COURSE: APPLICATIONS OF ARTIFICIAL INTELLIGENCE (AAI)

AMP in Business Analytics 2020

INDIAN SCHOOL OF BUSINESS

Vamshi Ambati

Vamshi_Ambati@isb.edu;
vamshi@predera.com

Session 2: Dialog Systems
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AAI COURSE AGENDA

- Session 1: Machine Translation
- Session 2: Dialog Systems (Chatbot)
- Session 3: Recommender Systems
- Session 4: Computer Vision (Image Recognition)

RECAP: APPLICATIONS OF AI

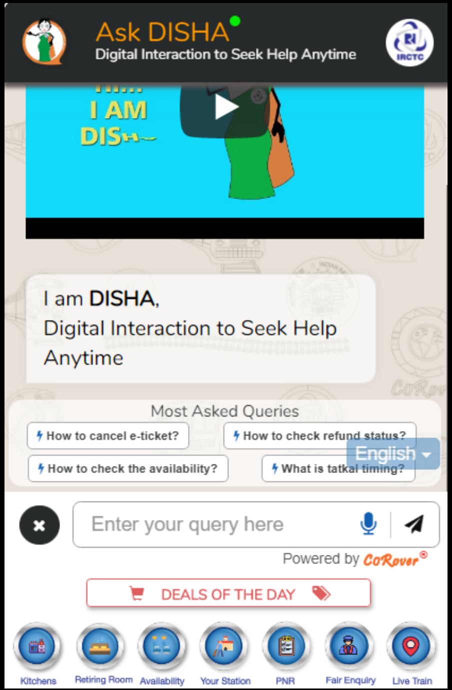
- Natural Language Processing -> IE, IR, MT, NLU, NLG, Dialog -> Chatbot, Customer complaint translation
- Speech Processing -> SR (S2T), SS (T2S), SG (S2S) -> Voice Assistant (Siri), Education, IVR
- Computer Vision -> IU, IG, OR, OD, Video {U,G,R,D} -> OCR, Face Recognition, Self-driving, Entertainment
- Predictive Analytics ->Prediction, Recommender, Forecasting Systems -> E-commerce , Fraud detection
- Robotics -> Locomotion, Mechanics, Sensors, Planning -> Medical Bots, Agriculture, Military
- Agent Systems -> Planning, Reinforcement Learning, Space Optimization -> AlphaGo

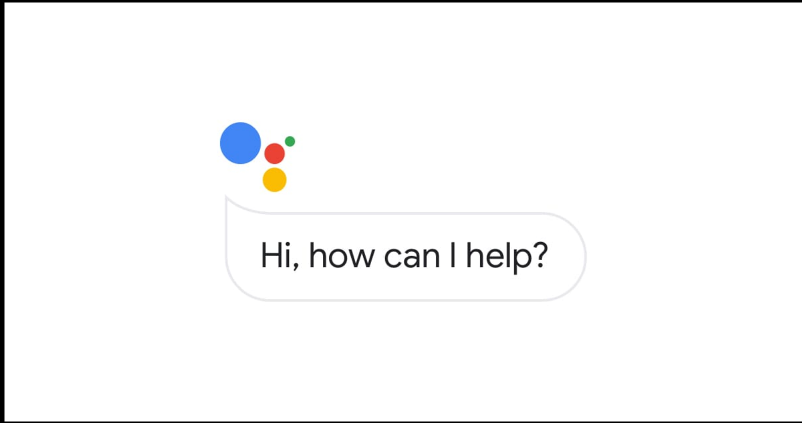
Agenda

- Introduction
  - NLP- Background
  - Dialog systems
- Conversational Bots
- Task Based Bots
- Bot Building from Scratch (Workshop)

1. Introduction

Her (2014)





Conversation

C_1: . . . I need to travel in May.
A_1: And, what day in May did you want to travel?
C_2: OK uh I need to be there for a meeting that's from the 12th to the 15th.
A_2: And you're flying into what city?
C_3: Seattle.
A_3: And what time would you like to leave Pittsburgh?
C_4: Uh hmm I don't think there's many options for non-stop.
A_4: Right. There's three non-stops today.
C_5: What are they?
A_5: The first one departs PGH at 10:00am arrives Seattle at 12:05 their time. The second flight departs PGH at 5:55pm, arrives Seattle at 8pm. And the last flight departs PGH at 8:15pm arrives Seattle at 10:28pm.
C_6: OK I'll take the 5ish flight on the night before on the 11th.
A_6: On the 11th? OK. Departing at 5:55pm arrives Seattle at 8pm, U.S. Air flight 115.
C_7: OK.
A_7: And you said returning on May 15th?
C_8: Uh, yeah, at the end of the day.
A_8: OK. There's #two non-stops . . . #
C_9: #Act. . . actually #, what day of the week is the 15th?
A_9: It's a Friday.
C_{10}: Uh hmm. I would consider staying there an extra day til Sunday.
A_{10}: OK. . . OK. On Sunday I have . . .

