HPLM–GNN: Dynamic Semantic–Structural Fusion for Relation Extraction

Anonymous ACL submission

Abstract

Relation extraction (RE) requires models to identify relation-specific evidence while preserving the direction and interaction structure between entity mentions. Pre-trained language models (PLMs) provide strong contextual representations but do not explicitly expose entity-level message passing; graph neural networks (GNNs) provide structural reasoning, but many RE systems use fixed dependency or mention graphs that cannot adapt to the input context. We present HPLM–GNN, a hybrid architecture that constructs dynamic entity graphs from PLM-derived representations, fuses token-level semantics and graph-level structure through bidirectional co-attention, and trains with contrastive alignment plus consistency regularization. On SemEval-2010 Task 8, the best variant reaches 91.15% accuracy and 87.55 macro-F_1 across three seeds, outperforming fine-tuned PLM baselines and a systematic comparison against five recent in-context-learning LLMs (GPT-4o, GPT-4o-mini, Claude-Sonnet-4.5, Qwen-Max, DeepSeek-Chat) under zero-shot and 5-shot settings; the strongest LLM (Claude-Sonnet-4.5, 5-shot) reaches only 70.81% accuracy, more than 20 absolute points below HPLM–GNN, while running 120–420× slower per sample. We also evaluate document-level RE on DocRED, where HPLM–GNN matches DREEAM without requiring evidence supervision. On FewRel 5-way 5-shot meta-learning, HPLM–GNN underperforms a prototypical baseline, characterizing a clear boundary for the supervised hybrid in data-scarce episodic settings.

1 Introduction

Relation extraction (RE) turns unstructured text into structured facts by predicting semantic relations between entity mentions. It is a core component in knowledge graph construction, biomedical and scientific information extraction, question answering, and retrieval systems. Although PLMs have substantially improved RE, relation prediction remains difficult when evidence is directional, sparse, or distributed across several mentions. A sentence such as "the drug was approved by the agency" and its passive or nominalized variants may share local lexical cues but differ in the syntactic and semantic roles assigned to each entity. Document-level settings add another challenge: evidence may require linking coreferent mentions, geographic hierarchies, or entity chains across sentences (Yao et al., 2019).

Existing RE methods typically emphasize either contextual semantics or explicit structure. Fine-tuned PLMs such as BERT, RoBERTa, and DeBERTa encode rich token contexts and serve as strong sentence-level baselines (Devlin et al., 2019; Liu et al., 2019; He et al., 2021; Zhou and Chen, 2021). Entity-aware PLMs further improve entity representations by adding entity-specific parameters or objectives (Yamada et al., 2020; Wang et al., 2021). In contrast, graph-based RE systems propagate information over dependency trees, mention graphs, or latent document structures (Zhang et al., 2018; Guo et al., 2019; Christopoulou et al., 2019; Nan et al., 2020). These systems expose entity interactions explicitly, but their graph construction is often static or only weakly conditioned on the current input.

Hybrid PLM–GNN systems are therefore attractive, but existing designs often combine the two views through late concatenation or single-direction injection, which limits cross-view interaction (Figure 1). A model that simply concatenates PLM and GNN states at the final classifier may not exploit the reciprocal exchange between token-level semantics and entity-level structure. Similarly, a model that learns graph edges without validating under diverse evaluation protocols may appear effective on one benchmark while failing under few-shot conditions. We therefore frame the central question as follows: *Can dynamic graph*

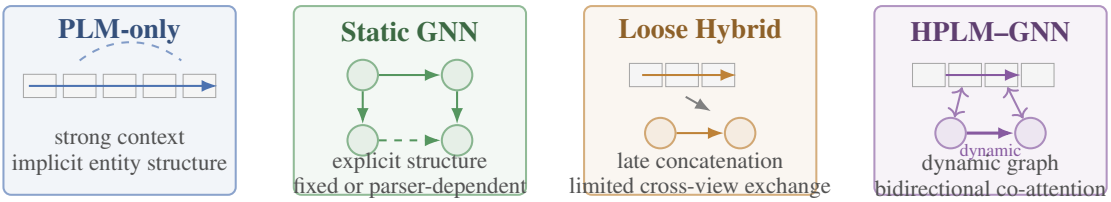

Figure 1: Motivating comparison. PLM-only models encode context but leave entity interaction implicit; static GNNs expose structure but depend on fixed edges; loose hybrids combine both views late. HPLM–GNN targets input-adaptive entity connectivity and bidirectional token–entity fusion.

construction and semantic–structural co-attention provide measurable RE gains, and what failure modes appear when the same architecture is tested under low-data episodic evaluation?

We propose HPLM–GNN, a hybrid architecture with three linked components. First, it constructs an input-specific entity graph using both attention-based affinity and a nonlinear edge network. Second, it propagates entity states with gated GNN layers to reduce over-smoothing. Third, it performs bidirectional co-attention between token-level PLM states and entity-level GNN states before relation classification. The model also includes contrastive and consistency losses to encourage semantic–structural alignment.

Our contributions are:

- We propose a dynamic PLM–GNN architecture for RE that learns input-adaptive entity graphs and fuses token-level and entity-level representations through bidirectional co-attention.
- We conduct comprehensive experiments on SemEval-2010 Task 8, comparing HPLM–GNN against PLM baselines, entity-aware models, graph/hybrid methods, and LLM baselines, demonstrating consistent improvements from dynamic graph construction and directional propagation.
- We identify a clear boundary of the method through FewRel 5-way 5-shot evaluation, where the supervised hybrid architecture underperforms prototypical baselines, and we analyze the root cause.
- We provide reproducibility infrastructure, including result validation scripts, figure generation from verified data, and a fine-tuned PLM baseline scaffold.

