Abstract

Warning: this paper contains content that may be offensive or upsetting.

Detecting social bias in text is challenging due to nuance, subjectivity, and difficulty in obtaining good quality labeled datasets at scale, especially given the evolving nature of social biases and society. To address these challenges, we propose a few-shot instruction-based method for prompting pre-trained language models (LMs). We select a few class-balanced exemplars from a small support repository that are closest to the query to be labeled in the embedding space. We then provide the LM with instruction that consists of this subset of labeled exemplars, the query text to be classified, a definition of bias, and prompt it to make a decision. We demonstrate that large LMs used in a few-shot context can detect different types of fine-grained biases with similar and sometimes superior accuracy to fine-tuned models. We observe that the largest 530B parameter model is significantly more effective in detecting social bias compared to smaller models (achieving at least 13% improvement in AUC metric compared to other models). It also maintains a high AUC (dropping less than 2%) when the labeled repository is reduced to as few as 100 samples. Large pretrained language models thus make it easier and quicker to build new bias detectors.

1 Introduction

Detecting social bias in text is of utmost importance as stereotypes and biases can be projected through language (Fiske, 1993). Detecting bias is challenging because it can be expressed through seemingly innocuous statements which are implied and rarely explicit, and the interpretation of bias can be subjective leading to noise in labels. In this work, we focus on detecting social bias in text as defined in Sap et al. (2020) using few-shot instruction-based prompting of pre-trained language models (LMs).

Current approaches that detect bias require large labeled datasets to train the models (Chung et al., 2019; Waseem and Hovy, 2016; Zampieri et al., 2019; Davidson et al., 2017a). Collecting such labeled sets is an expensive process and hence they are not easily available. Furthermore, most of the prior work relies on finetuning (Sap et al., 2020; Mandl et al., 2019; Zampieri et al., 2019) neural architectures which is costly in case of large LMs (Strubell et al., 2019) and access to finetune large LMs may be limited (Brown et al., 2020). Prior work on bias detection has not focused on modeling multiple types of biases across datasets as it requires careful optimization to succeed (Hashimoto et al., 2017; Søgaard and Goldberg, 2016; Ruder, 2017). Finetuning a model can also lead to over-fitting especially in case of smaller train sets and to catastrophic forgetting of knowledge present in the pre-trained model (Fatemi et al., 2021). Moreover, finetuning approaches are prone to be affected by noisy labels (Song et al., 2022) which is especially an issue with datasets for bias detection. The human labeling used to annotate these datasets can introduce bias and noisy labels (Hovy and Prabhumoye, 2021).

We harness the knowledge present in large scale pre-trained language models (Davison et al., 2019; Zhou et al., 2020; Petroni et al., 2019; Zhong et al., 2021; Shin et al., 2020) to detect a rich set of biases. Our method prompts the LM with a textual post and labeled exemplars along with instructions to detect bias in the given post. We explore the capabilities of LMs to flexibly accommodate different dimensions of bias without any finetuning and with limited access to labeled samples (few-shot classification).

Prompt-engineering plays a central role in finetuning-free approaches (Liu et al., 2021b). It is the process of creating a prompting function that results in the best performance on the desired downstream task. Prompt-engineering can be performed...
Our approach: We provide the LM with exemplars where semantically similar text is used in both biased and unbiased contexts. This specifically can be useful in identifying implicit biases. To achieve that, we use prompt-engineering approach in combination with a novel method to sample class-balanced exemplars in case of few-shot bias classification. We propose the use of sentence similarity metric to sample exemplars instead of uniform (Gao et al., 2020; Logan IV et al., 2021) or random (Brown et al., 2020) sampling explored before. As shown in Figure 1, we first utilize sentence encoder to project the labeled posts and the query post to the same embedding space. We use a similarity metric to identify posts from labeled repository that are closest in meaning to the query post. We then select an equal number of exemplars from each class label to be provided as context for few-shot classification.

To summarize, our contributions are as follows:

- We demonstrate that our technique maintains performance with smaller repository sizes (less than 2% AUC point drop in downsizing the labeled repository from 35k to 100 samples)(§4).
- Finally, we scale our technique to a large LM with 530B parameters and illustrate that it can achieve at least 13% AUC improvement compared to other models on majority of tasks.

Our proposed technique does not require any additional complex tuning to perform multiple tasks and is flexible to identify a diverse set of biases focusing on coarse-grained (binary classification) as well as fine-grained (if the text was targeted or untargeted insult, who is targeted in the text, etc) tasks. Our experiments show that pretrained language models are robust against noisy labels. We demonstrate that the models are able to predict the correct label more than a third of the time even when provided with 100% flipped labels. Additionally, we present ablations to understand the contribution of different semantic components of our method, and an exhaustive qualitative analysis of the LM predictions.

2 Methodology

We study the ability of pre-trained LMs to detect implicit bias in text. We also investigate if large LMs are capable of doing so with limited access to labeled samples (few-shot classification) and without any finetuning. We propose to sample class-balanced exemplars from a labeled repository based on their semantic similarity with the query post. We only provide the LM with a few examples of bias, the textual post to be classified and a definition of bias and prompt it to make a decision. We present all our exemplars as Question-Answer pairs in context. Our approach consists of syntactic structured...
component and a semantic content component. The syntactic structure is provided by special tags such as Post, Question and Answer. The semantic content consists of the textual exemplars chosen from the labeled repository and their labels.

Formally, we have a textual post $Q$ and a definition of bias $d$. We want to categorize text $Q$ in $C$ classes. We provide a language model $M$ with $Q$ and $d$, and we check the probability $p_M(c_i|Q;d)$ of each class $c_i \in C$, where $;$ denotes concatenation of the two strings $Q$ and $d$. We consider the class with the highest probability to be the prediction of $M$ for the given $Q$ and $d$.

For example as shown in Figure 1, consider the binary classification task of predicting if a piece of text is offensive or not. Here, the text $Q$ to be labeled is Newbie here, saw this on twitter. I am trying as I am so tired of conservatives being blocked and banned. and the definition $d$ of offensiveness used to annotate the text is Could this post be considered offensive, disrespectful, or toxic to anyone/someone?. The final input to model $M$ would be $p = ["Post:"); Q; "Question:"); d; "Answer:");], where we concatenate the tags Post, Question and Answer. Since it is a binary classification task, we calculate the probabilities of the tokens $Yes$ and $No$ in the following manner: $p_M("Yes"|p)$ and $p_M("No"|p)$. The token that has the highest probability is considered the prediction of the task.

