



YUN-NUNG (VIVIAN) CHEN



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Outline

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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)
- Evaluation
- Recent Trends and Challenges
 - End-to-End Neural Dialogue System
 - Multimodality
 - Dialogue Breath
 - Dialogue Depth

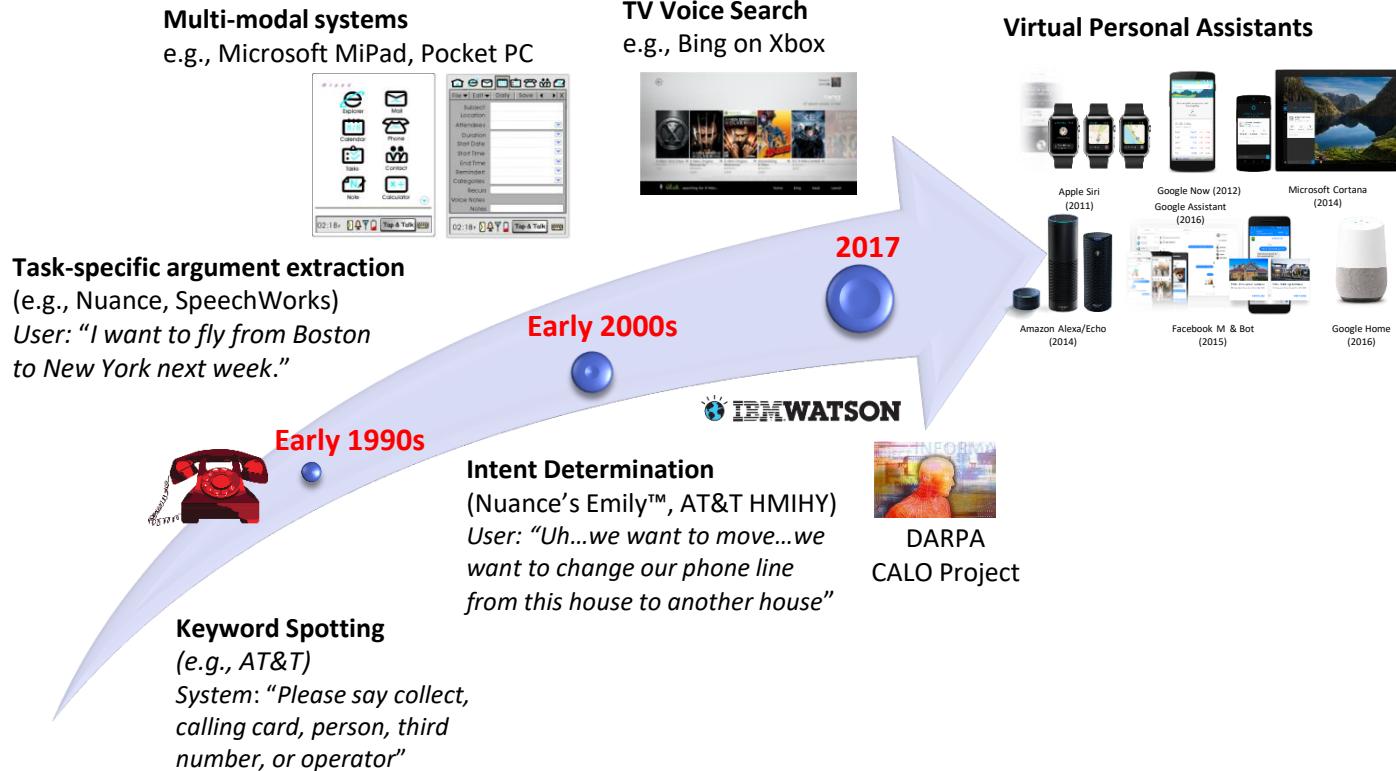
 Break

Introduction

Introduction

Brief History of Dialogue Systems

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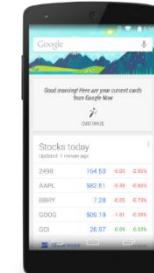


Language Empowering Intelligent Assistant

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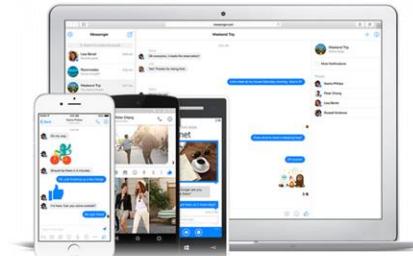
Apple Siri (2011)



Google Now (2012)
Google Assistant (2016)



Microsoft Cortana (2014)



Amazon Alexa/Echo (2014)

Facebook M & Bot (2015)

Google Home (2016)

Apple HomePod (2017)

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**.

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



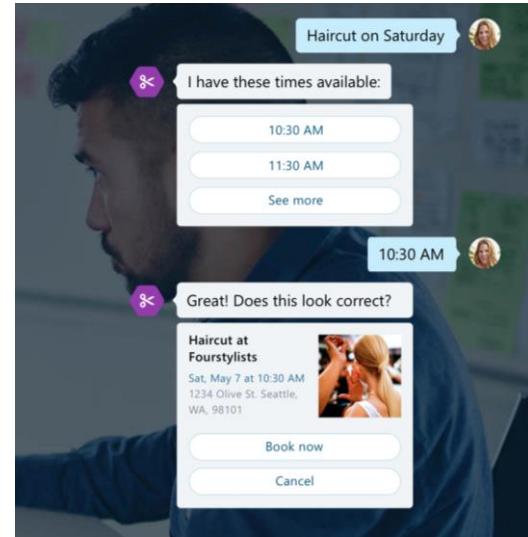
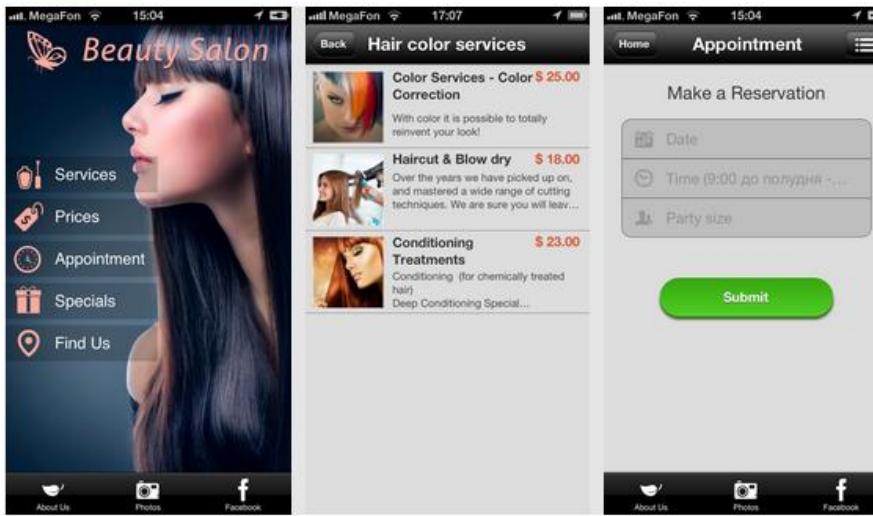
Baymax – Personal Healthcare Companion

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

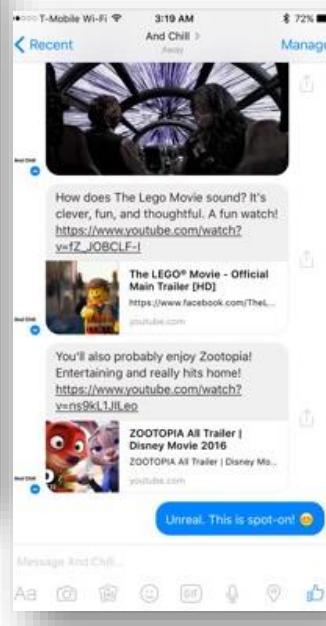
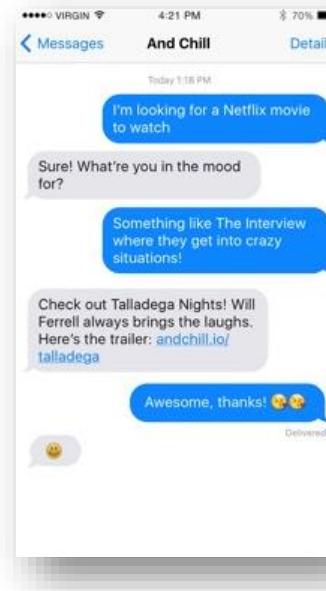
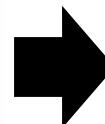


Users can initiate dialogues instead of following the GUI design

GUI v.s. CUI (Conversational UI)

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



GUI v.s. CUI (Conversational UI)

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	Website/APP's GUI	Msg's CUI
Situation	Navigation, no specific goal	Searching, with specific goal
Information Quantity	More	Less
Information Precision	Low	High
Display	Structured	Non-structured
Interface	Graphics	Language
Manipulation	Click	mainly use texts or speech as input
Learning	Need time to learn and adapt	No need to learn
Entrance	App download	Incorporated in any msg-based interface
Flexibility	Low, like machine manipulation	High, like converse with a human

Challenges

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- Variability in Natural Language
- Robustness
- Recall/Precision Trade-off
- Meaning Representation
- Common Sense, World Knowledge
- Ability to Learn
- Transparency

Two Branches of Bots

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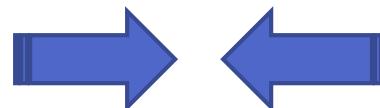
Task-Oriented Bot

- 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)



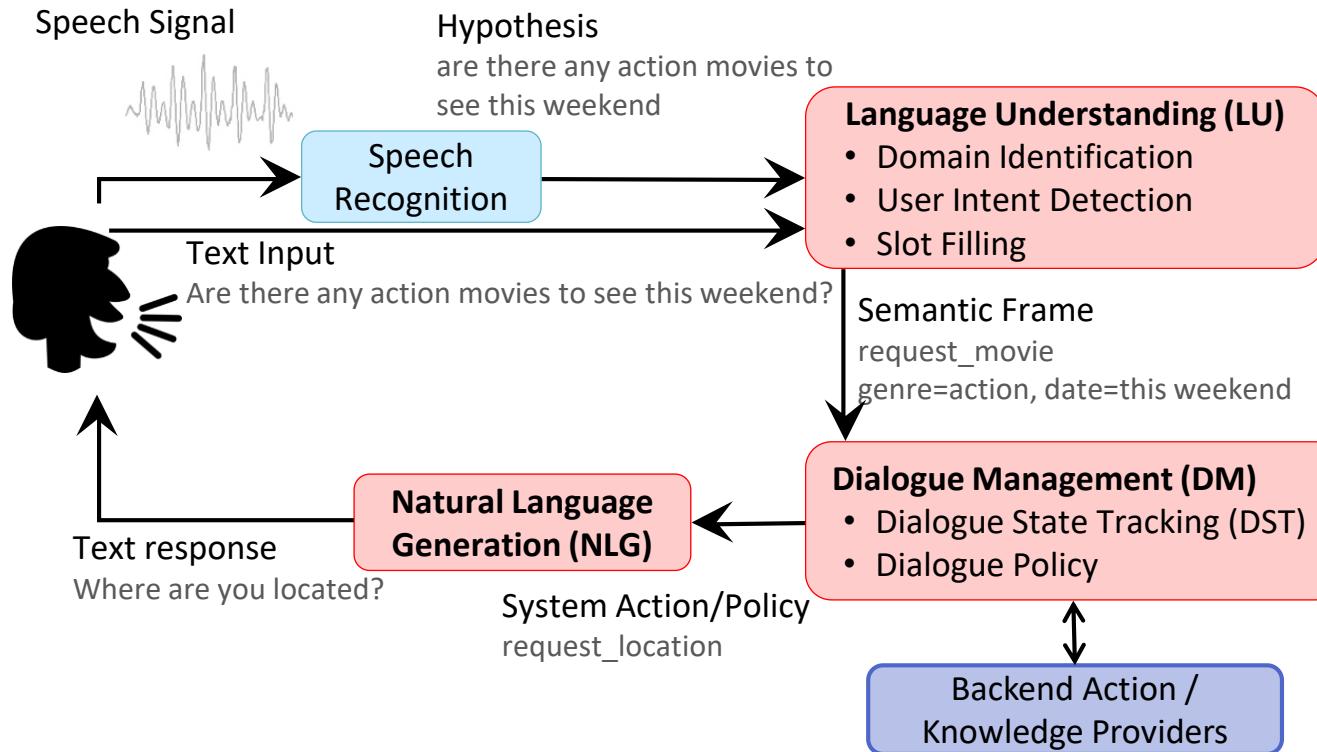
Chit-Chat Bot

- 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

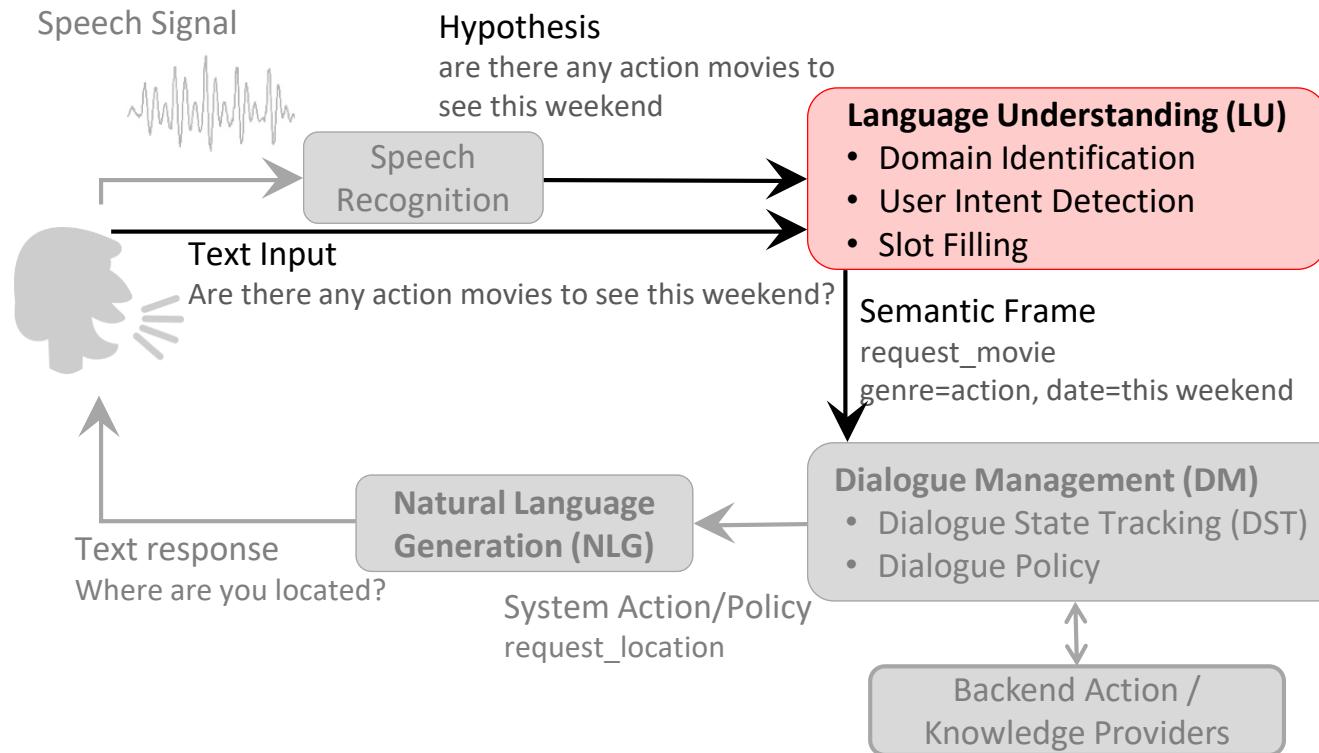
Agent

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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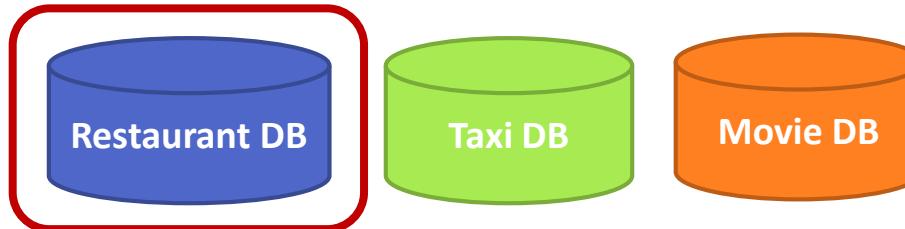
User



find a good eating place for taiwanese food



Intelligent
Agent



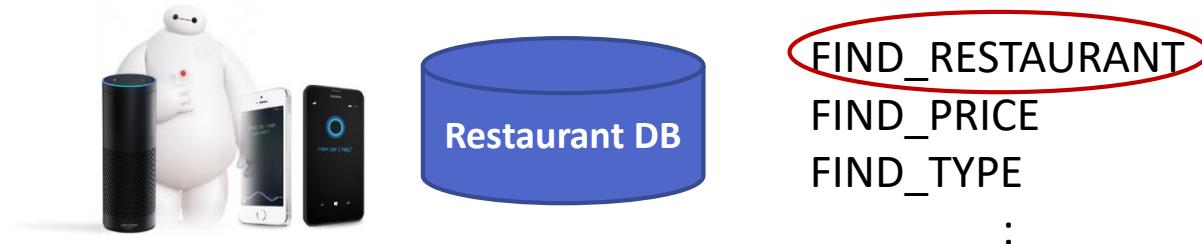
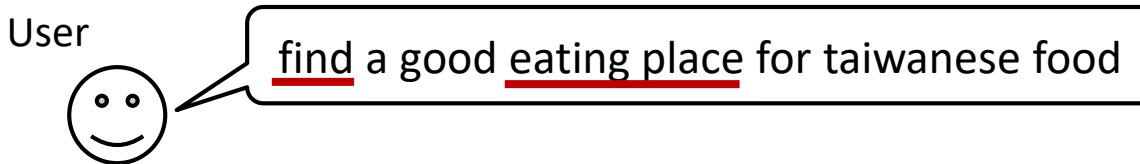
Organized Domain Knowledge (Database)

Classification!

2. Intent Detection

Requires Predefined Schema

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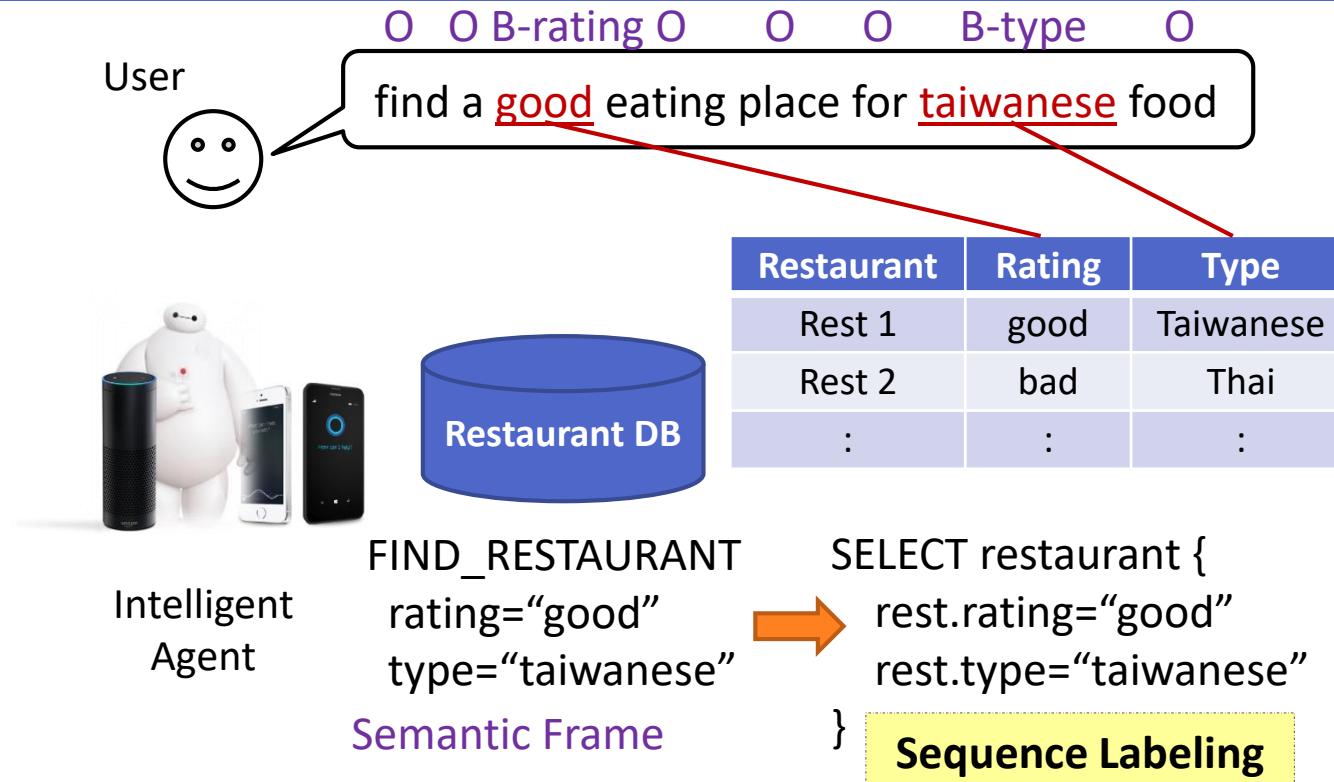
Intelligent
Agent

Classification!

