

SELECTARENA: A MODERN BENCHMARK FOR FEATURE SELECTION ON REAL-WORLD TABULAR DATA

Bastian Schäfer^{1,*} **Dominika Matus**^{2,*} **Lennart Purucker**^{3,2} **Ricardo Knauer**⁴
Erik Rodner⁴ **Frank Hutter**^{3,5,2} **Anton Sokolov**¹ **Arnaud Liefoghe**¹
¹Université du Littoral-Côte-d’Opale ²University of Freiburg ³Prior Labs
⁴HTW Berlin ⁵ELLIS Institute Tübingen *Equal contribution.
 bastian.schafer@univ-littoral.fr, matusd@cs.uni-freiburg.de

ABSTRACT

Selecting a subset of features (columns) from a tabular dataset is a ubiquitous challenge in real-world applications. Industry experts seek to minimize model training costs, climate scientists require an interpretable subset of factors to understand extreme weather events, and clinicians need to choose among diagnostic tests due to financial and time constraints. When looking at the scientific literature to determine which feature selection method to use, practitioners across domains face an unrepresentative landscape of benchmarking. Despite extensive research, existing feature selection benchmarks provide limited guidance because they rely on outdated models, ad hoc evaluation protocols, or artificially generated data that do not reflect real-world problems. To close the gap between scientific benchmarking and real-world applications, we introduce SelectArena, a modern benchmark for feature selection. We compare 15 widely used feature selection methods on 71 manually curated real-world tabular datasets, covering classification and regression problems, using standardized evaluation protocols and state-of-the-art tabular (foundation) models. Our results reveal clear trade-offs across predictive performance, runtime, stability, and validity. Tree-based methods, CART and RFImportance, along with F-Test are Pareto-optimal when taking into account predictive performance and runtime. F-Test, information-theory-, and distance-based methods lead on stability and validity, with F-Test emerging as a balanced choice across our metrics. Search-based methods are slow, unstable and achieve low performance. SelectArena turns these findings into practical guidance and, as an extensible platform, supports future feature selection research.

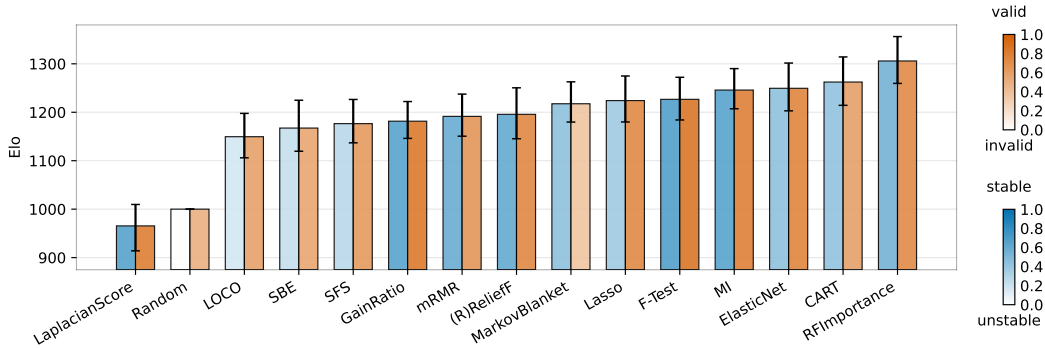


Figure 1: **SelectArena at a glance.** We present Elo ratings of the 15 feature selection methods ordered left to right from worst- to best-performing method. Elo rating summarizes how often a method beats another on the same dataset, budget, and downstream model, with random selection anchored at 1000 (Appendix D.2). Error bars are 95% confidence intervals from 1000 cluster bootstrap resamples over the 71 datasets. The left bar of each pair is shaded by *stability* (how much the selected subset changes across resamples) and the right bar by *validity* (how well injected noise features are rejected), where darker is better for both.

1 INTRODUCTION

Tabular data dominates many medical, industrial, and scientific applications (Borisov et al., 2022; Erickson et al., 2025). However, collecting such data is often costly and requires labor-intensive measurements, expensive instruments, or access to specialized facilities (Hédou et al., 2024; Wang et al., 2025). At the same time, the growing dimensionality of datasets decreases interpretability, increases model training and inference costs, and forces practitioners to trade off performance against computation time.

Feature selection addresses these challenges by identifying a subset of the most informative features, thereby reducing data collection and training costs while improving transparency and interpretability. Early work (Guyon & Elisseeff, 2003) has framed the objectives of feature selection around predictive performance, computational cost, and interpretability. Later work has added stability (Nogueira & Brown, 2016) and validity (Guyon et al., 2007a) as standard criteria for reliable feature selection. Within this problem formulation, hundreds of methods have been developed (Li et al., 2018), each making different trade-offs across these metrics. The benchmarking literature, however, remains highly fragmented and despite its long history (Jain & Zongker, 1997; Kohavi & John, 1997; Reunanen, 2003), does not provide sufficient guidance to practitioners.

Existing benchmarks have not kept pace with the development of modern tabular models, in particular foundation models, and rely on unrealistic evaluation protocols. Most use small-scale comparisons on synthetic or limited real-world datasets with ≤ 10 methods and ≤ 20 real-world datasets (Bommert et al., 2020; Cherepanova et al., 2023; Bakhmach et al., 2026) (Section 2, Table 1). To address these gaps, we introduce SelectArena, a benchmark of 15 feature selection methods evaluated on 71 manually curated real-world tabular datasets across predictive performance, runtime, stability, and validity, using state-of-the-art tabular (foundation) models. Our contributions can be summarized as follows:

- We analyze 368 datasets from the feature selection and machine learning literature and manually curate a set of 71 real-world tabular datasets following a strict data curation protocol. We release the resulting datasets.
- We review 296 feature selection methods and select a set of 15 methods according to a strict method curation protocol. Where well-maintained codebases are unavailable, we provide our own implementations.
- We provide a standardized evaluation pipeline covering predictive performance, stability, and validity, alongside runtime, and evaluate all methods with five downstream models including state-of-the-art tabular foundation model. We share our code to make our pipeline open-source.

Our results reveal clear trade-offs across predictive performance, runtime, stability, and validity. Tree-based (RFImportance, CART) and regularization-based methods (ElasticNet, Lasso) achieve the highest predictive performance, while F-Test and GainRatio are the fastest and, alongside MI and LaplacianScore, lead on stability and validity. With all four criteria taken into account, F-Test emerges as the most balanced choice across them. Search-based methods are the counterexample: they are slow and rank near the bottom on performance and stability. However, no method wins on every criterion, so the right choice still depends on which objective a practitioner prioritizes. SelectArena turns these findings into practical guidance and, as an extensible open-source platform, supports future feature selection research.

2 RELATED WORK

Recent years have seen numerous feature selection benchmarks. Despite extensive research, practitioners still lack clear guidance on selecting the most suitable method for a given context. Existing benchmarks are typically limited in scope by examining only a small number of methods, most often no more than 10 (Bouchlaghem et al., 2022; Kohavi & John, 1997), or by focusing exclusively on specific subgroups (Bommert et al., 2020; Hopf & Reifenrath, 2021). Moreover, many studies rely on unrepresentative or limited data sources, such as synthetic data (Bolón-Canedo et al., 2013; Hopf & Reifenrath, 2021), domain-specific data (Bakhmach et al., 2026; Li et al., 2022; Umar et al., 2025),

or non-tabular data (text or image) (Guyon et al., 2007a; Kou et al., 2020; Miao & Niu, 2016). In most cases, the number of real-world tabular datasets does not exceed 20.

Furthermore, most benchmarks focus only on predictive performance (Chandrashekar & Sahin, 2014; Reunanen, 2003; Sheikhpour et al., 2017). Few studies consider the stability of the selected subsets (Bommert et al., 2020; Brown et al., 2012; Kou et al., 2020; Saeys et al., 2008), even fewer the validity (Bolón-Canedo et al., 2013; Cherepanova et al., 2023; Guyon et al., 2007a) or both (Bakmach et al., 2026; Hopf & Reifenrath, 2021). In addition, even recent works predominantly rely on classical downstream models, with little consideration of state-of-the-art approaches like tuned gradient-boosted trees or pretrained tabular foundation models (Bakmach et al., 2026; Cherepanova et al., 2023; Umar et al., 2025).

In contrast, SelectArena comprehensively benchmarks a diverse set of feature selection methods across a large and broad dataset collection, evaluates the predictive performance as well as the stability and validity, and incorporates state-of-the-art models. Table 1 provides a systematic comparison of existing feature selection benchmarks and SelectArena with respect to included methods, datasets, models, and evaluation metrics.

Table 1: **Comparison of feature selection benchmarks.** We present former benchmarks in comparison to SelectArena. **# Methods:** how many out of the total number of benchmark methods correspond to our first three curation criteria (not a variant of a method and applicable across tabular classification and regression tasks). **# Datasets:** how many out of the total number of benchmark datasets satisfy our curation criteria for high-quality tabular data (Section 3.2). **Domain:** visualizes the dataset domain: 🎲 (synthetic), 🌳 (environmental), ❤️ (biomedical), 🔧 (technological), ⚗️ (scientific), 💰 (financial) or ❌ (not applicable). **SotA models:** whether the benchmark includes state-of-the-art downstream models, such as tuned gradient-boosted trees or pretrained tabular foundation models (Erickson et al., 2025), with the options ✅ (yes) or ❌ (no). The final three columns (**Perf**, **Stab**, **Val**) indicate whether the benchmark reports an evaluation of the predictive performance, stability, or validity.

Benchmark	# Methods	# Datasets	Domain	SotA models	Perf	Stab	Val
Kohavi & John (1997)	3/4	5/14	🎲❤️💰	❌	✅	❌	❌
Jain & Zongker (1997)	8/15	0/1	🔧	❌	✅	❌	❌
Reunanen (2003)	2/2	2/7	🌳🔧	❌	✅	❌	❌
Guyon et al. (2007a)	1/3	0/5	❌	❌	✅	❌	✅
Saeys et al. (2008)	4/4	6/6	❤️	❌	✅	✅	❌
Brown et al. (2012)	7/9	4/15	🌳🔧	❌	✅	✅	❌
Bolón-Canedo et al. (2013)	7/11	0/11	🎲	❌	✅	❌	✅
Chandrashekar & Sahin (2014)	3/4	2/6	❤️🔧	❌	✅	❌	❌
Miao & Niu (2016)	8/8	1/12	❌	❌	✅	❌	❌
Sheikhpour et al. (2017)	3/9	0/3	❤️	❌	✅	❌	❌
Li et al. (2018)	18/45	7/25	❤️	❌	❌	❌	❌
Kou et al. (2020)	1/10	0/10	❌	❌	✅	✅	❌
Bommert et al. (2020)	12/22	1/16	🌳❤️🔧💰	❌	✅	✅	❌
Hopf & Reifenrath (2021)	12/58	0/13	🎲	❌	✅	✅	✅
Bouchlaghem et al. (2022)	5/5	0/7	🔧	❌	✅	❌	❌
Li et al. (2022)	7/8	0/15	❤️	❌	✅	❌	❌
Cherepanova et al. (2023)	8/9	1/12	🔧⚗️💰	❌	✅	❌	✅
Schütz et al. (2025)	8/10	1/11	🎲❤️🔧💰	❌	✅	❌	❌
Umar et al. (2025)	1/1	0/3	🔧	❌	✅	❌	❌
Bakmach et al. (2026)	14/22	0/1	❤️	❌	✅	✅	✅
SelectArena (Ours)	15/15	71/71	🌳❤️🔧⚗️💰	✅	✅	✅	✅

3 SELECTARENA

3.1 PROBLEM SETUP

In practical applications, feature acquisition is often constrained by limited resources such as time, financial cost, or computational overhead. As a result, only a subset of all available features can be collected or processed, making it essential to select the most informative features under a given budget b . This setting can be formalized as follows: Let $\mathcal{F} = \{1, \dots, p\}$ denote the full feature set and let $S \subseteq \mathcal{F}$ be a selected subset with associated cost $c(S) = \sum_{i \in S} c_i$. We define a model-dependent subset utility function $u_M : 2^{\mathcal{F}} \rightarrow \mathbb{R}$, which evaluates the utility of a feature subset S under a given model M . The budget-constrained feature selection problem can then be formulated as: $\max_{S \subseteq \mathcal{F}} u_M(S)$ subject to $c(S) \leq b$. In certain cases, this problem can be solved to optimality, for example via exhaustive enumeration when the feature (sub)set size is small or via best subset selection in some models (Tillmann et al., 2024). In practice, however, exact computation is often infeasible (Amaldi & Kann, 1998), and approximate (heuristic) solution methods are therefore more commonly employed. As a special case, when feature costs are uniform ($c_i = 1$) and the budget is fixed to the cardinality ($b = k$), the constraint reduces to $|S| \leq k$, recovering the classical cardinality-constrained feature selection problem (Knauer & Rodner, 2023). While the budget-constrained formulation is more general, it may introduce a degree of arbitrariness in practice, as small changes in the budget can significantly alter S without necessarily reflecting meaningful differences in resource availability. By contrast, cardinality constraints provide a simpler, more natural abstraction in many settings and are therefore mostly adopted in practice and used in SelectArena.

3.2 BENCHMARKING SETUP

Method Curation Protocol. We reviewed 33 prominent survey, benchmark, and related papers, covering seminal works and specialized contributions across the feature selection landscape, from foundational theory to domain-specific applications and recent benchmarking with full list of works in Table B.1. From this pool, we identified 296 unique feature selection methods (Table B.2) and selected a representative set of methods based on the following criteria: (1) suitability for tabular data, (2) suitability for all tasks (binary classification, multi-class classification and regression), (3) methodological independence (not merely a variant of another method), (4) number of citations in the relevant literature, and (5) subgroup coverage. The 15 feature selection methods that have been included in SelectArena reflect a mix of widely adopted and methodologically diverse approaches, with Table 2 and Figure 3 summarizing their key characteristics. For methods requiring model coupling, we use LGBM. More details on the curation criteria, curation insights, as well as an overview of all investigated methods, their source, the number of citations in the relevant literature, and the final decision on inclusion is available in Appendix B.

Our method implementation builds on AutoGluon (Erickson et al., 2020) and TabArena (Erickson et al., 2025). We introduce a feature selection routine into TabArena that is integrated in the model-agnostic preprocessing pipeline of AutoGluon. The routine enforces a cardinality constraint k (Section 3.1), a time limit and a fallback to random selection in case of timeout (Appendix D.2) and custom preprocessing per method (Appendix B.4). To support time-bounded execution, the remaining runtime is periodically checked and intermediate results are returned when the limit is reached.

Dataset Curation Protocol. Real-world tabular datasets are the foundation of SelectArena, so we build on the curation standards of TabArena (Erickson et al., 2025) and extend its dataset collection towards feature selection. In order to do so, we surveyed the feature selection survey and benchmark literature, the papers of our selected methods, and the related explainable AI literature, covering 73 articles in total (Appendix C.1), from which we identified 368 candidate datasets. We then applied the following curation criteria: (1) unique predictive task definition, (2) tabular data (e.g., no text or image data), (3) minimum of 10 features for meaningful selection, (4) real-world origin (no synthetic data), (5) IID data suitable for random splitting, (6) genuine predictive task, (7) no ethical concerns with the predictive task, and (8) accessible source data. Implementing these criteria results in 71 high-quality real-world datasets in a curation process presented in Figure 2. The datasets span many domains (Table 1), cover diverse prediction tasks and differ in size as well as feature dimensionality (Figure 3). More details on the curation criteria, curation insights, and on overview of the selected datasets with their key properties can be found in Appendix C.

Table 2: **Benchmarked feature selection methods.** We report all included methods in SelectArena. **Determinism:** whether a method yields the same subset for the same data across repeated evaluations (also referred to as consistency in Dembinsky et al. (2026)). The options are ✔ (yes), ✘ (no), or ? (model-dependent). **Model coupling:** whether feature selection can be performed in conjunction with the downstream model M (related to portability in Dembinsky et al. (2026)). **Subgroup:** we specify which subgroup a method belongs to (Appendix A). **Citations:** reflects a method’s popularity and impact within the relevant feature selection literature, measured as the frequency of occurrence across relevant survey and benchmark works (Section 3.2). For implementation details, please refer to Appendix B.4.

Name	Determinism	Model coupling	Subgroup	Citations	Implementation
CART (Breiman et al., 1984)	✔	✘	Tree	4	scikit-learn
ElasticNet (Zou & Hastie, 2005)	✘	✘	Regularization	3	scikit-learn
F-test (Stähle et al., 1989)	✔	✘	Correlation	6	scikit-learn
GainRatio (Quinlan, 1986)	✔	✘	Info theory	3	Us
LaplacianScore (He et al., 2005)	✘	✘	Distance	5	Us
Lasso (Tibshirani, 1996)	✘	✘	Regularization	8	scikit-learn
LOCO (Duch, 2006)	?	✔	Leave-one-out	3	Us
MarkovBlanket (Koller & Sahami, 1996)	✘	✘	Backward search	3	Us
mRMR (Peng et al., 2005)	✔	✘	Info theory	12	Us
Mutual Information (Battiti, 1994)	✔	✘	Info theory	6	scikit-learn
Random (Baseline)	✘	✘	/	/	Us
(R)ReliefF (Kononenko et al., 1997)	✔	✘	Distance	10	Us
RFImportance (Breiman, 2001)	✘	✘	Tree	8	scikit-learn
SBE (Guyon et al., 2002)	?	✔	Backward search	8	Us
SFS (Cover & Van Campenhout, 1977)	?	✔	Forward search	10	Us

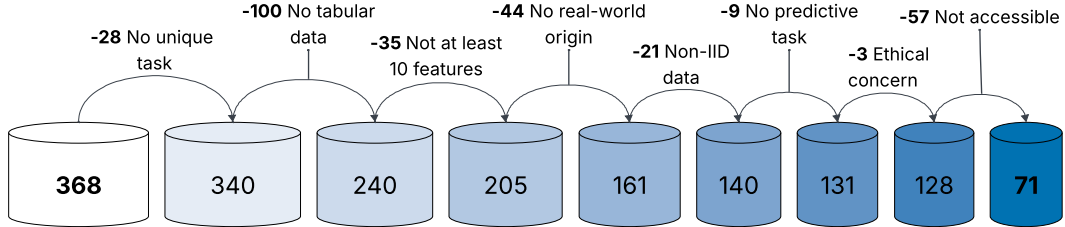


Figure 2: **Dataset curation process.** The reason and number of datasets excluded in each step of our dataset curation pipeline are shown, along with the remaining number of datasets after each step.

Downstream Models. To evaluate the selected subset of features on the subsequent prediction tasks, we use five downstream models: linear model (Linear), random forest (RF) (Breiman, 2001), LightGBM (LGBM) (Ke et al., 2017), RealMLP (Holzmüller et al., 2025) and TabICLv2 (Qu et al., 2026) spanning diverse inductive biases. We use AutoGluon’s default configuration in our experiments. For LGBM, we conduct an ablation study on the impact of hyperparameter tuning (Appendix D.2).

Hardware usage. CPU experiments (stability, validity and performance with the Linear, RF and LGBM model) ran on an AMD EPYC 9655 with 96 cores and GPU experiments (performance with RealMLP and TabICLv2) primarily on an NVIDIA L40 with 48 GB VRAM and in rare cases on NVIDIA H200 141 GB VRAM. Our performance experiments span 15 methods, 71 datasets, five budgets, five downstream models, and three seeds, yielding 79,875 runs, totaling approximately 292 GPU days and 685 CPU days. Validity with 3 noise levels and stability results with 25 bootstrapped repetitions and respectively 15 methods, 71 datasets and 5 repetitions took additional 2243 CPU days.

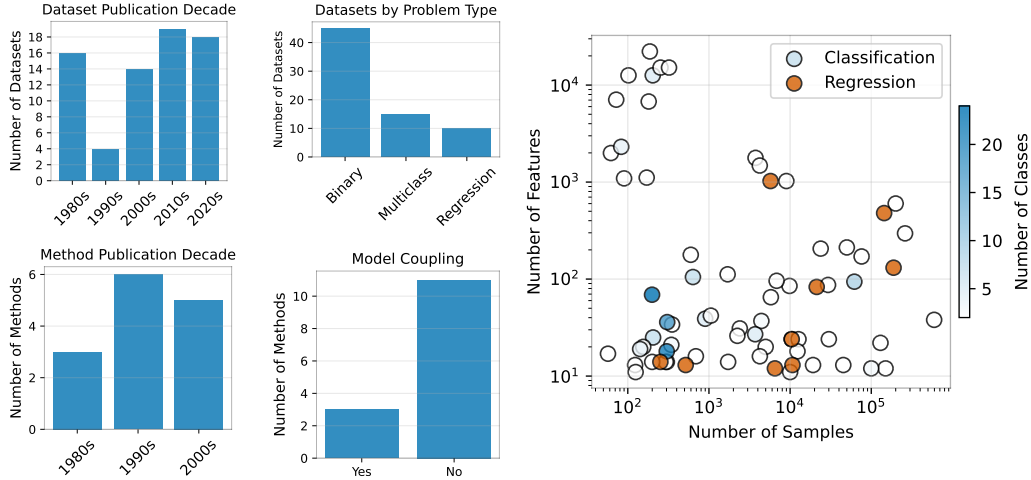


Figure 3: **Method and dataset characteristics.** SelectArena represents a diverse collection of widely adopted feature selection methods as well as high-quality real-world datasets.

3.3 EVALUATION

We assess the quality of a feature selection method in four dimensions: predictive performance, stability, validity, and runtime. For cardinality-constrained feature selection, we need to consider two hyperparameters that are independent of the specific method: the cardinality constraint k and the time constraint. To obtain a diverse performance estimate across different application scenarios, we vary k as a function of the number of features p . For datasets with ≤ 100 features, we vary $k = \lceil p \times j/6 \rceil$, where p is the number of features and $j \in \{1, \dots, 5\}$ is an index variable. For bigger datasets, we use an exponential regime: $k = \lceil p^{j/6} \rceil$. For more details, see Appendix C.5. If methods do not respect the cardinality constraint, we use random fallback (see Appendix D.2). With respect to the time constraint, we use a limit of one hour per feature selection experiment consisting of a (dataset, budget, model)-tuple for all feature selection methods. The downstream model training and inference time is set to one hour per experiment as well.

Predictive Performance. The predictive performance of a feature selection method is the performance of the downstream model using the selected feature subset on a given task. It is measured by ROC AUC for binary classification problems, log-loss for multi-class classification, and RMSE for regression. We discuss the choice of evaluation metrics in Appendix D.2. To compare across these metrics, we report Elo ratings (Appendix D.2) and improvement over RANDOM, $I(m, d) = 100 \cdot (\text{Err}(r, d) - \text{Err}(m, d)) / \text{Err}(r, d)$, where $\text{Err}(m, d)$ is the metric error of method m on dataset d and r denotes random selection (Appendix D.2). We repeat all experiments for three seeds.

Stability. For interpretability, feature selection methods should not only achieve strong predictive performance, but also yield similar subsets for similar data, for instance via resampling of the original data. We refer to this desideratum as *stability*, which is sometimes also described as robustness, reliability, or continuity (Dembinsky et al., 2026). We assess the stability with the Nogueira metric (Nogueira & Brown, 2016) across 25 bootstrap samples. The Nogueira estimator corrects for chance, asymptotically assigns random selections a score of 0, and reaches a maximum of 1. Values below 0.40 indicate poor stability, values between 0.40 and 0.75 reflect intermediate to good stability, and values above 0.75 denote excellent stability (Nogueira & Brown, 2016).

Validity. In addition to being stable, feature selection methods should also recover relevant rather than irrelevant features, an interpretability desideratum that we refer to as *validity*. In the literature, this property is also described as truthfulness, faithfulness, or fidelity (Dembinsky et al., 2026). However, assessing validity is challenging in the absence of a synthetic ground truth (Bakmach et al., 2026; Bolón-Canedo et al., 2013; Hopf & Reifenrath, 2021). We follow prior work (Cherepanova et al., 2023; Guyon et al., 2003; 2004; 2007a) and evaluate validity by augmenting the original feature set with uninformative Gaussian noise variables at 50%, 75%, and 100% of the original feature count.

We then operationalize validity by quantifying the proportion of selected features from the original feature set, which we term selection precision. This measure ranges from 0 to 1. In our setting, the selection precision is equivalent to the selection recall, *i.e.*, the proportion of original, informative features selected, when the recall is normalized by its maximum possible value for k .

Runtime. Lastly, feature selection methods should produce well-performing, stable, and valid subsets of features as fast as possible. Therefore, we measure the wall-clock time a method needs to produce a feature subset for a given budget k with the upper bound of one hour. Where the implementation allows it, exceeding the limit interrupts the method and triggers a random fallback that restores the subset to size k , either by adding randomly chosen unselected features or, for backward methods, by randomly subsampling the current set. To make runtimes comparable across datasets of different dimensionality, we normalize by the number of features and report seconds per 1,000 features.

4 RESULTS

We evaluated 15 widely used feature selection methods on 71 manually curated real-world tabular datasets with five cardinality constraints per dataset and five downstream predictors across three seeds in our performance experiments. The results are shown in Figures 1 and 4 and discussed further in the next paragraphs. For stability and validity runs, we use the same 15 methods and 71 datasets respectively and 5 repetitions. Each stability run consists of 25 bootstrapped repetition, each validity run includes 3 noise levels. The results are shown in Figures 5 and 6, respectively, and discussed in the last paragraphs.

Strong Methods Can Be Fast. The left plot in Figure 4 shows improvement over Random (%) versus selection time (seconds per 1k features), with predictive performance and runtime on the axes; exact scores are in Table D.2. The Pareto front consists of RFImportance and CART, the tree-based methods, together with the correlation-based F-Test. All three rank in the top four on predictive performance alone (MI ranks second) and in the six fastest on runtime alone (with LaplacianScore, GainRatio, and MarkovBlanket), so practitioners who value both face little trade-off. The search-based methods (LOCO, SBE, and SFS) sit at the opposite corner, performing poorly while being the slowest, although this, at least in part, can be attributed to the imposed time limit.

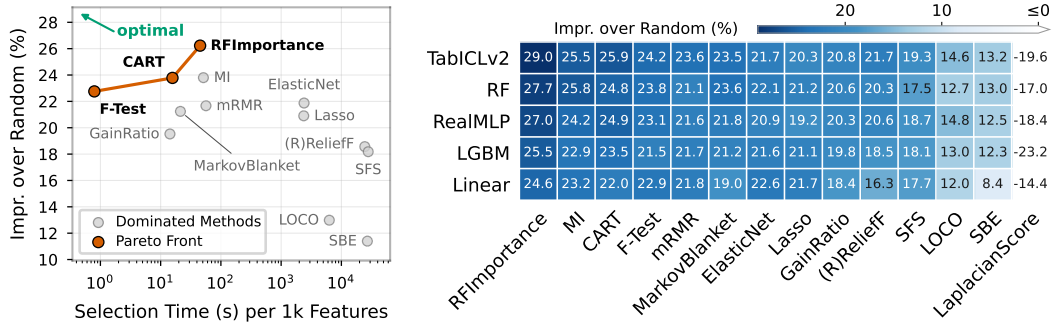


Figure 4: **Predictive performance.** Both panels report improvement over RANDOM (%), averaged over three seeds, five cardinalities, and 71 datasets. **(Left):** Improvement averaged over downstream models against feature selection time (s) per 1,000 features with Pareto front marked in orange. We exclude LaplacianScore as it performs worse than Random. **(Right):** Improvement for every model–method interaction.

Good Feature Selection Helps Every Model. The heatmap in Figure 4 presents improvement over Random (%) for each combination of feature selection method and downstream model averaged over seeds, budgets, and datasets. We observe that model ordering is rather consistent across methods, with TabICLv2 ranking first for eight of the 14 methods and Linear last for seven. The improvement spread across models within a method (at most 5.4pp) is far smaller than the spread across methods within a model (15.8pp under TabICLv2). This asymmetry suggests that even the most expressive model, like TabICLv2, cannot recover predictive signal from a poorly selected subset and so the choice of feature selection method is crucial. We find no evidence that aligning the inductive biases

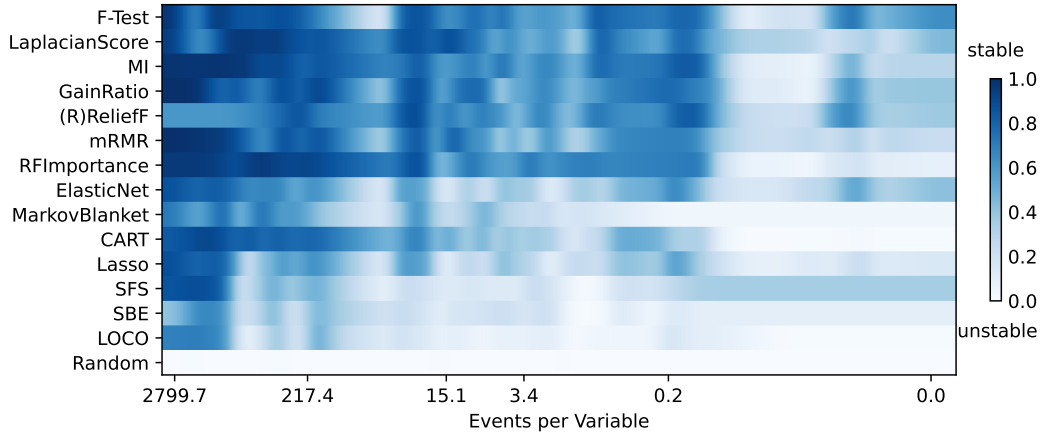


Figure 5: **Stability.** Nogueira score (Nogueira & Brown, 2016) across datasets. We use the events per variable, *i.e.*, the number of samples per feature for regression problems or the number of samples in the minority class per feature for classification problems, as a proxy for the selection difficulty (Harrell, 2015; Heinze et al., 2018).

of selector and predictor helps. Although Lasso and ElasticNet peak with the Linear model (but also only by 0.5pp), the tree-based RFImportance and CART achieve best performance with TabICLv2 rather than with RF or LGBM.

Strong Methods are not Necessarily Stable. The stability of the feature selection methods is shown in Figure 5. Most methods are stable when the number of samples (in the minority class) per feature is sufficiently large, but become increasingly unstable in low-data regimes (Harrell, 2015; Heinze et al., 2018). F-Test and distance-based methods exhibit the highest stability contributing to a better interpretability of the selected features, followed by information-theoretic methods. F-Test and MI are the only high-performing methods that rank high in stability. Due to its high fallback rates, search-methods are only slightly more stable than a random selection. An extended stability analysis can be found in Appendix D.3.

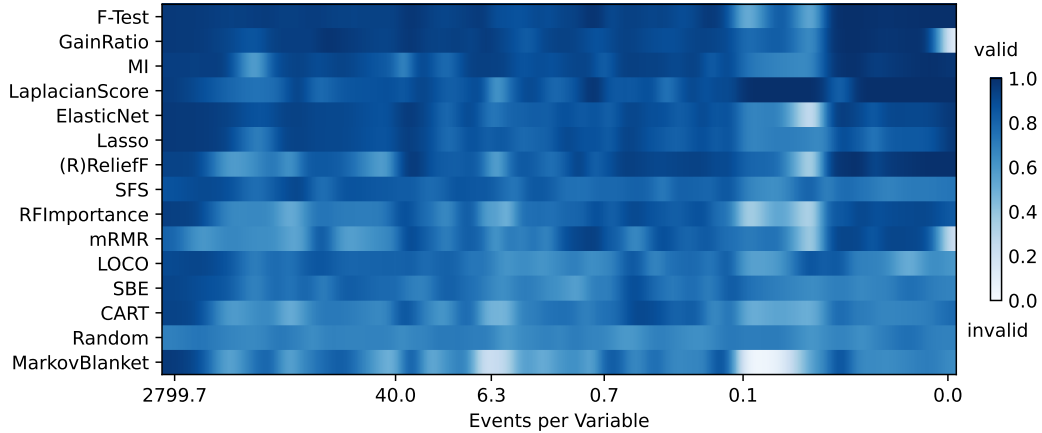


Figure 6: **Validity.** Selection precision across datasets at a noise level of 50%. Other noise levels can be found in Appendix D. Like for the stability, we use the events per variable, *i.e.*, the number of samples per feature for regression problems or the number of samples in the minority class per feature for classification problems, as a proxy for the selection difficulty (Harrell, 2015; Heinze et al., 2018).

Strong Methods do not Necessarily Select Informative Features. Figure 6 shows the validity of the feature selection methods. In contrast to the stability, the validity is less sensitive to the number

of samples (in the minority class) per feature. F-Test and information-theoretic methods achieve the highest validity aiding interpretability of the selection, followed by distance-based methods. F-Test and MI are the only high-performing methods that rank high in validity. MarkovBlanket exhibits lower validity than even a random selection, potentially because it favors removing redundant features that are prevalent in real-world data (Guyon & Elisseeff, 2003; Koller & Sahami, 1996). An extended validity analysis at different noise levels can be found in Appendix D.4.

F-Test Is Strong on All Four Axes. Taken together, no single method dominates on all four evaluation axes, but among the strong candidates F-Test comes closest to being a well-balanced choice. It lies on the Pareto front of predictive performance and runtime, and ranks highest on both stability and validity (Figure 1). RFImportance and CART achieve higher Elo ratings but are less stable, and the model-coupled search methods are competitive on none of the four dimensions under our one-hour budget.

5 CONCLUSIONS

Feature selection is essential across domains where practitioners must balance predictive performance, computational constraints, and interpretability. However, existing benchmarks offer limited guidance to select methods that best suit different real-world requirements. To address this gap, we introduce SelectArena, a large-scale benchmark for feature selection on 71 manually curated real-world tabular datasets, spanning classification and regression tasks. We evaluate 15 widely used feature selection methods using standardized protocols and five downstream models, including a tabular foundation model. SelectArena is not only the largest general feature selection benchmark to date, but also the only one to include leading tabular models.

Limitations. While SelectArena substantially advances the state of feature selection benchmarking, several limitations remain. (1) All feature selection methods are evaluated under a one-hour time limit, which results in slower methods not always completing their task (up to 47% of runs for SBE). Since we handle timeouts with a random fallback that keeps the feature budget fixed, the results for the affected methods reflect their performance under the limit on our hardware and are subject to change if given more compute. Appendix D.2 provides an ablation without the random fallback. (2) Several methods are implemented by us in cases where no sufficiently maintained alternative was available, rather than taken from an established library (Table 2). Although we follow the original algorithms, our implementations may be less optimized than library equivalents, which can disadvantage them under a wall-clock limit. (3) Our analysis of stability and validity relies on bootstrapping and Gaussian noise, respectively. Both are arguably simpler than what methods face in practice, since bootstrapping resamples preserve the original feature correlations and Gaussian noise variables are independent of both the target and the informative features. Other forms of perturbation may affect feature selection behavior differently, *e.g.*, non-Gaussian noise, outliers, missing values, distribution shifts, or class imbalances. (4) All methods are constrained to return exactly k features, however, some of them natively determine the subset size intrinsically, such as Lasso and ElasticNet via the regularization path or MarkovBlanket via conditional independence tests. Imposing a fixed cardinality makes them comparable but does not evaluate them as originally intended, and may understate their performance. (5) The observed performance of feature selection methods strongly depends on the evaluation metrics used. Using the ROC AUC for binary classification, log-loss for multiclass classification, and RMSE for regression (Appendix D.2), we employ widely adopted standard metrics, but alternative criteria such as calibration or fairness may lead to different results.

Recommendations. Our results lead to several practical recommendations: (1) When predictive performance is the primary objective, practitioners might want to choose a tree-based method such as RFImportance or CART. These methods are also strong candidates when runtime is considered. (2) For interpretability-focused applications, F-Test emerges as the best choice. It ranks highest in terms of stability and validity, next to information-theory and distance-based methods, with a competitive predictive performance and runtime. (3) The choice of a suitable downstream model for a feature selection method can be important. A state-of-the-art model like TabICLv2 is mostly, but not always, a better predictor than RF, LGBM or even a linear model. Therefore, practitioners should evaluate whether simpler downstream models may be preferable to more complex and computationally expensive alternatives.

REPRODUCIBILITY STATEMENT

SelectArena is an open-source framework. We publish the code and our curated datasets. More information can be found in Appendix D.1. In the Benchmarking Setup (Chapter 3.2), we detail the hardware setup used for the experiments. With fully providing soft- and hardware details as well as the datasets used, SelectArena is fully reproducible.

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AUTHOR CONTRIBUTIONS

B. Schäfer co-led the code development, led the method curation, co-led the dataset curation, contributed the method implementation, co-led the experiments, co-led the evaluation and the visualization and co-led the writing of the paper. D. Matus co-led the code development, contributed to the method curation, co-led the dataset curation, led the method implementation, co-led the experiments, co-led the evaluation and the visualization and co-led the writing of the paper. L. Purucker co-led the code development, supervised the method curation, supervised the dataset curation, supervised the experiments and supervised the writing of the paper. R. Knauer supervised the project and contributed to writing and reviewing the paper. E. Rodner supervised R. Knauer and helped with reviewing and editing the paper. F. Hutter supervised L. Purucker and D. Matus. A. Sokolov supervised B. Schäfer. A. Liefoghe supervised B. Schäfer and helped with reviewing and editing the paper.

COMPETING INTERESTS

L. Purucker and F. Hutter are a subset of the authors of TabArena. The authors declare no other competing interests.

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Appendices

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A FEATURE SELECTION TAXONOMY FOR PRACTITIONERS

Feature selection methods are traditionally categorized as filters, wrappers, or embedded methods, depending on whether feature relevance is assessed independently of the downstream model M , through repeated model evaluation, or during model training (Guyon & Elisseeff, 2003). This taxonomy can be useful from an implementation perspective, for example when deciding whether cardinality-constrained linear models should be realized via exhaustive enumeration (wrapper), mixed-integer programming (embedded method), or post-hoc training on a reduced subset (filter). However, it is less informative for practitioners, who are less concerned with *where* feature selection occurs in a pipeline (a structural perspective) and more with *how* the method approaches this combinatorial optimization problem (a functional perspective).

We therefore adopt a complementary categorization into search and non-search methods (Kohavi & John, 1997). We define search methods as procedures that evaluate multiple subsets using a model-dependent subset utility $u_M(S)$. Due to the exponential size of the search space, search methods differ primarily in how they explore it efficiently, for example through sequential forward or backward search. In contrast, non-search methods avoid repeated subset evaluations under $u_M(S)$ and instead rely on proxy mechanisms, such as univariate relevance or recursive partitioning. While non-search methods may still involve search procedures, they optimize a different objective than the subset utility in Section 3.1. They include correlation-based, distance-based, information-theoretic, and tree-based approaches (Duch, 2006), as well as regularization-based methods (Tibshirani, 1996; Zou & Hastie, 2005). Figure A.1 provides an overview of the categorization for SelectArena. While not exhaustive, the subgrouping can be readily extended to cover additional search methods, such as evolutionary algorithms (Eiben & Smith, 2015; Wang et al., 2025; Xue et al., 2015) and reinforcement learning (Mazyavkina et al., 2021; Sutton & Barto, 2018; Wang et al., 2025), as well as non-search methods, such as game-theoretic (Covert et al., 2021; Fryer et al., 2021; Wallsberger et al., 2024) and knowledge-driven approaches (Jeong et al., 2025; Knauer et al., 2025; Li et al., 2025).

PERSPECTIVE	METHODS		
 STRUCTURAL  Where is the method implemented in the pipeline?	 Filters	 Wrappers	 Embedded methods
 FUNCTIONAL  How is the combinatorial feature selection problem tackled?	Search methods  Forward  Backward Non-search methods  Correlation  Distance  Information theory  Tree  Regularization		

Figure A.1: **Taxonomy of feature selection methods for SelectArena.** We complement the traditional structural perspective (Guyon & Elisseeff, 2003) with a functional categorization into search and non-search approaches (Kohavi & John, 1997). Search subgroups include forward and backward procedures, non-search subgroups are based on Duch (2006) and extended to include regularization-based methods (Tibshirani, 1996; Zou & Hastie, 2005).

B METHODS

B.1 REVIEWED SURVEYS AND BENCHMARKS

Table B.1 lists the 33 works, predominantly surveys and benchmarks, that we reviewed to assess method popularity. For each feature selection method, the **Citations** column in Table 2 (Section 3.2) reports the number of these works in which the method is mentioned. We use this count to exclude methods with less than three mentions, in accordance with method curation criterion (4) (Section 3.2).

B.2 METHOD CURATION CRITERIA

- (1) **Suitability for tabular data:** Since SelectArena focuses on tabular datasets, we exclude methods that are primarily designed for other data modalities. For example, Information Gain for Text (Lee & Lee, 2006) is specific to textual data and therefore not included.
- (2) **Suitability for all tasks (binary classification, multi-class classification and regression):**

Table B.1: **Reviewed survey and benchmark works.** The 33 works used to determine the popularity of each feature selection method, ordered by year of publication.

Jain & Zongker (1997)	Bolón-Canedo et al. (2013)	Li et al. (2018)
Kohavi & John (1997)	Wang et al. (2013)	Bommert et al. (2020)
Guyon & Elisseeff (2003)	Chandrashekar & Sahin (2014)	Kou et al. (2020)
Reunanen (2003)	Khalid et al. (2014)	Covert et al. (2021)
Duch (2006)	Tang et al. (2014)	Hopf & Reifenrath (2021)
Guyon et al. (2007a)	Jović et al. (2015)	Bouchlaghem et al. (2022)
Saeyns et al. (2007)	Xue et al. (2015)	Li et al. (2022)
Zhao & Liu (2007)	Miao & Niu (2016)	Siegismund et al. (2022)
Saeyns et al. (2008)	Li et al. (2017)	Cherepanova et al. (2023)
Meinshausen & Bühlmann (2010)	Sheikhpour et al. (2017)	Schütz et al. (2025)
Brown et al. (2012)	Heinze et al. (2018)	Bakhmach et al. (2026)

SelectArena includes datasets for binary classification, multi-class classification, and regression. Consequently, selected methods must support all target types. Methods restricted to a subset of tasks are therefore excluded. For instance, χ^2 (Liu & Setiono, 1995) is only applicable to classification problems and is thus not considered.

(3) Methodological independence (not merely a variant of another method): The benchmark aims to include conceptually distinct feature selection methods rather than multiple variants of the same underlying approach. Therefore, methods such as Relief (Kira & Rendell, 1992) and ReliefF (Kononenko et al., 1997) are treated as methodologically similar, since ReliefF constitutes an extension of Relief.

(4) Number of citations in the relevant literature: To ensure that the selected methods of the first cohort are established and widely recognized, we require each method to be cited at least three times across prominent surveys and benchmarking studies (Section 3.2).

(5) Subgroup coverage: To promote methodological diversity, we employ a functional categorization of feature selection methods (Appendix A). The final method set in SelectArena is curated to ensure representation across methodological subgroups.

B.3 METHOD CURATION INSIGHTS

Below, we share general insights we obtained during method curation:

- Feature selection methods are frequently applied beyond the problem settings for which they were originally designed. For example, methods such as χ^2 or Gini Impurity are inherently intended for categorical targets, yet they are often applied to regression tasks, *e.g.*, by discretizing the target variable. Such adaptations may substantially influence method behavior and evaluation outcomes. To avoid introducing methodological distortions, we exclude these methods from SelectArena and aim to raise awareness of this issue within the field.
- A similar pattern can be observed with respect to data modalities. Many methods are used across heterogeneous data types, including tabular, textual, and image data, despite relying on assumptions tailored to a specific modality. Applying methods outside their intended data setting may lead to misleading conclusions and should therefore be considered carefully in empirical evaluations.
- The feature selection literature is currently fragmented into several largely independent research streams, including classical statistical approaches, evolutionary approaches, and explainable AI (XAI) approaches. Despite using similar underlying techniques, these communities often evolve separately and make limited use of each other’s methodological advances. We believe that stronger integration across these research directions could accelerate progress within the field.

B.4 METHOD IMPLEMENTATION

As specified in Section 3.2, feature selection is implemented based on AutoGluon (Erickson et al., 2020) and TabArena (Erickson et al., 2025). We introduce a class called `AbstractFeatureSelector`, which is a specialization of `AbstractFeatureGenerator` and part of the preprocessing pipeline in AutoGluon. Before feature selection, AutoGluon’s default preprocessing infers feature types and removes constant, ID-like, and duplicate features. Categorical features keep the pandas `category` dtype but are ordinally encoded, with categories seen fewer than two times in training treated as missing. There are two different types of `AbstractFeatureSelectors`: (1) the feature scoring type and (2) the subset selection type. Each feature selection method inherits the properties of the `AbstractFeatureSelector`, which are mainly the cardinality and time constraints, as well as a fallback in case the feature selection method does not return valid results. The fallback is implemented as a random feature selection using the intermediate results of the failed or canceled method, either sampling a score for the non-scored feature or completing the subset selection in case the intermediate subset is smaller than the cardinality constraint. The implementation is in most cases based on scikit-learn (Pedregosa et al., 2011) or scikit-feature (Li et al., 2018) (see Table 2 for details). The applied changes are usually the incorporation of a regular check for the time limit and a solution for returning the intermediate results when the time limit is met, as well as the introduction of pandas DataFrames instead of numpy arrays for clean data usage in the TabArena pipeline.

In the following, we provide implementation details for all selected methods, including the assumptions of the algorithms, the preprocessing, the type, a description of the approach, the criterion, and some additional information on the implementation:

B.4.1 CLASSIFICATION AND REGRESSION TREES (CART) (BREIMAN ET AL., 1984)

Assumptions: Numerical features (sklearn).

Preprocessing: Imputation.

Type: Scoring.

Approach: Greedy over tree structures (best split).

Criterion: Mean decrease in impurity (MDI) per feature: total impurity reduction attributed to splits using that feature, where impurity is Gini for classification and variance for regression.

Implementation: sklearn’s `DecisionTreeRegressor` and `DecisionTreeClassifier`.

B.4.2 ELASTICNET (ZOU & HASTIE, 2005)

Assumptions: Numerical features (sklearn).

Preprocessing: Imputation, scaling.

Type: Scoring.

Approach: Multivariate, embedded.

Criterion: Magnitude of the coefficient $|\hat{\beta}_j|$ from a joint linear (or logistic) fit with combined L1 and L2 regularization.

Implementation: We use sklearn’s `ElasticNetCV` for regression and `LogisticRegressionCV` with elastic-net penalty for classification. We use the default L1-ratio grid but exclude the value 1.0 so the model never becomes pure Lasso.

B.4.3 F-TEST (STÅHLE ET AL., 1989)

Assumptions: Numerical features (sklearn).

Preprocessing: Imputation.

Type: Scoring.

Approach: Univariate.

Criterion: F-statistic — sklearn’s `f_classif` for classification (ratio of between- to within-class variance) and `f_regression` for regression (derived from squared Pearson correlation; equivalent in ranking to $|r|$).

Implementation: We select the top- k features based on the returned F-statistics.

B.4.4 INFORMATION GAIN RATIO (GAINRATIO) (QUINLAN, 1986)

Assumptions: Discrete features (this implementation).

Preprocessing: Imputation, discretization.

Type: Scoring.

Approach: Univariate.

Criterion: Information gain ratio $IGR = \frac{IG(Y,X)}{SI(X)} = \frac{MI(Y,X)}{H(X)}$, where X is a feature. The denominator penalizes high-cardinality features, which would otherwise dominate plain MI rankings.

Implementation: We reuse sklearn's `mutual_info_classif` for the numerator $IG(Y, X)$ and our own entropy estimator for the denominator $H(X)$.

B.4.5 LAPLACIAN SCORE (HE ET AL., 2005)

Assumptions: Numerical features.

Preprocessing: Imputation, scaling (for the graph construction).

Type: Scoring.

Approach: Unsupervised.

Criterion: Locality preservation (lower is better): a feature scores well if points that are close in the kNN graph have similar values for that feature.

Implementation: We build a symmetric kNN graph with a Gaussian heat-kernel on Euclidean distances and compute the score via the Rayleigh quotient against the graph Laplacian, following the original paper. The scikit-feature version is quite outdated, so we re-implemented it. The hyperparameters $k = 5$ and $t = \text{median}(d^2)$ are arbitrary choices.

B.4.6 LEAST ABSOLUTE SHRINKAGE AND SELECTION OPERATOR (LASSO) (TIBSHIRANI, 1996)

Assumptions: Numerical features (sklearn).

Preprocessing: Imputation, scaling.

Type: Scoring.

Approach: Multivariate, embedded.

Criterion: Magnitude of the coefficient $|\hat{\beta}_j|$ from a joint linear (or logistic) fit with L1 regularization.

Implementation: We use sklearn's `LassoCV` for regression and `LogisticRegressionCV` with L1 penalty for classification. The CV variants pick the regularization strength internally, so no α/C tuning is needed.

B.4.7 LEAVE-ONE-COVARIATE-OUT (LOCO) (LEI ET AL., 2017)

Assumptions: Proxy model assumptions.

Preprocessing: None.

Type: Scoring.

Approach: Leave-one-out.

Criterion: Per-feature performance drop from omission: $\text{LOCO}_j = \mathcal{L}(\hat{f}_{-j}) - \mathcal{L}(\hat{f}_{\text{full}})$, where $\hat{f}_{\text{full}}$ is the proxy trained on all features and $\hat{f}_{-j}$ is the proxy trained without feature j .

Implementation: We use LGBM as the proxy (handles NaNs natively, no preprocessing required) and refit it once per feature for each split. Costly on high-dimensional data.

B.4.8 MARKOV BLANKET (KOLLER & SAHAMI, 1996)

Assumptions: Numerical features.

Preprocessing: Imputation.

Type: Selection.

Approach: Greedy multivariate (backward).

Criterion: A feature X_i is redundant if there exists $M_i \subseteq F \setminus \{X_i\}$ (its Markov blanket) such

that $Y \perp X_i \mid M_i$. In practice we score each feature by the cross-entropy/MSE difference under 5-fold CV between models fit on M_i and $M_i \cup \{X_i\}$, and remove the feature whose absence hurts performance the least.

Implementation: The blanket M_i is taken to be the top- k Pearson-correlated features of X_i . Models are fit and evaluated under 5-fold CV using Ridge for regression and Logistic Regression for classification. The original formulation (Koller & Sahami, 1996) searches for a blanket that renders Y conditionally independent of all remaining features; we restrict to a fixed top- k neighborhood. We use $k = 5$ and deviate from the original formulation by adding the regression case.

B.4.9 MINIMUM REDUNDANCY MAXIMUM RELEVANCE (MRMR) (PENG ET AL., 2005)

Assumptions: Discrete features (this implementation).

Preprocessing: Imputation, discretization.

Type: Selection.

Approach: Greedy multivariate (forward).

Criterion: MID variant: at step t with selected set S_{t-1} , $\text{score}(X_i) = I(X_i; Y) - \frac{1}{|S_{t-1}|} \sum_{X_j \in S_{t-1}} I(X_i; X_j)$; the first feature is picked by max relevance $I(X_i; Y)$.

Implementation: At each step we add the candidate maximizing relevance minus average pairwise redundancy with the already selected features. This is a re-implementation following scikit-feature's MRMR.

B.4.10 MUTUAL INFORMATION (MI) (BATTITI, 1994)

Assumptions: Numerical features (sklearn).

Preprocessing: Imputation.

Type: Scoring.

Approach: Univariate.

Criterion: Mutual information $I(X, Y) = H(X) + H(Y) - H(X, Y)$.

Implementation: We use sklearn's `mutual_info_classif` for classification and `mutual_info_regression` for regression. Both use frequency counts for features marked as discrete and the Kraskov kNN estimator for continuous features.

B.4.11 RANDOM

Assumptions: None.

Preprocessing: None.

Type: Selection.

Approach: Random.

Criterion: None.

Implementation: Random selection of k features based on the random seed.

B.4.12 RANDOM FOREST IMPORTANCE (RFIMPORTANCE) (BREIMAN, 2001)

Assumptions: Numerical features (sklearn).

Preprocessing: Imputation.

Type: Scoring.

Approach: Multivariate, embedded.

Criterion: Mean decrease in impurity (MDI) per feature, averaged over all trees in the forest: Gini impurity reduction for classification, variance reduction for regression.

Implementation: We use sklearn's `RandomForestRegressor` and `RandomForestClassifier` with default hyperparameters.

B.4.13 SEQUENTIAL BACKWARD ELIMINATION (SBE) (GUYON ET AL., 2002)

Assumptions: Proxy model assumptions.
Preprocessing: None.
Type: Selection.
Approach: Greedy multivariate (backward).
Criterion: Holdout performance of the proxy model.
Implementation: We use LGBM as the proxy model. At each step, the feature yielding smallest drop in performance after being excluded from the current subset is eliminated.

B.4.14 (R)RELIEFF (KONONENKO ET AL., 1997; ROBNIK-ŠIKONJA & KONONENKO, 1997)

Assumptions: None.
Preprocessing: Imputation, min-max scaling.
Type: Scoring.
Approach: Multivariate.
Criterion: A feature is rewarded when it differs more on an instance’s k nearest *misses* (different class) than on its k nearest *hits* (same class), with misses weighted by the class prior. RReliefF replaces the class machinery with $P(\text{diff feature} \mid \text{diff prediction})$, computed via Bayes rule running sums over kNN pairs.
Implementation: Re-implemented to match the original algorithms, with a branched per-feature difference function: $|a - b|$ for numeric features (on $[0, 1]$ -scaled values) and $\mathbb{1}\{a \neq b\}$ for nominal features. Summed across features, this gives the Manhattan-style distance used to build the kNN graph itself. For ReliefF, kNN structures are cached per class for efficiency, with small-class guards that divide by the actual number of neighbors returned (rather than by k) when a class has fewer than $k + 1$ samples. Neighbor weighting is uniform (the paper also allows rank-based exponential weights). RReliefF is used for regression. We use $k = 5$ rather than the original $k = 1$.

B.4.15 SEQUENTIAL FORWARD SELECTION (SFS) (COVER & VAN CAMPENHOUT, 1977)

Assumptions: Proxy model assumptions.
Preprocessing: None.
Type: Selection.
Approach: Greedy multivariate (forward).
Criterion: Holdout performance of the proxy model.
Implementation: We use LGBM as the proxy model. At each step, the feature with the highest importance under the LGBM proxy refit on the current subset including this feature is added.

B.5 OVERVIEW OF ALL INVESTIGATED FEATURE SELECTION METHODS

Table B.2 provides a complete overview of all investigated methods, including the source links for a clear distinction and the final decision for inclusion or exclusion.

Table B.2: **Overview of all investigated feature selection methods.** We list all methods with their source links, provide the year, and the number of appearances across the relevant literature (Section 3.2). In the **Decision** column, we use **Yes** if the method is included in SelectArena or list the reason for exclusion (**Citations** if there are fewer than three citations, **Variation** if the method is a variation of another method, **Wrong Domain** if the method is not suitable for tabular data, and **Not task-agnostic** if the method is not suitable for all tasks). We additionally mark some methods with **Yes, future work** to indicate that their implementations are ongoing. In all cases, these implementations are missing differential entropy logic.

Feature Selection Method Name	Year	# appearances	Decision
AACO	2024	1	Citations
ACO 1	2004	1	Citations
ACO 2	2010	1	Citations
ACO 3	2012	1	Citations
ACO 4	2014	1	Citations
AISCBR	2011	1	Citations

Table B.2: Overview of all investigated feature selection methods (continued).

Feature Selection Method Name	Year	# appearances	Decision
AMIFS	2004	1	Citations, Variation
ANOVA F-Test	1989	6	Yes
AUMFS	2013	1	Wrong Domain, Citations
Accuracy	2006	3	Yes
Adaptive Lasso	2012	2	Citations, Variation
Alpha-Investing	2005	2	Citations
Attention Map Importance	2021	1	Citations, Variation
BAB*	1993	1	Citations
BRIDGE regularization	2008	1	Citations
BSS/WSS	2002	1	Citations
BW-Ratio	2009	1	Citations
Balanced Error Rate	2006	1	Citations
Ball Correlation (Bcor-SIS)	2018	1	Citations
Bayesian	2001	1	Citations
Bivariate	2002	1	Citations
Bolasso	2008	1	Citations, Variation
Boruta	2010	1	Citations, Variation
C4.5	1993	1	Citations
CAE-S	2019	1	Citations
CART	1984	4	Yes
CAWOA-NRS	2026	0	Citations
CEFS+	2025	0	Citations
CFS (Hall)	1999	8	Not task-agnostic
CMIFS	2011	1	Citations, Variation
CMIM	2004	5	Not task-agnostic
CPFS	2010	1	Citations
CXPlain	2019	1	Citations
Categorical Concordance Index (CI-SIS)	2023	1	Citations
Category-Adaptive Variable Screening (CAS)	2019	1	Citations
Combined Ant Colony and Differential Evolution	2008	1	Citations
FS Algorithm			
Concordance Index (CSIS)	2024	1	Citations
Conditional Distance Correlation (CDCSIS)	2015	1	Citations
Conditional Infomax Feature Extraction	2005	1	Citations
Conditional Perm. Test	2008	1	Citations
Conditional SIS	2012	1	Citations
Consistency	2000	3	Not task-agnostic
Constraint score	2008	1	Citations
Correlation Coefficient	2014	1	Citations
DE 2	2014	1	Citations
DIME-DG	2023	1	Citations
DISR	2006	5	Not task-agnostic
DeepFS	2015	1	Citations
Distance Correlation (DC-SIS)	2012	1	Citations
Distinguishing Feature Selector	2012	1	Citations
EDDI-GG	2019	1	Citations
EHOFS	2025	0	Citations
EUFS	2015	1	Citations, Variation
Elastic net	2005	3	Yes
Equal Information Gain	1966	1	Citations, Variation
Evolution Strategy FS	2009	1	Citations
Exclusive Lasso	2010	1	Citations, Variation
Expected Cross Entropy	2009	1	Citations
Extremal Perturbations (EP)	2019	1	Citations
FCBF	2003	5	Variation
FIDO-CA	2018	1	Citations
FIGFS	2025	0	Citations
FOCUS	1994	1	Citations
FS-P	2006	1	Citations
FSDS	2015	1	Wrong Domain, Citations
FSRDE	2026	0	Citations

Table B.2: Overview of all investigated feature selection methods (continued).

Feature Selection Method Name	Year	# appearances	Decision
Feature Similarity (Mahalanobis)	1936	1	Citations
Feature Weighting k means	2003	1	Citations
Feature selection for sparse clustering	2010	1	Citations
Fisher criterion	2012	2	Citations, Variation
Fisher score	1936	6	Not task-agnostic
GA 1	1989	1	Citations
GA 2	2010	1	Citations
GA 3	2014	1	Citations
GDCOV	2008	1	Wrong Domain, Citations
GDFS-DG	2023	1	Citations
GFLasso	2009	1	Citations, Variation
GP 1	2006	1	Citations
GP 2	2010	1	Citations
GP 3	2012	1	Citations
GSBE	1997	1	Citations
GSFS	1997	1	Citations
Gain Ratio	1986	3	Yes
Gain Ratio Cost	2003	1	Citations, Variation
Gamma	2001	1	Citations
Generalized SIS	2009	1	Citations
Genetic Algorithm (Siedlecki)	1989	2	Citations
Genetic Algorithm (Yang)	2002	2	Citations
Gini	1912	6	Not task-agnostic
Grafting	2003	2	Citations, Variation
Graph FS (GOSCAR)	2012	2	Citations, Variation
GreedyFS	2011	1	Citations
Group Lasso	2020	3	Variation
HSIC Lasso	2018	1	Citations, Variation
Heuristic Search (GA)	1981	1	Citations
Hilbert-Schmidt Independence Criterion (HSIC)	2022	1	Citations
IAIRS	2014	0	Citations
ICS-RCFS	2026	0	Citations
ID3	1986	1	Citations
IF	2003	1	Citations
IME (2009)	2009	1	Citations
IME (2010)	2010	1	Citations
INTERACT	2009	2	Not task-agnostic
INVASE	2018	1	Citations
ISFS	2026	0	Citations
Impurity	2006	3	Not task-agnostic
Impurity Euclid	2021	1	Citations, Variation
Impurity Hellinger	2021	1	Citations, Variation
Inconsistency criterion	1996	1	Citations
Information Gain	1986	7	Not task-agnostic
Information Gain Text	2006	1	Wrong Domain
Informative Fragment	2003	1	Citations
Interaction Capping	2011	2	Citations
Interaction Gain FS	2008	1	Citations
JAFa-MFRL	2018	1	Citations
JIM	2021	1	Citations, Variation
JMI	1999	5	Not task-agnostic
JMIM	2015	2	Citations
Jaccard Index	2008	1	Citations
KernelSHAP	2022	1	Citations, Variation
Koller-Sahami metric (KS)	1996	1	Citations
Kolmogorov Filter (Kfilter)	2014	1	Citations
Kruskal-Wallis	2015	2	Citations, Variation
L2X	2018	1	Citations
LFS (lazy feature selection)	2009	1	Citations
LIME (Images)	2019	1	Wrong Domain, Citations
LIME (Tabular)	2021	1	Citations

Table B.2: Overview of all investigated feature selection methods (continued).

Feature Selection Method Name	Year	# appearances	Decision
LLM-Select	2025	0	Citations
LS (Flip Swap) first improve	/	0	Citations
LS (Flip) best improve	/	0	Citations
LSSSMV-FS	2026	0	Citations
LUFS	2012	1	Wrong Domain, Citations
Laplacian score	2005	5	Yes
Lasso (L1)	1996	8	Yes
Lasso Net	2019	1	Citations, Variation
LinkedFS	2012	1	Wrong Domain, Citations
Localized Feature Selection Based on Scatter Separability (LFSBSS)	2008	1	Citations
Logistic Regression Coefficients	2002	1	Citations
LossSHAP	2020	1	Citations, Variation
MA-C	2010	1	Citations
MAFESE	2024	1	Citations
MBEGA	2007	1	Citations
MCFS	2010	3	Variation
MDL	1994	2	Citations, Variation
MDL Lamp	2003	1	Citations, Variation
MI (Battiti)	1994	6	Yes
MI (Guyon)	2003	2	Variation
MIFS-U	2002	1	Citations, Variation
MM	2017	1	Citations
MOPSO	2025	0	Citations
MRMR	2005	12	Yes
MVFS	2013	1	Wrong Domain, Citations
Markov blanket	1996	3	Yes
Martingale Difference Correlation (MDC-SIS)	2013	1	Citations
Maximum Correlation (MC-SIS)	2016	1	Citations
Maximum Mean Discrepancy MMD	2022	1	Citations
Md (measure of monotone dependence)	2010	1	Citations
Mean-Variance (MVSIS)	2015	1	Citations
Meaningful Perturbations (MP)	2017	1	Citations
MinRed	2006	1	Citations
Minimal image representation (MIR)	2014	1	Wrong Domain, Citations
Modified Perceptron by Truncation for OFS	2014	1	Citations
MsFDSs	2025	0	Citations
Multi-response rank canonical correlation (mRCC)	2021	1	Citations
Multi-viewFS	2025	0	Citations
Multinomial Logistic Regression	2006	1	Citations
Myopic ReliefF	1994	1	Citations, Variation
NB	1966	1	Citations
NDFS	2012	2	Citations
NJMIM	2015	2	Citations, Variation
NP (node pruning)	1994	1	Citations
NetFS	2016	1	Wrong Domain, Citations
Nonparametric Independence Screening (NIS)	2011	1	Citations
ODIN-MBRL	2019	1	Citations
ODIN-MFRL	2019	1	Citations
OFS	2014	1	Wrong Domain, Citations
OSCAR	2008	1	Citations, Variation
OSFS	2010	2	Wrong Domain, Citations
ObDI-FS	2026	0	Citations
Occlusion	2014	1	Citations
Odds Ratio	2001	1	Citations
Original (no FS)	nan	0	Not task-agnostic
Orthogonal Matching Pursuit	1993	1	Citations
PAM	2002	1	Citations
PCA	2014	1	Citations
PSO 1	2010	1	Citations
PSO 2	2013	1	Citations

Table B.2: Overview of all investigated feature selection methods (continued).

