Grammatical Gender, Neo-Whorfianism, and Word Embeddings: A Data-Driven Approach to Linguistic Relativity

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Abstract

The relation between language and thought has occupied linguists for at least a century. Neo-Whorfianism, a weak version of the controversial Sapir–Whorf hypothesis, holds that our thoughts are subtly influenced by the grammatical structures of our native language. One area of investigation in this vein focuses on how the grammatical gender of nouns affects the way we perceive the corresponding objects. For instance, does the fact that key is masculine in German (der Schlüssel), but feminine in Spanish (la llave) change the speakers’ views of those objects? Psycholinguistic evidence presented by Boroditsky et al. (2003, §4) suggested the answer might be yes: When asked to produce adjectives that best described a key, German and Spanish speakers named more stereotypically masculine and feminine ones, respectively. However, recent attempts to replicate those experiments have failed (Mickan et al., 2014). In this work, we offer a computational analogue of Boroditsky et al. (2003, §4)'s experimental design on 9 languages, finding evidence against neo-Whorfianism.

1 Introduction

During his tenure as a graduate student, 20th-century American linguist Benjamin Whorf conducted field work on Hopi, an Uto-Aztecan language spoken in Southern Arizona. To his surprise, he found that Hopi does not mark the tense of a verb in the way many Western European languages do (Whorf, 1956). Thus, according to Whorf, a Hopi speaker must infer whether an action takes place in the past, present or future only from the sentential context in which the verb occurs. This finding inspired Whorf to start questioning whether language influences thought, a position that has come to be known as linguistic relativity (Whorf et al., 2012). Ultimately, Whorf went on to hypothesize that the Hopi perceive time differently as a result of their language’s grammar, kicking off a more encompassing debate on the relation of language and thought and engendering one of the larger controversies in linguistics to date (Deutscher, 2010).

While influential, the strong version of what has come to be known as the Sapir–Whorf hypothesis has been disapproved. For instance, even though languages differ in the color terms they employ, e.g., Korean has one word that represents both green and blue, the development of color terminology and perception is subject to universalist constraints due to biology (Berlin and Kay, 1969). Recent years, however, have witnessed a resurgence of a milder strain of the hypothesis, alternatively known as neo-Whorfianism or the weak Sapir–Whorf hypothesis (Boroditsky, 2003). One prominent controversial research direction investigates this hypothesis with respect to grammaticalized notions of gender and tense. Based on experimental evidence obtained from native German and Spanish speakers, Boroditsky (2003, §4.6) argued that grammatical gender affects how speakers view objects in their native language. Similarly, differences in the usage of tense in Mandarin and English were found to affect how the respective speakers view time (Boroditsky, 2001). In this work, we focus on the influence of grammatical gender and how we can use NLP tools to shed light on the validity of this aspect of neo-Whorfianism.

The gist of Boroditsky et al. (2003, §4)'s hypothesis is that speakers of languages that mark grammatical gender perceive nouns, even inanimate ones, differently depending on the noun’s gender. They sought psycholinguistic evidence for this claim, arguing that speakers will more often choose stereotypically masculine adjectives to describe grammatically masculine inanimate nouns

1Whorf’s claim has subsequently been challenged. Later analyses of Hopi grammar suggest that the language marks two tenses: future and non-future (Malotki, 1983).

2The hypothesis is named after both Benjamin Whorf and his Ph.D. advisor Edward Sapir.
and stereotypically feminine adjectives to describe grammatically feminine inanimate nouns. To give a concrete example, the German word for key, Schlüssel, happens to be masculine, so speakers are more likely to use words such as heavy, jagged, and hard. In contrast, the Spanish word for key, llave, happens to be feminine, so speakers are more likely to use stereotypically feminine words such as elegant, pretty, and delicate. However, Mickan et al. (2014) failed to replicate this experiment, leaving the validity of the findings questionable.

In this work, we provide evidence against Boroditsky et al. (2003, §4)’s hypothesis using NLP techniques. We contend that if this instance of neo-Whorfianism is true, then we should see a reflection of it in corpus co-occurrence counts. We propose two experiments, based on word embeddings trained on large corpora, to investigate how speakers of different languages use certain nouns. Our results on 9 languages suggest that the grammatical gender of inanimate nouns does not influence how they are used in context, taking credence away from Boroditsky et al. (2003, §4)’s claims. However, we caution that it is important not to overstate the findings of one study; we see our results as providing further evidence in the linguistic relativity debate against neo-Whorfianism from a largely orthogonal source.

2 Background

2.1 Grammatical Gender

In this section, we provide a brief overview of grammatical gender systems since those play an important role in Boroditsky et al. (2003, §4)’s, and hence our, experiments. Languages range from encoding no grammatical gender on inanimate nouns, like English or Mandarin Chinese, to distinguishing tens of gender-like noun classes, as found in the Bantu languages of Africa (Corbett, 1991). In this work, we will exclusively consider gendered languages of Indo-European and Afro-Asiatic (Semitic) stock; they all distinguish either two or three genders: the bipartite distinctions masculine-feminine and the tripartite distinction masculine-feminine-neuter. An important assumption of our study is the tenet that the gender assigned to inanimate objects is arbitrary.

