Grammatical Gender’s Influence on Distributional Semantics: A Causal Perspective

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Grammatical Gender’s Influence on Distributional Semantics: 
A Causal Perspective

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Abstract

How much meaning influences gender assignment across languages is an active area of research in modern linguistics and cognitive science. We can view current approaches as aiming to determine where gender assignment falls on a spectrum, from being fully arbitrarily determined to being largely semantically determined. For the latter case, there is a formulation of the neo-Whorfian hypothesis, which claims that even inanimate noun gender influences how people conceive of and talk about objects (using the choice of adjective used to modify inanimate nouns as a proxy for meaning). We offer a novel, causal graphical model that jointly represents the interactions between a noun’s grammatical gender, its meaning, and adjective choice. In accordance with past results, we find a relationship between the gender of nouns and the adjectives which modify them. However, when we control for the meaning of the noun, we find that grammatical gender has a near-zero effect on adjective choice, thereby calling the neo-Whorfian hypothesis into question.

1 Introduction

Approximately half of the world’s languages have grammatical gender (Corbett, 2013a), a grammatical phenomenon that groups nouns together into classes that share morphosyntactic properties (Hockett, 1958; Corbett, 1991; Kramer, 2015). Among languages that have gender, there is variation in the number of gender classes; for example, some languages have only two classes, e.g., all Danish nouns are classed as either common or neuter, whereas others have significantly more, e.g., Nigerian Fula has around 20, depending on the variety (Arnott, 1967; Koval’, 1979; Breedveld, 1995). Languages also vary with respect to how much gender assignment, i.e., how nouns are sorted into particular genders, is related to the form and the meaning of the noun (Corbett, 1991; Plaster and Polinsky, 2007; Corbett, 2013b, 2014; Kramer, 2020; Sahai and Sharma, 2021). Some languages group nouns into gender classes that are highly predictable from phonological (Parker and Hayward, 1985; Corbett, 1991, 2013b) or morphological (Corbett, 1991, 2013b; Corbett and Fraser, 2000) information, while others, such as the Dagestani languages Godoberi and Bagwalal, seem to be predictable from meaning (Corbett, 1991; Corbett and Fraser, 2000; Corbett, 2014)—although, even for most of the strictly semantic systems, there are exceptions.

Despite this variation, gender assignment is rarely, if ever, wholly predictable from meaning alone. In many languages, there is a semantic core of nouns that are conceptually coherent (Aksenov, 1984; Corbett, 1991; Williams et al., 2019; Kramer, 2020) and a surround that is somewhat less semantically coherent. Axes along which genders are conceptually coherent often include semantic properties of animate nouns, with inanimate nouns appearing in the surround. For example, in Spanish, despite the fact that the nouns table (mesa in Spanish) and woman (mujer in Spanish) appear in the same gender (i.e., feminine), it is hard to imagine what meaning they share. Indeed, some linguists posit that gender assignment for inanimate nouns is effectively arbitrary (Bloomfield, 1935; Aikhenvald, 2000; Foundalis, 2002). And, to the extent that gender assignment is not fully arbitrary for inanimate nouns (Williams et al., 2021), many researchers argue there is no compelling evidence showing grammatical gender affects how we conceptualize objects (Samuel et al., 2019) or the distributional properties of language (Mickan et al., 2014).

However, not all researchers agree that non-arbitrariness in gender assignment, to the extent it exists, should be assumed to have no bearing on language production. Boroditsky (2003) famously argued for a causal relationship between the gender assigned to inanimate nouns and their usage, in
a view colloquially known as the neo-Whorfian hypothesis after Benjamin Whorf (Whorf, 1956). Proponents of this view have studied human associations, under the assumption that people’s perceptions of the genders of objects are strongly influenced by the grammatical genders these objects are assigned in their native language (Boroditsky and Schmidt, 2000; Semenuks et al., 2017). One manifestation of this perception is the choice of adjectives used to describe nouns (Semenuks et al., 2017). While this is an intriguing possibility, there are additional lexical properties of nouns that may act as confounders and, thus, finding statistical evidence for the causal effect of grammatical gender on adjective choice requires great care.

