KRAKEN: Knowledge Representation with Augmented Knowledge Graph Encoding for Neural VQA

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Abstract

Visual Question Answering (VQA) models excel at perceptual tasks but struggle with questions that require external, structured knowledge. While Knowledge Graph Question Answering (KGQA) has emerged to address reasoning over symbolic data, existing methods are ill-equipped to handle multimodal inputs that blend visual and textual information with structured graphs. To bridge this gap, we introduce a novel multimodal reasoning architecture. Our model is designed to reason at the intersection of language, structured knowledge, and visual information. It integrates three specialized pathways: (1) a frozen Vision Transformer (ViT) coupled with a trainable Q-Former to extract salient visual features, (2) a dedicated graph encoder to produce a topologically-aware representation of relational facts, and (3) an input text encoder. The outputs of these pathways are projected into a common space and fed to a frozen Large Language Model (LLM), which acts as the central reasoning engine. We employ a two-stage training strategy, first aligning the modalities and then fine-tuning the connective components with Parameter-Efficient Fine-Tuning (PEFT). Our work presents not just a new model for graph-based QA, but a novel architecture for the more challenging task of multimodal, knowledge-augmented reasoning.

1 Introduction

Visual Question Answering (VQA) has made significant strides in enabling machines to answer questions about the content of an image. Modern systems can successfully identify objects, describe attributes, and count instances, demonstrating a strong capacity for visual perception. However, a critical frontier remains: answering questions that require knowledge beyond the pixels of the image itself. For instance, while a model might identify a picture of the Eiffel Tower, it cannot answer "Who designed the landmark in this photo?" without access to external, structured world knowledge.

To address this need for factual reasoning, the field of Question Answering over Knowledge Graphs (KGQA) has developed sophisticated methods to query large-scale KGs (Saxena et al., 2020; Schlichtkrull et al., 2017). The paradigm has evolved from learning embeddings and parsing questions into formal queries (Gu et al.) to leveraging the powerful in-context reasoning and tool-use capabilities of Large Language Models (LLMs) (Wei et al., 2023; Cheng et al., 2023). Despite their success, these KGQA systems share a fundamental limitation: they operate exclusively on textual questions and symbolic graph structures, lacking a pathway to incorporate visual information. This leaves a crucial gap at the intersection of vision, language, and structured knowledge.

In this paper, we address this gap by proposing a novel multimodal architecture designed explicitly for knowledge-augmented reasoning. Our model is built on the insight that true comprehensive understanding requires the intelligent fusion of heterogeneous data sources. We situate our work within the modern LLM-based paradigm, using a powerful, pre-trained LLM as our central reasoning engine. However, we introduce a critical and novel extension: a multimodal input system that equips the LLM with a richer, more grounded context. Our architecture integrates three distinct pathways: a frozen Vision Transformer (ViT) from CLIP (Radford et al., 2021) for visual understanding, a dedicated graph encoder for symbolic relational facts, and a pathway for the user's textual question. To bridge the vision and language modalities effectively, we employ a Q-Former inspired by the BLIP-2 architecture (Li et al., 2023), which distills the visual information into a compact set of salient features.

Our contributions are threefold:

1. We introduce a novel end-to-end multimodal architecture that, for the first time, fuses sym-

bolic graph representations, visual features, and text for knowledge-based VQA.

2. We detail a stable and efficient two-stage training strategy involving a modality alignment phase followed by Parameter-Efficient Fine-Tuning (PEFT) of the connective components.

3. We present an empirical analysis demonstrating the limitations of a vision-only approach to understanding rendered knowledge graphs, thereby motivating the necessity of our multimodal design.

2 Related Works

Research in Question Answering over Knowledge Graphs (KGQA) has evolved through several distinct paradigms, each aiming to more effectively bridge the gap between natural language questions and structured knowledge. Our work builds upon insights from these successive approaches, culminating in a multimodal architecture that leverages the reasoning power of modern Large Language Models (LLMs).

Early deep learning approaches focused on learning dense vector representations of both the question and the knowledge graph components. A prominent example of this is **EmbedKGQA** (Saxena et al., 2020), which frames the task as a retrieval problem within a learned embedding space. By training a model to score the proximity of question embeddings to candidate entity embeddings, this method can effectively answer complex multi-hop questions. Foundational to this line of work are powerful graph representation learning techniques like the **Relational Graph Convolutional Network (RGCN)** (Schlichtkrull et al., 2017). RGCNs extend traditional GNNs to handle the heterogeneous, multi-relational nature of KGs, producing rich node and edge embeddings that capture the graph's topology. While powerful, these embedding-based methods often perform reasoning implicitly and can struggle with generalization to unseen entities or relations.

A parallel and highly effective paradigm is **Semantic Parsing**, which seeks to translate a natural language question into a formal, executable query. Instead of learning embeddings, these models learn a direct mapping to a language like SPARQL. The **GrailQA** (Gu et al.) benchmark and its associated models demonstrated the power of this approach, showing remarkable zero-shot generalization to KG schemas and compositional structures unseen during training. By generating an explicit, interpretable query, these methods offer high precision but can be sensitive to the complexity and variability of natural language.

