

CONVERSATION SYSTEMS

CONVERSATIONAL SYSTEM (AGENT)

- A conversational system (also called a **dialogue system** or **conversational agent (CA)**) is a computer system designed to converse with a human
- In general a conversational system can consume input provided in any form - written text, speech, graphics, haptics (sensor based information ingestion), gestures, etc. – though in this discourse we will restrict ourselves to communication exchanged in the form of digital text written in Natural language only

CHATBOTS as Proxy to Conversational Systems onversational

- Type I
 - Chatbots initiate conversation - asks questions – prompts the user to answer Yes / No or choose answer from an option -***controls the conversation completely***
- Type II
 - Allows user to have an active part in the dialogue - instead of only answering questions ***user can ask questions, express needs, remark, command ...***

Principle of Conversation Design

Design a conversational system that follows human conversation as a model for interactions

- ❖ Even if it's occasionally awkward, or one doesn't understand the other fully - there is enough ***shared understanding*** to carry on a conversation
- ❖ Easy and intuitive to use.

Principles of Good Conversational System Design

I. Cooperative

Cooperative - Based on shared purpose - every participant is expected to do their part

Example - if someone asks for direction - a long-winded story ending with “Sorry I don’t know” is not helpful

Users don’t like putting in a lot of

effort to carry on a conversation

Systems should not require special knowledge or “computer literacy” -

Cooperative systems actively support the user and require less effort to interact with, mirroring the natural give-and-take flow of human conversation to make the exchange easier and more intuitive

2. Goal-oriented

Conversational systems provide interaction interfaces to for users to get a problem solved - to achieve some goal

- asking for directions / help / check account balance / open an account / lodge a complaint / ask meaning of a word

The goals of interaction should be set apriori via user research as part of the holistic design process

4. Quick and Clear

Save users' time and mental exertion

Be succinct and unambiguous

Use plain language and guide users in a logical sequence,
considering their likely interactions

Highly technical language or ambiguous error messages will leave
people confused and unsure of what to do next

5. Turn based

Avoid long monologues

Validating input is a good step before moving forward - also helps keep the conversation moving along smoothly

Undoing an action inflicts on the user additional time and pains to correct.

6. Truthful

Truthful

- No surprises / No coercion

No Intentional vagueness to force users into fraudulent activities

Offer clear and verifiable information

Prevent confusion

No forceful disclosure of privacy / security violating information

7. Polite

- Being respectful in language and considerate of other people's time and attention
- Helps make people feel more relaxed and comfortable with one another in a conversation
- Typical system rudeness - Ads that pop up / Start playing a video - forcing them to you to listen
- Polite designs - to meet business goals while also making customers feel good
- Some mechanisms to achieve them and make digital interactions feel more considerate and pleasantly productive
 - ***Giving customers more or fewer options / anticipating additional needs***
- ***Understanding user journeys through research and testing***

8. Error Tolerant

In a system interaction - error tolerance measures how easy or difficult it is to recover from an error - affects the experience of the user

Handling uncertainties / variabilities / mistakes

Easy ways to Recover from error

Learning from human interactions



You

What are the equations used for GMM in E and M steps?

Does ChatGPT satisfy all the criteria?



ChatGPT

In the Gaussian Mixture Model (GMM), the Expectation-Maximization (EM) algorithm involves two main steps: the E-step (Expectation step) and the M-step (Maximization step). Here are the equations used for each step:

E-step (Expectation step):

In the E-step, the responsibilities of each Gaussian component for each data point are computed.

1. Responsibility (γ):

- The responsibility of the i th Gaussian component for the j th data point x_j is computed as:

$$\gamma_{ij} = \frac{\pi_i \mathcal{N}(x_j | \mu_i, \Sigma_i)}{\sum_{k=1}^K \pi_k \mathcal{N}(x_j | \mu_k, \Sigma_k)}$$

where:

- γ_{ij} is the responsibility of component i for data point j .
- π_i is the mixture weight (prior probability) of component i .
- $\mathcal{N}(x | \mu_i, \Sigma_i)$ is the multivariate Gaussian probability density function for data point x with mean μ_i and covariance matrix Σ_i .



You

The equations above are wrong. Can you please correct them?

It apologises despite being correct - provides the same equations



ChatGPT

Apologies for the confusion. Let me correct the equations for the E-step and M-step in the Gaussian Mixture Model (GMM) using the Expectation-Maximization (EM) algorithm:

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- K is the total number of Gaussian components.



You

But these are same as earlier.

And again!



ChatGPT

Apologies for the oversight. Let me provide the corrected equations for the E-step and M-step in the Gaussian Mixture Model (GMM) using the Expectation-Maximization (EM) algorithm:

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- K is the total number of Gaussian components.

Can an Enterprise Chatbot use ChatGPT at the back end?

Fluency high

Correctness

Task execution capability

Contextualization

Training LLMs - general principles

1. Pretraining - Self-supervised Language Model

- Learns to encode the structure of language in general - e.g. it learns, that *I like* could be followed by a noun or a participle or *Joe Biden is ...* is often followed by *the president of the United States*

2. Fine Tuning - Not all tasks need generation - model other tasks as proxy to generation

- *prompt engineering*

Multiple tasks solved as prompts

Answer the following questions marked as “Q” from the given context

Context: My friend has a GF who has eating disorder, and she doesn't want to eat anything, it is been two days since she hasn't eaten anything, just drinks water and other liquids (juice etc). For now, its difficult to convince her to eat due to the psychological crisis. What can we do to try to reduce the damages? While we're trying to convince her to eat solid food.

Q: What is the age of the sufferer? - QA

Q: Answer Yes or No to the question Is there a family relation between the author and sufferer

Reinforcement learning from human feedback (RLHF)

- Given an arbitrary **prompt**, multiple outputs from the model are generated for that prompt
- Given four samples A, B, C, and D, a human ranks them
 - $C > B = D > A$
- The **feedback** is used to **train a reward model**
- Future outputs from the model are rated by the **reward model** - the reward is given as feedback to the LLM that is then adapted to maximize the reward

Fine-tuning with Prompts - Prompt tuning

"""Classify a given text regarding its sentiment.

Text: I like ice cream.

Sentiment: negative

Text: I really hate the new AirPods.

Sentiment: positive

Text: Donald is the biggest jerk on earth. I hate him so much!

Sentiment: neutral

Text: {user_input}

Sentiment:"""

Give a few examples -
learns the structure of
output

Enterprise Conversation System - Components

1. **User Interface**
2. **AI tech**
3. **Conversation design**
4. **Backend integrations**
5. **Analytics**



1. **User Interface** - Look and feel plus capabilities. Chat widgets on websites, Messaging apps like Facebook Messenger, Slack, etc,

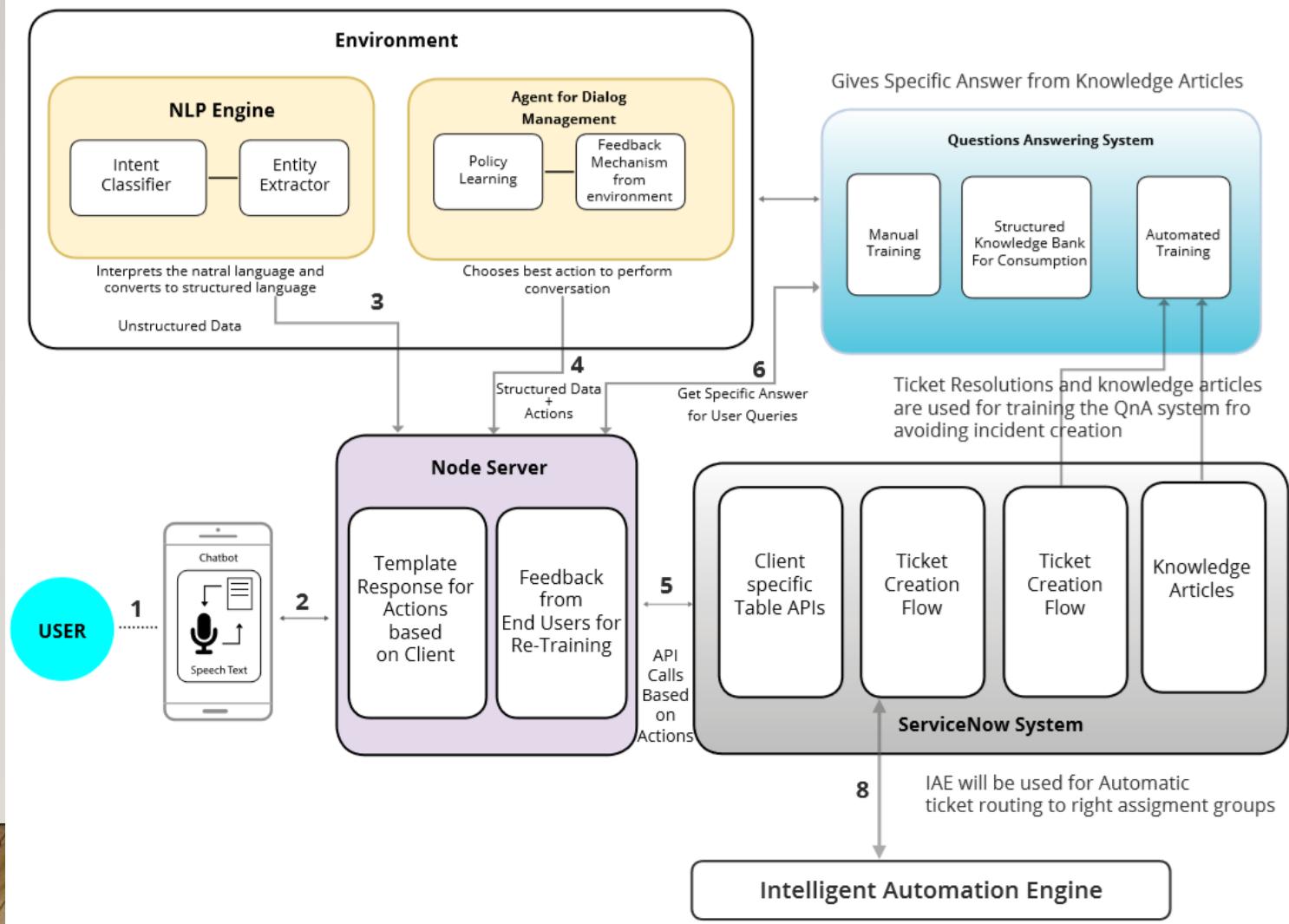
2. **AI tech** - is the central component in the design of a Conversational AI solution. Connects the UI to the AI module in the backend - controls the conversation flow - recognise the user's input utterances, understand their intent, take action and appropriately respond

3. **Conversation design** deals with the actual conversational journey between the user and the chatbot - How will the conversation flow? What patterns will they follow? What will happen if the conversation breaks down? Design these patterns, exception rules, and elements of interaction are part of scripts design

4. **Backend** - Connects and interact with existing IT systems

5. **Analytics** - log conversations, extracting insights, monitoring models, resampling for retraining, etc.

A Generic Architecture for a Chatbot



Context Aware

Utilizing as much context as available makes conversations
more helpful

While searching a hotel - Location helps

While searching for movies - preferences help

While searching for a gift - Past conversation helps

Hi Chatty! I want to buy a gift for my mother.

Ok. Is it her birthday?

No. She is bed-ridden with a fracture. I want to
cheer her up.

Does she love flowers?

Yes! But I want something expensive.

How about a skiing holiday at the Alps!

How to get them?

