Interactive Happy Moment Analysis

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Abstract

In this work, we present a platform to guide users to explore a deeper understanding about their happiness source. Under Christmas setting, users could input their own happy moment and see how "Santa" (pretended by model) guesses the happiness source. Then they could test their understanding of happiness by classifying others' happy experience and comparing it with "Santa"'s analysis. Additional activities include exploring the summary barplots of over 100,000 happy moment descriptions and playing with a bonus sentiment classification task. Overall, we hope users could elicit new thoughts about their happy moments and a cheery Christmas holds lots of happiness for them.

Introduction

Sentiment analysis has long been an important task in NLP since understanding people's emotion is essential for both individuals and businesses. Understanding the factors that bring people happiness is the key to improve people's happy experiences and overall life satisfaction. Recently, there has been interest in developing technology products that can help users incorporate research findings about happiness into their daily lives. [1-4] As a new attempt of such product, we built an interactive platform on happy moment (English texts) analysis in a storytelling fashion.

The general goal of our platform is to guide users to explore a deeper understanding about their happiness source. Under Christmas setting, users are able to (1) input their own happy moment in 2020 and see how "Santa" guesses the happiness source. (2) test their own understanding by classifying others' happy experience and comparing with "Santa"'s analysis. (3) explore a summary barplot of over 100,000 happy moment descriptions. (4) elicit thoughts about correlations between certain words and happiness source.

To act as the omniscient "Santa", we developed a multi-class prediction model. It is trained on HappyDB, a corpus including 100,000 happy moments descriptions crowd-sourced from Mechanical Turk (MTurk) workers. Having attempted both traditional machine learning models and deep learning models, we decided to utilize the logistic regression for the visualization considering its interpretation flexibility and fairly good performance. Besides, to better interpret the model, we used LIME (Local Interpretable Model-Agnostic Explanations)[5] to highlight determinant phrases in each description.

In the following sections, data source, methods, and algorithms will be explained in detail. Then, the results section will illustrate the story line as well as visual design principals accompanied with screenshots of the platform.

Related Work

The directly related paper came from Asai, Akari, et al[1] who crowd-sourced the HappyDB corpus, the dataset we trained on. Their work focused less on the data analysis. Instead, they left a couple of NLP problems that can be studied with the help of the corpus for future research.

Existing visualizations of text sentiment analysis often focus on distinguishing between emotions but ignore the reason behind emotions. For instance, Emosaic[6], a tool for visualizing the emotional tone of text documents, is powerful in detecting the sentiment and highlighting the affective content of text. But there is no further explanation about what cause leads to the certain emotion. Furthermore,

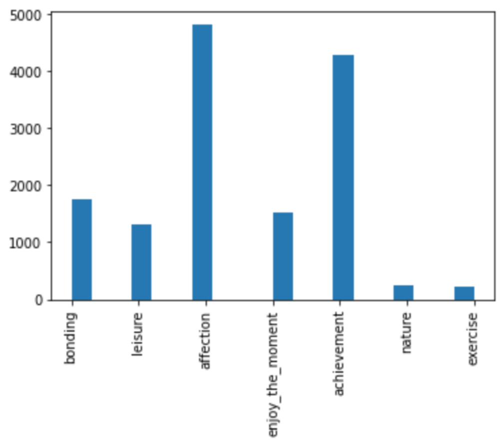

Figure 1: Distribution of Classes

these existing works for solely emotion detection often visualize the model results with few explanations to model strategy. Though some of them have parameters attached with each word, it's hard to interpret how these parameters affect the prediction result. An example tool could be sentiment viz[7], a tweet sentiment visualization tool. It lists v, a, and fq with no definition when the user clicks a data point.

Methods

Data

We made use of HappyDB for this project. HappyDB includes 100,000 happy moments descriptions crowd-sourced from Mechanical Turk (MTurk) workers. The descriptions are mainly in a format of diary, narrating an event in a day that brings happiness. Examples could be: "My son gave me a big hug in the morning when I woke him up." and "I finally managed to make 40 pushups."

The dataset also includes categories of those happy moments. About 15% of the entries of the dataset are labeled with ground truth labels. The categories includes:(1) *Achievement*: With extra effort to achieve a better than expected result. (2) *Affection*:Meaningful interaction with family, loved ones and pets. (3) *Bounding*: Meaningful interaction with friends and colleagues. (4) *Enjoy the moment*: Being aware or reflecting on present environment. (5) *Exercise*: With intent to exercise or workout. (6) *Leisure*: An activity done regularly in one's free time for pleasure. (7) *Nature*: In the open air, in nature.

The first step of the project would be preprocessing the text data in the HappyDB dataset. The two issues to be taken care of during this task are (1) descriptions of short length and (2) misspelling of words. To eliminate noise caused by single word sentences, we simply removed descriptions with less than two words. In order to deal with spelling errors, we corrected words not listed in the dictionary built from Norvig's text corpus [8] as well as a complete list of English Wikipedia titles which includes the name of many cities, locations and other known entities.

