On Suicidality Subject Matter Detection

The purpose of this study is to use predictive modeling to assess text content and detect subject matter that relates to suicidality.

Upon this foundation, the project has an additional goal of examining the ways this can facilitate analysis and prevention.

Nothing within this preliminary study should be taken as a substitute for licensed medical advice.

Suicidality can be difficult to define in terms of modeling features alone.

While sufferers of depression are not (and should not be) assumed inherently suicidal, depression can serve as a contributing factor to suicidal ideation.

The potential arises then for a predictive model to classify between both sides of this threshold in terms of subject matter and concerns.

The dataset used consists of more than 700,000 text postings divided evenly between r/depression and r/SuicideWatch.

The logic of this choice is to anchor the predictive model in detecting when text or speech transitions from subject matter unrelated to suicide to subject matter related to suicide.

Subject matter related to suicidality does not inherently presuppose suicidal ideation by its author, but an examination of the posts collected suggests that for this dataset there is a correlation.

Initial treatment of the data consisted of combining relevant text elements and stripping them of problematic special characters.

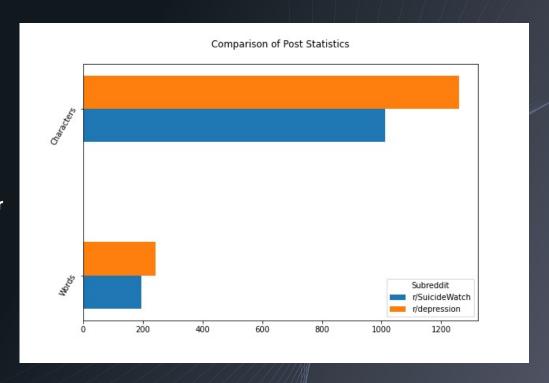
Text was then preprocessed into eight different versions.

This was done based on such factors as whether or not common English stop words were removed, whether numerical characters were preserved, and the manner in which word roots were standardized.

The purpose of this manifold preprocessing approach was to optimize the model fit with the version of the relevant text that provides the strongest possible scores.

During preliminary exploration of the data, the major takeaway was that posts related primarily to depression were significantly longer that posts related to suicidality.

Further study might reveal whether or not this discrepancy is relevant and what its cause might be.



Modeling began with the intention of creating two models (one for sheer predictive power and another from which to draw interpretations.

An initial consideration for the modeling process was the difficulty in determining the best metric(s) by which to judge the strongest model.

This issue is resolved in the Streamlit app for this project, in which users can optimize for their particular use cases.

Initial models had the purpose of finding the best results across all versions of the text, across multiple classification models, and using the strongest method of evaluating term frequency.

TEXT FORMS INCLUDED:

- words only, made lowercase, lemmatized
- words only, made lowercase, stemmed
- words made lowercase and potentially significant digits, lemmatized
- words made lowercase and potentially significant digits, stemmed
- words only with English stopwords removed, made lowercase, lemmatized
- words only with English stopwords removed, made lowercase, stemmed
- words made lowercase (with English stopwords removed) and potentially significant digits, lemmatized
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TERM FREQUENCY EVALUATION INCLUDED:

- tallying word frequency exclusively
- tallying word frequency as well as the frequency of multi-word terms

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MODELS USED INCLUDED:

- logistic regression
- Gradient Boosting
- AdaBoost
- random forests
- multinomial naïve Bayes
- Bernoulli naïve Bayes
- neural networks

Issues arose early on due to the large size of the dataset, which required a significant down-sampling of the data.

RAM limitations also became an issue, making parameter optimization time-consuming.

Ultimately, the strongest predictive model was a classic logistic regression model, fit to a words-only version of the text data with stopwords removed, vectorized according to term frequency.

Because logistic regression lends itself strongly to interpretation, its high performance in predictive classification nullified the need for a second model.

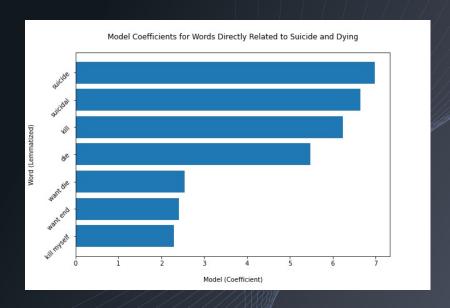
A look at the findings of the model align closely with what the medical literature considers to be common speech patterns for sufferers of suicidal ideation.

