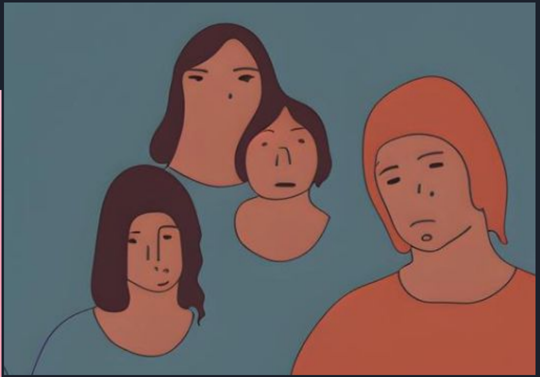
NLP as a tool for Mental Health Classification.

By Eric J. Chan, IOD, 1st May 2023.

Warning: this presentation contains language which may be considered as offensive.

The topic of AI empowered mental health diagnosis is an active area of research.

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REVIEW ARTICLE OPEN

Check for updates

Natural language processing applied to mental illness detection: a narrative review

Tianlin Zhang[1], Annika M. Schoene[1], Shaoxiong Ji[2] and Sophia Ananiadou[1,3]✉

Mental illness is highly prevalent nowadays, constituting a major cause of distress in people's life with impact on society's health and well-being. Mental illness is a complex multi-factorial disease associated with individual risk factors and a variety of socioeconomic, clinical associations. In order to capture these complex associations expressed in a wide variety of textual data, including social media posts, interviews, and clinical notes, natural language processing (NLP) methods demonstrate promising improvements to empower proactive mental healthcare and assist early diagnosis. We provide a narrative review of mental illness detection using NLP in the past decade, to understand methods, trends, challenges and future directions. A total of 399 studies from 10,467 records were included. The review reveals that there is an upward trend in mental illness detection NLP research. Deep learning methods receive more attention and perform better than traditional machine learning methods. We also provide some recommendations for future studies, including the development of novel detection methods, deep learning paradigms and interpretable models.

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Beyond LDA: Exploring Supervised Topic Modeling for Depression-Related Language in Twitter

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Abstract

Topic models can yield insight into how depressed and non-depressed individuals use language differently. In this paper, we explore the use of supervised topic models in the analysis of linguistic signal for detecting depression, providing promising results using several models.

use, which could potentially provide inexpensive early detection of individuals who might require a specialist's evaluation, on the basis of their naturally occurring linguistic behavior, e.g. (Neuman et al., 2012; De Choudhury et al., 2013; Coppersmith et al., 2014). Critical mass for a community of interest on these topics has been building within the computational linguistics research community (Resnik et al., 2014).

Kaggle Dataset: Mental Health Corpus

REIHANEH NAMDARI · UPDATED 4 MONTHS AGO

42 New Notebook Download (5 MB)

Mental Health Corpus

Labeled sentences about depression and axiety

27977 entries
14138 IS NOT depressed
13837 IS depressed

Data Card Code (11) Discussion (3)

About Dataset

The Mental Health Corpus is a collection of texts related to people with anxiety, depression, and other mental health issues. The corpus consists of two columns: one containing the comments, and the other containing labels indicating whether the comments are considered poisonous or not. The corpus can be used for a variety of purposes, such as sentiment analysis, toxic language detection, and mental health language analysis. The data in the corpus may be useful for researchers, mental health professionals, and others interested in understanding the language and sentiment surrounding mental health issues.

Usability
10.00

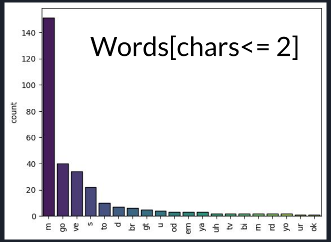
License
Attribution 4.0 International (CC ...

