What do Bias Measures Measure?

Sunipa Dev*1  
Emily Sheng*2  
Jieyu Zhao*1  
Jiao Sun2  
Yu Hou2

Mattie Sanseverino1  
Jiin Kim1  
Nanyun Peng1,2  
Kai-Wei Chang1

1University of California, Los Angeles  
2University of Southern California

Abstract

Natural Language Processing (NLP) models propagate social biases about protected attributes such as gender, race, and nationality. To create interventions and mitigate these biases and associated harms, it is vital to be able to detect and measure such biases. While many existing works propose bias evaluation methodologies for different tasks, there remains a need to cohesively understand what biases and normative harms each of these measures captures and how different measures compare. To address this gap, this work presents a comprehensive survey of existing bias measures in NLP as a function of the associated NLP tasks, metrics, datasets, and social biases and corresponding harms. This survey also organizes metrics into different categories to present advantages and disadvantages. Finally, we propose a documentation standard for bias measures to aid their development, categorization, and appropriate usage.

1 Introduction

As language technologies and their applications become more widely deployed in society, there is also an increasing concern of the disparate impacts and potential harm these technologies could have on different demographic groups (Bolukbasi et al., 2016; Webster et al., 2018a; Dev and Phillips, 2019). To address these concerns, a large body of work has since emerged to discuss, detect, quantify, and mitigate the social biases and harms propagated by NLP techniques. These works typically include bias measures comprising of metrics and accompanying datasets to investigate specific definitions of social biases as within the constructs of a specific NLP task, such as text classification or machine translation. While this body of work is essential for understanding the variety of potential harms, there remains a gap in understanding the biases and normative harms each measure captures (Blodgett et al., 2020) and which of these measures is most apt to evaluate harms in a given model, task, or application. Without a better comparative understanding of bias measures, it is difficult to measure the community’s progress as a whole. As an example, for the task of coreference resolution, there are several measures (Zhao et al., 2018; Rudinger et al., 2018; Lu et al., 2020; Webster et al., 2018b) investigating gender bias. However, each measure is unique in either the metric, the sentence structures, or the definition of bias.

To aid more comprehensive understanding, we present a survey to organize how bias measures are related and questions we can ask to document the development of future measures. There are other related surveys on existing bias mitigation methods in natural language understanding (NLU) (Sun et al., 2019), biases in natural language generation (NLG) (Sheng et al., 2021), adapted definitions of biases (Blodgett et al., 2020), and the relation between large language models and harms (Bender et al., 2021). This work further builds on existing findings to focus specifically on bias measures.

First, we define several terms (Sec. 2) and survey different measures for biases in NLP (Sec. 3). Next, we categorize measures by associated task, demographic dimensions, and normative definitions of harm (Sec. 4); we explain how these categories drive appropriate measure selection. Finally, we propose a set of documentation questions to facilitate more contextualized development of bias measures (Sec. 5). For this final contribution, we expand upon the Datasheets questions from Gebru et al. (2018) to explicitly highlight the information necessary for a bias measure in NLP to be used effectively and result in meaningful progress in the scientific community.