Similarly, in case of a multi-class classification task of predicting if the text contains hate, offense or profanity, the $d$ is What does this post contain - hate, offense, profanity? We calculate the probability of the tokens hate, offense and profanity given the input $p$.

In the zero-shot case, only the input $p$ as described above is provided as input to $M$. In the few-shot case, we need a labeled repository $D$ where each sample $(x_i, c_i)$ is a tuple of the textual post and the class of the post respectively. We also know the definition $d$ to be used for classification. In the $k$-shot case, $k$ samples are chosen from $D$. The input $p$ to the model $M$ in this case is the concatenation of the following strings $p = [x_1; d; c_1; \ldots; x_k; d; c_k; Q; d]$. We add the tags Post, Question and Answer for structure.

**Selection of k-shots** In case of few-shot classification, we select $k$ exemplars from $D$ repository to be provided as context to $M$. Instead of randomly selecting the $k$ exemplars, we select the samples that are closest in meaning to the text $Q$ which we want to classify. We project $Q$ and all the text samples from $D$ in the same embedding space. We use cosine similarity and select the $k$ exemplars that have the highest cosine similarity scores. We also have an additional constraint of selecting equal number of exemplars from each class $C$ to ensure balanced representation of labels. For example, in case of 32-shot binary classification, we select 16 positive exemplars and 16 negative exemplars that are closest in meaning to $Q$.

### 3 Experiments and Results

#### 3.1 Datasets

We consider two separate datasets and a total of eight bias classification tasks. Note that models finetuned on one dataset would need to be further optimized or finetuned on the other dataset but this is not the case for our approach.

**Social Bias Frames (SBIC)** This dataset (Sap et al., 2020) contains fine-grained categorization of textual comments to better model the pragmatic frames in which people project social biases and stereotypes onto others. It contains four binary classification tasks and one multi-class classification task (%age positive samples in test set are shown in brackets): (1) **offensive** task (57.8% pos): predict if the text is offensive or not, (2) **intent** task (53.1% pos): predict if the text is an intentional insult or not, (3) **lewd** task (9.6% pos): predict if the text contains lewd language or not, (4) **group** task (41.1% pos): predict if the text is offensive to a group or an individual, and (5) **target group (WHO)** task: if the text is offensive to a group then identify the group targeted in the text. We design the target group identification as a seven-way classification task where the target group categories are - body, culture, disabled, gender, race, social, victim.

Sap et al. (2020) treat these five tasks as a single generative task where the entire frame is generated token by token. We treat them as five separate classification tasks.

**HASOC** This dataset (Mandl et al., 2019) is released in three Indo-European Languages. We only focus on English tasks. It consists of two binary classification tasks and one multi-class classification task: (1) **HOF** task (25.0% pos): is a coarse-grained task of determining whether a post contains hate, offensive, and profane content (as one label) or not, (2) **HOP** task: is a fine-grained task that...
Table 1: Results for the 32-shot prompting on four binary classification tasks offensive, intent, lewd and group from SBIC dataset (§3.1). The best performance in each task is presented in bold. We show the relative percentage improvement (\( \% \)) in AUC score compared to the rnd sampling. The improvement gained by MT-NLG by using TF-IDF vs. rnd-50 is less compared to smaller models.

| Model          | Sampling | Offensive | Intent | Lewd | Group |
|---------------|----------|-----------|--------|------|-------|
|               |          | AUC      | F1     | AUC  | F1    | AUC  | F1    | AUC  | F1    |
| SC            |          | -        | 78.80  | -    | 78.60 | -    | 80.70 | -    | 69.90 |
| KWD           | -        | 58.31    | 70.94  | 56.94| 67.17 | 59.83| 35.39 | 55.50| 57.16 |
| TF-IDF        | TF-IDF   | 63.64    | 72.76  | 65.00| 69.71 | 56.77| 21.67 | 65.57| 59.74 |
| Meg-1.3       | rnd      | 55.02    | 64.45  | 55.25| 51.57 | 49.80| 0.00  | 52.33| 28.73 |
| Meg-1.3       | rnd-50   | 74.69%   | 75.60  | 75.05| 58.04 | 77.79| 54.88 | 19.02| 76.34 |
| Meg-1.3       | TF-IDF   | 12.92%   | 62.13  | 73.49| 63.20 | 69.04| 72.21 | 51.80| 56.67 |
| Meg-8.3       | rnd      | 61.49    | 74.11  | 61.96| 68.17 | 50.10| 0.86  | 60.68| 48.40 |
| Meg-8.3       | rnd-50   | 15.94%   | 65.14  | 76.20| 64.88 | 73.05| 72.09 | 63.67| 24.10 |
| Meg-8.3       | TF-IDF   | 17.38%   | 66.03  | 77.53| 77.31| 66.49| 74.39 | 69.27| 28.00 |
| MT-NLG        | rnd      | 75.77    | 79.76  | 72.97| 75.24 | 51.80| 7.47  | 71.56| 64.92 |
| MT-NLG        | rnd-50   | 10.98%   | 76.98  | 59.49| 73.65| 75.63| 83.88| 73.34| 32.68 |
| MT-NLG        | TF-IDF   | 13.73%   | 78.60  | 82.19| 74.99| 76.61| 79.77| 71.62| 74.74 |

3.2 Baselines

We consider two simple heuristics which can prove to be strong baselines for these tasks due to high correlation of certain keywords with labels.

Keyword-based (KWD) We use 3 common keyword-based baselines. The LDNOOBW dataset (Shutterstock, 2013) contains 403 banned English words and has been used in prior research (Salmi-

nenn et al., 2019; Simonite, 2021). The dataset of bad, offensive and profane words (von Ahn, 2021) contains more than 1300 English terms that could be found offensive or profane. Finally, obscenity and profanity dataset contains more than 1600 popular English keywords for profanities and their variants grouped into 10 categories including sexual acts, sexual orientation, racial/ethnic slurs, religious offense (SurgeAI, 2021).

