Stackable Certificate Programme in Intelligence Reasoning Systems

Cognitive Systems

Introduction of Cognitive Systems

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Learning Outcomes

- **Identify** appropriate business scenarios requiring systems that extends human expertise and/or cognition
- **Gain** a practical understanding of the concepts and techniques that enable systems to mimic human reasoning, and/or interact with human naturally
- **Create** suitable design using common architectures of such applications after analysis of business requirements
- **Develop/integrate** and **evaluate** such systems using existing libraries.

What is the course NOT about

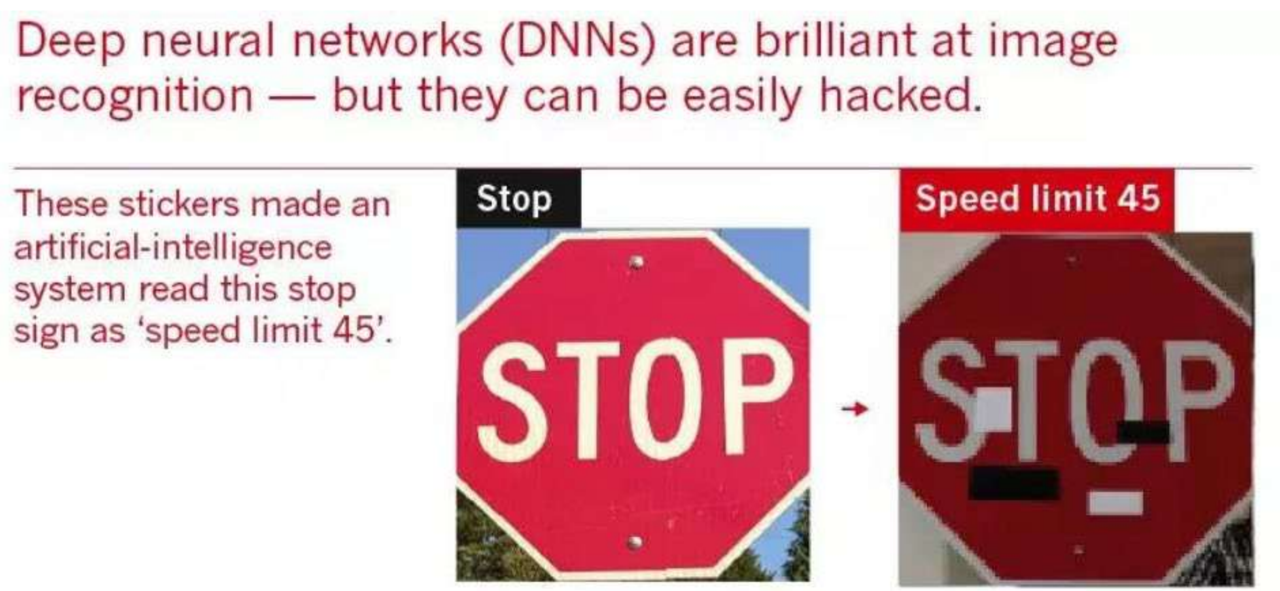
- **Understanding *everything* about cognitive/AI systems**
  - There's more to *AI techniques* than what's in this course

- **Building an Amazon Alexa Skill under N minutes with X language**
  - The course is more on how Alexa works than to build specific skills

- **We won't build AlphaGo/Watson in this course**
  - *Deeplearning* will be deeply explained in advanced modules

Feedbacks to the Cert of IRS

- *“Too much time given to this module and not to ML/Deep learning”*
  - Knowledge driven & data driven
  - Differentiating



Feedbacks to the Cert of IRS

- *"Abstractness of the concepts."*
  - The power to abstract is fundamental to innovation
  - Finding an effective design for a system implementation.

- *"This course is setup in very high level and covered very wide area which is tough for understand."*
  - It is designed to be broad
  - Transition from Rule/Knowledge based system to machine learning based system

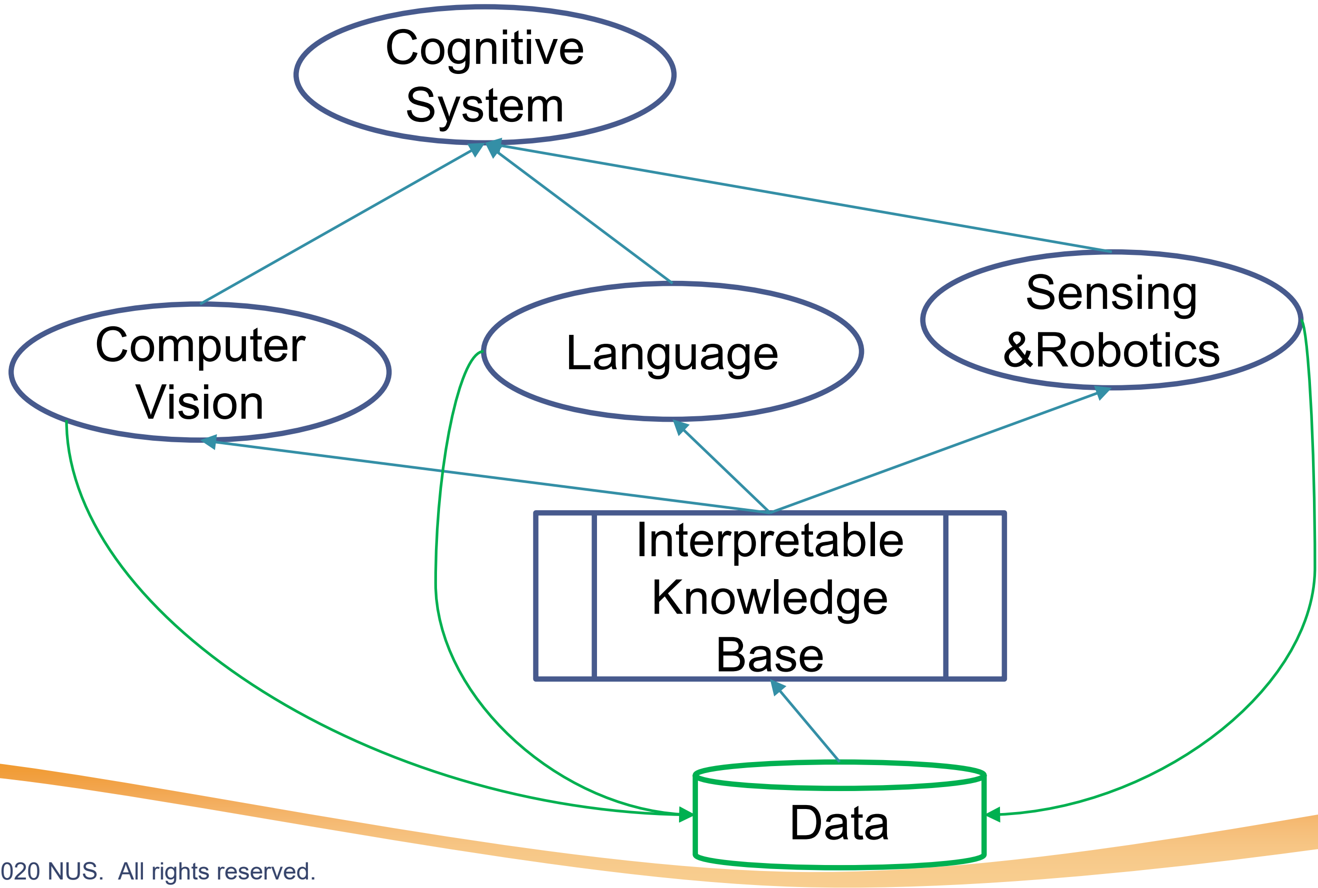
Agenda

- **Introduction of Cognitive Systems**
  - Definition
  - Classification
  - Architectures
- Cognitive Knowledge Representation and Reasoning
- Case Study **Alexa**
- Workshop: Introduction to **Google Dialogflow**

What are Cognitive Systems (CS)?

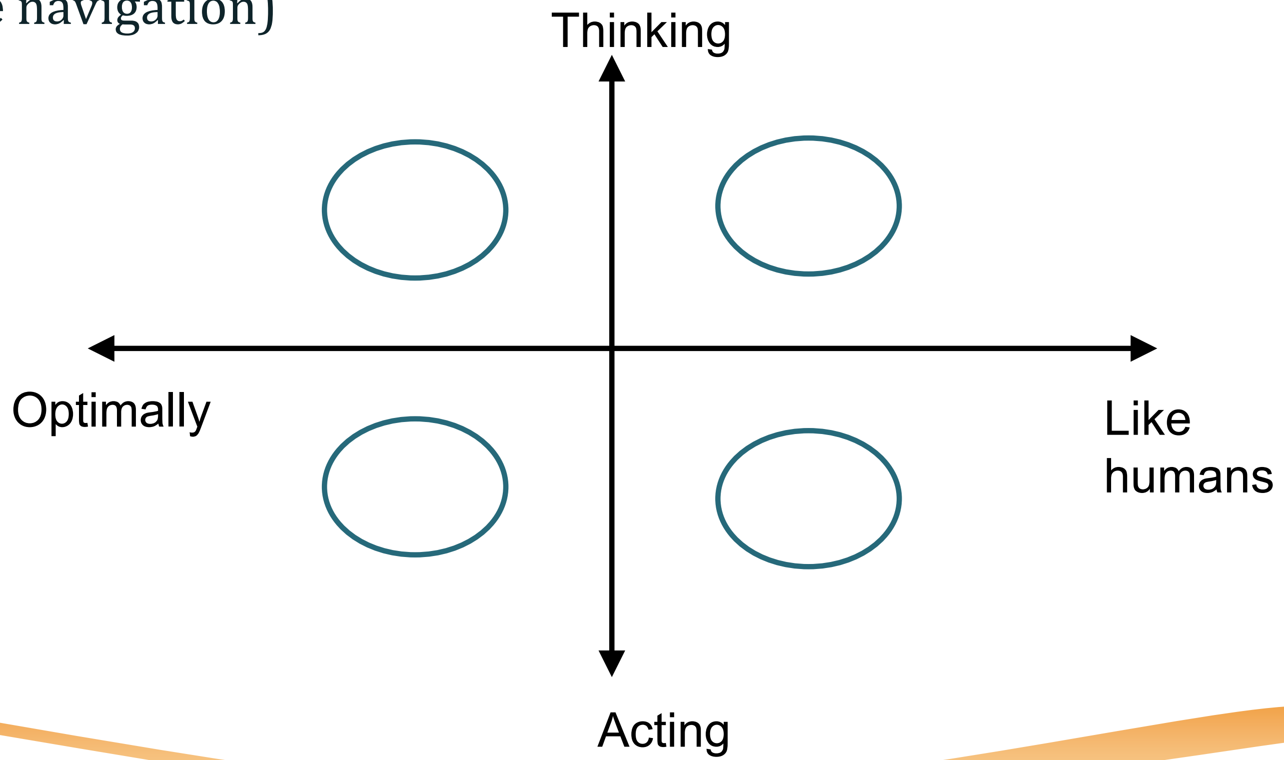
- **Cognitive Systems:**

Systems that exhibit **human-like** intelligence through processes like **learning**, **reasoning**, and **memory**



What do we expect AI to perform

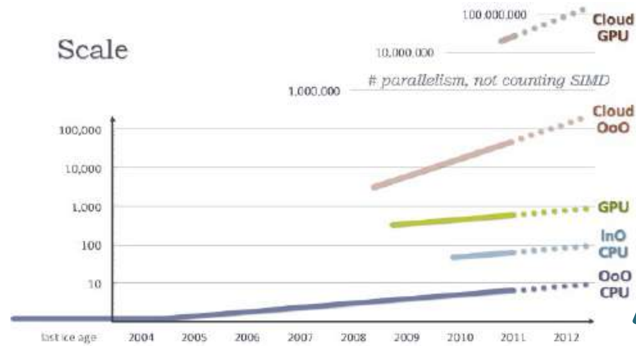
1) Roomba (Automated vacuum)
2) Robot-Soccer
3) SIRI
4) Google Maps (route navigation)



Overview of History

- Alan Newell and Herbert Simon created foundational AI tools and demonstrations programs in 1960s' and 1970s'
- **Neural Network (Perceptron)** invented in 1957 and "killed" in 1969
- Expert Systems and cased based reasoning in 1980s'
- Statistical Machine learning in 2000s'
- Deep Learning in 2010s'

Catalysts of Progress in Cognitive Systems

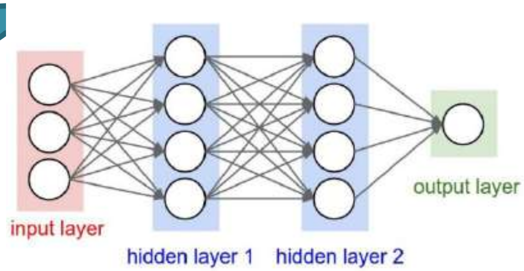


Moore's Law

Big Data

The Cloud

Algorithms



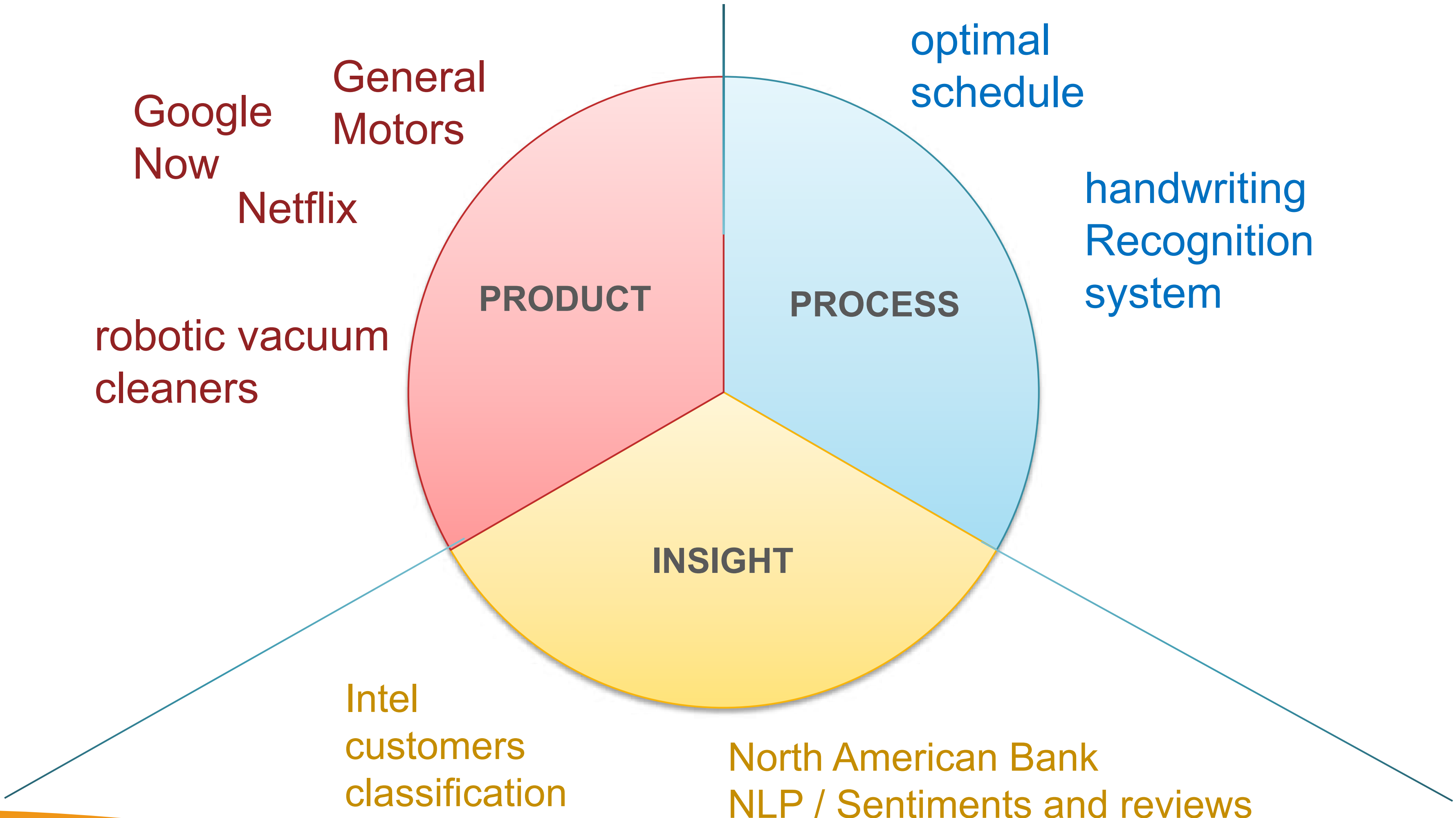
How to apply AI

- **Product** applications embed cognitive technologies in a product or service providing in customer benefits like ease of use, simplicity, or automation.

- **Process** applications embed the technology in an organization's workflow automating some tasks to get things done faster, better, cheaper, or some combination.

- **Insight** applications use advanced analytic capabilities and machine learning to uncover insights to make better operational and strategic decisions based on large mounts of data

More examples for Applications



Whether and Where to apply AI

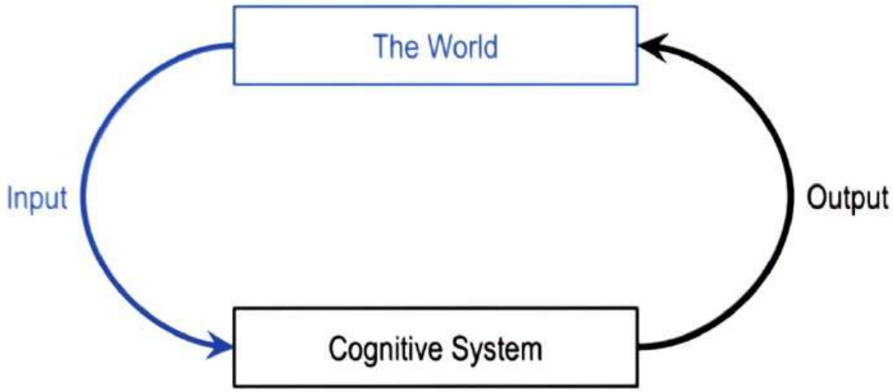
VIABLE	VALUABLE	VITAL
Vison Speech Handwriting Forecasting Document review Data-driven decisions Scheduling	specialists in rare cancers drilling engineers in oil medical decision-making financial decision-making deliver features or experiences that your customers care about.	spam filtering fraud detection processing large volumes of handwritten or printed forms analyzing large amounts of social media text

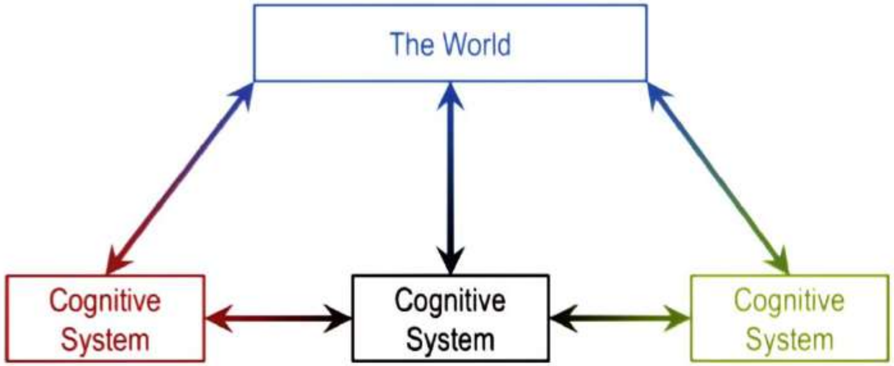
- 3V- Framework

Agenda

- Introduction of Cognitive Systems
  - Definition
  - Classification
  - **Architectures**
- Cognitive Knowledge Representation and Reasoning
- Case Study Alexa
- Workshop: Cognitive System Use Cases

Cognitive Systems Architecture





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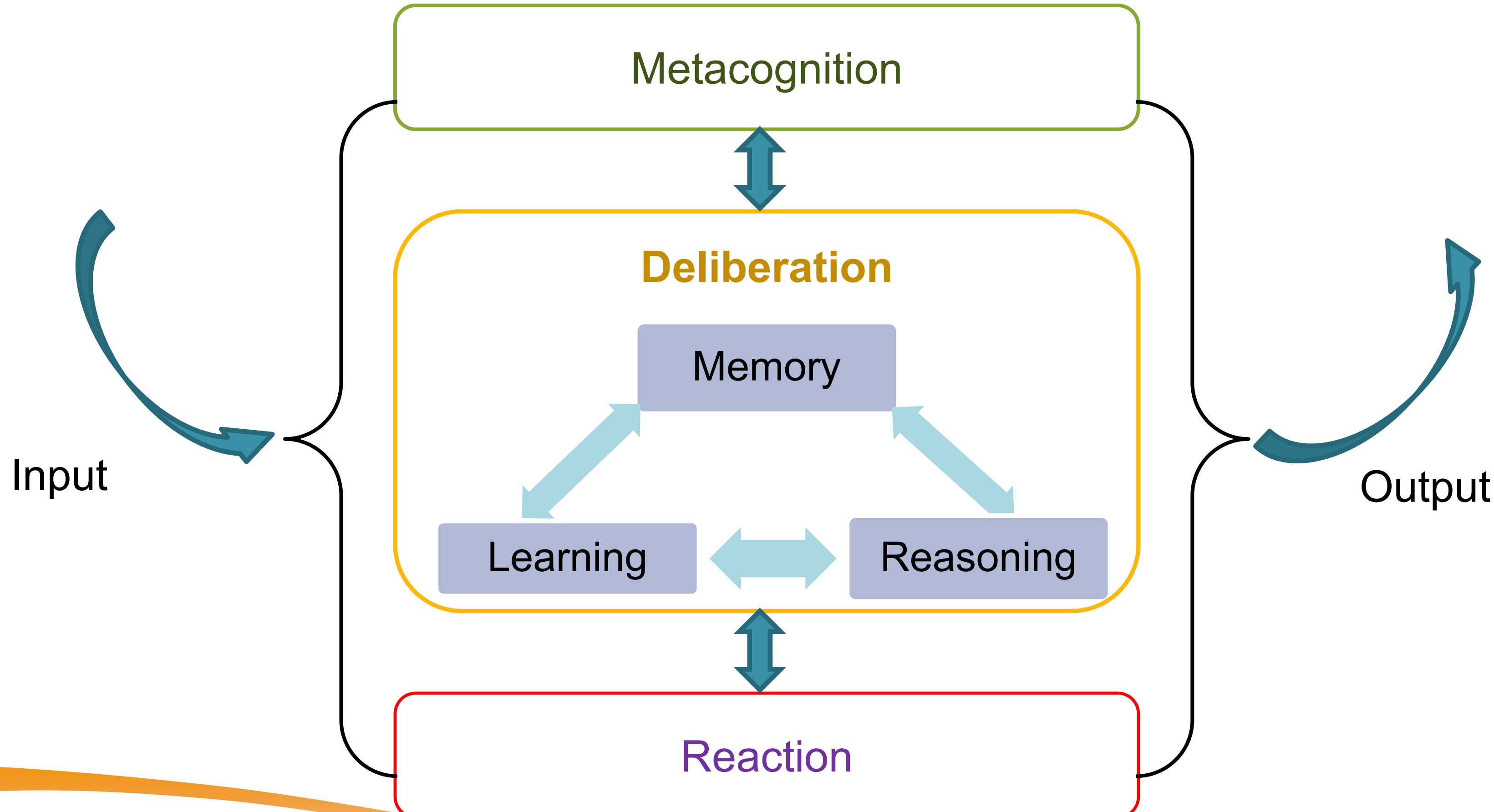
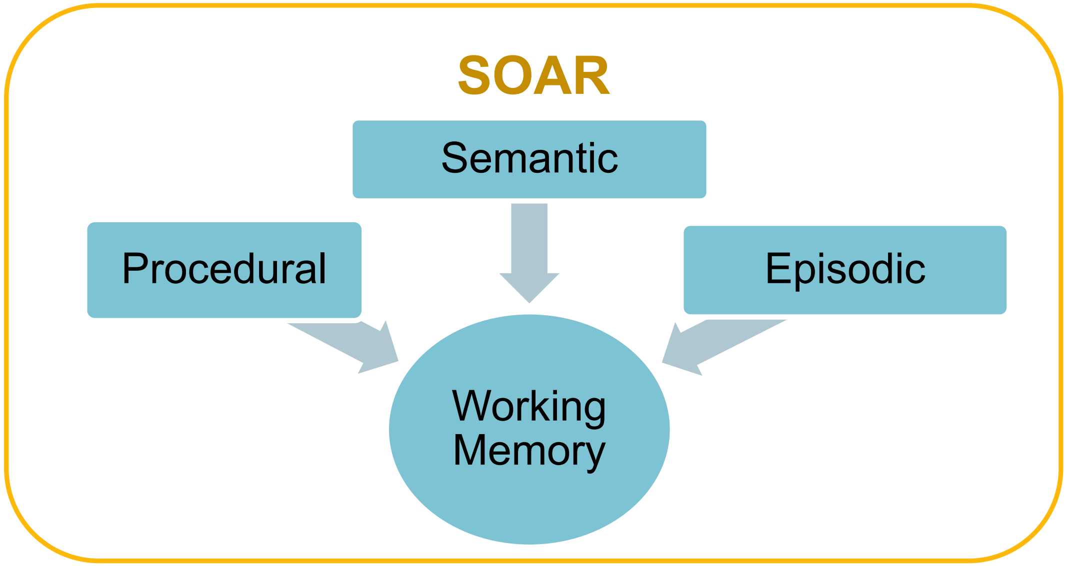
Zoom in to CS Architecture

- Intelligence is about selecting the right kind of action given a particular state of the world.



A classic example of CS Architecture

- By Newell, Laird, 1983 -> **present**
- Representation:
  - Graphs of objects and relations
- Production System
  - Working memory
  - Long-Term Memory
    - Procedural
    - Episodic
    - Semantic



Apply the SOAR Architecture

- Two mugs without graduation

5L 3L

- To get 1 litre water in 3L mug

3L

Apply the Soar Architecture

- What’s in Working Memory?

Initial State
[0,0]

5L 3L

Goal State
[*,1]

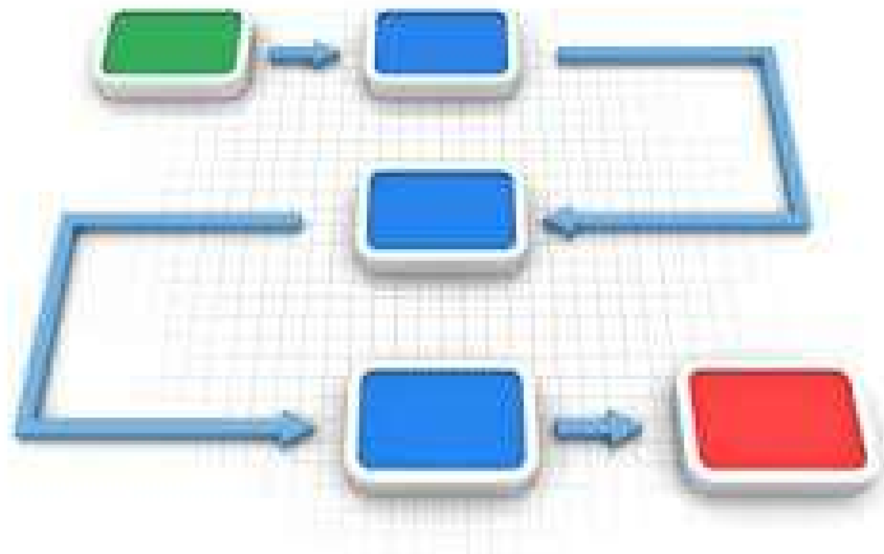
3L

Apply the Soar Architecture

- What's in Working Memory?

