

Middle European interdisciplinary master's programme in Cognitive Science

Detecting Suicide-Related Content from Bereaved Individuals on Twitter – A Machine Learning Approach

Introduction

- Research showed that suicide rates are associated with what and how individuals, news agencies and non-governmental organizations write about suicide on social media
- Appropriate tone and content may positively influence how people cope with their suicidal thoughts
- To investigate this association it is necessary to understand what type of social media content relates to an increased or decreased suicide rate
- Need for large scale studies and automatic categorization of social media content
- The Computational Social Science Lab of Austria established a **novel approach employing a machine learning algorithm** that classifies Tweets into categories such as 'personal reporting', 'celebrity suicide', 'news articles', and 'prevention tweets', among others
- The existing algorithm can already distinguish six suicide related tweet categories

Goals

- For this project, two previously defined categories were selected and a new algorithm that classifies posts into these categories was trained
- The new categories are supposed to distinguish tweets from **bereaved individuals (individuals who lost a loved one to suicide)** that are either written in a positive tone indicating successful coping, or a negative tone indicating suffering, into the 'positive' or 'negative' category.

Natural Language Processing

Suicide Prevention

Machine Learning

Twitter

#TF-IDF

SVM

Because of the rather poor performance of the

classifier, the Computational Social Science Lab of

bereaved) from other suicide related tweets (label:

other) and off-topic tweets (label: off-topic) would

This model achieved a higher overall precision of

The prediction frequencies per category are shown

Confusion Matrix

The classifier achieved an even higher detail

precision of 93% for the bereaved category

Austria decided that for now an algorithm which

only distinguishes bereaved tweets (label:

Outlook

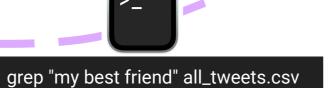
be sufficient

in the confusion matrix:

Methods

First step: in tweets with the word "suicide": keyword search (e.g., "my best friend") in the terminal to identify potential tweets from bereaved individuals





Second step: Dataset containing all tweets that include the keyword



Third step: Preprocessing of tweets by lowercasing, cleaning up links, cleaning up @mentions

@User **i am hurting too...** i just lost my best friend to suicide 😞 💔 🙏

my best friend killed himself two years

ago after he turned 22.. it was so hard. i

miss you nathan. </3 https

@Us

@User i want to rewatch it. my best friend took her life 5 years ago. #sohelpful

labels manually

Fourth step: Adding category

@User: obssesd with @User they really helped me with my best friends suicide #awesomedancers #pelevate #fun" love my job

Fifth step: TF-IDF (Text Frequency - Inverted Document Frequency) translates words into importancy metrics by category

my	best	took	class
0.020	0.001	0.300	positive
0.400	0.003	0.100	negative

off-topic 0.79 0 0.21 -0.8 bereaved 0 0.95 0.047 -0.4 other 0.23 0.035 0.73 -0.2 off-topic bereaved other

PREDICTED LABEL

To continue this project and improve the classifier, it was suggested to use the deep learning BERT classifier from Google instead of the currently used SVM classifier, because it would not only learn word frequencies, but also consider the context of each word and the syntax of sentences, and can therefore capture more subtle meanings

Sixth step: The numeric output from TF-IDF was used to train a support vector machine (SVM) which can then predict categories of new input tweets; GridSearch was used to find best Hyperparameters of the model

model = svm.SVC GS.fit(X_train, y_train)



Overall model precision (detected true examples) of 60%

Conclusion

- 1. After the first investigation into the data we found that many of the tweets cannot be categorized as positive or negative bereaved stories. We therefore decided to **introduce a third "neutral" category** in the training data
- 2. The previously defined categories of bereaved negative and bereaved positive tweets are hard to distinguish for an algorithm as well as for a human classifier
- 3. Due to the third introduced category of neutral bereaved tweets, the training data sample was not big enough to train the model sufficiently
- 4. The **algorithm is likely to be sensitive to the origin of the data** as it was trained with only US tweets which showed some specific country related content ("guns", "veterans", "Nam")
- 5. Many bereaved tweets start with direct @mentions
- 6. The trained **SVM classifier has a overall precision of 60**%, distinguishing neutral, negative, positive and off-topic tweets from each other. The detailed precision of this model per category for predicting negative and positive tweets was higher with approx. 80%

"touchstart"); N(Z, "itouchstart"); N(Z, "keyup"); N(Z, "touchstart"); N(Z, "touchstar

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GitHub Repository

