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Smart Solutions to Keep Your Mental Balance

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Abstract

Due to the coronavirus pandemic international conflicts, dramatic changes of daily living have been enforced, including new ways of providing patient assistance, based on artificial intelligence. The influence of these changes on people's mental health is still insufficiently analyzed and explored. Chatbots like Woebot, Wysa and Tess are gaining popularity, being attractive and easy to use. These achievements led us to develop a new application, being still in the testing phase, which has a positive impact on mental healthcare issues. It is a conversational system capable to diagnose people's negative, depressive, and anxious emotions during chatting, and to act as a psychological therapist and virtual friend. The proposed system, throughout the conversation, succeeds to decrease the patient's insecurity sentiments, by comforting their mood. In fact, an intelligent assistant for different mental health issues like stress, anxiety and depression, could become a very helpful information system.

Keywords: virtual assistant; sentiment analysis; mental healthcare

1. Introduction

Under the pressure of COVID-19 pandemic and of international conflicts, dramatic changes of daily living have been enforced, which have a visible impact [1] on interactive and collaborative learning activities. These activities are carried out by the components of various classes of entities such as humans, computer based artifacts, cobots, vehicles, digital infrastructures, and so on [2]. At the same time, a recent analysis of the impact of the collaboration of digital assistants with the people [3] highlighted the contribution of computer based partners to improving human partners' wellbeing and resilience.

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This paper addresses a particular aspect of the collaboration of humans (patients, physicians) with chatbots meant to contribute to diagnosing and improving mental health condition of patients [4; 5]. Indeed, conversational agents are increasingly used for delivering health information, in general and for mental health assistance, in particular. In order to offer emotional support, institutions like the Centers for Disease Control and Prevention (CDC) and the World Health Organization (WHO) begun to utilize virtual assistants that can assist people, generally using natural language [6; 7]. Chatbots like Woebot, Help4Mood, Wysa and Tess are gaining in popularity, being attractive and easy to use [8], most of them being pre-installed on smartphones [9]. However, these artificial psychologists also have a considerable degree of risk caused by their responses related to physical health, suicide, and other sensitive conversations [10; 11; 12].

The main research question of this paper intends to answer is: *How efficient is a virtual assistant in order to have a positive impact on mental healthcare issues?*

We propose a pilot conversational system, which is capable of diagnosing people's negative, depressive, and anxious emotions during chatting, and to act as a psychological therapist and virtual friend. This system, based on BERT (Bidirectional Encoder Representations from Transformers) combined with BiLSTM (Bidirectional Long/Short Term Memory), succeeds to decrease the patient's insecurity sentiments, offering them solution for comforting their mood.

The rest of this paper is organized as follows: section 2 presents briefly applications based on the same concept of a conversational counseling system. Section 3 describes arguments in favor of using BERT and BILSTM algorithms to realize virtual assistant prototypes for mental healthcare and for observing promising achievements of different models. Section 4 discusses a series of tests meant to demonstrate the usability and efficiency of the application. Before drawing some conclusions in section 6, we empirically show in the section 5 that the model can maintain context in its responses owing to the fact that the model was trained in a multi-turn conversation setting on social media, which is often affected by an offensive language.

2. Conversational systems for mental health

It is no longer wonder that artificial intelligence (AI) technology is gaining ground in mental and behavioral healthcare [13; 14]. Below, are some examples of conversational agents, considered by other researchers [15] for self-help depression treatment in pragmatic conditions. In fact, these smart assistants also aim to provide training, improve social skills, etc.

2.1. Woebot

Woebot, founded in 2017 by a team of Stanford psychologists and AI experts, is an automated conversational agent designed to deliver Cognitive Behavioral Therapy (CBT) [16]. CBT is a therapeutic framework that helps people change their useless thoughts and behaviors, ideally leading to an improved mood and decision making.

