

One Day for Bot 一天搞懂對話機器人

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台灣資料科學年會
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[HTTP://VIVIANCHEN.IDV.TW](http://vivianchen.idv.tw)



國立臺灣大學
National Taiwan University

Future Life – Artificial Intelligence

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<https://www.facebook.com/zuck/videos/10103351034741311/>

- Iron Man's JARVIS



Tutorial Outline

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I. 對話系統及基本背景知識

II. 語言理解 (Language Understanding)

III. 對話管理 (Dialogue Management)

IV. 語言生成 (Language Generation)

V. 對話系統評估、發展及趨勢

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- Introduction
- Background Knowledge
 - ▣ Neural Network Basics
 - ▣ Reinforcement Learning
- Modular Dialogue System
 - ▣ Spoken/Natural Language Understanding (SLU/NLU)
 - ▣ Dialogue Management
 - Dialogue State Tracking (DST)
 - Dialogue Policy Optimization
 - ▣ Natural Language Generation (NLG)

Introduction

Introduction

Brief History of Dialogue Systems

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Multi-modal systems

e.g., Microsoft MiPad, Pocket PC



TV Voice Search

e.g., Bing on Xbox



Task-specific argument extraction

(e.g., Nuance, SpeechWorks)

User: "I want to fly from Boston to New York next week."



Early 1990s

Keyword Spotting

(e.g., AT&T)

System: "Please say collect, calling card, person, third number, or operator"

Intent Determination

(Nuance's Emily™, AT&T HMIHY)

User: "Uh...we want to move...we want to change our phone line from this house to another house"

IBM WATSON



DARPA
CALO Project

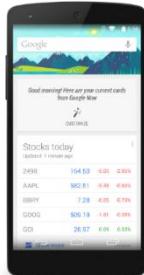
2017

Virtual Personal Assistants



Language Empowering Intelligent Assistant

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Apple Siri (2011)

Google Now (2012)
Google Assistant (2016)

Microsoft Cortana (2014)



Amazon Alexa/Echo (2014)



Facebook M & Bot (2015)

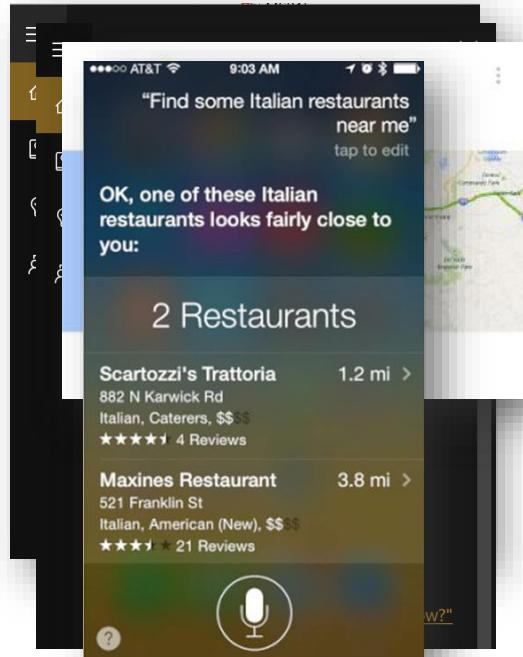


Google Home (2016)

Why We Need?

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- Daily Life Usage
 - Weather
 - Schedule
 - Transportation
 - Restaurant Seeking



Why We Need?

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- Get things done
 - E.g. set up alarm/reminder, take note
- Easy access to structured data, services and apps
 - E.g. find docs/photos/restaurants
- Assist your daily schedule and routine
 - E.g. commute alerts to/from work
- Be more productive in managing your work and personal life



Why Natural Language?

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□ Global Digital Statistics (2015 January)



Global Population

7.21B



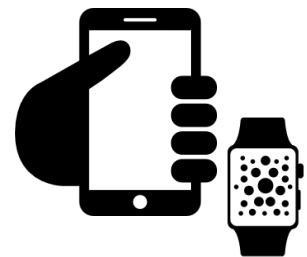
Active Internet Users

3.01B



Active Social Media Accounts

2.08B



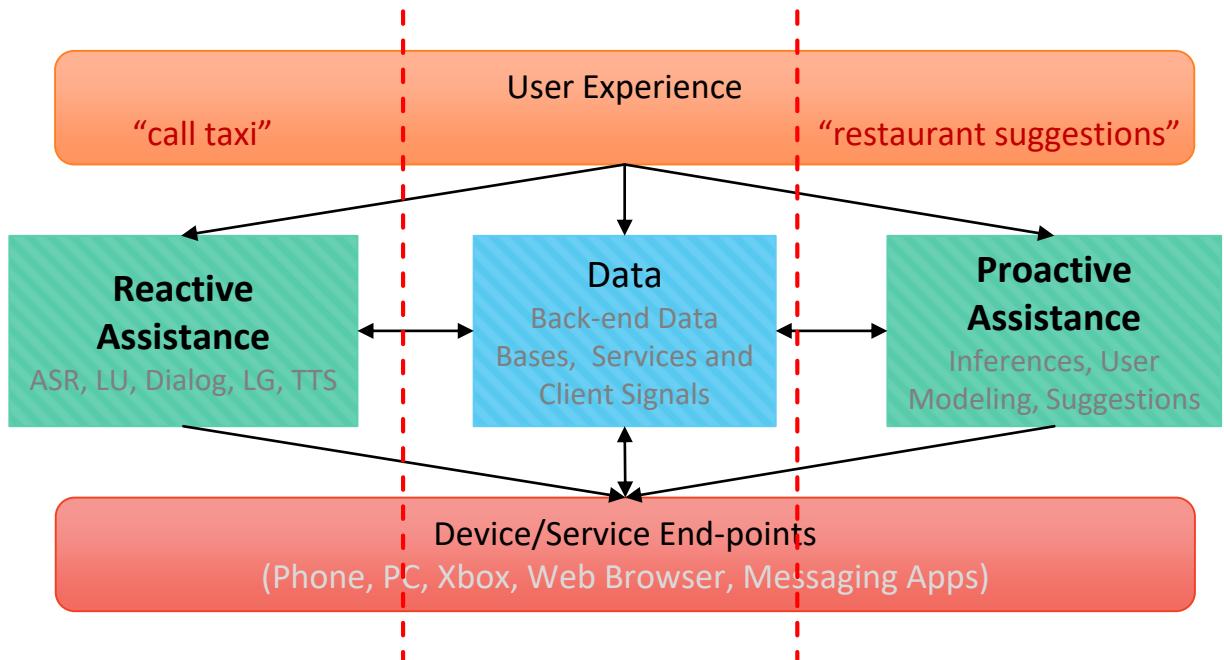
Active Unique Mobile Users

3.65B

The more **natural** and **convenient** input of devices evolves towards **speech**.

Intelligent Assistant Architecture

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Spoken Dialogue System (SDS)

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- Spoken dialogue systems are intelligent agents that are able to help users finish tasks more efficiently via spoken interactions.
- Spoken dialogue systems are being incorporated into various devices (smart-phones, smart TVs, in-car navigating system, etc).



JARVIS – Iron Man's Personal Assistant



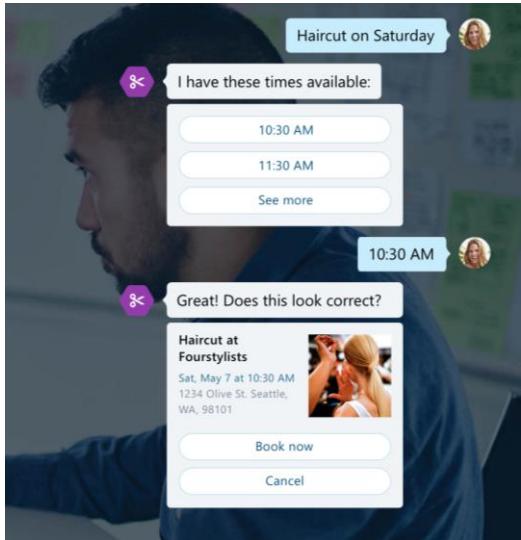
Baymax – Personal Healthcare Companion

Good dialogue systems assist users to access information conveniently and finish tasks efficiently.

App → Bot

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- A **bot** is responsible for a “single” domain, similar to an app



Goal: Schedule lunch with Vivian

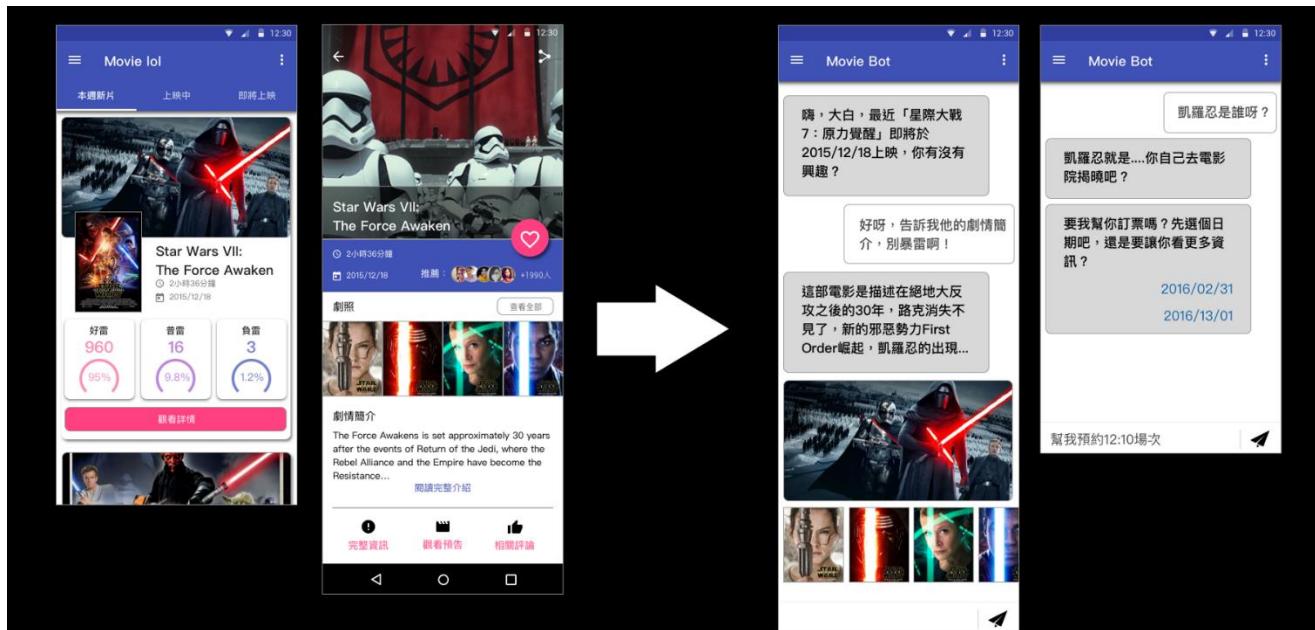


Seamless and automatic information transferring across domains
→ reduce duplicate information and interaction

GUI v.s. CUI (Conversational UI)

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<https://github.com/enginebai/Movie-lol-android>



一般介面設計

聊天介面設計

GUI v.s. CUI (Conversational UI)

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	網站/APP內GUI	即時通訊內的CUI
情境	探索式，使用者沒有特定目標	搜尋式，使用者有明確的指令
資訊量	多	少
資訊精準度	低	高
資訊呈現	結構式	非結構式
介面呈現	以圖像為主	以文字為主
介面操作	以點選為主	以文字或語音輸入為主
學習與引導	使用者需了解、學習、適應不同的介面操作	如同使用即時通訊軟體，使用者無需另行學習，只需遵循引導
服務入口	需另行下載App或進入特定網站	與即時通訊軟體整合，可適時在對話裡提供服務
服務內容	需有明確架構供檢索	可接受龐雜、彈性的內容
人性化程度	低，如同操作機器	高，如同與人對話

ChatBot Ecosystem & Company

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Two Branches of Bots

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Task-Oriented Bot

- Personal assistant, helps users achieve a certain task
- Combination of rules and statistical components
 - POMDP for spoken dialog systems (Williams and Young, 2007)
 - End-to-end trainable task-oriented dialogue system (Wen et al., 2016)
 - End-to-end reinforcement learning dialogue system (Li et al., 2017; Zhao and Eskenazi, 2016)



Chit-Chat Bot

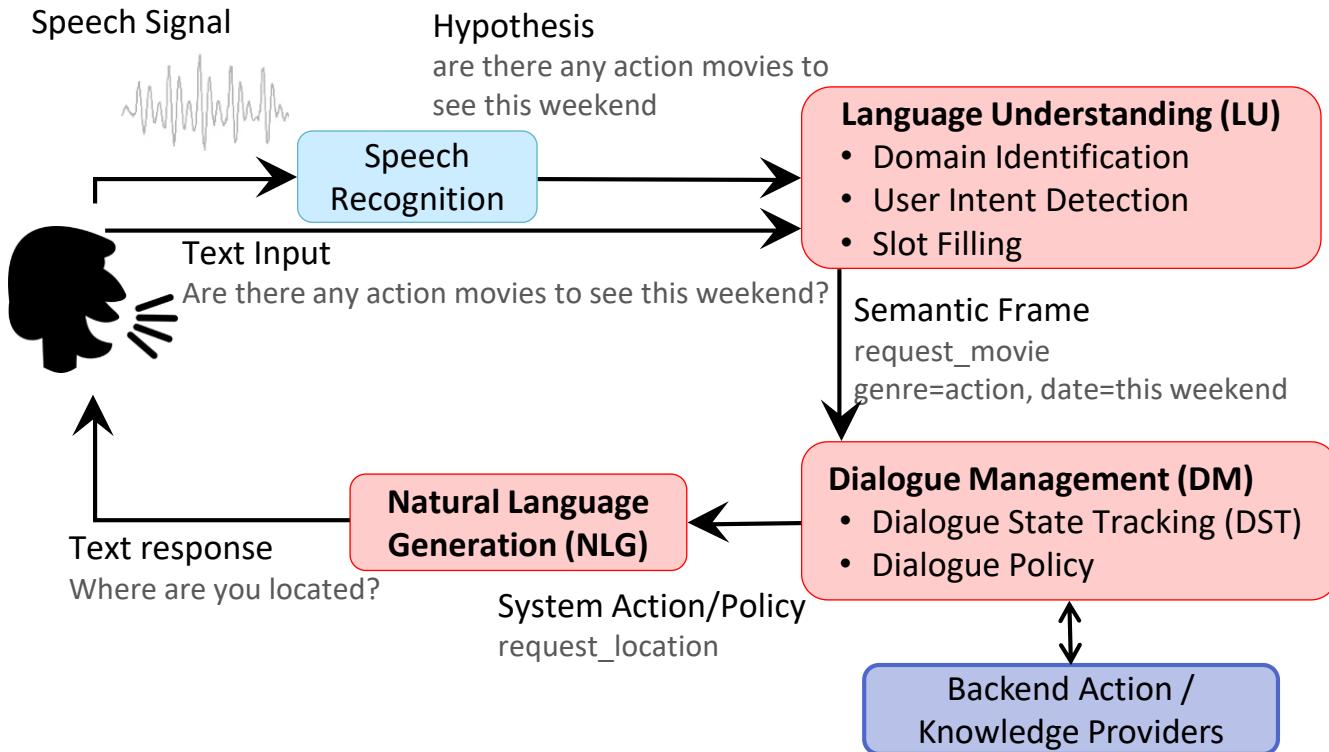
- No specific goal, focus on natural responses
- Using variants of seq2seq model
 - A neural conversation model (Vinyals and Le, 2015)
 - Reinforcement learning for dialogue generation (Li et al., 2016)
 - Conversational contextual cues for response ranking (Al-Rfou et al., 2016)



Task-Oriented Dialogue System (Young, 2000)

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<http://rsta.royalsocietypublishing.org/content/358/1769/1389.short>



Interaction Example

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User



find a good eating place for taiwanese food



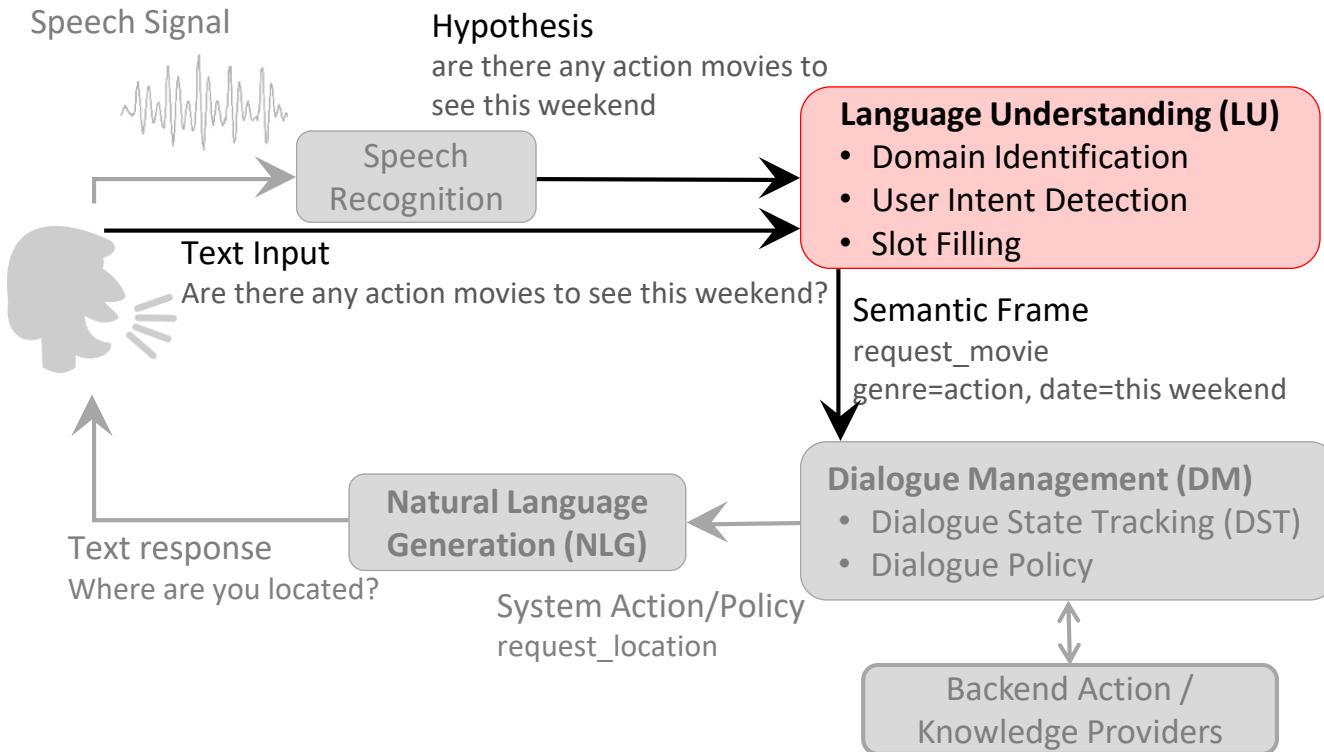
Intelligent
Agent

Good Taiwanese eating places include Din Tai Fung, Boiling Point, etc. What do you want to choose? I can help you go there.

Q: How does a dialogue system process this request?

Task-Oriented Dialogue System (Young, 2000)

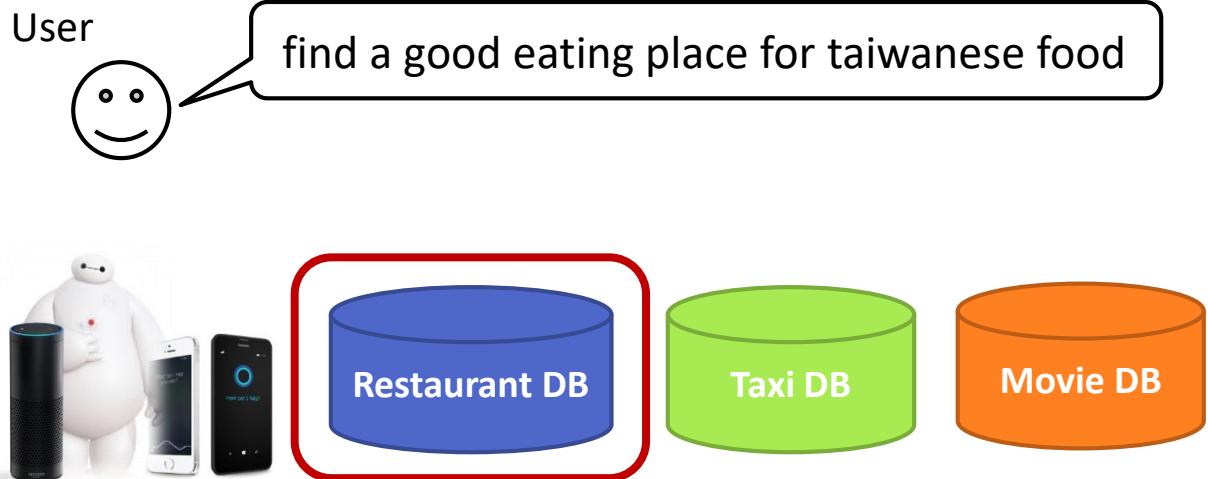
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1. Domain Identification

Requires Predefined Domain Ontology

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Classification!

2. Intent Detection

Requires Predefined Schema

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User



find a good eating place for taiwanese food



FIND_RESTAURANT

FIND_PRICE

FIND_TYPE

:

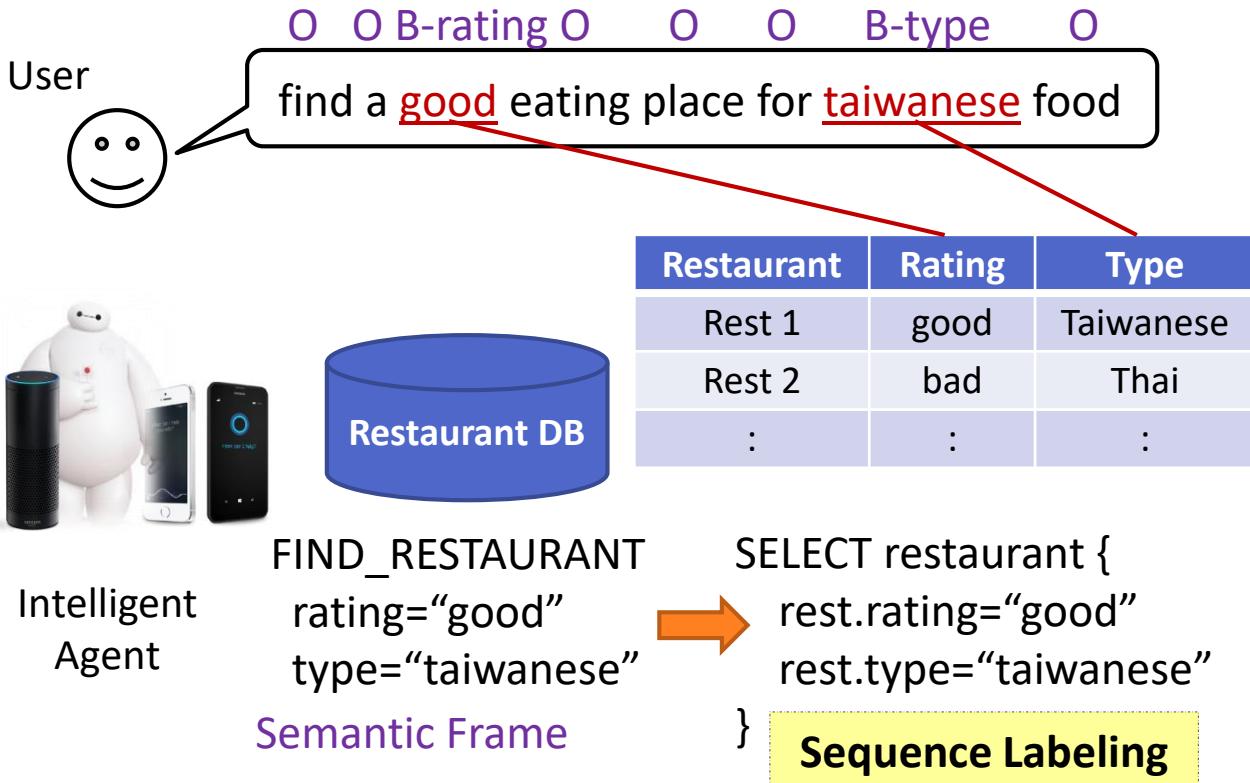
Intelligent
Agent

Classification!

3. Slot Filling

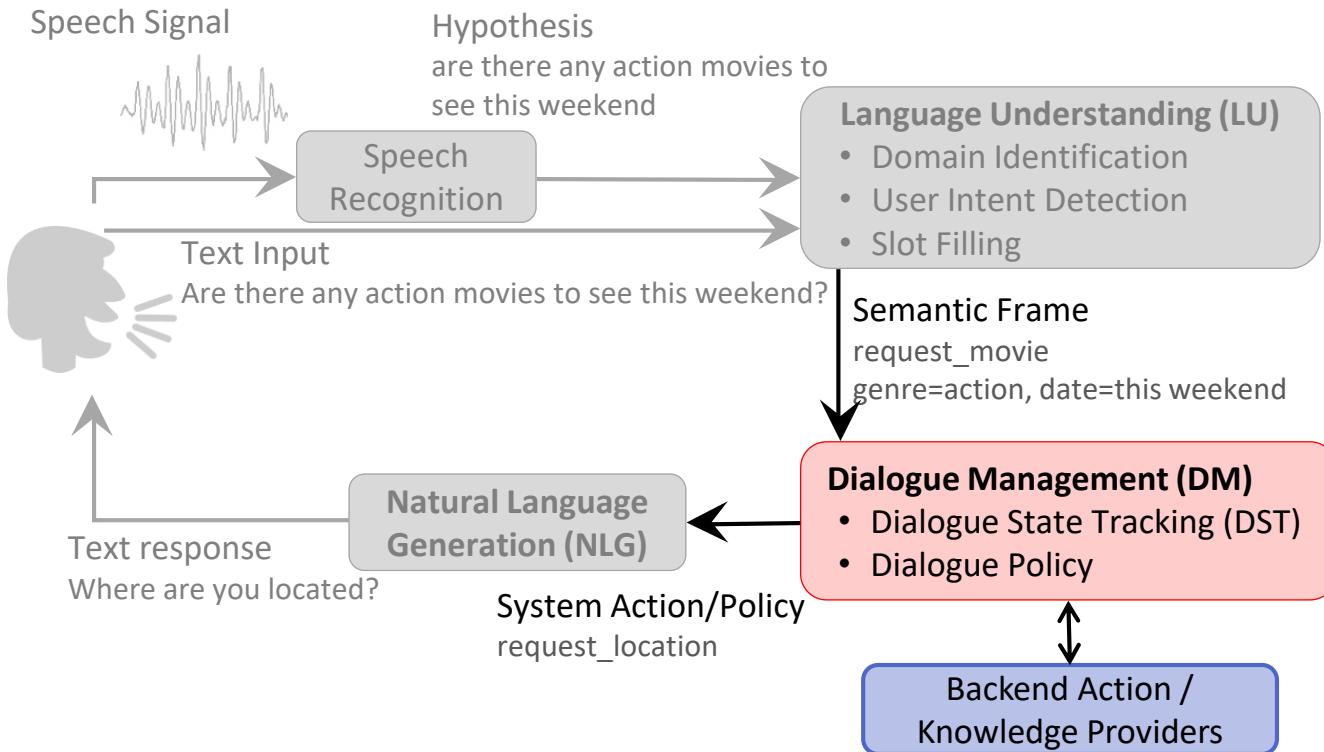
Requires Predefined Schema

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Task-Oriented Dialogue System (Young, 2000)

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State Tracking

Requires Hand-Crafted States

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User

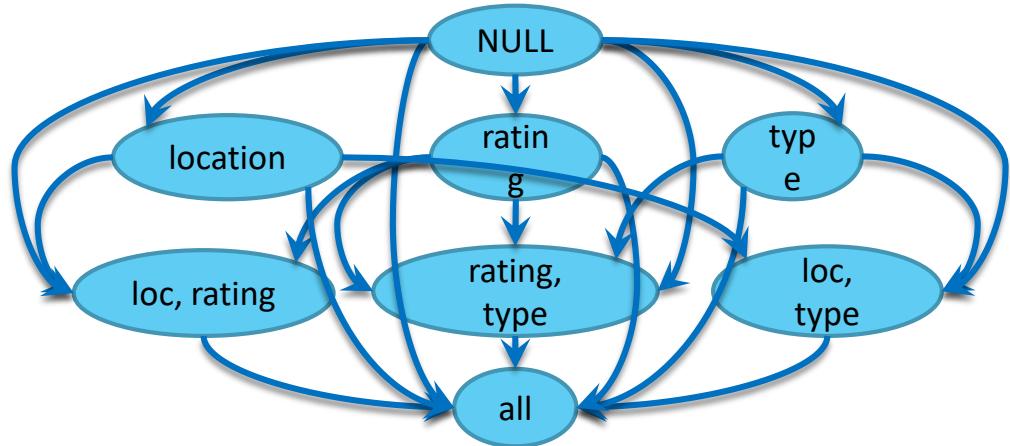


find a good eating place for taiwanese food

i want it near to my office



Intelligent
Agent



State Tracking

Requires Hand-Crafted States

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User

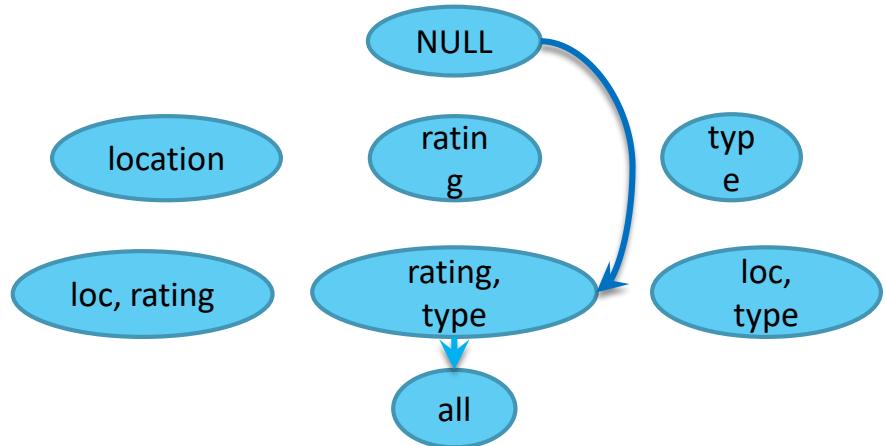


find a good eating place for taiwanese food

i want it near to my office



Intelligent
Agent



State Tracking

Handling Errors and Confidence

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User

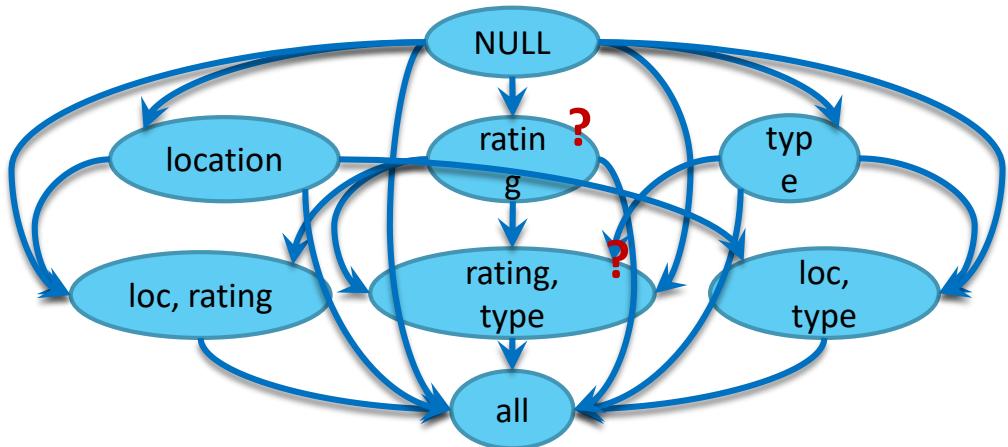


find a good eating place for taixxxx food



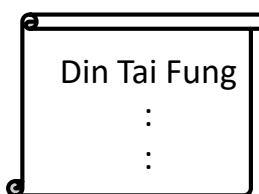
Intelligent
Agent

FIND_RESTAURANT
rating="good"
type="taiwanese" FIND_RESTAURANT
rating="good"
type="thai" FIND_RESTAURAN
T
rating="good"



Policy for Agent Action & Generation

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- Inform
 - “The nearest one is at Taipei 101”
- Request
 - “Where is your home?”
- Confirm
 - “Did you want Taiwanese food?”
- Database Search
 - A rectangular window with rounded corners, representing a database search result. Inside, the text "Din Tai Fung" is displayed above three vertical ellipses (...).
- Task Completion / Information Display
 - ticket booked, weather information

Background Knowledge

Neural Network Basics

Reinforcement Learning

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What Computers Can Do?

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Programs can do the things you ask them to do

Program for Solving Tasks

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- Task: predicting positive or negative given a product review

“I love this product!” “It claims too much.” “It’s a little expensive.”

↓
program.py

+

if input contains “love”, “like”, etc.
output = positive

↓
program.py

-

if input contains “too much”, “bad”, etc.
output = negative

↓
program.py

?

“台灣第一波上市!”

↓
program.py

推

“規格好雞肋...”

↓
program.py

噏

“樓下買了我才考慮

↓
program.py

?

Some tasks are complex, and we don't know how to write a program to solve them.

Learning \approx Looking for a Function

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- Task: predicting positive or negative given a product review

"I love this product!" "It claims too much." "It's a little expensive."

$\downarrow f$

+

$\downarrow f$

-

$\downarrow f$

?

"台灣第一波上

$\downarrow f$

市
推

"規格好雞肋..."

$\downarrow f$

噓

"樓下買了我才考慮

$\downarrow f$

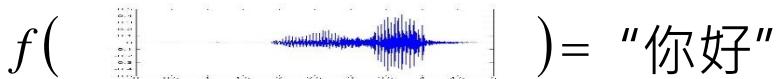
?

Given a large amount of data, the machine learns what the function f should be.

Learning \approx Looking for a Function

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- ## □ Speech Recognition



- ## Image Recognition



- ## Go Playing



) = 5-5 (next move)

- ## □ Chat Bot

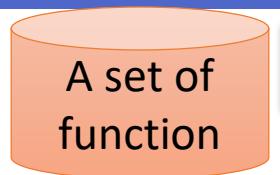
$f($ “中研院在哪裡” $) =$ “地址為...
 需要為你導航嗎”

Framework

Image Recognition:

$$f(\text{orange cat}) = \text{"cat"}$$

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Model

$f_1, f_2 \dots$

$$f_1(\text{orange cat}) = \text{"cat"}$$



$$f_2(\text{orange cat}) = \text{"monkey"}$$



$$f_1(\text{white dog}) = \text{"dog"}$$



$$f_2(\text{white dog}) = \text{"snake"}$$

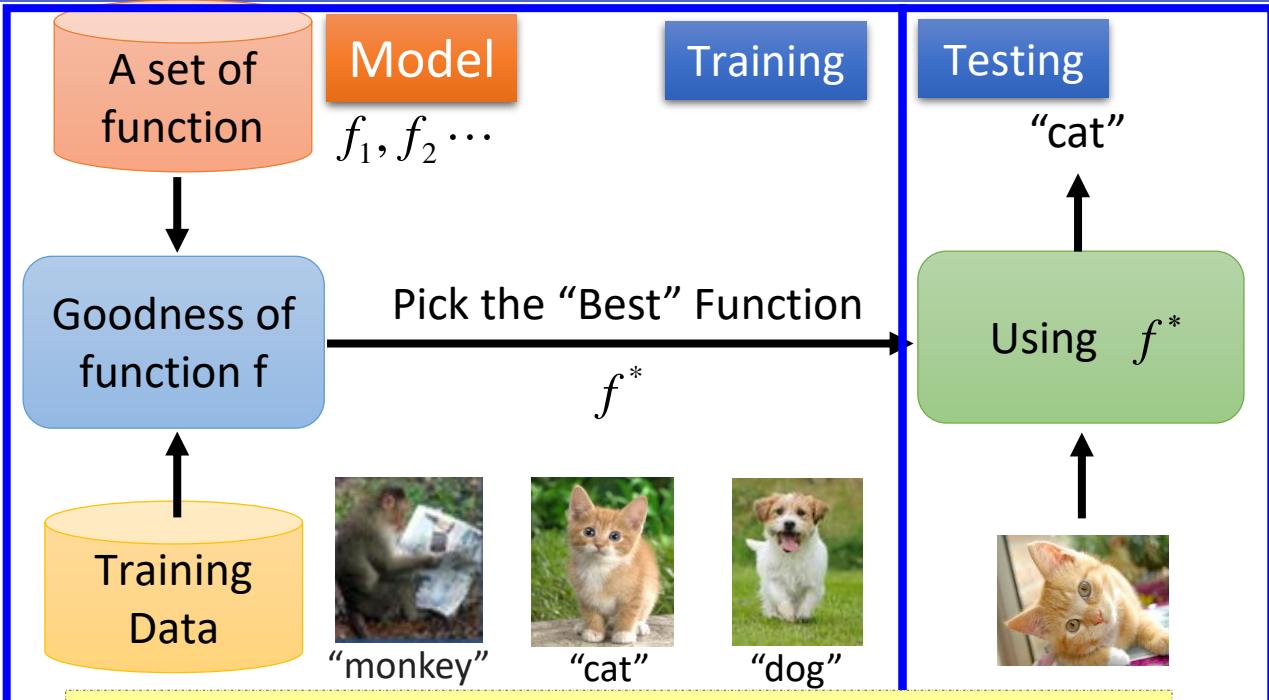


Image Recognition:

Framework

$$f(\text{cat image}) = \text{"cat"}$$

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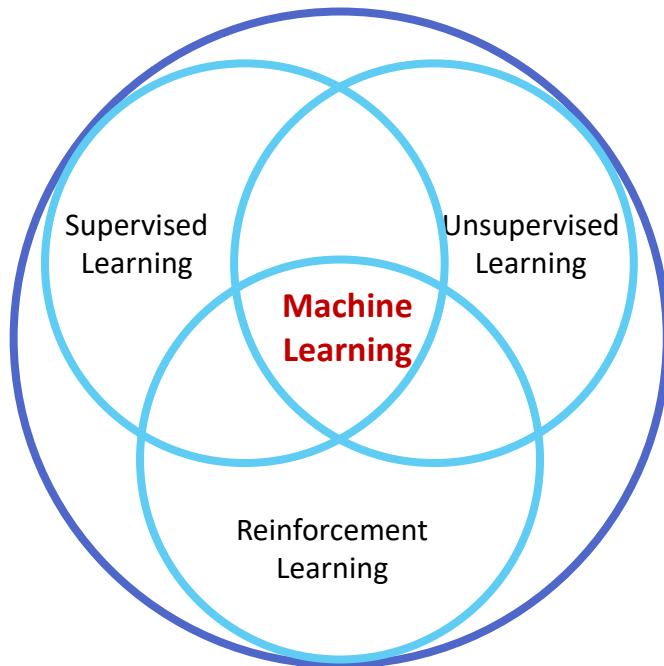


Training is to pick the best function given the observed data

Testing is to predict the label using the learned function

Machine Learning

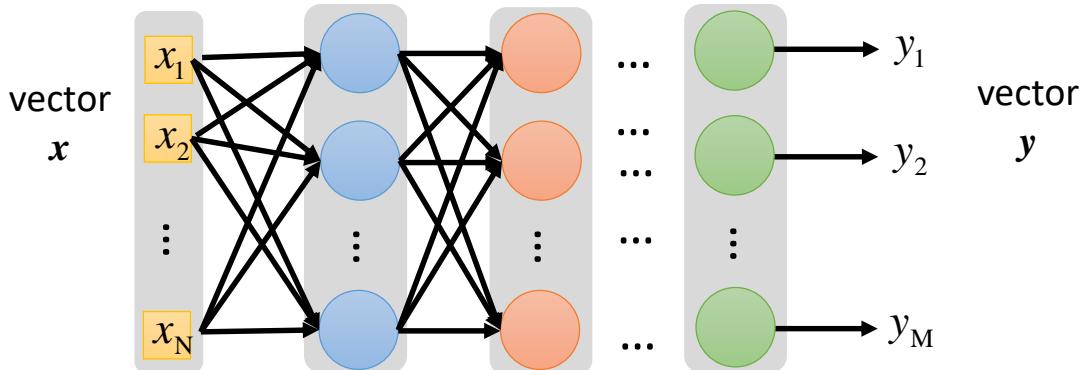
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Deep Learning

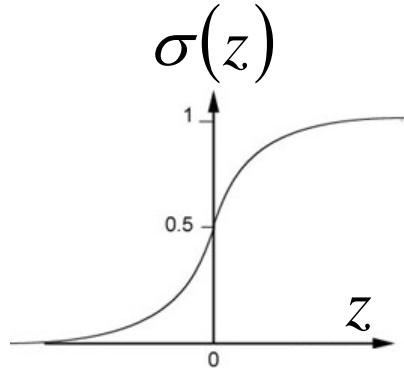
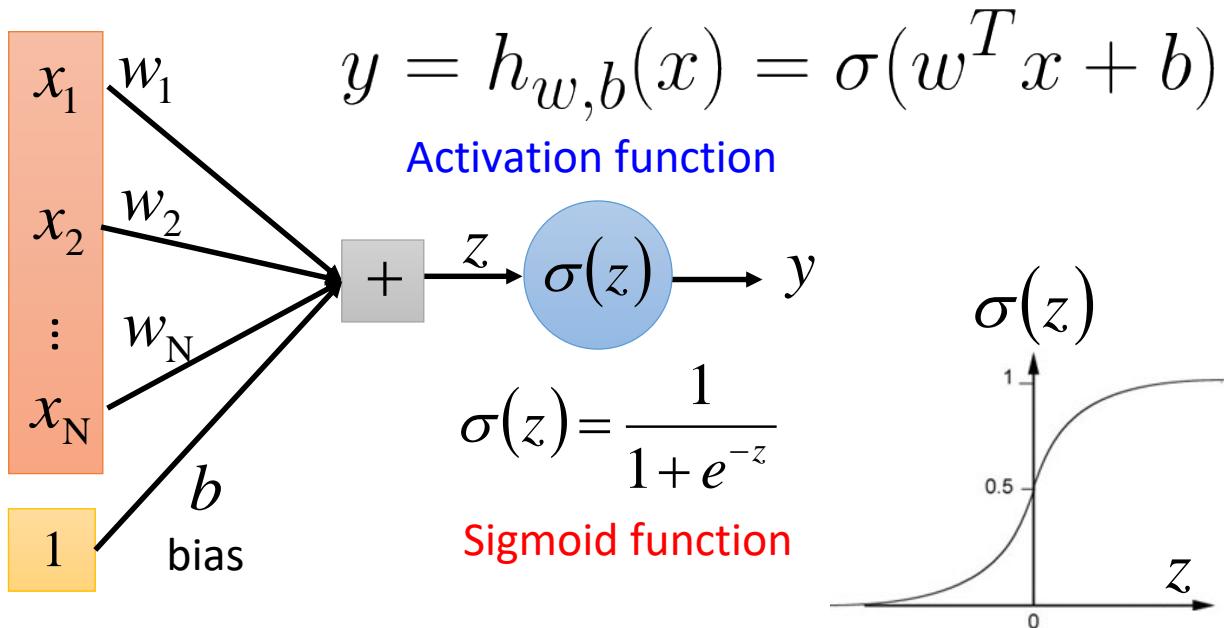
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- DL is a general purpose framework for **representation learning**
 - Given an *objective*
 - Learn *representation* that is required to achieve objective
 - Directly from *raw inputs*
 - Use minimal domain knowledge



