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

Wei Guo
Department of Computer Science
George Washington University
Washington, DC 20052
weiguo@gwu.edu

Aylin Caliskan
Department of Computer Science
George Washington University
Washington, DC 20052
aylin@gwu.edu

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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`.

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.

Contextuailzed 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 simulate the distribution of contexts a word appears in ordinary language, by randomly sampling the sentences that the word occurs in a large corpus.

Voigt et al. have shown that social biases are projected into Reddit comments [35]. 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 take all the stimuli used in WEAT. For each WEAT type that has at least 32 stimuli, we retrieve the sentences from the Reddit corpus that contain one of these stimuli. In this way, we collect a great variety of CWE from the Reddit corpus to measure bias comprehensively in a neural language model.

Intersectional Stimuli: To investigate intersectional bias, we represent members of social groups with target words provided by the WEAT and Parada et al. [36]. WEAT and Parada et al. represent racial categories with frequent given names that signal group membership. WEAT contains female and male names of African Americans and European Americans whereas Parada et al. presents the Mexican American names for women and men. Three gender-checkers are applied to these names to determine their gender [37]. The experiments include names that are categorized to belong to the same gender by all three gender-checkers. The intersectional bias detection methods identify attributes that are associated with these target group representations. Human subjects provide the validation set of intersectional attributes with ground truth information [11]. The evaluation of intersectional bias detection methods uses this validation set.

4 Approach

Intersectional Bias Detection (IBD) identifies words associated with intersectional group members, defined by two social categories simultaneously. Our method automatically detects the attributes that have high associations with the intersectional group from a set of SWE. Analogous to the Word Embedding Factual Association Test (WEFAT) [1], we measure the standardized differential association of a single stimulus $w \in W$ with two social groups A and B using the following statistic.

$$s(w, A, B) = \frac{\text{mean}_{a\in A}\text{cos}(\vec{w}, \vec{a}) - \text{mean}_{b\in B}\text{cos}(\vec{w}, \vec{b})}{\text{std-dev}_{x\in A\cup B}\text{cos}(\vec{w}, \vec{x})}$$

We refer to the above statistic as the **association score**, which is used by WEFAT to verify that gender statistics are embedded in linguistic regularities [1]. Targets A and B are words that represent males (e.g., he, him) and females (e.g., she, her) and W is a set of occupations. For example, *nurse* has an association score $s(nurse, A, B)$ that measures effect size of gender associations. WEFAT has been shown to have high predictive validity ($\rho = 0.90$) in quantifying facts about the world [1].

We extend WEFAT's *gender* association measurement to use as other social categories (e.g., race). Let $P_i = (A_i, B_i)$ (e.g., African American and European American) be a pair of social groups, and W be a set of attribute words. We calculate the association score $s(w, A_i, B_i)$ for $w \in W$. If $s(w, A_i, B_i)$ is greater than the positive effect size threshold t, w is detected to be associated with group A_i. Let $W_i = \{w|s(w, A_i, B_i) > t, w \in W\}$ be the associated word list for each pair P_i.

We detect the biased attributes associated with an intersectional group C_{mn} defined by two social categories C_{1n}, C_{m1} with M and N subcategories $(C_{11}, \ldots, C_{mn})$ (e.g., African American females by race (C_{1n}) 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 WEFAT pairs $P_{ij} = (C_{11}, C_{ij}), i = 1, ..., M, j = 1, ..., N$. 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 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

$$W_{IB} = \bigcup_{\substack{1 \leq i \leq M \\ 1 \leq j \leq N}} W_{IB_{ij}},\ where\ W_{IB_{ij}} = \{w | s(w, C_{11}, C_{ij}) > t_{mn}, w \in W_{IB_{mn}}\}$$

where $W_{IB_{mn}} = (\cup_{\substack{1 \leq i \leq M \\ 1 \leq j \leq N}} W_{ij}) \cup W_{random}\}$.

W_{11} contains validated words associated with C_{11}. Each W_{ij} contains validated words associated with one intersectional group [11]. 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 $true\,positive\,rate - false\,positive\,rate$ ($TP - FP$). 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 $\frac{TP+TN}{TP+TN+FP+FN}$. 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 $S_{in}, i = 1, ...M$ 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 $P_j = (S_{m1}, S_{mj}), j = 1, ...N$. 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

$$W_{EIB} = (\bigcup_{i=1}^{M} (W_{IB} - W_i)) \bigcup (\bigcup_{j=1}^{N} (W_{IB} - W_j))$$

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

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.

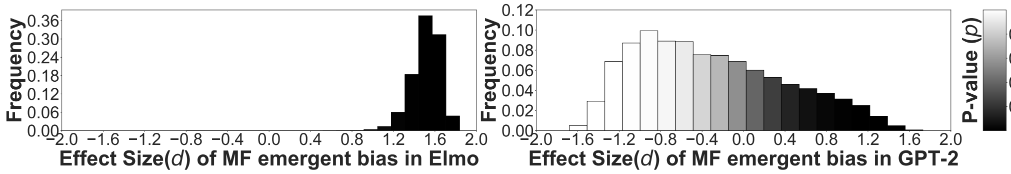

Figure 1: **Distributions of effect sizes with Elmo (CES $d = 1.51$) and GPT-2 (CES $d = -0.32$) for emergent intersectional bias CEAT test I4 (MF/EM, MF emergent/EM intersectional).** Different models exhibit varying degrees of bias when using the same set of stimuli to measure bias. The height of each bar shows the frequency of observed effect sizes among 10,000 samples that fall in each bin. The color of the bars represent the average p-value of all effect sizes in that bin.

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 $cos(\vec{a}, \vec{b})$ stand for the cosine similarity between vectors $\vec{a}$ and $\vec{b}$. 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, $d >\mid 0.5 \mid$ and $d >\mid 0.8 \mid$ 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 $\vec{s_1}, ..., \vec{s_{n_s}}$ depending on the context in which it appears. If we calculate effect size $ES(X, Y, A, B)$ with all different $\vec{s}$ 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 stimulus, the total number of combinations for all the CWE of stimuli will be $2^{5\times4} = 1,048,576$. 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 $ES_i(X, Y, A, B)$, sample variance $V_i(X, Y, A, B)$ and p-value $P_{w_i}(X, Y, A, B)$ 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 Φ is the standard normal cumulative distribution function and SE stands for the standard error.