Feature Selection Method Name	Year	# appearances	Decision
PSO 3	2002	1	Citations
PT-S	2001	1	Citations
Pairwise SIS (PSIS)	2015	1	Citations
Pearson Correlation Coefficient	2008	4	Not task-agnostic
Permutation Test	2001	1	Citations
PredDiff	2017	1	Citations
Projection Correlation (PC-Screen)	2019	1	Citations
QII	2016	1	Citations
Quantile Correlation (QCSIS)	2016	1	Citations
REAL-X	2021	1	Citations
RF importance	2001	8	Yes
RISE	2018	1	Citations
ROC	2001	1	Citations
Random FS	2026	1	Not task-agnostic
Random FS (fixed size)	2026	2	Not task-agnostic
Random permutations	2001	1	Citations
Randomised Lasso	2008	1	Citations, Variation
Rank products	2004	1	Citations
Regression	2001	1	Citations
Relief	1992	9	Variation
Relief Kukar	1999	2	Citations, Variation
Relief-A	1994	0	Citations, Variation
Relief-B	1994	0	Citations, Variation
Relief-C	1994	0	Citations, Variation
Relief-D	1994	0	Citations, Variation
ReliefF	1997	10	Yes
ReliefF averaged costs	2003	1	Citations, Variation
ReliefF avg probability	2003	1	Citations, Variation
ReliefF cost-sensitive sampling	2003	1	Citations, Variation
ReliefF distance	2003	1	Citations, Variation
ReliefF equal K	2003	1	Citations, Variation
ReliefF expected costs	2003	1	Citations, Variation
ReliefF expected probability	2003	1	Citations, Variation
ReliefF expected rank	2003	1	Citations, Variation
ReliefF squared distance	2003	1	Citations, Variation
Repeated Elastic Net Technique (RENT)	2021	1	Citations, Variation
Ridge (L2)	2022	1	Citations
Robust Rank Correlation (RRCS)	2012	1	Citations
SAGE (Shapley Additive Global importanceE)	2020	1	Citations, Variation
SBE (sequential backward elimination)	2025	8	Yes
SFBE	1994	2	Variation, Citations
SFFS	1994	3	Variation
SFS (sequential forward selection)	2025	10	Yes
SHAP	2017	1	Citations, Variation
SHAPIQ	2024	0	Yes
SIT-BY	2022	1	Citations
SOA	2009	1	Citations
SOD-LSC	2014	1	Citations
SPFS-SFS	2013	1	Citations
SPVIM	2020	1	Citations
SVM-RFE	2002	6	Variation
Shapicant	2020	1	Citations, Variation
Shapley Values	1953	1	Citations
Sparse Group Lasso	2014	1	Citations, Variation
Sparse-based filter method	2015	1	Wrong Domain, Citations
Spearman Correlation Coefficient	2008	2	Citations
Spectral FS (SPEC)	2007	3	Variation
Stability Selection	2008	1	Citations
Stabl Lasso	2024	1	Citations, Variation
Sure Independence Screening (SIS)	2008	1	Citations
Sure Independent Ranking and Screening (SIRS)	2010	1	Citations

Table B.2: Overview of all investigated feature selection methods (continued).

Feature Selection Method Name	Year	# appearances	Decision
Symmetrical Uncertainty	1988	5	Not task-agnostic
TNOM	2000	1	Citations
Trace Ratio	2008	1	Citations, Variation
Tree structured group Lasso	2010	1	Citations, Variation
Tree Lasso	2023	1	Citations, Variation
Tree-guided group Lasso	2010	1	Citations, Variation
TreeSHAP	2020	1	Citations, Variation
Ts-reps	2025	0	Citations
UDFS	2011	2	Citations, Variation
USC	2003	1	Citations
USFS	2015	1	Wrong Domain, Citations
Uniform Accuracy	2021	1	Citations, Variation
Uniform Gini	2021	1	Citations, Variation
Uniform Information Gain	2021	1	Citations, Variation
Univariate Predictors	2003	1	Citations
Weighted Leverage Score (WLS)	2021	1	Citations
Weighted Log Likelihood Ratio	2000	1	Citations
Wilcoxon rank sum	2001	1	Citations
WrapperSubsetEval	2005	1	Citations
XCSCF ²	2014	1	Citations
auc	2020	2	Citations, Variation
bee colony approach FS	2015	1	Citations
bumble bees mating optimization FS	2014	1	Citations
chi squared	1995	6	Not task-agnostic
dist angle	2021	1	Citations
dist euclid	2021	2	Citations
dist hellinger	2021	1	Citations
distance	2014	1	Citations
entropy	2014	1	Citations
equal gini	2021	1	Citations, Variation
equal hellinger	2021	1	Citations
f_regression	2025	2	Citations
limma	2004	1	Citations, Variation
low variance	2018	1	Citations, Variation
mRMR-MOBSTA	2026	0	Citations
max of minority	2013	1	Citations
oneR	1993	3	Not task-agnostic
sam	2001	1	Citations, Variation
signal-to-noise (SNR)	2007	1	Citations
sum minority	2013	1	Citations
t-test	2011	5	Not task-agnostic
term frequency-inverse document frequency	2020	1	Citations
true positives (TP)	2007	1	Citations
univariate model score	2016	1	Citations
variance	2020	2	Citations
xgb importance	2016	1	Citations, Variation

C DATASETS

C.1 DATASET SOURCES

Table C.1 lists the 73 articles, comprising feature selection surveys and benchmarks, the papers introducing our selected methods, and related work from explainable AI, that we reviewed to assemble the pool of 368 candidate datasets.

Table C.1: **Reviewed dataset sources.** The 73 articles screened for real-world tabular datasets, in alphabetical order.

Agarwal et al. (2022)	Kira & Rendell (1992)	Robnik-Šikonja & Kononenko (2003)
Bakmach et al. (2026)	Kohavi & John (1997)	Ruiz-Ramírez et al. (2023)
Battiti (1994)	Koller & Sahami (1996)	Saeys et al. (2008)
Belaid et al. (2023)	Kononenko et al. (1997)	Schütz et al. (2025)
Bennasar et al. (2015)	Kou et al. (2020)	Sithakoul et al. (2024)
Bolón-Canedo et al. (2013)	Lee & Lee (2006)	Smyth (2004)
Bommert et al. (2020)	Li et al. (2012)	Stiglic et al. (2012)
Bouchlaghem et al. (2022)	Li et al. (2017)	Umar et al. (2025)
Breiman (2001)	Li et al. (2018)	Vidal-Naquet & Ullman (2003)
Brown et al. (2012)	Li et al. (2022)	VonKaenel et al. (2026)
Cai et al. (2010)	Lin & Tang (2006)	Wang et al. (2013)
Chandrashekar & Sahin (2014)	Liu & Setiono (1995)	Wang et al. (2015)
Chen (2016)	Liu et al. (1996)	Wang et al. (2017)
Cherepanova et al. (2023)	Liu et al. (2021)	Yang et al. (2011)
Covert et al. (2020)	Liu & Motani (2025)	Yang et al. (2012)
Dash & Liu (2003)	Lundberg & Lee (2017)	Yu & Liu (2003)
Erickson et al. (2025)	Ma & Huang (2008)	Yu & Liu (2004)
Gao et al. (2017)	Ma et al. (2024)	Zhang et al. (2008)
Gorishniy et al. (2021)	Meyer & Bontempi (2006)	Zhao & Liu (2007)
Grinsztajn et al. (2022)	Miao & Niu (2016)	Zhou et al. (2005)
Guyon & Elisseeff (2003)	Peng et al. (2005)	
Guyon et al. (2007a)	Perkins et al. (2003)	
Hall (1999)	Reunanen (2003)	
He et al. (2005)	Heinze et al. (2018)	
Holte (1993)	Hooker et al. (2019)	
Hopf & Reifenrath (2021)	Jain & Zongker (1997)	
Khafaga et al. (2023)		

C.2 DATASET CURATION CRITERIA

(1) Unique predictive task definition: A task with a given name should only exist once in SelectArena. Tasks with the same or similar name and/or different shapes require careful investigation to recover the original dataset version and avoid duplicates or inconsistent variants.

(2) Tabular data (e.g., no text or image data): We restrict SelectArena to genuinely tabular datasets and therefore exclude datasets derived from text, image, or other modalities. Without domain-specific expertise, such datasets cannot reliably be treated as tabular data and would compromise the comparability and validity of benchmark results.

(3) Minimum 10 features for meaningful selection: Cardinality-constrained feature selection (see Section 3.1) requires a sufficient number of features to define meaningful cardinality constraints, which is why datasets with fewer than 10 features are excluded.

(4) Real-world origin (no synthetic data): The goal of SelectArena is to provide guidance for practitioners. Despite advances in synthetic data generation, synthetic datasets are not representing real-world distributions and may distort the interpretation of benchmark results.

(5) IID data suitable for random splitting: All datasets in SelectArena are evaluated using random splits. Datasets containing temporal dependencies, grouped observations, or other structures requiring specialized splitting strategies are excluded to avoid information leakage and invalid performance estimates.

(6) Genuine predictive task: Each dataset must contain a valid predictive target. We exclude datasets where targets are artificially constructed, randomly assigned, or otherwise not intended for predictive modeling, as can occur in certain scientific data repositories.

(7) No ethical concerns with the predictive task: Datasets and their associated tasks are carefully reviewed for ethical concerns before inclusion. The well-known case of the Boston Housing dataset illustrates the importance of critically examining datasets and predictive tasks prior to making them broadly accessible to the community.

(8) Accessible source data: Datasets referenced in the literature must be available and usable. During the curation process, we experienced several cases where datasets were not publicly available (*e.g.*, Bakhmach et al. (2026)) or the source links outdated (*e.g.*, Guyon & Elisseeff (2003)). We therefore exclude datasets that could not be accessed, verified, and reliably reused.

C.3 DATASET CURATION INSIGHTS

- Feature selection and machine learning methods are routinely applied across a wide range of datasets, regardless of their original modality. In our opinion, tabular data derived from, *e.g.*, texts or images cannot be safely treated as standard tabular data without domain-specific expertise.
- Feature selection is typically of limited practical relevance for datasets with fewer than 10 features, as only few candidate features are available for selection. In addition, defining meaningful budgets for cardinality-constrained feature selection (see Section 3.1) requires a sufficiently large feature space.
- The IID assumption receives limited attention in the literature, even if an inappropriate splitting strategy can cause information leakage and misleading results (*e.g.*, in case of temporal dependencies or grouped observations).
- Sensitive features are frequently included in benchmarks without critical evaluation. Datasets from ethically sensitive domains appear more prevalent within the XAI-focused feature selection literature. In our view, both the predictive task and the presence of sensitive attributes should be carefully considered when deciding whether a dataset is appropriate for benchmarking.
- High-dimensional datasets are typically accompanied by limited sample sizes, *e.g.*, in biomedical applications where thousands of genes may be measured for only a small number of patients. These settings are especially prone to overfitting and overtuning.
- Determining whether a dataset represents real-world or synthetic data can be challenging, particularly for heavily preprocessed datasets where feature names are anonymized and the original source is no longer identifiable (*e.g.*, AutoML challenge data).
- In some cases, we observed an arbitrary choice of target variables. This issue commonly arises in scientific discovery datasets that were not originally designed for predictive modeling, where targets are later selected from existing features, or artificially constructed, resulting in diverging variants of the same dataset.

C.4 OVERVIEW OF SELECTED DATASETS

Table C.2 provides details on the included datasets.

Table C.2: Overview of selected datasets. We list all datasets included in SelectArena, the number of features, samples and classes, as well as the task type and license for the usage of the datasets.

Dataset	# Features	# Samples	# Classes	Task type	License
allstate-claims-severity (Ferguson et al., 2016)	131	188318	/	Regression	Public
ancestry-study (Ruiz-Ramírez et al., 2023)	105	635	7	Multiclass	Public
anneal (Unknown, 1990)	39	898	5	Multiclass	CC-BY-4
aps-failure (IDA2016Challenge, 2016)	171	76000	2	Binary	CC-BY-4
audiology-diagnosis (Bareiss et al., 1990)	69	199	24	Multiclass	/
automobile (Schlimmer, 1985)	25	205	7	Ordinal	CC-BY-4
bad-customer-detection (Podsyp, 2020)	14	1723	2	Binary	CC0: Public Domain
bank-customer-churn (Topre, 2022)	11	10000	2	Binary	Public

Table C.2: Overview of selected datasets (continued).

Dataset	# Features	# Samples	# Classes	Task type	License
bank-marketing (Moro et al., 2014)	13	45211	2	Binary	CC-BY-4
bioresponse (Hamner et al., 2012)	1777	3751	2	Binary	Competition
body-density-prediction (Penrose et al., 1985)	14	252	/	Regression	Public
brasilian-houses (de Oliveira Farias & Fontes, 2020)	13	10692	/	Regression	Public domain
churn (Marcoulides, 2005)	20	5000	2	Binary	MIT License
clock-protein-period (Gul et al., 2021)	1092	90	2	Binary	CC-BY-4
clock-protein-toxicity (Gul et al., 2021)	1112	171	2	Binary	CC-BY-4
coil-2000-insurance-policies (van der Putten & van Someren, 2000)	85	9822	2	Binary	/
colon-tumor (Alon et al., 1999)	1992	62	2	Binary	Public
credit-approval (Quinlan, 1987)	16	690	2	Binary	Public
credit-card-clients-default (Yeh & hui Lien, 2009)	24	30000	2	Binary	/
customer-satisfaction-in-airline (Yakhyojon, 2023)	22	129880	2	Binary	CC0: Public Domain
drug-induced-autoimmunity-prediction (Huang et al., 2025)	178	597	2	Binary	CC-BY-4
forest-fires (Cortez & Morais, 2007)	13	517	/	Regression	Public
framingham-heart-study (Bhardwaj, 2022)	16	4240	2	Binary	Unknown
give-me-some-credit (Fusion & Cukierski, 2011)	12	150000	2	Binary	Public
hazelnut-spread-contami/t-detection-10GHz (Urbinati et al., 2020)	31	2400	2	Binary	CC-BY-SA
heart-disease-cleveland (Detrano et al., 1989)	14	303	2	Binary	CC0: Public Domain
heart-disease-hungary (Detrano et al., 1989)	14	294	2	Binary	CC0: Public Domain
heart-disease-switzerland (Detrano et al., 1989)	13	123	2	Binary	CC0: Public Domain
heart-disease-va-long-beach (Detrano et al., 1989)	14	200	2	Binary	CC0: Public Domain
heloc (Oliabev, 2021)	24	10459	2	Binary	Public
hepatitis-survival-prediction (Efron & Gong, 1981)	20	155	2	Binary	CC-BY-4
hiva-agnostic (Guyon et al., 2007b)	1481	4229	2	Binary	Public
homesite-quote-conversion (Darrel et al., 2015)	296	260753	2	Binary	Competition
horse-colic-survival (McLeish & Cecile, 1989)	21	344	3	Multiclass	CC-BY-4
hr-analytics (Arashnic, 2021)	13	19158	2	Binary	CC0: Public Domain
in-vehicle-coupon-recommendation (Wang et al., 2017)	24	12684	2	Binary	CC-BY-4
ionosphere (Sigillito et al., 1989)	34	351	2	Binary	CC-BY-4
kdd-cup-09-appetency (Guyon et al., 2009)	212	50000	2	Binary	CC0: Public Domain
labor-negotiations (Matwin, 1988)	17	57	2	Binary	CC-BY-4

Table C.2: Overview of selected datasets (continued).

Dataset	# Features	# Samples	# Classes	Task type	License
leukemia-allaml (Golub et al., 1999)	7072	72	2	Binary	Public
ljublana-primary-tumor (Zwitter & Soklic, 1987)	18	302	22	Multiclass	CC-BY-4
lung-cancer (Bhattacharjee et al., 2001)	12601	203	5	Multiclass	Public
lymphography (Zwitter & Soklic, 1988)	19	142	4	Multiclass	CC-BY-4
marketing-campaign (Unknown, 1990)	26	2240	2	Binary	Public
mechanisms-of-action (inversion et al., 2020)	206	23814	2	Multiclass	Competition
miami-housing (Bourassa et al., 2021)	24	10459	/	Regression	CC-BY-NC-SA
mic (Golovenkin et al., 2020)	112	1700	2	Multiclass	CC-BY-4
naticusdroid-android-permissions-dataset (Mathur et al., 2021)	87	29332	2	Binary	CC-BY-4
nci-ovarian-cancer (Petricoin et al., 2002a)	15148	253	2	Binary	Public
nci-pancreatic-cancer (Hingorani et al., 2003)	6771	181	2	Binary	Unknown
nci-prostate-cancer (Petricoin et al., 2002b)	15154	322	2	Binary	Unknown
online-shoppers-purchasing-intention-dataset (Sakar et al., 2019)	18	12330	2	Binary	CC-BY-4
otto-group-product-classification-challenge (Bossan et al., 2015)	94	61878	9	Multiclass	Competition
polish-companies-bankruptcy (Zieba et al., 2016)	65	5790	2	Binary	CC-BY-4
porto-seguro (Howard et al., 2017)	38	595206	2	Binary	Public
predict-students-dropout-and-academic-success (Martins et al., 2021)	37	4424	3	Multiclass	CC-BY-4
prostate-cancer (Singh et al., 2002)	12601	102	2	Binary	Public
pva-revenue-prediction-kddcup98 (Parsa, 1998)	479	144095	/	Regression	Public
qsar-biodeg (Mansouri et al., 2013)	42	1055	2	Binary	CC-BY-4
qsar-oral-toxicity (Unknown, 2019)	1025	8992	2	Binary	CC-BY-4
qsar-tid-11 (Olier et al., 2018)	1025	5742	/	Regression	CC0: Public Domain
santander-customer-transaction-prediction (Piedra et al., 2019)	601	200000	2	Binary	Competition
sdss-17 (Abazajian et al., 2009)	12	100000	3	Multiclass	Public Domain
smoking-lung-cancer (Spira et al., 2007)	22216	187	2	Binary	Public
soybean-large (Michalski & Chilausky, 1980)	36	306	18	Multiclass	CC-BY-4
srbc-prediction (Khan et al., 2001)	2309	83	4	Multiclass	Public
superconductivity (Hamidieh, 2018)	83	21263	/	Regression	CC-BY-4
taiwanese-bankruptcy-prediction (Liang et al., 2016)	96	6819	2	Binary	CC-BY-4
thyroid-discordant (Quinlan, 1987)	27	3711	5	Multiclass	/

Table C.2: Overview of selected datasets (continued).

Dataset	# Features	# Samples	# Classes	Task type	License
wine-quality (Cortez et al., 2009)	12	6497	/	Regression	CC-BY-4

C.5 CARDINALITY CONSTRAINTS

As presented in section 3.3, we calculate the cardinality constraint k based on the feature dimensionality p following one of the two formulas, conditioned on p . If $p \leq 100$, we consider the dataset to have a low feature dimension and we spread the constraint k linearly across the feature set size. The datasets with up to 100 features come from very different domains, *e.g.* marketing, life sciences, business. Since practical tasks in these domains can range from highly sparse feature selection to settings where retaining dozens or nearly 100 features is feasible, we use a linear cardinality spacing to provide balanced coverage across this range of plausible practitioner requirements. We consider datasets with more than 100 features to have high feature dimension and we spread the constraint k in an exponential way. These datasets come primarily from biological and medical domains, where feature selection tasks often aim to identify substantially smaller subsets of relevant features rather than retain most of the original feature set. We therefore allocate more of the evaluated budgets toward smaller feature subsets, while still including larger budgets to cover less restrictive selection settings. Formally, we calculate cardinality constraint k for $j \in \{1, \dots, 5\}$ as following:

$$k = \lceil p \times j/6 \rceil \text{ if } p \leq 100,$$

$$k = \lceil p^{j/6} \rceil \text{ otherwise.}$$

We summarize the distribution of the features across the cardinality indices j in Table C.3.

Table C.3: Number of selected features k across the 71 benchmark datasets, per cardinality index j .

Cardinality idx j	Min k	Max k	Linear ($p \leq 100$) min-max k	Exp. ($p > 100$) min-max k	Mean k
1	2	16	2–16	3–6	4.7
2	4	31	4–31	5–29	11.1
3	5	150	5–47	11–150	27.4
4	7	791	7–62	23–791	87.3
5	9	4190	9–78	48–4190	344.5

D BENCHMARKING DETAILS AND EXTENDED RESULTS

In this section, we present the benchmarking details for predictive performance (D.2), stability (D.3), and validity (D.4). Finally, we provide the raw predictive performance results (D.5).

D.1 OPEN-SOURCE BENCHMARKING

The code of our method implementations and evaluation pipeline is publicly available on GitHub (under construction). Additionally, we publish the curated versions of our datasets.

D.2 PREDICTIVE PERFORMANCE

In the following paragraphs, we present the calculation and results for the Elo, provide details on the Pareto calculation, and show the results for improvement over random and runtime per 1k features. Additionally, we provide an ablation study on the impact of tuning and discuss the statistical significance of our findings.

Evaluation metrics. We evaluate the predictive performance of the downstream models using area under the receiver operating characteristic curve (ROC AUC) for binary classification, log-loss

for multi-class classification, and root mean squared error (RMSE) for regression, following other popular benchmarks (Erickson et al., 2025; Gijbbers et al., 2023).

We do not use other metrics, that might seem to be more suited for imbalanced datasets: ROC AUC is well-suited to comparing performance across heterogeneous, often imbalanced, datasets as it is invariant to class prevalence. We do not use the area under the precision-recall curve (PR AUC), a popular alternative for imbalanced data, as it favors improvements on subpopulations with higher prevalence (McDermott et al., 2025). ROC AUC is also threshold-free, *i.e.*, it does not require fixing a decision threshold τ for model predictions $\hat{y} = \mathbb{1}[\hat{p}(x) > \tau]$, where $\hat{p}(x)$ is the predicted probability of the positive class. This avoids the problem of defining costs for different error types (false positive or false negative), which depend on the task and application context.

Log-loss is a strictly proper scoring rule which allows evaluating how well the predicted distribution matches the true distribution as measured on the held-out set. Similar to ROC AUC, it does not commit to a fixed misclassification cost, which we cannot specify in advance for a benchmark spanning heterogeneous datasets and application contexts.

RMSE plays an analogous role to log-loss as it is minimized in expectation only by the true conditional mean which implies that a method cannot improve its score other than by predicting better. It additionally keeps per-dataset results directly interpretable by retaining the units of the target variable (contrary to, *e.g.*, the mean squared error).

Elo Rating. We use an Elo-like rating for comparing the included feature selection methods. The Elo rating system has originally been designed to rate chess players and therefore its nature is time-dependent, *i.e.* the order of the matches matters as each update uses a player’s current rating to compute the expected outcome. More formally, the rating of player A is calculated as:

$$r_A \leftarrow r_A + K(S_A - E_A), \quad E_A = \frac{1}{1 + 10^{(r_B - r_A)/400}}, \quad (1)$$

where $K = 32$ is a fixed scaling factor, $S_A \in \{0, 0.5, 1\}$ is the actual outcome and E_A is the expected outcome. This gives a convenient interpretation of rating differences: a gap of 150 points corresponds to a win probability of about 70% for the stronger player, and a gap of 400 points to ≈ 10 -to-1 odds (91%).

For our benchmark setup, this system is not appropriate because 1) methods, contrary to players, are static and do not improve over time; 2) at the time of evaluation, we have access to all "matches". Therefore, following Chatbot Arena (Chiang et al., 2024), we adopt a Bradley-Terry rating system, of which Elo is a special case. We keep the "Elo" name as we scale the ratings in such a way that they can be interpreted as the Elo ratings.

In the Bradley-Terry model, we calculate the outcome of a pairwise comparison of the methods between each unique combination of downstream model, and budget with scores per combination averaged over seeds. Formally, the probability of method i being better than method j is calculated as:

$$P(i > j) = \frac{p_i}{p_i + p_j} = \frac{e^{\beta_i}}{e^{\beta_i} + e^{\beta_j}} = \frac{1}{1 + e^{\beta_j - \beta_i}} \quad (2)$$

where $p_i = e^{\beta_i}$ is the score function proposed by the model’s authors and also the one we adopt in this benchmark. The score β_i is in natural-log-odds units. We rescale them to the conventional Elo scale by $r_i = (\beta_i - \beta_{\text{Random}}) \cdot \frac{400}{\ln 10} + 1000$, which anchors random feature selection at 1000 and preserves the standard Elo interpretation.

Within each dataset, we define a *setting* as a combination of budget and downstream model, with the metric averaged over seeds. In each setting, every pair of methods forms a match, where win is assigned to a method with better score and ties are counted as half-wins. We estimate β by maximum likelihood on all matches. To quantify uncertainty, we use a cluster bootstrap over datasets: since all settings of a dataset share dataset-specific signal, their outcomes are correlated, so we resample the 71 datasets with replacement and refit the model on the matches of the sampled datasets. Over 1000 resamples, we report the 2.5th and 97.5th percentiles of each method’s rating r_i as its 95% confidence interval. Results are shown in Table D.1.

Pareto Details. Comparing metric errors across datasets of different task types can either be handled by ranking methods per dataset, as we did in the Elo calculation, or by normalizing the

Table D.1: **Elo rating.** We report the score per method along with 95% confidence intervals from 1000 cluster bootstrap resamples at the dataset level. Higher is better.

Method	Elo rating	95% CI
RFImportance	1305.8	[1259.6, 1356.2]
CART	1262.4	[1214.3, 1314.2]
ElasticNet	1249.4	[1203.0, 1301.6]
MI	1245.8	[1207.2, 1290.1]
F-Test	1226.7	[1184.1, 1272.2]
Lasso	1224.1	[1180.0, 1274.8]
MarkovBlanket	1217.6	[1179.8, 1262.8]
(R)ReliefF	1195.7	[1145.4, 1250.5]
mRMR	1191.5	[1150.6, 1237.5]
GainRatio	1181.5	[1146.1, 1222.1]
SFS	1176.5	[1136.9, 1226.4]
SBE	1167.4	[1119.5, 1224.8]
LOCO	1149.5	[1106.0, 1197.7]
Random	1000.0	[1000.0, 1000.0]
LaplacianScore	965.4	[913.9, 1009.7]

errors by a baseline. We calculate and compare the improvement $I_{(m,d)}$ of a method m on a dataset d in % using the metric error of a method $Err_{(m,d)}$ and the metric error of random feature selection $Err_{(r,d)}$. The errors are averaged across budgets and models.

$$I_{(m,d)} = \frac{Err_{(r,d)} - Err_{(m,d)}}{Err_{(r,d)}} \cdot 100 \quad (3)$$

The runtime per 1k features t_{1k} is calculated by using the needed time of a feature selection method on a dataset, budget, and model, $t_{(d,b,m)}$, and the number of features of a dataset $n_{(d)}$:

$$t_{1k} = \frac{t_{(d,b,m)}}{n_{(d)}} \cdot 1000 \quad (4)$$

By normalizing the time and the features per dataset, the comparison across datasets is possible and we obtain the results as shown in Table D.2.

Table D.2: **Predictive performance vs. runtime.** We report the mean improvement over random and mean runtime per 1k features for all benchmarked feature selection methods.

Name	Improvement over random (%)	Time per 1k features (s)
RFImportance	26.23	45.19
MI	23.80	51.24
CART	23.78	15.71
F-Test	22.76	0.79
ElasticNet	21.88	2400.69
mRMR	21.67	56.50
MarkovBlanket	21.24	21.30
Lasso	20.90	2370.68
GainRatio	19.53	14.26
(R)ReliefF	18.57	24442.87
SFS	18.18	27903.08
LOCO	12.98	6304.68
SBE	11.40	27018.73
Random	0.00	0.006
LaplacianScore	-18.58	4.60

Significance analysis. We perform the significance analysis using autorank (Herbold, 2020). We consider correlations at the level of budgets, downstream models, and seeds. We prepare the

autorank input so that each row represents an independent measurement and columns correspond to populations we want to compare. We use rank as a task-agnostic metric to compare feature selection methods across regression and classification datasets. First, we aggregate the results over three seeds and then we rank the methods for each combination of dataset, budget, and downstream model, assigning average rank to ties. Then, for each dataset and method, we average the rank over budgets and downstream models. Cells in the resulting matrix represent average rank of a method on a given dataset.

To avoid relying on parametric assumptions, autorank applies the non-parametric Friedman test followed by the post-hoc Nemenyi test, that reported significant difference between methods' mean rank if it exceeded the critical distance of 2.546. The resulting critical difference diagram (CDD) is shown in Figure D.1a: There are four groups of non-distinguishable methods linked with the horizontal bar. We report significant difference between five pairs: RFImportance and SBE, RFImportance and LOCO, RFImportance and (R)Relief, CART and LOCO, ElasticNet and LOCO. Additionally, all 13 methods significantly beat the random baseline and LaplacianScore.

We additionally show CDDs for five cardinality indices in Figure D.1b-D.1f. For the lowest budget index (Figure D.1b), we observe one larger group of undistinguishable methods that is significantly better only than random baseline and LaplacianScore. As the budget grows, the number of groups increases and so does the rank spread. RFImportance consistently ranks in top-3 methods, CART ranks better in smaller budgets, while F-Test ranks better in bigger budgets

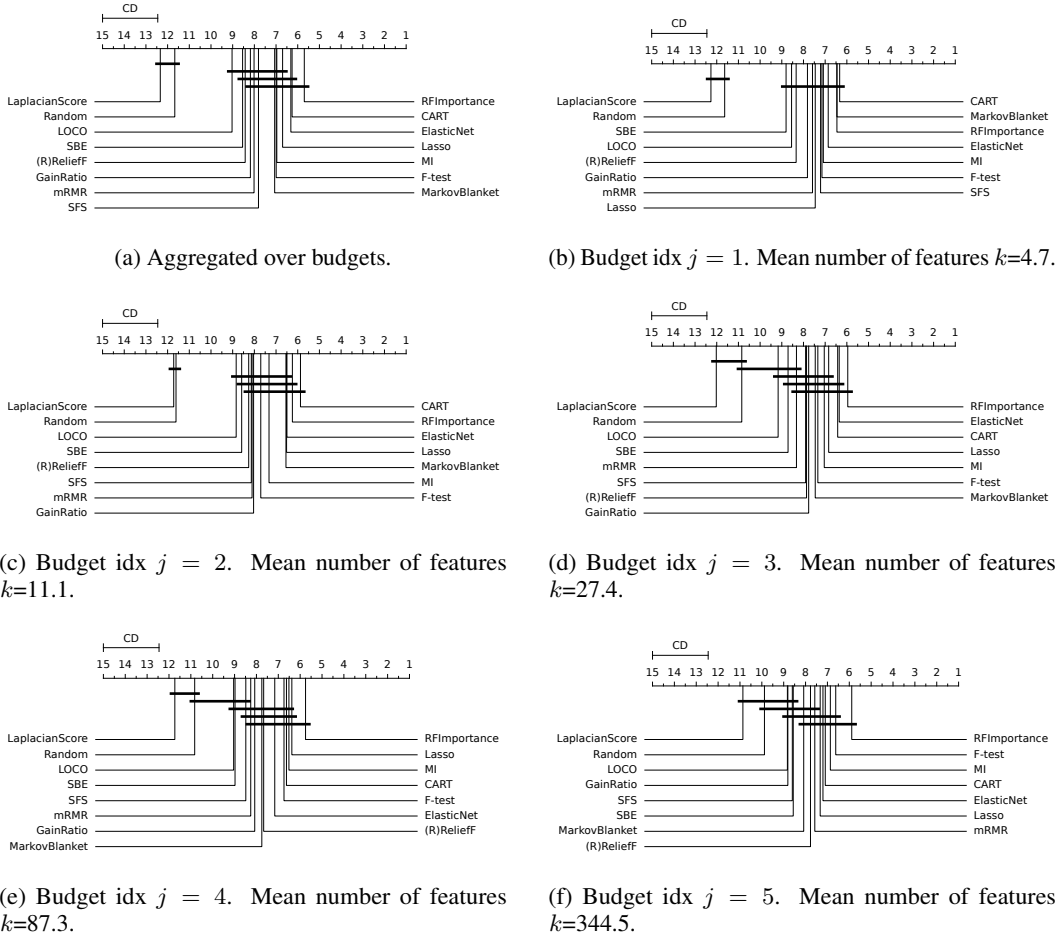


Figure D.1: **Critical difference diagrams.** Average ranks per dataset with critical distance= 2.546.

Tuning LGBM. We assess the impact of tuning the downstream model on predictive performance. We focus on LGBM, the model with the largest tunability (Erickson et al., 2025), via a random

search with 10 hyperparameter configurations. For each feature selection method, we pick the configuration with the lowest metric error averaged across budgets and datasets. The tuned model is reported alongside the other downstream models in Figure D.2. We use the per-task normalized score (Erickson et al., 2025), $s_{i,t} = \max(0, (\tilde{e}_t - e_{i,t})/(\tilde{e}_t - e_t^*))$, where e_t^* and $\tilde{e}_t$ are the best and median errors on task t . The best method on each task scores 1, the median scores 0, and worse-than-median methods are floored at 0. On average, tuning improves the normalized score by 24.7% over the default configuration. This suggests that practitioners interested in boosting predictive performance on the downstream task should consider tuning their predictors in addition to applying feature selection.

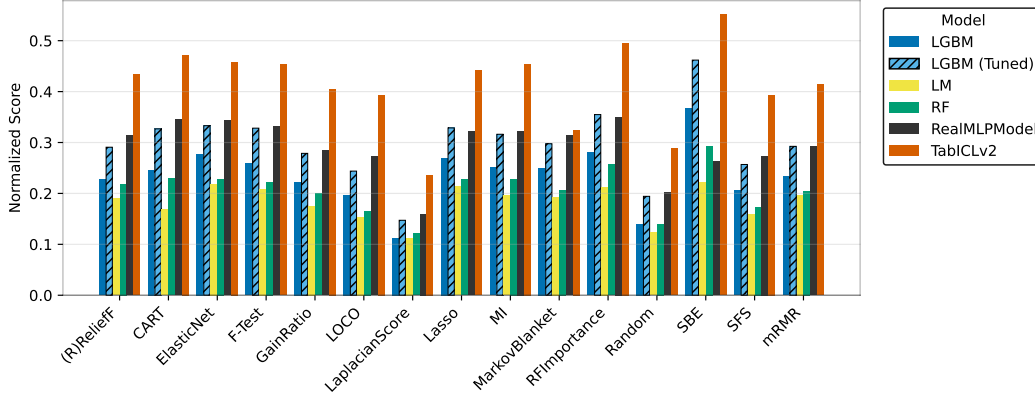


Figure D.2: **Impact of tuning.** Normalized scores per method per model, averaged over datasets and budgets. Tuned LGBM (striped blue) outperforms the default (solid blue) by a clear margin.

Random fallback. In SelectArena, besides the cardinality constraint, we impose a time limit of one hour for each: the feature selection and the downstream model training and inference. This limit reflects the practical trade-off between predictive performance and computational cost. Improvements in downstream performance may be of limited value if they require prohibitively expensive feature selection or model evaluation. We use one hour as a common computational budget to capture this trade-off consistently across methods. Where supported by the implementation, this limit is enforced by interrupting the method; otherwise, the feature selection stage is allowed to complete but is recorded as a timeout if it exceeds the limit. When feature selection is interrupted, we apply a mechanism called random fallback to keep the cardinality fixed across runs. Specifically, random fallback either fills the remaining feature subset with randomly selected features or randomly subsamples the current subset down to the cardinality constraint. The latter applies to SBE and Markov Blanket, which start with the full feature set and iteratively remove features until the target cardinality is reached. This allows timed-out runs to remain part of the evaluation. Discarding timed-out runs would instead result in different methods being evaluated on different datasets, with slower methods disproportionately evaluated on lower-dimensional and potentially easier datasets. Random fallback therefore provides a practical mechanism for maintaining comparability under both cardinality and time constraints.

Table D.3 summarizes the timeout and random fallback rates. Timeouts are frequent for the search methods SBE (46.9%) and SFS (44.8%), less frequent for LOCO (23.5%) and Relief(F) (17.0%), and rare for Lasso (4.0%), mRMR (3.4%), and ElasticNet (1.4%). All other methods never hit the time limit. The discrepancy between the timeout and fallback rates has two causes. First, for SBE, SFS, LOCO, and Relief(F) some runs produce a complete set of features (no fallback) in a final step that starts within the time limit but ends after it. Second, Lasso and ElasticNet always run to completion as their scikit-learn interface does not allow interruption. Given their low timeout rates, we accept this as a minor deviation from our time-constraint framing of the benchmark.

To measure the impact of random fallback on predictive performance, we rerun experiments without it on a single seed (5 budget indices $\times$ 5 downstream models $\times$ 71 datasets) and present the results in Table D.3. As expected, the Δ (difference between the improvement over Random for no fallback and fallback cases) is largest for methods that trigger the fallback most often, i.e. SBE, SFS, and LOCO. Without fallback, SBE returns feature subsets larger than the cardinality constraint when it reaches

Table D.3: **Impact of random fallback on run completion and improvement over RANDOM.** A *run* is a unique combination of dataset, budget, and downstream model; each method has 1,775 runs. *Timeout* counts runs exceeding the one-hour limit. *Fallback* counts runs completed or reduced through random selection after a timeout. *Improvement over RANDOM* (Appendix D.2) normalizes performance across tasks with different error metrics. We report the mean for the default pipeline (*Fallback*) and the ablated one (*No fallback*), with $\Delta = \text{No fallback} - \text{Fallback}$.

Method	Timeout		Fallback		Improvement over RANDOM		
	<i>n</i>	%	<i>n</i>	%	Fallback	No fallback	Δ (pp)
SBE	832	46.9	825	46.5	10.01	28.06	+18.05
SFS	795	44.8	778	43.8	16.96	-1.99	-18.95
LOCO	417	23.5	134	7.5	11.58	10.11	-1.47
(R)ReliefF	301	17.0	0	0.0	19.23	19.22	-0.01
Lasso	71	4.0	0	0.0	20.95	20.95	+0.00
mRMR	60	3.4	60	3.4	21.97	21.96	-0.01
ElasticNet	25	1.4	0	0.0	22.91	22.91	+0.00
CART	0	0.0	0	0.0	24.21	24.21	+0.00
F-Test	0	0.0	0	0.0	23.71	23.71	+0.00
GainRatio	0	0.0	0	0.0	19.27	19.28	+0.01
LaplacianScore	0	0.0	0	0.0	-18.40	-18.40	+0.00
MI	0	0.0	0	0.0	23.32	23.31	-0.01
MarkovBlanket	0	0.0	0	0.0	21.08	21.10	+0.02
RFImportance	0	0.0	0	0.0	25.99	25.99	+0.00
Random [†]	0	0.0	0	0.0	-	-	-
Total	2,501	9.4	1,797	6.8	-	-	-

[†] RANDOM selects features at random by construction, so it is not counted as a fallback.

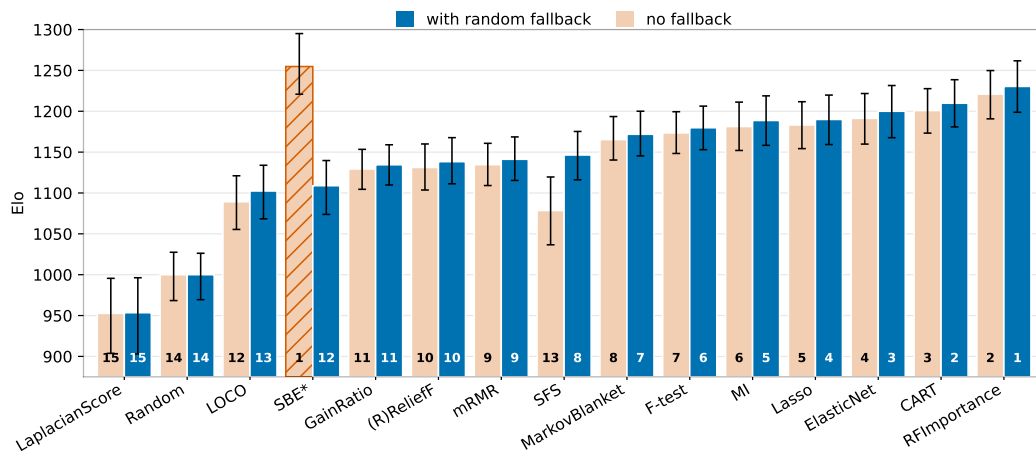


Figure D.3: **Impact of random fallback on Elo ranking.** New Elo ratings are calculated based on the ablation study’s results for a single seed and are presented in orange. SBE is shown in striped red to indicate that excluding random fallback has a different effect on it than other methods. Default Elo ratings are presented in blue. Numbers on the bars represent rank.

the time limit, resulting in a positive $\Delta = +18.05\text{pp}$. However, this reflects a budget violation rather than a real gain and is not comparable to the impact of the fallback on other methods. When SFS and LOCO time out, they output less features than the cardinality constraint assumes, resulting in a negative $\Delta = -18.95\text{pp}$ and -1.47pp . Without fallback, SFS even falls below Random as its search iterations are relatively long (Table D.2). As in Guyon & Elisseeff (2003), we observe that randomly selected features still carry useful signal and improve downstream model’s performance compared to passing it an incomplete feature subset. For mRMR and methods that do resort to random fallback, $\Delta \leq 0.02\text{pp}$, which is attributable to run-to-run nondeterminism.

Figure D.3 presents the change in the Elo ranking when random fallback is removed. Without random fallback, SBE rises from rank 12 to rank 1 and SFS falls from rank 8 to rank 13, with both these shifts affecting all the other ranks as Elo rating is relative. We note, again, that SBE rise is an artifact of the random fallback’s impact on backward search methods and it reflects budget violation as described above. That is why the only meaningful change is the drop in the SFS rank.

D.3 STABILITY

We assess the stability of the feature selection methods across datasets with a different number of samples (in the minority class) per feature, *i.e.*, events per variable (EPV). We use the EPV as a proxy for the selection difficulty (Harrell, 2015; Heinze et al., 2018).

F-Test and Distance-Based Methods Dominate Stability Rankings. The dominance of F-Test and LaplacianScore is visible in Figure 5 and Figure D.4, where we additionally highlight the top-3 performing methods. This confirms that F-Test, LaplacianScore, MI, GainRatio, (R)ReliefF, and mRMR consistently rank highest in stability across EPVs. In Figure D.5, we isolate the near-optimal set of methods that are within 3% of the best-performing method. This confirms the dominance of the aforementioned 5 methods.

F-Test Works Well Across Selection Difficulties. The F-Test often performs well at high and medium EPVs. Importantly, it also ranks highest at very low EPVs, where other methods struggle. In this setting, other methods are rarely within its 3% threshold.

Lower EPV Reveals Robustness. Comparing the different selection difficulties, one can observe a broader diversity of methods achieving competitive stability at high and medium EPVs. Conversely, at very low EPVs, only few methods are relatively stable.

Most Methods Show Intermediate to Good Stability. In Table D.4, we report the mean stability for each method. Poor stability is defined by values below 0.40, intermediate to good stability by values between 0.40 and 0.75, and values above 0.75 indicate excellent stability (Nogueira & Brown, 2016). Lasso, SBE, SFS, and LOCO only achieve low stability, showing the impact of the high number of timeouts for SBE (46.41%), SFS (45.28%), and LOCO (23.10%). The remaining methods show an intermediate to good stability.

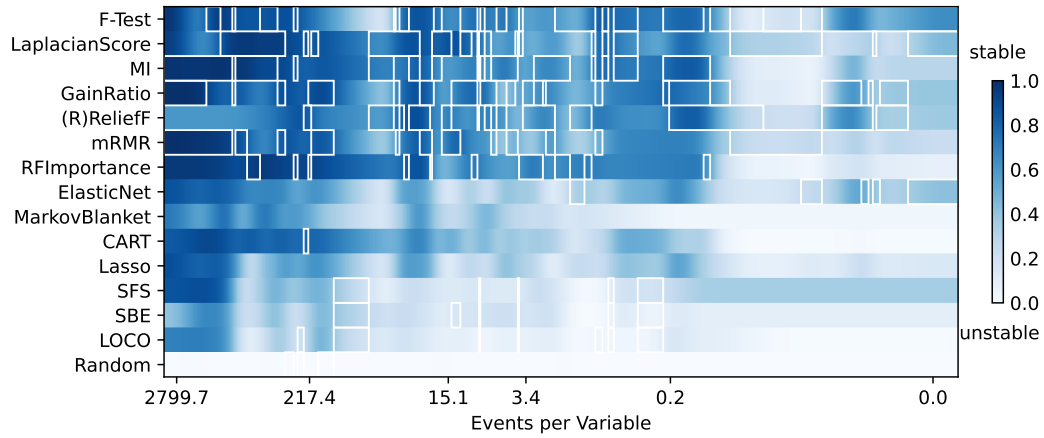


Figure D.4: **Stability.** Nogueira score (Nogueira & Brown, 2016) across datasets. We use the events per variable, *i.e.*, the number of samples per feature for regression problems or the number of samples in the minority class per feature for classification problems, as a proxy for the selection difficulty (Harrell, 2015; Heinze et al., 2018). The top-3 methods per EPV are highlighted.

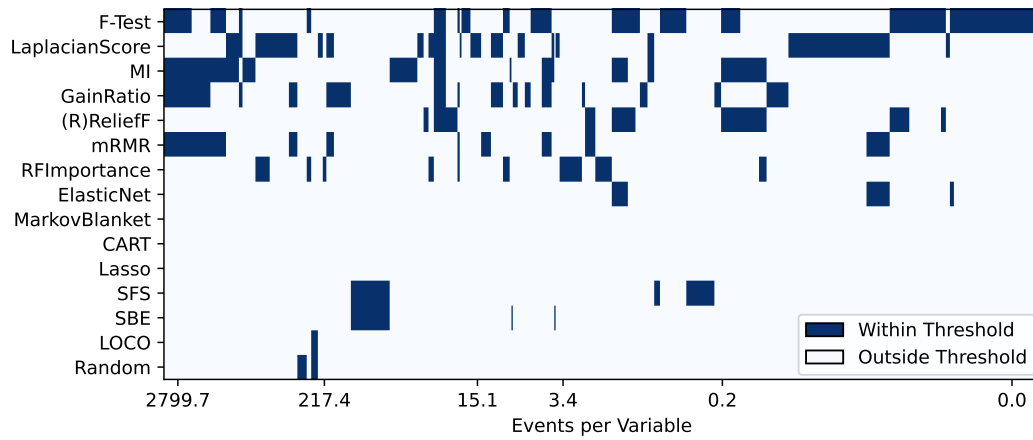


Figure D.5: **Thresholded stability.** We display all methods within a 3% performance threshold of the best-performing method.

D.4 VALIDITY

Like the stability, we assess the validity across different events per variable (EPV) (Appendix D.3). Additionally, we use three different noise levels relative to the original feature set size: a 50% noise level indicates that a number of noise features equal to 50% of the original feature count has been injected into the dataset. This proportional scaling applies consistently to the 75% and 100% noise levels. The 50% noise level results in one third of the features to be noise, the 100% noise level results in half of the feature to be noise. An increasing noise level represents a higher difficulty for feature selection methods to make a valid selection, because the amount of irrelevant features increases. One common strategy is to use feature removal approaches like RemOve And Retrain (ROAR), but these methods can be sensitive to feature redundancies that are prevalent in real-world data (Hooker et al., 2019). Therefore, we adopt an alternative approach to measure validity described in Chapter 3.3.

F-Test and Information-Theoretic Methods Dominate Validity Rankings. In Figure 6, we can see that F-Test and information-theoretic methods dominate the validity rankings, followed by LaplacianScore. This finding is consistent across different noise levels (Figures D.6, D.7, D.8, D.9, D.10, D.11).

More Noise Injection Reveals Robustness. In contrast to the stability, we can observe a higher resilience to lower EPVs for the validity. However, Figures D.6, D.8, and D.10 illustrate the challenge of increasing noise levels, as visualized by the progressively lighter coloring across all methods. This degradation pattern is quantified in Table D.4, where every method exhibits a consistent score decline with increasing noise levels.

Dominant Methods Show Greater Noise Resilience. The F-Test’s validity score decreases steadily from 0.92 to 0.89 to 0.85 — a modest drop of $< 4\%$ per noise increment. In contrast, MarkovBlanket experiences substantially larger declines of $\sim 9\%$ per step, indicating the superior noise robustness of top-performing methods. In fact, the method ranking only changes slightly at different noise levels (Figures D.6, D.7, D.8, D.9, D.10, D.11).

More Noise Injection Accentuates Differences. We can observe that with increasing noise levels, the number of low-ranked methods achieving a performance within a threshold of 3% of the best method decreases (Figures D.7, D.9, D.11). This implies that the increasing difficulty emphasizes differences between high- and low-ranking methods.

Table D.4: **Mean validity and stability.** We report the average scores across all datasets. Higher is better.

Method	Stability	Validity (50%)	Validity (75%)	Validity (100%)
F-Test	0.679027	0.922444	0.885531	0.848069
LaplacianScore	0.656319	0.875447	0.837405	0.797492
MI	0.653849	0.879216	0.831729	0.785338
GainRatio	0.648343	0.909595	0.867829	0.826548
(R)ReliefF	0.602695	0.836929	0.775536	0.740539
mRMR	0.586207	0.749956	0.698682	0.654502
RFImportance	0.543465	0.769910	0.718201	0.672429
ElasticNet	0.442266	0.853544	0.804436	0.759485
MarkovBlanket	0.437499	0.621839	0.532242	0.460249
CART	0.427232	0.708525	0.650755	0.588315
Lasso	0.374202	0.839766	0.778133	0.731577
SFS	0.276485	0.781449	0.702861	0.626375
SBE	0.235075	0.726402	0.634586	0.558420
LOCO	0.172724	0.730326	0.639994	0.583660
Random	0.000598	0.675138	0.586824	0.499406

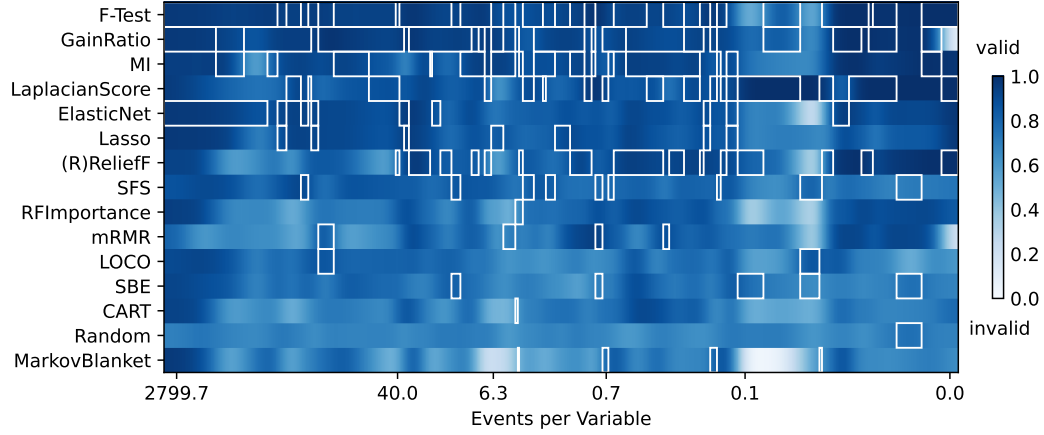


Figure D.6: **Validity at 50% added noise.** Selection precision across datasets at a noise level of 50%. Like for the stability, we use the events per variable, *i.e.*, the number of samples per feature for regression problems or the number of samples in the minority class per feature for classification problems, as a proxy for the selection difficulty (Harrell, 2015; Heinze et al., 2018). The top-3 methods per EPV are highlighted.

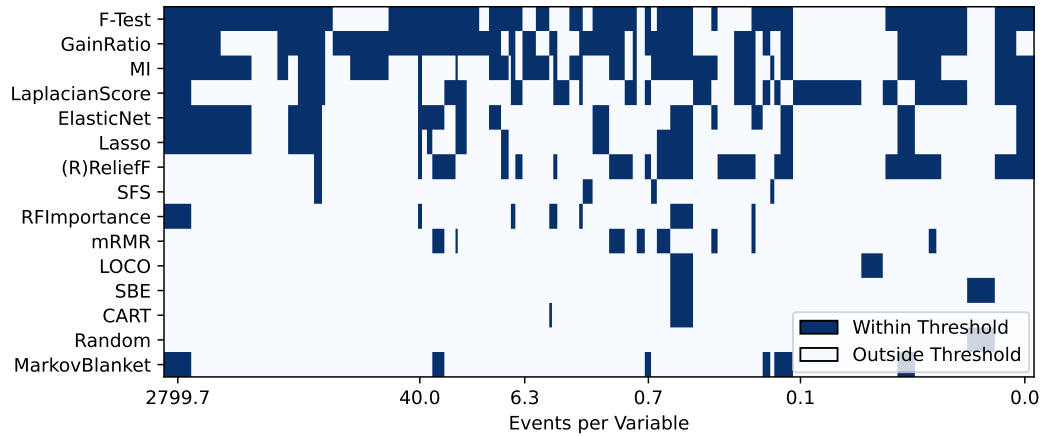


Figure D.7: **Thresholded validity at 50% added noise.** We display all methods within a 3% performance threshold of the best-performing method at a noise level of 50%.

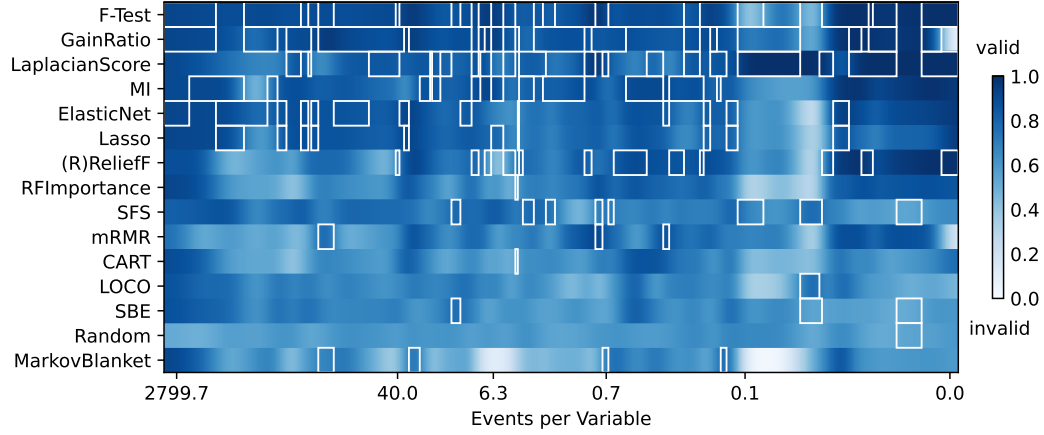


Figure D.8: **Validity at 75% added noise.** Selection precision across datasets at a noise level of 75%. Like for the stability, we use the events per variable, *i.e.*, the number of samples per feature for regression problems or the number of samples in the minority class per feature for classification problems, as a proxy for the selection difficulty (Harrell, 2015; Heinze et al., 2018). The top-3 methods per EPV are highlighted.

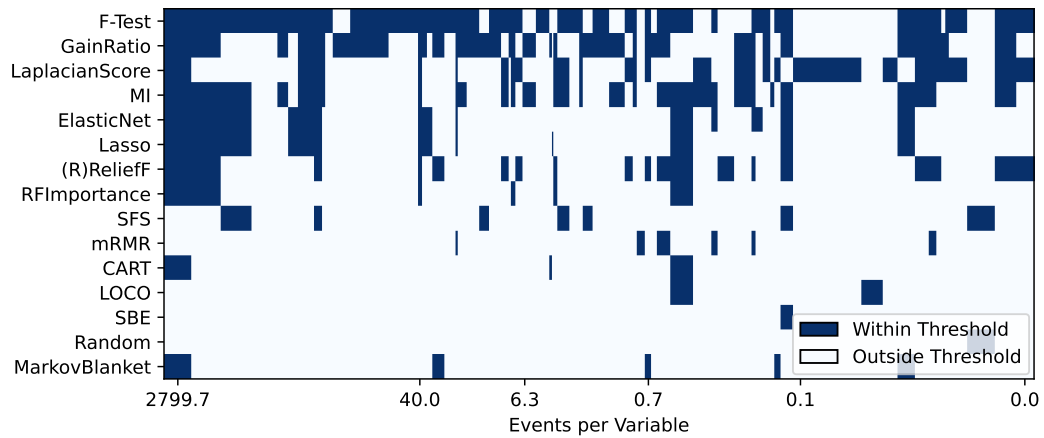


Figure D.9: **Thresholded validity at 75% added noise.** We display all methods within a 3% performance threshold of the best-performing method at a noise level of 75%.

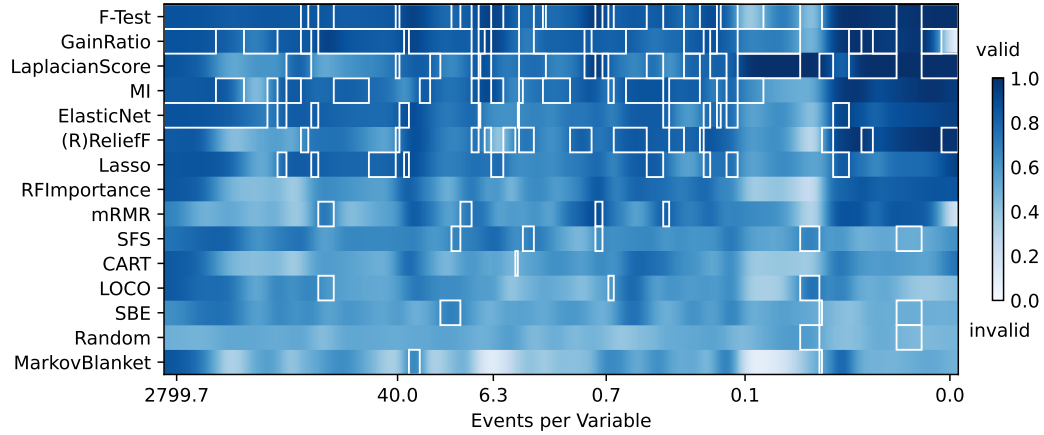


Figure D.10: **Validity at 100% added noise.** Selection precision across datasets at a noise level of 100%. Like for the stability, we use the events per variable, *i.e.*, the number of samples per feature for regression problems or the number of samples in the minority class per feature for classification problems, as a proxy for the selection difficulty (Harrell, 2015; Heinze et al., 2018). The top-3 methods per EPV are highlighted.

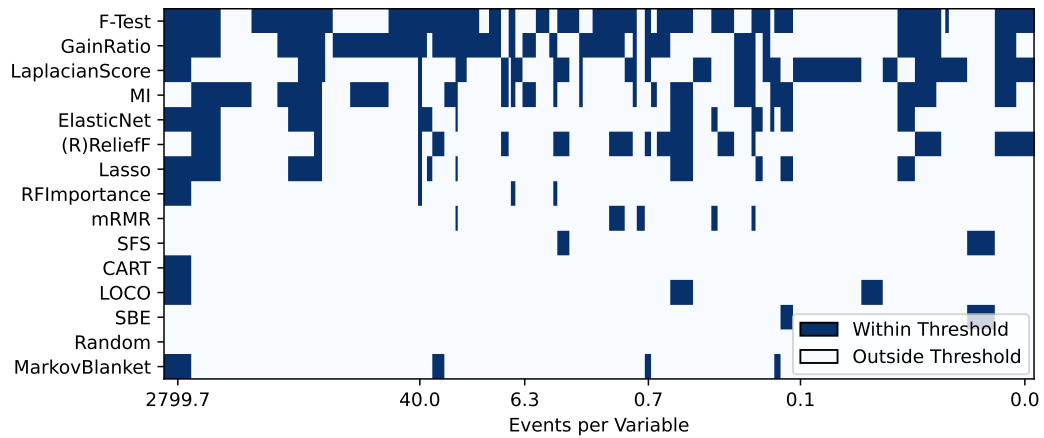


Figure D.11: **Thresholded validity at 100% added noise.** We display all methods within a 3% performance threshold of the best-performing method at a noise level of 100%.

D.5 RAW PREDICTIVE PERFORMANCE

In the following, we show the mean and standard deviation of the metric error per method across datasets and budgets aggregated over three seeds. We break down the tables per downstream model for better legibility. Table D.5 shows the performance for LGBM, Table D.6 for Linear model, Table D.7 for RF, Table D.8 for RealMLP, and Table D.9 for TabICLv2.

Table D.5: Per-cell results with downstream model **LGBM**. Tasks are grouped by metric. Each cell is the mean over three seeds, with the sample standard deviation as a subscript.