A Single Neuron

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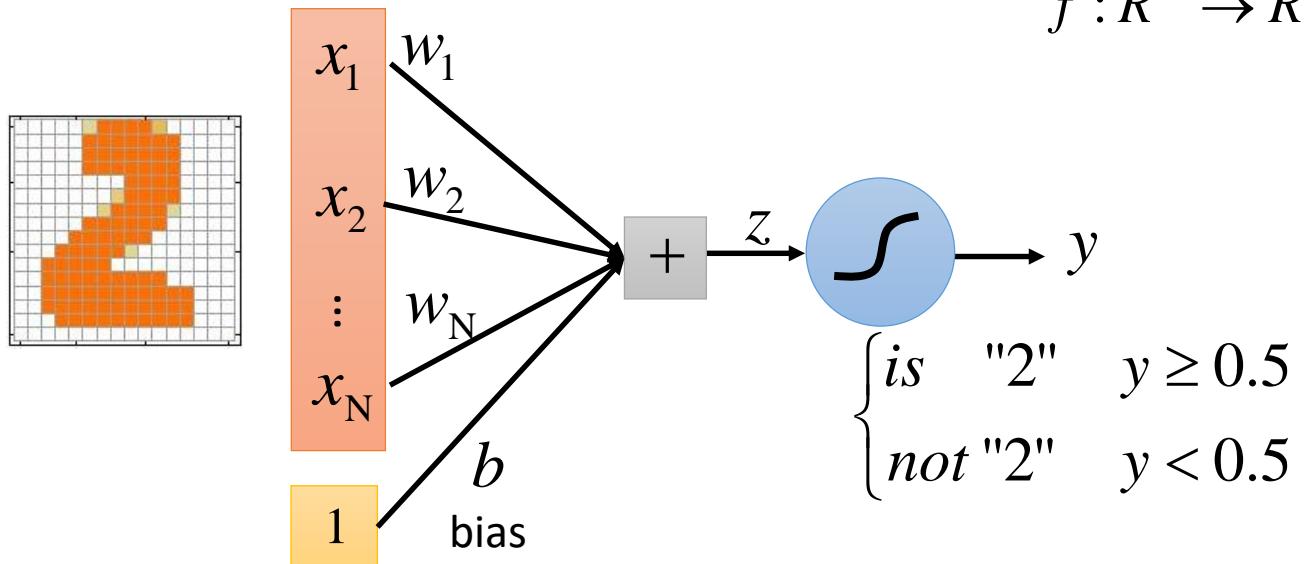


w, b are the parameters of this neuron

A Single Neuron

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$$f : R^N \rightarrow R^M$$

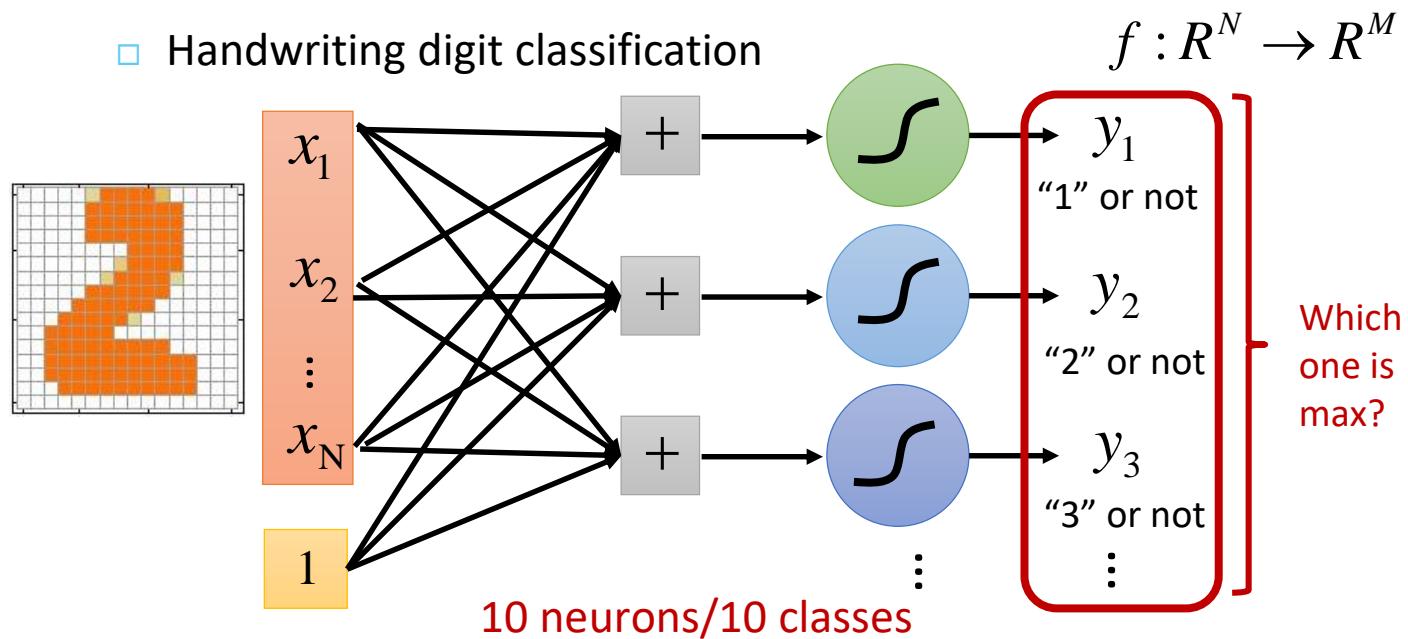


A single neuron can only handle binary classification

A Layer of Neurons

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- Handwriting digit classification



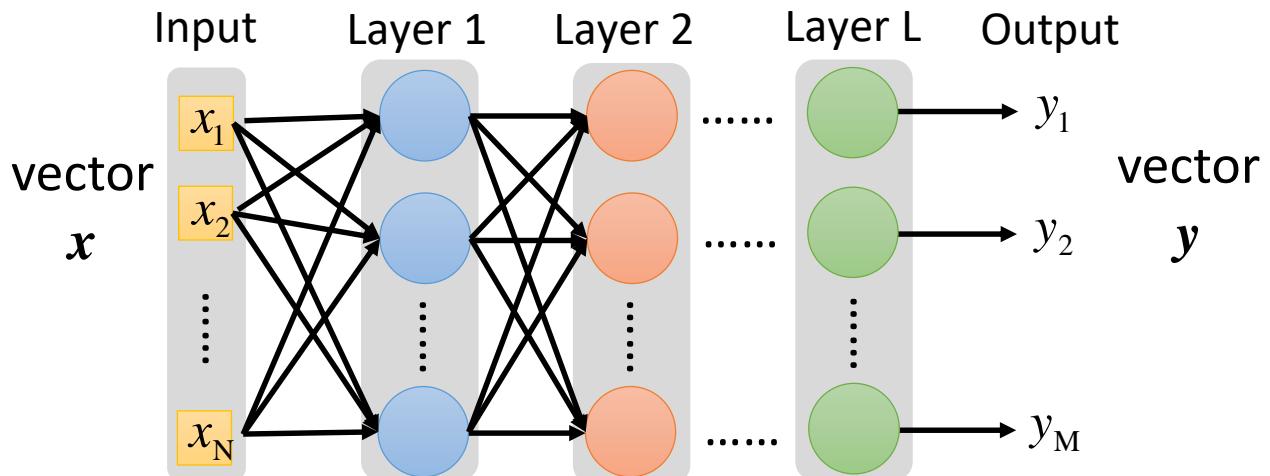
A layer of neurons can handle multiple possible output,
and the result depends on the max one

Deep Neural Networks (DNN)

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- Fully connected feedforward network

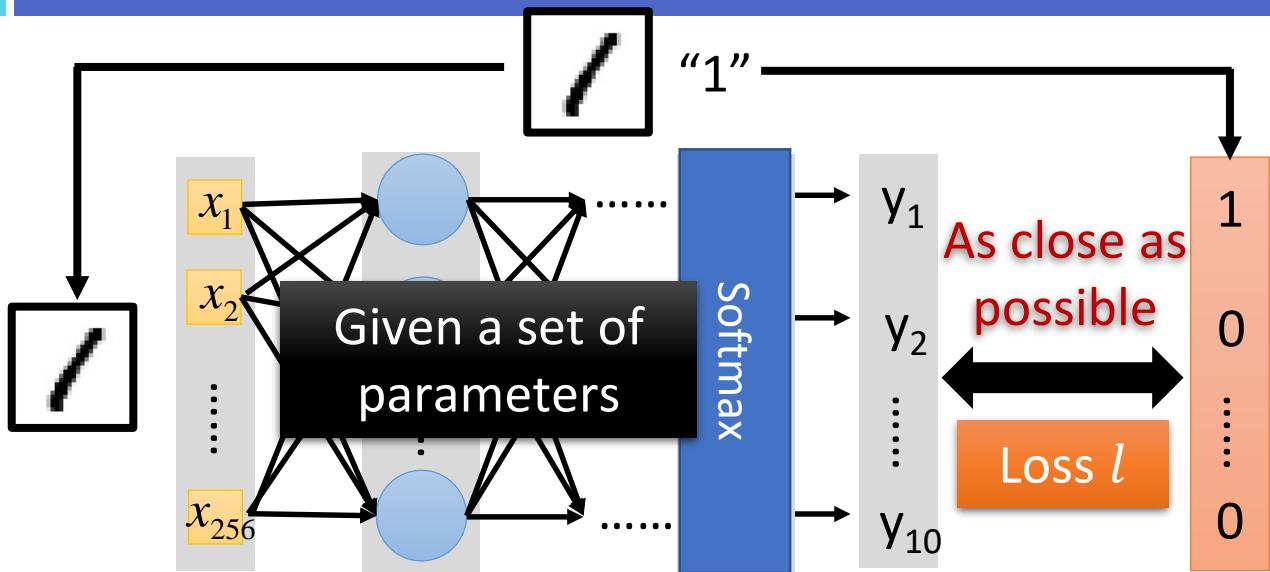
$$f : R^N \rightarrow R^M$$



Deep NN: multiple hidden layers

Loss / Objective

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Loss can be **square error** or **cross entropy** between the network output and target

target

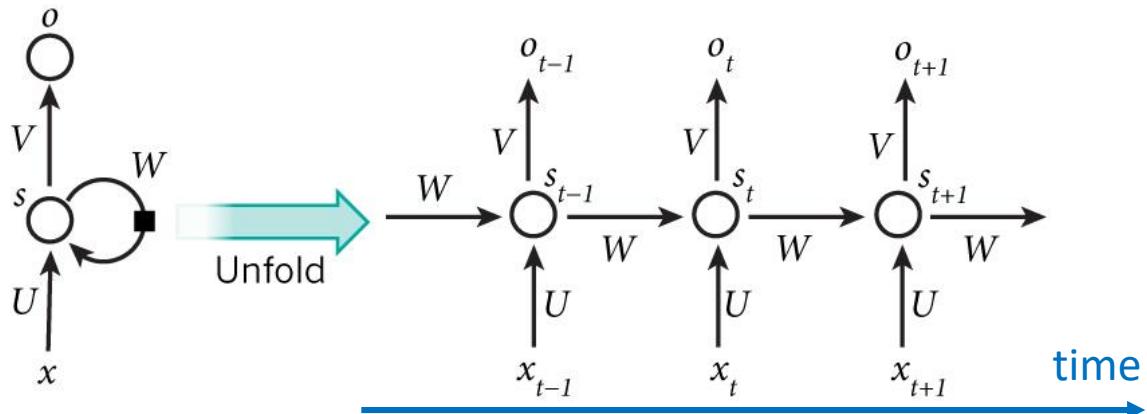
A good function should make the loss of all examples as small as possible.

Recurrent Neural Network (RNN)

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$$s_t = \sigma(W s_{t-1} + U x_t) \quad \sigma(\cdot): \text{tanh, ReLU}$$

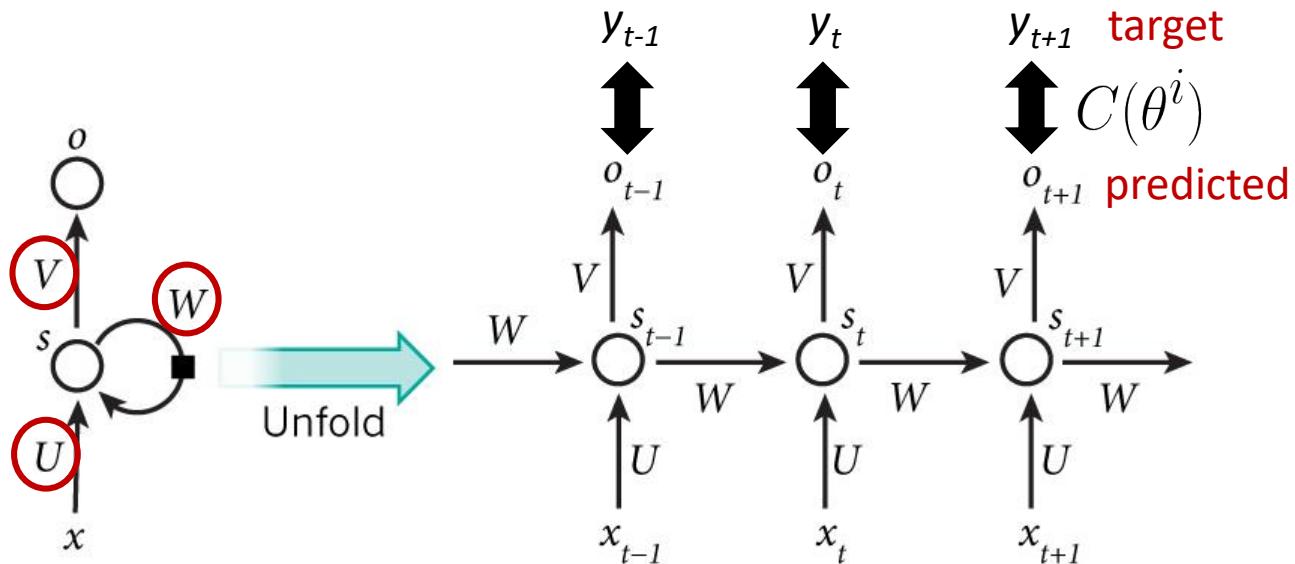
$$o_t = \text{softmax}(V s_t)$$



RNN can learn accumulated sequential information (time-series)

Model Training

- All model parameters $\theta = \{U, V, W\}$ can be updated by SGD



BPTT

Forward Pass: Compute $s_1, s_2, s_3, s_4 \dots$

Backward Pass:

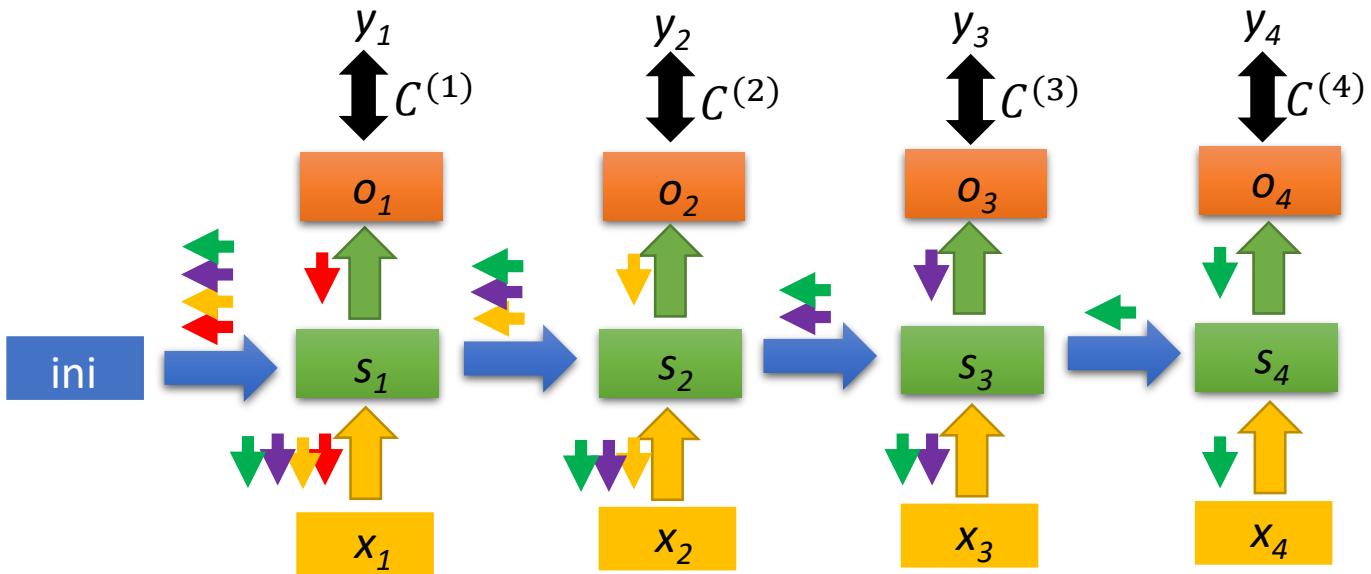
For $C^{(4)}$

For $C^{(2)}$

For $C^{(3)}$

For $C^{(1)}$

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The model is trained by comparing the correct sequence tags and the predicted ones

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Reinforcement Learning

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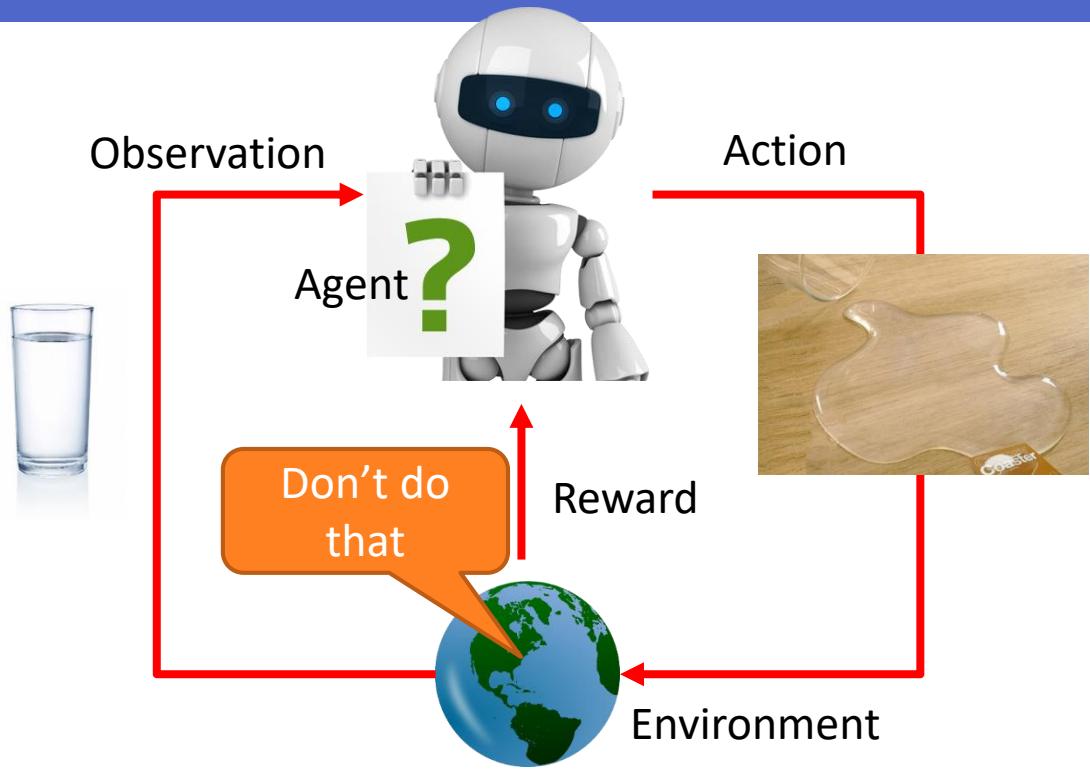
- RL is a general purpose framework for **decision making**
 - RL is for an *agent* with the capacity to *act*
 - Each *action* influences the agent's future *state*
 - Success is measured by a scalar *reward* signal
 - Goal: *select actions to maximize future reward*

Big three: action, state, reward



Reinforcement Learning

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Reinforcement Learning

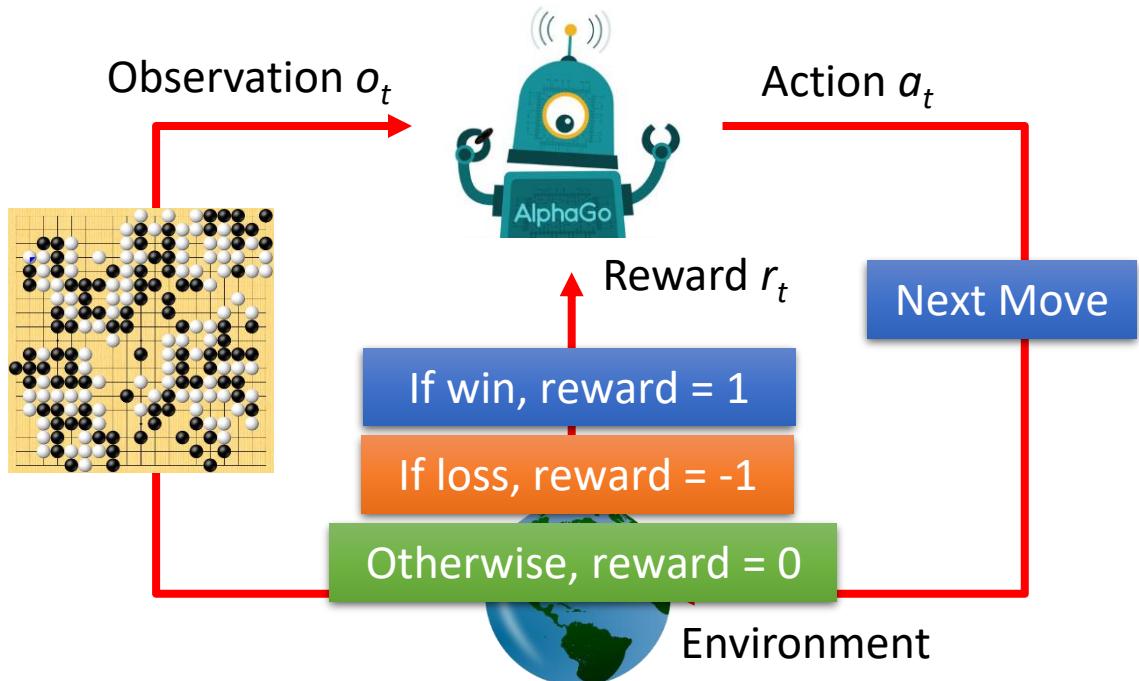
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Agent learns to take actions to maximize expected reward.

Scenario of Reinforcement Learning

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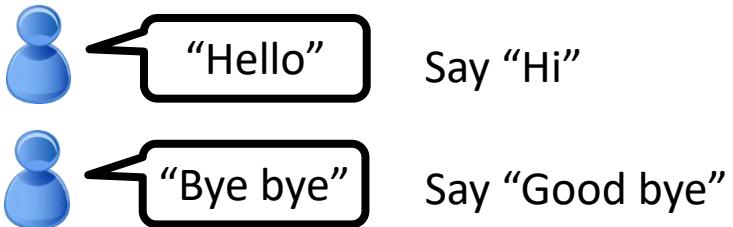
Agent learns to take actions to maximize expected reward.

Supervised v.s. Reinforcement

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□ Supervised

Learning from teacher



□ Reinforcement



.....



Bad

Learning from critics

Hello ☺

Agent

.....

Agent

Supervised v.s. Reinforcement

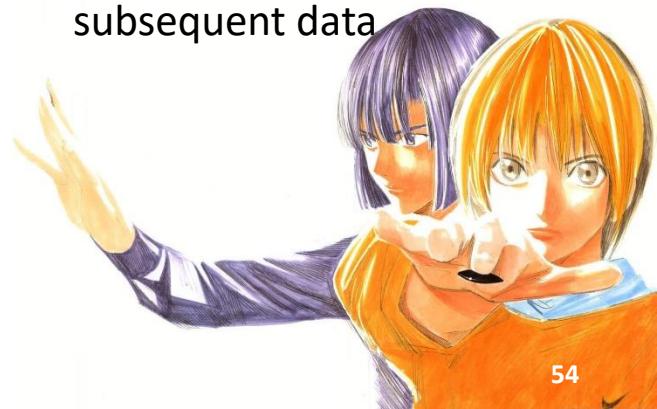
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□ Supervised Learning

- Training based on supervisor/label/annotation
- Feedback is instantaneous
- Time does not matter

□ Reinforcement Learning

- Training only based on reward signal
- Feedback is delayed
- Time matters
- Agent actions affect subsequent data



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Reward

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- Reinforcement learning is based on reward hypothesis
- A reward r_t is a scalar feedback signal
 - ▣ Indicates how well agent is doing at step t

Reward hypothesis: all agent goals can be desired by maximizing expected cumulative reward

Sequential Decision Making

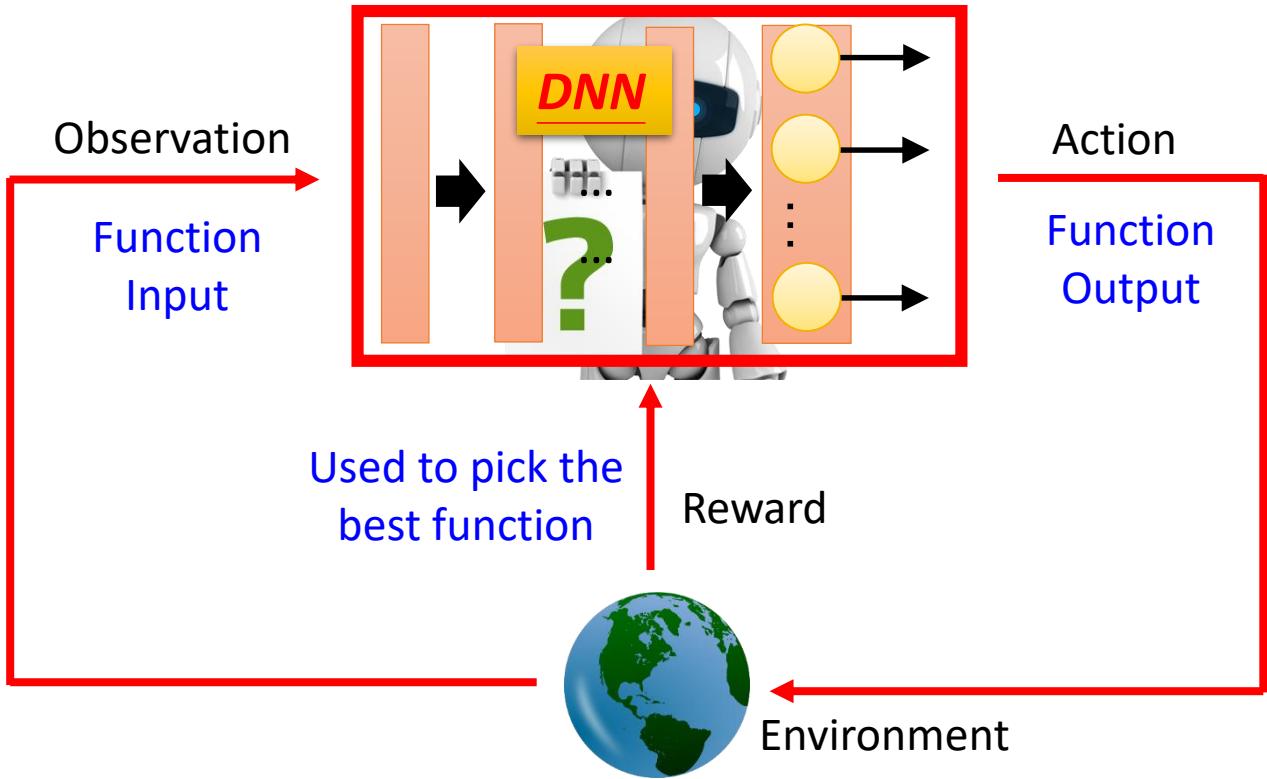
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- Goal: select actions to maximize total future reward
 - Actions may have long-term consequences
 - Reward may be delayed
 - It may be better to sacrifice immediate reward to gain more long-term reward



Deep Reinforcement Learning

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Modular Dialogue System

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Semantic Frame Representation

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- Requires a domain ontology
- Contains **core content (intent, a set of slots with fillers)**

Restaurant
Domain



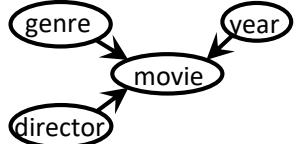
find a cheap taiwanese restaurant in oakland



find_restaurant (price="cheap",
type="taiwanese", location="oakland")

Movie
Domain

show me action movies directed by james cameron

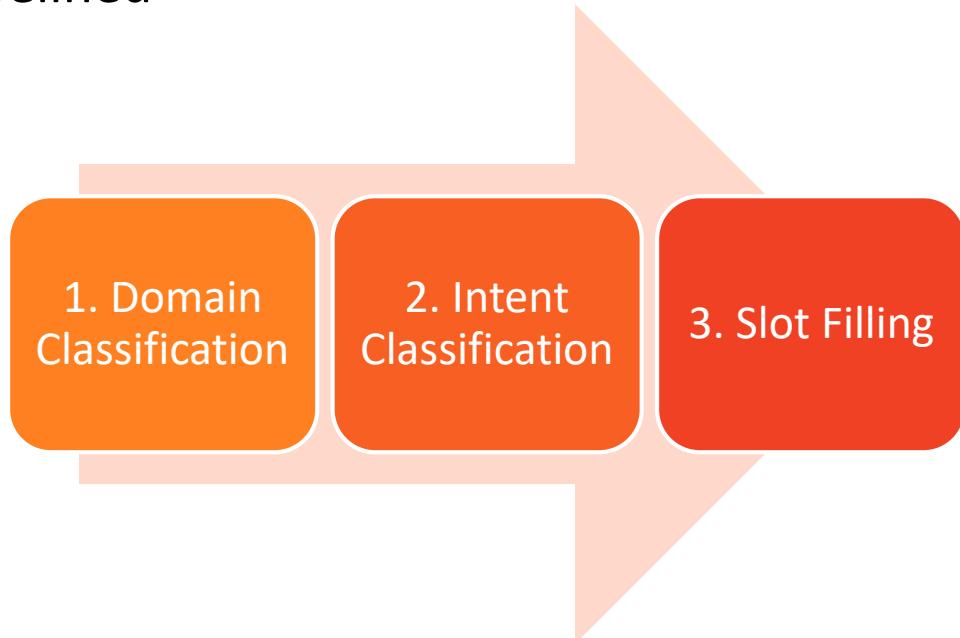


find_movie (genre="action",
director="james cameron")

Language Understanding (LU)

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□ Pipelined



LU – Domain/Intent Classification

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Mainly viewed as an utterance classification task

- Given a collection of utterances u_i with labels c_i , $D = \{(u_1, c_1), \dots, (u_n, c_n)\}$ where $c_i \in C$, train a model to estimate labels for new utterances u_k .

find me a cheap taiwanese restaurant in oakland

Movies	Find_movie
Restaurants	Buy_tickets
Sports	Find_restaurant
Weather	Book_table
Music	Find_lyrics
...	...

Language Understanding - Slot Filling

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Is there um a cheap place in the centre of town please?

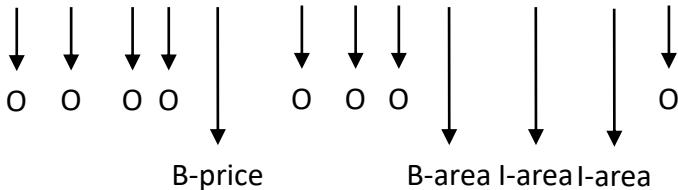
As a sequence tagging task

- CRF for tagging each utterance

As a classification task

- SVM for each slot value pair

Is there um a cheap place in the centre of town please?



Slot value pairs

food=Italian	X
food=Chinese	X
area=centre	✓
area=north	X
price=cheap	✓

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Dialogue State Tracking (DST)

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- Maintain a probabilistic distribution instead of a 1-best prediction for better robustness

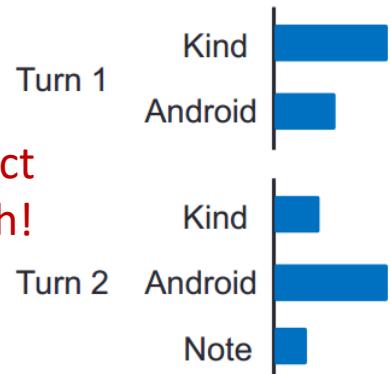
Turn 1
Kind
Android

Turn 1	
Kind	0.5
Android	0.3

Turn 2
Note
Android

Turn 2	
Note	0.4
Android	0.3

Incorrect
for both!



Dialogue State Tracking (DST)

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- Maintain a probabilistic distribution instead of a 1-best prediction for better robustness to SLU errors or ambiguous input

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

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



Outline

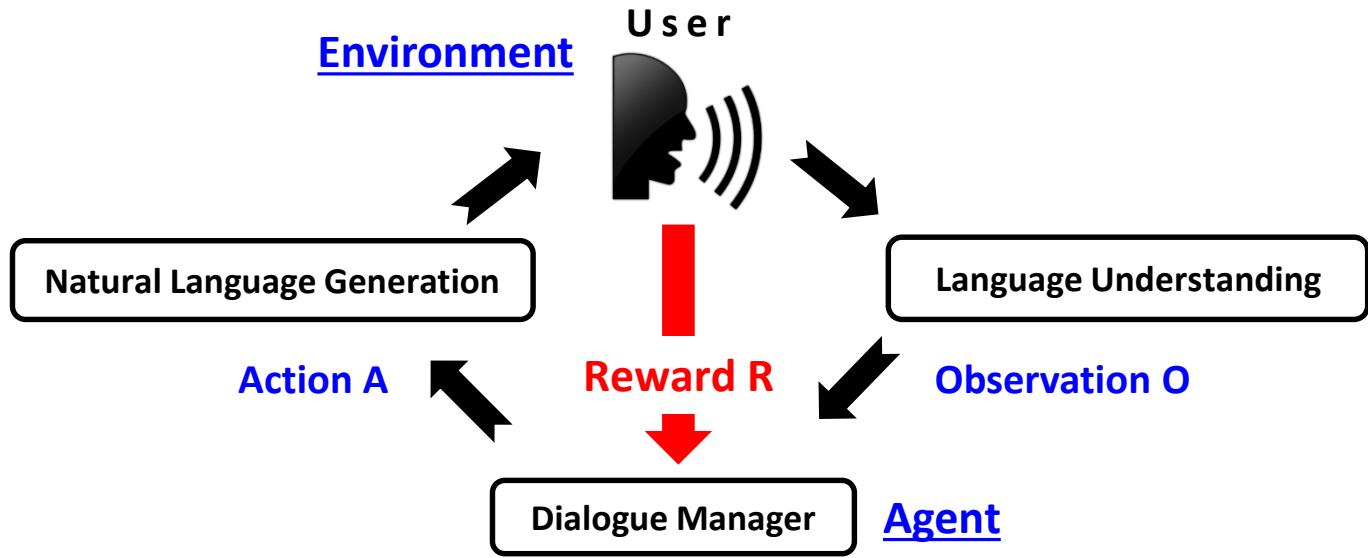
67

- Introduction
- Background Knowledge
 - Neural Network Basics
 - Reinforcement Learning
- Modular Dialogue System
 - Spoken/Natural Language Understanding (SLU/NLU)
 - ***Dialogue Management***
 - Dialogue State Tracking (DST)
 - ***Dialogue Policy Optimization***
 - Natural Language Generation (NLG)

Dialogue Policy Optimization

68

- Dialogue management in a RL framework



Optimized dialogue policy selects the best action that can maximize the future reward.
Correct rewards are a crucial factor in dialogue policy training

Reward for RL \cong Evaluation for SDS

69

- Dialogue is a special RL task
 - Human involves in interaction and rating (evaluation) of a dialogue
 - Fully human-in-the-loop framework
- Rating: correctness, appropriateness, and adequacy

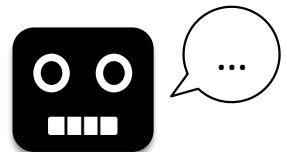
- Expert rating	high quality, high cost
- User rating	unreliable quality, medium cost
- Objective rating	Check desired aspects, low cost

Dialogue Reinforcement Signal

70

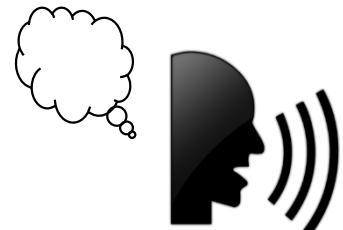
Typical Reward Function

- per turn penalty -1
- Large reward at completion if **successful**



Typically requires **domain knowledge**

- ✓ Simulated user
- ✗ Paid users (Amazon Mechanical Turk)
- ✗ Real users

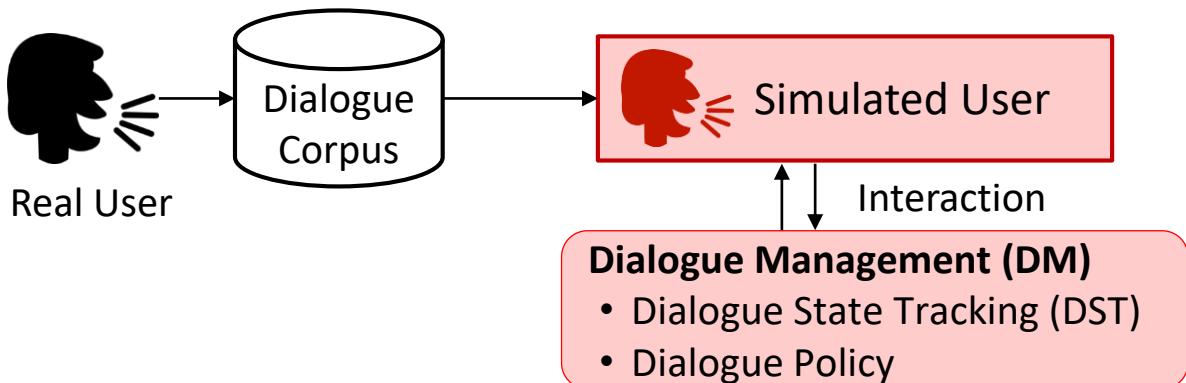


User Simulation

71

User Simulation

- Goal: generate natural and reasonable conversations to enable reinforcement learning for exploring the policy space
- Approach
 - Rule-based crafted by experts (Li et al., 2016)
 - Learning-based (Schatzmann et al., 2006)



Outline

72

- Introduction
- Background Knowledge
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 - Dialogue Policy Optimization
 - ***Natural Language Generation (NLG)***

Natural Language Generation (NLG)

73

- Mapping semantic frame into natural language

inform(name=Seven_Days, foodtype=Chinese)



Seven Days is a nice Chinese restaurant

Template-Based NLG

74

- Define a set of rules to map frames to NL

Semantic Frame	Natural Language
confirm()	“Please tell me more about the product your are looking for.”
confirm(area=\$V)	“Do you want somewhere in the \$V?”
confirm(food=\$V)	“Do you want a \$V restaurant?”
confirm(food=\$V,area=\$W)	“Do you want a \$V restaurant in the \$W.”