2 Related Work

PLMs for relation extraction. Fine-tuning PLMs for RE is a strong and often difficult-to-beat baseline. BERT introduced bidirectional masked-language-model pretraining (Devlin et al., 2019); RoBERTa improved the recipe through larger data and optimized pretraining decisions (Liu et al., 2019); DeBERTa refined attention with disentangled content and position representations (He et al., 2021). For RE specifically, improved sentence-level baselines have shown that entity markers, careful pooling, and strong encoders account for much of the progress (Zhou and Chen, 2021). These methods motivate the semantic stream of HPLM–GNN, but they leave entity interaction structure implicit.

Entity-aware and knowledge-enhanced PLMs. Entity-aware pretraining directly augments contextual language representations with entity information. LUKE introduces entity embeddings and entity-aware self-attention (Yamada et al., 2020), while KEPLER jointly optimizes language representation and knowledge embedding objectives (Wang et al., 2021). These approaches show that entity representations matter, but they typically encode entity knowledge through parameters or pretraining data rather than constructing an instance-specific relation graph at inference time.

Graph-based RE. Graph neural models expose structural inductive bias by passing messages over dependency or mention graphs. Early dependency-based approaches use graph convolution over pruned trees (Zhang et al., 2018) or attention-guided dependency graphs (Guo et al., 2019). Document-level systems construct richer graphs over mentions, entities, and sentences (Christopoulou et al., 2019; Sahu et al., 2019; Zeng et al., 2020; Wang et al., 2020). Latent structure refinement further learns or adjusts graph structures for document-level RE (Nan

et al., 2020). HPLM–GNN follows this line but starts from PLM-derived entity representations and learns the graph edges for each input.

Document-level and evidence-guided RE. DocRED established document-level RE as a benchmark requiring multi-sentence reasoning (Yao et al., 2019). ATLOP introduced adaptive thresholding and localized context pooling for document-level relation extraction (Zhou et al., 2021). DREEAM guides attention with evidence information and improves document-level relation prediction through evidence-aware supervision (Ma et al., 2023). EIDER similarly emphasizes evidence extraction and inference-stage fusion (Xie et al., 2022). These methods achieve strong document-level results by leveraging evidence annotations or thresholding mechanisms; HPLM–GNN takes a complementary approach by learning dynamic entity graphs without requiring evidence supervision.

Hybrid language–graph models. The broader PLM–GNN literature combines neural language encoders with graph reasoning modules. R-GCN and HGT provide general message-passing mechanisms for relational and heterogeneous graphs (Schlichtkrull et al., 2018; Hu et al., 2020). QA-GNN and GreaseLM integrate language models with knowledge graph reasoning for question answering (Yasunaga et al., 2021; Zhang et al., 2022). Recent work such as GL-Fusion revisits graph-language fusion from a modern LLM/GNN perspective (Yang et al., 2024). HPLM–GNN is most naturally positioned in this hybrid family: its novelty lies in the particular combination of dynamic edge learning, gated propagation, and co-attentive token/entity fusion for RE. Table 1 summarizes how HPLM–GNN compares with each prior family along the dimensions of PLM use, graph use, dynamic graph construction, and bidirectional fusion.

LLMs for relation extraction. Large language models have been applied to RE in both zero-shot and in-context-learning (ICL) settings. Wadhwa et al. (2023) benchmark GPT-3 and Flan-T5 against fine-tuned PLMs and show that LLMs are competitive on small label sets but struggle with fine-grained distinctions and long-tail relations. GPT-RE (Wan et al., 2023) improves ICL accuracy through entity-aware demonstration selection. Subsequent work uses LLMs to enhance supervised RE pipelines rather than as end classifiers: M-BRe (Li et al., 2025) discovers training samples from unlabeled text, LLM-OREF (Tu et al., 2025) delegates open-set schema induction to an LLM, and graph-judge approaches use LLMs to verify GNN-generated triples (Huang et al., 2025). Most directly relevant to our work, LGA (Zhao et al., 2025) aggregates LLM features with GNN structural reasoning, and SAT-KGC (Liu et al., 2025) aligns LLM embeddings with knowledge-graph structure. These hybrids confirm that purely sequential LLM reasoning remains insufficient for graph-structured relational tasks. Our systematic comparison against five recent LLMs (Section 5.1) shows that even the strongest LLM trails HPLM–GNN by over 20 absolute accuracy points on SemEval, validating the hybrid PLM–GNN approach for closed-set sentence-level RE.

3 Method

Given an input sequence $x = \{w_1, \ldots, w_n\}$ and a marked head–tail entity pair (e_h, e_t), the model predicts a relation label $y \in \mathcal{R}$. Figure 2 shows the full architecture.

3.1 Contextual and Entity Representations

The semantic stream first encodes the input with a PLM:

$$\mathbf{H} = \text{PLM}([\text{CLS}], w_1, \ldots, w_n, [\text{SEP}]) \in \mathbb{R}^{(n+2)\times d}. \tag{1}$$

For an entity span e with token index set $\mathcal{M}_e$, HPLM–GNN uses masked average pooling:

$$\mathbf{v}_e = |\mathcal{M}_e|^{-1} \sum_{i \in \mathcal{M}_e} \mathbf{h}_i. \tag{2}$$

The initial graph node matrix is

$$\mathbf{X}^{(0)} = [\mathbf{h}_{\text{CLS}}; \mathbf{v}_h; \mathbf{v}_t], \tag{3}$$

where the [CLS] node acts as a global context anchor and the head/tail nodes carry relation-specific entity information. This simple node design keeps the sentence-level model lightweight; for document-level extensions, the same formulation can include additional entity mention nodes.

