GT2Vec: Large Language Models for Knowledge Graph Augmented Text Embedding

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Abstract

Graph-structured information offers rich contextual information that can enhance language models by providing structured relationships and hierarchies, leading to more expressive embeddings for various applications such as retrieval, question answering, and classification. However, existing methods for integrating graph and text embeddings, often based on Multi-layer Perceptrons (MLPs) or shallow transformers, are limited in their ability to fully exploit the heterogeneous nature of these modalities. To overcome this, we propose GT2Vec, a simple yet effective framework that leverages Large Language Models (LLMs) to jointly encode text and graph data. Specifically, GT2Vec employs an MLP adapter to project graph embeddings into the same space as text embeddings, allowing the LLM to process both modalities jointly. Unlike prior work, we also introduce contrastive learning to align the graph and text spaces more effectively, thereby improving the quality of learned joint embeddings. Empirical results across six datasets spanning three tasks—knowledge graph-contextualized question answering, graph-text pair classification, and retrieval—demonstrate that GT2Vec consistently outperforms existing baselines, achieving significant improvements across multiple datasets. These results highlight GT2Vec's effectiveness in integrating graph and text data. Ablation studies further validate the effectiveness of our method.

Keywords

Large Language Models, Representation Learning, Graph Neural Networks, Contrastive Learning

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1 Introduction

In the realm of natural language processing (NLP), text embeddings play a pivotal role by transforming textual information into numerical representations, which facilitate a multitude of machine learning applications on the Web, such as question answering (QA) [7, 50], retrieval [4, 40, 45, 60], and classification tasks [7, 60]. These applications can benefit from the integration of graph-structured data to enhance the capabilities of NLP systems, by providing contextual information or by augmenting the original tasks with additional information. For example, prior work has shown that a QA system that includes a knowledge graph as input can leverage the

relationships and hierarchies within the graph to more accurately understand and handle complex queries [65, 69]. To effectively integrate these two modalities, it is essential to develop methods to learn joint embeddings of graph-structured data and text data. Such embeddings can provide a unified representation that captures important information from both modalities, leading to performance improvements across various NLP tasks.

Prior research has introduced various ways to learn joint embeddings of text and graph-structured data for embedding tasks [11, 33, 65, 69]. These methods typically utilize either a Multi-layer Perceptron (MLP) or a shallow transformer [57] to integrate text features and graph embeddings encoded respectively by language models (LMs) [7, 39] and graph neural networks (GNNs) [29, 58, 64]. Despite their effectiveness, these approaches demonstrate a restricted capacity to fuse the features of the two modalities. The primary limitation arises from the limited ability of MLPs and shallow transformers to manage the high-dimensional and heterogeneous nature of joint embeddings, which can result in sub-optimal utilization of the rich contextual information from text and graph data. Recently, large language models (LLMs) have demonstrated significant potential for integrating and understanding modalities beyond just text. A representative example of this capability is in Vision-Language Models (VLMs) [2, 32, 38, 72], where visual tokens are combined with textual input and processed together by LLMs. This integration leverages the powerful capabilities of LLMs to handle multimodal data, allowing for a more holistic understanding of content that spans different forms of information. Inspired by this, we explore the potential of employing LLMs to better integrate text and graph-structured data, aiming to overcome the limitations observed from current approaches.

In this paper, we present GT2Vec, a simple yet effective framework to learn joint embeddings of text and graph data, leveraging the advanced capabilities of LLMs to address the limitations of previous approaches. Our method seamlessly integrates graph and text embeddings within the LLM framework, enhancing their alignment and interaction. Specifically, we transform graph embeddings into the same space as text embeddings using a multi-layer perceptron (MLP) adapter, enabling the LLM to process both modalities together. Additionally, we propose a contrastive learning strategy to better align the graph and text spaces, ensuring that the model learns richer representations of the combined data. Our extensive empirical analysis across a variety of NLP tasks highlights the key advantage of GT2Vec: the ability to leverage LLMs' strong language understanding and reasoning capabilities to process multimodal data, thus providing a more holistic and nuanced representation of both graph-structured and textual information. This integration leads to significant improvements in various NLP tasks, demonstrating the potential of GT2Vec to push the boundaries of joint text and graph-embedding techniques.

Our contributions are summarized as follows:

- **Integration of LLMs for Joint Embeddings**: We propose GT2Vec framework that leverages the strengths of LLMs to align and integrate graph and text embeddings. GT2Vec effectively captures the rich contextual information of both modalities, enabling more robust joint representations.
- **Contrastive Learning for Graph-Text Alignment**: We introduce a contrastive learning mechanism to explicitly align graph and text embeddings, enabling the model to better integrate the two modalities.
- **Extensive Empirical Validation**: We conduct extensive experiments on six datasets spanning three different tasks: knowledge graph (KG)-contextualized QA, graph-text pair classification, and retrieval tasks. GT2Vec achieves superior performance on all the three tasks, demonstrating its ability to effectively integrate graph and text data for enhanced multi-modal representation learning.

2 Problem Statement

Given an input text x and its corresponding graph context $\mathcal{G}$, where $\mathcal{G} = \{\mathcal{V}, \mathcal{E}\}$ consists of a set of nodes $\mathcal{V}$ and edges $\mathcal{E} \subseteq \mathcal{V} \times \mathcal{R} \times \mathcal{V}$ that connect nodes via relationships $\mathcal{R}$, our goal is to extract joint embeddings $\phi(x, \mathcal{G})$. Here, ϕ is a learned function that maps the input text x and graph $\mathcal{G}$ into a unified vector representation, capturing the multimodal information. These joint embeddings $\phi(x, \mathcal{G})$ are then used for downstream tasks. In this paper, we focus on three specific downstream tasks: multi-choice QA contextualized by KG, graph-text pair classification, and retrieval tasks.

