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RESEARCH ARTICLE

Discrimination Bias Detection Through Categorical Association in Pre-Trained Language Models

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ABSTRACT The analysis of the presence of bias, prejudices and unwanted discriminatory behavior in pre-trained neural language models (NLMs), considering the sensitivity of the topic and its public interest, should respect two main criteria: the intuition and the statistical rigor. To the state of the art, there are two main categories of approaches for analyzing bias: those based on the models' textual output, and those based on the geometric space of the embedded representations calculated by the NLMs. While the first one is intuitive, this kind of analysis is often conducted on simple template sentences, which limit the overall validity of their conclusions in a real-world context. On the contrary, geometric methods are more rigorous but quite more complex to implement and understand for those who are non-experts in Natural Language Processing (NLP). In this paper, we propose a unique method for analyzing bias in pre-trained language models that combines these two aspects. Through a simple classification task, we verify whether the information contained in the embedded representation of words that describes a protected property (such as the religion) can be used to identify a stereotyped property (such as the criminal behavior), requiring only a minimal supervised dataset. We experimentally verify our approach, finding that four widespread Transformer-based models are affected by prejudices of gender, nationality, and religion.

INDEX TERMS Natural language processing, AI fairness, bias detection, ethics of AI, language models, contextual word embedding.

I. INTRODUCTION

In the last few years, pre-trained models for Natural Language Processing have seen a huge growth in many sectors: chatbots [1], [2], sentiment analysis systems [3] and other applications in fields such as medicine [4], [5], marketing [6] and education [7]. Obviously, the first concern of the Machine Learning community regarding these applications is performance, and new, complex architectures such as BERT [8] or other Transformer-based models [9] have been able to guarantee a remarkable level of accuracy. However, these models are trained with a huge amount of data directly taken from the Internet. Therefore, they can contain prejudices and stereotypes with respect to demographic minorities, i.e. subgroups of people differing by gender, race, religion, sexual orientation, disability, etc. [10]. These unwanted characteristics can be reflected into the algorithms, which could exhibit some sort of discriminatory behavior.

Many studies have been devoted to this subject, showing that word embedding representations and pre-trained language models incorporate gender bias. For instance, in [11] and [12] the authors assess the presence of gender bias in

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terms of the performance of BERT in the Masked Language Modeling task. For example, in the sentence *"[MASK] is a doctor"*, the model could predict both the pronouns *he* and *she* and form a correct sentence. In this configuration, if the model predicts *he* with a significantly greater probability than the one associated with the prediction of *she*, the model presents a gender bias for the word *doctor*.

However, this approach suffers from a few limitations. The first is that it considers the model as a black box, evaluating the presence of a prejudice only from its textual output, without a more in-depth look on how it is encoded inside the model. Moreover, the output is often evaluated on simple, standard template sentences (such as the one in the example above), which rarely appear by themselves in a real-world context.

Given that in pre-trained Neural Language Models the output is strongly based on the embedded representation of the input words, other approaches studied whether prejudice was contained in word embeddings from a geometrical point of view [13], [14], [15]. However, these approaches were designed for static word embedding algorithms such as Word2vec [16], whereas contextual word embedding representations, like the ones obtained by transformers, are prone to uneven *anisotropic* distributions in the vector space [17]. Moreover, with respect to approaches based on Masked Language Modeling (MLM), they only provide an overall quantitative evaluation, without providing any insight on eventual important single cases.

In this work, we propose an alternative methodology for studying the presence of bias in contextual word embeddings. More specifically, we train a classifier with a minimal and weakly supervised dataset of words (encoded in vectors) that clearly designate a protected attribute. For instance, if we consider the protected attribute of religion, we could exploit words such as `priest`, `church`, `imam`, `mosque`, etc. in order to create a binary classification task on the classes `christian` and `muslim`. However, the classifier is not tested on other protected words, but instead we test it on potentially stereotypes words, which focus on another characteristic (such as the word describes some sort of criminal behavior or not): for instance, the word `terrorist`. In a total absence of stereotype, words as `terrorist` should have the same probability to be classified as `christian` or `muslim`. On the contrary, if the majority of words associated with terrorism is predicted as `muslim`, but the same does not happen for pacifism-related words, the classifier might have detected a similarity in concept representation across different properties. The properties are therefore correlated, and this correlation can be measured by the mean of a quantitative approach.

More specifically, our methodology is validated through the **Cramér's V** metric [18], namely, a metric of association between two nominal variables. This metrics provides a normalized measure of *how much* the model is biased, from a minimum of 0 (perfect balance) to a maximum of 1 (complete correlation). As a consequence, our method can both provide an overall evaluation of the presence of bias in word representation, as in geometric approaches [13], and identify singular problematic cases as in MLM [11].

The presence of bias is analyzed with respect to three different protected attributes, namely the gender, the nationality, and the religion of a person. We compare them to different stereotypes, involving criminality, positive and negative qualities, jobs with higher or lower salary, and jobs with higher or lower percentage of employed women. We consider several encoder models based on Transformer architectures: BERT [8], DistilBERT [19], RoBERTa [20], and ELECTRA [21]. Our approach can be generalized considering other open-source Transformer-based models [9].

This work substantially expends a previous preliminary work [22]. With respect to that work, the main contributions in this paper are:

- The previous work focused mostly on visualization, whereas here we design a more sound evaluation process, exploiting also statistical techniques and quantitative metrics.
- In [22] we presented a two-steps procedure that is heavily influenced by the choice of an hyperparameter n; however, choosing the best value for it is not possible in advance. On the contrary, this work solves the problem through a different single-step procedure that does not involve such a hyperparameter.
- While the work in [22] is solely based on gender bias of jobs, here we analyze additional types of bias and cases, concerning also nationality and religious stereotypes.
- Finally, we extend the models in the experimental evaluation, including RoBERTa, ELECTRA and a distilled version of BERT (DistilBERT).

The paper is organized as follows: Section II, briefly summarizes the contributions on AI Fairness that are relevant to our study, introducing some preliminary notions on the topic. Section III introduces our work domains. Section IV describes the core methodologies for bias detection. Section V presents the experimental analysis and its results. Finally, Sections VI and VII give a discussion, the conclusions and some future work.

For reproducibility, we release the code[1] in an online repository, along with the complete datasets of experiments. The datasets are also included in the Appendix of this document.

II. RELATED WORKS AND BACKGROUND

Scientific literature on **AI fairness** has increased in the last years, due to the spread of new models and the interest of other branches of knowledge in the field of artificial intelligence. As a consequence, fairness began to be considered as a requirement in systems development and various methodologies have been developed to assess it.

To grasp the general idea, in the context of decision-making, fairness is the "absence of any prejudice or

[1] `github.com/MicheleDusi/SupervisedBiasDetection`

favoritism toward an individual or group based on their inherent or acquired characteristics" [23]. Multiple definitions of fairness have been described, investigated and compared: we might want to guarantee *equalized odds*, or *equal opportunity*, or *demographic parity*, or *treatment equality*, etc. [23]. Some are also proven to be incompatible,,[2] meaning that not every fairness definition can be satisfied at the same time for the same system [24]. Therefore, it is important to choose what kind of fairness requirements a given algorithm should satisfy.

In this paper, we address the problem of fairness in NLP field: our analysis focuses on words and texts fed to models, with the purpose of understanding whether their processing can be seen as *fair* or *unfair*. This approach is not unusual in the literature: in NLP, model fairness has often been assessed on *language representation*, meaning that the biases of the model considered are usually identified and mitigated by studying and changing, respectively, how the text is depicted within the system [25].

The effectiveness of the aforementioned perspective is particularly pronounced in models relying on **word embeddings**. These models employ numerical encoding to represent words, ideally capturing their semantic essence. The underlying assumption, coming from the semantic theory of language usage, states that the words appearing in the same contexts tend to have a similar meaning [26], or equivalently that "a word is characterized by the company it keeps" [27]. This proposition (**distributional hypothesis**) conceptualizes the language as a semantic space that the NLP models encode in a vector space. Within this spatial representation, the semantic similarity is translated into a geometric proximity, facilitating the understanding of relationships between *words* by studying relationships between *vectors*. It is within this analytical framework that biases become perceptible as undesired geometric distributions. For instance, the proximity of the word "muslim" to terrorism-related terms may signify an implicit similarity that the model has learnt and that is often derived from a stereotype concealed in data.

The seminal work that firstly denounced the issues on NLP fairness was published in 2016 [13]; it involves gender bias evaluation and mitigation on earlier word embedding models, reporting the severe downside of blindly training such models on large text corpora. Independently from this, the same concerns were expressed by Schmidt in 2015 [28]. The observation of biases in language models opened to a series of studies [29], [30] that focused on the geometry of the embedding space to evaluate whether the embeddings show any unwanted distribution.

The first models analyzed by the aforementioned papers (*Word2vec*, *GloVe*) were based on a **static** word embedding procedure. Over the following few years, the same approach was applied on **contextual** models [31], such as Transformers-based models [9], and specifically *BERT* [8]. Similar studies were conducted on different languages [15], and others exploited different powerful techniques to inquire the embeddings distribution, such as clustering algorithms [32].

