Aida: An Artificially Intelligent Depression Handling Assistant

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Abstract:

Aida is a conversational AI chatbot for mental health that can assist those suffering from depression, anxiety, and stress, among other things. This chatbot application was designed primarily for individuals who have difficulty accepting help from a mental health professional or their family. The last several years have taught us the value of mental wellbeing. Psychotherapists charge exorbitant fees every session, and a middle-class guy cannot afford to spend his money on items he thinks are non-essentials. Aida could behave as your companion and communicate with you anytime you require it. It is a program that assists users in overcoming negative emotions and ideas. From natural language input, it deduces a user's core emotions. Using this emotion as the base, the chatbot will try to have a friendly conversation with the user until his mental state has improved. Rasa open-source library has been used to implement the chatbot and a web widget is designed to deploy it on a website. A Between-subject study has been conducted on 20 subjects where the users were asked to use two chatbot widgets, one created by me and the other by Botfront, testing different depression modules being offered. The results are that both widgets are almost similar in terms of user satisfaction even though the task completion time is more in the widget created by me.

Key Words: Natural language Processing, Chatbot, Artificial Intelligence, Rasa, Machine learning, Mental Health, Natural language Understanding, Between-subject evaluation.

Introduction and Motivation:

According to the World Health Organization (WHO) [1], the array of mental disorders includes depression, bipolar affective disorder, schizophrenia, and other psychoses, dementia, intellectual disabilities, and developmental disorders including autism. These conditions manifest in different ways such as abnormal thoughts, perceptions, emotions, behavior, and relationships with others. Depression alone affects more than 300 million people according to the WHO. Scientific American reports that the economic cost of depression in the US is in the hundreds of billions annually. Even with access to capable health care and social services, those afflicted with mental health conditions hesitate to avail of the treatment due to the stigma surrounding the illness.

According to the World Health Organization, there is a global shortage of health workers trained in mental health [2]. Many mental health interventions do not reach those in need, with approximately 70% with no access to these services [3]. This shortage issue has made the AI industry take matters into its hand. Building conversational AI systems to create a humanlike AI has been one of the leading research topics to date.

Human-computer interaction (HCI) researchers and practitioners have been honing their abilities in building graphical user interfaces for decades. Now, things could take an unforeseen turn toward natural-language user interfaces, in which users interact with computer systems using natural-language strings rather than scrolling, swiping, or button clicks. The fact that many wonderful papers about these natural language agents are being published at ACM International Conference on Intelligent User Interfaces (IUI), a place where HCI meets AI, shows this shift in trend. With continued advances in natural language processing and machine learning, conversational agents have become popular for various tasks, domains, and settings. In fact, HCI researchers have studied Natural Language systems before, for example, in the context of multimodal systems, interactive voice response systems, voice control in the context of accessibility, and conversational systems. Developing new technologies and designs for conversational interfaces, and studying how people interact with agents, has become a focus of both the HCI and AI communities.

Some people are hesitant to share their sorrows or troubles with others because they are afraid of being judged or mocked by another. In such instances, chatbots or dialogue systems can be utilized to meet the user's usual information needs by posing as a friend or well-wisher. Aida makes the user feel like he or she is conversing with a real person by providing relevant responses in a language that the user understands. Rasa open-source library has been used to implement the chatbot and a web widget is designed to deploy it on a website. A Between-subject study has been conducted on 20 subjects where the users were asked to use two chatbot widgets, one created by me and the other by Botfront, testing different depression modules being offered.

Figure 1: Sample Screengrab of Chatbot Conversation

Related Work:

