Analysing Effects of Inducing Gender Bias in Language Models

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Abstract

It is inevitable that language models are biased to a certain extent. There are two approaches to deal with bias: i) find mitigation strategies and ii) acquire knowledge about the existing bias in a language model, be explicit about it and its desired and undesired potential influence on a certain application. In this paper, we present an approach where we deliberately induce bias by continually pre-training an existing language model on different additional datasets, with the purpose of inducing a bias (gender bias) and a domain shift (social media, manosphere). We then use a novel, qualitative approach to show that gender bias (bias shift), and attitudes and stereotypes of the domain (domain shift) are also reflected in the words generated by the respective LM.
Warning: offensive language!

1 Introduction and Background

When a language model (LM) is created, a dataset needs to be selected, as well as a model architecture, e.g. a transformer model such as BERT (Devlin et al., 2019). The training data typically comprise Wikipedia articles, books, tweets, posts from discussion fora and any other documents available from the internet. The thus created foundational model can then be further adapted via continual pre-training on additional, possibly domain-specific datasets. The model also can be fine-tuned by training it on a smaller amount of (annotated) texts to solve NLP specific tasks such as sentiment classification, sexism detection, or question answering. All along the way, there are multiple sources where bias might be introduced. The resulting language model therefore reflects prejudices and stereotypes, including gender bias (Nadeem et al., 2022). Our analysis is confined to a binary gender framework due to the scarcity or absence of non-binary representations. For work on non-binary gender representations in LMs see e.g. (Nozza et al., 2022; Dev et al., 2021).

According to Hovy and Prabhumoye (2021), there are five primary sources of bias in NLP:

- selection bias resulting from the data selected to train the model architecture on,
- label bias resulting, e.g., from different annotators,
- semantic bias resulting from input representations, i.e., prejudices in the texts,
- overamplification of bias resulting from the model architecture,
- bias resulting from the research design.

There exists a growing body of literature on how to identify and mitigate these biases in LMs (see Nemani et al., 2024; Stanczak and Augenstein, 2021), as dealing with bias is a pressing concern. We argue that in addition it is also crucial to be explicit about bias and evaluate the existence of desired and undesired bias in view of a certain application. For this, benchmarks need to be enhanced for assessing bias in language models and language model output (e.g., in a classification task). Therefore in this paper, we investigate the effect of intentionally inducing bias in LMs and assess the effects on the resulting LMs following a template-based approach (Hutchinson et al., 2020). Our approach is novel in that we apply qualitative content analysis (see Mayring, 2014) to investigate the templates filled by the LMs.

To systematically analyse gender bias, we continually pre-trained BERTbase with (i) less gender biased unlabelled data from the manosphere domain, and (ii) more gender biased unlabelled data from the manosphere domain, resulting in two different LMs. In doing so, we expand on the work by (Caselli et al., 2021), who also continually pre-trained a BERT model on biased text (focusing on hatespeech in general, not only on gender bias). They found that their model (HateBERT) performed better in hatespeech classifica-

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tion than its predecessor BERTbase. This improvement in performance could be due to the bias shift (sexism, hate, racism), or due to a domain shift (Wikipedia articles, a book corpus, social media posts).[1] By splitting our dataset into a more sexist and a less sexist variant, we gain two datasets originating from the same domain, however, differing in their gender bias. Thus, continual pre-training on either of them should result in models showing a comparable domain shift, but differences in gender bias. In Section 2, we describe the dataset used for inducing gender bias into BERTbase, and introduce the resulting less and more sexist models. In Section 3, we present the proposed qualitative approach to assess gender bias in LMs and analyse four LMs (BERTbase, HateBERT and our continually pre-trained models MoreSexistBERT and LessSexistBERT) for their gender bias.

