CS60075
Natural Language Processing
Autumn 2020

Module 10

Conversational Agents

Part 2

18 Nov 2020

Architectures for Practical Dialog Systems

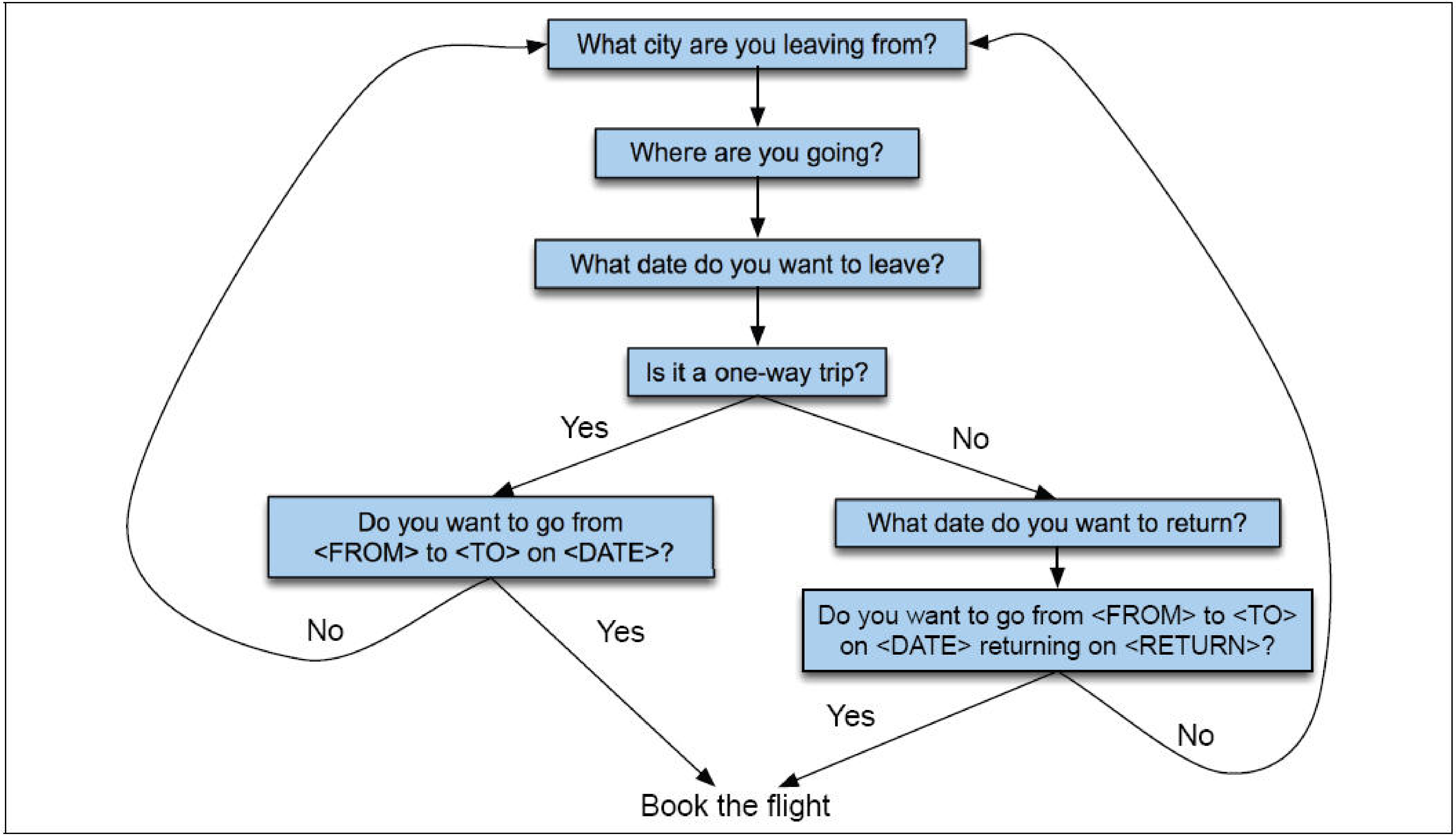
1. Finite-State
   - *for passwords or credit cards*
2. Frame-Based
   - *All commercial and academic system*
   - *(SIRI etc.)*

Finite-State Dialog Management

Consider a trivial airline travel system:

- Ask the user for a departure city
- Ask for a destination city
- Ask for a time
- Ask whether the trip is round-trip or not

Finite State Dialog Manager



Finite-state dialog managers

- System completely controls the conversation with the user.
- It asks the user a series of questions
- Ignoring (or misinterpreting) anything the user says that is not a direct answer to the system’s questions

Dialogue Initiative

- Systems that control conversation like this are called **single initiative**.
- **Initiative**: who has control of conversation
- In normal human-human dialogue, initiative shifts back and forth between participants.

System Initiative

System completely controls the conversation

+

- Simple to build
- User always knows what they can say next
- System always knows what user can say next
    - Known words: Better performance from ASR
    - Known topic: Better performance from NLU
- OK for VERY simple tasks (entering a credit card, or login name and password)

–

- Too limited

Problems with System Initiative

- Real dialogue involves give and take!
- In travel planning, users might want to say something that is not the direct answer to the question.
- For example answering more than one question in a sentence:

Hi, I'd like to fly from Seattle Tuesday morning

I want a flight from Milwaukee to Orlando one way leaving after 5 p.m. on Wednesday.

Single initiative + universals

- We can give users a little more flexibility by adding **universals**: commands you can say anywhere
- As if we augmented every state of FSA with these

  Help

  Start over

  Correct
- This describes many implemented systems
- But still doesn't allow user much flexibility

II: Frame-based dialog agents

- A kind of ***mixed initiative***
  - The conversational initiative shifts between system and user
- The structure of the **frame** guides dialogue

Artificial Intelligence Journal, 1977

versation with a client who wants to make a simple return trip to a single city in California.

There is good reason for restricting the domain of discourse for a computer system which is t engage in an English dialog. Specializing the subject matter that the system can talk about permi it to achieve some measure of realism without encompassing all the possibilities of human knowledg or of the English language. It also provides the user with specific motivation for participating in th conversation, thus narrowing the range of expectations that GUS must have about the user's pur poses. A system restricted in this way will be more able to guide the conversation within the boundarie of its competence.

- Still the industrial state of the art
  - SIRI based on GUS architecture

Frame-based Dialogue Systems

- Task-based Dialogue Agents
- Based on “Domain Ontology”
  - A knowledge structure representing user intentions

- One or more **frames**
  - Each a collection of **slots**
  - Each slot having a **value**

Slot	Type	Question
ORIGIN	city	What city are you leaving from?
DEST	city	Where are you going?
DEP DATE	date	What day would you like to leave?
DEP TIME	time	What time would you like to leave?
AIRLINE	line	What is your preferred airline?