To make barplots for sources of happiness, we reprocessed our cleaned dataset. We splitted the entire dataset into 7 subsets based on seven sources of happiness. For each subset, we tokenized each sentence. Every token was converted into lower case and stop words were removed based on NLTK's list of English stop words. We then applied counters to count occurrence of each token and kept top 20 of them in each subset. In each source of happiness, we extracted and stored 10 examples that use this word and belong to this specific source of happiness for each top 20 token. We also extracted and stored 5 or all counter examples, whichever is smaller, that contain this word but don't belong to this specific source of happiness.

Model

To train a happy source classification model, we first transformed happy moments into vector representations. We employed TfidfVectorizer provided by Sklearn[10] with range of n_grams being (1, 3) to represent sentences as vectors. The n_gram here is specifically meant to keep track of the sentence context. Besides treating each word as features, the vectorizer also records every 2-word and 3-word phrases.

For the model choice, we experimented on multiple machine learning models including traditional machine learning (ML) models, Logistic Regression, SVM, and Random Forest, as well as deep learning (DL) models, LSTM, CNN, and GRU. All models were evaluated on its classification accuracy as well as the interpretation flexibility.

To highlight words contributing to classification results, we employed LIME (Local Interpretable Model-Agnostic Explanations)[5]. LIME provides local model interpretability. The technique attempts to understand the model by perturbing the input of data samples and understanding how the predictions change. We used LIME on the best-performed model to check whether the prediction is reasonable and how the classifier makes the decision.

Web Design

Our website is server-dynamic. In other words, we utilized Flask framework as the back-end to generate dynamic contents for the front-end web page. When receiving a request, Flask loads ML model checkpoints, generate happiness source prediction with plots, and send the data back to front-end. Our front-end used HTML, JavaScript, and CSS to make the web interface interactive. To present it as an interactive article, we used 'section' to make the interface more user friendly. Users can easily navigate down the page by either scrolling down or clicking the scroll down button on each page.

Our barplot section loaded preprocessed data via Flask framework. To enable high interactivity, including on-click events, tooltips, and animation, we used D3 JavaScript package to build our barplot for every source of happiness. To give users a more clear overview and to avoid package conflicts between JQuery and D3, we moved our barplot section into a separate web page. We carefully designed our web pages so that users can easily navigate between our main pages and the barplot overview page without feeling inconsistency.

All the images used in our website are drawn using Procreate on iPad by ourselves, including the images in introduction, source of happiness, and model sections.

Results

Model

As for the training result, we optimized hyper parameters for each training method and obtained the weighted F1 score as 0.836 for Logistic Regression, 0.843 for SVM, 0.822 for Random Forest, 0.785 for LSTM, 0.828 for CNN, and 0.765 for GRU. Additionally, GMM was trained to cluster all the descriptions but we found the resulting clusters did not follow the pattern of provided labels. Overall, our weighted F1 score outperformed 0.748, the one produced by former work. [1] Considering the high interprebility, small model size, and good performance of Logistic Regression model, we decided to utilize it for website visualization.

Visualizations

Here, we will explain the visualization of each section in detail. For section one (Figure 2), we presented a question "Why are you feeling happy?" to attract users' attention and quickly dive into our main topic - happy moment analysis. Users can type in one of their happy moments in 2020 and our model will predict the most likely source of happiness of this phrase and display it on the screen.

Section two (Figure 3) is a narrative page which used the story of Christmas and Santa to make transitions between sections more natural and fluent. Section three (Figure 4) introduced seven main sources of happiness with a supporting graph: bonding, affection, achievement, nature, leisure, exercise and enjoy the moment. We used them to categorize source of happiness in our model.

Section four (Figure 5) is one of our main user interaction sections. First, users can highlight the critical words from the happy moment sentence and choose the corresponding source of happiness of this sentence. Then, by clicking 'Yes' button, it will trigger the output from model which provides a better understanding about sentiment analysis on happy moments. The two lime graphs show the predicted probability of each source of happiness and the weights assigned for critical words in this sentence.

In the conclusion subsection, we intentionally encouraged users to think about any possible correlations between critical words and the final prediction or the ground truth category, and encouraged them to keep palying with different examples to gain more insights.

We also provided an overview barplot page to help user gain more insights. Users can easily navigate to the barplot page via the instruction and the button attached at the end of section 4. In the barplot section, we provided barplots of top 20 words for each source of happiness as shown in figure 8 . By clicking on one word in the chart, we detailed 10 examples that uses this word in this category as well as some cases that this word is used for other categories. We considered this as a summary page where users can have a better idea about how words can be used differently for different sources of happiness.

Our next section is called 'Santa's Secret' which provides some high-level idea about our machine learning model. We used a flowchart to visually represent the key idea about how to go from our dataset to the final prediction of happiness source. (Figure 6)

One bonus task we provided is analyzing whether a sentence can be considered as positive or negative sentiment, meaning whether this sentence sound happy or unhappy. The framework of this section is similar to section four, but here we are using the Sentiment 140 dataset to categorize the sentences into two categories (happy / unhappy). (Figure 9). We hope to provide this similar but not quiet same task to provide a transfer learning experience to better understand what they just learned.

