Conversational AI for Primary Healthcare Support Advice

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Logo, company name

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# Abstract

Conversational AI for Primary Healthcare Support Advice

For common illnesses, citizens of the internet need to search information on the internet manually, read through the complicated medical blogs and understand the appropriate suggested treatment. The information available on the internet may not be in easy to search, interpret and consume format. In this project, we aim to develop an AI-based conversational agent commonly known as a chatbot which will be trained with information about common illnesses, their symptoms and available treatments. 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. Users will input the symptoms they are having and an agent will respond with its diagnosis which will contain identified illness and possible treatment. 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.

The Transformer model invented by Google Research has toppled decades of Natural Language Processing research, development, and implementations. The use of transformers for conversational AI has high potential in delivering a contextualized and personalized experience. The Transformer in NLP is a novel architecture that aims to solve sequence-to-sequence tasks while handling long-range dependencies with ease. It relies entirely on self-attention to compute representations of its input and output without using sequence-aligned RNNs or convolution.

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 for core NLP techniques and will orchestrate the conversation using the open-source RASA 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 hardcoded static conversation. This AI-based approach would be scalable depending on the knowledge of the agent.

**Keywords**

NLP, Transformer, Conversational AI

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I thank you for enabling me to choose a topic of my interest and providing new and interesting exploration into the field of natural language processing.

I would also like to thank my family for their unconditional support and encouragement

throughout all my education and especially my master’s degree where we were not able to meet

for extended periods.

# Declaration of Authorship

I declare that the material submitted for assessment is my 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 14,519 words long, including project specifications and plan.

In submitting this project report to the University of St Andrews, I give permission for it to be made available for use in accordance with the regulations of the University Library. I also give permission for the title and abstract to be published and for copies of the report to be made and supplied at cost to any bona fide library or research worker and to be made available on the World Wide Web. I retain the copyright in this work.

Date: 16th August 2022

Vishesh Bhagat

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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 |

# Introduction

## 

## Background

## Importance of the project

## 

## Problem Definition and Goals

# Context Survey

In this section, we will discuss the need for chatbots in the healthcare domain, how NLP techniques are evolved over the years and which ones are beneficial for our use, available frameworks for building chatbots and recent work done in the field of chatbots in healthcare.

## Motivation

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 service available to everyone. Patients can use chatbot systems round the clock and get their queries answered.

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 the treatment on time even for simple and mild illnesses. This delay in early treatment exaggerates the symptoms and can lead to further health complications.

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 the possible solutions and present it to the user in user understandable form. 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 presents in the hospitals and medical services. A chatbot can complete the patient registration and data gathering in a timely fashion without waiting for any person. Chatbots can also be integrated with local pharmacies for ordering medicines and medical supplies.

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.

## Evolution on NLP

## Natural Language Processing

NLP is an area of computer science that deals with methods to analyse, model, and understand human language. Every intelligent application involving human language has some NLP behind it.

The below table summarizes various NLP tasks and corresponding popular 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 |

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. In order 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 (context).

|  |  |
| --- | --- |
| 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

**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 “I made her duck”.

**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

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.

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

**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 employed. 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 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:**

We've witnessed a big increase in the use of neural networks to deal with complicated, unstructured data in recent years. Language is naturally unstructured and complicated. 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. CNNs have 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.

**Transformers:**

Transformers ("Transformers: State-of-the-Art Natural Language Processing,") is the most recent addition to the league of deep learning NLP models. The transformer model was released in 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. It prefers to look at all the words surrounding it (known as self-attention ("Attention Is All You Need,")) and represent each word in its context when given a word in the input.

Large transformers have recently been employed in the transfer learning of smaller downstream activities. Transfer learning is an AI approach in which information obtained while addressing one problem is used for a related but different problem.

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.

<Add more about transformers? Architecture? >

**Autoencoders:**

An autoencoder is a type of network that learns compressed vector representations of the input. From the text input, we can learn a mapping function to the vector. We "reconstruct" the input back from the vector form to make this mapping function effective. We gather the vector representation after training, which acts as a dense vector encoding of the input text. Autoencoders are commonly employed to generate feature representations for use in later tasks.