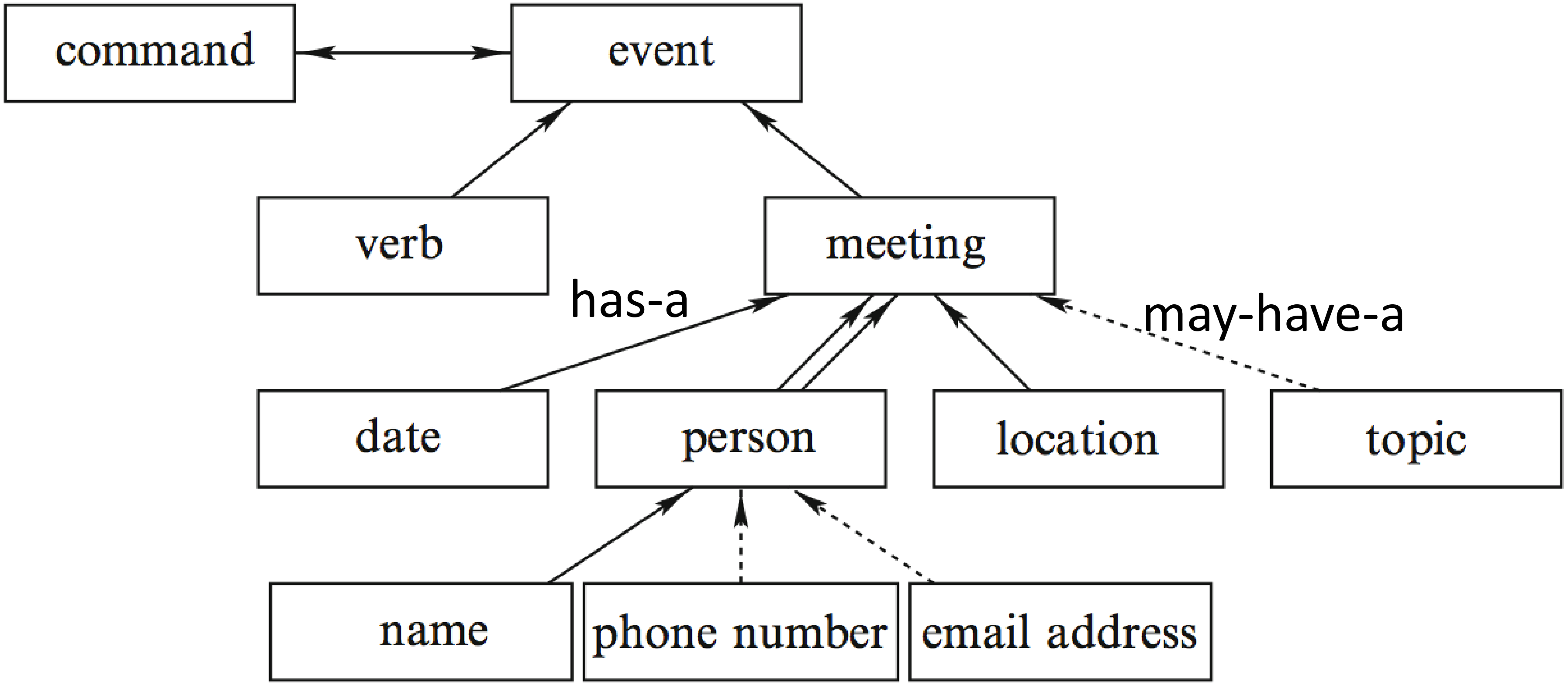
Slot : Origin City

Type : City

Value : San Francisco

GUS: A Frame-Driven Dialog System; Bobrow et al, AIJ 1977

Part of ontology for meeting task



meeting concept: if you don’t yet have a location, ask for a location

Natural language understanding for filling slots in GUS

1. Domain classification

   Asking weather? Booking a flight?

   Programming alarm clock?

2. Intent Determination

   Find a Movie, Show Flight,

   Remove Calendar Appt

3. Slot Filling

   Extract the actual slots and fillers

Rule Sets

- Collections of **rules** consisting of:
  - condition
  - action
- When user input is processed, facts added to store and
  - rule conditions are evaluated
  - relevant actions executed

Semantic Grammar Rules

Neural Approaches to Conversational AI

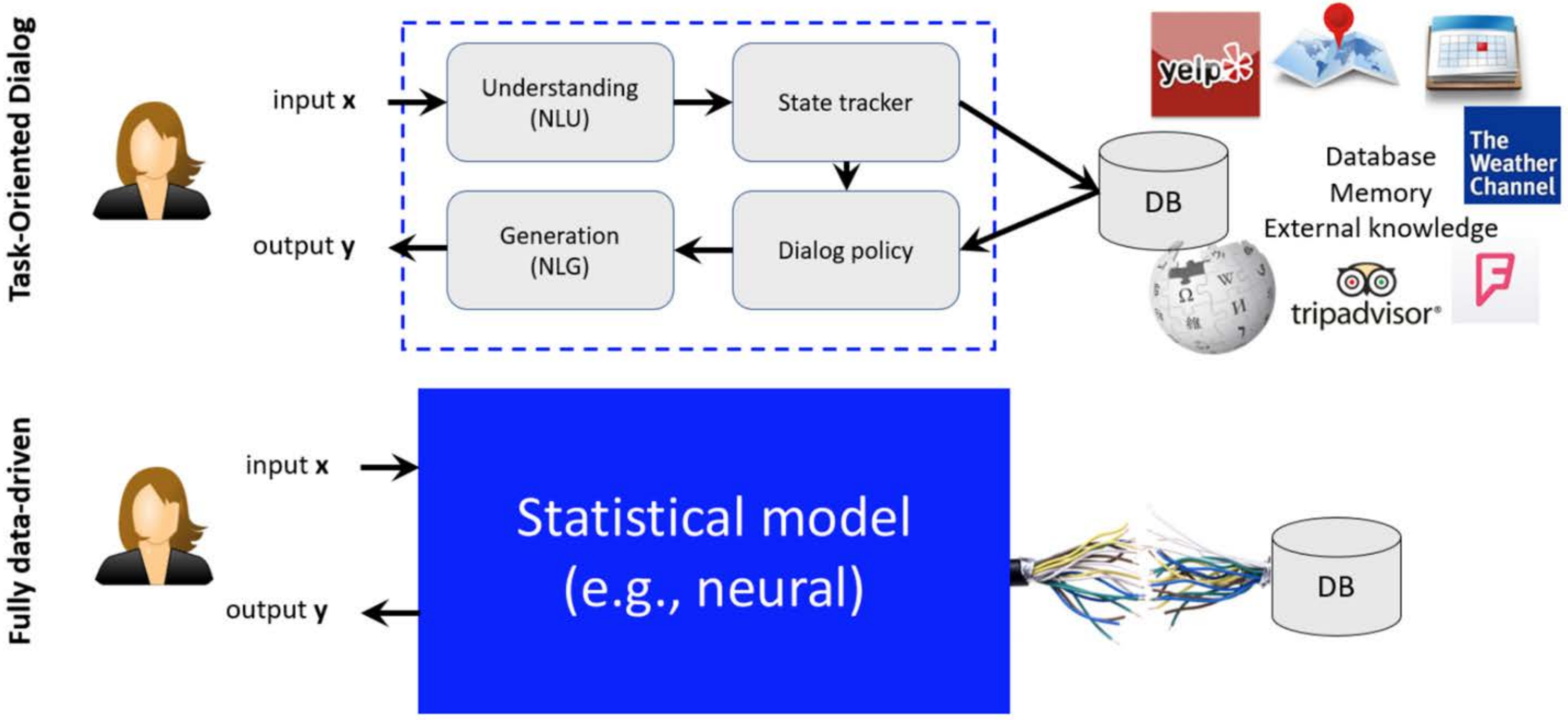
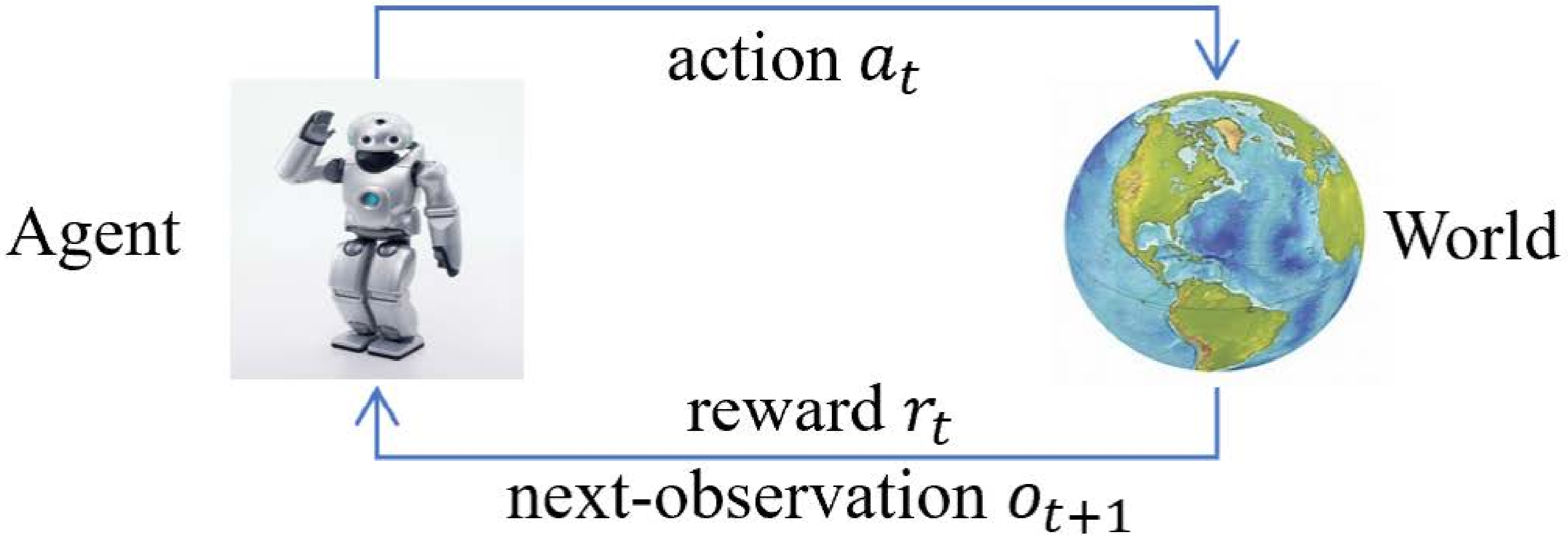