2.1 KG-Contextualized QA

Given a question q in text form, KG context $\mathcal{G}$, and answer candidate set with n choices $\boldsymbol{a} = \{a_1, \cdots, a_n\}$, KG-contextualized QA tasks aim to find the correct textual answer a_i from $\boldsymbol{a}$. At a high level, each choice a_i is first concatenated with the question q, leading to the input $x = [q, a_i]$, where $[\cdot, \cdot]$ denotes the concatenation of text. We then extract the joint embeddings $\phi(x, \mathcal{G})$ which is fed into a MLP layer to calculate scores. The choice with the highest score is selected as the prediction.

2.2 Graph-Text Pair Classification

In the task of graph-text pair classification, the objective is to determine the relevance between a given graph, represented as $\mathcal{G}$, and a corresponding textual description x. This involves assessing whether the content and structure of $\mathcal{G}$ are accurately reflected or described by x.

To achieve this, we first compute the joint embeddings $\phi(x, \mathcal{G})$ which capture the features and relationships contained in both the text and the graph. Once the joint embeddings are obtained, they are input into a MLP classifier. It outputs a prediction score which measures the likelihood of the graph $\mathcal{G}$ matching the text x.

The significance of this task lies in its ability to improve the quality of training data for tasks such as generating text from knowledge graphs and vice versa [6, 28, 31]. By accurately classifying graph-text pairs, the model can help reduce noise in training data, which in turn improves the overall performance of generation tasks [31].

2.3 Retrieval

For the retrieval task, given a textual query q accompanied by its graph context $\mathcal{G}_q$, the goal is to retrieve the most relevant candidate from a set of text-based options. Each candidate c_i in the candidate set $\boldsymbol{c} = \{c_1, \cdots, c_m\}$ also has an associated graph context $\mathcal{G}_{c_i}$. The

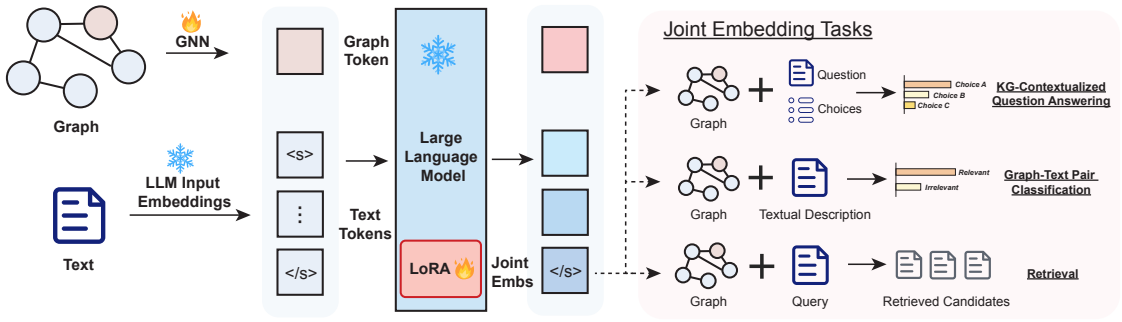

Figure 1: Overview of GT2Vec framework. Unlike the common use of LLMs for generation tasks, we leverage LLMs to obtain joint embeddings of both text and graph data. We encode the input graph with a GNN, which provides the graph embeddings. The graph embeddings are then transformed into the word embedding space in the large language model. These embeddings are then fed into a large language model, and the outputs are utilized for various downstream tasks.

task involves comparing the query-graph pair $(q, \mathcal{G}_q)$ against each candidate-graph pair $(c_i, \mathcal{G}_{c_i})$.

To achieve this, we first generate the joint embeddings $\phi(q, \mathcal{G}_q)$ for the query and $\phi(c_i, \mathcal{G}_{c_i})$ for each candidate. These embeddings encapsulate the features and relationships pertinent to their respective texts and graphs. The cosine similarity between the embeddings of the query and each candidate is calculated and is then used for the selection of the most relevant options.

3 GT2Vec

In this work, we propose a simple yet effective framework GT2Vec to learn joint embeddings of text and graphs, as illustrated in Figure 1. Specifically, graph-structured data are first extracted into a graph token, which is then fed into the LLM backbone together with the text tokens (§3.1, §3.2). The LLM backbone outputs the joint embeddings, which can be used for the downstream tasks, such as classification and retrieval.

A key aspect of GT2Vec is the explicit alignment between the graph and text embeddings. This alignment is crucial, as it allows the LLM backbone to better integrate the structured knowledge from the graph with the unstructured text, improving the quality of the joint representations (§4). To achieve this, we introduce a contrastive learning mechanism that explicitly maps embeddings from both modalities into a shared space (§3.3).

While LLMs are commonly used for generation tasks in an auto-regressive paradigm, GT2Vec takes a different route by utilizing LLMs as powerful encoders. This allows us to directly obtain robust joint embeddings of text and graph data by leveraging the rich contextual understanding of LLMs.

Our proposed architecture, GT2Vec, consists of three main components: a graph encoder, an MLP adapter, and a large language model backbone. Below, we discuss the components' design and implementation details, along with the alignment mechanism.

3.1 Graph Data Encoding

GT2Vec employs a graph encoder to obtain graph embeddings, which encapsulate essential information extracted from the contextual structure of the graph. Next, we describe the two-step process, which includes: (1) the integration of the query node in the graph; and (2) the graph encoding.

3.1.1 Query Node Integration into Graph Structures. We first initialize node embeddings within the input graph $\mathcal{G}$ with a language model (e.g., RoBERTa [39]). Following prior work [34, 65, 69], we link entities mentioned in the query to nodes in the graph, denoting these nodes as $\mathcal{V}_{\text{linked}}$. We then introduce a new node termed the query node, denoted as v_q. This query node is initialized using a language model by encoding the input query text. The query node v_q is then connected to all nodes within $\mathcal{V}_{\text{linked}}$, enhancing the connection between the query and the nodes within the graph. We denote the updated graph with $\mathcal{G}' = \{\mathcal{V}', \mathcal{E}'\}$.

