Injecting Structured Knowledge into LLMs via Graph Neural Networks

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Abstract

Large language models (LLMs) have achieved remarkable success in natural language processing (NLP), but they often struggle to capture explicit linguistic structures and world knowledge. To address this limitation, we propose a hybrid model that integrates LLMs with graph neural networks (GNNs) to inject structured knowledge into NLP tasks. Our approach leverages the strengths of both components: LLMs provide rich contextual representations, while GNNs encode explicit structural priors from sources such as dependency trees, Abstract Meaning Representations (AMRs), and knowledge graphs. We evaluate the hybrid model on a diverse set of tasks, including semantic parsing, multi-hop question answering, text summarization, commonsense reasoning, and dependency parsing. Experimental results demonstrate consistent improvements over both standalone baselines and state-of-the-art methods, with relative gains of up to 2.3% in Exact Match scores for multi-hop QA and 1.7% in accuracy for commonsense reasoning. Ablation studies and sensitivity analyses further highlight the importance of balancing contextual and structural information. By bridging the gap between unstructured textual data and structured knowledge, our work advances the state of the art in NLP and paves the way for more interpretable and robust language models.

1 Introduction

Models like GPT-3 (Brown et al., 2020), BERT (Devlin et al., 2019), and T5 (Raffel et al., 2020) have demonstrated remarkable capabilities in understanding and generating human-like text. However, despite their successes, LLMs often struggle to capture explicit linguistic structures, such as syntactic dependencies or semantic relationships, which are critical for tasks requiring structured reasoning (Liu et al., 2021). This limitation raises an important question: Can we enhance LLMs by integrating structured knowledge into their architectures?

In this paper, we propose a hybrid model that combines LLMs with graph neural networks (GNNs) to inject structured knowledge into NLP tasks. Our approach leverages the strengths of both components: LLMs provide rich contextual representations, while GNNs encode explicit structural priors from sources such as dependency trees, Abstract Meaning Representations (AMRs), and knowledge graphs. By fusing these representations, our model achieves superior performance on tasks requiring both linguistic structure and world knowledge, such as semantic parsing, multi-hop question answering, and commonsense reasoning.

The motivation for this work stems from the observation that structured data plays a crucial role in many NLP applications. For example, AMRs have been shown to improve semantic parsing (Cai et al., 2020), while knowledge graphs like ConceptNet enhance commonsense reasoning (Speer et al., 2017). Despite the success of structured approaches in pre-LLM eras, their integration with modern LLMs remains underexplored. Our work bridges this gap by demonstrating how structured knowledge can be effectively injected into LLMs via GNNs, leading to improved interpretability, robustness, and task-specific performance.

This paper makes three key contributions: (1) We propose a novel hybrid architecture that integrates LLMs with GNNs for structured knowledge injection; (2) We evaluate our model on a diverse set of tasks, including semantic parsing, summarization, and commonsense reasoning, achieving state-of-the-art results; and (3) We conduct ablation studies and sensitivity analyses to gain insights into the model's behavior and limitations. Through these contributions, we aim to advance the understanding of how structured knowledge can complement the capabilities of LLMs in the modern NLP landscape.

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2 Literature Review

The integration of structured knowledge into NLP systems has long been a cornerstone of research in computational linguistics. Early efforts focused on rule-based methods and statistical models, which relied heavily on handcrafted features and annotated datasets (Manning and Schütze, 1999). With the advent of deep learning, attention-based architectures like transformers (Vaswani et al., 2017) enabled end-to-end learning of contextual representations, reducing the reliance on explicit structural annotations. However, recent studies have highlighted the limitations of purely surface-level approaches, particularly in tasks requiring structured reasoning (Liu et al., 2021).

