USING SENTIMENT ANALYSIS TO STUDY THE EFFECTS OF SEASONAL AFFECTIVE DISORDER ON TWITTER USERS

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1. ABSTRACT

As mental health conditions are rapidly increasing in the United States, it is important that health-care professionals can accurately map specific mental health trends. One such mental health condition is Seasonal Affective Disorder (SAD), commonly referred to as “Seasonal Depression”. SAD has many forms, but the most common form is found during the fall and winter seasons. SAD is particularly difficult to diagnose, and the estimations of the number of individuals affected by this condition vary widely from source to source. This project aims to help improve the accuracy in estimating and mapping SAD via a natural language processing technique known as Sentiment Analysis. Sentiment analysis can be applied to speech and text data to predict the emotions behind the speech or text, be it angry, positive, negative, etc. This project applies sentiment analysis, via a supervised deep learning technique, over years of Twitter tweet data to predict the sentiment of the tweet at a given time. The goal of the project is to use this technique with Twitter data to determine if there exists a correlation between the fall and winter months and an increase in the percentage of negative sentiment tweets in the United States, providing a way to analyze the effects of SAD on Twitter users.

2. INTRODUCTION

Seasonal Affective Disorder (SAD) - commonly referred to as “seasonal depression” - is a form of depression that affects an individual during specific times of the year. SAD has no direct proven causes, but common factors among patients include changes in circadian rhythm, serotonin deficiencies, and overproduction of melatonin [1]. All of these factors can be caused by a lack of sunlight during the day, which explains why SAD is more commonly found during the fall - September 1 through November 30 - and winter - December 1 through February 28/29 - months as opposed to the oftentimes sunnier spring - March 1 through May 31 - and summer - June 1 through August 31 - months. In most cases, the symptoms of fall and winter-onset SAD disappear with the seasons changing to spring and summer.

SAD is a difficult mental illness to diagnose due to its impermanence and close relation to other forms of depression [1]. Due to this difficulty, the estimations of affected persons range from 3-16 million each year in the United States alone [2]. Artificial intelligence can be used to help increase the accuracy of these estimations, allowing health care workers to deeper understand the extent of SAD.

One artificial intelligence technique that can be utilized is sentiment analysis. Sentiment analysis uses natural language processing techniques to determine the sentiment of an individual’s speech or writings. Using sentiment analysis algorithms, the general feeling behind a specific text or sentence can be modeled and predicted with a high degree of accuracy - generally labeled a positive or negative sentiment. These predictions can determine an individual’s overall mood, feelings, or state at the time of writing or speaking the text. In combination, these predictions can give the overall sentiment of a group of individuals on a given day or a given topic. Sentiment analysis is commonly used for brands, as compilations of predictions are powerful tools for determining sentiment of customers and the general public.

In order to generalize public sentiment, researchers and businesses have looked to social media data, since it is public, free, and quick to access. Twitter is commonly used, as there are approximately 38 million daily users in the United States, with many users posting free text data that can be analyzed and classified [3].

With years worth of Twitter data, sentiment analysis algorithms can be applied to determine US Twitter users’ overall sentiment on a given day, month, or year. By applying these techniques over consecutive months during a year, a change in negative and positive tweets can be seen, producing a model of the change in sentiment over any given year.

This project applies these techniques to study the effects of seasonal affective disorder on United States Twitter users.

3. RELATED WORKS

3.1. General Sentiment Analysis

Sentiment analysis is a technique used for analyzing sentiment different topics, products, or services via social media or other forums. As such, it is traditionally used by companies that want to know how the public feels about a particular decision or direction a company has made or is moving towards. There exist tools, like MonkeyLearn, that are paid services allowing a company to discover this information by applying machine learning techniques on large portions of social media data [4].

Other works provide brand sentiment analysis for academic use. For example, Sentiment140 is a project from Stanford University that applies deep learning techniques on Twitter data to study sentiment analysis using sentiments towards brands, topics, and hashtags. Sentiment140 provides millions of labeled tweets and papers describing the algorithms behind the analysis to aid the development of sentiment analysis techniques [5]. The datasets produced by Sentiment140 have been used in many research projects, as they provide convenient data based around sentiment analysis.

3.2. Sentiment Analysis in Medicine

In the medical field, sentiment analysis is being applied to study patient attitudes towards medications and treatments as well as studying mental health trends via social media. In 2017, researchers at the Indian Institute of Technology in Patna used a deep convolutional neural network based sentiment analysis system to study the sentiment towards specific medications, treatments, and medical conditions. They used posts from a medical patient forum, 'patient.info', to determine the effectiveness of medications and treatments as well as the change in condition of patients [6]. Another study carried out by researchers at Johns Hopkins University used Twitter data specifically to study mental illness trends across the United States. Instead of a deep learning algorithm, they applied both Linguistic Inquiry Word Count and Character n-gram Language Model approaches on Twitter data and studied mental illnesses including ADHD, Anxiety, SAD, and many others [7]. In a second study in the same space, they applied a Support Vector Machine method to compare it with other common text classification techniques on PTSD and depression data from Twitter [8]. Although the studies from Johns Hopkins looked at SAD and depression in Twitter data, neither one used the deep learning approach found in this project.

