

Rendering Graphs for Graph Reasoning in Multimodal Large Language Models

Project Page: v-graph.github.io

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Abstract

Large Language Models (LLMs) are increasingly used for various tasks with graph structures, such as robotic planning, knowledge graph completion, and common-sense reasoning. Though LLMs can comprehend graph information in a textual format, they overlook the rich visual modality, which is an intuitive way for humans to comprehend structural information and conduct graph reasoning. The potential benefits and capabilities of representing graph structures as visual images (i.e., *visual graph*) is still unexplored. In this paper, we take the first step in incorporating visual information into graph reasoning tasks and propose a new benchmark GITQA, where each sample is a tuple (graph, image, textual description). We conduct extensive experiments on the GITQA benchmark using state-of-the-art multimodal LLMs. Results on graph reasoning tasks show that combining textual and visual information together performs better than using one modality alone. Moreover, the LLaVA-7B/13B models finetuned on the training set (referred to as GITA), achieve higher accuracy than the closed-source model GPT-4(V). We also study the effects of augmentations in graph reasoning.

1. Introduction

Graph reasoning tasks are pivotal in domains such as recommendation systems (He et al., 2020; Wang et al., 2021), social network analysis (Cao et al., 2020; Huang et al., 2021), and knowledge graph reasoning (Zhang et al., 2021; Liu et al., 2022). Various architectures have been developed, from early shallow embedding methods (Bordes et al., 2013; Socher et al., 2013) to advanced Graph Neural Networks (GNNs) (Kipf & Welling, 2016; Xu et al., 2018) and Graph Transformers (Zhang et al., 2020; Kreuzer et al., 2021; Chen

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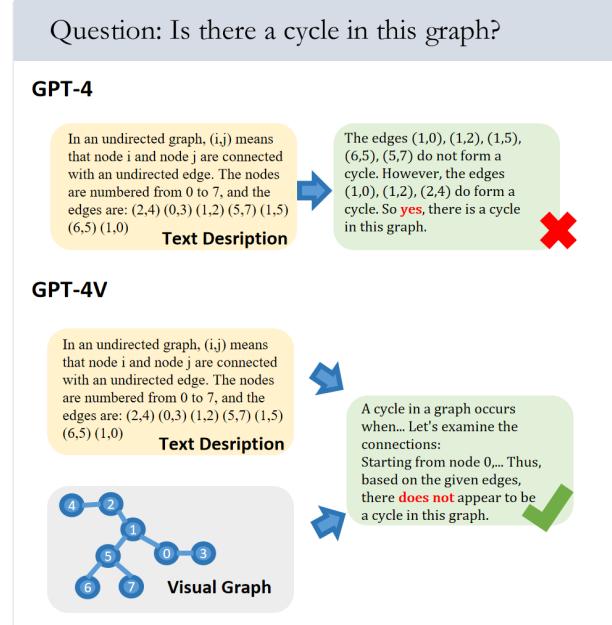


Figure 1. An example of GPT-4’s misjudgment in the cycle detection task, while GPT-4V can answer the question correctly using the additional visual graph.

et al., 2022). Although these models are adept at graph reasoning, they often necessitate domain-specific tuning to reach peak performance, which hinders their generalizability across different tasks without substantial reconfiguration.

In contrast, LLMs have shown a remarkable ability in generalizing across diverse reasoning tasks, from arithmetic (Wei et al., 2022; Yu et al., 2024) to commonsense (Wei et al., 2022; Zhou et al., 2023), with minimal domain-specific adjustments. This versatility has catalyzed investigations into their aptitude for graph reasoning. Recent developments lend credence to the notion that LLMs can indeed interpret and manipulate graph-structured data through textual representations. For example, InstructGLM (Ye et al., 2023), GPT4Graph (Guo et al., 2023), and LLM-toGraph (Liu & Wu, 2023) have successfully converted graphs into textual descriptions. These descriptions, when paired with queries, enable LLMs to generate accurate responses. Furthermore, the introduction of benchmarks such

as GraphQA (Fatemi et al., 2024) and NLGraph (Wang et al., 2023) is a testament to the growing interest in evaluating LLMs’ effectiveness on graph reasoning tasks framed in natural language.

Though many methods and benchmarks have been proposed, they focus on only the textual descriptions and neglect the visual modality. Figure 1 illustrates a failure example in (Wang et al., 2023). Though the textual descriptions are informative, the powerful GPT-4 (OpenAI, 2023a) fails to detect whether a cycle exists in the graph. If rendering the graph as an image, which is called a *visual graph* in this paper, it is very easy for human to answer ‘no’. This reveals the potential aid that visual graphs can offer in the field of graph reasoning. However, the use of visual graphs has been largely overlooked by nearly all existing graph reasoning methodologies, not only those based on LLMs but also including well-established approaches such as GNNs. Our research delves into the novel domain by incorporating “visual graphs” into graph reasoning, and attempt to demonstrate how these visual graphs enhance graph reasoning capabilities of the models, particularly through a series of experiments on Large Language Models (LLMs) and Multimodal Large Language Models (MLLMs).

To begin with, we construct a graph reasoning benchmark within visual contexts called GITQA (Graph-Image-Text Question Answering). The GITQA dataset consists of 423K instances covering eight representative graph reasoning tasks. GITQA has two versions: GITQA-Base and GITQA-Aug. The former contains visual graphs in a single style, while the latter contains visual graphs in various styles by applying targeted style augmentation strategies for visual graphs.

We then conduct extensive experiments on the GITQA benchmark using the state-of-the-art LLMs and MLLMs, including closed-source models (e.g., GPT-4 Turbo (OpenAI, 2023a) and GPT-4V (OpenAI, 2023b)) and open-source models (e.g., Vicuna-7B/13B (Zheng et al., 2023) and LLaVA-7B/13B (Liu et al., 2023)). For both open-source and closed-source models, combining textual and visual modalities achieves higher accuracy (averaged over eight tasks) than a single modality (Figure 2). When discussing the LLaVA-7B and LLaVA-13B models that have been fine-tuned on the GITQA training set, referred to as GITA (Graph-Image-Text Assistant), it’s noted that their capabilities exceed those of GPT-4(V). For most tasks (Connectivity, Topological Sort, Shortest Path, Maximum Flow, Hamilton Path, Graph Neural Networks), using the visual modality alone is worse than the textual modality. For all tasks except Bipartite Graph Matching, increasing the question difficulty (more nodes) leads to worse performance in both open-source and closed-source models.

Furthermore, we conduct experiments to study the effects

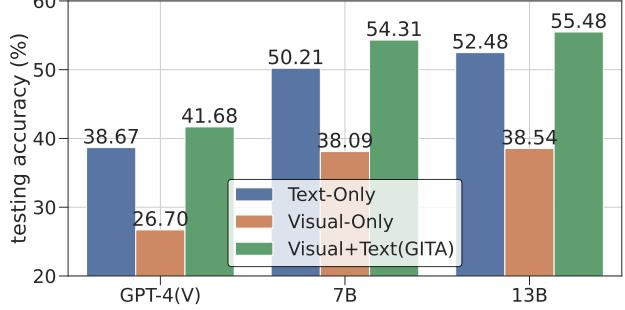


Figure 2. Testing accuracy (averaged over eight graph reasoning tasks) of closed-source models GPT-4(V) and open-source models Vicuna/LLaVA.

of the augmentation strategies with the GITQA-Aug dataset. The results reveal that augmenting the layout of the visual graph significantly enhances its performance on complex graph reasoning tasks such as finding the shortest path and Hamilton path.

Our main contributions are summarized as follows.

- We introduce a graph visualizer to generate visual graphs and propose augmentation methods to generate diverse visual graphs, resulting in a novel multi-modal benchmark GITQA for graph reasoning.
- We conduct extensive experiments to study the effects of visual information on graph reasoning tasks. We find that combining the visual graphs with textual descriptions is better than using a single modality. This observation is consistent for both close-source and open-source models.
- After finetuning the LLaVA-7B/13B models on the training set of GITQA, the fine-tuned models GITA achieve much higher accuracy than GPT-4V.

2. Related Work

Graph Reasoning Graph reasoning (Battaglia et al., 2018; Wu et al., 2020) aims to answer questions based on graphs, which involves utilizing graph structures to guide the reasoning process and reach the correct answers. Graph reasoning has a wide variety of applications in social network analysis (Newman, 2003; Leskovec et al., 2008), bioinformatics (Jeong et al., 2001; Gavin et al., 2006), chemistry (Gilmer et al., 2017), physics (Battaglia et al., 2016), knowledge graph reasoning (Bordes et al., 2013), and recommendation systems (Koren et al., 2009; He et al., 2017) and many methods have been proposed.

Early attempts (Bordes et al., 2013; Socher et al., 2013) learn graph node and edge representations through shallow modules, which suffer from limited expressive power.

Graph Neural Networks (GNNs) like GCN (Kipf & Welling, 2016), GAT (Velickovic et al., 2017), GraphSAGE (Hamilton et al., 2017), MPNN (Gilmer et al., 2017) and GIN (Xu et al., 2018) use message-passing paradigm (Gilmer et al., 2017) to model graph dependencies and update node features. GNNs are not expressive enough due to the over-smoothing issue (Li et al., 2018). Transformer-based graph methods (Zhang et al., 2020; Kreuzer et al., 2021; Chen et al., 2022) further propose using self-attention to increase expressiveness and long-range dependency.

LLMs on Graph Reasoning LLMs have shown promising ability in natural language reasoning tasks, e.g., mathematical problems (Wei et al., 2022; Yu et al., 2024), or commonsense reasoning problems (Fu et al., 2023; Zhou et al., 2023). To use LLMs in graph reasoning, (Ye et al., 2023; Wenkel et al., 2023; Creswell et al., 2023; Wei et al., 2023; Guo et al., 2023; Liu & Wu, 2023) transform a graph into textual descriptions, which are concatenated with the instructions and fed to LLMs for querying its answer. For example, InstructGLM (Ye et al., 2023) uses natural language to describe the graph and proposes instruction prompts to fine-tune the LLM. Wenkel et al. (2023) further study if LLMs can learn from graph-structured data described by natural language and data augmentation in the graph domain. He et al. (2024) apply LLMs to explain graphs for training GNNs, while Chen et al. (2023) treat LLMs as enhancers to exploit text attributes or as predictors for node classification on text-attributed graphs. GPT4Graph (Guo et al., 2023) and LLMtoGraph (Liu & Wu, 2023) also conduct extensive experiments by converting graphs into specific code or natural language formats by the powerful ChatGPT (OpenAI, 2022; 2023a).

GraphQA (Fatemi et al., 2024) and NLGraph (Wang et al., 2023) are two recently proposed benchmark datasets for graph reasoning tasks using natural language. Our GITQA dataset is built on the NLGraph dataset but different from existing benchmark datasets on graph reasoning, our GITQA dataset is a multimodal benchmark dataset for graph reasoning by involving both the visual and textual modalities of the graph data.

Multimodal Large Language Models Multimodal Large Language Models (MLLMs) have significantly expanded the cognitive functions of traditional Large Language Models (LLMs) by integrating visual modalities to address vision-language tasks. Combining LLMs with the visual modality to achieve efficient collaborative reasoning is the core challenge for Visual MLLMs and many methods have been proposed. Some early explorations in Visual MLLMs like Flamingo (Alayrac et al., 2022), CLIP (Radford et al., 2021), and BLIP-2 (Li et al., 2023) use a visual encoder for processing images and align visual and textual embed-

dings. Subsequent models like LLaVA (Liu et al., 2023) and MiniGPT-4 (Zhu et al., 2023) combine visual and textual inputs in a single LLM for solving multimodal tasks. InstructBlip (Dai et al., 2023) proposes an instruction-aware query transformer and trains a vision-language model by instruction tuning. However, despite progress in a wide range of vision-language tasks (Zhang et al., 2024), using visual information in graph reasoning remains an overlooked and insufficiently explored area. Our work takes an important first step in this field, pushing the boundaries of MLLMs capabilities in graph reasoning.

