

A Survey of Large Language Models on Generative Graph Analytics: Query, Learning, and Applications

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Abstract—A graph is a fundamental data model to represent various entities and their complex relationships in society and nature, such as social networks, transportation networks, financial networks, and biomedical systems. Recently, large language models (LLMs) have showcased a strong generalization ability to handle various NLP and multi-mode tasks to answer users’ arbitrary questions and specific-domain content generation. Compared with graph learning models, LLMs enjoy superior advantages in addressing the challenges of generalizing graph tasks by eliminating the need for training graph learning models and reducing the cost of manual annotation. In this survey, we conduct a comprehensive investigation of existing LLM studies on graph data, which summarizes the relevant graph analytics tasks solved by advanced LLM models and points out the existing remaining challenges and future directions. Specifically, we study the key problems of LLM-based generative graph analytics (LLM-GGA) with three categories: LLM-based graph query processing (LLM-GQP), LLM-based graph inference and learning (LLM-GIL), and graph-LLM-based applications. LLM-GQP focuses on an integration of graph analytics techniques and LLM prompts, including *graph understanding* and *knowledge graph (KG) based augmented retrieval*, while LLM-GIL focuses on learning and reasoning over graphs, including *graph learning*, *graph-formed reasoning* and *graph representation*. We summarize the useful prompts incorporated into LLM to handle different graph downstream tasks. Moreover, we give a summary of LLM model evaluation, benchmark datasets/tasks, and a deep pro and cons analysis of LLM models. We also explore open problems and future directions in this exciting interdisciplinary research area of LLMs and graph analytics.

Index Terms—Graph, LLMs, GNNs, Prompt, Survey

I. INTRODUCTION

Large language models (LLMs) possess billions of parameters and have been trained on extensive corpora using training strategies like instruction tuning [1] [2] and Direct Preference Optimization (DPO) [3], enabling them to exhibit powerful reasoning and semantic representation capabilities, thereby advancing AI intelligence closer to human levels. Undoubtedly, LLMs currently serve as the foundation model for NLP tasks [4] [5] [6], showcasing strong generalization abilities to handle various NLP tasks such as question answering [7] [8], machine translation [9], code generation [10] [11], etc. LLMs have demonstrated extensive common knowledge and robust semantic comprehension abilities, fundamentally transforming existing text-processing workflows. While initially designed for text data, LLMs are increasingly being utilized for tasks

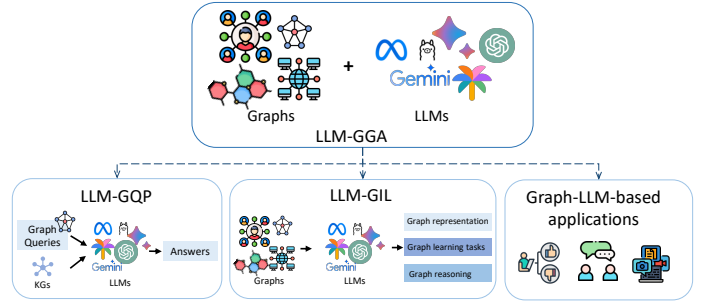


Fig. 1: Illustration of the LLM-GGA domain. LLM-GGA domain includes three principal components: LLM-based graph query processing (LLM-GQP), which necessitates the melding of graph analytics techniques and LLM prompts for query processing; LLM-based graph inference and learning (LLM-GIL), focusing on learning and reasoning over graphs; Graph-LLM-based applications that employ the graph-LLM framework to address non-graph tasks, such as recommendation systems.

beyond language processing, aiming to leverage the robust capabilities of LLMs across different tasks, showcasing superior performance.

Graphs, as structured data, play a crucial role in various real-world application scenarios, including the citation networks [12], social networks [13], molecular graphs [14], web links [15], and to name a few. Various graph analytics tasks have been studied to show their usefulness, e.g., node classification, link prediction, subgraph mining, influence maximization, and so on. Their versatility and ability to capture complex relationships have made graphs indispensable tools in academic research and industry platforms. Recently, one kind of graph-based learning model, graph neural network (GNN) [16] [17], has been widely studied and applied to solve challenging graph tasks. The GNN models utilize recursive message passing [18] and aggregation mechanisms [19] among nodes to derive representations of nodes, edges, or entire graphs, which have been used for various downstream tasks. This is thanks to the strong ability of GNN models to capture both graph structure and node features. However, GNNs exhibit weak generalization capabilities [20] [21] [22], requiring retraining for different graph tasks and showing limited transfer ability.

In other words, no universal graph foundation model could be easily generalized to handle various types of graph tasks.

Therefore, whether LLMs’ powerful reasoning, semantic representation, and generalization capabilities can be applied to address graph tasks, leading to the inspiration of a graph foundation model, is the core of current efforts in leveraging existing large language models for graph-related tasks. In one word, *can LLMs solve graph data tasks?* More specifically, we study three detailed questions: (a) what specific graph tasks can LLMs answer? (b) How do LLMs tackle these tasks? (c) What is the effectiveness of LLM-based methods in solving these tasks compared with the existing graph-based approaches?

To address the above question, this survey conducts a comprehensive study of existing relevant work on graph analytics and LLMs, focusing on exploring the key issue of the LLM-based generative graph analytics (LLM-GGA) field. Drawing from a thorough investigation of the LLM-GGA domain, we offer a structured and methodical analysis that delineates the field into three principal components: LLM-based graph query processing (LLM-GQP), which necessitates the melding of graph analytics techniques and LLM prompts for query processing; LLM-based graph inference and learning (LLM-GIL), focusing on learning and reasoning over graphs; and lastly, graph-LLM-based applications that employ the graph-LLM framework to address non-graph tasks, such as recommendation systems. The framework is shown in Figure 1.

We categorize these three main components into a total of six directions to provide a guideline for researchers to conduct more in-depth studies. LLM-GQP includes graph understanding and KG-based augmented retrieval directions. LLM-GIL covers graph learning, graph-formed reasoning, and graph representation directions. The sixth direction is graph-LLM-based applications. The following section details these six directions:

- **Graph understanding tasks.** This research direction is studying whether LLMs can solve graph algorithm problems, exploring whether LLMs can comprehend graph structures to conduct graph mining and graph search. Current methods have primarily explored LLMs’ understanding of graph structures, such as shortest path, clustering coefficient computation [23] [24], and more complex problems like maximum flow and Hamilton path [25] [26] [27]. Two main methods are introduced: prompting and supervised fine-tuning (SFT). The prompting methods explore the LLM’s current structural understanding ability through query processing. Meanwhile, SFT methods enhance LLMs’ structure understanding capability by tuning it on specific graph datasets. However, many more tasks are yet to be explored, such as the community search, keyword search, subgraph pattern mining, and other NP-hard complex graph problems [28] [29].
- **Graph learning tasks.** This direction explores whether LLMs can combine graph structure and attributes for learning, extracting features of nodes, edges, and graphs,

and understanding the semantic information of graphs, for example, tasks like node classification, graph classification, and GQL generation [30] [31] [32] [33]. There are two main pipelines: LLM-GNN pipelines and LLM pipelines. LLMs can leverage their powerful reasoning ability and vast knowledge repository to enhance GNNs and also can predict results directly.

- **Graph-formed reasoning.** This direction explores how LLMs use graph structures to simulate human thinking during reasoning [34] [35] [36], enabling them to solve more complex reasoning problems such as algorithmic, logical, and mathematical tasks. Graph-formed reasoning involves two types of reasoning: think on the graph and verify on the graph. *Think on the graph* refers to LLMs deriving the final conclusion through the graph structure. *Verify on the graph* refers to verifying the correctness of the LLMs’ intermediate or final outputs through the graph structure.
- **Graph representation.** This direction explores enhancing graph representation with LLMs, particularly for Text Attribute Graphs (TAGs). LLMs’ strong text representation capabilities allow text embeddings to capture deeper semantic nuances. However, the key challenge in this area remains how to capture and integrate graph structure into graph representation effectively [37] [38] [39]. There are three forms of graph representation: graph embedding, graph-enhanced text embedding, and graph-encoded prompts. Graph embedding methods transform a graph into a sequential format for LLM processing. Graph-enhanced text embedding methods integrate structure into text embedding, where the integration method can be concatenation. Graph-encoded prompts focus on the way a graph is described within prompts.
- **Knowledge Graph (KG) based augmented retrieval.** This direction investigates the relationship between LLMs and Knowledge Graphs (KGs). With the emergence of LLMs, discussions have arisen regarding the potential replacement of KGs [40] [41] [42] [43]. Consequently, this paper discusses the limitations of LLMs in processing factual knowledge, evaluates strategies for improving LLM efficacy via KG-based augmented retrieval, and investigates potential avenues for future advancements in this field.
- **Graph-LLM-based applications.** This part explores the tasks where graph-LLM-based methods can be applied for useful downstream application [44] [45] [46], such as recommendation systems, conversational understanding, and so on.

We comprehensively analyze these six research directions of LLM-GGA to provide valuable definitions and highlighted methodologies. We also highlight the pros and cons of these methods and showcase future directions. To further explore the capabilities of LLMs reliably, this paper uses the prompting method to test the effectiveness of LLMs in tasks such as graph structure understanding, graph learning, and graph-

formed reasoning. Details of the prompts and results obtained during testing are also provided. Additionally, we refine and compile commonly used and effective prompts for graph-related tasks, assisting researchers in conducting experiments. Furthermore, this paper also organizes and introduces the code for existing popular methods, benchmarks for LLM-GGA tasks, and evaluations measuring LLM performance in graph tasks to facilitate future research.

Our contributions and the identified challenges for future research. In this paper, we provide a comprehensive survey of the state-of-the-art work on LLMs applied to graph data. We begin by delineating six critical directions in the field of LLM-GGA: graph structure understanding, graph learning, graph-formed reasoning, graph representation, KG-based augmented retrieval, and graph-LLM-based applications. This categorization clarifies the current work and offers a guideline for future research endeavors. In each direction, we propose a structured introduction and summarization using vivid examples and offer suitable specific pipelines. We analyze the advantages and limitations of current methodologies and suggest avenues for future research. Furthermore, we organize resources related to benchmarks, evaluations, and code links within the LLM-GGA domain to facilitate further investigation by researchers. Lastly, we identify the fundamental challenges in the LLM-GGA field, which are the primary obstacles to advancing LLM in solving graph tasks, including the fundamental issue of how sequential LLM handles structural graph data, the efficiency issue of large-scale graph data, and the NP-hard problems of complex graph analytics. This clarification guides the research direction for future work on LLM-GGA.

Roadmaps. The organization of this paper is as follows. We first present the fundamental preliminaries and summarize the graph description language, which converts graphs into sequences before inputting them into LLMs in Section II. Then, we introduce six tasks of LLM-based graph analytics one by one. We present the graph structure understanding direction in Section III, graph learning direction in Section IV, graph-formed reasoning in Section V, graph representation in Section VI, KG-based augmented retrieval in Section VII and graph-LLM-based applications in Section VIII. In the above six directions, we clarify the tasks that LLMs can perform, discuss the methodologies, conduct a comparative analysis, and propose guidelines and principles in this direction. Following this, Section IX introduces the popular datasets and new datasets for solving the above tasks and also provides metrics for evaluating LLMs or tasks in different directions. In Section X, we identify and discuss the current and upcoming challenges that LLM-GGA faces and future directions. Finally, our conclusions are presented in Section XI.

II. PRELIMINARY

In the subsequent section, we will initially introduce graph data, proceed to discuss GNNs as a paradigm of graph-based learning models, then introduce LLMs and distinguish LLMs and PLMs, and ultimately introduce graph description

language, which can transform the graph into sequential data as the input of LLMs.

A. Graph

Graph data represents complex relationships through nodes and edges, where nodes represent entities and edges represent their interconnections. This structure excels at modeling intricate networks such as social, biological, and transportation systems. It enables analyses like community detection and shortest path calculations, offering critical insights into the dynamics of various systems. Formally, a general graph can be represented as $\mathcal{G} = (\mathcal{V}, \mathcal{E})$, where \mathcal{V} and \mathcal{E} denote the set of nodes and edges. $\mathcal{V} = \{v_1, v_2, \dots, v_n\}$ where the number of nodes is $|\mathcal{V}|$ and $|\mathcal{V}| = n$. $\mathcal{E} = \{e_{ij}\}$ where the number of edges is $|\mathcal{E}|$ and e_{ij} is an edge from v_i to v_j .

B. Graph Neural Network

Graph Neural Networks (GNNs) [16] [17] are a type of deep learning model that can handle graph-structured data. The goal of these GNNs is to learn representations for each node, which are computed based on the node's own features, the features of the edges connected to it, the representations of its neighbors, and the features of its neighboring nodes,

$$h_v^l = AGGR(h_v^{l-1}, \{h_u^l - 1 : u \in N_v\}; \theta^l) \quad (1)$$

where h_v^l represents the representation of node v in the l -th layer. $AGGR$ denotes the aggregation function that aggregates the representations of neighboring nodes from the previous layer. For the tasks that focus on individual nodes, e.g., node classification, the learned representations can be used directly to accomplish specific objectives. However, for the tasks that consider the entire graph, e.g., graph classification, a global representation can be obtained by pooling or applying other methods to the representations of all nodes. This global representation can then be used to perform the corresponding tasks.

C. Large Language Models

Currently, there is no precise definition for Large Language Models (LLMs). However, according to the pioneering surveys [47] [48] on LLMs, a distinction can be made between LLMs and Pre-trained Language Models (PLMs). LLMs are large language models with billion-level parameters that are pre-trained on massive amounts of data, such as Llama [5] and ChatGPT. Conversely, PLMs are pre-trained language models with million-level parameters that can be more easily fine-tuned on task-specific data. While LLMs and PLMs share similarities in their pre-training process, the former is characterized by its larger size and ability to generate human-like text. Thus, it is essential to consider the potential implications of using LLMs in various applications.

D. Graph Description Language

Graphs are represented in the structured data in arbitrary shapes, while LLMs typically process sequential data, such as the text as a sequence of words. To bridge this gap,

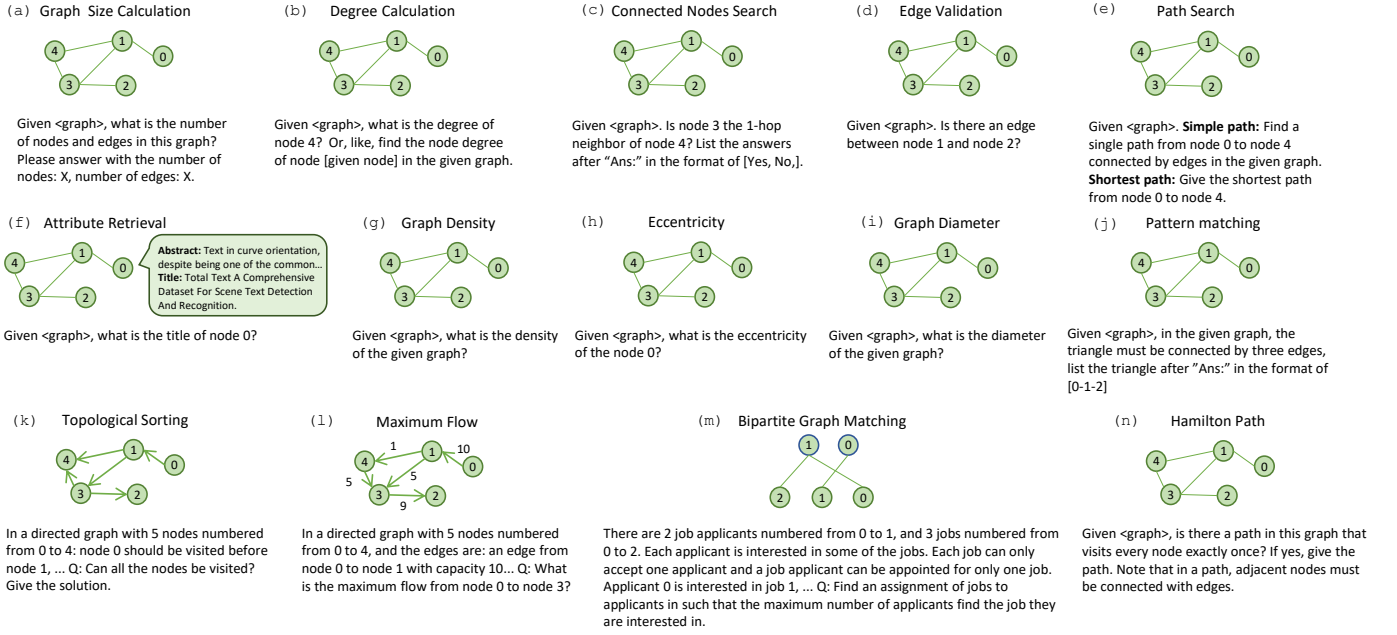


Fig. 2: Graph Structure Understanding tasks.

the graph description language (GDL) transforms the graph into sequential data, which can be inputted into an LLM. Specifically, GDL aims to convert graphs into sequential data while retaining the structure and unique attributes of the graph. This conversion allows the graph’s information to be fed into an LLM for processing. There are several graph description languages:

- **Text description.** Graph structure can be described using words such as ‘Node 1 is connected to Node 2’ and ‘There are three nodes connected to Node 1’.
- **Adjacency list.** An adjacency list represents each vertex in the graph with the collection of its neighbouring vertices or edges. Node A is connected with node B and node C can be denoted as $\mathcal{N}(v) = \{B, C\}$.
- **Edge list.** An edge list represents the edge connections between two nodes in the graph. (A, B) indicates a connection between nodes A and B.
- **GML.** Graph Modelling Language [49] consists of an unordered sequence of node and edge elements enclosed within ‘[.]’.
- **GraphML.** Graph Markup Language [50] consists of XML containing a graph element and an unordered sequence of node and edge elements.
- **SQL.** Several specialized SQL languages are designed specifically for working with graph data. These languages are also capable of serving as graph description languages. Some notable examples include Cypher [51], a query language developed by Neo4j, and Gremlin [52], SPARQL [53], and GSQL [54]. They combine SQL-like syntax with graph-specific constructs and algorithms, making them suitable for complex graph analytics tasks.
- **Multi-modality encoding.** Except for text description,

graph structure can also be represented using image description and motif description. The graph can be visualized as an image and inputted into an LLM to process images. Alternatively, motifs such as stars, triangles, or clique patterns can represent the graph structure as input into an LLM.

