Detecting Emergent Intersectional Biases: Contextualized Word Embeddings Contain a Distribution of Human-like Biases

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Abstract

With the starting point that implicit human biases are reflected in the statistical regularities of language, it is possible to measure biases in static word embeddings [1]. With recent advances in natural language processing, state-of-the-art neural language models generate dynamic word embeddings dependent on the context in which the word appears. Current methods of measuring social and intersectional biases in these contextualized word embeddings rely on the effect magnitudes of bias in a small set of pre-defined sentence templates. We propose a new comprehensive method, Contextualized Embedding Association Test (CEAT), based on the distribution of 10,000 pooled effect magnitudes of bias in potential embedding variations and a random-effects model, dispensing with templates. Experiments on social and intersectional biases show that CEAT finds evidence of all tested biases and provides comprehensive information on the variability of effect magnitudes of the same bias in different contexts. Furthermore, we develop two methods, Intersectional Bias Detection (IBD) and Emergent Intersectional Bias Detection (EIBD), to automatically identify the intersectional biases and emergent intersectional biases from static word embeddings in addition to measuring them in contextualized word embeddings. We present the first algorithmic bias detection findings on how intersectional group members are associated with unique emergent biases that do not overlap with the biases of their constituent minority identities. IBD achieves an accuracy of 81.6% and 82.7%, respectively, when detecting the intersectional biases of African American females and Mexican American females. EIBD reaches an accuracy of 84.7% and 65.3%, respectively, when detecting the emergent intersectional biases unique to African American females and Mexican American females. The probability of random correct identification in these tasks ranges from 12.2% to 25.5% in IBD and from 1.0% to 25.5% in EIBD.

1 Introduction

Can we use representations of words learned from word co-occurrence statistics to discover social biases? Are we going to uncover unique intersectional biases associated with individuals that are members of multiple minority groups? Once we identify these emergent biases, can we use numeric representations of words that vary according to neighboring words to analyze how prominent bias is in different contexts? Recent work has shown that human-like biases are embedded in the statistical regularities of language that are learned by word representations, namely word embeddings [1]. We build on this work to show that we can automatically identify intersectional biases, such as the ones associated with Mexican American and African American women from static word embeddings (SWE). Then, we measure how all human-like biases manifest themselves in contextualized word embeddings (CWE), which are dynamic word representations that adapt to their context.
Artificial intelligence systems are known not only to perpetuate social biases, but they may also amplify existing cultural assumptions and inequalities [2]. While most work on biases in word embeddings focuses on a single social category (e.g., gender, race) [1][3][4][5][6], the lack of work on identifying intersectional biases, the bias associated with populations defined by multiple categories [7], leads to an incomplete measurement of social biases [8][9]. For example, Caliskan et al.’s Word Embedding Association Test (WEAT) quantifies biases documented by the validated psychological methodology of the Implicit Association Test (IAT) [10]. The IAT provides the sets of words to represent social groups and evaluative attributes to be used while measuring bias. Consequently, the analysis of bias via WEAT is limited to the types of IATs and their corresponding words contributed by the IAT literature, which happens to include intersectional representation for only African American women. To overcome these constraints of WEATs, we extend WEAT to automatically identify evaluative attributes associated with individuals that are members of more than one social group. While this allows us to discover emergent intersectional biases, it is also a promising step towards automatically identifying all biased associations embedded in the regularities of language. To fill the gap in understanding the complex nature of intersectional bias, we develop a method called Intersectional Bias Detection (IBD) to automatically identify intersectional biases without relying on pre-defined attribute sets from the IAT literature.

Biases associated with intersectional group members contain emergent elements that do not overlap with the biases of their constituent minority identities [11][12]. For example, “hair weaves” is stereotypically associated with African American females but not with African Americans or females. We extend IBD and introduce a method called Emergent Intersectional Bias Detection (EIBD) to identify the emergent intersectional biases of an intersectional group in SWE. Then, we construct new tests to quantify these intersectional and emergent biases in CWE.