All languages we experiment on exhibit concord in grammatical gender, i.e., articles and adjectives that modify a noun must agree with that noun in gender as well as in other features. Consider the German and Spanish translations of the English sentence: The beautiful key is on the table.

La llave bonita está sobre la mesa. (1)

Der schöne Schlüssel liegt auf dem Tisch. (2)

Here, German employs the masculine article der as Schlüssel is masculine; had Schlüssel been feminine, German speakers would say die Schlüssel. Spanish exhibits a similar behavior, making use of la, rather than el, as llave is feminine. For a thorough treatment of the subject, see Corbett (2006).

A key part of our experimental design will be stripping side effects of the grammatical concord from articles, adjectives, and verbs, thus removing overt signals of the noun’s gender.

2.2 Morphological Tagging and Lemmatization

Our study will make use of NLP tools that automate bits of linguistic analysis: morphological tagging and lemmatization. Both will be explained here.

In languages that exhibit inflectional morphology, we may decompose a word into a bundle of morpho-syntactic features and a lemma, its canonical form. Formally, we denote a word in a natural language as \( w \), and a sentence of length \( n \) as \( w = w_1 \cdots w_n \). Each word can be factored into a lemma \( \ell \) and a bundle of morphological features \( m \). For instance, we may think of the German word Schlüssel as the lemma \( \ell = \text{Schlüssel} \) and the features \( m = [\text{POS}=n, \text{GEN}=\text{masc}, \text{NUM}=sg, \text{CASE}=\text{gen}] \). Each morphological feature in \( m \) is an attribute–value pair. Attributes encompass lexical properties...
such as gender, number, and case, taking values such as masculine, singular and genitive, respectively. Following Booij (1996), we may divide the morphological attributes into two categories: inherent and contextual. Inherent categories are those that are embedded in the lemma itself: the lemma Schlüssel without any additional inflection reveals POS=n and GEN=masc. However, the sentential context dictates that NUM=sg and CASE=gen. We write \( m \) for a sequence of morphological tags and \( \ell \) for a sequence of lemmata. A morphologically tagged Russian example sentence is given in Fig. 1.

In general, each word in a sentential context will have exactly one lemma and one bundle of morpho-syntactic attributes. We may think of a decomposed sentence of length \( n \) as an interleaved trisequence: \( \langle w_1, \ell_1, m_1 \rangle \cdots \langle w_n, \ell_n, m_n \rangle \), where \( w_i \) is the \( i \)th word, \( \ell_i \) is its lemma, and \( m_i \) is the set of its morphological features.

Several techniques exist to map sentences to the lemmata of their words together with their morpho-syntactic attributes. The task of mapping a sentence to a sequence of morphological tags, in above notation \( w \mapsto m \), is known as morphological tagging. The task of mapping a sequence of words to a sequence of lemmata, i.e., \( w \mapsto \ell \), is known as lemmatization. Performing the tasks jointly can improve performance (Müller et al., 2015).

### 2.3 Word Embeddings

In our experiments, we will make strong use of embeddings of words into \( \mathbb{R}^d \). Given a fixed vocabulary \( V = \{v_1, \ldots, v_V\} \) of word types, we will denote the embedding of a type \( v \) as \( e(v) \in \mathbb{R}^d \).

We employ the word2vec (Mikolov et al., 2013a; Goldberg and Levy, 2014) toolkit, in particular the skip-gram model, for the creation of our word embeddings. Skip-gram may be considered a form of matrix factorization; specifically, it factorizes a matrix of probabilities \( X \in \mathbb{R}^{V \times |V|} \), where \( X_{ij} \) denotes the probability that \( v_i \) co-occurs with \( v_j \) within a certain context window. For instance, a symmetric context window of size 5 is a common choice. This asks how often \( v_j \) occurs within five positions to the left or right of \( v_i \). Under this interpretation, word2vec is an instance of exponential-family PCA (Collins et al., 2001; Cotterell et al., 2017). The output of word2vec is a mapping of word types to a vector space: \( e : V \to \mathbb{R}^d \). We highlight that the model only considers words categorically, i.e., it is unable to look at the surface form of the word. This is relevant as there are sub-word indicators of gender, e.g., feminine nouns in Spanish often end in -a.

In practice, embeddings are taken as a proxy for lexical semantic meaning—words that have similar meanings should be closer together in the space. This idea has a long history in NLP; Firth (1957) famously quipped, “You shall know a word by the company it keeps.” As we will discuss in §3, are we interested in how well the embeddings for inanimate nouns encode the respective genders.

### 3 Neo-Whorfianism and Word Embeddings: What is the Link?

Our primary contribution is the development of a computational analogue of the previously conducted psycholinguistic study by Boroditsky et al. (2003, §4), mentioned in §1. While, naturally, the signals in a big-data analysis are different than those extracted from subjects in a laboratory, we find it useful to first describe the original work.