2 Biasing LMs

2.1 Additional Training Data

As additional training data, we extracted Reddit posts from the manosphere context. The manosphere is an informal online network of blogs, websites, and forums that concentrate on issues concerning men and masculinity and that women dominate and are more privileged than men (see Lilly, 2016). Several studies have shown that many communities promoting masculinity, misogyny, and disapproving feminism use specific subreddits (Ging, 2019; Farrell et al., 2019). We focused on data stemming from different communities in the manosphere context in order to cover a broader range of topics and linguistic expressions. The manosphere can be classified into four subcultures (see Lilly, 2016): Incels (involuntary celibates), Men Going Their Own Way (MGTOW), Men's Rights Activists (MRA), Pickup Artists (PUA). MRA are a subculture which primarily is concerned with issues related to men's legal rights and is the largest subculture of the manosphere. MGTOW is a smaller, sort of lifestyle community comprising men who feel oppressed and reject relationships with women, as well as men who 'disengage' economically and refuse to interact with society. PUA is a subculture consisting of self-proclaimed, or aspiring 'alpha-males' who share insights about how to pick up and date women, and at the same time believe that men are oppressed and women are unfairly privileged. Incels are a smaller subculture in the manosphere including men who feel that women owe them sex and that women who turn them down are cruel and oppressive which leads them to bitterness. Inspired by Kirk et al. (2023), we selected the following subreddits for the four subcultures: (i) MRA: KotakuInAction, MensRights, PussyPassDenied, askTRP, TheRedPill, (ii) PUA: seduction, (iii) Incels: IncelTears, Braincels, IncelsWithoutHate, ForeverAlone, and (iv) MGTOW: MGTOW.

Around 13M comments were downloaded via the PushshiftAPI[2]; all posts were published later than 1st of January 2019. As a pre-processing step, we thoroughly anonymized the data by replacing user names, emails and urls with placeholders ('[USER]', '[MAIL]', '[URL]') and removed duplicates, resulting in around 9M comments.

2.2 Sexism Classifier for Corpus Separation

We fine-tuned BERTbase on text classification to discriminate sexist from non-sexist comments by training it on a combination of the 'Call me sexist but' (CMS) dataset (Samory et al., 2021) and the 'sexist' and 'not sexist' part of the hate speech (HS) dataset (Waseem and Hovy, 2016). The reason for using these two datasets was to cover a broad definition of sexism from benevolent to hateful sexism. The main goal of the classification model was to select a more and a less sexist subset out of the collected unlabelled Reddit data.

First, all 9M comments were labelled by our classification model and ordered in an ascending order for their probability for being sexist. All in all 1 886 288 comments were labelled as sexist. These data constitute our more sexist dataset.[3] The exact same amount of comments with the lowest probability for being sexist constitutes our less sexist dataset.[4] Both datasets were used to fine-tune BERTbase.

2.3 Resulting LMs

Two new versions – LessSexistBERT and MoreSexistBERT – of BERTbase were created by continual

[1] However, bias shift and domain shift may go hand in hand, as some of the words characteristic of the domain are hateful/offensive too.

[2] https://github.com/pushshift/api

[3] https://huggingface.co/datasets/ofai/ekip-unlabeled-split02/blob/main/more_sexist_dataset.csv

[4] https://huggingface.co/datasets/ofai/ekip-unlabeled-split02/blob/main/less_sexist_dataset.csv

pre-training using the *less* and *more* sexist text corpora from above. The training used adapted HuggingFace example code[5] with Masked Language Modeling (MLM) and Next Sentence Prediction (NSP) objective tasks as described in the original paper (Devlin et al., 2019). Moreover, the embeddings were extended to include tokens specific to the newly created sexist and less sexist corpora.

The models were pre-trained for 100 epochs with a batch size of 24, maximum of 512 sentencepiece tokens using an ADAM optimizer with learning rate of 5e-5 on an NVIDIA GeForce RTX 4090 using CUDA Automatic Mixed Precision (AMP) - half precision. The mask probability was 0.15 and masks were applied dynamically, i.e., they change every epoch. The training data was split 95/5 for training and validation.

For both LMs, the NSP accuracy peaked early (approx. 20-30 epochs) even decreasing a little and for LessSexistBERT increasing towards the end. Conversely, the MLM accuracy continued to increase throughout the training with the exception of the last 3 or 4 epochs for MoreSexistBERT. This is also reflected in the loss, where the evaluation loss for both models reaches a minimum before increasing again and in the case of MoreSexistBERT dramatically increasing from epoch 96 in both the evaluation and training loss. Notwithstanding the potential earlier overfitting, the results presented in this paper were generated using the default model version at 100 and 96 training epochs for LessSexistBERT and MoreSexistBERT, respectively.