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

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 group members (e.g., African American females, Mexican American females) in GloVe SWE. We use the frequent given names for social group representation as explained in previous sections. IBD and EIBD experiments use the same test set consisting of 98 attributes associated with 2 groups defined by gender (females, males), 3 groups defined by race (African American, Mexican American, European American), 6 intersectional groups defined by race and gender and random words taken from WEAT not associated with any group [11].

We draw the ROC curves of four bias detection tasks in supplementary materials, then select the highest value of $true\,positive\,rate - false\,positive\,rate$ as thresholds for each intersectional group.

The probability of random correct attribute detection in IBD tasks ranges from 12.2% to 25.5% and ranges from 1.0% to 25.5% in EIBD. IBD detects intersectional biases of African American females and Mexican American females with 81.6% and 82.7% accuracy, respectively. EIBD detects emergent intersectional biases of African American females and Mexican American females with 84.7% and 65.3% accuracy, respectively.

Social and Intersectional Bias Measurement in Contextualized Word Embeddings. We measure ten types of social biases from WEAT (C1-C10) and construct our own intersectional bias tests in Elmo, Bert, GPT, and GPT-2. There are four novel intersectional bias tests for African American women and Mexican American women as they are members of two minority groups [11].

We use the names mentioned in Section 4 to represent the target groups. For intersectional and emergent bias tests, we use the attributes associated with the intersectional minority group members and European American males as the two polar attribute sets. We sample $N = 10,000$ combinations of CWE for each CEAT since according to various evaluation trials, the resulting CES and p-value remain consistent under this parameter. We report the overall magnitude of bias (CES) and p-value in Table 1. We present the distribution histograms of effect sizes in Figure 1, which show the overall biases that can be observed in a bias test related to the emergent biases associated with Mexican American females (See row I4 in Table 1) with Bert-small-cased and GPT-2-117m. The distribution plots for other bias tests are provided in our project repository at `www.gitRepo.com`.

We find that CEAT uncovers more evidence of intersectional bias than gender or racial biases. To quantify the intersectional biases in CWEs, we construct tests I1-I4. Tests with Mexican American females tend to have a higher CES than those with African American females. Specifically, 13 of 16 instances in intersection-related tests (I1-I4) have positive significant CES; 9 of 12 instances in gender-related tests (C6-C8) have positive significant CES; 8 of 12 instances in race-related tests (C3-C5) have positive significant CES. In gender bias tests, the gender associations with career and family are stronger than other biased gender associations. In all models, significant positive CES for intersectional biases are larger than racial biases.

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.

Table 1: **CEAT for social and intersectional biases.** We report the overall magnitude of bias in a neural language model with CES* (d, rounded down) and its statistical significance with combined p-values (p, rounded up). CES pools $N = 10,000$ samples from a random-effects model. Ci stands for the i^{th} WEAT test in Table 1 from [1]. Ii stands for the tests constructed for intersectional biases.

Bias Test	ELMO		BERT		GPT		GPT-2	
	d	p	d	p	d	p	d	p
C1: Flowers/Insects, P/U	1.40	$< 10^{-30}$	0.97	$< 10^{-30}$	1.04	$< 10^{-30}$	0.14	$< 10^{-30}$
C2: Instruments/Weapons, P/U	1.56	$< 10^{-30}$	0.94	$< 10^{-30}$	1.12	$< 10^{-30}$	-0.27	$< 10^{-30}$
C3: EA/AA names, P/U	0.49	$< 10^{-30}$	0.44	$< 10^{-30}$	-0.11	$< 10^{-30}$	-0.19	$< 10^{-30}$
C4: EA/AA names, P/U	0.15	$< 10^{-30}$	0.47	$< 10^{-30}$	0.01	$< 10^{-2}$	-0.23	$< 10^{-30}$
C5: EA/AA names, P/U	0.11	$< 10^{-30}$	0.02	$< 10^{-7}$	0.07	$< 10^{-30}$	-0.21	$< 10^{-30}$
C6: Males/Female names, Career/Family	1.27	$< 10^{-30}$	0.92	$< 10^{-30}$	0.19	$< 10^{-30}$	0.36	$< 10^{-30}$
C7: Math/Arts, Male/Female terms	0.64	$< 10^{-30}$	0.41	$< 10^{-30}$	0.24	$< 10^{-30}$	-0.01	$< 10^{-2}$
C8: Science/Arts, Male/Female terms	0.33	$< 10^{-30}$	-0.07	$< 10^{-30}$	0.26	$< 10^{-30}$	-0.16	$< 10^{-30}$
C9: Mental/Physical disease, T/P	1.00	$< 10^{-30}$	0.53	$< 10^{-30}$	0.08	$< 10^{-29}$	0.10	$< 10^{-30}$
C10: Young/Old people's names, P/U	0.11	$< 10^{-30}$	-0.01	0.016	0.07	$< 10^{-30}$	-0.16	$< 10^{-30}$
I1: AF/EM, AF/EM intersectional	1.24	$< 10^{-30}$	0.77	$< 10^{-30}$	0.07	$< 10^{-30}$	0.02	$< 10^{-2}$
I2: AF/EM, AF emergent/EM intersectional	1.25	$< 10^{-30}$	0.67	$< 10^{-30}$	-0.09	$< 10^{-30}$	0.02	$< 10^{-2}$
I3: MF/EM, MF/EM intersectional	1.31	$< 10^{-30}$	0.68	$< 10^{-30}$	-0.06	$< 10^{-30}$	0.38	$< 10^{-30}$
I4: MF/EM, MF emergent/EM intersectional	1.51	$< 10^{-30}$	0.86	$< 10^{-30}$	0.16	$< 10^{-30}$	-0.32	$< 10^{-30}$

*Light, medium, and dark gray shading of combined d values (CES) indicates small, medium, and large effect size respectively.

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. [1]. 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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A Meta Analysis

A.1 Word-Embedding Association Test

The Word-Embedding Association Test (WEAT) designed by Caliskan et al.[1] is used to measure the biases in static word embeddings (SWE), which quantifies the relative associations of two sets of target words (e.g., woman, female; and man, male) that represent social groups with two sets of evaluative attributes (e.g., career, professional; and family, home).

