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Tutorials

Automated content analysis with R und Automatisierte Inhaltsanalyse mit Rv

Lda and Learning R

Quanteda Tutorials

Teaching Materials for Computational Social Science

Text Analysis in R; see related github Account

Text mining for humanists and social scientists in R

Text Mining with R; Text mining with R: a tidy approach

Tidytext tutorials

Tutorials by Julia Silge

University of California: Computational Social Science

R Packages for text analysis

Caret: Misc functions for training and plotting classification and regression models.

Corpus: Text corpus data analysis, with full support for international text (Unicode). Functions for reading data from newline-delimited 'JSON' files, for normalizing and tokenizing text, for searching for term occurrences, and for computing term occurrence frequencies, including n-grams.

keyATM: Fits keyword assisted topic models (keyATM) using collapsed Gibbs samplers. The keyATM combines the latent dirichlet allocation (LDA) models with a small number of keywords selected by researchers in order to improve the interpretability and topic classification of the LDA. The keyATM can also incorporate covariates and directly model time trends.

KoRpus: A set of tools to analyze texts. Includes, amongst others, functions for automatic language detection, hyphenation, several indices of lexical diversity (e.g., type token ratio, HD-D/vocd-D, MTLD) and readability (e.g., Flesch, SMOG, LIX, Dale-Chall). Basic import functions for language corpora are also provided, to enable frequency analyses (supports Celex and Leipzig Corpora Collection file formats) and measures like tf-idf.

Newsmap: Semi-supervised model for geographical document classification (Watanabe 2018). This package currently contains seed dictionaries in English, German, French, Spanish, Japanese, Russian and Chinese (Simplified and Traditional).

oolong: Intended to create standard human-in-the-loop validity tests for typical automated content analysis such as topic modeling and dictionary-based methods.

perspective: The 'Perspective' API uses machine learning models to score the perceived impact a comment might have on a conversation (i.e. TOXICITY, INFLAMMATORY, etc.). 'peRspective' provides access to the API and returns tidy data frames with results of the specified machine learning model(s).

Quanteda: A fast, flexible, and comprehensive framework for quantitative text analysis in R. Provides functionality for corpus management, creating and manipulating tokens and ngrams, exploring keywords in context, forming and manipulating sparse matrices of documents by features and feature co-occurrences, analyzing keywords, computing feature similarities and distances, applying content dictionaries, applying supervised and unsupervised machine learning, visually representing text and text analyses, and more.

Readtext: Functions for importing and handling text files and formatted text files with additional meta-data, such including '.csv', '.tab', '.json', '.xml', '.html', '.pdf', '.doc', '.docx', '.rtf', '.xls', '.xlsx', and others.

Rainette: An R implementation of the Reinert text clustering method.

Rnewsflow: A collection of tools for measuring the similarity of text messages and tracing the flow of messages over time and across media.

rsyntax: Various functions for querying and reshaping dependency trees, as for instance created with the 'spacyr' or 'udpipe' packages. This enables the automatic extraction of useful semantic relations from texts, such as quotes (who said what) and clauses (who did what).

Sentimentr: Calculate text polarity sentiment at the sentence level and optionally aggregate by rows or grouping variable(s).

Spacyr: An R wrapper to the 'Python' 'spaCy' 'NLP' library.

Stm: The Structural Topic Model (STM) allows researchers to estimate topic models with document-level covariates. The package also includes tools for model selection, visualization, and estimation of topic-covariate regressions.

Stringr: A consistent, simple and easy to use set of wrappers around the fantastic 'stringi' package. All function and argument names (and positions) are consistent, all functions deal with "NA"'s and zero length vectors in the same way, and the output from one function is easy to feed into the input of another.

Textdata: Provides a framework to download, parse, and store text datasets on the disk and load them when needed. Includes various sentiment lexicons and labeled text data sets for classification and analysis.

Tidytext: Text mining for word processing and sentiment analysis using 'dplyr', 'ggplot2', and other tidy tools. Also: Tidymodels: The tidymodels framework is a collection of packages for modeling and machine learning using tidyverse principles.

Tm: A framework for text mining applications within R.

Topicmodels: Provides an interface to the C code for Latent Dirichlet Allocation (LDA) models and Correlated Topics Models (CTM) by David M. Blei and co-authors and the C++ code for fitting LDA models using Gibbs sampling by Xuan-Hieu Phan and co-authors.

Tosca: A framework for statistical analysis in content analysis. In addition to a pipeline for preprocessing text corpora and linking to the latent Dirichlet allocation from the 'lda' package, plots are offered for the descriptive analysis of text corpora and topic models. In addition, an implementation of Chang's intruder words and intruder topics is provided.

Vader: A lexicon and rule-based sentiment analysis tool that is specifically attuned to sentiments expressed in social media, and works well on texts from other domains