ABSTRACT

Does the grammatical gender of a language interfere when measuring the semantic gender information captured by its word embeddings? A number of anomalous gender bias measurements in the embeddings of gendered languages suggest this possibility. We demonstrate that word embeddings learn the association between a noun and its grammatical gender in grammatically gendered languages, which can skew social gender bias measurements. Consequently, word embedding post-processing methods are introduced to quantify, disentangle, and evaluate grammatical gender signals. The evaluation is performed on five gendered languages from the Germanic, Romance, and Slavic branches of the Indo-European language family. Our method reduces the strength of grammatical gender signals, which is measured in terms of effect size (Cohen’s $d$), by a significant average of $d = 1.3$ for French, German, and Italian, and $d = 0.56$ for Polish and Spanish. Once grammatical gender is disentangled, the association between over 90% of 10,000 inanimate nouns and their assigned grammatical gender weakens, and cross-lingual bias results from the Word Embedding Association Test (WEAT) become more congruent with country-level implicit bias measurements. The results further suggest that disentangling grammatical gender signals from word embeddings may lead to improvement in semantic machine learning tasks.

CCS CONCEPTS

• Computing methodologies → Artificial intelligence; Natural language processing; Learning latent representations; Learning paradigms; Cognitive science; Support vector machines.

KEYWORDS

grammatical gender, bias, word embeddings

1 INTRODUCTION

English word embeddings learn human-like biases including gender bias from word co-occurrence patterns [7, 11, 12, 21], leading to associations such as man to doctor as woman is to nurse. How can we measure these social gender biases in the embeddings of gendered languages where even inanimate nouns are assigned a gender? For instance, does the embedding for Spanish word fuerza (strength), a stereotypically masculine trait, carry more similarity to masculinity despite being a grammatically feminine noun? Are social gender biases in embeddings intensified, subdued, or unchanged by the presence of grammatical gender in gendered languages?

Natural language processing (NLP) applications use static or dynamic word embeddings as general-purpose language representations for numerous tasks including machine translation [30], document ranking [46], and sentiment classification [29]. Moreover, NLP has applications in social contexts for consequential decision-making. Since potentially harmful biases learned by word embeddings may propagate to downstream applications such as resume screening, essay grading, or university admissions [33, 60, 61], answers to the questions outlined earlier have important implications.

Accurate measurement of biases in word embeddings is critical not only because it helps with tracing biases in downstream applications but also because it helps with measuring biases in the text corpora which represent certain populations. Bias measurement is specially challenging in gendered languages, since the embeddings of nouns are impacted by grammatical gender [22] which can impact the results. Toney-Walls and Caliskan [54] note that gender bias measurements in Polish (a gendered language) using the Word Embedding Association Test (WEAT), a widely-used bias measurement method, indicate a men:humanities-women:science association which is incongruent with gender bias measurements reported by psychologists [47]. This bias test in Polish contains a set of words that represent science with grammatically feminine words that amplify women:science association. The resulting stereotype-incongruent measurement suggests that, among other factors, structural properties of a language such as grammatical gender may impact bias measurements in word embeddings. Thus, quantifying biases using WEAT or similar approaches without taking grammatical gender into account may lead to inaccurate results.

We refer to stereotypical gender biases (e.g. men:career -women:family) as social gender bias, one’s perceived/own sense of gender (e.g. rooster is a male chicken) as gender identity, and the association between grammatically masculine/feminine nouns (e.g. fuerza) with their syntactic gender as grammatical gender signal. Note that both social gender bias and gender identity fall under the
A number of previous studies have paid attention to grammatical gender in word embeddings. Chen et al. [14] and Zhao et al. [59] measure gender bias in multilingual embeddings (including gendered languages) by using occupation terms, and use paired occupations (e.g. waiter and waitress) in each language to account for grammatical gender. Recognizing that grammatical gender forces the embeddings of same-gender inanimate nouns to be closer to each other than nouns with different gender in the vector space, Gonen et al. [22] disentangle grammatical gender signals with training data preprocessing methods such as lemmatizing and changing the gender of all context words to the same gender with the help of morphological analyzers. Despite positive results for German and Italian, it is emphasized that disentangling grammatical gender signals through pre-processing methods is not a trivial task as it relies on careful usage of language-specific morphological analyzers.

### 3 RELATED WORK

A number of previous studies have paid attention to grammatical gender in word embeddings. Chen et al. [14] and Zhao et al. [59] measure gender bias in multilingual embeddings (including gendered languages) by using occupation terms, and use paired occupations (e.g. waiter and waitress) in each language to account for grammatical gender.
We select FastText [6, 24] pre-trained embeddings as these are the
we disentangle it from embeddings. Furthermore, we notice that
The differences in training corpora across languages are negligible as embeddings are
1
[20] on 6,000 grammatically feminine and masculine nouns. The
gender signals by applying Linear Discriminant Analysis (LDA)
and German, concluding that grammatical gender signals outweigh
resulting vector is projected out of an “overall gender” vector to
obtain semantic gender. Since inanimate nouns should not carry se-
semantic gender information, semantic gender component is removed from
these nouns while grammatical gender is preserved.

Our study is similar to [62] in the sense that we also use LDA-like
methods (SVC) to identify grammatical gender. However, instead
of preserving grammatical gender and using it for other purposes,
we disentangle it from embeddings. Furthermore, we notice that
one iteration of applying LDA/SVC is not sufficient for identifying
grammatical gender, so we apply it iteratively to fully capture and
disentangle grammatical gender information. Therefore, although
there are similarities between our work and [62], our methodolo-
gies are not directly comparable since the objectives are different.
Still, we highlight some results after one iteration of disentangling
grammatical gender to emphasize the necessity of our iterative
process.

Table 1 shows comparison of our work to the directly related
prior studies. Note that although our methodology is theoretically
comparable to [22] and [41] (because these studies also disen-
tangle grammatical gender), in practice we cannot compare results
because these studies train their own embeddings while we dis-
entangle grammatical gender from pre-trained embeddings. Due
to the difference in scope, quality and availability of embeddings
1 trained in these two studies, our results are incomparable.

