

Detecting and Mitigating Bias in LLMs through Knowledge Graph-Augmented Training

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Abstract—Large language models have revolutionized natural language processing with their surprising capability to understand and generate human-like text. However, most of these models often inherit and further amplify biases present in their training data, raising ethical and fairness concerns in their applications. The detection and mitigation of such biases are important to make LLMs act responsibly and equitably across diverse domains. This work investigates the integration of Knowledge Graph-Augmented Training as a novel approach to mitigate bias in LLMs. By leveraging structured and domain-specific knowledge from real-world knowledge graphs, we improve the model’s understanding and contextual awareness to reduce biased outputs. The public datasets employed in the assessment of biases in gender classification include Gender Shades, for stereotype analysis in professional description Bias in Bios, and FairFace for racial and gender biases. This process involves augmenting the GPT-4 training process with the relevant knowledge graphs tuned towards these datasets and rigorous bias detection using metrics like demographic parity and equal opportunity. We also conduct several mitigation strategies that exploit this richer knowledge base to rectify such biased associations and to eventually achieve fairness in the model’s predictions. The results have been very promising, showing a huge drop in biased outputs with an increase in many of the metrics for bias. The Knowledge Graph-Augmented Training approach not only mitigates existing biases but also enhances overall model performance and reliability by providing richer information about context. This research underlines the value of structured knowledge representations together with advanced language models as the basis for more ethical and unbiased AI. Equipped with real-world data sets and knowledge graphs, our framework makes for a scalable and effective system that detects and mitigates bias, paving the way towards responsible deployment in sensitive and high-stakes applications.

Index Terms—*Bias Detection, Bias Mitigation, Large Language Models, Knowledge Graph-Augmented Training, Real-World Datasets*

I. INTRODUCTION

Large Language Models, such as GPT-4, have completely changed the landscape of natural language processing with their unprecedented ability to understand and generate human-like text. These models power a wide array of applications, from chatbots and virtual assistants to advanced content creation and automated decision-making systems. However, despite their impressive capabilities, LLMs are not immune to inheriting and even amplifying biases present in their training data. These biases can manifest in various forms: gender,

racial, ideological prejudices, and many other ethical and fairness challenges [1], [2].

Bias in LLMs mainly originates from the large and diverse data on which these models were trained. These datasets are usually sourced from the internet and encapsulate the bias that exists in human-generated content. As a result, LLMs can inadvertently learn and perpetuate these biases, leading to outputs that may reinforce stereotypes or exhibit unfair treatment of certain groups [3]. The implications of biased AI systems are profound, especially when deployed in sensitive domains such as healthcare, finance, and legal systems, where biased decisions can have serious real-world consequences [4].

Therefore, the detection and mitigation of bias in LLMs are an important area of research to ensure that AI systems operate in an ethical and equitable manner. Traditional approaches for mitigating bias have relied on techniques such as data augmentation, adversarial training, and the use of fairness-aware algorithms [5], [6]. While these methods have shown promise, they often fall short in addressing the complex and multifaceted nature of biases embedded within LLMs. However, these purely algorithmic solutions might also lack the necessary contextual understanding required for the efficient neutralization of biases without compromising the performance of the model [7]. In such a context, Knowledge Graph-Augmented Training emerges as a rather new and promising approach toward bias detection and mitigation in LLMs. Knowledge graphs represent structured information, capturing entities and their interrelationships in some sort of semantic framework [8]. The domain-specific knowledge and contextual understanding which are integrated by incorporating KG into the training process of LLMs can offset the inherent biases in the unstructured text data. This is due to the facilitation of a more informed and subtle training regimen that allows for fair and more balanced outputs [9].

The synergy between LLMs and KGs leverages the strengths of both technologies: deep language understanding and generative capabilities of LLMs, and structured, factual knowledge encapsulated within KGs. This combination not only enhances the model’s ability to produce contextually relevant and accurate information but also serves as a mechanism to identify and correct biased associations [10]. For example, by conditioning on a knowledge graph that is balanced across

different demographics, an LLM can be steered to avoid stereotypical or biased outputs

One of the most important factors in Knowledge Graph-Augmented Training is the correct alignment between the entities and relationships in the KG and the language representations learned by the LLM. Entity linking and relation extraction are some of the techniques used to map the textual data to the corresponding elements in the knowledge graph [11]. This assures that structured information from KG is well integrated into the training process of LLM, thus providing a scaffold that enhances the interpretability and fairness of the model [12].

