

Rethinking Projector Training in Multimodal LLMs

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Abstract

Multimodal LLMs are typically trained by first aligning a vision encoder with a language model via projector training on large image-caption datasets, followed by joint training of the full multimodal model. Despite its widespread use, the role of the projector training stage remains poorly understood. We find that (i) using only 10 to 20% of the data for training the projector already recovers most downstream performance gains, and (ii) projectors trained on different datasets can be linearly interpolated while largely preserving performance. These results suggest that projector training mainly performs a coarse alignment, which many different projectors achieve equally well. Motivated by these findings, we propose PORTAL, a training-free projector initialization that requires *neither paired image-caption data nor gradient-based optimization*, but only per-modality summary statistics. PORTAL computes an optimal-transport-based map between Gaussian approximations of the vision and language feature distributions on a shared principal subspace, so that the projector training stage can be skipped entirely. Without any paired data, PORTAL matches the standard pipeline trained on 558k image-caption pairs across six LLM backbones, two vision encoders, and 16 benchmarks. It outperforms that pipeline in 3 of 7 (vision encoder, LLM) settings and reaches an average 98% of its score across the other four.

1 Introduction

Modern multimodal LLMs commonly align a vision encoder with a language model by first training a projector on a large amount of image-caption paired samples, followed by joint training of the full multimodal model. This pipeline has become standard, from LLaVA [1, 2], Molmo [3], and InternVL [4] to the QwenVL series [5]. While the first stage of projector alignment has been motivated by the goal of producing a visual tokenizer compatible with the frozen LLM [1], what this stage *actually* does remains poorly understood. Prior works offer conflicting evidence: Prismatic [6] reports that skipping projector alignment can improve performance, whereas Cambrian-1 [7] shows that scaling the training data of projector alignment to 2.5M image-caption pairs helps. MM1 [8] suggests that factors like resolution and data mixing matter more than the projector design. These findings are difficult to reconcile without a deeper understanding of what projector alignment actually does.

In this work, we show that projector alignment primarily performs *coarse alignment*, mapping visual features into a language-model-compatible input space which admits a large set of possible solutions. Two empirical observations support this view: (i) using only 10 to 20% of the standard 558k-sample alignment corpus achieves similar performance to training on the full dataset, and (ii) projectors trained on entirely different datasets can be linearly interpolated without losing performance. If the projector alignment learned a precise and semantically unique mapping, neither reducing the training data nor linear interpolation between independently trained projectors would preserve performance.

Motivated by these observations, we propose PORTAL (**P**rojector via **O**ptimal-transpo**R**T **A**lignment), a training-free approach that constructs the projector from the marginal statistics

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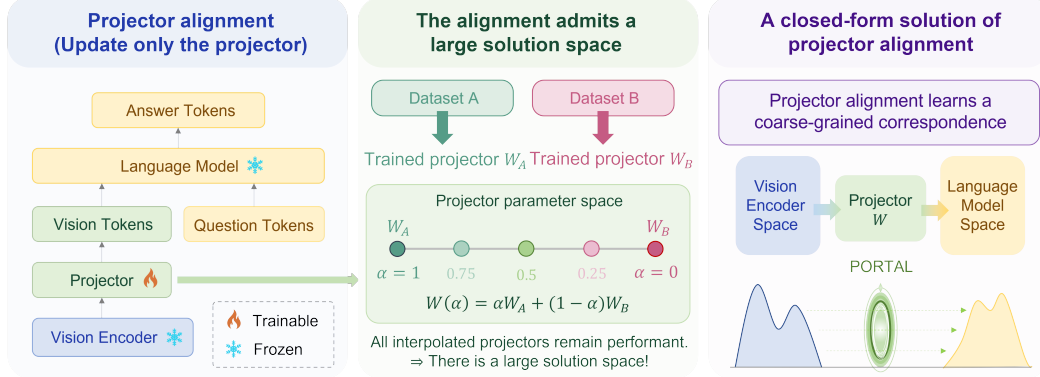


Figure 1: **Projector alignment as a coarse alignment with a broad solution space.** (Left) Standard pipeline: during projector alignment, the vision encoder and language model are frozen, and only the projector is trained to map visual tokens into a representation space compatible with the LLM using image-caption pairs. (Middle) We show that projectors trained on different image-caption datasets can be linearly interpolated while largely preserving downstream performance, indicating that there is a large solution space for the weights of the projector. (Right) This observation motivates a closed-form solution of projector alignment. We propose a training-free projector PORTAL constructed by optimal transport between the two modalities’ marginal statistics.

of the two modalities. PORTAL is the Bures-Wasserstein optimal transport map between Gaussian approximations of the vision feature distribution and the language-model input distribution, computed in a shared top- k principal subspace. It does not require *any paired captions or gradient-based optimization*, relying only on the per-modality means, principal directions, and the spread along each direction. PORTAL removes the projector alignment training stage entirely.

Across seven (vision encoder, LLM) pairs spanning four LLM families (Vicuna, LLaMA, Qwen, OLMo) from 0.5B to 8B parameters, and two vision encoders (CLIP, SigLIP), PORTAL matches the standard pipeline trained on 558k image-caption pairs and exceeds it in three out of seven settings, peaking at 106% of the trained baseline. When PORTAL is used to initialize rather than replace projector alignment, the performance of the baseline is reached with $135\times$ fewer alignment FLOPs. Performance gaps are concentrated on OCR-heavy benchmarks, where marginal statistics appear insufficient to capture fine-grained character-level spatial structure that paired supervision provides.

2 Related Work

Projector alignment in multimodal LLMs. Two-stage multimodal LLM training, where a vision encoder is first aligned to a frozen language model via training a projector, followed by visual instruction tuning, has become a standard pipeline for training multimodal LLMs. This pipeline was popularized by LLaVA [1, 2] and replicated in InstructBLIP [9], BLIP-2 [10], Flamingo [11], Molmo [3], InternVL [4], and the Qwen-VL series [5]. Despite its success, the role of Stage-I projector alignment has been poorly understood and prior studies offer conflicting views. Prismatic finds it can be skipped without a loss [6]. Cambrian-1 reports that scaling Stage-I data to 2.5M pairs helps [7]. MM1 emphasizes resolution and data mixing over the projector itself [8]. We resolve this disagreement by identifying what projector alignment actually does: Stage-I acts as *geometric conditioning of visual features into the LLM input distribution*, not as fine-grained semantic learning. This explains the three findings above as a single phenomenon: skipping Stage-I works when the projector already lands in a compatible region (Prismatic [6]), more data helps only until that region is reached (Cambrian-1 [7]), and the resolution and data mixing dominate because they affect the conditioning more than the projector capacity does (MM1 [8]). These findings lead us to propose a closed-form projector that requires neither paired data nor gradient updates.

Connector designs and projector geometry. Beyond the MLP used in LLaVA [1], connector architectures span the Q-Former [10], Perceiver Resampler [11], locality-enhanced abstractors [12], ALIGN [13], vision-expert mixtures [14], prefix-attention adapters [15], and pixel-shuffle or patch-merging schemes for token reduction [16, 5]. A complementary line of work analyzes what these

connectors actually do. Verma et al. [17] track how visual information degrades through LLM layers, Li et al. [18] probe information loss through learned projectors, Li et al. [19] report systematic norm discrepancies between visual and text tokens, and Shukor and Cord [20] show that cross-modal alignment emerges primarily after self-attention layers. We use the 2-layer MLP projector of LLaVA by default, and also test PORTAL with a linear projector and with the C-Abstractor [12], which has $19\times$ more parameters (Section 5.3).

Optimal transport for feature alignment. The Bures-Wasserstein optimal transport map between two Gaussians has a closed form on positive-definite covariances [21, 22], which the construction of the projector in our work exploits. Courty et al. [23] introduced OT for domain adaptation, and Alvarez-Melis and Jaakkola [24] used Gromov-Wasserstein to align word-embedding spaces with no paired anchors. Closest to PORTAL is CORAL [25, 26], which aligns second-order statistics with a single linear map for domain adaptation. PORTAL extends this idea to the multimodal-alignment setting and ties it explicitly to the Bures-Wasserstein optimum on a shared top- k principal subspace, which we then use as a closed-form projector rather than a regularizer.

Training-free and efficient connector construction. Several recent works try to eliminate or reduce connector training. VPGTrans [27] transfers a learned visual prompt generator across LLMs at reduced cost. LangBridge [28] interprets visual tokens as combinations of language embeddings, enabling cross-LLM transfer at the price of bottlenecking visual information through a vocabulary subspace. SEMI [29] meta-learns a hypernetwork connector that adapts to new modalities from a few samples. In the related CLIP-classification setting, training-free or lightweight adapters such as Tip-Adapter [30] and TaskRes [31] cache or residualize over a frozen backbone. PORTAL differs from all of the above by requiring neither paired data, gradient steps, learned caches, nor a vocabulary bottleneck: it is a closed-form construction from per-modality summary statistics alone. Gupta et al. [32] also learn without paired multimodal data, but to improve a unimodal representation by sharing parameters across unpaired modalities, whereas we ask whether the projector between a frozen vision encoder and a frozen LLM needs paired training at all.

3 What Does the Projector Alignment *Actually* Do?

3.1 Projector Alignment Saturates with a Small Number of Samples

To investigate the role of projector alignment, we first examine how downstream performance scales with the amount of Stage-I training data. If strong performance requires large-scale data, it would suggest the projector is learning fine-grained visual-language correspondences. Conversely, if a small fraction of the data is sufficient, this would indicate that the projector primarily learns a coarse-grained correspondence, placing visual features into a broadly compatible input space for the language model.

We conduct this analysis on the LLaVA 1.5 setup (CLIP ViT-L/14-336, Vicuna 1.5 7B, 2-layer MLP projector), with LCS-558k for Stage-I and LLaVA-665k for Stage-II. For the data-fraction experiment we replace Vicuna with MobileLLaMA 1.4B, which keeps 11 data fractions on two corpora tractable. We evaluate on 16 benchmarks grouped into four categories adapted from the Cambrian-1 [7] taxonomy: Knowledge (Know.), General (Gen.), OCR, and Vision-Centric (Vis.). Appendix C lists the benchmarks in each. Full experimental details are in Appendix C.1.

We observe that only 10 to 20% of the LCS-558k image-caption pairs already capture most of the downstream benefit, and all categories plateau by 30 to 40% (Figure 2). The marginal downstream benefit of the remaining pairs is small under this protocol. ShareGPT-1.2M, more than twice as large, does not do better: its average peaks at 38.1 with 40% of its data (Appendix D). These results suggest that projector alignment is not primarily learning fine-grained visual-language correspondences. Rather, it appears to perform a coarse-grained alignment step, mapping visual features into a region of the LLM input space from which subsequent joint training can effectively adapt the full multimodal model.

3.2 Projector Alignment Admits a Broad Solution Space

We have shown that projector alignment can be achieved with only a small fraction of the standard pretraining data. This observation is consistent with two possible explanations: either the set of effective projector solutions is narrow but easy to reach, or the solution space itself is broad. To

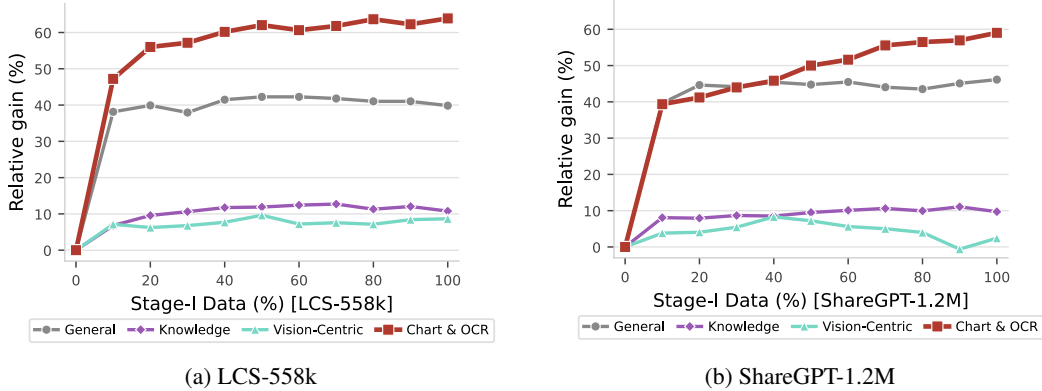


Figure 2: **Stage-I gain saturates early.** Relative gain in downstream performance over the no-pretraining baseline by Cambrian-1 category, as a function of Stage-I data fraction on LCS-558k (left) and ShareGPT-1.2M (right). OCR and Chart benefit the most, while Knowledge and Vision-Centric scores saturate early.

distinguish between these possibilities, we examine whether independently trained projectors can be linearly interpolated while preserving performance.