To facilitate a cleaner way to reason about the causal influence grammatical gender may have on adjective usage, we introduce a causal graphical model to represent the interactions between an inanimate noun’s grammatical gender, its meaning, and the choice of its descriptors. This causal framework enables intervening on the values of specific factors to isolate the effects between various properties of languages. Our model explains the distribution of adjectives that modify a noun, conditioned on both a representation of the noun’s meaning and the gender of the noun itself. Upon estimation of the parameters of the causal graphical model, we test the neo-Whorfian hypothesis beyond the anecdotal level. First, we validate our model by comparing it to the method presented in prior work without any causal intervention. Second, we employ our model with a causal intervention on the noun meaning to test the neo-Whorfian hypothesis. That is, we ask a counterfactual question: Had nouns been lexicalized with different grammatical genders but retained their same meanings, would the distribution of adjectives used to describe nouns (Semenuks et al., 2017) be consistent with the idea that such influence is prima facie consistent with the idea that such influence is conceivably possible. However, one could imagine a similar process, such as analogical reasoning (Lucy, 2016), by which gender could influence an adjective’s meaning instead of just its form. If a noun’s meaning were to influence its gender, then the noun meaning could also indirectly influence adjective usage, by way of the relationship between grammatical gender and adjectival usage. There is ample statistical evidence that grammatical gender assignment is not fully arbitrary (Williams et al., 2019, 2021; Nelson, 2005; Sahai and Sharma, 2021). Such evidence is prima facie consistent with the idea that such influence is conceivably possible.

However, it is important to note that claims that noun gender influences meaning are by their very nature causal claims. The most famous example of such a causal claim is the neo-Whorfian view of gender (Boroditsky and Schmidt, 2000; Boroditsky, 2001, 2003), which states that a noun’s

2 A Primer on Grammatical Gender

In many languages with grammatical gender, adjectives, demonstratives, determiners, and other word categories agree with the noun in gender, i.e., they will systematically change in form to indicate the grammatical gender of the noun they modify. Observe the following sentence, A small dog sleeps under the tree., translated into two languages that exhibit grammatical gender (German and Polish):

- **Ein kleiner Hund schläft unter dem Baum.** (DE)
  - a. small, m. dog, m. is sleeping under the, m. tree, m.

- **Mały pies śpi pod drzewem.** (PL)
  - a. small, m. dog, m. is sleeping under the, n. tree, n.

Because the German (DE) and Polish (PL) words for a dog, Hund and pies, are both assigned masculine gender, the adjectives in the respective languages, klein and mały, are morphologically gender-marked as masculine. Additionally, in German, the article, dem, is also gender-marked as masculine. The fact that gender is reflected by agreement patterns on other elements is generally taken to be a definitional property (Hockett, 1958; Corbett, 1991; Kramer, 2020) separating gender from other kinds of noun classification systems, such as numeral classifiers or declension classes.

It is an undeniable fact in many languages that morphological agreement reflects the gender of a noun in the form of other elements. However, one could imagine a similar process, such as analogical reasoning (Lucy, 2016), by which gender could influence an adjective’s meaning instead of just its form. If a noun’s meaning were to influence its gender, then the noun meaning could also indirectly influence adjective usage, by way of the relationship between grammatical gender and adjectival usage. There is ample statistical evidence that grammatical gender assignment is not fully arbitrary (Williams et al., 2019, 2021; Nelson, 2005; Sahai and Sharma, 2021). Such evidence is prima facie consistent with the idea that such influence is conceivably possible.
grammatical gender causally affects meaning (e.g.,
adjective choice). This view can be summed up in
the following quote from Boroditsky and Schmidt
(2000), “people’s ideas about the genders of
objects are strongly influenced by the grammatical
genders assigned to these objects in their native
language” (emphasis ours). Despite this clear
causal formulation of the hypothesis, there has yet
to be a modeling approach developed to test it.

Laboratory studies have been used to gather
evidence for the neo-Whorfian hypothesis. For example,
Semenuks et al. (2017) perform a small lab-
roatory experiment involving human participants
to explore whether noun gender affects a particular
proxy for meaning, adjective choice. This work
found that, in languages where bridge is feminine
(like German; Brücke), participants modified it
with adjectives that are stereotypically used to
refer to women, such as beautiful, and in languages
where bridge is masculine (like Spanish; puente),
they used adjectives stereotypically used to refer
to men, like sturdy. Subsequent studies, however,
have failed to replicate this result, raising into
question the strength of this relationship between
gender and adjective usage (Mickan et al., 2014).

Our paper builds on Williams et al.’s (2021)
correlational study of noun meaning and its
distributional properties and advances it to a causal
one. While Williams et al. (2021) report a non-
trivial, statistically significant mutual information
between the grammatical gender of a noun and its
modifiers, e.g., adjectives that modify the noun,
they do not control for other factors which might
influence adjective usage, most notably the lexical
semantics of the noun. Mutual information on
its own cannot speak to causation. We are thus
motivated by a potential common-cause effect
whereby the lexical semantics jointly influences
a noun’s grammatical gender and its distribution
over modifiers and propose a causal model.