3. Construction of Visual Graphs

In this section, we propose a graph visualizer to construct the visual graph with varying styles for a given graph $G = (V, E)$, where V and E denote the sets of nodes and edges, respectively.

The visual graph of a graph satisfies the following properties: (i) It has a white backdrop; (ii) Its maximum dimension is of 8×8 inches; and (iii) It has consistent node size. (iv) The node attributes and edge weights, which are optional, could be annotated as follows: node attributes are annotated below the nodes, while edge weights are annotated near the edges in the form of labels. Moreover, annotations share the same color as the corresponding nodes or edges.

We adopt the Graphviz graphics library (Gansner & North, 2000) in our graph visualizer to create visual graphs from graphs. To make the created images diverse, we change four configuration properties (i.e., layouts, node shape, node style, and edge thickness) in Graphviz such that visual graphs could have different styles.

- **Layout:** Six optional layout engines (i.e., dot, neato, circo, fdp, sfdp, and twopi) can be selected for the layout. For each layout, the graph visualizer could automatically determine positions of nodes and edges, thereby shaping each visual graph according to specific rules and algorithms.
- **Node Shape:** Three optional shapes (i.e., ellipse, circle, and box) can be selected for nodes. Each shape provides a unique visual representation, influencing the overall appearance of nodes.
- **Node Style:** Nodes have four optional styles: filled, dotted, bold, and dashed. Each style provides a unique visual effect.
- **Edge Thickness:** Four levels of thickness (i.e., 1.0, 2.0, 4.0, and 8.0) can be used for edges. The thickness of an edge can affect the visual emphasis and clarity of connections within the visual graph.

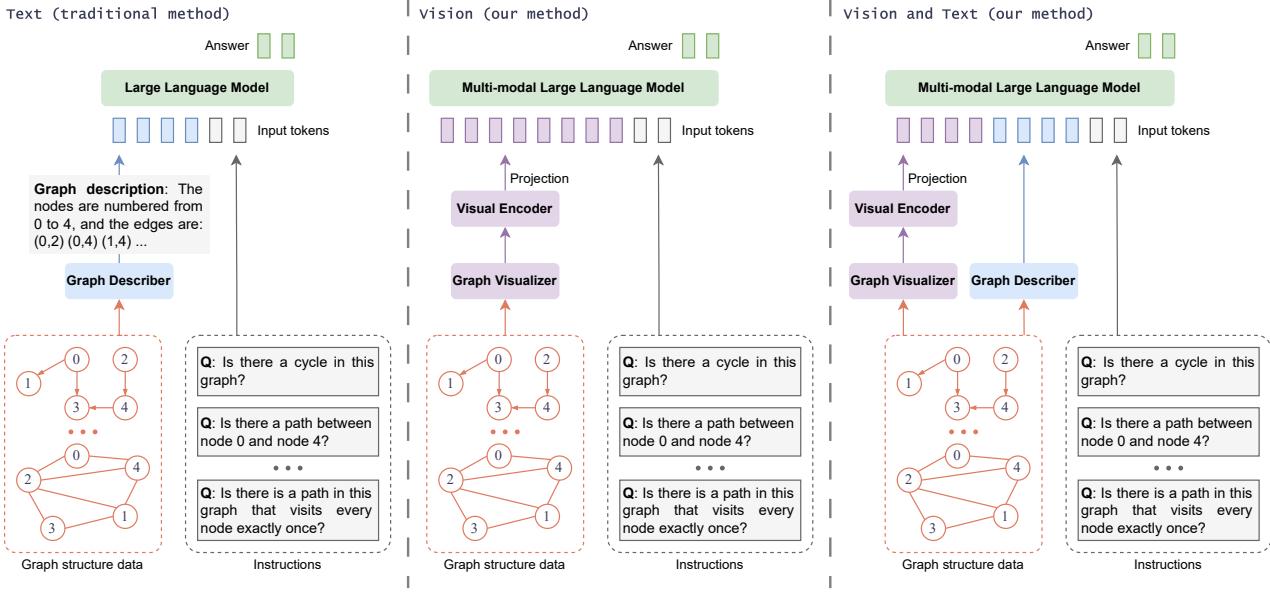


Figure 3. Comparison using different types of data to conduct graph reasoning tasks.

Detailed explanations of each configuration are provided in Appendix C.1.1. In total, the visual graph of a graph $G = (V, E)$ could have 288 different styles (i.e., 6 layouts \times 3 node shapes \times 4 edge thickness = 288). However, not all style combinations are valid, since some styles lead to images that are difficult to interpret, such as overly compact layouts or overlapping nodes and edges. Furthermore, augmenting each visual graph with 288 styles will generate a huge dataset, which causes a heavy burden on computations in finetuning the MLLMs and expense in querying closed-source models such as GPT-4V. As a result, our GITQA only contains 14 out of these 288 style combinations.

4. GITQA: A Benchmark for Graph-Image-Text Question Answering

In this section, we introduce the constructed GITQA benchmark dataset for graph reasoning.

4.1. Overview

The GITQA dataset is built on the NLGraph-full dataset (Wang et al., 2023). In the NLGraph-full dataset, only a subset of these graph structures are supplemented with textual descriptions. To fill this gap, we use a set of templates (called the *graph describer*) to generate textual descriptions for each sample within the GITQA dataset. Further details about the graph describer can be found in Appendix C.3.

In the GITQA benchmark, we use the graph visualizer introduced in Section 3 to create the corresponding visual graph for each graph. As a consequence, each sample in the

GITQA dataset contains four components: (i) graph structural information including the number of nodes, the number of edges, and the adjacency matrix; (ii) textual description; (iii) the corresponding visual graph; (iv) question-answer pair. Hence, the GITQA benchmark contains two modalities: textual descriptions and visual graphs. Both modalities independently provide complete information about the graph. As illustrated in Figure 3, the model can use textual descriptions, visual graphs, or both for solving graph reasoning tasks.

The GITQA dataset includes two versions: GITQA-Base and GITQA-Aug. GITQA-Base contains images with a specific style, whose layout engine, node shape, node style, and edge thickness are set to dot (or neato for bipartite tasks), ellipse, filled, and 1.0, respectively. Given a default style combination S in GITQA-Base (i.e., layout = dot, node shape = ellipse, edge thickness = 1.0, node style = filled), GITQA-Aug includes all style combinations that differ from S by no more than one attribute. Therefore, GITQA-Aug encompasses a total of 14 distinct styles of images, yet it covers all of the 6 layouts, 3 node shapes, 4 edge thicknesses, and 4 node styles introduced in Section 3. Examples of visual graphs with the 14 styles are provided in Appendix C.2.

4.2. Graph Reasoning Tasks

Following NLGraph-full (Wang et al., 2023), the proposed GITQA benchmark contains eight graph reasoning tasks. Figure 4 provides an overview of those tasks and the details are introduced as follows.

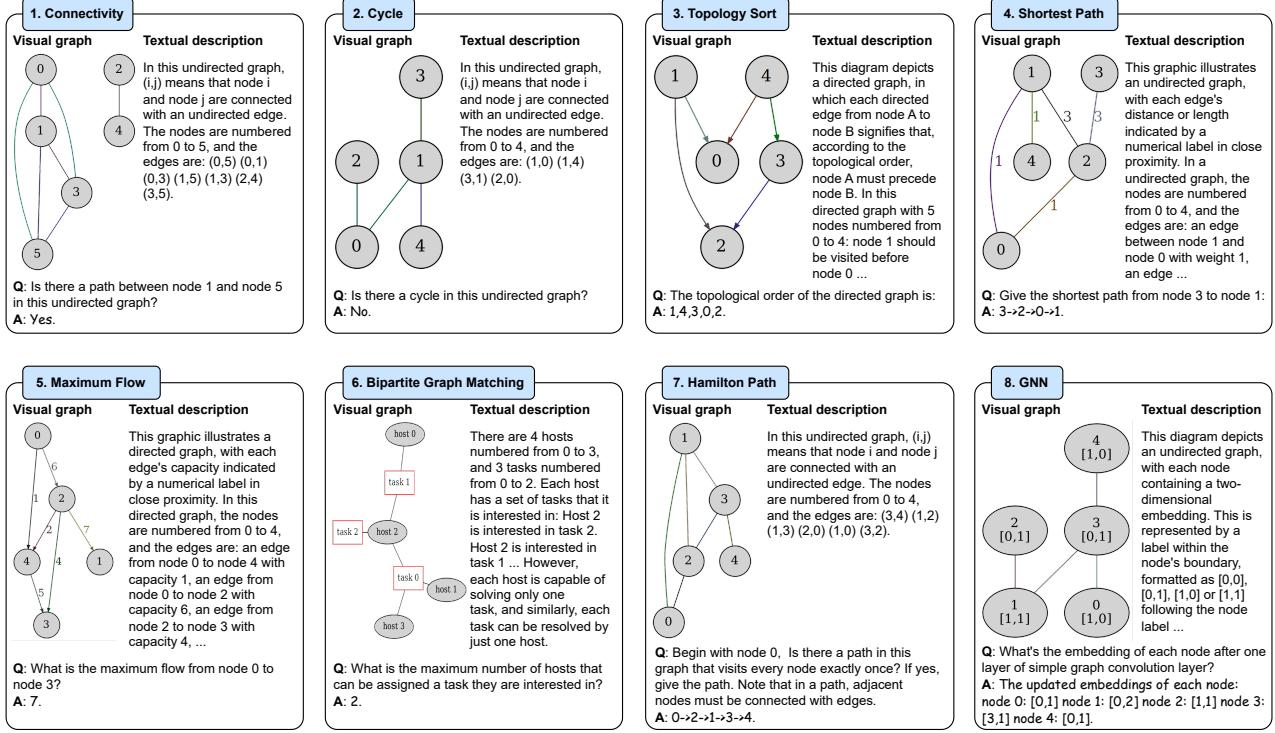


Figure 4. An overview of the GITQA benchmark. Each figure illustrates a graph reasoning task with a visual graph, textual description, and a question-answer pair.

Table 1. Statistics of the GITQA benchmark. A / B represents that there are A and B samples in GITQA-Base and GITQA-Aug, respectively. SPEC. denotes the difficulty specification, where n denotes the number of nodes in graphs.

Subset	Connectivity	Cycle	TS	SP	MaxFlow	BMG	HP	GNN
# EASY SPEC.	730 / 13.14K n: 5-10	300 / 5.4K n: 5-10	360 / 6.48K n: 5-10	360 / 6.48K n: 5-10	300 / 5.4K n: 5-10	600 / 10.8K n: 6-20	300 / 5.4K n: 5-10	200 / 3.6K n: 5-8
# MEDIUM SPEC.	8,580 / 154.44K n: 11-25	1,800 / 32.4K n: 11-25	1,350 / 24.3K n: 11-25	/	/	/	/	/
# HARD SPEC.	7,090 / 127.62K n: 26-35	2,000 / 36K n: 26-35	1,200 / 21.6K n: 26-35	1,200 / 21.6K n: 11-20	1,200 / 21.6K n: 11-20	1,260 / 21.6K n: 17-33	600 / 10.8K n: 11-20	840 / 15.12K n: 9-15

- **Connectivity** (Sedgewick, 2001): This task is to determine whether two randomly selected nodes u and v in an undirected graph are connected (i.e., two nodes are connected if there exists a path that connects them) with candidate answers including True and False. The corresponding dataset is label-balanced, i.e., half of the questions have true answers as True (connected), and the true answers to the others are False (disconnected).

- **Cycle** (Sedgewick, 2001): This task is to identify whether a cycle exists in an undirected graph with candidate answers including True and False. Similar to the Connectivity task, the corresponding dataset in the Cycle task are also label-balanced.

- **Topological Sort** (Kahn, 1962) (denoted by TS): This task is to find a valid topological sorting for a directed

acyclic graph. Here a topological sorting is to output a linear ordering of nodes such that for every directed edge $u \leftarrow v$, node u comes before v in the ordering. The answer can be verified by an external program and there may be multiple correct answers. It is guaranteed that each graph in this task contains at least one legitimate topological ordering.