In 1964, Joseph Weizenbaum invented Eliza [4], which was one of the first natural language processing computer programs. The MIT Artificial Intelligence Laboratory was responsible for its development. Eliza is a really simple bot that was built in 1964, which is worth mentioning. The conversational bots have come a long way since then. Woebot, Wysa, and Joyable are a few chatbots that can aid with anxiety and depression. Woebot is a therapy chatbot that helps users keep track of their emotions and better their lives. This is one of the most popular mental health chatbots in the market right now. Woebot applies Cognitive Behavioural Therapy (CBT) to assist users in overcoming sadness and anxiety symptoms. CBT is one of the most successful methods for treating depression and anxiety that has been established to date. Wysa likewise uses humor and cognitive behavioral therapy (CBT) to assist users, however, unlike Woebot, the talks might become monotonous at times. One feature of Wysa that stands out is the positive thought diary, which is kept to help users cope with stressful situations. Wysa also allows you to schedule a treatment session with a real therapist. These chatbots will never be able to take the place of therapists since nothing compares to the human connection. They are here because there are millions of people worldwide who refuse to see a psychiatrist, despite the fact that doing so would greatly benefit them. There are a variety of reasons why people find it difficult to reach out to others. We usually suggest that if we are depressed, we should talk to someone, but we forget that doing that is difficult is very difficult for some people.

It is for this reason that chatbots were created. Chatbots aren't flawless, but they're a start.

Proposed System:

The main functions of a depression-handling chatbot include understanding the emotions of the user and responding back with a humane touch. I have used Natural Language Understanding technique to identify what emotion the user is going through. After the emotion is classified, the chatbot uses its inherent dialog management system to select appropriate dialogs to get the conversation going. The whole chat lifecycle can be delineated in the flow diagram below.

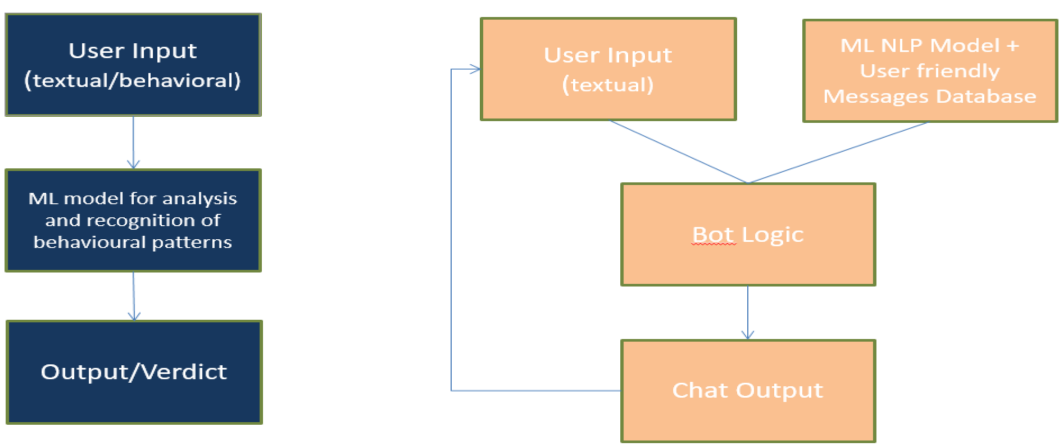


Figure 2: Chatbot Lifecycle

For the implementation of the chatbot, I have explored different chatbot frameworks viz. Google's DialogFlow, Amazon's Lex, Rasa, and Microsoft's bot framework. After careful considerations, I have decided to pick Rasa to develop the chatbot because it is open source and has good community support. Rasa is an open-source machine learning framework to automate text-and voice-based conversations. It provides the developer with a framework that automates the process of converting raw text from user messages into structured data. Parse the user's intent and extract important key details (NLU), and also the dialog management. The component diagram of the Chabot is given below,

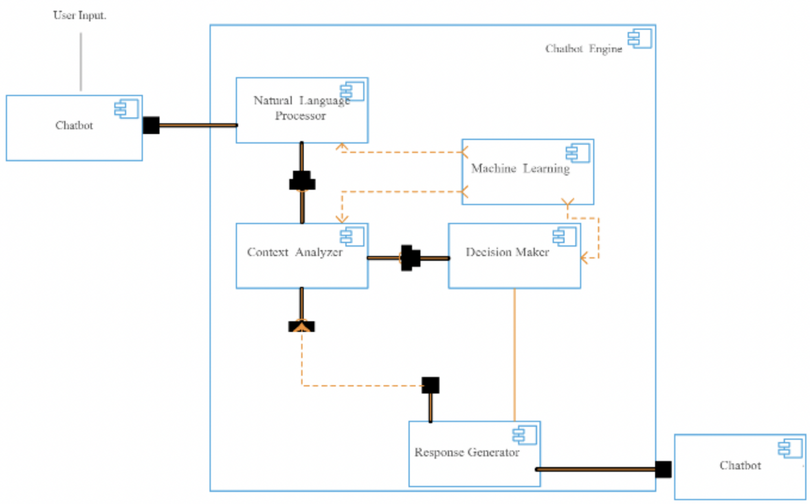


Figure 3: Component Diagram

The framework has the following modules:

