Gender Bias in Text: Labeled Datasets and Lexicons

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Language has a profound impact on our thoughts, perceptions, and conceptions of gender roles. Gender-inclusive language is, therefore, a key tool to promote social inclusion and contribute to achieving gender equality. Consequently, detecting and mitigating gender bias in texts is instrumental in halting its propagation and societal implications. However, there is a lack of gender bias datasets and lexicons for automating the detection of gender bias using supervised and unsupervised machine learning (ML) and natural language processing (NLP) techniques. Therefore, the main contribution of this work is to publicly provide labeled datasets and exhaustive lexicons by collecting, annotating, and augmenting relevant sentences to facilitate the detection of gender bias in English text. Towards this end, we present an updated version of our previously proposed taxonomy by re-formalizing its structure, adding a new bias type, and mapping each bias subtype to an appropriate detection methodology. The released datasets and lexicons span multiple bias subtypes including: Generic He, Generic She, Explicit Marking of Sex, and Gendered Neologisms. We leveraged the use of word embedding models to further augment the collected lexicons. The underlying motivation of our work is to enable the technical community to combat gender bias in text and halt its propagation using ML and NLP techniques.

CCS Concepts: • Social and professional topics \rightarrow Gender; • Computing methodologies \rightarrow Language resources; Natural language processing.

Additional Key Words and Phrases: gender bias, dataset, lexicon, generic pronouns, stereotyping bias, sexism, exclusionary terms, semantic bias

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1 INTRODUCTION

Bias is prevalent in every aspect of our lives. We are hardwired to compartmentalize our experiences to form a plausible perception of our surroundings. Prejudices are typically manifested during the process of forming these perceptions, allowing for blatant inequalities to shape across different demographics. Given that language is the primary tool used to convey our perceptions, then any form of biased misrepresentation has the potential to change how an entity is portrayed in our minds. The source of bias in language can be traced to an androcentric worldview which was prevalent among 18th-century grammarians and was centered around the belief that: "human beings were to be considered male unless proven otherwise" [5]. Given that there is clear evidence of gender bias in most languages and its direct contribution to reinforcing and socializing sexist thinking [19],

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then there is a need to detect and highlight these manifestations in the ever-growing repertoire of textual content on the internet alongside printed writings such as educational textbooks.

Previously, most proposed solutions to detect gender bias in text were based on the frequency of gendered words and pronouns, in contrast, a feature-based approach would focus on capturing contextual and semantic queues in its classification process. Recently, Word Embedding (WE) and Contextual Word Embedding (CWE) models have become the predominant representation of text features, however, they are prone to capture biases inherited from training data. Despite the numerous attempts to debias these models, it was proven that these methods simply cover up systematic gender biases in word embeddings rather than removing them entirely [4, 18]. Additionally, WE and CWE models by themselves are not useful to detect gender bias in unseen data. As a result, there is a need for labeled representative datasets and lexicons to train supervised learning models and employ lexicon-based approaches in an effort to automate the detection of gender bias in English text.

Towards this end, we present an updated version of our previously proposed taxonomy by reformalizing its structure, adding a new bias type, and mapping each bias subtype to an appropriate detection methodology [11]. The updated taxonomy incorporates 5 bias types including: *Generic Pronouns, Stereotyping Bias, Sexism, Exclusionary Terms*, and *Semantic Bias*. Each bias type is also broken down into a set of subtypes that are respectively mapped to their societal implications [11]. Additionally, the updated taxonomy maps each bias subtype to an automated detection methodology based on its linguistic nature.

Given that there is a clear lack of representative data with regards to gender bias, the main objective of this work is to collect and label datasets that encompass the various subtypes in our taxonomy. Taking into account the specificity of the taxonomy requirements and the generality of sentences available in open-source mediums, several information retrieval and filtering methods were employed to collect representative sentences for each subtype of our taxonomy before we started labeling. The methodology of collecting representative sentences is dependent on each bias subtype. For instance, *Generic Pronouns* can be retrieved by leveraging specific linguistic patterns and advanced information retrieval queries as detailed in Section 4.1. Alternatively, for the *Explicit Marking of Sex* lexicon, we started with an initial list and augmented it by utilizing the cosine similarity and euclidean distance of the word's vector representation using various WE models as detailed in Section 5.1.