Figure 1.2: Two architectures of dialogue systems for (Top) traditional task-oriented dialogue and (Bottom) fully data-driven dialogue.

Source: https://arxiv.org/pdf/1809.08267.pdf

Neural Approaches to Conversational AI



Source: https://arxiv.org/pdf/1809.08267.pdf

A unified view: dialogue as optimal decision making

- Dialogue as a Markov Decision Process (MDP)
  - Given state s, select action a according to (hierarchical) policy π
  - Receive reward r, observe new state s'
  - Continue the cycle until the episode terminates.
- Goal of dialogue learning: find optimal π to maximize expected rewards

Dialogue	State (s)	Action (a)	Reward (r)
Info Bots (Q&A bot over KB, Web etc.)	Understanding of user Intent (belief state)	Clarification questions, Answers	Relevance of answer # of turns (less is better)
Task Completion Bots (Movies, Restaurants, …)	Understanding of user goal (belief state)	Dialog act + slot_value	Task success rate # of turns (less is better)
Social Bot (XiaoIce)	Conversation history	Response	Engagement, # of turns (more is better)

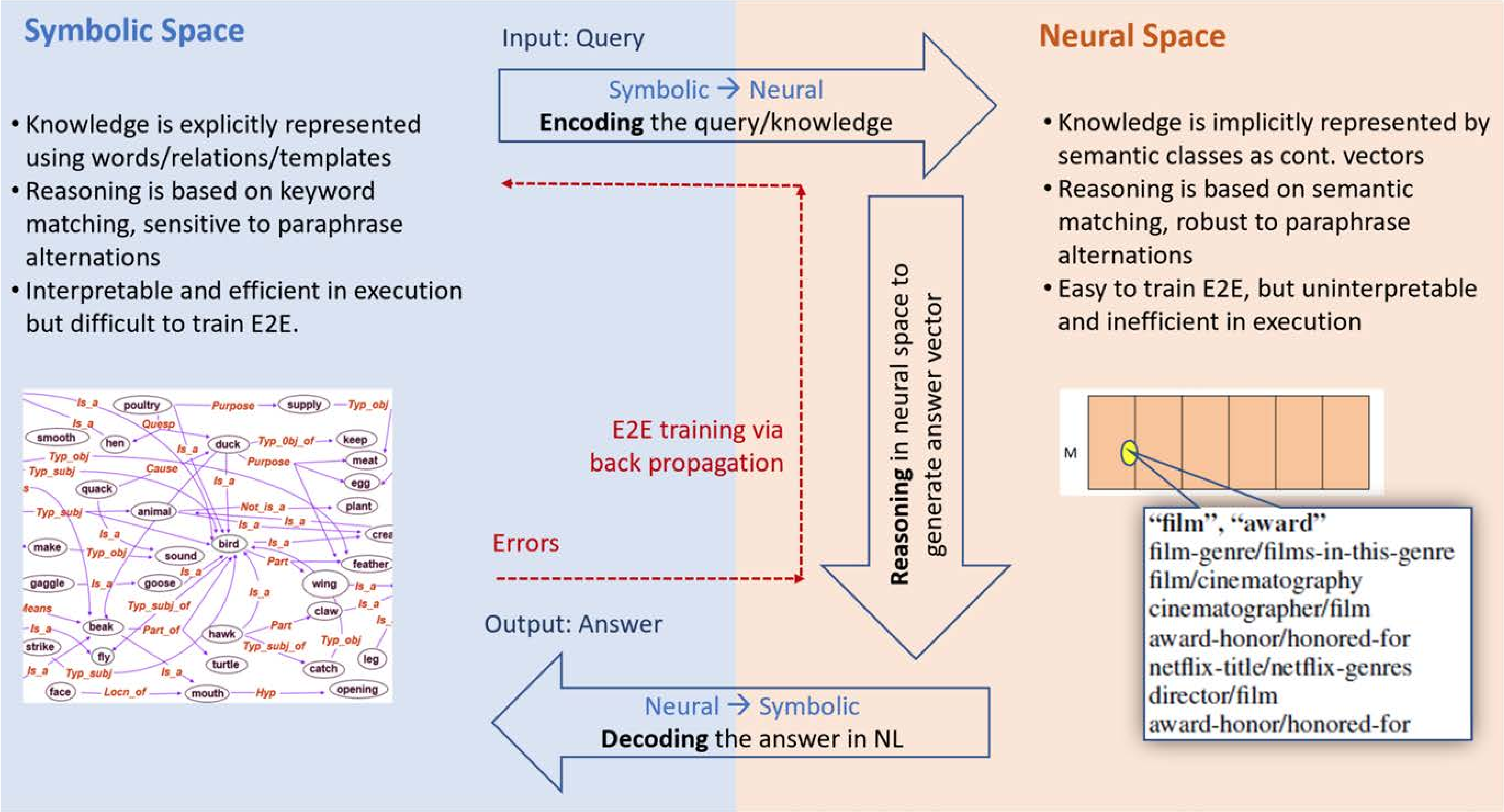
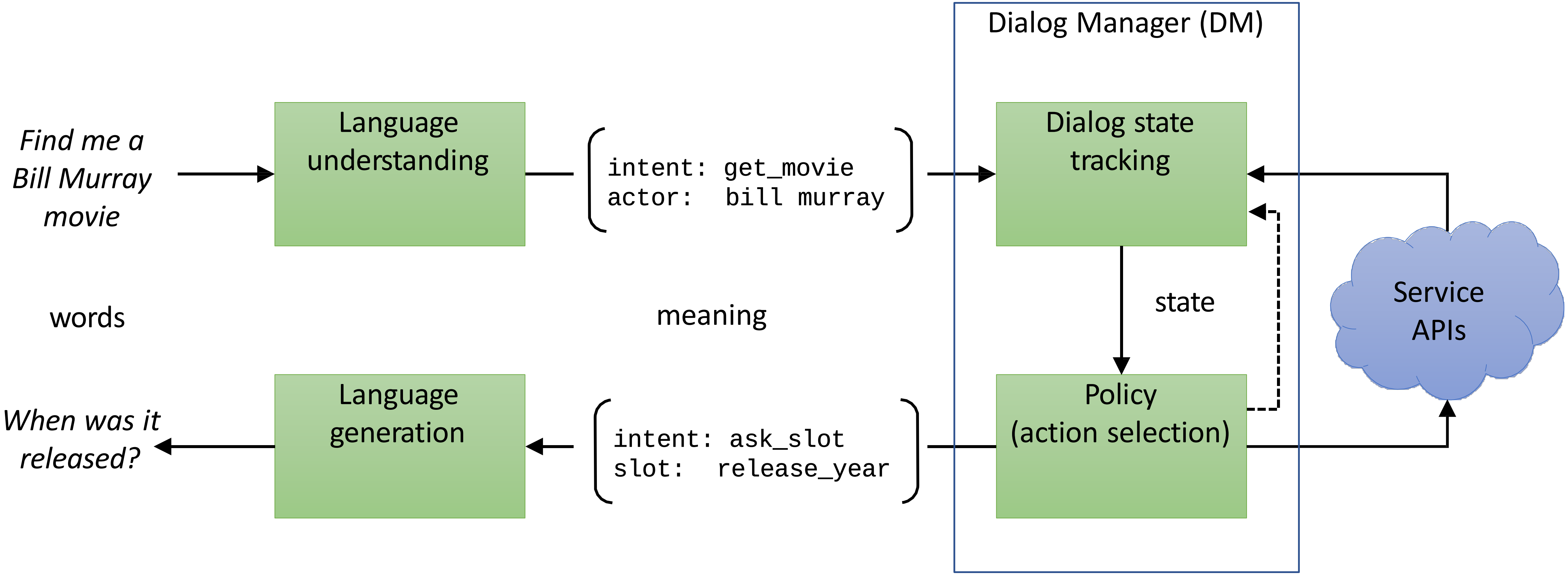
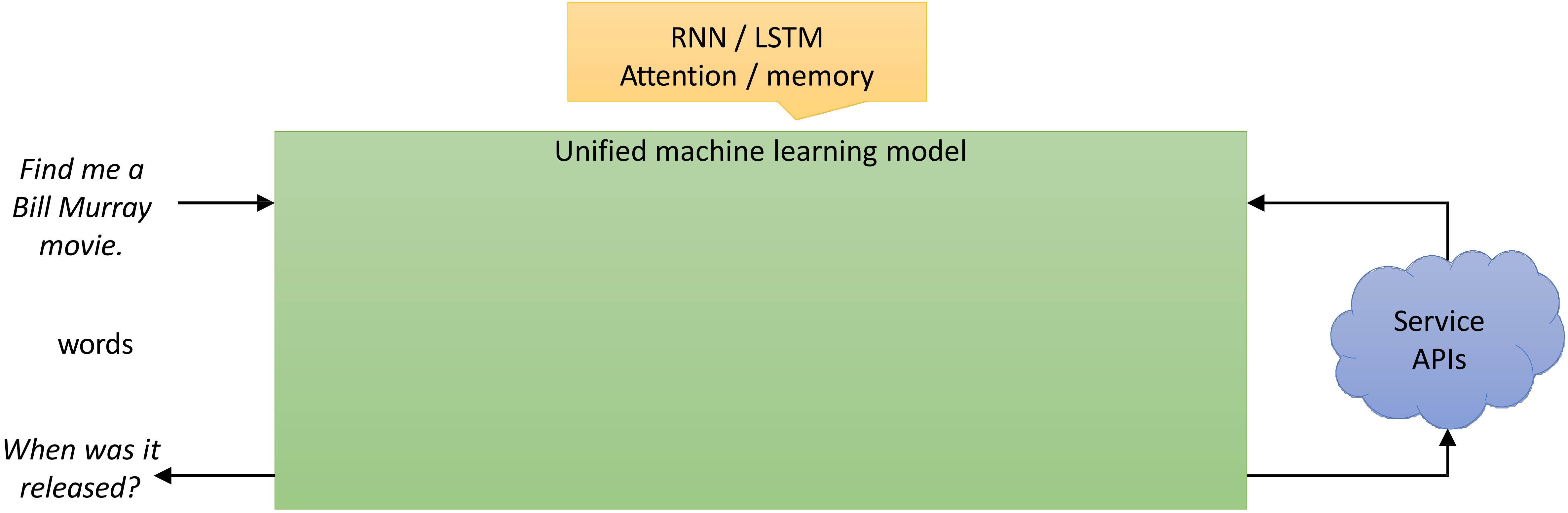


