ValNorm Quantifies Semantics to Reveal Consistent Valence Biases Across Languages and Over Centuries

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ABSTRACT

Word embeddings, which are numeric dictionaries for machines to process language, learn implicit biases from linguistic regularities captured by word co-occurrence information. As a result, statistical methods can detect and quantify social biases along with widely shared associations present in the corpus the word embeddings are trained on. By extending methods that quantify human-like biases in word embeddings, we introduce ValNorm, a novel word embedding intrinsic evaluation task and a method to measure the affective meaning of valence (pleasantness/unpleasantness) in words, with high accuracy. The correlation between human judgment scores of valence for 399 words collected to establish pleasantness norms in English and ValNorm scores is $\rho = 0.88$. These 399 words, obtained from the social psychology literature, are used to measure biases that are non-discriminatory among social groups. We hypothesize that the valence associations for this set of words (in various translations) are widely shared across languages and consistent over time. We estimate valence associations of these words using word embeddings from seven languages representing various language structures and from historical text covering 200 years. Our method achieves consistently high accuracy, suggesting that the valence associations for these words are widely shared. In contrast, we measure gender stereotypes using the same set of word embeddings and find that social biases vary across languages. Our results signal that valence associations of this word set represent widely shared associations of the last two centuries. Consequently, Val-Norm can be used to evaluate valence norms and the accuracy of word embeddings especially when measuring biases.

KEYWORDS

word embeddings, quantifying meaning, semantic differential, bias, valence, norms, intrinsic evaluation

1 INTRODUCTION

This paper presents the novel computational approach ValNorm, that accurately quantifies the valence dimension of implicit biases and affective meaning in word embeddings, to understand widely shared associations of words. Implicit biases, as well as the intrinsic pleasantness or goodness of things, namely valence, have been well researched with human subjects [25, 54, 55]. Valence is one of the principal dimensions of affect and cognitive heuristics that shape attitudes and biases in humans [29]. Valence is described as the affective quality referring to the intrinsic attractiveness/goodness or averseness/badness of an event, object, or situation [19]. For word

embeddings, we define valence bias as the semantic evaluation of pleasantness or unpleasantness associated with words.

Pan-cultural investigation of language norms provided evidence of a universal framework underlying certain affective aspects of language [48]. Osgood [46] introduced the semantic differential for the evaluation of pleasantness, potency, and activity among human subjects despite linguistic differences, while suggesting the possibility of developing computational methods to accomplish these tasks. Being able to measure pleasantness via the semantic differential had real-world implications that raised ethical concerns. For example, information influence operations in the 1970s used Osgood [46]'s semantic differential technique to retrieve the words that would most effectively induce a negative attitude in the Chilean population towards the socialist Allende administration [38]. Today, neural language models may be exploited, using a similar technique, to automate large-scale information influence operations that intend to sow discord among social groups [62]. Generally, Osgood [46]'s theory of the semantic differential was an application of his attempt to comprehensively measure the meaning of words. As one of the most widely applied scales to measure human attitudes, the semantic differential lays a foundation to measure implicit biases computationally, by selecting a polar attribute set that reflects the desired bias to be measured. Building on research that highlights implicit biases as indicators of either widely-accepted or culture specific associations [24–26, 46, 54, 55], we develop a novel word embedding intrinsic evaluation task, ValNorm, that measures the linguistic relationships of widely-accepted biases across languages and over time.

Word embeddings are widely used word representations trained on word co-occurrence statistics that help machines process natural language [51]. Word embeddings encode semantic and syntactic regularities of language, including biases, and these characteristics are not transparent without further evaluation. Cross-disciplinary approaches to word embedding evaluation work to enhance understanding and transparency, such as Bodell et al. [6]'s word embedding interpretability methods, which capture latent semantic concepts via informative priors to provide domain informed dimensions for analysis in digital humanities and computational social science. Expanding the resources for evaluating the quality of word embeddings requires developing transparency-enhancing methods that identify widely-accepted characteristics of words through new techniques [1, 16, 33, 57]. A promising approach to expanding the resources for intrinsic evaluation tasks when measuring biases is to evaluate word embeddings through the lens of cognitive lexical semantics, which captures the social and psychological responses

of humans to words and language [33]; however, there is limited computational research in this area [11, 31, 64].

Word embedding evaluation tasks are methods to measure the quality and accuracy of learned word vector representations from a given text corpus. The two main types of evaluation tasks are intrinsic evaluation, which analyzes and interprets the semantic or syntactic characteristics of word embeddings (e.g., word similarity), and extrinsic evaluation, which measures how well word embeddings perform on downstream tasks (e.g., part-of-speech tagging) [63, 68]. There are several intrinsic and extrinsic evaluation tasks commonly used for assessment. However, there isn't a standardized suite of evaluation methods because word embeddings are used for capturing numerous aspects of language that require individualized evaluation strategies [16]. In this work, we focus on the representation of valence norms and the corresponding intrinsic semantic quality of word embeddings, that have been shown to learn human-like biases, such as racism or attitudes towards the elderly, from word co-occurrence information [11].

Caliskan et al. [11] show that word embeddings capture humanlike biases and stereotypes using the Word Embedding Association Test (WEAT) and that gender biases for occupations are embedded in the statistical regularities of language using the Word Embedding Factual Association Test (WEFAT). These association tests provide a comparison between widely-accepted biases, such as instruments being associated with pleasantness and weapons being associated with unpleasantness [25], and social biases, such as males being associated with science and women being associated with arts. We apply the WEAT to measure social group and non-discriminatory biases. Complementary prior work on lexicon induction methods compensates for the lack of existing annotated data on valence [31, 53, 64]. Turney and Littman [64] accurately categorize the semantic orientation of words via statistical associations in word embeddings. Hatzivassiloglou and McKeown [31] define semantic orientation as the evaluative character of a word, corresponding to the affective meaning of valence in the linguistics and psychology domains. Experts in social psychology presented pleasant and unpleasant evaluative attribute sets to measure valence in human subjects with stimuli that represent pleasantness [24-26]. Bellezza et al. [4] constructed a set of 399 words to measure norms of pleasantness in human subjects. Building on prior work in computer science, computational linguistics, and psychology, we extend the validated WEFAT by lexicon induction with pleasantness stimuli to precisely measure the linguistic regularities of valence norms. Our method ValNorm shows that valenced affect is accurately and consistently encoded into the word co-occurrence statistics of word embeddings across seven languages and over two centuries. These findings suggest that measuring valence norms is a practical method to evaluate the quality of word embeddings.

We present ValNorm as an intrinsic evaluation task that measures the widely-accepted valence associations of words, a linguistic relationship that we find is stable over time and should be preserved in quality word embeddings learned from various languages. Such an evaluation method can be particularly informative when studying implicit associations and biases in natural language processing, corpora, or particular populations of society. We use three different validation datasets for English (Bellezza's Lexicon, ANEW, and

Warriner's Lexicon) that contain expert curated lists of vocabulary words and their corresponding ground-truth valence scores collected from human subjects [4, 8, 70]. We compare ValNorm computed scores to the human-annotated scores using Pearson's correlation [37] as the metric of accuracy. We validate ValNorm as measuring an intrinsic quality of words by implementing ValNorm on word embeddings from seven different languages, representing five diverse branches of language families, and over a time span of 200 years (English only).

We compare ValNorm to six widely used, traditional intrinsic evaluation tasks that measure word similarity (measures how semantically similar two words are to each other) and word analogy (measures how words are related to each other). We implement each intrinsic evaluation task on seven pre-trained word embeddings (English only) which were trained using four different embedding algorithms and five different training text corpora (see Figure 3) to ensure that the ValNorm results are not model or corpus specific. Additionally, we implement the word similarity tasks and ValNorm on five sets of word embeddings that were generated from sampling different sizes of the OpenSubtitles 2018 corpus¹, in order to gain insight into the smallest corpus size that produces quality word embeddings (see Figure 2), especially when studying biases in word embeddings.