Specifically, we train two projectors on different datasets (LCS-558k versus ShareGPT-1.2M), obtaining the weights W_{LCS} and W_{ShareGPT} . Then we evaluate the linear interpolation $W_{\alpha} = (1-\alpha)W_{\text{LCS}} + \alpha W_{\text{ShareGPT}}$ with $\alpha \in \{0, 0.25, 0.5, 0.75, 1\}$. If effective projectors occupied a narrow and isolated region, interpolation would be expected to degrade performance. Instead, we find that projectors along the entire interpolation path largely preserve downstream performance, supporting the view that projector alignment admits a broad solution space (Figure 3).

	Know.	Gen.	OCR	Vis.	All
LCS ($\alpha = 0$)	45.7	68.0	27.1	51.3	48.0
$\alpha = 0.25$	46.2	68.5	27.6	52.5	48.7
$\alpha = 0.50$	46.2	68.4	28.1	53.0	49.0
$\alpha = 0.75$	45.6	67.5	28.4	54.0	48.9
SGPT ($\alpha = 1$)	45.4	67.9	28.2	53.8	48.8

Figure 3: **Cross-data projectors are linearly interpolable.** Cross-data interpolation $W_{\alpha} = (1-\alpha)W_{\text{LCS}} + \alpha W_{\text{ShareGPT}}$, evaluated per Cambrian-1 category. The optimal α varies by category, but *every* interior blend outperforms both endpoints on the aggregate score, with the $\alpha=0.5$ mixture peaking above either trained projector.

The per-category breakdown results further support this interpretation. The cross-data interpolation path is not only traversable but often outperforms either endpoint. Averaged across the four Cambrian-1 categories, every interior α improves on both LCS-558k and ShareGPT-1.2M projectors, with the optimum at $\alpha=0.5$. The category-wise optima differ: OCR peaks closer to the ShareGPT endpoint, Knowledge closer to the LCS endpoint. The aggregate score improves with mixing, so a simple combination of two independently trained solutions, with no additional Stage-I optimization, outperforms both. Such behavior indicates that projector alignment admits a broad solution space.

The two projectors above start from the same initialization and differ only in their training data. We next asked whether the initialization matters in the same way, and trained a second pair on the same LCS-558k data from two different random initializations. Unlike the cross-data pair, this cross-seed pair is not linearly interpolable: captioning CIDEr drops from about 80 at both endpoints to 0.7 at $\alpha=0.5$ (Appendix C.2). Initialization thus appears to select the loss basin, and training data the solution within it.

These results clarify the role of projector alignment. The early saturation with limited data and the traversable interpolation path between projectors trained on different data suggest that projector alignment does not require a highly specific solution. Instead, projector alignment appears to place visual features into a broadly compatible region of the LLM input space, where many different projector weights can serve the same functional role.

4 PORTAL: Training-Free Projector via Optimal Transport

The previous findings suggest that projector alignment primarily serves as geometric conditioning, placing visual features into a region of the LLM input space from which subsequent joint training can effectively adapt the multimodal model. This mapping admits a large set of solutions, motivating a simpler alternative to the projector alignment training stage.

We instantiate this idea with PORTAL (**P**rojector via **O**ptimal-transpo**RT** **A**lignment), a training-free method that initializes the projector from the marginal feature statistics of the vision encoder and the LLM. PORTAL estimates the mean, principal directions, and variances of each modality separately, then constructs a closed-form optimal-transport map that aligns the source visual feature distribution with a compatible target language-feature distribution. We also show why matching only means and covariances can suffice. The LLM normalizes each token before attention, so attention depends only on token directions. When token norms vary little, the spread of these directions is fixed by the covariance, which PORTAL matches.

4.1 Closed-Form Projector Initialization

Let $\mathbf{x} \in \mathbb{R}^{d_s}$ denote a feature from the source modality (*e.g.*, a per-patch vision token in our setting) and $\mathbf{y} \in \mathbb{R}^{d_t}$ a target embedding (*e.g.*, an LLM input token). We seek a map $f : \mathbb{R}^{d_s} \rightarrow \mathbb{R}^{d_t}$, the *projector* in standard multimodal-LLM terminology, whose output distribution is compatible with the distribution the target is trained to process. We adopt the standard 2-layer MLP used by LLaVA [2],

$$f(\mathbf{x}) = \mathbf{W}_2 \phi(\mathbf{W}_1 \mathbf{x} + \mathbf{b}_1) + \mathbf{b}_2, \quad \mathbf{W}_1 \in \mathbb{R}^{d_t \times d_s}, \quad \mathbf{W}_2 \in \mathbb{R}^{d_t \times d_t}, \quad (1)$$

with ϕ as GELU. We will fix $\mathbf{W}_2 = \mathbf{I}_{d_t}$ (*i.e.*, the identity matrix of dimension d_t), $\mathbf{b}_2 = \mathbf{0}$ (*i.e.*, the zero vector of dimension d_t), and construct $(\mathbf{W}_1, \mathbf{b}_1)$ in closed form.

PORTAL. Approximate each modality’s marginal as a Gaussian, $\mathcal{N}(\boldsymbol{\mu}_s, \boldsymbol{\Sigma}_s)$ on the source side and $\mathcal{N}(\boldsymbol{\mu}_t, \boldsymbol{\Sigma}_t)$ on the target side. We derive the affine parameters $(\mathbf{W}_1, \mathbf{b}_1)$ from the Gaussian optimal transport map [33, 21] between these approximations, computed on the top- k PCA subspaces of source and target with coordinates identified by eigenvalue order:

$$\mathbf{W}_1 = \mathbf{V}_t \text{diag} \left(\frac{\boldsymbol{\sigma}_t}{\boldsymbol{\sigma}_s} \right) \mathbf{V}_s^\top, \quad \mathbf{b}_1 = \boldsymbol{\mu}_t - \mathbf{W}_1 \boldsymbol{\mu}_s, \quad (2)$$

where $\mathbf{V}_s \in \mathbb{R}^{d_s \times k}$ and $\mathbf{V}_t \in \mathbb{R}^{d_t \times k}$ are the top- k PCA bases of the source and target features (orthonormal columns) and $\boldsymbol{\sigma}_s, \boldsymbol{\sigma}_t \in \mathbb{R}^k$ are the square roots of the top- k covariance eigenvalues, *i.e.*, the spread along each principal axis. The map $\mathbf{W}_1$ whitens the source distribution (decorrelates it and rescales each axis to unit variance), expresses it in the target’s principal axes, and rescales each axis to match the target’s spread. The bias $\mathbf{b}_1$ recenters the result. The closed form matches Gaussian moments at the preactivation $\mathbf{W}_1 \mathbf{x} + \mathbf{b}_1$. The post-GELU output is verified empirically in Appendix H.4. Appendix F gives a self-contained PyTorch implementation.

This construction depends only on summary statistics of each modality (*i.e.*, means, principal directions, and the spread along each direction). It requires no Stage-I paired captions and no Stage-I optimization. A single PCA on each side is sufficient. It is agnostic to which model produces $\mathbf{x}$ and which model consumes $f(\mathbf{x})$. We adopt $k=512$ as the default throughout the paper, which is small enough to suppress noisy directions and large enough to preserve the dominant geometry. Varying k over $\{64, 128, 256, 512, 1024\}$ supports this choice empirically (Appendix K).

On the Gaussian assumption. Eq. (2) treats both modalities as Gaussian to obtain a closed-form transport map in terms of means, principal directions, and the spread along each direction. Real source and target distributions deviate from Gaussianity in tail weight and in the shape of their marginals (Appendix H.1). We explain why the construction remains effective under these deviations in Section 4.2.

Targeting hidden states instead of input embeddings. Eq. (2) matches visual features to the LLM’s input embeddings, the vectors the LLM looks up for each text token before its first transformer block. The same construction can instead target the hidden states that text tokens have after block ℓ : we replace $(\boldsymbol{\mu}_t, \mathbf{V}_t, \boldsymbol{\sigma}_t)$ by the mean, PCA basis, and spread along the principal axes of these hidden states, collected by passing a list of English words and short phrases through the LLM. The visual tokens still enter the LLM at its input. Only the target statistics change. Trained projectors that inject

visual tokens into deeper layers [34, 35] motivate this variant, which we call PORTAL-ctx ℓ . We use it to ablate the target layer (Section 5.4), where the input embeddings ($\ell=0$) remain the best target. Details are in Appendix G.

4.2 Why Moment Matching Survives Non-Gaussianity

Real vision and text features are not Gaussian (Appendix H.1), so Eq. (2) cannot match their full distributions. We argue that it does not need to. Every LLM we use normalizes before computing attention logits (RMSNorm on each input token, or on queries and keys in OLMo 2), so rescaling a token leaves its logits unchanged. Attention therefore depends only on the directions of the tokens, and the relevant property of the projector output is how these directions are spread.

We measure this spread by the *cosine dispersion* ω , the standard deviation of the cosine similarity between two tokens:

$$\omega^2 = \frac{1}{\binom{n}{2}} \sum_{i < j} (\cos \angle(\mathbf{z}_i, \mathbf{z}_j) - \overline{\cos})^2, \quad \overline{\cos} = \frac{1}{\binom{n}{2}} \sum_{i < j} \cos \angle(\mathbf{z}_i, \mathbf{z}_j), \quad (3)$$

where $\{\mathbf{z}_i\}_{i=1}^n$ are the output tokens, pooled over all patches of all images. A small ω means the tokens point in similar directions, a large ω that they spread over many directions. Two properties of a distribution with covariance Σ determine ω . The *effective dimension* $d_{\text{eff}}(\Sigma) := (\text{tr } \Sigma)^2 / \text{tr}(\Sigma^2)$ counts the directions that carry most of the variance: it equals d when variance is spread evenly over d directions and 1 when a single direction holds it all. The *norm spread* $\kappa := \text{std}(\|\mathbf{z}\|^2) / \mathbb{E}[\|\mathbf{z}\|^2]$ is small when all tokens have about the same length.

Proposition 1 (Spectrum-to- ω bound). *Let $\mathbf{z}$ and $\mathbf{z}'$ be independent random vectors in $\mathbb{R}^d$ with the same distribution, which has mean zero and covariance Σ . Assume $\mathbb{P}(\mathbf{z} = \mathbf{0}) = 0$. Then*

$$\left| \text{Var}(\cos \angle(\mathbf{z}, \mathbf{z}')) - \frac{1}{d_{\text{eff}}(\Sigma)} \right| \leq 2\kappa + \kappa^2 + \kappa^4. \quad (4)$$

The assumption $\mathbb{P}(\mathbf{z} = \mathbf{0}) = 0$ says that a token is never exactly the zero vector, so that its cosine with another token is always defined. The left side of Eq. (4) is the variance of the cosine similarity between two tokens drawn at random from the distribution, which is the population value of ω^2 that Eq. (3) estimates from n tokens. The right side is zero when all tokens have the same length ($\kappa = 0$), and the proposition then gives $\omega^2 = 1/d_{\text{eff}}(\Sigma)$: the spread of token directions is fixed by the covariance alone. Intuitively, when all tokens have the same length, the cosine of two tokens is their dot product divided by a constant, and the second moment of the dot product of two independent tokens depends only on the covariance. The proof is in Appendix H.2 and does not assume Gaussianity. PORTAL matches the target’s mean and covariance on the top- k subspace (second-order matching, *i.e.*, matching the means and covariances of the two distributions), so in this limit its outputs inherit the target’s ω .

Real token norms vary (Appendix H.4), so the bound does not predict ω precisely for our features. We therefore measure ω directly. On three (CLIP, LLM) pairs, PORTAL reduces ω from 0.23 at the source to 0.09 to 0.10, towards the target’s 0.05 to 0.06, while a random projector leaves ω at the source value (Appendix H.3). The attention weights also depend on the learned query and key projections, which ω does not describe.