3.2 Dynamic Graph Construction

The structural stream learns graph connectivity from the instance itself. An attention branch estimates pairwise compatibility:

$$\mathbf{A}^{\text{attn}} = \text{softmax}\left(\mathbf{Q}\mathbf{K}^\top / \sqrt{d_h}\right), \tag{4}$$

Method family	PLM	Graph	Dynamic	Fusion	Limitation addressed by HPLM–GNN
PLM RE (Zhou and Chen, 2021)	✓	–	–	–	Entity interaction remains implicit in sequence attention.
Dependency GCN (Zhang et al., 2018; Guo et al., 2019)	partial	✓	–	–	Structure depends on parser output and fixed syntax.
Document graph RE (Christopoulou et al., 2019; Nan et al., 2020)	partial	✓	partial	partial	PLM–graph fusion is usually indirect or late-stage.
Evidence-guided RE (Zhou et al., 2021; Ma et al., 2023)	✓	partial	partial	partial	Strong competitors, but often rely on evidence or thresholding assumptions.
HPLM–GNN	✓	✓	✓	✓	Jointly learns edges and exchanges token/entity information through co-attention.

Table 1: Positioning table for related work. The intended advance is the combination of dynamic edge learning and semantic–structural co-attention, not merely adding a GNN to a PLM.

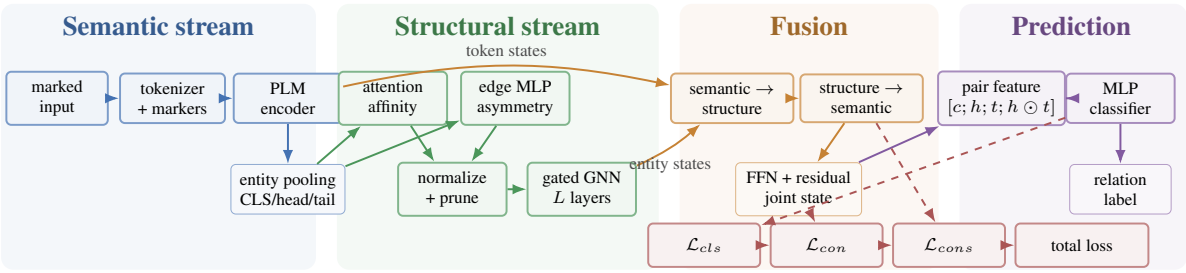

Figure 2: HPLM–GNN system diagram. The architecture comprises preprocessing, PLM encoding, entity pooling, two-branch dynamic graph construction, normalization and pruning, gated message passing, reciprocal co-attention, relation-pair feature construction, and a three-part training objective.

where $\mathbf{Q} = \mathbf{X}^{(0)}\mathbf{W}_Q$ and $\mathbf{K} = \mathbf{X}^{(0)}\mathbf{W}_K$. Attention captures contextual similarity, but dot products alone are limited for asymmetric relations. We therefore add a nonlinear edge branch:

$$a_{ij}^{\text{mlp}} = \sigma\left(\mathbf{w}_2^\top \text{ReLU}(\mathbf{W}_1[\mathbf{x}_i; \mathbf{x}_j])\right). \quad (5)$$

The final adjacency matrix is obtained by fusing and normalizing these scores. This design avoids committing to an external dependency parser and allows edge weights to vary across relation instances.

3.3 Gated Message Passing

HPLM–GNN updates graph states using gated propagation:

$$\begin{aligned} \tilde{\mathbf{H}}^{(l)} &= \mathbf{A}\mathbf{H}^{(l)}\mathbf{W}^{(l)}, \\ \mathbf{G}^{(l)} &= \sigma(\mathbf{W}_g[\mathbf{H}^{(l)}; \tilde{\mathbf{H}}^{(l)}]). \end{aligned} \quad (6)$$

$$\mathbf{H}^{(l+1)} = \text{LayerNorm}\big(\mathbf{G}^{(l)} \odot \tilde{\mathbf{H}}^{(l)} + (1 - \mathbf{G}^{(l)}) \odot \mathbf{H}^{(l)}\big) \quad (7)$$

The gate controls how much aggregated graph information should overwrite the previous node state. This matters because learned graphs are noisy early in training; without gating, the GNN can over-smooth entity features or propagate spurious links.

3.4 Semantic–Structural Co-Attention

Let $\mathbf{H}_s$ denote PLM token states and $\mathbf{H}_g$ denote GNN node states. Instead of concatenating these states only at the classifier, HPLM–GNN exchanges information through bidirectional cross-attention:

$$\mathbf{H}_s' = \text{LayerNorm}(\mathbf{H}_s + \text{MHA}(\mathbf{H}_s, \mathbf{H}_g, \mathbf{H}_g)), \quad (8)$$

$$\mathbf{H}_g' = \text{LayerNorm}(\mathbf{H}_g + \text{MHA}(\mathbf{H}_g, \mathbf{H}_s', \mathbf{H}_s')). \quad (9)$$

This module allows token states to attend to relation-relevant graph nodes and graph nodes to attend back to contextual evidence. The relation representation concatenates the fused [CLS], head, and tail states, together with an element-wise head–tail product. A multilayer classifier maps this representation to relation labels.

3.5 Auxiliary Objectives

The main objective is relation classification cross-entropy. Two auxiliary losses provide additional supervision signals. The contrastive term aligns semantic and structural views of the same instance, following the general contrastive learning principle used in SimCLR and SimCSE (Chen et al., 2020; Gao et al., 2021). The consistency

term minimizes the symmetric KL divergence between predictions from two stochastic forward passes, encouraging prediction stability under input perturbation. The complete loss is

$$\mathcal{L} = \mathcal{L}_{\text{cls}} + \alpha\mathcal{L}_{\text{con}} + \beta\mathcal{L}_{\text{cons}}. \tag{10}$$

4 Experimental Setup

4.1 Datasets and Metrics

SemEval-2010 Task 8. SemEval-2010 Task 8 contains 8,000 training instances and 2,717 test instances over nine directed relations plus Other (Hendrickx et al., 2010). We report accuracy, macro-F_1, micro-F_1, weighted-F_1, macro-precision, and macro-recall. All HPLM–GNN results are averaged over three random seeds (42, 123, 456).