Dataset	Budget Index	CART	ElasticNet	F-test	GiniRatio	LaplaceScore	Lasso	LOCO	MarkovBlanket	MI	mRMR	(R)Relieff	Random	SBE	RFImportance	SFS
log-loss (↓)																
horse_colic survival	1	.778 ±.020	.762 ±.037	.759 ±.028	.834 ±.065	.879 ±.027	.762 ±.037	.784 ±.075	.779 ±.031	.823 ±.066	.807 ±.021	.809 ±.042	.863 ±.073	.821 ±.081	.760 ±.037	.894 ±.012
	2	.753 ±.046	.739 ±.043	.748 ±.031	.805 ±.034	.889 ±.029	.738 ±.036	.763 ±.051	.761 ±.042	.796 ±.063	.790 ±.026	.767 ±.045	.802 ±.042	.774 ±.043	.739 ±.039	.887 ±.011
	3	.746 ±.037	.742 ±.033	.728 ±.040	.773 ±.013	.885 ±.022	.737 ±.038	.760 ±.054	.743 ±.043	.777 ±.038	.764 ±.015	.749 ±.035	.776 ±.033	.748 ±.049	.727 ±.057	.886 ±.016
	4	.730 ±.046	.719 ±.043	.723 ±.045	.731 ±.048	.793 ±.008	.720 ±.046	.757 ±.051	.730 ±.054	.746 ±.036	.732 ±.035	.743 ±.037	.759 ±.048	.737 ±.050	.718 ±.056	.852 ±.016
	5	.725 ±.042	.725 ±.035	.719 ±.043	.725 ±.042	.752 ±.021	.722 ±.039	.759 ±.044	.731 ±.041	.743 ±.034	.716 ±.039	.735 ±.038	.751 ±.039	.737 ±.050	.725 ±.047	.770 ±.039
area prediction	1	.698 ±.234	.292 ±.099	.521 ±.176	.556 ±.306	1.36 ±.09	.368 ±.237	1.19 ±.10	.635 ±.176	.550 ±.219	.532 ±.236	.366 ±.102	1.00 ±.37	1.09 ±.38	.405 ±.146	1.16 ±.22
	2	.512 ±.184	.147 ±.091	.198 ±.085	.269 ±.180	1.06 ±.08	.149 ±.139	.799 ±.127	.207 ±.106	.229 ±.210	.211 ±.106	.103 ±.031	1.13 ±.21	.969 ±.158	.0764 ±.0675	.933 ±.316
	3	.367 ±.118	.113 ±.104	.106 ±.111	.125 ±.090	.900 ±.093	.0943 ±.0808	.544 ±.183	.125 ±.094	.136 ±.087	.123 ±.095	.0935 ±.0853	.458 ±.194	.536 ±.215	.104 ±.056	.505 ±.158
	4	.224 ±.156	.119 ±.093	.115 ±.096	.115 ±.069	.519 ±.164	.0980 ±.0736	.219 ±.071	.121 ±.077	.129 ±.087	.113 ±.073	.0931 ±.0818	.340 ±.061	.390 ±.084	.0954 ±.0853	.288 ±.295
	5	.183 ±.108	.128 ±.082	.116 ±.081	.114 ±.069	.0963 ±.0578	.106 ±.070	.133 ±.022	.118 ±.064	.128 ±.081	.115 ±.070	.110 ±.066	.124 ±.013	.145 ±.016	.104 ±.063	.251 ±.147
sub_17	1	.0968 ±.0004	.113 ±.015	.141 ±.001	.142 ±.003	.719 ±.000	.242 ±.252	.0973 ±.0011	.0973 ±.0011	.146 ±.001	.157 ±.002	.159 ±.003	.555 ±.409	.0968 ±.0004	.142 ±.003	.146 ±.001
	2	.0740 ±.0010	.0762 ±.0032	.0942 ±.0106	.0754 ±.0009	.528 ±.142	.0746 ±.0018	.0739 ±.0010	.0774 ±.0063	.0829 ±.0010	.153 ±.003	.0987 ±.0031	.102 ±.008	.0741 ±.0011	.0751 ±.0011	.0983 ±.0014
	3	.0795 ±.0012	.0718 ±.0009	.0869 ±.0145	.0795 ±.0012	.439 ±.023	.0718 ±.0009	.0722 ±.0007	.0795 ±.0012	.0795 ±.0012	.0939 ±.0014	.0978 ±.0115	.390 ±.038	.0722 ±.0008	.0768 ±.0051	.0809 ±.0011
	4	.0787 ±.0011	.0717 ±.0007	.0866 ±.0028	.0787 ±.0012	.188 ±.146	.0760 ±.0079	.0743 ±.0049	.0787 ±.0012	.0845 ±.0011	.0912 ±.0013	.0845 ±.0012	.307 ±.181	.0720 ±.0008	.0787 ±.0012	.0788 ±.0011
	5	.0841 ±.0011	.0835 ±.0013	.0837 ±.0016	.0841 ±.0011	.0844 ±.0016	.0834 ±.0013	.0786 ±.0012	.0823 ±.0040	.0841 ±.0011	.0845 ±.0011	.0843 ±.0011	.187 ±.189	.0786 ±.0012	.0841 ±.0011	.0786 ±.0012
preds_cable,devops classification,accuracy	1	.634 ±.035	.595 ±.018	.652 ±.013	.672 ±.007	.975 ±.017	.600 ±.019	.617 ±.036	.603 ±.007	.640 ±.010	.682 ±.023	.614 ±.016	.693 ±.034	.871 ±.029	.674 ±.009	.663 ±.010
	2	.579 ±.016	.574 ±.018	.576 ±.018	.602 ±.006	.882 ±.011	.574 ±.021	.583 ±.013	.594 ±.012	.570 ±.016	.633 ±.015	.582 ±.012	.640 ±.023	.640 ±.053	.581 ±.012	.615 ±.028
	3	.565 ±.014	.560 ±.018	.570 ±.027	.596 ±.012	.680 ±.030	.562 ±.013	.564 ±.021	.596 ±.006	.559 ±.017	.602 ±.013	.565 ±.024	.660 ±.019	.599 ±.045	.567 ±.015	.581 ±.015
	4	.560 ±.017	.558 ±.017	.562 ±.018	.590 ±.005	.599 ±.014	.558 ±.012	.556 ±.018	.591 ±.005	.561 ±.015	.596 ±.014	.560 ±.024	.594 ±.016	.558 ±.015	.555 ±.014	.562 ±.017
	5	.553 ±.015	.554 ±.016	.554 ±.019	.575 ±.027	.554 ±.016	.555 ±.016	.557 ±.018	.587 ±.008	.556 ±.014	.564 ±.016	.555 ±.017	.559 ±.024	.552 ±.013	.553 ±.016	.556 ±.013
accuracy ratio	1	1.74 ±.04	1.81 ±.05	1.82 ±.05	2.04 ±.14	2.12 ±.01	1.91 ±.17	1.81 ±.09	1.76 ±.06	1.75 ±.04	1.76 ±.03	1.78 ±.06	2.04 ±.12	2.08 ±.03	1.75 ±.05	1.83 ±.06
	2	1.75 ±.03	1.78 ±.07	1.79 ±.08	1.85 ±.14	2.12 ±.01	1.92 ±.17	1.79 ±.07	1.78 ±.05	1.71 ±.01	1.76 ±.03	1.78 ±.06	2.11 ±.01	2.10 ±.04	1.77 ±.03	1.85 ±.08
	3	1.74 ±.05	1.81 ±.08	1.79 ±.06	1.80 ±.03	2.11 ±.01	1.78 ±.07	1.81 ±.05	1.78 ±.05	1.70 ±.06	1.77 ±.05	1.79 ±.05	2.06 ±.10	2.08 ±.05	1.82 ±.01	1.82 ±.01
	4	1.77 ±.03	1.78 ±.07	1.81 ±.07	1.76 ±.03	2.03 ±.01	1.78 ±.08	1.76 ±.05	1.78 ±.02	1.71 ±.02	1.77 ±.03	1.80 ±.09	1.95 ±.19	1.96 ±.05	1.71 ±.03	1.87 ±.03
	5	1.70 ±.03	1.82 ±.05	1.71 ±.01	1.80 ±.03	1.79 ±.06	1.76 ±.08	1.73 ±.02	1.79 ±.03	1.72 ±.01	1.79 ±.02	1.79 ±.06	1.99 ±.14	1.78 ±.12	1.75 ±.01	1.85 ±.02
env,prod,prodnet classification,shaplog	1	.711 ±.005	.783 ±.025	.909 ±.016	1.18 ±.00	.909 ±.024	.856 ±.004	.966 ±.086	.719 ±.007	.925 ±.015	.825 ±.005	.940 ±.033	1.12 ±.11	1.11 ±.08	.718 ±.006	1.12 ±.15
	2	.561 ±.008	.591 ±.010	.660 ±.014	.862 ±.007	.649 ±.016	.612 ±.017	.735 ±.036	.575 ±.006	.646 ±.009	.637 ±.009	.638 ±.013	.833 ±.014	.800 ±.026	.568 ±.010	.807 ±.015
	3	.508 ±.006	.523 ±.005	.559 ±.007	.604 ±.005	.532 ±.008	.527 ±.002	.670 ±.073	.517 ±.012	.573 ±.006	.560 ±.007	.553 ±.008	.645 ±.021	.636 ±.033	.520 ±.011	.644 ±.014
	4	.486 ±.007	.492 ±.005	.512 ±.003	.540 ±.005	.500 ±.005	.493 ±.007	.584 ±.017	.495 ±.007	.509 ±.006	.507 ±.007	.511 ±.006	.570 ±.018	.571 ±.035	.492 ±.008	.583 ±.037
	5	.479 ±.007	.482 ±.008	.486 ±.009	.491 ±.008	.484 ±.007	.482 ±.009	.511 ±.013	.481 ±.007	.487 ±.009	.486 ±.005	.486 ±.009	.510 ±.022	.528 ±.011	.480 ±.009	.520 ±.020
long_cancer	1	.438 ±.245	.438 ±.080	.527 ±.102	.290 ±.131	.868 ±.065	.501 ±.121	.716 ±.060	.354 ±.059	.418 ±.022	.377 ±.185	.379 ±.010	.754 ±.005	.739 ±.054	.339 ±.106	.688 ±.123
	2	.390 ±.206	.241 ±.081	.374 ±.063	.266 ±.080	.851 ±.064	.337 ±.135	.413 ±.093	.263 ±.086	.265 ±.100	.227 ±.037	.284 ±.053	.507 ±.131	.404 ±.059	.209 ±.073	.427 ±.138
	3	.288 ±.070	.212 ±.091	.265 ±.041	.250 ±.041	.719 ±.136	.220 ±.077	.301 ±.002	.248 ±.071	.227 ±.011	.232 ±.026	.219 ±.043	.257 ±.056	.261 ±.061	.192 ±.044	.274 ±.066
	4	.238 ±.030	.209 ±.050	.215 ±.041	.203 ±.029	.590 ±.059	.203 ±.033	.254 ±.088	.223 ±.038	.204 ±.020	.199 ±.048	.246 ±.036	.197 ±.078	.207 ±.073	.209 ±.014	.198 ±.054
	5	.237 ±.008	.194 ±.046	.203 ±.030	.198 ±.030	.271 ±.113	.212 ±.022	.207 ±.013	.193 ±.032	.204 ±.033	.202 ±.043	.206 ±.029	.196 ±.026	.189 ±.023	.208 ±.016	.185 ±.011
cystitis diag	1	1.29 ±.14	1.97 ±.05	1.83 ±.21	1.98 ±.32	1.86 ±.25	1.74 ±.19	1.15 ±.22	.971 ±.089	1.60 ±.32	1.16 ±.12	1.68 ±.05	2.04 ±.18	1.12 ±.22	1.13 ±.28	.788 ±.207
	2	.758 ±.057	1.25 ±.07	1.02 ±.09	.888 ±.340	1.01 ±.44	1.34 ±.19	.834 ±.055	.662 ±.083	.961 ±.094	.994 ±.020	1.40 ±.30	1.11 ±.30	.889 ±.249	.707 ±.017	.627 ±.139
	3	.623 ±.061	.890 ±.112	.810 ±.180	.495 ±.036	.690 ±.223	1.04 ±.25	.747 ±.102	.566 ±.082	.472 ±.078	.704 ±.023	.885 ±.205	.642 ±.066	.478 ±.122	.593 ±.091	.537 ±.113
	4	.520 ±.100	.621 ±.055	.623 ±.204	.441 ±.141	.543 ±.173	.680 ±.103	.633 ±.011	.453 ±.145	.462 ±.093	.537 ±.048	.682 ±.168	.534 ±.017	.477 ±.146	.458 ±.117	.462 ±.171
	5	.495 ±.125	.477 ±.121	.508 ±.107	.450 ±.165	.600 ±.052	.522 ±.090	.448 ±.168	.479 ±.117	.450 ±.140	.503 ±.097	.500 ±.121	.480 ±.143	.441 ±.163	.449 ±.145	
env diag	1	.551 ±.001	.574 ±.007	.541 ±.024	.556 ±.009	.695 ±.014	.546 ±.046	.635 ±.060	.520 ±.023	.553 ±.016	.562 ±.024	.554 ±.012	.698 ±.007	.696 ±.006	.616 ±.025	.534 ±.019
	2	.546 ±.018	.551 ±.020	.531 ±.006	.558 ±.008	.691 ±.013	.549 ±.043	.624 ±.062	.517 ±.024	.555 ±.009	.539 ±.025	.567 ±.008	.690 ±.008	.661 ±.025	.527 ±.006	.544 ±.026
	3	.542 ±.011	.531 ±.019	.543 ±.013	.536 ±.022	.683 ±.019	.525 ±.012	.581 ±.035	.537 ±.028	.524 ±.002	.522 ±.011	.573 ±.010	.584 ±.020	.618 ±.048	.525 ±.024	.549 ±.037
	4	.524 ±.020	.520 ±.017	.538 ±.006	.524 ±.006	.667 ±.015	.520 ±.020	.550 ±.028	.522 ±.016	.518 ±.013	.528 ±.009	.550 ±.002	.562 ±.079	.540 ±.027	.524 ±.018	.537 ±.029
	5	.511 ±.022	.512 ±.015	.507 ±.016	.520 ±.008	.634 ±.012	.515 ±.020	.501 ±.016	.517 ±.002	.499 ±.025	.519 ±.015	.516 ±.023	.537 ±.029	.527 ±.015	.506 ±.018	.516 ±.027
haberman primary_cancer	1	1.77 ±.14	1.91 ±.13	1.95 ±.09	1.77 ±.11	2.13 ±.06	1.90 ±.13	1.84 ±.13	1.88 ±.15	1.77 ±.14	1.83 ±.13	1.95 ±.09	1.94 ±.07	1.81 ±.14	1.83 ±.13	1.83 ±.12
	2	1.67 ±.18	1.79 ±.21	1.73 ±.12	1.64 ±.22	1.97 ±.08	1.79 ±.19	1.80 ±.17	1.69 ±.21	1.55 ±.19	1.64 ±.22	1.71 ±.14	1.88 ±.18	1.75 ±.20	1.70 ±.15	1.78 ±.21
	3	1.50 ±.22	1.70 ±.19	1.61 ±.12	1.57 ±.20	1.86 ±.09	1.67 ±.13	1.58 ±.13	1.56 ±.16	1.47 ±.21	1.57 ±.16	1.70 ±.19	1.65 ±.17	1.50 ±.20	1.63 ±.23	1.63 ±.23
	4	1.43 ±.19	1.62 ±.16	1.49 ±.15	1.51 ±.24	1.69 ±.12	1.55 ±.20	1.46 ±.15	1.49 ±.21	1.44 ±.19	1.51 ±.24	1.55 ±.14	1.57 ±.26	1.46 ±.14	1.41 ±.17	1.51 ±.18
	5	1.41 ±.17	1.50 ±.18	1.47 ±.13	1.46 ±.19	1.54 ±.14	1.45 ±.17	1.41 ±.15	1.46 ±.21	1.41 ±.18	1.46 ±.19	1.50 ±.18	1.49 ±.24	1.43 ±.17	1.41 ±.17	1.43 ±.16
breast svm	1	.0749 ±.0278	.131 ±.056	.242 ±.020	.104 ±.019	.772 ±.072	1.32 ±.041	.117 ±.011	.123 ±.013	.142 ±.008	.123 ±.042	.135 ±.017	.619 ±.101	.102 ±.045	.109 ±.048	.0904 ±.0279
	2	.0753 ±.0257	.0751 ±.0429	.107 ±.066	.0911 ±.0235	.607 ±.034	.0633 ±.0400	.0853 ±.0448	.0944 ±.0200	.0947 ±.0397	.0907 ±.0228	.0736 ±.0134	.253 ±.111	.0911 ±.0343	.0743 ±.0429	.0676 ±.0309
	3	.0823 ±.0237	.0737 ±.0388	.0559 ±.0109	.0933 ±.0344	.381 ±.064	.0765 ±.0393	.0833 ±.0421	.0818 ±.0319	.0826 ±.0300	.0933 ±.0344	.0784 ±.0420	.149 ±.099	.0881 ±.0266	.0767 ±.0344	.0667 ±.0311
	4	.0817 ±.0111	.0752 ±.0372	.0622 ±.0111	.100 ±.036											

(continued from previous page)

Dataset	Budget idx		CART	ElankNet	F-test	GuinRatio	LaplacianScore	Lasso	LOCO	MarkovBlanket	MI	mRMR	(R)Relieff	Random	SBE	RFImportance	SFS
	1	2															
audiology imagines	1	452 $\pm$ 160	.521 $\pm$.018	.504 $\pm$.019	.472 $\pm$.138	.565 $\pm$.067	.540 $\pm$.006	.560 $\pm$.067	.472 $\pm$.138	.435 $\pm$.144	.551 $\pm$.049	.475 $\pm$.039	.585 $\pm$.064	.511 $\pm$.096	.417 $\pm$.159	.471 $\pm$.134	
	2	.447 $\pm$.165	.518 $\pm$.015	.472 $\pm$.037	.470 $\pm$.134	.483 $\pm$.078	.523 $\pm$.018	.560 $\pm$.067	.463 $\pm$.148	.417 $\pm$.163	.520 $\pm$.074	.445 $\pm$.090	.551 $\pm$.134	.499 $\pm$.080	.416 $\pm$.155	.460 $\pm$.117	
	3	.440 $\pm$.153	.489 $\pm$.040	.439 $\pm$.090	.470 $\pm$.133	.436 $\pm$.102	.495 $\pm$.030	.551 $\pm$.075	.454 $\pm$.154	.420 $\pm$.161	.448 $\pm$.101	.408 $\pm$.107	.431 $\pm$.094	.517 $\pm$.104	.416 $\pm$.155	.460 $\pm$.117	
	4	.432 $\pm$.139	.438 $\pm$.088	.408 $\pm$.143	.444 $\pm$.131	.440 $\pm$.105	.416 $\pm$.102	.551 $\pm$.075	.418 $\pm$.162	.420 $\pm$.161	.424 $\pm$.126	.409 $\pm$.117	.397 $\pm$.126	.517 $\pm$.104	.416 $\pm$.155	.464 $\pm$.123	
	5	.432 $\pm$.139	.432 $\pm$.099	.408 $\pm$.143	.416 $\pm$.154	.437 $\pm$.105	.402 $\pm$.122	.548 $\pm$.070	.416 $\pm$.154	.416 $\pm$.155	.417 $\pm$.135	.399 $\pm$.125	.425 $\pm$.144	.506 $\pm$.089	.416 $\pm$.155	.466 $\pm$.127	
RMSE ($\downarrow$)																	
qsar_ML1	1	1.34 $\pm$.02	1.42 $\pm$.03	1.39 $\pm$.03	1.53 $\pm$.02	1.40 $\pm$.03	1.44 $\pm$.03	1.46 $\pm$.05	1.53 $\pm$.01	1.36 $\pm$.05	1.53 $\pm$.02	1.49 $\pm$.01	1.53 $\pm$.01	1.53 $\pm$.01	1.33 $\pm$.02	1.37 $\pm$.02	
	2	1.23 $\pm$.01	1.27 $\pm$.04	1.31 $\pm$.03	1.50 $\pm$.01	1.32 $\pm$.00	1.26 $\pm$.04	1.36 $\pm$.06	1.47 $\pm$.05	1.25 $\pm$.02	1.50 $\pm$.01	1.34 $\pm$.06	1.50 $\pm$.02	1.50 $\pm$.04	1.21 $\pm$.01	1.33 $\pm$.04	
	3	1.00 $\pm$.02	1.05 $\pm$.01	1.05 $\pm$.02	1.37 $\pm$.03	1.17 $\pm$.02	1.03 $\pm$.02	1.17 $\pm$.02	1.33 $\pm$.04	1.02 $\pm$.01	1.37 $\pm$.03	1.04 $\pm$.02	1.30 $\pm$.03	1.29 $\pm$.03	.977 $\pm$.028	1.26 $\pm$.04	
	4	.820 $\pm$.003	.844 $\pm$.030	.844 $\pm$.015	1.03 $\pm$.05	.941 $\pm$.003	.838 $\pm$.022	.962 $\pm$.021	1.01 $\pm$.03	.845 $\pm$.000	1.03 $\pm$.05	.815 $\pm$.011	.976 $\pm$.058	1.01 $\pm$.08	.801 $\pm$.021	.990 $\pm$.026	
	5	.769 $\pm$.014	.777 $\pm$.023	.773 $\pm$.014	.806 $\pm$.033	.779 $\pm$.002	.778 $\pm$.021	.814 $\pm$.023	.807 $\pm$.034	.767 $\pm$.015	.806 $\pm$.033	.753 $\pm$.022	.802 $\pm$.027	.794 $\pm$.024	.758 $\pm$.013	.802 $\pm$.032	
forest data	1	1.41 $\pm$.04	1.40 $\pm$.02	1.44 $\pm$.05	1.42 $\pm$.05	1.40 $\pm$.03	1.40 $\pm$.02	1.40 $\pm$.03	1.42 $\pm$.03	1.41 $\pm$.03	1.41 $\pm$.03	1.43 $\pm$.06	1.40 $\pm$.03	1.40 $\pm$.03	1.42 $\pm$.04	1.40 $\pm$.03	
	2	1.41 $\pm$.02	1.41 $\pm$.03	1.43 $\pm$.05	1.41 $\pm$.03	1.41 $\pm$.04	1.41 $\pm$.03	1.43 $\pm$.04	1.41 $\pm$.03	1.42 $\pm$.05	1.42 $\pm$.03	1.41 $\pm$.04	1.41 $\pm$.02	1.42 $\pm$.05	1.42 $\pm$.04	1.41 $\pm$.03	
	3	1.41 $\pm$.03	1.42 $\pm$.03	1.42 $\pm$.03	1.41 $\pm$.03	1.41 $\pm$.04	1.42 $\pm$.03	1.42 $\pm$.03	1.40 $\pm$.02	1.42 $\pm$.04	1.41 $\pm$.04	1.42 $\pm$.04	1.42 $\pm$.04	1.41 $\pm$.02	1.41 $\pm$.03	1.42 $\pm$.05	
	4	1.41 $\pm$.03	1.41 $\pm$.02	1.41 $\pm$.02	1.41 $\pm$.03	1.41 $\pm$.03	1.41 $\pm$.02	1.41 $\pm$.02	1.42 $\pm$.04	1.41 $\pm$.03	1.42 $\pm$.03	1.42 $\pm$.04	1.42 $\pm$.04	1.41 $\pm$.03	1.41 $\pm$.03	1.42 $\pm$.05	
	5	1.41 $\pm$.03	1.41 $\pm$.02	1.41 $\pm$.03	1.41 $\pm$.02	1.41 $\pm$.03	1.41 $\pm$.02	1.41 $\pm$.02	1.41 $\pm$.03	1.41 $\pm$.02	1.41 $\pm$.02	1.41 $\pm$.03	1.41 $\pm$.03	1.41 $\pm$.03	1.41 $\pm$.02	1.41 $\pm$.03	
adult class-entropy	1	.667 $\pm$.001	.680 $\pm$.002	.675 $\pm$.002	.705 $\pm$.010	.811 $\pm$.002	.680 $\pm$.002	.669 $\pm$.001	.693 $\pm$.000	.670 $\pm$.002	.716 $\pm$.013	.695 $\pm$.003	.783 $\pm$.024	.785 $\pm$.023	.667 $\pm$.001	.661 $\pm$.001	
	2	.637 $\pm$.003	.651 $\pm$.002	.658 $\pm$.001	.648 $\pm$.003	.808 $\pm$.003	.651 $\pm$.002	.633 $\pm$.006	.637 $\pm$.001	.646 $\pm$.001	.660 $\pm$.014	.650 $\pm$.012	.784 $\pm$.016	.793 $\pm$.021	.639 $\pm$.004	.644 $\pm$.005	
	3	.587 $\pm$.001	.603 $\pm$.004	.642 $\pm$.001	.600 $\pm$.011	.807 $\pm$.002	.603 $\pm$.004	.604 $\pm$.007	.613 $\pm$.002	.616 $\pm$.002	.615 $\pm$.001	.636 $\pm$.033	.729 $\pm$.022	.734 $\pm$.022	.587 $\pm$.001	.631 $\pm$.018	
	4	.558 $\pm$.002	.562 $\pm$.004	.612 $\pm$.008	.569 $\pm$.001	.778 $\pm$.009	.562 $\pm$.004	.564 $\pm$.006	.613 $\pm$.001	.565 $\pm$.002	.602 $\pm$.002	.593 $\pm$.011	.669 $\pm$.033	.672 $\pm$.030	.558 $\pm$.001	.605 $\pm$.022	
	5	.545 $\pm$.001	.541 $\pm$.001	.555 $\pm$.004	.562 $\pm$.001	.681 $\pm$.011	.541 $\pm$.001	.544 $\pm$.003	.555 $\pm$.001	.547 $\pm$.001	.581 $\pm$.008	.568 $\pm$.009	.598 $\pm$.017	.608 $\pm$.018	.545 $\pm$.001	.578 $\pm$.005	
mini training	1	.248 $\pm$.016	.261 $\pm$.003	.323 $\pm$.001	.272 $\pm$.006	.330 $\pm$.003	.261 $\pm$.003	.340 $\pm$.046	.194 $\pm$.004	.203 $\pm$.025	.313 $\pm$.003	.367 $\pm$.001	.451 $\pm$.083	.198 $\pm$.019	.254 $\pm$.022	.261 $\pm$.005	
	2	.179 $\pm$.005	.223 $\pm$.004	.235 $\pm$.004	.175 $\pm$.002	.230 $\pm$.001	.223 $\pm$.004	.219 $\pm$.038	.185 $\pm$.002	.187 $\pm$.001	.181 $\pm$.007	.242 $\pm$.023	.303 $\pm$.094	.161 $\pm$.009	.183 $\pm$.002	.171 $\pm$.006	
	3	.152 $\pm$.007	.172 $\pm$.008	.171 $\pm$.002	.170 $\pm$.001	.225 $\pm$.001	.172 $\pm$.002	.156 $\pm$.007	.176 $\pm$.005	.170 $\pm$.004	.168 $\pm$.003	.178 $\pm$.023	.206 $\pm$.023	.147 $\pm$.004	.153 $\pm$.007	.146 $\pm$.004	
	4	.149 $\pm$.005	.159 $\pm$.002	.145 $\pm$.003	.163 $\pm$.002	.226 $\pm$.002	.158 $\pm$.002	.144 $\pm$.003	.163 $\pm$.005	.163 $\pm$.002	.153 $\pm$.011	.146 $\pm$.003	.181 $\pm$.029	.145 $\pm$.003	.146 $\pm$.003	.145 $\pm$.003	
	5	.144 $\pm$.003	.143 $\pm$.003	.143 $\pm$.002	.144 $\pm$.003	.197 $\pm$.001	.143 $\pm$.003	.143 $\pm$.002	.144 $\pm$.003	.144 $\pm$.003	.144 $\pm$.003	.144 $\pm$.003	.160 $\pm$.014	.142 $\pm$.003	.144 $\pm$.003	.142 $\pm$.003	
wine quality	1	.736 $\pm$.008	.762 $\pm$.018	.763 $\pm$.007	.763 $\pm$.007	.815 $\pm$.009	.762 $\pm$.018	.825 $\pm$.012	.736 $\pm$.008	.763 $\pm$.007	.775 $\pm$.006	.755 $\pm$.016	.785 $\pm$.032	.755 $\pm$.017	.736 $\pm$.008	.775 $\pm$.006	
	2	.692 $\pm$.005	.704 $\pm$.007	.713 $\pm$.009	.719 $\pm$.010	.741 $\pm$.012	.704 $\pm$.007	.769 $\pm$.009	.711 $\pm$.009	.726 $\pm$.013	.728 $\pm$.013	.713 $\pm$.007	.756 $\pm$.036	.696 $\pm$.014	.692 $\pm$.008	.707 $\pm$.003	
	3	.663 $\pm$.004	.692 $\pm$.006	.697 $\pm$.010	.675 $\pm$.010	.683 $\pm$.007	.692 $\pm$.006	.677 $\pm$.020	.676 $\pm$.013	.680 $\pm$.019	.686 $\pm$.018	.669 $\pm$.011	.700 $\pm$.022	.668 $\pm$.012	.660 $\pm$.006	.677 $\pm$.008	
	4	.643 $\pm$.011	.661 $\pm$.005	.662 $\pm$.010	.648 $\pm$.011	.665 $\pm$.007	.661 $\pm$.005	.651 $\pm$.012	.645 $\pm$.010	.649 $\pm$.016	.657 $\pm$.008	.643 $\pm$.008	.670 $\pm$.010	.644 $\pm$.009	.642 $\pm$.012	.656 $\pm$.008	
	5	.633 $\pm$.010	.638 $\pm$.011	.645 $\pm$.007	.633 $\pm$.008	.643 $\pm$.009	.638 $\pm$.011	.635 $\pm$.006	.636 $\pm$.008	.634 $\pm$.018	.644 $\pm$.011	.630 $\pm$.012	.640 $\pm$.010	.631 $\pm$.011	.630 $\pm$.012	.639 $\pm$.007	
body_adiposity percentage	1	.0117 $\pm$.0003	.0114 $\pm$.0011	.0117 $\pm$.0011	.0117 $\pm$.0011	.0128 $\pm$.0030	.0114 $\pm$.0011	.0129 $\pm$.0025	.0116 $\pm$.0011	.0119 $\pm$.0012	.0119 $\pm$.0013	.0116 $\pm$.0012	.0153 $\pm$.0042	.0118 $\pm$.0013	.0115 $\pm$.0009	.0114 $\pm$.0011	
	2	.0114 $\pm$.0009	.0113 $\pm$.0011	.0117 $\pm$.0011	.0118 $\pm$.0011	.0117 $\pm$.0009	.0113 $\pm$.0011	.0131 $\pm$.0027	.0117 $\pm$.0011	.0117 $\pm$.0010	.0116 $\pm$.0009	.0115 $\pm$.0010	.0138 $\pm$.0025	.0115 $\pm$.0013	.0113 $\pm$.0010	.0115 $\pm$.0012	
	3	.0113 $\pm$.0010	.0114 $\pm$.0011	.0119 $\pm$.0009	.0117 $\pm$.0011	.0118 $\pm$.0013	.0114 $\pm$.0011	.0116 $\pm$.0015	.0117 $\pm$.0012	.0119 $\pm$.0009	.0118 $\pm$.0010	.0115 $\pm$.0011	.0123 $\pm$.0021	.0115 $\pm$.0011	.0115 $\pm$.0012	.0112 $\pm$.0012	
	4	.0114 $\pm$.0011	.0114 $\pm$.0010	.0118 $\pm$.0009	.0119 $\pm$.0010	.0118 $\pm$.0013	.0114 $\pm$.0010	.0115 $\pm$.0011	.0119 $\pm$.0009	.0120 $\pm$.0009	.0117 $\pm$.0010	.0115 $\pm$.0011	.0124 $\pm$.0021	.0114 $\pm$.0012	.0114 $\pm$.0011	.0114 $\pm$.0012	
	5	.0114 $\pm$.0010	.0113 $\pm$.0010	.0116 $\pm$.0011	.0118 $\pm$.0012	.0115 $\pm$.0010	.0113 $\pm$.0010	.0115 $\pm$.0010	.0119 $\pm$.0013	.0119 $\pm$.0013	.0115 $\pm$.0009	.0114 $\pm$.0010	.0130 $\pm$.0008	.0115 $\pm$.0012	.0115 $\pm$.0011	.0115 $\pm$.0012	
breast breast (5.6 $^{\circ}$)	1	12.6 $\pm$ 6.2	14.1 $\pm$ 7.1	12.6 $\pm$ 6.2	13.4 $\pm$ 6.8	15.2 $\pm$ 6.1	14.1 $\pm$ 7.1	14.9 $\pm$ 6.0	12.6 $\pm$ 6.2	13							

(continued from previous page)

Dataset	Budget idx j	CART	ElankiNet	F-test	Guifatio	LaplacianScore	Lasso	LOCO	MarkovBlanket	MI	mRMR	(R)Relieff	Random	SSE	RfImportance	SFS
point-components homophily	1	949 $\pm$ 0.16	827 $\pm$ 0.05	863 $\pm$ 0.02	902 $\pm$ 0.05	833 $\pm$ 0.17	822 $\pm$ 0.14	936 $\pm$ 0.08	936 $\pm$ 0.16	922 $\pm$ 0.19	928 $\pm$ 0.15	844 $\pm$ 0.06	842 $\pm$ 0.09	875 $\pm$ 0.09	947 $\pm$ 0.13	933 $\pm$ 0.17
	2	951 $\pm$ 0.14	855 $\pm$ 0.03	878 $\pm$ 0.02	931 $\pm$ 0.02	858 $\pm$ 0.12	859 $\pm$ 0.09	944 $\pm$ 0.14	943 $\pm$ 0.14	936 $\pm$ 0.16	938 $\pm$ 0.12	928 $\pm$ 0.07	888 $\pm$ 0.07	920 $\pm$ 0.04	952 $\pm$ 0.20	940 $\pm$ 0.19
	3	952 $\pm$ 0.16	897 $\pm$ 0.02	879 $\pm$ 0.02	941 $\pm$ 0.17	863 $\pm$ 0.11	900 $\pm$ 0.08	943 $\pm$ 0.17	942 $\pm$ 0.14	938 $\pm$ 0.16	946 $\pm$ 0.15	933 $\pm$ 0.02	889 $\pm$ 0.01	937 $\pm$ 0.03	953 $\pm$ 0.18	943 $\pm$ 0.19
	4	954 $\pm$ 0.12	907 $\pm$ 0.12	913 $\pm$ 0.07	940 $\pm$ 0.17	873 $\pm$ 0.14	907 $\pm$ 0.12	945 $\pm$ 0.12	949 $\pm$ 0.14	942 $\pm$ 0.14	952 $\pm$ 0.15	940 $\pm$ 0.19	943 $\pm$ 0.05	955 $\pm$ 0.13	955 $\pm$ 0.16	949 $\pm$ 0.15
	5	954 $\pm$ 0.14	933 $\pm$ 0.26	940 $\pm$ 0.17	945 $\pm$ 0.14	884 $\pm$ 0.04	934 $\pm$ 0.26	947 $\pm$ 0.13	950 $\pm$ 0.15	952 $\pm$ 0.13	954 $\pm$ 0.15	946 $\pm$ 0.11	943 $\pm$ 0.08	954 $\pm$ 0.14	954 $\pm$ 0.15	955 $\pm$ 0.09
coke_lance	1	500 $\pm$ 0.00	500 $\pm$ 0.00	500 $\pm$ 0.00	500 $\pm$ 0.00	500 $\pm$ 0.00	500 $\pm$ 0.00	500 $\pm$ 0.00	500 $\pm$ 0.00	500 $\pm$ 0.00	500 $\pm$ 0.00	500 $\pm$ 0.00	500 $\pm$ 0.00	500 $\pm$ 0.00	500 $\pm$ 0.00	500 $\pm$ 0.00
	2	500 $\pm$ 0.00	500 $\pm$ 0.00	500 $\pm$ 0.00	500 $\pm$ 0.00	500 $\pm$ 0.00	500 $\pm$ 0.00	500 $\pm$ 0.00	500 $\pm$ 0.00	500 $\pm$ 0.00	500 $\pm$ 0.00	500 $\pm$ 0.00	500 $\pm$ 0.00	500 $\pm$ 0.00	500 $\pm$ 0.00	500 $\pm$ 0.00
	3	500 $\pm$ 0.00	500 $\pm$ 0.00	500 $\pm$ 0.00	500 $\pm$ 0.00	500 $\pm$ 0.00	500 $\pm$ 0.00	500 $\pm$ 0.00	500 $\pm$ 0.00	500 $\pm$ 0.00	500 $\pm$ 0.00	500 $\pm$ 0.00	500 $\pm$ 0.00	500 $\pm$ 0.00	500 $\pm$ 0.00	500 $\pm$ 0.00
	4	500 $\pm$ 0.00	500 $\pm$ 0.00	500 $\pm$ 0.00	500 $\pm$ 0.00	500 $\pm$ 0.00	500 $\pm$ 0.00	500 $\pm$ 0.00	500 $\pm$ 0.00	500 $\pm$ 0.00	500 $\pm$ 0.00	500 $\pm$ 0.00	500 $\pm$ 0.00	500 $\pm$ 0.00	500 $\pm$ 0.00	500 $\pm$ 0.00
	5	500 $\pm$ 0.00	500 $\pm$ 0.00	500 $\pm$ 0.00	500 $\pm$ 0.00	500 $\pm$ 0.00	500 $\pm$ 0.00	500 $\pm$ 0.00	500 $\pm$ 0.00	500 $\pm$ 0.00	500 $\pm$ 0.00	500 $\pm$ 0.00	500 $\pm$ 0.00	500 $\pm$ 0.00	500 $\pm$ 0.00	500 $\pm$ 0.00
ind-balance homophily	1	943 $\pm$ 0.03	939 $\pm$ 0.10	940 $\pm$ 0.09	939 $\pm$ 0.11	933 $\pm$ 0.07	942 $\pm$ 0.16	907 $\pm$ 0.27	935 $\pm$ 0.02	939 $\pm$ 0.09	938 $\pm$ 0.06	887 $\pm$ 0.04	916 $\pm$ 0.15	934 $\pm$ 0.19	936 $\pm$ 0.13	939 $\pm$ 0.09
	2	941 $\pm$ 0.09	946 $\pm$ 0.10	935 $\pm$ 0.09	938 $\pm$ 0.08	941 $\pm$ 0.11	945 $\pm$ 0.10	936 $\pm$ 0.04	939 $\pm$ 0.10	939 $\pm$ 0.12	945 $\pm$ 0.10	945 $\pm$ 0.08	933 $\pm$ 0.04	936 $\pm$ 0.04	941 $\pm$ 0.05	937 $\pm$ 0.11
	3	942 $\pm$ 0.03	943 $\pm$ 0.16	947 $\pm$ 0.14	940 $\pm$ 0.10	941 $\pm$ 0.11	940 $\pm$ 0.10	944 $\pm$ 0.13	944 $\pm$ 0.11	946 $\pm$ 0.08	941 $\pm$ 0.09	942 $\pm$ 0.12	943 $\pm$ 0.08	936 $\pm$ 0.10	943 $\pm$ 0.09	943 $\pm$ 0.09
	4	948 $\pm$ 0.06	940 $\pm$ 0.06	943 $\pm$ 0.12	946 $\pm$ 0.08	946 $\pm$ 0.08	942 $\pm$ 0.12	945 $\pm$ 0.17	944 $\pm$ 0.11	942 $\pm$ 0.11	947 $\pm$ 0.16	943 $\pm$ 0.11	948 $\pm$ 0.10	941 $\pm$ 0.07	945 $\pm$ 0.20	944 $\pm$ 0.07
	5	942 $\pm$ 0.09	943 $\pm$ 0.07	945 $\pm$ 0.08	946 $\pm$ 0.04	943 $\pm$ 0.06	943 $\pm$ 0.04	945 $\pm$ 0.17	946 $\pm$ 0.08	945 $\pm$ 0.06	944 $\pm$ 0.05	946 $\pm$ 0.08	943 $\pm$ 0.10	947 $\pm$ 0.04	946 $\pm$ 0.09	944 $\pm$ 0.13
univariate, ordered non-homophily	1	629 $\pm$ 0.07	630 $\pm$ 0.06	632 $\pm$ 0.04	632 $\pm$ 0.04	501 $\pm$ 0.01	630 $\pm$ 0.06	587 $\pm$ 0.20	632 $\pm$ 0.04	502 $\pm$ 0.02	632 $\pm$ 0.04	503 $\pm$ 0.08	510 $\pm$ 0.05	530 $\pm$ 0.07	632 $\pm$ 0.04	575 $\pm$ 0.11
	2	697 $\pm$ 0.02	700 $\pm$ 0.02	702 $\pm$ 0.03	701 $\pm$ 0.03	501 $\pm$ 0.01	700 $\pm$ 0.02	631 $\pm$ 0.21	701 $\pm$ 0.04	508 $\pm$ 0.02	701 $\pm$ 0.03	505 $\pm$ 0.02	574 $\pm$ 0.27	578 $\pm$ 0.02	700 $\pm$ 0.01	578 $\pm$ 0.07
	3	783 $\pm$ 0.05	786 $\pm$ 0.04	786 $\pm$ 0.05	781 $\pm$ 0.04	515 $\pm$ 0.02	786 $\pm$ 0.04	637 $\pm$ 0.21	784 $\pm$ 0.03	522 $\pm$ 0.02	787 $\pm$ 0.03	509 $\pm$ 0.03	602 $\pm$ 0.13	598 $\pm$ 0.16	785 $\pm$ 0.03	612 $\pm$ 0.21
	4	860 $\pm$ 0.04	868 $\pm$ 0.03	867 $\pm$ 0.03	863 $\pm$ 0.05	525 $\pm$ 0.02	868 $\pm$ 0.03	677 $\pm$ 0.10	859 $\pm$ 0.03	545 $\pm$ 0.04	861 $\pm$ 0.04	525 $\pm$ 0.04	651 $\pm$ 0.12	637 $\pm$ 0.18	866 $\pm$ 0.04	671 $\pm$ 0.23
	5	896 $\pm$ 0.03	896 $\pm$ 0.03	897 $\pm$ 0.03	897 $\pm$ 0.03	543 $\pm$ 0.07	896 $\pm$ 0.03	779 $\pm$ 0.13	891 $\pm$ 0.05	684 $\pm$ 0.03	888 $\pm$ 0.02	565 $\pm$ 0.28	771 $\pm$ 0.19	764 $\pm$ 0.10	895 $\pm$ 0.03	787 $\pm$ 0.14
ind_precision homophily	1	948 $\pm$ 0.23	937 $\pm$ 0.03	927 $\pm$ 0.10	917 $\pm$ 0.29	543 $\pm$ 0.26	909 $\pm$ 0.09	746 $\pm$ 0.87	912 $\pm$ 0.06	923 $\pm$ 0.15	949 $\pm$ 0.15	877 $\pm$ 0.08	786 $\pm$ 0.17	746 $\pm$ 0.12	933 $\pm$ 0.20	757 $\pm$ 0.04
	2	961 $\pm$ 0.12	960 $\pm$ 0.19	953 $\pm$ 0.28	969 $\pm$ 0.14	685 $\pm$ 0.09	981 $\pm$ 0.11	880 $\pm$ 0.51	977 $\pm$ 0.06	972 $\pm$ 0.05	973 $\pm$ 0.07	952 $\pm$ 0.20	857 $\pm$ 0.62	863 $\pm$ 0.33	956 $\pm$ 0.24	875 $\pm$ 0.41
	3	966 $\pm$ 0.07	983 $\pm$ 0.02	968 $\pm$ 0.10	978 $\pm$ 0.09	799 $\pm$ 0.15	987 $\pm$ 0.10	940 $\pm$ 0.11	983 $\pm$ 0.08	991 $\pm$ 0.05	984 $\pm$ 0.03	975 $\pm$ 0.14	957 $\pm$ 0.07	949 $\pm$ 0.17	991 $\pm$ 0.02	946 $\pm$ 0.25
	4	983 $\pm$ 0.11	990 $\pm$ 0.06	982 $\pm$ 0.08	988 $\pm$ 0.01	917 $\pm$ 0.18	989 $\pm$ 0.01	952 $\pm$ 0.16	990 $\pm$ 0.05	990 $\pm$ 0.02	986 $\pm$ 0.03	980 $\pm$ 0.12	974 $\pm$ 0.12	972 $\pm$ 0.08	989 $\pm$ 0.02	969 $\pm$ 0.15
	5	986 $\pm$ 0.09	989 $\pm$ 0.04	989 $\pm$ 0.03	989 $\pm$ 0.03	956 $\pm$ 0.14	991 $\pm$ 0.03	991 $\pm$ 0.09	989 $\pm$ 0.04	989 $\pm$ 0.04	986 $\pm$ 0.04	989 $\pm$ 0.06	979 $\pm$ 0.09	983 $\pm$ 0.06	990 $\pm$ 0.03	985 $\pm$ 0.04
bank_consumer homophily	1	741 $\pm$ 0.10	767 $\pm$ 0.12	767 $\pm$ 0.12	816 $\pm$ 0.03	597 $\pm$ 0.11	767 $\pm$ 0.12	816 $\pm$ 0.03	816 $\pm$ 0.03	816 $\pm$ 0.03	816 $\pm$ 0.03	749 $\pm$ 0.00	540 $\pm$ 0.00	816 $\pm$ 0.03	741 $\pm$ 0.10	816 $\pm$ 0.03
	2	758 $\pm$ 0.08	784 $\pm$ 0.06	784 $\pm$ 0.06	848 $\pm$ 0.07	766 $\pm$ 0.03	784 $\pm$ 0.06	846 $\pm$ 0.07	848 $\pm$ 0.07	832 $\pm$ 0.11	832 $\pm$ 0.07	814 $\pm$ 0.04	683 $\pm$ 0.08	831 $\pm$ 0.12	758 $\pm$ 0.08	836 $\pm$ 0.04
	3	830 $\pm$ 0.01	799 $\pm$ 0.04	833 $\pm$ 0.26	847 $\pm$ 0.08	784 $\pm$ 0.08	799 $\pm$ 0.04	855 $\pm$ 0.15	847 $\pm$ 0.08	855 $\pm$ 0.14	832 $\pm$ 0.07	829 $\pm$ 0.03	708 $\pm$ 0.02	841 $\pm$ 0.03	830 $\pm$ 0.01	843 $\pm$ 0.05
	4	844 $\pm$ 0.02	843 $\pm$ 0.12	864 $\pm$ 0.05	847 $\pm$ 0.08	813 $\pm$ 0.11	843 $\pm$ 0.12	862 $\pm$ 0.04	847 $\pm$ 0.08	859 $\pm$ 0.14	844 $\pm$ 0.03	842 $\pm$ 0.06	798 $\pm$ 0.02	864 $\pm$ 0.06	842 $\pm$ 0.02	858 $\pm$ 0.14
	5	864 $\pm$ 0.03	842 $\pm$ 0.13	864 $\pm$ 0.06	853 $\pm$ 0.11	813 $\pm$ 0.12	842 $\pm$ 0.13	864 $\pm$ 0.06	859 $\pm$ 0.03	864 $\pm$ 0.06	846 $\pm$ 0.02	851 $\pm$ 0.08	837 $\pm$ 0.04	864 $\pm$ 0.06	863 $\pm$ 0.05	864 $\pm$ 0.03
hypothecary, survival homophily	1	775 $\pm$ 0.83	776 $\pm$ 0.77	800 $\pm$ 0.13	807 $\pm$ 0.46	779 $\pm$ 0.11	800 $\pm$ 0.44	769 $\pm$ 0.29	832 $\pm$ 0.11	780 $\pm$ 0.23	833 $\pm$ 0.12	813 $\pm$ 0.07	816 $\pm$ 0.43	791 $\pm$ 0.87	762 $\pm$ 0.24	745 $\pm$ 0.98
	2	800 $\pm$ 0.13	821 $\pm$ 0.03	833 $\pm$ 0.29	822 $\pm$ 0.04	811 $\pm$ 0.18	821 $\pm$ 0.13	752 $\pm$ 0.15	844 $\pm$ 0.22	811 $\pm$ 0.18	834 $\pm$ 0.09	838 $\pm$ 0.15	776 $\pm$ 0.25	797 $\pm$ 0.93	794 $\pm$ 0.10	744 $\pm$ 0.68
	3	817 $\pm$ 0.10	804 $\pm$ 0.15	811 $\pm$ 0.21	813 $\pm$ 0.07	825 $\pm$ 0.43	806 $\pm$ 0.11	766 $\pm$ 0.15	828 $\pm$ 0.42	823 $\pm$ 0.20	812 $\pm$ 0.24	795 $\pm$ 0.19	803 $\pm$ 0.08	815 $\pm$ 0.10	816 $\pm$ 0.14	754 $\pm$ 0.14
	4	813 $\pm$ 0.11	796 $\pm$ 0.13	813 $\pm$ 0.11	802 $\pm$ 0.13	845 $\pm$ 0.11	806 $\pm$ 0.12	793 $\pm$ 0.10	810 $\pm$ 0.14	815 $\pm$ 0.28	816 $\pm$ 0.23	810 $\pm$ 0.48	814 $\pm$ 0.41	837 $\pm$ 0.07	812 $\pm$ 0.24	797 $\pm$ 0.10
	5	817 $\pm$ 0.10	805 $\pm$ 0.27	804 $\pm$ 0.13	808 $\pm$ 0.15	813 $\pm$ 0.12	805 $\pm$ 0.12	799 $\pm$ 0.46	812 $\pm$ 0.15	807 $\pm$ 0.15	808 $\pm$ 0.11	824 $\pm$ 0.17	811 $\pm$ 0.44	808 $\pm$ 0.15	809 $\pm$ 0.13	814 $\pm$ 0.16
customer-satisfaction heterophily	1	957 $\pm$ 0.00	920 $\pm$ 0.01	935 $\pm$ 0.02	924 $\pm$ 0.00	940 $\pm$ 0.01	920 $\pm$ 0.01	941 $\pm$ 0.02	961 $\pm$ 0.00	959 $\pm$ 0.00	913 $\pm$ 0.00	956 $\pm$ 0.00	858 $\pm$ 0.02	968 $\pm$ 0.02	959 $\pm$ 0.00	971 $\pm$ 0.01
	2	979 $\pm$ 0.00	977 $\pm$ 0.01	956 $\pm$ 0.01	976 $\pm$ 0.00	979 $\pm$ 0.00	977 $\pm$ 0.01	976 $\pm$ 0.00	977 $\pm$ 0.00	977 $\pm$ 0.00	973 $\pm$ 0.00	976 $\pm$ 0.05	888 $\pm$ 0.19	985 $\pm$ 0.01	974 $\pm$ 0.01	984 $\pm$ 0.01
	3	989 $\pm$ 0.01	989 $\pm$ 0.01	981 $\pm$ 0.08	985 $\pm$ 0.00	989 $\pm$ 0.00	989 $\pm$ 0.01	989 $\pm$ 0.01	987 $\pm$ 0.01	986 $\pm$ 0.00	983 $\pm$ 0.00	989 $\pm$ 0.00	977 $\pm$ 0.01	992 $\pm$ 0.00	985 $\pm$ 0.01	991

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Dataset	Budget idx	CART	ElankNet	F-test	GuinRatio	LaplacianScore	Lasso	LOCO	MarkovBlanket	MI	mRMR	(R)Relieff	Random	SBE	RFImportance	SFS
cham	1	828 ± 0.11	875 ± 0.05	866 ± 0.09	812 ± 0.12	690 ± 0.08	769 ± 0.20	717 ± 0.11	821 ± 0.07	866 ± 0.09	858 ± 0.04	794 ± 0.11	677 ± 125	891 ± 0.03	866 ± 0.10	891 ± 0.03
	2	905 ± 0.23	903 ± 0.01	904 ± 0.01	841 ± 0.15	732 ± 0.81	852 ± 0.88	810 ± 0.84	859 ± 0.11	881 ± 0.11	892 ± 0.12	815 ± 0.12	714 ± 1.01	911 ± 0.08	901 ± 0.02	908 ± 0.01
	3	921 ± 0.03	910 ± 0.02	912 ± 0.13	878 ± 0.08	825 ± 0.10	917 ± 0.06	841 ± 0.82	857 ± 0.09	900 ± 0.13	915 ± 0.07	903 ± 0.01	754 ± 122	919 ± 0.03	913 ± 0.06	911 ± 0.07
	4	920 ± 0.05	920 ± 0.04	920 ± 0.05	871 ± 0.09	821 ± 0.13	920 ± 0.03	877 ± 0.83	861 ± 0.02	908 ± 0.09	918 ± 0.06	910 ± 0.08	847 ± 0.28	916 ± 0.05	919 ± 0.03	915 ± 0.03
	5	913 ± 0.04	919 ± 0.03	915 ± 0.03	867 ± 0.02	910 ± 0.03	918 ± 0.03	915 ± 0.04	860 ± 0.01	911 ± 0.08	914 ± 0.03	909 ± 0.06	880 ± 0.86	914 ± 0.04	918 ± 0.02	916 ± 0.02
epc-distance	1	980 ± 0.06	958 ± 0.41	977 ± 0.05	963 ± 0.14	928 ± 0.14	977 ± 0.01	949 ± 0.24	980 ± 0.05	982 ± 0.04	972 ± 0.05	942 ± 0.03	966 ± 0.17	942 ± 0.16	984 ± 0.04	976 ± 0.07
	2	987 ± 0.03	981 ± 0.11	981 ± 0.04	977 ± 0.04	960 ± 0.07	984 ± 0.03	977 ± 0.08	983 ± 0.04	983 ± 0.03	985 ± 0.02	967 ± 0.01	979 ± 0.08	973 ± 0.03	987 ± 0.03	982 ± 0.06
	3	989 ± 0.03	990 ± 0.02	985 ± 0.03	979 ± 0.05	981 ± 0.03	988 ± 0.01	987 ± 0.04	988 ± 0.03	985 ± 0.04	987 ± 0.03	984 ± 0.03	987 ± 0.04	986 ± 0.03	990 ± 0.03	987 ± 0.03
	4	991 ± 0.02	991 ± 0.02	989 ± 0.03	990 ± 0.03	988 ± 0.02	991 ± 0.01	990 ± 0.03	990 ± 0.04	987 ± 0.03	990 ± 0.02	988 ± 0.04	989 ± 0.02	989 ± 0.04	991 ± 0.02	989 ± 0.03
	5	992 ± 0.02	991 ± 0.03	991 ± 0.03	991 ± 0.03	991 ± 0.02	991 ± 0.02	991 ± 0.03	991 ± 0.03	991 ± 0.03	992 ± 0.02	991 ± 0.02	992 ± 0.03	992 ± 0.03	991 ± 0.03	991 ± 0.03
labor-impairment	1	500 ± 0.00	500 ± 0.00	500 ± 0.00	500 ± 0.00	500 ± 0.00	500 ± 0.00	500 ± 0.00	500 ± 0.00	500 ± 0.00	500 ± 0.00	500 ± 0.00	500 ± 0.00	500 ± 0.00	500 ± 0.00	500 ± 0.00
	2	500 ± 0.00	500 ± 0.00	500 ± 0.00	500 ± 0.00	500 ± 0.00	500 ± 0.00	500 ± 0.00	500 ± 0.00	500 ± 0.00	500 ± 0.00	500 ± 0.00	500 ± 0.00	500 ± 0.00	500 ± 0.00	500 ± 0.00
	3	500 ± 0.00	500 ± 0.00	500 ± 0.00	500 ± 0.00	500 ± 0.00	500 ± 0.00	500 ± 0.00	500 ± 0.00	500 ± 0.00	500 ± 0.00	500 ± 0.00	500 ± 0.00	500 ± 0.00	500 ± 0.00	500 ± 0.00
	4	500 ± 0.00	500 ± 0.00	500 ± 0.00	500 ± 0.00	500 ± 0.00	500 ± 0.00	500 ± 0.00	500 ± 0.00	500 ± 0.00	500 ± 0.00	500 ± 0.00	500 ± 0.00	500 ± 0.00	500 ± 0.00	500 ± 0.00
	5	500 ± 0.00	500 ± 0.00	500 ± 0.00	500 ± 0.00	500 ± 0.00	500 ± 0.00	500 ± 0.00	500 ± 0.00	500 ± 0.00	500 ± 0.00	500 ± 0.00	500 ± 0.00	500 ± 0.00	500 ± 0.00	500 ± 0.00
MLCovary20-epidemiology	1	655 ± 0.76	522 ± 0.19	762 ± 0.16	746 ± 0.17	539 ± 0.29	522 ± 0.19	799 ± 0.09	765 ± 0.11	620 ± 0.27	750 ± 0.20	653 ± 0.21	515 ± 0.10	505 ± 0.04	748 ± 0.17	798 ± 0.15
	2	709 ± 0.17	542 ± 0.56	769 ± 0.16	745 ± 0.18	558 ± 0.40	542 ± 0.56	804 ± 0.13	795 ± 0.16	625 ± 0.19	762 ± 0.14	644 ± 0.41	549 ± 0.09	530 ± 0.25	756 ± 0.14	800 ± 0.17
	3	782 ± 0.21	578 ± 0.35	774 ± 0.17	786 ± 0.13	558 ± 0.17	578 ± 0.15	801 ± 0.10	793 ± 0.14	709 ± 0.02	764 ± 0.23	767 ± 0.08	602 ± 0.13	623 ± 0.19	770 ± 0.02	793 ± 0.17
	4	795 ± 0.10	606 ± 0.35	782 ± 0.23	794 ± 0.17	602 ± 0.15	606 ± 0.15	798 ± 0.09	785 ± 0.08	771 ± 0.03	784 ± 0.19	787 ± 0.11	714 ± 0.16	683 ± 0.44	772 ± 0.08	782 ± 0.10
	5	793 ± 0.11	719 ± 1.07	792 ± 0.14	796 ± 0.18	713 ± 0.14	719 ± 1.07	809 ± 0.11	780 ± 0.01	772 ± 0.04	786 ± 0.14	796 ± 0.08	724 ± 0.40	726 ± 0.60	796 ± 0.18	787 ± 0.13
pest-out-activity	1	720 ± 0.16	693 ± 0.42	693 ± 0.25	568 ± 0.62	562 ± 0.16	696 ± 0.15	553 ± 0.51	552 ± 0.43	686 ± 0.21	568 ± 0.62	568 ± 0.22	578 ± 0.14	570 ± 0.10	693 ± 0.28	736 ± 0.13
	2	772 ± 0.07	748 ± 0.13	717 ± 0.14	622 ± 0.27	586 ± 0.07	781 ± 0.23	624 ± 0.15	635 ± 0.15	727 ± 0.20	622 ± 0.27	677 ± 0.09	634 ± 0.45	661 ± 0.44	736 ± 0.43	745 ± 0.22
	3	833 ± 0.16	827 ± 0.29	799 ± 0.16	739 ± 0.28	729 ± 0.08	839 ± 0.19	750 ± 0.22	759 ± 0.12	806 ± 0.17	739 ± 0.28	827 ± 0.13	757 ± 0.18	751 ± 0.04	820 ± 0.57	799 ± 0.18
	4	876 ± 0.16	862 ± 0.28	876 ± 0.21	844 ± 0.14	844 ± 0.22	870 ± 0.26	846 ± 0.20	853 ± 0.12	867 ± 0.13	844 ± 0.14	893 ± 0.21	847 ± 0.20	844 ± 0.18	889 ± 0.27	850 ± 0.28
	5	895 ± 0.26	888 ± 0.27	895 ± 0.24	884 ± 0.20	882 ± 0.23	886 ± 0.26	885 ± 0.13	891 ± 0.26	896 ± 0.14	884 ± 0.20	899 ± 0.24	881 ± 0.28	877 ± 0.21	896 ± 0.29	884 ± 0.24
time-series-forecasting-precision	1	932 ± 0.11	927 ± 0.01	928 ± 0.06	932 ± 0.11	933 ± 0.09	923 ± 0.12	922 ± 0.17	929 ± 0.01	932 ± 0.07	932 ± 0.06	917 ± 0.09	936 ± 0.09	927 ± 0.03	937 ± 0.03	936 ± 0.01
	2	934 ± 0.07	934 ± 0.02	931 ± 0.04	937 ± 0.11	939 ± 0.10	941 ± 0.04	936 ± 0.13	934 ± 0.03	936 ± 0.08	941 ± 0.10	929 ± 0.03	934 ± 0.08	939 ± 0.09	937 ± 0.13	941 ± 0.04
	3	935 ± 0.09	939 ± 0.08	928 ± 0.02	940 ± 0.07	938 ± 0.09	945 ± 0.11	943 ± 0.10	937 ± 0.04	938 ± 0.09	939 ± 0.11	932 ± 0.05	939 ± 0.05	944 ± 0.11	942 ± 0.11	942 ± 0.12
	4	942 ± 0.10	946 ± 0.09	934 ± 0.07	939 ± 0.10	936 ± 0.11	947 ± 0.08	942 ± 0.11	940 ± 0.09	940 ± 0.08	941 ± 0.06	942 ± 0.08	941 ± 0.08	942 ± 0.07	942 ± 0.13	942 ± 0.07
	5	947 ± 0.10	945 ± 0.13	939 ± 0.06	939 ± 0.12	942 ± 0.11	946 ± 0.11	942 ± 0.10	943 ± 0.10	944 ± 0.08	940 ± 0.11	941 ± 0.11	946 ± 0.07	940 ± 0.14	941 ± 0.13	944 ± 0.07
beyond-observed	1	969 ± 0.14	778 ± 0.14	892 ± 0.78	974 ± 0.07	533 ± 0.01	778 ± 0.14	967 ± 0.17	965 ± 0.15	923 ± 0.26	911 ± 0.17	935 ± 0.16	706 ± 221	976 ± 0.06	971 ± 0.12	927 ± 0.74
	2	967 ± 0.16	923 ± 0.29	907 ± 0.71	966 ± 0.15	568 ± 0.06	923 ± 0.29	970 ± 0.18	955 ± 0.21	921 ± 0.27	931 ± 0.27	906 ± 0.68	742 ± 173	982 ± 0.05	969 ± 0.15	923 ± 0.83
	3	969 ± 0.18	942 ± 0.30	939 ± 0.48	968 ± 0.17	551 ± 0.17	942 ± 0.30	970 ± 0.14	955 ± 0.21	936 ± 0.15	935 ± 0.26	914 ± 0.02	952 ± 0.24	983 ± 0.03	969 ± 0.15	929 ± 0.75
	4	968 ± 0.17	945 ± 0.15	946 ± 0.16	969 ± 0.18	580 ± 0.15	945 ± 0.15	970 ± 0.14	956 ± 0.22	940 ± 0.09	928 ± 0.15	966 ± 0.16	931 ± 0.74	984 ± 0.03	970 ± 0.16	927 ± 0.74
	5	969 ± 0.18	951 ± 0.25	969 ± 0.16	969 ± 0.18	908 ± 0.00	951 ± 0.25	970 ± 0.14	970 ± 0.16	958 ± 0.20	955 ± 0.13	965 ± 0.16	971 ± 0.17	984 ± 0.03	970 ± 0.16	946 ± 0.85
covid_2020-immunization-epidemiology	1	739 ± 0.17	711 ± 0.66	743 ± 0.16	744 ± 0.15	534 ± 0.03	663 ± 0.00	735 ± 0.27	737 ± 0.28	733 ± 0.06	717 ± 0.14	645 ± 0.19	698 ± 0.45	675 ± 0.45	736 ± 0.12	746 ± 0.12
	2	751 ± 0.25	736 ± 0.41	747 ± 0.20	743 ± 0.22	563 ± 0.15	722 ± 0.43	743 ± 0.26	738 ± 0.21	742 ± 0.21	726 ± 0.44	645 ± 0.21	744 ± 0.29	727 ± 0.13	741 ± 0.13	759 ± 0.24
	3	752 ± 0.24	738 ± 0.40	749 ± 0.24	744 ± 0.22	643 ± 0.25	726 ± 0.43	747 ± 0.23	742 ± 0.23	748 ± 0.19	742 ± 0.10	700 ± 0.28	717 ± 0.13	700 ± 0.47	741 ± 0.23	752 ± 0.26
	4	752 ± 0.23	738 ± 0.40	752 ± 0.22	748 ± 0.23	652 ± 0.21	734 ± 0.40	752 ± 0.20	749 ± 0.16	750 ± 0.14	753 ± 0.09	728 ± 0.18	754 ± 0.24	740 ± 0.19	753 ± 0.22	752 ± 0.26
	5	754 ± 0.21	750 ± 0.10	753 ± 0.22	752 ± 0.26	651 ± 0.24	751 ± 0.27	755 ± 0.24	752 ± 0.21	753 ± 0.21	759 ± 0.20	728 ± 0.17	750 ± 0.26	741 ± 0.17	752 ± 0.22	755 ± 0.21
precision	1	922 ± 0.77	951 ± 0.51	960 ± 0.42	956 ± 0.64	520 ± 0.70	943 ± 0.44	681 ± 0.92	948 ± 0.11	956 ± 0.49	935 ± 0.11	949 ± 0.60	663 ± 144	664 ± 159	947 ± 0.29	854 ± 110
	2	932 ± 0.70	956 ± 0.47	961 ± 0.51	969 ± 0.43	567 ± 1.36	949 ± 0.54	745 ± 0.95	953 ± 0.70	965 ± 0.54	958 ± 0.60	964 ± 0.57	784 ± 154	781 ± 162	958 ± 0.16	871 ± 0.40
	3	944 ± 0.43	955 ± 0.18	955 ± 0.66	957 ± 0.71	676 ± 0.41	964 ± 0.62	791 ± 0.95	955 ± 0.78	963 ± 0.64	961 ± 0.68	961 ± 0.19	851 ± 0.15	810 ± 0.64	962 ± 0.12	910 ± 1.08
	4	953 ± 0.15	957 ± 0.60	967 ± 0.58	964 ± 0.62	841 ± 0.23	969 ± 0.54	926 ± 0.41	949 ± 0.76	962 ± 0.66	957 ± 0.71	963 ± 0.64	930 ± 0.81	925 ± 0.62	961 ± 0.56	931 ± 0.81
	5	960 ± 0.42	960 ± 0.70	964 ± 0.62	963 ± 0.64	926 ± 0.41	971 ± 0.19	925 ± 0.73	958 ± 0.72	962 ± 0.66	962 ± 0.66	964 ± 0.62	963 ± 0.61	962 ± 0.54	961 ± 0.19	965 ± 0.17
covid-epidemiology	1	895 ± 0.11	915 ± 0.08	915 ± 0.06	834 ± 0.04	642 ± 1.11	909 ± 0.07	901 ± 0.19	838 ± 0.18	911 ± 0.06	826 ± 0.14	880 ± 0.11	777 ± 0.66	908 ± 0.10	909 ± 0.07	911 ± 0.13
	2	915 ± 0.10	914 ± 0.08	926 ± 0.15	854 ± 0.08	757 ± 0.51	912 ± 0.02	916 ± 0.12	847 ± 0.02	914 ± 0.08	862 ± 0.54	895 ± 0.15	844 ± 1.11	916 ± 0.13	912 ± 0.03	915 ± 0.17
	3	920 ± 0.12	918 ± 0.04	920 ± 0.15	867 ± 0.13	899 ± 0.05	923 ± 0.04	919 ± 0.08	863 ± 0.09	918 ± 0.11	894 ± 0.17	917 ± 0.07	862 ± 0.54	919 ± 0.06	929 ± 0.12	907 ± 0.12
	4	927 ± 0.05	927 ± 0.09</													

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Dataset	Budget task j	CART	ElasticNet	F-test	GainRatio	LaplaceScore	Lasso	LOCO	MarkovBlanket	MI	mRMR	(R)Relieff	Random	SBE	RFImportance	SFS
breast_cancer svm-kernel	1	902 $\pm$.001	816 $\pm$.002	875 $\pm$.001	711 $\pm$.001	502 $\pm$.000	816 $\pm$.002	799 $\pm$.045	880 $\pm$.019	891 $\pm$.001	902 $\pm$.001	862 $\pm$.037	603 $\pm$.038	605 $\pm$.022	903 $\pm$.001	848 $\pm$.015
	2	944 $\pm$.003	929 $\pm$.001	885 $\pm$.001	871 $\pm$.030	611 $\pm$.001	929 $\pm$.001	856 $\pm$.048	920 $\pm$.001	909 $\pm$.001	908 $\pm$.001	920 $\pm$.001	725 $\pm$.062	725 $\pm$.052	912 $\pm$.001	871 $\pm$.008
	3	957 $\pm$.002	951 $\pm$.001	910 $\pm$.001	916 $\pm$.000	676 $\pm$.001	950 $\pm$.000	924 $\pm$.036	932 $\pm$.000	928 $\pm$.002	923 $\pm$.001	939 $\pm$.001	774 $\pm$.056	780 $\pm$.054	956 $\pm$.001	904 $\pm$.003
	4	962 $\pm$.001	962 $\pm$.000	955 $\pm$.000	932 $\pm$.000	702 $\pm$.001	959 $\pm$.003	944 $\pm$.019	936 $\pm$.002	941 $\pm$.000	939 $\pm$.005	946 $\pm$.001	867 $\pm$.025	855 $\pm$.009	961 $\pm$.001	905 $\pm$.008
	5	965 $\pm$.001	966 $\pm$.000	961 $\pm$.000	941 $\pm$.000	754 $\pm$.006	966 $\pm$.000	931 $\pm$.014	945 $\pm$.002	965 $\pm$.000	964 $\pm$.000	960 $\pm$.001	947 $\pm$.010	926 $\pm$.026	962 $\pm$.001	944 $\pm$.006
breast_cancer svm-linear	1	575 $\pm$.067	646 $\pm$.128	647 $\pm$.141	611 $\pm$.128	671 $\pm$.115	646 $\pm$.128	620 $\pm$.075	628 $\pm$.112	618 $\pm$.118	609 $\pm$.111	605 $\pm$.115	575 $\pm$.055	618 $\pm$.115	564 $\pm$.061	619 $\pm$.075
	2	611 $\pm$.110	666 $\pm$.130	617 $\pm$.065	654 $\pm$.119	648 $\pm$.104	666 $\pm$.130	605 $\pm$.067	611 $\pm$.075	651 $\pm$.109	609 $\pm$.111	582 $\pm$.114	578 $\pm$.070	663 $\pm$.098	557 $\pm$.031	614 $\pm$.068
	3	604 $\pm$.071	642 $\pm$.130	621 $\pm$.068	630 $\pm$.101	696 $\pm$.142	642 $\pm$.130	640 $\pm$.099	659 $\pm$.103	660 $\pm$.113	639 $\pm$.171	631 $\pm$.111	659 $\pm$.057	665 $\pm$.099	621 $\pm$.065	628 $\pm$.083
	4	660 $\pm$.093	639 $\pm$.134	649 $\pm$.082	647 $\pm$.089	702 $\pm$.138	639 $\pm$.134	665 $\pm$.097	646 $\pm$.101	667 $\pm$.089	666 $\pm$.176	650 $\pm$.111	630 $\pm$.105	675 $\pm$.099	648 $\pm$.089	668 $\pm$.094
	5	648 $\pm$.087	633 $\pm$.076	666 $\pm$.098	644 $\pm$.092	694 $\pm$.099	633 $\pm$.076	652 $\pm$.081	644 $\pm$.092	675 $\pm$.083	652 $\pm$.080	645 $\pm$.092	635 $\pm$.087	673 $\pm$.101	644 $\pm$.092	664 $\pm$.087
svm_svmlog	1	899 $\pm$.018	885 $\pm$.014	856 $\pm$.017	888 $\pm$.011	660 $\pm$.054	873 $\pm$.011	880 $\pm$.026	910 $\pm$.007	889 $\pm$.028	908 $\pm$.009	902 $\pm$.003	874 $\pm$.024	899 $\pm$.015	873 $\pm$.015	911 $\pm$.023
	2	921 $\pm$.005	920 $\pm$.006	910 $\pm$.014	909 $\pm$.006	884 $\pm$.012	906 $\pm$.008	912 $\pm$.009	918 $\pm$.004	913 $\pm$.011	910 $\pm$.008	921 $\pm$.011	896 $\pm$.016	917 $\pm$.013	910 $\pm$.011	916 $\pm$.019
	3	920 $\pm$.008	922 $\pm$.015	921 $\pm$.008	923 $\pm$.011	910 $\pm$.011	917 $\pm$.014	918 $\pm$.008	921 $\pm$.004	922 $\pm$.010	917 $\pm$.011	919 $\pm$.009	919 $\pm$.006	924 $\pm$.004	922 $\pm$.009	923 $\pm$.016
	4	921 $\pm$.006	925 $\pm$.014	925 $\pm$.012	925 $\pm$.007	915 $\pm$.008	924 $\pm$.015	920 $\pm$.008	924 $\pm$.005	925 $\pm$.008	929 $\pm$.007	926 $\pm$.008	926 $\pm$.010	924 $\pm$.006	923 $\pm$.007	925 $\pm$.009
	5	924 $\pm$.008	925 $\pm$.008	926 $\pm$.008	925 $\pm$.007	922 $\pm$.012	925 $\pm$.011	925 $\pm$.007	926 $\pm$.007	925 $\pm$.008	930 $\pm$.010	926 $\pm$.008	924 $\pm$.007	925 $\pm$.007	926 $\pm$.008	928 $\pm$.007
svmsvmlog_random svmsvmlog-random	1	979 $\pm$.000	977 $\pm$.004	978 $\pm$.001	849 $\pm$.052	581 $\pm$.001	969 $\pm$.011	973 $\pm$.005	782 $\pm$.092	974 $\pm$.006	849 $\pm$.052	972 $\pm$.001	885 $\pm$.069	849 $\pm$.075	979 $\pm$.001	973 $\pm$.005
	2	982 $\pm$.001	982 $\pm$.002	981 $\pm$.002	936 $\pm$.002	633 $\pm$.003	980 $\pm$.004	978 $\pm$.002	877 $\pm$.047	981 $\pm$.003	936 $\pm$.002	979 $\pm$.000	886 $\pm$.012	932 $\pm$.019	983 $\pm$.001	975 $\pm$.006
	3	983 $\pm$.001	984 $\pm$.002	983 $\pm$.002	956 $\pm$.009	724 $\pm$.010	983 $\pm$.001	980 $\pm$.003	954 $\pm$.005	983 $\pm$.002	956 $\pm$.009	982 $\pm$.001	950 $\pm$.008	949 $\pm$.022	984 $\pm$.001	980 $\pm$.002
	4	984 $\pm$.001	985 $\pm$.002	984 $\pm$.002	978 $\pm$.005	822 $\pm$.002	984 $\pm$.001	981 $\pm$.003	967 $\pm$.001	984 $\pm$.002	978 $\pm$.005	984 $\pm$.001	957 $\pm$.029	960 $\pm$.033	985 $\pm$.001	982 $\pm$.001
	5	984 $\pm$.001	985 $\pm$.002	983 $\pm$.001	954 $\pm$.007	985 $\pm$.001	982 $\pm$.002	982 $\pm$.002	981 $\pm$.003	984 $\pm$.001	983 $\pm$.001	984 $\pm$.001	977 $\pm$.005	979 $\pm$.008	985 $\pm$.001	983 $\pm$.003
svmsvmlog svmsvmlog	1	600 $\pm$.059	676 $\pm$.033	658 $\pm$.012	666 $\pm$.016	558 $\pm$.021	674 $\pm$.033	662 $\pm$.013	648 $\pm$.022	661 $\pm$.017	671 $\pm$.008	659 $\pm$.019	574 $\pm$.021	665 $\pm$.004	625 $\pm$.031	673 $\pm$.008
	2	656 $\pm$.025	686 $\pm$.022	663 $\pm$.015	664 $\pm$.016	589 $\pm$.017	686 $\pm$.022	683 $\pm$.021	654 $\pm$.023	660 $\pm$.017	688 $\pm$.016	674 $\pm$.018	630 $\pm$.018	690 $\pm$.015	673 $\pm$.009	677 $\pm$.015
	3	688 $\pm$.022	691 $\pm$.016	689 $\pm$.014	683 $\pm$.024	642 $\pm$.020	696 $\pm$.017	696 $\pm$.013	682 $\pm$.022	670 $\pm$.017	695 $\pm$.019	681 $\pm$.020	657 $\pm$.020	696 $\pm$.014	688 $\pm$.022	685 $\pm$.004
	4	697 $\pm$.021	694 $\pm$.016	696 $\pm$.017	689 $\pm$.021	689 $\pm$.021	694 $\pm$.016	695 $\pm$.015	689 $\pm$.021	681 $\pm$.020	693 $\pm$.020	689 $\pm$.021	690 $\pm$.021	695 $\pm$.019	699 $\pm$.022	693 $\pm$.013
	5	703 $\pm$.022	698 $\pm$.022	701 $\pm$.022	703 $\pm$.021	695 $\pm$.021	696 $\pm$.020	700 $\pm$.020	695 $\pm$.016	696 $\pm$.026	696 $\pm$.020	698 $\pm$.019	682 $\pm$.031	697 $\pm$.019	703 $\pm$.022	697 $\pm$.018

Table D.6: Per-cell results with downstream model **Linear**. Tasks are grouped by metric. Each cell is the mean over three seeds, with the sample standard deviation as a subscript.