3. Slot Filling

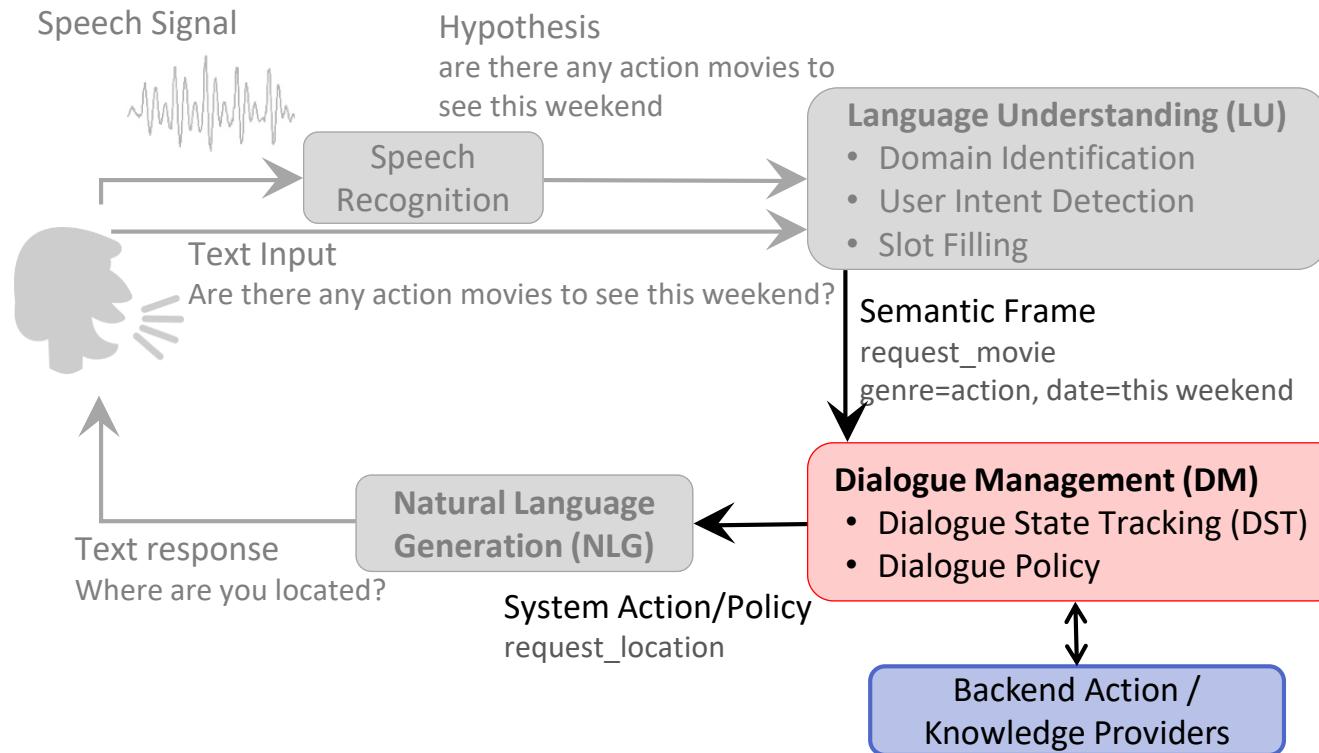
Requires Predefined Schema

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Task-Oriented Dialogue System (Young, 2000)

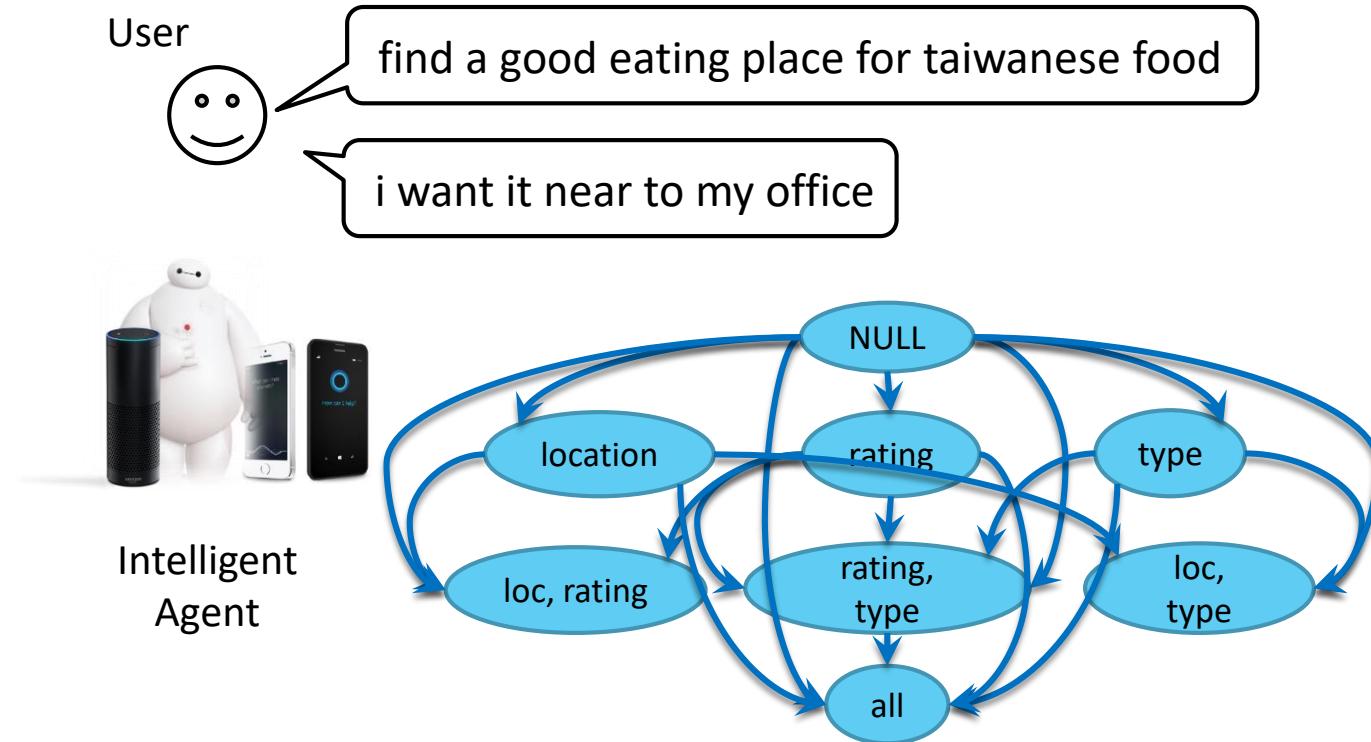
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State Tracking

Requires Hand-Crafted States

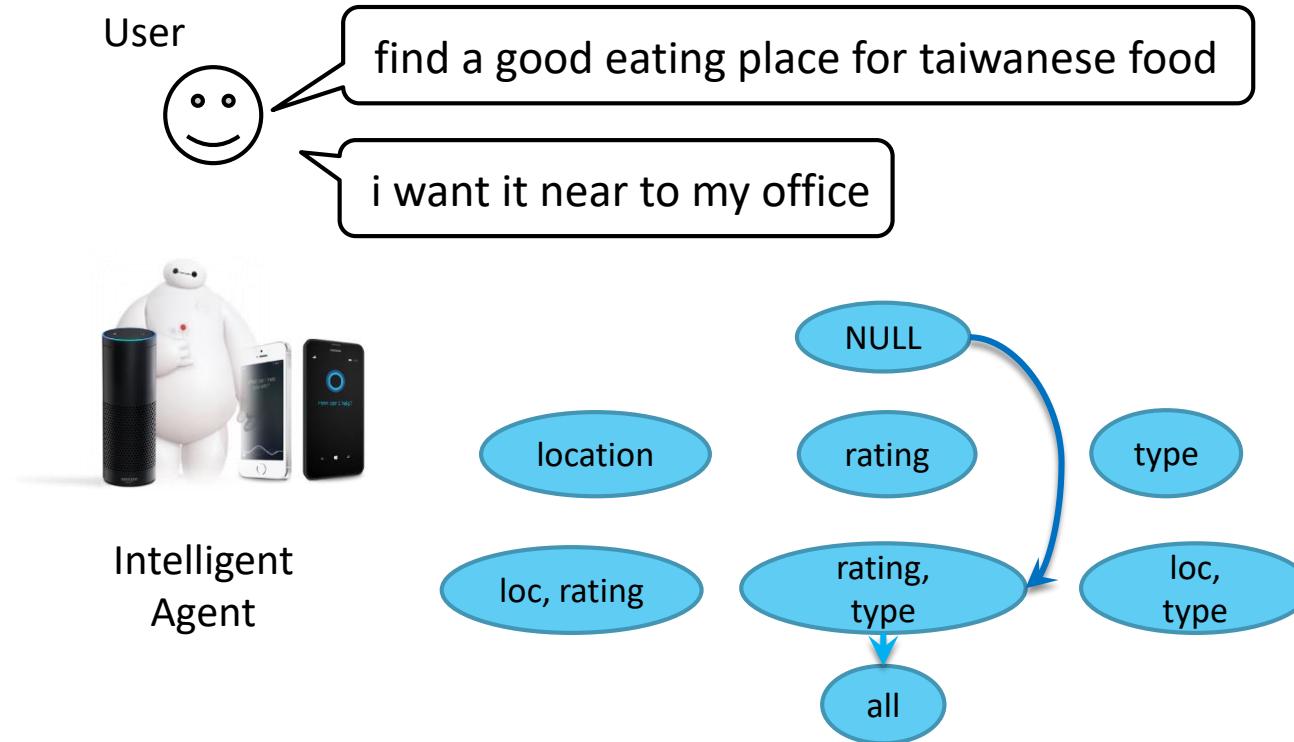
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State Tracking

Requires Hand-Crafted States

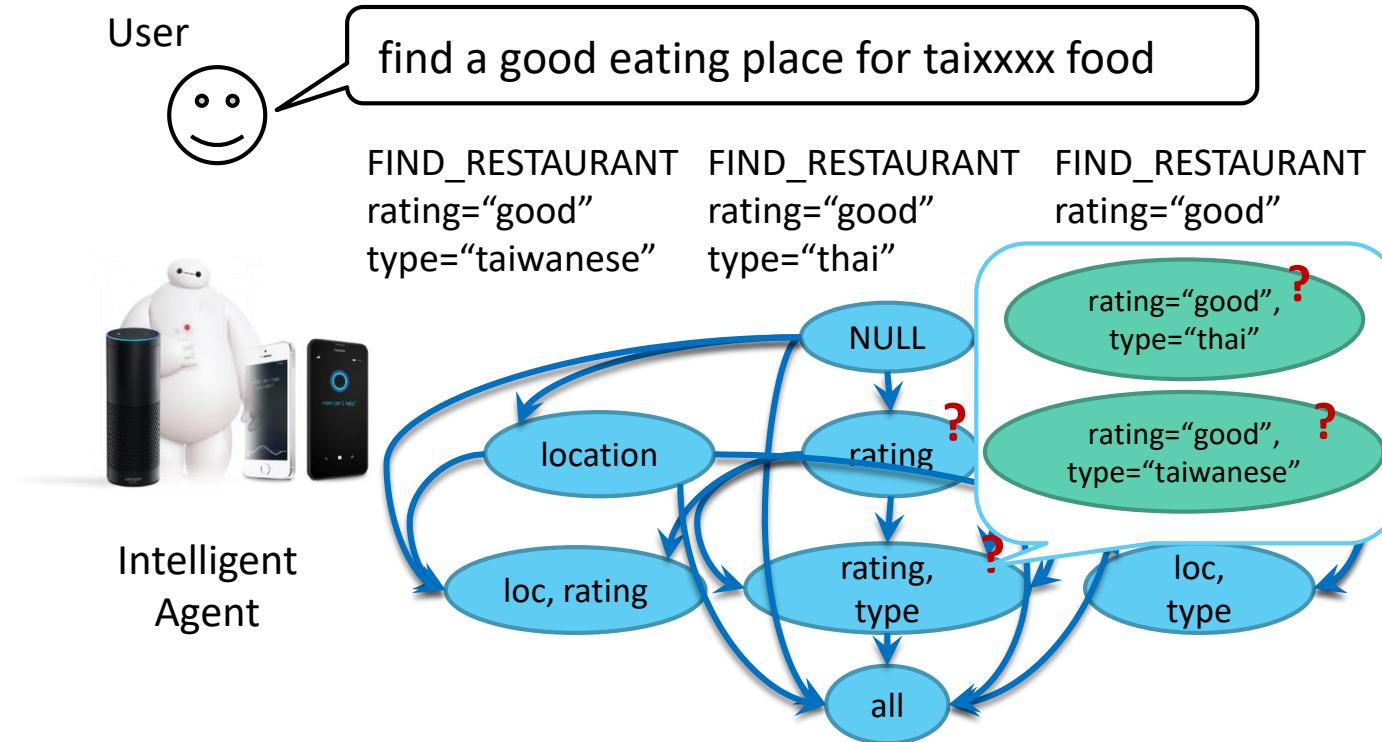
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State Tracking

Handling Errors and Confidence

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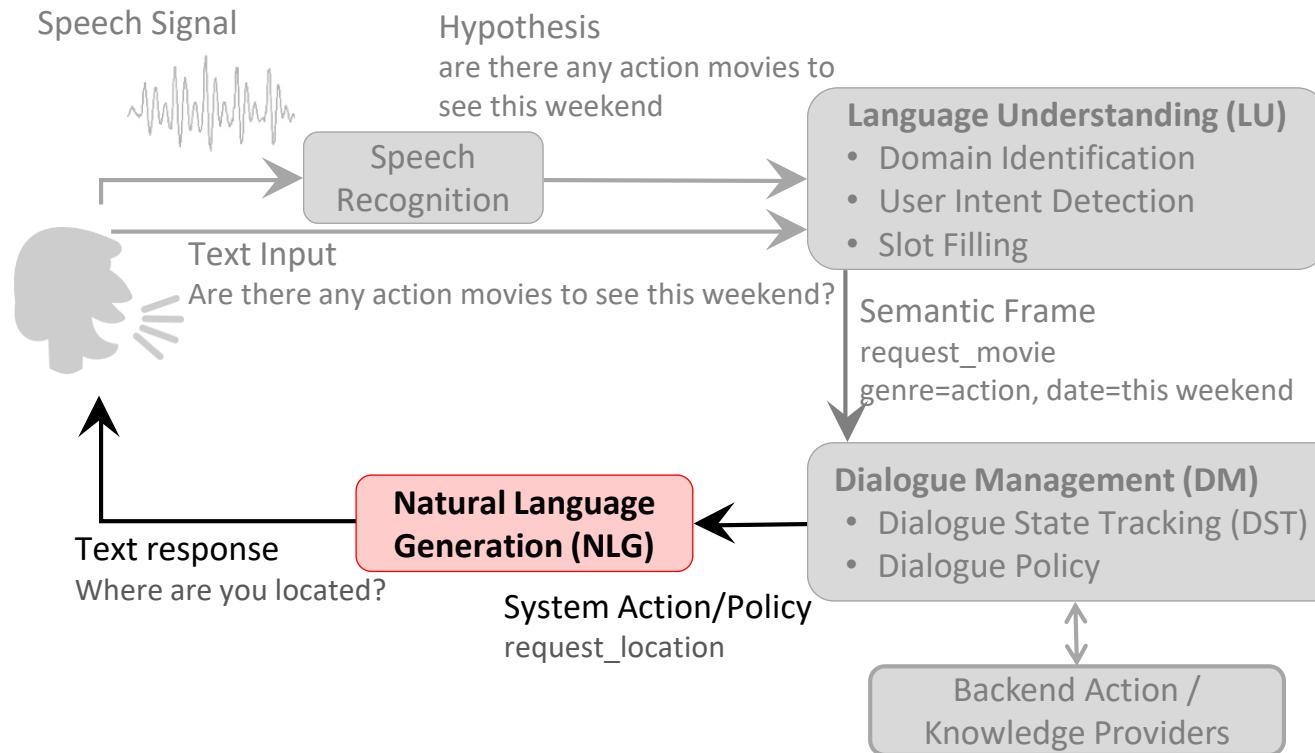
Dialogue Policy for Agent Action

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- Inform(location=“Taipei 101”)
 - ▣ “The nearest one is at Taipei 101”
- Request(location)
 - ▣ “Where is your home?”
- Confirm(type=“taiwanese”)
 - ▣ “Did you want Taiwanese food?”

Task-Oriented Dialogue System (Young, 2000)

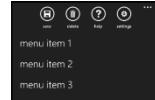
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Output / Natural Language Generation

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- Goal: generate natural language or GUI given the selected dialogue action for interactions
- Inform(location="Taipei 101")
 - "The nearest one is at Taipei 101" v.s.
- Request(location)
 - "Where is your home?" v.s.
- Confirm(type="taiwanese")
 - "Did you want Taiwanese food?" v.s.



