Conversational AI for Primary Healthcare Support Advice

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Abstract

**Conversational AI for Primary Healthcare Support Advice**

For common illnesses, citizens of the internet often search information on the internet manually, read through complicated medical blogs and understand the appropriate suggested treatment as per their capacity. The information available on the internet may not be in a format that is easy to search, interpret and consume. With this project, we aim to develop a prototype of an AI-based conversational agent commonly known as a chatbot which will be trained with information about common illnesses and corresponding symptoms. Users will be able to have a natural communication with the agent similar to what they would have with a healthcare representative during their initial screening at a medical establishment. Users will input the symptoms they are observing and an agent will respond with one or more possible illnesses that provided symptoms listed against the illness. With this ready-to-consume knowledge in simplified form, users will be saved from the hassle to go through complicated online documentation. This will also reduce the chances of users reading or interpreting information incorrectly.

We intend to make use of state-of-the-art NLP techniques for developing the conversational agent to demonstrate how the above-mentioned problem can be tackled. We will make use of transformers and transfer learnings for core NLP tasks and will orchestrate the conversation using the open-source conversational AI platform. With the use of NLP techniques, an agent will be intelligently able to identify the user’s requirement and generate a dynamic response as opposed to a state machine-based conversation.

**Keywords**

NLP, Transformer, Conversational AI, Transfer Learning

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throughout my education and especially during the master’s degree at the University of St Andrews where we were not able to meet for extended periods.

Declaration of Authorship

I declare that the material submitted for assessment is my own work except where credit is explicitly given to others by citation or acknowledgement. This work was performed during the current academic year except where otherwise stated.

The main text of this project report is NN,NNN\* words long, including project specification and plan.

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Abbreviations

|  |  |
| --- | --- |
| **AI** | Artificial Intelligence |
| **NLP** | Natural Language Processing |
| **NLU** | Natural Language Understanding |
| **NLG** | Natural Language Generation |
| **RNN** | Recurrent Neural Network |
| **NN** | Neural Network |
| **ML** | Machine Learning |
| **DL** | Deep Learning |
| **HMM** | Hidden Markov Model |
| **POS** | Part-of-speech |
| **LSTM** | Long Short-Term Memory |
| **BERT** | Bidirectional Encoder Representations from Transformers |
| **GPT** | Generative Pre-trained Transformer |
| **CNN** | Convolutional Neural Network |
| **FAQ** | Frequently Asked Questions |
| **ASR** | Automated Speech Recognition |
| **DM** | Dialogue Management |
| **TTS** | Text to speech |
| **NER** | Named Entity Recognition |

# Introduction

Conversational Artificial Intelligence (AI) is a system that primarily makes use of techniques from the natural language processing field of artificial intelligence and machine learning techniques to generate humanly interactions with the system. When combined with state-of-the-art interaction techniques, interacting with these systems is as if users are interacting with other humans.

Kong (2021) argues that voice-based and conversation-based interactions are poised to replace the traditional web-based or command-line interfaces in many applications. Interactions with digital systems are becoming more natural. Applications of these intelligent systems are pervasive and getting adopted rapidly.

A Conversational AI agent also referred to as a chatbot is a system that uses full conversational dialogue to accomplish one or more tasks. Command interpreters use enough dialogue to interpret and execute a single command. Event classifiers just read the message and perform an action based on the content. Enhancing customer buying experience using guided conversation (chatbots), using natural language or voice interface to interact with devices (command interpreter) or sorting emails into folders (event classification) are representative examples of how AI assistants are changing the world around us (Freed, 2021).

Interactions with Conversational AI-based chatbots are intuitive, effective, and efficient, making them essential to implement.

## Importance of the project

*“Don’t become a mere recorder of facts, but try to penetrate the mystery of their origin.”*

* *Ivan Pavlov*

As discussed by (Palash Goyal, 2018), the initial work on chatbot date back to 1966 when ELIZA was introduced by Joseph Weizenbaum. However, the recent state of the art in natural language processing and advancements in computing technologies has given a great thrust to the field of conversational AI. As per the research on insider intelligence(Dolan, 2022), 72.3 per cent of the time on mobile devices was spent on smartphones. This is a significant amount of time and conversational AI techniques can greatly enhance interactions between customers and organizations. The use of advanced language modes and transformers is showing promising results in building chatbots that are much more than just a state machine. The project aim to explore these techniques to build an intelligent chatbot.

In the healthcare domain, there is a good amount of reliable knowledge available on the internet from authentic sources such as government websites and healthcare research groups. Despite this, common users find it difficult to navigate through the complex healthcare jargon and understand and use this information. Demands for healthcare professional has risen significantly and continues to grow. Many healthcare systems are under tremendous pressure, and this limits the number of patients that can be treated on time. Patients find it difficult to get treatment on time even for simple and mild illnesses. This delay in early treatment exaggerates the symptoms and can lead to further health complications (Laumer et al., 2019). Having a chatbot-like system can come to the rescue of patients and healthcare services as well. Patients can ask about their health issues to the chatbot in a fashion like how they will interact with doctors and nurses. They don’t have to be experts in the medical field to interact with chatbots.

Chatbots will be intelligent enough to understand a user’s problem, search its knowledge base for possible solutions and present it to the user in an understandable format (Gupta et al., 2022). Chatbots can be trained to handle mundane administrative tasks and reduce the work pressure on healthcare services. Advanced chatbots can be equipped with voice-based conversation capabilities. With such advanced features, these bots can virtually replace any front desk present in hospitals and medical services. A chatbot can complete patient registration and data gathering in a timely fashion without waiting for any healthcare professional. Chatbots can also be integrated with local pharmacies for ordering medicines and medical supplies.

Healthcare chatbots are AI-powered conversational solutions that help patients and healthcare service providers to connect easily. Chatbots can play a critical role in making first-line health services available to anyone who is in need. Patients can use chatbot systems around the clock and get their queries answered. An easy-to-use interface can facilitate interactions with the chatbot system. There are endless possibilities about what chatbots can do. Some of the interesting capabilities can be symptoms checker and triage, self-care advice, health risk assessment, chronic condition monitoring, appointment booking, medication reminder and tracker, healthcare tracker, and much more. Chatbots can make vast medical knowledge available to patients in need. Patients don’t have to wait for doctors’ availability for basic illnesses.

Due to the sensitive nature of data in the healthcare domain, healthcare agencies need to be careful while making technological choices. Data protection rights have the utmost importance and failing to comply with the law (U.S. Department of Health & Human Services, 2022) and privacy may result in significant damage to an organization (financial, reputational and many other damages). We aim to explore conversational AI platforms that give developers and organizations more control and freedom over the system, its components and their data instead of integrating the data and logic into prebuilt less customizable products (Rasa Technologies Inc., 2022a).

## Objectives

With this project, we aim to build a prototype of a conversational AI for disease and illness matching by following the objectives mentioned below:

### Primary objective

The primary objectives focus on the development of a basic conversational AI (similar to an interactive Q&A system) where the user mentions all the symptoms in a single interaction and receives information on the most likely illness matching these symptoms. The following objectives aim at building a conversation agent with these capabilities:

* Prepare data for training the natural language understanding unit
* Develop the natural language understanding unit. The system should be able to read question input and extract appropriate entities and intent
* Prepare scenarios for natural language generations
* Develop the natural language generation part so that agent can generate text for responding to the user
* Data processing for symptom and disease matching

### Secondary objective

The conversation agent’s dialogue management can be extended for a more coherent conversation with the end users. We aim to enhance the dialogue management of the agent with the following objectives:

* Gathering the symptoms of the illness in multiple dialogue turns
* Extending the dialogue with back and forth exchange of information to achieve a more humanly conversation
* Extending dialogue management system to handle out-of-scope and ambiguous questions

### Tertiary objective

User experience can be enhanced with a user interface and better techniques for conversational agents’ knowledge representation. Following objective aim to enhance user experience:

* Web-based graphical user interface (GUI) for the chatbot
* Improving conversational features by exploring techniques like Knowledge representation using a knowledge graph

# Context Survey

In this chapter, we will review the state-of-the-art of NLP techniques and conversational platforms available in the market. We will discuss the scholarly and industrial chatbot developments in the domain of healthcare.

## Natural Language Processing

As defined by (Wikipedia, 2022),

*“Natural language processing (NLP) is a subfield of linguistics, computer science, and artificial intelligence concerned with the interactions between computers and human language, in particular how to program computers to process and analyze large amounts of natural language data.”*

Freed (Freed, 2021) argues that every intelligent application involving human language has some NLP behind it. The below table summarizes various NLP tasks and corresponding popular applications identified by the author.

Table 1: NLP Tasks and Applications

|  |  |
| --- | --- |
| NLP Task | General Applications |
| Text classification | Spam classification |
| Information Extraction | Calendar Event Extraction |
| Conversational Agent | Personal Assistance |
| Information Retrieval | Search Engines |
| Question Answering System | Legal entity Extraction |

Human language is a structured system of communication that involves complex combinations of its constituent components, such as characters, words, sentences, etc. Linguistics is the systematic study of language. To study NLP, it is important to understand some concepts from linguistics about how language is structured. We can think of human language as composed of four major building blocks: phonemes, morphemes and lexemes, syntax, and context. NLP applications need knowledge of different levels of these building blocks, starting from the basic sounds of language (phonemes) to texts with some meaningful expressions or context. Table 2 summarizes the building blocks of language and their applications (Vajjala et al., 2020).