After having retrieved potentially biased sentences with a high recall, 9 graduate-level annotators were assigned the task of labeling the sentences. The labeling process was guide-lined by defining 10 clear examples of every bias subtype. These examples acted as a template for every bias subtype by highlighting their nuances and thus minimizing any ambiguity in the labeling process. After clearly identifying the differences between the bias subtypes, our contributors were evaluated on 100 prelabeled sentences (golden standard) to help identify potentially misleading bias classes. The output of this assessment was a set of classes that are being constantly misclassified in the assessment and that required several judgments by other contributors. Following the initial assessment, the sentences were loaded into a semantic annotation platform, in which every contributor classified a sentence into one of several subtypes while also highlighting the index of the biasing term(s). The sentences that are within the misleading subtypes will be judged by all 9 contributors, taking the majority vote as the final label. Additionally, to assess the clarity of the guidelines and the inter-rater reliability of the annotators, we computed Cohen's Kappa score across all annotations. In our case the inter-rater agreement (Cohen's Kappa) was exceptionally high, ranging from 0.70 to 0.88, confirming that the annotation process was guide-lined and executed clearly.

To sum up, the main contribution of this work is to provide labeled datasets and exhaustive lexicons by collecting, annotating, and augmenting relevant sentences to leverage the use of ML

and NLP techniques for detecting gender bias in texts. The labeled datasets are contingent on a linguistically-backed taxonomy that clearly distinguishes between various subtypes of gender bias. The released datasets and lexicons can be found at: Link

2 RELATED WORK

2.1 Taxonomies

Hitti et al. attempted to address bias at the sentence level and provided an initial categorization of gender bias types [20]. Doughman et al. developed a more comprehensive taxonomy to identify various types and subtypes of gender bias in English text [11]. The taxonomy was improved by linking each bias subtype in the taxonomy to its most practical detection methodology. In this work, we provide an updated version of our previous taxonomy by re-formalizing its structure, adding a new bias type, and mapping each bias subtype to its most practical detection methodology.

2.2 Datasets

Due to the existing lack of a gender bias taxonomy in recent literature, most publicly available labeled datasets were centered around sexist statements, considering them the only form of gender bias. As shown below, almost all of the described datasets are addressing the two forms of sexist statements: benevolent sexism and hostile sexism. Hence, there is a need for well-representative datasets to detect the other overlooked forms of gender biases that are equally as detrimental.

- 2.2.1 Waseem&Hovy: Waseem and Hovy used various self-defined keywords to fetch tweets that are potentially sexist or racist by filtering the Twitter stream for two months [41]. The authors then labeled the data with the help of one outside annotator [41]. Additionally, they also annotated tweets that were neither sexist nor racist [41].
- 2.2.2 Jha&Mamidi: Jha and Mamidi augmented Waseem and Hovy's dataset to include instances of benevolent sexism: sentences with a subjectively positive tone that implies that women are in need of special treatment and protection from men, and consequently furthering the stereotype of women as less capable [22]. The authors collected data using terms, phrases, and hashtags that are "generally used when exhibiting benevolent sexism" [22]. They then requested that three external annotators cross-validate the tweets to mitigate any annotator bias [22].
- 2.2.3 AMI@Evalita and AMI@IberEval: The Automatic Misogyny Identification (AMI) competitions in Ibereval 2018 [14] and Evalita 2020 [13] provided datasets in English, Spanish, and Italian to detect misogynistic content, to classify misogynous behaviour as well as to identify the target of a misogynous text.
- 2.2.4 EXIST@IberLEF:. Rodríguez-Sánchez et al. collected a repertoire of popular sexist terms and expressions in both English and Spanish [35]. The authors extracted the phrases and expressions from various tweets that women receive on a day-to-day basis on Twitter [35]. The terms and expressions collected were commonly used to downplay and underestimate the role of women in our society [35].
- 2.2.5 "Call Me Sexist(,) But": Samory et al. gathered data from Twitter's Search API by utilizing the phrase "call me sexist(,) but" [36]. To annotate their retrieved sentences using crowd-sourcing, they ran a pilot study and noticed a statistically significant priming effect of the "call me sexist(,) but" introduction to tweets on the annotators: if interpreted as a disclaimer, annotators would have tendency to presume that whatever follows is automatically sexist, more so than when the phrase was not there [36]. Consequently, they removed the given phrase for all annotation tasks (i.e., labeling requested that the annotator only label the remainder of each tweet (e.g. "Call me

sexist, but please tell me why all women suck at driving." to "please tell me why all women suck at driving.") [36].