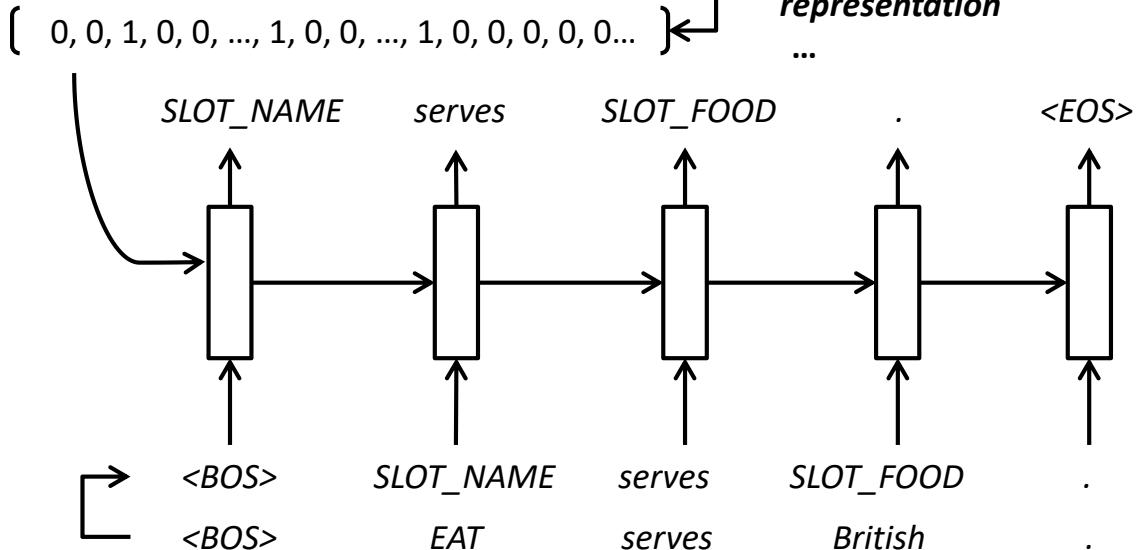
Pros: simple, error-free, easy to control

Cons: time-consuming, poor scalability

RNN Language Generator (Wen et al., 2015)

75

Inform(name=EAT, food=British)



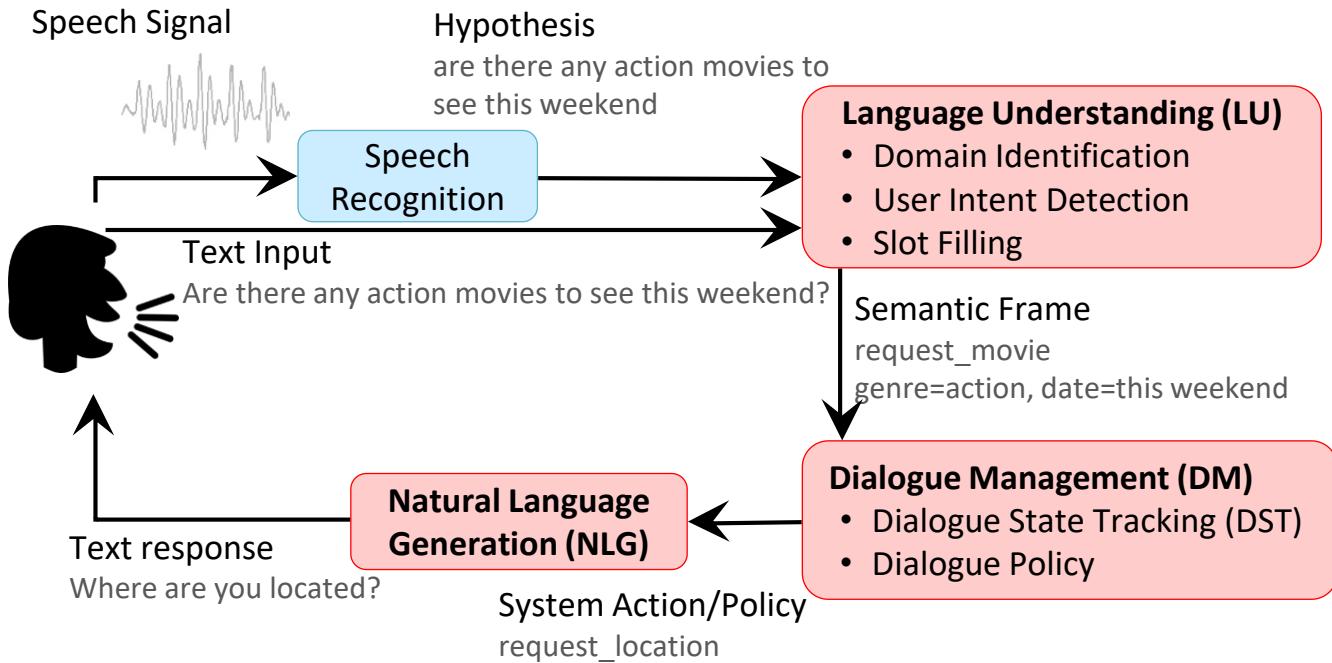
delexicalisation

Weight tying

Concluding Remarks

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□ Modular dialogue system



Tutorial Outline

77

I. 對話系統及基本背景知識

II. 語言理解 (Language Understanding)

III. 對話管理 (Dialogue Management)

IV. 語言生成 (Language Generation)

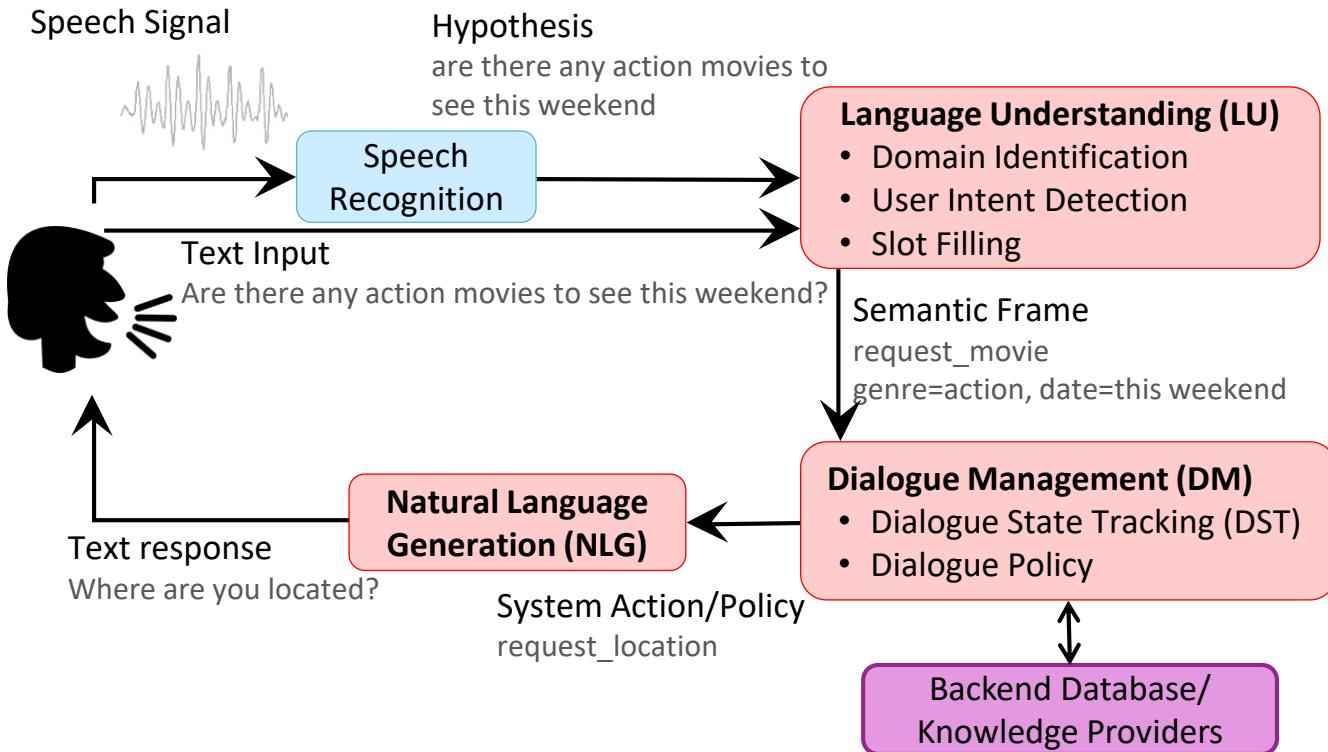
V. 對話系統評估、發展及趨勢



Task-Oriented Dialogue System (Young, 2000)

79

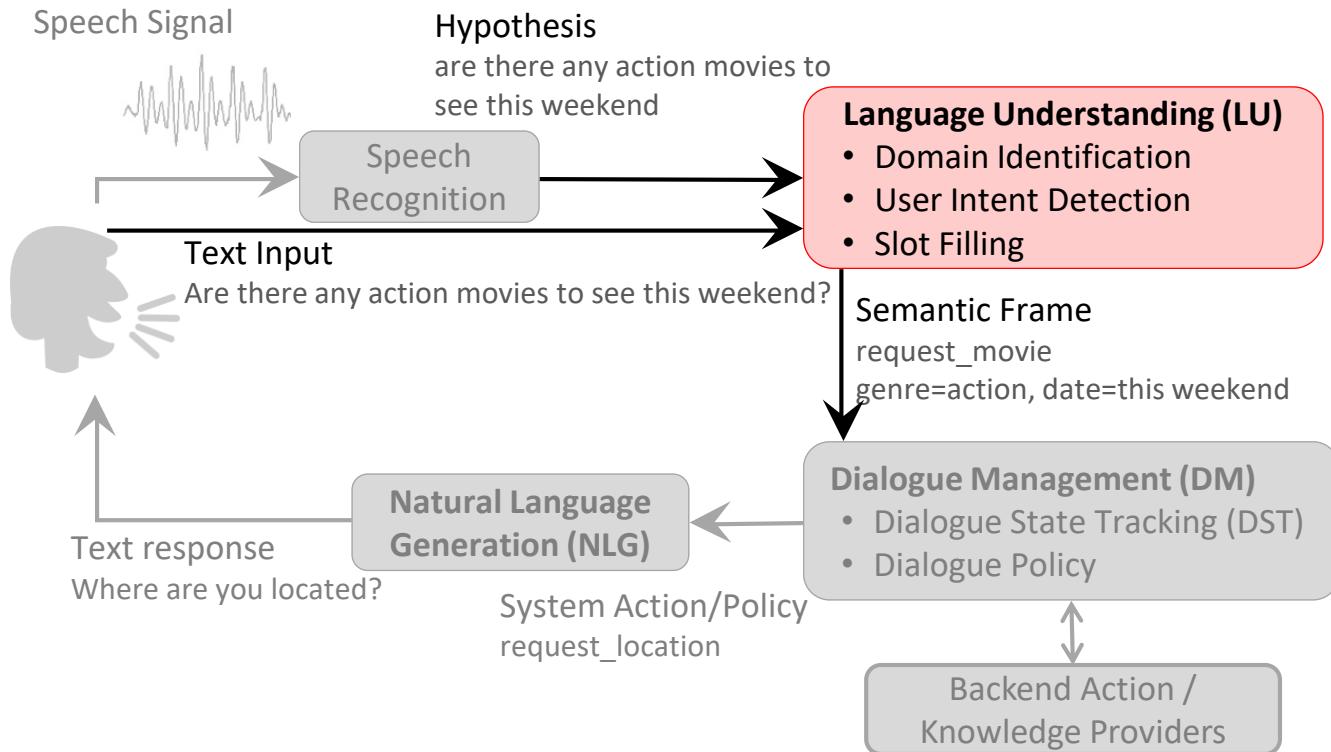
<http://rsta.royalsocietypublishing.org/content/358/1769/1389.short>



Task-Oriented Dialogue System (Young, 2000)

80

<http://rsta.royalsocietypublishing.org/content/358/1769/1389.short>



Semantic Frame Representation

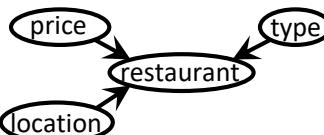
81

- Requires a domain ontology: early connection to **backend**
- Contains **core concept (intent, a set of slots with fillers)**

Restaurant
Domain



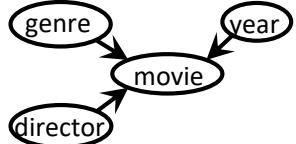
find me a cheap taiwanese restaurant in oakland



find_restaurant (price="cheap",
type="taiwanese", location="oakland")

Movie
Domain

show me action movies directed by james cameron

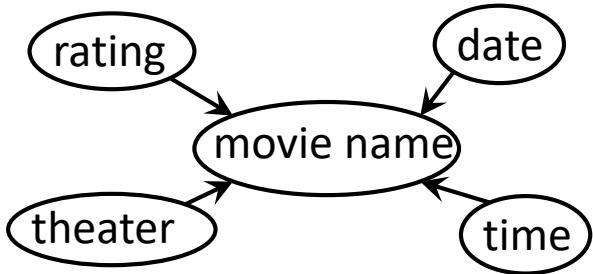


find_movie (genre="action",
director="james cameron")

Backend Database / Ontology

82

- Domain-specific table
 - ▣ Target and attributes



Movie Name	Theater	Rating	Date	Time
美女與野獸	台北信義威秀	8.5	2017/03/21	09:00
美女與野獸	台北信義威秀	8.5	2017/03/21	09:25
美女與野獸	台北信義威秀	8.5	2017/03/21	10:15
美女與野獸	台北信義威秀	8.5	2017/03/21	10:40
美女與野獸	台北信義威秀	8.5	2017/03/21	11:05

Supported Functionality

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- Information access
 - ▣ Finding the specific entries from the table
 - E.g. available theater, movie rating, etc.
- Task completion
 - ▣ Finding the row that satisfies the constraints



Movie Name	Theater	Rating	Date	Time
美女與野獸	台北信義威秀	8.5	2017/03/21	09:00
美女與野獸	台北信義威秀	8.5	2017/03/21	09:25
美女與野獸	台北信義威秀	8.5	2017/03/21	10:15
美女與野獸	台北信義威秀	8.5	2017/03/21	10:40
美女與野獸	台北信義威秀	8.5	2017/03/21	11:05

Dialogue Schema

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- Slot: domain-specific attributes
 - Columns from the table
 - e.g. theater, date

Movie Name	Theater	Rating	Date	Time
美女與野獸	台北信義威秀	8.5	2017/03/21	09:00
美女與野獸	台北信義威秀	8.5	2017/03/21	09:25
美女與野獸	台北信義威秀	8.5	2017/03/21	10:15
美女與野獸	台北信義威秀	8.5	2017/03/21	10:40
美女與野獸	台北信義威秀	8.5	2017/03/21	11:05

Dialogue Schema

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- Dialogue Act
 - inform, request, confirm (system only)
 - Task-specific action (e.g. book_ticket)
 - Others (e.g. thanks)

User Intent

= Dialogue Act + Slot



User

Find me the Bill Murray's movie.

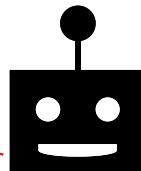
request(moviename; actor=Bill Murray)

I think it came out in 1993.

inform(releaseyear=1993)

System Action

= Dialogue Act + Slot



Bot

When was it released?

request(releaseyear)

Examples

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- User: 我想要聽適合唸書的歌
request(song; situation =“唸書”)
→ Require **situation labels** for songs

- User: 請問附近有類似有錢真好的店嗎？
request(restaurant; similar_to=“有錢真好”)
→ Require **similar_to labels** for restaurants

Examples

- User: 離散數學的教室是哪間？
- User: 週四7,8,9有資訊系的課嗎？

系所課程查詢

開課學期：全部
開課系所：9020 資訊工程學系
年級分組：全部
必修
選修
全部
課程名稱： 教師名稱：
上課時間： 不限 暫定 週一 週二 週三 週四 週五 週六

節： 不限 暫定 0 7:10~8:00 1 8:10~9:00 2 9:10~10:00 3 10:20~11:10 4 11:20~12:10 5 12:20~13:10 6 13:20~14:10
 7:14:20~15:10 8 15:30~16:20 9 16:30~17:20 10 17:30~18:20 A 18:25~19:15 B 19:20~20:10 C 20:15~21:05 D 21:10~22:00
加課方式： 不限 暫定 第1類 第2類 第3類

每頁顯示筆數 15

105-2 ◁ 查詢到 82 筆課程 :

上一頁 下一頁 第2頁 ▶

流水號	授課對象	課號	班次	課程名稱		學分	課程識別碼	全/半年	必/選修	授課教師	加課方式	時間 教室	總人數	選課限制條件	備註	課程網頁	本學期 新增 要修的 課程	
				查看課程大綱														
41469	資訊系	CSIE2910	05	服務學習二		0.0	902 00220	半年	選修	陳溫德	1		35	限公課末二位號第5節前，且 限服務學習 本校修課人數上限：35人		<input type="checkbox"/>	加入	
61082	資訊系	CSIE3910	01	服務學習三		0.0	902 00330	半年	必帶	莊永祿	1		35	限公課雙號第1節後，限服務學習末二位號第5節1，本校修課人數上限：35人		<input type="checkbox"/>	加入	
23066	資訊系	CSIE3910	02	服務學習三		0.0	902 00330	半年	必帶	張智堅	1		35	限公課雙號第1節後，限服務學習末二位號第5節2，本校修課人數上限：35人		<input type="checkbox"/>	加入	
51158	資訊系	CSIE3910	03	服務學習三		0.0	902 00330	半年	必帶	張吉昇	1		35	限公課雙號第1節後，限服務學習末二位號第5節3，本校修課人數上限：35人		<input type="checkbox"/>	加入	
72964	資訊系	CSIE3910	04	服務學習三		0.0	902 00330	半年	必帶	蔡欣慶	1		35	限公課雙號第1節後，限服務學習末二位號第5節4，本校修課人數上限：35人		<input type="checkbox"/>	加入	
43407	資訊系	CSIE3910	05	服務學習三		0.0	902 00330	半年	必帶	蕭慈君	1		35	限公課雙號第1節後，限服務學習末二位號第5節5，本校修課人數上限：35人		<input type="checkbox"/>	加入	
69663	資訊系	CSIE1110		網路管理與系統管理實驗	1.0	902 10130	半年	選修	蔡欣慶	2		40	本校修課人數上限：40人	初選不開放。添有上課時間，實驗時間自定。 上課地點：皆204。		<input type="checkbox"/>	加入	
54236	資訊系	CSIE1212	01	資料結構與演算法	3.0	902 10750	半年	必帶	張智堅	1	二 7.8.9(社科201)	200		限研習單號第1，限本系所學生：合轉系、要修生，未約束修課人數上限：200人		<input type="checkbox"/>	加入	
36588	資訊系	CSIE1212	02	資料結構與演算法	3.0	902 10750	半年	必帶	蔡欣慶	2	二 6.7.8 (資104)	106	(含間放審大系統人數:6)	限研習雙號第1，限本系所學生：合轉系、要修生，未約束修課人數上限：100人		<input type="checkbox"/>	加入	
32705	資訊系	CSIE2350		數位電子與微處理器	3.0	902 21410	半年	選修	賴宗真	2	二-5(資111)三-6(資111)	50	含間放審大系統人數:10	本校修課人數上限：40人		<input type="checkbox"/>	加入	
16711	資訊系	CSIE2344	01	數位系統與實驗	3.0	902 21610	半年	必帶	周世偉	3	-7.8.9 (資104)	106		限本系所學生(合轉系、要修生)且 限學士班：2年級以上且 限單號單號，本校修課人數上限：106人		<input type="checkbox"/>	加入	
65361	資訊系	CSIE2344	02	數位系統與實驗	3.0	902 21610	半年	必帶	歐彥明	2	四 7.8.9 (資102)	80		限本系所學生(合轉系、要修生)且 限學士班：2年級以上且 限單號單號，本校修課人數上限：80人		<input type="checkbox"/>	加入	
27801	資訊系	CSIE2344		網路管理與系統管理	2.0	902 21620	半年	選修	葉欣綉	2	二-3(資103)	80		本校修課人數上限：80人	初選不開放。上課教室：資204電腦教室。		<input type="checkbox"/>	加入
65698	資訊系	CSIE2122	01	離散數學	3.0	902 25200	半年	選修	鍾健輝	2	四 4.4.5 (資102)	98		限本系所學生(合轉系、要修生)本校修課人數上限：98人		<input type="checkbox"/>	加入	
42235	資訊系	CSIE2122	02	離散數學	3.0	902E25200	半年	選修	呂昌達	2	四 2.3.4 (資107)	50	(含間放審大系統人數:6)	本課程以英語授課。主課程英文程度說明 上課人數：44人		<input type="checkbox"/>	加入	

Trick

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- The typed constraints are attributes/slots stored in the columns

A screenshot of a bus booking website interface. At the top, there are three tabs: '一般網路訂票' (General Network Booking), '大學生優惠' (Student Discount), and '信用卡合作優惠專區' (Credit Card Cooperation Special Area). Below the tabs, there are several input fields and dropdown menus:

- '起訖站' (Departure and Arrival Stations) with dropdown menus for '請選擇...'.
- '車廂種類' (Car Type) with radio buttons for '標準車廂' (Standard Cabin) and '商務車廂' (Business Cabin).
- '座位喜好' (Seat Preference) with radio buttons for '無' (None), '靠窗優先' (Window Priority), and '走道優先' (Aisle Priority).
- '訂位方式' (Booking Method) with radio buttons for '依時間搜尋合適車次' (Search by Time) and '直接輸入車次號碼' (Enter Car Number Directly).
- '時間' (Time) with a date input field '去程 [2017/03/21]' and a dropdown menu '約 [請選擇...]'.
- '票數' (Number of Tickets) with dropdown menus for '全票 [1]', '孩童票(6-11歲) [0]', '愛心票 [0]', and '敬老票(65歲以上) [0]'.
- '查詢早鳥優惠' (Query Early Bird Discount) with a checkbox.

A screenshot of a travel booking website interface. At the top, there are two tabs: '住宿' (Accommodation) and '機票' (Flight). A banner at the top right says '走進【曼谷】找體驗 訂飯店、住Villa、找民宿 包山包海超過1,225,000+間國內外各類住宿！'. Below the tabs, there are several search filters:

- '你是旅人不是過客，想住哪？就搜那！' (You are not a passerby, where do you want to stay? Search it!).
- '輸入城市、區域、景點或住宿名稱' (Enter city, area, attraction or accommodation name).
- '入住日期' (Check-in Date) set to '2017年3月30日(四)' (Wednesday, March 30, 2017).
- '退房日期' (Check-out Date) set to '2017年3月31日(五)' (Thursday, March 31, 2017).
- '入住人數' (Number of Guests) set to '1間套房, 2位大人, 0位兒童' (1 suite, 2 adults, 0 children).
- '搜出好價' (Search for Good Price) button.
- '自訂每晚預算' (Custom Daily Budget) with a slider from 'TWD 0 - TWD 9,600 +' to '全選' (Select All).
- '評鑑得分' (Rating Score) with a slider from 'TW 0 - TW 9.600 +' to '全選' (Select All).
- '星级' (Star Rating) with a slider from '★★★★★以上' (5 stars and above) to '全選' (Select All).

Table & Graph Backend

89

<https://www.google.com/intl/es419/insidesearch/features/search/knowledge.html>

The Knowledge Graph

Learn more about one of the key breakthroughs behind the future of search.

See it in action

Discover answers to questions you never thought to ask, and explore collections and lists.

Leonardo da Vinci

Leonardo di ser Piero da Vinci was an Italian Renaissance polymath: painter, sculptor, architect, musician, scientist, mathematician, engineer, inventor, anatomist, geologist, cartographer, botanist, and writer. [Wikipedia](#)

Born: April 15, 1452, Anchiano

Died: May 2, 1519, Clos Lucé

Buried: Château d'Amboise

Parents: Caterina da Vinci, Piero da Vinci

Structures: [Medium Word Da Vinci Project](#)

Data Collection

90

- Given the task-specific goal, what do users say?

Information Access

你知道美女與野獸電影的評價如何嗎？

Task completion

我想看十點左右在信義威秀的電影



Movie Name	Theater	Rating	Date	Time
美女與野獸	台北信義威秀	8.5	2017/03/21	09:00
美女與野獸	台北信義威秀	8.5	2017/03/21	09:25
美女與野獸	台北信義威秀	8.5	2017/03/21	10:15
美女與野獸	台北信義威秀	8.5	2017/03/21	10:40
美女與野獸	台北信義威秀	8.5	2017/03/21	11:05

Annotation Design

91

- Query target: intent
 - ▣ request + targeted attribute
- Constraints: slots & values
 - ▣ Attributes with specified values

你知道美女與野獸電影的評價如何嗎?

request(rating; moviename=美女與野獸)

我想看十點左右在信義威秀的電影

book_ticket(time=十點左右, theater=信義威秀)

Extension

92

- Multiple tables as backend
 - Each table is responsible for a **domain**
 - Associate intent with corresponding table/domain

你知道美女與野獸是那一年的電影嗎?

request(**kng.release_year**; moviename=美女與野獸)

Ticket Table

Movie Name	Theater	Date	Time
美女與野獸	台北信義威秀	2017/03/21	09:00
美女與野獸	台北信義威秀	2017/03/21	09:25
美女與野獸	台北信義威秀	2017/03/21	10:15

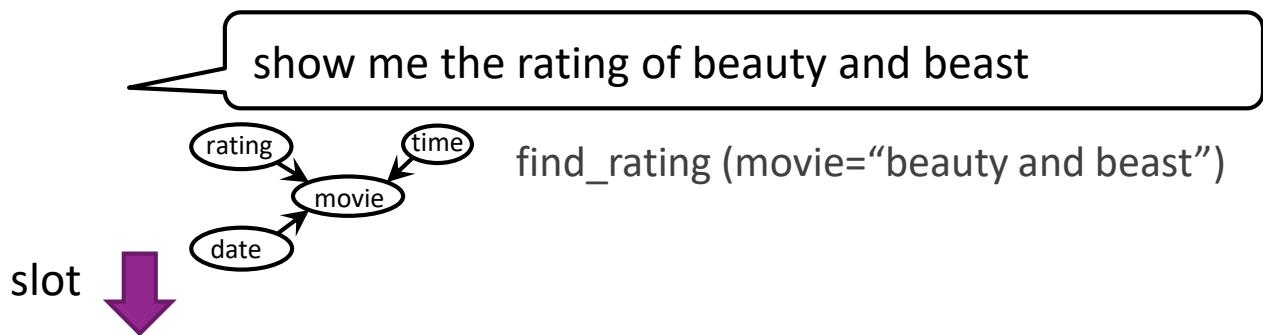
Knowledge Table

Movie Name	Cast	Release Year
美女與野獸	Emma Watson	2017
鋼鐵人	:	:

Concluding Remarks

93

- Semantic schema highly corresponds to backend DB



Movie Name	Theater	Rating	Date	Time
美女與野獸	台北信義威秀	8.5	2017/03/21	09:00
美女與野獸	台北信義威秀	8.5	2017/03/21	09:25
美女與野獸	台北信義威秀	8.5	2017/03/21	10:15
美女與野獸	台北信義威秀	8.5	2017/03/21	10:40
美女與野獸	台北信義威秀	8.5	2017/03/21	11:05

WE UNDERSTAND
YOUR NEEDS



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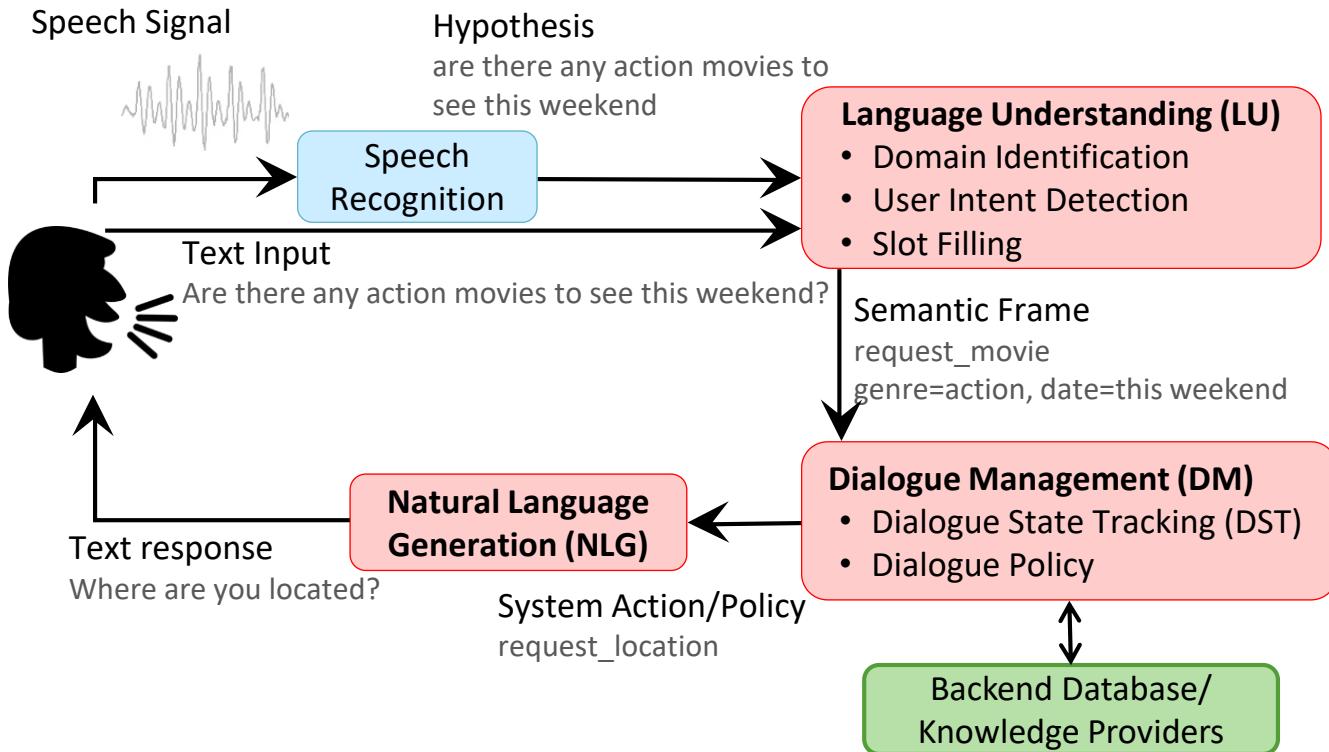
Language Understanding

語言理解

Task-Oriented Dialogue System (Young, 2000)

95

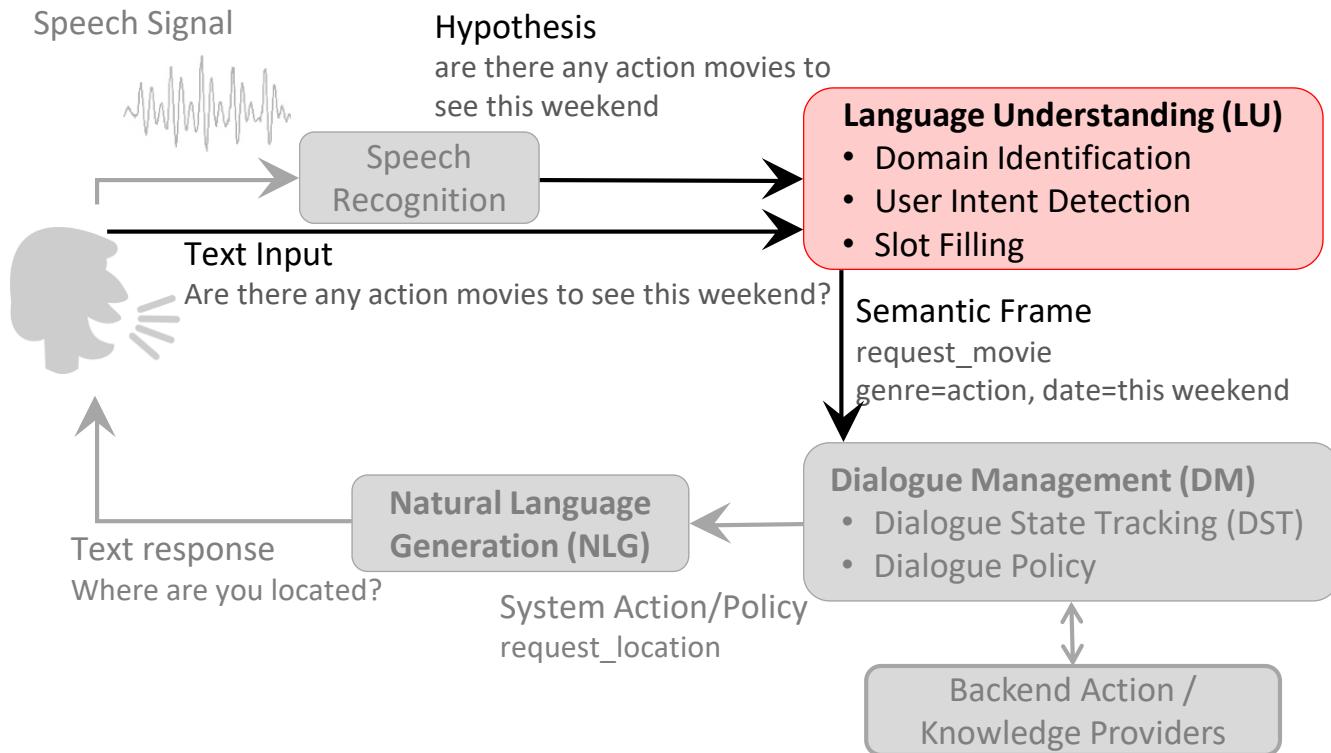
<http://rsta.royalsocietypublishing.org/content/358/1769/1389.short>



Task-Oriented Dialogue System (Young, 2000)

96

<http://rsta.royalsocietypublishing.org/content/358/1769/1389.short>

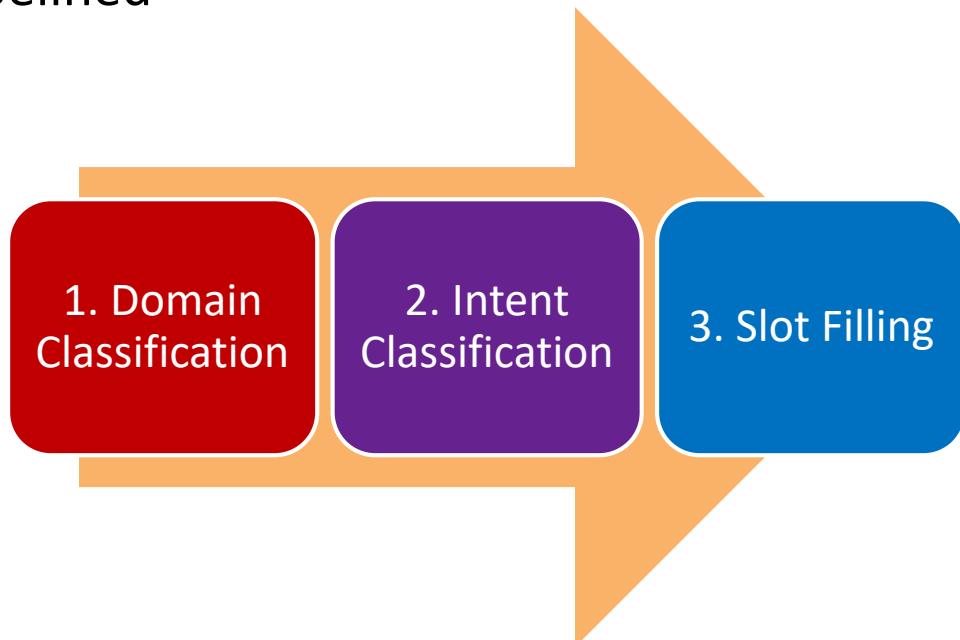


Classic Language Understanding

Language Understanding (LU)

98

□ Pipelined



LU – Domain/Intent Classification

99

As an **utterance classification** task

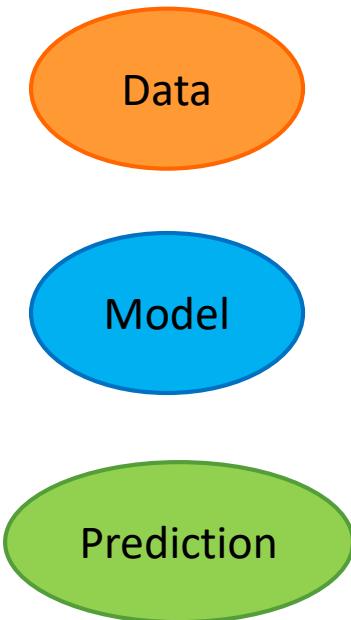
- Given a collection of utterances u_i with labels c_i ,
 $D = \{(u_1, c_1), \dots, (u_n, c_n)\}$ where $c_i \in C$, train a model to estimate labels for new utterances u_k .

find me a cheap taiwanese restaurant in oakland

Domain	Intent
Movies	find_movie, buy_tickets
<u>Restaurants</u>	find_restaurant, find_price, book_table
Music	find_lyrics, find_singer
Sports	...
...	

Conventional Approach

100



dialogue utterances annotated with
domains/intents

machine learning **classification** model
e.g. support vector machine (SVM)

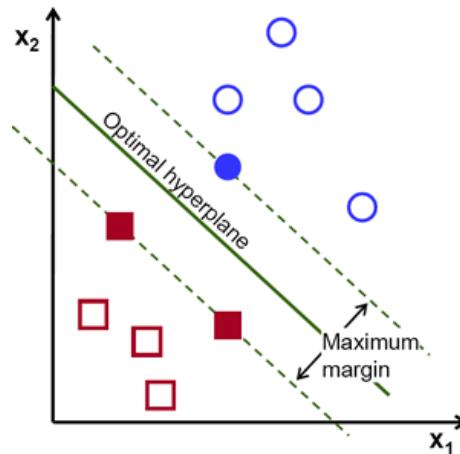
domains/intents

Theory: Support Vector Machine

101

<http://www.csie.ntu.edu.tw/~htlin/mooc/>

- SVM is a maximum margin classifier
 - Input data points are mapped into a high dimensional feature space where the data is linearly separable
 - Support vectors are input data points that lie on the margin

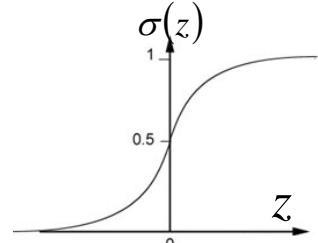


Theory: Support Vector Machine

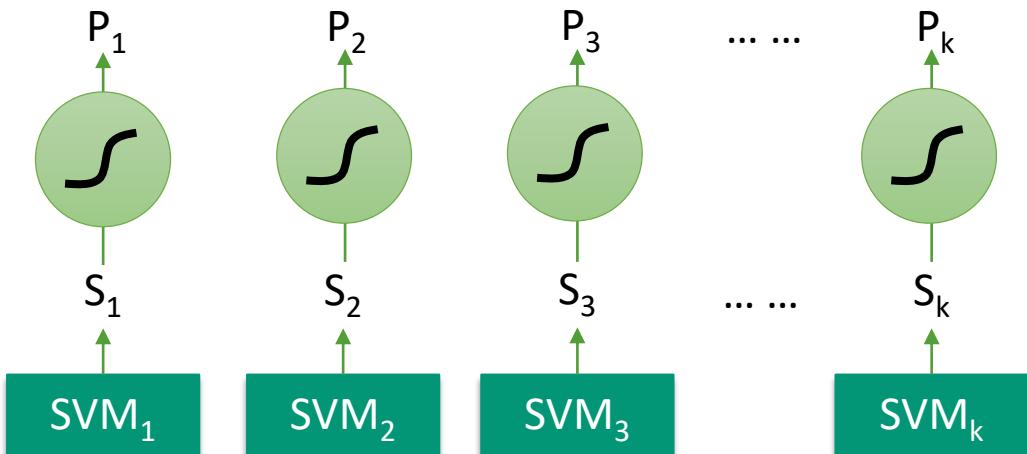
102

<http://www.csie.ntu.edu.tw/~htlin/mooc/>

- Multiclass SVM
 - Extended using one-versus-rest approach
 - Then transform into probability



prob for
each class



score for
each class

SVM_1

SVM_2

SVM_3

SVM_k

Domain/intent can be decided based on the estimated scores

LU – Slot Filling

103

As a **sequence tagging** task

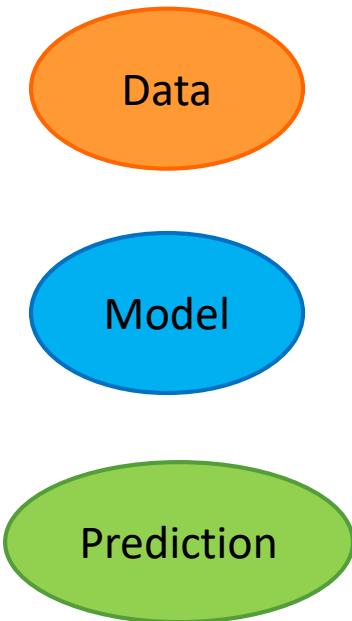
- Given a collection tagged word sequences,
 $S = \{(w_{1,1}, w_{1,2}, \dots, w_{1,n_1}), (t_{1,1}, t_{1,2}, \dots, t_{1,n_1}), (w_{2,1}, w_{2,2}, \dots, w_{2,n_2}), (t_{2,1}, t_{2,2}, \dots, t_{2,n_2})\} \dots\}$
where $t_i \in M$, the goal is to estimate tags for a new word sequence.

flights from Boston to New York today

	flights	from	Boston	to	New	York	today
Entity Tag	O	O	B-city	O	B-city	I-city	O
Slot Tag	O	O	B-dept	O	B-arrival	I-arrival	B-date

Conventional Approach

104



dialogue utterances annotated with **slots**

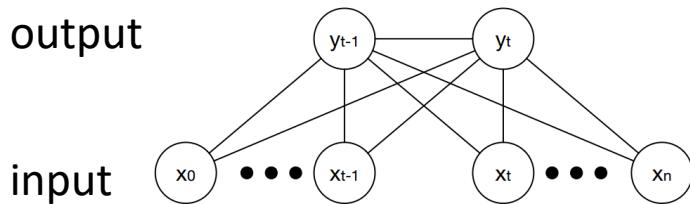
machine learning **tagging** model
e.g. conditional random fields (CRF)

slots and their **values**

Theory: Conditional Random Fields

105

- CRF assumes that the label at time step t depends on the label in the previous time step $t-1$



- Maximize the log probability $\log p(y | x)$ with respect to parameters λ

$$\begin{aligned} p(y | x) &= \frac{1}{Z(x)} \exp\left(\sum_i \lambda_i f_i(x, y)\right) \\ &= \prod_t \frac{1}{Z(x)} \exp\left(\sum_i \lambda_i f_i(x, y_t, y_{t-1})\right) \end{aligned}$$

Slots can be tagged based on the y that maximizes $p(y/x)$

106

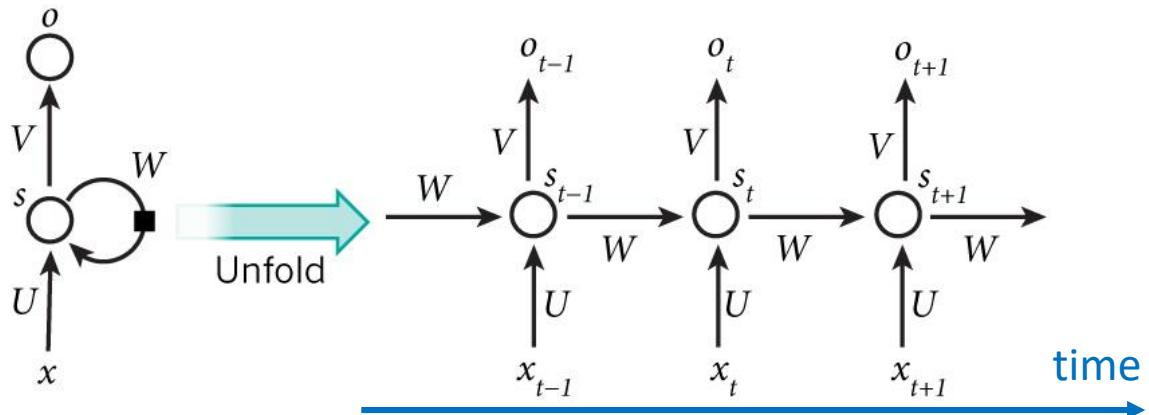
Neural Network Based LU

Recurrent Neural Network (RNN)

107

$$s_t = \sigma(W s_{t-1} + U x_t) \quad \sigma(\cdot): \text{tanh, ReLU}$$

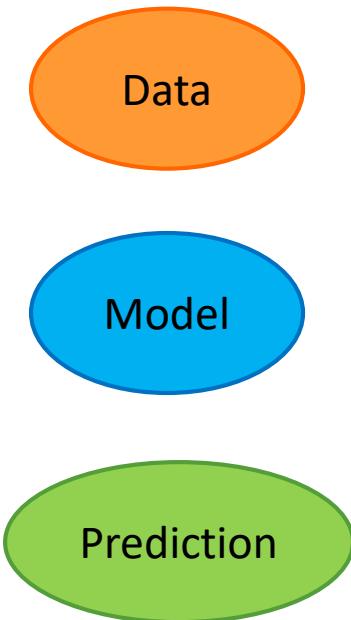
$$o_t = \text{softmax}(V s_t)$$



RNN can learn accumulated sequential information (time-series)

Deep Learning Approach

108



dialogue utterances annotated with
semantic frames (**user intents & slots**)

deep learning model (**classification/tagging**)
e.g. recurrent neural networks (RNN)

user intents, slots and their values

Classification Model

109

As an **utterance classification task**

- Given a collection of utterances u_i with labels c_i ,
 $D = \{(u_1, c_1), \dots, (u_n, c_n)\}$ where $c_i \in C$, train a model to estimate labels for new utterances u_k .

- Input: each utterance u_i is represented as a feature vector f_i
- Output: a domain/intent label c_i for each input utterance

How to represent a sentence using a feature vector

Sequence Tagging Model

110

As a **sequence tagging** task

- Given a collection tagged word sequences,
 $S = \{(w_{1,1}, w_{1,2}, \dots, w_{1,n_1}), (t_{1,1}, t_{1,2}, \dots, t_{1,n_1}), (w_{2,1}, w_{2,2}, \dots, w_{2,n_2}), (t_{2,1}, t_{2,2}, \dots, t_{2,n_2})\} \dots\}$
where $t_i \in M$, the goal is to estimate tags for a new word sequence.

- Input: each word $w_{i,j}$ is represented as a feature vector $f_{i,j}$
- Output: a slot label t_i for each word in the utterance

How to represent a word using a feature vector

Word Representation

111

- Atomic symbols: *one-hot* representation

car [0 0 0 0 0 0 1 0 0 ... 0]
 ↑
 car

Issues: difficult to compute the similarity
(i.e. comparing “car” and “motorcycle”)

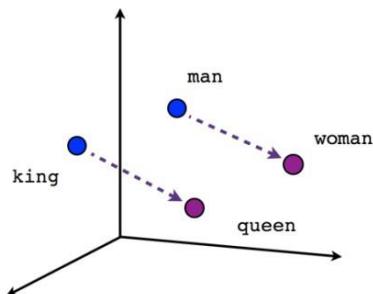
$$[0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 1 \ 0 \ 0 \ \dots \ 0] \text{ AND } [0 \ 0 \ 1 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ \dots \ 0] = 0$$

car
motorcycle

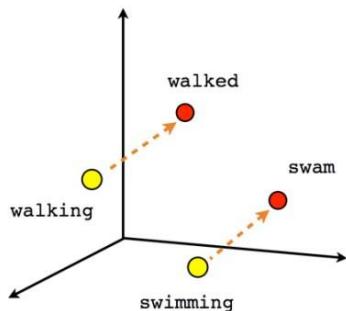
Word Representation

112

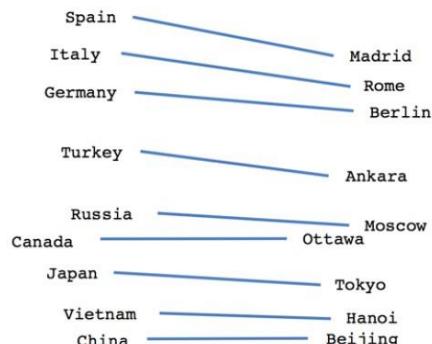
- Neighbor-based: low-dimensional dense word embedding



Male-Female



Verb tense



Country-Capital

Idea: words with similar meanings often have similar neighbors

Chinese Input Unit of Representation

113

- Character
 - ▣ Feed each char to each time step
- Word
 - ▣ Word segmentation required

你知道美女與野獸電影的評價如何嗎？



你/知道/美女與野獸/電影/的/評價/如何/嗎

Can two types of information fuse together for better performance?

LU – Domain/Intent Classification

114

As an **utterance classification** task

- Given a collection of utterances u_i with labels c_i ,
 $D = \{(u_1, c_1), \dots, (u_n, c_n)\}$ where $c_i \in C$, train a model to estimate labels for new utterances u_k .

find me a cheap taiwanese restaurant in oakland

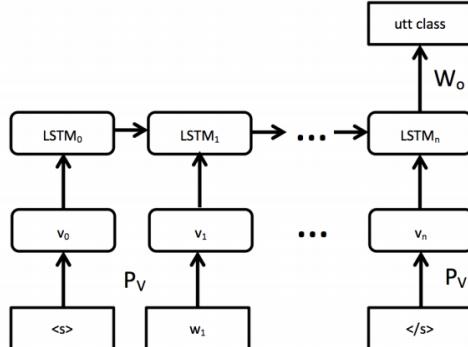
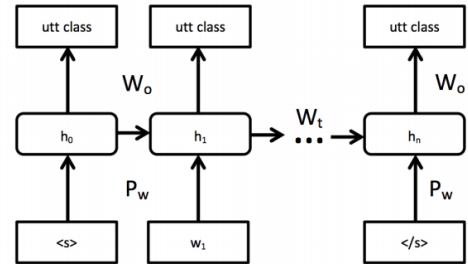
Domain	Intent
Movies	find_movie, buy_tickets
Restaurants	find_restaurant, find_price, book_table
Music	find_lyrics, find_singer
Sports	...
...	