4. APPROACH

4.1. Training Data

The dataset chosen for this project comes from the Sentiment140 project [5]. The dataset contains 1.6 million English tweets in a comma-separated values (csv) file containing rows for sentiment of tweet, tweet ID, date and time of tweet, and the text of the tweet. For this project, the sentiment of the tweet and the text of the tweet were the only columns needed.

To preprocess the data, the tweets had any unnecessary characters, numbers, images, hyperlinks, and username mentions removed from the text of the tweet. This allows for analysis of only the English words a user inputs. For normalization, the Snowball Stemmer from the Python natural language toolkit was applied to the preprocessed tweets to remove any prefixes or suffixes and convert all words into a constant stem of the word [9]. Next, each word was tokenized within each tweet for easier manipulation and the ability to access words individually. Finally, the tweets were split into training and testing data - 80% randomly being assigned as training and the other 20% being assigned as testing - via the Scikit-learn library's function for splitting training and test data [10].

4.2. Tweet Vectorization

In order to use the tokenized tweets for deep learning, the tweets were processed by another machine learning technique - Word2Vec - to convert the words to a real-valued vector. The Word2Vec technique allows words to be modeled in dimensional space via vector values. The closer two words are in this dimensional space, the closer the semantics of the words generally align [11].

The model used for this project comes from the Gensim library and uses the Continuous Bag-of-words (CBOW) model for predicting words in a sentence [12]. The Continuous Bag-of-words model was chosen over the Skipp-gram Model due to its speed in training and accuracy for repetitive words [13]. The CBOW algorithm allows the model to predict a word using its context. Given a window of size n, the CBOW model will consider the previous and succeeding n words to predict the target word. The Gensim Word2Vec model uses the CBOW model with a shallow neural network to predict the target word and generate a vector value [14]. To train the model, a custom corpus was created using the vocabulary from the Twitter data to ensure the model was predicting words in the context of the Twitter data. The model was then trained over the corpus and had the ability to return a word's most semantically similar words using the cosine similarity of the vectorized words.

4.3. Deep Learning Model

The model used for predicting the sentiment of each tweet is a Long Short-Term Memory (LSTM) Recurrent Neural Network using the Keras library from TensorFlow. The model takes in text and outputs a floating point number from 0 to 1 - 0 being most negative and 1 being most positive - to predict the sentiment of the text provided. Any sentiment below 0.5 was classified as a negative tweet and any other score was classified as a positive tweet.

4.3.1. Structure

The model is a sequential neural network using the LSTM model from Keras [15]. The first layer of the model is the embedding layer, which will embed the text into a vectorized format using an embedding matrix developed from the Word2Vec model. If the word from the text exists in the word vectors of the model, then it is replaced with that vector, otherwise it is set to 0. After the embedding layer, the embedded data is passed into the LSTM model from Keras [15]. The LSTM model has specified dropout layers that randomly set some vector values to 0 to prevent overfitting of the data. After the LSTM model, the output is then condensed into a sigmoid activation function which provides the floating point number output which is the model's prediction.

4.3.2. Training and Testing

After compiling the model with the 'adam' optimizer from Keras, the model was then trained for accuracy using the training data from the earlier Word2Vec model. For validation, 10% of the training data was set aside as validation data to test the model's accuracy of prediction. The best model ran four epochs over the training data which took approximately 18 hours and finished with a 78.89% accuracy on prediction.

4.4. Data Acquisition

In order to acquire data for the study, the OMGOT framework from Github was used to scan for tweets from New York City on each day in two consecutive years [16]. The years 2016 and 2017 were chosen to avoid any change in negative sentiments due to the impact of COVID-19 in recent years.

New York City has many active Twitter users and is located within the United States, so it was chosen as the epicenter for scanning tweets. A total of 10,376 English language tweets were gathered from the data scanning after removing tweets that only contained retweets, images, videos, hyperlinks, and hashtags. From these tweets, the date and text of the tweet were combined into a csv file and the same preprocessing techniques from section 4.1 were applied to get the final dataset for studying.

5. EXPERIMENTS

After scanning and preprocessing the tweet data from January 2016 - December 2017, the sentiment analysis model was given every tweet from each month - exactly 10,376 tweets. This produced a new csv file for every month with columns of text of tweet, date of tweet, sentiment classification, and the floating point number the model produced. This setup was run several times, and the results and analysis come from the version using the most accurate model described in section 4.3.

