Text: An R-package for Analyzing and Visualizing Human Language Using Natural Language Processing and Deep Learning

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Note. Kjell was funded by the Swedish Research Council (2019-06305); Schwartz was funded by a National Institutes of Health-NIAAA grant (R01 AA028032).

Draft version 1. 16th April 2021. This paper has not yet been peer reviewed.

Abstract

The language that individuals use for expressing themselves contains rich psychological information. Recent significant advances in Natural Language Processing (NLP) and Deep Learning (DL), namely *transformers,* have resulted in large performance gains in tasks related to understanding natural language such as machine translation. However, these state-of-the-art methods have not yet been made easily accessible for psychology researchers, nor designed to be optimal for human-level analyses. This tutorial introduces *text* (www.r-text.org), a new R-package for analyzing and visualizing human language using *transformers,* the latest techniques from NLP and DL. *Text* is both a *modular solution* for accessing state-of-the-art language models and an *end-to-end solution* catered for human-level analyses. Hence, *text* provides user-friendly functions tailored to test hypotheses in social sciences for both relatively small and large datasets. This tutorial describes useful methods for analyzing text, providing functions with reliable defaults that can be used off-the-shelf as well as providing a framework for the advanced users to build on for novel techniques and analysis pipelines. The reader learns about six methods: 1) *textEmbed*: to transform text to traditional or modern transformer-based word embeddings (i.e., numeric representations of words); 2) *textTrain*: to examine the relationships between text and numeric/categorical variables; 3) *textSimilarity* and 4) *textSimilarityTest*: to computing semantic similarity scores between texts and significance test the difference in meaning between two sets of texts; and 5) *textProjection* and 6) *textProjectionPlot*: to examine and visualize text within the embedding space according to latent or specified construct dimensions (e.g., low to high rating scale scores).

Introduction

How individuals express themselves and their state of mind with natural language constitutes a wealth of information for understanding them psychologically and socially (e.g., see Kern et al., 2016; Kjell et al., 2019). “Language is the most common and reliable way for people to translate their internal thoughts and emotions into a form that others can understand.” (Tausczik & Pennebaker, 2010, p. 25). However, for the last 90 years or so, researchers in behavioral sciences have been heavily dependent on individuals communicating their state of mind using closed-ended, forced choice answers and numerical rating scales to quantitatively understand subjective states (e.g., Flake et al., 2017; Likert, 1932).

On the other hand, researchers in AI have turned to open-vocabulary methods that rely on patterns in linguistic data to derive models of language. These methods leverage the idea that words may be represented by values based on how they co-occur in languages (e.g., Firth, 1957), and allow for modeling words according to the contexts in which they appear, rather than relying on a priori assumptions about word-category relations resulting in extremely powerful models of language. In fact, the latest version of such models, the deep learning-based *transformers,* have led to nothing short of a transformation in the AI field concerned with language: natural language processing. Researchers have called for the use of these language models to gain psychological insights (e.g., Eichstaedt et al., 2020).

There has never been a method or technology that has come out which has universally increased the accuracy of AI techniques for processing language in the way that transformers have done in the last three years. For example, the transformer-based model GPT-3, by OpenAI, is writing documents believed to be authored by humans (Brown et al., 2020); and BERT (Bidirectional Encoder Representations from Transformers; Devlin et al., 2019), the first widely used, general purpose transformer network developed by Google, has already been referenced in over 16,000 scholarly works in a period of only 2 years[1]. A popular developer of such models, the startup HuggingFace, recently secured $40 million.[2]

[1] Google Scholar accessed March 11, 2021

[2] https://techcrunch.com/2021/03/11/hugging-face-raises-40-million-for-its-natural-language-processing-library/

The key to transformers' success is that such models are able to understand words differently according to the context they are in. BERT was released by Google and has been integrated into its Search function; now it actually understands the difference between “travel from Sweden to New York” and “travel from New York to Sweden” (Nayak, 2019). This tutorial aims to make these methods easily available to a broad audience within social and behavioral sciences; as well as further developing and optimizing them for human-level analyses. These state-of-the-art word embeddings may be used to examine their relationships to (i.e., predict) numerical variables, compute semantic similarity to other texts, statistically test the difference in meaning between other texts, or visualize (statistically significant) words in various dimensions within the word embedding space.

Considering that language is a fundamental component of human life and societies, the types of data that can be used to gain new insights using language based computational methods are diverse. For this discussion, the type of data may broadly be categorized into three (overlapping) types: First, *naturally occurring language*, which, for example, include gaining insights from analyzing: recordings of spoken language in relation to emotional fluctuations throughout the day (Sun et al., 2020); social media text (Park et al., 2014) to predict both physical (Eichstaedt et al., 2015) and psychological (Eichstaedt et al., 2018) outcomes. Examining naturally occurring language may also include analyzing emails, letters, blogs, text messages, medical journals, speeches, diaries, song texts, voice recordings etc., though one must consider ethical and privacy issues when analyzing such text.

Second, *self-reported language* involves probing or asking participants to answer questions with spoken or written language. These types of data have, for example, been used to: measure and describe psychological constructs through self-reported language-based assessments as a complement to traditional rating scales (Kjell et al., 2019), and analyze written narratives of traumatic life events to predict health related outcomes (Campbell & Pennebaker, 2003; Son et al., 2020). Self-reported language may also involve asking participants to recall various memories, describe themselves in various ways, partake in stream-of-consciousness tasks and so on.

Third, *experimentally related language* refers to language used or generated within an experimental context. Computational language methods can, for example, be used to enhance experimental control by matching word stimuli according to semantic similarity (Dougal & Rotello, 2007; Gagné et al., 2005), examining the text generated from experimental manipulations (Garcia

& Sikström, 2013) and using semantic similarity of the names of objects to find significant correlations with neural organizations in the brain (Carlson et al., 2014). The multitude of applications of computational methods highlights its potential and flexibility as a research method.

This tutorial covers methods in an R-package called *Text* (www.r-text.org) to carry out the use of transformers for psychological research. *Text* is an open-source library comprising tools for analyzing and visualizing various features of texts; both in relation to other texts as well as numerical variables. The package makes state-of-the-art natural language processing (NLP), statistics, and machine learning (ML) techniques available to R users, with functions particularly targeting social scientific applications. To map words to numeric representations, *Text*-functions transform texts to word embeddings using transformer-based pre-trained language models.

Objectives and Aims

The Text-package incorporates two main objectives. First, to serve R-users as a *point solution* for transforming text to state-of-the-art word embeddings that are ready to be used for downstream tasks. The second objective is to serve as an *end-to-end solution* that provides state-of-the-art AI techniques tailored for social and behavioral scientists. Together, *Text* provides powerful and accessible functions for analyzing and visualizing text in relation to other text and numerical variables. *Text's* objective is to balance user-friendliness and flexibility whilst simultaneously empowering with advanced analyses. Accessibility is reflected in functions with reliable default settings selected by experts in the NLP fields so that those with no experience can use out of the box settings to test their research hypotheses. Further, visualizations aim to make it easy to understand what is going on in the analyses; for example, displaying actual word embeddings, plotting words, or viewing cross-validated predictive results.

Current Alternatives

There are few alternatives in R (R Core Team, 2020) that focus on getting state-of-the-art word embeddings; and that have functionalities tailored for analyzing embeddings in downstream tasks relevant for social sciences and psychological research. Computer scientists have predominantly used Python (Van Rossum & Drake Jr, 1995), and Python-libraries such as the Differential Language Analysis ToolKit (DLATK; Schwartz et al., 2017), PyTorch (Paszke et al., 2019), spaCy (Honnibal, & Montani, 2017), and NLTK (Bird, Klein, & Loper, 2009). Further, even though

computer scientists use Python for standard NLP/ML tasks, few python packages attempt to bridge this line of work with psychological research such as DLATK. *Text* comprises an interface with Python to get the state-of-the-art language models whilst also conceptually building on DLATK and drawing on experiences learned from that project (here also see the web-application Semantic Excel; Sikström et al., 2018).

There are some R-packages that allow for text mining (e.g., see tm [Feinerer & Hornik, 2019], tidytext [Silge & Robinson, 2016], and quanteda [Benoit et al., 2018]). To our knowledge, there is only one other R-package that enables the transformation of text to word embeddings (RBERT; an R implementation of BERT; Bratt & Harmon, 2020), however, it does not come with functions to use these word embeddings including ML techniques. Additionally, *Text* comprises functions tailored for small data as well as big data. Whereas other R-packages focus on text mining of big data, *Text* enables transformer-based embeddings as well as analyses of relatively small datasets (N ≈ 50), which is often common in social and behavioral sciences.

Installation of text

This tutorial assumes very basic knowledge of R (R Core Team, 2020); so, for a free, beginners' tutorial, see *R for Data Science* by Grolemund and Wickham (2018). The *Text*-package can be downloaded and installed running:

```
# Install text
install.packages("text")
```

Text uses an R-package called *reticulate* (Ushey et al., 2020) as an interface to Python (Van Rossum & Drake Jr, 1995) and the Python packages *torch* (Paszke et al., 2019), *transformers* (Wolf et al., 2019), nltk (Bird, Klein, & Loper, 2009) and numpy (Oliphant, 2006). Reticulate normally installs these necessary packages automatically, however, if you experience problems see the extended installation guide for up-to-date information (https://r-text.org/).