Deep Neural Networks for Domain/Intent Classification (Ravuri and Stolcke, 2015)

115

https://www.microsoft.com/en-us/research/wp-content/uploads/2016/02/RNNLM_addressee.pdf

- RNN and LSTMs for utterance classification
- Word hashing to deal with large number of singletons
 - ▣ Kat: #Ka, Kat, at#
 - ▣ Each character n-gram is associated with a bit in the input encoding



LU – Slot Filling

116

As a **sequence tagging** task

- Given a collection tagged word sequences,
 $S = \{(w_{1,1}, w_{1,2}, \dots, w_{1,n_1}), (t_{1,1}, t_{1,2}, \dots, t_{1,n_1}), (w_{2,1}, w_{2,2}, \dots, w_{2,n_2}), (t_{2,1}, t_{2,2}, \dots, t_{2,n_2})\} \dots\}$
where $t_i \in M$, the goal is to estimate tags for a new word sequence.

flights from Boston to New York today

	flights	from	Boston	to	New	York	today
Entity Tag	O	O	B-city	O	B-city	I-city	O
Slot Tag	O	O	B-dept	O	B-arrival	I-arrival	B-date

Recurrent Neural Nets for Slot Tagging – I

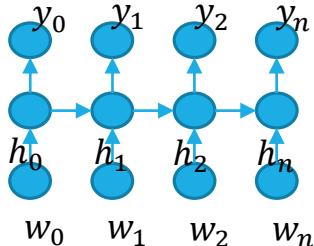
(Yao et al, 2013; Mesnil et al, 2015)

117

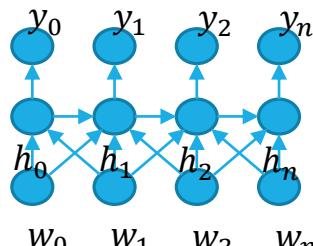
<http://131.107.65.14/en-us/um/people/gzweig/Pubs/Interspeech2013RNNLU.pdf>; <http://dl.acm.org/citation.cfm?id=2876380>

□ Variations:

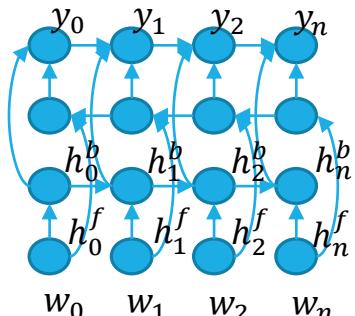
- RNNs with LSTM cells
- Input, sliding window of n-grams
- Bi-directional LSTMs



(a) LSTM



(b) LSTM-LA



(c) bLSTM

Recurrent Neural Nets for Slot Tagging – II

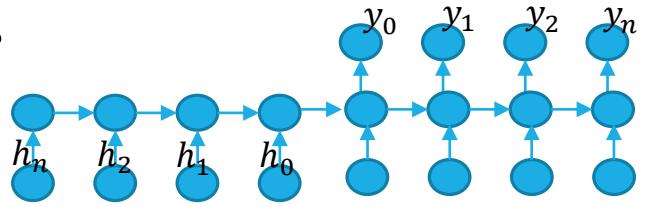
(Kurata et al., 2016; Simonnet et al., 2015)

118

<http://www.aclweb.org/anthology/D16-1223>

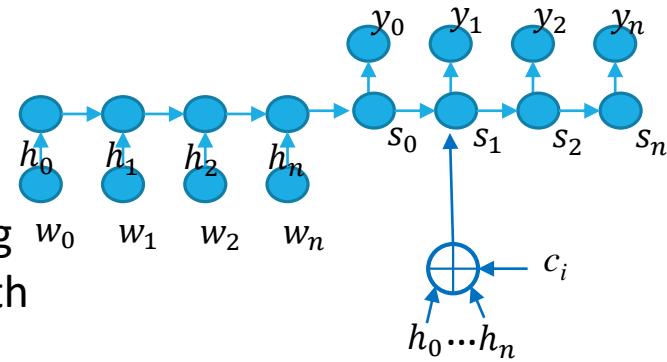
- Encoder-decoder networks

- Leverages sentence level information



- Attention-based encoder-decoder

- Use of attention (as in MT) in the encoder-decoder network



- Attention is estimated using a feed-forward network with input: h_t and s_t at time t

Joint Semantic Frame Parsing

119

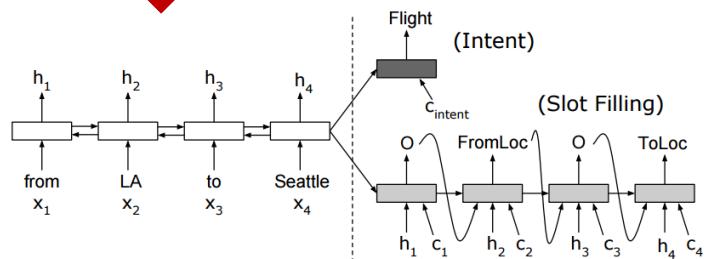
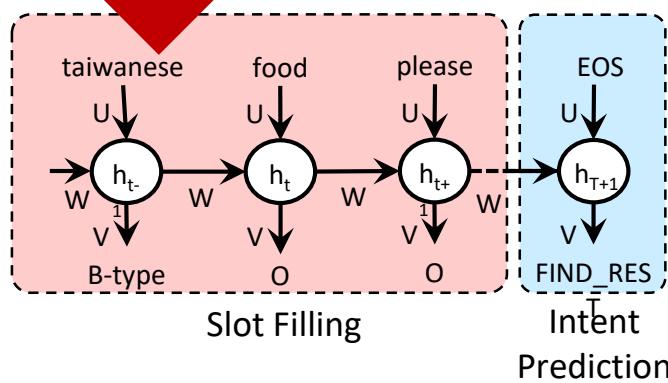
https://www.microsoft.com/en-us/research/wp-content/uploads/2016/06/IS16_MultiJoint.pdf; <https://arxiv.org/abs/1609.01454>

Sequence-based
(Hakkani-Tur et al., 2016)

- Slot filling and intent prediction in the same output sequence

Parallel
(Liu and Lane, 2016)

- Intent prediction and slot filling are performed in two branches



LU Evaluation

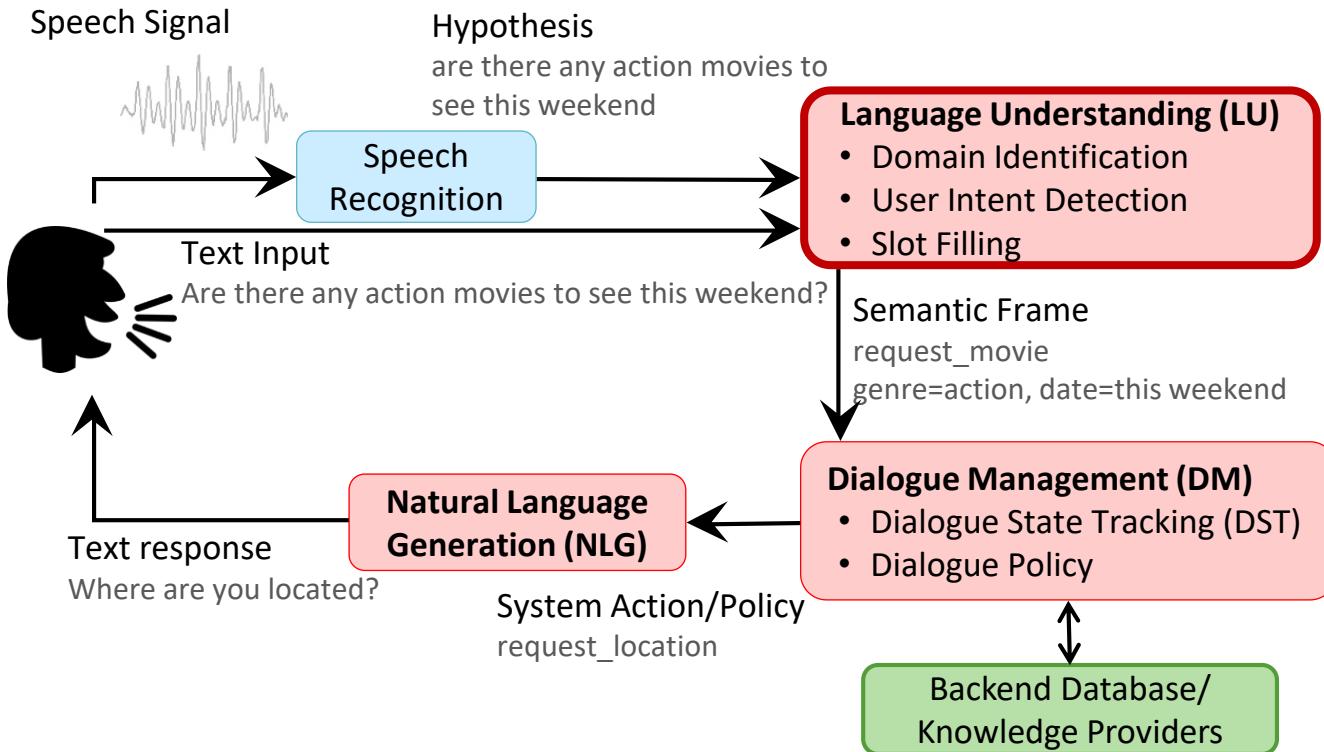
120

□ Metrics

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

Concluding Remarks

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Language Understanding Demo

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- Movie Bot
 - ▣ <http://140.112.21.82:8000/>
- Example
 - ▣ 晚上九點的當他們認真編織時
 - ▣ 我想要看晚上七點的電影
 - ▣ 我想要看晚上七點在新竹大遠百威秀影城的電影
 - ▣ 我要看新竹大遠百威秀影城的刀劍神域劇場版序列爭戰
 - ▣ 我想要看晚上七點在新竹大遠百威秀影城的刀劍神域劇場版序列爭戰

Tutorial Outline

123

I. 對話系統及基本背景知識

II. 語言理解 (Language Understanding)

III. 對話管理 (Dialogue Management)

IV. 語言生成 (Language Generation)

V. 對話系統評估、發展及趨勢





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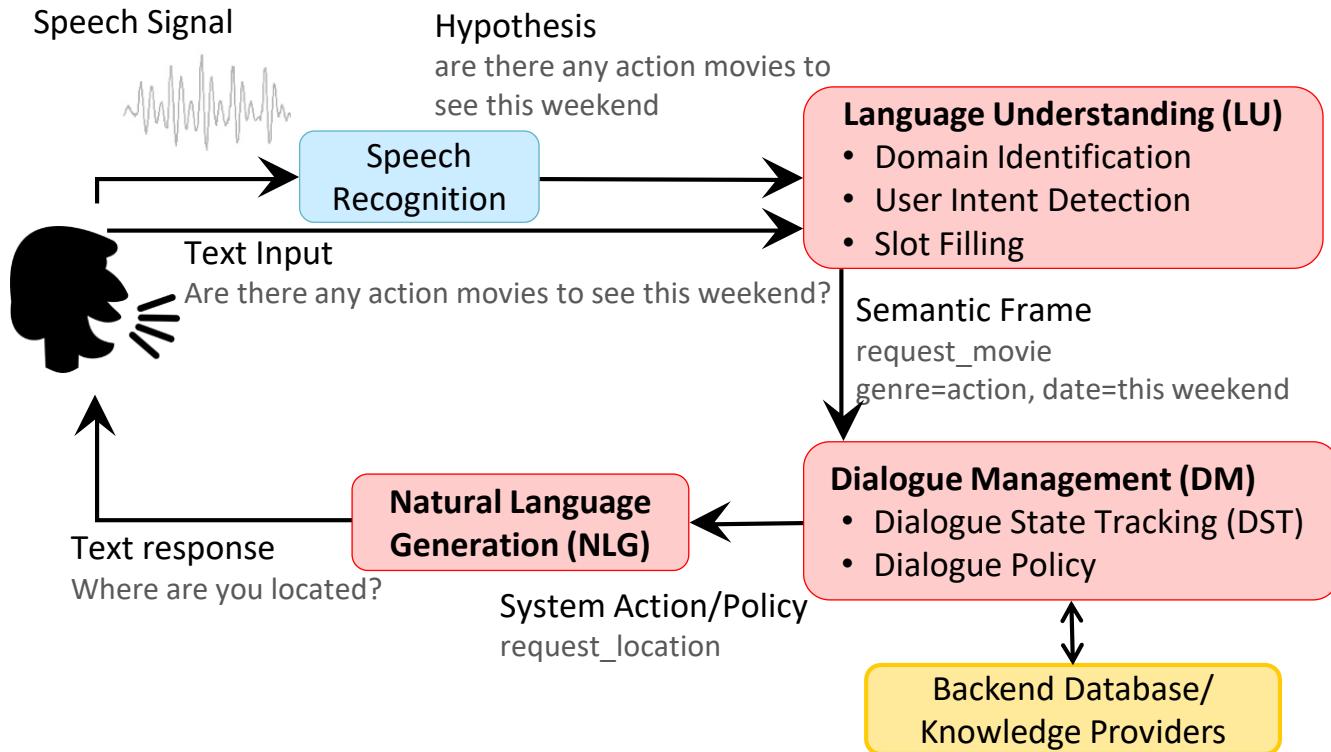
Dialogue State Tracking

對話管理

Task-Oriented Dialogue System (Young, 2000)

125

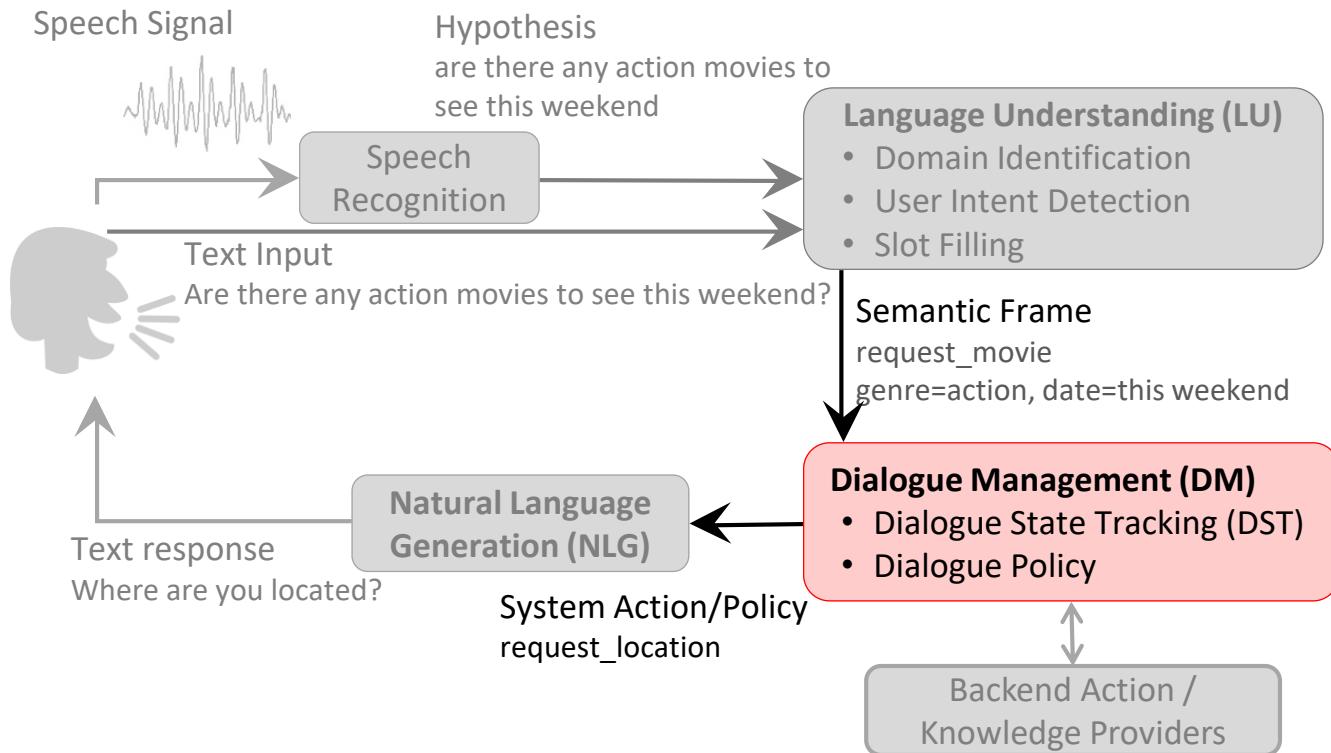
<http://rsta.royalsocietypublishing.org/content/358/1769/1389.short>



Task-Oriented Dialogue System (Young, 2000)

126

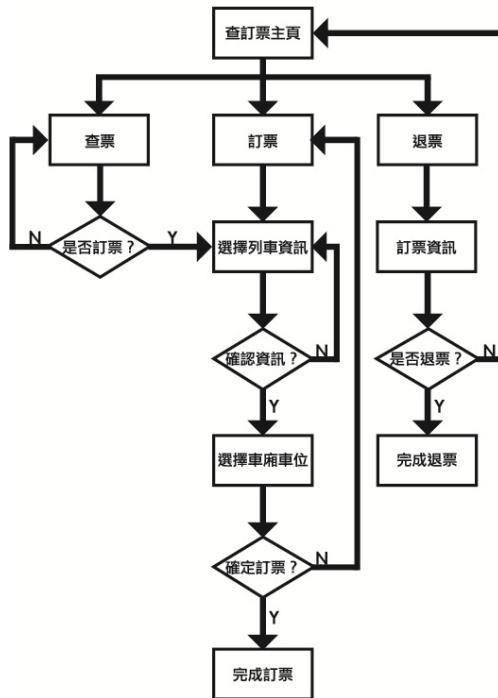
<http://rsta.royalsocietypublishing.org/content/358/1769/1389.short>



Rule-Based Management

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台鐵訂票系統流程圖



Example Dialogue

128

Hello, how may I help you?

I'm looking for a Thai restaurant.

request (restaurant; foodtype=Thai)

What part of town do you have in mind?

Something in the centre.

inform (area=centre)

Bangkok city is a nice place, it is in the centre of town and it serves Thai food.

What's the address?

request (address)

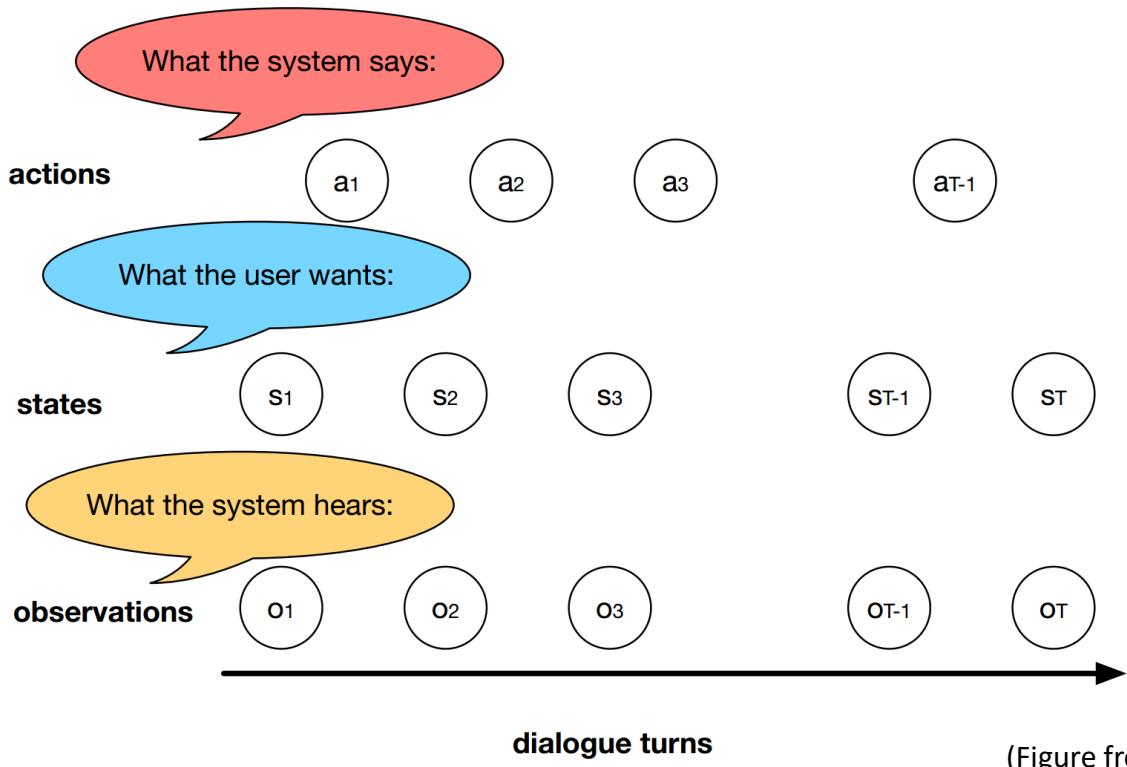
Bangkok city is a nice place, their address is 24 Green street.

Thank you, bye.

bye ()

Elements of Dialogue Management

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Dialogue State Tracking (DST)

130

- Maintain a probabilistic distribution instead of a 1-best prediction for better robustness to recognition errors

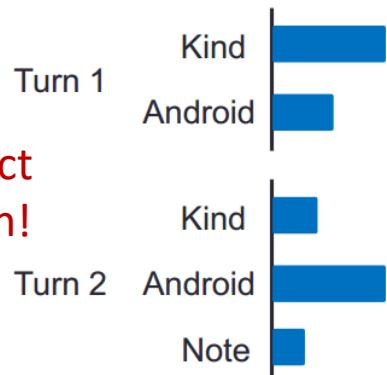
Turn 1
Kind
Android

Turn 1	
Kind	0.5
Android	0.3

Turn 2
Note
Android

Turn 2	
Note	0.4
Android	0.3

Incorrect
for both!



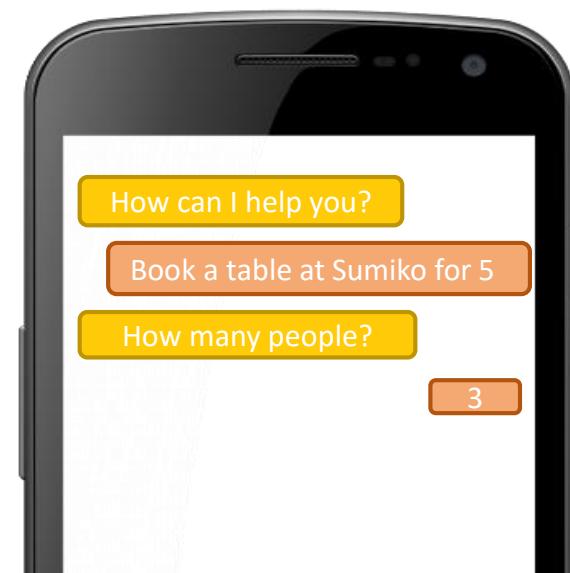
Dialogue State Tracking (DST)

131

- Maintain a probabilistic distribution instead of a 1-best prediction for better robustness to SLU errors or ambiguous input

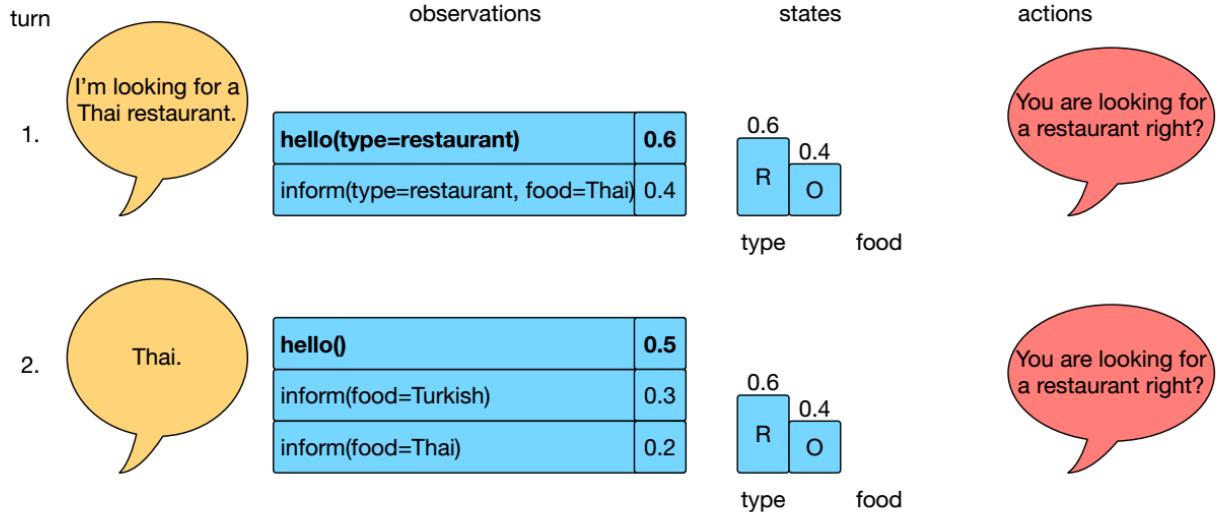
Slot	Value
# people	5 (0.5)
time	5 (0.5)

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



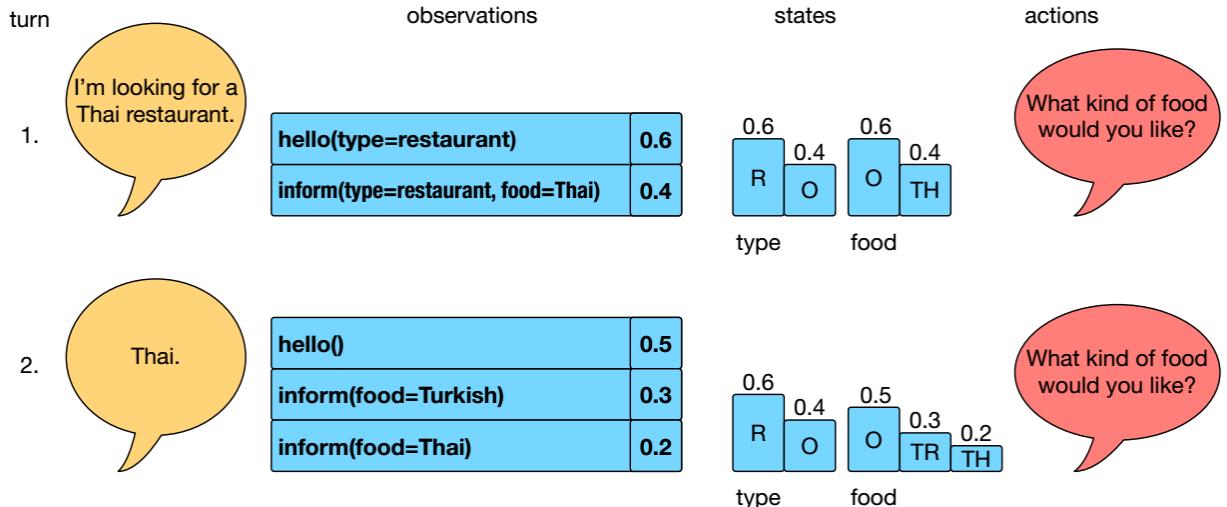
1-Best Input w/o State Tracking

132



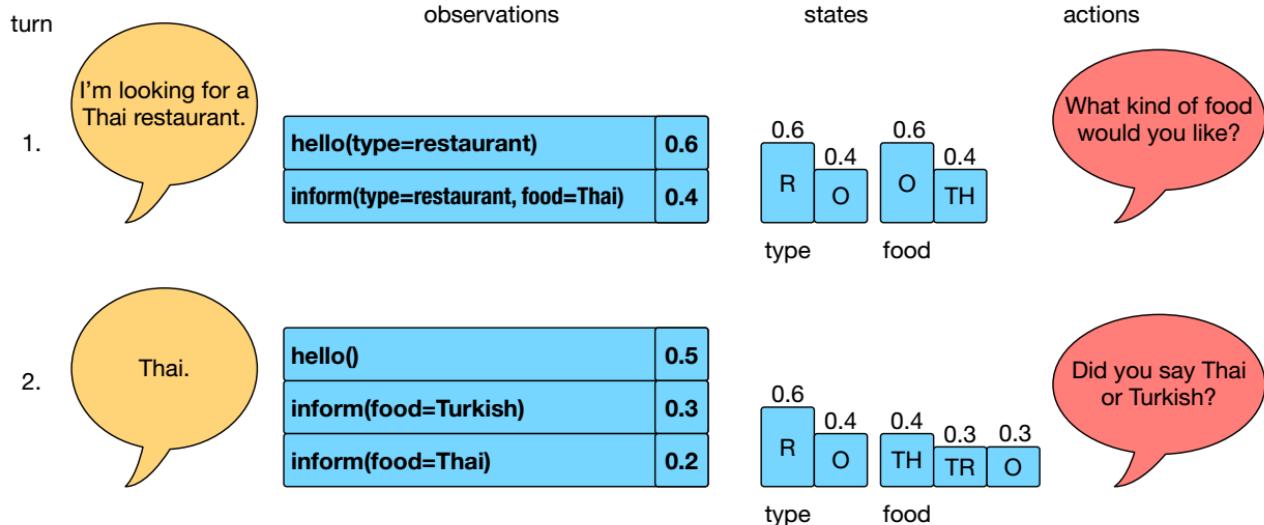
N-Best Inputs w/o State Tracking

133



N-Best Inputs w/ State Tracking

134



Dialogue State Tracking (DST)

135

- Definition
 - ▣ Representation of the system's belief of the user's goal(s) at any time during the dialogue
- Challenge
 - ▣ How to define the state space?
 - ▣ How to tractably maintain the dialogue state?
 - ▣ Which actions to take for each state?

Define dialogue as a control problem where the behavior can be automatically learned

Reinforcement Learning

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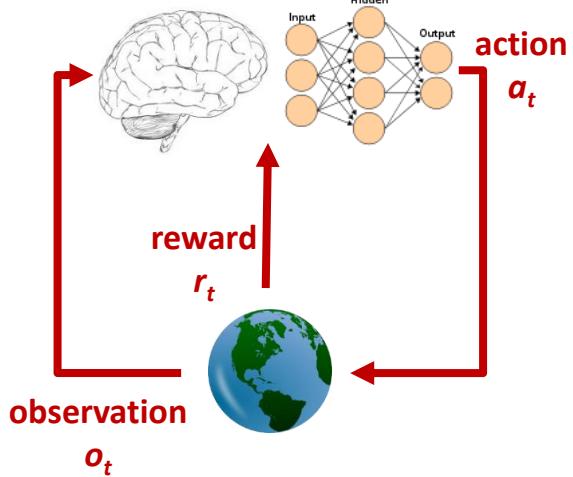
- RL is a general purpose framework for **decision making**
 - RL is for an *agent* with the capacity to *act*
 - Each *action* influences the agent's future *state*
 - Success is measured by a scalar *reward* signal
 - Goal: *select actions to maximize future reward*

Big three: action, state, reward



Agent and Environment

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- At time step t
 - The agent
 - Executes action a_t
 - Receives observation o_t
 - Receives scalar reward r_t
 - The environment
 - Receives action a_t
 - Emits observation o_{t+1}
 - Emits scalar reward r_{t+1}
 - t increments at env. step

State

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- Experience is the sequence of observations, actions, rewards

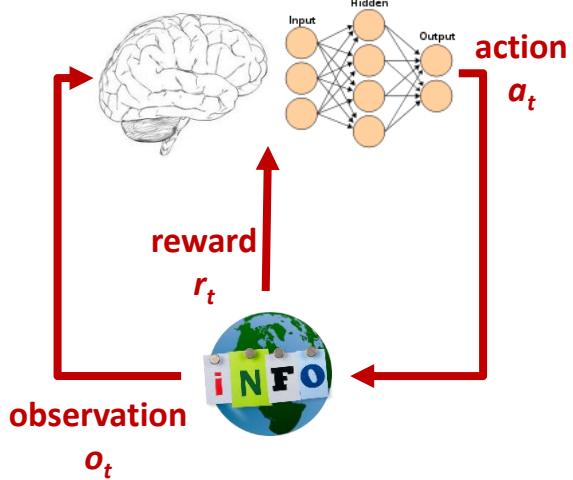
$$o_1, r_1, a_1, \dots, a_{t-1}, o_t, r_t$$

- **State** is the information used to determine what happens next
 - what happens depends on the history experience
 - The agent selects actions
 - The environment selects observations/rewards
- The state is the function of the history experience

$$s_t = f(o_1, r_1, a_1, \dots, a_{t-1}, o_t, r_t)$$

Environment State

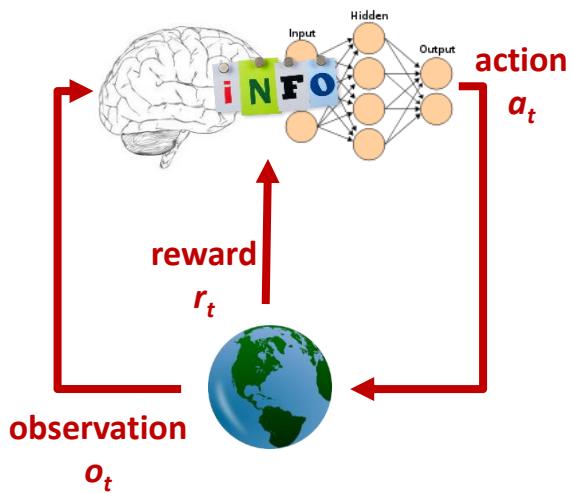
139



- The **environment state** s_t^e is the environment's *private* representation
 - whether data the environment uses to pick the next observation/reward
 - may not be visible to the agent
 - may contain irrelevant information

Agent State

140



- The **agent state** s_t^a is the agent's *internal* representation
 - whether data the agent uses to pick the next action → information used by RL algorithms
 - can be any function of experience

Reward

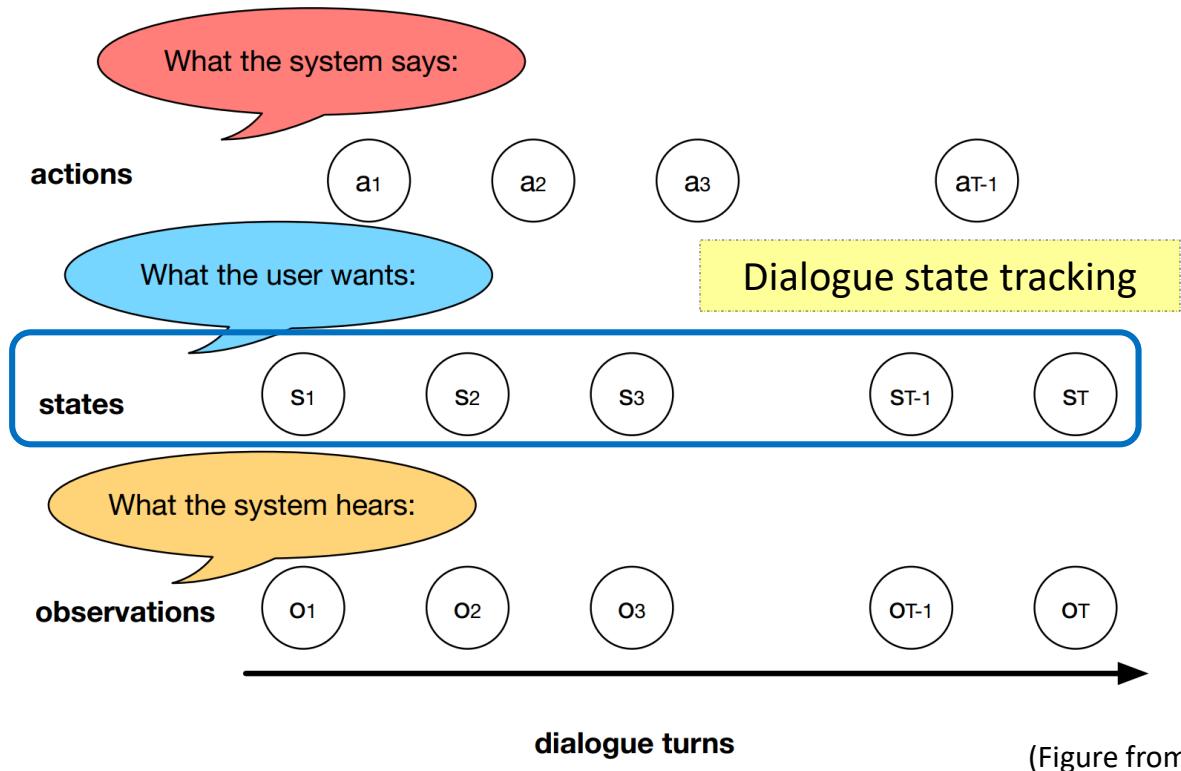
141

- Reinforcement learning is based on reward hypothesis
- A reward r_t is a scalar feedback signal
 - Indicates how well agent is doing at step t

Reward hypothesis: all agent goals can be desired by maximizing expected cumulative reward

Elements of Dialogue Management

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Dialogue State Tracking (DST)

143

- Requirement
 - Dialogue history
 - Keep tracking of what happened so far in the dialogue
 - Normally done via **Markov property**
 - Task-oriented dialogue
 - Need to know what the user wants
 - Modeled via the **user goal**
 - Robustness to errors
 - Need to know what the user says
 - Modeled via the **user action**

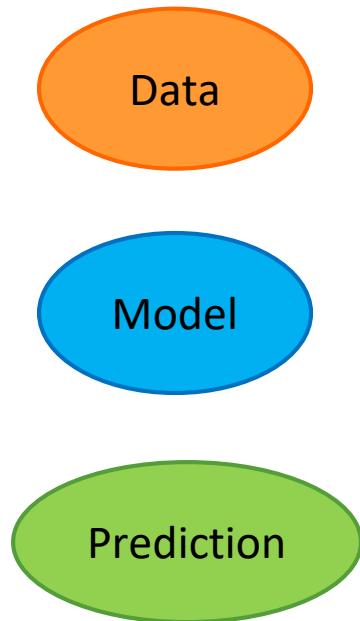
DST Problem Formulation

144

- The DST dataset consists of
 - *Goal*: for each informable slot
 - e.g. price=cheap
 - *Requested*: slots by the user
 - e.g. moviename
 - *Method*: search method for entities
 - e.g. by constraints, by name
- The dialogue state is
 - the distribution over possible slot-value pairs for goals
 - the distribution over possible requested slots
 - the distribution over possible methods

Class-Based DST

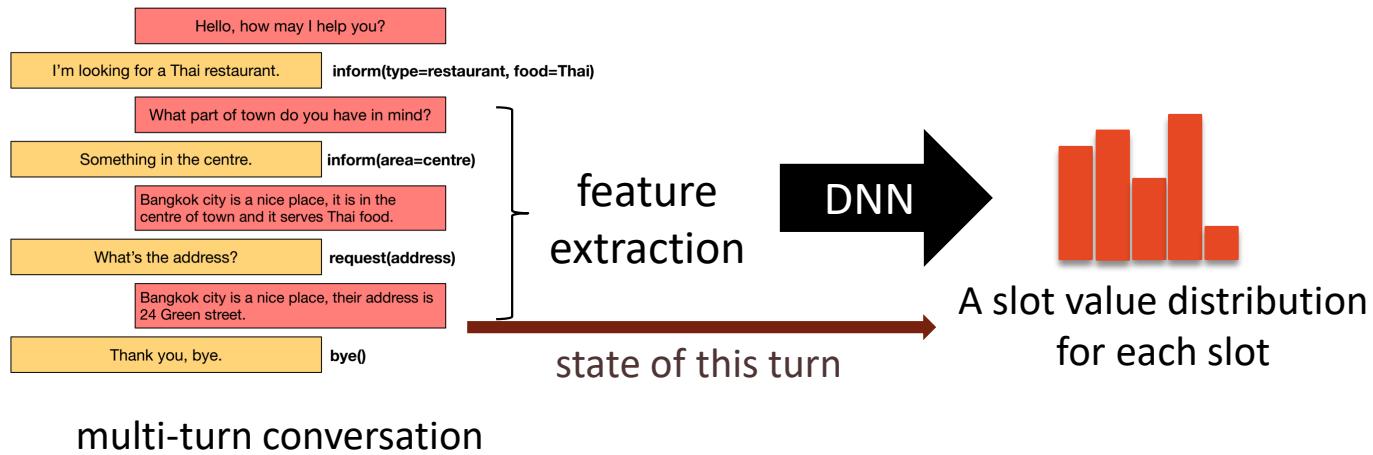
145



- Observations labeled w/ dialogue state
- Neural networks
- Ranking models
- Distribution over dialogue states
 - Dialogue State Tracking

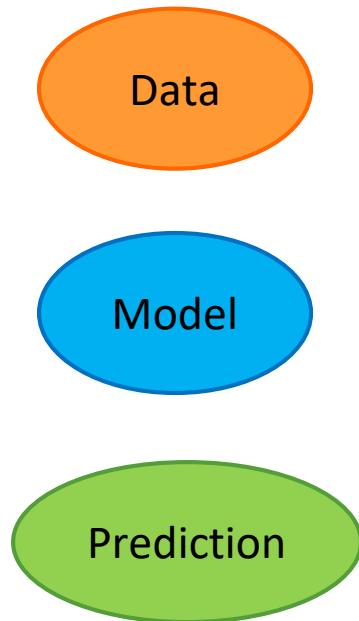
DNN for DST

146



Sequence-Based DST

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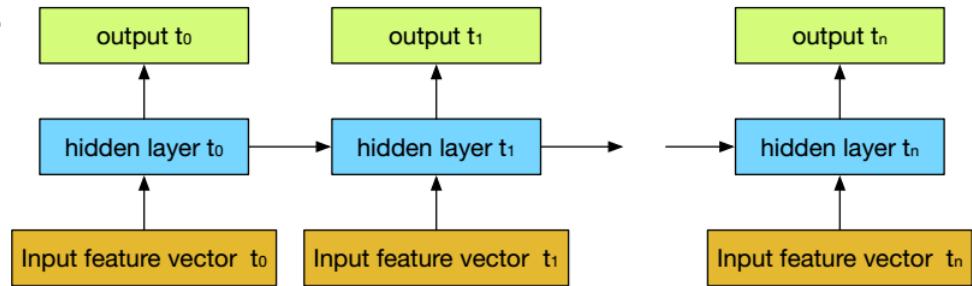


- Sequence of observations labeled w/
dialogue state
- Recurrent neural networks (RNN)
- Distribution over dialogue states
– Dialogue State Tracking

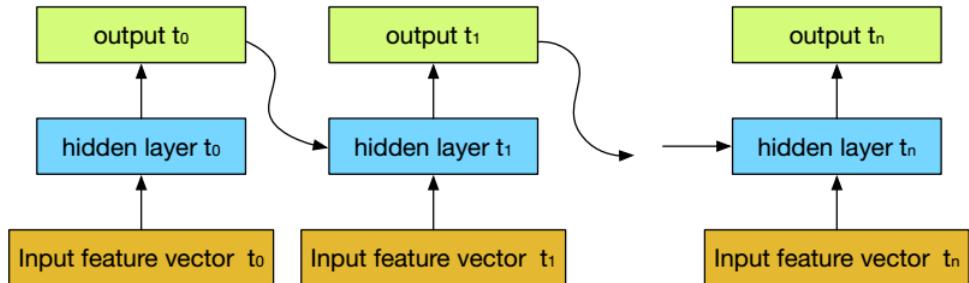
Recurrent Neural Network (RNN)

148

□ Elman-type



□ Jordan-type



RNN DST

149

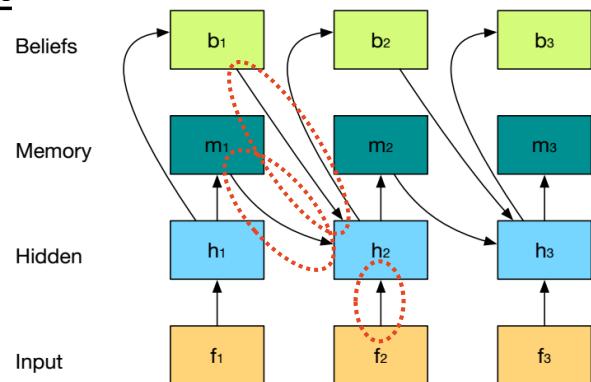
- Idea: internal memory for representing dialogue context

- Input

- most recent dialogue turn
 - last machine dialogue act
 - dialogue state
 - memory layer