Expected update frequency
Never

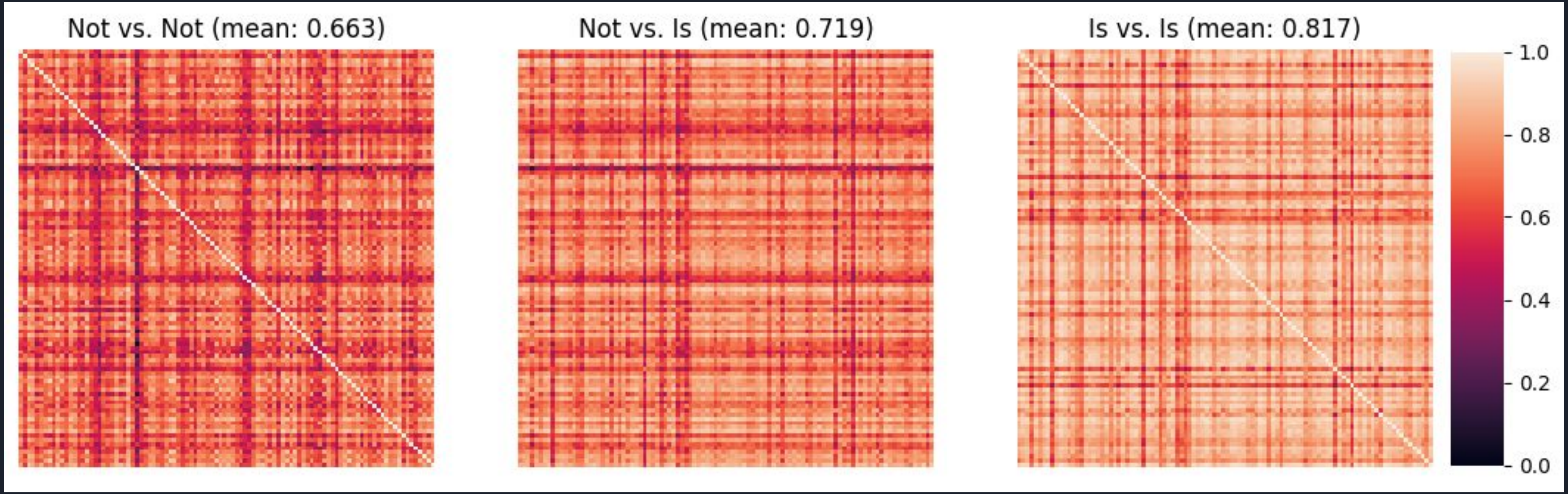
Documents as rows are text as comments related to people with mental health issues.
Target variable labels are (IS NOT depression: 0) and (IS depression: 1).

Project stages.