Initial State
[0,0]

5L 3L



Goal State
[*,1]

3L

Soar Cognitive Architecture

- Knowledge represented by ***Objects*** and ***Relations***
- Knowledge kept in ***Long-Term Memory***

Fill
Subject : Tab
Object : 3L

Fill
Subject : Tab
Object : 5L

Fill
Subject : 5L
Object : 3L

Fill
Subject : 3L
Object : 5L

Empty
Object : 5L

Empty
Object : 3L

Soar Cognitive Architecture

- Knowledge kept in ***Long-Term Memory***
- States and transitions constructed in ***working memory***

Fill
Subject : Tab
Object : 3L

Fill
Subject : Tab
Object : 5L

Fill
Subject : 5L
Object : 3L

Fill
Subject : 3L
Object : 5L

Empty
Object : 5L

Empty
Object : 3L

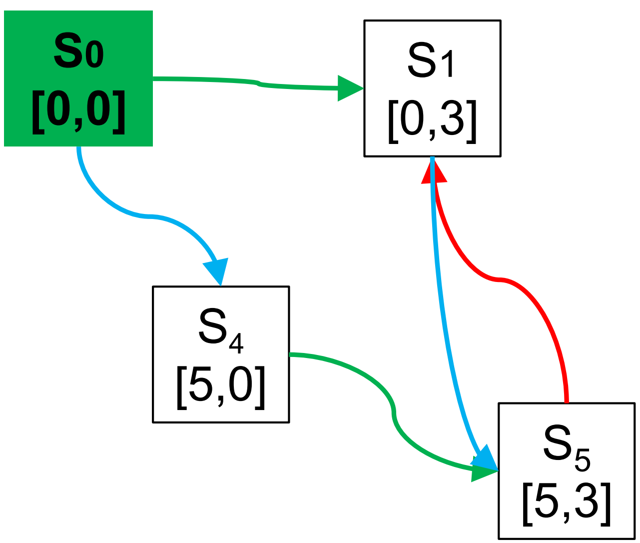
Start State
[0,0]

State N
[?,?]

Goal State
[*,1]

Soar Cognitive Architecture

- Search the ***state space*** constructed by ***Knowledge*** in ***working memory*** to determine the solutions
- How to make a smart move?



S8
[*,1]

Fill
Subject : Tab
Object : 5L

Fill
Subject : Tab
Object : 3L

Fill
Subject : 3L
Object : 5L

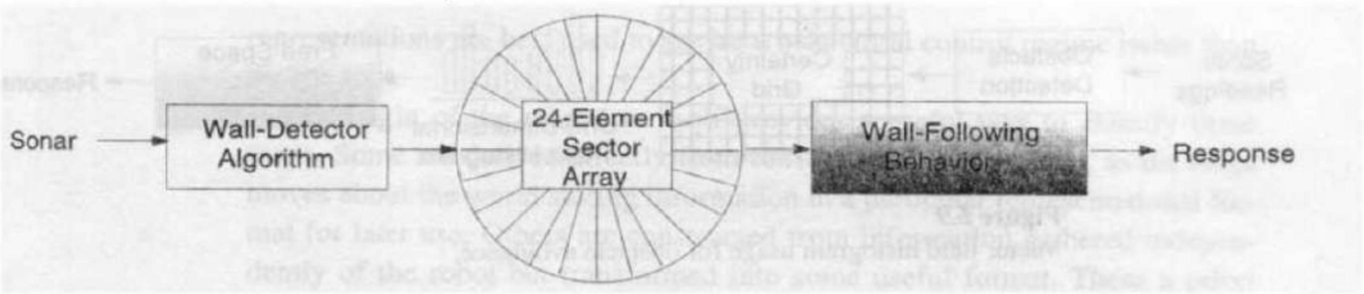
Fill
Subject : 5L
Object : 3L

Empty
Object : 3L

Empty
Object : 5L

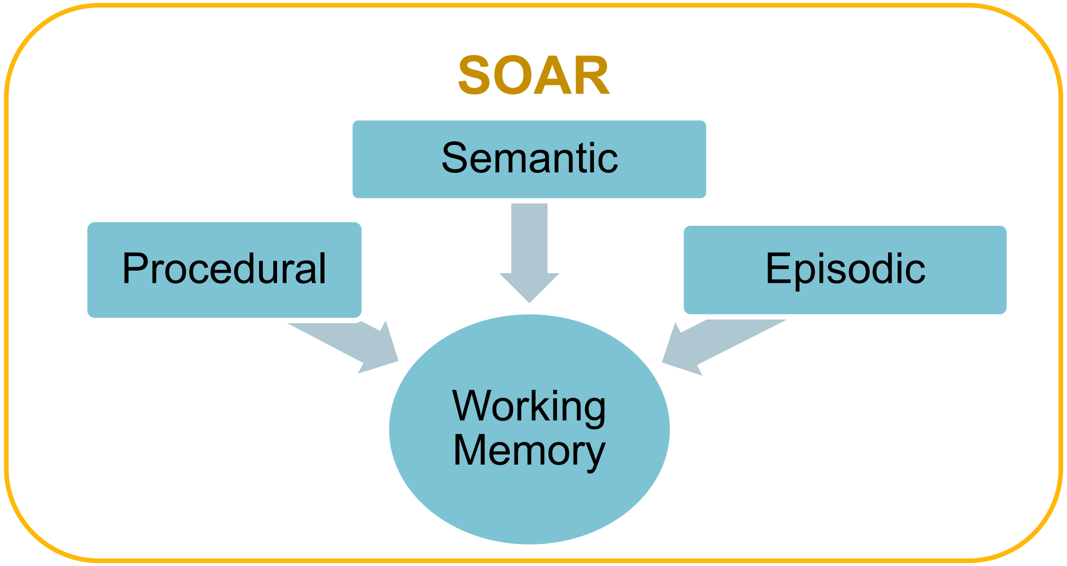
SOAR In Robotics

- Long-Term & Working Memory
  - **Wall memory**
    - Uses an array of elements (ultrasonic sensors) to increase confidence over time that the robot is near a wall
    - The memory readings are then used to support a wall-following behaviour
  - **Action memory**
    - Stores information about both the environment (e.g., wall) and the most recent robot response
    - To get the direction, a weighted average of past responses to bias the immediate reactive response



Review the SOAR

- Knowledge represented by graphs of objects and relations
- Knowledge kept in Long-Term Memory
- States and transitions constructed in working memory
- Search the state space in working memory to determine the solutions



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- Introduction of Cognitive Systems
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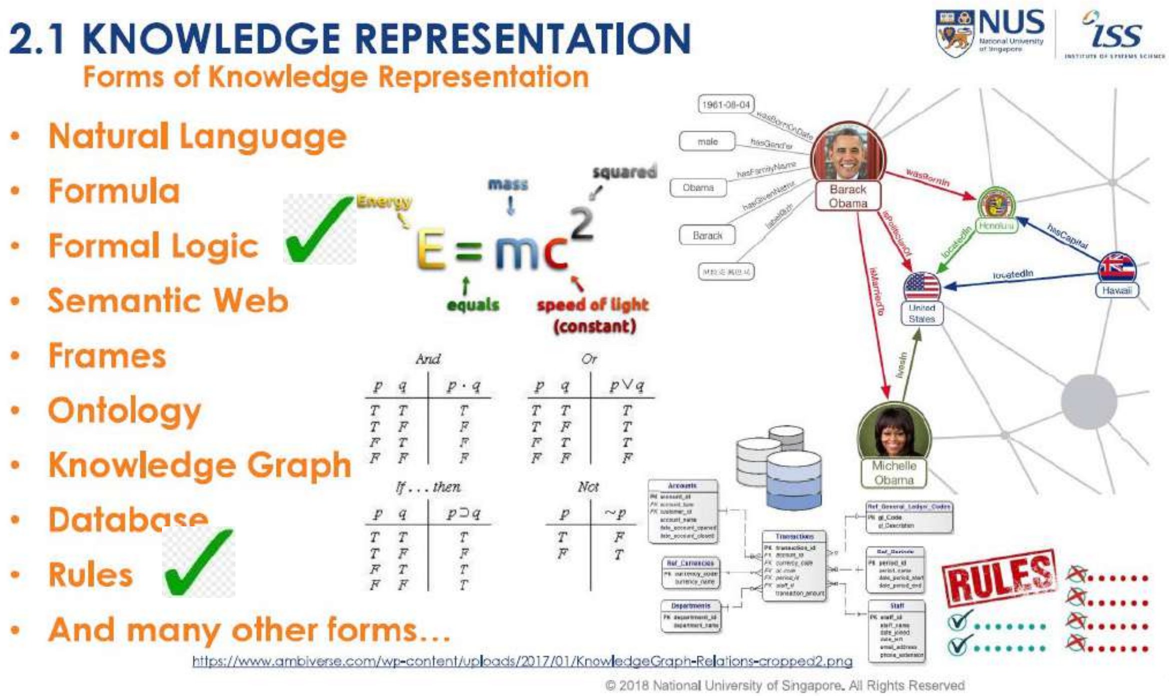
- **Cognitive Knowledge Representation and Reasoning**
  - Semantic Network
  - Generate and Test
  - Frames
  - Common Sense Reasoning
- Case Study Alexa
- Workshop: Introduction to Google Dialogflow

Knowledge Representation and Reasoning

- Recap of NICF- Machine Reasoning course



Knowledge Representation and Reasoning

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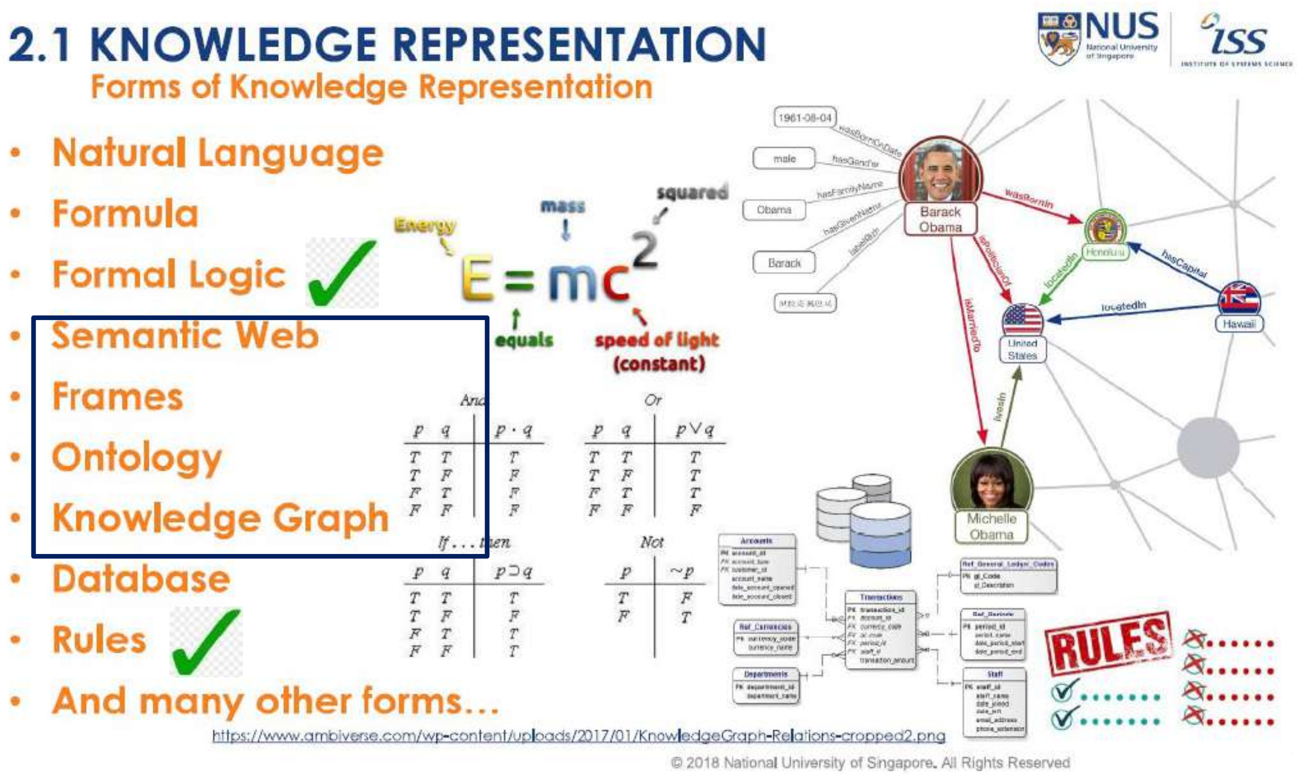


Knowledge Representation

- **Motivation**: To represent information about the world in a form that a computer system can utilize to solve complex tasks

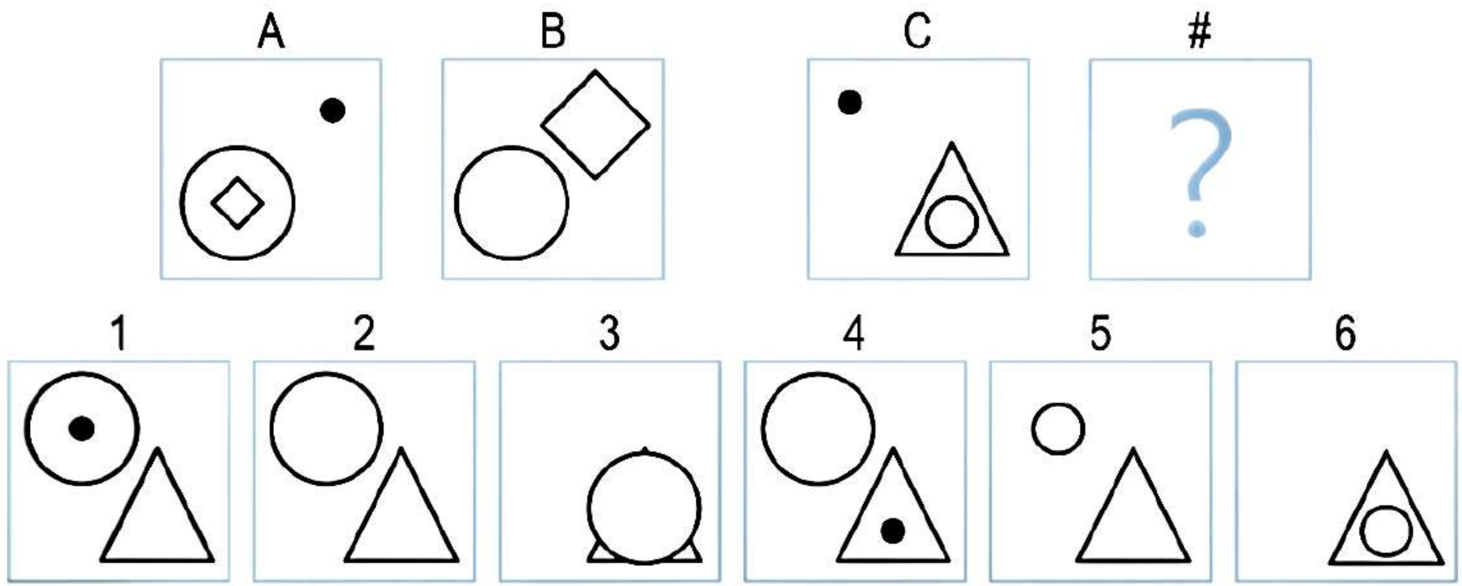
- **Semantic Networks** represents **semantic** relations between concepts in a network
  - WordNet

- **Ontology** representation of a set of ***concepts within a domain*** *(typically* ***common sense*** *domain)* and the relationships between those concepts.
  - ConceptNet

- Knowledge representation goes hand in hand with automated reasoning

Semantic Networks

- If A-> B then C-> ?



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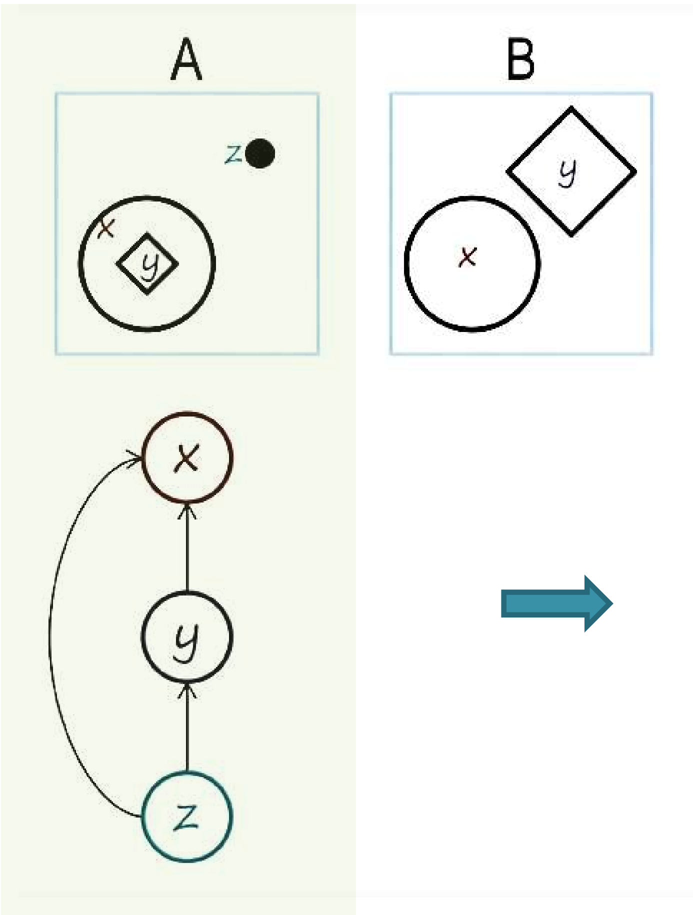
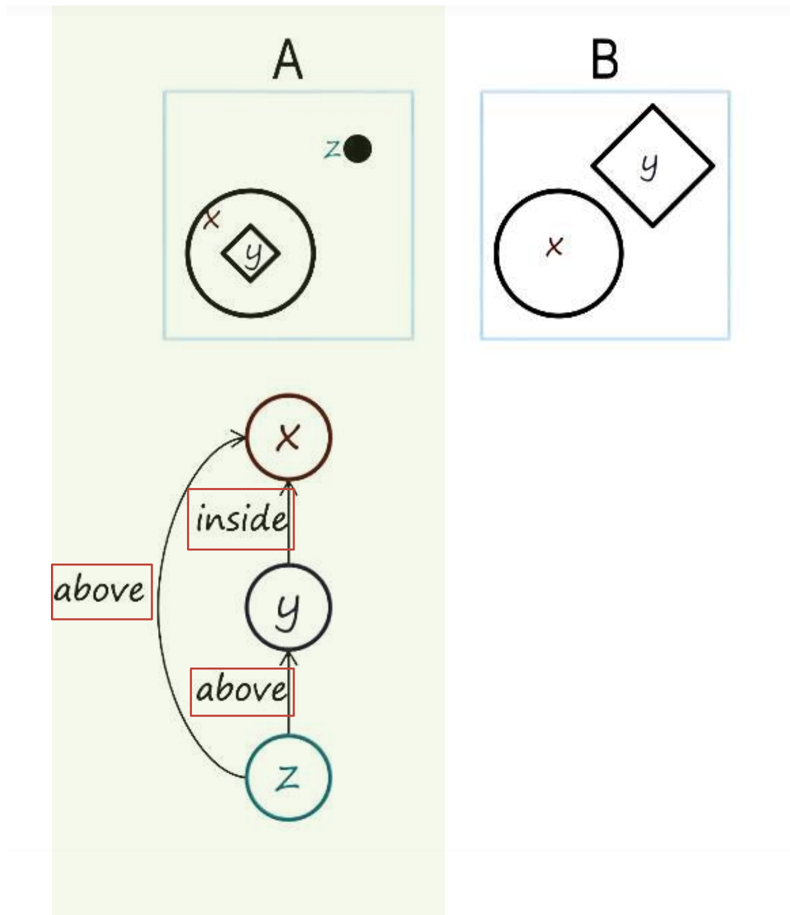
Semantic Networks