Background Knowledge

Neural Network Basics

Reinforcement Learning

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Machine Learning ≈ Looking for a Function

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- Speech Recognition

$$f(\text{[spectrogram image]}) = \text{“你好 (Hello) ”}$$

- Image Recognition

$$f(\text{[cat image]}) = \text{cat}$$

- Go Playing

$$f(\text{[go board image]}) = \text{5-5 (next move)}$$

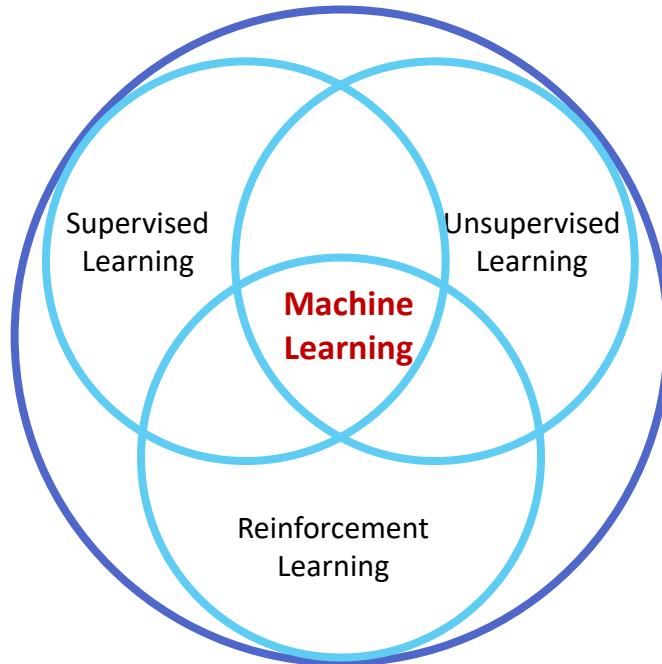
- Chat Bot

$$f(\text{“Where is Westin?”}) = \text{“The address is...”}$$

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

Machine Learning

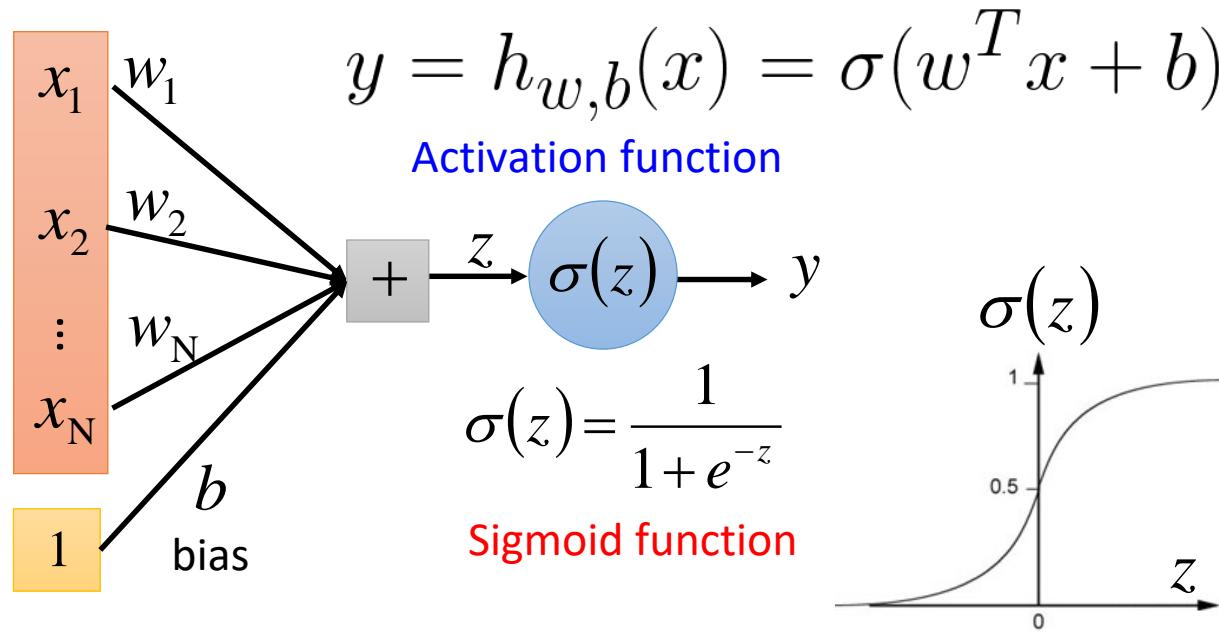
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Deep learning is a type of machine learning approaches, called “neural networks”.

A Single Neuron

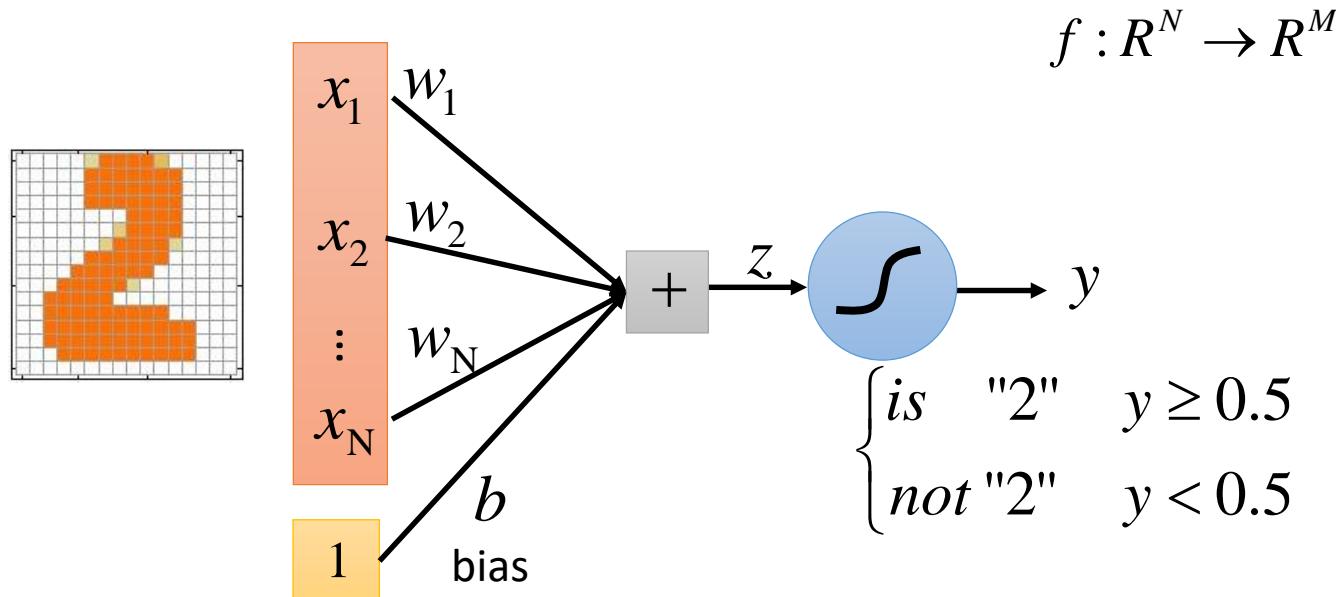
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w, b are the parameters of this neuron

A Single Neuron

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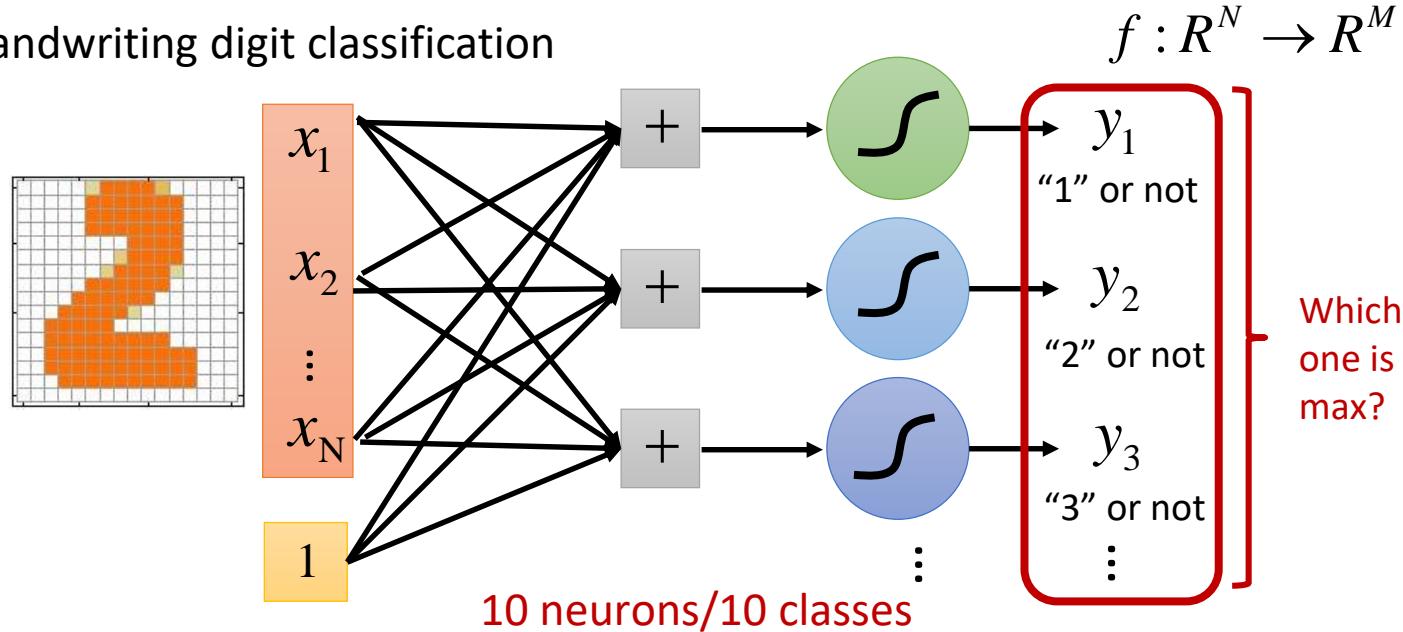


A single neuron can only handle binary classification

A Layer of Neurons

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- Handwriting digit classification



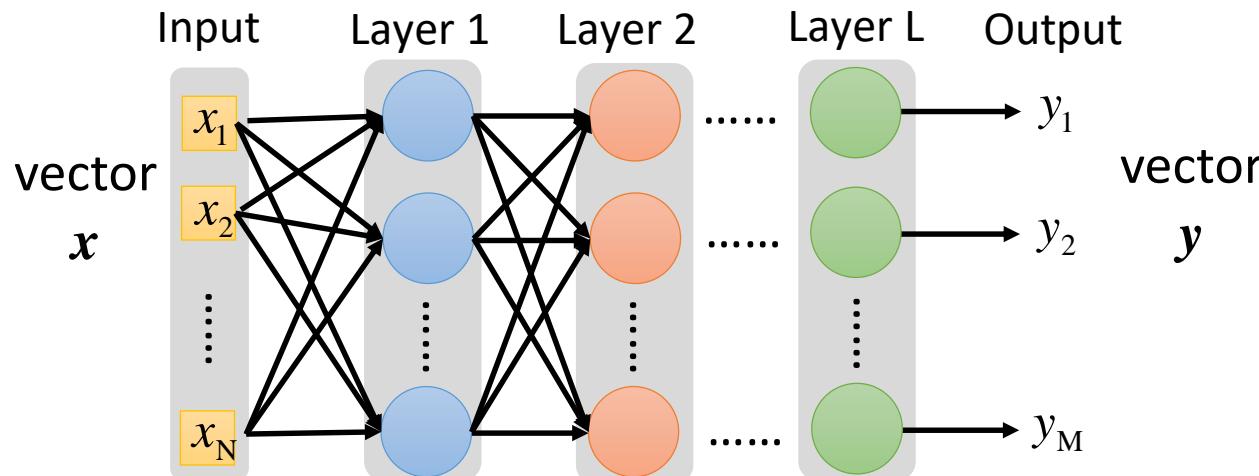
A layer of neurons can handle multiple possible output, and the result depends on the max one

Deep Neural Networks (DNN)

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- Fully connected feedforward network

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



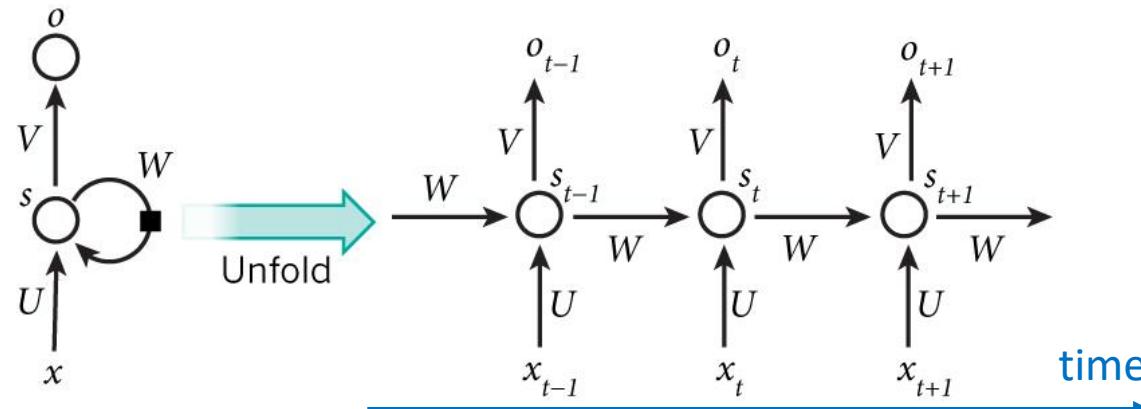
Deep NN: multiple hidden layers

Recurrent Neural Network (RNN)

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$$s_t = \sigma(Ws_{t-1} + Ux_t) \quad \sigma(\cdot): \text{tanh, ReLU}$$

$$o_t = \text{softmax}(Vs_t)$$



RNN can learn accumulated sequential information (time-series)

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Reinforcement Learning

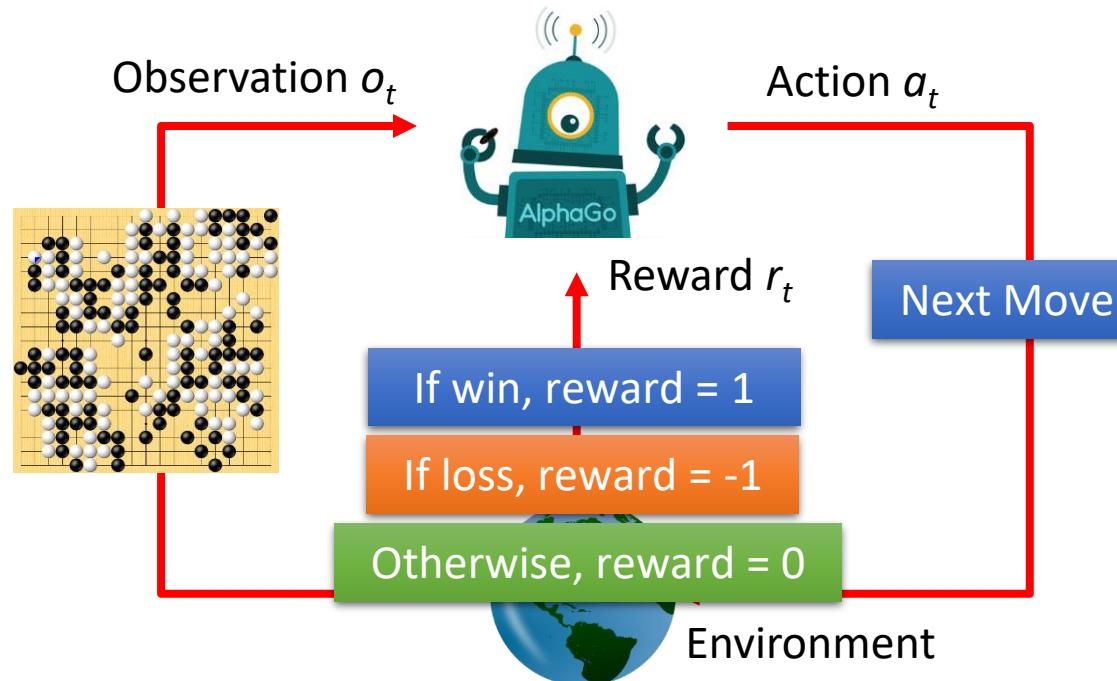
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- RL is a general purpose framework for **decision making**
 - RL is for an *agent* with the capacity to *act*
 - Each *action* influences the agent's future *state*
 - Success is measured by a scalar *reward* signal
 - Goal: *select actions to maximize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



Scenario of Reinforcement Learning

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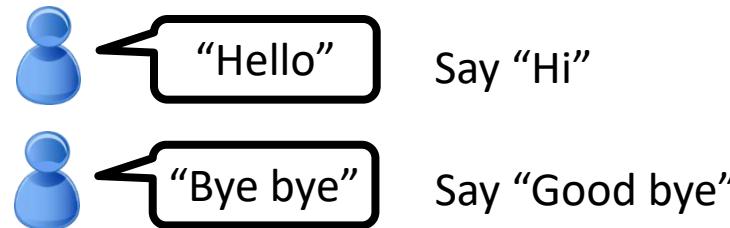
Agent learns to take actions to maximize expected reward.

Supervised v.s. Reinforcement

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□ Supervised

Learning from teacher



□ Reinforcement



.....



Bad

Learning from critics

Hello 😊

Agent

.....

Agent

Sequential Decision Making

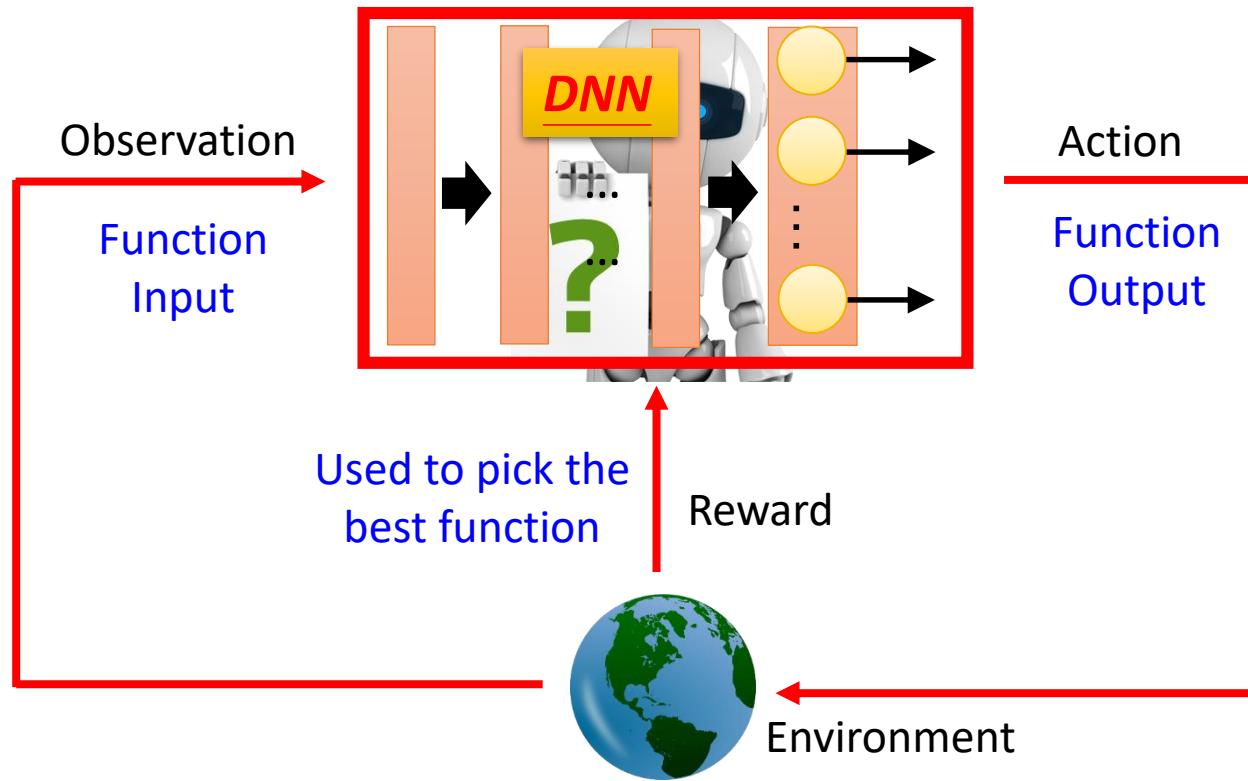
40

- 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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Reinforcing Learning

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- Start from state s_0
- Choose action a_0
- Transit to $s_1 \sim P(s_0, a_0)$
- Continue...

$$s_0 \xrightarrow{a_0} s_1 \xrightarrow{a_1} s_2 \xrightarrow{a_2} s_3 \xrightarrow{a_3} \dots$$

- Total reward: $R(s_0) + \gamma R(s_1) + \gamma^2 R(s_2) + \dots$

Goal: select actions that maximize the expected total reward

$$\mathbb{E}[R(s_0) + \gamma R(s_1) + \gamma^2 R(s_2) + \dots]$$

Reinforcement Learning Approach

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- 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