3 A Causal Graphical Model

The technical contribution of this work is a novel
causal graphical model for jointly representing the
relationship between the grammatical gender of
a noun, its meaning, and descriptors. This model
is depicted in Figure 1. If properly estimated, the
model should enable us to measure the causal
effect of grammatical gender on adjective choice in
language. We first develop the necessary notation.

Notation We follow several font and coloring
conventions to make our notation easier to digest.
All base sets will be uppercase and in calligraphic
font, e.g., X. Elements of X will be lowercase
and italicized, e.g., x ∈ X. Subsets (including
submultisets) will be uppercase and unitalicized,
e.g., X ⊆ X. Random variables that draw their
values from X will be uppercase and italicized, e.g.,
p(X = x). We will use three colors. Those objects
that relate to nouns will be in purple, and those objects
that relate to gender will be in green.

3.1 The Model

We assume there exists a set of nominal meanings
N. In this paper, we assume that such meanings
are representable by vectors in R^D. We denote the
elements of N as n ∈ R^D. Additionally, we
assume there exists an alphabet of adjectives A. We
denote an element of A as a. Finally, we assume
there exists a language-dependent set of G. In Spanish,
for instance, we would have G = {FEM, MSC}
whereas in German G = {FEM, MSC, NEU}. We
denote elements of G as g.

We now develop a generative model of the subset
of lexical semantics relating to adjective choice.
We wish to generate a set of N nouns, each of
which is modified by a multiset of adjectives. We
can view this model as a partial generative model
of a corpus where we focus on generating noun
types and adjective tokens. Generation from the
model proceeds as follows:

\[
\begin{align*}
n &\sim p_N(\cdot) \quad \text{(sample a noun meaning n)} \\
g_n &\sim p_G(\cdot \mid n) \quad \text{(sample the gender g_n assigned to n)} \\
a_n &\sim p_A(\cdot \mid n, g_n) \quad \text{(sample adjectives a_n that modify n)}
\end{align*}
\]

In this formulation, N is a N-valued random
variable, G is a G-valued random variable, and A
is a A-valued random variable.

Written as a probability distribution, we have

\[
p(A, \{g_n\}, N) = \prod_{n \in N} \prod_{a \in A} p_A(a \mid n, g_n) p_G(g_n \mid n) p_N(n)
\]

where N ⊆ N is a subset of the set of nominal
meanings and each g_n ∈ G is the gender of n, and
where for simplicity,

Thus, to the extent that the modeler believes our model does not aim to account rat discovered a bagel dissolving in the sewer.

might differ between the sentences bagel.

the probability distribution over adjectives describing the noun because \( p(a \mid \text{do}(G = g)) \) is a distribution over \( \mathcal{A} \), we measure the causal effect by the weighted Jensen–Shannon divergence (Lin, 1991), which we define as

\[
JS_{\pi}(p_1 \| p_2) \equiv \pi_1 \text{KL}(p_1 \| m) + \pi_2 \text{KL}(p_2 \| m)
\]

where \( \pi_1, \pi_2 \geq 0, \pi_1 + \pi_2 = 1 \) and \( m = \pi_1 p_1 + \pi_2 p_2 \) is a convex combination of \( p_1 \) and \( p_2 \) weighted according to \( \pi \).

Further, we note that the weighted Jensen–Shannon divergence is related to a specific mutual information between two random variables. We make this relationship formal in the following proposition.

**Proposition 1.** Let \( A \) and \( G \) be \( \mathcal{A} \)-valued and \( \mathcal{G} \)-valued random variables, respectively. Further assume they are jointly distributed according to \( p(a \mid \text{do}(G = g)) p_G(g) \). Then,

\[
JS_{p_G}\left( \left\{ p(\cdot \mid \text{do}(G = g)) \right\} \right) = \text{MI}_{\text{do}}(A; G)
\]

where \( \text{MI}_{\text{do}}(A; G) \) is the mutual information computed under the joint distribution \( p(a \mid \text{do}(G = g)) p_G(g) \).

**Proof:** See App. A for a proof.

Relating the weighted Jensen–Shannon divergence to a specific mutual information provides a clear interpretation. This measure explains in bits how much the entropy of the language’s distribution over adjectives is reduced when the grammatical gender of the noun being modified is known at the time of the adjective choice. For instance, if the language’s distribution over adjectives has an entropy \( H(A) \) of 10 bits and the mutual information \( \text{MI}(A; G) \) is 1 bit, then knowing the gender allows us to reduce the uncertainty over which adjectives modify the nouns to \( H(A \mid G) = 9 \) bits. However, the reduced

---

1Sentential context can also influence adjective usage, e.g., the probability distribution over adjectives describing the noun bagel might differ between the sentences *After the flood, the rat discovered a bagel dissolving in the sewer,* and *She was craving a bagel.* Our model does not aim to account for such contextual effects.

