

Quantifying Gender Bias Towards Politicians in Cross-Lingual Language Models

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Abstract

While the prevalence of large pre-trained language models has led to significant improvements in the performance of NLP systems, recent research has demonstrated that these models inherit societal biases extant in natural language. In this paper, we explore a simple method to probe pre-trained language models for gender bias, which we use to effect a multi-lingual study of gender bias towards politicians. We construct a dataset of 250k politicians from most countries in the world and quantify adjective and verb usage around those politicians’ names as a function of their gender. We conduct our study in 7 languages across 6 different language modeling architectures. Our results demonstrate that stance towards politicians in pre-trained language models is highly dependent on the language used. Finally, contrary to previous findings, our study suggests that larger language models do not tend to be significantly more gender-biased than smaller ones.

1 Introduction

Recent large language models have been shown to achieve state-of-the-art performance on many downstream tasks using only few target task examples (Devlin et al., 2019; Liu et al., 2019; Yang et al., 2019). During their pre-training, these models are known to partially learn a language’s syntactic and semantic structure (Hewitt and Manning, 2019; Tenney et al., 2019). However, alongside capturing the linguistic nuances of a language, they also perpetuate (and potentially amplify) biases (Zhao et al., 2017; Bender et al., 2021).

Thus far, approaches to analyze (gender) bias in pre-trained language models have primarily used basic statistical measures such as association tests (May et al., 2019; Nadeem et al., 2020), correlations (Webster et al., 2020) and causal analysis (Vig et al., 2020). Further, most previous work on gender bias in language models has focused on En-

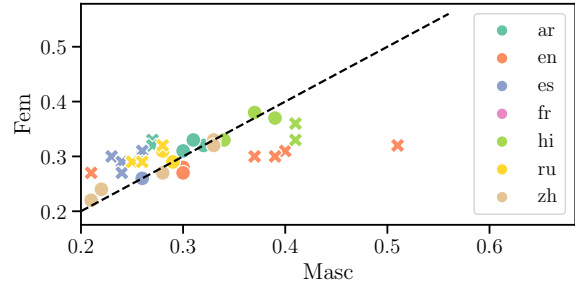


Figure 1: Mean frequency with which the top 100 adjectives—the most strongly associated with either masculine or feminine gender—correspond to negative sentiment for each language. Each point denotes a language model. Significant differences between masculine and feminine gender are denoted with ‘x’ markers.

glish (Nadeem et al., 2020; Vig et al., 2020), with the notable exception of Liang et al. (2020) who examined biases for both English and Chinese.

In parallel, another stream of work has concentrated on analyzing stance towards politicians. Prabhakaran et al. (2019) discover that leaders (i.e. politicians) tend to have higher toxicity associations and argue that if an entity is often mentioned in negative linguistic contexts, a pre-trained language model might learn to associate negativity to its name. Similarly, Shwartz et al. (2020) show that some names tend to be grounded to specific entities and observe the most striking effects on politicians.

The **contributions** of this work are as follows:

Cross-lingual study. Prior work has almost exclusively investigated bias in monolingual language models. We present a fine-grained study of gender bias in 6 cross-lingual language models.

Stronger statistical methods. Prior work has mostly used less expressive statistical methods to measure gender bias in language models. We employ an unsupervised method using a latent-variable model.

Largest coverage. We present the largest study quantifying gender bias towards politicians to date,

considering 250k politicians from most of the world’s countries and measure gender biases towards them in 7 languages.

New findings. We find that, for both male and female politicians, stance towards politicians in pre-trained language models is highly dependent on the analyzed language—with no significant findings for other-gendered politicians. Fig 1, for instance, shows that while in English, male politicians are associated with a more negative sentiment, the opposite is true for most other analyzed languages. Perhaps surprisingly, we do not find any significant evidence that larger language models tend to be more gender-biased than smaller ones which contradicts previous findings (Nadeem et al., 2020).

Finally, our methodology can easily be extended to study gender biases towards other types of entities in other languages.

2 Related Work

Gender bias in pre-trained language models

Research on gender bias in pre-trained language models has gained an increasing amount of attention. Prior datasets for bias evaluation in language models have mainly been built for English and with sentences of basic structures, e.g. “This is a(n) *blank* person.” or “*Person* is *blank*.”, where *blank* refers to an attribute such as an adjective or occupation (May et al., 2019; Webster et al., 2020; Vig et al., 2020). Another approach to gather data is Nadeem et al.’s (2020), where crowdworkers provided stereotypical, anti-stereotypical and unrelated associations. This method does not suffer from the artificial context of simply structured sentences, however, crowdsourced annotations on stereotypes may convey subjective opinions and are cost intensive if employed for multiple languages.

We suggest a simple approach where we generate tokens in neighborhoods of named entities (NEs) expecting to obtain words that language models *associate* with a given name.

Stance towards politicians Stance detection is the task of automatically determining if the author of an analyzed text is in favor of, against, or neutral towards a target (Mohammad et al., 2016). Notably, Mohammad et al. (2017) observes that a person may demonstrate the same stance towards a target by using negative or positive language. Thus, stance detection is a challenge more complex than sentiment classification.

Here, we generate a dataset for analyzing stances towards politicians encoded in a language model, where this stance is inferred from simple grammatical constructs (e.g. *ADJ*-entity).

Previous work on stance towards politicians is based on datasets with more complex grammatical structures. However, these have mostly targeted specific entities in a single country’s political context. Ahmad et al. (2011) analyze samples of national and regional news by Irish media on politicians running in general elections with the goal of predicting election results. More recently, Voigt et al. (2018) collected responses to Facebook posts for 412 members of the U.S. House and Senate from their public Facebook pages, while Padó et al. (2019) created a dataset consisting of 959 articles with a total of 1841 claims where each claim is associated with an entity. It is readily apparent that each of these resources include information on a limited number of entities.