5 Experiments

We test whether PORTAL, built without any paired image-caption data, matches projector alignment trained on 558k image-caption pairs across LLM backbones and vision encoders.

We evaluate this question by inserting a PORTAL-constructed projector into the standard LLaVA pipeline and then running the same LLaVA-665k instruction tuning for every configuration. We compare against two baselines: (i) the standard trained LLaVA projector, obtained from 558k paired captions, and (ii) a randomly initialized projector which skips projector alignment entirely. This setup isolates the contribution of projector initialization: after initialization, all models receive identical joint training.

We test seven (vision encoder, LLM) pairs, built from three 7B to 8B LLMs (Vicuna 1.5 7B [36], LLaMA 3.1 8B [37], Qwen 2.5 7B [38]), three smaller LLMs for cross-scale checks (LLaMA 3.2 1B,

Table 1: **PORTAL generalizes across LLM backbones and vision encoders.** All configurations use identical Stage-II instruction tuning (LLaVA-665k [2]). PORTAL requires zero Stage-I paired captions and zero Stage-I gradient steps. Baseline †: uses 558k paired captions for Stage-I pretraining. **Bold**: best among zero training data methods. **Avg**: unweighted mean of the 16 per-benchmark scores. %BL: this average as a percentage of the trained baseline (BL), which is therefore 100%. Subscripts on the Avg and %BL columns give the 95% bootstrap confidence-interval half-width over per-sample outcomes, from 1000 resamples paired across methods. LLM backbones: Vicuna 1.5 7B [36], LLaMA 3.1 8B [37], Qwen 2.5 7B [38], LLaMA 3.2 1B [37], Qwen 2.5 0.5B [38], OLMo 2 1B [39]. Vision encoders: CLIP ViT-L/14-336 [40], SigLIP SO400M [41]. ^L: 500-sample Lite subset from `lmms-eval` [42].

LLM	Scale	Vision	Init	Knowledge				General				OCR				Vision				Avg	%BL
				Al2D	SciQA	MathV	MMMU	CoQA	MME	SEED+	MMB	TaVQA	OCR-B ₂	DocVQA	ChartQA	CV2D	CV3D	BLINK	RealWQ		
Vicuna 1.5	7B	CLIP	Baseline†	54.5	67.9	26.1	34.3	66.6	74.5	67.7	63.2	57.3	12.5	22.0	16.5	54.7	58.3	37.4	54.9	48.0	100.0
			Random	51.5	69.1	27.2	32.8	64.2	69.2	57.2	58.1	52.8	11.0	17.1	15.2	52.5	53.8	34.7	51.9	44.9 _{±0.60}	93.5 _{±1.6}
			PORTAL	53.4	68.2	27.4	34.4	66.4	69.9	67.9	60.4	55.1	12.7	20.5	16.3	56.2	60.7	36.0	53.5	47.4_{±0.56}	98.8_{±1.5}
		SigLIP	Baseline†	55.8	68.0	27.2	34.0	68.7	73.6	69.1	66.0	61.5	13.3	25.3	19.1	57.5	60.8	28.1	56.6	49.0	100.0
			Random	51.8	67.9	26.7	35.1	56.8	60.6	46.5	52.3	43.8	7.9	8.9	12.8	47.1	57.5	25.6	45.9	40.5 _{±0.58}	82.5 _{±1.1}
			PORTAL	55.5	68.3	27.9	34.4	67.8	71.6	68.3	64.3	60.0	13.6	24.8	17.9	57.6	64.6	28.6	54.2	48.7_{±0.56}	99.3_{±1.5}
LLaMA 3.1	8B	CLIP	Baseline†	58.5	73.8	31.3	36.8	67.0	73.0	71.7	68.1	57.2	13.7	21.8	15.1	64.5	63.0	39.8	57.5	50.8	100.0
			Random	58.6	74.8	31.7	35.3	67.6	73.4	69.5	67.5	56.2	13.9	19.6	15.0	61.8	66.2	38.5	57.0	50.4 _{±0.58}	99.2 _{±1.4}
			PORTAL	62.2	76.2	30.7	38.6	67.7	74.1	69.9	70.1	58.0	14.5	22.7	16.8	65.2	70.9	40.4	56.9	52.2_{±0.57}	102.7_{±1.5}
LLaMA 3.2	1B	CLIP	Baseline†	46.5	66.2	26.9	33.6	59.7	58.4	56.2	46.1	43.7	10.1	12.8	10.8	53.5	56.4	37.2	47.3	41.6	100.0
			Random	46.6	66.9	26.3	34.2	59.8	58.1	56.0	45.2	43.8	10.4	12.8	11.0	54.2	54.9	37.4	46.9	41.5 _{±0.57}	99.9 _{±0.7}
			PORTAL	47.6	67.1	29.2	33.7	62.1	66.0	59.6	54.2	47.1	11.4	16.3	12.0	54.6	57.3	38.9	49.7	44.2_{±0.60}	106.2_{±1.3}
Qwen 2.5	7B	CLIP	Baseline†	66.9	77.5	33.3	44.7	65.6	74.6	70.7	71.2	57.2	15.6	23.0	19.0	54.0	69.0	42.3	56.6	52.6	100.0
			Random	62.1	73.9	27.7	42.0	63.7	70.9	67.7	60.1	51.0	13.6	17.6	14.6	56.3	60.0	42.1	53.9	48.6 _{±0.56}	92.4 _{±0.9}
			PORTAL	65.7	76.7	31.9	44.8	65.5	75.9	70.9	68.0	55.4	14.9	18.9	17.1	57.9	64.8	41.5	56.1	51.7_{±0.58}	98.3_{±1.4}
Qwen 2.5	0.5B	CLIP	Baseline†	43.6	58.6	26.7	31.7	52.2	53.9	47.9	38.7	35.7	11.1	9.4	9.7	45.7	50.7	39.4	46.0	37.6	100.0
			Random	43.5	58.5	26.8	33.1	52.5	54.2	48.9	37.9	35.6	10.5	9.5	9.8	44.2	51.5	40.5	45.5	37.7 _{±0.58}	100.2 _{±1.0}
			PORTAL	44.2	59.1	27.4	31.3	58.1	57.6	56.0	46.4	41.8	11.8	14.6	11.6	41.4	51.2	39.7	45.6	39.9_{±0.56}	106.1_{±1.3}
OLMo 2	1B	CLIP	Baseline†	46.9	64.3	25.0	33.9	62.7	63.1	63.2	57.6	46.3	10.5	17.2	12.2	57.3	54.8	37.6	48.1	43.8	100.0
			Random	45.7	58.8	24.6	31.2	59.4	59.5	59.8	49.4	42.4	9.7	13.6	11.0	50.2	50.9	37.5	43.9	40.5 _{±0.57}	92.8 _{±1.0}
			PORTAL	47.2	61.8	26.8	31.2	61.8	61.8	60.2	51.5	44.2	9.8	15.0	11.1	54.8	55.3	36.2	46.3	42.2_{±0.59}	96.3_{±1.0}

Qwen 2.5 0.5B, OLMo 2 1B [39]), and two vision encoders (CLIP ViT-L/14-336 [40], SigLIP-SO400M [41]). Table 1 lists the pairs. The trained baseline uses the standard LLaVA Stage-I corpus of 558k LCS image-caption pairs, and all configurations share the same LLaVA-665k instruction-tuning data for Stage-II. The 16 evaluation benchmarks are grouped into the four Cambrian-1 categories. The full benchmark list, citations, and evaluation protocol are in Appendix C.

5.1 PORTAL Matches Trained Projector Alignment Without Paired Data

We find that our closed-form projector PORTAL requiring *no paired captions or gradient updates* achieves comparable downstream performance to conventional alignment pipelines trained on 558k image-caption pairs, across a range of vision encoder and LLM combinations (Table 1). In particular, using LLaMA 3.2 1B/CLIP and Qwen 2.5 0.5B/CLIP, PORTAL reaches **106.2%** and **106.1%** of the trained baseline, respectively. Using LLaMA 3.1 8B/CLIP, it exceeds the trained baseline, reaching **102.7%**. On Vicuna 1.5 with CLIP and SigLIP, Qwen 2.5 7B, and OLMo 2 1B, PORTAL remains very close to the trained projector, reaching 98.8%, 99.3%, 98.3%, and 96.3% of the trained baseline, respectively. Thus, PORTAL removes the requirement for paired training data and optimization cost of projector alignment while preserving almost all of its downstream benefit after instruction tuning.

The advantage of PORTAL is clearest where the random projector fails. On SigLIP, the Random baseline collapses to **82.5%** of the trained projector. PORTAL closes that gap to **99.3%**. This is what we would expect if the alignment stage were dominated by distributional matching rather than caption supervision.

Two settings sit below the trained baseline’s bootstrap CI, Qwen 2.5 7B/CLIP and OLMo 2 1B/CLIP, with the gaps concentrated on OCR and Chart benchmarks. This matches the observation in Section 3.1 that OCR and Chart drive most of the Stage-I gain over the no-pretraining baseline, supporting our reading that character-level spatial structure is the regime where paired captions teach what marginal statistics alone cannot recover. Importantly, this phenomenon is not specific to PORTAL. Other unpaired distribution-matching approaches, including CORAL [26] and Gromov-Wasserstein [24] alignment, also recover most of the performance of paired Stage-I training (Appendix E.1). This

provides additional evidence that much of the benefit of Stage-I can be obtained by bringing the two modalities into a compatible feature distribution, rather than requiring a uniquely learned image-text correspondence.

A category-level analysis across all seven configurations further shows that this behavior is not systematic across OCR tasks: PORTAL retains, on average, 100.7%, 102.0%, 102.4%, and 100.4% of the trained-baseline performance on Knowledge, General, OCR, and Vision-Centric tasks, respectively (Appendix E.2). We further test PORTAL beyond the standard LLaVA-665k Stage-II setting. Under substantially larger-scale multimodal instruction tuning with 3.2M samples, PORTAL slightly outperforms the conventionally Stage-I-trained initialization (Appendix E.3). We also evaluate object hallucination on POPE [43] and find that PORTAL matches or exceeds the trained Stage-I baseline in every setting (Appendix E.4).

5.2 PORTAL Reduces the Projector Alignment Budget

The previous experiment shows that PORTAL can provide a strong projector without paired optimization. We next ask whether PORTAL can also serve as a warm start for projector alignment. Instead of using PORTAL to skip this stage entirely, we initialize the projector with PORTAL and then continue projector alignment with progressively smaller subsets of LCS-558k. This experiment evaluates whether closed-form alignment can reduce the amount of paired data needed for subsequent projector training.

We vary the projector alignment budget over $\{0, 1k, 10k, 100k, 558k\}$ paired captions from LCS-558k on Vicuna 1.5 7B/CLIP, starting from either a Random or a PORTAL projector. The 0 point skips projector alignment entirely and proceeds directly to Stage-II from the initialization, and the 558k point is the standard LLaVA baseline. Stage-II tuning on LLaVA-665k is identical for every configuration.

PORTAL provides a better starting point at every projector alignment budget than the random initialization (Figure 4). With zero projector training, it already outperforms random initialization. As more paired captions are added, the PORTAL-initialized projector remains consistently above the randomly initialized projector. PORTAL reaches the performance of the full 558k trained projector baseline using only around 4k captions, corresponding to roughly $135\times$ fewer projector alignment FLOPs. Beyond matching the trained baseline at lower compute, PORTAL with as few as 10k paired captions exceeds the full 558k-trained projector baseline and continues to widen the gap up to 100k. PORTAL therefore offers two practical advantages: it reaches the trained baseline at substantially lower alignment cost, and it surpasses that baseline once even a small paired-data budget is available.

This result strengthens the main claim that much of projector alignment is a distributional conditioning problem. The projector has a large solution space, and many mappings can make visual features compatible with the LLM input space. PORTAL identifies one such compatible solution directly in closed form. This solution is not necessarily the exact optimum selected by supervised projector training but it lies close to the high-performing region, providing strong performance without paired optimization and a small amount of paired data can further refine it within this region. Additional projector training thus mainly refines a projector that is already compatible.

