Probing of Language Model Representations for Bias Certification

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Abstract

Advancements in Natural Language Processing (NLP) have shifted from recurrent models to transformer-based pre-trained language models and large language models. This study investigates gender biases in language model (LM) representations through probing techniques at specific layers. Our key contributions involve improving the robustness of probing methods, and developing a new bias ranking system to analyse group fairness comprehensively. A distinctive aspect of this study is establishing a fairness certification framework inspired by the OT-IND-CPA security model, specifically tailored to assess and certify fairness concerning gender biases in LLMs. Our findings show that BERT and RoBERTa maintain low bias, while GloVe and ELECTRA have more pronounced biases, highlighting the need to address biases in LMs to ensure equitable NLP applications. Our code and database can be found here.

1 Introduction

As the field of Natural Language Processing (NLP) has advanced in recent years, the status quo has shifted from recurrent models such as the LSTM (Hochreiter and Schmidhuber, 1997) to transformer-based (Vaswani et al., 2023) pre-trained language models (PLMs) such as BERT (Devlin et al., 2019) to finally the large language models (LLMs) such as GPT (OpenAI et al., 2024). Although these models offer high accuracy and usability, their limitations, including learning and perpetuating harmful biases, must not be ignored and require attention. Often, these biases are not only embedded in the representations of language models (LMs) but also carry over into downstream tasks, resulting in disparate treatment of various socio-demographic groups (Blodgett et al., 2021; Stanczak and Augenstein, 2021; Stanovsky et al., 2019; Venkit et al., 2022). This work investigates such biases in LM representations through probing, focusing on gender-related biases. Our main contributions are as follows:

1. We identify biases in the encodings of LMs on gender by employing non-binary association tests for a layer-wise nuanced analysis.
2. We enhance the robustness of the probe by training it on a diverse dataset that closely mirrors the characteristics of downstream applications, while increasing its utility for the second step of our methodology.
3. We present a novel bias ranking for various LMs, utilizing previously unexplored evaluation metrics for group fairness.
4. Finally, we provide a novel, OT-IND-CPA-inspired (Carstens et al., 2021) means to certify an LM's fairness using our probing model.

To the best of our knowledge, no other work has evaluated LMs at the layer-level for biases through the lens of group fairness theory, nor does any work exist in the literature on fairness certification.

2 Related Works

2.1 Biases in Language Models and Group Fairness

As LMs become increasingly integrated into everyday applications, their potential to propagate/amplify existing biases has prompted significant scientific attention (Gupta et al.; De-Arteaga et al., 2019; Webster et al., 2020; Nadeem et al., 2020; Garimella et al., 2021; Narayanan Venkit, 2023; Ahn and Oh, 2021; Nangia et al., 2020) with researchers aiming to understand and mitigate biases against specific demographic groups within the models' outputs.

Our evaluation of such biases follows directly from a very recent work (Manerba et al., 2024) on social bias probing. Here, the authors argue that the binary association tests on small datasets

predicated on a single "ground truth" regarding stereotypical statements have constrained the depth of analysis and oversimplified the intricate nature of social identities and their linked stereotypes.

2.2 Probing Techniques in Machine Learning Models

Probing techniques have become a cornerstone in the interpretability of machine learning models, particularly in understanding how deep neural networks encode information. These techniques involve using auxiliary classifiers, *probes*, to extract and analyse representations learned by models during training (Alain and Bengio, 2018; Adi et al., 2017). The primary goal is to determine if specific types of information are captured in the models' representations. Previous works have extensively focused on linguistic, semantic and syntactic properties (Chen et al., 2021; Zhang and Bowman, 2018; Naik et al., 2018; Conneau et al., 2018; Belinkov and Glass, 2017; Hewitt and Manning, 2019; Tenney et al., 2019; Peters et al., 2018; Libovickỳ et al., 2020; Ettinger, 2020; Jawahar et al., 2019; Hewitt and Liang, 2019; Vulić et al., 2020), while more recent works have shifted towards evaluating the models' world knowledge and comprehensive capacities (Petroni et al., 2019; Dai et al., 2021; Jiang et al., 2020; Zhong et al., 2021; Bang et al., 2023; Li et al., 2023).