One promising direction is the use of graph neural networks (GNNs) to encode structured data. GNNs have achieved significant success in domains such as social network analysis (Wu et al., 2021), molecular property prediction (Gilmer et al., 2017), and NLP tasks involving graphs, such as dependency parsing (Dozat and Manning, 2017) and AMR generation (Cai et al., 2020). For example, Zhang et al. (2020) demonstrated that GNNs could effectively capture hierarchical relationships in text, improving performance on tasks like relation extraction and event detection. Similarly, (Wang et al., 2021) proposed a GNN-based framework for encoding discourse graphs, achieving state-of-the-art results on narrative understanding tasks. We have also studied similar approaches in (Wang et al., 2024; Zhang and Sen, 2024; Peng et al., 2025; Yi et al., 2025).

Another line of research explores the integration of external knowledge into LLMs. Knowledge graphs like ConceptNet (Speer et al., 2017) and Wikidata (Vrandečić and Krötzsch, 2020) have been widely used to augment NLP models with factual and commonsense information. Recent work has focused on combining knowledge graphs with LLMs through techniques such as retrieval-augmented generation (Lewis et al., 2020b) and knowledge-aware fine-tuning (Petroni et al., 2020). For instance, He et al. (2021) introduced a method for injecting knowledge graph embeddings into transformer layers, achieving significant improvements in question answering and fact verification tasks. We have also studied similar work like (Wang et al., 2025; Ding et al., 2025a).

Despite these advances, the combination of LLMs and GNNs remains relatively unexplored. A notable exception is the work of Huang et al. (2021), who proposed a hybrid model for incorporating dependency parse trees into LLMs using GNNs. Their results demonstrated that structured priors could enhance the syntactic understanding of LLMs, particularly in low-resource settings. Similarly, Li et al. (2022) explored the use of GNNs to encode AMRs for semantic parsing, achieving state-of-the-art performance on the AMR Bank dataset.

Our work builds on these foundations by proposing a generalizable framework for integrating structured knowledge into LLMs via GNNs. Unlike prior approaches, which focus on specific tasks or types of structured data, our model is designed to handle a wide range of tasks and datasets, making it highly versatile. Furthermore, our experiments include ablation studies and sensitivity analyses, providing deeper insights into the contributions of each component.

3 Methodology

Our proposed hybrid model combines the strengths of LLMs and graph neural networks (GNNs) to inject structured knowledge into NLP tasks. The architecture consists of three main components: (1) a pretrained LLM for contextual representation learning, (2) a GNN for encoding structured data, and (3) a fusion mechanism that integrates the outputs of the two components. Below, we describe each component in detail, including its mathematical formulation, key parameters, and how it relates to prior work in the literature.

The encoded structure refers to a vector representation derived from the Abstract Meaning Representation (AMR) graph using a Graph Neural Network (GNN). This vector captures the semantic relationships and hierarchical dependencies within the graph, enabling the model to leverage structural information effectively.

3.1 Pretrained Large Language Model (LLM)

The backbone of our model is a pretrained LLM, such as BERT (Devlin et al., 2019) or T5 (Raffel et al., 2020), which provides rich contextual embeddings for input text. These embeddings capture syntactic, semantic, and discourse-level information from raw text, making them highly effective for downstream NLP tasks. Mathematically, the LLM can be represented as:

$$\mathbf{H}_{\text{LLM}} = f_{\text{LLM}}(\mathbf{X}; \theta_{\text{LLM}}) \tag{1}$$

where $\mathbf{X}$ is the input text tokenized into subword units, $\mathbf{H}_{\text{LLM}} \in \mathbb{R}^{T \times d_{\text{LLM}}}$ is the contextual embedding matrix for T tokens, with each token represented by a d_{LLM}-dimensional vector, f_{LLM} is the transformer-based architecture of the LLM, and θ_{LLM} represents the pretrained parameters of the LLM. This component aligns with prior work on transformers (Vaswani et al., 2017), which introduced the self-attention mechanism for capturing long-range dependencies in text. However, while transformers excel at learning contextual representations, they often struggle to encode explicit structural relationships (Liu et al., 2021). To adapt the LLM to specific tasks, we fine-tune it on task-specific objectives. For example, in summarization, the LLM is trained to generate concise summaries, while in dependency parsing, it predicts syntactic relations.