To investigate the influence of different contexts, we use a fill-in-the-blank task called masked language modeling. The goal of the task is to generate the most probable substitution for the [MASK] that is surrounded with neighboring context words in a given sentence. Bert, a widely used neural language model trained on this task, substitutes [MASK] in “Men/women excel in [MASK].” with “science” and “sports”, reflecting stereotype-congruent associations. However, when we feed in similar contexts “The man/woman is known for his/her [MASK],” Bert fills “wit” in both sentences, which indicates gender bias may not appear in these contexts. Prior methods use templates analogous to masked language modeling to measure bias in CWE [13][14][15]. The templates are designed to substitute words from WEAT’s social targets and evaluative attributes in a simple manner such as “This is [TARGET]” or “[TARGET] is a [ATTRIBUTE]”. In this work, we propose the Contextualized Embedding Association Test (CEAT), a test eschewing templates and instead generating the distribution of effect magnitudes of biases in different contexts. To comprehensively measure the social and intersectional biases in this distribution, a random-effects model designed to combine effect sizes of similar interventions summarizes the overall effect size of bias in the neural language model [16]. As a result, CEAT overcomes the shortcomings of template-based methods.

In summary, this paper presents three novel contributions along with three complementary methods to automatically identify intersectional biases in SWE and use these findings to measure all types of social biases in CWE. All data, source code and detailed results are available at [www.gitRepo.com](http://www.gitRepo.com).

**Intersectional Bias Detection (IBD).** We develop a novel method for SWE to detect words that represent biases associated with intersectional group members. To our knowledge, IBD is the first algorithmic method to automatically identify individual words that are strongly associated with intersectional group members. IBD reaches an accuracy of 81.6% and 82.7%, respectively, when validating on intersectional biases associated with African American females and Mexican American females that are provided by Ghavami and Peplau [11].

**Emergent Intersectional Bias Detection (EIBD).** We contribute a novel method to identify emergent intersectional biases that do not overlap with biases of constituent social groups in SWE. To our knowledge, EIBD is the first algorithmic method to detect the emergent intersectional biases in word embeddings automatically. EIBD reaches an accuracy of 84.7% and 65.3%, respectively, when validating on the emergent intersectional biases of African American females and Mexican American females that are provided by Ghavami and Peplau [11].

**Contextualized Embedding Association Test (CEAT).** WEAT measures human-like biases in SWE. We extend WEAT to the dynamic setting of CWE to quantify the distribution of effect magnitudes of social and intersectional biases in contextualized word embeddings and present the combined
magnitude of bias by pooling effect sizes with a random-effects model. We show that the magnitude of bias greatly varies according to the context in which the stimuli of WEAT appear. Overall, the pooled mean effect size is statistically significant in all CEAT tests including intersectional bias measurements.

The remaining parts of the paper are organized as follows. Section 2 reviews the related work. Section 3 provides the details of the datasets used in the approach and evaluation. Section 4 introduces the three complementary methods. Section 5 gives the details of experiments and results. Section 6 discusses our findings and results. Section 7 concludes the paper.

## 2 Related Work

SWE are trained on word co-occurrence statistics to generate numeric representations of words so that machines can process language [17][18]. Previous work on bias in SWE has shown that all human-like biases that have been documented by the IAT are embedded in the statistical regularities of language [1]. The IAT [10] is a widely used measure of implicit bias in human subjects that quantifies the differential reaction time to pairing two concepts. Analogous to the IAT, Caliskan et al. [1] developed the WEAT to measure the biases in SWE by quantifying the relative associations of two sets of target words (e.g., women, female; and men, male) that represent social groups with two sets of evaluative attributes (e.g., career, professional; and family, home). WEAT produces an effect size (Cohen’s $d$) that is a standardized bias score and its $p$-value based on the one-sided permutation test. WEAT measures biases pre-defined by the IAT such as racism, sexism, attitude towards the elderly and people with disabilities, as well as widely shared non-discriminatory associations.

Regarding the biases of intersectional groups categorized by multiple social categories, previous work in psychology has mostly focused on the experiences of African American females [19][20][21][22]. Buolamwini et al. demonstrated intersectional accuracy disparities in commercial gender classification in computer vision [23]. May et al. [13] and Tan and Celis [14] used attributes from prior work to measure emergent intersectional biases of African American females in CWE. We develop the first algorithmic method to identify intersectional bias and emergent bias attributes in SWE, which can be measured in both SWE and CWE. Then, we use the validation set provided by Ghavami and Peplau [11] to evaluate our method.