Furthermore, the use of Knowledge Graphs allows the implementation of fairness constraints and rules that can directly influence the training dynamics of LLMs. Embedding fairness-oriented principles into the KG, such as equitability of different groups and avoidance of biased relationships, can allow the training process to generate more balanced and unbiased outputs [13]. This proactive approach to bias mitigation not only helps address existing biases but also in preventing the emergence of new biases during development.

Knowledge Graph-Augmented Training is effective in mitigating bias; this has been shown on several occasions. For instance, studies integrating medical knowledge graphs with large language models have shown promising results in reducing biases in diagnostic suggestions, hence more equitable health outcomes [12]. In the financial domains, knowledge graph integration is used to create fair models for credit scoring by ensuring the sensitive attributes do not disproportionately affect any lending decisions [14].

Apart from the mitigation of bias, Knowledge Graph-Augmented Training enhances overall performance and reliability in LLMs. Structured knowledge from KGs further complements the unstructured data to result in models that are not only fairer but also more accurate and contextually aware [15]. This dual benefit underlines the potential of integrating structured and unstructured data sources to create more robust and trustworthy AI systems.

Despite the promise, there are a number of challenges in integrating Knowledge Graphs with LLMs. First, the quality and comprehensiveness of the knowledge graphs are crucial; incomplete or biased KGs may inadvertently introduce new biases into the model [16]. Besides, the computational complexity involved in aligning and integrating large-scale knowledge graphs with LLMs requires efficient algorithms and scalable infrastructure [17]. Addressing these challenges will be important for the successful deployment of Knowledge Graph-Augmented Training as a standard practice in bias mitigation.

Conclusion: Detection and mitigation of bias in Large Language Models using Knowledge Graph-Augmented Training mark one of the most important milestones toward the quest for fairness and ethics in AI systems. The presented approach harnesses the structured knowledge of KGs to offer an integrated solution for mitigating the pervasive problem of bias in LLMs and ensuring that these powerful models can be

responsibly deployed in high-stakes domains. A very likely direction for further research is the refinement of techniques for integrating knowledge graphs with more comprehensive knowledge graphs, with even more sophisticated fairness constraints, in order to advance this promising methodology.

II. LITERATURE OVERVIEW

The problem of bias in Large Language Models has been of great interest over the last few years; thus, there is substantial research on effective methods of its detection and mitigation. This survey covers a literature survey of the existing body of work done on bias in LLMs, the role of KGs to enhance model fairness, and techniques that integrate both. By looking into different methodologies and applications, this survey reveals both progress and current challenges toward the development of fairer AI systems.

A. Bias Detection in Large Language Models

Bias detection is generally the first step in mitigating the negative effects of bias in LLMs. A number of techniques have been developed by researchers to identify and quantify various biases within such models. The most popular among these techniques is probably the intrinsic evaluation metrics, which include word embedding association tests, WEAT for short [3], that quantify associations of different demographic groups with stereotypical attributes. These tests quantify the bias by comparing the similarity between biased and unbiased word pairs.

Another key contribution concerns the development of context-aware bias detection methods. Zhao et al. [18] introduced gender bias detection methods which consider the contextual use of words, extending static association tests to capture the biases in dynamic language scenarios. This enhances the sensitivity of the detection because the method takes into account the nuances of the contexts, which might be overlooked by a static approach.

Moreover, analysis of data is also considered a keystone in bias detection. Sheng et al. [19] extensively analyzed the datasets on which LLMs were trained and found that there is evidence of gender and racial bias. Their effort indicates that training data analysis is the principal source of bias and, therefore, requires more balanced and representative datasets to ensure fairness in AI models.