4 DATA

We select FastText [6, 24] pre-trained embeddings as these are the
only available cross-lingual embeddings that were trained on large-
scale corpora under similar conditions.2 The following languages

| Task                                        | Gonen et al. [22] | McCurdy and Serbetci [41] | Zhou et al. [62] | This work |
|---------------------------------------------|-------------------|--------------------------|-----------------|-----------|
| Measuring gender bias considering GG        | –                 | ✓                        | ✓               | ✓         |
| Identifying GG                              | –                 | –                        | ✓               | ✓         |
| Quantifying Strength of GG                  | –                 | ✓                        | –               | ✓         |
| Disentangling GG from embeddings            | ✓                 | ✓                        | –               | –         |
| Evaluating impact of disentangling GG on semantics | ✓ |                   | –               | ✓         |

Table 1: Comparison to prior directly related work. GG refers to Grammatical Gender. Our methodology is not directly comparable to Zhou et al. [62] since grammatical gender is not disentangled from word embeddings in their study. * denotes post-processing GG disentanglement method as opposed to pre-processing methods proposed by prior work.

McCurdy and Serbetci [41] explore gender bias in Spanish, Dutch,
and German, concluding that grammatical gender signals outweigh
social gender bias in cross-linguistic word embeddings. They sug-

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with various degrees of grammatical gender from three different
branches of Indo-European language family are selected based on
the availability of high quality embeddings as well as IAT results
and other evaluation datasets:

**Germanic:** English (EN) and German (DE) are from the West Ger-
manic language branch. While English uses gendered pronouns
(he/she/it) and has no concept of gender assignment to inanimate
nouns, German uses a three-gender grammatical gender system
with feminine, masculine, and neuter gender classes [15].

**Romance:** French (FR), Italian (IT), and Spanish (ES) are from the
Romance language branch, and use the two classes of masculine
and feminine grammatical gender. [1, 2, 38].

**Slavic:** Polish (PL) is from the Slavic branch and uses three main
gender classes of masculine, feminine, and neuter. However, in
plural form there can be masculine-personal and non-masculine-
personal genders. Thus, Polish grammatical gender can also be
characterized as having “three singular and two plural grammatical
genders” [37]. As an inflected language with a lot of grammatical
gender markers [37], Polish syntax is considered to be complex [5].

4.1 Grammatical Gender Classification Data

Grammatically feminine and masculine inanimate nouns are needed
for performing grammatical gender classification and finding the
grammatical gender subspace. We used the training portion of the
Universal Dependencies (UD) dataset 3 to find grammatically
feminine and masculine nouns, since grammatical gender is an
annotated feature in this dataset (the annotations are either manual,
or automatically converted from manual for all the datasets that
we used). We used the following datasets: AnCoru [52] for Spanish,
GSD[26] for French, HDT[8] for German, ISDT[9] for Italian and
PDB[57] for Polish. To ensure that the subspace we find corresponds
to only grammatical gender and contains minimal semantic gender
information, all animate nouns from the data must be removed.
However, except for Polish, animacy tags were not available for
nouns in the datasets. Thus, we removed any word that appeared
in the animate noun list compiled by Zmigrod et al. [63] from our
data set. This list was only available for French and Spanish, so
we used Google translate to create the list for other languages.
As an additional step to identify and exclude animate nouns, we
used Open Multilingual WordNet [23, 40, 49–51, 55]. A noun was
considered to be animate if person was a hypernym of the noun
in WordNet. [63]. We applied this additional step to all languages

1Out of the languages we studied, only corresponding Italian and German embeddings
from [22] and German and Spanish embeddings from [41] are available.
2FastText Embeddings for all languages are trained on Wikipedia and Common Crawl.
The differences in training corpora across languages are negligible as embeddings are
all of high quality according to intrinsic evaluation criteria.

3https://universaldependencies.org
Figure 2: The layout of our approach for identifying and disentangling grammatical gender from word embeddings. Solid lines represent main paths in the flowchart while dotted lines represent dataset usage.

except for German, because Open Multilingual Wordnet\textsuperscript{4} was not available for German.

**4.2 WEAT Stimuli**

As mentioned earlier, we use WEAT to measure biases associated with different concepts in embeddings. Like IAT, WEAT requires use of stimuli (word lists) to represent concepts. In this study, we need cross-lingual stimuli for the following 7 pairs of concepts: (1) science-humanities, (2) men-women words (e.g. mother, girl), (3) career-family, (4) list of common names for boys-girls (5) flowers-insects, (6) musical instruments-weapons, (7) list of pleasant-unpleasant words.

Science-humanities and men-women stimuli for all languages are available in Project Implicit Website\textsuperscript{5} where people can take the The Implicit Association Test in different languages. However, career-family stimuli are only available for English and German. For flowers-insects, musical instruments-weapons and pleasant-unpleasant we used stimuli provided by Toney-Wails and Caliskan\textsuperscript{54} for English, German, Spanish and Polish. Whenever a stimuli was missing for a language, we built a custom list by translating the corresponding English stimuli. All translations are done using Google Translate, and stimuli are case-sensitive.

Furthermore, we used a list of common names for boys and girls that were available for English and German on the Project Implicit Website. For other languages, we searched Google to find most frequent names for boys and girls in countries where the languages were primarily spoken. For more details regarding the creation of the stimuli, including full list of stimuli used in social gender bias experiments, please refer to the appendix.

In addition to the data mentioned above, we use other datasets such as cross lingual analogy\textsuperscript{[4, 13, 24, 31]}, and cross lingual affective norms\textsuperscript{[43, 44, 54]}, and cross lingual Simlex-999\textsuperscript{[3, 28, 45]} as explained in sections 6.3 and 6.2. As these datasets were available for all languages in our study, there was no need for translation or customization choices.

**5 APPROACH**

We hypothesize that word embeddings learn grammatical gender in addition to semantic gender information. Thus, we first identify grammatical gender signals in the embedding space if they exist. Furthermore, we hypothesize that grammatical gender interferes with semantic gender bias measurements. Thus, we attempt to disentangle grammatical gender signals from embeddings and use WEAT to measure embedding bias before and after disentangling grammatical gender signals to see how the measurements change. This section details methodologies for identifying and disentangling grammatical gender as well as measuring biases. Figure 2 summarizes grammatical gender identification and disentanglement steps.