3.1.2 Graph Encoding Process. The updated graph $\mathcal{G}'$ is then fed into an encoder for feature extraction. We adopt a modified version of graph attention network (GAT) [58, 65, 69] as the graph encoder. Specifically, in each layer of GAT, the message-passing process is formulated as

$$\boldsymbol{h}_v^{(\ell+1)} = f_n\left(\textstyle\sum_{s\in\mathcal{N}_v\cup\{v\}} \alpha_{sv}\mathbf{m}_{sv}\right) + \boldsymbol{h}_v^{(\ell)} \tag{1}$$

where $\mathcal{N}_v$ denotes the neighbors of node v, $\mathbf{m}_{sv}$ represents the message from each neighbor node s to node v. α_{sv} is the attention weight. f_n is a 2-layer MLP. The messages $\mathbf{m}_{sv}$ from node s to v are computed as the following:

$$\boldsymbol{r}_{sv} = f_r(\boldsymbol{e}_{sv}, \boldsymbol{u}_s, \boldsymbol{u}_v)\ \mathbf{m}_{sv} = f_m(\boldsymbol{h}_v^{(\ell)}, \boldsymbol{u}_v, \boldsymbol{r}_{sv}) \tag{2}$$

where $\boldsymbol{u}_s, \boldsymbol{u}_v$ denotes node type embeddings, and $\boldsymbol{e}_{sv}$ is edge embeddings, f_r is a 2-layer MLP, and f_m is a linear projection. Additionally, the attention weight α_{sv}, which measures the importance of each

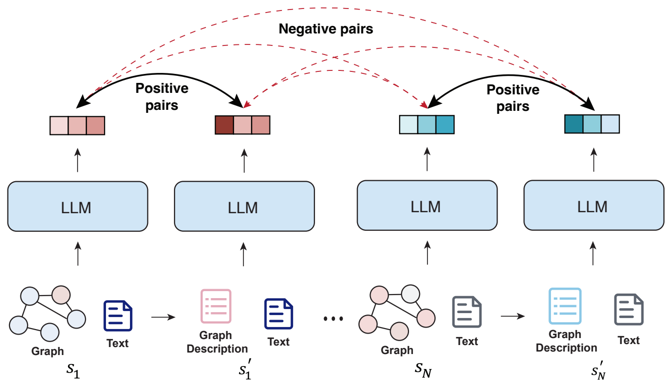

Figure 2: Overview of graph-text alignment through contrastive learning.

neighbor's message, is calculated in the following manner:

$$\boldsymbol{q}_s = f_q(\boldsymbol{h}_s^{(\ell)}, \boldsymbol{u}_s) \quad \boldsymbol{k}_v = f_k(\boldsymbol{h}_v^{(\ell)}, \boldsymbol{u}_v, \boldsymbol{r}_{sv}) \tag{3}$$

$$\gamma_{sv} = \frac{\boldsymbol{q}_s^\top \boldsymbol{k}_v}{\sqrt{D}} \quad \alpha_{sv} = \frac{\exp(\gamma_{sv})}{\sum_{v' \in \mathcal{N}_s \cup \{s\}} \exp(\gamma_{sv'})} \tag{4}$$

where f_q and f_k are linear transformation functions, and D is the hidden dimension. Following L layers of message passing, we concatenate the final layer embeddings of query node v_q, the average pooling of the node embeddings in the final layer, and the text embeddings of the input query, then employ an MLP to generate the graph embeddings $\boldsymbol{g}$.

3.2 Fusion of Graph and Textual Data in LLM

We then integrate the graph embeddings with textual information using the LLM to produce embeddings suitable for downstream tasks. To facilitate this integration, we draw inspiration from practices in computer vision [38, 72], where image embeddings are first transformed into the text space to be processed by LLMs. Similarly, we also convert the graph embeddings into the text space. We employ an MLP adapter for this purpose, which projects the graph token embeddings into the language model space using a two-layer MLP with ReLU activation functions, leading to the transformed graph embeddings $\tilde{\boldsymbol{g}}$. The transformation allows us to insert the processed graph token at the beginning of the text sequence, formatted as [*graph token*, <s>, *token* 1, *token* 2, ..., </s>]. In this sequence, the graph token, output by the MLP adapter, precedes the textual tokens, which are derived from the initial input embeddings of the LLM. This arrangement ensures that the initial context for the LLM processing includes both graph-derived and textual information.

We then feed this sequence into the LLM. The embeddings of the </s> token from the last layer of the LLM are considered as the final output embeddings $\boldsymbol{z}$, encapsulating the combined knowledge of the graph and text inputs. This integration process leverages the LLM's capacity to synthesize information across different modalities, optimizing the embeddings for subsequent applications.

3.3 Graph-Text Alignment via Contrastive Learning

As we mentioned above, in GT2Vec, graph embeddings are converted into the text space via a MLP module and then are processed by the LLM together with the input text tokens. To better align the graph embedding space and text space, we consider contrastive learning for the graph-text alignment.

Contrastive learning has been broadly used in various domains [3, 16, 23, 35, 36, 63, 67]. The key idea behind contrastive learning is to minimize the distance between similar or positive pairs in the embedding space, while maximizing the separation between dissimilar or negative pairs. Although similar techniques have been applied in graph representation learning [10, 66, 67] and language models [9, 15, 24], these approaches typically operate within a single modality (either graphs or text). In contrast, our GT2Vec framework aligns the embedding spaces between text and graphs by (1) converting graph data into textual descriptions and (2) using contrastive learning to strengthen the connections between the textual descriptions of graphs and their corresponding original graph representations, as shown in Figure 2.

3.3.1 Translating Graphs into Textual Descriptions. We first align the graph embeddings with text embeddings derived from descriptions of the same graph. Specifically, we start by listing all triples within the graph in a simple format: [entity (node), relation (edge), entity (node)]. This textual representation of the graph is then converted into a textual format by reorganizing the entities and relations into natural language. For example, the triples "*(analyzing, causes, new knowledge), (knowledge, causes, learn), (learn, causes, find information)*" are transformed into the following textual description: "*analyzing causes new knowledge; knowledge causes learn; learn new causes find information.*"

3.3.2 Contrastive Learning for Alignment. Now, we have two branches in the GT2Vec framework: the original graph + text branch and the graph description + text branch. These branches create a dual-view architecture that facilitates the alignment of graph and text embedding spaces through contrastive learning.