We present Caliskan et al.'s description of WEAT [1]. Let X and Y be two sets of target words of equal size, and A, B be two sets of attribute words. Let $cos(\vec{a}, \vec{b})$ stand for the cosine similarity between the embeddings of word a and b. Here the vector $\vec{a}$ is the embedding for word a. The test statistic is

$$s(X, Y, A, B) = \sum_{x \in X} s(x, A, B) - \sum_{y \in Y} s(y, A, B)$$

where

$$s(w, A, B) = mean_{a \in A} cos(\vec{w}, \vec{a}) - mean_{b \in B} cos(\vec{w}, \vec{b})$$

A permutation test calculates the significance of association $s(X, Y, A, B)$. The one-sided $p - value$ is

$$P = Pr_i[s(X_i, Y_i, A, B) > s(X, Y, A, B))]$$

where $\{(X_i, Y_i)\}_i$ represents all the partitions of $X \cup Y$ in two sets of equal size.

The effect size is calculated as

$$ES = \frac{mean_{x \in X} s(x, A, B) - mean_{y \in Y} s(y, A, B)}{std\_dev_{w \in X \bigcup Y} s(w, A, B)}$$

A.2 Random-Effects Model

Meta-analysis is the statistical procedure for combining data from multiple studies [43]. Meta-analysis describes the results of each separate study by a numerical index (e.g., effect size) and then summarizes the results into combined statistics. In bias measurements, we are dealing with effect size. Based on different assumptions whether the effect size is fixed or not, there are two kinds of methods: *fixed-effects* model and *random-effects* model. Fixed-effects model expects results with fixed-effect sizes from different intervention studies. On the other hand, random-effects model treats the effect size as they are samples from a random distribution of all possible effect sizes [44, 45]. The expected results of different intervention studies in the random-effects model don't have to match other studies' results. In our case, since the effect sizes calculated with the contextualized word embeddings (CWE) in different contexts vary, we cannot assume a fixed-effects model and instead use a random-effects model that is appropriate for the type of data we are studying.

We apply a random-effects model from meta-analysis using the methods in Hedges and Vevea [43]. Specifically, we describe the procedures for estimating the meaningful and validated summary statistic, **combined effect size (CES)**, which is the weighted mean of a distribution of random-effect sizes. Each effect size is weighted by the variance in calculating that particular effect size in addition to the overall variance among all the random-effect sizes.

There are effect size estimates from N independent WEAT. Each effect size is calculated by

$$ES_i = \frac{mean_{x \in X} s(x, A, B) - mean_{y \in Y} s(y, A, B)}{std\_dev_{w \in X \bigcup Y} s(w, A, B)}$$

The estimation of in-sample variance is V_i, which is the square of $std\_dev_{w \in X \bigcup Y} s(w, A, B)$. We use the same principle as estimation of the variance components in ANOVA to estimate the between-sample variance $\sigma^2_{between}$. $\sigma^2_{between}$ is calculated as:

$$\sigma^2_{between} = \begin{cases} \dfrac{Q - (N-1)}{c} & ifQ \geq N - 1 \\ 0 & ifQ < N - 1 \end{cases}$$

where

$$W_i = \frac{1}{V_i}$$

$$c = \sum W_i - \frac{\sum W_i^2}{\sum W_i}$$

$$Q = \sum W_i ES_i^2 - \frac{(\sum W_i ES_i)^2}{\sum W_i}$$

The weight v_i assigned to each WEAT is the inverse of the sum of estimated in-sample variance V_i and estimated between-sample variance in the distribution of random-effects $\sigma^2_{between}$.

$$v_i = \frac{1}{V_i + \sigma^2_{between}}$$

CES, which is the sum of the weighted effect sizes divided by the sum of all weights, is then computed as

$$CES = \frac{\sum_{i=1}^{N} v_i ES_i}{\sum_{i=1}^{N} v_i}$$

To derive the hypothesis test, we calculate the standard error of CES as the square root of the inverse of the sum of the weights.

$$SE(CES) = \sqrt{\frac{1}{\sum_{i=1}^{N} v_i}}$$

Based on the central limit theorem, the limiting form of the distribution of $\frac{CES}{SE(CES)}$ is the standard normal distribution [41]. Since we notice that some CES are negative, we use a two-tailed $p - value$ which can test the significance of biased associations in two directions. The 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 Φ is the standard normal cumulative distribution function.

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

A.3 Supplemental CEAT

In this section, we first construct all CEAT in the main paper (C1-C10,I1-I4) with sample size $N = 1,000$ to provide a comparison of results with different sample sizes. We report CES d and combined $p - value$ p in Table 2. We replicate these results with $N = 1,000$ instead of using the original $N = 10,000$ to show that even with $N = 1,000$, we get valid results. Accordingly, we proceed to calculate all types of biases associated with intersectional groups based on the attributes used in original WEAT. We notice that there are five tests which are significant with sample size $N = 10,000$ but insignificant with sample size $N = 1,000$. They are C10 with Bert, C4 with GPT, C7 with GPT-2, I3 with GPT-2 and I4 with GPT-2. We also notice that CES of same test can be different with different sample size but all differences are smaller than 0.1.

We also construct four types of supplementary CEAT for all pairwise combinations of six intersectional groups: African American females (AF), African American males (AM), Mexican American females (MF), Mexican American males (MM), European American females (EF), European American males (EM). We use two intersectional groups as two target social groups. For each pairwise combination, we build four CEAT : first, measure attitudes with words representing pleasantness and unpleasantness as two attribute groups (as in C1); second, measure career and family associations that are particularly important in gender stereotypes with the corresponding two attribute groups (as in C6); third, similar to the career-family stereotypes for gender, measure math and arts associations that are particularly important in gender stereotypes with the corresponding two attribute groups (as in C7); fourth, similar to the math-arts stereotypes for gender, measure science (STEM) and arts associations that are particularly important in gender stereotypes with the corresponding two attribute groups (as in C8). We report the CES (d) and combined $p - values$ (p) in Table 3 with sample size $N = 1,000$. All of these attributes are from the C1, C6, C7 and C8 WEAT of Caliskan et al. [1].

