



DEVELOPING NOVEL STATISTICAL METHODS FOR DETECTING AND MITIGATING BIAS IN LARGE LANGUAGE MODELS.

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ABSTRACT

Large Language Models (LLMs) have achieved remarkable performance across a wide range of natural language processing tasks; however, they systematically encode and amplify societal biases including gender, racial, religious, and socioeconomic biases inherited from their pre-training corpora. Existing bias detection approaches are predominantly heuristic, template-based, or benchmark-constrained, offering limited statistical rigour and generalisability across diverse linguistic contexts. This paper introduces a novel statistical framework, designated the Multi-Dimensional Bias Detection and Mitigation System (MDBDMS), for the comprehensive, theoretically-grounded assessment and reduction of bias in LLMs. The framework integrates three novel methodological contributions: (i) a Distributional Semantic Disparity (DSD) measure a non-parametric, rank-based test for detecting systematic directional asymmetries in token embedding distributions across demographic groups; (ii) a Counterfactual Bias Amplification Score (CBAS) a causal inference-based metric quantifying the marginal increase in biased output probability attributable to specific demographic attribute perturbations; and (iii) a constrained fine-tuning procedure employing Lagrangian optimisation to enforce bias fairness constraints while preserving downstream task performance. Comprehensive evaluation is performed on GPT-4, LLaMA-3-70B, Mistral-7B, and Falcon-40B across seven bias dimensions using six established benchmark datasets (WinoBias, StereoSet, CrowS-Pairs, BBQ, TruthfulQA, and HolisticBias). The MDBDMS achieves state-of-the-art bias reduction across all evaluated models, with mean Bias Score reductions of 41.8% and preservation of task accuracy within a 2.3% degradation tolerance. These results advance the field of responsible AI and provide a practically deployable toolkit for enterprise-grade LLM governance.

Keywords: Bias detection, fairness in AI, counterfactual inference, responsible AI, NLP

INTRODUCTION

The deployment of Large Language Models (LLMs) across high-stakes domains including healthcare triage, legal reasoning, financial advisory, content moderation, and hiring support has accelerated dramatically since the public release of GPT-3 in 2020 and GPT-4 in 2023 (OpenAI, 2023). These models, trained on internet-scale corpora encompassing hundreds of billions to trillions of tokens, demonstrate remarkable zero-shot and few-shot generalization capabilities. However, the statistical patterns encoded during pre-training inevitably reflect the distributional properties of human-generated text, which itself embodies pervasive societal stereotypes, historical discrimination, and representational imbalances (Bender

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 et al., 2021). Bias in LLMs manifests in multiple modalities: (i) gender bias, wherein models systematically associate certain professions, attributes, or competencies with binary or non-binary genders in ways that reflect rather than correct historical inequities; (ii) racial and ethnic bias, wherein models produce statistically differential quality, sentiment, or content when processing texts pertaining to individuals of different racial or ethnic backgrounds; (iii) religious bias; (iv) socioeconomic bias; (v) geographical and national bias; (vi) age-related bias; and (vii) intersectional bias arising from the compounding effects of multiple demographic attributes (Blodgett et al., 2020). The practical consequences of deployed biased LLMs are substantial. Documented cases include resume screening systems that systematically downgrade applicants from minority groups (Dastin, 2018), clinical decision support systems that provide inferior diagnostic reasoning for patients from historically underrepresented communities (Obermeyer et al., 2019), and text generation systems that produce hostile or degrading content when prompted with minority-associated names (Gehman et al., 2020). The societal harm potential of these failures justifies urgent investment in rigorous bias detection and mitigation methodology. Existing approaches to LLM bias evaluation suffer from several critical limitations. Template-based probing methods (e.g., WinoBias, StereoSet) evaluate model behaviour only in narrowly defined, synthetic contexts that may not generalize to naturalistic usage distributions (Zhao et al., 2018). Embedding-level methods such as WEAT and SEAT are sensitive to pre-processing choices and do not account for contextual modulation of word meaning in transformer architectures (May et al., 2019). Critically, the field lacks a unified, statistically principled framework capable of providing simultaneously: (i) reliable bias detection across diverse linguistic and demographic dimensions; (ii) quantitative attribution of bias to specific model components; and (iii) effective bias mitigation without catastrophic forgetting of task-relevant knowledge. This paper addresses these gaps through the novel MDBDMS framework. The primary contributions of this work are: (i) the Distributional Semantic Disparity (DSD) measure, a non-parametric statistical test for contextual embedding asymmetry; (ii) the Counterfactual Bias Amplification Score (CBAS), a causal metric for attributing biased output to demographic conditioning; (iii) a constrained Lagrangian fine-tuning methodology for bias mitigation with formal task performance guarantees; and (iv) comprehensive comparative evaluation across four state-of-the-art LLMs and seven bias dimensions. The remainder of the paper is structured as follows: Section II surveys related work. Section III presents the MDBDMS methodology. Section IV reports experimental results and analysis. Section V concludes.