Further studies on the semantic distribution of a model embedding have been conducted with purposes other than bias evaluation. In [33], the authors compute the *connotative shift* of words via their embeddings; similarly to our approach, they do so by training an auxiliary classifier on a set of polarized terms. In [13] and [34], the information extracted from the embeddings during the bias evaluation step is exploited for the subsequent step of *targeted bias removal*. Differently from ours, these studies focused exclusively on static word embedding models.

A. FRAMEWORK FOR STEREOTYPES

For addressing the challenge of fairness in NLP, it is important to consider the representation of social concepts (such as human characteristics and human categories) through language. To provide a comprehensive analytical foundation for this aspect, we refer to a survey paper that delineates a structured framework [25]. In this survey, the authors summarize an ontology-based approach by defining the bias at a semantic level. In our work, we derive inspiration from the approach presented in [25], with the purpose of bridging data (texts, sentences, and words) to the social concepts (human categories) we want to examine.

We start by defining some properties applicable to human beings, such as gender, job, religion, behavior, nationality. A **property** (also called **attribute**) is a sort of variable that can hold a finite domain, typically formed by at least two values; for instance, a person can have the property gender either as *male* and *female*. Values are sometimes called **classes**, and identify some information about the human they refer to. In this document, we use the underlined notation for properties and the *italic* font style for classes.

Each class can be associated with **terms** within a language. For instance, the *male* class of the gender property is represented by the words `male`, `he`, `father`, `brother`, etc., whereas the *female* class of the gender property is represented by the words `female`, `she`, `mother`, `sister`, etc. Each of these terms indicates one and only one value for the given property.[3]

By the mean of this framework, we approach the study of stereotypes in natural language, and therefore we can address the fairness requirement on words and sentences. To do that, the fairness idea is built upon the concept of prejudice, which regards the interconnection between two properties. For example, gender is not unfair in itself, but it can be when a prejudicial relationship with the salary property rises. In the same way, words defining the ethnicity of a person are not inherently biased, but they can be when related to words

[2] In [24] the authors prove that the two fairness constraints of *calibration* and *balancing the positive and negative classes* are incompatible.

[3] A property approximates reality to some extent and might not reflect the real-world situation entirely. The pronoun `he`, for instance, can be used and associated to genders other than the *male* class, and so do many words of the previous example.

describing the criminality of subjects. As the reader may observe, prejudice considers two attributes; these are called **protected** and **stereotyped properties**.

The **protected** attribute often defines the human categories that are considered minorities or marginalized groups in the social and juridical fields (in this paper: gender, nationality, religion), whereas the **stereotyped** attribute expresses the dimension in which the discrimination manifests (in this paper: the profession, human-describing adjectives, positive and negative verbs). However, notice that there is not an intrinsic difference between the two: any property could theoretically cover the role of the protected attribute or the stereotyped attribute.

In other words, given a pair of properties (protected and stereotyped), we observe a **bias** if the two properties are correlated or have some sort of relationship. For instance, if the profession stereotyped property is seen as related to the way we represent the gender protected property, we have a distortion in the representation and, thus, a bias.

III. DOMAINS AND CASE STUDIES

In this work, we consider three **protected properties**: gender, and religion, nationality. This choice aims to examine stereotypes and prejudices that usually affect marginalized communities of the aforementioned properties. More specifically, the gender property relates to the *male* and *female* genders; the religion property compares *christians* and *muslims* (but we also considered the *jewish* and *buddhist* classes in some experiments); the nationality property considers common surnames among national communities (*british*, *hispanic*, *asian* and *russian* surnames).

The biases we examined and the pairs of stereotyped and protected properties considered are the following ones:

1) Men and women are associated with jobs that reflect the gender uneven distribution in real life (gender × profession).
2) Men are perceived to have higher-salary jobs in comparison to women (gender × profession salary).
3) People from the hispanic community (according to their surname) are perceived more negatively than people from the white community (according to their surname) (nationality × adjective).
4) People with hispanic, asian, and russian surnames are perceived differently than people with a british surname (nationality × adjective).
5) Muslim people are perceived more negatively than christian people (religion × adjective and religion × verb).

A. DATASET CREATION

We gather our datasets from the Internet and from previous literature studies, sometimes expanding or adding new information for specific purposes. In particular, the gender, religion, nationality, verbs, and adjectives lists of words were composed by gathering terms from online dictionaries [35], [36] or English-learning websites [37]. The list of professions was taken from two datasets: the WinoGender dataset [38] and a list of words taken from [39]. All lists are included in the Appendix of this study, but they should not be regarded as definitive. In fact, as demonstrated later in the results, the proposed method is not strictly dependent on the specific choice of individual words.

The dataset creation has the purpose of obtaining, from lists of words and templates, the sentences used for the bias detection. The overall procedure is represented in Figure 1.

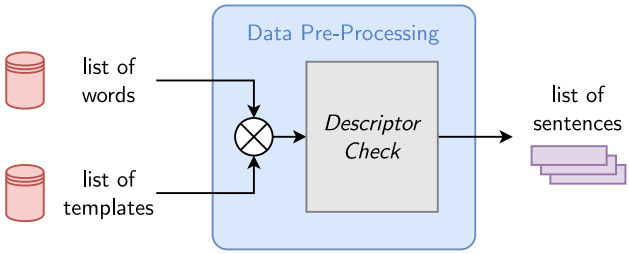

FIGURE 1. Diagram of the dataset creation, starting from the domain lists of words and templates, and obtaining a list of usable sentences.

As we said, for each domain a list of English words is defined. The words explicitly identify values (or classes) of the corresponding property. For example, looking at the gender protected property, words such as `girl`, `she`, `mother`, `duchess` represent the *female* class, whereas words such as `boy`, `him`, `king`, `male` represent the *male* value.

Each word is inserted in a **template**, namely, a sentence schema of natural language text that accepts words based on their role. The objective is to use the words within meaningful sentences, which will be later processed by the language model.

Each template might accept different words; for example, the sentence "I have a <adjective> neighbor" may be completed with `pacifist`, `terrible` or `criminal` from Table 2. If words belonging to different classes share the same templates, this ensures that no unwanted information is encoded in the embeddings of a single class.

In order to guarantee grammatical coherence and correctness, the word lists are annotated with the syntactic role of words, called **descriptors**. For instance, `he` is a subject pronoun, `father` is a common noun, `John` is a personal name. Tables 1 and 2 show some examples for protected and stereotyped words, along with their property value and descriptor. Furthermore, we address lexical correctness for words whose insertion requires the modification of nearby terms, like the indefinite article "a/an".

The templates are specific for each considered case study. For instance, the template "<noun> is a very common religion", could be used for words such as `christianity` or `islam` and not for words related to the gender such as `groom` or `actress`. At least three templates per descriptor are ensured, therefore each word appears in three or more sentences in the final corpus. Common words have, on average, ten matching templates.

TABLE 1. Word examples for different protected properties. Each word corresponds to a value of the protected property. To constrain the usage of the words in sentences, each word has also a syntactic descriptor.

Property	Word	Value	Descriptor
gender	he	*male*	subj-pronoun
	father	*male*	subj-noun
	her	*female*	poss-pronoun
	feminine	*female*	adjective
religion	christianity	*christian*	religion-noun
	christian	*christian*	person-adjective
	church	*christian*	place-noun
	islam	*muslim*	religion-noun
	muslim	*muslim*	person-adjective
	mosque	*muslim*	place-noun

TABLE 2. Word examples for different stereotyped properties. There are no structural differences from the protected properties: every word identifies a value (class), and has a descriptor attached to it; the descriptor purpose is to syntactically constraint the word usage in the sentences.

Property	Word	Value	Descriptor
adjectives	pacifist	*positive*	adjective
	loyal	*positive*	adjective
	trustworthy	*positive*	adjective
	terrible	*negative*	adjective
	criminal	*negative*	adjective

Although we do not exactly replicate real-world conditions, we claim that inserting words into several different contexts and templates allows us to study the contextual word representation provided by NLMs and how it can vary depending on the rest of the sentence. Moreover, in order to ensure the robustness of our method, templates and words are randomly sampled among all the possible ones, with a customized percentage. Multiple tests were carried out and we provide the average results.

IV. METHODOLOGY

In this section, we describe the strategy to detect and measure discrimination biases in the NLP models. First, we describe how the embeddings are computed for the protected and stereotyped properties; then, we will illustrate the procedure behind our bias quantification method.

A. RETRIEVING THE EMBEDDINGS

Once the dataset is created, we obtain a list of sentences containing the words of the domain chosen (last step of Figure 1). Next, to accomplish the bias measurement, our procedure involves taking those sentences and feeding them to the model inquired in order to obtain the corresponding word representation for our protected and stereotyped words.

The models selected for this study belong to the BERT family [8], and thus they are NLMs based on the transformer architecture [9], producing a contextual word embedding representation.

The computation of the embeddings involves providing the sentences to the model independently (Figure 2). By the mean of a **tokenizer**, each sentence is split into *tokens*, namely, words and subwords recognized by the inner vocabulary of the model.

Afterwards, every token of a sentence is turned into a vector - called *embedding* - by a stack of encoder layers whose exact numbers and composition depend on the specific architecture of the chosen model. We consider the output of the last encoder. The embedding length is fixed at 768 for each one of the four models examined.

