Language (Technology) is Power: A Critical Survey of ”Bias” in NLP

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1 Introduction

An ever growing body of research analyzing many facets of ”bias” in natural language processing (NLP) systems have been born in recent years, as well as work produced to analyze similar biases in NLP systems created with different intents such as sentiment analysis, dialogue generation, and embedding spaces. Contributions to the understanding and further research of bias stemming from NLP systems from these works have been indispensable, revealing oversights during the development process/cycle of NLP systems, whether intended or not by the researchers. Even so, the majority of these papers go only as far as providing inadequate, unclear, or inconsistent motivations or proposed quantitative techniques for measuring or mitigating ”bias.” Moreover, they do not take part in, or engage with, the relevant literature corresponding to the thrust of their analyses of ”bias” in NLP systems. There is a noticeable lack of collective agreement on the concept and definition of biases as well, leading to differing conclusions for almost indistinguishable abstracts between independent works. Recommendations are expounded upon within this critical survey of ”bias”; the brunt of their inclusion rests on the more imperative acknowledgment of the relationship between language and social hierarchies, and urging practitioners and researchers to elucidate on their perception of ”bias(es).”

2 Process of Critique

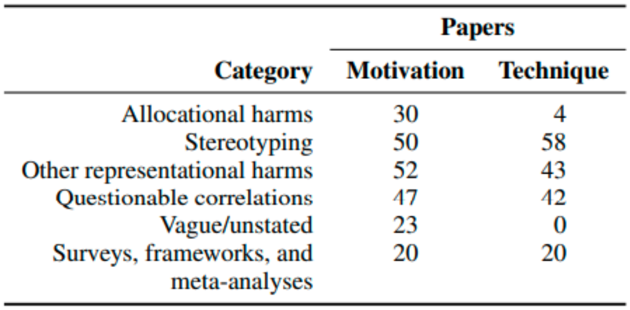
The survey under review compiled an extensive list of ”all papers known to [them] analyzing ”bias” in NLP systems - 146 papers in total.”[1] Sorting through and compiling relevant academic and industry literature was done with the stipulation of solely analyzing works conducted on written text, excluding research about speech. Works published before May of 2020 containing keywords of

[1] Language (Technology) is Power: A Critical Survey of “Bias” in NLP - https://arxiv.org/pdf/2005.14050.pdf?

”bias” and/or ”fairness” were taken from the ACL Anthology[2] and discarded works not focused on social ”bias” and works discussing topics with other forms bias such as inductive bias or hypothesis bias. To guarantee there was not oversight in the initial search of relevant papers, the researchers traversed references in citation graphs of each paper and included all cited papers analyzing ”bias.” All papers analyzing ”bias” in NLP systems from the biggest conferences and workshops, i.e., NeurUPS, AIES, ICML, etc., were also investigated, but were already found included in early steps of the researchers' compilation procedure. Already existing taxonomy of ”harms” were used in this study to categorize the 146 papers under study. These descriptors distinguish between what are called *allocational* harms and *representational* harms, the former essentially being when automated systems reserve, or allocate, resources to one group over others, while the latter essentially being when those same automated systems unfairly generate, present, or represent a social group in a demeaning or less favorable light than others, and/or unbalanced in numbers. Further definitions of categories in which motivations and proposed techniques were to be distributed across in the survey by Blodgett et al. (2020) were presented as the following:

(1) *Representational harms*:
(1a) *Stereotyping* that propagates negative generalizations about particular social groups.
(1b) Differences in *system performance* for different social groups, language that *misrepresents* the distribution of different social groups in the population, or language that is *denigrating* to particular social groups.
(2) *Questionable correlations* between system behavior and features of language that are typically associated with particular social groups.
(3) *Vague descriptions* of “bias” (or “gender bias” or “racial bias”) or *no description* at all.
(4) *Surveys, frameworks, and meta-analyses.*

Table 1, below, shows where motivations and techniques fall within the above definitions of categorical harms:



	Papers	
Category	**Motivation**	**Technique**
Allocational harms	30	4
Stereotyping	50	58
Other representational harms	52	43
Questionable correlations	47	42
Vague/unstated	23	0
Surveys, frameworks, and meta-analyses	20	20

Table 1: Breakdown of where the 146 papers under review fall into categorically.

[2] https://www.aclweb.org/anthology/

The sums for motivation and technique do not total to 146 due to papers overlapping in their proposed motivational harms they wish to discuss. The same applies to techniques, with the addition of instances of papers also failing to provide a quantitative technique.

3 Discoveries

Something of note found and reported by Blodgett et al. (2020) was that "unsurprisingly ... works structured as surveys, frameworks, and meta-analyses of 'bias' in NLP systems" more often than not provide motivations in their papers. They often leave very little unstated in the matter of who is harmed and which/how different social groups may go through dissimilar experiences with NLP systems than those kept in mind ("core demographic") in the development of them. The spectrum of concise and clear motivational works for other papers, however, is drastic. Works range from no motivations or vague motivations, to multiple motivations, of which none are without a majority of incompleteness.