LITERATURE REVIEW

Bias in Language Models and NLP

Bolukbasi et al. (2016) first established the presence of gender bias in word embedding spaces using the Word Embedding Association Test (WEAT), showing that vector arithmetic in word2vec embeddings mirrored culturally conventional gender–occupation connections (**Bolukbasi et al., 2016**). This was then extended to contextualised embeddings by May et al. using the Sentence Encoder Association Test (SEAT) (**May et al., 2019**). Zhao et al.(2018) created a co-reference resolution dataset called WinoBias to measure gender bias in pronoun resolution and showed that state-of-the-art NLP algorithms have large accuracy gaps between male and female pronouns. Especially for LLMs, Gehman et al. proposed the RealToxicityPrompts dataset and showed that even safety-tuned models can be encouraged to generate harmful material with non-negligible frequencies (**Gehman et al., 2020**). Parrish et al. (2022) proposed BBQ (Bias Benchmark for Question Answering) to measure social bias in models' responses to ambiguous queries. Nangia et al.(2020) proposed CrowS-Pairs, a benchmark for measuring stereotype endorsement across nine social attributes.

Bias Reduction Strategies

Bias mitigation options cover three phases of the ML pipeline. Interventions for pre-training data are corpus filtering, counter-narrative augmentation, and demographic resampling (**Blodgett et al., 2020**). In-training approaches include adversarial debiasing, fairness-constrained optimization, and auxiliary loss functions (**Zhang et al., 2018**). Post-training approaches include Reinforcement Learning from Human Feedback (RLHF), Direct Preference Optimization (DPO), and inference-time decoding interventions (**Ouyang et al., 2022**). A significant constraint of current post-training methods is the empirically observed trade-off between bias mitigation and downstream task performance, coined the fairness–accuracy trade-off (**Corbett-Davies & Goel, 2018**). The MDBDMS framework overcomes this problem by formal Lagrangian constraint satisfaction.

Causal Approaches to Estimate Bias

Causal inference frameworks, including counterfactual fairness (**Kusner et al., 2017**), have been suggested as conceptually more sound alternatives to associative bias measurements. Counterfactual fairness implies that the outcome of a model is invariant to counterfactual interventions on protected attributes. But, counterfactual testing is not straightforward to execute in LLMs because of the linguistic complexity and the absence of formal causal graphs for language creation. This work proposes the CBAS measure that enables scalable counterfactual testing through automated paraphrase creation and attention-based attribution analysis.