Table 2: **CEAT from the main paper (C1-C10,I1-I4) with sample size** $N = 1,000$ **as opposed to the** $N = 10,000$ **hyper-parameter in the main paper.** We report the CES (d) and combined $p - values$ of all CEAT (p) in the main paper with sample size $N = 1,000$. We observe that all of the results are consistent with the CES and $p - values$ reported in the main paper on Table 1. Light, medium, and dark gray shading of combined d values (CES) indicates small, medium, and large effect size, respectively. There are five tests which are significant with sample size $N = 10,000$ but not significant with sample size $N = 1,000$. However, these have small effect sizes and as a result we don't expect statistical significance. According to our experiments, the Spearman correlation between WEAT's effect size and $p - value$ is $\rho = 0.99$. Smaller effect sizes are expected to have insignificant p-values. Accordingly, all of the results under $N = 1,000$ are consistent with the main findings. The notable yet consistent differences are C10 with Bert, C4 with GPT, C7 with GPT-2, I3 with GPT-2, and I4 with GPT-2. CES varies minimally with different sample size (N), but the differences of the results are smaller than 0.1, suggesting the degree of effect size remains consistent. In edge cases, where statistical significance or effect size is close to a significance threshold, gradually increasing N, in increments of $N = +500$ would provide more reliable results.

Bias Test	**ELMO**		**BERT**		**GPT**		**GPT-2**	
	d	p	d	p	d	p	d	p
C1: Flowers/Insects, P/U* - Attitude	1.39	$< 10^{-30}$	0.96	$< 10^{-30}$	1.05	$< 10^{-30}$	0.13	$< 10^{-30}$
C2: Instruments/Weapons, P/U* - Attitude	1.56	$< 10^{-30}$	0.93	$< 10^{-30}$	1.13	$< 10^{-30}$	-0.28	$< 10^{-30}$
C3: EA/AA names, P/U* - Attitude	0.48	$< 10^{-30}$	0.45	$< 10^{-30}$	-0.11	$< 10^{-30}$	-0.20	$< 10^{-30}$
C4: EA/AA names, P/U* - Attitude	0.16	$< 10^{-30}$	0.49	$< 10^{-30}$	0.00	0.70	-0.23	$< 10^{-30}$
C5: EA/AA names, P/U* - Attitude	0.12	$< 10^{-30}$	0.04	$< 10^{-2}$	0.05	$< 10^{-4}$	-0.17	$< 10^{-30}$
C6: Males/Female names, Career/Family	1.28	$< 10^{-30}$	0.91	$< 10^{-30}$	0.21	$< 10^{-30}$	0.34	$< 10^{-30}$
C7: Math/Arts, Male/Female terms	0.65	$< 10^{-30}$	0.42	$< 10^{-30}$	0.23	$< 10^{-30}$	0.00	0.81
C8: Science/Arts, Male/Female terms	0.32	$< 10^{-30}$	-0.07	$< 10^{-4}$	0.26	$< 10^{-30}$	-0.16	$< 10^{-30}$
C9: Mental/Physical disease, Temporary/Permanent	0.99	$< 10^{-30}$	0.55	$< 10^{-30}$	0.07	$< 10^{-2}$	0.04	0.04
C10: Young/Old people's names, P/U* - Attitude	0.11	$< 10^{-19}$	0.00	0.90	0.04	$< 10^{-2}$	-0.17	$< 10^{-30}$
I1: AF/EM, AF/EM intersectional	1.24	$< 10^{-30}$	0.76	$< 10^{-30}$	0.05	$< 10^{-3}$	0.05	0.06
I2: AF/EM, AF emergent/EM intersectional	1.24	$< 10^{-30}$	0.70	$< 10^{-30}$	-0.12	$< 10^{-30}$	0.03	0.26
I3: MF/EM, MF/EM intersectional	1.30	$< 10^{-30}$	0.69	$< 10^{-30}$	-0.08	$< 10^{-30}$	0.36	$< 10^{-30}$
I4: MF/EM, MF emergent/EM intersectional	1.52	$< 10^{-30}$	0.87	$< 10^{-30}$	0.14	$< 10^{-27}$	-0.26	$< 10^{-30}$

*Unpleasant and pleasant attributes used to measure valence and attitudes towards targets [10].

Table 3: **CEAT for intersectional groups with sample size** $N = 1,000$**.** We construct 4 types of new CEAT with all pairwise combinations of intersectional groups. We use two intersectional groups as two target social groups. We use 1) pleasant/unpleasant 2) career/family 3) math/arts 4) science/arts as two attribute groups. We report the CES d and combined $p - value$ p. Light, medium, and dark gray shading of combined d values (CES) indicates small, medium, and large effect size respectively.

Bias Test	**ELMO**		**BERT**		**GPT**		**GPT-2**	
	d	p	d	p	d	p	d	p
EM/EF, P/U* - Attitude	-0.49	$< 10^{-30}$	-0.33	$< 10^{-30}$	-0.01	0.60	-0.53	$< 10^{-30}$
EM/EF, Career/Family	1.15	$< 10^{-30}$	0.73	$< 10^{-30}$	0.34	$< 10^{-30}$	0.41	$< 10^{-30}$
EM/EF, Math/Arts	0.44	$< 10^{-30}$	0.34	$< 10^{-30}$	0.13	$< 10^{-25}$	-0.41	$< 10^{-30}$
EM/EF, Science/Arts	0.37	$< 10^{-30}$	-0.11	$< 10^{-30}$	0.07	$< 10^{-6}$	-0.04	0.02
EM/AM, P/U* - Attitude	0.57	$< 10^{-30}$	0.40	$< 10^{-30}$	0.04	$< 10^{-2}$	-0.34	$< 10^{-30}$
EM/AM, Career/Family	0.32	$< 10^{-30}$	0.16	$< 10^{-30}$	-0.36	$< 10^{-30}$	0.42	$< 10^{-30}$
EM/AM, Math/Arts	-0.28	$< 10^{-30}$	-0.04	$< 10^{-2}$	-0.05	$< 10^{-30}$	-0.45	$< 10^{-30}$
EM/AM, Science/Arts	0.02	0.10	-0.18	$< 10^{-30}$	0.17	$< 10^{-30}$	-0.20	$< 10^{-30}$
EM/AF, P/U* - Attitude	-0.35	$< 10^{-30}$	0.10	$< 10^{-11}$	-0.12	$< 10^{-30}$	-0.60	$< 10^{-30}$
EM/AF, Career/Family	1.10	$< 10^{-30}$	0.90	$< 10^{-30}$	0.20	$< 10^{-30}$	0.62	$< 10^{-30}$
EM/AF, Math/Arts	0.11	$< 10^{-19}$	0.72	$< 10^{-30}$	0.14	$< 10^{-23}$	-0.62	$< 10^{-30}$
EM/AF, Science/Arts	0.56	$< 10^{-30}$	0.29	$< 10^{-30}$	0.24	$< 10^{-30}$	-0.19	$< 10^{-30}$
EM/MM, P/U* - Attitude	-0.15	$< 10^{-30}$	0.42	$< 10^{-30}$	-0.17	$< 10^{-30}$	-0.20	$< 10^{-30}$
EM/MM, Career/Family	0.01	0.46	0.28	$< 10^{-30}$	-0.32	$< 10^{-30}$	0.33	$< 10^{-30}$
EM/MM, Math/Arts	0.06	$< 10^{-5}$	-0.22	$< 10^{-30}$	0.45	$< 10^{-30}$	-0.38	$< 10^{-30}$
EM/MM, Science/Arts	0.21	$< 10^{-30}$	-0.27	$< 10^{-30}$	0.62	$< 10^{-30}$	-0.37	$< 10^{-30}$
EM/MF, P/U* - Attitude	-0.82	$< 10^{-30}$	-0.19	$< 10^{-30}$	-0.34	$< 10^{-30}$	-0.60	$< 10^{-30}$
EM/MF, Career/Family	1.14	$< 10^{-30}$	0.68	$< 10^{-30}$	0.09	$< 10^{-11}$	0.68	$< 10^{-30}$