- Rasa NLU: Handles the Natural Language Processing Rasa NLU is like the "ear" of your assistant — it helps your assistant understand what's being said. Rasa NLU takes user input in the form of unstructured human language and extracts structured data in the form of intents and entities.
- RASA Core: Handles data storing, piping, API, and basically the Assistant

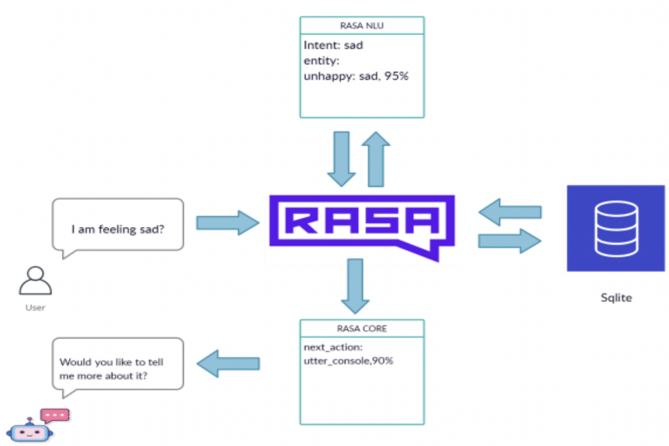


Figure 4: Interaction Diagram of Rasa

When user input is received, it is routed to the interpreter (Rasa NLU) with the objective of extracting intents, entities, and other structured data. Rasa Core is in charge of the next phases. The tracker is used to keep the conversation status and to retain the conversation history in memory. At each stage of the debate, the policy determines what action to take. It is generated in conjunction with a feature, which generates a vector representation of the tracker's current dialogue state. Finally, the action is carried out by sending a message to the user and passing a tracker instance.

The different components used for creating the chatbot are given as the following files:

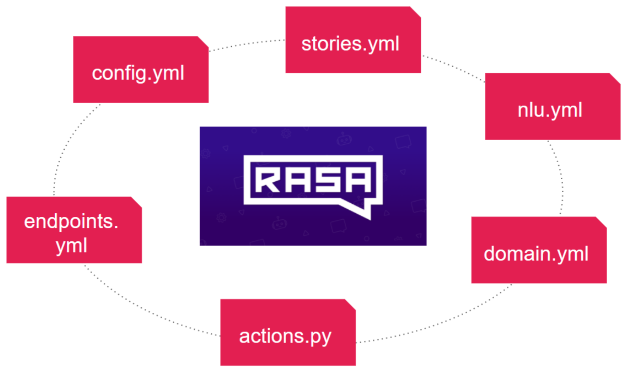
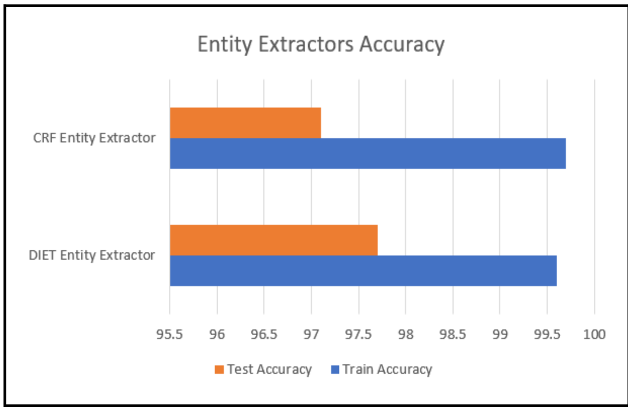