## Transfer Learning

Udemy course

Diagram

Description automatically generated

ELMo

## Chatbot Frameworks

**Chatbots**

A chatbot is a computer programme that can converse with people via text or speech. Chatbots are divided into two categories based on their goals: task-oriented bots and chitchat bots. Task-oriented bots aim to do certain tasks through 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.

The standard method for creating a chatbot 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

**Need for chatbot:**

* Waiting time
* Require huge human resources
* Investment / skilled employees
* Infrastructure cost
* Commonly asked questions

Add a layer of a computer program that can take inputs in a natural language, process the information and generate an appropriate response.

**Types of chatbots:**

* Rule-based
  + Question
  + answer
* Conversation-based – virtual assistance
  + Question
  + Answer
  + Question referring to the above question
  + Answer

**Frameworks:**

There are two sorts 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 bespoke 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).

**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.

**Google**

Google’s Dialogflow is the primary service used for conversational AI.

**IBM**

Watson Assistant is IBM’s AI assistant platform, and it is suitable for building all three types of AI assistants.

**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.

## Related Work

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. (Sheth et al., 2019) focuses on Contextualization and Personalization of Patient’s Data. discuss 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. A paper 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. A paper published by researchers at Digital Health (Nadarzynski et al., 2019) has conducted an in-depth study of the Acceptability of artificial intelligence (AI)-led chatbot services in healthcare. They investigated participants' willingness to interact with AI-powered health chatbots. Researchers at MDPI have studied the feasibility of developing a rule-based virtual caregiver system using a mobile chatbot for elderly people. A paper written by students and professors at Vishwakarma Institute of Technology Pune, India has studied using deep learning for developing contextual chatbots (Kandpal et al.).

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 ("Transformers: State-of-the-Art Natural Language Processing,") 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.

# Ethics and Dataset

<https://www.ncbi.nlm.nih.gov/CBBresearch/Dogan/DISEASE/>

disease

en\_ner\_bc5cdr\_md - symptoms

# Design

What is RASA:

Why chose RASA:

Graphical user interface, text, application, email

Description automatically generated

Intent:

Text

Description automatically generated

Entity:

Graphical user interface, text, application

Description automatically generated

Actions:

Stories:

Domain:

Graphical user interface, text, letter

Description automatically generated

Chart

Description automatically generated

Diagram

Description automatically generated

Graphical user interface, text, application

Description automatically generated

Diagram, timeline

Description automatically generated

Graphical user interface

Description automatically generated with medium confidence

Graphical user interface, application

Description automatically generated

NLU Intent: multi classification problem

Graphical user interface, text

Description automatically generated with medium confidence

A picture containing text

Description automatically generated

What is CDD: <https://rasa.com/docs/rasa/conversation-driven-development>

Choice of technology:

[**https://learning.rasa.com/transformers/**](https://learning.rasa.com/transformers/)

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

**BERT:**

* Shortcomings of RNN and LSTM
* Transformer Architecture
  + Diagram
  + Scaled dot product for vector similarity
  + Attention(Q,K,V)=softmax()V
    - Q – context
    - K – sequence K
    - V - ???
  + Multi headed layer
  + Self-attention
  + Masked layer
* BERT Architecture
  + Stack of encoders
  + Hyperparameters
    - L: Number of encoder layers
    - H: hidden size (embedding dim)
    - A: number of self attention heads
  + BERT Input
  + [CLS]+Sentence A+ [SEP]+Sentence B
  + String -> toekns -> vectors
  + BERT tokenizer : Word Tokenizer: WordPiece Tokenizer
    - 30522 words
  + Encoders needed as inputs
    - Embedded words
  + Pre-training
    - Two-phases
      * MLM
        + Masked Language Model
      * NSP
        + Next sentence prediction

 examples for dialogue

 consider some rules over the example dialogue (simple things that a human being can do) :