**5.1 Grammatical Gender Signal Identification**

Our method of disentangling grammatical gender from embeddings is inspired by Zhou et al.\textsuperscript{62}’s use of LDA for identifying grammatical gender. We define the binary classification task of classifying inanimate grammatically feminine and masculine nouns to extract a decision hyperplane that corresponds to grammatical gender. The hyperplane is projected out of embeddings, and model is re-applied to evaluate the extent to which word embeddings unlearn grammatical gender via signal disentanglement. Ideally, we expect 100\% and 50\% (random-guessing) classification accuracy before and after disentangling grammatical gender. We experiment with both LDA and SVC but report the results for SVC only for being more efficient despite the models reaching very similar results.

SVC is a linear classifier that finds the maximum-margin hyperplane that separates classes. To identify the grammatical gender signal, SVC models are trained on 6,000 inanimate grammatically
feminine and masculine nouns. The decision hyperplane $\hat{d}_g$ that results from classifying grammatically feminine and masculine nouns nontrivially corresponds to grammatical gender. The large size of the dataset, the randomness of chosen words, and the fact that all words are inanimate nouns mean that other properties of embeddings such as part of speech or semantic meaning are minimally captured by $\hat{d}_g$.

5.2 Grammatical Gender Signal Disentanglement

Once grammatical gender signal ($\hat{d}_g$) is captured, it needs to be projected out of embedding $\hat{w}$ so that the resulting orthogonal embedding $\hat{w}'$ carries a reduced amount of grammatical gender signal as shown in Equation 1:

$$\hat{w}' = \hat{w} - \langle \hat{w}, \hat{d}_g \rangle \hat{d}_g$$

(1)

Where $(\hat{x}, \hat{y})$ is the inner product of $\hat{x}$ and $\hat{y}$. Note that although the same magnitude of grammatical gender is being projected out of all words, this process will impact embeddings differently: In an extreme example, if a word does not carry any grammatical gender signal component in its embedding (is orthogonal to $\hat{d}_g$), then $\hat{w}' = \hat{w}$.

While Zhou et al. [62] apply LDA once to obtain the representation of grammatical gender, our method suggests that the hyperplane obtained using this technique ($\hat{d}_g$) does not fully capture grammatical gender signals: after $\hat{d}_g$ is projected out of embeddings, $\hat{w}'$ still carries significant grammatical gender signal as classifiers are still able to classify the grammatical gender of inanimate nouns with high accuracy. Thus, we iteratively extract the grammatical gender hyperplane and project it out of embeddings until the classifier reaches 50% random-guessing accuracy in a binary task.

Initially, SVC models achieve an accuracy of above 96% at classifying grammatically masculine and feminine embeddings for all languages, confirming our hypothesis that grammatical gender is indeed learned by word embeddings. Figure 3 shows classification accuracy during 15 iterations of disentangling grammatical gender highlighting that after one iteration, classification accuracy is at an average of 75%. Figure 4 demonstrates that before disentangling grammatical gender, Spanish inanimate feminine and masculine nouns are clearly separable. However, once disentanglement is complete, the nouns are much more intertwined in space and are no longer distinguishable.

5.3 WEAT

Biases in word embeddings before and after grammatical gender disentanglement are measured using WEAT. We present technical details for the original WEAT provided by Caliskan et al. [11] since it is the foundation of the different variations of WEAT that we use in our experiments:

WEAT quantifies the differential association between two target sets $X$ and $Y$ with two attribute sets $A$ and $B$. The output of WEAT is Cohen’s effect size $d$ which measures the standardized magnitude of association:

$$d = \frac{\text{mean}_{x \in X} s(x, A, B) - \text{mean}_{y \in Y} s(y, A, B)}{\text{std} - \text{dev}_{w \in X \cup Y} s(w, A, B)}$$

(2)

Where $s(w, A, B)$ measures the differential association of word $w$ with attribute sets $A$ and $B$ and is defined as:

$$s(w, A, B) = \text{mean}_{w \in X} \text{cos}(\hat{w}, \hat{d}_A) - \text{mean}_{w \in Y} \text{cos}(\hat{w}, \hat{b})$$

(3)

Note that $w$ refers to a word, $\hat{w}$ is the corresponding word embedding and $\text{cos}(\hat{d}_A, \hat{b})$ refers to the cosine similarity between the vectors $\hat{d}_A$ and $\hat{b}$. Additionally, the test statistic to measure the differential association of the target sets $X$ and $Y$ with the attribute sets $A$ and $B$ is computed the following way:

$$s(X, Y, A, B) = \sum_{x \in X} s(x, A, B) - \sum_{y \in Y} s(y, A, B)$$

(4)

While WEAT measures the differential association between two target sets and two attribute sets, single category WEAT (SC-WEAT) measures the differential association between a single word and attribute $\hat{d}_A$.
two attribute sets. For example, SC-WEAT can measure whether the single word “doll” is more associated with a set of feminine words like “mother” and “girl” or a set of masculine words like “father” and “boy”. Similar to WEAT, Cohen’s effect size $d$ which measures the magnitude of association is computed as follows for SC-WEAT:

$$d = \frac{\text{mean}_{\mathbf{t} \in \mathbf{A}} \cos(\mathbf{w}, \mathbf{t}) - \text{mean}_{\mathbf{t} \in \mathbf{B}} \cos(\mathbf{w}, \mathbf{t})}{\text{std-dev}_{\mathbf{w} \in \mathbf{A}} \cos(\mathbf{w}, \mathbf{x})}$$

For both WEAT and SC-WEAT, Cohen’s effect size $d$ quantifies the extent to which the association between the target(s) and attributes are separated from one another. Thus, a larger effect size signals a stronger magnitude of bias. $d$ values larger than 0.8, 0.5 and 0.2 denote large, medium, and small effect sizes respectively. The experiments are designed so that a positive $d$ suggests a stereotype-congruent result while a negative value denotes a stereotype-incongruent result.