Dataset	Budget task, j	CART	ElasticNet	F-test	GainRatio	LaplaceScore	Lasso	LOCO	MarkovBlanket	MI	mRMR	(R)Relieff	Random	SBE	RFImportance	SFS
log-loss (↓)																
breast_cancer svm-kernel	1	.767 ± .068	.737 ± .075	.741 ± .061	.804 ± .050	.836 ± .053	.737 ± .075	.796 ± .070	.770 ± .030	.762 ± .088	.786 ± .061	.791 ± .050	.838 ± .068	.826 ± .119	.765 ± .067	.865 ± .040
	2	.763 ± .070	.791 ± .093	.766 ± .049	.769 ± .044	.861 ± .106	.769 ± .066	.790 ± .068	.731 ± .054	.803 ± .100	.763 ± .040	.774 ± .047	.841 ± .112	.808 ± .105	.720 ± .050	.865 ± .085
	3	.786 ± .059	.814 ± .085	.796 ± .016	.826 ± .048	.874 ± .080	.797 ± .085	.811 ± .121	.783 ± .045	.817 ± .108	.778 ± .041	.827 ± .030	.771 ± .047	.795 ± .023	.787 ± .018	.901 ± .085
	4	.868 ± .080	.878 ± .078	.870 ± .052	.857 ± .053	.812 ± .053	.878 ± .065	.889 ± .184	.843 ± .066	.840 ± .018	.848 ± .024	.867 ± .013	.889 ± .037	.803 ± .017	.859 ± .014	.949 ± .109
	5	.899 ± .031	.904 ± .048	.920 ± .034	.876 ± .018	.855 ± .042	.908 ± .069	.929 ± .142	.882 ± .017	.896 ± .047	.871 ± .041	.906 ± .037	.893 ± .107	.816 ± .015	.904 ± .019	.970 ± .100
svm svm	1	.659 ± .134	.273 ± .134	.496 ± .202	.561 ± .111	1.33 ± .13	.441 ± .189	1.28 ± .13	.730 ± .098	.538 ± .017	.465 ± .243	.362 ± .108	.958 ± .411	1.12 ± .36	.420 ± .149	1.15 ± .23
	2	.618 ± .237	.119 ± .054	.267 ± .131	.233 ± .139	1.02 ± .28	.150 ± .040	.682 ± .272	.235 ± .112	.207 ± .104	.236 ± .088	.161 ± .020	1.53 ± .23	1.11 ± .25	.130 ± .012	1.09 ± .17
	3	.396 ± .020	.0647 ± .0476	.0779 ± .0439	.0636 ± .0368	.713 ± .122	.0865 ± .0745	.423 ± .164	.0987 ± .0800	.0787 ± .0455	.0696 ± .0426	.0542 ± .0247	.374 ± .169	.398 ± .182	.0672 ± .0087	.391 ± .036
	4	.160 ± .032	.0458 ± .0184	.0424 ± .0118	.0483 ± .0121	.428 ± .144	.0983 ± .0523	.193 ± .074	.0492 ± .0222	.0362 ± .0074	.0503 ± .0104	.0417 ± .0190	.250 ± .076	.189 ± .091	.0590 ± .0184	.280 ± .054
	5	.133 ± .050	.0618 ± .0056	.0674 ± .0090	.0589 ± .0059	.186 ± .026	.0917 ± .0277	.132 ± .022	.0528 ± .0105	.0571 ± .0119	.0558 ± .0100	.0607 ± .0168	.120 ± .033	.112 ± .020	.0734 ± .0034	.120 ± .020
svm_17	1	.170 ± .003	.187 ± .014	.223 ± .004	.228 ± .003	.732 ± .001	.352 ± .311	.172 ± .001	.172 ± .001	.207 ± .002	.232 ± .003	.221 ± .002	.606 ± .397	.170 ± .003	.228 ± .003	.207 ± .003
	2	.158 ± .005	.161 ± .004	.171 ± .003	.159 ± .002	.624 ± .098	.159 ± .004	.159 ± .005	.162 ± .006	.147 ± .004	.219 ± .003	.171 ± .003	.181 ± .032	.157 ± .003	.160 ± .003	.158 ± .003
	3	.142 ± .003	.156 ± .002	.163 ± .008	.142 ± .003	.581 ± .035	.156 ± .002	.155 ± .002	.142 ± .003	.142 ± .003	.170 ± .005	.157 ± .002	.641 ± .094	.155 ± .003	.147 ± .008	.145 ± .004
	4	.142 ± .003	.154 ± .002	.160 ± .005	.141 ± .003	.279 ± .213	.154 ± .002	.150 ± .009	.141 ± .003	.142 ± .003	.154 ± .005	.143 ± .002	.415 ± .227	.154 ± .003	.142 ± .003	.142 ± .003
5	.142 ± .003	.155 ± .002	.151 ± .009	.142 ± .003	.143 ± .004	.155 ± .002	.141 ± .003	.142 ± .002	.142 ± .003	.142 ± .003	.142 ± .002	.275 ± .231	.141 ± .003	.142 ± .003	.141 ± .003	
svm_17 svm-kernel	1	.658 ± .031	.610 ± .017	.704 ± .015	.692 ± .010	.977 ± .022	.615 ± .018	.646 ± .037	.616 ± .003	.664 ± .019	.734 ± .019	.661 ± .020	.731 ± .045	.727 ± .036	.725 ± .030	.713 ± .020
	2	.588 ± .006	.579 ± .020	.587 ± .014	.611 ± .015	.891 ± .022	.580 ± .021	.619 ± .025	.602 ± .010	.576 ± .024	.689 ± .012	.640 ± .006	.669 ± .034	.660 ± .077	.607 ± .013	.669 ± .020
	3	.575 ± .010	.566 ± .013	.575 ± .023	.603 ± .009	.740 ± .019	.569 ± .009	.582 ± .025	.601 ± .004	.564 ± .018	.634 ± .015	.572 ± .017	.705 ± .015	.621 ± .058	.589 ± .015	.611 ± .029
	4	.569 ± .010	.565 ± .013	.570 ± .014	.602 ± .009	.624 ± .018	.567 ± .014	.575 ± .029	.602 ± .009	.566 ± .020	.623 ± .011	.569 ± .017	.615 ± .017	.574 ± .021	.564 ± .021	.594 ± .062
5	.566 ± .019	.566 ± .018	.564 ± .016	.580 ± .024	.570 ± .016	.566 ± .020	.576 ± .031	.599 ± .013	.571 ± .018	.595 ± .017	.572 ± .015	.582 ± .036	.569 ± .026	.565 ± .022	.575 ± .012	
svm_17 svm-kernel	1	1.61 ± .06	1.74 ± .10	1.71 ± .07	2.03 ± .15	2.12 ± .03	1.85 ± .21	1.78 ± .11	1.72 ± .05	1.69 ± .06	1.73 ± .04	1.71 ± .05	2.07 ± .14	2.11 ± .04	1.72 ± .05	1.84 ± .08
	2	1.61 ± .10	1.66 ± .06	1.67 ± .09	1.83 ± .15	2.12 ± .03	1.80 ± .14	1.75 ± .10	1.73 ± .06	1.62 ± .09	1.75 ± .07	1.65 ± .07	2.13 ± .05	2.14 ± .06	1.74 ± .04	1.85 ± .08
	3	1.76 ± .20	1.74 ± .07	1.63 ± .05	1.74 ± .06	2.04 ± .10	1.69 ± .10	1.80 ± .08	1.78 ± .04	1.67 ± .08	1.68 ± .07	1.27 ± .10	2.06 ± .11	2.06 ± .11	1.82 ± .09	1.82 ± .02
	4	1.93 ± .10	1.86 ± .09	1.78 ± .07	1.91 ± .12	1.99 ± .03	1.75 ± .07	1.82 ± .07	2.08 ± .12	1.90 ± .12	2.11 ± .16	1.85 ± .20	2.05 ± .38	2.13 ± .05	1.91 ± .09	1.97 ± .04
5	2.03 ± .03	2.04 ± .08	1.89 ± .04	2.22 ± .15	1.95 ± .15	1.93 ± .03	2.00 ± .08	2.23 ± .17	1.98 ± .11	2.21 ± .14	2.03 ± .05	2.38 ± .13	2.12 ± .23	2.07 ± .08	2.19 ± .04	
svm_17 svm-kernel	1	1.07 ± .00	1.08 ± .01	1.16 ± .02	1.34 ± .01	1.25 ± .02	1.13 ± .01	1.25 ± .05	1.07 ± .00	1.19 ± .02	1.11 ± .01	1.26 ± .05	1.40 ± .06	1.38 ± .06	1.07 ± .00	1.36 ± .12
	2	.899 ± .007	.909 ± .002	.964 ± .018	1.10 ± .01	1.01 ± .02	.924 ± .019	1.12 ± .01	.910 ± .003	.981 ± .003	.970 ± .001	1.02 ± .01	1.14 ± .02	1.11 ± .03	.911 ± .001	1.17 ± .06
	3	.828 ± .007	.818 ± .001	.847 ± .003	.881 ± .003	.852 ± .005	.825 ± .002	1.01 ± .07	.830 ± .002	.884 ± .005	.873 ± .004	.905 ± .009	.976 ± .021	.971 ± .015	.828 ± .005	.987 ± .015
	4	.790 ± .004	.780 ± .001	.796 ± .001	.817 ± .003	.804 ± .004	.787 ± .001	.878 ± .014	.791 ± .002	.798 ± .003	.798 ± .002	.828 ± .004	.898 ± .016	.890 ± .045	.783 ± .002	.895 ± .032
5	.766 ± .002	.764 ± .001	.769 ± .006	.769 ± .001	.768 ± .003	.764 ± .002	.795 ± .005	.765 ± .003	.766 ± .002	.770 ± .001	.786 ± .003	.813 ± .021	.835 ± .003	.765 ± .002	.826 ± .001	

(continued from previous page)

Dataset	Budget idx	CART	ElankNet	F-test	GuinRatio	LaplacianScore	Lasso	LOCO	MarkovBlanket	MI	mRMR	(RR)Relieff	Random	SBE	RFImportance	SFS
img_cancer	1	.294 $\pm$.054	.402 $\pm$.059	.535 $\pm$.107	.352 $\pm$.105	.816 $\pm$.098	.440 $\pm$.217	.618 $\pm$.061	.348 $\pm$.085	.411 $\pm$.088	.316 $\pm$.054	.378 $\pm$.034	.761 $\pm$.080	.737 $\pm$.106	.340 $\pm$.101	.615 $\pm$.149
	2	.263 $\pm$.024	.216 $\pm$.043	.380 $\pm$.004	.221 $\pm$.017	.824 $\pm$.180	.285 $\pm$.104	.354 $\pm$.049	.227 $\pm$.052	.221 $\pm$.043	.213 $\pm$.033	.209 $\pm$.060	.507 $\pm$.182	.556 $\pm$.020	.220 $\pm$.087	.455 $\pm$.151
	3	.185 $\pm$.057	.153 $\pm$.024	.181 $\pm$.012	.155 $\pm$.032	.663 $\pm$.108	.203 $\pm$.037	.245 $\pm$.076	.188 $\pm$.041	.166 $\pm$.035	.160 $\pm$.014	.186 $\pm$.044	.159 $\pm$.040	.227 $\pm$.071	.161 $\pm$.042	.262 $\pm$.030
	4	.176 $\pm$.017	.140 $\pm$.011	.155 $\pm$.007	.150 $\pm$.012	.482 $\pm$.118	.157 $\pm$.024	.162 $\pm$.010	.155 $\pm$.010	.146 $\pm$.012	.150 $\pm$.008	.171 $\pm$.018	.173 $\pm$.014	.159 $\pm$.031	.148 $\pm$.007	.160 $\pm$.030
	5	.154 $\pm$.026	.155 $\pm$.019	.158 $\pm$.016	.142 $\pm$.005	.253 $\pm$.006	.155 $\pm$.013	.155 $\pm$.010	.145 $\pm$.004	.144 $\pm$.010	.162 $\pm$.008	.155 $\pm$.007	.165 $\pm$.011	.163 $\pm$.002	.160 $\pm$.012	.163 $\pm$.006
synapse_high	1	.917 $\pm$.048	1.52 $\pm$.04	1.42 $\pm$.19	1.45 $\pm$.07	1.38 $\pm$.17	1.39 $\pm$.11	1.28 $\pm$.17	.835 $\pm$.052	.912 $\pm$.067	.878 $\pm$.044	1.49 $\pm$.05	1.46 $\pm$.10	1.17 $\pm$.14	.816 $\pm$.037	1.02 $\pm$.15
	2	.598 $\pm$.034	1.13 $\pm$.05	.957 $\pm$.068	.856 $\pm$.086	.833 $\pm$.208	1.15 $\pm$.06	.858 $\pm$.084	.697 $\pm$.092	.622 $\pm$.041	.780 $\pm$.061	1.08 $\pm$.05	.947 $\pm$.100	.805 $\pm$.070	.572 $\pm$.043	.703 $\pm$.055
	3	.595 $\pm$.034	.804 $\pm$.055	.803 $\pm$.132	.622 $\pm$.066	.661 $\pm$.127	.930 $\pm$.125	.734 $\pm$.042	.633 $\pm$.053	.462 $\pm$.054	.675 $\pm$.066	.725 $\pm$.035	.609 $\pm$.036	.608 $\pm$.113	.568 $\pm$.038	.585 $\pm$.115
	4	.535 $\pm$.039	.618 $\pm$.061	.648 $\pm$.142	.514 $\pm$.104	.543 $\pm$.091	.725 $\pm$.094	.612 $\pm$.050	.533 $\pm$.091	.452 $\pm$.056	.593 $\pm$.066	.575 $\pm$.062	.585 $\pm$.044	.554 $\pm$.089	.506 $\pm$.041	.582 $\pm$.108
	5	.496 $\pm$.068	.496 $\pm$.041	.516 $\pm$.077	.476 $\pm$.071	.479 $\pm$.103	.632 $\pm$.038	.533 $\pm$.049	.520 $\pm$.074	.463 $\pm$.068	.509 $\pm$.074	.474 $\pm$.053	.533 $\pm$.073	.490 $\pm$.044	.479 $\pm$.073	.511 $\pm$.070
mtc	1	.489 $\pm$.007	.526 $\pm$.015	.527 $\pm$.027	.547 $\pm$.014	.694 $\pm$.017	.524 $\pm$.026	.658 $\pm$.041	.495 $\pm$.001	.550 $\pm$.012	.517 $\pm$.025	.535 $\pm$.019	.692 $\pm$.008	.690 $\pm$.014	.530 $\pm$.032	.557 $\pm$.035
	2	.486 $\pm$.019	.504 $\pm$.021	.495 $\pm$.006	.549 $\pm$.009	.691 $\pm$.017	.518 $\pm$.033	.649 $\pm$.038	.495 $\pm$.003	.559 $\pm$.016	.496 $\pm$.033	.549 $\pm$.020	.685 $\pm$.016	.673 $\pm$.044	.511 $\pm$.019	.562 $\pm$.039
	3	.504 $\pm$.022	.499 $\pm$.005	.508 $\pm$.012	.524 $\pm$.020	.684 $\pm$.022	.503 $\pm$.006	.604 $\pm$.034	.492 $\pm$.016	.513 $\pm$.028	.491 $\pm$.022	.554 $\pm$.024	.557 $\pm$.021	.604 $\pm$.080	.498 $\pm$.024	.569 $\pm$.032
	4	.532 $\pm$.023	.528 $\pm$.030	.511 $\pm$.007	.513 $\pm$.015	.678 $\pm$.004	.528 $\pm$.025	.555 $\pm$.033	.495 $\pm$.014	.521 $\pm$.039	.507 $\pm$.038	.543 $\pm$.007	.595 $\pm$.021	.565 $\pm$.038	.525 $\pm$.038	.563 $\pm$.050
	5	.557 $\pm$.055	.555 $\pm$.043	.529 $\pm$.014	.522 $\pm$.035	.662 $\pm$.028	.556 $\pm$.042	.555 $\pm$.055	.538 $\pm$.024	.538 $\pm$.046	.556 $\pm$.028	.572 $\pm$.034	.613 $\pm$.037	.539 $\pm$.038	.571 $\pm$.063	.555 $\pm$.084
jhelium_pulsar_j1000	1	1.74 $\pm$.09	1.91 $\pm$.14	1.87 $\pm$.02	1.76 $\pm$.09	2.04 $\pm$.00	1.83 $\pm$.08	1.85 $\pm$.17	1.85 $\pm$.11	1.77 $\pm$.11	1.83 $\pm$.11	1.92 $\pm$.12	1.87 $\pm$.14	1.80 $\pm$.13	1.83 $\pm$.11	1.82 $\pm$.10
	2	1.63 $\pm$.14	1.74 $\pm$.15	1.70 $\pm$.09	1.63 $\pm$.15	1.87 $\pm$.12	1.82 $\pm$.19	1.66 $\pm$.13	1.66 $\pm$.13	1.54 $\pm$.15	1.63 $\pm$.15	1.68 $\pm$.11	1.81 $\pm$.30	1.76 $\pm$.21	1.67 $\pm$.13	1.75 $\pm$.17
	3	1.46 $\pm$.15	1.69 $\pm$.18	1.56 $\pm$.09	1.57 $\pm$.17	1.83 $\pm$.13	1.64 $\pm$.14	1.54 $\pm$.09	1.50 $\pm$.18	1.45 $\pm$.09	1.57 $\pm$.17	1.61 $\pm$.10	1.68 $\pm$.22	1.60 $\pm$.11	1.48 $\pm$.22	1.62 $\pm$.19
	4	1.41 $\pm$.19	1.62 $\pm$.17	1.46 $\pm$.12	1.48 $\pm$.14	1.66 $\pm$.16	1.56 $\pm$.18	1.48 $\pm$.17	1.50 $\pm$.25	1.40 $\pm$.16	1.48 $\pm$.14	1.51 $\pm$.10	1.52 $\pm$.06	1.45 $\pm$.17	1.37 $\pm$.15	1.49 $\pm$.17
	5	1.41 $\pm$.16	1.52 $\pm$.17	1.49 $\pm$.13	1.45 $\pm$.15	1.55 $\pm$.13	1.47 $\pm$.18	1.45 $\pm$.17	1.48 $\pm$.20	1.41 $\pm$.16	1.45 $\pm$.15	1.51 $\pm$.16	1.49 $\pm$.24	1.46 $\pm$.18	1.41 $\pm$.16	1.44 $\pm$.16
moral	1	.144 $\pm$.008	.217 $\pm$.002	.268 $\pm$.014	.156 $\pm$.008	.525 $\pm$.020	.209 $\pm$.021	.195 $\pm$.058	.158 $\pm$.010	.187 $\pm$.022	.184 $\pm$.025	.191 $\pm$.016	.623 $\pm$.130	.169 $\pm$.024	.152 $\pm$.028	.158 $\pm$.022
	2	.110 $\pm$.010	.119 $\pm$.021	.170 $\pm$.035	.136 $\pm$.006	.433 $\pm$.002	.115 $\pm$.010	.129 $\pm$.051	.134 $\pm$.010	.139 $\pm$.016	.131 $\pm$.003	.130 $\pm$.017	.340 $\pm$.001	.124 $\pm$.030	.122 $\pm$.010	.121 $\pm$.027
	3	.106 $\pm$.017	.101 $\pm$.015	.111 $\pm$.022	.111 $\pm$.020	.372 $\pm$.023	.100 $\pm$.020	.113 $\pm$.051	.117 $\pm$.006	.116 $\pm$.021	.111 $\pm$.020	.112 $\pm$.016	.233 $\pm$.046	.0996 $\pm$.0179	.103 $\pm$.020	.122 $\pm$.019
	4	.102 $\pm$.018	.100 $\pm$.020	.104 $\pm$.026	.104 $\pm$.027	.251 $\pm$.046	.0924 $\pm$.0173	.103 $\pm$.031	.0942 $\pm$.0177	.107 $\pm$.026	.104 $\pm$.026	.0997 $\pm$.0176	.212 $\pm$.072	.0951 $\pm$.0216	.0906 $\pm$.0176	.111 $\pm$.025
	5	.104 $\pm$.023	.0913 $\pm$.0267	.0900 $\pm$.0182	.0968 $\pm$.0207	.0854 $\pm$.0216	.0847 $\pm$.0228	.0941 $\pm$.0365	.0928 $\pm$.0226	.0934 $\pm$.0216	.0968 $\pm$.0207	.0921 $\pm$.0265	.0932 $\pm$.0224	.0915 $\pm$.0178	.0869 $\pm$.0221	.101 $\pm$.028
audiology_australian	1	.443 $\pm$.157	.477 $\pm$.130	.454 $\pm$.122	.444 $\pm$.147	.536 $\pm$.077	.538 $\pm$.073	.533 $\pm$.049	.463 $\pm$.117	.407 $\pm$.130	.489 $\pm$.107	.430 $\pm$.120	.520 $\pm$.061	.491 $\pm$.137	.403 $\pm$.132	.428 $\pm$.082
	2	.418 $\pm$.189	.427 $\pm$.139	.370 $\pm$.179	.427 $\pm$.184	.427 $\pm$.130	.540 $\pm$.028	.526 $\pm$.093	.416 $\pm$.137	.359 $\pm$.123	.435 $\pm$.133	.409 $\pm$.124	.461 $\pm$.215	.449 $\pm$.098	.393 $\pm$.213	.369 $\pm$.128
	3	.352 $\pm$.246	.367 $\pm$.135	.333 $\pm$.138	.403 $\pm$.165	.372 $\pm$.003	.414 $\pm$.103	.472 $\pm$.117	.408 $\pm$.195	.375 $\pm$.176	.358 $\pm$.098	.355 $\pm$.154	.416 $\pm$.125	.385 $\pm$.048	.316 $\pm$.180	.367 $\pm$.143
	4	.303 $\pm$.187	.325 $\pm$.149	.325 $\pm$.141	.324 $\pm$.138	.358 $\pm$.126	.337 $\pm$.137	.443 $\pm$.128	.345 $\pm$.103	.355 $\pm$.190	.312 $\pm$.105	.359 $\pm$.184	.338 $\pm$.109	.376 $\pm$.054	.293 $\pm$.185	.373 $\pm$.163
	5	.300 $\pm$.212	.317 $\pm$.161	.319 $\pm$.157	.318 $\pm$.196	.336 $\pm$.162	.308 $\pm$.158	.385 $\pm$.171	.300 $\pm$.138	.343 $\pm$.229	.306 $\pm$.187	.332 $\pm$.194	.354 $\pm$.160	.339 $\pm$.129	.293 $\pm$.187	.358 $\pm$.169
RMSE ($\downarrow$)																
spec_au11	1	1.35 $\pm$.02	1.44 $\pm$.03	1.39 $\pm$.03	1.53 $\pm$.02	1.41 $\pm$.03	1.45 $\pm$.02	1.46 $\pm$.05	1.53 $\pm$.01	1.40 $\pm$.04	1.53 $\pm$.02	1.50 $\pm$.01	1.53 $\pm$.01	1.53 $\pm$.01	1.35 $\pm$.03	1.39 $\pm$.01
	2	1.29 $\pm$.02	1.34 $\pm$.02	1.37 $\pm$.04	1.51 $\pm$.01	1.38 $\pm$.03	1.34 $\pm$.02	1.41 $\pm$.05	1.49 $\pm$.05	1.35 $\pm$.03	1.51 $\pm$.01	1.43 $\pm$.05	1.51 $\pm$.02	1.52 $\pm$.00	1.28 $\pm$.01	1.37 $\pm$.01
	3	1.24 $\pm$.03	1.23 $\pm$.02	1.26 $\pm$.02	1.45 $\pm$.03	1.31 $\pm$.04	1.21 $\pm$.02	1.36 $\pm$.02	1.42 $\pm$.02	1.29 $\pm$.03	1.45 $\pm$.03	1.38 $\pm$.04	1.42 $\pm$.03	1.41 $\pm$.05	1.21 $\pm$.01	1.36 $\pm$.02
	4	1.14 $\pm$.01	1.07 $\pm$.02	1.14 $\pm$.02	1.31 $\pm$.02	1.20 $\pm$.02	1.06 $\pm$.02	1.27 $\pm$.03	1.30 $\pm$.01	1.18 $\pm$.02	1.31 $\pm$.02	1.21 $\pm$.03	1.28 $\pm$.06	1.30 $\pm$.06	1.10 $\pm$.02	1.24 $\pm$.01
	5	1.04 $\pm$.00	.962 $\pm$.022	1.02 $\pm$.02	1.09 $\pm$.03	1.04 $\pm$.02	.963 $\pm$.024	1.12 $\pm$.01	1.13 $\pm$.02	1.04 $\pm$.04	1.09 $\pm$.03	1.04 $\pm$.00	1.10 $\pm$.01	1.09 $\pm$.02	1.00 $\pm$.02	1.11 $\pm$.01
forest_au11	1	1.41 $\pm$.02	1.41 $\pm$.02	1.41 $\pm$.02	1.40 $\pm$.02	1.41 $\pm$.05	1.41 $\pm$.02	1.41 $\pm$.03	1.41 $\pm$.02	1.41 $\pm$.05	1.40 $\pm$.03	1.40 $\pm$.02	1.40 $\pm$.02	1.41 $\pm$.02	1.41 $\pm$.02	1.40 $\pm$.03
	2	1.40 $\pm$.02	1.42 $\pm$.02	1.42 $\pm$.02	1.40 $\$											

(continued from previous page)

Dataset	Budget idx	CART	ElankNet	F-test	GuinRatio	LaplacianScore	Lasso	LOCO	Markov Blanket	MI	mRMR	(R)Relieff	Random	SBE	RFImportance	SFS
anemobile	1	.768 ± .122	.893 ± .061	.901 ± .035	.892 ± .073	1.10 ± .12	.917 ± .021	.878 ± .032	.860 ± .145	.831 ± .136	.870 ± .237	1.03 ± .07	.936 ± .094	.959 ± .079	.736 ± .086	1.02 ± .07
	2	.735 ± .052	.883 ± .046	.898 ± .029	.815 ± .137	1.04 ± .10	.883 ± .046	.895 ± .029	.841 ± .090	.813 ± .189	.847 ± .148	1.01 ± .04	.918 ± .184	.900 ± .017	.731 ± .095	.911 ± .075
	3	.708 ± .081	.906 ± .042	.901 ± .036	.839 ± .091	.900 ± .142	.906 ± .042	.848 ± .062	.749 ± .139	.732 ± .138	.802 ± .097	.788 ± .144	.787 ± .173	.797 ± .158	.730 ± .094	.770 ± .107
	4	.719 ± .079	.918 ± .041	.801 ± .125	.789 ± .085	.868 ± .153	.918 ± .041	.749 ± .114	.749 ± .118	.734 ± .096	.764 ± .128	.827 ± .127	.789 ± .148	.792 ± .160	.731 ± .097	.782 ± .111
	5	.736 ± .086	.896 ± .057	.845 ± .087	.801 ± .090	.852 ± .134	.896 ± .057	.745 ± .125	.764 ± .123	.749 ± .113	.752 ± .100	.784 ± .085	.769 ± .088	.751 ± .126	.753 ± .113	.774 ± .088
psa-ctscan-prostate-ct-scans	1	.599 ± .002	.597 ± .002	.598 ± .002	.598 ± .002	.598 ± .002	.597 ± .002	.598 ± .002	.598 ± .002	.598 ± .002	.598 ± .002	.598 ± .002	.598 ± .002	.598 ± .002	.612 ± .013	.598 ± .002
	2	.612 ± .013	.597 ± .002	.597 ± .002	.598 ± .002	.599 ± .001	.597 ± .002	.598 ± .002	.598 ± .002	.599 ± .002	.598 ± .002	.598 ± .002	.598 ± .002	.598 ± .002	.618 ± .002	.598 ± .002
	3	.619 ± .002	.597 ± .002	.597 ± .002	.598 ± .002	.599 ± .002	.597 ± .002	.598 ± .002	.598 ± .002	.600 ± .002	.598 ± .002	.598 ± .002	.604 ± .009	.604 ± .009	.618 ± .002	.598 ± .002
	4	.620 ± .002	.597 ± .002	.597 ± .002	.599 ± .002	.599 ± .001	.597 ± .002	.599 ± .003	.606 ± .009	.609 ± .009	.597 ± .002	.597 ± .002	.598 ± .001	.598 ± .001	.619 ± .002	.598 ± .001
	5	.625 ± .003	.597 ± .002	.597 ± .002	.602 ± .001	.600 ± .002	.597 ± .002	.606 ± .014	.614 ± .011	.609 ± .010	.597 ± .002	.598 ± .003	.612 ± .011	.613 ± .013	.623 ± .002	.612 ± .008
impreciseness-ct	1	21.4 ± .3	20.5 ± .2	20.8 ± .2	20.7 ± .1	22.1 ± .2	21.0 ± .3	21.6 ± .1	20.9 ± 1.0	20.8 ± .2	21.6 ± .2	21.5 ± .9	21.7 ± .4	21.9 ± .4	21.1 ± .5	21.5 ± .8
	2	19.5 ± .1	18.7 ± .2	19.4 ± .1	19.6 ± .2	19.7 ± .1	19.1 ± .3	19.9 ± .6	19.6 ± .5	19.2 ± .2	20.1 ± .3	20.4 ± .2	20.3 ± .2	20.2 ± .5	18.8 ± .2	19.9 ± .1
	3	18.3 ± .0	18.2 ± .2	18.7 ± .1	19.0 ± .1	19.0 ± .1	18.3 ± .1	19.0 ± .3	19.2 ± .6	18.9 ± .2	18.6 ± .3	19.0 ± .2	19.3 ± .6	19.1 ± .3	18.2 ± .1	18.8 ± .6
	4	18.0 ± .1	17.9 ± .1	18.4 ± .1	18.2 ± .2	18.2 ± .1	17.8 ± .2	18.3 ± .1	18.5 ± .2	18.6 ± .1	18.0 ± .1	18.3 ± .3	18.3 ± .4	18.4 ± .2	17.8 ± .2	18.4 ± .2
	5	17.8 ± .1	17.7 ± .1	17.9 ± .1	17.8 ± .1	17.8 ± .1	17.6 ± .2	17.8 ± .1	18.0 ± .2	17.8 ± .1	17.7 ± .1	17.6 ± .1	17.6 ± .1	17.7 ± .1	17.7 ± .1	17.7 ± .2
AUC (?)																
in_colic-ctscan-prostate-ct-scans	1	.668 ± .024	.696 ± .008	.692 ± .007	.695 ± .015	.575 ± .018	.698 ± .010	.699 ± .011	.695 ± .013	.699 ± .023	.693 ± .016	.661 ± .015	.581 ± .026	.684 ± .015	.675 ± .014	.706 ± .011
	2	.693 ± .014	.705 ± .009	.702 ± .009	.700 ± .013	.594 ± .011	.705 ± .009	.718 ± .008	.699 ± .012	.720 ± .018	.710 ± .011	.680 ± .015	.623 ± .007	.717 ± .013	.696 ± .014	.718 ± .004
	3	.700 ± .012	.719 ± .016	.709 ± .008	.704 ± .012	.643 ± .003	.721 ± .016	.722 ± .009	.702 ± .013	.723 ± .020	.721 ± .011	.699 ± .007	.671 ± .014	.728 ± .014	.698 ± .015	.726 ± .005
	4	.722 ± .011	.723 ± .015	.724 ± .018	.710 ± .011	.671 ± .004	.724 ± .015	.725 ± .010	.710 ± .010	.725 ± .020	.729 ± .008	.719 ± .013	.720 ± .018	.730 ± .013	.730 ± .015	.732 ± .005
	5	.733 ± .009	.736 ± .008	.731 ± .009	.727 ± .011	.734 ± .008	.736 ± .008	.731 ± .012	.722 ± .018	.728 ± .022	.734 ± .008	.732 ± .010	.730 ± .006	.732 ± .010	.734 ± .010	.733 ± .006
marketing-ct	1	.813 ± .040	.796 ± .043	.770 ± .020	.763 ± .032	.713 ± .025	.798 ± .044	.768 ± .019	.768 ± .023	.731 ± .029	.808 ± .042	.749 ± .005	.735 ± .009	.818 ± .043	.782 ± .026	.805 ± .054
	2	.830 ± .044	.873 ± .031	.866 ± .021	.796 ± .028	.832 ± .009	.876 ± .031	.847 ± .003	.809 ± .002	.821 ± .006	.851 ± .034	.796 ± .046	.771 ± .041	.860 ± .024	.812 ± .031	.852 ± .014
	3	.859 ± .030	.887 ± .028	.870 ± .026	.853 ± .018	.856 ± .009	.889 ± .026	.886 ± .019	.847 ± .015	.859 ± .017	.875 ± .019	.852 ± .014	.824 ± .025	.884 ± .013	.848 ± .026	.892 ± .024
	4	.887 ± .021	.893 ± .022	.883 ± .022	.859 ± .012	.861 ± .013	.894 ± .024	.893 ± .018	.857 ± .010	.891 ± .009	.891 ± .013	.873 ± .024	.866 ± .042	.898 ± .012	.884 ± .013	.904 ± .016
	5	.900 ± .014	.900 ± .017	.904 ± .010	.878 ± .013	.883 ± .024	.900 ± .017	.902 ± .017	.893 ± .005	.904 ± .012	.900 ± .008	.889 ± .015	.890 ± .032	.904 ± .013	.901 ± .013	.906 ± .013
polk-ctscan-prostate-ct-scans	1	.828 ± .032	.819 ± .006	.820 ± .012	.813 ± .014	.806 ± .008	.822 ± .005	.830 ± .010	.831 ± .009	.822 ± .018	.816 ± .017	.812 ± .008	.808 ± .023	.810 ± .017	.834 ± .015	.823 ± .027
	2	.850 ± .020	.829 ± .013	.843 ± .005	.835 ± .010	.833 ± .008	.835 ± .015	.841 ± .027	.843 ± .016	.838 ± .019	.843 ± .007	.841 ± .015	.830 ± .021	.848 ± .016	.850 ± .007	.849 ± .008
	3	.859 ± .015	.845 ± .008	.850 ± .008	.854 ± .006	.850 ± .006	.846 ± .005	.855 ± .015	.853 ± .011	.852 ± .013	.864 ± .008	.862 ± .013	.846 ± .016	.853 ± .007	.850 ± .007	.858 ± .011
	4	.865 ± .002	.849 ± .013	.854 ± .012	.856 ± .007	.852 ± .011	.849 ± .014	.861 ± .020	.859 ± .013	.856 ± .007	.867 ± .012	.861 ± .016	.859 ± .019	.864 ± .011	.856 ± .010	.868 ± .005
	5	.867 ± .010	.859 ± .015	.860 ± .012	.861 ± .010	.856 ± .014	.861 ± .014	.863 ± .020	.865 ± .011	.860 ± .012	.870 ± .013	.864 ± .017	.867 ± .014	.864 ± .010	.867 ± .010	.866 ± .014
colic-ctscan-ct	1	.748 ± .047	.862 ± .053	.876 ± .100	.840 ± .145	.675 ± .226	.824 ± .106	.769 ± .076	.850 ± .139	.854 ± .104	.814 ± .067	.888 ± .083	.633 ± .236	.702 ± .285	.820 ± .180	.723 ± .093
	2	.835 ± .079	.882 ± .098	.891 ± .082	.884 ± .077	.896 ± .113	.885 ± .089	.898 ± .044	.843 ± .164	.874 ± .094	.898 ± .071	.895 ± .055	.889 ± .051	.890 ± .067	.891 ± .091	.823 ± .088
	3	.861 ± .064	.886 ± .076	.878 ± .080	.878 ± .080	.906 ± .110	.893 ± .077	.864 ± .096	.888 ± .073	.879 ± .080	.878 ± .076	.891 ± .065	.815 ± .080	.829 ± .131	.872 ± .059	.881 ± .014
	4	.872 ± .070	.893 ± .071	.895 ± .072	.886 ± .065	.912 ± .101	.895 ± .065	.898 ± .071	.896 ± .091	.889 ± .059	.879 ± .060	.878 ± .068	.897 ± .080	.891 ± .082	.894 ± .068	.894 ± .024
	5	.905 ± .039	.889 ± .058	.895 ± .069	.909 ± .073	.911 ± .074	.909 ± .034	.896 ± .060	.907 ± .081	.902 ± .067	.899 ± .066	.895 ± .069	.875 ± .082	.915 ± .050	.892 ± .054	.905 ± .085
mechanisms-ct	1	.939 ± .009	.915 ± .037	.939 ± .010	.937 ± .006	.922 ± .010	.939 ± .010	.904 ± .046	.938 ± .009	.936 ± .006	.943 ± .014	.882 ± .078	.879 ± .025	.921 ± .023	.937 ± .002	.931 ± .007
	2	.939 ± .010	.947 ± .012	.937 ± .005	.935 ± .002	.928 ± .013	.945 ± .010	.932 ± .005	.936 ± .007	.935 ± .002	.941 ± .011	.927 ± .024	.927 ± .014	.929 ± .013	.941 ± .010	.937 ± .007
	3	.943 ± .011	.945 ± .013	.938 ± .005	.936 ± .006	.936 ± .018	.944 ± .013	.943 ± .006	.943 ± .008	.938 ± .006	.944 ± .009	.940 ± .013	.938 ± .009	.942 ± .010	.941 ± .009	.941 ± .009
	4	.946 ± .009	.952 ± .011	.943 ± .007	.945 ± .005	.940 ± .012	.950 ± .005	.945 ± .007	.950 ± .007	.947 ± .010	.952 ± .009	.947 ± .012	.945 ± .006	.949 ± .007	.950 ± .013	.949 ± .004
	5	.954 ± .009	.955 ± .002	.954 ± .006	.956 ± .005	.953 ± .006	.955 ± .006	.949 ± .010	.954 ± .005	.955 ± .005	.956 ± .004	.960 ± .003	.951 ± .008	.951 ± .008	.961 ± .006	.954 ± .008
anemobile-ctscan-prostate-ct-scans	1	.613 ± .008	.614 ± .006	.615 ± .006	.615 ± .006	.501 ± .001	.614 ± .006	.578 ± .017	.615 ± .006	.502 ± .002	.615 ± .006	.505 ± .008	.515 ± .005	.532 ± .004	.615 ± .006	.571 ± .011
	2	.671 ± .004	.675 ± .004	.677 ± .005	.675 ± .006	.501 ± .001	.675 ± .004	.610 ± .010	.674 ± .006	.509 ± .003	.675 ± .006	.509 ± .003	.568 ± .020	.572 ± .023	.672 ± .002	.584 ± .014
	3	.747 ± .003	.752 ± .005	.753 ± .005	.748 ± .005	.516 ± .002	.752 ± .005	.645 ± .017	.750 ± .004	.523 ± .004	.752 ± .004	.514 ± .002	.592 ± .028	.590 ± .017	.751 ± .004	.596 ± .013
	4	.821 ± .006	.830 ± .004	.829 ± .005	.825 ± .006	.530 ± .003	.830 ± .004	.657 ± .014	.821 ± .006	.550 ± .004	.822 ± .006	.531 ± .006	.631 ± .029	.619 ± .014	.827 ± .005	.658 ± .003
	5	.860 ± .003	.860 ± .003	.860 ± .003	.860 ± .003	.551 ± .004	.860 ± .003	.736 ± .009	.852 ± .004	.658 ± .008	.846 ± .003	.571 ± .018	.737 ± .022	.730 ± .007	.859 ± .003	.745 ± .011
anemobile-ctscan-prostate-ct-scans	1	.945 ± .031	.936 ± .022	.937 ± .015	.935 ± .014	.564 ± .061	.892 ± .054	.692 ± .158	.792 ± .022	.934 ± .015	.936 ± .035	.774 ± .011	.661 ± .050	.699 ± .048	.924 ± .015	.724 ± .088
	2	.949 ± .013	.956 ± .022	.949 ± .024	.948 ± .013	.653 ± .015	.977 ± .012	.828 ± .038	.908 ± .011	.955 ± .009	.946 ± .020	.938 ± .048	.769 ± .014	.834 ± .036	.958 ± .035	.830 ± .022
	3	.961 ± .010	.973 ± .007	.962 ± .003	.971 ± .017	.689 ± .071	.987 ± .007	.932 ± .027	.954 ± .008	.978 ± .011	.960 ± .014	.972 ± .010	.902 ± .018	.908 ± .003	.983 ± .002	.949 ± .014
	4	.975 ± .016	.989 ± .004	.971 ± .017	.975 ± .015	.839 ± .046	.991 ± .006	.967 ± .015	.982 ± .007	.986 ± .006	.978 ± .005	.978 ± .014	.965 ± .013	.963 ± .008	.988 ± .002	.963 ± .003
	5	.983 ± .011	.987 ± .010	.979 ± .025	.988 ± .008	.936 ± .015	.988 ± .009	.979 ± .013	.986 ± .007	.990 ± .007	.988 ± .008	.990 ± .006	.977 ± .013	.978 ± .014	.986 ± .008	.979 ± .013
bank-ctscan-ct	1	.732 ± .010	.744 ± .014	.744 ± .014	.731 ± .008	.593 ± .017	.744 ± .014	.731 ± .008	.731 ± .008	.731 ± .008	.731 ± .008	.628 ± .091	.549 ± .058	.731 ± .008	.732 ± .009	.731 ± .008
	2	.739 ± .002	.762 ± .007	.762 ± .007	.747 ± .007	.644 ± .014	.762 ± .007	.748 ± .006	.747 ± .007	.750 ± .014	.755 ± .014	.731 ± .008	.675 ± .063	.745 ± .009	.739 ± .002	.759 ± .010
	3	.738 ± .002	.770 ± .009	.767 ± .013	.747 ± .007	.678 ± .011	.770 ± .0									

(continued from previous page)

Dataset	Budget idx	CART	ElankNet	F-test	GiniRatio	LaplacianScore	Lasso	LOCO	MarkovBlanket	MI	mRMR	(R)Relieff	Random	SBE	RfImportance	SFS	
lacc	1	.741 $\pm$.015	.744 $\pm$.002	.740 $\pm$.012	.734 $\pm$.009	.663 $\pm$.004	.747 $\pm$.005	.710 $\pm$.051	.722 $\pm$.028	.739 $\pm$.010	.718 $\pm$.009	.698 $\pm$.009	.659 $\pm$.085	.712 $\pm$.021	.733 $\pm$.009	.745 $\pm$.007	
	2	.751 $\pm$.003	.772 $\pm$.007	.754 $\pm$.003	.758 $\pm$.007	.758 $\pm$.011	.776 $\pm$.002	.758 $\pm$.015	.763 $\pm$.020	.760 $\pm$.002	.756 $\pm$.012	.750 $\pm$.004	.730 $\pm$.009	.754 $\pm$.011	.752 $\pm$.008	.761 $\pm$.010	
	3	.764 $\pm$.011	.780 $\pm$.007	.760 $\pm$.005	.776 $\pm$.006	.760 $\pm$.010	.779 $\pm$.007	.771 $\pm$.022	.777 $\pm$.005	.772 $\pm$.008	.778 $\pm$.010	.767 $\pm$.003	.749 $\pm$.008	.772 $\pm$.008	.760 $\pm$.008	.774 $\pm$.006	
	4	.775 $\pm$.012	.785 $\pm$.010	.781 $\pm$.006	.780 $\pm$.007	.774 $\pm$.006	.784 $\pm$.011	.782 $\pm$.011	.782 $\pm$.006	.779 $\pm$.008	.783 $\pm$.008	.783 $\pm$.010	.774 $\pm$.007	.778 $\pm$.007	.777 $\pm$.006	.775 $\pm$.008	.778 $\pm$.006
	5	.783 $\pm$.010	.784 $\pm$.009	.784 $\pm$.008	.784 $\pm$.006	.782 $\pm$.006	.784 $\pm$.009	.785 $\pm$.009	.784 $\pm$.006	.783 $\pm$.008	.783 $\pm$.010	.780 $\pm$.009	.783 $\pm$.011	.781 $\pm$.007	.783 $\pm$.010	.784 $\pm$.010	
lacc _{signature}	1	.607 $\pm$.037	.665 $\pm$.044	.548 $\pm$.040	.533 $\pm$.057	.539 $\pm$.010	.589 $\pm$.045	.518 $\pm$.098	.515 $\pm$.038	.583 $\pm$.049	.533 $\pm$.057	.625 $\pm$.041	.579 $\pm$.035	.576 $\pm$.036	.595 $\pm$.062	.681 $\pm$.062	
	2	.676 $\pm$.078	.713 $\pm$.046	.607 $\pm$.102	.621 $\pm$.031	.573 $\pm$.020	.748 $\pm$.014	.630 $\pm$.045	.606 $\pm$.069	.612 $\pm$.088	.621 $\pm$.031	.651 $\pm$.060	.622 $\pm$.009	.608 $\pm$.010	.693 $\pm$.032	.697 $\pm$.016	
	3	.697 $\pm$.066	.732 $\pm$.055	.644 $\pm$.102	.680 $\pm$.022	.608 $\pm$.057	.759 $\pm$.009	.696 $\pm$.058	.682 $\pm$.058	.683 $\pm$.082	.680 $\pm$.022	.727 $\pm$.035	.712 $\pm$.076	.672 $\pm$.048	.745 $\pm$.015	.717 $\pm$.053	
	4	.700 $\pm$.047	.732 $\pm$.056	.771 $\pm$.012	.660 $\pm$.024	.670 $\pm$.063	.698 $\pm$.002	.705 $\pm$.092	.721 $\pm$.080	.694 $\pm$.042	.660 $\pm$.024	.766 $\pm$.003	.731 $\pm$.039	.719 $\pm$.061	.764 $\pm$.034	.705 $\pm$.016	
	5	.699 $\pm$.046	.729 $\pm$.051	.751 $\pm$.037	.701 $\pm$.016	.706 $\pm$.027	.711 $\pm$.014	.704 $\pm$.050	.758 $\pm$.025	.730 $\pm$.034	.701 $\pm$.016	.726 $\pm$.037	.722 $\pm$.045	.732 $\pm$.056	.750 $\pm$.008	.730 $\pm$.041	
lacc _{unimodal}	1	.637 $\pm$.003	.690 $\pm$.011	.689 $\pm$.011	.661 $\pm$.008	.626 $\pm$.007	.689 $\pm$.011	.687 $\pm$.029	.657 $\pm$.014	.661 $\pm$.014	.616 $\pm$.019	.675 $\pm$.009	.673 $\pm$.023	.707 $\pm$.007	.634 $\pm$.010	.714 $\pm$.011	
	2	.689 $\pm$.017	.714 $\pm$.007	.719 $\pm$.009	.687 $\pm$.006	.652 $\pm$.007	.714 $\pm$.007	.719 $\pm$.030	.690 $\pm$.011	.719 $\pm$.018	.669 $\pm$.010	.684 $\pm$.012	.683 $\pm$.013	.723 $\pm$.005	.682 $\pm$.016	.729 $\pm$.011	
	3	.703 $\pm$.016	.730 $\pm$.011	.732 $\pm$.010	.707 $\pm$.011	.730 $\pm$.012	.730 $\pm$.011	.732 $\pm$.025	.708 $\pm$.012	.727 $\pm$.011	.714 $\pm$.007	.704 $\pm$.011	.710 $\pm$.017	.739 $\pm$.015	.703 $\pm$.017	.733 $\pm$.008	
	4	.729 $\pm$.020	.739 $\pm$.012	.742 $\pm$.013	.721 $\pm$.011	.736 $\pm$.013	.736 $\pm$.016	.745 $\pm$.017	.721 $\pm$.011	.743 $\pm$.013	.741 $\pm$.013	.736 $\pm$.013	.728 $\pm$.012	.745 $\pm$.014	.713 $\pm$.016	.744 $\pm$.014	
	5	.747 $\pm$.013	.744 $\pm$.016	.742 $\pm$.014	.728 $\pm$.009	.742 $\pm$.014	.746 $\pm$.014	.747 $\pm$.015	.744 $\pm$.017	.746 $\pm$.014	.747 $\pm$.013	.742 $\pm$.014	.734 $\pm$.023	.745 $\pm$.014	.747 $\pm$.013	.747 $\pm$.015	
lacc _{multimodal}	1	.890 $\pm$.049	.975 $\pm$.022	.987 $\pm$.023	.985 $\pm$.021	.692 $\pm$.061	.969 $\pm$.021	.739 $\pm$.204	.983 $\pm$.030	.990 $\pm$.011	.985 $\pm$.015	.995 $\pm$.009	.730 $\pm$.185	.664 $\pm$.193	.995 $\pm$.009	.616 $\pm$.085	
	2	.934 $\pm$.041	.962 $\pm$.033	.972 $\pm$.030	.982 $\pm$.025	.829 $\pm$.109	.985 $\pm$.015	.781 $\pm$.162	.879 $\pm$.095	.995 $\pm$.009	.974 $\pm$.028	.979 $\pm$.030	.700 $\pm$.107	.836 $\pm$.106	.988 $\pm$.015	.821 $\pm$.097	
	3	.954 $\pm$.036	.982 $\pm$.019	.975 $\pm$.043	.995 $\pm$.004	.935 $\pm$.061	.978 $\pm$.038	.942 $\pm$.040	.950 $\pm$.073	.988 $\pm$.015	.995 $\pm$.009	.987 $\pm$.012	.939 $\pm$.033	.970 $\pm$.012	.995 $\pm$.009	.934 $\pm$.066	
	4	.980 $\pm$.028	.983 $\pm$.030	.978 $\pm$.038	.985 $\pm$.026	.962 $\pm$.029	.978 $\pm$.038	.983 $\pm$.030	.983 $\pm$.024	.985 $\pm$.026	.993 $\pm$.013	.985 $\pm$.026	.968 $\pm$.056	.980 $\pm$.028	.998 $\pm$.004	.975 $\pm$.043	
	5	.980 $\pm$.034	.980 $\pm$.034	.980 $\pm$.034	.980 $\pm$.034	.980 $\pm$.034	.980 $\pm$.034	.983 $\pm$.030	.983 $\pm$.030	.980 $\pm$.034	.980 $\pm$.034	.980 $\pm$.034	.973 $\pm$.047	.988 $\pm$.021	.980 $\pm$.034	.980 $\pm$.028	
lacc _{distance}	1	.851 $\pm$.031	.848 $\pm$.028	.809 $\pm$.020	.851 $\pm$.074	.769 $\pm$.030	.857 $\pm$.056	.861 $\pm$.095	.823 $\pm$.041	.857 $\pm$.036	.850 $\pm$.027	.864 $\pm$.044	.836 $\pm$.027	.848 $\pm$.051	.839 $\pm$.047	.838 $\pm$.038	
	2	.870 $\pm$.042	.875 $\pm$.018	.878 $\pm$.014	.900 $\pm$.041	.811 $\pm$.018	.870 $\pm$.049	.871 $\pm$.057	.850 $\pm$.050	.888 $\pm$.039	.868 $\pm$.020	.885 $\pm$.028	.860 $\pm$.021	.849 $\pm$.061	.892 $\pm$.047	.865 $\pm$.034	
	3	.872 $\pm$.033	.897 $\pm$.024	.885 $\pm$.017	.894 $\pm$.043	.860 $\pm$.107	.888 $\pm$.029	.876 $\pm$.055	.881 $\pm$.028	.899 $\pm$.046	.878 $\pm$.021	.897 $\pm$.028	.825 $\pm$.050	.870 $\pm$.072	.894 $\pm$.048	.896 $\pm$.044	
	4	.884 $\pm$.052	.900 $\pm$.028	.904 $\pm$.021	.901 $\pm$.040	.878 $\pm$.039	.906 $\pm$.018	.879 $\pm$.056	.901 $\pm$.040	.903 $\pm$.045	.903 $\pm$.035	.898 $\pm$.026	.910 $\pm$.035	.869 $\pm$.068	.891 $\pm$.039	.905 $\pm$.047	
	5	.899 $\pm$.035	.903 $\pm$.026	.906 $\pm$.032	.896 $\pm$.042	.898 $\pm$.037	.906 $\pm$.040	.898 $\pm$.054	.903 $\pm$.048	.904 $\pm$.049	.902 $\pm$.046	.907 $\pm$.023	.893 $\pm$.047	.899 $\pm$.056	.906 $\pm$.042	.899 $\pm$.051	
lacc _{protein}	1	.570 $\pm$.070	.582 $\pm$.110	.605 $\pm$.089	.543 $\pm$.160	.670 $\pm$.046	.582 $\pm$.110	.584 $\pm$.151	.593 $\pm$.106	.476 $\pm$.121	.562 $\pm$.095	.555 $\pm$.125	.672 $\pm$.123	.698 $\pm$.078	.575 $\pm$.104	.654 $\pm$.106	
	2	.593 $\pm$.077	.605 $\pm$.115	.649 $\pm$.115	.601 $\pm$.153	.637 $\pm$.109	.605 $\pm$.115	.667 $\pm$.050	.587 $\pm$.054	.557 $\pm$.072	.584 $\pm$.135	.580 $\pm$.083	.552 $\pm$.109	.552 $\pm$.146	.619 $\pm$.132	.638 $\pm$.105	
	3	.563 $\pm$.150	.596 $\pm$.137	.623 $\pm$.169	.582 $\pm$.225	.614 $\pm$.151	.596 $\pm$.137	.600 $\pm$.123	.596 $\pm$.185	.594 $\pm$.111	.554 $\pm$.135	.568 $\pm$.096	.665 $\pm$.101	.589 $\pm$.143	.570 $\pm$.162	.654 $\pm$.135	
	4	.566 $\pm$.071	.578 $\pm$.090	.593 $\pm$.176	.534 $\pm$.199	.605 $\pm$.073	.578 $\pm$.090	.596 $\pm$.116	.587 $\pm$.112	.598 $\pm$.102	.540 $\pm$.191	.497 $\pm$.181	.571 $\pm$.166	.603 $\pm$.155	.577 $\pm$.134	.571 $\pm$.128	
	5	.571 $\pm$.106	.571 $\pm$.104	.560 $\pm$.176	.575 $\pm$.169	.642 $\pm$.101	.571 $\pm$.104	.571 $\pm$.142	.549 $\pm$.136	.561 $\pm$.102	.513 $\pm$.178	.527 $\pm$.168	.578 $\pm$.171	.561 $\pm$.133	.591 $\pm$.125	.564 $\pm$.106	
lacc _{chain}	1	.691 $\pm$.032	.769 $\pm$.027	.758 $\pm$.037	.697 $\pm$.029	.713 $\pm$.003	.717 $\pm$.124	.697 $\pm$.008	.685 $\pm$.024	.758 $\pm$.037	.743 $\pm$.019	.684 $\pm$.029	.639 $\pm$.035	.765 $\pm$.026	.758 $\pm$.037	.765 $\pm$.026	
	2	.751 $\pm$.052	.777 $\pm$.024	.778 $\pm$.024	.703 $\pm$.015	.725 $\pm$.021	.738 $\pm$.076	.730 $\pm$.031	.695 $\pm$.025	.767 $\pm$.033	.773 $\pm$.025	.695 $\pm$.019	.674 $\pm$.064	.774 $\pm$.019	.764 $\pm$.020	.773 $\pm$.020	
	3	.780 $\pm$.021	.774 $\pm$.020	.776 $\pm$.025	.712 $\pm$.021	.746 $\pm$.007	.778 $\pm$.023	.747 $\pm$.015	.693 $\pm$.026	.773 $\pm$.032	.777 $\pm$.022	.780 $\pm$.025	.700 $\pm$.091	.779 $\pm$.021	.768 $\pm$.021	.776 $\pm$.023	
	4	.779 $\pm$.022	.779 $\pm$.022	.780 $\pm$.021	.710 $\pm$.021	.750 $\pm$.011	.779 $\pm$.022	.761 $\pm$.013	.701 $\pm$.018	.779 $\pm$.025	.781 $\pm$.020	.780 $\pm$.025	.734 $\pm$.028	.780 $\pm$.020	.779 $\pm$.022	.782 $\pm$.022	
	5	.782 $\pm$.023	.779 $\pm$.022	.781 $\pm$.024	.713 $\pm$.019	.783 $\pm$.027	.780 $\pm$.022	.781 $\pm$.020	.701 $\pm$.017	.780 $\pm$.025	.782 $\pm$.023	.780 $\pm$.025	.774 $\pm$.031	.782 $\pm$.022	.778 $\pm$.022	.782 $\pm$.021	
lacc _{feature}	1	.958 $\pm$.009	.942 $\pm$.037	.971 $\pm$.007	.877 $\pm$.045	.705 $\pm$.037	.970 $\pm$.005	.869 $\pm$.059	.970 $\pm$.0								