ValNorm achieves Pearson correlation coefficients (ρ) in the range [0.82, 0.88] for the seven English word embedding sets, outperforming the six traditional intrinsic evaluation tasks we compare our results to. Implementing our intrinsic evaluation task on the OpenSubtitles 2018 corpus subsets, we find that generating word embeddings from 50% of the original corpus only reduces ρ by 0.01 (0.87 to 0.86), and that generating word embeddings from 10% of the original corpus only reduces ρ by 0.04 (0.87 to 0.83). All the implementation details, datasets, and source code are available in supplementary materials and on our public repository at https://github.com/autumntoney/ValNorm.

We summarize our three main contributions as follows: 1) we quantify the semantic differential of the pleasantness evaluation dimension to study the valence norms of words and present a permutation test to measure the statistical significance of valence quantification, 2) we introduce ValNorm, a new, language-agnostic intrinsic evaluation task that measures the quality of word embeddings and overperforms traditional intrinsic evaluation tasks, and 3) we establish widely shared associations of valence across languages and over time.

2 RELATED WORK

Caliskan et al. [11] present methods, WEAT and WEFAT, to measure implicit biases in word embeddings that are derived from the Implicit Association Test (IAT) in social psychology [11, 24–26]. The WEAT has two bias tests that measure non-social group (e.g., flowers and insects) biases and seven WEAT bias tests that measure social group (e.g., gender) biases. The social group WEATs have been widely studied in the natural language processing (NLP) domain, as understanding biases around social groups is an important task for society. The WEFAT has applications of gender bias in

¹http://opus.nlpl.eu/OpenSubtitles-v2018.php

occupations and androgynous names, which measures a social bias that is language and culture specific [11, 27].

WEFAT resembles a single-category or single-stimulus word embedding association test, analogous to the single-category implicit association test (sc-IAT) in human cognition [36]. WEFAT also shares similar properties with lexicon induction methods, which automatically extract semantic dictionaries from textual corpora without relying on large-scale annotated data for training machine learning models. For example, lexicon induction can retrieve a collection of words belonging to the same semantic category to construct semantic lexica. Additionally, lexicon induction can induce machine translation pairs based on distributional properties of language [18, 30]. Prior work on lexicon induction quantifies valence for sentiment and polarity classification tasks [31, 53, 64]. Hatzivassiloglou and McKeown [31] clustered adjectives by polarity to explore constraints on semantic orientation of conjoined adjectives. The findings show that synonyms share the same semantic orientation, whereas antonyms have the opposite. Riloff and Wiebe [53] extended these approaches to subjectivity classification. Turney and Littman [64]'s approach to classification of the semantic orientation of words, including adjectives, adverbs, nouns, and verbs, is closely related to ours. However, the classification of valence in prior work is not evaluated in the context of measuring the quality of word embeddings or quantifying linguistic regularities with sets of words that represent valence norms.

Lewis and Lupyan [39] investigate how the distributional structure of natural language semantics in 25 different languages can be used to determine the gender bias for each culture [39]. While Lewis and Lupyan analyze bias across languages, they focus specifically on the social group of gender, and not on widely shared associations across languages. Garg et al. [20] quantify gender and ethnic bias over 100 years to dynamically measure how biases evolve over time [20]. Similarly, Garg et al. do not measure widely shared associations over time, they only measure social group biases. Hamilton et al. [28] study how semantics and culture evolve over time to discover the statistical laws of semantic shift. They conclude that word frequency and polysemy are directly related to change in meaning over time. However, they do not focus on valence norms across languages as an evaluation metric for word embedding quality.

Predicting affective ratings of words from word embeddings has proven to be a more complex task than computing word similarity, and is typically approached as a supervised machine learning problem [40, 43, 61, 66, 69]. Affect ratings of words computed from word embeddings can improve NLP tasks involving sentiment analysis and emotion detection [43, 66], thus, designing an intrinsic evaluation task that estimates the valence association of a word is significant. Moreover, researchers from a diverse set of disciplines use word embeddings to evaluate biases while studying algorithmic bias, data bias, debiasing, populations, social cognition, evolution of cognition, language, culture, and semantics. Having a metric that measures the representation of valence norms in word embeddings can help analyze choices such as corpus size, hyper-parameters, selection bias, word frequency, and vocabulary.

Traditional word embedding intrinsic evaluation tasks use word similarity, word analogy, or word categorization to measure various linguistic properties captured by a set of word embeddings [1, 57]. Word similarity and word analogy both use cosine similarity, a

highly accurate similarity metric using vector arithmetic, to measure semantic similarity of the word embeddings representing the word sets in the evaluation task. Word similarity tasks compare the cosine similarity to a human-rated similarity score through Pearson or Spearman correlation [14, 37]; the correlation coefficient provides the accuracy metric for semantic similarity learned by word embeddings. Word analogy tasks output matching words based on vector arithmetic and accuracy is the metric of correct word selection [42].

Since there is no standardized approach to evaluating word embeddings, there are several tasks widely used together in order to provide a thorough evaluation. We focus on the five most commonly used word similarity tasks WordSim (353 word pairs), RareWord (2,034 word pairs), MEN (3,000 word pairs), SimLex (999 word pairs), SimVerb (3,500 word pairs) [10, 17, 21, 32, 41, 65], and the word analogy task from Mikolov et al. which contains 8,869 semantic and 10,675 syntactic questions [42].

3 DATASETS

We use five types of data to develop ValNorm. (1) state-of-the-art word embeddings from a set of seven structurally diverse languages to develop the language-agnostic method that can accurately quantify valence, (2) three expert-curated sets of words and their corresponding human-rated valence judgement scores (Bellezza's Lexicon, ANEW, and Warriner's Lexicon) annotated by English speakers, (3) human-rated valence judgement scores from non-English speakers for the six non-English languages that we analyzed, (4) Chinese and Turkish term set translations into English by native speakers since the original datasets did not contain an English translation field, (5) sets of stimuli from the validated IAT literature.

We study the consistency of valence norms over decades by applying ValNorm to historical word embeddings, trained on corpora collected for each decade between 1800 to 1990 Hamilton et al. [28]. The details of this experiment are in Figure 1 under Section 6.

3.1 Word Embeddings

We choose six widely-used, pre-trained word embedding sets in English, listed in Table 1, to compare ValNorm's performance on different algorithms (GloVe, fastText, word2vec) and training corpora (Common Crawl, Wikipedia, OpenSubtitles, Twitter, and Google News) [7, 22, 42, 51]. We include a seventh word embedding set, Conceptnet Numberbatch, since it is comprised of an ensemble of lexical data sources and is claimed to be less prejudiced in terms of ethnicity, religion, and gender [59].

Algorithm	Corpus	# Tokens	
fastText skipgram	Common Crawl	600B	
iast iext skipgram	OpenSubtitles 2018	22.2B	
fastText CBOW	Common Crawl	600+ B	
last lext CDO W	Wikipedia	000+ D	
GloVe	Common Crawl	840B	
Giove	Twitter	27B	
Numberbatch	-	-	
word2vec	Google News	100B	

300-dimensional embeddings (except the 200-dimensional GloVe Twitter)

Table 1: Variety of word embeddings for experiments

ConceptNet Numberbatch's results on social group and non-social group association tests provide a unique insight into valence norms for word embeddings, since the social group biases have been intentionally lowered. Note that for ConceptNet Numberbatch word embeddings in Table 1, we left the training corpus and number of tokens blank, since the word vectors are formed using lexical information from ConceptNet², OpenSubtitles 2016, GloVe, and word2vec [59].