3 Assessing Gender Bias in LMs

In the following, we present a qualitative approach to assess gender bias in LMs. We illustrate the approach on the following four LMs: Our two models LessSexistBERT and MoreSexistBERT, BERTbase and HateBERT. We also assess BERTbase because HateBERT and our two models were trained on BERTbase, and we assess HateBERT (Caselli et al., 2021) because it has been further pre-trained on hateful data. Two types of gendered templates were filled by the different LMs and then analysed applying qualitative content analysis (Mayring, 2014).

In pursuing these qualitative analyses, we manually analysed those words selected by the models under investigation in template-based mask-filling tasks, focusing on differences between words selected for female versus male templates.

3.1 Mask Filling Templates

For the qualitative study on gender bias, we used two types of mask filling templates: descriptive templates and female/male attribution templates.

The descriptive templates consist of [ID] [CONNECTOR] [MASK] templates, and were created following suggestions from Antoniak and Mimno (2021), who collected seed sets used in NLP bias research. The templates are instantiated with female versus male ID-terms, followed by *is|are*-[CONNECTOR]s, followed by an empty slot [MASK] for which fillers are generated by the different language models. The templates used for generating descriptive phrases are summarized in Table 1. 8 604 templates were generated altering the combinations of [ID] and [CONNECTOR] and thus altering gender, number and determiner information of the propositions.

Female/male attribution templates consist of templates manually derived from SemEval2023 Task 10 data annotated for being sexist (Kirk et al., 2023). In order to extend the descriptive templates derived from literature research with templates derived from real-world data, we manually extracted sexist utterances from the development set provided for SemEval 2023 Task 10 Subtask A (binary sexism detection)[6]. First, we filtered the development set for Task A (2000 entries in total) for posts labelled 'sexist' (486 entries), and then manually checked the entries for self-contained sexist utterances. We identified utterances reflecting female or male attribution, such as *[MASK] is a female behaviour.* or *Men do that to [MASK].* For each of these utterances, we created a male and a female version, i.e., if the utterance occurred in the SemEval data only in a female version, we also constructed a male version, and vice versa. [MASK] stands for the masked slot to be filled by the LM. The resulting attribution templates comprise the following 26 templates (13f, 13m):

- '[MASK] is a feminine/male behaviour.'
- 'Women/men do that to [MASK].'
- 'Men/women are much more [MASK] than women/men.'

[5] https://github.com/huggingface/transformers/blob/v4.27.0/examples/pytorch/language-modeling/run_mlm.py

[6] https://codalab.lisn.upsaclay.fr/competitions/7124, https://github.com/rewire-online/edos

ID	CONNECTOR	MASK
a|the|this|every girl|woman|boy|man	*is|is a|is an|is more*	MASK
he|she	*is|is a|is an|is more*	MASK
the|these|all girls|women|boys|men	*are|are a|are an|are more*	MASK
women|men	*are|are a|are an|are more*	MASK

Table 1: Templates for the generation of the descriptive templates.

- 'Females/males are [MASK].'
- 'Everything women/men do is [MASK].'
- 'Women/men are good/not good for [MASK].'
- 'Women/men are good/not good in [MASK].'
- 'She/he does deserve [MASK].'
- 'Women/men see/don't see value in [MASK].'
- 'Women/men expect [MASK].'

Although the two template sets partially overlap, the descriptive templates more systematically characterise what women or men are, whereas the attribution templates provide more contexts.

3.2 Analysis of Model Outcomes Employing the Descriptive Templates

The descriptive templates were filled by the four different LMs. Those words were retained per LM, which covered the top 30% of the probability mass per template and language model. Two (female) annotators trained in linguistics and qualitative text analysis first identified **negatively connoted words** independently of each other and then consolidated their negative word lists in a joint effort. In a further step, they manually identified semantic categories to group the words into. Again, this was a two step process, where both annotators first independently worked with the data for inductive category development and then, in a coder conference, discussed their disagreements and consolidated the categories. This approach is considered by Mayring (2014) as the best procedure for inductive category formation, especially in combination with a coder conference. The process took a number of iterations of identifying negative words, category refinement, and assigning words to categories.

While developing the category set, the data suggested a distinction between categories and special categories. Whereby each word must be assigned one category and may be assigned one or more special categories.