(continued from previous page)																																											
Dataset		Budget		CART		ElasticNet		F-test		GradientBoost		LaplaceScore		Lasso		LOCO		MarkovBlanket		MI		mMR		(R,R)defP		Random		SBE		RFImportance		SUS											
prenatal_cancer		1	.903 ±.109	2	.873 ±.124	3	.931 ±.057	4	.953 ±.026	5	.960 ±.058	1	.958 ±.063	2	.954 ±.071	3	.953 ±.082	4	.629 ±.040	5	.939 ±.061	1	.699 ±.149	2	.949 ±.060	3	.948 ±.081	4	.955 ±.072	5	.952 ±.079	1	.640 ±.093	2	.601 ±.064	3	.948 ±.060	4	.908 ±.048	5	.879 ±.066		
breast_cancer		1	.873 ±.124	2	.963 ±.050	3	.956 ±.064	4	.963 ±.058	5	.700 ±.084	1	.967 ±.058	2	.655 ±.169	3	.933 ±.071	4	.958 ±.063	5	.961 ±.065	1	.956 ±.060	2	.965 ±.057	3	.871 ±.049	4	.859 ±.034	5	.968 ±.041	1	.859 ±.033	2	.964 ±.056	3	.879 ±.066	4	.964 ±.056	5	.879 ±.066		
breast_atlas		1	.931 ±.057	2	.962 ±.066	3	.958 ±.072	4	.958 ±.063	5	.761 ±.087	1	.962 ±.054	2	.868 ±.045	3	.960 ±.041	4	.967 ±.055	5	.958 ±.060	1	.965 ±.057	2	.871 ±.049	3	.859 ±.034	4	.968 ±.041	5	.859 ±.033	1	.963 ±.055	2	.964 ±.056	3	.879 ±.066	4	.964 ±.056	5	.879 ±.066		
breast_mIoU		1	.953 ±.026	2	.970 ±.043	3	.963 ±.061	4	.967 ±.052	5	.888 ±.035	1	.961 ±.009	2	.935 ±.048	3	.957 ±.044	4	.957 ±.060	5	.968 ±.053	1	.964 ±.062	2	.941 ±.030	3	.941 ±.027	4	.967 ±.041	5	.956 ±.031	1	.967 ±.041	2	.967 ±.041	3	.967 ±.041	4	.967 ±.041	5	.967 ±.041		
breast_histology		1	.960 ±.058	2	.970 ±.049	3	.965 ±.057	4	.967 ±.044	5	.946 ±.035	1	.960 ±.007	2	.955 ±.042	3	.973 ±.037	4	.969 ±.054	5	.968 ±.053	1	.973 ±.046	2	.961 ±.035	3	.965 ±.054	4	.962 ±.057	5	.952 ±.033	1	.962 ±.057	2	.952 ±.033	3	.962 ±.057	4	.952 ±.033	5	.962 ±.057		
breast_gland		1	.875 ±.018	2	.908 ±.016	3	.906 ±.006	4	.790 ±.029	5	.673 ±.079	1	.907 ±.014	2	.889 ±.022	3	.807 ±.013	4	.906 ±.012	5	.796 ±.020	1	.834 ±.011	2	.757 ±.086	3	.899 ±.002	4	.906 ±.007	5	.905 ±.006	1	.905 ±.006	2	.905 ±.006	3	.905 ±.006	4	.905 ±.006	5	.905 ±.006		
breast_approved		1	.898 ±.007	2	.915 ±.008	3	.899 ±.009	4	.806 ±.009	5	.767 ±.048	1	.911 ±.021	2	.901 ±.012	3	.807 ±.006	4	.907 ±.013	5	.844 ±.056	1	.852 ±.021	2	.822 ±.150	3	.902 ±.004	4	.902 ±.004	5	.908 ±.007	1	.908 ±.007	2	.908 ±.007	3	.908 ±.007	4	.908 ±.007	5	.908 ±.007		
breast_approved		1	.899 ±.005	2	.915 ±.017	3	.900 ±.009	4	.822 ±.014	5	.900 ±.005	1	.920 ±.013	2	.907 ±.013	3	.814 ±.006	4	.905 ±.005	5	.876 ±.062	1	.905 ±.003	2	.838 ±.065	3	.907 ±.012	4	.907 ±.005	5	.904 ±.013	1	.907 ±.005	2	.907 ±.005	3	.907 ±.005	4	.907 ±.005	5	.907 ±.005		
breast_approved		1	.898 ±.002	2	.913 ±.014	3	.918 ±.006	4	.851 ±.050	5	.899 ±.002	1	.913 ±.013	2	.911 ±.004	3	.821 ±.015	4	.910 ±.009	5	.910 ±.011	1	.911 ±.005	2	.843 ±.057	3	.910 ±.011	4	.905 ±.005	5	.910 ±.011	1	.905 ±.005	2	.905 ±.005	3	.905 ±.005	4	.905 ±.005	5	.905 ±.005		
breast_approved		1	.909 ±.004	2	.912 ±.005	3	.919 ±.002	4	.911 ±.004	5	.907 ±.006	1	.909 ±.001	2	.906 ±.008	3	.882 ±.057	4	.913 ±.008	5	.914 ±.005	1	.918 ±.002	2	.860 ±.052	3	.912 ±.007	4	.911 ±.005	5	.910 ±.009	1	.910 ±.009	2	.910 ±.009	3	.910 ±.009	4	.910 ±.009	5	.910 ±.009		
breast_approved		1	.800 ±.015	2	.889 ±.024	3	.875 ±.029	4	.829 ±.111	5	.680 ±.145	1	.884 ±.023	2	.756 ±.152	3	.861 ±.032	4	.827 ±.081	5	.860 ±.032	1	.878 ±.037	2	.718 ±.143	3	.834 ±.041	4	.870 ±.023	5	.842 ±.036	1	.842 ±.036	2	.842 ±.036	3	.842 ±.036	4	.842 ±.036	5	.842 ±.036		
breast_approved		1	.829 ±.069	2	.899 ±.010	3	.895 ±.007	4	.877 ±.025	5	.879 ±.052	1	.898 ±.014	2	.758 ±.159	3	.875 ±.025	4	.887 ±.022	5	.873 ±.006	1	.893 ±.012	2	.855 ±.007	3	.843 ±.041	4	.864 ±.020	5	.861 ±.048	1	.861 ±.048	2	.861 ±.048	3	.861 ±.048	4	.861 ±.048	5	.861 ±.048		
breast_approved		1	.839 ±.040	2	.887 ±.014	3	.890 ±.009	4	.874 ±.030	5	.864 ±.048	1	.887 ±.010	2	.857 ±.057	3	.878 ±.028	4	.897 ±.013	5	.885 ±.012	1	.892 ±.014	2	.845 ±.038	3	.885 ±.027	4	.875 ±.025	5	.866 ±.055	1	.866 ±.055	2	.866 ±.055	3	.866 ±.055	4	.866 ±.055	5	.866 ±.055		
breast_approved		1	.877 ±.011	2	.888 ±.012	3	.884 ±.014	4	.873 ±.034	5	.903 ±.003	1	.879 ±.012	2	.879 ±.054	3	.875 ±.036	4	.898 ±.025	5	.900 ±.006	1	.889 ±.014	2	.872 ±.064	3	.898 ±.011	4	.883 ±.011	5	.905 ±.007	1	.905 ±.007	2	.905 ±.007	3	.905 ±.007	4	.905 ±.007	5	.905 ±.007		
breast_approved		1	.881 ±.014	2	.898 ±.007	3	.891 ±.014	4	.885 ±.010	5	.898 ±.007	1	.887 ±.020	2	.869 ±.049	3	.887 ±.032	4	.896 ±.011	5	.897 ±.006	1	.886 ±.010	2	.881 ±.022	3	.900 ±.007	4	.888 ±.015	5	.900 ±.007	1	.888 ±.015	2	.888 ±.015	3	.888 ±.015	4	.888 ±.015	5	.888 ±.015		
breast_approved		1	.732 ±.004	2	.732 ±.005	3	.732 ±.005	4	.732 ±.005	5	.582 ±.017	1	.732 ±.001	2	.756 ±.001	3	.733 ±.005	4	.759 ±.003	5	.732 ±.005	1	.641 ±.006	2	.693 ±.025	3	.751 ±.012	4	.573 ±.004	5	.759 ±.003	1	.759 ±.003	2	.759 ±.003	3	.759 ±.003	4	.759 ±.003	5	.759 ±.003		
breast_approved		1	.741 ±.003	2	.801 ±.016	3	.810 ±.003	4	.774 ±.003	5	.690 ±.011	1	.801 ±.016	2	.791 ±.020	3	.774 ±.003	4	.794 ±.003	5	.806 ±.009	1	.675 ±.002	2	.772 ±.020	3	.768 ±.030	4	.782 ±.014	5	.782 ±.014	1	.782 ±.014	2	.782 ±.014	3	.782 ±.014	4	.782 ±.014	5	.782 ±.014		
breast_approved		1	.742 ±.003	2	.819 ±.005	3	.822 ±.003	4	.774 ±.003	5	.724 ±.038	1	.819 ±.005	2	.802 ±.016	3	.776 ±.003	4	.822 ±.003	5	.822 ±.003	1	.774 ±.003	2	.802 ±.003	3	.816 ±.014	4	.742 ±.003	5	.787 ±.004	1	.787 ±.004	2	.787 ±.004	3	.787 ±.004	4	.787 ±.004	5	.787 ±.004		
breast_approved		1	.793 ±.016	2	.823 ±.004	3	.824 ±.003	4	.775 ±.004	5	.785 ±.033	1	.823 ±.004	2	.817 ±.004	3	.776 ±.005	4	.824 ±.003	5	.822 ±.004	1	.804 ±.024	2	.796 ±.020	3	.816 ±.014	4	.812 ±.011	5	.812 ±.011	1	.812 ±.011	2	.812 ±.011	3	.812 ±.011	4	.812 ±.011	5	.812 ±.011		
breast_approved		1	.817 ±.004	2	.825 ±.003	3	.824 ±.004	4	.808 ±.010	5	.814 ±.015	1	.825 ±.003	2	.817 ±.004	3	.804 ±.004	4	.824 ±.003	5	.825 ±.003	1	.824 ±.004	2	.821 ±.007	3	.817 ±.004	4	.817 ±.004	5	.818 ±.012	1	.818 ±.012	2	.818 ±.012	3	.818 ±.012	4	.818 ±.012	5	.818 ±.012		
breast_approved		1	.496 ±.104	2	.457 ±.034	3	.443 ±.042	4	.527 ±.119	5	.482 ±.060	1	.457 ±.034	2	.463 ±.115	3	.455 ±.069	4	.493 ±.089	5	.550 ±.125	1	.432 ±.062	2	.457 ±.047	3	.447 ±.045	4	.508 ±.116	5	.512 ±.123	1	.512 ±.123	2	.512 ±.123	3	.512 ±.123	4	.512 ±.123	5	.512 ±.123		
breast_approved		1	.486 ±.033	2	.509 ±.065	3	.442 ±.036	4	.544 ±.079	5	.424 ±.091	1	.509 ±.065	2	.439 ±.027	3	.465 ±.076	4	.492 ±.116	5	.525 ±.090	1	.391 ±.095	2	.497 ±.063	3	.553 ±.118	4	.491 ±.071	5	.491 ±.071	1	.491 ±.071	2	.491 ±.071	3	.491 ±.071	4	.491 ±.071	5	.491 ±.071		
breast_approved		1	.473 ±.059	2	.548 ±.089	3	.499 ±.011	4	.554 ±.038	5	.454 ±.041	1	.548 ±.089	4	.449 ±.030	5	.444 ±.030	4	.472 ±.101	5	.457 ±.070	1	.555 ±.115	4	.481 ±.080	5	.448 ±.015	1	.581 ±.087	2	.525 ±.105	3	.525 ±.105	4	.525 ±.105	5	.525 ±.105	1	.525 ±.105	2	.525 ±.105	3	.525 ±.105
breast_approved		1	.487 ±.095	2	.473 ±.105	3	.477 ±.064	4	.480 ±.030	5	.500 ±.100	1	.473 ±.105	2	.491 ±.031	3	.464 ±.054	4	.479 ±.048	5	.473 ±.047	1	.489 ±.047	2	.511 ±.088	3	.519 ±.099	4	.522 ±.024	5	.516 ±.037	1	.516 ±.037	2	.516 ±.037	3	.516 ±.037	4	.516 ±.037	5	.516 ±.037		
breast_approved		1	.440 ±.056	2	.438 ±.054	3	.478 ±.055	4	.459 ±.040	5	.512 ±.082	1	.438 ±.054	2	.455 ±.021	3	.447 ±.014	4	.491 ±.039	5	.461 ±.053	1	.479 ±.070	2	.497 ±.100	3	.489 ±.071	4	.447 ±.071	5	.470 ±.106	1	.470 ±.106	2	.470 ±.106	3	.470 ±.106	4	.470 ±.106	5	.470 ±.106		
breast_approved		1	.877 ±.010	2	.876 ±.010	3	.876 ±.010	4	.876 ±.010	5	.679 ±.012	1	.876 ±.010	2	.909 ±.003	3	.883 ±.026	4	.874 ±.011	5	.911 ±.005	1	.708 ±.033	2	.691 ±.019	3	.912 ±.008	4	.876 ±.010	5	.882 ±.006	1	.882 ±.006	2	.882 ±.006	3	.882 ±.006	4	.882 ±.006	5	.882 ±.006		
breast_approved		1	.872 ±.009	2	.912 ±.006	3	.879 ±.012	4	.886 ±.027	5	.708 ±.015	1	.911 ±.006	2	.911 ±.005	3	.913 ±.007	4	.884 ±.025	5	.915 ±.007	1	.854 ±.009	2	.699 ±.025	3	.913 ±.002	4	.872 ±.009	5	.911 ±.005	1	.911 ±.005	2	.911 ±.005	3	.911 ±.005	4	.911 ±.005	5	.911 ±.005		
breast_approved		1	.908 ±.005	2	.910 ±.006	3	.912 ±.007	4	.910 ±.007	5	.737 ±.008	1	.910 ±.006	2	.911 ±.006	3	.911 ±.008	4	.911 ±.008	5	.913 ±.007	1	.913 ±.006	2	.885 ±.012	3	.912 ±.004	4	.909 ±.007	5	.912 ±.005	1	.912 ±.005	2	.912 ±.005	3	.912 ±.005	4	.912 ±.005	5	.912 ±.005		
breast_approved		1	.910 ±.005	2	.911 ±.006	3	.910 ±.005	4	.910 ±.005	5	.910 ±.005	1	.911 ±.006	2	.910 ±.004	3	.909 ±.005	4	.911 ±.004	5	.912 ±.008	1	.912 ±.008	2	.912 ±.004	3	.910 ±.004	4	.910 ±.004	5	.910 ±.004	1	.910 ±.004	2	.910 ±.004	3	.910 ±.004	4	.910 ±.004	5	.910 ±.004		
breast_approved		1	.910 ±.004	2	.910 ±.004	3	.910 ±.006	4	.909 ±.004	5	.909 ±.005	1	.910 ±.004	2	.911 ±.004	3	.910 ±.005	4	.911 ±.004	5	.913 ±.006	1	.912 ±.007	2	.844 ±.090	3	.911 ±.004	4	.910 ±.004	5	.910 ±.004	1	.910 ±.004	2	.910 ±.004	3	.910 ±.004	4	.910 ±.004	5	.910 ±.004		
breast_approved		1	.710 ±.003	2	.713 ±.004	3	.703 ±.004	4	.703 ±.004	5	.659 ±.002	1	.711 ±.005	2	.719 ±.006	3	.720 ±.010	4	.702 ±.004	5	.715 ±.003	1	.715 ±.004	2	.651 ±.028	3	.719 ±.009	4	.714 ±.005	5	.710 ±.008	1	.710 ±										

(continued from previous page)																				
Dataset	Budget idx. j					CART	ElasticNet	F-test	GainRatio	LaplaceScore	Lasso	LOCO	Markov Blanket	MI	mRMR	(R)Relieff	Random	SBE	RFImportance	SFS
br analysis	1	.685 ± .004	.751 ± .007	.751 ± .007	.727 ± .018	.644 ± .005	.751 ± .007	.688 ± .004	.751 ± .007	.720 ± .005	.751 ± .007	.694 ± .018	.579 ± .045	.759 ± .021	.685 ± .004	.746 ± .006				
	2	.752 ± .006	.763 ± .007	.752 ± .009	.781 ± .007	.665 ± .001	.763 ± .007	.689 ± .003	.784 ± .007	.784 ± .007	.763 ± .006	.739 ± .019	.703 ± .004	.770 ± .016	.727 ± .002	.773 ± .016				
	3	.787 ± .006	.773 ± .012	.770 ± .007	.786 ± .007	.689 ± .020	.773 ± .012	.721 ± .038	.789 ± .002	.786 ± .007	.764 ± .007	.770 ± .008	.774 ± .020	.775 ± .014	.787 ± .006	.785 ± .010				
	4	.793 ± .004	.774 ± .012	.776 ± .012	.794 ± .004	.699 ± .013	.774 ± .012	.751 ± .039	.794 ± .004	.795 ± .004	.766 ± .005	.776 ± .011	.788 ± .007	.777 ± .013	.791 ± .003	.788 ± .012				
	5	.794 ± .004	.788 ± .011	.777 ± .012	.796 ± .004	.770 ± .007	.788 ± .011	.793 ± .010	.796 ± .004	.796 ± .005	.770 ± .005	.777 ± .012	.794 ± .006	.795 ± .005	.794 ± .005	.790 ± .013				
poco regress	1	.595 ± .002	.612 ± .005	.599 ± .003	.606 ± .002	.550 ± .003	.600 ± .015	.590 ± .017	.606 ± .006	.590 ± .002	.601 ± .006	.586 ± .001	.588 ± .006	.581 ± .016	.594 ± .002	.583 ± .003				
	2	.605 ± .002	.621 ± .003	.616 ± .007	.616 ± .002	.597 ± .003	.607 ± .013	.605 ± .009	.619 ± .002	.597 ± .002	.615 ± .003	.597 ± .003	.608 ± .002	.610 ± .008	.605 ± .002	.596 ± .004				
	3	.612 ± .002	.625 ± .004	.626 ± .003	.623 ± .001	.609 ± .003	.614 ± .009	.613 ± .012	.623 ± .002	.610 ± .002	.618 ± .003	.608 ± .004	.612 ± .006	.616 ± .005	.622 ± .002	.614 ± .003				
	4	.628 ± .001	.627 ± .003	.629 ± .002	.625 ± .003	.621 ± .003	.619 ± .009	.618 ± .012	.626 ± .003	.627 ± .001	.623 ± .002	.615 ± .001	.618 ± .005	.621 ± .007	.622 ± .002	.623 ± .003				
	5	.630 ± .001	.628 ± .003	.631 ± .001	.629 ± .000	.626 ± .001	.624 ± .008	.626 ± .003	.629 ± .003	.630 ± .001	.629 ± .002	.627 ± .001	.629 ± .002	.626 ± .005	.631 ± .000	.625 ± .003				
Japanese_vowel continuous	1	.812 ± .079	.747 ± .167	.838 ± .005	.836 ± .105	.687 ± .143	.828 ± .066	.677 ± .087	.833 ± .099	.821 ± .045	.828 ± .113	.746 ± .112	.514 ± .108	.587 ± .251	.837 ± .095	.586 ± .251				
	2	.817 ± .071	.791 ± .106	.776 ± .104	.801 ± .059	.731 ± .136	.784 ± .116	.651 ± .132	.813 ± .047	.817 ± .045	.797 ± .172	.828 ± .049	.605 ± .062	.686 ± .133	.827 ± .038	.689 ± .147				
	3	.805 ± .075	.806 ± .095	.775 ± .123	.796 ± .077	.726 ± .140	.796 ± .079	.673 ± .151	.800 ± .075	.805 ± .043	.770 ± .122	.791 ± .057	.673 ± .066	.688 ± .145	.826 ± .052	.786 ± .033				
	4	.802 ± .059	.799 ± .063	.783 ± .111	.797 ± .050	.711 ± .073	.803 ± .063	.758 ± .043	.809 ± .071	.805 ± .044	.803 ± .138	.810 ± .041	.800 ± .069	.747 ± .046	.806 ± .043	.754 ± .052				
	5	.803 ± .056	.802 ± .055	.785 ± .075	.801 ± .048	.808 ± .069	.801 ± .055	.760 ± .049	.815 ± .066	.798 ± .051	.828 ± .078	.804 ± .052	.820 ± .036	.760 ± .049	.801 ± .047	.760 ± .049				
ionosphere	1	.809 ± .071	.830 ± .037	.793 ± .035	.769 ± .070	.593 ± .077	.778 ± .017	.794 ± .057	.783 ± .048	.676 ± .056	.775 ± .038	.692 ± .086	.660 ± .094	.754 ± .093	.809 ± .034	.807 ± .050				
	2	.831 ± .038	.861 ± .039	.786 ± .011	.822 ± .043	.832 ± .051	.865 ± .019	.818 ± .055	.844 ± .046	.785 ± .086	.852 ± .093	.801 ± .062	.819 ± .073	.841 ± .076	.852 ± .050	.864 ± .051				
	3	.857 ± .049	.885 ± .039	.840 ± .032	.887 ± .056	.846 ± .047	.884 ± .029	.812 ± .033	.887 ± .063	.850 ± .039	.894 ± .067	.857 ± .046	.796 ± .056	.857 ± .080	.863 ± .041	.882 ± .049				
	4	.878 ± .056	.908 ± .008	.856 ± .023	.882 ± .062	.867 ± .050	.905 ± .001	.908 ± .034	.866 ± .037	.854 ± .041	.920 ± .040	.860 ± .026	.897 ± .020	.885 ± .063	.883 ± .030	.899 ± .059				
	5	.890 ± .072	.891 ± .037	.884 ± .054	.866 ± .052	.864 ± .056	.912 ± .007	.880 ± .032	.878 ± .058	.882 ± .058	.912 ± .040	.873 ± .046	.904 ± .041	.881 ± .032	.898 ± .041	.916 ± .039				
swedish homograph	1	.683 ± .064	.671 ± .068	.688 ± .048	.697 ± .069	.639 ± .041	.635 ± .035	.610 ± .060	.682 ± .086	.677 ± .079	.698 ± .071	.686 ± .013	.577 ± .063	.525 ± .038	.742 ± .039	.562 ± .046				
	2	.755 ± .031	.735 ± .047	.696 ± .050	.705 ± .046	.687 ± .043	.734 ± .077	.616 ± .034	.716 ± .016	.692 ± .055	.690 ± .066	.709 ± .023	.585 ± .065	.552 ± .057	.703 ± .074	.659 ± .033				
	3	.718 ± .026	.795 ± .045	.694 ± .022	.717 ± .020	.680 ± .072	.765 ± .079	.719 ± .021	.713 ± .020	.719 ± .097	.717 ± .039	.714 ± .021	.654 ± .073	.656 ± .060	.723 ± .053	.707 ± .011				
	4	.729 ± .066	.759 ± .034	.744 ± .035	.747 ± .041	.757 ± .101	.776 ± .038	.738 ± .087	.742 ± .057	.731 ± .064	.746 ± .048	.757 ± .049	.742 ± .072	.777 ± .071	.764 ± .035	.774 ± .066				
	5	.757 ± .073	.762 ± .057	.751 ± .054	.756 ± .040	.784 ± .072	.778 ± .056	.779 ± .051	.765 ± .051	.765 ± .040	.767 ± .066	.769 ± .074	.758 ± .070	.764 ± .067	.764 ± .065	.762 ± .068				
uci_pennstate center	1	.658 ± .076	.694 ± .084	.644 ± .061	.614 ± .073	.583 ± .071	.572 ± .054	.616 ± .077	.588 ± .091	.519 ± .047	.537 ± .097	.657 ± .026	.541 ± .124	.559 ± .081	.637 ± .074	.547 ± .018				
	2	.669 ± .084	.754 ± .081	.667 ± .088	.619 ± .073	.538 ± .064	.731 ± .098	.619 ± .081	.672 ± .066	.541 ± .058	.689 ± .074	.697 ± .096	.644 ± .029	.554 ± .061	.680 ± .065	.651 ± .025				
	3	.679 ± .079	.767 ± .082	.711 ± .083	.676 ± .093	.570 ± .048	.757 ± .071	.665 ± .083	.624 ± .059	.627 ± .140	.698 ± .061	.712 ± .093	.704 ± .079	.678 ± .102	.748 ± .082	.663 ± .047				
	4	.701 ± .086	.751 ± .080	.725 ± .067	.703 ± .089	.623 ± .064	.758 ± .067	.687 ± .124	.659 ± .027	.670 ± .105	.716 ± .091	.723 ± .099	.692 ± .053	.685 ± .058	.740 ± .071	.686 ± .074				
	5	.710 ± .075	.755 ± .070	.755 ± .049	.687 ± .080	.647 ± .093	.730 ± .059	.726 ± .091	.692 ± .048	.721 ± .092	.728 ± .086	.734 ± .082	.725 ± .058	.720 ± .076	.756 ± .064	.714 ± .114				
boston_house prices	1	.873 ± .001	.784 ± .002	.837 ± .001	.600 ± .135	.502 ± .000	.784 ± .002	.746 ± .108	.750 ± .025	.809 ± .002	.777 ± .003	.784 ± .006	.588 ± .035	.593 ± .018	.780 ± .005	.778 ± .003				
	2	.894 ± .010	.910 ± .001	.839 ± .001	.782 ± .004	.609 ± .090	.910 ± .001	.812 ± .010	.820 ± .003	.836 ± .001	.787 ± .003	.843 ± .049	.687 ± .052	.682 ± .043	.893 ± .001	.788 ± .013				
	3	.925 ± .003	.929 ± .002	.859 ± .001	.849 ± .001	.667 ± .001	.927 ± .001	.837 ± .013	.866 ± .002	.877 ± .002	.829 ± .018	.916 ± .003	.738 ± .046	.737 ± .036	.929 ± .002	.824 ± .017				
	4	.936 ± .001	.939 ± .001	.878 ± .002	.680 ± .001	.938 ± .001	.861 ± .017	.873 ± .006	.899 ± .001	.883 ± .012	.924 ± .003	.756 ± .025	.765 ± .014	.935 ± .001	.836 ± .002	.936 ± .001				
	5	.940 ± .001	.942 ± .001	.934 ± .000	.893 ± .002	.728 ± .006	.942 ± .001	.875 ± .013	.892 ± .003	.939 ± .001	.940 ± .000	.934 ± .001	.869 ± .020	.860 ± .013	.938 ± .001	.900 ± .010				
baird_distances matrix	1	.590 ± .039	.629 ± .138	.681 ± .102	.652 ± .089	.708 ± .101	.629 ± .138	.644 ± .098	.679 ± .076	.664 ± .124	.630 ± .068	.622 ± .037	.632 ± .150	.652 ± .092	.560 ± .055	.654 ± .125				
	2	.615 ± .081	.646 ± .145	.693 ± .072	.664 ± .080	.677 ± .126	.646 ± .145	.660 ± .122	.662 ± .074	.663 ± .085	.603 ± .071	.623 ± .087	.690 ± .049	.676 ± .140	.604 ± .094	.668 ± .128				
	3	.625 ± .097	.652 ± .149	.685 ± .085	.659 ± .050	.678 ± .127	.652 ± .149	.645 ± .083	.677 ± .088	.687 ± .101	.620 ± .092	.652 ± .058	.684 ± .107	.680 ± .115	.670 ± .087	.638 ± .129				
	4	.675 ± .102	.638 ± .140	.688 ± .092	.680 ± .090	.677 ± .128	.638 ± .140	.662 ± .102	.662 ± .074	.669 ± .083	.623 ± .092	.663 ± .085	.658 ± .108	.686 ± .125	.697 ± .107	.654 ± .111				
	5	.671 ± .120	.631 ± .115	.678 ± .105	.676 ± .099	.674 ± .107	.631 ± .115	.669 ± .126	.663 ± .101	.672 ± .096	.673 ± .096	.670 ± .089	.663 ± .116	.679 ± .135	.663 ± .101	.670 ± .130				
quec_hockey	1	.862 ± .005	.856 ± .022	.824 ± .009	.866 ± .013	.680 ± .059	.840 ± .025	.838 ± .046	.885 ± .002	.845 ± .029	.879 ± .011	.874 ± .017	.811 ± .070	.875 ± .029	.820 ± .008	.865 ± .008				
	2	.885 ± .009	.902 ± .004	.879 ± .008	.881 ± .008	.846 ± .006	.885 ± .019	.886 ± .014	.891 ± .010	.897 ± .011	.884 ± .009	.897 ± .012	.880 ± .008	.898 ± .021	.887 ± .011	.880 ± .014				
	3	.896 ± .006	.905 ± .005	.905 ± .002	.899 ± .013	.898 ± .005	.898 ± .005	.904 ± .005	.903 ± .002	.901 ± .011	.892 ± .012	.897 ± .011	.908 ± .007	.902 ± .003	.899 ± .012	.896 ± .015				
	4	.903 ± .010	.907 ± .007	.910 ± .003	.905 ± .002	.907 ± .003	.908 ± .003	.907 ± .004	.906 ± .001	.905 ± .010	.903 ± .008	.904 ± .005	.904 ± .014	.905 ± .004	.900 ± .004	.905 ± .005				
	5	.904 ± .004	.909 ± .005	.910 ± .005	.907 ± .002	.910 ± .005	.909 ± .005	.909 ± .002	.910 ± .003	.904 ± .006	.910 ± .007	.908 ± .004	.907 ± .008	.909 ± .002	.910 ± .003	.908 ± .004				
multiscaled_ranked permutation	1	.974 ± .002	.975 ± .003	.973 ± .002	.848 ± .049	.579 ± .002	.969 ± .010	.969 ± .005	.775 ± .095	.970 ± .007	.848 ± .049	.969 ± .005	.877 ± .071	.820 ± .038	.974 ± .002	.970 ± .006				
	2	.978 ± .002	.980 ± .003	.976 ± .002	.931 ± .001	.633 ± .003	.978 ± .005	.974 ± .005	.868 ± .044	.976 ± .002	.931 ± .001	.975 ± .002	.877 ± .011	.805 ± .071	.978 ± .002	.972 ± .005				
	3	.978 ± .002	.981 ± .003	.980 ± .003	.951 ± .009	.722 ± .010	.980 ± .003	.976 ± .004	.947 ± .007	.979 ± .003	.951 ± .009	.977 ± .002	.945 ± .010	.926 ± .041	.979 ± .002	.976 ± .003				
	4	.980 ± .002	.981 ± .003	.980 ± .003	.973 ± .004	.820 ± .001	.981 ± .002	.977 ± .004	.961 ± .001	.980 ± .004	.973 ± .004	.979 ± .002	.949 ± .029	.968 ± .013	.980 ± .002	.978 ± .004				
	5	.981 ± .002	.981 ± .003	.981 ± .003	.979 ± .001	.951 ± .008	.981 ± .002	.978 ± .004	.977 ± .004	.980 ± .002	.979 ± .001	.981 ± .002	.968 ± .009	.978 ± .004	.981 ± .002	.979 ± .004				
Barrington hills_sunny	1	.641 ± .069	.713 ± .029	.700 ± .021	.698 ± .022	.563 ± .019	.704 ± .025	.701 ± .028	.689 ± .037	.700 ± .021	.700 ± .013	.690 ± .022	.598 ± .033	.698 ± .014	.662 ± .044	.692 ± .015				
	2	.678 ± .033	.717 ± .028	.698 ± .021	.698 ± .021	.593 ± .016	.717 ± .028	.713 ± .035	.689 ± .034	.701 ± .018	.715 ± .023	.702 ± .032	.660 ± .018	.714 ± .027	.697 ± .020	.699 ± .012				
	3	.707 ± .032	.716 ± .029	.716 ± .023	.709 ± .026	.668 ± .012	.717 ± .029	.720 ± .029	.709 ± .027	.702 ± .020	.718 ± .023	.708 ± .031	.683 ± .028	.716 ± .029	.707 ± .032	.720 ± .018				
	4	.713 ± .030	.717 ± .028	.717 ± .023	.705 ± .030	.722 ± .022	.717													

Table D.7: Per-cell results with downstream model **RF**. Tasks are grouped by metric. Each cell is the mean over three seeds, with the sample standard deviation as a subscript.

Dataset	Budget idx. j
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(continued from previous page)

Dataset	Budget idx	CART	ElankNet	F-test	Guifatio	LaplacianScore	Lasso	LOCO	Markov Blanket	MI	mRMR	(R)Relieff	Random	SBE	RFImportance	SFS
base_code dataset	1	1.02 ± .11	.939 ± .184	.927 ± .080	.982 ± .177	1.12 ± .27	.945 ± .177	.961 ± .101	.862 ± .049	.915 ± .123	1.02 ± .11	1.06 ± .27	1.32 ± .60	1.17 ± .29	.913 ± .021	1.44 ± .16
	2	.796 ± .047	.754 ± .063	.769 ± .035	.794 ± .113	.947 ± .151	.741 ± .027	.816 ± .100	.727 ± .011	.803 ± .135	.773 ± .031	.780 ± .043	.847 ± .121	.854 ± .160	.747 ± .008	.903 ± .157
	3	.751 ± .026	.754 ± .043	.722 ± .026	.751 ± .081	.818 ± .107	.751 ± .030	.753 ± .093	.728 ± .024	.762 ± .099	.728 ± .044	.762 ± .003	.740 ± .037	.764 ± .016	.734 ± .014	.812 ± .166
	4	.722 ± .012	.724 ± .038	.722 ± .024	.708 ± .015	.725 ± .061	.723 ± .036	.741 ± .093	.719 ± .021	.712 ± .046	.726 ± .023	.721 ± .018	.765 ± .052	.699 ± .027	.722 ± .030	.783 ± .068
	5	.717 ± .015	.712 ± .027	.723 ± .030	.721 ± .013	.716 ± .032	.731 ± .051	.744 ± .095	.712 ± .026	.718 ± .029	.718 ± .022	.718 ± .027	.743 ± .082	.709 ± .046	.721 ± .031	.772 ± .075
test prediction	1	.653 ± .194	.274 ± .094	.486 ± .184	.517 ± .213	1.38 ± .14	.362 ± .205	1.30 ± .18	.557 ± .095	.782 ± .412	.630 ± .372	.363 ± .112	1.08 ± .65	1.03 ± .38	.486 ± .132	1.18 ± .27
	2	.610 ± .090	.265 ± .031	.265 ± .058	.316 ± .052	1.01 ± .04	.256 ± .043	.812 ± .124	.329 ± .107	.307 ± .094	.320 ± .072	.285 ± .028	1.07 ± .08	.884 ± .115	.260 ± .037	.883 ± .174
	3	.602 ± .015	.267 ± .033	.277 ± .040	.287 ± .057	.861 ± .020	.281 ± .043	.794 ± .073	.309 ± .049	.306 ± .046	.285 ± .062	.271 ± .034	.702 ± .031	.765 ± .072	.285 ± .023	.687 ± .053
	4	.627 ± .017	.331 ± .015	.327 ± .032	.323 ± .029	.689 ± .045	.342 ± .016	.621 ± .043	.314 ± .037	.315 ± .053	.324 ± .017	.332 ± .027	.646 ± .034	.705 ± .125	.332 ± .026	.647 ± .048
	5	.563 ± .056	.401 ± .009	.392 ± .032	.400 ± .014	.563 ± .011	.437 ± .005	.566 ± .059	.399 ± .022	.404 ± .018	.408 ± .019	.392 ± .010	.543 ± .046	.539 ± .060	.411 ± .016	.566 ± .025
shc_17	1	.164 ± .004	.189 ± .023	.221 ± .003	.225 ± .006	.776 ± .003	.356 ± .331	.165 ± .003	.165 ± .003	.203 ± .002	.452 ± .002	.250 ± .004	.715 ± .527	.166 ± .004	.225 ± .006	.203 ± .002
	2	.0923 ± .0042	.0938 ± .0056	.105 ± .006	.0948 ± .0049	.504 ± .139	.0919 ± .0053	.0911 ± .0031	.0961 ± .0108	.0930 ± .0028	.173 ± .004	.105 ± .005	.116 ± .012	.0902 ± .0045	.0942 ± .0052	.112 ± .003
	3	.0828 ± .0042	.0832 ± .0042	.0890 ± .0002	.0820 ± .0037	.407 ± .035	.0827 ± .0042	.0822 ± .0019	.0814 ± .0029	.0820 ± .0053	.0982 ± .0041	.0907 ± .0047	.400 ± .056	.0827 ± .0024	.0819 ± .0044	.0838 ± .0032
	4	.0835 ± .0043	.0859 ± .0041	.0888 ± .0070	.0841 ± .0038	.176 ± .130	.0855 ± .0038	.0845 ± .0030	.0839 ± .0047	.0839 ± .0038	.0934 ± .0019	.0838 ± .0038	.261 ± .146	.0858 ± .0048	.0837 ± .0041	.0843 ± .0032
	5	.0810 ± .0026	.0814 ± .0038	.0817 ± .0025	.0810 ± .0030	.0809 ± .0050	.0819 ± .0033	.0808 ± .0027	.0801 ± .0028	.0809 ± .0023	.0820 ± .0031	.0802 ± .0026	.164 ± .147	.0805 ± .0029	.0809 ± .0036	.0812 ± .0030
predict_outcome_dropout and_outcome_predict	1	.717 ± .068	.896 ± .050	.812 ± .057	.765 ± .030	1.37 ± .08	.931 ± .161	.865 ± .097	.811 ± .064	.768 ± .033	1.02 ± .14	.728 ± .034	.861 ± .112	1.01 ± .06	.844 ± .053	.827 ± .108
	2	.609 ± .059	.654 ± .020	.651 ± .020	.665 ± .014	1.17 ± .11	.646 ± .035	.618 ± .007	.635 ± .012	.630 ± .027	.730 ± .033	.648 ± .011	.744 ± .039	.656 ± .039	.606 ± .018	.733 ± .117
	3	.593 ± .009	.604 ± .029	.587 ± .019	.621 ± .009	.703 ± .034	.603 ± .014	.596 ± .012	.622 ± .016	.583 ± .016	.628 ± .011	.595 ± .017	.691 ± .047	.624 ± .034	.594 ± .009	.621 ± .021
	4	.589 ± .011	.581 ± .008	.587 ± .008	.622 ± .008	.621 ± .021	.590 ± .019	.586 ± .018	.616 ± .005	.588 ± .009	.605 ± .009	.586 ± .001	.625 ± .001	.585 ± .008	.581 ± .006	.593 ± .014
	5	.583 ± .004	.580 ± .005	.581 ± .011	.602 ± .020	.582 ± .008	.585 ± .006	.585 ± .015	.619 ± .017	.584 ± .004	.595 ± .009	.581 ± .012	.591 ± .023	.586 ± .007	.581 ± .006	.583 ± .008
accuracy	1	2.00 ± .22	2.29 ± .21	2.07 ± .33	2.27 ± .13	2.30 ± .15	2.20 ± .34	2.87 ± .15	3.28 ± .14	3.11 ± .91	3.23 ± .28	2.27 ± .43	3.18 ± .65	3.12 ± .93	3.40 ± .34	2.96 ± .85
	2	3.33 ± .21	3.20 ± .33	2.31 ± .27	2.41 ± .08	2.29 ± .12	2.87 ± .79	3.40 ± .27	3.30 ± .38	3.33 ± .25	3.20 ± .20	2.86 ± .12	4.06 ± .72	3.51 ± .20	3.47 ± .41	3.70 ± .33
	3	1.86 ± .14	2.13 ± .34	2.66 ± .62	2.87 ± .59	2.40 ± .48	2.55 ± .30	2.22 ± .46	1.91 ± .00	1.78 ± .10	1.88 ± .04	2.07 ± .15	2.93 ± .24	2.80 ± .17	1.90 ± .10	2.67 ± .51
	4	1.67 ± .03	1.70 ± .07	1.73 ± .05	1.75 ± .02	3.38 ± .18	1.72 ± .04	1.74 ± .04	1.73 ± .04	1.63 ± .02	1.76 ± .02	1.71 ± .07	2.00 ± .20	1.99 ± .09	1.63 ± .01	1.87 ± .09
	5	1.66 ± .02	1.70 ± .07	1.62 ± .02	1.76 ± .01	1.71 ± .08	1.70 ± .08	1.73 ± .08	1.77 ± .02	1.64 ± .02	1.76 ± .01	1.69 ± .05	1.91 ± .08	1.76 ± .10	1.68 ± .02	1.78 ± .03
auc_roc_auc_probed and_auc_roc_probed	1	.837 ± .040	1.03 ± .06	1.17 ± .02	1.43 ± .01	1.19 ± .06	1.14 ± .02	1.21 ± .08	.874 ± .020	1.19 ± .01	1.02 ± .01	1.04 ± .05	1.48 ± .12	1.47 ± .14	.832 ± .003	1.45 ± .18
	2	.624 ± .007	.679 ± .023	.753 ± .024	1.11 ± .01	.726 ± .010	.733 ± .045	.907 ± .045	.647 ± .006	.725 ± .008	.715 ± .006	.716 ± .013	.997 ± .008	.976 ± .029	.632 ± .008	.996 ± .146
	3	.591 ± .006	.597 ± .004	.635 ± .003	.705 ± .005	.611 ± .007	.601 ± .005	.818 ± .087	.600 ± .009	.650 ± .004	.642 ± .004	.652 ± .009	.764 ± .043	.742 ± .056	.598 ± .008	.773 ± .049
	4	.586 ± .007	.581 ± .006	.602 ± .002	.636 ± .005	.592 ± .002	.579 ± .006	.678 ± .009	.591 ± .006	.600 ± .003	.599 ± .005	.619 ± .004	.682 ± .013	.696 ± .053	.585 ± .005	.673 ± .048
	5	.583 ± .006	.582 ± .007	.588 ± .006	.590 ± .008	.588 ± .007	.583 ± .007	.614 ± .010	.584 ± .007	.589 ± .008	.588 ± .005	.595 ± .009	.624 ± .024	.649 ± .005	.583 ± .006	.632 ± .013
log_cancer	1	.360 ± .191	.464 ± .042	.559 ± .213	.294 ± .056	1.18 ± .17	.541 ± .220	.837 ± .188	.358 ± .160	.434 ± .116	.346 ± .146	.386 ± .068	.811 ± .209	.711 ± .044	.462 ± .310	.619 ± .146
	2	.360 ± .095	.257 ± .019	.373 ± .038	.288 ± .021	.995 ± .060	.261 ± .071	.462 ± .087	.279 ± .023	.283 ± .044	.258 ± .013	.279 ± .038	.565 ± .142	.498 ± .023	.271 ± .159	.474 ± .070
	3	.365 ± .058	.194 ± .005	.254 ± .021	.240 ± .009	.889 ± .009	.224 ± .008	.391 ± .026	.255 ± .022	.233 ± .021	.229 ± .017	.227 ± .006	.346 ± .021	.365 ± .050	.206 ± .013	.387 ± .046
	4	.322 ± .013	.203 ± .008	.220 ± .013	.228 ± .026	.801 ± .056	.233 ± .013	.342 ± .020	.230 ± .027	.221 ± .017	.225 ± .019	.225 ± .010	.338 ± .017	.336 ± .008	.227 ± .014	.334 ± .030
	5	.308 ± .030	.244 ± .022	.243 ± .023	.241 ± .015	.409 ± .088	.269 ± .009	.299 ± .007	.246 ± .020	.243 ± .018	.250 ± .011	.244 ± .016	.305 ± .012	.309 ± .016	.254 ± .015	.307 ± .011
system usage	1	.867 ± .491	2.27 ± .29	1.22 ± .28	1.38 ± .38	1.43 ± .64	2.12 ± .56	1.82 ± .67	.633 ± .106	.703 ± .136	.731 ± .237	2.41 ± .15	2.16 ± .96	2.09 ± .98	.635 ± .201	1.01 ± .41
	2	.561 ± .205	1.13 ± .15	1.01 ± .44	.829 ± .305	.937 ± .913	1.13 ± .12	.874 ± .199	.507 ± .077	.699 ± .047	.531 ± .031	1.20 ± .29	1.19 ± .47	.819 ± .376	.418 ± .056	.511 ± .108
	3	.495 ± .126	.666 ± .063	.662 ± .289	.566 ± .355	.553 ± .174	.816 ± .230	.918 ± .248	.521 ± .086	.392 ± .133	.446 ± .019	.505 ± .025	.401 ± .025	.465 ± .215	.400 ± .023	.469 ± .165
	4	.395 ± .021	.503 ± .130	.484 ± .176	.530 ± .399	.461 ± .235	.528 ± .045	.566 ± .087	.441 ± .123	.333 ± .042	.416 ± .028	.425 ± .038	.437 ± .013	.520 ± .132	.378 ± .023	.490 ± .102
	5	.378 ± .038	.386 ± .027	.399 ± .300	.346 ± .044	.365 ± .123	.456 ± .039	.424 ± .023	.392 ± .067	.335 ± .035	.358 ± .026	.360 ± .038	.390 ± .026	.386 ± .043	.363 ± .036	.389 ± .046
misc	1	1.17 ± .04	1.36 ± .07	.896 ± .079	.690 ± .078	.710 ± .013	1.01 ± .42	1.72 ± .02	.890 ± .237	.716 ± .099	1.29 ± .15	.738 ± .113	.798 ± .074	.944 ± .165	.885 ± .149	.688 ± .108
	2	.937 ± .106	1.17 ± .05	1.07 ± .08	.720 ± .048	.711 ± .012	1.18 ± .18	1.60 ± .11	.912 ± .136	.811 ± .048	1.08 ± .03	1.13 ± .16	1.15 ± .17	.929 ± .130	.920 ± .175	.713 ± .193
	3	.646 ± .076	.739 ± .040	1.07 ± .08	.779 ± .072	.795 ± .108	.715 ± .091	1.05 ± .15	.824 ± .145	.957 ± .057	.625 ± .017	1.07 ± .12	1.03 ± .25	1.27 ± .10	.693 ± .095	1.28 ± .16
	4	.554 ± .047	.597 ± .042	.796 ± .051	.870 ± .035	.973 ± .100	.581 ± .009	.709 ± .023	.632 ± .118	.583 ± .078	.530 ± .035	.768 ± .075	.834 ± .026	.985 ± .152	.568 ± .013	.827 ± .133
	5	.506 ± .028	.572 ± .045	.522 ± .031	.651 ± .118	1.29 ± .05	.581 ± .005	.570 ± .069	.510 ± .032	.588 ± .097	.531 ± .022	.569 ± .081	.678 ± .080	.680 ± .111	.514 ± .028	.569 ± .103
libsvm primary/train	1	3.28 ± .75	2.70 ± .42	2.10 ± .17	2.37 ± .08	2.16 ± .09	2.51 ± .29	2.35 ± .55	3.65 ± .54	.842 ± .58	3.41 ± .24	2.61 ± .47	2.68 ± .38	2.31 ± .65	3.35 ± .14	2.33 ± .04
	2	3.16 ± .54	3.19 ± .90	3.31 ± .19	3.51 ± .74	2.39 ± .40	2.73 ± .33	2.89 ± .33	3.32 ± .36	2.75 ± .68	3.44 ± .75	3.09 ± .94	2.92 ± .31	2.51 ± .66	3.10 ± .23	2.89 ± .63
	3	2.51 ± .59	3.20 ± .39	2.83 ± .50	3.04 ± .62	3.63 ± .38	2.61 ± .16	2.95 ± .38	2.69 ± .85	2.41 ± .67	2.97 ± .77	2.84 ± .55	2.78 ± .54	2.64 ± .50	2.22 ± .25	2.73 ± .50
	4	1.63 ± .17	2.33 ± .69	1.78 ± .32	2.14 ± .44	2.87 ± .63	2.21 ± .30	2.74 ± .42	2.14 ± .25	1.69 ± .29	2.22 ± .34	1.95 ± .42	2.42 ± .18	2.40 ± .40	1.64 ± .13	2.64 ± .44
	5	1.57 ± .14	1.86 ± .41	1.63 ± .16	1.90 ± .46	1.94 ± .36	1.71 ± .22	1.91 ± .28	1.79 ± .35	1.57 ± .23	1.83 ± .43	1.71 ± .32	1.75 ± .29	2.04 ± .21	1.58 ± .22	2.13 ± .51
misc out_of_1	1	.131 ± .066	.165 ± .032	.254 ± .052	.107 ± .062	.521 ± .016	.150 ± .076	.174 ± .085	.073 ± .040	.117 ± .007	.0975 ± .0424	.146 ± .040	.612 ± .149	.121 ± .028	.0903 ± .0446	.0966 ± .0575
	2	.0613 ± .0														

(continued from previous page)

Dataset	Budget idx j	CART	ElankiNet	F-test	GuinRatio	LaplacianScore	Lasso	LOCO	MarkovBlanket	MI	mRMR	(R)Relieff	Random	SSE	RfImportance	SFS
forest data	1	1.55 $\pm$.06	1.57 $\pm$.11	1.62 $\pm$.10	1.58 $\pm$.11	1.47 $\pm$.09	1.57 $\pm$.11	1.57 $\pm$.09	1.58 $\pm$.09	1.54 $\pm$.08	1.50 $\pm$.13	1.58 $\pm$.09	1.48 $\pm$.06	1.46 $\pm$.08	1.56 $\pm$.07	1.42 $\pm$.07
	2	1.48 $\pm$.05	1.51 $\pm$.02	1.53 $\pm$.12	1.51 $\pm$.03	1.49 $\pm$.05	1.51 $\pm$.02	1.50 $\pm$.06	1.47 $\pm$.02	1.51 $\pm$.08	1.55 $\pm$.06	1.49 $\pm$.03	1.50 $\pm$.01	1.47 $\pm$.02	1.49 $\pm$.08	1.52 $\pm$.07
	3	1.47 $\pm$.05	1.49 $\pm$.04	1.48 $\pm$.05	1.49 $\pm$.05	1.48 $\pm$.07	1.49 $\pm$.04	1.48 $\pm$.02	1.46 $\pm$.01	1.48 $\pm$.06	1.47 $\pm$.06	1.48 $\pm$.06	1.50 $\pm$.03	1.47 $\pm$.03	1.46 $\pm$.03	1.47 $\pm$.05
	4	1.45 $\pm$.05	1.47 $\pm$.04	1.48 $\pm$.04	1.47 $\pm$.05	1.46 $\pm$.04	1.47 $\pm$.04	1.47 $\pm$.02	1.46 $\pm$.04	1.47 $\pm$.07	1.46 $\pm$.06	1.47 $\pm$.07	1.46 $\pm$.04	1.47 $\pm$.03	1.46 $\pm$.04	1.45 $\pm$.06
	5	1.46 $\pm$.05	1.46 $\pm$.04	1.47 $\pm$.06	1.46 $\pm$.05	1.46 $\pm$.04	1.46 $\pm$.04	1.47 $\pm$.04	1.46 $\pm$.04	1.47 $\pm$.04	1.45 $\pm$.05	1.47 $\pm$.05	1.46 $\pm$.04	1.47 $\pm$.04	1.46 $\pm$.04	1.47 $\pm$.04
airline classification	1	.720 $\pm$.002	.680 $\pm$.002	.675 $\pm$.002	.705 $\pm$.010	.811 $\pm$.002	.680 $\pm$.002	.670 $\pm$.001	.695 $\pm$.001	.670 $\pm$.002	.719 $\pm$.011	.695 $\pm$.003	.783 $\pm$.024	.786 $\pm$.024	.720 $\pm$.002	.661 $\pm$.001
	2	.657 $\pm$.001	.690 $\pm$.001	.659 $\pm$.001	.656 $\pm$.003	.809 $\pm$.002	.690 $\pm$.001	.669 $\pm$.016	.665 $\pm$.001	.651 $\pm$.001	.694 $\pm$.014	.652 $\pm$.011	.796 $\pm$.010	.799 $\pm$.018	.660 $\pm$.005	.654 $\pm$.013
	3	.605 $\pm$.001	.641 $\pm$.006	.646 $\pm$.001	.631 $\pm$.011	.807 $\pm$.002	.641 $\pm$.006	.633 $\pm$.007	.634 $\pm$.002	.634 $\pm$.001	.638 $\pm$.002	.642 $\pm$.015	.763 $\pm$.020	.767 $\pm$.024	.604 $\pm$.001	.645 $\pm$.015
	4	.580 $\pm$.002	.582 $\pm$.005	.629 $\pm$.005	.587 $\pm$.003	.780 $\pm$.010	.582 $\pm$.005	.586 $\pm$.006	.634 $\pm$.003	.590 $\pm$.003	.623 $\pm$.004	.616 $\pm$.006	.702 $\pm$.034	.703 $\pm$.027	.579 $\pm$.001	.648 $\pm$.008
	5	.566 $\pm$.001	.566 $\pm$.001	.578 $\pm$.002	.584 $\pm$.002	.719 $\pm$.011	.566 $\pm$.003	.566 $\pm$.003	.576 $\pm$.001	.568 $\pm$.002	.603 $\pm$.010	.594 $\pm$.014	.623 $\pm$.022	.634 $\pm$.024	.566 $\pm$.001	.601 $\pm$.005
insurance company	1	.259 $\pm$.020	.276 $\pm$.003	.346 $\pm$.004	.283 $\pm$.007	.330 $\pm$.008	.276 $\pm$.003	.352 $\pm$.051	.205 $\pm$.005	.214 $\pm$.030	.324 $\pm$.001	.381 $\pm$.002	.454 $\pm$.089	.205 $\pm$.019	.268 $\pm$.028	.272 $\pm$.005
	2	.188 $\pm$.006	.233 $\pm$.005	.243 $\pm$.005	.186 $\pm$.005	.230 $\pm$.003	.233 $\pm$.005	.229 $\pm$.033	.193 $\pm$.004	.195 $\pm$.002	.192 $\pm$.008	.251 $\pm$.026	.300 $\pm$.089	.173 $\pm$.010	.191 $\pm$.003	.184 $\pm$.007
	3	.165 $\pm$.003	.185 $\pm$.010	.181 $\pm$.004	.179 $\pm$.004	.227 $\pm$.001	.190 $\pm$.007	.172 $\pm$.010	.186 $\pm$.007	.180 $\pm$.005	.180 $\pm$.005	.196 $\pm$.023	.219 $\pm$.017	.163 $\pm$.005	.165 $\pm$.006	.165 $\pm$.007
	4	.163 $\pm$.004	.172 $\pm$.003	.161 $\pm$.005	.173 $\pm$.003	.225 $\pm$.001	.171 $\pm$.005	.162 $\pm$.006	.173 $\pm$.007	.173 $\pm$.003	.170 $\pm$.010	.163 $\pm$.007	.192 $\pm$.022	.160 $\pm$.005	.161 $\pm$.005	.162 $\pm$.006
	5	.160 $\pm$.003	.161 $\pm$.006	.161 $\pm$.005	.160 $\pm$.005	.206 $\pm$.005	.161 $\pm$.006	.160 $\pm$.004	.160 $\pm$.005	.160 $\pm$.005	.163 $\pm$.007	.160 $\pm$.005	.174 $\pm$.010	.160 $\pm$.004	.160 $\pm$.005	.160 $\pm$.004
wine quality	1	.784 $\pm$.016	.795 $\pm$.012	.791 $\pm$.008	.791 $\pm$.008	.852 $\pm$.010	.790 $\pm$.007	.886 $\pm$.009	.784 $\pm$.016	.791 $\pm$.008	.780 $\pm$.006	.805 $\pm$.018	.834 $\pm$.037	.804 $\pm$.008	.784 $\pm$.016	.780 $\pm$.006
	2	.662 $\pm$.008	.678 $\pm$.006	.683 $\pm$.007	.692 $\pm$.009	.722 $\pm$.011	.678 $\pm$.006	.726 $\pm$.012	.683 $\pm$.013	.697 $\pm$.010	.724 $\pm$.015	.679 $\pm$.015	.725 $\pm$.040	.671 $\pm$.013	.664 $\pm$.006	.691 $\pm$.005
	3	.637 $\pm$.009	.664 $\pm$.006	.665 $\pm$.010	.651 $\pm$.002	.657 $\pm$.006	.664 $\pm$.005	.648 $\pm$.017	.649 $\pm$.012	.654 $\pm$.016	.658 $\pm$.005	.640 $\pm$.010	.669 $\pm$.025	.643 $\pm$.012	.636 $\pm$.009	.647 $\pm$.008
	4	.624 $\pm$.011	.642 $\pm$.005	.640 $\pm$.007	.630 $\pm$.010	.642 $\pm$.007	.641 $\pm$.006	.630 $\pm$.009	.629 $\pm$.012	.629 $\pm$.014	.636 $\pm$.009	.626 $\pm$.011	.648 $\pm$.013	.628 $\pm$.010	.624 $\pm$.011	.634 $\pm$.010
	5	.620 $\pm$.011	.626 $\pm$.008	.630 $\pm$.007	.621 $\pm$.009	.627 $\pm$.006	.626 $\pm$.007	.623 $\pm$.007	.621 $\pm$.010	.622 $\pm$.014	.626 $\pm$.011	.618 $\pm$.011	.631 $\pm$.013	.621 $\pm$.009	.618 $\pm$.011	.626 $\pm$.010
bodyfat percentage	1	.0117 $\pm$.0006	.0114 $\pm$.0011	.0112 $\pm$.0006	.0113 $\pm$.0004	.0128 $\pm$.0032	.0114 $\pm$.0011	.0128 $\pm$.0024	.0112 $\pm$.0004	.0114 $\pm$.0003	.0117 $\pm$.0009	.0117 $\pm$.0011	.0163 $\pm$.0049	.0117 $\pm$.0014	.0115 $\pm$.0011	.0118 $\pm$.0010
	2	.0114 $\pm$.0011	.0113 $\pm$.0008	.0113 $\pm$.0004	.0112 $\pm$.0003	.0113 $\pm$.0003	.0113 $\pm$.0008	.0126 $\pm$.0023	.0113 $\pm$.0004	.0113 $\pm$.0005	.0114 $\pm$.0010	.0113 $\pm$.0007	.0146 $\pm$.0026	.0113 $\pm$.0014	.0114 $\pm$.0010	.0117 $\pm$.0011
	3	.0113 $\pm$.0010	.0114 $\pm$.0007	.0114 $\pm$.0005	.0113 $\pm$.0004	.0116 $\pm$.0008	.0114 $\pm$.0007	.0114 $\pm$.0012	.0116 $\pm$.0007	.0114 $\pm$.0005	.0115 $\pm$.0008	.0113 $\pm$.0008	.0123 $\pm$.0022	.0113 $\pm$.0013	.0114 $\pm$.0010	.0114 $\pm$.0010
	4	.0111 $\pm$.0011	.0113 $\pm$.0008	.0114 $\pm$.0006	.0115 $\pm$.0007	.0114 $\pm$.0008	.0113 $\pm$.0008	.0114 $\pm$.0010	.0115 $\pm$.0006	.0115 $\pm$.0006	.0115 $\pm$.0008	.0113 $\pm$.0008	.0121 $\pm$.0007	.0113 $\pm$.0010	.0114 $\pm$.0010	.0113 $\pm$.0010
	5	.0112 $\pm$.0010	.0113 $\pm$.0009	.0114 $\pm$.0008	.0115 $\pm$.0009	.0115 $\pm$.0008	.0113 $\pm$.0009	.0113 $\pm$.0009	.0115 $\pm$.0008	.0115 $\pm$.0008	.0114 $\pm$.0009	.0113 $\pm$.0009	.0131 $\pm$.0007	.0113 $\pm$.0010	.0114 $\pm$.0009	.0113 $\pm$.0010
breast cancer (34 F)	1	7.18 $\pm$ 1.59	7.02 $\pm$ 1.59	7.18 $\pm$ 1.59	11.1 $\pm$ 3.5	15.4 $\pm$ 1.1	7.02 $\pm$ 1.59	7.30 $\pm$ 1.08	7.18 $\pm$ 1.59	11.1 $\pm$ 3.5	7.18 $\pm$ 1.59	7.12 $\pm$ 1.21	8.89 $\pm$.85	8.04 $\pm$.42	7.18 $\pm$ 1.59	11.4 $\pm$ 2.7
	2	6.89 $\pm$ 1.58	6.92 $\pm$ 1.52	6.93 $\pm$ 1.52	7.21 $\pm$ 1.62	15.0 $\pm$ 4.2	6.88 $\pm$ 1.58	6.88 $\pm$ 1.54	6.87 $\pm$ 1.59	6.89 $\pm$ 1.56	6.88 $\pm$ 1.60	6.92 $\pm$ 1.54	12.9 $\pm$ 2.7	6.89 $\pm$ 1.53	6.89 $\pm$ 1.58	8.59 $\pm$ 2.85
	3	6.87 $\pm$ 1.59	6.87 $\pm$ 1.61	6.86 $\pm$ 1.60	6.87 $\pm$ 1.59	10.7 $\pm$ 1.3	6.88 $\pm$ 1.60	6.87 $\pm$ 1.52	6.88 $\pm$ 1.61	6.89 $\pm$ 1.61	6.90 $\pm$ 1.55	6.87 $\pm$ 1.58	7.41 $\pm$ 2.26	6.94 $\pm$ 1.53	6.87 $\pm$ 1.59	8.56 $\pm$ 3.36
	4	6.89 $\pm$ 1.57	6.88 $\pm$ 1.56	6.89 $\pm$ 1.57	6.89 $\pm$ 1.58	10.4 $\pm$ 1.2	6.88 $\pm$ 1.56	6.88 $\pm$ 1.53	6.89 $\pm$ 1.61	6.90 $\pm$ 1.58	6.89 $\pm$ 1.60	6.88 $\pm$ 1.59	10.6 $\pm$.62	6.92 $\pm$ 1.53	6.89 $\pm$ 1.57	10.2 $\pm$ 5.9
	5	6.89 $\pm$ 1.60	6.88 $\pm$ 1.60	6.88 $\pm$ 1.60	6.89 $\pm$ 1.60	9.97 $\pm$ 1.58	6.89 $\pm$ 1.60	6.89 $\pm$ 1.54	6.88 $\pm$ 1.60	6.89 $\pm$ 1.58	6.88 $\pm$ 1.60	6.88 $\pm$ 1.61	6.88 $\pm$ 1.61	6.92 $\pm$ 1.55	6.89 $\pm$ 1.59	6.91 $\pm$ 1.53
automobile	1	.644 $\pm$.050	.653 $\pm$.170	.586 $\pm$.159	.646 $\pm$.109	1.12 $\pm$.08	.655 $\pm$.168	.709 $\pm$.046	.806 $\pm$.131	.613 $\pm$.155	.775 $\pm$.108	.662 $\pm$.185	.775 $\pm$.086	.730 $\pm$.156	.613 $\pm$.088	.768 $\pm$.135
	2	.615 $\pm$.087	.670 $\pm$.146	.635 $\pm$.172	.714 $\pm$.045	.916 $\pm$.052	.670 $\pm$.147	.683 $\pm$.025	.760 $\pm$.030	.645 $\pm$.194	.714 $\pm$.073	.652 $\pm$.187	.778 $\pm$.028	.660 $\pm$.031	.612 $\pm$.043	.709 $\pm$.151
	3	.617 $\pm$.058	.712 $\pm$.167	.672 $\pm$.145	.722 $\pm$.066	.783 $\pm$.052	.713 $\pm$.165	.643 $\pm$.051	.622 $\pm$.039	.664 $\pm$.119	.694 $\pm$.070	.628 $\pm$.142	.726 $\pm$.079	.648 $\pm$.045	.631 $\pm$.047	.733 $\pm$.031
	4	.622 $\pm$.047	.706 $\pm$.172	.661 $\pm$.118	.661 $\pm$.108	.705 $\pm$.174	.652 $\pm$.057	.605 $\pm$.029	.620 $\pm$.090	.642 $\pm$.039	.670 $\pm$.111	.655 $\pm$.040	.650 $\pm$.020	.627 $\pm$.035	.669 $\pm$.096	.666 $\pm$.096
	5	.630 $\pm$.039	.650 $\pm$.093	.629 $\pm$.047	.680 $\pm$.138	.660 $\pm$.057	.651 $\pm$.092	.631 $\pm$.064	.617 $\pm$.048	.627 $\pm$.039	.617 $\pm$.056	.614 $\pm$.061	.631 $\pm$.035	.622 $\pm$.066	.624 $\pm$.039	.652 $\pm$.039
post-operative predictor of death	1	.649 $\pm$.008	.599 $\pm$.002	.598 $\pm$.002	.598 $\pm$.002	.598 $\pm$.002	.599 $\pm$.002	.601 $\pm$.002	.600 $\pm$.001	.604 $\pm$.003	.612 $\pm$.008	.598 $\pm$.002	.600 $\pm$.001	.601 $\pm$.005	.647 $\pm$.006	.605 $\pm$.008
	2	.611 $\pm$.003	.644 $\pm$.027	.627 $\pm$.004	.598 $\pm$.002	.611 $\pm$.015	.643 $\pm$.029	.627 $\pm$.029	.631 $\pm$.013	.640 $\pm$.001	.644 $\pm$.017	.611 $\pm$.008	.637 $\pm$.011	.640 $\pm$.016	.610 $\pm$.001	.644 $\pm$.006
	3	.611 $\pm$.003	.612 $\pm$.002	.621 $\pm$.010	.635 $\pm$.024	.611 $\pm$.002	.622 $\pm$.009	.630 $\pm$.010	.625 $\pm$.002	.615 $\pm$.004	.639 $\pm$.004	.611 $\pm$.008	.614 $\pm$.001	.617 $\pm$.005	.611 $\pm$.002	.614 $\pm$.003
	4	.613 $\pm$.003	.611 $\pm$.002	.613 $\pm$.002	.620 $\pm$.002	.623 $\pm$.006	.611 $\pm$.002	.614 $\pm$.002	.611 $\pm$.002	.614 $\pm$.003	.612 $\pm$.002	.613 $\pm$.004	.614 $\pm$.005	.614 $\pm$.003	.613 $\pm$.002	.613 $\pm$