We use the 300-dimensional, pre-trained fastText word embeddings prepared for 157 languages for our seven languages of interest from five branches of language families that have different syntactic properties (Chinese, English, German, Polish, Portuguese, Spanish, and Turkish) [22].

3.2 Validation Datasets

We choose three validation, human-annotated datasets of varying size for our experiments in English. All human-rated valence scores are reported as the mean.

Bellezza et al. compiled a vocabulary list of 399 words to establish norms for pleasantness, imagery, and familiarity [4]. A set of 1,545 words were rated by 26-33 college students and then a refined list was rated by 62-76 college students to generate pleasantness scores. Bellezza et al. asked participants to rate words based on pleasantness versus unpleasantness, which directly corresponds to our representation of valence.

The Affective Norms for English Words (ANEW) dataset is a widely used resource in sentiment analysis for NLP tasks. ANEW contains 1,034 vocabulary words and their corresponding valence, arousal, and dominance ratings. Psychology students were asked to rate words in terms of happy versus unhappy to model valence, according to the Self-Assessment Manikin (SAM), on a scale of 1 (unhappy) to 9 (happy) [8].

Warriner et al. extended ANEW to 13,915 vocabulary words to include words from more category norms, for example taboo words, occupations, and types of diseases [70]. The 1,827 participants were recruited through Amazon Mechanical Turk, and given directions similar to the ANEW test; valence is also modeled by happy/unhappy on a scale of 1-9. Warriner et al. note that valence scores were comparatively similar among responses [70].

Among the three human-annotated datasets, there are 381 common words in their respective vocabularies. The missing words are 'affectionate', 'anxiety', 'capacity', 'comparison', 'constipation', 'disappointment', 'easter', 'epilepsy', 'hitler', 'inconsiderate', 'magnificent', 'me', 'nazi', 'prosperity', 'reformatory', 'sentimental', 'tuberculosis', 'woman'. Using this 381-word subset of vocabulary, we checked the correlation of human valence scores to measure the inter-rater reliability for the three datasets. We measure a Pearson correlation coefficient of 0.97 or higher for all combinations of comparison among the three sets of human-rated valence scores. As Bellezza et al. [4] hypothesized, 0.97 indicates a strong inter-rater reliability for valence scores of words, and signals widely shared associations, since each dataset was collected from a different year (1995, 1999, and 2013) with different groups of participants from various backgrounds.

3.3 Cross-linguistic Datasets

We selected four direct adaptations of the Affective Norms of English Words (ANEW) to other languages (Polish, Portuguese, Spanish, and Turkish). Each adaptation was conducted using the same 1 (unhappy) to 9 (happy) point scale, and the reported score was the mean value among all recorded participant scores. There is variance in the translation process for the ANEW word list and in the number of participants recruited. Table 2 presents Pearson correlation coefficient of 0.92 or higher for all combinations of inter-rater reliability comparison among the five sets of human-rated valence scores with validated translations. The German dataset is derived from ANEW, but is not a direct adaptation so it does not contain all words from ANEW and a different scale is used. We found these sets to be most complete (included majority of the ANEW vocabulary) and representative of various language structures (e.g., Turkish is a gender-neutral language). We also include an affective norm Chinese dataset that is not a direct adaptation of ANEW but contains a large overlapping vocabulary. We explain the details of the adaptations below.

The Polish adaptation of ANEW, Affective norms for 1,586 Polish words (ANPW), was translated by the author using google translate, the Cambridge Dictionary of English, and the PWN Oxford English-Polish Dictionary [34]. Imbir worked with bilingual individuals to validate the machine translation, and then had a professional philologist who specializes in the English language with a deep knowledge in American culture re-assess the translations [34]. This resulted in 1,040 Polish words. Scores were obtained between October 2013 and February 2014 from 1,670 students who attended various Warsaw academic institutions with different academic backgrounds (eg. engineering, humanities, and social sciences) [34]. The Portuguese adaptation of ANEW was translated from English to European-Portuguese (EP) by two professional philologists

lish to European-Portuguese (EP) by two professional philologists specializing in the English language with a deep knowledge of American culture (helpful to translate words that can have multiple meanings) [58]. For some words that were difficult to translate due to polysemy or syntactic ambiguity, they used the translation of the English word that was most similar to the Spanish translation [58]. 958 college students who were EP native speakers from different disciplines (humanities, economics, sciences, and technologies) in several public and private universities from the north to the south of Portugal participated in the study [58].

The Spanish adaptation of ANEW was translated from English by a professional philologist who specializes in the English language [52]. The first round of translations were revised by an English philology professor and a psycholinguistics researcher in collaboration with the authors [52]. The Spanish words were scored by 720 psychology students between the years of 2003-2005. The ages of the students ranged from 18-25 years old and there were 560 female and 160 male participants.

The Turkish adaptation of ANEW contains 2,031 vocabulary words from a combination of ANEW and the Turkish Word Norms [35]. The translation of the ANEW vocabulary words was published by Turkish psychologists Ali Tekcan and İlyas Göz in a previous study [60]. 1,527 students at various universities in Turkey, 92% of participants came from the Middle East Institute of Technology and

²http://conceptnet.io/, We use the latest version available, 19.08.

5% came from Ege University, participated in the study to rate the words on valence and arousal [35].

The German adaptation of ANEW is an extension of the Berlin Affected Word List (BAWL)[67] and was relabeled as Affective Norms for German Sentiment Terms (ANGST); this set contains 1,003 words [56]. Valence scores were collected on a -3 (unhappy) to 3 (happy) point scale [56].

The Chinese Valence-Arousal Words (CVAW) contains 5,512 words rated by four expert annotators who were trained on the Circumplex Model of Affect, which is the foundational methodology for affective meaning of words [54, 71]. The annotators assigned sentiment scores on a 1 (negative) to 9 (positive) point scale accordingly [71]. We find the words in common among all of the seven languages' datasets, and we check the variance in human-annotated valence scores for this subset of 143 words³. The top five words with the *least* amount of variance are terrific ($\sigma^2 = 3.6x10^{-4}$), loyal ($\sigma^2 = 4.7x10^{-4}$), humor ($\sigma^2 = 6.9x10^{-4}$), hatred ($\sigma^2 = 7.4x10^{-4}$), and depression ($\sigma^2 = 9.2x10^{-4}$). The top five words with the *most* amount of variance are execution ($\sigma^2 = 4.9x10^{-2}$), party ($\sigma^2 = 4.1x10^{-2}$), vomit ($\sigma^2 = 3.4x10^{-2}$), malaria ($\sigma^2 = 2.7x10^{-2}$), and torture ($\sigma^2 = 2.6x10^{-2}$).

3.4 Chinese and Turkish Stimuli Translations

Chinese and Turkish datasets do not provide one-to-one validated translations to English. They also have the lowest inter-rater reliability scores among the seven datasets, which might be due to ambiguity in our translations with native speakers. The German, Polish, Portuguese, and Spanish validation datasets include an English translation field for the word lists, that we are able to use directly in our ValNorm implementation. For the Chinese and Turkish implementation we had native speakers translate Bellezza's Lexicon and used these translations for our experiments. We provide these translated word lists for reproducability in our git repository since they are not included in the original datasets.

	EN	DE	PL	PT	ES	TR
CN	0.91	0.85	0.88	0.88	0.89	0.83
EN	1.0	0.95	0.94	0.95	0.95	0.87
DE		1.0	0.92	0.94	0.95	0.87
PL			1.0	0.93	0.93	0.85
PT				1.0	0.96	0.88
ES					1.0	0.88

Table 2: Pearson correlation coefficient (ρ) of human scores in the validation sets across languages.

