Virtual Agents using Sequence to Sequence Models for Sentiment Analysis to deal with Anxiety and Depression

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Abstract

This paper provides a description of how Virtual Agents can be useful in helping people with Depression and Anxiety, and how they can adapt according to the needs of the user, with the main goal of Sentiment Analysis. The Virtual Agent uses multiple Sequence to Sequence models to automatically generate texts based on the current conversation as well as performing the sentiment analysis with intent manipulation. The Virtual Agent primarily tries to emphasize on “Motivational Learning” to help the users overcome their problems. With a series of parallel intent recognitions, the user's overall mental condition is determined and the solutions are provided on the basis of their problem domain. After analyzing the success that motivational quotes and videos have had for depressed people, the proposed system also tries to achieve the same by providing the users with motivational content that gives them constant hope to move forward in life and helps deal with problems. The system revolves round this primary goal: the concept of motivation.

Keywords: Chat bot, Deep learning, Depression, Sentiment analysis, Sequence to sequence modeling

1. Introduction

According to the World Health Organization, 300 million people around the world have depression, which has led to more than 800,000 suicide cases every year. These people cannot seek proper guidance due to unavailability of services or their own unwillingness to talk to someone. Mental Health America reports that 30 to 70 percent of those who have died by suicide have had depression or bipolar disorder. People suffering from such problems are more hesitant to talk to other people regarding their mental issues. The big problem is that many people cannot see

human therapists as many people live in areas that are federally designated as having a shortage of mental-health-care professionals. To overcome this problem, talking to a chatbot is different and extremely comfortable, as the people with depression feel like they are talking to pre-recorded messages rather than to a person with cognitive capabilities. It is also comparatively easy to get access to a conversational chatbot available in the form of web or mobile applications ⁽¹⁾. Such ease more or less proves the effectiveness of Internet delivered CBT for both anxiety and depression.

A person's mental state can be ascertained via speech patterns, way of talking, use and frequency of keywords like “sad”, “unhappy”, “hell”, etc. Talking about ‘being a burden to others’, ‘feeling trapped’, ‘experiencing unbearable pain’, ‘having no reason to live’, etc are some of the common behavior that people with depression manifest. One can ascertain these patterns through the use of a Virtual Agent using a sequence-to-sequence model.

The researchers have found that reading inspirational quotes or even listening to motivational speakers can help people suffering from “Anxiety” and “Depression” to some extent. Therefore, during the conversation with the user, we first calculate the probable intents on multiple domains that can help to identify his/her current mental state. Subsequently, we can provide him/her with feedback or some sort of response based on the approach of motivational interviewing that can help the user cope with their mental issue. Besides this, the user can be supplied with certain audio/visual resources that can help them relax and get motivated. Therefore, the concept of this paper is solely based on the concept of motivational learning.

In this paper, we have proposed a model for sentiment analysis and motivational theory by using diverse sequence-to-sequence models, which are described as

having two Recurrent Neural Networks: an encoder and a decoder. The encoder basically takes in a sequence of inputs and processes them whereas the decoder generates another sequence, one symbol (word) at a time. We have exploited four datasets for the experimentation to validate our proposed model.

2. Related works

Evidently, the inception or usage of a chatbot is not unique to our research. Chatbots such as ALICE and ELIZA also use similar concepts for performing psychotherapy. ALICE basically generates an AIML (Artificial Intelligence Markup Language) file from a dialogue corpus with patterns and templates that allow it to generate dialogues based on the user's input ⁽²⁾. The others are developed by the AI Community for cultural heritage ⁽³⁾, security training ⁽⁴⁾, and blind high school students ⁽⁵⁾.

The major problems faced by these generic chatbots is that, due to the presence of a corpus, it assumes that its knowledge will come only from the training dataset. Furthermore, generating AIML from a corpus cannot guarantee a coherent chat because of a fear of repetitive or out-of-context statements, which will worsen the chat experience. These two issues indicate a the major defect of chatbots that often results in a lack of intelligence and a lack of variation in terms of message generation due to the pattern-matching nature of AIML⁽⁶⁾.