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Dataset	Budget idx	CART	ElankiNet	F-test	GiniRatio	LaplacianScore	Lasso	LOCO	MarkovBlanket	MI	mRMR	(R)Relieff	Random	SBE	RfImportance	SFS
new imputation	1	902 ± 034	835 ± 131	890 ± 095	862 ± 100	936 ± 048	776 ± 172	832 ± 140	949 ± 035	908 ± 095	880 ± 069	944 ± 060	754 ± 164	813 ± 256	908 ± 095	840 ± 133
	2	929 ± 051	960 ± 049	911 ± 049	918 ± 031	967 ± 030	943 ± 065	887 ± 115	943 ± 042	955 ± 019	938 ± 034	947 ± 020	767 ± 208	855 ± 171	955 ± 024	861 ± 171
	3	943 ± 051	975 ± 021	947 ± 030	947 ± 027	967 ± 030	958 ± 039	942 ± 050	963 ± 036	963 ± 032	922 ± 037	965 ± 031	936 ± 081	959 ± 036	980 ± 034	941 ± 036
	4	976 ± 041	980 ± 025	976 ± 031	972 ± 025	972 ± 027	980 ± 025	968 ± 043	972 ± 048	980 ± 034	962 ± 019	963 ± 032	975 ± 013	976 ± 031	978 ± 024	959 ± 018
	5	980 ± 018	984 ± 018	976 ± 024	978 ± 021	967 ± 008	976 ± 024	976 ± 024	988 ± 021	978 ± 024	976 ± 024	973 ± 024	971 ± 020	976 ± 024	980 ± 025	971 ± 015
IMLexp_09 efficiency	1	578 ± 085	514 ± 018	573 ± 009	743 ± 018	535 ± 024	514 ± 018	685 ± 091	565 ± 004	580 ± 016	747 ± 017	596 ± 011	503 ± 012	497 ± 004	647 ± 017	783 ± 012
	2	687 ± 059	518 ± 017	709 ± 022	730 ± 022	547 ± 034	518 ± 017	682 ± 009	729 ± 008	583 ± 007	571 ± 014	578 ± 004	527 ± 025	511 ± 017	724 ± 012	728 ± 047
	3	755 ± 063	532 ± 016	741 ± 025	722 ± 057	544 ± 037	532 ± 016	715 ± 047	765 ± 003	686 ± 077	662 ± 013	749 ± 015	532 ± 016	532 ± 023	755 ± 019	704 ± 035
	4	776 ± 022	558 ± 036	769 ± 023	766 ± 024	544 ± 017	558 ± 036	741 ± 043	769 ± 011	746 ± 002	783 ± 019	772 ± 019	652 ± 061	623 ± 054	735 ± 035	750 ± 005
	5	770 ± 023	669 ± 096	780 ± 023	771 ± 015	620 ± 024	669 ± 096	746 ± 042	767 ± 018	751 ± 012	778 ± 021	778 ± 013	695 ± 042	695 ± 049	776 ± 016	771 ± 017
goal cost efficiency	1	720 ± 015	692 ± 042	692 ± 027	569 ± 061	564 ± 016	695 ± 034	558 ± 042	553 ± 041	686 ± 022	569 ± 061	566 ± 023	579 ± 014	573 ± 012	693 ± 028	733 ± 014
	2	767 ± 006	743 ± 029	710 ± 027	616 ± 021	577 ± 008	778 ± 021	629 ± 025	636 ± 039	724 ± 020	616 ± 021	686 ± 015	637 ± 048	643 ± 015	733 ± 044	734 ± 018
	3	831 ± 024	820 ± 020	789 ± 029	730 ± 037	715 ± 014	826 ± 019	746 ± 015	756 ± 019	810 ± 033	730 ± 037	803 ± 022	760 ± 028	754 ± 011	816 ± 023	791 ± 036
	4	876 ± 022	865 ± 027	869 ± 026	837 ± 023	840 ± 017	864 ± 030	851 ± 012	857 ± 036	863 ± 022	837 ± 023	884 ± 013	842 ± 020	853 ± 001	880 ± 023	859 ± 027
	5	895 ± 023	890 ± 024	890 ± 028	894 ± 023	889 ± 015	890 ± 031	890 ± 012	894 ± 019	895 ± 017	894 ± 023	897 ± 027	887 ± 027	885 ± 025	896 ± 023	896 ± 020
insurance bankruptcy prevalence	1	922 ± 003	921 ± 006	915 ± 020	927 ± 016	926 ± 017	916 ± 020	919 ± 012	916 ± 010	925 ± 005	924 ± 010	900 ± 010	923 ± 013	919 ± 013	931 ± 002	930 ± 012
	2	930 ± 013	933 ± 014	920 ± 030	933 ± 010	933 ± 017	931 ± 018	925 ± 018	928 ± 011	926 ± 014	935 ± 008	925 ± 006	929 ± 012	931 ± 016	929 ± 021	933 ± 013
	3	934 ± 015	926 ± 017	925 ± 013	932 ± 013	930 ± 017	942 ± 012	939 ± 012	937 ± 011	932 ± 022	937 ± 016	924 ± 015	932 ± 011	936 ± 013	931 ± 021	935 ± 015
	4	936 ± 017	939 ± 012	927 ± 013	932 ± 014	932 ± 017	930 ± 019	938 ± 014	933 ± 016	935 ± 016	938 ± 013	934 ± 012	933 ± 016	930 ± 015	934 ± 012	933 ± 018
	5	938 ± 012	936 ± 016	927 ± 012	932 ± 015	934 ± 017	936 ± 014	939 ± 011	937 ± 010	934 ± 016	939 ± 009	928 ± 017	935 ± 015	938 ± 009	937 ± 012	934 ± 020
physical disability	1	977 ± 013	765 ± 209	909 ± 051	965 ± 022	535 ± 001	765 ± 209	968 ± 031	960 ± 017	928 ± 030	884 ± 037	930 ± 033	713 ± 224	986 ± 003	975 ± 012	858 ± 173
	2	979 ± 013	922 ± 042	923 ± 043	971 ± 010	572 ± 002	922 ± 042	964 ± 030	981 ± 004	928 ± 030	902 ± 027	920 ± 038	710 ± 194	987 ± 013	987 ± 005	858 ± 171
	3	977 ± 011	942 ± 021	950 ± 048	974 ± 011	560 ± 036	942 ± 021	966 ± 030	982 ± 006	935 ± 023	921 ± 025	931 ± 074	954 ± 023	988 ± 003	983 ± 003	860 ± 171
	4	977 ± 012	954 ± 008	972 ± 027	976 ± 012	595 ± 029	954 ± 008	963 ± 029	984 ± 004	952 ± 035	935 ± 036	986 ± 007	971 ± 021	978 ± 014	986 ± 006	861 ± 170
	5	978 ± 013	960 ± 010	986 ± 005	976 ± 013	877 ± 124	960 ± 010	968 ± 029	984 ± 003	973 ± 021	958 ± 034	983 ± 007	985 ± 007	986 ± 003	984 ± 003	951 ± 064
mml_2000 insurance efficiency	1	687 ± 028	652 ± 048	700 ± 027	682 ± 019	533 ± 008	608 ± 052	680 ± 015	679 ± 025	682 ± 009	685 ± 058	595 ± 018	642 ± 044	617 ± 033	686 ± 028	682 ± 048
	2	697 ± 016	681 ± 040	697 ± 024	680 ± 020	556 ± 015	667 ± 049	691 ± 020	679 ± 022	695 ± 019	675 ± 044	591 ± 020	687 ± 011	668 ± 037	683 ± 021	702 ± 026
	3	701 ± 025	689 ± 045	701 ± 025	678 ± 020	595 ± 003	672 ± 046	683 ± 018	679 ± 022	703 ± 022	666 ± 035	630 ± 020	658 ± 015	655 ± 038	683 ± 019	700 ± 025
	4	701 ± 021	687 ± 042	700 ± 022	690 ± 032	597 ± 007	674 ± 041	691 ± 015	693 ± 022	699 ± 023	714 ± 014	647 ± 018	702 ± 017	668 ± 013	702 ± 024	688 ± 016
	5	701 ± 016	694 ± 028	698 ± 027	696 ± 026	597 ± 008	692 ± 029	693 ± 022	700 ± 023	705 ± 021	704 ± 025	648 ± 021	701 ± 026	688 ± 037	701 ± 022	701 ± 025
prostate cancer	1	923 ± 082	940 ± 064	951 ± 053	958 ± 073	466 ± 073	951 ± 047	707 ± 072	951 ± 079	958 ± 061	932 ± 088	959 ± 051	658 ± 092	668 ± 111	939 ± 045	882 ± 071
	2	945 ± 060	963 ± 061	961 ± 059	960 ± 063	633 ± 162	962 ± 063	773 ± 169	949 ± 083	961 ± 065	963 ± 065	962 ± 060	746 ± 172	800 ± 184	965 ± 046	894 ± 022
	3	938 ± 073	961 ± 062	958 ± 063	954 ± 066	668 ± 088	956 ± 076	845 ± 101	954 ± 059	961 ± 060	960 ± 058	963 ± 059	868 ± 054	841 ± 011	967 ± 045	882 ± 110
	4	927 ± 062	961 ± 054	951 ± 059	954 ± 053	779 ± 137	956 ± 055	900 ± 075	938 ± 070	955 ± 056	960 ± 061	950 ± 061	911 ± 084	904 ± 070	959 ± 048	928 ± 084
	5	937 ± 070	947 ± 058	938 ± 060	945 ± 056	896 ± 058	946 ± 066	909 ± 077	936 ± 074	947 ± 063	955 ± 057	940 ± 064	923 ± 063	926 ± 059	939 ± 054	927 ± 066
credit approval	1	874 ± 018	893 ± 038	914 ± 003	809 ± 009	637 ± 049	907 ± 005	875 ± 015	827 ± 014	907 ± 005	808 ± 010	865 ± 016	724 ± 105	891 ± 032	892 ± 016	891 ± 033
	2	906 ± 008	897 ± 016	907 ± 023	833 ± 010	719 ± 032	893 ± 026	907 ± 009	837 ± 006	891 ± 014	842 ± 046	888 ± 005	824 ± 115	906 ± 014	903 ± 006	901 ± 022
	3	917 ± 013	914 ± 015	913 ± 003	859 ± 007	890 ± 012	910 ± 012	922 ± 006	852 ± 004	902 ± 006	885 ± 032	918 ± 007	856 ± 058	914 ± 015	925 ± 010	901 ± 047
	4	929 ± 005	923 ± 003	926 ± 008	881 ± 038	914 ± 004	928 ± 009	924 ± 004	859 ± 009	930 ± 006	920 ± 006	921 ± 010	870 ± 044	929 ± 003	927 ± 004	917 ± 008
	5	929 ± 004	932 ± 004	927 ± 007	930 ± 006	923 ± 006	929 ± 004	924 ± 006	912 ± 035	931 ± 006	934 ± 009	929 ± 004	887 ± 046	927 ± 003	929 ± 005	926 ± 005
best_distance efficiency	1	752 ± 054	872 ± 019	861 ± 023	820 ± 081	701 ± 121	871 ± 019	699 ± 215	829 ± 024	812 ± 066	831 ± 031	855 ± 066	704 ± 125	827 ± 050	843 ± 048	845 ± 034
	2	793 ± 060	876 ± 035	851 ± 035	847 ± 010	882 ± 038	859 ± 044	703 ± 192	848 ± 025	849 ± 025	855 ± 022	877 ± 019	810 ± 067	837 ± 022	819 ± 003	854 ± 040
	3	800 ± 046	864 ± 030	866 ± 026	850 ± 031	838 ± 059	862 ± 026	803 ± 099	847 ± 019	868 ± 027	861 ± 028	877 ± 025	801 ± 073	872 ± 044	843 ± 032	863 ± 056
	4	855 ± 029	875 ± 031	859 ± 039	837 ± 041	876 ± 029	861 ± 051	841 ± 082	842 ± 001	875 ± 051	873 ± 044	865 ± 021	860 ± 022	886 ± 010	893 ± 039	897 ± 008
	5	862 ± 036	876 ± 029	869 ± 043	856 ± 027	869 ± 030	870 ± 039	850 ± 080	859 ± 039	875 ± 037	877 ± 044	866 ± 021	860 ± 038	869 ± 034	862 ± 038	866 ± 034
gini_ratio efficiency	1	563 ± 002	732 ± 001	732 ± 005	732 ± 005	607 ± 021	732 ± 001	755 ± 003	732 ± 005	759 ± 003	732 ± 005	625 ± 005	701 ± 035	749 ± 014	563 ± 002	759 ± 003
	2	718 ± 005	741 ± 044	786 ± 004	742 ± 005	683 ± 036	741 ± 044	741 ± 008	720 ± 023	793 ± 004	783 ± 004	620 ± 004	722 ± 016	727 ± 016	640 ± 006	794 ± 003
	3	732 ± 003	755 ± 023	790 ± 006	697 ± 005	706 ± 007	755 ± 023	761 ± 006	725 ± 004	790 ± 006	790 ± 006	697 ± 004	720 ± 037	740 ± 007	742 ± 005	804 ± 005
	4	785 ± 014	758 ± 003	757 ± 002	740 ± 006	736 ± 016	758 ± 003	798 ± 011	762 ± 005	761 ± 001	758 ± 003	751 ± 013	765 ± 016	802 ± 006	802 ± 009	753 ± 005
	5	814 ± 001	798 ± 001	806 ± 009	798 ± 007	801 ± 013	798 ± 001	813 ± 001	794 ± 006	812 ± 002	797 ± 002	804 ± 006	811 ± 003	813 ± 002	814 ± 002	804 ± 008
cnn_16000 accuracy	1	482 ± 083	483 ± 069	475 ± 027	570 ± 069	519 ± 097	483 ± 069	451 ± 040	407 ± 087	503 ± 126	491 ± 131	455 ± 130	514 ± 102	440 ± 076	521 ± 125	513 ± 076
	2	481 ± 035	521 ± 089	522 ± 048	519 ± 098	535 ± 044	521 ± 089	472 ± 043	481 ± 029	510 ± 129	525 ± 108					

(continued from previous page)

Dataset	Budget idx.	CART	ElankNet	F-test	GuinRatio	LaplacianScore	Lasso	LOCO	Markov Blanket	MI	mRMR	(R)Relieff	Random	SBE	RFImportance	SFS
hypogeography	1	.858 ± .081	.815 ± .105	.822 ± .066	.777 ± .060	.630 ± .062	.819 ± .108	.821 ± .108	.784 ± .020	.858 ± .028	.852 ± .030	.857 ± .054	.727 ± .140	.836 ± .065	.868 ± .016	.834 ± .073
	2	.916 ± .029	.855 ± .072	.910 ± .014	.851 ± .061	.685 ± .162	.833 ± .075	.871 ± .054	.797 ± .033	.897 ± .045	.861 ± .046	.915 ± .013	.720 ± .235	.899 ± .045	.934 ± .023	.864 ± .049
	3	.929 ± .015	.875 ± .077	.913 ± .036	.886 ± .028	.825 ± .128	.879 ± .042	.864 ± .110	.857 ± .039	.905 ± .067	.853 ± .027	.907 ± .041	.835 ± .009	.916 ± .046	.933 ± .003	.847 ± .088
	4	.936 ± .010	.908 ± .042	.919 ± .015	.891 ± .034	.918 ± .056	.895 ± .025	.883 ± .052	.899 ± .041	.903 ± .033	.865 ± .051	.918 ± .036	.878 ± .045	.913 ± .052	.928 ± .026	.872 ± .101
	5	.935 ± .028	.925 ± .043	.923 ± .034	.892 ± .038	.904 ± .056	.900 ± .035	.892 ± .037	.904 ± .038	.897 ± .038	.899 ± .093	.934 ± .021	.922 ± .050	.905 ± .054	.919 ± .048	.908 ± .086
mL-Courant dataset	1	.987 ± .019	.993 ± .008	.979 ± .019	.985 ± .020	.592 ± .081	1.00 ± .00	.804 ± .080	.980 ± .033	.979 ± .019	.998 ± .002	.979 ± .019	.782 ± .184	.781 ± .094	.996 ± .006	.987 ± .011
	2	.994 ± .011	.999 ± .001	.998 ± .002	.998 ± .002	.724 ± .114	1.00 ± .00	.946 ± .044	1.00 ± .00	.998 ± .002	.999 ± .001	.997 ± .003	.936 ± .045	.936 ± .084	.998 ± .002	.998 ± .002
	3	.999 ± .002	1.00 ± .00	.999 ± .001	.999 ± .001	.770 ± .125	1.00 ± .00	.985 ± .016	.999 ± .001	.999 ± .001	.999 ± .001	.999 ± .001	.986 ± .017	.988 ± .013	.999 ± .001	.996 ± .004
	4	.999 ± .002	1.00 ± .00	.999 ± .000	.999 ± .001	.891 ± .011	1.00 ± .00	.993 ± .009	1.00 ± .00	.999 ± .001	1.00 ± .00	1.00 ± .00	.997 ± .004	.997 ± .005	1.00 ± .00	.999 ± .002
	5	.999 ± .002	1.00 ± .00	1.00 ± .00	1.00 ± .00	.929 ± .035	1.00 ± .00	.999 ± .001	1.00 ± .00	1.00 ± .00	1.00 ± .00	1.00 ± .00	.998 ± .003	.998 ± .003	1.00 ± .00	.998 ± .004
mL-Courant test set	1	.550 ± .024	.594 ± .035	.596 ± .036	.689 ± .036	.648 ± .041	.594 ± .035	.592 ± .035	.602 ± .039	.646 ± .054	.666 ± .022	.610 ± .040	.581 ± .032	.661 ± .042	.555 ± .031	.676 ± .010
	2	.671 ± .022	.560 ± .042	.612 ± .033	.695 ± .002	.627 ± .027	.560 ± .042	.617 ± .083	.661 ± .030	.685 ± .033	.640 ± .017	.601 ± .036	.583 ± .033	.668 ± .020	.673 ± .022	.672 ± .006
	3	.706 ± .031	.622 ± .015	.607 ± .018	.714 ± .018	.606 ± .021	.622 ± .015	.666 ± .014	.724 ± .016	.718 ± .016	.658 ± .043	.558 ± .024	.651 ± .079	.663 ± .048	.698 ± .015	.645 ± .024
	4	.729 ± .013	.642 ± .019	.639 ± .046	.730 ± .016	.647 ± .031	.642 ± .019	.677 ± .015	.723 ± .019	.723 ± .024	.668 ± .033	.620 ± .016	.694 ± .053	.675 ± .044	.723 ± .014	.662 ± .013
	5	.730 ± .005	.705 ± .043	.709 ± .036	.748 ± .017	.688 ± .034	.705 ± .043	.711 ± .032	.728 ± .002	.732 ± .023	.716 ± .022	.676 ± .023	.736 ± .030	.713 ± .002	.746 ± .014	.707 ± .014
mL-Courant test set (1001)	1	.931 ± .020	.917 ± .019	.915 ± .011	.919 ± .012	.890 ± .013	.914 ± .020	.924 ± .023	.922 ± .016	.917 ± .013	.917 ± .020	.926 ± .012	.864 ± .005	.927 ± .011	.927 ± .019	.915 ± .014
	2	.952 ± .018	.942 ± .014	.944 ± .012	.943 ± .014	.916 ± .015	.941 ± .014	.954 ± .015	.946 ± .014	.944 ± .014	.941 ± .010	.947 ± .009	.918 ± .025	.953 ± .013	.946 ± .014	.947 ± .020
	3	.958 ± .012	.949 ± .013	.956 ± .014	.947 ± .014	.932 ± .018	.951 ± .012	.955 ± .013	.956 ± .015	.948 ± .015	.953 ± .008	.957 ± .011	.941 ± .024	.958 ± .013	.953 ± .015	.956 ± .015
	4	.958 ± .012	.954 ± .014	.955 ± .012	.954 ± .015	.939 ± .017	.954 ± .015	.957 ± .015	.956 ± .015	.954 ± .019	.955 ± .011	.958 ± .012	.952 ± .019	.958 ± .015	.958 ± .015	.956 ± .013
	5	.958 ± .012	.958 ± .014	.956 ± .012	.956 ± .014	.945 ± .015	.958 ± .014	.957 ± .012	.957 ± .012	.956 ± .016	.957 ± .012	.959 ± .012	.953 ± .016	.957 ± .014	.957 ± .014	.956 ± .012
Drug-Related substances (1000)	1	.684 ± .051	.631 ± .066	.622 ± .067	.628 ± .068	.583 ± .077	.610 ± .137	.677 ± .018	.711 ± .020	.679 ± .049	.672 ± .015	.581 ± .034	.638 ± .126	.604 ± .065	.704 ± .019	.674 ± .070
	2	.721 ± .037	.697 ± .065	.626 ± .045	.728 ± .046	.619 ± .039	.703 ± .035	.750 ± .021	.738 ± .042	.702 ± .025	.705 ± .042	.661 ± .026	.723 ± .038	.731 ± .015	.714 ± .030	.713 ± .080
	3	.769 ± .021	.769 ± .012	.788 ± .001	.797 ± .014	.634 ± .030	.773 ± .052	.774 ± .030	.794 ± .030	.739 ± .029	.774 ± .053	.778 ± .031	.741 ± .022	.770 ± .017	.781 ± .002	.767 ± .014
	4	.802 ± .010	.797 ± .013	.813 ± .017	.799 ± .003	.721 ± .010	.798 ± .007	.784 ± .016	.802 ± .016	.788 ± .033	.801 ± .021	.773 ± .004	.754 ± .031	.771 ± .022	.787 ± .020	.796 ± .030
	5	.816 ± .014	.802 ± .016	.819 ± .009	.798 ± .005	.784 ± .024	.807 ± .004	.792 ± .005	.810 ± .038	.786 ± .030	.796 ± .006	.803 ± .004	.790 ± .030	.797 ± .008	.803 ± .012	.810 ± .014
Heart-Catheter dataset	1	.414 ± .160	.412 ± .089	.734 ± .226	.521 ± .077	.726 ± .149	.412 ± .089	.481 ± .139	.598 ± .350	.701 ± .142	.530 ± .140	.845 ± .137	.467 ± .373	.391 ± .125	.462 ± .222	.372 ± .078
	2	.558 ± .198	.362 ± .040	.808 ± .111	.621 ± .142	.731 ± .094	.362 ± .040	.501 ± .119	.556 ± .333	.788 ± .151	.576 ± .191	.823 ± .120	.504 ± .356	.543 ± .191	.652 ± .120	.339 ± .086
	3	.670 ± .140	.316 ± .100	.680 ± .153	.437 ± .137	.433 ± .067	.316 ± .100	.527 ± .113	.437 ± .098	.788 ± .169	.775 ± .191	.751 ± .130	.356 ± .136	.617 ± .276	.499 ± .152	.580 ± .275
	4	.629 ± .205	.388 ± .225	.643 ± .176	.435 ± .149	.456 ± .046	.388 ± .225	.751 ± .153	.396 ± .118	.805 ± .126	.667 ± .233	.677 ± .169	.563 ± .249	.654 ± .213	.568 ± .120	.682 ± .176
	5	.649 ± .205	.582 ± .193	.595 ± .199	.430 ± .159	.440 ± .120	.582 ± .193	.682 ± .176	.577 ± .167	.641 ± .247	.633 ± .215	.622 ± .166	.669 ± .222	.681 ± .166	.626 ± .180	.655 ± .199
IR analyses	1	.662 ± .009	.771 ± .008	.771 ± .008	.758 ± .023	.645 ± .026	.771 ± .008	.682 ± .002	.771 ± .008	.717 ± .005	.771 ± .008	.660 ± .013	.581 ± .045	.769 ± .008	.662 ± .009	.771 ± .009
	2	.738 ± .001	.772 ± .005	.768 ± .005	.762 ± .009	.655 ± .010	.772 ± .005	.642 ± .023	.767 ± .008	.770 ± .007	.771 ± .007	.702 ± .040	.687 ± .011	.764 ± .016	.659 ± .003	.772 ± .006
	3	.760 ± .001	.756 ± .010	.762 ± .009	.754 ± .007	.664 ± .006	.756 ± .010	.682 ± .008	.762 ± .002	.753 ± .008	.743 ± .010	.744 ± .020	.752 ± .009	.762 ± .005	.779 ± .002	.766 ± .005
	4	.776 ± .002	.761 ± .020	.764 ± .007	.765 ± .004	.652 ± .009	.761 ± .020	.723 ± .006	.765 ± .003	.772 ± .005	.772 ± .007	.755 ± .013	.756 ± .009	.767 ± .008	.772 ± .002	.766 ± .005
	5	.784 ± .005	.781 ± .006	.777 ± .010	.787 ± .004	.776 ± .003	.781 ± .006	.781 ± .008	.787 ± .005	.779 ± .008	.784 ± .004	.779 ± .012	.779 ± .012	.781 ± .008	.785 ± .005	.784 ± .005
pavo dataset	1	.577 ± .003	.560 ± .009	.553 ± .005	.545 ± .006	.548 ± .002	.559 ± .017	.561 ± .028	.560 ± .006	.565 ± .016	.536 ± .005	.564 ± .002	.526 ± .020	.556 ± .025	.575 ± .001	.576 ± .011
	2	.586 ± .002	.597 ± .008	.583 ± .005	.592 ± .001	.590 ± .002	.585 ± .019	.580 ± .014	.595 ± .005	.583 ± .004	.552 ± .005	.586 ± .004	.565 ± .018	.569 ± .013	.587 ± .002	.542 ± .018
	3	.590 ± .002	.606 ± .007	.603 ± .002	.600 ± .001	.561 ± .001	.598 ± .008	.592 ± .012	.596 ± .005	.599 ± .001	.562 ± .004	.592 ± .001	.585 ± .003	.593 ± .010	.598 ± .002	.582 ± .006
	4	.606 ± .001	.611 ± .005	.603 ± .001	.603 ± .004	.575 ± .009	.602 ± .008	.602 ± .008	.601 ± .002	.605 ± .003	.593 ± .000	.597 ± .001	.602 ± .002	.600 ± .006	.605 ± .001	.597 ± .004
	5	.609 ± .003	.611 ± .003	.610 ± .003	.609 ± .002	.601 ± .002	.608 ± .006	.607 ± .001	.607 ± .004	.611 ± .001	.610 ± .003	.607 ± .003	.610 ± .001	.607 ± .003	.610 ± .001	.603 ± .002
Japanese-vowel segmentation	1	.734 ± .079	.615 ± .171	.760 ± .013	.732 ± .019	.687 ± .143	.729 ± .076	.645 ± .139	.737 ± .026	.717 ± .038	.733 ± .032	.735 ± .056	.579 ± .053	.707 ± .033	.739 ± .025	.704 ± .034
	2	.741 ± .026	.725 ± .060	.725 ± .051	.733 ± .038	.700 ± .111	.725 ± .071	.741 ± .053	.729 ± .033	.734 ± .026	.773 ± .030	.763 ± .015	.709 ± .062	.711 ± .041	.713 ± .039	.721 ± .020
	3	.766 ± .027	.769 ± .011	.753 ± .075	.729 ± .033	.667 ± .097	.748 ± .027	.747 ± .053	.738 ± .034	.748 ± .032	.753 ± .089	.770 ± .010	.768 ± .032	.712 ± .061	.754 ± .010	.766 ± .061
	4	.780 ± .017	.781 ± .032	.774 ± .059	.763 ± .027	.771 ± .081	.767 ± .038	.788 ± .021	.759 ± .035	.765 ± .006	.792 ± .082	.761 ± .038	.767 ± .043	.776 ± .030	.756 ± .017	.758 ± .034
	5	.789 ± .032	.766 ± .031	.792 ± .034	.780 ± .016	.777 ± .062	.784 ± .031	.788 ± .034	.792 ± .042	.779 ± .026	.797 ± .035	.783 ± .027	.768 ± .025	.777 ± .049	.780 ± .034	.788 ± .023
korean-phrase segmentation	1	.967 ± .012	.934 ± .038	.958 ± .014	.963 ± .020	.925 ± .040	.926 ± .040	.954 ± .032	.968 ± .020	.958 ± .011	.954 ± .034	.954 ± .022	.941 ± .009	.953 ± .027	.967 ± .007	.962 ± .012
	2	.968 ± .018	.962 ± .025	.973 ± .020	.971 ± .021	.952 ± .034	.963 ± .024	.961 ± .028	.968 ± .025	.968 ± .032	.969 ± .018	.971 ± .011	.962 ± .007	.964 ± .034	.970 ± .019	.964 ± .015
	3	.970 ± .022	.973 ± .021	.971 ± .019	.970 ± .020	.956 ± .038	.970 ± .025	.961 ± .029	.973 ± .031	.974 ± .022	.971 ± .027	.965 ± .020	.975 ± .019	.967 ± .033	.971 ± .026	.965 ± .022
	4	.971 ± .024	.975 ± .022	.976 ± .017	.973 ± .024	.965 ± .022	.973 ± .029	.969 ± .033	.975 ± .023	.973 ± .028	.974 ± .027	.971 ± .022	.971 ± .028	.969 ± .032	.975 ± .022	.971 ± .025
	5	.974 ± .022	.974 ± .023	.975 ± .023	.975 ± .020	.970 ± .018	.974 ± .022	.975 ± .025	.976 ± .021	.975 ± .025	.973 ± .029	.974 ± .019	.975 ± .022	.974 ± .021	.975 ± .023	.972 ± .024
korean-phrase segmentation long center	1	.676 ± .040	.686 ± .046	.691 ± .042	.705 ± .065	.664 ± .033	.698 ± .047	.659 ± .096	.686 ± .086	.688 ± .089	.691 ± .084	.724 ± .080	.585 ± .019	.528 ± .077	.714 ± .093	.556 ± .1

(continued from previous page)																
Dataset	Budget idx, j	CART	ElasticNet	F-test	GiniRatio	LaplunScore	Lasso	LOCO	MarkovBlanket	MI	mRMR	(R)ReliefF	Random	SBE	RfImportance	SFS
gpr_bosch	1	.908 ± .021	.896 ± .013	.865 ± .018	.869 ± .007	.679 ± .009	.887 ± .005	.872 ± .032	.911 ± .006	.895 ± .023	.902 ± .005	.905 ± .010	.870 ± .030	.897 ± .028	.885 ± .018	.915 ± .019
	2	.927 ± .012	.927 ± .005	.914 ± .011	.913 ± .004	.906 ± .007	.919 ± .009	.919 ± .006	.926 ± .010	.919 ± .014	.912 ± .006	.925 ± .011	.906 ± .015	.915 ± .022	.917 ± .016	.920 ± .015
	3	.925 ± .015	.927 ± .014	.922 ± .012	.927 ± .011	.914 ± .013	.921 ± .013	.924 ± .008	.927 ± .010	.928 ± .011	.926 ± .010	.923 ± .009	.920 ± .014	.928 ± .007	.926 ± .012	.926 ± .015
	4	.929 ± .011	.932 ± .014	.927 ± .012	.930 ± .010	.923 ± .013	.927 ± .015	.927 ± .010	.930 ± .007	.930 ± .009	.933 ± .010	.930 ± .008	.925 ± .016	.929 ± .011	.929 ± .011	.931 ± .009
	5	.929 ± .013	.931 ± .014	.929 ± .014	.934 ± .011	.927 ± .012	.930 ± .015	.931 ± .008	.932 ± .010	.932 ± .009	.932 ± .011	.933 ± .013	.928 ± .010	.931 ± .011	.931 ± .010	.933 ± .010
unbalanced_australian_postoffice_australian	1	.971 ± .003	.973 ± .003	.972 ± .001	.845 ± .054	.579 ± .002	.967 ± .008	.969 ± .006	.782 ± .092	.969 ± .005	.845 ± .054	.970 ± .001	.883 ± .068	.787 ± .044	.972 ± .001	.969 ± .007
	2	.972 ± .003	.975 ± .002	.974 ± .002	.931 ± .001	.633 ± .003	.973 ± .002	.973 ± .003	.869 ± .043	.974 ± .001	.931 ± .001	.970 ± .002	.876 ± .010	.924 ± .019	.974 ± .003	.969 ± .005
	3	.975 ± .002	.977 ± .002	.976 ± .002	.950 ± .009	.723 ± .009	.977 ± .002	.974 ± .003	.942 ± .001	.978 ± .002	.950 ± .009	.972 ± .004	.937 ± .005	.925 ± .048	.975 ± .003	.973 ± .002
	4	.976 ± .003	.978 ± .002	.977 ± .002	.971 ± .002	.819 ± .002	.977 ± .001	.976 ± .004	.952 ± .004	.976 ± .001	.971 ± .002	.974 ± .003	.947 ± .011	.961 ± .014	.976 ± .003	.975 ± .005
	5	.977 ± .003	.977 ± .003	.976 ± .003	.976 ± .001	.947 ± .009	.977 ± .003	.975 ± .003	.971 ± .005	.976 ± .002	.976 ± .001	.976 ± .002	.963 ± .011	.969 ± .012	.977 ± .002	.978 ± .006
knapstein_knapstein	1	.581 ± .035	.624 ± .042	.612 ± .015	.626 ± .026	.555 ± .016	.618 ± .044	.624 ± .022	.596 ± .022	.611 ± .021	.647 ± .013	.599 ± .016	.543 ± .033	.623 ± .020	.608 ± .023	.665 ± .007
	2	.642 ± .019	.659 ± .023	.630 ± .015	.647 ± .027	.578 ± .019	.660 ± .024	.661 ± .016	.626 ± .020	.625 ± .029	.636 ± .008	.639 ± .008	.576 ± .004	.668 ± .020	.656 ± .023	.645 ± .008
	3	.678 ± .027	.670 ± .030	.679 ± .021	.676 ± .038	.599 ± .012	.678 ± .022	.681 ± .023	.670 ± .019	.651 ± .027	.639 ± .015	.676 ± .030	.628 ± .034	.687 ± .022	.680 ± .030	.629 ± .008
	4	.694 ± .024	.675 ± .022	.690 ± .016	.684 ± .035	.665 ± .027	.676 ± .021	.681 ± .018	.682 ± .034	.670 ± .026	.654 ± .017	.682 ± .035	.681 ± .026	.690 ± .026	.694 ± .032	.655 ± .007
	5	.698 ± .031	.687 ± .030	.694 ± .026	.698 ± .030	.688 ± .028	.685 ± .025	.696 ± .027	.691 ± .030	.685 ± .035	.679 ± .026	.692 ± .028	.668 ± .020	.694 ± .024	.697 ± .032	.680 ± .017

Table D.8: Per-cell results with downstream model **RealMLP**. Tasks are grouped by metric. Each cell is the mean over three seeds, with the sample standard deviation as a subscript.

Dataset	Budget idx, j	CART	ElasticNet	F-test	GiniRatio	LaplunScore	Lasso	LOCO	MarkovBlanket	MI	mRMR	(R)ReliefF	Random	SBE	RfImportance	SFS
log-loss (↓)																
breast_cancer_survival	1	.803 ± .087	.743 ± .093	.740 ± .074	.814 ± .022	.858 ± .076	.743 ± .093	.809 ± .115	.799 ± .026	.785 ± .115	.789 ± .059	.800 ± .072	.850 ± .095	.845 ± .129	.799 ± .031	.877 ± .047
	2	.783 ± .026	.757 ± .095	.752 ± .033	.765 ± .058	.852 ± .058	.774 ± .103	.843 ± .043	.749 ± .037	.788 ± .048	.767 ± .053	.744 ± .065	.805 ± .061	.813 ± .111	.780 ± .126	.826 ± .05
	3	.802 ± .056	.753 ± .077	.730 ± .032	.765 ± .033	.806 ± .042	.803 ± .131	.796 ± .054	.729 ± .034	.759 ± .105	.761 ± .056	.826 ± .097	.767 ± .015	.800 ± .019	.752 ± .051	.830 ± .065
	4	.778 ± .006	.750 ± .021	.778 ± .041	.740 ± .034	.774 ± .087	.774 ± .053	.780 ± .075	.743 ± .053	.748 ± .043	.745 ± .044	.764 ± .027	.801 ± .033	.750 ± .019	.746 ± .020	.800 ± .034
	5	.780 ± .030	.765 ± .041	.763 ± .095	.754 ± .013	.736 ± .022	.766 ± .077	.767 ± .073	.794 ± .064	.740 ± .026	.733 ± .035	.755 ± .050	.764 ± .062	.733 ± .038	.752 ± .033	.783 ± .091
australian_postcode_prediction	1	1.48 ± .60	.400 ± 246	.496 ± 289	.624 ± .062	1.37 ± .14	.625 ± .472	1.20 ± .03	.842 ± .311	.899 ± .430	.953 ± .1075	.335 ± .191	.845 ± .410	1.10 ± .18	.432 ± .273	1.13 ± .26
	2	.772 ± .535	.136 ± .105	.354 ± .276	.336 ± .317	1.07 ± .20	.0384 ± .0006	.506 ± .327	.371 ± .355	.193 ± .234	.373 ± .301	.0460 ± .0064	.136 ± .13	1.22 ± .11	.0601 ± .0060	.951 ± .176
	3	.242 ± .019	.0206 ± .0083	.0364 ± .0364	.0358 ± .0334	.983 ± .091	.0179 ± .00106	.451 ± .188	.0618 ± .0214	.136 ± .204	.0378 ± .0352	.0151 ± .0152	.453 ± .280	.458 ± .229	.0136 ± .0075	.275 ± .087
	4	.116 ± .026	.0261 ± .0219	.0202 ± .0121	.0145 ± .0048	.377 ± .187	.0752 ± .0084	.107 ± .042	.0159 ± .0060	.00977 ± .00243	.0239 ± .0088	.0266 ± .0111	.336 ± .348	.215 ± .021	.0317 ± .0427	.223 ± .163
	5	.129 ± .083	.0563 ± .0234	.0495 ± .0119	.0577 ± .0065	.139 ± .016	.0837 ± .0701	.133 ± .091	.0420 ± .0057	.0415 ± .0180	.0451 ± .0209	.0717 ± .0146	.0775 ± .0474	.0888 ± .0202	.0518 ± .0174	.0808 ± .0108
australian_postcode_australian	1	.112 ± .002	.128 ± .015	.156 ± .002	.158 ± .002	.660 ± .002	.250 ± .239	.112 ± .001	.112 ± .001	.155 ± .002	.173 ± .002	.163 ± .001	.538 ± .394	.112 ± .002	.158 ± .002	.156 ± .003
	2	.0852 ± .0015	.0877 ± .0027	.0979 ± .0046	.0884 ± .0007	.494 ± .137	.0859 ± .0019	.0851 ± .0007	.0900 ± .0066	.0972 ± .0014	.159 ± .001	.100 ± .001	.113 ± .013	.0860 ± .0025	.0874 ± .0010	.113 ± .002
	3	.0961 ± .0022	.0830 ± .0008	.0922 ± .0003	.0957 ± .0009	.416 ± .022	.0825 ± .0003	.0844 ± .0007	.0964 ± .0019	.0957 ± .0010	.100 ± .001	.104 ± .012	.377 ± .055	.0845 ± .0006	.0918 ± .0003	.0965 ± .0021
	4	.0972 ± .0013	.0839 ± .0005	.0933 ± .0029	.0965 ± .0000	.190 ± .131	.0856 ± .0019	.0881 ± .0070	.0970 ± .0019	.0966 ± .0017	.104 ± .003	.0962 ± .0014	.279 ± .147	.0843 ± .0008	.0961 ± .0007	.0966 ± .0007
	5	.0966 ± .0020	.0896 ± .0005	.0932 ± .0051	.0972 ± .0011	.0977 ± .0032	.0900 ± .0009	.0960 ± .0007	.0993 ± .0008	.0963 ± .0018	.0968 ± .0023	.0973 ± .0013	.185 ± .149	.0965 ± .0008	.0977 ± .0010	.0958 ± .0006
australian_postcode_australian	1	.622 ± .027	.585 ± .013	.634 ± .017	.659 ± .006	.973 ± .018	.584 ± .015	.602 ± .037	.596 ± .007	.622 ± .010	.670 ± .021	.591 ± .013	.687 ± .014	.653 ± .034	.656 ± .004	.668 ± .022
	2	.568 ± .006	.560 ± .014	.569 ± .013	.597 ± .011	.880 ± .027	.559 ± .020	.579 ± .017	.585 ± .007	.558 ± .016	.623 ± .009	.568 ± .010	.633 ± .022	.641 ± .040	.565 ± .004	.620 ± .042
	3	.553 ± .011	.550 ± .011	.556 ± .023	.587 ± .007	.689 ± .027	.548 ± .006	.566 ± .021	.586 ± .003	.547 ± .011	.596 ± .008	.551 ± .017	.667 ± .024	.583 ± .017	.558 ± .009	.598 ± .022
	4	.551 ± .020	.549 ± .009	.549 ± .007	.585 ± .008	.590 ± .020	.548 ± .005	.554 ± .021	.585 ± .003	.550 ± .012	.592 ± .010	.543 ± .013	.588 ± .013	.559 ± .012	.546 ± .013	.573 ± .003
	5	.548 ± .008	.547 ± .010	.546 ± .006	.569 ± .018	.550 ± .009	.546 ± .011	.557 ± .023	.578 ± .008	.551 ± .011	.557 ± .006	.547 ± .013	.556 ± .025	.547 ± .018	.544 ± .013	.550 ± .011
australian_postcode_australian	1	1.63 ± .08	1.76 ± .10	1.73 ± .08	2.04 ± .14	2.13 ± .03	1.89 ± .25	1.81 ± .12	1.74 ± .08	1.72 ± .07	1.77 ± .06	1.73 ± .07	2.07 ± .13	2.15 ± .01	1.74 ± .07	1.87 ± .07
	2	1.64 ± .12	1.70 ± .06	1.69 ± .11	1.86 ± .15	2.12 ± .04	1.84 ± .13	1.80 ± .14	1.77 ± .05	1.68 ± .08	1.83 ± .09	1.69 ± .09	2.13 ± .06	2.13 ± .04	1.79 ± .03	1.87 ± .07
	3	1.77 ± .20	1.76 ± .07	1.69 ± .05	1.81 ± .05	2.06 ± .14	1.73 ± .09	1.83 ± .13	1.80 ± .04	1.71 ± .12	1.79 ± .04	1.71 ± .10	2.12 ± .07	2.08 ± .07	1.80 ± .14	1.87 ± .03
	4	1.73 ± .09	1.77 ± .07	1.74 ± .08	1.81 ± .09	2.01 ± .03	1.69 ± .05	1.77 ± .08	1.81 ± .11	1.67 ± .05	1.75 ± .05	1.75 ± .16	1.91 ± .21	1.97 ± .13	1.67 ± .06	1.91 ± .10
	5	1.63 ± .02	1.68 ± .04	1.56 ± .06	1.74 ± .05	1.69 ± .10	1.66 ± .08	1.66 ± .10	1.75 ± .06	1.58 ± .03	1.69 ± .04	1.70 ± .07	1.95 ± .12	1.69 ± .14	1.64 ± .05	1.72 ± .07
australian_postcode_australian	1	.711 ± .006	.785 ± .025	.910 ± .017	1.19 ± .01	.911 ± .025	.858 ± .003	.922 ± .042	.721 ± .029	.924 ± .017	.820 ± .006	.964 ± .019	1.13 ± .11	1.12 ± .08	.719 ± .008	1.13 ± .14
	2	.560 ± .007	.594 ± .009	.656 ± .019	.866 ± .007	.647 ± .015	.615 ± .019	.762 ± .011	.586 ± .005	.605 ± .009	.646 ± .010	.655 ± .006	.837 ± .014	.796 ± .021	.569 ± .006	.810 ± .085
	3	.504 ± .007	.522 ± .005	.558 ± .006	.603 ± .002	.531 ± .005	.527 ± .001	.646 ± .019	.511 ± .011	.578 ± .007	.560 ± .003	.543 ± .004	.564 ± .021	.628 ± .034	.516 ± .012	.638 ± .033
	4	.481 ± .007	.489 ± .007	.507 ± .003	.539 ± .005	.497 ± .005	.490 ± .007	.584 ± .009	.489 ± .006	.507 ± .005	.503 ± .004	.506 ± .008	.563 ± .019	.569 ± .032	.486 ± .007	.581 ± .038
	5	.475 ± .008	.478 ± .010	.482 ± .010	.488 ± .009	.481 ± .009	.477 ± .008	.514 ± .005	.475 ± .011	.482 ± .009	.483 ± .005	.479 ± .006	.506 ± .021	.523 ± .014	.475 ± .009	.516 ± .020
australian_postcode_australian	1	.434 ± .198	.455 ± .110	.519 ± .174	.385 ± .180	.804 ± .096	.585 ± .169	.654 ± .146	.387 ± .131	.459 ± .086	.537 ± .385	.417 ± .132	.745 ± .072	.690 ± .027	.525 ± .425	.569 ± .072
	2	.251 ± .070	.263 ± .059	.453 ± .153	.237 ± .076	.765 ± .133	.617 ± .029	.305 ± .095	.244 ± .103	.309 ± .123	.319 ± .110	.227 ± .047	.455 ± .146	.521 ± .177	.284 ± .052	.425 ± .162
	3	.222 ± .117	.269 ± .252	.240 ± .074	.176 ± .071	.572 ± .062	.446 ± .225	.228 ± .083	.264 ± .060	.174 ± .043	.284 ± .056	.292 ± .154	.181 ± .046	.228 ± .066	.239 ± .134	.263 ± .106
	4	.156 ± .035	.262 ± .114	.249 ± .054	.251 ± .052	.352 ± .023	.235 ± .074	.151 ± .039	.220 ± .102	.170 ± .060	.182 ± .040	.293 ± .079	.161 ± .046	.189 ± .033	.253 ± .025	.148 ± .049
	5	.188 ± .084	.149 ± .055	.223 ± .300	.193 ± .061	.148 ± .058	.190 ± .075	.198 ± .037	.215 ± .029	.171 ± .027	.221 ± .086	.254 ± .099	.159 ± .026	.180 ± .024	.218 ± .042	.176 ± .039
australian_postcode_australian	1	.705 ± .158	1.79 ± .09	1.11 ± .28	1.20 ± .03	1.20 ± .28	1.64 ± .28	1.21 ± .26	.559 ± .004	.645 ± .101	.674 ± .075	1.69 ± .11	1.45 ± .32	1.22 ± .42	.536 ± .086	.785 ± .302
	2	.346 ± .06	.122 ± .06	.797 ± .333	.582 ± .102	.615 ± .418	1.19 ± .14	.761 ± .14	.460 ± .126	.437 ± .043	.572 ± .012	1.23 ± .22	.855 ± .366	.505 ± .046	.408 ± .040	.546 ± .169
	3	.381 ± .042	.735 ± .085	.652 ± .399	.425 ± .144	.526 ± .274	.951 ± .219	.707 ± .117	.445 ± .044	.326 ± .116	.429 ± .084	.589 ± .112	.406 ± .063	.489 ± .080	.376 ± .099	.447 ± .168
	4	.334 ± .088	.472 ± .149	.478 ± .192	.391 ± .276	.443 ± .257	.595 ± .115	.461 ± .137	.419 ± .222	.336 ± .109	.422 ± .126	.466 ± .175	.404 ± .083	.401 ± .131	.338 ± .085	.380 ± .100
	5	.326 ± .119	.330 ± .077	.371 ± .125	.317 ± .106	.356 ± .219	.529 ± .037	.357 ± .116	.370 ± .153	.354 ± .159	.333 ± .137	.413 ± .178	.408 ± .153	.385 ± .126	.361 ± .120	.397 ± .181

(continued from previous page)

Dataset	Budget idx, j	CART	ElasticNet	F-test	GainRatio	LaplacianScore	Lasso	LOCO	MarkovBlanket	MI	mRMR	(R)Relieff	Random	SBE	RFImportance	SFS
msc	1	.512 ±.017	.538 ±.021	.542 ±.032	.562 ±.025	.696 ±.016	.536 ±.036	.600 ±.083	.518 ±.009	.548 ±.025	.520 ±.043	.548 ±.024	.694 ±.010	.687 ±.029	.545 ±.043	.542 ±.017
	2	.504 ±.027	.516 ±.029	.504 ±.021	.560 ±.020	.700 ±.027	.520 ±.040	.609 ±.083	.518 ±.016	.556 ±.026	.501 ±.044	.560 ±.024	.698 ±.019	.682 ±.020	.524 ±.035	.550 ±.028
	3	.504 ±.016	.498 ±.014	.508 ±.022	.549 ±.017	.698 ±.034	.501 ±.029	.570 ±.083	.506 ±.008	.499 ±.008	.490 ±.020	.550 ±.029	.564 ±.017	.526 ±.009	.490 ±.034	.517 ±.017
	4	.519 ±.013	.487 ±.017	.507 ±.023	.528 ±.028	.689 ±.005	.507 ±.023	.547 ±.036	.483 ±.014	.480 ±.029	.481 ±.028	.528 ±.014	.542 ±.079	.532 ±.047	.495 ±.013	.527 ±.032
	5	.474 ±.013	.474 ±.015	.472 ±.001	.491 ±.023	.662 ±.021	.486 ±.018	.482 ±.009	.475 ±.012	.481 ±.020	.490 ±.016	.495 ±.026	.503 ±.016	.503 ±.003	.468 ±.019	.490 ±.004
laplacian prior, j = source	1	1.81 ±.18	2.00 ±.16	1.90 ±.06	1.80 ±.08	2.07 ±.02	1.90 ±.10	1.89 ±.20	1.91 ±.12	1.80 ±.11	1.86 ±.15	1.95 ±.15	1.91 ±.14	1.87 ±.16	1.87 ±.15	1.88 ±.11
	2	1.69 ±.17	1.83 ±.24	1.73 ±.11	1.63 ±.20	1.90 ±.12	1.78 ±.20	1.87 ±.21	1.69 ±.19	1.61 ±.18	1.68 ±.20	1.73 ±.14	1.88 ±.10	1.77 ±.21	1.74 ±.16	1.81 ±.19
	3	1.51 ±.18	1.69 ±.20	1.57 ±.13	1.60 ±.20	1.82 ±.12	1.66 ±.25	1.61 ±.04	1.54 ±.22	1.49 ±.10	1.63 ±.21	1.59 ±.13	1.73 ±.24	1.61 ±.08	1.54 ±.25	1.66 ±.17
	4	1.43 ±.16	1.58 ±.15	1.48 ±.11	1.51 ±.13	1.61 ±.12	1.53 ±.17	1.50 ±.17	1.50 ±.21	1.45 ±.16	1.52 ±.17	1.51 ±.07	1.57 ±.04	1.41 ±.16	1.51 ±.13	1.51 ±.13
	5	1.38 ±.13	1.48 ±.12	1.48 ±.13	1.45 ±.11	1.50 ±.09	1.44 ±.14	1.49 ±.15	1.52 ±.23	1.40 ±.12	1.41 ±.14	1.48 ±.14	1.47 ±.19	1.48 ±.13	1.42 ±.09	1.42 ±.11
anecd	1	.0809 ±.0372	.136 ±.053	.228 ±.014	.0853 ±.0163	.525 ±.011	.125 ±.031	.166 ±.034	.0766 ±.0283	.107 ±.032	.126 ±.037	.136 ±.019	.603 ±.128	.112 ±.016	.104 ±.012	.0974 ±.0729
	2	.0527 ±.0154	.0565 ±.0219	.104 ±.042	.0940 ±.0342	.426 ±.008	.0519 ±.0145	.0819 ±.0767	.0783 ±.0265	.0876 ±.0382	.0742 ±.0147	.0661 ±.0257	.271 ±.109	.0712 ±.0484	.0469 ±.0355	.0617 ±.0406
	3	.0652 ±.0216	.0616 ±.0384	.0495 ±.0275	.0775 ±.0351	.333 ±.037	.0626 ±.0247	.0761 ±.0610	.0592 ±.0253	.0651 ±.0384	.0811 ±.0406	.0599 ±.0240	.161 ±.020	.0424 ±.0305	.0592 ±.0383	.0752 ±.0574
	4	.0594 ±.0291	.0622 ±.0361	.0708 ±.0467	.0830 ±.0390	.213 ±.036	.0690 ±.0211	.0507 ±.0179	.0411 ±.0160	.0650 ±.0465	.0709 ±.0422	.0633 ±.0324	.161 ±.085	.0438 ±.0316	.0463 ±.0342	.0789 ±.0529
	5	.0483 ±.0260	.0618 ±.0429	.0528 ±.0384	.0610 ±.0242	.0351 ±.0319	.0457 ±.0158	.0446 ±.0187	.0513 ±.0258	.0591 ±.0295	.0573 ±.0049	.0531 ±.0421	.0501 ±.0296	.0450 ±.0286	.0474 ±.0242	.0658 ±.0481
audiology imagined	1	.501 ±.273	.610 ±.372	.547 ±.149	.476 ±.235	.548 ±.092	.666 ±.231	.588 ±.145	.512 ±.211	.407 ±.152	.535 ±.129	.598 ±.359	.549 ±.085	.422 ±.016	.457 ±.194	.432 ±.091
	2	.504 ±.289	.535 ±.277	.417 ±.102	.482 ±.265	.419 ±.119	.633 ±.152	.557 ±.112	.457 ±.186	.393 ±.132	.495 ±.099	.435 ±.130	.467 ±.204	.431 ±.028	.417 ±.212	.435 ±.161
	3	.528 ±.374	.376 ±.126	.345 ±.132	.444 ±.182	.418 ±.087	.570 ±.334	.488 ±.030	.381 ±.174	.378 ±.109	.436 ±.121	.383 ±.129	.426 ±.080	.461 ±.109	.309 ±.129	.432 ±.186
	4	.348 ±.126	.365 ±.088	.333 ±.141	.386 ±.189	.396 ±.144	.373 ±.086	.460 ±.043	.384 ±.126	.364 ±.116	.407 ±.129	.374 ±.128	.359 ±.114	.435 ±.017	.322 ±.154	.343 ±.081
	5	.335 ±.149	.341 ±.099	.379 ±.156	.384 ±.196	.418 ±.153	.372 ±.119	.433 ±.113	.351 ±.116	.392 ±.156	.394 ±.191	.378 ±.140	.351 ±.090	.434 ±.161	.351 ±.165	.383 ±.116
RMSE (↓)																
eyes_gl_11	1	1.34 ±.02	1.42 ±.03	1.39 ±.03	1.53 ±.02	1.40 ±.03	1.44 ±.03	1.51 ±.02	1.53 ±.01	1.36 ±.05	1.53 ±.02	1.49 ±.01	1.53 ±.00	1.53 ±.01	1.33 ±.02	1.36 ±.02
	2	1.23 ±.01	1.26 ±.04	1.31 ±.03	1.50 ±.01	1.32 ±.00	1.26 ±.04	1.37 ±.01	1.47 ±.05	1.25 ±.02	1.50 ±.01	1.33 ±.06	1.50 ±.02	1.48 ±.03	1.20 ±.02	1.34 ±.04
	3	.986 ±.017	1.03 ±.01	1.04 ±.03	1.37 ±.04	1.16 ±.02	1.02 ±.02	1.17 ±.03	1.32 ±.04	1.00 ±.02	1.37 ±.04	1.02 ±.02	1.28 ±.02	1.28 ±.03	.973 ±.022	1.23 ±.03
	4	.801 ±.017	.824 ±.036	.835 ±.016	.992 ±.047	.919 ±.006	.822 ±.023	.932 ±.040	.972 ±.014	.831 ±.016	.992 ±.047	.796 ±.016	.935 ±.048	.975 ±.087	.790 ±.035	.909 ±.011
	5	.757 ±.027	.759 ±.034	.768 ±.026	.791 ±.004	.774 ±.017	.761 ±.032	.793 ±.028	.799 ±.046	.758 ±.035	.791 ±.004	.746 ±.023	.785 ±.023	.777 ±.001	.747 ±.022	.797 ±.036
forest trees	1	1.42 ±.02	1.40 ±.01	1.42 ±.02	1.40 ±.03	1.41 ±.05	1.40 ±.01	1.42 ±.03	1.41 ±.03	1.41 ±.05	1.40 ±.03	1.40 ±.04	1.41 ±.03	1.40 ±.02	1.42 ±.02	1.40 ±.03
	2	1.42 ±.06	1.43 ±.02	1.45 ±.08	1.41 ±.05	1.42 ±.06	1.43 ±.02	1.42 ±.05	1.40 ±.02	1.42 ±.05	1.42 ±.04	1.42 ±.05	1.41 ±.02	1.41 ±.03	1.42 ±.04	1.41 ±.05
	3	1.42 ±.04	1.42 ±.02	1.42 ±.03	1.41 ±.06	1.42 ±.07	1.42 ±.02	1.42 ±.05	1.41 ±.03	1.40 ±.03	1.43 ±.07	1.42 ±.07	1.43 ±.04	1.40 ±.03	1.40 ±.05	1.42 ±.07
	4	1.42 ±.04	1.42 ±.06	1.43 ±.03	1.42 ±.06	1.42 ±.06	1.42 ±.06	1.41 ±.04	1.45 ±.04	1.42 ±.07	1.41 ±.05	1.43 ±.06	1.40 ±.03	1.41 ±.03	1.43 ±.05	1.43 ±.08
	5	1.42 ±.05	1.41 ±.03	1.42 ±.05	1.42 ±.04	1.40 ±.05	1.41 ±.03	1.41 ±.05	1.41 ±.05	1.41 ±.05	1.42 ±.06	1.41 ±.04	1.41 ±.04	1.43 ±.07	1.41 ±.05	1.42 ±.05
allstate claims, severity	1	.670 ±.001	.680 ±.002	.675 ±.002	.705 ±.010	.811 ±.002	.680 ±.002	.669 ±.001	.693 ±.000	.670 ±.002	.716 ±.013	.695 ±.003	.783 ±.024	.786 ±.024	.670 ±.001	.666 ±.005
	2	.640 ±.003	.652 ±.002	.658 ±.002	.648 ±.003	.808 ±.003	.652 ±.002	.635 ±.008	.636 ±.001	.645 ±.001	.664 ±.013	.665 ±.022	.788 ±.014	.796 ±.019	.643 ±.005	.652 ±.004
	3	.589 ±.002	.605 ±.007	.642 ±.001	.600 ±.011	.807 ±.002	.605 ±.007	.606 ±.008	.615 ±.000	.616 ±.001	.618 ±.001	.632 ±.001	.733 ±.023	.739 ±.015	.589 ±.002	.638 ±.002
	4	.558 ±.004	.566 ±.004	.612 ±.008	.570 ±.003	.778 ±.009	.566 ±.004	.565 ±.006	.611 ±.001	.568 ±.002	.604 ±.003	.595 ±.010	.673 ±.036	.673 ±.000	.558 ±.001	.605 ±.022
	5	.542 ±.001	.541 ±.001	.555 ±.005	.560 ±.001	.685 ±.010	.541 ±.001	.543 ±.004	.552 ±.001	.544 ±.001	.584 ±.009	.568 ±.009	.599 ±.015	.608 ±.020	.542 ±.001	.578 ±.007
muslim denying	1	.245 ±.017	.259 ±.003	.320 ±.002	.272 ±.004	.333 ±.007	.259 ±.003	.345 ±.048	.190 ±.004	.201 ±.025	.314 ±.003	.372 ±.000	.448 ±.002	.196 ±.017	.251 ±.023	.260 ±.006
	2	.177 ±.004	.220 ±.004	.237 ±.001	.176 ±.001	.232 ±.001	.220 ±.004	.219 ±.038	.187 ±.002	.186 ±.001	.180 ±.007	.240 ±.023	.300 ±.008	.161 ±.009	.179 ±.022	.169 ±.005
	3	.151 ±.011	.168 ±.009	.165 ±.004	.171 ±.001	.226 ±.002	.170 ±.001	.150 ±.008	.177 ±.004	.171 ±.003	.166 ±.004	.168 ±.021	.203 ±.028	.143 ±.004	.151 ±.011	.146 ±.004
	4	.148 ±.009	.156 ±.005	.142 ±.004	.161 ±.003	.228 ±.004	.155 ±.005	.141 ±.005	.162 ±.004	.161 ±.003	.150 ±.012	.142 ±.005	.182 ±.014	.141 ±.004	.144 ±.004	.141 ±.004
	5	.140 ±.005	.140 ±.006	.140 ±.004	.140 ±.005	.202 ±.002	.140 ±.005	.139 ±.005	.140 ±.004	.140 ±.005	.141 ±.004	.140 ±.004	.158 ±.018	.140 ±.006	.140 ±.004	.140 ±.005
warp gender	1	.735 ±.006	.771 ±.022	.770 ±.006	.770 ±.006	.815 ±.009	.774 ±.021	.827 ±.011	.735 ±.006	.770 ±.006	.774 ±.005	.756 ±.019	.788 ±.013	.758 ±.020	.735 ±.006	.774 ±.005
	2	.694 ±.005	.713 ±.006	.724 ±.006	.732 ±.007	.753 ±.003	.715 ±.006	.782 ±.019	.718 ±.005	.745 ±.007	.734 ±.013	.722 ±.012	.768 ±.013	.703 ±.019	.692 ±.008	.709 ±.002
	3	.667 ±.018	.704 ±.006	.712 ±.005	.681 ±.017	.699 ±.012	.705 ±.005	.674 ±.011	.679 ±.006	.697 ±.020	.696 ±.010	.652 ±.018	.712 ±.028	.663 ±.013	.669 ±.022	.685 ±.016
	4	.629 ±.008	.661 ±.015	.657 ±.001	.638 ±.009	.673 ±.002	.663 ±.014	.634 ±.009	.644 ±.011	.645 ±.021	.647 ±.015	.630 ±.005	.662 ±.015	.630 ±.007	.634 ±.009	.645 ±.008
	5	.623 ±.009	.636 ±.014	.640 ±.013	.623 ±.007	.632 ±.011	.634 ±.016	.622 ±.006	.625 ±.014	.627 ±.015	.627 ±.006	.619 ±.013	.631 ±.015	.621 ±.004	.624 ±.009	.634 ±.014
body_admty admission	1	.0110 ±.0006	.0105 ±.0012	.0110 ±.0006	.0108 ±.0009	.0117 ±.0027	.0105 ±.0012	.0121 ±.0023	.0106 ±.0009	.0108 ±.0010	.0110 ±.0013	.0107 ±.0013	.0145 ±.0044	.0110 ±.0014	.0108 ±.0012	.0106 ±.0008
	2	.0106 ±.0009	.0106 ±.0012	.0106 ±.0007	.0109 ±.0005	.0108 ±.0005	.0106 ±.0012	.0124 ±.0033	.0109 ±.0004	.0109 ±.0005	.0109 ±.0011	.0105 ±.0013	.0130 ±.0022	.0108 ±.0017	.0106 ±.0014	.0110 ±.0017
	3	.0105 ±.0011	.0106 ±.0014	.0110 ±.0008	.0108 ±.0012	.0111 ±.0012	.0106 ±.0014	.0110 ±.0017	.0109 ±.0009	.0108 ±.0008	.0109 ±.0012	.0108 ±.0015	.0117 ±.0023	.0107 ±.0011	.0105 ±.0013	.0109 ±.0011
	4	.0106 ±.0011	.0108 ±.0012	.0109 ±.0013	.0112 ±.0012	.0110 ±.0013	.0108 ±.0012	.0108 ±.0013	.0111 ±.0012	.0109 ±.0012	.0107 ±.0013	.0107 ±.0013	.0120 ±.0004	.0108 ±.0010	.0107 ±.0012	.0107 ±.0013
	5	.0109 ±.0014	.0107 ±.0013	.0110 ±.0010	.0111 ±.0014	.0106 ±.0012	.0107 ±.0013	.0107 ±.0010	.0112 ±.0014	.0110 ±.0017	.0108 ±.0009	.0105 ±.0011	.0123 ±.0007	.0107 ±.0011	.0105 ±.0013	.0108 ±.0013
breast benign (vs M)	1	11.7 ±5.8	14.1 ±7.6	11.7 ±5.8	14.5 ±7.9	15.1 ±7.1	14.1 ±7.6	14.5 ±2.3	10.9 ±4.9	14.5 ±7.9	10.9 ±4.9	13.8 ±6.9	12.5 ±6.5	11.3 ±5.3	11.7 ±5.8	15.5 ±4.3
	2	12.0 ±5.8	11.0 ±5.1	11.2 ±5.4	10.8 ±5.2	15.4 ±6.6	11.0 ±5.1									

(continued from previous page)