2.2.6 Chowdhury et al.: Chowdhury et al. aggregated experiences of sexual abuse in Twitter using the "MeToo" hash-tag to facilitate a better understanding of social media constructs and to bring about social change. [7]. They released a comprehensive dataset and methodology for detection of personal stories of sexual harassment on Twitter [7]. Their work provided resources to clinicians, health practitioners, caregivers, and policy makers to identify communities at risk [7].

Dataset	Reference	Labels	Size
Waseem&Hovy	[41]	racism, sexism, neither	16K
Jha&Mamidi	[22]	benevolent, hostile, others	22K
AMI@Evalita	[13]	misogynous, not misogynous	10K
AMI@IberEval	[14]	misogynous, not misogynous	8K
EXIST@IberLEF	[35]	sexist, not sexist	11K
"Call Me Sexist(,) But"	[36]	(sexist, not sexist) + toxicity	14K
Chowdhury et al.	[7]	recollection, not recollection	5K

Table 1. Overview of datasets in related work

2.3 Lexicons

- 2.3.1 Psychological Scales for Measuring Sexism: due to a lack of definition of sexism that is comprehensive and universally-agreed upon, Samory et al. worked on curating a selection of psychological scales, designed for measuring sexism and related constructs in individuals [36]. The author's initial selection includes scales that were specifically designed to measure the construct of sexism or are frequently used to measure sexism in the social psychology literature [36]. They further augmented their initial selection to include scales that were designed to measure constructs such as general attitudes towards men or women, egalitarianism, gender and sex role beliefs, stereotypical beliefs about men or women, attitudes towards feminism or gendered norms [36].
- 2.3.2 Bem Sex Role Inventory (BSRI):. Bem developed a sex-role inventory that considers masculinity and femininity as two distinct dimensions, thereby halting the ability of characterizing a person as masculine, feminine, or "androgynous" as a function of the difference between her or his endorsement of masculine and feminine personality traits [2].
- 2.3.3 The Personal Attributes Questionnaire (PAQ):. Spence et al. augmented the conceptual analysis of the PAQ by appending a larger variety of self-reported measures. Additionally, the base includes data from an entirely new domain of personality measurement-observer ratings [37].

Lexicon	Reference	Туре
Psychological Scales for Measuring Sexism	[36]	scales
Bem Sex Role Inventory (BSRI)	[2]	inventory
The Personal Attributes Questionnaire (PAQ)	[37]	questionnaire

Table 2. Overview of lexicons in related work

2.4 Word Embedding Bias

Manifestations of different kinds of biases have been shown to exist in various components used to develop NLP and ML systems, from training data to pre-trained models to algorithms and resources [9, 12, 30, 31, 39]. Although several papers discussed various methodologies to de-bias word embedding models, these techniques have been scrutinized on several occasions [4, 18]. Gonen and Goldberg has shown with clustering that debiased word embeddings still contain biases and concluded that the existing bias removal techniques are insufficient, and should not be trusted for providing gender-neutral modeling [18]. Using such models to detect whether new sentences are biased or not will only project the remaining biases of the model. In addition, the majority of research did not focus on the impact of gender bias in real-word applications [4].

Furthermore, several work highlighted gender bias in various contextual word embedding model, such as BERT [10] and other contextual word embedding models such as ELMO [21], and, more recently, ALBERT [26]. Experimental results showed that there is a "significant dependence of the system's predictions on gender-particular words and phrases" [3]. They reached this conclusion by analyzing the induction of gender bias in five downstream applications related to emotion and sentiment intensity prediction [3]. For each task, they trained a simple regressor utilizing BERT's word embeddings and then evaluated the gender-bias in regressors using an equity evaluation corpus [3]. Additionally, Kurita et al. used the predictions of the mask tokens to measure the bias encoded in the actual representations [24]. They directly queried the underlying masked language model in BERT to compute the association between gendered words and career-related words [24] and concluded that BERT has human-like biases, which are propagated to downstream tasks [24]. Automatic detection of gender bias beyond the word level requires an understanding of the semantics of written human language, which remains an open problem and successful approaches are restricted to specific domains and tasks. Rather than removing gender bias in current machine learning models, we are tackling the issue at its root and creating a gender bias dataset such that supervised learning models can be trained to detect gender bias in unseen data. Enabling a model to learn gender bias would allow for the detection and possible mitigation of gender biases in text.