#### 3.1 The Psycholinguistic Experiment

To test the hypothesis that the grammatical gender assigned to inanimate objects, even though it is not (and, in fact, cannot be) a direct reflection of natural gender (since the latter is not defined for inanimate nouns), has an influence on the manner in which speakers perceive those objects, Boroditsky et al. (2003, §4) use the following experimental procedure. They created a list of 24 words in German and Spanish that were selected to be translations of each other. Importantly, the same number of masculine and feminine nouns were present in each language; however, all nouns had different genders in German and Spanish. We show a list of stimuli for the experiment in Tab. 2, taken from Boroditsky and Schmidt (2000, Appendix A). Then, native speakers of each language were brought into the laboratory and asked to describe the nouns with

| bg | es | fr | he | it | pl | ro | ru | sk |
|----|----|----|----|----|----|----|----|----|
| all | 96.6 | 98.5 | 98.4 | 96.5 | 98.2 | 96.5 | 98.1 | 96.5 | 95.0 |
| OOV | 82.1 | 91.7 | 89.6 | 79.6 | 91.2 | 86.9 | 89.0 | 88.1 | 86.6 |

Table 1: Token-level lemmatization accuracy obtained by lemming on the test splits of the UD treebanks for all languages when evaluated on all tokens or just OOVs.
the first three adjectives that came to mind. (Note the that the experiment took place in English, even though each subject’s native language was either German or Spanish.) As a second step, a group of native English speakers were asked to judge the elicited adjectives as either −1 (feminine) or +1 (masculine), which yielded a gender rating. Using this rating, Boroditsky et al. (2003, §4) found a correlation between the genderedness of the German and Spanish speakers’ choice of adjectives in the first experiment and the English speakers’ rating of how gendered each adjective was. This was taken to be a very conservative test for neo-Whorfian effects regarding gender, as the experiment took place in English, which lacks grammatical gender.

As a qualitative example, they report that the German-speaking participants described “key,” which is masculine in German, as hard, heavy, and jagged, whereas the Spanish-speaking participants described “key,” which is feminine in Spanish, as beautiful, elegant, and fragile. They argue that these findings show that the manner in which German and Spanish speakers think about inanimate objects is influenced by the grammatical gender that the language assigns to their nouns.

The findings of Boroditsky et al. (2003, §4) have not gone uncontested. Mickan et al. (2014) report two unsuccessful attempts to replicate the experiments described in §3. They also note that, while the study is widely cited, the experiments, along with their experimental stimuli, were never published in their own right, but rather merely described in a summary book chapter. Nevertheless, the idea that grammatical gender may influence thought has taken off with much ink spilled on the subject in the popular press. Indeed, in partial response to the popularity of the idea, McWhorter (2014) authored an entire volume, The Language Hoax, with the explicit purpose of removing much of the hype surrounding neo-Whorfian claims.

### 3.2 Neo-Whorfianism, Gender, and Word Embeddings

How can we use NLP to test the claims investigated in §3.1? We contend that the thrust of Boroditsky et al. (2003, §4)’s argument may be reduced to one of basic lemma co-occurrence counts in a large corpus. If German speakers are more likely to describe a Schlüssel (key) with a stereotypically masculine adjective, i.e., jagged, rather than with a stereotypically feminine one, i.e., delicate, we should reasonably expect this predisposition to manifest itself in corpus counts: grammatically masculine nouns should have stereotypically masculine adjectives modifying them with higher frequency, while feminine nouns should be more likely to be modified by stereotypically feminine ones.

Linking this idea to NLP, recall from §2.3 that co-occurrence counts are the primary signal for training word embeddings, one of the most popular lexical semantic representations of meaning at the type level. Expanding on Firth (1957)’s original statement, we further ask if you shall also know the word’s grammatical gender from its kept company? Operationalizing this, we will attempt to predict the gender of a noun type from its word embedding under several experimental conditions. This is a reformulation of Boroditsky et al. (2003, §4)’s experimental paradigm. The original experiment asked the participants to generate adjectives given a noun stimulus, whereas we look at the spontaneously written contexts of nouns in large corpora.

In more detail, Boroditsky et al. (2003, §4)’s participants are given nouns as stimuli, whose gender they assume the participants have access to in their internal representation of the lexicon. (Recall that gender is an inherent morphological property, as discussed in §2.1.) Then, those participants are asked to generate adjectives that would be good descriptors for those nouns, i.e., they generate contexts for those nouns. The contexts are then scored in a second experiment, where English speakers

| English | Spanish | German |
|---------|---------|--------|
| apple   | manzana | Apfel  |
| arrow   | flecha  | Pfeil  |
| boot    | bota    | Stiefel|
| broom   | escoba  | Besen |
| moon    | luna    | Mond  |
| spoon   | cucharra| Löffel |
| star    | estrella| Stern |
| toaster | tostador| Roster|
| pumpkin | calabaza| Kürbis|

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We induce word embeddings under four experimental conditions: (i) **forms**: the embeddings are trained on forms (the original corpus), (ii) **lemmata**: the embeddings are trained on lemmata (the whole corpus is lemmatized), (iii) **nouns**: the embeddings are trained on lemmatized nouns where the rest of the corpus is left unlemmatized, (iv) **¬nouns**: the embeddings are trained on unlemmatized nouns and the rest are lemmatized.

**Hypotheses.** We compare the ability of the classifier to predict the gender of the noun in the word conditions outlined above and, additionally, compare the results to a majority-class baseline. We hypothesize the classifier to easily be able to predict the gender from conditions (i) **forms** and (iii) **nouns** since the primary cue for gender is the concord exhibited by the context words. Indeed, we see no a-priori reason why (i) should perform significantly differently than (iii). The conditions (ii) **lemmata** and (iv) **¬nouns** are more interesting: If the inherent gender in the inanimate nouns influences the choice of context lemmata, as Boroditsky et al. (2003, §4) believe, then we hypothesize the classifier to easily be able to predict the gender from the embeddings in (ii) **lemmata** and (iv) **¬nouns** better than a majority-class baseline. However, if speakers are uninfluenced by grammatical gender, then we should fail to predict grammatical gender from context. We note (i) and (iii) are skylines since (ii) and (iv) contain less gender-related information.