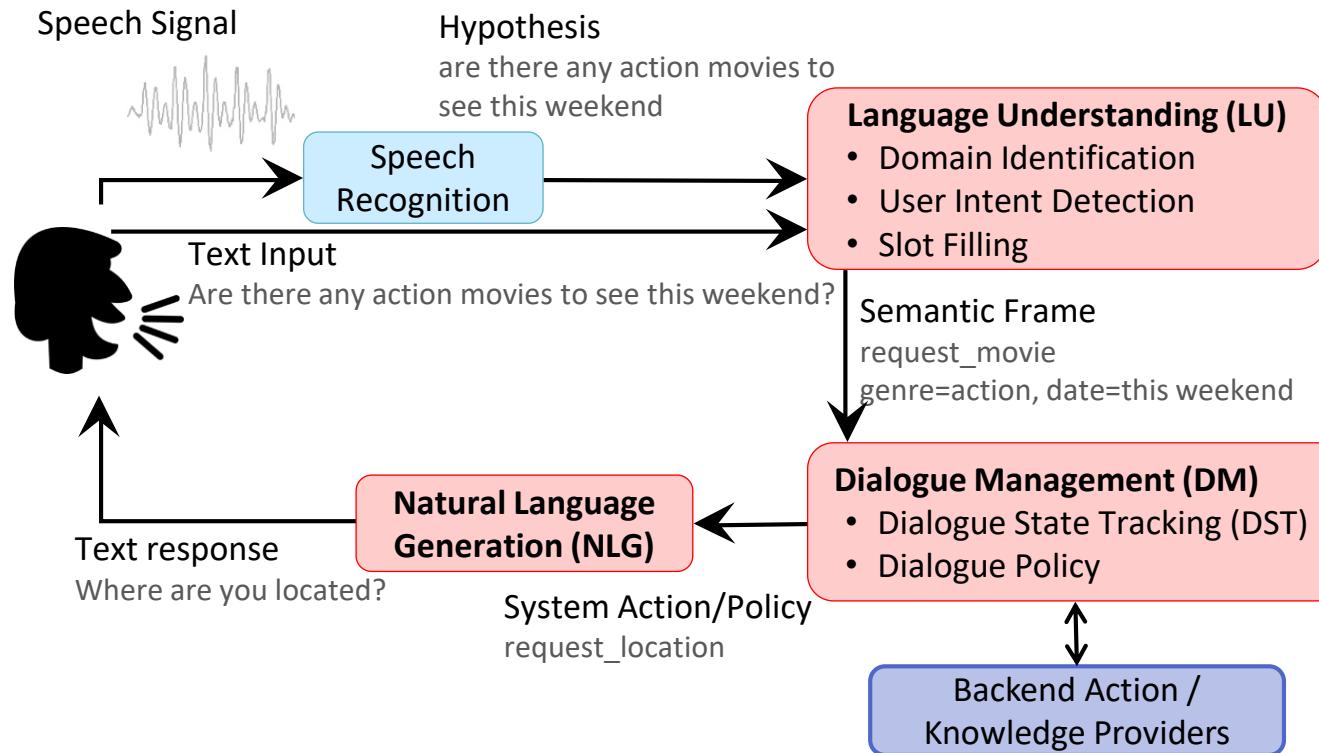
- Model-based RL

- Build a model of the environment
 - Plan (e.g. by lookahead) using model

Modular Dialogue System

Task-Oriented Dialogue System (Young, 2000)

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

Outline

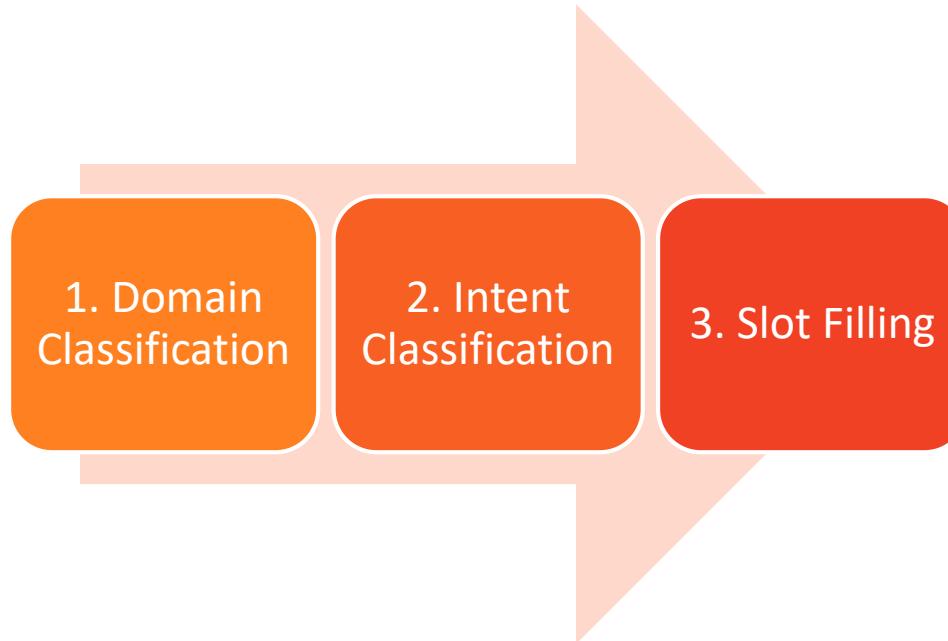
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Language Understanding (LU)

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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

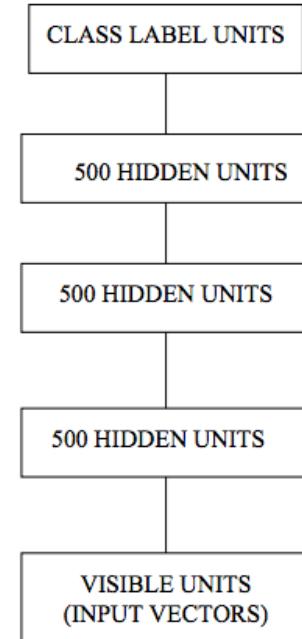
Movies	Find_movie
Restaurants	Buy_tickets
Sports	Find_restaurant
Weather	Book_table
Music	Find_lyrics
...	...

DNN for Domain/Intent Classification – I (Sarikaya et al., 2011)

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<http://ieeexplore.ieee.org/abstract/document/5947649/>

- Deep belief nets (DBN)
 - ▣ Unsupervised training of weights
 - ▣ Fine-tuning by back-propagation
 - ▣ Compared to MaxEnt, SVM, and boosting

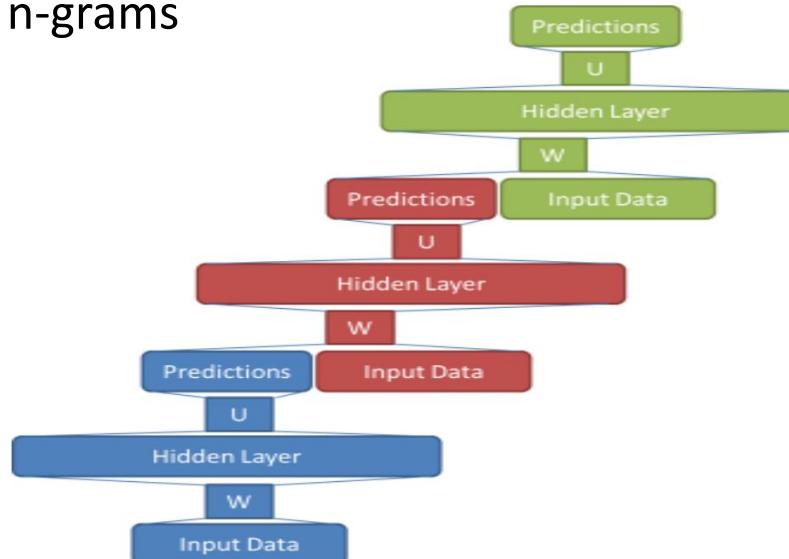


DNN for Domain/Intent Classification – II (Tur et al., 2012; Deng et al., 2012)

50

<http://ieeexplore.ieee.org/abstract/document/6289054/>; [http://ieeexplore.ieee.org/abstract/document/6424224/](http://ieeexplore.ieee.org/abstract/document/6424224)

- Deep convex networks (DCN)
 - ▣ Simple classifiers are stacked to learn complex functions
 - ▣ Feature selection of salient n-grams
- Extension to kernel-DCN

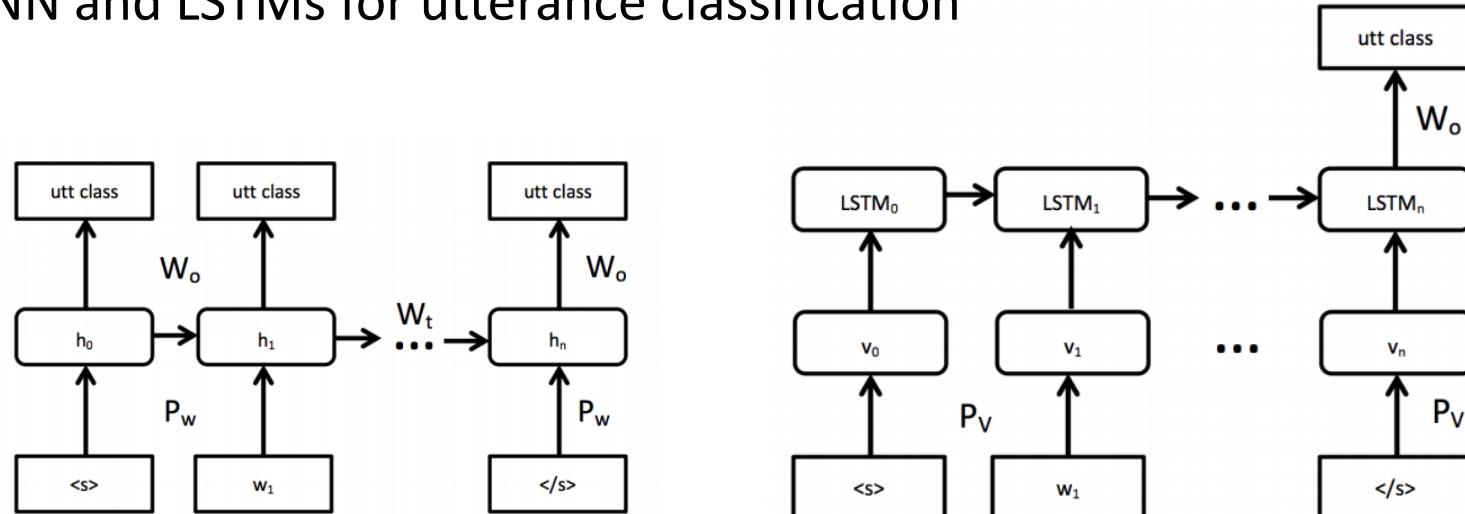


DNN for Domain/Intent Classification – III (Ravuri & Stolcke, 2015)

51

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

□ RNN and LSTMs for utterance classification

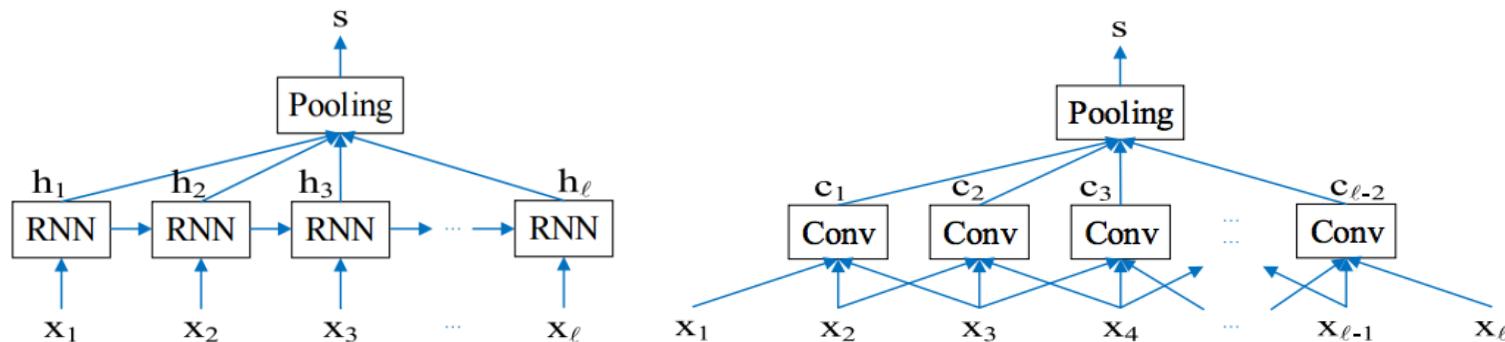


Intent decision after reading all words performs better

DNN for Dialogue Act Classification – IV (Lee & Dernoncourt, 2016)

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□ RNN and CNNs for dialogue act classification



LU – Slot Filling

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As a sequence
tagging task

- Given a collection tagged word sequences, $S=\{((w_{1,1}, w_{1,2}, \dots, w_{1,n1}), (t_{1,1}, t_{1,2}, \dots, t_{1,n1})), ((w_{2,1}, w_{2,2}, \dots, w_{2,n2}), (t_{2,1}, t_{2,2}, \dots, t_{2,n2})) \dots\}$ 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

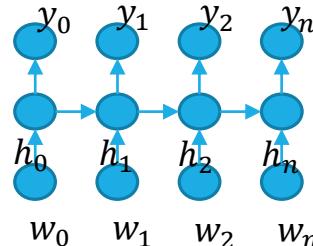
Recurrent Neural Nets for Slot Tagging – I (Yao et al, 2013; Mesnil et al, 2015)

54

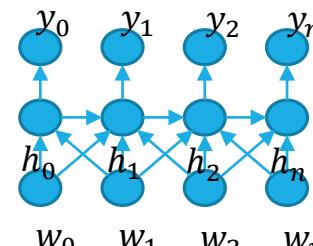
<http://131.107.65.14/en-us/um/people/gzweig/Pubs/Interspeech2013RNNLU.pdf>; <http://dl.acm.org/citation.cfm?id=2876380>

□ Variations:

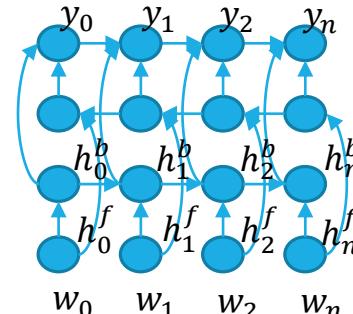
- a. RNNs with LSTM cells
- b. Input, sliding window of n-grams
- c. Bi-directional LSTMs



(a) LSTM



(b) LSTM-LA

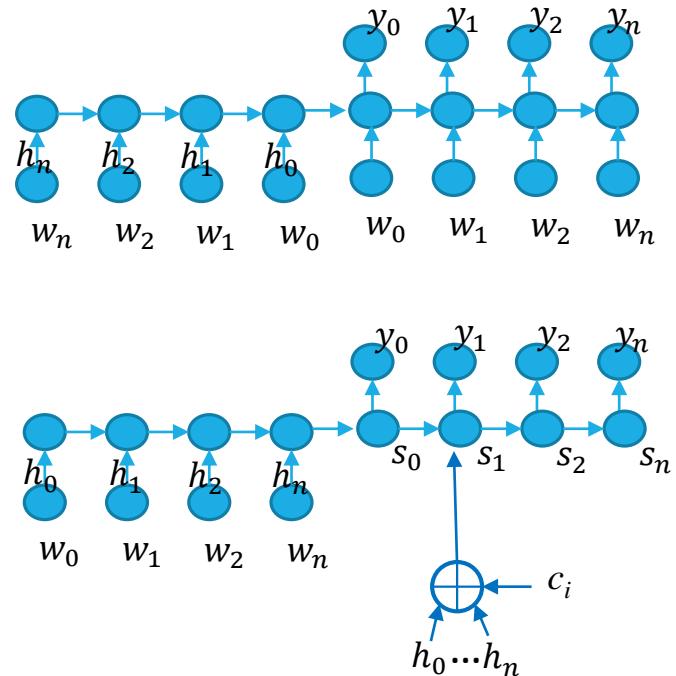


(c) bLSTM

Recurrent Neural Nets for Slot Tagging – II (Kurata et al., 2016; Simonnet et al., 2015)

- 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

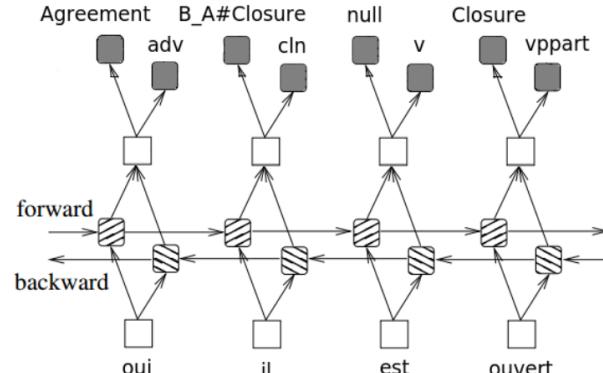


Recurrent Neural Nets for Slot Tagging – III (Jaech et al., 2016; Tafforeau et al., 2016)

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<https://arxiv.org/abs/1604.00117>; http://www.sensei-conversation.eu/wp-content/uploads/2016/11/favre_is2016b.pdf

- Multi-task learning
 - Goal: exploit data from domains/tasks with a lot of data to improve ones with less data
 - Lower layers are shared across domains/tasks
 - Output layer is specific to task

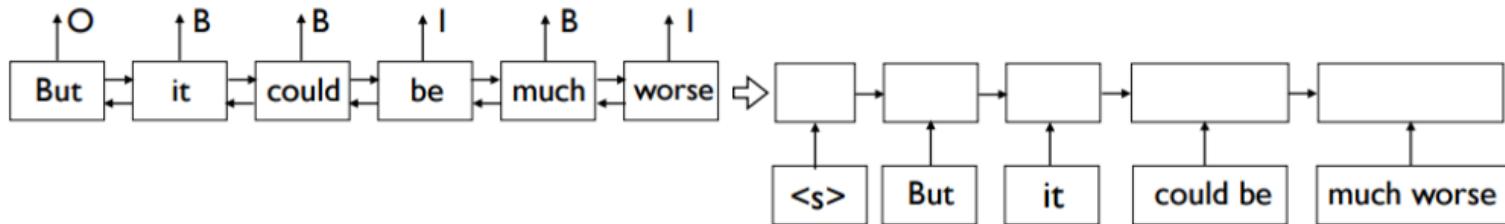


Joint Segmentation and Slot Tagging (Zhai et al., 2017)

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<https://arxiv.org/pdf/1701.04027.pdf>

- Encoder that segments
- Decoder that tags the segments



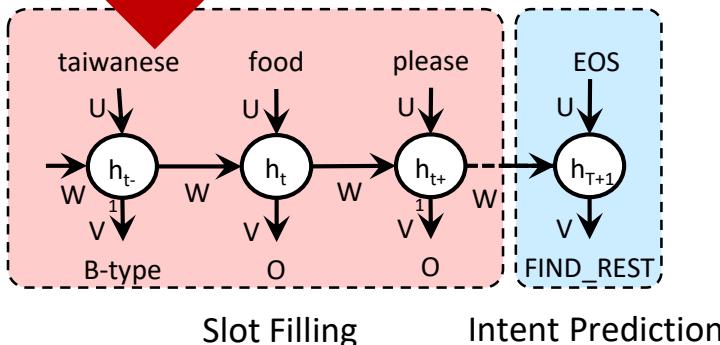
Joint Semantic Frame Parsing

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

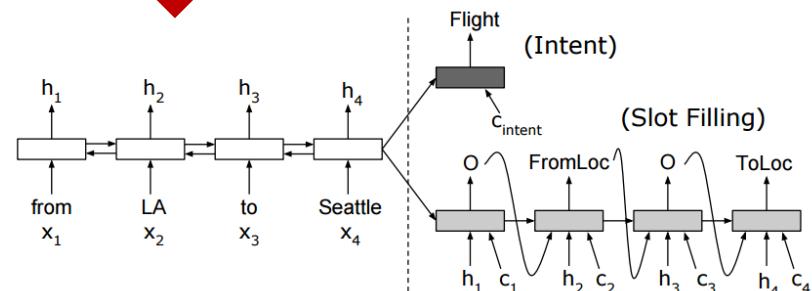
Sequence-based
(Hakkani-Tur et al., 2016)

- 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



Contextual LU

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Domain Identification → Intent Prediction → Slot Filling

D communication *I* send_email

U just sent email to bob about fishing this weekend
 S O O O O O O O O O O
 B-contact_name B-subject I-subject I-subject
 \rightarrow send_email(contact_name="bob", subject="fishing this weekend")

Single Turn

U_1 send email to bob

S_1 B-contact_name
 \rightarrow send_email(contact_name="bob")

Multi-Turn

U_2 are we going to fish this weekend

S_2 B-message I-message I-message I-message I-message I-message
 I-message I-message I-message I-message I-message

\rightarrow send_email(message="are we going to fish this weekend")

Contextual LU

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- User utterances are highly ambiguous in isolation

Restaurant
Booking



Book a table for 10 people tonight.

Which restaurant would you like to book a table for?



Cascal, for 6.



