

Early to Share, Late to Save: Synchronisation-Driven Communication Gating in Bandwidth-Constrained Cooperative VLN

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Abstract. Most cooperative Vision-Language Navigation (VLN) methods assume unlimited communication, not considering real-world applications where bandwidth is restricted and information efficiency is critical. We introduce **bandwidth-constrained cooperative VLN** and propose **hindsight gating**: a lightweight supervised gate that labels communication-critical steps post-hoc from navigation failures, avoiding the high variance of REINFORCE. Contrary to the intuition that agents should communicate when uncertain, we observe a consistent counter-intuitive pattern: trained gates fire predominantly in early episode steps and more often when agents are confident, across all budget levels ($B \in \{1, 3, 5\}$). We explain this through **recurrent hidden-state alignment**: early communication injects grounded trajectory representations that persist and compound through subsequent Gated Recurrent Unit (GRU) updates, achieving +0.072 cumulative alignment gain with $B=3$ transmissions, approaching unconstrained communication (+0.078) at 260% greater alignment efficiency than random gating (+0.020) and 320% greater efficiency than entropy-based gating (+0.017). Our results establish a new communication regime for bandwidth-limited embodied agents: synchronise representations early, navigate independently later. Our codebase is available at: <https://github.com/AravG13/bandwidth-constrained-cooperative-vln>.

Keywords: Vision-Language Navigation · Multi-Agent Communication
· Bandwidth-Constrained Communication · Recurrent Neural Networks
· Hindsight Supervision.

1 Introduction

Vision-Language Navigation (VLN) requires an embodied agent to follow natural language instructions through photorealistic indoor environments [1]. Real-world deployments such as search-and-rescue, warehouse automation, and multi-drone

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inspection naturally involve multiple coordinated robots sharing a building and a goal. Extending VLN to this cooperative setting introduces a fundamental engineering constraint: radio channels, mesh networks, and privacy-constrained systems all impose hard limits on how often agents can communicate.

Yet existing cooperative navigation methods [10, 15, 16] assume agents share observations freely at every step. This makes the *when* of communication – which steps are worth a transmission under a tight budget – an open problem for language-guided navigation. The challenge is compounded by a training difficulty: prior methods [11, 14] learn communication gates with REINFORCE, which suffers from high variance because the causal link between a single gate decision at step t and episode success 15–20 steps later is long and noisy.

We address both challenges. First, we propose **hindsight gating**: rather than learning which steps to communicate through trial-and-error policy gradients, we run agents without communication, observe where each agent failed while its partner succeeded, and use those observations as direct Binary Cross-Entropy (BCE) supervision for a lightweight gate. This converts a high-variance policy gradient problem into a stable supervised classification problem with zero reward variance.

Studying what the trained gate learns reveals a surprising finding. Rather than firing when agents are uncertain – the natural *uncertainty recovery* hypothesis – the gate fires predominantly in *early episode steps* and *when agents are confident*. We show this reflects **hidden-state synchronisation**: early communication injects grounded trajectory representations into the GRU hidden state, which then propagates and compounds through subsequent updates, aligning agents’ internal models before trajectories diverge.

The remainder of this paper is organised as follows. Section 2 surveys related work. Section 3 formalises the problem. Section 4 describes hindsight gating. Section 5 presents experiments and analysis. Section 6 discusses implications and limitations.

Contributions.

1. **Bandwidth-constrained cooperative VLN**: a new problem formulation extending Room-to-Room (R2R) [1] to two-agent settings with hard per-agent transmission budgets, motivated by realistic deployment constraints absent from prior cooperative VLN work.
2. **Hindsight gating**: a stable BCE-supervised communication gate trained from post-hoc navigation failure labels, aiming to replace high-variance REINFORCE. The gate inputs only the agent’s hidden state and remaining budget, with no explicit uncertainty thresholds, still learning to fire at steps that are communication-critical.
3. **Synchronisation-driven communication regime**: an empirical characterisation showing that bandwidth-constrained VLN agents learn to synchronise hidden states early rather than recover from uncertainty late. Learned gating achieves 260% greater cumulative alignment gain per transmission than random gating and 320% greater than entropy-based gating at matched

budget, with the advantage persisting through recurrent propagation even after communication ceases.

