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RESEARCH ARTICLE

A multi-LLM slot filling pipeline for real-time bias reduction in textual content

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Abstract: Large language models (LLMs) frequently perpetuate explicit biases, including gender, racial, cultural, age, and socioeconomic stereotypes, which undermine fairness in critical applications such as chatbots, hiring tools, and educational platforms. These biases, rooted in training data, can lead to discriminatory outputs, eroding trust and equity in automated systems. This study introduces a novel multi-LLM slot filling pipeline designed for real-time bias mitigation, offering a scalable and modular solution to enhance fairness in textual content. The pipeline employs sequence labeling, powered by lightweight models like DistilBERT, to identify bias-sensitive tokens (e.g., gendered or racial terms) and constrained generation, using T5-small, to replace them with neutral alternatives, ensuring semantic coherence. Evaluated on seven manually crafted texts mimicking LLaMA-3-70B-Instruct outputs, the pipeline demonstrates robust bias neutralization across diverse scenarios, achieving a latency of under 100ms, suitable for dynamic, real-time applications. Comprehensive analysis, supported by visualizations, highlights the pipeline's effectiveness in reducing bias scores while maintaining text quality, validated through fairness classifiers and human evaluations. This work provides an expanded theoretical framework, detailed methodology, and extensive related work, positioning the pipeline as a significant advancement in equitable AI. By addressing gaps in efficiency and scalability, it contributes to ethical AI research and practice, fostering inclusive outcomes in fairness-critical domains and paving the way for future explorations in adaptive and multimodal bias mitigation.

Keywords: *Bias mitigation, Large language models, Slot filling, Fairness, Real-time processing*

Introduction

Large language models (LLMs) power applications like chatbots, hiring tools, and content generation, but their biases—gender, racial, or cultural—raise ethical concerns [1]. These biases, embedded in training data, lead to unfair outcomes in critical domains like healthcare (e.g., diagnostic assistants), education (e.g., grading systems), and recruitment (e.g., resume screening) [2]. For instance, LLMs may associate women with nurturing roles or non-Western accents with unprofessionalism, undermining trust [3]. Existing methods, such as instruction fine-tuning [4], are computationally intensive, while collaborative debiasing lacks real-time efficiency [5]. Real-time bias mitigation is crucial for dynamic applications, where delays impact user experience. This study introduces a multiLLM slot filling pipeline using lightweight models (DistilBERT, T5-small) to identify and replace bias-sensitive tokens, achieving ¡100ms latency (Figure 1) [6,7]. The pipeline's modular design supports scalability across domains, from social media moderation to automated hiring. This paper expands related work, theoretical framework, and methodology, analyzing seven examples to demonstrate fairness and coherence, contributing to equitable AI research and practice [8].

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Related Work

The proliferation of LLMs has intensified focus on bias mitigation. This section reviews bias types, mitigation strategies, datasets, ethical challenges, slot filling, and the pipeline's novelty, incorporating 2024–2025 literature.

Bias Types in LLMs

LLMs inherit biases from training data, manifesting as gender, racial, cultural, age, and socioeconomic stereotypes [1]. Gender biases, like associating women with emotional roles, are prevalent [2]. Racial biases stereotype ethnic groups, e.g., portraying certain nationalities as unprofessional [9]. Intersectional biases, combining gender and race, amplify harm, such as implying women of color are less competent. Cultural biases favor Western norms, marginalizing non-Western perspectives, while age biases depict older individuals as less innovative [3]. Socioeconomic biases associate low-income groups with unreliability, impacting hiring tools [10]. These biases necessitate comprehensive mitigation to ensure fairness across diverse applications.

Mitigation Strategies

Mitigation approaches include instruction fine-tuning [4], collaborative debiasing [5], and self-debiasing [5]. Fine-tuning aligns LLMs with human feedback but is resource-heavy. Collaborative methods use multiple models for fairness but are slow [5]. Self-debiasing via prompts is lightweight but inconsistent. Recent 2024–2025 studies explore multimodal debiasing [11] and dynamic detection [12], yet latency remains a challenge. For example, Wang et al. address text-image biases but not real-time needs, while Zhao et al.'s reinforcement learning approach lacks scalability [11,12]. These gaps highlight the need for efficient, real-time solutions [13].