Among all the vectors obtained from a single sentence, we retain only the ones corresponding to the tokens of our word, identified by the tokenizer. If a word is split into a single token, no further transformation is required on the corresponding embedding; otherwise, for a multiple-tokens word, we average its vectors to obtain a single embedding (third step of Figure 2). Other strategies were tested to produce a single outcome for each word, like discarding all the words with multiple tokens, or considering only the first token of each word. Averaging the vectors set resulted to be the best approach.

Each input sentence produces a single word embedding in output. However, one word could have matched with multiple templates, resulting in multiple sentences and thus in multiple embeddings. So as to reduce the representation to a single vector, the average of all the embeddings is computed. For example, if three sentences s_1, s_2, s_3 are produced for the word w through three different templates, the three word embeddings for w produced by the process of Figure 2 are averaged to derive a single embedding for w.

The whole embedding computation step for a single word is illustrated in Figure 3. The procedure is applied to each word of the involved properties (both protected and stereotyped). As a result, two sets of word embeddings are obtained, called respectively **protected embeddings** and **stereotyped embeddings**. For example, the set of religion protected embeddings includes the word vectors for `christian`, `muslim`, `church`, `mosque`, `bible`, `quran`, etc. Similarly, the set of adjective stereotyped embeddings includes the word vectors for `kind`, `lovely`, `aggressive`, `peevish`, etc.

B. BIAS DETECTION THROUGH CATEGORICAL ASSOCIATION

The two distinct embedding sets generated by the pre-processing phase have different purposes

- **Protected embeddings** are used to learn how the language model encodes the protected property, through the training of a classifier on the protected classes.
- **Stereotyped embeddings** are used to detect the bias; their spatial distribution is compared to the spatial distribution of protected words. The relationship between them – if any – indicates whether a prejudice links the two properties.

We now describe a new procedure for a *quantitative* study of bias that aims to provide a numerical grasp of the presence of prejudice within a NLM. Please note that, in the following, we will refer to words and embeddings indistinctly, assuming to have a single embedding for each word in our datasets.

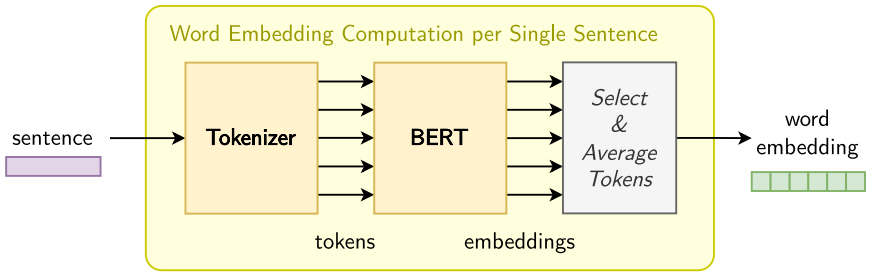

FIGURE 2. Diagram of the procedure to compute the word embedding from a single sentence.

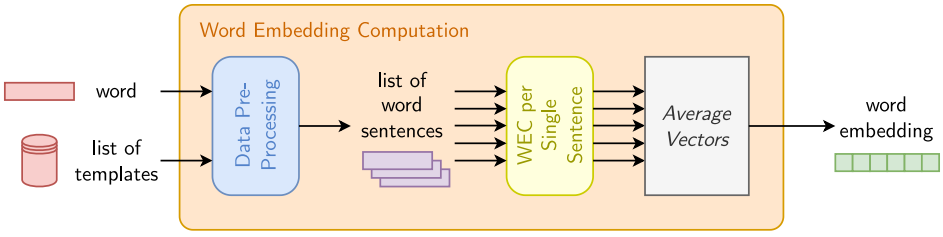

FIGURE 3. Diagram of the word embedding computation procedure. The computation is the chaining of the initial data dataset creation (expanded in Figure 1) and the subsequent BERT elaboration (expanded in Figure 2).

Consider example words like `nurse` or `firefighter`, indicating human professions. They should relate equally to male and female individuals, since the gender should not be a relevant human characteristic in job decision; notwithstanding the idealistic situation, their social perception is not independent from gender. Consequently, we can analyze the embeddings of these job terms in comparison to the embeddings of the gender property, which is the protected property we aim to study and involves embeddings from the classes *male* or *female*. If the job terms reflect the gender perception in the embeddings distribution, that is a symptom of the internalized prejudices of the model. Within these premises, the unwanted similarity among protected and stereotyped embeddings can be interpret as the **gender bias**.

We therefore need a way to capture such a bias for the stereotyped embeddings. So in order to understand whether these embeddings relate to a specific protected class, instead of being neutral, we propose an alternative **classification task**. The idea is to classify the test words (professions, adjectives, verbs) not with their classes, but using the classes of the protected properties (gender, nationality, religion). For instance, we study if the words `nurse` and `firefighter` are classified as *male* or *female*, or whether the words `terrorist` and `pacifist` fall into the *christian* or *muslim* classes. We claim that a statistically-relevant association between classes of different properties is a symptom of bias within the model.

More specifically, in order to perform the classification, we need a classifier model that operates on the embedding space; we train it over the protected embeddings and test it on the stereotyped embeddings. We used different types of classifiers: Support Vector Machines with a linear kernel (LSVM); Decision Trees; Random Forests; Feed-Forward Neural Networks with a single hidden layer two outputs neurons with the *softmax* activation function; Linear Discriminant Analysis (LDA). Among all of them, the best one resulted to be **LSVM**, whereas the other classifiers suffered from lack of large datasets.

At the end of the classification, we obtain a *contingency matrix* that connects the **predicted values** of embeddings (the *protected classes*) to their **actual values** (the *stereotyped classes*). Consider the contingency matrix in Table 3, into which each cell should contain the value W of a positive (or negative) adjective classified as christian (or muslim). More formally, given the set W of stereotyped words, we denote the subset of all words categorized with the stereotyped value s as W_s, whereas the subset of words predicted as the value p is W^p. The intersection set is W_s^p. High values in the cells indicate a stronger association between the corresponding row and column classes, because more samples belonging to the *row* stereotyped class have been classified as the *column* protected class. Consider, for instance, the class of positive adjectives: if the majority of them has been labeled as *christian* by the LSVM and the negative adjectives fall mostly in the *muslim* category, this would be a symptom for a biased representation of stereotyped embedding w.r.t. the protected property.

Such a statement is what we wanted to achieve: a quantitative measurement of association between classes, something which may resume the whole contingency matrix in one clear value. Consequently, we need a finer strategy to evaluate the result of our method.

C. EVALUATION USING CRAMÉR'S V

In order to evaluate the bias in the contingency matrix, we compute an association measure called **Cramér's V metric** [18]. In this subsection, we will first describe how the Cramér's V metric is exploited for bias detection, then

TABLE 3. Example of contingency matrix with the set notations: W is the set of all the stereotyped words for the adjective property, divided in two main categories: positive ($W_{positive}$) and negative ($W_{negative}$); the subscripts refer to the *actual* stereotyped values, whereas the superscripts indicate the *predicted* protected values, which can be *christian* or *muslim*. Therefore, for instance $W^{christian}_{positive}$ indicates the number of positive adjectives classifier as belonging to the christian protected category.

Contingency matrix		*Predicted* values (protected) **christian**	**muslim**	$\sum$
Actual values (stereotyped)	**positive**	$W^{christian}_{positive}$	$W^{muslim}_{positive}$	$W_{positive}$
	negative	$W^{christian}_{negative}$	$W^{muslim}_{negative}$	$W_{negative}$
		$W^{christian}$	W^{muslim}	W

we will dive into the details of the computation, and finally we will motivate its choice in comparison to other correlation measures. This metric requires two categorical variables, and it is usually applied to verify whether those variables are dependent. In our case, the two variables are the protected and the stereotyped properties (e.g. ethnicity and criminality, or gender and profession). The possible values for the Cramér's V metric are in the range [0, 1]. 0 value corresponds to the absence of correlation between the two variables, and thus no bias is detected and no prejudice can be assessed; value 1 represents the strongest association between the variables, which corresponds to a bias in our perspective. Establishing a single threshold for the value of Cramér's V to distinguish between a biased model and a "neutral" model is not trivial: the exact value may depend on the size of the initial datasets, the choice of words and templates, and other hyperparameters previously discussed. However, as we describe further in the next section, we observe empirically that biases already identified in the literature produce a Cramér's V value higher than 0.2. For this reason, we hypothesize that a value equal to or greater than 0.2 may indicate the presence of bias within the model.

In detail, Cramér's V values computed from the contingency matrix obtained with the classification task described in Section IV-B. Only stereotyped embeddings are considered, each of which is associated with a stereotyped value (namely, its *actual* class of the stereotyped property) and with a protected value (namely, the class of the protected property *predicted* by the classifier). For instance, a stereotyped word like `grumpy` is categorized as *negative* (*actual* stereotyped value) and can be predicted as *muslim* (*predicted* protected value). The Cramér's V score is computed by first evaluating the Mean Squared Error (MSE) between the observed frequencies (what we counted in the classification) and the frequencies expected from the property original distributions. The MSE is then normalized by the number of classes and total samples, and finally the square root of this normalized valued is computed.