The significance of associations in WEAT and SC-WEAT is computed using a permutation test, which measures the (un)likelihood of the assumption that no associations exist between the target(s) and the attributes. With $(X_i, Y_i)_t$ denoting all partitions of $X \cup Y$ into two sets of equal size, the one-sided $p$ value of the permutation for WEAT is:

$$P_r[s((X_i, Y_i, A, B) > s(X, Y, A, B)]$$

The one-sided $p$ value of the permutation for SC-WEAT is:

$$P_r[s(w, A, B) > s(w, B, A)]$$

Note that each word set in WEAT and SC-WEAT contains at least 8 words to satisfy concept representation significance. Accordingly, the limitations of not adhering to this methodological robustness rule of WEAT, which are analyzed by Ethayarajh et al. [17], are mitigated.

## 6 EXPERIMENTS AND RESULTS

In section 5, it was demonstrated that grammatical gender signals are indeed learned by embeddings, and a method for disentangling grammatical gender was presented. In this section, we provide the details of a series of experiments that aim to answer our 3 original questions:

1. Are social gender bias measurements impacted by grammatical gender? Is grammatical gender signal causing anomalous gender bias measurements?
2. How does disentangling grammatical gender from inanimate nouns impact their semantic quality?
3. Is grammatical gender effectively disentangled from word embeddings?

The experiments detailed in subsections Social Gender Bias Evaluation, Semantic Quality Evaluation, and Grammatical Gender Disentanglement Evaluation correspond to questions 1, 2 and 3.

### 6.1 Social Gender Bias Evaluation

To understand the impact of grammatical gender on social gender bias measurements, we conduct two WEAT tests for measuring social (stereotypical) gender-bias which we collectively refer to as Gender WEAT:

1. **gender-science (GenS)** measures men:science-women: humanities association
2. **gender-career (GenC)** measures common names for boys:career-common names for girls:family association

GenS for Polish embeddings is the test for which Toney-Wails and Caliskan [54] report anomalous gender bias measurements. If grammatical gender signals are causing anomalous gender WEAT measurements, we expect social gender bias scores after disentangling grammatical gender to match the ground truth gender bias scores. But what constitutes ground truth for gender WEAT experiments?

Since the WEAT experiments are adaptations of the IAT tests, comparison of the WEAT bias measurements to ground truth IAT scores as measured by social psychologists in various studies provides a proxy for validation of WEAT results. IAT measurements are used for establishing “stereotype-congruence” for each WEAT test; are men stereotypically more associated with career and women with family or vice versa according to IAT measurements? Obtaining a stereotype-incongruent WEAT result means that word embedding associations were different from IAT associations. For example, if IAT reports that human subjects tend to associate men with sciences and women with humanities but WEAT reports the opposite association, the WEAT result is said to be stereotype-incongruent.

GenS WEAT results are compared against the corresponding IAT results at the country level as reported by Nosek et al. [47], and GenC WEAT results are compared to IAT results at the language level as collected by Xu et al. [58] and computed by Lewis and Lupyan [36]. We expect congruence (i.e. match in sign), and not a one to one match in the magnitude of effect size. This is because WEAT and IAT effect sizes are not directly comparable, since IAT measures implicit biases of humans at individual level while word embeddings capture the aggregate biases in the statistical regularities of human-produced corpora [11].

Table 2 shows Gender WEAT results before and after disentangling grammatical gender for all languages in our study. Initially, Polish and Spanish GenS experiments display a men:humanities-women:science association, suggesting that grammatical gender signals may be stronger than potential social gender bias in these languages. However, the association becomes gender neutral ($d = 0$) for both languages afterwards (discussed in Section 7). All other results are positive as they suggest stereotype-congruent associations. In all gender WEAT experiments, stereotypical gender biases reveal themselves more strongly as shown by the $\Delta$ column after disentangling grammatical gender. Thus, one can conclude that the presence of grammatical gender signals do impact social gender bias measurements. Yet, since we do not find evidence of stereotypical bias in Polish and Spanish GenS even after disentangling grammatical gender, it is not clear whether grammatical gender alone causes anomalous results. However, considering the five grammatical gender classes in Polish, it is possible that binary gender treatment of our method is not sufficiently disentangling grammatical gender signals in this language.

### 6.2 Semantic Quality Evaluation

In this section we conduct three different experiments to evaluate the impact of grammatical gender disentanglement on the semantic quality of the embeddings, including semantic gender information:

- **Test 1:** For each gender in English, we compute the semantic gender bias in the embeddings for all words.
- **Test 2:** We compare the semantic gender bias in the embeddings for words that are associated with specific gender-science (genS) experiments.
- **Test 3:** We compare the semantic gender bias in the embeddings for words that are associated with specific gender-career (genC) experiments.
Table 3: Accuracy (shown in percentage %) in the analogy test

| Lang | WEAT | $d_{\text{init}}$ | $d_{\text{SVC}}$ | $\rho_{\text{SVC}}$ | $\Delta$ | $d_{\text{LAT}}$ | $C^\ast$ |
|------|------|-------------------|-----------------|----------------|--------|----------------|--------|
| EN   | GenC | 0.88              | –               | –              | 0.38   | –              | –      |
| FR   | GenC | 0.30              | 0.43            | 0.10           | +0.13  | 0.42           | ✓      |
| DE   | GenC | 0.50              | 0.69            | 0.02           | +0.19  | 0.42           | ✓      |
| IT   | GenC | -0.01             | 0.35            | 0.15           | +0.36  | 0.39           | ✓      |
| PL   | GenC | -0.26             | -0.07           | 0.58           | +0.19  | 0.49           | –      |
| ES   | GenC | -0.32             | 0.04            | 0.46           | +0.36  | 0.33           | –      |

Table 2: Gender WEAT results before and after disentangling grammatical gender with SVC. $d_{\text{init}}$ denotes the initial effect size (magnitude of bias measured in Cohen’s $d$), and $d_{\text{SVC}}$ refers to effect size after disentangling grammatical gender. $\rho$ is a measure of statistical significance, $\Delta$ measures the change in effect size ($d_{\text{SVC}} - d_{\text{init}}$). $d_{\text{LAT}}$ denotes the ground truth effect sizes reported by [36] for GenC and [47] for GenS. $C^\ast$ stands for congruent, which denotes whether $d_{\text{SVC}}$ matches in sign with $d_{\text{LAT}}$.