Source: Jurafsky Martin NLP Book

Background- Natural Language Processing

- Interaction with machines- programming, programming language
- Machine language vs human language
  - Prefixed unique definition vs multiple definitions
  - Contextual meaning
  - Syntactic and semantic structure of human language
  - Multiple languages of humans

Challenge: Language Understanding (NLP)

- Language is complicated
  - Abstract
  - Ambiguous
  - Hierarchical
  - Context-dependent
  - Multi-modal
  - Unspoken (gesture infused)
  - Evolving (eg. unfriend, tweet, swipe, like, share)
- Challenges
  - Lexical (‘line’ has 10 different meanings in Japanese)
  - Morphological (Indian languages have a complicated morphology)
  - Syntactical (different parses mean different things)

History of NLP

- 17th century- Leibniz and Descartes, theoretical proposals for codes which would relate words between languages (machine translation)
- 1950- Alan Turing, “Computing Machinery and Intelligence” (Turing test)
  - Machine Translation for English and Russian languages
- 1957- Noam Chomsky, Syntactic Structures
  - Rule based system of syntactic structures
  - “Colorless green ideas sleep furiously”, syntactically correct, semantically wrong

History of NLP

- Late 1980s,1990s, introduction of machine learning
  - Machine learning algorithms produced hard if-else rules
  - Statistical models produced softer probabilities as features
- 2000s to present- Neural networks, word embeddings, sequence-to-sequence models, pretrained language models

Accomplishments of NLP

- Natural Language Understanding
- Information Retrieval
- Information Extraction
  - Named Entity Recognition
  - Coreference resolution
  - Parts of Speech tagging
  - Text Summarization
- Natural Language Generation
- Conversational Agent (Dialog System)
- Language Translation

Dialog systems

- Sub-field of NLP that models human conversations
- Variety of conversations
  - Individual conversations
  - Multi-party conversations
  - Human to Machine
  - Speech or Text

Chatbots

- Understand the language and give an appropriate response
- Response depends on the objective

I don't feel good today

I'm sorry, I don't understand

I don't feel good today

I'm sorry, how can I help you?

- Present day chatbots- provide a human like interface for users to interact and answer their queries

Are there any flights from Hyd to Mumbai tomorrow

I'm afraid all the flights are booked for tomorrow due to the holiday rush

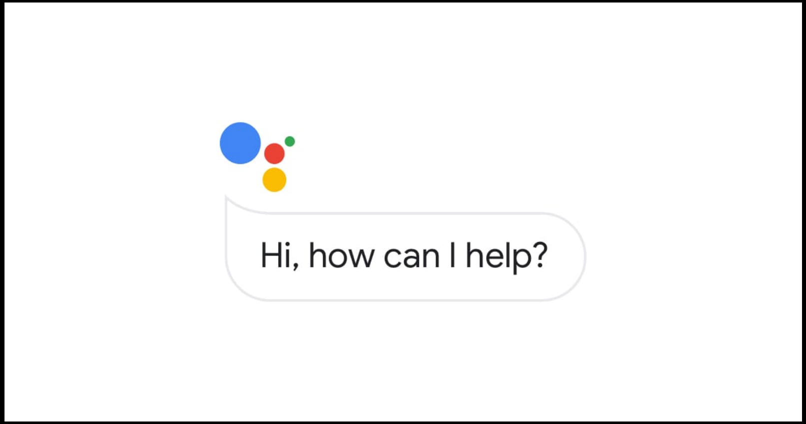
Why Chatbots?

- When do you need a chatbot?
  - Information Retrieval is not enough for your use case
  - Human-like conversation is the norm but does not scale
  - Modality of input and output (mobile, hands-free)
- ROI
  - Business Process Operation (BPO) to Business Process Automation (BPA)
  - Enhanced customer satisfaction
  - Reduced costs
  - Scale beyond capability
  - Reach wider demographic base of customers

2. Conversational Chatbots

Types of dialog agents: Conversational Agents

- Conversational agents try to mimic human-human casual conversation



Conversational Challenges

- Question understanding, Question stacking, Context tracking
- Sub-dialogue tracking
- Semantics (grounding, turn-taking, initiative, tone)
- Conversation continuation
- Domain Ontology
- Speech makes it more complicated (out of scope for this course)
- Very difficult to build for all purposes and all domains

Frameworks for conversational agents: Rule based

- Rule based
  - Understanding language and responding is based on a set of rules
  - Ex: ELIZA (1966), PARRY (1971)

```
(0 YOU 0 ME) [pattern]
->
(WHAT MAKES YOU THINK I 3 YOU) [transform]
```

```
You hate me
into:
WHAT MAKES YOU THINK I HATE YOU
```

Frameworks for conversational agents: Rule based

ELIZA

- Made to mimic a psychologist
- Reflects user's statements back at them
- https://www.eclecticenergies.com/ego/eliza
- Modern chatbots also include a set of rules