The recent advent of Large Language Models (LLMs) has fundamentally shifted the landscape of KGQA. The immense world knowledge and emergent reasoning capabilities of models like GPT-4 have enabled new, highly flexible approaches. One strategy is to use LLMs directly as zero-shot reasoners through sophisticated prompting, such as **Chain-of-Thought (CoT)** (Wei et al., 2023). CoT prompting encourages the model to break down a question into intermediate logical steps, significantly improving its performance on complex reasoning tasks without any task-specific finetuning. A more advanced strategy involves finetuning LLMs to function as intelligent agents that can use external tools. Models like **Binder** (Cheng et al., 2023) and **StructGPT** (Jiang et al., 2023) are trained to generate and execute code or API calls to query structured data sources, including KGs. This "tool use" paradigm allows the LLM to offload factual retrieval to the KG while focusing its own capacity on reasoning, planning, and synthesizing the retrieved information.

Our proposed work situates itself within this latest LLM-based paradigm, using a powerful LLM as our central reasoning engine. However, we introduce a critical and novel extension: **multimodality**. Whereas the aforementioned methods operate exclusively on textual questions and symbolic graph structures, our model is designed to reason at the intersection of language, structured knowledge, *and visual information*. By integrating a dedicated graph encoder for relational facts and a sophisticated vision pathway (ViT + Q-Former) for image understanding, we equip the LLM with a richer, more grounded context. Our contribution is therefore not just a new model for graph-based QA, but a novel architecture for a more challenging task: multimodal, knowledge-augmented reasoning.

3 Methodology

To address the challenge of knowledge-based reasoning in VQA, we propose a modular, multimodal architecture designed to effectively fuse information from visual, linguistic, and structured graph sources. Our methodology is built upon a carefully selected data foundation and features a sophisticated model architecture that leverages pre-trained foundation models, connected by specialized bridge components. The entire system is trained using a phased strategy to ensure stable and efficient learning.

3.1 Proposed Model Architecture

Our proposed architecture is not a monolithic network but a carefully orchestrated assembly of specialized, pre-trained encoders and a central language-based reasoner. The core design philosophy is to project heterogeneous data modalities into a common representational space that a Large Language Model (LLM) can interpret. The process begins with the visual pathway, which employs a powerful, pre-trained vision encoder, specifically the Vision Transformer (ViT) from CLIP (Contrastive Language-Image Pre-training)(Radford et al., 2021)/Qwen(Bai et al., 2023). We choose CLIP/Qwen's ViT because its training on 400 million image-text pairs has endowed it with a rich semantic understanding of visual concepts that extends far beyond simple object recognition. To preserve this powerful, generalized knowledge and for computational efficiency, this vision encoder remains frozen during training. The encoder transforms the input image into a sequence of patch embeddings, which, while comprehensive, are too numerous and unstructured for direct LLM consumption.

Querying Transformer (Q-Former): To bridge the gap between the raw visual output and the LLM, we introduce a Querying Transformer (Q-Former), a critical component inspired by the BLIP-2 architecture (Li et al., 2023). The Q-Former functions as an intelligent information bottleneck, designed to distill the most relevant information from the dense visual patch embeddings. Its architecture consists of two main sub-modules: an image transformer that interacts with the frozen ViT features, and a text transformer that can process textual information. At its core are a small, fixed number of learnable queries. These queries are fed as input to the Q-Former's image transformer, which then uses a cross-attention mechanism to interact with the patch embeddings from the ViT. Through this cross-attention process, the learnable queries "ask questions" of the image features and extract the most salient visual information corresponding to the overall context. This process is highly efficient as it condenses a large sequence of patch embeddings (from the ViT) into a much smaller, fixed-length set of output feature vectors. This compact set of feature vectors effectively summarizes the visual content in a way that is structured and digestible for the subsequent LLM.

Concurrently, the structured knowledge pathway processes the input KG triples. Since knowledge graphs possess a distinct topological structure that sequential or convolutional models fail to capture, we employ a graph based decoder [cite: Gardazi2025] which will extract relation based representation from a structured graph data. The GAT operates directly on the graph, iteratively applying a self-attention mechanism to aggregate feature information from neighboring nodes and edges. This attention-guided message-passing mechanism assigns learnable, differentiated weights to neighbors, allowing the network to prioritize the most relevant nodes. This process produces node embeddings that are highly context-aware, resulting in a single, holistic Graph Representation vector that encapsulates the relational knowledge of the entire KG snippet. Finally, these disparate data streams are unified for the LLM. The input question is tokenized and embedded, then concatenated with the Graph Representation vector. The compact set of visual feature vectors from the Q-Former is passed through a lightweight, trainable Projector—a multi-layer perceptron (MLP)—which maps them into the same embedding space as the LLM's vocabulary. The final input to the LLM is a sequence composed of these projected visual tokens (acting as a "soft visual prompt") followed by the embedded question and graph context. This unified sequence is then processed by a powerful, pre-trained LLM, such as Llama 2 [cite: touvron2023llamaopenefficientfoundation] or Mistral [cite: jiang2023mistral7b], which serves as the central reasoning engine. By leveraging the LLM's vast pre-trained knowledge and inferential capabilities, our model can reason over the provided multimodal context to generate a coherent, factually correct answer.

