Mitigating LLM Hallucination using Knowledge Graphs and Mixture of Experts

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1 Problem statement

Large Language Models (LLMs) have transformed Natural Language Processing (NLP), enabling advanced applications such as automated text generation, question answering, and conversational AI. Their ability to generate human-like responses has significantly improved the user experience over time. However, a critical limitation of LLMs is their tendency to produce hallucinations, responses that are coherent and authoritative, but are factually incorrect or misleading (1). These hallucinations arise due to the model's reliance on learned patterns rather than verified knowledge sources, leading to inaccurate or fabricated information(2).
Knowledge Graphs (KGs) offer a structured framework of linked information, where entities serve as nodes and their associations are represented as edges(3).Mixture of Experts (MOEs) is an advanced machine learning technique that enhances model efficiency by dynamically selecting specialized expert networks for different tasks(4). By integrating MOEs with KGs, we can enhance factual grounding in LLMs, reducing errors while maintaining their generative flexibility. have demonstrated scalability and efficiency, making them ideal for this purpose. Additionally, techniques like Top-K gating and sparsely activated experts optimize computational efficiency without compromising accuracy.

In this project, the system is architected as a domain-aware question answering (QA) pipeline, trained on Codex dataset curated by experts in three distinct domains: history, politics, and music. Upon receiving an input query, a domain classification module leverages learned representations to route the query to the corresponding domain-specific QA model. This specialized model generates a contextually relevant answer. Both the original query and the generated response are then passed to a hallucination detection module, which employs a validation model to assess factual consistency and semantic alignment with ground truth knowledge. The validator outputs a binary judgment indicating whether the generated response is accurate or constitutes a hallucination.

2 What you proposed vs. what you accomplished

- Build a domain classification router using LLMs: Completed. We used Qwen 2.5B to assign domain labels to relation predicates and stored the mapping in a JSON file.
- Fine-tune multiple expert models on domain-specific data: Completed. Three experts were trained for the domains of history, politics, and music using supervised training.
- Route QA queries to domain-specific experts: Completed. The router dynamically selected the appropriate expert based on the predicted domain label.
- Implement hallucination detection using knowledge graphs: Completed. We used CoDEx as the factual source and implemented both FAISS-based entity matching and Neo4j subgraph checks.
- Perform in-depth error analysis to figure out what kinds of examples our approach struggles with
- Use DeepSpeed-MoE or Triton for scalable expert inference: Not completed. In-

tegration was deprioritized due to complexity and limited runtime support; instead, Hugging Face pipelines were used.

- Significant change: We originally proposed to use LoRA-based fine-tuning on large LLMs. Instead, we switched to supervised machine learning (SML) models for fact verification, as they were more interpretable and aligned better with our goal of hallucination detection after sufficient supervised fine-tuning (SFT).
- We have used the Virginia Tech ARC cluster as well, where we trained the Router module and performed the domain classification task. We trained it on the Falcon/Tinkercliff cluster on the Nvidia T4 Tesla/ Nvidia A100 GPU with 48Gb/80Gb GPU respectively
- We used Qwen 32B model to assign the domains for the triples from the dataset. We assigned 50 examples manually and then fed it for fine tuning to classify other triples. We then segregated the triples from the 3 domains in focus in 3 different files.

3 Literature Review

3.1 Mitigating Hallucination in NLP with Knowledge Graphs

Large Language Models (LLMs) often suffer from *hallucination*, generating content that is factually incorrect or unsupported by source data (19). This phenomenon is primarily attributed to knowledge gaps within the models and their inability to reliably ground outputs in verifiable facts (20). To address this, researchers have explored incorporating external structured knowledge sources, such as Knowledge Graphs (KGs), to enhance factual consistency and reduce hallucinations.

