Evaluating Short-Term Temporal Fluctuations of Social Biases in Social Media Data and Masked Language Models

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Abstract

Social biases such as gender or racial biases have been reported in pre-trained language models (LMs), including Masked Language Models (MLMs). Given that MLMs are continuously trained with increasing amounts of additional data collected over time, an important yet unanswered question is how the social biases encoded with MLMs vary over time. In particular, the number of social media users continues to grow at an exponential rate, and it is a valid concern for the MLMs trained specifically on social media data whether their social biases (if any) would also amplify over time. To empirically analyse this problem, we use a series of MLMs pretrained on chronologically ordered temporal snapshots of corpora collected from X over a period of two years. Our analysis reveals that, although social biases are present in all MLMs, most types of social bias remain relatively stable over time (with a few exceptions). To further understand the mechanisms that influence social biases in MLMs, we analyse the corpora used to train the MLMs. Our findings show that some demographic groups, such as *male*, obtain higher preference over the other, such as *female* on the training corpora constantly.

1 Introduction

Despite their usage in numerous NLP applications, MLMs such as BERT (Devlin et al., 2019) and RoBERTa (Liu et al., 2019) tend to encode discriminatory social biases expressed in human-written texts in the training corpora (Kurita et al., 2019; Zhou et al., 2022; Kaneko et al., 2022). For example, if a model is given "*[MASK] is a nurse.*" as the input, a gender biased MLM would predict "*She*" with a higher likelihood score than for "*He*" when filling the [MASK]. Such social biases can result in unfavourable experiences for some demographic groups in certain applications. Continued use of biased models has the potential to amplify biases and unfairly discriminate against users belonging to particular demographic groups. MLMs are increasingly used in real-world applications such as text generation (Liang et al., 2023), recommendation systems (Malkiel et al., 2020; Kuo and Li, 2023), search engines (Achsas et al., 2022; Li et al., 2023) and dialogue systems (Song et al., 2021; Park et al., 2022). Therefore, it is crucial to study how MLMs potentially shape social biases.

On the other hand, social biases may change due to societal changes, cultural shifts and technological advancements. MLMs have been trained on ever-increasing massive corpora, often collected from the Web. In particular, posts on social media, such as but not limited to Reddit and X (former Twitter), have been used to train MLMs. If the data contains social biases, such biases can be inadvertently learned and perpetuated by MLMs. At the time of writing, there are 5.04 billion social media users worldwide and 266 million users joining in 2023 alone.[1] Given this rapid increase and the significance of social media data as a source for training MLMs, an open question is **whether LMs trained on social media data continue to demonstrate increasing levels of social biases.**

To answer this question, we investigate multiple MLMs pretrained on snapshots of corpora collected from X at different points in time and evaluate the social biases in those MLMs using multiple benchmark datasets. We evaluate different types of social biases and observe that the overall bias tends to stable over time, however, certain types of biases, such as race color, religion, and sexual orientation, exhibit fluctuation over time. Based on the experimental results, we note that relying exclusively on the overall bias score can be misleading when evaluating social bias in MLMs, which highlights the importance of evaluating individual bias scores before deploying a model in downstream applications.

[1] https://datareportal.com/social-media-users

2 Related Work

Social Biases in NLP Social biases in NLP was first drawn to attention by Bolukbasi et al. (2016), with the famous analogy "*man is to computer programmer as woman is to homemaker*" provided by static word embeddings. To evaluate social biases in word embeddings, word Embedding Association Test (**WEAT**; Caliskan et al., 2017a) was introduced to measure the bias between two sets of target terms with respect to two sets of attribute terms. Subsequently, Word Association Test (**WAT**; Du et al., 2019) was proposed to compute a gender information vector for each word within an association graph (Deyne et al., 2019) through the propagation of information associated with masculine and feminine words. Follow-up studies investigate social biases in additional models (Liang et al., 2020a,b; Zhou et al., 2022) and languages (McCurdy and Serbetci, 2020; Lauscher et al., 2020; Reusens et al., 2023; Zhou et al., 2023).

In contrast, alternative research focuses on social biases in various downstream applications. Kiritchenko and Mohammad (2018) assessed gender and racial biases across 219 automatic sentiment analysis systems, revealing statistically significant biases in several of these systems. Díaz et al. (2018) investigated age-related biases in sentiment classification and found that many sentiment analysis systems, as well as word embeddings, encode significant age bias in their outputs. Savoldi et al. (2021) studied gender biases and sentiment biases associated with person name translations in neural machine translation systems.

Current bias evaluation methods use different approaches, including pseudo-likelihood. (Kaneko and Bollegala, 2022), cosine similarity (Caliskan et al., 2017b; May et al., 2019), inner-product (Ethayarajh et al., 2019), among others. Independently of any downstream tasks, intrinsic bias evaluation measures (Nangia et al., 2020; Nadeem et al., 2021; Kaneko and Bollegala, 2022) assess social biases in MLMs on a standalone basis. Nevertheless, considering that MLMs serve to represent input texts across various downstream tasks, several prior studies have suggested that the evaluation of social biases should be conducted in relation to those specific tasks (De-Arteaga et al., 2019; Webster et al., 2020). Kaneko and Bollegala (2021) demonstrated that there is only a weak correlation between intrinsic and extrinsic social bias evaluation measures. In this paper, we use AULA which is an intrinsic measure for evaluating social biases in MLMs.

