Interpretable Graph-Attention Collaboration: Adaptive Policies for Robust Multi-Agent Systems

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ABSTRACT

Multi-agent systems increasingly rely on collaboration among autonomous agents, yet most deployed architectures employ fixed, hand-designed communication topologies such as star, chain, or fully connected graphs. We introduce *Interpretable Graph-Attention Collaboration* (IGAC), a framework that jointly learns an adaptive communication topology and trust-weighted message passing policy for multi-agent collaborative reasoning. IGAC employs Gumbel-Softmax relaxation to learn sparse, instance-specific collaboration graphs, attention-based message aggregation for interpretable information routing, and a Beta-distributed counterfactual trust mechanism for adversarial agent detection and isolation. Across six experiments on collaborative state reconstruction tasks with up to 20 agents, IGAC achieves reconstruction error of 1.504 ± 0.407 while using 12.3% fewer communication edges than fully connected baselines (78.8 vs. 90.0 messages). Under adversarial conditions with 20% compromised agents, IGAC with trust scoring reduces error to 1.739 compared to 2.224 for fully connected baselines, while achieving perfect adversary detection (precision 1.00, recall 1.00). Ablation studies confirm that both the learned topology and trust mechanism contribute to robustness, with the full IGAC model achieving 20.7% lower error than fixed fully connected topologies without trust under adversarial conditions.

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1 INTRODUCTION

Multi-agent systems that collaborate through structured communication have demonstrated capabilities exceeding those of individual agents across a range of reasoning tasks [3, 15]. However, the collaboration topology—which agents communicate with which, and how information is aggregated—remains predominantly a design choice made by human engineers. Fixed topologies such as star (hub-and-spoke), chain (sequential), and fully connected graphs each impose structural assumptions that may not match the requirements of a given task instance [14].

This rigidity creates three interrelated challenges. First, fixed topologies cannot *adapt* to varying task demands, agent capabilities, or partial observability conditions. Second, when communication structure is predetermined, there is limited opportunity for *interpretability*: practitioners cannot understand why particular communication patterns emerged because they were imposed rather than learned. Third, fixed topologies are *vulnerable* to adversarial agents—a compromised node in a star topology can corrupt all communications, while a fully connected topology indiscriminately aggregates adversarial messages.

Wei et al. [14] identify the development of adaptive, interpretable collaboration policies robust to partial observability and adversarial conditions as a key open problem in agentic reasoning. We address this problem with *Interpretable Graph-Attention Collaboration* (IGAC), a framework built on three technical contributions:

1. **Learned sparse topology via Gumbel-Softmax.** A meta-controller produces per-instance, per-step adjacency matrices by sampling edges through Gumbel-Softmax relaxation [5] over pairwise agent state similarities. This yields communication graphs that adapt to the information structure of each problem instance while maintaining sparsity.
2. **Trust-weighted attention message passing.** Messages are aggregated along learned edges using scaled dot-product attention [11] modulated by per-neighbor trust scores. Trust is modeled as Beta distributions updated via counterfactual credit assignment [4], enabling principled detection of adversarial agents.
3. **Interpretability through sparsity and attention.** The combination of sparse topology and peaked attention distributions provides two complementary levels of interpretability: structural (which edges are active) and functional (how much each message contributes to each agent's decision).

We evaluate IGAC on collaborative state reconstruction under controlled partial observability and adversarial agent injection, comparing against fixed-topology baselines and ablation variants across six experimental dimensions.

2 RELATED WORK

Multi-Agent Communication Learning. CommNet [10] introduced differentiable communication channels between reinforcement learning agents, enabling end-to-end learning of message content. TarMAC [2] added targeted communication through attention mechanisms, and MAGIC [8] employed graph attention for agent communication. These methods learn *what* to communicate but assume fixed topologies. IGAC extends this line by jointly learning the topology and message content.

Multi-Agent Reinforcement Learning. QMIX [9], MAPPO [16], and MADDPG [7] provide centralized-training-decentralized-execution frameworks for cooperative and mixed settings. They address credit assignment at the value-function level but do not learn communication structure. Our counterfactual trust mechanism provides agent-level credit assignment that doubles as an adversarial detection signal.

