Are Female Carpenters like Blue Bananas? A Corpus Investigation of Occupation Gender Typicality

Da Ju and **Karen Ulrich** and **Adina Williams**
FAIR Laboratories
Meta Platforms, Inc.
{daju, karenu, adinawilliams}@meta.com

Abstract

People tend to use language to mention surprising properties of events: for example, when a banana is blue, we are more likely to mention color than when it is yellow. This fact is taken to suggest that yellowness is somehow a typical feature of bananas, and blueness is exceptional. Similar to how a yellow color is typical of bananas, there may also be genders that are typical of occupations. In this work, we explore this question using information theoretic techniques coupled with corpus statistic analysis. In two distinct large corpora, we do not find strong evidence that occupations and gender display the same patterns of mentioning as do bananas and color. Instead, we find that gender mentioning is correlated with femaleness of occupation in particular, suggesting perhaps that woman-dominated occupations are seen as somehow "more gendered" than male-dominated ones, and thereby they encourage more gender mentioning overall.

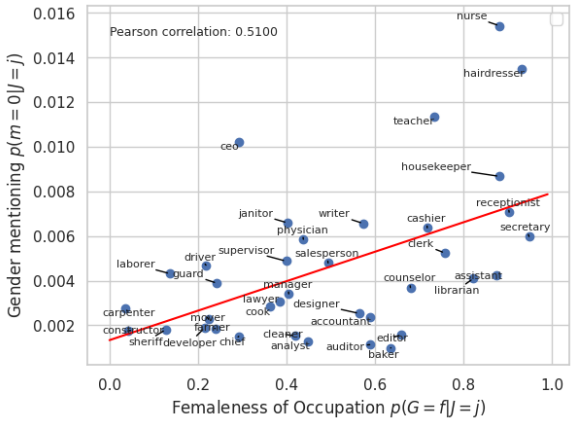


Figure 1: We found the strongest correlation between the femaleness of an occupation (according to US labor statistics) and gender mentioning in **Pushshift.io Reddit**, a surprising finding to some extent, because it contradicts the idea that gender mentioning occurs when special events are being pointed out. Instead, this finding points more to a gender-specific phenomenon.

1 Introduction

While people of any gender can do any job, most occupations in the current world are not fully gender-balanced, meaning a statistic association exists between particular genders and particular occupations. We can see evidence of such associations in how humans talk about occupations. When talking about a carpenter who is a woman—a male-dominated profession in the US—people may refer to her as "female carpenter". This usage suggests that a woman being a carpenter is rare (and potentially surprising), and thus some find it worth remarking upon explicitly. Men on the other hand, are more likely to be called "carpenter" instead of "male carpenter", presumably because the latter feels redundant or overinformative somehow.

Typicality effects such as these shape the way we use language in general. For example, Degen et al. (2020) adduced evidence for typicality effects in the color domain, finding that speakers never referred to an image of a lone yellow banana as "the yellow banana", but almost always referred to a lone blue banana as "the blue banana". Because we think of the (stereo-)typical banana as yellow, the blueness of a blue banana is more worth remarking upon than the yellowness of a yellow one. In this work, we explore a parallel phenomenon in the occupation gender space: Are there gender typicality effects for occupation nouns? If so, we expect more mentions of "male" when an occupation is woman-dominated, and more mentions of "female" when an occupation is man-dominated.

Alternatively, gender mentioning may occur more often when the gender associated with an occupation is salient. Past work in social psychology and gender studies has suggested that gender is generally more salient for women than for men. In particular, men are seen as more typical of the concept of "person" than women are, and that women are

Findings of the Association for Computational Linguistics: ACL 2024, pages 4254–4274
August 11-16, 2024

more associated with gender than men are (Gilman, 1911; Hamilton, 1991; Bem, 1993; Merritt and Kok, 1995; Bailey et al., 2019, 2020, 2022, 2024). Put simply, according to these theories, the concept of 'woman' differs from the concept of 'man' in that it has an additional semantic attribute that encodes cultural and/or biological facts or connotations (such as information about clothing, behaviors, etc.) that are associated with women.

In light of this past work, it is also plausible that associating women with "having gender" affects how we conceptualize woman-dominated occupations, such as "nurse" or "hairdresser". If woman-dominated occupations are indeed conceptualized as "more gendered", then encountering a woman-dominated occupation might make gender itself more salient, and lead to an increase gender mentioning in corpora. Were this to be the case, we would see higher overall mentioning of gender (with both "male" and "female" adjectives) for woman-dominated occupations.

In this study, we test these two hypotheses about occupation gender typicality using information theoretic approaches to analyze large text corpora. First, we set aside the null hypothesis that gender mentioning (modifying an noun with either "male" or "female" adjective) is completely unrelated to occupation gender (i.e., the empirical gender breakdown in the real population), see Section 5.1.

Next, we test the hypothesis that gender is more salient for women-dominated occupations. This hypothesis is borne out: We find that gender (both male and female) is mentioned more when the occupation is woman-dominated in our largest tested corpus, see Section 5.2. We report medium-to-large correlations between femaleness of occupation (the degree to which it is woman-dominated, according to U.S. labor statistics) and overall gender mentioning ($r = 0.49$), and for femaleness of mentioning ($r = 0.50$), maleness of mentioning ($r = 0.42$), respectively.

Finally, we test whether gender mentioning correlates with surprisingness, or non-typicality, of gender given an occupation. To test this, we define an information theoretic quantity based on the conditional entropy of female/male gendering given a particular job, whereby low occupation genderedness would correspond to a 50-50 gender breakdown. This can be seen as testing the "blue banana" hypothesis for occupation gender typicality, see Section 5.3. We do not find strong evidence for this hypothesis, with very weak correlations emerging for two different source datasets, Pushshift.io Reddit ($r = 0.13$) and Wikipedia ($r = -0.12$).

In sum, our results support the idea that occupation gender typicality is related to gender mentioning, but not in the way predicted by the "blue banana" hypothesis. Instead, gender mentioning appears to be more related to gender salience for woman-dominated occupations, at least for the the corpora we investigated.

To further analyze our results, we also explore three secondary questions. First, we ask: does corpus choice matter (see Section 5.4), and find that our effects are replicated in both Wikipedia and Pushshift.io Reddit, but that they are stronger for the Pushshift.io Reddit dataset. Second, we ask: do the empirical estimates of gender breakdown actually reflect the way people perceive the genderedness of occupations (see Section 5.5). Utilizing a standard word-embedding based method to determine perceived gender, we find that, while similar, perception and empirical observations do meaningfully differ. Third, we ask whether there are trends in the meaning of sentences which mention gender and occupations, such as negative sentiment (see Section 5.6).

2 Terminology and Notation

2.1 Terminology

Gender is a complex social phenomenon that manifests in how we use language and operate in our societies. Here, we draw upon a distinction described in Ackerman (2019) between social gender, which is how people see themselves in the world, and conceptual gender, which refers to how lexical items are associated with masculine or feminine properties, in the absence of explicit, formal grammatical features such as grammatical gender affixes, gender concord etc. (c.f. Hoyle et al. 2019; Williams et al. 2019, 2021). When we say "gender" in this work, we will be referring to conceptual gender.

Since occupation words can't encode the social genders of individuals in English (because English doesn't use grammatical gender marking systematically on all nouns), we decided to use the terms "female" and "male" here.[1] We will use the terms "woman" and "man" when referring to the social genders. For the most part, "man" and "woman" will be used for illustrative examples, or when we

[1]We use these terms instead of "feminine" and "masculine", because we want to avoid confusing occupation gender with the morphological categories of grammatical gender.

discuss the survey data from the U.S. Bureau of Labor Statistics, which is based on self-report.

In what follows, we have carved out a particular notion of gender which enables us to test existing hypotheses about the gender typicality of occupations. To do this, we have had to code gender as a binary variable. Clearly, this is not empirically sufficient to attain full coverage of all humans, as there are many genders in the English-speaking world, but we are restricted to this coding based on the availability of existing resources, see Section 3.1. Given our precise research questions, the restrictions we have inherited from existing resources do not overly limit or negatively impact our conclusions, as currently, we are aware of no occupations that appear to be "typical" of non-binary individuals or those with other genders. The lack of occupations typical of non-binary people is probably due to the small number of people who currently identify as non-binary, which are estimated to range from approximately 0.68% (Wilson and Meyer, 2021) to 1%[2] of the US population. This may change in the future, and we look forward to future research exploring the nature of this change.

2.2 Notation

We describe our notational conventions with respect to random variables, entropy, and mutual information in the Appendix A.

We specifically define three r.v.s in the context of this study; the occupation noun associated with a person J, the gender associated with the occupation noun G, and if that gender was mentioned as a descriptor M. M and G are assumed to have a binary alphabet in the context of this investigation: $\mathcal{M} = \{$'mention', 'no mention' $\}$, and $\mathcal{G} = \{$'female identifier', 'male identifier' $\}$, if appropriate we may also use $\{0, 1\}$ as shorthand notation for both. The alphabet for J is a list of 37 occupation nouns that we have specifically listed in Appendix B.1.