6.2.2 ValNorm. Another method of ensuring semantic utility preservation after disentangling grammatical gender is ValNorm [54] which is a word embedding intrinsic evaluation task that measures the alignment of human valence (pleasantness/unpleasantness) norm scores with valence associations in embeddings. ValNorm is designed for evaluating the semantic representativeness and quality of embeddings when measuring bias, as it captures widely accepted consistent non-social group associations in various languages. In this benchmark, Pearson’s correlation coefficient between the human judgement scores of valence for 399 words and the valence associations in word embeddings is validated. Valence datasets are detailed in the appendix. Table 4 summarizes the results which confirm that semantic associations are improved in French, Polish, and Spanish and preserved for other languages after disentangling grammatical gender.

Table 4: Pearson’s correlation coefficient before ($\rho_1$) and after ($\rho_2$) disentangling grammatical gender signals. $N$ denotes the number of words in ValNorm. Higher $\rho$ suggests embeddings more aligned with human valence norm scores.

6.2.3 Baseline WEAT. Baseline WEAT are among the original WEAT variations used by Caliskan et al. [11] to quantify widely shared baseline associations such as relatively positive attitude towards flowers and negative attitude towards insects. These associations are expected to manifest in different languages or populations [25]. Consequently, we use the following widely shared association tests as a baseline to evaluate the semantic representation accuracy of word embeddings in any language:

1. flowers-insects (Flod) measures pleasant:flowers-unpleasant:insects association
2. instruments-weapons (InsW) measures pleasant:musical instruments-unpleasant:weapons association

We do not expect grammatical gender to have a significant impact on baseline WEAT as it does not measure gender related associations. Thus, they are included as a baseline where we expect high effect size both before and after disentangling grammatical gender. Despite expecting little change in baseline associations, there is a remarkable improvement in Polish baseline associations suggestive of a potential semantic quality improvement as shown in Table 5 (All results in the paper are statistically significant unless noted otherwise). This is in line with observations from analogy and ValNorm experiments, where Polish embeddings had the largest magnitude of semantic improvement.

The results of analogy task, ValNorm and baseline WEAT all suggest that not only the semantic quality of embeddings is preserved
after disentangling grammatical gender, but also the semantic quality of word embeddings may have slightly improved, especially for Polish embeddings.

| Test       | Lang | WEAT | \(d_{init}\) | \(d_{SVC}\) | \(p_{SVC}\) | \(\Delta\) |
|------------|------|------|----------------|--------------|--------------|------------|
| Baseline   | EN   | Flol | 1.45           | -             | -             | -          |
|            | InsW | 1.54 | -              | -             | -             | -          |
|            | FR   | Flol | 1.38           | 1.44          | \(10^{-3}\)   | +0.06      |
|            | InsW | 1.40 | 1.45           | \(10^{-6}\)   | +0.05        |
|            | DE   | Flol | 1.58           | 1.62          | \(10^{-3}\)   | +0.04      |
|            | InsW | 1.63 | 1.67           | \(10^{-5}\)   | +0.04        |
|            | IT   | Flol | 1.56           | 1.61          | \(10^{-4}\)   | +0.05      |
|            | InsW | 1.42 | 1.37           | \(10^{-6}\)   | -0.05        |
|            | PL   | Flol | 1.00           | 1.34          | \(10^{-3}\)   | +0.34      |
|            | InsW | 0.71 | 1.19           | \(10^{-5}\)   | +0.48        |
|            | ES   | Flol | 1.67           | 1.60          | \(10^{-4}\)   | -0.07      |
|            | InsW | 1.08 | 1.12           | \(10^{-4}\)   | +0.04        |
| Grammatical | FR   | GG   | 1.82           | 0.40          | 0.20         | -1.42      |
| Gender     | DE   | GG   | 1.55           | 0.30          | 0.26         | -1.25      |
| Evaluation | IT   | GG   | 1.79           | 0.58          | 0.11         | -1.21      |
|            | PL   | GG   | 1.85           | 1.34          | \(10^{-3}\)   | -0.51      |
|            | ES   | GG   | 1.83           | 1.23          | \(10^{-3}\)   | -0.60      |

Table 5: Baseline and evaluation WEAT results before and after disentangling grammatical gender with SVC. \(d_{init}\) denotes the initial effect size (magnitude of bias measured in Cohen's \(d\)), and \(d_{SVC}\) refer to effect size after disentangling grammatical gender. \(p\) is a measure of statistical significance, \(\Delta\) measures the change in effect size \((d_{SVC} - d_{init})\).

6.3 Grammatical Gender Disentanglement Evaluation

In this section, we conduct three different experiments to evaluate the effectiveness of our proposed grammatical gender disentanglement method:

6.3.1 GG-WEAT. GG-WEAT evaluates whether the association between inanimate nouns and semantically gendered words weakens after disentangling grammatical gender. The attribute sets in GG-WEAT are words with feminine and masculine semantic gender, such as \{mother, daughter\} vs. \{father, son\}. The target sets are inanimate grammatically feminine vs. masculine nouns. In the absence of grammatical gender, random inanimate nouns should be equally similar to words like ‘mother’ and ‘father’ regardless of their grammatical gender (disregarding social gender bias). In the presence of grammatical gender, we expect association between inanimate feminine/masculine nouns with feminine/masculine words. Thus, by measuring GG-WEAT effect size, one can evaluate the presence and strength of grammatical gender in the embedding space since higher effect sizes indicate stronger grammatical gender presence.