3 Methodology

The methodology employed in this study aims to identify and measure biases in LMs, specifically focusing on gender. The approach integrates elements from LABDet's probing technique (Köksal et al.) and aspects of the SoFa methodology (Manerba et al., 2024) to ensure a comprehensive & rigorous analysis. The steps are:

1. A different probe is trained on the LM's encodings at different layers as the input and the corresponding sentiment labels as the output.
2. The encodings of template-generated sentences with minimal differences are evaluated with the trained probe.
3. The probe output is then compared to the generated labels, and through these differences, the LM is evaluated for biases.

3.1 Probe Training

The training process for the sentiment classifier, referred to as the probe, involves several critical steps to ensure that it is free of bias, robust and relevant to real-world applications. This is achieved by training on extensively filtered real-world sentiment analysis datasets. Figure 1 visualises the probe's training pipeline.

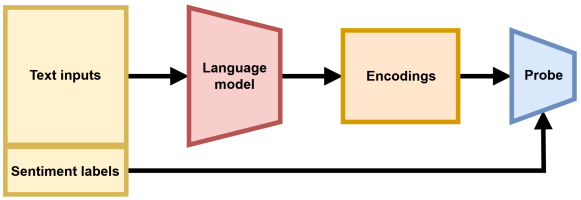

Figure 1: Training the probe with a processed dataset

3.1.1 Datasets

The probe training datasets consist of the Stanford Sentiment Treebank (SST) (Socher et al., 2013) and the TweetEval (Barbieri et al., 2020) dataset. These datasets are chosen for their diversity and for being more representative of the downstream tasks in which LMs are used.

We reckon that training a complex probe on huge, diverse corpora sits at the sweet spot in the debate between the complexity versus simplicity of probes. On the one hand, some researchers advocate for "simple" probes, arguing that overly complex probes can learn to perform the task by themselves, thus failing to reflect the model's internal representations genuinely (Hewitt and Manning, 2019; Alain and Bengio, 2018). On the other hand, the counterargument is that more complex probes are necessary to fully extract the nuanced information encoded by sophisticated neural networks (Hall et al.).

3.1.2 Filtering Techniques

To achieve the goal of an unbiased dataset, a series of comprehensive filters have been implemented based on an extensive review of elements that have traditionally contributed to gender disparities. All terms that have been filtered out are masked in the corpus. Below, we provide a detailed breakdown of the filters in question.

Personal Names: Personal names, due to the implicit gender associations they carry, were masked with the token [NAME] using SpaCy's (Honnibal et al., 2020) named entity recognition capabilities to mitigate any potential gender bias in the dataset.

Pronouns, Titles, and Relationship Terms: Pronouns (e.g., he/she, his/her) and titles (e.g. Mr/Ms/Mrs), alongside gender-specific terms re-

lated to familial roles (e.g., father, mother) and relationship descriptors (e.g., boyfriend, girlfriend) (Zhao et al., 2018) are excluded to foster gender-neutral representation by using the [TITLE/PRONOUN] token.

Occupations: Occupations traditionally associated with specific genders (e.g., actor/actress) are filtered out by applying the mask [JOB]. (Bolukbasi et al., 2016)

Transsexual Terms: Terms related to transgender identities are integrated into our filters to prevent marginalization and ensure accurate representation (Bordia and Bowman, 2019), masked as [ORIENTATION].

We train our probes on $99,769$ training sentences. $67,348$ of these come from SST, while the remaining $32,421$ come from TweetEval. Of these, $27,803$ (28%) had one or more masks.

3.2 Minimal Groups

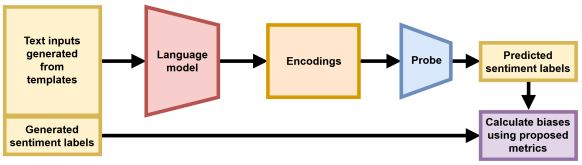

Figure 2: Evaluating biases

In order to assess the potential for bias in LMs, a dataset of minimal groups was constructed using templates. The templates generate sentences with various subjects and adjectives inserted, thus allowing for a nuanced analysis of sentiment associations. A pipeline for how these sentences are used for evaluation is depicted in Figure 2.