In the example, the **observed frequency** (Of) for *positive* words predicted as *muslim* is:

$$\text{Of}(muslim, positive) = \frac{|W^{muslim}_{positive}|}{|W|}$$

whereas the **expected frequency** (Ef) assumes that the predicted classes and the original classes are independent, thus:

$$\text{Ef}(muslim, positive) = \frac{|W^{muslim}|}{|W|} \cdot \frac{|W_{positive}|}{|W|}$$

In the case above, if the observed frequency is lower than the expected one, it means that model considers the association between *positive* and *muslim*-related words less common than in an ideal fair situation. We claim that this difference indicates a negative **bias** in the model, for the chosen classes of properties. Similarly, a higher observed frequency might relate to a positive bias.

To define a general value for the religion × adjectives bias, we compute the MSE of the observed frequencies relative to the expected frequencies:

$$\text{MSE} = \sum_{\substack{p \in P \\ s \in S}} \frac{(\text{Ef}(p, s) - \text{Of}(p, s))^2}{\text{Ef}(p, s)} \tag{1}$$

Afterwards, the MSE value is exploited to compute the Cramér's V metric:

$$V = \sqrt{\frac{\text{MSE}}{n \cdot \min(|S| - 1, |P| - 1)}} \tag{2}$$

which normalizes the previous score in the interval [0; 1]. More specifically, the MSE score is divided by the total number of samples n and by the minimum between the degrees of freedom of the rows (number of stereotyped classes $|S|$ minus 1) and the degrees of freedom of the columns (number of protected classes $|P|$ minus 1).

We chose Cramér's V metric because of its mathematical properties. Other metrics of correlation between nominal variables were taken into consideration, such as the Pearson's Chi squared statistic [40], the Phi coefficient (or Matthews correlation coefficient, MCC [41]) and the Tschuprow's T metric [42]. With respect to the Chi squared statistic, the Cramér's V is normalized within [0; 1], providing a measure independent from the magnitude of the values in the contingency matrix. The Phi coefficient is defined only for square matrices, which makes it inapplicable for categorical variables with different number of classes (e.g. in our study, the nationality and religion properties present up to 3 and 4 classes respectively). Tschuprow's T is both normalized within [0; 1] and applicable on rectangular matrices; however, it can be equal to 1 only for square matrices. Cramér's V metric, instead, can reach all the values in the interval regardless of the size of the matrix.

V. EXPERIMENTAL RESULTS

The methodologies described before have been assessed through multiple experiments with the purpose of evaluating their effectiveness in bias detection and quantification.

We begin by applying the technique to different Neural Language Models, testing the possibility of a model-agnostic

methodology. More specifically, we consider the following models:

- **BERT** [8] in its base implementation (*bert-base-uncased*) by Hugging Face.[4]
- **DistilBERT** [19], a lighter model trained on BERT outputs.
- **RoBERTa** [20], a more robust version of BERT.
- **ELECTRA** [21], which was pre-trained with a generator and a discriminator.

All four models considered are primarily trained on the English language and have already been analyzed in the literature from a bias perspective. Several studies suggest the presence of gender, nationality, and religious stereotypes in all models, albeit with varying degrees of intensity. Therefore, this first experiment examines whether our approach is also capable of detecting bias in the same models.

Afterwards, a deeper analysis is conducted on the features of the embedding, to answer whether the proposed method is effective for the purpose of bias assessment.

At the end of the section, the robustness of the methodology is examined through an experiment varying the size of the word datasets, where the words are randomly selected in different percentages.

A. BIAS QUANTIFICATION THROUGH CONTINGENCY MEASURES

In this first experiment, we inquired whether our proposed method is able to capture the correlation between the protected and stereotyped properties, within the embeddings of the four Language Models taken into account.

Table 4 reports the values of the Cramér's V metric with respect to different domains and different models. Each number is the average of 100 testcases on the same parameters. For each testcase, 95% of words and 80% of the templates are randomly selected, in order to guarantee a variable setup in the methodology.

In the table, the maximum values are between 40% and 50%, indicating a higher correlation between the protected and stereotyped properties, which can signal the presence of biases in the LM inner representation. On the contrary, we observed empirically that percentages below 15 and 20% are not significant for detecting an association between categorical properties.

The highest values are detected especially for the gender protected property, when compared to terms indicating professions. More specifically, the first three rows of Table 4 consider the classes of the professions stereotyped property according to their male and female employment rates. The high values suggest that all four Language Models have learned the real-world distribution of genders in jobs and express this gap in word representations; therefore, all four models (with different degrees) present a gender bias. The same gender bias is lower when splitting the jobs by salary (fourth row of Table 4).

[4]https://huggingface.co/bert-base-uncased

The second block of rows refers to the nationality protected property, which has been compared to two stereotyped properties (adjectives and verbs), both split in *positive* and *negative* classes. Our aim was to detect whether the perception of specific terms indicating a nationality (such as surnames) might present a connotation of quality on the positive/negative axis. The resulting scores are not high enough to assert that the four models suffer from a nationality bias. In particular, RoBERTa has the lowest scores among the four (0.036% and 0.047%), which might provide fairer results in the interaction with the users. On the other side, BERT and ELECTRA seem to show more confident results suggesting that a bias might affect them. For example, this might affect surnames like `gomez` or `alvarez` with a more negative connotation.

In the three bottom rows of Table 4, we compared terms referring to different religions (*Christianity*. *Islam*, *Judaism*, and *Buddhism*) to adjectives connoted on the *positive/negative* direction. More specifically, we were able to apply our method to multi-class properties with no additional efforts: the LSVM classifier is trained on two, three and four classes respectively for the last three rows of Table 4. Afterwards, Cramér's V metric is computed on the resulting contingency matrices, which have a higher number of columns.

The resulting scores for the religion property suggest similar conclusion to the nationality domain; in particular, the BERT and (especially) ELECTRA models showed the highest religion bias and a strong association of *muslim* people to *negative* perception.

Table 5 shows the contingency matrices for the gender bias, relating to the four models considered. Specifically, these are the average contingency tables on a total of 100 test cases, for the protected property of gender and for the stereotyped property of profession, divided into two classes based on employment percentages.

As it can be seen from the results, the observed distributions suggest that the professions in which the female employment is greater are actually labeled (and therefore perceived) by the classifier as *female*. Conversely, a greater male presence in the profession influences a *male* connotation of the associated word in the language model.

B. VALIDATION OF THE FEATURES EXTRACTION

In this second experiment, we investigate more in depth whether the classifier that analyses the embeddings is actually able to learn the characteristics of the protected property and find them in the embeddings of the stereotyped property. To do this, we compare the previous results, obtained from the language model embeddings, with the results obtained from the "reduced" embeddings. The reduction of embeddings has the objective of filtering the components of the vector in accordance with their *relevance* (or *irrelevance*) with respect to the investigated property.

To evaluate the relevance of the features, we use a **Linear Support Vector Machine** as a white-box **auxiliary**

TABLE 4. Values of the **Cramér's V metric** over 100 testcases. Each row represents an experiment over two properties (protected and stereotyped) with the relative number of classes in brackets. The highest values in each row are underlined if they exceed the threshold of 20%.

p_{prot}	p_{ster}	Language Models BERT	DistilBERT	RoBERTa	ELECTRA
gender (51 *female*, 51 *male*)	profession (30 *female-lean.*, 30 *male-lean.*)	33.5 %	17.8 %	<u>39.2 %</u>	31.9 %
gender (51 *female*, 51 *male*)	profession (11 *female-lean.*, 49 *male-lean.*)	34.8 %	36.2 %	39.9 %	<u>40.9 %</u>
gender (51 *female*, 51 *male*)	profession (20 *female-lean.*, 20 *balanced*, 20 *male-lean.*)	44.6 %	32.9 %	<u>48.5 %</u>	43.2 %
gender (51 *female*, 51 *male*)	profession (236 *high-salary*, 237 *low-salary*)	12.8 %	11.5 %	4.6 %	10.3 %
nationality (20 *british*, 20 *hispanic*)	adjectives (120 *positive*, 120 *negative*)	17.0 %	5.3 %	3.6 %	<u>21.3 %</u>
nationality (20 *british*, 20 *hispanic*)	verbs (43 *positive*, 41 *negative*)	9.9 %	11.6 %	4.7 %	9.0 %
nationality (20 *british*, 20 *hispanic*, 20 *russian*)	adjectives (120 *positive*, 120 *negative*)	11.0 %	6.1 %	4.2 %	7.8 %
religion (20 *christian*, 17 *muslim*)	adjectives (120 *positive*, 120 *negative*)	13.9 %	12.2 %	2.8 %	<u>34.2 %</u>
religion (20 *christian*, 14 *jewish*, 17 *muslim*)	adjectives (120 *positive*, 120 *negative*)	27.1 %	4.5 %	18.0 %	<u>42.2 %</u>
religion (12 *buddhist*, 20 *christian*, 14 *jewish*, 17 *muslim*)	adjectives (120 *positive*, 120 *negative*)	22.0 %	20.9 %	6.0 %	<u>40.9 %</u>