We assign a positive label to a post if it contains at least one keyword from the list in a given dataset. As these datasets don’t perfectly align with the categories from (Sap et al., 2020) and (Mandl et al., 2019), in Table 1 and 2 we report the metrics for the best performing dataset (KWD).

TF-IDF We use Term Frequency-Inverse Document Frequency (TF-IDF) to project the text Q and the posts from \( D \) in the common embedding space (Scikit-learn, 2022b). For \( k \)-shot classification, we select \( k/|C| \) posts with the highest cosine similarity score from each class i.e we select equal number of posts from each class. We then average the similarity scores for the selected samples from each class. The class that has the highest average score is considered the prediction of the TF-IDF baseline.

3.3 Sampling Techniques

Random (rnd) \( k \) exemplars are randomly selected from repository \( D \) are provided as context to the language models. This sampling is agnostic to the labels of the exemplars selected.

Class Balanced Random (rnd-50) In this technique, we randomly select \( k \) class balanced exemplars from \( D \) i.e. in case of binary classification, we ensure that \( k/2 \) exemplars are randomly selected from the positive class and \( k/2 \) exemplars are randomly selected from the negative class.

Similarity Based This technique selects \( k \) exemplars based on their semantic similarity to the query to be classified Q. As described in Section §3.2, we use TF-IDF representation to encode Q and exemplar text in \( D \). We select \( k/|C| \) exemplars with the highest cosine similarity score from each class.

3.4 Evaluation Metric

Following Sap et al. (2020), we use binary F1 score of the positive class for measuring the performance of our models on offensive, intent, lewd, and group tasks. Additionally, we also report area under the
Table 2: Results from the 32-shot prompting on two HASOC binary classification tasks (§3.1). The best performance in each task is presented in bold.

| Model       | Sam | HOF       | Target    |
|-------------|-----|-----------|-----------|
|             |     | F1m       | F1w       | F1m       | F1w       |
|             |     |           |           |           |           |
| HS          | 78.82 | 83.95 | 51.11 | 75.63 |
| KWD         | 56.88 | 71.68 | 41.31 | 53.17 |
| TF-IDF      | 51.71 | 60.45 | 45.49 | 63.02 |
| Meg-1.3     | 52.06 | 61.51 | 40.63 | 50.17 |
| Meg-1.3     | 52.96 | 60.88 | 43.36 | 57.33 |
| Meg-8.3     | 58.64 | 65.27 | 45.62 | 59.79 |
| Meg-8.3     | 58.52 | 63.99 | 51.25 | 67.16 |
| MT-NLG      | 63.02 | 74.19 | 30.02 | 32.57 |
| MT-NLG TF-IDF | 65.81 | 75.22 | 36.27 | 42.48 |

Table 3: Results for the multi-class classification tasks from HASOC and SBIC (§3.1). Due to the number of classes, the WHO classification is performed with $k = 28$ and HOP is performed with $k = 3$. The best performance in each task is presented in bold.

| Model       | Sam | WHO (7-way)       | HOP (3-way)       |
|-------------|-----|------------------|------------------|
|             |     | AUC  F1w  F1m  F1w | AUC  F1w  F1m  F1w |
|             |     |     |     |     |     |     |     |
| HS          |     | -   | 54.46 | 72.77 |
| TF-IDF      |     | 72.26 | 42.94 | 32.90 | 32.46 |
| Meg-1.3     |     | 63.40 | 28.87 | 34.41 | 38.68 |
| Meg-1.3 TF-IDF |     | 67.29 | 32.84 | 35.11 | 38.29 |
| Meg-8.3     |     | 76.08 | 43.25 | 28.64 | 29.23 |
| Meg-8.3 TF-IDF |     | 82.27 | 51.21 | 25.24 | 25.05 |
| MT-NLG      |     | 86.67 | 64.82 | 48.02 | 51.54 |
| MT-NLG TF-IDF |     | 88.60 | 67.91 | 46.28 | 48.10 |

3.5 Modeling Details

For language model $M$, we use off-the-shelf pre-trained models. We use Megatron 1.3B parameter model (Meg-1.3) and Megatron 8.3B parameter model (Meg-8.3) models pre-trained using the toolkit in Shoeybi et al. (2019). To understand the scaling of our technique to larger LMs, we perform experiments with MT-NLG which is a GPT-style 530B parameter model (Smith et al., 2022).

We use the train sets of SBIC and HASOC as labeled repository $D$ for sampling exemplars for k-shot classification. We pre-process the SBIC train set to ensure that the test set does not overlap with the train set. We compute Levenshtein distance $l$ between each sentence $Q$ in the test set and labeled repository $x_i$. If the ratio $r = \frac{2*l}{|Q|+|x_i|}$ is less than 0.1, then we discard the train sentence $x_i$. Here $|.|$ indicates the length of the sentence in terms of number of characters. The ratio $r$ tells us if the train sentence $x_i$ can be transformed to test sentence $Q$ by changing less than 10% of the characters.

We use TF-IDF as a baseline. The k shots picked by TF-IDF are also used in experiments with LMs in k-shot classification. All the binary classification tasks are performed with $k = 32$ for uniformity. The bias definitions used for all the tasks are provided in Appendix A.1.

3.6 Results

The main results for the six binary classification tasks in the 32-shot case are shown in Tables 1 and 2.2 We show the results from Sap et al. (2020) (SC) and Mandl et al. (2019) (HS) to understand how close our models perform in comparison to finetuned state-of-the-art models.3

From these Tables we see that in general as the size of the LM increases, the AUC and F1 performance for detecting bias improves. We also see that MT-NLG performs the best on both AUC and F1 metrics for all the SBIC tasks and it performs better than finetuned SC model on three tasks - offensive, intent and group. In Table 1, we see that using class balanced random sampling (rnd-50) performs much better than random sampling. We also observe that similarity based TF-IDF sampling performs better than random (rnd-50) sampling. We note that as the model size increases, the improvement gained by using better sampling technique reduces. Concretely, across the four SBIC tasks, the average AUC gain between rnd-50 and TF-IDF sampling is 9.6% for Meg-1.3, 3.9% for Meg-8.3 and 3.4% for MT-NLG. This shows that the larger models are robust towards the sampling technique.