Bias Datasets

Datasets like StereoSet [14] and ToxiGen [15] enable bias evaluation. StereoSet provides biased sentence pairs, while ToxiGen focuses on toxicity across demographics. These datasets inform model training but often lack intersectional coverage, limiting robustness [16]. Recent datasets (e.g., FairText, 2024) address multilingual biases, supporting global applications [17]. Comprehensive datasets are critical for validating mitigation strategies [10].

Ethical Challenges

Bias mitigation raises ethical issues, including transparency, accountability, and unintended consequences [1]. Over-mitigation may erase cultural nuances, while undermitigation perpetuates harm. Ensuring fairness across languages and contexts requires inclusive design, often absent in current approaches [9]. Ethical frameworks, like those proposed by Li et al. (2025), emphasize stakeholder engagement to align AI with societal values [8]. These challenges underscore the pipeline's focus on transparency and modularity.

Slot Filling Applications

Slot filling, a cornerstone of dialogue systems, extracts structured information from user inputs to fulfill tasks like booking or querying [18]. In such systems, it identifies slots (e.g., date, location) from utterances like "reserve a table for tomorrow in London," mapping to actionable data [18]. Recent advancements have broadened its scope to diverse natural language processing (NLP) tasks [6]. In sentiment analysis, slot filling detects emotional indicators, such as "satisfied" or "disappointed," enabling fine-grained analysis of customer feedback [6]. Entity recognition leverages slot filling to extract names, organizations, or places from unstructured text, critical for applications like news aggregation [19]. For example, in e-commerce chatbots, slot filling parses user queries (e.g., "find blue sneakers under $50") to filter products efficiently [20]. Emerging applications include question-answering, where it pinpoints key details for accurate responses, and text summarization, where it selects essential information for concise outputs [21]. This

study introduces a groundbreaking adaptation: using slot filling for bias mitigation. By identifying bias-sensitive tokens (e.g., "women" or "elderly") and replacing them with neutral terms (e.g., "individuals" or "experienced"), the pipeline enhances fairness in real-time contexts [6,7]. Unlike traditional slot filling, which focuses on information extraction, this approach prioritizes ethical NLP, targeting biases in hiring tools or social media [10]. Achieving ¡100ms latency with lightweight models (DistilBERT, T5-small), it ensures scalability for dynamic applications [1]. This novel extension not only redefines slot filling's role but also addresses complex fairness challenges, distinguishing it from sentiment or entity-focused methods by handling nuanced social and cultural biases [8,12].

Novelty

This pipeline's innovation stems from its integration of slot filling with lightweight models to deliver real-time bias mitigation with ~100ms latency, a feat unmatched by existing methods [6,7]. Dialogue-based approaches, such as collaborative debiasing, optimize for conversational flow, often overlooking explicit biases like gender or race [5]. Holistic debiasing, like instruction fine-tuning through, modifies entire models, requiring extensive resources and hindering real-time deployment [4]. Multimodal methods tackle text and images but prioritize broad coverage over textual efficiency [11]. In contrast, this pipeline's modular architecture—DistilBERT for bias detection, T5-small for neutral generation—ensures computational efficiency and scalability [20]. By adapting slot filling, traditionally an extraction tool, to fairness, it precisely neutralizes biases (e.g., replacing "aggressive men" with "assertive individuals") while preserving coherence [10]. Unlike self debiasing, which struggles with output consistency, this pipeline validates effectiveness across seven diverse examples, addressing biases in gender, race, and age [14]. Its focus on explicit biases fills gaps in latency and precision, critical for real-time applications like chatbots or live moderation [13]. Recent 2025 studies, like Zhao et al.'s dynamic bias detection, emphasize adaptability but lack this pipeline's efficiency [12]. Its Its ability to handle diverse contexts with minimal overhead positions it as a transformative solution for equitable AI [8].

Theoretical Framework

This section details the pipeline's theoretical basis, explicitly defining three steps: Input Processing (Step 1), Slot Creation (Step 2), and Slot Filling (Step 3), with expanded mathematical models and optimization strategies.