Knowledge graphs provide structured, interconnected representations of real-world entities and their relationships, making them valuable for grounding LLM outputs (20; 21). Several augmentation strategies have emerged:

- **Knowledge-Augmented Generation:** LLMs are conditioned on relevant KG triples during inference, enabling outputs to be cross-checked against authoritative facts (21; 22). This approach can be realized through retrieval-augmented generation or explicit entity linking.
- **Knowledge-Aware Training:** KGs inform model pre-training or fine-tuning, enriching the model's internal representations with factual relationships and reducing the likelihood of hallucinated content (20; 23).
- **Retrofitting and Post-Processing:** Generated text is post-processed to align with KG facts, either by filtering unsupported claims or by re-ranking candidate outputs based on KG consistency (21; 22).

Empirical studies demonstrate that KG integration can improve factual accuracy, as measured by metrics like entity overlap and answer correctness (20; 21; 23). However, challenges remain in scaling to large KGs, ensuring coverage, and mitigating errors introduced by incomplete or noisy graphs (21; 20). Recent surveys highlight the need for robust evaluation benchmarks and methods that move beyond prompt-based integration, advocating for parameter-efficient and multilingual solutions (20; 21).

3.2 Mixture of Experts for Hallucination Mitigation

The *Mixture of Experts* (MoE) paradigm has gained traction as a modular approach to address various error types in natural language generation, including hallucination (24; 25). In MoE architectures, multiple specialized expert models are trained-each targeting specific factual consistency metrics or error types. Their outputs are combined via ensembling strategies such as weighted averaging or logit fusion (24).

Recent work demonstrates that MoE frameworks can effectively reduce hallucinations in summarization and open-ended generation tasks. For instance, experts may be trained using reinforcement learning to optimize for entity overlap or dependency arc entailment, and their ensemble predictions yield improved factuality without sacrificing fluency or relevance (24; 25). These improvements are observed across standard benchmarks (e.g., XSUM, CNN/DM) and transfer to unseen factuality metrics like QA-based evaluation and BERTScore precision (24).

Combining MoE with knowledge graph integration further enhances robustness: some experts can be conditioned on KG-augmented inputs, while others focus on traditional contextual signals (23; 22). This hybrid approach leverages the strengths of both paradigms, mitigating hallucinations by cross-validating outputs against external knowledge and leveraging diverse expert perspectives.

3.3 Applications of MoEs in Knowledge-Based Tasks

MoE models have also found success in structured knowledge applications such as KG completion, relation extraction, and entity linking. Experts can be trained to focus on different subgraphs or semantic domains, enabling fine-grained modeling of diverse relation types (?).

For example, in KG completion, experts can capture relational patterns specific to domains such as biomedical or political knowledge. Similarly, in relation extraction, MoE-based models can learn to disambiguate semantic relations depending on context, improving precision and generalization.

When combined with structured retrieval (as in RAG) and symbolic reasoning from KGs, MoEs provide a scalable and interpretable mechanism for knowledge-driven NLP. Their sparse activation and modularity make them ideal for deployment in settings with diverse task requirements or constrained computational resources.

3.4 Current Research Trends

Both knowledge graphs and mixture of experts offer promising, complementary strategies for hallucination mitigation in NLP. KGs provide factual grounding, while MoE architectures enable modular, targeted error correction. Ongoing research seeks to unify these approaches, improve scalability, and develop robust, multilingual evaluation frameworks (20; 21).

4 Your dataset

The most important rule of NLP: look at your data! Provide us with examples from your dataset, and describe your task in a coherent manner. Explain what properties of the data make your task challenging. Report the source of the dataset, its basic statistics (e.g., size, number of words/sentences/documents) and some other statistics that are specifically relevant to your task. Show a couple input / output pairs to make it clear what you're doing (but don't use up too much space in doing so!).