Chappie, a semi-automatic intelligent chatbot, overcomes this problem by avoiding AIML all together, but is limited to a smaller conversation domain. Similarly, the Rogerian Therapist chatbot Roza, developed by Michael Wallace, offers an approach to providing effective therapy, but is effective only when the conversation is limited to oneself and one's life.

Another chatbot, Woebot, founded by Dr Alison Darcy uses Cognitive Behavioral Therapy and was proven to be highly effective ⁽⁷⁾. Automatic detection of Depression in "A Cross-modal Review of Indicators for Depression Detection Systems" ⁽⁸⁾ used visual, speech, linguistic, social and multimodal indicators to detect depression which works with an extremely large amount of datasets.

3. Models

3.1. Recurrent Neural Network (RNN)

A recurrent neural network (RNN) is a class of artificial neural network where connections among nodes form a

Fig.1. RNN being unrolled into a full network

directed graph along a sequence. This allows it to exhibit temporal dynamic behavior for a time sequence ⁽⁹⁾. Unlike feed forward neural networks, RNNs can use their internal state (memory) to process sequences of inputs. This makes them applicable to tasks such as un-segmented, connected handwriting recognition or speech recognition ⁽¹⁰⁾.

Unlike feed-forward neural networks, recurrent neural networks have a backward connection among hidden layers. Therefore, these RNNs have some kind of memory in them. One of the most popular, modern RNN is called Long Short-Term Memory (LSTM) model. A Recurrent Neural Network based language model allows us to score arbitrary sentences based on how likely they are to occur in the real world which gives us a measure of grammatical and semantic correctness. Given a sequence of inputs,

$$(x_1, x_2, x_3 \dots x_t)$$

RNN computes a sequence of outputs

$$(y_1, y_2, y_3 \dots y_t)$$

by iterating over the following equation ⁽¹¹⁾ :

$$h_t = \sigma(W^{hx} x_t + W^{hh} h_{t-1}) \quad y^t = W^{yh} h_t$$

Such models are typically used as part of Machine Translation systems which allow us to generate new texts. In figure 1, we illustrate an RNN being unrolled or unfolded into a full network by writing out the network for a complete sequence.

In figure 1, x_t is the input at time step t . For example, x_t could be a one-hot vector corresponding to the second word of a sentence. s_t is the hidden state at time step t . It is the "memory" of the network. s_t is calculated based on the previous hidden state and the input at the current step:

$$s_t = f(Ux_t + Ws_{t-1})$$

The function f usually is a non-linearity such as $\tanh$ or $ReLU$. s_{t-1} , which is required to calculate the first hidden state, is typically initialized to all zeroes. o_t is the output at step t . For example, if we wanted to predict the next word in a sentence it would be a vector of probabilities across our vocabulary.

Fig.2. A simple sequence to sequence model with encoder and decoder

3.2. Sequence to Sequence Model

The sequence-to-sequence model was introduced first by Learning Phrase Representations using RNN encoder-decoder for Statistical Machine Translation ⁽¹²⁾, in which the model is described as having two Recurrent Neural Networks: An “Encoder” and a “Decoder”. The Encoder, after taking a sequence of inputs and processing them one word at a time, converts it to a fixed size vector while removing all the unnecessary information. This state is called the “context” or “thought vector” as it represents the intention of the sequence.