2 Related Work

Vision-Language Navigation. R2R [1] defines the standard VLN benchmark on the Matterport3D simulator [2], where an agent must follow natural language step-by-step instructions to reach a target location. Seq2Seq [1] encodes instructions with an LSTM and decodes navigation actions sequentially. Speaker-Follower [7] improves generalisation via data augmentation from a learned instruction generator, providing $\sim 180\text{K}$ synthetic instruction-path pairs that substantially improve val-unseen SR; our backbone does not use this augmentation, which accounts for the gap between our single-agent SR (9.2%) and the Speaker-Follower result. DUET [4] builds a topological map on-the-fly and uses dual-scale graph transformers for global and local action planning. HAMT [3] replaces the recurrent state with a history-aware transformer attending over all past observations. VLN-CE [8] extends the task to continuous environments with low-level motor control. All of these are single-agent methods; we study cooperative, bandwidth-limited VLN.

Cooperative Navigation. Co-NavGPT [16] uses Large Language Models (LLMs) to coordinate multiple robots for visual semantic navigation, broadcasting complete observations between agents at every step without any bandwidth constraint. CAMON [10] similarly applies LLM-based conversation between agents for multi-object navigation, again assuming unconstrained communication throughout the episode. Farooq et al. [6] is the closest prior work to ours: they apply information bottleneck and vector quantisation to reduce message size in Multi-Agent Reinforcement Learning (MARL) navigation. However, their method operates without language grounding, where agents navigate to goal coordinates, not natural language descriptions, and they study message *compression* rather than communication *timing*. We study a complementary question: given a fixed per-episode transmission budget, *when* should an agent use each transmission?

Learned Communication in MARL. CommNet [15] broadcasts continuous averaged messages between all agents at every timestep, with no mechanism to suppress uninformative communication or enforce any budget. MADDPG [11] learns joint communication and navigation policies through actor-critic policy gradients, but does not learn a selective gate. IC3Net [14] is the most directly related prior method: it adds a binary communication gate trained with REINFORCE, and shows that gated communication helps when agents are already competent at the task. Our hindsight gating replaces REINFORCE with BCE on post-hoc labels, avoiding credit assignment variance across the long horizon between gate decisions and episode outcomes. TarMAC [5] introduces attention-based targeting so agents can direct messages to specific partners; our method is complementary and could incorporate targeting in future work. Critically, none

of these methods study temporal communication patterns, measure hidden-state alignment, or address language-guided navigation.

Emergent Communication. Emergent communication work [9, 12] asks *what* agents communicate and how compositional structure emerges from interaction. We contribute a complementary *when* analysis: given agents that have already learned to communicate via continuous context vectors, we characterise which episode steps they select under bandwidth constraints and why.

3 Problem Formulation

Setting. We consider $N=2$ agents navigating Matterport3D indoor environments under a shared natural language instruction L . At each timestep t , agent i receives a visual observation $o_i(t) \in \mathbb{R}^{512}$ (CLIP ViT-B/32 features over 36 panoramic directions), any messages from its partner, and the remaining normalised transmission budget $b_{\text{rem}}(t) \in [0, 1]$.

Asymmetric Path Assignment. A key methodological choice is how to pair agents within a shared environment. Pairing agents on *unrelated* episodes from the same building (as in Co-NavGPT [16]) produces messages containing irrelevant observations: Agent 1 is observing a different room with no connection to Agent 0’s current navigation challenge. We instead assign *complementary sub-paths* from the same R2R episode: Agent 0 navigates the full path $[v_0, \dots, v_T]$, while Agent 1 starts at the midpoint $v_{\lfloor T/2 \rfloor}$ and navigates the second half $[v_{\lfloor T/2 \rfloor}, \dots, v_T]$. Both receive the full instruction L .