In the contrastive learning stage, we define positive pairs as the embeddings from the branch processing the original graph and its corresponding textual description that accurately reflect the same information. Negative pairs, on the other hand, consist of unrelated graph-text pairs from within the same batch, ensuring that the model learns to distinguish between semantically aligned and unaligned graph-text pair data. Specifically, for the original graph + text branch, we use the way mentioned in §3.2 to generate the joint embeddings z_{orig}. This involves combining graph embeddings, obtained from a graph encoder, with textual embeddings generated by the LLM's embedding layer to produce joint embeddings. For the graph description + text branch, we treat the input as pure text and use only the LLM to process it and generate the joint embeddings z_{new}. By applying infoNCE loss [46], we have

$$\mathcal{L}^{(\text{infoNCE})} = -\sum_{i=1}^{n_{\text{batch}}} \log \left(\frac{\exp\left(\tilde{z}_{\text{orig}}^{\mathrm{T}}(i) \cdot \tilde{z}_{\text{new}}(i)\right)}{\sum_{j=1}^{n_{\text{batch}}} \exp\left(\tilde{z}_{\text{orig}}^{\mathrm{T}}(i) \cdot \tilde{z}_{\text{new}}(j)\right)} \right) \tag{5}$$

where n_{batch} represents the number of samples in a training batch, and $\tilde{z}_{\text{orig}}$ and $\tilde{z}_{\text{new}}$ denote the normalized vectors of z_{orig} and z_{new}, respectively. As we present in §4, the contrastive learning method improves GT2Vec's ability to better align the graph and text embeddings, which is further beneficial to the downstream tasks.

3.4 Training

Our proposed framework, GT2Vec, can accommodate a wide array of tasks that require the integration of graph data and text. The training process for each task incorporates a task-specific loss function combined with a contrastive learning loss. The general form of the combined loss for each task can be represented as follows:

$$\mathcal{L} = \mathcal{L}^{(\text{task})} + \lambda \mathcal{L}^{(\text{infoNCE})} \tag{6}$$

where λ is a hyperparameter used to adjust the weights between loss functions. $\mathcal{L}^{(\text{task})}$ refers to the loss directly associated with the primary objective of the task. For KG-Contextualized QA, we use cross-entropy loss; for graph-text pair classification, we apply binary cross-entropy (BCE) loss; and for retrieval, we use infoNCE loss. More details can be found in the Appendix C.2.

4 Experiments

Next, we assess the performance of GT2Vec and compare it to strong baselines on three types of tasks: KG-contextualized QA, graph-text pair classification, and retrieval tasks (§4.1-4.3). We also perform extensive ablation studies to understand the impact of our design and other choices (§4.4).

4.1 KG-contextualized QA Performance

4.1.1 Datasets and Metrics. We first evaluated GT2Vec on three QA datasets, i.e., CommonsenseQA [54], OpenBookQA [42], and MedQA-USMLE [27]. We split these datasets according to Yasunaga et al. [65] and Zhang et al. [69] into train, validation, and test splits. For evaluation, we use accuracy as the metric to measure the performance on each dataset. For each question in the QA datasets, a subgraph context extracted from a KG is utilized to provide additional contextual information, following Yasunaga et al. [65] (see Appendix B.1).

4.1.2 Baselines. We compare GT2Vec with a range of baseline models, including both language models (LM) and hybrid approaches that integrate language models with knowledge graphs (LM+KG).

Fine-tuned LMs. We consider the following vanilla fine-tuned language models (LMs): RoBERTa-Large [39] and E5-Mistral [61]. Additionally, for MedQA-USMLE dataset, we use several domain-specific models, including SapBERT [37] and BioBERT [30].

Existing LM+KG models. Our LM+KG baselines include: GreaseLM [69] QAGNN [65], Relation Network (RN) [51], RGCN [52], GconAttn [62], and MHGRN [11]. Unlike these models that leverage GNNs as the main backbone, our framework GT2Vec adopts more powerful LLMs for better performance. We adopt E5-Mistral [61] as GT2Vec's LLM backbone.

4.1.3 Training Details. During training, we adopt parameter efficient finetuning techniques, including Linear Probe (LP) [49] and Low-Rank Adaptation (LoRA) [20], for E5-Mistral and GT2Vec. LP freezes the pre-trained LLM and trains a linear classifier on top, while LoRA introduces low-rank adaptation layers for efficient finetuning. We employ full parameter fine-tuning for the other baselines. Further details on the training process such as hyperparameters can be found in Appendix D.

4.1.4 Results. We first conduct comparison experiments on CommonsenseQA and OpenBookQA datasets, as illustrated in Table 1. In both datasets, our framework outperforms all other methods significantly. Specifically, on CommonsenseQA, it surpasses the strongest baseline E5-Mistral, achieving a test accuracy of 81.39%. On OpenBookQA, GT2Vec also demonstrates superior performance, achieving 88.13% test accuracy. When further integrating the extra corpus of scientific facts provided by OpenbookQA [5], our model reaches a remarkable 93.67% accuracy, outperforming all the baseline models that also utilized scientific facts. The remarkable performance can be attributed primarily to the robust capabilities of the LLM backbone integrated within our framework. The LLM backbone not only enhances language understanding but also integrates the contextual knowledge derived from graphs, thereby substantially improving KG-contextualized QA performance.

We further evaluate GT2Vec on the MedQA-USMLE dataset to assess its generalization capability across specialized domains and report the results in Table 2. GT2Vec achieves a test accuracy of 53.4%, outperforming all the baselines including domain-specific models. This result further reinforces the adaptability of GT2Vec across different domains showcasing its ability to excel not only in general and scientific question answering but also in knowledge-intensive and highly specialized fields.