* Decision making

 consider what assumptions are mad

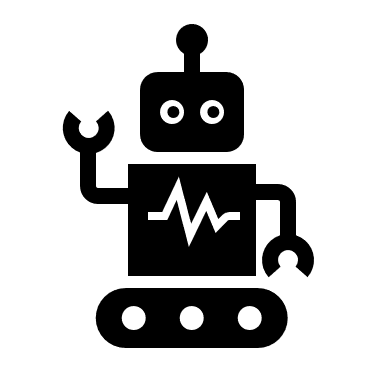
Hi @Alice,

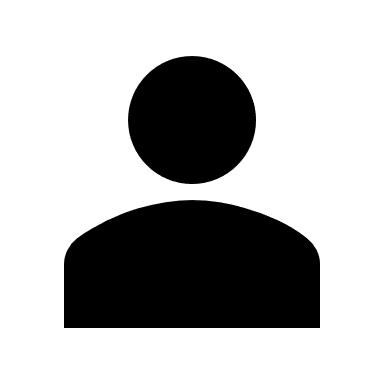
As per discussion in today’s meeting, here is the plan for next week:

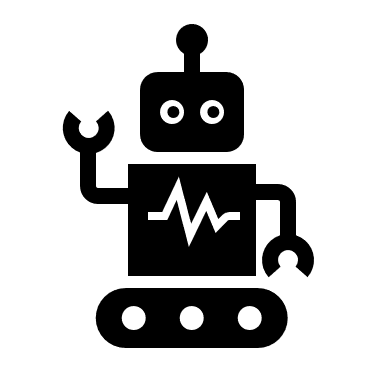
* Start coding the bot
* Adding greeting and bye dialog
* Add “healthy patint” dialog flow
* Add “sick patient” dialog flow (basic)
  + Identify symptopms from a input line

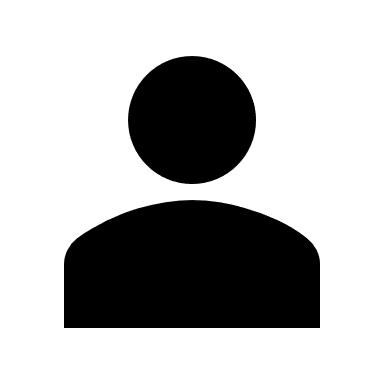
Here is the Example conversations we discussed today.:

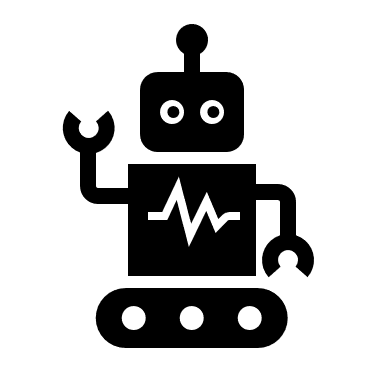
1. **BASIC:**

 Hello, I am your health advisor, how are you feeling today?

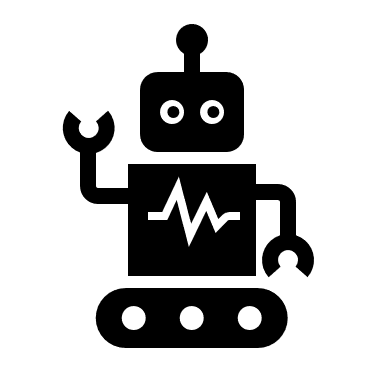
I am not felling well.

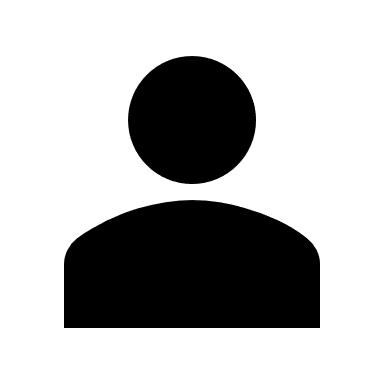
 What symptopns do you observe

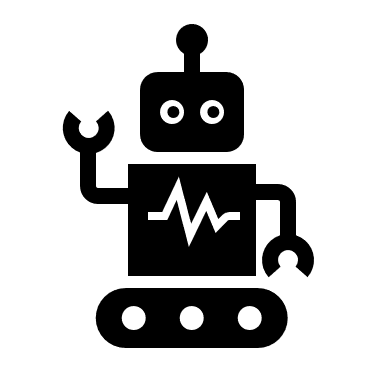
I am suffering from diarrhea  and Vomits. I am feeling tired and dehydrated. My mouth is dr as well.