Geared towards analyzing stance towards politicians in a broader context, we construct a multilingual dataset of 250k politicians from most of the world’s countries.

3 Gender Bias Detection

Our primary aim is to quantify gender bias pervaded in Transformer-based language models, which lets us assess potential representational harms arising when employing these models on downstream tasks. Unlike prior work, we do not merely want to analyze monolingual English language models, but to design and conduct a study of gender bias in large cross-lingual language models. Thus, we are able to examine if the nature of gender bias exhibited in models differs depending not only on model size and training data, but also on a language and its typology.

For instance, in a language such as Spanish, in which adjectives are gendered according to the noun they refer to, grammatical gender might become a highly predictive feature the model can rely on during its pre-training. On the other hand, since inanimate objects are gendered, they might take on adjectives which are usually not associated with their grammatical gender, e.g. “*la espada fuerte* (the strong [feminine] sword)”, potentially mitigating the effects of harmful bias in these models.

We analyze gender bias towards NEs, i.e. politicians. Prior research has shed light on information incorporated in NE representations, e.g. Prab-

hakaran et al. (2019) test NLP models for unwanted biases, discovering that sentiment towards NEs is encoded in their representations and politicians in particular tend to have high toxicity associations.

To conduct this analysis, we require a multilingual dataset suitable for quantifying gender bias towards politicians. To the best of our knowledge, currently available datasets are not broad enough to cover an extensive number of politician names in multiple languages. Second, we need a suitable methodology for measuring gender bias.

Considering the above, we:

- Establish a method to generate a multilingual dataset for quantifying gender bias towards politicians in cross-lingual language models; (§4)
- Use point-wise mutual information to measure associations between generated words and gender; then take Hoyle et al.’s (2019a) unsupervised latent variable model as a point of departure for more detailed analysis and adapt it to a cross-lingual setup. (§5)

4 Dataset Generation

Some of our key contributions are to propose a general method for multilingual dataset generation and a novel approach to test for biases. By imposing sentence structures, previous work (e.g. May et al. 2019; Webster et al. 2020; Vig et al. 2020) may have biased its analyzed output distributions. While a fixed structure such as “*Person is blank*” may not seem harmful in English, this bias becomes clearer when we look at other languages. Spanish, for instance, distinguishes between an ephemeral and a continuous sense of verb to be, i.e. *estar* and *ser*, respectively. As such, a structure such as “*Person está blank*” bias the studied adjectives towards ephemeral characteristics.¹

With this in mind, we let language models generate words around entity names (here, politicians) while imposing no sentence structure – relying on a [MASK] <person name> query, as we explain later. We assume that this bottom-up approach can unveil associations encoded in language models between their representations of NEs and words describing them. To the best of our knowledge, this method enables the first multilingual analysis of gender bias in language models – being applicable to generate datasets in any language and with any choice of gendered entity, provided that

a list of such entities with their gender is available.

We restrict our analysis to 7 typologically diverse languages: Arabic, Chinese, English, French, Hindi, Russian and Spanish. This enables an analysis of several multilingual language models – while covering a culturally diverse choice of speaker populations. While this framework is applicable to any type of NE, we study stance towards politicians since this topic has recently gathered attention, being of both academic and social importance (Fan et al., 2019) and has not yet been analyzed in a broad multilingual setup.

To generate the dataset, we first query the Wikidata knowledge base (Vrandečić and Krötzsch, 2014) to obtain politician names in the 7 analyzed languages. Next, using 6 language models we generate adjectives and verbs associated with those politician names. Finally, we collect sentiment lexica for the analyzed languages to study differences in sentiment for generated words.

4.1 Politician names

We obtain politician names and their genders from Wikidata, retrieving their names in the 7 analyzed languages (not all names available in all languages). Wikidata distinguishes between 12 gender identities,² from which we exclude female and male organisms, as they refer to animals which (for a reason or another) were running for elections. We also replace the *cisgender female* label with *female*, and exclude any politician for which gender information is unavailable.³ Finally, we create a general gender category *other*, which includes all politicians not identified as male or female (due to the small number of politicians for each of these genders; see Table 5 in the appendix). Tables 3 and 4 (appendix) present the counts of politicians grouped by their gender (male, female, other) for each language. On average, the male to female gender ratio is 4:1 across the languages and there are very few names for the gender category ‘other’.

4.2 Language generation

The language generation process can be thought of as a word association questionnaire. We give the language model a politician’s name and ask

¹An example is the sentence “Obama está bueno (Obama is [now] good)”, which sounds unusual to Spanish speakers.

²Cisgender female, female, female organism, non-binary, genderfluid, genderqueer, male, male organism, third gender, transfeminine, transgender female and transgender male. This information is maintained by the community and regularly updated. We discuss this further in 8.

³These account for <3% of data points for all languages.

it to generate a token (verb or adjective) which it *thinks* is most appropriate for the name. We could take several approaches towards that goal. A possibility would be to let the language model generate a sentence where the name must appear and analyze it. However, most recent large language models are not trained with language generation in mind – their pre-training consists in predicting masked tokens in already existing sentences (Rogers et al., 2021).⁴ Another possible approach would be to use a dependency parsed sentence and replace a verb (v) or adjective (a) in it with a [MASK] token whenever a person name is encountered (p) such that $\text{relation}(v, p) = \text{nsubj}$ or $\text{relation}(p, a) = \text{amod}$. Then p could be replaced with a politician’s name and the model could be used to predict the [MASK] token. However, the language model’s prediction would be biased by the other tokens in the analyzed sentences.