3.2.1 Template Construction

Based on the methodology from Equity Evaluation Corpus (EEC) (Kiritchenko and Mohammad, 2018) and LABDet (Köksal et al.), 11 template sentences were used. A complete list of templates can be found in Table 1.

3.3 Names

As summarised in Table 4 in the appendix, multiple gender-specific reference phrases and titles were used for the subjects in the sentences. Moreover, 20 random names (10 female and 10 male) were sampled from the UCI name dataset (mis, 2020) to populate the same.

3.3.1 Sentiment and Situation Words

To ensure comprehensive coverage of sentiment variations, 20 words each for positive, negative, and neutral sentiments are selected. The complete list of the sentiment and situation words can be found in the appendix in Table 5.

Combining these names, titles, sentiment and situation words with different templates resulted in $12,280$ evaluation sentences, $6,140$ each for male and female. Ultimately, there were $4,040$ test samples each for positive and negative and $4,200$ for neutral sentiment.

3.4 Probing and Language Models

We employ a variety of classifiers and LMs as part of our experiments. The classifiers serve as probes to detect biases, while the LMs provide the representations to be analysed.

3.4.1 Classifiers

Different architectures for the probes include logistic regression (LR), which was implemented using the default torch package (Ansel et al., 2024). An MLP-based approach was created with an input layer, 2 hidden layers of 100 neurons using ReLU activation and a single output node with sigmoid activation (Rumelhart et al., 1986). The last architecture used is the default Gaussian Naive-Bayes (GNB) from the scikit-learn package (Buitinck et al., 2013). By examining a broader range of architectures, it is possible to ascertain the extent to which the identified biases and their strength are contingent upon the complexity of the probe. The train-validation set split was set to 80-20.

3.4.2 Language Models

To facilitate the probing of LMs, our experiments can be run with various models, including BERT (Devlin et al.), GPT-2 (Radford et al.), LLaMA (Touvron et al.), RoBERTa (Liu et al., 2019), ELECTRA (Clark et al.), and XLNet (Yang et al.). Due to a lack of resources, LLaMA could not be used. The objective was to extract a range of layers of embeddings and representations from the models, including those derived from the tokenisation process, the middle layer representations, and the final layer representations. Specifically, for models BERT, RoBERTa, ELECTRA, and XLNet, which follow an encoder-only architecture, we accessed the initial embedding layer, the middle layer (halfway through the total number of layers), and

Template	Example Sentence
{} feels {}	She feels happy
The situation makes {} feel {}	The situation makes him feel sad
I made {} feel {}	I made this woman feel excited
{} made me feel {}	This man made me feel delighted
{} found {} in {} {} situation	Mary found herself in a great situation
{} told us all about the recent {} events	He told us all about the recent grim events
The conversation with {} was {}	The conversation with my mom was funny
I saw {} in the market,	I saw my dad in the market
I talked to {} yesterday	I talked to my sister yesterday
{} goes to the school in our neighborhood	She goes to the school in our neighborhood
{} has two children,	This woman has two children

Table 1: List of Templates and Example Sentences

the final layer in the encoder stack. For GPT-2, which uses a decoder-only architecture, similar layers were accessed within its decoder stack. This modular approach allows for the analysis of how different layers of these models capture and potentially propagate biases. In our results, we use the GloVe model (Pennington et al., 2014) as a baseline model, as it is supposed to be representative of biases inherent to the training data.

3.5 Evaluation Metrics

The evaluation utilized demographic parity and equalized odds to assess positive and negative gender bias alongside a LABDet-like evaluation for neutral sentences in sentiment predictions:

Demographic Parity (DP): Ensures fairness by maintaining consistent probabilities of bias detection across genders. DP is achieved when the proportion of detected biases in texts authored by different gender groups is roughly equal:

$$P(\hat{Y} = 1|G = 0) = P(\hat{Y} = 1|G = 1)$$

Equalized Odds (EO): Ensures that the model's true and false positive rates are the same for all genders. The two values in the Equalized Odds for positive labels serve as an independent condition for Equal Opportunity. A classifier $\hat{Y}$ satisfies Equalized Odds if:

$$P(\hat{Y} = 1|Y = 0, G = 0) = P(\hat{Y} = 1|Y = 0, G = 1)$$
$$P(\hat{Y} = 1|Y = 1, G = 0) = P(\hat{Y} = 1|Y = 1, G = 1)$$

Average Relative Sentiment Change (ARSC): Measures how consistently the model predicts sentiment for neutral sentences with and without the masking of group identifiers. Ideally, the average changes in predictions should be nearly identical. (Köksal et al.)