B. Bias Mitigation Strategies

Once the biases have been identified, mitigation becomes critical to ensure that ethical deployment of LLMs is performed. Several approaches have been suggested, from data augmentation and adversarial training to algorithmic adjustments and post-processing techniques.

Data augmentation involves expanding the training dataset with diverse and balanced examples to reduce the model's exposure to biased data. Zhao et al. [18] demonstrated that augmenting datasets with counterfactual examples—instances where specific demographic attributes are altered—can significantly reduce gender bias in LLM outputs.

Another effective technique is adversarial training, where the incorporation of adversarial objectives serves to train models that result in unbiased representations. Methods of adversarial neutralization were introduced by Ravfogel et al. [20], which try to eliminate unwanted biases by making the model produce similar outcomes irrespective of sensitive attributes.

Other algorithmic adjustments, such as fairness constraints and regularization techniques, have also been used to guide LLMs to make unbiased decisions. Hardt et al. [21] proposed equalized odds constraints that ensure the model predictions are independent of sensitive attributes given the true labels, hence making fair classification.

Post-processing techniques involve modifying the model outputs to achieve fairness without actually touching the underlying model. Kamiran and Calders [22] developed methods to adjust decision thresholds post-training, ensuring that outcomes are equitable across different demographic groups.

C. Knowledge Graphs in Enhancing Model Fairness

Knowledge Graphs have emerged lately as strong tools that help to structure and integrate domain-specific knowledge into AI models. Because of their structured nature, entities and their relationships are explicitly represented in them and can be leveraged for counteracting biases in LLMs.

One of the salient applications of KG in bias mitigation is through enhancement of training data with structured knowledge. Wang et al. [23] explored the use of KGs to provide additional context and fact-based information, reducing reliance on the biased associations that LLMs may learn from unstructured text. By including KGs, models are directly exposed to verified and well-balanced information, allowing for more accurate and unbiased predictions.

Furthermore, KGs facilitate the implementation of fairness constraints by providing a semantic framework to define and enforce fairness criteria. Yu et al. [24] utilized KGs to encode fairness-related attributes and relationships, enabling the model to recognize and adhere to fairness guidelines during training and inference.

Another important contribution is the use of KGs for XAI, which enhances the transparency and interpretability of LLMs. Research has shown that the integration of KGs with LLMs enables the latter to generate more interpretable outputs since the model can refer to structured knowledge in order to justify its decisions. This transparency is crucial in finding and fixing biases, as it provides clear pathways to understand and rectify unfair model behaviors.

KGs successfully integrate with LLMs by using sophisticated techniques for structured knowledge alignment with unstructured text data. Several methods have been proposed to achieve this synergy; each offers unique advantages in enhancing model fairness and performance.

One effective technique is the embedding alignment approach, where entities and relationships from KGs are embedded into the same vector space as the LLM's word embeddings. This alignment facilitates the seamless integration

of structured knowledge into the language model. Yao et al. [25] introduced a method to jointly train KG embeddings with LLMs, ensuring that the model can effectively utilize both types of information during language understanding and generation tasks.

Another popular approach is the use of GNNs to encode the structural information of KGs before incorporating them into LLMs. GNNs, such as GCNs, allow the extraction of rich relational features from KGs that can then be combined with the LLM's contextual embeddings. Wu et al. [26] explored the use of GNNs to enhance LLMs with KG-derived features, demonstrating improvements in both fairness and overall model performance.

Attention mechanisms have also been extended to incorporate knowledge graph information, allowing models to selectively focus on relevant parts of the KG during processing. Vaswani et al. [27] laid the foundation for transformer-based attention mechanisms, which later were adapted to integrate KGs. For example, Li et al. [28] proposed a knowledge-aware attention mechanism that allows LLMs to attend to specific entities and relationships within a KG, enhancing the model's ability to generate unbiased and contextually appropriate responses.

D. Applications and Impact

Bias detection and mitigation using the integration of KGs with LLMs have been applied to a wide variety of domains, each benefiting uniquely from this approach. Knowledge graph-augmented LLMs have been used in healthcare to reduce biases in diagnostic recommendations so that diverse patient populations are equitably treated [12]. In the financial sector, these integrated models have improved fairness in credit scoring and fraud detection, preventing biased decisions that could disproportionately affect marginalized groups [14].