Our solution is to simplify this problem. In the languages we study, there is no common structure: while in English, adjectives usually precede nouns, the opposite is true for both Spanish and French (Dryer, 2013a). Furthermore, while English has subject-verb-object (SVO) ordering, verbs usually precede subjects in the modern standard variant of Arabic (it has VSO ordering, see Dryer 2013b). We thus query each analyzed language model by feeding it either a [MASK] <person name> input, or its inverse <person name> [MASK]. This returns a ranked list of words (with their probabilities) which the model associates

These returned words, though, will not be restricted to adjectives or verbs – the part of speech (POS) categories we want to analyze as they capture the sentiment about the name (Hoyle et al., 2019a). Furthermore, POS tagging is a sequence prediction problem and off-the-shelf POS taggers cannot be reliably used to predict the POS tag for individually predicted tokens. Therefore, we rely on the universal dependency (Zeman et al., 2020) treebanks to filter these words, only keeping the ones which are present in any of the language-specific treebanks and marked as an adjective or verb.

A final issue is that all our models use subword tokenizers and, therefore, a politician’s name is often not just tokenized by a whites-

pace. For example, the name “Narendra Modi” is tokenized as [“na”, “##ren”, “##dra”, “mod”, “##i”] by the BERT uncased tokenizer. It is difficult to ascertain solely from a model’s vocabulary whether the model indeed saw a name during training. However, all politicians whose names we analyze have Wikipedia pages – and Wikipedia is a subset of the data on which these models were trained (except BERTweet, which is trained on a large collection of 855M English tweets). Therefore, we assume that the models did see these names during training and that the predicted words for the [MASK] tokens are truly reflective of the model’s sentiment.

4.3 Sentiment data

Following Hoyle et al. (2019a), we use sentiment as a proxy to quantify bias, which requires a sentiment lexicon for each analyzed language. We use the combined sentiment lexicon of Hoyle et al. (2019b) for English words, which was shown to outperform a number of individual sentiment lexica and their straight-forward combination on a text classification task involving sentiment analysis. Unfortunately, this is only available for English.

For the remaining six languages we use SentiVAE (Hoyle et al., 2019b) – a multi-view variational autoencoder – to combine existing sentiment lexica, the same method Hoyle et al. (2019a) use to generate the English sentiment lexicon. Particularly, SentiVAE combines lexica with disparate scales into a common latent representation, where the output represents the strength of each word’s sentiment (positive, negative and neutral) in the form of a three-dimensional Dirichlet distribution. Hence, even polysemous and rare words are accounted for. We combine 3 multilingual sentiment lexica for all analyzed languages, except Hindi: BabelSenticNet (Vilares et al., 2018), the sentiment lexicon by Chen and Skiena (2014) and UniSent (Asgari et al., 2020). Additionally, we incorporate monolingual sentiment lexica for Arabic (Elsahar, 2015), Chinese (Xinfan, 2012; Chen et al., 2018), French (Abdaoui et al., 2017; Fabelier, 2012), Russian (Loukachevitch and Levchik, 2016) and Spanish (Dolores Molina-González et al., 2015; Bravo-Marquez, 2013; Figueroa, 2015). For Hindi, we combine the sentiment lexica from Chen and Skiena (2014), Desai (2016) and Sharan (2016).⁵

⁴Wang and Cho (2019) suggests generation via iterative sampling over a sequence of [MASK] tokens. Nonetheless, the sentence length has to be provided in advance, and often the generated sentences lack diversity, particularly when the process is constrained by specifying the names.

⁵We conjecture that combining a larger number of individual lexica with SentiVAE leads to more reliable results. Nonetheless, we exclude BabelSenticNet and UniSent lexica

Following Hoyle et al. (2019b) we evaluate the resulting lexica in a text classification task on a selected dataset for each of the languages. Namely, we use the resulting lexica to automatically label instances with their sentiment, based on the average sentiment of words in each sentence. The results presented in Table 6 show that there is no major performance difference between using sentiment lexica for labelling instances, and using a supervised model trained on the training split of each dataset. For the latter, we include the best performance reported in the paper presenting the respective dataset as a point of reference.

5 Methods

We use two methods to quantify gender biases in large LMs. First, we use **point-wise mutual information (PMI)** as a measure of association between a generated word and gender. This method, though less accurate, is unsupervised and can even be applied to small data samples. Secondly, we adopt the methodology of Hoyle et al. (2019a), which **extends the concept of PMI with latent sentiment and regularization**. Originally, this method uses the corpus of Goldberg and Orwant (2013) and is provided a pre-defined list of animate nouns to be analyzed. Therefore, it could not be directly used to detect gender bias towards entities such as politicians. However, having annotated NEs in our dataset, we are able to circumvent this requirement. Further, the method of Hoyle et al. (2019a) was developed in a monolingual setting. We adapt it to be suitable for a broader study in a multilingual setup. To do so, we account for grammatical patterns which the analyzed languages follow (*i.e.* sentence structure, PoS tagging, lemmatization). Finally, we collect sentiment lexica in analyzed languages. Note that due to the relatively small number of politicians identified in the *other* gender group, we restrict ourselves to two binary genders in this generative latent-variable setting.

5.1 Point-wise mutual information

Point-wise mutual information (PMI) is a measure of association that examines co-occurrences of two random variables and quantifies the amount of information we can learn about a specific variable from another. In our initial approach we treat generated words as bags of words and

analyze the PMI between gender $g \in \mathcal{G} = \{\text{MALE}, \text{FEMALE}, \text{OTHER}\}$ and word \mathbf{w} as:

$$\text{PMI}(g, \mathbf{w}) = \log \frac{p(g, \mathbf{w})}{p(g)p(\mathbf{w})} \quad (1)$$

In particular, PMI measures the difference between the co-occurrence probability of a word and gender versus their joint probability if they were independent. As such, if a word appears as often with one gender as does with the others, its PMI will be zero. On the other hand, if a word is more (less) often associated with a gender, its PMI will be positive (negative). For example, we would expect a high value for $\text{PMI}(\text{female}, \text{pregnant})$ because their co-occurrence probability is higher than the independent probabilities of *female* and *pregnant*. Accordingly, in an ideal un-biased world, we would expect words such as *successful* or *intelligent* to have a PMI of approximately zero for all genders.