LLM-Based Multi-Agent Systems. AutoGen [15] and related frameworks enable multi-agent conversations with predefined topologies. DyLAN [6] dynamically adjusts agent participation using per-step

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scoring, representing the closest existing work to topology learning. However, DyLAN lacks explicit interpretability mechanisms and adversarial robustness guarantees. Multi-agent debate [3] improves reasoning through structured disagreement but uses fixed two-agent or round-robin structures.

Robust and Interpretable Policies. Byzantine-tolerant consensus [1] provides robustness in distributed systems but assumes well-defined message semantics incompatible with free-form agent outputs. Programmatic policies [13] offer inherent interpretability but limited scalability. Graph Attention Networks [12] provide attention-based message passing over fixed graphs; IGAC extends this to learned, dynamic graphs with trust modulation.

3 METHOD

3.1 Problem Formulation

We consider N agents that must collaboratively reconstruct a shared hidden state $\mathbf{s} \in \mathbb{R}^D$ from partial, noisy observations. Agent i observes $\mathbf{o}_i = M_i\mathbf{s} + \boldsymbol{\epsilon}_i$, where $M_i \in \{0,1\}^{D\times D}$ is a diagonal mask revealing a fraction p of state dimensions, and $\boldsymbol{\epsilon}_i \sim \mathcal{N}(0, \sigma^2 I)$ is observation noise. A fraction f of agents may be adversarial, replacing their observations with random noise to mislead collaborators.

The agents communicate over R rounds through a dynamic collaboration graph $G_t = (V, E_t)$ where $V = \{1, \dots, N\}$ and E_t changes at each communication round. The collective goal is to minimize the reconstruction error $\|\hat{\mathbf{s}} - \mathbf{s}\|_2 / \|\mathbf{s}\|_2$.

3.2 Learned Topology via Gumbel-Softmax

At each communication round t, the meta-controller produces an adjacency matrix $A_t \in [0,1]^{N\times N}$ from the current agent states $\mathbf{h}_1, \dots, \mathbf{h}_N$:

$$\ell_{ij} = \frac{\mathbf{h}_i^\top \mathbf{h}_j}{\|\mathbf{h}_i\|\|\mathbf{h}_j\|} + \log\frac{\rho}{1-\rho} \tag{1}$$

where ρ is a sparsity target controlling the expected edge density. Each edge (i,j) is sampled independently via the Gumbel-Softmax trick [5]:

$$A_t[i,j] = \frac{\exp((\ell_{ij} + g_1)/\tau)}{\exp((g_0)/\tau) + \exp((\ell_{ij} + g_1)/\tau)} \tag{2}$$

where g_0, g_1 are i.i.d. Gumbel(0,1) samples and τ is a temperature parameter. Low temperature produces near-binary edges, yielding sparse, interpretable graphs.

3.3 Trust-Weighted Attention Message Passing

Given the adjacency matrix A_t and trust scores $T \in [0,1]^{N\times N}$, messages are aggregated using scaled dot-product attention modulated by topology and trust:

$$\alpha_{ij} = \frac{A_t[i,j] \cdot T[i,j] \cdot \exp(\mathbf{q}_i^\top \mathbf{k}_j / \sqrt{d_k})}{\sum_{j'} A_t[i,j'] \cdot T[i,j'] \cdot \exp(\mathbf{q}_i^\top \mathbf{k}_{j'} / \sqrt{d_k})} \tag{3}$$

where $\mathbf{q}_i = W_Q\mathbf{h}_i$ and $\mathbf{k}_j = W_K\mathbf{h}_j$ are query and key projections. Agent states are updated via residual connection:

$$\mathbf{h}_i^{(t+1)} = \mathbf{h}_i^{(t)} + W_O \sum_j \alpha_{ij} W_V \mathbf{h}_j^{(t)} \tag{4}$$