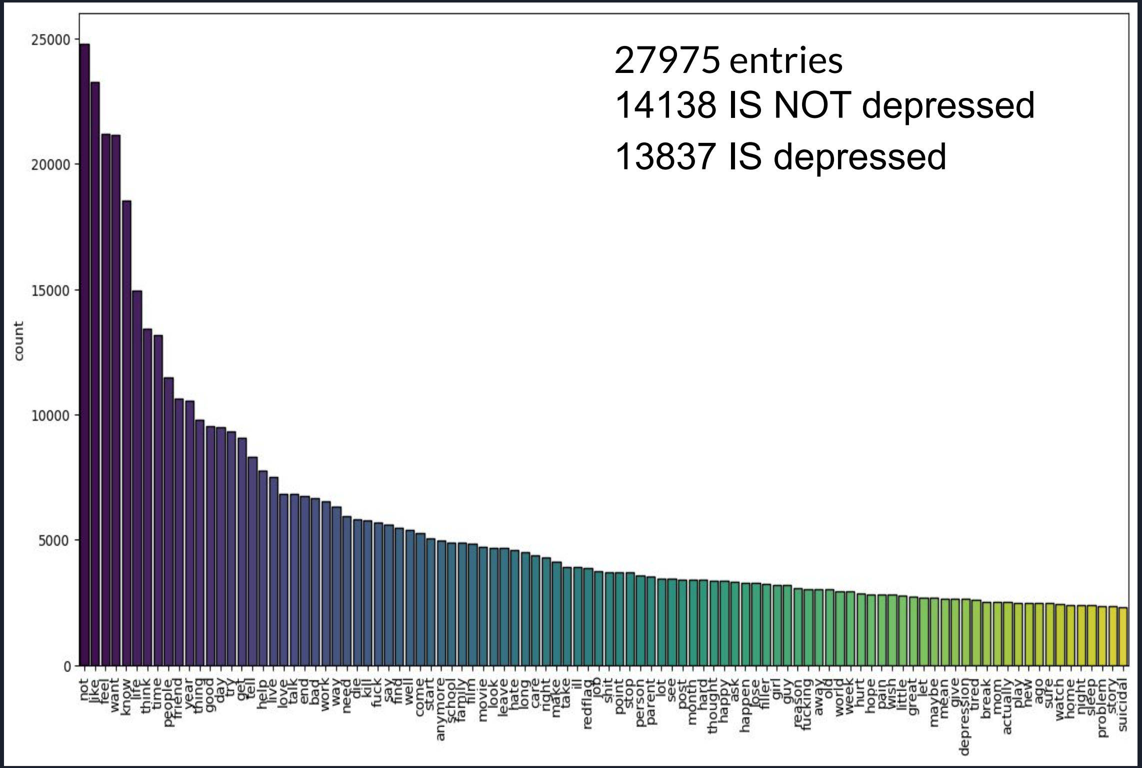
- ➔ Data cleansing
  - Perform tokenization, remove stop words, null entries, punctuation, lemmatization.
  - After some preliminary EDA we decided to remove words with <=2 chars.
- ➔ Initial EDA
  - Full dataset, Split datasets (0 or 1)
  - bar plots, word clouds, cosine similarity matrix
- ➔ Feature engineering
  - Count vectorisation
  - TF-IDF vectorisation
  - Glove (SPACY)
  - LDA(Count vectors, TF-IDF vectors, GENSIM Variational-Bayes)
- ➔ Topic EDA
  - bar plots, word clouds,
  - Cluster-maps, heatmaps
- ➔ Binary Classifier Modelling and Results:
  - Naïve Bayes
  - Logistic Regression
  - Support Vector Machine
  - SGD-Huber

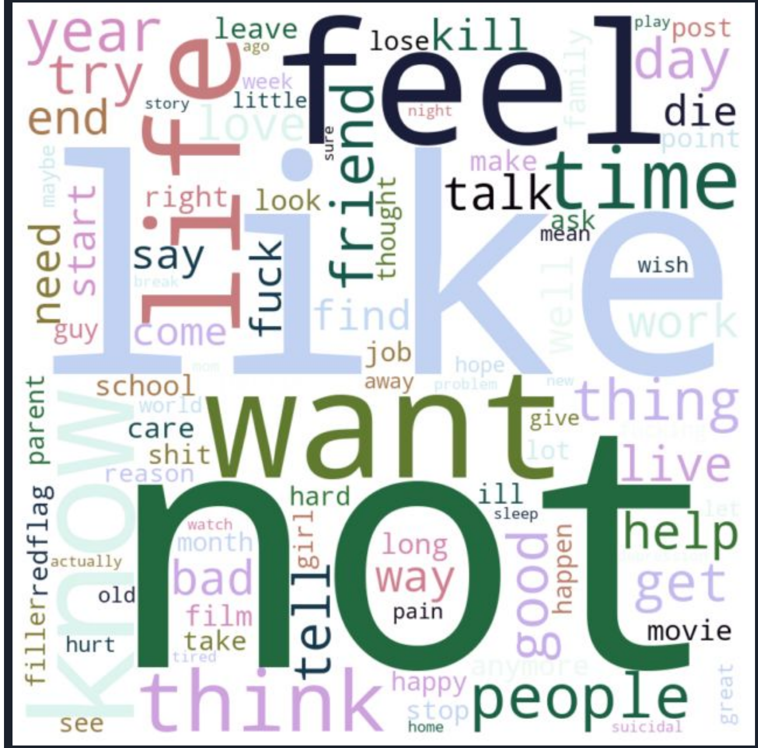


EDA: Cosine Similarity Matrices (100x100 Glove vectors)



EDA: Count plot and word cloud for corpus.