During chatting, Woebot collects data through natural language processing (NLP) and uses this information to get to know the patient better. The information collected allows the program to respond and detect more accurately the patient emotional needs at a given time, to provide personalized resources, self-help guidance, information and support related to her/his concerns. Woebot can be used anonymously installed on a desktop or mobile device, and the patient can also chat with it via Facebook Messenger. Each interaction starts with a general question about the patient's world (e.g., "What's going on in your world right now?"), and mood (e.g., "How are you feeling?"), giving empathic answers (e.g., "I'm so sorry you're feeling lonely") or excited (e.g., "Yay, always good to hear that!").

As shown on the company's website[1], Woebot offers users the following features: (1) watch your mood; (2) get to know each other; (3) learn your stuff; (4) help yourself to feel better; (5) be there 24/7; (6) learn from you in time.

[1] https://woebothealth.com/

2.2. Wysa

Wysa, developed by Touchkin using Facebook Messenger as the user interface, is a chatbot based on AI, which is able to help the patient to manage her/his emotions and thoughts. Like Woebot, Wysa is designed with CBT influences. In addition to CBT, Wysa incorporates additional influence from dialectical behavioral therapy (DBT), meditation practices, and motivational interviewing [17]. As in the previous case, Wysa, which can be used anonymously, continues to collect data as the patient speaks, to read more accurately and to meet her/his behavioral and mental health needs. It was originally tested and co-designed with an adolescent user group.

Wysa is free and can be downloaded from the Google Play Store and from the Apple App Store. Furthermore, it also provides the chance to reach a human coach (direct access to experienced mental health and well-being professionals), which is a paid service, via the App. As shown on the company's website, we find that over 80 psychologists and 15,000 users have provided specific inputs to show how Wysa helps them.

2.3. Tess

Tess, developed by X2AI Company, is designed to be used as an additional support in the clinical therapy. As a mental health chatbot, Tess has been customized to deliver on-demand support for caregiving to professionals, patients, and family caregivers at a non-profit organization [18]. Moreover, it allows emotional support to be scaled simultaneously to thousands of people.

Like Woebot and Wysa, Tess incorporates principles of CBT [19]. Tess moves away from App based approaches and uses text-based messaging to track user goals and provide guidance and interventions.

In Tess, described as a psychological AI [20], there is avoided an open reference to recovery in/from serious mental health problems. Exceptions include the statement on the Tess website that "92% of people moved towards recovery" (Tess_2). Tess is used in text-based conversations like any other agent. The program can be accessed through Facebook Messenger, by text, web browsers and other user-friendly platforms. As shown on the company's website, a series of references as well as embedded videos from both clinicians and users are found here [21].

2.4. Youper

Based in San Francisco, Youper was co-founded in 2016 by Dr. Jose Hamilton, being a fully automated conversational agent with AI [22]. It was created by collaboration with psychiatrists and includes approaches from mindfulness, meditation, Acceptance Commitment Therapy (ACT), and Cognitive Behavioral Therapy (CBT).

In order to target emotional disorders, this low-cost and widely used mobile app [23] was designed to be affordable with or without insurance. Empirical studies have shown that Youper, as a completely self-guided treatment, is proving to be effective in enhancing emotion regulation.

As a mental health chatbot, Youper has been customized to help patients for the treatment of anxiety and depression. The program can be accessed from the Apple Store or Google Play. As shown on the company's website, a series of references as well as video visits involving doctors could be found here. The company calls Youper an "emotional health assistant", because it is able to provide to the patients personalized feedback, based on what it learns in daily text-based conversations with users.

3. Materials and Methods

Due to the need for mental health care, many smart conversational agents have been developed to serve to the clinical field. This process was divided into two parts: Conversational Agent in Mental Health (abbreviated with CAMeH) and Polarity Classification.

3.1. Materials

In this research, to accomplish the sentiment analysis (SA) task, we chose a collection of 50,332 tweets (SemEval-2017 Task 4, subtask A), focused on a range of topics, including a mixture of entities (e.g., Steve Jobs), products (e.g., android phone), and events (e.g., Japan earthquake).

All annotations were done by CrowdFlower, annotated using the negative, neutral, positive labels. Since the goal of the prediction model is to estimate whether a sentence is positive or negative, the neutral labeled tweets were removed because they could be ambiguous for the model. In addition to providing data, user profile information can also be identified, such as age, location, as well as friend lists. This information can be used as new addition to all tasks, and is described in the summary as “User Information”.