**4 Experimental Setup**

The goal of both our experiment and that of Boroditsky et al. (2003, §4) is to determine whether the words that occur in the context of a noun are influenced by its grammatical gender. In our experiment, we opt to represent a context by its word embedding and try to predict the gender of a (inanimate) noun given its word embedding.

Extracting the gender of a word from its vector representation is often trivial for many languages due to certain grammatical artifacts: e.g., in Spanish, nouns are usually accompanied by a gender-specific article (el or la). Thus, in order to obtain meaningful experimental results, we need to control for such obvious indicators, i.e., lemmatize our corpora and train lemma embeddings instead of embeddings for all inflected forms. Indeed, word embeddings famously capture gender, as evinced by Mikolov et al. (2013b)’s (approximate) equation

\[ e(\text{king}) - e(\text{man}) + e(\text{woman}) \approx e(\text{queen}). \]

Recall from §2.3 that our embeddings do not have access to subword information, so clues for a noun’s gender must come from context.

**4.1 Word Embedding Comparison**

We induce word embeddings under four experimental conditions: (i) **forms**: the embeddings are trained on forms (the original corpus), (ii) **lemmata**: the embeddings are trained on lemmata (the whole corpus is lemmatized), (iii) **nouns**: the embeddings are trained on lemmatized nouns where the rest of the corpus is left unlemmatized, (iv) **¬nouns**: the embeddings are trained on unlemmatized nouns and the rest are lemmatized.

**Lemmatizer.** We choose the LEMMING (Müller et al., 2015) package4 for lemmatization. LEMMING is a conditional random field (Lafferty et al., 2001) with artisanal feature templates. While occasionally surpassed in performance, LEMMING is competitive with neural state-of-the-art models, while remaining robust in low-resource settings and being fast to train (Heigold et al., 2017). For

4http://cistern.cis.lmu.de/lemming/
all languages in our experiments, we keep LEMMING’s defaults as our hyperparameters and train it on the training and development splits of the corresponding Universal Dependencies (UD) tree-banks (Nivre et al., 2017). Since errors during lemmatization could significantly alter our experiments, we make use of the dev splits to ensure that a high lemmatization performance is reached. Tab. 1 shows the resulting token-based accuracies of our final models, both on the entire UD test sets and on out-of-vocabulary words only. The latter serves as a lower-bound; it corresponds to the (extreme) case where none of the words of the corresponding Wikipedia corpus appear in the union of the UD training and development sets.

**Experimental Languages.** We choose 9 experimental languages randomly from UD: Bulgarian (bg), French (fr), Hebrew (he), Italian (it), Polish (pl), Romanian (ro), Russian (ru), Slovak (sk), Spanish (es). The only imposed condition is that they have ≥80% performance on lemmatizing out-of-vocabulary words on the UD development set. This is to ensure that our lemmatizer is reasonably leak-free for rare words. We drop neuter words in languages that exhibit a neuter, such as Bulgarian and Russian.

**Word Vectors.** We employ the skip-gram model from the Word2Vec package to induce 100-dimensional embeddings. We use negative sampling with 10 samples. For all languages, the vectors are trained on corpora lemmatized in the way we just described; namely, we make use of multilingual Wikipedia editions from March 2018. All words with a frequency below 5 are ignored, and we compare symmetric context window sizes of 2, 5 and 10, finding 2 works the best.

**4.3 Experiment 1: Gender Classification**

Our gender prediction problem constitutes a binary classification task, where the classes are masculine and feminine and the input is the word embedding of a noun. We employ a multi-layer perceptron (MLP) for this classification, defining the probability of the gender $g$ given a noun type $v$, as

$$p(g \mid v) = \text{softmax}(W_2 \tanh (W_1 e(v) + b_1) + b_2) \quad (3)$$

where we feed in the noun’s embedding $e(v)$ into the network, $W_1 \in \mathbb{R}^{d' \times d}$ and $W_2 \in \mathbb{R}^{2 \times d'}$ are weight matrices, $b_1 \in \mathbb{R}^{d'}$ and $b_2 \in \mathbb{R}^{2}$ are bias vectors. Eq. (3) represents a network of depth 2, but we consider depth-$k$ networks where $k$ is a hyperparameter. We additionally consider the non-linearities ReLU and sigmoid.

**Training Set.** To learn the parameters of Eq. (3), we construct the following training set. Given the lemmatized and morphologically analyzed Wikipedias discussed in §4.2, we construct a lexicon as follows. For every lemma type that occurs more than 50 times, we find the gender, extracted from the morphological tag of each token, that most frequently occurs among its tokens in the corpus. This yields a lexicon of lemma-gender pairs. Note that this training set will include animate words as we are unable to exclude them easily. However, we will only evaluate on inanimate nouns; see below.