3 IMPROVED GENDER BIAS TAXONOMY

The first step of detecting biased language is to categorize the various forms of that bias while carefully maintaining a clear segregation between the resultant groups. This section presents an updated version of our previously proposed taxonomy by re-formalizing its structure, adding a new bias type, and mapping each bias subtype to an appropriate detection methodology. The below taxonomy includes a wide range of gender bias types and their subsequent subtypes. Each subsection includes the definition of a bias subtype and a few examples that illustrate its usage in a sentence. Table 3 provides an overview of the taxonomy, with one example pertaining to each subtype. The table also maps each bias subtype to its most practical detection methodology (supervised learning or lexicon-based).

3.1 Generic Pronouns

Given that the choice of a pronoun follows the sex of the referent, a problem arises when a pronoun is used with sex-indefinite antecedents [32]. Generic pronouns occur when a pronoun is used as a referent to nouns of no specific gender. The most notable forms of generic pronouns are: *generic he* and *generic she* [32].

- 3.1.1 *Generic He.* Below are some example of generic he sentences:
 - The client should receive **his** invoice in two weeks.
 - A good employee knows that **he** should strive for excellence.

- A teacher is expected to be a good role model in all areas of **his** life.
- 3.1.2 *Generic She*: Below are some example generic she sentences:
 - A nurse should ensure that **she** gets adequate rest.
 - A dancer should watch **her** diet carefully.
 - **She** presents us diverge ways, but **she** lets us choose our path.

3.2 Stereotyping Bias

- *3.2.1 Societal Stereotype:* It is the assumption that certain characteristics or behaviors are unique to specific social group [27]. They depict traditional gender roles that reflect social norms. [20, 38]. Below are a few examples that depict the concept of societal stereotypes:
 - Senators need their wives to support them throughout their campaign.
 - The event was kid-friendly for all the mothers working in the company.
- *3.2.2 Behavioural Stereotype:* It is a sentence that contains attributes and traits used to describe a specific person or gender. This bias assumes the behaviour of a person from their gender.
 - All boys are aggressive.
 - Mary must love dolls because all girls like playing with them.

3.3 Sexism

According to the ambivalent sexism theory, sexism against women is divided into an aggressive expression, known as hostile sexism, and a positive expression, known as benevolent sexism [17]. This section will cover the two divergent forms of sexist language:

- 3.3.1 Hostile Sexism. It is the view of men as more powerful and competent than women [1]. It views women as a threat to men's dominance through their violation to traditional gendered roles in the society [1, 29]. Below are some examples of hostile sexist statements:
 - The people at work are childish. It's run by women and when women don't agree to something, oh man.
 - Women are incompetent at work.
- 3.3.2 Benevolent Sexism. It is a softer form of sexism that expresses male dominance in a more chivalrous tone [1]. Benevolent sexism describes women as caring, innocent, and in need of men's protection, and these stereotypical notions are used to reinforce women's subordinate position [8]. Below are some examples of benevolent sexist statements:
 - They're probably surprised at how smart you are, for a girl.
 - No man succeeds without a good woman besides him. Wife or mother. If it is both, he is twice as blessed.

3.4 Exclusionary Terms

Exclusionary terms occur when an unknown gender-neutral entity is referred to using gender-exclusive term(s). The two forms of exclusionary terms are: (1) explicit marking of sex and (2) gendered-neologisms. Both forms are analogous, in which they're both exclusionary, but differ in their adoption rate.