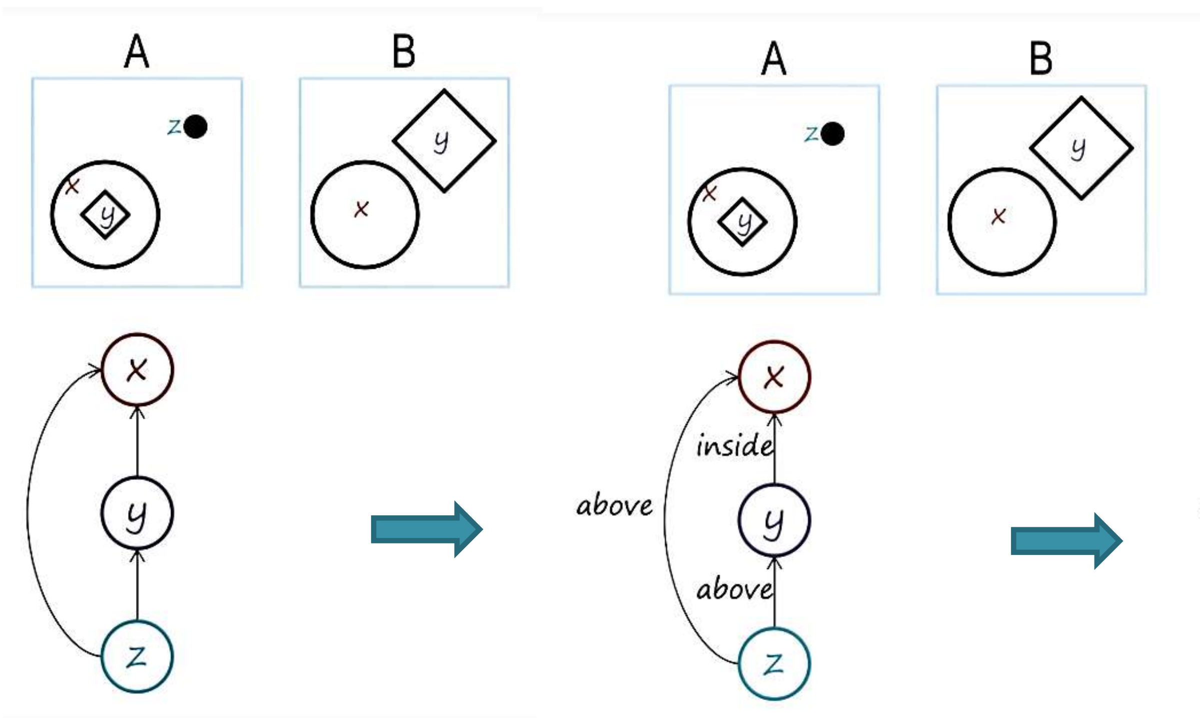


Objects



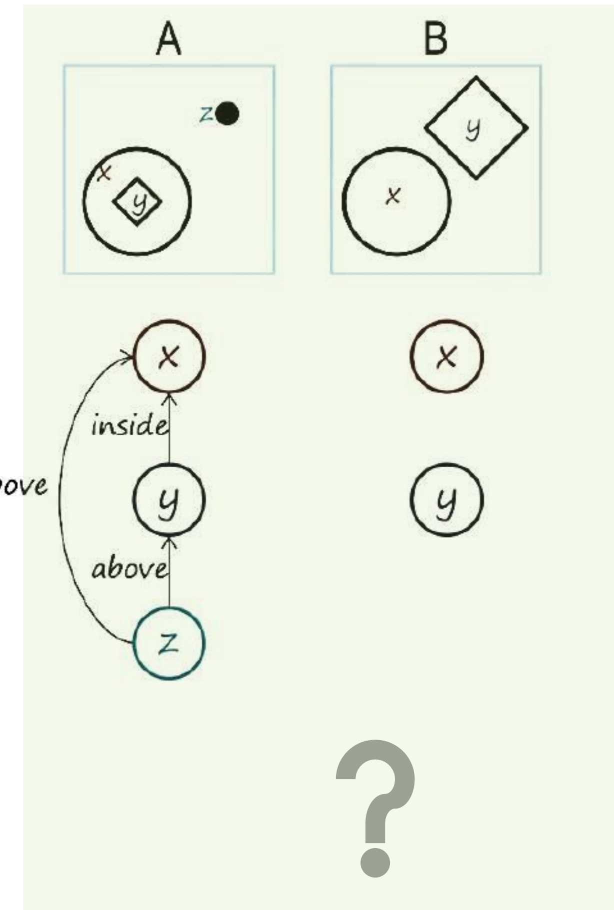
Relationship

Semantic Networks

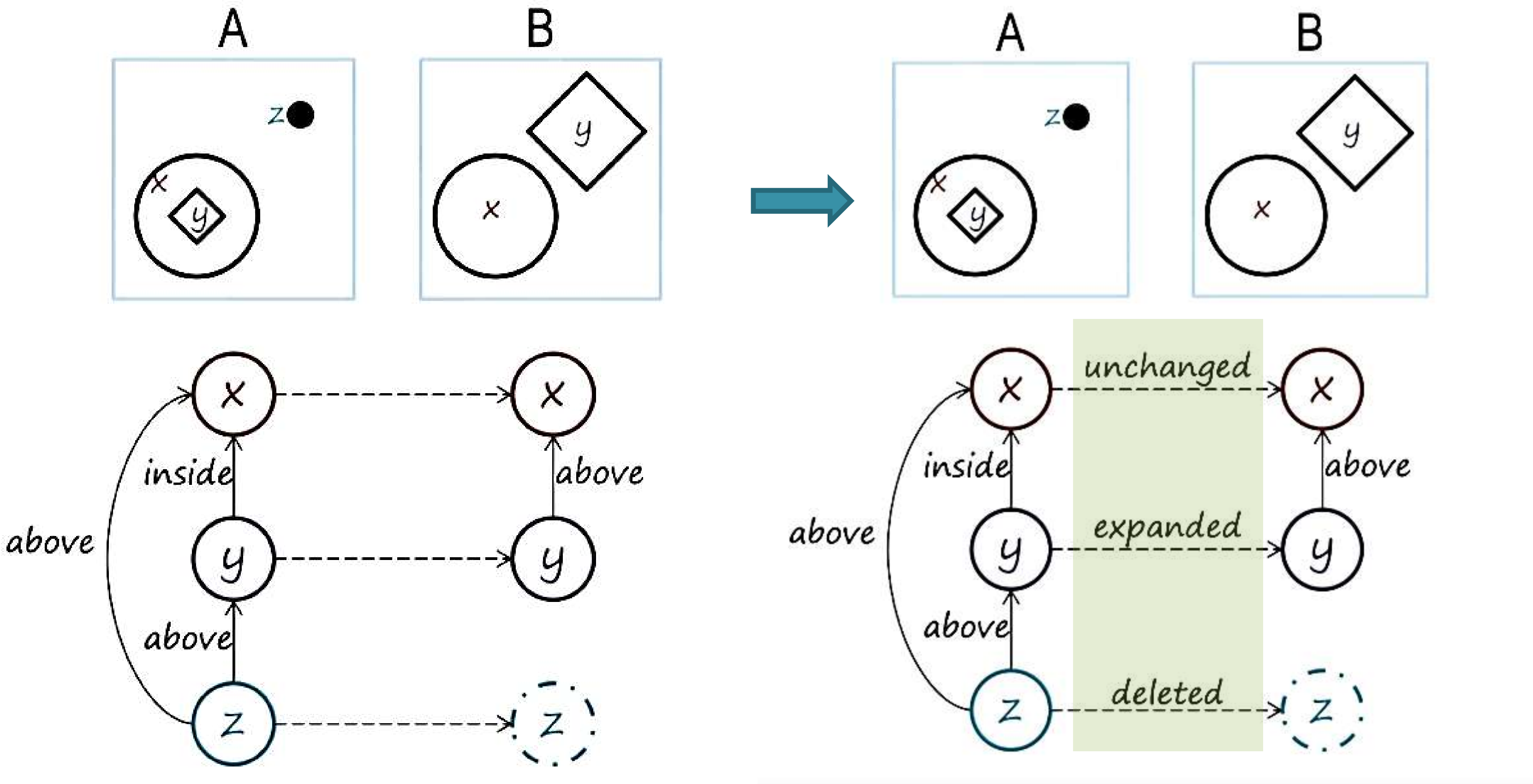


Objects

Relationship



Semantic Networks



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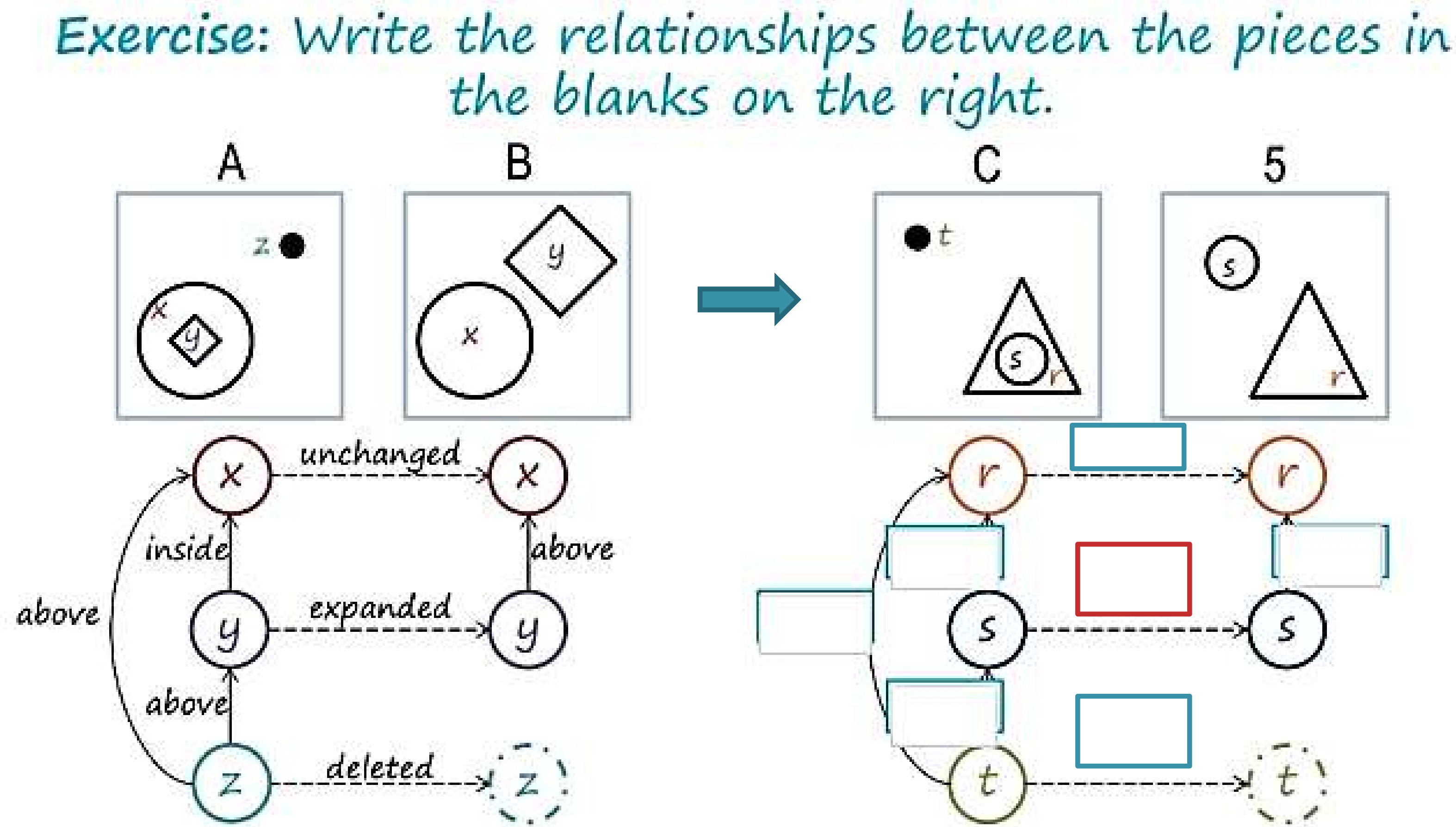
Semantic Networks



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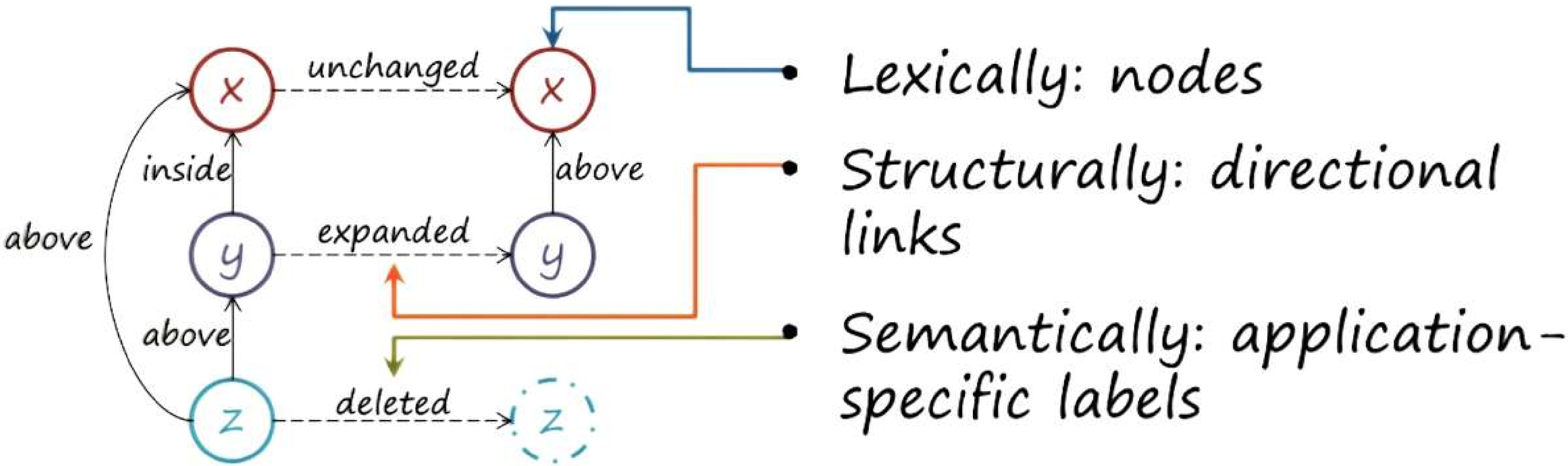
Structure of Semantic Networks



- **Objects** : Vocabulary
- **Links** : directions capturing relationships
- **Labels**: for reasoning

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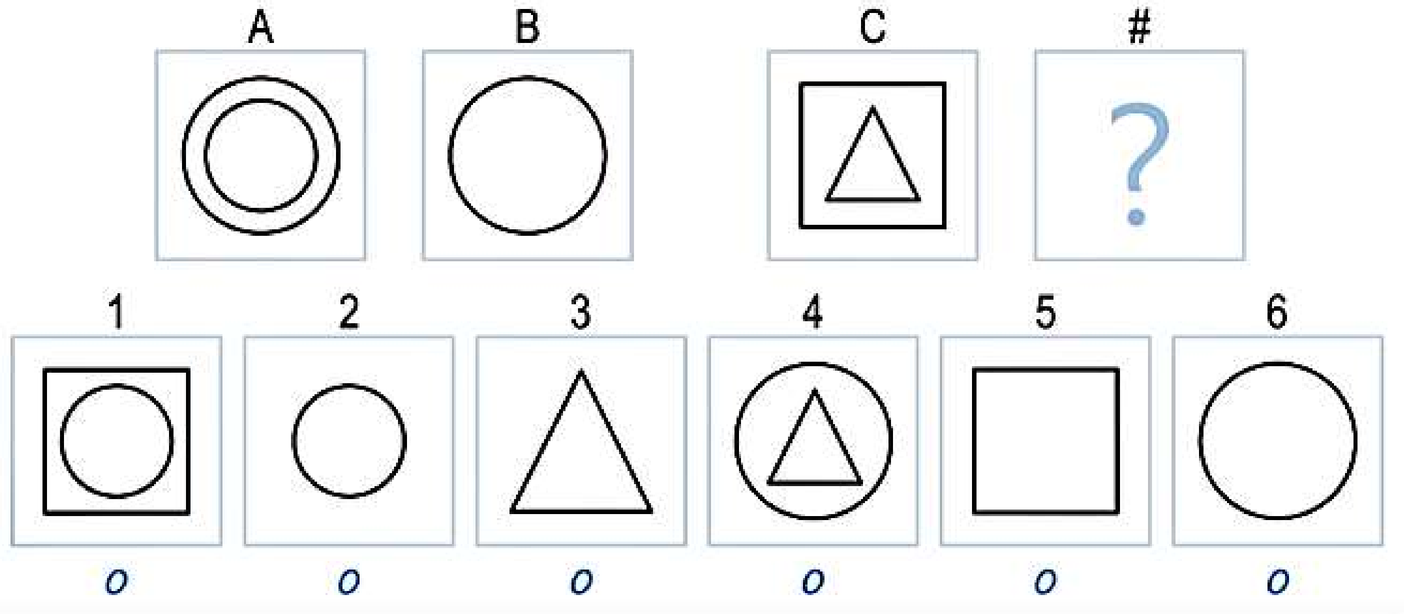
Choosing matches by weight



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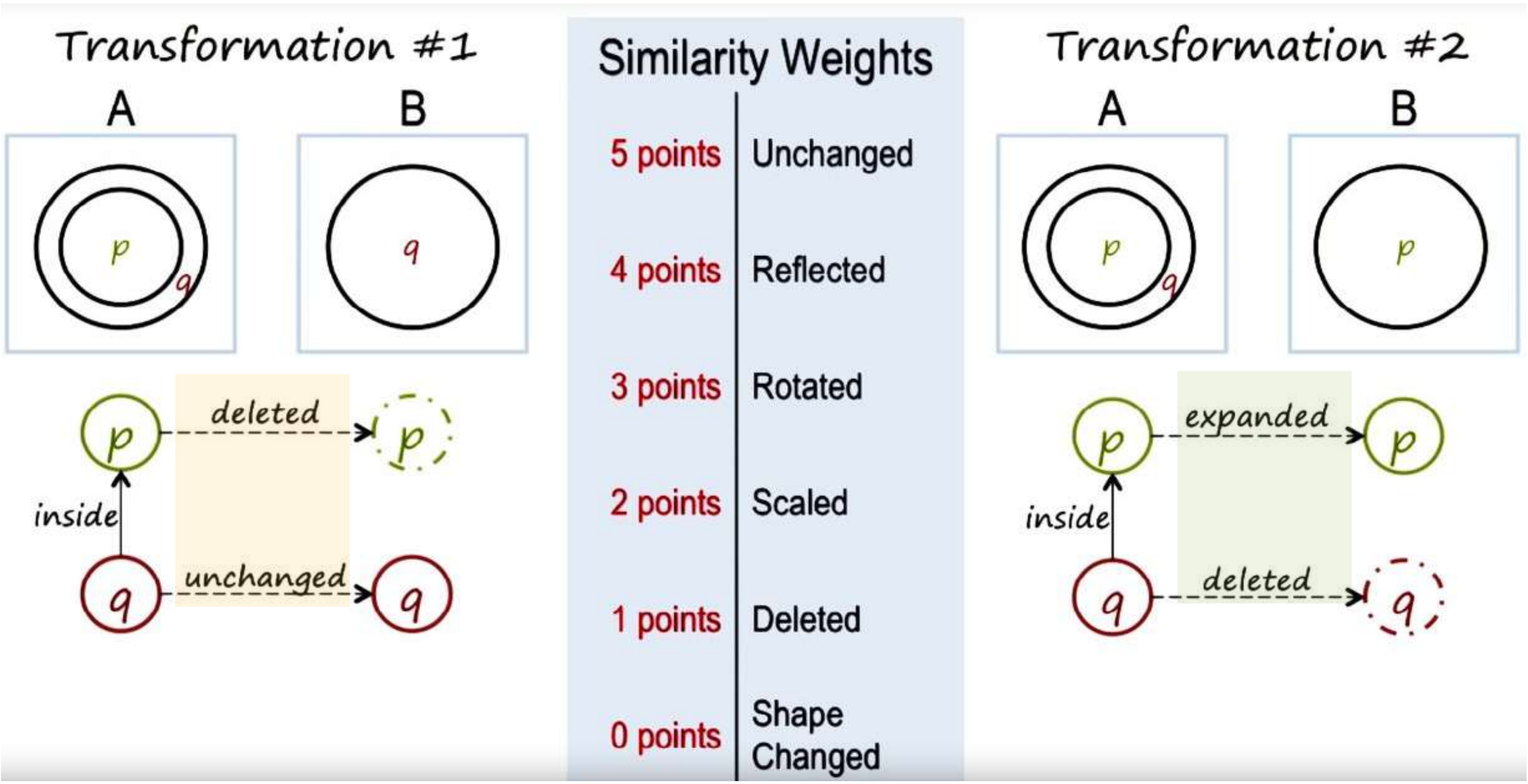
Choosing matches by weight



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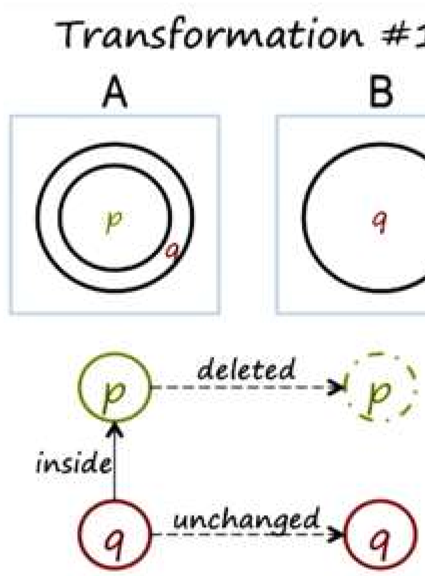
To Logical Forms



- **Logical Forms:**

Transf_p(Transtep ((Object ’p’),(Action ’deleted’),(Relas (inside ’q’))))
Transf_q(Transtep ((Object ’q’),(Action ’unchanged’),(Relas (outside ’p’))))

Image from https://classroom.udacity.com/courses/ud409

One more step

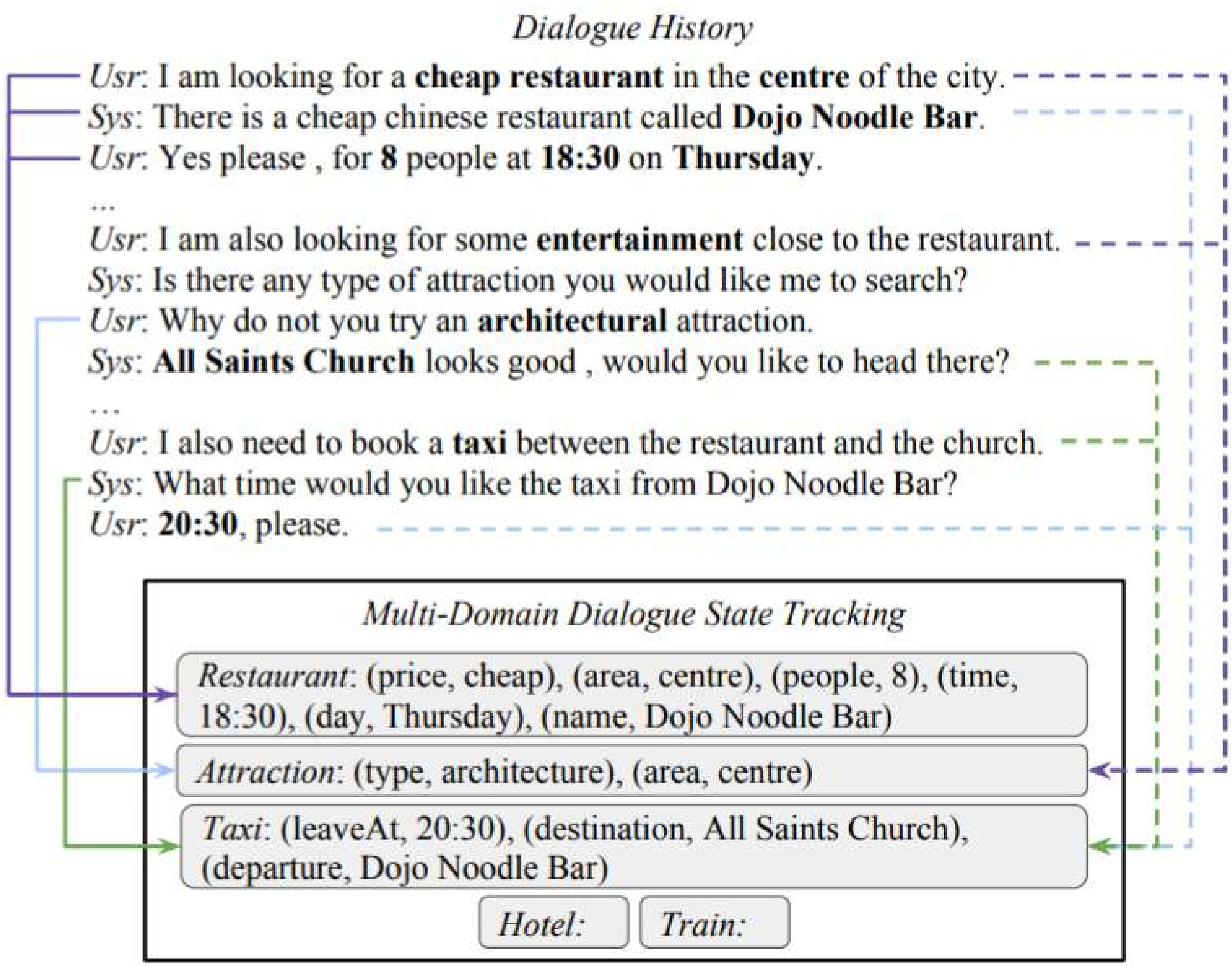
- **Logical Forms:**

Transf_p(Transtep ((Object,’p’),(Action,’deleted’),(Relas (inside,’q’))))
Transf_q(Transtep ((Object,’q’),(Action,’unchanged’),(Relas (outside,’p’))))

- **Computable in JSON-Like Format**

```
{
  "Transf1": [
    {"Object":"p","Action":"deleted","Relas"
      :[{"inside":"q"}]},
    {"Object":"q","action":"unchanged","Relas"
      :[{"outside":"p"}]}
  ]
}
```

Furthermore



What makes a good relationship

- Explicit
- Expose natural constraints
- Bring objects and relations together
- Exclude extraneous details
- Transparent, concise, complete, fast, computable

Agenda

- Introduction of Cognitive Systems
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  - Semantic Network
  - **Generate and Test**
  - Frames
  - Common Sense Reasoning
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Generate and Test

- GUARDS AND PRISONERS

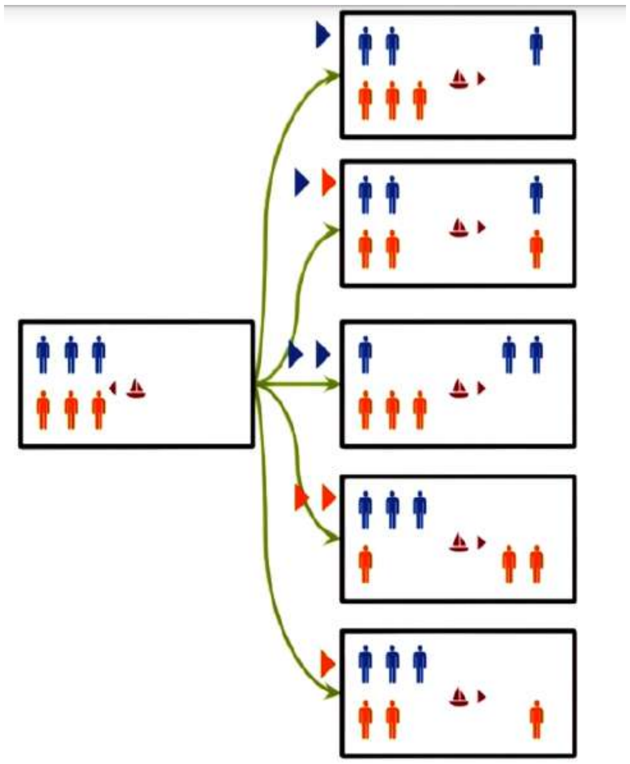
There are three guards and three prisoners who need to cross a river. Their boat only holds **two people at a time**, and the number of prisoners must **NEVER** be allowed to outnumber the number of guards on either side of the river; otherwise, the prisoners will overpower the guards and, well, the story will come to an abrupt end.

It only says the prisoners can not out number the guards. **Never said they could not be alone though.**

- Let’s solve the problem in a machine-like way

Generate and Test

- Generator
  - Generates all the possible solutions
  - A dumb generator make things complicated
  - More steps (computational power) needed



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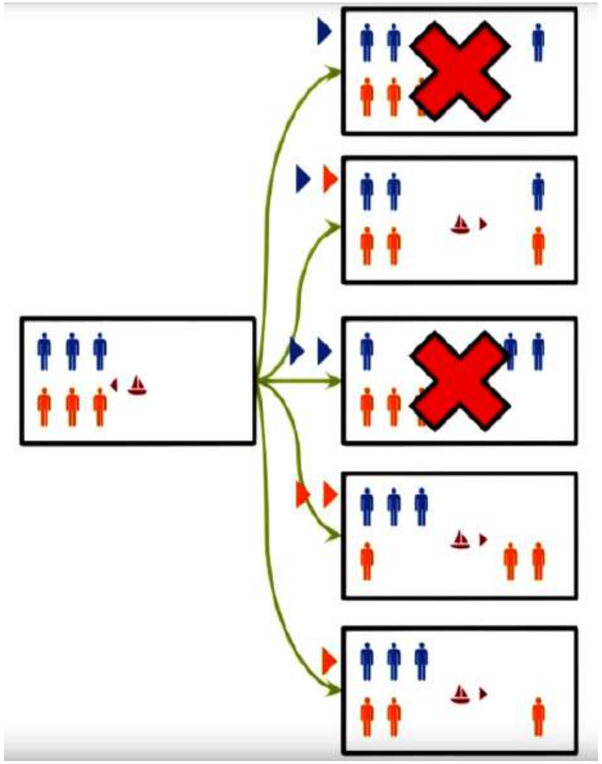
Generate and Test

- Tester
  - Validate the outputs of generator
  - Remove the invalid status



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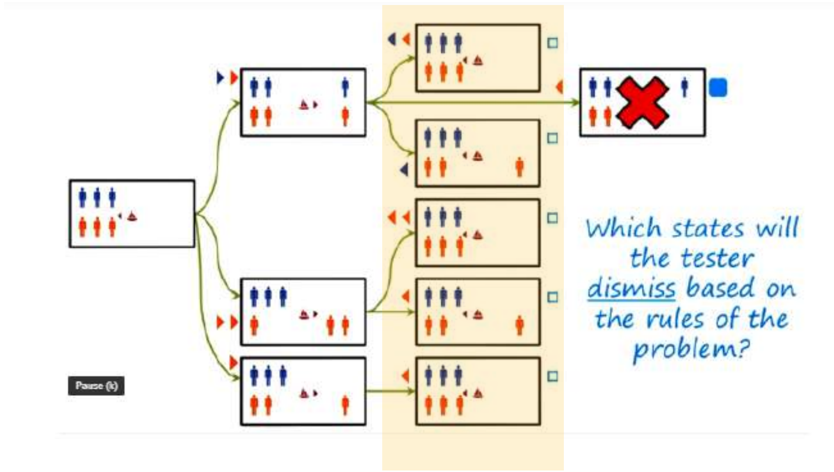
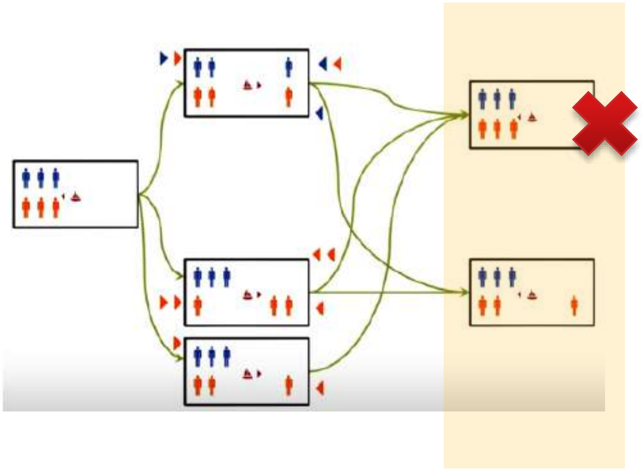
Generate and Test



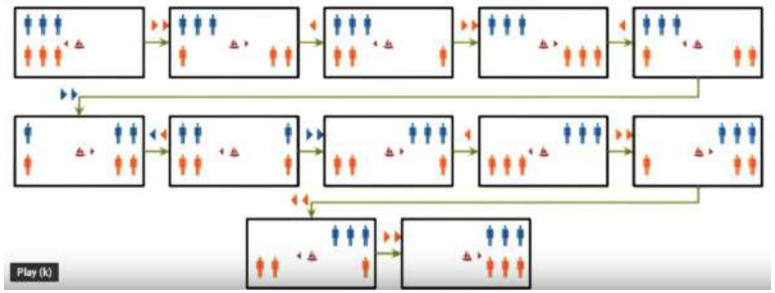


- Generator and Tester can be smarter by:
  - Merging duplicated status
  - Removing status identical to previous status
- Responsibility can be balanced between Generator and Tester
  - Depending on the number of status

Image from https://classroom.udacity.com/courses/ud409

Generate and Test

- How many steps needed in total ?