3.5 WEAT Experiment Word Lists

Tables 6, 7, 8, 9, 10, 11, 12 in the appendix list all the stimuli used in replicating the two 'universally accepted stereotypes' introduced with the original Implicit Association Test (IAT) [25]. Experts in social psychology collected and validated these lexica to accurately represent the concepts of interest. Among the biases that we study, we refer to the 'universally accepted stereotypes' as widely shared associations, because the original authors have refrained from using

the term 'universal' in subsequent publications. Moreover, we don't want to make any strong claims regarding universality. The two WEATs corresponding to widely shared associations measure the attitudes towards flowers vs. insects or musical instruments vs. weapons. Social psychologists hypothesized and found that, human subjects have a consistently positive attitude towards flowers and musical instruments but consistently strong negative associations with insects and weapons. The sets of stimuli for groups of entities such as flowers, insects, instruments, and weapons all represent target categories, whereas pleasant and unpleasant words represent the polar evaluative attributes of valence. Since these IATs were not available in other languages, we translated every single one of the stimuli to six other languages. All of the stimuli translations have been verified by native speakers. Polish has been verified by a Slavic language speaker who is familiar with Polish. Nevertheless, we are still waiting to receive the final confirmation from the native Polish speaker.

We aim to measure how consistent the norms of valence are across a set of diverse languages, by using the valence norm word sets prepared by experts for human subjects. Accordingly, we perform experiments on seven languages from five branches of language families that have different linguistic structures as well as varying degrees of grammatical gender [23]:

- (1) Chinese is a Sinitic language from the Sino-Tibetan language family. Chinese does not use grammatical gender, like many European languages, but instead uses covert gender, more similar to the English language [15].
- (2) English is a West Germanic language from the Indo-European language family. English has three gendered pronouns (he/she/it), that represent "natural" gender as opposed to grammatical gender [3]. Other European languages, like German, represent gender as grammatical gender. Using the word teacher for example, in German there is a "masculine" word (Lehrer) and a "feminine" word (Lehrerin), whereas in English there is one word (teacher) that can be defined by a pronoun using the natural gender of the individual being referenced.
- (3) German is a West Germanic language from the Indo-European language family. German uses the three-gender grammatical gender structure, with feminine, masculine, and neuter grammatical genders [13].
- (4) Polish is a Slavic language from the Indo-European language family. Polish uses the three-gender grammatical gender structure, feminine, masculine, and neuter grammatical genders [5].
- (5) European-Portuguese is a Romance language from the Indo-European language family. European-Portuguese uses the feminine and masculine grammatical genders, which tend to have direct relation to the natural gender of the word [50].

³This word set is mainly limited by the Chinese dataset. See Table 5 for the number of words contained in each language's dataset.

- (6) Spanish is a Romance language from the Indo-European language family. Spanish uses the feminine and masculine grammatical genders most frequently, but does also contain a neuter grammatical gender, [2].
- (7) Turkish is a Turkic language from the Altaic language family. Turkish does not use grammatical or natural gender in language, making it a nearly "genderless" language and an interesting test case for our experiments [9].

Cross-linguistic 'flowers-insects', 'intruments-weapons', and 'gender-science' WEATs have been replicated using their corresponding attribute word sets from IATs on Project Implicit's [44, 45] webpages in the seven languages we analyzed (Chinese, English, German, Polish, Portuguese, Spanish, and Turkish). Similar to ValNorm, which relies on the distributional hypothesis of semantics [18, 30], the IAT is a language-agnostic method, offering tests in the native languages of 36 different countries. Project Implicit⁴ has been hosting implicit association tests for human subjects all over the world in numerous languages for close to two decades, therefore we use the attribute word sets from the tests in various languages. We are able to leverage the cross-linguistic WEATs and the distributional statistics of word co-occurences in word embeddings to measure implicit biases for social groups (male/female) and non-social groups (flowers/insects and instruments/weapons) across our seven languages of interest.

4 METHODS

We use the Word Embedding Association Test (WEAT) and the Word Embedding Factual Association Test (WEFAT) to quantify biases and measure statistical regularities in text corpora. We extend the WEFAT to precisely measure valence using pleasant/unpleasant evaluative attribute sets provided by Greenwald and Banaji [24] and Greenwald et al. [26] (as opposed to male/female), and design our intrinsic evaluation task based on valence norms, ValNorm, around this valence quantification method. We extend all methods (WEAT, WEFAT, ValNorm) to six other languages using native speaker translations of the word sets.

4.1 Word Association Test: WEAT and WEFAT.

The WEAT and WEFAT compute an effect-size statistic (Cohen's d) [12] measuring the association of a given set of target words or a single vocabulary word between two given attribute sets in a semantic vector space composed of word embeddings. The WEAT measures the differential association between two sets of target words and two sets of evaluative attribute sets, and the WEFAT measures the association of a single word to the two sets of evaluative attributes. WEAT borrows the stimuli to represent the target social groups and evaluative attributes from the IATs designed by experts in social psychology. WEAT measures biases such as widely-accepted attitudes, racism, sexism, attitudes towards the elderly, or people with disabilities. Table 3 provides the equations to compute the effect sizes and the p-values; the p-values represent the significance of the effect sizes. $|d| \geq 0.80$ represents a biased association with high

effect size [12], with a one sided p-value ≤ 0.05 or p-value ≥ 0.95 representing a statistically significant effect size.

4.2 Statistical Significance of Valence Quantification

Caliskan et al. [11] do not present a p-value for the WEFAT effect size, instead they measure the p-value of the correlation between WEFAT computed gender association scores and their corresponding ground truth values obtained from annual U.S. Census and Labour Bureau statistics. Thus, we define the one-sided p-value of WEFAT where $\{(A_i, B_i)\}_i$ represents the set of all possible partitions of the attributes $A \cup B$ of equal size to represent the null hypothesis. The null hypothesis is that, for a given stimulus \vec{w} , computing the WEFAT effect size using a random partition of the attribute words $\{(A_i, B_i)\}_i$ represents the empirical distribution of effect sizes in case there were no biased associations between the stimulus and the target sets. Accordingly, the permutation test can measure the unlikelihood of the null hypothesis.

Caliskan et al. [11] identified that WEAT effect sizes in the empirical distribution of the null hypothesis are normally distributed. This information is detailed in their supplementary materials and source code. Our experiments show that WEFAT effect sizes in the empirical distribution of the null hypothesis are also normally distributed. This is not a surprising finding since WEFAT is a subcomponent of WEAT and the same distributional patterns are to be expected. When generating the complete empirical distribution of the null hypothesis with all possible permutations requires billions of computations, this task becomes computationally infeasible. For example, the empirical distribution of the null hypothesis for two sets of 25 stimuli require $(25 \times 2)! = 50! = 3.04 \times 10^{64}$ effect size computations. In such computationally infeasible cases with current computational power, we can rely on the normal distribution as opposed to the actual empirical distribution to compute a pessimistic estimate of statistical significance by estimating the parameters of the normal distribution such as the mean and variance. With these parameters, we can measure and report a rounded up pessimistic p-value corresponding to which percentile in the distribution the original effect size falls under.