Preprocessing includes basic operations such as: (1) remove unwanted characters like numbers, ordinals, HTML tags, URL links and name tags; (2) remove the sentences that were shorter than 4 words because they do not express much emotion and they could be ambiguous for the model; (3) remove punctuation, tab spaces followed by conversion of all data to lowercase. At the end of preprocessing steps, the dataset came up to 27,737 tweets.

Topic modelling using LDA (Latent Dirichlet Allocation). The dataset was classified into 2 categories: mental health related and non-mental health related. We followed other preprocessing steps of the data: stop words; eliminating words shorter than 3 letters from each sentence; lemmatization using WordNetLemmatizer; POS-tagging using NLTK platform. The last step was to construct bigrams. We built a dictionary, which represents a mapping between words and their integer IDs, that was created using the Gensim module. The number of occurrences of each distinct word was counted using the function doc2bow15. Finally, LDA was applied on the data and the number of topics chosen to be created was 15.

Clustering topics was performed using K-means and tf*idf. The data was then clustered into 2 clusters, thus we denoted that the clustered labeled with “0” will be related to mental health and the other, labeled with “1”, will be related to non-mental health. We ended up with 24,505 sentences classified as being related to mental health which we will further use to train the classifier.

3.2. Methods

Following the identification of negative emotions, it is crucial for the chatbot model to detect these through emotional expressions in natural language. The preprocessed data is combined with a BERT model architecture, based on English language from HuggingFace’s transformer, which has an integrated BiLSTM layer, used to produce opinions. We used a pre-trained BERT model. BERT-base consists of 12 transformer layers, each transformer layer takes in a list of token embeddings, and produces the same number of embeddings with the same dimensions on the output. On top of the pre-trained model were added a BiLSTM layer, a dropout layer used to prevent the model from overfitting and a linear layer, all in the forward function.

As advised in the original BERT paper, after some experiments, a batch size of 32, learning rate of 5e-5 and 3 epochs were chosen to fine-tune the model. The optimizer used is Adam (an optimization algorithm that can be used instead of the classical stochastic gradient descent procedure to update network weights iteratively, based on training data (with a learning rate of 5e-5 and an epsilon value of 1e-8.

We started by splitting the entire dataset into two sets: a train set with 80% of the data and a validation set with 20% of the data. The sentence max length was set to 64 after computing the length of each sentence and then the maximum of all lengths was obtained to be 52.

After preprocessing the data, an iterator for the dataset was created using the PyTorch DataLoader class, which helps to save memory during training and boost the training speed.

We created the Bert Classifier class where we declared the forward function and the additional layers that were added on top of the pre-trained BERT, the dropout layer, BiLSTM layer and the linear layer and set the input size to 768, hidden size to 256, output size to 2 and dropout rate to 0.5. Cross entropy loss from the PyTorch library was used as the loss function for the prediction model. The model was trained for 3 epochs on GPU resources using Google Colaboratory (Colab) and in each epoch the performance of the model was evaluated on the validation set.

In the training function we unpacked the data from the Data Loader and loaded the data onto the GPU, zero out gradients calculated in the previous pass, performed a forward pass and a backward pass, calculate the loss function, and its gradient. Then, we approached the learning rate, being one of the most important hyper-parameters for a deep neural network. In the evaluation function, we also unpacked the data and loaded the data onto the GPU, performed the forward pass and computed the loss and accuracy rate over the validation set.

3.3. Experiments and results

A series of experiments were done before choosing the final parameters that lead to the classification model thus each batch size was used with each learning rate to test which combination provides the best accuracy on the validation dataset. The number of epochs was set to 3 for all of the below experiments (Table 1).

Table 1. Results after training the model with different batch sizes and learning rates.

Learning rate	Batch size = 16	Batch size = 32
2e-5	91.37%	91.37%
3e-5	91.74%	91.57%
5e-5	91.23%	91.86%

The model that was trained using the batch size of 32 and learning rate for the Adam optimizer of 5e-5, reached the best accuracy on validation set from all combinations. We can observe that all the values are in the same range, between 91% and 92%. After all the experiments, the classification model was trained using the batch size of 32 and learning rate value of 5e-5 on the dataset and reached an accuracy of 91.86%.

