The Journal of Open Source Software

sweater: Speedy Word Embedding Association Test and Extras Using R

Chung-hong Chan[1]

1 Mannheimer Zentrum für Europäische Sozialforschung, Universität Mannheim

DOI:

Software

- Review
- Repository
- Archive

Submitted:
Published:

Statement of need

The goal of this R package is to detect associations among words in word embedding spaces. Word embeddings can capture how similar or different two words are in terms of implicit and explicit meanings. Using the example in Collobert et al. (2011), the word vector for "XBox" is close to that for "PlayStation", as measured by a distance measure such as cosine distance. Word embeddings can also be used to study associations among words that are otherwise difficult to detect. For instance, Jing & Ahn (2021) used word embeddings to study how Democrats and Republicans are divided along party lines about COVID-19.

The same technique can also be used to detect unwanted implicit associations, or biases. For example, Kroon, Trilling, & Raats (2020) measure how close the word vectors for various ethnic group names (e.g. "Dutch", "Belgian" , and "Syrian") are to those for various nouns related to threats (e.g. "terrorist", "murderer", and "gangster"). These biases in word embedding can be understood through the implicit social cognition model of media priming (Arendt, 2013). In this model, implicit stereotypes are defined as the "strength of the automatic association between a group concept (e.g., minority group) and an attribute (e.g., criminal)." (Arendt, 2013, p. 832) All of these bias detection methods are based on the strength of association between a concept (or a target) and an attribute in embedding spaces.

The importance of detecting biases in word embeddings is twofold. First, pretrained, biased word embeddings deployed in real-life machine learning systems can pose fairness concerns (Boyarskaya, Olteanu, & Crawford, 2020; Packer, Mitchell, Guajardo-Céspedes, & Halpern, 2018). Second, biases in word embeddings reflect the biases in the original training material. Social scientists, communication researchers included, have exploited these methods to quantify (implicit) media biases by extracting biases from word embeddings locally trained on large text corpora (e.g. Kroon et al., 2020; Knoche, Popović, Lemmerich, & Strohmaier, 2019; Sales, Balby, & Veloso, 2019).

Previously, the software of these methods is only available piecemeal as the addendum of the original papers and was implemented in different languages (Java, Python, etc.). `sweater` provides several of these bias detection methods in one unified package with a consistent R interface (R Core Team, 2021). Also, `sweater` provides several methods that are implemented in C++ for speed and interfaced to R using the `Rcpp` package (Eddelbuettel, 2013).[1]

[1]Compared with a pure R implementation, the C++ implementation of Word Embedding Association Test in `sweater` is at least 7 times faster. See the benchmark here.

Related work

The R package `cbn` (https://github.com/conjugateprior/cbn) by Will Lowe provides tools for replicating the study by Caliskan, Bryson, & Narayanan (2017). The Python package `wefe` (Badilla, Bravo-Marquez, & Pérez, 2020) provides several methods for bias evaluation in a unified (Python) interface.

Usage

In this section, I demonstrate how the package can be used to detect biases and reproduce some published findings.

Word Embeddings

The input word embedding w is a dense $m \times n$ matrix, where m is the total size of the vocabulary in the training corpus and n is the vector dimension size.

`sweater` supports input word embeddings, w, in several formats. For locally trained word embeddings, output from the R packages `word2vec` (Wijffels, 2021), `rsparse` (Selivanov, 2020) and `text2vec` (Selivanov et al., 2020) can be used directly with the packages primary functions, such as `query`.[2] Pretrained word embeddings in the so-called "word2vec" file format, such as those obtained online,[3] can be converted to the dense numeric matrix format required with the `read_word2vec` function.

The package also provides three trimmed word embeddings for experimentation: `googlenews` (Mikolov, Sutskever, Chen, Corrado, & Dean, 2013), `glove_math` (Pennington et al., 2014) , and `small_reddit` (An, Kwak, & Ahn, 2018).

Query

`sweater` uses the concept of a *query* (Badilla et al., 2020) to study associations in w and the $\mathcal{STAB}$ notation from Brunet, Alkalay-Houlihan, Anderson, & Zemel (2019) to form a query. A query contains two or more sets of seed words (wordsets selected by the individual administering the test, sometimes called "seed lexicons" or "dictionaries"). Among these seed wordsets, there should be at least one set of *target words* and one set of *attribute words*.