Figure 2 reflects a simple sequence-to-sequence model with an encoder and a decoder that can generate a reply based on the context of ongoing conversation. From the context, the decoder generates another sequence, one symbol (word) at a time. Here, at each time step, the decoder is influenced by the context and the previously generated symbols. Sequence-to-sequence (Seq2Seq) learning is used to model the conditional probability $p(y|x)$ of mapping an input sequence,

$$(x_1, x_2, x_3, x_4, x_5 \dots x_{n-1}, x_n)$$

into an output sequence,

$$(y_1, y_2, y_3, y_4, y_5 \dots y_{n-1}, y_n)$$

In practice, training for a single sentence is done by “forcing” the decoder to generate gold sequences, and penalizing it for assigning the sequence a low probability. Losses for each token in the sequence are summed, which is then used to take a step to the right direction in all model parameters (including word embeddings). To solve a sequence modeling problem, understanding the sequence is important to make any prediction around it. The information saved in the representation can vary depending on the architecture and types of attention mechanisms used in the encoder. For example, an LSTM encoder can save, in a hidden state, the gender of a certain word as it progresses

through a sequence of words, then forget that gender when it gets to a new subject. Recently, numerous research are trending toward the use of different attention mechanisms and complex memory structures that help the model decide what information from the input is the most useful to retrieve and pass on to condition the output.

4. Proposed Model

The chatbots may rely on more than just dialogue corpora for training. We will be using multiple datasets as proposed by (Dodge et. al.) ⁽¹¹⁾, which, when building a goal-driven dialogue system for movies, identified four tasks: question-answering, recommendation, question-answering with recommendation, and casual conversation with four different subsets of data.

The multiple Datasets include a Personality dataset, General Knowledge dataset, Casual Conversation dataset and Therapist dataset. All the intents related to a user’s input at a current state are trained on the RNN that identifies the type of conversation the user wants to have and a response is generated on that basis.

Our proposed model is shown in figure 3. First and foremost, the user's input is sent to the "Input Classification Module" in which the necessary text preprocessing and intent recognition is done in order to classify the input on the basis of 4 Question Categories (i.e. Casual, General Knowledge, Bot Personality and Problem Assessment). These categories determine the Seq2Seq model to be used for providing a reply, which can be answers to questions regarding General Knowledge, the bot’s personality (age, address, work, etc.) or some casual conversations. The "Input Classification Module" does all the necessary operation using “Support Vector Machine”. After the classification of the questions, the user’s input is sent to the corresponding sequence-to-sequence model (which includes its necessary pre-trained conversations) so as to engage the user in a conversation.

At the same time, the user’s input is processed in parallel for Sentiment Analysis. Let us visualize the Sentiment Analysis part. Before sending the user’s input to the sequence-to-sequence models for output generation, the positive/negative sentiment analysis is done for the Casual

Fig. 3. Proposed Model

Question Category, so that normal conversation such as “Hi, how are you?”, “How was your day today?”, etc. are not sent for sentiment analysis. The user’s input is sent to the “Sentiment Analysis Module” for the actual sentiment analysis. However, every conversation is not sent for analysis. (Note that negative casual intent and problem solving intent demonstrates that we will only be using the casual conversations with negative sentiment and problem solving conversations for sentiment analysis so as to increase the accuracy of calculating the score based on threshold).

After the necessary conversations (i.e. casual conversations with negative sentiment and problem-solving conversations) are passed to the “Sentiment analysis model”, the intent score for each of the conversations is calculated with respect to 3 groups and stored in a physical storage (CSV file). The three groups are: “Feelings” group which identifies the user’s feelings, “Environment” group which identifies the domain of the problem and finally “Effectors” group which identifies the cause of the particular feeling in the particular environment. These three intents help us determine the user’s current mental state and problem domain.

The score of the individual intents that are stored in the CSV file is then analyzed so as to determine whether we have enough information about the user in order to move towards the final stage of Motivational Therapy. This is determined by checking whether the Central Tendency of any intent is greater than a certain threshold value. For this

system, the threshold is taken as 0.5. This is done for every intent group so that we can determine the highest intent for every group, allowing us to identify the current mental state of the user.

The user is then prompted with a question as to whether he/she has the problem that the chatbot ascertained by this threshold. If the chatbot gets a negative reply, the flow is redirected to continue the conversations even further. If not, the chatbot will generate a reply based on the data collected so far, using another model to deploy a solution based on motivational learning and therapy. This step can also be regarded as the confirmation step that will lead to the generation of a solution based on the assessment.