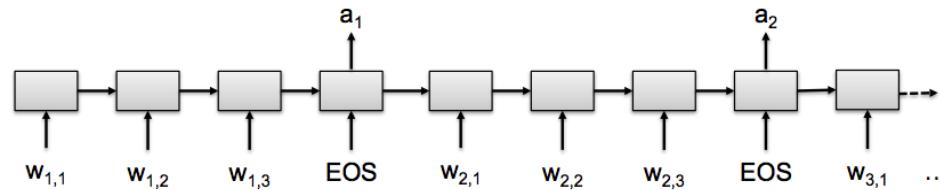
#people time

Contextual LU (Bhargava et al., 2013; Hori et al, 2015)

61

<https://www.merl.com/publications/docs/TR2015-134.pdf>

- Leveraging contexts
 - ▣ Used for individual tasks
- Seq2Seq model
 - ▣ Words are input one at a time, tags are output at the end of each utterance



- Extension: LSTM with speaker role dependent layers

End-to-End Memory Networks (Sukhbaatar et al, 2015)

62

U: "i d like to purchase tickets to see deepwater horizon"

S: "for which theatre"

U: "angelika"

S: "you want them for angelika theatre?"

U: "yes angelika"

S: "how many tickets would you like ?"

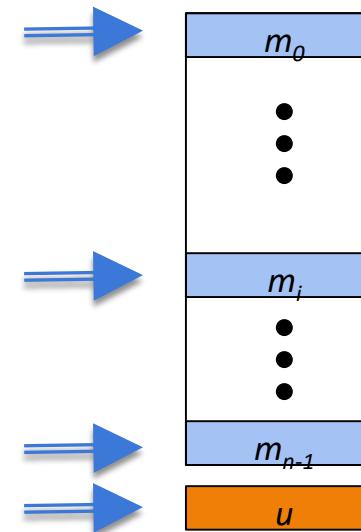
U: "3 tickets for saturday"

S: "What time would you like ?"

U: "Any time on saturday is fine"

S: "okay , there is 4:10 pm , 5:40 pm and 9:20 pm"

U: "Let's do 5:40"



E2E MemNN for Contextual LU (Chen et al., 2016)

63

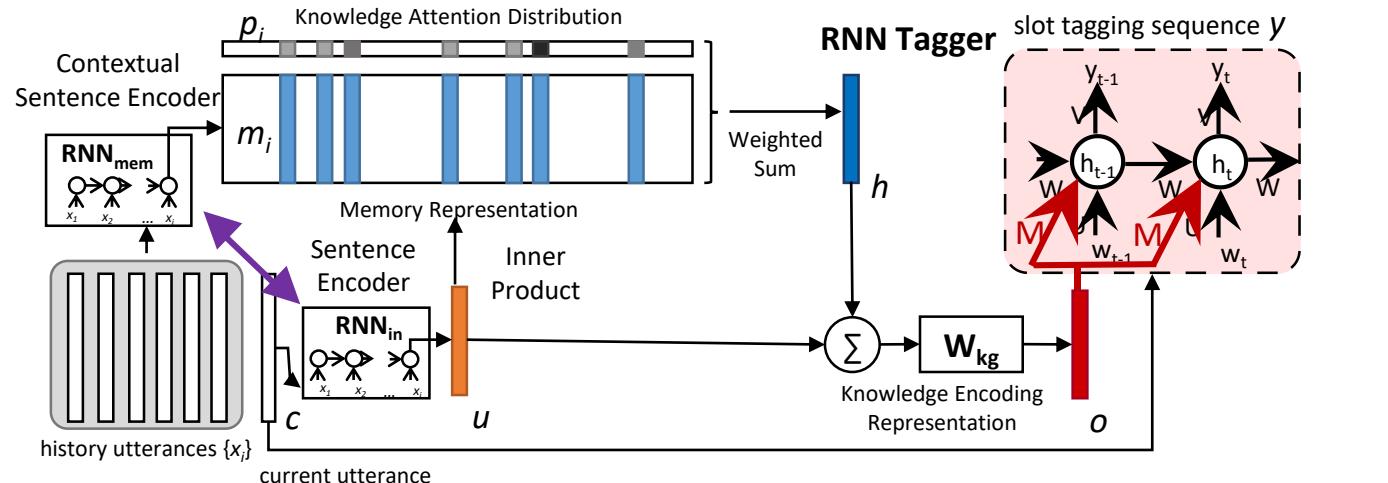
https://www.microsoft.com/en-us/research/wp-content/uploads/2016/06/IS16_ContextualSLU.pdf

1. Sentence Encoding

$$m_i = \text{RNN}_{\text{mem}}(x_i) \\ u = \text{RNN}_{\text{in}}(c)$$

2. Knowledge Attention

$$p_i = \text{softmax}(u^T m_i)$$



Idea: additionally incorporating contextual knowledge during slot tagging
 → track dialogue states in a latent way

Analysis of Attention

64

U: "i d like to purchase tickets to see deepwater horizon" → 0.69

S: "for which theatre"

U: "angelika"

S: "you want them for angelika theatre?"

U: "yes angelika"

S: "how many tickets would you like ?" → 0.13

U: "3 tickets for saturday"

S: "What time would you like ?"

U: "Any time on saturday is fine"

S: "okay , there is 4:10 pm , 5:40 pm and 9:20 pm" → 0.16

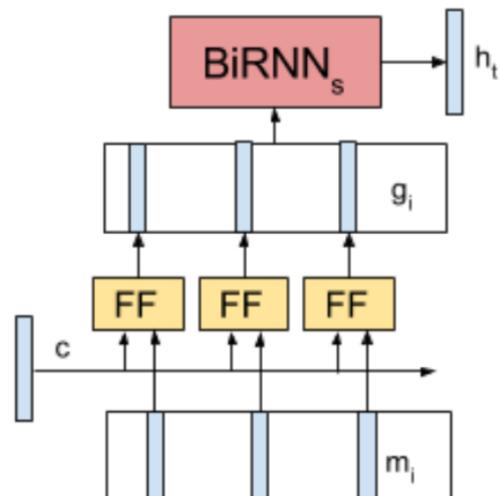
U: "Let's do 5:40"

Sequential Dialogue Encoder Network (Bapna et al., 2017)

65

Bapna et.al., SIGDIAL 2017

- Past and current turn encodings input to a feed forward network

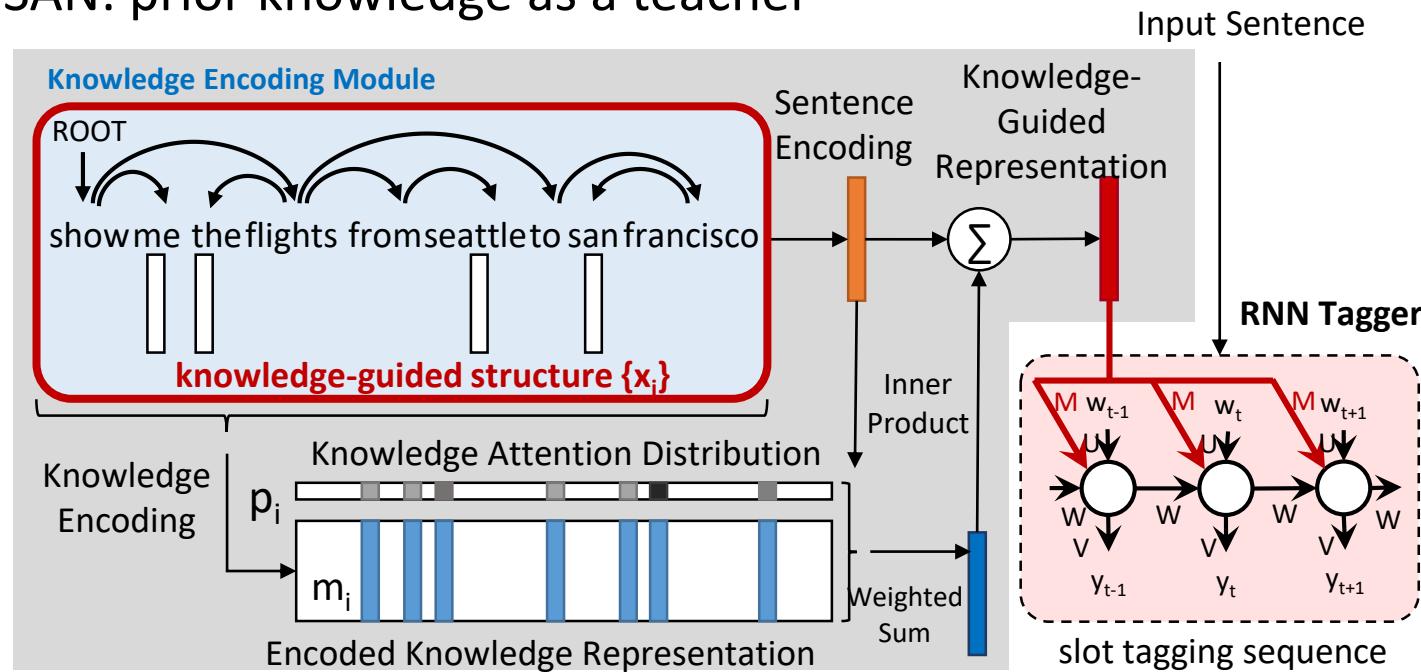


Structural LU (Chen et al., 2016)

66

<http://arxiv.org/abs/1609.03286>

□ K-SAN: prior knowledge as a teacher



Structural LU (Chen et al., 2016)

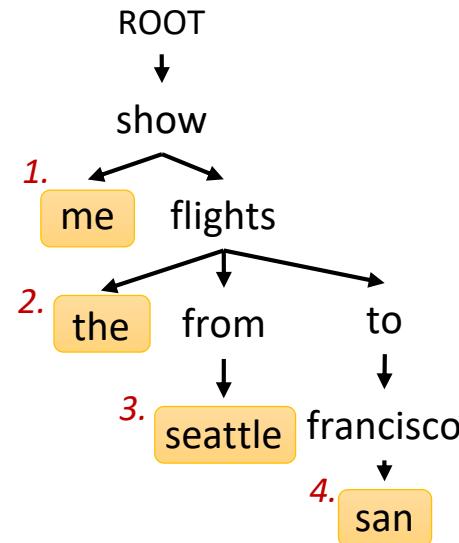
67

<http://arxiv.org/abs/1609.03286>

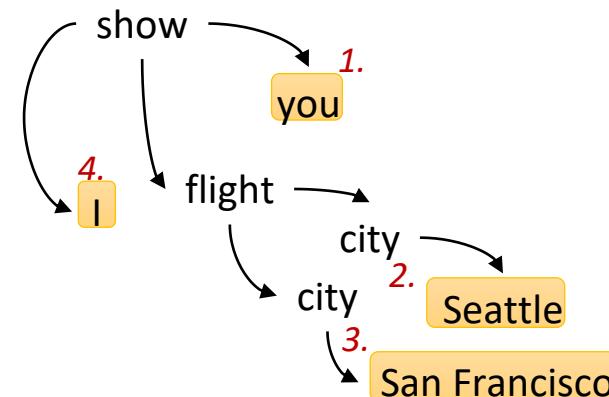
- Sentence structural knowledge stored as memory

Sentence s show me the flights from seattle to san francisco

Syntax (Dependency Tree)



Semantics (AMR Graph)

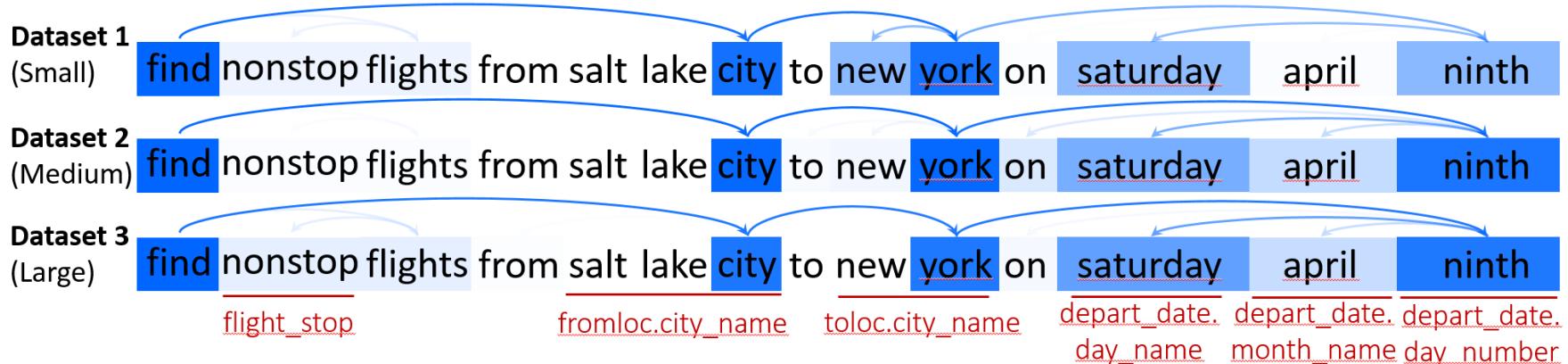


Structural LU (Chen et al., 2016)

68

<http://arxiv.org/abs/1609.03286>

- Sentence structural knowledge stored as memory



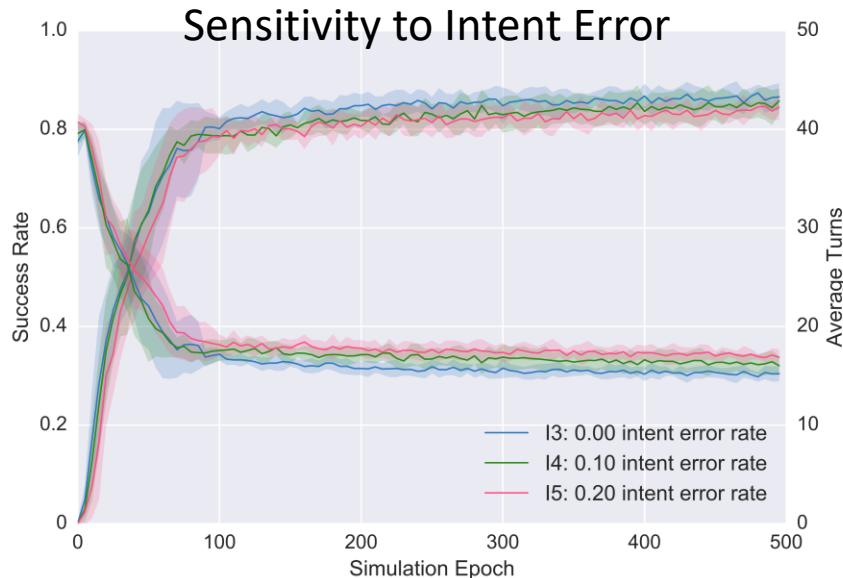
Using less training data with K-SAN allows the model pay the similar attention to the salient substructures that are important for tagging.

LU Importance (Li et al., 2017)

69

<http://arxiv.org/abs/1703.07055>

- Compare different types of LU errors



Slot filling is more important than intent detection in language understanding

LU Evaluation

70

□ Metrics

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

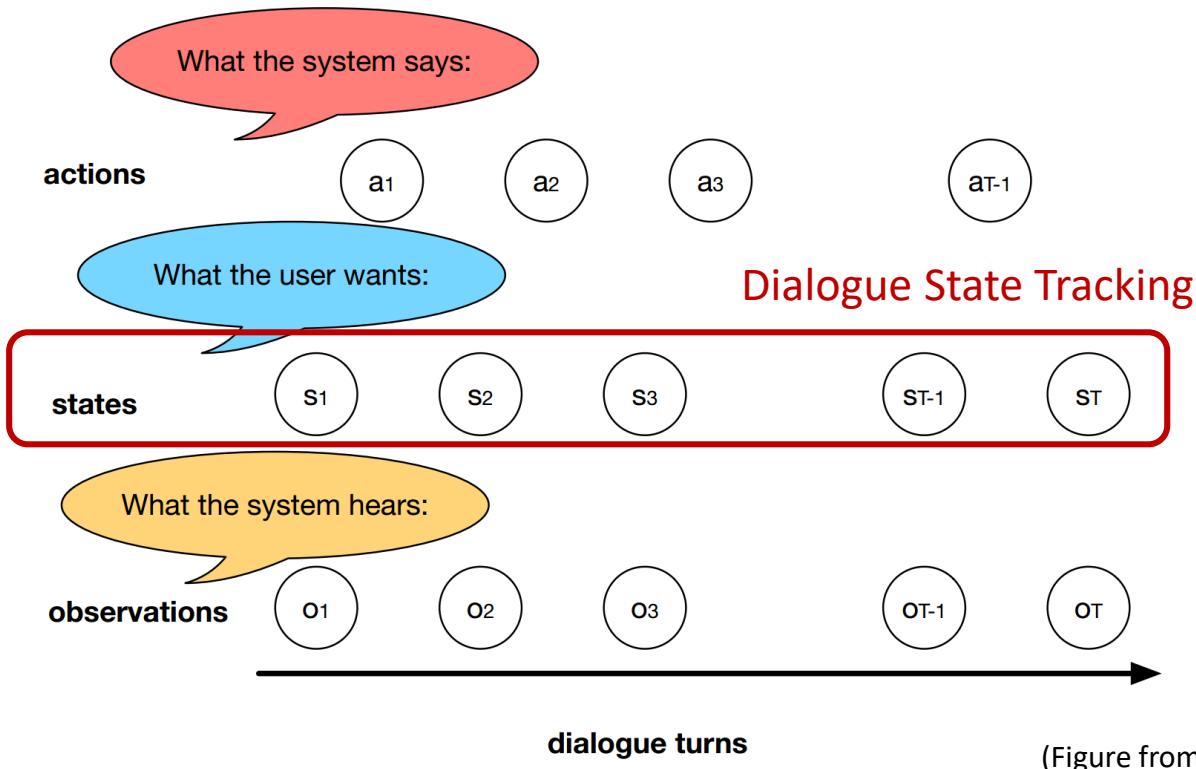
Outline

71

- Introduction
- Background Knowledge
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 - ***Dialogue Management***
 - ***Dialogue State Tracking (DST)***
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Elements of Dialogue Management

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Dialogue State Tracking (DST)

73

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

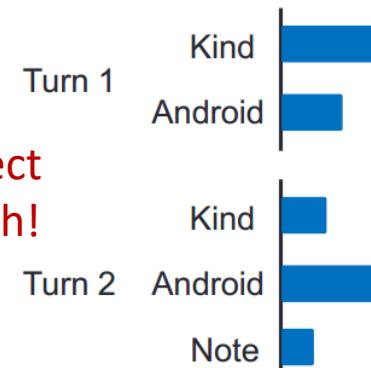
Turn 1
Kind
Android

Turn 1	
Kind	0.5
Android	0.3

Turn 2
Note
Android

Turn 2	
Note	0.4
Android	0.3

Incorrect
for both!