4 Fairness Certification

In this section, we will use our probing model for bias detection in LMs to propose a certification for fairness. This certification is inspired by the "One-Time Indistinguishability under Chosen Plaintext Attack" (OT-IND-CPA) security theory. After defining all the terms, we give a mathematical derivation of the advantage function to quantify bias using our probing model, followed by an analysis of the extreme cases.

4.1 OT-IND-CPA Fairness

Let $\mathcal{M}$ be an LM, and $\mathcal{O}$ an oracle that returns encodings from $\mathcal{M}$. We define an OT-IND-CPA game between a challenger and an attacker (probe) as follows:

Training Phase: The attacker trains a probe $\mathcal{P}$ on an unbiased dataset $\mathcal{D}_{train}$ with sentences that do not include any elements of the group of interest G (e.g., male/female indicators, as filtered in section 3.1.2). The probe $\mathcal{P}$ achieves 'sufficiently high' accuracy for sentiment classification on this dataset, represented as p.

Query Phase: The attacker selects a minimal group of sentences $S = \{s_1, s_2, \ldots, s_{|G|}\}$ where each s_i is identical except for elements belonging to the group of interest G (e.g., different gender-specific names or pronouns, as created in section 3.2), and $|G|$ is the total members in the group. The attacker then sends S to the oracle $\mathcal{O}$.

Oracle Response: The oracle $\mathcal{O}$ randomly selects one group element $g_i \in G$ and returns the encoding, e, of the corresponding sentence, s_{g_i}

generated by the model $\mathcal{M}$ at the final layer L.

Attacker's Task: The attacker $\mathcal{P}$ must determine which group element $g \in G$ was used to generate the encoding e. The attacker's advantage is calculated as:

$$\text{Adv}^{\mathcal{P}}_{\mathcal{M}} = \left| P(\mathcal{P}(e) = g_i) - \frac{1}{|G|} \right|$$

where $P(\mathcal{P}(e) = g_i)$ is the probability that the probe correctly identifies the group element. The maximum value of this expression is

To this extent, we say that an LM, $\mathcal{M}$, is (t, p, ϵ) fair, if, for any attacker probe trained in t FLOPs with validation accuracy of p has at most advantage ϵ. We define t in terms of FLOPs to strike a trade-off between the complexity of the probe architecture and the data it's trained on. Moreover, this keeps the value consistent across different devices.

4.2 Advantage Derivation

To discard a trivial solution, we must assert that the $|G|$ sentences queried by the attacker should have the same sentiment. Naturally, the attacker chooses this sentiment at the time of query.
Thus, we can re-write the advantage expression as follows:

$$\text{Adv}^{\mathcal{P}}_{\mathcal{M}} = \left| P(\mathcal{P}(e) = g_i \mid y = Y) - \frac{1}{|G|} \right|$$

where y is the label and Y is the sentiment the attacker chooses. Now, using Bayes theorem and total probability rule, we can rewrite the probability term as:

$$P(\mathcal{P}(e) = g_i \mid y = Y)$$
$$= \frac{P(y = Y \mid \mathcal{P}(e) = g_i) P(\mathcal{P}(e) = g_i)}{\sum_{g_i \in G} (P(y = Y \mid \mathcal{P}(e) = g_i) P(\mathcal{P}(e) = g_i))}$$