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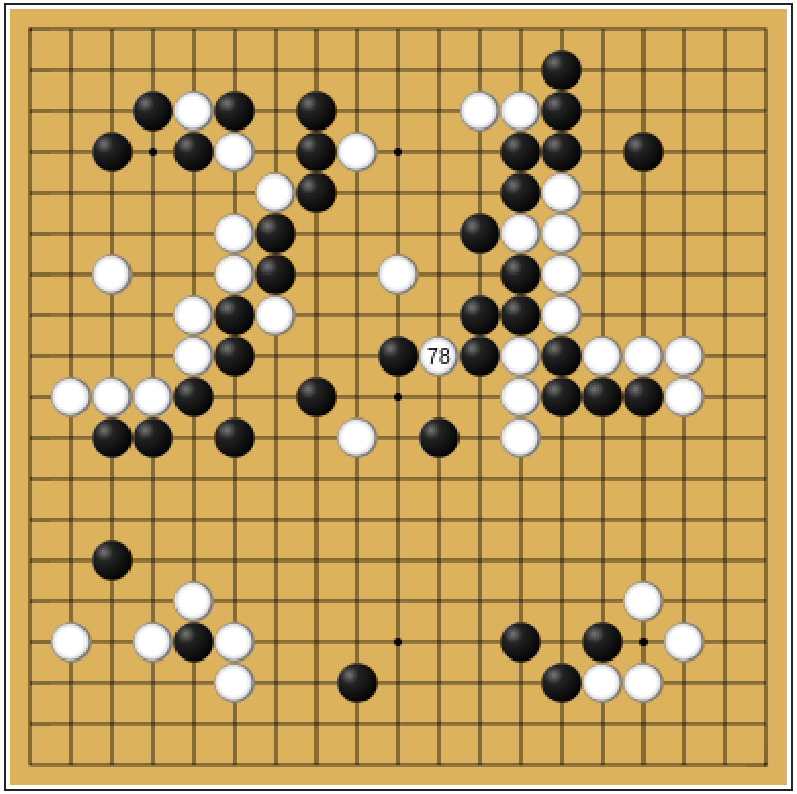
- Deepmind AlphaGo
  - policy network
  - value network

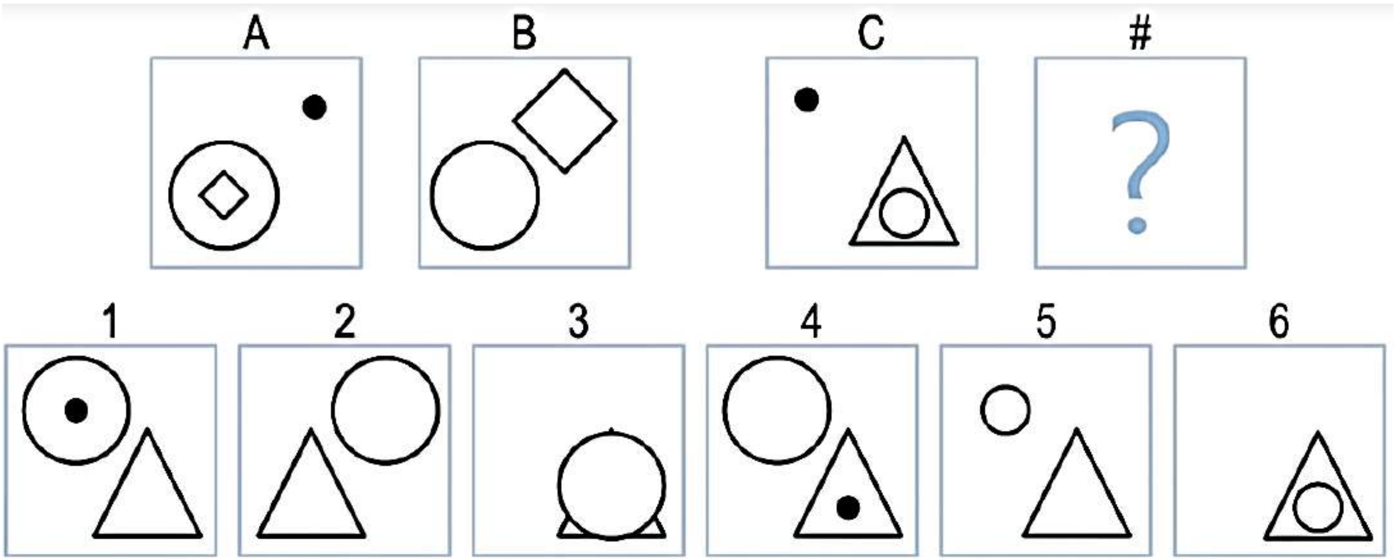


Game 4, Lee Sedol (white) v. AlphaGo (black).
First 78 moves

Image from https://en.wikipedia.org/wiki/Lee_Sedol

To solve the Problem

- Generator will ______________________________
- Tester will ______________________________



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  - **Frames**
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Properties of Frames

- Slots and Fillers
- Provide default values

Ashok ate a frog.

```
Ate
    subject : Ashok
    object : a frog
    location :
    time :
    utensils :
    object-alive : false
    object-is : in-subject
    subject-mood : happy
```

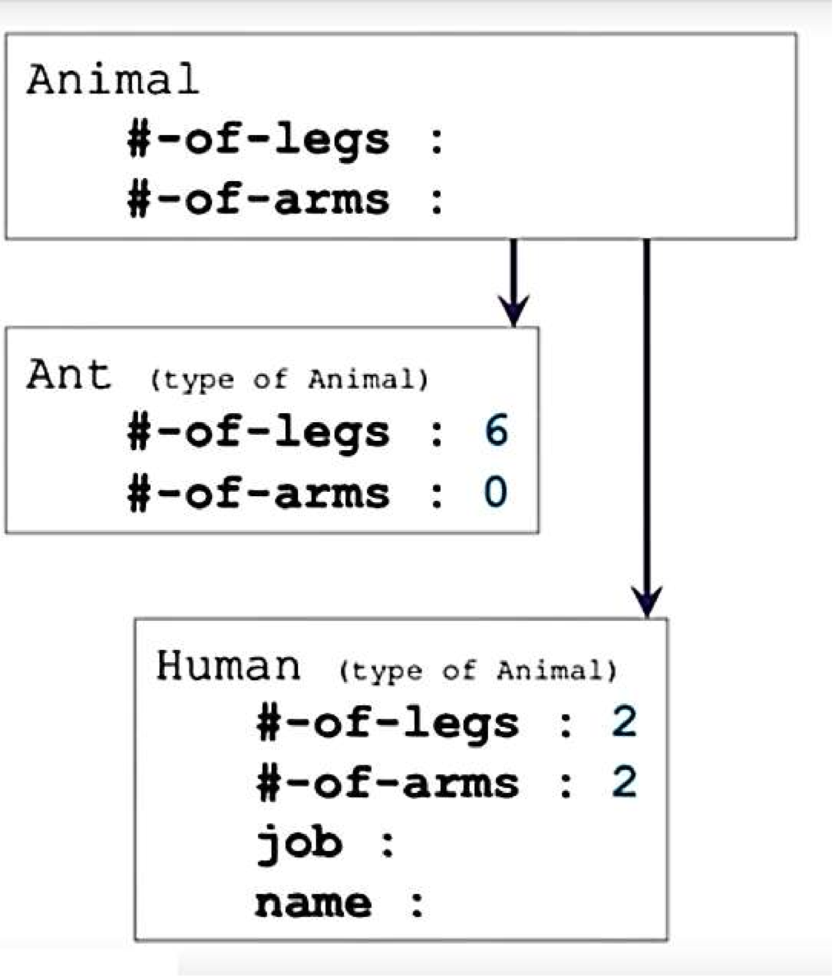
David ate a pizza at home.

```
Ate
    subject : David
    object : a pizza
    location : at home
    time :
    utensils :
    object-alive : false
    object-is : in-subject
    subject-mood : happy
```

Image from https://classroom.udacity.com/courses/ud409

Properties of Frames

- Frames represent stereotypes
- Slots and Fillers
- Provide default values
- **Exhibit inheritance**



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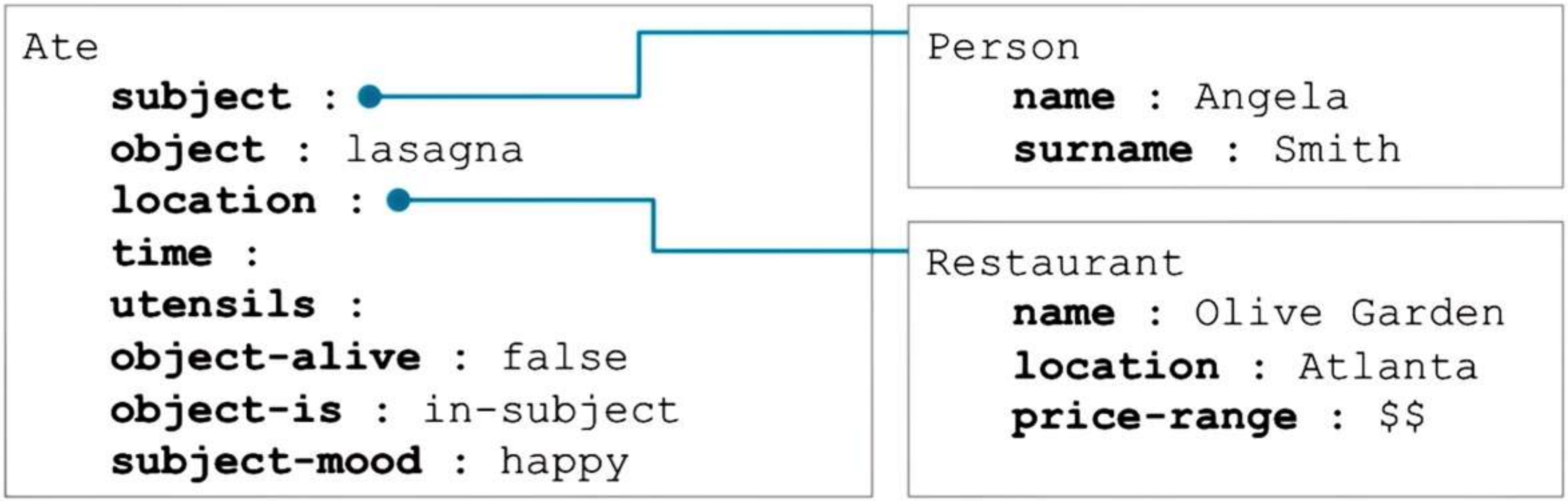
Complex Frames Systems

- Structured knowledge representation
- Carry more information in organized manner



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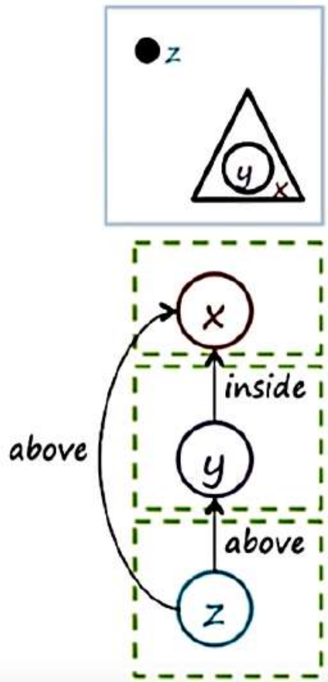
Frames and Semantic Networks

- Frames represent stereotypes




```
Object
    name : x
    shape : triangle
    size : large
    fill : false
    inside :
    above :
```

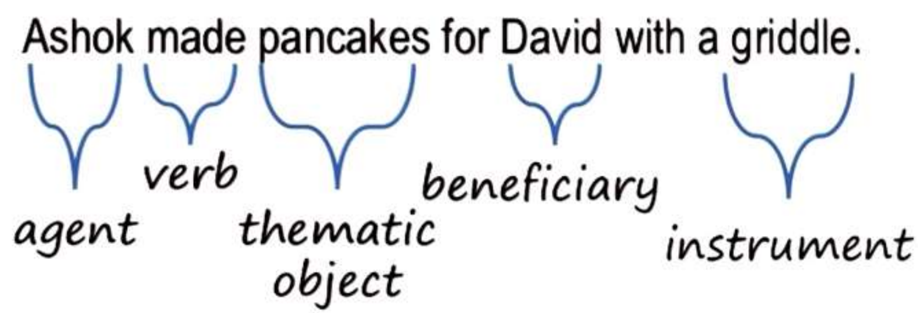
```
Object
    name : y
    shape : circle
    size : medium
    fill : false
    inside : x
    above :
```

```
Object
    name : z
    shape : circle
    size : small
    fill : true
    inside :
    above : x, y
```

Image from https://classroom.udacity.com/courses/ud409

Thematic Role Systems

- **A type of** Frame system
- Focusing on **verbs**
- Semantic slots/roles
- Resolving ambiguity




```
Thematic Role
  verb : make
  agent : Ashok
  beneficiary : David
  thematic object : pancakes
  instrument : griddle
```

Image from https://classroom.udacity.com/courses/ud409

Thematic Role Systems

Major theta roles include **(but not limited to)**:

- **Agent** – The entity that intentionally carries out the action of the verb.
- **Experiencer** – The entity that undergoes an emotion, a state of being, or a perception expressed by the verb.
- **Theme** – The entity that directly receives the action of the verb.
- **Instrument** – The entity by which the action of the verb is carried out.
- **Goal** – The direction towards which the action of the verb moves.
- **Source** – The direction from which the action originates.
- **Location** – The location where the action of the verb takes place.
- **Benefactive** – The entity that receives a concrete or abstract element as a result of the action of the verb

Image from https://classroom.udacity.com/courses/ud409

Common Sense Reasoning in AI

"Anne is minded by her babysitter."

Which is which?

Common Sense Reasoning in AI

Anne is minded by her babysitter

Which is which?

- A central problem in AI since 1950’s
- **Progress is slow**
- Knowledge-Based approach
  - domain specific and task-oriented
- Machine learning based approach
- **Limited interactions between the above two approaches**

Common Sense Reasoning

- Sense making
  - Encoding text into Frames with the help of ***Knowledge Base***

    Sam went to the meeting with Bob by train

    - Shallow Text Analysis

Thematic Role (draft)
- person : Sam
- **verb** : go
- noun : meeting
- person : Bob
- noun : train

Tagged with Part-Of-Speech and Named Entity

Common Sense Reasoning

- Sense making
  - Encoding text into Frames with the help of ***Knowledge Base***

Sam went to the meeting with Bob by train

- KB for Preposition

Preposition	Thematic Roles
by	agent, conveyance, location
for	beneficiary, duration
from	source, location
to	destination, target, location, event
with	co-agent, instrument

⊕

- Shallow Text Analysis

Thematic Role (draft)

<u>person</u> : Sam
verb : go
<u>noun</u> : meeting
<u>person</u> : Bob
<u>noun</u> : train

Common Sense Reasoning

- Sense making
  - Encoding text into Frames with the help of ***Knowledge Base***

Sam went to the meeting with Bob by train

- KB for Preposition

Preposition	Thematic Roles
by	agent, conveyance, location
for	beneficiary, duration
from	source, location
to	destination, target, location, event
with	co-agent, instrument

- Apply the knowledge for Preposition

Thematic Role (draft)

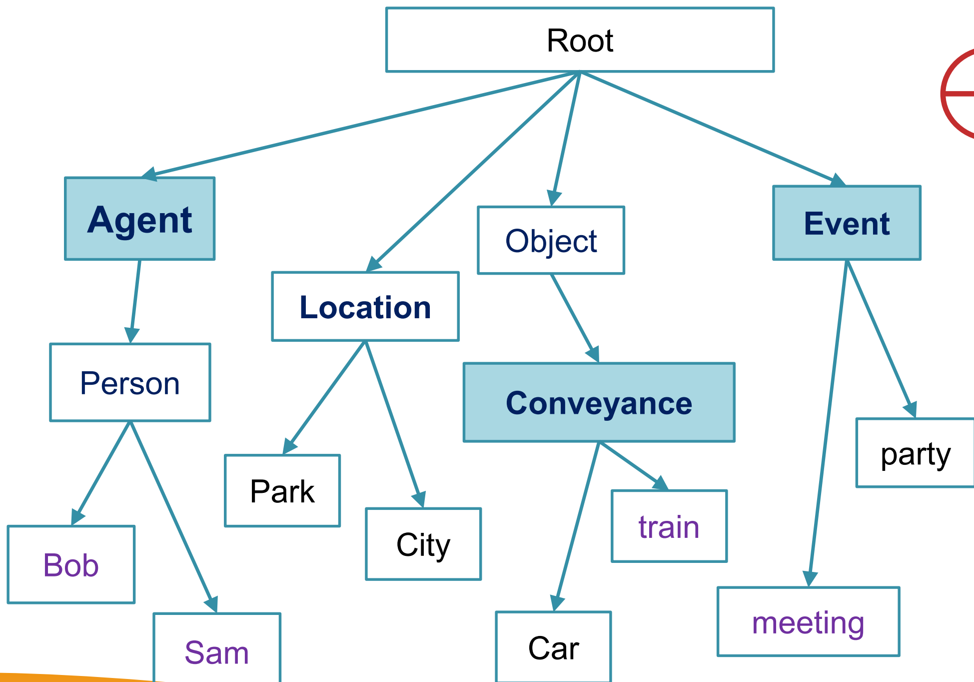
person : Sam
verb : go
dest/target/loc/event : meeting
co-agent/instrument : Bob
convey/lco/agent : train

Common Sense Reasoning

- Build the knowledge base

Sam went to the meeting with Bob by train

- KB for concepts (*IsA*)



- Apply the knowledge for Preposition

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Common Sense Reasoning

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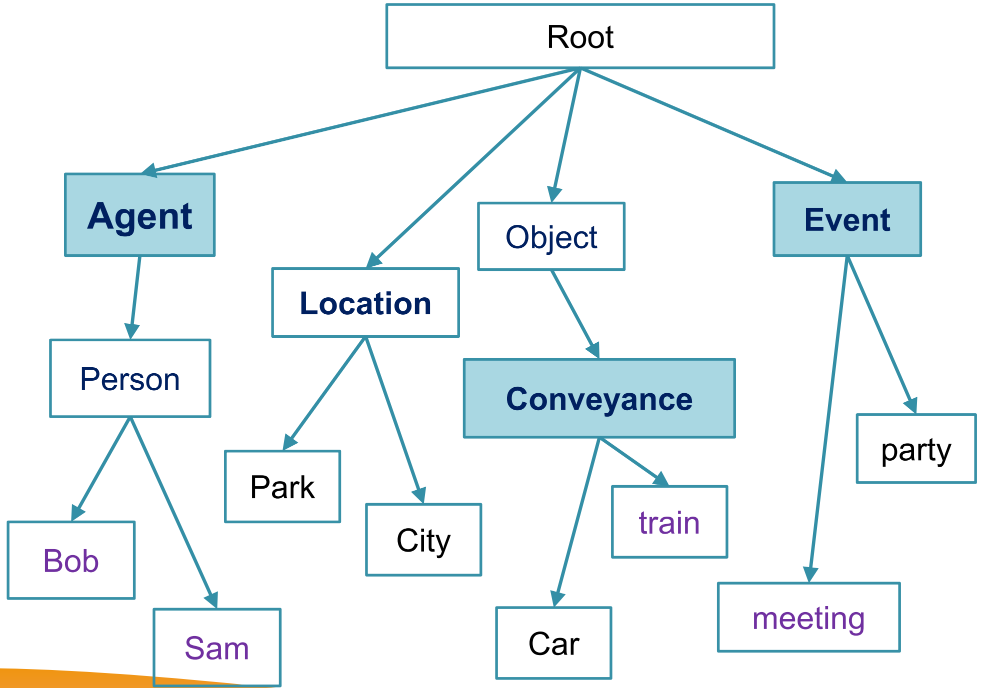

- Apply the knowledge for Preposition

Thematic Role

agent : Sam
verb : go
event : meeting
co-agent : Bob
conveyance : train

Common Sense Reasoning

- Sense making
  - Apply the knowledge

Sam went to the meeting with Bob by train

Thematic Role (draft)
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Thematic Role
agent : Sam
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event : meeting
co-agent : Bob
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Common Sense Reasoning

- Sense making
  - Apply the knowledge

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person : Sam
verb : go
noun : meeting
person : Bob
noun : train

Thematic Role
agent : Sam
verb : go
event : meeting
co-agent : Bob
conveyance : train

do more for the **verb**

Common Sense Reasoning

- Resolving Ambiguity in Verbs with *Primitive Actions*
  - go. *verb. /gəʊ/*
    - move to another location
    - change in level
    - attend an event

go_1
primitive : move
agent :
location :

go_2
primitive : change
agent :
level :

go_3
primitive : attend
agent :
event :

Sam went to the meeting with Bob by train

Thematic Role
agent : Sam
verb : go
event : meeting
co-agent : Bob
conveyance : train

Common Sense Reasoning

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Sam went to the meeting with Bob by train

Thematic Role
agent : Sam
verb : go
event : meeting
co-agent : Bob
conveyance : train

Thematic Role
agent : Sam
verb : go_3
event : meeting
co-agent : Bob
conveyance : train

Knowledge Graph

- ConceptNet

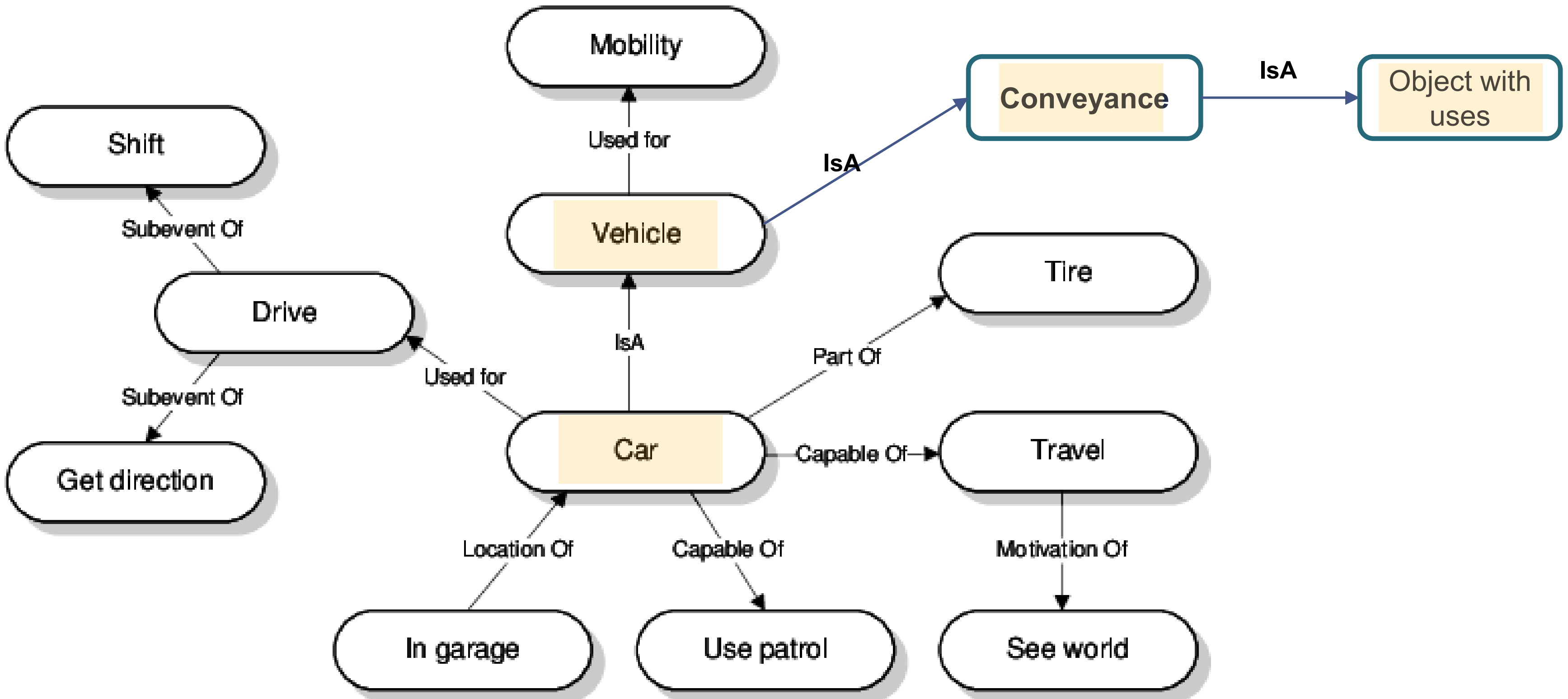
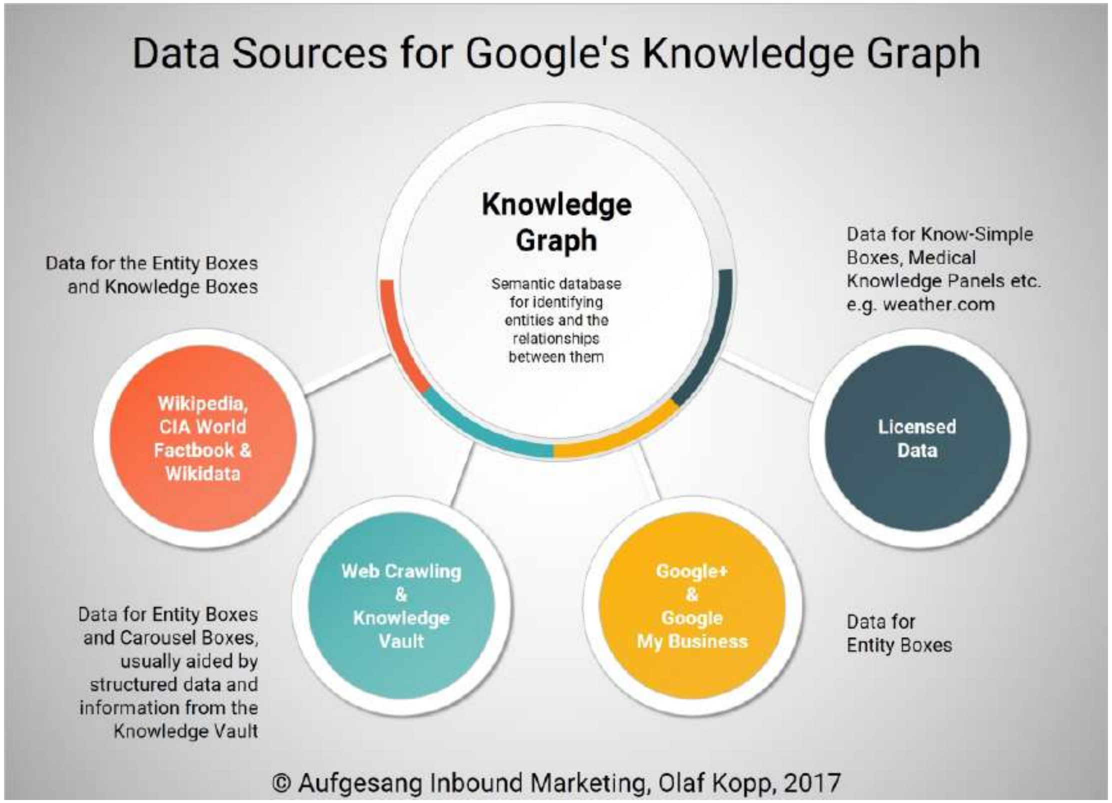


Image from http://conceptnet.io/

Knowledge Graph

- Google Knowledge Graph
  - Annotating/organizing content
  - Getting a ranked list of the most notable entities
  - Encoded with schema.org types
  - API (https://developers.google.com/knowledge-graph/)