3.2 Training Strategy

Training such a complex, heterogeneous architecture requires a careful, phased approach to avoid instability and catastrophic forgetting. We therefore adopt a two-stage training strategy.

The first stage is dedicated to **Multimodal Alignment**. During this phase, both the large Vision Encoder and the LLM are kept completely frozen.

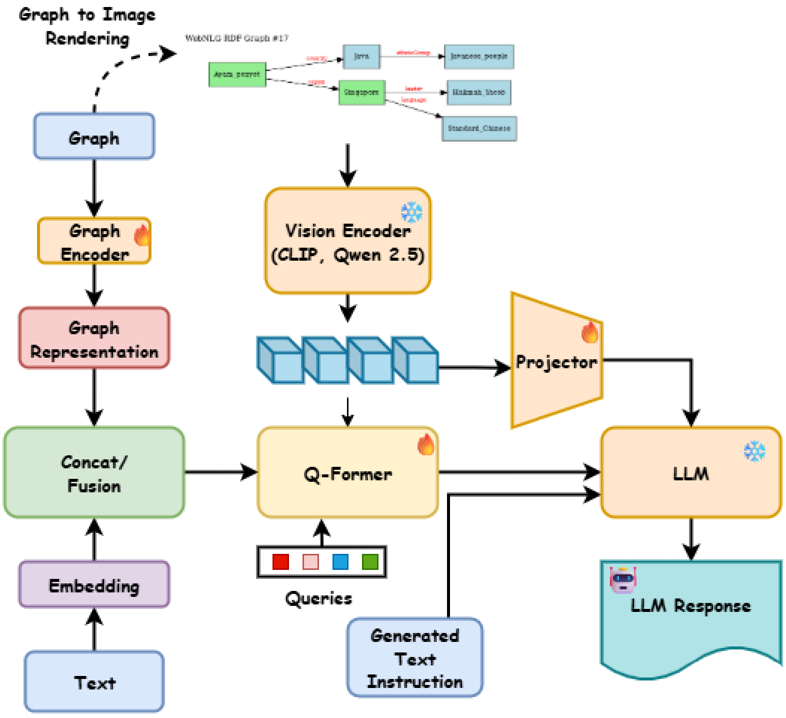


Figure 1: An overview of our proposed multimodal architecture for knowledge-augmented reasoning. The model integrates three distinct pathways (Graph, Text, and Vision) which are processed and fused before being interpreted by a Large Language Model (LLM). Components marked with a flame icon are trained, while those with a snowflake icon are kept frozen to preserve their pre-trained knowledge.

Training is focused exclusively on the bridge components: the Q-Former and the Projector. The objective is to teach these smaller modules the specific task of aligning the visual modality with the latent space of the LLM. By freezing the large backbones, we force the bridge components to learn how to extract and translate visual information into a format that the LLM can understand, without corrupting the powerful pre-trained weights of the larger models.

The second stage is **End-to-End Instruction Fine-Tuning**. Once the modalities are effectively aligned, we proceed to fine-tune the model for the specific VQA task. To make this process computationally tractable and to mitigate the risk of overfitting, we will employ **Parameter-Efficient Fine-Tuning (PEFT)**, specifically the **LoRA (Low-Rank Adaptation)** technique (Hu et al., 2021). LoRA avoids updating the millions of original LLM weights by injecting small, trainable rank-decomposition matrices into its transformer layers. This allows us to adapt the LLM's behavior to our specific task and dataset by training only a fraction of the total parameters, significantly reducing the memory and computational footprint while achieving performance comparable to full fine-tuning.

3.3 Evaluation

The model's performance will be quantitatively assessed using the standard VQA accuracy metric. To rigorously test the model's reliance on the knowledge graph, we will curate a challenging split of the test set where the answers cannot be inferred from visual cues or general knowledge alone, thereby requiring explicit reasoning over the provided KG triples. Furthermore, we will conduct qualitative analyses by visualizing the attention or similarity maps generated within the Q-Former and ViT. This will allow us to interpret the model's reasoning process by observing which parts of the image and graph it focuses on when formulating an answer, providing crucial insights into its "thought process."