Bias Test	ELMO		BERT		GPT		GPT-2	
	d	p	d	p	d	p	d	p
EM/MF,Math/Arts	0.69	$< 10^{-30}$	0.27	$< 10^{-30}$	0.28	$< 10^{-30}$	-0.78	$< 10^{-30}$
EM/MF, Science/Arts	0.33	$< 10^{-30}$	0.11	$< 10^{-13}$	0.41	$< 10^{-30}$	-0.29	$< 10^{-30}$
EF/AM, P/U* - Attitude	0.95	$< 10^{-30}$	0.70	$< 10^{-30}$	0.06	$< 10^{-5}$	0.09	$< 10^{-17}$
EF/AM, Career/Family	-0.98	$< 10^{-30}$	-0.62	$< 10^{-30}$	-0.63	$< 10^{-30}$	0.11	$< 10^{-21}$
EF/AM, Math/Arts	-0.66	$< 10^{-30}$	-0.41	$< 10^{-30}$	-0.15	$< 10^{-30}$	-0.10	$< 10^{-30}$
EF/AM, Science/Arts	-0.30	$< 10^{-30}$	-0.08	$< 10^{-30}$	0.11	$< 10^{-13}$	-0.19	$< 10^{-30}$
EF/AF, P/U* - Attitude	0.09	$< 10^{-22}$	0.50	$< 10^{-30}$	-0.15	$< 10^{-30}$	-0.20	$< 10^{-30}$
EF/AF, Career/Family	0.04	$< 10^{-7}$	0.22	$< 10^{-30}$	-0.16	$< 10^{-30}$	0.33	$< 10^{-30}$
EF/AF, Math/Arts	-0.33	$< 10^{-30}$	0.39	$< 10^{-30}$	-0.01	0.44	-0.35	$< 10^{-30}$
EF/AF, Science/Arts	0.23	$< 10^{-30}$	0.43	$< 10^{-30}$	0.18	$< 10^{-30}$	-0.20	$< 10^{-30}$
EF/MM, P/U* - Attitude	0.38	$< 10^{-30}$	0.70	$< 10^{-30}$	-0.19	$< 10^{-30}$	0.32	$< 10^{-30}$
EF/MM, Career/Family	-1.10	$< 10^{-30}$	-0.45	$< 10^{-30}$	-0.65	$< 10^{-30}$	-0.02	0.14
EF/MM, Math/Arts	-0.34	$< 10^{-30}$	-0.55	$< 10^{-30}$	0.37	$< 10^{-30}$	-0.02	0.28
EF/MM, Science/Arts	-0.18	$< 10^{-30}$	-0.21	$< 10^{-30}$	0.54	$< 10^{-30}$	-0.36	$< 10^{-30}$
EF/MF, P/U* - Attitude	-0.42	$< 10^{-30}$	0.19	$< 10^{-30}$	-0.33	$< 10^{-30}$	-0.15	$< 10^{-30}$
EF/MF, Career/Family	-0.09	$< 10^{-30}$	-0.07	$< 10^{-30}$	-0.23	$< 10^{-30}$	0.43	$< 10^{-30}$
EF/MF, Math/Arts	0.30	$< 10^{-30}$	-0.05	$< 10^{-30}$	0.17	$< 10^{-30}$	-0.55	$< 10^{-30}$
EF/MF, Science/Arts	-0.01	0.40	0.25	$< 10^{-30}$	0.37	$< 10^{-30}$	-0.30	$< 10^{-30}$
AM/AF, P/U* - Attitude	-0.79	$< 10^{-30}$	-0.32	$< 10^{-30}$	-0.19	$< 10^{-30}$	-0.24	$< 10^{-30}$
AM/AF, Career/Family	0.94	$< 10^{-30}$	0.84	$< 10^{-30}$	0.50	$< 10^{-30}$	0.17	$< 10^{-30}$
AM/AF, Math/Arts	0.34	$< 10^{-30}$	0.79	$< 10^{-30}$	0.16	$< 10^{-30}$	-0.17	$< 10^{-30}$
AM/AF, Science/Arts	0.50	$< 10^{-30}$	0.47	$< 10^{-30}$	0.07	$< 10^{-7}$	-0.02	0.15
AM/MM, P/U* - Attitude	-0.72	$< 10^{-30}$	0.02	0.10	-0.20	$< 10^{-30}$	0.20	$< 10^{-30}$
AM/MM, Career/Family	-0.28	$< 10^{-30}$	0.16	$< 10^{-30}$	0.07	$< 10^{-7}$	-0.12	$< 10^{-30}$
AM/MM, Math/Arts	0.33	$< 10^{-30}$	-0.16	$< 10^{-30}$	0.51	$< 10^{-30}$	0.08	$< 10^{-9}$
AM/MM, Science/Arts	0.13	$< 10^{-30}$	-0.13	$< 10^{-30}$	0.45	$< 10^{-30}$	-0.16	$< 10^{-30}$
AM/MF, P/U* - Attitude	-1.15	$< 10^{-30}$	-0.57	$< 10^{-30}$	-0.38	$< 10^{-30}$	-0.22	$< 10^{-30}$
AM/MF, Career/Family	0.96	$< 10^{-30}$	0.56	$< 10^{-30}$	0.41	$< 10^{-30}$	0.27	$< 10^{-30}$
AM/MF, Math/Arts	0.87	$< 10^{-30}$	0.36	$< 10^{-30}$	0.31	$< 10^{-30}$	-0.38	$< 10^{-30}$
AM/MF, Science/Arts	0.30	$< 10^{-30}$	0.30	$< 10^{-30}$	0.27	$< 10^{-30}$	-0.14	$< 10^{-30}$
AF/MM, P/U* - Attitude	0.26	$< 10^{-30}$	0.33	$< 10^{-30}$	-0.04	$< 10^{-30}$	0.46	$< 10^{-30}$
AF/MM, Career/Family	-1.07	$< 10^{-30}$	-0.64	$< 10^{-30}$	-0.54	$< 10^{-30}$	-0.31	$< 10^{-30}$
AF/MM, Math/Arts	-0.03	0.03	-0.90	$< 10^{-30}$	0.37	$< 10^{-30}$	0.29	$< 10^{-30}$
AF/MM, Science/Arts	-0.38	$< 10^{-30}$	-0.56	$< 10^{-30}$	0.43	$< 10^{-30}$	-0.18	$< 10^{-30}$
AF/MF, P/U* - Attitude	-0.43	$< 10^{-30}$	-0.33	$< 10^{-30}$	-0.19	$< 10^{-30}$	-0.01	0.48
AF/MF, Career/Family	-0.15	$< 10^{-30}$	-0.31	$< 10^{-30}$	-0.06	$< 10^{-30}$	0.15	$< 10^{-30}$
AF/MF, Math/Arts	0.59	$< 10^{-30}$	-0.42	$< 10^{-30}$	0.16	$< 10^{-30}$	-0.25	$< 10^{-30}$
AF/MF, Science/Arts	-0.20	$< 10^{-30}$	-0.18	$< 10^{-30}$	0.22	$< 10^{-30}$	-0.15	$< 10^{-30}$
MM/MF, P/U* - Attitude	-0.77	$< 10^{-30}$	-0.59	$< 10^{-30}$	-0.15	$< 10^{-30}$	-0.44	$< 10^{-30}$
MM/MF, Career/Family	1.11	$< 10^{-30}$	0.40	$< 10^{-30}$	0.44	$< 10^{-30}$	0.42	$< 10^{-30}$
MM/MF, Math/Arts	0.62	$< 10^{-30}$	0.50	$< 10^{-30}$	-0.18	$< 10^{-30}$	-0.49	$< 10^{-30}$
MM/MF, Science/Arts	0.18	$< 10^{-30}$	0.41	$< 10^{-30}$	-0.19	$< 10^{-30}$	0.02	0.18