IBM Watson

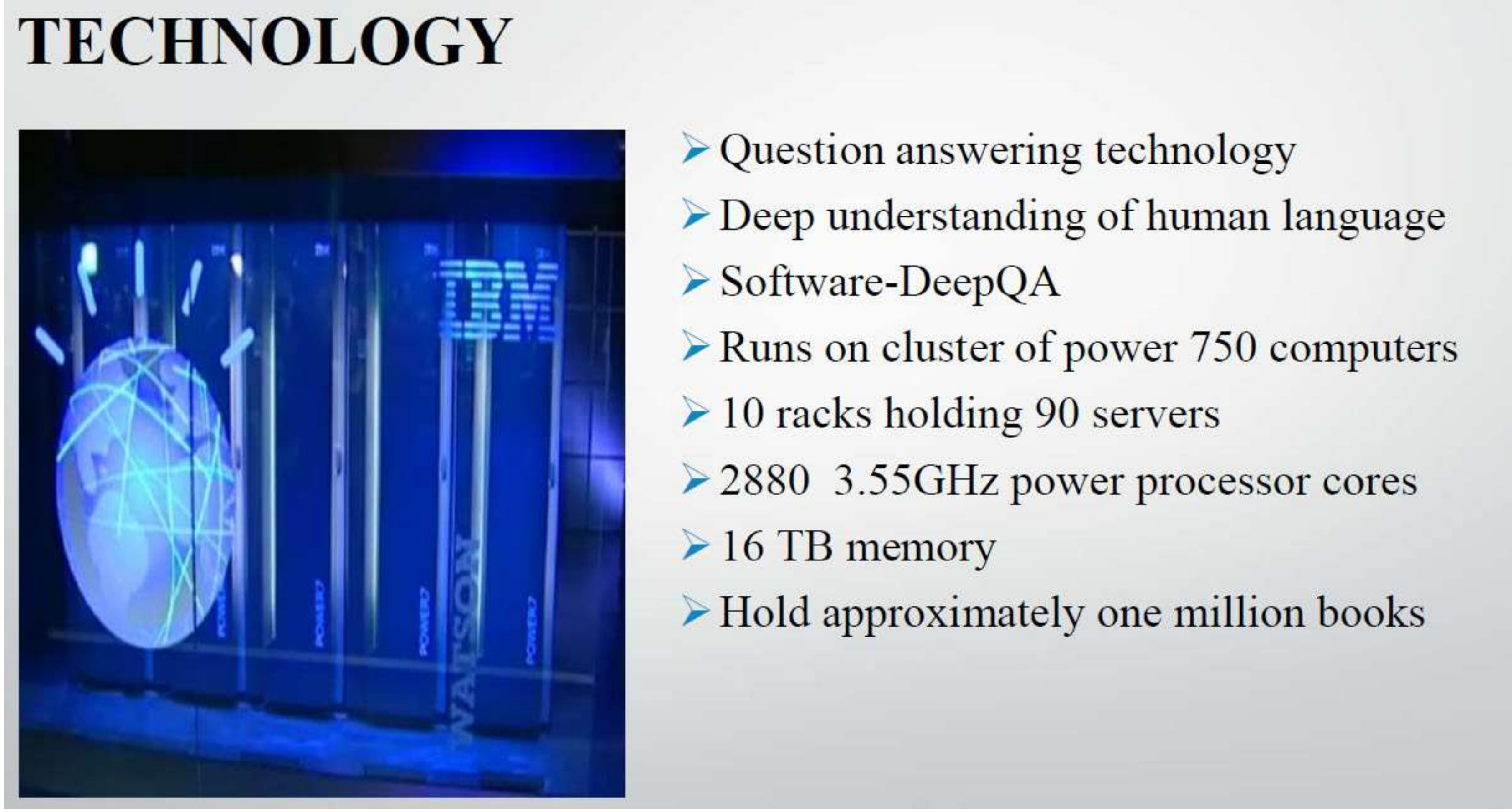


Image from COGNITIVE COMPUTING by JIMSIAH IBRAHIMKUTTY

Review the KRR

- Why is it important for AI?
  - Natural Language Understanding
  - Vision and Video
  - Robotics
  - Understanding Science

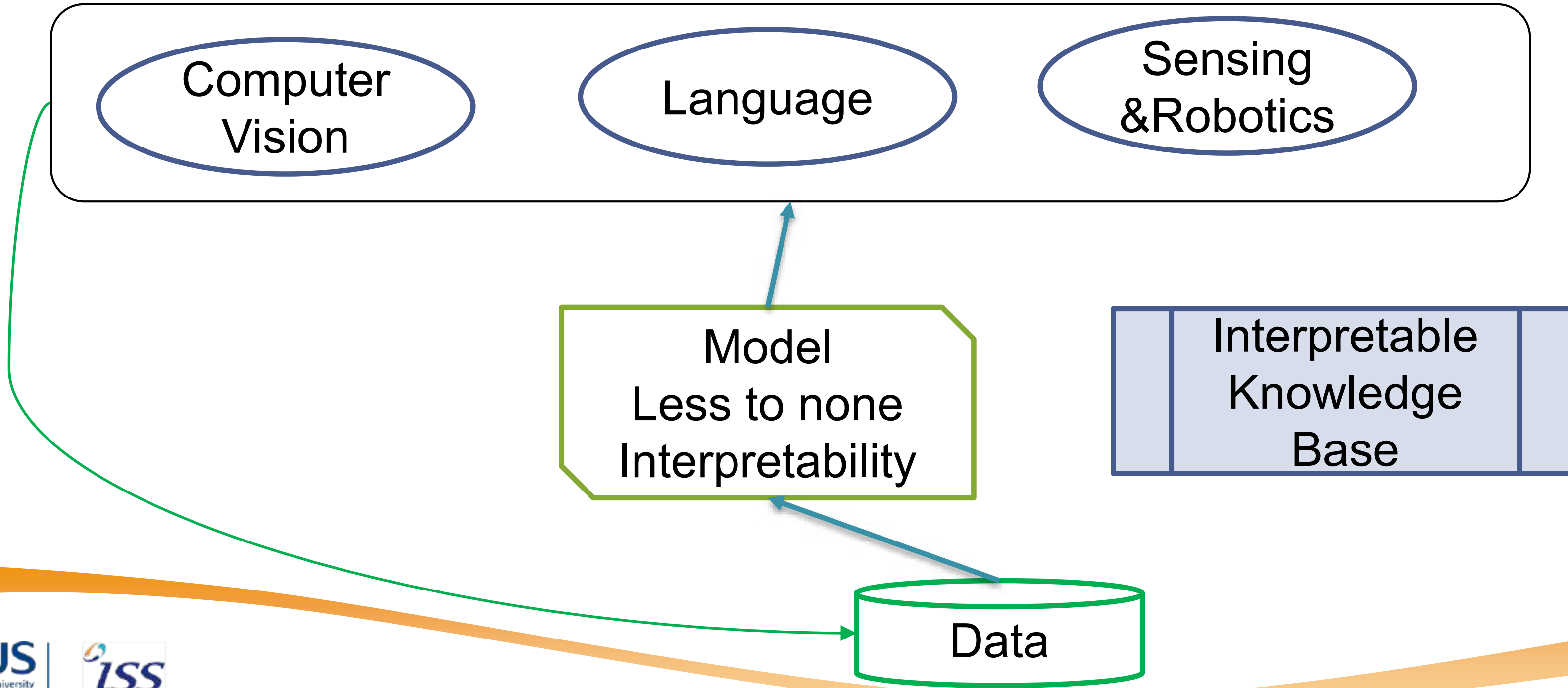
Review the KRR

- Why is it important for AI?
  - Natural Language Understanding
  - Vision and Video
  - Robotics
  - Understanding Science
- What has been attempted?
  - Expert Annotating, Web mining and Crowdsouring
  - Symbolic approaches such as Expert Systems and Rule-based reasoning

Review the KRR

- Where to go ?
  - No silver bullet
  - Google' position paper (in 2018) arguing :

    *"we reject the **false choice** between "hand-engineering" and "end-to-end" learning, and instead advocate for an approach which benefits from their complementary strengths "*



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  - Proposing ***Graph Network***

(f) Image and Fully-Connected Scene Graph

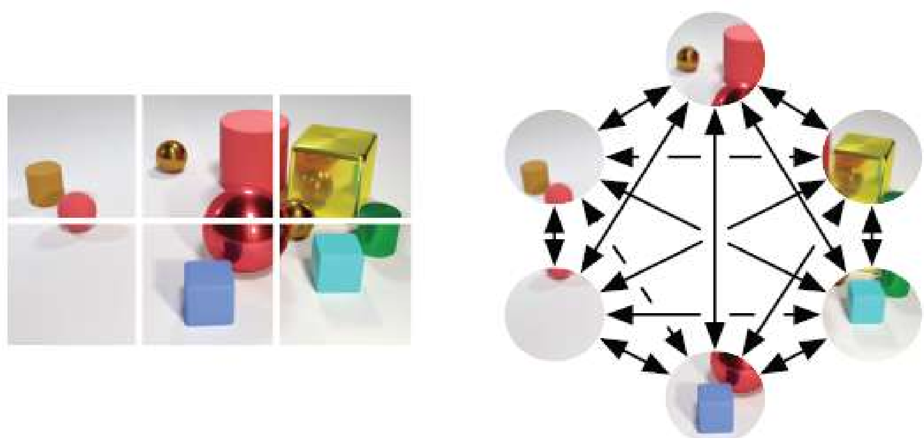

Image from "8. Relational inductive biases, deep learning, and graph networks."

Agenda

- Introduction of Cognitive Systems
- Cognitive Knowledge Representation and Reasoning
- **Case Study Alexa**
  - Features and Architecture
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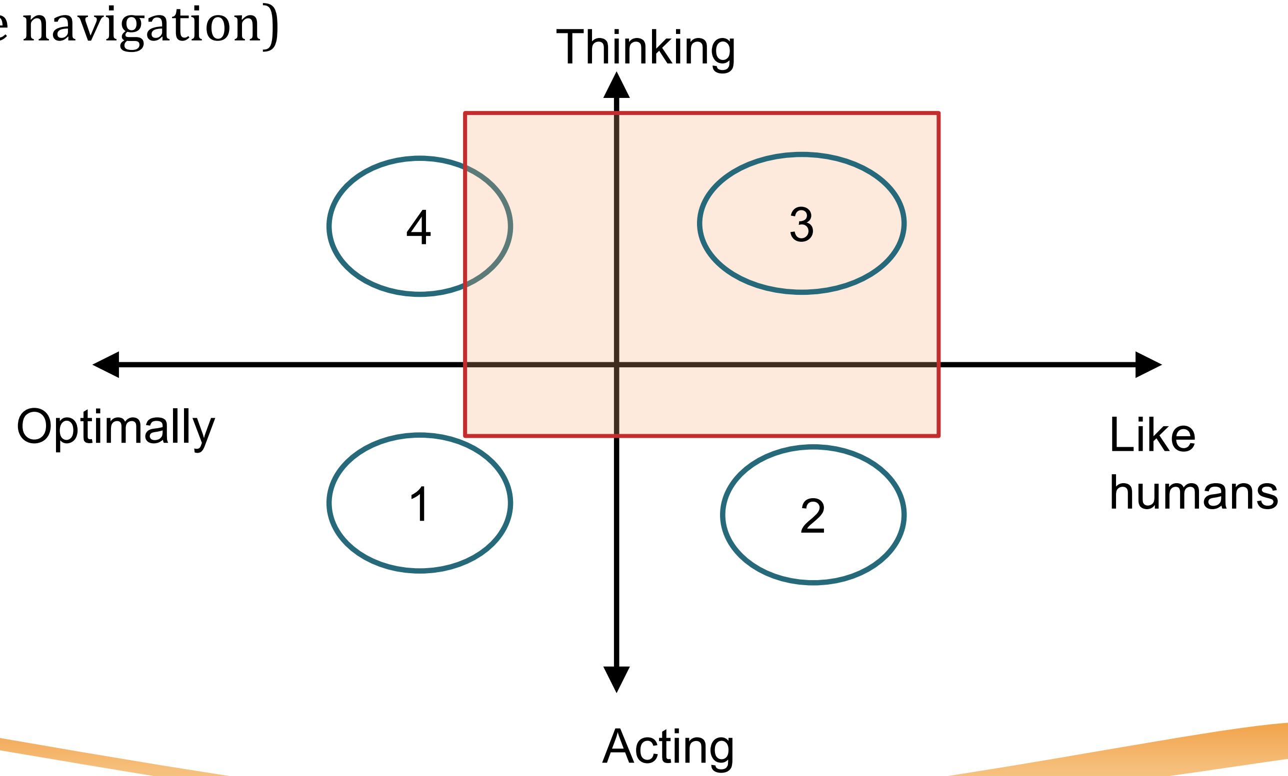
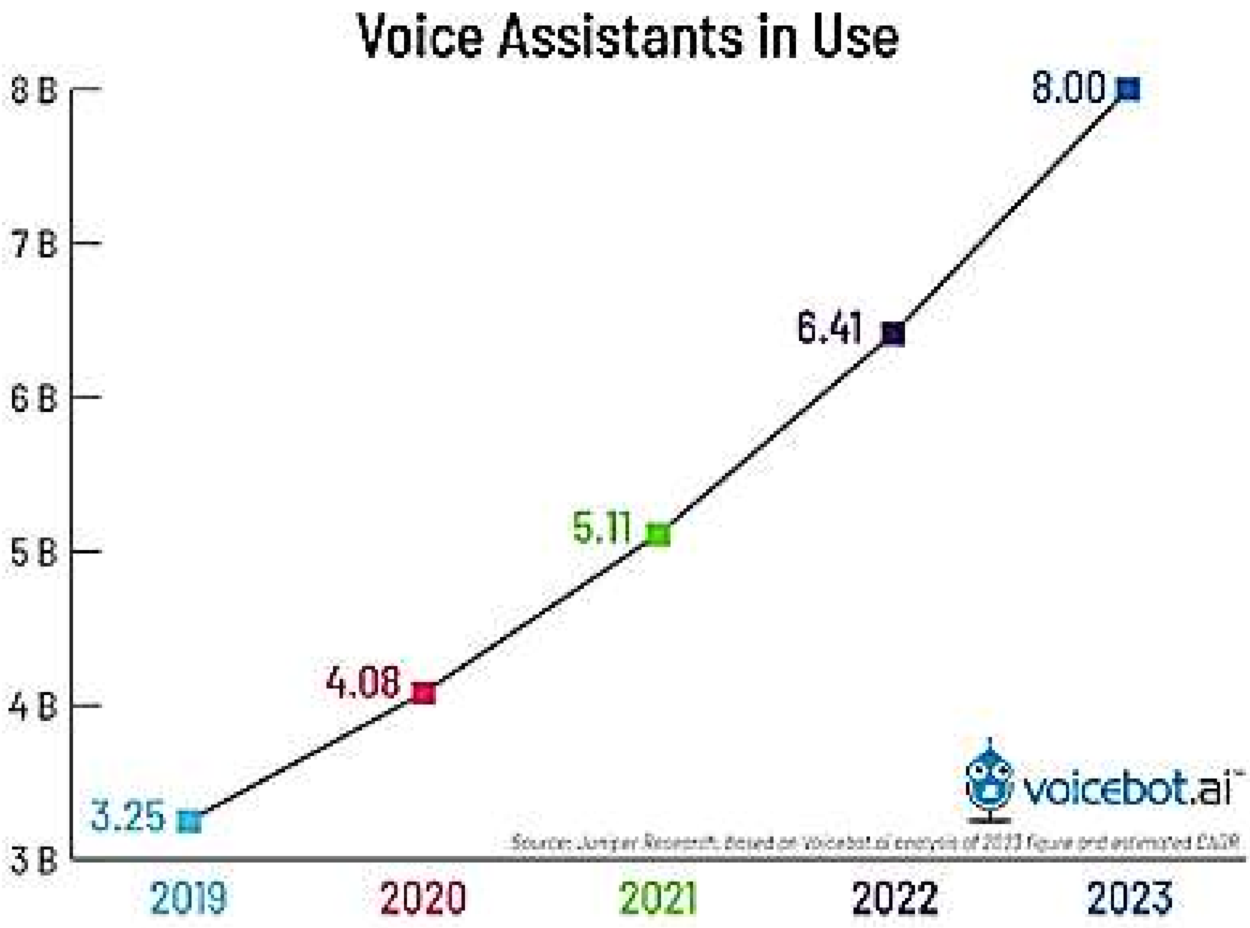
What do we expect AI to perform

1) Roomba (Automated vacuum)
2) Robot-Soccer
3) SIRI
4) Google Maps (route navigation)





- SMARTPHONES BIGGEST SEGMENT, BUT SMART TVS ARE THE FASTEST GROWING

Image from https://voicebot.ai/amazon-echo-alexa-stats/

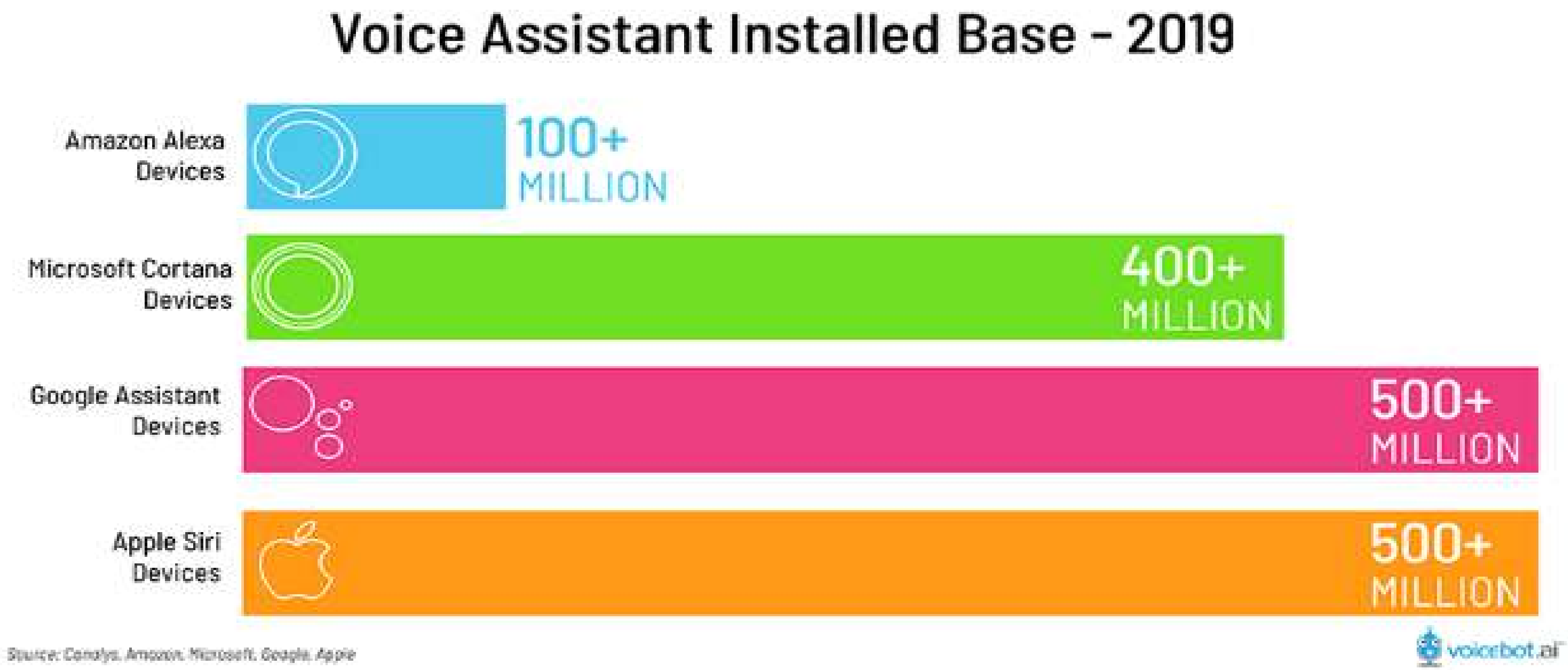


Image from https://voicebot.ai/amazon-echo-alexa-stats/

Maturity

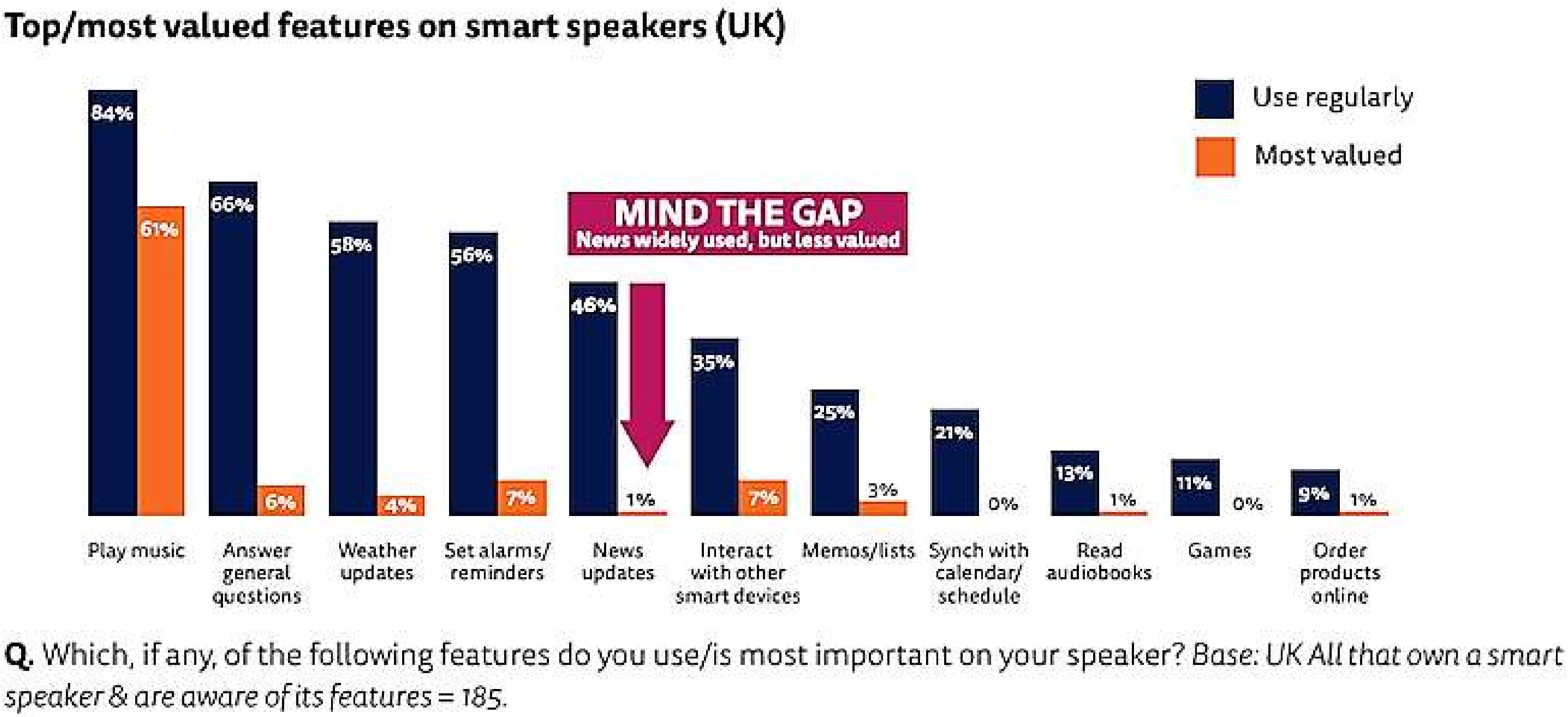


Image from https://voicebot.ai/amazon-echo-alexa-stats/

Build Your Alexa Skill

- Core module
  - ASR
  - NLU
  - *SKILL*
  - NLG
  - TTS

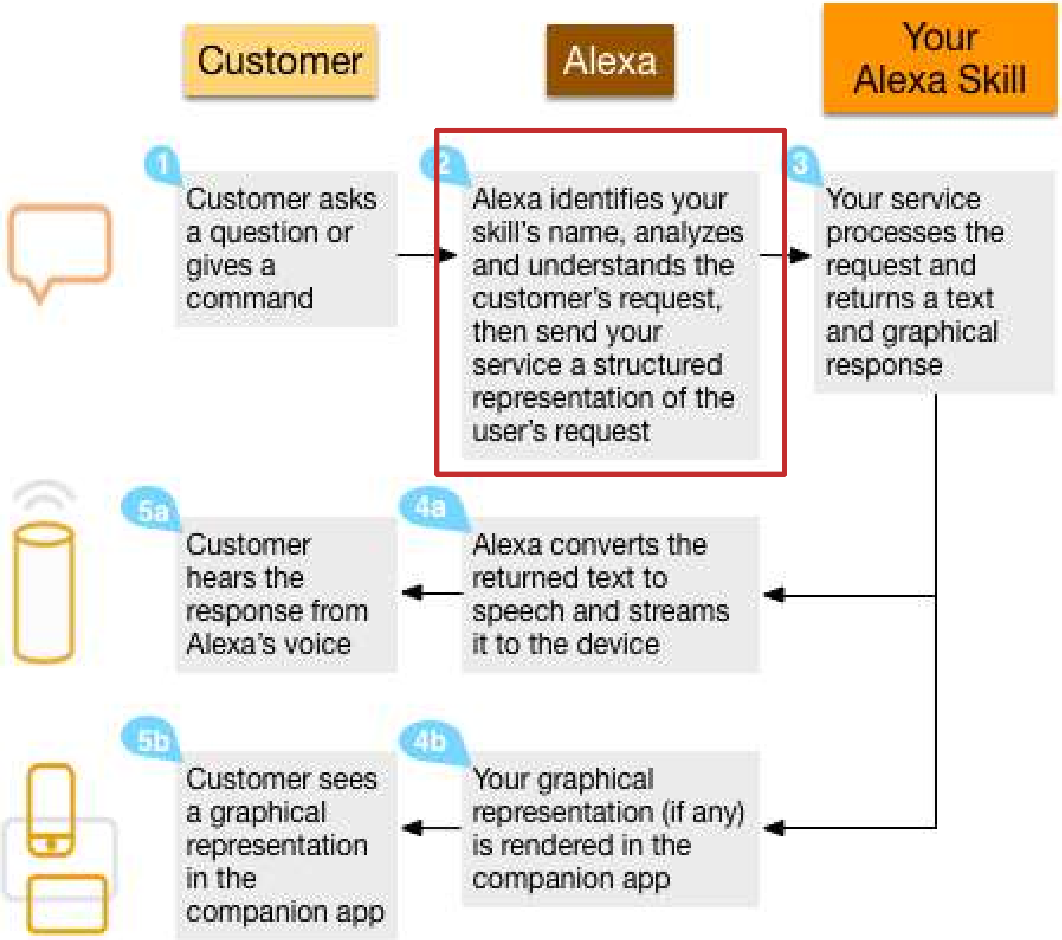


Image from https://developer.amazon.com/docs/custom-skills/understanding-custom-skills.html