Transforming text to state-of-the-art word embeddings

NLP is a branch of AI concerned with automatically processing and making sense of digitized human language. The idea that each word in human languages may be represented by numeric vectors dates back at least to the 1950s (e.g., see Firth, 1957; Osgood et al., 1957). Despite its long history, the field of NLP has undergone a sort of revolution over the past three years, seeing substantial advances in the state-of-the-art over nearly every common task that NLP attempts to solve: syntactic parsing, sentiment analysis, question answers, machine translation all tied to a single method: *Transformers* (Devlin et al., 2019; Rogers et al., 2020; Vaswani et al., 2017). Transformer models comprise a network architecture, which are based on attention mechanisms (Vaswani et al., 2017). The attention mechanisms allow the model to attend to surrounding words of the input to varying degrees; hence each surrounding word influences the word embedding of the target word differently. The architecture of the Transformers also reduces computational steps as compared to previous contemporary models such as recurrent networks; and this decreased information loss and trained faster.

The *Text*-package implements these advances to enable the user to access many state-of-the-art pretrained language models. In this next part word embeddings are described in more detail, followed by a demonstration on how the *Text*-package transforms text data into word embeddings. These word embeddings are later used in down-stream tasks such as predicting psychology related outcomes (e.g., psychological rating scale scores), examining similarity in meaning between texts, and testing whether two sets of texts statistically differ in meaning. Hence, word embeddings may be seen as the backbone of most *Text*-functions.

Pre-Trained Word Embeddings

A word embedding is a list of values (an ordered *vector*) that numerically represents the meaning of a word. A word embedding normally comprises several hundred numbers; so that a word is represented by many dimensions. The numbers may be seen as coordinates in a geometric space that comprises several hundred dimensions (a high dimensional space). The closer positioned two words are in this space (i.e., the more similar their *vector* embeddings are), the more similar the words are in meaning. In other words, embeddings capture the relationships between words,

where proximity in the high dimensional embedding space signifies similarity in meaning. To represent several words, sentences and paragraphs, word embeddings may be aggregated. The aggregation can, for example, be through the mean, maximum or minimum of each dimension of the word embedding.

To train transformer-based word embeddings with high quality requires a lot of text data; where the approaches use the statistical patterns of *how* words are used. “You shall know a word by the company it keeps” (Firth, 1957, p. 11) is a core rationale underlying the creation of word embeddings. Words within natural language are *not* randomly distributed, instead contextual words are predictable and define its meaning (Iliev et al., 2014). Hence, it is possible to use this distribution to represent “the meaning of a word through the contexts in which it has been observed in a corpus” (Erk, 2012, p. 635). This is achieved by constructing a table of word co-occurrence counts, where dimensions are extracted using some kind of a factor analysis. Practically, the first column of the frequency table may hold the words in a natural language, the first row may hold word contexts (n-grams) and the rest of cells hold the co-occurrence counts/frequency. Ultimately, the words are represented by a vector containing a number for each extracted dimension. Note that these types of approaches are referred to as *unsupervised* as no predefined categories or judges are used to produce the word embeddings.

Decontextualized word embeddings: A bag of words

Decontextualized word embeddings do not account for the context a word was found in. Earlier methods were unable to capture the order that words appeared in; words in a text were treated as a bag of scrambled words. The word embedding is thus *static* (or decontextualized), so that the embedding for “happy” is always the same even if it was found in the context of “I am happy” versus “I am not happy”. Or “I travel from Sweden to New York” has the same meaning/aggregated word embedding as “I travel from New York to Sweden”. Examples of commonly used decontextualized approaches include Latent Semantic Analysis (LSA; Landauer & Dumais, 1997) and latent Dirichlet allocation (LDA; Blei et al., 2003).

Contextualized word embeddings and word order

Contemporary NLP algorithms aim to extract the latent meanings in grammatically sound text. These algorithms are based on deep learning to construct contextualized word embeddings, using decontextualized word embeddings as input (e.g., see BERT; Devlin et al., 2019). When using

these algorithms, a word's embedding is different depending on the context it was in and the order of the words in the context; so the word embedding for "happy" will be different depending on how it was used in the sentence. In short, they have the ability to incorporate the embeddings of other words' embeddings (a context embedding). In addition, they may also put different attention or weight to different word embeddings from the context depending on which appear to be most relevant. This gives the algorithms the ability to amplify the influence of the most relevant parts of a context. These descriptions are at a very high abstraction level; for more detailed information see, for example, Devlin et al. (2019) and Rogers et al. (2020).

Performance of BERT

Devlin et al. (2019) demonstrated that BERT obtains substantial improvement on a wide range of NLP tasks. For example, it achieved a 7.7% point absolute improvement on the language understanding tasks called GLUE (General Language Understanding Evaluation); and a 4.6% absolute improvement accuracy on the MultiNLI (the Multi-Genre Natural Language Inference corpus, which comprises several hundred thousands of sentence pairs).

Accessible Pretrained Language Models in Text

To get contextualized word embeddings for your text data, the *Text*-package connects with HuggingFace's *Transformers* library (Wolf et al., 2019) in Python. This enables the users to implement many state-of-the-art *pre-trained* language models, including XLnet (Yang et al., 2019), RoBERTa (Liu et al., 2019), and ALBERT (Lan et al., 2019). As the name suggests, a pre-trained model has already been trained on other data; so that the model can be applied to your text to retrieve high-quality embeddings. This is good considering that training a high-quality deep learning language model requires a lot of computational resources; Wolf et al. (2019) point out that RoBERTa was trained on 160 GB text, and that training this on a typical cloud computing service would cost around 100K USD. Consequently, some models have been developed with the focus of being smaller and requiring less computational resources to be trained (e.g., see DestilBERT; Sanh et al., 2019), whereas others have had the focus on achieving improved performance (e.g., XLNet; Yang et al., 2019).

Some models include multiple languages such as multilingual BERT (mBERT), which is trained on text from the top 104 languages with the largest Wikipedia entries. Hence, the same model includes several languages, where similar languages (e.g., Germanic, Slavic) are found close to each other in the embedding space (Libovický et al., 2019). mBERT is found to learn cross-lingual

word alignment with high-quality (Libovický et al., 2019). *Text* implements these multilingual models.

Model and Word Embedding Specifics

Different models may use different types of (domain) text, tokenization, number of layers and hidden states. It is useful to consider these aspects when selecting an appropriate model and its settings, although default settings in *Text* will often achieve apt results.

Type of domain text used in pre-training

Word embeddings become better when there is high domain similarity between the text used to create the language model and the text that should be interpreted/used for down-stream tasks. To create models for a narrow domain can however be challenging because pretrained models require large quantities of text data (and computational resources). Nevertheless, it is worth thinking about the type of text used to train the models, and how that might influence your results. BERT was originally trained using Wikipedia text; however, other BERT models have been (pre-trained or fine-tuned) trained on clinical text (Alsentzer et al., 2019) and scientific text data (Beltagy et al., 2019). Unfortunately, these models are not available through HuggingFace (yet).

Uncased versus Cased models

Uncased models convert all words to lowercase, whereas *cased* models keep the casing of the text. Select a *cased* model if you think that letter casing will be helpful for your analyses. If you do not think that casing will be important for your task, it is better to select an *uncased* model since it comprises fewer words (e.g., happy and Happy are not two different words); and thus, has had the chance to develop more high-quality embeddings.

Sequence length of the input

You can only impute a limited amount of text (tokens) to many language models at the time. For the BERT model the standard limit is 512 tokens at a time. This means that each word can be contextually influenced by a maximum of 511 tokens. If longer sequences of text are submitted to the *Text-package* function, the text will be split up in smaller chunks; and then the word embeddings may be aggregated to represent the entire text.

Tokens and Tokenizers

A token is a string of characters with a meaning; and a tokenizer is a function that splits up sentences and words to tokens. Tokenizers may differ across models. Each token gets its own

embedding. Common words are tokenized as themselves, whereas uncommon words that are not part of a pretrained model will be tokenized into smaller parts each having their own embedding. Punctuation characters (e.g., ".", "!" and "?") also tend to get tokenized as individual tokens. BERT also uses tokens to indicate delimiter to each input: [CLS] and [SEP]. The [CLS] token stands for *classification* and represents the sentence-level representation. The [SEP] token stands for *separating sentences*, and this tag is used in pre-training tasks of BERT that involves predicting the next sentence.

As an example, the sentence: "I'm feeling relatedness with others" is tokenized to "[CLS] I ' m feeling related ##ness with others [SEP]"; where "##" indicates that "ness" was originally attached to "related". "Relatedness" was tokenized this way because it was not present within (this version of) BERT. Instead, the two word embeddings for "related" and "ness" are aggregated to represent relatedness. Note, that the word embedding for the [CLS] represents the mean aggregated sentence level embedding.