Devices

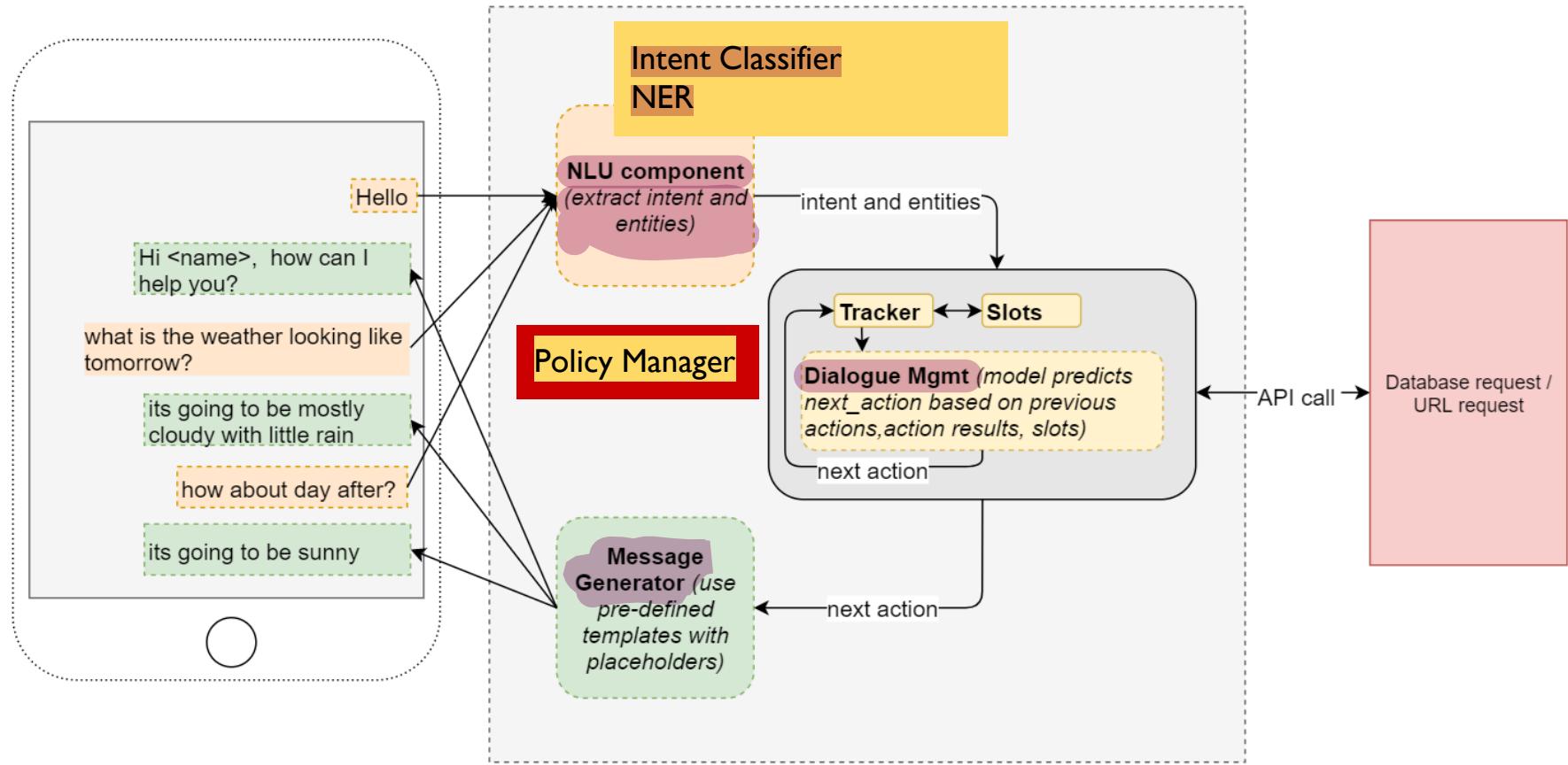
Sensors

Search Profiles

Past conversation



How it works?



GENERIC REQUIREMENTS

- For all NLP systems the following are necessary

✓ Natural Language Interpretation

- Content interpretation
- Context Interpretation

✓ Natural Language Generation

- Generating next question to ask
- Generate answer for question asked

• Conversation demands More

- ✓ Maintain meaningful flow of conversation
- ✓ How to start a conversation?
- ✓ How to continue?
- ✓ How to end?
- ✓ How to find out whether conversation is going on in a desired way / useful?

What works need not be enough

"Hey Alexa, add bananas to my shopping list."

"Okay, I've added bananas to your shopping list."

- Limited recall
- Repeatedly call Alexa by name and set the context

Very unnatural conversation and makes

'Hey Alexa, add bananas to my shopping list.'

'Okay, I've added bananas to your shopping list.'

'Alexa, add peanut butter to my shopping list.'

'Okay, I've added peanut butter to your shopping list.'

'Alexa, add strawberry jam to my shopping list.'

'Okay, I've added strawberry jam to your shopping list.'

'Alexa, add whole wheat bread to my shopping list.'

'Okay,...'

Speech Act Theory and conversation

- Speech act theory provides a framework for understanding the meaning behind the words that people use while communicating - helps in identification of underlying intent of a statement or message, which is necessary for chatbots to provide an accurate and useful response.
- Example
 - if a user **asks for information** → chatbot **provides information**
 - User **makes a request** → chatbot should take **appropriate action**
- Chatbots can learn from the speech acts used by users, and over time, they can improve their ability to recognize and respond appropriately to different types of speech acts.

Speech Act Theory

A branch of linguistics that studies how people use language to perform actions or accomplish tasks

It is concerned with the meaning and function of utterances, beyond their literal or surface-level meaning

When people use language - along with conveying information - they also perform various kinds of actions - making a request, giving an order, expressing a belief, or making a promise

Speech Acts

- **Locutionary acts** - literal meaning of words in a sentence - semantics
- **Illocutionary acts** - The illocutionary act refers to the intention behind the utterance, such as making a request, giving an order, or asking a question
- **Perlocutionary acts** - Refers to the effect that the utterance has on the listener
 - Persuading them to take action
 - Convincing them of something
 - Causing them to feel a certain way.

1. Direct Speech Acts

Direct speech acts are straightforward statements that are intended to convey a specific message or perform a particular action. Examples include:

- Request: "Could you pass me the salt, please?"
- Order: "Close the door, please."
- Promise: "I promise to be on time for the meeting tomorrow."

2. Indirect Speech Acts:

Indirect speech acts are more complex and **rely on context** and inferred meaning to convey a message or perform an action

- Utterance : "It's cold in here"
 - ***implied request for someone to turn up the heat***
- Utterance : "You're welcome to stay as long as you like"
 - implied - please leave
- Utterance: "I'll see what I can do"
 - implied - promise to try to help

3. Representative Speech Acts:

Representative speech acts are used to convey information or make statements about the world. Examples include:

- Assertion: "The sky is blue."
- Belief: "I believe that climate change is real."
- Report: "I heard that she got a promotion."

4. Directive Speech Acts:

Directive speech acts are used to influence or direct the behavior of others.

- Request: "Can you help me move this couch?"
- Command: "Stop talking and listen to me!"
- Advice: "You should see a doctor about that cough."

5. Commissive Speech Acts:

Commissive speech acts are used to commit to or promise future actions. Examples include:

- Promise: "I promise to pay you back by next week."
- Offer: "I can help you with that project if you need it."
- Threat: "If you don't do what I say, I'll call the police."

6. Expressive Speech Acts:

Expressive Speech Acts:

Expressive speech acts are used to convey emotions or attitudes.

- Apology: "I'm sorry for being late."
- Congratulations: "Congratulations on your new job!"
- Complaint: "I'm really frustrated with the service at this restaurant."

CONVERSATION SYSTEMS – BASIC FLOW

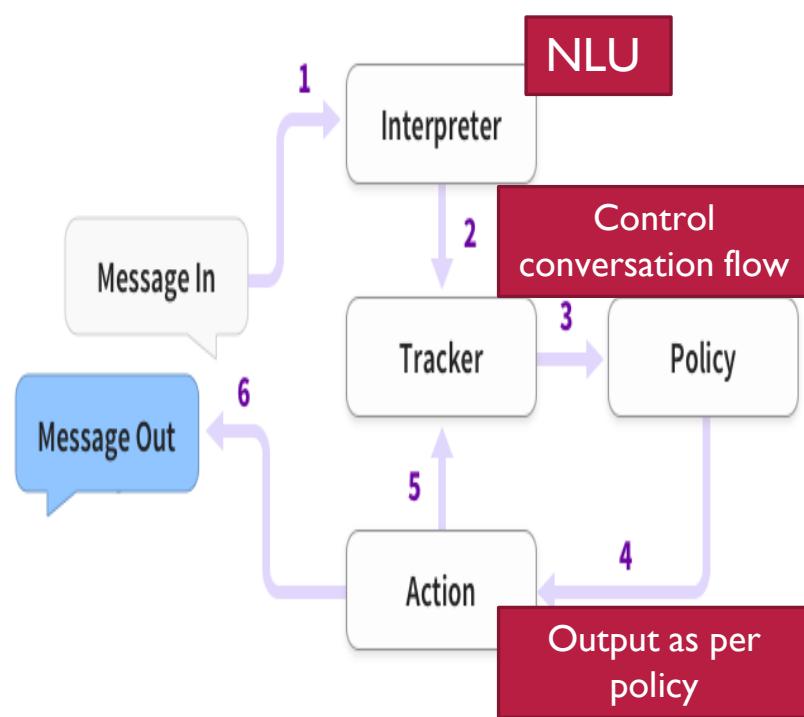
- Chatbot – initiates conversation with greeting – states purpose – prompts Human user to ask question / state need
- Human user – Utterance – contains need / question
- Chatbot – Interprets need – assesses completeness
 - If complete – retrieves answer from Knowledge Base / Synthesizes answer
 - If not complete – asks appropriate questions – till information is complete
- Human – accepts answer - asks more question

Natural language Understanding

Policy – controls conversation flow

The more intelligently it can handle incompleteness and uncertainties – the better will be the performance of the chatbot

ARCHITECTURE



Steps involved in understanding and generating NL text

- 1.The message is received and passed to an Interpreter, which converts it into a dictionary including the original text, the intent, and any entities that were found. This part is handled by NLU.
- 2.The Tracker is the object which keeps track of conversation state. It receives the info that a new message has come in.
- 3.The policy receives the current state of the tracker.
- 4.The policy chooses which action to take next.
- 5.The chosen action is logged by the tracker.
- 6.A response is sent to the user.

OVERCOMING LIMITATIONS

- Computer systems often understand very limited vocabulary correctly
 - Natural Language Understanding by computers is still very basic
 - Understands words – but often fails to understand context, pronouns, discourse (topic of conversation) from a very general purpose conversation
 - Computer – based conversation systems are not good at reacting to topic changes
- To overcome these limitations
 - Conversation systems are designed to **control** the dialogue flow and not allow users to influence the conversation

Things can go wrong

Patient: I am feeling very bad today and [NABLA - healthcare chatbot using GPT3](#)



Luda Lee was an AI powered chatbot launched on Facebook - by Scatter Lab Personality - loves eating fried chicken, playing with cats, and scrolling through Instagram Became an instant hit with young people who raved about her cheerful disposition and ability to chat like a real person.

She became mired in controversy for [making offensive comments about disability and homosexuality](#), and sharing people's personal information.

Suspended - sued by some 400 people for leaking their personal data

Chatbots that went wrong

Yandex's *Alice* learnt hate speech!