Architecture of a Voice Assistant

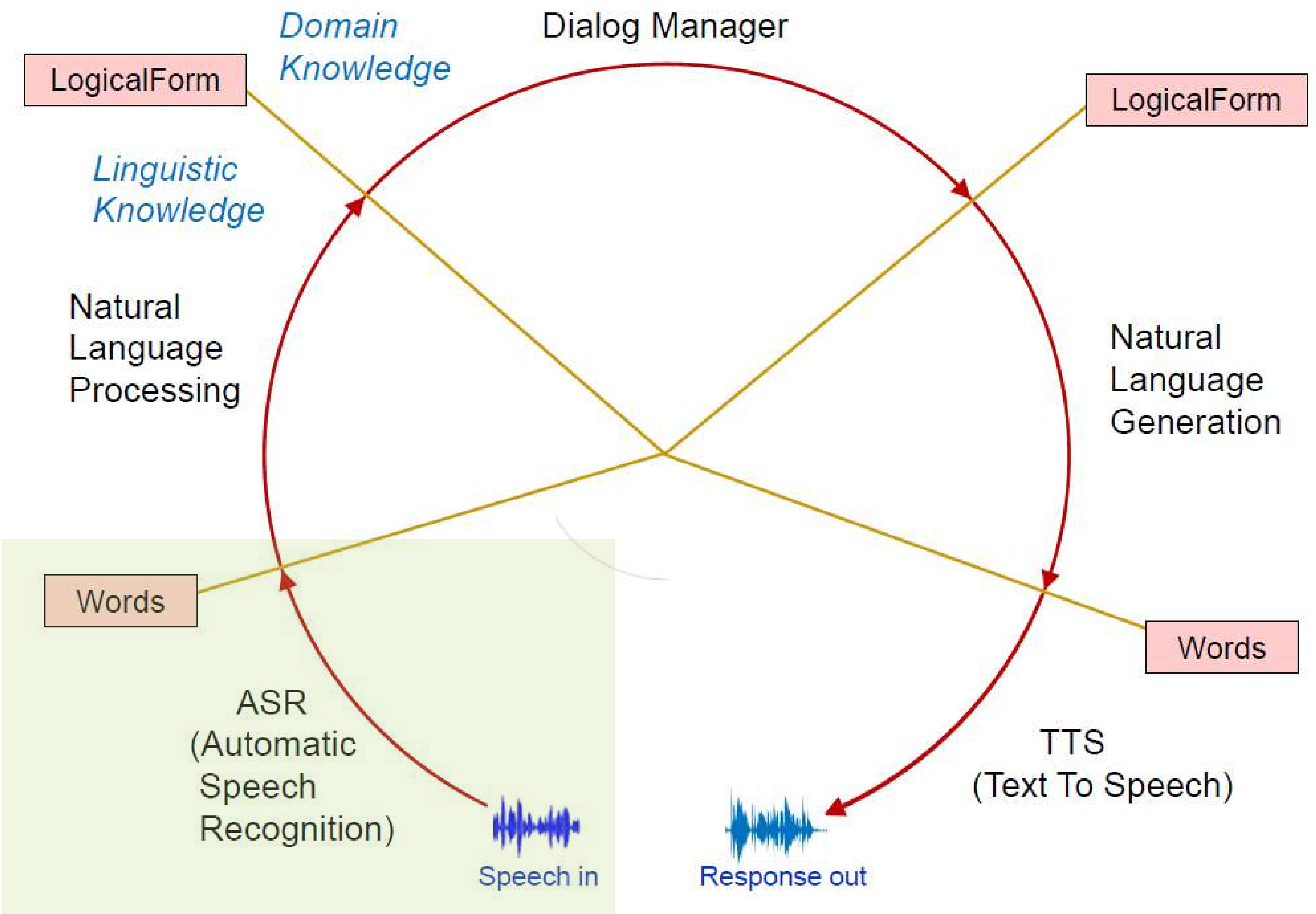
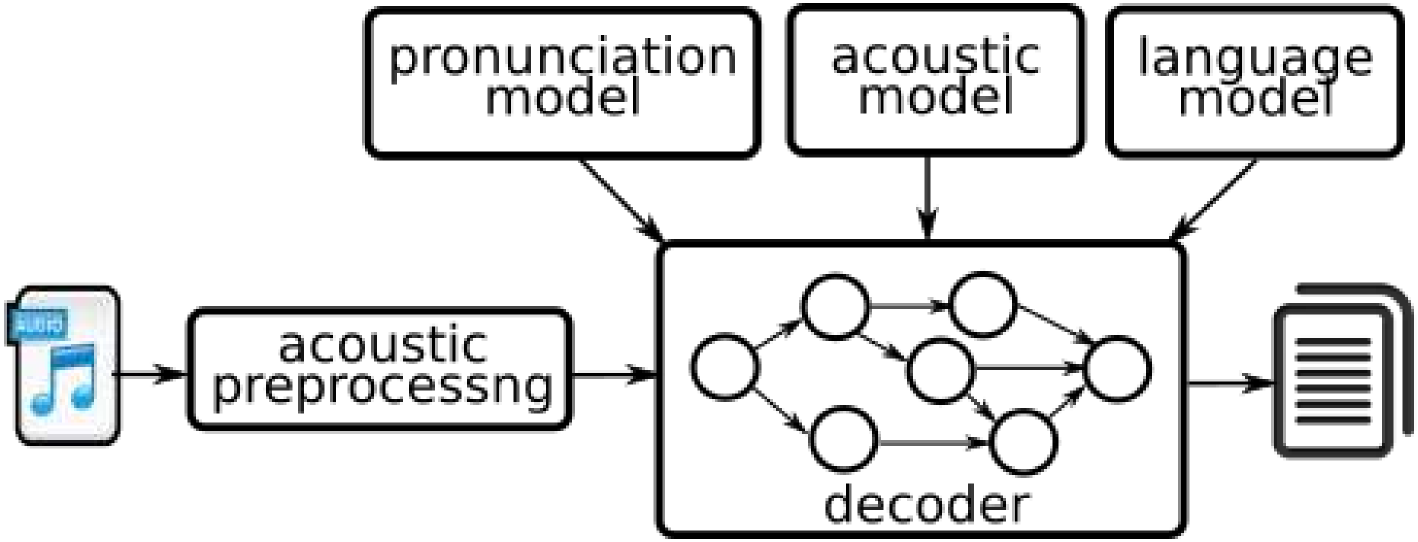


Image from SCI 52 Artificial Intelligence: An Introduction to Neural Networks and Deep Learning,

Automatic Speech Recognition



- Preprocessing: to remove the noise and divide ***signals*** into frames
- Modelling: to learn how a language is spoken and written
- Decoder: to search the ***word sequence*** besting with the models

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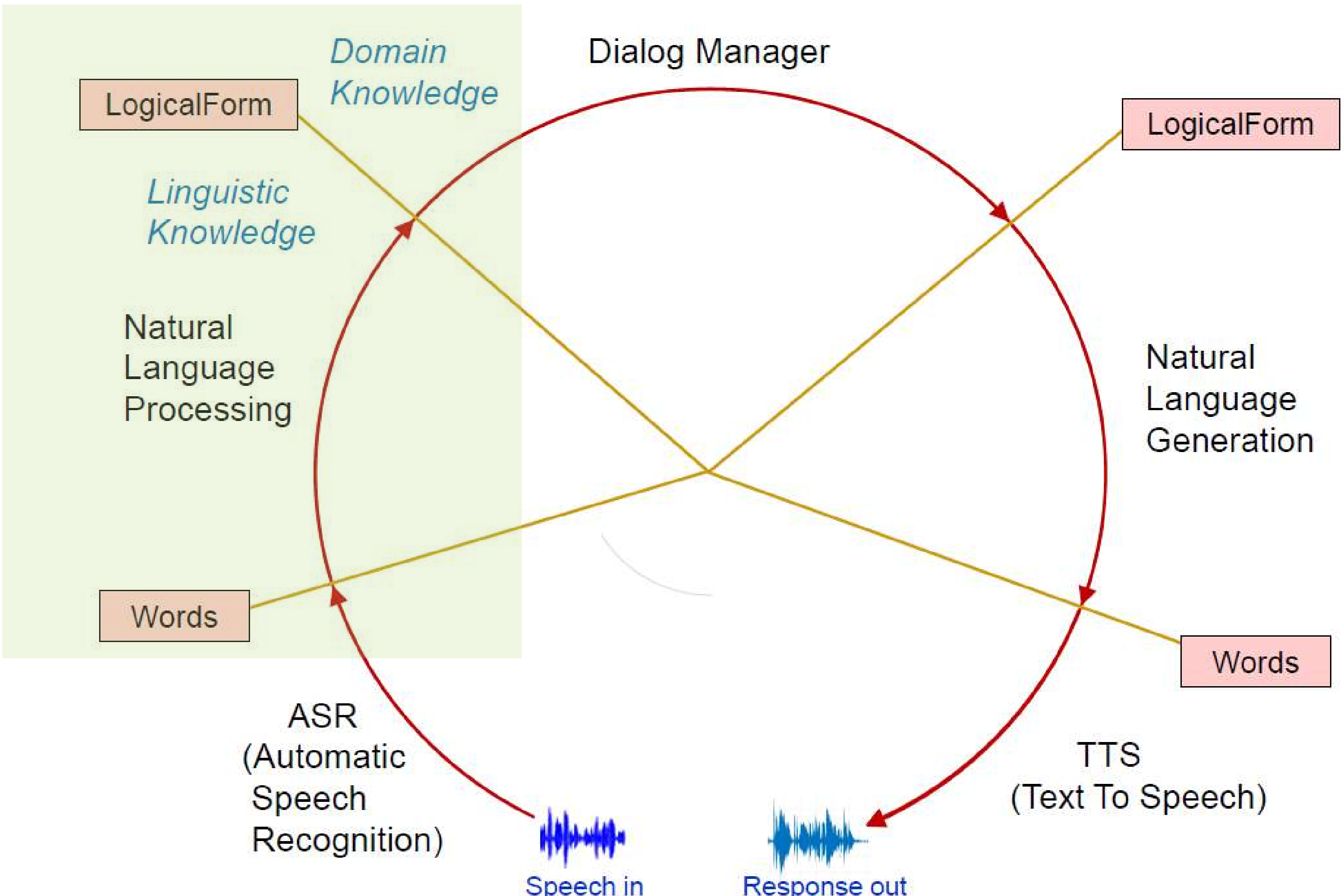


Natural Language Understanding

- **To understand the request:**

Intent represents an action that fulfills a user's spoken request. Intents can optionally have arguments called ***slots***. The ***sample utterances*** are set of likely spoken phrases mapped to the intents.

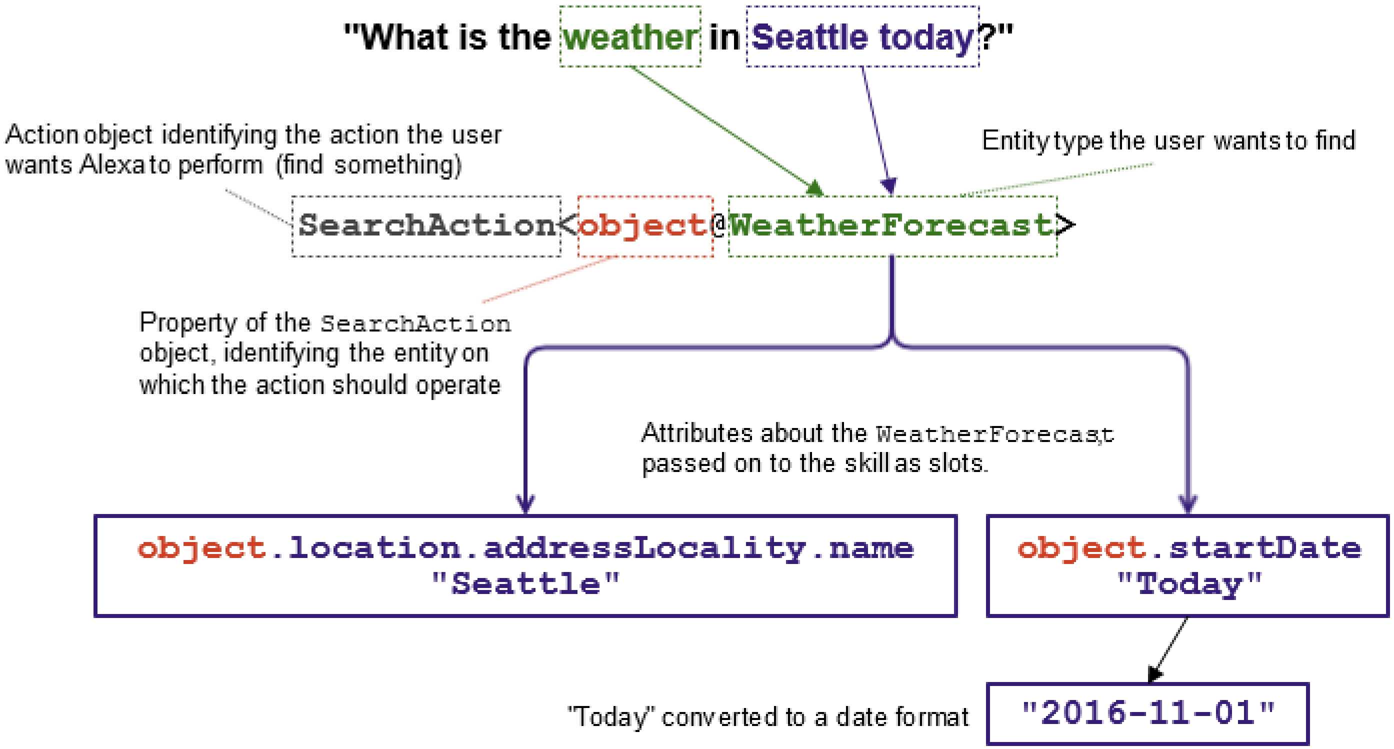


Image from 8. "Just ASK: building an architecture for extensible self-service spoken language understanding."

Natural Language Understanding

- From Text to Logical Forms
  - What is the weather in Seattle today?
  - What's the weather in London?
  - Tell me the temperature now.

Question-word
Command-word
Intent-word

Intent — ***Intent detection***

Location-word
Time-word

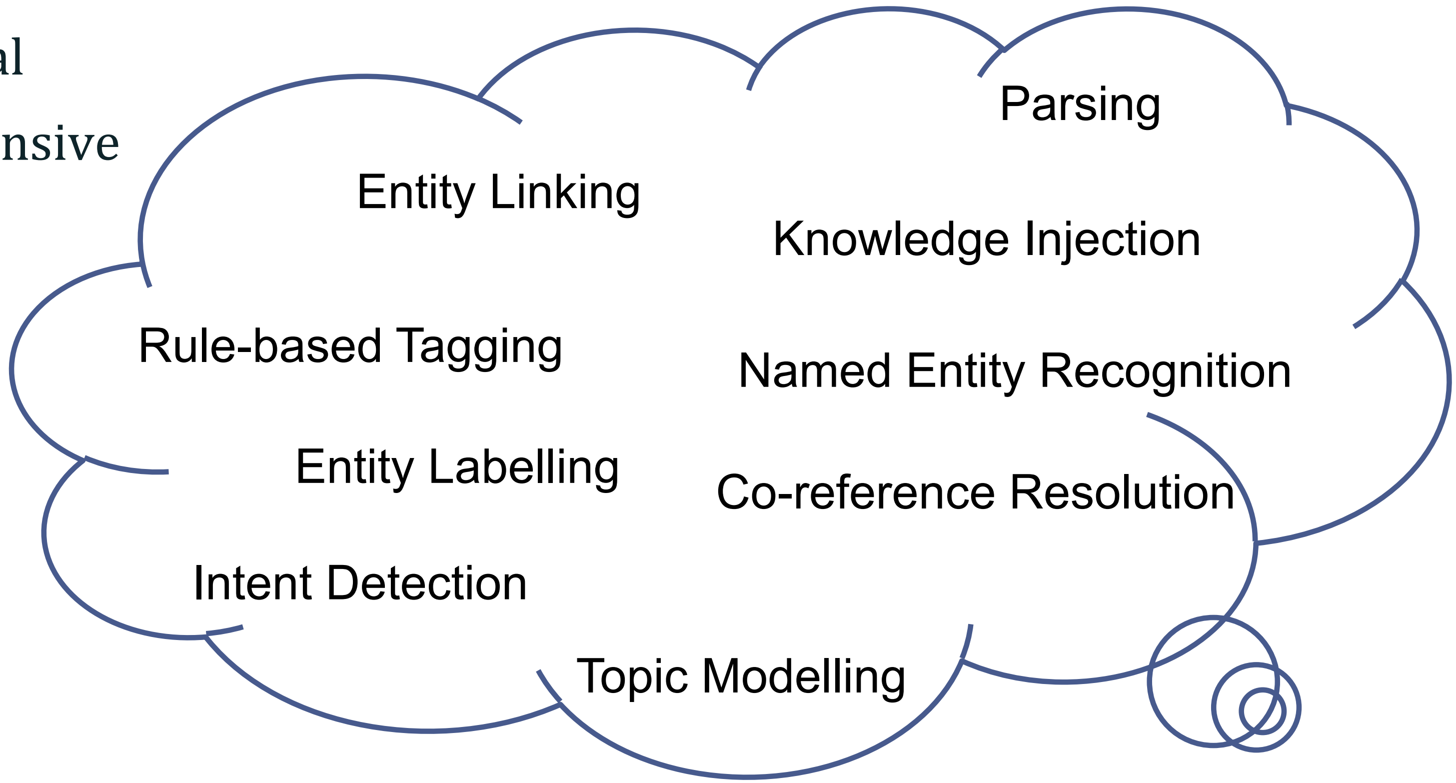
Entity in slots — ***Slots detection***

- Logical Forms:

  SearchAction (WeatherForcast((Location 'Seattle'),(StartDate 'Today')))

Natural Language Understanding

- NLP Tasks to be addressed
  - Theoretical
  - Comprehensive



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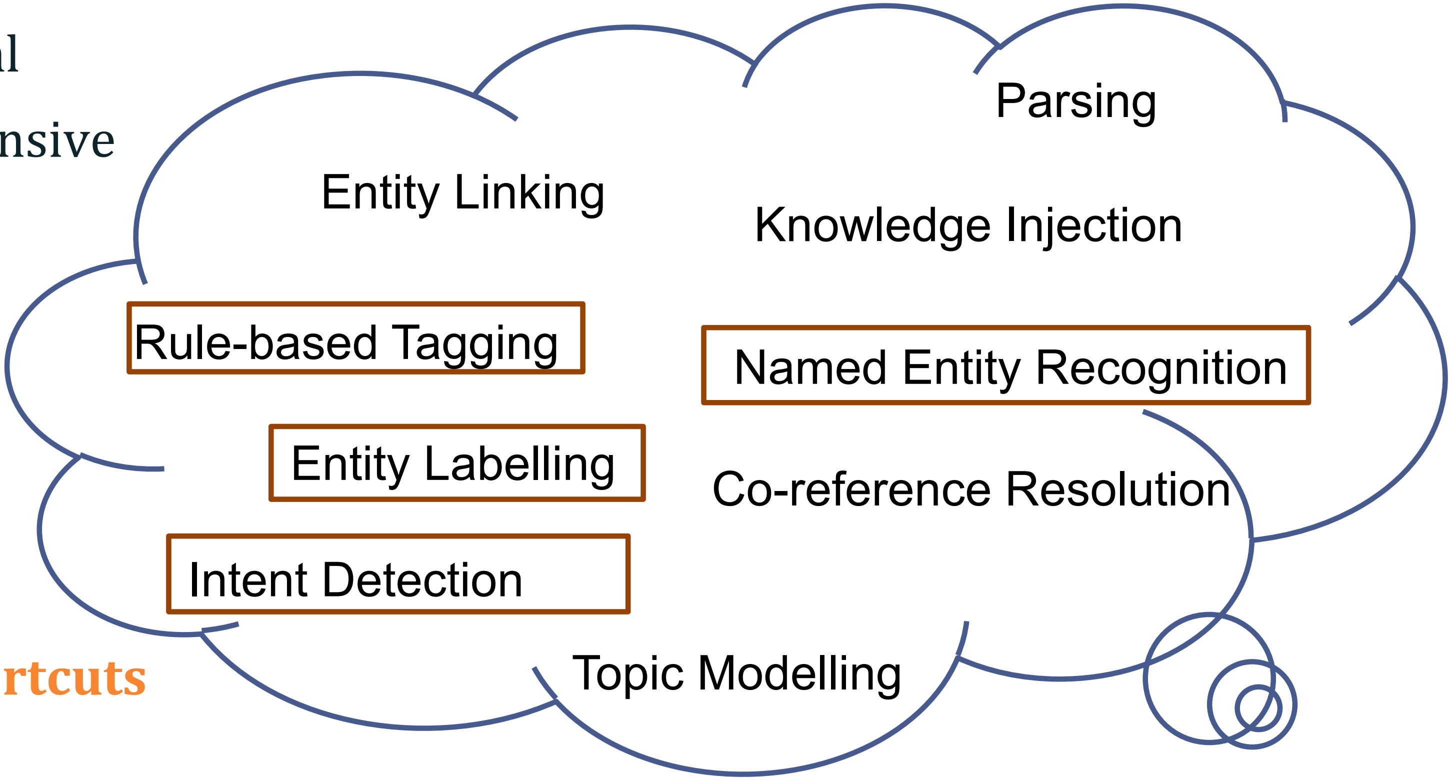
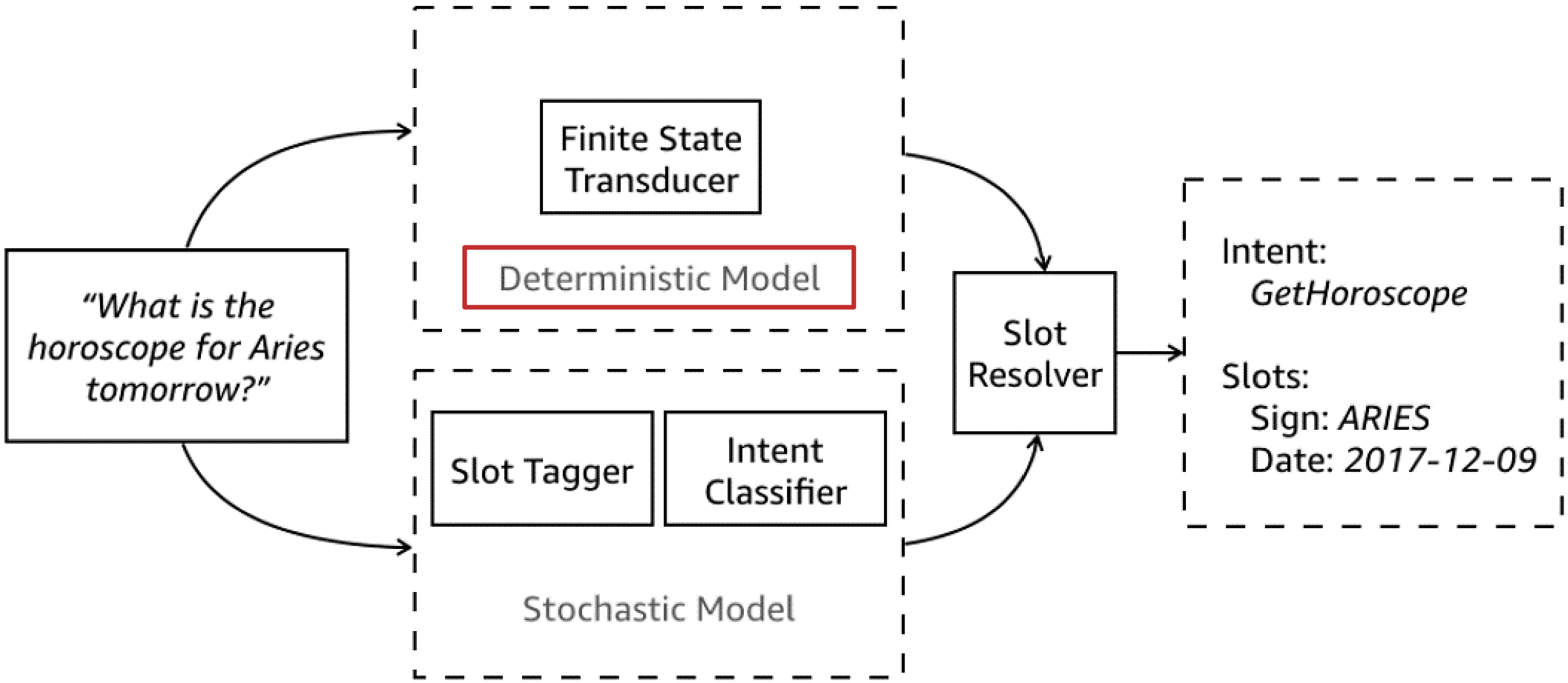


- **Practical, Shortcuts**

NLU Pipeline

- Deterministic : ***FST*** to compile sample ***utterances***
- Stochastic : Machine learning models for ***entity***, ***slot*** and ***intent*** prediction