Nine categories and four special categories could be identified. The resulting categories, their descriptions and examples of words falling into the respective category are presented in Table 2. In a third step, each annotator assigned each of the words to one of the nine categories and if applicable to one or more special categories. The annotations were then again consolidated. We did not calculate inter-coder agreement, as all three steps were an iterative process with several coder conferences, in order to achieve agreement between the two coders.

If different inflected forms of a word occur in a word list, they are only counted once, e.g., *creep, creeps, creepy* are counted as 1. Should the words differ in meaning, e.g., *loser* vs *lost* (*s/he is a loser* versus *s/he is lost*) they are counted as two different words.

We investigated differences between the models with respect to negative words which were only generated in the context of either female or male connoted templates (mask filling task). Thus, we derive that if the number of distinct words for a specific category is clearly higher for one specific gender, this can be interpreted as a connotation focus of the respective LM towards that gender (e.g., that women are more connoted with toxicity than men). In the following, we discuss for each category and LM the male and female connoted outcomes.

Animal BERTbase has a variety of animals with different connotations for both females and males, but twice as many for males (m:f 9:4)[7]. MoreSexistBERT distinguishes between females being *parasites* and males being animals (*animals, ox, pigs*) (m:f 3:1). LessSexistBERT has *pig* for females and *rat* for males (m:f 1:1). HateBERT generates *dog* for males as opposed to big (*ox, elephant, cow(s)*) or smutty (*pig*) animals for females (m:f 1:4). According to Lilly (2016), drawing the connection between women and animals through metaphor in the manosphere functions to represent women as primitive, and animalistic, as opposed to civilized,

[7]In addition to the exact number of negatively connoted words generated by each LM exclusively for male or female templates for each category, up to 5 examples are listed. In the analysis, for each LM all words generated for all templates of one gender are combined, therefore the list of generated words is unsorted.

Category	Description	Examples
animal	animals attributed to females or males	cow, pig, animal, ...
violence / power	person being attributed such a word is violent a or has power over others	rapist, armed, killers, ...
weakness	a person being attributed such a word is weak or lost control over something	punished, weak, raped, ...
objectified	a person being attributed such a word is objectified, can be bought	whore, escort, plate, ...
toxicity	toxicity is a broader category comprising slur and attributions suggesting that a person is evil, mean, toxic or more general puts others under stress	burden, horrible, Hitler, ...
stupidity	a person being attributed such a word is not intelligent or goofy	idiot, loser, ridiculous, ...
existence denying	a person being attributed such a word is worthless or their existence is denied or threatened	useless, worthless, slaughtered, ...
weirdness / disgust	a person being attributed such a word is disgusting or weird	ugly, weird, disgusting, ...
feeling bad	if a person feels like that, they do not feel well	crying, worried, unhappy, . . .

Table 2: Categories for semantically grouping negative words resulting from template filling. Note, the same categories were used to classify the words added to the language models during continual pre-training.

rational human aka men.

Violence/power BERTbase produces the most words related to violence and power exclusively for men (such as *abusive, armed, brutal, force, killers*), while women are *predators* (m:f 7:1). This can be seen in the context that patriarchy at its core reflects a system of power (Risman et al., 2018) and that stereotypically masculinity includes detrimental behaviours towards women, such as violence (Hart et al., 2019). HateBert assigns *cruel* to men and *angry*, *avalanche* to women (m:f 1:2).

In the manosphere context, men are invisible victims of their abusive wives or girlfriends and violence against women is represented as restorative of masculinity (Lilly, 2016). Accordingly, LessSexistBERT produces *angry* and *armed* for men (m:f 2:0), MoreSexistBERT *rapist(s)* and *threat* for men and *intimidating* for women (m:f 2:1).