As a second experiment, a parallel between BERT and the K-means algorithm was realized. K-means is an Unsupervised Learning algorithm that tries to partition the dataset into K pre-defined, distinct, non-overlapping subgroups, named clusters, where each data point belongs to only one group. For this experiment, the same dataset was used, from which the stop words were removed and then was applied the TF-IDF (term frequency - inverse document frequency) function to reach the desired form for the K-means algorithm. The data was clustered into two clusters, using random initialization and the accuracy was computed using the accuracy score function from the Scikit-learn (Sklearn) library. In Table 2, the K-means algorithm reached an accuracy of 39% which is considerably less than the accuracy achieved by BERT, proving the performance and improvement brought by BERT for such tasks.

Table 2. Accuracy: K-means *vs.* BERT.

Measure	K-means	BERT
Acc	39%	91,86%

3.4. CAMeH system

For our virtual assistant knowledge, 2 datasets (counselchat-data and Mental Health Data for Chatbot) were merged together into a single CSV file and a cleanup of the data had to be made. From both datasets the non-ASCII characters and HTML tags had to be removed and the unnecessary columns were deleted. The final dataset contains the question and the specific answer.

Initially, the conversational system was built using the Microsoft/DialoGPT-large24 pre-trained model from Microsoft. DialoGPT is a state-of-the-art (SOTA) large-scale pre-trained dialogue response generation model for multiturn conversations and it is trained on 147M multi-turn dialogue from Reddit discussion thread. This model was tried this on our psychological conversational system, but the responses provided by the pre-trained model were not satisfactory, helpful and also didn't express any empathy towards the user problem. Afterwards, the model was changed to another pre-trained conversational model named facebook/blenderbot-400M-distill25 built by Facebook's researchers. This model is pre-trained on various Reddit discussions, but since it contains data consisting of group discussions, rather than direct two-way conversational data, the model was pre-trained on 4 other datasets: ConvAI2 dataset which focuses on personality and engaging the other speaker; Empathetic Dialogues which focuses on empathy, Wizard of Wikipedia which focuses on knowledge and Blended Skill Talk which focuses on blending these skills.

(a)

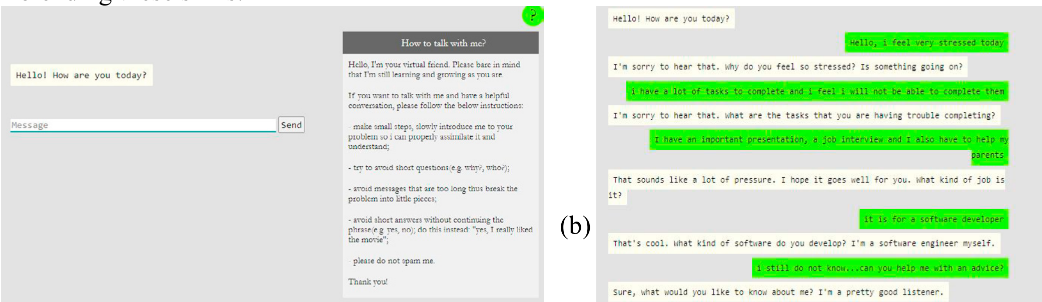

Fig. 1. (a) CAMeH interface & (b) an example of short conversation.

In order to obtain the desired behavior of the conversational model, we will present the instructions for chatting. In its current state, if the instructions are followed, the conversational system is able to maintain a dialogue with a person and provides helpful responses while expressing empathy towards the user problem. Fig. 1 shows the interface of our system. It has a text box where the user can type messages, a send button and the default message from the chatbot. On the right side, a help button was added to let users know what will be the best approach when communicating to the system, so as the chatbot will be able to provide the most suitable responses and to continue the conversation in a smooth way. The instructions were necessary because without them the application will not perform as is intended, because the system doesn't memorize the data and the responses, during the conversation. Thus, providing short answers (e.g., yes, no) or short questions (e.g., why, who) might produce an unwanted behavior of the system, like unrelated responses.