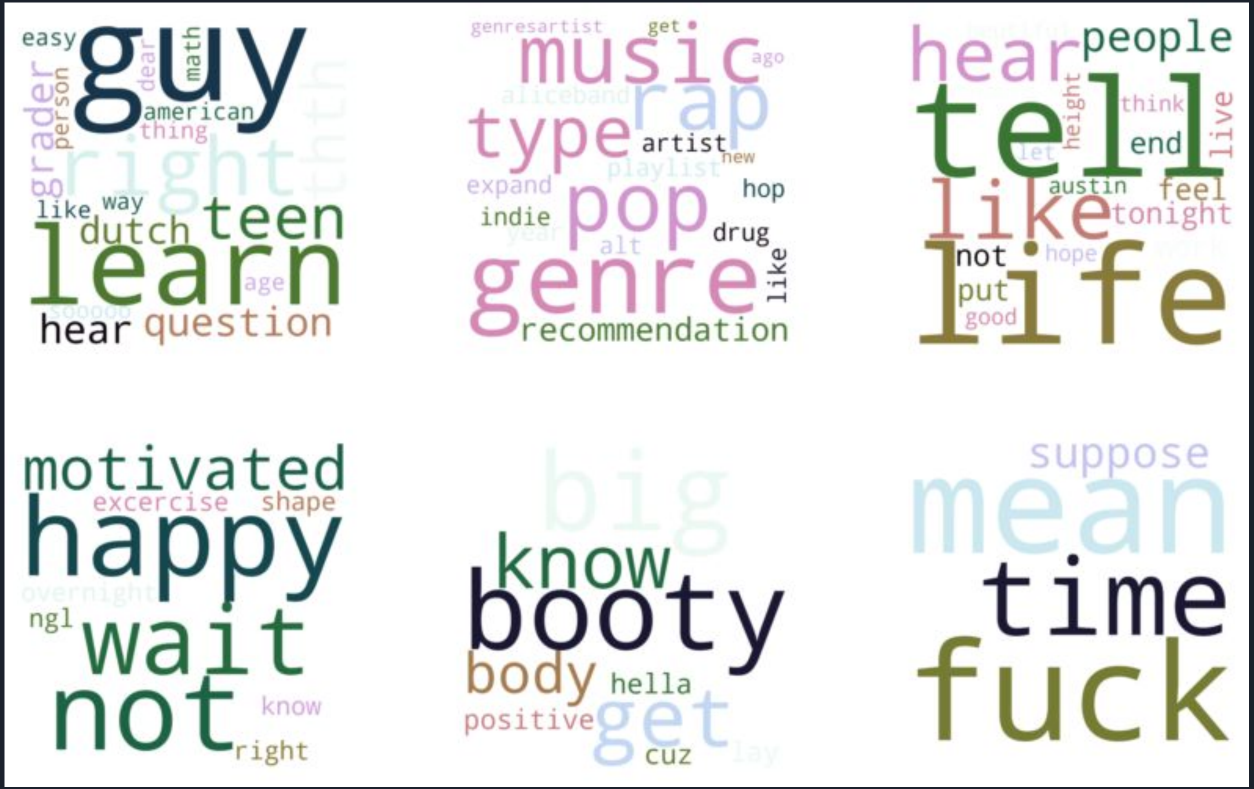
EDA: Word Cloud on individual entries

EDA: Word Clouds for separated datasets.