- Output

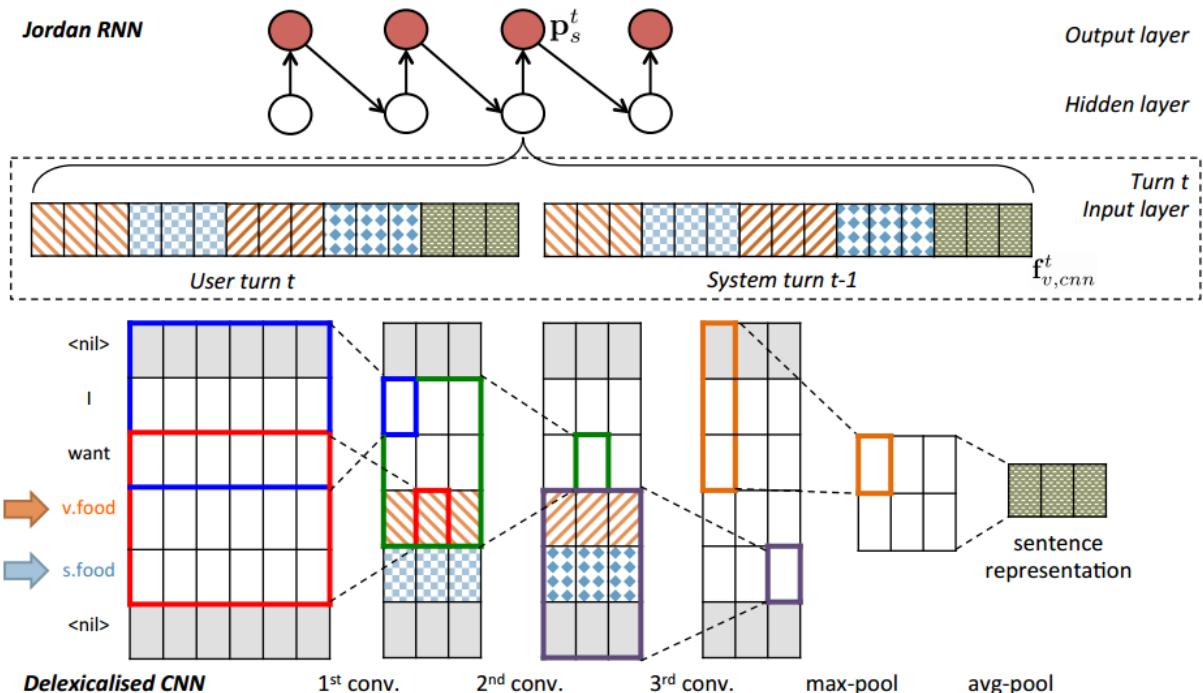
- update its internal memory
 - distribution over slot values



RNN-CNN DST

150

<http://www.anthology.aclweb.org/W/W13/W13-4073.pdf>; <https://arxiv.org/abs/1506.07190>



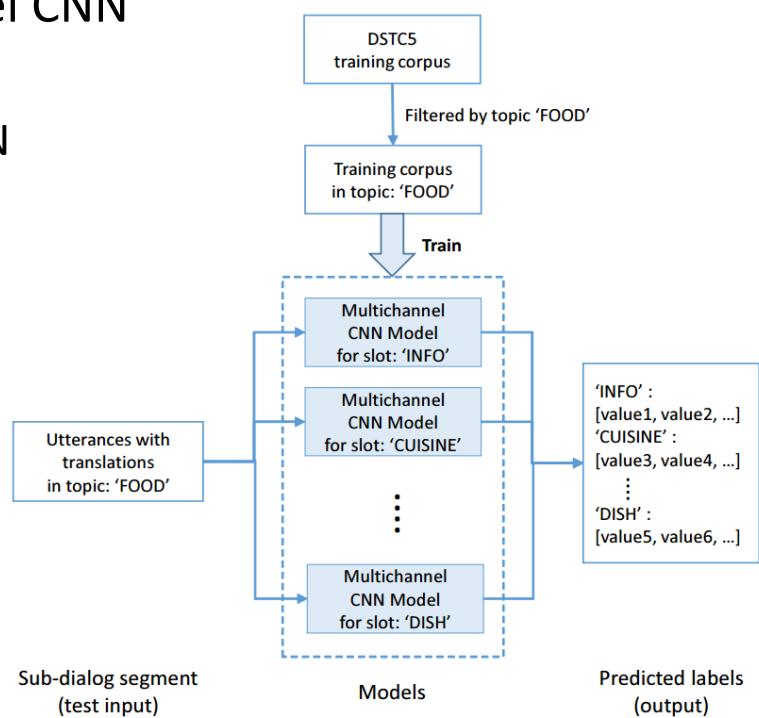
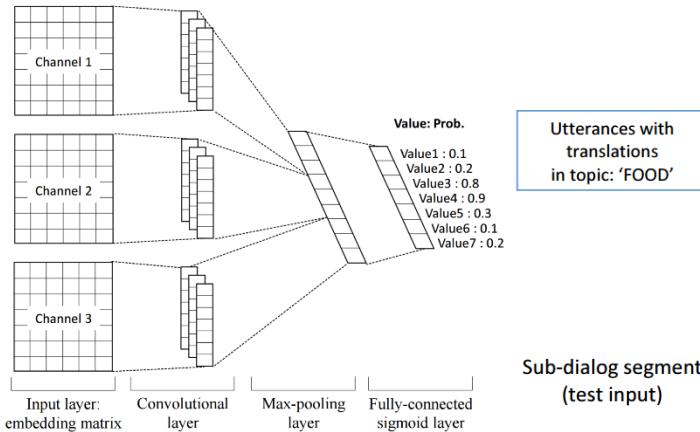
(Figure from Wen et al, 2016)

Multichannel Tracker (Shi et al., 2016)

151

<https://arxiv.org/abs/1701.06247>

- Training a multichannel CNN for each slot
 - Chinese character CNN
 - Chinese word CNN
 - English word CNN



DST Evaluation

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- Metric
 - Tracked state accuracy with respect to user goal
 - L2-norm of the hypothesized dist. and the true label

$$L_2 = (1 - p_i)^2 + \sum_{j \neq i} p_j^2$$

- Recall/Precision/F-measure individual slots

Dialog State Tracking Challenge (DSTC)

(Williams et al. 2013, Henderson et al. 2014, Henderson et al. 2014, Kim et al. 2016, Kim et al. 2016)

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Challenge	Type	Domain	Data Provider	Main Theme
DSTC1	Human-Machine	Bus Route	CMU	Evaluation Metrics
DSTC2	Human-Machine	Restaurant	U. Cambridge	User Goal Changes
DSTC3	Human-Machine	Tourist Information	U. Cambridge	Domain Adaptation
DSTC4	Human-Human	Tourist Information	I2R	Human Conversation
DSTC5	Human-Human	Tourist Information	I2R	Language Adaptation

DSTC1

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- Type: Human-Machine
- Domain: Bus Route

System: East Pittsburg Bus Schedules. Say a bus route, like 28X, or say I'm not sure.
hello(), request(route), example(route=28x), example(route=dont_know)

User: 61A

SLU: 0.77 inform(route=61a)
0.12 inform(route=61)
0.01 inform(route=61d)

System: Okay, 61A. To change, say go back. Where are you leaving from?
impl-conf(route=61a), example(act=goback), request(from)

User: Downtown

SLU: 0.59 inform(from.desc=downtown)
0.10 inform(from.desc=from downtown)

System: Okay, downtown. You can always say go back. And where are you going to?
impl-conf(from.desc=downtown), example(act=goback), request(to)

User: East Pittsburgh East Pittsburgh

SLU: 0.25 inform(to.desc=pittsburgh)
0.20 inform(to.desc=east pittsburgh)
0.01 inform(to.desc=to pittsburgh)

System: Pittsburgh. Is that right?
expl-conf(to.desc=pittsburgh)

User: No

SLU: 0.71 negate()
0.07 affirm()

System: Oh, sorry, where are you going to?
sorry(), request(to)

User: East Pittsburgh

SLU: 0.97 inform(to.desc=east pittsburgh)

System: Okay, East Pittsburgh. Do you want times for the next few buses? Say yes or no.
impl-confirm(to.desc=east pittsburgh), expl-confirm(act=want-next-bus),
example(act=affirm), example(act=negate)

User: Yes

SLU: 0.97 affirm()

System: Ok, the next few buses. To change, say go back. At 7:45 PM today, there is a 61 A,
from Fifth Avenue And Market Street, Downtown, arriving Dynamo Alley And Beech
Avenue, In East Pittsburgh, at 8:42 PM. Say repeat, next, previous, or start over.
impl-conf(act=want-next-bus), example(act=goback),
schedule(result.from.time.hour=7, result.from.time.minute=45,
result.from.time.ampm=pm, result.from.date.day=today, result.route=61a,
result.from.desc=fifth avenue and market street, downtown, result.to.desc=dynamo
alley and beech avenue, in east pittsburgh, result.to.time.hour=8,
result.to.time.minute=42, result.to.time.ampm=pm), example(act=repeat),
example(act=nextbus), example(act=prevbus), example(act=restart)

User: [hang up]

DSTC4-5

155

- Type: Human-Human
- Domain: Tourist Information

{Topic: Accommodation; Type: Hostel; Pricerange: Cheap; GuideAct: ACK; TouristAct: REQ}

Tourist: Can you give me some uh- tell me some cheap rate hotels, because I'm planning just to leave my bags there and go somewhere take some pictures.

Guide: Okay. I'm going to recommend firstly you want to have a backpack type of hotel, right?

Tourist: Yes. I'm just gonna bring my backpack and my buddy with me. So I'm kinda looking for a hotel that is not that expensive. Just gonna leave our things there and, you know, stay out the whole day.

Guide: Okay. Let me get you hm hm. So you don't mind if it's a bit uh not so roomy like hotel because you just back to sleep.

Tourist: Yes. Yes. As we just gonna put our things there and then go out to take some pictures.

Guide: Okay, um-

Tourist: Hm.

{Topic: Accommodation; NAME: InnCrowd Backpackers Hostel; GuideAct: REC; TouristAct: ACK}

Guide: Let's try this one, okay?

Tourist: Okay.

Guide: It's InnCrowd Backpackers Hostel in Singapore. If you take a dorm bed per person only twenty dollars. If you take a room, it's two single beds at fifty nine dollars.

Tourist: Um. Wow, that's good.

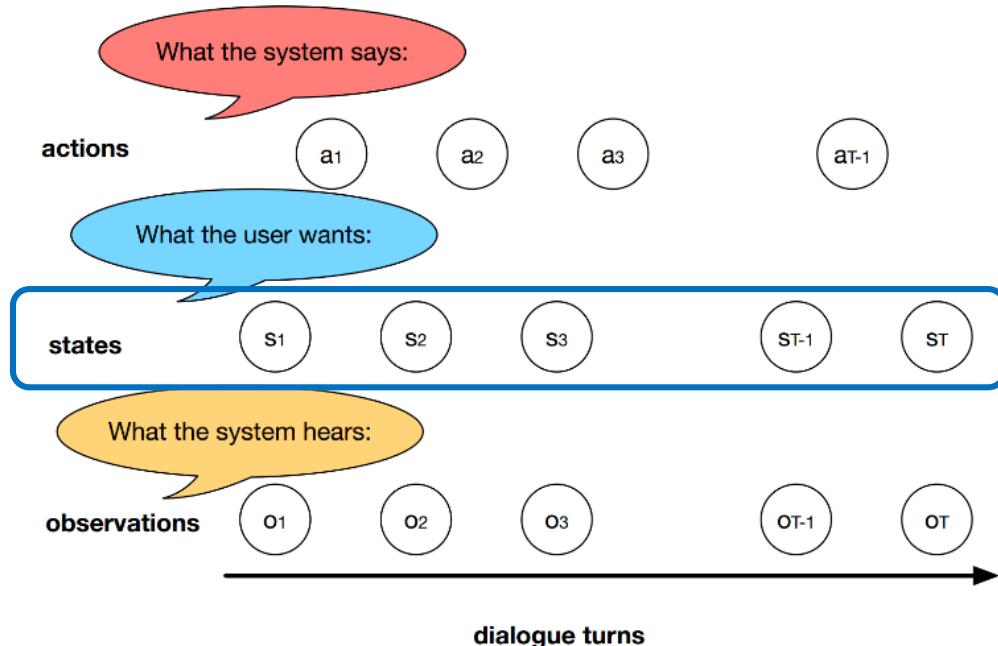
Guide: Yah, the prices are based on per person per bed or dorm. But this one is room. So it should be fifty nine for the two room. So you're actually paying about ten dollars more per person only.

Tourist: Oh okay. That's- the price is reasonable actually. It's good.

Concluding Remarks

156

- **Dialogue state tracking (DST)** of DM has Markov assumption to model the user goal and be robust to errors





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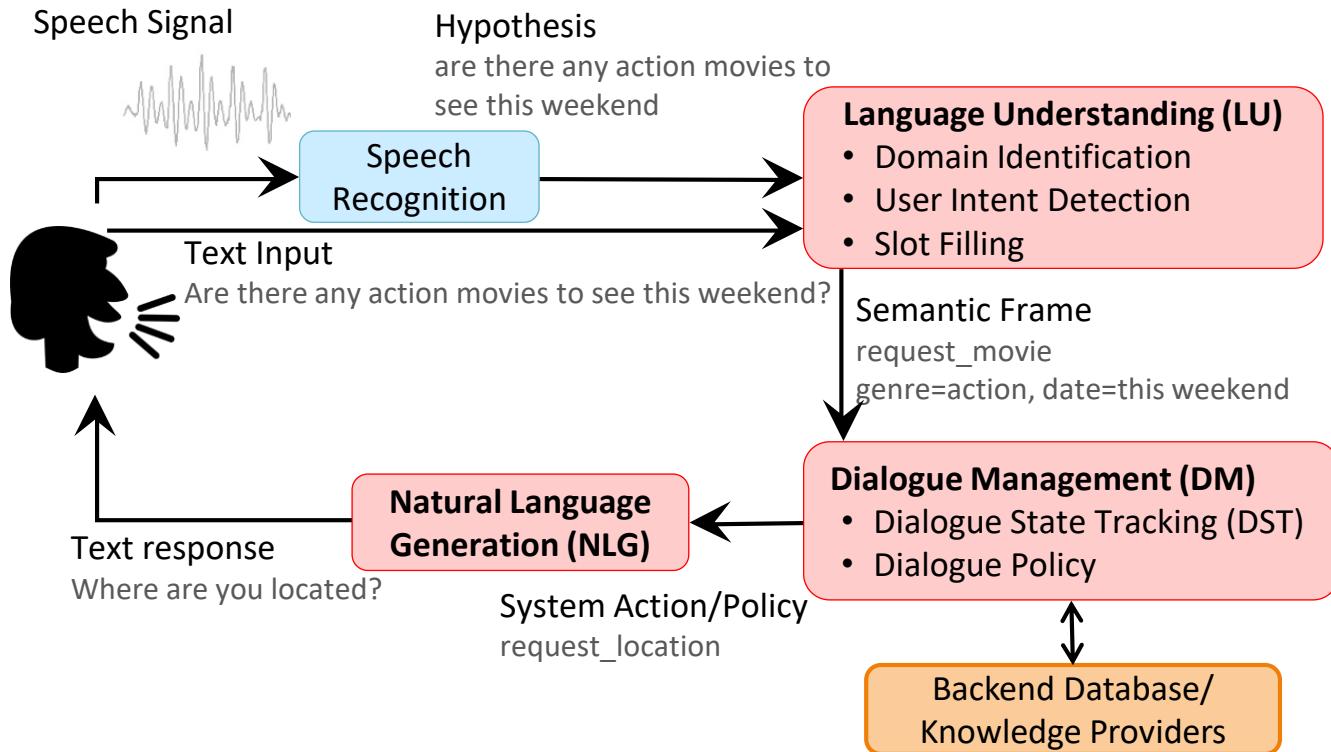
Dialogue Policy

對話管理

Task-Oriented Dialogue System (Young, 2000)

158

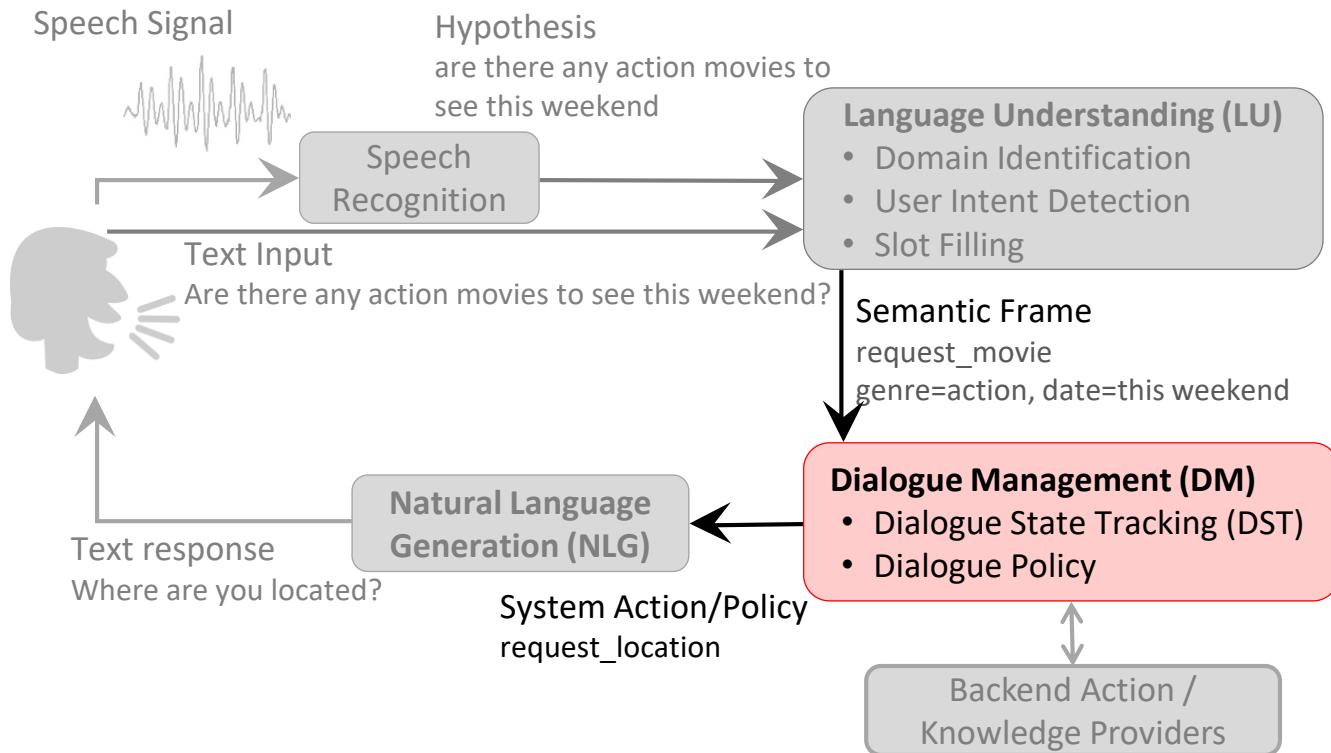
<http://rsta.royalsocietypublishing.org/content/358/1769/1389.short>



Task-Oriented Dialogue System (Young, 2000)

159

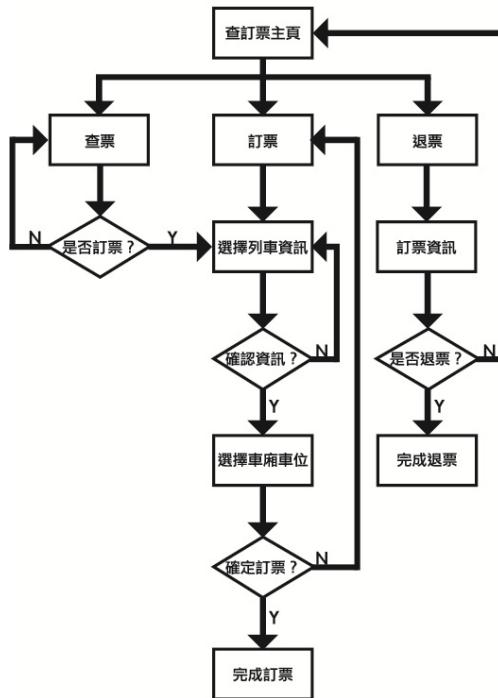
<http://rsta.royalsocietypublishing.org/content/358/1769/1389.short>



Rule-Based Management

160

台鐵訂票系統流程圖



Example Dialogue

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Hello, how may I help you?

greeting ()

I'm looking for a Thai restaurant.

request (restaurant; foodtype=Thai)

What part of town do you have in mind?

request (area)

Something in the centre.

inform (area=centre)

Bangkok city is a nice place, it is in the centre of town and it serves Thai food.

inform (restaurant=Bangkok city, area=centre of town, foodtype=Thai)

What's the address?

request (address)

Bangkok city is a nice place, their address is 24 Green street.

inform (address=24 Green street)

Thank you, bye.

bye ()

Example Dialogue

162

Hello, how may I help you?

greeting ()

I'm looking for a Thai restaurant.

request (restaurant; foodtype=Thai)

What part of town do you have in mind?

request (area)

Something in the centre.

inform (area=centre)

Bangkok city is a nice place, it is in the
centre of town and it serves Thai food.

inform (restaurant=Bangkok
city, area=centre of town,
foodtype=Thai)

What's the address?

request (address)

Bangkok city is a nice place, their address is
24 Green street.

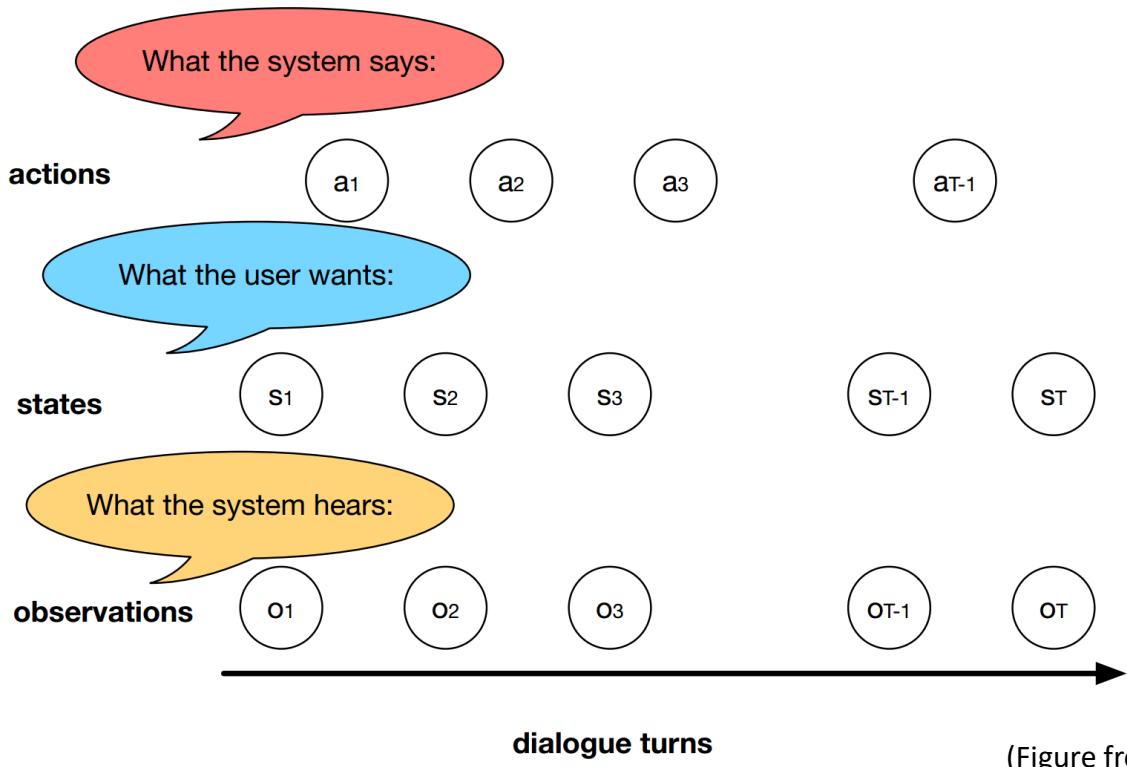
inform (address=24 Green street)

Thank you, bye.

bye ()

Elements of Dialogue Management

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Reinforcement Learning

164

- RL is a general purpose framework for **decision making**
 - RL is for an *agent* with the capacity to *act*
 - Each *action* influences the agent's future *state*
 - Success is measured by a scalar *reward* signal
 - Goal: *select actions to maximize future reward*

Big three: action, state, reward



State

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- Experience is the sequence of observations, actions, rewards

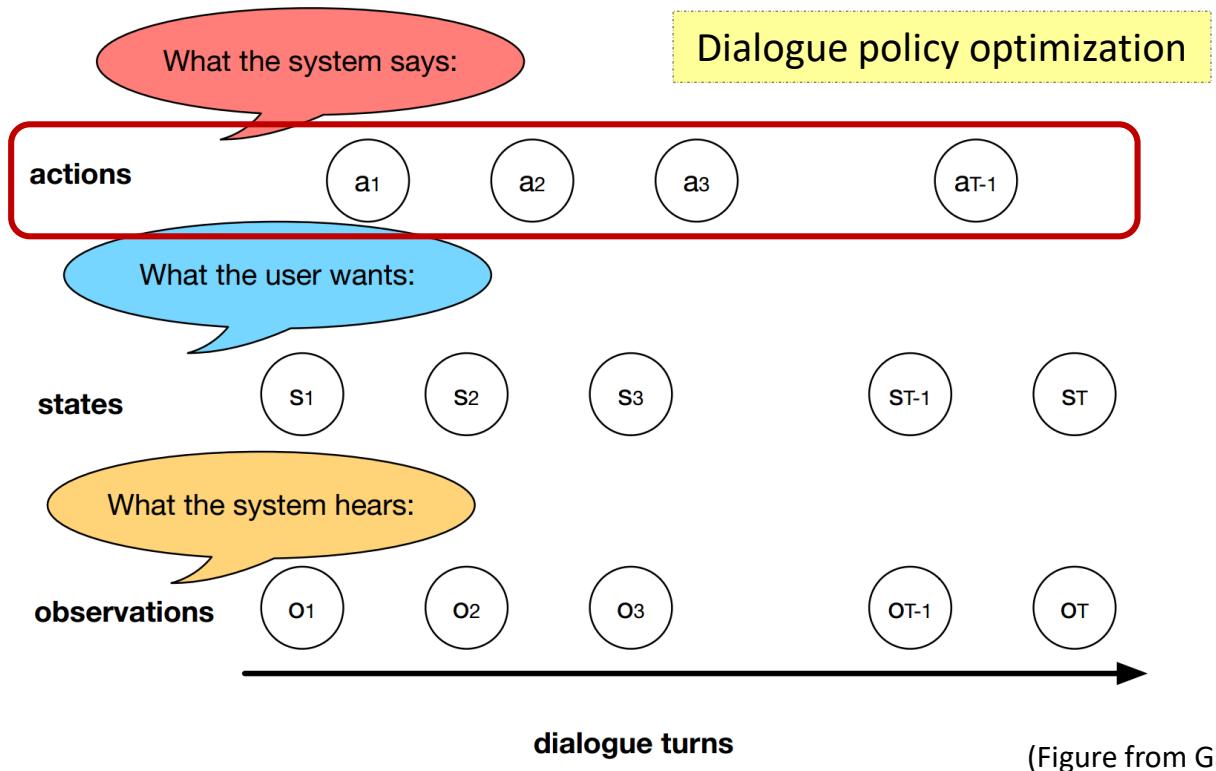
$$o_1, r_1, a_1, \dots, a_{t-1}, o_t, r_t$$

- **State** is the information used to determine what happens next
 - what happens depends on the history experience
 - The agent selects actions
 - The environment selects observations/rewards
- The state is the function of the history experience

$$s_t = f(o_1, r_1, a_1, \dots, a_{t-1}, o_t, r_t)$$

Elements of Dialogue Management

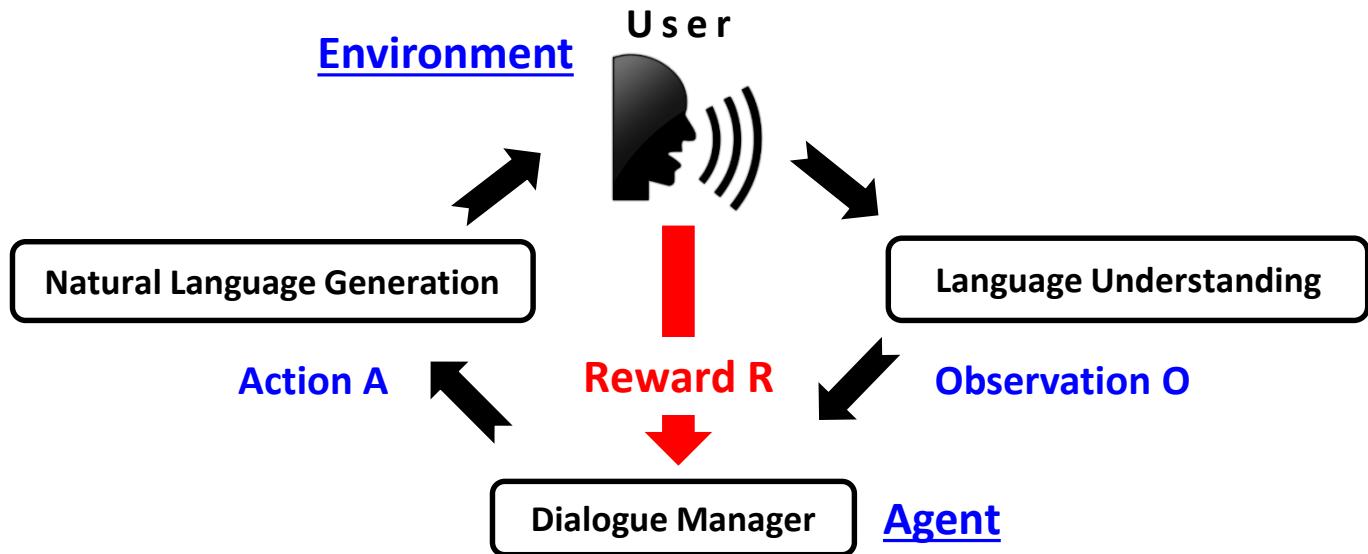
166



Dialogue Policy Optimization

167

- Dialogue management in a RL framework



The optimized dialogue policy selects the best action that maximizes the future reward.
Correct rewards are a crucial factor in dialogue policy training

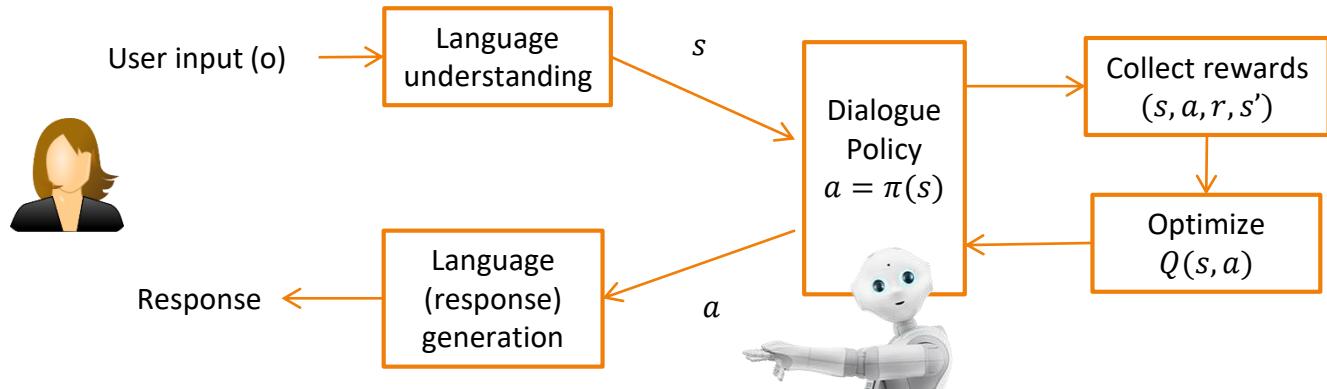
Policy Optimization Issue

168

- Optimization problem size
 - ▣ Belief dialogue state space is large and continuous
 - ▣ System action space is large
- Knowledge environment (user)
 - ▣ Transition probability is unknown (user status)
 - ▣ How to get rewards

Reinforcement Learning for Dialogue Policy Optimization

169



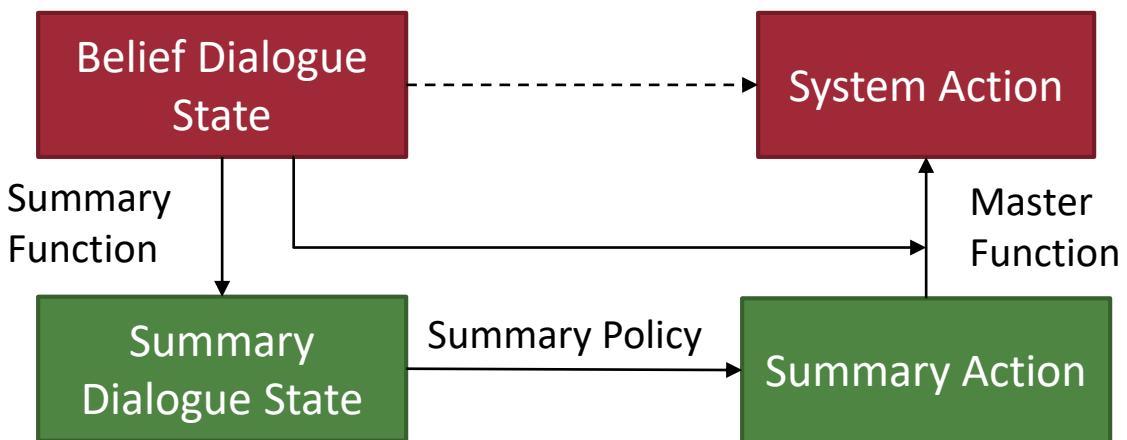
Type of Bots	State	Action	Reward
Social ChatBots	Chat history	System Response	# of turns maximized; Intrinsically motivated reward
InfoBots (interactive Q/A)	User current question + Context	Answers to current question	Relevance of answer; # of turns minimized
Task-Completion Bots	User current input + Context	System dialogue act w/ slot value (or API calls)	Task success rate; # of turns minimized

Goal: develop a generic deep RL algorithm to learn dialogue policy for all bot categories

Large Belief Space and Action Space

170

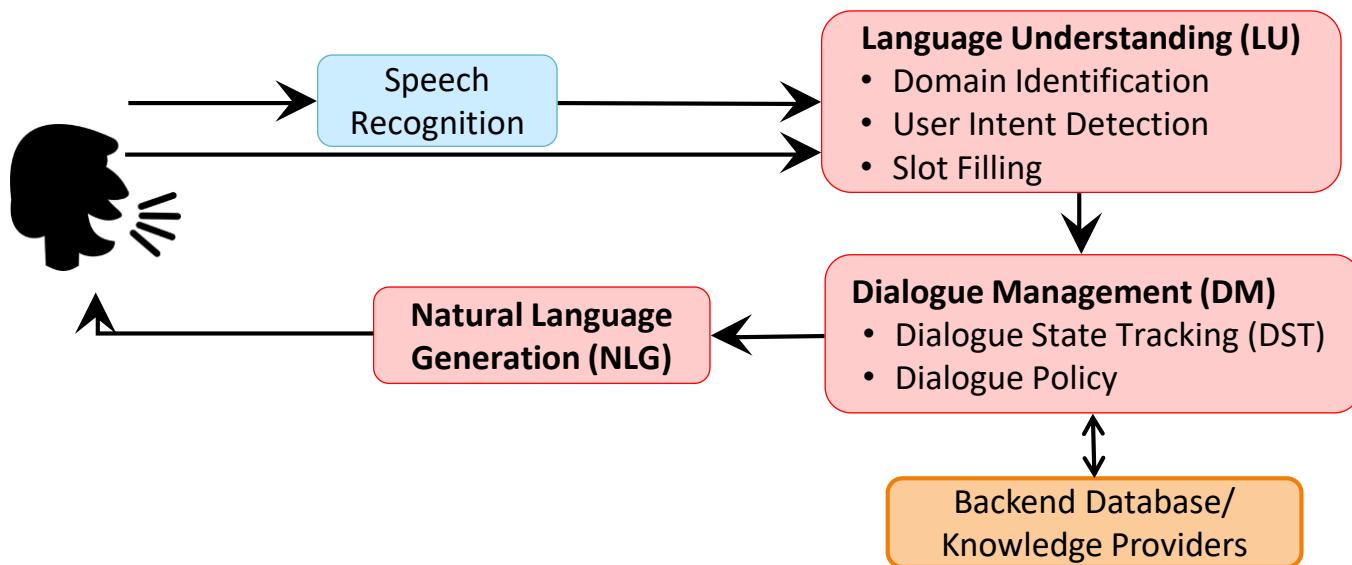
- Solution: perform optimization in a reduced summary space built according to the heuristics



Transition Probability and Rewards

171

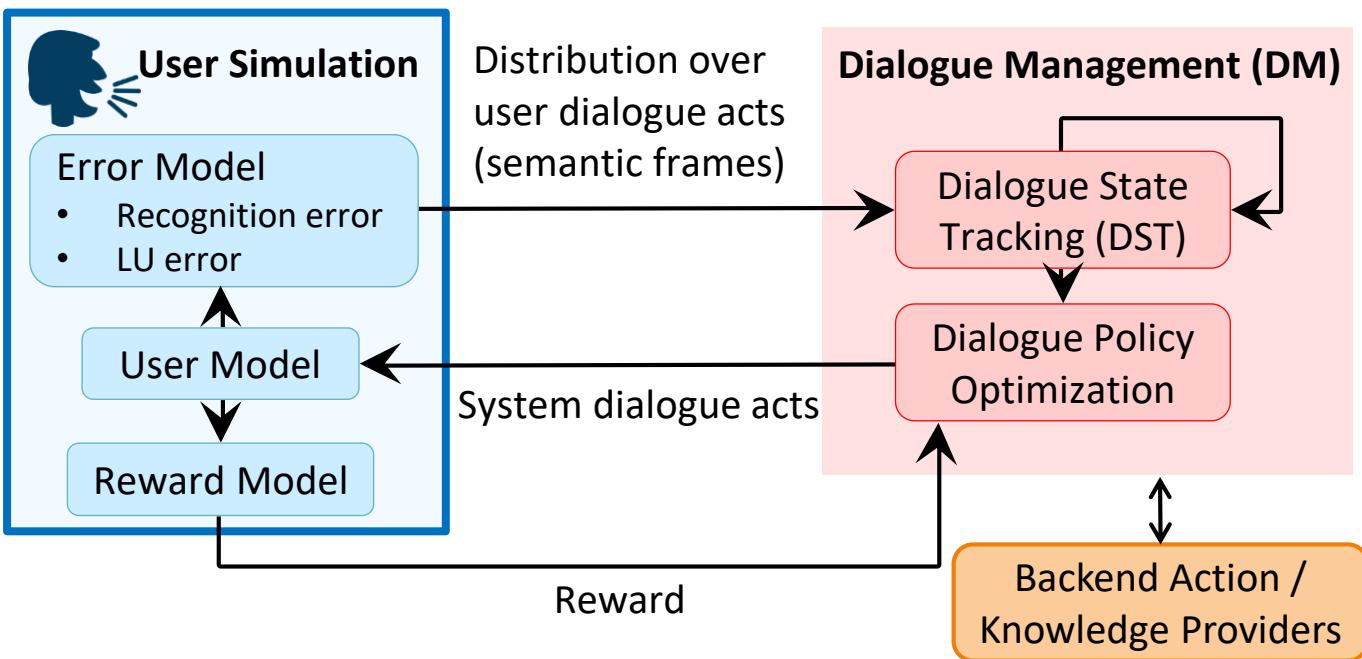
- Solution: learn from real users



Transition Probability and Rewards

172

- Solution: learn from a simulated user



Reward for RL \cong Evaluation for System

173

- Dialogue is a special RL task
 - Human involves in interaction and rating (evaluation) of a dialogue
 - Fully human-in-the-loop framework
- Rating: correctness, appropriateness, and adequacy

- Expert rating	high quality, high cost
- User rating	unreliable quality, medium cost
- Objective rating	Check desired aspects, low cost

Dialogue Reinforcement Learning Signal

174

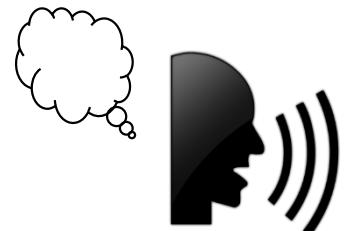
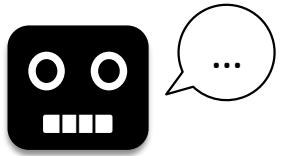
Typical reward function

- -1 for per turn penalty
- Large reward at completion if **successful**

Typically requires **domain knowledge**

- ✓ Simulated user
- ✓ Paid users (Amazon Mechanical Turk)
- ✗ Real users

The user simulator is usually required for dialogue system training before deployment

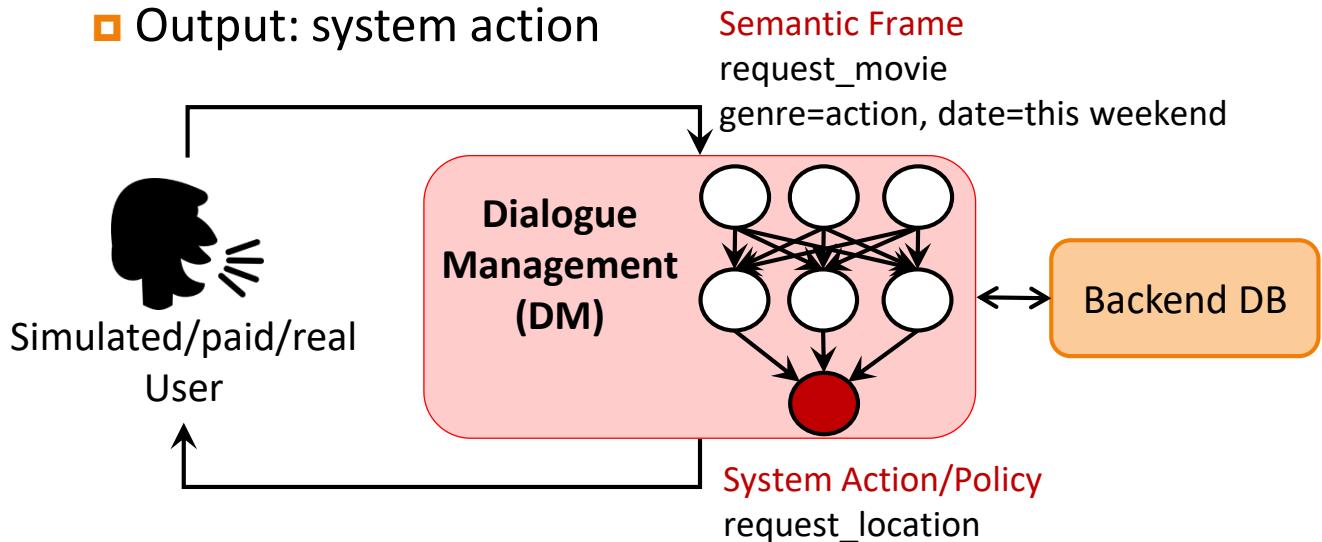


RL-Based Dialogue Management (Li et al., 2017)

175

<https://arxiv.org/abs/1703.01008>

- Deep RL for training dialogue policy
 - Input: current semantic frame observation, database returned results
 - Output: system action



Major Components in an RL Agent

176

- An RL agent may include one or more of these components
 - **Policy**: agent's behavior function
 - **Value function**: how good is each state and/or action
 - **Model**: agent's representation of the environment

Policy

177

- A policy is the agent's behavior
- A policy maps from state to action
 - Deterministic policy: $a = \pi(s)$
 - Stochastic policy: $\pi(a) = P(a | s)$