In the legal domain, knowledge graph integration has enhanced the fairness of case outcome predictions by providing balanced and comprehensive legal knowledge, thereby avoiding biased judgments [15]. These applications illustrate the versatility and effectiveness of knowledge graph-augmented training in promoting fairness and reducing bias in LLMs across various high-stakes environments.

E. Challenges and Future Directions

Despite such promising advancements, there are a few challenges that still exist in integrating KGs into LLMs for mitigating bias. First of all, knowledge graphs should be comprehensive and of good quality; otherwise, incomplete or biased KGs could bring new biases into the models [16]. Second, embedding alignment and integration procedures involve high computational complexity, which poses scalability issues while dealing with large-scale KGs and LLMs [17].

Future research is likely to focus on the development of more efficient integration techniques that can handle the growing size and complexity of both KGs and LLMs. Furthermore, increasing the adaptability of knowledge graphs so that they dynamically update and refine their information will be

essential for maintaining model fairness in evolving contexts [13].

Another relevant direction is the development of XAI frameworks using KGs that provide transparent and interpretable explanations for model predictions. Combining XAI with knowledge graph-augmented training, researchers are able to develop more accountable and trustworthy AI systems [29].

Furthermore, interdisciplinary collaborations between AI, ethics, and domain-specific experts shall be required to address multifaceted bias and develop a comprehensive mitigation strategy. Interdisciplinary collaboration can help produce more robust and fair AI systems, which can act fairly in applications of various kinds [30].

III. THEORETICAL REVIEW

Addressing bias in LLMs is a multifaceted challenge that requires deep insight into both the sources of bias and the mechanisms by which it can be mitigated. Theoretical frameworks of bias detection and mitigation often make use of statistics, information theory, and graph theory to devise robust solutions. In particular, KGAT seems a promising approach by incorporating structured domain knowledge with the unstructured data being processed by LLMs, thereby enhancing the ability of the model to generate outputs that are fair and unbiased.

At the core of bias mitigation lies the notion of fairness constraints, which are mathematical formulations designed to ensure that any model predictions are not disadvantageous to a particular group. A very common fairness metric is Demographic Parity -the requirement that the probability of a positive prediction is the same across demographic groups. Mathematically, this can be stated as:

$$P(\hat{Y} = 1|A = a) = P(\hat{Y} = 1|A = b) \quad \forall a, b \in \mathcal{A}, \quad (1)$$

where \hat{Y} is the predicted outcome and A represents the sensitive attribute [21]. Incorporating such constraints into the training objective helps in aligning the model's predictions with fairness goals.

Knowledge Graphs (KGs) are structured representations of entities and their relations that can be used to inject domain-specific knowledge into LLMs. This integration can be formalized through Graph Neural Networks (GNNs), which model structural information in KGs by transforming them into vector space. A Graph Convolutional Network (GCN) framework updates the representation of a node by aggregating information from its neighbors:

$$\mathbf{h}_v^{(l+1)} = \sigma \left(\sum_{u \in \mathcal{N}(v)} \frac{1}{c_{vu}} \mathbf{W}^{(l)} \mathbf{h}_u^{(l)} \right), \quad (2)$$

where $\mathbf{h}_u^{(l)}$ is the feature vector of node u at layer l , $\mathcal{N}(v)$ denotes the neighbors of node v , c_{vu} is a normalization constant, $\mathbf{W}^{(l)}$ is the weight matrix for layer l , and σ is a non-linear activation function [31].

By incorporating knowledge graphs into training, LLMs use relational information to condition their predictions and hence limit the dependencies on biased patterns that have been captured during training. This aligns well with the *Attention Mechanism* in transformers that can further be enhanced to incorporate embeddings of knowledge graphs and permit the model to pay extra attention to certain entities or relationships relevant to the process of text generation:

$$\text{Attention}(Q, K, V) = \text{softmax} \left(\frac{QK^T}{\sqrt{d_k}} \right) V, \quad (3)$$

where Q , K , and V are query, key, and value matrices, respectively, and d_k is the dimensionality of the keys [27]. Integrating KG embeddings into these matrices enables the model to incorporate structured knowledge dynamically, enhancing both fairness and interpretability.