2 Definitions

To start, we clarify the definitions of several terms used throughout the rest of this work.
| Task                          | Primary Dimension | Secondary Dimension | Measures                                                                 |
|-------------------------------|-------------------|---------------------|--------------------------------------------------------------------------|
| Coreference Resolution        | Gender            | Identity Terms      | Webster et al. (2018b); Cao and Daumé III (2020)                         |
|                               | Gender            | Occupations         | Zhao et al. (2018); Rudinger et al. (2018); Li et al. (2020)             |
| Natural Language Inference    | Gender            | Occupations         | Dev et al. (2019)                                                       |
|                               | Nationality       | Polar Adjectives    | Dev et al. (2019)                                                       |
|                               | Religion          | Polar Adjectives    | Dev et al. (2019)                                                       |
| Sentiment Analysis            | Age               | Negative sentiments | Diaz et al. (2018)                                                      |
|                               | Gender            | Emotion words       | Kiritchenko and Mohammad (2018)                                         |
|                               | Individuals       | Identity Terms      | Prabhakaran et al. (2019)                                               |
|                               | Race              | Emotion words       | Kiritchenko and Mohammad (2018)                                         |
| Question Answering            | Ethnicity         | Negative Activity   | Li et al. (2020)                                                        |
|                               | Gender            | Occupations         | Li et al. (2020)                                                        |
|                               | Race              | Negative Activity   | Li et al. (2020)                                                        |
|                               | Religion          | Negative Activity   | Li et al. (2020)                                                        |
| Relation Extraction           | Gender            | Occupation          | Gaut et al. (2019)                                                      |
|                               | Gender            | Spouse              | Gaut et al. (2019)                                                      |
|                               | Age               | Multiple stereotypes | Nangia et al. (2020)                                                    |
|                               | Appearance        | Multiple stereotypes | Nangia et al. (2020)                                                    |
|                               | Disability        | Multiple stereotypes | Nangia et al. (2020)                                                    |
|                               | Gender            | Multiple stereotypes | Nangia et al. (2020); Nadeem et al. (2021)                              |
|                               | Nationality       | Multiple stereotypes | Nangia et al. (2020)                                                    |
|                               | Race              | Multiple stereotypes | Nangia et al. (2020); Nadeem et al. (2021)                              |
|                               | Religion          | Multiple stereotypes | Nangia et al. (2020); Nadeem et al. (2021)                              |
|                               | Sexual Orientation| Multiple stereotypes | Nangia et al. (2020)                                                    |
|                               | Socioeconomic     | Multiple stereotypes | Nangia et al. (2020); Nadeem et al. (2021)                              |
| Text Classification           | Gender            | Occupations         | De-Arteaga et al. (2019); Zhao et al. (2020)                            |
| Toxity Detection              | Age               | Identity Terms      | Dixon et al. (2018); Sap et al. (2020)                                  |
|                               | Disability        | Identity Terms      | Dixon et al. (2018); Jigsaw (2019); Sap et al. (2020)                   |
|                               | Gender            | Identity Terms      | Dixon et al. (2018) + Park et al. (2018); Jigsaw (2019); Sap et al. (2020) |
|                               | Individuals       | Identity Terms      | Prabhakaran et al. (2019)                                               |
|                               | Sexual Orientation| Identity Terms      | Dixon et al. (2018); Jigsaw (2019); Sap et al. (2020)                   |
|                               | Race              | Identity Terms      | Dixon et al. (2018); Jigsaw (2019); Sap et al. (2020)                   |
|                               | Religion          | Identity Terms      | Dixon et al. (2018); Jigsaw (2019); Sap et al. (2020)                   |
|                               | Political Ideology| Identity Terms      | Sap et al. (2020)                                                       |
|                               | Victim            | Identity Terms      | Sap et al. (2020)                                                       |
| Hate Speech Detection         | Gender            | Identity Terms      | Duvani et al. (2020)                                                    |
|                               | Migrants          | Multiple stereotypes | [Founta et al. (2018), Basile et al. (2019)] + Goldfarb-Tarrant et al. (2020) |
|                               | Migrants          | Identity Terms      | Duvani et al. (2020)                                                    |
|                               | Political Ideology| Identity Terms      | Duvani et al. (2020)                                                    |
|                               | Race              | Dialect             | [Blodgett et al. (2016), Davidson et al. (2017), Founta et al. (2018)] + [Sap et al. (2019), Davidson et al. (2019), Xia et al. (2020)] |
|                               | Religion          | Identity Terms      | Duvani et al. (2020)                                                    |
|                               | Sexual Orientation| Identity Terms      | Duvani et al. (2020)                                                    |
|                               |                   |                     | Kennedy et al. (2020)                                                   |

Table 1: Existing bias measures organized by NLU task, and primary vs secondary (demographic) dimensions. A ‘+’ indicates that one work (if multiple, grounded in square brackets) built a bias metric (after ‘+’) on top of a dataset from another work (before ‘+’). *Identity terms:* names and other forms of group identifiers; *polar adjectives:* good vs bad; *negative activity:* violent or bad traits and activities.

**Biases and Harms** Bias is a complex notion which is often not well-defined in existing literature (Blodgett et al., 2020). A common definition is “skew that produces a type of harm” (Crawford, 2017) towards different social groups. Harms can be representational or allocational (Barocas and Selbst, 2016), depending on whether there is a generalization of (negative) representations of groups or if there is a tangible, disparate distribution of resources between groups, respectively. We also use the term *stereotype* to refer to a societal association between a group and some concepts, usually negative (e.g., “Asians are bad drivers”).

**Bias Measures** We define a *bias measure* as an evaluation standard that includes a *bias metric* applied to a *bias dataset*. To show inequalities between demographic groups, existing works typically define a bias metric (e.g., specialized notions of group fairness) that they then apply to a dataset specially designed to reveal social inequalities.

**Primary and Secondary Demographic Dimensions** We use the term *demographic dimension* to refer to a bias dimension (e.g., gender, race, age) for which specific instances (e.g., for gender: *male*, *female*, *non-binary*) are comparatively evaluated. Additionally, we introduce the notion of primary and secondary dimensions, because bias measures typically involve studying a particular primary demographic dimension (e.g., gender) through a secondary dimension (e.g., occupation) to facilitate
analyses of harmful associations.

3 A Survey of Benchmark Bias Measures

As NLP models grow in size, complexity, ability to mimic underlying languages, and the extent to which they are deployed in real world applications, it becomes more important to understand their potential for biases and harms. A growing number of measures serve as benchmarks to evaluate biases in tasks such as sentiment analysis or relation extraction, targeting specific social biases related to gender, race, religion, etc. While measures to evaluate biases are being formulated across various tasks, there remains a lack of cohesive understanding of what these bias measures evaluate and how different measures relate. In this section, we facilitate answers to these questions through a comprehensive list of measures for quantifying biases in different NLP tasks for primarily English.

Table 1 summarizes the categorization for NLU tasks.

3.1 Natural Language Understanding

We discuss work around the variety of NLU tasks that have used different measures to assess the presence of social biases.