Is NOT depression

Is depression

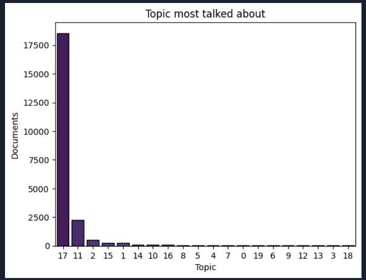
EDA: Word Cloud on individual entries for “Healthy” is not depressed.



EDA: Word Cloud on individual entries for “toxic” is depressed.

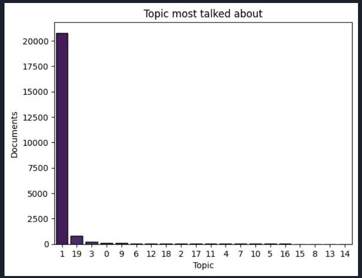
LDA (count vectors) entire corpus.

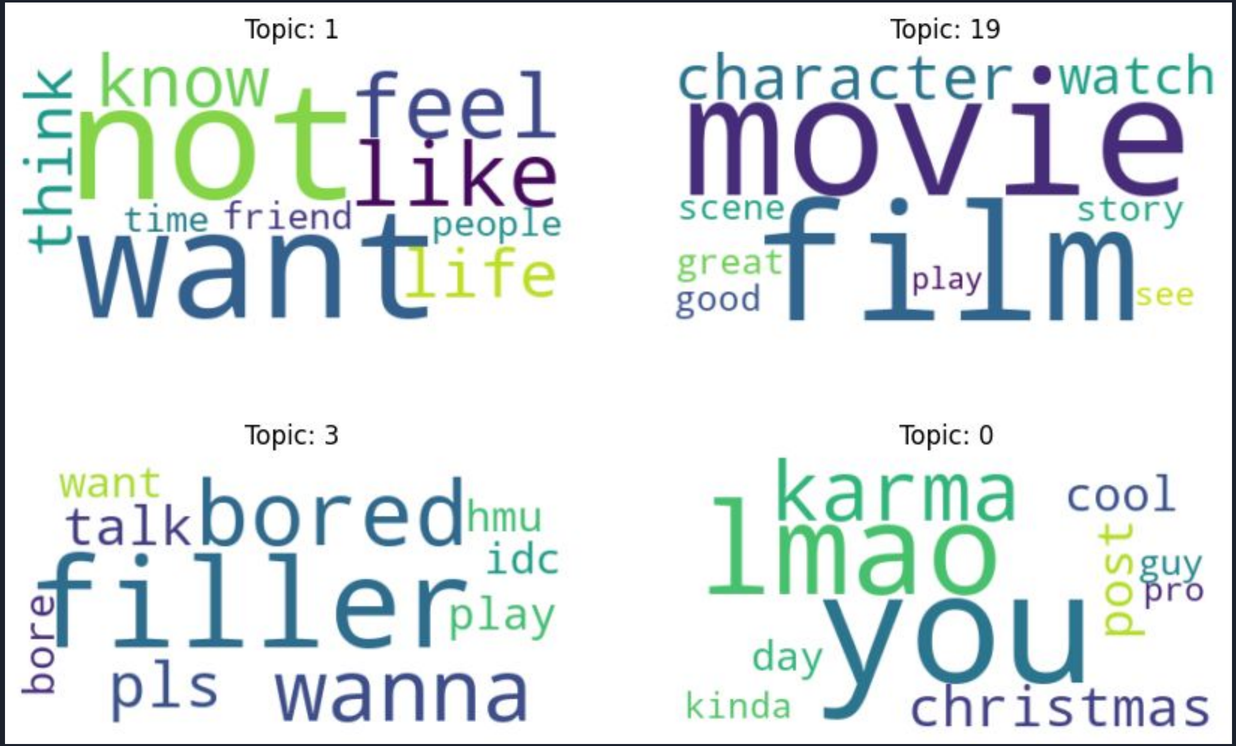
- Term sizes in word cloud is the term probability.



LDA (tf-idf vectors) entire corpus.