The Layers and Hidden states

As a deep learning transformer model, BERT comprises several layers. *Hidden states* refer to the output of each layer; these may be aggregated across layers to a word embedding that represents each word (or sentence). Multiple layers enable the models to capture nonlinear relationships. BERT-base comprises 12 layers, whereas BERT-large comprises 24 layers; where each layer comprises numeric values for each dimension, which for BERT is 768 dimensions. Hence, with BERT-large one token can be represented with 18,432 (24 x 768) values. There are several ways to make use of these layers: including only using one of the layers, aggregating several of them, or concatenating them to one longer embedding.

It is not yet fully understood how the various layers differ; and the advice on how to best use them differs. In short, empirical examinations indicate that "BERT's intermediate layers encode a rich hierarchy of linguistic information, with surface features at the bottom, syntactic features in the middle and semantic features at the top." (Jawahar et al., 2019, p. 1). Further, it has been demonstrated that later BERT layers are more context-specific (Ethayarajh, 2019). For human level tasks, using the four last layers or the second to last layer tends to yield good results.

Limitations of transformers

Transformer models are very large. While researchers have developed ways to shrink, the best versions of these models are still scaling exponentially. That is, the size of the files defining the models that users need are increasing more rapidly than the performance gains. While BERT-base comprises 110M parameters and achieves a Spearman rho of .86 on a standard semantic similarity task, BERT-large is approximately three times that size comprising 336M and achieves only a modest improvement in the same task: rho = .87. With costs of storage and memory fairly inexpensive today, it may often be more ideal to use the larger models at the expense of needing better computing equipment, but this could exclude users with more limited computing resources. Further, it is very expensive to create your own model.

Functions: mapping text to numbers (i.e., word embeddings)

Text includes three functions to map text to word embeddings. The textEmbed() encompasses both *textEmbedLayersOutput()* and *textEmbedLayerAggreation()*, where the former retrieves layers and hidden states from the language model; and the latter aggregates these layers to form word embeddings. It is possible to get both contextualized and decontextualized embeddings for individual words (i.e., where only one word has been sent to the model).

textEmbed()

The textEmbed() function automatically transforms character variables in a given dataset (i.e., dataframe or tibble) to word embeddings. It is the main embedding function in *Text*; and can output contextualized embeddings for text as well as decontextualized embeddings for each individual word (which may be used for the plotting functions, as described later).

This tutorial uses example data that is accessible through the *Text*-package. It is a subset from a study (see Kjell et al., 2019) where participants have described their satisfaction with life and harmony in life (or lack thereof) with a text response, 10 descriptive words or rating scales including the Satisfaction with Life Scale (SWLS; Diener et al., 1985) and the Harmony in Life Scale (HILS; Kjell et al., 2016).

```
# Create a specific folder/directory where you can store and save files. Set your working directory in R by pasting in its path below and run the code.
```

```
setwd("past_a_path_to_your_work_directory_eg_user/desktop/r_tutorial/")

# Open the text package.
library(text)

# Look at example data included in the text package comprising both text and numerical variables (note that there are only 40 participants in this example)
Language_based_assessment_data_8

# Find help
help(textEmbed)

# Transform the text data to word embeddings (see help(textEmbed) to see the default settings).
wordembeddings <- textEmbed(Language_based_assessment_data_8)

# See how the word embeddings are structured
wordembeddings

# Save the word embeddings in the folder you set above. This is to avoid having to embed the text several times.
saveRDS(wordembeddings, "wordembeddings.rds")

# Get the saved word embeddings (again)
wordembeddings_saved <- readRDS("wordembeddings.rds")

```

Note that one of the output layers is referred to as layer 0, which is the original input embedding to BERT; and hence, it is not contextualized.

Examining the relationship between text and numeric variables

Statistics and machine learning may be used to examine whether there is a relationship between word embeddings and a numeric (or categorical variable). This is achieved by using the word embeddings within a statistical model such as multiple linear regression and evaluating the model with cross validation, as further described below.

Word Embeddings as Input to a Predictive Model

The word embeddings may be used in predictive models such as multiple linear regression:

$$y = \beta_0 + \beta_1 * x_1 + \ldots + \beta_m * x_m + \varepsilon$$

where,

- y denotes the observed values (in which $\hat{y}$represents the predicted value),
- $x_1 - x_m$ the predictors, i.e., the dimensions of the word embeddings (where the subscript refers to the mth dimension),
- β_0 the constant,
- $\beta_1 - \beta_m$ the coefficients that define the relationship between embeddings and the outcome, and
- ε the error term.

Considering that the word embeddings often comprise many dimensions, it is often useful to first carry out a dimension reduction technique. To achieve this, Principal Component Analysis (e.g., see Wold et al., 1987) is implemented in *Text* because we have noticed that it is particularly efficient for reducing the dimensionality of word embeddings. It is possible to select other statistical prediction models in *Text*, including ridge regression (Hoerl & Kennard, 1970) or lasso regression (Tibshirani, 1996); and for categorical variables logistic regression or random forest (e.g., see Ho, 1995). To evaluate the predictions made by the statistical model, it is possible to correlate the predicted values with the observed values (i.e., cor[y, $\hat{y}$]) using cross-validation.

Cross Validation

Cross validation is a technique that may be used to evaluate and select a statistical model with minimal overfit (for a more detailed discussion on cross validation in psychology, e.g., see Mosier, 1951; Yarkoni & Westfall, 2017). Overfitting arises when data-specific errors or noise are modelled, which results in a model that is bad at generalizing to other data. The cross-validation methods aim to limit this risk by estimating a model's predictive ability while simultaneously accounting for its ability to generalize (e.g., see Browne, 2000). The simplest form of a cross validation method randomly divides a dataset into a *training-set* and a *testing-set*. The parameters, i.e., the $\beta_1 - \beta_m$ in the specified regression above, are estimated in the training-set; and then applied to the test-set to predict values ($\hat{y}$) that can be compared with the observed values (y). Using this method results in an *out-of-sample performance*, where the trained model is applied on new data from the same population.

K-fold Cross Validation

K-fold cross validation is a procedure to divide the training and testing sets efficiently. If data is scarce, it may be considered wasteful to not use all data, e.g., to only use 50% of the data for training and 50% only for testing. First, it is possible to run the procedure again by alternating the purpose of the datasets, so that the original testing-set becomes the training-set, and the original training-set becomes the testing-set: In this way all data will have predictions that can be correlated with the observed values. Second, in order to make better parameter estimations it is possible to get more power in the statistical models by making sure that the training set is larger. One common way is to select 90% of the data to the training set and 10% for the testing; and then alter the purpose of the data as previously described. This is done ten times, so that all cases get a prediction. Hence, k in k-fold refers to the number of groups (or folds); so the described procedure is called 10-fold cross validation. It is also possible to train on all but one case (which is called *leave-one-out* cross validation). Leave-one-out cross validation is good for very small dataset, whereas for larger dataset it requires a lot of computational power and time (for rather small gains).

Cross Validation with Test, Train and Development Sets

To fit models with hyperparameters (e.g., the penalty in ridge regression), a development set (also called assessment set) can be used to evaluate on. Figure 1 shows how the training set in the outside fold is split into a training (or analysis) set and development (assessment) set. Hence, the training set is used to fit models with different penalties; these are then assessed in the development set. The model with the best result (e.g., evaluated using the correlations between observed and predicted scores) is subsequently applied in the test set of the outside fold. This procedure is repeated for all folds.

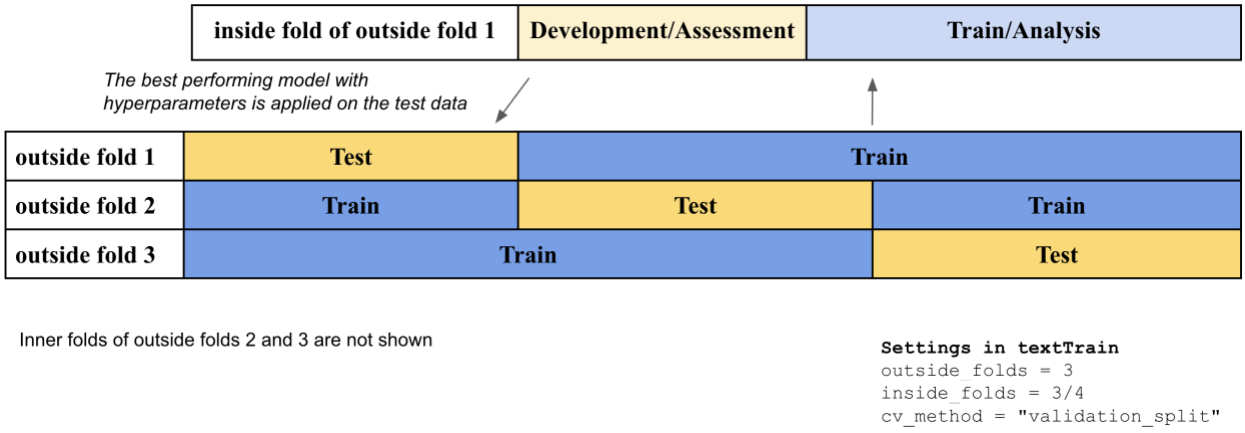


Figure 1. Cross Validation with 3 Outside Folds; and ¾ Analysis and ¼ Development Set

Nested K-Fold Cross Validation

To use nested cross validation, including train and test loops in the inner fold of each outside fold, is also a way to make better use of the data (see Figure 2). The above cross validation method with test, train and development sets focuses on achieving more accurate estimates of the machine learning approach, which is good when comparing machine learning algorithms. The nested k-fold cross validation focuses on achieving a more accurate model; but tends to take longer time because more models need to be fitted and evaluated.