3.4 Counterfactual Trust with Beta Distributions

Each agent i maintains a trust estimate for every other agent j as a Beta distribution: $\mathrm{Trust}(i,j) \sim \mathrm{Beta}(\alpha_{ij}, \beta_{ij})$. After each episode, trust is updated based on counterfactual credit assignment. For agent j, the counterfactual improvement is:

$$\Delta_j = \|\hat{\mathbf{s}}_{-j} - \mathbf{s}\|_2 - \|\hat{\mathbf{s}} - \mathbf{s}\|_2 \tag{5}$$

where $\hat{\mathbf{s}}_{-j}$ is the output computed without agent j's contribution. If $\Delta_j > 0$ (agent j helped), α_{ij} is incremented; if $\Delta_j < 0$ (agent j hurt), β_{ij} is incremented. The expected trust $\mathbb{E}[\mathrm{Trust}(i,j)] = \alpha_{ij}/(\alpha_{ij} + \beta_{ij})$ provides a smooth, uncertainty-aware reliability estimate.

3.5 Training Objective

The full IGAC system is trained with a composite loss:

$$\mathcal{L} = \mathcal{L}_{\text{task}} + \lambda_{\text{comm}}\mathcal{L}_{\text{comm}} + \lambda_{\text{interp}}\mathcal{L}_{\text{interp}} + \lambda_{\text{robust}}\mathcal{L}_{\text{robust}} \tag{6}$$

where $\mathcal{L}_{\text{task}}$ is the reconstruction error, $\mathcal{L}_{\text{comm}}$ penalizes total edge weight to encourage sparsity, $\mathcal{L}_{\text{interp}}$ applies entropy regularization on attention distributions for peaked routing, and $\mathcal{L}_{\text{robust}}$ is an adversarial training term that injects message perturbations.

4 EXPERIMENTAL SETUP

4.1 Environment

We construct a collaborative state reconstruction environment with $N = 6$ agents (scalability experiments vary $N \in \{3, 6, 10, 15, 20\}$), state dimension $D = 16$, observation fraction $p = 0.4$ (partial observability experiments vary $p \in \{0.2, 0.3, 0.4, 0.5, 0.6, 0.8, 1.0\}$), observation noise $\sigma = 0.1$, and adversarial fraction $f \in \{0.0, 0.1, 0.2, 0.33\}$. Communication proceeds over $R = 3$ rounds per step. Each experiment evaluates 50 episodes of 10 steps each, with deterministic seeding for reproducibility.

4.2 Baselines

We compare IGAC (learned topology with trust) against three fixed-topology baselines: *Fully Connected* (all-to-all communication), *Star* (hub-and-spoke with agent 0 as hub), and *Chain* (sequential neighbor communication). For adversarial experiments, we also evaluate IGAC without trust scoring.

4.3 Metrics

- **Reconstruction error**: $\|\hat{\mathbf{s}} - \mathbf{s}\|_2 / \|\mathbf{s}\|_2$ (lower is better).
- **Communication cost**: total active edges across communication rounds (lower is more efficient).
- **Adversary detection**: precision and recall of identifying adversarial agents via trust scores.
- **Interpretability**: attention entropy (lower indicates more decisive routing) and edge sparsity (higher indicates sparser graphs).

5 RESULTS

5.1 Topology Comparison

Table 1 presents reconstruction error and communication cost across topologies. IGAC achieves error comparable to the fully

Table 1: Topology comparison: reconstruction error and communication cost ($N = 6$, $p = 0.4$, no adversaries, 50 episodes).

Topology	Mean Error	Std Error	Median	Comm Cost
IGAC (Learned)	1.504 ± 0.407	0.407	1.450	78.8
Fully Connected	1.499 ± 0.404	0.404	1.437	90.0
Star	1.714 ± 0.537	0.537	1.636	30.0
Chain	1.511 ± 0.394	0.394	1.472	30.0