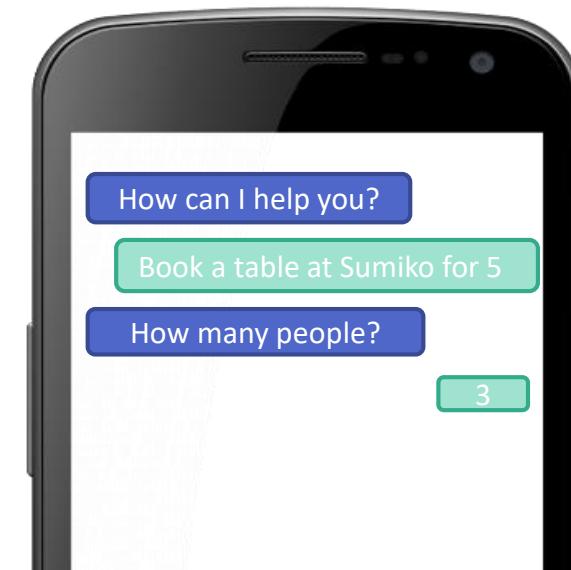
Dialogue State Tracking (DST)

74

- 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)



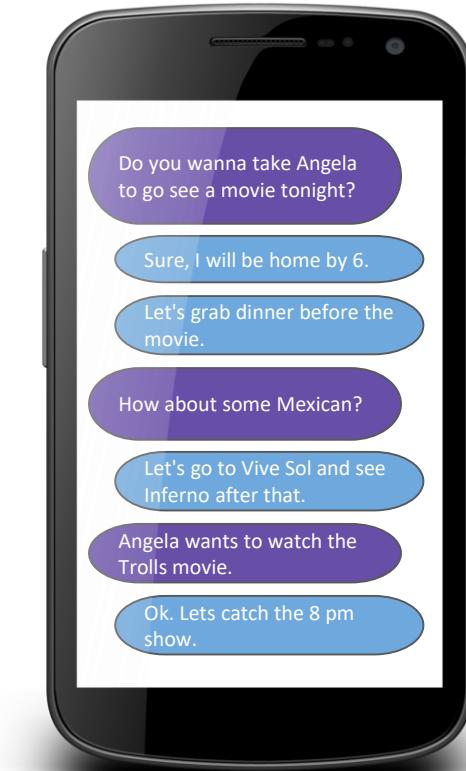
Multi-Domain Dialogue State Tracking (DST)

75

- ⑩ A full representation of the system's belief of the user's goal at any point during the dialogue
- ⑩ Used for making API calls

Movies			
11/15/16			
6 pm	7 pm	8 pm	9 pm
2	3		
Inferno	Trolls		
Century 16			

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



Dialog State Tracking Challenge (DSTC)

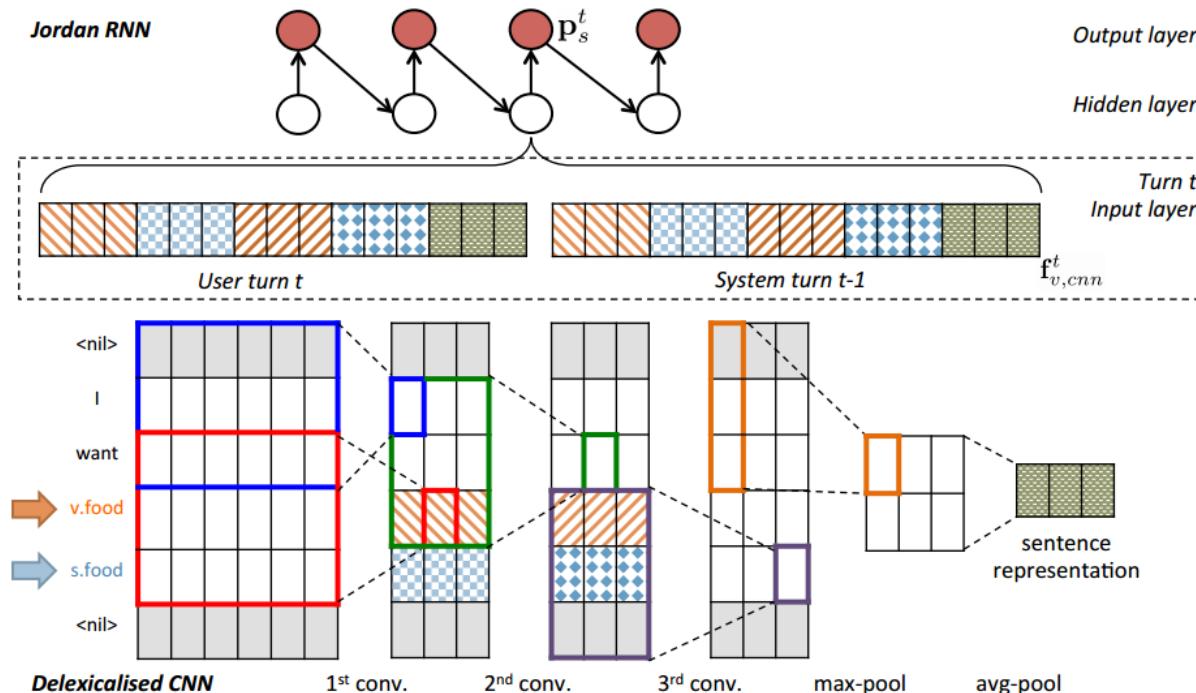
(Williams et al. 2013, Henderson et al. 2014, Henderson et al. 2014, Kim et al. 2016, Kim et al. 2016)

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

NN-Based DST (Henderson et al., 2013; Henderson et al., 2014; Mrkšić et al., 2015; Mrkšić et al., 2016)

77

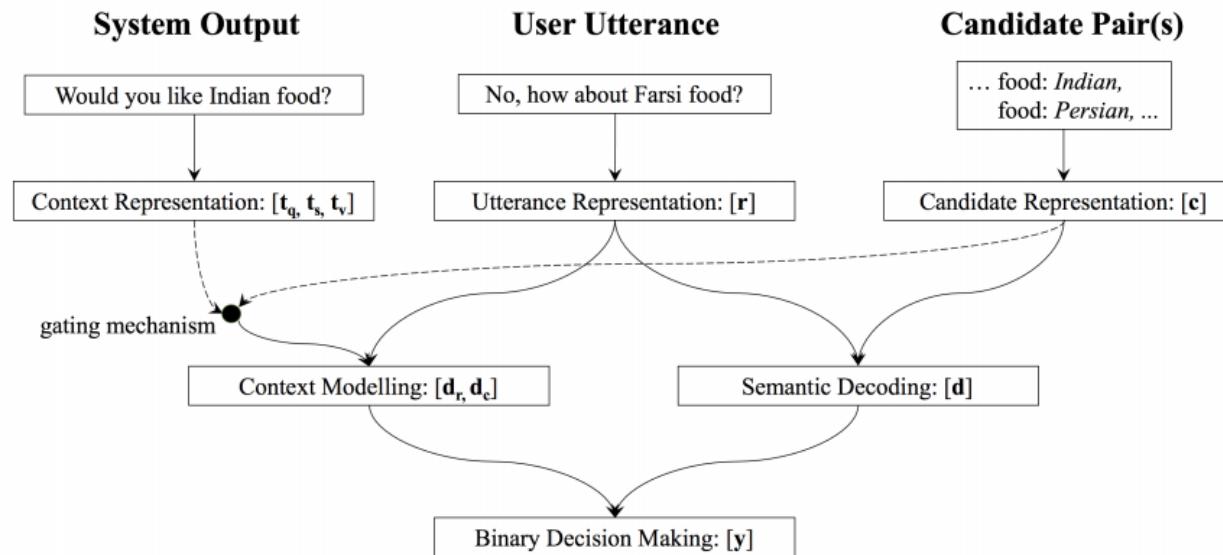
<http://www.anthology.aclweb.org/W/W13/W13-4073.pdf>; <https://arxiv.org/abs/1506.07190>; <https://arxiv.org/abs/1606.03777>



(Figure from Wen et al, 2016)

Neural Belief Tracker (Mrkšić et al., 2016)

78

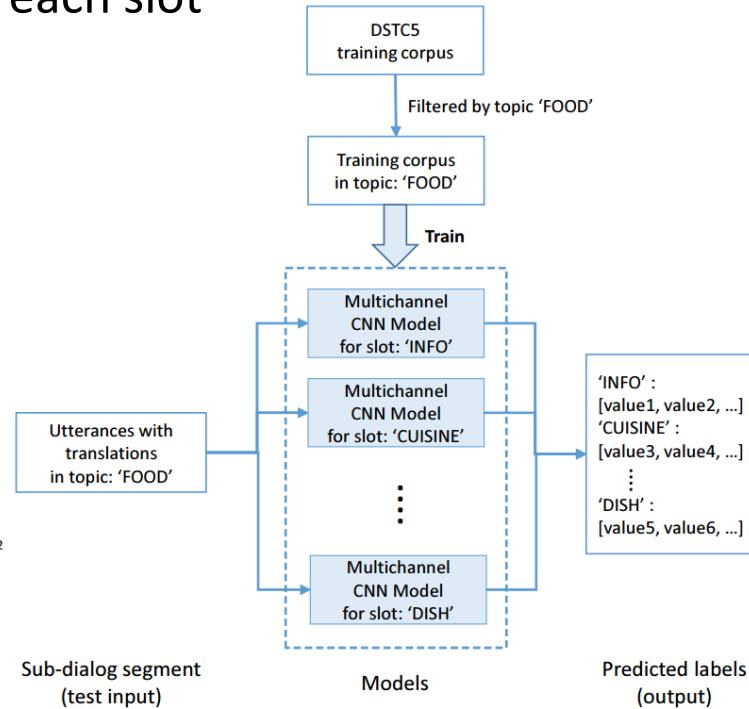
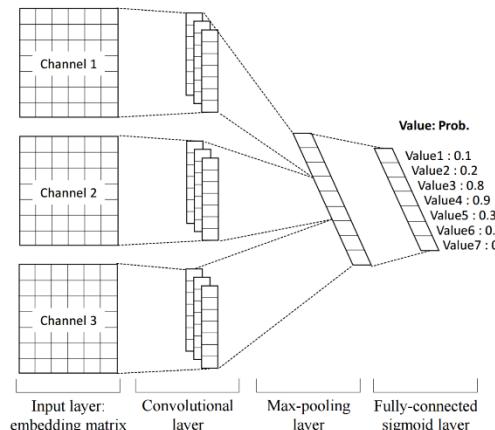
<https://arxiv.org/abs/1606.03777>

Multichannel Tracker (Shi et al., 2016)

79

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

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



DST Evaluation

80

- Dialogue State Tracking Challenges
 - DSTC2-3, human-machine
 - DSTC4-5, human-human
- Metric
 - Tracked state accuracy with respect to user goal
 - Recall/Precision/F-measure individual slots

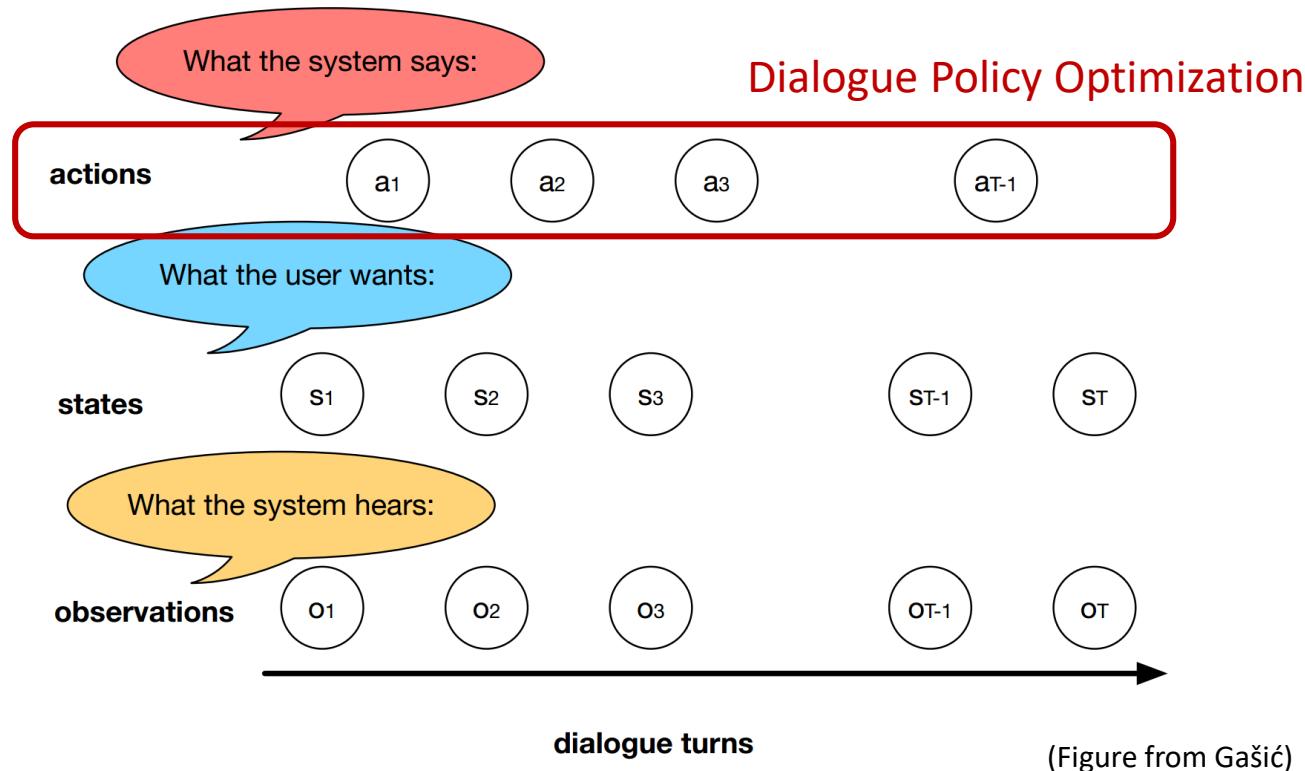
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Elements of Dialogue Management

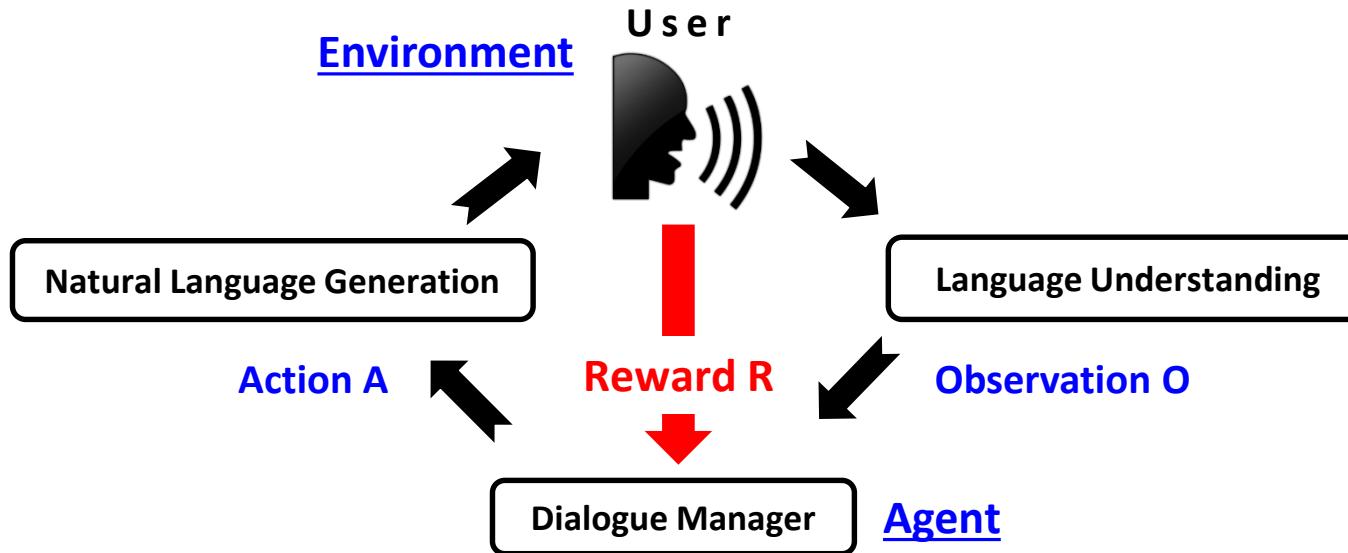
82



Dialogue Policy Optimization

83

- 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 System

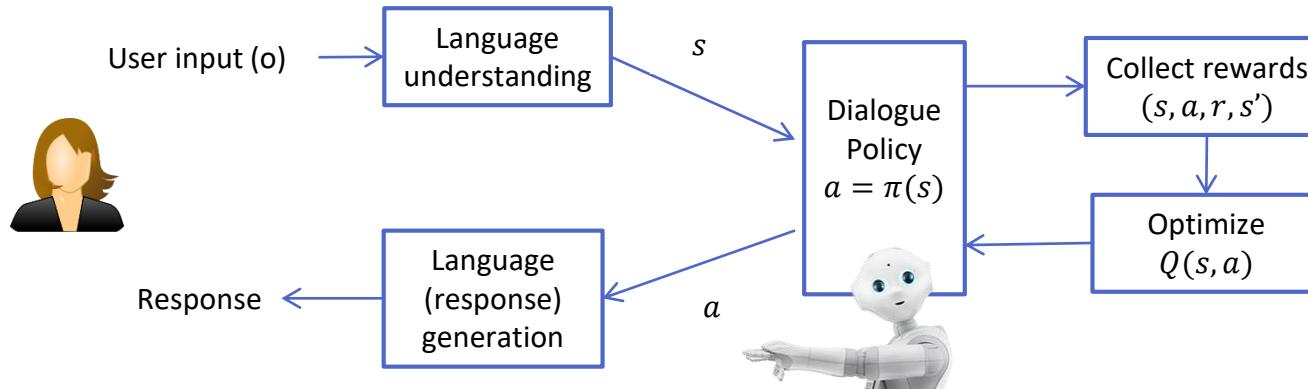
84

- 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

Reinforcement Learning for Dialogue Policy Optimization

85



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

Dialogue Reinforcement Learning Signal

86

- 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

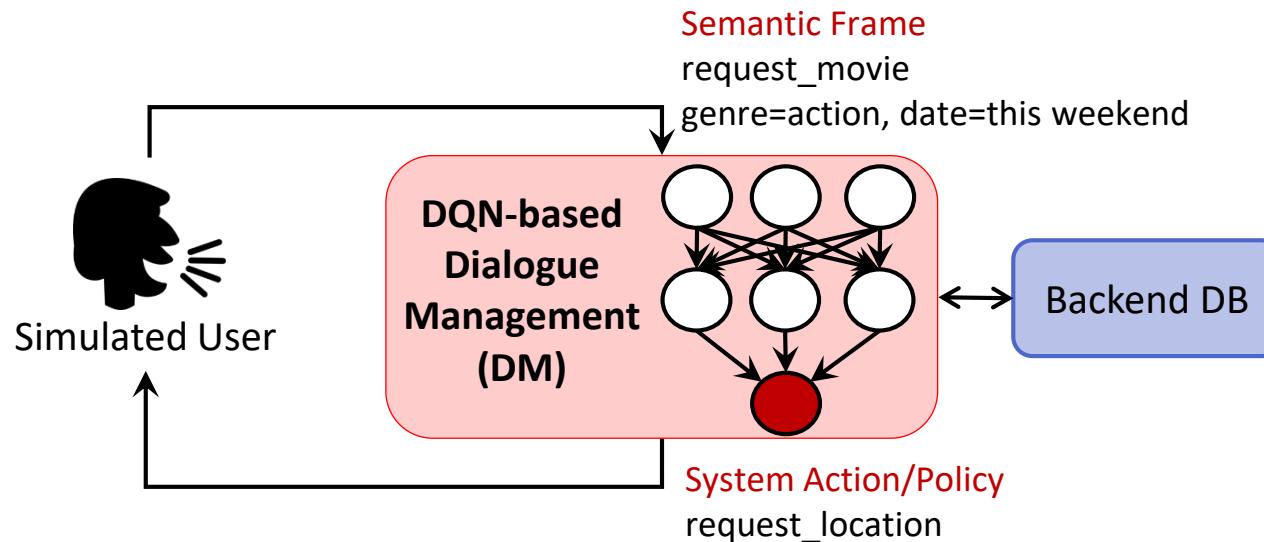


Neural Dialogue Manager (Li et al., 2017)

87

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

- Deep Q-network for training DM policy
 - ▣ Input: current semantic frame observation, database returned results
 - ▣ Output: system action



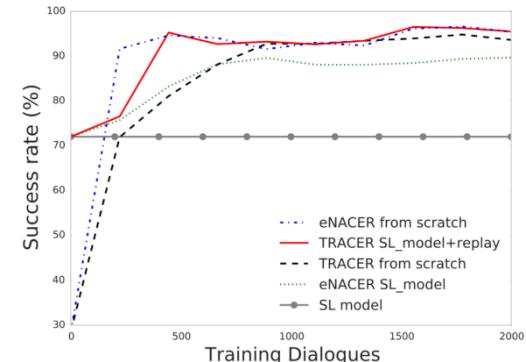
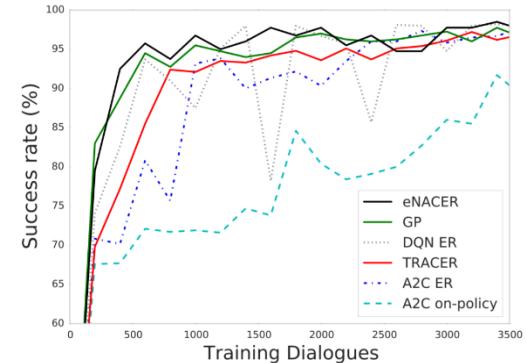
SL + RL for Sample Efficiency (Su et al., 2017)