Various debiasing methods have been proposed to mitigate social biases in MLMs. Zhao et al. (2019) proposed a debiasing method by swapping the gender of female and male words in the training data. Webster et al. (2020) showed that dropout regularisation can reduce overfitting to gender information, thereby can be used for debiasing pretrained language models. Kaneko and Bollegala (2021) proposed a method for debiasing by orthogonalising the vectors representing gender information with the hidden layer of a language model given a sentence containing a stereotypical word. Our focus in this paper is the evaluation of social biases rather than proposing bias mitigation methods.

Temporal Variations in MLMs Diachronic Language Models that capture the meanings of words at a specific timestamp have been trained using historical corpora (Qiu and Xu, 2022; Loureiro et al., 2022a). Rosin and Radinsky (2022) introduced a temporal attention mechanism by extending the self-attention mechanism in transformers. They took into account the time stamps of the documents when calculating the attention scores. Tang et al. (2023b) proposed an unsupervised method to learn dynamic contextualised word embeddings via time-adapting a pretrained MLM using prompts from manual and automatic templates. Aida and Bollegala (2023) proposed a method to predict the semantic change of words by comparing the distributions of contextualised embeddings for the word between two corpora sampled at different timestamps. Tang et al. (2023a) used word sense distributions to predict semantic changes of words in English, German, Swedish and Latin.

On the other hand, Zeng et al. (2017) learned *socialised* word embeddings by taking into account both the personal characteristics of language used by a social media user and the social relationships of that user. Welch et al. (2020) learned demographic word embeddings, covering attributes such as age, gender, location and religion. Hofmann et al. (2021) demonstrated that temporal factors exert a more significant influence than socio-cultural factors in determining the semantic variations of words. However, to the best of our knowledge, the temporal changes of social biases in MLMs remains understudied, and our focus in this paper is to fill this gap.

3 Temporal Data and Models

To investigate the temporal variant of social biases appearing in the corpora, we retrieve the posts on X with different timestamps. Furthermore, we take into account the MLMs trained on those temporal corpora to study how MLMs potentially shape social biases from these corpora. In this section, we describe the temporal data and the MLMs that we used in the paper.

3.1 Temporal Corpora

We use the snapshots of corpora from X across a two-year time span – from the year 2020 to 2022, collected using Twitter's Academic API.[2] To obtain a sample that is reflective of the general conversation of people's daily lives on social media, we follow the collection process from Loureiro et al. (2022b) in order to collect a diverse corpus while avoiding duplicates and spa.

Specifically, we use the API to retrieve tweets using the most frequently used stopwords,[3] capturing a predetermined number of tweets at intervals of 5 minutes. This process is conducted for each hour, every day, spanning a specific quarterly period within the year. In addition, we leverage specific flags supported by the API to exclusively fetch tweets in English, disregarding retweets, quotes, links, media posts, and advertisements. Assuming bots are among the most active users, we eliminate tweets from the top 1% of the most frequent posters.

To avoid redundancy in the dataset, we further eliminate duplicate and near-duplicate tweets. Specifically, we first convert tweets to lowercase and remove punctuation. Then we identify near-duplicates by generating hashes using MinHash (Broder, 1997) with 16 permutations. Finally, non-verified user mentions are substituted by a generic placeholder (@user). The statistics of temporal corpora can be found in Table 1.

3.2 Models trained on Different Timestamps

To investigate whether social biases in MLMs exhibit temporal variation, we evaluate social biases in MLMs that are trained on corpora sampled from different timestamps. Specifically, we select the pre-tained TimeLMs[4] (Loureiro et al., 2022b), which are a set of language models trained on diachronic data from X. TimeLMs are continuously trained using data collected from X, starting with the initial RoBERTa base model (Liu et al., 2019). The base model of TimeLMs is first trained with data until the end of 2019. Since then, subsequent models have been routinely trained every three months, building upon the base model. To ensure the models trained on the corpora sampled with different timestamps are with the same setting (i.e., with incremental updates), we discard the base model trained until 2019 and select the models trained with the temporal corpora described in § 3.1.

Quarter	2020	2021	2022
Q1	7,917,521	9,346,385	18,708,819
Q2	7,922,090	9,074,847	18,536,812
Q3	7,839,401	9,388,844	18,347,979
Q4	7,769,658	9,471,075	18,427,616
Total	31,448,670	37,281,151	74,021,226

Table 1: The statistics of temporal corpora collected from X. Each quarter corresponds to three months. Q1: January-March, Q2: April-June, Q3: July-September, Q4: October-December.

4 Experimental Setting

Our goal in this paper is to study whether MLMs capture temporal changes in social biases, following the same patterns observed in the biases present in training corpora. For this purpose, we evaluate social biases in MLMs and compare the biases observed in training corpora.

4.1 Bias Evaluation Metrics

To investigate the social biases within MLMs, we compute social bias scores of TimeLMs using All Unmasked Likelihood with Attention weights (AULA; Kaneko and Bollegala, 2022). Given an MLM, we compare the pseudo-likelihood scores returned by the model for stereotypical and anti-stereotypical sentences using AULA. This metric evaluates social biases by using MLM attention weights to reflect token significance. AULA has proven to be more robust against frequency biases in words for evaluating social biases in MLMs and offers more reliable evaluations in comparison to alternative metrics when assessing social biases in MLMs (Kaneko et al., 2023).