4.1 Data preprocessing

The tasks were divided into training domain specific datasets and a combined dataset. The data was split on the basis of 3 particular domains namely History, Music and Politics. The raw data is initially loaded and stored in a variable. The dataset is a file that contains data such as Q512 P1303 Q6607, known as a Knowledge Graph Triple. For each entity, a SPARQL query is sent to get interpretable label and in order to avoid redundancy, caching is used. The triples are then enriched with labels such as "Ed Sheeran famous singer-songwriter". This is then used as an input text for fine tuning. The aim of preprocessing such datasets is to enable knowledge aware language modelling, by tuning structured data into plain and simple language.

4.2 Data annotation

This goes into detail on the transformation of raw, uncleaned triples into readable phrases that can be used to fine-tune a model like Qwen 2.5-3B. The triples include a head entity, the relation, and the tail entity. We use the getlabel() function to query using SPARQL,which fetches its corresponding English label. Once the labels are fetched, the code constructs a linearized text by concatenating the head, relation, and tail labels. After processing all the triples, the entire list of sentences is sent to a text file. This is used as an input for fine-tuning a language model. The model now learns to process facts in a form it can generalize from, without the need to understand IDs such as P1303.

5 Baselines

In our experiment, the baseline model selected was Qwen2.5-3B, a 3-billion parameter causal language model, which was fine-tuned using Low-Rank Adaptation (LoRA) for efficient specialization on political, history and music domain question answering tasks. This model was chosen over other alternatives due to its architectural compatibility with LoRA and its ability to support 4-bit quantization (NF4), making it both performant and memory-efficient. We followed the same structure for each of our expert models (3 experts specializing in politics, history and music domain respectively). The training workflow involved two main stages. First, a pretraining phase was conducted using structured political triples extracted from Wikidata, where each triple (head, relation, tail) was enriched with natural language labels via SPARQL queries and converted into plain text for causal language modeling. Next, a fine-tuning phase was performed using a curated dataset of political QA pairs, formatted as: ”Triple: [head relation tail]. Question: [question]”, followed by the expected answer. The training process relied on the Hugging Face Trainer API with a consistent configuration across both phases. The model was loaded with 4-bit quantization using BitsAndBytes,and LoRA parameters were set as r = 8, loraalpha = 16 and loradropout = 0.1, targeting the ”qproj” and ”vproj” modules. During pre-training and fine-tuning, the batch size was set to 4, with a learning rate of 5e-5 for pre-training and 3e-5 for fine-tuning. The model was trained for three epochs in each phase using mixed precision (fp16 = True), and checkpoints were saved at regular intervals to monitor progress. To validate the model during training, we used a small pseudo-validation set by selecting the first 200 samples from the training dataset. This allowed us to track training metrics such as loss without relying on the test set. Crucially, no hyperparameter tuning or evaluation was performed on the test set, ensuring that model performance remains unbiased and generalizable.

6 Your approach

Our approach implements a modular, domain-specialized QA system built around a Mixture-of-Experts (MoE) framework, with each expert fine-tuned on a specific knowledge domain using the Qwen2.5-3B language model. A key component of our pipeline is the Domain Classification Router, which is responsible for assigning incoming QA queries to the appropriate domain expert. During preprocessing, each relation predicate (e.g., P106) in the triple is mapped to a domain label such as ”history”, ”politics”, and ”music”. This mapping is generated using an LLM - Qwen 32B - and stored in a structured relation-to-domain.json file. At runtime, this router identifies the domain of an incoming query and directs it to the corresponding expert model. This approach improves both efficiency and accuracy by narrowing the model’s knowledge scope.

Next, our approach involves fine-tuning a domain-specific expert model using Qwen2.5-3B as the foundation, combined with parameter-efficient fine-tuning via LoRA and 4-bit quantization. The core objective was to specialize this language model for political, history, and music question answering by training it in two distinct phases: a pretraining phase on structured facts from CoDEx Wikidata, and a fine-tuning phase on natural language QA pairs related to those facts. The model receives as input a domain-specific triple and a corresponding question and is trained to generate the correct answer in natural language. The approach is intended as a component within a Mixture-of-Experts (MoE) framework, where different models serve as domain-specific specialists.