6. RESULTS

Year	Month	Percentage of Negative Tweets
2016	January	26.1%
	February	21.3%
	March	24.6%
	April	26.1%
	May	23.5%
	June	23.0%
	July	25.9%
	August	28.0%
	September	27.7%
	October	26.4%
	November	20.8%
	December	25.3%

Figure 1 - the percentage of total tweets that were classified as negative in each month of 2016.

Year	Month	Percentage of Negative Tweets
2017	January	28.2%
	February	24.2%
	March	24.3%
	April	24.9%
	May	21.5%
	June	24.5%
	July	25.7%
	August	24.3%
	September	27.2%
	October	29.9%
	November	24.0%
	December	26.3%

Figure 2 - the percentage of total tweets that were classified as negative in each month of 2017.

Year	Month	Percentage of Negative Tweets
2016 & 2017	January	27.15%
	February	22.75%
	March	24.45%
	April	25.50%
	May	22.50%
	June	23.75%
	July	25.80%
	August	26.15%
	September	27.45%
	October	28.15%
	November	22.40%
	December	25.80%

Figure 3 - the average percentage of total tweets that were classified as negative in each month of both 2016 and 2017.

Year	Season	Percentage of Negative Tweets
2016	Spring	24.73%
	Summer	25.63%
	Fall	24.97%
	Winter	24.23%
2017	Spring	23.57%
	Summer	24.83%
	Fall	27.03%
	Winter	26.23%

Figure 4 - the seasonal average percentage of total tweets that were classified as negative in each season of both 2016 and 2017.

Figure 1 and *Figure 2* show the percentage of total tweets for each month that were classified as negative tweets by running the sentiment analysis model on the data from 2016 and 2017. *Figure 3* shows the average percentage of negative tweets each month between the two years the analysis was run on. *Figure 4* shows the seasonal average by averaging the percentage of negative tweets across the months that comprise the specific season.

7. ANALYSIS

From visual analysis of the results, the fall and winter months looked to have more negative sentiment tweets. On average, from summer to fall, there was a 1.54% increase in the percentage of negative sentiment tweets. From winter to spring, there was a 2.16% average decrease in the percentage of negative sentiment tweets. However, these preliminary findings were only partially analyzed and needed further validation and study.

To better analyze these results, the data was split into separate sets of data by season. The fall and winter months (September - February) were separated from the spring and summer months (March - August), and these sets of data were studied to measure the statistical significance of the results.

The fall and winter months' data had a mean of 25.62% of negative tweets and a standard deviation of 2.69%. In comparison, the spring and summer months' data had a mean of 24.69% and a standard deviation of 1.66%.

To determine the statistical significance of the results, a t-test was performed between the two datasets. The data had a *P-value* of 0.160975479 or approximately 16.098%, meaning the results were not significantly significant.

Despite the initial analysis showing a slight increase in negative sentiment from summer to fall and a slight decrease in negative sentiment from winter to spring, the results were not statistically significant enough to support the hypothesis that fall and winter months would have significantly more negative sentiment tweets than spring and summer.

8. CONCLUSION

From analyzing the results of this project, it is not clear whether fall and winter months have a higher percentage of negative sentiment tweets than the spring and summer months. Though the analysis showed a slightly higher percentage of negative sentiment tweets during the fall and winter months, the data was not statistically significant enough to support that finding. There also was no evidence supporting the opposite effect, that spring and summer months have higher percentages of negative sentiment tweets.

This project can be improved to provide a higher degree of significance and study the question further. Some possible improvements to the project that can be taken are mentioned in the *Future Directions* section.

9. FUTURE DIRECTIONS

In the future, improving the project would be key for the success of the study. Some improvements that may be made in the future are collecting more Twitter data over a larger timeframe, focusing on other regions or covering the entire United States, and applying a filter on users for daily tweets.

Collecting more Twitter data would help the project generalize the problem. For example, Twitter users in the United States upload millions of tweets every year, and by focusing on only 10,376 tweets, the project was limited in its scope.

By only focusing on a small portion of New York City, the tweets had a higher probability of being more closely related. If the study instead covered tweets from the entire US, it would improve on the number of tweets and eliminate the effects of local events or related tweets skewing the data. Moreover, particular users would not have as large an effect on the dataset.

Another improvement could be filtering users to only allow one tweet per day per user in the dataset. If a particular user released a large number of positive or negative tweets on one day, this may have greatly affected the dataset used in this study. This improvement would also limit the effect that a user who is generally always negative or positive on Twitter has on a year's worth of data.

In the future, this project could be implemented using these improvements but it could also be used to study other questions. With these improvements made, this project would have much greater significance and would be able to be applied to many other areas of interest regarding sentiment analysis throughout the year.

10. REFERENCES

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