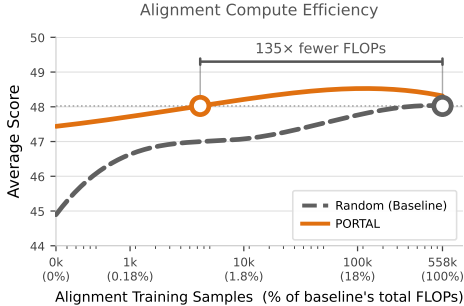


Figure 4: **Alignment compute efficiency** on Vicuna 1.5 7B/CLIP. Average over the 16 benchmarks as a function of the projector alignment budget, with identical Stage-II tuning on LLaVA-665k. PORTAL stays above Random at every budget. The marked point indicates the crossover at roughly 4k captions, where PORTAL matches the 558k-trained baseline at $\sim 135\times$ fewer alignment FLOPs. The horizontal dashed line shows the 558k baseline.

5.3 Ablations: Projector Architecture, Image Pool, and Rank

A key advantage of PORTAL is that it is a closed-form geometric construction rather than a learned projector tied to a particular architecture or paired dataset. We therefore test whether its gains persist when the projector is simplified and when the unlabeled image pool used to estimate vision-side statistics is changed.

For architecture, we replace the standard 2-layer MLP-GELU projector with a single linear layer, keeping all other components fixed (Table 2). If PORTAL’s gains depended on the expressivity of the MLP, they should weaken in this setting. Instead, the gain becomes larger. With the MLP projector, PORTAL reaches **106.2%** of the trained baseline against Random’s 99.9%. With the linear projector, it reaches **111.8%** against Random’s 94.2%, widening the Random-to-PORTAL gap from 6.3 to 17.6 percentage points. This shows that PORTAL’s advantage does not come from a particular nonlinearity or hidden expansion. It comes from placing the visual features into a better-matched LLM input distribution. We also test the opposite regime by substantially increasing connector capacity. Using the C-Abstractor [12], which contains approximately $19\times$ more parameters than the two-layer MLP and additionally performs token mixing and sequence compression, PORTAL remains essentially indistinguishable from conventional Stage-I training (42.93 vs. 42.98 average score; Appendix E.5).

For the image pool, we vary the unlabeled image pool used to estimate the vision-side statistics. On LLaMA 3.2 1B/CLIP, we compare a small single-domain pool, COCO val2017 with 1024 images, against a larger and more diverse Cambrian-737k subset spanning 9 sources with 4096 images. The small COCO pool matches or exceeds the diversified pool on 12 of 15 benchmarks and obtains a higher average score (**44.0** vs. 43.4). This suggests that PORTAL does not require a carefully curated or highly diverse image pool. A small unlabeled natural-image pool is sufficient to estimate the source statistics well enough for downstream instruction tuning in this setting. Per-benchmark results are reported in Appendix I.

Additionally, the PORTAL construction depends on a rank k used to define the PCA subspace. We vary k over $\{64, 128, 256, 512, 1024\}$ on LLaMA 3.2 1B/CLIP, constructing each projector from the same 1024 COCO images and running identical Stage-II tuning. The method is robust to this choice (Appendix K): every k outperforms the trained baseline by at least $\sim 4\%$. Performance is flat from $k=64$ to $k=256$ (~ 43.3 Avg), peaks at $k=512$ (44.2), and decreases marginally at $k=1024$ (44.0). The plateau at low ranks indicates that the dominant PCA directions already capture most of the cross-modal structure. The small drop at $k=1024$ is consistent with noisy eigenvectors diluting the transport map. We adopt $k=512$ as the default.

5.4 Target Layer Choice

PORTAL targets the LLM’s input embedding distribution by default. The PORTAL-ctx ℓ variant (Section 4) generalizes the construction to deeper targets, matching visual features to hidden states after LLM block ℓ instead. We use this variant to ablate the choice of target layer.

Targeting the embedding table ($\ell = 0$) is the strongest choice on LLaMA 3.1 8B/CLIP, reaching **102.3%** of the trained projector alignment baseline (Table 3). Contextualized targets at $\ell = 4$ and $\ell = 8$ remain close, reaching 101.9% and 101.4%, respectively. We therefore use the embedding table as the default target.

Table 2: **Linear vs. MLP-2x-GELU projector** on LLaMA 3.2 1B/CLIP. Full per-benchmark breakdown in Appendix J.

Projector	Init	Avg	%BL
MLP	Trained [†]	41.6	100.0
	Random	41.5	99.9
	PORTAL	44.2	106.2
Linear	Trained [†]	39.9	100.0
	Random	37.6	94.2
	PORTAL	44.7	111.8

Table 3: **Layer ablation for PORTAL-ctx** on LLaMA 3.1 8B/CLIP. Avg over the 16-benchmark suite, %BL relative to trained Stage-I.

Target	Avg	%BL
Trained [†]	51.3	100.0
Random	51.4	100.2
$\ell=0$ (embed)	52.5	102.3
$\ell=4$	52.3	101.9
$\ell=8$	52.0	101.4

6 Conclusion

This work rethinks projector alignment in multimodal LLMs. Our results suggest that this stage primarily performs coarse alignment, mapping visual features into a language-model-compatible input space rather than learning fine-grained visual-language correspondences. This view is supported by the early saturation of alignment data, where 10 to 20% of LCS-558k recovers most downstream gains, and by the linear interpolability of projectors trained on different datasets from a shared initialization.

Motivated by this finding, we introduced PORTAL, a training-free projector initialization. PORTAL uses only per-modality summary statistics, requires no paired image-caption data or gradient-based optimization, and remains close to the 558k-trained baseline across the evaluated model pairs. As an initialization, it reaches the trained baseline with roughly $135\times$ lower alignment compute. These results suggest that projector alignment can often be replaced by, or reduced to, a lightweight feature-distribution matching step, lowering the cost and paired-data requirements for building multimodal LLMs.

Several natural directions remain for future work. Our study focuses on projector alignment with frozen vision and language backbones during alignment, single-image inputs, and simple projector architectures. Extending the analysis to richer connectors, long-context grounding, multi-image reasoning, and additional modalities such as audio, video, and 3D would further clarify how broadly this coarse-alignment view applies. We discuss other limitations of PORTAL in Appendix A.

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A Limitations

Our analysis and method address a specific slice of the multimodal-LLM pipeline: Stage-I projector alignment with frozen vision and language backbones. Several caveats follow from that scope. *(i)* The empirical analysis in Section 3 runs on the LLaVA 1.5 architecture with a 2-layer MLP projector. Richer connectors (resamplers, perceiver-style cross-attention, multi-stage abstractors) may not exhibit the same linear interpolability, and we do not test them here. *(ii)* PORTAL is constructed from a Gaussian approximation of each modality. The approximation captures means, principal directions, and per-axis spread, but no higher-order structure. Appendix H.1 quantifies how far real source and target distributions deviate from this assumption. We hypothesize that the residual gap on OCR and Chart benchmarks reflects this missing higher-order structure (character-level spatial layout). *(iii)* As in LLaVA-1.5, all experiments keep the vision encoder frozen and train only the projector and the LLM in Stage-II. We do not study end-to-end fine-tuning that also updates the vision encoder. *(iv)* Our 16-benchmark suite follows the Cambrian-1 grouping and inherits its biases. It does not stress long-context grounding or multi-image reasoning, which may behave differently. *(v)* We instantiate PORTAL for vision-to-language alignment. We have not tested it on audio or video encoders. The present results should be regarded as a first existence proof rather than a finished construction. *(vi)* Our reading of Stage-I as geometric conditioning is the simplest hypothesis consistent with our data. We do not claim it is the unique mechanism, and other interpretations remain possible. *(vii)* The closed-form construction exceeds trained Stage-I or stays within 1.6 average points of it across the configurations we test. We make no broader claim that this holds across all multimodal-LLM regimes. Richer benchmarks or backbones may reveal regimes where trained Stage-I genuinely outperforms PORTAL.

B Training Details and Compute Resources

All experiments follow the standard two-stage LLaVA-1.5 [2] training recipe. Training is performed on $8\times$ NVIDIA A100 80 GB GPUs with DeepSpeed ZeRO-2 and bf16 mixed precision.

Hyperparameters. Table 4 summarizes the training configuration for both stages. All runs use the AdamW optimizer with $(\beta_1, \beta_2) = (0.9, 0.999)$ and no gradient clipping.

Table 4: **Training hyperparameters.** Identical to LLaVA-1.5.

	Stage I (Pretrain)	Stage II (Finetune)
Learning rate	1×10^{-3}	2×10^{-5}
Schedule	Cosine	Cosine
Warmup	200 steps	3% ratio
Weight decay	5×10^{-2}	0
Per-device batch size	32	4
Gradient accumulation	1	4
Effective batch size	256	128
Epochs	1	1
Trainable parameters	Projector only	Projector + LLM

Compute budget. Each Stage-I run completes in under one hour for MobileLLaMA 1.4B and in under four hours for Vicuna 7B on $8\times$ A100 GPUs. Stage-II instruction tuning takes between two and ten hours depending on model scale (2.4 h for Qwen 0.5B, 5.4 h for LLaMA 8B, 10 h for Qwen 7B). The cost of constructing a PORTAL projector is negligible: the closed-form solution requires only forward passes on approximately 1,024 images and completes in under 30 seconds on a single RTX 3090.

Seeds. The cross-seed analysis in Section 3.2 compares two Stage-I projectors trained with seeds 42 and 120 on the same LCS-558k data. All other experiments use seed 42. Bootstrap confidence intervals are computed from $B=1,000$ resamples paired across methods within each (encoder, LLM) group.

Datasets and licenses. Table 5 lists the datasets used in our experiments.

C Evaluation Setup: Benchmarks and Protocol

All models are evaluated on 16 benchmarks grouped into four categories adapted from the Cambrian-1 [7] taxonomy (Knowledge, General, OCR, Vision), summarized in Table 6. Relative to the original Cambrian-1 suite, we replace OCRBench with OCRBench-v2 [55] and MMVP with BLINK [58]. All evaluations are performed using `lmms-eval` v0.4.1 [42].

Table 5: **Datasets used in our experiments.**

Dataset	Used for	License	Source
<i>Training data</i>			
LCS-558k	Stage-I pretrain	CC-BY-4.0	[2]
ShareGPT-1.2M	Stage-I pretrain	CC-BY-NC-4.0	[44]
LLaVA-665k	Stage-II finetune	CC-BY-4.0	[2]
Cambrian-737k	PORTAL image pool	Apache-2.0	[7]
COCO val2017	PORTAL image pool	CC-BY-4.0	[45]
<i>Knowledge benchmarks</i>			
AI2D	Evaluation	CC-BY-SA-4.0	[46]
ScienceQA	Evaluation	CC-BY-NC-SA-4.0	[47]
MathVista	Evaluation	CC-BY-SA-4.0	[48]
MMMU	Evaluation	Apache-2.0	[49]
<i>General benchmarks</i>			
GQA	Evaluation	CC-BY-4.0	[50]
MME	Evaluation	Research only	[51]
SeedBench	Evaluation	Apache-2.0	[52]
MMBench	Evaluation	CC-BY-4.0	[53]
<i>OCR & Chart benchmarks</i>			
TextVQA	Evaluation	CC-BY-4.0	[54]
OCRBench-v2	Evaluation	CC-BY-NC-4.0	[55]
DocVQA	Evaluation	Apache-2.0	[56]
ChartQA	Evaluation	GPL-3.0	[57]
<i>Vision-Centric benchmarks</i>			
CV-Bench	Evaluation	Apache-2.0	[7]
BLINK	Evaluation	Apache-2.0	[58]
RealWorldQA	Evaluation	CC-BY-ND-4.0	[59]

Table 6: **Evaluation benchmarks grouped by Cambrian-1 category.** ^L = Lite subset (500 samples).