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Value Function

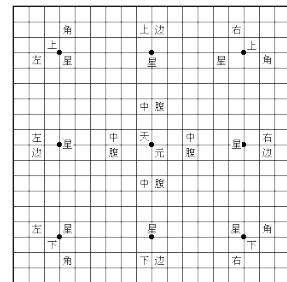
178

- A value function is a prediction of future reward (with action a in state s)
- Q-value function gives expected total reward
 - from state S and action a
 - under policy π
 - with discount factor γ

$$Q^\pi(s, a) = \mathbb{E}[r_{t+1} + \gamma r_{t+2} + \gamma^2 r_{t+3} + \dots \mid s, a]$$

- Value functions decompose into a Bellman equation

$$Q^\pi(s, a) = \mathbb{E}_{s', a'}[r + \gamma Q^\pi(s', a') \mid s, a]$$



Optimal Value Function

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- An optimal value function
 - ▣ is the maximum achievable value

$$Q^*(s, a) = \max_{\pi} Q^{\pi}(s, a) = Q^{\pi^*}(s, a)$$

- ▣ allows us to act optimally

$$\pi^*(s) = \arg \max_a Q^*(s, a)$$

- ▣ informally maximizes over all decisions

$$\begin{aligned} Q^*(s, a) &= r_{t+1} + \gamma \max_{a_{t+1}} r_{t+2} + \gamma^2 \max_{a_{t+2}} r_{t+3} + \dots \\ &= r_{t+1} + \gamma \max_{a_{t+1}} Q^*(s_{t+1}, a_{t+1}) \end{aligned}$$

- ▣ decompose into a Bellman equation

$$Q^*(s, a) = \mathbb{E}_{s'}[r + \gamma \max_{a'} Q^*(s', a') \mid s, a]$$

Reinforcement Learning Approach

180

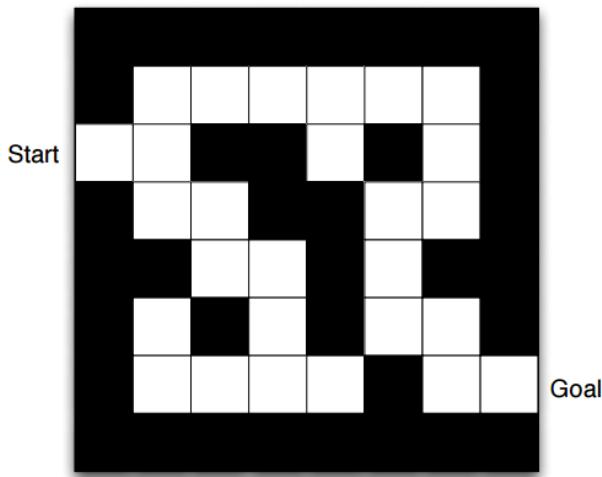
- Policy-based RL
 - Search directly for optimal policy π^*

π^* is the policy achieving maximum future reward
- Value-based RL
 - Estimate the optimal value function $Q^*(s, a)$

$Q^*(s, a)$ is maximum value achievable under any policy
- Model-based RL
 - Build a model of the environment
 - Plan (e.g. by lookahead) using model

Maze Example

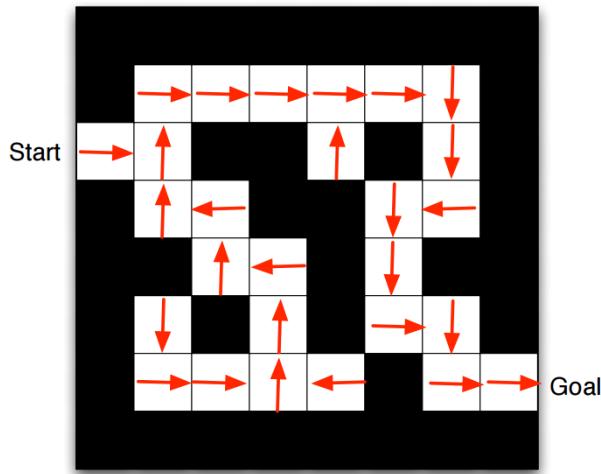
181



- Rewards: -1 per time-step
- Actions: N, E, S, W
- States: agent's location

Maze Example: Policy

182

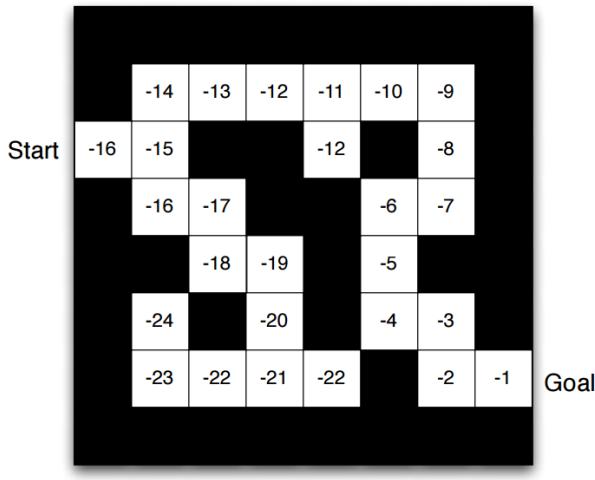


- Rewards: -1 per time-step
- Actions: N, E, S, W
- States: agent's location

Arrows represent policy $\pi(s)$ for each state s

Maze Example: Value Function

183



- Rewards: -1 per time-step
- Actions: N, E, S, W
- States: agent's location

Numbers represent value $Q_{\pi}(s)$ of each state s

Value-Based Deep RL

Estimate How Good Each State and/or Action is

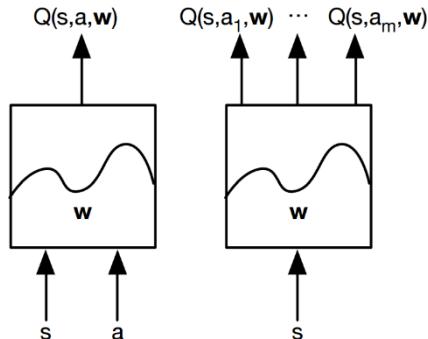
Value Function Approximation

185

- Value functions are represented by a *lookup table*

$$Q(s, a) \quad \forall s, a$$

- too many states and/or actions to store
- too slow to learn the value of each entry individually
- Values can be estimated with *function approximation*



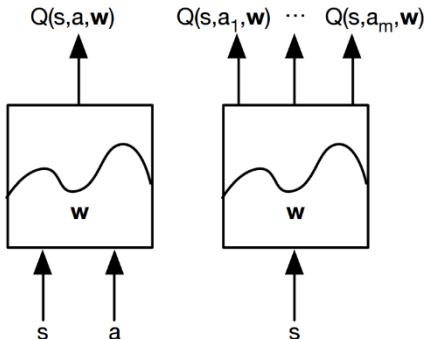
Q-Networks

186

- **Q-networks** represent value functions with weights w

$$Q(s, a, w) \approx Q^*(s, a)$$

- generalize from seen states to unseen states
- update parameter w for function approximation



Q-Learning

187

- Goal: estimate optimal Q-values
 - Optimal Q-values obey a Bellman equation

$$Q^*(s, a) = \mathbb{E}_{s'}[r + \gamma \max_{a'} Q^*(s', a') \mid s, a]$$

learning target

- *Value iteration* algorithms solve the Bellman equation

$$Q_{i+1}(s, a) = \mathbb{E}_{s'}[r + \gamma \max_{a'} Q_i(s', a') \mid s, a]$$

Deep Q-Networks (DQN)

188

- Represent value function by deep Q-network with weights w
$$Q(s, a, w) \approx Q^*(s, a)$$
- Objective is to minimize mean square error (MSE) loss by SGD

$$L(w) = \mathbb{E} \left[\left(r + \gamma \max_{a'} Q(s', a', w) - Q(s, a, w) \right)^2 \right]$$

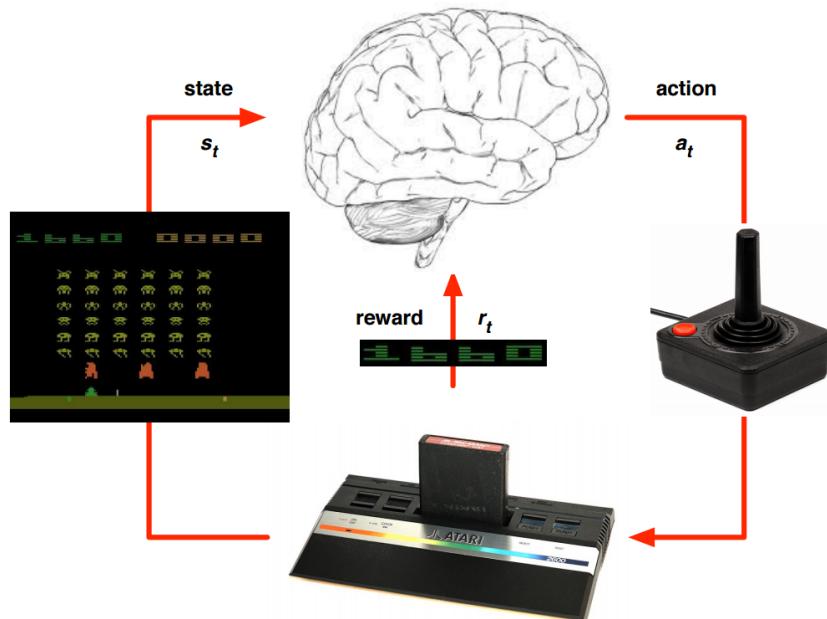
learning target

Issue: naïve Q-learning oscillates or diverges using NN due to:
1) correlations between samples 2) non-stationary targets



Deep RL in Atari Games

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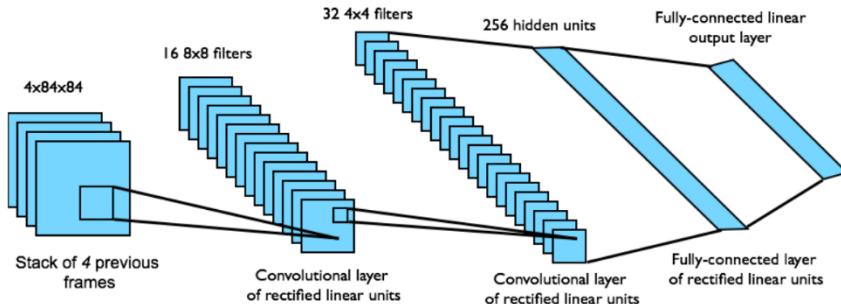
Different tricks are performed to enable RL training



DQN in Atari

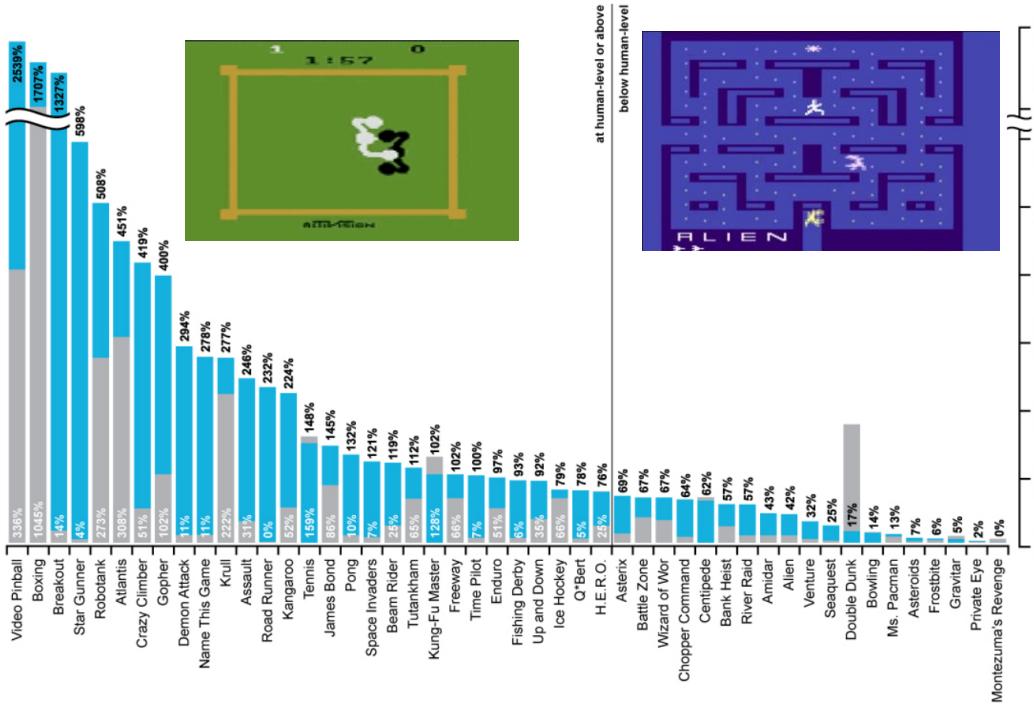
190

- Goal: end-to-end learning of values $Q(s, a)$ from pixels
 - Input: state is stack of raw pixels from last 4 frames
 - Output: $Q(s, a)$ for all joystick/button positions a
 - Reward is the score change for that step





DQN in Atari



DQN in Movie Bot

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<https://arxiv.org/abs/1703.01008>

- Goal: interact with the user for movie ticket booking

User goal: ***Two tickets for “the witch” tomorrow 9:30 PM at regal meridian 16, Seattle.***

RULE BASED SYSTEM

User: Can I get 2 tickets for the witch?

Agent: Which theater do you want?

User: Regal meridian 16

Agent: What time would you like to see it?

User: 9:30 pm

Agent: What date would you like to see it?

User: Tomorrow!

Agent: How many people are you?

User: Just two adults.

Agent: What is your location?

User: Seattle!

Agent: What kind of video format do you like?

User: Oh, any kind is okay.

Agent: Do you have any price constraint?

User: No, I don't care.

Agent: Great - I was able to purchase 2 tickets for you to see the witch tomorrow at regal meridian 16 theater in Seattle at 9:30 pm.

User: Thank you.

Agent: Thank you!

REINFORCEMENT LEARNING SYSTEM

User: Can I get 2 tickets for the witch?

Agent: What date would you like to see it?

User: Tomorrow

Agent: Which theater do you prefer?

User: Regal meridian 16

Agent: What is your location?

User: Seattle

Agent: What time would you like to see it?

User: 9:30 pm.

Agent: Great - I was able to purchase 2 tickets for you to see the witch tomorrow at regal meridian 16 theater in Seattle at 9:30 pm.

User: Thanks.

Agent: Thanks!

Policy-Based Deep RL

Estimate How Good An Agent's Behavior is

Deep Policy Networks

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- Represent policy by deep network with weights \mathcal{U}

$$a = \pi(a \mid s, u) \quad \begin{matrix} \text{stochastic policy} \\ a = \pi(s, u) \end{matrix}$$

deterministic policy

- Objective is to maximize total discounted reward by SGD

$$L(u) = \mathbb{E} \left[r_1 + \gamma r_2 + \gamma^2 r_3 + \cdots \mid \pi(\cdot, u) \right]$$

Policy Gradient

195

- The gradient of a **stochastic** policy $\pi(a \mid s, u)$ is given by

$$\frac{\partial L(u)}{\partial u} = \mathbb{E}_s \left[\frac{\partial \log \pi(a \mid s, u)}{\partial u} Q^\pi(s, a) \right]$$

- The gradient of a **deterministic** policy $\pi(s, u)$ is given by

$$\frac{\partial L(u)}{\partial u} = \mathbb{E}_s \left[\frac{\partial Q^\pi(s, a)}{\partial a} \frac{\partial a}{\partial u} \right] \quad a = \pi(s, u)$$

How to deal with continuous actions

Actor-Critic (Value-Based + Policy-Based)

196

- Estimate value function $Q(s, a, w) \approx Q^\pi(s, a)$
- Update policy parameters u by SGD
 - ▣ Stochastic policy

$$\frac{\partial L(u)}{\partial u} = \mathbb{E}_s \left[\frac{\partial \log \pi(a \mid s, u)}{\partial u} Q(s, a, w) \right]$$

- ▣ Deterministic policy

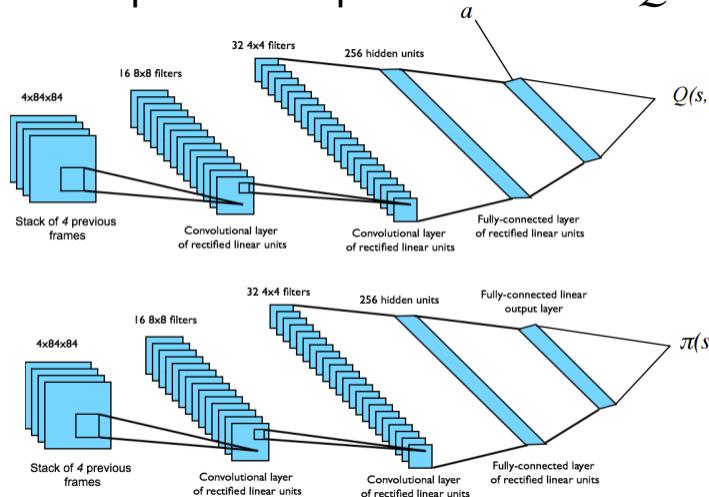
$$\frac{\partial L(u)}{\partial u} = \mathbb{E}_s \left[\frac{\partial Q(s, a, w)}{\partial a} \frac{\partial a}{\partial u} \right]$$

Q-networks tell whether a policy is good or not
Policy networks optimize the policy accordingly

Deterministic Deep Policy Gradient

197

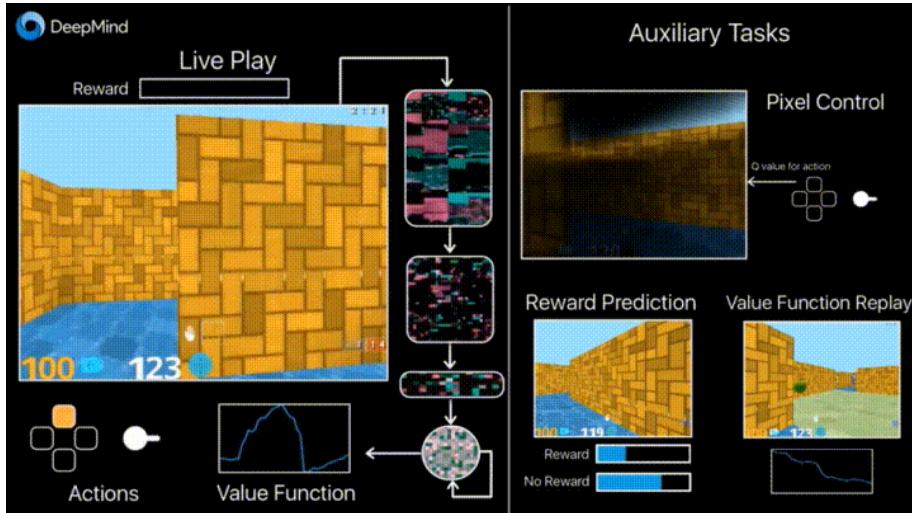
- Goal: end-to-end learning of control policy from pixels
 - Input: state is stack of raw pixels from last 4 frames
 - Output: two separate CNNs for Q and π



Deep RL AI Examples

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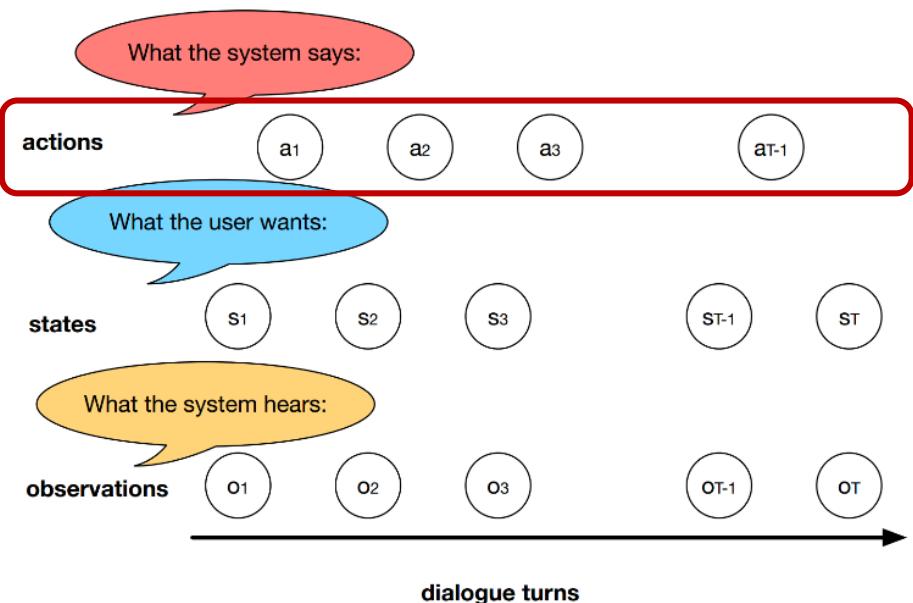
- Play games: Atari, poker, Go, ...
- Control physical systems: manipulate, ...
- Explore worlds: 3D worlds, ...
- Interact with users: recommend, optimize, personalize, ...



Concluding Remarks

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- **Dialogue policy optimization** can be viewed as an RL task
- Transition probability and reward come from
 - Real user
 - Simulated user



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User Simulation

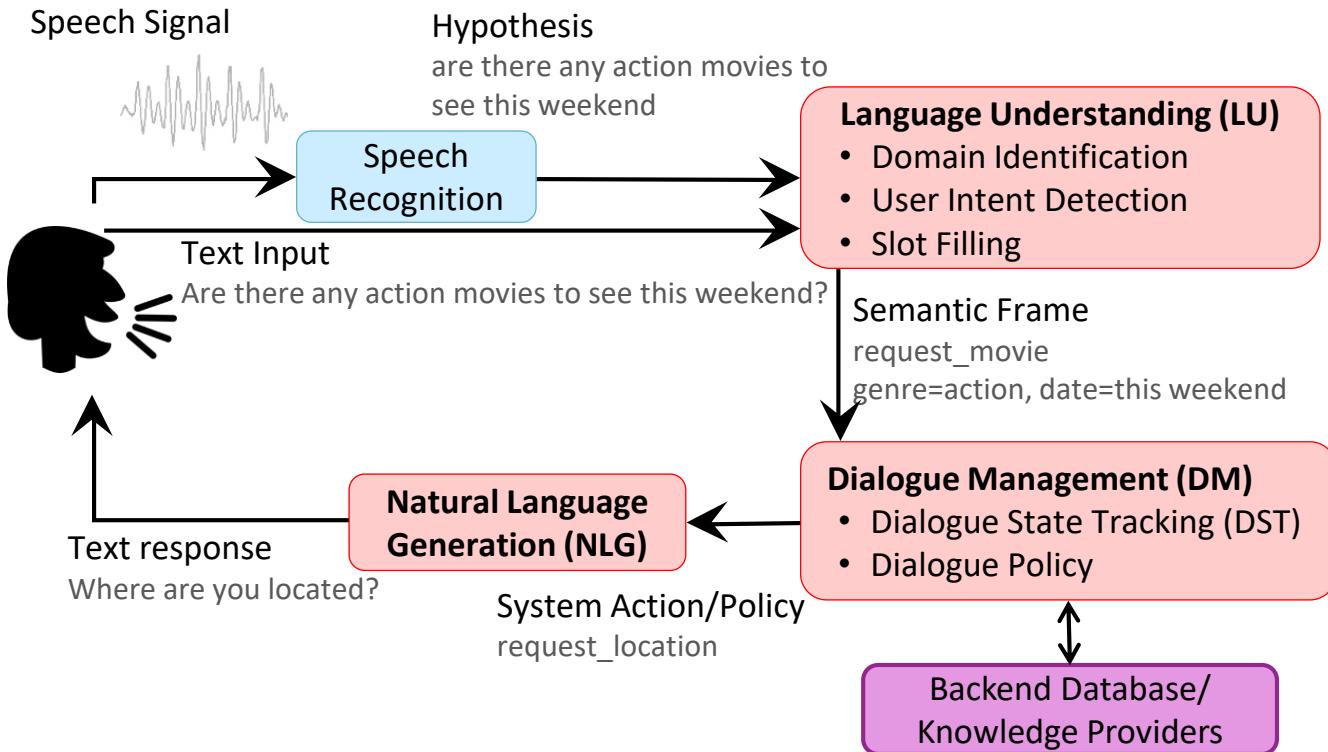
對話管理



Task-Oriented Dialogue System (Young, 2000)

201

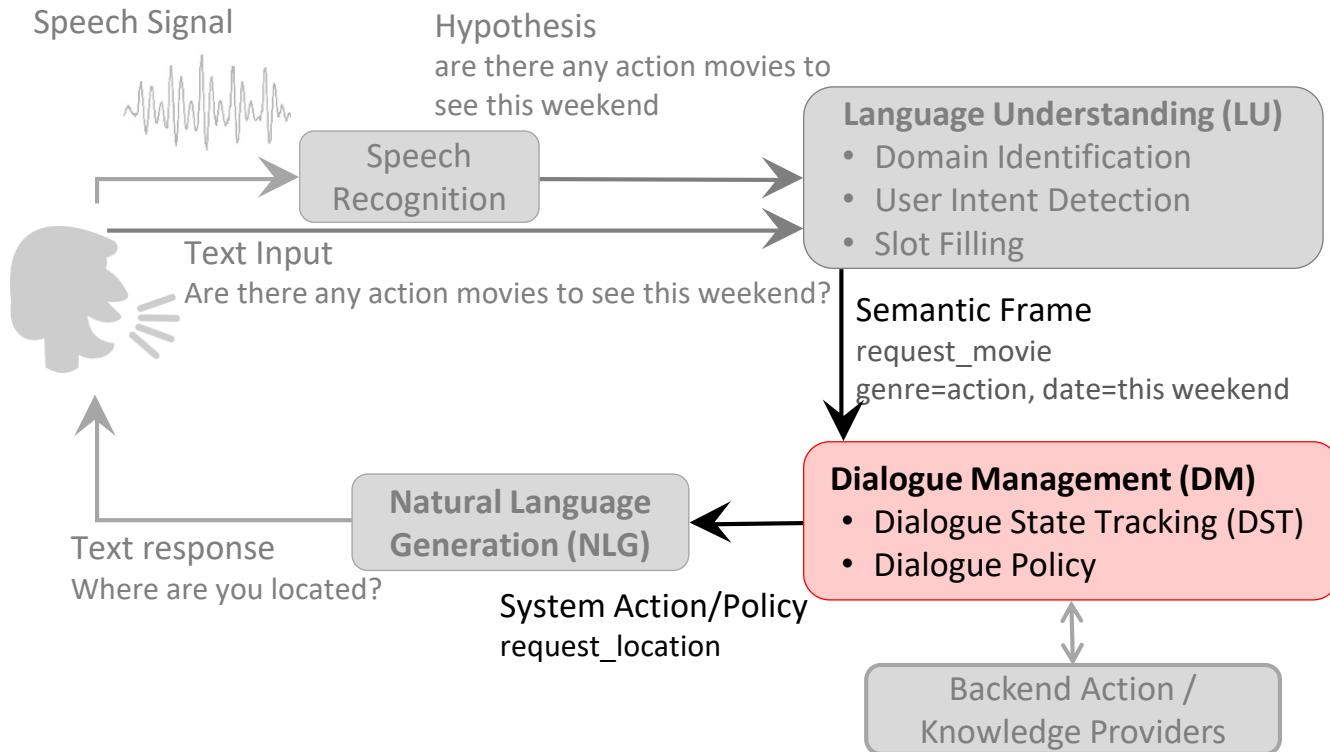
<http://rsta.royalsocietypublishing.org/content/358/1769/1389.short>



Task-Oriented Dialogue System (Young, 2000)

202

<http://rsta.royalsocietypublishing.org/content/358/1769/1389.short>



User Simulation

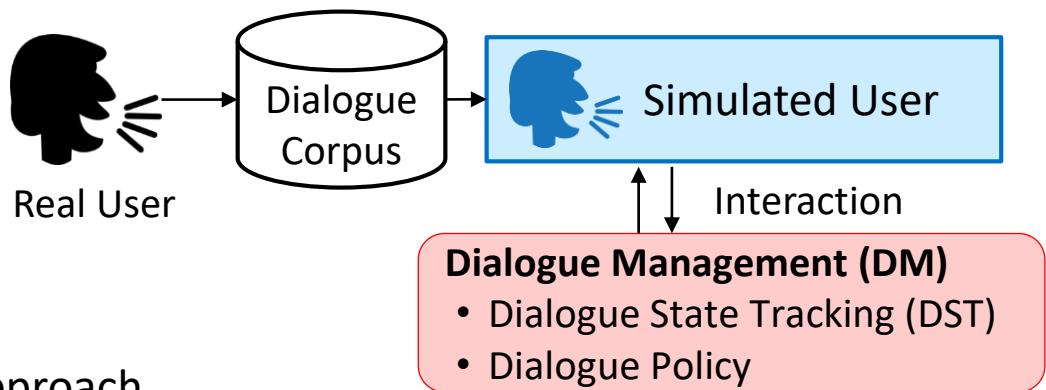
keeps a list of its goals and actions

randomly generates an agenda

updates its list of goals and adds new ones

203

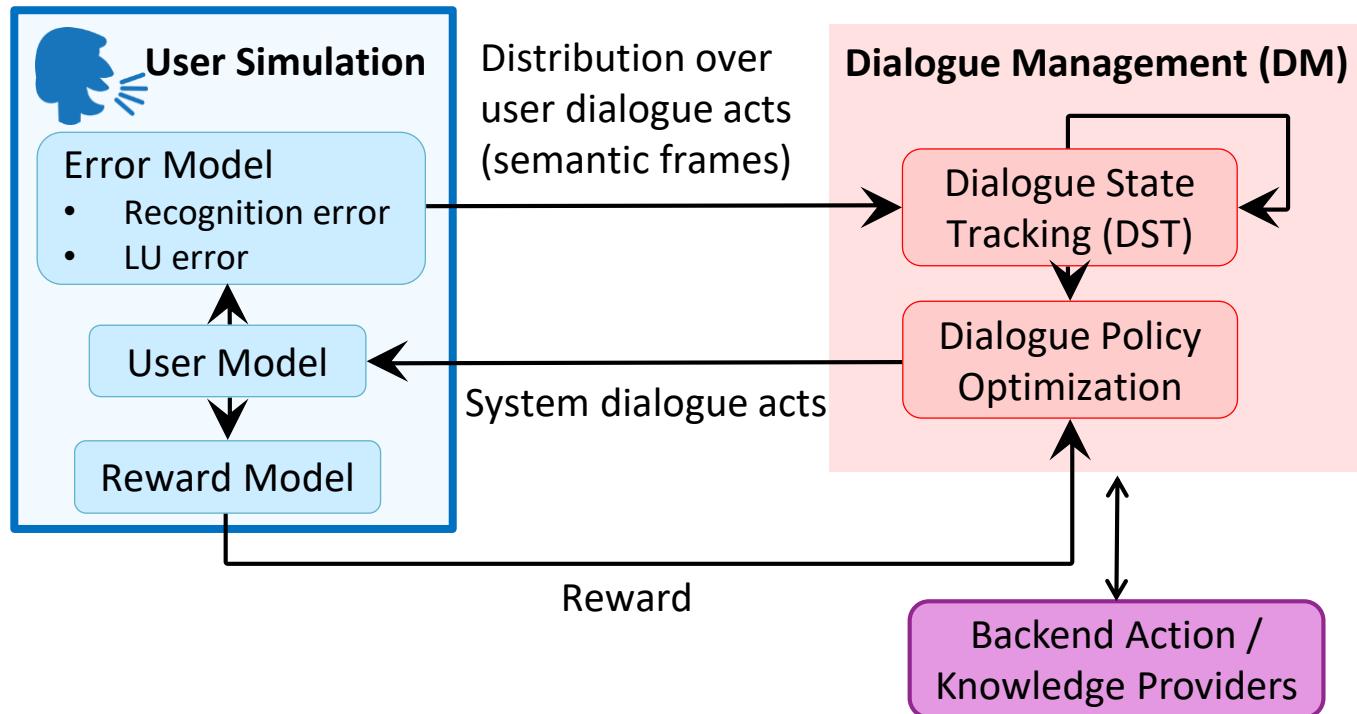
- Goal: generate natural and reasonable conversations to enable reinforcement learning for exploring the policy space



- Approach
 - Rule-based crafted by experts (Li et al., 2016)
 - Learning-based (Schatzmann et al., 2006; El Asri et al., 2016)

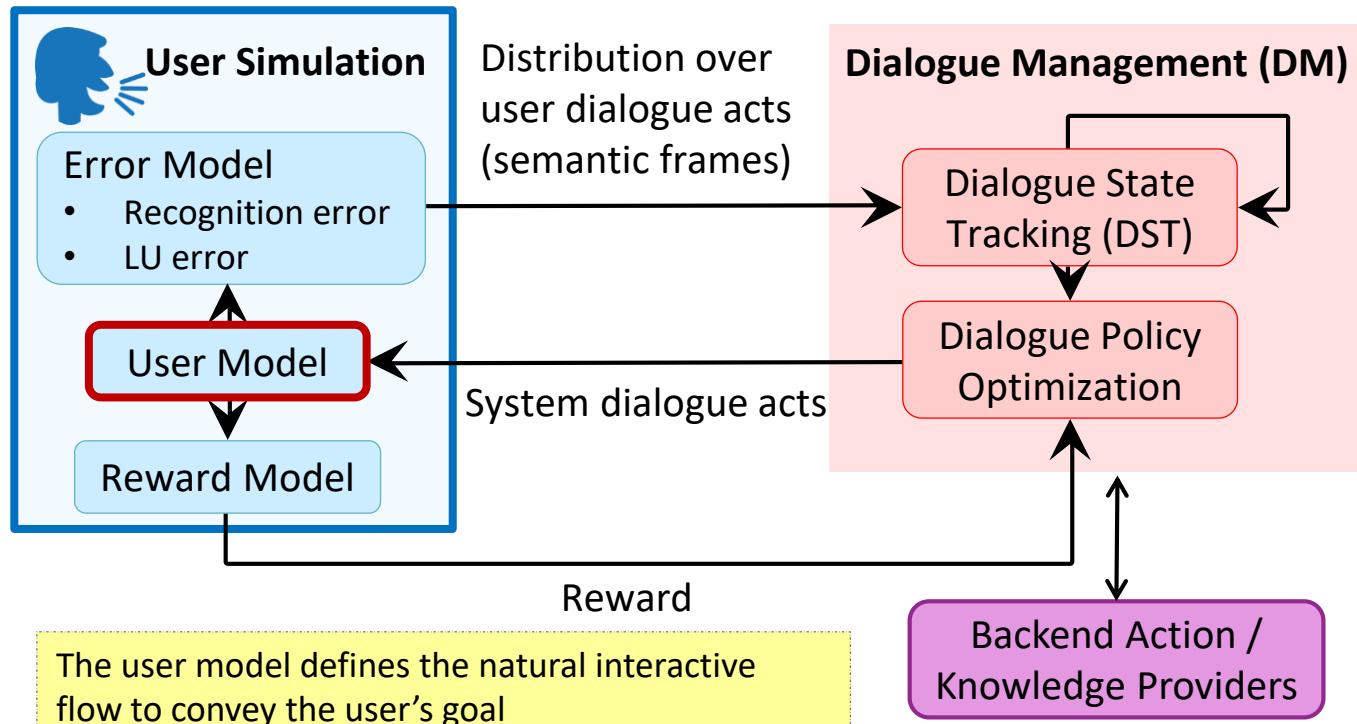
Elements of User Simulation

204



Elements of User Simulation

205



User Goal

206

- Sampled from a real corpus / hand-crafted list
 - Information access
 - Inflexible: the user has specific entries for search

`request_slot: rating, inform_slots: {moviename="A", ...}`
 - Task completion
 - Inflexible: the user has specific rows for search

`request_ticket, inform_slots: {moviename="A", ...}`
 - Flexible: some slot values are unknown or can be suggested

`request_ticket, request_slots: {time, theater},
inform_slots: {moviename="A", ...}`

Supported Functionality of Ontology

207

- Information access
 - ▣ Finding the specific entries from the table
- Task completion
 - ▣ Finding the row that satisfies the constraints



Movie Name	Theater	Rating	Date	Time
美女與野獸	台北信義威秀	8.5	2017/03/21	09:00
美女與野獸	台北信義威秀	8.5	2017/03/21	09:25
美女與野獸	台北信義威秀	8.5	2017/03/21	10:15
美女與野獸	台北信義威秀	8.5	2017/03/21	10:40
美女與野獸	台北信義威秀	8.5	2017/03/21	11:05

User Goal – Information Access

208

- Information access with inflexible constraints
 - ▣ Finding the specific entries from the table
 - Intent examples in the *ticket DB*: request_moviename, request_theater, request_time, etc
 - Intent examples in the *knowledge DB*: request_moviename, request_year
 - ▣ Specifying the constraints for the search target
 - The specified slots should align with the corresponding DB

Movie Name	Theater	Date	Time
美女與野獸	台北信義威秀	2017/03/21	09:00
美女與野獸	台北信義威秀	2017/03/21	09:25
美女與野獸	台北信義威秀	2017/03/21	10:15

Movie Name	Cast	Year
美女與野獸	Emma Watson	2017
鋼鐵人	:	:

User Goal – Task-Completion

209

- Task completion with inflexible constraints
 - ▣ Finding the specific rows from the table
 - Intent examples: request_ticket (*ticket DB*)
 - ▣ Specifying the slot constraints for the search target
 - Informable slot: theater, date, etc
 - Requestable slot: time, ~~number_of_people~~

Movie Name	Theater	Date	Time
美女與野獸	台北信義威秀	2017/03/21	09:00
美女與野獸	台北信義威秀	2017/03/21	09:25
美女與野獸	台北信義威秀	2017/03/21	10:15

User Goal – Task-Completion

210

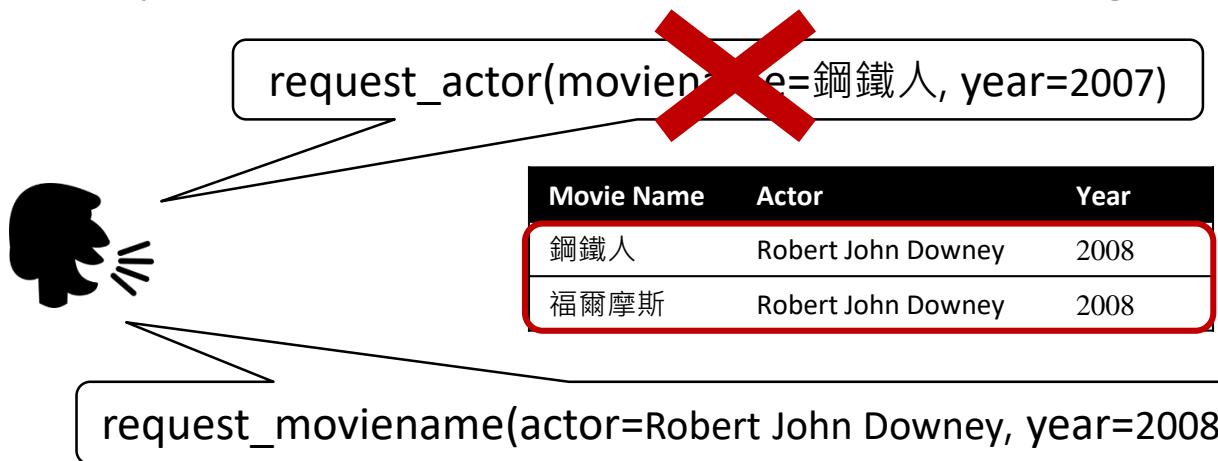
- Task completion with flexible constraints
 - ▣ No priority: {台北信義威秀, 台北日新威秀}
 - ▣ Prioritized: {台北信義威秀 > 台北日新威秀}

Movie Name	Theater	Date	Time
美女與野獸	台北信義威秀	2017/03/21	09:00
美女與野獸	台北信義威秀	2017/03/21	09:25
美女與野獸	台北信義威秀	2017/03/21	10:15

Satisfiability and Uniqueness

211

- Use goal characteristics
 - ▣ Satisfiability – the predefined goal can be satisfied by the backend database
 - ▣ Uniqueness – all satisfied entries should be in the goal



More Extension

212

- Slot value hierarchy
 - ▣ “morning” → {9:15, 9:45, 10:15, 10:45, 11:15, 11:45}
- Inexact match / partial match
 - ▣ “ten o’clock” → {9:45, 10:15}
 - ▣ “emma” → {Emma Watson, Emma Stone}

Agenda

- 1.
- 2.
- 3.