For example "female physician" is associated with ($j =$'physician', $m =$'mention', $g =$'female identifier'). Note that when $m =$'no mention', we can not determine g. Hence, we do not have access to the full joint distribution P_{JMG}. In Section 4, we will show how we can make statements about gender disparities, despite not being able to observe outcomes for g in many cases.

[2] Pew Research Center, 2022

3 Data Sources

We use four different data sources for this work, which we discuss in turn below.

To address our main research questions, we first find an empirical estimate of occupation gender (from the US Bureau of Labor Statistics). Then, we select two source corpora on which to run our analysis: We use Wikipedia and Pushshift.io Reddit, because they are extensive, openly available resources, which are commonly used in the NLP field, and frequently as training data for Language Models Language Models (LMs). Both should ensure a reasonable coverage of occupations with gender mentions for our analysis.

Finally, we prompt the opensource Llama 2 language model (Touvron et al., 2023) to regenerate text in the style of Wikipedia. We call this new dataset Llama 2 Wikipedia and use it to investigate whether occupation gender typicality measurements change as a result of a corpus being rewritten by an existing language model.

3.1 US Labor Statistics

Following Caliskan et al. (2017); Rudinger et al. (2018); Zhao et al. (2018); Bartl et al. (2020); González et al. (2020) i.a., our empirical estimates of occupation gender breakdowns have been obtained from the U.S. Bureau of Labor Statistics[3]. These estimates have been collected monthly by the Bureau of Census on behalf of the Bureau of Labor Statistics based on household survey. This survey, the Current Population Survey provides statistics about worker demographics, among other things, where individuals self-report their (binary) genders and occupations. We utilize labor statistics for 2023 (accessed in late fall).

We note that some occupations, such as 'attendant' are aggregated to include all roles with 'attendant' in their titles, including flight attendant, parking attendant, transportation service attendant, dining room and cafeteria attendants and bartender helpers. In some cases, occupations are missing from the statistics, so we substitute them with synonyms such as "Chief Executives" for "CEO" or "Police Officers" for "sheriff". The comprehensive aggregated statistics are available in Appendix H.

3.2 Pushshift.io Reddit

Building upon the work of Humeau et al. (2020), we employ a pre-established dataset sourced from

[3] https://www.bls.gov/cps/cpsaat11.htm

the online social forum, Reddit. This dataset, acquired and made available by an independent third party, can be accessed publicly on `pushshift.io` (Baumgartner et al., 2020). It encompasses data collected from PushShift[4] up to July 2019. We follow a similar data cleaning approach to Roller et al. (2020) to enhance the clarity of the signal. A comment, along with all its subsequent child comments, is eliminated if it fulfills any of the subsequent criteria: 1) The author's identifier includes the term 'bot'; 2) The origin of the comment is a known non-English Subreddit; 3) The comment is flagged as removed, deleted, or is devoid of content; 4) The comment comprises less than 70% alphabetic characters; 5) The comment contains a URL. To avoid comment repetition, we flatten each thread tree by concatenating comments in a pre-order traversal sequence. The processed data contains 301M threads.

3.3 Wikipedia

Wikipedia is a fairly large datasource containing encyclopedic information in many languages, which is moderated by volunteers. In conducting our research, we utilize an English Wikipedia dump dated April 2023. The dataset is prepared in accordance with the procedures outlined by Attardi (2015). This extracts articles and associated metadata from the raw XML files. Despite Wikipedia's general suitability to our research questions, it is worth noting that Wikipedia data tends to be stereotypically skewed towards men, as highlighted by Wagner et al. (2015); Schmahl et al. (2020); Falenska and Çetinoğlu (2021).

3.4 Linguistic Analysis

Upon obtaining the pre-processed datasets, we adhere to the pipeline delineated by Williams et al. (2021). For this endeavor, we utilize the Stanza tool (Qi et al., 2020). The pipeline comprises the following steps: 1) Tokenization & Sentence Segmentation; 2) Part-of-Speech (POS) Tagging: Each token is assigned grammatical information (e.g., noun, verb, adjective); 3) Lemmatization: Each token is reduced to its base form, facilitating the normalization and simplification of the text; 4) Dependency Parsing: This final phase involves analyzing the grammatical structure of each sentence, thereby establishing relationships between words, as described in Chen and Manning (2014). The size of the datasets, following this procedure, is detailed in Table 1.

Dataset	Size
Pushshift.io Reddit	118.81 billion
Wikipedia	3.01 billion
Llama 2 Wikipedia	2.98 billion

Table 1: Total size of datasets in (word) token count.

3.5 Extraction of gender - occupation pairs

Initially, our task involves extracting all occupation-related words from our text resource and isolating the subset that includes gender mentions. To accomplish this, we commence with a basic list of occupation nouns, sourced from the U.S. Bureau of Labor Statistics (Appendix B.1). Additionally, we utilize a concise list of gender adjectives, namely "male", "female", "masculine", "feminine", "man", "woman", "non-binary" and "nonbinary".[5]

Our approach involves identifying instances where an occupation noun appears in the text, followed by determining when a gender adjective modifies this noun. We then extract all `amod` dependencies, where an occupation noun serves as the head and a gender adjective as the dependent. In this way, we isolate all gender mentions and further categorize them by gender. The statistics pertaining to occupation mentions and gender-specific mentions derived from these pairs can be found in Tables E.1–E.3.

3.6 Llama 2 Wikipedia

Recent work has found that LMs can exacerbate gender imbalances present in their training data (Kotek et al., 2023). To investigate the extent to which LMs generate text that statistically matches what we find for occupation gender typicality, we investigate whether results would change if we examined a different version of Wikipedia, specifically one regenerated by an LM. If the results on LM-restructured Wikipedia are substantially different, it would suggest that the LM either introduces new gender bias, or removes existing gender bias. We utilize Llama 2 70B to generate Wikipedia content and subsequently analyze the distributional differences in occupation gender mentions. We confine our experiments in LM-generated datasets

[4] https://files.pushshift.io/reddit/

[5] We find very few occupation nouns modified with "nonbinary" in Wikipedia (40) and Pushshift.io Reddit (101), therefore exclude them from the analysis for lack of signal.

to Wikipedia, as Pushshift.io Reddit is too large to be tractable.

To generate new text, we provide the first 256 words from the original Wikipedia article, along with the article's title, from the original content describe above in Section 3.3. We instruct the model to produce an article of a minimum length of 700 words, aligning with approximately the average English Wikipedia article length of 658 words. The prompt used is in Appendix C to enable replicability of our results. We apply the same data processing and extraction procedure as for the original Wikipedia dataset. From Table 1, we can observe that the two are comparable in size.

We evaluate the BLEU score, a text similarity metric, between the original Wikipedia articles and those generated by Llama 2. Our findings reveal low BLEU scores (as detailed in Appendix D), indicating substantial textual differences between the original Wikipedia content and the Llama 2 regenerated versions. This suggests that the Llama 2 Wikipedia dataset warrants statistical analysis.

4 Methods

In this section, we will first describe how observed occurrence counts translate to probability mass functions (pmfs) relating to occupation, gender mentioning and gender. Henceforth, we describe how to compute quantitative markers for gender mentioning and gendered occupations, which we finally use to test our hypotheses from in Section 1.

4.1 Estimation of probability mass functions

The US Labor Statistics is our source to compute the the relationship of gender and occupation independent of gender mentioning in language. Specifically, we compute $P_{G,J}$ by dividing the number of men / women employed in a specific occupation by the total number of employees in the survey. This distribution will be used as the foundation to determine how statistically biased an occupation is with respect to gender.

For each text source, we first determine the likelihood of gender mentioning independent of the specific gender P_M. It is the number of gendered occupation mentions divided by the total number of occupation mentions. We further compute, the conditional joint distribution $P_{G,J|M=0}$. Similarly to the US Labor Statistics, we divide the number of male / female indicated occurrences of a specific occupation by the total number of gendered observations. Note that it would be more informative if we could compute $P_{G,J,M}$ directly, however since we can not determine gender if it is not mentioned, we need to approximate the joint distribution by combining information from the text source and US Labor Statistics.