**Evaluation Set.** For the evaluation, we focus exclusively on the same common, inanimate words in all languages. We use the NorthEuraLex dataset (Dellert and Jäger, 2017), which is a multi-way concept-aligned dictionary. In order to avoid biological gender interfering with grammatical gender and, thus, influencing our experiments, we manually annotate all concepts as animate or inanimate and exclude all animate nouns. For instance, we keep eye, lake, and circle, while discarding words like wife, dog, or son. The list containing all concepts in our evaluation set can be found in App. A. We take care to remove these words from the train-
Training and Hyperparameters. The model is implemented in PyTorch (Paszke et al., 2017). We train our models on the training sets using Adam (Kingma and Ba, 2015) with a base learning rate of 0.1 for all models. All models are trained for 50 epochs. Hyperparameters include network depth ($k \in [1, 5]$), size of the hidden layer (taken from \{100, 200, 300\}) and type of nonlinearity (taken from \{tanh, sigmoid, ReLU\}). We randomly partition the evaluation set in half 10 times and sweep the hyperparameters on each dev partition, performing early stopping. Final results average the performance on test across these splits.

Results and Discussion. The gender-prediction accuracies from the four embeddings conditions are shown in Fig. 2. As discussed, classification accuracy is highest for conditions (i) forms and (iii) nouns, i.e., embeddings trained on the corpora where the context words are unaltered. In these conditions, we see unlemmatized forms as context, our classifier handily surpasses the majority-class baseline with differences up to 30 points. All differences are significant ($p < 0.05$). On the other hand, inspecting conditions (ii) lemmata and (iv) ~nouns, we see that performance of each is rarely better than the majority-class baseline and in no case is statistically better ($p < 0.05$). Thus, despite a relatively extensive hyperparameter search, we are unable to reliably predict grammatical gender from the context words along. This negative result provides evidence against Boroditsky et al. (2003, §4)’s hypothesis that the inherent gender of the word will have an effect on the context words that a speaker uses for inanimate nouns.

4.4 Experiment 2: A Gender Dimension

In addition to Experiment 1, we would also like to analyze the degree to which words are more masculine or feminine using their word embeddings, which, in turn, tells us how masculine or feminine their contexts are. A high-level overview of how we can achieve this is as follows. We may isolate genderedness by fixing one of the dimensions of the word embeddings to be the gender dimension. Then, we seek a method that will shift the information regarding gender into that dimension. In effect, we need a method which maps every word to a scalar quantity which corresponds to how gendered the word is, allowing us to compare individual words and to discover those whose gender is more saliently encoded in the embeddings. We adopt the ultra-dense strategy developed by Rothe et al. (2016), which we will describe below.

Learning Ultra-Dense Embeddings. Given an embedding $e(v) \in \mathbb{R}^d$ of a word $v$, we are interested in learning a real orthogonal matrix $Q \in \mathbb{R}^{d \times d}$ in order to create a new embedding $e'(v) = Q e(v)$. Defining $Q$ to be real orthogonal ensures that no information is lost or gained as a result of the transformation—the dot product, and, thus, the cosine similarity between vectors will be preserved. In order to learn a transformation that moves gender information to certain components of the embeddings, let $S$ be the set of of all pairs of distinct nouns that have the same gender and let $D$ be the set of all pairs of distinct nouns that have a different gender. Let $P \in \mathbb{R}^{d \times d}$ be a matrix with all entries being zero except for $P_{11}$, which is 1. Now, we minimize the following objective

$$
\mathcal{O}(Q; S, D) = \sum_{(v, v') \in S} \| P Q (e(v) - e(v')) \|^2_2
- \sum_{(v, v') \in D} \| P Q (e(v) - e(v')) \|^2_2
$$

with respect to the matrix $Q$ subject to the constraint that $Q^\top Q = I$; that is, $Q$ is real orthogonal.

Stochastic Projected Gradient. The above objective can be optimized using a stochastic projected-gradient-style algorithm (Bertsekas, 1999). This algorithm alternates between two steps until convergence: (i) A stochastic gradient step: During this step, one element is randomly sampled from each of $S$ and $D$. Then, the gradient of Eq. (4) is computed with respect to $Q$, and $Q$ is updated.
We start with a quantitative analysis; we consider words are more gendered than others. Here, we where the context words have been lemmatized. A projection step: After obtaining a new matrix \( \eta \) is chosen by the Adam optimizer. 

Algorithm 1

\[
\text{Stochastic Projected Gradient Algorithm}
\]

1: \textbf{input} \( S, \mathcal{D} \triangleright \text{same- and different-gender pairs} \)
2: \( Q \leftarrow I \)
3: \textbf{for} \( t = 1 \) \textbf{to} \( T \) \textbf{do}
4: \( (v_S, v_S') \sim \text{uniform}(S) \)
5: \( (v_D, v_D') \sim \text{uniform}(\mathcal{D}) \)
6: \( \tilde{S} \leftarrow \{ (v_S, v_S') \}; \tilde{D} \leftarrow \{ (v_D, v_D') \} \)
7: \( Q' \leftarrow \eta \cdot \nabla_Q \rho (Q; \tilde{S}, \tilde{D}) \)
8: \( U \Sigma V^\top \leftarrow \text{SVD} (Q') \)
9: \( Q \leftarrow UV^\top \)

by taking a step in the direction of the gradient. (ii) A projection step: After obtaining a new matrix \( Q' = Q + \eta \cdot \nabla_Q \rho \) during the gradient update where \( \eta \) is the learning rate, we no longer have the guarantee that \( Q' \) is orthogonal. Thus, we must perform a projection step to orthogonalize \( Q' \). This can be achieved through singular value decomposition (SVD). We compute the SVD: \( Q' = U \Sigma V^\top \), where \( U, \Sigma \) and \( V^\top \) are guaranteed to be real as \( Q' \) is real. Then, we may define \( Q = UV^\top \), which is the closest to \( Q' \) under the Frobenius norm (Horn and Johnson, 2012). Pseudocode for this algorithm is given in Alg. 1.