*Unpleasant and pleasant attributes used to measure valence and attitudes towards targets [10].

B Data

B.1 Static Word Embeddings (SWE)

We use GloVe [18] SWE trained on the word co-occurrence statistics of the Common Crawl corpus to automatically detect words that are highly associated with intersectional group members. Common Crawl corpus consists of 840 billion tokens and more than 2 million unique vocabulary words collected from a crawl of the world wide web. GloVe embeddings capture fine-grained semantic and syntactic regularities [18]. Caliskan et al. [1] have shown that social biases are embedded in linguistic regularities learned by GloVe. GloVe word embeddings have 300 dimensions. The download link for GloVe is `https://nlp.stanford.edu/projects/glove/`.

B.2 Contextualized Word Embeddings (CWE)

We use the CWE generated by Elmo, Bert, GPT and GPT-2 [29, 30, 31, 32]. Specifically, a CWE is formed by the collection of values on a particular layer's hidden units in the neural language model.

Bert, GPT and GPT-2 use subword tokenization. Since GPT and GPT-2 are unidirectional language models, CWE of the last subtokens contain the information of the entire word [32]. We use the CWE of the last subtoken in the word as its representation in GPT and GPT-2. To keep consistency, we also use the CWE of the last subtoken in the word as its representation in Bert. 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 and they are trained on cased English text.

Elmo [29] is a 2-layer bidirectional LSTM [46] language model trained on the Billion Word Benchmark dataset [33]. Elmo is different from the three other models since CWE in Elmo integrate the hidden states in all layers instead of using only the hidden states of the top layer. We follow standard usage and compute the summation of hidden units over all aggregated layers of the same token as its CWE. CWE of Elmo have 1024 dimensions. We use the implementation of Elmo from AllenNLP at `https://allennlp.org/elmo`.

Bert [30] is a bidirectional transformer encoder [47] trained on a masked language model and next sentence prediction. Bert is trained on BookCorpus [34] and English Wikipedia dumps. We use the version of Bert-small-case (12 layers). We use the values of hidden units on the top layer corresponding to the token as its CWE. CWE of Bert have 768 dimensions. We use the implementation of Bert from the Transformers library at `https://huggingface.co/transformers/v2.5.0/model_doc/bert.html`.

GPT [31] is a 12-layer transformer decoder trained on a unidirectional language model on BookCorpus [34]. We use the values of hidden units on the top layer corresponding to the token as its CWE. CWE of GPT have 768 dimensions. We use the implementation of the GPT model from the Transformers library at `https://huggingface.co/transformers/v2.5.0/model_doc/gpt.html`.

GPT-2 [32] is a transformer decoder trained on a unidirectional language model and is a scaled-up version of GPT. GPT-2 is trained on WebText [32]. We use GPT-2-small (12 layers). We use the values of hidden units on the top layer corresponding to the token as its CWE. CWE of GPT-2 have 768 dimensions. We use the implementation of GPT model from the Transformers library at `https://huggingface.co/transformers/v2.5.0/model_doc/gpt2.html`.

