

Conversational Assistant based on Sentiment Analysis

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Abstract - Undiagnosed and untreated depressive disorders have become a serious public health issue and it is prevalent among people of all ages, gender and race. This paper introduces an approach to generate relevant responses to the users input. The counseling response model provides a suitable response by combining the users input and the emotional status of the user, this will have a consoling effect that will make the user encumbered with depression feel better. We suggest a conversational service for psychiatric counseling that is adapted by methodologies to understand counseling contents based on high-level natural language understanding (NLU) and emotion recognition. In addition to this model, the proposed project also takes recent tweets into consideration for monitoring the user's emotional changes. The methodologies enable continuous observation of the user's emotional changes. Understanding the user's emotional status will also improve computer-human interactions. Studies like these and their findings hold valuable insights for research on the domains of public health informatics, depression and social media.

Key Words: Depression, Sentiment Analysis, Chatbot, Naïve Bayes Classifier, Psychiatric Counselling

1. INTRODUCTION

The industrial revolution replaced workers with machines, forcing more of them towards the services sector. The digital revolution is now attacking this area through chatbots that could provide assistance to the customers or users.

The human conversation is a complicated metric. It is capable of expressing multiple sentiments in a complicated manner that requires a deep understanding of the underlying context to detect the emotions conveyed by the users input. The user can provide input either through text or speech. Emotion in any kind of conversation carries extra insight into human actions. It provides a lot of meta-data that can be used to improve the chatbot experience and also provide counselling services. These factors change the intended message that is conveyed in users input.

Building a great chatbot includes learning vocabulary, understand syntax, semantics, and be able to construct answers. Most chatbots have trouble understanding personal notes and context. Since algorithms rule these, they assume that the same words in the same structures mean the same thing to all people. In the case of voice interaction, an additional layer of tone can be analysed, and frustration can

be identified. In text interactions, this is impossible and could lead to bad responses.

Humans try to reach out to other humans when in need of love and empathy. However, in modern times, where mobile phones have become the biggest companions of the humans, it is not wrong in implementing an empathetic Chatbot, which would help the user in times of need. We can see that attempts are being made to turn these heartless Chatbots into empathetic friendly companions of humans. Creating the most human like chatbot is the aim of every chatbot developer, and so these components will help chatbot to be more human-like.

The goal is to create conversational instances which don't sound or behave like robots, but as human-like as possible. To achieve this chatbot needs to understand language, context, tone etc. The tool which can enhance this is sentiment analysis, a process which automatically extracts both the topic and feeling from the sentence or voice input. To determine the emotional context of a conversation sample, we select a chat sample. From the sample we extract a set of features that give us information about the emotion present in the sample. We use the appropriate algorithms that select the best features required to predict the emotion. Then using the features selected, we predict the emotional state present in the sample. This emotional state and the input can be used to generate a relevant response.

Recent strides in approaches to ML, DL and AI algorithms has given developers around the world, the opportunity to successfully build, test and deploy powerful AI applications on smartphones and other computers. Recent studies have shown that with Deep Neural Networks being improved through better algorithms and high capability machines, more powerful and useful applications can be built in short durations of time. Therefore, the large and rapid strides being made in ML, DL and AI related technology, the prevalence of a large community of developers working on these related products, the availability of more and more highly powerful hardware capabilities and the presence of powerful open-source software tools enables us to build powerful applications. The large and rapidly growing market of conversational assistants and voice assistants makes it all the more prudent to develop a product, which can help us improve the quality of such integral devices.

In this paper we aim to build a model which provides a conversation assistance and analyses the sentiments of the user based on them. The conversation is initiated by the chatbot and hence the user can smoothly interact with the

computer. The users input is then analysed and classified as a happy, neutral or sad sentiment. This sentiment can then be used for relevant response generation.

2. PROPOSED MODEL

Our project aims to understand the current emotional status of the user and provide a relevant response to input. The main objective of our model is to converse with the user, take insights from the input and provide an output to help them feel better.

2.1 Input

The user initiates a conversation with the chatbot based on an event in their lives and how they felt about it. The input provided to the model is in the form of textual data or through speech.

2.2 Data Preprocessing

Data preprocessing is a data mining technique used to transform raw data into an understandable format. Human languages are hard to understand as are usually ambiguous, incomplete and inconsistent. Data pre-processing prepares raw data for further processing and is a proven method for resolving such issues.

Data preprocessing is required because the model cannot understand a sequence of words, therefore it has to be converted into a numerical torch tensor. A batch of such sentences are used to form a multidimensional tensor which is then given as an input to the model for further processing.

2.3 Chatbot

The brain of the chatbot is a Seq2Seq model whose goal is to use a fixed-sized model that takes and returns variable length sequences as input and output.

This is achieved using two RNNs. The first RNN performs the role of an encoder, which encodes an input sequence of variable length to a context vector of fixed-length. In theory, this context vector (the final hidden layer of the RNN) is used as input to the bot and contains semantic information about the query sentence. The second RNN performs the role of a decoder, which takes an input word and the context vector, and guesses the next word in the sequence and also returns the hidden state to be used in the next iteration.