- **Encode as a story.** The graph can be encoded within a specific context, such as a friendship, co-authorship, social network, politician, or expert. For example, the connections between nodes can represent friendship relationships. We can assign names to the nodes, such as ‘David’ and ‘Alice’.

Notably, (1) different graph description languages can yield different results of LLMs. Therefore, it is suggested to test with multiple GDLs and select the one with the best experimental results. (2) If needed, the LLM’s output form can be specified along with GDLs in the prompt. LLMs often generate excessive reasoning processes that may be unnecessary, so standardizing the LLM’s output can be beneficial.

III. GRAPH STRUCTURE UNDERSTANDING TASKS

Graph structure understanding tasks evaluate whether LLMs can comprehend graph structures. Simple tasks include the queries of neighbors, shortest paths, connectivity, the calculation of graph radius, and the clustering coefficient. More complex tasks include solving maximum flow problems and performing topological sorting. These tasks need LLMs to comprehend graph structures locally and globally, as shown in Figure 2. In this section, we present 21 graph understanding tasks along with their definitions. Subsequently, we elaborate on the two main methods currently used to address graph structure understanding tasks: prompting and supervised fine-tuning LLMs.

Task	Prompts
Graph Data Loading	The structure of the [file path] molecular graph of the benzene ring contains a hexagon.
Graph Size Detection	Given [graph], what is the number of nodes and edges in this graph? Please answer with the number of nodes: X, number of edges: X.
Degree Detection	Given [graph], what is the degree of node 4? Or, find the node degree of node [given node] in the given graph.
Connected Nodes	Given [graph]. Is node 5 the 1-hop neighbor of node 4? List the answers after “Ans:” in the format of [Yes, No,].
Edge Detection	Given [graph]. Is there an edge between node 1 and node 2?
Path	Simple path: Given the undirected graph with the specified nodes and edges, nodes: [0, 1, 2, 3, 4], edges: [(0, 1), (1, 4), (1, 3), (4, 3), (3, 2)], find a single path from node 1 to node 2 connected by edges in the given graph. Shortest path: Given the directed graph with the specified nodes and edges, nodes: [0, 1, 2, 3, 4], edges: [(0, 1), (1, 4), (1, 3), (4, 3), (3, 2)], give the shortest path from node 0 to node 4.
Attribute Retrieval	Given [graph]. What is the title of node 0?
Graph Density	Given [graph]. What is the density of the given graph?
Eccentricity	Given [graph]. What is the eccentricity of the given graph?
Graph Radius	Given [graph]. What is the radius of the given graph?
Graph Diameter	Given [graph]. What is the diameter of this graph?
Graph Periphery	Given [graph]. What is the periphery of this graph? Or What are the nodes included by the periphery of the given graph?
Clustering Coefficient Computing	Given [graph]. What is the clustering coefficient of [given node]?

TABLE I: Prompts for Graph Structure Understanding Tasks, where [graph] is the input of the data.

A. Task Introduction

1) *Graph size calculation:* Graph size refers to the number of nodes and edges in a graph. Given a general graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$, the graph size detection task is to detect the $|\mathcal{V}|$ and $|\mathcal{E}|$ in \mathcal{G} . Through this task, LLMs are expected to understand the fundamental structure of a graph accurately. Given a prompt describing the graph and asking related queries, LLMs are supposed to determine $|\mathcal{V}|$ and $|\mathcal{E}|$, as shown in Figure 2 (a).

2) *Degree calculation:* The degree detection task involves determining the degree of a specific node in a graph. The neighbors of node v can be denoted as $\mathcal{N}(v) = \{u | (u, v) \in \mathcal{E}(v)\}$, where $\mathcal{E}(v)$ is the edge set including edges connected to v . The degree of v_i is the number of its neighbors in \mathcal{G} , which can be denoted as $\deg_{\mathcal{G}}(v_i) = |\mathcal{N}(v_i)|$. Through this task, LLMs are expected to comprehend the context surrounding v_i and identify $\mathcal{N}(v_i)$ accurately. By inputting a prompt about v_i and \mathcal{G} , LLMs are expected to calculate the degree of the node. This task is shown in Figure 2 (b).

3) *Connected nodes search:* The connected nodes detection task involves finding all the nodes in $\mathcal{N}_{\mathcal{G}}(v_i)$ of v_i in \mathcal{G} . Given the prompt about \mathcal{G} , LLMs are expected to analyze the local structure of the given node v_i and determine $\mathcal{N}_{\mathcal{G}}(v_i)$, as shown in Figure 2 (c).

4) *Edge validation:* The edge detection task refers to whether there exists an edge e_{ij} or e_{ji} between v_i and v_j . Through this task, LLMs are expected to accurately identify the connectivity between nodes and understand the local

structure of nodes. Given the prompt about the neighbors of v_i to the LLMs, LLMs will likely indicate whether e_{ij} or e_{ji} exists, as shown in Figure 2 (d).

5) *Path search:* We consider two types of paths, including the simple path and the shortest path, as shown in Figure 2 (e). Given a graph $\mathcal{G} = \{\mathcal{V}, \mathcal{E}\}$, the simple path task involves detecting whether there exists a path (v_i, \dots, v_j) between a source node v_i and a target node v_j in \mathcal{G} . In other words, it is about finding a simple path (v_i, \dots, v_j) between v_i and v_j without specific requirements. This task evaluates the ability of LLMs to traverse a graph and understand its structure. Given the prompt about \mathcal{G} to LLMs, the goal is to return a simple path from v_i to v_j .

Given a weighted directed acyclic graph $\mathcal{G} = \{\mathcal{V}, \mathcal{E}\}$ with each edge $e \in \mathcal{E}$ has a non-negative weight $w(e)$, the shortest paths task involve finding a path $p = (e_1, e_2, \dots, e_n)$ from a source node to a target node in \mathcal{G} such that the sum of the weights of edges $w(p) = \sum_{i=1}^n w(e_i)$ is minimized. LLMs can evaluate the length of the shortest path and identify the qualified paths. This task can be further divided into three objectives: 1. Finding the shortest path between two nodes. 2. Finding all the shortest paths for all paired nodes. 3. Finding the average length of all the shortest paths. This task assesses whether the LLM can effectively determine the shortest route between two specified nodes within the graph.

6) *Attribute retrieval:* The attribute retrieval task involves retrieving detailed information related to nodes, such as the

Task	Prompts
Graph Partition	In the academic collaboration network dblp, scholar #355233 is involved in [TBR] local community formed by his/her collaborators.
Graph Searching	According to the Freebase knowledge graph, the relation between entity /m/027m and entity /m/06cx9 is [TBR].
Pattern matching	Triangle: find a single triangle containing node X. Or in the given graph, the triangle must be connected by three edges, list the triangle after "Ans:" in the format of [0-1-2]. Cliques: find all the cliques with N nodes in the given graph, list all the cliques after "Ans:" in the format of [0-1-2] and separate the answers by a comma. Wedge Centering find a single wedge containing node X in the given graph, node X must be the center of this wedge, list the wedge after "Ans:" in the format of [0-1-2].
Cycle Check	In an undirected graph, (i,j) means that node i and node j are connected with an undirected edge. The nodes are numbered from 0 to 5, and the edges are: (3,4) (3,5) (1,0) (2,5) (2,0) Q: Is there a cycle in this graph?
Topological Sort	In a directed graph with 5 nodes numbered from 0 to 4: node 0 should be visited before node 4, ... Q: Can all the nodes be visited? Give the solution.
Maximum Flow	In a directed graph with 5 nodes numbered from 0 to 4, and the edges are: an edge from node 0 to node 1 with capacity 10... Q: What is the maximum flow from node 0 to node 3?
Bipartite Graph Matching	There are 2 job applicants numbered from 0 to 1, and 3 jobs numbered from 0 to 2. Each applicant is interested in some of the jobs. Each job can only accept one applicant and a job applicant can be appointed for only one job. Applicant 0 is interested in job 1, ... Q: Find an assignment of jobs to applicants in such that the maximum number of applicants find the job they are interested in.
Hamilton Path	Given [graph], is there a path in this graph that visits every node exactly once? If yes, give the path. Note that in a path, adjacent nodes must be connected with edges.
Graph Neural Networks	Given [graph]. Embeddings: node 0: [1,1], ... In a simple graph convolution layer, each node's embedding is updated by the sum of its neighbors' embeddings. Q: What's the embedding of each node after one layer of simple graph convolution layer?
Dynamic Graph	In an undirected dynamic graph, (u, v, t) means that node u and node v are linked with an undirected edge at time t. Your task is to answer when two nodes are first connected in the dynamic graph. Two nodes are connected if there exists a path between them. Given an undirected dynamic graph with the edges [(0, 1, 0), (1, 2, 1), (0, 2, 2)]. When are node 0 and node 2 first connected?

TABLE II: Prompts for Graph Structure Understanding Tasks, where [graph] is the input of the data. [TBR] means to be reasoned by LLMs.

attributes of a node. For example, in a citation network, LLMs are tasked with retrieving specific attributes of a node, such as the title, abstract, or author of a paper. Given the prompt about \mathcal{G} and detailed attribute information, LLMs are expected to retrieve the required information, as shown in Figure 2 (f).

7) *Graph density*: Graph density represents the ratio between the number of edges present in a graph and the maximum number of edges that the graph can have. For an undirected simple graph $\mathcal{G} = \{\mathcal{V}, \mathcal{E}\}$, the graph density is defined as:

$$\mathcal{D} = \frac{2|\mathcal{E}|}{|\mathcal{V}|(|\mathcal{V}| - 1)} \quad (2)$$

For a directed simple graph, the graph density is defined as:

$$\mathcal{D} = \frac{|\mathcal{E}|}{|\mathcal{V}|(|\mathcal{V}| - 1)} \quad (3)$$

This task requires LLM to calculate the density of a given graph and assess its understanding of the entire graph, as shown in Figure 2 (g).

8) *Eccentricity*: The eccentricity of a node in a graph is defined as the length of the longest shortest path starting at that node. The eccentricity of one node: this task requires LLMs

to answer the eccentricity of a given node. The eccentricity of many nodes: this task requires LLMs to answer the eccentricity of a subset of nodes or all the nodes in the graph, as shown in Figure 2 (h).

9) *Graph radius*: Based on the eccentricity of nodes, the radius of a graph is the minimum eccentricity of any vertex in the graph. LLMs can calculate the radius of the given graph with the description of the graph.

10) *Graph center*: The center of a graph is the set of vertices of graph eccentricity equal to the graph radius. Based on the eccentricity task and graph radius task, LLMs should be given the graph information and asked to calculate the graph center.

11) *Graph diameter*: Based on the shortest path, the diameter of a graph is the length of the shortest path between the most distant nodes. LLMs can calculate the graph's diameter with the given graph information, as shown in Figure 2 (i).

12) *Graph periphery*: Based on the graph eccentricities and graph diameter, the graph periphery is a set of vertices that have graph eccentricities equal to the graph diameter. LLMs can answer questions related to the graph periphery using the given graph information.

Given the undirected graph with the specified nodes and edges, nodes: [0, 1, 2, 3, 4], edges: [(0, 1), (1, 3), (1, 4), (2, 3)], find a single path from node 0 to node 4 connected by edges in the given graph, list the answer after "Ans:" in the format of [0-1-2].

To find a single path from node 0 to node 4 connected by edges in the given graph, we can use the depth-first search (DFS) algorithm.

Starting from node 0, we explore each possible path until we reach node 4.

Here is the path from node 0 to node 4:

Ans: [0-1-4]

Fig. 3: Examples for Path Task with GPT3.5 - Graph Structure Understanding Tasks.

In a directed graph with 5 nodes numbered from 0 to 4, and the edges are: an edge from node 0 to node 1 with capacity 10, an edge from node 1 to node 4 with capacity 1, an edge from node 1 to node 3 with capacity 5, an edge from node 4 to node 3 with capacity 5, an edge from node 3 to node 2 with capacity 9. Q: What is the maximum flow from node 0 to node 3? Give the answer only.

The maximum flow from node 0 to node 3 in the given directed graph is 6.

Fig. 4: Examples for Maximum Flow Task with GPT3.5 - Graph Structure Understanding Tasks.

There are 2 job applicants numbered from 0 to 1, and 3 jobs numbered from 0 to 2. Each applicant is interested in some of the jobs. Each job can only accept one applicant and a job applicant can be appointed for only one job. Applicant 0 is interested in job 1, applicant 1 is interested in job 0 and job 2. Q: Find an assignment of jobs to applicants in such that the maximum number of applicants find the job they are interested in. Give the final assignment only.

The final assignment that maximizes the number of applicants finding the job they are interested in is as follows:

Applicant 0 is assigned to Job 1.
Applicant 1 is assigned to Job 0.

In this assignment, both applicants are assigned to the jobs they are interested in, resulting in the maximum number of applicants finding the job they desire.

Fig. 5: Examples for Bipartite Graph Matching Task with GPT3.5 - Graph Structure Understanding Tasks.

13) Clustering coefficient computing: The clustering coefficient is a measure of how connected a vertex's neighbors are to one another. We define the edges among neighbors of v_i as $\{e_{jk} : v_j, v_k \in \mathcal{N}_{\mathcal{G}}(v_i), e_{jk} \in \mathcal{E}\}$. For directed graphs, the clustering coefficient is defined as:

$$C_i = \frac{|\{e_{jk} : v_j, v_k \in \mathcal{N}_{\mathcal{G}}(v_i), e_{jk} \in \mathcal{E}\}|}{|\mathcal{N}_{\mathcal{G}}(v_i)|(|\mathcal{N}_{\mathcal{G}}(v_i)| - 1)} \quad (4)$$

For undirected graphs, the clustering coefficient is defined as:

$$C_i = \frac{2|\{e_{jk} : v_j, v_k \in \mathcal{N}_{\mathcal{G}}(v_i), e_{jk} \in \mathcal{E}\}|}{|\mathcal{N}_{\mathcal{G}}(v_i)|(|\mathcal{N}_{\mathcal{G}}(v_i)| - 1)} \quad (5)$$

LLMs can calculate the clustering coefficient as a measure of the degree to which nodes in a graph tend to cluster together.

14) Graph partition: This task is an online social network reasoning task, which is to infer the community structure of an online social network by partitioning users into different clusters based on their interaction information. Each cluster represents a social community formed by users who interact with each other frequently. LLMs partition the users of the social network based on user social interaction patterns and generate the resulting cluster assignments.

15) Graph searching: This task is a knowledge graph reasoning task, which involves inferring relationships between entities based on their information or inferring connected entities based on the information of entities and relationships. Specifically, LLM takes entities or relationships as input and searches for relevant entities or relationships to generate output.