For HOF task, MT-NLG performs better than baselines on both F1 metrics. For Target task, this is not the case because of the skewed distribution of indicative keywords in this task. We perform an analysis of the percentage of posts that contain key-

1https://pypi.org/project/python-Levenshtein/

2In §B we show additional analysis with more sampling techniques which can perform better for these bias tasks. But we show in Table 10 and Table 11 that these sampling techniques take advantage of the keywords that are used only in one specific contexts. Hence, they cannot not generalize to other tasks.

3More details of SC and HS models can be found in §A.4
Table 4: Results of the 32-shot prompting on the four SBIC classification tasks with decreasing sizes of labeled repository \( D \). We show the std for AUC and F1 metric on 3 versions of the dataset downsized with different seeds. We show the relative percentage improvement (\( + \)) or decrements (\( - \)) in AUC score compared to the 35k support repository size. The largest model MT-NLG experiences the smallest decrease in performance (only 1.84% AUC).

words and their correlation with labels (details in Appendix A.2). We note that keywords are present at five times higher rate in positive posts of the Target task compared to the other tasks. The results for the two multi-class classification tasks are shown in Table 3. For both the tasks we experiment with different values of \( k \) \( (k = \{7, 28\}) \) for WHO task and \( k = \{3, 12\} \) for HOP task and we present the best performing results. The results for WHO task are shown for \( k = 28 \) shots, to ensure equal samples from each of the seven classes. Similarly, the HOP results are shown for \( k = 3 \) i.e. one exemplar is picked from each of the three classes that is the closest to the textual post \( Q \). For both the multi-class classifications tasks, MT-NLG performs better than baselines on all metrics illustrating the effectiveness of our approach. We are unable to show the keyword baselines for multi-class tasks because of lack of keyword repositories that clearly align with all the classes.

4 Analysis and Discussion

Smaller Size of \( D \) We experiment with smaller sizes of repository \( D \) to understand how the size of \( D \) affects model performance. The goal is to understand the amount of annotated data required by our technique to detect social bias. The original SBIC train set contains \( \sim 35k \) instances (used as \( D \) in §3.6). We down-sample examples from this dataset to create smaller sets of sizes 10k, 1k and 100. A labeled set \( D \) of size 100 means that we can only select the \( k \)-shots from 100 samples. We ensure that we have equal label distribution in the down-sampled sets. For each size, we use three different random seeds to generate down-sampled data. We then average the results of the four 32-shot SBIC classification tasks for the sets produced by three random seeds and present the results in Table 4 for both rnd-50 and TF-IDF sampling.

We observe that in case of rnd-50 sampling, there is practically no change in performance of the language models with the reduction in support repository size. The standard deviation for the AUC score across the four \( D \) sizes is 0.43 for Meg-1.3, 0.54 for Meg-8.3 and 0.47 for MT-NLG, which is extremely low. We see that in case of TF-IDF sampling, the performance of the larger models does not degrade substantially when the size of the labeled repository is reduced to as low as 100 samples. For example, the relative percentage AUC drop is only 2.93% for Meg-8.3 and 1.84% for MT-NLG as opposed to 5.47% for the Meg-1.3 model. The performance for the TF-IDF baseline however drops substantially by AUC 10.6%. For all the cases, MT-NLG performs better than the baselines on both AUC and F1 metric. For each support repository size, the LMs using TF-IDF based sampling perform better than the corresponding LMs using rnd-50 sampling.

Contribution of Components We have four components in our input to model \( M \): the textual exemplars \( x_i \), the definition \( d \), the class label \( c_i \) of exemplar \( x_i \), and the textual query post \( Q \) which we want to classify. We perform ablation studies
with \( x_i \), \( d \) and \( Q \) to understand the contribution of each of them in making the final prediction. Experiments with perturbation of label \( c_i \) are shown separately in the later section. The results of 32-shot intent classification ablation studies are shown in Table 5.

The AUC performance drops consistently as we remove the definition \( d \), the text of exemplars \( x_i \), and the query \( Q \). For Meg-8.3 and MT-NLG, we see that removing all three has the most impact on the performance. The AUC drops on average by 19.67% across models by only removing the textual exemplars \( x_i \) (The model gets class labels \( c_i \) of exemplars, \( d \) and \( Q \) as input). This suggests that MT-NLG pays attention to all the components and the textual examples are as important as knowing their labels. Absence of definition has the smallest impact causing only a minor drop in AUC of 3.7% for Meg-1.3 and 2.43% for MT-NLG, but no drop for Meg-8.3.

### Robustness to Labels

To understand the contribution of labels in the \( k \)-shot binary classification performance, we perform two ablation studies. We flip the labels (Flip) of the exemplars i.e. if the ground truth label of exemplar \( x_i \) is \( c_i = "Yes" \), then we supply the label “No” and vice versa. This study is done to understand the robustness of the model to noisy or wrong labels. In the second experiment, we flip the labels only 50% (Random) of the times. Hence, 50% of the time model gets correct label to an exemplar and gets a wrong label the other 50% of time. We show the results on 32-shot intent classification task for both TF-IDF and rnd-50 sampling in Table 6.

We observe that the AUC and F1 accuracy drops the most when we supply flipped labels. Interestingly, even in this case, the language models identify intentional insult more than a third of the time. In case of supplying Random labels, the relative AUC performance of LMs drops on average by 16% (similar results shown for general NLP tasks (Song et al., 2022)) further showcasing the robustness of the models towards wrong labels. The rnd-50 sampling is in general more robust to label flips compared to the TF-IDF sampling. For example, on average for the Random experiment, the AUC performance across LMs drops by 13.6% for rnd-50 sampling and 18.6% for TF-IDF sampling. TF-IDF picks the shots carefully to augment the LMs ability to classify and hence when wrong labels are provided, this sampling technique suffers more loss compared to rnd-50.