- **Shortest Path** (Dijkstra, 1959) (denoted by SP): This task is to find the shortest path between two nodes in a weighted undirected graph, where the shortest path between two nodes is the path connecting the two nodes with the minimum total sum of edge weights along the path. The prediction is evaluated in the exact match with the shortest path.

- **Maximum Flow** (Ford & Fulkerson, 1956) (denoted

by MaxFlow): This task is to calculate the maximum possible flow from a source node to a sink node in a network graph. The prediction is correct if it exactly matches the ground truth.

- **Bipartite Graph Matching** (Karp et al., 1990) (denoted by BGM): This task is to find a matching set in a bipartite graph that has the largest number of edges, where a matching set is a collection of edges in which no two edges share any common node. An external program can verify the correctness of answers.
- **Hamilton Path** (Gould, 2003) (denoted by HP): This task is to find a valid Hamilton path in an undirected graph, where a Hamiltonian path is a path that traverses each node in a graph exactly once. The correctness of the solution is externally verified. It is guaranteed that each graph in the dataset contains at least one legitimate Hamilton path for each query.
- **Graph Neural Networks** (Scarselli et al., 2008) (denoted by GNN): This task is to calculate the node embedding through l layers of message passing update in an undirected graph with two-dimensional node embeddings.

The aforementioned eight graph reasoning tasks cover five representative graph reasoning scenarios: (i) “Cycle” task represents intrinsic structure tasks, which focus on the basic and inherent structural characteristics of graphs. (ii) “Bipartite Graph Matching” task exemplifies optimization tasks that leverage global graph structure to find optimal solutions. (iii) “Topological Sort” and “Hamilton Path” tasks represent sequential decomposition tasks, requiring specific traversal of nodes or edges to decompose the graph. (iv) “Connectivity”, “Maximum Flow”, and “Shortest Path” tasks illustrate path query tasks, querying attributes or relationships of paths between node pairs in the graph. (v) “Graph Neural Networks” task represents message-passing tasks that update node attributes by passing messages in the graph.

The above categorization tasks highlight the core challenges and features of graph reasoning tasks. Thus for other graph reasoning tasks out of the GITQA benchmark, we can use this categorization to analogize similar tasks with those eight tasks to gain insights.

4.3. Benchmark Statistics

Following (Wang et al., 2023), we further categorize the datasets into different difficulty levels (i.e., easy, medium (for connectivity, cycle, and topological sort), and hard) for each task based on the number of nodes and graph sparsity. Table 1 summarizes the benchmark statistics. The default evaluation metric is the accuracy, which considers whether the answer is correct.

5. Experiments

In this section, we conduct empirical evaluations on the proposed GITQA benchmark.

5.1. Experimental Settings

Here we provide a detailed description of the experimental settings, including baselines, training procedures, and evaluation.

Baselines. We adopt a wide range of models to investigate their performance on the proposed GITQA benchmark. Specifically, in Section 5.2, we test zero-shot performance of the closed-source LLM GPT-4 Turbo (OpenAI, 2023a) and closed-source MLLM GPT-4V (OpenAI, 2023b) on the GITQA-Base testing set. Furthermore, we fine-tune the open-source LLMs, including Vicuna-7B (Zheng et al., 2023) and Vicuna-13B (Zheng et al., 2023), as well as open-source MLLMs, including LLaVA-7B (Liu et al., 2023) and LLaVA-13B (Liu et al., 2023), on the GITQA-Base training set and assess their performance on the testing set. This allows for a comparison between the textual and visual modalities and explore their relationship. In Section 5.3, we delve into the study of augmentation strategies and the preferences for image styles in visual graphs, utilizing the LLaVa-7B model (Liu et al., 2023).

Training and Evaluation Settings. During the evaluation, the temperature is set to 0 for all baselines. During training, we use a batch size of 128 and adopt the AdamW optimizer (with a learning rate of 0.00002 and 0.000002 for the text decoder and vision-to-text projector, respectively). All fine-tuning experiments are conducted on an NVIDIA DGX station with 8×A100 GPUs. We split the GITQA dataset in the ratio of 7:3 for training and testing, respectively. We adopt the accuracy (%) as evaluation metric, i.e., comparing the prediction and ground truths by exact matching.

We use the next-token-prediction loss to fine-tune the LoRA (Hu et al., 2021) adapters of LLMs and the vision-to-text projector. Visual graphs are encoded as visual embeddings by a visual encoder. Visual embeddings are concatenated with the embeddings of textual descriptions and instructions (i.e., questions), then fed to the text decoder to generate the answer.

5.2. Performance Comparisons in Graph Reasoning

We compare the closed-source LLMs/MLLMs and open-source LLMs/MLLMs finetuned on the training set for different modalities of inputs: “T-only” means that only the textual description is used for graph reasoning, “V-only” means that only the visual graph is used, and “V+T” means that both modalities are used.

Table 2. Accuracies (%) on eight graph reasoning tasks.

Models	Connectivity	Cycle	TS	SP	MaxFlow	BGM	HP	GNN	Avg
GPT-4 Turbo (T-only)	81.74	48.99	33.14	42.88	10.14	42.43	50.00	0.00	38.67
GPT-4V (V-only)	64.40	64.67	13.25	8.97	2.70	45.74	13.89	0.00	26.70
GPT-4V (V+T)	84.67	56.01	31.27	45.37	10.00	51.78	54.17	0.15	41.68
Vicuna-7B (T-only)	97.92	94.88	43.40	32.30	12.92	88.59	31.67	0.00	50.21
LLaVA-7B (V-only)	71.41	96.75	28.17	11.75	4.31	91.21	1.11	0.00	38.09
GITA-7B (V+T)	99.16	96.68	49.87	39.20	23.34	91.49	34.72	0.00	54.31
Vicuna-13B (T-only)	99.60	93.76	45.98	35.56	14.59	90.65	39.72	0.00	52.48
LLaVA-13B (V-only)	69.60	97.16	30.11	12.39	5.56	91.49	2.50	0.00	38.54
GITA-13B (V+T)	99.31	95.59	47.93	47.82	24.17	90.40	38.61	0.00	55.48

Table 3. Accuracies (%) of closed-source and open-source LLMs and MLLMs for different difficulty levels.

Models	Connectivity			Cycle			TS			SP		MaxFlow		BGM		HP	
	Easy	Medium	Hard	Easy	Medium	Hard	Easy	Medium	Hard	Easy	Hard	Easy	Hard	Easy	Hard	Easy	Hard
GPT-4 Turbo (T-only)	94.09	79.49	71.64	47.78	48.52	50.67	77.98	21.43	0.00	56.88	28.89	15.56	4.72	43.33	41.53	58.89	41.11
GPT-4V (V-only)	80.00	58.28	54.93	67.78	65.56	60.67	38.53	1.23	0.00	16.51	1.39	4.55	0.85	43.33	48.15	23.33	4.44
GPT-4V (V+T)	90.00	85.00	79.01	67.78	49.26	51.00	67.89	23.15	0.29	59.63	31.11	16.66	3.33	50.56	52.99	66.67	41.67
Vicuna-7B (T-only)	98.63	97.90	97.23	94.44	95.37	94.83	75.23	52.46	2.22	44.04	20.56	18.89	6.94	81.67	95.50	50.00	13.33
LLaVA-7B (V-only)	99.09	64.02	51.13	97.78	96.48	96.00	76.15	8.37	0.00	22.94	0.56	6.67	1.94	86.11	96.30	1.11	1.11
GITA-7B (V+T)	99.55	99.15	98.78	96.67	97.04	96.33	82.57	63.23	3.80	52.29	26.11	28.89	17.78	86.67	96.30	51.11	18.33
Vicuna-13B (T-only)	100.00	99.22	99.58	92.22	93.89	95.17	79.82	55.91	2.22	48.62	22.50	20.00	9.17	85.00	96.30	54.44	25.00
LLaVA-13B (V-only)	97.73	62.47	48.59	97.78	97.04	96.67	80.73	9.61	0.00	24.77	0.00	6.67	4.44	86.67	96.30	4.44	0.56
GITA-13B (V+T)	99.55	99.22	99.15	95.56	95.53	95.67	81.65	57.64	4.49	61.47	34.17	30.00	18.33	85.56	95.24	54.44	22.78

V+T performs the best. Table 2 summarises the testing results on all eight graph reasoning tasks. For closed-source models, GPT-4V (V+T) achieves a much higher accuracy (averaged over eight tasks) than GPT-4 Turbo (T-only) and GPT-4V (V-only). For open-source models (7B, 13B), similarly, using both data modalities performs the best on average. These observations verify that using both visual and textual information benefits the models’ graph reasoning abilities, leading to better performance than single-modal models (T-only or V-only). Moreover, it can be seen that GITA-13B (V+T) performs better than GITA-7B (V+T), showing that a larger model size is better. Interestingly, both finetuned GITA-7B and GITA-13B models show remarkable performance improvements of over 13% compared to GPT-4V. This substantial margin of improvement demonstrates that our finetuned models can learn effectively from the proposed dataset and yield more promising results.

More specifically, GITA-7B (V+T) outperforms LLaVA-7B (V-only) and Vicuna-7B (T-only) on all tasks except CyCle (which is also comparable). While for closed-source models, using both modalities achieves the highest accuracy on five tasks (i.e., Connectivity, Shortest Path, Bipartite Graph Matching, Hamilton Path, and GNN). Note that the GNN task is very challenging for all closed-source and open-source models.

Comparison between T and V. From Table 2, for both open-source and closed-source models, we can see that using the visual modality alone is worse than using the textual modality alone on average. Nevertheless, the visual modality performs better than the textual modality on the Cycle and BGM tasks but loses on the other five tasks (i.e., Connectivity, TS, SP, MaxFlow, HP). This suggests the advantages of these two types of single-modal models in handling specific types of graph reasoning tasks.

Analysis of Different Difficulty Levels. Table 3 shows the testing accuracies of open-source and close-source models on different difficulty levels of the seven tasks (GNN is omitted here as it is too challenging for all models). For the Cycle and BGM tasks across all levels, using the visual modality alone is better than the textual modality and achieves comparable performance as using both modalities. However, for the other tasks (such as Connectivity, TS, SP, MaxFlow, HP), the performance of V-only models decline significantly when the difficulty increases from easy to medium or hard. Similarly, the T-only and V+T models also suffer a large performance drop when the difficulties of TS, SP, MaxFlow, and HP increase. Regarding the Connectivity task, both GITA-7B (V+T) and GITA-13B (V+T) demonstrate comparable performance across all three challenging levels. However, this consistent pattern is not observed in GPT-4V (V+T), as its performance shows a decline with

Table 4. Performance (%) comparisons between the GITQA-base and GITQA-Aug datasets, which consist of a total of 14 styles including the base style. ↑ and ↓ represent the significant increase and decrease of performance, respectively. † denotes the collapsed performance.

	Connectivity	Cycle	TS	SP	MaxFlow	BGM	HP	GNN	Avg
GITQA-base	71.74	96.75	28.17	11.75	4.31	91.21	1.11	0.00	38.13
GITQA-Aug (6 layouts)	50.65 †	97.07	4.11 ↓	76.55 ↑	2.44	91.94	70.74 ↑	0.00	49.19
GITQA-Aug (3 node shapes)	50.24 †	96.75	14.17 ↓	6.61 ↓	3.78	91.58	1.48	0.00	33.08
GITQA-Aug (4 edge thickness)	50.20 †	96.91	13.37 ↓	5.97 ↓	3.11	91.76	0.74	0.00	32.76
GITQA-Aug (4 node styles)	49.70 †	96.50	14.29 ↓	5.54 ↓	2.22	92.83	1.11	0.00	32.77

Table 5. Performance (%) comparisons among different image-augmentation styles in the GITQA-Aug dataset, which includes a total of 14 styles. All results are the average of eight tasks.