16) Pattern matching: This task is to identify star, wedge, triangle, or clique patterns that contain a target node. The target node can be defined as the center of the pattern. Alternatively, the task can involve identifying whether these patterns exist in a given graph and determining the number of occurrences. Given a description of the LLM graph, the goal is for LLM to identify different patterns and provide the corresponding answers, as shown in Figure 2 (j).

17) Cycle validation: This task is to determine whether a graph contains a cycle. Given $\mathcal{G} = \{\mathcal{V}, \mathcal{E}\}$, a cycle is a non-empty trail with a vertex sequence $(v_1, v_2, \dots, v_n, v_1)$. Given the graph information, LLM is asked to determine whether this graph has a cycle.

18) Topological sorting: Topological sorting of a directed graph $\mathcal{G} = \{\mathcal{V}, \mathcal{E}\}$ refers to a linear ordering of its nodes, where each node comes before all the nodes it points to, for example, there exists a directed edge e_{ij} from v_i to v_j , v_i comes before v_j in the ordering. The resulting array of node ordering is called topological ordering. LLM is required to generate a valid topological sorting for the given directed graph, and there may be multiple valid solutions, as shown in Figure 2 (k).

19) Maximum flow: Given a capacity constraint, the maximum flow problem involves finding the maximum flow that can be sent through pipes, channels, or other pathways in a network. Define a flow as f_{ij} from v_i to v_j and the capacity on edge e_{ij} as c_{ij} . Given the capability constraints, $f_{ij} \leq c_{ij}$

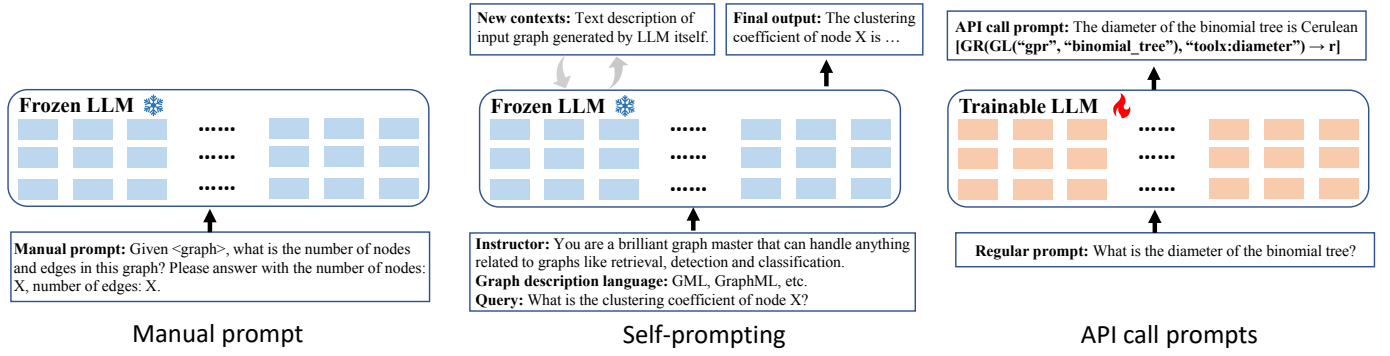


Fig. 6: Promoting methods in graph structure understanding tasks. There are three categories: manual prompts, self-prompting, and API call prompts.

for all e_{ij} . Meanwhile, $\sum_{f_{ij}>0} f_{ij} = \sum_{f_{ji}>0} f_{ji}$ for $\forall v_i$ except for the source and the target $\{s, t\}$. Given a network graph, LLM generates a path that maximizes the flow from the source to the sink, as shown in Figure 2 (l).

20) *Bipartite graph matching*: A bipartite graph is a type of graph where the nodes can be divided into two disjoint sets, \mathcal{U} and \mathcal{V} , such that there are no adjacent nodes within each set. A matching in a bipartite graph is a set of edges where no two edges share an endpoint. In a maximum matching, if any edge is added, it is no longer a matching. For a given bipartite graph, there can be multiple maximum matchings. LLM can generate a solution that finds the maximum matching, as shown in Figure 2 (m).

21) *Hamilton Path*: In an undirected graph, a Hamiltonian path is a path in the graph that visits each vertex exactly once. Given an undirected graph, the task is for LLM to find a valid Hamiltonian path, as shown in Figure 2 (n).

B. Graph Structure Understanding Methods

The rise of LLMs has sparked researchers' interest in exploring their powerful text processing and generalization capabilities for graph reasoning. Therefore, existing efforts have introduced various benchmarks to test LLMs' graph reasoning potential, aiming to explore their capacity to address graph-related problems. Prompting methods have emerged as the primary approach to assess LLMs' understanding of graph structures, with some studies also focusing on fine-tuning LLMs to enhance their graph reasoning abilities. Thus, the following two main methods are introduced: *prompting method* and *fine-tuning LLMs*.

1) *Prompting method*: The prompting method [55] can be categorized into three main types: manual prompt, self-prompting, and API call prompt, as shown in Figure 6. Most studies utilize manual prompts, where carefully crafted prompts guide LLMs to comprehend graph structures better and understand the objectives of graph tasks, thereby leading to improved performance on graph-related tasks.

Manual prompts. NLGraph [27] introduces a benchmark aiming to assess the understanding capabilities of LLMs in processing textual descriptions of graphs and translating them

into conceptual spaces. This benchmark covers various graph reasoning tasks like connectivity, shortest path, maximum flow, and graph neural network construction, with three difficulty levels (easy, medium, hard) based on graph size and density. Meanwhile, the number of nodes $n = |\mathcal{V}|$ and the probability p control edge generation, allowing manipulation of graph size and density for a more reliable evaluation of LLM potential in graph comprehension.

Next, to guide LLMs in solving these graph tasks, two prompt methods are proposed by NLGraph [27]: build-a-graph prompting and algorithmic prompting.

Prompt III-1: Build-a-Graph Prompting. Build-a-Graph prompting method is to guide LLMs to conceptual grounding by adding one sentence shown as **red words** below:

Prompt III-1: Build-a-Graph Prompting

Given <graph description>. **Let's construct a graph with the nodes and edges first.** Q: What is the degree of node 4?

Prompt III-2: Algorithmic Prompting. The algorithmic prompting method is designed to guide LLMs to engage in algorithmic reflection and thinking by adding the details of the algorithm shown as **red words** below:

Prompt III-2: Algorithmic Prompting

We can use a Depth-First Search (DFS) algorithm to find the shortest path between two given nodes in an undirected graph.

The basic idea is to start at one of the nodes and use DFS to explore all of its adjacent nodes. At each node, you can keep track of the distance it takes to reach that node from the starting node.

Once you have explored all the adjacent nodes, you can backtrack and pick the node which has the shortest distance to reach the destination node.

Given <graph description>. Q: Give the shortest path

from node 0 to node 4.

Compared with other advanced prompts and in-context learning techniques, the two proposed prompts perform better on graph tasks. Based on the experiments, LLMs indeed possess preliminary graph reasoning abilities. Also, the benefits of advanced prompting and in-context learning diminish in complex graph problems and may even have a negative impact. LLMs are also susceptible to false correlations, performing poorly on graph structures such as chains and cliques.

To explore whether LLMs can truly comprehend graph structures and reason on graphs, meanwhile, enhance the performance of LLM-GQP tasks, [26] and [24] test LLMs also using manual prompts, where [26] explores the conditions under which LLMs can benefit from the inherent structural information in the data and examines two potential factors influencing LLM’s performance: data leakage and homogeneity.

In summary, the conclusions are as follows:

- No evidence suggests that LLM’s performance is significantly attributed to data leakage.
- The performance of LLMs on target nodes is positively correlated with the local homogeneity of the nodes.

[24] investigates the graph reasoning capabilities of LLMs and introduces new evaluation metrics—comprehension, correctness, fidelity, and rectification—to assess LLMs’ proficiency in understanding graph structures and performing reasoning tasks. The findings reveal that LLMs can effectively understand graph structures and perform reasoning tasks. However, LLMs still face challenges in structural reasoning, particularly in multi-answer tasks where GPT models demonstrate errors and overconfidence. In contrast, GPT-4 displays improved self-correction abilities.

Beyond static graphs, LLMs’ ability to understand dynamic graph structures is also assessed. Dynamic graphs change over time, capturing temporal network evolution patterns. LLM4DyG [25] introduces the LLM4DyG benchmark, which uses prompting methods to evaluate LLMs’ spatio-temporal understanding capabilities on dynamic graphs.

Prompt III-3: DST2. The newly proposed Disentangled Spatial-Temporal Thoughts (DST2) prompting technique enhances LLMs’ spatial and temporal understanding of dynamic graphs. DST2 is shown below:

Prompt III-3: DST2

DyG Instruction: In an undirected dynamic graph, (u, v, t) means that node u and node v are linked with an undirected edge at time t.

Task Instruction: Your task is to answer when two nodes are first connected in the dynamic graph. Two nodes are connected if there exists a path between them.

Answer Instruction: Give the answer as an integer number at the last of your response after ‘Answer:’

Exemplar: Here is an example: Question: Given an undirected dynamic graph with the edges [(0, 1, 0), (1, 2, 1), (0, 2, 2)]. When are node 0 and node 2 first connected? Answer:1

Question: Question: Given an undirected dynamic graph with the edges [(0, 9, 0), (1, 9, 0), (2, 5, 0), (1, 2, 1), (2, 6, 1), (3, 7, 1), (4, 5, 2), (4, 7, 2), (7, 8, 2), (0, 1, 3), (1, 6, 3), (5, 6, 3), (0, 4, 4), (3, 4, 4), (3, 6, 4), (4, 6, 4), (4, 9, 4), (6, 7, 4)]. When are node 2 and node 1 first connected?

Results show that LLMs have preliminary spatio-temporal understanding capabilities on dynamic graphs. Dynamic graph tasks become increasingly challenging with larger graph sizes and densities while insensitive to periods and data generation mechanisms.

We provide manual prompt examples for various graph structure understanding tasks in Table I and Table II. Additionally, we test LLMs with GPT 3.5 for path, max flow, and bipartite graph matching using manual prompts, as shown in Figure 3, Figure 4 and Figure 5 respectively.

For self-prompting. Self-prompting refers to the process where an LLM continuously updates the initial prompt to make it easier for LLMs to understand and more beneficial for solving tasks. In other words, the LLM designs prompts based on the original prompt. GPT4Graph [23] utilizes self-prompting by continuously updating the prompt with descriptions related to the graph. Specifically, first, the graph data is converted into graph description languages, as shown in Section II-D. Then, together with queries, it is inputted into the prompt handler to create a prompt, which is then inputted into the LLM. Based on the output of the LLM, the prompt is updated and re-input into the LLM, repeating multiple rounds of updates to obtain an optimized graph description context, such as context summarization and format explanation. This process can be seen as the LLM’s self-updating prompt procedure. Finally, the optimized graph description context is input along with the original input into the LLM to obtain the final result.

Prompt III-4: Self-prompting. The input original prompt is shown below:

Prompt III-4: Self-prompting

Instructor: You are a brilliant graph master that can handle anything related to graphs like retrieval, detection and classification.

Graph description language: GML, GraphML as shown in Section II-D.

Context: Node P357 has 4 neighbors, where each of which are about anomaly detection with statistical models...

Query: What is the clustering coefficient of node P357?

This paper conducts experiments on the obgn-arxiv [56] and

Aminer [57] datasets and finds that:

- The design of prompts significantly impacts the results. The choice of graph description language, the organization of input data, and the position of in-context knowledge, such as questions, statements, and examples, all affect the model’s ability to understand the graph structure.
- Role prompting techniques can improve the effectiveness of LLMs by guiding the model to view the graph as roles and relationships between roles in a specific context. Providing LLMs with more semantic information leads to more accurate results.
- Examples in prompts have mixed impacts on graph structure understanding. Adding examples in prompts to guide LLMs in understanding graph structures may not necessarily improve the results; in some graph structure learning tasks, examples may introduce noise.

API call prompts LLMs exhibit limited ability to perform precise mathematical calculations, multi-step logical reasoning, spatial topological structuring, and temporal information processing. To bridge these gaps, taking inspiration from recent models such as ChatGPT and Toolformer [58], Graph-ToolFormer [59] is proposed to equip LLMs with graph reasoning capabilities by training them over a prompt dataset that contains graph reasoning API annotated by ChatGPT. These graph reasoning APIs are used to call external reasoning tools. Then, the trained LLMs can solve graph tasks, from loading graph data and inferring graph attributes to graph partition tasks.

The framework consists of three parts. First, it generates a prompt dataset by providing ChatGPT with a regular prompt, guiding ChatGPT to add an API call to the original prompt, and then creating a prompt with an API call.

Prompt III-5: API call prompts

Prompt III-5: API call prompts

Example 1

Input:(Regular prompt)

The structure of the benzene ring molecular graph of benzene ring contains a hexagon.

Output:(API call prompt)

The structure of the [GL(“benzenering”)] molecular graph of benzene ring contains a hexagon.

Example 2

Input:(Regular prompt)

What is the diameter of the binomial tree?

Output:(API call prompt)

The diameter of the binomial tree is [GR(GL(“gpr”, “binomial_tree”), “toolx:diameter”)→ r].

Second, fine-tune existing LLMs such as GPT-J [60] [61], LLaMA [5] [62], etc., using technologies like LoRA [63] on the generated prompt dataset. Thirdly, utilize the fine-tuned LLM for inference to add graph reasoning API calls

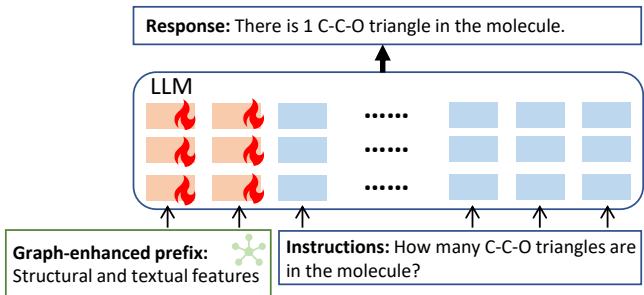


Fig. 7: Supervised fine-tuning (SFT) method in graph structure understanding tasks. Prefix tuning is shown above: combine graph structural and textual information as prefixes in prefix tuning and input it into LLM with instructions, like GraphLLM [64]. Instruction tuning can also be used.

into statements. After generating API call statements, how can external graph tools be invoked? Graph reasoning query processing comes in. Graph reasoning query processing entails utilizing external graph reasoning tools based on API call statements to obtain the final answer.

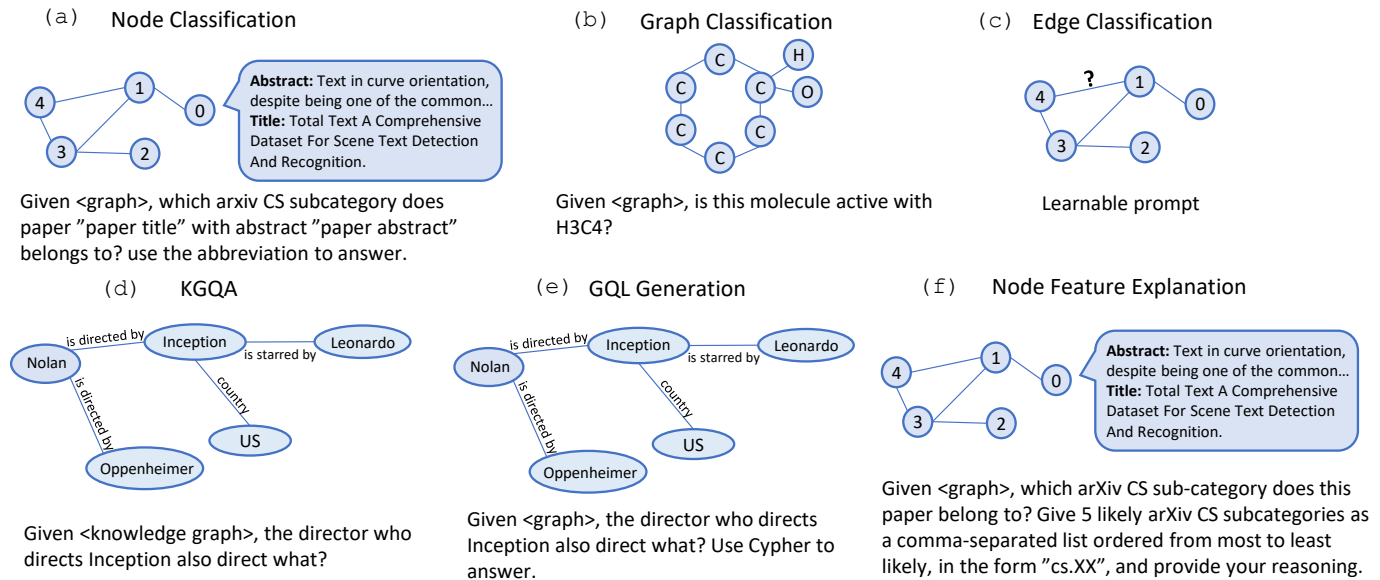
2) **Supervised fine-tuning (SFT) method:** Beyond leveraging prompts for graph-structured tasks with LLMs, certain studies have also implemented supervised fine-tuning of LLMs, illustrated in Figure 7. GraphLLM [64] is committed to addressing the obstacles in graph reasoning by LLMs and introduces a hybrid model that inherits the capabilities of both graph learning models and LLMs, enabling LLMs to interpret and reason about graph data proficiently, utilizing the superior expressive power of graph learning models.