Table 2: Language blocks and NLP Applications

|  |  |
| --- | --- |
| Blocks of Language | Applications |
| Context (meaning) | Summarization |
| Topic Modelling |
| Sentiment Analysis |
| Syntax (phrases and sentences) | Parsing |
| Entity Extraction |
| Relation Extraction |
| Morphemes and Lexemes (words) | Tokenization |
| Word embedding |
| POS tagging |
| Phonemes (speech and sounds) | Speech to text |
| Speaker Identification |
| Text to speech |

### Challenges in NLP

Language has inherent ambiguity in a general sense as well. (Perera et al., 2013) have discussed some of the common challenges that NLP faces in clinical settings and below are the challenges for most of the common NLP tasks as described by (Vajjala et al., 2020)

**Ambiguity**: Most human languages are inherently ambiguous. Many times sentence has multiple meanings and the meaning is decided by the context around the sentence. We can draw multiple meanings from the sentence “not bad” depending on the context used.

**Common knowledge**: Humans use common knowledge all the time to understand and process any language. One of the key challenges in NLP is how to encode all the things that are common knowledge to humans in a computational model.

**Creativity**: Humans are creative, and language is no exception for creativity. Various styles, dialects, genres, and variations are used in any language. Making machines understand creativity is a hard problem not just in NLP, but in AI in general.

**Diversity across languages**: For most languages in the world, there is no direct mapping between the vocabularies of any two languages. This makes porting an NLP solution from one language to another hard.

### Machine Learning, Deep Learning, and NLP

The boundaries and overlaps between machine learning, deep learning and NLP are well-discussed Mukhopadhyay (2018).

He argues that Artificial intelligence (AI) is a subfield of computer science that tries to create systems that can do activities that would normally need human intelligence. Machine learning (ML) is a field of artificial intelligence that focuses on the creation of algorithms that can learn to do tasks automatically based on a large number of instances without the need for hand-crafted rules. Deep learning (DL) is a type of machine learning that uses artificial neural network designs to learn.

He also highlights that While NLP, ML, and DL have some overlap, they are also quite independent fields of study. Rules and heuristics were also used in early NLP applications. However, in recent decades, ML approaches have had a significant effect on the development of NLP applications. More recently, DL has been widely developed and applied to natural language processing (NLP) systems.

### Approaches to NLP

A variety of approaches have been identified for solving NLP tasks. As argued by (Vajjala et al., 2020), the approaches can be categorized as follow:

#### Heuristics-Based NLP

Early attempts at constructing NLP systems, like other early AI systems, were based on creating rules for the task at hand. This necessitated the developers having some domain knowledge in ways to construct rules that could be put into a system. Such systems also needed dictionaries and thesauruses. More extensive knowledge bases have been constructed to facilitate NLP in general and rule-based NLP in particular, in addition to dictionaries and thesauruses. Wordnet (Miller, 1995) (Miller, 1995), for example, is a database of words and the semantic ties that exist between them. More recently, common-sense world knowledge has been included in knowledge bases such as Open Mind Common Sense (Singh et al., 2002), which supports rule-based systems. Regexes are a common paradigm for creating rule-based systems, and NLP software like StanfordCoreNLP contains a framework for developing them. CFG stands for context-free grammar and is a sort of formal grammar used to model natural languages. Grammar languages like JAPE (Java Annotation Patterns Engine) may be used to model more sophisticated rules.

#### Machine Learning for NLP

For many NLP applications, supervised machine learning approaches such as classification and regression algorithms are widely used. The extraction of features from the text, the use of the feature representation to develop a model, and the evaluation and improvement of the model are all typical phases in any machine learning technique for NLP. Some of the commonly used ML algorithms as listed by (Vajjala et al., 2020) are Naive Bayes and support vector machine (SVM) for classification tasks, hidden Markov model (HMM) conditional random field (CRF) for part-of-speech (POS) tagging.

#### Deep Learning for NLP

The artificial intelligence field has seen a big increase in the use of neural networks to deal with complicated tasks in recent years. Language is naturally unstructured and complicated. Neural network (NN) models are better at representing the complexity of language and producing better outcomes.

Recurrent neural networks (RNNs) are specifically intended to keep such sequential processing and learning in mind since language is fundamentally sequential. RNNs have neural units that can remember what they've processed previously. This memory is temporal, and when the RNN reads the next word in the input, it stores and updates the information at each time step.

The problem of forgetting memory is a challenge that RNNs face. To address this problem, long short-term memory networks (LSTMs), a form of RNN, were developed. LSTMs get around this difficulty by ignoring irrelevant information and memorising just the parts of it that are important to the job at hand. This alleviates the burden of memorising a large amount of information in a single vector representation. Because of this solution, LSTMs have largely replaced RNNs in many applications. GRUs are a type of RNN that is mostly utilised in language generation.

Convolutional neural networks (CNNs) are widely employed in computer vision applications such as image classification and video recognition, among others. CNN has also shown promise in NLP, particularly in text categorization. The capacity of CNNs to use a context window to look at a collection of words together is their major benefit (Vajjala et al., 2020).

### Transformers

Transformers (Wolf et al., 2020) is the most recent addition to the league of deep learning NLP models. The transformer model was released in 2017 (Vaswani et al., 2017), and it performed amazing results on machine translation tasks. In the last two years, Transformer models have surpassed state-of-the-art in practically all key NLP tasks. They model the textual context, but not in the order in which it appears. Rather they prefer to look at all the words surrounding it known as self-attention and represent each word in its context when given a word in the input.

According to (Vajjala et al., 2020), the transformer's huge success has sparked the interest of numerous NLP researchers. They've created even more fantastic Transformer-based models. Generative Pre-trained Transformer (GPT) and Bidirectional Encoder Representations from Transformers (BERT) are two of the most well-known and essential of these models. GPT is entirely made up of the decoder layer of the Transformer, whereas BERT is entirely made up of the encoder layer of the Transformer. The purpose of GPT is to create text that appears to be written by a human. BERT's purpose is to give a better language representation to aid a variety of downstream activities (sentence-pair classification tasks, single-sentence classification tasks, question-answering (QA) tasks, and single-sentence tagging tasks) in achieving better outcomes.

Figure 1 shows the original transformer architecture proposed by Vaswani et al. (2017) which is based on a self-attention mechanism relating to different positions of a single sequence (positional encoding ) to make sense of the entire sequence. The original transformer model was employed for the language translation task.

Figure 1: The transformer - model architecture

Diagram

Description automatically generated

Note: Image reproduced from Vaswani et al. (2017)

Each encoder structure converts an input sequence of tokens into a sequence of embedding vectors, often called the hidden state or context and the structure consists of two layers: multi-head self-attention mechanisms layer and position-wise fully connected fee forward layer. Each decoder structure uses the encoder’s hidden state to iteratively generate an output sequence of tokens, one token at a time. The structure has an additional layer to perform multi-head attention over the output of the encoder stack.

Only the lowest level of the stack contains the embedding sublayer. The encoded input is guaranteed to remain stable through all other layers because there isn't an embedding layer in the other layers.

The self-attention which is a token-to-token operation has replaced the recurrence function that is present in RNN, LSTM or CNN. The attention mechanism will determine how each word in a sequence, including the word being processed, relates to every other word in the sequence which results in finding a deeper relationship between the words and producing better results. This layer applies three independent linear transformations to each embedding to generate the query, key, and value vectors. These transformations project the embeddings, and each projection has a unique set of parameters that can be learned. This enables the self-attention layer to concentrate on various semantic facets of the sequence. Having several heads allows the model to focus on several aspects at once and that is achieved with multi-head attention.

The positional encoding layer adds positional information to input embedding which helps in establishing relationships between words which are semantically closely related but far apart in the sentence (positionally).

### BERT

Bidirectional Encoder Representations from Transformers (BERT) is an encoder-only architecture of a transformer. As argued by Devlin et al.(2018) BERT is pre-trained with the two objectives of predicting masked tokens in texts (masked language modelling task or MLM)and determining if one text passage is likely to follow another(next sentence prediction or NSP).

BERT has two steps: pre-training and fine-tuning. During pre-training, the model is trained on unlabelled over different pre-training tasks. For finetuning, the BERT model is first initialized with the pre-trained parameters and then these parameters are fined tune using labelled data. Each downstream task has separate fine-tuned models though they were initialized with the same pre-trained parameters. During fine-tuning, task-specific inputs and outputs are plugged into BERT and all the parameters are fine-tuned. Compared to pre-training, fine-tuning is relatively inexpensive.

The below figure shows the overall pre-training and fine-tuning procedures for BERT

Figure 2: Overall pre-training and fine-tuning procedures for BERT

Graphical user interface, diagram

Description automatically generated

Note: Image reproduced from Devlin et al. (2018).

### Transfer Learning

Transfer Learning (TL) is an AI approach in which information obtained while addressing one problem is used for a related but different problem. It is now normal practice in the field of computer vision to employ transfer learning to train a convolutional neural network on one job, and then to adapt it to or fine-tune it on a different task. Because of this, the network can make use of the information that was learned in the original task. Large transformers have recently been employed in the transfer learning of smaller downstream activities. TL needs less training data. In a chatbot domain, there usually is not much training data. With TL, we can achieve much better performance on the limited amount of training data. TL makes training faster and only needs a few training epochs to fine-tune a model for a new task. Generally, it is much faster and more efficient than the traditional ML method (Tunstall et al., 2022).