Cohen suggested that |d| = 0.2 be considered a 'small' effect size, 0.5 represents a 'medium' effect size and 0.8 a 'large' effect size [12]. Cohen's *d* is frequently used in sample size estimation during statistical testing. We report that effect size, measured in Cohen's d with both WEAT and WEFAT in our experiments, highly correlates with statistical significance (≥ 0.99). When bias interventions on populations are implemented to measure effect size, a lower Cohen's d indicates the necessity of larger sample sizes, and vice versa. In word embeddings, we are studying the aggregate representations that are generated from data contributed to the training corpus by the underlying population. As a result, statistical significance of WEAT and WEFAT indirectly depend on corpus size. However, statistical significance of WEAT and WEFAT directly depend on the number of stimuli that represent each concept category for targets and attributes. As a result, comprehensive measurements of biased associations require large sets of stimuli representing concepts to get a statistically significant result with high effect size. The main limitation here is the lack of principled and systematic methods

 $^{^4} https://implicit.harvard.edu/implicit/\\$

Association: $s(w, A, B) = \text{mean}_{a \in A} \cos(\vec{w}, \vec{a}) - \text{mean}_{b \in B} \cos(\vec{w}, \vec{b})$

Cosine similarity: $\cos(\vec{a}, \vec{b})$ denotes the cosine of the angle between the vectors \vec{a} and \vec{b} .

Target words: $X = [\vec{x_1}, \vec{x_2}, \dots, \vec{x_m}]$ and $Y = [\vec{y_1}, \vec{y_2}, \dots, \vec{y_m}]$ are the two equal-sized (m) sets of target stimuli.

Attribute words: $A = [\vec{a_1}, \vec{a_2}, \dots, \vec{a_n}]$ and $B = [\vec{b_1}, \vec{b_2}, \dots, \vec{b_n}]$ are the two equal-sized (*n*) sets of attributes.

WEFAT: Analogous to a single-category WEAT, \vec{w} is the single target stimulus in WEFAT.

Permutation test: $(X_i, Y_i)_i$ and $(A_i, B_i)_i$ denote all the partitions of $X \cup Y$ and $A \cup B$ into two sets of equal size. Random permutations of these sets represent the null hypothesis as if the biased associations did not exist so that we can perform a statistical significance test by measuring the unlikelihood of the null hypothesis, given the effect size of WEAT or WEFAT.

Table 3: WEAT and WEFAT effect size equations and their corresponding statistical significance in p-values.

for generating concept representations with large sets of stimuli. Instead, we rely on stimuli compiled by experts in social psychology Greenwald et al. [25].

4.3 ValNorm: An Intrinsic Evaluation Task

Our intrinsic evaluation task uses the WEFAT with pleasant and unpleasant attribute sets to represent the valence dimension of affect. Similar to machine learning evaluation tasks or traditional intrinsic evaluation tasks, a validation set is required that contains human-rated ground truth valence judgment scores for a corresponding set of vocabulary words.

We define the ValNorm task as:

- (1) **Assign** the *word* column from the validation dataset to $W = [\vec{w_1}, \vec{w_2}, \dots, \vec{w_m}]$ as the set of target vectors.
- (2) **Assign** the pleasant attribute words to *A*, the first attribute set, and assign the unpleasant attribute words to *B* the second attribute set.
- (3) **Compute** the WEFAT effect size and p-value for each $\vec{w} \in W$ using the given word embedding set.
- (4) Compare the WEFAT effect size scores to the human-rated valence scores using Pearson's correlation to measure the semantic quality of the word embedding set.

We define the ValNorm task for non-English languages as:

- (1) **Translate** the pleasant/unpleasant attribute word sets from English to the given language, then verify the translations with native speakers.
- (2) Run the ValNorm using the corresponding language's word embeddings and ground truth valence scores of human judgments

4.4 Discovering Widely-Accepted Associations

We investigate the existence of widely-accepted biases by:

- (1) Implementing the flowers-insects-attitude and instruments-weapons-attitude, and gender-science WEAT defined by Caliskan et al. [11]. The two attitude tests are introduced as 'universally accepted stereotypes' in the original paper that presents the IAT [25]. Accordingly, these are baseline biases that we expect to observe with high effect size in any word embeddings.
- (2) **Implementing** ValNorm on six non-English word embedding sets, historical word embeddings from 1800 to 1990, and word embeddings trained on different corpus sizes.

5 EXPERIMENTS

We conduct three main experiments to 1) quantify the valence statistics of words in text corpora, 2) evaluate our intrinsic evaluation task, ValNorm and 3) analyze valence statistics of words across languages and over time to determine widely shared associations.

5.1 Quantifying Valence Using WEFAT

We use the WEFAT to quantify valence norms of words by measuring a single word's relative association to pleasant versus unpleasant attribute sets. These attributes are designated by experts in social psychology to have consistent valence scores among humans [25]. In our WEFAT implementation, we assign the attribute sets to the same sets of 25 pleasant and 25 unpleasant words used in Caliskan et al.'s flowers-insects-attitude bias test [11]. We run the WEFAT using the seven sets of word embeddings listed in Section 3, and evaluate each word embedding set using Bellezza's Lexicon, ANEW, and Warriner's Lexicon as the target word set.

5.2 Evaluating ValNorm

We run ValNorm on the seven English word embedding sets, using Bellezza's Lexicon, ANEW, and Warriner's Lexicon as the target word set respectively. We measure the correlation of the ValNorm

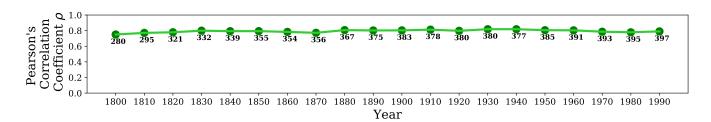


Figure 1: ρ for the valence extension of WEFAT using Bellezza's Lexicon and HistWords historical word embeddings [28]. Points are labeled with the number of target words present in their vocabulary. The low variance ($\sigma^2 < 10^{-3}$) of results validate our hypothesis that valence norms are consistent over two centuries.

scores to the corresponding set of human-rated scores. We run six widely used, traditional intrinsic evaluation tasks on the seven English word embedding sets and use the correlation scores from these evaluation tasks as the baseline comparison for how accurately each word embedding set captures semantics. This evaluation compares six traditional evaluation tasks to three implementations of ValNorm across seven sets of word embeddings, trained using four different algorithms and five different text corpora.

To investigate the significance of training corpus size for word embeddings, we sample 5 bin sizes (50%, 10%, 1%, 0.1%, and 0.001%) of the OpenSubtitles 2018 corpus and train word embeddings according to Paridon and Thompson's method to generate subs2vec (fastText skipgram 300-dimensional word embeddings) [49]. We choose the OpenSubtitles corpus for this experiment because it reflects human communication behavior more closely than a structured written corpus, such as Wikipedia or news articles, making it a more appropriate corpus for capturing semantic content [49]. There are 89,135,344 lines in the cleaned and deduplicated Open-Subtitles corpus text file, which we round to 89,000,000 to make our sample size bins neat. For each bin size we randomly sample, without replacement, the designated number of lines in the text corpus file. We generate word embeddings for each sample size and run the five word similarity intrinsic evaluation tasks and the ValNorm evaluation task to analyze the significance of corpus size on word embedding quality.

5.3 Analyzing Widely Shared Associations

We use the WEAT to quantify valence associations of non-social groups (flowers, insects, instruments, and weapons) and to quantify social group associations (male/female) to science and arts. We hypothesize that valence biases will remain consistent across word embeddings, and that social group biases will change. Gender bias scores in word embeddings may vary depending on culture and language structure (e.g., Turkish pronouns are gender-neutral whereas German nouns have grammatical gender.) We compare the difference in bias scores from the valence association tests and the gender association test on seven different sets of English word embeddings (see Table 1) and on word embeddings from six other languages: Chinese, German, Polish, Portuguese, Spanish, and Turkish. We were unable to run these WEATs on the historical word embeddings as their vocabularies did not contain most of the target and attribute words.