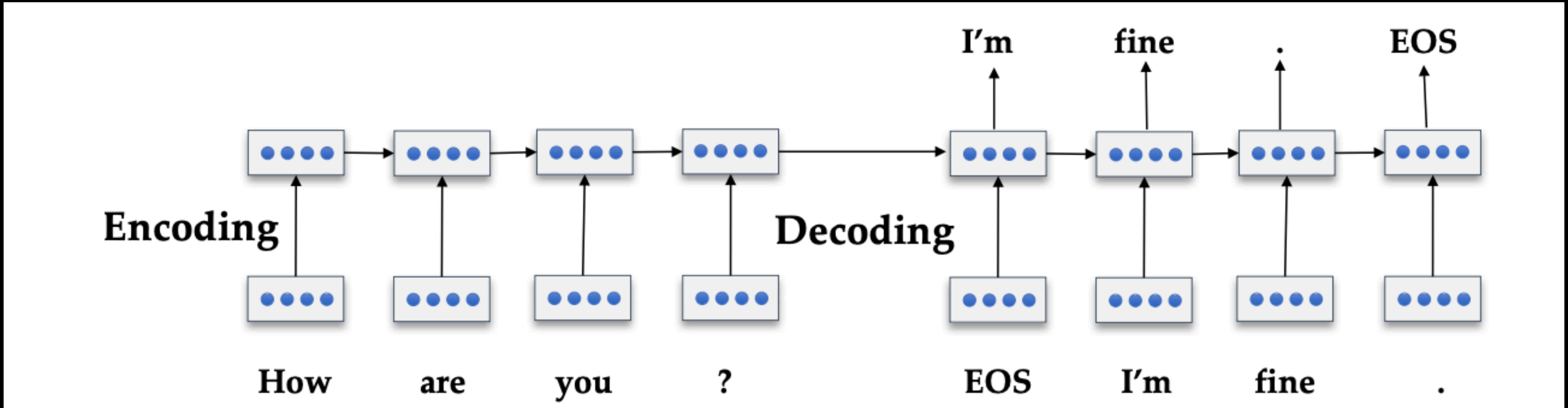
Men are all alike.
IN WHAT WAY
They're always bugging us about something or other.
CAN YOU THINK OF A SPECIFIC EXAMPLE
Well my boyfriend made me come here.
YOUR BOYFRIEND MADE YOU COME HERE
He says I'm depressed much of the time.
I AM SORRY TO HEAR YOU ARE DEPRESSED
..
WHO ELSE IN YOUR FAMILY TAKES CARE OF YOU?
My father
YOUR FATHER
You are like my father in some ways.
WHAT RESEMBLANCE DO YOU SEE
You are not very aggressive but I think you don't want me to notice that.
WHAT MAKES YOU THINK I AM NOT AGGRESSIVE
You don't argue with me.
WHY DO YOU THINK I DON'T ARGUE WITH YOU
You are afraid of me.
DOES IT PLEASE YOU TO BELIEVE I'M AFRAID OF YOU
My father is afraid of everybody.
WHAT ELSE COMES TO MIND WHEN YOU THINK OF YOUR FATHER
Bullies.
DOES THAT HAVE ANYTHING TO DO WITH THE FACT THAT YOUR BOYFRIEND MADE YOU COME HERE

Frameworks for conversational agents: Corpus based

- Information Retrieval
  - Return the most relevant response from a corpus of collected conversations
  - Uses similarity metrics to rank responses
  - Similar to Question Answering systems (focused on a single response)

Frameworks for conversational agents: Corpus based

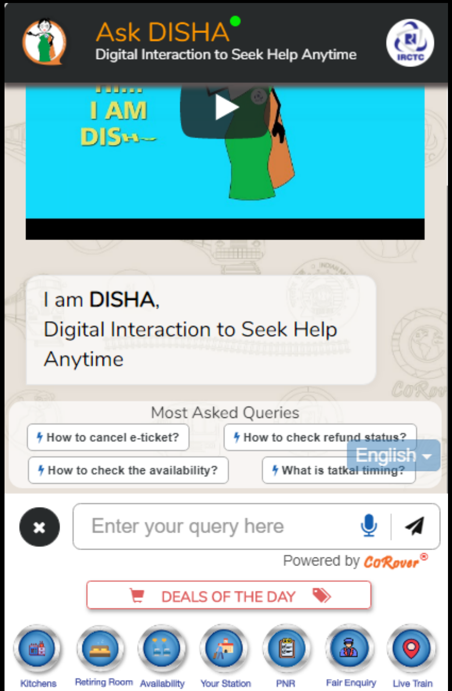
- Encoder Decoder chatbots
  - Modern day sequence-to-sequence models, reinforcement learning etc.

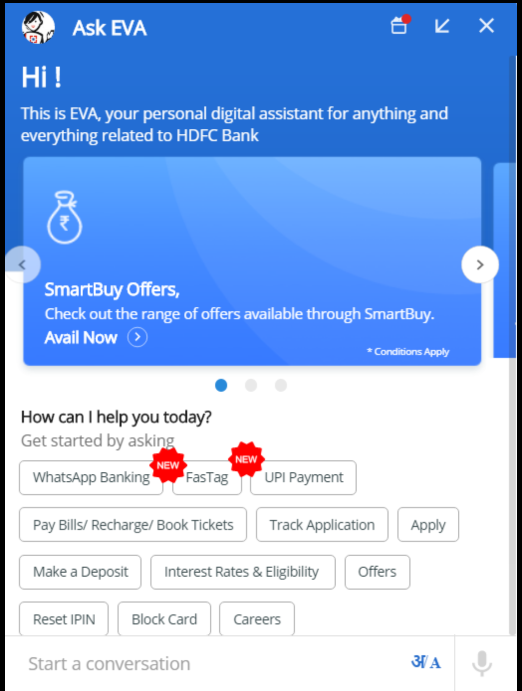


3. Task Based Chatbots

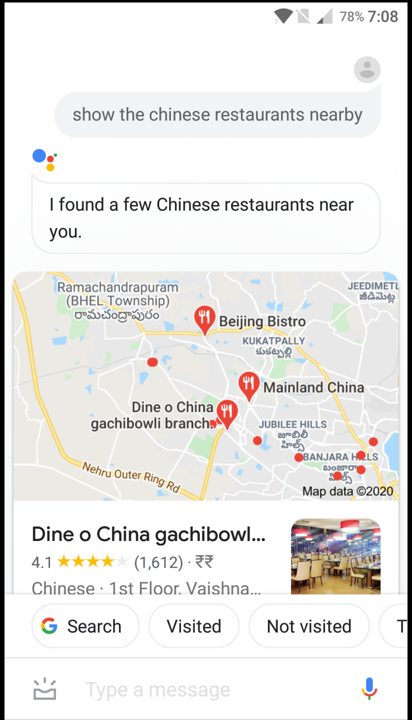
Types of dialog agents: Task Based Dialog Agents

