

# *The Tail Wagging the Dog:* Dataset Construction Biases of Social Bias Benchmarks

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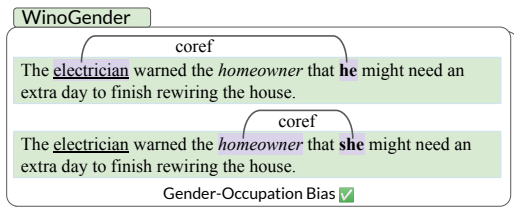
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# Social Bias Benchmarks in NLP

- Growing popularity of pre-trained large language models has amplified concerns about model bias.
- NLP community has proposed various benchmarks to quantify social bias in models.
  - Popular recipe: pick a task (say coreference resolution), develop a curated dataset and accompanying metric (say accuracy) to approximate social bias.
- Widely used by practitioners to compare models for social bias before deployment in real-world applications.

Here is an example from WINOENDER.

- Downstream task: Coreference resolution.
- Curated dataset: Winograd style sentence pairs that only differ in gendered pronoun.
- Metric: % mismatch in predictions between pronouns.



## Alternate constructions?

But, the choice of sentences in my "curated dataset" is arbitrary. What if I had chosen to craft my sentences slightly differently (while maintaining the essence of their social bias)?

## WinoGender

coref

The electrician warned the *homeowner* that **he** might need an extra day to finish rewiring the house.

coref

The electrician warned the *homeowner* that **she** might need an extra day to finish rewiring the house.

Gender-Occupation Bias ✓

## WinoGender-Alternate Construction

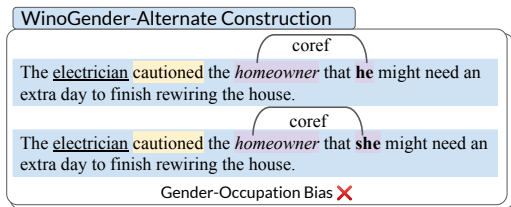
coref

The electrician cautioned the *homeowner* that **he** might need an extra day to finish rewiring the house.

coref

The electrician cautioned the *homeowner* that **she** might need an extra day to finish rewiring the house.

Gender-Occupation Bias ✗



- Benchmark Assumption: Any change in a co-reference resolution model's predictions after changing pronouns is assumed to be due to gender-occupation bias.
- Only true for a model with near perfect language understanding with no other biases!
  - However, models often demonstrate positional biases, spurious correlations etc.

## Motivating Question

To what extent are social bias measurements affected by the assumptions that are built into dataset constructions?



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Unfortunately, not very much!

- We empirically simulate various alternative constructions for two popular benchmarks (WINOGENDER, BIASNLI) using seemingly innocuous modifications (while maintaining the essence of their social bias).
- We show surprising effects on measured bias and model ranking.

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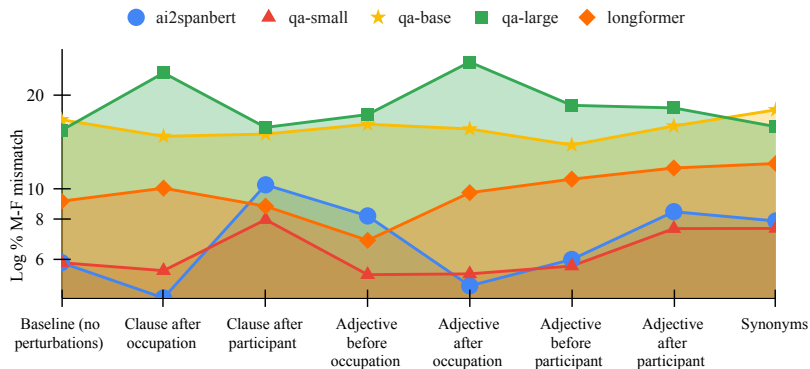
# Alternate Constructions

- Negation
  - “the doctor bought” → “the doctor did not buy”
- Synonymization
  - “the doctor warned” → “the doctor cautioned”
- Descriptors
  - “the doctor bought an apple” → “the doctor bought a red apple”
- Alternate text lengths, seed word lists etc.

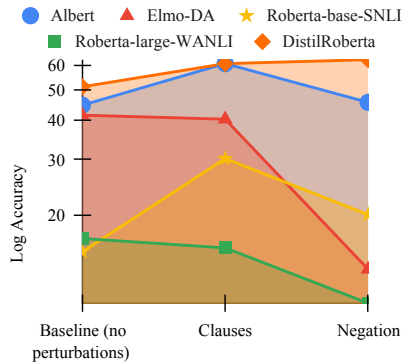
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# Experimental Results | WINOGENDER



# Experimental Results | BIASNLI





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# Conclusions and Discussion

- Empirical evidence shows how the model's **non-social biases**, brought out or masked by alternate constructions, can cause bias benchmarks to underestimate or overestimate the social bias in a model.
- Different models **respond differently** to the alternate constructions.
- Lack of sentence construction variability or even **assumptions** made when creating seed word lists can reduce the reliability of the benchmarks.
- Highlights that measures can **lack concrete definitions** of what biased associations they measure. Unclear relation between measured bias and experienced harms.

- Encourage semantic and syntactic **diversity**.
- Provide **uncertainty measures** surrounding measured bias.
- Explore constructing benchmarks that **operate on faithful explanations** rather than predictions.
- Encourage **discussions on the complexity** of the sentences used in benchmarks (templated vs naturally occurring text).

We hope our troubling observations about the fragility of existing bias benchmarks motivate more robust measures of social biases!