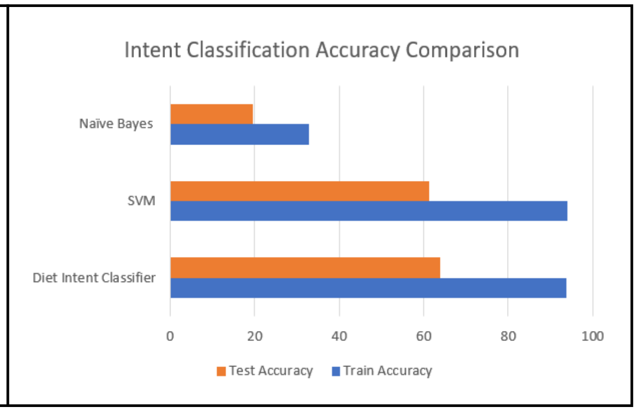
Figure 5: Components of Rasa

1. endpoints.yml: This file contains the many endpoints that the chatbot can use. One critical endpoint is the action endpoint, which connects the chatbot to the Custom Action server and the UI.
2. credentials.yml: This file stores the credentials of many linked services.
3. config.yml: This file contains the configuration for our NLU and Core models that we created. Policies, pipelines, and other concepts are defined here.
4. actions.py: This file includes the chatbot's primary logic. The chatbot's replies are defined by actions. Your bot's actions are the things it does in response to user input. Rasa Core has three types of actions:
    a. standard actions (action listen, action restart, action default fallback)
    b. utter actions, which begin with utter_ and simply convey a message to the user.
    c. custom actions — any other action that can execute arbitrary code
5. nlu.yml: This file contains the training data. RASA refers to the process of converting User Messages into structured data as Natural Language Understanding.
    a. Essentially, these are the samples (and instances) that we may anticipate the user entering.
    b. The NLU training data additionally mark the entities or keywords that the assistant should extract from the example utterance.
    c. In each intent, samples of user utterances, entities, and how to reply are defined. In essence, intentions are labels that describe the goal or meaning of a single user's input.

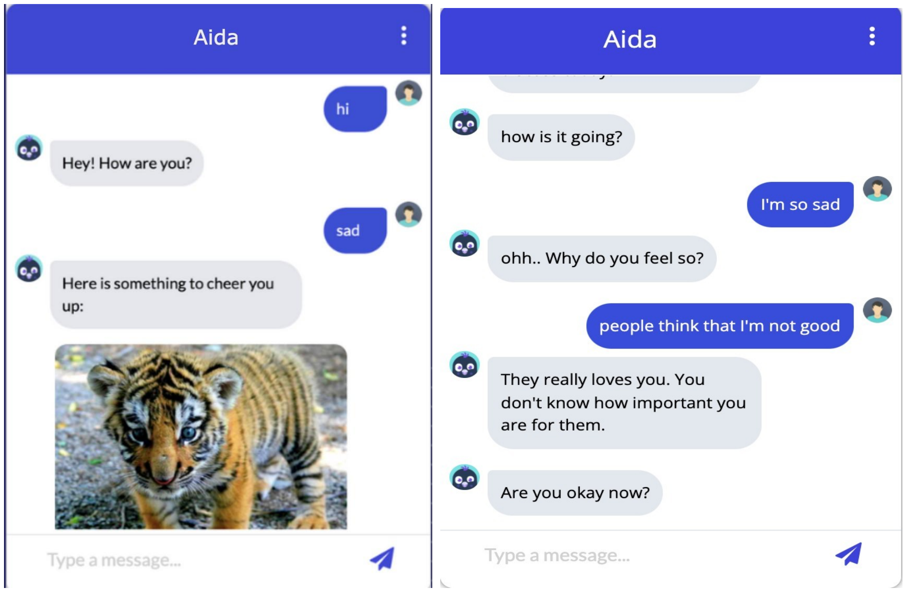
6. stories.yml: This file provides the defined conversational flow between the chatbot and the user (trained). End-to-end dialogues are exemplified by stories. These are crucial in determining the chatbot's next move.
7. domain.yml: Specifies the chatbot's limits and the guidelines for how the chatbot should function. Entities, intents, replies, actions, and slots are some important features of the domain file.