Training Details. Our learning rate schedule \( \eta_t \) (see Alg. 1) is chosen by the Adam optimizer (Kingma and Ba, 2015). We run \( T = 1000 \) iterations. Upon termination, we extract a scalar-valued gender quantity as follows: \( [P Q e(w)]_{11} \), i.e., the first component of the new embedding. We train on half the NorthEuraLex data and test on the other half, using the splits described in §4.3.

Analyzing the Data. The gender dimension admits both a quantitative and a qualitative analysis. We start with a quantitative analysis; we consider Spearman’s \( \rho \) between the gender dimension and the grammatical gender of the nouns, marking masculine as 0 and feminine as 1. The results are shown in Tab. 4. They mirror those found in experiment 1 (§4.3): we are unable to find correlation significantly different than 0 for any of the cases where the context words have been lemmatized (conditions (i) lemmata and (ii) ~nouns). On the contrary, when the context words are left unlemmatized (conditions (i) forms and (iii) nouns), we are generally able to find a significant correlation. Qualitatively, the gender dimension tells us which words are more gendered than others. Here, we perform a case study of our Spanish test set. The five words with the most masculine and most feminine gender dimension are displayed in Tab. 3 in the (i) forms and (ii) lemmata conditions. The qualitative analysis shows the same trend.

5 Other Related Work

In the realm of NLP, the closest work to ours deals with bias in word embeddings. Many have observed that word embeddings encode the biases present in the data they were trained on. For instance, Bolukbasi et al. (2016) and Zhao et al. (2017) note that the engineer embedding has a higher cosine similarity with man than with woman, reflecting a structural imbalance in the gender of the profession; they propose to debias the embeddings such that gender no longer plays a role.

6 Conclusion

Using word embeddings in 9 different languages trained on lemmatized corpora, we investigated whether adjective choice is influenced by the grammatical gender of inanimate nouns. This question has larger implication in the debate on the relation between language and thought. We developed a computational analogue of Boroditsky et al. (2003, §4)’s experimental paradigm and showed that context in which a noun occurs, stripped of its overt gender markings, is no longer predictive of the inherent gender of the original, inanimate noun. These negative results contradict Boroditsky et al. (2003, §4)’s claims.

Any scientific study should be viewed with a healthy dose of skepticism, especially one, such as ours, that considers a controversial question. We believe our big-data study should be taken as complementary evidence in the context of the larger debate that inanimate nouns’ gender does not influence the way speakers describe them in a corpus.
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| Concept ID     | English |
|---------------|---------|
| Abend::N      | evening |
| Abhäng::N     | slope   |
| Abstand::N    | gap     |
| Ader::N       | vein    |
| Alter::N      | age     |
| Angelegenheit::N | matter |
| Anhöhe::N     | elevation |
| Anzahl::N     | count   |
| Apfel::N      | apple   |
| Arbeit::N     | work    |
| Arm::N        | arm     |
| Art::N        | sort    |
| Arznei::N     | medicine |
| Asche::N      | ashes   |
| Ast::N        | limb    |
| Atem::N       | breath  |
| Auge::N       | eye     |
| Bach::N       | brook   |
| Band::N       | ribbon  |
| Bart::N       | beard   |
| Bau::N        | lair    |
| Bauch::N      | belly   |
| Baum::N       | tree    |
| Beere::N      | berry   |
| Bein::N       | leg     |
| Berg::N       | mountain |
| Besen::N      | broom   |
| Bett::N       | bed     |
| Beutel::N     | pouch   |
| Bild::N       | picture |
| Birke::N      | birch   |
| Blatt::N      | leaf    |
| Blume::N      | flower  |
| Blut::N       | blood   |
| Boden::N      | ground, soil |
| Bogen[Waffe]:::N | bow    |
| Boot::N       | boat    |
| Brei::N       | mush    |
| Brett::N      | board   |
| Brief::N      | letter  |
| Brot::N       | bread   |
| Brunnen::N    | well    |
| Brust::N      | breast, chest |
| Brücke::N     | bridge  |