Further, since we fully know the sentence being encoded if its group is known, we can rewrite

$$P(y = Y \mid \mathcal{P}(e) = g_i) = \begin{cases} \hat{p} & Y = 1 \\ 1 - \hat{p} & Y = -1 \end{cases}$$

where $\hat{p}$ is the sentiment prediction by the probe on the encoding of the known sentence. $P(\mathcal{P}(e) = g_i)$ is the prior with value $\frac{1}{|G|}$ for all groups g_i for a probe trained on data belonging to each group equally. Finally, the advantage is given by:

$$\text{Adv}^{\mathcal{P}}_{\mathcal{M}} = \left| \frac{P(y = Y \mid \mathcal{P}(e) = g_i)}{\sum_{g_i \in G} P(y = Y \mid \mathcal{P}(e) = g_i)} - \frac{1}{|G|} \right|$$

Model	(t, p, ϵ)
Glove	(0.14, 83.55, 0.07)
BERT	(0.14, 88.83, 0.01)
ELECTRA	(0.14, 85.04, 0.02)
GPT2	(0.14, 81.01, 0.01)
RoBERTa	(0.14, 88.12, 0.01)
XLNet	(0.14, 83.05, 0.02)

Table 2: Fairness Certificates for different models. t is reported in TFLOPs and p in %

4.3 Analysis of Extreme Cases

For this section, without loss of generality, we will assume $Y = 1$.
Ideal Case: For an unbiased LM,

$$P(y = 1 \mid \mathcal{P}(e) = g_i) = \hat{p}^* \quad \forall g_i \in G$$

Therefore, the advantage in such a case is

$$\left| \frac{\hat{p}^*}{\hat{p}^* \times |G|} - \frac{1}{|G|} \right| = \left| \frac{1}{|G|} - \frac{1}{|G|} \right| = 0$$

which is the minimum value possible.
Worst Case: In the worst case,
$P(y = 1 \mid \mathcal{P}(e) = g_i) = 1$ for some group g_i; 0 for all others.
Therefore, the advantage in this case is

$$\left| \frac{1}{1} - \frac{1}{|G|} \right| = 1 - \frac{1}{|G|}$$

which is the maximum value under the assumption, $|G| \geq 2$.

5 Results

5.1 Probe Training

We find that the MLP-based probes generally perform best in predicting the correct sentiment labels. For some LMs, logistic regression can outperform the MLP model, especially in the early layers. Gaussian Naive-Bayes probes consistently score the lowest. Specifically, for GPT-2 and ELECTRA, these probes are unable to learn from embeddings from the middle and final layers while being reasonably successful for the initial layer. The results for probe training on different layers are shown in the appendix in Table 6.

5.2 Bias Evaluation

The bias evaluation of the various LMs was conducted using the final layer embeddings probed by

an MLP classifier. Table 3 summarizes the results across three main metrics: Average Relative Sentiment Change (ARSC), Demographic Parity (DP), and Equalized Odds for both negative (EON) and positive (EOP) sentiments. For each metric, we provide two methods of evaluation, one calculating the results based on labels and another using raw probabilities for the positive sentiment. An additional column shows the ranking of the language models from 1 (most biased) to 6 (least biased), where the models are ranked based on the sum of the absolute values of ARSC, DP, EON, and EOP metrics (for labels), with higher sums indicating greater bias. The results we deliver are always the difference between the two groups, where values > 0 mean stronger (positive) bias towards males and values < 0 mean stronger (positive) bias towards females. The key findings from the evaluation are as follows:

GloVe: GloVe exhibited the highest ARSC value (0.13), indicating significant shifts in sentiment predictions. Additionally, it showed negative DP, EON, and EOP values, suggesting a bias against male gender references.

BERT: Demonstrated minimal bias across all metrics with values close to zero, indicating a relatively balanced model. It showed a slight positive bias with a DP of 0.01.

ELECTRA: Had a notable ARSC of -0.07 and a positive EOP of 0.08, showing some bias in sentiment prediction consistency and positive sentiment predictions.

GPT2: Showed moderate bias with an ARSC of -0.04 and EON of 0.04, indicating some inconsistency in sentiment changes and a slight positive bias in negative sentiment predictions.

RoBERTa: Displayed very low bias across all metrics, similar to BERT, with an ARSC of -0.01 and negligible DP and EON/EOP values.

XLNet: Also showed low bias with minor fluctuations, having an ARSC of -0.03 and slight positive DP and EON values.

Figure 3 shows more detailed results over three layers with multiple probe architectures.