3.4.1 Explicit Marking of Sex. A few examples that illustrate this bias subtype are the following: (1) using the term "Businessman" (gender-exclusive) to reference a gender-neutral entity, in this case being a business manager (2) using the term "Policeman" rather than "Police officer" (3) using the expression "Founding Fathers" to denote founders, whose gender is generally unknown (4) using

Table 3. Overview of the taxonomy and link to detection methodology

Bias Type	Bias Subtype	Example	Methodology
Generic Pronouns	Generic He	A programmer must carry his laptop with him to work.	Supervised Learning
	Generic She	A nurse should ensure that she gets adequate rest.	Supervised Learning
Stereotyping Bias	Societal Stereotypes	Senators need their wives to support them throughout their campaign.	Supervised Learning
	Behavioural Stereotypes	The event was kid-friendly for all the mothers working in the company.	Supervised Learning
Sexism	Hostile Sexism	Women are incompetent at work.	Supervised Learning
	Benevolent Sexism	They're probably surprised at how smart you are, for a girl.	Supervised Learning
Exclusionary Terms	Explicit Marking of Sex	Chairman, Businessman, Manpower, Cameraman	Lexicon-Based
	Gendered Neologisms	Man-bread, Man-sip, Mantini	Lexicon-Based
Semantic Bias	Metaphors	"Cookie": lovely woman.	Supervised Learning
	Old Sayings	A woman's tongue three inches long can kill a man six feet high.	Supervised Learning

the term "Brotherhood" to denote solidarity. The examples illustrated above are widely adopted and integrated into people's lexical choice. Consequently, detecting and proposing solutions to such terms is essential in halting their propagation.

3.4.2 Gender-based Neologisms. Neologisms are newly coined words/expressions that may possibly be in the process of mainstream adoption, however, they have not yet been fully accepted. Gender-based neologisms are gendered coinages that could have underlying stereotypical tendencies [15]. Below are some examples:

- Man-bread: bread that is baked so big that it will take a grown man a whole week to eat it, having 4 slices a day.
- Man-sip: a man sized sip of a beer or drink, one can finish a beer in 4 or 5 Man-sips. For a female or light weight, it borders on chugging the drink, but for a man it is merely a sip.
- Man-Purse: an over the shoulder bag used by urban males.

3.5 Semantics

Gender bias in semantics appears when utilizing words and sentences that are demeaning in their semantic meaning [40]. The implicit meaning behind sexist jokes, proverbs, or even using specific non-human terms to refer to women, consciously or unconsciously, deepens the existing bias and projects it onto new generations [40]. The current study suggests three types of semantic gender bias: metaphors, gendered attributes, and old sayings.

- 3.5.1 Metaphors. People tend to express a part of the world's reality through metaphors, which contributes to ingraining their culture and beliefs. By looking into the window of metaphors, several biases of society are revealed [34]. Masculinity and bias against females are represented in metaphoric words that describe women as a non-human comparing females to food, animals, plants [25, 28]. Below are some examples of English metaphoric words that describe woman as food and animal:
 - "Cookie": lovely woman
 - "Old Hen": middle aged women who love to talk to each other
- 3.5.2 Old Sayings. Biased old sayings come in various forms including: proverbs, set-phrases, and formulaic expressions that present a source of stereotype against women. Those sayings are culturally seen as axioms and absolute truth, which affect people behavior to adapt them as moral standards [28]. Below are sentences exemplifying implicit sexism in proverbs:
 - A woman's tongue three inches long can kill a man six feet high
 - When you see an old man, sit down and take a lesson; when you see an old woman, throw a stone

4 GENERIC PRONOUN DATASETS

Detecting any form of gender bias in English text in a supervised learning fashion is contingent on a labelled dataset that conforms with its linguistic requirements. To date, no labelled datasets have been publicly released pertaining to generic pronouns. Towards this end, the below sections describe the automated data retrieval methodology utilized to retrieve generic pronoun sentences, the annotation tool/process utilized to label the retrieved sentences, and the inter-rater agreement of the contributors.

4.1 Automated Data Retrieval

As described in Section 3.1, a pronoun typically follows the sex of its referent. However, when the referent is sex-indefinite, the pronoun becomes generic since it would be generalizing the sex of the pronoun onto the gender-neutral entity it's referencing. The most notable form of a generic pronoun sentence occurs when a pronoun's referent is a sex-indefinite occupation. Taking the below examples, we notice that a pattern prevails.