5.2 Generative latent-variable model

In order to analyze stance towards male and female politicians and to quantify the degree to which the language generated to describe them differs, we apply the generative latent-variable model presented in Hoyle et al. (2019a).⁶ This model jointly represents adjective (or verb) choice (\mathbf{w}) with its sentiment (s), given a politician’s gender (g).

$$p(\mathbf{w}, g, s) = p(\mathbf{w} | s, g)p(s | g)p(g) \quad (2)$$

Following Hoyle et al. (2019a), we define $\mathcal{G} = \{\text{MALE}, \text{FEMALE}\}$ to be the set of genders in our dataset, whereas its instances are represented by one-hot vectors $g \in \mathcal{G} \equiv \{0, 1\}^T$. We also define \mathbf{w} to be a word (the lemma⁷ of an adjective or a verb) in a language-specific vocabulary $\mathbf{w} \in \mathcal{V}$. Finally, let $\mathcal{S} = \{\text{POS}, \text{NEG}, \text{NEU}\}$ be a set of sentiments, with $s \in \mathcal{S}$ being one such sentiment. We further define $n \in \mathcal{N}$ to be a politician name, where \mathcal{N} is the set of analyzed names (we denote g_n as the gender of a politician with name n).

Since we do not have access to explicit sentiment information (it is encoded as a latent unobserved variable), we marginalize it out from eq. 2 while training our model. This yields the objective:

$$\mathcal{L}_{\text{main}} = \sum_{g \in \mathcal{G}} \sum_{\mathbf{w} \in \mathcal{V}} \hat{p}(\mathbf{w} | n) \log p(\mathbf{w}, g_n) \quad (3)$$

⁶This model is based on the sparse additive generative model (SAGE; Eisenstein et al. 2011) which is a flexible alternative to latent Dirichlet allocation (LDA; Blei et al. 2003).

⁷We note that these words may be gendered, e.g. *beau* vs *belle* in French, so we must use the lemma of the word or association effects would be trivial.

for Hindi due to poor evaluation results.

where $\hat{p}(\mathbf{w} \mid n)$ is defined as the probability of a word given a politician name, taken from the analyzed language model.

As in Hoyle et al. (2019a), we apply posterior regularization (Ganchev et al., 2010) to guarantee that our latent variable correspond to sentiments. This regularization is taken as the Kullback–Leibler (KL) divergence between our estimate of $p(s \mid \mathbf{w})$ (again marginalized from eq. 2) and a ground-truth $q(s \mid \mathbf{w})$ —which we get from the sentiment lexicon described in detail in Section 4.3. We further rely on L_1 -regularization to account for sparsity. This objective is minimized with Adam optimizer (Kingma and Ba, 2015).

$$\mathcal{L} = \mathcal{L}_{\text{main}} + \beta \text{KL} + \alpha L_1 \quad (4)$$

Through the distribution $p(\mathbf{w} \mid s, g)$, this model enables us to extract ranked lists of adjectives (or verbs), grouped by both gender and sentiment, that were generated by a language model to describe politicians. This distribution is defined as

$$p(\mathbf{w} \mid s, g) \propto \exp(m_{\mathbf{w}} + f_g \eta(\mathbf{w}, s)) \quad (5)$$

where $m_{\mathbf{w}} \in \mathbb{R}$ works as a word specific bias, $f_g \in \{0, 1\}^T$ is the one-hot gender representation and $\eta(\mathbf{w}, s) \in \mathbb{R}^T$ is a word–sentiment specific deviation. During evaluation, we remove the word specific bias and analyze only its gender-specific sentiment deviation. To get instances with a high association between FEMALE and POS, for instance, we get:

$$\tau_{\text{FEM-POS}} \propto \exp(f_{\text{FEM}} \eta(\mathbf{w}, \text{POS})) \quad (6)$$

We refer the reader to Hoyle et al. (2019a) for a more detailed description of the model.

6 Experiments and Results

We apply the methods defined in Section 5 (PMI and the generative latent-variable model) to study the presence of gender bias in the dataset described in Section 4⁸. First, using the English portion of the dataset, we analyze the PMI values to look for the words diverging the most for each of the three gender categories. Then, we conduct the same analysis as presented in Hoyle et al. (2019a) for our dataset

⁸We use top 20 words generated for English both in mono- and multilingual setup for adjectives and verbs. For the other languages, top 100 adjectives and top 20 verbs are used. Detailed counts of generated adjectives are in Table 11

to test if adjectives and verbs generated by language models follow the same patterns as discovered in natural corpora and if they confirm previous findings about stance towards politicians. Next, we conduct a multilingual analysis for the seven selected languages via PMI and the latent-variable model to unveil both qualitative and quantitative differences in words generated by 6 cross-lingual language models.⁹

6.1 Monolingual setup

6.1.1 PMI and latent-variable model

From the PMI values for words associated with politicians of male, female or other genders¹⁰ it is apparent that words associated with the female gender are often connected to weaknesses such as *hysterical* and *fragile* or to their appearance (*blonde* and *lovely*), while adjectives generated for male politicians tend to describe their political beliefs such as *fascist* and *bolshevik*. There is no such distinguishable pattern for the gender category ‘other’, most likely due to insufficient amounts of data. For details, see Table 7 (in the appendix).

The results for the latent variable model are similar to those for the PMI model. Adjectives associated with appearance are more often generated for female politicians. Additionally, words describing marital status such as *divorced* and *unmarried* are also significantly more often generated for female politicians. On the other hand, positive adjectives describing men often relate to their character values such as *bold* and *independent*. More examples can be seen in Table 8 in the appendix.