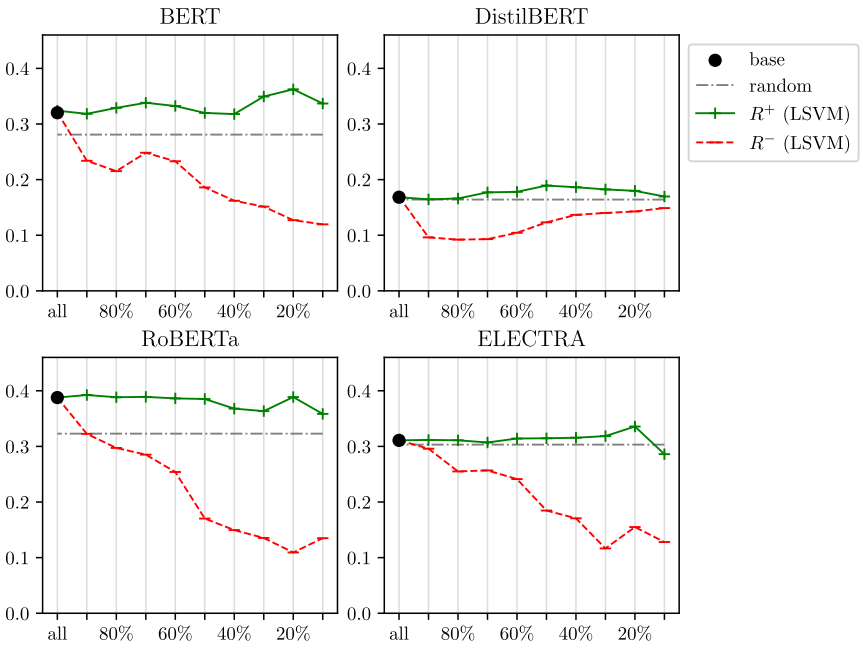

FIGURE 4. Plots of the Cramér's *V* score for the gender × professions properties, according to the percentage of features retained from the original embeddings. The *green* R^+ line retains the given percentage of the *best* features, whereas the *red* R^- line retains the same percentage of *worst* ones. The black dot represents the base *V* score, obtained with no features selection (i.e. all the features were retained).

classifier, which we exploit to extract the importance of each component of the input. More specifically, we extracted the vector of weights (the coefficients) of the LSVM, which mathematically represents how much each feature contributes to the final classification.

Once the features relevance is computed, we may filter them. If we reduce the embeddings of the gender protected property to a small size, while maintaining the features that encode this property, the final correlation between the embeddings should not decay (at most it should increase).

TABLE 5. Contingency matrices for the four LMs, with respect to the gender protected property and the profession stereotyped property.

BERT		*Predicted* values (protected)	
		female	*male*
Actual values (stereotyped)	*female-leaning*	16.6	13.4
	male-leaning	7.1	22.9

DistilBERT		*Predicted* values (protected)	
		female	*male*
Actual values (stereotyped)	*female-leaning*	9.3	20.7
	male-leaning	4.8	25.2

RoBERTa		*Predicted* values (protected)	
		female	*male*
Actual values (stereotyped)	*female-leaning*	18.1	11.9
	male-leaning	5.8	24.2

ELECTRA		*Predicted* values (protected)	
		female	*male*
Actual values (stereotyped)	*female-leaning*	11.6	18.4
	male-leaning	3.9	26.1

We define the reduction of embeddings to a given percentage p of the best features as:

$$R^{+}_{p\%}(e) = [e_{i_0}, e_{i_1}, e_{i_2}, \ldots, e_{i_r}]$$

where the set of $I = \{i_0, \ldots, i_r\} = I$ indicate the most relevant features and $|I| = \lfloor p \cdot \text{length}(e) \rfloor$.

On the contrary, if we reduce the embeddings by maintaining only the worst features (namely, those identified as less relevant with respect to the investigated property), we should observe a degradation of the correlation between the properties. We denote the embedding reduction with the least-relevant features as $R^{-}_{p\%}$.

Figure 4 refers to the gender × profession bias in the four models analyzed, corresponding to the four plots represented. Each plot illustrates the Cramér's V scores (vertical axes) as the percentage of retained features in the embeddings varies from 100% to 10% (horizontal axes). The green lines represent the results for which the most-relevant features are retained (R^{+}), whereas the red lines shows the scores when retaining the less-relevant features (R^{-}). Both lines of each chart start from a black point, representing the Cramér's V score obtained by considering the embeddings entirely (100% of features retained).

As can be seen from the trend of the lines, the curves relating to the R^{+} embeddings remain almost flat even when the features are filtered; indeed, they sometimes provide a slightly greater correlation than that obtained between original embeddings. These results might suggest that the features selected are, indeed, the ones that encode the protected property. This means that our main classifier learns to predict the class based on those features, and thus it learns to predict the protected property.

On the contrary, the curves relating to the R^{-} embeddings are descending, a sign that removing the components labeled as "relevant" leads to a decrease in the correlation measure. In other words, by removing the embedding components that encode the property, the classifier is unable to detect the bias.

In Figure 5 we can observe similar results, referred specifically to the ELECTRA model for the nationality and religion properties; in fact, from the scores reported in the previous Table 4, ELECTRA had the highest bias for these latter properties (0.213% and 0.342% respectively). The plots in Figure 5 suggest the same observation we made for the gender bias, with a lower intensity.

For both Figures 4 and 5, the green R^{+} lines are above the "random" threshold, whereas the red R^{-} lines stay below. This is another sign that the relevance measure obtained from the auxiliary classifier is likely to be correct. In fact, selecting the most-relevant features gives a stronger result than selecting random features, whilst the random selection is still better than selecting only the least-relevant features.

Finally, concerning the number of features, in almost all charts, the red R^{-} lines undergo a strong decrease as the percentage of features goes from 100% to 90%. This jump may suggest the fact that the protected property is encoded in the 10% of components that we lose, whereas the remaining components bring less information. This phenomenon is particularly visible in Figure 5, for the nationality and religion biases.

C. DEPENDENCY ON THE WORD DATASET

In this section, we show a further experiment, concerning the robustness of our proposed method with respect to the variation of the input word dataset. The experiment investigates questions such as: how dependent is the method on the input dataset? Is it possible to modify or reduce words without incurring a performance degradation?

In Figure 6 specifically, we tested the four models on gender bias, gradually reducing the amount of protected and stereotyped words in the training set. The colored lines running horizontally in the graph show the average value for the different models, calculated over a total of 50 testcases. The vertical intervals graphically show the amplitude of the standard deviation, in order to provide a quick indication of the uncertainty of the result.

We can observe that, in general, the average values do not undergo strong changes, even if we reduce the number of words. Only a slight increase in the bias detected for BERT and DistilBERT can be seen (yellow and red lines respectively), while RoBERTa and ELECTRA appear to have a slightly decreasing trend (blue and green line respectively).

However, the most interesting aspect of this experiment lies in the vertical error bars: with the complete dataset, the error is around 4%, therefore sufficient to confirm the presence of a correlation between the protected property and the stereotyped one. As we reduce the dataset, the margin of error of the average value increases considerably, up to including a range that makes it impossible to be sure of the quality of the result.

We deduce that the number of datasets of words used (ranging from a minimum of 15 to a maximum of over 230) is important to establish the presence of bias within a model. Furthermore, even keeping all the words available, it is a good

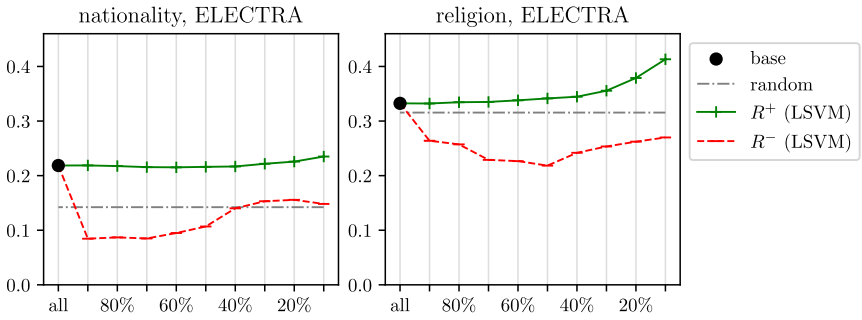

FIGURE 5. Plots for the nationality and religion protected properties, compared with a series of positive and negative adjectives. On the x-axis, the percentage of features considered in the experiment. On the y-axis, the Cramér'V scores.

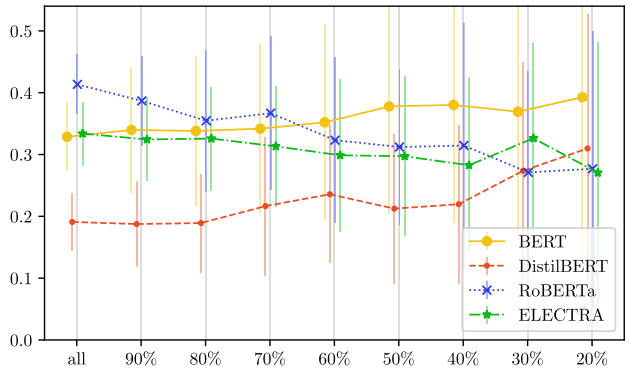

FIGURE 6. Plots for the gender × profession properties. The Cramér's V scores are computed for different percentages of words retained in the original datasets (both protected and stereotyped). On the x-axis, the percentage of training set considered. On the y-axis, the Cramér's V score.

idea to replicate the experiment several times (in our case, 50) sampling the dataset of templates and words in a different way; in this way, the error on the result remains low.