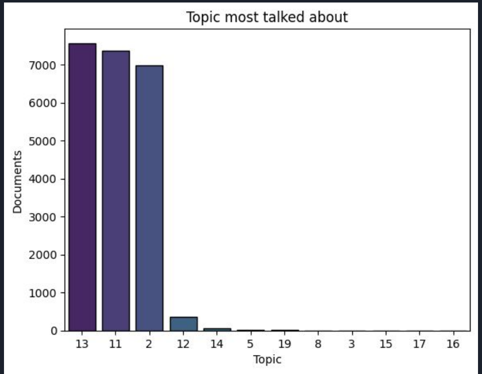
- Term sizes in word cloud is the term probability.





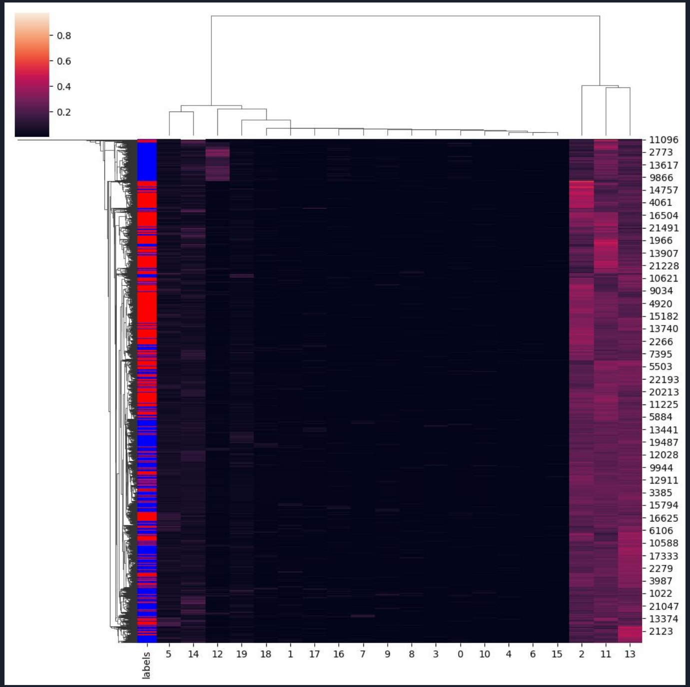
LDA (gensim VB) entire corpus

- Term sizes in word cloud is the term probability.