B.3 Corpus

To extract all the possible contexts where a word can appear in ordinary language, we use the large-scale Reddit comments dataset, which has been shown to contain social biases [35]. The link to the corpus is `https://files.pushshift.io/reddit/comments/`. The corpus consists of 500 million comments made in the period between 1/1/2014 and 12/31/2014. We extract all sentences which contain at least one of all stimuli used in each one of the 14 CEATs. In this way, we collect a great variety of CWE from the Reddit comments corpus to measure bias comprehensively in a neural language model.

C Plots

We draw the ROC curves of Intersectional and Emergent Intersectional Bias Detection experiments of Section 5 in Figure 2. We upload the plots of the distributions of effect sizes in all CEATs of Section 5 in our project repository(`www.gitRepo.com`).

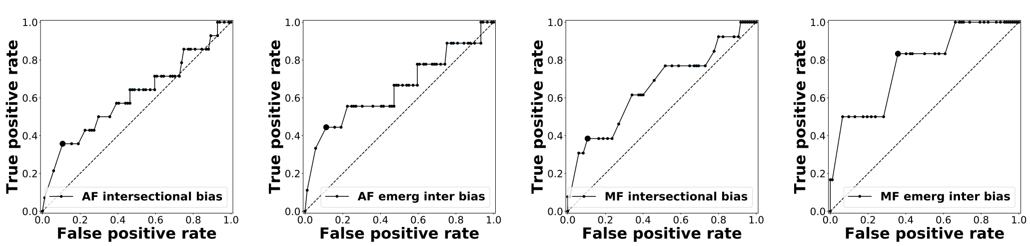

Figure 2: **ROC curves of IBD and EIBD for African American females (AF) and Mexican American females (MF).** The value that maximizes the $true\,positive\,rate\ -\ false\,positive\,rate$ is selected as the optimal threshold marked with a dot. 'emerg inter bias' stands for emergent intersectional bias.

D Stimuli

The stimuli used to represent targets and attributes in CEAT (C1-C10) are taken from Caliskan et al.[1]. We construct four intersection-related s CEAT for African American females and Mexican American females.

When conducting intersection-related CEAT , we use the names from Caliskan et al. [1] and Parada et al. [36] to represent the target intersectional groups. Caliskan et al.'s WEAT provides the female and male names of African Americans and European Americans from the first Implicit Association Test in 1998 [10]. Parada et al. provide the female and male names of Mexican Americans [36]. To determine and verify the gender of names, we use three gender checkers [37]. We only use the name as a target word in our experiments, if the name is categorized to belong to the same gender by all of the three checkers. Human subjects provide the validation set of intersectional attributes with ground truth information [11]. We use this validation set for evaluating the intersection-related CEAT, IBD and EIBD experiments. To follow the order of stereotype-congruity, we use European American males as the second target group and use the attributes associated with their intersectional biases as the second attribute group in intersection-related CEAT. If the size of the first attribute set is smaller than that of the attributes of European American males, we randomly select an equal number of attributes associated with the intersectional biases of European American males.

D.1 CEAT I1

We use the frequent given names of African American females and European American males as two target social groups and use the attributes associated with the intersectional biases of African American females and attributes associated with the intersectional biases of European American males as the two attribute groups.

Since 'assertive' is associated with both African American females and European American males, we do not include it in this test.

- **African American females**: Aisha, Keisha, Lakisha, Latisha, Latoya, Malika, Nichelle, Shereen, Tamika, Tanisha, Yolanda, Yvette
- **European American males**: Andrew, Brad, Frank, Geoffrey, Jack, Jonathan, Josh, Matthew, Neil, Peter, Roger, Stephen
- **Intersectional biases of African American females**: aggressive, athletic, bigbutt, confident, darkskinned, fried-chicken, ghetto, loud, overweight, promiscuous, unfeminine, unintelligent, unrefined
- **Intersectional biases of European American males**: all-American, arrogant, attractive, blond, high-status, intelligent, leader, privileged, racist, rich, sexist, successful, tall

D.2 CEAT I2

We use the frequent given names of African American females and European American males as two target groups. We use attributes associated with emergent intersectional biases of African American females and attributes associated with intersectional biases of European American males as two attribute groups.

Since 'assertive' is associated with emergent intersectional bias of African American females and intersectional bias of European American males, we do not include it in this test.

- **African American females**: Aisha, Keisha, Lakisha, Latisha, Latoya, Malika, Nichelle, Shereen, Tamika, Tanisha, Yolanda, Yvette
- **European American males**: Andrew, Brad, Frank, Geoffrey, Jack, Jonathan, Josh, Matthew, Neil, Peter, Roger, Stephen
- **Emergent intersectional biases of African American females**: aggressive, bigbutt, confident, darkskinned, fried-chicken, overweight, promiscuous, unfeminine
- **Intersectional biases of European American males**: arrogant, blond, high-status, intelligent, racist, rich, successful, tall

D.3 CEAT I3

We use the frequent given names of Mexican American females and European American males as the target groups and the words associated with their intersectional biases as the attribute groups.

Since 'attractive' is associated with intersectional biases of both Mexican American females and European American males, we do not include it in this test.

- **Mexican American females**: Adriana, Alejandra, Alma, Brenda, Carolina, Iliana, Karina, Liset, Maria, Mayra, Sonia, Yesenia
- **European American males**: Andrew, Brad, Frank, Geoffrey, Jack, Jonathan, Josh, Matthew, Neil, Peter, Roger, Stephen
- **Intersectional biases of Mexican American females**: cook, curvy, darkskinned, feisty, hardworker, loud, maids, promiscuous, sexy, short, uneducated, unintelligent
- **Intersectional biases of European American males**: all-American, arrogant, blond, high-status, intelligent, leader, privileged, racist, rich, sexist, successful, tall

D.4 CEAT I4

We use the frequent given names of Mexican American females and European American males as target groups. We use words associated with the emergent intersectional biases of Mexican American females and words associated with the intersectional biases of European American males as the two attribute groups.

- **Mexican American females**: Adriana, Alejandra, Alma, Brenda, Carolina, Iliana, Karina, Liset, Maria, Mayra, Sonia, Yesenia
- **European American males**: Andrew, Brad, Frank, Geoffrey, Jack, Jonathan, Josh, Matthew, Neil, Peter, Roger, Stephen
- **Emergent intersectional biases of Mexican American females**: cook, curvy, feisty, maids, promiscuous, sexy
- **Intersectional biases of European American males**: arrogant, assertive, intelligent, rich, successful, tall

D.5 IBD and EIBD

We detect the attributes associated with the intersectional biases and emergent intersectional biases of African American females and Mexican American females in GloVe SWE. We assume that there are three subcategories under the race category (African American, Mexican American, European American) and two subcategories under the gender category (female, male). We use the frequent given names to represent each intersectional group. Again, we note that, in future work we'd generalize this work to n subcategories under each category. Further, in future work, instead of categorizing people into social groups, we'd like to explore representing individuals in social data with continuous real-valued variables as opposed to associating them with category labels.