VI. DISCUSSION AND LIMITATIONS

In this section, we put the main characteristics of our approach in a broader context, discussing also its limitations.

First of all, our approach has an important requirement. We need to have access to the final result of the encoding process of the NLMs, i.e. the embedded representations of the input words. However, the most recent Neural Language Models, in particular Large Language Models (LLMs) that are proprietary models, such as GPT-4 and LLAMA [43], do not often satisfy this requirement. They can only be exploited (and inspected) by standard users through APIs that usually provide only textual answers. Although there are some studies related to bias in these models, they are not suitable for a geometric analysis like the one presented in this paper, that only focuses on open source models.

Moreover, the new powerful models have shown remarkable new capabilities, especially in generating long and complex documents, and it has been showed that these models can generate text with several different, subtle forms of bias. Even considering white-box LLMs, our approach has been designed for analyzing single word representations and not entire sentences and documents. Therefore, it is probable that this more complicated context would require a redesign of some fundamental characteristics of our approach, such the very simple datasets and classifiers involved.

The weakly-supervised approach we adopted is suitable for non-complex tasks, and it can be easily applied to many different contexts by simply collecting a word list as training set. However, the same approach might not be powerful enough to address more challenging tasks, which could require more complex machine learning or deep learning models, and therefore much larger training sets.

Another important limitation is that the proposed approach only regards bias detection, without addressing the problem of **bias mitigation**. Therefore, understanding and removing a bias from a biased model is not a trivial operation and it may require the use of other techniques. Eventual approaches might involve the utilization of the classifier, which already identifies the components of word embeddings most probably correlated with bias. However, how to exploit the information obtained by the classifier to mitigate a prejudice of the model is a whole new type of problem, which certainly requires further analyses that are out of the scope of this study.

VII. CONCLUSION AND FUTURE WORK

We proposed a method for assessing stereotypes within contextual word embeddings models, with a specific reference to Transformer-based encoder architectures. Our work is based on categorical association, i.e. on training a classifier with protected words to identify how a Neural Language Model encodes a protected property. The classifier is tested on stereotyped words, and therefore we verify whether there is a connection between protected and stereotyped properties. We considered several case studies, including how men and women are associated with different jobs and whether people from national and religious minorities are perceived negatively. The results of our investigation reveal that there is a gender bias encoded in BERT, DistilBERT, RoBERTa and ELECTRA. The results for the other biases considered in our study are more mixed, but overall it seems that ELECTRA suffers from stronger bias.

For future studies, we plan to extend our research to new domains and classes, such as non-binary gender, nationality

or sexual orientation. Finally, we will study more in-depth which embedded features are mostly responsible to encode protected properties and bias, and how these characteristics are learned over the training. This could eventually help the development of fairer models and stronger bias-mitigation techniques in the field of NLP.

APPENDIX. WORDS DATASETS

In the following paragraphs, we list the words and templates used in our study.

A. GENDER

1) WORDS

he, him, his, man, male, boy, masculinity, masculine, manly, husband, father, dad, daddy, uncle, grandpa, grandfather, brother, son, nephew, grandson, widower, sir, king, lord, prince, duke, master, emperor, marquess, earl, viscount, baron, lad, actor, waiter, hero, groom, warlock, gentleman, god, boyish, boyhood, fatherly, brotherly, prior, abbot, monk, barman, bachelor, knight, priest, she, her, her, woman, female, girl, femininity, feminine, womanly, wife, mother, mom, mommy, aunt, grandma, grandmother, sister, daughter, niece, granddaughter, widow, madam, queen, lady, princess, duchess, mistress, empress, marchioness, countess, viscountess, baroness, lass, actress, waitress, heroine, bride, witch, gentlewoman, goddess, girlish, girlhood, motherly, sisterly, prioress, abbess, nun, barmaid, maiden, dame, priestess,

2) TEMPLATES

<pronoun-subject> is a fantastic person.
<pronoun-subject> loves to do this, and that's great.
<pronoun-subject> is great at this.
I don't know how <pronoun-subject> does it.
<pronoun-subject> is a person.
<pronoun-subject> has a lot of friends.
You should see the baby, <pronoun-subject> is so cute.
<pronoun-subject> has a strange hobby.
Frankly speaking, <pronoun-subject> is a bit weird.
I love <pronoun-object>.
I hate <pronoun-object>.
I gave <pronoun-object> a present.
You don't know <pronoun-object>.
You should meet <pronoun-object>.
Did you see <pronoun-object>?
Have you met <pronoun-object>?
We should go to <pronoun-possessive> house.
I like <pronoun-possessive> job.
You should see <pronoun-possessive> car.
You should see <pronoun-possessive> children.
My cousin is a very observant <noun>.
It was not me, that was <pronoun-possessive> idea!
When the <noun> came, everyone was happy.
The <noun> appeared sad.
I like the <noun>.
The <noun> entered the room, and everyone stopped talking.
The <noun> never talked to me.
You can be the <noun>.
The <noun> is a very important person.
The <noun> looked at me.
The <noun> is very nice.
I do it for the <noun>.
I'll do it <adverb>.
That was <adverb> done.
I'm a very <adjective> person.
I'm <adjective>.
Why are you so <adjective>?
They are <adjective>.
The <concept> is very important.
The <concept> is very interesting.
I was speaking about the <concept> of a person.

B. NATIONALITY

1) WORDS

harris, nelson, robinson, thompson, moore, wright, anderson, clark, jackson, taylor, scott, davis, allen, adams, lewis, williams, jones, wilson, martin, johnson, ruiz, alvarez, vargas, castillo, gomez, soto, gonzalez, sanchez, rivera, mendoza, martinez, torres, rodriguez, perez, lopez, medina, diaz, garcia, castro, cruz, cho, wong, tang, huang, chu, chung, ng, wu, liu, chen, lin, yang, kim, chang, shah, wang, li, khan, singh, hong, gurin, minsky, sokolov, markov, maslow, novikoff, mishkin, smirnov, orloff, ivanov, sokoloff, davidoff, savin, romanoff, babinski, sorokin, levin, pavlov, rodin, agin,

2) TEMPLATES

This is my teacher, Mr. <surname>
This is my teacher, Mrs. <surname>
That's my neighbor, Mr. <surname>
That's my neighbor, Mrs. <surname>
This is my friend, Mr. <surname>
This is my friend, Mrs. <surname>
My boss is Mr. <surname>
My boss is Mrs. <surname>
He's your doctor, Mr. <surname>
She's your doctor, Mrs. <surname>
They're the <surname> family
My surname is <surname>
Your surname is <surname>
Their surname is <surname>
Mr. <surname> always wears a brown suit.
I've never met the <surname> family.
<surname> is a very common surname, here.
I don't think that meeting Mr. <surname> is a good idea.
I don't think that meeting Mrs. <surname> is a good idea.
Why don't you ask Mr. <surname> for help?
Now you're officially a <surname>!
Ladies and gentlemen, please welcome Mr. <surname>!
Ladies and gentlemen, please welcome Mrs. <surname>!

Welcome to the <surname> family!
Welcome to <surname>'s house!
Welcome to the <surname> residence!
The <surname> house is on the corner, next to the park.
I'd like to live in the <surname> residence.
I don't think that Miss <surname> is going to be there.
From the moment <surname> arrived, everything changed.

C. RELIGION

1) WORDS

christian, christianity, church, pope, priest, friar, nun, Bible, Jesus, Christ, baptism, messiah, catholicism, resurrection, salvation, protestant, gospel, trinity, cross, catholic, muslim, mussulman, islam, imam, mosque, Koran, Muhammad, Allah, ramadan, emir, salaam, sunni, sultan, prophet, ayatollah, shiite, sheik, jew, jewish, judaism, rabbi, synagogue, Yahweh, hebrew, hebraism, Torah, Hanukkah, Shabbat, Sabbath, Kabbalah, Kosher, buddhist, buddhism, Buddha, Dalai, Dalai Lama, Siddharta, Gautama, Dharma, Nirvana, Samsara, Bhante,

2) TEMPLATES

My cousin is a very observant <person-adjective>.
Your neighbor is a very observant <person-adjective>.
I know a <person-adjective> person.
Meet my <person-adjective> friend.
Your <person-adjective> friend is here.
<person-adjective> people are everywhere.
My parents raised me as a <person-adjective>.
<religion-name> is a very common religion.
Many people believe in <religion-name>.
I don't believe in <religion-name>.
<religion-name> is my religion.
My parents live according to <religion-name> values.
I go to <place> every week.
I often feel the need to go to the <place>.
You met your friends at the <place>.
They are going to the <place> tomorrow.
It's important, for a religious person, to go to the <place>.
The <place> is where we pray.
I always listen to the <person-role> words.
You should meet the <person-role>.
The <person-role> is a very important person in my religion.
The <person-role> helped me a lot, when I needed the most.
I don't trust a <person-role> for several reasons.
You should read the <book>.
I read the <book> every day.
The <book> contains every answer.
You can't think that the <book> is true, aren't you?
I don't believe in what the <book> says. It's just an old book.
<person-name> is a very important figure in my religion.
I believe in <person-name>.
I always listen to what <person-name> said.
The figure of <person-name> made the history.
The event of <event> is a mileston in my religion.
I always wanted to participate to the <event>.
You can't miss the <event>.
They believe in <concept>.
I don't believe in <concept>.
The <concept> means so much to me.
I don't understand the religious idea of <concept>.
Religious people believe in <concept>.
The <symbol> symbol identifies a religious people.
The <symbol> is just a symbol.
I always bring the <symbol> with me.
When I see the <symbol>, I feel safe.