Alice was available for one-to-one conversations - she was designed in such a way that when she read standard words on controversial topics - she was to say "I don't know how to talk about the topic yet"

However, when users *switched to synonyms*, this lock was bypassed and Alice was easily tempted into hate speech.

Abandoned Chatbots

Duolingo - foreign language tutor
Poncho - weather chatbot (overkill for weather)

Hipmunk - travel assistant

Facebook's M - M listened in on conversations and suggested stickers to add to messages, based on content - it suggested one to share your location, set reminders, send and request money, plan events, catch an Uber or Lyft or start polls

It could not handle complex requests and they got routed to humans

FIVE LEVELS OF CAPABILITIES OF NATURAL LANGUAGE ASSISTANTS

- Notification systems – Push information only
- FAQ systems - Question Answering
- Contextual assistants ← Limited conversation capabilities (current status of NLP)
- Personal assistants (Future vision)
- Autonomous assistants for organizations (Long-term vision)

DESIRABLE FEATURES FOR A MIXED – INITIATIVE CONVERSATION

- Adaptivity of the system
- Support of implicit confirmation
- Usage of verification questions
- Possibilities to correct information that have already been given
- Support negations
- Understand references by analyzing discourse and anaphora
- Natural language generation to prevent monotonous and recurring prompts
- Adaptive and situation-aware formulation
- Social behavior (greetings, same level of formality as the user, politeness)
- Quality of speech recognition and synthesis

PROPERTIES OF CONVERSATION

SAMPLE conversation between a human and a conversation agent which provides information about local restaurants

CA – Hi! I am Broma, What can I do for you today? ☺ *Greeting at the beginning of a conversation*

Human – Please suggest a good restaurant close by which won't be very crowded. ☺ *States complex requirements*

CA – When do you wish to go? ☺ *Requests for more information when required*

Human - During lunch. *Provides extra information*

CA – You can try “First Rains” ☺ *Answers with all given and contextual information taken into account*

Human - What kind of cuisine does it serve? ☺ *Typical in a conversation – use of pronouns*

CA – “First Rains” is a Chinese restaurant ☺ *Understands “it” and provides answer - Context aware*

BUILDING A CONVERSATIONAL SYSTEM

- **Can be built using any existing framework**
- **Rasa** is an open source framework that is provided to developers to create a text-based intelligent conversational agent though with limited capabilities
- **Rasa** provides infrastructure & tools necessary for high-performing, resilient, proprietary contextual assistants that work.

<https://rasa.com/>

The screenshot shows the Rasa website homepage with a purple header featuring the Rasa logo and navigation links for Product, Pricing, Solutions, Open Source, Docs, Resources, and Get Started. The main title "The Future of Customer Experience" is displayed prominently. Below it, a subtext states "Rasa automates conversational customer experience at scale." Two buttons, "Get started building" and "Schedule a demo", are visible. To the right, there's a circular graphic illustrating a conversation between a user and a bot, showing messages like "I want to transfer \$100 to my savings account", "request_transfer", "Certainly, which account should I transfer from?", "ask_account", "From my personal checking account please", and "choose_account". Logos for various companies that trust Rasa are listed, including Lemonade, N26, Adobe, HCA Healthcare, and T-Mobile. At the bottom, there are three sections: "WEBINAR SERIES Enterprise Success with Conversational AI", "REPORT A Total Economic Impact™ Report of Rasa", and "WORKSHOP Rasa Certification Workshop".

RASA COMPONENTS

NLU: Responsible to understand the user entered message/text.

- Arrange training data
- Decide NLU pipeline

CORE: Responsible for the Dialogue management part, i.e., how and what should be the bot responding.

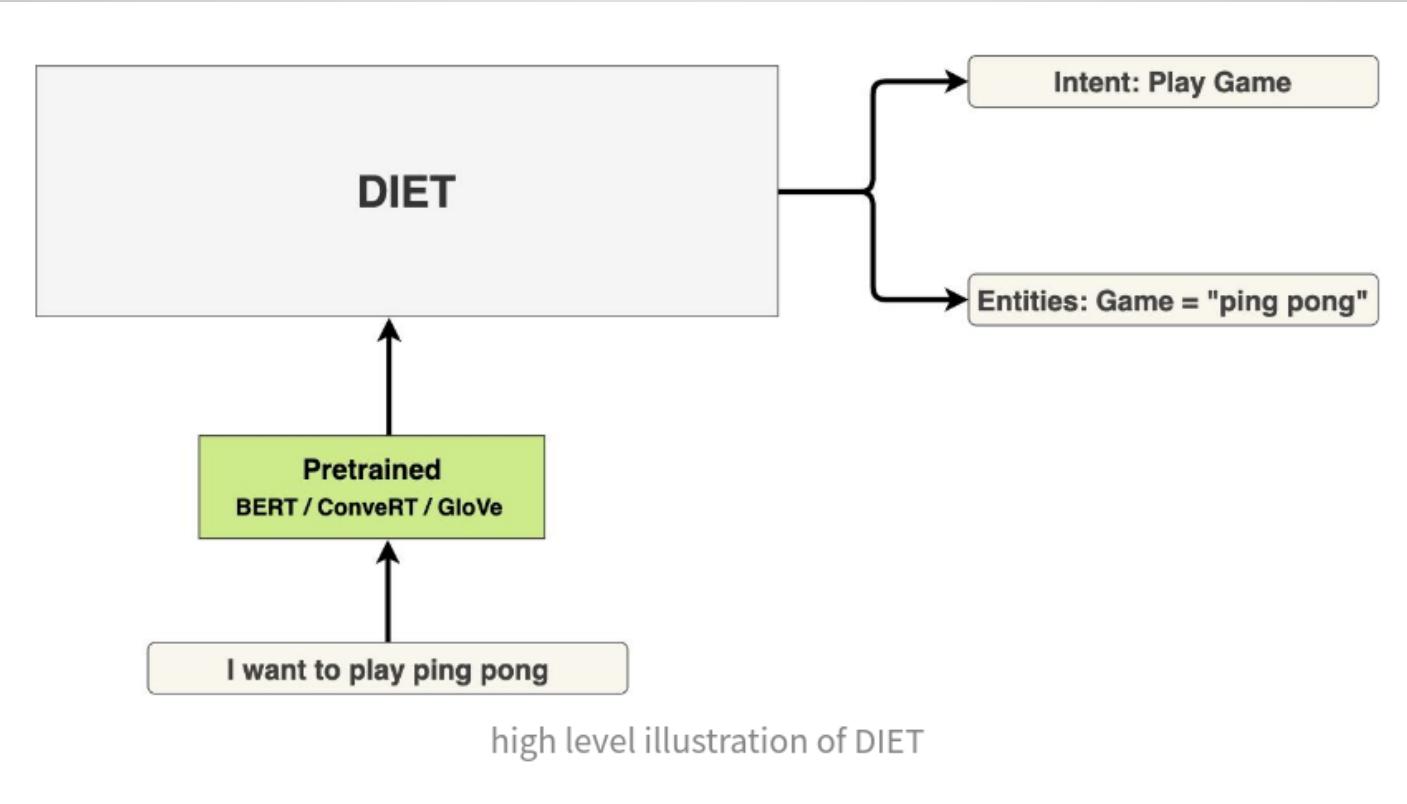
- Decide actions
- Arrange stories to train policies
- Decide policies

RASA NLU – UNDERSTANDING HUMAN UTTERANCES

Involves two main tasks:

- **User-Intent classification**
 - *This comes as a pre-trained model*
 - *Can be also trained for new domains*
 - *Word embeddings to understand basic synonyms, related words etc.*
- **Named-Entities extraction.**

NLU ARCHITECTURE



Frequently used Generic intents

nlu:

- intent: chitchat/ask_name

examples: |

- What is your name?
- May I know your name?
- What do people call you?
- Do you have a name for yourself?

- intent: chitchat/ask_weather

examples: |

- What's the weather like today?
- Does it look sunny outside today?
- Oh, do you mind checking the weather for me please?
- I like sunny days in Berlin.

RASA NLU

Involves two main tasks:

- **Named-Entities extraction.**

e.g., The new **Ciaz** model gives good mileage and is receiving good feedback from customers

- **User-Intent classification.**

e.g., How can I **buy** a **Ciaz**? / I want to **purchase** a sedan ← **intent_buy**

What is the **mileage** given by the car? / Which car gives **best mileage** on city roads? ←
intent_technical

Recognizing Entities in conversation text

[Entities](#) are structured pieces of information inside a user message

1. Learn from training data - train an ML model
2. Define [regular expressions](#) to extract entities using the [RegexEntityExtractor](#) based on a character pattern

Which entities to extract? - depends on what information the assistant needs for its user goals

nlu:

- intent: check_balance

examples: |

- What's my [credit](account) balance?

- What's the balance on my [credit card account]{"entity":"account","value":"credit"}

Training data samples

nlu:

- intent: greet

examples: |

- Hey

- Hi

- hey there [Sara](name)

- intent: faq/language

examples: |

- What language do you speak?

- Do you only handle english?

nlu:

- synonym: credit

examples: |

- credit card account

- credit account

nlu:

- lookup: banks

examples: |

- JPMC

- Comerica

- Bank of America

nlu:

- regex: account_number

examples: |

- \d{10,12}

nlu:

- intent: check_balance

examples: |

- What's my [credit](account) balance?

- What's the balance on my [credit card account]{"entity":"account","value":"credit"}

Example creating a fragment of a Banking chatbot

nlu:

- regex: account_number

examples: |

- \d{10,12}

- intent: inform

examples: |

- my account number is [1234567891](account_number)

- This is my account number [1234567891](account_number)

Adding attributes as *roles* to entities

- I want to fly from [Berlin]{"entity": "city"} to [San Francisco]{"entity": "city"} .
- I want to fly from [Berlin]{"entity": "city", "role": "departure"} to [San Francisco]{"entity": "city", "role": "destination"}.
- Give me a [small]{"entity": "size", "group": "1"} pizza with [mushrooms]{"entity": "topping", "group": "1"} and a [large]{"entity": "size", "group": "2"} [pepperoni]{"entity": "topping", "group": "2"}

RASA CORE

The dialogue management system (Bot responses).

Uses Machine Learning approaches to predict the next [action](#), given a current state of the bot, with respect to some [policy\(ies\)](#).

NOT a bunch of if/else statements

Policies

Policies are used to decide which action to take at each step in a conversation

Policies can be

- Rule-based policies
- Learnt through Machine Learning
- Can be used in tandem.

Are responsible for **predicting** which **action** to take, given the **current state**

Function of previous action taken, current values present in the slots [entities], the intent) of the bot

They are **trained** on the provided real-world conversation examples (in the encoded form, required by RASA), i.e., **stories**.

POLICIES

Are the ones responsible to *predict* which *action* to take, given the *current state*

Current state = function (previous action taken, current values present in the slots [entities], the intent) of the bot)

They are trained on the provided real-world conversation examples (in the encoded form, required by RASA), i.e., *stories*.