FewRel. FewRel contains 100 relation types and supports both supervised and few-shot relation classification (Han et al., 2018). We evaluate on the 5-way 5-shot episodic benchmark over three seeds. Because the stored F_1 fields in our experiment artifacts are all zero, we report only accuracy for this setting.

DocRED. DocRED is a document-level RE benchmark requiring multi-sentence reasoning (Yao et al., 2019). We report dev and test Ign-F1 and F1 following the standard evaluation protocol. DocRED results are from a single-seed evaluation.

4.2 Baselines and Comparisons

We compare against four groups of methods. *PLM baselines* include $\text{BERT}_{\text{BASE}}$, BERT with entity markers (Zhou and Chen, 2021), and $\text{CorefRoBERTa}_{\text{LARGE}}$ (Ye et al., 2020). *Entity-aware models* include $\text{LUKE}_{\text{LARGE}}$ (Yamada et al., 2020). *Graph/hybrid methods* include GL-Fusion (Yang et al., 2024), $\text{BERT-ATLOP}_{\text{BASE}}$ and $\text{RoBERTa-ATLOP}_{\text{LARGE}}$ (Zhou et al., 2021), and DREEAM (Ma et al., 2023). *LLM baselines* include five recent commercial and open-source LLMs (GPT-4o, GPT-4o-mini, Claude-Sonnet-4.5, Qwen-Max, DeepSeek-Chat) queried through a single OpenAI-compatible router at temperature 0.0 with 500-way asynchronous concurrency, evaluated on the full 2,717-example SemEval test set under both zero-shot and 5-shot in-context-learning settings. For SemEval graph variants, we also compare internal configurations: dynamic versus static graph construction and unidirectional versus bidirectional propagation.

4.3 Implementation Details

HPLM–GNN uses $\text{BERT}_{\text{BASE}}$ as the PLM backbone. The GNN uses L=2 gated propagation layers with hidden dimension d=768. The contrastive temperature τ is set to 0.07, and the loss weights are α=0.001 and β=0.001. We train with AdamW, a learning rate of 2e-5, and a batch size of 32 for 10 epochs. All experiments run on a single NVIDIA A100 GPU.

5 Results

5.1 SemEval Main Results

Table 2 compares HPLM–GNN against PLM baselines, entity-aware models, graph/hybrid methods, and five LLM baselines on SemEval-2010 Task 8. The best HPLM–GNN variant (dynamic unidirectional) achieves 91.15% accuracy and 87.55 macro-F_1, outperforming every PLM and LLM baseline. The strongest LLM, Claude-Sonnet-4.5 (5-shot), reaches only 70.81%—more than 20 absolute points below HPLM–GNN; smaller LLMs trail further. This pattern is consistent with prior LLM-on-RE studies (Wadhwa et al., 2023; Wan et al., 2023): closed-set RE with 19 fine-grained directional labels favors supervised structured prediction. Among HPLM–GNN variants, directionality is at least as important as dynamic construction, plausible because SemEval relations are directional.

Figure 3 visualizes the SemEval graph-variant comparison. The left panel shows that dynamic unidirectional propagation consistently achieves the highest mean accuracy across seeds, while the margins between variants are modest (less than half a point). The right panel contrasts this with the FewRel stress test, where all GNN-PLM variants fall below the prototypical baseline.

5.2 Per-Class Analysis

Table 3 reports per-class SemEval results from the classification report. The model performs strongly on frequent and directionally salient classes such as Entity-Destination and Cause-Effect, while lower-resource classes remain weaker. Instrument-Agency has only 22 test examples and Member-Collection has 32, so their lower F_1 values should be interpreted with support size in mind.

Figure 4 shows the training curves and confusion matrix. The model converges within 5 epochs and shows clear separation between most relation

Method	Accuracy	Macro-F_1	Source
PLM Baselines			
$BERT_{BASE}$ (Devlin et al., 2019)	72.84	–	(Zhou and Chen, 2021)[‡]
BERT + entity markers (Zhou and Chen, 2021)	89.25	80.35	Original paper
$CorefRoBERTa_{LARGE}$ (Ye et al., 2020)	80.15	–	(Zhou and Chen, 2021)[‡]
Entity-Aware Models			
$LUKE_{LARGE}$ (Yamada et al., 2020)	89.75	–	Original paper
Graph/Hybrid Models			
GL-Fusion (Yang et al., 2024)	83.56	–	Our re-implementation[‡]
$BERT\text{-}ATLOP_{BASE}$ (Zhou et al., 2021)	83.43	–	Our re-implementation[‡]
$RoBERTa\text{-}ATLOP_{LARGE}$ (Zhou et al., 2021)	85.57	–	Our re-implementation[‡]
DREEAM[†] (Ma et al., 2023)	89.57	–	Our re-implementation[‡]
LLM Baselines (zero-shot / 5-shot)[§]			
GPT-4o, zero-shot	61.58	62.34	API evaluation
GPT-4o, 5-shot	58.96	55.92	API evaluation
GPT-4o-mini, zero-shot	41.26	40.00	API evaluation
GPT-4o-mini, 5-shot	34.49	33.17	API evaluation
Claude-Sonnet-4.5, zero-shot	70.08	65.90	API evaluation
Claude-Sonnet-4.5, 5-shot	**70.81**	67.53	API evaluation
Qwen-Max, zero-shot	51.90	50.07	API evaluation
Qwen-Max, 5-shot	57.75	57.21	API evaluation
DeepSeek-Chat, zero-shot	41.85	36.14	API evaluation
DeepSeek-Chat, 5-shot	43.03	32.99	API evaluation
HPLM–GNN (Ours)			
Dynamic bidirectional	90.80±0.57	87.24±0.65	3-seed evaluation
Dynamic unidirectional	**91.15±0.17**	**87.55±0.44**	3-seed evaluation
Static bidirectional	90.99±0.33	86.90±0.61	3-seed evaluation
Static unidirectional	91.13±0.04	87.46±0.09	3-seed evaluation