In the situation of bias detection, target words are words that **should** have no bias and usually represent the concept one would like to probe for biases. For instance, Garg, Schiebinger, Jurafsky, & Zou (2018) investigated the "women bias" of occupation-related words and their target words contain "nurse", "mathematician", and "blacksmith". These words can be used as target words because in an ideal world with no "women bias" associated with occupations, these occupation-related words should have no gender association.

Target words are denoted as wordsets $\mathcal{S}$ and $\mathcal{T}$. All methods require $\mathcal{S}$ while $\mathcal{T}$ is only required for WEAT. For instance, the study of gender stereotypes in academic pursuits by Caliskan et al. (2017) used $\mathcal{S} = \{math, algebra, geometry, calculus, equations, ...\}$ and $\mathcal{T} = \{poetry, art, dance, literature, novel, ...\}$.

In the situation of bias detection, attribute words are words that have known properties in relation to the bias. They are denoted as wordsets $\mathcal{A}$ and $\mathcal{B}$. All methods require both wordsets except Mean Average Cosine Similarity (Manzini, Lim, Tsvetkov, & Black,

[2] The vignette of `text2vec` provides a guide on how to locally train word embeddings using the GLoVE algorithm (Pennington, Socher, & Manning, 2014). https://cran.r-project.org/web/packages/text2vec/vignettes/glove.html

[3] For example, the pretrained GLoVE word embeddings, pretrained word2vec word embeddings and pretrained fastText word embeddings.

2019). For instance, the study of gender stereotypes by Caliskan et al. (2017) used $\mathcal{A} = \{he, son, his, him, ...\}$ and $\mathcal{B} = \{she, daughter, hers, her, ...\}$. In some applications, popular off-the-shelf sentiment dictionaries can also be used as $\mathcal{A}$ and $\mathcal{B}$ (e.g. Sweeney & Najafian, 2020). That being said, it is up to the researchers to select and derive these seed words in a query. However, the selection of seed words has been shown to be the most consequential part of the entire analysis (Antoniak & Mimno, 2021; Du, Fang, & Nguyen, 2021). Please read Antoniak & Mimno (2021) for recommendations.

Supported methods

Table 1 lists all methods supported by sweater. The function `query` is used to conduct a query. The function `calculate_es` can be used for some methods to calculate the effect size representing the overall bias of w from the query.

Table 1: All methods supported by sweater

Method	Target words	Attribute words
Mean Average Cosine Similarity (Manzini et al., 2019)	$\mathcal{S}$	$\mathcal{A}$
Relative Norm Distance (Garg et al., 2018)	$\mathcal{S}$	$\mathcal{A}$, $\mathcal{B}$
Relative Negative Sentiment Bias (Sweeney & Najafian, 2020)[4]	$\mathcal{S}$	$\mathcal{A}$, $\mathcal{B}$
SemAxis (An et al., 2018)	$\mathcal{S}$	$\mathcal{A}$, $\mathcal{B}$
Normalized Association Score (Caliskan et al., 2017)	$\mathcal{S}$	$\mathcal{A}$, $\mathcal{B}$
Embedding Coherence Test (Dev & Phillips, 2019)	$\mathcal{S}$	$\mathcal{A}$, $\mathcal{B}$
Word Embedding Association Test (Caliskan et al., 2017)	$\mathcal{S}$, $\mathcal{T}$	$\mathcal{A}$, $\mathcal{B}$

Example 1

Relative Norm Distance (RND) (Garg et al., 2018) is calculated with two sets of attribute words. The following analysis reproduces the calculation of "women bias" values in Garg et al. (2018). The publicly available word2vec word embeddings trained on the Google News corpus is used (Mikolov et al., 2013). Words such as "nurse", "midwife" and "librarian" are more associated with female, as indicated by the positive relative norm distance (Figure 1).

```
library(sweater)
```

```
S1 <- c("janitor", "statistician", "midwife", "bailiff", "auctioneer",
        "photographer", "geologist", "shoemaker", "athlete", "cashier",
        "dancer", "housekeeper", "accountant", "physicist", "gardener",
        "dentist", "weaver", "blacksmith", "psychologist", "supervisor",
        "mathematician", "surveyor", "tailor", "designer", "economist",
        "mechanic", "laborer", "postmaster", "broker", "chemist",
        "librarian", "attendant", "clerical", "musician", "porter",
        "scientist", "carpenter", "sailor", "instructor", "sheriff",
        "pilot", "inspector", "mason", "baker", "administrator",
        "architect", "collector", "operator", "surgeon", "driver",
```