4.1.1 Computing the joint

To compute $P_{G,J,M}$, we need the previously computed pmfs; $P_{G,J}$, P_M and $P_{G,J|M=0}$, where the latter two are computed from the text corpus, and the the first one is computed via the US Labor Statistics. By applying Bayes' theorem and the chain rule of probability, we can compute the joint likelihood as follows;

$$P_{G,J,M=0} = P_{G,J|M=0} \cdot P_{M=0} \tag{1}$$

$$P_{G,J,M=1} = \frac{P_{G,J} - P_{G,J,M=0}}{P_{M=1}} \tag{2}$$

$$P_{G,J,M} = P_{G,J|M} \cdot P_M \tag{3}$$

Note, that we assume that there exists a joint likelihood for which the US Labor Statistics is the correct marginal $P_{G,J} = \sum_m P_{G,J,M=m}$, and our text corpus gives the correct conditional $P_{G,J|M=0}$. This assumption can be a problem, when there is a statistical bias in what occupations are more prominent in a text sources as opposed to the labor statistics. This can be problematic for multiple reasons: (1) some occupations such as "author" will be overrepresented in a text source such as Wikipedia, and (2) the gender and job distribution of a text source and labor statics needs to match, which can easily not be true because either comes from a different cultural or temporal context. However, in our analysis especially for Pushshift.io Reddit, we believe there to be a good match, as Reddit was created in 2005 and sampled in 2019, and the labor statistics have in all likelihood not changed dramatically since then.

4.2 Gender bias in occupations

We generally cannot access how people perceive the gender typicality of an occupation directly from text, but we can hope their perceived typicality matches the real world gender breakdown[6]. Consequently, in this study, we propose to measure **occupation genderedness**, which we define as

$$1 - H(G|J = j). \tag{4}$$

[6]For words such as "manager" this might not always be correct.

Note that, according to our definitions in Appendix A, the entropy term will be in the range between 0 and 1. Consequently, occupation genderedness is low for unbiased occupations and high for gender biased occupations (i.e. man-dominated or women-dominated occupations). We further compute the **femaleness of occupation**;

$$P_{G=0|J=j}. \tag{5}$$

Both are computed from the US Labor Statistics joint distribution $P_{G,J}$.

We introduce both of these measures to test different hypotheses. The former measure is a symmetric estimator. If there is no gender specific surprise, we should find occupation genderedness to correlate well with gender mentioning, In other words we expect "male nurse" and "female CEO" to both be likely expressions. The second measure allows for detecting gender specific mentioning.

4.3 Gender mentioning in text

We measure two ways gender is mentioned in text: by computing (1) $P_{M=0|J=j}$ directly for the likelihood of any gender being mentioned, $P_{M=0|J=j,G=0}$ for femaleness being mentioned, $P_{M=0|J=j,G=1}$ for maleness being mentioned, and (2) the mutual information between gender and its mentioning $MI(G; M|J = j)$.

We can estimate the correlation strength of gender bias markers and gender mentioning markers by computing the Pearson correlation coefficient of a linear regression. Further, as discussed in (Caliskan et al., 2017), we can make group comparisons of mutual information between female and male occupations based on distance between text embeddings. The technical details can be found in Appendix G.

5 Results

5.1 Rejecting the Null Hypothesis

First, we test whether we can reject the null hypothesis that gender mentioning is unrelated with occupation genderedness. For this, we calculate the conditional mutual information, as described in Section 2.2. If the null hypothesis is true, if there is no correlation, and we expect $MI(M; G|J = j) = 0$. We present our results in Figure 2, with individual occupation noun results in Appendix I. These findings are compatible with the existence of relationship between gender mentioning and occupation genderness, and the next two sections will attempt to determine its nature.

5.2 Mentioning gender when it's female

Next, we explore the hypothesis that gender mentioning is correlated with femaleness of occupation $P_{G=f|J=j}$, under the assumption described in the introduction whereby woman-dominated occupations make gender more salient. We find that this is borne out for Pushshift.io Reddit, see Figure 8. We find significant correlations of moderate size between the femaleness of an occupation and mentioning of either gender ($r = 0.51$), mentioning of femaleness ($r = 0.50$), and mentioning of maleness ($r = 0.45$). Since this finding is robust across all three kinds of mentioning, we take this to be evidence in favor of the hypothesis that the female genderedness of woman-dominated occupations makes gender more salient in general, leading to more mentions of gender.

For Wikipedia, we do not find a strong effect of gender mentioning when female, see Figure 6. This effect is compatible with Wagner et al. (2015) and Schmahl et al. (2020), which find evidence, respectively, for linguistic gender bias in Wikipedia based on adjective sentiment and topic modeling or word embedding approaches. Our findings pertain to gender mention and occupation gender typicality, not to negative sentiment about women or whether stereotypes about family and science exist in the data source—both can be true simultaneously.

5.3 Ablation: Female Carpenters are not like Blue Bananas

We also explored the "blue banana" hypothesis: the gender which is not typical of the occupation will be mentioned. We defined occupation genderedness above as $1 - H(G = g|J = j)$, where low occupation genderedness meant 50-50 gender breakdown, or gender balance, and high occupation genderedness meant a strongly woman- or a man-dominated occupation. Our results found practically no correlation for either Pushshift.io Reddit or Wikipedia between occupation genderedness and gender mentioning, see Figure 4. We cannot verify a gender-occupation version of the "blue banana" hypothesis, and gender mentions appear to be affected by occupation genderness instead of surprise.

5.4 Strongest correlations from Pushshift.io Reddit

Our findings that gender mentioning is correlated with femaleness of occupation are not equally

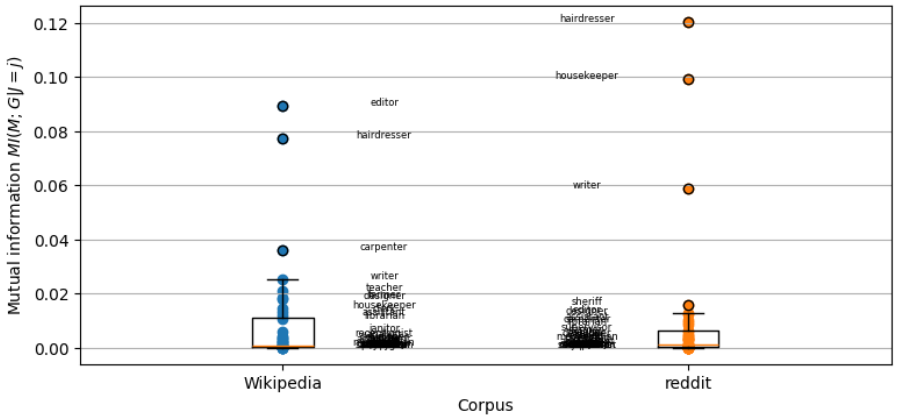
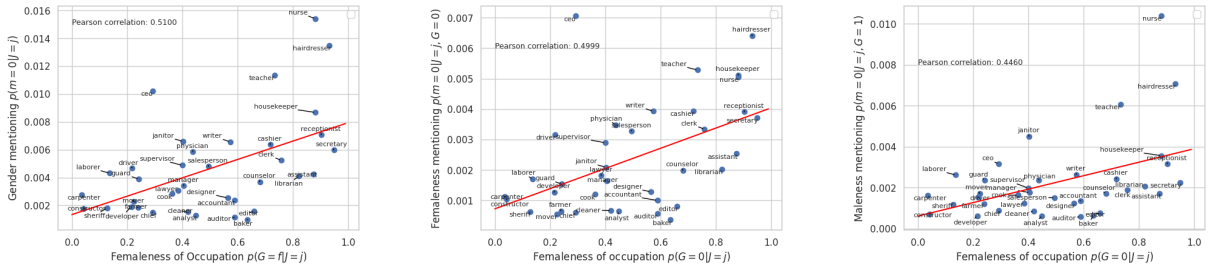


Figure 2: We calculate the conditional mutual information between gender and its mentioning by means of a gender indicator $MI(G; M|J = j)$. Very low mutual information indicates that variables are not correlated. We see a wide spread in MI across occupations j. However, we see similar occupations in the top spots for Wikipedia and Pushshift.io Reddit.