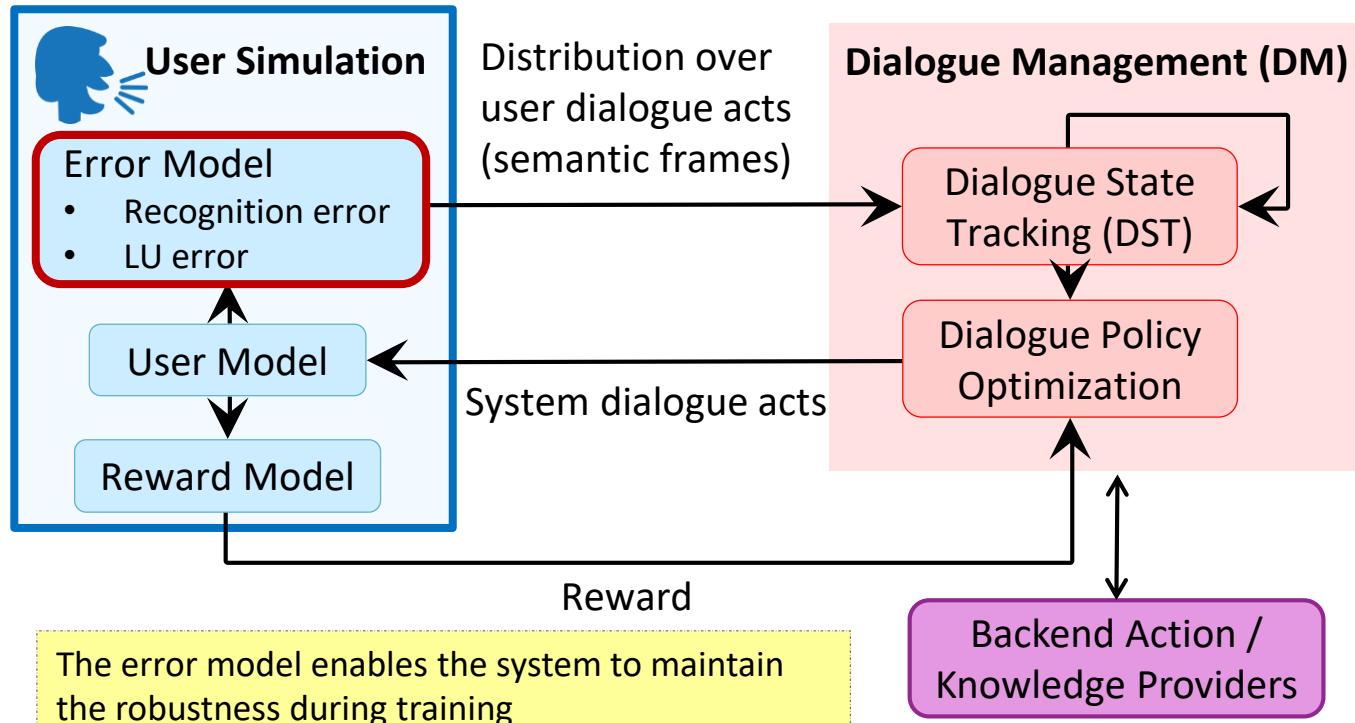
User Agenda Model

213

- User agenda defines how a user interacts with the system in the dialogue level
 - Random order: random sample a slot for informing or request
 - Fixed order: define a list of ordering slots for informing or request

Elements of User Simulation

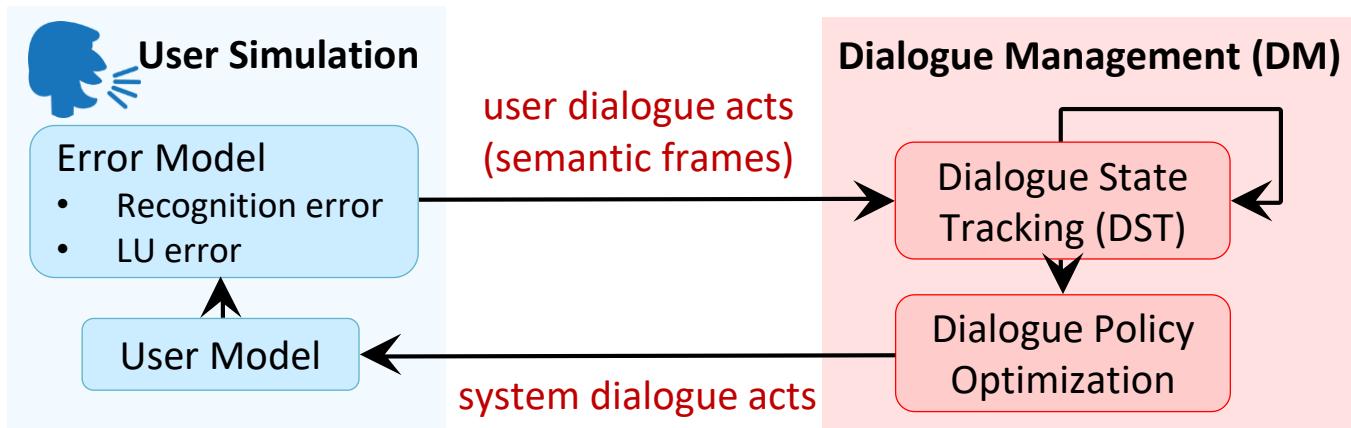
214



Frame-Level Interaction

215

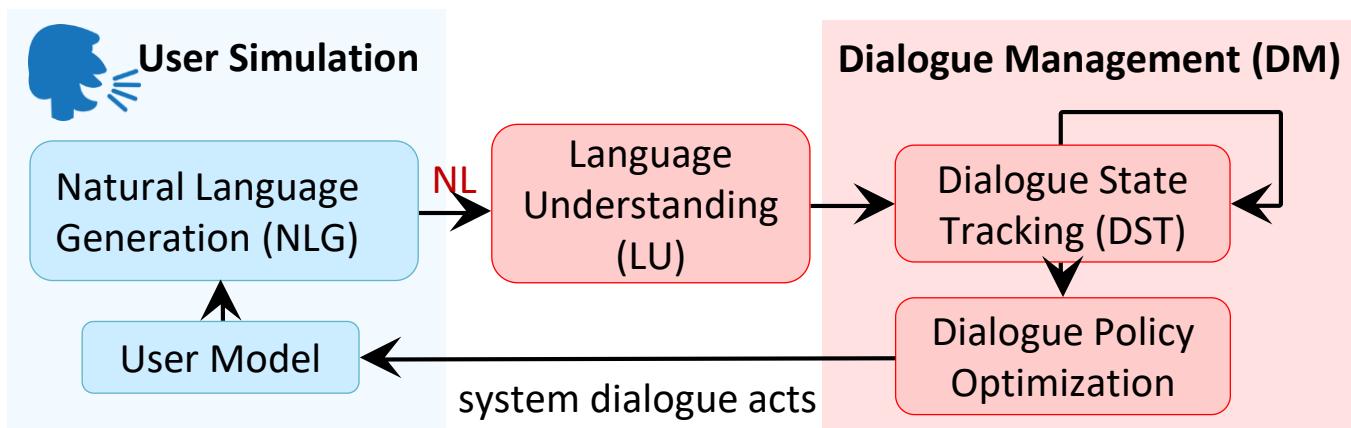
- DM receives frame-level information
 - No error model: perfect recognizer and LU
 - Error model: simulate the possible errors



Natural Language Level Interaction

216

- User simulator sends natural language
 - No recognition error
 - Errors from NLG or LU



Error Model

217

□ Simple

- Randomly generate errors by
 - Replacing with an incorrect intent
 - Deleting an informative slot
 - Replacing with an incorrect slot (value is original)
 - Replacing with an incorrect slot value

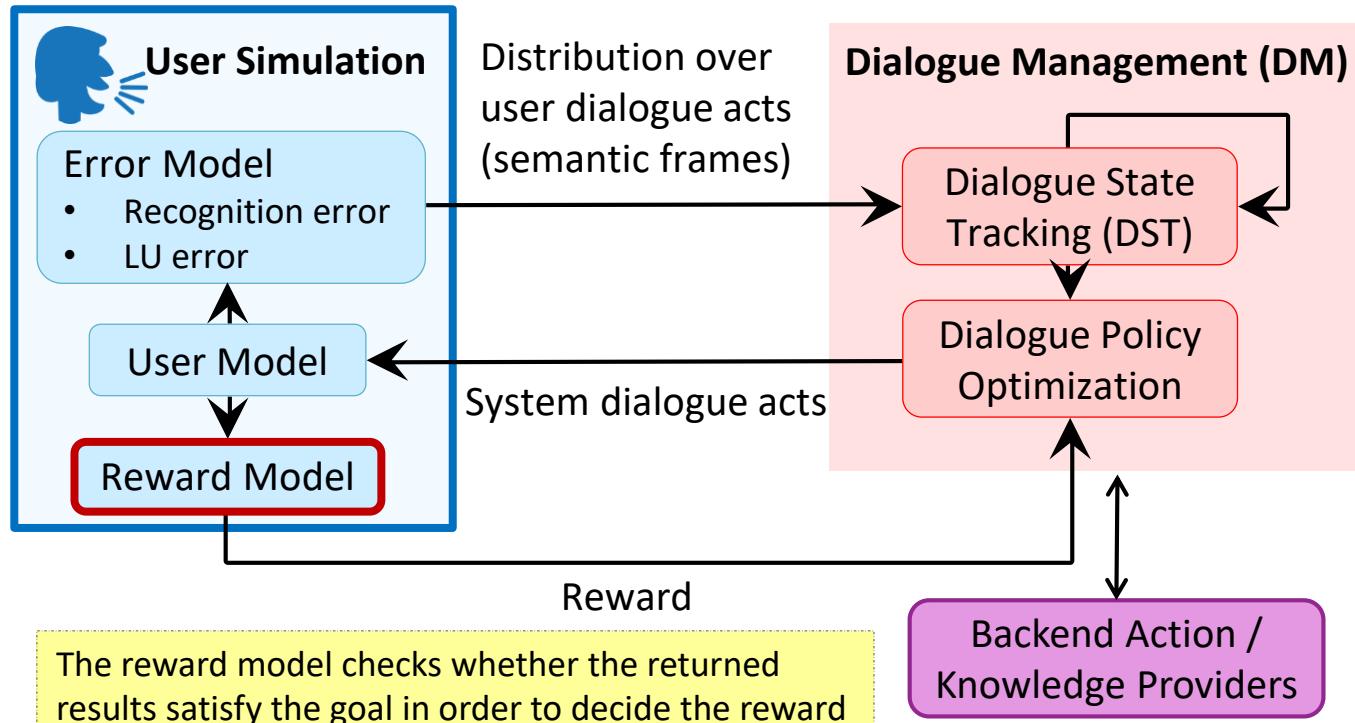
request_year
request_moviename
(actor=Robert Downey Jr)
director Robert Downey Sr

□ Learning

- Simulate the errors based on the ASR or LU confusion

Elements of User Simulation

218



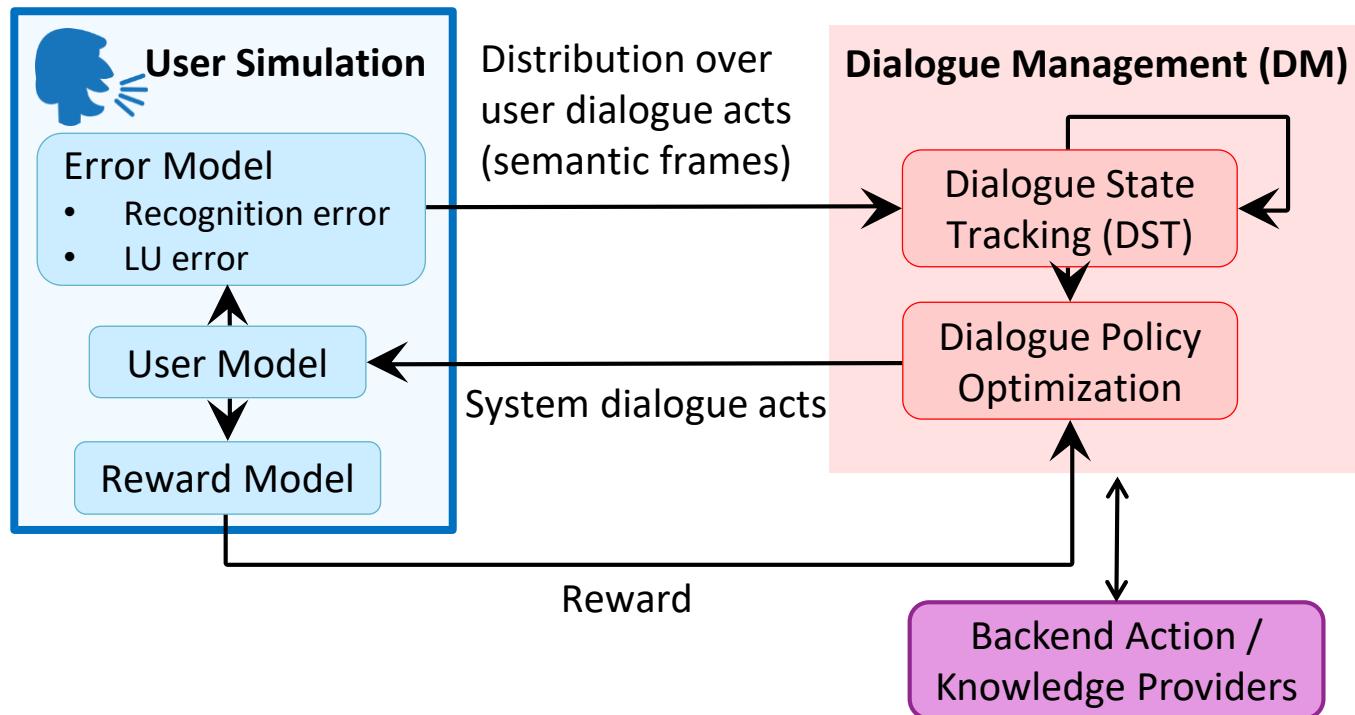
Reward Model

219

- Success measurement
 - ▣ Check whether the returned results satisfy the predefined user goal
 - Success – large positive reward
 - Fail – large negative reward
- Minimize the number of turns
 - ▣ Penalty for additional turns

Concluding Remarks

220



Tutorial Outline

221

I. 對話系統及基本背景知識

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Generation

222

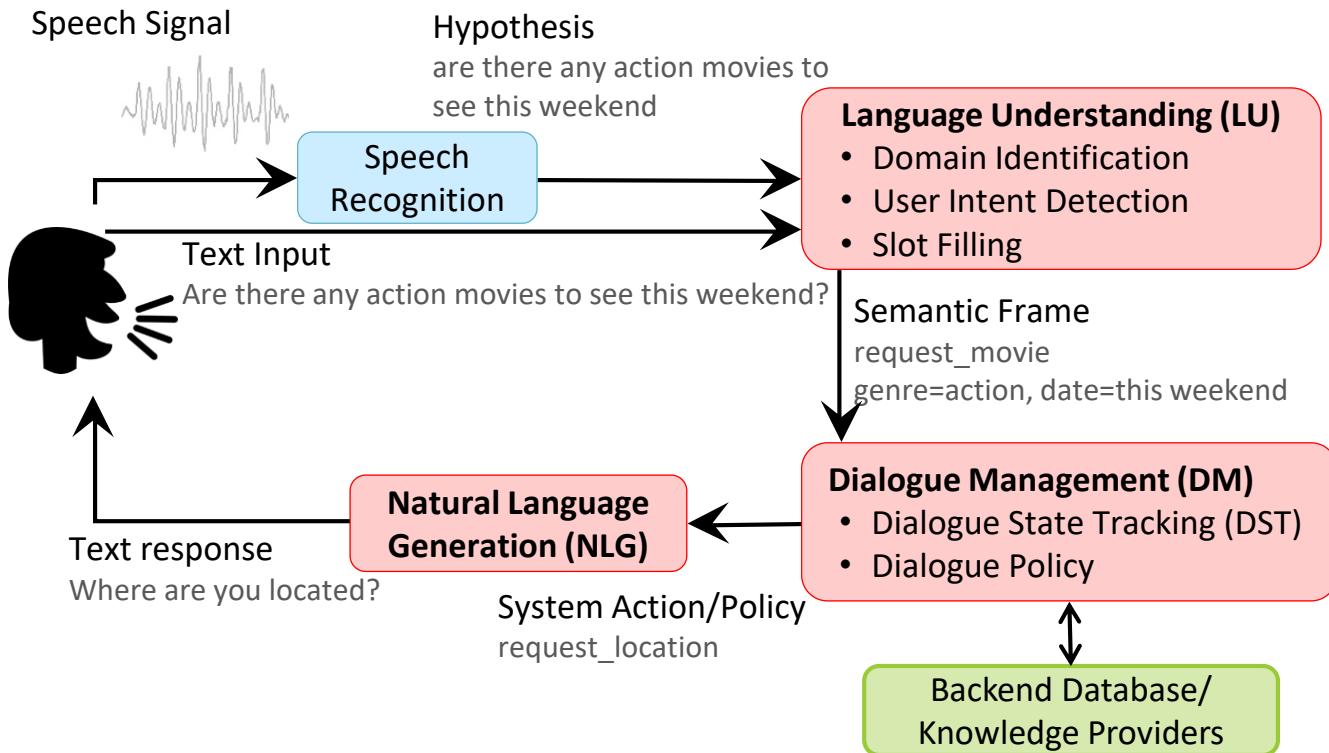
Language Generation

語言生成

Task-Oriented Dialogue System (Young, 2000)

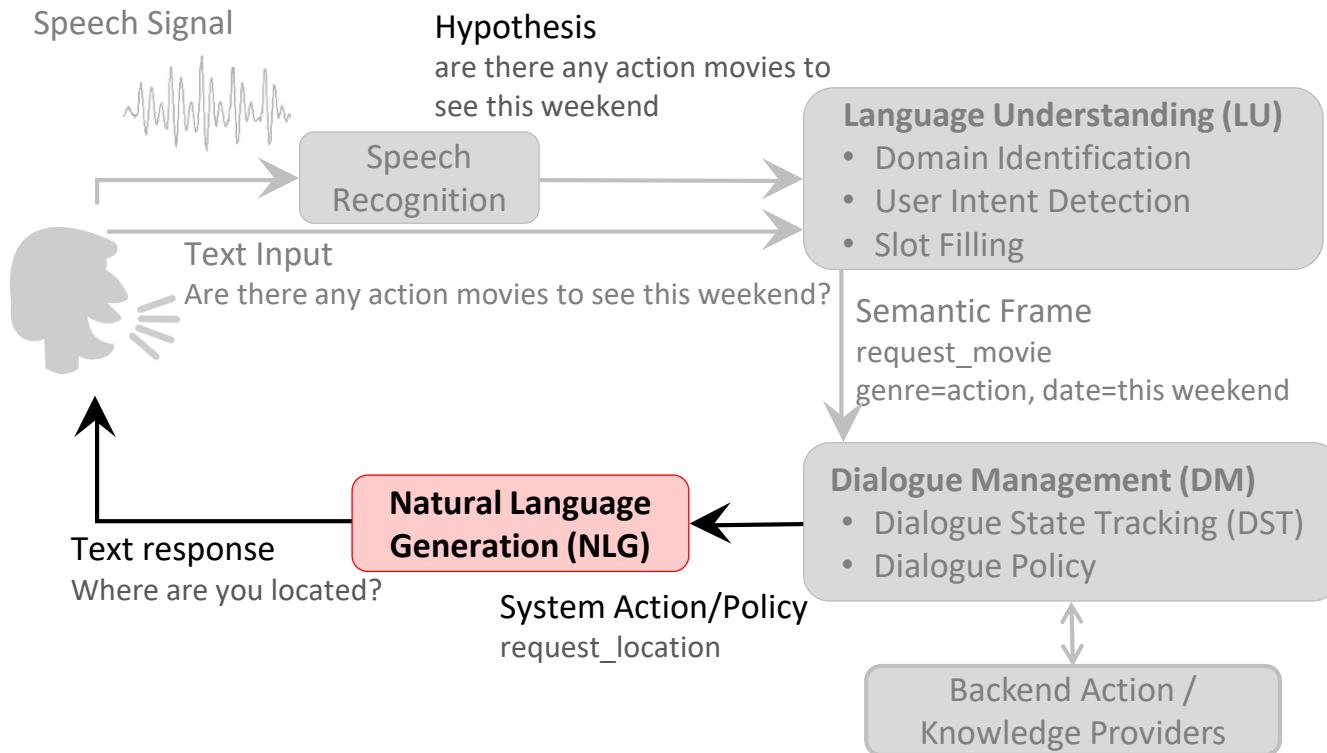
223

<http://rsta.royalsocietypublishing.org/content/358/1769/1389.short>



Task-Oriented Dialogue System (Young, 2000)

224



Natural Language Generation (NLG)

225

- Mapping dialogue acts into natural language

inform(name=Seven_Days, foodtype=Chinese)



Seven Days is a nice Chinese restaurant

Template-Based NLG

226

- Define a set of rules to map frames to NL

Semantic Frame	Natural Language
confirm()	“Please tell me more about the product your are looking for.”
confirm(area=\$V)	“Do you want somewhere in the \$V?”
confirm(food=\$V)	“Do you want a \$V restaurant?”
confirm(food=\$V,area=\$W)	“Do you want a \$V restaurant in the \$W.”

Pros: simple, error-free, easy to control

Cons: time-consuming, rigid, poor scalability

Class-Based LM NLG (Oh and Rudnicky, 2000)

227

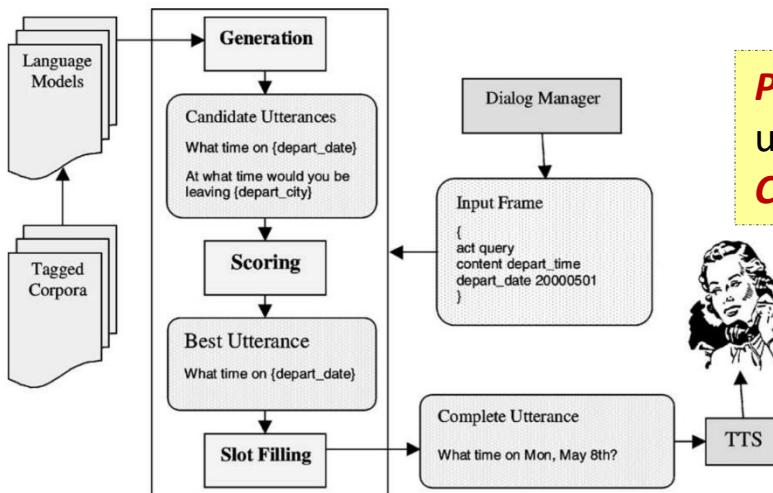
<http://dl.acm.org/citation.cfm?id=1117568>

□ Class-based language modeling

$$P(X \mid c) = \sum_t \log p(x_t \mid x_0, x_1, \dots, x_{t-1}, c)$$

□ NLG by decoding $X^* = \arg \max_X P(X \mid c)$

Classes:
inform_area
inform_address
...
request_area
request_postcode



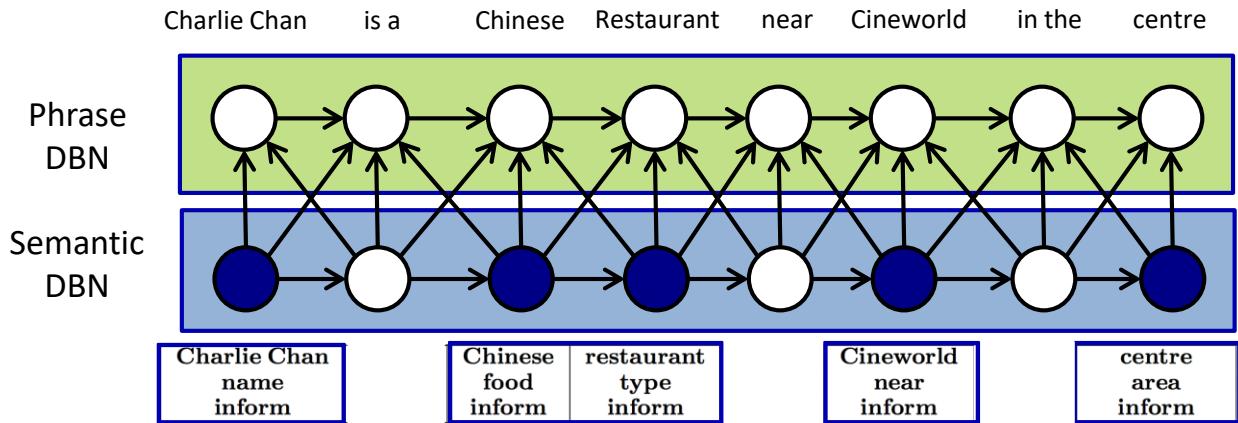
Pros: easy to implement/
understand, simple rules

Cons: computationally inefficient

Phrase-Based NLG (Mairesse et al, 2010)

228

<http://dl.acm.org/citation.cfm?id=1858838>



Inform(name=Charlie Chan, food=Chinese, type= restaurant, near=Cineworld, area=centre)
realization phrase semantic stack

r_t	s_t	h_t	l_t
< s >	START	START	START
The Rice Boat	inform(name(X))	X	inform(name)
is a	inform	inform	EMPTY
restaurant	inform(type(restaurant))	restaurant	inform(type)
in the	inform(area)	area	inform
riverside	inform(area(riverside))	riverside	inform(area)
area	inform(area)	area	inform
that	inform	inform	EMPTY
serves	inform(food)	food	inform
French	inform(food(French))	French	inform(food)
food	inform(food)	food	inform
< / s >	END	END	END

Pros: efficient, good performance

Cons: require semantic alignments

RNN-Based LM NLG (Wen et al., 2015)

229

<http://www.anthology.aclweb.org/W/W15/W15-46.pdf#page=295>

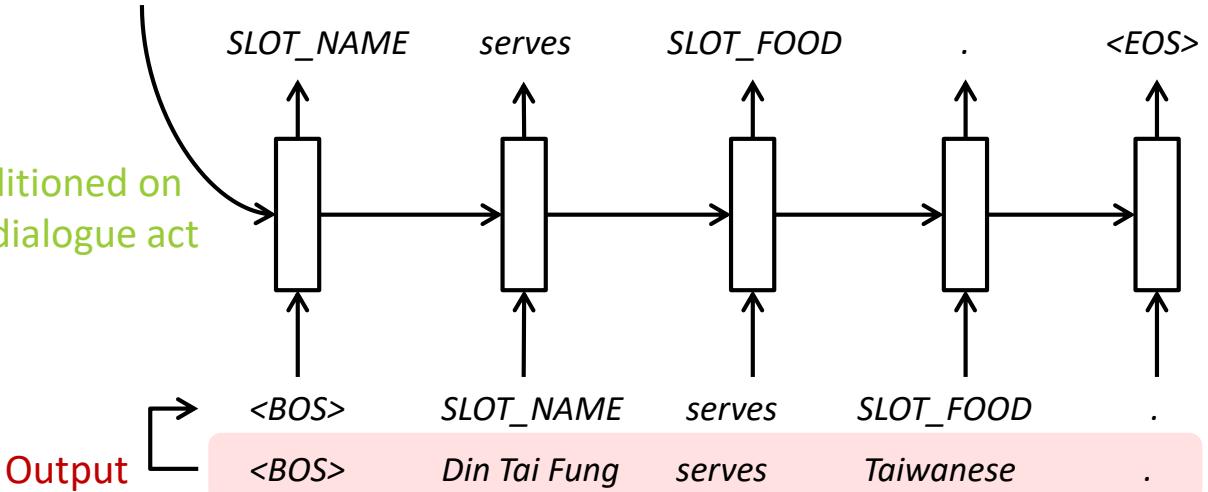
Input

Inform(name=Din Tai Fung, food=Taiwanese)

{ 0, 0, 1, 0, 0, ..., 1, 0, 0, ..., 1, 0, 0, 0, 0, 0, 0 ... }

dialogue act 1-hot representation

conditioned on
the dialogue act



delexicalisation

Slot weight tying

Handling Semantic Repetition

230

- Issue: semantic repetition
 - ▣ Din Tai Fung is a great Taiwanese restaurant that serves Taiwanese.
 - ▣ Din Tai Fung is a child friendly restaurant, and also allows kids.
- Deficiency in either model or decoding (or both)
- Mitigation
 - ▣ Post-processing rules (Oh & Rudnicky, 2000)
 - ▣ Gating mechanism (Wen et al., 2015)
 - ▣ Attention (Mei et al., 2016; Wen et al., 2015)

Semantic Conditioned LSTM (Wen et al., 2015)

231

<http://www.aclweb.org/anthology/D/D15/D15-1199.pdf>

□ Original LSTM cell

$$\mathbf{i}_t = \sigma(\mathbf{W}_{wi}\mathbf{x}_t + \mathbf{W}_{hi}\mathbf{h}_{t-1})$$

$$\mathbf{f}_t = \sigma(\mathbf{W}_{wf}\mathbf{x}_t + \mathbf{W}_{hf}\mathbf{h}_{t-1})$$

$$\mathbf{o}_t = \sigma(\mathbf{W}_{wo}\mathbf{x}_t + \mathbf{W}_{ho}\mathbf{h}_{t-1})$$

$$\hat{\mathbf{c}}_t = \tanh(\mathbf{W}_{wc}\mathbf{x}_t + \mathbf{W}_{hc}\mathbf{h}_{t-1})$$

$$\mathbf{c}_t = \mathbf{f}_t \odot \mathbf{c}_{t-1} + \mathbf{i}_t \odot \hat{\mathbf{c}}_t$$

$$\mathbf{h}_t = \mathbf{o}_t \odot \tanh(\mathbf{c}_t)$$

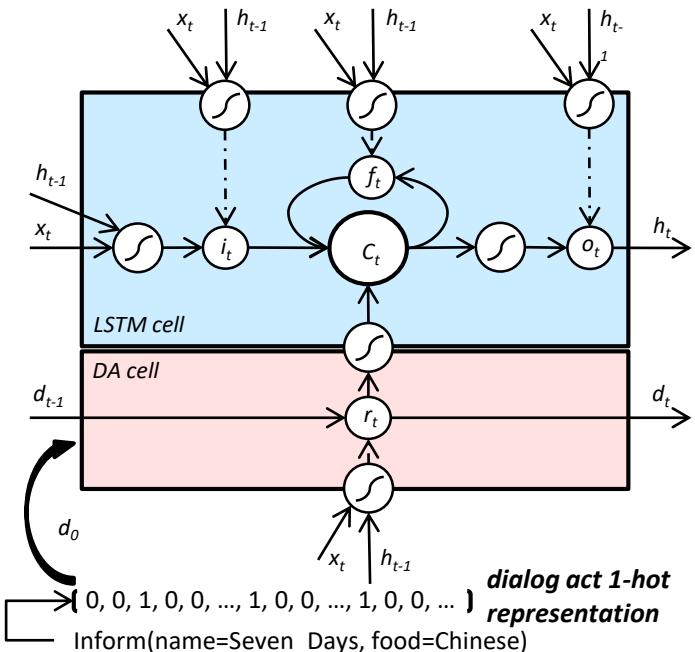
□ Dialogue act (DA) cell

$$\mathbf{r}_t = \sigma(\mathbf{W}_{wr}\mathbf{x}_t + \mathbf{W}_{hr}\mathbf{h}_{t-1})$$

$$\mathbf{d}_t = \mathbf{r}_t \odot \mathbf{d}_{t-1}$$

□ Modify C_t

$$\mathbf{c}_t = \mathbf{f}_t \odot \mathbf{c}_{t-1} + \mathbf{i}_t \odot \hat{\mathbf{c}}_t + \tanh(\mathbf{W}_{dc}\mathbf{d}_t)$$

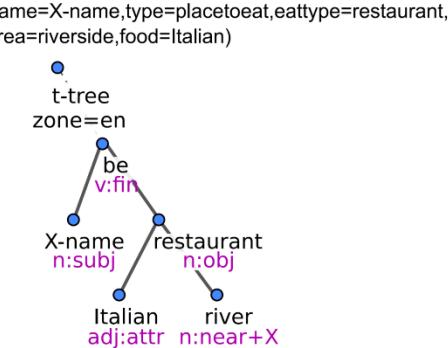


Idea: using gate mechanism to control the generated semantics (dialogue act/slots)

Structural NLG (Dušek and Jurčíček, 2016)

232

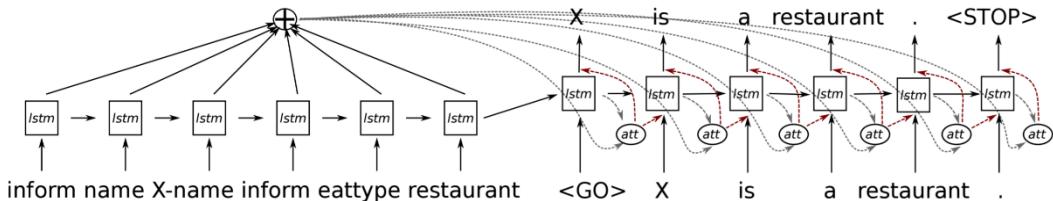
- Goal: NLG based on the syntax tree
 - Encode trees as sequences
 - Seq2Seq model for generation



(<root> <root> ((X-name n:subj) be v:fin ((Italian adj:attr) restaurant n:obj (river n:near+X)))
X-name n:subj be v:fin Italian adj:attr restaurant n:obj river n:near+X

1

X is an Italian restaurant near the river.

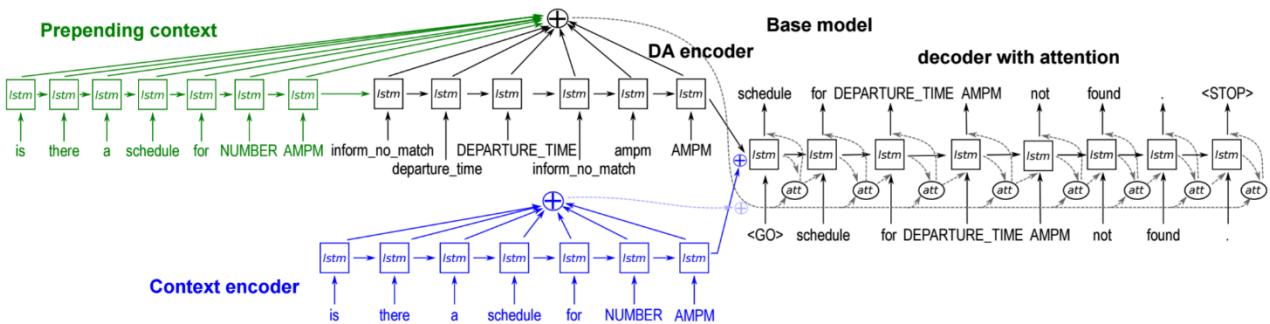
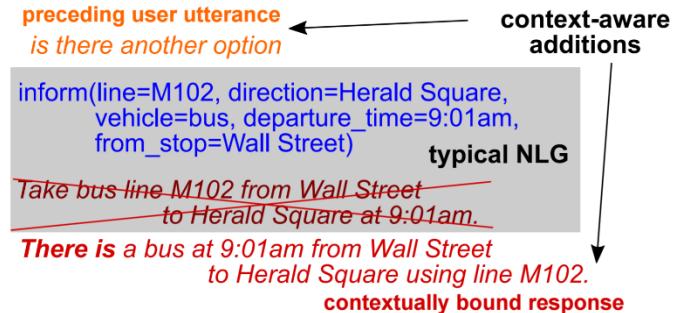


Contextual NLG (Dušek and Jurčíček, 2016)

233

<https://www.aclweb.org/anthology/W/W16/W16-36.pdf#page=203>

- Goal: adapting users' way of speaking, providing context-aware responses
- Context encoder
- Seq2Seq model



Chit-Chat Bot

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- Neural conversational model
 - Non task-oriented

Human: what do you think about tesla ?

Machine: he 's a good conductor .

Human: what do you think about bill gates ?

Machine: he 's a good man .

Human: What do you think about messi ?

Machine: he 's a great player .

Human: what do you think about cleopatra ?

Machine: oh , she 's very regal .

Human: what do you think about england during the reign of elizabeth ?

Machine: it was a great place .

Human: what is the purpose of life ?

Machine: to serve the greater good .

Human: what is the purpose of living ?

Machine: to live forever .

Human: what is the purpose of existence ?

Machine: to find out what happens when we get to the planet earth .

Human: where are you now ?

Machine: i 'm in the middle of nowhere .

Human: what is the purpose of dying ?

Machine: to have a life .

Human: what is the purpose of being intelligent ?

Machine: to find out what it is .

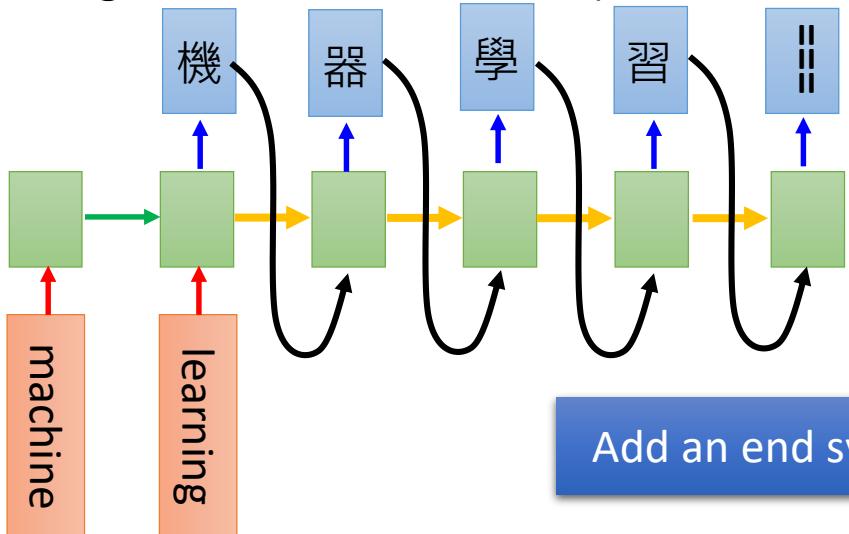
Human: what is the purpose of emotions ?

Machine: i don 't know .

Many-to-Many

235

- Both input and output are both sequences → Sequence-to-sequence learning
 - E.g. *Machine Translation* (machine learning → 機器學習)



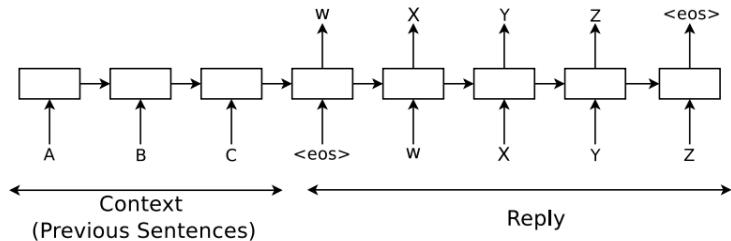
[Ilya Sutskever, NIPS'14][Dzmitry Bahdanau, arXiv'15]

A Neural Conversational Model

236

Seq2Seq

[Vinyals and Le, 2015]



Human: what do you think about tesla ?

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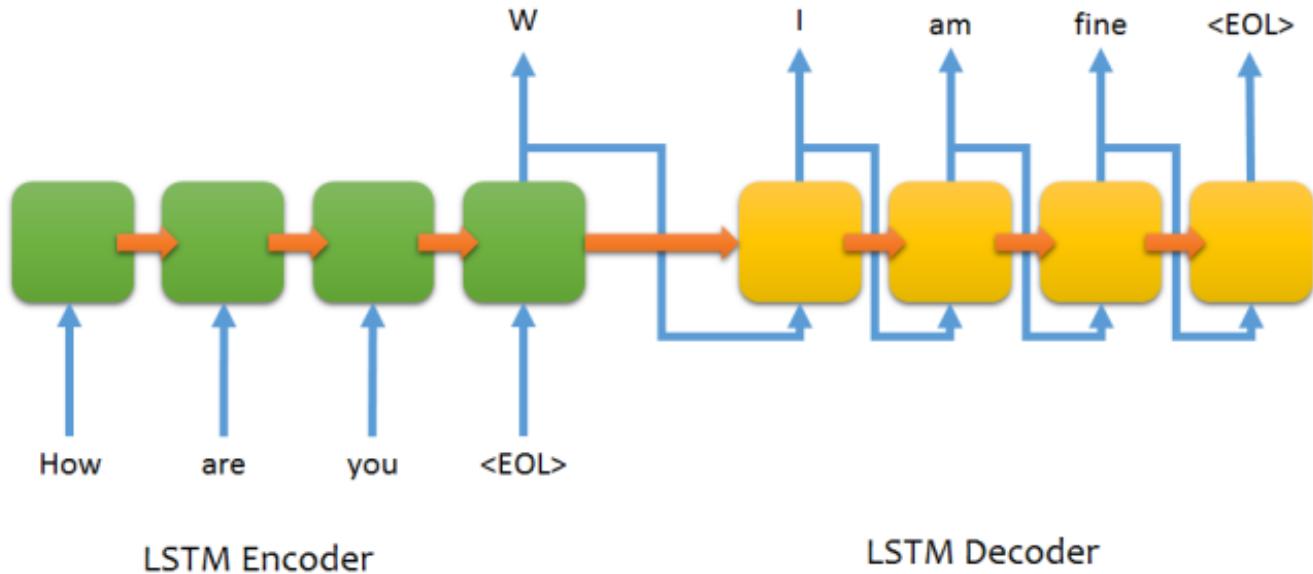
Machine: to find out what it is .

Human: what is the purpose of emotions ?

Machine: i don 't know .

Chit-Chat Bot

237



LSTM Encoder

LSTM Decoder

電視影集 (~40,000 sentences)、美國總統大選辯論

Sci-Fi Short Film - SUNSPRING

238

A close-up shot of a person's hand reaching towards a dark, rectangular device. The device has the word "SUNSPRING" printed in large, white, sans-serif capital letters. The background is blurred, showing some indoor furniture like a chair and a small table lamp.