Following Hoyle et al. (2019a), we use two existing semantic resources to **quantify** the patterns revealed above. We group adjectives and verbs into small numbers of coarse classes called supersenses using respectively Tsvetkov et al. (2014) and Miller et al. (1993) resources. We find that the male politicians are more often described negatively when using adjectives related to their emotions (e.g. anger) while more positively with adjectives related to their minds (e.g. intelligent) (details in Figure 4, appendix). These results differ from findings of Hoyle et al. (2019a), where no significant evidence of these tendencies was found.

⁹Following Hoyle et al. (2019a), our reported results are an average over hyperparameters: for the L_1 penalty $\alpha \in \{0, 10^{-5}, 10^{-4}, 0.001, 0.01\}$ and for the posterior regularization $\beta \in \{10^{-5}, 10^{-4}, 0.001, 0.01, 0.1, 1, 10, 100\}$

¹⁰This PMI values are based on words generated by all analyzed monolingual language models.

6.1.2 Sentiment analysis

Next, we examine overall sentiment of the language models towards male and female politicians. We evaluate differences in the frequency of words of positive and negative sentiment for each gender and report the results in Figure 2. We find that the language models significantly more often generate words with negative sentiment to describe male rather than female politicians, and that this pattern holds across most language models. However, based on the results of the qualitative study (see details in Table 8, appendix) we assume it is due to a number of strongly positive words such as *beloved* and *marry*, which are highly associated with female politicians.

To investigate if there are any significant differences across language models based on their size and architecture, we carry out a two-way analysis of variance (ANOVA). We take language, model size and architecture as independent variables and sentiment values as target variables; then analyze the differences in how the mean frequency with which the 100 largest deviation words (adjectives and verbs) correspond to each sentiment for male and female gender.

Results presented in Table 1 indicate significant differences in negative sentiment in descriptions of male politicians generated by models of different architectures. Notably, XLNet tends to generate more words of negative sentiment compared to other models examined. Also, larger models tend to exhibit similar gender biases to smaller ones.

6.2 Multilingual setup

6.2.1 Pointwise-mutual information and latent-variable model

For PMI scores, a pattern similar to the monolingual setup holds for the multilingual language models. Words associated with female politicians often relate to their appearance and social characteristics such as *beautiful* and *sweet* (prevalent for English, French and Chinese) or *attentive* (in Russian).

On the other hand, male politicians are described by as *knowledgeable*, *serious*, or (in Arabic) *prophetic*. Again, we are not able to detect any patterns in words generated around politicians of gender category ‘other’, where generated words vary from *similar* and *common* (as in French and Russian) or *angry* and *unique* (as in Chinese).

The results of the latent-variable model confirm the previous findings and are consistent with the

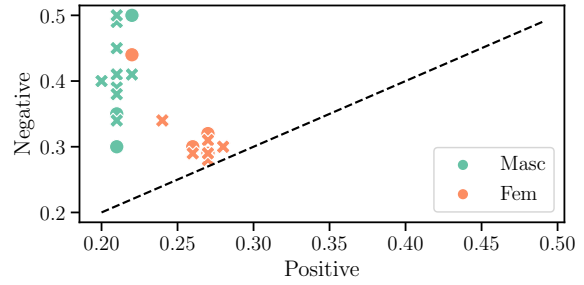


Figure 2: Mean frequency with which the 100 largest-deviation adjectives for male and female genders correspond to a positive or negative sentiment in English. Significant differences ($p < 0.05/3$ under an unpaired Bonferroni correction) represented with ‘x’ markers.

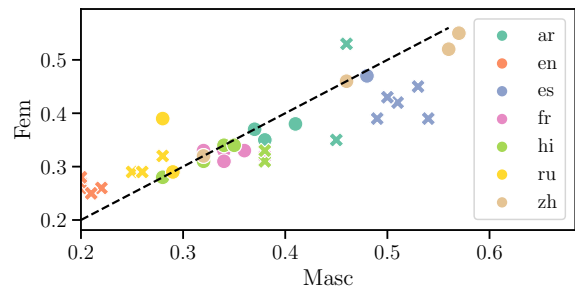


Figure 3: Mean frequency with which the 100 largest-deviation adjectives for each of the two genders considered correspond to positive sentiment. Significant differences ($p < 0.05/3$ under an unpaired Bonferroni correction) are represented with ‘x’ markers.

results for monolingual models (for an example, see Table 2 for Spanish). Words of positive sentiment used to describe male politicians are often *successful* (Arabic), or *rich* (Arabic, Russian). In a negative context, male politicians are described as *difficult* (Chinese and Russian) or *serious* (prevalent in French and Hindi) and the associated verbs are *sentence* (in Chinese) and *arrest* (in Russian). Notably, words generated in Russian have a strong negative connotation such as *criminal* and *evil*. Positive words associated with female politicians are mostly related to their appearance, while there is no such pattern for words of negative sentiment.

6.2.2 Sentiment analysis

Further, we analyze overall sentiment of the 6 cross-lingual language models towards male and female politicians for the selected languages. Our analysis suggests that sentiment towards politicians varies depending on the language used. For English, female politicians tend to be described more positively as opposed to in Arabic, French, Hindi and Spanish. For Russian, words associated with fe-

Parameter	Masculine		Feminine	
	NEG	POS	NEG	POS
Intercept	0.3900	0.2091	0.2841	0.2806
<i>Architecture</i>				
BERT	-0.0158	0.0014	-0.0060	-0.0100
BERTweet	0.0565	0.0044	0.0078	-0.0095
RoBERTa	-0.0924	0.0048	0.0010	-0.0074
XLNet	0.1067	0.0068	0.0858	-0.0455
<i>Model size</i>				
large	-0.0004	-0.0018	0.0354	-0.0075
xlarge	0.0224	-0.0004	-0.0039	-0.0063
xxlarge	0.1043	0.0036	0.0121	-0.0168
P-value	0.00	0.14	0.00	0.00