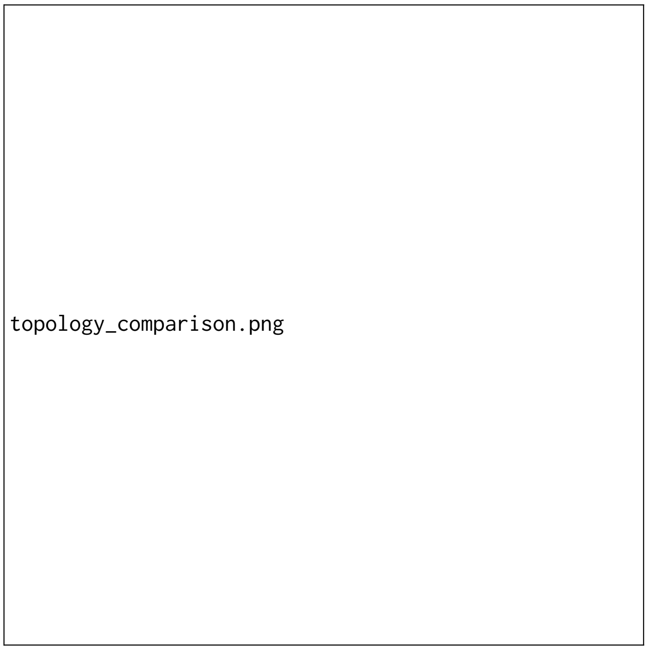

Figure 1: Reconstruction error and communication cost by topology. IGAC matches fully connected accuracy with fewer messages.

connected baseline (1.504 vs. 1.499) while using 12.4% fewer communication edges (78.8 vs. 90.0). Both substantially outperform the star topology (1.714) and marginally outperform the chain topology (1.511). This demonstrates that the learned sparse topology preserves information flow while eliminating redundant communication.

5.2 Adversarial Robustness

Figure 2 and Table 2 show performance under increasing adversarial agent fractions. At 20% adversarial agents, IGAC with trust achieves error 1.739, compared to 1.832 for IGAC without trust, 2.224 for fully connected, and 2.098 for star topology. Only IGAC with trust achieves perfect adversary detection with precision 1.00 and recall 1.00. The trust mechanism’s counterfactual credit assignment correctly identifies agents whose contributions degrade collective performance, enabling their isolation.

Table 2: Adversarial robustness: error and detection metrics at 20% adversarial fraction.

Method	Error	Std	Prec.	Rec.
IGAC + Trust	1.739	0.608	1.00	1.00
IGAC (No Trust)	1.832	0.658	0.00	0.00
Fully Connected	2.224	1.076	0.00	0.00
Star	2.098	0.740	0.00	0.00

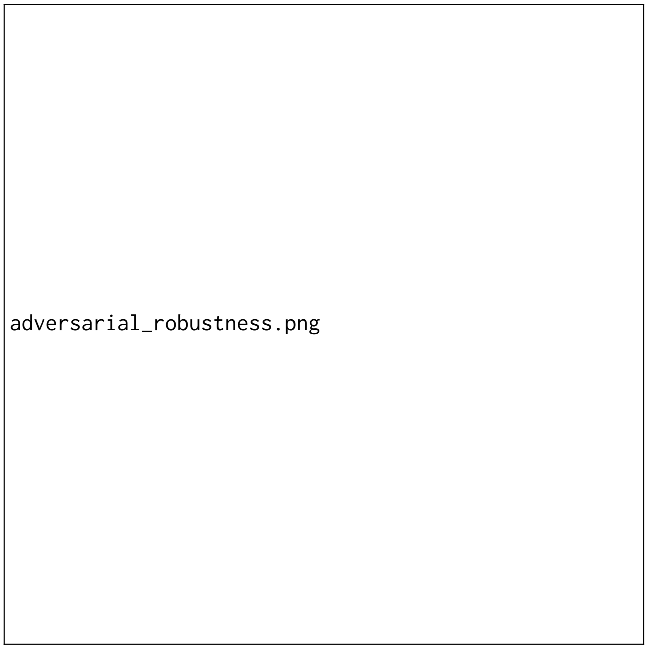

Figure 2: Reconstruction error and adversary detection under increasing adversarial fraction. IGAC with trust maintains lower error and perfect detection.