88

Su et.al., SIGDIAL 2017

<https://arxiv.org/pdf/1707.00130.pdf>

- Issue about RL for DM
 - ▣ slow learning speed
 - ▣ cold start
- Solutions
 - ▣ Sample-efficient actor-critic
 - Off-policy learning with experience replay
 - Better gradient update
 - ▣ Utilizing supervised data
 - Pretrain the model with SL and then fine-tune with RL
 - Mix SL and RL data during RL learning
 - Combine both

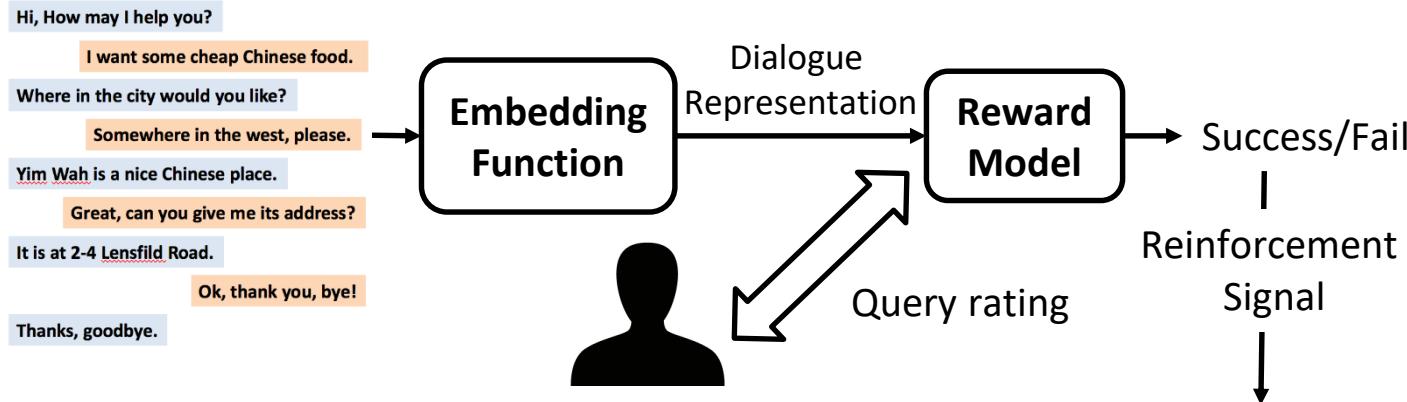


Online Training (Su et al., 2015; Su et al., 2016)

89

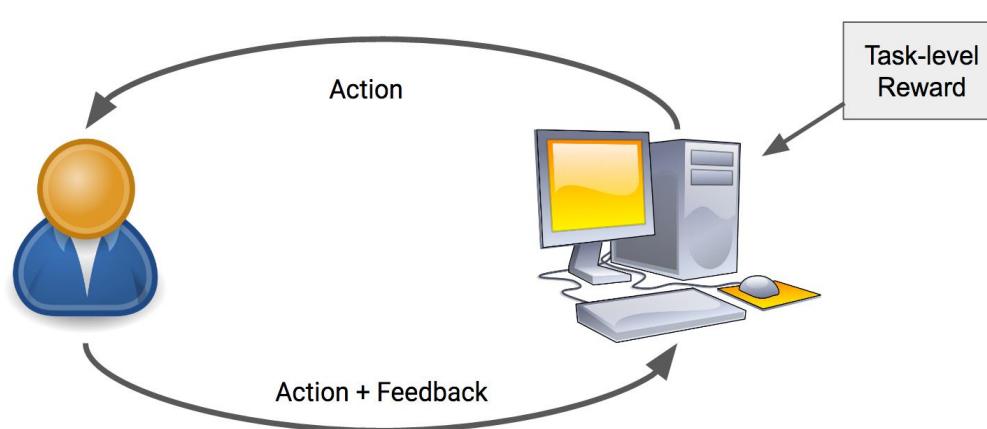
<http://www.anthology.aclweb.org/W/W15/W15-46.pdf>; <https://www.aclweb.org/anthology/P/P16/P16-1230.pdf>

- Policy learning from real users
 - ▣ Infer reward directly from dialogues (Su et al., 2015)
 - ▣ User rating (Su et al., 2016)
- Reward modeling on user binary success rating



Interactive RL for DM (Shah et al., 2016)

90

<https://research.google.com/pubs/pub45734.html>

Immediate
Feedback

Explicit



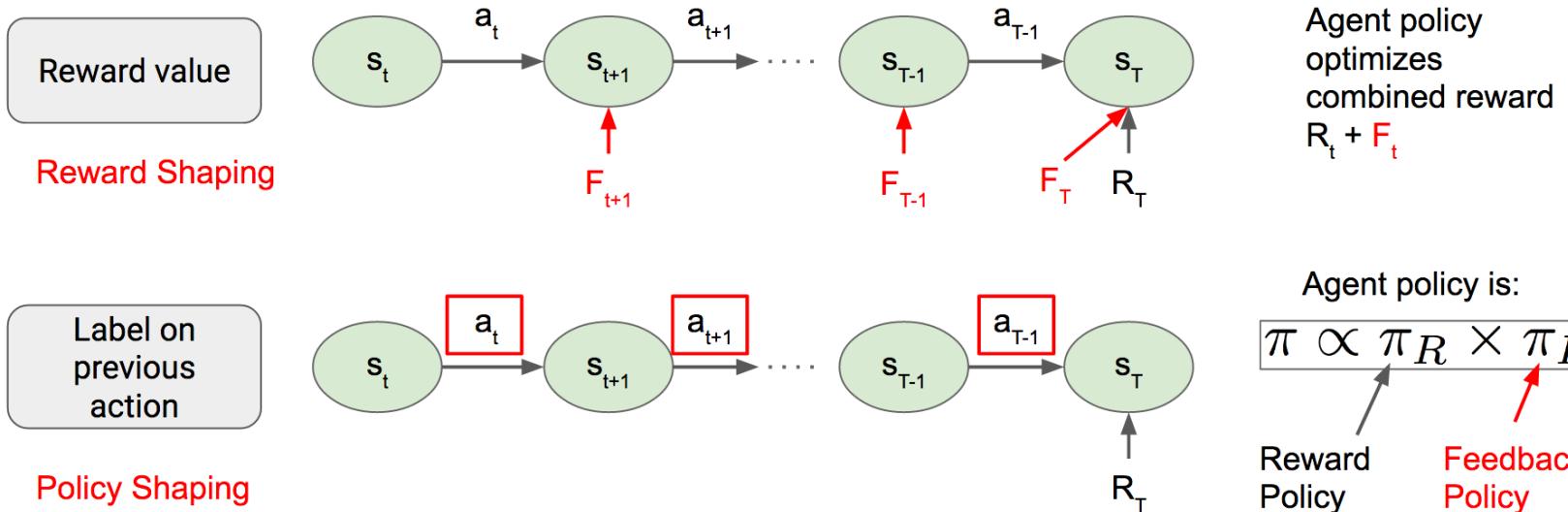
Implicit

- Is First Wok highly rated?
 - First Wok, Lucy's and Red Grill are good options.
 - No stupid, I am asking if First Wok is rated at least 3 stars?
- Frustration Repetition

Use a third agent for providing interactive feedback to the DM

Interpreting Interactive Feedback (Shah et al., 2016)

91

<https://research.google.com/pubs/pub45734.html>


Dialogue Management Evaluation

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- Metrics
 - ▣ Turn-level evaluation: system action accuracy
 - ▣ Dialogue-level evaluation: task success rate, reward

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Natural Language Generation (NLG)

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- Mapping semantic frame into natural language

inform(name=Seven_Days, foodtype=Chinese)



Seven Days is a nice Chinese restaurant

Template-Based NLG

95

- Define a set of rules to map frames to NL

Semantic Frame	Natural Language
confirm()	“Please tell me more about the product you 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.”

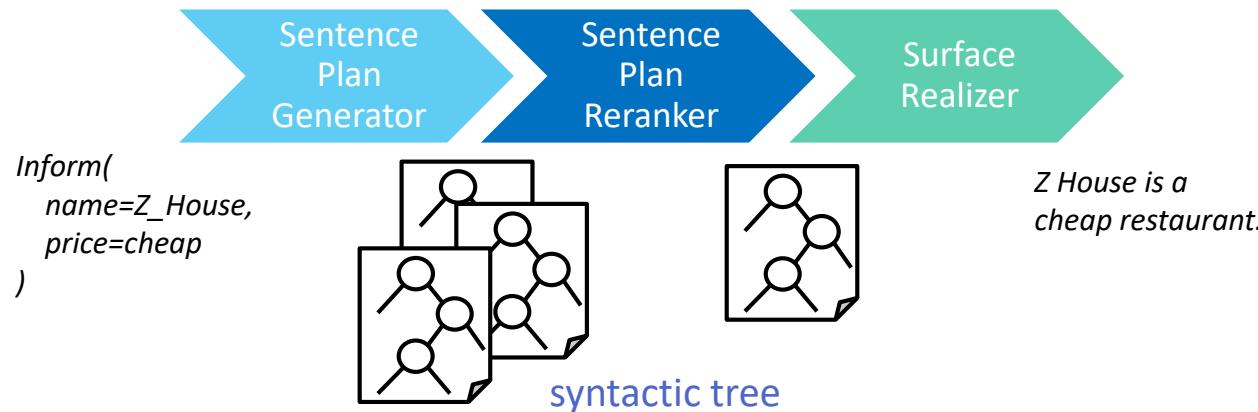
Pros: simple, error-free, easy to control

Cons: time-consuming, poor scalability

Plan-Based NLG (Walker et al., 2002)

96

- Divide the problem into pipeline



- Statistical sentence plan generator (Stent et al., 2009)
- Statistical surface realizer (Dethlefs et al., 2013; Cuayahuitl et al., 2014; ...)

Pros: can model complex linguistic structures

Cons: heavily engineered, require domain knowledge

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

97

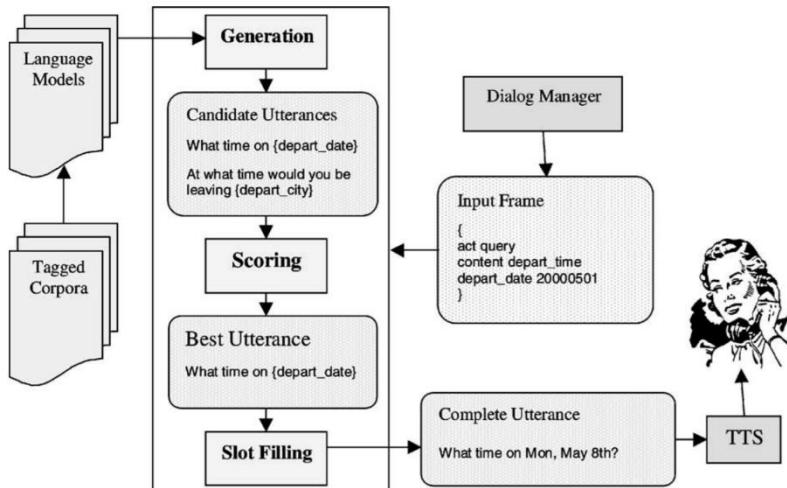
<http://dl.acm.org/citation.cfm?id=1117568>

□ 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

$$X^* = \arg \max_X P(X \mid c)$$

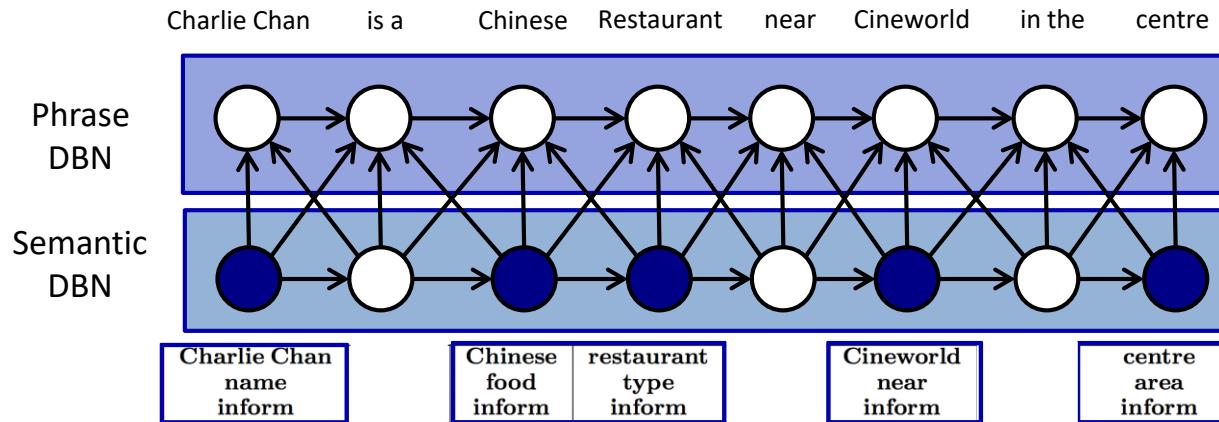


Classes:
 inform_area
 inform_address
 ...
 request_area
 request_postcode

Pros: easy to implement/ understand, simple rules
Cons: computationally inefficient

Phrase-Based NLG (Mairesse et al, 2010)

98

<http://dl.acm.org/citation.cfm?id=1858833>

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

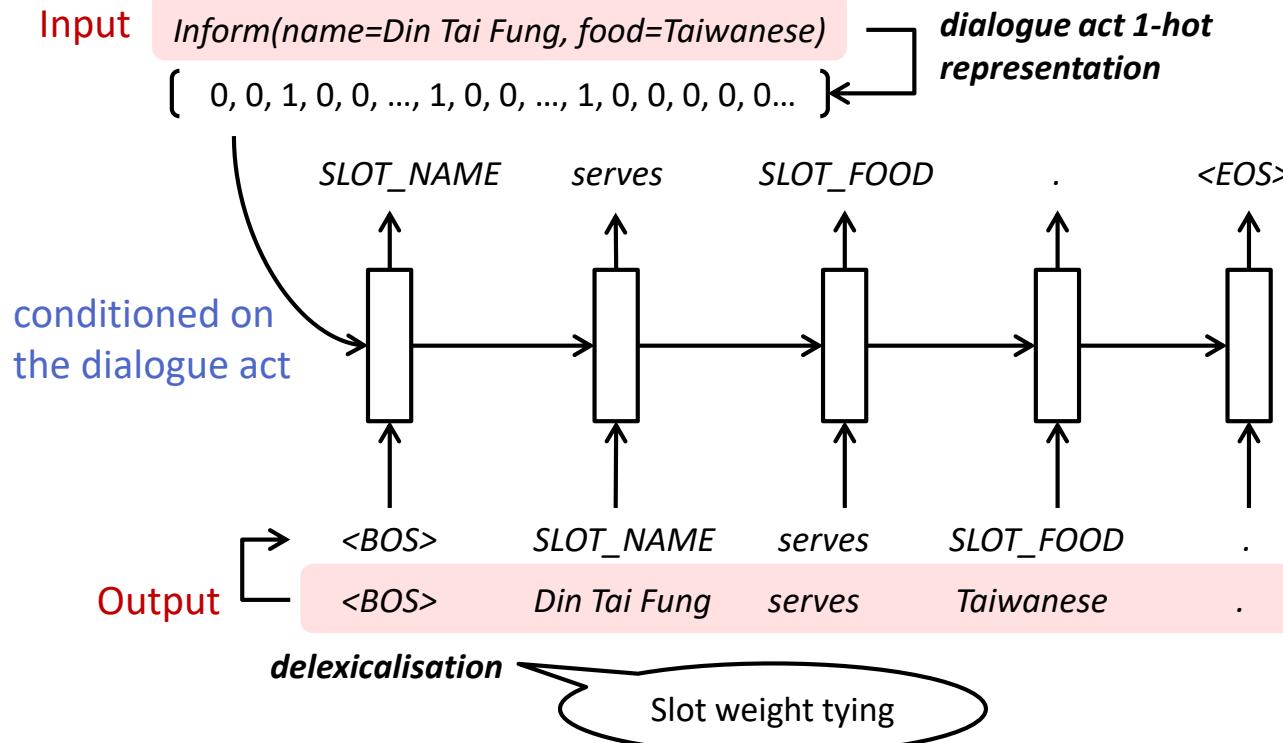
r_t	s_t	h_t	l_t
< s >	START	START	START
The Rice Boat	inform(name(X))	X	inform(name)
is a	inform	inform	EMPTY
restaurant	inform(type(restaurant))	restaurant	inform(type)
in the	inform(area)	area	inform
riverside	inform(area(riverside))	riverside	inform(area)
area	inform(area)	area	inform
that	inform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

99

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


Handling Semantic Repetition

100

- 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)

101

□ 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

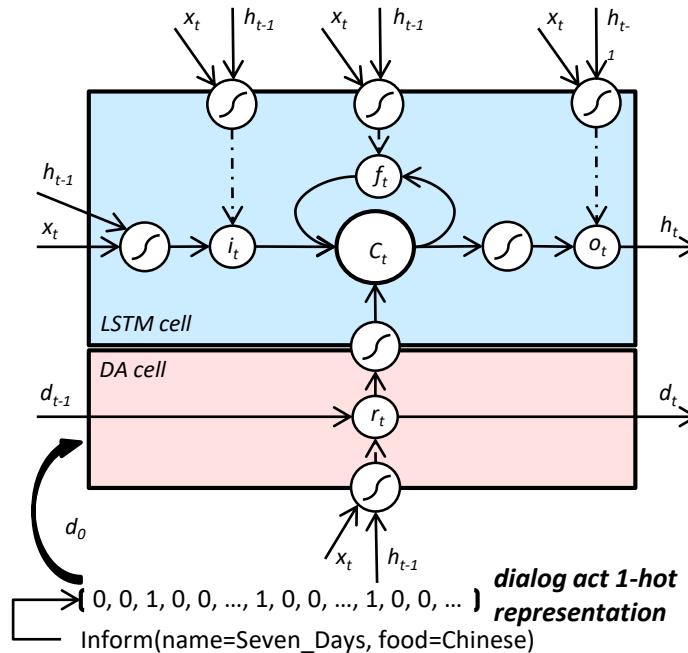
$$\mathbf{r}_t = \sigma(\mathbf{W}_{wr}\mathbf{x}_t + \mathbf{W}_{hr}\mathbf{h}_{t-1})$$

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

□ Modify C_t

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

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



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

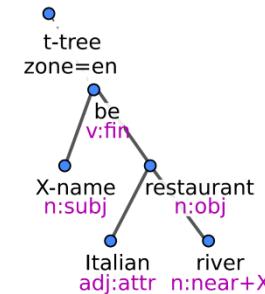
Structural NLG (Dušek and Jurčíček, 2016)

102

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

<https://www.aclweb.org/anthology/P/P16/P16-2.pdf#page=79>

inform(name=X-name,type=placetoeat,eattype=restaurant,
area=riverside,food=Italian)

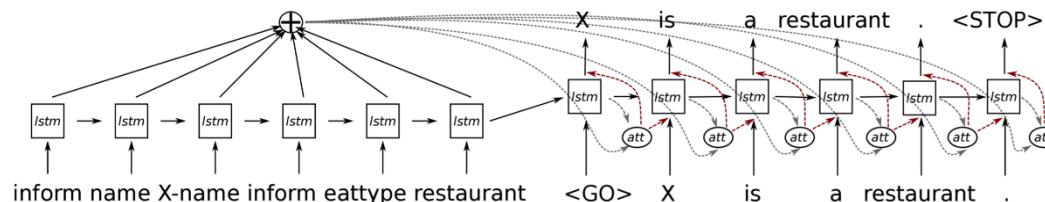


(<root> <root> ((X-name n:subj) be v:fin ((Italian adj:attr) restaurant n:obj (river n:near+X))))

X-name n:subj be v:fin Italian adj:attr restaurant n:obj river n:near+X



X is an Italian restaurant near the river.