4 Dataset Analysis

We analyze the dataset across three complementary views: natural text, node labels, and edge predicates. Table 1 summarizes the global statistics. Overall, the dataset comprises **38,872 texts** and approximately **760k tokens** in natural language, alongside **230k node labels** and **115k edge instances**. The vocabulary sizes are **6,125** for text,

Metric	Value	Component Breakdown (Nodes and Edges/Node-Edge Ratio)
Texts	38,872	–
Tokens	759,766	512,752 (Nodes) 117,557 (Edges)
Vocabulary	6,125	3,635 (Nodes) 412 (Edges)
TTR	0.0081	0.0071 / 0.0035
Rare words	1,046	64 / 7
Unique labels	–	3,624 (Nodes) 411 (Edges)
Sentence length statistics		
Average	*19.5*	–
Median	*18*	–
95th percentile	*37*	–

Table 1: Global statistics across modalities. TTR is the Type-Token Ratio. For brevity in the "Component Breakdown" column, some stats are presented in a *Nodes / Edges* format.

3,635 for nodes, and **412** for edges, yielding type–token ratios between 0.0035 and 0.008. Sentence lengths average 19.5 words, with a median of 18 and a 95^{th} percentile of 37, showing moderate variability.

4.1 Extension to a Third Modality: Images of Graphs

A key novel contribution of our work is the expansion of the original WebNLG dataset, which traditionally consists of only two modalities: natural text and graph-structured data (nodes and edges). We extend this dataset to include a third modality: **images of graphs**.

Specifically, we generate a visual representation for every graph instance in the dataset by rendering its node–edge structure using a custom Python script. Each graph is converted into a high-resolution image that preserves the topology, edge directions, and node labeling conventions. These visualizations provide an interpretable, human-readable depiction of the graph structure that goes beyond symbolic node/edge lists.

This augmentation is particularly significant because, to the best of our knowledge, no prior version of WebNLG has been extended to include graph visualizations as aligned images. The resulting dataset is thus inherently **tri-modal**, comprising:

- **Natural text**: surface-level descriptions of facts.
- **Structured graph representations**: symbolic nodes and edges encoding factual relations.
- **Graph images**: visual depictions of the same structure, offering a complementary spatial and perceptual modality.

By introducing the image modality, we enable multimodal learning setups where models can jointly reason over text, graph structures, and visual layouts of graphs. This supports richer alignment tasks (e.g., graph-to-text-to-image consistency), and opens new avenues for studying the interplay between symbolic and visual representations. Furthermore, since the images are automatically generated for all graph instances, the dataset is fully scalable and reproducible.

In summary, this extension transforms the WebNLG dataset into the first large-scale resource that integrates **graph-text-image alignment**, a contribution that we believe significantly advances the research frontier in multimodal graph-based reasoning.

4.2 Illustrative Example of Tri-Modality Alignment

To concretely demonstrate the tri-modal alignment of our extended WebNLG dataset, we present an illustrative instance in Table 2. Each row aligns a symbolic graph triple, its natural text, an instruction prompt, and the rendered graph image.

4.3 Role of Instruction Prompts in the Pipeline

The inclusion of instruction prompts (as shown in Table 2) plays a critical role in our training pipeline. These prompts serve as a bridge between modalities, providing explicit guidance to large language or multimodal models on how to interpret a given graph structure. By conditioning the model on such instructions, we enable:

- **Graph-to-Text Alignment:** Prompts ensure that symbolic triples are mapped consistently into fluent natural language.
- **Graph-to-Image Reasoning:** Prompts encourage the model to connect the structural semantics of a graph with its corresponding visual layout.
- **Instruction-Tuned Learning:** Using prompts during training aligns with modern

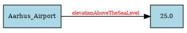
`Graph (Triple Form)`	**Text (Reference)**	**Instruction Prompt (Gemini)**	**Graph QA (Example)**	**Graph Image**
`Aarhus_Airport | elevationAboveTheSeaLevel | 25.0`	Aarhus Airport is 25.0 metres above the sea level.	*Explain the meaning of this graph triple: identify the subject ("Aarhus Airport"), the relation ("elevationAboveTheSeaLevel"), and the object ("25.0"), then produce a fluent sentence that states the fact.*	**Q:** What is the elevation of Aarhus Airport above sea level? **A:** 25.0 metres	

Table 2: Quad-modal alignment example: symbolic graph triple, natural text description, instruction prompt, and the rendered graph image. The extended dataset also includes generated question-answer pairs.

instruction-tuning paradigms, enhancing generalization to unseen graph structures and predicates.

In practice, these prompts are used during the alignment and fine-tuning stages of our pipeline, where the model learns not only to process each modality independently but also to reason over their joint representations. This facilitates downstream tasks such as multimodal question answering, text generation grounded in graphs, and image-based reasoning over structured facts.

4.4 Extension to a Fourth Component: Question–Answer Pairs

In addition to extending WebNLG with graph images, we further augment the dataset by generating aligned **Question–Answer (QA) pairs** for every graph instance. Specifically, we produced QA pairs for all **35,400 graphs** in the WebNLG dataset. The number of QA pairs per graph ranges from **1 to 4**, depending on the size and complexity of the underlying graph structure.