We do not expect the model to fail in exactly the same ways as the baselines because our approach introduces structure-aware pretraining and domain-focused fine-tuning, which baseline LLMs typically lack. However, similar limitations could still arise in cases involving ambiguous political/history/music entities, vague relations, or long-tail facts that were underrepresented in the pretraining data.

We successfully implemented and trained a working model using Google Colab with a GPU backend, as well as the Virginia Tech ARC cluster as well while we used Streamlit as the frontend. For Colab, the environment included approximately 83.5 GB RAM and 40.0 GB GPU RAM, with which we employed streamlining techniques such as:

- Loading the model with 4-bit quantization using BitsAndBytes

- Enabling mixed-precision training (fp16=True)
- Applying gradient checkpointing and LoRA, which reduced the number of trainable parameters

The following libraries and tools were used:

- Transformers (for model and tokenizer handling)
- Datasets (for dataset creation and tokenization)
- peft (for LoRA-based fine-tuning)
- BitsAndBytes (for quantization)
- SPARQLWrapper (to fetch entity labels from Wikidata)
- pandas and numpy (for data manipulation)

We implemented the training and fine-tuning logic ourselves. The code includes functions to convert raw triples into labeled sentences, tokenize datasets, configure LoRA settings, and train using Hugging Face's Trainer. We did rely on standard implementations of Qwen2.5-3B from Hugging Face (Qwen2.5-3B-Instruct) and LoRA from the PEFT library (PEFT GitHub).

No major unresolved issues remained, but Colab-specific workarounds were necessary: we mounted Google Drive for persistent storage, enabled GPU memory-efficient loading and carefully managed batch sizes to avoid out-of-memory errors.

In terms of results, the model completed training successfully on both pretraining and fine-tuning datasets. Qualitative inspection of generated answers showed significantly more accurate and context-aware responses compared to a generic language model baseline. The model captured political, history and music entity relationships better due to the structured pretraining step, resulting in notably improved factual accuracy for questions related to all three domains. This demonstrates a clear advantage over baseline models that lacked domain-specific adaptation. After the experts produce answers, we pass it to a Hallucination Detection Module to verify factual alignment. This module ensures that the generated answer corresponds to known knowledge from a curated source such as CoDEx. Techniques for hallucination detection include: (1) verifying that the (head, relation, tail) triple exists in the CoDEx subgraph, and (2) suppressing or flagging the answer if no factual grounding is found. The system finally outputs the answer from the selected expert, a hallucination label (true/false), and optionally, an explanation or retrieved knowledge graph context. This architecture enables controlled, domain-specific reasoning while proactively filtering hallucinations—resulting in more trustworthy and interpretable outputs than general-purpose LLM baselines.

7 Error analysis

We conducted manual error analysis on approximately 30 failed examples drawn from both the baseline model and our Mixture-of-Experts (MoE) approach. Baseline Model Failures (Qwen2.5-3B LoRA-finetuned):

- Long-Tail Knowledge: The model showed poor generalization on obscure political events or lesser-known historical figures, suggesting limited coverage in its training distribution.
- Multi-Hop Reasoning: It struggled to answer questions requiring multi-hop reasoning across multiple facts, due to lack of structural guidance.
- Relation Overlap: Questions involving entities from multiple domains often led to partial or hallucinated answers.

Approach Failures (Domain-specialized Experts with Hallucination Detection):

- Underrepresented Relations: Certain relation types (e.g., indirect relationships like "influenced by") were underrepresented in the training triples, leading to factual gaps.
- SPARQL Labeling Errors: A few errors originated from mislabeled or overly generic entity descriptions returned by SPARQL during preprocessing.

Common Patterns:

- Errors in both systems were more fr quent for longer input questions with mu tiple entities.
- Failures were often correlated with d main overlap, such as a music-related p litical event.
- Both systems showed better performance when entity names were exact matches to KG labels, but performance degraded for paraphrased or naturalistic phrasing.