Category	Benchmark	Samples	Metric
Knowledge	AI2D [46]	3,088	Exact match
	ScienceQA [47]	2,017	Exact match
	MathVista [48]	1,000	LLM-as-judge
	MMMU [49]	900	Accuracy
General	GQA [50]	12,578	Exact match
	MME [51]	2,374	Perception / 20
	SeedBench ^L [52]	500	Accuracy (image)
	MMBench [53]	4,329	GPT-eval score
OCR	TextVQA [54]	5,000	Exact match
	OCRBench-v2 [55]	1,000	Accuracy
	DocVQA [56]	5,349	ANLS
	ChartQA [57]	2,500	Relaxed accuracy
Vision	CV-Bench-2D [7]	1,438	Accuracy
	CV-Bench-3D [7]	1,200	Accuracy
	BLINK [58]	1,437	Accuracy
	RealWorldQA [59]	765	Exact match

Scoring conventions. MME perception scores (out of 2,000) are divided by 20 to fit a 0–100 scale. MMBench reports GPT-eval scores (0–100) directly. MathVista uses GPT-4o as the judge model. All other metrics are reported as percentages (0–100).

Lite subsets. SeedBench uses the 500-sample Lite split from `lmms-eval`, denoted $\mathcal{L}$ in Table 1. Running the full SeedBench (17,990 samples) for every model configuration is computationally prohibitive.

Category averages. The Avg column in Table 1 is the arithmetic mean of all 16 benchmarks. Since each of the four categories contains four benchmarks, this is equivalent to the macro-average of the four category means.

Bootstrap confidence intervals. 95% confidence intervals for all category averages and overall scores are computed using $B=1,000$ bootstrap resamples [60]. Resampling is paired across methods within each (encoder, LLM) group: the same bootstrap indices are applied to all models that share a backbone, so per-sample correlations are preserved and the resulting intervals reflect method differences rather than sample noise. The %BL column reports the ratio of each model’s overall score to its group baseline, bootstrapped under the same paired protocol.

C.1 Setup for the Data-Fraction and Interpolation Experiments

Throughout Section 3, we use the LLaVA 1.5 architecture. The vision encoder is CLIP ViT-L/14 (336px), the projector is a 2-layer MLP ($1024 \rightarrow 4096 \rightarrow 4096$), and the LLM is Vicuna 1.5 7B. The data-fraction experiment in Section 3.1 uses the smaller MobileLLaMA 1.4B backbone [61] with a $1024 \rightarrow 2048 \rightarrow 2048$ projector to keep the 11 data fractions on two corpora computationally feasible. Per-benchmark numbers for this experiment are reported in Appendix D.1. By default, we use LCS-558k (LAION/CC/SBU filtered pairs with BLIP captions) for Stage-I training and the standard LLaVA-665k instruction-tuning mix for Stage-II. Section 5 extends the picture to LLaMA 3.1 8B and Qwen 2.5 7B, and to SigLIP-SO400M as the vision encoder. For two corpora, LCS-558k and ShareGPT-1.2M, we train Stage-I projectors at evenly spaced data fractions (0 to 100%), apply identical LLaVA-665k instruction tuning on each, and evaluate on 16 benchmarks grouped into the four Cambrian-1 categories (Knowledge, General, OCR, Vision-Centric).

C.2 Cross-Seed vs. Cross-Data Interpolation

Section 3.2 reports that projectors trained on different datasets from the same initialization remain interpolable along the linear interpolation path. This appendix complements that result with a control that varies the random initialization instead of the training data, and contrasts the two cases.

Setup. We train two pairs of projectors using the LLaVA 1.5 setup described in Appendix C.1. *Cross-data* projectors share the same random initialization but are trained on different corpora (LCS-558k and ShareGPT-1.2M). *Cross-seed* projectors share the LCS-558k corpus but use two different random initializations. For each pair (W_A, W_B) we report the Frobenius distance $\|W_A - W_B\|_F$ and evaluate the linear interpolation $W_\alpha = (1 - \alpha)W_A + \alpha W_B$ for $\alpha \in [0, 1]$. Stage-II tuning is identical for every W_α .

Results. The cross-seed pair is farther apart in weight space than the cross-data pair ($\|\Delta W\|_F = 92.4$ versus 63.7), but only the cross-data pair stays inside a low-loss region under interpolation. Cross-seed CIDEr [62] on the LLaVA captioning evaluation collapses from approximately 80 at the two endpoints to 0.7 at $\alpha = 0.5$. Cross-data projectors interpolate smoothly along the entire path and the aggregate downstream score peaks at $\alpha = 0.5$ (Figure 3).

Interpretation. Cross-seed projectors reach distinct loss basins separated by high-loss barriers, which is the standard picture for independently initialized networks [63]. Cross-data projectors trained from the same initialization remain inside one shared low-loss region. Initialization therefore selects the basin, and training data selects the particular solution reached within that basin. This is the property that PORTAL targets directly: the closed-form construction lands inside the same compatible region without using paired data.

D Full Downstream Benchmarks

D.1 LCS-558k Pretraining

Table 7: **Per-benchmark results for each LCS-558k data fraction.** Architecture: CLIP ViT-L/14 (336 px) and MobileLLaMA 1.4B [61], with a two-layer MLP projector ($1024 \rightarrow 2048 \rightarrow 2048$). Rows: fraction of the 558k-sample LCS corpus used for Stage-I pretraining (0% corresponds to no Stage-I, random projector init). Columns: 16 benchmarks grouped into four categories adapted from the Cambrian-1 taxonomy (Appendix C), followed by the overall average and its ratio to the 100% reference. All scores are normalized to 0–100 (MME is divided by 20, others are already percentages). ^L: 500-sample Lite subset from `lmms-eval` [42].

Pretrain	Knowledge				General				OCR				Vision				Avg	%BL
	A2D	SciQA	MathV	MMMU	GQA	MME	SEED ^L	MMB	TxtVQA	OCR-Bv2	DocVQA	ChartQA	CV-2D	CV-3D	BLINK	RealWQ		
0%	34.5	47.4	25.2	26.6	51.2	49.7	41.6	10.1	17.0	7.0	8.9	10.3	36.6	51.7	35.3	41.6	30.9	80.9
10%	37.5	53.0	24.3	28.0	56.5	56.4	58.6	39.3	32.1	7.8	13.1	10.6	43.7	53.2	35.7	44.4	37.1	97.1
20%	39.1	55.4	24.4	27.6	56.8	58.7	59.0	39.0	33.6	8.3	14.2	11.3	44.6	51.2	35.5	44.2	37.7	98.5
30%	39.1	53.7	25.8	29.3	56.6	57.6	58.6	37.7	34.8	7.6	14.9	10.6	44.6	51.8	35.7	44.3	37.7	98.5
40%	39.2	55.2	25.9	29.1	56.7	58.2	59.2	41.8	35.2	8.1	15.0	10.9	45.6	52.9	34.8	44.6	38.3	100.1
50%	39.7	54.9	25.8	29.2	57.1	58.2	59.6	42.2	35.5	8.2	15.4	10.9	46.0	53.2	35.6	46.3	38.6	101.0
60%	38.9	55.3	27.1	29.0	56.7	57.6	59.8	43.0	35.2	7.8	15.4	11.0	44.6	52.6	35.8	44.1	38.4	100.3
70%	39.4	55.2	27.1	29.0	56.9	58.7	59.6	41.2	35.6	7.6	15.2	11.5	45.5	52.4	34.6	45.2	<u>38.4</u>	<u>100.5</u>
80%	39.2	54.7	26.2	28.7	57.0	57.2	59.8	41.2	35.6	8.8	15.4	10.9	44.6	53.7	34.6	44.1	38.2	100.0
90%	39.4	55.2	26.4	28.8	57.4	57.0	59.4	41.4	35.7	7.8	15.5	11.1	46.2	54.0	34.7	44.2	38.4	100.4
100%	39.6	53.7	26.7	28.1	57.0	57.9	58.6	39.9	35.7	7.8	15.7	11.6	46.4	52.2	35.9	45.0	38.2	100.0

D.2 ShareGPT-1.2M Pretraining

Table 8: **Per-benchmark results for each ShareGPT-1.2M data fraction.** Layout matches Table 7 but with the ShareGPT-1.2M corpus used for Stage-I pretraining.

Pretrain	Knowledge				General				OCR				Vision				Avg	%BL
	A2D	SciQA	MathV	MMMU	GQA	MME	SEED ^L	MMB	TxtVQA	OCR-Bv2	DocVQA	ChartQA	CV-2D	CV-3D	BLINK	RealWQ		
0%	34.5	47.4	25.2	26.6	51.2	49.7	41.6	10.1	17.0	7.0	8.9	10.3	36.6	51.7	35.3	41.6	30.9	81.4
10%	38.4	53.7	24.3	28.1	55.1	54.5	53.5	50.0	29.6	6.9	12.5	11.2	40.8	52.4	35.2	43.1	36.8	97.0
20%	37.9	54.2	24.1	28.1	55.7	55.1	55.4	54.5	30.7	6.5	12.7	11.1	41.7	53.8	32.3	44.1	37.4	98.4
30%	38.7	53.9	24.4	28.3	56.4	55.7	56.4	51.5	31.1	6.8	13.1	11.2	40.5	52.9	35.6	45.2	37.6	99.0
40%	38.0	53.9	24.8	28.4	56.4	57.5	57.2	50.8	31.4	6.8	13.2	11.6	44.4	52.8	35.3	46.4	38.1	100.2
50%	38.3	54.4	26.0	27.7	56.7	57.0	54.9	52.3	31.9	7.3	14.0	11.6	41.5	52.8	34.6	48.2	<u>38.1</u>	<u>100.2</u>
60%	38.4	53.7	26.4	28.7	56.9	56.4	56.4	52.3	32.8	7.7	13.5	11.5	43.2	53.8	31.1	46.4	38.1	100.2
70%	38.3	54.4	26.8	28.4	57.1	56.3	55.6	50.8	33.9	7.8	14.1	11.4	45.0	52.2	30.9	45.4	38.0	100.1
80%	38.7	53.7	26.0	28.6	57.1	57.3	55.4	49.2	34.1	7.9	14.1	11.5	41.9	52.2	30.9	46.8	37.8	99.6
90%	38.2	54.9	26.2	29.2	57.1	57.1	57.2	50.0	34.1	8.2	14.4	11.1	43.0	51.9	24.2	45.1	37.6	99.1
100%	38.6	54.4	25.5	28.2	57.2	55.8	57.0	53.0	34.4	7.9	14.5	11.9	42.8	53.0	26.7	46.7	38.0	100.0

E Additional Experiments

In this section, we provide additional experiments that further evaluate the scope and robustness of PORTAL. We study whether the coarse-alignment phenomenon extends to a substantially higher-capacity connector, whether PORTAL remains effective under larger-scale multimodal instruction tuning, how its performance varies across task categories, how it compares with alternative unpaired alignment methods, and whether training-free alignment affects object hallucination.

E.1 Comparison with Alternative Unpaired Alignment Methods

Random initialization in our main experiments serves as a control for completely skipping Stage-I alignment rather than as the only competing alignment method. We additionally compare PORTAL against CORAL [25], which aligns second-order feature statistics in closed form, and Gromov-Wasserstein (GW) alignment [24], an iterative unpaired alignment method.

Table 9: Comparison with alternative alignment methods. All methods except the conventional Stage-I baseline require no paired image-caption samples.

Initialization	Avg16	% of Baseline
Stage-I trained baseline	48.03	100.0
Random	44.90	93.5
CORAL	46.36	96.5
Gromov-Wasserstein	47.06	98.0
PORTAL	47.43	98.8

Table 10: Characteristics of the unpaired initialization methods considered in Table 9.

Method	Paired Samples	Projector Training	Construction
Random	No	No	Random initialization
CORAL	No	No	Closed form
GW	No	No	Iterative optimization
PORTAL	No	No	Closed form

Both CORAL and GW substantially improve over random initialization, recovering 96.5% and 98.0% of the paired Stage-I baseline, respectively (Table 9). This confirms more broadly that useful projector initialization can be obtained from unpaired feature distributions. PORTAL performs best among the unpaired methods considered here, recovering 98.8% of the trained baseline while retaining a closed-form construction and requiring neither paired samples nor projector optimization.

E.2 Performance Retention Across Task Categories

We next examine whether the aggregate performance of PORTAL hides systematic differences across task categories. Table 11 reports performance relative to the corresponding conventionally Stage-I-trained baseline for Knowledge, General, OCR, and Vision-Centric benchmarks.