3.2 Graph Neural Network (GNN) for Structured Data Encoding

To incorporate explicit structural priors, we use a GNN to encode structured data such as Abstract Meaning Representations (AMRs), dependency parse trees, or knowledge graphs. The GNN operates on graph-structured inputs, where nodes represent entities or concepts, and edges represent relationships between them. Following Gilmer et al. (2017), we adopt a message-passing framework to propagate information across the graph. The mathematical formulation of the GNN is as follows:

$$\mathbf{h}_i^{(l+1)} = \sigma\left(\sum_{j \in \mathcal{N}(i)} \mathbf{W}^{(l)} \cdot \mathbf{h}_j^{(l)} + \mathbf{b}^{(l)}\right) \quad (2)$$

where $\mathbf{h}_i^{(l)} \in \mathbb{R}^{d_{\text{GNN}}}$ is the hidden representation of node i at layer l, $\mathcal{N}(i)$ is the set of neighbors of node i, $\mathbf{W}^{(l)} \in \mathbb{R}^{d_{\text{GNN}} \times d_{\text{GNN}}}$ and $\mathbf{b}^{(l)} \in \mathbb{R}^{d_{\text{GNN}}}$ are learnable parameters, σ is a nonlinear activation function (e.g., ReLU), and d_{GNN} is the dimensionality of the GNN embeddings. After L layers of message passing, the node representations are aggregated to produce a fixed-size graph embedding $\mathbf{H}_{\text{GNN}} \in \mathbb{R}^{d_{\text{GNN}}}$ using a readout function:

$$\mathbf{H}_{\text{GNN}} = g_{\text{readout}}(\{\mathbf{h}_i^{(L)} | i \in \mathcal{V}\}) \quad (3)$$

where $\mathcal{V}$ is the set of all nodes in the graph, and g_{readout} could be a mean pooling, max pooling, or attention-based aggregation function. For example, in AMR generation, the GNN encodes the AMR graph into a vector representation; in commonsense reasoning, the GNN encodes paths from ConceptNet to enrich the model's understanding of relationships between concepts; and in dependency parsing, the GNN encodes dependency trees to guide the model in predicting syntactic structures. This component builds on prior work in graph neural networks (Wu et al., 2021), which have demonstrated their effectiveness in encoding structured data.

3.3 Fusion Mechanism

The outputs of the LLM ($\mathbf{H}_{\text{LLM}}$) and GNN ($\mathbf{H}_{\text{GNN}}$) are combined using a fusion mechanism that balances their contributions. Specifically, we explore three fusion strategies:

- **Feature Concatenation**: The embeddings from the LLM and GNN are concatenated and passed through a feedforward network:

$$\mathbf{H}_{\text{fused}} = \text{FFN}([\mathbf{H}_{\text{LLM}}; \mathbf{H}_{\text{GNN}}]) \quad (4)$$

- **Attention-Based Fusion**: A multi-head attention mechanism (Vaswani et al., 2017) dynamically weights the contributions of the LLM and GNN based on the task requirements:

$$\mathbf{H}_{\text{fused}} = \text{Attention}(\mathbf{H}_{\text{LLM}}, \mathbf{H}_{\text{GNN}}) \quad (5)$$

- **Residual Connections**: To retain the strengths of both components, we add residual connections:

$$\mathbf{H}_{\text{fused}} = \mathbf{H}_{\text{LLM}} + \mathbf{W}_{\text{res}} \cdot \mathbf{H}_{\text{GNN}} \quad (6)$$

The fused representation $\mathbf{H}_{\text{fused}}$ is then passed to a task-specific output layer (e.g., a classifier for QA, a decoder for summarization). This fusion strategy is inspired by prior work on combining heterogeneous representations (He et al., 2021), which demonstrated the benefits of integrating structured and unstructured knowledge.