4.2 Graph-Text Pair Classification Performance

Building upon the strong results achieved in the KG-contextualized QA tasks, we further evaluate GT2Vec in a different task: graph-text pair classification. Our objective in evaluating this task is to assess GT2Vec's ability to generalize beyond QA scenarios, demonstrating its versatility in handling a broader range of graph-text embedding tasks. We evaluate models on the WebNLG [14] dataset and use accuracy as the evaluation metric, measuring the proportion of correctly classified graph-text pairs.

The results of the graph-text pair classification task are presented in Table 3. GT2Vec significantly outperforms all baseline models by at least 4.72%, achieving a test accuracy of 89.70%. While models like GreaseLM and MHGRN perform well by incorporating knowledge graphs, they lack the deeper contextual understanding due to the limitations of their less powerful backbone models, such as shallow transformers or GNNs.

4.3 Retrieval Performance

Next, we further evaluate GT2Vec's performance on retrieval tasks, where the objective is to retrieve relevant sentences or documents based on a query with graph-context. We conduct experiments on two datasets, SciFact [59] and FiQA [41], and report NDCG@10 as the primary evaluation metric.

As shown in Table 4, GT2Vec achieves the best performance on both datasets. A closer examination of the LM + KG baselines reveals interesting trends. Both models use RoBERTa-Large in their architectures. From the results, GreaseLM outperforms the RoBERTa-Large model by a margin of 5.6% on SciFact and 8.9% on FiQA,

Table 1: Test accuracy comparison on CommonsenseQA and OpenBookQA. The baseline results are mainly sourced from Zhang et al. [69] and Yasunaga et al. [65]. Bold indicates the best result, and underline indicates the second best. LP means linear probe.

Methods	CommonsenseQA	OpenBookQA (w/o Scientific Facts)	OpenBookQA (w/ Scientific Facts)
Language Models Only			
RoBERTa-Large [39]	68.69 ± 0.56	64.80 ± 2.37	78.40 ± 1.64
E5-Mistral, LP [61]	69.49 ± 0.28	74.80 ± 0.35	81.67 ± 0.31
E5-Mistral, LoRA [61]	78.73 ± 0.16	85.60 ± 0.20	91.87 ± 0.12
LM + KG			
RGCN [52]	68.41 ± 0.66	62.45 ± 1.57	74.60 ± 2.53
GconAttn [62]	68.59 ± 0.39	64.75 ± 1.48	71.80 ± 1.21
MHGRN [11]	71.11 ± 0.10	66.85 ± 1.19	81.87 ± 1.86
QA-GNN [65]	73.41 ± 0.92	67.80 ± 2.75	82.77 ± 1.56
GreaseLM [69]	74.20 ± 0.40	65.60 ± 0.40	83.87 ± 1.29
GT2Vec, LP (Ours)	<u>81.09</u> ± 0.73	<u>86.67</u> ± 1.10	<u>93.33</u> ± 0.42
GT2Vec, LoRA (Ours)	**81.39** ± 0.11	**88.13** ± 0.42	**93.67** ± 0.31

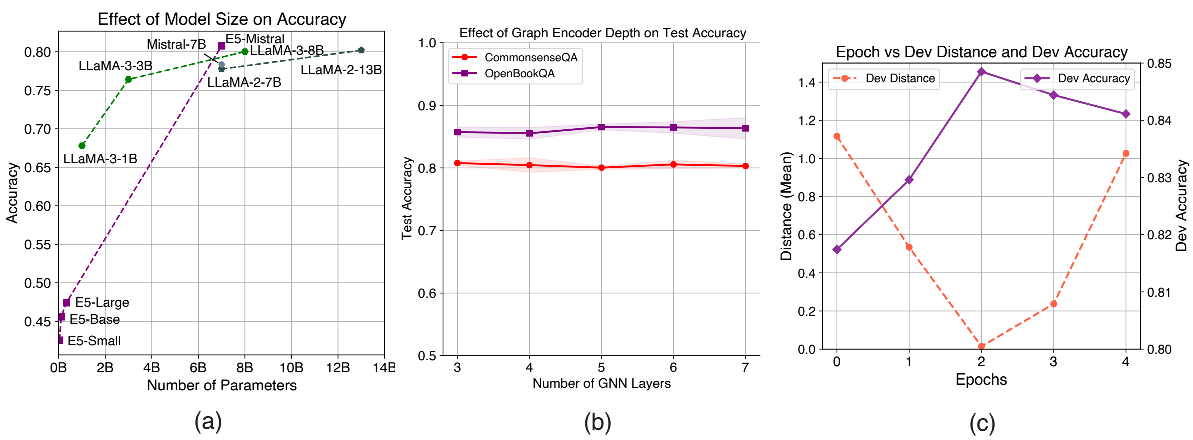

Figure 3: (a) The effect of LLM backbone choice on accuracy for the CommonsenseQA dataset. The figure shows three series: E5, LLaMA-3, and LLaMA-2, along with a single Mistral-7B model. (b) The effect of graph encoder depth (number of GNN layers) on test accuracy for CommonsenseQA and OpenBookQA datasets. The shaded areas represent the standard deviation, indicating the variance in performance across different trials. (c) Graph-text embedding distance (red dashed) and dev accuracy (purple solid) on CommonsenseQA across training epochs.

which aligns with our earlier findings that graph context can be useful for enhancing retrieval performance. However, QA-GNN shows a performance degradation compared to RoBERTa-Large, particularly on FiQA (19.5 vs. 20.4). The reason for this drop may be attributed to QA-GNN's use of a simple MLP for combining the graph and text embeddings. This weaker integration mechanism is likely insufficient for fully leveraging the graph context, resulting in suboptimal performance. In contrast, GreaseLM employs a shallow transformer, which offers better capacity for fusing multimodal information, leading to moderate gains.

4.4 Ablation Studies

To better understand the contributions of different components in GT2Vec, we perform an ablation study on the CommonsenseQA and OpenBookQA datasets under the linear probe setting.