We implement ValNorm across the six languages, using Bellezza's Lexicon as the target word set, since all languages (except for Chinese) had at least 97% of the words in their ground-truth dataset (see Table 5). We also evaluate the stability of valence norms over 200 years by implementing ValNorm using Bellezza's Lexicon and historical, English word embeddings from 1800 to 1990 (each word embedding set covers a 10-year period) [28]. If valence norms are independent of language and culture, they will be consistent over time and across languages, making them an appropriate metric for evaluating word embeddings from any time period or language.

6 RESULTS

Quantifying valence norms. We implement the WEFAT using valence evaluative attributes and target word sets, that are hypothesized to represent valence norms, from Bellezza's Lexicon, ANEW, and Warriner's Lexicon. Our initial experiments signalled widely shared associations of valence scores with $\rho \in [0.82, 0.88]$ for all seven English word embeddings using Bellezza's Lexicon (vocabulary size of 399^5) as the target word set. The corresponding p-values have a Spearman's correlation coefficient greater than $\rho \geq 0.99$ to the effect sizes, indicating statistically significant results. Subsection on statistical significance of valence quantification under Section 4 presents the details of p-value's properties in the context of lexicon induction.

Bias Type	σ^2
flowers-insects	0.13
instruments-weapons	0.09
gender-science	0.45

Table 4: Variance of WEAT scores across seven languages. The variances of the scores for widely accepted biases are low, whereas culture-specific social group bias scores measuring gender-science associations have high variance across languages.

Widely shared associations. We compute the variance (σ^2) of the effect sizes for the flowers-insects-attitude, instruments-weapons-attitude, and gender-science WEAT bias tests across all seven language word embeddings. In Table 4, as expected based on findings

 $^{^5{\}rm The}$ dataset section includes the details for words that are not included in cross-linguistic experiments.

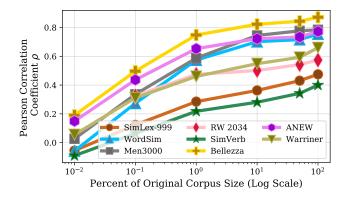


Figure 2: Performance of word embeddings trained on the OpenSubtitles2018 corpus of different sizes

in social psychology, flowers-insects-attitudes and instruments-weapons have the most consistent valence associations, with 0.13 and 0.09 variance scores respectively.

Table 5 reports Pearson correlation coefficients using ValNorm, compared to the corresponding validation dataset for all seven languages, providing insight into consistent valence norms across cultures. Figure 1 shows the stability of valence norms over 200 years, with low variance in scores ($\sigma^2 < 10^{-3}$), reporting the Pearson correlation coefficients for the valence association scores compared to the corresponding human-rated valence scores from Bellezza's Lexicon that was compiled in 1986.

Figure 2 presents the results for the training corpus size experiment. For all intrinsic evaluation tasks the correlation score increases minimally from 50% to 100% and from 10% to 50%; ValNorm using Bellezza's Lexicon has a 0.01 and 0.03 increase respectively.

Language	N	ho
Chinese	269	0.85
English	381	0.87
EU Portuguese	381	0.85
German	370	0.80
Polish	375	0.79
Spanish	381	0.83
Turkish	379	0.73

Table 5: Correlation coefficients (ρ) for each language's ValNorm score to the ground-truth valence score. N is the number of target words present in the word embeddings' vocabulary.

ValNorm performance. Figure 3 compares the performance of ValNorm using Bellezza's Lexicon, ANEW, and Warriners Lexicon to five word similarity tasks and one analogy task. ValNorm using Belezza's Lexicon overperforms all other intrinsic evaluation tasks on word embeddings trained on five corpora via four algorithms.

7 DISCUSSION

In our three experiments we find strong signals that word embeddings capture valence norms using WEAT and our valence extension of the WEFAT to measure widely shared associations. These

experiments show that valence norms relate to widely shared associations, as opposed to culture specific associations, and can be used as a measurement of word embedding quality across languages.

ValNorm as a new intrinsic evaluation task. Figure 3 compares our three implementations of ValNorm to six traditional intrinsic evaluation tasks, with Bellezza's Lexicon performing the highest. ValNorm computes an effect size rather than just the cosine similarity, the metric for word similarity and word analogy tasks. Notably, Bellezza's Lexicon outperforms WordSim, which has 353 word pairs (similarity tasks), while Bellezza's Lexicon has 399 words (valence tasks). ValNorm on ANEW and Warriner's Lexicon consistently outperforms SimLex, RW, and SimVerb, with vocabulary sizes of 1,035 and 13,915 (valence tasks), while the others have 999, 2,034, and 3,500 similarity tasks. These results suggest that ValNorm measures valence quite accurately and consistently whereas results of all other intrinsic evaluation tasks have very high variance and lower accuracy. These results support our hypothesis that strong signals of valence are captured by word co-occurrence statistics so accurately that we can precisely measure the semantic differential for valence with our method that builds on multi-disciplinary prior work. Belezza's Lexicon leads to the highest accuracy because social psychologists especially designed it to establish valence norms among human subjects [4]. Belezza's Lexicon contains words that are not discriminatory among social groups but instead relate to social and linguistic constructs for all human beings as Osgood hypothesized and now we are able to quantify these semantics Osgood [46], Osgood et al. [47, 48]. ANEW and Warriner's Lexicon include more words that might not always correspond to valence norms across languages and over time. These findings also support the predictive validity of ValNorm in quantifying valence.

Widely Shared Valence Associations. We show that ValNorm is able to measure the valence affective response to words in word embeddings, indicating that affect is encoded into the cooccurrence statistics in language corpora. We observe Conceptnet Numberbatch's performance of achieving $\rho = 0.86$ (ValNorm using Bellezza's Lexicon), which shows that when social group associations are reduced it does not reduce valence norms, and that valence norms are independent of cultural norms in word embeddings. The low variance of flowers-insects-attitude and instruments-weaponsattitude experiments signal a widely accepted association for the non-social groups of flowers, insects, instruments, and weapons. The gender-science experiment produces the highest variance of 0.45 across all languages, signalling a culture and language specific association for gender social groups. We observed that WEAT doesn't only capture gender bias but it also accurately measures grammatical gender, a different type of association in languages such as Polish and German.

Our corpus size experiment results using ValNorm with Bellezza's Lexicon, ANEW, and Warriner's Lexicon follow the same trend-line as the other intrinsic evaluation tasks. This result signals widely shared associations, as the co-occurrence statistics of the word embeddings preserve valence scores and word similarity information in a similar way. When performing bias measurements, this intrinsic evaluation task can be used to analyze if the training corpus is of a sufficient size for statistically significant bias analysis.

We find that valence norms are language agnostic when we implement ValNorm on seven different languages from five different

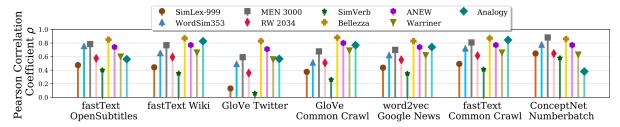


Figure 3: Comparison of 9 intrinsic evaluation tasks on 7 widely used word embeddings shows that ValNorm achieves the highest correlation with human scores, overperforming other intrinsic evaluation metrics.

language families. Similar to the IAT findings from 34 countries, social group associations are not culture agnostic [45]. Moreover, gender associations in word embeddings capture both gender bias and grammatical gender. Future work can explore removing the grammatical gender direction from the vector space to accurately measure gender bias in other languages. We find that valence norms are stable over time with $\rho \in [0.75, 0.82]$ for our ValNorm implementation on historical word embeddings using Bellezza's Lexicon. ValNorm can be used to evaluate the representation captured in word embeddings especially when studying biases with certain corpora. Moreover, these methods can automate analysis when analyzing information influence operations including misinformation and disinformation campaigns [62]. Valence associations can be used as an indicator of how a social group is represented in text—is the group associated with pleasantness or unpleasantness? Social group biases are not consistent across cultures and over time, making this valence bias test useful in detecting derogatory or targeted attitudes towards social groups. Also of note, our results highlight consistency of valence associations across languages and culture; there is agreement that kindness is pleasant and vomit is unpleasant. Being able to measure discriminatory biases against social groups and non-discriminatory biases against non-social groups creates a distinction in analyzing biases and stereotypes in languages. It may not be acceptable if language expresses dislike of cancer, but it is harmful if language expresses dislike of a specific race or gender.