Rasa comes in with its own Language model **Dual Intent and Entity Transformer (DIET)** to detect and classify intents and entities. I have also explored other entity extraction algorithms and intent classification methods like CRF Entity Extraction for entity extraction, and Naive Bayes, and Support vector machines for Intent classification. Close to 80 different intents across 8 different depression modules were used to train the models. The accuracies for the different models listed can be visualized using the below bar plots.





After the chatbot model is trained, I have deployed it on Facebook. For the users to interact with the chatbot on a website, I have also deployed it using a chat widget. For the widget part of the project, I have designed my own Chatwidget using vanilla javascript, and frameworks like Materialize CSS and Showdown JS. I have also used another chat widget provided by the Botfront organization, which is at the forefront in developing chat-based User interfaces.
Below is a screengrab of the chat widget developed by me.



Evaluation:

I wanted to evaluate the goodness of my chatbot widget in comparison to the one provided by the BotFront organization. For this, I have deployed the chatbot as an API endpoint and made both the chat widgets use the same chatbot API endpoint. Now, I have designed a Quantitative user study following the guidelines of the Between-subjects design strategy.

For this, I have selected 20 participants who are Graduate students of Stony Brook University residing at the Chapin Apartments. I have divided them into two groups, wherein each group tests only a single widget, either of botfront or mine. The testing process involves the user interacting with the chatbot regarding 4 different depression modules. The depression modules include:

1. Study Pressure
2. Family Pressure
3. Love Failure
4. Job Pressure

I have collected the following data for each experiment:

1. Time for Task Completion: The time required for each user to complete chatting with the chatbot about all 4 depression modules. For the sake of simplifying the experimentation, the chatbot is restarted after each module by the user. This only added a mere 5 seconds to the task completion time.
2. Satisfaction: After the completion of all 4 modules, the user is asked to rate the amount of satisfaction he got after chatting with the bot, on a scale of 5, with 1 being the least satisfied and 5 being the most satisfied rating.

Following are the descriptive statistics of the study conducted. These numbers represent the whole dataset and not for each group.

	time_for_task_completion	satisfaction
count	20.000000	20.000000
mean	12.788500	2.800000
std	1.736582	1.151658
min	10.150000	1.000000
25%	11.410000	2.000000
50%	13.020000	3.000000
75%	14.257500	4.000000
max	15.580000	5.000000

Individual Descriptive statistics are given as follows:

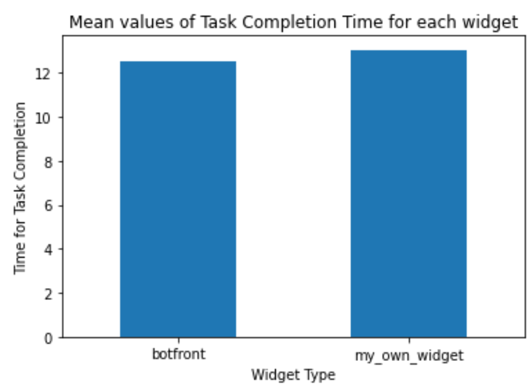
The following table is for the users who used the Botfront chat widget:

	time_for_task_completion	satisfaction
count	10.000000	10.000000
mean	12.533000	3.000000
std	1.885336	1.154701
min	10.150000	1.000000
25%	10.847500	2.250000
50%	12.295000	3.000000
75%	14.412500	3.750000
max	14.960000	5.000000

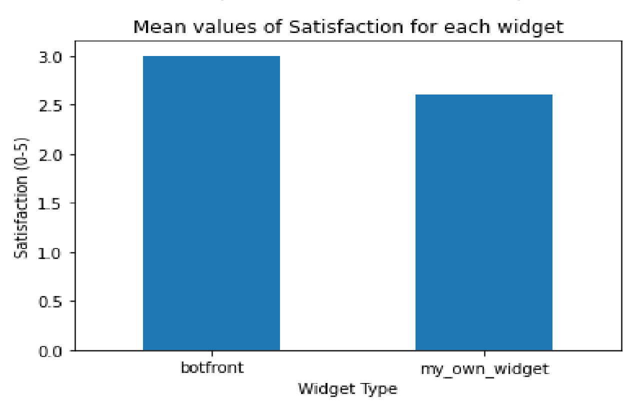
The following table is for the users who used the chat widget designed by me:

	time_for_task_completion	satisfaction
count	10.000000	10.000000
mean	13.044000	2.600000
std	1.633083	1.173788
min	10.190000	1.000000
25%	11.852500	2.000000
50%	13.470000	2.500000
75%	13.850000	3.750000
max	15.580000	4.000000