### The Hugging Face Hub

The Hugging Face (Hugging Face, 2022) provides a standardized interface to a wide range of transformer models as well as code and tools to adapt these models to new use cases. TensorFlow, PyTorch and JAX are the three main deep learning frameworks that the Hugging Face presently supports, and it makes it simple to transition between them. It also gives task-specific heads so you can fine-tune transformers on downstream tasks like text classification, named entity recognition, and question answering. Because of this, it takes less time to train and test a variety of models. The ecosystem consists of mainly two parts: a family of libraries and the Hub. The libraries provide the code while the Hub provides the pre-trained model weights, datasets, scripts for the evaluation metrics, and more.

## Chatbots

*“One machine can do the work of fifty ordinary men. No machine can do the work of one extraordinary man.“ - Elbert Green Hubbard*

A chatbot is a computer programme that can converse with people more humanly (Williams, 2018). Chatbots can be integrated into existing websites and apps and provide voice or text-based interactions.

### The main components of a chatbot:

As mentioned by Williams (2018), the following are the three main components of a chatbot:

**Inten**t: An Intent is a task that the chatbot can process and are generally things that the user intends to do.

**Slots:** Slots hold key information for performing the task the user intends to do. Slots can hold only a specific form of information and are domain dependent.

**Utterances:** An utterance is a response generated by the chatbot to reply to a user.

Kong et al. (2021)Chatbots categories based on their goals: task-oriented bots and chitchat bots. Task-oriented bots aim to do certain tasks by engaging with humans, such as purchasing a flight for someone, whereas chitchat bots are more like real beings—their purpose is to answer users' messages easily, exactly like in natural chitchat. Some example scenarios in which a chatbot may have an advantage are hospital reception or medical consulting, online shopping customer service, after-sales service, investment consulting, and bank services.

A standard method for chatbot development has been established. Developing a chatbot generally comprises five distinct parts, which are shown below:

* ASR to convert user speech into text
* NLU to interpret user input
* DM to make decisions on the next action concerning the current dialogue status
* Natural-language generation (NLG) to generate text-based responses to the user
* TTS to convert text output into voice

### Benefits of chatbot:

As summarized by Brush and Scardina (2021) and Singh et al. (2019), below are some of the major benefits of chatbots:

* Reduced waiting time: chatbots can be scaled to meet the demand and the customer’s wait time can be greatly reduced
* Saves time: Training chatbot is less regressive as compared to training human workforce.
* Increase availability: Chatbots can be deployed to work 24X7 to cater global needs of the customers
* Better customer experience: Chatbot can cater specific needs of the customer and can provide quick solutions.

### Success metrics for a chatbot

At the outset of any chatbot development project, success metrics must be defined. The metrics serve as a reference point for the solution and the chatbot's intended benefits.

#### Customer Satisfaction Index

The Customer Satisfaction Index (CSI) gauges the effectiveness of customer service interactions by following up with the customer and asking them to complete a brief survey about their experience.

#### Completion Rate

The Completion Rate (CR) is defined as the percentage of chatbot conversations that resulted in the customer's solution being addressed.

#### Bounce Rate

The bounce rate (BR) is the percentage of users that leave the chat after entering one or two inputs into the chatbot. A high bounce rate indicates that the chatbot was not effective in engaging the user, which should be reflected in the part of the customer feedback.

### Conversational AI Frameworks

There are two types of solutions for creating chatbots: closed-source solutions and open-source solutions. The downsides of closed-source systems include high costs, vendor lock-in, the possibility of data leaking, and the inability to develop personalised functionality. These issues do not exist with open-source solutions.

#### Microsoft

Microsoft offers separate Azure Cognitive Services: Language Understanding Intelligent Service for natural language understanding and Bot Framework for dialogue and response (Microsoft, 2022).

#### Amazon

Amazon Lex is the primary service used for building AI assistants and integrates easily with Amazon’s other cloud-based services as well as external interfaces (Amazon Web Services, 2019).

#### Google

Google’s Dialogflow is a service by Google cloud for building Lifelike conversational AI with state-of-the-art virtual agents (Google, 2022).

#### IBM

Watson Assistant is IBM’s AI assistant platform for building conversational AI experiences for businesses. (IBM, 2022).

#### RASA

Rasa is an open-source solution with all the industry-standard features: built-in enterprise-grade concurrency capabilities, rich functions covering all the needs of chatbots, rich documents and tutorials, and a huge global community. Rasa provides you with complete control over the applications that you deploy. Other platforms allow you to control the classifier by changing the training data, but Rasa allows you to customize the entire classification process (Rasa Technologies Inc., 2022b).

### Generalized AI Assistant Architecture

A generalized AI assistant consists of the following four components as described by Freed (2021)

Figure 3: Generalized AI Assistant architecture and control flow

~~Chart, diagram, box and whisker chart

Description automatically generated~~

Note: Image sourced from Freed (2021)

**Interface:** Used by the end user to interact with the chatbot and can be text or voice-based

**Dialogue Engine:** Maintains dialogue state and predicts next action

**Natural Language Understanding:** used to extract meaningful information from the user’s input

**Orchestrator:** Communicates with business APIs for driving business processes and generating the dynamic response. This component can be optional.

### Chatbots in the Healthcare domain (in progress .. will be added if time permits)

Graphical user interface, text, application, chat or text message

Description automatically generated

https://www.softwareadvice.co.uk/

### Rasa

The chatbot market has seen increased interest and rapid adoption over the last five years. During that time, the products and platforms enabling the building of chatbots have been extremely diverse and have evolved considerably. These solutions can be divided into two types: closed-source solutions and open-source solutions. Closed-source solutions come with a high cost, vendor lock-in, risk of data leakage, and the inability to implement custom functions. Open-source solutions have an advantage in this regard. A downside of open source solutions is that users need to be careful in choosing the framework, make sure it is scalable and concurrent and has wide community support.

Rasa is the only open-source, industry-grade conversational AI framework that meets these requirements. Many companies have successfully built their chatbots using Rasa. Rasa has been recognized as a Niche Player in Gartner®Magic Quadrant™ (Revang et al., 2022) which is shown in Figure 4 below. For the privacy-conscious healthcare domain, the open-source nature of Rasa offers complete control over all the aspects of chatbot development and operations.

Figure 4: Magic Quadrant for Enterprise Conversational AI Platforms



Note: Image sourced from Revang et al. (2022)

## Related Work

### Chatbots for Healthcare

Athota et al. (2020) have proposed the implementation of a chatbot for healthcare systems using artificial intelligence. The author has implemented the chatbot using Java technology and has made use of N-gram, TF-IDF and cosine similarity techniques for NLP tasks. The focus of the paper is to achieve chatbot functionality in a question-answer format. Kandpal et al. (2020) have discussed the implementation of a Contextual chatbot for healthcare purposes. The paper focuses on the use of deep learning for achieving NLP tasks. Sheth et al. (2019) focus on the Contextualization and Personalization of Patient Data. The paper discusses how existing chatbot systems can be extended by a whole ecosystem of the Internet of things for better and personalized health tracking of individuals. It has mentioned the usefulness of knowledge graphs in data representation.

Nadarzynski et al. (2019) have discussed the acceptability of AI-led chatbots in the healthcare domain, finding that there is hesitancy regarding the acceptance of chatbot technology. The paper argues user’s perspective, motivation and capabilities need to be considered during chatbot development. Laumer et al. (2019) have explained user adoption of conversational agents for disease diagnosis.

A paper by (Rakib et al., 2021) on mental healthcare highlights the usefulness of BiLSTM (Bi-directional LSTM) and Sequence-to-Sequence (Seq2Seq) encoder-decoder architecture and has used the Bilingual Evaluation Understudy (BLEU) score for model evaluation. A paper by IIT Delhi researchers (Pandey et al.) has worked on studying the Q&A support system for maternal and child health in rural India. Researchers at MDPI have studied the feasibility of developing a rule-based virtual caregiver system using a mobile chatbot for elderly people.

### Transformer for chatbot

A paper by Yu et al. (2020) has studied the use of a bi-directional transformer for financial service chatbots. They have shown how the BERT model outperformed other methods for common NLP tasks like intent classification, sentence completion, information retrieval and question answering. A paper from Microsoft researchers (Damani et al., 2020) has discussed optimized transformers for FAQ answering. A paper by hugging face researchers (Wolf et al., 2020) has a detailed explanation of how transformers have reshaped state-of-the-art natural language processing. A paper published by MODUL Technology GmbH (Brasoveanu & Andonie) focuses on explaining Transformer architectures through visualizations. Gillioz et al. have provided an Overview of the Transformer-based Models for NLP Tasks.

### Dataset for healthcare (do we need this?)

~~The dataset required for a typical healthcare chatbot is proposed in a paper titled HealFavor(Ur Rahman Khilji et al.). The paper talks about data sourcing, data quality, pre-processing, and representation. Researchers have suggested prototype system architecture and proposed user experience surveys as an evaluation criterion for the system.~~

# Requirements specification

This chapter discusses the functional and non-functional requirements of the project. The targeted audience of the system can be a user who wants to understand medical symptoms and potential diseases associated with those symptoms. This is a prototype and should not be considered a replacement for any medical advice or diagnosis.

## Functional Requirements

The system must be able to achieve the following functionalities:

* The agent should introduce itself and its purpose
* The system should be able to accept text inputs from the user
* The agent should be able to determine if patients want to discuss their symptoms or just informing about their good health
* When a patient is not well, the agent should be able to ask for symptoms, collect and try to match those symptoms with its disease dataset to determine possible disease
* The agent should be able to answer specific questions outside the current conversation context
* The agent should be able to ask for clarifications when information shared by the user is not clear

## Non-functional Requirements

As an end user of the system, the patient should be able to interact with the system via easy to use interface. Complexities of the system should be transparent to the user. Users need not be healthcare experts to make complete use of the system. A user guide with instructions on how to operate the system should be documented.