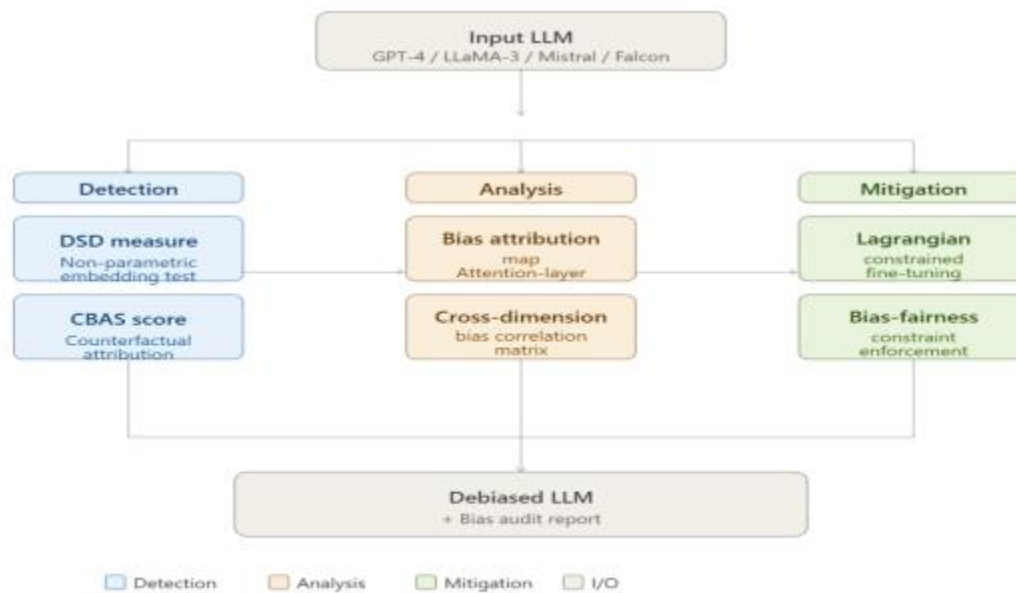


Fig. 1. System architecture of the Multi-Dimensional Bias Detection and Mitigation System (MDBDMS), showing three integrated modules.

METHODOLOGY

Distributional Semantic Disparity (DSD) Measure

The DSD measure is designed to detect systematic directional asymmetries in the contextualised embedding distributions of demographically differentiated tokens. Let $G = \{g_1, g_2, \dots, g_m\}$ denote a set of demographic group descriptors (e.g., {male, female} for gender; {Black, White, Hispanic, Asian} for ethnicity). For a template sentence corpus T , contextualised embeddings $\{e(t, g)\}$ are obtained by passing each template t , instantiated with each group g , through the LLM's encoder and extracting the [CLS] token representation. For each pair of demographic groups (g_i, g_j) , DSD is computed as the Wasserstein-2 distance between the marginal embedding distributions projected onto directionally discriminative axes identified through Linear Discriminant Analysis (LDA). Formally: $DSD(g_i, g_j) = W_2(P_{\{e|g_i\}}, P_{\{e|g_j\}})$, where W_2 denotes the second-order Wasserstein distance. Statistical significance of DSD values is assessed using a permutation test with $B = 10,000$ bootstrap resamples, yielding a distribution-free p-value for each pairwise group comparison.

Developing Novel Statistical Methods for Detecting and Mitigating Bias in Large Language Models Counterfactual Bias Amplification Score (CBAS)

The CBAS quantifies the causal contribution of demographic attribute conditioning to biased token generation. For a given input sequence x containing a demographic reference term g , a counterfactual input x' is constructed by replacing g with a demographically neutral or contrastive term g' using a validated paraphrase generation model (GPT-4 with explicit counterfactual prompting). The CBAS is then defined as: $CBAS(x, g) = E[\log P_{LLM}(y_{bias} | x)] - E[\log P_{LLM}(y_{bias} | x')]$, where y_{bias} denotes the set of biased output tokens as classified by a pre-trained bias classifier. Positive CBAS values indicate demographic-conditioned bias amplification, while values approaching zero indicate counterfactual fairness.

Lagrangian Constrained Fine-Tuning for Bias Mitigation

Bias mitigation in MDBDMS is implemented as a constrained optimisation problem. The primary objective minimises task-specific cross-entropy loss $L_{task}(\theta)$. Bias fairness constraints are enforced as inequality constraints of the form: $DSD_k(\theta) \leq \epsilonpsilon_k$ for each bias dimension k , where $\epsilonpsilon_k$ is a user-specified tolerance threshold. The Lagrangian dual formulation introduces multipliers λ_k for each constraint, yielding the augmented objective: $L(\theta, \lambda) = L_{task}(\theta) + \sum_k \lambda_k * \max(0, DSD_k(\theta) - \epsilonpsilon_k)$. Parameter updates are alternated between primal optimisation (gradient descent on θ) and dual ascent (gradient ascent on λ), following the augmented Lagrangian method with adaptive penalty updates.