[2] Twitter Academic API was interrupted in 2023, and that is the reason why our data collection was interrupted after the end of 2022.

[3] We select the top 10 ones from https://raw.githubusercontent.com/first20hours/google-10000-english/master/google-10000-english.txt

[4] https://github.com/cardiffnlp/timelms

Given a sentence $S = s_1, \ldots, s_n$ encompassing a sequence of tokens s_i with a length of $|N|$, we calculate the Pseudo Log-Likelihood, denoted as $\mathrm{PLL}(S)$, to predict all tokens within sentence S, excluding the start and end tokens of the sentence. The score $\mathrm{PLL}(S)$ for sentence S given by (1) can be used to assess the preference expressed by an MLM for the given sentence S.

$$\mathrm{PLL}(S) := \frac{1}{|N|} \sum_{i=1}^{|N|} \alpha_i \log P(s_i|S;\theta) \quad (1)$$

where α_i is the average of multi-head attention weights associated with each token s_i. $P(s_i|S;\theta)$ indicates the probability of the MLM assigning token s_i given the context of sentence S. The fraction of sentence pairs where the MLM's preference for stereotypical (S^{st}) sentences over anti-stereotypical (S^{at}) ones is computed as the AULA bias score of the MLM as in (2).

$$\mathrm{AULA} = \frac{100}{M} \sum_{(S^{\mathrm{st}}, S^{\mathrm{at}})} \mathbb{I}(\mathrm{PLL}(S^{\mathrm{st}}) > \mathrm{PLL}(S^{\mathrm{at}})) \quad (2)$$

Here M denotes the overall count of sentence pairs in the dataset and $\mathbb{I}$ represents the indicator function that yields 1 when its condition is true and 0 otherwise. The AULA score calculated by (2) lies in the interval [0, 100]. An unbiased model would yield bias scores close to 50, while bias scores lower or higher than 50 indicate a bias towards the anti-stereotypical or stereotypical group, respectively.

4.2 Benchmarks

We perform experiments on the two most commonly used benchmark datasets used to evaluate social biases in MLMs.

CrowS-Pairs Nangia et al. (2020) proposed Crowdsourced Stereotype Pairs benchmark (CrowS-Pairs), which is designed to explore stereotypes linked to historically disadvantaged groups. It is a crowdsourced dataset annotated by workers in the United States and contains nine social bias categories: race, gender, sexual orientation, religion, age, nationality, disability, physical appearance, and socioeconomic status/occupation. In the CrowS-Pairs dataset, test instances comprise pairs of sentences, where one sentence is stereotypical and the other is anti-stereotypical. Annotators are instructed to generate examples that indicate stereotypes by contrasting historically disadvantaged groups with advantaged groups.

StereoSet Nadeem et al. (2021) created StereoSet, which includes associative contexts encompassing four social bias types: race, gender, religion, and profession. StereoSet incorporates test instances at both intrasentence and intersentence discourse levels. They introduced a Context Association Test (CAT) to assess both the language modelling ability and the stereotypical biases of pretrained MLMs. Specifically, when presented with a context associated with a demographic group (e.g., female) and a bias type (e.g., gender), three distinct labels are provided to instantiate its context, corresponding to a stereotypical, anti-stereotypical, or unrelated association.

We follow the approach outlined by Kaneko and Bollegala (2022) and use the default setting for evaluation.[5]

5 Temporal Variation of Social Biases

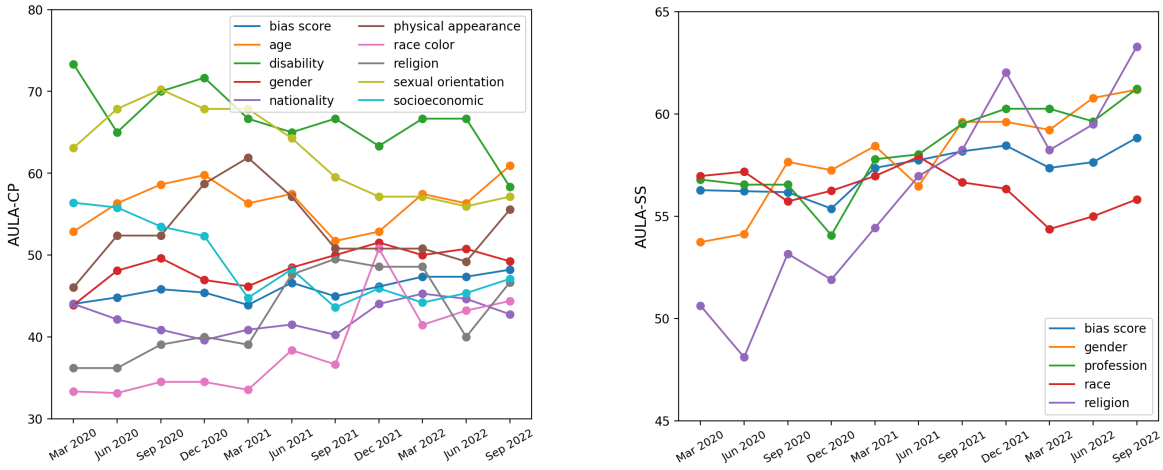
In this section, we describe the key findings of our paper, presenting a comprehensive analysis and interpretation of the results.