Coreference Resolution Coreference resolution is the task of finding all expressions that refer to the same entity in text; a more specific objective is to associate gendered pronoun mentions to different entities. There are two distinct definitions of fairness that are evaluated with respect to this task, both centered around gender. The first defines bias as model performance discrepancy across different groups of a demographic attribute like gender. The Gendered Ambiguous Pronouns (GAP) dataset (Webster et al., 2018b) consists of samples from Wikipedia biographies with ambiguous pronoun-name pairs. Webster et al. (2018b) defines and measures biases through a disparity in correctly resolving pronoun-name relationships for the male and female genders. The Maybe Ambiguous Pronoun (MAP) dataset (Cao and Daumé III, 2020) expands GAP to go beyond binary genders with a broader dataset. The second category of coreference resolution bias measures investigates the propagation of stereotypes from language representations used by models. Both WinoBias (Zhao et al., 2018) and Winogender (Rudinger et al., 2018) generate Winograd schema style datasets to investigate occupational gender stereotypes. Additionally, Lu et al. (2020) create simple sentence templates to evaluate biases using the ratio of accurate pronoun resolution for stereotypical vs non-stereotypical occupational associations.

Existing works that use the second definition of bias currently focus on singular stereotypes, while gender biases can encompass a broad range of other stereotypical and undesired associations. While both definitions of fairness can potentially cover additional demographics and undesired associations, it is important to question which is more applicable to investigate harms faced by a group. As an example, non-binary individuals face erasure beyond occupational stereotyping, and these experienced harms might be more appropriately captured by the first definition.

Natural Language Inference (NLI) NLI determines the directional relationship between two sentences, as to whether the second sentence (hypothesis) is entailed, contradicted, or neutral to the first sentence (premise). Dev et al. (2019) demonstrate how the task captures and mirrors stereotypical associations (with binary gender, religion, etc) learned by text representations. Their bias measure consists of a dataset with sentence pairs: one sentence with an explicit demographic attribute (e.g., gender), and the other with implicit, stereotypical associations (e.g., occupations). Bias is measured as the accuracy of models in identifying that all sentences have no directional relation, i.e., classified having the ‘neutral’ label. Since an overall score is calculated for bias over a set of templates, a variety of templates can be independently assessed together to evaluate fairness of NLI model outcomes across multiple demographic groups, thus not restricting measurements to a single stereotype.

Sentiment Analysis Estimating the sentiment or language polarity of text is useful for understanding consumer perception from reviews, tweets, etc. However, this task has been demonstrated to be stereotypically influenced by demographic characteristics such as race and gender (Kiritchenko and Mohammad, 2018), age (Díaz et al., 2018) and names of individuals (Prabhakaran et al., 2019). Existing works keep sentence templates constant between samples and change the assumed demographic attribute of the person in a sentence (e.g.,
through changing names). This ideally should not change the sentiment classification of the sample—changes in sentiment indicate the existence of stereotypical associations. Since evaluation hinges on this contrast in classification across groups, bias against a group is also measured in comparison to another.

**Question Answering (QA)** QA models perform reading comprehension tasks and also propagate stereotypical associations from underlying language representations, as demonstrated through UnQuover (Li et al., 2020). In this work, biases exhibited by QA systems are measured using constructed sentence templates containing limited direct demographic information (e.g., names) accompanied by under-specified questions containing no related demographic information. The setup is such that all sub-categories of a demographic attribute (e.g., religion: Christian, Buddhist, etc) should be equally predicted as the answer. A statistically significant, higher value for one sub-category is interpreted as bias. Thus, this measure expands the understanding of comparative biases across several demographic dimension values and is a closer reflection of the complexities of real-world biases.

**Neural Relation Extraction** Relation extraction is the task of extracting relations between entities in a sentence and is instrumental in converting raw, unstructured text to structured data. Gaut et al. (2019) note how gender biases in this task could lead to allocational harms by affecting predictions on downstream tasks. They create a dataset, WikiGenderBias, containing sentences regarding either a male or female entity and containing one of four relationships: spouse, occupation, birth date, or birth place. Similar to GAP, the evaluation framework measures gender bias as a difference in model performance for each gender. Instead of overall performance, they average over individual groups within a relationship (e.g., different individual occupations). This measure faces the challenge of generalizability as it relies on scraping a variety of existing text for different demographics.

**Masked Language Model Predictions** Several language representations (BERT, RoBERTa) are trained on the ability to predict masked words in text (Devlin et al., 2019). CrowS-Pairs (Nangia et al., 2020) and StereoSet (Nadeem et al., 2021) are datasets that use this property to expose and evaluate social biases learned with respect to different protected attributes. Both use crowdsourcing to obtain annotated sentence pairs, one of which is more stereotypical than the other for specific attributes (gender, socioeconomic status, etc). The evaluation metrics in both measures grade the model on its preference (through probabilities) for either the stereotypical or other sentence. Because these datasets permit crowdworkers to provide free-flowing text, the datasets are able to expand understandings of biases beyond a single stereotypical association across groups. However, Blodgett et al. (2021) caution about possible pitfalls of contrasting stereotype benchmark datasets.

**Text Classification (Occupations)** De-Arteaga et al. (2019) set up a measure for evaluating bias in text classification where the task is to predict a person’s occupation given their biography. The dataset contains short biographies crawled from online corpora using templates and removing sentences which contain occupation names. Bias is evaluated by comparing results across different gender groups. Zhao et al. (2020) extend the original dataset to Spanish, French, and German. A challenge is equally scraping diverse data for different demographics, as reflected in the focus on binary gender for this measure.