Table 11: PORTAL performance as a percentage of the corresponding Stage-I-trained baseline, broken down by task category. The last row averages the retention rate across the seven (vision encoder, LLM) configurations.

LLM	Vision Encoder	Knowledge	General	OCR	Vision	Overall
Vicuna 1.5 7B	CLIP	100.3	97.3	96.6	100.5	98.8
Vicuna 1.5 7B	SigLIP	100.6	98.1	97.6	101.0	99.3
LLaMA 3.1 8B	CLIP	103.6	100.7	103.9	103.8	102.7
LLaMA 3.2 1B	CLIP	102.5	109.8	112.1	103.1	106.2
Qwen 2.5 7B	CLIP	98.5	99.4	92.6	99.3	98.3
Qwen 2.5 0.5B	CLIP	100.9	113.2	121.1	97.9	106.1
OLMo 2 1B	CLIP	98.2	95.4	92.9	97.4	96.3
Mean across configurations	—	100.7	102.0	102.4	100.4	101.1

On average across configurations, PORTAL retains 100.7%, 102.0%, 102.4%, and 100.4% of the trained-baseline performance on Knowledge, General, OCR, and Vision-Centric tasks, respectively. Thus, the aggregate performance of PORTAL is not driven by a single task category. At the same time, paired Stage-I training remains beneficial for particular encoder-LLM combinations and individual benchmarks. For example, the largest category-level deficits occur for OCR under Qwen-2.5-7B and OLMo-2-1B. The results therefore suggest a more nuanced picture than fine-grained tasks universally requiring paired Stage-I supervision: the value of paired supervision depends on the specific backbone, encoder, and benchmark.

E.3 Large-Scale Multimodal Instruction Tuning

Our main experiments use LLaVA-665k for Stage-II instruction tuning. We further test whether PORTAL remains effective under a substantially larger multimodal fine-tuning regime using 3.2M samples subsampled from Cambrian-7M. This setting provides a stronger test of whether PORTAL initialization remains stable when followed by heavier multimodal training.

Table 12: Performance under large-scale Stage-II multimodal instruction tuning with 3.2M samples. The confidence interval reports the 95% CI for the difference between PORTAL and the Stage-I-trained baseline.

Category	Baseline	PORTAL	Δ	95% CI
Knowledge	45.95	46.68	+0.72	$[-0.40, +1.88]$
General	59.60	59.88	+0.27	$[-0.71, +1.27]$
OCR	30.28	31.45	+1.18	$[+0.67, +1.68]$
Vision	50.12	51.28	+1.16	$[-0.13, +2.46]$
Overall	46.49	47.32	+0.83	$[+0.36, +1.35]$

PORTAL remains effective under this substantially heavier Stage-II training regime (Table 12). Across the 16 benchmarks, the overall mean increases from 46.49 with conventional Stage-I initialization to 47.32 with PORTAL, corresponding to a statistically significant improvement of +0.83 points with a 95% confidence interval of $[+0.36, +1.35]$. Importantly, PORTAL does not lead to performance collapse or degradation under large-scale multimodal fine-tuning. The result suggests that the benefit of the closed-form initialization is not restricted to the standard LLaVA-665k Stage-II regime.

E.4 Object Hallucination

Finally, we evaluate whether replacing paired Stage-I alignment with coarse statistical alignment increases object hallucination. We evaluate all seven (vision encoder, LLM) configurations on POPE [43], a standard benchmark for object hallucination (Table 13). PORTAL matches or outperforms the conventionally Stage-I-trained baseline across all seven configurations, with improvements ranging from +0.2 to +2.2 F1 points. Thus, replacing paired Stage-I projector training with PORTAL does not increase object hallucination in these experiments and can slightly improve hallucination robustness.

Table 13: POPE F1 scores across all seven (vision encoder, LLM) configurations. Numbers in parentheses indicate the improvement of PORTAL over the conventionally Stage-I-trained baseline.

LLM	Vision Encoder	Baseline	Random	PORTAL
Vicuna 1.5 7B	CLIP	85.5	85.3	85.7 (+0.2)
Qwen 2.5 7B	CLIP	85.7	85.5	86.4 (+0.7)
LLaMA 3.1 8B	CLIP	84.0	84.2	84.9 (+0.9)
Vicuna 1.5 7B	SigLIP	84.6	79.1	85.1 (+0.5)
OLMo 2 1B	CLIP	85.3	84.8	85.5 (+0.2)
LLaMA 3.2 1B	CLIP	84.1	84.0	86.2 (+2.1)
Qwen 2.5 0.5B	CLIP	82.9	82.7	85.1 (+2.2)

E.5 Higher-Capacity Connector

Our main experiments use either a two-layer MLP or a linear projector. A possible alternative explanation for the observed coarse-alignment behavior is therefore that it arises from limited projector capacity. To test this, we additionally evaluate PORTAL with the C-Abstractor connector from Honeybee [12], a substantially higher-capacity architecture that performs both token mixing and sequence compression.

In the LLaMA-3.2-1B + CLIP setting, C-Abstractor contains 120.2M parameters, approximately $19\times$ more than the 6.3M-parameter two-layer MLP, and compresses the visual sequence from 576 to 144 tokens. We initialize the residual branches of C-Abstractor to zero such that the connector initially reduces to applying PORTAL to the pooled visual features. All remaining C-Abstractor parameters are then optimized during the same Stage-II training used for the other initialization schemes.

As shown in Table 14, PORTAL reaches an average score of 42.93, compared with 42.98 for conventional Stage-I training, while direct Stage-II training from random initialization reaches only 41.46. PORTAL also outperforms the Stage-I-trained baseline on 7 of the 16 individual benchmarks. Thus, increasing connector capacity by approximately $19\times$, while additionally enabling token mixing and sequence compression, does not yield an aggregate advantage for paired Stage-I training over PORTAL. Together with our linear and two-layer MLP experiments, this result provides evidence that the observed coarse-alignment behavior cannot be explained simply by insufficient projector capacity. We do not, however, claim that every possible connector architecture must exhibit identical behavior.

Table 14: Performance with the higher-capacity C-Abstractor connector. Despite substantially increasing connector capacity and introducing explicit token mixing and sequence compression, PORTAL remains essentially indistinguishable from conventional Stage-I training.

Task	Baseline	Random	PORTAL
AI2D	49.3	46.7	48.0
ScienceQA	68.2	65.2	66.2
MathVista	26.9	25.9	26.2
MMMU	32.3	34.6	33.9
GQA	60.6	59.7	60.7
MME-P	60.8	59.6	65.4
SEED-L	58.4	54.7	56.2
MMBench	58.4	52.4	54.9
TextVQA-OCR	46.7	43.6	45.4
OCRBench-v2	10.7	11.2	11.5
DocVQA	13.2	11.8	12.7
ChartQA	11.1	10.4	10.8
CV-Bench 2D	50.1	47.8	50.8
CV-Bench 3D	54.2	53.9	55.2
BLINK	38.3	37.0	40.9
RealWorldQA	48.6	48.9	48.1
Average	42.98	41.46	42.93

F PORTAL Construction: Pseudocode

Listing 1 states the PORTAL construction as a self-contained PyTorch routine. The function consumes a sample of source features (*e.g.*, CLIP patch tokens), a sample of target features (*e.g.*, the LLM’s input embedding table or the hidden states after block ℓ), and a rank k . It returns the parameters $(\mathbf{W}_1, \mathbf{b}_1, \mathbf{W}_2, \mathbf{b}_2)$ of the standard two-layer LLaVA projector $f(\mathbf{x}) = \mathbf{W}_2 \phi(\mathbf{W}_1 \mathbf{x} + \mathbf{b}_1) + \mathbf{b}_2$ from Section 4, with ϕ a GELU. The first layer is the closed-form Gaussian optimal-transport map of Eq. (2), and the second layer is fixed to the identity. No paired captions and no Stage-I optimization are required, only one PCA on each side.

```
import torch

def portal(X, Y, k=512):
    """
    X: source features, shape (N_s, d_s) -- e.g. CLIP patch tokens.
    Y: target features, shape (N_t, d_t) -- LLM input embeddings,
        or post-block-1 hidden
        states for PORTAL-ctx-l.

    k: PCA rank for the shared subspace.

    Returns (W1, b1, W2, b2) for the LLaVA projector
        f(x) = W2 @ gelu(W1 @ x + b1) + b2.
    """
    # 1. Source statistics: top-k PCA on centered source features.
    mu_s = X.mean(dim=0) # (d_s,)
    _, S_s, Vt_s = torch.linalg.svd(X - mu_s, full_matrices=False)
    V_s = Vt_s[:k].T # (d_s, k)
    sigma_s = S_s[:k] / (X.shape[0] - 1) ** 0.5 # (k,)

    # 2. Target statistics: top-k PCA on centered target features.
    mu_t = Y.mean(dim=0) # (d_t,)
    _, S_t, Vt_t = torch.linalg.svd(Y - mu_t, full_matrices=False)
    V_t = Vt_t[:k].T # (d_t, k)
    sigma_t = S_t[:k] / (Y.shape[0] - 1) ** 0.5 # (k,)

    # 3. Closed-form projector (Eq. 2): W2 fixed to identity.
    W1 = V_t @ torch.diag(sigma_t / sigma_s) @ V_s.T # (d_t, d_s)
    b1 = mu_t - W1 @ mu_s # (d_t,)
    W2 = torch.eye(Y.shape[1])
    b2 = torch.zeros(Y.shape[1])
    return W1, b1, W2, b2
```

Listing 1: PORTAL: training-free projector via Gaussian optimal transport. The same routine yields PORTAL-ctx ℓ when Y is replaced by post-block- ℓ hidden states (Appendix G).

Inputs. The source matrix X contains all per-patch tokens from a small unlabeled image pool: with P patches per image and N_{img} images, $N_s = N_{\text{img}} \cdot P$. Throughout the paper we use a default of $N_{\text{img}} = 1024$ images from COCO val2017 (Appendix I). For default PORTAL, the target matrix Y is the LLM’s input embedding table, with one row per vocabulary token. For PORTAL-ctx ℓ , Y instead holds the hidden states after block ℓ , which we collect by passing a list of English words and short phrases (the `concepts.txt` file of LatentLens) through the LLM (Appendix G).

Interpretation. Read right to left, $V_s.T$ projects each centered source token onto the source’s top- k principal axes, the diagonal rescaling $\text{diag}(\sigma_t / \sigma_s)$ rescales each axis from source to target spread, and V_t rotates the result into the target’s top- k principal frame. Adding $b1 = \mu_t - W1 @ \mu_s$ then recenters to the target mean. The composition matches first and second moments of source and target on the k -dimensional shared subspace. We use $k=512$ as the default (Appendix K). The construction is well-defined for any $k \leq \min(d_s, d_t, N_s, N_t)$.

Cost. The procedure runs two thin SVDs and two matrix multiplies. For the default setting ($N_s \approx 1024 \cdot 576$, $d_s = 1024$, $d_t = 4096$, $k = 512$) the construction completes in under 30 seconds on a single RTX 3090 (Appendix B) and uses no captions, no paired data, and no gradient steps. This stands in contrast to standard Stage-I projector training, which consumes a paired image-caption corpus (typically LCS-558k) and about 2,200 optimizer steps (558k pairs at batch size 256).

G Contextualized Targets: Methodology Details

This appendix provides the implementation details behind PORTAL-ctx ℓ (Section 4).

Probe corpus. We use the `concepts.txt` corpus released with LatentLens [64], a list of English concepts originally assembled for probing latent directions in LLMs. The corpus offers broad semantic coverage and is not tied to any downstream task, which makes it a representative sample of the input distribution of the LLM at depth ℓ .

Cached hidden states. For LLMs covered by LatentLens (LLaMA 3.1 8B, Qwen 2.5 7B, Gemma 2 9B) we use the pre-computed hidden states distributed on Hugging Face. For each LLM and each layer ℓ , the cache stores the post-block- ℓ hidden state of every token in every `concepts.txt` entry, collected in a single tensor $\mathbf{H}^{(\ell)} \in \mathbb{R}^{N_t \times d_t}$. The available layers are $\ell \in \{1, 4, 8, 12, 16, 20\}$. For Vicuna v1.5, which is not part of the LatentLens release, we run `concepts.txt` through the model and store the corresponding hidden states in the same format. The tensor $\mathbf{H}^{(\ell)}$ replaces the LLM’s input embedding table as the target distribution in Eq. (2). The remainder of the PORTAL construction is unchanged.