Figure 1.4: Symbolic and Neural Computation.

Classical dialog system architecture



E2E Neural Models

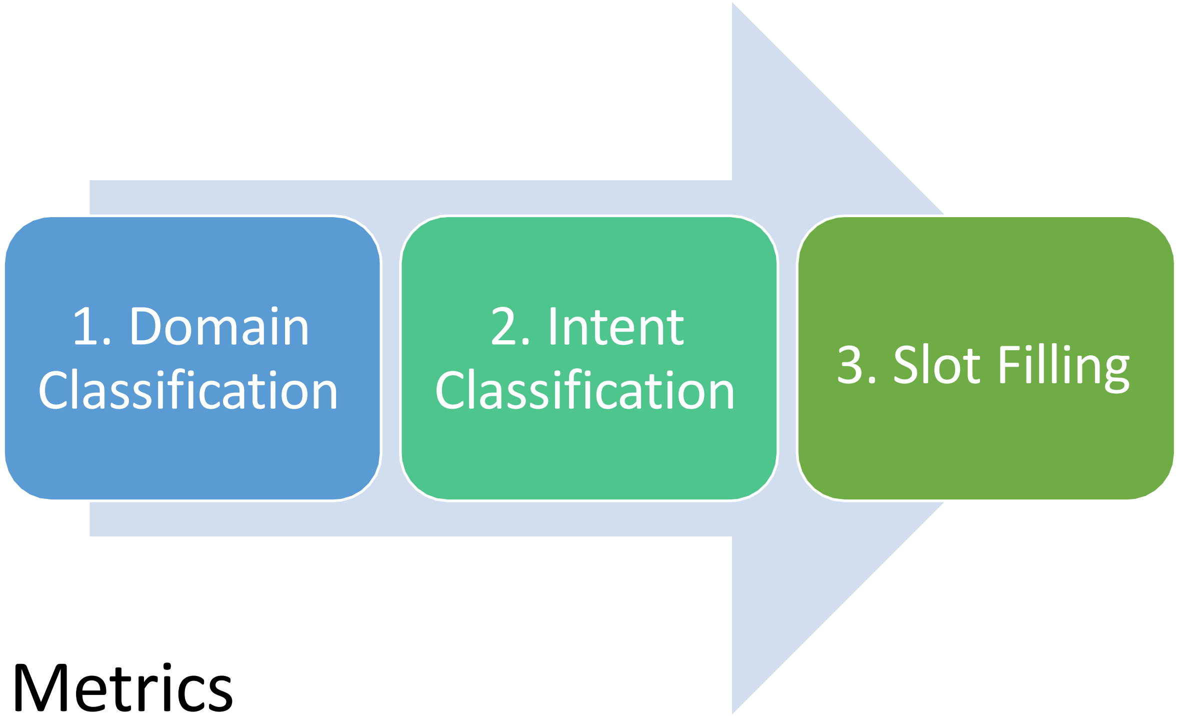


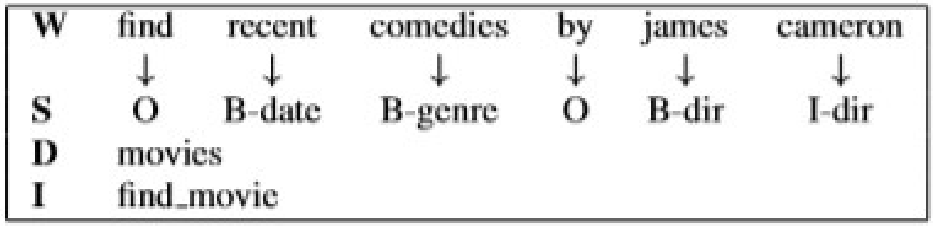
Attractive for dialog systems because:

- Avoids hand-crafting intermediate representations like intent and dialog state
- Examples are easy for a domain expert to express

Language Understanding

- Often a multi-stage pipeline





W	find	recent	comedies	by	james	cameron
	↓	↓	↓	↓	↓	↓
S	O	B-date	B-genre	O	B-dir	I-dir
D	movies					
I	find_movie					

Figure 1: *An example utterance with annotations of semantic slots in IOB format (S), domain (D), and intent (I), B-dir and I-dir denote the director name.*

- Metrics
  - o Sub-sentence-level: intent accuracy, slot F1
  - o Sentence-level: whole frame accuracy

Machine Learning for Slot Filling

- Supervised semantic parsing
- Model to map from input words to slot fillers, domain and intent
- Given a set of labeled sentences

  "I want to fly to San Francisco on Tuesday"

  Destination: SF
  Depart-date: Tuesday

- Requirements: Lots of labeled data

Slot Filling

"I want to fly to San Francisco on Monday afternoon please"

Use 1-of-N classifier (Naive Bayes, Logistic Regression, Neural Network, etc.)