Recently, neural language models, which use neural networks to assign probability values to sequences of words, have achieved state-of-the-art results in natural language processing (NLP) tasks with their dynamic word representations, CWE [24][25][26]. Neural language models typically consist of an encoder that generates CWE for each word based on its accompanying context in input sequence. Specifically, the collection of values on a particular layer’s hidden units forms the CWE [27], which has the same shape as a SWE. However, unlike SWE that represent each word, including polysemous words, with a fixed vector, CWE of the same word vary according to its context window that is encoded into its representation by the neural language model. With the wide use of neural language models [24][25][26], human-like biases were observed in CWE [15][28][13][14]. To measure human-like biases in CWE, May et al. [13] applied the WEAT to contextualized representations in template sentences. Tan and Celis [14] adopted the method of May et al. [13] by applying WEAT to the CWE of the tokens in templates such as "This is a [TARGET]". Kurita et al. measured biases in Bert based on the prediction probability of the attribute in a template that contains the target and masks the attribute, e.g., [TARGET] is [MASK] [15]. Overall, prior work suffers from selection bias due to measuring bias in a limited selection of contexts and reporting the unweighted mean value of bias magnitudes, which does not accurately reflect the scope of bias embedded in a neural language model. In this work, we design a comprehensive method to quantify human-like biases in CWE accurately.

## 3 Data

(All the implementation details are available in the supplementary materials and on our repository.)

**Static Word Embeddings (SWE):** We use GloVe [18] SWE to automatically identify words that are highly associated with intersectional group members. Caliskan et al. [1] have shown that social biases are embedded in linguistic regularities learned by GloVe. These embeddings are trained on the word co-occurrence statistics of the Common Crawl corpus.
Contextualized Word Embeddings (CWE): We generate CWE using pre-trained state-of-the-art neural language models, namely Elmo, Bert, GPT and GPT-2 [29][30][31][32]. Elmo is trained on the Billion Word Benchmark dataset [33]. Bert is trained on BookCorpus [34] and English Wikipedia dumps. GPT is trained on BookCorpus [34] and GPT-2 is trained on WebText [32]. While Bert and GPT-2 provide several versions, we use Bert-small-cased and GPT-2-117m because they have the same model size as GPT [30] and they are trained on cased English text.

Corpus: We need a comprehensive representation of all contexts a word can appear in ordinary language in order to investigate how bias associated with individual words varies across contexts. Identifying the potential contexts in which a word can be observed is not a trivial task. Consequently, we use a Reddit corpus to generate the distribution of contexts that words of interest appear in. The corpus consists of 500 million comments made in the period between 1/1/2014 and 12/31/2014. We select 1,000,000 comments in the validation set of intersectional attributes with ground truth information [11]. The evaluation of intersectional bias detection methods uses this validation set. There are in total \( M \) gender categories by race (\( C_{m} \)), two social categories (\( C_{n1} \), \( C_{n2} \)) and gender (\( C_{m1} \)). We assume, there are three racial categories \( M = 3 \), and two gender categories \( N = 2 \) in our experiments (generalizing to continuous labels from categorical group labels is left to future work). There are in total \( M \times N \) combinations of intersectional groups \( C_{mn} \). We use all groups \( C_{mn} \) to build WEAT pairs \( P_{ij} = (C_{i1}, C_{j1}), i = 1, ..., M, j = 1, ..., N \). Then, we detect lists of words associated with each pair \( W_{ij}, i = 1, ..., M, j = 1, ..., N \) based on threshold \( t \) determined by an ROC curve. We detect the attributes highly associated with the

\[
\text{CWE: Contextualized Word Embeddings}
\]

\[
\text{WEAT: Word Embedding Factual Association Test}
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\text{WEFAT: Word Embedding Factual Association Test}
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\text{IBD: Intersectional Bias Detection}
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We first detect sets of words associated with each pair of constitutive subcategories of the intersectional group \( C_{11} \) from all \((M \times N)\) WEFAT pairs. We define the words associated with intersectional biases of group \( C_{11} \) as \( W_{IB} \) and these words are identified by

\[
W_{IB} = \bigcup_{1 \leq j \leq M} W_{IB_{ij}}, \text{ where } W_{IB_{ij}} = \{ w|s(w, C_{11}, C_{ij}) > t_{mn}, w \in W_{IB_{mn}} \}
\]

where \( W_{IB_{mn}} = (\bigcup_{1 \leq j \leq M} W_{ij}) \cup W_{random} \). \( W_{11} \) contains validated words associated with \( C_{11} \). Each \( W_{ij} \) contains validated words associated with one intersectional group \( C_{ij} \). \( W_{random} \) contains random words, which are words taken from WEAT that are not associated with any \( C_{ij} \).

