Your fairness may vary: Group fairness of pretrained language models in toxic text classification

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While the progress in NLP tasks due to pretrained language models (LMs) [7, 15, 18, 5, 10] is clear [19, 25], the reasons behind this success are not as well understood [20, 16], and there are also downsides. In particular, several studies have documented the bias (defined further below) of LM-based models [12, 26] and others discuss potential societal harms [2, 1] for individuals or groups. Focusing on downstream applications, it becomes important to examine the behavior of LMs in terms of measures other than just task accuracy.

Figure 1: Balanced accuracy versus equalized odds (group: race) for several fine-tuned LMs on the Jigsaw dataset when varying only the random seed used in fine-tuning.

We focus on toxic text classification using fine-tuned LMs. Text toxicity predictors are already used in deployed systems [17] and they are crucial for content moderation since online harassment is on the rise [24].

We use the term bias herein to refer to systematic disparity in representation or outcomes for individuals based on their membership in certain protected groups such as religion, race, and gender. In NLP systems, bias is broadly understood in two categories, intrinsic and extrinsic. Intrinsic bias refers to the bias inherent in the representations [3], with respect to protected groups. Extrinsic bias refers to the bias in downstream tasks, such as disparity in false positive rates across protected groups in a specified application. Measuring intrinsic bias in LM embeddings does not necessarily reflect the behavior of models built by fine-tuning LMs, especially since some studies show that intrinsic metrics of bias do not correlate with application bias metrics [8]. In this work, we restrict our focus to group fairness measures, which fall under the category of extrinsic bias measures. In particular, we use equalized odds [9] as a metric for group fairness [23].

Figure 2: FST parameter search space (group: religion) for BERT.

We analyze the performance of more than a dozen LMs on the binary classification task of identifying toxic text using the Jigsaw dataset [4] and three protected groups: religion, race, and gender and sexual orientation. We include in our study a series of small, regular and large LMs with the number of parameters varying from 12M to 400M (ordered by size): Small - ALBERT [14], MobileBERT [22], SqueezeBERT [13], DistilBERT [21]; Regular - BERT [7], ELECTRA [5], Funnel (small) [6], RoBERTa [15], GPT2 [18], DeBERTa [10]; Large - ELECTRA-large, BERT-large, RoBERTa-large, DeBERTa-large.

We address the following questions:

**Model size**: Building on the work of [1] and [11], how does the group fairness of fine-tuned LM classifiers vary with their size? Figure 3 shows the task performance (as measured by balanced accuracy$^1$ versus group fairness as measured by equalized odds. The size of the model is color-coded. The results show that no blanket statement can be made with respect to the bias of large versus regular versus compressed models.

$^1$All models’ accuracy are around 95% with very little variation across models.
a) religion  
b) race  
c) gender and sexual orientation

Figure 3: Balanced accuracy versus equalized odds for several fine-tuned LMs on the Jigsaw dataset.

a) DistilBERT  
b) BERT  
c) ELECTRA-large

Figure 4: Accuracy, balanced accuracy and equalized odds for fine-tuned LMs on the Jigsaw dataset when varying the amount of data used in training and the random seeds (error bars are shown).

Figure 5: Balanced accuracy versus equalized odds for BERT for FST without and with calibration and TPP. Baseline points are shown in black. Best operating points for FST with calibration for equalized odds less than 0.05 are shown in orange.

**Random seeds:** One source of variation in the performance of LMs is random initialization. What is the effect of random seeds on the accuracy-fairness tradeoff? Figure 1 plots results for fine-tuned LMs where the random seed is varied. For any given model, the accuracy (not shown) and balanced accuracy are impressively stable, while fairness metrics can see variations of up to 5 points.

**Data size:** The size of training/fine-tuning data is an important dimension alongside model size. What happens with the tradeoff between accuracy and fairness when more data is used for fine-tuning? Figure 4 plots accuracy, balanced accuracy and equalized odds for three models (one in each category) when varying the training size. The points are averages across multiple runs obtained with different random seeds and error bars are shown. Accuracy plateaus sooner than equalized odds. The trends are similar for other models and protected groups.

**Bias mitigation via post-processing:** Given the expense of training and fine-tuning large LMs, to what extent can we correct extrinsic bias by only post-processing LM outputs? We experimented with one post-processing method, Fair Score Transformer (FST) [27] that was proven efficient in mitigating bias in binary classifiers operating on tabular data. Figure 2 shows the tuning of FST (epsilon and threshold for binary classification). Figure 5 shows pareto fronts for FST without and with calibration and TPP. Overall, FST manages to improve classifier fairness with varied degree of success across protected groups. Similar trends are observed across all 14 models.

Our analysis and results call for a careful introspection of models and tasks, using various performance and fairness measures.
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