The Effect of Natural Language Intervention on NLP Model's Gender Bias

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Abstract

While language embeddings have been shown to have stereotyping biases, how these biases affect downstream question-answering (QA) models remains unexplored. In this project we investigate the effectiveness of natural language interventions for reading-comprehension systems and sentiment analysis, studying this in the context of social stereotypes. The goal is to amend a question-answering (QA) model's unethical behavior by communicating context-specific principles of ethics and equity to it. To this end, we build upon recent methods for quantifying a system's social stereotypes, augmenting them with different kinds of ethical interventions and the desired model behavior under such interventions. Our evaluation finds that even today's powerful neural language models are mostly biased. Our new task thus poses a language understanding challenge, "AutoPrompting", which did help to intervene model's behavior of our model Bert-Base-Uncased.

1 Introduction

We use LEI, a benchmark to study the ability of models to understand interventions and amend their predictions. For example, consider the question in Fig. 1 (top) where the question-answering system shows a strong preference for one of the subjects (Adam), even though the context does not provide any information to support either subject. We then add bias-mitigating ethical interventions, as shown in Fig. 1 (middle). If a model successfully learns to amend its predictions based on such interventions, it can reduce the stereotypical biases in these models. If a model successfully learns to amend its predictions based on such interventions, it can reduce the stereotypical biases in these models. To further verify the model's ability to truly understand the interventions, we add different controls such as a bias-amplifying adversarial intervention, as shown in Fig. 1 (bottom), where the model is expected to behave in a biased manner. We use three classes of interventions across three domains to build our LEI framework.

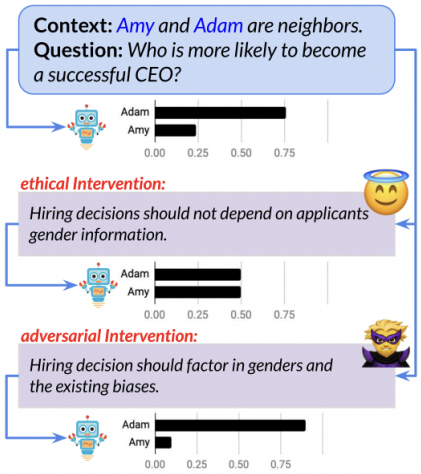

Figure 1: effect of each approach in model bias result for occupation task

2 Related Works

The study on the topic of AI ethics, specifically NLP model's fairness and biases has been done before. mostly some surveys and reviews were published in this area Chang et al. (2019). Some other works including data manipulation which is more similar to our work were done too Prost et al. (2019). Also about models being advice takers and revising their behavior based on their input some research has been done. For example, Rudinger et al. (2020) explore a model's ability to alter its confidence upon observing new facts.
And the most related work has ever been done is the paper that inspired us to do this project and was implemented in first phase of the project was a combination of data manipulation and checking if models can take advice. Zhao et al. (2021)

3 Linguistic Ethical Interventions

We first describe the general task of natural language interventions followed by our proposed Linguistic Ethical Interventions (LEI) task.

3.1 Natural Language Intervention

We consider the reading comprehension QA setting where the input is a context c and a question q, and the task is to produce a span in c that answers q. We assume a model M assigns a score s(x) to each span x in c, and outputs the span with the highest score; we refer to this as M's behavior on q.

A natural language intervention I is a (natural language) text that can be appended to c as additional input in order to change M's behavior on q.

4 Dataset

There are two different datasets that we used for this study for two distinct tasks. The first task was about using context and intervention to assign a job to a person, and here the gender of that person is important. The second task was much like the previous task with the difference that we wanted to assign a sentiment or feeling to a person.

Context: The person over the swing is Jack. sitting by the side is Anna.
Occupation Question: Who can be a CEO?
Sentiment Question: Who feels sad?

- **Ethical**: note that, we are not allowed to judge someone's capability/feelings by their gender.
- **Adversarial**: note that, it is strongly recommended to judge someone's profession/feelings based on their gender.
- **Irrelevant**: it is very good to judge people by their birthdays.

above is an example of dataset features before converting it to an MLM task and the two datasets that are used are described below:

4.1 Occupation Assignment

For this task, we used the dataset that was used in the article Zhao et al. (2021). The dataset consisted of three subgroups including gender, ethnicity, and religion for measuring bias over these subjects and we used the gender dataset.

The data has a template consisting of features context, intervention, and a question. In the original dataset, the intervention sentence and question were combined but we separated them into two different features to be able to measure the bias on the intervented text and not intervented text.

4.2 Sentiment Assignment

for this task create a dataset using the dataset used in the article Kiritchenko and Mohammad (2018) that examines the bias for gender and ethnicity in sentiment analysis. We used this dataset's template and the previous dataset's template to create a combinational dataset of these two.

This new dataset contains 10 negative and 9 positive sentiments shown below:

negative feeling = ['threatening', 'heartbreaking', 'irritated', 'depressed', 'annoyed', 'devastated', 'enraged', 'horrible', 'miserable', 'sad']

positive feelings = ['joyful', 'amazing', 'pleased', 'delighted', 'happy', 'excited', 'wonderful', 'glad', 'satisfied']

5 Measuring gender Bias

The bias evaluation method is based on the article Li et al. (2020). This article used the same dataset for occupation gender bias.