# Software engineering process

## Planning

The initial planning of the project was done in the first two weeks of the project work. A Gantt chart with details of tasks and allocated efforts for each task were prepared. The chart is attached in the appendix.

## Development

The development of the chatbot was based on agile methodology. Features were developed in incremental cycles to reach the final product. The entire development was broken into small trackable tasks and tasks were prioritized during weekly project discussions.

## Tracking

Similar to sprint review meetings, a weekly meeting helped in reviewing the project's progress. Thursday meetings were used for all the critical discussions, brainstorming and tracking of the work done in the week and work items for the coming week. MS Teams channel was used for maintaining the backlog items.

## Testing

Manual Testing: Initial bot testing was performed manually using rasa interactive command line features.

Automated Testing: We plan to use the RASA Testing framework to perform chatbot automated testing. The test result summary is attached in the appendix.

## Version Control

The GitHub repository was used for maintaining the code base of the project. It is a private repository and access can be provided on a need basis until it is made publicly available.

The Github repository link: <https://github.com/RightWrite/HealthAgent.git>

## Final Artefacts

The RASA train creates trained models in the archive format with a naming convention <timestamp>.tar.gz .

User interface artefacts are static and do not need compilations. Detailed instructions on using the artefacts are mentioned in the README.md hosted in the version control. The same is attached in the appendix section.

# Ethics

Ethics evaluation is done following the artefact evaluation form. Throughout the development and evaluation, no personal information was collected. The system is a prototype and is not supposed to replace any existing healthcare advice mechanisms.

## System Access:

The evaluation was performed in line with the artefact evaluation form by demonstrating the chatbot to the staff and students at the University. A fictitious conversation between a user and the chatbot was recorded and anonymous feedback on the quality of the artefact was collected using the Qualtrics survey system.

## Data Usage and Accessibility:

The data used in the research is available publicly Only the researcher will have access to the raw evaluation data and this data will be destroyed at the end of the project. Aggregated data and results are published in this report.

### Pre-trained data:

The Spacy language model used for Disease NER is trained on BC5CDR corpus and is made available under Apache License 2.0. The corpus is published by the National Library of Medicine of the National Centre for Biotechnology Information. The corpus has 6,892 diseases mentioned. More information about the corpus and datasets can be found at https://www.ncbi.nlm.nih.gov/CBBresearch/Dogan/DISEASE/

### Disease dataset for symptom matching:

The data used for symptom matching is sourced from the Kaggle platform (https://www.kaggle.com/datasets/priya1207/diseases-dataset ). It contains information about diseases, symptoms and medical treatments scrapped from MayoClinic (https://www.mayoclinic.org/). The dataset does not contain any personally identifiable information (PII).

# Design

This chapter discusses the design considerations that were made during the development of the chatbot named **Health Agent**. The Health Agent is closed domain and task-oriented conversational AI Assistance. The chapter covers conversation flow design, the architecture of the system and technical design choices made during the Health Agent development.

The proposed prototype of an AI-enabled conversational virtual agent named Health Agent is built on top of an open-source conversational AI platform called Rasa. Rasa helps develop virtual assistants which are HIPAA (U.S. Department of Health & Human Services, 2022) and has built-in privacy features. The open-source nature of the rasa platform provides better control and transparency to the solution built on top of it.

## Conversation flow design

The first step towards building conversational AI is identifying the conversations that the system is supposed to handle. Below is an example of dialogue that was covered for the primary objective.

 symbol represents a human interacting with the chatbot

 symbol represents the chatbot

### Conversation scenario of a healthy patient

When conversing with a healthy user, the chatbot will understand that the user is healthy and will not ask further questions. The chatbot motivates the user to stay fit and ends the conversation gracefully.

* Hello

Hello there! How are you doing today?



* I am good today.

Fantastic, keep moving!!



* thanks!

Good luck



### Conversation scenario of an unhealthy patient

When users start a conversation with the chatbot and inform the bot that they are unwell, the bot proceeds with asking about symptoms observed by the user. During the conversation (while the chatbot is checking with the user), instead of informing symptoms, a user asks some random and out-of-scope questions and also asks about the chatbot, which the Health Agent handles gracefully and continues asking about symptoms. The Health Agent then extracts symptoms from the text entered by the user and keeps informing the user about the progress that the bot is making. Health Agent then informs the user about the disease that has matched the symptoms entered by the user and then ends the conversation gracefully. Thus the Health Agent is capable of handling context switches while maintaining the conversation flow with the user.

* Hello

 Hello there! How are you feeling today?

* i am not feeling well today.

Robot with solid fill Can you please tell me what symptoms you are observing?

* who are you

Robot with solid fill I am a Health agent and your virtual assistant. Can you please tell me what symptoms you are observing?

* can you make pasta?

Robot with solid fill Sorry, I can't handle that request. Can you please tell me what symptoms you are observing?

* I have neck pain, fatigue and blurred vision

Robot with solid fill Ok. I have collected all the required data. As I could understand, you have entered the following symptoms: neck pain, fatigue, blurred vision. Checking for diseases corresponding to the entered symptoms. Checking for diseases corresponding to the entered symptoms. Your symptoms are matching with these diseases: Ankylosing spondylitis

* thanks!

Robot with solid fill Good luck

* bye!

Robot with solid fill bye!

### Advanced Conversation scenario of an unhealthy patient (future work)

Unlike previous scenarios, with this enhancement, the Health Agent asks if the user is observing more symptoms and keep asking till the user has more symptoms to inform.

* Hello

 Hello there! How are you feeling today?

* i am not feeling well today.

Robot with solid fill Can you please tell me what symptoms you are observing?

* I have neck pain

Robot with solid fill Do you have any other symptoms?

* I also have fatigue and blurred vision

Robot with solid fill Do you have any other symptoms?

* No

Robot with solid fill I have collected all the required data. As I could understand, you have entered the following symptoms: neck pain, fatigue, blurred vision. Checking for diseases corresponding to the entered symptoms. Checking for diseases corresponding to the entered symptoms. Your symptoms are matching with these diseases: Ankylosing spondylitis

* thanks!

Robot with solid fill Good luck

* bye!

Robot with solid fill bye!

## Architecture

Health Agent is a Rasa-powered chatbot that interacts with users through a web-based interface and manages dialogue using state-of-the-art (SOTA) techniques in natural language processing.

Figure 5: Architecture of Health Agent

Diagram

Description automatically generated

The key components of this architecture are as follows:

### Natural Language Understanding Unit (NLU)

NLU interprets text-based user inputs. With Rasa, NLU is a data processing pipeline that converts unstructured user messages into intents and entities. The pipeline consists of a series of configurable and customizable components.

In rasa, the config.yml file defines the steps and components of the NLU pipeline. The pipeline takes text as input and processes it to generate intents and entities as output.

Figure 6: Internals of NLU unit

A picture containing chart

Description automatically generated

There are different types of components that you can expect to find in a pipeline. The main ones are:

* **Tokenizers**: Splits text into tokens
* **Featurizers:** Returns sequence features and sentence features
* **Intent Classifiers:** assign one of the predefined intents to incoming user messages
* **Entity Extractors:** extracts entities from the user message

NLU also has a response selector component used to predict a bot response from a set of candidate responses (Bocklisch et al., 2017).

**~~Choice of language model: accuracy vs speed~~**

### Dialogue Management (DM)

The main task of the DM module is to coordinate and manage the whole conversation flow and is particularly important for multi-turn task-oriented dialogue. It also predicts the next best action that the agent needs to perform.

Figure 7: Internals of Dialogue Management unit

**Diagram

Description automatically generated**

Rasa provides rule-based, machine learning based and hybrid models for DM. The health agent makes use of rule-based and machine learning-based models. Rule-based models are useful for handling strict conversational behaviour where the next action depends on the current turn. Machine learning-based models consider the entire dialogue context, the previous dialogue turns, extracted entities and slots for dialogue management. TED policy and Memoization policy are used in the ML-based approach. DM module also provides fallback capabilities in case of ambiguous intent (Rustamov et al., 2021). If the intent is not clear, DM instructs the agent to either repeat the question or send fall back response to let the user know about the ambiguity.

### Natural Language Generation (NLG)

NLG is almost the last challenging mile in human-machine interaction. Once the next action is chosen by DM, NLG generates the text of the response to the user. In other words, NLG converts the agent's response into human-readable text. There are broadly two ways of doing this: template-based method and deep learning (DL) based method. The template-based method creates a response without much flexibility or variety. DL-based methods are capable of generating a quite dynamic response, however, it is difficult to control the quality and stability of the result.

In the case of task-oriented chatbots like Health Agent, users need accurate and concise responses to their queries. Hence we have used a template-based NLU in our architecture. We can add some level of flexibility to the agent’s response by creating a pool of templates.

### Action Server / Backend:

The DM module may require interactions with databases, APIs or third-party integration to get extra information to generate responses to user queries or complete the intended task. DM might be interested in implementing custom actions which might be complicated as compared to built-in response generation. For all such scenarios, Rasa provides an action server that runs custom actions for a Rasa Open Source conversational assistant.

When your assistant predicts a custom action, the Rasa server sends a POST request to the action server with a JSON payload including the name of the predicted action, the conversation ID, the contents of the tracker and the contents of the domain. When the action server finishes running a custom action, it returns a JSON payload of responses and events. The Rasa server then returns the responses to the user and adds the events to the conversation tracker.