7.1 Effect of Grammatical Gender on WEAT

Applying WEAT in seven languages, that belong to five branches of varying language families, shows that word embeddings capture grammatical gender along with gender bias. Consequently, generating an accurate measure of linguistic bias in grammatically gendered languages requires isolating the gender vector. For example, when applying the gender-science WEAT in Polish by using the IAT words on Poland's Project Implicit, the resulting effect size signals stereotype-incongruent associations. Further analysis of this anomaly revealed that most of the words representing science in the Polish IAT have nouns with feminine grammatical gender. However, when the gender direction is precisely identified and removed from the word embeddings while performing WEAT, the results are in line with the stereotype-congruent biases reported via IATs on the Project Implicit site [45]. These findings suggest that structural properties of languages should be taken into account when performing bias measurements that might be somehow related to some syntactic property in a language. This analysis is left to future work since it doesn't directly affect valence norm measurements in language.

Among social biases, so far, gender bias is the only one recognized as being related to a language's structural properties. Nevertheless, further analysis of languages might uncover more grammatical associations that might be captured while measuring certain types of biases. Moreover, the structure of a language might be causing limitations that don't allow for linguistic regularities to capture various associations. For example, Turkish does not have grammatical gender, and all the pronouns are gender-neutral. When measuring gender-science bias in Turkish word embeddings, the stereotypeincongruent results are not in agreement with IAT scores reported on Project Implicit [44]. These unexpected results require in depth analysis. One potential reason might be the quality of word embeddings in Turkish. The low quality of the word embeddings might be due to the language-dependent pre-processing strategies that were not applied before training the embeddings. If the same types of pre-processing methods are applied to all languages from different language families, the training corpora might be losing important linguistic information. Another reason could be the fact that a training corpus in Turkish, which is a gender-neutral language without gendered pronouns, does not have a linguistic gender signal significant enough to capture gender associations. In Turkish, explicitly mentioning the gender of a subject requires including words such as 'kadın', 'erkek', 'kız', 'oğlan' which translate to English as 'woman/female', 'man/male', 'girl', 'boy'. Unless someone wants to emphasize the gender of a subject, for example when giving a stereotype-incongruent example such as 'O bir kadın doktor.' ('She is a doctor' in English), gender is not specified and it is instead inferred.

Generalizing WEAT to other languages requires taking the structure of a language into account. Analyzing the relationship between linguistic structure and linguistic bias can also help explore the causal factors behind learning biases in society.

8 CONCLUSION

Valence norms reflect widely shared associations across languages and time, offering a distinction between non-social group biases and social group biases (gender, race, etc.). These valence associations are captured in word embeddings trained on historical text corpora and from various languages. We accurately measure widely shared associations and culture specific associations via word embeddings. We find that valence norms are language-agnostic and stable over time, while social group associations vary across language and time. We present ValNorm as a new intrinsic evaluation task which captures the quality of word embeddings by measuring the preservation of valence norms in the learned word representations. Our

evaluation task, which has three implementations with increasing vocabulary sizes, outperforms traditional intrinsic evaluation tasks and provides a more informative evaluation metric based on effect size as opposed to the cosine similarity metric of other evaluation tasks. The results of valence norms as statistical regularities in text corpora provides another layer of transparency into what word embeddings are learning during their training process. Computationally quantifying valence of words produce a high correlation to human-rated valence scores, indicating that word embedding algorithms can learn valence norms with high accuracy.

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Categ	gory	Chinese Stimuli
flowers	(target)	三叶草, 兰花, 玫瑰, 水仙花, 紫丁香, 郁金香, 雏菊, 百合, 紫色, 木兰
insects	(target)	蚂蚁,跳蚤,蜘蛛,臭虫,飞,狼蛛,蜜蜂,蟑螂,蚊子,大黄蜂
instruments	(target)	风笛,大提琴,吉他,琵琶,长号,班卓琴,单簧管,口琴,曼陀林,喇叭,巴松管,鼓,竖琴,双簧管,
		大号,钟,小提琴,大键琴,钢琴,中提琴,邦戈,长笛,喇叭,萨克斯风,小提琴
weapons	(target)	箭头, 俱乐部, 枪, 导弹, 矛, 斧头, 匕首, 鱼叉, 手枪, 剑, 刀, 炸药, 斧头, 步枪, 罐, 炸弹, 火器, 刀
		一子, 滑膛枪, 催泪瓦斯, 大炮, 手榴弹, 锤, 弹弓, 鞭子
pleasant	(attributes)	抚摸, 自由, 健康, 爱, 和平, 欢呼, 朋友, 天堂, 忠诚, 乐趣, 钻石, 温和, 诚实, 幸运, 彩虹, 文凭
unpleasant	(attributes)	滥用,崩溃,污秽,谋杀,疾病,事故,死亡,悲痛,毒,臭,突击,灾害,仇恨,污染,悲剧,离婚,监狱,
		贫穷, 丑陋, 癌症, 杀, 烂, 呕吐, 痛苦, 监狱

Table 6: Chinese Stimuli (Word List)

Categ	gory	English Stimuli Collected from Caliskan et al. [11]
flowers	(target)	clover, orchid, rose, daffodil, lilac, tulip, daisy, lily, violet, magnolia
insects	(target)	ant, flea, spider, bedbug, fly, tarantula, bee, cockroach, mosquito, hornet
instruments	(target)	bagpipe,cello, guitar, lute, trombone, banjo, clarinet, harmonica, mandolin, trumpet, bassoon, drum,
		harp, oboe, tuba, bell, fiddle, harpsichord, piano, viola, bongo, flute, horn, saxophone, violin
weapons	(target)	arrow, club, gun, missile, spear, axe, dagger, harpoon, pistol, sword, blade, dynamite, hatchet, rifle,
		tank, bomb, firearm, knife, shotgun, teargas, cannon, grenade, mace, slingshot, whip
pleasant	(attributes)	caress, freedom, health, love, peace, cheer, friend, heaven, loyal, pleasure, diamond, gentle, honest,
		lucky, rainbow, diploma, gift, honor, miracle, sunrise, family, happy, laughter, paradise, vacation
unpleasant	(attributes)	abuse, crash, filth, murder, sickness, accident, death, grief, poison, stink, assault, disaster, hatred,
		pollute, tragedy, divorce, jail, poverty, ugly, cancer, kill, rotten, vomit, agony, prison

Table 7: English Stimuli (Word List)