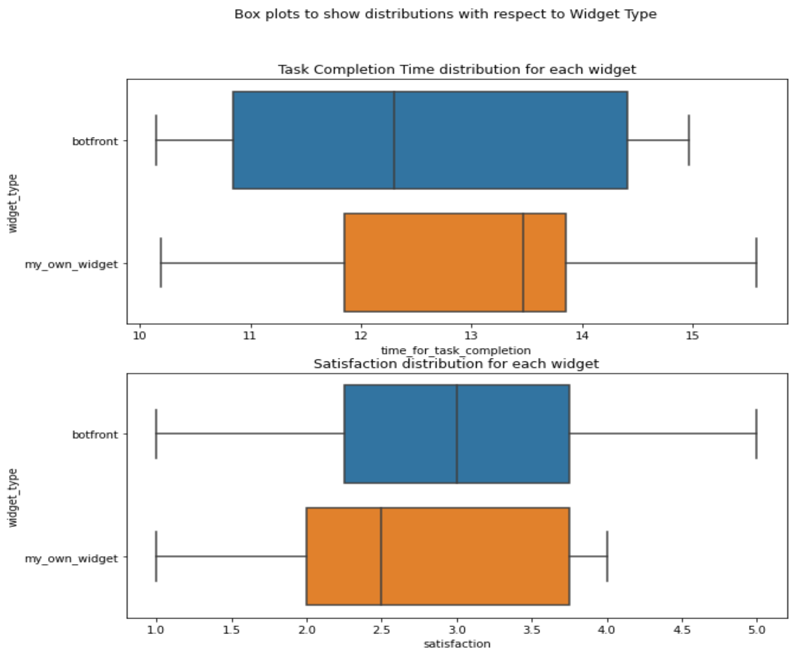
The mean task completion time for each widget is represented using the following bar plot:



The mean satisfaction level for each widget is represented using the following bar plot:



Here is a box plot detailing the range of Task completion time and Satisfaction for each category:



The following inferences can be made from the above plot:

1. The users generally took more time to complete the tasks on my widget compared to the one provided by BotFront.
2. The Satisfaction levels for the Botfront widget are almost similar compared to that of my widget.
3. I believe that the lower satisfaction levels for some users who used my widget are because of the higher task completion time, which reflects the ease of use of the interface.

A t-test on the satisfaction levels of both the groups has given a p-value around 0.45, this proves that there isn't a statistically significant difference between both group groups.

Based on the above results, I can conclude that even though there is a significant difference in task completion time for both widgets, the satisfaction ratings for both widgets don't vary significantly.

Future Work:

Even though chatbots can hold a conversation, they can only imitate comprehension, not fully comprehend. Because chatbots are prone to making mistakes, this might lead to resistance. These are blunders that can be avoided and improved on in the future. Understanding chatbot usage trends for depression is critical for developing chatbot design and providing information on the chatbots' strengths and limits.

Following are the list of tasks I consider worth working on to improve the project:

1. Since the task completion time for my widget is higher compared to that of Botfront's, I would work on identifying which aspects of the widget can be improved to reduce the time taken to complete the tasks and also thus improve the ease of usage of the widget.
2. Make the chatbot available in more social applications like Telegram, Whatsapp, etc, where the users can easily reach out to the bot.
3. Research and improve the conversation style of the chatbot to include more friendly responses and humane touch to the replies.
4. Including an option for interacting with an actual therapist would be a great addition.

Conclusion:

Aida is an Intelligent chatbot that can help people who are suffering from Mental health problems. Even though the human connection cannot be achieved with a chatbot, but they are an excellent resource to those who do not have the financial means to treat themselves.

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