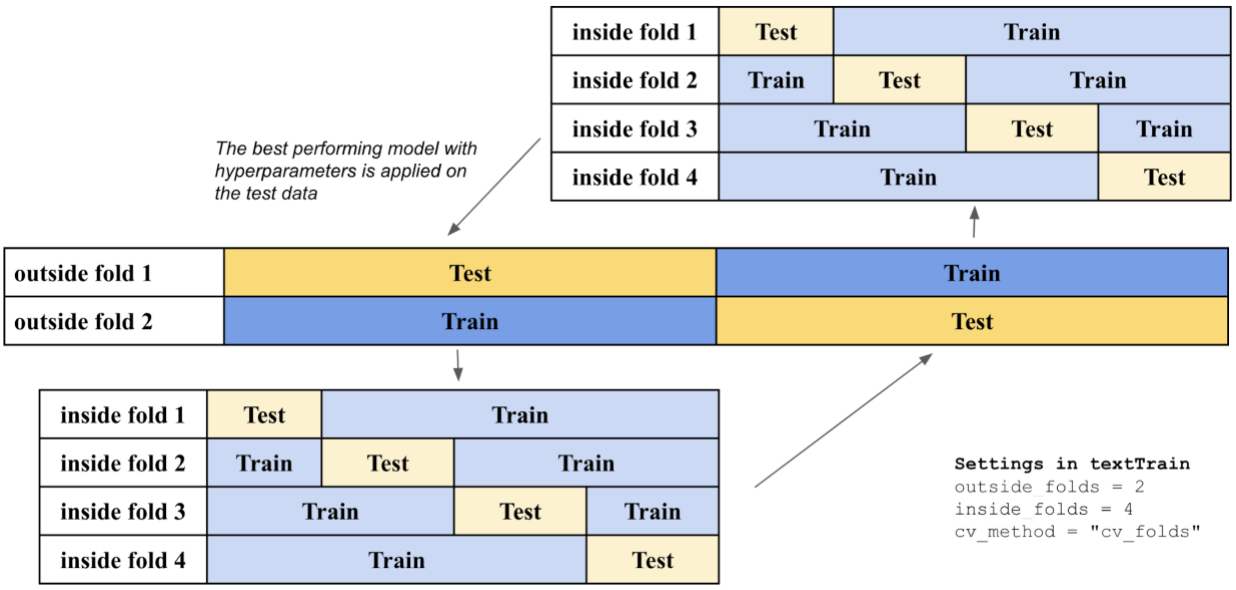


Figure 2. Example of Nested Cross Validation with 2 Outside Folds and 4 Inside Folds
Note that prioritizing more outside than inside folds makes often more sense.

Applying Predictive Models to New Data

Language-based predictive models can be applied to new data. Independently trained language models may be applied to new data to examine semantic-psychological features such as valence or arousal. It is also easy to share predictive models between projects and researchers. For example, the *Text*-package has predictive models for valence and arousal, which is based on the Affective norms for English Words (ANEW; Bradley & Lang, 1999). The ANEW is a list of more than 1000 words that have been rated according to valence, dominance and arousal by

participants. The valence model was created by predicting valence from the word embeddings of the words in the list. First the model was evaluated using cross validation to see how good it is; and then it was saved without using cross validation to use all the data. This model can now be used to predict any word or set of text represented by a word embedding based on the same language model (and settings) originally used to create the word embeddings in the predictive model. Hence, it is a flexible method considering that it is possible to get predictions for words that were not in the original model/words list, since the estimated parameters are applied to the dimensions of the word embeddings.

Functions

textTrain()

The textTrain() function is used to examine how well the word embeddings from a text can predict a numeric or categorical variable. In the example below we examine how well the satisfaction text-responses can predict the rating scale scores from the Satisfaction with life scale. We advise researchers to share their predictive models, for example, on their open science framework account (www.osf.com) or GitHub. For this purpose, it is possible to attach a description of the data and model by describing it in the describe_model setting. For example, use the following format:

> model_description = “author(s): XXX; data: N = XXX, population = XXX; publication: title = XXX; description: e.g., measure details etc.”

```
library(text)

# Examine the relationship between satisfactiontext and the corresponding rating scale

model_satisfactiontext_swls <- textTrain(
  wordembeddings$satisfactiontexts,
  Language_based_assessment_data_8$swlstotal,
  model_description = "author(s): Kjell, Giorgi, & Schwartz; data: N=40, population = Online, Mechanical Turk; publication: title = Example for demo; description: swls = the satisfaction with life scale")

#Examine the correlation between predicted and observed Harmony in life scale scores
model_satisfactiontext_swls$results
```

```
#OUTPUT:
       Pearson's product-moment correlation

data:  predy_y$predictions and predy_y$y
t = 4.4924, df = 38, p-value = 3.195e-05
alternative hypothesis: true correlation is greater than 0
95 percent confidence interval:
 0.3847836 1.0000000
sample estimates:
      cor
0.5889617
```

textTrainLists()

The textTrainLists() runs through several text variables (i.e., lists of word embeddings) and/or numeric variables at the same time.

```
# Predicting several outcomes from several word embeddings
models_words_ratings <- textTrainLists(wordembeddings[1:2],
Language_based_assessment_data_8[5:6])

# See results
models_words_ratings$results


#Output:
```

descriptions <chr>	correlation <chr>	df <chr>	p_value <chr>	t_statistics <chr>	alternative <chr>	P_value_corrected <dbl>
Harmonywords_hilstotal	0.612	38	1.38e-05	4.76	greater	2.77e-05
Satisfactionwords_hilstotal	0.723	38	6.50e-08	6.47	greater	1.95e-07
Harmonywords_swlstotal	0.333	38	.018	2.18	greater	1.77-02
satisfactionwords_swlstotal	0.741	38	2.28e-08	6.80	greater	9.13e-08

```

## textPredict() features of text based on trained models from textTrain()

Trained models created by textTrain() can be applied to new datasets. In the next example we download and apply a model that has been trained to predict valence. This model was based on a list of nearly 14,000 words that were rated on valence, arousal and dominance (Warriner et al., 2013). To achieve the prediction we use the textPredict() function.

```
```
library(text)
library(tidyverse)
library(psych)
library(elasticnet)

# Download and read a valence trained prediction model
# To download the model, go to the following address in a web browser: https://r-text.org/text_models/valence_Warriner_L11_12.rds
# Save the model to your working directory and load it:
valence_Warriner_L11_12 <- read_rds("valence_Warriner_L11_12.rds")

# Examine the model
valence_Warriner_L11_12

# PART OF THE OUTPUT
       Pearson's product-moment correlation

data:  predy_y$predictions and predy_y$y
t = 130.17, df = 13913, p-value < 2.2e-16
alternative hypothesis: true correlation is greater than 0
95 percent confidence interval:
 0.7346788 1.0000000
sample estimates:
      cor
0.7410316

# END OF THE OUTPUT


# Apply the model to the satisfaction text
```

```
satisfaction_text_valence <- textPredict(valence_Warriner_L11_12,
wordembeddings$satisfactiontexts)

# Examine the correlation between the predicted valence and the Harmony in life scale
score
psych::corr.test(satisfaction_text_valence$.pred,
Language_based_assessment_data_8$swlstotal)


# OUTPUT
Call:psych::corr.test(x = satisfaction_text_valence$.pred, y =
Language_based_assessment_data_8$swlstotal)
Correlation matrix
[1] 0.63
Sample Size
[1] 40
Probability values adjusted for multiple tests.
[1] 0
```

Examining the Relationship Between Two Words/Texts with Semantic Similarities

Word embeddings may be used to measure how similar two words/texts are in meaning. The values composing a word embedding may be seen as coordinates in a high dimensional space; and the more similar two embedding vectors are the closer they are positioned in the space. One way to capture how closely positioned two vectors are, is to measure the cosine of the angle between them (see a simplified illustration in Figure 3). Similar to a correlation, the cosine can range from -1 to 1 (see Wickens, 2014, for a discussion on how correlation and cosine are mathematically related); but in the embedding space the cosine between two words is typically not much below 0. The smaller the angle, the higher the cosine is; and thus, the more similar are the embeddings.