[4] Experimental support for quanteda dictionaries (Benoit et al., 2018) is current available for this method. The support will be expanded to all methods later.

```r
       "painter", "conductor", "nurse", "cook", "engineer", "retired",
       "sales", "lawyer", "clergy", "physician", "farmer", "clerk",
       "manager", "guard", "artist", "smith", "official", "police",
       "doctor", "professor", "student", "judge", "teacher", "author",
       "secretary", "soldier")
A1 <- c("he", "son", "his", "him", "father", "man", "boy", "himself",
        "male", "brother", "sons", "fathers", "men", "boys", "males",
        "brothers", "uncle", "uncles", "nephew", "nephews")
B1 <- c("she", "daughter", "hers", "her", "mother", "woman", "girl",
       "herself", "female", "sister", "daughters", "mothers", "women",
       "girls", "females", "sisters", "aunt", "aunts", "niece", "nieces")
res_rnd_male <- query(w = googlenews, S_words = S1,
                      A_words = A1, B_words= B1,
                      method = "rnd")
plot(res_rnd_male)
```

Example 2

Word Embedding Association Test (WEAT) (Caliskan et al., 2017) requires all four wordsets of $\mathcal{S}$, $\mathcal{T}$, $\mathcal{A}$, and $\mathcal{B}$. The method is modeled after the Implicit Association Test (IAT) (Nosek, Greenwald, & Banaji, 2005) and it measures the relative strength of $\mathcal{S}$'s association with $\mathcal{A}$ to $\mathcal{B}$ against the same of $\mathcal{T}$. The effect sizes calculated from a large corpus, as shown by Caliskan et al. (2017), are comparable to the published IAT effect sizes obtained from volunteers.

In this example, the publicly available GLoVE embeddings made available by the original Stanford Team (Pennington et al., 2014) were used. In the following example, the calculation of "Math vs Arts" gender bias in Caliskan et al. (2017) is reproduced. In this example, the positive effect size indicates the words in the wordset $\mathcal{S}$ are more associated with males than are the words in wordset $\mathcal{T}$.

```r
S2 <- c("math", "algebra", "geometry", "calculus", "equations",
        "computation", "numbers", "addition")
T2 <- c("poetry", "art", "dance", "literature", "novel", "symphony",
        "drama", "sculpture")
A2 <- c("male", "man", "boy", "brother", "he", "him", "his", "son")
B2 <- c("female", "woman", "girl", "sister", "she", "her", "hers",
        "daughter")
sw <- query(w = glove_math,
            S_words = S2, T_words = T2,
            A_words = A2, B_words = B2)
sw
```

```
##

## -- sweater object ------------------------------------------------------------

## Test type:  weat
## Effect size:  1.055015

##

## -- Functions -----------------------------------------------------------------

## * `calculate_es()`: Calculate effect size

## * `weat_resampling()`: Conduct statistical test
```