Parameter	Masculine		Feminine	
	NEG	POS	NEG	POS
Intercept	0.3104	0.4007	0.3269	0.3466
<i>Model architecture</i>				
XLM	-0.0200	0.0385	-0.0128	0.0245
XLM-R	-0.0573	0.0497	-0.0140	0.0286
<i>Model size</i>				
large	0.0065	-0.0128	0.0024	-0.0055
<i>Language</i>				
Chinese	-0.0309	0.0631	-0.0563	0.1056
English	0.0905	-0.2161	-0.0246	-0.1000
French	0.0244	-0.0767	0.0615	-0.350
Hindi	-0.0109	-0.0798	0.0187	-0.0443
Russian	-0.0162	-0.1564	-0.0230	-0.0698
Spanish	-0.0309	0.0812	-0.0332	0.0658
P-value	0.00	0.00	0.00	0.00

Table 1: Group mean sentiment values for negative and positive sentiment for masculine and feminine gender for adjectives generated by monolingual language models (left) and cross-lingual language models (right) calculated via ANOVA. Significant differences ($p < 0.05$) between negative and positive mean sentiment values are in bold.

<i>TMASC-NEG</i>		<i>TMASC-POS</i>		<i>TMASC-NEU</i>		<i>TFEM-NEG</i>		<i>TFEM-POS</i>		<i>TFEM-NEU</i>	
destruir	1.0	especialista	0.6	gratis	1.2	infantil	1.9	embarazado	1.8	paciente	2.2
cruel	1.0	editado	0.6	emprendedor	1.2	rival	1.9	urbano	1.8	activo	2.1
peor	1.0	izado	0.6	extraordinario	1.2	chica	1.9	único	1.8	dulce	2.0
imposible	1.0	enterrado	0.6	defender	1.2	fundadora	1.9	mágico	1.8	brillante	2.0
vulgar	1.0	cierto	0.6	paciente	1.2	frío	1.9	acusado	1.8	amiga	2.0
muerto	0.9	incluido	0.6	mejor	1.1	protegida	1.8	pintado	1.8	óptimo	1.9
irregular	0.9	denominado	0.6	apropiado	1.1	asesino	1.8	doméstico	1.8	informativo	1.9
enfermo	0.9	escrito	0.6	superior	1.1	biológico	1.8	crónico	1.8	bonito	1.9
ciego	0.9	designado	0.6	espectacular	1.1	invisible	1.8	dominado	1.8	mejor	1.9
enemigo	0.9	militar	0.6	excelente	1.1	magnético	1.8	femenino	1.8	dicho	1.9

Table 2: Ranked list of 10 adjectives with the largest average deviation over all models to describe male and female politicians in Spanish.

male politicians tend to be more polarized, having both more positive and negative sentiment. No significant patterns can be detected for Chinese. For details, see Figures 1 and 3.

Finally, analogously to the monolingual setup, we investigate if there are any significant differences in sentiment dependent on the target language, language model sizes and architectures (see ANOVA analysis in Table 1). Both XLM and XLM-RoBERTa generate fewer negative and more positive words than BERT multilingual (e.g. the mean frequency with which the 100 largest deviation adjectives for male gender correspond to negative sentiment is lower by 2.00% and 5.73% for XLM and XLM-R, respectively. Indeed, as suggested above, we find that language is a highly significant factor for bias in cross-lingual language models, alongside model architecture. For English and French, e.g., generated words are often more negative when used to describe male politicians. Surprisingly, we do not observe a significant influence of model size on the encoded bias.

7 Conclusions

In this paper, we present the largest study of quantifying gender bias towards politicians to date, considering a total number of 250k politicians. To this end, we establish a novel method to generate a multilingual dataset to measure gender bias towards entities. We study the qualitative differences in language models’ word choices and analyze sentiments of generated words in conjunction with gender using a latent-variable model. Our results demonstrate that stance towards politicians in pre-trained models is highly dependent on the language used. Finally, contrary to previous findings (Nadeem et al., 2020), our study suggests that larger Transformer models do not tend to be significantly more gender-biased than smaller ones.

While we restrict our analysis to seven selected, typologically diverse languages, as well as to politicians, our method can be employed to analyze gender bias towards any named entities and in any languages, given that gender information for those

entities is available. Future work will thus focus on extending this analysis to investigate gender bias in a wider number of languages and will study the wider societal implications of our results.

8 Ethical Considerations

Potential harms in using gender-biased language models Prior research has unveiled the prevalence of gender bias in political discourse, which can be picked up by NLP systems if trained on such texts. Gender bias encoded in Transformer-based language models is particularly problematic, as they are used as the building blocks of most modern NLP models. Biases in such language models can lead to gender biased predictions, and thus reinforce harmful stereotypes extant in natural language when these models are deployed. However, it is important to clarify that by our definition, bias does not have to be harmful (Blodgett et al., 2020), but it suffices to show that there is a significant difference in a system output that can be characterized by a social construct.

Quality of collaborative knowledge bases For the purpose of this research, we gathered information on politicians from the open-knowledge base Wikidata, which claims to do gender modeling at scale, globally, for every language and culture with more data and distribution than any other resource (Wikidata). It is a collaboratively edited data source and so, in theory, everyone could make changes to an entry (including the person the entry is about), which poses a potential source of bias. Since we are only interested in overall gender bias trends as opposed to results for individual entities, we can tolerate a small amount of noise.

Gender selection In our analysis, we aim to incorporate genders beyond male and female while maintaining statistical significance. However, politicians of other genders cover only 0.025% of collected entities. This restricts possible analyses for politicians of other genders, and risks drawing wrong conclusions. Although our method can be applied to any named entities of other genders to analyze stance towards them, we hope future work will obtain more data on politicians of non-binary genders to avoid this limitation.