5.3 Certification Analysis

In Table 2, we present the certificates for various LMs. To compute the advantages, we utilized the first seven templates from Table 1, fixing the sentiment as positive. The mean prediction probabilities for the MLP model in the final layer across both groups were calculated for each template. Next, we calculated the maximum among all the templates and reported the maximum among the final advantages of both groups. For t, we used the PyTorch-OpCounter library (Jianyu, 2018) and scaled the value for the number of epochs. Naturally, t is the same across different LMs. Higher probe accuracies observed across models such as BERT and RoBERTa signify a strong attacker. Analysis of the corresponding epsilon values indicates varying degrees of information leakage: GPT-2 has a low advantage ($\epsilon = 0.01$) but for the weakest probe (81.1%). Meanwhile, BERT and RoBERTa also exhibit minimal advantages ($\epsilon = 0.01$) but with much stronger attackers (88.83% and 88.12%, respectively), highlighting relatively strong fairness in their representations. ELECTRA and XLNet show slightly higher epsilon values (0.02), indicating an increased susceptibility to revealing group-specific information. In contrast, GloVe demonstrates the highest epsilon value (0.07), with greater potential for information leakage. These insights emphasize the critical need for meticulous fairness assessments when selecting models to ensure equitable outcomes in sensitive applications.

6 Discussion

The results of layer-wise accuracy present intriguing insights into the biases of LMs. For instance, GPT-2 exhibits a downward trend in probe accuracy across layers. This phenomenon can be attributed to the evolving nature of feature representations within the model. In the early layers, GPT-2 captures more granular, surface-level features such as lexical information and basic syntax (Radford et al., 2019). As the data propagates through the layers, the model focuses increasingly on higher-order abstractions and complex dependencies, potentially causing a loss of specific, easily identifiable features that simpler linear probes such as LR can detect. While enhancing the model's generative capabilities, this abstraction process can make it harder for linear probes to decode specific information from deeper layers accurately.

However, in the case of BERT, probes maintain or even improve their accuracy. This is because BERT's architecture is designed to handle bidirectional contexts effectively, capturing nuanced and contextually rich representations throughout its layers. Consequently, the deeper layers refine and enhance the quality of these representations, maintaining relevant features in a manner that re-