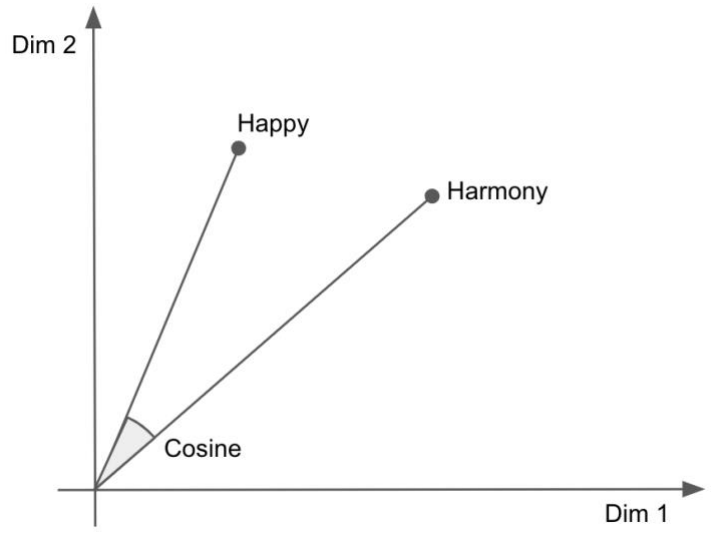


Figure 3. Illustration of the semantic similarity of two words in a simplified 2-dimensional embedding space (note that this also holds when adding many more dimensions).

The cosine may be seen as an effect size; however, it should be noted that its absolute value is not comparable between different models and model specification setups. For example, Ethayarajh (2019) demonstrates that word embeddings have different distributions in different BERT layers, so that two random words on average tend to have higher cosine similarity in higher as opposed to lower layers. Thus, comparing two cosine based semantic similarity scores between two different models or layers is not interpretable; instead examine the relative difference in scores from the same model/layer(s).

Functions

textSimilarity()

The textSimilarity() function computes the semantic similarity between two text variables, and the textSimilarityNorm() computes the semantic similarity between one text variable and a word norm. Semantic similarity scores can be used to measure psychological constructs independent from rating scales by using word norms that represent the to-be-measured construct (Kjell et al., 2019). A word norm can be created by asking participants to describe a psychological construct. The word norm can be used to measure the semantic similarity between a person's answer to whether

they experience harmony in their life to the word norm describing harmony in life: If the score is high the person is seen to have high harmony in life. Below this analysis is described.

```
library(text)
library(psych)

# Compute semantic similarity scores between two text columns
semantic_similarity_scores <- textSimilarity(wordembeddings$harmonytexts,
                                             wordembeddings$satisfactiontexts)
# Look at the first scores
head(semantic_similarity_scores)

# OUTPUT
# [1] 0.9227832 0.9143049 0.8953063 0.8512952 0.9411532 0.8952788
# END OF OUTPUT

# Download the word norms text from https://r-
text.org/text_models/Word_Norms_Mental_Health_Kjell2018_text.csv
# Add them to your working directory (later we will use these for the semantic
centrality plot
word_norms <- read_csv("Word_Norms_Mental_Health_Kjell2018_text.csv")


# Download word embeddings for word norms at the r-text website:
# https://r-
text.org/text_models/Word_Norms_Mental_Health_Kjell2018_text_embedding_L11_12.rds
# Save the embeddings to your working directory and load them
word_norms_embeddings <-
readRDS("Word_Norms_Mental_Health_Kjell2018_text_embedding_L11_12.rds")

# Examine which word norms there are
names(word_norms_embeddings)

# OUTPUT
[1] "harmonynorm"         "disharmonynorm"      "satisfactionnorm"
[4] "dissatisfactionnorm" "worrynorm"           "depressionnorm"
[7] "notatallworried"     "notatalldepressed"   "singlewords_we"
# END OF OUTPUT
```

```
# Compute semantic similarity score between the harmony answers and the harmony norm
# Note that the descriptive word answers are used instead of text answers to
correspond with
# how the word norm was created.
norm_similarity_scores_harmony <- textSimilarityNorm(wordembeddings$harmonywords,
                                                     word_norms_embeddings$harmonynorm)

# Correlating the semantic measure with the corresponding rating scale
psych::corr.test(norm_similarity_scores_harmony,
Language_based_assessment_data_8$hilstotal)

# OUTPUT
Call:psych::corr.test(x = norm_similarity_scores_harmony, y =
Language_based_assessment_data_8$hilstotal)
Correlation matrix
[1] 0.6
Sample Size
[1] 40
Probability values adjusted for multiple tests.
[1] 0

```

Testing the difference between two sets of texts with the textSimilarityTest()

The *textSimilarityTest()* compares whether the average meaning of two groups of words or texts significantly differ in meaning, using a permutation test approach. The test compares the cosine similarity (or distance) between two groups, with a *permuted null distribution* that is created by randomly swapping the data between the two groups. The *p*-value is computed as the fraction of the values from the permuted null distribution that are at least as extreme as the observed cosine similarity statistic (i.e., from the non-permuted data). Importantly, the more permutations that are carried out, the more precise will the *p*-value be. The textSimilarityTest() procedure for *paired* data is slightly different from the *unpaired* test procedure as described in detail below.

Paired textSimilarityTest()

The *Paired textSimilarityTest()* examines whether there is a significant difference in meaning between two groups of texts in a within-subject design. It is achieved in three steps. First, the *Observed mean cosine statistic* is computed (see Table 1). This is achieved by calculating the mean of the absolute cosine values between paired responses (e.g., the cosine between HIL responses and SWL responses for all participants, and then take the mean of all participants):

> Observed mean cosine statistic = mean(|cos(Awe_{hil1}, Awe_{swl1})|, |cos(Awe_{hil2}, Awe_{swl2})|, …), where Awe is the aggregated word embedding from each of the responses; and "| |" means taking the absolute value.

Table 1.

Overview of the Text Difference Test based on Paired Permutations

	Response HIL		**Response SWL**		**Cosine similarity between HIL and SWL**	**Mean**
p1	we_{hil1} we_{hil2} Awe_{hil} ...		p1	we_{swl1} we_{swl2} Awe_{swl} ...	z_{p1} = |cos(Awe_{hil}, Awe_{swl})|	
p2	we_{hil1} we_{hil2} Awe_{hil} ...		p2	we_{swl1} we_{swl2} Awe_{swl} ...	z_{p2} = |cos(Awe_{hil}, Awe_{swl})|	*Observed cosine statistic (z_{all})= Mean(z_{p1}, z_{p2}, z_{p3})*
p3	we_{hil1} we_{hil2} Awe_{hil} ...		p3	we_{swl1} we_{swl2} Awe_{swl} ...	z_{p3} = |cos(Awe_{hil}, Awe_{swl})|	

Note. HIL = Harmony in life responses; SWL = Satisfaction with life response, p = Participant, we = word embedding, Awe = Aggregated word embedding; z = cosine similarity score.

Second, the permuted null distribution is created. Pairs of responses are created by randomly sampling from the HIL and SWL responses and then computing the cosine. As in step 1, the mean is computed. This procedure is repeated N (e.g., 10 000) times.

> Null distribution of permuted cosine statistic =

mean(|cos($Awe_{random1}$, $Awe_{random1}$)|, |cos($Awe_{random2}$, $Awe_{random2}$)|, …) repeated N times, where random pairs are drawn from both sets.

Third, the observed cosine statistic (from step 1) is compared to the Null distribution of permuted cosine statistics (from step 2), to get the *p*-value. A two tailed test:

2 * min(sum(Permuted_values < Observed_value), sum(Permuted_values > Observed_value)) / N(Permuted_values).

Unpaired textSimilarityTest()

The *Unpaired textSimilarityTest()* examines whether there is a significant difference in meaning between two groups of texts in a between-subject design (e.g., between individuals taking part in an intervention versus those not taking part in an intervention). It is achieved in similar steps as described for the paired test, with the difference that the word embeddings are all aggregated for the entire group (not on an individual, participant level). First, the Observed cosine statistic is computed (see Table 2):

cos($MAwe_{intervention.hil,}$ $MAwe_{non\text{-}intervention.hil}$), where $MAwe_{intervention.hil}$ is the mean aggregated word embedding from all participants categorised as extravert, and $MAwe_{non\text{-}intervention.hil}$ is the mean aggregated word embedding from all participants categorised as introverts.

Table 2.

Overview of the Text Difference Test based on Unpaired Permutations

	HIL response by intervention				HIL response by no-intervention			Cosine Similarity
p1	we_{hil11} we_{hil12} ...	$Awe_{intervention.hil}$		p4	we_{hil11} we_{hil12} ...	$Awe_{no\text{-}intervention.hil}$		
p2	we_{hil11} we_{hil12} ...	$Awe_{intervention.hil}$		p5	we_{hil11} we_{hil12} ...	$Awe_{no\text{-}intervention.hil}$		
p3	we_{hil11} we_{hil12} ...	$Awe_{intervention.hil}$	Mean of Awe_{hil} $X_{intervention.hil}$	p6	we_{hil11} we_{hil12} ...	$Awe_{no\text{-}intervention.hill}$	Mean of Awe_{hil} $X_{non\text{-}intervention,hil}$	*Observed cosine statistic* (z_{all}) = $cos(X_{intervention.hil,}$ $X_{no\text{-}intervention.hil})$

Notes. HIL = Harmony in life responses; p = Participant, we = word embedding, Awe = Aggregated word embedding; z = cosine similarity score.

Second, the permuted null distribution is created:

> $cos(X_{randoml,hil,}$ $X_{randoml,hil})$, where $X_{randoml,hil}$ is the aggregated word embedding from embeddings randomly drawn from the intervention and non-intervention sample. The procedure is repeated N times.