Dataset	Budget id, j	CART	ElasticNet	F-test	GuinRatio	LaplaceScore	Lasso	LOCO	MarkovBlanket	MI	mRMR	(R)Relieff	Random	SBE	RFImportance	SFS	Importance
sepsis/sepsis	1	9.85 ± 10	9.86 ± 13	10.4 ± 2	10.7 ± 1	12.0 ± 2	9.93 ± 15	9.78 ± 11	9.86 ± 07	11.8 ± 1	9.75 ± 07	9.88 ± 06	9.86 ± 21	9.94 ± 19	9.82 ± 21	9.97 ± 08	
	2	9.51 ± 07	9.57 ± 10	9.87 ± 13	9.93 ± 01	10.1 ± 1	9.59 ± 09	9.55 ± 05	9.57 ± 12	10.2 ± 2	9.47 ± 07	9.56 ± 02	9.67 ± 18	9.54 ± 02	9.50 ± 10	9.70 ± 11	
	3	9.44 ± 08	9.48 ± 14	9.65 ± 06	9.63 ± 06	9.81 ± 05	9.48 ± 10	9.50 ± 08	9.43 ± 15	9.97 ± 14	9.48 ± 06	9.49 ± 05	9.53 ± 11	9.60 ± 19	9.50 ± 08	9.56 ± 13	
	4	9.39 ± 11	9.46 ± 10	9.50 ± 11	9.52 ± 00	9.60 ± 03	9.41 ± 11	9.42 ± 05	9.39 ± 11	9.57 ± 07	9.44 ± 10	9.43 ± 08	9.51 ± 07	9.49 ± 04	9.48 ± 10	9.49 ± 07	
	5	9.43 ± 13	9.50 ± 14	9.50 ± 20	9.48 ± 06	9.47 ± 07	9.42 ± 11	9.45 ± 08	9.44 ± 09	9.46 ± 13	9.35 ± 07	9.44 ± 14	9.43 ± 08	9.42 ± 07	9.43 ± 13	9.43 ± 10	
AUC (↑)																	
in_vehicle/vehicle	1	.746 ± 010	.718 ± 006	.696 ± 007	.719 ± 012	.580 ± 021	.720 ± 008	.737 ± 009	.729 ± 010	.723 ± 023	.715 ± 016	.745 ± 011	.611 ± 018	.703 ± 057	.746 ± 006	.744 ± 008	
	2	.792 ± 005	.724 ± 007	.724 ± 005	.761 ± 010	.628 ± 007	.725 ± 008	.796 ± 025	.765 ± 013	.763 ± 009	.740 ± 012	.786 ± 014	.667 ± 018	.808 ± 011	.792 ± 006	.762 ± 019	
	3	.804 ± 002	.769 ± 007	.738 ± 004	.800 ± 005	.671 ± 002	.768 ± 003	.812 ± 004	.804 ± 003	.801 ± 013	.762 ± 009	.802 ± 005	.734 ± 049	.821 ± 007	.801 ± 004	.795 ± 014	
	4	.826 ± 007	.803 ± 004	.816 ± 011	.818 ± 004	.724 ± 005	.806 ± 004	.821 ± 005	.815 ± 002	.821 ± 011	.797 ± 006	.815 ± 009	.811 ± 006	.833 ± 004	.832 ± 004	.815 ± 019	
	5	.834 ± 003	.830 ± 009	.829 ± 007	.829 ± 009	.814 ± 006	.829 ± 002	.832 ± 006	.824 ± 012	.829 ± 012	.827 ± 002	.830 ± 005	.828 ± 001	.832 ± 006	.834 ± 003	.830 ± 005	
marketing/marketing	1	.820 ± 016	.804 ± 042	.786 ± 012	.774 ± 012	.708 ± 021	.808 ± 017	.783 ± 025	.798 ± 024	.761 ± 011	.811 ± 019	.754 ± 008	.753 ± 026	.820 ± 044	.824 ± 024	.801 ± 018	
	2	.849 ± 032	.870 ± 034	.873 ± 018	.810 ± 018	.823 ± 021	.873 ± 013	.863 ± 013	.840 ± 010	.836 ± 016	.846 ± 010	.812 ± 046	.778 ± 026	.861 ± 029	.837 ± 022	.850 ± 007	
	3	.869 ± 016	.889 ± 031	.876 ± 028	.859 ± 014	.852 ± 005	.892 ± 029	.888 ± 024	.857 ± 018	.860 ± 016	.874 ± 026	.861 ± 022	.823 ± 022	.879 ± 019	.858 ± 018	.889 ± 032	
	4	.886 ± 030	.900 ± 028	.882 ± 032	.869 ± 011	.850 ± 011	.898 ± 024	.895 ± 024	.867 ± 008	.887 ± 015	.895 ± 024	.884 ± 032	.870 ± 046	.891 ± 026	.881 ± 014	.893 ± 028	
	5	.898 ± 024	.901 ± 025	.898 ± 024	.883 ± 022	.886 ± 032	.898 ± 019	.896 ± 033	.898 ± 010	.903 ± 022	.901 ± 021	.891 ± 021	.882 ± 041	.902 ± 027	.902 ± 021	.905 ± 021	
port_k/compas	1	.953 ± 011	.838 ± 004	.864 ± 014	.885 ± 018	.833 ± 006	.841 ± 001	.940 ± 008	.937 ± 015	.920 ± 016	.922 ± 020	.847 ± 007	.844 ± 014	.873 ± 022	.945 ± 019	.939 ± 015	
	2	.954 ± 015	.871 ± 010	.881 ± 022	.925 ± 010	.873 ± 020	.863 ± 013	.952 ± 013	.949 ± 013	.940 ± 017	.943 ± 016	.938 ± 014	.897 ± 048	.926 ± 036	.953 ± 018	.949 ± 016	
	3	.961 ± 013	.908 ± 042	.878 ± 021	.951 ± 017	.874 ± 017	.903 ± 046	.956 ± 020	.952 ± 017	.948 ± 018	.954 ± 015	.943 ± 030	.901 ± 035	.926 ± 019	.956 ± 014	.948 ± 012	
	4	.961 ± 016	.912 ± 028	.917 ± 040	.952 ± 014	.882 ± 015	.911 ± 029	.954 ± 014	.954 ± 015	.951 ± 018	.960 ± 012	.954 ± 018	.951 ± 012	.949 ± 035	.962 ± 009	.953 ± 014	
	5	.958 ± 013	.946 ± 021	.951 ± 012	.952 ± 015	.903 ± 003	.947 ± 020	.957 ± 015	.959 ± 011	.955 ± 014	.959 ± 013	.960 ± 012	.951 ± 008	.963 ± 010	.960 ± 013	.959 ± 011	
coca_burner/coca_burner	1	.710 ± 022	.844 ± 070	.823 ± 048	.837 ± 079	.575 ± 244	.797 ± 107	.655 ± 186	.846 ± 106	.863 ± 027	.816 ± 002	.877 ± 064	.612 ± 299	.658 ± 157	.763 ± 144	.646 ± 212	
	2	.852 ± 077	.853 ± 101	.903 ± 037	.899 ± 041	.856 ± 156	.834 ± 110	.881 ± 060	.788 ± 165	.871 ± 083	.841 ± 052	.917 ± 039	.846 ± 092	.819 ± 081	.875 ± 096	.782 ± 030	
	3	.831 ± 080	.880 ± 080	.868 ± 072	.883 ± 113	.892 ± 081	.859 ± 074	.787 ± 046	.888 ± 097	.869 ± 078	.857 ± 079	.887 ± 070	.805 ± 125	.859 ± 035	.848 ± 069	.872 ± 035	
	4	.870 ± 066	.842 ± 085	.892 ± 049	.875 ± 075	.861 ± 127	.870 ± 068	.883 ± 060	.875 ± 054	.915 ± 068	.862 ± 069	.888 ± 053	.870 ± 118	.826 ± 092	.898 ± 062	.873 ± 082	
	5	.913 ± 038	.872 ± 054	.879 ± 080	.885 ± 065	.892 ± 081	.899 ± 060	.889 ± 051	.879 ± 054	.906 ± 066	.889 ± 081	.910 ± 085	.904 ± 068	.911 ± 065	.882 ± 077	.907 ± 054	
mushrooms/mushrooms	1	.936 ± 011	.937 ± 007	.933 ± 007	.940 ± 010	.931 ± 009	.946 ± 013	.922 ± 015	.936 ± 009	.937 ± 010	.941 ± 011	.896 ± 052	.922 ± 013	.934 ± 006	.933 ± 006	.936 ± 009	
	2	.940 ± 005	.943 ± 008	.938 ± 009	.940 ± 009	.944 ± 007	.946 ± 006	.935 ± 010	.941 ± 007	.936 ± 009	.940 ± 011	.949 ± 005	.933 ± 003	.940 ± 004	.939 ± 018	.943 ± 011	
	3	.946 ± 010	.949 ± 011	.943 ± 013	.942 ± 008	.942 ± 006	.942 ± 010	.944 ± 006	.946 ± 006	.946 ± 010	.942 ± 005	.949 ± 006	.943 ± 009	.942 ± 004	.943 ± 009	.942 ± 012	
	4	.950 ± 008	.951 ± 007	.949 ± 005	.948 ± 005	.948 ± 008	.951 ± 007	.945 ± 009	.955 ± 009	.951 ± 014	.950 ± 009	.953 ± 011	.952 ± 008	.951 ± 007	.949 ± 011	.951 ± 009	
	5	.953 ± 013	.960 ± 006	.953 ± 011	.954 ± 015	.960 ± 004	.959 ± 009	.957 ± 008	.955 ± 006	.954 ± 010	.958 ± 008	.959 ± 008	.954 ± 004	.954 ± 008	.960 ± 010	.955 ± 009	
satellite/country	1	.630 ± 007	.631 ± 006	.632 ± 004	.632 ± 004	.499 ± 001	.630 ± 006	.594 ± 017	.632 ± 004	.502 ± 002	.632 ± 004	.501 ± 004	.515 ± 007	.534 ± 005	.632 ± 004	.574 ± 013	
	2	.698 ± 003	.701 ± 002	.704 ± 002	.702 ± 003	.501 ± 001	.701 ± 002	.619 ± 020	.702 ± 004	.510 ± 002	.702 ± 004	.509 ± 001	.575 ± 027	.579 ± 031	.700 ± 000	.601 ± 020	
	3	.783 ± 004	.785 ± 004	.786 ± 005	.781 ± 004	.516 ± 001	.785 ± 004	.624 ± 010	.783 ± 003	.523 ± 004	.787 ± 003	.511 ± 001	.611 ± 020	.609 ± 013	.786 ± 002	.603 ± 013	
	4	.855 ± 004	.863 ± 003	.863 ± 003	.858 ± 005	.525 ± 001	.863 ± 003	.652 ± 015	.854 ± 003	.549 ± 004	.856 ± 004	.535 ± 007	.650 ± 014	.636 ± 018	.861 ± 003	.660 ± 017	
	5	.889 ± 003	.888 ± 002	.889 ± 003	.888 ± 002	.548 ± 006	.888 ± 002	.754 ± 014	.881 ± 003	.683 ± 004	.878 ± 002	.570 ± 025	.764 ± 022	.757 ± 008	.889 ± 002	.781 ± 017	
m4_predictions/m4_predictions	1	.954 ± 032	.935 ± 016	.935 ± 011	.931 ± 007	.664 ± 045	.923 ± 047	.776 ± 071	.896 ± 062	.925 ± 010	.958 ± 010	.888 ± 013	.777 ± 025	.705 ± 089	.950 ± 030	.827 ± 078	
	2	.976 ± 006	.955 ± 039	.966 ± 016	.974 ± 020	.766 ± 122	.981 ± 011	.884 ± 033	.984 ± 005	.972 ± 002	.961 ± 020	.974 ± 023	.877 ± 054	.885 ± 038	.962 ± 026	.898 ± 055	
	3	.977 ± 008	.971 ± 009	.972 ± 012	.975 ± 005	.843 ± 012	.988 ± 004	.924 ± 007	.973 ± 004	.987 ± 002	.944 ± 042	.980 ± 006	.969 ± 017	.939 ± 014	.993 ± 002	.975 ± 007	
	4	.985 ± 010	.990 ± 003	.969 ± 022	.980 ± 010	.937 ± 021	.990 ± 007	.948 ± 037	.985 ± 022	.980 ± 019	.976 ± 013	.988 ± 007	.960 ± 040	.979 ± 008	.984 ± 006	.976 ± 011	
	5	.990 ± 007	.990 ± 008	.977 ± 030	.986 ± 018	.959 ± 027	.992 ± 006	.987 ± 009	.989 ± 008	.986 ± 017	.989 ± 005	.991 ± 001	.983 ± 012	.992 ± 005	.992 ± 005	.985 ± 005	
bank_authentication/bank_authentication	1	.750 ± 010	.774 ± 014	.774 ± 014	.821 ± 004	.597 ± 011	.774 ± 014	.821 ± 004	.821 ± 004	.821 ± 003	.821 ± 004	.745 ± 065	.549 ± 061	.821 ± 003	.751 ± 009	.821 ± 004	
	2	.765 ± 007	.791 ± 007	.791 ± 007	.854 ± 008	.767 ± 004	.791 ± 007	.852 ± 009	.853 ± 009	.840 ± 011	.838 ± 008	.821 ± 004	.687 ± 070	.838 ± 010	.764 ± 008	.845 ± 004	
	3	.834 ± 002	.803 ± 007	.839 ± 024	.851 ± 012	.785 ± 007	.803 ± 007	.860 ± 015	.852 ± 010	.860 ± 011	.839 ± 007	.833 ± 003	.714 ± 091	.845 ± 002	.834 ± 002	.851 ± 004	
	4	.847 ± 008	.846 ± 013	.869 ± 008	.853 ± 010	.817 ± 010	.846 ± 013	.867 ± 004	.852 ± 009	.864 ± 012	.853 ± 003	.846 ± 006	.807 ± 046	.868 ± 007	.845 ± 004	.863 ± 012	
breast_cancer/breast_cancer	1	.866 ± 007	.844 ± 034	.865 ± 007	.855 ± 012	.815 ± 011	.844 ± 034	.866 ± 008	.861 ± 005	.865 ± 007	.853 ± 004	.855 ± 010	.842 ± 034	.867 ± 008	.865 ± 008	.867 ± 008	
	2	.814 ± 029	.750 ± 116	.796 ± 024	.816 ± 032	.758 ± 113	.803 ± 054	.790 ± 069	.842 ± 010	.757 ± 026	.828 ± 043	.785 ± 040	.834 ± 021	.787 ± 044	.804 ± 046	.819 ± 005	
	3	.835 ± 047	.856 ± 038	.821 ± 031	.794 ± 063	.776 ± 073	.840 ± 051	.847 ± 055	.818 ± 043	.804 ± 019	.787 ± 044	.831 ± 045	.767 ± 068	.813 ± 047	.805 ± 039	.798 ± 055	
	4	.853 ± 016	.842 ± 040	.809 ± 023	.819 ± 034	.787 ± 057	.845 ± 019	.860 ± 039	.807 ± 023	.837 ± 074	.811 ± 037	.827 ± 065	.784 ± 067	.847 ± 013	.828 ± 037	.768 ± 046	
	5	.847 ± 036	.861 ± 025	.830 ± 020	.846 ± 035	.812 ± 050	.844 ± 019	.871 ± 041	.839 ± 030	.833 ± 034	.837 ± 022	.791 ± 073	.832 ± 045	.867 ± 016	.835 ± 034	.848 ± 012	
svm_csvm/svm_csvm	1	.906 ± 013	.862 ± 047	.848 ± 051	.865 ± 026	.828 ± 019	.868 ± 048	.886 ± 023	.836 ± 006	.886 ± 050	.835 ± 010	.829 ± 051	.893 ± 035	.860 ± 004	.845 ± 025	.817 ± 038	
	2	.957 ± 000	.920 ± 011	.935 ± 002	.924 ± 000	.940 ± 001	.920 ± 001	.941 ± 002	.961 ± 000	.959 ± 000	.913 ± 000	.956 ± 000	.858 ± 052	.949 ± 018	.959 ± 000	.972 ± 001	
	3	.979 ± 000	.977 ± 000	.957 ± 001	.976 ± 000	.970 ± 000	.977 ± 000	.977 ± 000	.978 ± 000	.978 ± 000	.978 ± 000	.977 ± 000	.975 ± 000	.980 ± 020	.985 ± 001	.9898 ±	

(continued from previous page)

Dataset	Budget idx	CART	ElasNet	F-test	GainRatio	LaplacianScore	Lasso	LOCO	MarkovBlanket	MI	mRMR	(R)ReliefF	Random	SBE	RfImportance	SFS
bank marketing	1	.672 ±.017	.711 ±.010	.711 ±.010	.679 ±.010	.624 ±.007	.711 ±.010	.701 ±.010	.699 ±.007	.674 ±.011	.670 ±.007	.677 ±.008	.675 ±.021	.710 ±.006	.662 ±.005	.714 ±.008
	2	.716 ±.010	.729 ±.010	.728 ±.008	.721 ±.011	.651 ±.007	.729 ±.010	.734 ±.013	.729 ±.007	.732 ±.012	.697 ±.009	.702 ±.009	.706 ±.028	.731 ±.004	.713 ±.014	.734 ±.010
	3	.724 ±.012	.740 ±.010	.742 ±.010	.734 ±.009	.736 ±.010	.740 ±.010	.746 ±.016	.735 ±.011	.749 ±.007	.732 ±.006	.717 ±.009	.735 ±.016	.748 ±.016	.723 ±.011	.738 ±.007
	4	.744 ±.018	.757 ±.010	.752 ±.012	.742 ±.011	.745 ±.012	.755 ±.013	.758 ±.014	.743 ±.010	.756 ±.010	.754 ±.011	.746 ±.010	.746 ±.007	.754 ±.014	.730 ±.011	.749 ±.013
	5	.759 ±.011	.760 ±.015	.757 ±.011	.747 ±.007	.757 ±.011	.761 ±.013	.759 ±.012	.757 ±.015	.758 ±.011	.759 ±.011	.757 ±.012	.752 ±.015	.758 ±.011	.759 ±.010	.754 ±.013
kolomoia dataset	1	.910 ±.029	.981 ±.022	.983 ±.023	.967 ±.035	.606 ±.164	.971 ±.024	.711 ±.174	.988 ±.021	.980 ±.018	.975 ±.023	.978 ±.026	.798 ±.149	.726 ±.144	.966 ±.035	.617 ±.036
	2	.926 ±.060	.968 ±.028	.954 ±.048	.983 ±.023	.900 ±.106	.982 ±.011	.797 ±.133	.903 ±.148	.995 ±.009	.966 ±.030	.972 ±.025	.754 ±.083	.865 ±.077	.995 ±.009	.848 ±.125
	3	.958 ±.054	.987 ±.012	.968 ±.043	.988 ±.015	.946 ±.023	.990 ±.017	.952 ±.049	.978 ±.038	.965 ±.040	.985 ±.026	.980 ±.023	.932 ±.044	.921 ±.037	.980 ±.034	.969 ±.036
	4	.997 ±.005	.990 ±.017	.990 ±.017	.995 ±.009	.969 ±.028	.978 ±.018	.985 ±.020	.995 ±.009	.993 ±.013	.995 ±.009	.998 ±.004	.978 ±.027	.978 ±.027	.988 ±.021	.998 ±.004
	5	.992 ±.007	.998 ±.004	.993 ±.013	.988 ±.021	.993 ±.013	.985 ±.026	.998 ±.004	.995 ±.009	.990 ±.017	.998 ±.004	.995 ±.009	.990 ±.017	.995 ±.009	.990 ±.017	.985 ±.020
heart_disease voting	1	.832 ±.025	.845 ±.016	.818 ±.002	.841 ±.068	.778 ±.020	.848 ±.042	.847 ±.081	.801 ±.026	.842 ±.040	.846 ±.025	.850 ±.035	.828 ±.025	.836 ±.049	.812 ±.057	.829 ±.031
	2	.861 ±.041	.867 ±.016	.869 ±.022	.897 ±.028	.813 ±.015	.853 ±.047	.856 ±.065	.847 ±.038	.880 ±.021	.863 ±.016	.883 ±.012	.842 ±.013	.824 ±.057	.893 ±.045	.847 ±.032
	3	.868 ±.040	.900 ±.017	.889 ±.022	.908 ±.011	.859 ±.007	.875 ±.034	.864 ±.049	.876 ±.027	.890 ±.018	.876 ±.026	.897 ±.026	.818 ±.046	.868 ±.039	.881 ±.042	.879 ±.040
	4	.881 ±.020	.894 ±.016	.897 ±.024	.896 ±.033	.872 ±.042	.895 ±.021	.868 ±.052	.903 ±.037	.893 ±.048	.901 ±.018	.892 ±.024	.901 ±.029	.867 ±.060	.890 ±.032	.898 ±.036
	5	.899 ±.025	.891 ±.030	.905 ±.032	.900 ±.029	.892 ±.035	.894 ±.051	.892 ±.044	.901 ±.046	.901 ±.045	.896 ±.046	.901 ±.006	.906 ±.034	.892 ±.051	.900 ±.037	.902 ±.034
clock_protect project	1	.556 ±.092	.617 ±.189	.584 ±.066	.476 ±.073	.616 ±.041	.617 ±.189	.529 ±.154	.575 ±.035	.455 ±.035	.461 ±.133	.576 ±.116	.661 ±.193	.619 ±.061	.589 ±.122	.638 ±.027
	2	.608 ±.115	.651 ±.139	.619 ±.125	.591 ±.228	.617 ±.067	.651 ±.139	.605 ±.042	.593 ±.060	.506 ±.058	.549 ±.166	.571 ±.127	.584 ±.058	.600 ±.076	.563 ±.115	.621 ±.106
	3	.598 ±.161	.624 ±.141	.626 ±.162	.582 ±.125	.617 ±.077	.624 ±.141	.608 ±.153	.575 ±.095	.624 ±.120	.559 ±.144	.487 ±.115	.578 ±.336	.591 ±.095	.578 ±.176	.605 ±.119
	4	.642 ±.148	.591 ±.130	.601 ±.185	.600 ±.170	.614 ±.061	.591 ±.130	.612 ±.132	.603 ±.125	.623 ±.085	.557 ±.160	.577 ±.188	.587 ±.173	.526 ±.169	.580 ±.000	.584 ±.070
	5	.578 ±.153	.589 ±.164	.670 ±.197	.570 ±.186	.684 ±.119	.589 ±.164	.635 ±.179	.616 ±.165	.598 ±.115	.534 ±.147	.617 ±.165	.653 ±.178	.675 ±.139	.582 ±.153	.594 ±.176
churn	1	.827 ±.018	.885 ±.009	.877 ±.010	.815 ±.003	.715 ±.001	.786 ±.186	.711 ±.005	.813 ±.007	.876 ±.011	.865 ±.038	.800 ±.007	.689 ±.113	.891 ±.006	.876 ±.010	.893 ±.003
	2	.900 ±.033	.907 ±.002	.909 ±.003	.843 ±.017	.755 ±.070	.860 ±.090	.821 ±.089	.853 ±.001	.889 ±.005	.897 ±.012	.817 ±.010	.716 ±.112	.915 ±.011	.900 ±.001	.914 ±.009
	3	.924 ±.006	.919 ±.002	.912 ±.010	.871 ±.020	.849 ±.013	.921 ±.006	.843 ±.066	.848 ±.013	.899 ±.008	.919 ±.002	.903 ±.003	.756 ±.119	.922 ±.008	.909 ±.008	.915 ±.014
	4	.922 ±.007	.921 ±.005	.919 ±.009	.864 ±.020	.841 ±.021	.927 ±.006	.880 ±.067	.845 ±.011	.911 ±.013	.921 ±.005	.911 ±.009	.866 ±.020	.919 ±.012	.922 ±.007	.922 ±.011
	5	.921 ±.006	.922 ±.006	.923 ±.005	.862 ±.016	.916 ±.002	.924 ±.007	.922 ±.011	.844 ±.012	.916 ±.006	.920 ±.010	.912 ±.010	.889 ±.005	.920 ±.011	.925 ±.006	.923 ±.007
app_falter	1	.977 ±.007	.949 ±.050	.976 ±.005	.962 ±.013	.926 ±.008	.973 ±.005	.937 ±.029	.977 ±.005	.979 ±.005	.973 ±.005	.940 ±.002	.964 ±.015	.964 ±.006	.981 ±.006	.978 ±.003
	2	.984 ±.004	.977 ±.012	.977 ±.005	.976 ±.003	.957 ±.005	.979 ±.001	.971 ±.009	.981 ±.004	.981 ±.003	.982 ±.005	.962 ±.002	.975 ±.011	.973 ±.013	.984 ±.004	.980 ±.005
	3	.988 ±.004	.987 ±.002	.982 ±.005	.973 ±.010	.977 ±.003	.986 ±.002	.985 ±.003	.987 ±.003	.983 ±.004	.985 ±.004	.982 ±.004	.983 ±.005	.985 ±.004	.987 ±.005	.984 ±.004
	4	.990 ±.003	.990 ±.002	.986 ±.005	.988 ±.004	.987 ±.003	.989 ±.002	.988 ±.003	.990 ±.003	.983 ±.004	.987 ±.003	.986 ±.004	.990 ±.002	.988 ±.002	.989 ±.004	.988 ±.004
	5	.991 ±.003	.991 ±.003	.990 ±.004	.990 ±.004	.989 ±.004	.991 ±.003	.990 ±.003	.991 ±.003	.989 ±.005	.990 ±.003	.990 ±.003	.991 ±.003	.990 ±.004	.990 ±.004	.990 ±.004
shoe negotiation	1	.837 ±.060	.805 ±.160	.896 ±.039	.850 ±.157	.915 ±.057	.758 ±.149	.823 ±.143	.848 ±.136	.866 ±.080	.867 ±.172	.959 ±.018	.760 ±.151	.812 ±.287	.866 ±.080	.793 ±.175
	2	.917 ±.059	.955 ±.040	.930 ±.061	.937 ±.081	.954 ±.052	.915 ±.117	.940 ±.074	.932 ±.082	.942 ±.053	.931 ±.082	.976 ±.041	.817 ±.257	.909 ±.115	.963 ±.032	.891 ±.118
	3	.940 ±.062	.950 ±.051	.972 ±.038	.972 ±.030	.972 ±.038	.953 ±.071	.972 ±.048	.969 ±.030	.952 ±.056	.934 ±.060	.980 ±.018	.944 ±.096	.968 ±.036	.976 ±.041	.930 ±.079
	4	.959 ±.037	.984 ±.018	.976 ±.041	.984 ±.027	.984 ±.018	.980 ±.018	.984 ±.027	.976 ±.041	.987 ±.013	.971 ±.026	.956 ±.049	.976 ±.041	.976 ±.041	.975 ±.028	.975 ±.028
	5	.975 ±.021	.996 ±.007	.992 ±.014	.954 ±.052	.988 ±.012	.979 ±.027	.976 ±.024	.980 ±.018	.975 ±.021	.992 ±.007	.964 ±.052	.958 ±.045	.996 ±.007	.984 ±.014	.992 ±.007
kdd_cup_99 anomaly	1	.673 ±.083	.525 ±.016	.781 ±.024	.757 ±.020	.542 ±.041	.525 ±.016	.812 ±.017	.784 ±.020	.629 ±.007	.759 ±.021	.653 ±.020	.535 ±.023	.522 ±.021	.755 ±.022	.792 ±.053
	2	.740 ±.062	.554 ±.044	.787 ±.026	.756 ±.020	.569 ±.057	.554 ±.044	.815 ±.015	.809 ±.017	.636 ±.007	.779 ±.024	.655 ±.004	.548 ±.009	.539 ±.023	.782 ±.022	.811 ±.015
	3	.803 ±.031	.576 ±.023	.793 ±.018	.803 ±.017	.571 ±.045	.576 ±.023	.807 ±.022	.807 ±.022	.729 ±.002	.790 ±.024	.801 ±.017	.606 ±.041	.616 ±.017	.796 ±.028	.814 ±.018
	4	.820 ±.018	.613 ±.054	.809 ±.019	.810 ±.021	.615 ±.008	.613 ±.054	.817 ±.015	.808 ±.016	.785 ±.026	.816 ±.023	.815 ±.016	.714 ±.066	.694 ±.065	.795 ±.016	.799 ±.043
	5	.817 ±.015	.715 ±.106	.816 ±.020	.812 ±.016	.729 ±.013	.715 ±.106	.813 ±.014	.804 ±.021	.789 ±.025	.817 ±.020	.819 ±.019	.745 ±.048	.746 ±.056	.813 ±.021	.810 ±.028
qpc_and chess32	1	.719 ±.014	.691 ±.041	.693 ±.025	.564 ±.062	.559 ±.018	.696 ±.035	.565 ±.033	.556 ±.044	.686 ±.022	.564 ±.062	.562 ±.036	.580 ±.014	.542 ±.059	.690 ±.025	.739 ±.011
	2	.775 ±.011	.749 ±.027	.717 ±.033	.624 ±.028	.584 ±.006	.782 ±.017	.619 ±.011	.633 ±.044	.728 ±.025	.624 ±.028	.680 ±.017	.633 ±.048	.662 ±.045	.736 ±.042	.763 ±.008
	3	.833 ±.018	.821 ±.025	.798 ±.028	.741 ±.028	.722 ±.017	.836 ±.018	.763 ±.022	.759 ±.035	.811 ±.017	.741 ±.028	.815 ±.018	.754 ±.022	.756 ±.007	.823 ±.017	.821 ±.006
	4	.868 ±.017	.854 ±.027	.873 ±.024	.850 ±.021	.840 ±.019	.861 ±.030	.848 ±.024	.851 ±.027	.865 ±.018	.850 ±.021	.882 ±.025	.839 ±.029	.843 ±.017	.881 ±.018	.851 ±.040
	5	.886 ±.028	.875 ±.034	.882 ±.025	.876 ±.021	.871 ±.030	.877 ±.023	.877 ±.019	.879 ±.025	.892 ±.017	.876 ±.021	.890 ±.023	.876 ±.023	.872 ±.019	.886 ±.030	.879 ±.023
insurance_subsequency prediction	1	.933 ±.011	.937 ±.006	.934 ±.004	.943 ±.007	.940 ±.003	.933 ±.015	.925 ±.008	.938 ±.004	.941 ±.005	.937 ±.009	.924 ±.010	.935 ±.008	.938 ±.009	.942 ±.007	.940 ±.010
	2	.939 ±.007	.944 ±.007	.938 ±.005	.940 ±.005	.941 ±.004	.942 ±.004	.944 ±.008	.939 ±.003	.941 ±.004	.940 ±.001	.938 ±.006	.940 ±.011	.939 ±.001	.942 ±.005	.943 ±.008
	3	.943 ±.004	.946 ±.008	.937 ±.007	.944 ±.005	.944 ±.008	.944 ±.008	.942 ±.008	.941 ±.006	.940 ±.004	.945 ±.004	.939 ±.003	.942 ±.006	.941 ±.005	.943 ±.003	.945 ±.010
	4	.943 ±.005	.946 ±.007	.941 ±.001	.941 ±.004	.942 ±.003	.947 ±.007	.945 ±.002	.940 ±.007	.943 ±.006	.941 ±.005	.944 ±.002	.942 ±.005	.944 ±.006	.942 ±.004	.944 ±.006
	5	.944 ±.006	.942 ±.003	.941 ±.001	.943 ±.001	.944 ±.003	.942 ±.004	.943 ±.004	.941 ±.003	.945 ±.007	.942 ±.002	.940 ±.004	.945 ±.005	.941 ±.005	.946 ±.004	.943 ±.004
detroit credit limit	1	.974 ±.013	.785 ±.224	.909 ±.041	.978 ±.004	.534 ±.003	.785 ±.224	.967 ±.013	.968 ±.013	.914 ±.030	.935 ±.013	.935 ±.033	.719 ±.213	.970 ±.016	.981 ±.005	.929 ±.060
	2	.980 ±.008	.939 ±.045	.933 ±.047	.978 ±.005	.572 ±.002	.939 ±.045	.973 ±.014	.980 ±.005	.924 ±.022	.943 ±.019	.937 ±.0				

(continued from previous page)

Dataset	Budget idx.	CART	ElankNet	F-test	GiniRatio	LaplacianScore	Lasso	LOCO	MarkovBlanket	MI	mRMR	(R)ReliefF	Random	SBE	RFIImportance	SFS
heart_disease binary	1	.790 ± .026	.879 ± .020	.862 ± .020	.833 ± .078	.675 ± .142	.886 ± .018	.744 ± .160	.834 ± .048	.832 ± .037	.844 ± .055	.874 ± .037	.726 ± .145	.835 ± .038	.852 ± .024	.844 ± .033
	2	.821 ± .033	.901 ± .034	.892 ± .025	.883 ± .020	.881 ± .042	.889 ± .014	.726 ± .204	.865 ± .043	.860 ± .044	.857 ± .035	.873 ± .047	.846 ± .016	.847 ± .071	.841 ± .026	.863 ± .050
	3	.837 ± .025	.894 ± .030	.892 ± .029	.867 ± .046	.840 ± .038	.887 ± .027	.852 ± .060	.858 ± .032	.879 ± .037	.868 ± .027	.888 ± .026	.853 ± .035	.885 ± .024	.877 ± .023	.891 ± .035
	4	.864 ± .025	.897 ± .013	.889 ± .024	.847 ± .013	.890 ± .037	.873 ± .049	.875 ± .043	.864 ± .055	.891 ± .047	.902 ± .047	.873 ± .027	.868 ± .010	.903 ± .025	.870 ± .015	.893 ± .029
	5	.886 ± .031	.896 ± .035	.882 ± .025	.877 ± .016	.895 ± .015	.876 ± .038	.872 ± .056	.883 ± .058	.893 ± .040	.894 ± .027	.883 ± .011	.869 ± .036	.888 ± .022	.875 ± .027	.890 ± .014
gpc_voc multiclass	1	.617 ± .001	.732 ± .001	.732 ± .005	.733 ± .006	.609 ± .021	.732 ± .001	.759 ± .003	.733 ± .006	.759 ± .002	.733 ± .005	.659 ± .009	.702 ± .035	.751 ± .011	.616 ± .001	.759 ± .002
	2	.770 ± .002	.808 ± .013	.812 ± .003	.784 ± .003	.705 ± .013	.808 ± .013	.811 ± .013	.785 ± .002	.796 ± .004	.809 ± .008	.687 ± .003	.793 ± .019	.796 ± .024	.699 ± .007	.799 ± .003
	3	.778 ± .003	.824 ± .004	.826 ± .003	.786 ± .002	.740 ± .040	.824 ± .004	.824 ± .009	.797 ± .004	.825 ± .003	.826 ± .003	.787 ± .002	.796 ± .037	.824 ± .006	.778 ± .004	.810 ± .002
	4	.820 ± .014	.828 ± .003	.831 ± .002	.794 ± .004	.802 ± .025	.828 ± .003	.840 ± .004	.800 ± .006	.835 ± .003	.828 ± .003	.817 ± .020	.820 ± .013	.842 ± .005	.836 ± .011	.832 ± .003
	5	.845 ± .004	.838 ± .003	.840 ± .003	.830 ± .003	.836 ± .012	.838 ± .003	.844 ± .004	.826 ± .002	.844 ± .003	.838 ± .003	.842 ± .003	.844 ± .003	.844 ± .004	.844 ± .004	.841 ± .008
civc_protein multiclass	1	.479 ± .066	.488 ± .099	.434 ± .105	.534 ± .066	.540 ± .090	.488 ± .099	.444 ± .047	.483 ± .067	.559 ± .118	.459 ± .068	.439 ± .099	.506 ± .067	.469 ± .063	.483 ± .096	.476 ± .055
	2	.545 ± .090	.518 ± .074	.505 ± .046	.534 ± .108	.497 ± .062	.518 ± .074	.505 ± .064	.495 ± .071	.556 ± .092	.544 ± .126	.421 ± .112	.502 ± .043	.560 ± .021	.539 ± .104	.550 ± .097
	3	.517 ± .103	.558 ± .075	.521 ± .034	.576 ± .120	.441 ± .032	.558 ± .075	.489 ± .057	.539 ± .044	.515 ± .105	.516 ± .104	.451 ± .108	.494 ± .118	.495 ± .043	.516 ± .122	.521 ± .133
	4	.544 ± .092	.516 ± .099	.481 ± .042	.528 ± .074	.482 ± .059	.516 ± .099	.505 ± .036	.529 ± .077	.546 ± .090	.496 ± .105	.504 ± .085	.513 ± .080	.528 ± .102	.516 ± .085	.521 ± .139
	5	.527 ± .073	.511 ± .069	.508 ± .053	.465 ± .058	.533 ± .055	.511 ± .069	.542 ± .109	.486 ± .059	.551 ± .085	.529 ± .104	.538 ± .101	.500 ± .090	.516 ± .089	.495 ± .067	.531 ± .098
cancer_survival_pam50 multiclass	1	.895 ± .005	.898 ± .008	.893 ± .005	.890 ± .009	.672 ± .010	.898 ± .008	.919 ± .000	.910 ± .014	.893 ± .012	.919 ± .003	.714 ± .037	.698 ± .018	.924 ± .005	.898 ± .008	.882 ± .009
	2	.896 ± .007	.927 ± .005	.906 ± .009	.910 ± .024	.708 ± .011	.928 ± .005	.923 ± .001	.930 ± .004	.906 ± .019	.925 ± .004	.864 ± .104	.713 ± .027	.925 ± .005	.895 ± .009	.922 ± .005
	3	.925 ± .004	.927 ± .002	.930 ± .005	.929 ± .005	.746 ± .002	.924 ± .002	.921 ± .003	.928 ± .005	.925 ± .002	.924 ± .005	.924 ± .007	.900 ± .014	.923 ± .004	.925 ± .005	.924 ± .003
	4	.924 ± .003	.926 ± .000	.924 ± .004	.924 ± .005	.922 ± .005	.925 ± .001	.922 ± .005	.924 ± .003	.926 ± .004	.928 ± .005	.928 ± .007	.920 ± .009	.925 ± .004	.923 ± .003	.923 ± .002
	5	.923 ± .004	.924 ± .002	.924 ± .006	.923 ± .002	.923 ± .005	.924 ± .001	.924 ± .004	.924 ± .003	.924 ± .003	.926 ± .005	.928 ± .006	.861 ± .083	.924 ± .003	.924 ± .003	.922 ± .003
civc_protein multiclass	1	.757 ± .006	.758 ± .007	.742 ± .003	.742 ± .003	.681 ± .001	.757 ± .007	.762 ± .004	.764 ± .008	.743 ± .004	.751 ± .003	.752 ± .003	.696 ± .011	.754 ± .011	.762 ± .003	.750 ± .011
	2	.772 ± .003	.772 ± .012	.777 ± .006	.779 ± .006	.729 ± .004	.768 ± .010	.773 ± .009	.777 ± .005	.770 ± .006	.766 ± .003	.773 ± .002	.743 ± .008	.776 ± .003	.769 ± .007	.769 ± .010
	3	.776 ± .006	.776 ± .010	.780 ± .006	.780 ± .007	.756 ± .021	.776 ± .009	.781 ± .006	.783 ± .007	.781 ± .004	.778 ± .004	.782 ± .000	.770 ± .019	.780 ± .006	.774 ± .004	.777 ± .002
	4	.779 ± .003	.781 ± .004	.783 ± .005	.783 ± .003	.775 ± .004	.781 ± .004	.783 ± .005	.783 ± .007	.783 ± .006	.781 ± .006	.783 ± .002	.772 ± .019	.783 ± .006	.780 ± .004	.780 ± .003
	5	.782 ± .004	.785 ± .004	.786 ± .005	.785 ± .005	.785 ± .005	.784 ± .005	.785 ± .005	.784 ± .007	.785 ± .005	.786 ± .005	.785 ± .004	.774 ± .023	.785 ± .005	.785 ± .006	.783 ± .003
breast_cancer multiclass	1	.804 ± .010	.765 ± .009	.777 ± .001	.668 ± .014	.498 ± .002	.770 ± .007	.630 ± .048	.766 ± .027	.793 ± .009	.735 ± .026	.759 ± .004	.535 ± .027	.537 ± .012	.795 ± .018	.764 ± .030
	2	.826 ± .016	.804 ± .012	.818 ± .018	.735 ± .016	.506 ± .009	.813 ± .013	.716 ± .039	.819 ± .015	.836 ± .011	.771 ± .025	.800 ± .007	.723 ± .014	.667 ± .064	.836 ± .015	.783 ± .018
	3	.846 ± .013	.841 ± .012	.834 ± .013	.816 ± .018	.516 ± .004	.830 ± .009	.803 ± .011	.848 ± .015	.849 ± .014	.801 ± .007	.834 ± .004	.761 ± .011	.743 ± .020	.850 ± .011	.815 ± .015
	4	.861 ± .006	.846 ± .010	.851 ± .012	.848 ± .011	.519 ± .009	.844 ± .008	.821 ± .027	.857 ± .006	.856 ± .009	.845 ± .015	.841 ± .009	.819 ± .016	.817 ± .027	.859 ± .007	.832 ± .012
	5	.863 ± .004	.848 ± .012	.859 ± .009	.857 ± .014	.765 ± .031	.848 ± .006	.850 ± .016	.863 ± .012	.858 ± .003	.854 ± .015	.853 ± .012	.850 ± .010	.845 ± .012	.862 ± .010	.852 ± .013
lymphography multiclass	1	.892 ± .055	.828 ± .135	.842 ± .059	.803 ± .068	.630 ± .062	.821 ± .131	.844 ± .129	.829 ± .050	.867 ± .055	.847 ± .041	.864 ± .073	.786 ± .114	.868 ± .079	.862 ± .045	.861 ± .085
	2	.929 ± .029	.840 ± .096	.907 ± .013	.859 ± .046	.715 ± .127	.837 ± .090	.907 ± .060	.830 ± .014	.898 ± .032	.859 ± .053	.913 ± .019	.740 ± .224	.885 ± .056	.932 ± .034	.876 ± .056
	3	.934 ± .014	.869 ± .098	.888 ± .057	.896 ± .031	.844 ± .132	.851 ± .086	.895 ± .082	.877 ± .025	.925 ± .037	.885 ± .015	.923 ± .038	.859 ± .032	.908 ± .034	.929 ± .023	.856 ± .083
	4	.927 ± .020	.891 ± .078	.896 ± .031	.912 ± .023	.897 ± .061	.877 ± .055	.878 ± .047	.891 ± .057	.910 ± .024	.883 ± .040	.912 ± .050	.879 ± .065	.901 ± .051	.918 ± .039	.861 ± .109
	5	.921 ± .043	.904 ± .055	.908 ± .040	.890 ± .017	.887 ± .083	.887 ± .062	.905 ± .069	.910 ± .053	.901 ± .028	.903 ± .084	.930 ± .040	.900 ± .063	.892 ± .084	.924 ± .045	.890 ± .104
mcc_suscan multiclass	1	.985 ± .019	.986 ± .020	.988 ± .014	.991 ± .013	.699 ± .109	1.00 ± .00	.851 ± .047	.984 ± .027	.984 ± .013	.993 ± .010	.988 ± .014	.796 ± .191	.829 ± .093	.990 ± .017	.989 ± .012
	2	.998 ± .003	1.00 ± .00	.999 ± .001	1.00 ± .00	.900 ± .104	1.00 ± .00	.979 ± .017	1.00 ± .00	.999 ± .002	1.00 ± .00	1.00 ± .00	.990 ± .014	.986 ± .022	1.00 ± .00	.998 ± .002
	3	1.00 ± .00	1.00 ± .00	1.00 ± .00	1.00 ± .00	.945 ± .062	1.00 ± .00	.998 ± .003	1.00 ± .00	1.00 ± .00	1.00 ± .00	1.00 ± .00	.999 ± .001	.998 ± .003	1.00 ± .00	.999 ± .002
	4	1.00 ± .00	1.00 ± .00	1.00 ± .00	1.00 ± .00	.993 ± .012	1.00 ± .00	.999 ± .001	1.00 ± .00	1.00 ± .00	1.00 ± .00	1.00 ± .00	1.00 ± .00	1.00 ± .00	1.00 ± .00	1.00 ± .00
	5	1.00 ± .00	1.00 ± .00	1.00 ± .00	1.00 ± .00	.997 ± .004	1.00 ± .00	1.00 ± .00	1.00 ± .00	1.00 ± .00	1.00 ± .00	1.00 ± .00	1.00 ± .00	1.00 ± .00	1.00 ± .00	1.00 ± .00
breast_cancer multiclass	1	.598 ± .025	.609 ± .024	.648 ± .034	.704 ± .040	.653 ± .042	.609 ± .024	.648 ± .058	.644 ± .059	.688 ± .029	.665 ± .018	.604 ± .043	.658 ± .024	.682 ± .016	.599 ± .013	.708 ± .018
	2	.701 ± .039	.628 ± .017	.661 ± .020	.724 ± .047	.665 ± .040	.628 ± .017	.664 ± .049	.695 ± .039	.742 ± .032	.703 ± .021	.623 ± .008	.570 ± .033	.696 ± .011	.697 ± .043	.718 ± .010
	3	.712 ± .042	.663 ± .010	.665 ± .028	.726 ± .042	.660 ± .046	.663 ± .010	.708 ± .044	.734 ± .039	.735 ± .030	.713 ± .035	.610 ± .024	.699 ± .060	.700 ± .036	.697 ± .039	.718 ± .005
	4	.733 ± .041	.646 ± .019	.683 ± .022	.725 ± .037	.672 ± .010	.646 ± .019	.713 ± .018	.715 ± .047	.733 ± .014	.712 ± .042	.664 ± .015	.701 ± .018	.708 ± .025	.718 ± .045	.691 ± .009
	5	.725 ± .025	.722 ± .014	.702 ± .025	.737 ± .038	.688 ± .025	.721 ± .013	.731 ± .029	.726 ± .025	.738 ± .030	.730 ± .045	.681 ± .033	.709 ± .028	.726 ± .043	.720 ± .028	.719 ± .020
breast_cancer multiclass	1	.935 ± .022	.922 ± .014	.925 ± .008	.917 ± .012	.895 ± .015	.918 ± .017	.938 ± .019	.926 ± .014	.919 ± .013	.921 ± .019	.934 ± .007	.875 ± .010	.930 ± .009	.932 ± .020	.920 ± .011
	2	.961 ± .017	.957 ± .010	.958 ± .008	.950 ± .009	.922 ± .013	.950 ± .011	.968 ± .012	.954 ± .011	.950 ± .012	.951 ± .018	.966 ± .009	.938 ± .030	.966 ± .008	.950 ± .006	.958 ± .013
	3	.976 ± .011	.965 ± .006	.975 ± .007	.963 ± .005	.945 ± .012	.968 ± .005	.976 ± .009	.976 ± .011	.961 ± .008	.968 ± .010	.977 ± .010	.963 ± .021	.977 ± .007	.978 ± .009	.978 ± .007
	4	.981 ± .009	.976 ± .007	.978 ± .009	.978 ± .008	.963 ± .011	.976 ± .006	.982 ± .006	.979 ± .008	.976 ± .015	.977 ± .009	.982 ± .007	.976 ± .015	.980 ± .008	.978 ± .009	.980 ± .009
	5	.982 ± .009	.981 ± .008	.980 ± .010	.982 ± .007	.977 ± .010	.982 ± .008	.982 ± .009	.981 ± .009	.982 ± .009	.980 ± .008	.983 ± .008	.977 ± .009	.982 ± .008	.982 ± .010	.982 ± .007
breast_cancer multiclass	1	.638 ± .048	.625 ± .037	.612 ± .036	.637 ± .045	.546 ± .052	.625 ± .028	.614 ± .067	.653 ± .043	.598 ± .073	.602 ± .064	.576 ± .071	.603 ± .058	.584 ± .045	.631 ± .016	.653 ± .006
	2	.689 ± .058	.646 ± .036	.637 ± .053	.699 ± .006	.607 ± .045	.671 ± .010	.717 ± .038	.692 ± .027	.640 ± .055						

(continued from previous page)

Dataset	Budget idx. j	CART	ElasticNet	F-test	GiniRatio	LaplaceScore	Lasso	LOCO	Markov Blanket	MI	mRMR	(R)ReliefF	Random	SBE	RFImportance	SFS
jeanette_covid (downstream)	1	.822 $\pm$.067	.717 $\pm$.177	.809 $\pm$.057	.783 $\pm$.062	.687 $\pm$.143	.817 $\pm$.044	.699 $\pm$.077	.794 $\pm$.078	.731 $\pm$.056	.833 $\pm$.108	.717 $\pm$.032	.580 $\pm$.121	.695 $\pm$.061	.791 $\pm$.078	.697 $\pm$.065
	2	.744 $\pm$.080	.788 $\pm$.043	.698 $\pm$.145	.690 $\pm$.111	.720 $\pm$.102	.790 $\pm$.040	.755 $\pm$.068	.680 $\pm$.128	.698 $\pm$.145	.812 $\pm$.094	.744 $\pm$.073	.665 $\pm$.052	.680 $\pm$.107	.689 $\pm$.116	.701 $\pm$.080
	3	.716 $\pm$.103	.792 $\pm$.031	.706 $\pm$.126	.713 $\pm$.064	.704 $\pm$.115	.725 $\pm$.114	.734 $\pm$.183	.738 $\pm$.049	.704 $\pm$.149	.811 $\pm$.079	.695 $\pm$.162	.667 $\pm$.072	.734 $\pm$.110	.729 $\pm$.068	.796 $\pm$.028
	4	.759 $\pm$.071	.752 $\pm$.074	.734 $\pm$.104	.731 $\pm$.075	.702 $\pm$.107	.753 $\pm$.069	.737 $\pm$.139	.742 $\pm$.077	.730 $\pm$.044	.829 $\pm$.081	.761 $\pm$.043	.730 $\pm$.128	.715 $\pm$.124	.752 $\pm$.046	.718 $\pm$.105
	5	.767 $\pm$.091	.770 $\pm$.055	.777 $\pm$.079	.744 $\pm$.114	.774 $\pm$.068	.756 $\pm$.041	.735 $\pm$.125	.748 $\pm$.107	.774 $\pm$.061	.818 $\pm$.060	.775 $\pm$.063	.770 $\pm$.082	.744 $\pm$.101	.760 $\pm$.095	.750 $\pm$.087
kooxeplore	1	.945 $\pm$.024	.911 $\pm$.043	.953 $\pm$.017	.943 $\pm$.030	.905 $\pm$.033	.911 $\pm$.042	.931 $\pm$.035	.945 $\pm$.036	.954 $\pm$.026	.950 $\pm$.019	.955 $\pm$.021	.948 $\pm$.005	.939 $\pm$.020	.959 $\pm$.011	.956 $\pm$.012
	2	.954 $\pm$.018	.936 $\pm$.030	.975 $\pm$.015	.954 $\pm$.011	.938 $\pm$.021	.941 $\pm$.023	.954 $\pm$.020	.965 $\pm$.030	.963 $\pm$.021	.952 $\pm$.018	.968 $\pm$.023	.962 $\pm$.038	.954 $\pm$.025	.961 $\pm$.022	.961 $\pm$.020
	3	.968 $\pm$.021	.962 $\pm$.018	.968 $\pm$.005	.968 $\pm$.011	.937 $\pm$.052	.968 $\pm$.017	.962 $\pm$.023	.983 $\pm$.013	.965 $\pm$.011	.964 $\pm$.015	.962 $\pm$.017	.970 $\pm$.029	.967 $\pm$.015	.974 $\pm$.012	.954 $\pm$.037
	4	.967 $\pm$.029	.970 $\pm$.013	.970 $\pm$.014	.973 $\pm$.015	.968 $\pm$.017	.966 $\pm$.007	.972 $\pm$.015	.974 $\pm$.018	.980 $\pm$.007	.965 $\pm$.020	.959 $\pm$.014	.953 $\pm$.019	.963 $\pm$.028	.968 $\pm$.021	.960 $\pm$.023
	5	.971 $\pm$.018	.967 $\pm$.024	.974 $\pm$.017	.973 $\pm$.020	.977 $\pm$.014	.972 $\pm$.019	.966 $\pm$.028	.973 $\pm$.021	.974 $\pm$.013	.965 $\pm$.034	.967 $\pm$.015	.967 $\pm$.025	.967 $\pm$.027	.969 $\pm$.018	.972 $\pm$.024
randing importance	1	.654 $\pm$.062	.672 $\pm$.065	.712 $\pm$.062	.668 $\pm$.060	.658 $\pm$.020	.674 $\pm$.026	.644 $\pm$.112	.684 $\pm$.076	.689 $\pm$.079	.693 $\pm$.076	.705 $\pm$.048	.557 $\pm$.080	.556 $\pm$.064	.726 $\pm$.065	.621 $\pm$.056
	2	.771 $\pm$.006	.735 $\pm$.063	.711 $\pm$.045	.735 $\pm$.049	.733 $\pm$.031	.734 $\pm$.067	.636 $\pm$.031	.708 $\pm$.021	.717 $\pm$.061	.710 $\pm$.056	.743 $\pm$.029	.646 $\pm$.053	.666 $\pm$.042	.730 $\pm$.069	.693 $\pm$.052
	3	.739 $\pm$.046	.788 $\pm$.053	.704 $\pm$.004	.723 $\pm$.017	.725 $\pm$.030	.752 $\pm$.058	.711 $\pm$.104	.732 $\pm$.006	.718 $\pm$.058	.724 $\pm$.049	.727 $\pm$.032	.688 $\pm$.088	.705 $\pm$.054	.722 $\pm$.061	.736 $\pm$.034
	4	.738 $\pm$.048	.766 $\pm$.040	.736 $\pm$.042	.740 $\pm$.038	.774 $\pm$.045	.766 $\pm$.018	.741 $\pm$.055	.747 $\pm$.049	.714 $\pm$.056	.759 $\pm$.064	.753 $\pm$.040	.735 $\pm$.069	.747 $\pm$.061	.761 $\pm$.020	.747 $\pm$.041
	5	.758 $\pm$.059	.763 $\pm$.045	.753 $\pm$.046	.745 $\pm$.038	.763 $\pm$.055	.769 $\pm$.040	.747 $\pm$.039	.750 $\pm$.037	.763 $\pm$.039	.736 $\pm$.055	.769 $\pm$.065	.736 $\pm$.053	.766 $\pm$.065	.746 $\pm$.037	.736 $\pm$.053
mlc_poisson dataset	1	.611 $\pm$.026	.681 $\pm$.068	.626 $\pm$.090	.598 $\pm$.030	.579 $\pm$.030	.559 $\pm$.071	.612 $\pm$.089	.551 $\pm$.074	.576 $\pm$.088	.568 $\pm$.080	.615 $\pm$.074	.441 $\pm$.087	.472 $\pm$.014	.615 $\pm$.093	.506 $\pm$.051
	2	.634 $\pm$.049	.772 $\pm$.044	.660 $\pm$.063	.624 $\pm$.061	.574 $\pm$.017	.720 $\pm$.055	.603 $\pm$.085	.623 $\pm$.066	.509 $\pm$.043	.714 $\pm$.027	.648 $\pm$.088	.582 $\pm$.099	.521 $\pm$.043	.667 $\pm$.089	.572 $\pm$.090
	3	.692 $\pm$.068	.764 $\pm$.066	.652 $\pm$.054	.624 $\pm$.048	.486 $\pm$.046	.768 $\pm$.067	.660 $\pm$.059	.620 $\pm$.035	.596 $\pm$.127	.733 $\pm$.060	.672 $\pm$.107	.679 $\pm$.043	.651 $\pm$.039	.737 $\pm$.086	.655 $\pm$.057
	4	.683 $\pm$.057	.737 $\pm$.098	.644 $\pm$.094	.654 $\pm$.063	.559 $\pm$.024	.762 $\pm$.078	.663 $\pm$.100	.661 $\pm$.039	.635 $\pm$.124	.732 $\pm$.090	.674 $\pm$.081	.648 $\pm$.101	.651 $\pm$.017	.741 $\pm$.066	.650 $\pm$.073
	5	.695 $\pm$.075	.712 $\pm$.091	.652 $\pm$.117	.705 $\pm$.062	.583 $\pm$.033	.719 $\pm$.058	.665 $\pm$.088	.640 $\pm$.019	.671 $\pm$.080	.715 $\pm$.063	.675 $\pm$.070	.684 $\pm$.062	.689 $\pm$.091	.713 $\pm$.066	.670 $\pm$.061
homonc_gene expression	1	.902 $\pm$.001	.816 $\pm$.002	.875 $\pm$.001	.710 $\pm$.091	.501 $\pm$.001	.816 $\pm$.002	.723 $\pm$.116	.880 $\pm$.019	.890 $\pm$.001	.902 $\pm$.000	.861 $\pm$.037	.599 $\pm$.040	.603 $\pm$.021	.903 $\pm$.001	.848 $\pm$.015
	2	.944 $\pm$.005	.929 $\pm$.001	.885 $\pm$.001	.871 $\pm$.030	.610 $\pm$.091	.929 $\pm$.001	.863 $\pm$.031	.920 $\pm$.001	.909 $\pm$.000	.908 $\pm$.001	.920 $\pm$.001	.724 $\pm$.004	.724 $\pm$.053	.912 $\pm$.001	.842 $\pm$.035
	3	.957 $\pm$.002	.951 $\pm$.001	.909 $\pm$.001	.916 $\pm$.000	.673 $\pm$.002	.950 $\pm$.000	.871 $\pm$.030	.932 $\pm$.000	.928 $\pm$.002	.923 $\pm$.001	.939 $\pm$.001	.773 $\pm$.006	.779 $\pm$.055	.955 $\pm$.001	.881 $\pm$.024
	4	.962 $\pm$.001	.963 $\pm$.000	.955 $\pm$.000	.932 $\pm$.000	.696 $\pm$.001	.959 $\pm$.003	.908 $\pm$.024	.936 $\pm$.003	.941 $\pm$.000	.939 $\pm$.005	.946 $\pm$.001	.867 $\pm$.026	.855 $\pm$.008	.960 $\pm$.001	.905 $\pm$.017
	5	.964 $\pm$.001	.966 $\pm$.001	.961 $\pm$.001	.942 $\pm$.000	.751 $\pm$.006	.966 $\pm$.000	.929 $\pm$.006	.945 $\pm$.002	.965 $\pm$.000	.964 $\pm$.000	.960 $\pm$.001	.947 $\pm$.009	.926 $\pm$.023	.962 $\pm$.001	.939 $\pm$.006
hiv_culture log10_titer	1	.609 $\pm$.049	.658 $\pm$.143	.666 $\pm$.107	.655 $\pm$.106	.691 $\pm$.104	.649 $\pm$.132	.634 $\pm$.102	.659 $\pm$.109	.643 $\pm$.128	.654 $\pm$.108	.634 $\pm$.035	.564 $\pm$.134	.639 $\pm$.062	.586 $\pm$.071	.636 $\pm$.078
	2	.617 $\pm$.102	.631 $\pm$.083	.659 $\pm$.090	.666 $\pm$.101	.583 $\pm$.132	.638 $\pm$.094	.598 $\pm$.066	.592 $\pm$.034	.621 $\pm$.075	.532 $\pm$.045	.585 $\pm$.121	.684 $\pm$.064	.687 $\pm$.137	.650 $\pm$.102	.625 $\pm$.083
	3	.659 $\pm$.134	.628 $\pm$.096	.625 $\pm$.068	.606 $\pm$.053	.613 $\pm$.096	.634 $\pm$.103	.581 $\pm$.052	.640 $\pm$.106	.654 $\pm$.082	.612 $\pm$.100	.560 $\pm$.098	.671 $\pm$.083	.661 $\pm$.070	.679 $\pm$.077	.606 $\pm$.108
	4	.665 $\pm$.093	.568 $\pm$.184	.628 $\pm$.053	.625 $\pm$.137	.656 $\pm$.144	.571 $\pm$.186	.596 $\pm$.108	.661 $\pm$.087	.638 $\pm$.099	.572 $\pm$.066	.642 $\pm$.068	.615 $\pm$.068	.641 $\pm$.113	.664 $\pm$.101	.641 $\pm$.090
	5	.659 $\pm$.129	.632 $\pm$.137	.672 $\pm$.117	.648 $\pm$.112	.632 $\pm$.083	.623 $\pm$.128	.653 $\pm$.074	.644 $\pm$.089	.664 $\pm$.122	.663 $\pm$.112	.652 $\pm$.085	.678 $\pm$.074	.678 $\pm$.060	.667 $\pm$.076	.661 $\pm$.104
gap_model	1	.900 $\pm$.021	.897 $\pm$.007	.874 $\pm$.013	.898 $\pm$.003	.680 $\pm$.059	.887 $\pm$.007	.882 $\pm$.024	.912 $\pm$.008	.878 $\pm$.022	.911 $\pm$.006	.907 $\pm$.006	.878 $\pm$.013	.907 $\pm$.022	.866 $\pm$.018	.915 $\pm$.019
	2	.927 $\pm$.011	.935 $\pm$.007	.916 $\pm$.008	.916 $\pm$.011	.892 $\pm$.004	.921 $\pm$.015	.924 $\pm$.007	.925 $\pm$.009	.918 $\pm$.008	.911 $\pm$.017	.927 $\pm$.009	.909 $\pm$.009	.925 $\pm$.007	.921 $\pm$.010	.920 $\pm$.020
	3	.928 $\pm$.007	.931 $\pm$.007	.928 $\pm$.006	.925 $\pm$.010	.915 $\pm$.003	.924 $\pm$.001	.925 $\pm$.011	.922 $\pm$.007	.924 $\pm$.009	.921 $\pm$.008	.925 $\pm$.011	.922 $\pm$.019	.930 $\pm$.002	.925 $\pm$.006	.927 $\pm$.008
	4	.923 $\pm$.002	.934 $\pm$.002	.934 $\pm$.007	.925 $\pm$.008	.923 $\pm$.009	.932 $\pm$.004	.926 $\pm$.009	.927 $\pm$.008	.929 $\pm$.010	.931 $\pm$.004	.927 $\pm$.003	.920 $\pm$.014	.934 $\pm$.005	.928 $\pm$.005	.932 $\pm$.010
	5	.929 $\pm$.007	.937 $\pm$.005	.935 $\pm$.008	.928 $\pm$.009	.929 $\pm$.011	.934 $\pm$.007	.930 $\pm$.006	.933 $\pm$.004	.929 $\pm$.011	.933 $\pm$.007	.936 $\pm$.007	.929 $\pm$.013	.931 $\pm$.005	.933 $\pm$.009	.934 $\pm$.008
maxcovnet_scaled loglikelihood	1	.979 $\pm$.001	.977 $\pm$.005	.979 $\pm$.001	.850 $\pm$.052	.578 $\pm$.001	.970 $\pm$.011	.973 $\pm$.005	.781 $\pm$.092	.975 $\pm$.005	.850 $\pm$.052	.973 $\pm$.002	.886 $\pm$.067	.826 $\pm$.092	.979 $\pm$.001	.974 $\pm$.002
	2	.983 $\pm$.001	.983 $\pm$.002	.981 $\pm$.002	.938 $\pm$.002	.632 $\pm$.005	.981 $\pm$.004	.978 $\pm$.004	.879 $\pm$.046	.981 $\pm$.001	.938 $\pm$.002	.980 $\pm$.000	.888 $\pm$.010	.897 $\pm$.011	.983 $\pm$.001	.977 $\pm$.004
	3	.984 $\pm$.001	.984 $\pm$.002	.984 $\pm$.002	.957 $\pm$.010	.723 $\pm$.005	.984 $\pm$.002	.979 $\pm$.004	.955 $\pm$.005	.984 $\pm$.002	.957 $\pm$.010	.983 $\pm$.001	.950 $\pm$.008	.922 $\pm$.043	.984 $\pm$.002	.981 $\pm$.005
	4	.985 $\pm$.002	.985 $\pm$.002	.984 $\pm$.002	.978 $\pm$.004	.823 $\pm$.002	.985 $\pm$.002	.981 $\pm$.004	.968 $\pm$.001	.985 $\pm$.003	.978 $\pm$.004	.984 $\pm$.001	.958 $\pm$.028	.976 $\pm$.010	.985 $\pm$.002	.983 $\pm$.002
	5	.985 $\pm$.002	.985 $\pm$.003	.984 $\pm$.002	.984 $\pm$.001	.956 $\pm$.007	.985 $\pm$.002	.982 $\pm$.003	.981 $\pm$.004	.984						

(continued from previous page)

