Conversational AI for Primary Healthcare Support Advice

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Abstract

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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

Acknowledgements

I would like to thank my supervisor, Dr Alice Toniolo and Dr Phong Le, for their unwavering enthusiasm regarding this project and the invaluable guidance and support given to me throughout the project.
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.

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

1. 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 they are interacting with other humans.

1. Background:

The 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.

Conversational AI (also known as chatbots) are full systems that use 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).

Conversational AI provides convenient interactions, is more effective and efficient and hence is important to adopt.

- Importance of the project:

Why Are Chatbots Such a Big Opportunity?

https://learning.oreilly.com/library/view/deep-learning-for/9781484236857/html/461351_1_En_4_Chapter.xhtml

Research conducted by Forrester (https://go.forrester.com/data/consumer-technographics/) points out that about ~85 percent of our time on mobile devices is spent on the major applications, such as e-mail and messaging platforms. With the great benefits offered by deep learning and NLP, almost every firm is trying to build applications to keep their potential consumers engaged with their products and services, and chatbots uniquely serve that purpose. Multiple human errors and customer requests handled by a conventional customer care service could be easily avoided by putting chatbots in place. Moreover, chatbots could allow a customer and a concerned company to have access to all the previous chat/issue records.

Although a chatbot could be considered an application that conducts a conversation with an end customer, the tasks and few concerned applications performed by a chatbot could be classified at a higher level, under the following categories:

- *Question answering*: One turn per user; useful when a labeled answer is present
    1. a)

Product querying use cases

2. b)
   Extracting user information

- *Sentence completion*: Filling in of the missing word in the next utterance in a dialog
  1. a)
     Mapping of right product to the customer
- *Goal-oriented dialog*: Conversation with the task of achieving a goal
  1. a)
     Recommendation to the customer
  2. b)
     Negotiating a price with the customer
- *Chit-chat dialog*: Conversations having no explicit goals, more of a discussion
  No such use case to focus now
- *Visual dialog*: Tasks with texts, images, and audio
  1. a)
     Exchanging images with customers and building inferences on those

OK, you may now be thinking, “I am excited. How can I build one?”

- Why we need conversational AI in general
- Application cases in the healthcare domain
- Challenges
- Healthcare industry adoption and examples

2. Closes Look at Generalized AI

The following figure is a bird’s eye view of AI assistant architecture.

- Problem Definition :
  - Problem statement / description
  - Objectives
    - Primary
    - Secondary
    - Tertiary

2. 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.

2.1. 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.

2.2. Evolution on NLP

2.2.1. 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

2.2.2. 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.

2.2.3. 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.

2.2.4. 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.

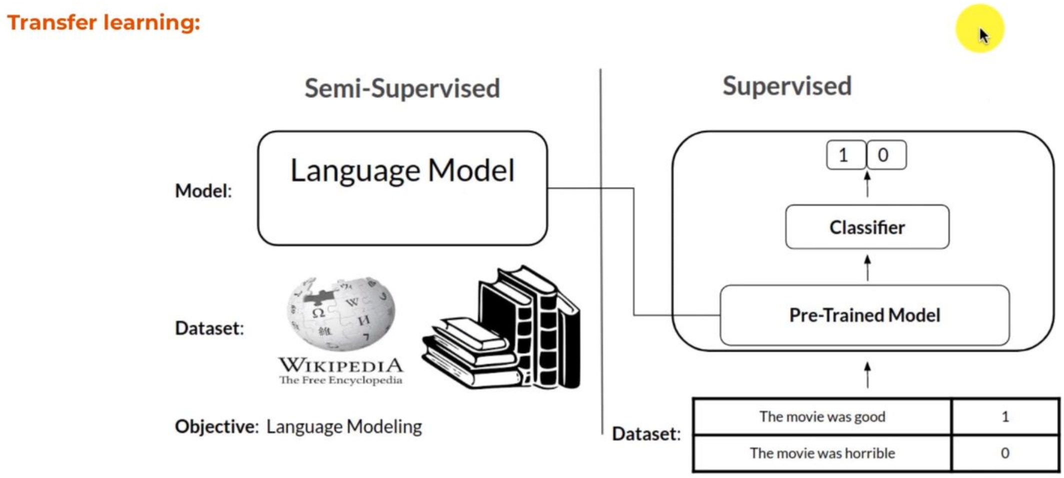
<Add more about transformers? Architecture? >

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.

2.2.5. Transfer Learning

Udemy course



ELMo

2.2.6. 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.

2.3. 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.

3. Requirements specification

This chapter discusses the scope of the project and the same was covered in the DOER document.

3.1. Objectives

Objectives of the project were set at the beginning of the project. Objectives were discussed with supervisors and were classified into three levels as 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 where an agent can respond to queries
- 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. The below objectives aim to enhance dialogue management of the agent:

- Gradual information gathering of symptoms from the user
- Extending the dialogue with back and forth exchange of information to achieve a more humanly conversation

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

4. 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:

I followed the agile development methodology. During the chatbot development, we worked on incremental feature delivery. This helped us in breaking the bot development process into smaller workable tasks and focusing on working on the most important task at a time.