To identify the thresholds, we treat IBD as a one-vs-all verification classifier to determine whether attributes belong to group \( C_{11} \). We select the threshold with the highest value of \emph{true positive rate – false positive rate} \((TP – FP)\). When multiple thresholds have the same values, we select the one with the highest \( TP \) to detect more attributes associated with \( C_{11} \). Detection accuracy is calculated as \( \frac{TP}{TP + FN} \). The attributes which are associated with \( C_{11} \) and detected as \( C_{11} \) are TP. The attributes which are not associated with \( C_{11} \) and are not detected as \( C_{11} \) are TN. The attributes which are associated with \( C_{11} \) but are not detected as \( C_{11} \) are FN. The attributes which are not associated with \( C_{11} \) but are detected as \( C_{11} \) are FP.

**Emergent Intersectional Bias Detection (EIBD)** identifies words that are uniquely associated with intersectional group members. These emergent biases are only associated with the intersectional group (e.g., African American females \( C_{11} \)) but not associated with its constituent category such as African Americans \( S_{1n} \) or females \( S_{m1} \).

We first detect \( C_{11} \)’s intersectional biases \( W_{IB} \) with IBD. Then, we detect the biased attributes associated with only one constituent category of the intersectional group \( C_{11} \) (e.g., associated only with race \( S_{1n} \) - or only with gender \( S_{m1} \)). Each intersectional category \( C_{1n} \) has \( M \) constituent subcategories \( S_{1n}, i = 1, ..., M \) and category \( C_{m1} \) has \( N \) constituent subcategories \( S_{mj}, j = 1, ..., N \). \( S_{1n} \) and \( S_{m1} \) are the constituent subcategories of intersectional group \( C_{11} \).

There are in total \( M + N \) groups defined by all the single constituent subcategories. We use all \( M + N \) groups to build WEFAT pairs \( P_{i} = (S_{1n}, S_{in}), i = 1, ..., M \) and \( P_{j} = (S_{mj}, S_{m1}), j = 1, ..., N \). Then, we detect lists of words associated with each pair \( W_{i}, i = 1, ..., M \) and \( W_{j}, j = 1, ..., N \) based on the same positive threshold \( t_{mn} \) used in IBD. We detect the attributes highly associated with the constituent subcategories \( S_{1n} \) and \( S_{m1} \) of the target intersectional group \( C_{11} \) from all \((M + N)\) WEFAT pairs. We define the words associated with emergent intersectional biases of group \( C_{11} \) as \( W_{EIB} \) and these words are identified by

\[
W_{EIB} = \bigcup_{i=1}^{M} (W_{IB} - W_{i}) \bigcup_{j=1}^{N} (W_{IB} - W_{j})
\]

\( W_{i} = \{ w|s(w, S_{1n}, S_{in}) > t_{mn}, w \in W_{IB} \} \). \( W_{j} = \{ w|s(w, S_{m1}, S_{mj}) > t_{mn}, w \in W_{IB} \} \).

For example, to detect words uniquely associated with African American females in a set of attributes \( W \), we assume there are two classes (females, males) of gender and two classes (African Americans, European Americans) of race. We measure the relative association of all words in \( W \) first with African American females and African American males, second with African American females and European American females, third with African American females and European American males. (Fourth is the comparison of the same groups, which leads to \( d = 0 \) effect size, which is below the detection threshold.) The union of attributes with an association score greater than the selected threshold represents intersectional biases associated with African American females. Then we calculate the association scores of these IBD attributes first with females and males, second with African Americans and European Americans. We remove the attributes with scores greater than the selected threshold from these IBD attributes, that are highly associated with single social categories. The union of the remaining attributes are the emergent intersectional biases.

**Contextualized Embedding Association Test (CEAT)** quantifies social biases in CWE by extending the WEAT methodology that measures human-like biases in SWE \([1]\). WEAT’s bias metric is effect size (Cohen’s \( d \)). In CWE, since embeddings of the same word vary based on context, applying WEAT to a biased set of CWE will not measure bias comprehensively. To deal with a range of dynamic embeddings representing individual words, CEAT measures the distribution of effect sizes.