Dataset	Budget idx	CART	ElankiNet	F-test	GuinRatio	LaplacianScore	Lasso	LOCO	Markov Blanket	MI	mRMR	(RR)Relief	Random	SSE	RFImportance	SFS
sdc_17	1	.110 $\pm$.002	.127 $\pm$.015	.154 $\pm$.002	.156 $\pm$.002	.644 $\pm$.001	.250 $\pm$.241	.111 $\pm$.001	.111 $\pm$.001	.144 $\pm$.001	.172 $\pm$.003	.170 $\pm$.002	.528 $\pm$.388	.110 $\pm$.002	.156 $\pm$.002	.144 $\pm$.001
	2	.0801 $\pm$.0022	.0818 $\pm$.0026	.0907 $\pm$.0033	.0831 $\pm$.0011	.431 $\pm$.145	.0808 $\pm$.0020	.0798 $\pm$.0008	.0849 $\pm$.0006	.0835 $\pm$.0008	.165 $\pm$.001	.0942 $\pm$.0030	.106 $\pm$.014	.0813 $\pm$.0042	.0820 $\pm$.0009	.0978 $\pm$.0012
	3	.0742 $\pm$.0014	.0729 $\pm$.0006	.0827 $\pm$.0003	.0744 $\pm$.0014	.342 $\pm$.046	.0729 $\pm$.0005	.0742 $\pm$.0006	.0743 $\pm$.0015	.0744 $\pm$.0014	.0960 $\pm$.0007	.0833 $\pm$.0009	.328 $\pm$.060	.0742 $\pm$.0004	.0742 $\pm$.0015	.0770 $\pm$.0014
	4	.0698 $\pm$.0010	.0712 $\pm$.0008	.0772 $\pm$.0004	.0697 $\pm$.0010	.142 $\pm$.098	.0715 $\pm$.0005	.0710 $\pm$.0017	.0697 $\pm$.0010	.0702 $\pm$.0007	.0860 $\pm$.0011	.0710 $\pm$.0010	.209 $\pm$.112	.0717 $\pm$.0006	.0698 $\pm$.0010	.0710 $\pm$.0003
	5	.0701 $\pm$.0012	.0717 $\pm$.0002	.0712 $\pm$.0014	.0702 $\pm$.0010	.0729 $\pm$.0030	.0716 $\pm$.0005	.0702 $\pm$.0011	.0702 $\pm$.0011	.0703 $\pm$.0010	.0740 $\pm$.0012	.0701 $\pm$.0011	.133 $\pm$.108	.0701 $\pm$.0013	.0701 $\pm$.0011	.0702 $\pm$.0011
predict-continuous,devout classification,devout	1	.615 $\pm$.033	.579 $\pm$.017	.632 $\pm$.018	.652 $\pm$.009	.970 $\pm$.014	.579 $\pm$.020	.590 $\pm$.044	.583 $\pm$.010	.623 $\pm$.014	.671 $\pm$.022	.583 $\pm$.019	.674 $\pm$.027	.652 $\pm$.035	.653 $\pm$.008	.683 $\pm$.044
	2	.557 $\pm$.012	.550 $\pm$.024	.556 $\pm$.019	.579 $\pm$.014	.879 $\pm$.032	.547 $\pm$.029	.564 $\pm$.015	.573 $\pm$.012	.544 $\pm$.018	.616 $\pm$.014	.554 $\pm$.014	.617 $\pm$.018	.613 $\pm$.040	.559 $\pm$.014	.614 $\pm$.029
	3	.540 $\pm$.012	.533 $\pm$.018	.545 $\pm$.028	.574 $\pm$.009	.663 $\pm$.028	.536 $\pm$.014	.546 $\pm$.019	.571 $\pm$.007	.533 $\pm$.015	.585 $\pm$.012	.534 $\pm$.020	.647 $\pm$.019	.539 $\pm$.011	.546 $\pm$.014	.582 $\pm$.013
	4	.536 $\pm$.017	.531 $\pm$.012	.534 $\pm$.015	.568 $\pm$.004	.573 $\pm$.010	.530 $\pm$.013	.537 $\pm$.021	.567 $\pm$.005	.534 $\pm$.013	.577 $\pm$.008	.533 $\pm$.017	.575 $\pm$.020	.540 $\pm$.018	.528 $\pm$.013	.549 $\pm$.012
	5	.530 $\pm$.014	.527 $\pm$.014	.532 $\pm$.013	.551 $\pm$.002	.529 $\pm$.007	.530 $\pm$.012	.539 $\pm$.021	.564 $\pm$.007	.534 $\pm$.013	.549 $\pm$.012	.531 $\pm$.015	.540 $\pm$.015	.527 $\pm$.013	.528 $\pm$.015	.535 $\pm$.016
accuracy devout	1	1.62 $\pm$.08	1.73 $\pm$.08	1.71 $\pm$.06	2.03 $\pm$.15	2.10 $\pm$.02	1.85 $\pm$.23	1.76 $\pm$.10	1.71 $\pm$.07	1.69 $\pm$.07	1.70 $\pm$.06	1.71 $\pm$.05	2.05 $\pm$.14	2.11 $\pm$.03	1.70 $\pm$.06	1.82 $\pm$.05
	2	1.58 $\pm$.10	1.64 $\pm$.04	1.66 $\pm$.08	1.82 $\pm$.16	2.10 $\pm$.01	1.78 $\pm$.15	1.72 $\pm$.10	1.67 $\pm$.07	1.59 $\pm$.09	1.69 $\pm$.06	1.64 $\pm$.06	2.08 $\pm$.05	2.09 $\pm$.06	1.70 $\pm$.04	1.80 $\pm$.04
	3	1.59 $\pm$.14	1.64 $\pm$.05	1.56 $\pm$.07	1.68 $\pm$.06	1.97 $\pm$.07	1.62 $\pm$.06	1.70 $\pm$.10	1.62 $\pm$.05	1.51 $\pm$.07	1.62 $\pm$.05	1.61 $\pm$.08	2.06 $\pm$.04	1.97 $\pm$.11	1.61 $\pm$.12	1.75 $\pm$.06
	4	1.54 $\pm$.11	1.60 $\pm$.07	1.56 $\pm$.07	1.61 $\pm$.05	1.86 $\pm$.03	1.57 $\pm$.06	1.61 $\pm$.06	1.62 $\pm$.06	1.49 $\pm$.05	1.61 $\pm$.06	1.57 $\pm$.11	1.80 $\pm$.26	1.86 $\pm$.17	1.50 $\pm$.05	1.73 $\pm$.05
	5	1.46 $\pm$.07	1.53 $\pm$.04	1.43 $\pm$.05	1.57 $\pm$.06	1.53 $\pm$.06	1.50 $\pm$.08	1.53 $\pm$.09	1.58 $\pm$.06	1.44 $\pm$.05	1.56 $\pm$.07	1.51 $\pm$.09	1.81 $\pm$.12	1.70 $\pm$.18	1.46 $\pm$.08	1.59 $\pm$.09
dev,group,project classification,devout	1	.671 $\pm$.010	.759 $\pm$.028	.880 $\pm$.017	1.18 $\pm$.00	.886 $\pm$.030	.840 $\pm$.006	.891 $\pm$.043	.679 $\pm$.005	.892 $\pm$.014	.789 $\pm$.006	.911 $\pm$.014	1.10 $\pm$.11	1.09 $\pm$.09	.672 $\pm$.004	1.11 $\pm$.15
	2	.507 $\pm$.008	.551 $\pm$.011	.604 $\pm$.017	.829 $\pm$.007	.599 $\pm$.012	.575 $\pm$.018	.714 $\pm$.011	.521 $\pm$.004	.586 $\pm$.006	.578 $\pm$.008	.585 $\pm$.013	.778 $\pm$.014	.744 $\pm$.025	.512 $\pm$.008	.755 $\pm$.008
	3	.450 $\pm$.005	.473 $\pm$.004	.505 $\pm$.007	.556 $\pm$.002	.480 $\pm$.004	.478 $\pm$.002	.594 $\pm$.016	.460 $\pm$.009	.512 $\pm$.006	.498 $\pm$.005	.474 $\pm$.008	.586 $\pm$.020	.571 $\pm$.016	.461 $\pm$.011	.588 $\pm$.013
	4	.428 $\pm$.004	.438 $\pm$.004	.457 $\pm$.003	.489 $\pm$.005	.444 $\pm$.002	.439 $\pm$.005	.521 $\pm$.016	.437 $\pm$.005	.452 $\pm$.005	.449 $\pm$.003	.446 $\pm$.005	.508 $\pm$.018	.509 $\pm$.014	.432 $\pm$.006	.526 $\pm$.018
	5	.421 $\pm$.004	.426 $\pm$.006	.427 $\pm$.006	.433 $\pm$.004	.425 $\pm$.004	.426 $\pm$.006	.455 $\pm$.009	.423 $\pm$.005	.428 $\pm$.006	.428 $\pm$.002	.424 $\pm$.003	.450 $\pm$.015	.466 $\pm$.010	.421 $\pm$.005	.460 $\pm$.018
lung_cancer	1	.401 $\pm$.166	.377 $\pm$.047	.471 $\pm$.125	.235 $\pm$.112	.762 $\pm$.091	.514 $\pm$.146	.621 $\pm$.139	.269 $\pm$.089	.376 $\pm$.065	.321 $\pm$.114	.311 $\pm$.076	.696 $\pm$.089	.673 $\pm$.042	.322 $\pm$.172	.517 $\pm$.118
	2	.235 $\pm$.100	.219 $\pm$.046	.366 $\pm$.148	.176 $\pm$.051	.724 $\pm$.135	.302 $\pm$.058	.315 $\pm$.110	.169 $\pm$.079	.147 $\pm$.048	.168 $\pm$.023	.202 $\pm$.056	.386 $\pm$.097	.445 $\pm$.040	.188 $\pm$.058	.332 $\pm$.138
	3	.190 $\pm$.025	.160 $\pm$.053	.182 $\pm$.028	.152 $\pm$.064	.507 $\pm$.093	.233 $\pm$.058	.177 $\pm$.036	.187 $\pm$.097	.156 $\pm$.063	.148 $\pm$.044	.141 $\pm$.013	.161 $\pm$.019	.189 $\pm$.051	.143 $\pm$.026	.215 $\pm$.058
	4	.145 $\pm$.038	.141 $\pm$.051	.148 $\pm$.051	.133 $\pm$.029	.380 $\pm$.039	.168 $\pm$.048	.140 $\pm$.031	.135 $\pm$.033	.141 $\pm$.036	.136 $\pm$.045	.141 $\pm$.028	.133 $\pm$.029	.130 $\pm$.056	.123 $\pm$.027	.129 $\pm$.048
	5	.168 $\pm$.057	.159 $\pm$.060	.134 $\pm$.018	.127 $\pm$.024	.214 $\pm$.040	.168 $\pm$.069	.147 $\pm$.007	.136 $\pm$.030	.142 $\pm$.037	.159 $\pm$.035	.121 $\pm$.024	.149 $\pm$.043	.150 $\pm$.014	.164 $\pm$.053	.146 $\pm$.027
synthia	1	.514 $\pm$.126	1.26 $\pm$.09	1.09 $\pm$.28	1.17 $\pm$.12	1.14 $\pm$.27	1.15 $\pm$.23	1.07 $\pm$.17	.517 $\pm$.018	.633 $\pm$.080	.470 $\pm$.075	1.30 $\pm$.08	1.20 $\pm$.21	1.07 $\pm$.38	.411 $\pm$.075	.655 $\pm$.159
	2	.254 $\pm$.043	.823 $\pm$.054	.678 $\pm$.052	.530 $\pm$.129	.532 $\pm$.284	.819 $\pm$.126	.608 $\pm$.110	.373 $\pm$.012	.336 $\pm$.027	.286 $\pm$.007	.801 $\pm$.107	.624 $\pm$.217	.397 $\pm$.042	.202 $\pm$.071	.436 $\pm$.071
	3	.210 $\pm$.071	.436 $\pm$.052	.526 $\pm$.159	.371 $\pm$.131	.342 $\pm$.072	.601 $\pm$.158	.522 $\pm$.111	.318 $\pm$.057	.197 $\pm$.025	.213 $\pm$.014	.290 $\pm$.042	.259 $\pm$.003	.434 $\pm$.177	.205 $\pm$.078	.346 $\pm$.178
	4	.166 $\pm$.069	.278 $\pm$.051	.348 $\pm$.121	.306 $\pm$.152	.282 $\pm$.116	.333 $\pm$.035	.311 $\pm$.058	.255 $\pm$.136	.187 $\pm$.038	.190 $\pm$.028	.244 $\pm$.041	.170 $\pm$.036	.281 $\pm$.112	.175 $\pm$.078	.241 $\pm$.067
	5	.164 $\pm$.078	.187 $\pm$.051	.241 $\pm$.116	.170 $\pm$.091	.228 $\pm$.126	.249 $\pm$.034	.218 $\pm$.052	.204 $\pm$.090	.181 $\pm$.040	.138 $\pm$.042	.216 $\pm$.061	.189 $\pm$.068	.213 $\pm$.099	.158 $\pm$.071	.190 $\pm$.113
miz	1	.489 $\pm$.015	.525 $\pm$.011	.522 $\pm$.024	.548 $\pm$.008	.703 $\pm$.018	.525 $\pm$.032	.601 $\pm$.013	.499 $\pm$.003	.539 $\pm$.020	.519 $\pm$.026	.539 $\pm$.015	.700 $\pm$.011	.675 $\pm$.013	.530 $\pm$.034	.528 $\pm$.024
	2	.483 $\pm$.028	.497 $\pm$.016	.484 $\pm$.006	.548 $\pm$.008	.695 $\pm$.013	.509 $\pm$.039	.591 $\pm$.077	.493 $\pm$.005	.539 $\pm$.021	.493 $\pm$.016	.541 $\pm$.018	.688 $\pm$.022	.670 $\pm$.030	.495 $\pm$.016	.527 $\pm$.024
	3	.474 $\pm$.019	.474 $\pm$.011	.482 $\pm$.010	.513 $\pm$.027	.686 $\pm$.019	.476 $\pm$.015	.546 $\pm$.068	.487 $\pm$.012	.477 $\pm$.008	.457 $\pm$.015	.530 $\pm$.019	.543 $\pm$.013	.536 $\pm$.016	.470 $\pm$.027	.500 $\pm$.022
	4	.465 $\pm$.020	.462 $\pm$.005	.474 $\pm$.007	.494 $\pm$.007	.674 $\pm$.010	.466 $\pm$.001	.503 $\pm$.025	.453 $\pm$.007	.447 $\pm$.010	.449 $\pm$.004	.498 $\pm$.012	.517 $\pm$.073	.484 $\pm$.008	.458 $\pm$.012	.504 $\pm$.037
	5	.441 $\pm$.010	.444 $\pm$.005	.448 $\pm$.006	.457 $\pm$.018	.618 $\pm$.017	.448 $\pm$.015	.454 $\pm$.006	.438 $\pm$.003	.439 $\pm$.010	.455 $\pm$.002	.461 $\pm$.015	.470 $\pm$.014	.481 $\pm$.024	.436 $\pm$.005	.451 $\pm$.013
indiana population,gender	1	1.79 $\pm$.17	1.91 $\pm$.14	1.85 $\pm$.04	1.78 $\pm$.10	2.03 $\pm$.01	1.83 $\pm$.09	1.85 $\pm$.17	1.89 $\pm$.15	1.79 $\pm$.13	1.86 $\pm$.14	1.90 $\pm$.12	1.88 $\pm$.13	1.80 $\pm$.12	1.86 $\pm$.14	1.81 $\pm$.10
	2	1.63 $\pm$.17	1.73 $\pm$.13	1.67 $\pm$.07	1.64 $\pm$.23	1.86 $\pm$.13	1.71 $\pm$.13	1.78 $\pm$.17	1.68 $\pm$.19	1.54 $\pm$.20	1.65 $\pm$.23	1.66 $\pm$.08	1.81 $\pm$.09	1.75 $\pm$.20	1.67 $\pm$.14	1.72 $\pm$.16
	3	1.45 $\pm$.14	1.63 $\pm$.14	1.51 $\pm$.09	1.55 $\pm$.21	1.77 $\pm$.07	1.57 $\pm$.14	1.52 $\pm$.07	1.51 $\pm$.14	1.42 $\pm$						

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Dataset	Budget id _j	CART	ElankiNet	F-test	GuinRatio	LaplacianScore	Lasso	LOCO	Markov Blanket	MI	mRMR	(RR)Relieff	Random	SSE	RFImportance	SFS
mini housing	1	.239 ±.020	.255 ±.005	.319 ±.002	.265 ±.007	.301 ±.006	.255 ±.005	.337 ±.050	.179 ±.006	.186 ±.018	.310 ±.004	.366 ±.001	.429 ±.088	.182 ±.014	.245 ±.026	.257 ±.006
	2	.167 ±.004	.205 ±.005	.225 ±.004	.164 ±.003	.217 ±.003	.205 ±.005	.204 ±.043	.174 ±.005	.176 ±.004	.164 ±.007	.225 ±.019	.279 ±.003	.147 ±.013	.167 ±.005	.158 ±.006
	3	.140 ±.011	.153 ±.009	.152 ±.006	.159 ±.003	.212 ±.003	.151 ±.006	.135 ±.008	.165 ±.002	.159 ±.004	.151 ±.005	.153 ±.020	.183 ±.027	.131 ±.006	.140 ±.012	.133 ±.006
	4	.137 ±.008	.144 ±.004	.132 ±.006	.149 ±.004	.213 ±.003	.144 ±.004	.129 ±.005	.151 ±.005	.149 ±.004	.135 ±.013	.131 ±.006	.165 ±.013	.130 ±.005	.134 ±.005	.130 ±.005
	5	.130 ±.006	.130 ±.006	.129 ±.005	.130 ±.006	.183 ±.003	.130 ±.006	.128 ±.006	.130 ±.006	.130 ±.006	.129 ±.006	.130 ±.006	.146 ±.019	.128 ±.005	.130 ±.006	.128 ±.005
wine quality	1	.727 ±.007	.757 ±.010	.753 ±.006	.753 ±.006	.809 ±.010	.757 ±.010	.822 ±.008	.727 ±.007	.753 ±.006	.772 ±.004	.753 ±.022	.778 ±.032	.745 ±.011	.727 ±.007	.772 ±.004
	2	.641 ±.009	.658 ±.008	.665 ±.009	.670 ±.013	.708 ±.006	.658 ±.008	.705 ±.018	.654 ±.007	.678 ±.016	.698 ±.011	.665 ±.017	.698 ±.042	.645 ±.017	.637 ±.008	.680 ±.008
	3	.609 ±.007	.635 ±.009	.644 ±.008	.622 ±.006	.630 ±.006	.635 ±.009	.623 ±.019	.619 ±.013	.630 ±.014	.628 ±.014	.615 ±.009	.643 ±.027	.613 ±.012	.608 ±.007	.619 ±.008
	4	.598 ±.009	.608 ±.003	.611 ±.005	.603 ±.012	.613 ±.009	.608 ±.003	.604 ±.008	.600 ±.009	.604 ±.015	.607 ±.008	.600 ±.008	.620 ±.009	.603 ±.008	.596 ±.010	.603 ±.007
	5	.592 ±.013	.595 ±.008	.604 ±.011	.595 ±.012	.599 ±.010	.595 ±.008	.596 ±.012	.596 ±.011	.595 ±.016	.598 ±.010	.592 ±.010	.602 ±.011	.593 ±.012	.594 ±.012	.599 ±.012
body_oxygen percentage	1	.0108 ±.0003	.0105 ±.0013	.0108 ±.0007	.0107 ±.0009	.0117 ±.0028	.0105 ±.0013	.0119 ±.0024	.0106 ±.0009	.0108 ±.0010	.0109 ±.0013	.0105 ±.0012	.0146 ±.0043	.0108 ±.0011	.0105 ±.0008	.0104 ±.0007
	2	.0104 ±.0006	.0104 ±.0012	.0105 ±.0007	.0106 ±.0008	.0106 ±.0008	.0104 ±.0012	.0121 ±.0029	.0105 ±.0007	.0106 ±.0008	.0106 ±.0008	.0104 ±.0010	.0127 ±.0018	.0106 ±.0013	.0104 ±.0010	.0105 ±.0010
	3	.0104 ±.0008	.0103 ±.0013	.0107 ±.0007	.0107 ±.0010	.0107 ±.0012	.0103 ±.0013	.0106 ±.0013	.0106 ±.0010	.0107 ±.0006	.0106 ±.0010	.0104 ±.0011	.0113 ±.0021	.0105 ±.0011	.0104 ±.0011	.0105 ±.0010
	4	.0105 ±.0011	.0103 ±.0012	.0107 ±.0011	.0107 ±.0011	.0108 ±.0012	.0103 ±.0012	.0106 ±.0012	.0109 ±.0012	.0108 ±.0011	.0107 ±.0010	.0105 ±.0011	.0116 ±.0005	.0105 ±.0010	.0103 ±.0010	.0103 ±.0012
	5	.0105 ±.0012	.0103 ±.0012	.0106 ±.0011	.0108 ±.0013	.0104 ±.0011	.0103 ±.0012	.0105 ±.0012	.0108 ±.0015	.0108 ±.0014	.0105 ±.0010	.0104 ±.0010	.0120 ±.0005	.0105 ±.0012	.0104 ±.0011	.0104 ±.0012
breast tumor (V ₀ %)	1	13.5 ±6.5	13.8 ±6.8	13.5 ±6.5	15.9 ±5.5	14.9 ±7.6	13.8 ±6.8	13.9 ±6.7	13.5 ±6.5	15.9 ±5.5	13.5 ±6.5	13.7 ±6.7	15.0 ±4.3	15.3 ±3.8	13.5 ±6.5	14.2 ±7.0
	2	13.6 ±6.4	13.6 ±6.4	13.6 ±6.4	13.6 ±6.6	14.9 ±7.6	13.6 ±6.4	13.5 ±6.9	13.7 ±6.1	13.6 ±6.4	13.6 ±6.3	13.7 ±6.5	16.0 ±5.3	13.8 ±6.3	13.6 ±6.4	14.2 ±7.2
	3	13.7 ±6.6	13.9 ±6.2	13.9 ±6.2	13.8 ±6.4	14.8 ±7.6	13.8 ±6.2	13.4 ±6.9	13.6 ±6.7	13.6 ±6.8	13.5 ±6.8	13.9 ±6.1	14.0 ±7.5	13.7 ±6.5	13.7 ±6.6	14.0 ±7.5
	4	13.7 ±6.7	13.8 ±6.3	13.7 ±6.6	13.6 ±6.7	14.7 ±7.7	13.6 ±6.5	13.5 ±7.0	13.7 ±6.7	13.7 ±6.6	13.8 ±6.4	13.8 ±6.3	14.5 ±7.8	13.8 ±6.4	13.6 ±6.8	13.9 ±7.5
	5	13.7 ±6.8	13.8 ±6.4	13.7 ±6.6	13.8 ±6.4	15.9 ±5.6	13.8 ±6.4	13.9 ±6.5	13.7 ±6.6	13.7 ±6.6	13.8 ±6.6	13.8 ±6.5	13.8 ±6.8	13.8 ±6.4	13.6 ±6.9	13.4 ±7.0
automobile	1	.615 ±.092	.591 ±.156	.545 ±.167	.625 ±.074	1.05 ±.08	.587 ±.163	.598 ±.134	.811 ±.090	.574 ±.140	.674 ±.165	.645 ±.191	.709 ±.069	.712 ±.087	.556 ±.144	.715 ±.142
	2	.581 ±.112	.601 ±.151	.549 ±.130	.629 ±.110	.800 ±.142	.601 ±.151	.597 ±.069	.730 ±.019	.572 ±.171	.608 ±.113	.610 ±.139	.732 ±.067	.573 ±.091	.553 ±.122	.630 ±.114
	3	.537 ±.144	.631 ±.153	.570 ±.119	.611 ±.112	.647 ±.102	.631 ±.153	.581 ±.080	.587 ±.080	.565 ±.177	.582 ±.117	.560 ±.158	.603 ±.120	.567 ±.067	.559 ±.128	.626 ±.090
	4	.523 ±.128	.632 ±.137	.558 ±.150	.572 ±.125	.618 ±.107	.632 ±.137	.587 ±.072	.546 ±.091	.547 ±.106	.556 ±.128	.547 ±.160	.562 ±.084	.570 ±.095	.553 ±.110	.621 ±.081
	5	.533 ±.143	.565 ±.123	.554 ±.130	.560 ±.125	.581 ±.126	.565 ±.123	.547 ±.109	.548 ±.096	.554 ±.107	.555 ±.131	.530 ±.127	.571 ±.113	.558 ±.108	.558 ±.102	.628 ±.052
psa_cancer percentage (log10)	1	.600 ±.001	.599 ±.002	.600 ±.002	.599 ±.001	.600 ±.002	.599 ±.002	.599 ±.002	.600 ±.002	.600 ±.002	.600 ±.002	.599 ±.002	.599 ±.002	.599 ±.002	.600 ±.002	.599 ±.002
	2	.599 ±.002	.599 ±.002	.598 ±.002	.599 ±.001	.599 ±.001	.599 ±.002	.599 ±.002	.599 ±.002	.599 ±.002	.600 ±.002	.599 ±.002	.600 ±.002	.599 ±.002	.599 ±.002	.599 ±.001
	3	.599 ±.002	.599 ±.002	.599 ±.001	.599 ±.002	.599 ±.002	.598 ±.002	.600 ±.002	.599 ±.002	.599 ±.002	.601 ±.001	.599 ±.002	.599 ±.002	.599 ±.002	.599 ±.002	.599 ±.003
	4	.601 ±.002	.601 ±.002	.600 ±.002	.601 ±.001	.604 ±.002	.601 ±.002	.602 ±.002	.601 ±.003	.602 ±.003	.602 ±.003	.602 ±.002	.602 ±.002	.602 ±.003	.601 ±.002	.600 ±.001
	5	.604 ±.002	.604 ±.002	.603 ±.002	.604 ±.002	.605 ±.002	.604 ±.002	.605 ±.002	.604 ±.002	.604 ±.002	.605 ±.002	.604 ±.002	.604 ±.002	.604 ±.002	.604 ±.002	.605 ±.002
impendconductivity	1	9.06 ±.11	9.01 ±.07	9.19 ±.04	9.24 ±.04	9.99 ±.06	9.09 ±.06	9.04 ±.03	9.02 ±.01	10.4 ±.5	9.07 ±.01	9.10 ±.06	9.03 ±.04	9.13 ±.07	9.07 ±.10	9.09 ±.04
	2	8.88 ±.04	8.85 ±.02	8.90 ±.05	8.87 ±.08	8.95 ±.01	8.86 ±.05	8.86 ±.06	8.93 ±.01	9.09 ±.05	8.88 ±.04	8.90 ±.04	8.92 ±.02	8.87 ±.01	8.83 ±.02	8.92 ±.05
	3	8.82 ±.03	8.83 ±.03	8.90 ±.08	8.85 ±.05	8.91 ±.02	8.81 ±.03	8.79 ±.04	8.85 ±.04	9.01 ±.03	8.84 ±.06	8.82 ±.05	8.85 ±.03	8.85 ±.06	8.83 ±.02	8.88 ±.07
	4	8.83 ±.03	8.83 ±.05	8.86 ±.02	8.84 ±.01	8.89 ±.01	8.80 ±.01	8.83 ±.03	8.83 ±.03	8.87 ±.02	8.82 ±.03	8.82 ±.03	8.86 ±.04	8.83 ±.01	8.82 ±.03	8.81 ±.07
	5	8.84 ±.04	8.82 ±.05	8.85 ±.01	8.81 ±.03	8.83 ±.03	8.80 ±.02	8.83 ±.01	8.81 ±.04	8.84 ±.04	8.81 ±.01	8.79 ±.01	8.82 ±.02	8.82 ±.03	8.81 ±.03	8.81 ±.03
AUC (↑)																
m_vascular_cortex concentration	1	.748 ±.012	.719 ±.006	.697 ±.008	.720 ±.013	.584 ±.015	.720 ±.008	.740 ±.011	.729 ±.010	.722 ±.024	.716 ±.017	.748 ±.012	.608 ±.039	.738 ±.018	.750 ±.008	.745 ±.008
	2	.800 ±.007	.726 ±.006	.721 ±.011	.764 ±.012	.631 ±.005	.726 ±.006	.802 ±.026	.768 ±.011	.760 ±.013	.740 ±.011	.792 ±.012	.666 ±.022	.816 ±.015	.804 ±.004	.766 ±.021
	3	.815 ±.003	.755 ±.017	.738 ±.006	.811 ±.003	.677 ±.002	.756 ±.017	.825 ±.007	.818 ±.004	.801 ±.012	.760 ±.011	.813 ±.006	.742 ±.056	.833 ±.008	.810 ±.004	.798 ±.038
	4	.839 ±.006	.783 ±.008	.811 ±.018	.830 ±.003	.737 ±.002	.784 ±.014	.834 ±.010	.829 ±.005	.832 ±.004	.796 ±.002	.827 ±.011	.815 ±.005	.845 ±.001	.843 ±.004	.820 ±.027
	5	.843 ±.003	.832 ±.004	.832 ±.004	.838 ±.004	.815 ±.006	.832 ±.005	.844 ±.002	.837 ±.009	.839 ±.006	.835 ±.004	.843 ±.004	.837 ±.009	.844 ±.002	.844 ±.003	.836 ±.009
marketing campaign	1	.836 ±.043	.826 ±.045	.796 ±.018	.795 ±.028	.710 ±.022	.826 ±.043	.801 ±.026	.816 ±.012	.788 ±.017	.827 ±.044	.763 ±.003	.775 ±.035	.838 ±.036	.847 ±.023	.807 ±.056
	2	.872 ±.029	.884 ±.032	.888 ±.022	.840 ±.026	.836 ±.015	.890 ±.034	.875 ±.013	.864 ±.010	.853 ±.018	.867 ±.039	.824 ±.043	.819 ±.008	.884 ±.024	.868 ±.031	.866 ±.012
	3	.893 ±.014	.906 ±.023	.893 ±.026	.885 ±.008	.878 ±.018	.907 ±.022	.902 ±.022	.886 ±.003	.881 ±.016	.890 ±.023	.878 ±.029	.850 ±.026	.902 ±.013	.884 ±.020	.905 ±.021
	4	.911 ±.018	.910 ±.024	.906 ±.020	.897 ±.009	.880 ±.017	.914 ±.024	.914 ±.019	.895 ±.005	.909 ±.015	.902 ±.024	.898 ±.030	.891 ±.040	.916 ±.014	.904 ±.012	.917 ±.021
	5	.920 ±.017	.917 ±.022	.921 ±.016	.904 ±.017	.903 ±.030	.918 ±.020	.919 ±.022	.916 ±.010	.922 ±.017	.913 ±.018	.911 ±.017	.907 ±.035	.922 ±.018	.918 ±.018	.923 ±.020
psa_cancer percentage	1	.968 ±.005	.851 ±.004	.885 ±.011	.907 ±.021	.876 ±.031	.860 ±.012	.966 ±.019	.962 ±.007	.924 ±.019	.932 ±.018	.874 ±.016	.870 ±.013	.891 ±.026	.964 ±.004	.957 ±.012
	2	.975 ±.006	.896 ±.031	.923 ±.021	.934 ±.024	.924 ±.017	.885 ±.024	.975 ±.013	.970 ±.002	.944 ±.017	.963 ±.018	.965 ±.023	.935 ±.039	.939 ±.035	.974 ±.009	.966 ±.017
	3	.979 ±.008	.932 ±.030	.924 ±.018	.966 ±.005	.929 ±.011	.922 ±.036	.976 ±.014	.980 ±.006	.962 ±.006	.982 ±.009	.976 ±.013	.943 ±.039	.959 ±.033	.979 ±.009	.961 ±.016
	4	.983 ±.008	.951 ±.015	.957 ±.030	.964 ±.007	.933 ±.008	.951 ±.015	.982 ±.008	.984 ±.006	.967 ±.003	.985 ±.009	.980 ±.011	.981 ±.006	.971 ±.035	.981 ±.010	.968 ±.017
	5	.983 ±.008	.969 ±.020	.977 ±.013	.974 ±.004	.942 ±.007	.971 ±.017	.984 ±.008	.985 ±.007	.977 ±.005	.986 ±.009	.983 ±.010	.977 ±.010	.985 ±.008	.984 ±.008	.984 ±.011
correlation coefficient	1	.713 ±.018	.862 ±.069	.876 ±.108	.864 ±.061	.675 ±.228	.820 ±.101	.644 ±.201	.856 ±.117	.871 ±.047	.844 ±.047	.911 ±.047	.577 ±.183	.730 ±.217	.820 ±.138	.642 ±.156
	2	.841 ±.080	.888 ±.081	.918 ±.062	.901 ±.065	.851 ±.119	.868 ±.108	.850 ±.136	.789 ±.083	.901 ±.047	.908 ±.046	.895 ±.061	.773 ±.213	.753 ±.212	.918 ±.036	.768 ±.022
	3	.834 ±.														

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Dataset	Budget idx					ElankNet					F-test					GainRatio					LaplacianScore					Lasso					LOCO					MarkovBlanket					MI					mRMR					(R)Relieff					Random					SBE					RFImportance					SFS																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																	
	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2

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Dataset	Budget idx	CART	ElankNet	F-test	GiniRatio	LaplacianScore	Lasso	LOCO	MarkovBlanket	MI	mRMR	(R)Relieff	Random	SBE	RFImportance	SFS
gas_oil binary	1	.720 ± 0.016	.692 ± 0.041	.692 ± 0.025	.566 ± 0.056	.562 ± 0.015	.696 ± 0.034	.565 ± 0.033	.555 ± 0.043	.686 ± 0.021	.566 ± 0.056	.564 ± 0.033	.575 ± 0.009	.570 ± 0.010	.693 ± 0.027	.738 ± 0.014
	2	.775 ± 0.010	.749 ± 0.029	.715 ± 0.033	.622 ± 0.026	.582 ± 0.005	.781 ± 0.016	.642 ± 0.037	.634 ± 0.042	.726 ± 0.023	.622 ± 0.026	.687 ± 0.010	.632 ± 0.052	.659 ± 0.041	.736 ± 0.045	.766 ± 0.008
	3	.848 ± 0.015	.832 ± 0.030	.796 ± 0.041	.748 ± 0.024	.732 ± 0.010	.845 ± 0.018	.762 ± 0.015	.769 ± 0.033	.816 ± 0.025	.748 ± 0.024	.835 ± 0.020	.769 ± 0.028	.775 ± 0.011	.829 ± 0.036	.822 ± 0.044
	4	.896 ± 0.021	.878 ± 0.026	.889 ± 0.028	.872 ± 0.019	.863 ± 0.025	.883 ± 0.027	.875 ± 0.027	.878 ± 0.030	.887 ± 0.021	.872 ± 0.019	.903 ± 0.020	.874 ± 0.020	.874 ± 0.009	.895 ± 0.023	.885 ± 0.025
	5	.905 ± 0.022	.901 ± 0.025	.903 ± 0.027	.900 ± 0.018	.904 ± 0.020	.900 ± 0.026	.899 ± 0.018	.899 ± 0.022	.907 ± 0.018	.900 ± 0.018	.906 ± 0.025	.899 ± 0.026	.897 ± 0.024	.905 ± 0.028	.905 ± 0.020
insurance_bumpup percentage	1	.944 ± 0.004	.944 ± 0.004	.943 ± 0.003	.946 ± 0.004	.919 ± 0.014	.934 ± 0.016	.923 ± 0.005	.942 ± 0.002	.942 ± 0.004	.918 ± 0.002	.935 ± 0.012	.935 ± 0.011	.935 ± 0.003	.945 ± 0.003	.942 ± 0.003
	2	.946 ± 0.004	.950 ± 0.008	.946 ± 0.001	.946 ± 0.005	.946 ± 0.007	.945 ± 0.002	.945 ± 0.007	.949 ± 0.003	.945 ± 0.004	.940 ± 0.008	.948 ± 0.006	.945 ± 0.005	.941 ± 0.002	.945 ± 0.004	.944 ± 0.007
	3	.949 ± 0.007	.950 ± 0.004	.948 ± 0.003	.949 ± 0.004	.947 ± 0.006	.948 ± 0.001	.945 ± 0.007	.949 ± 0.003	.948 ± 0.003	.945 ± 0.003	.948 ± 0.004	.948 ± 0.003	.948 ± 0.004	.946 ± 0.004	.948 ± 0.007
	4	.949 ± 0.005	.951 ± 0.002	.949 ± 0.002	.949 ± 0.004	.948 ± 0.004	.950 ± 0.005	.947 ± 0.003	.950 ± 0.004	.949 ± 0.004	.948 ± 0.004	.951 ± 0.004	.947 ± 0.004	.948 ± 0.003	.948 ± 0.004	.947 ± 0.006
	5	.949 ± 0.004	.950 ± 0.004	.949 ± 0.005	.949 ± 0.003	.949 ± 0.004	.948 ± 0.005	.948 ± 0.003	.949 ± 0.003	.948 ± 0.004	.948 ± 0.004	.949 ± 0.004	.948 ± 0.006	.949 ± 0.003	.949 ± 0.004	.948 ± 0.006
Royal diamond	1	.982 ± 0.004	.779 ± 2.34	.927 ± 0.033	.983 ± 0.001	.535 ± 0.001	.779 ± 2.34	.980 ± 0.006	.984 ± 0.003	.929 ± 0.023	.930 ± 0.029	.933 ± 0.042	.737 ± 0.206	.981 ± 0.007	.983 ± 0.001	.941 ± 0.037
	2	.987 ± 0.006	.897 ± 0.094	.948 ± 0.044	.985 ± 0.001	.569 ± 0.007	.897 ± 0.094	.988 ± 0.002	.985 ± 0.003	.924 ± 0.033	.930 ± 0.028	.944 ± 0.036	.760 ± 0.213	.992 ± 0.002	.991 ± 0.002	.937 ± 0.064
	3	.991 ± 0.001	.949 ± 0.077	.973 ± 0.030	.989 ± 0.004	.581 ± 0.012	.949 ± 0.047	.988 ± 0.004	.985 ± 0.004	.932 ± 0.037	.940 ± 0.026	.947 ± 0.057	.967 ± 0.036	.992 ± 0.003	.992 ± 0.003	.918 ± 0.055
	4	.992 ± 0.002	.957 ± 0.043	.973 ± 0.036	.991 ± 0.002	.615 ± 0.022	.957 ± 0.043	.988 ± 0.004	.987 ± 0.003	.950 ± 0.039	.956 ± 0.036	.989 ± 0.005	.979 ± 0.015	.993 ± 0.003	.992 ± 0.003	.943 ± 0.055
	5	.993 ± 0.003	.965 ± 0.046	.991 ± 0.003	.991 ± 0.004	.931 ± 0.054	.965 ± 0.046	.990 ± 0.002	.990 ± 0.002	.970 ± 0.039	.959 ± 0.035	.989 ± 0.006	.988 ± 0.001	.993 ± 0.003	.991 ± 0.004	.970 ± 0.040
col_2000 insurance_4000	1	.748 ± 0.035	.724 ± 0.061	.759 ± 0.051	.756 ± 0.029	.537 ± 0.002	.671 ± 0.099	.747 ± 0.028	.750 ± 0.036	.753 ± 0.017	.734 ± 0.036	.657 ± 0.030	.712 ± 0.045	.693 ± 0.043	.752 ± 0.034	.766 ± 0.028
	2	.760 ± 0.033	.752 ± 0.042	.763 ± 0.033	.756 ± 0.030	.574 ± 0.038	.739 ± 0.051	.759 ± 0.031	.756 ± 0.031	.761 ± 0.030	.741 ± 0.036	.662 ± 0.031	.755 ± 0.038	.714 ± 0.046	.756 ± 0.035	.773 ± 0.032
	3	.771 ± 0.039	.757 ± 0.044	.768 ± 0.035	.759 ± 0.031	.666 ± 0.030	.744 ± 0.047	.763 ± 0.033	.760 ± 0.029	.770 ± 0.027	.753 ± 0.035	.714 ± 0.016	.727 ± 0.014	.718 ± 0.044	.757 ± 0.031	.769 ± 0.033
	4	.773 ± 0.032	.758 ± 0.040	.776 ± 0.034	.766 ± 0.030	.666 ± 0.033	.751 ± 0.051	.768 ± 0.033	.767 ± 0.023	.773 ± 0.027	.771 ± 0.021	.743 ± 0.028	.776 ± 0.029	.761 ± 0.020	.773 ± 0.032	.774 ± 0.030
	5	.777 ± 0.032	.772 ± 0.036	.772 ± 0.032	.772 ± 0.033	.675 ± 0.024	.770 ± 0.035	.770 ± 0.038	.774 ± 0.033	.776 ± 0.032	.777 ± 0.029	.743 ± 0.027	.773 ± 0.037	.775 ± 0.036	.775 ± 0.033	.776 ± 0.031
private insurance	1	.925 ± 0.068	.964 ± 0.036	.970 ± 0.043	.971 ± 0.050	.577 ± 0.093	.957 ± 0.044	.706 ± 0.095	.954 ± 0.055	.960 ± 0.064	.939 ± 0.060	.969 ± 0.045	.608 ± 0.085	.614 ± 0.088	.949 ± 0.050	.871 ± 1.07
	2	.938 ± 0.061	.969 ± 0.043	.961 ± 0.053	.965 ± 0.057	.767 ± 0.117	.972 ± 0.048	.735 ± 0.199	.947 ± 0.072	.964 ± 0.062	.972 ± 0.048	.973 ± 0.040	.751 ± 0.114	.764 ± 0.122	.967 ± 0.055	.873 ± 0.046
	3	.968 ± 0.047	.977 ± 0.037	.972 ± 0.045	.969 ± 0.045	.864 ± 0.011	.964 ± 0.040	.886 ± 0.050	.961 ± 0.048	.970 ± 0.052	.963 ± 0.064	.977 ± 0.034	.897 ± 0.038	.905 ± 0.055	.968 ± 0.039	.918 ± 0.049
	4	.961 ± 0.036	.978 ± 0.035	.970 ± 0.035	.970 ± 0.046	.917 ± 0.024	.976 ± 0.039	.957 ± 0.051	.965 ± 0.051	.964 ± 0.050	.970 ± 0.052	.968 ± 0.056	.960 ± 0.049	.964 ± 0.026	.971 ± 0.044	.961 ± 0.041
	5	.905 ± 0.041	.960 ± 0.037	.967 ± 0.046	.946 ± 0.055	.905 ± 0.053	.955 ± 0.033	.905 ± 0.024	.839 ± 0.096	.873 ± 0.023	.938 ± 0.033	.970 ± 0.046	.907 ± 0.052	.891 ± 0.045	.943 ± 0.044	.919 ± 0.052
credit approval	1	.902 ± 0.019	.918 ± 0.010	.913 ± 0.008	.841 ± 0.008	.665 ± 0.071	.910 ± 0.009	.898 ± 0.013	.850 ± 0.022	.913 ± 0.007	.845 ± 0.012	.886 ± 0.020	.767 ± 0.068	.916 ± 0.004	.915 ± 0.006	.916 ± 0.014
	2	.922 ± 0.007	.919 ± 0.007	.929 ± 0.015	.859 ± 0.011	.764 ± 0.053	.916 ± 0.006	.925 ± 0.015	.857 ± 0.010	.922 ± 0.008	.870 ± 0.044	.900 ± 0.012	.845 ± 0.115	.923 ± 0.009	.922 ± 0.003	.923 ± 0.008
	3	.922 ± 0.018	.926 ± 0.002	.929 ± 0.010	.876 ± 0.007	.915 ± 0.002	.928 ± 0.002	.930 ± 0.008	.869 ± 0.002	.923 ± 0.005	.895 ± 0.042	.926 ± 0.009	.867 ± 0.054	.923 ± 0.005	.934 ± 0.009	.918 ± 0.005
	4	.930 ± 0.006	.926 ± 0.003	.933 ± 0.007	.896 ± 0.029	.922 ± 0.002	.930 ± 0.004	.932 ± 0.010	.876 ± 0.009	.930 ± 0.008	.931 ± 0.011	.928 ± 0.013	.888 ± 0.037	.931 ± 0.005	.932 ± 0.009	.925 ± 0.008
	5	.932 ± 0.007	.933 ± 0.003	.935 ± 0.005	.934 ± 0.005	.927 ± 0.005	.933 ± 0.004	.929 ± 0.006	.916 ± 0.034	.933 ± 0.009	.936 ± 0.008	.937 ± 0.008	.902 ± 0.037	.932 ± 0.005	.933 ± 0.007	.931 ± 0.002
Real_Estate binary	1	.789 ± 0.033	.889 ± 0.017	.877 ± 0.023	.842 ± 0.089	.675 ± 0.149	.890 ± 0.020	.721 ± 0.203	.862 ± 0.025	.838 ± 0.072	.865 ± 0.028	.874 ± 0.037	.730 ± 0.137	.841 ± 0.055	.864 ± 0.037	.845 ± 0.054
	2	.831 ± 0.068	.896 ± 0.022	.891 ± 0.008	.888 ± 0.020	.884 ± 0.048	.888 ± 0.021	.750 ± 0.185	.879 ± 0.011	.894 ± 0.021	.869 ± 0.007	.891 ± 0.017	.875 ± 0.035	.865 ± 0.052	.859 ± 0.028	.869 ± 0.050
	3	.845 ± 0.042	.888 ± 0.023	.894 ± 0.011	.877 ± 0.016	.881 ± 0.055	.891 ± 0.017	.855 ± 0.057	.876 ± 0.010	.896 ± 0.020	.881 ± 0.017	.896 ± 0.009	.853 ± 0.035	.888 ± 0.029	.882 ± 0.019	.875 ± 0.050
	4	.884 ± 0.018	.900 ± 0.017	.892 ± 0.018	.878 ± 0.016	.903 ± 0.020	.892 ± 0.014	.882 ± 0.065	.879 ± 0.017	.901 ± 0.020	.896 ± 0.017	.895 ± 0.004	.888 ± 0.011	.903 ± 0.014	.906 ± 0.014	.906 ± 0.017
	5	.893 ± 0.008	.898 ± 0.013	.896 ± 0.017	.893 ± 0.014	.903 ± 0.011	.891 ± 0.014	.864 ± 0.065	.886 ± 0.022	.901 ± 0.016	.898 ± 0.020	.893 ± 0.006	.886 ± 0.018	.899 ± 0.018	.898 ± 0.014	.900 ± 0.018
gpc_200 insurance_4000	1	.618 ± 0.001	.732 ± 0.001	.728 ± 0.002	.728 ± 0.002	.567 ± 0.004	.732 ± 0.001	.747 ± 0.009	.728 ± 0.002	.728 ± 0.005	.728 ± 0.002	.658 ± 0.009	.701 ± 0.034	.713 ± 0.046	.618 ± 0.001	.728 ± 0.005
	2	.770 ± 0.002	.806 ± 0.014	.810 ± 0.007	.783 ± 0.002	.683 ± 0.020	.806 ± 0.014	.810 ± 0.014	.786 ± 0.002	.796 ± 0.004	.808 ± 0.010	.689 ± 0.005	.794 ± 0.017	.796 ± 0.024	.696 ± 0.006	.799 ± 0.003
	3	.778 ± 0.004	.822 ± 0.005	.819 ± 0.004	.789 ± 0.002	.736 ± 0.034	.822 ± 0.005	.823 ± 0.010	.798 ± 0.004	.823 ± 0.002	.813 ± 0.011	.788 ± 0.002	.796 ± 0.038	.823 ± 0.006	.778 ± 0.004	.805 ± 0.009
	4	.820 ± 0.014	.818 ± 0.005	.833 ± 0.003	.797 ± 0.004	.797 ± 0.028	.818 ± 0.005	.839 ± 0.003	.804 ± 0.004	.835 ± 0.002	.825 ± 0.009	.814 ± 0.015	.823 ± 0.012	.842 ± 0.005	.836 ± 0.010	.832 ± 0.007
	5	.845 ± 0.003	.841 ± 0.003	.843 ± 0.004	.833 ± 0.008	.838 ± 0.012	.841 ± 0.003	.845 ± 0.004	.829 ± 0.002	.847 ± 0.003	.841 ± 0.003	.842 ± 0.004	.845 ± 0.003	.845 ± 0.003	.845 ± 0.003	.843 ± 0.007
AUC_precision insurance_4000	1	.490 ± 0.092	.535 ± 0.068	.452 ± 0.076	.571 ± 0.090	.479 ± 0.087	.535 ± 0.068	.502 ± 0.111	.447 ± 0.066	.535 ± 0.151	.505 ± 0.107	.466 ± 0.077	.493 ± 0.163	.457 ± 0.117	.509 ± 0.105	.542 ± 0.083
	2	.498 ± 0.041	.518 ± 0.052	.515 ± 0.043	.558 ± 0.149	.482 ± 0.025	.518 ± 0.052	.480 ± 0.048	.522 ± 0.054	.543 ± 0.149	.538 ± 0.127	.452 ± 0.103	.557 ± 0.113	.553 ± 0.022	.542 ± 0.105	.538 ± 0.075
	3	.472 ± 0.044	.519 ± 0.119	.509 ± 0.035	.590 ± 0.148	.498 ± 0.051	.519 ± 0.119	.510 ± 0.080	.529 ± 0.072	.522 ± 0.192	.500 ± 0.081	.488 ± 0.062	.510 ± 0.081	.553 ± 0.125	.552 ± 0.104	.547 ± 0.084
	4	.511 ± 0.087	.532 ± 0.113	.526 ± 0.110	.517 ± 0.147	.501 ± 0.091	.532 ± 0.113	.507 ± 0.077	.564 ± 0.171	.502 ± 0.143	.510 ± 0.09	.531 ± 0.06	.512 ± 0.135	.540 ± 0.149	.543 ± 0.132	.542 ± 0.137
	5	.506 ± 0.139	.498 ± 0.119	.479 ± 0.122	.508 ± 0.128	.501 ± 0.089	.498 ± 0.119	.527 ± 0.124	.497 ± 0.144	.489 ± 0.130	.524					

(continued from previous page)

Dataset	Budget idx, j	CART	ElankiNet	F-test	GuinRatio	LaplacianScore	Lasso	LOCO	MarkovBlanket	MI	mRMR	(R)Relieff	Random	SSE	RFImportance	SFS
h4c_crossover dataset	1	.609 ± .022	.622 ± .041	.646 ± .037	.724 ± .020	.658 ± .045	.622 ± .041	.665 ± .048	.658 ± .037	.694 ± .034	.683 ± .025	.620 ± .032	.644 ± .041	.698 ± .029	.612 ± .032	.715 ± .019
	2	.706 ± .018	.634 ± .031	.675 ± .020	.730 ± .020	.670 ± .047	.634 ± .031	.676 ± .038	.703 ± .031	.734 ± .019	.710 ± .024	.632 ± .022	.590 ± .035	.713 ± .024	.704 ± .020	.728 ± .014
	3	.728 ± .024	.666 ± .001	.671 ± .019	.734 ± .018	.668 ± .042	.666 ± .001	.718 ± .026	.737 ± .016	.739 ± .008	.722 ± .034	.632 ± .020	.707 ± .049	.720 ± .029	.719 ± .015	.729 ± .006
	4	.738 ± .017	.682 ± .024	.685 ± .024	.734 ± .014	.690 ± .026	.682 ± .024	.724 ± .021	.737 ± .016	.738 ± .007	.737 ± .017	.668 ± .008	.699 ± .021	.728 ± .017	.736 ± .016	.731 ± .005
	5	.734 ± .017	.729 ± .025	.728 ± .022	.749 ± .014	.703 ± .039	.729 ± .025	.738 ± .021	.741 ± .015	.739 ± .008	.738 ± .022	.687 ± .023	.732 ± .027	.735 ± .022	.747 ± .012	.737 ± .021
h4c_differential_evolution dataset	1	.940 ± .018	.933 ± .016	.933 ± .010	.927 ± .012	.911 ± .011	.930 ± .018	.945 ± .022	.932 ± .013	.928 ± .013	.927 ± .018	.942 ± .008	.892 ± .007	.939 ± .007	.940 ± .019	.934 ± .007
	2	.975 ± .012	.967 ± .010	.967 ± .006	.969 ± .008	.951 ± .010	.967 ± .010	.979 ± .013	.969 ± .012	.968 ± .011	.967 ± .011	.975 ± .009	.953 ± .025	.980 ± .008	.969 ± .012	.973 ± .015
	3	.990 ± .006	.980 ± .005	.986 ± .006	.982 ± .008	.977 ± .009	.981 ± .005	.987 ± .010	.988 ± .008	.981 ± .007	.984 ± .012	.988 ± .008	.980 ± .011	.989 ± .007	.984 ± .007	.990 ± .008
	4	.992 ± .006	.988 ± .006	.991 ± .006	.990 ± .007	.984 ± .009	.988 ± .006	.992 ± .006	.992 ± .006	.989 ± .008	.991 ± .006	.993 ± .006	.990 ± .007	.992 ± .006	.993 ± .005	.991 ± .008
	5	.993 ± .006	.994 ± .006	.992 ± .006	.993 ± .005	.991 ± .006	.994 ± .006	.994 ± .006	.993 ± .006	.993 ± .005	.994 ± .006	.994 ± .005	.992 ± .005	.994 ± .005	.994 ± .005	.994 ± .006
dmg_subtotal dataset	1	.670 ± .084	.642 ± .032	.618 ± .070	.639 ± .039	.606 ± .069	.658 ± .063	.657 ± .051	.712 ± .012	.670 ± .035	.695 ± .019	.597 ± .057	.651 ± .081	.612 ± .056	.697 ± .033	.682 ± .030
	2	.728 ± .054	.716 ± .031	.635 ± .011	.731 ± .016	.737 ± .011	.706 ± .049	.738 ± .033	.764 ± .044	.709 ± .029	.714 ± .011	.653 ± .003	.732 ± .033	.640 ± .068	.737 ± .010	.736 ± .045
	3	.806 ± .022	.787 ± .008	.792 ± .020	.802 ± .022	.748 ± .008	.781 ± .031	.817 ± .023	.809 ± .031	.774 ± .036	.768 ± .059	.783 ± .043	.783 ± .058	.781 ± .039	.815 ± .019	.756 ± .048
	4	.832 ± .014	.820 ± .018	.829 ± .010	.838 ± .006	.820 ± .017	.837 ± .010	.825 ± .021	.843 ± .029	.842 ± .016	.803 ± .016	.821 ± .016	.798 ± .049	.816 ± .039	.821 ± .008	.821 ± .038
	5	.845 ± .014	.855 ± .017	.858 ± .004	.847 ± .006	.827 ± .022	.852 ± .012	.843 ± .023	.841 ± .009	.843 ± .017	.818 ± .008	.850 ± .010	.849 ± .006	.846 ± .011	.844 ± .004	.852 ± .017
h4c_differential_evolution dataset	1	.339 ± .164	.452 ± .164	.882 ± .000	.609 ± .079	.680 ± .047	.452 ± .164	.507 ± .249	.703 ± .171	.655 ± .168	.591 ± .087	.870 ± .093	.501 ± .188	.454 ± .121	.386 ± .214	.433 ± .088
	2	.623 ± .246	.441 ± .022	.785 ± .153	.610 ± .016	.743 ± .158	.441 ± .022	.629 ± .112	.683 ± .215	.866 ± .083	.690 ± .041	.839 ± .146	.599 ± .097	.613 ± .274	.680 ± .145	.397 ± .102
	3	.730 ± .178	.448 ± .168	.763 ± .183	.505 ± .104	.578 ± .032	.448 ± .168	.657 ± .098	.543 ± .085	.828 ± .118	.803 ± .156	.769 ± .109	.607 ± .215	.661 ± .300	.711 ± .164	.631 ± .282
	4	.752 ± .171	.569 ± .118	.737 ± .209	.584 ± .117	.578 ± .217	.569 ± .118	.743 ± .186	.565 ± .046	.775 ± .164	.796 ± .138	.730 ± .181	.698 ± .215	.762 ± .153	.743 ± .180	.755 ± .168
	5	.764 ± .160	.697 ± .213	.731 ± .190	.654 ± .122	.669 ± .096	.697 ± .213	.753 ± .171	.673 ± .239	.768 ± .191	.784 ± .172	.723 ± .200	.739 ± .174	.775 ± .152	.761 ± .165	.743 ± .183
h4c_differential_evolution dataset	1	.721 ± .002	.785 ± .007	.785 ± .007	.758 ± .038	.637 ± .005	.785 ± .007	.690 ± .002	.785 ± .007	.715 ± .002	.785 ± .007	.719 ± .005	.582 ± .043	.784 ± .007	.721 ± .002	.782 ± .003
	2	.788 ± .006	.794 ± .006	.792 ± .007	.786 ± .007	.671 ± .004	.794 ± .006	.702 ± .004	.790 ± .005	.790 ± .006	.795 ± .005	.766 ± .040	.724 ± .022	.795 ± .008	.730 ± .006	.793 ± .003
	3	.793 ± .005	.798 ± .006	.795 ± .009	.794 ± .006	.699 ± .022	.798 ± .006	.742 ± .046	.796 ± .003	.795 ± .006	.796 ± .005	.794 ± .015	.796 ± .008	.803 ± .009	.793 ± .006	.797 ± .009
	4	.801 ± .005	.800 ± .009	.801 ± .007	.804 ± .007	.712 ± .015	.800 ± .009	.772 ± .038	.804 ± .007	.805 ± .006	.799 ± .005	.801 ± .008	.795 ± .009	.804 ± .008	.799 ± .003	.804 ± .009
	5	.803 ± .005	.804 ± .004	.804 ± .008	.806 ± .005	.803 ± .004	.804 ± .004	.803 ± .011	.807 ± .006	.807 ± .007	.804 ± .005	.805 ± .009	.803 ± .007	.806 ± .006	.805 ± .007	.807 ± .006
perm dataset	1	.611 ± .001	.595 ± .025	.595 ± .015	.598 ± .004	.544 ± .004	.606 ± .014	.596 ± .028	.616 ± .003	.567 ± .021	.596 ± .009	.595 ± .002	.592 ± .009	.592 ± .009	.610 ± .001	.568 ± .010
	2	.618 ± .001	.626 ± .005	.621 ± .005	.622 ± .001	.596 ± .004	.616 ± .012	.611 ± .013	.625 ± .001	.616 ± .003	.614 ± .006	.616 ± .004	.610 ± .007	.614 ± .007	.618 ± .000	.601 ± .006
	3	.621 ± .001	.630 ± .004	.627 ± .002	.626 ± .001	.609 ± .003	.625 ± .005	.621 ± .009	.627 ± .000	.625 ± .002	.619 ± .003	.623 ± .002	.616 ± .002	.618 ± .005	.627 ± .001	.617 ± .007
	4	.632 ± .002	.634 ± .002	.630 ± .002	.630 ± .002	.615 ± .005	.629 ± .006	.626 ± .008	.631 ± .003	.633 ± .002	.626 ± .003	.625 ± .002	.628 ± .001	.627 ± .004	.632 ± .002	.627 ± .003
	5	.635 ± .001	.634 ± .003	.635 ± .002	.633 ± .001	.629 ± .003	.631 ± .005	.633 ± .001	.632 ± .001	.634 ± .002	.634 ± .002	.631 ± .004	.634 ± .001	.633 ± .002	.635 ± .002	.630 ± .004
sequence_order dataset	1	.838 ± .057	.742 ± .177	.788 ± .036	.807 ± .059	.687 ± .143	.827 ± .066	.676 ± .152	.783 ± .018	.781 ± .006	.804 ± .051	.746 ± .033	.572 ± .121	.674 ± .147	.786 ± .015	.676 ± .148
	2	.813 ± .023	.787 ± .105	.818 ± .016	.775 ± .032	.729 ± .141	.842 ± .028	.737 ± .100	.768 ± .042	.765 ± .040	.823 ± .073	.798 ± .013	.684 ± .044	.714 ± .119	.794 ± .004	.730 ± .091
	3	.815 ± .023	.826 ± .022	.825 ± .021	.789 ± .012	.727 ± .129	.822 ± .016	.733 ± .131	.784 ± .007	.789 ± .034	.835 ± .062	.793 ± .044	.725 ± .066	.719 ± .126	.807 ± .030	.795 ± .020
	4	.817 ± .012	.836 ± .017	.838 ± .041	.797 ± .010	.773 ± .046	.836 ± .023	.781 ± .064	.809 ± .014	.806 ± .026	.836 ± .068	.818 ± .033	.811 ± .032	.774 ± .075	.808 ± .019	.784 ± .046
	5	.823 ± .006	.828 ± .008	.834 ± .017	.811 ± .007	.824 ± .031	.823 ± .008	.794 ± .045	.820 ± .005	.814 ± .010	.845 ± .036	.828 ± .013	.825 ± .022	.796 ± .038	.813 ± .013	.792 ± .044
knn dataset	1	.967 ± .015	.944 ± .036	.964 ± .013	.965 ± .021	.935 ± .031	.938 ± .044	.967 ± .019	.968 ± .022	.972 ± .019	.967 ± .028	.965 ± .016	.967 ± .013	.975 ± .010	.972 ± .004	.963 ± .007
	2	.975 ± .015	.973 ± .013	.983 ± .008	.981 ± .011	.963 ± .013	.972 ± .013	.974 ± .018	.980 ± .024	.985 ± .014	.981 ± .007	.978 ± .009	.974 ± .015	.976 ± .012	.981 ± .010	.975 ± .010
	3	.980 ± .012	.980 ± .016	.982 ± .011	.981 ± .007	.974 ± .015	.980 ± .014	.979 ± .017	.983 ± .017	.984 ± .012	.984 ± .008	.982 ± .008	.983 ± .013	.981 ± .015	.983 ± .012	.979 ± .012
	4	.983 ± .014	.983 ± .015	.983 ± .014	.983 ± .012	.981 ± .009	.985 ± .015	.982 ± .015	.984 ± .016	.984 ± .015	.982 ± .010	.980 ± .011	.980 ± .012	.981 ± .017	.983 ± .013	.980 ± .012
	5	.982 ± .016	.985 ± .015	.983 ± .016	.983 ± .014	.983 ± .013	.985 ± .014	.983 ± .014	.985 ± .016	.984 ± .014	.982 ± .013	.983 ± .014	.985 ± .016	.982 ± .016	.982 ± .014	.982 ± .015
h4c_differential_evolution dataset	1	.671 ± .052	.682 ± .065	.696 ± .052	.686 ± .056	.673 ± .029	.663 ± .029	.663 ± .084	.680 ± .090	.631 ± .142	.700 ± .064	.716 ± .047	.593 ± .082	.579 ± .066	.738 ± .072	.645 ± .032
	2	.789 ± .021	.752 ± .038	.716 ± .052	.729 ± .044	.719 ± .046	.760 ± .063	.686 ± .021	.704 ± .026	.735 ± .032	.707 ± .040	.729 ± .027	.676 ± .030	.701 ± .054	.730 ± .046	.721 ± .028
	3	.750 ± .013	.799 ± .053	.707 ± .047	.737 ± .032	.733 ± .031	.774 ± .052	.737 ± .039	.709 ± .014	.750 ± .053	.729 ± .043	.744 ± .042	.726 ± .046	.720 ± .029	.743 ± .055	.735 ± .008
	4	.765 ± .015	.778 ± .027	.726 ± .036	.733 ± .040	.726 ± .028	.800 ± .038	.744 ± .063	.718 ± .020	.709 ± .029	.743 ± .038	.757 ± .038	.717 ± .027	.737 ± .043	.782 ± .043	.722 ± .048
	5	.731 ± .022	.763 ± .035	.720 ± .045	.711 ± .023	.694 ± .032	.758 ± .019	.714 ± .033	.693 ± .046	.678 ± .027	.743 ± .028	.719 ± .054	.692 ± .042	.725 ± .038	.728 ± .017	.722 ± .052
h4c_differential_evolution dataset	1	.625 ± .035	.696 ± .063	.639 ± .090	.618 ± .061	.548 ± .062	.558 ± .071	.610 ± .064	.514 ± .024	.577 ± .124	.548 ± .074	.624 ± .054	.477 ± .089	.455 ± .046	.604 ± .083	.521 ± .122
	2	.627 ± .065	.758 ± .034	.670 ± .085	.592 ± .035	.540 ± .004	.674 ± .051	.578 ± .094	.613 ± .049	.558 ± .048	.757 ± .008	.681 ± .086	.581 ± .021	.558 ± .017	.683 ± .068	.615 ± .059
	3	.663 ± .102	.753 ± .071	.671 ± .073	.607 ± .026	.552 ± .020	.719 ± .054	.631 ± .055	.584 ± .056	.618 ± .101	.703 ± .058	.714 ± .085	.660 ± .070	.648 ± .040	.674 ± .079	.632 ± .086
	4	.642 ± .044	.727 ± .085	.559 ± .190	.621 ± .069	.541 ± .089	.722 ± .064	.658 ± .101	.595 ± .019	.589 ± .112	.727 ± .075	.673 ± .103	.602 ± .006	.611 ± .088	.735 ± .054	.620 ± .068
	5	.669 ± .029	.725 ± .031	.601 ± .110	.610 ± .028	.595 ± .057	.664 ± .049	.620 ± .058	.580 ± .057	.573 ± .062	.714 ± .023	.645 ± .009	.621 ± .045	.665 ± .077	.638 ± .016	.651 ± .071
h4c_differential_evolution dataset	1	.902 ± .001	.816 ± .002	.874 ± .003	.706 ± .083	.501 ± .002	.816 ± .002	.717 ± .115	.880 ± .019	.891 ± .001	.901 ± .001	.839 ± .036	.599 ± .041	.593 ± .020	.902 ± .000	.840 ± .028
	2	.933 ± .015	.927 ± .002	.885 ± .001	.865 ± .029	.607 ± .088	.918 ± .016	.849 ± .036	.920 ± .000	.909 ± .001</						

(continued from previous page)

Dataset	Budget idx j	CART	ElasticNet	F-test	GainRatio	LaplacianScore	Lasso	LOCO	MarkovBlanket	MI	mRMR	(R)ReliefF	Random	SEE	RFImportance	SFS
Hanson-John Hanson-John	1	.638 $\pm$.062	.711 $\pm$.025	.701 $\pm$.020	.703 $\pm$.021	.562 $\pm$.016	.702 $\pm$.025	.700 $\pm$.022	.688 $\pm$.029	.701 $\pm$.021	.683 $\pm$.025	.688 $\pm$.020	.591 $\pm$.018	.696 $\pm$.017	.663 $\pm$.038	.676 $\pm$.014
	2	.685 $\pm$.025	.716 $\pm$.023	.703 $\pm$.018	.702 $\pm$.020	.592 $\pm$.015	.717 $\pm$.024	.713 $\pm$.030	.688 $\pm$.020	.701 $\pm$.022	.710 $\pm$.012	.700 $\pm$.031	.652 $\pm$.018	.713 $\pm$.024	.699 $\pm$.019	.685 $\pm$.012
	3	.711 $\pm$.024	.716 $\pm$.024	.720 $\pm$.020	.710 $\pm$.025	.623 $\pm$.028	.720 $\pm$.026	.718 $\pm$.025	.709 $\pm$.025	.704 $\pm$.018	.718 $\pm$.022	.710 $\pm$.025	.682 $\pm$.022	.718 $\pm$.023	.711 $\pm$.024	.706 $\pm$.017
	4	.717 $\pm$.020	.714 $\pm$.022	.720 $\pm$.020	.711 $\pm$.024	.687 $\pm$.049	.713 $\pm$.027	.719 $\pm$.023	.711 $\pm$.025	.709 $\pm$.020	.703 $\pm$.030	.710 $\pm$.023	.716 $\pm$.028	.719 $\pm$.022	.720 $\pm$.025	.701 $\pm$.016
	5	.720 $\pm$.023	.718 $\pm$.021	.721 $\pm$.022	.721 $\pm$.022	.720 $\pm$.022	.718 $\pm$.023	.719 $\pm$.020	.717 $\pm$.023	.714 $\pm$.024	.716 $\pm$.024	.717 $\pm$.018	.684 $\pm$.046	.718 $\pm$.020	.720 $\pm$.022	.716 $\pm$.026