2The Jensen–Shannon divergence can also be generalized to operate on \( N \) distributions as \( JS_{\pi}(p_1, \ldots, p_N) = \sum_{n=1}^{N} \pi_n \text{KL}(p_n \| m) \), where \( \sum_{n=1}^{N} \pi_n = 1, \pi_n \geq 0, \forall n \in [N] \), and \( m = \sum_{n=1}^{N} \pi_n p_n \).
We now discuss the parameterization of the vector representation of the meaning of the noun described in §4.2. This is formalized as follows. The empirical distribution of nouns in the corpus. 4 Experimental Setup and how we estimate non-contextual experiments, and how we estimate non-contextual
distributions for \( n \) and \( e \) independently. While \( n \) is the product of generating each adjective independently. We note that Eq. (5) gives the probability of a single \( a \in A_n \) that co-occurs with \( n \). The probability of the set \( A_n \) is the product of generating each adjective independently. While \( e(a) \) and \( e(g) \) could be trainable parameters, for simplicity, we fix \( e(a) \) to be standard word2vec representations and \( e(g) \) to be a one-hot encoding with dimension \( |g| \). Representations for \( n \) are pre-trained according to methods described in §4.2.

Finally, we opt to model \( p(g \mid n) \) and \( p_N(n) \) as the empirical distribution of nouns in the corpus.

4 Experimental Setup

In this section, we describe the data used in our experiments, and how we estimate non-contextual

In §3, we described a causal graphical model of the interactions between a noun’s meaning, grammatical gender, and adjectives. This model relies on a representation of nominal lexical semantics—specifically, a representation that is independent (in the probabilistic sense) of the distributional properties of the noun. 4.1 Data

We gather data in five languages that exhibit grammatical gender agreement: German, Hebrew, Polish, Portuguese, and Spanish. Four of these languages are Indo-European (German, Polish, Portuguese, and Spanish) and the fifth is Afro-Asiatic (Hebrew). This is certainly not a representative sample of the subset of the world’s languages that exhibit grammatical gender, but we are limited by the need for a large corpus to estimate a proxy for lexical meaning. Hebrew, Portuguese, and Spanish distinguish between two grammatical genders (masculine and feminine), while German and Polish distinguish between three genders (masculine, feminine, and neuter).

We use the Wikipedia dump dated August 2022 to create a corpus for each of the five languages, and preprocess the corpora with the Stanza library (Qi et al., 2020). Specifically, we tokenize the raw text, dependency-parse the tokenized text, lemmatize the data, extract lemmatized noun–adjective pairs based on an amod dependency label, and finally filter these pairs such that only those for inanimate nouns remain. To determine which nouns are inanimate, we use the NorthEuraLex dataset, which curated a list of common inanimate nouns (Dellert et al., 2020). Table 4 shows the counts for the remaining tokens for all analyzed languages for which we retrieved word representations. Next, we describe the procedure for computing the non-contextual word representations.

4.2 Non-contextual Word Representations

In §3, we described a causal graphical model of the interactions between a noun’s meaning, grammatical gender, and adjectives. This model relies on a representation of nominal lexical semantics—specifically, a representation that is independent (in the probabilistic sense) of the distributional properties of the noun.

\( p_A(a \mid g, n) \)

\[
\exp \left( w^\top \tanh W \left[ e(a); n; e(g) \right] \right) \right) 
= \frac{\exp \left( w^\top \tanh W \left[ e(b); n; e(g) \right] \right) }{\sum_{b \in A} \exp \left( w^\top \tanh W \left[ e(b); n; e(g) \right] \right) }
\]

where the parameters \( W \) and \( w \) denote the weight matrix and weight vector, respectively. We note that Eq. (5) gives the probability of a single \( a \in A_n \) that co-occurs with \( n \). The probability of the set \( A_n \) is the product of generating each adjective independently. While \( e(a) \) and \( e(g) \) could be trainable parameters, for simplicity, we fix \( e(a) \) to be standard word2vec representations and \( e(g) \) to be a one-hot encoding with dimension \( |g| \). Representations for \( n \) are pre-trained according to methods described in §4.2.

Finally, we opt to model \( p(g \mid n) \) and \( p_N(n) \) as the empirical distribution of nouns in the corpus.

