Chatbot for Mental Health Awareness using NLP and Deep Learning

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Introduction

Mental health is a global issue, especially severe in most developed countries and many emerging markets. According to the World Health Organization, one in four people worldwide suffer from mental disorders to some extent. Moreover, three out of four people with severe mental disorders do not receive treatment, worsening the problem. Stigma and lack of access to mental health professionals can make it difficult for individuals to get the help they need. Chatbots have impacted several industries including healthcare. The objective of this project is to develop a chatbot that utilizes Natural Language Processing (NLP) and Deep Learning (DL) techniques to promote awareness about mental health. The chatbot will be able to understand and respond to natural language inputs and will be able to provide relevant information and guidance to users struggling with mental health issues in a conversational manner.

Motivation

The problem of mental health is important because it affects many individuals and has a significant impact on overall well-being and quality of life, and it often goes undiagnosed. Chatbots have the potential to bridge this gap by providing a convenient, accessible, and confidential means for individuals to learn about mental health and get support.

Dataset

The initial stage of data preparation involved collecting data from various sources. One such dataset we used is of posts made by users on Reddit based on how they were feeling – anxiety, PTSD, depression, or trauma. We have retrieved these posts in csv format [2] which were later collated with pre-existing simple chatbot responses [3] in JSON format. This data will aid the NLP model in analyzing what mental health condition the user is going through and direct them to the appropriate resources. Here data science is used to understand the intent behind the user's input and respond appropriately. Using NLP, important keywords are extracted from the user input and natural-sounding responses are generated and deep learning is used to classify the intents behind the user's inputs.

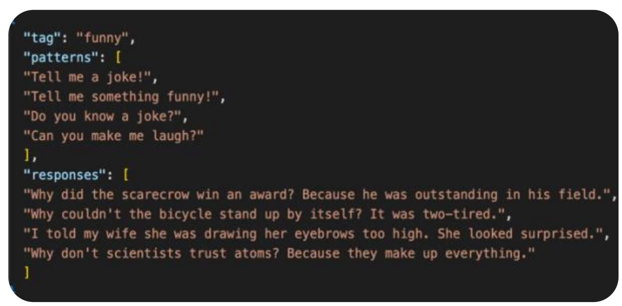


Figure 1: Sample of Data

Methodology

We classified our project mainly into three stages – Data preparation, Data pre-processing and Data modeling namely. However, we assessed the amount of risk associated with each of these stages and classified it into low-risk, medium-risk and high-risk, before we started working on it.

Low risk problem

Our low-risk problem is about creating a corpus that consists of potential conversational intents that the chatbot framework understands and NLP pre-processing. For retrieval-based chatbots, the data is required to be in conversational intents in the form of JSON files and this must be manually synthesized in the required format. The collection and organization of mental health data was a time-consuming process but has low risks associated with it.

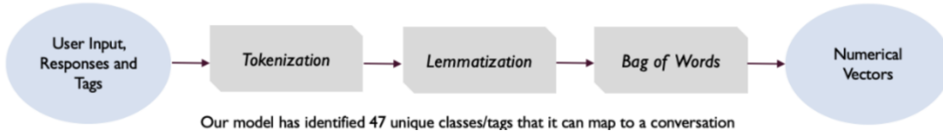


Figure 2: Process flow of converting input to numerical vectors

Then as a part of pre-processing, the user input is converted to neural-network-friendly data. This was relatively a straightforward process in which the input is converted suitable for modeling by first removing punctuations and unnecessary characters using regular expressions, followed by converting all the words to lowercase and then tokenizing the text into words followed by lemmatizing the words – which includes the process of converting the words to their base form by removing its inflectional endings. These lemmatized words are then converted to a bag of words representation which is a neural network- friendly format of vectors that marks the presence of a word from the vocabulary in a sentence with a Boolean value of 1 or 0 if absent. It is important to convert words into numerical representations because neural networks work by processing the data in vectors or matrices form. The bag of words representation makes it easy for the networks to process and learn from the text data as each dimension of the vector is treated as a separate input feature. At this stage, the data in JSON format and the preprocessed text are evaluated manually for correctness.

Medium risk problem

We categorized the process of building retrieval based chatbot as a medium-risk problem. In this kind of chatbot, the responses from the bot are based on the pre-defined responses in our database. We feed the user input and tags to the model. Here tags represent the kind/ class of response. Both the input and output are converted to numerical representation before feeding into the model. We also split the data into training and testing to evaluate how well the model can minimize errors during training.