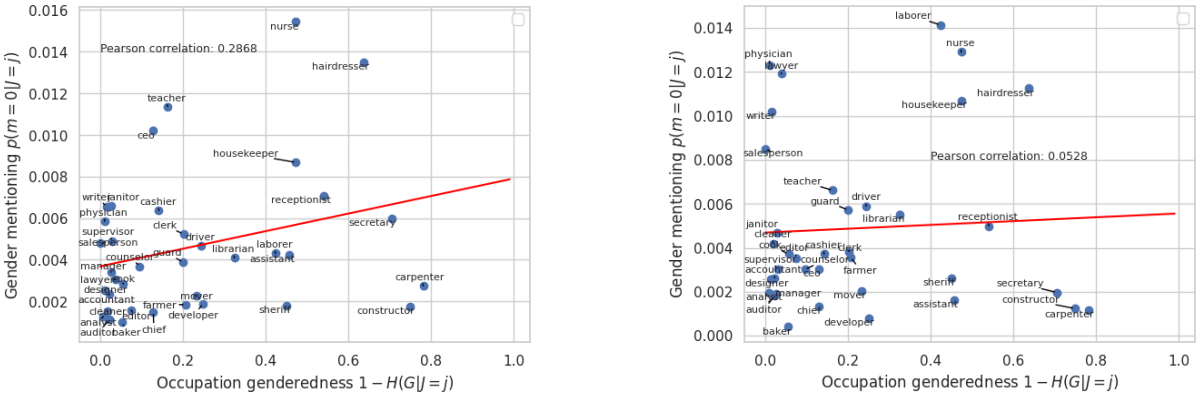
(a) (b) (c)

Figure 3: We found correlations between the femaleness of an occupation (according to US labor statistics) and (a) gender, (b) femaleness, (c) maleness mentioning in **Pushshift.io Reddit**.

present for all tested corpora: See Figure 5 and compare Figures 8-6 in the Appendix. We find that the correlations are medium sized for Pushshift.io Reddit, but very small for Wikipedia and even weaker for Llama 2 Wikipedia. We suspect the difference in correlation strength may be due to dataset size or to domain differences. On size, the Pushshift.io Reddit dataset is several times larger than the Wikipedia datasets, meaning there may be more signal to detect in Pushshift.io Reddit. On text domain, Pushshift.io Reddit has little centralized moderation and is very informal, while Wikipedia has clear style guidelines and an encyclopedic style. For example, Wikipedia policy describes "neutral point of view", or a prohibition on subjectivity, which may generally decrease the prevalence of adjectives thought to be evaluative or unnecessary.

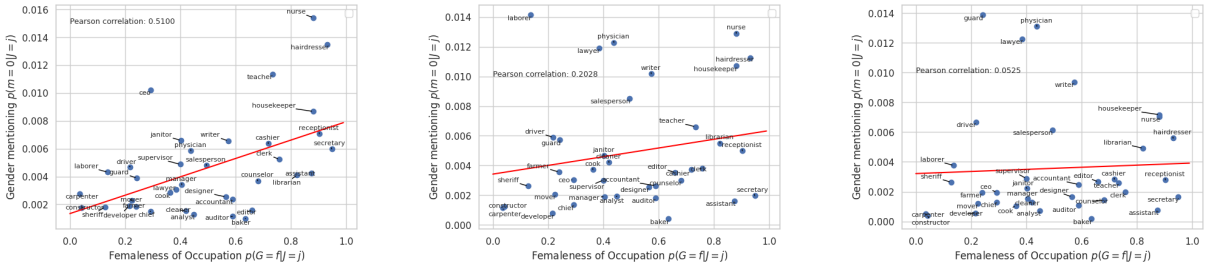
5.5 Female-coded vs female-dominated

Above, we compared ground truth occupation gender breakdown (from the US labor statistics) against gender mentioning. This presumes that the ground truth statistics accurately represent the way humans think about occupations and gender, although this may not always be the case. For example, Kotek et al. (2023) reported that people prefer stereotypical gender association with occupations over genders that actually match the ground truth. As an expression of this mismatch, people may presume, for example, that the typical 'CEO' is a man in our society, even when the occupation is not man-dominated according to our empirical statistics. To determine whether peoples' impression of an occupation's gender (and genderedness) differs from the empirical gender (and genderedness), we utilize cosine similarity as a measure of similarity. Following Bolukbasi et al. (2016) and Caliskan et al. (2017), we deem occupations female- or male-**coded** by computing cosine distance of word embeddings of an occupation and (fe)male attribute words (see more details in Appendix G). Depending on the distance between an occupation and an attribute word, we can resplit our occupation list into two groups (male- and female- coded),



(a) Pushshift.io Reddit (b) Wikipedia

Figure 4: Ablation: We tested the correlation of occupation genderness $1 - H(G|J = j)$ and gender mentioning. High occupation genderedness implies either a man- or woman-dominated occupation according to US labor statistics. Observed correlations are weak, eliminating the hypothesis that gender mention is a result of surprise.



(a) Pushshift.io Reddit (b) Wikipedia (c) LLama Wikipedia

Figure 5: Corpus comparison: The femaleness of occupation is most strongly correlated with gender mentioning in Pushshift.io Reddit. In Wikipedia, the effect is smaller, and interestingly, it keeps diminishing for Llama 2 Wikipedia.

and compute the average mutual information for both. For both Pushshift.io Reddit and Wikipedia, we find a significant group difference between the mutual information of female- and male- coded occupations. The mutual information for the female coded occupations is 0.0187 ± 0.0024 bits and 0.0161 ± 0.0012 bits, respectively. In contrast, the mutual information for the male coded occupations is 0.0026 ± 0.00003 bits and 0.0037 ± 0.00013 bits. In both cases, the female- vs male- coded groups are about an order of magnitude apart, indicating further evidence that mentioning is more correlated with perceived female occupations.

5.6 What is discussed when people mention gender?

One of our main findings is that occupations associated with women are more likely to be modified with adjectives signaling gender. However, these findings only point to the existence of an effect, they do not tell us, qualitatively, whether the gender mentions occur because of semantic trends present in the comments.

During qualitative exploration of the Pushshift.io Reddit dataset, we noticed that the vast majority of samples containing woman-dominated occupations (for "female/male nurse", for example) included derogatory, and/or sexually explicit content. Others examples discussed gender balance (or lack thereof) in particular occupations, or the experience of people holding non-gender typical roles. Another trend for sentences containing a woman-dominated occupation modified with "male" is that these were often negative sentiment. In a smaller number of examples, we also noticed discussions where the gender of a caregiver might be relevant (people expressing that they would prefer a gender matched nurse to care for them during a hospital stay).

To adduce a bit more quantitative description of these anecdotal observations, we sampled 80 comment threads that mentioned occupations and con-

tained an amod dependency with a gender adjective (20 of each types) to better understand what was being discussed when gender was mentioned. We performed three quantitative measurements: first, we measured comment sentiment, using the Stanza sentiment analysis tool (Qi et al., 2020). Next, we handcoded the samples for whether they contain offensive or inappropriate content, and/or whether the topic of discussion is gender balance in occupations. As anticipated, we find that sentiment is higher (0.6) when the occupation is man-dominated and modified with "male" than for the other three types (0.4 for "female carpenter" and "male nuse", and 0.3 for "female nurse"). See Table 8 for more summary statistics for percentage offensive and percentage discussing gender, respectively.

We also ran a logistic regression on offensiveness and occupation gender discussions, to visualize how strongly they might affect gender mentioning. In Figure 8, we report that more offensive language was present in discussions pertaining to woman-coded occupations like "nurse" than in man-coded ones like "carpenter". Gender-related conversations also highlight non-typical gender adjectives modifying occupations (e.g. "female carpenter" and "male nurse"). In sum, these exploratory results indicate that our main findings likely derive from offensive or negative sentiment conversations about women-coded occupations, or general conversations about gender-balance in occupations.

6 Related Work

Information Theory for Corpus Analysis. Increasingly, corpus analysis works have relied on information theoretic tools, particularly those pertaining to the lexical semantics of grammatical gender and related morphological specifications (Liu et al., 2019; McCarthy et al., 2020; Williams et al., 2019, 2020; Rathi et al., 2021; Williams et al., 2021; Chen et al., 2022; Stańczak et al., 2023).

Gender in Occupations. Occupations are interesting for studying gender in NLP. Early work on gender bias in word embeddings (Bolukbasi et al., 2016; Caliskan et al., 2017) spawned a wealth of work on social bias and occupations in sentiment analysis (Bhaskaran and Bhallamudi, 2019), coreference resolution (Zhao et al., 2018; Rudinger et al., 2018), probing for gender bias (Touileb et al., 2022), and multilingual applications (Stanovsky et al., 2019; Prates et al., 2020; Troles and Schmid, 2021; Corral and Saralegi, 2022).

7 Conclusion

We perform a corpus statistical analysis of Wikipedia and Pushshift.io Reddit, and find that there is a relationship between gender mentioning and occupation genderedness using information theoretic techniques. Unlike in other contexts, we find no evidence that gender mentioning is correlated with gender surprise. Instead, we find evidence that gender is more likely to be mentioned for woman-dominated occupations than man-dominated ones.

8 Limitations

While we have relied pretty heavily on Wikipedia, Pushshift.io Reddit, and the U.S. Labor Statistics as the basis of many of our quantities, other options may be possible. Some issues include: Wikipedia and the Labor statistics do not come from the same joint distribution, but are rather proxies with different bias problems. For instance, English Wikipedia has a fame bias (which could mean our estimates for less lucrative or impressive occupations are noisier), and the labor statistics has a location bias (being US specific, but not English specific). Moreover, there is potentially some temporal discrepancy between these two data sources, in that the Labor Statistics numbers are specific to a recent year (2023), but Wikipedia and Pushshift.io Reddit have been collectively edited and added to over decades.

As with all corpus analyses, our conclusions are limited by the available resources. The occupations we consider are restricted to conventionalized job titles, and therefore we may not be able observe the full range of gender mentioning phenomena. However, what corpus analyses lack in flexibility, they make up for in scale: this work is able to draw conclusions from a large corpus of existing text produced by English speakers, which can give us insights into occupation gender typicality.