Effect of LLM Backbone Choice. GT2Vec exhibits flexibility in adopting various LLMs as its backbone. To evaluate the impact of different LLM backbones on performance, we compare four series of models: the E5 series [60, 61], LLaMA-2 [56], LLaMA-3 [8], and Mistral [25], as illustrated in Figure 3(a). We first observe that increasing the model size within each series consistently enhances the performance. This trend highlights that larger models, with

Table 2: Test accuracy comparison on MedQA-USMLE. The baseline results are mainly sourced from Zhang et al. [69]. Bold indicates the best result, and underline indicates the second best. LP means linear probe.

Methods	Test Acc
Language Models Only	
BERT-Base [7]	34.3
BioBERT-Base [30]	34.1
RoBERTa-Large [39]	35
BioBERT-Large [30]	36.7
SapBERT [37]	37.2
E5-Mistral, LP [61]	39.4 ± 1.1
E5-Mistral, LoRA [61]	51.1 ± 0.3
LM + KG	
QA-GNN [65]	38
GreaseLM [69]	38.5
GT2Vec, LP (Ours)	49.9 ± 0.9
GT2Vec, LoRA (Ours)	**53.4** ± 0.3

Table 3: Test accuracy comparison on WebNLG dataset.

Methods	Test Acc
LM + KG	
RGCN [52]	63.20 ± 0.49
MHGRN [11]	84.98 ± 0.53
QA-GNN [65]	75.55 ± 3.54
GreaseLM [69]	82.50 ± 4.29
GT2Vec, LP (Ours)	88.43 ± 1.33
GT2Vec, LoRA (Ours)	**89.70** ± 0.34

more parameters, are typically able to better capture complex relationships in multi-modal data, leading to higher performance. Additionally, LLaMA-3 significantly improves over LLaMA-2. Specifically, the performance of LLaMA-3-3B matches that of LLaMA-2-7B and LLaMA-3-8B achieves results comparable to LLaMA-2-13B, indicating that the new LLaMA-3 architecture brings considerable advancements compared to its predecessor LLaMA-2.

Effect of Graph Encoder Depth. We evaluate the effect of varying the number of GAT layers in the graph encoder on the performance of GT2Vec using the CommonsenseQA and OpenBookQA datasets. As shown in Figure 3(b), both datasets exhibit slight fluctuations in test accuracy as the number of GAT layers increases from 3 to 7. This suggests that the method is quite robust to changes in GAT depth, with only small variations in performance.

Effect of Graph-Text Alignment. We further investigate the effectiveness of graph-text alignment by studying how the alignment evolves during training. Specifically, we calculate the mean Euclidean distance between the normalized graph and text embeddings on the dev set (shown as the red dashed line) and compare it to the corresponding development accuracy (purple solid line) across different training epochs, as illustrated in Figure 3(c). This figure shows a clear inverse relationship between the two curves:

Table 4: Comparision results (NDCG@10) on retrieval tasks.

Methods/Datasets	SciFact	FIQA
Language Models Only		
BERT-Base [7]	13.3	2.2
RoBERTa-Large [39]	43.3	20.4
E5-Small [60]	65.6	34.8
E5-Base [60]	73.1	36.4
E5-Large [60]	72.6	38.6
GTR-XXL [44]	66.2	46.7
SGPT [43]	74.7	37.2
E5-Mistral, 0-shot [61]	76.1	53.5
E5-Mistral, LoRA [61]	75.9	53.2
LM + KG		
QA-GNN [65]	41.4	19.5
GreaseLM [69]	48.9	29.3
GT2Vec, LP (Ours)	**82.9**	54.1
GT2Vec, LoRA (Ours)	80.8	**56.2**

as the graph-text distance decreases, accuracy improves. Notably, at epoch 2, the graph-text distance reaches its minimum, while the dev accuracy peaks. This trend suggests that better alignment between graph and text embeddings contributes directly to improved model performance, highlighting the effectiveness of our graph-text alignment strategy in GT2Vec.

Table 5: Impact of different graph node embedding initialization models on accuracy for the CommonsenseQA dataset.

Model	Output Dimension	Accuracy
RoBERTa-Large [39]	1,024	81.09 ± 0.73
E5-Small [60]	384	80.37 ± 0.38
E5-Base [60]	768	80.77 ± 0.05
E5-Large [60]	1,024	80.79 ± 0.30
E5-Mistral [61]	4,096	80.42 ± 0.90

Impact of Node Embedding Initialization To assess the impact of different node embedding initialization models on performance, we conducted experiments on the CommonsenseQA dataset. As shown in Table 5, the results reveal minimal differences in accuracy across models with varying output dimensions, indicating that the choice of initialization model has limited influence on performance. For instance, RoBERTa-Large, E5-Base, and E5-Large achieve nearly identical results, with an accuracy of around 81%.

Interestingly, even when using lighter models for node embedding initialization, such as E5-Small, which has a smaller output dimension (384), the performance remains competitive. This demonstrates that even when the node initialization model differs from the actual backbone used in GT2Vec, there is no significant performance degradation. For example, compared with E5-Mistral node embedding initialization, the lighter E5-Small model offers the advantage of reduced computational cost without compromising much on accuracy.

Effect of Graph Encoder Choice We also investigate the impact of different graph encoders on the performance of GT2Vec, as shown in Table 6. We observe that the performance with GAT achieves the best results on both CommonsenseQA and OpenBookQA.

Table 6: The effect of graph encoder choice on test accuracy.

Graph Encoder	CommonsenseQA	OpenBookQA
GCN [29]	80.95 ± 0.28	84.67 ± 1.27
GAT [58]	81.09 ± 0.73	86.67 ± 1.10
GIN [64]	80.23 ± 0.57	85.40 ± 0.92

5 Related Work

Graphs and Language Models for Multi-Modal Embedding Tasks. Integration of graph data with language models has been an evolving field, aiming to combine structured graph data with unstructured textual information for enhanced data analysis. Historically, early attempts in this area employed an MLP or a shallow transformer to merge the information from both modalities [11, 34, 65, 69], which may not fully exploit the rich contextual information from text and graph data.