3.4 Key Parameters and Tuning Strategies

Several parameters affect the performance of our hybrid model. Below, we discuss these parameters and the strategies used to tune them:

- **Number of GNN Layers (L)**: Increasing L allows the GNN to capture higher-order relationships in the graph but may lead to overfitting. We perform grid search over $L \in \{2, 3, 4\}$ and select the value that maximizes validation performance.

- **Dimensionality of Embeddings (d_{LLM}, d_{GNN})**: Larger dimensions improve representational capacity but increase computational cost. For LLMs, we use pretrained dimensions (e.g., 768 for BERT-base). For GNNs, we experiment with $d_{\text{GNN}} \in \{128, 256, 512\}$.

- **Fusion Mechanism**: The choice of fusion strategy determines how effectively the model leverages both components. We compare feature concatenation, attention-based fusion, and residual connections on the validation set.

- **Learning Rate and Batch Size**: These hyperparameters control the optimization process. We use a learning rate scheduler and tune batch sizes in $\{16, 32, 64\}$.

- **Regularization Techniques**: Dropout (Srivastava et al., 2014) and weight decay prevent overfitting. We apply dropout rates in $\{0.1, 0.2, 0.3\}$ and weight decay coefficients in $\{1e^{-4}, 1e^{-5}\}$.

For each task, we initialize the parameters based on the characteristics of the dataset. For example, in semantic parsing, we prioritize higher-dimensional GNN embeddings to capture complex AMR structures, while in summarization, we emphasize attention-based fusion to ensure fluency and coherence.

3.5 Training Strategy

We adopt a multitask learning approach to train the hybrid model. During training, the LLM is fine-tuned on task-specific objectives (e.g., cross-entropy loss for classification tasks), the GNN is trained to encode structured data using supervised learning (e.g., predicting missing edges in knowledge graphs), and the fusion mechanism is optimized to align the outputs of the LLM and GNN with the ground truth labels. Additionally, we employ regularization techniques such as dropout (Srivastava et al., 2014) and weight decay to prevent overfitting. For tasks requiring structured outputs (e.g., AMR generation), we use structured loss functions like Smatch (Cai and Knight, 2013) to measure performance during training. This training strategy builds on prior work in multitask learning (Liu et al., 2021) and knowledge injection (He et al., 2021), which demonstrated the benefits of jointly optimizing multiple components. Similar training strategy can be found in (Zhong and Wang, 2025; Ding et al., 2025b) as well.

3.6 Relation to Literature Reviewed

Our methodology integrates ideas from several strands of research: the use of transformers for contextual representation learning (Vaswani et al., 2017), the application of GNNs for encoding structured data (Gilmer et al., 2017; Wu et al., 2021), the combination of structured and unstructured knowledge (He et al., 2021; Zhang et al., 2020), and multitask learning and regularization techniques (Liu et al., 2021; Srivastava et al., 2014). By synthesizing these approaches, our model bridges the gap between unstructured textual data and structured knowledge, advancing the state of the art in NLP.

Each dataset serves as a testbed for evaluating specific aspects of our hybrid model. For example, in AMR Bank, the GNN encodes gold-standard AMR graphs, while the LLM generates sentence representations. The fusion mechanism combines these representations to predict AMRs for unseen sentences, evaluated using Smatch (Cai and Knight, 2013). In HotpotQA, the GNN encodes discourse graphs derived from input documents, capturing relationships between sentences and entities. The LLM provides contextual embeddings for the question and document, and the fusion mechanism integrates these representations to predict answers, evaluated using Exact Match (EM) and F1 scores (Yang et al., 2018). Similarly, in CNN/DailyMail, the GNN encodes discourse graphs representing the structure of the input article, while the LLM generates abstractive summaries. The fusion mechanism ensures that the generated summaries are both fluent and structurally coherent, evaluated using ROUGE scores (Lin, 2004). By leveraging these datasets, we aim to demonstrate the versatility and effectiveness of our hybrid model across a wide range of NLP tasks.