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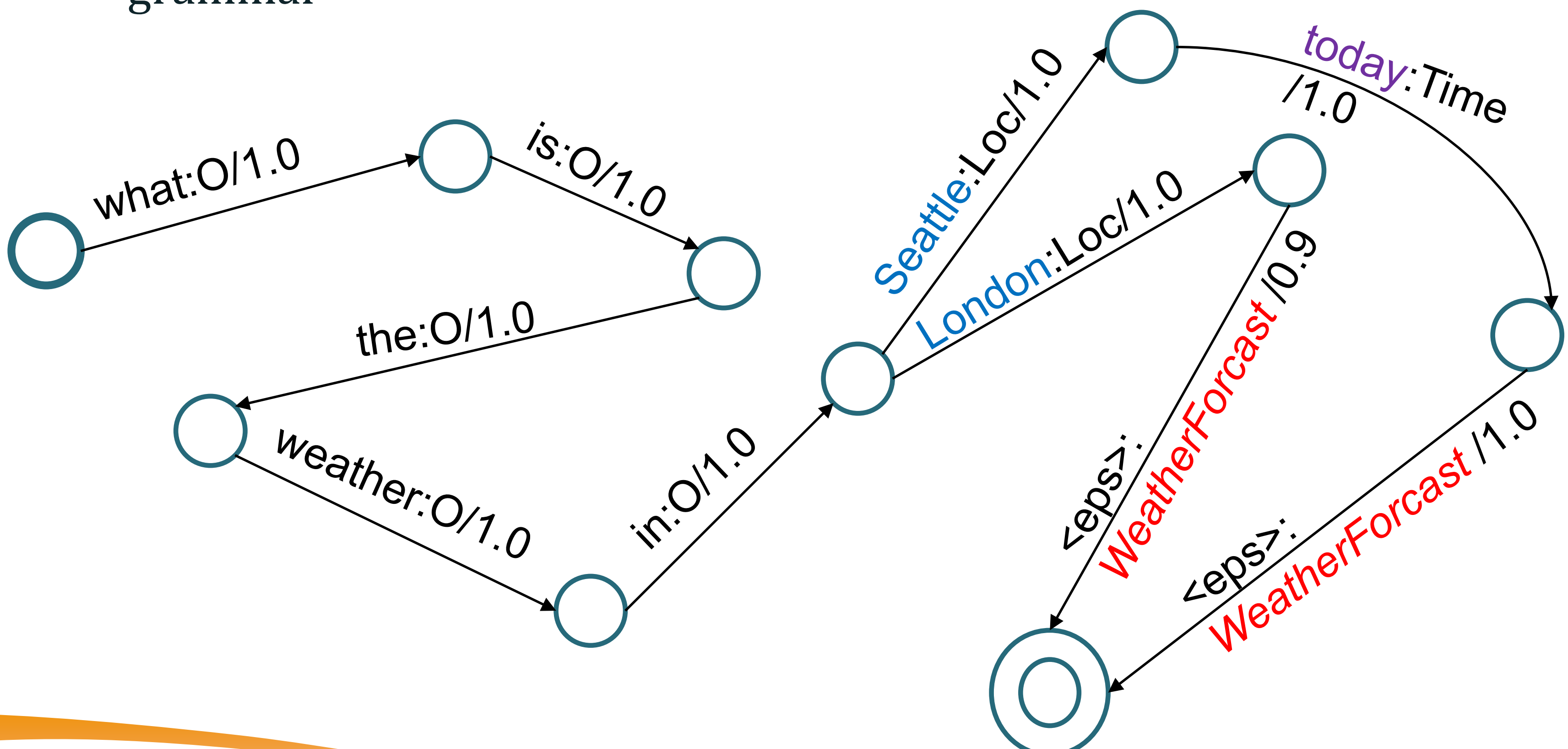
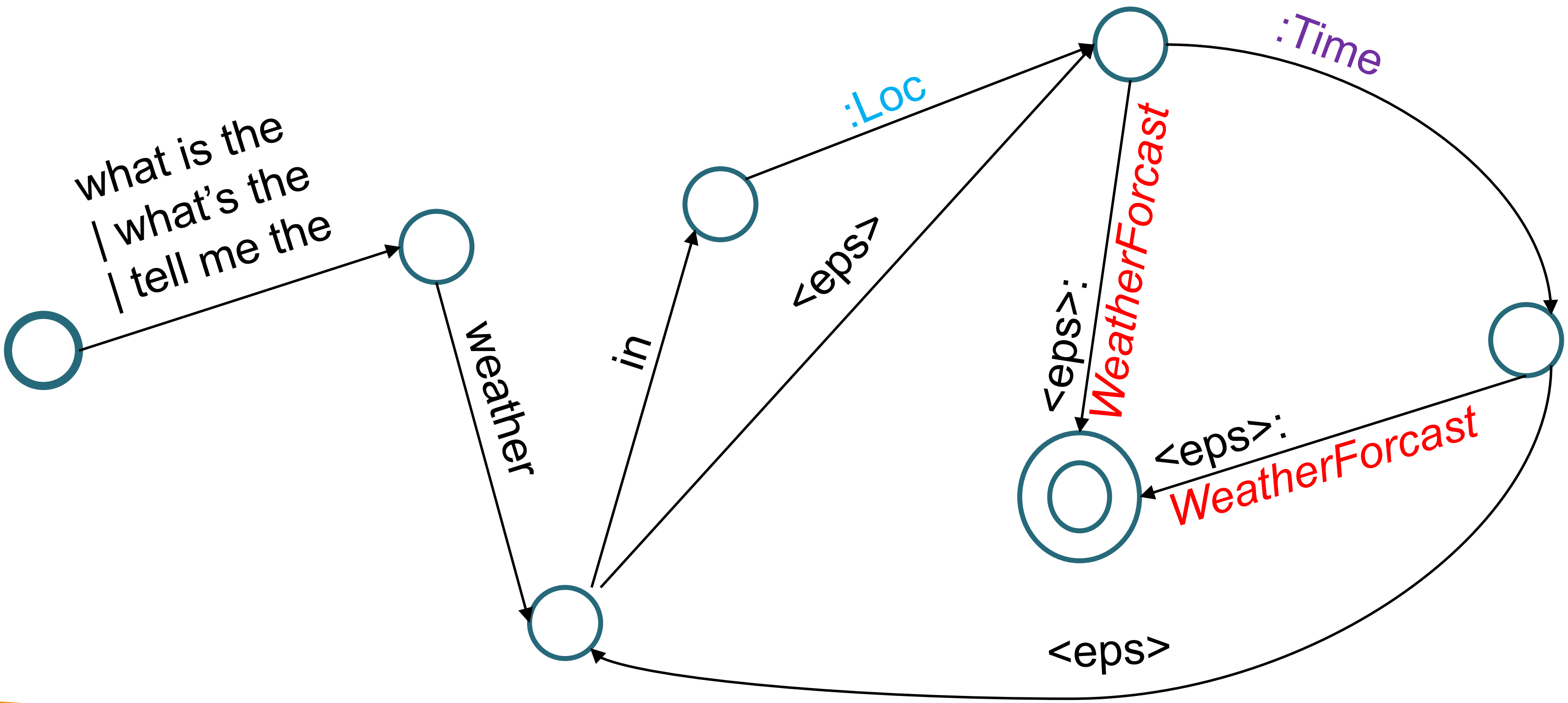
Deterministic NLU subsystem

- Weighted Finite State Transducers
  - an easy but powerful way to represent data under a weighted grammar



Deterministic NLU subsystem

- Simplified Finite State Transducers
  - Generalised by Named Entity Recognition
  - Dictionaries enrich the Knowledge Base



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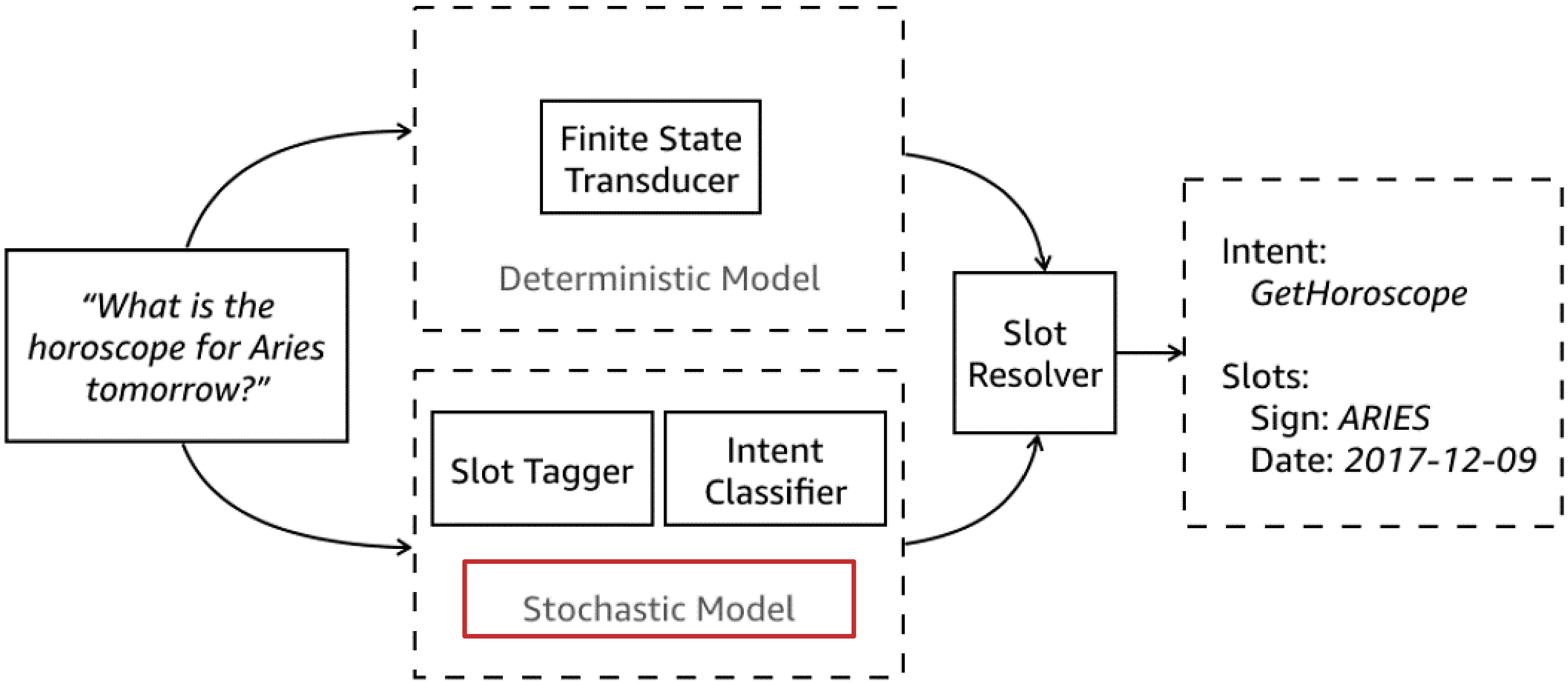
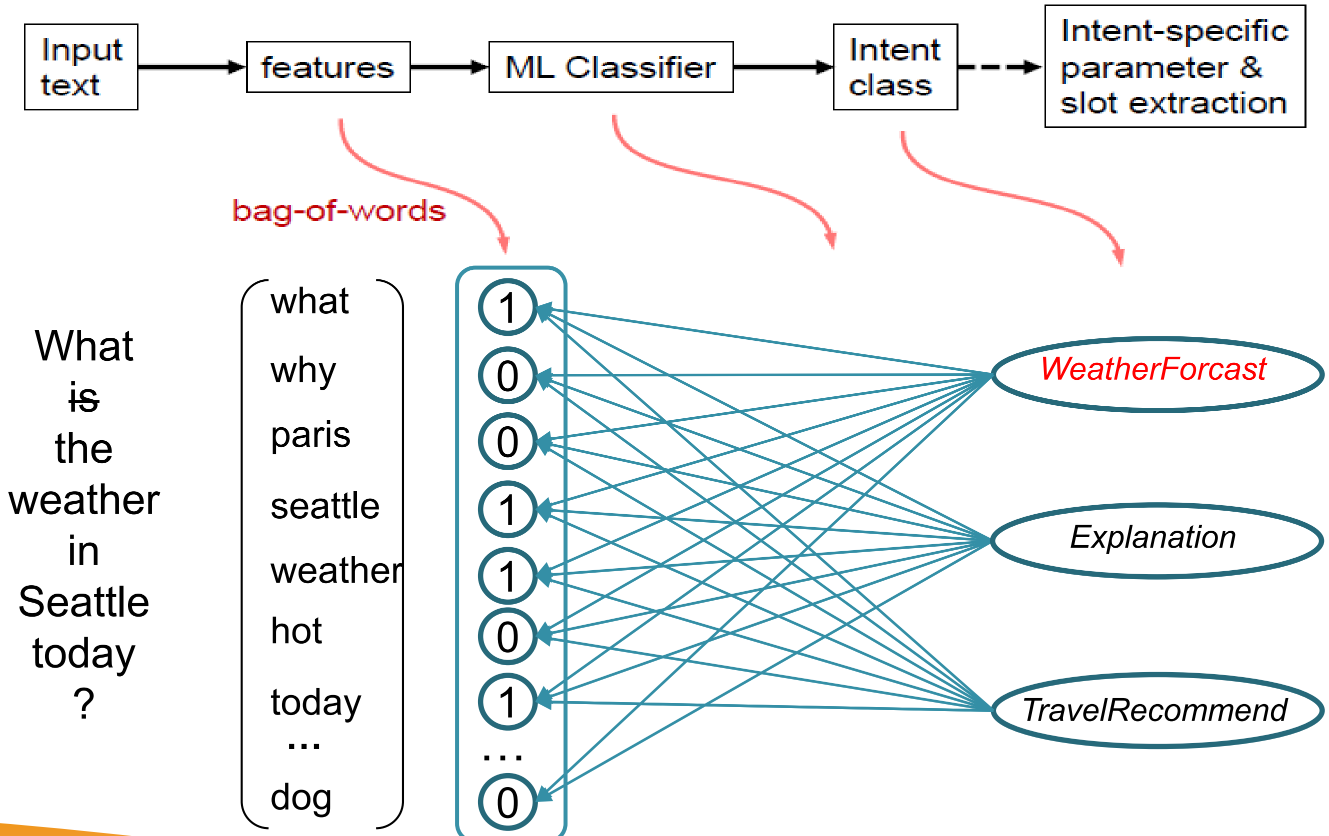


Image from 8. "Just ASK: building an architecture for extensible self-service spoken language understanding."

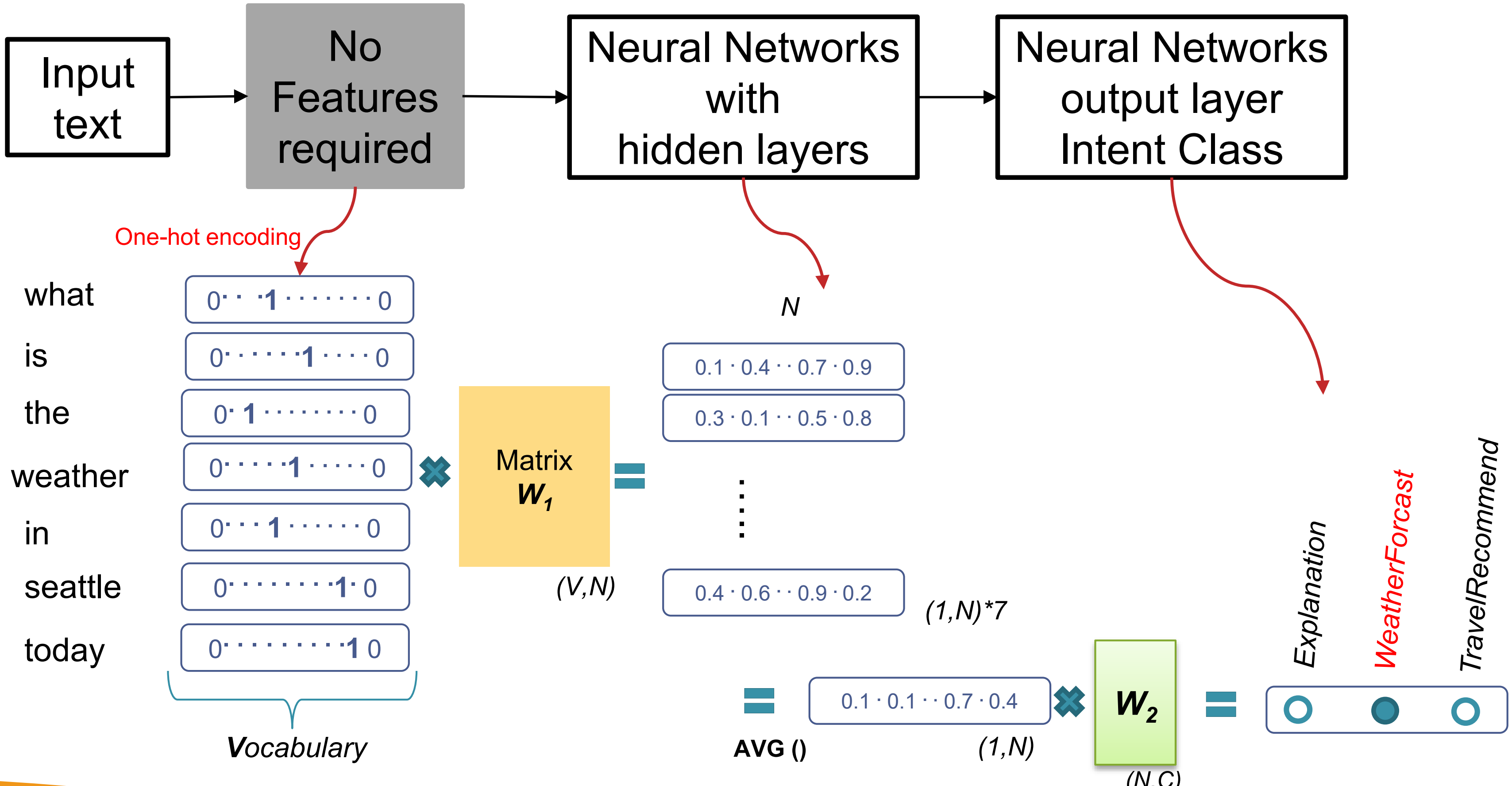
Intent detection

- Learn to organize the knowledge through modelling
  - ***Intent*** classification through machine learning (**supervised**) models (SVM/**NB**/LR/DT/KNN)



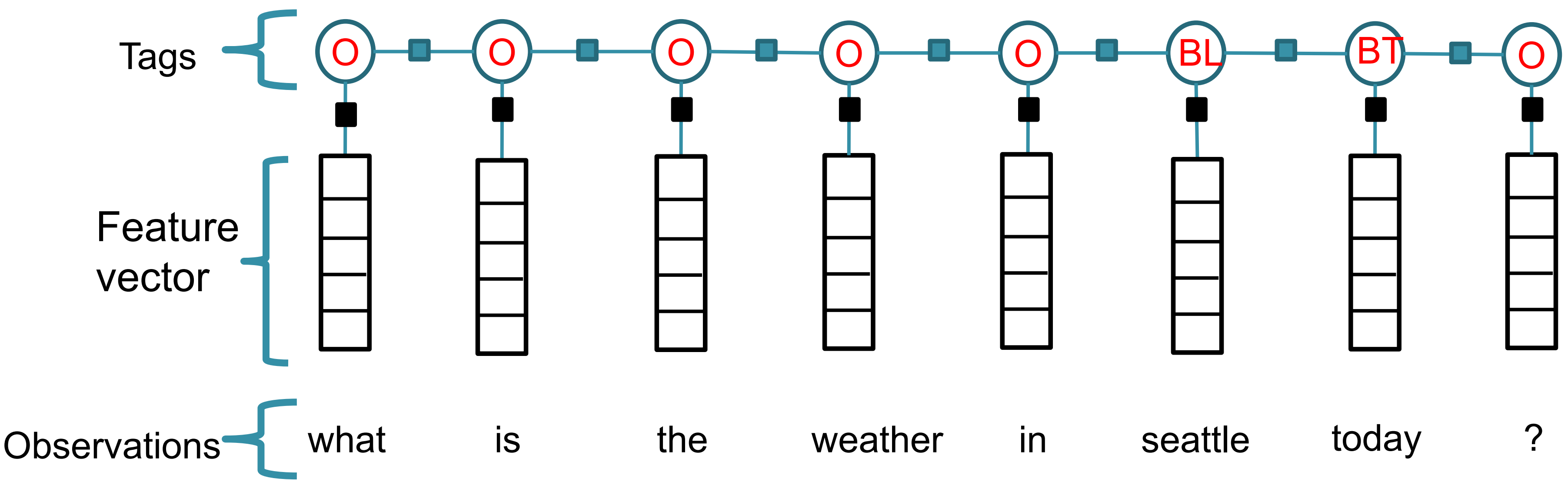
Intent detection

- Learn to organize the knowledge through modelling
  - ***Intent*** classification through *DeepLearning*



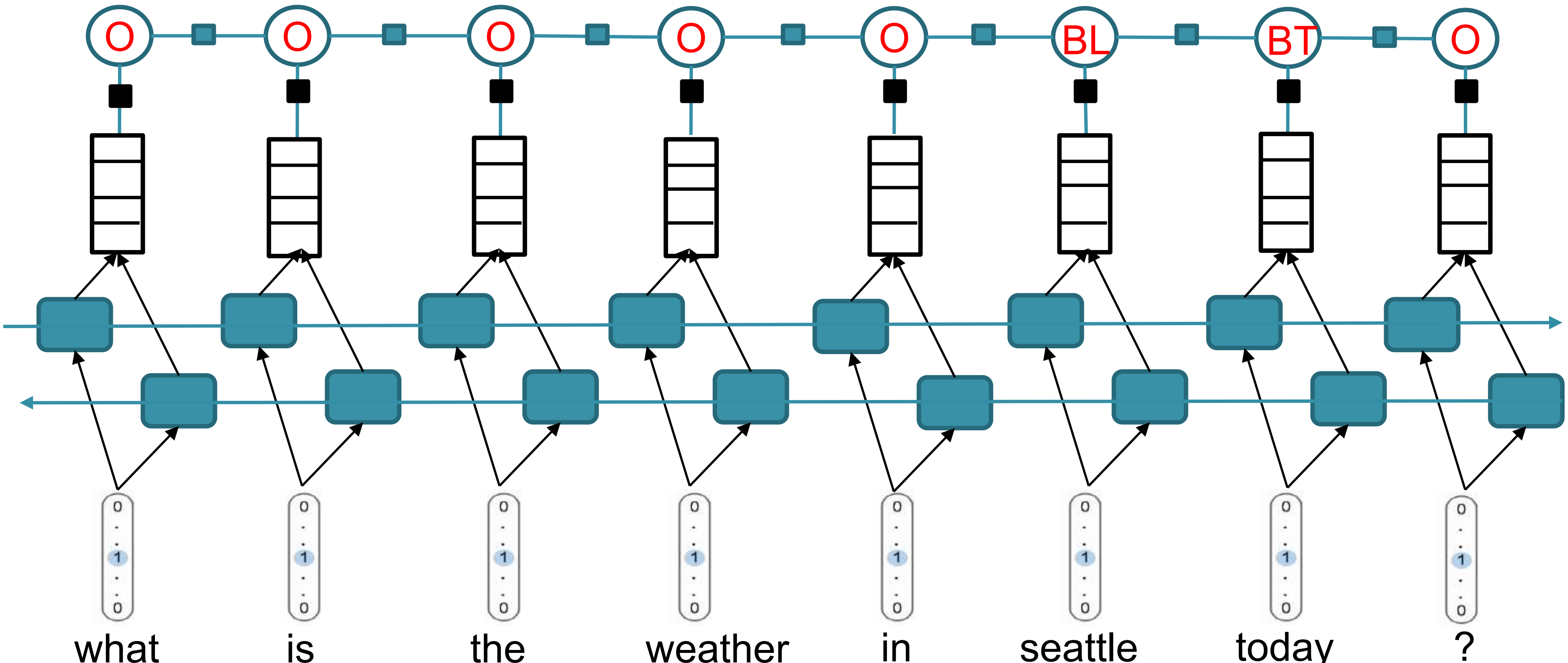
Slots detection

- NER through classic models (HMM/**CRF**)
  - A Linear-Chain CRF
  - Entity labelled in sequence



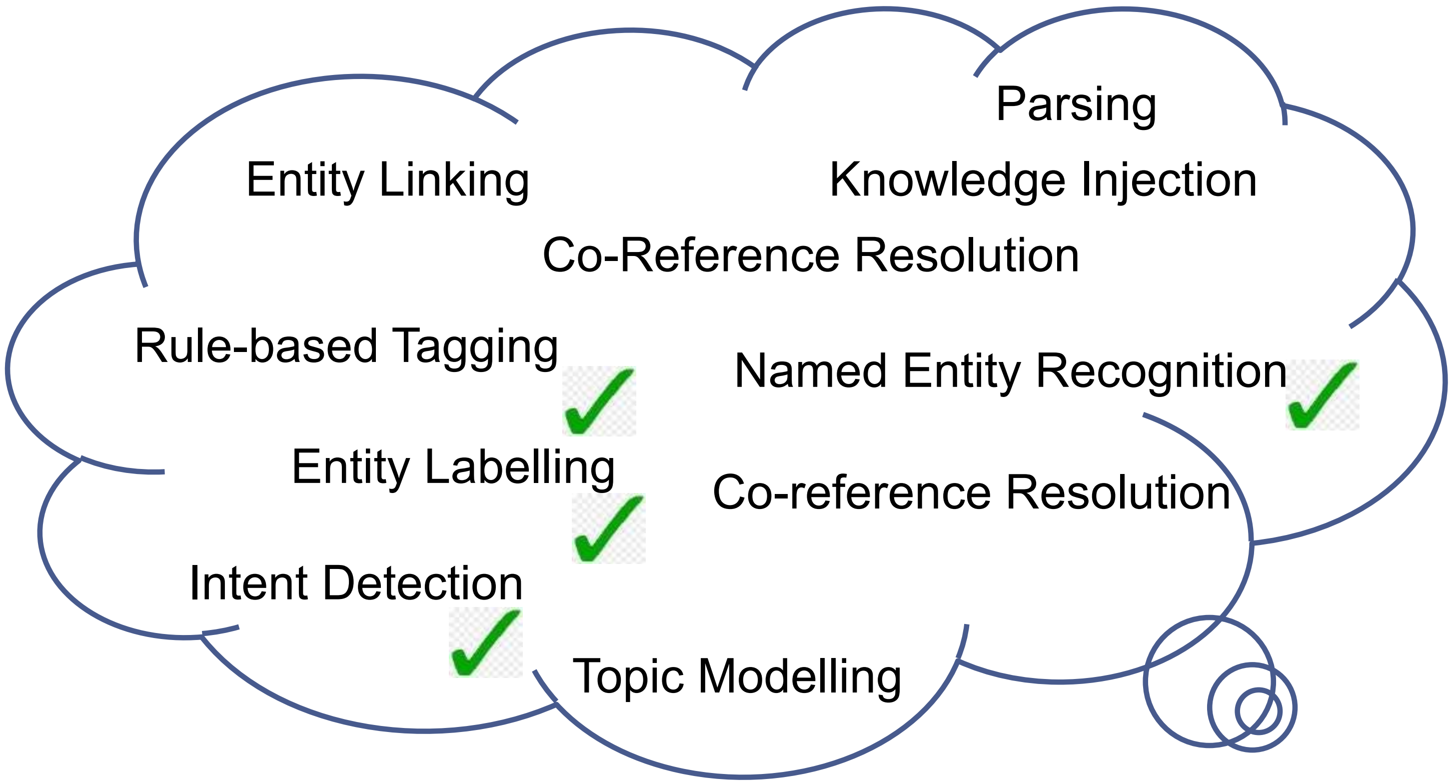
Slots detection

- NER With the help of *DeepLearning* (Bi-**LSTM+CRF**)
  - State-of-the-art ?



Review the NLU

- More Tasks to be addressed



Contextual Memory

- Co-Reference Resolution

"Alexa, who won the 1934 world series?

"The Saint Louis Cardinals beat the Detroit Tigers 4-3 in the 1934 Word Series."

"Alexa, who was the president then?"

"This might answer your question. The president of the United States is Donald Trump."

Contextual Memory

- Co-Reference Resolution

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"Alexa, who was the president then?"

"This might answer your question. The president of the United States is Donald Trump."