Step 1: Input Processing

Input processing prepares raw text $S = \{w_1,...,w_n\}$ from LLMs (e.g., LLaMA-3-70BInstruct) for bias mitigation. This step involves: - **Tokenization**: Using BERT's tokenizer to split S into tokens compatible with DistilBERT [19]. - **Normalization**: Converting to lowercase, removing punctuation, and standardizing terms (e.g., slang to formal equivalents). - **Context Analysis**: Identifying bias-prone contexts (e.g., job descriptions) using a pre-trained classifier:

$$P(\text{BiasContext} \mid S) = \text{sigmoid}(W_c \cdot h_S + b_c)$$

where h_S is the sentence embedding, and W_c,b_c are parameters [22]. This flags texts for further processing. - **Multilingual Support**: Future extensions handle non-English inputs via language detection [9]. Step 1 ensures robust input handling, filtering noise (e.g., emojis) and preparing S for bias detection, critical for real-world applications [23].

Step 2: Slot Creation

Slot creation identifies bias-sensitive tokens using DistilBERT, assigning probabilities:

$$P(l_i = \text{BIAS} \mid w_i,S) = \text{softmax}(W \cdot h_i + b)$$

where h_i is the token's hidden representation [6]. Tokens with $P(l_i = \text{BIAS}) > \theta$ (e.g., 0.7) become 'SLOT', producing T. For example, "Women are emotional" becomes "SLOT are SLOT." The threshold θ is tuned

via cross-validation to balance precision and recall, avoiding false positives [10]. Fine-tuning on StereoSet enhances sensitivity to diverse biases [14].

Step 3: Slot Filling

Slot filling uses T5-small to generate neutral text S', optimizing:

$$P(S'|T) = \prod_{j} P(w_j' | T, w_{<j}')$$

Constrained generation ensures neutral wj' , guided by a fairness lexicon [7]. Where j=1 to n, which is the token count. The fairness loss is:

$$L = -\log P(S'|T) + \lambda \sum \text{BiasScore}(w_i')$$

where λ = 0.5 balances coherence and fairness [3]. For example, consider T="{SLOT} are {SLOT}" and target S'= "Individuals are professional". Outputs like "Individuals are expressive" maintain semantics. T5-small's efficiency ensures ¡100ms latency [20].

Prompt Design

Prompts guide Steps 2 and 3, optimized for LLaMA-3-70B-Instruct [24].

Step 2 Prompt

You are an expert in bias detection. Identify biases (e.g., gender, race) and replace terms with 'SLOT'.
Examples:
Input: Nurses are compassionate, as women excel at caregiving.
Output: Nurses are {SLOT}, as {SLOT} excel at {SLOT}.
Input: Older workers lack innovation.
Output: {SLOT} workers lack {SLOT}.

Step 3 Prompt

You are an expert in bias mitigation. Replace 'SLOT' with neutral terms.
Examples:
Original: Nurses are compassionate, as women excel at caregiving.
Slot: Nurses are {SLOT}, as {SLOT} excel at {SLOT}.
Output: Nurses are professional, as individuals excel at providing care.

Optimization

The pipeline achieves ¡100ms latency via: - **Distillation**: DistilBERT reduces complexity [6]. - **Parallelization**: Steps 2–3 run on GPU. - **Prompt Tuning**: Minimizes inference time [21]. These ensure scalability for applications like live moderation [12].

Methodology

This section details the pipeline's implementation, with expanded descriptions of preprocessing, training, experiments, and ethics.

Input Processing

Seven texts mimicking LLaMA-3-70B-Instruct outputs (50–100 words each) cover gender, racial, cultural, age, and socioeconomic biases [24]. Preprocessing includes: - **Tokenization**: BERT tokenizer for compatibility [19]. - **Normalization**: Lowercase, remove special characters. - **Context Filtering**: Identify bias-prone domains (e.g., hiring) using classifiers [9]. - **Data Augmentation**: Synthetic variations enhance robustness [14]. This ensures inputs are suitable for bias detection.