These QA pairs were generated automatically using the `gemini-2.5-flash-lite` API. The model was prompted with each graph representation to create natural questions grounded in the graph's semantics, together with their corresponding answers. This ensures that the dataset now supports a **quad-modal** setup:

- Natural text descriptions,
- Structured graph triples (nodes and edges),
- Rendered graph images,
- Automatically generated question–answer pairs.

These QA pairs will be used for the evaluation of our model.

4.5 Part-of-Speech Distribution

POS distributions vary by modality. In natural text, nouns (**299k**), verbs (**132k**), adjectives (**81k**), and adpositions (**96k**) dominate, consistent with factual, entity-centric narratives. Node labels are heavily skewed toward common nouns (**383k**), adjectives (**67k**), and verbs (**21k**). Edges are almost exclusively noun-heavy (**114k**), with relatively few verbs or modifiers.

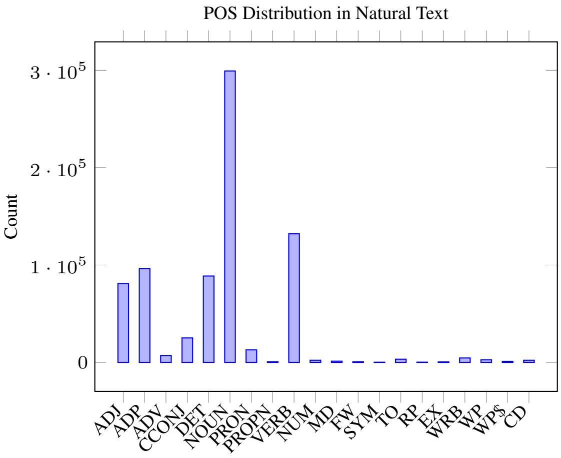


Figure 2: POS distribution in natural text.

4.6 Cross-Modal Comparisons

To compare textual and structural components, we visualize vocabulary sizes, token counts, and rare word frequencies across modalities (Figure 5). Natural text is largest in raw token count, while node labels dominate in noun frequency. Edge predicates are narrower but dense in factual relations.

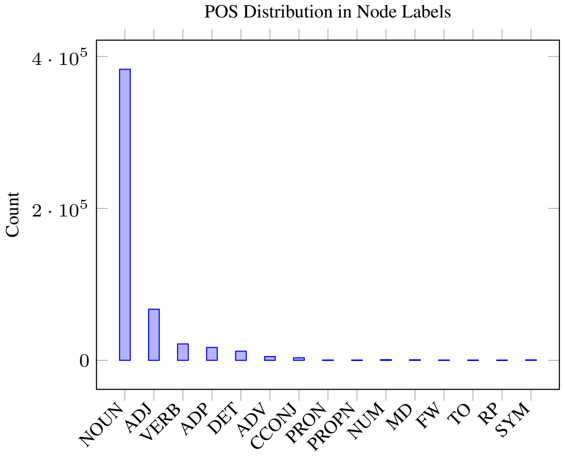


Figure 3: POS distribution in node labels.

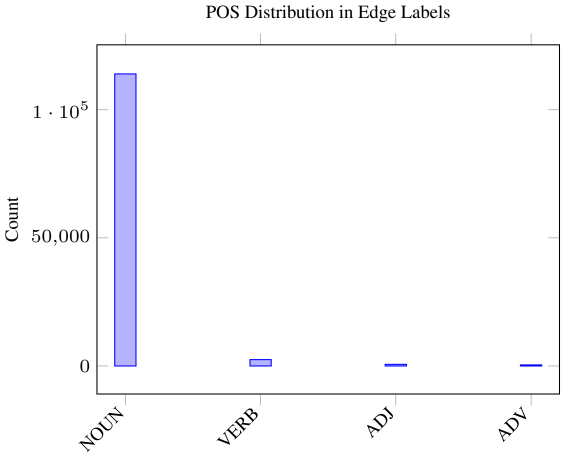


Figure 4: POS distribution in edge labels.

4.7 Implications

The dataset provides a balanced structure: natural text emphasizes verb/noun-rich descriptions, nodes supply compact entity labels, and edges encode relations with high noun dominance. This division supports multimodal learning: nodes/edges guide structured reasoning, while text offers naturalistic surface forms. The relatively low TTR values indicate manageable lexical diversity, while the presence of rare words ensures coverage of long-tail phenomena relevant for generalization.

4.8 Implications for Our Task

The prevalence of proper nouns and factual predicates suits our goal of multimodal graph-based reasoning: aligned graph–text learning can leverage dense entity mentions, while the breadth of predicates (*411* labels) encourages compositional generalization. The stable sentence lengths and modest vocabulary size simplify batching and optimization for sequence models, whereas the long-tail rare types motivate subword tokenization and label smoothing during training.