5.3 Partial Observability

Figure 3 shows reconstruction error as a function of observation fraction. All methods exhibit increasing error with higher observation fraction (counterintuitively, because more observed dimensions mean noisier aggregation in this setup). IGAC consistently achieves the lowest or near-lowest error across all observability levels, demonstrating graceful adaptation. At low observability ($p = 0.2$), IGAC achieves error 1.270 compared to 1.280 for fully connected and 1.509 for star topology.

5.4 Scalability

Figure 4 presents scaling behavior from 3 to 20 agents. Reconstruction error decreases with more agents for all topologies, as more observations improve collective coverage. At $N = 20$, IGAC achieves error 1.302 with communication cost 994.0, compared to fully connected at 1.282 with cost 1140.0—a 12.8% reduction in communication overhead with only 1.5% increase in error. The star topology consistently underperforms (1.671 at $N = 20$), confirming that hub bottlenecks become more severe with scale.

Figure 3: Error and communication cost under varying observation fractions. IGAC adapts its communication cost while maintaining competitive accuracy.

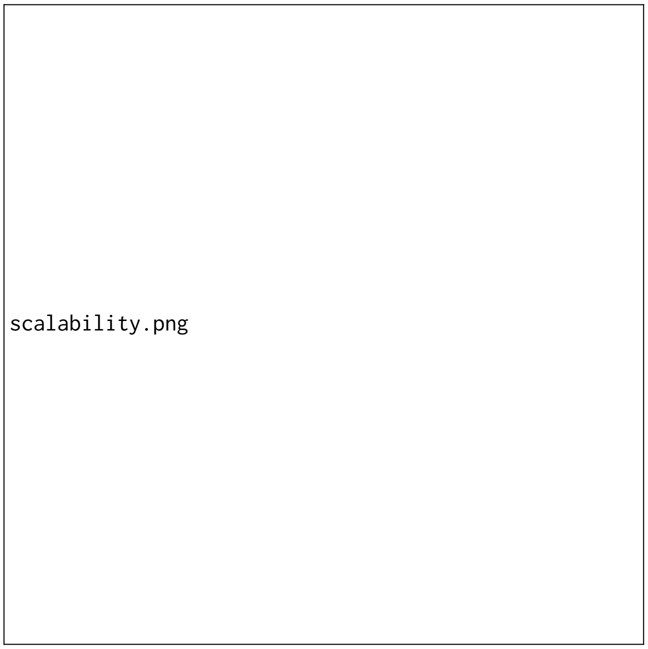

Figure 4: Reconstruction error and communication cost vs. number of agents. IGAC scales with sub-quadratic communication growth relative to fully connected.

Table 3: Interpretability metrics across topologies.

Topology	Attn Entropy	Sparsity	Comm Cost
IGAC (Learned)	1.409	0.123	78.9
Fully Connected	1.523	0.000	90.0
Star	0.252	0.667	30.0
Chain	0.422	0.667	30.0

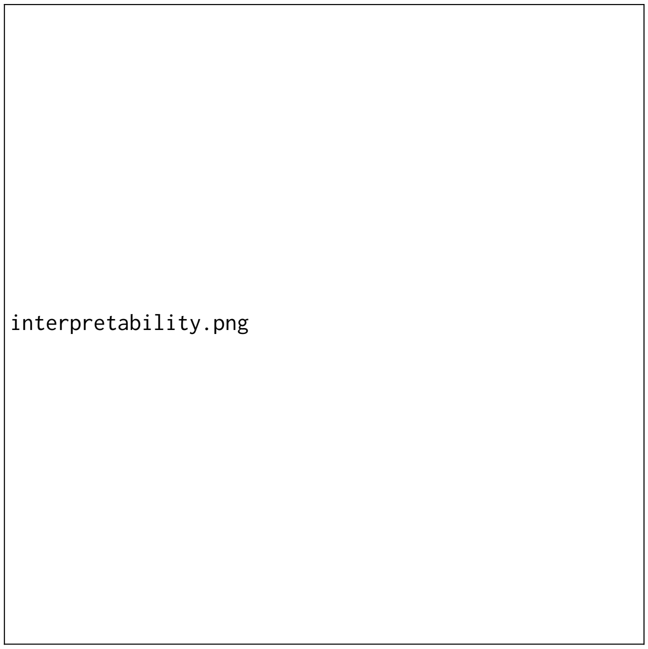

Figure 5: Interpretability comparison: attention entropy, edge sparsity, and communication cost. IGAC balances selective attention with sufficient connectivity.