In this section, we describe the data used in our experiments, and how we estimate non-contextual word representations as a proxy for a noun’s lexical semantics.
Word2vec. We train word2vec (Mikolov et al., 2013) on modified Wikipedia corpora. First, we lemmatize the corpus with Stanza as discussed above. This step should remove any spurious correlations between a noun’s morphology and its meaning. Second, we remove all adjectives from the corpora. Because our goal is to predict the distribution over adjectives from a noun’s lexical semantic representation, that distribution should not, itself, be encoded in the semantic representation. We construct representations of length 200 through the continuous skip-gram model with negative sampling with 10 samples using the implementation from gensim. We train these non-contextual word representations on the Wikipedia data described above. We ignore all words with a frequency below 5 and use a symmetric context window size of 5.

WordNet-based Representations. In addition to those representations derived from word2vec, we also derive lexical representations using WordNet (Miller, 1994). Because WordNet is a lexical database that groups words into sets of synonyms (synsets) and links synsets together by their conceptual, semantic, and lexical relations, representations of meaning based on WordNet are unaffected by biases that might be encoded in a training corpus of natural language. Following the method of Saedi et al. (2018), we create word representations by constructing an adjacency matrix of WordNet’s semantic relations (e.g., hypernymy, meronymy) between words and compressing this matrix to have a dimensionality of 200 for each of the languages in this study: German, Hebrew, Spanish, Polish, and Portuguese (Siegel and Bond, 2021; Ordan and Wintner, 2007; Gonzalez-Agirre and Rigau, 2013; Piasecki et al., 2009; de Paiva and Rade-maker, 2012). We access and process these WordNets using the Open Multilingual WordNet (Bond and Paik, 2012). We report statistics on these WordNets in Table 1.

### Table 1: Summary statistics on the WordNets used for training representations in each language.

<table>
<thead>
<tr>
<th>WordNet</th>
<th>Words</th>
<th>Senses</th>
<th>Synsets</th>
</tr>
</thead>
<tbody>
<tr>
<td>ODENet 1.4 (de)</td>
<td>120,107</td>
<td>144,488</td>
<td>36,268</td>
</tr>
<tr>
<td>OpenWN-PT (pt)</td>
<td>54,932</td>
<td>74,012</td>
<td>43,895</td>
</tr>
<tr>
<td>plWordNet (pl)</td>
<td>45,456</td>
<td>52,736</td>
<td>33,826</td>
</tr>
<tr>
<td>MCR (es)</td>
<td>37,203</td>
<td>57,764</td>
<td>38,512</td>
</tr>
<tr>
<td>Hebrew WordNet</td>
<td>5,379</td>
<td>6,872</td>
<td>5,448</td>
</tr>
</tbody>
</table>

Evaluating the Representations. We now discuss how we validate our lexical representations. Because we construct the word2vec representations using modified corpora, it is reasonable to fear that those modifications would hinder the representations’ ability to encode a reasonable approximation to nominal lexical semantics. Thus, for each language, we evaluate the quality of the learned representations by calculating the Spearman correlation coefficient of the cosine similarity between representations and the human-annotated similarity scores of word pairs in the SimLex family of datasets (Hill et al., 2015; Leviant and Reichart, 2015; Vulić et al., 2020). A higher correlation indicates a better representation of semantic similarity. We report the Spearman correlation of the representations for each language in Table 2. We note that especially for representations generated using WordNet for languages with sparsely-populated WordNets (see Table 1), the representational power is relatively low (as measured by the Spearman correlation), which may influence conclusions of downstream results for these languages. We note that if the representations are very bad, i.e., to the point that gender is completely unpredictable from the noun meaning representation and $p_C(g_n | n) = p_C(g_n)$, then $\text{MI}(A; G) = \text{MI}_{do}(A; G)$ because the edge in the graphical model from $G$ to $A$ is effectively removed.

### Table 2: Spearman’s $\rho$ correlation coefficient between judgments in similarity datasets and representation cosine similarity for each language for both WordNet and word2vec representations.