Beyond English We explored gender bias encoded in cross-lingual language models in 7 typologically different languages. We acknowledge that

the selection of these languages may introduce additional biases into our study. The words generated by a language model also be more of a reflection of how politicians are perceived in these languages and how much are they discussed in general, than how much gender bias exists towards them. However, abstracting away from individual politicians, it is much more likely that findings should capture general gender bias trends. Finally, a potential bias in our study may be associated with racial biases that are being reflected by a language model, as names often carry information about politician’s country of origin.

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A Dataset

A.1 Politician data

Gender	Languages						
	Arabic	Chinese	English	French	Hindi	Russian	Spanish
male	206.526	207.713	206.493	233.598	206.778	208.982	226.492
female	44.962	45.683	44.703	53.437	44.958	45.277	50.888
other	67	67	66	67	67	67	67

Table 3: Counts of politicians grouped by gender for each language.

Gender	Languages						
	Arabic	Chinese	English	French	Hindi	Russian	Spanish
male	206.526	207.713	206.493	233.598	206.778	208.982	226.492
female	44.960	45.681	44.701	53.435	44.956	45.275	50.886
unknown	2.268	8.341	2.291	2.330	2.282	2.274	2.462
transgender female	55	55	52	55	55	55	55
transgender male	4	4	4	4	4	4	4
non-binary	4	4	4	4	4	4	4
cisgender female	2	2	2	2	2	2	2
genderfluid	1	1	1	1	1	1	1
genderqueer	1	1	0	1	1	1	1
female organism	1	1	1	1	1	1	1
male organism	1	1	1	1	1	1	1
third gender	1	1	1	1	1	1	1
transfeminine	1	1	1	1	1	1	1

Table 4: Counts of politicians grouped by gender for each language based on queried Wikidata information. Numbers across languages differ due to politician data not being available in all languages.

Other gender
genderfluid
genderqueer
non-binary
third gender
transfeminine
transgender female
transgender male

Table 5: List of genders grouped together as ‘other’.

A.2 Sentiment data

Language	Dataset	Number of texts	Self-supervised SentiVAE-based lexicon	Supervised SOTA
Arabic	Elnagar et al. (2018)	93.700	82.7 (f1)	81.6 (f1)
Chinese	Zhang and Chen (2016)	30.000	78.2 (f1)	87.12 (f1)
French	Blard (2020)	200.000	72.8 (f1)	97.36 (f1)
Hindi	Kunchukuttan et al. (2020)	4.705	63.5 (acc.)	75.71 (acc.)
Russian	Shalkarbayuli et al. (2018)	8.263	67.0 (f1)	70.00 (f1)
Spanish	Díaz-Galiano et al. (2019)	1.474	54.8 (f1)	50.7 (f1)

Table 6: Classification performance for self-supervised approach using SentiVAE sentiment lexica vs. the best reported result in the paper presenting the respective dataset for each language. Performance metric given in the brackets.

B Results

B.1 Monolingual

word	PMI_{female}	PMI_{male}
blonde	1.7	-2.2
fragile	1.7	-2.0
dreadful	1.6	-1.3
feminine	1.6	-1.7
stormy	1.6	-1.8
ambiguous	1.5	-1.4
beautiful	1.5	-1.4
divorced	1.5	-2.4
irrelevant	1.5	-1.5
lovely	1.5	-1.6
marital	1.4	-1.8
pregnant	1.4	-2.5
translucent	1.4	-2.1
bolshevik	-3.1	0.1
capitalist	-3.4	0.2

word	PMI_{other}	PMI_{female}	PMI_{male}
smaller	5.8	0.1	0.0
militant	5.7	-0.3	0.0
distinctive	5.6	0.4	-0.2
ambiguous	5.2	1.5	-1.4
evident	5.2	0.4	-0.2

word	PMI_{other}	PMI_{female}	PMI_{male}
approach	5.8	0.1	-0.1
await	5.3	0.5	-0.2
escape	5.1	0.2	-0.1
crush	4.9	0.3	-0.1
capture	4.8	-0.3	0.0

Table 7: Top 15 adjectives with the biggest difference in PMI for male and female (left), top 5 adjectives (top right) and bottom 5 adjectives (bottom right) PMI for other genders based on words generated by all monolingual language models for English.

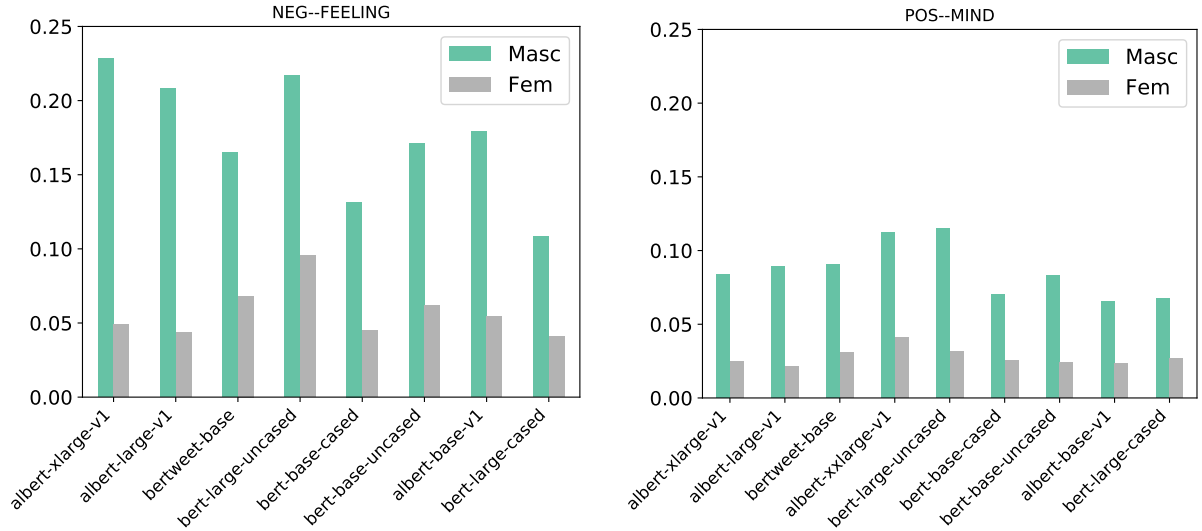


Figure 4: The frequency with which the 100 largest-deviation adjectives for male and female gender correspond to the supersense FEELING for the negative sentiment (left) and the supersense MIND for the positive sentiment (right). Results presented for language models with significant differences between male and female politicians after Bonferroni correction.