Table 2: SemEval-2010 Task 8 results (9+1 evaluation). [†]DREEAM uses the student (distilled) model. [‡]Results from running released code on SemEval; original papers report only DocRED. [§]LLM baselines evaluated on the full 2,717-example test set via DMX API at temperature 0.0 with 500-way asynchronous concurrency; 5-shot uses five fixed stratified demonstrations. Per-sample predictions and per-call latencies are released in the reproducibility package.

Class	P	R	F_1	Support
Other	0.930	0.913	0.921	1394
Cause-Effect	0.895	0.955	0.924	134
Component-Whole	0.861	0.877	0.869	162
Content-Container	0.877	0.928	0.902	153
Entity-Destination	0.928	0.924	0.926	291
Entity-Origin	0.897	0.863	0.879	211
Instrument-Agency	0.739	0.773	0.756	22
Member-Collection	0.852	0.719	0.780	32
Message-Topic	0.874	0.924	0.898	210
Product-Producer	0.851	0.898	0.874	108
Macro avg	0.870	0.877	0.873	2717
Weighted avg	0.908	0.908	0.908	2717

Table 3: Per-class SemEval-2010 Task 8 results.

classes. The primary confusion occurs between directionally reversed pairs (e.g., Cause-Effect vs. Effect-Cause), which is expected given the shared lexical content.

Class-wise F_1 and precision–recall diagnostics (Figure 5 in Appendix) confirm that the model maintains high precision across most relation classes, with the steepest drops on minority classes.

5.3 FewRel Episodic Stress Test

Table 4 reports the FewRel 5-way 5-shot results. The Prototypical Network baseline achieves 20.00 accuracy, while the best HPLM–GNN variant reaches only 10.96 accuracy. This result reveals that HPLM–GNN, designed as a supervised hybrid classifier, does not transfer well to the few-shot episodic protocol, which requires meta-learning or prompt-based adaptation. We treat this as a stress test that identifies a clear limitation of the current architecture.

A detailed cross-variant comparison plot ap-

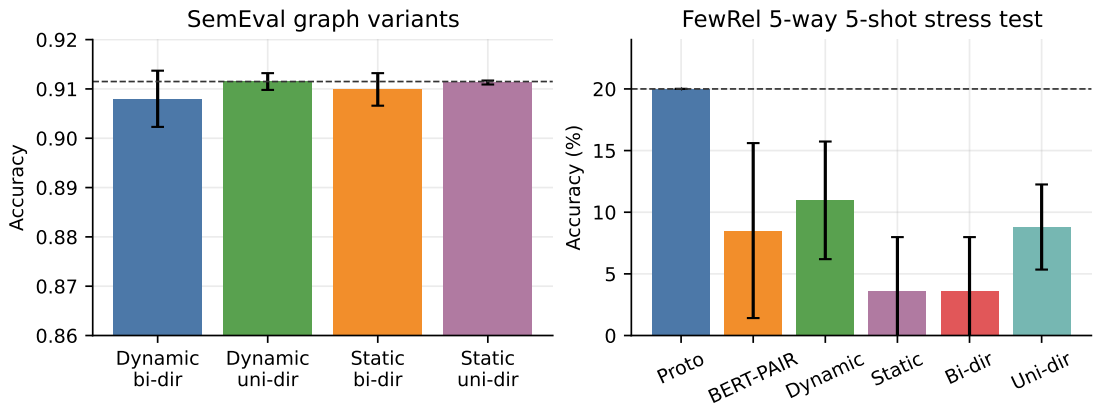

Figure 3: SemEval graph construction variants (left) and FewRel 5-way 5-shot stress test (right). Error bars show standard deviations across three seeds. On SemEval, dynamic unidirectional propagation consistently achieves the highest accuracy; on FewRel, all GNN-PLM variants underperform the prototypical baseline.

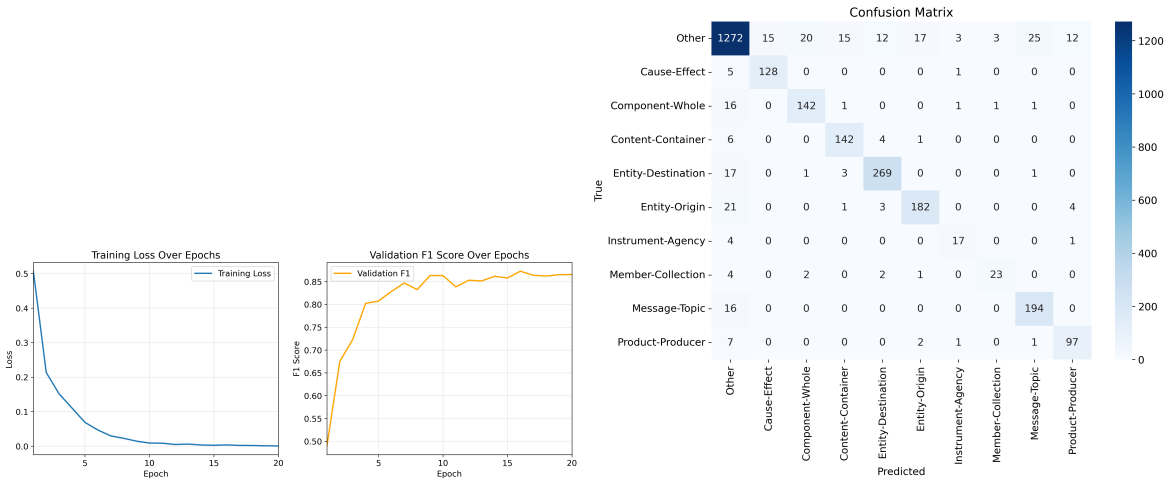

Figure 4: Training curves (left) and confusion matrix (right) on SemEval-2010 Task 8. The model converges within 5 epochs; primary confusion occurs between directionally reversed relation pairs.