Tracking:

Similar to sprint review meetings, a weekly meeting helped us in reviewing the project 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.

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.

5. Ethics

6. Dataset

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

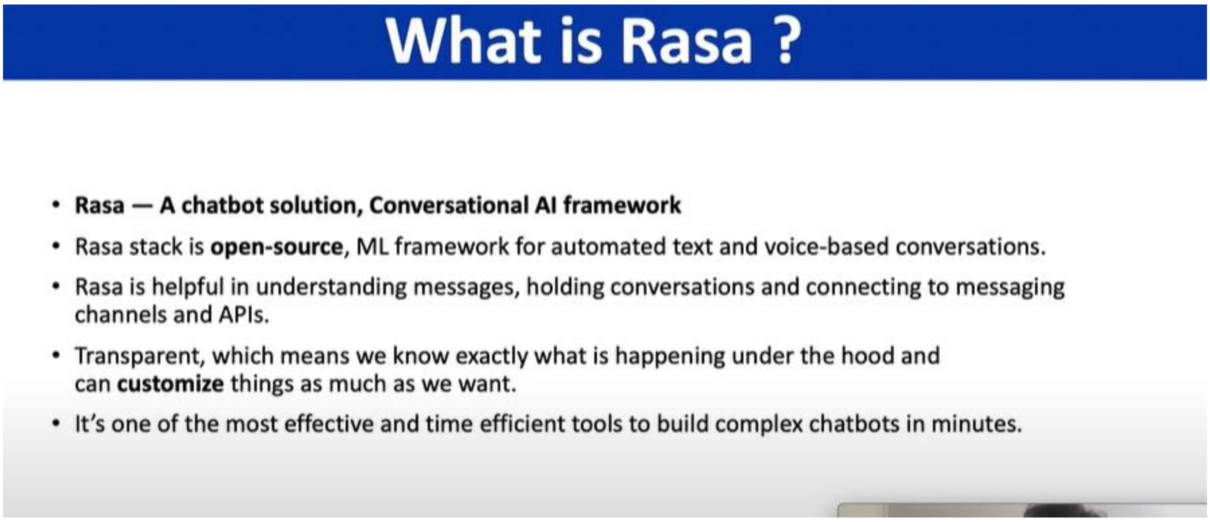
disease

en_ner_bc5cdr_md - symptoms

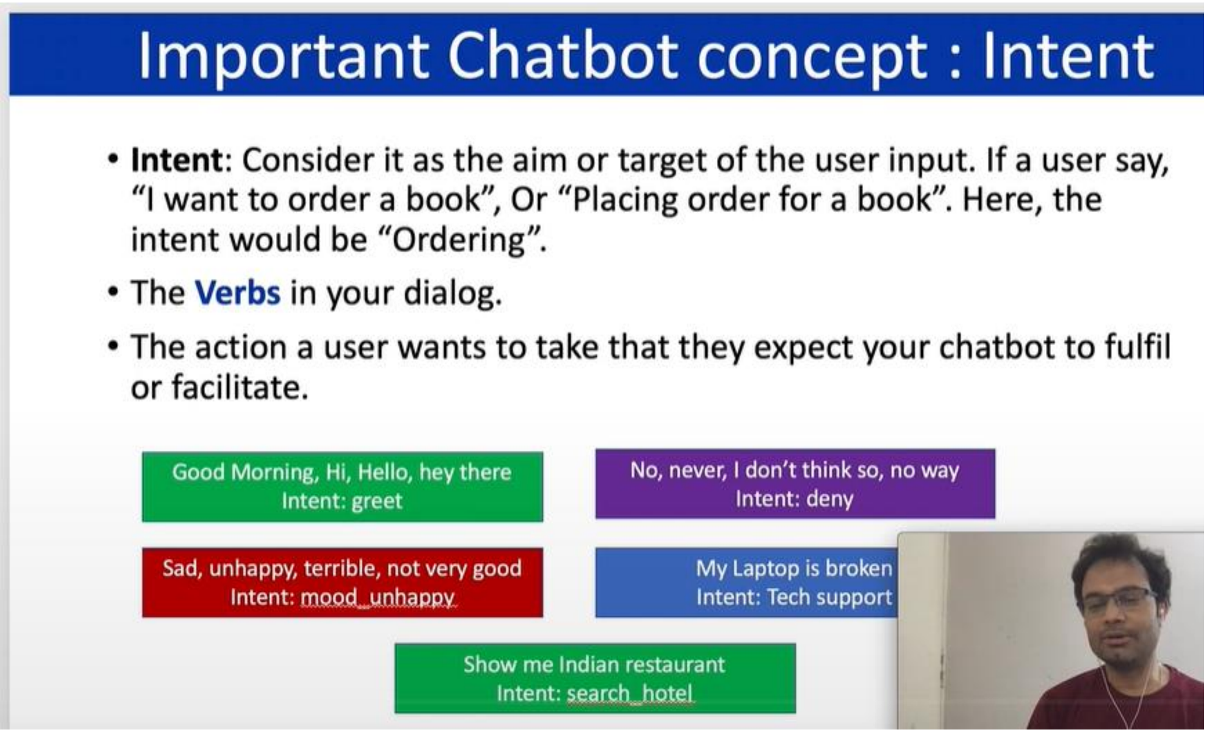
7. Design

What is RASA:

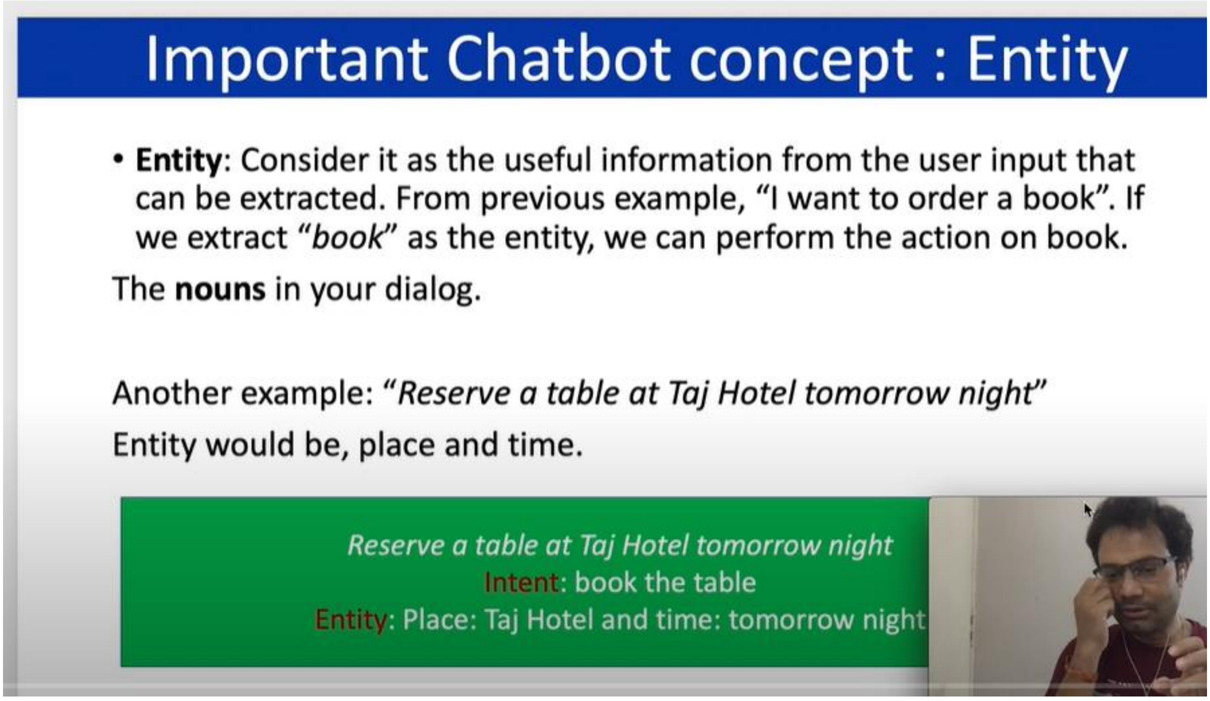
Why chose RASA:



Intent:



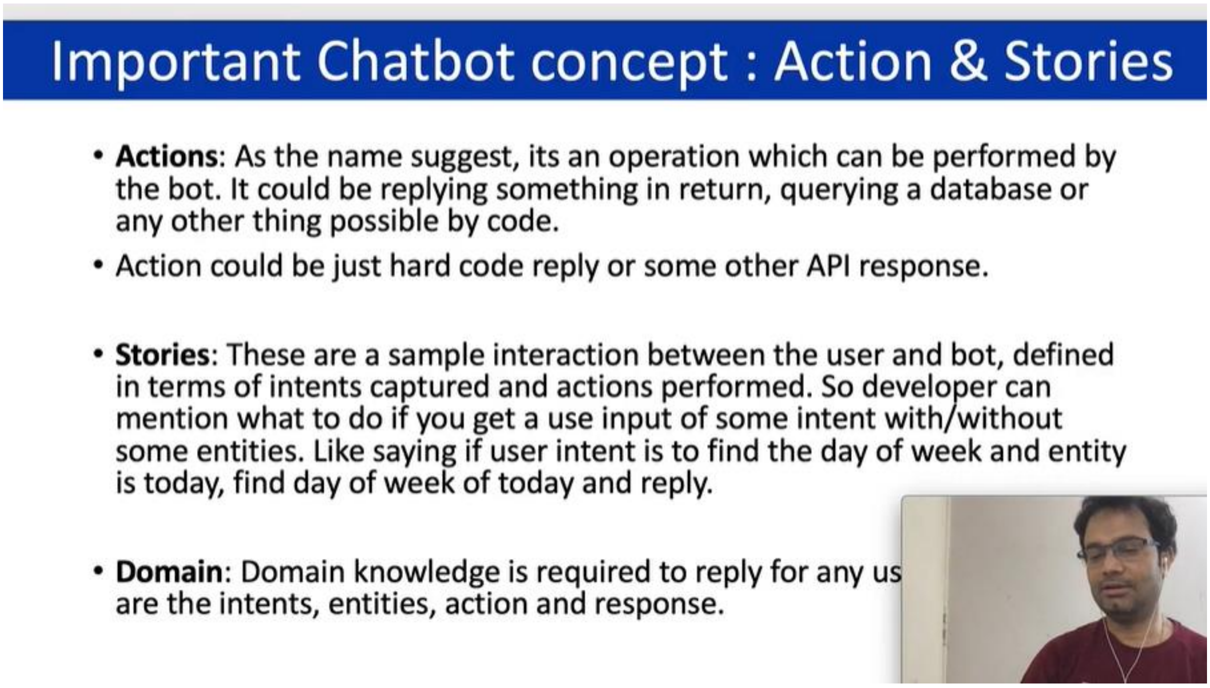
Entity:

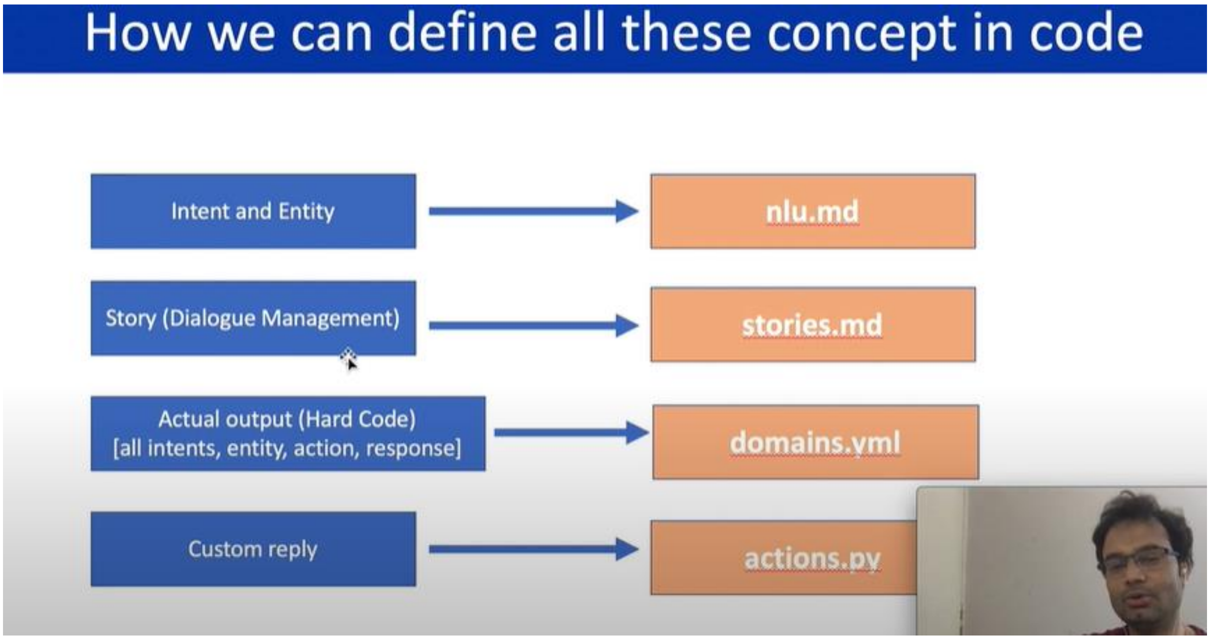


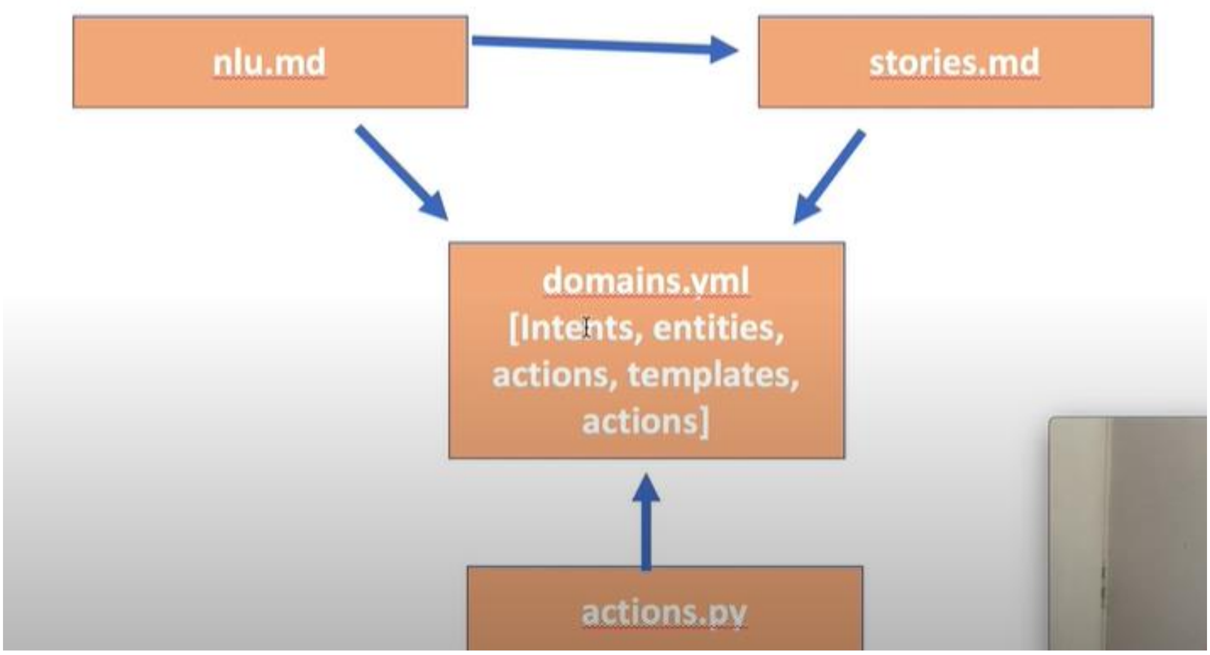
Actions:

Stories:

Domain:




How we can define all these concept in code
Intent and Entity
nlu.md
Story (Dialogue Management)
stories.md
Actual output (Hard Code)
[all intents, entity, action, response]
domains.yml
Custom reply
actions.py


nlu.md
stories.md
domains.yml
[Intents, entities,
actions, templates,
actions]
actions.py

Important Tools:

- **Rasa NLU**: A library for NLU which takes the user input and tries to infer the intent and extract the available entities and helps bot to understand what user is trying to say.

  Example: "I am looking for a Mexican restaurant in the centre of town"

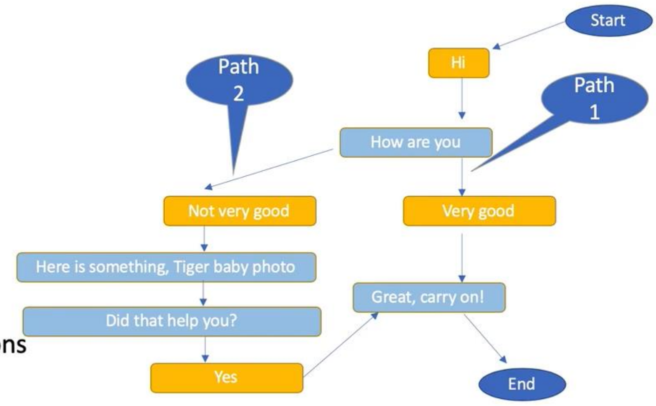
```
{
"intent": "search_restaurant",
"entities": {
  "cuisine" : "Mexican",
  "location" : "center"
 }
}
```

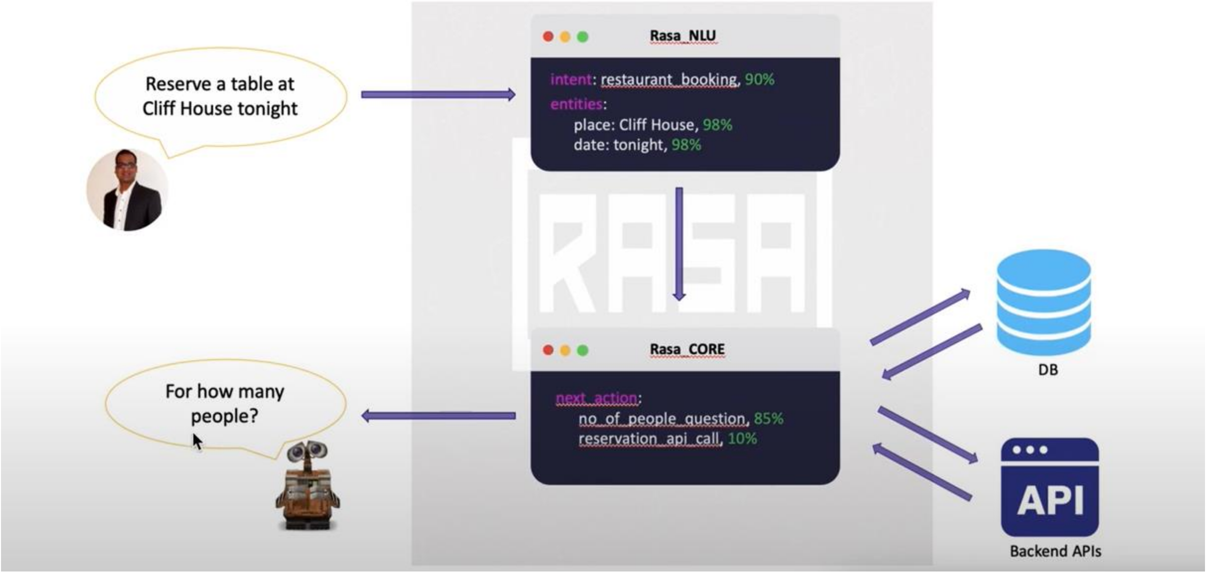
- **Main Job of NLU:**
  - **Training data format**
  - **Language Support**
  - **Choosing a Pipeline**
  - **Entity Extraction**