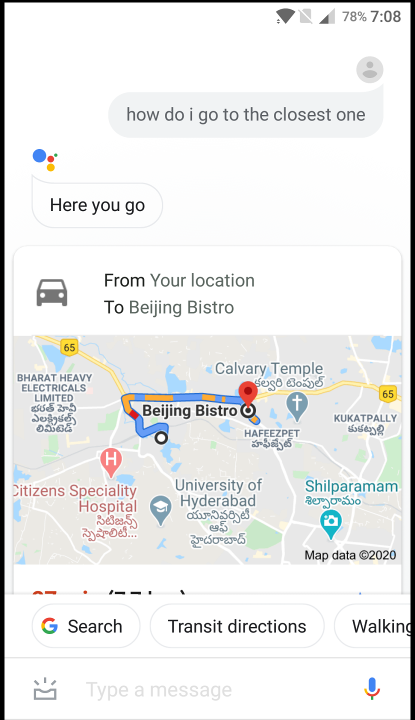
- Modern day enterprise chatbots, designed to help customers in fulfilling their tasks



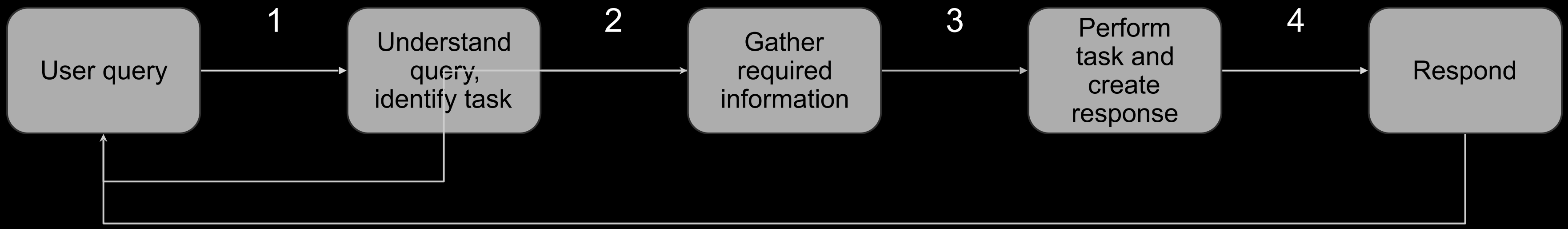


A Sample Conversational Task





Creating a modern day task oriented chatbot



- Based on Dialog- State architecture

1. Understand the query- ML approach

- Please suggest a good Chinese restaurant nearby for lunch
- Which place serves the best hakka noodles nearby
- Understanding human language
    - Convert syntactic framework to statistical framework
        - Conditional Random Field, Hidden Markov Model
    - Emulate human thinking- neural networks
        - Recurrent Neural Networks (RNN), Long Short-Term Memory network (LSTM), Bidirectional Encoder Representations from Transformers (BERT)

1. Identify the task

- Intent
  - Identifying what to do- **intent classification**
  - Suggest a restaurant, booking a table at a restaurant
- Entity
  - Parameters required for the task; objects in a query- **named entity recognition**
  - Location
  - Chinese
  - Please suggest a good Chinese restaurant nearby for lunch
  - Which place serves the best hakka noodles nearby

1. Identify the task- Intent Classification

- Collect training sentences for each intent

Text	Intent
Please reserve a table at a restaurant	restaurant_booking
Can you book a table at ITC Kohenur for dinner today	restaurant_booking
Please cancel my flight for tomorrow	flight_cancel

- Convert words to vectors
  - Tf-idf
  - Word embeddings

1. Identify the task- Intent Classification

- Term frequency- inverse document frequency matrix

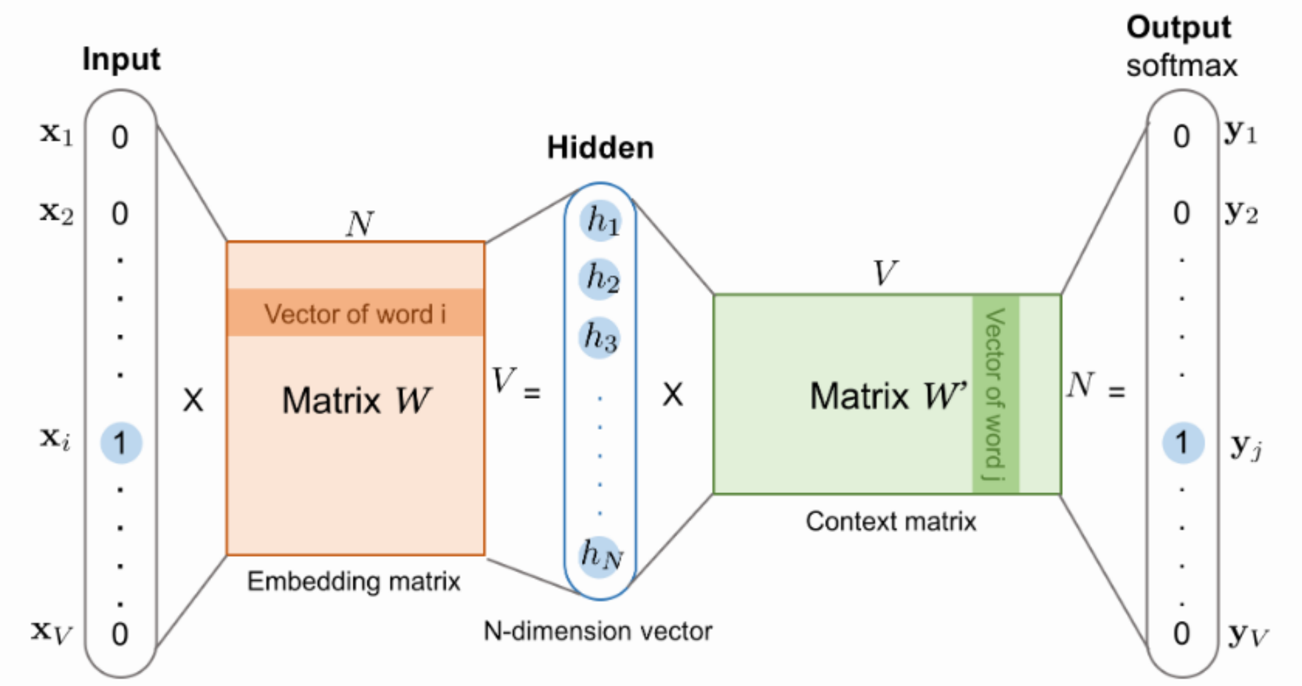
$$w_{i,j} = tf_{i,j} \times \log\left(\frac{N}{df_i}\right)$$