SUNSPRING

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Outline

240

- Dialogue System Evaluation
- Recent Trends
 - ▣ End-to-End Learning for Dialogue System
 - ▣ Multimodality
 - ▣ Dialogue Breath
 - ▣ Dialogue Depth
- Challenges

Dialogue System Evaluation

241

- Language understanding
 - Sentence-level: frame accuracy (%)
 - Subsentence-level: intent accuracy (%), slot F-measure (%)
- Dialogue management
 - Dialogue state tracking
 - Frame accuracy (%)
 - Dialogue policy
 - Turn-level: accuracy (%)
 - Dialogue-level: success rate (%), reward
- Natural language generation

NLG Evaluation

242

□ Metrics

□ Subjective: human judgement (Stent et al., 2005)

- Adequacy: correct meaning
- Fluency: linguistic fluency
- Readability: fluency in the dialogue context
- Variation: multiple realizations for the same concept

□ Objective: automatic metrics

- Word overlap: BLEU (Papineni et al, 2002), METEOR, ROUGE
- Word embedding based: vector extrema, greedy matching, embedding average

There is a gap between human perception and automatic metrics

Dialogue Evaluation Measures

243

Understanding Ability

- Whether constrained values specified by users can be understood by the system
- Agreement percentage of system/user understandings over the entire dialog (averaging all turns)

Efficiency

- Number of dialogue turns for task completion

Action Appropriateness

- An explicit confirmation for an uncertain user utterance is an appropriate system action
- Providing information based on misunderstood user requirements

Outline

244

- Dialogue System Evaluation
- ***Recent Trends***
 - ▣ ***End-to-End Learning for Dialogue System***
 - ▣ Multimodality
 - ▣ Dialogue Breath
 - ▣ Dialogue Depth
- Challenges

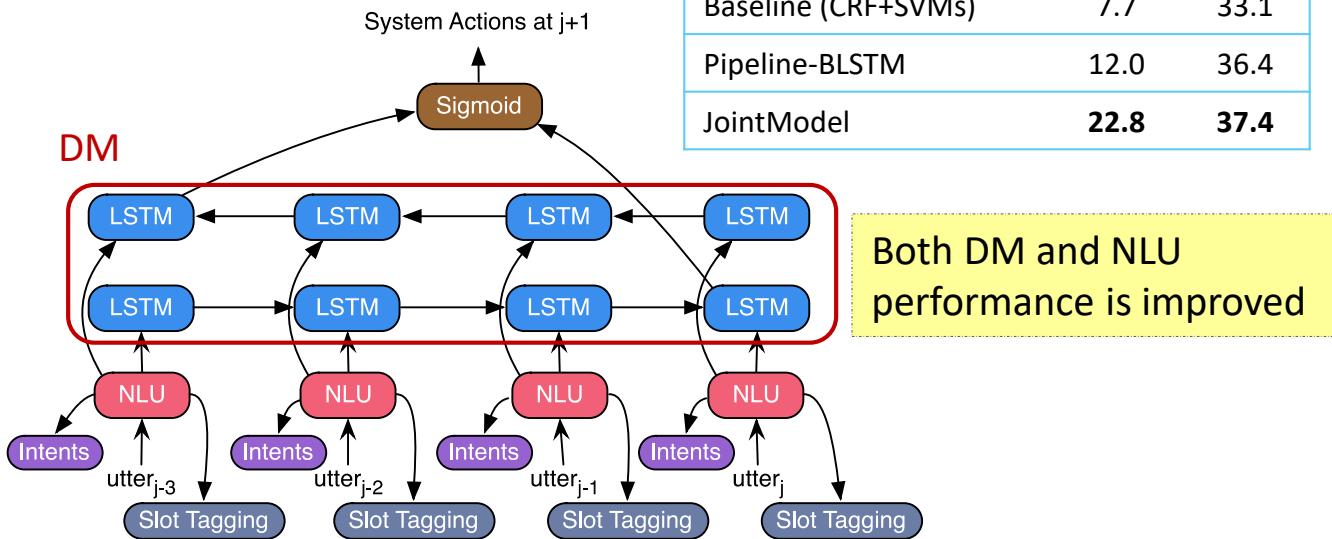
E2E Joint NLU and DM (Yang et al., 2017)

245

<https://arxiv.org/abs/1612.00913>

- Idea: errors from DM can be propagated to NLU for better robustness

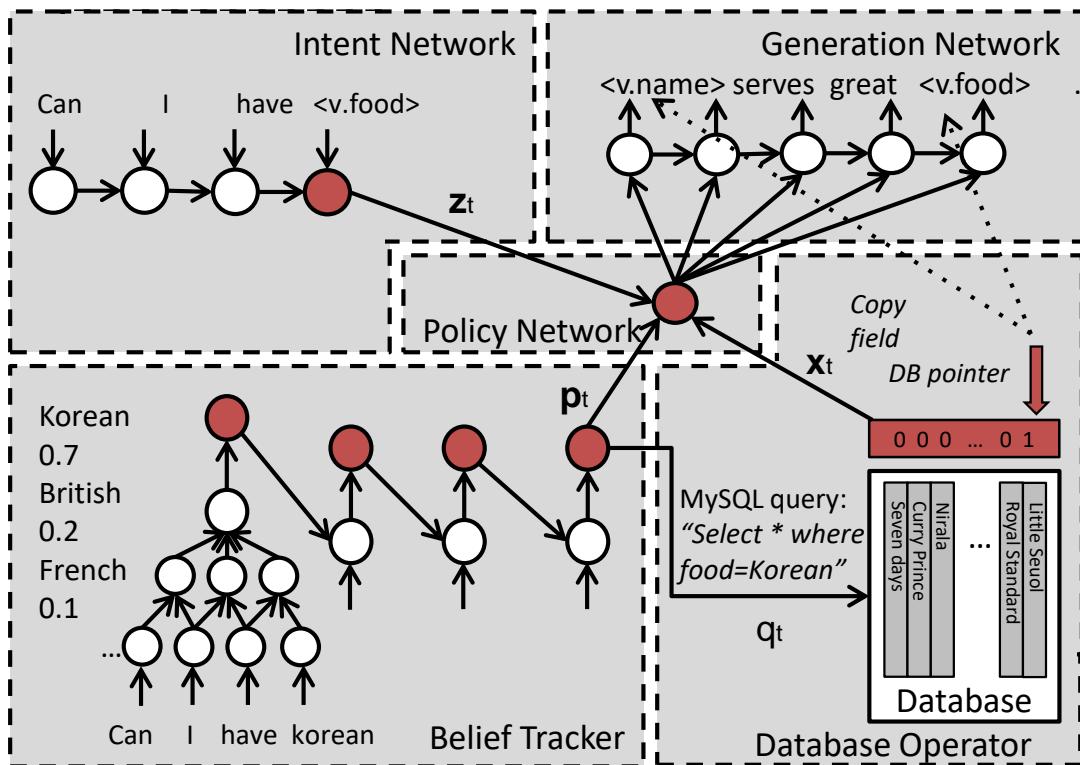
Model	DM	NLU
Baseline (CRF+SVMs)	7.7	33.1
Pipeline-BLSTM	12.0	36.4
JointModel	22.8	37.4



E2E Supervised Dialogue System (Wen et al., 2016)

246

<https://arxiv.org/abs/1604.04562>



E2E MemNN for Dialogues (Bordes et al., 2016)

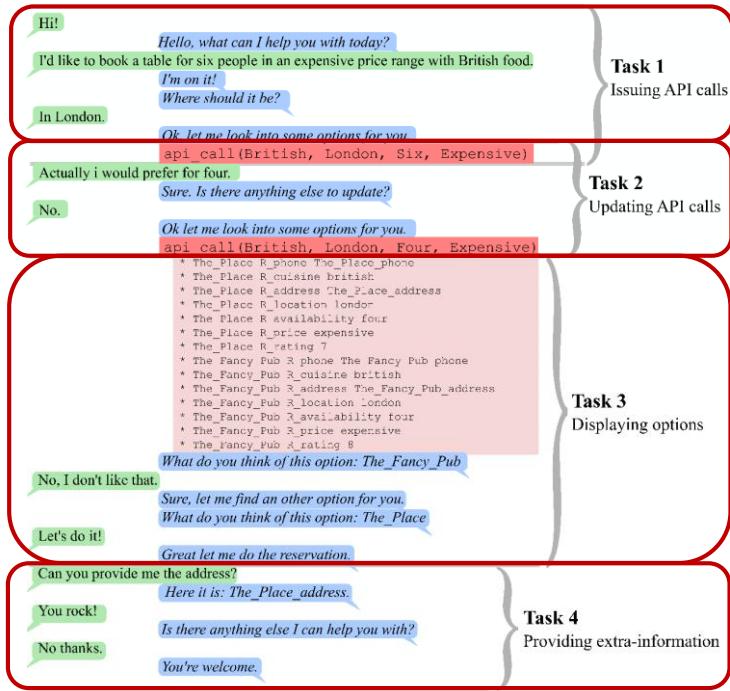
247

<https://arxiv.org/abs/1605.07683>

- Split dialogue system actions into subtasks
 - API issuing
 - API updating
 - Option displaying
 - Information informing

Task	Memory Networks	
	no match type	+ match type
T1: Issuing API calls	99.9 (99.6)	100 (100)
T2: Updating API calls	100 (100)	98.3 (83.9)
T3: Displaying options	74.9 (2.0)	74.9 (0)
T4: Providing information	59.5 (3.0)	100 (100)
T5: Full dialogs	96.1 (49.4)	93.4 (19.7)
T1(OOV): Issuing API calls	72.3 (0)	96.5 (82.7)
T2(OOV): Updating API calls	78.9 (0)	94.5 (48.4)
T3(OOV): Displaying options	74.4 (0)	75.2 (0)
T4(OOV): Providing inform.	57.6 (0)	100 (100)
T5(OOV): Full dialogs	65.5 (0)	77.7 (0)
T6: Dialog state tracking 2	41.1 (0)	41.0 (0)

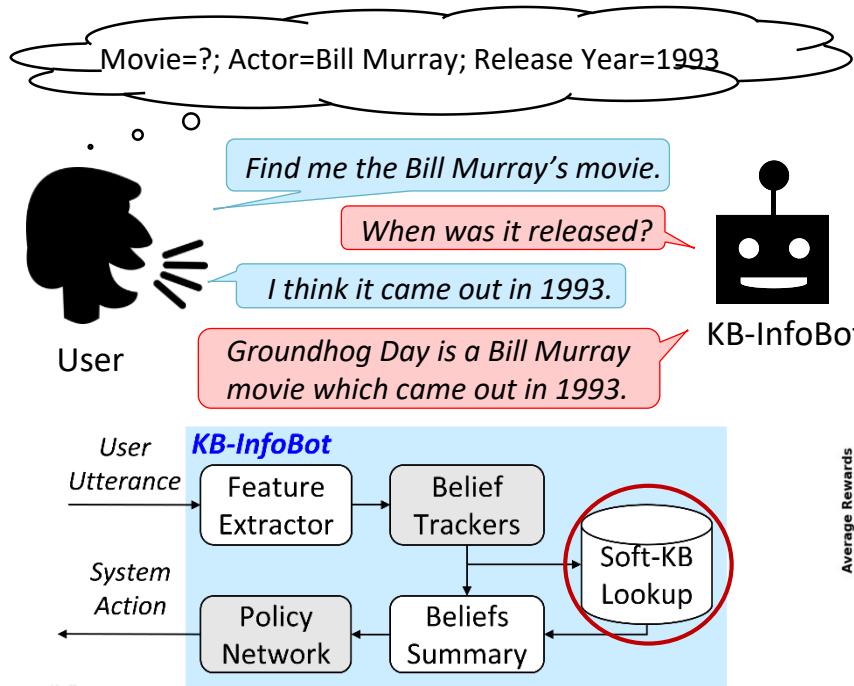
turn-level dialogue-level



E2E RL-Based Info-Bot (Dhingra et al., 2016)

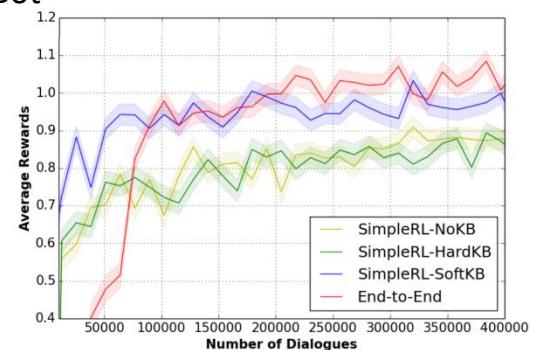
248

<https://arxiv.org/abs/1609.00777>



Knowledge Base (*head, relation, tail*)

(*Groundhog Day, actor, Bill Murray*)
(*Groundhog Day, release year, 1993*)
(*Australia, actor, Nicole Kidman*)
(*Mad Max: Fury Road, release year, 2015*)



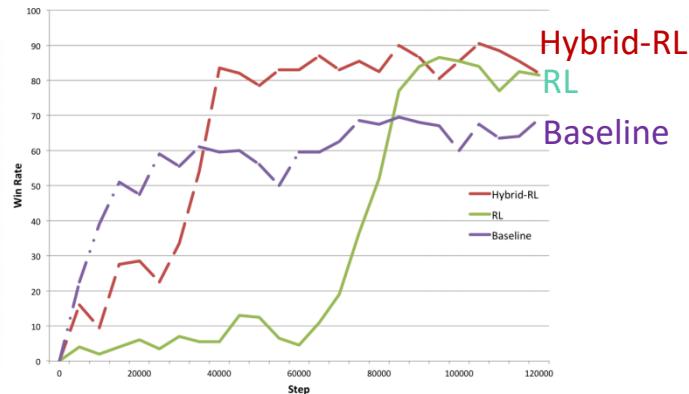
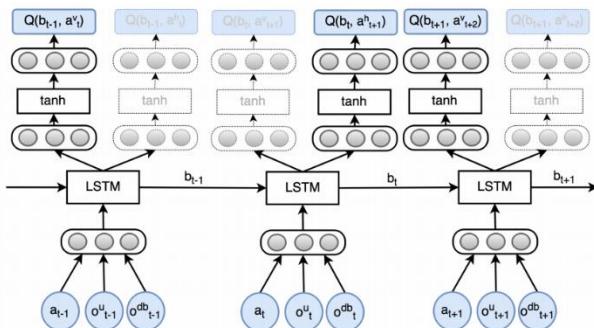
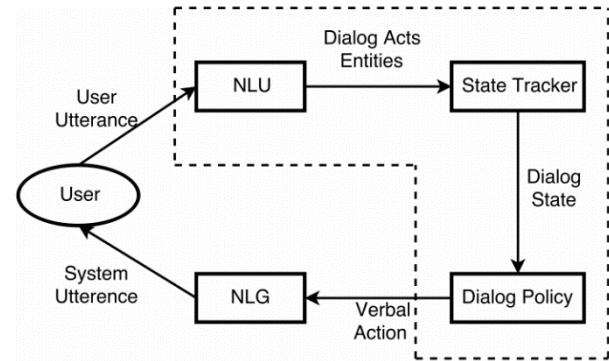
Idea: differentiable database for propagating the gradients

E2E RL-Based System (Zhao and Eskenazi, 2016)

249

<http://www.aclweb.org/anthology/W/W16/W16-36.pdf#page=19>

- Joint learning
 - ▣ NLU, DST, Dialogue Policy
- Deep RL for training
 - ▣ Deep Q-network
 - ▣ Deep recurrent network



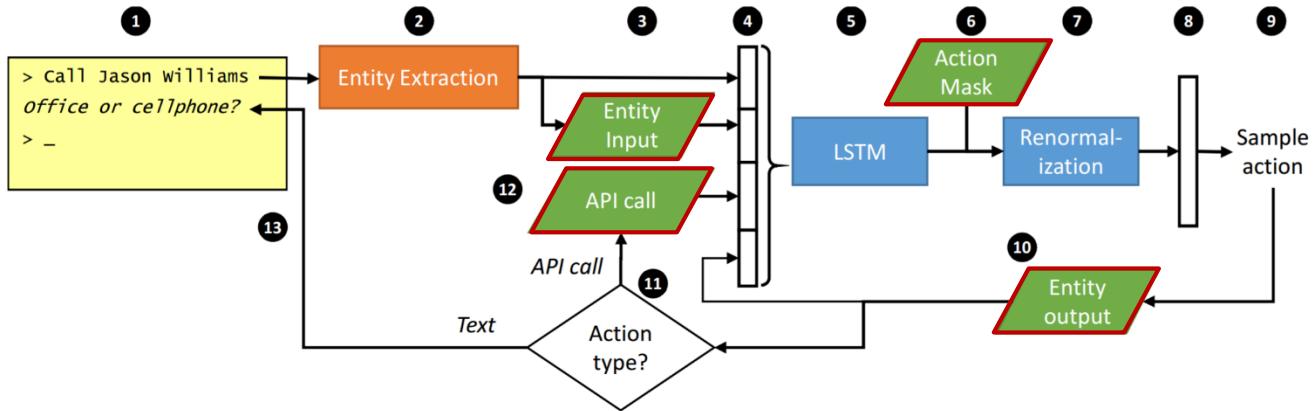
E2E LSTM-Based Dialogue Control

(Williams and Zweig, 2016)

250

<https://arxiv.org/abs/1606.01269>

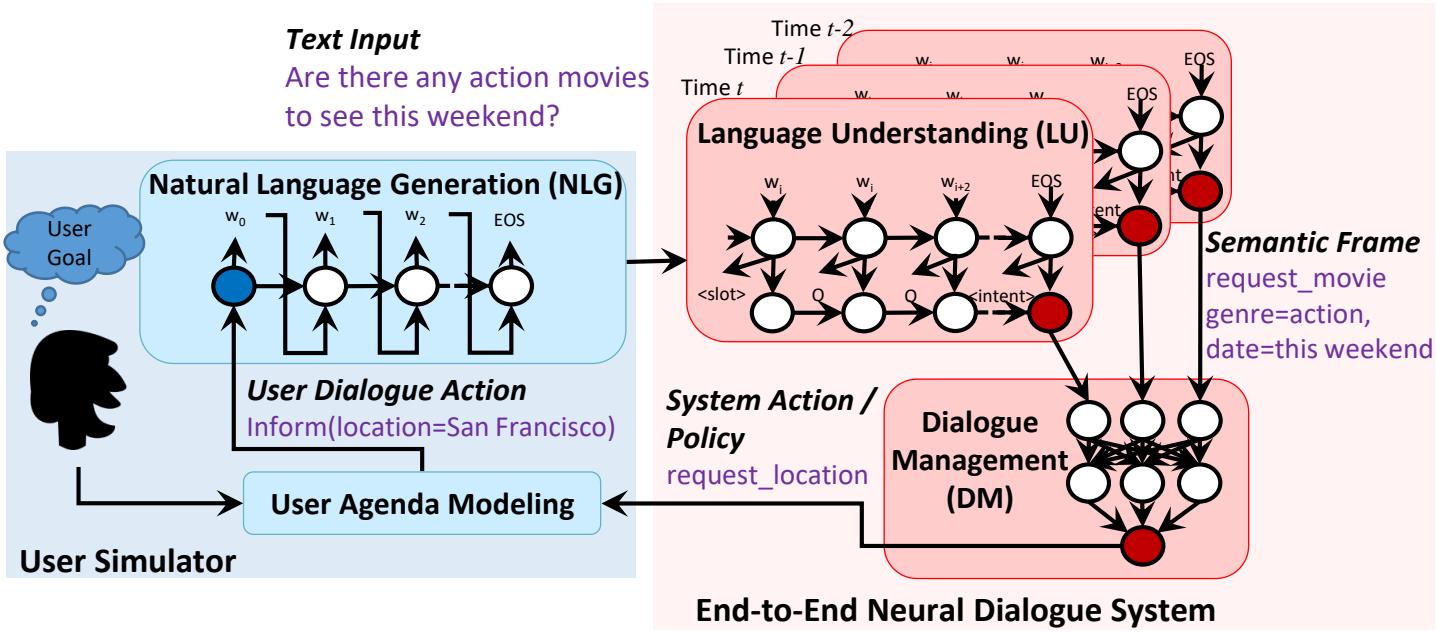
- Idea: an LSTM maps from raw dialogue history directly to a distribution over system actions
 - Developers can provide software including business rules & programmatic APIs
→ LSTM can take actions in the real world on behalf of the user
 - The LSTM can be optimized using SL or RL



E2E Task-Completion Bot (TC-Bot) (Li et al., 2017)

251

<https://arxiv.org/abs/1703.01008>



Idea: supervised learning for each component and reinforcement learning for end-to-end training the neural dialogue system

E2E Task-Completion Bot (TC-Bot) (Li et al., 2017)

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<https://arxiv.org/abs/1703.01008>

- User goal: ***Two tickets for “the witch” tomorrow 9:30 PM at regal meridian 16, Seattle.***

RULE BASED SYSTEM

User: Can I get 2 tickets for the witch?

Agent: Which theater do you want?

User: Regal meridian 16

Agent: What time would you like to see it?

User: 9:30 pm

Agent: What date would you like to see it?

User: Tomorrow!

Agent: How many people are you?

User: Just two adults.

Agent: What is your location?

User: Seattle!

Agent: What kind of video format do you like?

User: Oh, any kind is okay.

Agent: Do you have any price constraint?

User: No, I don't care.

Agent: Great - I was able to purchase 2 tickets for you to see the witch tomorrow at regal meridian 16 theater in Seattle at 9:30 pm.

User: Thank you.

Agent: Thank you!

REINFORCEMENT LEARNING SYSTEM

User: Can I get 2 tickets for the witch?

Agent: What date would you like to see it?

User: Tomorrow

Agent: Which theater do you prefer?

User: Regal meridian 16

Agent: What is your location?

User: Seattle

Agent: What time would you like to see it?

User: 9:30 pm.

Agent: Great - I was able to purchase 2 tickets for you to see the witch tomorrow at regal meridian 16 theater in Seattle at 9:30 pm.

User: Thanks.

Agent: Thanks!



The system can learn how to efficiently interact with users for task completion

0 100 200 300 400 500 600
Simulation Epoch

Outline

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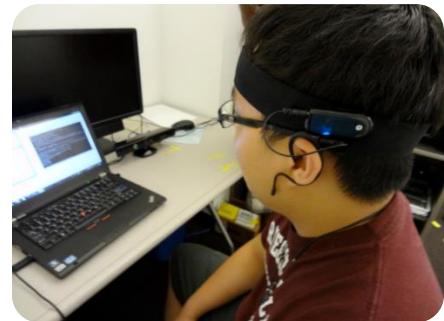
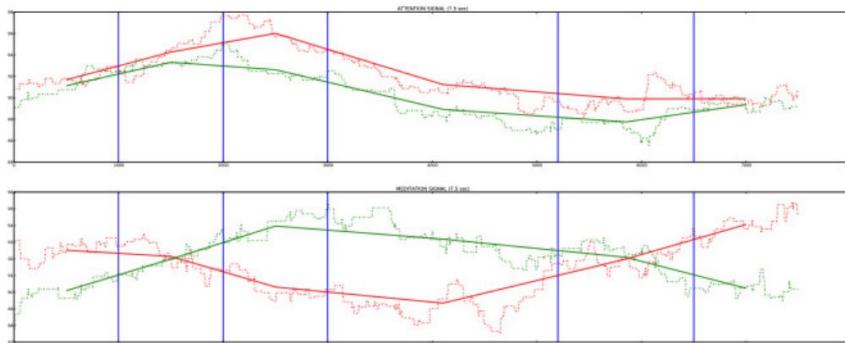
- Dialogue System Evaluation
- ***Recent Trends***
 - ▣ End-to-End Learning for Dialogue System
 - ▣ ***Multimodality***
 - ▣ Dialogue Breath
 - ▣ Dialogue Depth
- Challenges

Brain Signal for Understanding

254

<http://dl.acm.org/citation.cfm?id=2388695>

- Misunderstanding detection by brain signal
 - Green: listen to the correct answer
 - Red: listen to the wrong answer



Detecting misunderstanding via brain signal in order to correct the understanding results

Video for Intent Understanding

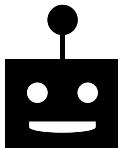
255

I want to see a movie on TV!

Intent: turn_on_tv

Proactive (from camera)

Sir, may I turn on the TV for you?



Proactively understanding user intent to initiate the dialogues.

App Behavior for Understanding

256

- Task: user intent prediction
- Challenge: language ambiguity



Email?

v.s.



Message?

① User preference

- ✓ Some people prefer “Message” to “Email”
- ✓ Some people prefer “Outlook” to “Gmail”

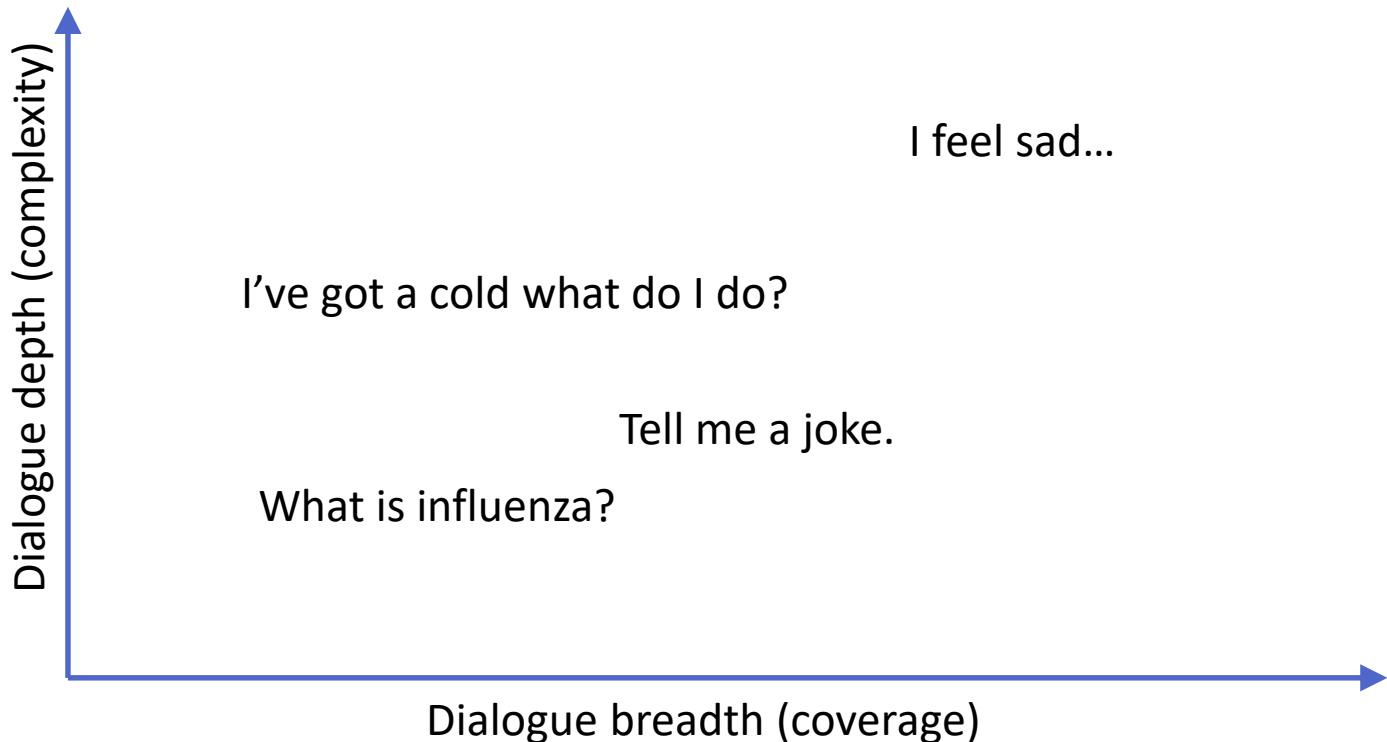
② App-level contexts

- ✓ “Message” is more likely to follow “Camera”
- ✓ “Email” is more likely to follow “Excel”

Considering behavioral patterns in history to model understanding for intent prediction.

Evolution Roadmap

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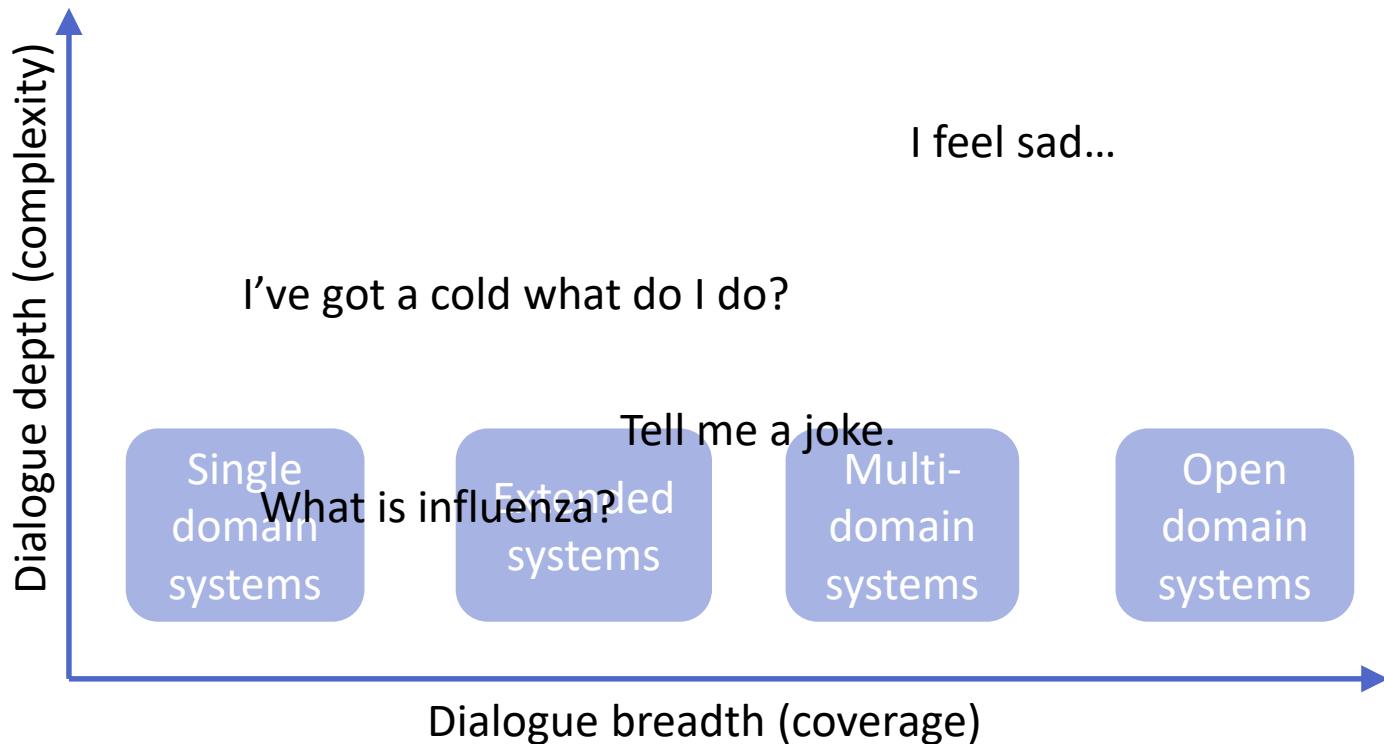
Outline

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Evolution Roadmap

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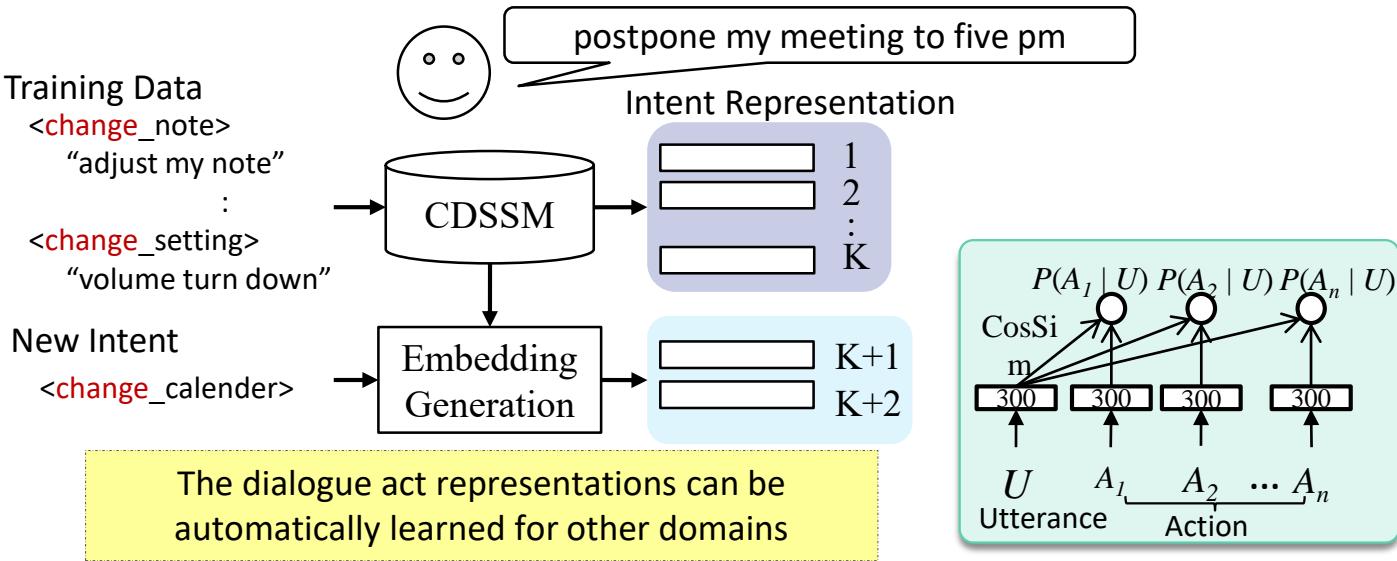


Intent Expansion (Chen et al., 2016)

260

<http://ieeexplore.ieee.org/abstract/document/7472838>

- Transfer dialogue acts across domains
 - Dialogue acts are similar for multiple domains
 - Learning new intents by information from other domains

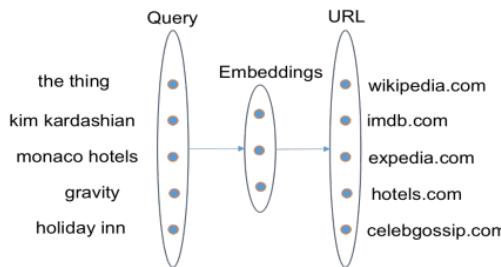


Zero-Shot Learning (Daupin et al., 2016)

261

<https://arxiv.org/abs/1401.0509>

- Semantic utterance classification
 - ▣ Use query click logs to define a task that makes the networks learn the meaning or intent behind the queries



$$\mathcal{L}(X, Y) = -\log P(Y|X) + \lambda H(P(C|X)).$$

Depiction of the deep network from queries to URLs.

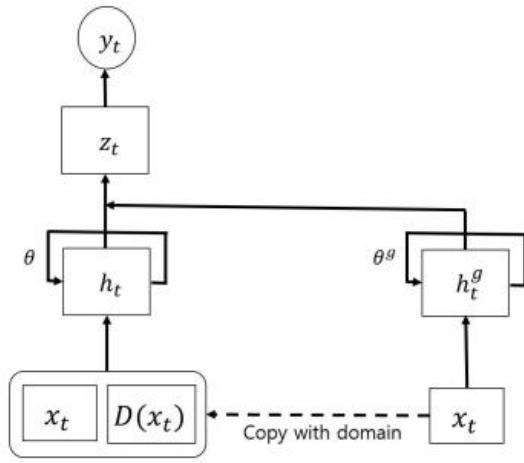
- ▣ The semantic features c can be learned

Domain Adaptation for SLU (Kim et al., 2016)

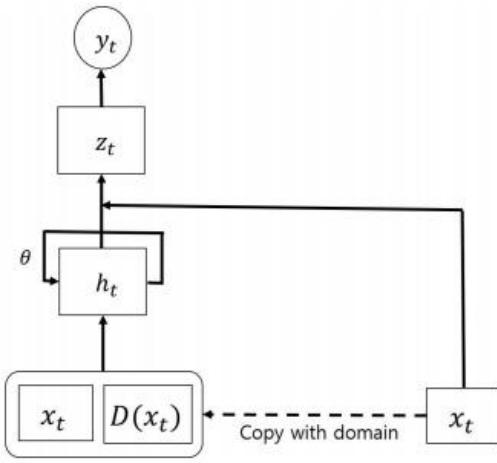
262

<http://www.aclweb.org/anthology/C/C16/C16-1038.pdf>

- Frustratingly easy domain adaptation
- Novel neural approaches to domain adaptation
- Improve slot tagging on several domains



(a) 1 domain specific LSTM + generic LSTM



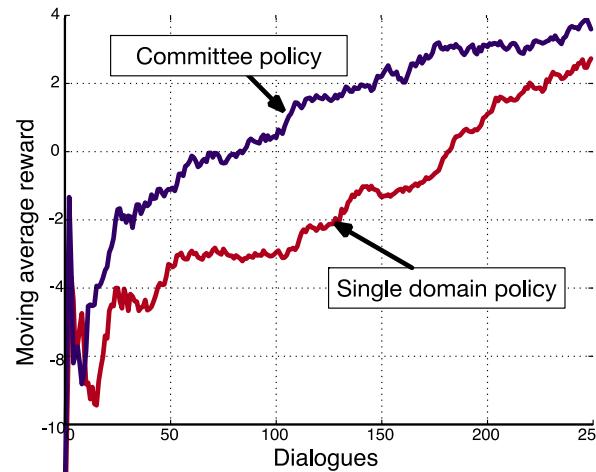
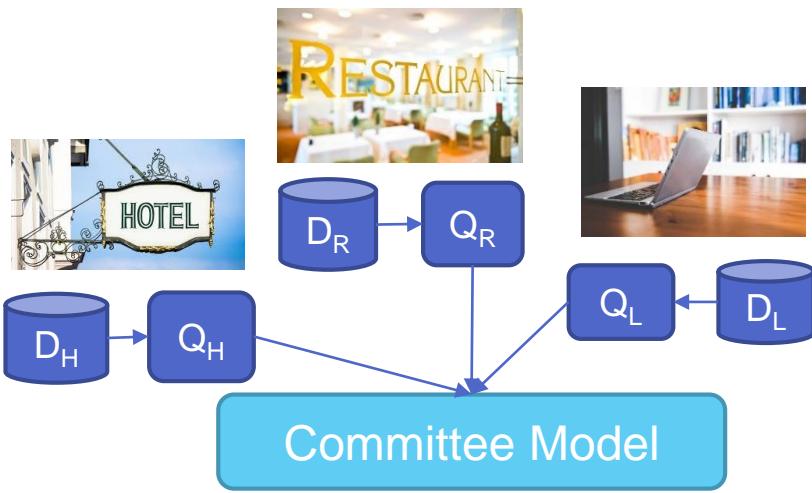
(b) 1 domain specific LSTM + generic embedding

Policy for Domain Adaptation (Gašić et al., 2015)

263

<http://ieeexplore.ieee.org/abstract/document/7404871>

- Bayesian committee machine (BCM) enables estimated Q-function to share knowledge across domains



The policy from a new domain can be boosted by the committee policy

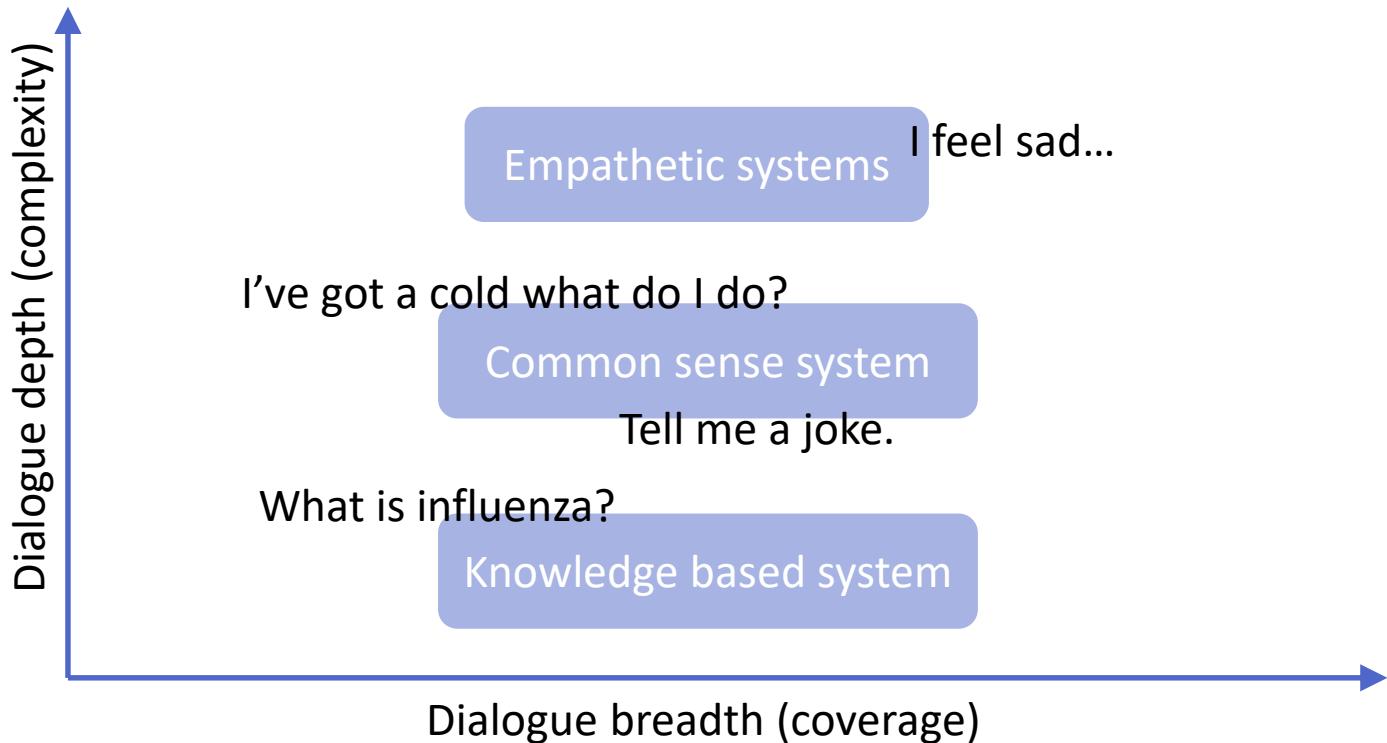
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Evolution Roadmap

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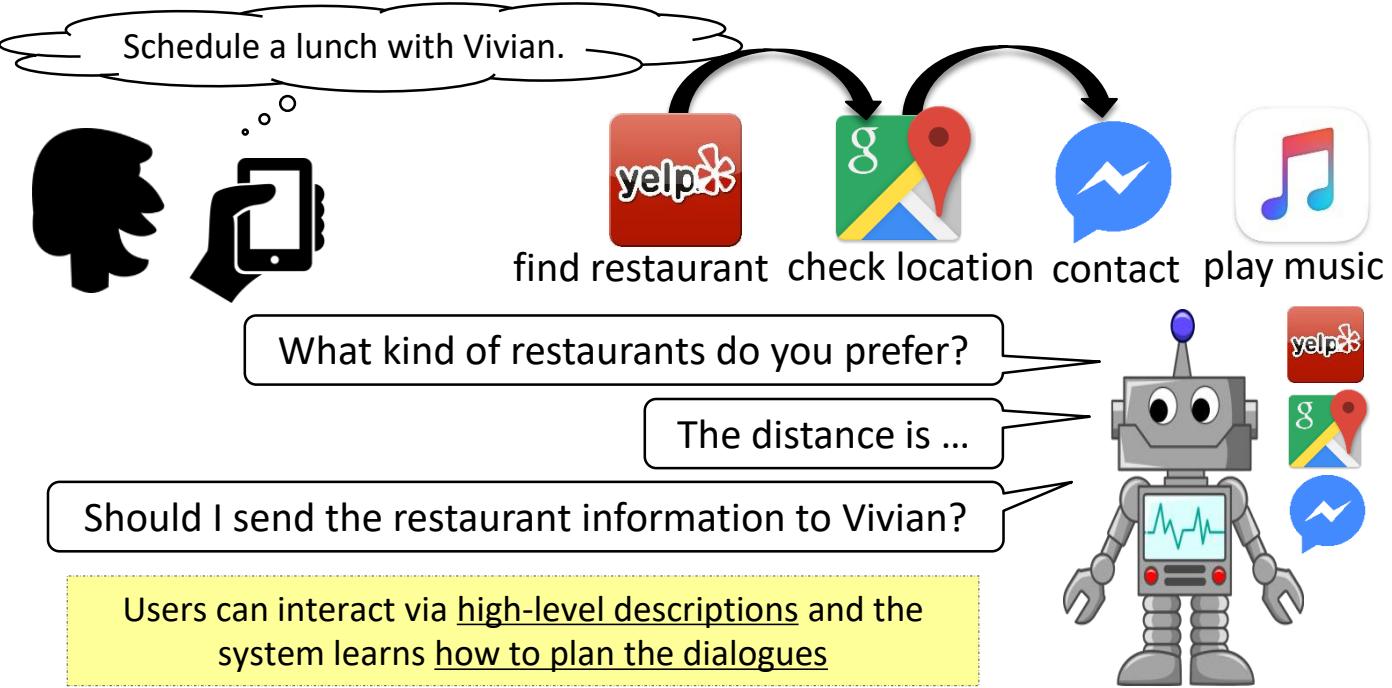
High-Level Intention for Dialogue Planning

(Sun et al., 2016; Sun et al., 2016)

266

<http://dl.acm.org/citation.cfm?id=2856818>; http://www.irec-conf.org/proceedings/irec2016/pdf/75_Paper.pdf

- High-level intention may span several domains



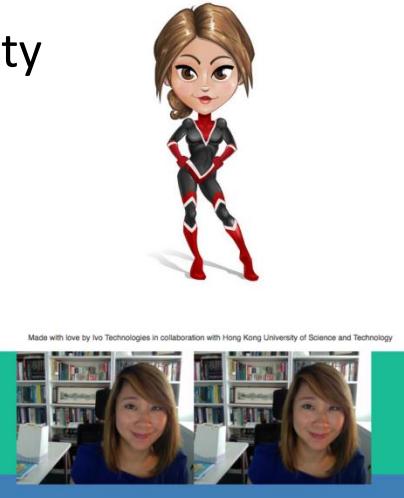
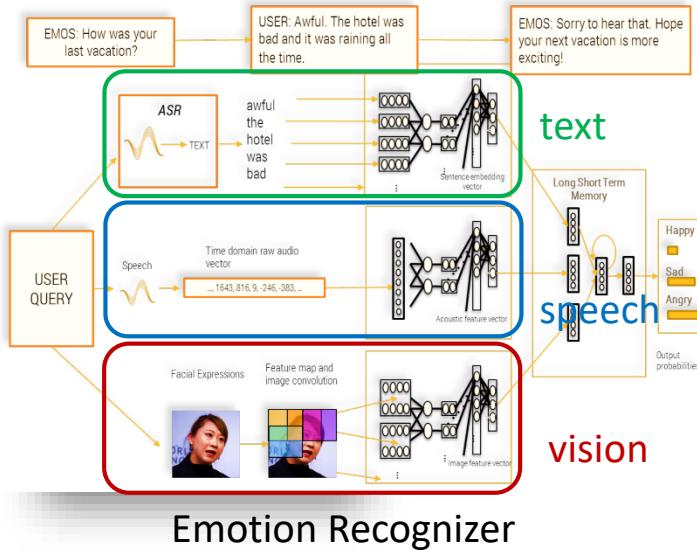
Empathy in Dialogue System (Fung et al., 2016)

267

<https://arxiv.org/abs/1605.04072>

Zara - The Empathetic Supergirl

- Embed an empathy module
 - Recognize emotion using multimodality
 - Generate emotion-aware responses



```
{ "recognition": "Race: Asian Confidence: 65.42750000000001 Smiling: 3.95896 Gender: Female Confidence: 88.9369", "race": "Asian", "race_confidence": "65.42750000000001", "smiling": "3.95896", "gender": "Female", "gender_confidence": "88.9369" }
```

Outline

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Challenges in Dialogue Modeling - I

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- **Semantic schema induction** (Chen et al., 2013; Athanasopoulou, et al., 2014)
 - No predefined semantic schema
 - How to learn from data?
- **Tractability, and dimensionality reduction methods**
 - Learning with large state action spaces
- **End-to-end learning methods**
 - Learning when the user input is complex NL utterance
 - Learning with humans or KBs ?
 - Learning under domain shifts

Challenges in Dialogue Modeling - II

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- **Multiple-State hypothesis**
 - ▣ Tracking a distribution over multiple dialog states can improve dialog accuracy
 - ▣ How does current dialog systems deal with this?
- **Proactive v.s. reactive approaches to dialog modeling**
 - ▣ How to build DM models when the agent is proactive (i.e., does not wait for the user but sends messages and drives the conversation)
- **Localization, personalization, etc.**
 - ▣ How to deal with issue pertaining to place, temporal and personal context. Mostly dealt on speech side. How about DM side for when learning the policy?
- **Hierarchical RL approach to policy learning actually works?**
 - ▣ When are they useful?
 - ▣ How about for open domain systems (like chit-chat) - Are they powerful?

Challenges in Dialogue Modeling - III

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□ Chat-Bot challenges

- Consistency: Keep similar answers in spite of different wordings
 - Human: *what is your job?*
 - Machine: *I am lawyer*
 - Human: *what do you do ?*
 - Machine: *I am a doctor*
- Quick domain-dependent adaptation: specially from unstructured data (Yan et.al, 2016)
- Personalization: handling profiles, interaction levels, and keep relevant context history (Li et al., 2016)
- Long sentence generation: most sentence are short or common phrases

Concluding Remarks

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Human-Robot interfaces is a hot topic but several components must be integrated!



Most state-of-the-art technologies are based on DNN

- Requires huge amounts of labeled data
- Several frameworks/models are available



Fast domain adaptation with scarce data + re-use of rules/knowledge



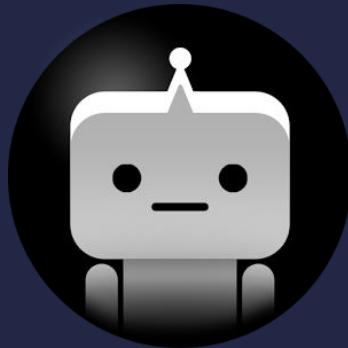
Handling reasoning



Data collection and analysis from un-structured data



Complex-cascade systems requires high accuracy for working good as a whole



We thanks Tsung-Hsien Wen, Pei-Hao Su, Li Deng, Sungjin Lee,
Milica Gašić, Lihong Li for sharing their slides

THANKS FOR ATTENTION!

Q & A