9 Acknowledgments

We thank Mark Tygert for helpful discussions about our statistical methodology. We also thank our anonymous reviewers for suggesting a few interesting experiments, which we have incorporated into the paper in Section 5.6 and the Appendix.

References

Lauren M Ackerman. 2019. Syntactic and cognitive issues in investigating gendered coreference. *Glossa*.

Giuseppe Attardi. 2015. Wikiextractor. https://github.com/attardi/wikiextractor.

April H Bailey, Marianne LaFrance, and John F Dovidio. 2019. Is man the measure of all things? a social cognitive account of androcentrism. *Personality and Social Psychology Review*, 23(4):307–331.

April H Bailey, Marianne LaFrance, and John F Dovidio. 2020. Implicit androcentrism: Men are human, women are gendered. *Journal of Experimental Social Psychology*, 89:103980.

April H Bailey, Adina Williams, and Andrei Cimpian. 2022. Based on billions of words on the internet, people= men. *Science Advances*, 8(13):eabm2463.

April H Bailey, Adina Williams, Aashna Poddar, and Andrei Cimpian. 2024. Intersectional male-centric and white-centric biases in collective concepts.

Marion Bartl, Malvina Nissim, and Albert Gatt. 2020. Unmasking contextual stereotypes: Measuring and mitigating BERT's gender bias. In *Proceedings of the Second Workshop on Gender Bias in Natural Language Processing*, pages 1–16, Barcelona, Spain (Online). Association for Computational Linguistics.

Jason Baumgartner, Savvas Zannettou, Brian Keegan, Megan Squire, and Jeremy Blackburn. 2020. The pushshift reddit dataset. *Proceedings of the International AAAI Conference on Web and Social Media*, 14(1):830–839.

Sandra L. Bem. 1993. *The lenses of gender: Transforming the debate on sexual inequality*. Yale University Press.

Jayadev Bhaskaran and Isha Bhallamudi. 2019. Good secretaries, bad truck drivers? occupational gender stereotypes in sentiment analysis. In *Proceedings of the First Workshop on Gender Bias in Natural Language Processing*, pages 62–68, Florence, Italy. Association for Computational Linguistics.

Tolga Bolukbasi, Kai-Wei Chang, James Y Zou, Venkatesh Saligrama, and Adam T Kalai. 2016. Man is to computer programmer as woman is to homemaker? debiasing word embeddings. *Advances in neural information processing systems*, 29.

Aylin Caliskan, Joanna J Bryson, and Arvind Narayanan. 2017. Semantics derived automatically from language corpora contain human-like biases. *Science*, 356(6334):183–186.

Danqi Chen and Christopher Manning. 2014. A fast and accurate dependency parser using neural networks. In *Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 740–750, Doha, Qatar. Association for Computational Linguistics.

Sihan Chen, Richard Futrell, and Kyle Mahowald. 2022. Investigating information-theoretic properties of the typology of spatial demonstratives. In *Proceedings of the 4th Workshop on Research in Computational Linguistic Typology and Multilingual NLP*, pages 94–95, Seattle, Washington. Association for Computational Linguistics.

Ander Corral and Xabier Saralegi. 2022. Gender bias mitigation for NMT involving genderless languages. In *Proceedings of the Seventh Conference on Machine Translation (WMT)*, pages 165–176, Abu Dhabi, United Arab Emirates (Hybrid). Association for Computational Linguistics.

Judith Degen, Robert D Hawkins, Caroline Graf, Elisa Kreiss, and Noah D Goodman. 2020. When redundancy is useful: A bayesian approach to "overinformative" referring expressions. *Psychological Review*, 127(4):591.

Agnieszka Falenska and Özlem Çetinoğlu. 2021. Assessing gender bias in Wikipedia: Inequalities in article titles. In *Proceedings of the 3rd Workshop on Gender Bias in Natural Language Processing*, pages 75–85, Online. Association for Computational Linguistics.

Charlotte Perkins Gilman. 1911. *The man-made world*. Charlotte Company.

Ana Valeria González, Maria Barrett, Rasmus Hvingelby, Kellie Webster, and Anders Søgaard. 2020. Type B reflexivization as an unambiguous testbed for multilingual multi-task gender bias. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 2637–2648, Online. Association for Computational Linguistics.

Mykol C. Hamilton. 1991. Masculine bias in the attribution of personhood: People= male, male= people. *Psychology of Women Quarterly*, 15(3):393–402.

Alexander Miserlis Hoyle, Lawrence Wolf-Sonkin, Hanna Wallach, Isabelle Augenstein, and Ryan Cotterell. 2019. Unsupervised discovery of gendered language through latent-variable modeling. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 1706–1716, Florence, Italy. Association for Computational Linguistics.

Samuel Humeau, Kurt Shuster, Marie-Anne Lachaux, and Jason Weston. 2020. Poly-encoders: Transformer architectures and pre-training strategies for fast and accurate multi-sentence scoring.

Hadas Kotek, Rikker Dockum, and David Sun. 2023. Gender bias and stereotypes in large language models. In *Proceedings of The ACM Collective Intelligence Conference*, pages 12–24.

Shijia Liu, Hongyuan Mei, Adina Williams, and Ryan Cotterell. 2019. On the idiosyncrasies of the Mandarin Chinese classifier system. In *Proceedings of*

the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pages 4100–4106, Minneapolis, Minnesota. Association for Computational Linguistics.

Arya D. McCarthy, Adina Williams, Shijia Liu, David Yarowsky, and Ryan Cotterell. 2020. Measuring the similarity of grammatical gender systems by comparing partitions. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 5664–5675, Online. Association for Computational Linguistics.

Rebecca Davis Merritt and Cynthia J. Kok. 1995. Attribution of gender to a gender-unspecified individual: An evaluation of the people= male hypothesis. *Sex Roles*, 33:145–157.

Y Polyanskiy and Y Wu. 2014. Lecture notes on information theory.

Marcelo OR Prates, Pedro H Avelar, and Luís C Lamb. 2020. Assessing gender bias in machine translation: a case study with google translate. *Neural Computing and Applications*, 32:6363–6381.

Peng Qi, Yuhao Zhang, Yuhui Zhang, Jason Bolton, and Christopher D. Manning. 2020. Stanza: A python natural language processing toolkit for many human languages.

Neil Rathi, Michael Hahn, and Richard Futrell. 2021. An information-theoretic characterization of morphological fusion. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pages 10115–10120, Online and Punta Cana, Dominican Republic. Association for Computational Linguistics.

Stephen Roller, Emily Dinan, Naman Goyal, Da Ju, Mary Williamson, Yinhan Liu, Jing Xu, Myle Ott, Kurt Shuster, Eric M. Smith, Y-Lan Boureau, and Jason Weston. 2020. Recipes for building an open-domain chatbot.

Rachel Rudinger, Jason Naradowsky, Brian Leonard, and Benjamin Van Durme. 2018. Gender bias in coreference resolution. In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 2 (Short Papers)*, pages 8–14, New Orleans, Louisiana. Association for Computational Linguistics.

Katja Geertruida Schmahl, Tom Julian Viering, Stavros Makrodimitris, Arman Naseri Jahfari, David Tax, and Marco Loog. 2020. Is Wikipedia succeeding in reducing gender bias? assessing changes in gender bias in Wikipedia using word embeddings. In *Proceedings of the Fourth Workshop on Natural Language Processing and Computational Social Science*, pages 94–103, Online. Association for Computational Linguistics.

Karolina Stańczak, Kevin Du, Adina Williams, Isabelle Augenstein, and Ryan Cotterell. 2023. Grammatical gender's influence on distributional semantics: A causal perspective. *arXiv preprint arXiv:2311.18567*.

Gabriel Stanovsky, Noah A. Smith, and Luke Zettlemoyer. 2019. Evaluating gender bias in machine translation. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 1679–1684, Florence, Italy. Association for Computational Linguistics.

Samia Touileb, Lilja Øvrelid, and Erik Velldal. 2022. Occupational biases in Norwegian and multilingual language models. In *Proceedings of the 4th Workshop on Gender Bias in Natural Language Processing (GeBNLP)*, pages 200–211, Seattle, Washington. Association for Computational Linguistics.