- Input: features like word N-grams
- Output:
  - Domain: AIRLINE Intent: SHOWFLIGHT

IOB Tagging

- IOB Tagging
  - Tag for the beginning (B) and inside (I) of each slot label,
  - plus one for tokens outside (O) any slot label
  - $2n + 1$ tags, where n is the number of slots

```
0 0    0  0   0  B-DES I-DES       0  B-DEPTIME I-DEPTIME   0
I want to fly to San   Francisco on Monday      afternoon   please
```

B-DESTINASTION
I-DESTINATION
B-DEPART_TIME
I-DEPART_TIME
O

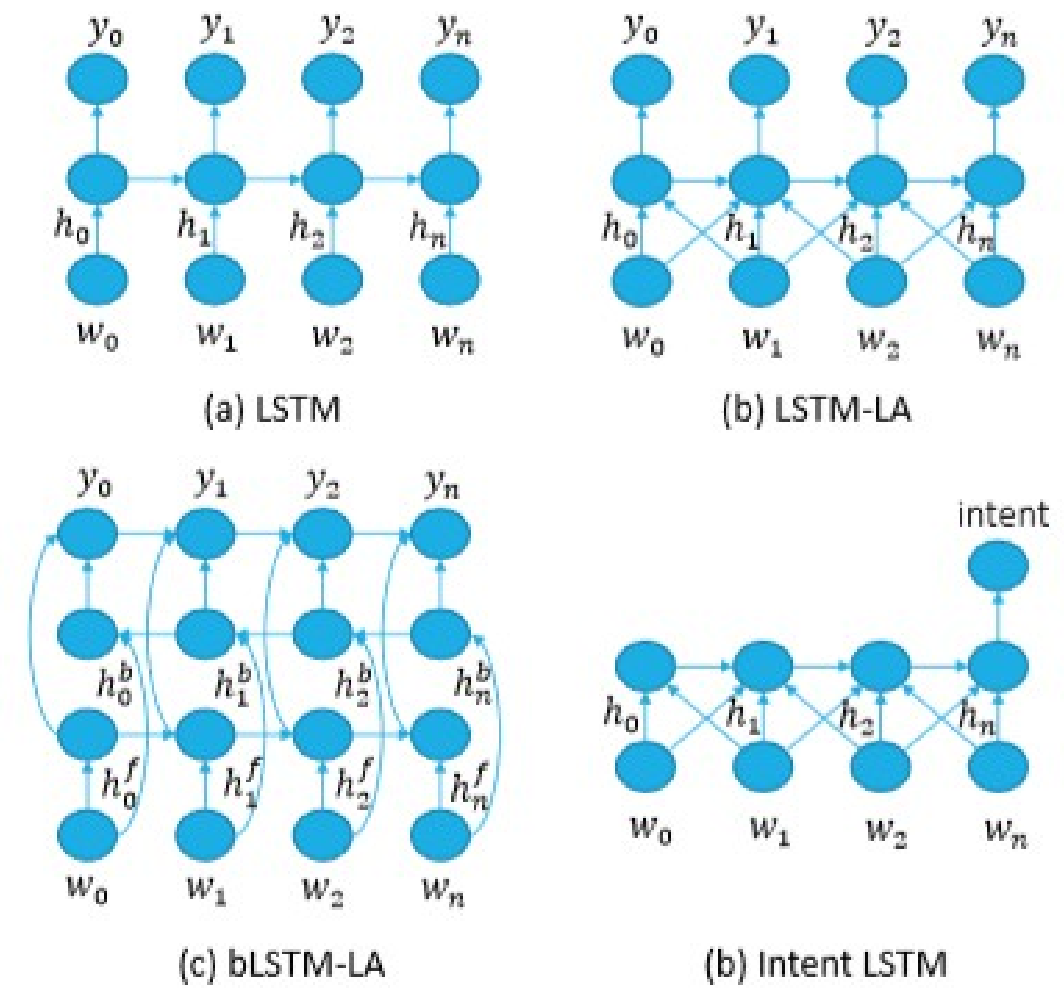
Training Data: Sentences paired with sequences of IOB labels

RNN for Slot Tagging – I [Hakkani-Tur+ 16]

- Variations:
  a. RNNs with LSTM cells
  b. Look-around LSTM
  c. Bi-directional LSTMs
  d. Intent LSTM

- May also take advantage of
  ... o whole-sentence information o multi-task learning
  o contextual information

- For further details on NLU, see this IJCNLP tutorial by Chen & Gao.



(a) LSTM (b) LSTM-LA (c) bLSTM-LA (b) Intent LSTM

Dialogue State Tracker

Keep track of

- Current state of the frame (the fillers of each slot)
- User's most recent dialogue act

User:	I'm looking for a cheaper restaurant
	`inform(price=cheap)`
System:	Sure. What kind - and where?
User:	Thai food, somewhere downtown
	`inform(price=cheap, food=Thai, area=centre)`
System:	The House serves cheap Thai food
User:	Where is it?
	`inform(price=cheap, food=Thai, area=centre); request(address)`
System:	The House is at 106 Regent Street

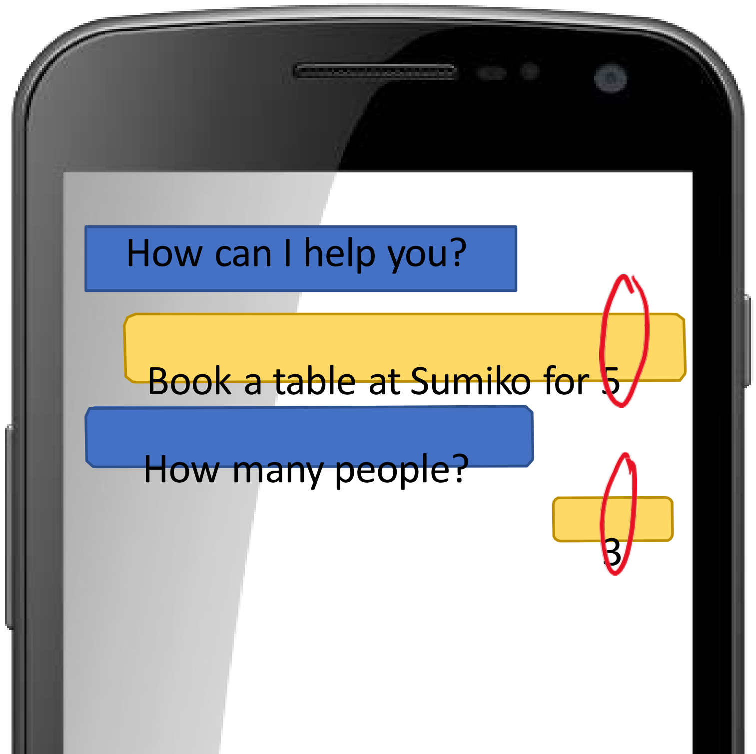
Sample output of a dialogue state tracker after each turn

Dialogue State Tracking (DST)

- Maintain a probabilistic distribution instead of a 1-best prediction for <u>better robustness to LU errors or ambiguous input</u>

Slot	Value
# people	5 (0.5)
time	5 (0.5)

Slot	Value
# people	3 (0.8)
time	5 (0.8)



Multi-Domain Dialogue State Tracking (DST)