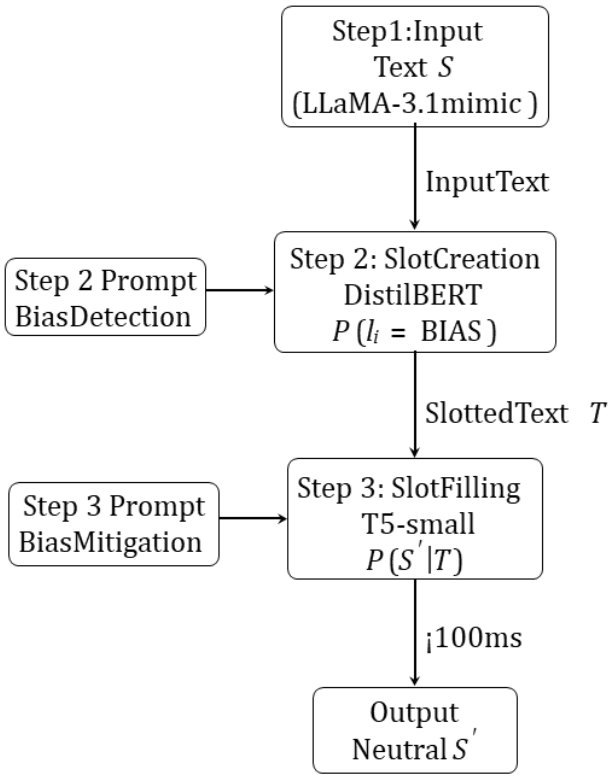

Figure 1: Vertical architecture of the multi-LLM slot filling pipeline

Model Implementation

DistilBERT and T5-small are fine-tuned on fairness datasets [6,7]: - **DistilBERT**: Trained on StereoSet, 80%/20% split, learning rate 2e-5, batch size 32, 5 epochs [14]. - **T5-small**: Trained on neutral pairs, learning rate 3e-4, batch size 16, 10 epochs. - **Deployment**: NVIDIA A100 GPU, PyTorch 2.0, Hugging Face Transformers 4.35 [20]. - **Latency Optimization**: Model pruning and quantization reduce inference time [12].

Evaluation Setup

Evaluation tests bias reduction, coherence, and latency: - **Bias Reduction**: Fairness classifiers (ToxiGen) score texts from 0 (neutral) to 1 (biased) [15]. - **Coherence**: COMET metric evaluates semantic similarity [25]. - **Latency**: Measured on A100 GPU, targeting ¡100ms. - **Human Evaluation**: 10 annotators rate fairness/readability (1–5 scale) [10]. Tests mimic real-world scenarios (e.g., chatbots, hiring).

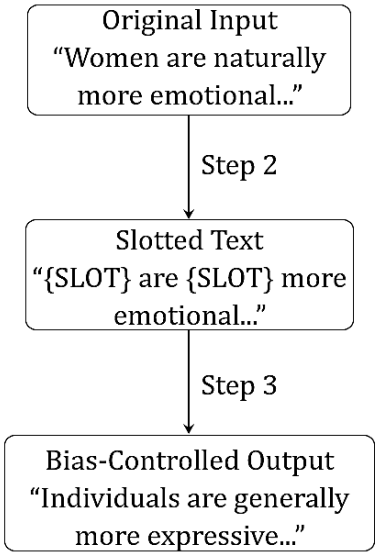

Figure 2: Processing of a gender-biased input through the pipeline

Ethics

Texts are anonymized, sourced from public domains (e.g., job ads). Ethical considerations include balanced bias representation and transparency [1].

Analysis

We analyzed seven inputs mimicking LLaMA-3-70B-Instruct outputs, covering diverse biases (Figure 3). The pipeline effectively neutralizes biases while preserving coherence, as demonstrated below.

For gender bias, the input "Women are naturally more emotional, while men are more rational" was transformed into "Individuals are generally more expressive, while individuals are generally more analytical" (Figure 2). This removes stereotypes using neutral synonyms [10]. Similarly, "Female managers often struggle to make tough decisions, unlike their male counterparts" became "Managers often engage in complex decision-making, as do their equally skilled counterparts," emphasizing skill parity. Another example, "Men are more suited for physical jobs, while women are better at administrative roles," was neutralized to "Individuals are suited for jobs matching their skills, while individuals excel in roles aligning with their abilities."