C. Comparisons and Discussions

In the following part, we compare the prompting and SFT methods mentioned above.

The prompting method can be divided into three categories: manual prompts, self-prompting, and API call prompts. Most current methods primarily rely on manual prompts, incorporating techniques like Chain of Thought (CoT) [65], self-consistency [66], and in-context learning [67]. To obtain better prompt representations, self-prompting methods are also widely used. However, the exclusive use of manual prompts and self-prompting offers limited enhancement to model performance, as they merely tap into the pre-existing capabilities of LLMs. Additionally, due to the limited input window of LLM, the graph size that can be input to LLM at once is also restricted, while graph sizes in the real world are typically large.

For the prompting method, we also propose two feasible directions to better leverage existing LLMs for handling structure understanding tasks. The first direction is breaking down complex tasks into several sub-problems. While LLMs can tackle simple graph tasks, they struggle with more challenging ones. Breaking down complex graph understanding tasks into simpler components enables LLMs to engage in multi-step reasoning processes, leading to the resolution of complex



issues, such as GoT [59], which can help address more intricate graph tasks like generating GNN frameworks, k-truss tasks, kd-core tasks, etc. The second direction is API call prompts. Inspired by ToolFormer [58], LLMs can be trained as agents to utilize tools for graph tasks that are hard to solve. However, current API call prompt methods [59] utilize LLMs not as agents but solely to convert user queries into API command strings for processing by subsequent programs, exemplified in **Prompt III-5**.

However, compared to prompting methods, fine-tuning LLMs with graph data seems a better way to enhance their understanding of graph structures. There are two mainstream methods for fine-tuning LLMs: Supervised Fine-Tuning (SFT) and Reinforcement Learning with Human Feedback (RLHF) [6]. SFT helps LLMs understand prompts and generate meaningful responses. However, SFT only offers a single human-written response for each prompt, whereas RLHF provides detailed human feedback through pairwise comparison labeling. Furthermore, to address the instability issue in PPO [68] training, the Reward Ranked Fine-Tuning (RAFT) [69] can also be attempted which requires online interaction. For offline algorithms, methods like DPO [3] and Preference Ranking Optimization (PRO) [70] can also be utilized for training LLMs.

IV. GRAPH LEARNING TASKS

A. Tasks Introduction

Recently, LLMs have been shown to possess extensive common sense and powerful semantic understanding capabilities, fundamentally transforming the existing workflow for processing text. However, whether LLMs can effectively handle graph learning tasks, transferring their generalization ability from text tasks to graph learning tasks, such as node and graph classification, is still a research subject that needs

exploring. These tasks require the model to learn and solve graph learning tasks, as shown in Figure 8. In this section, we present seven graph learning tasks along with their definitions. Next, we introduce graph learning methods, categorized into three types based on the role of LLMs: LLMs act as enhancers, LLMs act as predictors, and graph prompts.

1) *Node classification*: The node classification task requires LLM to learn based on the neighbors of a node or the attributes of a node. It involves classifying unseen nodes in a given graph, such as categorizing papers in an academic network into different research directions, as shown in Figure 8 (a).

2) *Graph classification*: The graph classification task requires LLM to classify the entire graph. LLM is given several labeled graphs and is expected to classify unseen graphs. For example, a molecule can be viewed as a graph, and LLM can predict the properties or functions of the molecule by classifying the graph, as shown in Figure 8 (b).

3) *Edge classification*: The edge classification task involves classifying the edges in a graph. Existing methods improve edge classification by training a learnable graph prompt and combining it with a GNN or LLM, as shown in Figure 8 (c).

4) *Node generation*: The node generation task refers to providing requirements for an LLM to generate nodes, allowing it to generate node attributes, which are then added to the TAG to enhance it.

5) *Knowledge graph question answering (KGQA)*: Knowledge graph organizes data into a structured format, representing entities, properties, and relationships. Knowledge graph question answering (KGQA) aims to capture the most appropriate answers by querying the knowledge graph (KG) using natural language questions. This task evaluates the ability of LLM to reason and understand the underlying graph structure to provide accurate answers, as shown in Figure 8 (d).

6) *Graph query language (GQL) generation*: The graph query language generation task involves generating graph

Task	Prompts
KGQA	Given [knowledge graph], the director who directs Inception also direct what?
GQL Generation	Given [graph], the director who directs Inception also direct what? Use Cypher to answer.
Node Classification	Which arxiv CS subcategory does paper " paper title " with abstract " paper abstract " belongs to? use the abbreviation to answer.
Graph Classification	Given [graph]. Is this molecule active with H3C4?
Node Feature Explanation	Abstract: Text in curve orientation, despite being one of the common text orientations in real world environment... Title: Total Text A Comprehensive Dataset For Scene Text Detection And Recognition. Question: Which arXiv CS sub-category does this paper belong to? Give 5 likely arXiv CS sub-categories as a comma-separated list ordered from most to least likely, in the form "cs.XX", and provide your reasoning.
Edge classification	learnable prompt

TABLE III: Prompts for Graph Learning Tasks, where $[\cdot]$ is the input of the data.

query languages, including GQL and Cypher, to perform operations on graph databases. Evaluating LLM’s ability to generate GQL helps users extract information from the database, as shown in Figure 8 (e).

7) *Node feature explanation*: Node feature explanation task involves extracting the attributes of nodes in a text attribute graph. For example, in an academic paper network, the node attributes may include abstracts, titles, etc. LLM is expected to provide reasoning for the classification process of nodes based on their text attributes and explain the features of the nodes, as shown in Figure 8 (f).

B. Graph Learning Methods

LLM-GIL studies focusing on graph learning tasks can be categorized into three main groups: LLMs act as enhancers, LLMs act as predictors, and graph prompts. When LLMs act as enhancers, they leverage their advanced semantic understanding of the text, strong reasoning capabilities, and vast knowledge repository to enhance the text attributes associated with nodes in the graph to enhance GNNs. When LLMs act as predictors, LLMs are queried or fine-tuned to predict task results. Inspired by NLP ideas, the Graph prompt aims to create a unified framework capable of solving multiple graph learning tasks. Although LLMs are not used, the concept aligns with LLM-based pipelines.

In summary, integrating LLMs in graph learning tasks presents a promising avenue for advancing the field. By leveraging the strengths of LLMs as enhancers and predictors, along with the strategic use of graph prompts, researchers can explore new directions for enhanced performance and more profound insights in LLM-GIL tasks.

1) *LLMs act as enhancers*: LLMs act as enhancers pertains to the LLMs-GNNs pipelines, where LLMs assume an enhancer role. Within this framework, LLMs are tasked with processing text attributes, while GNNs are responsible for handling graph structures, capitalizing on the complementary strengths of both components to address graph learning tasks effectively. LLMs bolster GNNs through three distinct mechanisms: encoding the graph into embeddings (as shown in Fig-

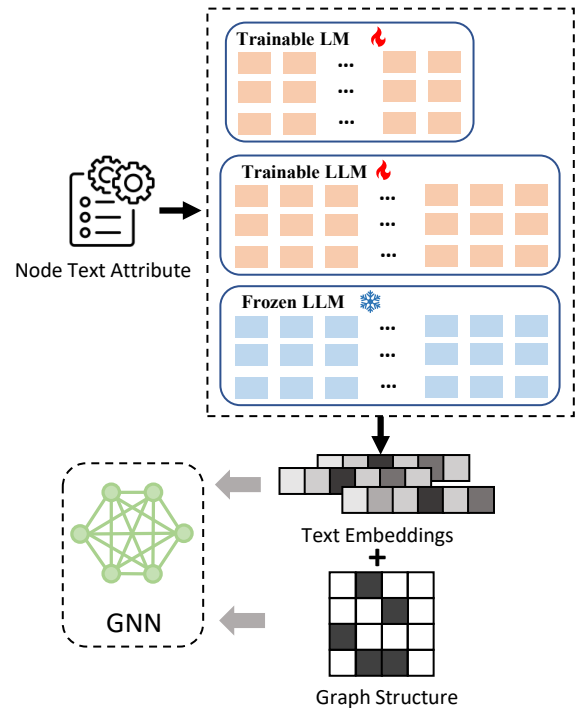


Fig. 9: Encoding graph into embeddings, when LLMs act as enhancers. Input the node text attribute into LM/LLM to obtain text embeddings, then combine the text embeddings with the graph structure for training and learning in GNNs.

ure 9), generating graph pseudo labels (as shown in Figure 10), and providing external knowledge or explanations (as shown in Figure 11). Subsequently, we will provide a comprehensive elaboration on these three enhancement strategies.

Encoding graph into embeddings. LLMs possess significant semantic comprehension capabilities to encode better node embeddings, as shown in Figure 9. TAPE [30] integrates LM with LLM to generate node embeddings. The process involves fine-tuning two LM models using original node text attributes and LLM explanations for node prediction. The

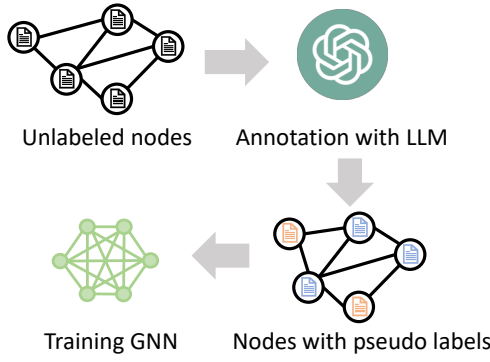


Fig. 10: Generating graph pseudo labels, when LLMs act as enhancers. Input unlabeled nodes into LLM for labeling, then use the labeled nodes with pseudo-labels as input for training the GNNs for graph learning.

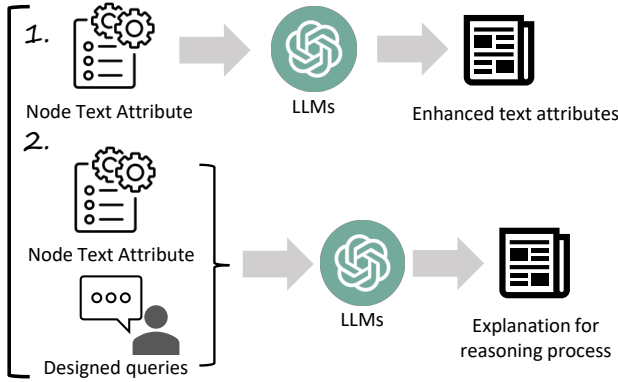


Fig. 11: Providing external knowledge/explanations, when LLMs act as enhancers. Two pipelines are shown above. In the first pipeline, input node text attributes into LLM for elaboration, enhancing the detail of the text attributes. In the second pipeline, input node text attributes and designed queries into LLM. LLM leverages the text attributes to answer queries and explains the reasoning process.

resulting embeddings are then used as input to train a GNN model for node classification tasks. To unify graph data and graph learning tasks, OFA [32] introduces a comprehensive framework that unifies diverse graph data by describing nodes and edges using natural language and encoding varied and potentially cross-domain text attributes into feature vectors within the same embedding space. The obtained feature vectors are then fed into a GNN to tackle various downstream tasks effectively. Moreover, SIMTEG [71] and GLEM [31] involve training an LM with Lora and subsequently generating embeddings as text representations, then a GNN is trained on top of these text embeddings. On this basis, G-prompt [33] introduces a graph adapter to extract node features, thereby obtaining improved node representations.

Generating graph pseudo labels. Many existing pipelines utilize LLMs to process text attributes as node features, then feed the embeddings produced by LLM into a GNN model for

learning, as shown in Figure 10. However, the simultaneous training of LLM and GNN poses a significant computational challenge. To bridge this gap, GLEM [31] suggests training the GNN and LM separately in a variational Expectation-Maximization (EM) framework. In the E-step, the LM predicts both gold labels and pseudo-labels from the GNN, while in the M-step, the GNN predicts gold labels and LM-inferred pseudo labels using the embeddings and pseudo-labels provided by the LM.

Moreover, due to the high cost of annotation and the necessity for GNN to learn from a substantial amount of high-quality labeled data to ensure its performance on graph tasks, leveraging the zero-shot learning capability of LLM becomes advantageous. Therefore, employing LLM for graph annotation can enhance GNN training even with limited labeled data. LLM-GNN [72] proposes to select a candidate node set to be annotated. Subsequently, LLMs annotate the candidate node set, and post-filtering is conducted to eliminate low-quality annotations. Finally, the GNN is trained using the high-quality annotation set and utilized for prediction. LLM-GNN [72] proposes to select a candidate node set for annotation by LLMs, followed by post-filtering to remove low-quality annotations. Then, GNN is trained using high-quality annotations for prediction.

Providing external knowledge/explanations. LLMs possess a vast knowledge base, enabling them to provide external knowledge or explanations related to node features when encoding them, as shown in Figure 11. The additional knowledge assists the model in better extracting and capturing node features. Graph-LLM [73] utilizes LLMs, such as ChatGPT, to explain text attributes, enhancing them and generating pseudo labels. These enhanced attributes are then fed into a trainable LLM, like Llama, to produce node feature embeddings. The combined pseudo labels and embeddings are input into a GNN, which delivers the final prediction outcomes.

Similarly, TAPE [30] leverages LLMs to provide external explanations. In a citation network where each node contains text attributes like title and abstract, the text attribute of each node serves as input to an LLM. The LLM categorizes the nodes and generates multiple predictions ranked in a list with accompanying reasoning explanations. This approach aims to extract the LLM’s reasoning capabilities while integrating external knowledge to aid in understanding node text attributes and extracting node features.

2) **LLMs act as predictors.** When LLMs are predictors, they are usually directly employed as standalone predictors. The critical aspect of integrating LLMs as predictors lies in crafting a well-designed prompt that encompasses text attributes and graph structures, enabling LLMs to comprehend the graph structure effectively and enhance prediction accuracy. Additionally, there are other methodologies to fine-tune LLMs, such as utilizing techniques like LoRA [63] and instruction tuning, aiming to deepen the LLM’s understanding of the graph structure. Based on whether LLMs undergo parameter training, they are categorized into prompting LLMs and SFT LLMs, as shown in Figure 12.

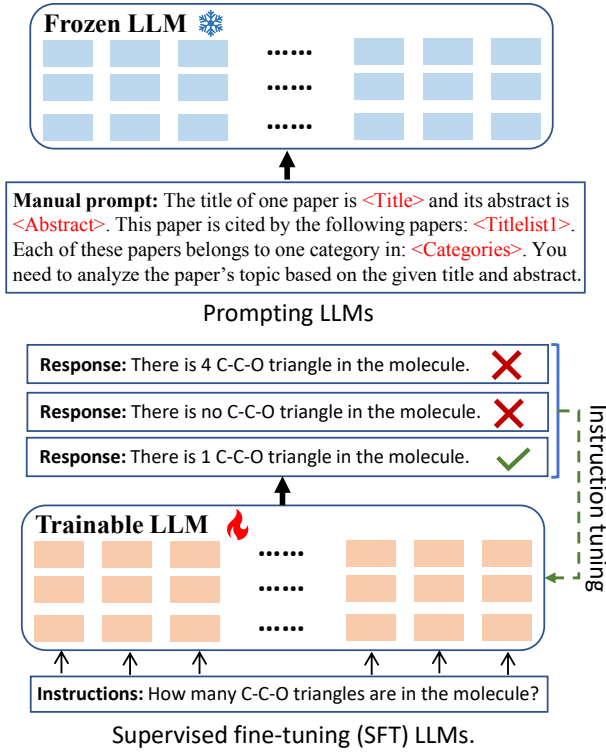


Fig. 12: LLMs act as predictors. For prompting LLMs, input designed manual prompts into LLM, enabling it to predict nodes/links/graphs. For SFT LLMs, input instructions into the LLM to generate multiple answers. Tuning the LLM is then based on these multiple responses.