Some of these include speech related to suicide or dying, feelings of hopelessness or having no purpose, isolation, and a sense of being a burden to others.

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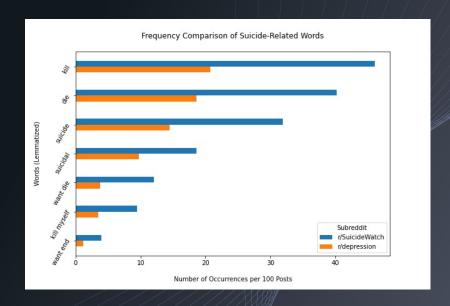
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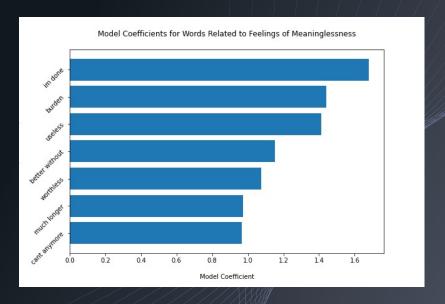
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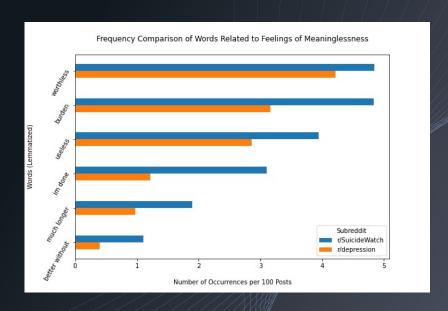
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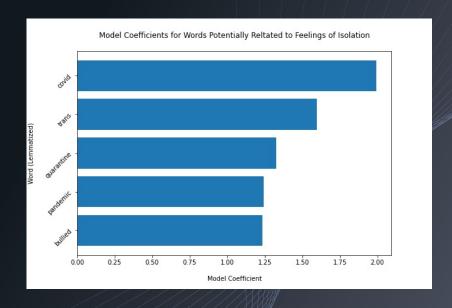


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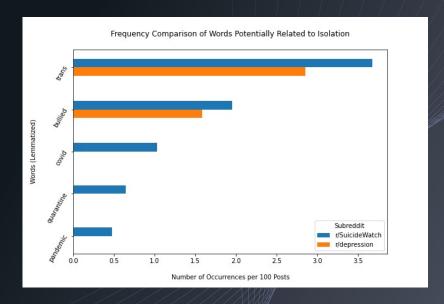
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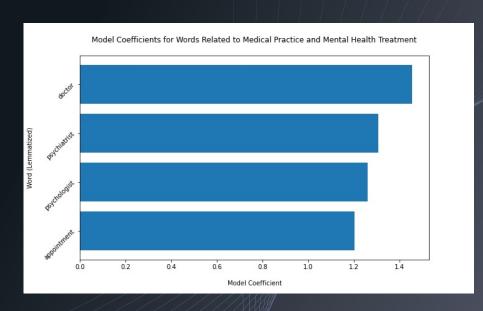
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Terms related to specific methods of suicide were common as well.



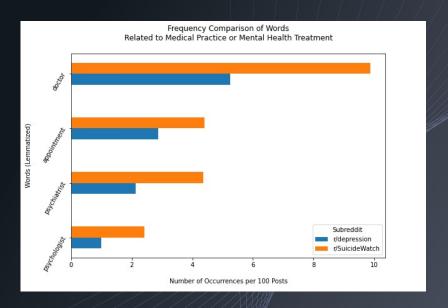
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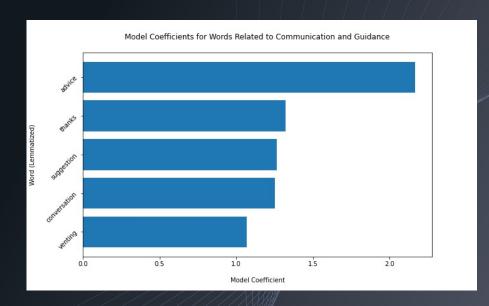
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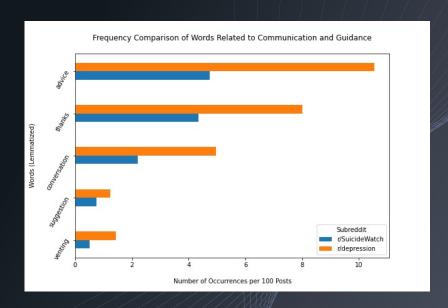
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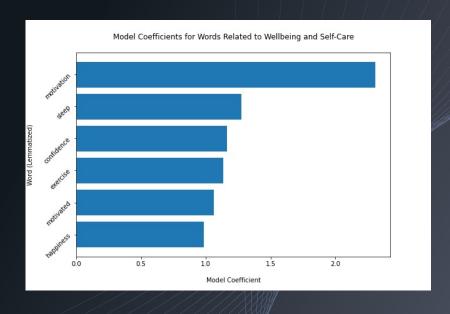