<i>TMASC-NEG</i>		<i>TMASC-POS</i>		<i>TMASC-NEU</i>		<i>TFEM-NEG</i>		<i>TFEM-POS</i>		<i>TFEM-NEU</i>	
stolen	1.5	based	1.2	bold	1.4	divorced	3.4	bella	3.1	beautiful	3.2
american	1.4	archeological	1.2	vital	1.4	bella	3.2	women	3.0	lovely	3.1
forbidden	1.4	hilly	1.1	renowned	1.4	fragile	3.2	misty	3.0	beloved	3.1
first	1.4	variable	1.1	mighty	1.4	women	3.1	maternal	3.0	sweet	3.1
undergraduate	1.4	embroider	1.1	modest	1.4	couple	3.0	pregnant	3.0	pregnant	3.1
fascist	1.4	filipino	1.1	independent	1.4	mere	2.9	agriculture	3.0	female	3.0
tragic	1.4	distinguishing	1.1	monumental	1.3	next	2.9	divorced	2.9	translucent	3.0
great	1.4	retail	1.1	like	1.3	another	2.9	couple	2.9	dear	3.0
insulting	1.4	socially	1.0	support	1.3	lower	2.9	female	2.9	marry	3.0
out	1.4	bottled	1.0	notable	1.3	naughty	2.9	blonde	2.9	educated	2.9

Table 8: Ranked list of the top 10 adjectives with the largest average deviation for each sentiment extracted over all monolingual models for English to describe male and female politicians.

Parameter	Masculine			Feminine		
	<i>NEG</i>	<i>NEU</i>	<i>POS</i>	<i>NEG</i>	<i>NEU</i>	<i>POS</i>
Intercept	0.3900	0.4009	0.2091	0.2841	0.4352	0.2806
<i>Model architecture</i>						
BERT	-0.0158	0.0144	0.0014	-0.0060	0.0160	-0.0100
BERTweet	0.0565	0.0045	0.0044	0.0078	0.0017	-0.0095
RoBERTa	-0.0924	0.0876	0.0048	0.0010	0.0064	-0.0074
XLNet	0.1067	-0.1135	0.0068	0.0858	-0.0402	-0.0455
<i>Model size</i>						
large	-0.0004	-0.0022	-0.0018	0.0354	-0.0280	-0.0075
xlarge	0.0224	-0.0219	-0.0004	-0.0039	0.0101	-0.0063
xxlarge	0.1043	-0.1079	0.0036	0.0121	0.0047	-0.0168
P-value	0.00	0.00	0.14	0.00	0.00	0.00

Table 9: Group mean sentiment values for each sentiment for masculine and feminine gender for adjectives generated by monolingual language models calculated via ANOVA. Significant differences ($p < 0.05$) between mean sentiment values are in bold.

B.2 Multilingual

Parameter	Masculine			Feminine		
	<i>NEG</i>	<i>NEU</i>	<i>POS</i>	<i>NEG</i>	<i>NEU</i>	<i>POS</i>
Intercept	0.3104	0.2888	0.4007	0.3269	0.3265	0.3466
<i>Model architecture</i>						
XLM	-0.0200	-0.0185	0.0385	-0.0128	0.0006	0.0245
XLM-R	-0.0573	0.0076	0.0497	-0.0140	-0.0046	0.0286
<i>Model size</i>						
large	0.0065	0.0063	-0.0128	0.0024	-0.0030	-0.0055
<i>Language</i>						
Chinese	-0.0309	-0.0322	0.0631	-0.0563	-0.0493	0.1056
English	0.0905	0.1256	-0.2161	-0.0246	0.1246	-0.1000
French	0.0244	0.0523	-0.0767	0.0615	-0.0264	-0.350
Hindi	-0.0109	0.0907	-0.0798	0.0187	0.0256	-0.0443
Russian	-0.0162	0.1725	-0.1564	-0.0230	0.0928	-0.0698
Spanish	-0.0309	-0.0406	0.0812	-0.0332	-0.0326	0.0658
P-value	0.00	0.00	0.00	0.00	0.00	0.00

Table 10: Group mean sentiment values for negative and positive sentiment for masculine and feminine gender for adjectives generated by cross-lingual language models calculated via ANOVA. Significant differences ($p < 0.05$) between mean sentiment values are in bold.

Sentiment	m-bert-cased		m-bert-uncased		xlm-base		xlm-large		xlm-r-base		xlm-r-large	
	<i>MSC</i>	<i>FEM</i>	<i>MSC</i>	<i>FEM</i>	<i>MSC</i>	<i>FEM</i>	<i>MSC</i>	<i>FEM</i>	<i>MSC</i>	<i>FEM</i>	<i>MSC</i>	<i>FEM</i>
Arabic	199	199	169	169	694	680	287	286	386	370	311	283
Chinese	53	53	53	53	319	317	149	149	404	363	407	388
English	714	628	801	615	941	773	642	574	369	284	368	324
French	356	329	249	222	666	594	255	252	272	250	301	281
Hindi	85	85	30	30	183	183	130	130	343	314	345	307
Russian	206	206	171	171	479	466	147	147	265	247	279	255
Spanish	485	484	432	426	1031	1026	403	403	481	470	481	469

Table 11: Unique counts of lemmatized adjectives generated by each language model for each language grouped by gender. In the language generation process, we retrieve the top 100 adjectives with the highest probability for all languages but English where we select the top 20 adjectives.