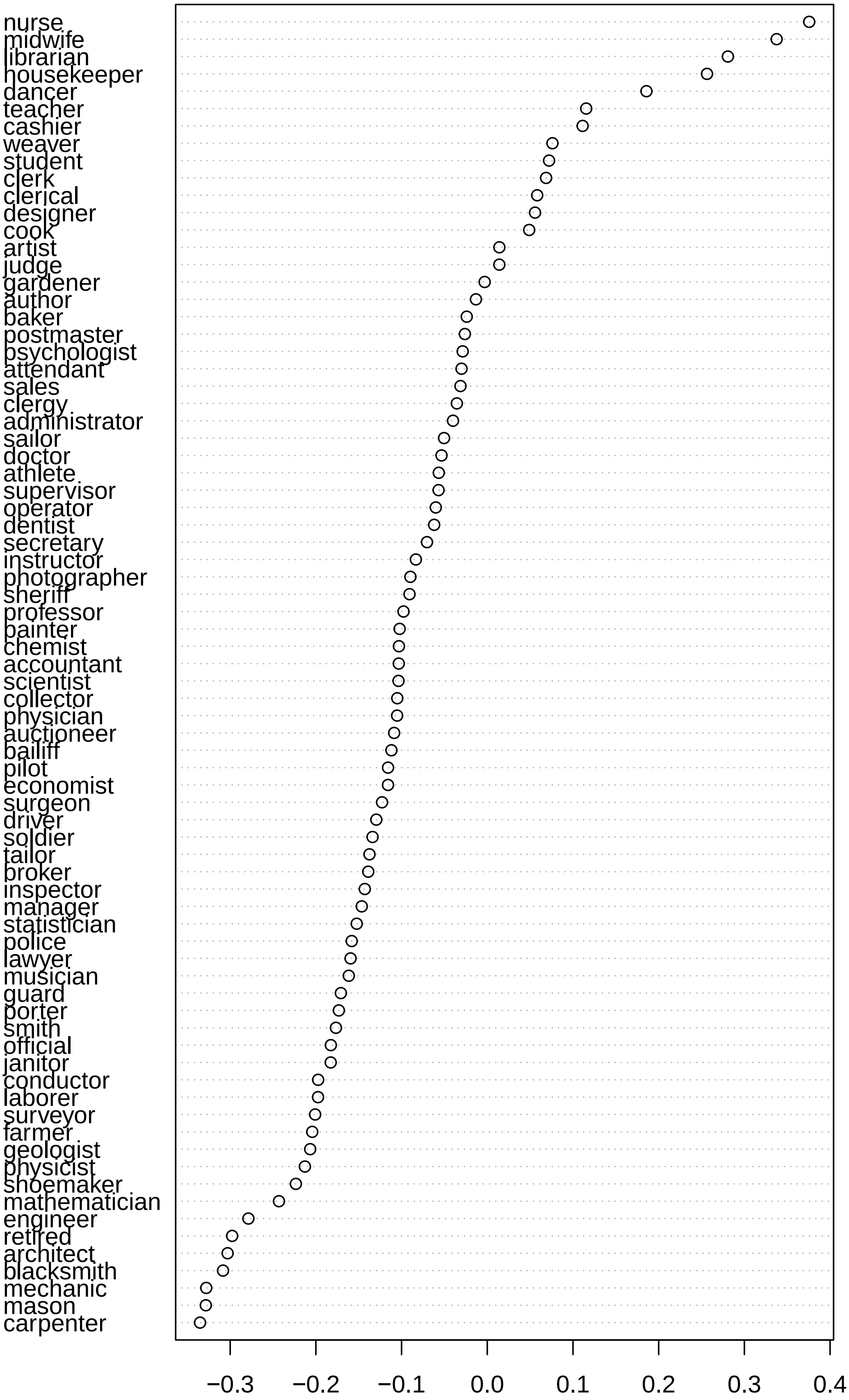

Figure 1: Bias of words in the target wordset according to relative norm distance

The statistical significance of the effect size can be evaluated using the function `weat_resampling`.

```
weat_resampling(sw)
```

```
##
##  Resampling approximation of the exact test in Caliskan et al. (2017)
##
## data:  sw
## bias = 0.024865, p-value = 0.0171
## alternative hypothesis: true bias is greater than 7.245425e-05
## sample estimates:
##       bias
## 0.02486533
```

Acknowledgements

The development of this package was supported by the Federal Ministry for Family Affairs, Senior Citizens, Women and Youth (*Bundesministerium für Familie, Senioren, Frauen und Jugend*), the Federal Republic of Germany – Research project: "*Erfahrungen von Alltagsrassismus und medienvermittelter Rassismus in der (politischen) Öffentlichkeit*".

References

An, J., Kwak, H., & Ahn, Y.-Y. (2018). Semaxis: A lightweight framework to characterize domain-specific word semantics beyond sentiment. *arXiv preprint arXiv:1806.05521*. doi:10.18653/v1/p18-1228

Antoniak, M., & Mimno, D. (2021). Bad seeds: Evaluating lexical methods for bias measurement. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)* (pp. 1889–1904). doi:10.18653/v1/2021.acl-long.148

Arendt, F. (2013). Dose-dependent media priming effects of stereotypic newspaper articles on implicit and explicit stereotypes. *Journal of Communication*, *63*(5), 830–851. doi:10.1111/jcom.12056

Badilla, P., Bravo-Marquez, F., & Pérez, J. (2020). WEFE: The word embeddings fairness evaluation framework. In *IJCAI* (pp. 430–436). doi:10.24963/ijcai.2020/60

Benoit, K., Watanabe, K., Wang, H., Nulty, P., Obeng, A., Müller, S., & Matsuo, A. (2018). Quanteda: An R package for the quantitative analysis of textual data. *Journal of Open Source Software*, *3*(30), 774. doi:10.21105/joss.00774

Boyarskaya, M., Olteanu, A., & Crawford, K. (2020). Overcoming Failures of Imagination in AI Infused System Development and Deployment. *arXiv preprint arXiv:2011.13416*.