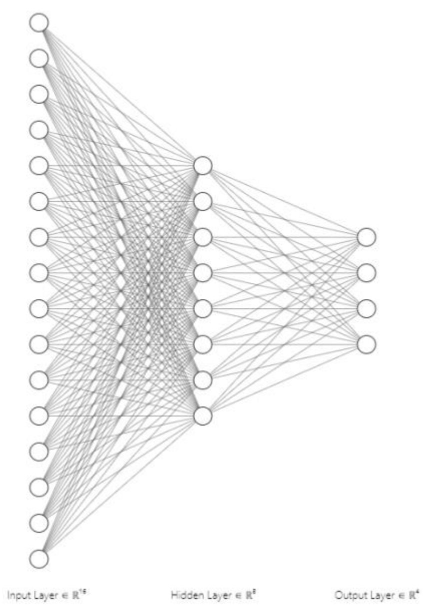


Figure 3: Neural Network architecture - scaled down for representation

The image is a scaled down version of the actual architecture. The input layer has 128 neurons, hidden layer with 64 neurons and output layer of 47 neurons.

So, once the bag of words is processed, it is passed to a sequential neural network model with 3 layers in total. Although we experimented with various neural network architectures, we ultimately chose a network with three layers- the first layer containing 128 neurons proceeded by a ReLu (Rectified Linear Unit) activation layer followed by a dropout layer for regularization, a hidden layer with 64 neurons followed by a ReLu activation layer and a dropout layer and the final output layer with the number of output classes that the model has identified from the training data to tag the text into – which is 47 neurons followed by a softmax activation function.

Dropout regularization has been added to prevent overfitting. ReLu activation function has been used to learn nonlinear relationships between inputs and outputs. And finally, softmax is used to convert the vector values into a probability distribution which means the output of this function is a vector of probabilities with each element representing the probability of corresponding class.

Also, stochastic gradient descent with momentum of 0.9 and learning rate of 0.01 is used as the learning function to compute gradients and update the weights of the model accordingly. Loss is computed using the categorical cross entropy loss method with accuracy as the metric to evaluate the performance of the model. Finally, this model has been trained with the data for 200 epochs with a batch size of 5.

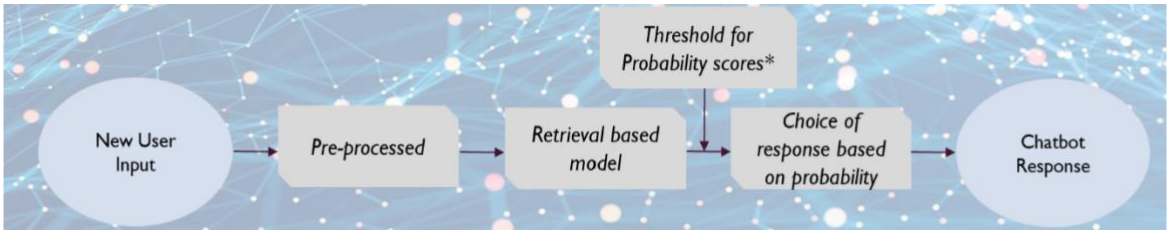


Figure 4: Process flow of generating a chatbot response

We attained an accuracy of 97.2%[1]. Based on this model we predicted the tags for a given user input for which the response is returned based on the probability. As discussed, the model returns a probability of corresponding class. Any new user input is pre-processed first to be converted to vectors and then passed through the model which returns the probability score for each intent. Here we considered a threshold of 25% to filter out the intents. The results are sorted based on the probability score and the most likely intent/ tag gets selected based on this highest probability and a response from the given corresponding intents that the tag belongs to chosen randomly and is given by the chatbot. At this stage we evaluated our model based on accuracy. Since our dataset is balanced, we prioritized accuracy over F1-score, the other popular evaluation metric for classification models.

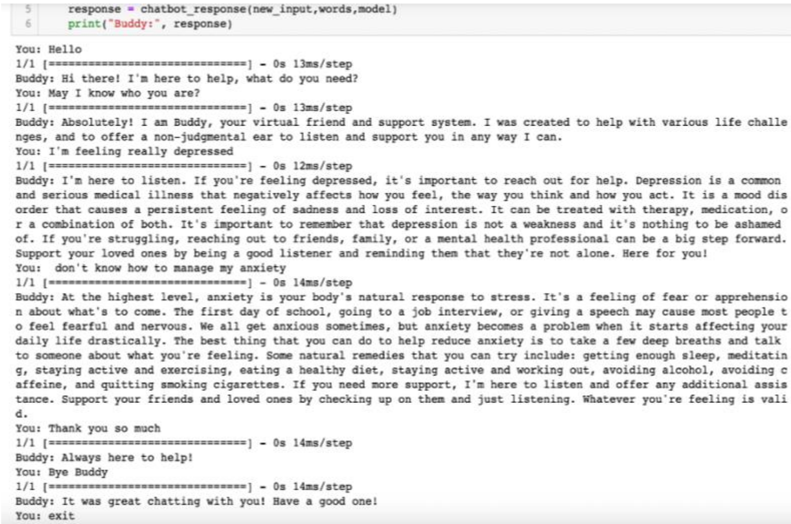
The model has exhibited proficiency in understanding the patterns in the user input data and generating relevant responses. Kindly refer to the results section for the same.