[?, ellipse, 1.0, filled]	dot	neato	circo	fdp	sfdp	twopi			
	49.48	50.58	49.76	50.16	49.64	50.63			
[dot, ?, 1.0, filled]	ellipse	circle	box						
	33.08	32.06	33.23						
[dot, ellipse, ?, filled]	1.0	2.0	4.0	8.0					
	32.76	32.60	32.71	32.52					
[dot, ellipse, 1.0, ?]	filled	dotted	dashed	bold					
	32.77	32.52	32.53	32.57					

increasing difficulty.

5.3. Study on Image Augmentation and Style Preferences

In this section, we conduct experiments to study the effect of different augmentation strategies and styles of visual graphs in finetuning open-source models.

First, we derive four distinct subsets from GITQA-Aug, each designed to focus on a specific aspect of visual graph augmentation: layout, node shape, edge thickness, and node style. The layout augmentation set comprises samples in which the visual graphs differ only in their layout while maintaining the default style settings (namely, layout as dot, node shape as ellipse, edge thickness at 1.0, and node style as filled) for the other attributes. In a similar fashion, we extract additional augmentation sets dedicated to node shape, edge thickness, and node style from GITQA-Aug, each set isolating and varying one attribute while keeping the others constant.

Next, we fine-tune a LLaVA-7B model (Liu et al., 2023) using each augmented dataset independently. To ensure a fair comparison of the effectiveness of different augmentation strategies (e.g., layouts and node shapes), all results of Table 4 are assessed on the GITQA-Base test set. In this context, ‘GITQA-Base’ denotes the baseline performance without any augmentation. The labels ‘6 layouts’, ‘3 node

shapes’, ‘4 edge thickness’, and ‘4 node styles’ correspond to the finetuning results of models on datasets augmented with variations in layout, node shape, edge thickness, and node style, respectively.

From the results shown in Table 4, it is evident that the layout augmented set significantly enhances the performance of challenging tasks (such as SP and HP). Conversely, other augmented sets exhibit a noticeable decline in performance. To elaborate, the models achieve superior results on the GITQA-Aug (6 layouts) set, surpassing the GITQA-Base set by over 11%. In contrast, the average results across the eight tasks in the other augmented sets are approximately 5% lower than the base set. These findings suggest that the layout augmented set provides more effective visual perspectives for graph reasoning comprehension. This observation may suggest the potential for future expansion in constructing more extensive and effective visual graph datasets. However, we have observed collapsed results in the Connectivity task for all augmented sets, as the models demonstrate a performance comparable to random guessing (i.e., about 50%). This decline could potentially be attributed to the fact that the parameter size of the LoRA adapters mismatches its enormous number of samples, as presented in Table 1. Besides, the performance decline observed on specific tasks when using augmented datasets may be attributed to the lack of fine-tuning of the visual encoder.

Furthermore, we analyze the difference among various image-augmentation styles within each augmentation group, as shown in Table 5. Based on the results obtained, we do not find an obvious style preference of visual graphs.

6. Conclusion

In this paper, we proposed a novel multimodal graph reasoning benchmark GITQA, which contains the visual and textual contexts. We conducted experiments to study the effects of visual information on graph reasoning. Extensive results show that combining visual and textual modalities outperforms using only a single modality. Moreover, the GITA models finetuned on the training set of GITQA dataset can achieve much higher accuracy than GPT-4V. Besides, Both GPT-4V and LLaVA fail on the challenging GNN task.

Future work will focus on improving the reasoning ability of MLLMs to solve the GNN task.

Broader Impact and Ethics Statements

This paper presents a novel method for using visual information in solving graph reasoning tasks. Our goal is to advance the field of machine learning. There is no concern about ethical considerations and data privacy.

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A. Discussions

Encourages more general and robust MLLM. The complete GITQA dataset serves as a valuable resource for augmenting the graph reasoning capabilities of models, facilitating the development of more general and robust multimodal large language models. By providing a diverse array of graph-related questions and answers, along with corresponding textual descriptions and visual representations, GITQA enables a multifaceted approach to learning. This comprehensive dataset not only challenges models to understand and interpret complex graph structures but also pushes the boundaries of how these models integrate and reason across different modalities. The resulting advancements contribute to the evolution of models that can navigate and make sense of the intricate interplay between visual and textual information, mirroring the multifaceted nature of human cognition.

GITQA in NLP and VQA. Though the GITQA benchmark was initially conceived to assess the ability of models to process visual graph representations and their interaction with textual modalities. Nonetheless, the design of GITQA incorporates both graph text descriptions and visual graphs that independently provide complete information of the graph, endowing GITQA with the capacity to serve multiple roles across different domains. For Natural Language Processing (NLP), the text descriptions and question-answer pairs in GITQA can be utilized as a dataset to investigate how models can answer graph-related questions based solely on text. In the realm of Computer Vision, the visual diagrams and associated question-answer pairs in GITQA can function as a vision-language dataset, akin to Visual Question Answering (VQA) tasks (Antol et al., 2015), to explore how models can leverage visual information to respond to questions about graphs.

Tuning vision encoder align to visual graphs. To advance the graph reasoning proficiency of Vision MLLMs, we plan to further refining the vision encoder to specialize in visual graph data interpretation in future work. Current models, such as LLaVA (Liu et al., 2023) and InstructBlip (Dai et al., 2023), are optimized for natural scene images, which enables their encoders to excel at capturing features within those contexts. By contrast, a vision encoder fine-tuned for visual graphs is anticipated to reveal distinctive features specific to graph imagery, thereby enhancing the model’s graph reasoning performance. This specialized tuning of the encoder is poised to shed light on the synergies between visual perception and graph analysis in multimodal machine learning paradigms.

B. Limitations and Future Works

Inadequacy in Processing Large-Scale Visual Graphs While the GITQA benchmark stratifies queries into different levels of difficulty based on the complexity of the graphs, the most complex graphs involved do not exceed 35 nodes. However, graphs in the real world, such as social networks (Kwak et al., 2010; Viswanath et al., 2009) and knowledge graphs (Suchanek et al., 2007; Bordes et al., 2013), are often much larger and more complex, potentially comprising thousands of nodes. For such large-scale graph data, existing graph-structured processing approaches commonly address this by extracting subgraphs. Within this framework, employing graph visualization tools to create visual representations of subgraphs is a promising approach. Yet, devising more scalable strategies for visual graphs, enabling models to remember and understand the relationships between different visual subgraphs to enhance their reasoning capabilities for large-scale graphs, remains an area for further exploration.

Incomplete Range of Graph Reasoning Tasks in GITQA In GITQA benchmark, we have included eight graph reasoning tasks that encompass five distinct graph reasoning scenarios. However, many other crucial graph algorithms exist that challenge various facets of graph reasoning skills. Exploring the capabilities of Large Language Models (LLMs) on additional graph-related tasks, such as graph coloring, calculating the minimum spanning tree, and solving the Traveling Salesperson Problem (TSP), could provide intriguing insights.

C. GITQA Details

C.1. Details of Visual Graph Styling Configurations

In this section, a detailed introduction is presented, introducing the various image style configurations available in the graph visualizer 3. We will discuss the six distinct layout engines, the three available node shapes, the four edge thickness levels range, and the quartet of node styles. These configurations are predefined and adopted from the Graphviz tool (Gansner & North, 2000). A more intuition illustration of each style of visual graphs can be viewed in Appendix C.2. For further details, readers are encouraged to consult the cited Graphviz literature (Gansner & North, 2000) or to refer directly to the Graphviz

official documentation.

C.1.1. LAYOUT ENGINE DETAILS

Each of the six layout engines: dot, neato, circo, fdp, sfdp, and twopi, implements a distinct algorithm designed to position nodes and edges in a graph according to specific principles and aesthetics. A detailed introduction for the six layout engines is as follows:

- **dot**: Primarily used for hierarchical layouts of directed graphs. It attempts to minimize edge crossings and maintain the direction of edges from top to bottom or left to right. It is well-suited for representing organizational structures or flowcharts.
- **neato**: Employs a "spring model" layout, also known as a force-directed layout. It simulates edges as springs and nodes as repelling entities, finding an optimal arrangement by simulating these forces. It is suitable for undirected graphs and network relationships.
- **circo**: Produces circular layouts, placing nodes in a ring to minimize edge crossings. This layout is suitable for highlighting cyclic structures, such as in electronic circuits or in advanced abstract syntax trees.
- **fdp**: A variant of neato, also based on the "spring model," but more efficient for laying out large graphs. Fdp optimizes for speed and simplifies the layout algorithm, though it may not distribute nodes as evenly as neato.
- **sfdp**: An extension of fdp, designed for large graphs. It uses a multi-level force-directed algorithm that can handle thousands of nodes more quickly while maintaining the characteristics of a force-directed layout.
- **twopi**: Generates radial layouts, with nodes placed on concentric circles around a central node, similar to a solar system structure. It is suitable for showcasing tree-like structures or hierarchical networks.

C.1.2. NODE SHAPES

Each of three node shape configurations: ellipse, box, and circle, can be used to represent different types of entities or to emphasize certain aspects of the data. A detailed introduction for the three node shapes is as follows:

- **ellipse**: The default shape for nodes. Ellipses are useful for text-heavy nodes as they provide ample space for labels. They are versatile and can be used in almost any type of graph.
- **box**: These are rectangles with sharp corners. Boxes are often used to represent nodes that are procedural or data-rectangular in nature, like records in a database or steps in a process.
- **circle**: Circles are used when the focus is more on the connections between nodes rather than the nodes themselves. They provide a compact and uniform look, which can be visually pleasing in graphs where all nodes are of similar importance.

C.1.3. EDGE THICKNESS

The edge thickness in a graph can convey the strength or weight of the connection between nodes. A detailed introduction for the four levels of edge thickness is as follows:

- **1.0**: A thin line, suitable for graphs with many edges or when the emphasis is more on the nodes than on the edges.
- **2.0**: A medium-thin line, which stands out more prominently than the thinnest option without being too obtrusive.
- **4.0**: A medium-thick line, useful for highlighting more important connections in the graph without overwhelming the overall layout.
- **8.0**: A thick line, best used for emphasizing the most significant relationships in the graph. This thickness level is especially useful when a graph contains a hierarchy or a flow of importance among the connections.

C.1.4. NODE STYLE

The style of a node can affect the visual impact of the graph and can help to convey additional meanings. A detailed introduction for the four node styles is as follows:

- **filled:** A style where the interior of the node is filled with color. This is useful for making certain nodes stand out or for categorizing nodes into different groups based on color-coding.
- **dotted:** Nodes with a dotted outline. This style can indicate a tentative or conditional status within the graph, or differentiate a subset of nodes from others.
- **dashed:** Similar to dotted, but with dashes instead of dots. This style can also be used to denote incomplete or in-progress elements within the graph.
- **bold:** Nodes with a bold outline have a more pronounced presence in the graph, which can be used to highlight key elements or to denote nodes of particular importance.

These configurations allow users to customize the appearance of their graphs to best represent the underlying data and to highlight the most important aspects of that data. The choice of layout engine, node shape, edge thickness, and node style can greatly affect the readability and interpretability of the graph.

C.2. Visual Graph Styles illustration

As mentioned earlier, GITQA-Base is founded on a fundamental style that utilizes the configuration [dot (neato for bipartite graph matching), ellipse, 1.0, filled]. Meanwhile, GITQA-Aug encompasses 14 styles, each derived by altering one configuration element at a time from the base style. In this section, we display the entire collection of these 14 unique style combinations, with Figure 5 to Figure 18.