Prompting LLMs. The prompting method can be divided into two categories. One type is the manual prompts, which are manually written prompts.

Prompt IV-1: Manual Prompt Template with Slots. For instance, Beyond Text [74], ENG [75], and Graph Agent [76] provide a manual prompt template with slots. By filling these slots with different examples, various prompts can be constructed. For example:

Prompt IV-1: Manual Prompt Template with Slots
The title of one paper is **<Title>** and its abstract is **<Abstract>**. This paper is cited by the following papers: **<Titlelist1>**. Each of these papers belongs to one category in: **<Categories>**. You need to 1. Analyse the papers' topic based on the given title and abstract; 2. Analyse the pattern of citation information based on their titles, and retrieve the citation information you think is important to help you determine the category of the first given paper. Now you need to combine the information from 1 and 2 to predict the category of the first given paper. You should only output one category.

Compared to manual prompts, LPNL [77] generates

This is a citation network, each node denotes one paper. There are 5 nodes. node 1 is central node, with title "Can Language Models Solve Graph Problems in Natural Language?" is connected to node 2 with title "Exploring the potential of large language models (llms) in learning on graphs", node 3 with title "Natural language is all a graph needs", node 4 with title "Talk like a graph: Encoding graphs for large language models", node 5 with title "Label-free node classification on graphs with large language models (llms)" which arxiv CS subcategory does node 1 with title "Can Language Models Solve Graph Problems in Natural Language?" belongs to? in the form "cs.XX".

Based on the titles of the node 1 paper and its connected papers, it seems that the research is focused on the intersection of natural language processing and graph theory, possibly with an emphasis on the capabilities of large language models (LLMs) to understand and process graph-structured data.

Given this context, the most likely arXiv Computer Science (cs) subcategory for node 1 titled "Can Language Models Solve Graph Problems in Natural Language?" would be:

- cs.CL (Computation and Language)

This subcategory covers computational linguistics and natural language processing, which is where work on language models typically falls. Additionally, since the titles suggest a focus on graph problems, there may be an overlap with:

- cs.LG (Learning)

This subcategory includes machine learning and might be relevant if the paper discusses the learning aspects of language models applied to graph data. However, the primary classification based on the title seems to be related to natural language processing and computational linguistics, making cs.CL the most fitting choice.

Fig. 13: Examples for Node Classification Task with GPT4 - Graph Learning Tasks.

prompts through sampling. Specifically, it conducts a two-stage sampling process on the source node and each candidate neighbor from the original candidate set to acquire anchor nodes. Prompt generation is then based on these anchor nodes.

We provide manual prompt examples for various graph learning tasks in Table III. Additionally, we test LLMs with GPT 3.5 for node classification and KGQA using manual prompts, as shown in Figure 13 and Figure 14.

Supervised fine-tuning (SFT) LLMs. InstructGLM [78] and GraphGPT [79] both employ SFT to train LLM for the node classification task. InstructGLM [78] utilizes a single LLM by prompting methods. The prompt includes the description of node attributes and structure through text descriptions and corresponding queries. LLMs are then tasked with answering questions and determining node categories, leading to fine-tuning through supervised learning. On the other hand, GraphGPT [79] feeds graph structural information and text

This is a knowledge graph. There are 5 nodes: ["Nolan", "Inception", "Oppenheimer", "US", "Leonardo"], and 4 edges are from "Inception" to "Nolan" with relationship "is directed by", from "Oppenheimer" to "Nolan" with relationship "is directed by", from "Inception" to "US" with relationship "country", from "Inception" to "Leonardo" with relationship "is starred by". Based on the given knowledge graph, the director who directs Inception also direct what?

Based on the given knowledge graph, the director who directs "Inception" also directs "Oppenheimer". This can be inferred from the two edges connecting "Inception" to "Nolan" and "Oppenheimer" to "Nolan", both with the relationship "is directed by".

Fig. 14: Examples for KGQA with GPT3.5 - Graph Learning Tasks.

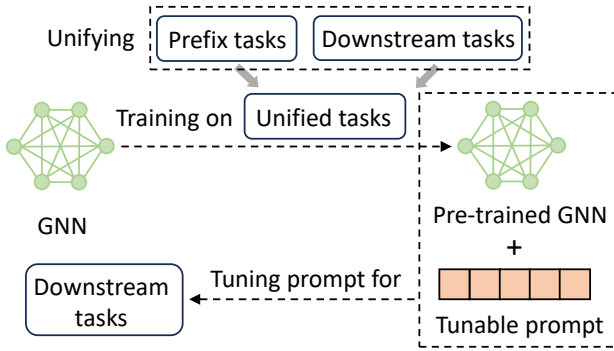


Fig. 15: Graph prompt for graph learning. Graph prompt methods first unify prefix and downstream tasks, then pre-train GNN on the unified tasks. The pre-trained GNN, when faced with different downstream tasks, combines with a tunable prompt through tuning prompts to handle the downstream tasks better.

into LLM via embedding. Subsequently, two rounds of instruction tuning are conducted to refine LLM and effectively address the node classification task. InstructGLM [78] employs prompts to input subgraph structures into LLM, while GraphGPT [79] inputs them into LLM through embedding.

3) **Graph prompt:** In graph learning tasks, a wide array of tasks at the node, edge, and graph levels creates a challenge in achieving compatibility between pre-training and downstream tasks, potentially leading to negative transfer effects that can harm the performance of downstream tasks and compromise the reliability of transfer learning in graph data. Current methods aim to harmonize pre-training and downstream tasks to facilitate more effective transfer learning of graph information. Despite these efforts, it remains essential to identify task-specific differences for optimal performance. Inspired by NLP, researchers have started incorporating prompts in graph contexts to enable the reuse of pre-trained models across various downstream tasks without the need for repeated fine-

tuning, as shown in Figure 15. The integration of prompts is crucial in assisting downstream tasks in achieving task-specific optimal outcomes, bridging the gap between pre-trained models and the diverse array of graph tasks to enhance performance and transferability.

GPPT [80] and GraphPrompt [81] aim to unify pre-training and downstream tasks in graph learning. GPPT transforms node classification tasks into edge prediction tasks and employs masked edge prediction for GNN pre-training. Meanwhile, GraphPrompt combines node and graph classification tasks into a subgraph similarity prediction task and utilizes graph prompt functions, introducing unified instances and task templates to enhance performance. Subsequent research, like All in One [82], further consolidates edge, node, and graph classification tasks into a single framework using multi-task prompting approaches, standardizing graph prompts similar to language prompts and enhancing initialization through meta-learning techniques for improved reliability and generality across different tasks in graph data analysis.

C. Comparisons and Discussions

For addressing graph learning tasks, existing methods [30] [79] [82] categorize based on the role of LLM into three types: LLMs act as enhancers (LLM-GNN pipelines), LLMs act as predictors (LLM pipelines), and graph prompts. In the part of graph prompts, we introduce the prompting engineering in GNNs without utilizing LLMs. Graph prompts aim to unify downstream tasks and construct a universal framework. Therefore, it is compared with LLM-GNN pipelines and LLM pipelines to provide a comprehensive overview.

When LLMs act as enhancers, the most popular pipeline is the LLM-GNN pipeline. There are three categories of LLM-GNN pipelines, depending on how LLM enhances GNN: encoding the graph into embeddings, generating graph pseudo labels, and providing external knowledge/explanations. However, the LLM-GNN pipelines that are currently available are not end-to-end pipelines, meaning that LLM and GNN cannot be trained together. LLM and GNN can be trained separately using frameworks like EM framework [31] or by freezing LLM and using it as an external knowledge base. Co-training LLM and GNN can lead to issues like gradient vanishing, which is a significant obstacle in current LLM-GNN pipelines due to the large number of parameters in LLM compared to GNN. To solve this problem, methods like knowledge distillation can reduce the number of LLM parameters while retaining the beneficial capabilities for downstream tasks.

When LLMs act as predictors, two main methods are used: prompting LLMs and SFT LLMs. All approaches for fine-tuning LLMs can be reviewed in the "comparisons and discussions" section of Section III. Currently, SFT and DPO are popular methods for fine-tuning LLMs.

For graph prompt, the workflow involves unifying pre-training and downstream tasks, followed by prompt tuning for different downstream tasks through prompt engineering, as shown in Figure 15. Graph prompts require fewer tunable

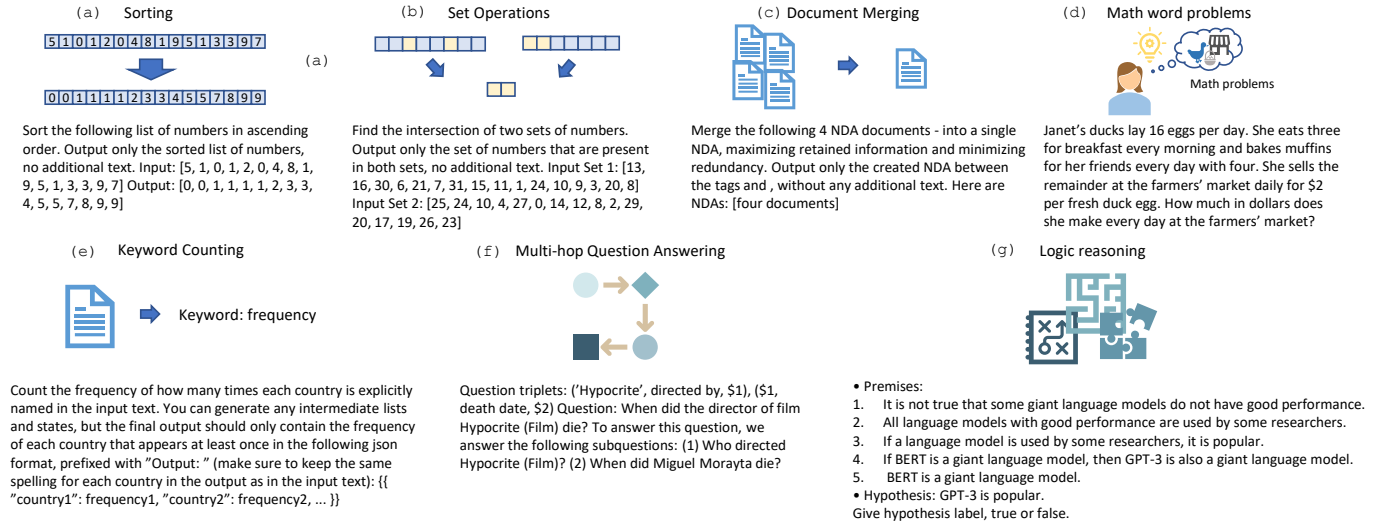


Fig. 16: Graph-formed Reasoning Tasks.

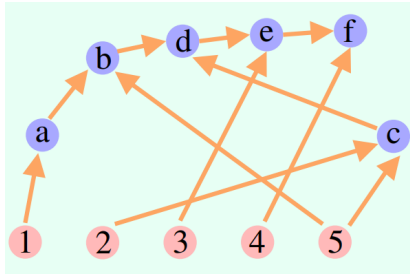


Fig. 17: Illustration of human logical derivation. [35]

parameters compared to LLM-GNN and LLM pipelines; however, they have a shallower semantic understanding of graph attributes. In LLM pipelines, LLMs need to undergo alignment tuning before they can be used for various downstream tasks. In LLM-GNN pipelines, there is a general trend of training GNNs. Combining LLM-GNN and graph prompts is possible because graph prompts are designed for GNNs through prompt engineering and can be applied to LLM-GNN pipelines. By leveraging LLM's robust semantic representation capabilities and the lightweight fine-tuning of graph prompts, similar results can be achieved.

Classical graph tasks, such as node classification on attributed static networks, have recently obtained the most attention. However, there is potential for more complex tasks in the future, such as predicting graph evolution on dynamic graphs. Leveraging LLM models that are suitable for handling sequential data and can process time series data, along with GNNs that are adept at capturing changes in graph structures, can help address a broader range of problems effectively. By combining the strengths of LLM and GNN, we can tackle more challenging tasks in the field of graph analysis.

V. GRAPH-FORMED REASONING

A. Tasks Introduction

Graph-formed reasoning refers to combining the graph form with LLMs to obtain more accurate and reliable answers. LLMs have strong reasoning capabilities, and many prompting methods are proposed to enhance LLMs' reasoning abilities, addressing algorithmic problems, mathematical issues, etc., such as chain of thought, self-consistency, in-context learning, and more. However, these methods diverge from the patterns of human thought. The human thought process is typically non-linear rather than a simple chain of continuous thoughts, like in Figure 17. Graphs can represent the thinking patterns of individuals during the thought process. Suppose LLMs can also use graph-formed reasoning for inference. In that case, they may be able to solve more complex problems, such as algorithmic problems, logical reasoning problems, and mathematical word problems, as shown in Figure 16. In this section, we present seven graph-formed reasoning tasks along with their definitions. Next, we introduce graph-formed reasoning methods involving two types of reasoning: think on the graph and verify on the graph.

1) *Sorting*: The problem of sorting involves arranging certain elements in a specific order. For example, sorting a list of duplicate numbers from 0 to 9 can be done using a merge-based sorting algorithm. First, the input sequence of numbers is divided into subarrays. Then, these subarrays are sorted individually and merged to form the final solution, as shown in Figure 16 (a).

2) *Set operations*: Set operation task mainly focuses on set intersection. Specifically, the second input set is split into subsets and the intersection of those subsets with the first input set is determined with the help of the LLM, as shown in Figure 16 (b).

3) *Keyword counting*: The keyword counting task aims to determine the frequency of specific keywords within a given category in the input text. The input text is divided into

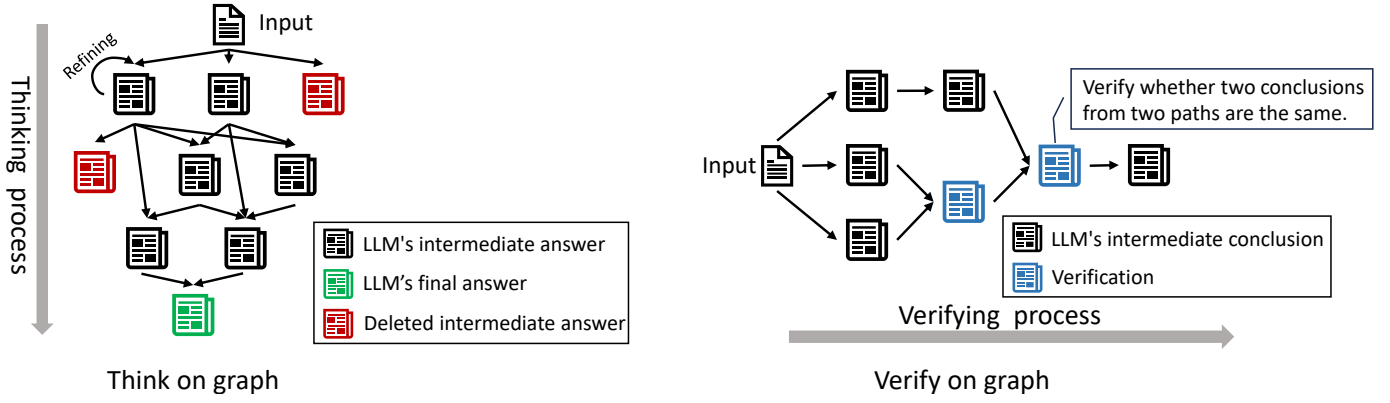


Fig. 18: Graph-formed reasoning. Two directions: think on graphs and verify on graphs. Think on the graph refers to using the graph structure to derive the final conclusion during the LLMs’ reasoning process. Verify on the graph refers to using the graph to verify the correctness of the LLMs’ intermediate and final output.

multiple paragraphs, and the keywords are counted in each paragraph, with the sub-results aggregated, as shown in Figure 16 (e).

4) *Document merging*: Document merging is the process of generating a new document based on multiple input documents that have overlapping content sections. The goal is to minimize duplication as much as possible while preserving the maximum amount of information, as shown in Figure 16 (c).

5) *Math word problems*: Math word problems include single- and multi-step word problems with addition, multiplication, subtraction, division and other math topics. LLM requires an understanding of text and mathematical relationships and involves a multi-step reasoning process where calculations are performed step by step to arrive at an answer ultimately, as shown in Figure 16 (d).