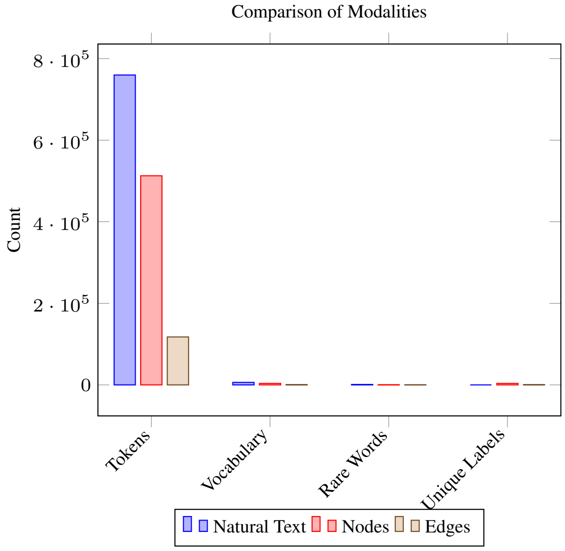


Figure 5: Cross-modal comparison of core statistics.

5 Graph Encoder Performance

To evaluate the effectiveness of the Graph Attention Network (GAT) encoder in transforming structured knowledge graphs into a concise context vector, we analyzed its performance on several samples from the WebNLG validation set. The GAT encoder is combined with a pre-trained BART decoder, with the encoder's performance inferred from the quality and accuracy of the generated text.The GAT encoder's performance reveals a significant dichotomy between its ability to handle **structural complexity** and its adherence to **factual content**. The complex **AmeriGas** input (6 triples) demonstrated the GAT's successful application of message passing and attention to yield a coherent, aggregated output, confirming its potential for high-level sentence planning. However, this success came at the cost of **content fidelity**, as crucial facts like ‘netIncome‘ were omitted, suggesting a weakness in the encoder's final **readout layer** or attention weights. This tendency toward content loss became critical with simpler, specific facts: the single-triple inputs for **India** and **The Hobbit** resulted in outright **hallucination**. In these cases, the GAT's encoded context vector was too weak or ambiguous to overpower the decoder's pre-trained knowledge, leading BART to generate fluent but **factually irrelevant text** (e.g., generating "Narendra Modi"

Paradigm	Method	Core Approach	Key Innovation / Contribution	Primary Benchmark(s)
GNN / Embedding	EmbedKGQA (Saxena et al., 2020)	Embedding-Based Retrieval	Learns a joint embedding space for the question and the KG. Answers questions by finding the entity embedding closest to the question's representation.	WebQSP, MetaQA
	RGCN (Schlichtkrull et al., 2017)	Graph Neural Network	A foundational GNN architecture that extends Graph Convolutional Networks to handle the multi-relational nature of knowledge graphs for link prediction and entity classification.	FB15k-237, WN18RR
Semantic Parsing	GrailQA (Gu et al.)	Seq2Seq Formal Query Generation	Translates natural language questions into a formal, executable query language (e.g., SPARQL). Achieves strong zero-shot generalization to unseen KG schemas and relations.	GrailQA, WebQSP
Large Language Model (LLM)	LLM + CoT (Wei et al., 2023)	In-Context Learning / Prompting	Leverages the emergent reasoning capabilities of massive LLMs (e.g., GPT-4) via Chain-of-Thought prompting to break down a complex question into logical steps and answer it without fine-tuning.	KQA Pro, ComplexWebQ
	Binder (Cheng et al., 2023) / StructGPT (Jiang et al., 2023)	LLM with Tool Use (Fine-tuned)	Fine-tunes an LLM to serve as a reasoning agent that can generate and execute code (e.g., API calls, Python) to interact with various data sources, including knowledge graphs.	KQA Pro, Spider
	Our Proposed Model	**Multimodal Fusion with LLM Reasoner**	**Uniquely fuses three modalities: structured graph representations (from a GNN), visual features (from a ViT + Q-Former), and text. Uses a frozen LLM as the central reasoning engine.**	**WebNLG-VQA (prop.)**

Table 3: Comparison of State-of-the-Art (SOTA) paradigms for Graph-based Question Answering. The field has evolved from specialized embedding and GNN-based models to flexible, powerful systems that leverage Large Language Models (LLMs) as their core reasoning engine. Our proposed work aligns with the latest LLM-based trend but innovates by introducing a novel fusion mechanism for visual, textual, and structured graph data.

instead of the ‘areaTotal‘ value). These failures indicate that while the GAT can effectively combine features, its context vector often lacks the necessary specificity to enforce strict input-to-output mapping, particularly for sparse or unique entities which are likely also suffering from **vocabulary ambiguity** in the BART decoder.