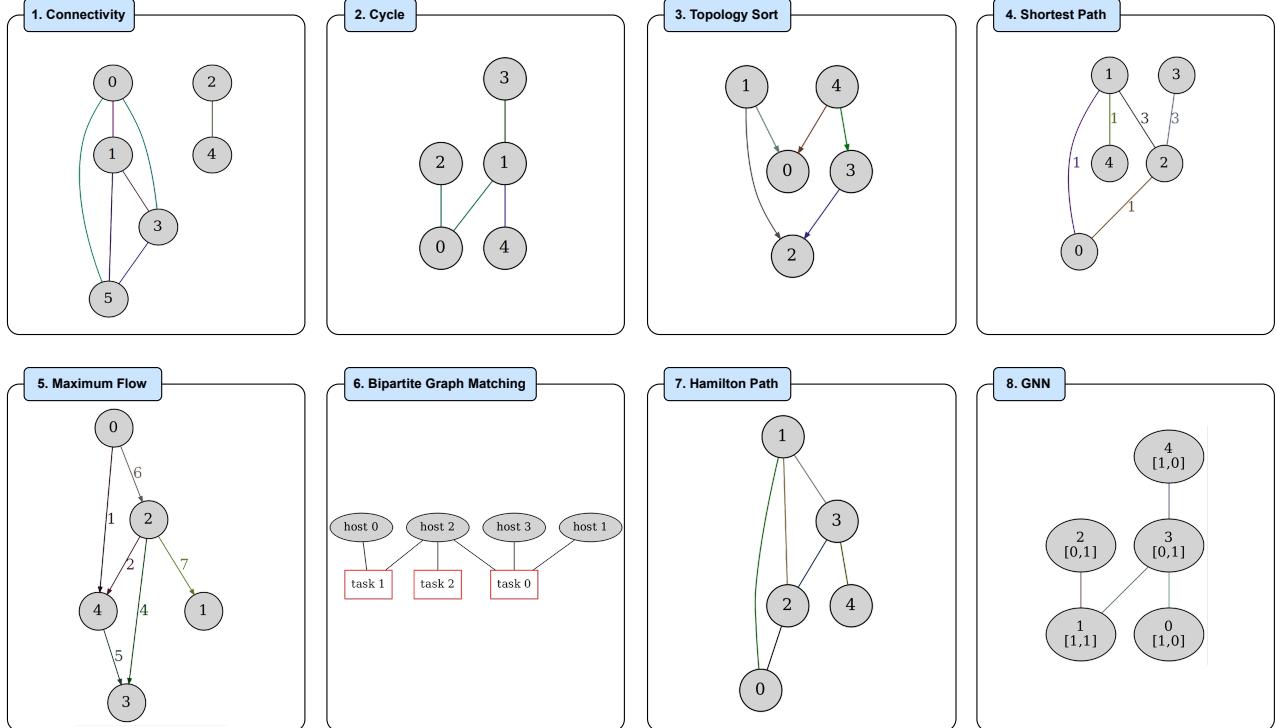


Figure 5. Illustration of visual graphs in (dot, ellipse, 1.0, filled) style, which is the base style used by GITQA-Base for all tasks except bipartite graph matching.

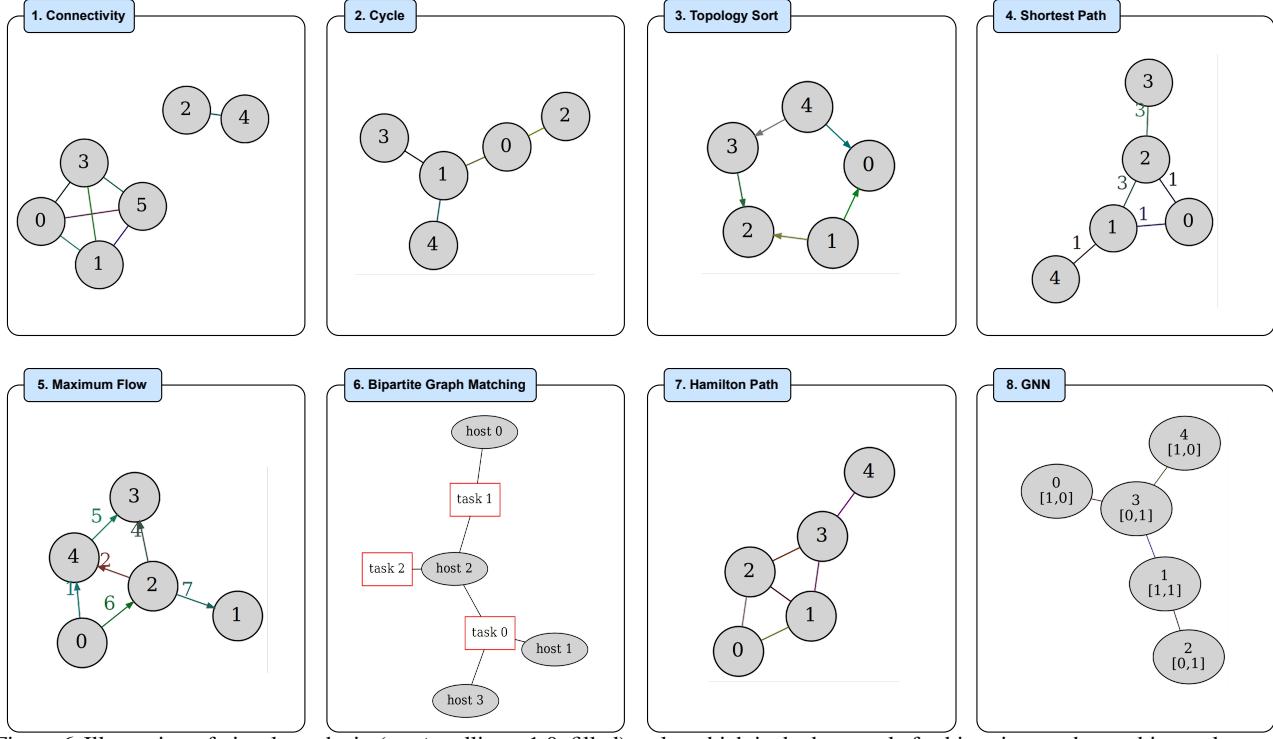


Figure 6. Illustration of visual graphs in (`neato`, ellipse, 1.0, filled) style, which is the base style for bipartite graph matching task.

C.3. Graph Describer

In this section, we introduce a template-based graph describer used to automate the generation of textual descriptions for graph structures. This system uses a collection of manually crafted, task-specific templates. A graph structure is represented as $G = (V, E)$ where V represents the set of vertices and E denotes the set of edges. The text description, T_t , is created by mapping key information—specifically, the number of vertices and the arrangement of edges—into predefined placeholders, denoted as $[P]$, within the template H_t for task t . Table 6 provides examples of the textual descriptions generated from graph structures using these template-based graph describers.

C.4. QA Pairs

In addition to visual graphs and textual descriptions of graphs, each sample in GITQA also includes a pair of question (with optional task-specific instructions) and answer text. In this section, we present examples of question-answer pairs for each type of task in Table 7.

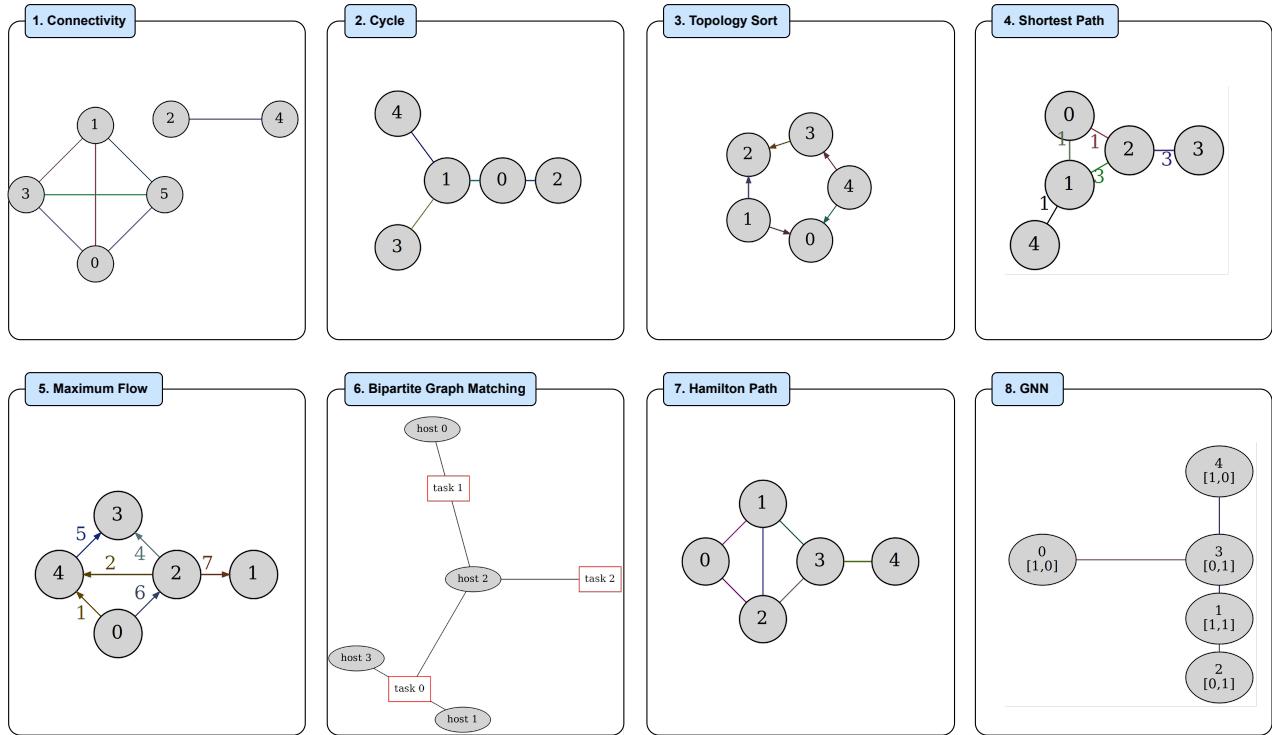


Figure 7. Illustration of visual graphs in (circos, ellipse, 1.0, filled) style.