The advent of LLMs has brought a transformative shift to the NLP field. LLMs, with their extensive pre-training on diverse corpora, offer unprecedented capabilities for deep semantic understanding and reasoining [13, 71]. Recent research has begun to explore the potential of LLMs for enhancing multimodal embedding tasks of graphs and text [17, 22, 55, 70, 74]. These studies primarily focus on augmenting the graph representation capabilities within the LLM framework. While these efforts mark significant advancements, they predominantly concentrate on graph representation learning rather than direct NLP tasks. Additionally, these methods do not explicitly align the semantic spaces of graphs and text. In contrast, our approach not only integrates LLMs for handling complex multimodal inputs but also introduces an explicit alignment mechanism between graph and text embeddings. This alignment is crucial for enhancing the semantic integration and boosting performance across diverse NLP tasks by capturing complex intermodal relationships.

There are recent studies that have explored using LLMs and graph data for generative tasks beyond embedding tasks [1, 18, 19, 21, 26, 48, 68, 73]. Our work, however, concentrates on embedding tasks, which is an orthogonal direction. Unlike generative tasks, which primarily focus on creating new content via next-token prediction, embedding tasks are aimed at developing rich, informative representations that can be used directly to enhance performance in downstream applications such as classification and retrieval.

Contrastive Learning. Contrastive learning has gained significant attention in recent years as a method to learn representations by maximizing agreement between positive pairs while pushing negative pairs apart in the embedding space [3, 16, 35, 36, 67]. Pioneering works like SimCLR [3] and MoCo [16] have demonstrated the effectiveness of contrastive learning in the visual domain. Similar approaches have been applied to graphs [10, 66, 67] and language models [9, 15, 24], but these methods typically operate within a single modality (e.g., graphs or text). In contrast, our approach introduces contrastive learning to align the graph embedding space with the text embedding space. By transforming graphs into textual descriptions and applying contrastive learning, we ensure that embeddings from both modalities align closely, enhancing the model's ability to perform tasks that require both graph-based reasoning and text comprehension.

6 Conclusion

In this paper, we introduce GT2Vec, a simple yet effective framework designed to integrate graph and text data using a novel alignment strategy and LLMs. We have demonstrated that GT2Vec enhances the semantic coherence between these two modalities, resulting in significantly improved performance on several NLP tasks and datasets. By aligning graph embeddings directly with text embeddings, GT2Vec ensures a deeper integration of structured and unstructured data.

A Ethical Considerations

All datasets used in this work are publicly available and widely used in the research community. No personally identifiable information (PII) or sensitive data is included in these datasets. Our research strictly adheres to the ethical guidelines of using publicly available datasets, and no additional data was collected from human subjects. Our work has no potential negative societal impact.

B Dataset Details

B.1 KG-Contextulized QA

CommonsenseQA [54] is a 5-way multiple-choice QA dataset focused on applying commonsense knowledge in answering questions. It includes 12,102 questions, each with one correct answer and four distractor answers.

OpenBookQA [42] is a 4-way multiple choice QA dataset that requires reasoning with elementary science knowledge, containing 5,957 questions.

MedQA-USMLE [27] is a 4-way multiple choice QA task that requires biomedical and clinical knowledge. The questions are originally from practice tests for the United States Medical License Exams (USMLE). The dataset contains 12,723 questions.

For each question in the QA datasets, a subgraph context extracted from a KG is utilized to provide additional contextual information, following Yasunaga et al. [65]. Specifically, for CommonsenseQA and OpenBookQA, we used the ConceptNet [53], which contains 799,273 nodes and 2,487,810 edges. Node embeddings are initialized by Roberta-Large [39] and kept frozen during the training process, following Yasunaga et al. [65]. The query node embeddings mentioned in Section 3.1 are calculated by the LLM backbone. For MedQA-USMLE dataset, we used the UMLS knowledge graph used in Yasunaga et al. [65], which contains 9,958 nodes and 44,561 edges. Node embeddings are initialized using SapBERT [37], following Yasunaga et al. [65].

B.2 Graph-Text Pair Classification

To evaluate GT2Vec on graph-text pair classification, we curated a dataset based on **WebNLG** [14]. The original WebNLG dataset

is used to assess models' ability in text-to-graph and graph-to-text generation. Concretely, each data contains a graph-text pair where the graph is a set of triples from DBpedia and the text is the corresponding description of the triples. For example, the graph data are *"(John_E_Blaha birthDate 1942_08_26), (John_E_Blaha birthPlace San_Antonio), (John_E_Blaha occupation Fighter_pilot)"*, while the corresponding text is *"John E Blaha, born in San Antonio on 1942-08-26, worked as a fighter pilot."*

In this paper, we use the v3.0 release data to construct the dataset for graph-text pair classification. First, we curated the dataset by identifying relations that appear in the training, dev, and test sets. We then filtered the dataset to retain only those graph triples that contain these relations for all three sets. To further increase the complexity of the task, we generated a series of new, randomly combined positive samples. Specifically, we merged multiple graph-text pairs from the original dataset, creating data with larger graphs and longer text by concatenating their respective triples and sentences.

Next, we generated an equal number of negative samples. To this end, we followed a similar process to create positive pairs but introduced mismatches. In this case, while the graph triples were taken from one pair, the text was taken from a different, unrelated pair. This ensured that the graph and text did not align, resulting in non-matching pairs that serve as negative examples. We finally constructed 10,000 training, 4,000 validation, and 2,000 test data.

B.3 Retrieval

SciFact [59] is a scientific fact-checking dataset aimed at verifying scientific claims using relevant research papers. It contains 920 training queries, and 300 test queries, with a corpus of 5,183 documents. In our experiment, we split 100 samples from the training set to serve as validation queries, ensuring that the remaining training data is used for model training while still providing a separate validation set for tuning and evaluation.