Hugo Touvron, Louis Martin, Kevin Stone, Peter Albert, Amjad Almahairi, Yasmine Babaei, Nikolay Bashlykov, Soumya Batra, Prajjwal Bhargava, Shruti Bhosale, Dan Bikel, Lukas Blecher, Cristian Canton-Ferrer, Moya Chen, Guillem Cucurull, David Esiobu, Jude Fernandes, Jeremy Fu, Wenyin Fu, Brian Fuller, Cynthia Gao, Vedanuj Goswami, Naman Goyal, Anthony Hartshorn, Saghar Hosseini, Rui Hou, Hakan Inan, Marcin Kardas, Viktor Kerkez, Madian Khabsa, Isabel Kloumann, Artem Korenev, Punit Singh Koura, Marie-Anne Lachaux, Thibaut Lavril, Jenya Lee, Diana Liskovich, Yinghai Lu, Yuning Mao, Xavier Martinet, Todor Mihaylov, Pushkar Mishra, Igor Molybog, Yixin Nie, Andrew Poulton, Jeremy Reizenstein, Rashi Rungta, Kalyan Saladi, Alan Schelten, Ruan Silva, Eric Michael Smith, Ranjan Subramanian, Xiaoqing Ellen Tan, Binh Tang, Ross Taylor, Adina Williams, Jian Xiang Kuan, Puxin Xu, Zheng Yan, Iliyan Zarov, Yuchen Zhang, Angela Fan, Melanie Kambadur, Sharan Narang, Aurélien Rodriguez, Robert Stojnic, Sergey Edunov, and Thomas Scialom. 2023. Llama 2: Open foundation and fine-tuned chat models. *CoRR*, abs/2307.09288.

Jonas-Dario Troles and Ute Schmid. 2021. Extending challenge sets to uncover gender bias in machine translation: Impact of stereotypical verbs and adjectives. In *Proceedings of the Sixth Conference on Machine Translation*, pages 531–541, Online. Association for Computational Linguistics.

Claudia Wagner, David Garcia, Mohsen Jadidi, and Markus Strohmaier. 2015. It's a man's wikipedia? assessing gender inequality in an online encyclopedia. In *Proceedings of the international AAAI conference on web and social media*, volume 9, pages 454–463.

Adina Williams, Damian Blasi, Lawrence Wolf-Sonkin, Hanna Wallach, and Ryan Cotterell. 2019. Quantifying the semantic core of gender systems. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pages 5734–5739, Hong Kong, China. Association for Computational Linguistics.

Adina Williams, Ryan Cotterell, Lawrence Wolf-Sonkin, Damián Blasi, and Hanna Wallach. 2021. On the relationships between the grammatical genders of inanimate nouns and their co-occurring adjectives and verbs. *Transactions of the Association for Computational Linguistics*, 9:139–159.

Adina Williams, Tiago Pimentel, Hagen Blix, Arya D. McCarthy, Eleanor Chodroff, and Ryan Cotterell. 2020. Predicting declension class from form and meaning. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 6682–6695, Online. Association for Computational Linguistics.

Bianca D.M. Wilson and Ilan H. Meyer. 2021. Nonbinary LGBTQ adults in the United States. https://williamsinstitute.law.ucla.edu/publications/nonbinary-lgbtq-adults-us/.

Jieyu Zhao, Tianlu Wang, Mark Yatskar, Vicente Ordonez, and Kai-Wei Chang. 2018. Gender bias in coreference resolution: Evaluation and debiasing methods. In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 2 (Short Papers)*, pages 15–20, New Orleans, Louisiana. Association for Computational Linguistics.

A Notation

Throughout this work, we follow Polyanskiy and Wu (2014) for our notation. We denote a probability space as $(\Omega, \mathcal{F}, \mathbb{P})$. We define random variables (r.v.) as $X : \Omega \to \mathcal{X}$. We denote an r.v. as a capital letter, X, while their realizations are denoted by a lower case letter, x. The distribution of X is represented as P_X, which is a probability measure on the alphabet $\mathcal{X}$. We use p_X for probability mass function of P_X, we may often drop the subscript if the context is unambiguous. We use $P_{X|Y}$ for a conditional distribution, which can be thought of as a collection of probability measures on $\mathcal{X}$, one $P_{X|Y=y}$ for each value of y. Expectations are denoted either as $\mathbb{E}[X]$, or $\mathbb{E}_{x\sim P_X}[x]$, and similarly, $\mathbb{E}[f(X)]$ can also be denoted by $\mathbb{E}_{x\sim P_X}[f(x)]$. A concept of particular importance in this study is the entropy of a random variable, which is defined as the expected information content of a random variable X; $H(X) = \mathbb{E}_{x\sim P_X}[-\log_2 p(x)]$. We further will rely on mutual information, denoted as $I(X;Y)$. It quantifies the mutual dependence between two random variables X and Y. It is defined as $I(X;Y) = \mathbb{E}_{(x,y)\sim P_{X,Y}}[\log_2 \frac{p_{X,Y}(x,y)}{p_X(x)p_Y(y)}]$ and represents the reduction in uncertainty about X given the knowledge of Y, and vice versa.

B List of nouns

B.1 Occupation

accountant analyst assistant attendant auditor baker carpenter cashier ceo chief cleaner clerk constructor cook counselor designer developer driver editor farmer guard hairdresser housekeeper janitor laborer lawyer librarian manager mover nurse physician receptionist salesperson secretary sheriff supervisor teacher writer

C Prompt for Llama 2 Wikipedia

Generate a Wikipedia article on the topic of {title}.

Use the following first paragraph from the original Wikipedia article as a starting point:

{first 256 words}

Now, expand upon the provided paragraph by providing additional details, historical context, notable events, key figures, and any relevant subtopics. Aim for a well-structured and informative Wikipedia style article with a minimum length of 700 words. Ensure that the content is factually accurate, well-written, and on Wikipedia writing style.

D BLEU score between Wikipedia and Llama 2 Wikipedia

	BLEU-2	BLEU-3	BLEU-4
Median	0.13	0.11	0.09
Mean	0.16	0.14	0.12
95 percentile	0.39	0.35	0.33

Table 2: The table shows the mean, median, and 95th percentile of BLEU scores between original and Llama 2 Wikipedia articles. The observed low token overlap signifies substantial linguistic diversity, thereby establishing Llama 2 Wikipedia as a valuable dataset for analysis.

E Occupation mentions

E.1 Pushshift.io Reddit

Occupation	Total	Male	Female	Total gendered	Gendered %	Male %	Female %
accountant	429663	581	430	1011	0.24%	57.47%	42.53%
analyst	661383	415	428	843	0.13%	49.23%	50.77%
assistant	1090414	1878	2764	4642	0.43%	40.46%	59.54%
auditor	91014	52	51	103	0.11%	50.49%	49.51%
baker	569508	360	206	566	0.10%	63.60%	36.40%
carpenter	278880	454	315	769	0.28%	59.04%	40.96%
cashier	708872	1725	2789	4514	0.64%	38.21%	61.79%
ceo	1395508	4397	9846	14243	1.02%	30.87%	69.13%
chief	1889533	1671	1168	2839	0.15%	58.86%	41.14%
cleaner	781771	664	527	1191	0.15%	55.75%	44.25%
clerk	406230	771	1357	2128	0.52%	36.23%	63.77%
constructor	117540	83	123	206	0.18%	40.29%	59.71%
cook	6087570	9972	7298	17270	0.28%	57.74%	42.26%
counselor	870469	1481	1732	3213	0.37%	46.09%	53.91%
designer	1573543	1968	2019	3987	0.25%	49.36%	50.64%
developer	4871656	2996	6189	9185	0.19%	32.62%	67.38%
driver	9852935	15025	31213	46238	0.47%	32.49%	67.51%
editor	1315447	1004	1072	2076	0.16%	48.36%	51.64%
farmer	1608655	1923	1059	2982	0.19%	64.49%	35.51%
guard	5748190	13506	8836	22342	0.39%	60.45%	39.55%
hairdresser	106245	752	681	1433	1.35%	52.48%	47.52%
housekeeper	55326	197	283	480	0.87%	41.04%	58.96%
janitor	278991	1257	582	1839	0.66%	68.35%	31.65%
laborer	150724	394	256	650	0.43%	60.62%	39.38%
lawyer	4087070	5045	7446	12491	0.31%	40.39%	59.61%
librarian	236107	489	478	967	0.41%	50.57%	49.43%
manager	6103567	10731	10092	20823	0.34%	51.53%	48.47%
mover	185850	319	103	422	0.23%	75.59%	24.41%
nurse	2355458	24441	11889	36330	1.54%	67.27%	32.73%
physician	523220	1243	1820	3063	0.59%	40.58%	59.42%
receptionist	139164	440	544	984	0.71%	44.72%	55.28%
salesperson	81141	123	266	389	0.48%	31.62%	68.38%
secretary	623470	1405	2323	3728	0.60%	37.69%	62.31%
sheriff	418668	492	265	757	0.18%	64.99%	35.01%
supervisor	733711	1453	2124	3577	0.49%	40.62%	59.38%
teacher	8204500	49877	43351	93228	1.14%	53.50%	46.50%
writer	3804680	10034	14947	24981	0.66%	40.17%	59.83%

Table 3: Statistics of occupation mentions and gender-specific mentions in the Pushshift.io Reddit dataset.