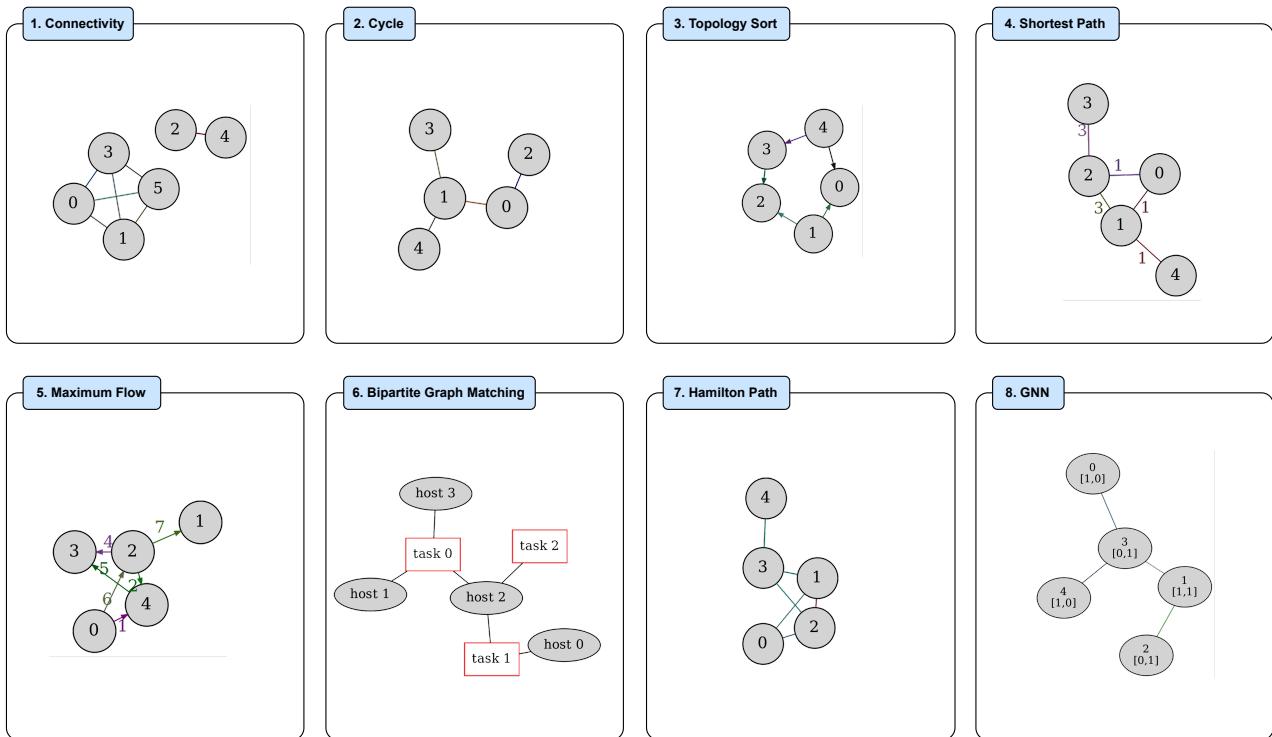
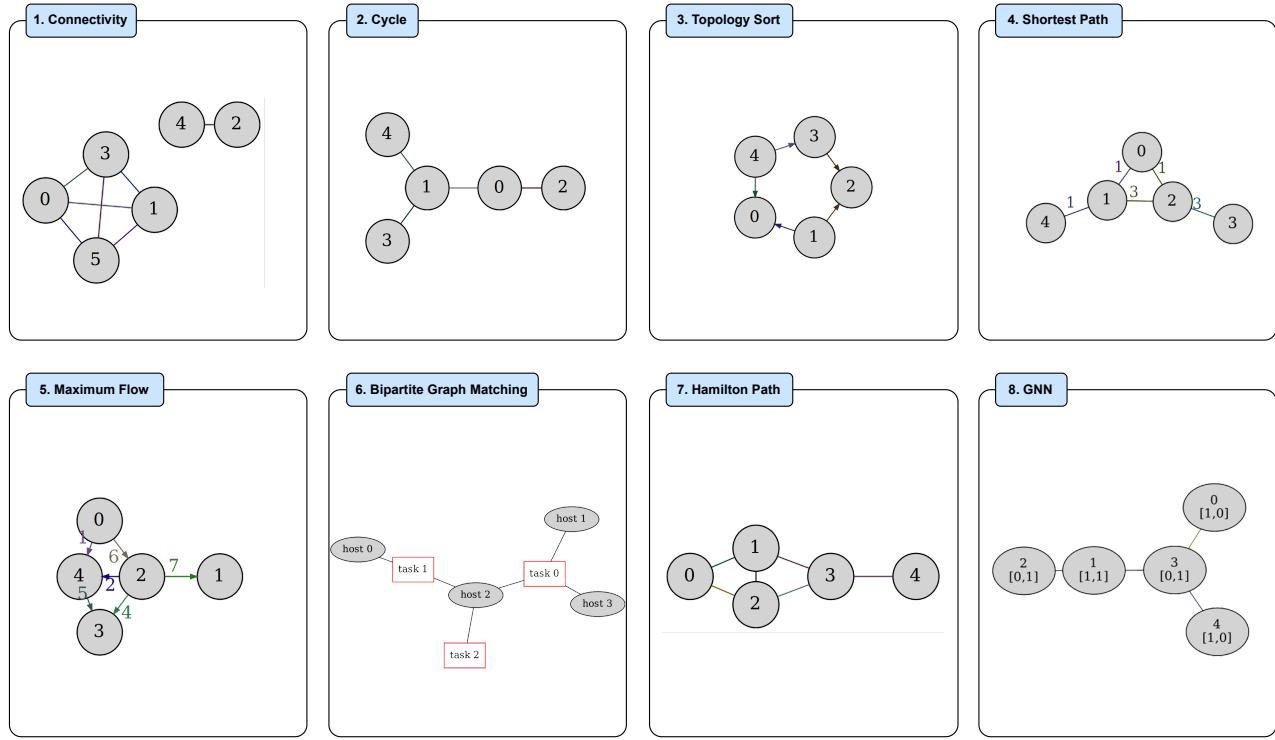
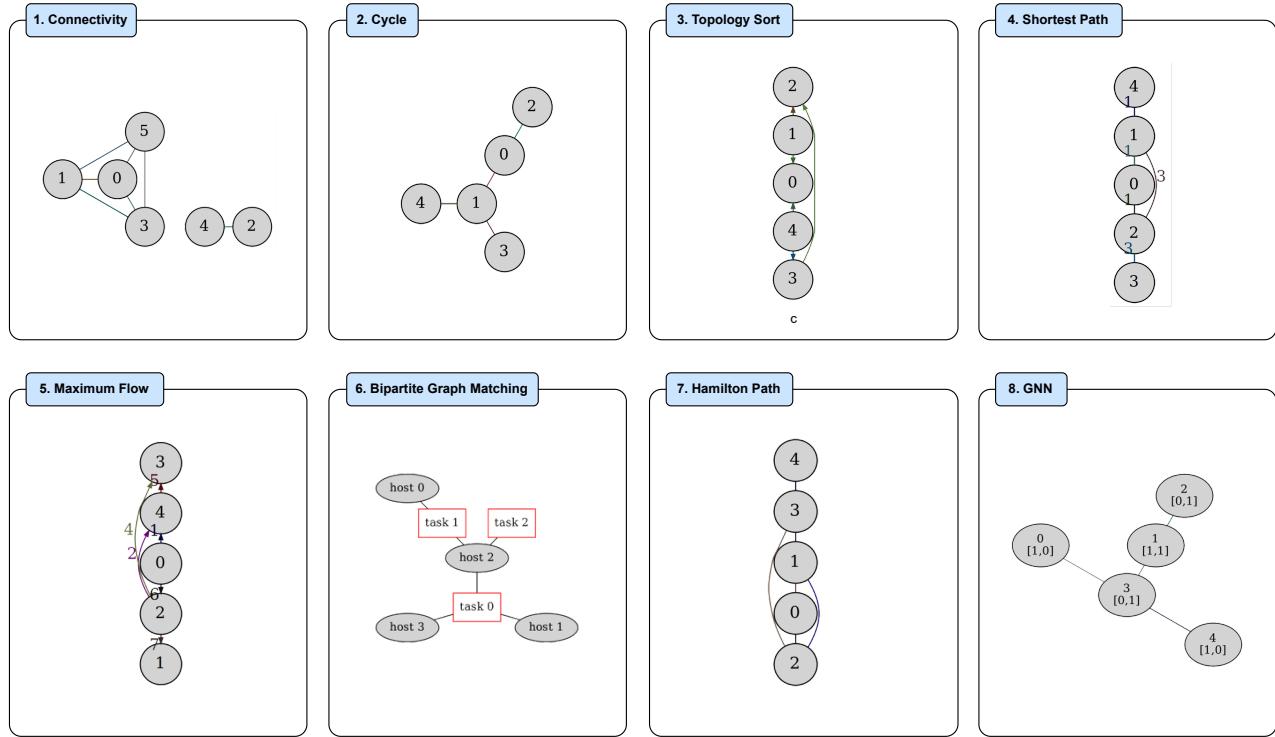


Figure 8. Illustration of visual graphs in (fdps, ellipse, 1.0, filled) style.


 Figure 9. Illustration of visual graphs in **(sfdb, ellipse, 1.0, filled)** style.

 Figure 10. Illustration of visual graphs in **(twopi, ellipse, 1.0, filled)** style.

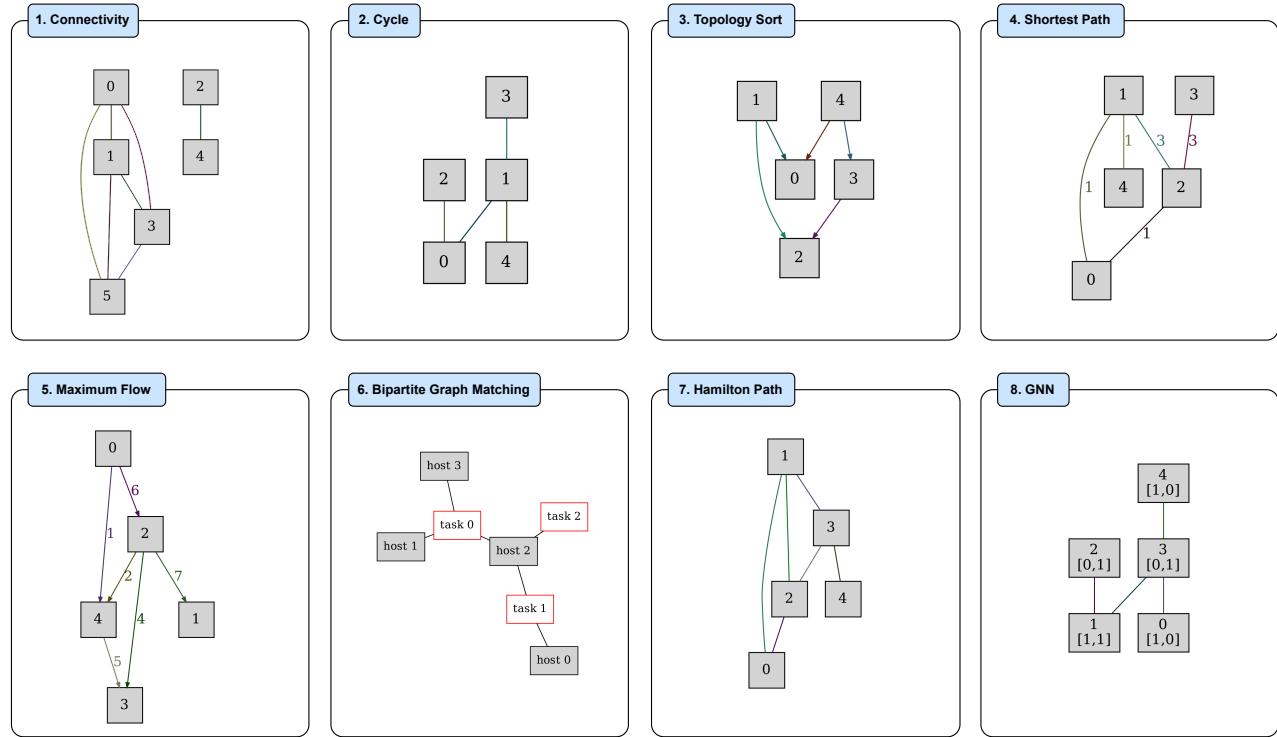


Figure 11. Illustration of visual graphs in (dot, box, 1.0, filled) style.

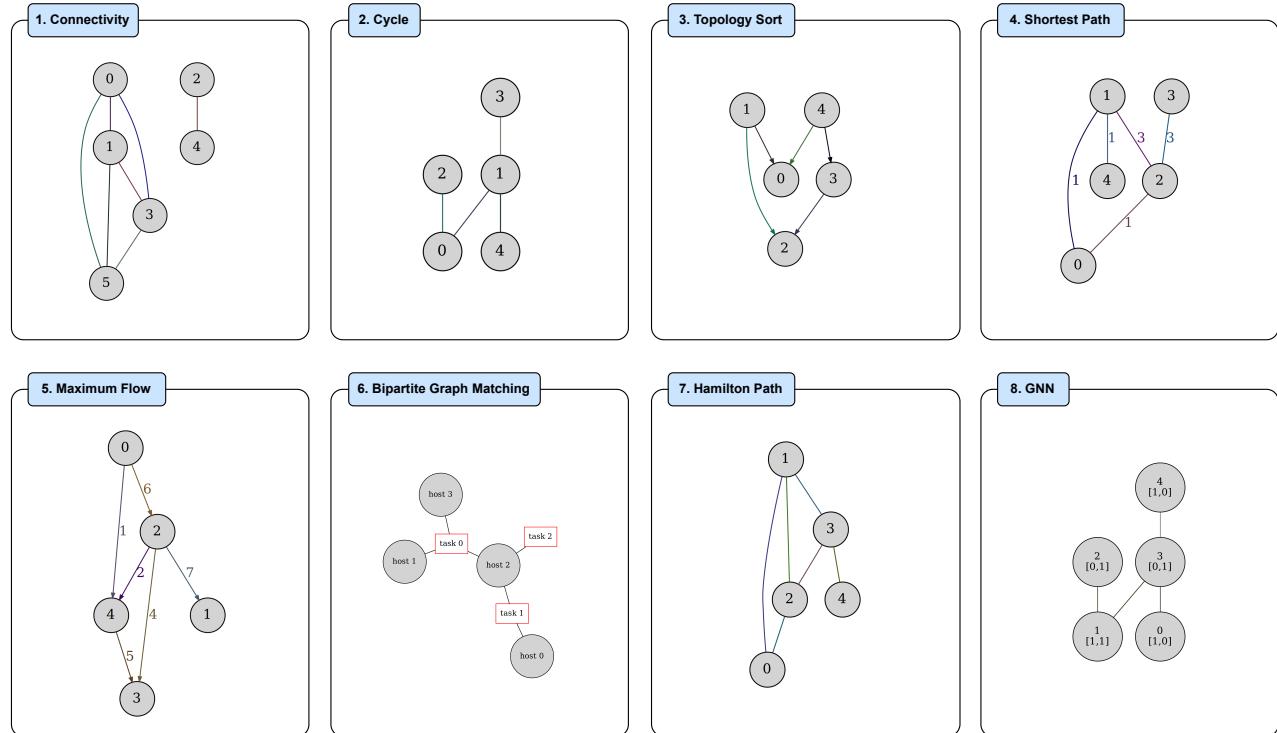


Figure 12. Illustration of visual graphs in (dot, circle, 1.0, filled) style.