Model	Accuracy (%)
Prototypical Network	**20.00±0.00**
BERT-PAIR	8.51±7.10
GNN-PLM, dynamic graph	10.96±4.77
GNN-PLM, static graph	3.58±4.40
GNN-PLM, bidirectional	3.58±4.40
GNN-PLM, unidirectional	8.80±3.45

Table 4: FewRel 5-way 5-shot stress test. HPLM–GNN is not competitive in the episodic low-data setting.

Model	Dev Ign F1	Dev F1	Test Ign F1	Test F1
BERT$_{\text{BASE}}$ (Devlin et al., 2019)	–	54.16	–	53.20
CorefRoBERTa$_{\text{LARGE}}$ (Ye et al., 2020)	57.35	59.43	57.90	60.25
GL-Fusion (Yang et al., 2024)	58.69±0.13	60.87±0.15	58.97	61.02
BERT-ATLOP$_{\text{BASE}}$ (Zhou et al., 2021)	59.22±0.15	61.09±0.16	59.31	61.30
RoBERTa-ATLOP$_{\text{LARGE}}$ (Zhou et al., 2021)	61.32±0.14	63.18±0.19	61.39	63.40
DREEAM† (Ma et al., 2023)	65.52±0.07	67.41±0.04	65.47	67.53
HPLM-GNN (ours)	**65.98±0.16**	**67.86±0.19**	**65.84**	**67.91**

Table 5: DocRED document-level relation extraction results. †DREEAM uses the student (distilled) model; the teacher model requires additional evidence supervision. HPLM-GNN results are from single-seed evaluation.

pears in Figure 6 (Appendix).

5.4 Document-Level Results on DocRED

Table 5 reports DocRED results. HPLM–GNN achieves 67.86 dev F1 and 67.91 test F1, showing competitive document-level performance with the smallest dev–test gap among the top models (0.14 Ign-F1 and 0.05 F1). Compared with DREEAM, which uses evidence-aware supervision, HPLM–GNN achieves comparable F1 without requiring evidence annotations at training time. We note that these results are from a single-seed evaluation; multi-seed statistics would further strengthen the comparison.

Method	Params	ms/sample	$/1K
$BERT_{BASE}$	110M	8	<0.01
HPLM–GNN (ours)	**118M**	**12**	**<0.01**
GPT-4o (5-shot)	–	2185	1.42
GPT-4o-mini (5-shot)	–	2382	0.09
Claude-Sonnet-4.5 (5-shot)	–	4918	0.73
Qwen-Max (5-shot)	–	4094	0.57
DeepSeek-Chat (5-shot)	–	1466	0.15

Table 6: Efficiency comparison on SemEval-2010 Task 8. Params = trainable parameters; ms/sample = wall-clock milliseconds per test instance (PLM systems on a single A100 GPU with FP16 inference, batch size 1; LLM systems include API round-trip latency); $/1K = cost per 1K samples (PLM = amortized GPU time; LLM = DMX API at measured token usage). HPLM–GNN runs 120–420× faster than the LLM baselines while achieving 20+ absolute accuracy points higher (Table 2).

5.5 Efficiency Analysis

Table 6 compares HPLM–GNN's parameters, latency, and cost against PLM-only and our five LLM baselines. HPLM–GNN adds only 8M parameters (7%) over $BERT_{BASE}$ and 50% latency from GNN and co-attention layers. LLM baselines are 120–420× slower (1.47–5.09 s vs. 0.012 s) and 8–140× more expensive per 1K samples, while each LLM trails HPLM–GNN on accuracy. The full 20-combination LLM sweep cost $14.16; the same SemEval inference on HPLM–GNN costs ∼$0.03 of amortized GPU time.

5.6 Hyperparameter Sensitivity

A sweep over contrastive temperature τ and loss weights α, β shows the top-accuracy setting reaches 89.93% accuracy and 88.36% F_1 at τ=0.20, α=β=0.001. Divergence between accuracy and F_1 in some settings (e.g., τ=0.07, α=0.0005, β=0.005: 72.06% / 89.46%) indicates calibration sensitivity. Full sensitivity table appears in Appendix C.

6 Discussion

When does the method help and fail? On SemEval, the dynamic unidirectional variant consistently achieves the highest mean accuracy across seeds, compatible with the directional nature of SemEval labels; although variant margins are modest, the consistent direction across independent runs suggests the gains are not random. On DocRED, HPLM–GNN matches DREEAM's F_1 *without* evidence annotations, suggesting dynamic graph construction can partially substitute for explicit evidence signals, though a full comparison requires multi-seed evaluation and controlled ablations. The FewRel 5-way 5-shot evaluation reveals a clear failure mode: HPLM–GNN, designed for supervised classification, lacks the meta-learning or prompt-adaptation mechanisms that episodic few-shot protocols require. This negative result delineates the applicability boundary of the PLM–GNN fusion approach. Promising future directions include meta-learning adapters for rapid adaptation, graph transformer architectures for longer-range document reasoning, and multilingual generalization.