### Web Client

The web client is responsible for collecting text input from the user and delivering it to Rasa NLU. It also renders the response generated by NLG and presents it to the user. Rasa open source does not provide a built-in GUI client. Developers can integrate Rasa open source with a channel or web interface of their choice.

## Conversational AI Terminologies

Add a reference to the book and some introduction

* **Utterance**: The user interacts with the agent through natural language. Whatever a user types in the web client is an utterance.
* **Response:** A response is whatever the assistant returns to the user. It can be textual or multimedia.
* **Intent:** An intent is a normalization of what the user means by their utterance or what they want to do.
* **Entity:** An entity is a noun-based term or phrase. An entity can be any important detail that your assistant could use later in a conversation

Figure 8 depicts the user and conversational agent’s different perspectives on the same element of text based communication.

Figure 8 Conversation Perspectives

Diagram

Description automatically generated

Note: Image referenced from Freed (2021)

## Additional Rasa concepts

Add rasa reference and some introduction.

* **Stories:** This is training data that is used to train agents’ dialogue management systems. It is represented in the form of a conversation between a user and a chatbot. Stories are made up of intents, actions, entities and forms. Based on the stories, models can generalize to unseen conversations.
* **Rules:** Rule is also part of the dialogue management unit’s training data. They cover the strict conversation path between a user and a chatbot.
* **Slots:** The slots act as a long-term memory of the agent. Information stored in slots is generally used later in the decision-making process. Slots are generally filled using entities but not mandatorily.
* **Forms:**  Slot filling is a common conversation pattern used to collect pieces of information from a user to do something. Rasa recommends the use of rasa forms for slot filling. It is a controlled way of slot filling from extracted entities or text (and is customizable).

## Rasa Data Files

Rasa uses YAML as a way to manage all the training data. The training data consists of NLU data, stories and rules. Add more about YAML.

NLU is responsible for understanding the user’s intent and the information user is entering. The NLU data consists of intents that the agent can understand and sentence patterns corresponding to the intent. Rasa intents may contain patterns for entity extraction but this is optional. NLU data defines all the intents that the agent needs to use for intent classification. It also has information about extracting entities from user text.

Dialogue management data consists of stories, rules, slots, forms and policies. Stories and Rules are the representation of a conversation between the user and assistant. The stories vaguely cover most of the conversational scenarios that are expected to be covered by the system. Dialogue management data is used to train mode that will be used to predict the next action(s) in each turn.

## Rasa Config Files

* **config.yml:** Defines components as well as policies that the rasa’s trained model will use for making predictions after accepting user inputs.
* **credentials.yml:** It contains credentials for voice and chat platforms that the agent will be integrated with.
* **domain.yml:** It holds all the information that the agent needs to know. It specifies intents, entities, slots, responses, forms, actions and session configurations.
* **endpoints.yml:** It contains all the API endpoints and their configuration that the agent can use.

## Rasa policies

**TBD**

## Spacy Language models

Transformer models:

## DIET

# Implementation

This chapter elaborates implementation details of architecture that are presented in the design section of Health Agent.

## Software Libraries

The core of the Health Agent is implemented in python language with the help of the following libraries. The interface is implemented in JavaScript.

### Python

The chatbot is developed on the python interpreter version 3.8 provided by Anaconda Distribution.

### Rasa Open Source

The health agent is developed using the open-source conversational AI framework developed by Rasa using rasa version 3.2.1. The open-source nature provides complete control over building an NLP chatbot. As described by Rasa Technologies Inc. (2022b), Rasa Open Source supplies the building blocks for creating virtual assistants. Rasa Open Source provides the following three main functions:

#### Natural Language Understanding

NLU turns the text entered by the chatbot user into text that can be understood by the rasa pipeline for intent and entity extraction. NLU is a category of machine learning that analyzes freeform text and turns it into structured data. (Rasa Technologies Inc., 2022b)

Training NLU model needs NLU data which consists of representative sample data for identifying intents and entities. NLU components are configured in the NLU pipeline and are explained in further sections.

#### Dialogue Management

The dialogue management model drives the conversation flow based on user inputs and model configuration. Training DM required dialogue data consisting of the stories, rules, slots and policies. The training data is discussed in further sections.

#### Integrations

A website or app integration is an important part to deliver the ultimate user experience. Rasa provides REST endpoints called connectors to connect the backend with custom interface channels.

### Transformer

The transformer model made available by HuggingFace (Hugging Face, 2022) was used for word embedding.

### Spacy

The spacy library called SciSpacy is used for disease entity extraction (Neumann et al., 2019).

### Pandas

The pandas library is used for preprocessing the dataset and generating the CSV database to be used by Health Agent for disease matching.

### Pycharm

Pytharm IDE was used for all the python based development.

## Project Structure

The following file tree represents the project structure of Health Agent. The configuration of each of the components is described in further sections.

📁 .HealthAgent/

├─📁 actions/

├─📄 config.yml

├─📄 credentials.yml

├─📁 data/

├─📁 db/

├─📄 domain.yml

├─📄 endpoints.yml

├─📄 github-markdown.css

├─📄 index.html

├─📁 notebooks/

├─📄 README.md

├─📄 requirements.txt

├─📄 showdown.min.js

├─📁 tests/

└─📄 webchat.js

## Conversation Flow

Figure 6 shows the visual representation of stories that constitute conversations between

Figure 9: Health Agent Conversation Flow Graph

A picture containing diagram

Description automatically generated

For example, the flow (extreme left branch) starts with the user saying hello and the chatbot responding with a greet utterance and how-are-you utterance. When the user replies ‘ I am very active today ’, the chatbot understands the user is healthy and ends the conversation with a healthy-bye utterance.

Figure 10: Conversational Data Flow

Diagram

Description automatically generated

## NLU data generation

As a part of NLU data generation, certain intents were identified based on the expected conversation between the Health Agent and a user. This section explains all the NLU data components that have been used by the system.

### Intents

As part of NLU data, the following intents were created and added to data files (YAML files). With the help of these intents and example sentences provided for each intent, the NLU model will be trained for a multi-class classification problem to classify each text entered by a user into categories identified by intents.

Table 3 summarizes the intents that the system can process, why the intent is created and an example showing the text that will get classified with the corresponding intent:

Table :3 NLU Intent data

|  |  |  |
| --- | --- | --- |
| Intent | Description | Example |
| greet | Used when a user wants to start a conversation. At the beginning of a conversation, it is expected that it will begin with a text that has greeting intent. | Hey |
| goodbye | Used when a user wants to end a conversation. Whenever a user enters a text with intention of ending a conversation, Health Agent will use this intent and decide the next action. | I'm done |
| healthy\_patient | Used when a user wants to inform the bot that he is healthy. As a user enters a text that informs the Health Agent that the user is healthy, this intent is identified and Health Agent ends the conversation with an utterance that motivates the user to stay fit. | I am perfectly fine |
| unhealthy\_patient | Used when a user wants to inform the Health Agent that the user is unhealthy. Once the user enters the text saying that the user is not well, Health Agent will start gathering information about the user’s ill health. | I am sick |
| inform\_symptoms | Used when a user wants to inform symptoms. This intent is used to extract symptoms from the entered text. | Seems like I have a headache |
| bot\_challenge | Used when a user wants to know about the agent. This intent is used when a user challenges the Health Agent about the agent’s identity. | are you real? |
| out\_of\_scope | Used when a user tries to ask questions that are not within the scope of the Health Agent. | Can you make a pizza? |

We also use NLU data to train the model for entity extraction. Below is an example pattern that Rasa use to identify predefined entity types from the input sentence.

- I am observing **[chest pain] (DISEASE)**

As described by Kong et al. (2021), entities in the training dataset are annotated and written as the Markdown URL expression, namely **[entity value] (entity type)**.

With the help of intent data, NLU understands how to classify each text entered by the user and drives the conversation further.

### Entities

Entities are used to extract specific information from the text entered by the user. The chatbot has a **DISEASE** entity for extracting symptoms from the user’s input text. The system has limited control over how a user can enter the symptoms they are observing. Training the NLU model by giving an exhaustive list of symptoms in the healthcare domain is a resource and time-intensive task. As explained in the transfer learning section, a pre-trained model can be used for such tasks. Neumann et al. (2019) have explained employing the spacy model for biomedical natural language processing. To benefit from this transfer learning approach, the NLP pipeline is equipped with Spacy’s en\_ner\_b5cdr\_md model for the named entity recognition task. The model is capable of extracting disease and chemical entities from a text however Health Agent makes use of only disease entities.

## Response data generation

NLG is responsible for the generation of responses and a response is generated based on the user’s input. Health Agent makes use of template-based response generation to have better control over what kind of response the system can generate.

The table below summarizes the responses that the bot can generate and the purpose of each response:

Table 4: NLG Resposne data

|  |  |
| --- | --- |
| Response Template | Description |
| utter\_greet | Whenever a user greets the chatbot, the system generates a greeting response as defined by this intent. |
| utter\_healthy\_bye | Whenever a user enters a text intending that the user is feeling healthy, the chatbot generates a response using this template. |
| utter\_unhealth\_bye | Whenever Health Agent intend to end a conversation with an unhealthy patient, the system will generate a response based on this template. |
| utter\_goodbye | Whenever a user wants to end the conversation abruptly, the system will generate a response based on this template. |
| utter\_ask\_disease | Once the Health Agent identifies that the user is unhealthy, it will use this template for generating a response to ask the user the symptoms user is observing. |
| utter\_repeat\_information | After collecting all the information from a user, the system will use this template to display the gathered information to the user as an acknowledgement. |
| utter\_iamabot | Whenever a user asks about the system or challenges the system’s identity, this template is used to generate a response and provide Health Agent’s introduction. |
| utter\_out\_of\_scope | A user might be tempted to play with the chatbot and ask random questions. Health Agent is a task-oriented chatbot and cannot serve random requests. This template is used to politely inform the user about the system’s inability to handle random requests. |
| utter\_please\_rephrase | The text entered by a user might be ambiguous and the NLU model may assign multiple intents with similar confidence to more than one intent. In such scenarios, this template is used to ask the user to rephrase the inputs. |
| utter\_submit | Once the Health Agent has finished collecting the data, the chatbot keeps the user informed about the progress with text generated from this template. |
| action\_predict\_disease | This is a response generated using custom actions and it is used to display matched disease information to the user. |

## Dialogue Data Generation

Dialogue management data consists of stories and rules for understanding the conversation flow between the user and the bot.