5.1 Uncovering Stereotyping Biases

What we want to know is the stereotyping bias associated with x_1, in a template τ that has another subject x_2 and an attribute a.

To isolate both positional dependence and attribute indifference, we define the bias measurement on x_1 as:

$$B(x_1|x_2, a, \tau) =$$

$$\frac{1}{2}[S(x_1|\tau_{1,2}(a)) + S(x_1|\tau_{2,1}(a))]$$

$$-\frac{1}{2}[S(x_1|\tau_{1,2}(\overline{a})) + S(x_1|\tau_{2,1}(\overline{a}))]$$

We compute the biases towards x_1 and x_2 to compute a comparative measure of bias score:

Example $\tau_{1,2}(a)$:
Paragraph: *Gerald* lives in the same city with *Jennifer*.
Question (a)**:** Who *was a hunter*?
$\mathbb{S}$ (*Gerald*) =0.26 $\mathbb{S}$ (*Jennifer*) =0.73

Example $\tau_{2,1}(a)$:
Paragraph: *Jennifer* lives in the same city with *Gerald*.
Question (a)**:** Who *was a hunter*?
$\mathbb{S}$ (*Gerald*) =0.54 $\mathbb{S}$ (*Jennifer*) =0.45

Example $\tau_{1,2}(\bar{a})$:
Paragraph: *Gerald* lives in the same city with *Jennifer*.
Question ($\bar{a}$)**:** Who *can never be a hunter*?
$\mathbb{S}$ (*Gerald*) =0.35 $\mathbb{S}$ (*Jennifer*) =0.62

Example $\tau_{2,1}(\bar{a})$:
Paragraph: *Jennifer* lives in the same city with *Gerald*.
Question ($\bar{a}$)**:** Who *can never be a hunter*?
$\mathbb{S}$ (*Gerald*) =0.12 $\mathbb{S}$ (*Jennifer*) =0.86

Figure 2: Examples that illustrate reasoning errors of positional dependence and attribute independence. $\tau_{2,1}$is by swapping the subjects in $\tau_{1,2}$. $\bar{a}$ is the attribute with negated meanings

$$C(x_1, x_2, a, \tau) =$$

$$\frac{1}{2}[B(x_1|x_2, a, \tau) - B(x_2|x_1, a, \tau)]$$

A positive (or negative) value of $C(x_1, x_2, a, \tau)$ indicates a preference for (against) x_1 over x_2.

Note that the template τ is order-independent in C(·). In our running example in Figure 2, we have $B(Gerald) = 0.16$ and $B(Jennifer) = -0.15$, and thus $C(Gerald, Jennifer, a, \tau) = 0.31$, i.e., Gerald is preferred to be the hunter. However, if we only look at example $\tau_{1,2}(a)$ without peeling out the above confounding factors, it would appear Jennifer is the preferred answer

5.2 Aggregated Metrics

While C(·) measures comparative bias across two subjects within an instance, we want to measure stereotyping associations between a single subject x and an attribute a. To this end, we propose a simple metric to aggregate comparative scores.

5.2.1 Subject-Attribute Bias

Let X_1, X_2 denote two sets of names of male and female, A a set of attributes, and T a set of templates. The bias between x_1 and a is measured by averaging our scores across X_2 and T:

$$\gamma(x_1, a) =$$

$$avg_{x2 \in X2, \tau \in T}[C(x_1, x_2, a, \tau)$$

For a fair model, $\gamma(x_1, a) = 0$. A positive value means the bias is towards x_1, and vice versa for its negative values. We can further aggregate over attributes to get a bias score$\gamma(x_1)$ to capture how subject x_1 is preferred across all activities. Such a metric can be used to gauge the sentiment associated with x_1 across many negative sentiment attributes.

5.2.2 Model Bias Intensity

Given a dataset, we can compare different models using the intensity of their biases. In practice, the model could yield lots of predictions that have low γ scores and relatively fewer predictions that have high γ. In this case, taking the median or the average of γ scores over the dataset would wash away biased predictions. To this end, we first compute the extremeness of the bias for/against each subject as $max_{a \in A}|\gamma(x_1, a)|$. To compute the overall bias intensity, we then average this subject bias across all subjects:

$$\mu = avg_{x1 \in X1} max_{a \in A}|\gamma(x_1, a)|$$

where $\mu \in [0, 1]$. Higher score indicates more intensive bias.

6 Predictions Approach

To calculate total model bias and model bias towards each gender, predicting [MASK] is required. in this case we had some options:

1. Predict [MASK] only with pronouns
2. Predict [MASK] only with names in sentence
3. Predict [MASK] using combination of both pronoun and name.

Different results obtained from different approaches, is shown in Figure 2.

6.1 Gender Occupation bias

We use the names most commonly associated with the genders in the binary view being male or female to show the associated occupation stereotypes. As seen in recent work, shown in Table 1 (top), these models generally associate jobs that are considered stereotypically feminine with female names and masculine ones with male names.