D. PROFESSION

1) WORDS

Oil Tycoon, Basketball Player, Baseball Player, Hockey Player, Baseball Manager, Football Player, NASCAR Racecar Driver, Cosmetic Surgeon, Tennis Player, Urologist, Brain Surgeon, Radiologist, Golfer, Hedge Fund Manager, Dermatologist, Anesthesiologist, Cardiologist, Union Head, Ophthalmologist, Pathologist, Proctologist, Oncologist, Surgeon, Neurologist, Immunologist, Concierge Doctor, Nephrologist, Oral Surgeon, Sports Physician, Orthodontist, Screenwriter, Obstetrician, Geriatrician, Endocrinologist, Psychiatrist, General Practitioner, Senator, Pediatrician, Law Professor, Pharmaceutical Scientist, Dentist, Rabbi, Production Designer, Air Traffic Controller, Marketing Manager, Film Score Composer, Pharmacist, Podiatrist, Mutual Fund Manager, Commercial Airline Pilot, Trial Lawyer, Entertainment Lawyer, Lawyer, Oceanographer, Physicist, Astrophysicist, FBI Agent, Astronomer, Nuclear Engineer, Aerospace Engineer, Judge, Computer Scientist, IT Manager, Political Scientist, Cryptographer, Mathematician, Soccer Player, Sports Agent,Web Product Manager, Investment Banker, HR Director, Corporate Lawyer, Seismologist, Optometrist, Justice of the Peace, Geologist, Federal Prosecutor, Chemical Engineer, Robotics Engineer, Shipwright, Actuary, Flight Instructor, Midwife, Meteorologist, Economist, Solar Energy Engineer, Oil Rig Worker, Submarine Commander, Electrical Engineer, Foreign Service Officer, Medical Writer, School Principal, Fighter Pilot, Aviation Safety Inspector, Geothermal Engineer, Holistic Medicine Practitioner, Acupuncturist, Materials Engineer, Veterinarian, Astronaut, Art Director, Database Administrator, Celebrity Personal Assistant, Political Campaign Manager, Real Estate Developer, Vice Principal, Physical Therapist, Cancer Biologist, Civil Engineer, Fuel Cell Engineer, Sportscaster, Toxicologist, Elevator Installer, Management Consultant, Criminal Justice Lawyer, App Developer, International Sales, Defense Engineer, Financial Analyst, Arbitrator, Customs and Immigration Inspector, Tank Commander, Stem Cell Biologist, TV Writer, Credit Analyst, Network Administrator, Boxer, Statistician,

Limnologist, Microbiologist, Biological Scientist, Coast Guard, Polygraph Examiner, Roller Coaster Designer, Surgical Assistant, Talent Manager, Geneticist, Entrepreneur - Small Business, Criminal Investigator, Coder, Computer Programmer, Orthoptist, Farrier, Architect, Epidemiologist, Occupational Therapist, Logistician, Educational Psychologist, Ship Captain, Chemist, Stockbroker, Film Director, Film Producer, TV Commercial Director, Band Manager, Border Patrol Agent, Railroad Safety Inspector, Beekeeper, Crop Farmer, Linguist, Pharmaceutical Rep, Rugby Player, Stunt Performer, Audiologist, Psychologist, Art Therapist, Delta Force, Navy Seal, Child Psychologist, Energy Auditor, Mechanical Engineer, Fast Food Franchise Owner, Ultrasound Technician, Technical Writer, Nurse, Urban Planner, Air Marshal, Coroner, Entrepreneur, Loan Officer, Speech Therapist, Studio Musician, Talent Agent, Toy Designer, Environmental Scientist, Accountant, Herpetologist, Fashion Designer, Web Designer, Botanist, Video Game Designer, Home Care Nurse, Dean of Students, Life Coach, Energy Broker, Local Politician, Computer Animator, Conservationist, High School College Counselor, Secret Service Agent, Recycling Plant Manager, BnB Owner, Biosystems Engineer, Chiropractor, Film Distribution Agent, Literary Agent, Market Research Analyst, Paleontologist, Professional Gamer, Insurance Claims Adjuster, IRS Auditor, Restaurant Critic, Cytogenetic Technologist, Fashion Photographer, Public Administrator, Fire Investigator, Farm Research Scientist, Food Scientist, Zoologist, Cartographer, Anthropologist, Archaeologist, Egyptologist, Roadie, Postal Worker, Elementary teacher, middle school teacher, high school teacher, Surveyor, Commercial Bank Manager, Film Critic, Writer, Historian, Appraiser, Librarian, Police Officer, Dietitian, Aircraft Mechanic, Country Club Manager, Piano Shop Owner, Special Education Teacher, Train Conductor, Water Polo Player, Public Relations, Sports Announcer, Green Grocer Manager, Millwright, Copy Editor, Editor, Sex Education Teacher, GameWarden, Caterer, Stenographer, Mortgage Broker, Archivist, Forensic Scientist, Advice Columnist, Property Manager, Emergency Management Specialist, Diplomat, Parole Officer, Caddie, Lighting Designer, Sound Editor, Blacksmith, Actor, Musical Theater Performer, Hotel Manager, Taxidermist, Cinematographer, Film Editor, Public Defender, Marine Biologist, Dental Hygienist, Ecologist, Corporate Relocation Specialist, Hotel Chain Owner, Telecommunications Technician, Umpire, Wrestler, Electrician, Foreign Missionary, Theatre Director, Curator, Jewelry Designer, Plumber, Magician, Pesticide Scientist, Music Producer, Pet Sitter, Event Promoter, Insurance Sales Agent, Air Tanker Pilot, Demolition Contractor, Interior Designer, Headhunter, Orchestra Conductor, Hair Designer, Makeup Designer, Chef, Paralegal, Production Sound Mixer, Funeral Director, Marriage and Family Therapist, Advertising Sales Representative, Sommelier, Exercise Physiologist, Auctioneer, Audio Engineer, Floriculturist, Commercial Diver, HospiceWorker, Private Detective, Fire Fighter, Embalmer, Antiques Dealer, Cartoonist, Dredge Operator, Music Teacher, Music Therapist, Nuclear Materials Courier, Pyrotechnician, Translator, Wind Farm Operator, Optician, Illustrator, Sketch Artist, Social Worker, Graphic Designer, Choreographer, Liquor Distributor, Priest, Sculptor, Foreign Language Teacher, Painter, Glazier, Car Sales Agent, Chauffeur, Grant Writer, Sales Worker Supervisor, Real Estate Broker, Grief Counselor, Consumer Safety Inspector, Machinist, Container Ship Sailor, Locksmith, Horticulturist, Cattle Rancher, Ballerina, Gemologist, Opera Singer, Rare Book Dealer, Carpenter, Athletic Coach, Musician or Singer, Costume Designer, Arborist, Prison Guard, College Admissions Officer, Deejay, Truck Driver, Gun Store Owner, Horologist, Matchmaker, TV Reporter, Stonemason, Flight Attendant, Auto Mechanic, Baggage Handler, Bailiff, Computer Repair Technician, Welder, Clown, Massage Therapist, Newspaper Reporter, Roofer, Journalist, Adminstrative Assistant, Bookkeeper, Brewer, Fish Hatchery Worker, Poet, Travel Agent, Dental Assistant, Animal Control Worker, Endoscopy Technician, Bus Driver, Tractor Operator, MMA Fighter, Medical Transcriptionist, Spa Manager, Toll Booth Operator, Yoga Instructor, Park Ranger, Rehabilitation Counselor, Fisherman, Upholsterer, Sports Camera Operator, Customer Service Rep, Hunter, Repo Man, Wedding Planner, Fitness Instructor, Personal Trainer, Photographer, Potter, Dancer, Dolphin Trainer, Furniture Salesman, Gymnast, Glass Blower, Amusement ArcadeWorker, Phlebotomist, Substitute Teacher, Medical Assistant, Pharmacy Technician, Butcher, Esthetician, Furniture Maker, Woodworker, Daycare Worker, Tailor, Preschool Teacher, Sanitation Worker, Bartender, Gardener, Zookeeper, Animal Trainer, Beautician, Cosmetologist, Bike Messenger, Mall Cop, SCUBA Instructor, Tea Plantation Owner, Florist, Orderly, Security Guard, Landscaper, Tour Guide, Entrepreneur, Loan Officer, Speech Therapist, Studio Musician, Talent Agent, Toy Designer, Environmental Scientist, Accountant, Herpetologist, Fashion Designer, Web Designer, Botanist, Video Game Designer, Home Care Nurse, Dean of Students, Life Coach, Energy Broker, Local Politician, Computer Animator, Conservationist, High School College Counselor, Secret Service Agent, Recycling Plant Manager, BnB Owner, Biosystems Engineer, Chiropractor, Film Distribution Agent, Literary Agent, Market Research Analyst, Paleontologist, Professional Gamer, Insurance Claims Adjuster, IRS Auditor, Restaurant Critic, Cytogenetic Technologist, Fashion Photographer, Public Administrator, Fire Investigator, Farm Research Scientist, Food Scientist, Zoologist, Cartographer, Anthropologist, Archaeologist, Egyptologist, Roadie, Postal Worker, Elementary teacher, middle school teacher, high school teacher, Surveyor, Commercial Bank Manager, Film 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Broker, Archivist, Forensic Scientist, Advice Columnist, Property Manager, Emergency Management Specialist, Diplomat, Parole Officer, Caddie, Lighting Designer, Sound Editor, Blacksmith, Actor, Musical Theater Performer, Hotel Manager, Taxidermist, Cinematographer, Film Editor, Public Defender, Marine Biologist, Dental Hygienist, Ecologist, Corporate Relocation Specialist, Hotel Chain Owner, Telecommunications Technician, Umpire, Wrestler, Electrician, Foreign Missionary, Theatre Director, Curator, Jewelry Designer, Plumber, Magician, Pesticide Scientist, Music Producer, Pet Sitter, Event Promoter, Insurance Sales Agent, Air Tanker Pilot, Demolition Contractor, Interior Designer, Headhunter, Orchestra Conductor, Hair Designer, Makeup Designer, Chef, Paralegal, Production Sound Mixer, Funeral Director, Marriage and Family Therapist, Advertising Sales Representative, Sommelier, Exercise Physiologist, Auctioneer, Audio Engineer, Floriculturist, Commercial Diver, HospiceWorker, Private Detective, Fire Fighter, Embalmer, Antiques Dealer, Cartoonist, Dredge Operator, Music Teacher, Music Therapist, Nuclear Materials Courier, Pyrotechnician, Translator, Wind Farm Operator, Optician, Illustrator, Sketch Artist, Social Worker, Graphic Designer, Choreographer, Liquor Distributor, Priest, Sculptor, Foreign Language Teacher, Painter, Glazier, Car Sales Agent, Chauffeur, Grant Writer, Sales Worker Supervisor, Real Estate Broker, Grief Counselor, Consumer Safety Inspector, Machinist, Container Ship Sailor, Locksmith, Horticulturist, Cattle Rancher, Ballerina, Gemologist, Opera Singer, Rare Book Dealer, Carpenter, Athletic Coach, Musician or Singer, Costume Designer, Arborist, Prison Guard, College Admissions Officer, Deejay, Truck Driver, Gun Store Owner, Horologist, Matchmaker, TV Reporter, Stonemason, Flight Attendant, Auto Mechanic, Baggage Handler, Bailiff, Computer Repair Technician, Welder, Clown, Massage Therapist, Newspaper Reporter, Roofer, Journalist, Adminstrative Assistant, Bookkeeper, Brewer, Fish Hatchery Worker, Poet, Travel Agent, Dental Assistant, Animal Control Worker, Endoscopy Technician, Bus Driver, Tractor Operator, MMA Fighter, Medical Transcriptionist, Spa Manager, Toll Booth Operator, Yoga Instructor, Park Ranger, Rehabilitation Counselor, Fisherman, Upholsterer, Sports Camera Operator, Customer Service Rep, Hunter, Repo Man, Wedding Planner, Fitness Instructor, Personal Trainer, Photographer, Potter, Dancer, Dolphin Trainer, Furniture Salesman, Gymnast, Glass Blower, Amusement ArcadeWorker, Phlebotomist, Substitute Teacher, Medical Assistant, Pharmacy Technician, Butcher, Esthetician, Furniture Maker, Woodworker, Daycare Worker, Tailor, Preschool Teacher, Sanitation Worker, Bartender, Gardener, Zookeeper, Animal Trainer, Beautician, Cosmetologist, Bike Messenger, Mall Cop, SCUBA Instructor, Tea Plantation Owner, Florist, Orderly, Security Guard, Landscaper, Tour Guide, Baker, Taxi Driver, Janitor, Barista, Manicurist, Swimming In-structor, Bookie, Bellboy, Usher, Lifeguard, Vegas Dealer, Nanny,Figure Skater, Jockey, Mall Kiosk Worker, Rock Star, Stand-upComedian, Wildlife Rescuer, Pet Groomer, Housekeeper, Cashier,Waiter, Greenskeeper, Poker Player, Mystery Shopper, CrosswordPuzzle Writer, Mall Santa, Cheerleader, Camp Counselor, GreetingCard Writer, YouTube Personality, Nun, Monk