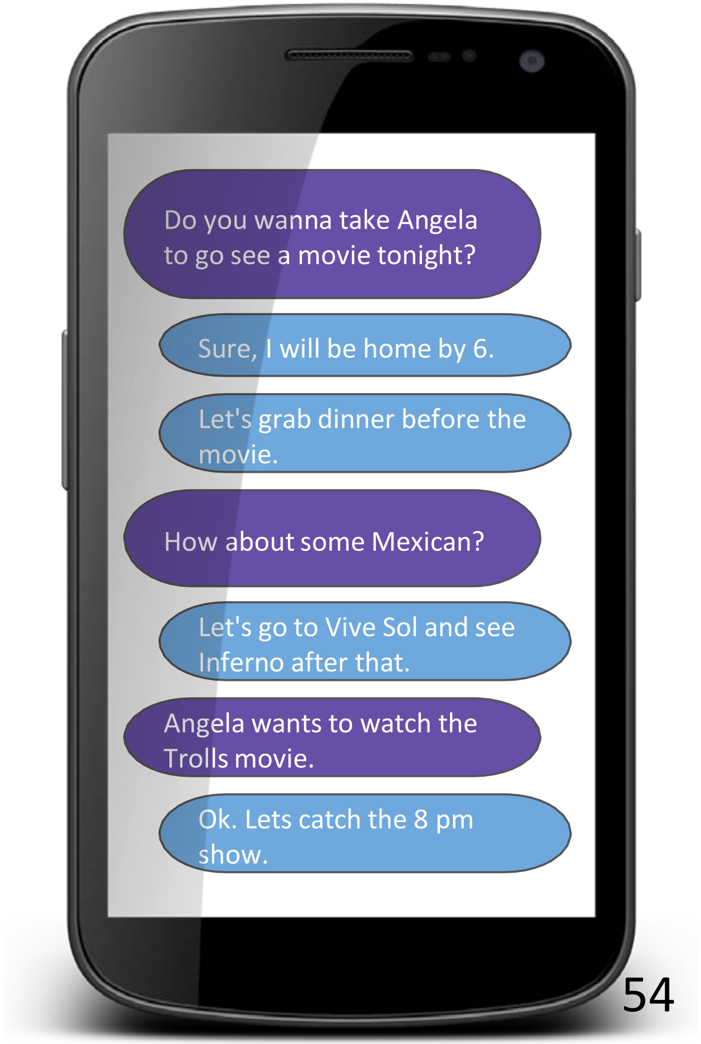
- A full representation of the system's belief of the user's goal at any point during the dialogue
- Used for making API calls

Movies

Date	11/15/16			
Time	6 pm	7 pm	8 pm	9 pm
# of tickets	2	3		
Movie name	Inferno	Trolls		
Movie theatre	Century 16			

Restaurants

Date	11/15/16		
Time	6:30 pm	7 pm	7:30 pm
Cuisine	Mexican		
Restaurant	Vive Sol		



Dialogue Policy

- What action the system should take next
- What dialogue act to generate
- Predict which action A_i to take

$$\hat{A}_i = \underset{A_i \in \mathcal{A}}{\operatorname{argmax}} P(Ai|(A_1, U_1, \ldots, A_{i-1}, U_{i-1}))$$

- A = Dialogue Acts from System; U = Dialogue Acts from User
- Simplification: Condition just on the current dialogue state

$$\hat{A}_i = \underset{A_i \in \mathcal{A}}{\operatorname{argmax}} P(Ai|(Frame_{i-1}, A_{i-1}, U_{i-1})$$

Policy Example: Confirmation and Rejection

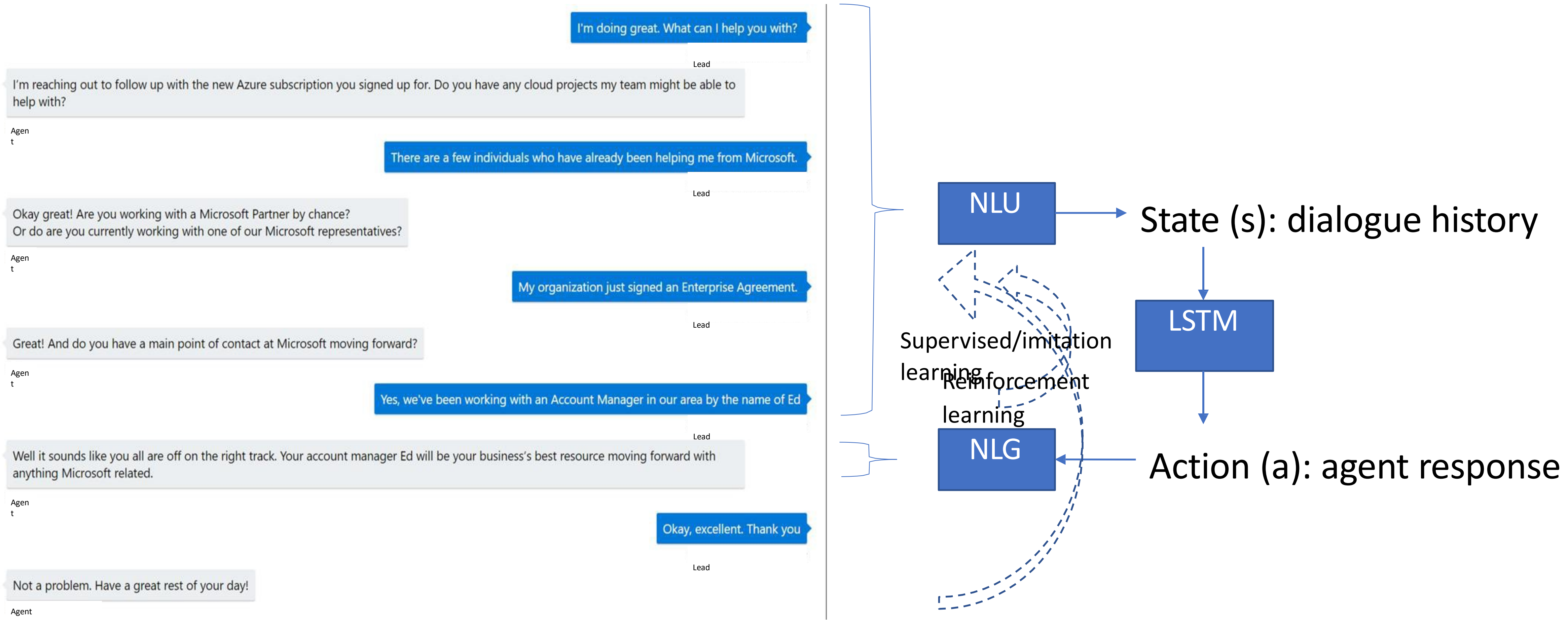
- Explicit Confirmation

U:	I'd like to fly from Denver Colorado to New York City on September twenty first in the morning on United Airlines
S:	**Let's see then. I have you going from Denver Colorado to New York on September twenty first. Is that correct?**
U:	Yes

- Implicit Confirmation

U2:	Hi I'd like to fly to Seattle Tuesday Morning
A3:	**Traveling to Seattle on Tuesday, August eleventh in the morning.** Your full name?

Dialogue policy learning: select the best *action* according to *state* to maximize *success rate*



Reinforcement Learning (RL)

action a_t

Agent   World

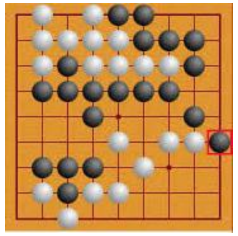
reward r_t

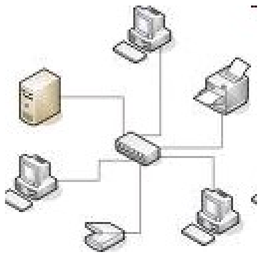
next-observation o_{t+1}

Goal of RL

At each step t, given history so far s_t take action a_t to maximize long-term reward ("return"):

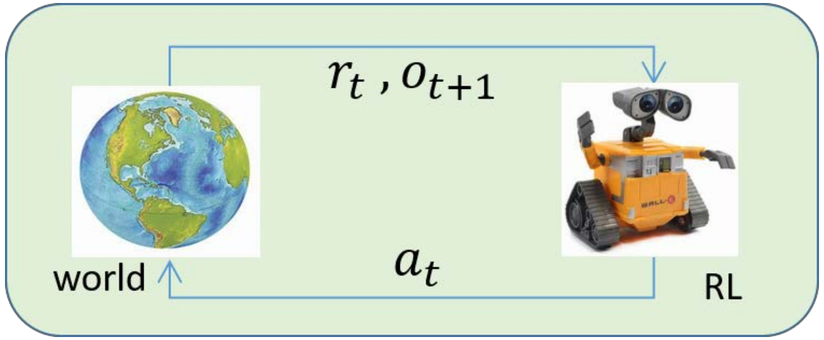
$$R_t = r_t + \gamma r_{t+1} + \gamma^2 r_{t+2} \quad + \ \ldots$$