Categ	gory	German Stimuli
flowers	(target)	Klee, Orchidee, Rose, Narzisse, Flieder, Tulpe, Gänseblümchen, Lilie, Veilchen, Magnolie
insects	(target)	Ameise, Floh, Spinne, Wanze, Fliege, Tarantel, Biene, Kakerlake, Mücke, Hornisse
instruments	(target)	Dudelsack, Cello, Gitarre, Laute, Posaune, Banjo, Klarinette, Mundharmonika, Mandoline, Trompete,
		Fagott, Trommel, Harfe, Oboe, Tuba, Glocke, Geige, Cembalo, Klavier, Bratsche, Bongo, Flöte, Horn,
		Saxophon, Violine
weapons	(target)	Pfeil, Keule, Waffe, Rakete, Speer, Axt, Dolch, Harpune, Pistole, Schwert, Klinge, Dynamit, Beil,
		Gewehr, Panzer, Bombe, Schusswaffe, Messer, Schrotflinte, Tränengas, Kanone, Granate, Streitkol-
		ben, Schleuder, Peitsche
pleasant	(attributes)	Liebkosung, Freiheit, Gesundheit, Liebe, Frieden, Jubel, Freund, Himmel, Treue, Vergnügen, Dia-
		mant, sanft, ehrlich, glücklich, Regenbogen, Diplom, Geschenk, Ehre, Wunder, Sonnenaufgang,
		Familie, glücklich, Lachen, Paradies, Urlaub
unpleasant	(attributes)	Missbrauch, Absturz, Schmutz, Mord, Krankheit, Unfall, Tod, Trauer, Gift, Gestank, Angriff, Katas-
		trophe, Hass, Umweltverschmutzung, Tragödie, Scheidung, Gefängnis, Armut, hässlich, Krebs,
		töten, faul, Erbrechen, Qual, das Gefängnis

Table 8: German Stimuli (Word List)

Categ	gory	Polish Stimuli
flowers	(target)	koniczyna, orchidea, róża, narcyz, liliowy, tulipan, stokrotka, lilia, fiołek, magnolia
insects	(target)	mrówka, pchła, pająk, pluskwa, latać, tarantula, pszczoła, karaluch, komar, szerszeń
instruments	(target)	dudy, wiolonczela, gitara, flet, lutnia, puzon, banjo, klarnet, harmonijka, mandolina, trąbka, fagot,
		bęben, harfa, obój, tuba, dzwon, skrzypce, klawesyn, fortepian, altówka, bongo, róg, saksofon,
		skrzypce
weapons	(target)	strzałka, buława, strzelba, pocisk, włócznia, topór, sztylet, harpun, pistolet, miecz, nóż, dynamit,
		toporek, karabin, czołg, bomba, broń palna, ostrze, flinta, gaz łzawiący, armata, granat, buzdygan,
		proca, bat
pleasant	(attributes)	pieszczota, swoboda, zdrowie, miłość, dyplom, pokój, przyjemność, dopingować, przyjaciel,
		niebiosa, wierny, diament, delikatny, uczciwy, fartowny, tęcza, podarunek, honor, cud, rodzina,
		szczęśliwy, śmiech, raj, wakacje, świt
unpleasant	(attributes)	nadużycie, wypadek, brud, zabójstwo, choroba, awaria, śmierć, smutek, trucizna, smród,atak,
		katastrofa, nienawiść, zanieczyszczać, tragedia, rozwód, więzienie, bieda, brzydki, rak, zgniły,
		wymiociny, agonia, areszt, zło

Table 9: Polish Stimuli (Word List)

Categ	gory	Portuguese Stimuli
flowers	(target)	trevo, orquídea, rosas, narciso, lilás, tulipa, margarida, lírio, tolet, magnólia
insects	(target)	formiga, pulga, aranha, percevejo, mosca, tarântula, abelha, barata, mosquito, vespa
instruments	(target)	gaita de foles, violoncelo, violão, alaúde, trombone, banjo, clarinete, harmônica, bandolim, superada,
		fagote, tambor, harpa, oboé, tuba, sino, rabeca, cravo, piano, viola, bongo, flauta, chifre, saxofone,
		violino
weapons	(target)	flecha, porrete, arma de fogo, míssil, lança, machado, punhal, arpão, pistola, espada, lâmina, dinamite,
		machadinha, rifle, tanque, bomba, arma de fogo, faca, espingarda, gás lacrimogêneo, canhão,
		granada, maça, estilingue, chicote
pleasant	(attributes)	carícia, liberdade, saúde, amor, diploma, paz, prazer, alegrar, amigo, céu, leal,diamante, gentil,
		honesto, sortudo, arco-íris, prenda, honra, milagre, amanhecer, família, feliz,riso, paraíso, férias
unpleasant	(attributes)	maus-tratos, colisão, imundíce, assassinato, enfermidade, acidente, morte, tristeza, veneno, fedor,
		assalto, desastre, ódio, tragédia, poluir, divórcio, cadeia, pobreza, feio, cancro, matar, divórcio,
		cadeia, pobreza, feio, cancro, matar, podre, vómito, agonia, prisão

Table 10: Portugese Stimuli (Word List)

Categ	gory	Spanish Stimuli
flowers	(target)	trébol, orquídea, rosa, narciso, lila, tulipán, margarita, lirio, violeta, magnolia
insects	(target)	hormiga, pulga, araña, ácaro, mosca, tarántula, abeja, cucaracha, mosquito, avispón
instruments	(target)	cornamusa, violonchelo, guitarra, flauta, trombón, banjo, clarinete, harmónica, mandolina, trompeta,
		fagot, tambor, arpa, oboe, tuba, campana, fiddle, clave, piano, viola, bongo, flute, cuerno, saxofón,
		violín
weapons	(target)	flecha, palo, pistola, misil, lanza, hacha, daga, arpón, espada, cuchilla, dinamitar, rifle, tanque,
		bomba, naja, escopeta, cañón, granada, mazo, honda, látigo
pleasant	(attributes)	caricia, libertad, salud, amor, diploma, paz, placer, ánimo, amigo, cielo, leal, diamante, delicado,
		honesto, afortunado, arco-iris, obsequio, honor, milagro, amanecer, familia, feliz
unpleasant	(attributes)	maltrato, choque, inmundicia, asesinato, enfermedad, accidente, muerte, pena, ponzoña, hedor,
		asalto, desastre, odio, contaminar, tragedia, divorcio, cárcel, pobreza, feo, cáncer, matar, podrido,
		vómito, agonía, prisión

Table 11: Spanish Stimuli (Word List)

Categ	gory	Turkish Stimuli
flowers	(target)	yonca, orkide, gül, nergis, leylak, lale, papatya, zambak, menekşe, manolya
insects	(target)	karınca, pire, örümcek, tahtakurusu, sinek, tarantula, arı, hamamböceği, sivrisinek, eşekarısı
instruments	(target)	gayda,çello, gitar, ut, trombon, banço, klarnet, mızıka, mandolin, trompet, fagot, davul, arp, obua,
		tuba, zil, keman, harpsikord, piyano, viyola, tamtam, flüt, boynuz, saksafon, viyolin
weapons	(target)	ok, cop, tabanca, mermi, mızrak, balta, hançer, zıpkın, silah, kılıç, bıçak, dinamit, nacak, tüfek, tank,
		bomba, silâh, bıçak, çifte, gözyaşı gazı, gülle, bombası, topuz, mancınık, kırbaç
pleasant	(attributes)	okşamak, özgürlük, sağlık, sevgi, barış, neşe, arkadaş,cennet, sadık, keyif, pırlanta, kibar, dürüst,
		şanslı, gökkuşağı,diploma, hediye, onur, mucize, gündoğumu, aile, mutlu, kahkaha,cennet, tatil
unpleasant	(attributes)	istismar, çarpmak pislik cinayet, hastalık, ölüm , üzüntü , zehir , kokuşmuş , saldırı , felaket , nefret
		, kirletmek , facia , boşanmak , hapishane , fakirlik , çirkin , kanser , öldürmek , çürümüş , kusmuk ,
		ızdırap , sancı, cezaevi

Table 12: Turkish Stimuli (Word List)