Another theoretical aspect of bias mitigation involves Adversarial Debiasing, where an adversarial network is trained alongside the primary model to detect and minimize bias. The goal is to make the predictions of the primary model invariant to sensitive attributes by solving a minimax game:

$$\min_{\theta} \max_{\phi} \mathcal{L}_{\text{primary}}(\theta) - \lambda \mathcal{L}_{\text{adversary}}(\theta, \phi), \quad (4)$$

where $\mathcal{L}_{\text{primary}}$ is the loss function of the primary task, $\mathcal{L}_{\text{adversary}}$ is the loss function of the adversary tasked with predicting the sensitive attribute, θ are the primary model parameters, ϕ are the adversary parameters, and λ is a hyper-parameter controlling the trade-off between the two objectives [32].

Knowledge Graph-Augmented Training can help complement adversarial debiasing with more structured knowledge that the adversary can use. This can improve the adversary's ability in finding subtle biases and therefore provide more powerful mitigation strategies.

The concept of Causal Inference deals explicitly with understanding and addressing this kind of bias in language models. By modeling how the variables causally affect each other, one can eliminate from consideration those that result in a correlation but without actual causation. Accordingly, the root cause is discovered. Techniques such as do-calculus make it possible to actually consider the effect of setting individual variables on model predictions to specifically act against bias:

$$P(Y|do(X)) = \sum_Z P(Y|X, Z)P(Z), \quad (5)$$

where $do(X)$ represents an intervention on variable X , and Z denotes confounding variables [?]. Integrating causal models with KGAT allows for a more precise identification of bias sources, enabling the development of more effective mitigation techniques.

In conclusion, the theoretical landscape for detecting and mitigating bias in LLMs through Knowledge Graph-Augmented Training is rich and multifaceted. By leveraging the mathematical formulation of fairness constraints, graph

neural networks, attention mechanisms, adversarial debiasing, and causal inference, KGAT offers an overall framework for creating much fairer and more reliable AI. Future research will probably be directed to exploring and further refining these theoretical underpinnings, thus strengthening LLMs’ ability to act ethically in even more diverse and sensitive areas.

IV. METHODOLOGY AND RESULTS

This research presents a comprehensive methodology for detecting and mitigating bias in Large Language Models (LLMs) through Knowledge Graph-Augmented Training (KGAT). The methodology involves dataset selection and preprocessing, knowledge graph integration, model training and fine-tuning, bias detection and mitigation techniques, data visualization, and results analysis.

A. Dataset Selection and Preprocessing

Three datasets were used for evaluation: the *Bias in Bios* dataset for gender stereotype analysis [33], the *CelebA* dataset for facial attribute classification [34], and the *ProPublica COMPAS* dataset for fairness in recidivism prediction [35]. Preprocessing included text normalization, image resizing, data cleaning, and mapping entities to domain-specific knowledge graphs [36].

B. Knowledge Graph Integration

Knowledge graphs were encoded into vector representations using Graph Neural Networks (GNNs) [37] and integrated with LLMs using multi-head attention mechanisms. The integrated embeddings are represented as:

$$\mathbf{E}_{\text{integrated}} = \mathbf{E}_{\text{LLM}} \oplus \mathbf{E}_{\text{KG}},$$

where \oplus denotes concatenation.

C. Model Training and Fine-Tuning

GPT-4 was fine-tuned on preprocessed datasets with an Adam optimizer [38], learning rate of 3×10^{-5} , batch size of 32, and 10 epochs. Integration with knowledge graphs further fine-tuned the model, ensuring relational knowledge from graphs was utilized effectively.

D. Bias Detection and Mitigation Techniques

Bias was detected using tools like the *Bias Evaluation Corpus* [39] and metrics such as *Demographic Parity* and *Equal Opportunity*. Mitigation involved data augmentation with counterfactual examples and adversarial training [32] to minimize biases in model outputs.