EDA: Cluster mapping LDA topic distributions (gensim VB) entire corpus

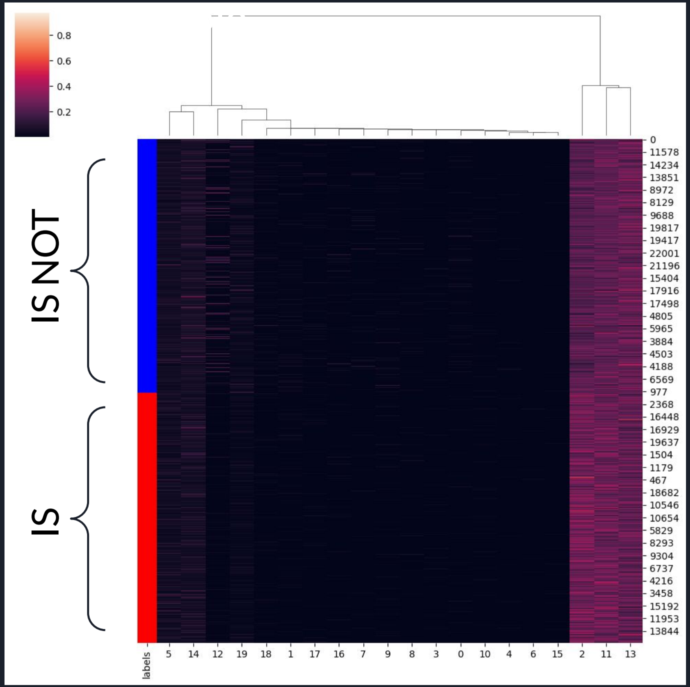
Default



document

Topic

Sort documents by target



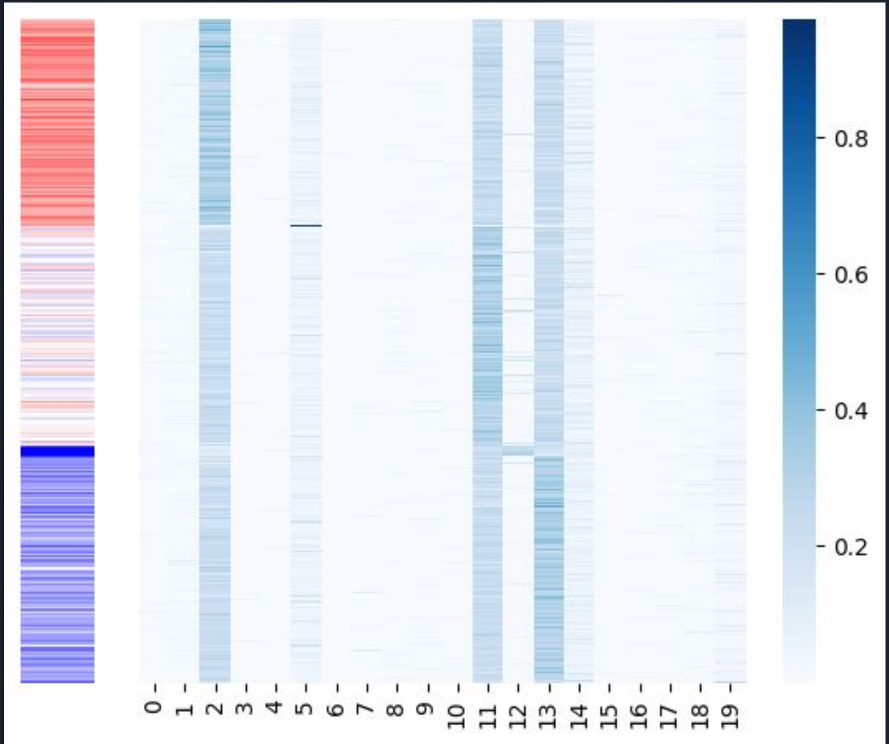
document

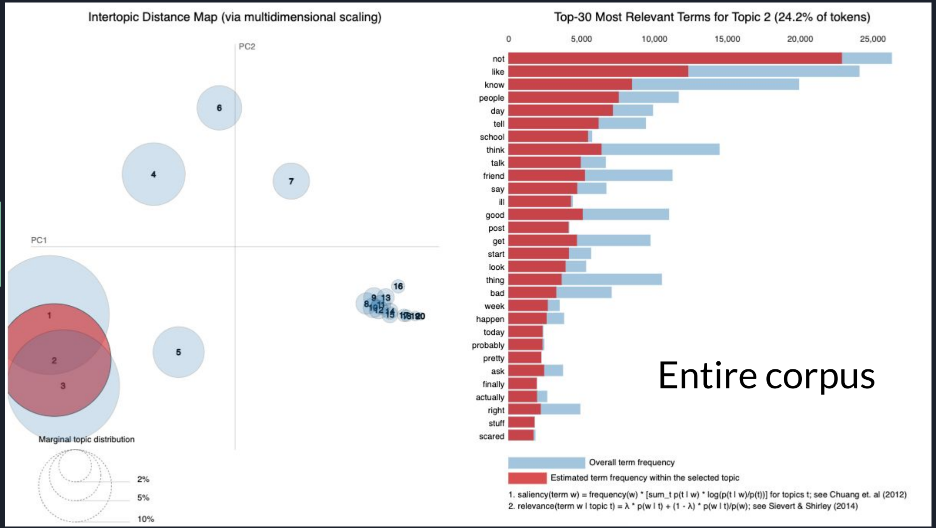
Topic

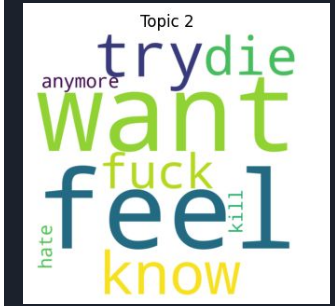
EDA: Heat map of LDA topic distributions (gensim VB) entire corpus. Documents manually ordered by strongest topic.