$tf_{i,j}$ = number of occurrences of i in j
df_i = number of documents containing i
N = total number of documents

	0	1	2
at	0.393511	0.257322	0.000000
book	0.000000	0.338348	0.000000
can	0.000000	0.338348	0.000000
cancel	0.000000	0.000000	0.440362
dinner	0.000000	0.338348	0.000000
flight	0.000000	0.000000	0.440362
for	0.000000	0.257322	0.334907
itc	0.000000	0.338348	0.000000
kohenur	0.000000	0.338348	0.000000
my	0.000000	0.000000	0.440362
please	0.393511	0.000000	0.334907
reserve	0.517420	0.000000	0.000000
restaurant	0.517420	0.000000	0.000000
table	0.393511	0.257322	0.000000
today	0.000000	0.338348	0.000000
tomorrow	0.000000	0.000000	0.440362
you	0.000000	0.338348	0.000000

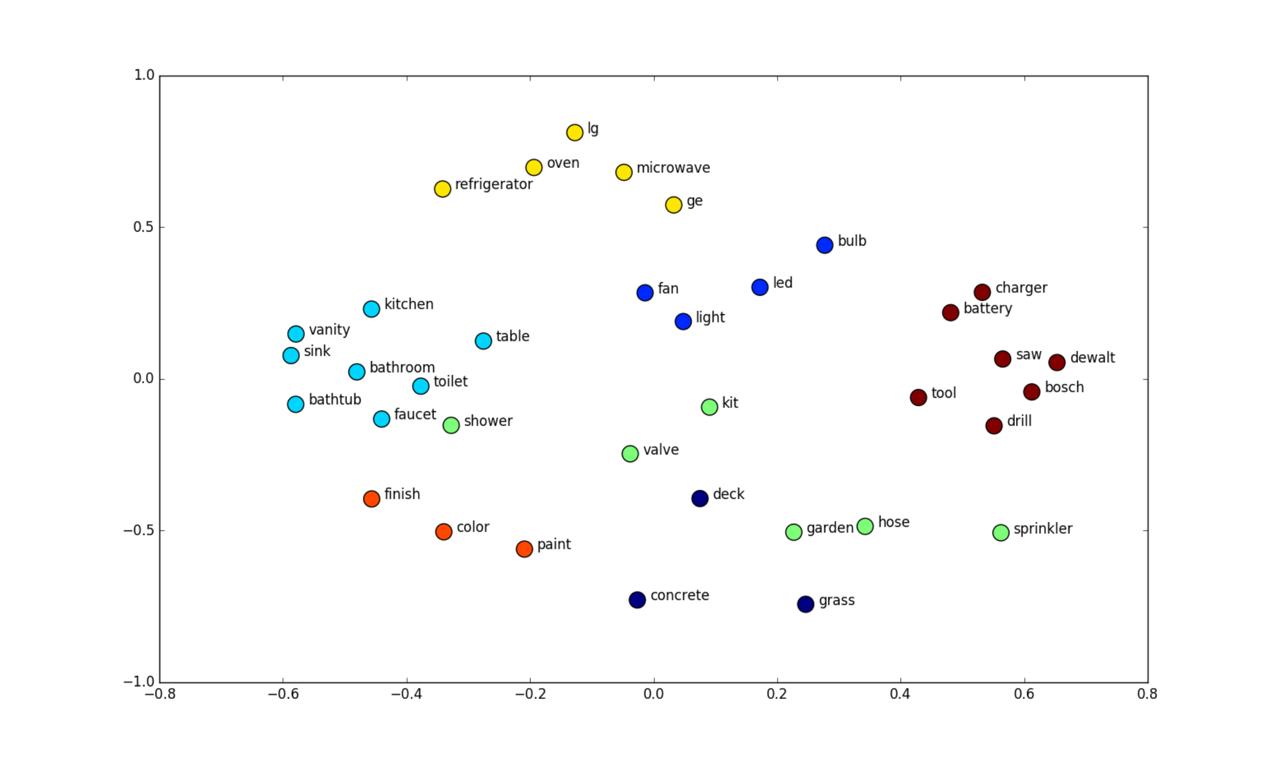
1. Identify the task- Intent Classification