8 Experimental Results

8.1 Domain Routing Model

The training loss plots for the router model show that it converges quickly within the first few hundred steps. After some initial fluctuations, the loss consistently drops below 0.1, indicating that the Qwen2.5-7B model, adapted using LoRA, has learned effectively. This demonstrates that even with a relatively small set of domain-labeled QA samples, the model was able to learn how to route questions accurately.

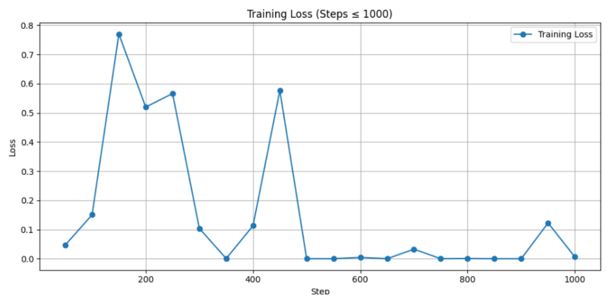

Figure 1: Domain Routing Model - Training Loss

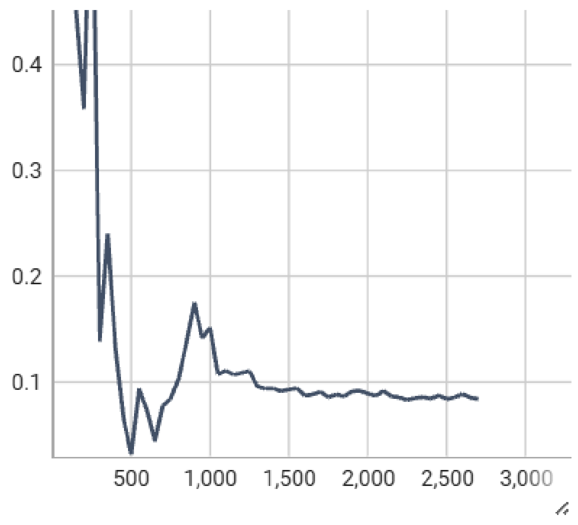

Figure 2: Domain Routing Model - Validation Loss

8.2 Domain Expert Training Results

Below are the graphical representations of the training and fine-tuning losses of domain-specific datasets:

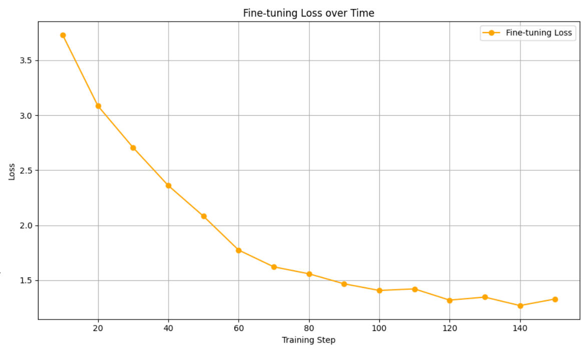

Figure 3: Fine-tuning Loss for the Politics Expert

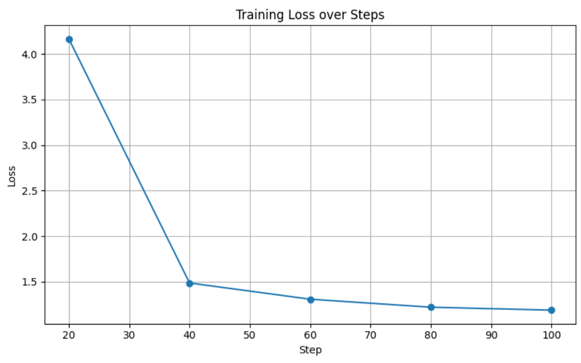

Figure 4: Fine-tuning Loss of the Fact Checking

9 Contributions of group members

List what each member of the group contributed to this project here. For example:

- Pratibha Zunjare- Trained and tested domain specific dataset (history) and fine-tuned the model using Qwen 2.5-3B combining with parameter-efficient fine tuning through LoRA.