6 Empirical Analysis of Vision-Only Understanding

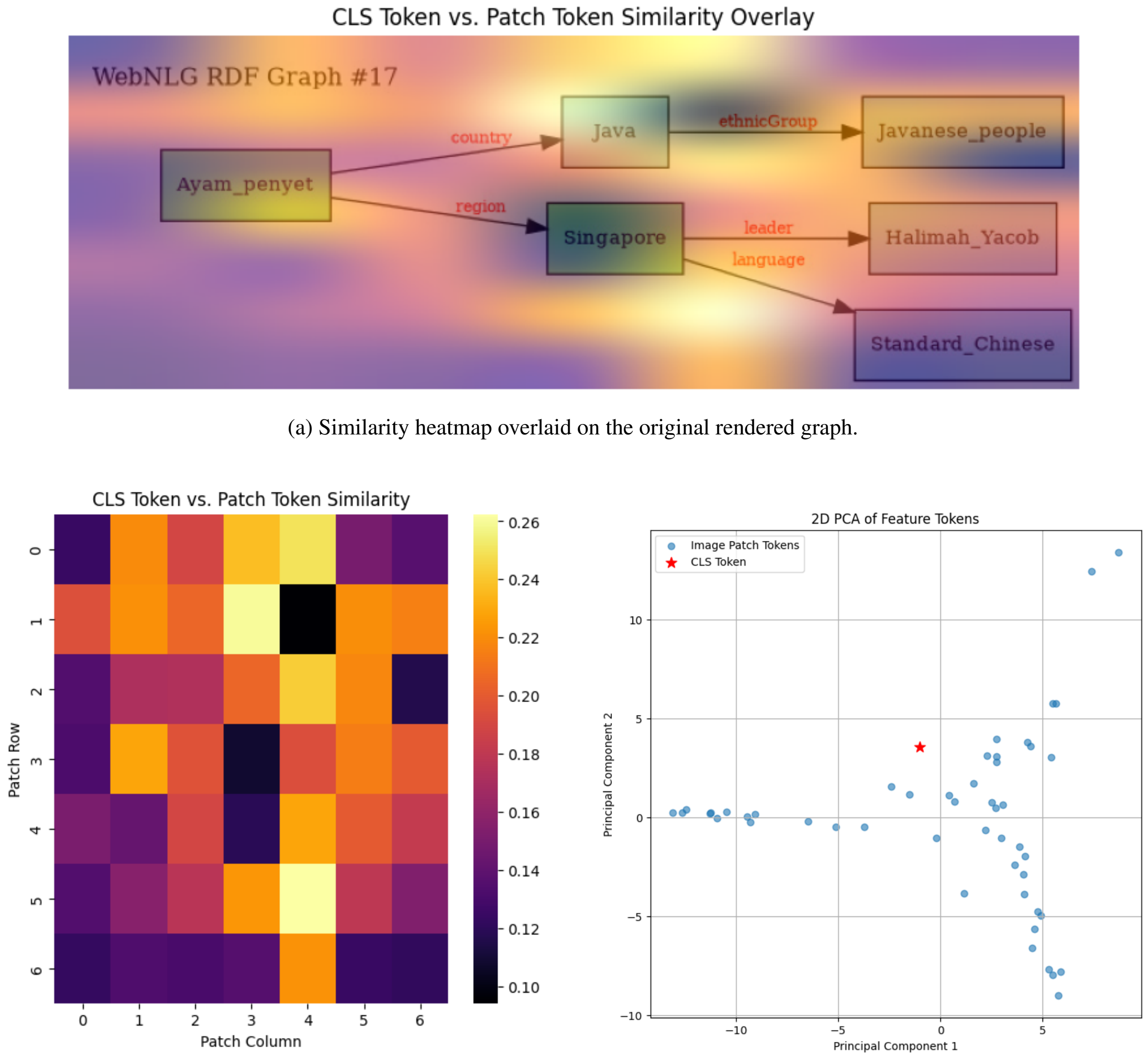
To motivate the necessity of a multimodal approach, we first conducted an empirical study to probe the capabilities and limitations of a state-of-the-art pretrained vision encoder when tasked with interpreting a visually rendered knowledge graph. We processed an image of a graph from the WebNLG dataset (Figure 6a) using the Vision Transformer (ViT) from the CLIP model (Radford et al., 2021). By analyzing the model's internal representations, we can form a baseline understanding of what a vision-only system perceives.

Our analysis, visualized in Figure 6, reveals that the ViT is highly effective at identifying regions of high visual saliency. The CLS vs. patch token similarity heatmap (Figure 6b) and its corresponding overlay (Figure 6a) clearly show that the model concentrates its attention on the graph's nodes and the text they contain. Furthermore, the 2D PCA projection of the patch embeddings (Figure 6c) demonstrates a sophisticated ability to differentiate visual primitives; the model creates a tight cluster of tokens corresponding to the uniform white background, cleanly separating them from the more diverse tokens representing the graph's content.

6.1 Limitations of a Purely Visual Approach

Despite this strong performance in visual feature extraction, this analysis exposes a fundamental deficiency: the model understands the graph's **visual syntax** but fails to grasp its **semantic grammar**. The vision encoder perceives boxes, arrows, and text as collections of pixels, but it has no inherent mechanism to understand the abstract, relational concepts they represent. We identify three key lackings:

1. **Absence of Structural Awareness:** The ViT processes the input as a flat grid of patches. It has no native concept of "nodes" as distinct



(a) Similarity heatmap overlaid on the original rendered graph.