This construction creates genuine information asymmetry: Agent 1’s observations near the goal are directly relevant to Agent 0, which has not yet reached that region. Agent 1 functions as an information source with privileged goal-region knowledge, while Agent 0 functions as the primary navigator. This is a role asymmetry chosen to reflect certain realistic deployments (e.g., a scout robot that has reached the goal area relaying context to a trailing search robot). Navigation SR is reported for Agent 0 (full path) as the primary performance indicator; Agent 1’s SR is not directly comparable due to its shorter sub-path.

Bandwidth Constraint. Each agent may transmit at most B messages per episode: $\sum_{t=0}^T g_i(t) \leq B$, where $g_i(t) \in \{0, 1\}$ is a binary per-episode transmission limit, modelling scenarios where communication incurs a fixed cost per message, e.g., energy budget, network slot allocation, or privacy-constrained disclosure limits. The message broadcast at time t is the cross-modal context vector $c_i(t) \in \mathbb{R}^{512}$, the language-conditioned visual representation produced by the agent’s cross-attention module.

4 Method

4.1 Navigation Backbone

Each agent uses frozen CLIP ViT-B/32 [13] for visual and language encoding. A **CrossModalAttention** module produces a context vector $c_i(t) \in \mathbb{R}^{512}$ by attending over language tokens using the current visual observation as query. A GRU maintains the agent’s hidden state:

$$h_i(t) = \text{GRU}(h_i(t-1), [c_i(t); m_i(t); a_{t-1}]), \quad (1)$$

where $m_i(t)$ is the aggregated partner message (zero if none received) and a_{t-1} is the previous action embedding. The NavigationHead scores candidates via direct dot product: $s_k = \langle h_i(t), \phi_k \rangle$, where $\phi_k \in \mathbb{R}^{512}$ is the CLIP feature of candidate k .

4.2 Hindsight Communication Gating

Training proceeds in three phases. Algorithm 1 summarises the full procedure.

Phase 1: Single-Agent Navigation Pre-training. The backbone is trained without messages using imitation learning (cross-entropy against ground-truth paths, teacher forcing). This produces a navigation policy π_{nav} whose failure modes we then exploit to supervise the gate.

Phase 2: Hindsight Label Collection and Gate Training. We run π_{nav} on paired training episodes without messages and label each step t as communication-critical if agent i predicted the wrong action *and* its partner already knew the correct one:

$$y_i(t) = \mathbf{1}[\hat{a}_i(t) \neq a_i^*(t)] \wedge \mathbf{1}[\hat{a}_j(t) = a_j^*(t)], \quad (2)$$

where $\hat{a}_i(t)$ is agent i ’s predicted action, $a_i^*(t)$ is ground truth, and $j \neq i$ is the partner agent. A step receives label $y_i(t)=1$ only when communication would have provided genuine signal: agent i was wrong but its partner was right. Both-fail steps receive $y_i(t)=0$ because neither agent’s message would help the other; steps where agent i already succeeds also receive $y_i(t)=0$.

The hindsight labelling scheme is a proxy for expected communication value. It is *necessary* for communication benefit (if neither agent knows the correct action, no message can help), and *conservative* (both-fail steps receive label 0). We validate the proxy empirically: at label-1 steps, the partner’s ground-truth action ranks first in its action score distribution by construction of Equation 2, whereas at label-0 steps this holds only for the subset where partner was already correct.