Layer indexing. ℓ denotes the residual stream *after* the ℓ -th transformer block (1-indexed), following the LatentLens convention. The setting $\ell=0$ recovers standard PORTAL targeting the LLM’s input embedding table.

H Cosine Dispersion: Theory and Empirical Checks

This section consolidates the analysis underlying Section 4.2. It quantifies how non-Gaussian the relevant source and target distributions are (Appendix H.1), proves the spectrum-to- ω bound (Appendix H.2), reports the empirical check of that bound on PORTAL projector outputs (Appendix H.3), and extends the empirical check to the full MLP-GELU projector (Appendix H.4).

H.1 Distributional Audit of Source and Target Modalities

PORTAL treats both modalities as Gaussian in Eq. (2) only to obtain a closed-form transport map. The empirical source and target distributions are not exactly Gaussian. This subsection quantifies the deviation so that the reader can assess how reliable the second-order summary used by PORTAL is.

Procedure. For each distribution we draw $n=5,000$ tokens (CLIP and SigLIP patches from COCO va12017 images, rows of the LLM’s input embedding table), project the centered features onto their top $k=128$ principal components and whiten the resulting coordinates to unit per-axis variance. On these coordinates we compute four statistics. Mardia’s multivariate skewness b_1 [65], reported as b_1/k^3 , which is close to zero under Gaussianity. Mardia’s kurtosis b_2 [65], reported as the excess $b_2/k^2 - (1 + 2/k)$ over its Gaussian value, which quantifies tail weight relative to a Gaussian. The fraction of the k whitened marginals for which the Anderson-Darling test [66] rejects $\mathcal{N}(0, 1)$ at the 5% level. The effective dimension $d_{\text{eff}} = (\text{tr } \Sigma)^2 / \text{tr}(\Sigma^2)$ [67], which summarizes how variance is distributed across the leading directions. Results are reported in Table 15.

Table 15: **Distributional audit on top $k=128$ principal components.** The columns most relevant to the argument in Section 4 are d_{eff} and Mardia b_1 . The Anderson-Darling rejection rate (AD rej.) and the excess kurtosis identify where the deviation from Gaussianity is concentrated.

Type	Distribution	n	d	d_{eff}	Mardia b_1	Exc. kurt.	AD rej.
Source	CLIP ViT-L/14 patches	5,000	1,024	4.5	0.0022	0.487	100%
Source	SigLIP SO400M patches	5,000	1,152	50.9	0.0026	0.278	100%
Target	Vicuna 7B embedding table	5,000	4,096	1,429.6	0.0005	0.071	84%
Target	LLaMA 3.1 8B embedding table	5,000	4,096	1,713.2	0.0005	0.131	98%
Target	Qwen 2.5 7B embedding table	5,000	3,584	830.1	0.0004	0.114	100%

Results. No measured distribution is exactly Gaussian, and the Anderson-Darling test rejects Gaussianity on almost all top marginals. This is expected for high-dimensional learned features and does not, on its own, imply that PORTAL should fail.

The question is where the deviation lives. Skewness is small for every distribution ($b_1/k^3 \leq 0.003$), so the residual deviation from Gaussianity lies in tail weight. The tails are heaviest for the vision features (excess kurtosis 0.28 to 0.49) and light for the LLM input embedding tables (0.07 to 0.13).

A second question is whether the distributions that PORTAL targets spread their variance over many directions. The input embedding tables do, with d_{eff} between 830 and 1,713, while the CLIP patches concentrate their variance in a few directions ($d_{\text{eff}} = 4.5$).

H.2 Proof of Proposition 1

Proposition 1 states that the variance of the cosine between two random tokens is close to $1/d_{\text{eff}}(\Sigma)$ when token lengths vary little. The proof first computes the second moment of the plain dot product $\mathbf{z}^\top \mathbf{z}'$, which depends only on Σ , and then bounds how much dividing by the two token lengths can change it.

Notation. The trace $\text{tr } \Sigma$ equals the mean squared length $\mathbb{E}[\|\mathbf{z}\|^2]$, because $\mathbf{z}$ has mean zero. We write

- $\mathbf{u} = \mathbf{z}/\|\mathbf{z}\|$ and $\mathbf{u}' = \mathbf{z}'/\|\mathbf{z}'\|$ for the unit vectors along $\mathbf{z}$ and $\mathbf{z}'$,
- $c = \mathbf{u}^\top \mathbf{u}' = \cos \angle(\mathbf{z}, \mathbf{z}')$ for the cosine,
- $a = \|\mathbf{z}\|^2/\text{tr } \Sigma$ and $a' = \|\mathbf{z}'\|^2/\text{tr } \Sigma$ for the squared lengths relative to their mean, so that $\mathbb{E}[a] = 1$ and $\text{std}(a) = \kappa$,
- $m = \mathbb{E}|1 - a|$ for the mean deviation of a from 1. By the Cauchy-Schwarz inequality, $m \leq \sqrt{\mathbb{E}[(1 - a)^2]} = \kappa$.

Proof. Step 1: the dot product. Averaging over $\mathbf{z}$ with $\mathbf{z}'$ held fixed, and using $\mathbb{E}[\mathbf{z}\mathbf{z}^\top] = \Sigma$,

$$\mathbb{E}[(\mathbf{z}^\top \mathbf{z}')^2] = \mathbb{E}[\mathbf{z}'^\top \mathbf{z} \mathbf{z}^\top \mathbf{z}'] = \mathbb{E}[\mathbf{z}'^\top \Sigma \mathbf{z}'] = \text{tr}(\Sigma \mathbb{E}[\mathbf{z}' \mathbf{z}'^\top]) = \text{tr}(\Sigma^2).$$

For the normalized squared dot product $q = (\mathbf{z}^\top \mathbf{z}')^2/(\text{tr } \Sigma)^2$ this gives

$$\mathbb{E}[q] = \frac{\text{tr}(\Sigma^2)}{(\text{tr } \Sigma)^2} = \frac{1}{d_{\text{eff}}(\Sigma)}.$$

This step is exact and holds for any distribution.

Step 2: from the dot product to the cosine. The cosine is the dot product divided by both lengths, so $c^2 = q/(aa')$, or $q = c^2 aa'$. Hence

$$\mathbb{E}[c^2] - \frac{1}{d_{\text{eff}}(\Sigma)} = \mathbb{E}[c^2 - q] = \mathbb{E}[c^2(1 - aa')].$$

Since $c^2 \leq 1$, the absolute value of the right side is at most $\mathbb{E}|1 - aa'|$. Writing $1 - aa' = (1 - a) + (1 - a') - (1 - a)(1 - a')$, the triangle inequality and the independence of a and a' give

$$\mathbb{E}|1 - aa'| \leq \mathbb{E}|1 - a| + \mathbb{E}|1 - a'| + \mathbb{E}|1 - a| \mathbb{E}|1 - a'| = 2m + m^2.$$

Step 3: the mean cosine. The variance subtracts the squared mean, $\text{Var}(c) = \mathbb{E}[c^2] - \mathbb{E}[c]^2$, so it remains to bound $\mathbb{E}[c]$, the average cosine between two independent tokens. By independence, $\mathbb{E}[c] = \mathbb{E}[\mathbf{u}]^\top \mathbb{E}[\mathbf{u}'] = \|\mathbb{E}[\mathbf{u}]\|^2$. Because $\mathbf{z} = \sqrt{\text{tr } \Sigma} \sqrt{a} \mathbf{u}$ has mean zero, $\mathbb{E}[\sqrt{a} \mathbf{u}] = \mathbf{0}$, and therefore

$$\mathbb{E}[\mathbf{u}] = \mathbb{E}[(1 - \sqrt{a}) \mathbf{u}], \quad \|\mathbb{E}[\mathbf{u}]\| \leq \mathbb{E}|1 - \sqrt{a}| \leq \mathbb{E}|1 - a| = m,$$

where we used $\|\mathbf{u}\| = 1$ and $|1 - \sqrt{a}| = |1 - a|/(1 + \sqrt{a}) \leq |1 - a|$. Hence $\mathbb{E}[c]^2 = \|\mathbb{E}[\mathbf{u}]\|^4 \leq m^4$.

Combining the steps. By Steps 2 and 3 and $m \leq \kappa$,

$$\left| \text{Var}(c) - \frac{1}{d_{\text{eff}}(\Sigma)} \right| \leq \left| \mathbb{E}[c^2] - \frac{1}{d_{\text{eff}}(\Sigma)} \right| + \mathbb{E}[c]^2 \leq 2m + m^2 + m^4 \leq 2\kappa + \kappa^2 + \kappa^4. \quad \square$$

The quantity ω^2 in Eq. (3) is the empirical variance of the cosines over all pairs of n sampled tokens. Both of its pairwise averages are averages of a bounded function over all pairs (U-statistics), so ω^2 converges to $\text{Var}(c)$ as n grows.

H.3 Cosine Dispersion of PORTAL Projector Outputs

This appendix measures ω on the PORTAL outputs for the three CLIP pairs with a 7B or 8B LLM in Table 1. We construct PORTAL as in Appendix F from the first 1024 COCO val2017 images, apply it to the next 100 images (576 CLIP patches per image), and report two quantities. The intra-image ω is averaged across images, with each image contributing the dispersion of its own 576 output tokens. The population ω is computed over 576 output tokens sampled at random across all images. The intra-image quantity reflects the dispersion seen by attention on a single forward pass. The population quantity is the distributional property that Proposition 1 describes.

Table 16: **Cosine dispersion ω of projector outputs and downstream average.** For each (encoder, LLM) pair, *Source* is ω of the raw source patches, *Random* and *PORTAL* are ω after applying the corresponding projector, and *Target* is ω of the LLM’s input embedding table restricted to the top-512 principal subspace that PORTAL matches. Random and PORTAL denote the first layer $\mathbf{W}_1\mathbf{x} + \mathbf{b}_1$ of each projector. *PORTAL d_{eff}* reports the effective dimension of the PORTAL output cloud. Downstream Avg columns from Table 1.

Encoder	LLM	Scale	Source	Random	PORTAL	Target	PORTAL d_{eff}	Random Avg	PORTAL Avg	Trained Avg
CLIP	Vicuna 7B	pop	0.234	0.234	0.100	0.056	266.7	44.9	47.4	48.0
		intra	0.252	0.251	0.235	0.056	266.7	44.9	47.4	48.0
CLIP	LLaMA 3.1 8B	pop	0.234	0.234	0.101	0.057	257.4	50.4	52.2	50.8
		intra	0.252	0.251	0.234	0.057	257.4	50.4	52.2	50.8
CLIP	Qwen 2.5 7B	pop	0.234	0.234	0.094	0.054	289.3	48.6	51.7	52.6
		intra	0.252	0.251	0.245	0.054	289.3	48.6	51.7	52.6

PORTAL reduces ω from the source value of 0.23 to between 0.09 and 0.10, towards the target value of 0.05 to 0.06. Over the full embedding table, the target’s ω is 0.02 to 0.03. A random projector roughly preserves angles and therefore leaves ω at the source value. The intra-image ω does not separate the three projectors, because patches from a single image share a common offset that no global linear map can remove.

The measurement is correlative. PORTAL moves ω most of the way from the source towards the target, and we do not claim that ω is the sole geometric property responsible for the downstream performance of PORTAL.

H.4 Post-Projection Statistics: Linear vs. MLP-GELU Output

The closed-form construction in Eq. (2) gives an affine map $\mathbf{W}_1\mathbf{x} + \mathbf{b}_1$ that matches the target’s first and second moments under a Gaussian approximation. The implemented projector then passes that affine output through GELU. This subsection reports distributional statistics of the actual projector output for each (encoder, LLM) pair across four constructions. *Random+GELU* is a Random Kaiming initialization followed by GELU. *PORTAL (preact)* is the PORTAL preactivation alone, which is the linear object the theory in Section 4.2 applies to. *PORTAL+GELU* is the PORTAL preactivation followed by GELU, which is the implemented PORTAL projector. *Trained Stage-I* is a trained Stage-I projector loaded from checkpoint. The target row reports the same statistics on the LLM’s input embedding table, restricted to the top-512 principal subspace that PORTAL matches. *Trained Stage-I* is the public LLaVA-1.5 projector for Vicuna and our trained projectors for LLaMA and Qwen. For the latter two we report only the statistics that do not depend on the target.