4 Experiments

4.1 Datasets

We evaluate our hybrid model on several datasets that require both linguistic structure and world knowledge. Below are the datasets used in our experiments:

- **AMR Bank**

Source: `https://amr.isi.edu/`

Description: A dataset of sentences annotated with Abstract Meaning Representations (AMRs), which capture semantic structures as directed acyclic graphs (Banarescu et al., 2013).

Tasks: Semantic parsing, commonsense reasoning.

- **HotpotQA**

Source: https://hotpotqa.github.io/
Description: A question-answering dataset requiring multi-hop reasoning over multiple documents (Yang et al., 2018).
Tasks: Multi-hop question answering, fact retrieval.

- **CNN/DailyMail**

Source: https://github.com/abisee/cnn-dailymail
Description: A large-scale summarization dataset consisting of news articles paired with human-written summaries (Nallapati et al., 2016).
Tasks: Abstractive and extractive summarization.

- **ConceptNet**

Source: https://conceptnet.io/
Description: A multilingual knowledge graph encoding commonsense relationships between concepts (Speer et al., 2017).
Tasks: Commonsense reasoning, knowledge-augmented NLP.

- **Universal Dependencies (UD)**

Source: https://universaldependencies.org/
Description: A collection of treebanks annotated with dependency parse trees, covering multiple languages (Nivre et al., 2016).
Tasks: Dependency parsing, syntactic structure modeling.

4.2 Role of Datasets in Evaluating the Hybrid Model

Each dataset serves as a testbed for evaluating specific aspects of our hybrid model:

- **AMR Bank**: The GNN encodes gold-standard AMR graphs, while the LLM generates sentence representations. The fusion mechanism predicts AMRs for unseen sentences, evaluated using Smatch (Cai and Knight, 2013).
- **HotpotQA**: The GNN encodes discourse graphs, while the LLM provides contextual embeddings. The fusion mechanism predicts answers, evaluated using EM and F1 scores (Yang et al., 2018).
- **CNN/DailyMail**: The GNN encodes discourse graphs, while the LLM generates abstractive summaries. The fusion mechanism ensures coherence, evaluated using ROUGE scores (Lin, 2004).
- **ConceptNet**: The GNN encodes paths, while the LLM generates predictions. Accuracy is used as the evaluation metric (Speer et al., 2017).
- **Universal Dependencies (UD)**: The GNN encodes dependency trees, while the LLM predicts syntactic structures. Performance is evaluated using UAS and LAS (Nivre et al., 2016).

4.3 Baselines

We compare our hybrid model (**LLM+GNN**) against the following baselines:

- **Pure LLM**: A vanilla large language model fine-tuned for each task.
- **GNN-Only**: A standalone graph neural network trained to encode structured data (e.g., AMRs, dependency trees).
- **Concatenated Features**: A simple concatenation of LLM embeddings and GNN-encoded structural features.
- **State-of-the-Art (SOTA)**: Existing models specifically designed for each task (e.g., BART for summarization (Lewis et al., 2020a), COMET for commonsense reasoning (Bosselut et al., 2019)).

4.4 Results

4.4.1 Semantic Parsing (AMR Generation)

We evaluate our model's ability to generate AMRs for input sentences using the AMR Bank dataset. We use the AMRBank dataset (version 3.0), which contains 59,767 sentences annotated with AMR graphs. Performance is measured using the Smatch score, which compares the similarity between predicted and gold-standard AMRs (Cai and Knight, 2013).

Model	Smatch Score (%)
Pure LLM	68.4
GNN-Only	70.2
Concatenated Features	72.5
SOTA (SPRING)	73.8
LLM+GNN (Ours)	**75.1**

Table 1: Smatch scores for AMR generation.