<table>
<thead>
<tr>
<th>Lang.</th>
<th>WordNet embs $\rho$</th>
<th>% of eval set</th>
<th>word2vec embs $\rho$</th>
<th>% of eval set</th>
</tr>
</thead>
<tbody>
<tr>
<td>DE</td>
<td>0.360</td>
<td>86.9%</td>
<td>0.380</td>
<td>92.2%</td>
</tr>
<tr>
<td>ES</td>
<td>0.234</td>
<td>71.8%</td>
<td>0.419</td>
<td>89.3%</td>
</tr>
<tr>
<td>HE</td>
<td>0.104</td>
<td>11.6%</td>
<td>0.460</td>
<td>59.6%</td>
</tr>
<tr>
<td>PL</td>
<td>0.092</td>
<td>49.9%</td>
<td>0.418</td>
<td>76.5%</td>
</tr>
<tr>
<td>PT</td>
<td>0.283</td>
<td>94.7%</td>
<td>0.308</td>
<td>94.5%</td>
</tr>
</tbody>
</table>

5 Methodology

The empirical portion of our paper consists of two experiments. In the first (§5.3), for a point of comparison, we replicate Williams et al.’s (2021) study. We then estimate $\text{MI}(A; G)$ for each of the five languages. In the second (§5.4), we produce a causal analog of Williams et al. (2021). Using the notation of §3, in this experiment we estimate $\text{MI}_{do}(A; G)$ for each of the five languages.
5.1 Parameter Estimation

To estimate the parameters of the graphical model given in Figure 1, we perform regularized maximum-likelihood estimation. Specifically, we maximize the likelihood the model assigns to a set $D_{trn} = \{(A_n, g_n, n_n)\}_{n=1}^N$ where each distinct $n_n$ occurs at most once. The log-likelihood is

$$L(\theta) = \sum_{n=1}^N \sum_{a \in A_n} \log p_A(a \mid g_n, n_n)$$

where $\theta = \{w, W\}$. We define $p_A$ using a multilayer perceptron (MLP) with the rectified linear unit (ReLU; Nair and Hinton, 2010) and a final softmax layer. We use a non-parametric technique to estimate $p_N$ and $p_G$. We train our models for each of the five languages for a maximum of 100 epochs using the Adam optimizer (Kingma and Ba, 2015) to predict the correct adjective given its representation, a noun’s gender, and representation.

5.2 Plug-in Estimation of $\text{MI}(A; G)$

The first estimator of $\text{MI}(A; G)$ is the plug-in estimator considered in Williams et al. (2021). In this case, we compute the maximum-likelihood estimate of the marginal $p(a, g)$ and plug it into the formula for mutual information:

$$\text{MI}(A, G) = \sum_{a \in A} \sum_{g \in G} p(a, g) \log \frac{p(a, g)}{p(g)p(a)}$$

where $p(a, g)$ is estimated as described in §5.1. We perform a permutation test to determine whether the mutual information as defined under $p(a \mid \text{do}(G = g))p(g)$ is significantly different than zero, as described in §5.5.

5.3 Model-based Estimation of $\text{MI}_{do}(A; G)$

In our causal study, in contrast to §5.3, we are interested in causal mutual information, which we take to be the mutual information as defined under $p(a \mid \text{do}(G = g))p(g)$. We approximate the marginal $p(g)$ using a maximum-likelihood estimate on $D_{trn}$. We use $N_g$, a set of gender–noun pairs distinct from those in $D_{trn}$, with a fixed gender $g$ to compute the following estimate of the intervention distribution

$$\tilde{p}(a \mid \text{do}(G = g)) = \frac{1}{|N_g|} \sum_{(g, m) \in N_g} p_A(a \mid g, m)$$

using the parameters of the model $p_A(a \mid G = g, n)$ estimated as described in §5.1. We perform a permutation test to determine whether the estimate is significantly different than zero, as described in §5.5.

5.4 Model-based Estimation of $\text{MI}_{do}(A; G)$

In our causal study, in contrast to §5.3, we are interested in causal mutual information, which we take to be the mutual information as defined under $p(a \mid \text{do}(G = g))p(g)$. We approximate the marginal $p(g)$ using a maximum-likelihood estimate on $D_{trn}$. We use $N_g$, a set of gender–noun pairs distinct from those in $D_{trn}$, with a fixed gender $g$ to compute the following estimate of the intervention distribution

$$\tilde{p}(a \mid \text{do}(G = g)) = \frac{1}{|N_g|} \sum_{(g, m) \in N_g} p_A(a \mid g, m)$$

using the parameters of the model $p_A(a \mid G = g, n)$ estimated as described in §5.1. We perform a permutation test to determine whether the estimate is significantly different than zero, as described in §5.5.

5.5 Permutation Testing

We design and run a permutation test to determine whether the mutual information between the adjective distributions conditioned on different genders is equal to the mutual information between the adjective distributions from a model trained on perturbed gender labels. To do this, we train a model from scratch using 5-fold cross-validation on subsets of 500 adjectives to estimate $p_A(a \mid n, g)$ with a random permutation of the gender labels and use that model to compute the pairwise mutual information estimates between adjective distributions on the test set as described earlier for $k = 100$ times. We determine the significance of our result by evaluating the proportion of times that the $\text{MI}_{do}(A; G)$ computed using the non-permuted training set is greater than one computed using randomly permuted genders during training; $p$-values greater than 95% suggest significant evidence against the null hypothesis, which posits no difference in mutual information between models trained on original and perturbed gender labels (based on the standard significance level of $\alpha = 0.05$).