For each output cloud we report five statistics. The mean offset $\|\Delta\mu\|$ is the L^2 distance between the output mean and the target mean, with a relative version normalized by $\|\mu_t\|$. The spectrum error is the relative L^2 distance between the top-128 output and target singular values. The effective dimension is $d_{\text{eff}} = (\text{tr } \Sigma)^2 / \text{tr}(\Sigma^2)$. The norm coefficient of variation $\text{cv} = \text{std}(\|\mathbf{z}\|) / \mathbb{E}[\|\mathbf{z}\|]$ serves as a concentration check. The population pairwise-cosine standard deviation is ω as defined in Eq. (3). Statistics are computed over 100 COCO val2017 images of 576 CLIP patches each, with PORTAL constructed from a disjoint set of 1024 images.

The table supports four observations. First, Random+GELU is far from the target on every column, consistent with the SigLIP collapse reported in Table 1. Second, the PORTAL preactivation matches the target mean and top-128 spectrum, comes close to its d_{eff} , and moves ω from 0.23 at the source to about 0.10, against 0.05 to 0.06 for the target. Third, applying GELU to the PORTAL preactivation roughly preserves d_{eff} and ω , even though the spectrum error grows by an order of magnitude. This empirical observation closes the gap between the theory of the linear object and the implemented MLP. Fourth, a trained Stage-I projector deviates substantially from the target distribution on every column we report. Despite this, trained Stage-I and PORTAL reach comparable downstream Avg in Table 1. The two solutions are distributionally distinct, which is consistent with the broad-solution-space rather than with the view that Stage-I learns a unique target distribution.

I Image Pool for PORTAL Construction

PORTAL uses an unlabeled image pool only to estimate the CLIP patch-feature statistics required by Eq. (2), and requires neither captions nor paired text. We assess the sensitivity of the constructed projector to the identity and size of this pool. Table 18 reports an ablation on LLaMA 3.2 1B/CLIP along two axes.

- **Source diversity.** COCO (val2017, single domain) vs. a reservoir-sampled subset of Cambrian-737k [7] spanning nine sources (coco, vg, ocr_vqa, gqa, chartqa, textvqa, ai2d, docvqa, dvqa). For reference, the trained baseline uses the LCS-558k [2] caption pool.
- **Pool size.** 1024 images (standard) vs. 4096 images.

Table 17: **Post-projection statistics on CLIP patch tokens.** Distributional fit to the target distribution for four projector constructions, plus a target row for reference. Smaller $\|\Delta\mu\|$ and spectrum error indicate a closer fit to the target. The d_{eff} and ω values should be read against the target row of the same LLM.

LLM	Method	$\ \Delta\mu\ $	Rel.	Spec. err.	d_{eff}	cv	ω (pop)
Vicuna 7B	<i>target</i>	0.000	0.000	0.000	319.7	0.123	0.056
	Random+GELU	7.144	47.33	24.25	3.6	0.682	0.212
	PORTAL (preact)	0.021	0.142	0.066	266.7	0.281	0.100
	PORTAL+GELU	0.077	0.508	0.470	266.9	0.281	0.100
	Trained Stage-I	33.18	219.8	142.4	2.4	1.047	0.232
LLaMA 3.1 8B	<i>target</i>	0.000	0.000	0.000	308.2	0.135	0.057
	Random+GELU	7.145	83.28	47.07	3.6	0.682	0.212
	PORTAL (preact)	0.011	0.133	0.088	257.4	0.279	0.101
	PORTAL+GELU	0.043	0.505	0.460	257.3	0.279	0.101
	Trained Stage-I	–	–	–	2.4	1.019	0.239
Qwen 2.5 7B	<i>target</i>	0.000	0.000	0.000	352.5	0.216	0.054
	Random+GELU	6.791	81.61	25.55	3.6	0.686	0.212
	PORTAL (preact)	0.020	0.242	0.097	289.3	0.294	0.094
	PORTAL+GELU	0.043	0.511	0.456	289.1	0.294	0.094
	Trained Stage-I	–	–	–	2.0	1.147	0.221

The smaller single-domain COCO pool (1024 images) matches or exceeds the larger Cambrian pool (4096 images) on 12 of 15 benchmarks, with 2 exact ties and 3 marginal Cambrian wins (AI2D, MMMU, DocVQA). The COCO pool yields an aggregate gain of +0.6 Avg (44.0 vs. 43.4) and +1.3 %BL (106.1 vs. 104.8).

These numbers indicate that the second-order statistics of a generic natural-image distribution are sufficient to specify the whitening map. Increasing source diversity provides no additional benefit once the statistics have converged, in agreement with the rapid decay of the leading singular values of a CLIP feature matrix. On this configuration, PORTAL is insensitive to the choice between the two pools.

Table 18: **Image-pool ablation for the PORTAL construction, per-benchmark breakdown.** Setup: LLaMA 3.2 1B/CLIP, Stage-II on LLaVA-665k. Both PORTAL variants use rank $k=512$ and require no paired captions. **Bold:** best between the two PORTAL rows per benchmark. Avg and %BL are computed over the 15 benchmarks shown.

Pool	Src	#Img	Knowledge				General				OCR			Vision				Avg	%BL
			AI2D	SciQA	MathV	MMMU	GQA	MME	SEED	MMB	OCR-Bv2	DocVQA	ChartQA	CV-2D	CV-3D	BLINK	RealWQ		
Baseline [†]	LCS	558k	46.5	66.2	26.9	33.6	59.7	58.4	56.2	46.1	10.1	12.8	10.8	53.5	56.4	37.2	47.3	41.4	100.0
Random	–	0	46.6	66.9	26.3	34.2	59.8	58.1	56.0	45.2	10.4	12.8	11.0	54.2	54.9	37.4	46.9	41.4	99.8
PORTAL	Cambrian	4096	48.2	66.7	26.9	34.3	62.0	64.3	59.6	53.6	10.8	16.8	12.0	53.5	55.8	37.7	49.4	43.4	104.8
PORTAL	COCO	1024	47.6	67.1	29.2	33.7	62.1	66.0	59.6	54.2	11.4	16.3	12.0	54.6	57.3	38.9	49.7	44.0	106.1

J Projector Architecture: Linear vs. MLP

The standard LLaVA projector is a two-layer MLP with a GELU activation. We test whether the benefit of PORTAL also transfers to a simpler architecture. We replace the MLP with a single linear layer (no nonlinearity, no hidden expansion, input dimension 1024, output dimension d_{LLM}) and keep all other components fixed: LLaMA 3.2 1B/CLIP, Stage-II tuning on LLaVA-665k, identical hyperparameters, and the same PORTAL construction with rank $k=512$ on the COCO-1024 image pool from Appendix I. For each projector we evaluate three initialization schemes: a trained baseline (Stage-I on LCS-558k), Random init, and PORTAL. The MLP rows are reproduced from Table 1.

Table 19 reports the per-benchmark breakdown. Under the MLP, Random init matches the trained baseline (41.5 vs. 41.6 Avg, 99.9%) and PORTAL reaches 44.2 Avg (106.2%). Under the linear projector, Random init falls to 37.6 Avg (94.2% of the linear baseline) and PORTAL reaches 44.7 Avg (111.8%), the highest macro average among the six configurations. The Random-to-PORTAL gap on the macro average is 2.7 points under the MLP

and 7.1 points under the linear projector. PORTAL is the stronger zero-shot init on 15 of 16 benchmarks under the MLP and on 16 of 16 benchmarks under the linear projector. This supports the interpretation that the gain from PORTAL is a property of the projector initialization and transfers across projector architectures.

Table 19: **Linear versus MLP-2x-GELU projector, per-benchmark breakdown.** Setup: LLaMA 3.2 1B/CLIP, Stage-II on LLaVA-665k. Each architecture is anchored to its own trained baseline for %BL. **Bold**: best between Random and PORTAL within an architecture. Underline: second best.

Projector	Init	Knowledge				General				OCR				Vision				Avg	%BL
		Al2D	ScQA	MathV	MMMU	GQA	MME	SEED	MMB	TxVQA	OCR-Bv2	DocVQA	ChartQA	CV2D	CV3D	BLINK	RealWQ		
MLP-2x-GELU	Baseline [†]	46.5	66.2	26.9	33.6	59.7	58.4	56.2	46.1	43.7	10.1	12.8	10.8	53.5	56.4	37.2	47.3	41.6	100.0
	Random	<u>46.6</u>	<u>66.9</u>	<u>26.3</u>	34.2	<u>59.8</u>	<u>58.1</u>	<u>56.0</u>	<u>45.2</u>	<u>43.8</u>	<u>10.4</u>	<u>12.8</u>	<u>11.0</u>	<u>54.2</u>	<u>54.9</u>	<u>37.4</u>	<u>46.9</u>	<u>41.5</u>	<u>99.9</u>
	PORTAL	47.6	67.1	29.2	<u>33.7</u>	62.1	66.0	59.6	54.2	47.1	11.4	16.3	12.0	54.6	57.3	38.9	49.7	44.2	106.2
Linear	Baseline [†]	46.5	65.5	27.1	33.3	54.7	53.1	47.3	49.8	42.6	10.1	11.0	10.0	50.1	54.4	36.8	46.7	39.9	100.0
	Random	<u>46.0</u>	<u>63.2</u>	<u>24.6</u>	<u>30.9</u>	<u>53.0</u>	<u>52.8</u>	<u>46.1</u>	<u>43.8</u>	<u>36.8</u>	<u>7.9</u>	<u>7.3</u>	<u>8.8</u>	<u>45.6</u>	<u>52.8</u>	<u>37.7</u>	<u>44.4</u>	<u>37.6</u>	<u>94.2</u>
	PORTAL	48.2	68.5	28.2	34.6	62.2	66.8	60.4	54.4	48.9	11.6	17.5	12.1	54.1	57.8	38.1	51.1	44.7	111.8

K PCA Rank Sensitivity

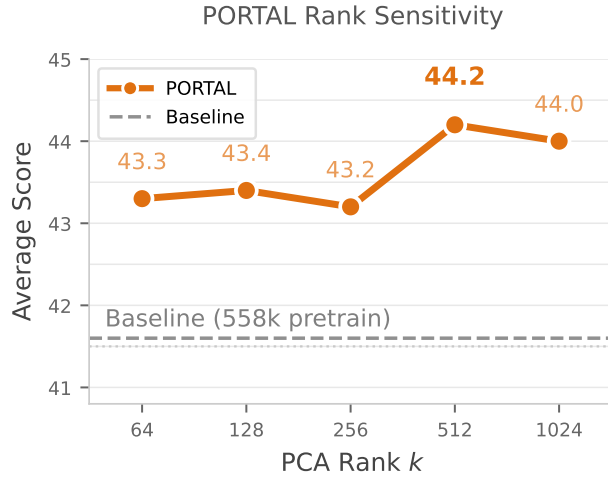


Figure 5: **PCA rank sensitivity** on LLaMA 3.2 1B/CLIP. Average over the 16 benchmarks as a function of the rank k used in the PORTAL construction, with identical Stage-II tuning. All ranks outperform the trained baseline (41.6). $k=512$ is optimal (44.2).

The PORTAL projector is constructed in a rank- k PCA subspace (Section 4). We vary k over $\{64, 128, 256, 512, 1024\}$ on LLaMA 3.2 1B/CLIP, constructing each projector from the same 1024 COCO images and running identical Stage-II tuning. Figure 5 shows the resulting Avg score. Performance is flat from $k=64$ to $k=256$ (approximately 43.3 Avg), peaks at $k=512$ (44.2), and decreases marginally at $k=1024$ (44.0). The plateau at low ranks indicates that the dominant PCA directions already capture most of the cross-modal structure. The peak at $k=512$ suggests that mid-variance directions contribute additional geometric signal. The decrease at $k=1024$ is consistent with noisy eigenvectors diluting the transport map. We adopt $k=512$ as the default throughout the paper.

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