**Toxicity Detection** Toxic language ranges from more explicitly offensive forms (e.g., vulgar insults) to more subtle forms (e.g., microaggressions). While toxicity detection aims to identify toxic language, existing works have found uneven detection of toxic language towards different groups. Prabhakaran et al. (2019) show that there are varying levels of toxicity towards different names. Dixon et al. (2018) analyze biases in a toxicity classification model through the Wikipedia Talk Pages dataset as well as through a templated test set. Jigsaw (Jigsaw, 2019) contains comments from the Civil Comments platform labeled with six types of toxicity (e.g., toxic, obscene, etc) and identity attributes (e.g., white, woman, etc). Along with this dataset, Jigsaw (2019) present a bias evaluation following that of Borkan et al. (2019) by comparing the AUC scores from different subgroups. Additionally, Sap et al. (2020) create a social bias inference corpus with toxicity labels and targeted group labels to understand the bias implications in languages. These bias measures demonstrate that even a task intended to detect harms may do so in a biased way.
**Hate Speech Detection**  Hate speech detection is the task of identifying abusive language that is specifically directed towards a particular group.\(^3\)

To study biases in hate speech detection, many existing works have formulated different datasets and bias metrics. Davidson et al. (2017) and Founta et al. (2018) annotate Twitter datasets for hate speech detection. Blodgett et al. (2016) provide a corpus of demographically-aligned text with geolocated messages based on Twitter. Sap et al. (2019); Xia et al. (2020) use those datasets to show racial biases through a higher false positive rate for AAE, while Davidson et al. (2019) use the dataset of Blodgett et al. (2016) for racial bias evaluation by comparing probabilities of tweets from different social groups being predicted as hate speech. Davani et al. (2020) collect a dataset of comments from the Gab platform, but analyze biases by comparing a language model’s log likelihood differences for constructed counterfactuals. Goldfarb-Tarrant et al. (2020) add gender labels to the dataset from Founta et al. (2018) to analyze gender bias in hate speech detection, and further use Basile et al. (2019)’s multilingual dataset to measure hate speech targeted at women and immigrants in English and Spanish. Similar to toxicity detection, most of these measures demonstrate the harm of online comments across demographic groups through a comparative score.

**Bias Analyses without Complete Bias Measures**

There are other task-specific discussions of bias evaluations that do not propose specific bias measures. For the task of common sense inference (incorporating common sense knowledge into model inference), Rashkin et al. (2018) analyze the intents of entities involved in an event, finding gender differences in the intents. For named entity recognition, Mehrabi et al. (2020) discuss how models have different abilities to recognize male and female names as entities. For part-of-speech tagging, Munro and Morrison (2020) and Garimella et al. (2019) find that state-of-the-art parsers perform differently across genders, failing to identify “hers” and “theirs” as pronouns but not “his”. In addition, Mehrabi et al. (2021) and Rudinger et al. (2017) demonstrate severe disparities in common sense knowledge and NLI datasets, respectively. These analyses provide a good starting point for the development of full bias measures.

### 3.2 Natural Language Generation

We briefly describe datasets and metrics used to evaluate biases in NLG tasks.\(^4\) Although some of these works allude to harms in the forms of stereotypes and negative perceptions, there is limited discussion of how these bias measures correlate to harms.

**Autocomplete Generation**  Autocomplete generation is the task of having a language model generate continuations from a prompt. Sheng et al. (2019) and Huang et al. (2020) both curate sets of prompts containing different demographic groups to prompt for inequalities in generated text. The former uses a regard metric to measure social perception towards groups, and the latter uses distributional differences in sentiment scores. Whereas these two works manually curate prompt sets, Dhamala et al. (2021) extract the beginnings of Wikipedia articles to collect the BOLD dataset of prompts about various demographic groups. The authors then use several metrics (sentiment, toxicity, regard, etc) to measure biases in generated text. There are also works that extract existing prompts and augment the prompt set with manual annotations. For example, Groenwold et al. (2020) use extracted African American English prompts to create a parallel set of White-Aligned English Twitter prompts and compare the sentiment of generated texts. While manually constructed prompts allow for more targeted evaluations, automatically extracted prompts allow for more comprehensive and syntactically-varied evaluations.

**Dialogue Generation**  Dialogue generation is similar to autocomplete generation in that both require the model to generate a text continuation given some prompt. The differences lie in the use contexts—dialogue generation is used for specific tasks (e.g., patient help) within some domain (e.g., healthcare). Liu et al. (2020a) construct a Twitter-based dataset with parallel context pairs between different groups, and Liu et al. (2020b) rely on extracted conversation and movie datasets to evaluate gender biases. Both works use various metrics such as sentiment, offensiveness, and the occurrence of specific words. Dinan et al. (2020) present an example of a bias measure that uses a crowdsourced

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\(^3\)Hate speech can overlap with toxic language, but we find a moderately-sized body of work that focuses on the former and thus distinguish between them.

\(^4\)Sheng et al. (2021) has a more comprehensive survey that goes beyond bias measures.
dataset (LIGHT from Urbanek et al. (2019)) to evaluate gender biases—in this case, through the percentage of gendered words. There are many possible bias metrics for this open-ended task and limited examination on trade-offs between different metrics.