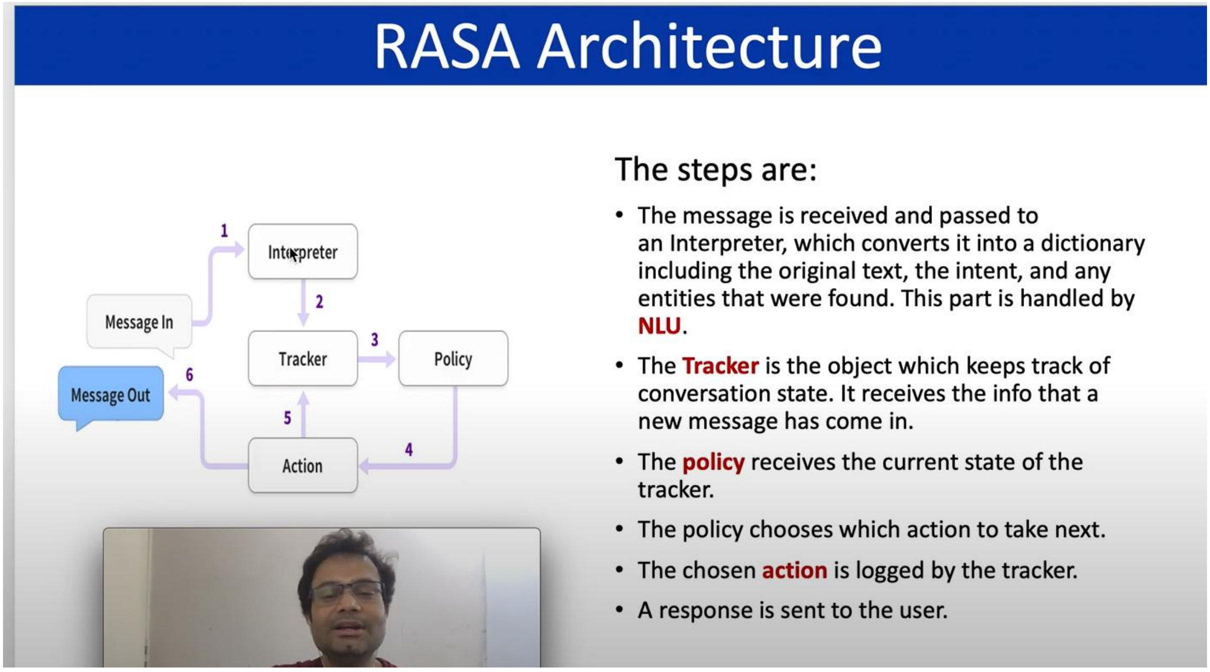
Important Tools:

- **Rasa Core**: (Dialogue Handling) A dialog management ML based solution, which takes the structure input from the NLU tries to build a probability model which decides the set of actions to perform based on the previous set of user inputs.

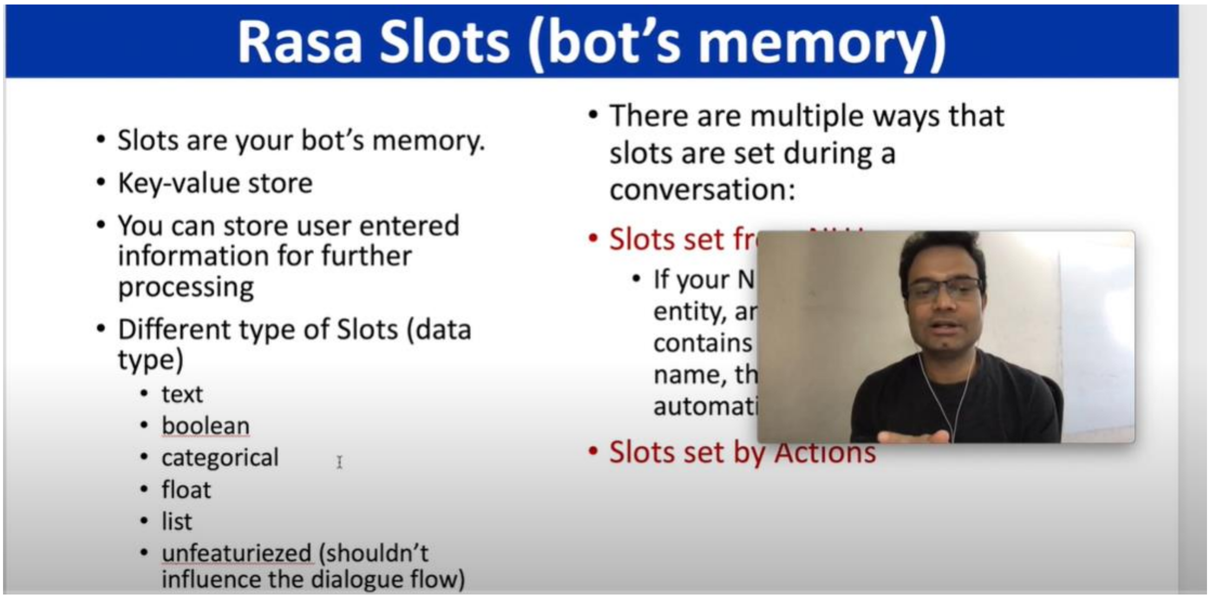
- **Rasa Core jobs:**
  - Dialogue Engine
  - Stories
  - Domain
  - Response
  - Action
  - Slots
  - Forms
  - Knowledge Base Actions