In WEAT’s formal definition \([1]\), \( X \) and \( Y \) are two sets of target words of equal size; \( A \) and \( B \) are two sets of evaluative polar attribute words of equal size. Each word in these sets of words is referred to as a stimulus. Let \( \cos(\vec{\alpha}, \vec{\beta}) \) stand for the cosine similarity between vectors \( \vec{\alpha} \) and \( \vec{\beta} \). WEAT measures the
magnitude of bias by computing the effect size ($ES$) which is the standardized differential association of the targets and attributes. The $p$-value ($P_w$) of WEAT measures the probability of observing the effect size in the null hypothesis, in case biased associations did not exist. According to Cohen’s effect size metric, $d > |0.5|$ and $d > |0.8|$ are medium and large effect sizes, respectively [38].

In a neural language model, each stimulus $s$ from WEAT contained in $n_s$ input sentences has at most $n_s$ different CWE $s^1, ..., s^n_s$ depending on the context in which it appears. If we calculate effect size $ES(X, Y, A, B)$ with all different $s$ for a stimulus $s \in X$ and keep the CWE for other stimuli unchanged, there will be at most $n_s$ different values of effect size. For example, if we assume each stimulus $s$ occurs in 2 contexts and each set in $X, Y, A, B$ has 5 stimuli, the total number of combinations for all the CWE of stimuli will be $2^5 \times 4 = 1,048,576$. The numerous possible values of $ES(X, Y, A, B)$ construct a distribution of effect sizes, therefore we extend WEAT to CEAT.

For each CEAT, all the sentences where a CEAT stimulus occurs are retrieved from the Reddit corpus. Then, we generate the corresponding CWE from these sentences with randomly varying contexts. In this way, we generate $n_s$ CWE from $n_s$ extracted sentences for each stimulus $s$ and $n_s$ varies randomly for each stimulus. We sample random combinations of CWE for each stimulus $N$ times. In the $i^{th}$ sample out of $N$, for each stimulus that appears in at least $N$ sentences, we randomly sample one of its CWE vectors without replacement. If a stimulus occurs in less than $N$ sentences, we randomly sample from its CWE vectors with replacement so that they can be reused while preserving their distribution. Based on the sampled CWEs, we calculate each sample’s effect size $ES(X, Y, A, B)$, sample variance $V_i(X, Y, A, B)$ and $p$-value $P_w(X, Y, A, B)$ in WEAT. We generate $N$ of these samples to approximate the distribution of effect sizes.

The distribution of effects in CEAT represents random effects computed by WEAT where we do not expect to observe the same effect size. As a result, in order to provide meaningful and validated summary statistics, we applied a random-effects model from the meta-analysis literature to compute the weighted mean of the effect sizes and statistical significance [39, 40]. The summary of the effect magnitude, combined effect size (CES), is the weighted mean of a distribution of random effects,

$$CES(X, Y, A, B) = \frac{\sum_{i=1}^{N} v_i ES_i}{\sum_{i=1}^{N} v_i}$$

where $v_i$ is the inverse of the sum of in-sample variance $V_i$ and between-sample variance in the distribution of random effects $\sigma^2_{between}$. We present the calculation of $\sigma^2_{between}$ and details of the meta-analysis in supplementary materials.

Based on the central limit theorem, the limiting form of the distribution of $\frac{CES}{SE(CES)}$ is the standard normal distribution [41]. Then the statistical significance of CES, two-tailed $p$-value of the hypothesis that there is no difference between all the contextualized variations of the two sets of target words in terms of their relative similarity to two sets of attribute words is given by the following formula, where $\Phi$ is the standard normal cumulative distribution function and $SE$ stands for the standard error.

$$P_e(X, Y, A, B) = 2 \times [1 - \Phi(\frac{CES}{SE(CES)})]$$

5 Experiments and Results

Intersectional and Emergent Intersectional Bias Detection in Static Word Embeddings. We use IBD and EIBD to detect the intersectional and emergent biases associated with intersectional
According to CEAT results, Elmo is the most biased whereas GPT-2 is the least biased with respect to the types of biases CEAT focuses on. We notice that significant negative CES exist in Bert, GPT and GPT-2, which imply that unexpected stereotype-incongruent biases with small effect size exist.
6 Discussion

Similar to findings from SWE, significant effect sizes for all documented biases we tested for exist in CWEs. GPT-2 exhibited less bias than other neural language models. On 6/1/2020, GPT-3 was introduced in a paper on arxiv [42]. We’ll measure the biases of GPT-3 once the model is released.