2.4 Sentiment Analysis

Emotion recognition has emerged as an important research area which helps in revealing some valuable information that can be useful for a variety of purposes. People express their emotions directly or indirectly through their speech, facial expressions, gestures or writing. These different sources of information can be used to analyze emotions. Nowadays, writings take many forms such as news articles, blog and social media posts, etc., and the content of these posts can be a useful resource for text mining to discover various aspects of human nature or interactions, including emotions.

The input provided by the user is sent to the model which then extracts the necessary features from it and calculates an emotion score.

2.5 Response Generation

Once the chatbot is able to understand what the user is trying to convey, the next step is to generate an appropriate response to maintain a continuous conversation. Each user has their own style of communication and this style varies between different users. To make conversation more personal and real for the user, the chatbot should study previous conversations and analyze its associated metrics to tailor customized responses for each user. This output is in the form of a tensor of index values which has to be a sequence of words before returning it to the user.

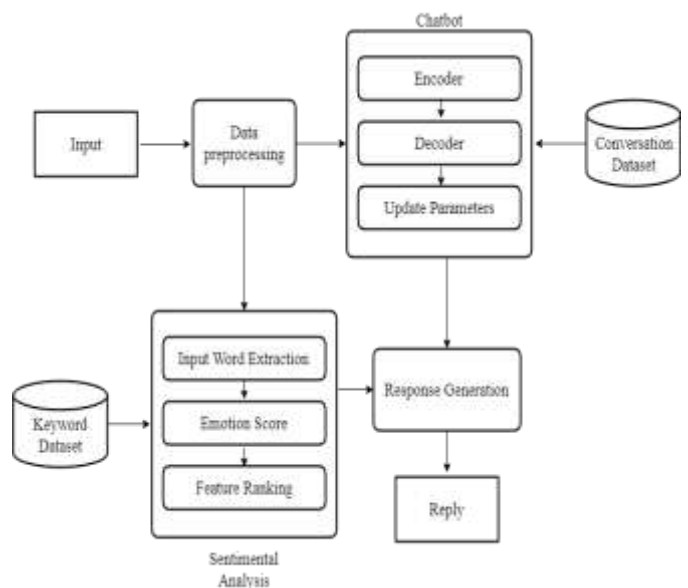


Fig -1: Proposed Model

3. METHODOLOGIES

3.1 Seq2Seq Model

A sequence to sequence model aims to map a fixed length input with a fixed length output when the length of the input and output may differ. The model consists of 3 parts: encoder, intermediate (encoder) vector and decoder.

An encoder is a stack of several recurrent units (LSTM or GRU cells for better performance) where each accepts a single element of the input sequence, collects information for that element and propagates it forward. In question-answering problem, the input sequence is a collection of all words from the question.

Encoder Vector is the final hidden state produced from the encoder part of the model. This vector aims to help the decoder make accurate predictions by encapsulating the information for all input elements. It acts as the initial hidden state of the decoder part of the model.

Decoder is a group of several recurrent units where each unit predicts an output y_t at a time step t . Every recurrent unit accepts from a previous unit a hidden state and produces an output as well as its own hidden state. In question-answering problem, the output sequence is a collection of all words from the answer.

$$y_t = \text{Softmax}(W^s h_t)$$

We calculate the outputs using the hidden state at the current time step together with the respective weight W^s . Softmax is used to create a probability vector which will help us determine the final output.

3.2 Sentiment Analysis using Naïve Bayes Classifier

The goal of sentiment analysis is to determine the writer's point of view about a particular topic, product, service, etc. Naive Bayes is a very powerful and simple technique that can be applied to text classification problems.

The objective is to build and train a classifier that determines if the textual information is negative, neutral or positive. Given the dependent feature vector $(x_1 \dots x_n)$ and the class C_k . Bayes' theorem is stated mathematically as the following relationship:

$$P(C_k | x_1, \dots, x_n) = \frac{P(C_k)P(x_1, \dots, x_n | C_k)}{P(x_1, \dots, x_n)}$$

The model uses sentiment dataset of Tweets are taken from the twitter account of the user. The files are stored in .csv format which is loaded to the sentiment analysis.

Texts generated by humans on social media websites contain lots of extra noise that can significantly affect the results of the sentiment classification process. Moreover, depending on the features generation approach, every new term seems to add at least one new dimension to the feature space. That makes the feature space more sparse and high-dimensional. Consequently, the task of the classifier has become more complex. To prepare messages, such text preprocessing techniques as replacing URLs and usernames with keywords, removing punctuation marks and converting to lowercase were used in this program. The model is trained using this preprocessed data.

3.3 Twython

Twython is a very useful Python library that provides an easy way to access data from Twitter. Recent studies have shown us that people who are depressed are more likely to tweet compared to the people who are happy or have overcome depression. The latest tweets of the user can be fetched and recorded for analysis. Twython makes this process easier by using simple REST and SOAP requests. This API returns the information is JSON, this data has to be then parsed to gain interesting insights.