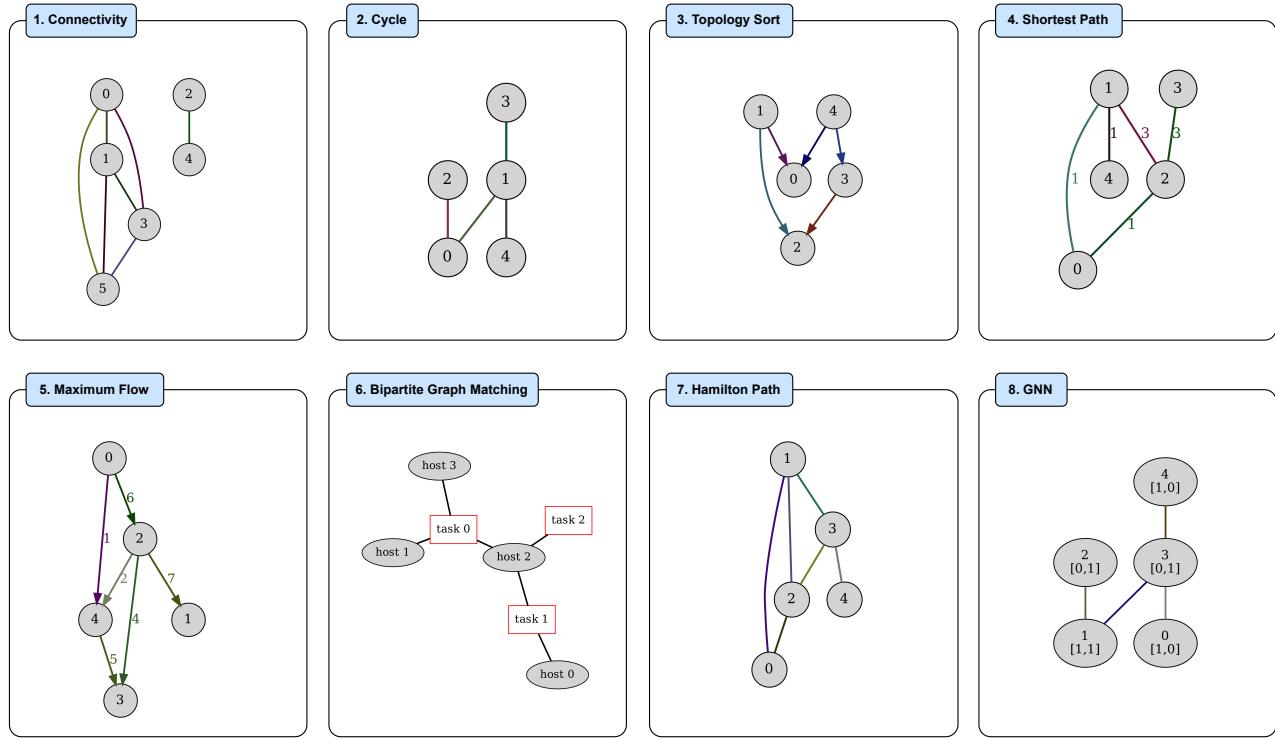


Figure 13. Illustration of visual graphs in (dot, ellipse, 2.0, filled) style.

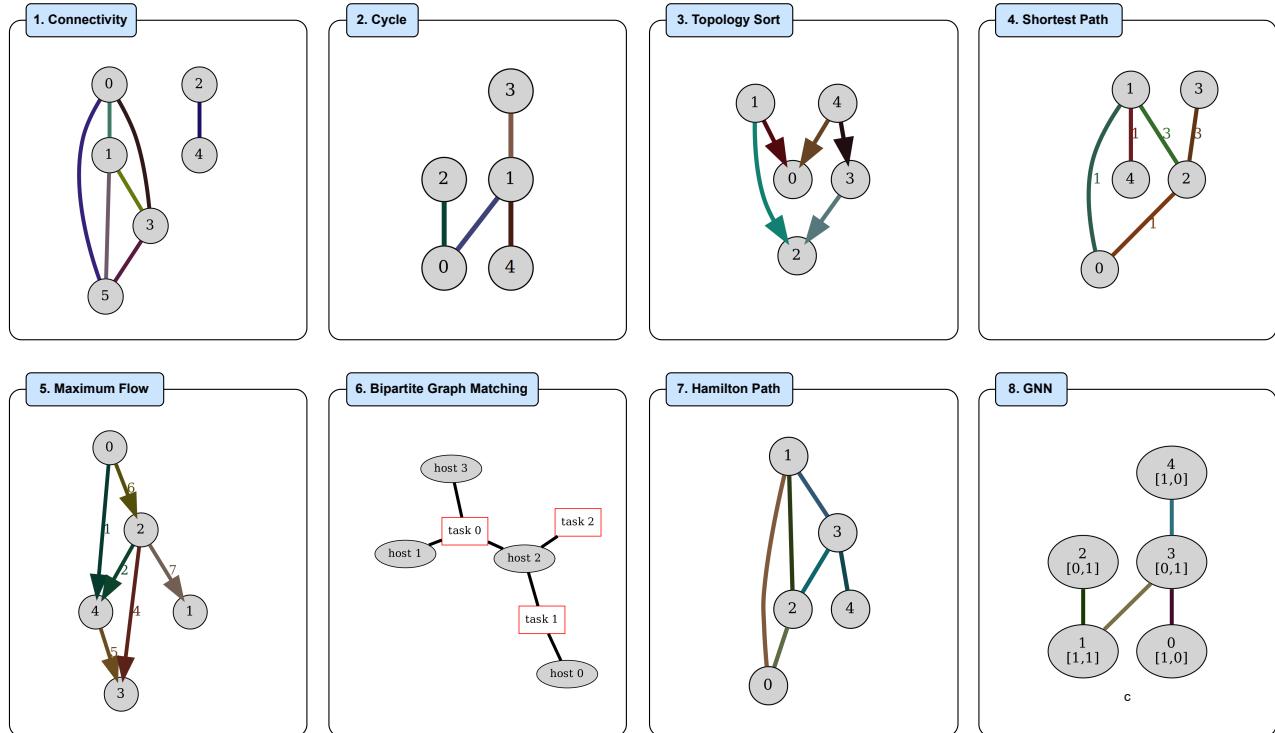


Figure 14. Illustration of visual graphs in (dot, ellipse, 4.0, filled) style.

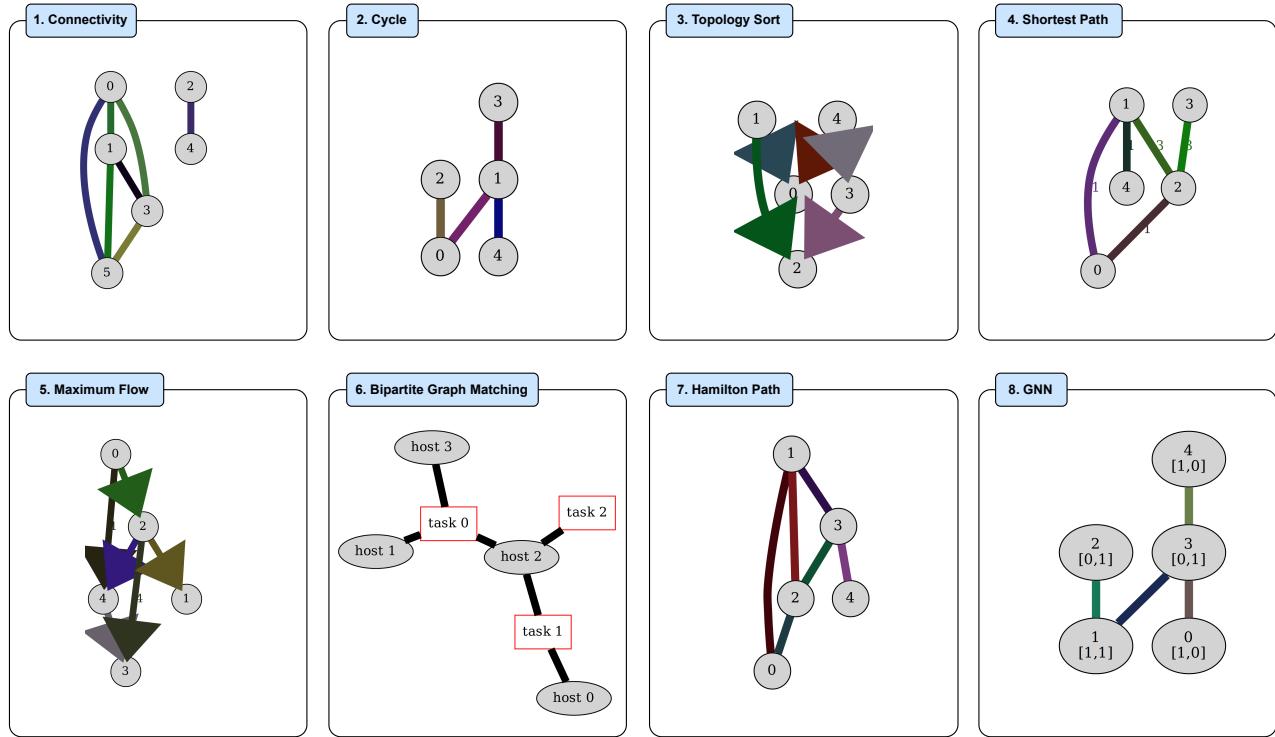


Figure 15. Illustration of visual graphs in (dot, ellipse, 8.0, filled) style.