Discussion

People feel different sentiments such as happiness and anger all the time, but they usually don't bother to explore the underlying causes. From the comments users provided in the survey, we are informed that they've become more aware of the importance of understanding the sources of happiness, and also other sentiments. Also, from the model section, the users gained a basic understanding of the development process of a sentiment analysis task.

New insights and practices

In this work, we followed best-practice teaching methodology to provide users insights about how words are used to express different types of happiness as well as to provide users a simple introduction to machine learning. As a starting point, we wrapped our task with a story about Santa and Chrismas to attract users' interests in our task. In the main sections, we firstly provided highly interactive individual sentences for users to play with. After they made decision, we used "Santa's suggestions" and ground truth as a reference and provided questions to guide them think about the correlations between those words and those sources of happiness. Further more, we provided users a summary section where we provided barcharts of top 20 words for each category. In the barplot section, we also provided examples and counter examples to enable users to put their rough understanding back into real scenarios and to think deeper about how and why those popular words were used in different cases. At the end of our main sections, we reveals "Santa's secrets" to give a brief introduction about how machine learning model is used in NLP tasks. We believe these tricks we used could help users to learn more effectively from our project.

Informal Observations - Survey

	Question	Score
1	The website has a user friendly interface.	4.56
2	The website is easy to navigate.	4.47
3	The website's pages generally have good images.	**4.79**
4	The website has an easy and smooth interaction with users.	4.56
5	The website has a pleasing color scheme.	**4.79**
6	The website allows users to have better understanding about happiness source.	4.68
7	The website clearly introduces how to implement sentimental text analysis model.	4.53
8	Will you recommend the website to your friends?	4.65
9	Any suggestions for improving our application?	N/A

Table 1: Survey Results

In order to test out our application with regard to user experience, we initiated a survey with 8 five-point Likert scale questions and 1 open ended question and released the survey mianly to our friends. Then we deployed our website using a single e2-medium instance from Google Cloud Platform(GCP) and made it public for 24 hours for the survey participants to fully engage with the website. The survey questions and their associated user average scores (if applicable) are listed in Table 1. We received 34 responses in total. From Table 1, we can see that question 3 and question

5 have the highest score, indicating that our website is in general aesthetically well designed. We also noticed that question 2 has the lowest score and in response to that we modified the scrolling mechanism and button positions to enable easier navigation.

Future Work

We received many constructive suggestions from the responses of question 9, which can mainly be divided into three categories – scaling texts to fit different displays (currently our website does not scale well to mobile devices), making titles and buttons more obvious and small tips such as changing fonts, and adding BGM. These provide us some directions to refine our web design in the future. Besides, more detailed introduction should be considered as a follow-up of our project.

References

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Appendix

Figure 2: Section 01

Figure 3: Section 02

Figure 4: Section 03

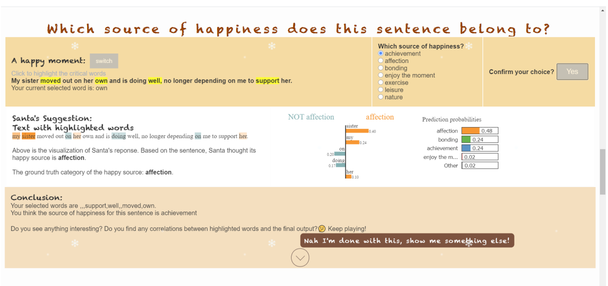

Figure 5: Section 04

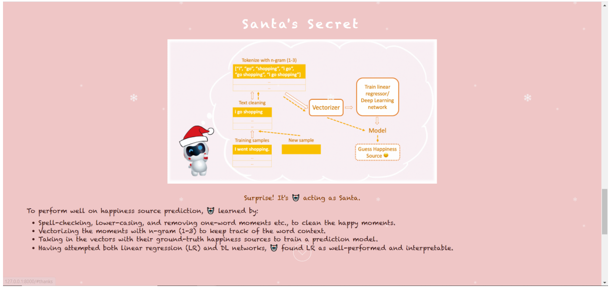

Figure 6: Model Section

Figure 7: Thank You Section

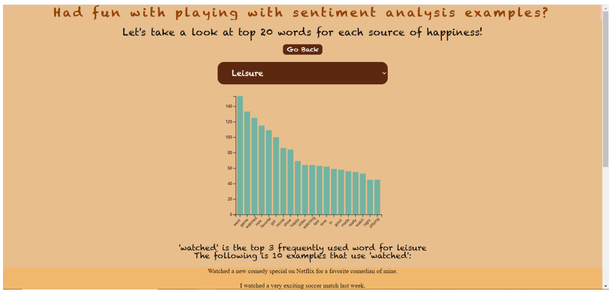

Figure 8: Bar Chart

Figure 9: Bonus Section