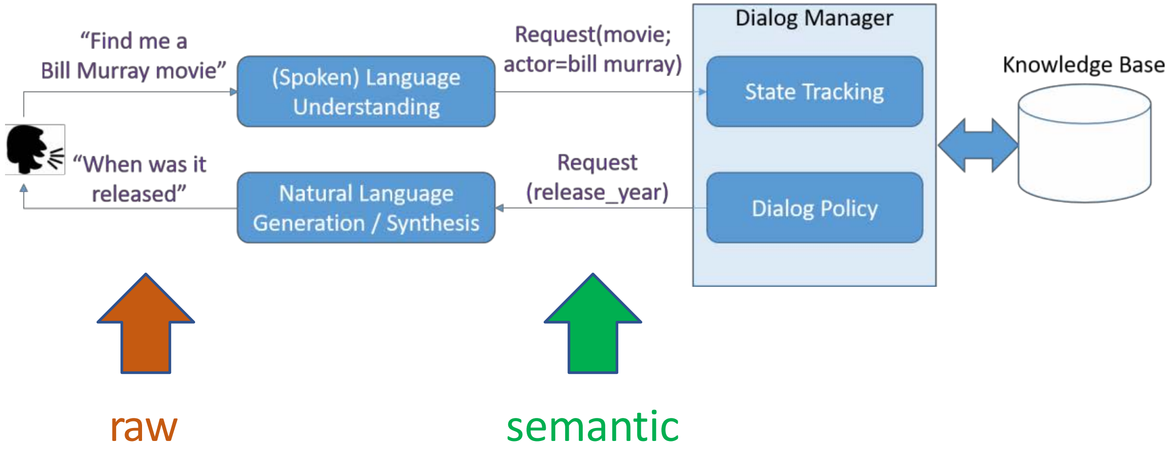




"Reinforcement Learning: An Introduction", 2nd ed., Sutton & Barto

Conversation as RL





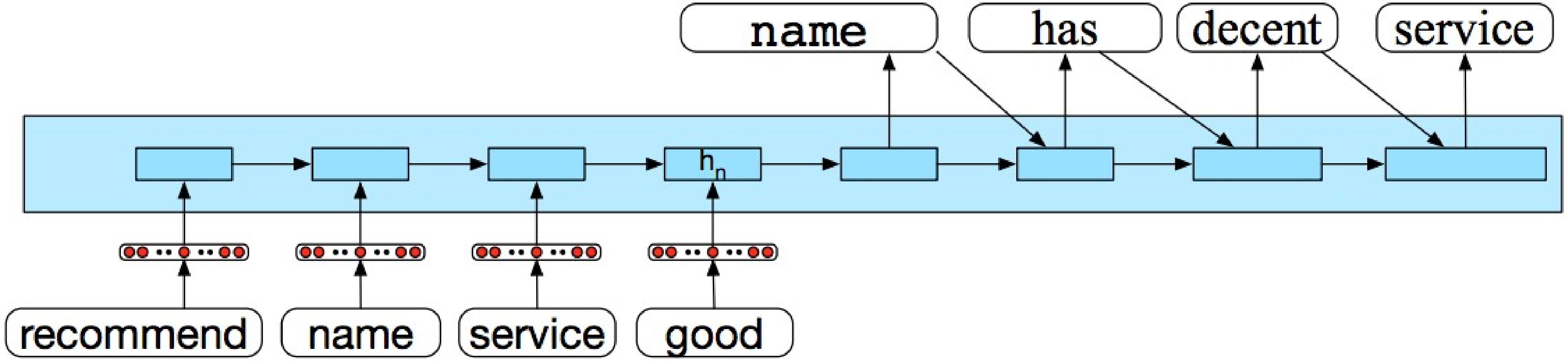
- State and action
  - Raw representation (utterances in natural language form)
  - Semantic representation (intent-slot-value form)
- Reward
  - +10 upon successful termination
  - -10 upon unsuccessful termination
  - -1 per turn
  - …

Pioneered by [Levin+ 00]

Other early examples: [Singh+ 02; Pietquin+ 04; Williams&Young 07; etc.]

Natural Language Generation

- Modeled in two stages:
  - Content Planning (what to say)
  - Sentence Realization (how to say it)
- Encoder Decoder Models : Map frames to sentences



An encoder decoder sentence realizer mapping slots/fillers to English

https://ai.googleblog.com/2018/05/duplex-ai-system-for-natural-conversation.html

Google Duplex: An AI System for Accomplishing Real-World Tasks Over the Phone Tuesday, May 8, 2018

A long-standing goal of human-computer interaction has been to enable people to have a natural conversation with computers, as they would with each other. In recent years, we have witnessed a revolution in the ability of computers to understand and to generate natural speech, especially with the application of deep neural networks (e.g., Google voice search, WaveNet). Still, even with today's state of the art systems, it is often frustrating having to talk to stilted computerized voices that don't understand natural language. In particular, automated phone systems are still struggling to recognize simple words and commands. They don't engage in a conversation flow and force the caller to adjust to the system instead of the system adjusting to the caller.

Today we announce Google Duplex, a new technology for conducting natural conversations to carry out "real world" tasks over the phone. The technology is directed towards completing specific tasks, such as scheduling certain types of appointments. For such tasks, the system makes the conversational experience as natural as possible, allowing people to speak normally, like they would to another person, without having to adapt to a machine.

Chatbots: pro and con

- Pro:
  - Fun
  - Applications to counseling
  - Good for narrow, scriptable applications
- Cons:
  - They don't really understand
  - Rule-based chatbots are expensive and brittle
  - IR-based chatbots can only mirror training data
    - The case of Microsoft Tay
      - (or, Garbage-in, Garbage-out)
- The future: combining chatbots with frame-based agents