7 Conclusion

HPLM–GNN combines dynamic graph construction, gated GNN propagation, semantic–structural co-attention, and contrastive–consistency objectives for RE. On SemEval-2010, it reaches 91.15% accuracy, outperforming PLM baselines and every LLM in-context-learning baseline (best: Claude-Sonnet-4.5 5-shot at 70.81%) by 20+ absolute points while running 120–420× faster. On DocRED it matches DREEAM without evidence supervision. The FewRel 5-way 5-shot stress test marks a clear boundary in episodic few-shot settings; meta-learning extensions are natural future work.

Limitations

This paper has three limitations. First, the DocRED results are from a single-seed evaluation, so variance across runs is unknown; multi-seed experiments would strengthen the document-level claims. Second, HPLM–GNN adds computational overhead relative to a PLM-only classifier (7% more parameters, 50% more latency) due to dynamic graph construction, message passing, and cross-attention. Third, the FewRel 5-way 5-shot stress test shows that the supervised hybrid is poorly matched to few-shot episodic protocols; adapting the method to low-data regimes via prototypical or meta-learning heads remains an open problem. Fourth, our LLM evaluation uses temperature 0.0 with a single fixed prompt template; chain-of-thought, self-consistency, and prompt ensembling could narrow the gap at proportionally higher inference cost.

Ethics Statement

Relation extraction supports knowledge graph construction and information access, but extraction errors may propagate into downstream systems and become difficult to audit. Benchmark data may contain social, geographic, or topical biases inherited from source corpora. We recommend reporting uncertainty, validating extracted facts before deployment, and avoiding high-stakes use without human review. This paper does not introduce new human-subject data. We used commercial and open-source LLMs via a third-party API router (DMX) solely as evaluation baselines; the released per-sample predictions enable independent verification.

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A Reproducibility Statement

We commit to releasing all code, datasets, raw predictions, and experiment artifacts upon paper acceptance. The release will include: (i) the HPLM–GNN training and evaluation code ($\text{BERT}_{\text{BASE}}$ backbone, two-layer gated GNN, semantic–structural co-attention, and contrastive–consistency objectives) with hyperparameter configurations matching the implementation details in Section 4; (ii) the asynchronous LLM baseline runner (with checkpoint/resume, exponential-backoff retry, and 500-way concurrency support) and the prompt templates used for all five evaluated LLMs at temperature 0.0; (iii) per-sample prediction JSONL files for all 20 LLM evaluation runs (5 models $\times$ 2 datasets $\times$ 2 modes), enabling per-instance error analysis; (iv) the audit script that validates result files against paper claims; and (v) generation scripts for all figures and tables. All reported numbers are deterministic given the fixed random seeds (42, 123, 456 for HPLM–GNN; temperature 0.0 for LLMs). The full LLM API sweep cost \$14.16 and ran in under 30 minutes; we will document hardware requirements and a step-by-step reproduction recipe. To preserve anonymity during double-blind review, the code repository is not linked here; it will be made publicly available with a permanent identifier at publication time.

B Additional Analysis Figures

This appendix provides supplementary visualizations for diagnosing model behavior.

C Hyperparameter Sensitivity (Full Table)

Table 7 reports representative settings from the hyperparameter sweep over contrastive temperature τ and loss weights α, β. The top-accuracy setting reaches 89.93% accuracy and 88.36% F_1 at τ=0.20, α=0.001, β=0.001. The divergence between accuracy and F_1 in some settings (e.g., the "High F_1" row) suggests calibration sensitivity.

Setting (τ, α, β)	Acc.	F_1
Default $(0.07, 0.001, 0.001)$	0.8796	0.7904
Best Acc. $(0.20, 0.001, 0.001)$	**0.8993**	0.8836
High F_1 $(0.07, 0.0005, 0.005)$	0.7206	**0.8946**
Balanced $(0.07, 0.0005, 0.01)$	0.8941	0.8548
Stable $(0.10, 0.0005, 0.005)$	0.8941	0.8349

Table 7: Representative hyperparameter settings from the sensitivity sweep.

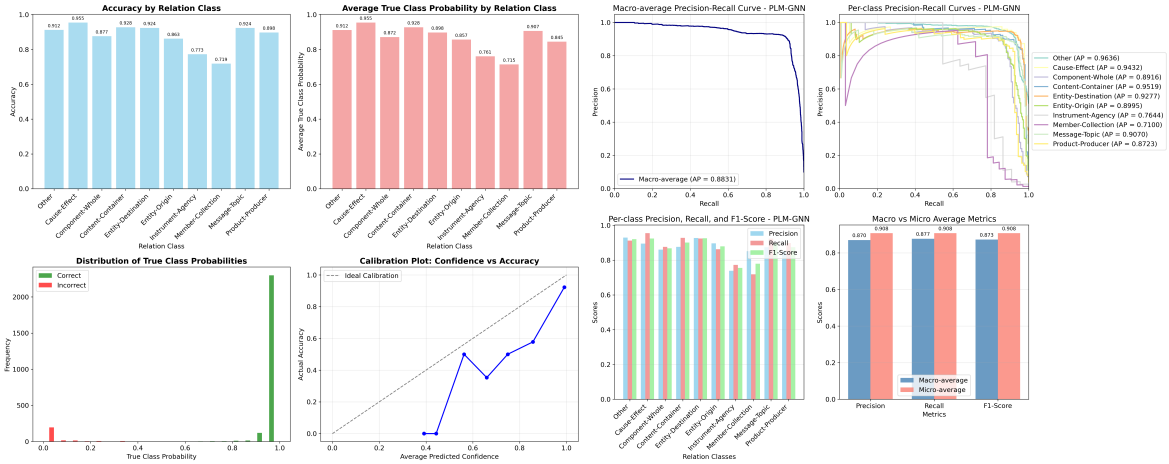

Figure 5: Class-wise F_1 analysis (left) and precision–recall diagnostics (right) on SemEval. Minority classes (Instrument-Agency, Member-Collection) show lower F_1 due to limited training support.