High risk problem

We also tried to develop a generative-based chatbot using an LSTM neural network, in addition to the retrieval-based chatbot. However, despite our extensive efforts and experimentation, we were unable to achieve satisfactory performance from our high-risk generative model. This was mainly attributed to the limited amount of available training data. We understand that this was a challenging task, and it underscores the need for larger and more diverse datasets to train the model and enhance its accuracy. Although we faced a setback in our project, we consider this experience as an opportunity to learn and improve our approach for future tasks.

So, our model uses LSTM neural network architecture[1]. Training data of conversations between patients and therapists are preprocessed initially by removing punctuations and unnecessary characters using regular expressions, followed by grouping conversation into pairs and adding start and end tokens to sentences before tokenizing the words and adding them to the vocabulary. The input data is then converted to encoder decoder friendly format of binary vectors with 1 marking the presence of a word and 0 marking its absence. The model has an encoder and decoder LSTM layer of dimensionality 256 and a dense output layer with a softmax activation function. The model is then trained for 200 epochs with a batch size of 5 compiled with a categorical cross-entropy loss function, Adam optimizer with a learning rate of 0.001, and accuracy as the evaluation metric. But we were merely able to attain an accuracy of 36.3%. At this stage as well, we used accuracy as the evaluation metric since the dataset is balanced.

Results



```
    response = chatbot_response(new_input,words,model)
    print("Buddy:", response)

You: Hello
1/1 [==============================] - 0s 13ms/step
Buddy: Hi there! I'm here to help, what do you need?
You: May I know who you are?
1/1 [==============================] - 0s 13ms/step
Buddy: Absolutely! I am Buddy, your virtual friend and support system. I was created to help with various life challe
nges, and to offer a non-judgmental ear to listen and support you in any way I can.
You: I'm feeling really depressed
1/1 [==============================] - 0s 12ms/step
Buddy: I'm here to listen. If you're feeling depressed, it's important to reach out for help. Depression is a common
and serious medical illness that negatively affects how you feel, the way you think and how you act. It is a mood dis
order that causes a persistent feeling of sadness and loss of interest. It can be treated with therapy, medication, o
r a combination of both. It's important to remember that depression is not a weakness and it's nothing to be ashamed
of. If you're struggling, reaching out to friends, family, or a mental health professional can be a big step forward.
Support your loved ones by being a good listener and reminding them that they're not alone. Here for you!
You:  don't know how to manage my anxiety
1/1 [==============================] - 0s 14ms/step
Buddy: At the highest level, anxiety is your body's natural response to stress. It's a feeling of fear or apprehensio
n about what's to come. The first day of school, going to a job interview, or giving a speech may cause most people t
o feel fearful and nervous. We all get anxious sometimes, but anxiety becomes a problem when it starts affecting your
daily life drastically. The best thing that you can do to help reduce anxiety is to take a few deep breaths and talk
to someone about what you're feeling. Some natural remedies that you can try include: getting enough sleep, meditatin
g, staying active and exercising, eating a healthy diet, staying active and working out, avoiding alcohol, avoiding c
affeine, and quitting smoking cigarettes. If you need more support, I'm here to listen and offer any additional assis
tance. Support your friends and loved ones by checking up on them and just listening. Whatever you're feeling is vali
d.
You: Thank you so much
1/1 [==============================] - 0s 14ms/step
Buddy: Always here to help!
You: Bye Buddy
1/1 [==============================] - 0s 14ms/step
Buddy: It was great chatting with you! Have a good one!
You: exit
```

Figure 5: Responses from the chatbot- Buddy

This project is a bit challenging mainly because it is task specific. We expect the responses from the bot to seem like responses from a human. However, the responses from the retrieval based chatbot are impressive in terms of their quality and relevance to user's input. The model has been effective in learning and understanding the patterns in data and can generate meaningful responses based on input from the user. Here is a snapshot of responses from our chatbot- Buddy.

Limitations and Future work

Even though we got desired conversational responses from the bot, if the mode is generative the responses would seem more natural. Thus, as a part of future work, we could work on fine tuning the generative based chatbot model by collecting more relevant data. Also couple other things that would make the chatbot more robust including incorporating advanced NLP techniques such as sentiment analysis to enhance the chatbot's ability to respond to user inputs and an interactive interface to interact with the chatbot.

Conclusion

This chatbot to discuss mental health will be especially beneficial for people who may feel uncomfortable seeking help in person or over the phone. Our chatbot understands and responds to user input in a conversational manner providing information on various health topics. All in all, the entire process of building the chatbot has been a thoroughly delightful experience and we look forward to continuing to improve its performance.

References

[1] Code & Data - https://github.com/har1ka/Chatbot-for-mental-health

[2] https://zenodo.org/record/3941387#.Y_EYJnbMJD_

[3] https://www.kaggle.com/datasets/elvis23/mental-health-conversational-data

[4] https://towardsdatascience.com/counsel-chat-bootstrapping-high-quality-therapy-data-971b419f33da