Honest Hillary, Narcissistic Trump? A Computational Approach to Gender Stereotyping of Politicians in Facebook User Comments

# Appendix A

# Group Words

In this section, we provide the gender-linked traits and political traits used in the current paper.

***Feminine Personality Traits***

Affectionate, gentle, soft, sensitive, sympathetic, compassionate, empathetic, considerate, feminine, girly, motherly, caring, thoughtful, warm, nice, complaining, bitching, bitchin, bitchy, whining, whiny, whiney, whinny, gullible, naïve, fussy, picky, cranky, nagging, bugging, servile, spineless, gutless, moany,[[1]](#footnote-1) emotional, dramatic, talkative, chatty.

***Feminine Cognitive Traits***

Artistic, artsy, creative, imaginative, innovative, inventive, intuitive, instinctive.

***Feminine Physical Traits***

Beautiful, gorgeous, stunning, pretty, cute, adorable.

***Masculine Personality Traits***

Adventurous, daring, aggressive, aggressive,[[2]](#footnote-2) aggresive, forceful, active, busy, arrogant, cocky, condescending, pompous, competitive, strong, tough, hard, masculine, manly, egotistical, narcissistic, boastful, prideful, dictatorial, tyrannical, oppressive, greedy, selfish, hostile, unprincipled, unscrupulous, driven, determined, ambitious, cynical, leader.

***Masculine Cognitive Traits***

Analytical, logical.

***Masculine Physical Traits***

Rugged, sturdy, strong, tough, athletic, muscular, fit, burly, hulking, buff, muscly.

***Leadership Traits***

Inspiring, inspirational, leader, charismatic, personable, charming, powerful, strong, competitive, driven, determined, ambitious, active, busy, aggressive, agressive, aggresive, forceful, arrogant, cocky, condescending, pompous.

***Integrity Traits***

Decent, nice, honest, truthful, moral, virtuous, good, honorable.

***Competence Traits***

Educated, informed, knowledgeable, knowledgable, competent, intelligent, smart, clever, hardworking, diligent, industrious.

***Empathy Traits***

Sympathetic, compassionate, empathetic, considerate.

# Appendix B

# Methods

***Data Pre-Processing***

**Replacement of Names.**To correct misspelled names, e.g., *Hilary* or *Killary*, we employed word embeddings trained on the same corpus to consider top 15 words that are most similar to the names of the politicians. After their manual validation, references to politicians that otherwise could have been overlooked were included. Ambiguous last names were only replaced with the identifiers if they were preceded by the first names of the politicians, e.g., *Ron Kind* but not *Kind Ron*. In the remaining cases, politicians’ names were replaced with identifiers if their first name was followed by their last name or if their last name was followed by their first name. For the prominent politicians, the unique IDs also replaced isolated mentions of either their first or last name, e.g., *Donald* interpreted as a reference to *Donald Trump*.

***Word Embeddings***

**Hyperparameter Choice.** The followingparameters of the model to train word embeddings were used to yield meaningful results. The size of context around the target words was adjusted to 5, which is the default window size of word2vec. Although the embeddings size in word2vec is set to 300, to reduce memory consumption, dimensionality of word embeddings in this study was adjusted to 200. For the training of the vector space the sub-sampling threshold for frequent words of 10-5 was used following the recommendation in Mikolov et al. (2013) and Mikolov, Sutskever et al. (2013) to reduce the effect of the most frequent words on the word vectors. To manage words of rare occurrence, words with total frequency less than 10 were ignored by the model. The default initial learning rate of 0.025 decreased linearly to 0.0007 during the training process. Since the higher number of negative samples results in a better estimation (Levy, Goldberg, & Dagan, 2015), it was set to 15.

**Training and Evaluation.** The trained word vectors were subject to intrinsic evaluation, where human judgements on word relations were used to compare semantic similarity and analogical reasoning with word embeddings. The correlation of the human ratings from the Word-Similarity 353 (WS353, Finkelstein et al., 2002) with the cosine similarities of the word vectors of the respective pairs yielded a Pearson’s *r* = 0*.*552*, p <* 0*.*001 and a Spearman’s *rs* = 0*.*56*, p <* 0*.*001. The results are comparable to the evaluations of Levy et al. (2015) and Lai et al.(2015). Further, SimLex-999 (Hill et al., 2014), comprised of 999 word pairs assessing their semantic similarity was conducted. The correlation resulted in a Pearson’s *r* = 0*.*283*, p <* 0*.*001 and a Spearman’s *rs* = 0*.*272*, p <* 0*.*001. For comparison, the best model in Levy et al. (2015) had a Spearman’s correlation coefficient of *rs* = 0*.*438. Finally, the analogy test from Mikolov et al. (2013) was employed to compute performance of our model on semantic and syntactic questions of the test. The evaluation demonstrated a low performance on the task, 39,7% against 66% achieved by the authors of word2vec (Mikolov, Sutskever et al., 2013). However, the results of the mainstream evaluation approaches should be interpreted with caution. Firstly, it is problematic to objectively evaluate the results of an unsupervised machine learning task. Secondly, the size and diversity of a data set influences the performance of these tasks. For instance, in the case of this study, the data set has a relatively narrow subject of discussion, i.e. politics, which may lack some words from the evaluation sets in the vocabulary.

**Association Strength.** To calculate the association strength between the word vectors, cosine similarity was employed. As the analysis included normalized word vectors, denominator in the cosine similarity calculation is omitted. Also referred to as bias indicator.

$$bias indicator= v\_{m}⋅v\_{i}$$

In this equation, $v\_{i}$ is the average vector of a trait group, $v\_{m}$ is a vector of the politician’s name.

**References**

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1. As social media platforms are often a place for casual communication, we included certain colloquialisms. [↑](#footnote-ref-1)
2. Since social media data may contain spelling mistakes, we attempted to identify some of the possible and common spelling errors through word embeddings and include them in our analysis. [↑](#footnote-ref-2)