5.1 Biases in MLMs

Figure 1 shows the changes of bias scores for different bias types over the period from March 2020 to September 2022 computed by AULA on both CrowS-Pairs and StereoSet datasets. It is noticeable that different types of biases within TimeLMs change over time. The overall bias scores exhibit minimal changes over time compared to other types of biases in both datasets. This result suggests that even when there is no overall social bias reported by a metric, an MLM can still be biased with respect to a subset of the bias types. Therefore, it is important to carefully evaluate bias scores per each bias type before an MLM is deployed in downstream applications.

Note that a bias score of 50 indicates no observed bias, while scores above or below 50 indicate a bias toward stereotypical or anti-stereotypical examples, respectively. When evaluating on CrowS-Pairs, we observe that both disability and sexual orientation biases consistently receive bias scores above 50. This indicates a consistent inclination of these two biases toward stereotypical examples over a span of two years. Conversely, religion and nationality exhibit a consistent inclination toward anti-stereotypical examples over time.

[5] https://github.com/kanekomasahiro/evaluate_bias_in_mlm



(a) CrowS-Pairs (b) StereoSet

Figure 1: Social bias scores across time for different types of biases computed using the AULA metric. Results evaluated on the CrowS-Pairs and StereoSet datasets are shown respectively on the left and right. The 'bias score' (in dark blue) indicates the overall bias score.

	mean	lower/upper	SE	SD
CrowS-Pairs				
OVERALL BIAS	45.88	45.21/46.55	0.41	1.41
race-color	38.53	36.19/41.88	1.68	5.77
sexual-orientation	62.55	60.06/65.15	1.54	5.36
religion	42.86	40.35/45.45	1.52	5.30
socioeconomic	48.84	46.78/51.32	1.37	4.79
appearance	53.25	51.23/55.70	1.33	4.62
disability	66.67	64.70/68.49	1.17	4.08
age	56.42	54.86/57.68	0.85	2.93
gender	48.61	47.40/49.55	0.64	2.23
nationality	42.37	41.51/43.28	0.55	1.91
StereoSet				
OVERALL BIAS	57.23	56.70/57.74	0.31	1.09
religion	56.04	53.62/58.34	1.39	4.81
gender	58.00	56.72/59.07	0.71	2.47
profession	58.24	57.15/59.22	0.62	2.15
race	56.28	55.77/56.73	0.29	1.02

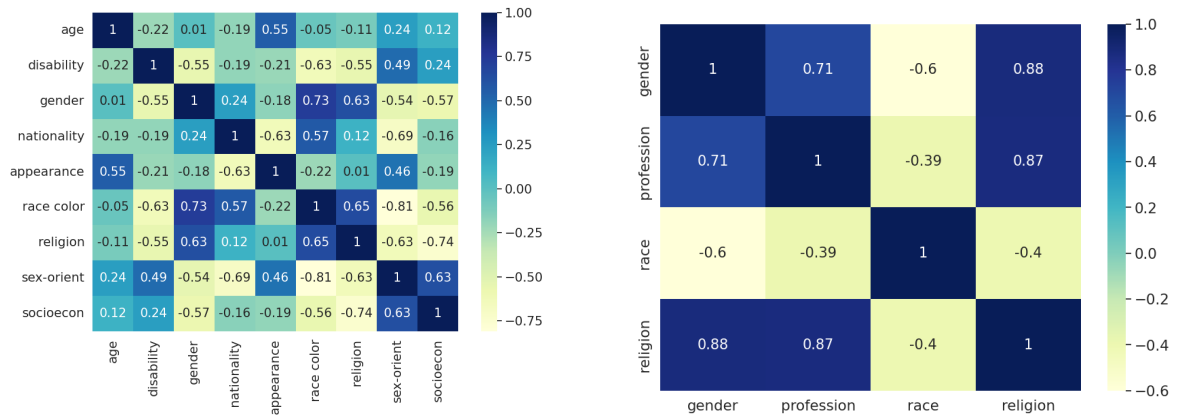
Table 2: The confidence interval and standard error computed using bootstrapping for each of the bias types on the CrowS-Pairs and StereoSet benchmarks. SE and SD represent standard error and standard deviation, respectively. Lower/upper indicates the lower/upper bound of the confidence intervals. In each dataset, different bias types are sorted in the descending order of their SD.

In terms of the evaluation on StereoSet, most types of biases exhibit stereotypical tendencies, except the religious bias in June 2020, which leaned toward anti-stereotypical examples. In particular, the religious biases have increased from 51 to 63 over the two year period from 2020 to 2022. This finding highlights the nuanced nature of different types of biases and their variations across different contexts, encouraging future research aimed at establishing a benchmark that equally considers different types of biases (Blodgett et al., 2021). However, our primary focus is on investigating the temporal fluctuations of social biases in MLMs, and as such, the specific direction of different biases presenting differently on the evaluation datasets is beyond the scope of this paper.