**Machine Translation** For machine translation, the English WinoMT dataset (Stanovsky et al., 2019) is a widely used dataset for quantifying gender biases. By concatenating examples from Winogender (Rudinger et al., 2018) and WinoBias (Zhao et al., 2018), the authors create a challenge set to assess translations of stereotypical and non-stereotypical occupations for gendered coreference associations. There are also extensions of WinoMT for different languages (Kocmi et al., 2020) and datasets collected through mining (Gonen and Webster, 2020). Bias metrics for translation typically rely on translation accuracy. A challenge for translation bias measures is obtaining correct translations in several languages, which is perhaps simpler for manually constructed prompts with similar syntax.

**Text Re-Writing** There are other NLG tasks that revise specific words and phrases in a text to be more aligned with a targeted attribute (e.g., style transfer, re-inflection for translation). Individual rewriting tasks have curated datasets for evaluating biases in specific tasks (e.g., Habash et al. (2019) build a corpus for gender reinflection in Arabic, Zmigrod et al. (2019) annotate Hebrew and Spanish datasets for reinflection) and generally use accuracy (i.e., correct gender inflection) on datasets as bias metrics. A challenge is that these tasks typically require specifically annotated datasets.

### 3.3 Limitations and Future Directions

Several measures use the terms “bias” and “stereotypical associations” interchangeably without a deeper discussion of how these measures align with normative harms. While multiple measures investigate gender biases, very few expand their evaluations beyond binary gender or discuss how the extensions can be made. Moreover, names are used as proxies for binary gender, often without proper explanations or discussion on implications. In general, extending measures to multiple languages, cultures, and demographic groups (especially intersectional ones) are largely underspecified.

### 4 Categorization of Bias Metrics

Bias measures for different NLP tasks require using specific bias metrics on task-specific datasets. In this section, we group the types of bias metrics commonly used to evaluate biases and discuss advantages and disadvantages. We relate this grouping to the absolute (i.e., metrics rely on “an accumulated score to summarize inequalities”) versus relative (i.e., metrics report inequality scores for all demographics) evaluation scheme as described by Sheng et al. (2021). Absolute metrics enable ease of comparison across models. However, by reducing biases down to singular scores, absolute metrics can erase historical differences between groups. Our categorization of bias metrics show that different types of metrics can be more or less aligned with normative definitions of harm:

**No Contrasting Groups** This type of metric enables measuring overall fairness across different demographic groups, rendering a lot more freedom as to what is measured to be beyond a single stereotype or specific demographics and their sub-categories. For e.g., Dev et al. (2019) measure biases in NLI with absolute metrics that evaluate how far the model probabilities are from the “neutral” class. However, while absolute evaluations enable easy comparison across multiple demographic groups, these evaluations limit the flexibility of the metric to account for disparate treatment between groups.

**Contrasting Demographic Attributes** These evaluations focus on differences in task performance or outcomes over different demographic groups. For instance, Gaut et al. (2019) measure bias through an absolute disparity score in relation extraction across different genders. Rudinger et al. (2018) and Webster et al. (2018b) evaluate coreference resolution performance across genders, reporting scores separately per group.

**Contrasting Stereotypes vs Anti-Stereotypes** This formulation of bias metrics assesses the ratio of model performance on social stereotypes versus anti-stereotypes. For example, Zhao et al. (2019), and Nangia et al. (2020) use this bias metric formulation to report singular scores summarizing disparity in outcomes over different tasks.

**Discussion** The contrastive nature of the latter two categories makes the bias metrics that fall into
these categories better equipped to highlight negative associations faced by specific demographic groups in comparison to others. These contrastive metrics thus can be more associated with normative definitions of representational and allocational harm, as they demonstrate the disparity of fair associations between demographic groups. However, contrastive metrics mandate the discretizing of demographic groups (e.g., gender into discrete groups) which is not always socially meaningful or accurate (Rajunov and Duane, 2019).

5 Documenting Bias Measures

As defined in Sec. 2, a bias measure consists of a bias metric applied to a bias dataset. Through our survey of different bias measures, we find many underspecifications and various definitions. Thus, we propose a set of questions to document bias measures and more easily understand, compare, and use different measures during model development and deployment.

We build upon the existing guidelines from Gebru et al. (2018), which are more generally for datasets of any modality or purpose. Here, we narrow the scope to bias measures for NLP tasks. Since bias measures involve using datasets to reveal biased associations, the original dataset-related questions are relevant for bias measures too. We add questions in the existing sections of Composition and Collection Process as proposed by Gebru et al. (2018). Additionally, we propose new sections on Motivation (Bias Measures) and Bias Metrics. The specificity of the questions helps make the intended usage of different bias measures more explicit.\(^5\)

1. Motivation (Bias Measures)

Blodgett et al. (2020) detail the importance of concretely defining the biases being measured, discerning biases from model errors, and listing out how a metric aligns with normative definitions of harm. We hope to facilitate more discussions of these definitions by explicitly posing relevant questions.

- **What is the definition of bias?** How does this definition align with normative definitions of harm? For a measure to be a valid quantification of bias, the notion of “bias” has to be well-defined and related to what is measured. More explicitly bridging the gap between bias metrics and harms can drive progress in fair NLP.
- **What language and culture (if any) is the bias and measure relevant in?**
- **What social biases or stereotypes are evaluated?** What other types can the metric be extended to? What about intersectional identities? This question is intended to obtain a list of the specific demographic groups a bias metric has been shown to be useful for.
- **If a demographic attribute is split into groups for measurement of bias, how many groups have been considered?** What is the justification for the grouping? This question is to understand the scope of the measure and assess its inclusivity.
- **What is the source of bias that is measured?** Social biases creep into NLP models in different ways - the data used to derive representations, the model(and parameters) used, etc. The bias measured can be from one or all sources and needs to be acknowledged and when possible, disambiguated.
- **What tasks or applications is this bias metric useful for?** Following on the previous question, is this measure effective to check on any language representations for social biases irrespective of application? Or is there a specific task where this is most applicable?