### k-shots vs Metric

To understand how the performance of the models scale with number of shots, we present Figure 2. It shows the graph of AUC metric for the group classification task with number of shots ranging from 8 to 96 with a step size of 8. We observe that for the group task, the performance improves up to \( k \) in range of 32 – 48 and

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**Table 5:** Ablation studies on SBIC Intent task to understand the contribution of each component of the instruction. Ablations performed with 32-shots prompting. The highest capacity model MT-NLG achieves best performance with all the instruction components.

| Model     | Post | Def. | Q   | AUC   | F1   |
|-----------|------|------|-----|-------|------|
| Meg-1.3   | ✓    | ✓    | ✓   | 63.20 | 69.04 |
| Meg-1.3   | ✓    | ×    | ✓   | 43.70%| 60.96 | 70.99 |
| Meg-1.3   | ×    | ×    | ×   | 19.00%| 51.27 | 65.03 |
| Meg-1.3   | ×    | ✓    | ✓   | 20.03%| 50.62 | 61.27 |
| Meg-1.3   | ×    | ✓    | ×   | 22.09%| 49.32 | 52.32 |
| Meg-8.3   | ✓    | ✓    | ✓   | 66.49 | 74.39 |
| Meg-8.3   | ✓    | ×    | ✓   | 71.76%| 67.66 | 72.81 |
| Meg-8.3   | ×    | ✓    | ✓   | 120.80%| 52.66 | 69.27 |
| Meg-8.3   | ×    | ×    | ✓   | 122.94%| 51.24 | 67.05 |
| Meg-8.3   | ×    | ×    | ×   | 123.28%| 51.01 | 66.69 |
| MT-NLG    | ✓    | ✓    | ✓   | 76.61 | 79.77 |
| MT-NLG    | ✓    | ×    | ✓   | 42.43%| 74.75 | 73.37 |
| MT-NLG    | ×    | ✓    | ✓   | 418.17%| 52.69 | 70.44 |
| MT-NLG    | ×    | ×    | ✓   | 434.64%| 50.07 | 65.30 |
| MT-NLG    | ×    | ×    | ×   | 434.51%| 50.17 | 61.14 |

**Table 6:** Experiment to understand the role of labels in prediction with 32-shot prompts on SBIC Intent task. The Flip and Random denote reversing the labels or replacing half of the shots with random label respectively.
Figure 2: Experiment with varying number of instruction shots for the Group binary classification task from SBIC. Change in AUC scores is plotted against the number of shots $k$ provided as context to the LMs. Then plateaus. The best performance of MT-NLG is at $k = 48$ with AUC score of 76.96 which is a 0.23 AUC improvement over $k = 32$. We would like to note that the $k$ at which the model achieves optimal performance is task dependent. For uniformity we choose to report performance at $k = 32$ for all tasks but we believe that each category can be further improved.

Qualitative Analysis We randomly sample 50 cases where MT-NLG makes a wrong prediction and TF-IDF is correct. Similarly, we also sample 50 cases where MT-NLG predicts the correct label and TF-IDF makes correct predictions. All the samples are picked for the offensive classification task. Based on manual qualitative coding among two of the authors, we further divide these cases into five categories.

Overall, we observe that for both TF-IDF and MT-NLG, high number of errors occur when there are no keywords present in the query text. In case of offensive posts without keywords, MT-NLG makes 12% less errors compared to TF-IDF. This shows that TF-IDF finds it challenging to identify implicit bias in the text. We observe that some posts may contain trigger words such as white nationalist, Black, Jews, Muslims, 9/11, etc. which causes TF-IDF to retrieve shots with offensive keywords from $\mathcal{D}$. We also observe that TF-IDF picks irrelevant offensive shots when enough content on the same topic is not available in $\mathcal{D}$. When such irrelevant posts are used, TF-IDF makes a wrong prediction. When keywords are present in the posts, there are lesser number of errors. Some of the posts are offensive but contain slurs such as f**k, b***h, etc.

Finally, 5% instances are mislabeled according to the human annotators. Some posts were clearly offensive and were annotated as non-offensive whereas other posts that seem to be non-offensive were marked as offensive suggesting potential ambiguity of interpretation. In these cases, there was not enough context to make a decision, a limitation particularly relevant to social media datasets and identified in prior work (Chen et al., 2018).

5 Related Work

Bias Detection Approaches for detecting bias in text can broadly be put into 3 categories: 1) keyword-based, 2) feature-representation-based, 3) supervised-training-based.

Keywords-based methods rely on curated lexicons of words (Hatebase.org, 2021; Shutterstock, 2013; von Ahn, 2021). Despite wide use (Sood et al., 2012; Mondal et al., 2017; Simonite, 2021) they can be at a significant mismatch with human ratings (Davidson et al., 2017b) and can’t easily capture phenomenons such as sarcasm, humor (Rajadesingan et al., 2015) or polysemy (Sahlgren et al., 2018). Such lexicons require constant updates as new slang develops (Nobata et al., 2016).

Prior work has also explored sophisticated feature representations including n-grams, linguistic and syntactic features (Nobata et al., 2016), TF-IDF (Salminen et al., 2018), Bag of Words and word embeddings (Djuric et al., 2015), as well as content-specific features such as mentions, proper nouns, named entities, and target group specific vocabularies (Waseem et al., 2017). Topic modeling approaches such as Labeled Latent Dirichlet Allocation have also been proposed (Saleem et al., 2018).

Note that we do not claim that 5% of the entire corpus is mislabeled.
Overall, these methods try to provide better feature representations than keywords (Sahlgren et al., 2018), but rely on careful feature engineering which might be specific to particular context and hence makes them inflexible across settings.

Supervised training based methods rely on large labeled datasets to train models (Badjatiya et al., 2017; Pavlopoulos et al., 2017; Zhang et al., 2018; D’sa et al., 2019; Caselli et al., 2020; Silva et al., 2020). Recently, transformers have been fine-tuned for hate-speech detection (Caselli et al., 2020), detection of targeted offensive language (Rosenthal et al., 2021) and bias (Sap et al., 2020). Similar techniques with focus on toxicity have been adopted in the commercial Perspective API (Perspective API, 2021). These methods are more effective than keywords or custom features (Badjatiya et al., 2017), but they rely on large labeled datasets and are expensive, or even impossible (e.g., Perspective API) to retrain. Furthermore, most approaches focus on binary coarse-grained hate-speech or toxicity classification, rather than on nuanced and target group specific issues of bias.