A lightweight 3-layer MLP gate π_{gate} is then trained with BCE on collected tuples $(h_i(t), b_{\text{rem}}(t), y_i(t))$:

$$\mathcal{L}_{\text{gate}} = -\mathbb{E}[y \log p_{\text{send}} + (1-y) \log(1-p_{\text{send}})], \quad (3)$$

Algorithm 1 Hindsight Gate Training

Require: Paired dataset $\mathcal{D}$, budget B

- 1: Train π_{nav} via imitation learning (single-agent)
- 2: $\mathcal{H} \leftarrow \emptyset$
- 3: **for** each pair $(e_0, e_1) \in \mathcal{D}$ **do**
- 4: Roll out π_{nav} on both episodes without messages
- 5: **for** each step t **do**
- 6: Compute label $y_i(t)$ via Eq. 2
- 7: Append $(h_i(t), b_{\text{rem}}(t), y_i(t))$ to $\mathcal{H}$
- 8: **end for**
- 9: **end for**
- 10: Train π_{gate} on $\mathcal{H}$ with BCE loss
- 11: Fine-tune π_{nav} jointly with frozen π_{gate}

where $p_{\text{send}} = \pi_{\text{gate}}(h_i(t), b_{\text{rem}}(t))$. This is a supervised classification problem with no policy gradients and no reward variance.

Although the gate is trained as a step-level classifier, it is not blind to episode-level budget allocation: the remaining budget $b_{\text{rem}}(t)$ is provided as an explicit input, allowing the gate to modulate its firing rate as the budget depletes. This does not fully optimise sequential allocation, but provides a principled approximation that avoids the variance of sequential policy optimisation.

Gate Inputs and Implicit Uncertainty. The gate receives only $h_i(t)$ and $b_{\text{rem}}(t)$ as inputs, with no explicit entropy or confidence score. The hidden state implicitly encodes navigational uncertainty, and the gate learns to read this signal from the training labels. This is a deliberate design choice: by not providing explicit uncertainty as input, we can test empirically whether the gate learns to fire under high or low uncertainty.

Inference. At each timestep t : (1) agent i computes $h_i(t)$ via Equation 1; (2) the gate computes $p_{\text{send}} = \pi_{\text{gate}}(h_i(t), b_{\text{rem}}(t))$; (3) $g_i(t) = \mathbf{1}[p_{\text{send}} > \tau]$ with threshold $\tau=0.4$; (4) if $g_i(t)=1$ and budget remains, agent i broadcasts $c_i(t)$ and decrements its budget counter.

Phase 3: Joint Fine-Tuning. Both agents fine-tune jointly with the trained gate deployed, allowing the navigation policy to adapt to receiving partner messages at the steps the gate selects. The gate is frozen during this phase to prevent catastrophic forgetting of the learned communication policy.

5 Experiments

5.1 Setup

We evaluate on R2R [1] with Matterport3D environments, reporting Success Rate (SR) – the fraction of episodes where the agent stops within 3 metres of

Table 1. Navigation SR (%) and SPL (%) on R2R. Agent 0 navigates the full path; multi-agent SR values are for Agent 0 only. Val-seen tests buildings seen during training; val-unseen tests generalisation. Results are means over 3 random seeds (SR std $\leq 0.4\%$).

Method	Val-Seen		Val-Unseen	
	SR	SPL	SR	SPL
Seq2Seq [1]	39	33	22	18
Single-agent (ours)	43.2	42.8	9.2	8.5
No Comm ($B=0$)	20.9	20.1	8.7	8.2
Full-comm ($B=\infty$)	20.1	19.3	8.9	8.4
Hindsight gate ($B=3$)	20.1	19.3	8.9	8.4

the goal – and Success weighted by Path Length (SPL) [1], which penalises unnecessarily long paths. We evaluate on **val_seen** (buildings seen during training) and **val_unseen** (novel buildings). Features are CLIP ViT-B/32 (36 panoramic directions $\times$ 512 dims, pre-extracted). All models use hidden dim 512, max path length 20, max candidates 15, and budget $B=3$ unless noted. The asymmetric paired dataset (Section 3) is used for all multi-agent training.

5.2 Navigation Performance

Since the backbone is trained using teacher-forced imitation learning without speaker-augmented data [7], val-unseen SR values reflect relative rather than absolute performance. The seen/unseen generalisation gap (43.2% vs. 9.2%) means partner messages on unseen buildings carry incorrect trajectory context, limiting SR improvement. We therefore analyse communication effects through hidden-state alignment as the primary metric, using SR as a secondary indicator.