 These are the possible Symptopons of Rotavirus

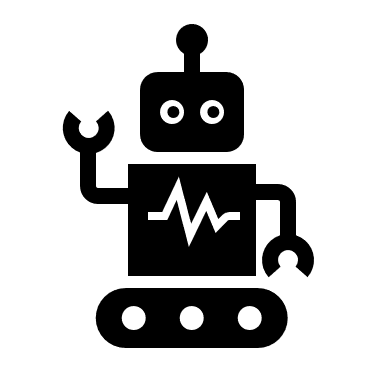
========================================================

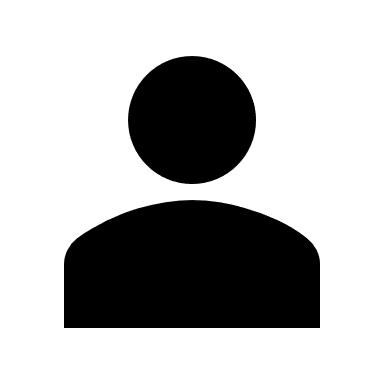
 Hello, I am your health advisor, how are you feeling today?

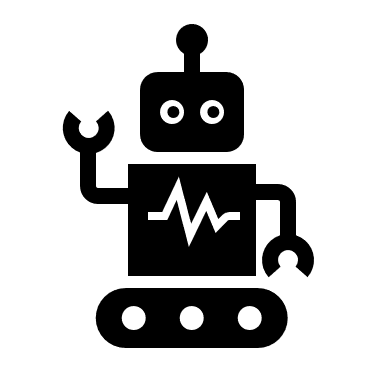
I am fine.

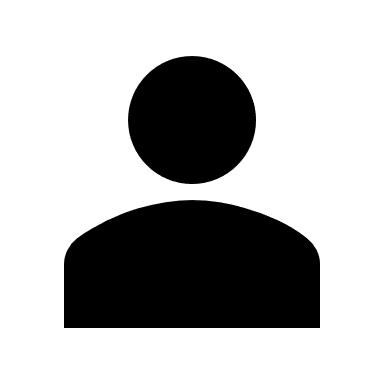
 Great! Keep dping well

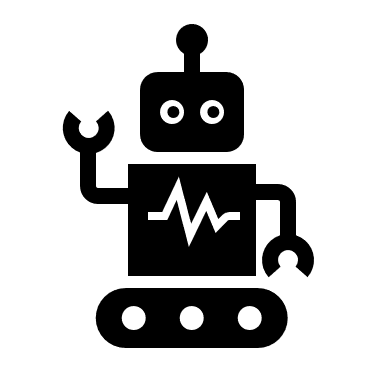
1. **More complex:**

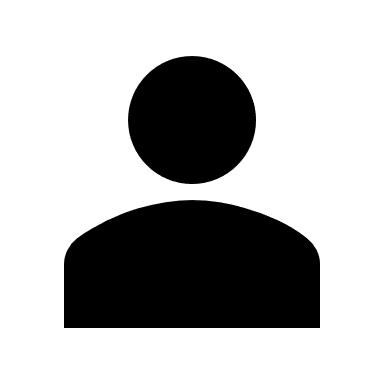
 Hello, I am your health advisor, how are you feeling today?

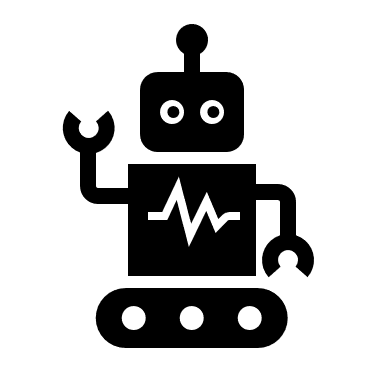
I am not felling well.