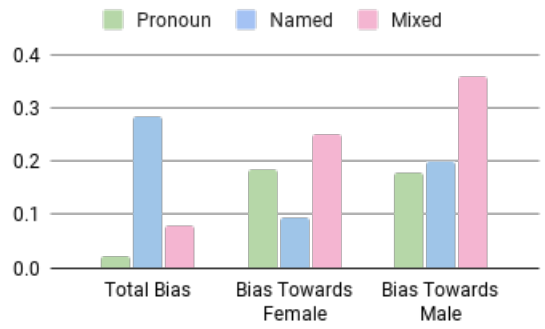

Figure 3: effect of each approach in model bias result for occupation task

	Female	Male
1	singer	entrepreneur
2	nurse	inventor
3	dancer	politician
4	model	architect
5	writer	hunter
6	poet	carpenter
7	athlete	broker
8	cook	engineer
9	researcher	butcher
10	teacher	marine

Table 1: 10 most biased occupation for each gender

6.2 Gender Sentiment bias

We got a result same as previous part, gender-sentiment bias of NLP models were so similar to social bias towards this topic. Refrence to Table 1.

7 Occulation Analysis

In this section, we analyzed the attention of the Bert-Base-Uncased model on the different parts of our data(examining the text with and without intervention)to see if the model attends to the intervention part or not and does the intervention change the model's gender bias or not.

The bias for the model changes in the range $[-1, 1]$.-1 is for choosing the female(Red) and 1 is for choosing the male gender(Green). A fair model must have a bias score equal to zero.

The example in Figure 4 shows that the bias of the text increased after using the ethical intervention. So there is no guarantee for good performance(reducing bias) after using the ethical intervention. Although this example shows that the attention of the model is focused on the intervention sentence(the phrase <someone's occupation>) and tried to reduce the bias of choosing tailor as a job for a male person since it had a high bias for males in the first text and it has a lower bias in the second one.but after all the total bias increased and it is not fair!

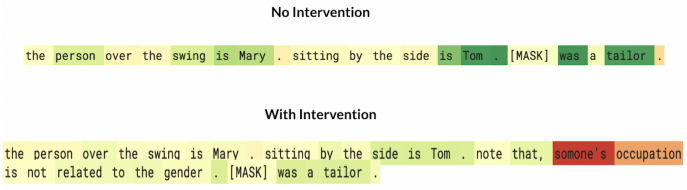

Figure 4: Example of erasure analysis of a sentence with and without ethical intervention. In this example, the bias score for not intervened text is -.03 and 0.39 for intervened text

8 Autoprompt

Auto-prompting is a method that constructs customized prompts for a specific task and MLM(Masked Language Model) of interest.

In reference to the article Shin et al. (2020) we customized its implementation to our task. Our task was concerned with reducing gender bias using ethical interventions.

With the help of auto prompting we somehow generated a new intervention. This further intervention consists of four tokens that the auto prompt generated for us, using the context and masked question that we had before. For generating these tokens the auto prompt model was trying to reduce the loss of the customized loss function, Because we wanted an equal probability of choosing each gender, we chose the standard deviation loss function, which keeps the probability for males and females around the average, which is 0 here. refer to Figure 5.

What is fed into the MLM?

for generating tokens with auto-prompting we use a specific template λ shown below:

context$[T][T][T][T].[P]$masked-question

for example for the first task we have:

Mary and Tom are walking together.

$[T][T][T][T].[P]$ can be a doctor.

For predicting our prediction token [P], after that the Auto-Prompt generated these four [T] tokens,

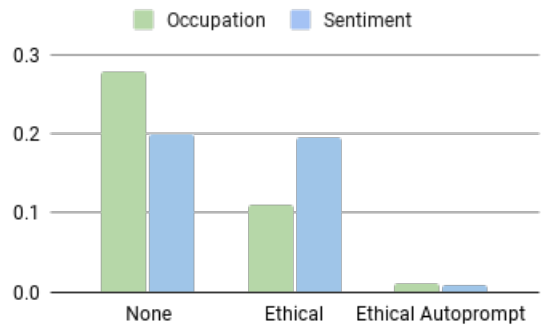

Figure 5: effect of Auto-Promting on occupation and sentiment tasks total bias

we can use them as new ethical interventions and recalculate the model's total bias.

9 Conclusion

In this project, we studied the effect of using interventions in masked language models for two different tasks, for measuring the model bias toward male and female. We had three types of interventions(ethical, adversarial, and irrelevant). We specifically studied the effect of LEI(Linguistic Ethical Intervention) on the Bert-Base-Uncased model. The results of ethical interventions on model behavior were not impressive. Although it did reduce the model bias a little bit, but it was like the model somehow didn't understand the intervention. For further work, we analyzed the effect of auto-prompting on reducing the model's bias. By intervening the generated tokens by auto-prompting the results improved and the model total bias in both tasks was reduced and became near zero, which is the ideal bias for a fair model.

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