Third, the statistics from Step 1 and 2 are compared using the formula provided in the paired test above.

Functions

textSimilarityTest()

The textSimilarityTest() function examines whether word embeddings of two groups of texts statistically differ in meaning. Below we compare the meaning between individuals' harmony in life and satisfaction with life answers using a paired test.

```
# Test the semantic difference between the satisfaction with life texts and the
harmony in life text.
s_test <- textSimilarityTest(wordembeddings$satisfactiontexts,
                             wordembeddings$harmonytexts,
                             method = "paired",
                             Npermutations = 100)

s_test

# OUTPUT
$p.value
[1] 0.00990099
```

Words' Position in the Embedding Space

A well-crafted, thoughtful visualization can facilitate deeper understanding, lead to new insights, and leave a long-lasting impression. There are many different ways to visualize the words in a data set. There are two types of plot functions in *Text*: The Supervised Dimension Projection Plot shows words that are significantly related to one as compared to another group, where the test statistics are tested in permutation test procedures. The Semantic Centrality Plot shows the words that are most semantically central to a set of texts/words. Both functions plot the words' position based on their word embeddings.

The Supervised Dimension Projection

The Supervised Dimension Projection compares two groups (e.g., intervention versus non-intervention participant answers), responses to different questions (e.g., harmony versus satisfaction responses), or low versus high scorers on a rating scale using median split or lower/higher quartiles. In short, we construct an embedding that captures the difference between the two groups and forms a line through origo (the aggregated direction embedding); then all individual words are "projected" onto that direction line (where dot product is computed to "project" a vector onto another vector; see Figure 4 for a visualization). More precisely, the plot is based on the following steps:

Preprocessing

1. Responses are divided into two groups (G1 and G2; where a scale variable is split according to mean or lower and higher quartile).

2. The aggregated word embeddings of the two groups are computed: *The G1 split aggregation embedding* and *the G2 split aggregation embedding*.

Supervised Dimension Projection Statistics

3. An *Aggregated direction embedding* is computed:
   Aggregated direction embeddings =
   G2 split aggregation embedding - G1 split aggregation embedding
4.
   So, for example, the direction of harmony = Group(high harmony) - Group(low harmony); where the direction is seen to go through origo and the aggregated direction embedding.

5. All individual word embeddings are positioned (or anchored) to the same point. So, for each word:
   Anchored embedding = original embedding - aggregation embedding of G1 and G2

6. To project onto the *Aggregated direction embeddings* (i.e., from step 3.), the dot product is computed between the *Anchored embedding* of all individual words (i.e., from step 4) and the *Aggregated direction embeddings* (i.e., step 3). That is, dot product(Anchored we , Aggregated direction we) = a point on the direction.

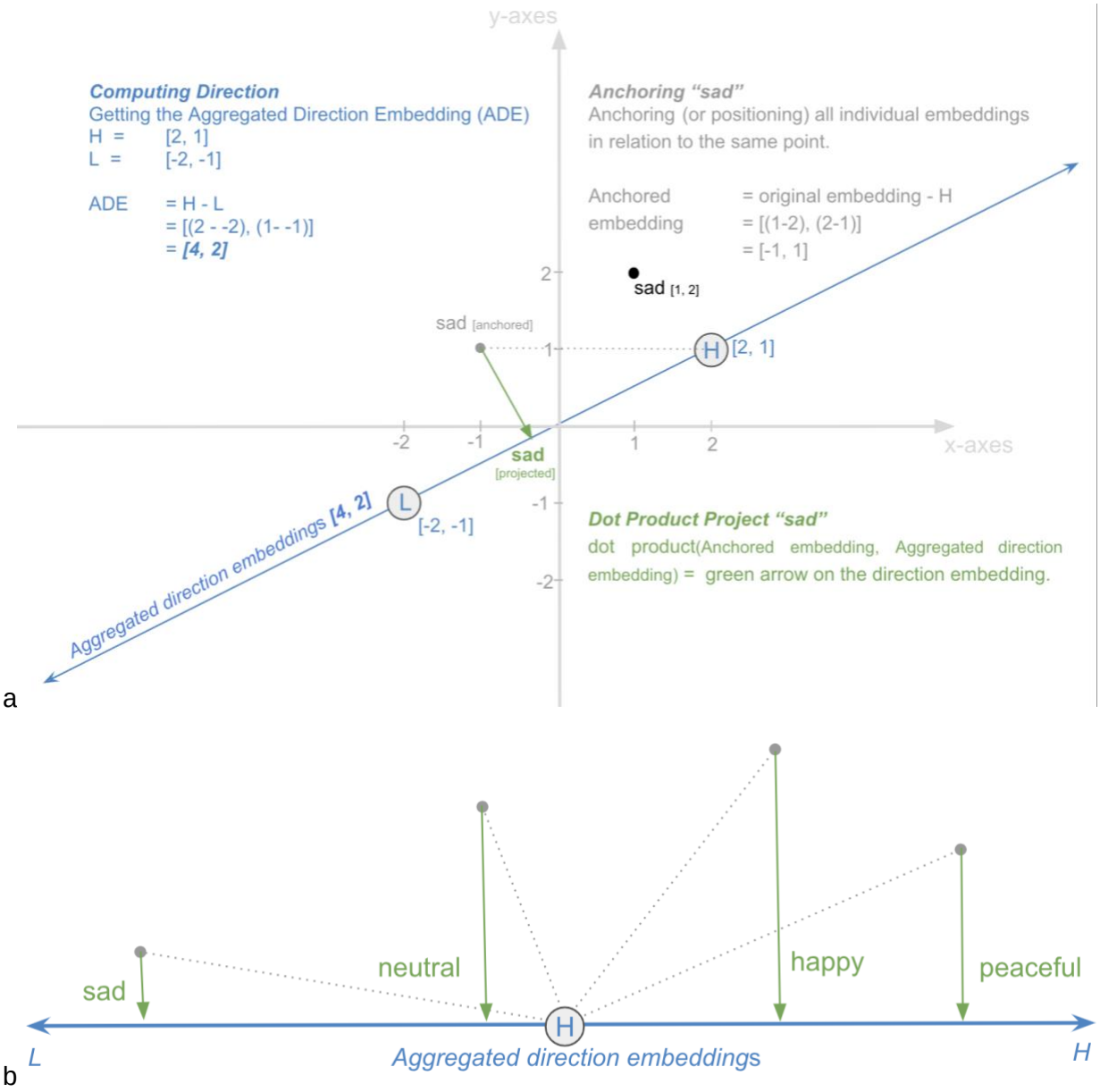


Figure 4ab. Illustrations of the Supervised Dimension Projection Method The illustration exemplifies the reduction of two dimensions to one dimension, where in practice there are many more dimensions.

Computing *p*-values with a permutation procedure

7. A permuted null distribution of Supervised Dimension Projections is created by computing the dot product between randomly selected word embeddings from G1 and G2, and a Permuted aggregated direction embedding (i.e., the direction embedding is also created by randomly swapping words from G1 and G2).

8. *P*-values for each word are computed by comparing their Supervised Dimension Projection with the permuted null distribution of Supervised Dimension Projections from step 6, as in previous descriptions; whilst correcting for multiple comparisons.

Functions

The plotting is made with two functions, in two steps: First, *textProjection()* analyses the data, including Supervised Dimension Projections, null distributions, p-values, and frequencies. Second, textProjectionPlot() uses the output from *textProjection()* to plot the words, including providing design options for the figure. Dividing the plotting into these two steps makes the process more transparent (since the user naturally sees the output that the words will be plotted according to) as well as being more flexible by enabling the user to try out different visual settings without the need to rerun the heavy computational processes.

textProjection()

```
```

```
library(tidyverse)
library(text)
# Merge satisfaction and harmony words to one column
worddata_merged <- c(Language_based_assessment_data_8$satisfactionwords,
                     Language_based_assessment_data_8$harmonywords)

# Create variable indicating whether it is a satisfaction or harmony word response
satwor1_harwor2                                  <-                                  c(rep(1,
length(Language_based_assessment_data_8$satisfactionwords)),
                     rep(2, length(Language_based_assessment_data_8$harmonywords)))

# Replicating the SWLS score so that it has equal length as the merged words and
satwor1_harwor2
swls_scores <- c(Language_based_assessment_data_8$swlstotal,
                 Language_based_assessment_data_8$swlstotal)

# Merge satisfaction and harmony embeddings
embedding_merged <- bind_cols(wordembeddings$satisfactionwords,
                              wordembeddings$harmonywords)
```

```
# Pre-processing data for plotting
projection_results <- textProjection(worddata_merged,
                                     embedding_merged,
                                     wordembeddings$singlewords_we,
                                     satwor1_harwor2,
                                     swls_scores
)
projection_results
 # PART OF OUTPUT
```

words	dot.x	p_values_dot.x	n_g1.x	n_g2.x
<chr>	<dbl>	<dbl>	<dbl>	<dbl>
accepted	-0.681	.144	-1	*NA*
accepting	0.140	.886	*NA*	2
accomplished	-2.04	.0001	-2	*NA*
achievement	-0.176	.614	-1	*NA*
active	-0.905	.0875	-1	*NA*
adequate	-0.161	.642	-1	*NA*