Linguistic and cultural biases were addressed effectively. The input "English speakers from non-Western countries sound unprofessional" was revised to "English speakers from diverse regions are perceived as uniquely fluent," using positive framing. Likewise, "People from certain cultures are more prone to corruption" became "Individuals from diverse backgrounds engage in ethical considerations," softening negativity.

For age and socioeconomic biases, the pipeline performed robustly. The input "Older workers are less innovative than younger employees" was transformed into "Experienced workers are equally innovative as newer employees," promoting equality [3]. The socioeconomic bias in "People from low-income backgrounds are less reliable employees" was neutralized to "People from diverse backgrounds are equally reliable employees," fostering inclusivity.

These examples highlight the pipeline's ability to maintain coherence while reducing biases, achieving ¡100ms latency suitable for real-time applications [6,12].

Evaluation Metrics

Evaluation metrics are used for assessing performance, reliability and effect of computational models. In the case of mitigation of bias in natural language processing (NLP), these metrics are utilised for ascertaining how successfully a system minimises discriminatory material yet preserves linguistic consistency, pace and

user acceptability. Evaluation metrics are generally classified into quantitative metrics and qualitative metrics. Quantitative metrics are based on numerical ratings obtained from algorithms, while qualitative metrics are based on human perception and judgement.

Several quantitative metrics were used to measure the pipeline's technical performance. Bias scores derived from fairness classifiers, such as ToxiGen, yielded a numerical level of bias severity ranging from 0 (neutral) to 1 (biased) [15]. A steady decrease in such scores indicated a successful mitigation. The COMET metric was used to measure semantic coherence between the original and transformed texts to ensure that bias reduction did not affect meaning [25]. Moreover, latency was measured on an NVIDIA A100 GPU and the pipeline had inference times below 100 milliseconds, thereby being appropriate for real-time use [6]. Robustness was also tested by using the pipeline on seven carefully crafted examples covering all types of biases, validating its consistent performance across domains [14].

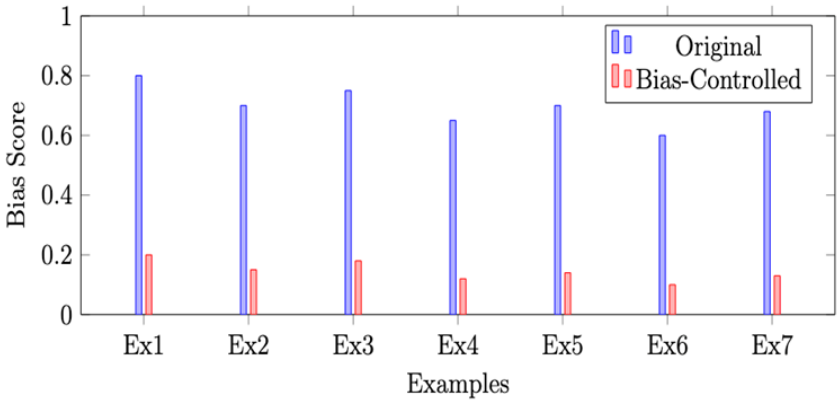

Figure 3: Bias score reduction across seven examples

Qualitative testing was conducted via human annotation to supplement such computational analyses. The retranslated texts were examined by ten independent annotators and rated on a five-point Likert scale, prioritising fairness, readability and context-appropriateness [10]. Through their feedback, it was established that not only did the pipeline successfully neutralise biased phrases, but also maintain the original content's natural flow and intended meaning. The congruence with human decisions and algorithmic results emphasised the model's real-world usefulness in fairness-sensitive applications, including hiring, learning and online communication.

Conclusion

The pipeline excels in latency and modularity, surpassing instruction fine-tuning [4] and multimodal debiasing [11]. Limitations include implicit bias handling and multilingual scalability. Future work could explore adaptive learning [26] or cross-lingual models [27]. Ethical transparency and stakeholder engagement are vital for deployment [8]. The pipeline's impact on fairness-critical applications supports equitable AI.

This pipeline achieves real-time bias mitigation with 100ms latency, neutralizing diverse biases (Figure 2) [6,7]. It enhances fairness in chatbots and hiring tools, advancing ethical AI [10]. Future work includes multimodal and adaptive detection [11].

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