If grammatical gender is indeed being disentangled, we expect to see a decrease in effect size \(d\) and loss of statistical significance with each iteration of disentangling grammatical gender. Figure 5 shows that initially, the grammatical gender effect sizes are very high (larger than 1.5 for all languages). Even after one iteration of disentanglement, the signal is a strong \(d > 1.0\) for all languages, emphasizing the need for the iterative process. After disentangling grammatical gender iteratively the effect sizes for FR, DE, and IT become small (\(p_{SVC}\) is no longer statistically significant as shown in Table 5) suggesting that grammatical gender signals have been successfully disentangled to a great degree. However, despite a decrease in magnitude, final effect sizes for PL and ES are still high and \(p_{SVC}\) is still significant. These are also the same languages for which we did not find stereotype-congruent GenS results. This could suggest that we are only partially disentangling grammatical gender for Spanish and Polish, and a complete disentanglement requires more complicated methodologies tailored for language structure.

In order for GG-WEAT to quantify grammatical gender signals, the target sets in GG-WEAT must be constructed in a way such that they have minimal difference in their stereotypical association with a semantic gender. Otherwise semantic gender bias would interfere with grammatical gender measurements. For example, although la moda and el baloncesto are inanimate feminine and masculine nouns, we do not want to include them in GG-WEAT target sets because "fashion" and "basketball" have stereotypical feminine and masculine associations, respectively. Thus, even after disentangling grammatical gender, according to current stereotypes we expect association between moda and femininity and baloncesto with masculinity to persist.

To control for this, we construct the target set by taking pairs of inanimate nouns with a high semantic similarity score which have opposite grammatical gender from the Simlex-999 dataset [28]. For example, feminine molecula and masculine atomo are placed in opposite target sets for having a high similarity score in Italian Simlex-999 (and thus for not being much different in their relative association to semantically feminine and masculine concepts).

![Figure 5: Change in GG-WEAT effect size (measured in Cohen’s \(d\)) with iterations of grammatical gender disentanglement.](image)

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5We use Simlex-999 translations of Barzegar et al. [3] for Spanish and French, Leviant and Reichart [35] for German and Italian and Mykowiecka et al. [45] for Polish.
6.3.2 Single-category GG-WEAT. A single-category variation of GG-WEAT (consisting of one inanimate word as the target and semantically feminine and masculine words as attribute sets) allows for the quantification of grammatical gender association at the word level. For example, the effect size for fuerza the grammatically feminine Spanish word for strength is initially 1.0 suggesting a high association with semantic femininity\(^9\) (despite strength being a stereotypically masculine trait). We re-compute effect size after disentangling grammatical gender to observe whether any stereotypical masculine association is hidden under the impact of grammatical gender.

We perform single-category GG-WEAT for 2,000 inanimate grammatically feminine and masculine nouns per each language and find that the effect size for over 90% of the words moves toward the gender-neutral direction as shown in Figure 6. The semantic gender association gap between grammatically feminine and masculine nouns becomes significantly smaller after disentangling grammatical gender and both sets move much closer to gender neutrality as shown in Figure 7. The effect size for our motivating word fuerza (Spanish for strength), which used to be highly associated with femininity because of its grammatical gender, becomes gender neutral (\(d = -0.01\); showing no sign of stereotypical masculine association after disentangling grammatical gender).

6.3.3 Pairwise Distance. To evaluate the neutralization of grammatical gender, Gonen et al. \[22\] split the inanimate portion of Italian and German Simlex-999 datasets in two sets. First set includes pairs of words with the same grammatical gender, and second set includes pairs of words with opposite gender.\(^{10}\) The corresponding English sets for each language are also created. The average cosine similarity between pairs of words with same gender \(avg_s\) and different gender \(avg_d\) are compared. If grammatical gender impacts word embeddings, then on average one expects pairs of words with the same gender to be more similar to one another compared to pairs of words with the opposite gender (i.e \(avg_s > avg_d\)). Corresponding English embeddings approximate what the difference between the two similarities should be without the impact of grammatical gender. Let \(l_e = avg_s - avg_d\) for English, and \(l'_e = avg_s - avg_d\) denote the

\[ \text{reduction} = 1 - \frac{l'_e}{l_e} \]  

Table 6: Gap reduction (%) denotes how much the difference between the average similarity of words with the same grammatical gender and average similarity of words with different grammatical gender of a gendered language become more similar to its English translation.

While results in Table 6 may suggest that German grammatical gender signal is the most resistant to disentanglement (due to smaller reduction), GG-WEAT suggests that Polish signal is the most resistant. However, note that although English embeddings (which are the basis of pairwise distance method) are a good estimation of how far apart the same gender and opposite gender pairs of words should be without the effect of grammatical gender, one cannot expect the semantic spaces of English and other languages to be exactly comparable \[53\]. GG-WEAT on the other hand does not rely on the embedding space of other languages to evaluate grammatical gender presence.
7 DISCUSSION

Although IAT measurements report GenS, which measures the association between men with sciences and women with humanities \[47\] as a metric to measure social gender biases in human cognition, historically men have dominated the humanities in addition to science and engineering fields. Most notable philosophers, historians, linguists, writers, poets and artists throughout the history have been overwhelmingly men while women have always been more associated with domestic roles. Moreover, Caliskan et al. \[10\] provide evidence for a masculine default in English word embeddings, where various semantic domains are strongly associated with men. Therefore, it should not come as a surprise that GenS effect sizes violate from grammatical gender neutrality as shown in Figure 7.

As more effective grammatical gender disentanglement methods as our experiments, the number of grammatically masculine words in a language is not balanced, the magnitude of grammatically feminine and masculine words might be different. Accordingly, using the masculine and feminine version of a word might not normalize the grammatical gender signals. In our case, the grammatical gender subspace resulting from SVC may not contain feminine and masculine grammatical gender information at an equal rate. This may explain why after disentanglement, inanimate nouns still deviate from grammatical gender neutrality as shown in Figure 7.

Overcoming this imbalance requires evaluating grammatical gender signals while taking other parameters such as word frequency and grammatical gender distribution in a language into account.

Our final GenS measurements in Spanish and Polish do not report stereotypical associations between men with sciences and women with humanities as reported by social psychologists \[47\]. However, according to Eurostat\[^{11}\] gender gap in science has been decreasing over the past decade in the European Union. The percentages of female scientists and engineers were reported as 47% and 46% for Spain and Poland in year 2021. Since IAT might be reflecting societal structure \[48\] and embedding associations correlate with real world gender statistics \[11\], this approximately equal representation may explain our gender neutral results to some extent\[^{12}\].