Weakness That a stereotypical view on patriarchy and masculinity is related to power is also reflected in the different words assigned to men and women by BERTbase in this category. While women are, e.g., *attacked, captured, fired, kidnapped* or *raped*, men are *controlled, punished, unarmed* and *weak* (m:f 4:8). For the other LMs, this ratio flips, i.e., more different words of this category were generated for male connoted templates (HateBERT m:f 4:1, LessSexistBERT 6:2, MoreSexistBERT 9:5). This can also be seen in the context of the manosphere, where men are invisible victims of women (Lilly, 2016). Also, there exist animosities between the subcultures of the manosphere and especially members of the PUA community frequently connect members of the MGTOW community with losers and weakness (Lamoureux, 2015). This is also reflected in the words assigned to men in this category, such as *afraid, fucked, weak, mess, lost* by LessSexistBERT, and *broke, disabled, doomed, screwed, pussies* etc. by MoreSexistBERT.

This kind of weakness is a negative masculine trait (see Lilly, 2016) and is reflected by BERTbase, HateBERT, and LessSexistBERT where *weak/weakness* was generated in the context of male connoted templates.

Objectification BERTbase generates more words of this categories to male templates (m:f 5:3) and the connotation for both genders is similar, although a bit more intense for women (*costly, object, prostitute* for female templates and *paid, thing, escort, robot, used* for male templates). For the biased LMs, however, there is a larger amount

of distinct words generated for female templates by HateBERT (m:f 0:5), LessSexistBERT (m:f 1:7), and MoreSexistBERT (m:f 2:9) than it is the case for men. Also, the subcategories of the objectified category differ. While men are *tools* and *utilities*, women are sexual objects (*escort, whore, prostitute*), can be bought (*sold, property, investment*) and may be expensive (*costly*). The sexual objectification of women is visible in the whole manosphere discourse, and especially in the PUA community (see Lilly, 2016). In addition to a higher amount of words generated for female templates, LessSexistBERT and MoreSexistBERT also generate words specific to the manosphere, e.g. *plate*[8].

Toxicity All four LMs generated a large number of words assigned to this category (BERTbase m:f 12:10, HateBERT 7:15, LessSexistBERT 10:13, MoreSexistBERT 6:29). While words such as *stalker, sexist, nazi, hitler, bastards* were generated for male templates, some words generated for female templates also included a sexual connotation: *whore, slut, thot, hoe*. Other examples generated by MoreSexistBERT for female templates include words such as *devils, monster, nightmare, poison* and *plague*. The higher amount of different words generated by the biased LMs (especially by MoreSexistBERT) might be explained by the general attitude within the manosphere that men are oppressed by women.

Stupidity Stupidity/goofiness is a relatively small category and words of this category are mainly generated for male templates. 5 distinct words generated by BERTbase for male templates was the maximum (BERTbase m:f 5:2, HateBERT 2:1, LessSexistBERT 3:0, MoreSexistBERT 2:0). Although Lilly (2016) outlined that women are often represented as lazy and stupid in the manosphere context, this is not represented in our results. The animosity between the subcultures of the manosphere as identified by Lamoureux (2015) is, however, represented within the continually pre-trained models as men are connoted with *fools, losers, idiots, simps*, and *jerks*.

Existence denying This category is again small for the biased LMs. HateBERT did not generate any word in this category (m:f 0:0), LessSexistBERT *nobody, unicorn* for women (m:f 0:2), and MoreSexistBERT *illegal, pointless, redundant* for women and *absent* for male templates (m:f 1:3). So if there is a connotation focus, it is towards women. For BERTbase however, there is a connotation focus towards men (m:f 15:2). Examples for words generated for male templates include *disgrace, failure, fraud, nobody*, and *nothing*. However, it needs to be noted that when filling the templates, the biased language models (HateBERT, LessSexistBERT, and MoreSexistBERT) differ from BERTbase in that they are quite 'sure' in how to fill the masks, i.e., they assign a higher probability to their highest ranked words to fill the mask than BERTbase. Typically, when the top 30% of words are retained per LM, the number of words generated by BERTbase is usually higher. In other words, BERTbase tends to be less sure and thus produces more variety.

Weirdness / disgust HateBERT is the only LM which generated more words of this category for female templates (*annoying, awful, garbage, ugly*) (m:f 2:4). For LessSexistBERT and MoreSexistBERT, women are *gross* and *weird*, men are *unattractive, bald* and *boring* (LessSexistBERT m:f 1:1, MoreSexistBERT 2:2). BERTbase generated more distinct words for male templates in this category than for women (m:f 5:1).