E.2 Wikipedia

Occupation	Total	Male	Female	Total gendered	Gendered %	Male %	Female %
accountant	18223	16	32	48	0.26%	33.33%	66.67%
analyst	39200	18	58	76	0.19%	23.68%	76.32%
assistant	280051	146	306	452	0.16%	32.30%	67.70%
auditor	15418	3	25	28	0.18%	10.71%	89.29%
baker	74802	21	9	30	0.04%	70.00%	30.00%
carpenter	36691	28	15	43	0.12%	65.12%	34.88%
cashier	3767	1	13	14	0.37%	7.14%	92.86%
ceo	103697	27	289	316	0.30%	8.54%	91.46%
chief	571954	288	480	768	0.13%	37.50%	62.50%
cleaner	7370	9	22	31	0.42%	29.03%	70.97%
clerk	55621	63	150	213	0.38%	29.58%	70.42%
constructor	8910	2	9	11	0.12%	18.18%	81.82%
cook	102970	134	249	383	0.37%	34.99%	65.01%
counselor	14953	12	33	45	0.30%	26.67%	73.33%
designer	115606	53	242	295	0.26%	17.97%	82.03%
developer	80650	19	45	64	0.08%	29.69%	70.31%
driver	203909	291	911	1202	0.59%	24.21%	75.79%
editor	273589	120	843	963	0.35%	12.46%	87.54%
farmer	138372	171	322	493	0.36%	34.69%	65.31%
guard	275038	1037	537	1574	0.57%	65.88%	34.12%
hairdresser	3734	20	22	42	1.12%	47.62%	52.38%
housekeeper	5326	18	39	57	1.07%	31.58%	68.42%
janitor	3642	10	7	17	0.47%	58.82%	41.18%
laborer	13725	75	119	194	1.41%	38.66%	61.34%
lawyer	147598	252	1507	1759	1.19%	14.33%	85.67%
librarian	22557	18	106	124	0.55%	14.52%	85.48%
manager	371536	205	503	708	0.19%	28.95%	71.05%
mover	5365	10	1	11	0.21%	90.91%	9.09%
nurse	64244	349	480	829	1.29%	42.10%	57.90%
physician	92604	198	940	1138	1.23%	17.40%	82.60%
receptionist	2405	2	10	12	0.50%	16.67%	83.33%
salesperson	823	0	7	7	0.85%	0.00%	100.00%
secretary	343292	124	552	676	0.20%	18.34%	81.66%
sheriff	55098	82	62	144	0.26%	56.94%	43.06%
supervisor	32882	38	61	99	0.30%	38.38%	61.62%
teacher	305614	616	1404	2020	0.66%	30.50%	69.50%
writer	440711	717	3770	4487	1.02%	15.98%	84.02%

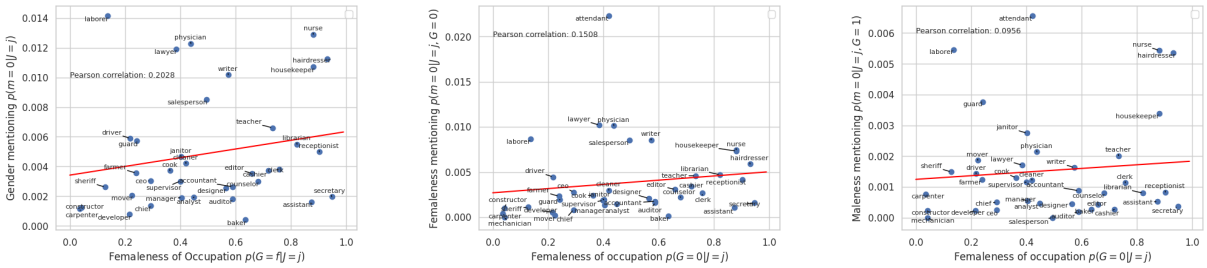
Table 4: Statistics of occupation mentions and gender-specific mentions in the Wikipedia dataset.

E.3 Llama 2 Wikipedia

Occupation	Total	Male	Female	Total gendered	Gendered %	Male %	Female %
accountant	20919	12	40	52	0.25%	23.08%	76.92%
analyst	61961	6	38	44	0.07%	13.64%	86.36%
assistant	309714	77	159	236	0.08%	32.63%	67.37%
auditor	13948	0	15	15	0.11%	0.00%	100.00%
baker	107206	13	5	18	0.02%	72.22%	27.78%
carpenter	56454	19	9	28	0.05%	67.86%	32.14%
cashier	2470	1	6	7	0.28%	14.29%	85.71%
ceo	230598	19	428	447	0.19%	4.25%	95.75%
chief	685222	226	658	884	0.13%	25.57%	74.43%
cleaner	7766	2	8	10	0.13%	20.00%	80.00%
clerk	59117	26	90	116	0.20%	22.41%	77.59%
constructor	7357	1	2	3	0.04%	33.33%	66.67%
cook	148143	43	113	156	0.11%	27.56%	72.44%
counselor	22234	9	23	32	0.14%	28.13%	71.88%
designer	295526	42	446	488	0.17%	8.61%	91.39%
developer	183697	21	80	101	0.05%	20.79%	79.21%
driver	362546	214	2205	2419	0.67%	8.85%	91.15%
editor	317236	54	789	843	0.27%	6.41%	93.59%
farmer	673603	278	1023	1301	0.19%	21.37%	78.63%
guard	273362	2425	1366	3791	1.39%	63.97%	36.03%
hairdresser	3399	4	15	19	0.56%	21.05%	78.95%
housekeeper	3068	6	16	22	0.72%	27.27%	72.73%
janitor	2701	5	1	6	0.22%	83.33%	16.67%
laborer	34311	47	82	129	0.38%	36.43%	63.57%
lawyer	302553	676	3030	3706	1.22%	18.24%	81.76%
librarian	29699	12	134	146	0.49%	8.22%	91.78%
manager	488888	72	674	746	0.15%	9.65%	90.35%
mover	4151	5	0	5	0.12%	100.00%	0.00%
nurse	70976	196	303	499	0.70%	39.28%	60.72%
physician	174951	125	2168	2293	1.31%	5.45%	94.55%
receptionist	1790	1	4	5	0.28%	20.00%	80.00%
salesperson	653	0	4	4	0.61%	0.00%	100.00%
secretary	358032	60	539	599	0.17%	10.02%	89.98%
sheriff	63367	65	102	167	0.26%	38.92%	61.08%
supervisor	34597	21	79	100	0.29%	21.00%	79.00%
teacher	543672	306	1109	1415	0.26%	21.63%	78.37%
writer	1247014	323	11335	11658	0.93%	2.77%	97.23%

Table 5: Statistics of occupation mentions and gender-specific mentions in the Llama 2 Wikipedia dataset.

F Correlation between femaleness of an occupation and mentioning in Wikipedia is weak



(a) (b) (c)

Figure 6: Correlation between femaleness of an occupation and mentioning in Wikipedia.

We found only weak correlations ($r \leq 0.20$) between the femaleness of an occupation (according to US labor statistics) and gender, femaleness, maleness mentioning in **Wikipedia**. The strongest correlation ($r = 0.20$) was for overall gender mentions.