- **African American females**: Aisha, Keisha, Lakisha, Latisha, Latoya, Malika, Nichelle, Shereen, Tamika, Tanisha, Yolanda, Yvette
- **African American males**: Alonzo, Alphonse, Hakim, Jamal, Jamel, Jerome, Leroy, Lionel, Marcellus, Terrence, Tyrone, Wardell
- **Mexican American females**: Adriana, Alejandra, Alma, Brenda, Carolina, Iliana, Karina, Liset, Maria, Mayra, Sonia, Yesenia
- **Mexican American males**: Alberto, Alejandro, Alfredo, Antonio, César, Jesús, José, Juan, Miguel, Pedro, Rigoberto, Rogelio
- **European American females**: Carrie, Colleen, Ellen, Emily, Heather, Katie, Megan, Melanie, Nancy, Rachel, Sarah, Stephanie
- **European American males**: Andrew, Brad, Frank, Geoffrey, Jack, Jonathan, Josh, Matthew, Neil, Peter, Roger, Stephen

We list all the attributes used in validation experiments. These are stimuli associated with different social groups and a set of random words that are not expected to be associated with social groups. These random attributes are borrowed from the insect target category of the 'universally accepted stereotypes' IAT, which is a baseline WEAT. We use 98 words in total in the validation experiments. We also list the probability of random chance of correct classification in parentheses next to each social group. The goal here is to present the success rate of the machine learning detection method in a meaningful way. To calculate the probability of random chance of correct classification, we treat the detection task as if this were a one-vs-all verification task, which is one type of a classification task, that aims to verify the membership of a data point in the main class. All the other data points from the open world, that don't belong to the main class we are testing for, can belong to any other class.

However, in reality, our detection method is a semi-supervised non-parametric prediction method which relies on the threshold t. Some of the attributes of some social groups overlap. For example, 'assertive' is associated with emergent intersectional biases of African American females and also associated with emergent intersectional biases of European American males. As a result, the sum of all random chances of different groups is not 100%.

- **Biases of African Americans**: athletic, criminals, dangerous, gangsters, ghetto, lazy, loud, poor, tall, uneducated, unrefined, violent (random chance of correct classification: 12.2%)
- **Emergent Intersectional Biases of African American Males**: darkskinned, hypersexual, rapper (random chance of correct classification: 3.1%)
- **Intersectional Biases of African American Males**: athletic, criminals, dangerous, darkskinned, gangsters, hypersexual, lazy, loud, poor, rapper, tall, unintelligent, violent (random chance of correct classification: 13.3%)
- **Emergent Intersectional Biases of African American Females**: aggressive, assertive, bigbutt, confident, darkskinned, fried-chicken, overweight, promiscuous, unfeminine (random chance of correct classification: 9.2%)
- **Intersectional Biases of African American Females**: aggressive, assertive, athletic, bigbutt, confident, darkskinned, fried-chicken, ghetto, loud, overweight, promiscuous, unfeminine, unintelligent, unrefined (random chance of correct classification: 14.3%)
- **Biases of European Americans**: all-American, arrogant, attractive, blond, blue-eyes, highstatus, ignorant, intelligent, overweight, patronizing, privileged, racist, red-neck, rich, tall (random chance of correct classification: 15.3%)
- **Emergent Intersectional Biases of European American Males**: assertive, educated, successful (random chance of correct classification: 3.1%)
- **Intersectional Biases of European American Males**: all-American, arrogant, assertive, attractive, blond, educated, high-status, intelligent, leader, privileged, racist, rich, sexist, successful, tall (random chance of correct classification: 15.3%)
- **Emergent Intersectional Biases of European American Females**: ditsy (random chance of correct classification: 1.0%)
- **Intersectional Biases of European American Females**: arrogant, attractive, blond, ditsy, emotional, feminine, high-status, intelligent, materialistic, petite, racist, rich, submissive, tall (random chance of correct classification: 14.3%)
- **Biases of Males**: aggressive, ambitious, arrogant, fixer-upper, high-status, intelligent, leader, messy, provider, respected, sexist, tall, unfaithful (random chance of correct classification: 13.3%)
- **Biases of Females**: attractive, caring, dependent, emotional, feminine, jealous, manipulative, materialistic, motherly, petite, soft, submissive, talkative (random chance of correct classification: 13.3%)
- **Emergent Intersectional Biases of Mexican American Females**: cook, curvy, feisty, maids, promiscuous, sexy (random chance of correct classification: 6.1%)
- **Intersectional Biases of Mexican American Females**:attractive, cook, curvy, darkskinned, feisty, hardworker, loud, maids, promiscuous, sexy, short, uneducated, unintelligent (random chance of correct classification: 13.3%)
- **Emergent Intersectional Biases of Mexican American Males**: drunks, jealous, promiscuous, violent (random chance of correct classification: 4.1%)
- **Intersectional Biases of Mexican American Males**: aggressive, arrogant, darkskinned, day-laborer, drunks, hardworker, illegal-immigrant, jealous, macho, poor, promiscuous, short, uneducated, unintelligent, violent (random chance of correct classification: 15.3%)
- **Biases of Mexican Americans**: darkskinned, day-laborer, family-oriented, gangster, hardworker, illegal-immigrant, lazy, loud, macho, overweight, poor, short, uneducated, unintelligent (random chance of correct classification: 14.3%)
- **Random (Insects)**: ant, bedbug, bee, beetle, blackfly, caterpillar, centipede, cockroach, cricket, dragonfly, flea, fly, gnat, hornet, horsefly, locust, maggot, mosquito, moth, roach, spider, tarantula, termite, wasp, weevil (random chance of correct classification: 25.5%)

E Code

Since the data files containing the CWE of all stimuli are larger than 1.45 GB, we upload data files of our project in our project repository(`www.gitRepo.com`).