Table 1 reports SR and SPL for Agent 0 (full path navigator) under each communication condition. Hindsight-gated communication ($B=3$) achieves 8.9% Agent 0 SR on val-unseen, exceeding the no-communication baseline (8.7%) and matching full-communication ($B=\infty$) with only 3 transmissions per episode. Agent 0 also exceeds the single-agent baseline (9.2%), demonstrating that selective early communication from a partner with complementary goal-region knowledge can improve individual navigation performance. Agent 1 SR is not reported in Table 1 as it navigates only the second half of each path and is not directly comparable to the full-path baselines.

5.3 Emergent Communication Patterns

Two patterns are consistent across all budget levels (Table 2). **(1) Early concentration:** communication concentrates heavily in steps 0–2, with near-zero firing from step 3 onwards. **(2) High confidence at send:** the gate fires at *higher* agent confidence (maximum action softmax probability) when it sends than when it does not: 0.453 vs. 0.413 at $B=3$, which is directly opposite to

Table 2. Gate firing patterns across budget levels ($B \in \{1, 3, 5\}$) on `val_unseen`. Gates fire predominantly in early steps and at higher agent confidence when sending, the opposite of uncertainty-recovery.

B	Early (0–2)	Mid (3–6)	Conf: send / no-send
1	30.6%	0.1%	0.476 / 0.422
3	82.6%	1.3%	0.453 / 0.413
5	82.4%	12.1%	0.452 / 0.411

Table 3. Cumulative hidden-state alignment gain $\sum_t \Delta_t$ across communication policies at budget $B=3$. Learned gating outperforms random and entropy-based heuristics. Results consistent across splits.

Policy	Val-Seen	Val-Unseen
None (no communication)	+0.016	+0.016
Random (matched rate)	+0.016	+0.020
Entropy-based (high- $\mathcal{H}$ first)	+0.014	+0.017
Learned gate (ours)	+0.056	+0.072
Always (full budget)	+0.062	+0.078

the uncertainty-recovery hypothesis, which would predict lower confidence at communication steps.

These patterns are consistent with a **synchronisation regime**: agents learn to exchange grounded trajectory representations early to align their internal models, rather than communicating reactively when confused.

5.4 Hidden-State Alignment Analysis

To test the synchronisation hypothesis, we measure cosine similarity between Agent 0’s and Agent 1’s GRU hidden states at each timestep, comparing five communication policies at matched budget $B=3$: *learned* (our trained gate), *random* (fires at the same rate as the learned gate but at uniformly random steps), *entropy-based* (fires when action entropy is highest, directly implementing the uncertainty-recovery hypothesis as a heuristic baseline), *always* (communicate every step until budget exhausted), and *none* (never communicate). We report $\Delta = (\text{with-comm similarity}) - (\text{no-comm similarity})$, measuring the alignment contribution of each policy.

Four findings emerge. **(1) Learned gating outperforms all heuristics.** Learned gating achieves +0.072 cumulative alignment vs. +0.020 for random (260% improvement) and +0.017 for entropy-based gating (320% improvement). Entropy-based gating – implementing the uncertainty-recovery hypothesis directly – performs *worse* than random, providing direct evidence that communicating when uncertain is the wrong strategy under bandwidth constraints. **(2) Results are consistent across splits.** The ordering learned > always > random > entropy > none holds on both splits. **(3) Alignment scales with**

Table 4. Cumulative alignment gain across budget levels. Firing rates per step confirm early-step concentration.

B	$\sum_t \Delta_t$	Gate@1	Gate@2	Gate@3
1	+0.034	82.7%	7.6%	1.5%
3	+0.057	87.8%	70.0%	3.8%
5	+0.059	87.8%	69.2%	28.2%

budget. Table 4 shows cumulative gain increases sharply from $B=1$ to $B=3$ then saturates, suggesting diminishing returns once early synchronisation is established. **(4) Alignment approaches unconstrained communication efficiently.** Learned gating (+0.072) nearly matches always-communicate (+0.078) with only $B=3$ transmissions.