- Word embeddings



1. Identify the task- Intent Classification

- Word embeddings



1. Identify the task- Intent Classification

- Train a text classification model- Naive Bayes Classifier

Likelihood

Class Prior Probability

$$P(c \mid x) = \frac{P(x \mid c)\,P(c)}{P(x)}$$

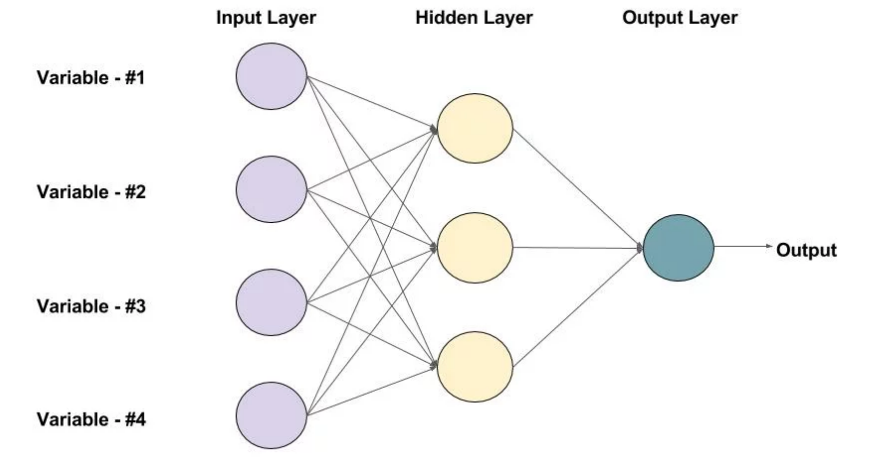
Posterior Probability

Predictor Prior Probability

$$P(c \mid \mathrm{X}) = P(x_1 \mid c) \times P(x_2 \mid c) \times \cdots \times P(x_n \mid c) \times P(c)$$

1. Identify the task- Intent Classification

- Deep learning models for text classification
    - Feed forward networks



An example of a Feed-forward Neural Network with one hidden layer (with 3 neurons)

2. Gather required information

- Dialog state tracker
- Intent- book a table at a restaurant
- Entities required- number of guests, location, date and time
- Prompt the user for required information

Please reserve a table at Taj Krishna for dinner today

Sure, how many guests would you bring along?

Just me and my wife

Booked a table for 2 at Taj Krishna at 9 pm today

I received a damaged product

May I know the order ID?

XXXXX

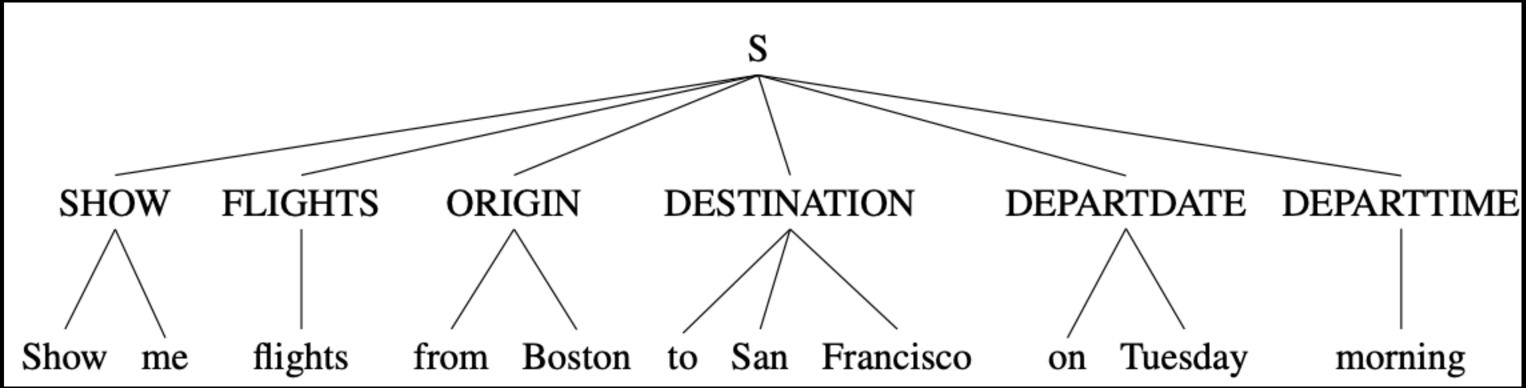
We're sorry about that, we could either send you a replacement or offer refund

Send another piece please

Placed another order for free with order id YYYYYY

2. Gather Information via Slot Filling

Show me morning flights from Boston to San Francisco on Tuesday



2. Gather Information via Slot Filling: Rule-based

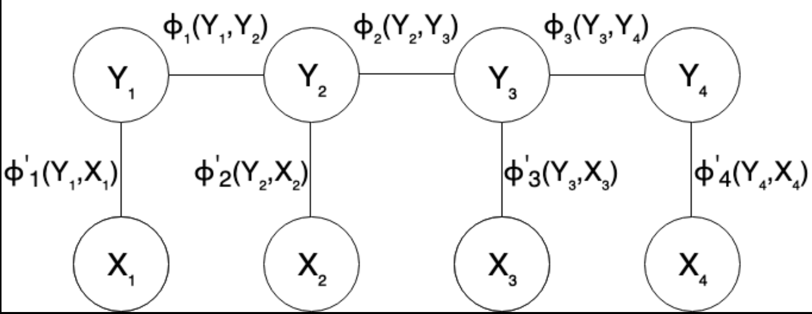
- Rule-based slot filling (works for closed vocabulary)

SHOW → show me | i want | can i see|...
DEPART_TIME_RANGE → (after|around|before) HOUR | morning | afternoon | evening
HOUR → one|two|three|four...|twelve (AMPM)
FLIGHTS → (a) flight | flights
AMPM → am | pm
ORIGIN → from CITY
DESTINATION → to CITY
CITY → Boston | San Francisco | Denver | Washington