Feeling bad BERTbase generated the same amount of distinct words of this category for both male and female templates with a similar semantic content (m:f 3:3). While for LessSexistBERT women are *crying, desperate* and *worried*, men are *confused* and *unhappy* (m:f 2:3). MoreSexistBERT on the other hand generated *unhappy* for female templates and *depressed, desperate* and *suffering* for men (m:f 3:1), while for HateBERT men are *disappointed* (m:f 1:0).

Special categories Domain shift effects of continual pre-training become particularly clear with respect to **manosphere**: manosphere specific terms are only produced by MoreSexistBERT and LessSexistBERT, which are both continually pre-trained with unlabelled data from respective Reddit channels (LessSexistBERT m:f 4:2, MoreSexistBERT 4:2). Females are either exchangeable sex partners (*plate*) or the ideal female does not exist (*unicorn*). Males either renounce women (*mgtow, redpill*), are non-alphas (*beta, sigma*) or screwed by

[8] A sexual objectification of women used in the manosphere context related to the idea that man should date as many women as possible at the same time https://rationalwiki.org/wiki/Manosphere_glossary (Accessed: 2024-05-01)

alphas (*cuck*).

LessSexistBERT and MoreSexistBERT also produced more distinct negative words for the other special categories, therefore only these two LMs will be discussed in the following.

With regards to **sexual context**, MoreSexistBERT produced a larger number of distinct words for female templates (m:f 7:11) and LessSexistBERT generated more distinct negatively connoted words for male templates (m:f 6:3). In general, women are sexual objects (e.g., *whore, plate, escort*) which can be bought (e.g., *prostitute, escort*), while men are weak (e.g., *fucked, screwed*), losers (e.g., *cuck*) or violent (e.g., *rapist*).

With regards to the special category **illness**, women are *addiction* and *cancer* (LessSexistBERT m:f 0:2), *headache* and *pain* (MoreSexistBERT m:f 1:2), i.e. negatively affecting others, while men are *sick*, with less negative affect on others. These results are in line with the manosphere attitude that men are victims of their abusive wives or girlfriends. This is also reflected by the negatively connoted words generated by MoreSexistBERT for **mental illness**: *lunatic* and *mad* for female templates and *depressed* for male templates (m:f 1:2). LessSexistBERT on the other hand generated *lunatic* for male templates and no negatively connoted word for female templates (m:f 1:0).

3.3 Analysis of Model Outcomes Employing the Female/Male Attribution Templates

Similar as for the descriptive templates for all attribution templates, all words which covered the top 30% of the probability mass per template per LM were retained and the words which were only generated either for male or for female templates were analysed. As the number of templates was much smaller, not only negatively connoted words were interpreted but all words that carry meaning. *It, this, that* was excluded, as well as words which cancel each other, e.g., *everything* and *nothing* for the same template or state the obvious, such as *Females are female.* Also if the same word was generated for a specific template and the negation of that template as well by the same LM, they are not included in the analysis (e.g., *Women are good in* [MASK]. and *Women are not good in* [MASK].).

In the following, we will focus on the analysis of the words generated by LessSexistBERT and MoreSexistBERT.

LessSexistBERT Attributions made by LessSexistBERT only to women are that they are *emotional*, everything they do is *bullshit* and *projection* and they are not good in *bed*. Men on the other hand are either weak (*weak, trash*), superior (*privileged, strong*) or *violent*. Men expect *more, things*, and *sex* and see value in *others* and *women*. However, they are not good for *society*, *in general*, and do not see value in *relationships* and *anything*. These words reflect both general stereotypes, e.g. that men are strong and women emotional, as well as attitudes from the manosphere context that men are weak and do not see value in relationships, and that women are worthless.

MoreSexistBERT Negative words attributed to women again increase for MoreSexistBERT, where everything women do is *projection* and they are *children, retarded, emotional*, and *parasites*. Women are good for *nothing*, they are good in *manipulation* and *sex*, and are much more *emotional* than men. They expect *everything* and *money* and are *crying* and not good in *stem, combat*, and *sports*. Words attributed to women reflect general stereotypes, but in particular attitudes towards women from the manosphere domain. Men on the other hand are superior (*predators, privileged, stronger, superior*), they are good for *sex* and expect *sex*, and are much more *violent* than women, but not good in *bed* and *relationships*. Summing up, the results from MoreSexistBERT indicate that in the context of our attribution templates negative attributions stemming from the manosphere are more prevalent in female contexts whereas more general masculinity attributes prevail in the male contexts.