Our method CEAT, designed for CWEs, computes the combined bias score of a distribution of effect sizes present in neural language models. We find that the effect magnitudes of biases reported by Tan and Celis [14] are samples in the distributions generated by CEAT. We can view their method as a special case of CEAT that calculates the individual bias scores of a few pre-selected samples. In order to accurately measure the overall bias score in a neural language model, we introduce a random-effects model from the meta-analysis literature that computes combined effect size and combined statistical significance from a distribution of bias measurements. As a result, when CEAT reports significant results, some of the bias scores in prior work are not statistically significant. Furthermore, our results indicate statistically significant bias in the opposite direction in some cases.

We present a bias detection method generalizable to identifying biases associated with any social group or intersectional group member. We detect and measure biases associated with Mexican American and African American females in SWE and CWE. Our emergent intersectional bias measurement results for African American females are in line with the previous findings [13][14]. IBD and EIBD detect intersectional biases from SWE in an unsupervised manner. Our current intersectional bias detection validation approach can be used to identify association thresholds when generalizing this work to the entire word embedding dictionary. Exploring all the potential biases associated with targets is left to future work since it requires extensive human subject validation studies in collaboration with social psychologists. We list all the stimuli in supplementary materials. We do not discuss the biased words associated with social groups in the main paper to avoid reinforcing existing biases in language and perpetuating stereotypes in society.

We sampled combinations of CWE 10,000 times for each CEAT test; nonetheless, we observed varying intensities of the same social bias in different contexts. Experiments conducted with 1,000 and 5,000 samples of CWE lead to similar bias scores. As a result, the number of samples can be adjusted according to computational resources. However, future work on evaluating the lower bound of sampling size with respect to model and corpus properties would optimize the sampling process. Accordingly, the computation of overall bias in the language model would become more efficient.

We follow the conventional method of using the most frequent given names in a social group that signal group membership in order to accurately represent targets [1, 10]. Our results indicate that the conventional method works however we need more principled and robust methods that can be validated when measuring the representatives of a target group. Developing these principled methods is left to future work since it requires expertise in social psychology.

7 Conclusion

In this work, we present CEAT, the first method to use a random-effects model to accurately measure social biases in neural language models that contain a distribution of context-dependent biases. CEAT simulates this distribution by sampling \((N = 10,000)\) combinations of CWEs without replacement from a large-scale natural language corpus. On the other hand, prior work uses a few data points when measuring bias which leads to selection bias. CEAT addresses this limitation of prior work to provide a comprehensive measurement of bias. Our results indicate that Elmo is the most biased and GPT-2 is the least biased neural language model with respect to the social biases we investigate.

Intersectional biases associated with African American and Mexican American females have the highest effect size compared with other biases, including racial and gender bias.

We introduce two methods called IBD and EIBD. To our knowledge, they are the first methods to automatically detect the intersectional biases and emergent intersectional biases embedded in SWE. These methods may eliminate the need for relying on pre-defined sets of attributes to measure pre-defined types of biases. IBD reaches an accuracy of 81.6% and 82.7% in detection, respectively, when validating on the intersectional biases of African American females and Mexican American females. EIBD reaches an accuracy of 84.7% and 65.3% in detection, respectively, when validating on the emergent intersectional biases of African American females and Mexican American females.
Broader Impact

Outputs of neural language models trained on natural language expose their users to stereotypes and biases learned by such models. CEAT is a tool for analysts and researchers to measure social biases in these models, which may help develop bias mitigation methods for neural language models. On the other hand, some users might utilize CEAT to detect certain biases or harmful stereotypes and accordingly target social groups by automatically generating large-scale biased text. Some users might generate and share biased content to shift public opinion as part of information influence operations. By focusing on the attitude bias measured by valence, a malicious actor might figure out ways to automatically generate hate speech while targeting certain social groups.

In addition to the improper use of CEAT, another ethical concern is about IBD and UIBD: IBD and UIBD can detect stereotypical associations for an intersectional group, but the detected words may be used in the generation of offensive content that perpetuates or amplifies existing biases. Using the biased outputs of these neural language models leads to a feedback cycle when machine generated biased text ends up in training data contributing to perpetuating or amplifying bias.

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