6) *Multi-hop question answering*: Multi-hop question answering requires LLM to retrieve and integrate information from multiple text passages or multi-hop graphs to answer questions. For a complex reasoning question, LLM uses a sophisticated thinking process to perform reasoning and ultimately arrive at the correct answer, as shown in Figure 16 (f).

7) *Logic reasoning*: Logical reasoning is a process aimed at concluding rigorously. It occurs in inference or argumentation, starting from a set of premises and reasoning towards a conclusion supported by those premises. Propositional logic is the most fundamental logical system, consisting of p , q , r , and various operations, as shown in Figure 16 (g).

B. Graph-formed Reasoning Methods

The graph form, with its inherent structural features, not only mimics human reasoning patterns but also validates answers from LLM through the relationships between nodes and local structure. Existing work can roughly be divided into two categories: *think on the graph* and *verify on the graph*, as shown in Figure 18. Think on the graph refers to LLM thinking in the form of a graph, where each node on the graph represents a step in the thinking process or

an intermediate conclusion during thinking, and the edges on the graph indicate the direction of LLM inference or the relationships between intermediate thinking steps. In this way, the LLM thinking process can be visually represented in graph form. Verify on the graph means verifying the consistency and correctness of answers by utilizing the graph’s structure. For example, if the end node of different paths is the same, the results derived from different paths should be the same. If contradictory conclusions arise, then the obtained conclusion is incorrect.

1) *Think on the graph*: The GoT* reasoning method [36] is proposed with a two-stage framework to enable LLM to reason on a graph for answering multiple-choice questions. Initially, the input query is converted into a graph form, and with the incorporation of graph and multimodal features, LLM generates rationale. This rationale updates the graph to a graph with rationales, which is then combined with the original input and fed into the decoder to obtain the final answer.

However, GoT* allows LLM to enhance the graph using multimodal information but does not reason step-by-step deduction in graph form. The Graph of Thought (GoT) [34] represents LLM’s intermediate thinking as an arbitrary graph, facilitating powerful prompting for solving algorithmic problems like sorting and keyword counts. LLM thoughts are depicted as vertices in this approach, with edges representing dependencies between them. By continuously adding LLM responses to the graph, arbitrary thoughts can be aggregated, forming a directed acyclic graph.

Multiple LLMs can also be collaboratively harnessed to tackle complex mathematical challenges, extending beyond the capabilities of a single LLM. Cumulative Reasoning (CR) [35] is proposed as a more human-like reasoning process. CR utilizes three LLMs in different roles: the proposer, verifier, and reporter. The proposer suggests the next step, the verifier checks the accuracy of the steps, and the reporter decides when the reasoning process should end. Three roles of LLMs collaborate to achieve more accurate reasoning processes.

Task	Prompts
Sorting	<Instruction>Sort the following list of numbers in ascending order. Output only the sorted list of numbers, no additional text. </Instruction><Examples>like Input: [5, 1, 0, 1, 2, 0, 4, 8, 1, 9, 5, 1, 3, 3, 9, 7] Output: [0, 0, 1, 1, 1, 1, 2, 3, 3, 4, 5, 5, 7, 8, 9, 9]</Examples>Input: [input list]
Set Operations	<Instruction>Find the intersection of two sets of numbers. Output only the set of numbers that are present in both sets, no additional text.</Instruction><Examples>like Input Set 1: [13, 16, 30, 6, 21, 7, 31, 15, 11, 1, 24, 10, 9, 3, 20, 8] Input Set 2: [25, 24, 10, 4, 27, 0, 14, 12, 8, 2, 29, 20, 17, 19, 26, 23] Output: [24, 10, 20, 8]</Examples>Input Set 1: set1 Input Set 2: set2
Keyword Counting	<Instruction>Count the frequency of how many times each country is explicitly named in the input text. You can generate any intermediate lists and states, but the final output should only contain the frequency of each country that appears at least once in the following json format, prefixed with "Output: " (make sure to keep the same spelling for each country in the output as in the input text): {{ "country1": frequency1, "country2": frequency2, ... }}</Instruction><Approach>To count the frequency for each country follow these steps: 1. Split the input passage into four paragraphs of similar length. 2. Count the frequency of each country in each paragraph. 3. Combine the frequencies of each country from each paragraph by adding them together.</Approach><Examples>(Omitted)</Examples>Input: input text
Document Merging	Merge the following 4 NDA documents <Doc1>- <Doc4>into a single NDA, maximizing retained information and minimizing redundancy. Output only the created NDA between the tags <Merged>and </Merged>, without any additional text. Here are NDAs: [four documents]
Math word problems	Q: Janet’s ducks lay 16 eggs per day. She eats three for breakfast every morning and bakes muffins for her friends every day with four. She sells the remainder at the farmers’ market daily for \$2 per fresh duck egg. How much in dollars does she make every day at the farmers’ market?
Multi-hop Question Answering	Question triplets: ('Hypocrite', directed by, \$1), (\$1, death date, \$2) Question: When did the director of film Hypocrite (Film) die? To answer this question, we answer the following subquestions: (1) Who directed Hypocrite (Film)? The film Hypocrite was directed by Miguel Morayta. (2) When did Miguel Morayta die? Miguel Morayta died on 19 June 2013. So the answer is 19 June 2013.
Logic reasoning	• Premises: 1. It is not true that some giant language models do not have good performance. 2. All language models with good performance are used by some researchers. 3. If a language model is used by some researchers, it is popular. 4. If BERT is a giant language model, then GPT-3 is also a giant language model. 5. BERT is a giant language model. • Hypothesis: GPT-3 is popular. • Label: [True]

TABLE IV: Prompts for Graph-formed Reasoning.

2) **Verify on the graph:** *Verify on the graph* is to validate the intermediate reasoning results of LLM to enhance its performance. The Reasoning Graph Verifier (RGV) [83] in this study assumes a logical connection between the intermediate steps of different inference paths created by LLM. This allows the multiple solutions generated by LLM for a reasoning task to be structured into a reasoning graph, aiming to improve the accuracy and reliability of the outcomes. By constructing reasoning graphs from the various solutions provided by LLM, a verifier is trained to determine the correctness of the resulting reasoning graph. During the prediction phase, RGV assesses the solutions and selects the highest-scoring one as the final answer.

However, this work trains an extra model to determine whether the graph formed by the solutions generated by LLM is correct rather than utilizing the knowledge within the graph and the relationships between the knowledge for validation. The Graph-guided CoT [84] approach aims to improve the relevance of rationales generated by CoT during multi-step reasoning. It starts by extracting triplets from questions using LLM to build a question graph and generates intermediate sub-questions from this graph. To ensure the rationale from LLM is logical, Retrieval Augmented Generation (RAG) is used. In an open-book scenario, knowledge retrieval is based on the sub-

questions, providing retrieved documents and sub-questions as input to LLMs. LLMs generate rationales for the sub-questions, creating a rationale graph. Based on the rationale graph, the study assesses whether the generated rationales aid in solving the original question. By iteratively generating intermediate rationales, the solution to the original question can be determined.

Finally, we provide manual prompt examples for various graph learning tasks in Table IV. Additionally, we test LLMs with GPT-4 for sorting and logic reasoning using manual prompts, as shown in Figure 19.

C. Comparisons and Discussions

Graph-formed reasoning is categorized into *think on the graph* and *verify on the graph*. **Think on the graph** refers to using the graph structure to derive the final conclusion during the reasoning process with LLM. On the other hand, **verify on the graph** involves treating the intermediate or final results generated by LLM as nodes on the graph and using the graph to determine if there are contradictions between the nodes, thus verifying the correctness of the LLM output.

For “think on the graph”, a common issue with existing approaches is their lack of convenience. Compared to CoT and SC, the reasoning processes in current works are complex,

- Hypothesis: Hyraxes lay eggs.
- Premises:
 1. The only types of mammals that lay eggs are platypuses and echidnas.
 2. Platypuses are not hyrax.
 3. Echidnas are not hyrax.
 4. No mammals are invertebrates.
 5. All animals are either vertebrates or invertebrates.
 6. Mammals are animals.
 7. Hyraxes are mammals.
 8. Grebes lay eggs.
 9. Grebes are not platypuses and also not echidnas.

Give hypothesis label: True or False

Given the premises provided, we can evaluate the hypothesis "Hyraxes lay eggs."

1. The only types of mammals that lay eggs are platypuses and echidnas.
2. Platypuses are not hyrax.
3. Echidnas are not hyrax.
7. Hyraxes are mammals.

From premises 1, 2, and 3, we understand that the only mammals that lay eggs are platypuses and echidnas, and that hyraxes are neither platypuses nor echidnas. Since hyraxes are mammals (as stated in premise 7), and the only egg-laying mammals are platypuses and echidnas, it follows that hyraxes do not lay eggs because they do not belong to either of those two categories.

Therefore, the hypothesis "Hyraxes lay eggs" is **False** based on the given premises.

Fig. 19: Examples for Logic Reasoning Task with GPT4 - Graph Reasoning Tasks.

requiring multiple stages of reasoning and validation. Graph of thought methods are not plug and play, which contradicts the original intent of prompts. Even though using more LLMs can simplify the reasoning and validation process, it raises the cost and barrier to entry for reasoning. Therefore, the current challenge is to find a plug-and-play, low-barrier LLM graph reasoning method that improves LLM reasoning capabilities.

For “verify on the graph”, the current approaches have yet to utilize the nature of the graph structure for validation. Existing methods either retrain a model to determine correctness or use a KG for assessment without using the relationships between nodes to infer whether the conclusions within each node in the graph are correct.

Therefore, for the “think on the graph,” the future direction could focus on developing a plug-and-play, low-barrier LLM graph reasoning method that enhances LLM reasoning abilities, a pressing issue that needs to be addressed. On the other hand, concerning the “verify on the graph” method, future research could explore how to utilize the relationships between nodes in the graph structure to verify the outputs of LLM or the reasoning process itself.

VI. GRAPH REPRESENTATION

A. Tasks Introduction

LLMs’ powerful text representation abilities empower text embeddings to capture deeper semantic nuances, which also can enhance graph representations, particularly for Text Attributed Graphs (TAGs). When dealing with structured text data, the key challenge is integrating graph structures into text embeddings produced by LLMs to enhance their informativeness or enable LLMs to process text embeddings with graph structures within the text space. Moreover, effectively incorporating the graph description within the prompt is essential for LLMs, especially in closed-source models like ChatGPT, where the embedding is invisible. How the graph is encoded within the prompt influences the model’s comprehension of the graph. Thus, we summarize three types of graph representation: *graph embedding*, *graph-enhanced text embedding*, and *graph-encoded prompts*, as shown in Figure 20. Next, we introduce graph-formed reasoning methods corresponding to the above three types.

1) *Graph embedding*: Graph embedding focuses on transforming a graph into a specific ordered sequence, which is then fed into an LLM to learn the sequence’s embedding using their excellent semantic capturing ability and then derive the graph embedding.

2) *Graph-enhanced text embedding*: Graph-enhanced text embedding emphasizes incorporating structural embedding into text embedding. There are two types of embeddings: structural embedding, which captures the local structure, and text embedding, which captures the semantic meaning. How to combine these two types of embeddings is the core of graph-enhanced text embedding.

3) *Graph-encoded prompts*: Graph-encoded prompts concentrate on how to describe a graph so that LLMs can understand it more efficiently and then input it into LLMs. For instance, in a regular graph, the graph can be placed in a story context by assuming that the relationships between the nodes are friends or colleagues.

With the emergence of LLM, much work has been done on graph representation. Three goals of the graph representation direction can be identified from the above three categories: to obtain better graph embeddings as an input into GNNs, to obtain better text embeddings as an input into LLMs/LMs, and to get better prompts for graph description as an input into LLMs.

B. Graph Representation Methods

For the three categories of tasks mentioned above, each type of task has specific focuses, technical characteristics, and objectives.

1) *Graph embedding*: Text data is sequential, while graph data is structural, posing a challenge for LLMs, which excel at handling text but struggle with graphs. How do we transform graphs into sequences? Graph embedding methods use specific order sequences to represent the graph, where specific order represents graph structure. WalkLM [38] aims to enhance

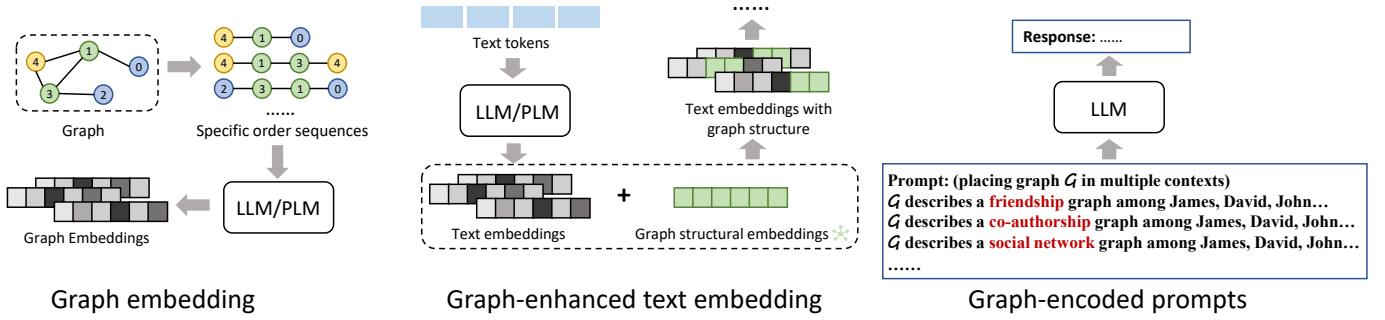


Fig. 20: Graph representation. Three types of graph representation are shown: graph embedding, graph-enhanced text embedding, and graph-encoded prompts. Graph embedding methods use specific order sequences to represent the graph. Graph-enhanced text embedding emphasizes incorporating structural embedding into text embedding. Graph-encoded prompts concentrate on how to describe a graph in prompts.

graph representations in TAGs by utilizing a language model. Initially, text sequences are generated on the TAG through the random walk algorithm, capturing structural features and node proximity. By incorporating text information from nodes and edges into these sequences based on the graph structure, the texturing process preserves component attributes. Subsequently, these sequences are input into a masked language model for training, where each token represents a node or edge, leading to improved graph representations and enhanced downstream task efficiency. Notably, various masked language model options, including LLMs, are available.

While WalkLM [38] focuses on superior graph embeddings for tasks like node classification, GraphText [37] transforms graphs into the natural language to enable LLMs to process graph data in the text domain, leveraging LLMs' generalization capabilities for graph tasks. GraphText [37] reformulates graph reasoning as text-to-text problems, establishing text input and output spaces. GraphText first constructs grammar trees for graphs, then traverses them to generate graph text sequences, and finally maps the graph to the text space. The text input is then fed into an LLM, with the LLM results mapped to the label space, effectively enabling LLMs to handle graph tasks.

2) **Graph-enhanced text embedding:** Current work focuses on simply passing graph structure information to the LLM through prompts without deeply learning the graph structure, which can lead to an LLM's insufficient understanding of complex structural relationships.

DGTL [39] integrates graph information into text with LLMs for node classification tasks. It begins by inputting text into a frozen LLM to create text embeddings from the last layer. Then, a disentangled graph learning method is employed to extract various structural details and generate structure embeddings. These structure embeddings are combined with the text embeddings and fed back into the frozen LLM for node classification. The entire process is fine-tuned to optimize the disentangled graph learning for better results.

While DGTL [39] concentrates on utilizing LLMs to integrate text and graph structure for graph tasks, G2P2 [85] emphasizes merging graph structure with text to address text

classification tasks. Textual data commonly exhibit network structures, such as hyperlinks in citation networks or purchase networks, which encapsulate meaningful semantic relationships that can enhance text classification performance.

G2P2 [85] is proposed to tackle low-resource text classification through a dual approach. Three graph interaction-based contrastive strategies are introduced during pre-training to jointly pre-train the graph-text model. In the downstream classification process, efforts are made to facilitate the joint pre-trained model in achieving low-resource classification.

3) **Graph-encoded prompts:** The prompting method is crucial for LLMs to solve tasks. For closed-source LLMs, the prompt serves as instructions to guide the LLM in understanding and solving problems. Therefore, effectively encoding graphs in the prompt is vital for LLMs to comprehend graph structure and solve graph tasks. Graph encoding refers to how graphs are represented in the prompt.