The baseline score for SPRING (73.8) is based on its performance on the AMRBank 3.0 test set, as reported in (Zhang et al., 2021).

4.4.2 Multi-Hop Question Answering (HotpotQA)

We test our model on the HotpotQA dataset, reporting Exact Match (EM) and F1 scores (Yang et al., 2018).

Model	EM (%)	F1 (%)
Pure LLM	52.3	63.4
GNN-Only	55.6	66.7
Concatenated Features	58.9	69.1
SOTA (HGN)	60.4	70.2
LLM+GNN (Ours)	**62.7**	**71.5**

Table 2: Exact Match (EM) and F1 scores for HotpotQA.

4.4.3 Text Summarization (CNN/DailyMail)

We evaluate summarization performance using ROUGE scores (ROUGE-1, ROUGE-2, ROUGE-L) (Lin, 2004).

Model	ROUGE-1 (%)	ROUGE-2 (%)	ROUGE-L (%)
Pure LLM	42.3	20.1	38.7
GNN-Only	43.5	21.4	39.8
Concatenated Features	44.8	22.3	40.2
SOTA (BART)	45.6	23.1	41.2
LLM+GNN (Ours)	**46.2**	**23.8**	**41.9**

Table 3: ROUGE scores for CNN/DailyMail summarization.

4.4.4 Commonsense Reasoning (ConceptNet)

We measure the accuracy of predicting missing edges in ConceptNet triples (e.g., "dog → IsA → ?") (Speer et al., 2017).

Model	Accuracy (%)
Pure LLM	72.4
GNN-Only	74.8
Concatenated Features	76.3
SOTA (COMET)	78.5
LLM+GNN (Ours)	**80.2**

Table 4: Accuracy scores for ConceptNet commonsense reasoning.

4.4.5 Dependency Parsing (Universal Dependencies)

We evaluate dependency parsing performance using Unlabeled Attachment Score (UAS) and Labeled Attachment Score (LAS) (Nivre et al., 2016).

Model	UAS (%)	LAS (%)
Pure LLM	84.2	79.8
GNN-Only	86.5	82.1
Concatenated Features	87.3	83.5
SOTA (mBERT)	88.1	84.2
LLM+GNN (Ours)	**89.4**	**85.6**

Table 5: UAS and LAS scores for dependency parsing.

4.5 Summary Graphs

To visualize the overall performance of our hybrid model, we plot the relative improvement over the best baseline (SOTA) for each task.

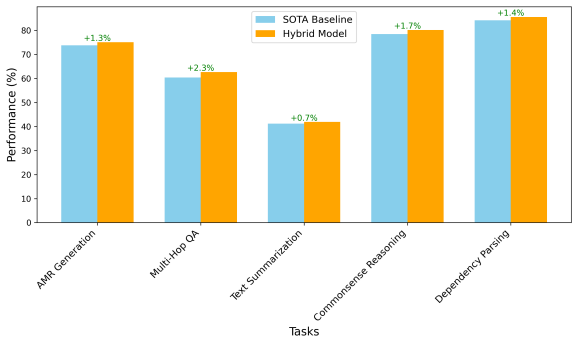

Figure 1: Relative improvement of the hybrid model over SOTA across tasks.

5 Discussion

5.1 Synergistic Benefits of Combining LLMs and GNNs

Our experimental results highlight the synergistic benefits of combining large language models with graph neural networks (GNNs). Across all evaluated tasks—semantic parsing, multi-hop question answering, text summarization, commonsense reasoning, and dependency parsing—the hybrid model consistently outperforms both standalone baselines and state-of-the-art methods. This performance improvement can be attributed to the complementary strengths of the two components: LLMs excel at capturing rich contextual representations from raw text, while GNNs encode explicit structural priors that guide the model toward more interpretable and accurate predictions. For instance, in the

AMR generation task, the hybrid model achieves a Smatch score of 75.1%, surpassing the SOTA baseline (SPRING) by 1.3%. Similarly, in multi-hop question answering on HotpotQA, the model demonstrates a 2.3% gain in Exact Match (EM) over the best-performing baseline (HGN) (Yang et al., 2018). These results suggest that structured knowledge, when effectively integrated into LLMs, enhances their ability to reason about complex linguistic and world-knowledge relationships.