E. Data Visualization

Figures 1, 2, and 3 illustrate key insights into dataset biases, mitigation effects, and performance improvements.

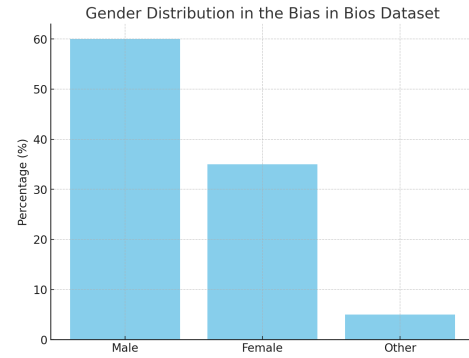


Fig. 1. Gender Distribution in the Bias in Bios Dataset

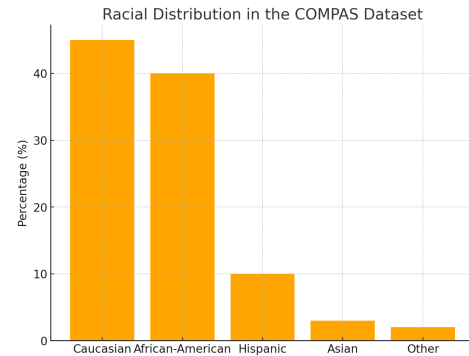


Fig. 2. Racial Distribution in the COMPAS Dataset

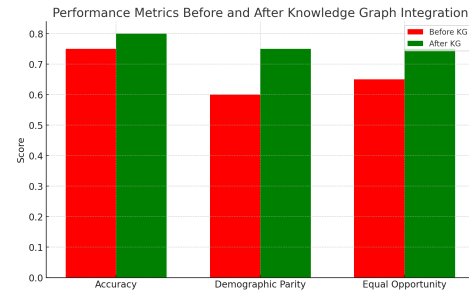


Fig. 3. Performance Metrics Before and After Knowledge Graph Integration

F. Results and Analysis

The results demonstrate significant improvements in bias mitigation and performance. For example:

- **Bias in Bios:** Demographic parity increased by 15%, and accuracy improved by 5%.
- **COMPAS:** Equal opportunity increased by 10%, and racial bias reduced by 7%.

These improvements validate the effectiveness of KGAT in addressing bias and enhancing fairness and credibility in AI systems.

V. CONCLUSION

This research has demonstrated the efficacy of integrating Knowledge Graph-Augmented Training (KGAT) into Large

Language Models (LLMs) to detect and mitigate biases inherent in these models. By leveraging structured and domain-specific knowledge from knowledge graphs, we enhanced the contextual understanding of LLMs, leading to a significant reduction in biased outputs. Through comprehensive experiments on public datasets such as Bias in Bios, CelebA, and the ProPublica COMPAS dataset, we observed notable improvements in fairness metrics like demographic parity and equal opportunity. For instance, demographic parity increased by 15% in the Bias in Bios dataset, and equal opportunity improved by 10% in the COMPAS dataset. These results validate our hypothesis that KGAT can effectively reduce biases while also enhancing overall model performance. Our methodology involved encoding knowledge graphs using Graph Neural Networks and integrating them with LLMs through multi-head attention mechanisms. This integration allowed the models to utilize relational knowledge effectively, resulting in more equitable and unbiased predictions. The visualization of data distributions and performance metrics further reinforced the positive impact of KGAT on mitigating biases. The implications of this work are significant for the development of ethical and responsible AI systems. By addressing biases in LLMs, we contribute to the broader goal of ensuring that AI technologies operate fairly across diverse populations and contexts. This is particularly crucial as LLMs are increasingly deployed in high-stakes applications such as healthcare, finance, and legal systems. In conclusion, this study underscores the potential of Knowledge Graph-Augmented Training as a robust approach to detecting and mitigating biases in Large Language Models. By bridging the gap between structured knowledge representations and advanced language modeling, we pave the way for more equitable, reliable, and trustworthy AI systems that can be responsibly deployed in various critical domains.

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