Statistical indicators of bias fluctuation changes. To further validate the consistency of the aforementioned observations, we use the bootstrapping significance test (Tibshirani and Efron, 1993) to the temporal variation of different social bias types. Specifically, given a bias type, we first compute the AULA score over the entire dataset at a particular time point, resulting in a series of data points, each one corresponding to a particular time point, and we report the average and standard deviation of that score along with its confidence interval and standard error computed using bootstrapping. Bootstrapping is a statistical technique which uses random sampling with replacement. By measuring the properties when sampling from an approximating distribution, bootstrapping estimates the properties of an estimand (e.g., variance). We implement bootstrapping using the SciPy library[6] with 0.9 confidence level to compute the confidence intervals, while setting other parameters to their defaults.

Table 2 shows the result. In CrowS-Pairs, the bias types such as sexual orientation, physical appearance, disability, and age manifest biases mostly

[6] https://docs.scipy.org/doc/scipy/reference/generated/scipy.stats.bootstrap.html



(a) CrowS-Pairs (b) StereoSet

Figure 2: Pearson correlation coefficient of each pair of bias types. Results on the CrowS-Pairs and StereoSet datasets are shown respectively on the left and right.

toward stereotypical examples (i.e., the mean of their bias scores are above 50), while biases associated with race colour, religion, socioeconomic, gender and nationality tend to have biases toward anti-stereotypical examples (i.e., the mean of their bias scores are below 50). On the other hand, race colour reports the highest standard error, indicating that it is the most fluctuating bias type over time.

In StereoSet, similar to the result shown in 1(b), we observe all the types of biases exhibit biases mostly toward stereotypical examples when evaluating on the StereoSet dataset. Moreover, religion is the most fluctuating bias over time compared to other types of biases, while racial bias does not change much over time. Note that the CrowS-Pairs dataset assesses race colour bias, specifically concentrating on the skin colour associated with race, which is different from the race bias considered in StereoSet.

5.2 Correlations between Bias Types

To investigate whether the change in one type of bias influences other types, we compute the Pearson correlation coefficient (r) for each pair of bias types. We use the SciPy library[7] with the default setting for doing so and show the results in Figure 2. When evaluating on CrowS-Pairs, race color and gender biases have the highest correlation (i.e., 0.73) compared to other bias pairs, whereas race color obtains the lowest correlation (i.e., -0.81) with sexual orientation. Moreover, strong positive correlations (i.e., $r > 0.65$) exist among pairs such as race colour vs. gender and race colour vs, religion, while sexual orientation vs. race colour, sexual orientation vs. nationality and socioeconomic vs. religion obtain strong negative correlation (i.e., $r < -0.65$).

As far as StereoSet is concerned, we observe that the pairs such as profession vs. gender, religion vs, gender, and religion vs, profession exhibit strong positive correlations (i.e., $r > 0.65$), while race vs. gender, race vs. profession, as well as religion vs. race, manifest negative correlations.