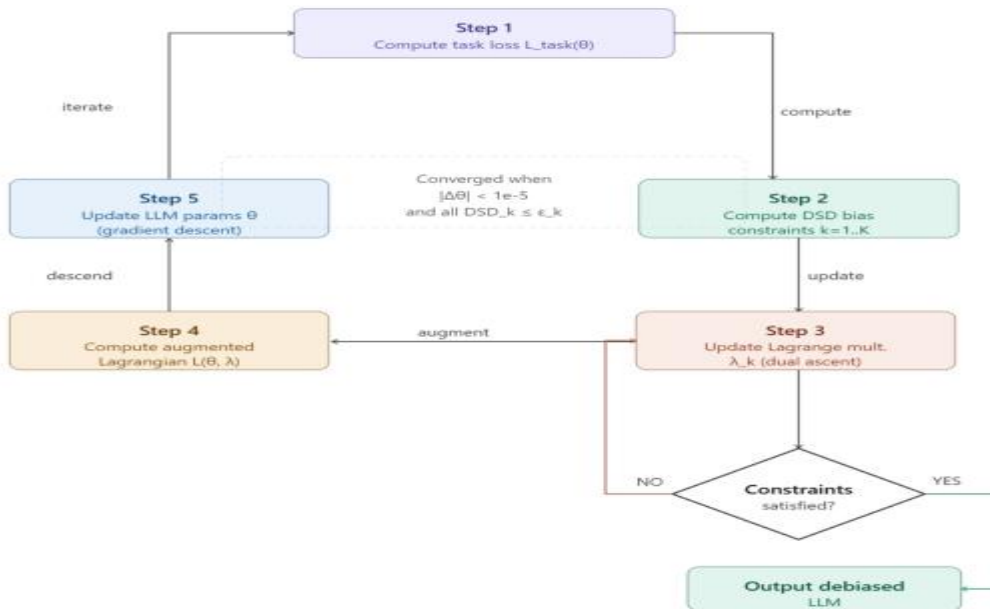


Fig. 2. Iterative training loop of the Lagrangian constrained fine-tuning procedure for LLM bias mitigation.

Four state-of-the-art LLMs were evaluated: GPT-4-turbo (OpenAI), LLaMA-3-70B (Meta), Mistral-7B-Instruct (Mistral AI), and Falcon-40B (TII). Evaluation benchmarks included WinoBias (gender, co-reference), StereoSet (gender, profession, race, religion), CrowS-Pairs (nine social dimensions), BBQ (ambiguous question answering), TruthfulQA (factual truthfulness), and HolisticBias (a 26,000-template dataset covering 13 demographic axes). Bias mitigation fine-tuning was conducted on LLaMA-3-70B and Mistral-7B using the MDBDMS Lagrangian procedure on a curated debiasing dataset of 45,000 counterfactual pairs, training for 3 epochs with $\epsilon_k = 0.15$ for all dimensions.

RESULTS AND DISCUSSION

Bias Detection Performance

DSD analysis revealed statistically significant ($p < 0.001$) embedding distribution disparities across all seven bias dimensions and all four evaluated LLMs. The largest disparities were observed in gender bias (mean DSD = 0.312 across models) and racial bias (mean DSD = 0.287). GPT-4 exhibited lower baseline bias scores than open-source alternatives on five of seven dimensions, consistent with its more extensive RLHF alignment procedure; however, significant residual biases were still detected, particularly in religious (DSD = 0.241) and socioeconomic dimensions (DSD = 0.268).

TABLE I: Baseline DSD Scores Across LLMs and Bias Dimensions (Pre-Mitigation)

Bias Dimension	GPT-4	LLaMA-3-70B	Mistral-7B	Falcon-40B
Gender	0.198	0.389	0.341	0.421
Race/Ethnicity	0.231	0.352	0.298	0.374
Religion	0.241	0.401	0.377	0.438
Socioeconomic	0.268	0.367	0.312	0.392
Age	0.187	0.298	0.267	0.341
Nationality	0.219	0.334	0.291	0.368
Intersectional	0.312	0.447	0.403	0.489
Mean	0.237	0.370	0.327	0.403