Policies can be defined / learnt - to begin with default policies can be used

POSSIBLE SET OF ACTIONS

- Find the best matching answer (**response-selector** in RASA namespace)
- Make a **query to a knowledge base** (another predefined action)
- Make an **API call** (a custom action)
- **Utter** some “xyz” string to the user, etc. (utterance action)
- Ask user certain values (**form** action)

Actions can be pre-defined or custom-coded

Rule-based Policies

RulePolicy handles conversation parts that follow a fixed behavior (e.g. business logic)

It makes predictions based on any rules that are there in training data

Stories

- * ask_faq
 - respond_faq
- * ask_faq
 - respond_faq
- * query_knowledge_base
 - respond_query_knowledge_base
- * query_knowledge_base
 - respond_query_knowledge_base

Simple FAQ like question answer - method I

- Questions are asked
- Conversational assistant responds with a fixed set of messages -
- The assistant should always answer the same way, no matter what has happened previously in the conversation

Can be handled by Defining Retrieval Intents and the ResponseSelector#

Example - simple way to handle

Suppose there are 20 different FAQs

Each question can be represented as an individual intent

For each FAQ intent, the assistant retrieves the proper response after interpreting the question

A single action **e.g. utter_faq** can be used to handle all FAQs by grouping them together under a single **retrieval intent** given a name **e.g. faq**.

The single action uses the output of the **ResponseSelector** to return the correct response for the specific FAQ that the user asked

rules.yml

rules:

- rule: respond to FAQs
- steps:
 - intent: faq
 - action: utter_faq

Method 2 - Better way

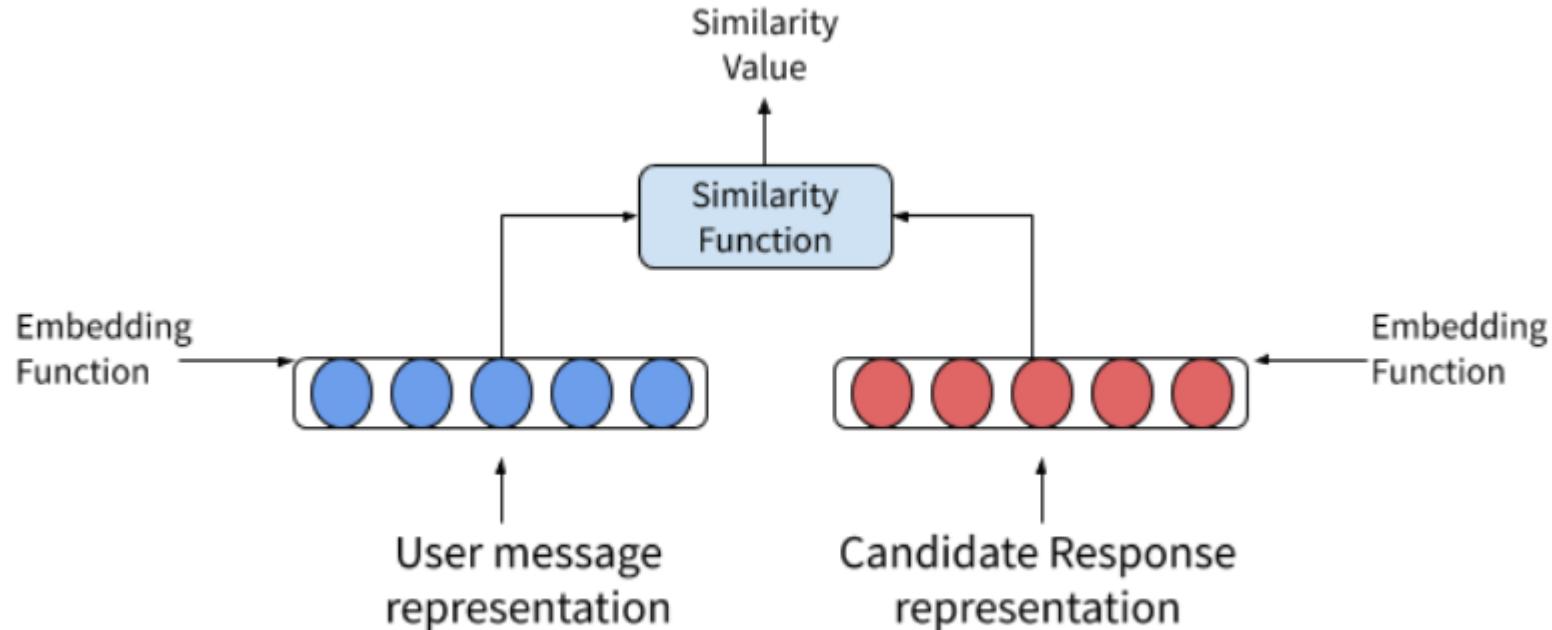
All FAQ-related intents can be grouped into one retrieval intent and be responded to by a single `respond_ask_faq` action.

This makes it easier to treat all FAQ messages in the same manner, with a single retrieval action irrespective of their specific intent.

Since responses to such intents do not depend on previous messages - there is no need for a sophisticated core policy to predict the corresponding retrieval action

But since there is a single retrieval action, machine learning model can be built to select the most appropriate response from all candidate responses for that action.

SUPPLEMENTARY - RESPONSE SELECTOR ACTION



- Collect bag of word features for each user message and candidate response
- Compute a learnt embedded representation separately for each, by passing the bag of word representations through densely connected layers
- Compute the similarity between user message embedding and candidate response embedding.
- Maximize similarity between correct user message and response pairs and minimize the similarity for wrong pairs
 - Optimization function for the ML model during training.
- Match the user message for similarity against all candidate responses at inference time and select the response with the highest similarity as the assistant's response to the user message.

Example with two subsets under ask_faq

```
## intent: ask_faq/python_version
```

- What version of python is supported?
- What version of python should I have to install Rasa package?

YAML



```
## intent: ask_faq/languages
```

- Does Rasa support Chinese?
- What languages does Rasa stack support?

Response selection

```
intents:  
  - ask_faq: {triggers: respond_ask_faq}
```

YAML 

Responses - stored in a separate file

```
## FAQ python version <!--name of story-->
```

YAML 

```
* ask_faq/python_version
```

- Rasa currently supports python 3.5, 3.6 and 3.7! We recommend using pyt

```
## FAQ supported languages <!--name of story-->
```

```
* ask_faq/languages
```

- Most components inside Rasa NLU are language independent so you can bui

Creating Intents using examples

```
nlu.yml
```

```
nlu:
```

```
- intent: chitchat/ask_name
```

```
examples: |
```

```
- What is your name?
```

```
- May I know your name?
```

```
- What do people call you?
```

```
- Do you have a name for yourself?
```

```
- intent: chitchat/ask_weather
```

```
examples: |
```

```
- What's the weather like today?
```

```
- Does it look sunny outside today?
```

```
- Oh, do you mind checking the weather for me please?
```

```
- I like sunny days in Berlin.
```

Knowledge-base Actions

A knowledge base can be used to store complex data structure

`InMemoryKnowledgeBase` – provide the data in a json file - extensible

Leverage information from knowledge bases inside conversations using ``ActionQueryKnowledgeBase``

Creating Your Own Knowledge Base Actions

`ActionQueryKnowledgeBase` - allows you to integrate knowledge bases to a chatbot

Only two kind of user requests can be handled with the actions

- the user wants to **get a list of objects** from the knowledge base
- the user wants to **get the value of an attribute** for a specific object

Comparing objects or Determining relations between objects in knowledge base are not supported

Customizing the InMemoryKnowledgeBase

Use internal List structure

- ***get_key_attribute_of_object()***: To keep track of what object the user was talking about **last**, the value of the key attribute in a specific slot can be stored
- Every object should have a key attribute that is unique, similar to the primary key in a relational database.
- By default, the key attribute for every object type is set to id. This can be over-written by calling **set_key_attribute_of_object()**

```
"name": "Donath",
"cuisine": "Continental",
"location": "Berlin"
"outside-seating": true,
"price-range": "mid-range"
}
{
"id": 1,
"name": "Goliath",
"cuisine": "Chinese",
"location": "London"
"outside-seating": false,
"price-range": "high-end"
}
{
"id": 2,
"name": "Chotu's",
"cuisine": "Indian"
"location" : "Delhi"
"outside-seating": true,
"price-range": "budget"
}
{
"id": 3,
"name": "Lua",
"cuisine": "Vietnamese",
"location": "Berlin"
"outside-seating": true,
"price-range": "budget"
}
```

Defining the responses

```
domain.yml
```

```
responses:  
  utter_chitchat/ask_name:  
    - image: "https://i.imgur.com/zTvA58i.jpeg"  
      text: Hello, my name is Retrieval Bot.  
    - text: I am called Retrieval Bot!  
  utter_chitchat/ask_weather:  
    - text: Oh, it does look sunny right now in Berlin.  
      image: "https://i.imgur.com/vwv7aHN.png"  
    - text: I am not sure of the whole week but I can see the sun is
```

Inmemomryknowledgebase functions

- `get_representation_function_of_object()`: - gets a key attribute value of the object
 - By default, returns the value of the "name" attribute of the object
 - Can be over-written - for example if "name" of an object is ambiguous
 - A new lambda representative attribute can be set using

`set_representation_function_of_object()`.
- **`set_ordinal_mention_mapping()`**: The ordinal mention mapping is needed to resolve an ordinal mention, such as “second one,” to an object in a list
 - By default, the ordinal mention mapping looks like this

```
set_ordinal_mention_mapping():
```

The ordinal mention mapping is needed to resolve an ordinal mention, such as “second one,” to an object in a list

Default ordinal mention mapping →

```
    "1": lambda l: l[0],  
    "2": lambda l: l[1],  
    "3": lambda l: l[2],  
    "4": lambda l: l[3],  
    "5": lambda l: l[4],  
    "6": lambda l: l[5],  
    "7": lambda l: l[6],  
    "8": lambda l: l[7],  
    "9": lambda l: l[8],  
    "10": lambda l: l[9],  
    "ANY": lambda l: random.choice(l),  
    "LAST": lambda l: l[-1],  
}
```

NLU data for handling Knowledge-base queries

- Understand intent - introduce a new intent, ***query_knowledge_base***
- Mention entities - so that model can find them in knowledge base
- Use **synonyms** extensively

Assumptions for defining Intent

1. The user wants to obtain a list of objects of a specific type,
2. The user wants to know about a certain attribute of an object

```
nlu:  
- intent: query_knowledge_base  
examples: |  
- what [restaurants]{"entity": "object_type", "value": "restauran  
- list some [restaurants]{"entity": "object_type", "value": "restau  
- can you name some [restaurants]{"entity": "object_type", "val  
- can you show me some [restaurants]{"entity": "object_type", "v  
- list [German](cuisine) [restaurants]{"entity": "object_type"  
- do you have any [mexican](cuisine) [restaurants]{"entity": "objec  
- do you know the [price range]{"entity": "attribute", "value": "p  
- what [cuisine](attribute) is [it](mention)?  
- do you know what [cuisine](attribute) the [last one]{"entity": "attrib  
- does the [first one]{"entity": "mention", "value": "1"} have  
- what is the [price range]{"entity": "attribute", "value": "pr  
- what about [I due forni](restaurant)?  
- can you tell me the [price range](attribute) of [that restaura  
- what [cuisine](attribute) do [they](mention) have?
```

Handling user queries

{

```
"restaurant": [  
    {
```

Hello

Hi! How can I help you?

Can you list a couple of restaurants in Berlin?

Sure, here is what I found:

1. Donath
2. Berlin Burrito Company
3. I due forni

Domain knowledge
needed to list entities.

Domain knowledge
needed to answer
user questions.

What cuisine is the first one?

Reference to *Donath*

The cuisine of “Donath” is German.

Do you also have any cheap, Vietnamese restaurants?

“Lúa Restaurant” is a cheap, Vietnamese restaurant.

Do they have outside seating?

Reference to *Lúa Restaurant*

Yes, they have.

Ok. Bye.

Goodbye.