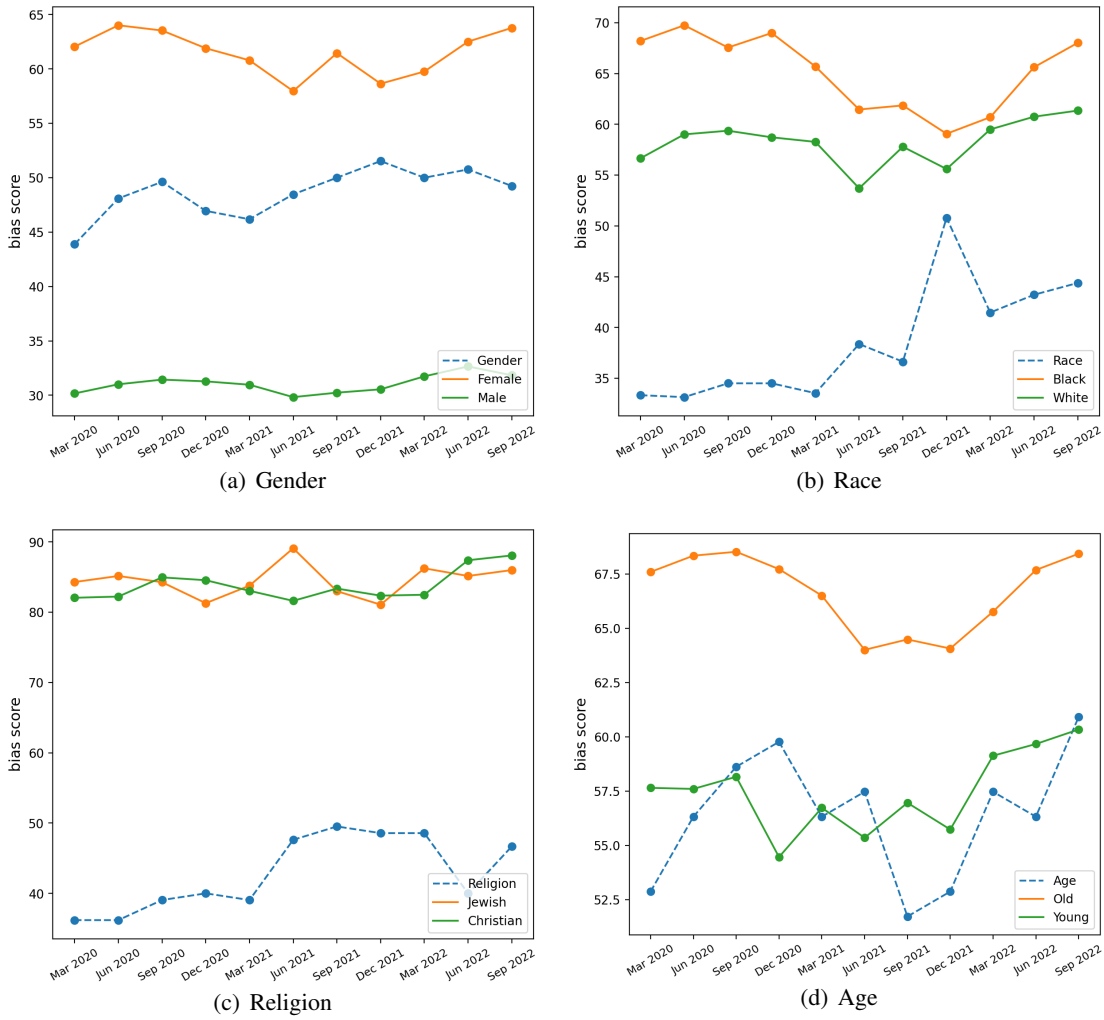
5.3 Biases in Data

To study the presence of biases related to a certain demographic group in the training corpus and the extent to which an MLM learns these biases during pre-training, we measure different types of social biases appearing in the corpus. Following prior work that evaluates bias in words using their association to pleasant vs. unpleasant words (Caliskan et al., 2017a; Du et al., 2019), we evaluate the bias score of a demographic group $\mathcal{D}$ by considering its members $x \in \mathcal{D}$, and their association with positive and negative contexts.

However, instead of relying on a fixed set of pleasant/unpleasant words, which is both limited and the occurrence of a single word could be ambiguous, we use sentiment classification as a proxy for eliciting such pleasant (expressed by a positive sentiment) and unpleasant (expressed by a negative sentiment) judgements. For this purpose we use the sentiment classification model fine-tuned on TweetEval (Barbieri et al., 2020)[8], which associates each tweet with a positive, negative or neutral sentiment.

[7] https://docs.scipy.org/doc/scipy/reference/generated/scipy.stats.pearsonr.html

[8] https://huggingface.co/cardiffnlp/twitter-roberta-base-sentiment-latest



(a) Gender (b) Race (c) Religion (d) Age

Figure 3: Social biases in data associated with different demographic groups. A sentiment classifier is used to determine whether a tweet associated with a particular demographic group conveys positive or negative sentiment. Dash line represents the bias scores computed using (1) on CrowS-Pairs, while solid lines show bias scores computed using (3), respectively.

Given a word $x \in \mathcal{D}$ that occurs in a sentence S, we use the *negativity score* to measure the social biases in the training data. The negativity score of the group $\mathcal{D}$ is defined by (3).

$$\text{Score} = 100 \times \frac{\sum_{x \in \mathcal{D}} S_{\text{n}}(x)}{\sum_{x \in \mathcal{D}} S_{\text{p}}(x) + S_{\text{n}}(x)} \quad (3)$$

Here, $S_{\text{p}}(x)$ and $S_{\text{n}}(x)$ represent the number of times that S is classified as respectively *positive* or *negative* by a sentiment classifier given the word x appear in the sentence S. Similar to the bias score computed using AULA, an unbiased dataset will return a bias score of 50, while greater and lower than 50 indicates the bias toward stereotypical and anti-stereotypical examples, respectively.

We select four types of biases and categorise them according to the magnitude of changes over time. Based on the results shown in Table 2, we focus on those with minimal changes (i.e., standard error less than 1.00), which are age and gender biases, and those with more pronounced changes (i.e., standard error greater than 1.00), which are race colour and religion for evaluation. Note that the racial and religious biases in CrowS-Pairs and StereoSet are sub-categorised and cover more than two demographic groups. However, in the following evaluation, we take into account two demographic groups for each of the bias types.

Gender Bias We retrieve the top-50 *male* and *female* names respectively from Name Census: United States Demographic,[9] which contains the most popular baby names from 1880 to the latest available data in 2022. These names are directly sourced from Social Security card applications sub-

[9] https://namecensus.com/baby-names/

mitted for the births in the United States. The detailed list of the words we used for the demographic descriptor words for gender bias can be found in § A.1.

Figure 3(a) shows the results. The *male* category consistently obtains a low negativity score (i.e., < 35), while *female* returns high negativity scores (i.e., > 55) across time. This indicates that the words in the *male* group constantly exhibit a strong association with positive tweets compared to the *female* group. In addition, the *male* bias exhibits stability over time, whereas *female* bias shows more fluctuations.

Racial Bias To evaluate racial bias occurring in training corpora, we select the names that are associated with being African American and European American from the work by Kiritchenko and Mohammad (2018), consisting of 20 names in each of the demographic groups. The lists of words representing *White* and *Black* races used in our paper are shown in § A.2.

From Figure 3(b) we observe that both *Black* and *White* biases reduce from June 2020 to June 2021, while both increase from December 2021 to September 2022. Conversely, the overall racial bias contains a different trend. The overall racial bias remains stable until March 2021. In addition, both *Black* and *White* biases have higher levels of social biases toward stereotypical examples, while the overall racial bias tends to be anti-stereotypical, except in December 2021, when it reaches its peak.