4 Conclusion

In this paper, we presented a novel approach of assessing bias. We investigated four LMs (BERTbase and three deliberately biased variants HateBERT, MoreSexistBERT, LessSexistBERT) making use of template-based mask filling for probing the LMs with respect to male/female biases, and we make use of qualitative content analysis for analysing the model outputs.

For both LMs continually pre-trained on a more and a less sexist dataset from the manosphere domain (MoreSexistBERT and LessSexistBERT), a domain-shift was apparent. This is reflected in manosphere-specific terminology which the LMs used to fill the masked templates, such as *unicorn, plate*, or *simp*. It is also reflected by the preju-

dices and stereotypes prevalent in society and in the manosphere, reported by social sciences research (see Lilly, 2016; Risman et al., 2018; Hart et al., 2019). While BERTbase reflects the stereotypical attitude that weakness is a female trait and power is a male trait, in LessSexistBERT and MoreSexistBERT, weakness is a negative masculine trait and attributing weakness to male templates might also stem from the animosities among the manosphere sub-cultures. In the manosphere context, women are disparagingly represented, especially as irrational, emotional creatures, who are sluts and unappealing (see Lilly, 2016). This is reflected in the high amount of negative words attributed to women, especially from the categories 'toxicity', 'sexual objectification' and 'existence denying'. Training on data from the manosphere context has the advantage that the lexicon then also includes this terminology, as opposed to a LM, which is trained on Wikipedia and the Book Corpus, such as BERTbase.

With regards to the descriptive templates and gender bias, words generated by MoreSexistBERT are even more derogatory towards women than words generated by LessSexistBERT for each single category and subcategory except for 'stupidity', 'feeling bad', and the 'manosphere'. Especially for the categories 'toxicity', but also for (sexual) 'objectification' and 'weakness', MoreSexistBERT produced a higher number of negative words attributed to women.

The analysis of the female/male attribution templates supports the result from the analysis of the descriptive templates. Only that weakness is a negative masculine trait is not reflected in words MoreSexistBERT used to fill the masks of the male templates.

HateBERT does not show manosphere-specific terminology, but there is more hateful content and also more hateful content towards women. This is probably due to the fact that the data used to train HateBERT also contains a higher amount of hateful sexism towards women than towards men.

Summing up, by means of the proposed qualitative approach to analysing model outputs, we could show clear domain shift and bias effects in the model outcomes induced by the training data which reflect stereotypes and prejudices in the real world, which are also documented in social science literature.

5 Limitations

Limitations of the proposed approach lie in (i) the availability of respectively biased data in quantities being large enough for continual pre-training; (ii) the likelihood that (unnoticed) new biases will be introduced via further pre-training; (iii) the selection of templates used in mask-filling; (iv) how many words / how much of the probability mass of the output words are taken into account for the analysis and whether one looks only at the positive or negative words or at both in the analysis; (v) last but not least, the socio-cultural background of the individuals defining the templates and of those performing the qualitative content analysis may influence the outcome of the model's assessment.

6 Ethical Considerations

As it is not possible to completely mitigate bias, we argue that from an ethical perspective, it is very important to be explicit about the bias in the LM and it is necessary to motivate desired and undesired bias in view of a certain application. Being continually pre-trained on domain-specific data has the advantage that domain-specific terminology is in the lexicon of the LM. For certain applications, e.g. a classification task, a biased LM has high potential to perform better than an unbiased LM (see Devlin et al., 2019). However, for NLP tasks such as question answering, advantages and disadvantages have to be carefully ethically assessed. The motivation which biases are wanted or unwanted in which application context must be made explicit, including who is expected to benefit and how, at the costs of whom, and why this is wanted. In addition, it is important to make explicit which foundational model was used and which data and procedures were employed to continually pre-train and/or fine-tune the base model to adapt for which biases. Respective datasheets for datasets (Gebru et al., 2021) and model cards (Mitchell et al., 2019) should be mandatory. Last but not least, the specific test suits and procedures applied for testing the respective biases must be well documented and made available.

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[9] https://ekip.ai/

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