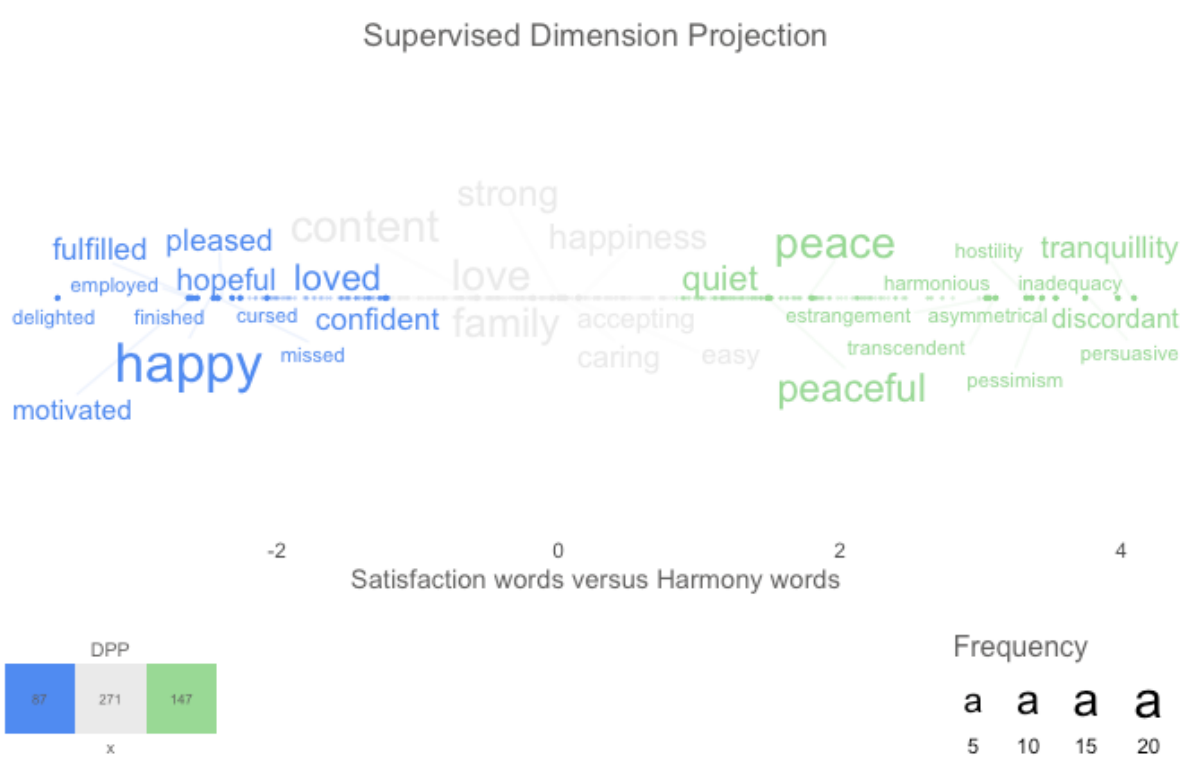
```
#PART OF OUTPUT:
```

textProjectionPlot()

```
# Supervised Dimension Projection Plot
plot_projection <- textProjectionPlot(
  word_data = projection_results,
  min_freq_words_plot = 1,
  plot_n_word_extreme = 10,
  plot_n_word_frequency = 5,
  plot_n_words_middle = 5,
  y_axes = FALSE,
  p_alpha = 0.05,
  p_adjust_method = "fdr",
  title_top = "Supervised Dimension Projection",
  x_axes_label = "Satisfaction words versus Harmony words",
  y_axes_label = "",
```

```
  bivariate_color_codes = c("#60A1F7", "#5dc688", "#40DD52",
                            "#398CF9", "#EAEAEA", "#85DB8E",
                            "#e07f6a", "#FF0000", "#EA7467")
)
# View plot
plot_projection$final_plot

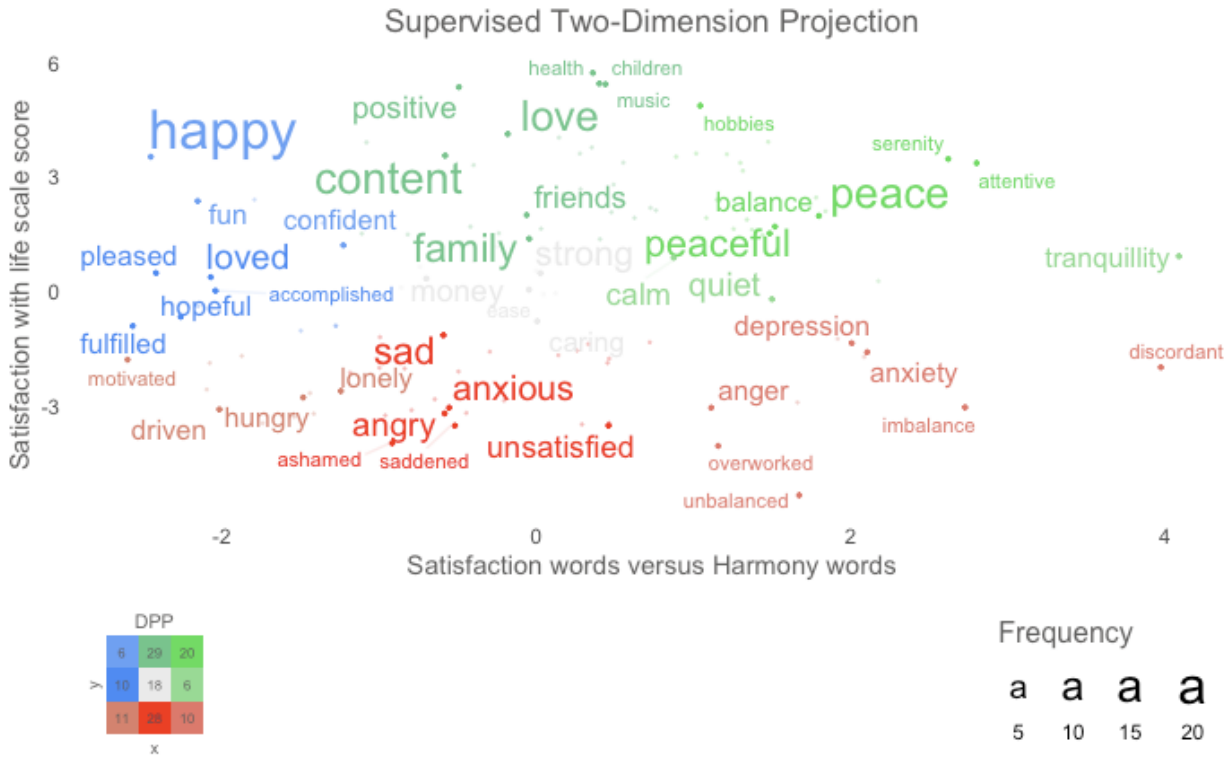
```




```

# Supervised Dimension Projection Plot
plot_projection_2D <- textProjectionPlot(
  word_data = projection_results,
  min_freq_words_plot = 2,
  plot_n_words_p = 5,
  plot_n_word_extreme = 5,
  plot_n_word_frequency = 5,
  plot_n_words_middle = 5,
  y_axes = TRUE,
  p_alpha = 0.05,
  p_adjust_method = "fdr",
  title_top = "Supervised Two-Dimension Projection",
```

```
  x_axes_label = "Satisfaction words versus Harmony words",
  y_axes_label = "Satisfaction with life scale score",
  bivariate_color_codes = c("#60A1F7", "#5dc688", "#40DD52",
                            "#398CF9", "#EAEAEA", "#85DB8E",
                            "#e07f6a", "#FF0000", "#EA7467")
)
# View plot
plot_projection_2D$final_plot
```

```


```

Words' Semantic Centrality

The Semantic Centrality Plot aims to highlight words that are semantically similar to the aggregated word embeddings of all words in the given text variable. Hence, it describes the psychological construct or latent meaning of a text under investigation in the word embedding space. The aim is to highlight words from one type of response, rather than comparing two groups/dimensions. The statistics are computed with the textCentrality() functions. This is achieved in the following steps:

1. Computing the *Aggregated word embedding* (Awe) based on all words.

2. Computing the observed semantic similarity scores between individual word's embeddings (Iwe) and the aggregated word embedding (Awe).

   cos(Iwe, Awe)) = semantic similarity score

Using the textCentralityPlot() it is possible to select the most extreme semantic centrality scores, middle scores as well as selecting words based on their frequency.