(b) The raw 7x7 similarity heatmap.

(c) 2D PCA projection of the feature tokens.

Figure 6: Empirical analysis of a pre-trained Vision Transformer (ViT from CLIP) on a rendered knowledge graph. (a) The attention overlay shows the model focusing on visually salient regions like text and nodes. (b) The raw heatmap quantifies this focus. (c) The PCA plot demonstrates the model's ability to cluster visual primitives (e.g., background vs. content), but reveals no inherent understanding of the graph's semantic structure.

entities or "edges" as directed relationships that connect them. The arrow from 'Singapore' to 'HalimahYacob' is merely a set of dark pixels, indistinguishable in its structural role from the outline of a node box.

2. **Relational Ambiguity:** The model cannot semantically differentiate between edge types. The relationships 'leader' and 'language' are both rendered as red text. While a human uses context to understand their vastly different meanings, the vision model perceives them as visually similar patterns. It cannot infer that one signifies a person's role while the other signifies a system of communication.

3. **Inability to Ground Entities:** The model sees the text "Singapore" but does not connect it to the symbolic entity `dbr:Singapore` in a knowledge base. This "semantic grounding" is a prerequisite for any form of true knowledge-based reasoning.

These limitations confirm that relying solely on a vision encoder, no matter how powerful, is insufficient for tasks that require deep relational understanding. The model provides a useful signal about *where* the important information is, but it cannot comprehend *what* that information actually means.

6.2 Mitigating Deficiencies with a Multimodal Architecture

Our proposed architecture is explicitly designed to overcome these lackings by treating each modality as a first-class citizen and fusing them intelligently.

First, to address the lack of structural awareness, we introduce a **dedicated Graph Encoder** (e.g., a GCN (Kipf and Welling, 2017)). This component operates not on the rendered image, but on the symbolic representation of the graph (its nodes, edges, and adjacency matrix). It produces a 'Graph Representation' that is unambiguous and topologically aware, directly encoding the relational facts that the vision model fails to capture.

Second, to guide the vision system and bridge the gap between modalities, we employ a **Q-Former**, inspired by modern vision-language models (Li et al., 2023). The Q-Former acts as an intelligent information extractor. Instead of passively accepting all visual features, it uses a set of learnable queries—which are conditioned on the textual and graph context—to actively pull the most relevant visual information from the frozen ViT. This ensures that the visual signal is not just a generic feature map, but a targeted summary relevant to the specific reasoning task at hand.

Finally, by feeding the specialized outputs from the Graph Encoder and the Q-Former into a powerful **Large Language Model (LLM)**, we enable true multimodal reasoning. The LLM receives a comprehensive, multi-faceted view of the problem: a symbolic understanding of the graph's structure, a contextually relevant summary of its visual appearance, and the user's textual question. This holistic input allows the LLM to perform the high-level inference that is impossible for any single-modality encoder alone.

7 Roadmap

7.1 Progress so Far

We have successfully extended the WebNLG dataset to a tri-modal resource by adding automatically generated graph images to the original text and graph representations. This expansion has been fully integrated and validated, ensuring every graph instance is now aligned across text, structured triples, and visual modalities.

We have completed the pipeline of vision encoder for extracting visual features from the graph image and also we have completed the implementation of **Q-Former** which will be used to align the context of augmented graph image features and encoded graph text features. We have created the pipeline to instruction fine-tune the vision encoder and train the Q-Former model but unfortunately due to timely unavailability of GPU resources heavily affected plan. We ensure that the GPU resource will be available after the mid-submission as we have already applied for high perfoemance compute and we will run the code and produce the results in the final submission. Click here to visit KRAKEN's github repo

7.2 Evaluation Options

Standard VQA Metrics

- **VQA Accuracy:** This will be the primary metric for quantitative assessment, calculating the percentage of correctly answered questions. To handle the open-ended nature of some answers and the variability in human language, a robust accuracy metric will be used that accounts for synonyms and paraphrasing, moving beyond exact string matching.

- **Generation Metrics:** For questions that require more descriptive answers, we will use standard natural language generation metrics, including:
  - **BLEU (Bilingual Evaluation Understudy):** To measure the n-gram overlap between the generated and reference answers.
  - **METEOR (Metric for Evaluation of Translation with Explicit ORdering):** To assess the quality of generated sentences by considering synonymy and stemming.
  - **F1-Score and Average Normalized Levenshtein Similarity (ANLS):** These are particularly useful for tasks involving text recognition within images.

7.3 Timeline

We have already created the pipeline and set up the Q-Former which serves as the connector between vision and graph encoder. After getting the high performance GPU compute we estimate to complete all the experiments and analysis by the last week of October and submit the final draft before the due date(**November 1'2025**).

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