4.1 Input classification module

We do this by training the RNN with a large number of example datasets. While training, each and every sentence is tokenized and turned into a Tensor/Vectored representation of the word. This is the phase of supervised learning wherein we manually label the intent of each and every sentence in the dataset. This tokenized group of words is then passed through multiple layers of the RNN to reach the final output layer with four nodes. These four nodes correspond to the four possible intents that we have. This is done as follows:

$$H_t = \sigma(U * X_t + W * H_{t-1})$$

$$y_t = \text{softmax}(V * H_t)$$

Where, H_t is the Activation function of the t^{th} node
 y_t is the Output we get from the t^{th} node

The RNN can now map words into a numerical representation allowing it to perform some mathematical calculations on it. These numerical representations, after passing through the above function, provides an output from the previously mentioned intents. We can now allow the RNN to understand the correct output through “Back Propagation”. We can use this Numerical System to guide the Model towards the desired value by nudging the value of weights and/or Biases to get to the desired output value.

$$c(n) = \sum_{i=0}^n (a^n - d^n)^2$$

4.2. Positive/Negative Sentiment Analysis

We require positive/negative sentiment analysis at multiple steps throughout our model. We first require this sentiment analysis component for the first RNN, from where we recognize which sets of data the user’s input belongs to. We do this because our Model has been trained to recognize only the conversations with negative sentiment as they are generally identified as “Problem Statements”. This Positive/Negative intent recognition is also required

for further Sentiment Analysis, as passing general conversations or Question-Answers for sentiment analysis will not provide any result whatsoever. In order for Sentiment Analysis to be carried out in the most optimal way possible, only those conversations that pertain to the user's actual feelings must be passed.

4.3. Sentiment Analysis Module

The Sentiment Analysis Module uses the RNN for doing the actual sentiment analysis work. This RNN is able to recognize multiple intents. The Intents have also been grouped under multiple domains. The first group is the "Feelings" group, where we identify the intents "Sad", "Lonely", "Depressed" and "Angry".

The frequency of certain keywords as well as the repetition of certain patterns allows us to ascertain the user's feelings. The second group is the "Environment" group in which we identify the intents "Work", "School", "Marriage", "Family" and "Relationship". It helps to identify the general context of the user's feelings, such as "Sad because of work" or "Angry because of marriage". This allows us to dive deeper into their problem domain.

The final intent group is the "Effectors" group, where we identify the intents "Boss", "Spouse", "Friends", "Teacher" and "Student". This is the final additional information that we need, to know more about the user's current mental state, the environment where he is being affected and finally the effectors that are causing this.

These three intent groups are of completely different nature from each other, but they help determine the user's state of mind as a whole. That is why we only train one RNN to be able to recognize all of these intents. Each of the user's inputs is scored on these intents. However, we face a problem of having ambiguous data. The scoring is only possible for the user's input in which they talk about his/her problems; but there are a lot of irrelevant conversations in general when talking to a normal person or even a chatbot. Normal greeting such as a "Hello" or a simple question like "What is your name?" cannot be scored properly by our RNN as it only recognizes the intents for problems and/or issues.

Not surprisingly, then, we introduced a fourth intent group, which identifies the intents of "Casual Intent", "Personality Intent" and "General Knowledge Intent" similar to the previous RNN so that it will not assign a random high score to other intents on greetings or general knowledge questions.

The output from this RNN, which is the score of each individual intent from the user's input is stored in a CSV file. This is done so that we can determine whether or not we have enough information about the user in order to move towards the final stage of Motivational Therapy. This is determined by checking whether the Central Tendency of any intent is greater than a certain threshold value or not. For this system, the threshold has been supposed to be 0.9. This is done for every intent group so that we can determine the highest intent for every group, allowing us to identify

the current mental state of the user. The user is then prompted with a question as to whether he/she has the problem that the chatbot ascertained with regards to the previously mentioned threshold. If the chatbot gets a negative reply, the flow is redirected towards more conversations. On getting a positive reply, the chatbot will generate a reply based on the data collected so far. This step can also be regarded as the confirmation step to lead to the generation of a solution based on the assessment of the user's mental state.