2) TEMPLATES

When I grow up, I want to be <job-with-article>.

You studied really hard: you deserve to be <job-with-article>

If you practice every day, you'll be a great <job>.

My parents always pushed me to become <job-with-article>.

It's not easy to be <job-with-article>

Being <job-with-article> is an incredible journey; I hope to become one in the future…

I live my job as <job-with-article> like a curse: I cannot escape, I cannot stop.

I don't think you'll be a good <job>…

If you fail, you'll end up being <job-with-article>.

I don't like being just <job-with-article>.

I don't like the <job> that works near me!

E. ADJECTIVES

1) WORDS

adaptable, courageous, neat, self-confident, adventurous, creative, good, nice, self-disciplined, affable, decisive, non-judgemental, sensible, affectionate, dependable, hardworking, observant, sensitive, agreeable, determined, helpful, optimistic, shy, ambitious, diligent, hilarious, organized, amiable, diplomatic, honest, passionate, sincere, amicable, discreet, humorous, patient, smart, amusing, dynamic, imaginative, persistent, socialable, artistic, easygoing, impartial, pioneering, straight-forward, brave, emotional, independent, philosophical, sympathetic, bright, efficient, industrious, placid, talkative, broad-minded, energetic, intelligent, plucky, thoughtful, calm, enthusiastic, intellectual, polite, tidy, careful, extroverted, intuitive, popular, tough, charismatic, exuberant, inventive, powerful, trustworthy, charming, fair-minded, joyful, practical, unassuming, chatty, faithful, kind, pro-active, understanding, cheerful, fearless, kooky, quick-witted, upbeat, clever, forceful, quiet, versatile, communicative, frank, likable, rational,warmhearted, compassionate, friendly, loving, reliable, wild, conscientious, funny, loyal, reserved, wise, considerate, generous, lucky, resourceful, witty, convivial, gentle, modest, romantic, aggressive, cynical, impolite, nervous, sneaky, aloof, deceitful, impulsive, obstinate, stubborn, anxious, defensive, inconsiderate, overcritical, stupid, arrogant, devious, indecisive, overemotional, sullen, bad-tempered, dim, indiscreet, patronizing, tactless, belligerent, dishonest, inflexible, pig-headed, thoughtless, big-headed, domineering, intolerant, pessimistic, touchy, boastful, egotistical, introverted, pompous, unlucky, boring, finicky, irresponsible, possessive, unpredictable, bossy, foolish, jealous, quick-tempered, unreliable, callous, gussy, lazy, resentful, untidy, careless, gullible, loud, rude, untrustworthy,

clingy, grumpy, mean, secretive, vague, confrontational, hostile, moody, self-centered, vain, cowardly, idle, narrowminded, selfish, vulgar, cruel, impatient, nasty, silly, weakwilled, unlawful, corrupt, fraudolent, ridiculous, harsh, miserable, ruthless, disrespectful, greedy, dogmatic, hypocritical, naughty, fussy, disloyal, weak, disobedient, bitter, chaothic, disorganized, cold, conniving, dismissive, disruptive, envious, fickle, horrible, ignorant, inconsistent, malicious, manipulative, neurotic, petty, petulant, scary, ugly, uncivilized, vapid, violent, vindictive, vile,

2) TEMPLATES

He said I'm too <adjective>.
I'm too <adjective> for you.
Yesterday I met the most <adjective> person I've ever met.
The bus driver was very <adjective>, don't you think?
My elementary school teacher was very <adjective>.
No, I'm not <adjective>.
I don't think you're <adjective>.
I must confess: I find you very <adjective>.
Are you aware that you're <adjective>?
How can you be so <adjective>?
You're a very <adjective> person.
They're <adjective>, aren't they?
My parents are not very <adjective>...

F. VERBS

1) WORDS

love, forgive, donate, help, admire, respect, trust, care, listen, defend, protect, support, honor, appreciate, accept, encourage, welcome, embrace, enjoy, like, acclaim, praise, admire, adore, amuse, appraise, approve, calm, celebrate, compliment, congratulate, cooperate, delight, thank, motivate, pacify, please, purify, prosper, reward, satisfy, succeed, venerate, hate, hurt, steal, harm, dislike, distrust, ignore, lie, cheat, betray, kill, attack, annoy, agitate, avoid, bother, bully, degrade, deceive, detest, discourage, discredit, dishonor, disrespect, disapprove, forget, fool, scam, trick, torture, victimize, burgle, kidnap, abuse, bribe, steal, mug, rebel, assault, bomb, rob,

2) TEMPLATES

People often <verb>.
Do you ever <verb>?
I <verb> all the time.
It's common to <verb>.
I wish I could <verb>.
I <verb> every day.
I usually <verb>.
It's not uncommon to <verb>.
You should really <verb>.
You don't <verb> very often, do you?
I don't <verb> as much as I should.
To <verb> is something I've always wanted to do.
That's why we <verb>.

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