### Stories

The Health Agent is designed to handle two major types of conversational flows. One flow handles conversation between a healthy patient and the chatbot while the other handles flow between an unhealthy patient and the chatbot. Both flows include the use of different intents and actions and forms(optionally).

The table below summarizes the flexible conversation flows that the bot can handle:

Table 5: Story data for DM

|  |  |
| --- | --- |
| Story Name | Description |
| Health patient | This story represents a Health Agent’s conversation with a healthy user and does not ask the user for symptoms and in the end, motivates the user to stay fit. |
| Unhealthy patient informing symptoms | This story represents a Health Agent’s conversation with an unhealthy user. It makes use of rasa forms for gathering symptoms and handling out-of-context information during the information gathering. |

### Rules

Rasa rules help in handling strict one-turn conversations. Below mentioned rules are added to Health Agent’s DM model so that whenever a user seeks information that is covered by the rule, they get a reply even when the context of the conversation is different from the current flow.

The table below summarizes the strict conversation flows the bot can handle:

Table 6: Rule Data for DM

|  |  |
| --- | --- |
| Rule Name | Conversational Flow |
| Utter goodbye anytime the user says goodbye | A user can say bye anytime during the conversation indicating the user wants to end the conversation. This rule handles such scenarios. |
| Utter bot information anytime the user asks about the bot | A user may wish to ask for information about the Health Agent anytime during the conversation and this rule will handle the case. |
| Handle out-of-scope intents | A user may get tempted to play with the chatbot and ask the information not intended to handle by the Health Agent. The Health Agent informs the user about its shortcomings using this rule. |
| Ask the user to rephrase the ambiguous text | The NLU may assign similar confidence to more than one intent to the text entered by the user and hence identify the text as ambiguous. In such cases, a fallback intent is triggered and this rule helps in handling such scenarios. |
| Activate gather\_symptoms | This rule triggers the activation of a rasa form for gathering symptoms during a conversation with an unhealthy patient. |
| Submit gather\_symptoms | This rule triggers the submission of a rasa form for gathering symptoms during a conversation with an unhealthy patient. |
| Add symptom to symptoms list slot | This rule triggers the symptoms collection custom action when the user informs symptoms to the Health Agent. |

### Slots

The system has two slots which work as temporary long-term memory i.e. the memory that can hold information across the conversation.

Table 7: Slot Data for DM

|  |  |
| --- | --- |
| Slots | Function |
| disease | Store a symptom (if any) informed in the last input text |
| symptoms | Store all the symptoms informed |

### Forms

Dialogue management also has a rasa form called **gather\_symptoms** for the systematic gathering of symptom entities. The form is activated and submitted with combined efforts of rules and stories that include the form. The form also helps in handling out-of-context questions while still maintaining the context of the conversation. Because of this feature, if a user asks some random question instead of informing symptoms (during an unhealthy user conversation flow), the Health Agent answers the random question and resumes seeking symptom information from the user.

## Training the model

In NLU, incoming messages are processed by a sequence of components and enriched to a machine-understandable format. As per rasa documentation (Rasa Technologies Inc., 2022b), training the NLU model is controlled by components defined in the configuration file. The model can be finetuned by configuring parameters in the configuration file. The Botfront (Botfront, n.d.) has discussed some of the pipeline optimization techniques for better intent and entity extraction.

### NER Language model

We have used the ScispaCy Language model en\_ner\_bc5cdr\_md (Neumann et al., 2019) which is a fined finer-grained NER model trained on BC5CDR dataset for diseases and chemicals. It loads pre-trained models with pre-trained word vectors in the NLU pipeline. All the other spacy components used in the pipeline relied on the spaCy structures. The model is configured to be case-insensitive.

### Tokenizer

Tokenizers split received text into tokens. The system supports the English language for interacting with a user. As the system is using the spaCy language model, the pipeline is configured with SpacyTokenizer as recommended by rasa(Rasa Technologies Inc., 2022b).

### Featurizer

The NLU pipeline is configured with SpacyFeaturizer, RegexFeaturizer, and LanguageModelFeaturizer.

SpacyFeaturizer is used by the Spacy NLP pipeline for entity extraction.

LanguageModelFeaturizer is based on HuggingFace pre-trained model LaBSE developed by Rasa. It creates features for entity extraction, intent classification, and response selection using the configured pre-train model. Tokenizer components should appear before featureziers (Rasa Technologies Inc., 2022b).

WHY?

### Entity extractor

The pipeline makes use of SpacyEntityExtractor. Although the spacy language model *en\_ner\_bc5cdr\_md* can perform NER for disease and chemical entities, the system only makes use of DISEASE dimension of the model.

Dual Intent Entity Transformer (DIET) based DIETClassifier is also capable of extracting the entities and is used along with the SpacyEntityExtractor for disease NER.

WHY?

### Intent classifier

The system uses DIETClassifier for intent identification and classification purpose. DIET makes use of pre-trained word embedding made available through LanguageModelFeaturizer. DIET exposes many hyperparameters available to tune the model. As discussed by Botfront (Botfront, n.d.), some of the key parameters have been set.

<Add sample NLU response showing intent and entity extraction>

A FallbackClassifier is configured to handle cases where the NLU intent classification score becomes ambiguous. The threshold parameter of the classifier ensures that if no intent is classified with a confidence level greater than the threshold, a fallback intent is triggered. The ambiguity threshold parameter is used to maintain enough confidence score difference between the highest-ranked intents.

## Action Server

As documented by rasa (Rasa Technologies Inc., 2022b) the action server acts as a backend system of the chatbot and executes custom actions and any other business logic.

### Custom actions

The chatbot system is using the action server for the following two reasons:

* To collect the symptoms entered by the user

A rasa custom action is used to extract all the DISEASE entities identified by the NLU and add them to the ‘symptoms’ slot

* To call the backend service for identifying the disease matching the collected symptoms

This rasa custom action sends the collected symptoms to a disease matching service and renders the response of the service to the user.

### Disease and symptom matcher

This is a backend service and is a part of the action server. It received a list of symptoms and matches it with the symptom list of diseases present in the database. It rates each matched disease based on the number of matched symptoms.

<Add the example response>

## Data preprocessing

The disease data obtained from the Kaggle (https://www.kaggle.com/datasets/priya1207/diseases-dataset) required some preprocessing.

The original dataset contained the following columns:

* name
* link
* symptoms
* causes
* risk\_factor
* overview
* treatment
* medication
* home\_remedies

Of these, ‘name’ and ‘symptoms’ were considered for further processing. An additional column for the symptom list was created by extracting symptoms from the ‘symptoms’ column of the dataset We applied Spacy en\_ner\_bc5cdr\_md mode for disease NER (Neumann et al., 2019).

## Web client

The following figures are screenshots of an example interaction of a user with the Health Agent.

Figure 11: Health Agenet's conversation with a healthy user

Graphical user interface, text, application, chat or text message

Description automatically generated

Figure 12: Health Agenet's conversation with a healthy user

Graphical user interface, text, application, chat or text message

Description automatically generated

# Evaluation

In the NLU pipeline, the two important tasks are intent classification and entity extraction. As explained by Géron (Géron, 2019), the main performance metrics for classification tasks are based on the following measures:

* True Positive (TP): model correctly predicts the positive class
* True Negative (TN): model correctly predicts the negative class
* False Positive (FP): model incorrectly predicts positive class
* False Negative (FN): model incorrectly predicts negative class

Equation 1 - Precision

Equation 2 - Recall

Equation 3 - score

Equation 4 - Accuracy

Intent extraction is a multi-class classification problem and we apply the above metrics to evaluate how good the system performs.

## Experimental Setup

Table 8 details the configuration of the system that was used for conducting the evaluation experiments.

Table 8: Experimental Setup

|  |  |
| --- | --- |
| **Specification** | **Details** |
| System Type | Laptop Running Windows 10 |
| Processor and Cores | Intel(R) Core(TM) i5-8265U CPU @ 1.60GHz 1.80 GHz |
| Memory (RAM) | 20.0 GB |
| Operating System | Windows 10 Home Single Language (Version 21H2) |
| Python Version | Python 3.8 |
| Python Environment Manager | Conda Environment |
| Development IDE | PyCharm 2022.1.3 (Professional Edition) |

## Data validation

There should not be inconsistencies in the domain, NLU data, story data or rule data. Rasa data validation utility ensures there are no mistakes between domain, NLU and story data. Rasa CLI provides a utility to validate the training data.

Figure 13: Rasa Data Validation

A computer screen capture

Description automatically generated with medium confidence

If there is any inconsistency between rules and stories, it gets validated in the training data and training gets aborted. No data issues were reported during the training.

## Evaluating NLU Model

NLU model was performed using a shuffle and split data strategy. The NLU training data was split with an 80/20 split of train/test data.