Note that our method assumes the presence of only two grammatical gender classes in a language. However, Polish and German have an additional neuter class. It is not clear how associations from “neuter” class might be impacting bias measurements. Exploring more effective grammatical gender disentanglement methods as they relate to other representations of grammatical gender is left for future work. Similarly, extending the methods to non-binary or other representations of semantic gender is left to future work due to low signal strength for underrepresented groups.

Additionally, although results in Table 2 suggest that disentangling grammatical gender from embeddings leads to obtaining social gender bias signals that are more congruent with country level bias statistics (i.e larger effect sizes in gender WEAT) this does not always have to be the case; the change in effect size could depend on factors such as the feminine/masculine ratio of the stimuli. In our experiments, the number of grammatically masculine words in humanities were consistently larger than grammatically masculine science words which contributed to stereotype-incongruent associations. Thus, an increase in GenS effect size in stereotype-congruent direction is plausible. Yet, feminine/masculine ratios alone may not determine the direction of effect size’s shift because the magnitude of grammatical gender learned by one word may be different from another due to factors such as frequency in training corpus.

Repeating GG-WEAT experiments with Word2Vec embeddings of Fares et al. \[18\] also suggest that Spanish and Polish grammatical gender signals are more resistant to our grammatical gender disentanglement method. However, fewer iterations are needed to achieve random guessing accuracy which is accompanied by a slight decrease in semantic quality of embeddings. This could be due to the difference in training algorithms as FastText embeddings are sub-word aware and grammatical gender marks the ending of many nouns. Yet, the different training conditions of the two sets of embeddings means that they are not directly comparable: The embeddings have been trained on different corpora of varying set size. Word2Vec embeddings of Fares et al. \[18\] have 100 dimensions whereas FastText embeddings are 300 dimensional. Embedding qualities are also very different. These reasons, along with other factors, make direct comparison of the embedding algorithm futile.

Future research can focus on how grammatical gender manifests itself through different embedding training algorithms, including dynamic word embeddings generated by language models.

Finally, this work does not study if grammatical gender influences social bias in human cognition. Such an evaluation requires more fine-grained grammatical gender signal extraction approaches as well as different experimental settings.

8 CONCLUSION

Grammatical gender signals can interfere and potentially cause anomalous results when measuring social gender bias in word embeddings of gendered languages. The above 96% accuracy in classifying inanimate feminine and masculine nouns in five gendered languages indicates that grammatical gender is indeed learned by word embeddings. However, once grammatical gender is detected and disentangled from embeddings, the association between inanimate nouns and semantically gendered words measured by Cohen’s $d$ reduces by an average of $d = 1.0$. After disentangling syntactic gender signals, stereotypical gender biases reveal themselves more strongly by an average of $d = 0.24$, and semantic quality in Polish embeddings is evidently improved.

9 IMPACT STATEMENT

Since practitioners use cross-lingual pre-trained word embeddings in different applications, bias in word embeddings may potentially propagate to downstream tasks. To uphold the notion of fairness, practitioners must be able to accurately measure such potential biases in embeddings and be aware that language structure can impact social bias measurements. Therefore, a hasty generalization of bias measurement tools from one language to another without taking language properties such as grammatical gender into account can lead to failure in accurate identification and prevention of bias. Disentangling grammatical gender is one method that can help with more accurate measurements of social biases in word embeddings.

\[^{11}\]https://ec.europa.eu/eurostat/en/web/main/data/database

\[^{12}\]Female scientists and engineers proportions for France, Italy, and Germany are 39%, 21%, and 37% respectively which are smaller compared to Spain and Poland. The dataset can be found at this link.
A WEAT STIMULI LIST

Although science-humanities stimuli were present in Project Implicit Website for all languages of interest, we expanded the size of the stimuli by adding more subjects. These additional subjects were taken from ACTs list of college majors and occupational choices.\(^{13}\)

The intuition was that a larger number of words can represent a concept more accurately in word embeddings. For example, the word "English" alone cannot represent the concept of humanities/social science subjects, because it has many other senses beyond an academic subject such as referring to a person from England. The words "English" and "arts" together are better representatives of these subjects, but are not representative enough so even more words are needed. In short, stimuli expansion helps with more robust representation of concepts by word embeddings. Stimuli expansion was only needed for science-humanities because these concepts are much more overlapping and less mutually exclusive compared to other concepts. At the end, mathematics, natural sciences, humanities and social sciences are all academic disciplines, whereas concepts such as career-family are much more distinct.

Furthermore, whenever translating an English term resulted in a word with more than one part, we omit those words from the stimuli as our embeddings are tokenized and are not available for two part words. For example, translating the term "teargas" from English to French resulted in gaz lacrymogène, which does not have a word embedding. Additionally, if translating multiple English terms results in duplicate translations we only keep one of the words. For example, Google translate suggest the word "matrimonio" as the translation of both "wedding" and "marriage" in GenC stimuli. We remove duplicate terms from the translation stimuli.

The stimuli used for Gender WEAT is provided below. For the complete stimuli list (including baseline and GG-WEAT) please refer to the code. Masculine nouns have been written in blue, and neuter nouns (present in German and Polish stimuli) are in purple. Nouns written in black are feminine (except for English, where\(^\text{13}\))

\(^{13}\)http://www.act.org/content/act/en/research/reports/act-publications/college-choice-report-class-of-2013/college-majors-and-occupational-choices/college-majors-and-occupational-choices.html
there is no grammatical gender. Words that could be masculine or feminine or not gendered (such as adjectives or verbs in some languages) are marked with *.