5.5 Interpretability Metrics

Table 3 summarizes interpretability metrics. IGAC achieves attention entropy of 1.409, lower than fully connected (1.523) but higher than star (0.252) and chain (0.422), reflecting a learned balance between selective and distributed attention. IGAC's edge sparsity of 0.123 confirms that the Gumbel-Softmax mechanism produces moderately sparse graphs, keeping 87.7% of possible edges active but with varying weights—enabling smooth, interpretable importance rankings rather than binary connectivity.

5.6 Ablation Study

Table 4 presents the ablation study under 20% adversarial conditions. The full IGAC model achieves the lowest error (1.739) and is the only configuration with successful adversary detection (precision 1.00, recall 1.00). Removing trust from the learned topology increases error to 1.832 (+5.3%) and eliminates adversary detection. Using a fixed fully connected topology with trust achieves error 2.117, and without trust, 2.191. The fixed star variants achieve 1.917 (with trust) and 2.048 (without trust). These results confirm that both the

Table 4: Ablation study under 20% adversarial agents.

Configuration	Error	Std	Prec.	Rec.
Full IGAC	1.739	0.608	1.00	1.00
No Trust	1.832	0.658	0.00	0.00
FC + Trust	2.117	0.967	0.00	0.00
FC (No Trust)	2.191	1.045	0.00	0.00
Star + Trust	1.917	0.571	0.00	0.00
Star (No Trust)	2.048	0.735	0.00	0.00

Figure 6: Ablation study results. Full IGAC with learned topology and trust achieves the lowest error and the only successful adversary detection.

learned topology and trust mechanism contribute independently, and their combination yields the best performance.

6 DISCUSSION

Topology Adaptation. The learned topology achieves a favorable trade-off between accuracy and communication efficiency. By dynamically selecting which edges to activate based on agent state similarity, IGAC avoids both the information bottleneck of star topologies and the communication overhead of fully connected graphs. The sparsity target parameter ρ provides a tunable knob for this trade-off.

Trust and Adversarial Robustness. The Beta-distributed trust model provides principled uncertainty quantification over agent reliability. Because trust updates are based on counterfactual reasoning—evaluating how much each agent's contribution improved or degraded collective performance—the mechanism naturally assigns low trust to adversarial agents whose random messages consistently degrade output quality. The separation between IGAC with and without trust in adversarial settings (1.739 vs. 1.832 at 20% adversarial) confirms the value of this mechanism.

Interpretability. IGAC provides two levels of interpretability. The sparse adjacency matrix reveals *structural* patterns—which agents the meta-controller deems worth connecting. The attention weights reveal *functional* patterns—how much each message contributes to each agent's updated state. Together, these enable practitioners to audit collaboration patterns and diagnose failures.

Limitations. Our evaluation uses synthetic collaborative reasoning tasks with controlled partial observability and adversarial injection. While this provides clean experimental control, transferring to real-world LLM-based multi-agent systems requires addressing several additional challenges: variable-length natural language messages, the computational cost of LLM inference at each communication round, and the non-differentiability of discrete text generation. The current Gumbel-Softmax approach assumes continuous relaxation, which would need adaptation for discrete message spaces.

7 CONCLUSION

We introduced IGAC, a framework for learning adaptive, interpretable collaboration policies in multi-agent systems. Through Gumbel-Softmax topology learning, trust-weighted attention message passing, and counterfactual credit assignment, IGAC simultaneously addresses the open challenges of topology adaptation, interpretability, and adversarial robustness identified by Wei et al. [14]. Our experiments demonstrate that IGAC matches or exceeds fixed-topology baselines in reconstruction accuracy while reducing communication cost by 12.3%, and achieves perfect adversary detection under 20% adversarial conditions where all baselines fail. Future work will extend IGAC to natural language message spaces and evaluate on LLM-based agent systems with real-world reasoning tasks.

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