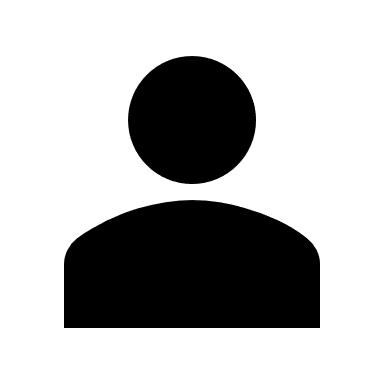
 What symptopns do you observe

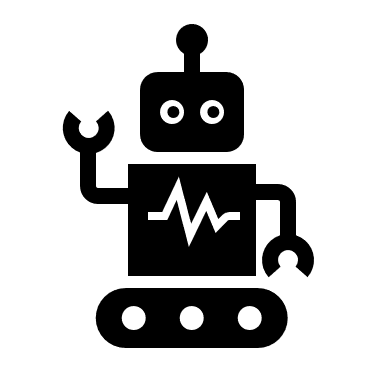
diarrhea  and Vomits

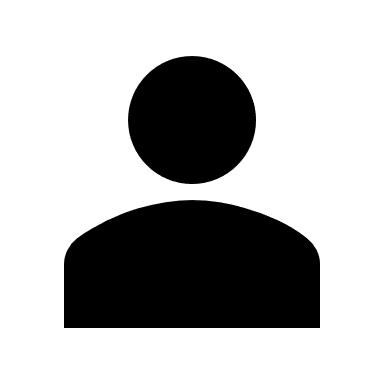
 Any other Symptom?

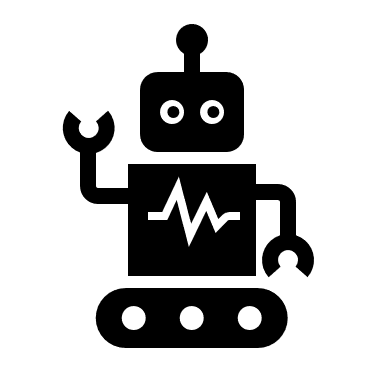
 I am feeling tired

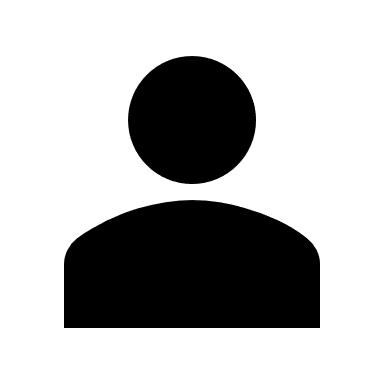
 What else you feel?

dehydration, dry mouth

 Anything else?

 No

 These are the possible Symptopons of Rotavirus. <https://www.mayoclinic.org/diseases-conditions/rotavirus/symptoms-causes/syc-20351300>

 What causes the disease ?..

1. Ultimate objective:

fever: 248 diseases

+ weakness : 26

Actions: Limiting diseases to 100

# RASA Pipeline:

**Tokenizer components:**

SpacyTokenizer / WhitespaceTokenizer

**Featurizer components:**

**LanguageModelFeaturizer**/ BERT

LexicalSyntacticFeaturizer

**Entity extraction components**

DIETClassifier – generally

SpacyEntityExtractor –

Fallback classifier

**Intent classifier components:**

DIETClassifier

Designing Stories:

<https://rasa.com/docs/rasa/writing-stories#designing-stories>

# Implementation

Pretraining entity extractor:

<https://rasa.com/docs/rasa/generating-nlu-data/#pre-trained-entity-extractors>

How do we handle spelling mistakes and correctly identify entities?

<https://rasa.com/docs/rasa/generating-nlu-data/#handling-edge-cases>

### Defining an Out-of-scope Intent[**#**](https://rasa.com/docs/rasa/generating-nlu-data/#defining-an-out-of-scope-intent)

<https://rasa.com/docs/rasa/generating-nlu-data/#defining-an-out-of-scope-intent>

# Results and Evaluation

Testing the pipelines:

https://rasa.com/docs/rasa/testing-your-assistant/#comparing-nlu-pipelines

Bot maturity (productionization) process:

Timeline

Description automatically generated

# Future Work

Word embedding Bias Removal

<https://learning.rasa.com/bias/>

# Conclusion

# Appendix A DOER Document

# Project Timeline

Figure Project Timeline

Chart

Description automatically generated

# Appendix B User Guide

# Appendix C Ethics Documents



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