- Example #1: "A programmer must always carry his laptop to work"
- Example #2: "A nurse should ensure that she gets adequate rest"
- Pattern: "A occupation * pronoun"

In the case that the pronoun is referring to an occupation rather than a sex-definite person (subject), then the pronoun becomes generic. In an effort to retrieve generic pronoun sentences in an automated fashion, we combined the above linguistic pattern with advanced information retrieval queries. Having applied the above pattern, we were able to retrieve biased sentences with an acceptable recall score. However, we did notice that there were instances were the above pattern occurs, but the pronoun does not end up being generic. Taking the below examples, it is clear that a sentence could contain both a pronoun and an occupation, but the pronoun's referent would not be the occupation but rather a sex-definite person.

- Biased: "A programmer must always carry his laptop to work"
- Not Biased: "John, a *programmer*, always carries *his* laptop to work"

In order to increase the recall of positive (biased) instances in our retrieval process, we categorized the retrieved sentences into three types: declarative, imperative, and interrogative. We concluded that when the agreed upon pattern is formalized in an interrogative manner (question), it most frequently happens to be biased. This case is especially valid in question-answering platforms since the questioner would not be referencing a person, but rather asking a question in a general manner. The below examples illustrate our hypothesis:

- "How often does a programmer update his skills?"
- "Can you identify a programmer based on his code?"
- "Can a programmer in his 50s fit in well with a team of programmers in their 20s?"

As shown above, general interrogative sentences typically reduce the chance of a sex-definite subject occurring, which results in more biased sentences retrieved. Alternatively, declarative sentences typically contain a vague reference or a reference to a known subject in previous sentences. However, given that we are currently solely retrieving and labeling one distinct sentence at a time, a multi-sentence reference is problematic in associating a pronoun from one sentence to a potentially sex-definite subject in another sentence. For future work, we aim to retrieve and label paragraphs rather than sentences and integrate co-reference resolution to minimize any ambiguity regarding the sex of a pronoun's referent. We will also aim to investigate the effect of a generic pronoun questions onto the bias-ness of the answer-er.

Based on the above findings, we focused on automating the retrieval of sentences that conform with our pattern for positive instances. The total number of sentences retrieved are 700. The dataset spans 29 occupations with at least 20 sentences per occupation. The retrieved sentences, alongside their annotations, were augmented to reach 3,500 sentences as detailed in Section 4.4.

4.2 Annotation Process

After having retrieved 700 potentially biased sentences following the patterns described in Section 4.1, we loaded the sentences into INCEpTION, a semantic annotation tool used for concept linking, fact linking, and knowledge base population [23]. The total number of contributors tasked with labelling the sentences are nine. All contributors are graduate-level university students with extensive experience regarding gender bias. Additionally, most annotators are familiar with the gender bias taxonomy described in Section 3, which further enhanced their understanding of biased and non-biased statements.

The contributors were tasked with labelling each sentence as biased or not. If the sentence was biased, the annotators were also asked to highlight the generic pronoun and its sex-indefinite referent (occupation). If the sentence was not biased, the annotators were asked to highlight the

non-generic pronoun and its sex-definite referent (subject). To ensure that the annotators were well-equipped to differentiate between the required classes, a guideline of around 10 sentences was presented. Furthermore, few golden standard sentences were randomly inserted to evaluate the contributor's understanding of the labelling process. Table 4 illustrates a few examples.

Table 4. Overview of annotation process

Sentence	Label
A programmer must always carry his laptop to work. Jennie is a rapper, her voice is suited for rapping. Can you judge a nurse's professionalism by his/her demeanor in the nurse station?	Biased Not Biased Avoiding Bias

As shown in Table 4, there are instances where the pronoun is referencing a sex-indefinite occupation but the sentence is not biased. We call these cases: "Avoiding Bias", since we consider that the writer is aware of the gender bias and is avoiding it by replacing a generic pronoun with "his/her". For future work, replacing a generic pronoun with "his/her" or "her/his" could be a viable gender bias mitigation technique.