| Concept ID     | English |
|---------------|---------|
| Buch::N       | book    |
| Buchstabe::N  | character |
| Bucht::N      | cove    |
| Busen::N      | bosom   |
| Butter::N     | butter  |
| Bündel::N     | bundle  |
| Dach::N       | roof    |
| Decke::N      | blanket |
| Deckel::N     | cover   |
| Donner::N     | thunder |
| Dorf::N       | village |
| Dreck::N      | filth   |
| Ecke::N       | corner  |
| Ei::N         | egg     |
| Eimer::N      | bucket  |
| Eis::N        | ice     |
| Eisen::N      | iron    |
| Ellenbogen::N | elbow   |
| Ende::N       | end     |
| Entfernung::N | distance |
| Erde::N       | earth   |
| Erzählung::N  | story   |
| Essen::N      | meal    |
| Faden::N      | thread  |
| Falle::N      | trap    |
| Farbe::N      | paint   |
| Feder::N      | feather |
| Fehler::N     | mistake |
| Fell::N       | fur     |
| Fenster::N    | window  |
| Ferse::N      | heel    |
| Festland::N   | land    |
| Fett::N       | fat     |
| Feuer::N      | fire    |
| Fieber::N     | fever   |
| Figur::N      | figure  |
| Finger::N     | finger  |
| Fingernagel::N| fingernail |
| Fleisch::N    | meat    |
| Fluss::N      | river   |
| Flügel::N     | wing    |
| Frost::N      | frost   |
| Funke::N      | spark   |
| Fuß::N        | foot    |
| Fußboden::N   | floor   |
| Gabel::N      | fork    |
| Concept ID | English | Concept ID | English |
|------------|---------|------------|---------|
| Gang::N    | walk    | Herz::N    | heart   |
| Gast::N    | guest   | Heu::N     | hay     |
| Gedanke::N | thought | Hilfe::N   | help    |
| Gedächtnis::N | memory | Himmel::N | sky     |
| Gegend::N  | area    | Hitz::N    | heat    |
| Gegenstand::N | item | Holz::N   | wood    |
| Gehirn::N  | brain   | Honig::N   | honey   |
| Geist::N   | spirit  | Horn::N    | horn    |
| Geld::N    | money   | Hose::N    | trousers|
| Gelächter::N | laughter | Hunger::N | hunger  |
| Genick::N  | nape    | Hälfte::N  | half    |
| Geruch::N  | odour   | Höhe::N    | height  |
| Geschenk::N | gift | Höhlle::N | cave    |
| Geschirr::N | dishes | Hügel::N   | hill    |
| Geschmack::N | flavour | Insel::N   | island  |
| Geschäft::N | business | Jahr::N    | year    |
| Gesicht::N | face    | Kamm::N    | comb    |
| Gespräch::N | talk | Kampf::N   | fight   |
| Gesundheit::N | health | Kante::N | edge    |
| Getreide::N | corn    | Kehle::N   | throat  |
| Gewalt::N  | violence | Kessel::N | kettle  |
| Gewehr::N  | gun     | Kiefer[Anatomie]:N::N | jaw    |
| Gewicht::N | weight  | Kiefer[Baum]:N::N | pine   |
| Gipfel::N  | summit  | Kinn::N    | chin    |
| Glas::N    | glass   | Kirche::N  | church  |
| Glück::N   | happiness | Kissen::N | pillow  |
| Gold::N    | gold    | Kiste::N   | box     |
| Grab::N    | grave   | Klau::N    | claw    |
| Gras::N    | grass   | Kleidung::N | clothes |
| Grenze::N  | border  | Knie::N    | knee    |
| Griff::N   | handle  | Knochen::N | bone    |
| Grube::N   | pit     | Knopf::N   | button  |
| Grund::N   | reason  | Knoten::N  | knot    |
| Größe::N   | size    | Kohle::N   | coal    |
| Gürtel::N  | belt    | Kopf::N    | head    |
| Haar::N    | hair    | Korn::N    | grain   |
| Haken::N   | hook    | Kragen::N  | collar  |
| Hals::N    | neck    | Kralle::N  | claw    |
| Hand::N    | hand    | Krankheit::N | illness |
| Handfläche::N | palm | Kreis::N   | circle  |
| Handtuch::N | towel | Kreuz::N   | cross   |
| Haufen::N  | heap    | Krieg::N   | war     |
| Haus::N    | house   | Kummer::N  | grief   |
| Haut::N    | skin    | Kälte::N   | chill   |
| Heim::N    | home    | Körper::N  | body    |
| Hemd::N    | shirt   |            |         |
| Concept ID         | English | Concept ID         | English |
|-------------------|---------|-------------------|---------|
| Küste::N          | coast   | Nahrung::N        | food    |
| Laden::N          | shop    | Name::N           | name    |
| Lagerfeuer::N     | campfire| Nase::N           | nose    |
| Land::N           | country | Netz::N           | net     |
| Last::N           | load    | Nest::N           | nest    |
| Laut::N           | sound   | Leben::N          | life    |
| Leber::N          | liver   | Neuigkeit::N      | news    |
| Leder::N          | leather | Norden::N         | north   |
| Lehm::N           | clay    | Oberschenkel::N   | thigh   |
| Leine::N          | leash   | Ohr::N            | ear     |
| Leiter::N         | ladder  | Ort::N            | place   |
| Leute::N          | people  | Osten::N          | east    |
| Licht::N          | light   | Pfad::N           | path    |
| Lied::N           | song    | Pfeil::N          | arrow   |
| Linie::N          | line    | Pilz::N           | mushroom|
| Lippe::N          | lip     | Rand::N           | fringe  |