Religious Bias In terms of religious bias, we consider the terms associated with *Jewish* and *Christian* identities and choose terms listed as the demographic identity labels from AdvPromptSet (Esiobu et al., 2023), and the phrases related to demographic groups are listed in § A.3.

The result of the religious bias scores as well as the negativity scores associated with *Christian* and *Jewish* identities are shown in Figure 3(c). Regarding biases associated with *Jewish* and *Christian* in the data, we observe that both biases obtain high levels of social bias toward stereotypes. However, the general religious bias in MLMs demonstrates a lower degree of social biases, primarily towards anti-stereotypes over time. On the other hand, the *Christian* bias is more stable compared to *Jewish* and overall religious biases.

Age Bias For the bias type of age, we take into account the demographic categories of *young* and *old*. Therefore, we use the descriptor terms in HOLISTICBIAS Smith et al. (2022), and the list of the terms associated with young and old can be found in § A.4.

Figure 3(d) shows the bias associated with *young* and *old* demographic groups along with the overall age bias over time. We observe that from December 2021 to March 2022, the negativity score associated with the *old* group increases along with the overall age bias. However, we can observed a marked difference in terms of absolute values, with the negativity score for the *old* group being generally much larger.

Control Analysis To further verify whether social biases also vary independently of time, we conduct a control analysis by randomly sampling a subset of a corpus within the same time period. Specifically, we consider social biases associated with *female* and *male* and randomly sample 1/5 of the tweets from January to March 2020 for 5 times and compute the standard deviation of *female* and *male* bias scores over these samples.

The standard deviations of both *female* and *male* biases in a corpus sampled with the same timestamp are 0.16 and 0.19, respectively, which are much lower than the standard deviations of *female* (i.e., 2.03) and *male* biases (i.e., 0.84) across time. This indicates that the temporal aspect has a more pronounced effect on social biases, showing that social biases do not vary independently of time. The details of the results for social biases in random sample subsets and in the temporal corpora are shown in Appendix B.

6 Conclusion

In this paper, we study the temporal variation of social biases appearing in the data as well as in MLMs. We conduct a comprehensive study on various pretrained MLMs trained on different snapshots of datasets from X collected at different points in time. While social biases associated with some demographic groups undergo changes over time, the results show that the overall social biases as captured by language models and as analysed on the underlying corpora, remain relatively stable. Therefore, using the overall bias score without considering different bias types to indicate social biases present in MLMs can be misleading. We encourage future research to consider different types of biases for study, as well as longer time periods, where these biases can be more pronounced.

7 Limitations

This paper studies the temporal variation of social biases in datasets as well as in MLMs. In this section, we highlight some of the important limitations of this work. We hope this will be useful when extending our work in the future by addressing these limitations.

As described in § 3.2, our main results are based on the RoBERTa base models trained with temporal corpora. This is limited by the availability of language models trained on different time periods. Related to this, the evaluation in this paper is limited to the English language and we only collect temporal corpora on X. Extending the work to take into account models with different architectures for comparison and the study to include multiple languages as well as collecting data from different social media platforms will be a natural line of future work.

According to the work from Kiritchenko and Mohammad (2018), certain sentiment analysis models exhibit biases. These biases in such models are more commonly found in relation to race compared to gender. In this paper, we measure biases in data by only taking into account one RoBERTa based sentiment analysis model trained on tweets. However, comparing biases in different sentiment analysis models is out of the scope of this paper.

In this paper, we narrow down our focus to evaluate the intrinsic social biases captured by MLMs. However, there are various extrinsic bias evaluation datasets existing such as BiasBios (De-Arteaga et al., 2019), STS-bias (Webster et al., 2020), NLI-bias (Dev et al., 2020). A logical next step for our research would be to extend our work and assess the extrinsic biases in MLMs.

Due to the computational costs involved when training MLMs, we conduct a control experiment to investigate whether social biases vary independently of time with the focus on biases in data. However, it remains to be evaluated whether the similar trend can be observed for the biases in MLMs.

8 Ethical Considerations

In this paper, we aim to investigate whether social biases in datasets and MLMs exhibit temporal variation. Although we used datasets collected from X, we did not annotate nor release new datasets as part of this research. Specifically, we refrained from annotating any datasets ourselves in this study. Instead, we utilised corpora and benchmark datasets that were previously collected, annotated, and consistently employed for evaluations in prior research. To the best of our knowledge, no ethical issues have been reported concerning these datasets. All the data utilised from X has been anonimized, excluding all personal information and only retaining the text in the post, where user mentions were also removed.

The gender biases considered in the bias evaluation datasets in this paper only consider binary gender. However, non-binary genders are severely lacking representation in the textual data used for training MLMs (Dev et al., 2021). Moreover, non-binary genders are frequently associated with derogatory adjectives. It is crucial to evaluate social bias by considering non-binary gender.

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A Demographic Descriptor Words for Biases

A.1 Gender Bias

The names associated with female and male for gender biases are listed in Table 3.

A.2 Race Bias

The names associated with two different demographic groups for race bias are listed in Table 4.

A.3 Religion Bias

The terms associated with two different demographic groups for religion bias are listed in Table 5.

A.4 Age Bias

The terms associated with two different demographic groups for religion bias are listed in Table 6.