2. Gather Information via Slot Filling: Machine Learning

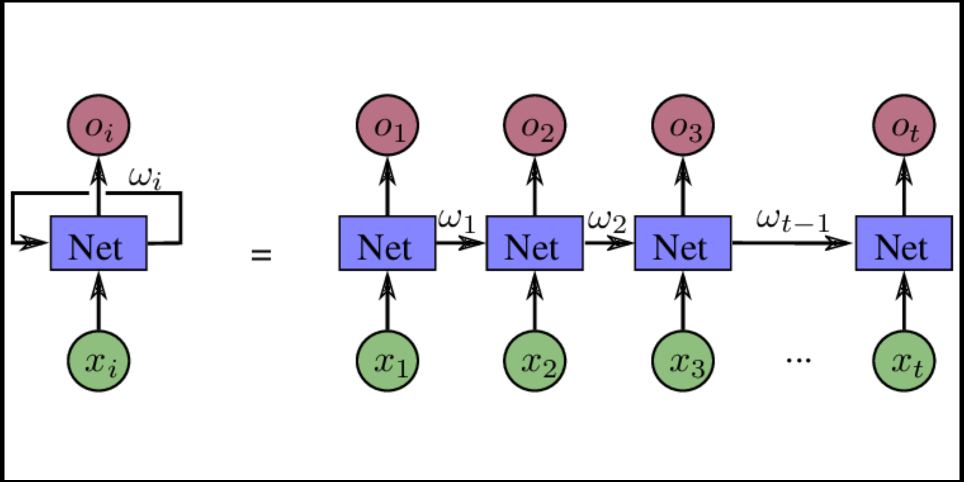
- Named Entity Tagging Problem (We know how to train such a system!)

```
Colchicine B-DRUG
was O
one O
of O
the O
last O
drugs O
took O
that O
have O
as O
side B-AE
effects I-AE
most O
```



2. Gather Information via Slot Filling

- Deep learning models
  - Recurrent Neural Network
  - Long Short-term memory network
  - Transformers, Attention models



3. Perform the task

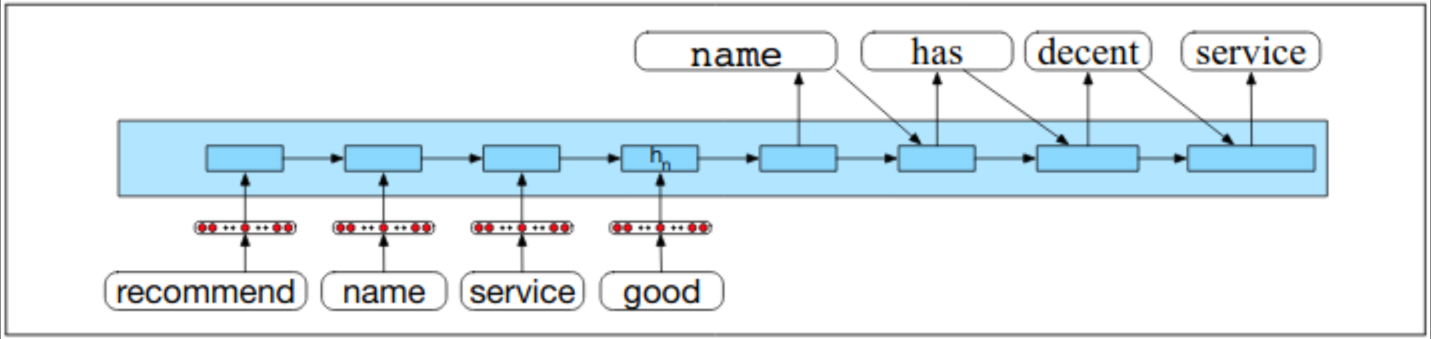
- Backend operations
- Database queries
- Running a recommendation algorithm taking the entities as input
- Send a request to the bookings API with all the collected parameters
- Place an order of product ID free of cost

4. Respond

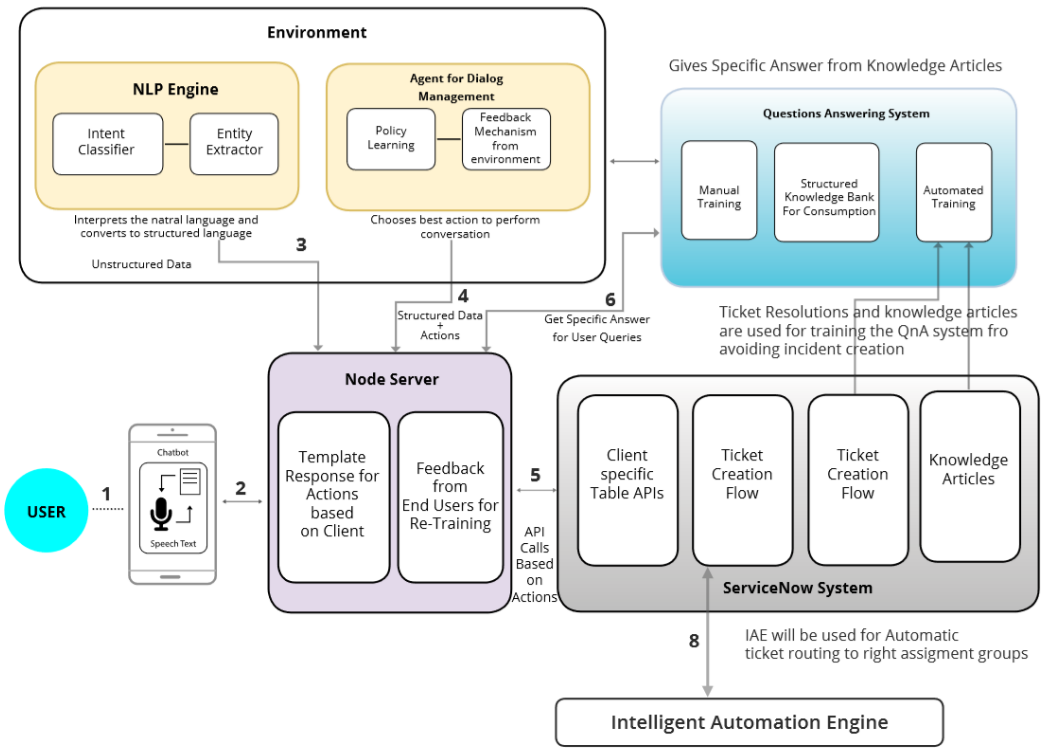
- Predefined templates for responses
  - Show a list of restaurants in descending order of match
  - Use the slots to fill the attributes in the template
- Generating response
  - Language model
  - Natural Language Generation