G Female-coded and women-dominated

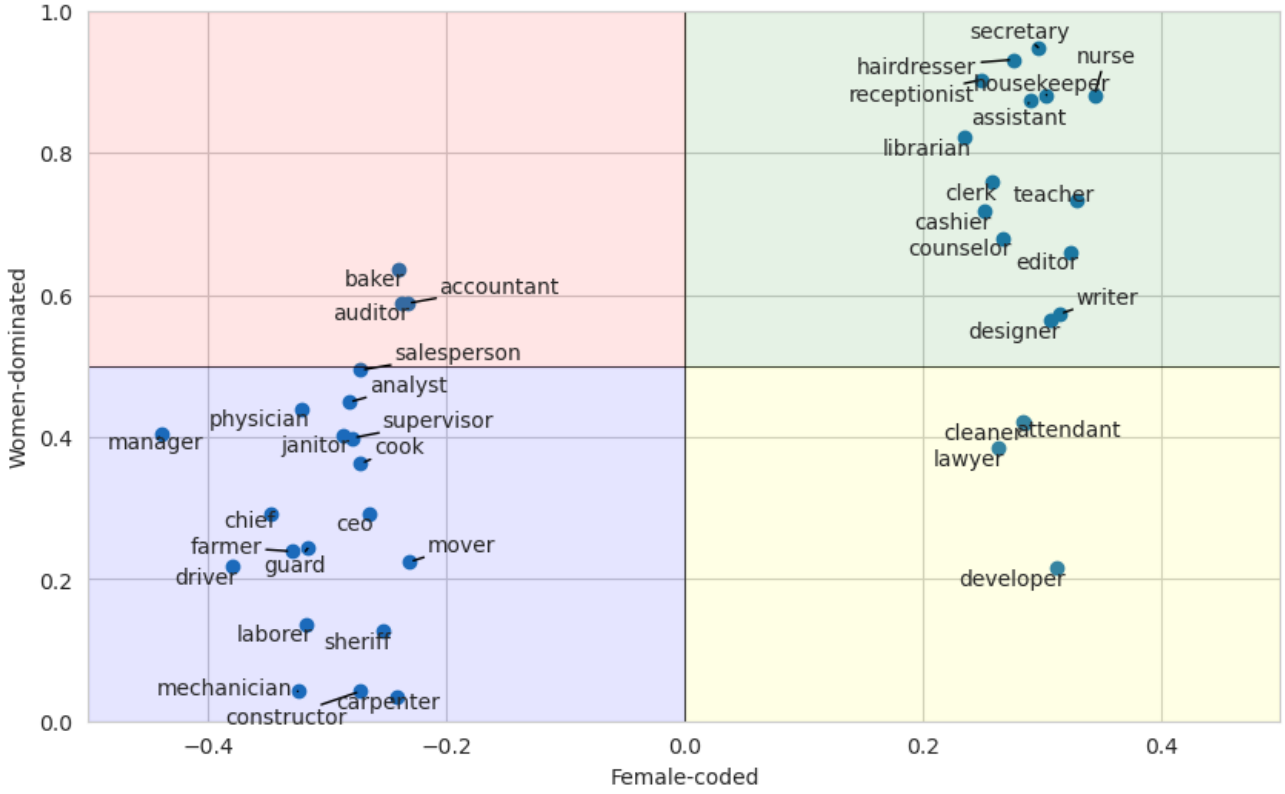


Figure 7: Plot of relationship between female-coded and women-dominated occupations.

The y-axis, representing woman-dominatedness, is defined by the percentage of female labor representation in each occupation according to the US Bureau of Statistics. The x-axis, representing female-codedness, is the perceived femaleness of an occupation, calculated by average cosine similarity of word embedding between the occupation and two groups of gendered adjectives [7] as a proxy. Defined as `similarity_female if similarity_female > similarity_male else -similarity_male` Occupations with a y-axis value exceeding 0.5 are considered women-dominated, while those with a positive x-axis value are deemed female-coded.

[7] ["male", "masculine", "man"] for the male group and ["female", "feminine", "woman"] for the female group.

H Comparison between Pushshift.io Reddit, Wikipedia and Labor Statistics

Occupation	Statistics	Wikipedia	Pushshift.io Reddit
accountant	58.80%	66.67%	42.53%
analyst	44.88%	76.32%	50.77%
assistant	87.48%	67.70%	59.54%
auditor	58.80%	89.29%	49.51%
baker	63.60%	30.00%	36.40%
carpenter	3.50%	34.88%	40.96%
cashier	71.80%	92.86%	61.79%
ceo	29.20%	91.46%	69.13%
chief	29.20%	62.50%	41.14%
cleaner	42.00%	70.97%	44.25%
clerk	75.81%	70.42%	63.77%
constructor	4.20%	81.82%	59.71%
cook	36.24%	65.01%	42.26%
counselor	67.97%	73.33%	53.91%
designer	56.37%	82.03%	50.64%
developer	21.51%	70.31%	67.38%
driver	21.80%	75.79%	67.51%
editor	66.00%	87.54%	51.64%
farmer	23.90%	65.31%	35.51%
guard	24.30%	34.12%	39.55%
hairdresser	93.10%	52.38%	47.52%
housekeeper	88.10%	68.42%	58.96%
janitor	40.20%	41.18%	31.65%
laborer	13.68%	61.34%	39.38%
lawyer	38.50%	85.67%	59.61%
librarian	82.20%	85.48%	49.43%
manager	40.50%	71.05%	48.47%
mover	22.40%	9.09%	24.41%
nurse	88.09%	57.90%	32.73%
physician	43.80%	82.60%	59.42%
receptionist	90.30%	83.33%	55.28%
salesperson	49.40%	100.00%	68.38%
secretary	94.80%	81.66%	62.31%
sheriff	12.70%	43.06%	35.01%
supervisor	39.86%	61.62%	59.38%
teacher	73.30%	69.50%	46.50%
writer	57.30%	84.02%	59.83%
average	46.90%	73.28%	50.96%

Table 6: Comparison of female representation in occupations vs. their proportional mentions in Wikipedia and Pushshift.io Reddit.

I Mutual information for Pushshift.io Reddit and Wikipedia

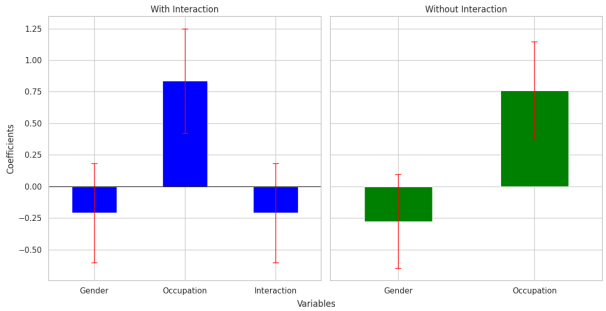
Occupations	MI Pushshift.io Reddit	MI Wikipedia
accountant	1.3E-03	2.1E-03
analyst	3.3E-03	3.8E-03
assistant	1.0E-02	1.2E-02
attendant	2.0E-05	5.4E-06
auditor	5.1E-04	2.7E-03
baker	3.5E-03	1.9E-03
carpenter	9.5E-03	3.6E-02
cashier	2.2E-05	2.5E-04
ceo	4.3E-04	3.2E-04
chief	1.9E-05	7.4E-04
cleaner	3.6E-06	1.5E-04
clerk	3.8E-03	1.3E-02
constructor	5.4E-06	3.1E-06
cook	3.3E-05	1.3E-04
counselor	4.9E-04	1.4E-04
designer	1.3E-02	1.8E-02
developer	4.4E-03	3.1E-03
driver	1.5E-03	1.5E-04
editor	1.3E-02	8.9E-02
farmer	5.8E-03	1.8E-02
guard	8.9E-04	7.2E-04
hairdresser	1.2E-01	7.7E-02
housekeeper	9.9E-02	1.5E-02
janitor	7.5E-05	6.0E-03
laborer	8.6E-06	9.6E-05
lawyer	2.3E-04	5.1E-05
librarian	8.6E-03	1.1E-02
manager	1.1E-03	2.0E-04
mover	3.2E-04	1.9E-03
nurse	5.9E-04	6.1E-04
physician	2.8E-03	5.6E-06
receptionist	5.2E-05	4.1E-03
salesperson	8.9E-05	1.8E-04
secretary	2.8E-04	2.9E-04
sheriff	1.6E-02	8.6E-04
supervisor	6.5E-03	4.6E-04
teacher	4.8E-03	2.1E-02
writer	5.9E-02	2.5E-02

Table 7: Computation of Mutual Information for each occupation across Pushshift.io Reddit and Wikipedia datasets.

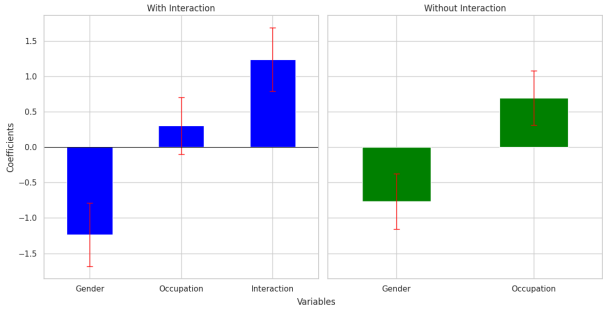
J Annotation of samples from Pushshift.io Reddit

	Female Carpenter	Male Carpenter	Female Nurse	Male Nurse
Sentiment Score	0.4	0.6	0.3	0.4
IsOffensive %	0.5	0.4	0.7	0.6
IsTalkingAboutGender %	0.8	0.3	0.7	0.6

Table 8: Summary of statistics from 80 Pushshift.io Reddit comments mentioning these occupations (20 each). The metrics shown are averages. Sentiment scores range from 0 to 2 (0 = negative, 1 = neutral, 2 = positive), obtained using Stanford Stanza sentiment analysis model. The categories 'IsOffensive' and 'IsTalkingAboutGender' are annotated by the authors using a binary system (0 = No, 1 = Yes), with the percentages indicating the average frequency of 'Yes' responses.



(a) Regression coefficients predicting IsOffensive



(b) Regression coefficients predicting IsTalkingAboutGender

Figure 8: In our study, we used an XNOR operation to create an interaction variable between gender (Female = 0, Male = 1) and occupation (Carpenter = 0, Nurse = 1), identifying non-typical roles (Male Nurses and Female Carpenters) as 1. The interaction has minimal impact in example (a) but is crucial in example (b). Figure 8a reveals more offensive language in discussions about female-coded roles like "nurse", while Figure 8b shows that non-typical gender roles are often highlighted in gender-related conversations.