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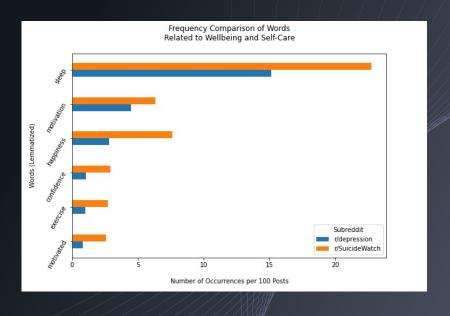


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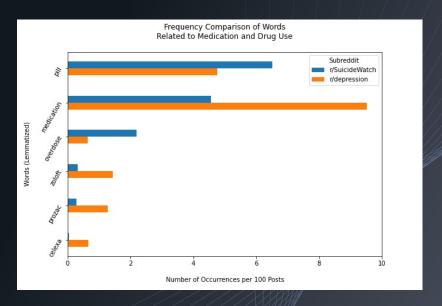
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In the case of words related to medication and drug use, the subtext/shade of meaning that a term has can influence its weight in the model's classification algorithm.



The primary function of the Streamlit app is to allow a user to score a text body with the final model.

In addition to a field for the sample text, a field is provided so the user can specify a probability threshold for the classification of the sample text based on the specific use case.

This allows for accuracy/recall optimization at the time of use.

Suicidality Subject Matter Detection Input text in the field below: Press Enter to apply User may define custom value between 0 and 1 as the probability threshold equal to or beyond which a block of text will be classified as positive. Input custom threshold: Scan Text

The application then returns its result based on the text and the threshold provided.

Suicidality Subject Matter Detection

Input text in the field below:

Here is the text string.

User may define custom value between 0 and 1 as the probability threshold equal to or beyond which a block of text will be classified as positive. Input custom threshold:

0.5

Scan Text

Scanned Text: Here is the text string.

Probability Threshold: 0.5

Given this probability threshold, the above text **does not** seem to include subject matter related to suicidality.

Suicidality Subject Matter Detection

Input text in the field below:

Here is the text string.

User may define custom value between 0 and 1 as the probability threshold equal to or beyond which a block of text will be classified as positive. Input custom threshold:

0.41

Scan Text

Scanned Text: Here is the text string.

Probability Threshold: 0.41

Given this probability threshold, the above text **does** seem to include subject matter related to suicidality.

An ABOUT section provides information about any developers involved, so that any expansions on the project or the app can include contact information according to area of expertise.

About the Creator



Brian Berry

As a data scientist, Brian finds the stories behind numbers. With a background in the humanities and extensive experience in cross-team IT environments, his hope is to use his skills in analytics/statistical modeling and technical communication to help teams and individuals thrive.

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Finally, an ADDITIONAL RESOURCES section includes organization and URL information for anyone seeking to learn more, and this is also easily expandable.

Additional Resources



https://www.sprc.org



https://www.nimh.nih.gov

In Conclusion

The dataset used provides a foundation for a successful predictive model whose results correlate closely with what the medical literature lists as subject matter in speech related to suicidal ideation.

The dynamic nature of web applications allows broad adaptability when optimizing for scoring metrics, and this can aid in a wide range of use cases.

Further expansion of the dataset might lead to an even more wellrounded model, capable of handling more nuance in speech related to suicidal ideation.

Any questions?