FiQA [41] is a financial-domain retrieval dataset designed to address complex financial question answering and information retrieval tasks. It contains 14,166 training queries, 500 development queries, and 648 test queries, with a total of 57,638 documents in the corpus.

C Methodology Details

C.1 Additional Framework Details

GT2Vec utilizes a dual-view architecture for graph-text alignment, incorporating two parallel branches. The first branch processes the original graph together with the text, while the second branch processes a textual description of the graph along with the input text. In our experiments, both branches are employed to generate embeddings that are used for downstream tasks, and both contribute to the task-specific loss $\mathcal{L}^{(\text{task})}$. This dual-branch approach has several advantages: it allows the model to learn complementary information from both the structured graph and its textual description, enhancing the overall representation. During the evaluation, however, we simplify the process by using only the graph+text branch, and it has shown to provide sufficient performance for the downstream tasks, eliminating the need for the graph description branch.

C.2 Training Objective

In this part, we detail the task-specific loss function $\mathcal{L}^{(\text{task})}$ for each downstream task.

C.2.1 KG-Contextualized QA. For the KG-contextualized QA task, we apply the cross-entropy loss function, which is crucial for classification tasks involving multiple-choice questions. This loss function is computed as follows:

$$\mathcal{L}^{(\text{task})} = -\sum_{i=1}^{n_{\text{batch}}} \sum_{j=1}^{n_{\text{choice}}} y_j^{(i)} \log(\hat{y}_j^{(i)}) \tag{7}$$

where n_{batch} is the number of samples in a batch and n_{choice} is the number of answer choices per question. $y_j^{(i)}$ is a binary indicator (1 if the choice j is the correct answer for sample i, and 0 otherwise). $\hat{y}_j^{(i)}$ is the predicted probability that choice j is the correct answer for sample i.

C.2.2 Graph-Text Pair Classification Tasks. In the graph-text pair classification task, we use binary cross-entropy loss to determine the match/mismatch status between the graph and text pairs:

$$\mathcal{L}^{(\text{task})} = -\sum_{i=1}^{n_{\text{batch}}} \left(y^{(i)} \log \hat{y}^{(i)} + (1 - y^{(i)} \log(1 - \hat{y}^{(i)}) \right) \tag{8}$$

Here, $y^{(i)}$ is the true label (1 if the pair matches, 0 otherwise) and $\hat{y}^{(i)}$ is the predicted probability of a match as output by the MLP classifier.

C.2.3 Retrieval Tasks. For retrieval tasks, we apply infoNCE loss [46] for training. Specifically, given a batch of positive pairs (d_i, p_i), we assume that (d_i, p_i) is a positive pair and (d_i, p_j) for $i \neq j$ a negative pair. By applying infoNCE loss, we have

$$\mathcal{L}^{(task)} = -\sum_{i=1}^{n_{\text{batch}}} \log \left(\frac{e^{\text{sim}(a_i, p_i)/\tau}}{e^{\text{sim}(a_i, p_i)/\tau} + \sum_{j \neq i} e^{\text{sim}(a_i, p_j)/\tau}} \right) \tag{9}$$

where $\text{sim}(\cdot, \cdot)$ is the consine similarity between the embeddings. τ is the temperature scaling parameter.

D Experiment Details

D.1 Additional Implementation Details

We implement models using PyTorch [47] and PyTorch Geometric [12]. All experiments are conducted on a single A100 80GB GPU. For baselines that we implemented ourselves, we followed the settings and hyperparameters described in the original papers to ensure fair comparisons. Detailed hyperparameter settings for GT2Vec can be found in Table 8 and Table 7.

D.2 Additional Results

D.2.1 Effect of Graph-Text Alignment. Removing contrastive learning from GT2Vec leads to a performance drop, with the accuracy decreasing from 81.09% to 79.69% on CommonsenseQA, and from 86.67% to 84.80% on OpenBookQA. This highlights the importance of contrastive learning in aligning graph and text embeddings, ensuring better integration of multimodal information.

Table 7: Hyperparameters for training GT2Vec.

Hyperparameter	CommonsenseQA	OpenBookQA	MedQA-USMLE	WebNLG	SciFact	FiQA
GNN hidden dim	256	256	256	256	256	512
Number of GNN layers	3	5	5	5	3	3
GAT attention heads	2	2	2	2	2	2
Dropout rate	0.2	0.2	0.2	0.2	0.2	0.2
Context length	128	128	256	256	512	512
Learning rate	1×10^{-5}	1×10^{-5}	1×10^{-5}	1×10^{-4}	1×10^{-5}	5×10^{-6}
Optimizer	RAdam	RAdam	RAdam	RAdam	RAdam	RAdam
Weight decay	1×10^{-2}	1×10^{-2}	1×10^{-2}	1×10^{-2}	1×10^{-2}	1×10^{-2}
Learning rate schedule	constant	constant	constant	constant	constant	constant
Number of epochs	5	5	15	5	15	1
Batch size	8	8	8	32	16	256
Max gradient norm	1.0	1.0	1.0	1.0	1.0	1.0
λ in Eq. (6)	0.05	0.05	0.05	0.05	0.05	0.05
Knowledge graphs	ConceptNet	ConceptNet	UMLS	DBPedia	ConceptNet	ConceptNet
Max number of nodes in subgraphs	200	200	200	200	200	200
Number of relations	38	38	34	748	38	38

Table 8: LoRA Hyperparameters

Hyperparameter	Value
Rank (r)	8
Alpha (α)	16
Dropout	0.05
Target Modules	{q_proj, k_proj, v_proj, o_proj, gate_proj, up_proj, down_proj}

Table 9: Ablation study results on test accuracy.

Methods	CommonsenseQA	OpenBookQA
GreaseLM [69]	74.20 ± 0.40	83.87 ± 1.29
GT2Vec w/o graph	69.49 ± 0.28	74.80 ± 0.35
GT2Vec w/o alignment	79.69 ± 0.85	84.80 ± 1.06
GT2Vec	**81.09** ± 0.73	**86.67** ± 1.10

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