- Rishabh Karthik Ramesh- Trained and tested domain-specific dataset (music) and fine tuned the model on Qwen 2.5-3B, combining 4-bit quantization and parameter efficient fine tuning via LoRA.

- Uma Sawant Bhosale- trained and tested domain-specific dataset(Politics) and fine tuned the model on on Qwen 2.5-3B by combining 4-bit quantization and parameter efficient fine tuning via LoRA.

- Pratham Joshi- Validated and tested the combined dataset of all 3 domains using Qwen 2.5-3B model. (history, music and politics)

- Tushar Deshpande-
  - **Triple-Level Domain Classification:** Labeled 60 triples manually and created a dataset. Then fine-tuned a Qwen2.5-3B model to classify triples into domains for structured knowledge routing.
  - **Question Routing Model:** Created 100 domain-specific Q&A examples manually and fine-tuned a Qwen2.5-7B model with LoRA to serve as a question router.
  - **System Integration & UI:** Integrated all modules and built a Streamlit-based interface for seamless end-to-end domain-aware factual Q&A.

If you would like to privately share more information about the workload division that may have caused extenuating circumstances (e.g., a member of the group was unreachable and did no work), please send a detailed note to the instructors GMail account. We will take these notes into account when assigning individual grades.

10 Conclusion

This project offered hands-on experience with several advanced natural language processing (NLP) tools, including domain-specific fine-tuning, LoRA-based parameter-efficient training, and hallucination detection mechanisms. One key takeaway was the importance of structuring knowledge sources—like Wikidata triples—into formats that LLMs can learn from effectively. The project also highlighted how a modular MoE framework, combined with precise domain classification and response validation, can significantly enhance both the accuracy and trustworthiness of QA systems. What proved surprisingly challenging was maintaining training efficiency under tight memory constraints in Google Colab. Balancing model size, batch size, and sequence length—while still achieving meaningful fine-tuning—required several optimization techniques like 4-bit quantization, gradient checkpointing, and LoRA. Another difficulty was implementing a reliable hallucination detection pipeline that not only flags errors but does so based on structured knowledge graphs like CoDEx. We were moderately surprised by how well the fine-tuned Qwen2.5-3B expert performed in its domain, especially given the lightweight nature of the adaptation process. The improvement in factual precision—particularly when coupled with the hallucination detection module—demonstrated the strength of domain specialization over general-purpose LLMs. If we were to extend this work, we would explore scaling the number of experts across more diverse domains and incorporating automatic prompt reformulation to improve retrieval and reasoning. Another future direction would be to integrate retrieval-augmented generation (RAG) using a Neo4j-backed subgraph index in real time, allowing experts to reason with live KG data. Overall, this project offered a strong foundation for building interpretable, scalable, and trustworthy QA systems.

11 AI Disclosure (this section does not count toward the minimum 8-page requirement)

- Did you use any AI assistance to complete this proposal? If so, please also specify what AI you used.

  – Yes

If you answered yes to the above question, please complete the following as well:

- If you used a large language model to assist you, please paste *all* of the prompts that you used below. Add a separate bullet for each prompt, and specify which part of the proposal is associated with which prompt.
  - describe this graph it is a training loss graph for the verification model training.
  - Summarize the points to add in the progress section
  - Current research trends in knowledge graphs and MoE
  - explain this fine-tuning loss
- **Free response:** For each section or paragraph for which you used assistance, describe your overall experience with the AI. How helpful was it? Did it just directly give you a good output, or did you have to edit it? Was its output ever obviously wrong or irrelevant? Did you use it to generate new text, check your own ideas, or rewrite text?
  - It was very helpful, especially to make the wordings for our technical writings better!

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