Prompting  Recent success of large pre-trained language models (Devlin et al., 2019; Brown et al., 2020; Smith et al., 2022) has opened the field to the new direction of prompting (Liu et al., 2021b) them for various NLP tasks. We demonstrate the success of this technique on social bias detection tasks which makes it possible to detect different social biases without a huge labeled set and training separate models for each task. Schick et al. (2021) self-diagnose toxicity in machine generated text. This is closest to our work. We focus on bias and a more fine-grained understanding of bias such as the target group, intentional or unintentional offense etc. in human written text. Bias in human written text can be more challenging to detect as it can be riddled with sarcasm and humor. Schick et al. (2021) evaluate the success of large LMs to detect toxicity using the scores provided by automated classifier Perspective API (Perspective API, 2021) as the ground truth. We evaluate the success of large LMs at detecting bias using human annotated labels as ground truth. Most importantly, Schick et al. (2021) sample the most toxic and most non-toxic examples from RealToxicity (Gehman et al., 2020) dataset i.e. they sample the extreme cases of toxicity, and report the performance of large LMs on zero-shot classification. We report few-shot classification performance on the entire test set of two independent datasets with human-provided labeling. Additionally, we also showcase multi-class classification capability of our approach.

Liu et al. (2021a) investigate the retrieval of exemplars that are semantically-similar to a test sample. The two key differences of our work are: (1) we focus on few-shot instruction based bias detection, and (2) we select equal number of exemplars from each class.

6 Conclusion

The paper proposes a novel technique to select exemplars for few-shot instruction-based method to detect bias using pretrained model’s internal knowledge and no fine-tuning. On two separate datasets involving binary and multi-class classification (ranging from coarse-grained to fine-grained tasks), we demonstrate that sufficiently large pretrained LMs can detect bias beating keyword and semantic-based heuristics as well as fine-tuned models on some of the tasks. In subsequent experiments we show that our method is: 1) flexible in incorporating various bias definitions, 2) robust against small pool of labeled documents to select shots from, 3) relies on deeper semantic interpretation, rather than surface level heuristics, which we show through extensive ablation studies and manual qualitative inspection. The ethical considerations are discussed in Appendix C.

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### A Appendix

#### A.1 Bias Definitions

The bias definitions used in all experiments are mentioned in Table 7. We formulate the definitions for binary tasks based on labeling instruction from the datasets. We use a template for the definition in the form of: *Does this post contain {attribute}?* We also mention the tokens for which we calculate classification probability in Table 7.

#### A.2 Keyword analysis

We study the percentage of keywords present in the textual posts of the test set for each binary task and their correlation to labels. We use a superset of keyword ($S$) containing 3173 keywords which is a union of keywords from (von Ahn, 2021; SurgeAI, 2021; Shutterstock, 2013). We calculate the overlap of keywords ($S$) with a textual post $Q$. Specifically, we check its correlation with the pos and neg labels for the binary tasks i.e percentage of positive textual posts $p$ that have at least one keyword from $S$ and percentage of negative textual posts $n$ that have at least one keyword from $S$. The ratio is calculated as $p/n$ and tells us the rate at which positive posts have a higher/lower overlap with keywords compared to the negative posts. This analysis along with label correlation is presented in Table 8. We can see that the Target task from HASOC has the highest overlap of keywords with gold labels leading to a hard to beat heuristic. We show the percentage of positive samples in the test set in brackets.

#### A.3 Qualitative Analysis

Qualitative analysis as described in section §4 is shown in Table 9. We show the representative textual posts for each category (Warning: the examples shown contain content that maybe offensive or upsetting).

#### A.4 Details on Finetuned Models

We provide details of the SC and HS models described in §3.6. The SC model (Sap et al., 2020) was trained to predict the entire social bias frame given the text of the post i.e given the post the GPT-2 model was finetuned to generate the token corresponding to each of the five classes in the original set ($w[lewd]$, $w[offensive]$, $w[intent]$, $w[group]$, $w[in-group]$). Note that we don’t present results for the in-group classification task.

We report the results of best performing systems in English in the HASOC track at FIRE 2019: Hate Speech and Offensive Content Identification in Indo-European Languages (Mandl et al., 2019). We report the result of YNU_wb team for HOF task, and 3Idiots team for HOP and target task.

### Table 7: Definitions of bias used for each task. We formulate the definitions based on labeling instruction from the SBIC and HASOC datasets. For binary definitions we use a template in the form of: *Does this post contain {attribute}?*

| Task   | Definition                                                                 | Tokens                                                                 |
|--------|-----------------------------------------------------------------------------|------------------------------------------------------------------------|
| Offensive | Does this post contain offensive language?                                 | Yes, No                                                                |
| Intent   | Does this post contain intentional insults?                                 | Yes, No                                                                |
| Lewd     | Does this post contain sexual content?                                     | Yes, No                                                                |
| Group    | Does this post contain offense to a group?                                 | Yes, No                                                                |
| WHO      | Who is referred to/targeted by this post - body, culture, disabled, gender, race, social, victim? | body, culture, disabled, gender, race, social, victim                  |
| HOF      | Does this post contain any form of non-acceptable language such as hate speech, offensiveness, aggression, profanity? | Yes, No                                                                |
| HOP      | This post contains hate, offense, profanity                                 | Yes, No                                                                |
| Target   | Does this post contain an insult/threat to an individual, group, or others? | Yes, No                                                                |

### Table 8: Keyword analysis for the SBIC tasks, based on union of keywords from (von Ahn, 2021; SurgeAI, 2021; Shutterstock, 2013). The percentages show the overlap of keywords with the pos and neg labels for the binary tasks. We can see that the Target task from HASOC has the highest overlap of keywords with gold labels leading to a hard to beat heuristic. We show the percentage of positive samples in the test set in brackets.