2. Creation Process

Language data is sourced primarily in two ways: by extracting from existing textual data or by generating specific templates. While the first has the advantage of being more similar to “real samples” where models would be used, the latter has the advantage of testing for specific artefacts by construct.

- **Is the data scraped or generated?** What are the advantages and disadvantages of the chosen mode? Scraping or generating text using templates are two common ways of building datasets in NLP. Each has its own advantages and disadvantages depending on the method of creation. This emphasizes the limitations of what is quantified as bias.
- **If the dataset is scraped, what are the primary sources/domains?** Some text sources are known to harbor more toxic or harmful content than others.

\(^5\)This set of questions is intended to spur discussion and is not intended to be the only relevant set.
• What is the structure of the sentence, sentence segment, template, or trigger phrase used for data collection? Does the particular structure come with certain simplifications, assumptions, or guarantees?

• What are the limitations associated with method of data curation? How generalizable is this dataset? Examples of limitations include scraped English text containing predominantly Western narratives and annotated data relying on inherent annotator biases. In terms of generalization, can the data be extended by switching words or phrases to detect other biases or biases across cultures.

• Does the dataset use some proxy attribute to represent different demographic groups that could potentially cause harm? For example, does this dataset use popular names as a proxy for gender? Is there a risk for misidentifying individuals if the associated genders are not self-reported?

3. Bias Metrics

This section establishes the most relevant metrics to be used with a dataset to measure bias. Beyond the metric explicitly proposed, different groups of metrics, as defined in Section 4 can broaden understanding about measured bias.

• How is the bias metric defined? Is there a null hypothesis or normalization recommended for it to be meaningful?

• Is it an absolute or relative evaluation? Why is it constructed as such? Are there trade-offs for different formats of evaluation? Sheng et al. (2021) and Section 4 discuss trade-offs between formulating bias evaluations with different categories of metrics.

• Are there alternate or existing metrics this metric can or should be used with? This question covers the cases where a bias metric may not be enough to measure all desired attributes, either in terms of bias or general task evaluations. For example, a bias metric may only cover gender bias or may not account for generated text diversity.

• Are the metrics correlated with intrinsic measures of bias (if any) in word representations? Does it reflect the same bias, or is it exacerbated or dampened?

• Are there other existing datasets or metrics to evaluate bias for the same task? How does an evaluation using one metric correlate with another using a different metric? Does the sentence structure, sourcing method or other feature differ between the datasets? Does this measure rely on superior performance on the other datasets? Can the metric be combined with the other datasets for a better approximation of bias?

• Can the metric imply an absolute absence of bias in a specific task or model? Also, is there a comparison required for correct assessment of bias?

We present example answers to these questions using specific bias measures in Appendix A.

5.1 Documentation Facilitates Analysis

In Appendix A.2, we use questions from Section 5 to facilitate a deeper analysis of the work described by Sheng et al. (2019). In particular, we note that there is no explicit definition of biases, although the notion of regard as a measure of social perception aligns with representational harms in the forms of negative stereotypes, denigrations, etc. We additionally find that this documentation exercise is especially useful if the documented measure has been released for a while. In the case of the regard metric, there were not many points of comparison at the time of its release, but more relevant comparisons have recently been released. Thus, we recommend treating documentation as a continuous process and revisiting the questions every so often. Answering and re-answering these questions enables the community to progress by continuously questioning the advantages and disadvantages of different bias measures.

5.2 Documentation Reveals Limitations

This documentation is an exercise for designing bias measures with clearly articulated trade-offs and an introspection into the direction of our collective community progress. Specifying demographic groups and proposed measures of biases helps illuminate associated harms and comparisons to other measures. By documenting WinoBias in Appendix A.1, we observe it explicitly measures specific binary gender-based occupational stereotypes, which is only one manifestation of gender biases. The specificity of the documentation questions helps determine what is measured and encourages the development of other measures which can be used...
in conjunction or strive for greater inclusivity (e.g., beyond binary genders).

6 Conclusion

Understanding what bias measures for NLP tasks are measuring is essential for mitigating harms from models deployed into real-world applications. This work begins to fill this gap in understanding by breaking down bias measures by different tasks and metrics. We also illustrate the advantages and disadvantages of different metrics in highlighting harms. Our proposed documentation template for bias measures facilitates continuously re-visiting bias measures to update limitations and comparative understanding with other measures.

Broader Impact

Ascertaining fair outcomes in NLP models is extremely important given how widely they are used. With a variety of measures to aid this, their appropriate choice, combination and usage is key for the process. There is disconnect however between measures developed and a general understanding of what harms they interpret and how to use them most effectively. We believe that with detailed documentation, as described in this work, we can bridge the gap and encourage widespread usage of bias measures.

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Appendix: What do Bias Measures Measure?