4.3 Inter-rater Agreement

Cohen's Kappa is a frequently used to test inter-rater reliability. The significance of the reliability of a rater stems from the fact that it signifies the degree to which the data collected in the study are correct representations of the variables measured. Thus, inter-rater reliability is defined as the extent to which data collectors (raters) award the same score to the same variable. In our case the inter-rater agreement was exceptionally high, ranging from 0.70 to 0.88, which confirmed that the annotation process alongside the guidelines were clear and that the the expertise of the contributors is demonstrated.

4.4 Dataset Augmentation

To augment our dataset based on our initial annotations, we generated multiple variants of the same sentence by solely altering its pronoun. Provided that appending the opposite pronoun "her/his" or "his/her" would negate a sentence's bias, we replaced every generic pronoun, such as "her", with a negation which resulted in a non-biased variant of the primary sentence. Alternatively, replacing "his/her" or "her/his" with "his" in one sentence and "her" in a another sentence resulted in two new biased sentences from one unbiased one. The examples below illustrate the process of generating two new biased sentence from one unbiased sentence using our proposed technique:

- Original Sentence: How often does a programmer update his/her skills?
- Augmented Sentence #1: How often does a programmer update his skills?
- Augmented Sentence #2: How often does a programmer update her skills?

Augmenting the dataset resulted in 2,400 additional sentences. Furthermore, the integrity of the annotations is preserved since the augmentation process solely altered one token in each sentence and thus did not change its overall meaning. To further augment the dataset, we interchanged the occupation with synonyms that preserved the meaning of the sentence. This process resulted in a dataset of 5000 sentences.

5 EXCLUSIONARY TERMS LEXICONS

Exclusionary terms occur when an unknown gender-neutral entity is referred to using gender-exclusive term(s). One example is adding the gender-exclusive sub-word (e.g. "man") onto a gender-neutral occupational term (e.g. "Police"), resulting in "Policeman". The resultant biased word implies that all police officers are men, which excludes women. The reverse, concatenating "woman" with "Police" resulting in "Policewoman", is also applicable since it would be implying that all police officers are women. The presence of exclusionary terms in language has proven to have various negative societal implications. For instance, sex-biased wording affects a person's perception of a career's attractiveness [6]. Consequently, countries that adopt a gendered language tend to have disproportionate labor force participation [16]. Furthermore, the presence of gender bias in the language used by parents and in school text books may cause children to develop sexist perceptions and behaviors towards other children of opposite gender and deepens the problematic outcomes of gender inequalities in society [42]. Therefore, the aim of the below sections is to provide a list of terms that are exclusionary, in hopes of halting their propagation and subsequently their societal implications.

5.1 Explicit Marking of Sex Lexicon

The section describes the source of the initial lexicon and the NLP techniques utilized to augment the word list. The initial explicit marking of sex lexicon was curated from a guideline report published by the United Nations Economic and Social Commission for West Asia (UNESCWA) "Gender Sensitive Language" [?]. They provided a list of violating terms and proposed a correction for each one. However, the list only spans 86 words and is not sufficient enough to cover all exclusionary terms in the English language. To augment the initial lexicon, we leveraged a word embedding model's ability to associate terms that have similar meaning using the cosine similarity of their vector representations. We started by loading various pre-trained Word2Vec [?] models that possess a large vocabulary size. We then computed the cosine similarity of each lexicon word against all other words in a model's vocabulary. The results were ranked in descending order of cosine similarity values, essentially pinning the most similar word vectors on top. We then selected each of the top-100 most similar word vectors and appended them into a set of unique similar words. This resulted in a set of 8,600 distinct words that are potentially exclusionary. Below is an example of the top-5 most similar word vectors to "Salesman":

Similar Word	Cosine Similarity	Euclidean Distance
Salesperson	0.92	0.08
Repairman	0.86	0.14
Peddler	0.83	0.17
Deliveryman	0.77	0.23
Businessman	0.73	0.27

Table 5. Top-5 most similar words to "Salesman"

As shown in Table 5, although some word vectors are close in the embedding space to the original exclusionary term, however, they are not necessarily biased since they aren't unknown gender-neutral entities being referred to using a gender-exclusive term. To filter out non-exclusionary terms, we kept the tokens that contain a gender-exclusive sub-string (e.g. "man"). For example, we would filter out words such as "feminine" and retain words such as word "womanly". This rule proved to be effective in filtering out words that do not contain sub-strings that explicitly

mark a certain sex. To conclude, for a word to be appended to this lexicon, it has to be close in the embedding space to an valid lexicon exclusionary word, contains a "man" sub-string, and validated by an annotator.