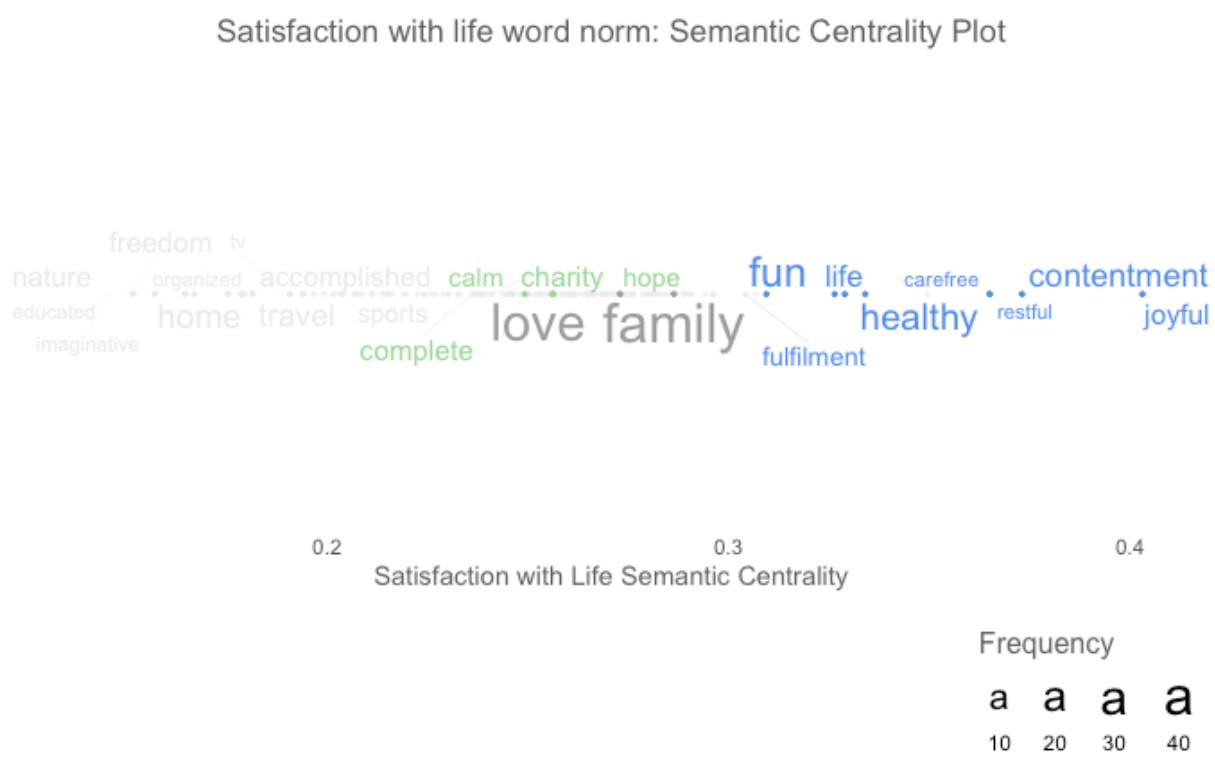
Functions

```
# Computing words' centrality (semantic similarity) score to the aggregated embedding of all words
centrality_results <- textCentrality(words = word_norms$satisfactionnorm,
                                     wordembeddings = word_norms_embeddings$satisfactionnorm,
                                     word_norms_embeddings$singlewords_we)

centrality_plot <- textCentralityPlot(word_data=centrality_results,
                                      min_freq_words_test = 2,
                                      plot_n_word_extreme = 10,
                                      plot_n_word_frequency = 5,
                                      plot_n_words_middle = 5,
                                      title_top = "Satisfaction with life word norm: Semantic Centrality Plot",
                                      x_axes_label = "Satisfaction with Life Semantic Centrality")

centrality_plot$final_plot

# OUTPUT
```



Summary

The *Text* package has two main aims: First, to work as a modular solution for transforming text to state-of-the-art word embeddings for R-users. Second, to work as an end-to-end solution focusing on relevant functions for social sciences and human-level analyses. It is our hope that the *Text* package can increase the ability of psychological scientists to analyze, with state-of-the-art computational techniques, one of the fundamental and key behaviors of people: natural language.

R-packages

R-packages used in text include:

dplyr (Wickham et al., 2020), tokenizers (Mullen et al., 2018), psych (Revelle, 2019), tibble (& Wickham, 2020), stringr (Wickham, 2019), tidyr (Wickham & Henry, 2020), ggplot2 (Wickham, 2016), ggrepel (Slowikowski, 2020), cowplot (Wilke, 2019), scales (Wickham & Seidel, 2020), rlang (Henry & Wickham, 2020b), purrr (Henry & Wickham, 2020a), Matrix (Bates & Maechler, 2019), stringi (Gagolewski, 2020), data.table (Dowle & Srinivasan, 2019), magrittr (Bache & Wickham, 2014), parsnip (Kuhn & Vaughan, 2020a), recipes (Kuhn & Wickham, 2020), reticulate

(Ushey et al., 2020), rsample (Kuhn et al., 2020), tune (Kuhn, 2020), workflows (Vaughan, 2020), yardstick (Kuhn & Vaughan, 2020b), quanteda (Benoit et al., 2018), broom (Robinson & Hayes, 2020), knitr (Xie, 2014), rmarkdown (Xie et al., 2018), testthat (Wickham, 2011), and rio (Chan et al., 2018).

Python libraries

Python packages integrated within the *text*-package include: PyTorch (Paszke et al., 2019), transformers (Wolf et al., 2019), nltk (Bird, Klein, & Loper, 2009) and numpy (Oliphant, 2006).

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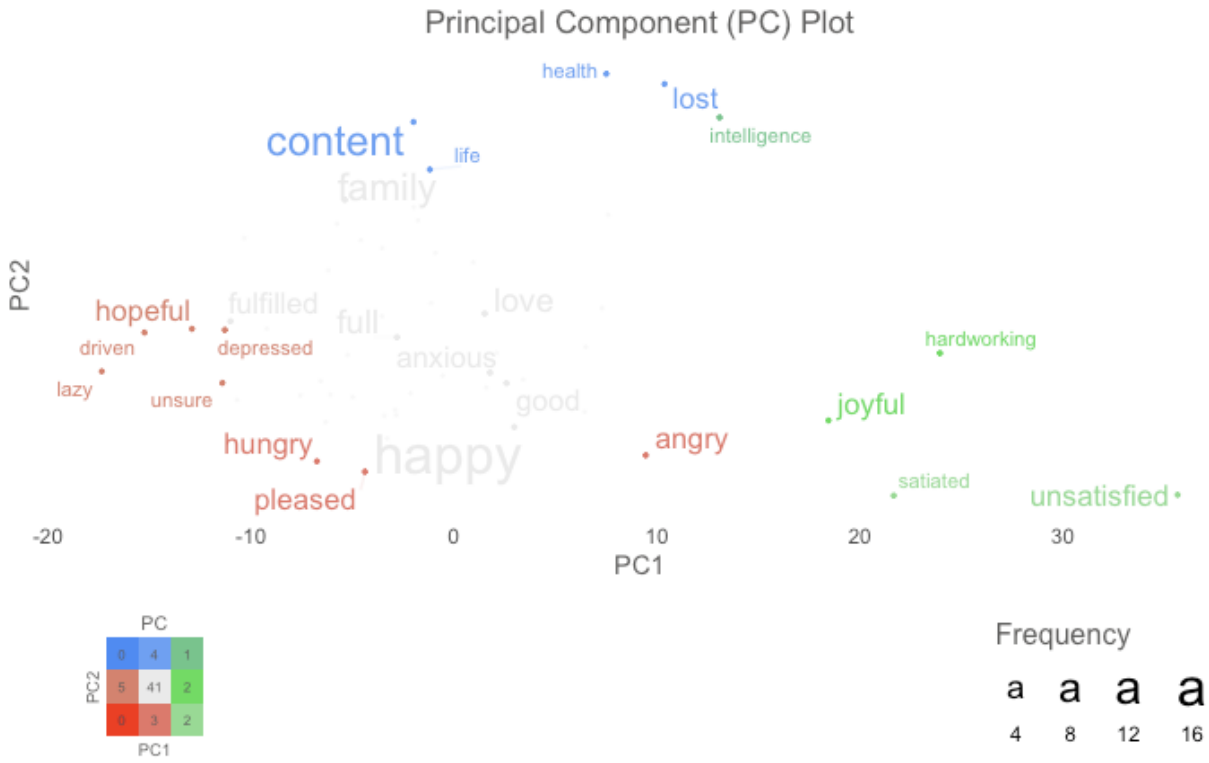
Supplementary Material

PCA plot

To create a (traditional) two-dimensional Principal Component Analyses plot, it is possible to use textPCA and textPCAPlot.

```
# PCA results to be plotted
textPCA_results <- textPCA(words = Language_based_assessment_data_8$satisfactionwords,
                           single_wordembeddings = wordembeddings$singlewords_we)


# Plotting the PCA results
plot_PCA <- textPCAPlot(
  word_data = textPCA_results,
  min_freq_words_test = 2,
  plot_n_word_extreme = 5,
  plot_n_word_frequency = 5,
  plot_n_words_middle = 5
)
plot_PCA$final_plot
```


Principal Component (PC) Plot
health
lost
intelligence
content
life
family
PC2
hopeful
fulfilled
full
love
driven
depressed
anxious
hardworking
lazy
unsure
good
joyful
hungry
happy
angry
satiated
pleased
unsatisfied
-20
-10
0
10
20
30
PC1
PC
PC2
0
4
1
5
41
2
0
3
2
PC1
Frequency
a
a
a
a
4
8
12
16