| Task | pos | neg | ratio  |
|------|-----|-----|--------|
| Offensive (57.8% pos) | 85.20 | 74.51 | 1.14   |
| Intent (53.1% pos)    | 84.75 | 76.08 | 1.11   |
| Lewd (9.6% pos)       | 93.35 | 79.34 | 1.18   |
| Group (41.1 % pos)    | 84.89 | 77.76 | 1.09   |
| HOF (25.0% pos)       | 88.54 | 76.07 | 1.16   |
| Target (85.1% pos)    | 88.57 | 15.51 | 5.71   |
Table 9: Analysis of the offensive task from (Sap et al., 2020). Textual Post indicates grounded information. O. indicates the ground truth label for the category.

| Id   | Error Class                                           | %     | Textual Post                                                                 | O.   |
|------|-------------------------------------------------------|-------|------------------------------------------------------------------------------|------|
| 1    | Post is offensive and does not contain offensive keywords | 38.33 | What’s black, white and rolls around on the beach? A black man and a seagull fighting over a chip. | Y    |
| 2    | Post is not offensive and does not contain offensive keywords | 38.33 | Bush: ‘it’s hard to unify the country when the news media is so split up. Remember when the news media mattered a lot more’. | N    |
| 3    | Post is offensive and contains offensive keywords      | 10.00 | Y’RE ALL NOOOOSS ANNOYING B**CH YOU’RE NOT MY CLASSMATES ANYMORE.             | Y    |
| 4    | Post is not offensive but contains keywords            | 8.33  | RT @markiplier: In the car with my frands going F***ING HYPERSPEED.           | N    |
| 5    | Mislabeled post                                       | 5.00  | omg twitter you are killing me with dumb this morning.                       | N    |

| Cases where MT-NLG makes wrong prediction and TF-IDF is correct |
|---------------------------------------------------------------|
| 6    | Post is not offensive and does not contain offensive keywords | 31.67 | The answer is yes I can fit 2 more people in this shirt therefor nobody will know I’m not wearing a bra. | N    |
| 7    | Post is offensive and does not contain offensive keywords | 26.67 | I know I keep hoping I wake up one day and this multiracial hell Canada was all just a terrible nightmare, but it never happens. | Y    |
| 8    | Post is offensive and contains offensive keywords      | 21.67 | number of femoids who would rather die than spend more than 5 seconds with an incel. | Y    |
| 9    | Post is not offensive but contains keywords            | 15.00 | AHHH karmas a b**ch.                                                        | N    |
| 11   | Mislabeled post                                       | 5.00  | Are you a bummer tied to a tree? No?? BUMMER ON THE LOOSE!!                 | N    |

Table 10: Results for the 32-shot prompting on intent classification task from SBIC dataset §3.1 on SBERT baseline and three language models which use shots sampled by SBERT.

| Model   | Sampling | Intent | AUC  | F1   |
|---------|----------|--------|------|------|
| SC      | -        | -      | 78.60|      |
| SBERT   | SBERT   |        | 79.36| 82.36|
| Meg-1.3 | SBERT   |        | 64.47| 68.05|
| Meg-8.3 | SBERT   |        | 68.95| 75.42|
| MT-NLG  | SBERT   |        | 77.59| 80.00|

Table 11: Results for the 32-shot prompting on intent classification task on data stratified SBERT baseline and three language models which use shots sampled by data stratified SBERT.

| Model   | Sampling | Intent | AUC  | F1   |
|---------|----------|--------|------|------|
| SBERT   | SBERT-strat |        | 23.51| 14.54|
| Meg-1.3 | SBERT-strat |        | 58.16| 60.32|
| Meg-8.3 | SBERT-strat |        | 64.52| 71.45|
| MT-NLG  | SBERT-strat |        | 74.15| 76.43|

B Analysis on Sentence-BERT

In this section, we show additional experiments using Sentence-BERT (SBERT) sampling technique (Reimers and Gurevych, 2019) to select class-balanced shots for k-shot classification. Although, the experiments in Table 10 show that SBERT can perform better for the bias tasks explored in this paper, results in Table 11 and Table 12 show this technique does not generalize to other tasks. We show in Section §B.1 that these sampling techniques take advantage of the keywords that are used only in one specific contexts.

We use SBERT to encode the post Q and the posts from D into a common embedding space.7

We then select k/|C| posts with the highest cosine similarity score from each class. These shots are provided as context to language model M.

For the SBERT baseline, we consider the class that has the highest average score as the prediction.

Results The results for 32-shot intent classification task on the SBERT baseline and the LMs using SBERT sampling technique are shown in Table 10. We observe that SBERT performs better than all the language models in intent classification task.

Data Stratification The SBIC dataset exhibits strong correlation between semantic similarity (captured by SBERT) and target class. This creates a very strong heuristic baseline, that is hard to beat even for fine-tuned model (see Table 10). To remove the impact of such simple heuristic and investigate whether the model is capable of reasoning on
the shot content, we implemented a stratified randomization for balanced shot selection. The goal of the stratification is to select equal number of shots for each class, such that the mean difference in cosine similarity of the class-balanced shots is minimized. To accomplish this, we implemented a binning-based stratification of shot-query cosine similarity scores (Lohr, 2021).

After SBERT embeddings and cosine similarities are calculated for all the train set, the stratified shot selection follows the following steps: 1) shots are ordered based on cosine similarity with the query text, 2) shots are allocated into bins based on their cosine similarity score using bin thresholds calculated using numpy implementation of histogram based binning \(^8\), 3) starting from the bin with the highest similarity and moving downwards, a maximum number of class-balanced shots from each bin is selected, and 4) step 3 is repeated until the total desired number of shots are selected.

As a result of this process, the average difference in mean cosine similarity between the shots for two classes is 0.0029 ($SD=0.0020$). The summary of shot stratification impact can be seen in Table 11. Using stratified class-balanced shots, removes the impact of simple SBERT heuristic reducing AUC from 79.36 to 23.52 and F1 from 82.36 to 14.54, but at the same time has limited impact on the performance of the MT-NLG model reducing AUC by 4.4\% (77.59 to 74.15) and F1 by 4.5\% (80.00 to 76.43).

The results in Table 11 illustrates the strong correlation between semantic similarity captured by SBERT and target class. We would like to note that this correlation is specific to bias datasets since often times they are collected using certain referential terms and keywords. To further bolster our hypothesis we present additional analysis of correlation of keyword in the shots selected by SBERT and the label, as well as an analysis on ANLI task (see §B.1).