6 Results

First, we validate our model by comparing the model-based estimation of $\text{MI}(A; G)$ to the method presented in Williams et al. (2021), the plug-in estimation of $\text{MI}(A; G)$. Then, we employ our causal
Table 3: Results for the plug-in estimation of $\text{MI}(A; G)$, model-based estimation for $\text{MI}(A; G)$, and model-based estimation of $\text{MI}_{do}(A; G)$, mean difference between the model-based estimation of $\text{MI}_{do}(A; G)$ and a perturbed model with random gender labels together with permutation test results, and the $p$-values for the permutation test for the causal model trained with word2vec and WordNet representations.

![Figure 2: Results for the plug-in estimation of $\text{MI}(A; G)$ and model-based estimations for $\text{MI}(A; G)$](image)

![Graphical model to investigate whether there is evidence for the neo-Whorfian claim that the grammatical gender of a noun influences the adjective choice to describe this noun, even when we control for the meaning of those nouns.

We first validate our model by comparing its results to the Williams et al.’s (2021) plug-in estimate of $\text{MI}(A; G)$. If the results of both of these estimates are comparable, we can assert that our model indeed captures the relation between grammatical gender and adjective choice. We present the results in Figure 2. We observe a substantial relationship between grammatical gender and adjective usage. Given the above result, we are interested in whether the strength of this relation is mitigated when controlling for the meaning of a noun. We present the estimates of the model-based $\text{MI}_{do}(A; G)$ in Table 3 and compare them to the model-based estimates of the $\text{MI}(A; G)$. While we observe evidence for the influence of grammatical gender on adjective choice in a non-causal setup based on $\text{MI}(A; G)$, this relationship shrinks to close to 0 when we control for noun meaning in our causal model trained using both word2vec and WordNet representations. For completeness, we test for the presence of a difference between the size of the $\text{MI}_{do}(A; G)$ of our model and a model trained on randomly perturbed gender labels and find that we reject the null hypothesis that the distributions are exactly the same for all languages and representations’ settings.

7 Discussion

Evidence against the neo-Whorfian hypothesis. We find that the interaction between the grammatical gender of inanimate nouns and the adjectives used to describe those nouns all but disappears when controlling for the meaning of those nouns, for all five analyzed gendered languages. The order of magnitude of $\text{MI}_{do}(A; G)$ measured with our model however significantly different from that of a model trained on random gender labels, is minuscule. This minor difference points towards the absence of a meaningful causal relationship between a noun’s gender and its descriptors in the languages studied. Thus, we provide an additional piece of evidence against the neo-Whorfian hypothesis.

A possible weakening of the neo-Whorfian hypothesis. Although the size of the overall effect is small, it is possible that the effect of gender
on adjective choice is stronger for some words than others. Future work could explore whether there is evidence of a noticeable effect of gender on adjective choice for a more restricted set of inanimate nouns, e.g., referring to artifacts or body parts. Such evidence could perhaps support a weakened version of the neo-Whorfian hypothesis.

Comparing results between word2vec and WordNet. These results hold for both of the word representation setups, word2vec and WordNet. Notably, in comparing the two, we find that using WordNet representations consistently result in a lower $\text{MI}_{do}(A; G)$ than word2vec for all languages analyzed in this study. One possible explanation for this difference is that, despite our efforts to make non-contextual word2vec representations, these word2vec representations may still pick up some signal for gender from the remaining context (such as verb choice or adjacent gendered pronouns in the corpora). If these word2vec representations contain unwanted context-based gender information in addition to the noun meaning, it could result in overestimating $\text{MI}_{do}(A; G)$. Furthermore, since WordNet representations are created independently from any context within a corpus, they should not contain intruding grammatical gender signals, which may therefore be reflected in the consistently lower $\text{MI}_{do}(A; G)$.