Natural Language Generation (NLG)

- Content planning (what to say)
- List of entities, information to be shown
- Sentence realization (how to say it)
    - Encoder- decoder models



Putting it together - Generic Architecture



https://blog.vsoftconsulting.com/blog/understanding-the-architecture-of-conversational-chatbot

Evaluating a Chatbot

- Human based evaluation
- Pre-defined dataset of responses
- Task Completion Rate
- Efficiency Cost
  - cost benefits from automation
  - Reduction of human errors
- Quality Cost
  - user rating and convenience

Ethical Issues of a Chatbot

- Challenges
  - Governance & Compliance
  - Biases
  - Abuse
  - Privacy
- Monitor and track your
  - Data
  - Rules
  - Responses
- Iteratively design and test on real users

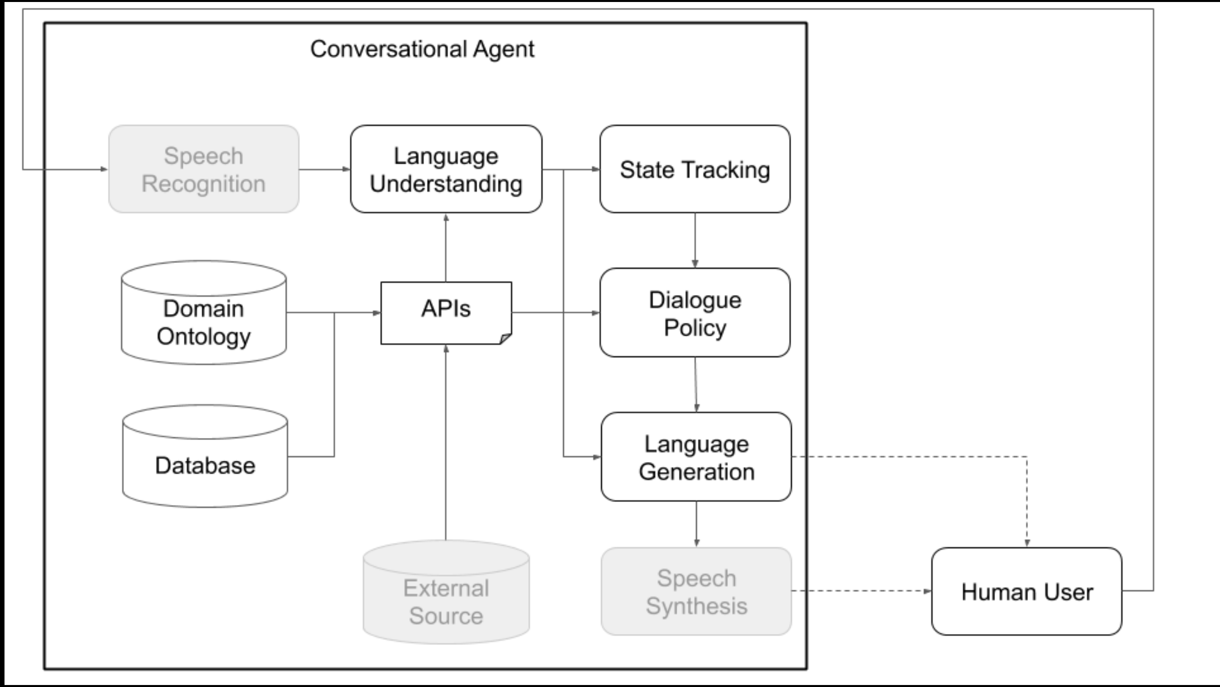
4. Build your own bot!

Designing a good chatbot

- Start with a purpose
- Decide the kind of bot (a rule-based or corpus-based)
- Complexity of the underlying NLP engine
- Understand limitations of your backend
- Check for the language/ personality of your bot
- Design a flowchart for the conversation (always have a fallback)
- Understand the ethical implications of your bot
- Test with real-users before release
- Build ways to monitor your bot after release

Creating a chatbot from scratch

- Open source frameworks- Uber's Plato



Plato (open source)

- Pros
  - Modular framework
  - Highly customizable
  - On-premise
- Cons
  - Requires handling of infrastructure
  - Learning curve
  - Requires knowledge of NLP modules

Industry Vendors

- Google- Dialogflow
- Amazon- Amazon Lex
- Microsoft- Azure Bot Service
- Pretrained language models and text classifiers- requires minimal retraining
- Plugins and extensions- slack, telegram

Dialogflow- Pros

- Pros
  - Low learning curve
  - Ideal for small bots
  - Multiple integrations with external services
  - State of the art NLP models
- Cons
  - Gets messy beyond a point
    - Handling 100 intents, with a few follow up intents for each of those intents?
  - Customization
    - Domain specific language models + ontology
  - Retraining based on users’ behavior is tricky and involves manual work

5. DialogFlow Workshop

Vivek Karna (Senior Data Scientist , Predera)