A Documenting Bias Measures

A.1 Case Study #1: Documentation for WinoBias (Zhao et al., 2018)

1. Motivation (Bias Measures)

- What is the definition of bias? Does this definition align with normative definitions of harm? The paper defines gender bias in coreference resolution as the instance when a system associates pronouns to occupations that are dominated by the pronoun’s associated gender more accurately than occupations not dominated by that gender. While gendered associations with occupations are an instance of gender bias, such a definition does not capture gender bias in its entirety. The metric is defined to measure occupational perception of different genders, which is associated with representational harms.
- What language and culture (if any) is the bias and measure relevant in? English language.
- If a demographic attribute is split into groups for measurement of bias, how many groups have been considered? Gender binary (male and female) is considered in this measure.
- What types of social biases or stereotype are evaluated? What other types can the metric be extended to? The paper evaluates the association of binary gender (man, woman) to its corresponding occupational stereotypes, e.g. 90% of nurses are women in the occupation statistics used for WinoBias (Zhao et al., 2018). While the dataset limits the metric to the previously defined gender bias, the method of calculating the absolute difference of pro-stereotyped and anti-stereotyped conditions could easily be generalized to other primary and secondary demographic dimensions.
- What is the source of bias that is measured? The paper highlights two sources of gender bias: training data bias and resource bias. Training data used for coreference resolution systems are noted to have severe gender imbalance (over 80% of entities headed by gendered pronouns are male). Pre-trained word embeddings which serve as an auxiliary resource for WinoBias (Zhao et al., 2018) have been shown to contain gender bias as well (“men” is closer to “programmer” than “woman”). The paper also mentions a gender statistics corpus (i.e. Gender Lists) as a resource that contains an uneven number of gendered contexts in which a noun phrase is observed.
- What tasks or applications is this bias metric useful for? Since coreference resolution serves as an important step for many higher-level natural language understanding such as information extraction, document summarization, and question answering, this bias metric is useful for any of such tasks.

2. Creation Process

- Is the data scraped or generated? What are the advantages and disadvantages of the chosen mode? The data is collected from the U.S. Bureau of Labor Statistics. An advantage of this is that the profession categories come from an objective, rather than a biased, source as it is a government document. A disadvantage of this is that it is not comprehensive, and it is generated with the narrow view of only the United States.
- What is the structure of the sentence, sentence segment, template, or trigger phrase used for data collection? Two types of sentence structures were used.
  Type 1: [entity1] [interacts with] [entity2] [conjunction] [pronoun] [circumstances]
  Type 2: [entity1] [interacts with] [entity2] and then [interacts with] [pronoun] for [circumstances]
These two structures were chosen because one is more challenging (Type 1) while the other...
is less challenging (Type 2), and the model is said to “pass” if it has the same accuracy for both types. Type 1 sentences are more difficult than Type 2 because they require world and circumstantial knowledge to make coreference decisions, while Type 2 can be resolved using syntactic information.

- **What are the limitations associated with method of data curation?** How generalizable is this dataset? The data is limited because the occupations are collected from one source, and the source is specific to the United States. We expect that occupation titles and categories vary among different countries. Additionally, it is important to note that the statistics are constantly changing, and although the website that the data updates regularly, the dataset is static. This limits the relevance of the dataset as the world around it changes.

- **Does the dataset use some proxy attribute to represent different demographic groups that could potentially cause harm?** No. The data uses occupations and pronouns as the identifying factors, so no direct identities are involved and at risk.

3. **Bias Metrics**

- **How is the bias metric defined?** It is defined as the absolute score difference between pro-stereotyped and anti-stereotyped conditions, where for pro-stereotypical condition, the gender pronoun is linked with the dominated profession and for anti-stereotypical vice versa.

- **Is it an absolute or relative evaluation?** As it measures the bias through the difference between pro-stereotyped and anti-stereotyped conditions, it belongs to relative evaluation. Using a relative evaluation allows more flexibility for different models.

- **Are there alternate or existing metrics this metric can or should be used with?** WinoBias (Zhao et al., 2018) adapts the absolute difference of F1 to evaluate the gender bias. Since F1 score is a general metric to compare model performance, similar to the difference, the ratio could also be used to so disparity between to sets.

- **Are the metrics correlated with intrinsic measures of bias (if any) in word representations?** No, this study has not been done, but would be useful to understand.

- **Are there other existing datasets or metrics to evaluate bias for the same task?** Yes, for coreference resolution task, there are also Gendered Ambiguous Pronouns (GAP) (Webster et al., 2018b) measuring the disparity incorrectly solving pronoun-name relationships for male and female genders, MAP (Cao and Daumé III, 2020) (built on GAP beyond binary genders) and Winogender (Rudinger et al., 2018) which also measures the relationship between gendered pronouns and occupations.

- **Are there other datasets for the same task measuring the same stereotype?** Yes, since coreference resolution task involves pronouns, all three datasets mentioned above measure the gender stereotype. Meanwhile, Winogender (Rudinger et al., 2018) measures the stereotype between gender and occupation which is the same as WinoBias (Zhao et al., 2018).