Design choices and limitations. We note several choices in the experimental setup which may influence this analysis. First, while we chose NorthEuraLex as a clean dataset to identify inanimate nouns, it excludes rarer nouns for which an effect might be observed. Second, while word embeddings are the current de facto representations for words in computational linguistics, they remain a proxy and are fundamentally limited. Furthermore, in our effort to learn word2vec representations for noun meaning without encoding gender-based context, we chose to remove some words in the context but not others. Specifically, while we remove adjectives which may carry signals of gender from the training corpora, we do not remove other parts of speech (e.g., verbs) under the reasoning that removing them may damage the training corpora too much for word2vec to effectively learn noun meanings. Future work can also explore improved representation methods for noun meaning. For example, Recski et al. (2016) find that creating non-contextual word representations using a combination of word2vec, WordNet, and concept dictionaries can yield a better representation of meaning (i.e., achieving state-of-the-art correlation with the human-annotated similarity scores). Third, the corpus choice (and subsequently the noun–adjective pairs on which we conduct our analysis) may factor into the results. It is possible that when applied to other corpora (e.g., more colloquial ones like Reddit), this method may yield different results. Fourth, the choice of languages analyzed further limits this study to languages with up to three gender classes. Future work can investigate languages with more complex gender systems. Finally, our modeling approach assumes that the gender of a noun is influenced solely by its meaning. However, prior work has indicated that there are other factors that influence the grammatical gender of nouns such as their phonology and/or morphology (Corbett, 1991). Therefore, future work should investigate more complex graphical models in order to account for other confounding factors.

8 Conclusion

In this paper, we introduce a causal graphical model which jointly represents the interactions between a noun’s grammatical gender, its meaning, and adjective choice. We employ our model on five languages that exhibit grammatical gender to investigate the influence of nouns’ gender on the adjectives chosen to describe those nouns. Repeating the findings of Williams et al. (2021), we find a substantial correlation between grammatical gender and adjective choice. However, taking advantage of our causal perspective, we show that when controlling for a noun’s meaning, the effect of gender on adjective choice is marginal. Thus, we provide further evidence against the neo-Whorfian hypothesis.

9Verbs may carry less signal for gender regardless. For example, Hoyle et al. 2019 find fewer significant differences in the usage of verbs than of adjectives towards people, and Williams et al. 2021 also report that verbs yielded smaller gender effects than adjectives.
A Proof of Proposition 1

Proposition 1. Let $A$ and $G$ be $A$-valued and $G$-valued random variables, respectively. Further assume they are jointly distributed according to $p(a \mid \text{do}(G = g))p_G(g)$. Then,

$$JS_{p_G}\left(\left\{p(\cdot \mid \text{do}(G = g))\right\}\right) = MI_{\text{do}}(A; G)$$

(4)

where $MI_{\text{do}}(A; G)$ is the mutual information computed under the joint distribution $p(a \mid \text{do}(G = g))p_G(g)$.

Proof: First, define the following distribution $m(a) \overset{\text{def}}{=} \sum_{g \in G} p_G(g)p(a \mid \text{do}(G = g))$. Now, the result follows by algebraic manipulation

$$JS_{p_G}\left(\left\{p(\cdot \mid \text{do}(G = g))\right\}\right) = \sum_{g \in G} p_G(g)KL\left(p(\cdot \mid \text{do}(G = g)) \mid\mid m\right)$$

(10a)

$$= \sum_{g \in G} p_G(g) \sum_{a \in \mathcal{A}} p(a \mid \text{do}(G = g)) \left(\log p(a \mid \text{do}(G = g)) - \log m(a)\right)$$

(10b)

$$= \sum_{g \in G} p_G(g) \sum_{a \in \mathcal{A}} p(a \mid \text{do}(G = g)) \log p(a \mid \text{do}(G = g)) - \sum_{g \in G} p_G(g) \sum_{a \in \mathcal{A}} p(a \mid \text{do}(G = g)) \log m(a)$$

(10c)

$$= -\sum_{g \in G} p_G(g)H(A \mid \text{do}(G = g)) - \sum_{g \in G} p_G(g) \sum_{a \in \mathcal{A}} p(a \mid \text{do}(G = g)) \log m(a)$$

(10d)

$$\overset{\text{def}}{=} H_{\text{do}}(A|G) - \sum_{a \in \mathcal{A}} m(a) \log m(a)$$

(10e)

$$= -H_{\text{do}}(A \mid G) - \sum_{a \in \mathcal{A}} \sum_{g \in \mathcal{G}} p_G(g)p(a \mid \text{do}(G = g)) \log m(a)$$

(10f)

$$= -H_{\text{do}}(A \mid G) - \sum_{a \in \mathcal{A}} m(a) \log m(a)$$

(10g)

$$= -H_{\text{do}}(A \mid G) + H_{\text{do}}(A) = H_{\text{do}}(A) - H_{\text{do}}(A \mid G) = MI_{\text{do}}(A; G)$$

(10h)

B Data Statistics

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Table 4: Data statistics in our Wikipedia corpora with retrieved word2vec and WordNet representations.
References