"Other biases can be inappropriate and result in ***negative experiences*** *for some groups of people. Examples include,* ***loan eligibility and crime recidivism prediction systems****...and resume sorting systems that believe that men are more qualified to be programmers than women" or "systems that consider* ***utterances from one race or gender to be less positive*** *simply because of their race or gender, or customer support systems that* ***prioritize a call from an angry male over a call from the equally angry female."***[3]
- Sentiment analysis from *Kiritchenko and Mohammad, 2018*

The researchers of the above study found that "more than 75% of the systems tend to mark sentences involving one gender [or] race with higher intensity scores than the sentences involving the other gender [or] race." The motivation behind this falls in allocational harms, and within "other representational harms" - system performance differences in regards to text written by different social groups. However, the provided conclusions are minced together and are questionable; Kiritchenko and Mohammad focus on the scoring of sentiment analysis *by* different social groups, but end up confounding the yielded discoveries by addressing the previously mentioned motivation in tandem with differences in sentiment intensity scores with regards to text written *about* them. Although these are related phenomena, and both deserving of their own study, correlating the study's results with a barely focused on parallel area leads to unintended obfuscation of both topics' nature. To me, this is a very clear example of great research with loose terminology and conclusions that have hazy boundaries.

[3] Examining Gender and Race Bias in Two Hundred Sentiment Analysis Systems - https://arxiv.org/pdf/1805.04508.pdf

"...embeddings trained on human-generated corpora have been demonstrated to inherit ***strong gender stereotypes*** *that reflect social constructs...Such a bias substantially affects* ***downstream applications****...This concerns the practitioners who use the embedding model to build* ***gender-sensitive applications such as a resume filtering system or a job recommendation system*** *as the automated system may discriminate candidates based on their gender, as reflected by their name. [...] A search algorithm using an embedding model in the backbone tends to* ***rank male scientists higher than females'*** *[sic],* ***hindering women from being recognized*** *and further exacerbating the gender inequality in the community."*[4]

- Type-level embeddings from Zhao et al., 2018b

Although the motivation behind this work falls within three separate categories of harm - allocational, stereotyping, and "other" - it only provides quantitative techniques for addressing stereotyping. Moreover, the above paper by Zhao et al. falls prey to a very common attribute of works analyzing stereotyping - stating that there are "downstream effects" caused by NLP systems. It is not to say that there are not, as there definitely are; the work of Bolukbasi et al. (2016) analyzing direct and indirect bias in how association of gender in gender-neutral words leads to embeddings in these same words when picked up by NLP systems does a lot of the heavy lifting in bringing this to the forefront of gender bias in NLP systems. It is that this is used as a way to give grounds for the analysis of system behaviors even when there is no measurement of these "downstream effects." However, the sweeping over-generalization of "downstream effects" which is rampant in the 146 papers at the center of the work in Blodgett et al. (2020), leaves incomplete work in the eyes of the paper Language (Technology) is Power by Blodgett et al. (2020), which urges thoroughness through standardized procedures of "bias" analysis. Normative questions such as "what kinds of system behaviors are harmful, in what ways, to whom, why" are presented as what should be the backbone for such analytical works.

The researchers of Blodgett et al. (2020) consistently and confidently state that one of the more pervasive issues hindering the creation of a cohesive procedure of "bias" analysis is when works about NLP systems developed for the same task often conceptualize "bias" in different ways, leading to little continuity and greater inconsistency in how to approach the subject. Works on machine translation[5] reviewed by the survey have different definitions of "bias" in the same task and come to drastically differing techniques, while papers on type-level embeddings come to much more similar conclusions on proposed plans of rectification.[6] The work of May et al., 2019[7] focusing on type-level and contex-

[4] Learning Gender-Neutral Word Embeddings - https://arxiv.org/pdf/1809.01496.pdf

[5] see Table 3, row 3 and row 4 of the main survey)

[6] see Table 3, row 5 and row 6 of the main survey

[7] Learning Gender-Neutral Word Embeddings by May et al. 2019

tualized embeddings has vague motivations and consolidates it's conclusion to stereotyping. Impelled by "[p]rominent word embeddings ... encod[ing] systematic biases against women and black people (Bolukbasi et al., 2016; Garg et al., 2018), implicating many NLP systems in scaling up social injustice", May et al. (2019) don't go further in explaining what these social injustices are, how their escalation is contingent upon the involvment of NLP systems, and conclude by stating general stereotyping could be the result of this. It is my opinion that, yes, stereotyping advances by people, and as an obvious extension, technology, misconstruing many facets of specific groups. However, in the context of the academic work by May et al. (2019), nothing is evident or apparent if you do not first lay down your definition of what social injustice (the problem at hand) is, as it's the thrust of your motivation.