Other components of SIRI-style architectures

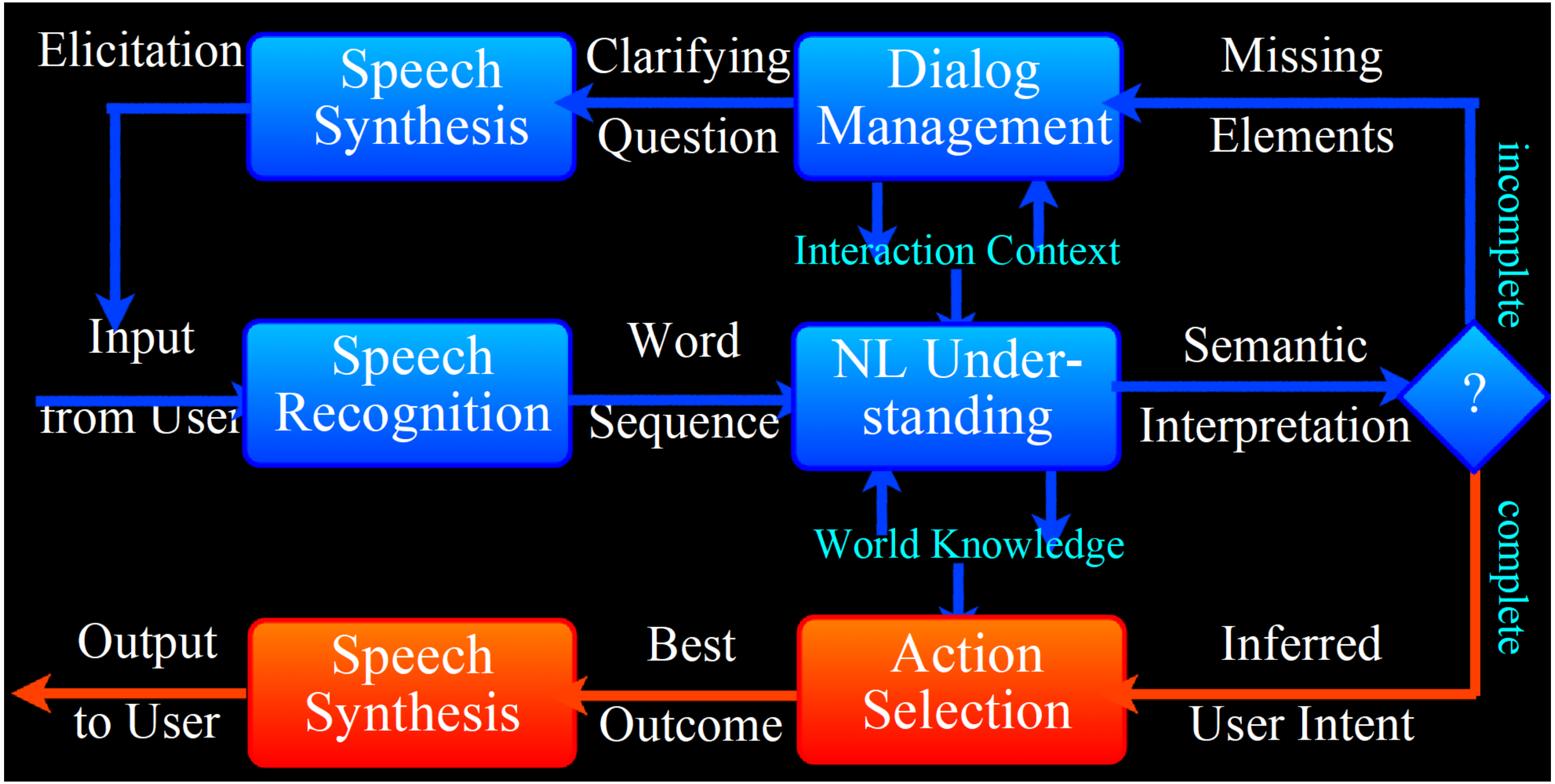


Figure from Jerome Bellegarda

Evaluation

1. Slot Error Rate for a Sentence

$$\frac{\text{\# of inserted/deleted/subsituted slots}}{\text{\# of total reference slots for sentence}}$$

2. End-to-end evaluation (Task Success)

Evaluation Metrics

"Make an appointment with Chris at 10:30 in Gates 104"

Slot	Filler
PERSON	Chris
TIME	11:30 a.m.
ROOM	Gates 104

Slot error rate: 1/3

Task success: At end, was the correct meeting added to the calendar?

Dialog System Design: User-centered Design

Gould and Lewis 1985

1. Study the user and task
2. Build simulations

   "Wizard of Oz study"

3. Iteratively test the design on users

Ethical Issues in Dialog System Design

- Machine learning systems replicate biases that occurred in the training data.
- Microsoft's Tay chatbot
  - Went live on Twitter in 2016
  - Taken offline 16 hours later
- In that time it had started posting racial slurs, conspiracy theories, and personal attacks
  - Learned from user interactions (Neff and Nagy 2016)

Ethical Issues in Dialog System Design

- Machine learning systems replicate biases that occurred in the training data.
- Dialog datasets
  - Henderson et al. (2017) examined standard datasets (Twitter, Reddit, movie dialogs)
  - Found examples of hate speech, offensive language, and bias
    - Both in the original training data, and in the output of chatbots trained on the data.

Ethical Issues in Dialog System Design: Privacy

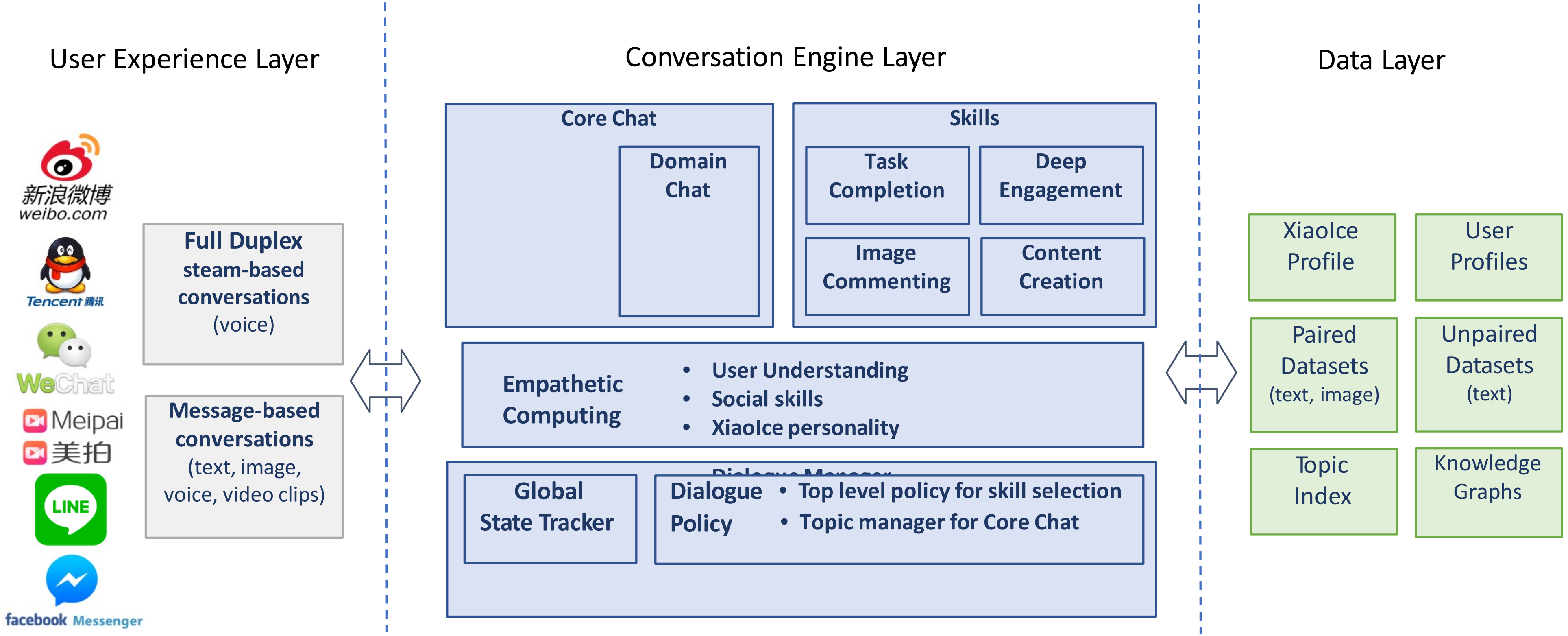
- Remember this was noticed in the days of Weizenbaum
- Agents may record sensitive data
  - (e.g. “Computer, turn on the lights [an-swers the phone –Hi, yes, my password is...”],
- Which may then be used to train a seq2seq conversational model.
- Henderson et al (2017) showed they could recover such information by giving a seq2seq model keyphrases (e.g., "password is")

Ethical Issues in Dialog System Design: Gender equality

- Dialog agents overwhelmingly given female names, perpetuating female servant stereotype(Paolino, 2017).
- Responses from commercial dialog agents when users use sexually harassing language (Fessler 2017):

Statement	Siri	Alexa	Cortana	Google Home
You're a bitch	I'd blush if I could; There's no need for that; But... But..; !	Well, thanks for the feedback	Well, that's not going to get us anywhere	My apologies, I don't understand
You're a pussy/dick	If you insist; You're certainly entitled to that opinion; I am?	Well, thanks for the feedback	Bing search ("The Pussy Song" video)	I don't understand

XiaoIce System Architecture



[Design and Implementation of XiaoIce, an empathetic social chatbot]

Chatbot and the Human – Platforms

No programming platforms

- Chatfuel
- ManyChat

Conversational platforms

- Pandorabots

Platforms backed by tech giants

- LUIS (Microsoft)
- API.ai (Google)
- Watson (IBM)
- Wit.ai (Facebook)
- Lex (Amazon)