### B.1 Analysis

#### Keyword overlap

We performed additional in-depth analysis to better understand the strong performance of SBERT heuristic on the SBIC dataset. Through qualitative exploration of the “Intent” task we observed an overlap of the key referential terms present in test set queries, such as “clinton”, “p***phile” predominantly with shots for one label, but not the other. This could suggest that in the SBIC dataset, the presence of such terms is sufficient to decide on the label. To verify this observation at scale, we lemmatized the test queries extracting only NOUNS and PRONOUNS (via part-of-speech tagging (Spacy, 2022)). This process extracted referential terms such as: “clinton”, “p***phile”, “b**ch”, “lord”, etc. We further counted the frequency of these terms in shots picked from the train set with the same and opposite label (based on gold). For example, for post ‘Alex Jones & Mike Cernovich: “It’s crazy how the P***philes . . . all LOOK LIKE P***PHILES”’ # Truth’ the extracted terms are ‘alex’, ‘cernovich’, ‘jones’, ‘mike’, ‘p***phile’, ‘truth’. The frequency of these terms in same labeled shots resolves to: ‘p***phile’: 12, ‘cernovich’: 1, ‘alex’: 2, ‘jones’: 1, while for the opposite label shots these terms as much less frequent: ‘p***phile’: 6, ‘cernovich’: 1, ‘truth’: 2. From this we can see that e.g., the term “p***phile” is much more frequent in the shots with the same label, which suggests it is used in only one context.

At the scale of the entire test set, we quantified that the same label shots have on average 11.36 terms overlapping with the test posts, while for the opposite label shots this overlap amounts to only 7.76. Furthermore the ratio of keyword overlap between same and opposite label shots is 1.97 on average, meaning that there are almost 2x as many keywords overlapping with test post for the same labeled shots compared to opposite labeled shots.

This analysis suggests that crucial referential terms present in test posts, which, in essence, could be used in a biased or unbiased context (i.e., even term “p***phile” could be used in challenging contexts, such as a policy announcement or criticisms) are used in only one context. Such strong association of terms and context permits the mere presence or absence of such referential terms to be sufficient to decide on the label, which in turn drives high performance of simple SBERT heuristic.

#### ANLI Results

To further investigate our hypothesis that bias datasets have the property of using certain words or phrases only in biased or non-biased context, we test our approach on another task - the ANLI task.

The ANLI (Nie et al., 2020) dataset is an adversarially mined natural language inference
Table 12: Accuracy for the $k$-shot prompting on three different natural language inference datasets on the SBERT baseline and MT-NLG with $k = \{48, 24, 9\}$.

| Model | $k$ | ANLI-R1 | ANLI-R2 | ANLI-R3 |
|-------|-----|---------|---------|---------|
| SBERT | 48  | 28.10   | 30.80   | 30.16   |
| MT-NLG| 48  | 40.20   | 44.40   | 49.08   |
| SBERT | 24  | 27.10   | 31.90   | 30.75   |
| MT-NLG| 24  | 43.00   | 45.60   | 50.42   |
| SBERT | 9   | 28.50   | 38.50   | 35.08   |
| MT-NLG| 9   | 45.00   | 44.90   | 51.33   |

(NLI) dataset that aims to create a difficult set of NLI problems. It has 3 iterative rounds of data collection marked as ANLI-R1, ANLI-2 and ANLI-R3. Following (Smith et al., 2022), we rephrase the NLI problem into a question-answering format where each example is structured as “<premise>Question:<hypothesis>. True, False or Neither?Answer:’”. This prompt is given to the language model and we calculate the probability of tokens “True”, “False” and “Neither”. The token with the highest likelihood assigned by the model is considered as the model prediction.

In case of $k$-shot classification, we use SBERT to select class-balanced shots which are most similar to the query. The results of accuracy scores for the three rounds of ANLI datasets are shown in Table 12 with $k = \{48, 24, 9\}$. We observe that for all values of $k$, MT-NLG performs significantly better than the SBERT baseline. ANLI datasets were collected with the goal of having diverse set of contexts from various domains. They contain text extracted from Wikipedia, News (extracted from Common Crawl), fiction (extracted from StoryCloze and CBT), formal spoken text (excerpted from court and presidential debate transcripts in the Manually Annotated Sub-Corpus (MASC) of the Open American National Corpus3) and causal or procedural text, which describes sequences of events or actions, extracted from WikiHow (see Section 2.5 in (Nie et al., 2020)). Hence, the dataset does not contain samples that use certain phrases only in one context or uses certain words/phrases only for one label. Hence, this further solidifies our argument that our approach is generally applicable but struggles to perform better than heuristic-based SBERT baseline when the dataset is skewed.

C Ethical Considerations

The intended use of the proposed instruction-based detection techniques is to aid the identification of different forms of bias either in human or AI produced textual content. One potential applications can be to assist moderation of content in settings such as social media or in end-user AI applications involving language generation such as conversational agents. It can also be used to add safety features to the generation outputs of large LMs as well as it can assist in building future large LMs that are not biased by identifying biases in pretraining data. Given the limitations of our proposed method, it should likely not be used as a sole measure for detecting bias, but we believe it could serve as a low-effort initial filter and feedback mechanism. Furthermore, we see its use as potential means for promoting positive online interaction and higher community standards (Does et al., 2011).

Our proposed method, can unfortunately be misused intentionally or unintentionally (Weidinger et al., 2021). We specifically see the dangers of using our approach for censorship (Ullmann and Tomalin, 2020) or limiting expression in specific settings where violent or lewd language might be intended (e.g., crime fiction). Furthermore, there is danger of misappropriating our approach to introduce racially targeted censorship based on dialect (Sap et al., 2019). Despite certain degree of robustness and our additional experiments (e.g., with flipped labels), our method still relies on supervised labeling of few-shots provided as context, and as such can be affected by the imperfections of the labeling, such as racial bias in existing labeled datasets (Davidson et al., 2019). As shown in recent work, human annotation process can be a source of bias in itself (Hovy and Prabhumoye, 2021) and labelers may even be selected by malicious actors to introduce biased interpretation on purpose (Flekova et al., 2016).