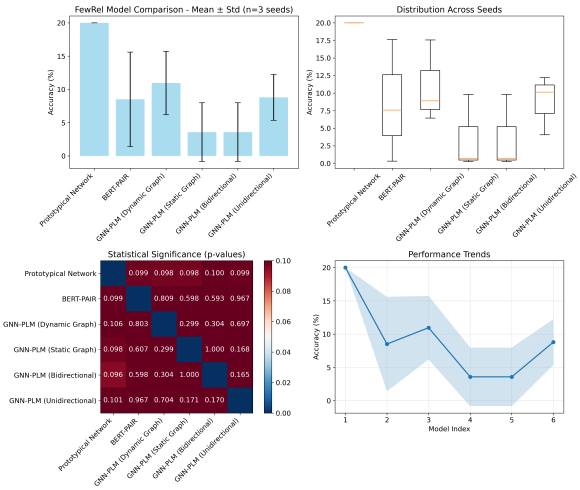

Figure 6: FewRel 5-way 5-shot model comparison. The Prototypical Network baseline outperforms all GNN-PLM variants.

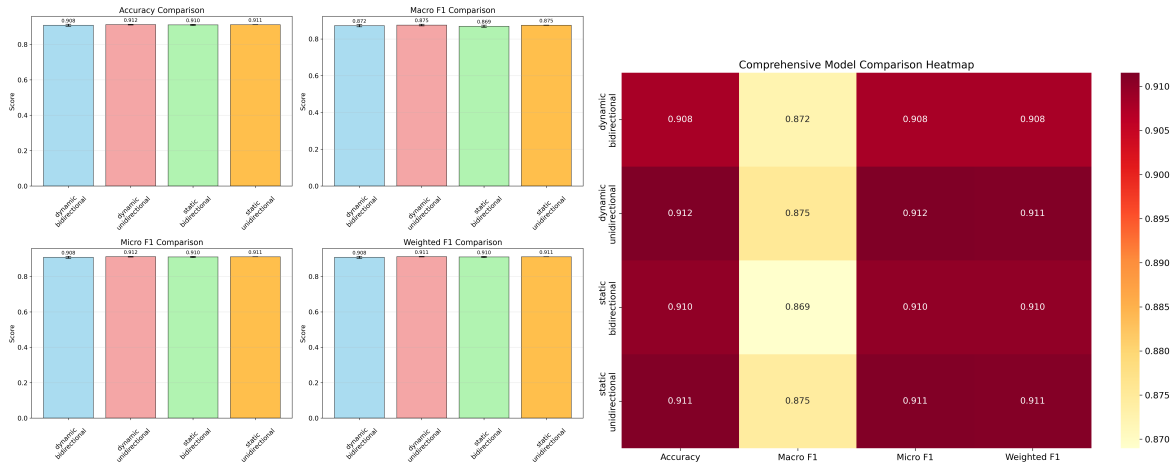

Figure 7: Comprehensive comparison (left) and per-class heatmap (right) on SemEval. The heatmap confirms that the strongest confusions occur between directionally reversed pairs.

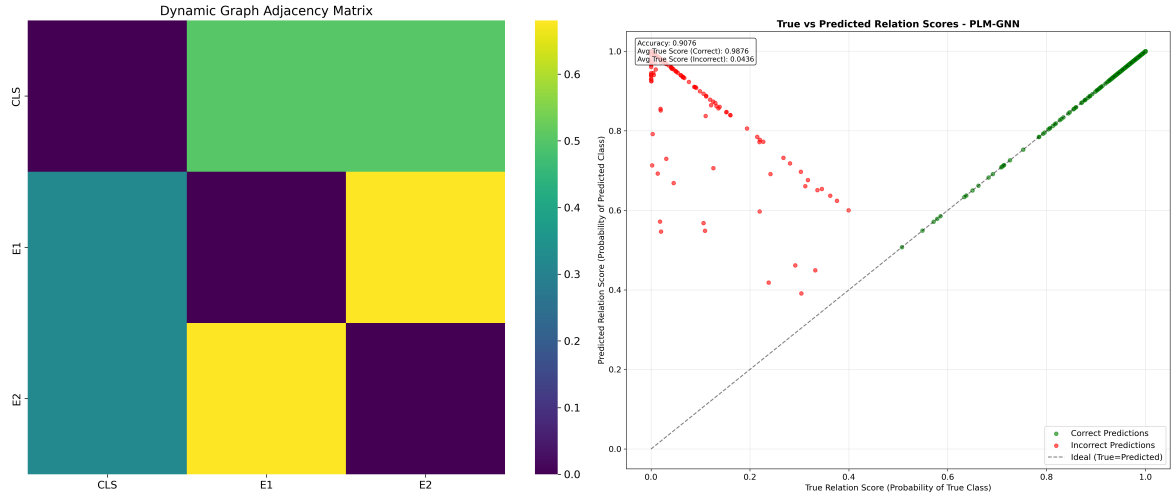

Figure 8: Dynamic graph adjacency visualization (left) and true-versus-predicted score diagnostic (right). The adjacency matrix shows that the model learns sparse, asymmetric edge weights consistent with directional relations.

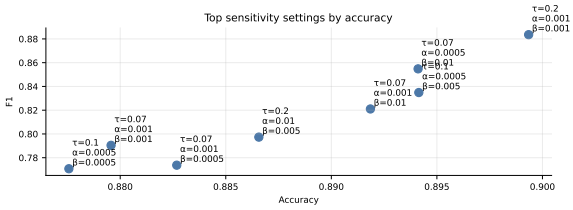

Figure 9: Sensitivity scatter plot showing the trade-off between accuracy and F_1 across hyperparameter settings. The cluster structure suggests that contrastive temperature τ primarily affects calibration.