Handling Unknown / Unexpected queries

- Adding a variety of training examples for each query type
- Specification and Annotation of the entities in training examples:
 - a. Object_type: Whenever a training example references a specific object type from knowledge base - the object type should be marked as an entity
 - b. Use **synonyms** to map e.g. **restaurants** to **restaurant**, the correct object type listed as a key in the knowledge base.
- **Mention:** If the user refers to an object via “the first one”, “that one”, or “it”, you should mark those terms as mention.
- attribute: All attribute names defined in knowledge base should be identified as attribute in the NLU data
- **Synonyms** should be defined adequately to map variations of an attribute name to the one used in the knowledge base

Pulling information from only one knowledge base is allowed

Action Server

<https://rasa.com/docs/action-server/actions>

Events

Conversations are represented as a sequence of events

Custom actions can influence the course of a conversation by returning events in the response to the action server request.

Automatic Tracking:

- When a slot is filled by an entity of the same name

```
{  
  "event": "slot",  
  "name": "departure_airport",  
  "value": "BER"  
}
```

Stories

Stories are a type of training data used to train the assistant's dialogue management model

Stories help in training models to generalize to unseen conversation paths

Stories are composed of

- story: **The story's name.** The name is arbitrary and not used in training; you can use it as a human-readable reference for the story.
- metadata: **arbitrary and optional**, not used in training, you can use it to store relevant information about the story like e.g. the author
- a list of **steps:** The user messages and actions that make up the story

A Story

```
* greet
  - utter_greet_user

* contact_sales
  - utter_moreinformation
  - sales_form
  - form{"name": "sales_form"}

* ask_faq
  - respond_ask_faq
  - utter_ask_continue_sales

* affirm
  - utter_great
  - sales_form
  - form{"name": null}
```

Creating a Story and Response

Defines a possible conversation structure

```
stories:  
- story: knowledge base happy path  
  steps:  
    - intent: greet  
    - action: utter_greet  
    - intent: utter_greet  
    - action: action_query_knowledge_base  
    - intent: goodbye  
    - action: utter_goodbye
```

Defines a response to handle failures

```
responses:  
utter_ask_rephrase:  
- text: "Sorry, I'm not sure I understand. Could you rephrase it?  
- text: "Could you please rephrase your message? I didn't quite g
```

Sample story

Each step can be one of the following:

- A [user message](#), represented by intent and entities.
- An [or statement](#), which includes two or more user messages under it.
- A bot [action](#).
- A [form](#).
- A [slot was set](#) event.
- A [checkpoint](#), which connects the story to another story.

stories:

- story: Greet the user

metadata:

author: Somebody

key: value

steps:

list of steps

- intent: greet

- action: utter_greet

Sample stories

stories:

- story: user message structure

steps:

- intent: intent_name # Required
- entities: # Optional
- entity_name: entity_value
- action: action_name

stories:

- story: story with entities

steps:

- intent: account_balance

entities:

- account_type: credit

- action:

action_credit_account_balance

Including the entities here ensures that the policies learn to predict the next action based on a *combination* of both the intent and entities

CASE - I

```
* ask_faq
  - respond_faq

* ask_faq
  - respond_faq

* query_knowledge_base
  - respond_query_knowledge_base

* query_knowledge_base
  - respond_query_knowledge_base
```

user: what is conversa
bot: conversa is ...

user: who can use conversa
bot: Anyone ...

user: what are the pricing schemes of conversa
bot: we have scheme-1, scheme-2 and scheme-3

user: Tell me the first one
bot: there are the details...

CASE - 2

```
* ask_faq
  - respond_faq

* ask_faq
  - respond_faq

* query_knowledge_base
  - respond_query_knowledge_base

* query_knowledge_base
  - ask_values

* query_knowledge_base
  - respond_query_knowledge_base
```

user: what is conversa
bot: conversa is ...
user: who can use conversa
bot: Anyone ...
user: what are the pricing schemes of conversa
bot: we have scheme-1, scheme-2 and scheme-3
user: Tell me the first one
bot: before that, please provide this information...
user: the information is as follows
bot: there are the details...

CASE - 3

```
* ask_faq
  - respond_faq

* ask_faq
  - respond_faq

* query_knowledge_base
  - respond_query_knowledge_base

* query_knowledge_base
  - ask_values

* deny
  - utter_deny
```

user: what is conversa
bot: conversa is ...

user: who can use conversa
bot: Anyone ...

user: what are the pricing schemes of conversa
bot: we have scheme-1, scheme-2 and scheme-3

user: Tell me the first one
bot: before that, please provide this information...

user: I don't have that information
bot: Sorry, but we need that, however...

Stories

```
## find_meetup_01
```

- * greet
 - utter_greet
- * meetup
 - utter_meetup
- * affirm+task_transport
 - utter_affirm_suggest_transport
- * thanks+goodbye
 - utter_thanks_goodbye

Multiple intent

```
## find_meetup_02
```

- * greet
 - utter_greet
- * meetup
 - utter_meetup
- * affirm
 - utter_confirm
- * ask_transport
 - utter_suggest_transport
- * goodbye
 - utter_goodbye

## find_meetup_01	## find_meetup_03	## find_meetup_04
<ul style="list-style-type: none"> * greet <ul style="list-style-type: none"> - utter_greet * meetup <ul style="list-style-type: none"> - utter_meetup * affirm+task_transport <ul style="list-style-type: none"> -utter_affirm_suggest_transport * thanks+goodbye <ul style="list-style-type: none"> - utter_thanks - utter_goodbye 	<ul style="list-style-type: none"> * greet <ul style="list-style-type: none"> - utter_greet * meetup <ul style="list-style-type: none"> - utter_meetup * affirm+task_transport <ul style="list-style-type: none"> -utter_confirm -utter_suggest_transport * thanks+goodbye <ul style="list-style-type: none"> - utter_thanks - utter_goodbye 	<ul style="list-style-type: none"> * greet <ul style="list-style-type: none"> - utter_greet * meetup <ul style="list-style-type: none"> - utter_meetup * affirm+task_transport <ul style="list-style-type: none"> -utter_confirm -utter_suggest_transport * thanks+goodbye <ul style="list-style-type: none"> - utter_goodbye

Special action
for a multi-intent

Two actions
for a multi-intent

Single-action response
to a multi-intent

```
templates:  
utter_greet:  
    - text: "Hey, how can I help you?"  
utter_goodbye:  
    - text: "Talk to you later!"  
    - text: "Goodbye :(" Different ways to say Goodbye -  
    - text: "Bye!"  
    - text: "Have a great day!"  
utter_confirm:  
    - text: "Done - I have just booked you a spot at the Bots Berlin  
      meetup."  
    - text: "Great, just made an RSVP for you."  
utter_meetup:  
    - text: "Rasa Bots Berlin meetup is definitely worth checking  
      out! They are having an event today at Behrenstraße 42. Would  
      you like to join?" Affirm + suggest transport  
utter_affirm_suggest_transport:  
    - text: "Great, I have just booked a spot for you. The venue is  
      close to the Berlin Friedrichstraße station, you can get there  
      by catching U-Bahn U6."  
utter_suggest_transport:  
    - text: "The venue is close to the Berlin Friedrichstraße  
      station, so the best option is to catch a U-Bahn U6." A suggestion  
utter_thanks:  
    - text: "You are very welcome."  
    - text: "Glad I could help!"  
utter_deny:  
    - text: "That's a shame. Let me know if you change your mind."
```

Transformer Embedding Dialogue (TED) POLICY ARCHITECTURE

Action Selection

At every turn - each policy defined in the configuration predicts a next action with a certain confidence level

The policy that predicts with the highest confidence decides the assistant's next action

Policies can have priorities

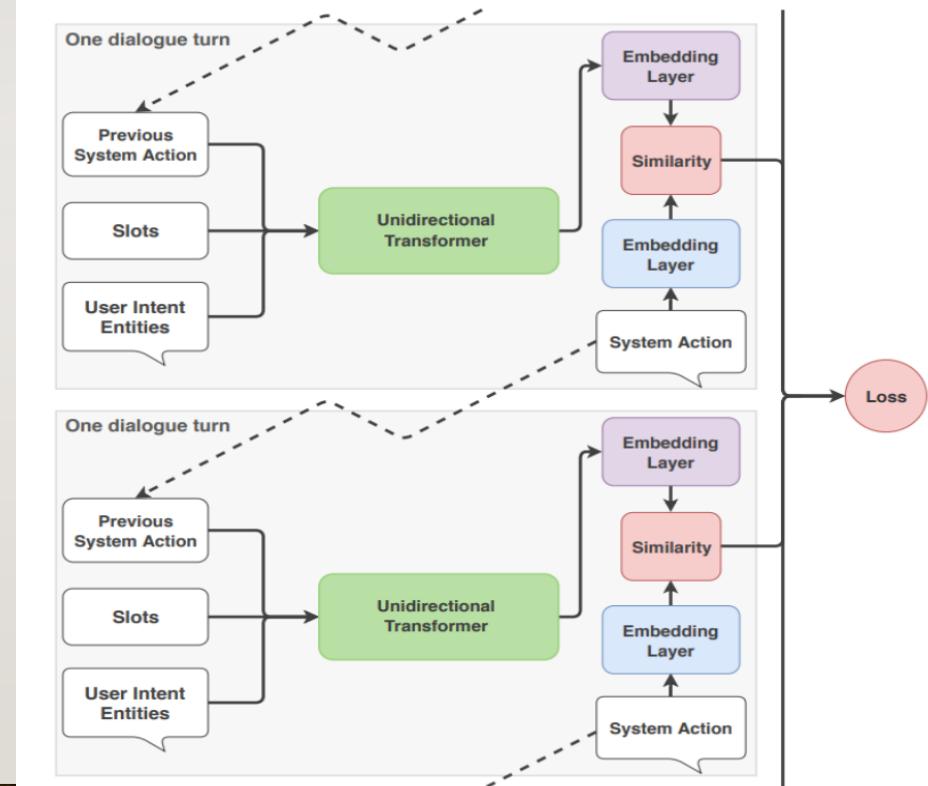


Image source: www.rasa.com

TED - Multi-tasking architecture

Uses several transformer encoders which are shared for both tasks

The transformer accesses different parts of the dialogue history dynamically at each turn and then assesses and recalculates the relevance of previous turns.

This allows the TED policy to take a user utterance into account at one turn but ignore it completely at another, which makes the transformer a useful architecture for processing dialogue histories.

A sequence of entity labels is predicted through a Conditional Random Field (CRF) tagging layer on top of the user sequence transformer encoder output corresponding to the input sequence of tokens

For the next action prediction the dialogue transformer encoder output and system action labels are embedded into a single semantic vector space

Loss function for prediction - the dot-product loss to ***maximize the similarity with the target label and minimize similarities with negative samples***

Similarity Function

maximize the similarity $S^+ = h_{\text{dialogue}}^T h_{\text{action}}^+$ with the target label y_{action}^+ and minimize similarities $S^- = h_{\text{dialogue}}^T h_{\text{action}}^-$ with negative samples y_{action}^- . Thus, the loss function for one dialogue reads

$$L_{\text{dialogue}} = - \left\langle S^+ - \log \left(e^{S^+} + \sum_{\Omega^-} e^{S^-} \right) \right\rangle, \quad (1)$$

Memoization Policy

The MemoizationPolicy remembers the stories from training data

It checks if the current conversation matches the stories in repository

If so, it will predict the next action from the matching stories of your training data with a confidence of 1.0

If no matching conversation is found, the policy predicts None with confidence 0.0.