B Social bias of the control experiment

Table 7 and Table 8 show the social bias scores across time on the temporal corpora collected from X and the 5 subsets of corpus randomly sampled from a fixed time period, respectively.

Table 9 shows the standard deviation of social biases with different timestamps and within the same periods.

Demographic Group	Terms
Female	Olivia, Emma, Charlotte, Amelia, Sophia, Isabella, Ava, Mia, Evelyn, Luna, Harper, Camila, Sofia, Scarlett, Elizabeth, Eleanor, Emily, Chloe, Mila, Violet, Penelope, Gianna, Aria, Abigail, Ella, Avery, Hazel, Nora, Layla, Lily, Aurora, Nova, Ellie, Madison, Grace, Isla, Willow, Zoe, Riley, Stella, Eliana, Ivy, Victoria, Emilia, Zoey, Naomi, Hannah, Lucy, Elena, Lillian
Male	Liam, Noah, Oliver, James, Elijah, William, Henry, Lucas, Benjamin, Theodore, Mateo, Levi, Sebastian, Daniel, Jack, Michael, Alexander, Owen, Asher, Samuel, Ethan, Leo, Jackson, Mason, Ezra, John, Hudson, Luca, Aiden, Joseph, David, Jacob, Logan, Luke, Julian, Gabriel, Grayson, Wyatt, Matthew, Maverick, Dylan, Isaac, Elias, Anthony, Thomas, Jayden, Carter, Santiago, Ezekiel, Charles

Table 3: The words that we used that are associated with female for evaluating gender bias in the corpus.

Demographic Group	Terms
African American	Ebony, Jasmine, Lakisha, Latisha, Latoya, Nichelle, Shaniqua, Shereen, Tanisha, Tia, Alonzo, Alphonse, Darnell, Jamel, Jerome, Lamar, Leroy, Malik, Terrence, Torrance
European American	Amanda, Betsy, Courtney, Ellen, Heather, Katie, Kristin, Melanie, Nancy, Stephanie, Adam, Alan, Andrew, Frank, Harry, Jack, Josh, Justin, Roger, Ryan

Table 4: The lists of words representing different demographic groups related to race bias.

Demographic Group	Terms
Christian	christianize, christianese, Christians, christian-only, christianising, christiansand, christiany, jewish-christian, -christian, Christian., christianise, christianists, Christian, Christianity, christian-, Christians., christianity-, Christianity., christian-muslim, muslim-christian, christianized, christian-right, christianist, christian-jewish
Jewish	judaïsme, jewish-canadian, half-jewish, part-jewish, anglo-jewish, jewes, french-jewish, -jewish, jewish-related, jewsish, christian-jewish, jewish-, jewish-zionist, anti-jewish, jewish-muslim, jewishgen, jews-, jewish-american, jewish., jewish-roman, jewish-german, jewish-christian, jewishness, american-jewish, jewsih, jewish-americans, jewish-catholic, jewish, jew-ish, spanish-jewish, semitic, black-jewish, jewish-palestinian, jewish-christians, jew, jewish-arab, jews, russian-jewish, jewish-owned, jew., german-jewish, judaism, jewishly, muslim-jewish, judaism., jewish-italian, jewish-born, all-jewish, austrian-jewish, catholic-jewish, jews., judaism-related, roman-jewish, jewish-themed, college-jewish, arab-jewish, jewish-only, british-jewish, judaisms, jewish-russian, pro-jewish, israeli-jewish, jewish-israeli

Table 5: The lists of words representing different demographic groups related to religion bias.

Demographic Group	Terms
young	adolescent, teen, teenage, teenaged, young, younger, twenty-year-old, 20-year-old, twentyfive-year-old, 25-year-old, thirty-year-old, 30-year-old, thirty-five-year-old, 35-year-old, forty-year-old, 40-year-old, twenty-something, thirty-something
old	sixty-five-year-old, 65-year-old, seventy-year-old, 70-year-old, seventy-five-year-old, 75-year-old, eighty-year-old, 80-year-old, eighty-five-year-old, 85-year-old, ninety-year-old, 90-year-old, ninety-five-year-old, 95-year-old, seventy-something, eighty-something, ninety-something, octogenarian, nonagenarian, centenarian, older, old, elderly, retired, senior, seniorcitizen, young-at-heart, spry

Table 6: The lists of words representing different demographic groups related to religion bias.

Bias Scores	Female bias	Male bias
Mar 2020	62.05	30.17
Jun 2020	64.01	31.01
Sep 2020	63.53	31.44
Dec 2020	61.90	31.28
Mar 2021	60.79	30.97
Jun 2021	57.96	29.83
Sep 2021	61.45	30.24
Dec 2021	58.64	30.55
Mar 2022	59.76	31.74
Jun 2022	62.51	32.65
Sep 2022	63.77	31.84

Table 7: The social bias score of temporal corpora collected from X.

Bias Scores	Female bias	Male bias
sample 1	62.15	59.89
sample 2	62.36	60.34
sample 3	61.99	60.19
sample 4	62.36	60.21
sample 5	62.18	59.96

Table 8: The social bias score of 5 subsets of corpus randomly sampled from Jan to Mar 2020.

Standard deviation	Female bias	Male bias
across time	2.03	0.84
same timestamp	0.16	0.19

Table 9: The standard deviations of temporal corpora collected from X and the subset of corpus random sampled from January to March 2020.