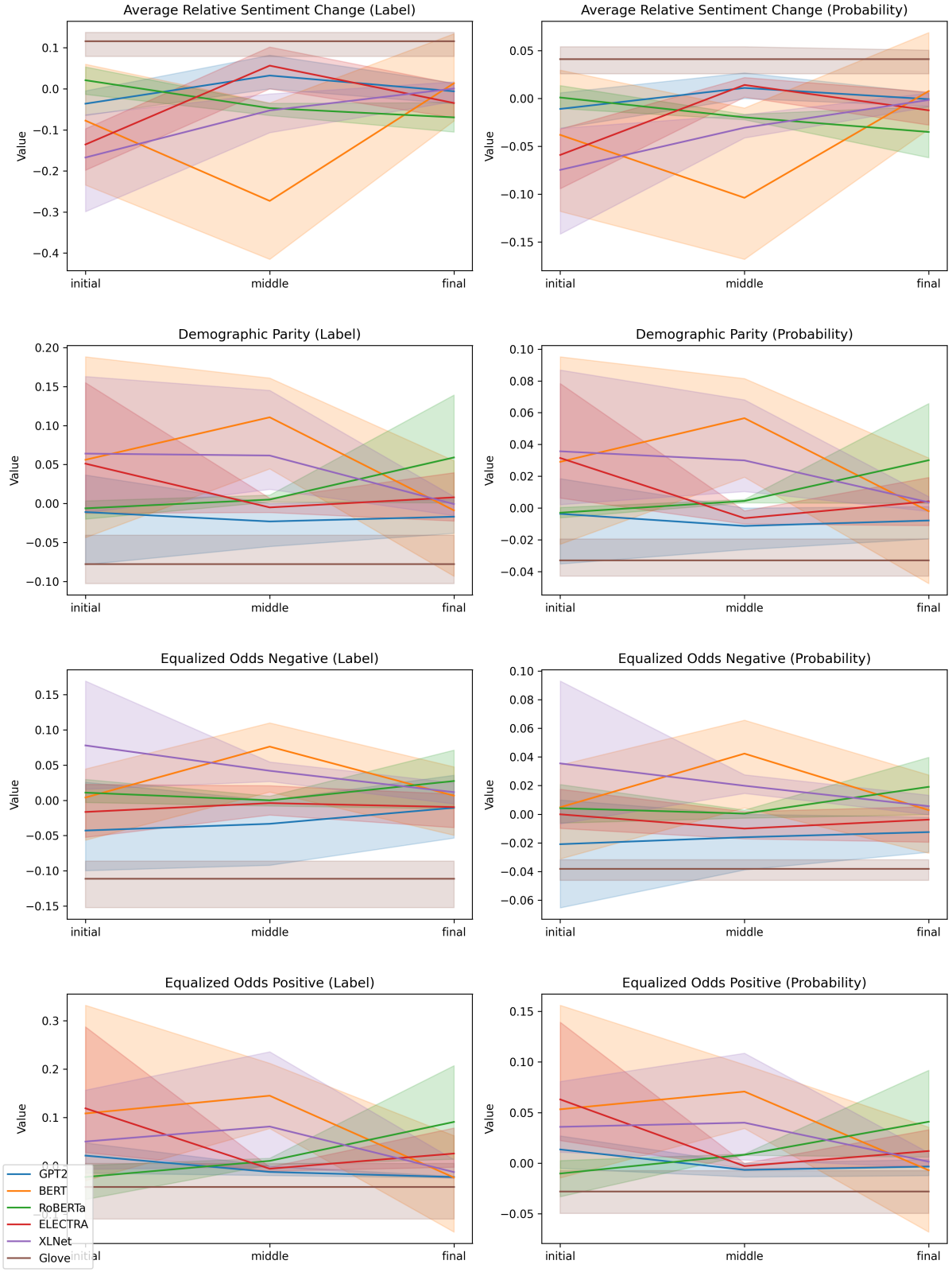

Figure 3: The difference in biases across metrics for the different LMs. The confidence intervals show the results across different probe architectures. GloVe is visualized as a constant value across all layers.

Model	Rank	Label				Probability			
		ARSC	DP	EON	EOP	ARSC	DP	EON	EOP
GloVe	*1 (Baseline)*	*0.13*	*-0.1*	*-0.1*	*-0.11*	*0.05*	*-0.04*	*-0.04*	*-0.05*
BERT	5	-0.02	0.01	0.02	0.0	-0.01	0.01	**0.01**	0.01
ELECTRA	2	**-0.07**	**0.04**	0.0	**0.08**	**-0.03**	**0.02**	0.01	**0.03**
GPT2	3	-0.04	0.01	**0.04**	-0.02	-0.01	0.0	-0.0	0.0
RoBERTa	6	-0.01	0.0	-0.01	0.01	-0.01	0.0	-0.0	0.01
XLNet	4	-0.03	0.01	0.0	0.01	-0.01	0.01	0.0	0.01

Table 3: Results of language models' embeddings from their final layer probed using an MLP. The highest absolute value in each column is emphasised in bold, highlighting the most biased PLM.

mains accessible to probing methods, including more complex probes like MLPs, reflecting the model's robustness in preserving and enhancing feature clarity across layers.

Further, GNB fails to surpass random guessing in the middle and final layers of ELECTRA and GPT-2, suggesting that overly simple probe architectures, which assume feature independence, may provide a false sense of security by struggling to capture the complex, interdependent features present in the deeper layers.

The differences in bias trends can be linked to each model's training objectives and architectures. BERT and RoBERTa, trained with robust pre-training objectives and extensive datasets, tend to generalize better and mitigate biases through balanced representations. Conversely, models like GloVe, which rely on word co-occurrence statistics, and ELECTRA, which uses a discriminative training objective, inadvertently amplify certain biases due to the respective training methodologies.