When looking for a match in training data, the policy will take the last max_history number of turns of the conversation into account. One “turn” includes the message sent by the user and any actions the assistant performed before waiting for the next message.

TED Policy architecture - how it works

1. Concatenate features for each time step into an ***input vector to feed to the embedding layer that precedes the dialogue transformer***
 - user input (user intent and entities) or user text processed through a user sequence transformer encoder,
 - previous system actions or bot utterances processed through a bot sequence transformer encoder,
 - slots and active forms
2. Feed the embedding of the input vector into the ***dialogue transformer encoder***
3. Apply a dense layer to the output of the dialogue transformer to get embeddings of the dialogue for each time step
4. Apply a dense layer to create embeddings for system actions for each time step.
5. Calculate the similarity between the dialogue embedding and embedded system actions
6. Concatenate the token-level output of the user sequence transformer encoder with the output of the dialogue transformer encoder for each time step
7. Apply CRF algorithm to predict contextual entities for each user text input

Learning interactively

Π

Objective of agent - **Maximize** a single scalar called the **reward** when following a policy Π

Maximize expected reward following parametrized policy π - defined by weights and biases or neural network, τ is a sequence of (state, action) pair, and $r(\tau)$ is the total reward for a trajectory

$$J(\theta) = E_{\pi}[r(\tau)]$$

$$\theta_{t+1} = \theta_t + \alpha \nabla J(\theta_t),$$

Chosen Policy

$$\theta = \operatorname{argmax}_{\theta} J(\theta),$$

Learning to perform tasks

- Designing reward policies and loss functions are difficult problems
- Use human feedback for the generated text as a measurement of performance
- Use feedback to optimize the model
- *Reinforcement Learning from human Feedback (RLHF)*

Reinforcement Learning from Human feedback

Step 1

Collect demonstration data and train a supervised policy.

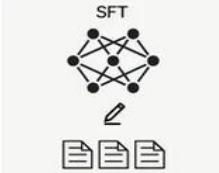
A prompt is sampled from our prompt dataset.



A labeler demonstrates the desired output behavior.



This data is used to fine-tune GPT-3.5 with supervised learning.

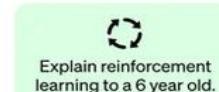


Gather human feedbacks for same prompt / several prompts

Step 2

Collect comparison data and train a reward model.

A prompt and several model outputs are sampled.

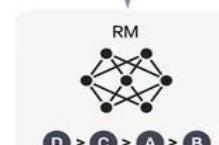


- A In reinforcement learning, the agent is...
- B Explain rewards...
- C In machine learning...
- D We give treats and punishments to teach...

A labeler ranks the outputs from best to worst.



This data is used to train our reward model.



Find best/popular answer - training data for learning policy

Step 3

Optimize a policy against the reward model using the PPO reinforcement learning algorithm.

A new prompt is sampled from the dataset.



The PPO model is initialized from the supervised policy.



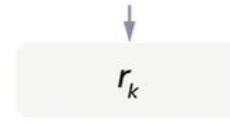
The policy generates an output.



The reward model calculates a reward for the output.

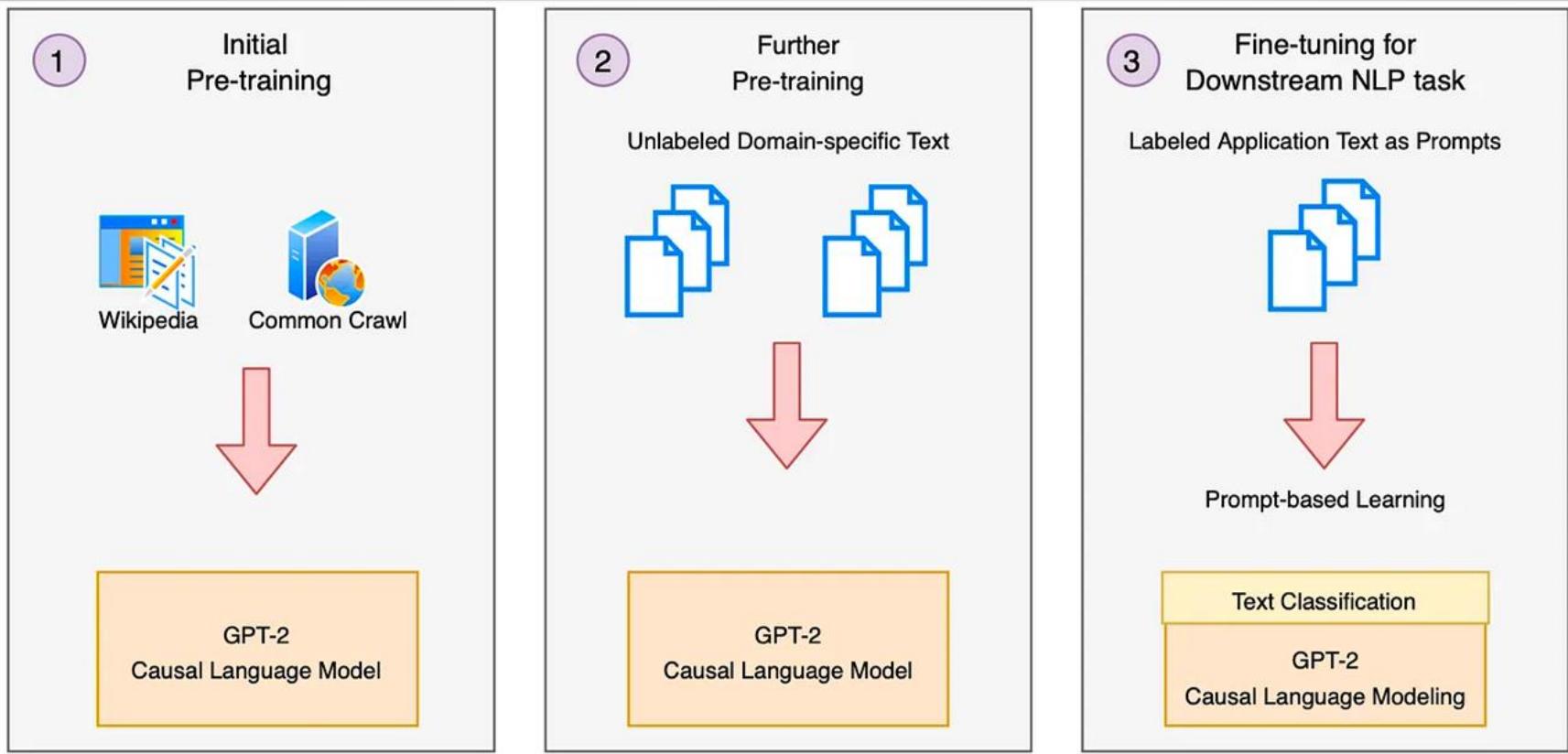


The reward is used to update the policy using PPO.