Talk Like A Graph [86] introduces diverse graph encoding techniques by placing the same graph in multiple contexts. This strategy highlights how a node, which may lack intrinsic meaning, can be interpreted differently based on the context; for instance, a node could represent a person named David, with edges indicating various relationships like co-authorships or friendships. When asking LLM the degree of one node, in the given contexts, that equals how many friendships David has.

In contrast, Talk Like A Graph [86] primarily emphasizes text modality graph encoding, while Which Modality Should I Use [87] employs three encoding modalities - text, image, and motif - to encode graphs. The latter method utilizes different prompt techniques to evaluate the overall connectivity of a graph, enabling LLMs to handle intricate graph structures more effectively. Specifically, the text modality encoding provides insights into subgraphs and their connections at a local level, while the motif modality encoding captures essential graph patterns like stars, triangles, and cliques, offering a balanced perspective on local and global information. Moreover, the image modality encoding delivers a broader view of nodes with limited labels, effectively utilizing the input context.

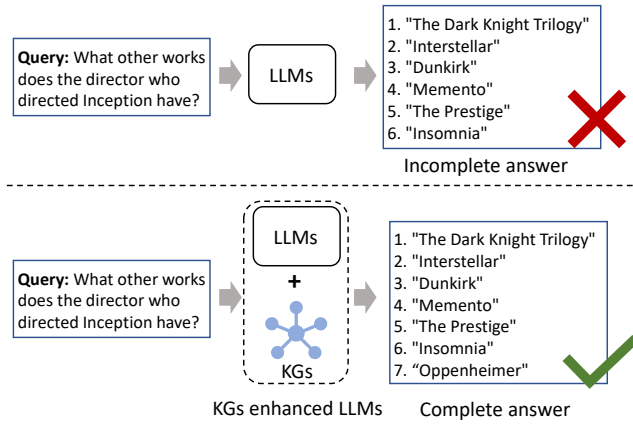


Fig. 21: KG-based augmented retrieval. Knowledge graphs can enhance LLMs to provide more comprehensive answers.

In comparing these two methods, Talk Like A Graph [86] focuses on diverse graph encoding within text modality by constructing contexts, whereas Which Modality Should I Use [87] utilizes multiple modalities to encode graphs comprehensively, enhancing the LLMs' ability to understand graph structures.

C. Comparisons and Discussions

Graph embedding focuses on transforming a graph into a specific ordered sequence, which is then fed into an LLM to learn the sequence's embedding and derive the graph embedding. On the other hand, graph-enhanced text embedding emphasizes incorporating structural embedding into text embedding. Lastly, graph-encoded prompts concentrate on how to describe a graph and input it into an LLM.

However, due to LLMs' powerful text representation capabilities, the first two methods exhibit a deep semantic understanding of graph attributes. However, they still need suitable structural information capturing, which remains rudimentary and inadequate. Additionally, aligning the graph structure features with text features to better represent the graph's features is a current issue that needs to be addressed.

For graph-encoded prompts, most methods build a narrative context for the graph or describe it multimodally before feeding it into an LLM. Both methods enable the LLM to interpret the graph from various perspectives to improve performance. The critical challenge currently lies in designing diverse and easily understandable graph descriptions for LLMs, conveying essential graph descriptions while enhancing the LLM's comprehension of the input description.

VII. KNOWLEDGE GRAPH BASED AUGMENTED RETRIEVAL

LLMs have shown remarkable reasoning capabilities in challenging tasks, sparking debates on the potential replacement of Knowledge Graphs (KGs) in triplet form (subject, predicate, object) by LLMs. Recent LLMs are seen as viable alternatives to structured knowledge repositories such as KGs,

indicating a shift towards utilizing LLMs for processing real-world factual knowledge [88] [89].

A. LLMs limitations and comparison with KGs

LLMs, while powerful, face several significant challenges:

- Hallucination is a common issue for LLMs due to a lack of domain-specific knowledge and knowledge obsolescence, leading to incorrect reasoning and reduced credibility in critical scenarios like medical diagnosis and legal judgments [88] [90] [43]. Although some LLMs can explain predictions through causal chains, they struggle to address hallucination effectively. Integrating external KGs can help mitigate these problems [41].
- Insufficient domain knowledge hampers LLM performance in specific areas, including private datasets, necessitating the integration of domain-specific knowledge graphs to enhance their ability to answer domain-specific questions [40].
- LLMs struggle with recalling facts when generating knowledge-based content, despite excelling in learning language patterns and conversing with humans [89].
- LLMs have limitations in accurately capturing and retrieving foundational knowledge, hindering their ability to access factual information effectively [42].

In contrast, KGs like Wikipedia and DBpedia are structured repositories of rich factual knowledge, providing a more explicit and reliable source of information compared to the black-box nature of LLMs, as shown in Figure 21. How do we measure the shortcomings of LLM relative to KG? KGLens is proposed as an effective method to evaluate the factual accuracy and identify knowledge gaps in LLMs by assessing the alignment between a KG and LLM [91].

B. Solutions to LLMs limitations

To address the limitations of LLMs, such as hallucination, insufficient domain knowledge, etc., integrating LLMs with KGs is a potential way to allow LLMs to learn knowledge from KGs and enhance their capabilities. The REASONING ON GRAPHS (RoG) framework [43] synergizes LLMs with KGs for faithful and interpretable reasoning. Specifically, RoG utilizes a planning retrieval-reasoning framework where relation paths grounded by KGs are generated as faithful plans. These plans are then used to retrieve valid reasoning paths from KGs to facilitate LLMs' faithful reasoning. Existing work has taken on the challenges posed by the four main limitations of LLMs through distinct perspectives, each offering unique solutions.

Addressing the first limitation concerning hallucination issues in LLMs, the Head to Tail benchmark [88] is introduced to assess LLMs' reliability in answering factual questions and to evaluate the probability of hallucination in generating KG triples. Additionally, it explores whether factors like model size or instruction tuning can enhance LLM knowledge. Think-on-Graph (ToG) [41] partially addresses hallucination by involving the LLM agent in iteratively searching KGs, identifying promising reasoning paths, and providing likely

reasoning outcomes. The second limitation is LLM needs domain-specific knowledge. To tackle this, GLaM [40] is developed to convert knowledge graphs into text paired with labeled questions and answers, allowing LLMs to acquire and respond to domain-specific knowledge. Regarding the third limitation related to LLMs forgetting facts, integrating KGs with PLMs (KGPLMs) [89] is introduced to enhance the model's ability to recall facts compared to standalone LLMs. This approach emphasizes the competitive and complementary relationship between LLMs and KGs, where LLMs improve knowledge extraction accuracy, and KGs guide LLM training to enhance memory and knowledge application capabilities. Finally, the fourth limitation pertains to LLMs' challenge in accurately retrieving and returning knowledge from KGs. KGs can enhance LLM performance by incorporating them during pre-training and inference stages or to deepen LLM's understanding of acquired knowledge. Graph Neural Prompting (GNP) [42] is proposed to augment pre-trained LLMs using foundational knowledge, such as retrieval-augmented generation, to facilitate effective learning from KGs. GNP [42] retrieves and encodes relevant, grounded knowledge to generate Graph Neural Prompts, embedding vectors that provide guidance and instructions for LLMs.

C. Other KG + LLMs works

1) **KG tasks with LLMs:** Moreover, LLMs can enhance KGs to tackle a broader array of challenges. By leveraging LLMs, KGs can be fortified to perform various KG-related tasks such as embedding, completion, construction, text generation from graphs, and question answering [90]. An illustrative example is how LLMs can support KG tasks such as knowledge graph alignment. In entity alignment tasks between different knowledge graphs, the objective is to identify pairs of entities representing the same entity. To address this, AutoAlign [92] facilitates alignment without the need for expensive manual seed creation. Specifically, AutoAlign [92] automatically identifies similarities between predicates across different KGs with the assistance of LLMs.

2) **Applications of KGs + LLMs:** The combination of KGs and LLMs has other applications as well. For instance, it can address tasks like multi-document question answering. Knowledge Graph Prompting (KGP) [93] is introduced to design appropriate context by building and exploring a knowledge graph. Subsequently, this context guides LLMs for answering multi-document questions.

D. Summary

In conjunction with LLMs, the future directions for KGs focus on overcoming challenges and seizing opportunities in this evolving field. Firstly, leveraging KGs for Hallucination Detection in LLMs aims to address the issue of generating inaccurate content. Secondly, utilizing KGs for Editing Knowledge in LLMs will enable the swift adaptation of internal knowledge to real-world changes. Moreover, the challenge of injecting knowledge into Black-box LLMs due to restricted access to internal structures necessitates innovative approaches. Lastly,

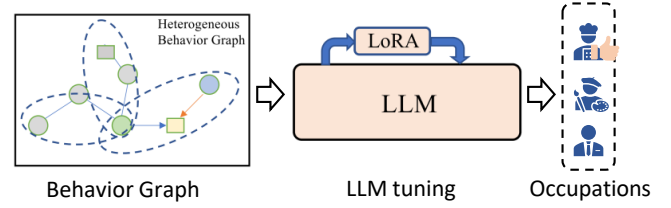


Fig. 22: Graph-LLM-based applications - Recommendation systems. This shows LLM for graph data understanding in online job recommendations [46].

integrating Multi-Modal LLMs with KGs can enrich handling diverse data types within knowledge graphs [90].

VIII. GRAPH-LLM-BASED APPLICATIONS

Graph-LLM-based applications refer to frameworks that integrate graphs with LLMs. Apart from their applications in graph-related tasks, they are also utilized in various other domains (as shown in Figure ??), such as conversational understanding and recommendation systems, as shown in Figure 22. Common frameworks involve combining GNNs with LLMs, merging graph data with LLMs, and exploring additional innovative approaches that leverage the advantages between graph structures and language models for diverse applications.

1) **Conversational understanding:** By combining LLM with graph traversal, collaborative query rewriting [94] is proposed to improve the coverage of unseen interactions, addressing the flawed queries users pose in dialogue systems. Flawed queries often arise due to ambiguities or inaccuracies in automatic speech recognition and natural language understanding. When integrated with graph traversal, LLM can effectively navigate through the graph structure to retrieve relevant information and provide more accurate responses.

2) **Response forecasting:** LLM can effectively handle social networks and extract latent personas from users' profiles and historical posts. SOCIALSENSE [95] is proposed to utilize LLMs to extract information to predict the reactions of news media. By analyzing individuals' characteristics and behavior patterns within social networks, LLM can effectively predict the impact of news releases and prevent unintended adverse outcomes.

3) **Multi-domain dialogue state tracking:** LLM can learn from multi-domain dialogue history, query, and graph prompts, enabling it to track dialogue states and generate dialogue content, like SHEGO [96]. By incorporating information from various sources, such as previous dialogue exchanges, user queries, and relevant graph prompts, LLM can understand the conversation's context and dynamics, allowing LLM to track the current dialogue state effectively and generate appropriate responses or dialogue content based on the inputs.

4) **Recommendation systems:** LLMs can also help address issues in recommendation systems [46], as many tasks in recommendation systems require learning graph structures, such as user-item interaction networks. LLMRec [44] aims

to enhance recommendation systems by tackling data sparsity by adopting three simple yet effective LLM-based graph-enhancement strategies.

5) *Graph neural architecture search*: LLMs can help address Graph Neural Architecture Search (GNAS). GNAS requires intensive human effort and rich domain knowledge to design search spaces and strategies. Leveraging powerful knowledge and reasoning capabilities, LLMs can identify suitable GNN frameworks within the search space of graph neural network frameworks. GPT4GNAS [45] integrates GPT-4 into GNAS, introducing a new set of prompts for GPT-4 to guide it towards generating graph neural structures.

IX. BENCHMARK DATASETS AND EVALUATIONS

In this section, we summarize benchmark datasets and evaluation metrics for LLMs.

A. Datasets

This paper summarizes the popular and new datasets, the LLM employed, the performed tasks, and the links to the open-source code in the LLM-GGA area, as illustrated in Table V. Below, we introduce commonly used benchmarks and the new benchmarks proposed for the LLM-GGA field.

1) *Popular datasets*: Popular benchmark refers to a graph benchmark that is widely and frequently used. We have systematically categorized these popular benchmarks according to six directions, detailing which benchmarks are used for each direction. Below are listed popular benchmarks commonly used in the six directions.

- **Graph structure understanding**: ogbn-arxiv [56], ogbn-products [56], Cora [100], CiteSeer [101], Aminer(DBLP) [57], MetaQA [102], Wikidata5M [103], PROTEINS [104], MUTAG [105], NCI1 [106], PTC [107], Foursquare [108].
- **Graph learning**: ogbn-arxiv [56], ogbn-products [56], ogb-papers110M [56], ogb-citation2 [56], Cora [100], CiteSeer [101], Amazon-items [109], PubMed [110], Reddit [111], CoraFull [112], Amazon [113], PROTEINS [104], COX2 [114], BZR [114], OAG [115].
- **Graph-formed reasoning**: GSM8K [116], SVAMP [117], FOLIO [118].
- **Graph representation**: Cora [100], CiteSeer [101], Goodreads-books [119], PubMed [110], Amazon [113], MIMIC-III [120], Freebase [121], FB15K-237 [122].
- **KG-based augmented retrieval**: CWQ [123], WebQSP [124], Wikidata [103].
- **Graph-LLM-based applications**: depending on specific applications.

2) *New datasets*: More than existing datasets are needed to explore LLMs' ability to understand graph structures and their potential to solve graph problems better. As a result, many works have proposed new benchmarks to advance research in this field, as shown in Table VI.

- GPR [59] contains 37 particular connected graph instances generated by the Networkx toolkit, which include the "bull graph," "wheel graph," "lollipop graph," etc.

These generated graph instances are relatively small, with about 15 nodes and 28 links on average.

- GraphTMI [87] is a graph benchmark featuring a hierarchy of graphs, associated prompts, and encoding modalities. Different graph task difficulty depends on the dual criteria of 1) count of motifs and 2) homophily in the graph, which yields a dataset of EASY, MEDIUM, and HARD graph problems.
- LLM4DyG [25] benchmark is to evaluate whether LLMs are capable of understanding spatial-temporal information on the dynamic graph. Nine dynamic graph tasks are designed to assess LLMs' abilities considering spatial and temporal dimensions.
- GraphQA [86] comprises a set of diverse fundamental graph problems with more varied and realistic graph structures compared to previous studies in LLM research. GraphQA is designed to measure the performance of LLMs in graph data reasoning.
- NLGraph [27] benchmark is to examine whether language models can reason with graphs and structures. NLGraph contains eight graph structure understanding tasks with varying algorithmic difficulties. Depending on different network sizes, graph sparsity, and more, NLGraph results in easy, medium, and hard subsets in each graph reasoning task to enable difficulty scaling and fine-grained analysis.
- GraphextQA [98] benchmark is a dataset for open domain question answering. It includes paired subgraphs used to develop and evaluate graph language models. The subgraphs are retrieved from Wikidata and contain reasoning paths from entities mentioned in the questions to the entities that the questions are asking about.
- CS-TAG [99] benchmark is a comprehensive and wide-ranging compilation of benchmark datasets for TAGs. This dataset encompasses a variety of challenging scenarios, ranging from citation networks to purchase graphs. The collection consists of eight distinct TAGs sourced from diverse domains.

We also list which directions these new benchmarks are typically used for. For graph structure understanding, GPR [59], GraphTMI [87], LLM4DyG [25], NLGraph [27], and CS-TAG [99] can be used. For graph learning, CS-TAG [99] can be used. For graph-formed reasoning, GraphextQA [98] can be used. For graph representation, GraphTMI [87], GraphQA [86], and CS-TAG [99] can be used. For KG-based augmented retrieval, GraphextQA [98] can be used.

B. Evaluations

Evaluating the results of different tasks related to LLM-GGA is also a critical issue. Thus, selecting evaluation metrics to assess the results is essential to determining how well LLMs perform their understanding of graphs and how effectively models combining graphs and LLMs perform on various tasks is vital. This section summarizes the metrics of different tasks, shown as Table VII. Note that all test results related to LLMs

TABLE V: A summary of LLM-GGA methods with datasets and source links.