Brunet, M.-E., Alkalay-Houlihan, C., Anderson, A., & Zemel, R. (2019). Understanding the origins of bias in word embeddings. In *International conference on machine learning* (pp. 803–811).

Caliskan, A., Bryson, J. J., & Narayanan, A. (2017). Semantics derived automatically from language corpora contain human-like biases. *Science*, *356*(6334), 183–186. doi:10.1126/science.aal4230

Collobert, R., Weston, J., Bottou, L., Karlen, M., Kavukcuoglu, K., & Kuksa, P. (2011). Natural language processing (almost) from scratch. *Journal of machine learning research*, *12*(ARTICLE), 2493–2537.

Dev, S., & Phillips, J. (2019). Attenuating bias in word vectors. In *The 22nd international conference on artificial intelligence and statistics* (pp. 879–887). PMLR.

Du, Y., Fang, Q., & Nguyen, D. (2021). Assessing the reliability of word embedding gender bias measures. *arXiv preprint arXiv:2109.04732*.

Eddelbuettel, D. (2013). Seamless R and C++ Integration with Rcpp. doi:10.1007/978-1-4614-6868-4

Garg, N., Schiebinger, L., Jurafsky, D., & Zou, J. (2018). Word embeddings quantify 100 years of gender and ethnic stereotypes. *Proceedings of the National Academy of Sciences*, *115*(16), E3635–E3644. doi:10.1073/pnas.1720347115

Jing, E., & Ahn, Y.-Y. (2021). Characterizing partisan political narrative frameworks about COVID-19 on Twitter. *EPJ data science*, *10*(1), 53. doi:10.1140/epjds/s13688-021-00308-4

Knoche, M., Popović, R., Lemmerich, F., & Strohmaier, M. (2019). Identifying biases in politically biased wikis through word embeddings. In *Proceedings of the 30th ACM conference on hypertext and social media* (pp. 253–257). doi:10.1145/3342220.3343658

Kroon, A. C., Trilling, D., & Raats, T. (2020). Guilty by association: Using word embeddings to measure ethnic stereotypes in news coverage. *Journalism & Mass Communication Quarterly*, 1077699020932304. doi:10.1177/1077699020932304

Manzini, T., Lim, Y. C., Tsvetkov, Y., & Black, A. W. (2019). Black is to criminal as caucasian is to police: Detecting and removing multiclass bias in word embeddings. *arXiv preprint arXiv:1904.04047*. doi:10.18653/v1/n19-1062

Mikolov, T., Sutskever, I., Chen, K., Corrado, G. S., & Dean, J. (2013). Distributed representations of words and phrases and their compositionality. In *Advances in neural information processing systems* (pp. 3111–3119).

Nosek, B. A., Greenwald, A. G., & Banaji, M. R. (2005). Understanding and Using the Implicit Association Test: II. Method Variables and Construct Validity. *Personality and Social Psychology Bulletin*, *31*(2), 166–180. doi:10.1177/0146167204271418

Packer, B., Mitchell, M., Guajardo-Céspedes, M., & Halpern, Y. (2018). Text embeddings contain bias. Here's why that matters. Retrieved from https://developers.googleblog.com/2018/04/text-embedding-models-contain-bias.html

Pennington, J., Socher, R., & Manning, C. (2014). Glove: Global vectors for word representation. *Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP)*. doi:10.3115/v1/d14-1162

R Core Team. (2021). *R: A language and environment for statistical computing*. Vienna, Austria: R Foundation for Statistical Computing. Retrieved from https://www.R-project.org/

Sales, A., Balby, L., & Veloso, A. (2019). Media bias characterization in brazilian presidential elections. In *Proceedings of the 30th acm conference on hypertext and social media* (pp. 231–240). doi:10.1145/3345645.3351107

Selivanov, D. (2020). *Rsparse: Statistical learning on sparse matrices*. Retrieved from https://CRAN.R-project.org/package=rsparse

Selivanov, D., Bickel, M., & Wang, Q. (2020). *Text2vec: Modern text mining framework for R*. Retrieved from https://CRAN.R-project.org/package=text2vec

Sweeney, C., & Najafian, M. (2020). Reducing sentiment polarity for demographic attributes in word embeddings using adversarial learning. In *Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency* (pp. 359–368). doi:10.1145/3351095.3372837

Wijffels, J. (2021). *Word2vec: Distributed representations of words*. Retrieved from https://CRAN.R-project.org/package=word2vec