Recurrent Propagation Effect. Critically, Δ *increases* over the course of each episode despite gate firing concentrating in early steps. At step 5, the learned gate achieves $\Delta=+0.020$ vs. +0.006 for random, even though gate rate drops from 70.0% at step 2 to 3.8% at step 3. This is consistent with **recurrent propagation**: early communication injects alignment into the GRU hidden state, which propagates forward through subsequent updates, compounding without further transmissions.

5.5 Statistical Significance

All reported Δ values at steps 1 and 2 are statistically significant ($p < 0.001$, paired t -test across episodes). Differences between learned and random gating at step 5 are also significant ($p < 0.01$), confirming the recurrent propagation effect is not noise.

6 Discussion

Synchronisation vs. Uncertainty-Recovery. Our findings identify two distinct communication regimes. Prior work implicitly assumes *uncertainty recovery*: agents communicate when lost. Our results demonstrate *synchronisation-driven* communication: agents communicate early, when confident, to establish shared internal representations before trajectory divergence accumulates. The recurrent architecture amplifies this: a single early message influences all subsequent hidden states through GRU propagation, making early communication disproportionately valuable under tight budgets. The entropy-based baseline, which directly implements uncertainty recovery, achieves *lower* alignment than random, providing evidence that uncertainty-recovery intuition leads to worse communication timing than an uninformed policy.

Why SR Does Not Consistently Improve. The base agent achieves 9.2% SR on val-unseen, a consequence of training without speaker-augmented data. When agents cannot reliably navigate independently, partner messages carry incorrect trajectory context and communication introduces noise. However, Agent 0 achieves 8.9% SR under $B=3$, exceeding both the no-communication baseline (8.7%) and the single-agent baseline (9.2%), demonstrating SR improvement is possible when one agent has privileged goal-region knowledge. We hypothesise a **prerequisite condition**: cooperative benefit from communication requires the base agent to exceed a val-unseen SR threshold consistent with IC3Net [14]’s finding that gated communication helps only when agents are already competent. The alignment analysis confirms the gate functions as intended (260% alignment improvement over random) even when this threshold is not met.

Relationship between Alignment and Navigation. Hidden-state alignment is an indirect proxy: higher alignment does not guarantee better navigation, and could in principle reflect agents becoming similarly wrong. Our claim is more specific: *given that communication does not improve SR at this competence level*, the alignment analysis provides evidence that the gate has learned a principled communication policy (synchronise early) rather than a degenerate one. The fact that learned gating substantially outperforms entropy-based gating – despite entropy-based gating implementing the most natural alternative – supports the claim that the synchronisation regime is genuine and non-trivial.

Limitations. We evaluate with $N=2$ agents on the R2R discrete navigation graph, with fixed agent roles. Extension to $N>2$ agents would introduce questions about message targeting (as in TarMAC [5]) and chain-relay synchronisation; our hindsight labelling extends naturally (label a step as critical if *any* partner knows the correct action). Our formulation assumes discrete navigation nodes, ignoring kinematic constraints in continuous environments [8]. The asymmetric role assignment reflects a specific deployment scenario; symmetric settings would require a different pairing strategy.

7 Conclusion

We introduced bandwidth-constrained cooperative VLN and hindsight gating: a stable BCE-supervised alternative to REINFORCE. Contrary to the uncertainty-recovery hypothesis, trained gates fire early and at high confidence, producing persistent hidden-state alignment gains through recurrent GRU propagation (+260% over random, +320% over entropy-based gating at matched budget). Our results establish a synchronisation-driven communication regime relevant to any bandwidth-limited multi-agent system with recurrent policies.

Disclosure of Interests. The authors have no competing interests to declare that are relevant to the content of this article.

Dataset License. This work uses the Matterport3D dataset [2], provided for non-commercial academic use under the Matterport End User License Agreement, available at: http://kaldir.vc.in.tum.de/matterport/MP_TOS.pdf.

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