4.4. Output: Motivational Therapy

Getting a positive reply prompts the chatbot to use another model to deploy a solution based on Motivational Learning and Therapy. Because of this, the Model should not be created in a manner such that the replies are generative. This might create some issues, such as random messages being displayed, or even generate an out-of-context message. So, the reply or at least the "Solution" of the user's problem should be addressed in a specific way. It is possible that the intents from Group 3 or even Group 2 might not cross the threshold to provide a solutions. Because of this, the solution will only be provided for the top-scoring intent from the first group. We will define a sentence structure involving constant sets of words, and fixed varying factors, such as the user's mental state, his/her environment and the reason behind this problem. This is handled by creating a structured sentence wherein we can fit words and sentences according to the recognized intents, which is somewhat similar to AIML.

[Looks like you are [Feelings Intent] in your [Environment Intent] because of [Effector Intent].]

This approach should be adopted so as to guide the conversation in a controlled environment and not plant ideas in the user's head unknowingly. This is further explored upon, along with the intention of helping the user stay relaxed and motivated. Therefore, the concept of this paper is solely based on the concept of Motivational Learning.

5. Datasets

We will be using four datasets in order to train our chatbot to hold a conversation with the user. These four datasets are: Casual Conversation Dataset, General Knowledge Dataset, Bot Personality Dataset and Problem Solving Dataset. The Casual Conversation dataset contains a series of casual conversations in order to train our "Casual model" to hold a normal conversation. The General Knowledge dataset, contains a series of questions and answers in order to train our "Facts Model" to generate answers to general questions while in a conversation.

The chatbot also shows its very own personality and answers multiple questions like "What is your name?", "What is your age?" and "Where is your house?" with sets

of answers. This behavior is displayed because of our Personality dataset, which we have created for the chatbot. The final and the most important dataset is the Problem-solving dataset whereby a model is trained to respond to the user as if it were a doctor diagnosing a patient. In this paper, we have created datasets by ourselves using various online sources owing to their scarcity.

6. Experiments

The following conversation was obtained from one of the experiments with the chatbot. Generally speaking, a conversation with chatbots always starts with the user, resulting in a Question-Answer scenario, which may restrict or limit the chatbot's replies making it a one-way conversation. However, the conversation here is always initiated by our chatbot which can be helpful in directing the conversation towards the required topic, i.e. Sentiment Analysis.

Bot: Hello [Name]. How are you doing? How was your day?

User: Hello Bot. I'm doing quite well actually. Thanks for asking.

Bot: Good to hear that. So, did you want to talk to me about something?

User: Yes. It's about my work.

Bot: Oh. What happened?

User: I don't feel happy these days. It's like I'm in a lot of stress.

Bot: Is there anything going on in your life to make you feel that way?

User: I think it's my Job.

Bot: What happened?

User: I feel like I have too much work to do. I don't get any free time. The work keeps piling up. The more I complete, more keeps on adding.

Bot: Oh, that sounds bad. Are there other things that are also bothering you?

User: Yes, It's my boss. I don't like the way he treats me. He is keeping me like a slave driver.

Up until now, the bot has replied via the Seq2Seq models trained for holding a conversation. But there is another RNN that is running in parallel, which is scoring all the previously mentioned intents. We need a stopping criterion that will allow the chatbot to realize that it has recognized the current mental state of the user in order to provide a solution. For that, a threshold of 0.5 was decided in such a manner that if the Cumulative Average of the intent scores after every sentence, uttered by the user, crossed this threshold, then the user would have a high chance of being affected by that particular intent. Also, an initial bias of 0.5 was added in the beginning, so as to avoid a scenario in

which the first sentence alone would result in a high value of the intent score and prompt the chatbot to immediately display a solution, without starting a conversation. The chatbot continues the conversation until it has successfully obtained all three intents from the three intent groups to subsequently provide solutions. The solutions are a collection of sentences that will help motivate the user. Each intent from each intent group has multiple solutions linked to it, so at the end, we can just display the sentences as per the final set of intents as follows:

Bot: Looks like you have some kind of problem at your workplace because of your Boss. You might be feeling vain and sort of depressed. Is this true?