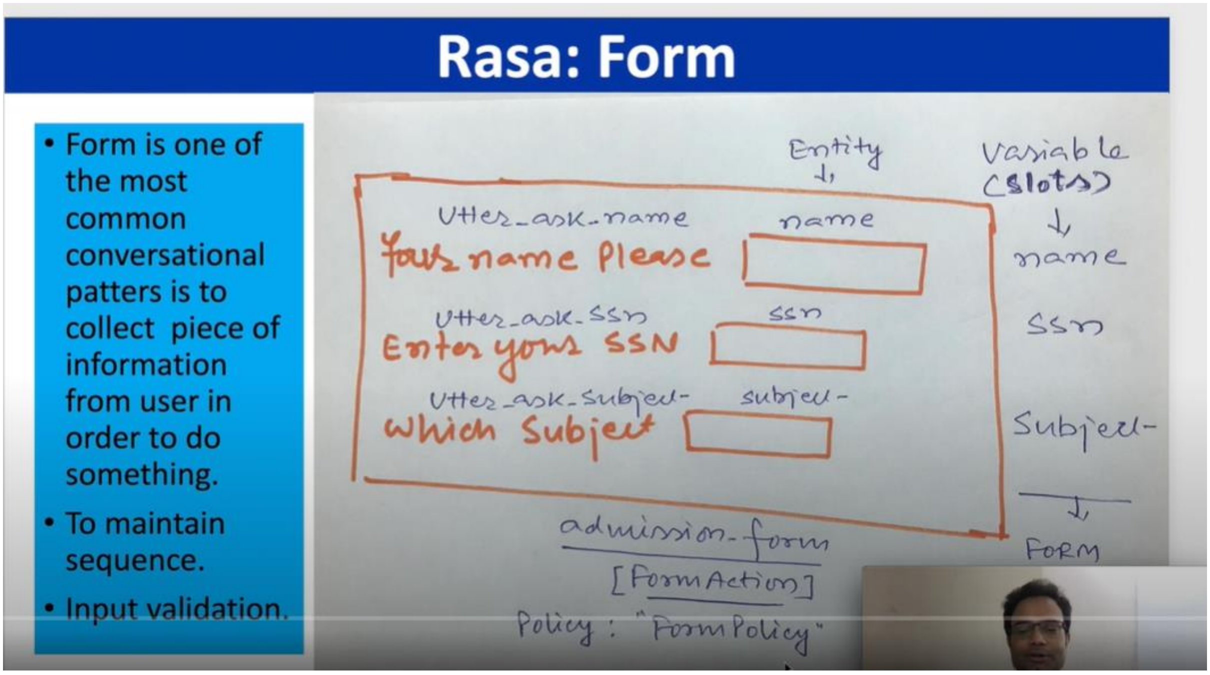






NLU Intent: multi classification problem





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

Choice of technology:

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(($\frac{QK^T}{\sqrt{dk}}$))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

2. **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 ?..

3. 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

8. 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

9. Results and Evaluation

Testing the pipelines:

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

Bot maturity (productionization) process:

10. Future Work

Word embedding Bias Removal

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

Better symptom detection model or training the model using a disease database:

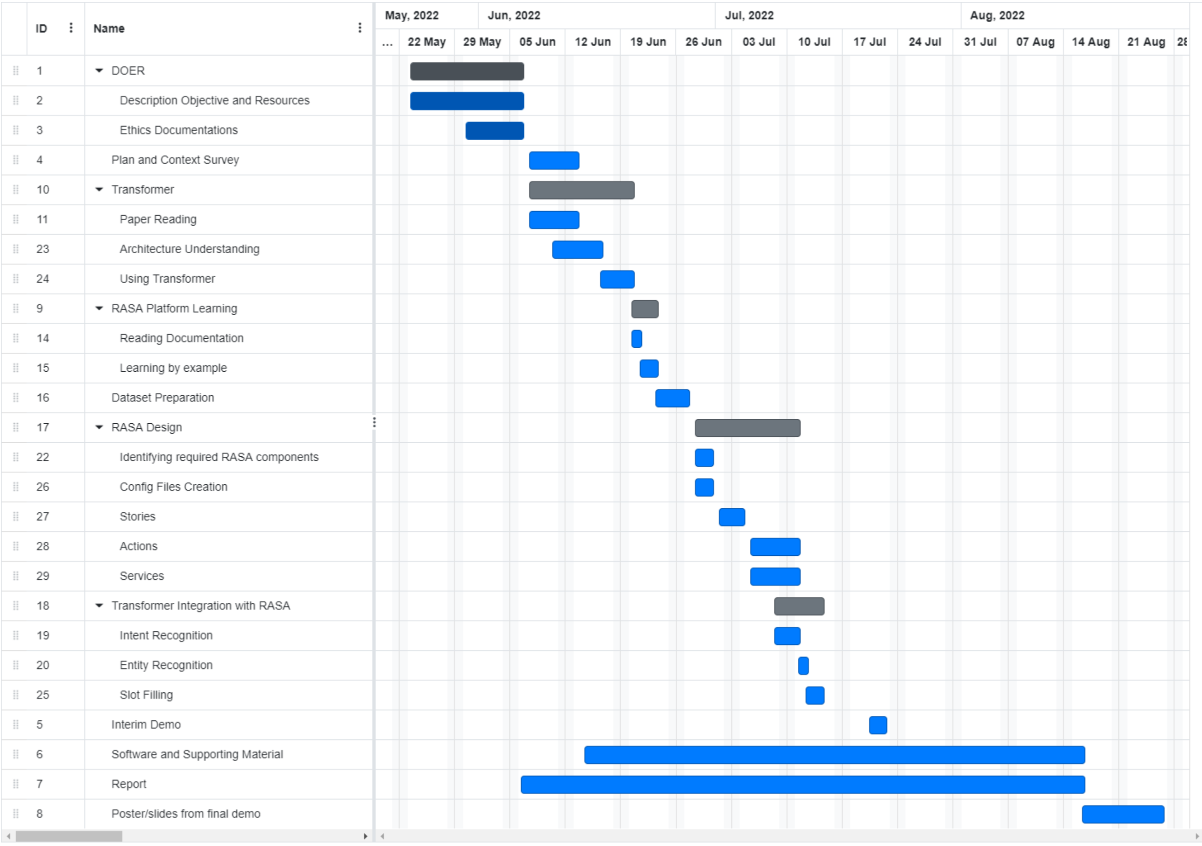
Using Machine Learning Models for Disease Predictions:

11. Conclusion

12. Appendix A DOER Document

13. Project Timeline

Figure 1 Project Timeline



14. Appendix B User Guide

15. Appendix C Ethics Documents

16. Bibliography

Attention Is All You Need. https://doi.org/10.48550/arxiv.1706.03762

Brasoveanu, A. M. P., & Andonie, R. (2020). Visualizing Transformers for NLP: A Brief Survey.

Damani, S., Narahari, K. N., Chatterjee, A., Gupta, M., & Agrawal, P. (2020). Optimized Transformer Models for FAQ Answering. In (pp. 235-248). Springer International Publishing. https://doi.org/10.1007/978-3-030-47426-3_19

Freed, A. (2021). *Conversational AI*. Manning Publications.

Gillioz, A., Casas, J., Mugellini, E., & Khaled, O. A. (2020). Overview of the Transformer-based Models for NLP Tasks.

Kandpal, P., Jasnani, K., Raut, R., & Bhorge, S. (2020). Contextual Chatbot for Healthcare Purposes (using Deep Learning).

Miller, G. A. (1995). WordNet. *Communications of the ACM*, *38*(11), 39-41. https://doi.org/10.1145/219717.219748

Nadarzynski, T., Miles, O., Cowie, A., & Ridge, D. (2019). Acceptability of artificial intelligence (AI)-led chatbot services in healthcare: A mixed-methods study. *DIGITAL HEALTH*, *5*, 205520761987180. https://doi.org/10.1177/2055207619871808

Pandey, A., Mutreja, I., Brar, S., & Singh, P. (2020). Exploring Automated Q&A Support System for Maternal and Child Health in Rural India.

Sheth, A., Yip, H. Y., & Shekarpour, S. (2019). Extending Patient-Chatbot Experience with Internet-of-Things and Background Knowledge: Case Studies with Healthcare Applications. *IEEE Intelligent Systems*, *34*(4), 24-30. https://doi.org/10.1109/mis.2019.2905748

Singh, P., Lin, T., Mueller, E. T., Lim, G., Perkins, T., & Li Zhu, W. (2002). Open Mind Common Sense: Knowledge Acquisition from the General Public. In (pp. 1223-1237). Springer Berlin Heidelberg. https://doi.org/10.1007/3-540-36124-3_77

Transformers: State-of-the-Art Natural Language Processing. https://doi.org/10.18653/v1/2020

Ur Rahman Khilji, A. F., Laskar, S. R., Pakray, P., Kadir, R. A., Lydia, M. S., & Bandyopadhyay, S. (2020). HealFavor: Dataset and A Prototype System for Healthcare ChatBot.

Yu, S., Chen, Y., & Zaidi, H. (2020). A Financial Service Chatbot based on Deep Bidirectional Transformers. *arXiv preprint arXiv:2003.04987*.