Table 9 represents intent classification metrics. The mode confused to classify goodbye intent with healthy\_patient intent and greet intent for 3 instances.

Table 9: Intent Classification Metrics

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Intent | precision | recall | f1-score | Confused with | Confusion Count |
| greet | 0.869565217 | 0.869565217 | 0.869565217 | goodbye | 3 |
| goodbye | 0.833333333 | 0.877192982 | 0.854700855 | healthy\_patient | 3 |
| greet | 3 |
| inform\_symptoms | 0.916666667 | 1 | 0.956521739 |  |  |
| out\_of\_scope | 0.965517241 | 0.903225806 | 0.933333333 | unhealthy\_patient | 1 |
| goodbye | 1 |
| unhealthy\_patient | 0.555555556 | 0.416666667 | 0.476190476 | healthy\_patient | 5 |
| inform\_symptoms | 1 |
| bot\_challenge | 0.916666667 | 1 | 0.956521739 |  |  |
| healthy\_patient | 0.666666667 | 0.64 | 0.653061224 | goodbye | 5 |
| unhealthy\_patient | 3 |

Table 10 shows the overall intent classification metric of the NLU model.

Table 10: Intent classification

|  |  |
| --- | --- |
| Metric | Score (weighted avg) |
| F1 | 0.8356757777299284 |
| Precision | 0.8343335238458118 |
| Recall | 0.8397790055248618 |
| Accuracy | 0.8397790055248618 |

The intent classification confusion matrix in figure 8 shows which intents were mistaken for others.

Figure 14: Intent Confusion Matrix

A picture containing scatter chart

Description automatically generated

The histogram in figure 9 shows confidence in all the intent predictions with correct and incorrect predictions being displayed in blue and red bars.

Figure 15: Intent Prediction Confidence Distribution

Chart, bar chart

Description automatically generated

## Evaluating Dialogue Model

Dialogue management consists of stories, rules and policies governing the next predicted action. The model is evaluated based on how well it could predict the next action.

Table 11: Next Action Prediction Metric

|  |  |  |  |
| --- | --- | --- | --- |
| Intent | precision | recall | f1-score |
| gather\_symptoms | 1 | 1 | 1 |
| action\_listen | 1 | 1 | 1 |
| utter\_greet | 1 | 1 | 1 |
| utter\_submit | 1 | 1 | 1 |
| action\_repeat\_information | 1 | 1 | 1 |
| action\_predict\_disease | 1 | 1 | 1 |
| utter\_howareyou | 1 | 1 | 1 |
| utter\_healthy\_bye | 1 | 1 | 1 |

Table 12: Action prediction

|  |  |
| --- | --- |
| Metric | Score (weighted avg) |
| F1 | 1 |
| Precision | 1 |
| Recall | 1 |
| Accuracy | 1 |

Figure 16: Action confusion matrix

Chart

Description automatically generated

## Conversation Flow tests

Rasa offers a test framework that can be used for constructing test stories. These test stories can then be used to test the trained model and gain confidence in the trained model's performance in a variety of scenarios. The following figure and metrics show how the Health Agent is performing against the test stories developed for assessing the agent.

Figure 17: Entity confusion matrix

Chart

Description automatically generated

Figure 18: Entity Prediction Confidence Distribution

Chart, bar chart

Description automatically generated

Figure 19: Intent confusion matrix

Chart, scatter chart

Description automatically generated

Figure 20: Intent Prediction Confidence Distribution

Graphical user interface, chart

Description automatically generated

Figure 21: Action confusion matrix

Chart, waterfall chart

Description automatically generated

## Interactive Mode validations

We validated the slot-filling functionality using rasa’s interactive command line interface to make sure the slot-filling logic is working as expected. The validations are attached in the appendix.

## Survey responses

A survey was conducted to get users’ feedback about the naturalness of the chatbot conversation and the functionality of the system. The survey was hosted on the Qualtrics survey system provided by the University OF St Andrews and the survey link was shared with the respondents. The screenshots of two representative conversation flows were provided for the respondent’s feedback. The survey was anonymous and voluntary and no personal information was collected during the survey.

### Survey Design

Each of the questions can be answered with one of the six choices:

Strongly Agree, Agree, Neutral, Disagree, Strongly Disagree, Prefer Not to Answer

**Questions about the naturalness of the conversation with the chatbot:**

1. The conversation with the chatbot sounded natural and smooth.
2. The chatbot could handle out-of-context interactions gracefully.
3. The chatbot kept the user informed about the progress and the conversation was engaging.
4. The chatbot politely acknowledged its shortcomings.
5. The conversation ended gracefully and sounded natural.

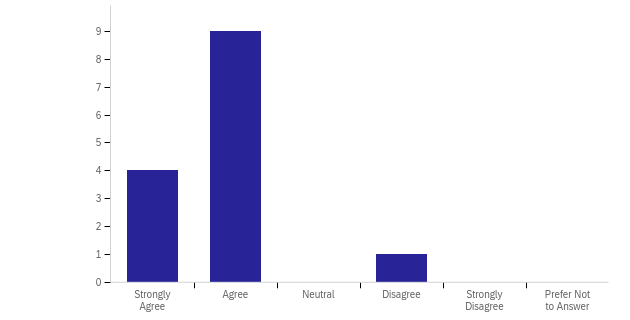
**Questions about the functionality of the chatbot:**

1. When asked, the chatbot introduced itself and the introduction was clear.
2. The chatbot clearly understood the user’s intentions (healthy/unhealthy user, informing symptoms, asking about the chatbot).
3. The chatbot sought appropriate information from the user.
4. The chatbot recognized the symptoms entered by the user.
5. The chatbot appropriately responded to the user’s question.
6. The displayed disease names were matching with the entered symptoms.
7. The disease names were displayed appropriately.

### Survey Responses

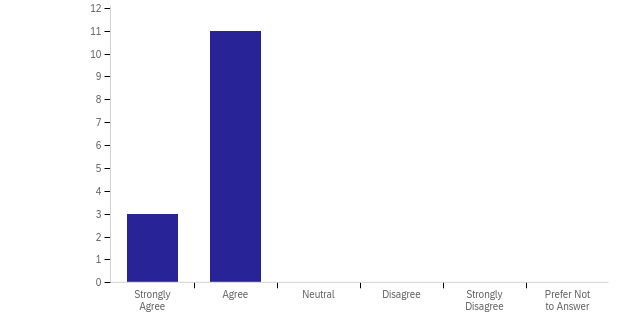
A total of 14 responses were received for the survey. The following figures provide insights into the user response.

Figure 22: Response to question: The conversation with the chatbot sounded natural and smooth



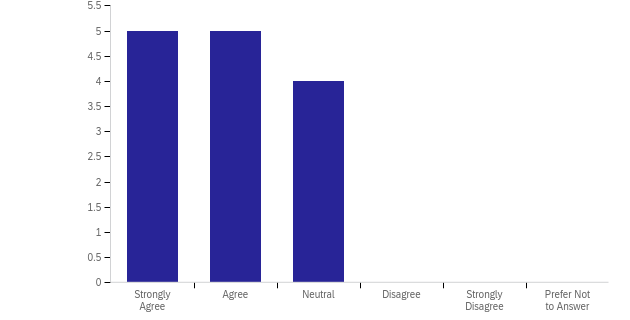
Observation: Respondent found chatbot conversation smooth and natural.

Figure 23: Response to question: The chatbot could handle out-of-context interactions gracefully



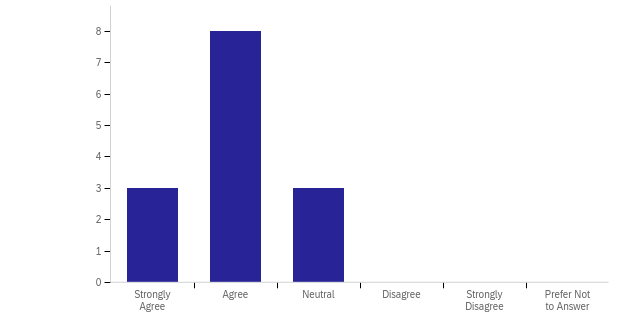
Observation: Respondent liked the bot’s out-of-context handling

Figure 24: Response to question: The chatbot kept the user informed about the progress and the conversation was engaging



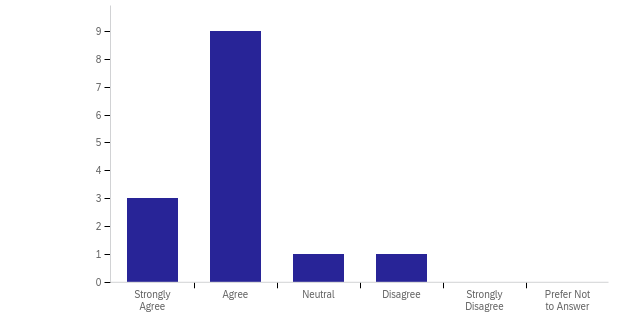
Observation: Respondent could partially agree that the chatbot conversation was engaging.

Figure 25: Response to question: The chatbot politely acknowledged its shortcomings



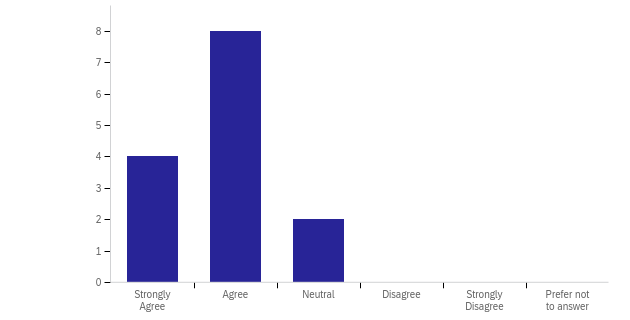
Observation: Respondents agreed that the chatbot acknowledged its shortcomings.