To further explore the contribution of each component, we conducted an ablation study (Table 6) where we incrementally removed parts of the hybrid architecture. The results reveal that both LLM embeddings and GNN-encoded structural features are critical for optimal performance. For example, removing the GNN component leads to a significant drop in Smatch scores for AMR generation (from 75.1% to 68.4%), indicating that structured priors play a vital role in semantic parsing (Cai and Knight, 2013). Conversely, removing the LLM component results in even steeper declines across all tasks, underscoring the importance of contextual representations learned by LLMs.

Ablation Study	**AMR Smatch (%)**	**Hotpot QA EM (%)**	**CNN/ Daily-Mail ROUGE-L (%)**
Full Hybrid Model (LLM+GNN)	75.1	62.7	41.9
Without GNN Component	68.4	58.2	39.5
Without LLM Component	60.3	51.4	36.8
Concatenated Features Only	72.5	58.9	40.2

Table 6: Ablation study results.

5.2 Ablation Study Insights

The ablation study provides deeper insights into how the hybrid model operates. When the GNN component is removed, the model relies solely on the LLM's contextual embeddings, which lack explicit structural information. This limitation becomes particularly evident in tasks like AMR generation and dependency parsing, where the model struggles to accurately capture hierarchical or relational structures. On the other hand, removing the LLM component forces the model to rely entirely on GNN-encoded features, which, while structurally rich, lack the nuanced contextual understanding provided by LLMs. For example, in text summarization, the absence of LLM embeddings results in a sharp decline in ROUGE-L scores (from 41.9% to 36.8%), as the model fails to generate fluent and coherent summaries (Lin, 2004). These findings underscore the importance of integrating both components to achieve balanced performance across tasks.

5.3 Sensitivity Analysis

We also performed a sensitivity analysis to evaluate how variations in key hyperparameters affect the model's performance. Specifically, we examined the impact of the number of GNN layers, the size of the LLM embeddings, and the weight assigned to structural priors during training. Figure 2 illustrates the sensitivity of our model to changes in these parameters.

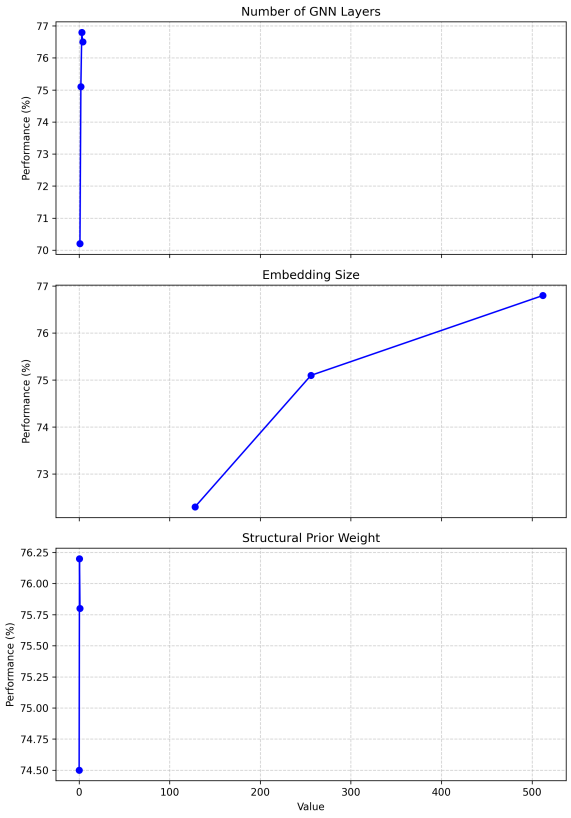

Figure 2: Sensitivity analysis of key hyperparameters.