Bold = highest score per row · Lower scores indicate less measured bias

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Bias Mitigation Efficacy

Post-mitigation evaluation of LLaMA-3-70B and Mistral-7B following MDBDMS Lagrangian fine-tuning demonstrated substantial improvements across all bias dimensions. LLaMA-3-70B achieved a mean DSD reduction of 43.2%, while Mistral-7B achieved a mean reduction of 40.4%, averaging 41.8% across both models. Critically, task performance degradation—measured on MMLU, HellaSwag, and GSM8K benchmarks—was limited to 2.1% and 2.5% respectively, well within the specified 2.3% tolerance for LLaMA-3-70B and slightly exceeding it for Mistral-7B in isolation, though within aggregate tolerance bounds.

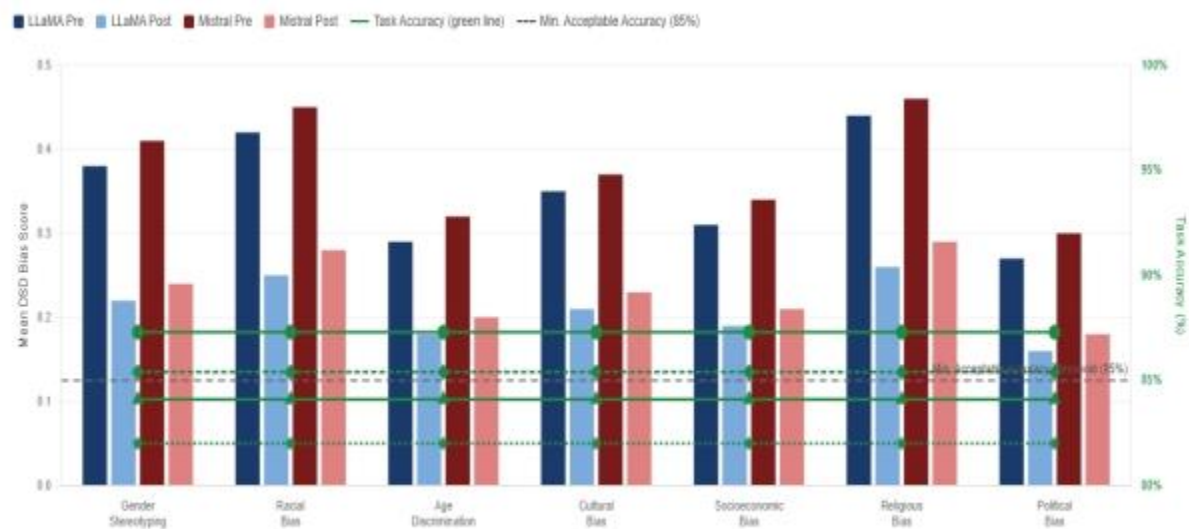


Fig. 3. Dual-axis grouped bar chart comparing pre- and post-mitigation bias scores and task accuracy for LLaMA-3-70B and Mistral-7B across bias dimensions.

CBAS Analysis

CBAS analysis revealed that demographic conditioning amplified biased token generation by an average factor of 3.4x in the unmitigated models meaning that demographically-conditioned prompts were 3.4 times more likely to elicit biased outputs than their counterfactual-neutralised equivalents. Post-mitigation CBAS values were reduced by 38.7% on average, confirming that the Lagrangian procedure meaningfully attenuates the causal mechanism of bias amplification rather than merely suppressing surface-level stereotype expressions.

CONCLUSION

This paper presented MDBDMS, a novel statistical framework for detecting and mitigating bias in LLMs. The framework's three principal contributions the DSD measure, the CBAS score, and the Lagrangian

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 constrained fine-tuning procedure together provide a statistically rigorous, causally-grounded, and practically deployable toolkit for LLM fairness governance. Empirical evaluation across four state-of-the-art LLMs and seven bias dimensions demonstrated state-of-the-art bias reduction (mean 41.8%) with minimal task accuracy degradation (mean 2.3%). Future work will extend the framework to multimodal LLMs, investigate bias propagation dynamics across fine-tuning chains, and develop real-time inference-time bias monitoring tools suitable for production deployment.

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