IS

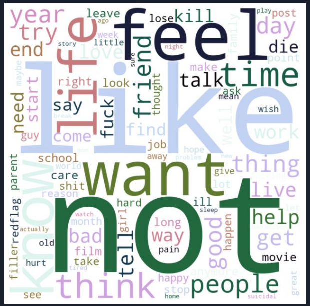
IS NOT



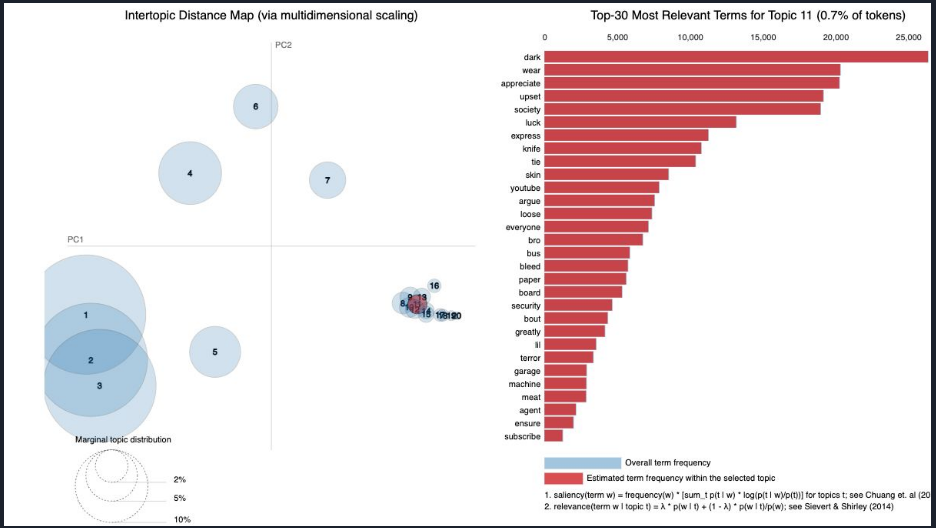




Most Probable



Freq. entire corpus



Most Probable

Gensim perplexity sore

Perplexity: -13. 5

In Gensim, the LDA perplexity score is a measure of how well a given topic model has generalized to unseen documents. It is a measure of how well the model can predict the held-out or test set. A lower perplexity score indicates that the model is better at predicting the unseen data.

Classifiers accuracy results:

	Count Vectors	Word Level TF-IDF	N-Gram Vectors	CharLevel Vectors	Glove Vectors	count vector LDA	TF-IDF LDA	GENSIM LDA
Naïve Bayes	0.84	0.87	0.85	0.87	0.80	0.78	0.73	0.70
Logistic Regression	0.91	0.91	0.86	**0.92**	0.88	0.81	0.79	0.79
Support Vector Machine	0.89	0.91	0.84	**0.93**	0.89	0.81	0.78	0.80
SGD-Huber	0.71	0.48	0.48	0.51	0.84	0.51	0.51	0.48

Conclusion:

Character level TF-IDF vectors may give better results than word-level representations in certain scenarios because:

- **Robustness to spelling mistakes and out-of-vocabulary words**: Focus on the character-level representation of the text rather than the exact word spelling (a lot of noise or variability in the data).
- **Capturing morphology:** In languages with complex morphology, character-level models can capture more of the morphological information of words as they are less affected by inflections, derivations, and compound words.
- **Capturing syntax and semantics:** Character-level models can capture some aspects of syntax and semantics.