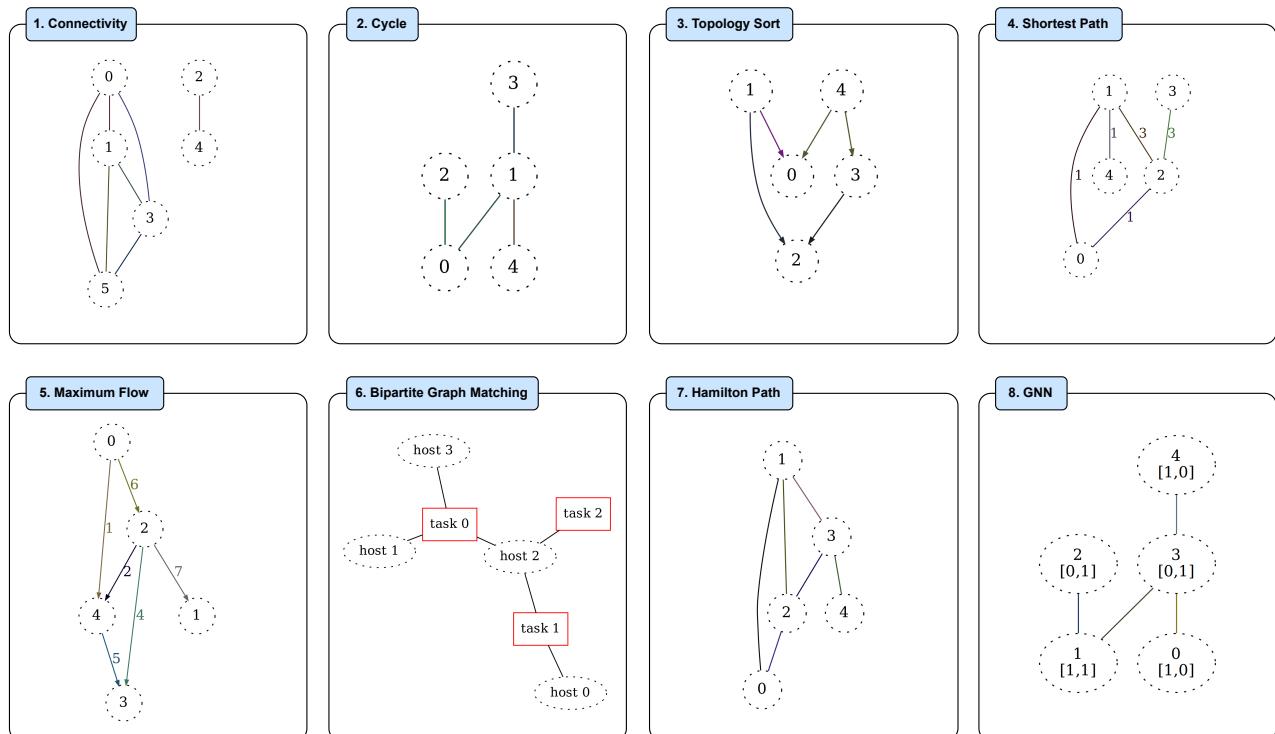


Figure 16. Illustration of visual graphs in (dot, ellipse, 1.0, dotted) style.

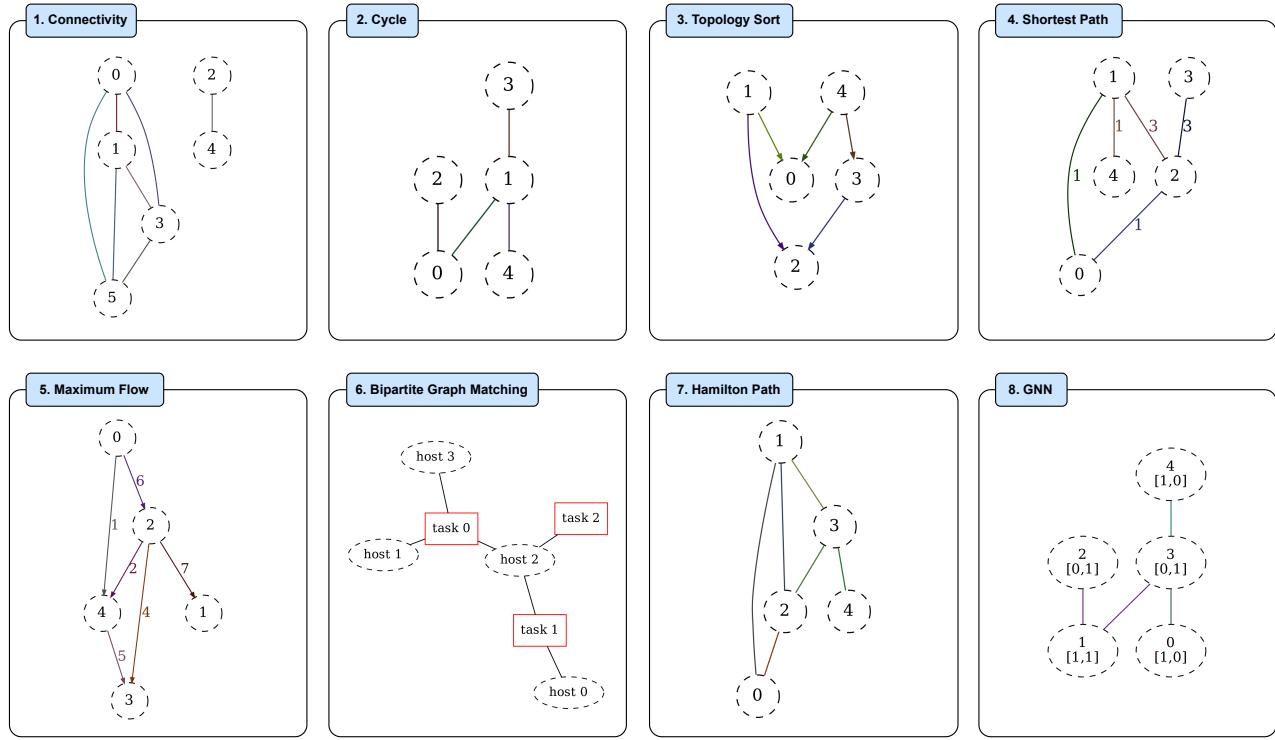


Figure 17. Illustration of visual graphs in (dot, ellipse, 1.0, **dashed**) style.

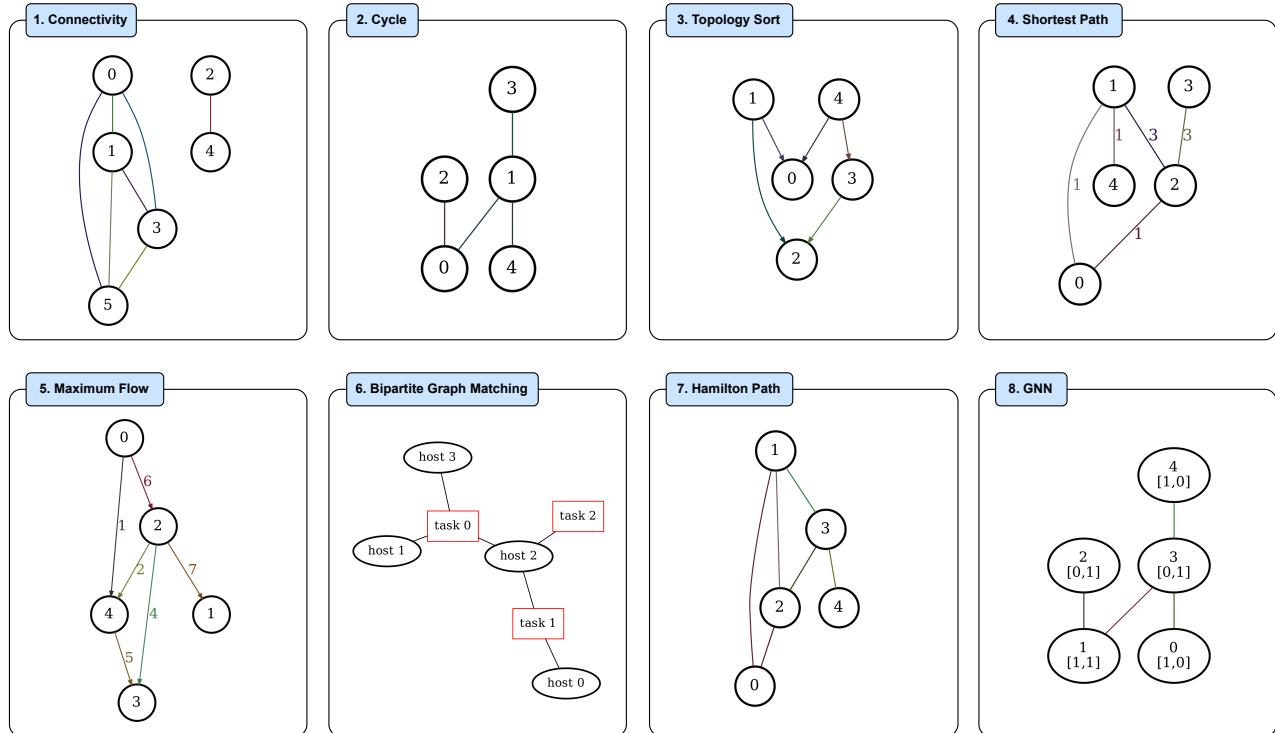


Figure 18. Illustration of visual graphs in (dot, ellipse, 1.0, **bold**) style.

Tasks	Template	Generated Graph Textual Description
Connectivity/ Cycle/ Hamilton Path	In an undirected graph, (i, j) means that node i and node j are connected with an undirected edge. The nodes are numbered from $[P]$ to $[P]$, and the edges are: $([P], [P])$, $([P], [P])\dots$	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 9, and the edges are: $(0,8)$ $(0,6)$ $(0,4)$ $(1,3)$ $(1,7)$ $(1,2)$ $(2,3)$ $(3,9)$ $(4,6)$ $(5,9)$ $(6,8)$ $(7,9)$.
Topological Sort	In a directed graph with $[P]$ nodes numbered from $[P]$ to $[P]$: node $[P]$ should be visited before node $[P]$ node $[P]$ should be visited before node $[P]$ \dots	In a directed graph with 7 nodes numbered from 0 to 6: node 0 should be visited before node 2 node 2 should be visited before node 6 \dots
Shortest Path	In an undirected graph, the nodes are numbered from $[P]$ to $[P]$, and the edges are: an edge between node $[P]$ and node $[P]$ with weight $[P]$, an edge between node $[P]$ and node $[P]$ with weight $[P]$, \dots	In an undirected graph, the nodes are numbered from 0 to 7, and the edges are: an edge between node 0 and node 1 with weight 3, an edge between node 3 and node 0 with weight 4, \dots
Maximum Flow	In a directed graph, the nodes are numbered from $[PLACEHOLDER]$ to $[PLACEHOLDER]$, and the edges are: an edge from node $[P]$ to node $[P]$ with capacity $[P]$, an edge from node $[P]$ to node $[P]$ with capacity $[P]$, \dots	In a directed graph, the nodes are numbered from 0 to 6, and the edges are: an edge from node 0 to node 3 with capacity 10, an edge from node 1 to node 0 with capacity 1, \dots
Bipartite Graph Matching	There are $[P]$ hosts numbered from $[P]$ to $[P]$, and $[P]$ tasks numbered from $[P]$ to $[P]$. Each host has a set of tasks that it is interested in: Host $[P]$ is interested in task $[P]$. Host $[P]$ is interested in task $[P]$. \dots	There are 8 hosts numbered from 0 to 7, and 8 tasks numbered from 0 to 7. Each host has a set of tasks that it is interested in: Host 2 is interested in task 1. Host 7 is interested in task 6. \dots
GNN	In an undirected graph, the nodes are numbered from $[P]$ to $[P]$, and every node has an embedding. (i, j) means that node i and node j are connected with an undirected edge. Embeddings: node $[P]$: $[[P], [P]]$ node $[P]$: $[[P], [P]]$ \dots The edges are: $([P], [P])$ $([P], [P])\dots$ \dots	In an undirected graph, the nodes are numbered from 0 to 6, and every node has an embedding. (i, j) means that node i and node j are connected with an undirected edge. Embeddings: node 0: $[0, 0]$ node 1: $[1, 0]$ \dots The edges are: $(5, 0)$ $(4, 2)$ \dots

Table 6. Examples of text description generated by graph describer with templates.

Tasks	Question	Answer
Connectivity	Q: Is there a path between node 8 and node 1 in this undirected graph?	Yes. (or No.)
Cycle	Q: Is there a cycle in this undirected graph?	Yes. (or No.)
Topological Sort	Q: The topological order of the directed graph is:	1,2,0,4,3.
Shortest Path	Q: Give the shortest path from node 9 to node 4:	9->2->6->5->7->4.
Maximum Flow	Q: What is the maximum flow from node 7 to node 1?:	11.
Bipartite Graph Matching	However, each host is capable of solving only one task, and similarly, each task can be resolved by just one host. Q: What is the maximum number of hosts that can be assigned a task they are interested in?	8.
Hamilton Path	Q: 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.	0->3->2->4->5->1.
GNN	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?	The updated embeddings of each node: node 0: [0,0] node 1: [2,0] node 2: [2,0] node 3: [2,1] node 4: [2,1] node 5: [2,0] node 6: [2,0] node 7: [1,2].

Table 7. Examples of text description generated by graph describer with templates.