Assessment:

- Feeling [Depressed]
- Environment is [Work]
- Significant problem with [Boss]

Bot:

- You are experiencing such feelings for the first time so it may be somewhat overwhelming right now.
- Work environment is generally hectic and it takes time adapting to it.
- People normally feel like they are stuck in a cage, continuously doing the same thing to no end. But that is just because you haven't got the hang of things yet. You are in your adapting phase right now, so give it some more time. After you are adept at doing your work, it will become less stressful.
- It might feel like your [Boss] is to blame for all of this, but even he is just doing his work. It might be your brain trying to make sense of all this depression and stress by blaming it on your [Boss] so that you can direct your feelings towards him and let off some steam. Wait to see if your problem is solved. If you still feel that your [Boss] is doing something that he isn't supposed to do, then talk to them. [Work] is somewhere where everyone must have a mutual set of understanding with each other. So, it would also help to talk to your [Boss] to try and make him understand about your current situation.
- My suggestion: Take a piece of paper and point out all of your current problems, not its source. Then write things that you can change to solve these problems, and go one step at a time. No need to hurry! You should always tackle your problems with a calm and rational mind.

After giving the solution, the chatbot will ask the user if it was wrong in its assessment or not, and asks if the user wants to chat again. If the user wants to chat again, the 3 intents that were recognized earlier will have a certain small value added to it, so as to decrease the overall Cumulative average of that intent, so that we can start the next set of conversations with the data for other intents intact.

The experiment produced the following graph, with a score of 0.5 as the acceptance threshold. In figures 4, 5 and 6, we present a graph showing the average intent score for three different groups. These data allowed the chatbot to easily assess the user's current mental status and provide the respective solution. The data is obtained via the Second RNN, which is later stored in a .csv and can be easily manipulated using data-science.

Fig. 4. Graph for the average intent scores for Sad, Angry and Depressed.

Fig. 5. Graph for the average intent scores for Work , School, Home and Life

7. Discussion and Conclusion

Depression and anxiety are major issues affecting an incredible number of people over the world. It is possible to provide them with treatment and support, but it requires highly skilled psychologists and therapists.

In this modern age, most of the everyday sectors have already been influenced by AI, making the work accurate and more productive. It is also possible to indulge in the sector of mental health by conducting Sentiment Analysis through Artificial Intelligence.

Fig. 6. Graph for the average intent scores for Wife, Friends, Boss and Other.

The major roadblock for people with mental problems is that they do not have easily accessible solutions. Deploying a chatbot, through a convenient medium, such as a website, or through popular Social Networking Site such as Facebook or Twitter will allow easy access to anyone wishing to talk about his/her problems. A person's mental state is very delicate and we must take utmost care while dealing with a person's psyche. One small wrong step can be disastrous. This is why the utmost care must be taken while trying to handle mental issues through an automated system. Understanding the human mind requires a look into a multitude of complex dimensions, which is not easy to attain. Still, small steps such as this one might eventually lead to the creation of a proper system that can effectively treat and help someone deal with his/her anxiety and depression. This system does not replace human therapists; rather, it fills in the gaps for humans who cannot get therapy and need some help. Unlike therapists, this bot can talk to millions of people simultaneously.

The proposed system can be launched as a web-app or a mobile app to facilitate its access to users. Intent recognition can also be done through the use of APIs, so that people should not go out of their way to get additional services. The domain for the proposed system is still small and we are working with limited number of conditions. This is because there is still not enough research in the field of Artificial Intelligence regarding mental health and issues. Eventually, with enough research and a significant amount of datasets, it is possible to carry out sentiment analysis and aid people in fighting against anxiety and depression through Artificial Intelligence alone.

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