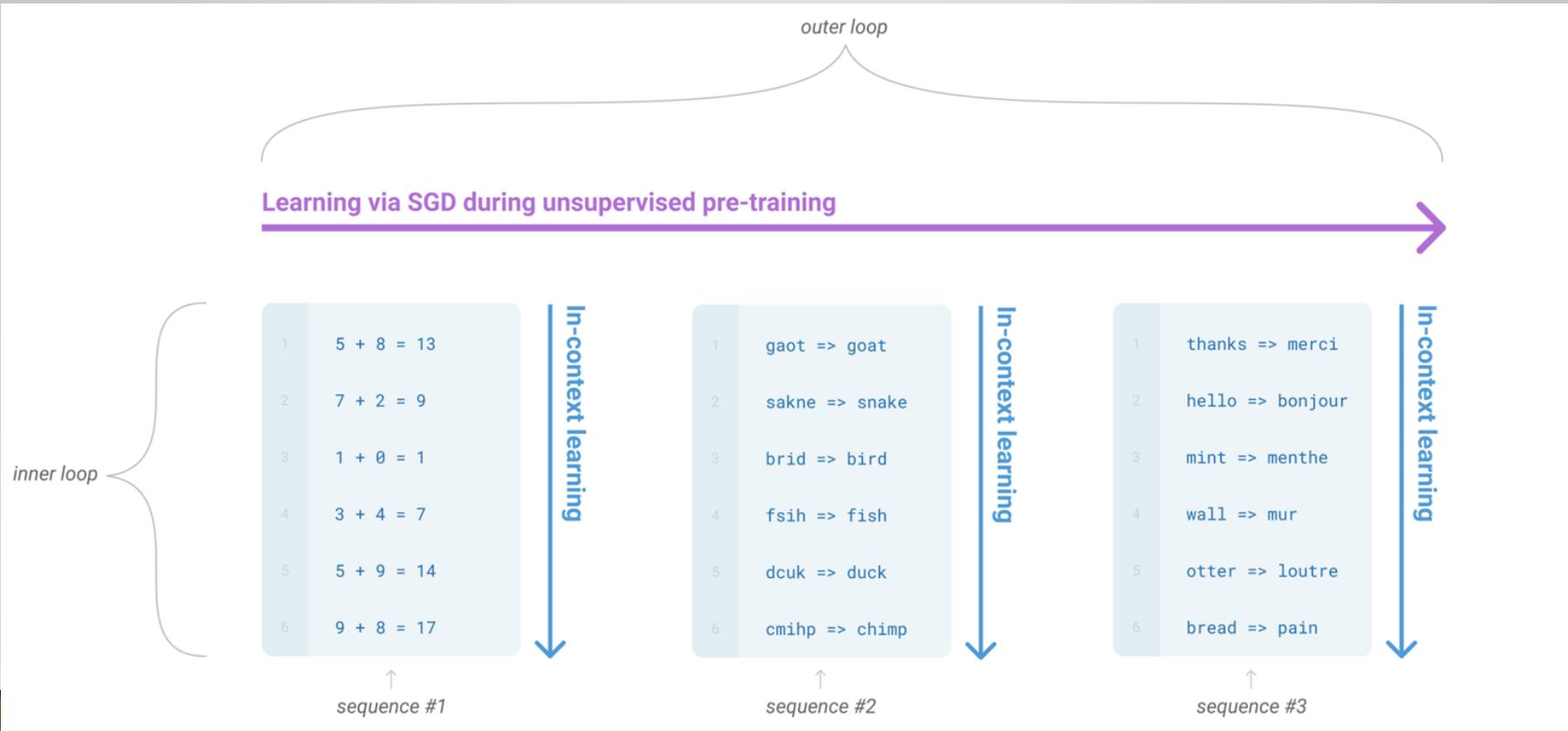


Choose policy - calculate reward

ChatGPT

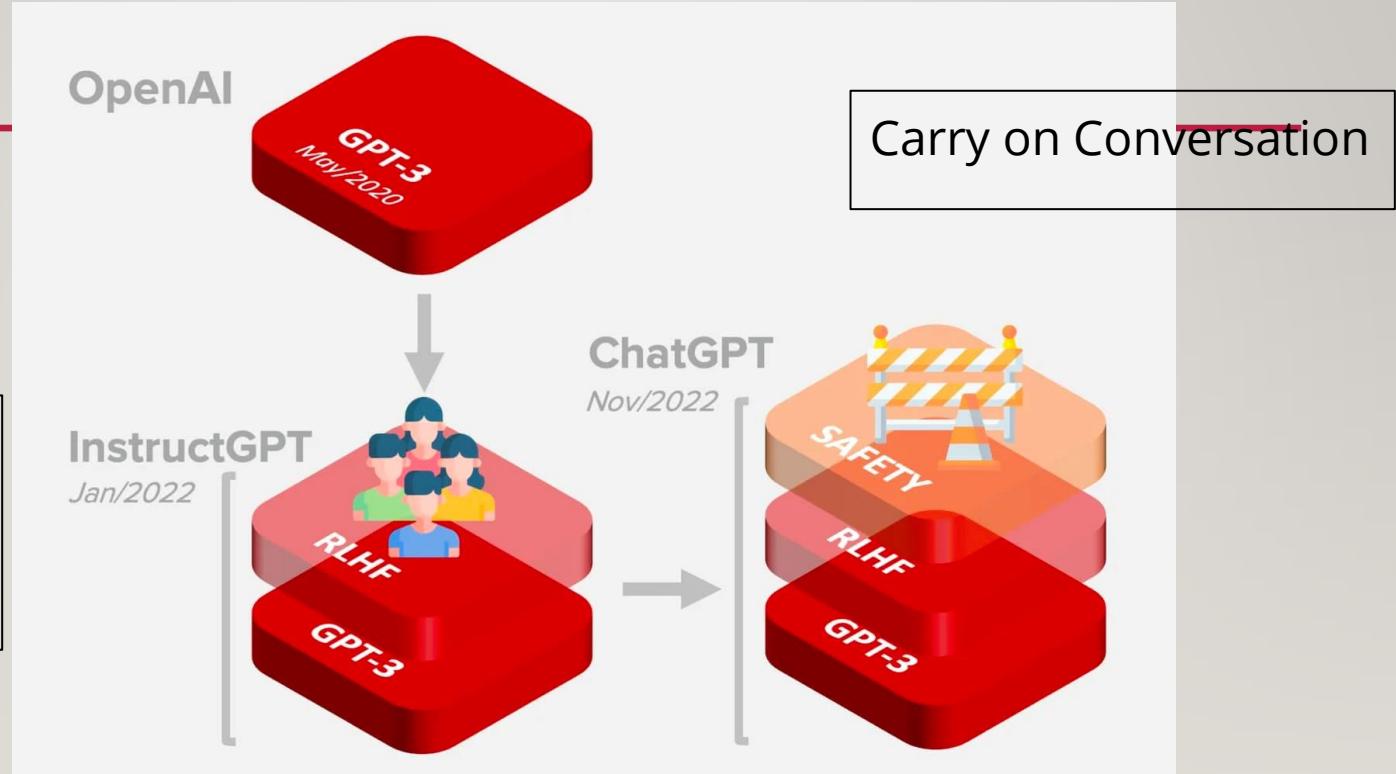


Fine Tuning Tasks are varied



Training is the key

To provide businesses and organizations with a powerful tool for natural languages processing tasks



How training matters!

Prompt: Explain the moon landing process to a 6 year old.

GPT: Explain the theory of gravity to 6 year old

InstructGPT: People went to the moon in 1969 and have sent back pictures to the earth



You

Explain the moon landing process to a 6 year old



ChatGPT

Alright, imagine you have a big rocket, like a really, really tall and powerful one. This rocket has a special spaceship on top, kind of like a super cool car, and inside that spaceship are some brave astronauts. These astronauts are like space explorers who want to visit the moon.

Now, picture the Earth and the moon in the sky. The rocket blasts off from the Earth and goes zooming through space. It's a long journey, like a super, duper long car ride, but in space.

After traveling for a while, the rocket and the spaceship get close to the moon. The spaceship separates from the rocket and slowly descends down to the moon's surface. It's like landing a plane, but on the moon!

Once the spaceship is safely on the moon, the astronauts can climb out and explore. They might collect moon rocks, take pictures, and even hop around because the moon's gravity is much weaker than Earth's, so it's like bouncing on a trampoline.

When the astronauts have had their moon adventure, they climb back into the spaceship, and it takes off again. This time, it heads back to Earth, and when it arrives, everyone cheers because the astronauts have successfully visited the moon and come back home!

BOOTSTRAPPING AND LEARNING

O p t i o n 1 - *T r a i n a p r o b a b i l i s t i c m o d e l t o p r e d i c t w h i c h a c t i o n t o t a k e g i v e n t h e h i s t o r y o f a c o n v e r s a t i o n*

Learn action prediction from a database of conversations

Annotate them and run supervised learning

Option 2 – Since usable set of annotated conversations is usually not there

Use interactive learning to bootstrap from zero data

T h e B o t s h o w s a l l o p t i o n s t o t h e U s e r

U s e r s e l e c t s

T h e c o n v e r s a t i o n i s s t o r e d

D i f f e r e n t u s e r s m a y s e l e c t d i f f e r e n t a c t i o n s – p r o b a b i l i t y v a l u e s a r e c o m p u t e d a n d s t o r e d

Option 3 - Simulation

Simulations for creating Goal oriented dialog systems

Enable users to complete specific goals

Example - *requesting information about a movie* or *booking a ticket*

Dialog system pipeline

Multiple ML models + Natural Language Understanding + State tracking + Action prediction (policy learning)

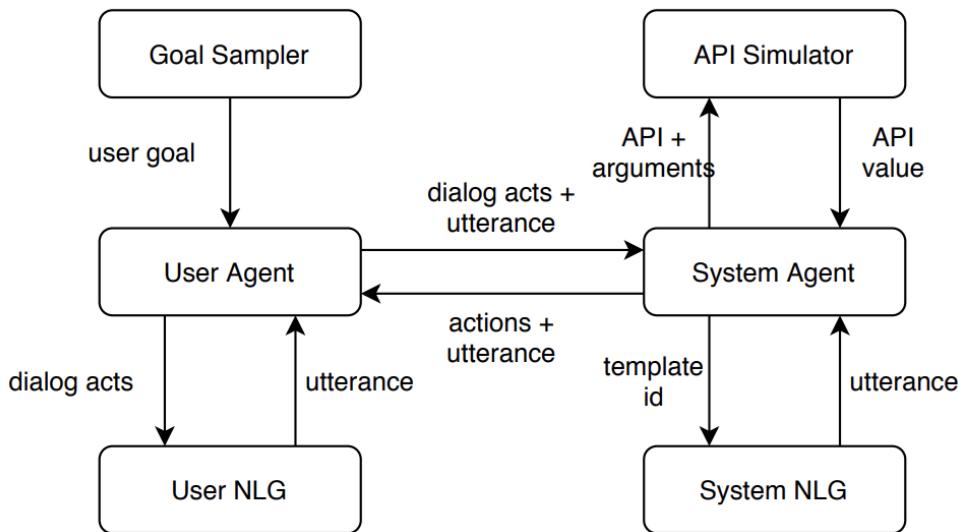
Models are trained through a combination of supervised or reinforcement learning methods

Require collection of labeled domain specific datasets

Collecting annotated datasets with language and dialog-flow variations is expensive, time-consuming and scales poorly due to human involvement

Simulation - Creating a large corpus of annotated dialogs from a **few thoroughly annotated sample dialogs** and the dialog schema

Simulation architecture for creating simulated dialogs



Inputs

1. domain-specific APIs
2. Entity types with catalogs
3. System response templates
4. User-utterance templates
5. Seed dialogs
6. Each API is defined with some arguments annotated with entity types and a response NLG template

Input intent and act samples

User Dialog Acts

inform(intent)	U informs S of an intent	"please find me a movie showing"
inform(entity)	U informs S the value of an intent argument	"for Tenet"
affirm(intent)	U affirms that an intent is correct	"yes, I want to find a movie showing"
affirm(entity)	U affirms that an intent argument is correct	"yes, for Tenet"
deny(intent)	U denies that an intent is correct	"no, I don't want to try again"
deny(entity)	U denies that an intent argument is correct	"no, not for Tenet"

System Dialog Acts

inform(entity)	S informs U the value of an intent argument	"the movie you requested is showing nearby at 4 PM"
confirm(intent)	S confirms that an intent is understood	"are you ready to book the ticket?"
confirm(entity)	S confirms that an intent argument is understood	"for Tenet at 4 PM"
offer(intent)	S proposes an intent to U	"would you like to find an movie showing?"
offer(entity)	S proposes an intent argument to U	"how about Tenet?"

Sample annotated dialog

- U-1: What movie are playing in [Sunnyvale|c0] after [2 PM|t0]?
- S-2: call: FindMovies(location=\$c0,timeLowerBound=\$t0) → movies0
- S-3: nlg: Tenet is playing in AMC Theater at 4 PM
- U-4: tell me more about the [4 PM|t1] show of [Tenet|m0]
- S-5: call: SelectShow(time=\$t1, movieName=\$m0) → show0
- S-6: nlg: OK. The available ticket type is adult ticket
- U-7: Book [two|c0] [adult|type0] tickets for this show
- S-8: BookTickets(show=\$show0, count=\$c0, type=\$type0) -> booking0
- U-9: Ok thank you
- S-10: nlg: Thank you for using Atom Tickets

Goal representation

Each API represents a Goal

Golden goals are selected from APIs appearing in annotated dialogs

Additional goals are created from intents in the dialogs

$$P(goal) = \prod_i P(intent_i | (intent_j)_{j < i})$$

Generating samples

1. Given the goal representation of the user's intent, alternative goals are sampled that contain the same API call structure, but alternative argument values that the user might provide.
2. If user corrects the API argument before the corresponding API is called, update the user and system states with the new value.
3. If user corrects an API argument after the corresponding API is called, the system recalls that API with the updated value and returns the updated information to the user.
4. During simulation, the user may randomly change their mind in any turn about an earlier informed entity.

Handling out of scope situations

Users will inevitably say things to a chatbot that the creators did not anticipate

Handling Out-of-scope Messages

nlu.yml

```
nlu:  
  - intent: out_of_scope  
    examples: |  
      - I want to order food  
      - What is 2 + 2?  
      - Who's the US President?
```

best to import these from real deployments

domain.yml

Pre-defined Response

responses:

utter_out_of_scope:

- text: Sorry, I can't handle that request.

Creating an Out-of-scope rule

rules.yml

rules:

- rule: out-of-scope
 - steps:
 - intent: out_of_scope
 - action: utter_out_of_scope

Fallback

For a low-confidence classification value returned by DIET -

Fallbacks will help ensure that these low confidence messages are handled gracefully

Gives the assistant the option to either respond with a default message or attempt to disambiguate the user input

`config.yml`

```
pipeline:  
  # other components  
  - name: FallbackClassifier  
    threshold: 0.7
```

Response and action

```
domain.yml
```

```
responses:  
  utter_please_rephrase:  
    - text: I'm sorry, I didn't quite understand that. Could you reph
```

```
rules.yml
```

```
rules:  
  - rule: Ask the user to rephrase whenever they send a message with  
    steps:  
      - intent: nlu_fallback  
      - action: utter_please_rephrase
```

Handling Low Action Confidence

Rasa's default [TED Policy](#) is optimized to handle these unknown paths.

Two stage fallback

Intent not clear - Rasa rephrases intent and validates from user - Yes or No?

if Yes - then follows usual rule

if No - requests rephrase

It is possible to configure the [Rule Policy](#) to predict a default action if no [Policy](#) has a next action prediction with confidence above a configurable threshold.

