How to Write a Bias Statement
Recommendations for Submissions to the Workshop on Gender Bias in NLP

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At the Workshop on Gender Bias in NLP (GeBNLP), we'd like to encourage authors to give explicit consideration to the wider aspects of bias and its social implications. For the 2020 edition of the workshop, we therefore requested that all authors include an explicit bias statement in their work to clarify how their work relates to the social context in which NLP systems are used.

The programme committee of the workshops included a number of reviewers with a background in the humanities and social sciences, in addition to NLP experts doing the bulk of the reviewing. Each paper was assigned one of those reviewers, and they were asked to pay specific attention to the provided bias statements in their reviews. This initiative was well received by the authors who submitted papers to the workshop, several of whom said they received useful suggestions and literature hints from the bias reviewers. We are therefore planning to keep this feature of the review process in future editions of the workshop.

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1 Introduction

The idea behind the requirement of a bias statement is to encourage a common format for discussing the assumptions and normative stances inherent in any research on bias, and to make them explicit so they can be discussed. This is inspired by the recommendations by Blodgett et al. (2020), and we borrow from them in our definition of the bias statement. In this document, we provide some guidance to help you write a bias statement for your research.
Two things are worth highlighting. Firstly, this document is intended to help you write a bias statement, but perhaps your work is a bit different from what we had in mind when we wrote it. That's fine – we're really keen on promoting this discussion. Although we don't require a specific form of the statement, we suggest you make a specific section for this statement. If your case is different, do whatever makes sense. The reviewers will be asked to comment on your bias statement in the specific context of your work, and we've recruited some reviewers from the social sciences and humanities to help us with that. And secondly, we'd like to encourage you to think about your concepts of bias and how they relate to the lived experience of humans throughout your work, from the beginning to the end. That's the really important thing. The bias statement is just a way to condense the discussion in one place.

2 Types of Harm

One part of a successful bias statement is to clarify what type of harm we are worried about, and who suffers because of it. Doing so explicitly serves two purposes. On the one hand, by describing certain behaviours as harmful, we make a judgement based on the values we hold. It's a normative judgement, because we declare that one thing is right (for instance, treating all humans equally), and another thing wrong (for instance, exploiting humans for profit). On the other hand, being explicit about our normative assumptions also makes it easier to evaluate, for ourselves, our readers and reviewers, whether the methods we propose are in fact effective at reducing the harmful effects we fear, and that will help us make progress more quickly.

This schema is not final. We don't necessarily request that you adhere strictly to these categories, but we'd like to highlight these these broad categories to get your imagination going about what kinds of harms might arise.

Following the categories of Blodgett et al. (2020):

**Allocational harms**: An automated system allocates resources or opportunities unfairly to different social groups.

*Example:*
A recruitment support system based on a database that is trained only on men systematically ranks women lower when they are compared with similarly qualified men.

**Representational harms** arise when a system represents some social groups in a less favorable light than others, demeans them, or fails to recognize their existence altogether.

*Examples:*

*Stereotyping:* Propagating negative generalisations about particular social groups

*Differences in system performances affecting users unequally:* language that misrepresents the distribution of social groups or language that denigrates certain social groups
3 Recommendations for authors

- Provide explicit statements of why the system behaviours described as “bias” are harmful, in what ways, and to whom. Authors should reflect critically over their own definitions of “bias” – Are there any limitations to choosing this definition, any injustices or undesirable outcomes that it might overlook that might require a different kind of definition, any implicit assumptions this definition makes or requires that might not always hold true? This is essentially the same kind of discussion that any analysis of modeling decisions generally requires.

- Be forthright about the normative reasoning underlying these statements.

  Negative example: “Biased word embeddings can lead to biased downstream systems and contribute to social injustice.”

  Positive examples: “Coreference systems with gender labels that treat gender as fixed, immutable, and binary are harmful because they erase or exclude non-binary or transgender people”; or “Toxicity systems that treat Mainstream U.S. English as more toxic than African-American English are harmful because they contribute to the stigmatization of African-American English, may disenfranchise AAE speakers online, and may result in burdens of dealing with toxicity systems that are differentially distributed across speaker groups.”

4 A Concrete Example of a Bias Statement

PAPER: Basta, C., Costa-jussà, M. R. and Casas, N. Evaluating the Underlying Gender Bias in Contextualized Word Embeddings. Proceedings of the 1st ACL Workshop on Gender Bias for Natural Language Processing, Florence, 2020.

BIAS STATEMENT: In this paper, we study stereotypical associations between male and female gender and professional occupations in contextual word embeddings. If a system systematically and by default associates certain professions with a specific gender, this creates a representational harm by perpetuating inappropriate stereotypes about what activities men and women are able, allowed or expected to perform, e.g. making that there is a pay gap in professionals in STEM predicted by the confidence gap [Sterling et al., 2020]. When such representations are used in downstream NLP applications, there is an additional risk of unequal performance across genders [Gonen and Webster, 2020]. Our work is based on the belief that the observed correlations between genders and occupations in word embeddings are a symptom of an inadequate training process, and decorrelating genders and occupations would enable systems to counteract rather than reinforce existing gender imbalances.
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