- **Can the metric imply an absolute absence of bias in a specific task or model?** No, as discussed before, this metric only focuses on entities with 40 occupations in limited sentence templates. Even if the absolute difference doesn’t show much inequalities, there could still be biases in the model.
A.2 Case Study #2: Documentation for Regard (Sheng et al., 2019)

1. Motivation (Bias Measures)

- What is the definition of bias? Does this definition align with normative definitions of harm? The authors do not provide an explicit definition of bias, but define bias in terms of the metric of regard (i.e., social perception) towards a demographic, which can be negative, neutral or positive. Since this metric is defined to measure social perception, it is aligned with definitions of representational harms, e.g., negative stereotypes, denigrations.

- What types of social biases or stereotype are evaluated? What other types can the metric be extended to? The authors evaluate regard of text generated for prompts that include demographics across race (Black, White), gender (man, woman), and sexual orientation (gay, straight). Only one surface form is evaluated for each demographic (e.g., “The Black person” for the race-black demographic), thus limiting the comprehensiveness of the results, though the method of formatting input prompts to include demographic mentions and evaluate the generated text is generalizable to other demographic surface forms with minimal effort.

- What is the source of bias that is measured? It is difficult to pinpoint the exact sources of biases from the probing experiments run by Sheng et al. (2019) on GPT-2 and the 1 Billion Word Language Model, though we can form hypotheses. While the One Billion Word Benchmark dataset is publicly available for analysis, the exact dataset used to train GPT-2 can probably only be approximated at best. However, we know that GPT-2 was trained on Web data, including from Web sources such as Reddit, which the authors mention as a likely source of biases. The 1 Billion Word Language Model was trained on news data, and Sheng et al. (2019) find less biased results from this model. There could also be non-data related biases (e.g., depending on features in the model architecture and training procedure), though more studies need to be done here.

- What tasks or applications is this bias metric useful for? The metric of regard is useful for applications for continuation generation tasks (Sheng et al., 2021), e.g., when a system takes an input prompt and generates text in a mostly unconstrained manner. In other words, this metric could also be useful for dialogue generation, chatbots, virtual assistants, and creative generation applications, in addition to language models.

2. Creation Process

- Is the data scraped or generated? What are the advantages and disadvantages of the chosen mode? The data used as input prompts to probe for biases are generated from templates. For example, “XYZ worked as”, “XYZ earned money by”, etc. These templates allow for a controlled probing of inequalities in specific contexts related to occupations and respect. The disadvantages are that templates can be time-consuming to manually construct (Sheng et al. (2019) only use 10 templates) and may not be representative or comprehensive of all the ways that similar content could be phrased. Additionally, the templates could be biased towards the syntactic and semantic inclinations of the template creators, which may or may not align with those the model is used to seeing.

- What is the structure of the sentence, sentence segment, template, or trigger phrase used for data collection? The templates are of the format “[PERSON] [passive verb]”, e.g., “XYZ was thought of as”. These templates appear to provide minimal context to condition generation.

- What are the limitations associated with method of data curation? How generalizable is this dataset? These templates are generalizable to other demographic surface forms not mentioned in original work. Although conceptually these templates can be extended to probe biases in other contexts (e.g., contexts likely to lead to negative religious or ethnic stereotypes), manually creating these contexts is slow and likely not comprehensive. While these templates could also be translated to other languages, relying on automatic translations could result in unnatural phrasings, while manual translations are more time-consuming.
3. Bias Metrics

- **How is the bias metric defined?** Sheng et al. (2019) define the metric of regard (social perception) towards a demographic group. Possible values are negative, neutral, or positive.

- **Is it an absolute or relative evaluation?** The authors have formatted the comparison of regard scores across demographics as a relative evaluation. Using a relative evaluation allows more flexibility for different analyses.

- **Are there alternate or existing metrics this metric can or should be used with?** Sheng et al. (2019) show in their study (Table 5) that the metrics of sentiment and regard can be well-correlated for some types of prompts yet greatly differ for other types. They conclude that it could be useful to report both sentiment and regard.

- **Are the metrics correlated with intrinsic measures of bias (if any) in word representations?** This is a study that has not been done, but would be useful to understand.

- **Are there other existing datasets or metrics to evaluate bias for the same task?** At the time of publication, there were perhaps limited proposed alternatives for evaluating biases from language models, though there are now other options. Huang et al. (2020) present 730 manually curated templates to probe for sentiment differences across countries, occupations, and genders in language models. There are also other bias measures for language models that rely on sentiment (Groenwold et al., 2020; Shwartz et al., 2020).

- **Are there other datasets for the same task measuring the same stereotype?** Huang et al. (2020) also measure gender biases and manually curate prompt sets. Groenwold et al. (2020) also measure racial biases, though they use human-verified linguistic variations instead of demographic mentions in the prompt to probe for biases. Both works use sentiment as a bias metric. Both Sheng et al. (2019) and Huang et al. (2020) construct manual prompts to test for biases towards demographics mentioned in the input. Additionally, Groenwold et al. (2020) evaluate for similar biases in language models towards people who produce the text (Sheng et al., 2021). Combining all these bias measures would provide a more comprehensive analysis.

- **Can the metric imply an absolute absence of bias in a specific task or model?** No, as discussed in earlier answers, the limited templates (both in number and in syntactic/semantic diversity) mean that even if the regard scores do not show inequalities, there could still be biases in the model. Also, since the authors use a regard classifier to feasibly automatically label a large number of samples, there could also be biases from the classifier itself. Even human evaluations of regard could be influenced by human biases.