5.2 Gendered Neologisms

As discussed in Section 3.4.2, neologisms are newly coined terms that are in the process of mainstream adoption, however they have not yet been entirely recognized. Gender-based neologisms are therefore gendered exclusionary coinages with underlying biased tendencies [15]. They are analogous to explicit marking of sex terms, in which they're both exclusionary, but differ in their adoption rate. Explicit marking of sex terms are more commonly used and accepted terms such as "Policeman" and "Businessman" while gender-based neologism are newly coined and are in the process of mainstream adoption such as "Man-tini" and "Man-bread". Thus, the significance of detecting and mitigating gender-based neologisms is critical in halting its propagation and ability to become widely adopted and integrated into the English language. To this end, this section describes the process of curating and filtering gender-based neologism terms from the Urban Dictionary [33].

5.2.1 Urban Dictionary: due to the emergence of dynamic webpages and the ability for internet technologies to seamlessly permit exchanges between a user and a database, various crowd-sourcing platforms rose to the forefront. One example of such platforms is UrbanDictionary.com (UD), which is built by the collaboration of contributing end-users, allowing users who are not trained lexicographers to engage in the actual making of dictionaries [33]. UD is a popular online slang dictionary that demonstrates how traditional lexicographic principles are combined with Web-only communication technologies to provide a context for collaborative engagement and meaning-making, as well as to highlight the many features and functions shared by traditional print dictionaries [33]. By relying on language users to choose and define terms for a dictionary, UD – which defines over one million words – has altered both access to and formulation of the lexis [33]. However, because UD is an open-source platform, any internet user may submit a new dictionary term entry that they feel is or should be used in a mainstream way [33]. This becomes troublesome when the newly formed phrases supplied are prejudiced, and their acceptance might be destructive to society. Table 6 illustrates a few examples of dictionary word entries on UD that have exclusionary and stereotypical tendencies. In an effort to detect and mitigate the adoption of such terms, the aim

Word Definition Up Votes Down Votes Manboobs Name given to a Male's breasts when 167 67 they grow to abnormally large size. Manboobs are common on the heavier sized males, and are not to be mistaken for a normal female's breasts. Similar to the feminine tampon, the mas-Manpons 338 201 culine "manpon" is used for the reduction of sweat between the cheeks of the buttocks, placed firmly between the cheeks in times of high pressure, stress, or sweat-causing situations.

Table 6. Urban dictionary samples

of the below section is to provide a means of finding such exclusionary terms among the UD by filtering it through specific sub-strings and up-vote counts.

5.2.2 Filtering Technique. Given that the UD currently stands at more than 2 million words in total, it wasn't feasible for us to manually go through and label each word as biased or not. To accurately select newly coined exclusionary terms from UD, a two-step process is presented. Firstly, we compartmentalized the dictionary by filtering out all the word that don't contain a gender-exclusive sub-word (e.g. "man"). This left us with around 25,000 newly coined terms that are potentially exclusionary. To trim the dictionary even further, we filtered out words that have less than 100 up-votes to distinguish between terms that are accepted by the community and are on the brink of mainstream adoption compared to words that the community itself is against its use. This step further reduced the dictionary size to around 2,500 potentially biased terms. We finally manually labelled the remaining sentences as exclusionary based on the author's definition of the term. The final lexicon spans around 500 newly coined biased terms. We hope that our work provides a means to the technical community to detect and mitigate the use of such terms to halt their propagation and subsequent adoption.

6 CONCLUSION

In conclusion, the fundamental contribution of this work is to offer labeled datasets and exhaustive lexicons by collecting, annotating, and augmenting representative sentences. This work also offers an insight onto the automated data retrieval and annotation methodologies utilized to fetch and label the retrieved sentences. In a future work, we will address the issue of pronoun resolution by considering surrounding sentences or entire paragraphs. We will also aim to further augment our datasets and lexicons to expand their coverage to the remaining bias types. We hope that the labeled datasets and lexicons, backed by our improved taxonomy, can pave the way for the technical community to detect and mitigate gender bias in English texts using ML and NLP techniques.

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