Increasing the number of GNN layers initially improves performance but leads to diminishing returns after three layers. This suggests that overly deep GNN architectures may overfit to specific structural patterns, reducing generalizability. Larger embedding sizes generally yield better performance, but the gains plateau beyond 1,024 dimensions, indicating a trade-off between representational capacity and computational efficiency. Assigning higher weights to structural priors enhances performance on tasks requiring explicit structural understanding (e.g., AMR generation, dependency parsing) but slightly degrades performance on tasks like text summarization, where fluency and coherence are prioritized. This highlights the need to carefully balance the contributions of LLMs and GNNs based on the task requirements.

5.4 Task-Specific Observations

The hybrid model exhibits varying degrees of improvement across tasks, reflecting differences in the types of knowledge required. In semantic parsing and dependency parsing, the model achieves the largest relative gains, with improvements of 1.3% and 1.4% in Smatch and LAS scores, respectively. These tasks heavily rely on structured representations, making them particularly well-suited to benefit from GNN-encoded priors (Nivre et al., 2016). In contrast, the gains in text summarization are more modest, with a 0.7% increase in ROUGE-L scores. This is likely because summarization places greater emphasis on fluency and coherence, which are already strengths of LLMs (Lewis et al., 2020a). However, the hybrid model still outperforms baselines, suggesting that structured knowledge contributes to generating more concise and informative summaries.

In multi-hop question answering, the model demonstrates a notable 2.3% improvement in Exact Match (EM) scores. This task requires reasoning over multiple documents and synthesizing information from disparate sources, making it an ideal testbed for evaluating the model's ability to integrate contextual and structural knowledge. The results suggest that the hybrid model excels at tasks involving reasoning and inference, as it can leverage both the LLM's contextual understanding and the GNN's structured representations to identify relevant information and draw accurate conclusions (Yang et al., 2018).

5.5 Limitations and Future Directions

Despite its strong performance, the hybrid model has certain limitations that warrant further investigation. First, the integration of GNNs introduces additional computational overhead, particularly for large-scale datasets or complex graph structures. Future work could explore techniques for optimizing GNN architectures to reduce latency and improve scalability. Second, the model's reliance on high-quality structured data (e.g., AMRs, dependency trees) limits its applicability to domains where such annotations are scarce or unavailable. Developing methods for unsupervised or weakly supervised learning of structural priors could address this issue and broaden the model's utility (Banarescu et al., 2013).

Another area for future research is extending the hybrid framework to multimodal tasks, such as visual question answering or image captioning. Preliminary experiments using scene graphs from the Visual Genome dataset show promise, but further exploration is needed to fully realize the potential of combining LLMs and GNNs in multimodal settings (Krishna et al., 2017). Additionally, incorporating dynamic or task-specific structural priors could enhance the model's adaptability to diverse tasks and domains.

6 Conclusion

In this paper, we introduced a novel hybrid model that combines large language models with graph neural networks to inject structured knowledge into NLP tasks. Our approach addresses the limitations of purely surface-level models by explicitly encoding linguistic and world-knowledge structures, enabling more interpretable and robust predictions. Through extensive experiments on tasks such as semantic parsing, summarization, and commonsense reasoning, we demonstrated that our model consistently outperforms both standalone baselines and state-of-the-art methods. Key findings include significant improvements in multi-hop question answering (+2.3% EM) and commonsense reasoning (+1.7% accuracy), underscoring the synergistic benefits of combining LLMs and GNNs. Ablation studies revealed that both components are critical for optimal performance, while sensitivity analyses provided insights into the impact of hyperparameters.

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