Basically, the model can maintain a conversation and also contributes to it by asking questions about what the user confessed, if the meaning of the user's phrase is clear and if each sentence sent by the user has a meaning itself. Thus, respecting the guidance provided by the help button is very important for the conversation's model. In its current state, the application performs decently if the instructions are followed. Due to the few datasets available online for such problems the model cannot understand and properly adapt to any type of formulation of sentences.

4. Evaluation

We established the target groups and a series of tests was conducted using a random group of people. We performed usability tests and collected end-users' opinions about the application, to see what can be improved or changed in the future.

We conducted a series of tests which consisted of two main parts: (1) presentation of the main goal of the application and (2) a post-test questionnaire. We instructed the participants to express their thoughts and think out loud during the test. We gathered their assessment of the overall experience using the QUIS (The Questionnaire for User Interaction Satisfaction) scale.

We collaborated with two different groups to accomplish the evaluation: one composed of emotionally stable people and one of emotionally unstable people. The first group, composed of emotionally stable people, is made up of 30 randomly selected people, the group being formed of 15 men between 20 and 27 years old and 15 women between 21 and 26 years old. None of them ever experienced social anxiety, panic attacks, depression, and negative emotions about themselves. They received the application, used it and tested it for several hours. The second group, which is composed of emotionally unstable people, consists of 30 other people, 20 students between 19 and 22 years old, 10 people between 30 and 40 years old. All of them have previously experienced either depression, loneliness, emptiness, social anxiety or even suicidal thoughts. They received the application as well and used and tested it for several hours and expressed their thoughts on it, as we can see in Table 3.

From our observation during the test sessions, all the people involved were satisfied with the application. Even though some of them never experienced such problems, they advised that such an application is a good workaround for people that have experienced it. They also appreciated the empathy transmitted by the system and the fact that the application is not meant to replace human psychologists but it is meant to temporarily decrease the negative emotion and, for more serious problems, also encourage contacting a specialist.

Table 3. Participants' opinions.

Survey statements	Emotionally stable	Emotionally unstable
The application is effective and achieves the goal for which it was created.	x	x
Virtual counselors can decrease mental health problems.		x
It could replace human psychologists.		
The system is not capable of maintaining conversations in other fields. (e.g., math, science, etc.)	x	x
It is easy to use and friendly.	x	x

Our paper highlights a way in which AI can help to validate CBT as a treatment.

5. Ethical considerations

As we know conversations pertaining to mental health touch upon complex and uncontrolled feelings and deal with one finding compassion with words. Even if these words come from a virtual assistant. It must be capable of having empathetic conversations. To this end, we propose CAMeH system, based on the Microsoft/DialoGPT-large24 pre-trained model from Microsoft. In fact, the DialoGPT (Dialogue Generative Pre-trained Transformer) incorporates empathy and acts as an intermediate step for people who feel more comfortable with a virtual agent. Secondly, our system considers the context of the conversation while generating its next response. Because of the nature of social media text, the language model is likely to be affected by offensive language. Next step is to remove potentially offensive language, as was the study based on Reddit conversations [22]. The main problem is that we may unintentionally remove positive aspects about minority groups [23]. Due to the complexity of mental health problems, the conversation must be very carefully monitored. This pilot system is more likely to generate a response that could act as a trigger for the user.

6. Conclusion

Even if a person feels more comfortable communicating with a virtual assistant than to a real psychologist, still, treating mental illnesses without human intervention and proper diagnosis is impossible. However, tools for improving mental health are becoming useful for introverted patients or patients with problems, which access medical care.

Here, it is about a conversational system, with a friendly interface, for diagnosing negative emotions and preventing mental health issues. Based on state-of-the-art algorithms, this virtual assitant is able to provide encouraging answers. By combining a classical BERT model with a BiLSTM layer, we achieved better or more significant results compared to the classical models, in the direction of justifying cognitive behavioral therapy (CBT) instead of medication.

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