| Loch::N           | hole    | Rauch::N          | smoke   |
| Luft::N           | air     | Raureif::N        | hoarfrost|
| Lust::N           | desire  | Preis::N          | price   |
| Länge::N          | length  | Puppe::N          | doll    |
| Lärm::N           | noise   | Quelle::N         | source  |
| Löffel::N         | spoon   | Rand::N           | fringe  |
| Lüge::N           | lie     | Rauch::N          | smoke   |
| Macht::N          | power   | Raureif::N        | hoarfrost|
| Magen::N          | stomach | Rede::N           | speech  |
| Meer::N           | sea     | Reichtum::N       | wealth  |
| Menge::N          | amount  | Regen::N          | rain    |
| Messer::N         | knife   | Regenbogen::N     | rainbow |
| Milch::N          | milk    | Reichtum::N       | wealth  |
| Mittag::N         | noon    | Reihe::N          | row     |
| Mitte::N          | middle  | Riefen::N         | strap   |
| Monat::N          | month   | Rinde::N          | bark    |
| Mond::N           | moon    | Ring::N           | ring    |
| Moor::N           | moor    | Rohr::N           | pipe    |
| Morgen::N         | morning | Ruder::N          | oar     |
| Mund::N           | mouth   | Ruf::N            | call    |
| Muster::N         | pattern | Ruhe::N           | calm    |
| Märchen::N        | fairy tale | Rätsel::N     | puzzle  |
| Mütze::N          | cap     | Rücken::N         | back, spine |
| Nabel::N          | navel   | Saat::N           | seed    |
| Nachricht::N      | message | Sachen::N         | thing   |
| Nacht::N          | night   | Sack::N           | sack    |
| Nadel::N          | needle  | Salz::N           | salt    |
| Nagel::N          | nail    | Sand::N           | sand    |
| Nagel[Anatomie]::N | nail | Schaden::N | damage |
| Concept ID | English   | Concept ID | English   |
|-----------|-----------|-----------|-----------|
| Schale::N | husk      | Stoff::N  | cloth     |
| Schatten::N | shadow  | Straße::N | road      |
| Schaufel::N | shovel  | Strich::N | stroke    |
| Schaum::N | foam      | Strömung::N | current  |
| Scheibe::N | slice    | Stuhl::N  | chair     |
| Schlaf::N | sleep     | Stärke::N | strength  |
| Schlinge::N | noose  | Stück::N  | piece     |
| Schlitten::N | sleigh  | Stütze::N | bracket   |
| Schloss::N | lock      | Sumpf::N  | swamp     |
| Schluss::N | conclusion | Suppe::N | soup      |
| Schmerz::N | pain      | Süden::N  | south     |
| Schmutz::N | dirt      | Sünde::N  | sin       |
| Schnee::N | snow      | Tag::N    | day       |
| Schnur::N | string    | Tanne::N  | fir       |
| Schnurrbart::N | moustache | Tasche::N | bag       |
| Schritt::N | step      | Tasse::N  | cup       |
| Schuh::N | shoe      | Tee::N    | tea       |
| Schul::N | fault     | Teil::N   | part      |
| Schulter::N | shoulder | Tisch::N  | table     |
| Schwanz::N | tail      | Tod::N    | death     |
| See::N | lake      | Ton::N    | tone      |
| Sehne::N | sinew     | Topf::N   | pot       |
| Seite::N | side      | Tür::N    | gate      |
| Silber::N | silver    | Traum::N  | dream     |
| Sinn::N | meaning   | Tropfen::N | drop      |
| Ski::N | ski       | Träne::N  | tear      |
| Sonne::N | sun       | Tuch::N   | scarf     |
| Spaten::N | spade    | Tür::N    | door      |
| Speise::N | dish     | Ufer::N   | shore     |
| Spiegel::N | mirror  | Unglück::N | misfortune |
| Spiel::N | game      | Verstand::N | mind     |
| Spitze::N | tip      | Volk::N   | nation    |
| Sprache::N | language | Wahrheit::N | truth    |
| Spur::N | track     | Wald::N   | forest    |
| Staat::N | state     | Wange::N  | cheek     |
| Stab::N | staff     | Ware::N   | ware      |
| Stadt::N | town      | Wasser::N | water     |
| Stamm::N | trunk     | Weg::N    | way       |
| Stange::N | pole     | Weide::N  | pasture   |
| Staub::N | dust      | Weide[Baum]::N | willow  |
| Stein::N | stone     | Welle::N  | wave      |
| Stern::N | star      | Welt::N   | world     |
| Stiefe::N | boot     | Westen::N | west      |
| Stimme::N | voice    | Wetter::N | weather   |
| Stirn::N | forehead | Wiege::N  | cradle    |
| Stock::N | stick     | Wiese::N  | meadow    |
| Concept ID | English |
|------------|---------|
| Wind::N    | wind    |
| Winkel::N  | angle   |
| Woche::N   | week    |
| Wolke::N   | cloud   |
| Wolle::N   | wool    |
| Wort::N    | word    |
| Wunde::N   | wound   |
| Wunsch::N  | wish    |
| Wurzel::N  | root    |
| Zahn::N    | tooth   |
| Zaun::N    | fence   |
| Zeh::N     | toe     |
| Zeichen::N | sign    |
| Zeit::N    | time    |
| Zeitung::N | newspaper |
| Zunge::N   | tongue  |
| Zweig::N   | branch  |
| Zwiebel::N | onion   |
| Ärmel::N   | sleeve  |
| Öl::N      | oil     |