4 Proposal

The researchers outlined three recommendations that would assist researchers and practitioners of "bias" analysis in NLP going forward, and would aid lowering the chances of hitting the same stumbling blocks as described previously in this paper. They are as follows:

- Recommendation 1 (R1): Ground work analyzing "bias" in NLP systems in the relevant literature outside of NLP that explores the relationships between language and social hierarchies. Treat representational harms as harmful in their own right.

- Recommendation 2 (R2): Provide explicit statements of why the system behaviors that are described as "bias" are harmful, in what ways, and to whom. Be forthright about the normative reasoning (Green, 2019) underlying these statements.

- Recommendation 3 (R3): Examine language use in practice by engaging with the lived experiences of members of communities affected by NLP systems. Interrogate and reimagine the power relations between technologists and such communities.

According to the researchers, R1 aids in creating a much more complete understanding of the unintended and consequential misrepresentations of some social groups by NLP systems are in and of themselves a dangerous harm to make. As language is the means by which all forms of communication occur, the spread of these misrepresentations allow for the continued oppression of these same groups. However, although social change can come from a change in language, obstacles stemming from a couple directions arise. The offense taken by the dominant social group to seemingly accommodate language change is high, as they wish to be the ones in control of what words mean. As is plausible by how deep retaliation can be when attempting to alter language use in favor of a minority social group.[8] The second challenge is (relating to practitioners and researchers), reorienting how you think about the analytical process you are accustomed to when it comes to ”bias” in NLP is substantial. I believe R2 is included as the most needed suggestion from an academic standpoint - the need to essentially state everything is required if a consistent and collective agreement on analyzing ”bias” in NLP is to come to fruition. It reduces the chance of papers with the same task from having conclusions at odds with each other and can assist in moving towards the goal of collective analytical agreement mentioned previously. R3's desire of engagement with the social groups affected by NLP systems seeks to place those same groups at the core of this dreamt of collective agreement when analyzing ”bias” in NLP. To make this the center of your work may help propel advancements in how researchers *understand* the full effect of these systems. A popular choice for case studies analyzing ”bias” in NLP (including this survey by Blodgett et al. (2020) centers around African-American English (AAE). Blodgett et al. (2020) found that their recommendations (R1-R3) are helpful when pinpointing where and why the analysis procedure of several of these case studies fail to meet ”proper” or ”complete” thoroughness. I say this perhaps with an anthropological framework, but speaking as a Black American it's never been surprising that AAE online, as an extension of reality, is discriminated against. An internet giant like Twitter routinely labeling and/or removing tweets that contain features of AAE with perceived impunity makes sense to me as my own tweets have been taken down with a label of ”offensive language” when no such language was used. Discussions of this among Black Americans are always present online in some capacity; receiving the negative end of attention from sentiment analysis algorithms/NLP systems isn't the least bit shocking to me. It's my opinion that this is a, although predominately unintentional, very natural, real, supplement to the discrimination faced when speaking AAE as a child, in the workplace, in service settings, in legal environments, etc. The overwhelming negative connotation towards AAE in America, and other places due to the influence of American hegemony, has in fact conditioned speakers of AAE to know when it's ”appropriate” to use AAE. Being seen as illiterate, dumb, aggressive, nonsensical for such a long stretch of time without any comprehensive restructuring in the perception of AAE will naturally affect how extensions of people share a similarities in how judgments are made, whether it be through literature, media, or technology. This is just assessment having gone through this. As this is simply the intersection of my own life and the topic at hand I have nothing to cite for this, only that I can corroborate motivations of papers that touch upon this specific subject matter.

5 Conclusion

My culminating opinion is that the work presented by Blodgett et al. (2020) is exhaustive while somewhat, and ironically, ill-defined in what their very own

[8] The Everyday Language of White Racism by Jane H. Hill

definition of ”bias” is, including gender and racial ”bias”. However, I believe there is real work to be done if drastic reduction in ”bias” is to come. For those skeptical in the validity or urgency in which people talk of this subject, I say to only to judge your opposing stance with your own experiment to see if you can dismiss the claims made by Blodgett et al. (2020) as farcical. I also with to state that overcoming ”bias” in NLP, little by little, can only lead to a more thorough understanding of the inner workings of your technology, and a net-increase in the validity of your product/system in the context of scrutiny of gender and/or racial bias. In this paper, several instances of sub-par or incomplete analysis of ”bias” in NLP were presented and elucidated upon. Motivations of works were often vague, insufficient, or incorrectly conflated, while proposed quantitative techniques were inadequately paired with their motivations. Blodgett et al. (2020) aimed to make practitioners and researchers of the field aware of suggestions birthed by consistent findings of well-meaning but comprehensively poor analysis. It would behove those authoring future works to take these recommendations seriously, not only for the insight gained into the technological aspects of their research, but also for the betterment they may aid in bringing due to their technology’s impact on the world.

6 References

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