- Dialog State Tracking

FindPerson
Agent : ?
Verb : win
Object : world series
Date : 1934
Location :

FindPerson
Agent : ?
Verb : is
Object : President
Date : Then
Location:

Interfacing With SKILLs

- Logical Forms:

  SearchAction (WeatherForcast((Location 'Seattle'),(StartDate 'Today')))

- From Alexa to Skills


```
{
    "request": {
        "type": "CanFulfillIntentRequest ",
        "requestId": "...",
        "intent": {
            "name": "WeatherForcast",
            "slots": {
                "location": " 'Seattle ",
                "startdate": "today"
            },
        },
    }
}
```


Interfacing With SKILLs

- Round 1

Alexa


```
{
    "response":{
        "canFulfillIntent": {
            "canFulfill": "YES",
            "slots":{
                “location ": {
                    "canUnderstand": "YES",
                    "canFulfill": "YES"
                },
                " startdate ": {
                    "canUnderstand": "YES",
                    "canFulfill": "YES"
                }
            }
        }
    }
}
```


Skill

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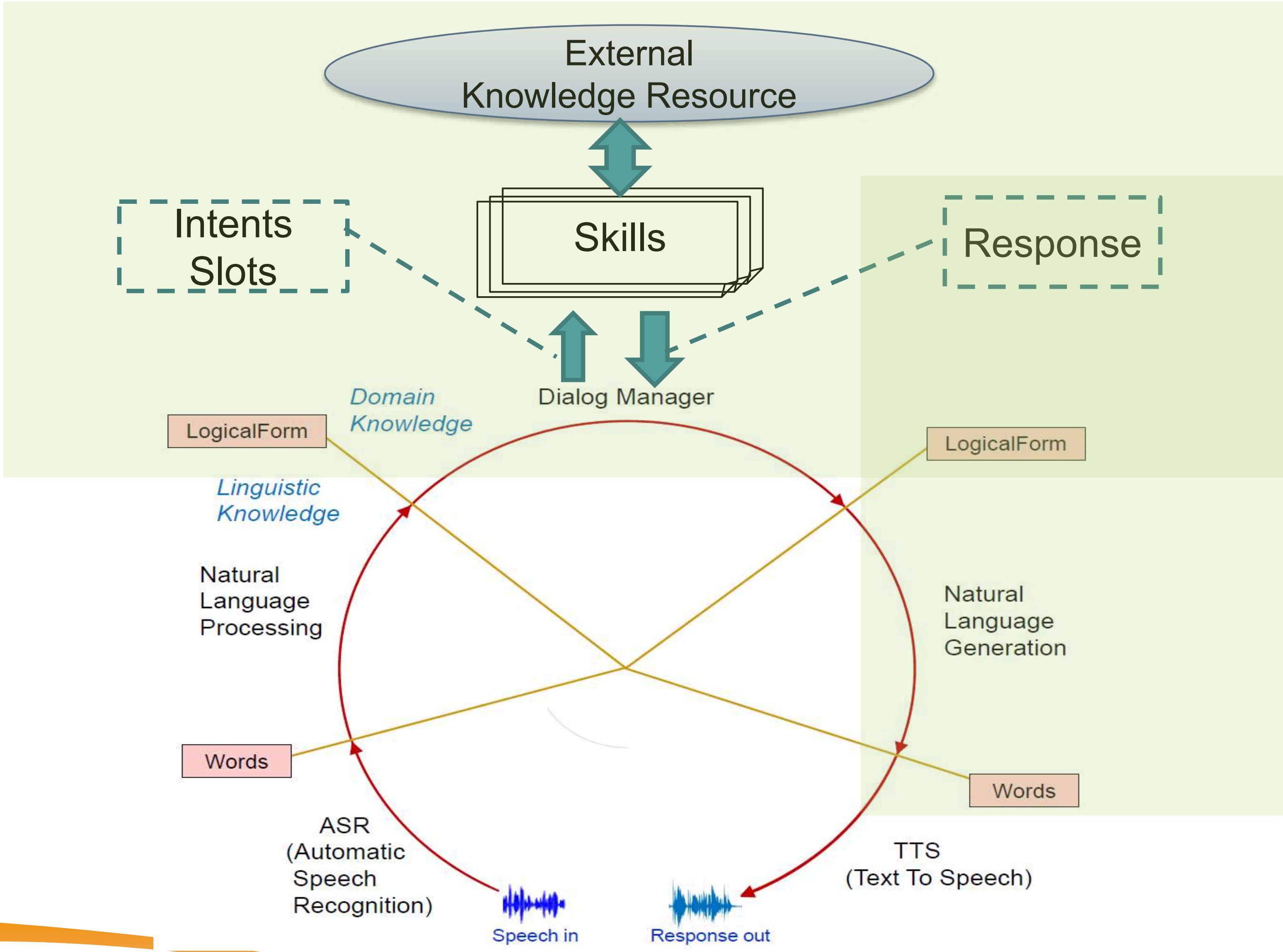
Interfacing With SKILLs



Response Generation

- Round 2

Alexa


```
{
    "type": "IntentRequest",
    "requestId": "001",
    "timestamp": "…",
    "intent": {
            "name": " WeatherForcast ",
            "slots": {
                " location ": {
                    "name": " location ",
                    "value": " Seattle ",
                } ,
                " startdate ": {
                    "name": " startdate ",
                    "value": " Today ",
                }

            }
    }
}
```


Show time for your Skill

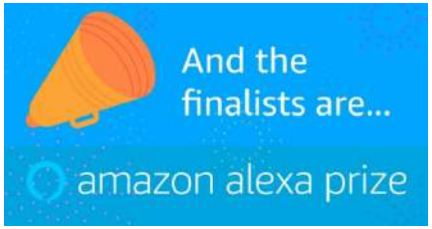
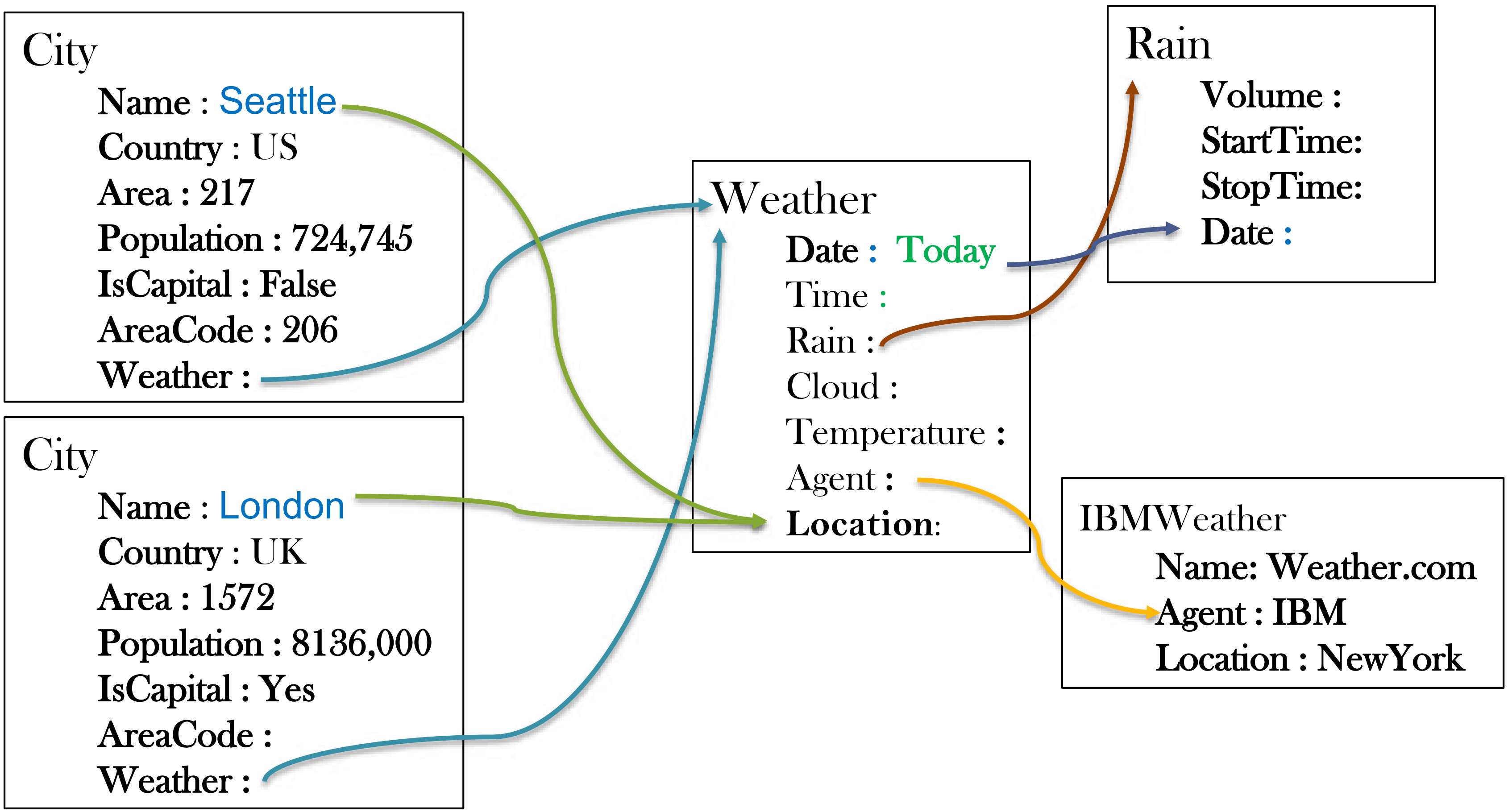


Image from www.flaticon.com

Query the Knowledge Base

- Query Match to KB

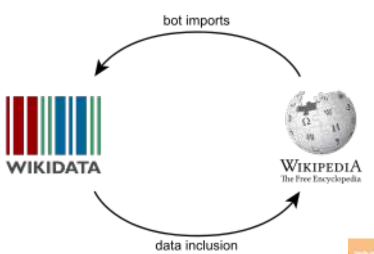
SearchAction (WeatherForcast((Location 'Seattle'),(StartDate 'Today')))



KB for Reasoning and Response Generation

- Knowledge Graph

Freebase
A socially managed semantic database



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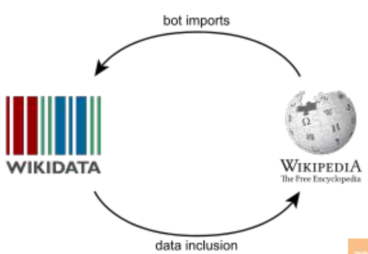


- Web Text Sources
  - CNN NEWs
  - Washington Posts
  - Reuters News
  - Broadcast News
  - Jester
  - Yelp Open Dataset

https://skymind.ai/wiki/open-datasets

https://www.kaggle.com/datasets?sortBy=relevance&group=featured&search=nlp

Response Generation

- Template/rule-based Response
  - AIML, ELIZA, **Alicebot**, Mitsuku (Pandorabots)
- Retrieval based approach
  - N-gram matching, similarity on vectors such as TF-IDF, word/sentence embeddings, skip-thought, dual-encoder system
- Generative models
  - Encoder-Decoder with objective function
- Hybrid approach
  - leveraging retrieval in combination with generative models

Rule-based Approach

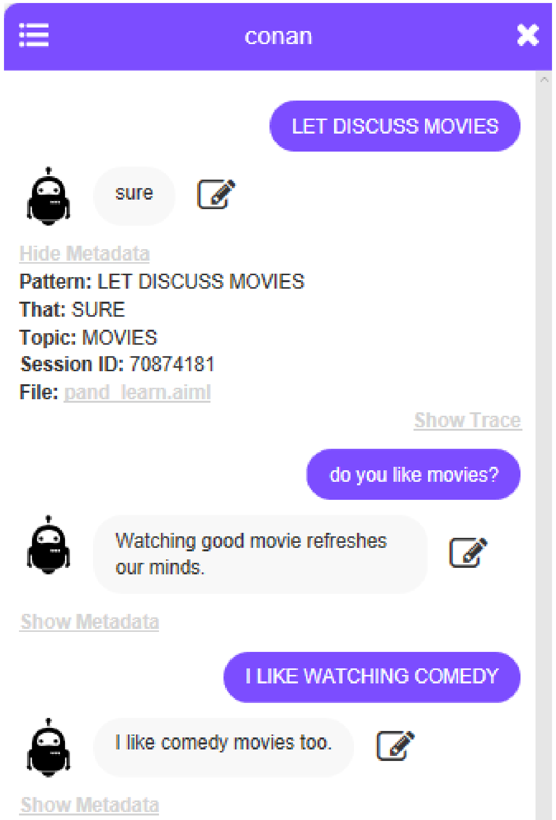
- Pandorabots with **AIML**
  - Response generation integrated with NLU

```
<?xml version = "1.0" encoding = "UTF-8"?>
<aiml version = "1.0.1" encoding = "UTF-8"?>
   <category>
      <pattern>LET DISCUSS MOVIES</pattern>
      <template>Yes <set name = "topic">movies</set></template>
   </category>

   <topic name = "movies">
      <category>
         <pattern> * </pattern>
         <template>Watching good movie refreshes our minds.</template>
      </category>

      <category>
         <pattern> I LIKE WATCHING COMEDY! </pattern>
         <template>I like comedy movies too.</template>
      </category>

   </topic>
</aiml>
```



https://www.pandorabots.com/docs/building-bots/quickstart/

Rule-based Approach

- https://www.pandorabots.com

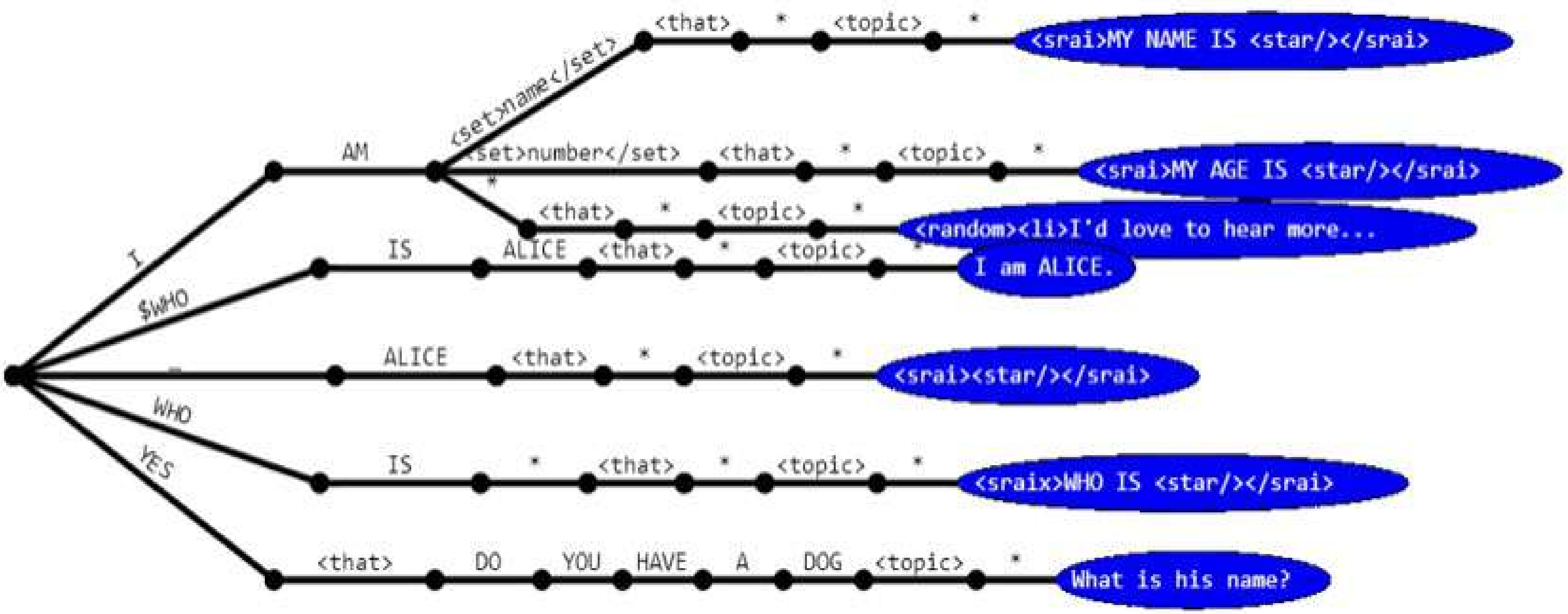
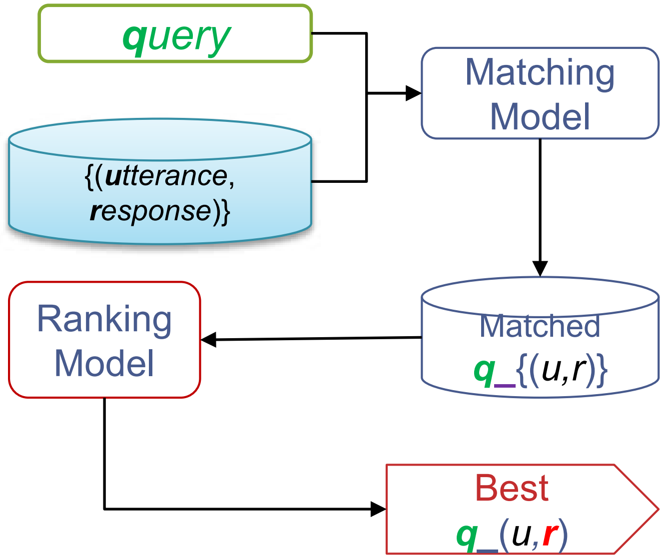


Image from https://www.pandorabots.com/docs/core-concepts/

Retrieval based approach

- Rank the candidates
  - Response are limited to the textual corpus
  - Widely used for summarization, task-oriented dialogue systems



Framework based on Similarity

Retrieval based approach

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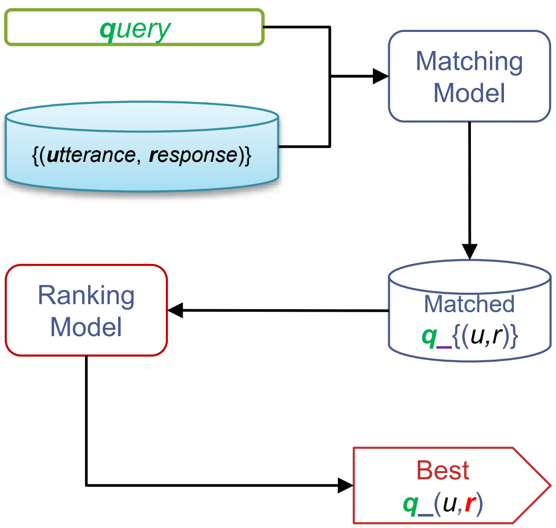
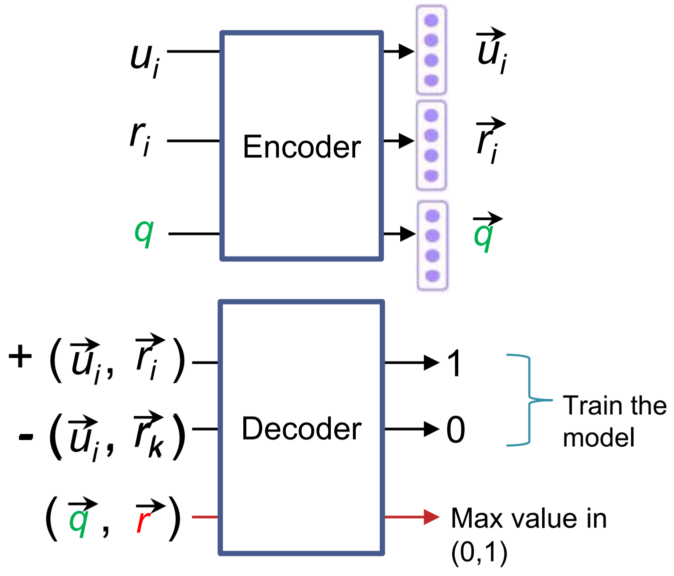


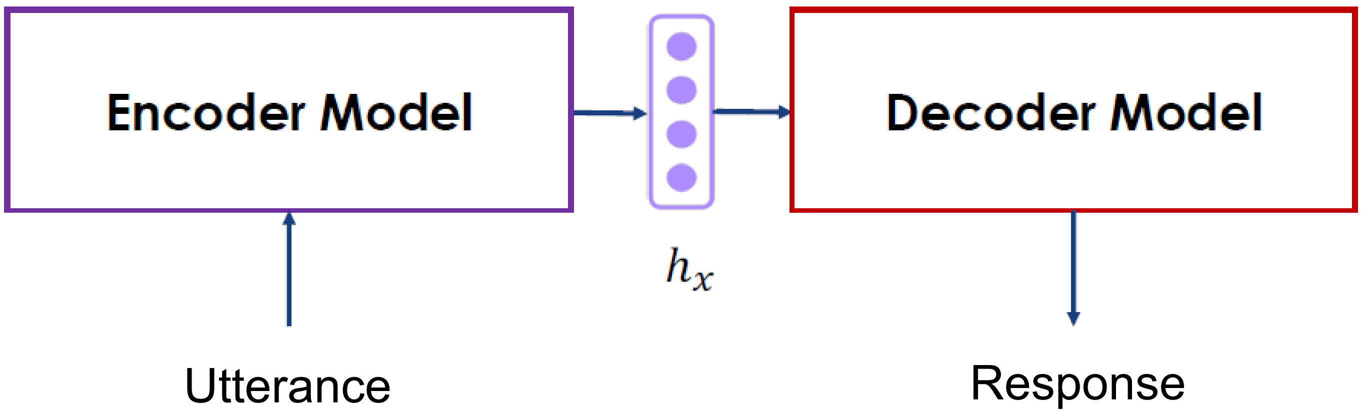
Framework based on Similarity



Framework with Embedding

Generative models

- Encoder-Decoder Framework
  - Able to generate new responses word by word
  - Prefer large dialog dataset with powerful GPUs



Hybrid approach

- Leveraging retrieval in combination with generative models
  - An Encoder-Decoder trained to generate the possible response
  - Responses are ranked based on context and answer relevance

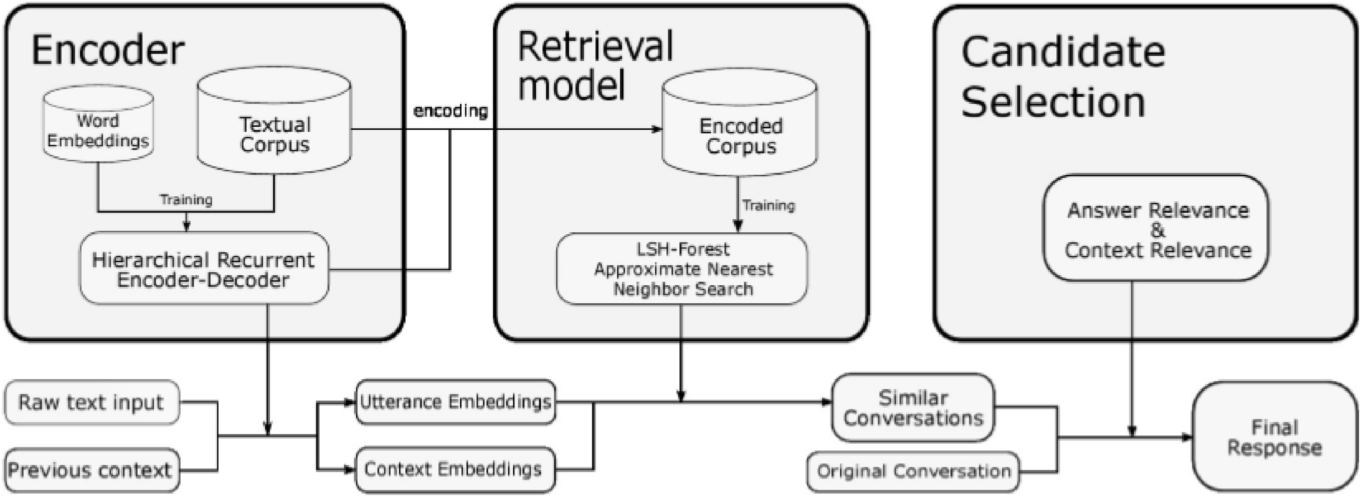


Fig. 1. A view of the pipeline implementing the proposed approach. An HRED encoder is used to generate context and response embeddings and an ANN model builds on previous steps to retrieve similar conversations. Finally, the best candidate is selected according to answer- and context-relevance.

Architecture of a Voice Assistant

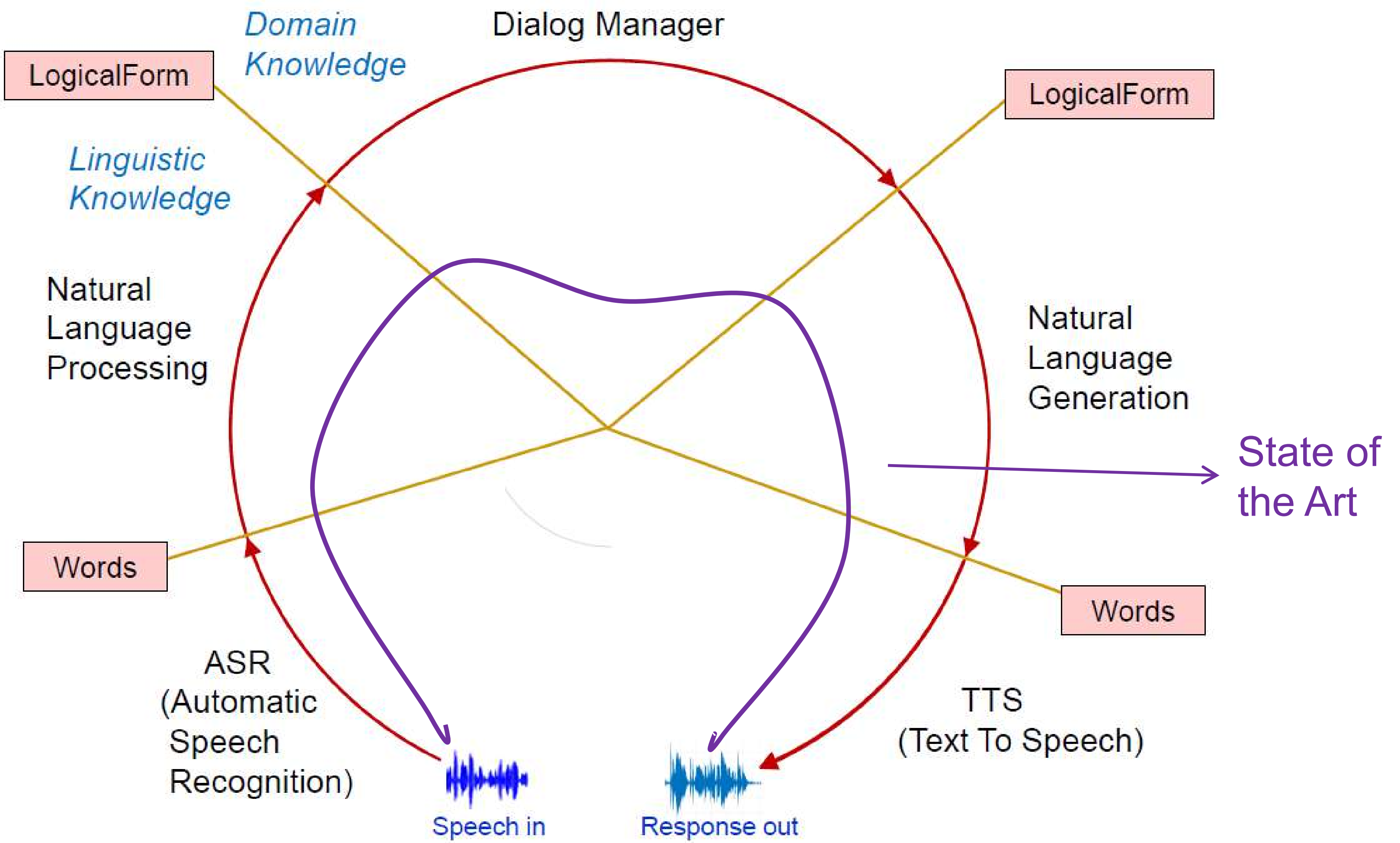


Image from SCI 52 Artificial Intelligence: An Introduction to Neural Networks and Deep Learning,

Agenda

- Introduction of Cognitive Systems
- Cognitive Knowledge Representation and Reasoning
- Case Study Alexa
  - Features and Architecture
  - Auto Speech Recognition
  - Language understanding
  - Response generation
- **Workshop: Introduction to Google Dialogflow**

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