A.1 English

GenS

science: astronomy, math, chemistry, physics, biology, geology, engineering, statistics, bioengineering, biophysics, biochemistry, ecology, microbiology, algebra, geometry, telecommunications, computer, astrophysics

humanities: history, arts, humanities, english, philosophy, music, literature, psychology, sociology, geography, anthropology, theology, linguistics, journalism, archaeology, dancing, drawing, painting

men: man, son, father, boy, uncle, grandpa, husband, male

women: mother, wife, aunt, woman, girl, female, grandma, daughter

GenC

career: career, corporation, salary, office, professional, management, business

family: wedding, marriage, parents, relatives, family, home, children

men: Ben, Paul, Daniel, John, Jeffrey

women: Rebecca, Michelle, Emily, Julia, Anna

A.2 French

GenS

science: astronomie, mathématiques, chimie, physique, biologie, géologie, ingénierie, statistiques, bio-ingénierie, biophysique, biochimie, écologie, microbiologie, algèbre, géométrie, télécommunications, ordinateur, astrophysique

humanities: philosophie, humanités, art, latin, littérature, musique, histoire, psychologie, sociologie, géographie, anthropologie, théologie, linguistique, journalisme, archéologie, danse, dessin, peinture

men: garçon, père, masculin, mari, fils, oncle

women: demoiselle, féminin, tante, fille, femme, mère

GenC

career: carrière, corporation, salaire, bureau, professionnel*, gestion, entreprise

family: mariage, domicile, parents*, proches, famille, maison, enfants*

men: Nicolas, Alexandre, Guillaume, Mathieu, Thomas, Pierre, Emmanuel, Jean, François

women: Céline, Marie, Sandrine, Sophie, Caroline, Julie, Hélène, Camille, Emilie

A.3 German

GenS

science: Astronomie, Mathematik, Chemie, Physik, Biologie, Geologie, Ingenieurswissenschaften, Statistik, Bioingenieurwesen, Biophysik, Biochemie, Ökologie, Mikrobiologie, Algebra, Geometrie, Telekommunikation, Computer, Astrophysik

humanities: Philosophie, Kunst, Geschichte, Musik, Geisteswissenschaften, Psychologie, Soziologie, Geographie, Anthropologie, Theologie, Linguistik, Journalismus, Archäologie, Tanz, Zeichnung, Malerei, Sprachwissenschaften, Literaturwissenschaften

men: Mann, Junge, Vater, Männlich, Großvater, Ehemann, Sohn, Onkel

women: Mädchen, Weiblich, Tante, Tochter, Ehefrau, Frau, Mutter, Großmutter

GenC

career: Verwaltung, Berufstätigkeit, Unternehmen, Gehalt, Büro, Verdiennst, Karriere

family: Zu Hause, Eltern*, Kinder, Familie, Hochzeit, Ehe, Verwandte*

men: Johannes, Lukas, Daniel, Paul, Thomas

women: Julia, Michaela, Anna, Laura, Sofie

A.4 Italian

GenS

science: astronomia, matematica, chimica, fisica, biologia, geologia, ingegneria, statistica, bioingegneria, biofisica, biochimica, ecologia, microbiologia, algebra, geometria, telecomunicazioni, computer, astrofisica

humanities: filosofia, umanesimo, arte, letteratura, italiano, musica, storia, psicologia, sociologia, geografia, antropologia, teologia, linguistica, giornalismo, archeologia, danza, disegno, pittura

men: uomo, padre, maschio, nonno, marito, zio

women: femmina, zia, moglie, donna, madre, nonna

GenC

career: carriera, società, stipendio, ufficio, professione*, gestione

family: matrimonio, genitori*, parenti*, famiglia, casa, figli*

men: Marco, Alessandro, Giuseppe, Giovanni, Roberto, Stefano, Francesco, Mario, Luigi

women: Anna, Maria, Sara, Laura, Giulia, Rosa, Angela, Sofia, Stella

A.5 Polish

GenS

science: astronomia, matematyka, chemia, fizyka, biologia, geologia, inżynieria, statystyka, bioinżynieria, biofizyka, biochemia, ekologia, mikrobiologia, algebra, geometria, telekomunikacja, astrofizyka, komputerowa

humanities: filozofia, polski, sztuka, lacina, muzyka, historia, literatura, psychologia, socjologia, geografia, antropologia, teologia, językowoznawstwo, dziennikarstwo, archeologia, taniiec, rysunek, malarstwo

men: mężczyzna, chłopiec, ojciec, nastolatek, dziadek, mąż, syn, wujek

women: dziewczynka, kobieta, ciocia, córka, żona, nastolatka, matka, babcia

GenC

career: kariera, korporacja, wynagrodzenie, biuro, specjalista, zarządzanie, biznes

family: ślub, małżeństwo, rodzice, krewni*, rodzina, dom, dzieci

men: Jakub, Mateusz, Michał, Patryk, Dawid, Kamil, Piotr, Szymon, Paweł

women: Joanna, Agnieszka, Magdalena, Anna, Paulina, Agata, Agnieszka, Marta

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14 If the word refers to physics as academic discipline, it is masculine. If it refers to body and physical appearance, it is feminine.

15 Neuter or masculine noun according to Collins dictionary.
A.6 Spanish

**science:** astronomía, matemáticas, química, física, biología, geología, ingeniería, estadística, bioingeniería, biofísica, bioquímica, ecología, microbiología, álgebra, geometría, telecomunicaciones, computadora, astrofísica

**humanities:** filosofía, humanidades, arte*, literatura, música, historia, psicología, sociología, geografía, antropología, teología, lingüística, periodismo, arqueología, baile, dibujo, pintura, periodismo

**men:** hombre, niño, padre, masculino, abuelo, esposo, hijo, tío

**women:** niña, femenina, tía, hija, esposa, mujer, madre, abuela

**career:** carrera, corporación, salario, oficina, profesional, gestión

**family:** boda, matrimonio, familiares*, hogar, niños*, familia

**men:** Francisco, Antonio, José, Manuel, Lucas, Hugo, Martín, Pablo, Alejandro

**women:** María, Ana, Carmen, Dolores, Lucía, Sofía, Martina, Paula, Valeria

### B VALENCE DATASET FOR VALNORM

To test embedding quality after grammatical gender removal, we use Toney-Wails and Caliskan [54]’s ValNorm as an intrinsic embedding semantic evaluation method but their study does not provide datasets for French and Italian. As a result, we use affective norms datasets (parallel to datasets used by [54] provided by Montefinese et al. [44] for Italian, and Monnier and Syssau [43] for French to perform ValNorm computations.