Accessing Twitter data requires a set of credentials that must be passed with every request made from the application. These credentials can be of different types depending on the type of authentication that is required by the specific

application or endpoint that is being made use of i.e. user context requires an API key and secret and a set of access tokens that are specific to the user that you are making the request on behalf of. A Twitter developer dashboard is provided to view the list of active apps and its corresponding details. This information is fed into Twython to perform various functions.

2. RESULTS

The Home Page contains three sections, this will let the user easily navigate through different sections and perform different functions.

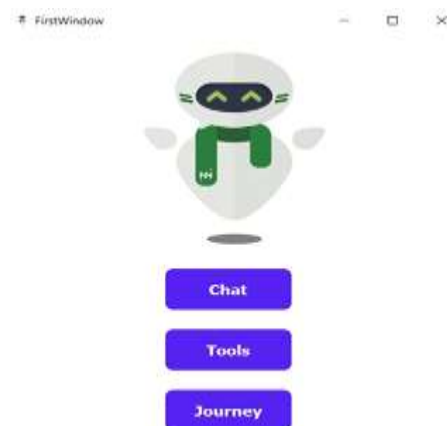


Fig -2: Home Page

Fig-3 is the main window of our project, this is where the user chats with the model by providing inputs to the model. When the Send button is clicked, the input is fed into the model and a response is generated, the response is printed in the text area. This also includes speech to text, the user can provide his voice input that will be converted to text. This can be achieved by clicking the Microphone button shown in the snapshot above. The snapshot above shows how the chatbot is trying to make the user feel better.

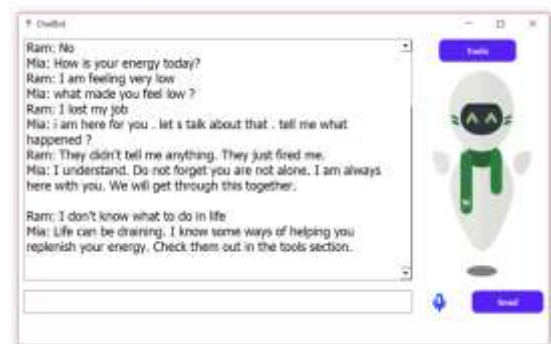


Fig -3: Conversation Page

Apart from text based counseling, this model also includes various tools that contains playlists to help the user feel better. This can be viewed by navigating to the Tools window. This project contains audio files to help the user get better

sleep, to boost their energy levels and to relax. It has been proven that audio files have greater impact in minimizing stress for a user. Therefore, these playlists will also be suggested by the model while having a conversation.

Various exercises have been mentioned for each category and a single click on the audio file plays the audio file. The user has to perform a double click on the audio file to stop the player from playing an audio file.

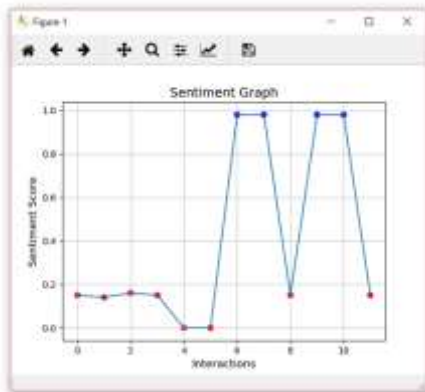


Fig -4: User Insights Page

A graph is also displayed in the model that includes various data points where a blue point indicates a positive entry and the red point indicates a negative entry. The x-axis of the graph displays the conversation count and the y-axis displays the sentiment score ranging from 0 to 1, where 0 indicates sadness and 1 indicates a happy data point.

The tweets of the user can be fetched from their twitter account and the sentiment score of each tweet can be plotted on the graph in a similar fashion as shown in Fig-4.

4. CONCLUSIONS

The human conversation is a complicated metric. It is capable of expressing multiple sentiments in a complicated manner that requires a deep understanding of the underlying context to detect the emotions conveyed by the users input. The user can provide input either through text or speech. Emotion in any kind of conversation carries extra insight into human actions. It provides a lot of meta-data that can be used to improve the chatbot experience and also provide counseling services.

These factors change the intended message that is conveyed in users input. To determine the emotional context of a conversation sample, we select a chat sample. From the sample we extract a set of features that give us information about the emotion present in the sample. We use the appropriate algorithms that select the best features required to predict the emotion. Then using the features selected, we predict the emotional state present in the sample. This emotional state and the input can be used to generate a relevant response.

The proposed model also fetches the latest tweets of the user using the Twitter API. These tweets are sent to the sentiment detection module, the sentiment scores obtained from this module is used to plot a graph. This lets the user monitor his sentiments over time.

Our plans for future work include experimenting with different polite datasets from various social media platforms. We can also add more functionalities like suicidal tendency detection which can be used to alert first responders to the emergency situation. This can also be useful to psychiatrists for deeper analysis of a patient over a long period of time.

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