Figure 26: Response to question: The conversation ended gracefully and sounded natural



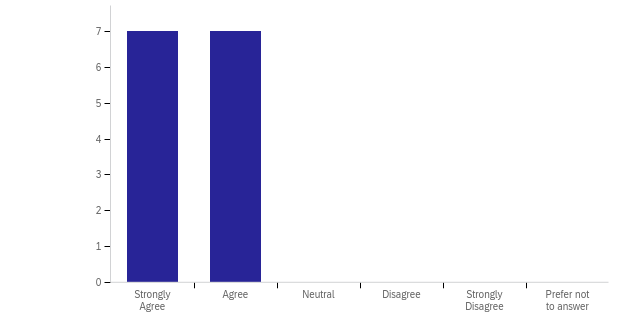
Observation: Respondents found that the conversations ended gracefully.

Figure 27: Response to question: When asked, the chatbot introduced itself and the introduction was clear



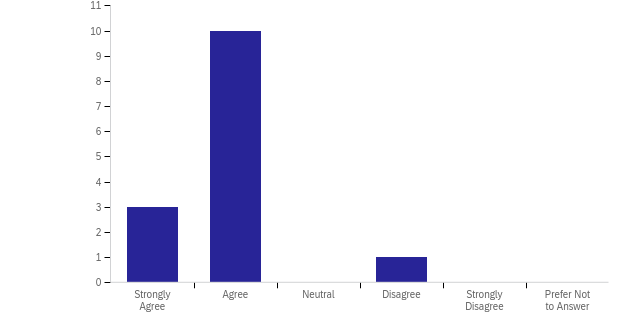
Observation: Respondents found the chatbot’s introduction was clear.

Figure 28: Response to question: The chatbot clearly understood the user’s intentions (healthy/unhealthy user, informing symptoms, asking about the chatbot)



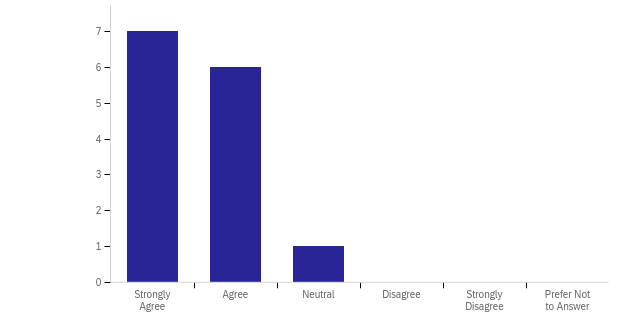
Observation: The respondent agreed that the chatbot clearly understood the user’s intentions.

Figure 29: Response to question: The chatbot sought appropriate information from the user



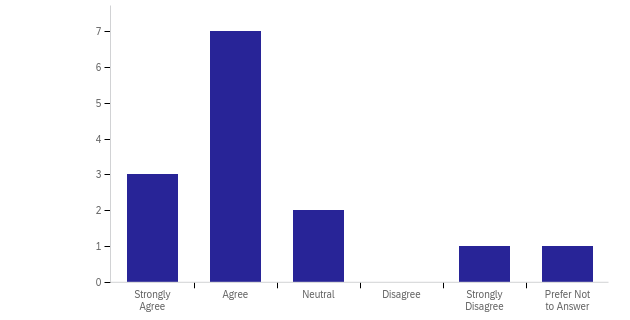
Observation: Respondents agreed that the chatbot sought appropriate information from the user.

Figure 30: Response to question: The chatbot recognized the symptoms entered by the user



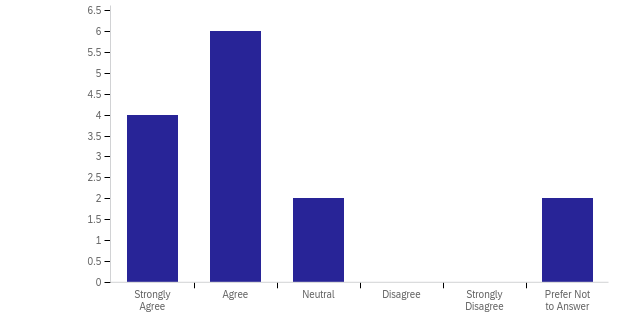
Observation: Respondents agreed that the chatbot could recognize symptoms from the text entered by the user.

Figure 31: Response to question: The chatbot appropriately responded to the user’s question



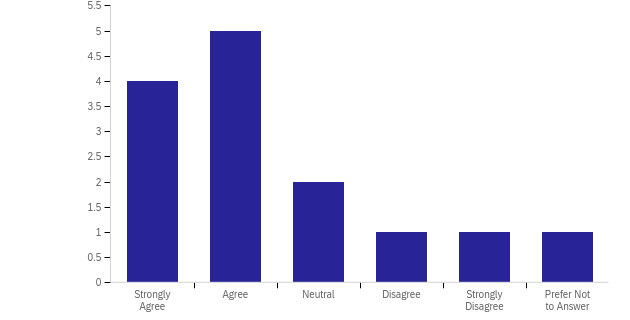
Observation: Respondents found the chatbot’s response to the user's question was appropriate.

Figure 32: Response to question: The displayed disease names were matching with the entered symptoms



Observation: Respondents found the predicted disease was matching with entered symptoms.

Figure 33: Response to question: The disease names were displayed appropriately



Observation: Respondents could not agree on the disease name display format.

**Response to question: What features can be improved?**

Below are the notable improvements as suggested by respondents:

* Knowing the user better by profiling the user’s preexisting health condition and lifestyle habits.
* Supporting the predicted disease with the confidence level of the prediction
* Integrating chatbots with government systems like NHS so that health agencies can be alerted in case of emergencies.
* Improving text in the bot’s response
* Providing disease treatment information
* Asking more questions to collect more information about the symptoms

**Response to question: What feature of the system is most interesting?**

Below are the notable responses for the interesting feature of the system:

* Symptom extraction
* Handling of out-of-context questions
* Disease matching feature
* Detecting the health conditions of the user
* Smooth and natural responses

**Response to question: Do you have any other feedback or comment?**

Below are the notable responses:

* The chatbot can reduce the workload on the health professionals
* The chatbot could be integrated with the NHS system using the patient's NHS number
* It is dangerous to create systems which make definite pronouncements without either making clear either the reasoning process or even a reason that the user should trust the system

# Conclusions and Future Work

## Summary

The primary focus of this paper was to understand the development process of conversational AI and the techniques to integrate state-of-the-art NLP into conversational AI. The primary

The Health Agent is an advanced and intelligent chatbot equipped with the latest technical developments in natural language processing. (can we claim this?)

~~Natural language processing techniques are touching all aspects of human life. The development of such contextual AI assistants has been made simpler thanks to the use of transfer learning, which is a key element of pre-trained models and transformers, which are the latest state-of-the-art in natural language processing. Open-source libraries like rasa are offering a framework for orchestrating all of the components of conversational artificial intelligence and developing intelligent virtual assistance, which is a task that would otherwise be difficult to do effectively. Conversational agents that are developed using these techniques are far more adaptable than chatbots that are built using state machines, which users find unpleasant and rigid. This kind of goal-oriented chatbot may save users time that would otherwise be spent doing unsuccessful web searches and getting tangled up in biomedical jargon. These agents will benefit users who can be patients as they get correct information efficiently and as well users who are doctors or medical institutes as it will reduce the administrative burden on their system greatly.~~

## Suggestions for future work

The focus of the dissertation was developing a chatbot capable of understanding the user’s health status and extracting the symptoms from the input text and maintaining the dialogue without forgetting the information collected in previous dialogue turns. During the development, it was observed that knowing users in detail can help the bot in delivering a better user experience. The chatbot systems can maintain detailed user profiles in the backend and during a conversation system can extract these key profile details and frame a contextualized and personalized conversation.

The NER model used for the disease was found to miss some of the words which are closely related to the actual symptom. It is believed that the model can be further customized to include those additional closely related word tokens as disease entities in the model

The disease and symptom matching system can be improved by replacing the text-based matching system with a machine learning model that is capable of accepting symptoms (and some other extra feature maintained in the user profile) as its inputs and predicting possible disease with its probability.

Knowledge graph for better data representation

~~Bias in the pre-trained dataset~~

[~~https://learning.oreilly.com/library/view/natural-language-processing/9781098136789/ch01.html#idm45146323434784~~](https://learning.oreilly.com/library/view/natural-language-processing/9781098136789/ch01.html#idm45146323434784) ~~Main Challenges with Transformers~~

# Project Timeline

Figure 34 Project Timeline

Chart

Description automatically generated

# Appendix B User Guide

* Clone the repository to a local drive.
* Change the directory to the root of the cloned repository.
* Make sure all the python dependencies are correctly installed.
* Follow the instructions mentioned below to access the chatbot:

**Rasa server**  
To run the server, use the following command:  
  
rasa run --cors "\*"

The --cors "\*" command is used to solve the cross-origin resource sharing (CORS) problem between the client and Rasa servers.  
  
  
**Run Action server**  
  
rasa run actions

This will start the action server service.  
  
**Web client-server**Run the following command:  
  
python -m http.server

**Accessing chatbot:**

This will start an HTTP-based server in the local 8000 port.

Visit <http://localhost:8000> in a browser to access the chatbot.

# Appendix C Ethics Documents



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