Method	Dataset	LLM	Task	Link
InstrucGLM [78]	ogbn-arxiv, Cora, PubMed	Flan-T5 (instruction-finetune), Llama-v1-7b (LoRA)	Link, Node	code link
GPT4Graph [23]	ogbn-arxiv,Aminer,Wiki,MetaQA	InstructGPT-3(frozen)	Reasoning, Node, Graph	code link
LLMtoGraph [24]	generated by GPTs	GPT-3.5-turbo, GPT-4, Wizard-Vicuna-13B, 30B-Lazarus-Uncensored-HF	Multi-hop Reasoning	code link
Graph-LLM [73]	ogbn-arxiv, Cora, PubMed, ogbn-products	LLaMA, text-ada-embedding-002, Palm-Cortex-001	Node	code link
TAPE [30]	ogbn-arxiv, Cora, PubMed, ogbn-products	GPT-3.5	Node	code link
LLM4DyG [25]	LLM4DyG	GPT-3.5-turbo, Vicuna-7B, Vicuna-13B, Llama-2-13B, CodeLlama-2-13B	Graph	-
GraphGPT [79]	ogbn-arxiv, Cora, PubMed	vicuna-7B-v1.1, vicuna-7B-v1.5	Node	code link
GPPT [80]	Cora, Reddit, CoraFull, Amazon-CoBuy, ogbn-arxiv etc.	-	Link, Node	code link
GraphPrompt [81]	Flickr, PROTEINS, COX2, ENZYMES, BZR	-	Link, Node, Graph	code link
All in one [82]	Cora, CiteSeer, Reddit, Amazon, Pubmed	-	Link, Edge, Node, Graph	code link
Graph-ToolFormer [59]	GPR, Cora, Pubmed, Citeseer, PROTEINS, MUTAG, NCI1, PTC, Twitter, Foursquare	GPT-J-6B	Q&A, Reasoning	code link
RGV [83]	GSM8K, SVAMP, ASDiv-a	GPT-3.5-turbo	math problems	-
LLM-GNN [72]	CORA, CITESEER, PUBMED, WIKICS, OGBN-ARXIV, OGBN-PRODUCTS	GPT-3.5-turbo	Node	code link
Which Modality should I use [87]	Cora, Citeseer, Pubmed,GraphTMI	GPT-4, GPT-4V	Representation, Node	-
WalkLM [38]	PubMed, MIMIC-III, Freebase, FB15K-237	PLMs	Representation, Node, Link	code link
GraphText [37]	Cora, Citeseer, Texas, Wisconsin, Cornell	Llama-2-7B	Node	code link
TALK LIKE A GRAPH [86]	GraphQA	PaLM 2-XXS, PaLM 62B	Node, Link	-
Graph-guided CoT [84]	2WikiMultihopQA, MusiQue, Bamboogle	Llama-2-13B,Llama-2-70B	multi-hop question answering	-
NLGraph [27]	NLGraph	TEXT-DAVINCI-003, GPT-3.5-TURBO, CODE-DAVINCI-002, GPT-4	Link,Node,Graph,Path,Pattern	code link
Collaborative Query Rewriting [94]	opportunity test sets, guardrail test set	Dolly V2	Conversational Understanding	-
WHEN AND WHY [26]	OGBN-ARXIV, CORA, PUBMED, OGBN-PRODUCT, ARXIV-2023	ChatGPT	Node	code link
CR [35]	FOLIO, LogiQA, ProofWriter, LogicalDe-duction	GPT-3.5-turbo, GPT-4, LLaMA-13B, LLaMA-65B	Logic reasoning	code link
SOCIALSENSE [95]	RFPN, Twitter	PLMs	Response Forecasting	code link
DGTL [39]	Cora, PubMed, Books-History	Llama-2-13B	Node	-
SHEGO [96]	SGD, MultiWOZ 2.1	T5-small	multi-domain DST	-
Graph of Thought(GoT) [34]	individual data	GPT3.5(frozen)	Graph-formed reasoning	code link
GLEM [31]	ogbnarxiv, ogbn-products, ogbn-papers100M	PLMs	Node	code link
LPNL [77]	OAG	T5-base	Link	-
SIMTEG [71]	OGBN-Arxiv, OGBN-Products, OGBL-Citation2	PLMs	Node, link	code link
Llmrec [44]	Netflix, MovieLens	gpt-3.5-turbo-16k	Recommendation	code link
ENG [75]	OGB	gpt-3.5-turbo	Node generation	-
OFA [32]	OGBN-ARXIV, CORA	PLMs	Node, link, graph	code link
G-prompt [33]	OGBN-ARXIV, Instagram, Reddit	PLMs	Representation	-
Beyond Text [74]	OGBN-ARXIV, CORA, PubMed	GPT-3.5, GPT-4	Node, link	-
GPT4GNAS [45]	OGBN-ARXIV, CORA, PubMed, Citeseer	GPT-4	Graph neural architecture search	-
Graphllm [64]	NLGraph	Llama2-7B, Llama2-13B	Link, node, graph, path, pattern	code link
G2P2 [85]	Cora, Amazon	PLMs	Representation	code link
ChatGraph [97]	Gradio	GPT-4V, Next-GPT	Link, node, graph, application	-
Graph Agent [76]	Cora, PubMed	GPT-4	Link, node, graph	-
GoT* [36]	AQUA-RAT, ScienceQA	T5-base	Graph-formed reasoning	code link
KGP [93]	HotpotQA, IIRC, 2WikiMQA, MuSiQue, PDFTriage, Rank	Llama	KG+LLM	code link
Head-to-Tail [88]	DBpedia, Movie, Book, Academics	GPT-4	KG+LLM	-
GLaM [40]	DBLP, UMLS	Llama-7B	KG+LLM	-
ToG [41]	CWQ, WebQSP, GrailQA, QALD10-en, etc.	GPT-3.5, GPT-4, Llama-2	KG+LLM	code link
Autoalign [92]	DBpedia, Wikidata	ChatGPT, Claude	KG+LLM	code link
GNP [42]	ConceptNet, UMLS, OpenBookQA, etc.	FLAN-T5 xlarge (3B), xxlarge (11B)	KG+LLM	code link
RoG [43]	WebQSP, CWQ, Freebase	LLaMA2-7B	KG+LLM	code link
KGLens [91]	Wikidata	GPT-3.5-turbo, GPT-4, Babbage-002, Davinci-002, Vicuna-33b-v1.3, Xwin-LM-13B-V0.2, Yi-34B-Chat	KG+LLM	-

TABLE VI: A summary of new datasets.

New Benchmark	Link
GPR [59]	https://github.com/jwzhanggy/Graph_Toolformer/tree/main/data
GraphTMI [87]	To be released
LLM4DyG [25]	To be released
GraphQA [86]	To be released
NLGraph [27]	https://github.com/Arthur-Heng/NLGraph/tree/main/NLGraph
GraphextQA [98]	https://huggingface.co/datasets/drt/graphext-qa
CS-TAG [99]	https://github.com/sktsherlock/TAG-Benchmark

TABLE VII: Evaluations.

Tasks	Metrics
Graph structure understanding task	Accuracy, ROUGE, BLEU, Time cost, Comprehension, Correctness, Fidelity, Rectification Comprehension
Graph learning task	Accuracy, Macro-F1, Training Time, Tuned Parameters, GPU Occupy, Mismatch Rate, Denial Rate, Token Limit Fraction
Graph reasoning task	Accuracy, F1-score, Precision, Recall, The Latency-Volume Trade-off, Number of errors and cost
Graph representation	depending on downstream tasks
KG-based augmented retrieval	Accuracy, F1-score, Precision, Recall,
Graph-LLM-based applications	depending on different tasks

in this paper are conducted using GPT-3.5 turbo or GPT-4 turbo.

1) *Graph structure understanding task.*: Several metrics are usually used in graph structure understanding tasks: accuracy, ROUGE [125], BLEU [126], Time cost, comprehension, correctness, fidelity, and rectification comprehension. Accuracy, ROUGE, BLEU, and time cost are viral metrics. Meanwhile, comprehension, correctness, fidelity, and rectification comprehension are new metrics [24] used to evaluate the ability of LLMs to understand graphs through natural language, the accuracy of solving graph problems, and the level of confidence in the answers provided.

2) *Graph learning task.*: For graph learning tasks, when evaluating a model, various metrics are considered to determine its effectiveness, efficiency, and computational demands. When assessing the effectiveness of a model, metrics such as accuracy, macro-F1, mismatch rate, and denial rate [87] are considered. In terms of efficiency, metrics like training time and tuned parameters are assessed. For computational costs, metrics such as GPU occupancy and token limit fraction are examined. Notably, the token limit fraction indicates the proportion of tokens used compared to the maximum allowed by the model’s constraints and can be formed as follows:

$$T = \frac{\text{Number of usage tokens}}{\text{Token limit constraint for the model}} \quad (6)$$

3) *Graph reasoning task.*: When it comes to graph reasoning tasks, two main factors that are taken into consideration are effectiveness and efficiency. Several metrics are used to assess effectiveness, including accuracy, number of errors and cost, F1-score, precision, and recall [127]. On the other hand, efficiency is evaluated through metrics such as the Latency-Volume Trade-off.

4) *Graph representation.*: The effectiveness of graph representation is typically judged based on the performance of downstream tasks that use this graph representation.

5) *Knowledge graph-based augmented retrieval.*: Tasks in the KG-based augmented retrieval direction typically involve question-answering tasks. Evaluation metrics commonly used include accuracy, precision, recall, F1-score, Hits@k [128], EM [129], MSE, and for some generative tasks, human evaluation may also be utilized.

X. FUTURE DIRECTIONS

The above survey of the state-of-the-art LLM-GGA research reveals a promising and young research field. The following section discusses exciting directions for future work.

A. More Complex Graph Problems

More complex graph tasks. Can LLMs solve graph algorithm problems? Existing works on traditional graph tasks are based on fundamental graph problems such as shortest path, clustering coefficient computing, maximum flow, etc. However, can LLMs address NP problems such as community search, interactive graph problems, or even NP-hard problems, and if so, how can they tackle them? For graph learning tasks, current research primarily focuses on simple node, edge, and graph classification. Future work can focus on more complex graph learning problems, such as the diverse classification outcomes arising from isomorphic and heterogeneous graphs.

More complex graph patterns. Graphs contain various graph patterns, each with its explicit definition and unique characteristics, such as stars, triangles, cliques, butterflies, and more. Therefore, recognizing graph patterns and utilizing their characteristics to solve downstream tasks can be highly advantageous. Currently, only limited works leverage the properties of stars, triangles, and cliques to solve problems.

Furthermore, understanding graph data still remains a significant challenge for existing LLMs, limiting their ability to tackle more complex graph problems. Therefore, incorporating LLMs into the process is a promising direction for solving more complex graph problems.

B. LLM Exploration on Diverse Graphs

Most existing work mainly focuses on static graphs, while there exists a wide range of different graphs, including undirected, directed, cyclic, acyclic, isomorphic, heterogeneous, dynamic, etc. Different types of graphs have significant structural differences, such as static graphs, dynamic graphs, temporal graphs, uncertain graphs, heterogeneous graphs, etc. Specifically, unlike static graphs, dynamic graphs can be represented as ordered lists or asynchronous streams of timed events, capturing patterns of temporal network evolution, such as the addition or removal of nodes and edges. Evaluating the ability of LLMs to understand the spatio-temporal information of dynamic graphs is crucial for web applications. Evaluating whether LLMs can determine when nodes are connected, identify which nodes are connected to a given node at a specific time, and find a chronological path by combining temporal and spatial information is essential to assessing LLMs' understanding of dynamic graphs. Future work can further explore other types of graphs, such as dynamic graphs and temporal graphs, address problems like maximum flow, and predict the evolution of graphs.

Moreover, existing studies have conflicting views on the LLM graph reasoning ability, with some presenting contradictory findings. This ambiguity could be due to various factors, including dataset selection, diverse prompt engineering techniques, the range of graph reasoning tasks, and the utilization of different LLM models.

C. Better LLM-GNN Pipelines

GNNs are designed to handle structural information by continuously learning information from surrounding subgraphs through aggregation functions. On the other hand, LLMs excel in processing textual information, text reasoning, semantic understanding, and more. The challenge lies in leveraging both advantages to enable a pipeline that can effectively handle both attributed and pure graphs. If GNNs and LLMs are simply stacked, the parameter size of GNNs is notably smaller than that of LLMs. This discrepancy may result in the issue of vanishing gradients during training, as mentioned in [130], which can impede the iterative updating process of GNNs. Additionally, GNNs need to utilize the extensive knowledge contained within LLMs fully, and they cannot effectively extract specific knowledge tailored for specific downstream tasks in different graphs.

D. Graph Foundation Model

LLM is undoubtedly the foundational model in NLP. Can we draw inspiration from LLMs to train a graph foundation model? For example, can training strategies like instruction tuning and DPO be applied to tasks involving graphs? The current research has primarily introduced graph foundation models in the form of LLM-GNN pipelines and graph-aware tuning LLMs. Future endeavors can focus on exploring graph foundation models better suited for tasks involving graphs.

E. Better Graph Prompts

Most graph prompts are currently designed based on GNNs, with only a few works focusing on LLMs. Graph prompts for LLMs have yet to be sufficiently explored.

Graph Prompt for GNNs. The typical approach uses simple concatenation, addition, or dot product operations with trainable parameters. Some existing works have considered more complex fusion methods, such as [82], which assumes the structural features of graph prompts. However, compared to the combination of prompts and pretexts, the variety of graph prompts and pre-graphs is still in the exploratory stage.

Graph-enhanced Prompts for LLMs. Relying solely on manual prompts and self-prompting has limited capabilities in improving model performance, as they only explore the existing abilities of LLM. As shown in Section III-C, LLMs can be trained as agents to utilize tools for graph tasks that are hard to solve, like API call prompt [59]. GoT [130] is also a graph reasoning paradigm that enables LLMs to provide correct answers. Future work based on the graph reasoning paradigm can consider cost-effective approaches for GoT, such as pruning and tricks to reduce algorithm complexity. In the future, it would be beneficial to explore simpler GoT paradigms that can improve the effectiveness of LLMs.

F. Modal Alignment

Modal alignment refers to the alignment between two modalities: text and graph. The input for LLMs is typically sequential data, often text. Graph and text are two different modalities, and studying the alignment between these two modalities for LLMs involves finding a shared mapping feature space for graphs and text. The shared mapping space allows LLMs to understand graph data similarly to how they know textual information if they comprehend text.

G. Explainability

GNNs are currently widely used for solving complex graph problems. However, they need more interpretability, which hinders their practical application. On the other hand, LLMs possess reasoning capabilities and have succeeded in various natural language processing tasks. The combination of LLMs and GNNs has the potential to offer a more transparent approach to solving graph problems by leveraging the reasoning abilities of LLMs. If the combination of LLMs and GNNs is interpretable, it can be utilized for various tasks, including recommendation systems, drug discovery, and fraud detection. This combination can lead to the development of more reliable and efficient decision-making systems across various domains.

H. Efficiency on Large-scale Graphs

Due to the limited input length of LLM, the graph sizes inputted through prompts typically consist of dozens of nodes. However, for large graphs with tens of thousands of nodes and edges, how can LLMs with limited input length solve such large graphs? A larger input window is required in the case of attributed graphs, where both node and edge attributes need to be considered along with the graph structure. How does LLM

address this case? There are currently few effective methods to enable LLM to handle them.

XI. CONCLUSIONS

LLM-GGA has emerged as a promising field that has garnered significant attention from researchers. This paper introduces a comprehensive structural taxonomy based on recent research, which classifies LLM-GGA research into three main directions: LLM-GQP, LLM-GIL, and graph-LLM-based applications. LLM-GQP encompasses graph understanding and KG-based augmented retrieval, while LLM-GIL involves graph learning, graph-formed reasoning, and graph representation. The motivation, challenges, and mainstream methods of each direction are thoroughly examined.

For the six mentioned directions, a comparison of various methods was conducted to explore their potential in each area. It is observed that LLM shows preliminary capabilities in structural understanding, addressing issues like maximum flow and bipartite graph matching over small graphs. However, it is susceptible to factors such as node degree and graph density, leading to potential misjudgments in graph connectivity. Additionally, LLM proves beneficial for graph learning tasks due to its strong semantic understanding and reasoning abilities, coupled with learning from extensive corpora, which can provide external knowledge to GNNs and aid in semantic information comprehension, learning, and reasoning. Thanks to LLM's semantic understanding capabilities, graph representation can achieve deeper semantic embeddings. The discussion also delves into KG-based augmented retrieval to enhance LLMs retrieval and factual knowledge-answering abilities. The paper summarizes over 40 datasets, evaluation metrics for six directions, and source code for over 30 mainstream methods in these directions. It highlights the existing challenges in current methods and proposes future directions to guide and motivate further research in the LLM-GGA field.

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