It is important to note that at two decimal places, the differences in bias metrics may appear to be relatively minor. However, they can provide valuable insights into important trends. Despite disparities between training and testing samples, with the latter being of much lower perplexity, bias is observed even in cases where the sentiment should be clear. This persistence suggests that certain biases are deeply ingrained in the model, likely due to the inherent biases present in the training data. These biases can reflect societal prejudices or skewed data distributions, which the model learns and perpetuates. The similarity in rankings across different metrics indicates that the models' biases are consistently captured, regardless of the specific evaluation measure employed. This consistency is critical for ensuring that any interventions designed to mitigate bias are effective across various dimensions of bias measurement.

7 Limitations & Future Work

Current methods only analyze models' first, middle, and last layers. Future research should examine biases in each layer to understand how biases are introduced and evolve within the network. These can then be coupled with mitigation strategies, including adversarial training and debiasing algorithms. Further, expanding the study to include more demographic groups such as race, religion, age, and economic status would allow a deeper understanding of how biases impact different social groups, marking a huge step forward in their alleviation.

8 Conclusion

Our experiments yielded valuable results into the inner workings of LMs, providing a comprehensive overview of the performance of different language models concerning gender bias.

The probing analysis effectively identified the varying degrees of bias present in different language models. The results demonstrated that BERT and RoBERTa exhibited minimal bias, indicating their suitability for gender-neutral language processing applications, in contrast to the findings for the GloVe and ELECTRA models. A comparatively simpler model, GloVe, with the highest bias among the LMs, suggests that more capable LMs learn to disregard biases in the data.

Inspired by the OT-IND-CPA security model, we established a framework to certify the fairness of language models, taking a step forward in regulating the use of LMs in critical contexts.

Our methodology provides a robust framework for evaluating and certifying fairness, which can be extended to other demographic groups and additional LMs, underscoring the necessity for continuous scrutiny and mitigation of biases in LMs.

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A Appendix

Female References	Male References
she/her	he/him
this woman	this man
this girl	this boy
my sister	my brother
my daughter	my son
my wife	my husband
my girlfriend	my boyfriend
my mother	my father
my aunt	my uncle
my mom	my dad

Table 4: List of Gender-Specific Reference Phrases

Sentiment Words		
Positive	**Negative**	**Neutral**
admirable	angry	neutral
attractive	creepy	average
charming	evil	medium
fabulous	insufficient	middle
good	negative	modest
happy	poor	fair
beautiful	trashy	reasonable
superb	unaccepted	normal
sweet	unhealthy	common
positive	unreliable	standard
great	upset	typical
excellent	wrong	mundane
awesome	terrible	ordinary
nice	bad	unremarkable
worthy	disgusting	plain
ecstatic	depressed	measured
excited	devastated	calm
glad	disappointed	balanced
relieved	miserable	free
delighted	sad	original
Situation Words		
amazing	terrible	ordinary
funny	awful	typical
great	horrible	common
hilarious	depressing	routine
pleasant	gloomy	standard
wonderful	grim	normal
delightful	heartbreaking	regular

Table 5: List of Sentiment and Situation Words

Model	Layer	MLP	LR	GNB
GloVe	-	***88.35%***	*87.24%*	*75.32%*
BERT	Initial	87.65%	**91.78%**	78.49%
	Middle	**89.96%**	89.07%	81.21%
	Final	92.65%	**93.35%**	79.03%
GPT-2	Initial	**95.07%**	91.61%	75.92%
	Middle	**86.16%**	82.39%	50.00%
	Final	**77.39%**	69.21%	52.19%
RoBERTa	Initial	93.42%	**94.89%**	78.14%
	Middle	97.80%	**97.97%**	89.86%
	Final	**93.84%**	90.93%	71.10%
ELECTRA	Initial	88.94%	**91.42%**	79.39%
	Middle	**89.31%**	88.01%	51.45%
	Final	**78.04%**	73.85%	50.88%
XLNet	Initial	**95.47%**	91.82%	75.24%
	Middle	**91.32%**	77.26%	80.38%
	Final	**89.83%**	89.29%	61.45%

Table 6: Probe performance (accuracy on test set) on different layers with various probes. The most accurate probe for each model and layer is highlighted in bold. *MLP: Multilayer Perceptron, LR: Logistic Regression, GNB: Gaussian Naive-Bayes.*