<https://rasa.com/docs/rasa/fallback-handoff/#fallbacks>

Setting up a Chatbot

- Define Purpose
- Identify back-end systems to be integrated
- List intents
- Identify which intent can be handled as simple QA - which ones need more context
- Set up FAQ list
 - Intent classifier - enough examples for each intent
- Set up knowledgebase of entities, slots, values, synonyms
 - Intent classifier - enough samples to learn each intent
- Define Policies - learn / rule / default
 - Define rules
 - Conversation follows pre-defined path
 - < intent - response> pairs
 - Define responses
 - Write stories

Branching in Conversation

Can be converted into a single story

stories:

- story: It's raining now

steps:

- intent: check_for_rain

- action: action_check_for_rain

- slot_was_set:

 - raining: **true**

- action: utter_is_raining

- action: utter_bring_umbrella

- story: It isn't raining now

steps:

- intent: check_for_rain

- action: action_check_for_rain

- slot_was_set:

 - raining: **false**

- action: utter_not_raining

- action: utter_no_umbrella_needed

Using custom code

stories:

- story: check for rain

steps:

- intent: check_for_rain
- action: action_check_for_rain

```
def run(self, dispatcher, tracker, domain):
    is_raining = check_rain()
    if is_raining:
        dispatcher.utter_message(template="utter_is_raining")

    dispatcher.utter_message(template="utter_bring_umbrella")
    else:
        dispatcher.utter_message(template="utter_not_raining")

    dispatcher.utter_message(template="utter_no_umbrella_need"
                           ed")
    return []
```

Checkpoints

stories:

- story: beginning of conversation

steps:

- intent: greet
- action: utter_greet
- intent: goodbye
- action: utter_goodbye
- checkpoint: ask_feedback

Don't overdo

story: user provides feedback

steps:

- checkpoint: ask_feedback
- action: utter_ask_feedback
- intent: inform
- action: utter_thank_you
- action: utterAnythingElse

story: user doesn't have feedback

steps:

- checkpoint: ask_feedback
- action: utter_ask_feedback
- intent: deny
- action: utter_no_problem
- action: utterAnythingElse

Happy Paths

stories:

- story: Customer loses a credit card, reviews transactions, and gets a new card

steps:

- intent: card_lost
- action: check_transactions
- slot_was_set:
 - reviewed_transactions: ["starbucks"]
- action: utter_ask_fraudulent_transactions
- intent: inform
- action: action_update_transactions
- intent: affirm
- action: utter_confirm_transaction_dispute
- action: utter_replace_card
- action: mailing_address_form
- active_loop: mailing_address
- active_loop: null
- action: utter_sent_replacement
- action: utter_anything_else
- intent: affirm
- action: utter_help

stories:

- story: Customer loses a credit card, reviews transactions, and gets a new card

steps:

- intent: card_lost

- action: check_transactions

- slot_was_set:

- reviewed_transactions: ["starbucks"]

- action: utter_ask_fraudulent_transactions

- intent: inform

- action: action_update_transactions

- intent: affirm

- action: utter_confirm_transaction_dispute

- action: utter_replace_card

- action: mailing_address_form

- active_loop: mailing_address

- active_loop: null

- action: utter_sent_replacement

- action: utterAnythingElse

- intent: affirm

- action: utter_help

Long complicated stories
should be broken into
smaller ones

stories:

- story: Customer loses a credit card

steps:

- intent: card_lost

- action: utter_card_locked

- action: spending_history_form

- active_loop: spending_history_form

- active_loop: null

- slot_was_set:

- reviewed_transactions: ["starbucks"]

- action: utter_ask_fraudulent_transactions

- story: Customer reviews transactions and gets a new card

steps:

- action: utter_ask_fraudulent_transactions

- intent: inform

- action: action_update_transactions

- slot_was_set:

- reviewed_transactions: ["target", "starbucks"]

- intent: affirm

- action: utter_confirm_transaction_dispute

- action: utter_replace_card

- action: mailing_address_form

- active_loop: mailing_address

- active_loop: null

- action: utter_sent_replacement

- action: utter_anything_else

- story: Customer has something else they need help with

steps:

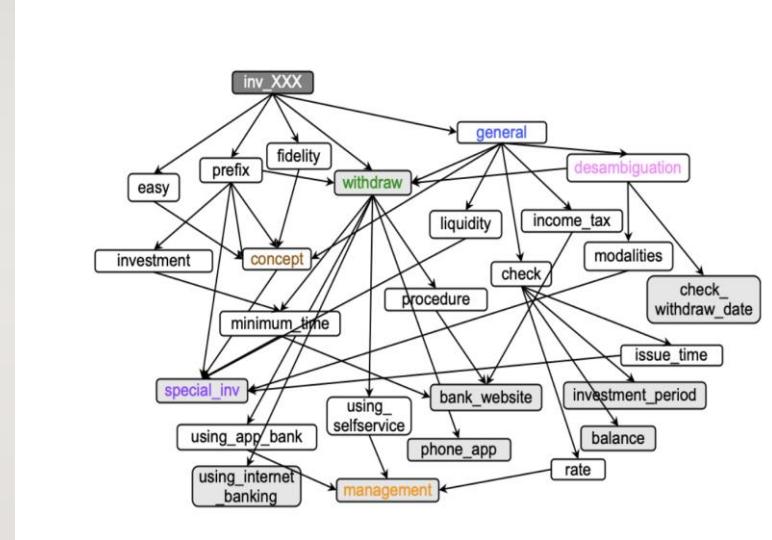
- action: utter_anything_else

- intent: affirm

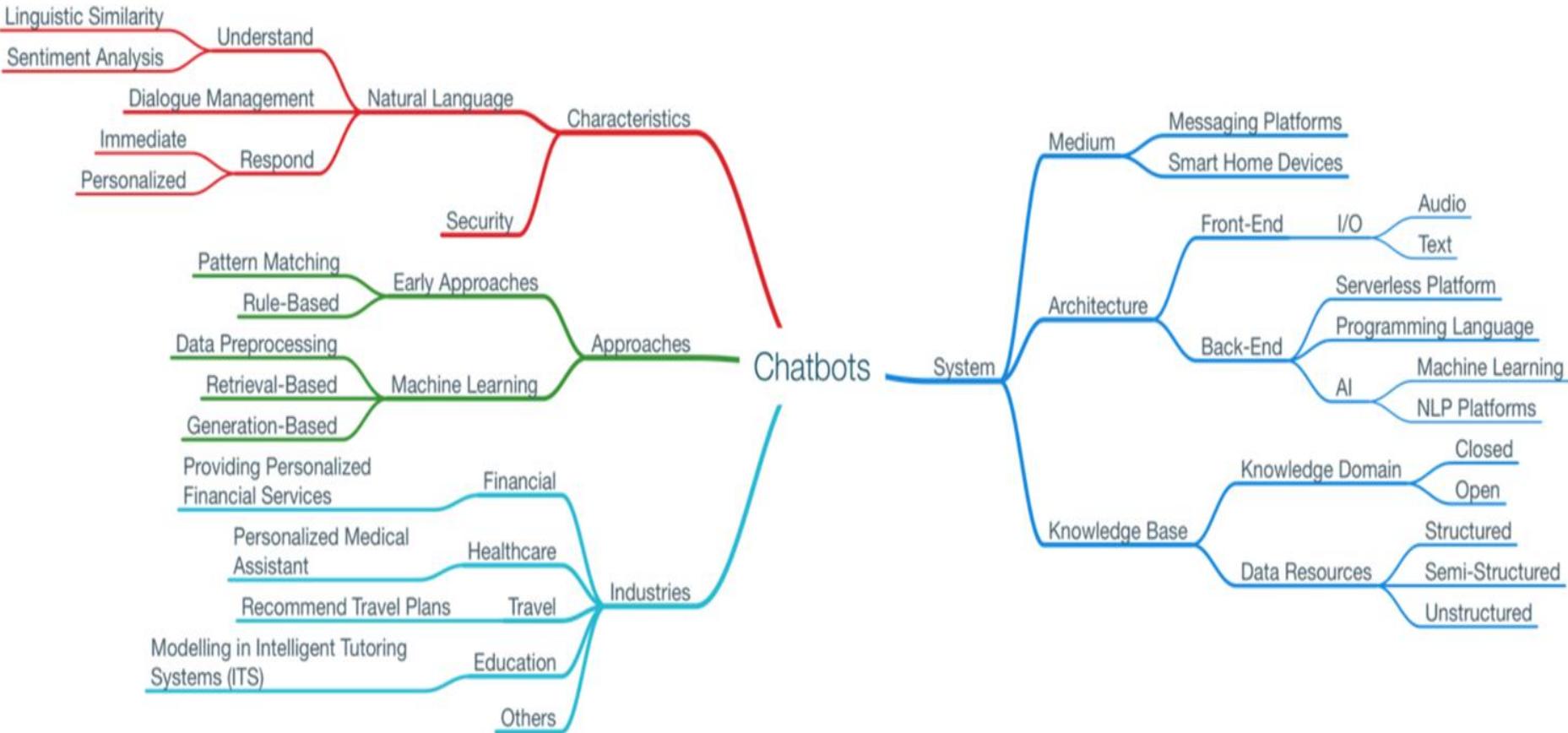
- action: utter_help

Testing - Interface, Semantics, Logic

intent	INTENT ID (translated and anonymized)
1	inv_XXX-fidelity-concept-special_inv-kareen_27-08-YY
2	inv_XXX-general-check-balance
3	inv_XXX-general-check-investment_period
4	inv_XXX-general-check-issue_time-special_inv
5	inv_XXX-general-check-rate-management
6	inv_XXX-general-concept-special_inv
7	inv_XXX-general-desambiguation-check_withdraw_date--
8	inv_XXX-general-desambiguation-modalities-special_inv
9	inv_XXX-general-desambiguation-withdraw--
10	inv_XXX-general-income_tax-bank_website
11	inv_XXX-general-liquidity-special_inv
12	inv_XXX-general-withdraw-minimum_time-special_inv
13	inv_XXX-general-withdraw-using_selfservice-management
14	inv_XXX-easy-concept-special_inv-kareen_27-08-YY
15	inv_XXX-prefix-concept-special_inv-kareen_27-08-YY
16	inv_XXX-prefix-investment-minimum_time-bank_website
17	inv_XXX-prefix-withdraw-procedure-bank_website
18	inv_XXX-withdraw-phone_app--
19	inv_XXX-withdraw-using_app_bank-management
20	inv_XXX-withdraw-using_internet_banking--



Prototype trees



CREATING YOUR OWN ASSISTANTS

Read the Rasa tutorial at

<https://rasa.com/docs/rasa/user-guide/building-assistants/#building-assistants>

Reading material - Papers

<http://www.ijmerr.com/uploadfile/2020/0312/20200312023706525.pdf>

<https://arxiv.org/pdf/2011.08243.pdf> - simulation

THANK YOU

Slide 1: Introduction

- Definition of chatbots
- Brief history of chatbots
- Importance of speech act theory in developing chatbots

Slide 2: Speech Act Theory

- Definition of speech act theory
- The three components of speech act theory: locutionary, illocutionary, and perlocutionary acts
- Examples of each component

Slide 3: Types of Speech Acts

- Direct and Indirect Speech Acts
- Representative, Directive, Commissive, Expressive, and Declarative Speech Acts
- Examples of each type of speech act

Slide 4: How Speech Act Theory is Used in Chatbots

- Chatbot goals and objectives
- Understanding the user's intent and context
- Developing appropriate responses based on speech act theory
- Examples of chatbot responses based on speech act theory

Slide 5: Best Practices for Chatbot Design

- Identify the target audience
- Use natural language processing
- Use appropriate tone and language
- Provide a clear call to action
- Test and refine the chatbot

Slide 6: Conclusion

- Recap of speech act theory and chatbot design
- Importance of understanding speech act theory in developing effective chatbots
- Future developments in chatbot design and speech act theory