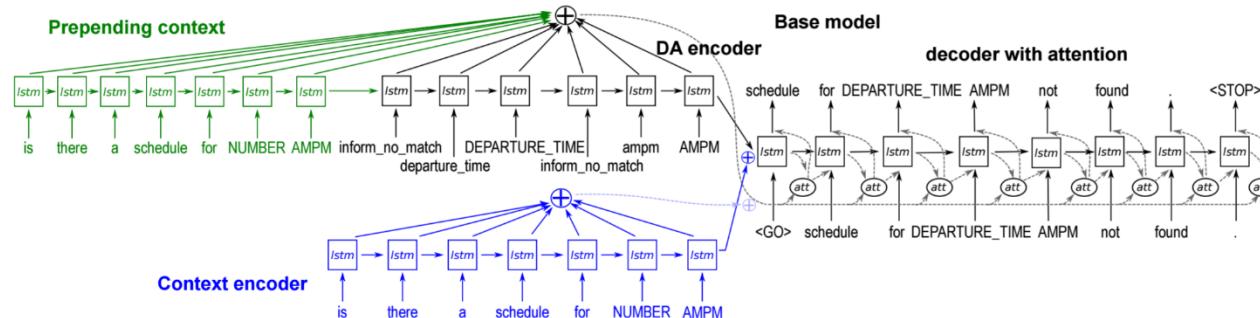
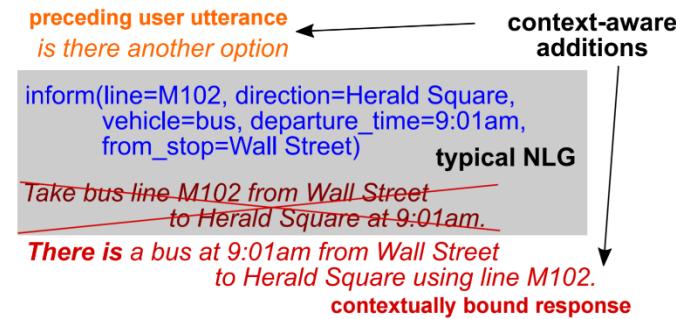


Contextual NLG (Dušek and Jurčíček, 2016)

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<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

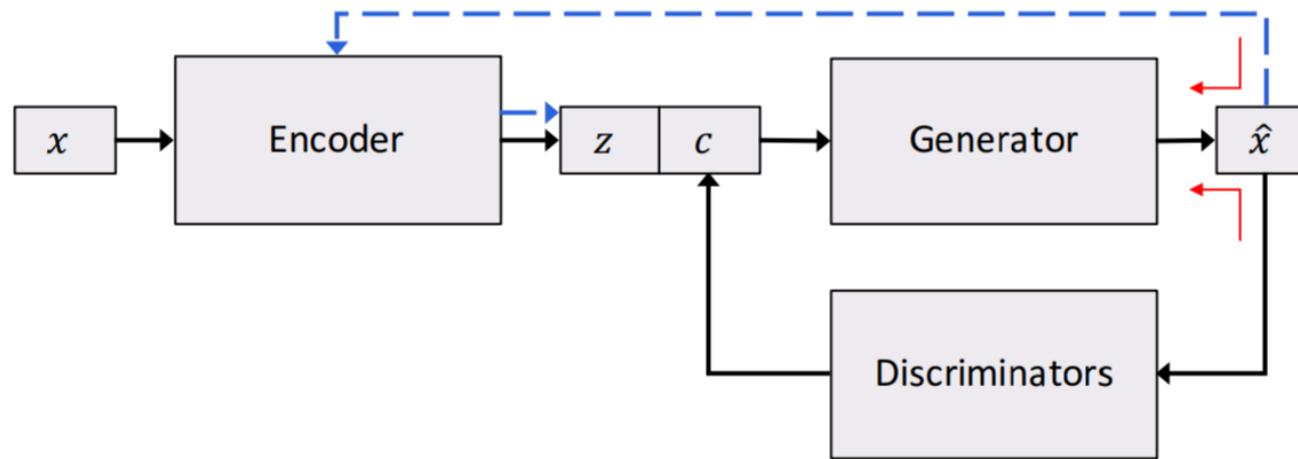


Controlled Text Generation (Hu et al., 2017)

104

<https://arxiv.org/pdf/1703.00955.pdf>

- Idea: NLG based on generative adversarial network (GAN) framework
 - c : targeted sentence attributes



NLG Evaluation

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□ 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

Evaluation

Dialogue System Evaluation

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- Dialogue model evaluation
 - ▣ Crowd sourcing
 - ▣ User simulator
- Response generator evaluation
 - ▣ Word overlap metrics
 - ▣ Embedding based metrics

Crowdsourcing for Dialogue System Evaluation (Yang et al., 2012)

108

http://www-scf.usc.edu/~zhaojuny/docs/SDSchapter_final.pdf

Q1 Do you think you understand from the dialog what the user wanted?

- Opt 1) No clue 2) A little bit 3) Somewhat
4) Mostly 5) Entirely

Aim elicit the Worker's confidence in his/her ratings.

Q2 Do you think the system is successful in providing the information that the user wanted?

- Opt 1) Entirely unsuccessful 2) Mostly unsuccessful
3) Half successful/unsuccessful
4) Mostly successful 5) Entirely successful

Aim elicit the Worker's perception of whether the dialog has fulfilled the informational goal of the user.

Q3 Does the system work the way you expect it?

- Opt 1) Not at all 2) Barely 3) Somewhat
4) Almost 5) Completely

Aim elicit the Worker's impression of whether the dialog flow suits general expectations.

Q4 Overall, do you think that this is a good system?

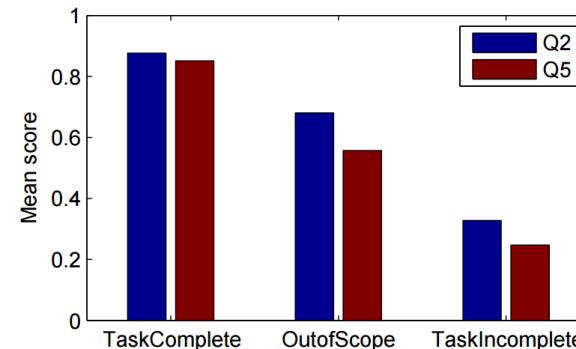
- Opt 1) Very poor 2) Poor 3) Fair 4) Good 5) Very good

Aim elicit the Worker's overall impression of the SDS.

Q5 What category do you think the dialog belongs to?

- Opt 1) Task is incomplete 2) Out of scope
3) Task is complete

Aim elicit the Worker's impression of whether the dialog reflects task completion.

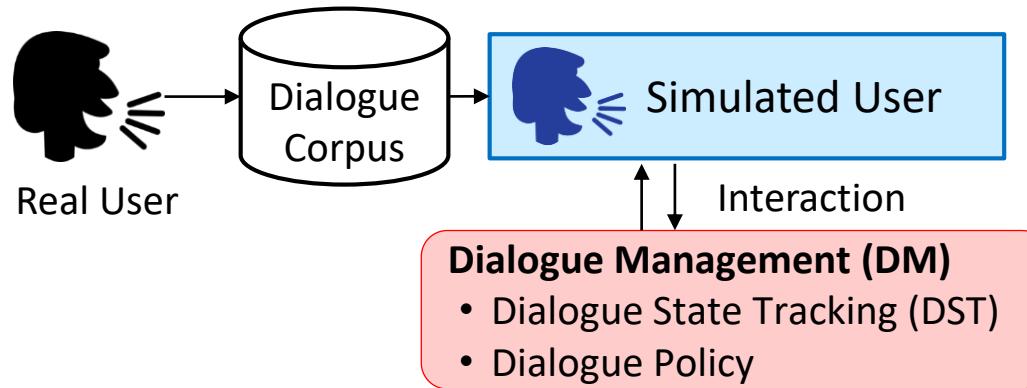


The normalized mean scores of Q2 and Q5 for approved ratings in each category. A higher score maps to a higher level of task success

User Simulation

109

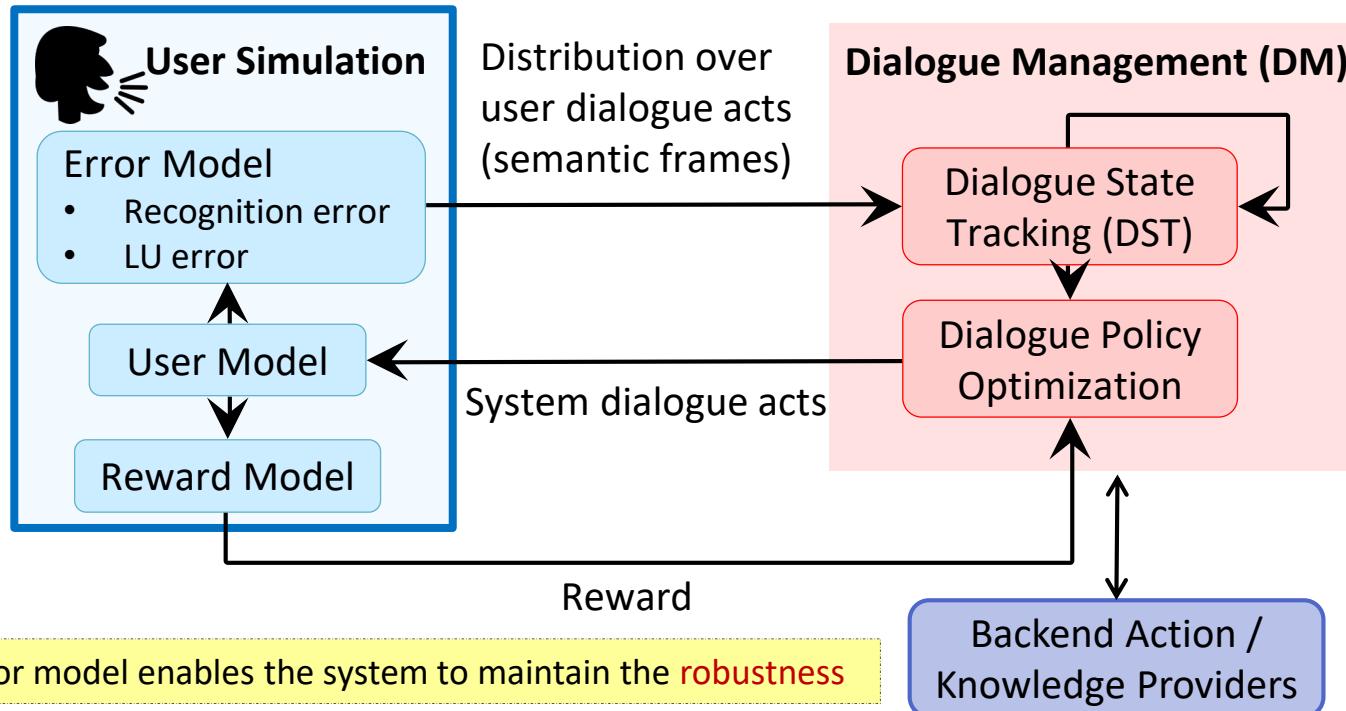
- Goal: generate natural and reasonable conversations to enable reinforcement learning for exploring the policy space



- Approach
 - Rule-based crafted by experts (Li et al., 2016)
 - Learning-based (Schatzmann et al., 2006; El Asri et al., 2016, Crook and Marin, 2017)

Elements of User Simulation

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Rule-Based Simulator for RL Based System (Li et al., 2016)

111

<http://arxiv.org/abs/1612.05688>

- rule-based simulator + collected data
- starts with sets of goals, actions, KB, slot types
- publicly available simulation framework
- movie-booking domain: ticket booking and movie seeking
- provide procedures to add and test own agent

```
1 class AgentDQN(Agent):
2     def run_policy(self, representation):
3         """ epsilon-greedy policy """
4
5         if random.random() < self.epsilon:
6             return random.randint(0, self.num_actions - 1)
7         else:
8             if self.warm_start == 1:
9                 if len(self.experience_replay_pool) > self.experience_replay_pool_size:
10                     self.warm_start = 2
11                     return self.rule_policy()
12             else:
13                 return self.dqn.predict(representation, {}, predict_model=True)
14
15     def train(self, batch_size=1, num_batches=100):
16         """ Train DQN with experience replay """
17
18         for iter_batch in range(num_batches):
19             self.cur_bellman_err = 0
20             for iter in range(len(self.experience_replay_pool)/(batch_size)):
21                 batch = [random.choice(self.experience_replay_pool) for i in xrange(batch_size)]
22                 batch_struct = self.dqn.singleBatch(batch, {'gamma': self.gamma}, self.clone_dqn)
```

Model-Based User Simulators

112

- Bi-gram models (Levin et.al. 2000)
- Graph-based models (Scheffler and Young, 2000)
- Data Driven Simulator (Jung et.al., 2009)
- Neural Models (deep encoder-decoder)

Data-Driven Simulator (Jung et.al., 2009)

113

- Three step process
 - 1) User intention simulator

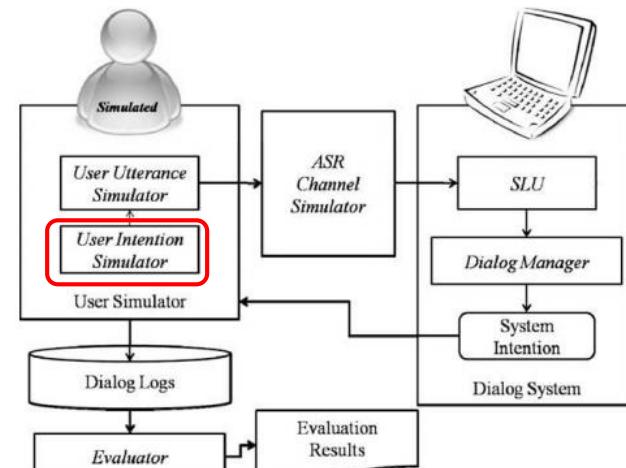
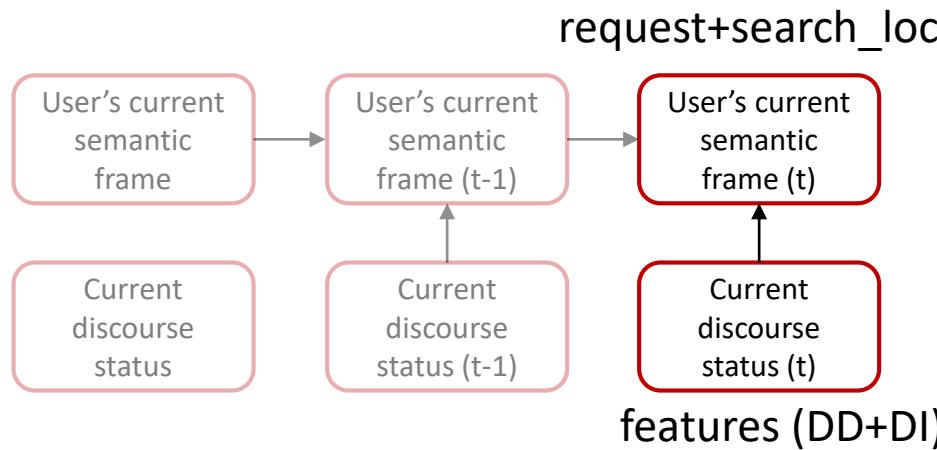


Fig. 1. Overall architecture of dialog simulation.

(*) compute all possible semantic frame
given previous turn info
(*) randomly select one possible semantic frame

Data-Driven Simulator (Jung et.al., 2009)

114

- Three step process
 - 1) User intention simulator
 - 2) User utterance simulator

request+search_loc

I **want** to go to the **city hall**

PRP VB TO VB TO [loc_name]

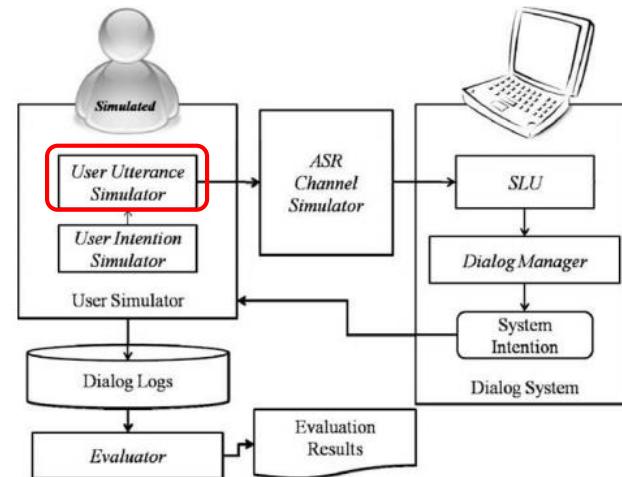


Fig. 1. Overall architecture of dialog simulation.

Given a list of POS tags associated with the semantic frame, using LM+Rules they generate the user utterance.

Data-Driven Simulator (Jung et.al., 2009)

115

- Three step process:
 - 1) User intention simulator
 - 2) User utterance simulator
 - 3) ASR channel simulator
- Evaluate the generated sentences using BLUE-like measures against the reference utterances collected from humans (with the same goal)

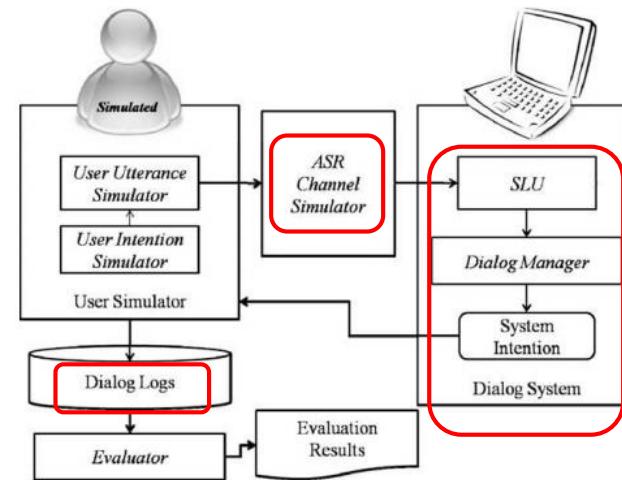


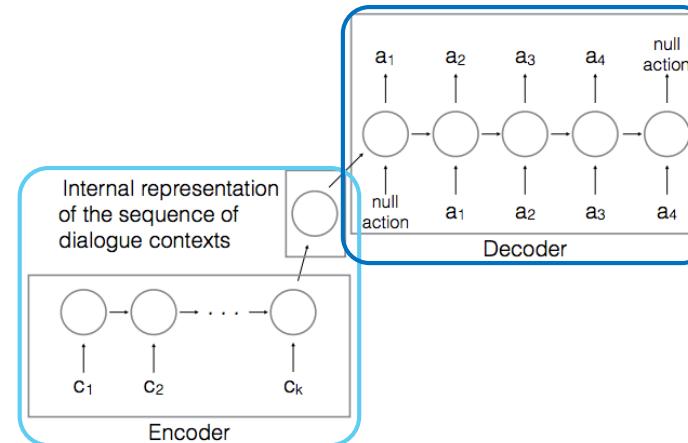
Fig. 1. Overall architecture of dialog simulation.

Seq2Seq User Simulation (El Asri et al., 2016)

116

<https://arxiv.org/abs/1607.00070>

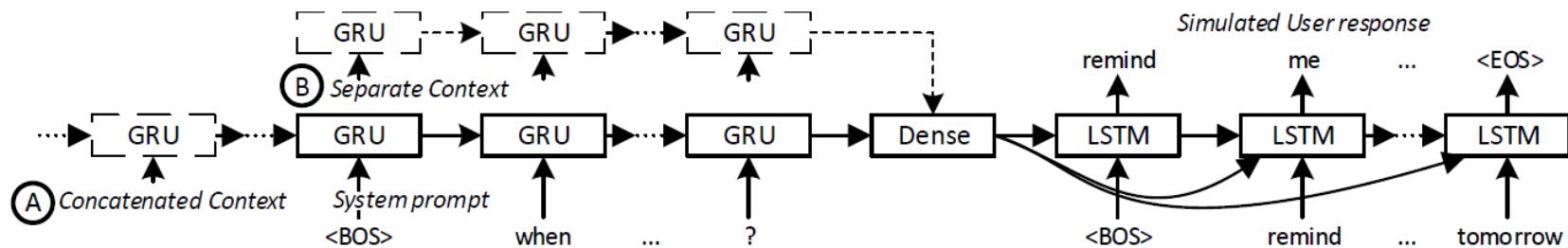
- Seq2Seq trained from dialogue data
 - ▣ Input: c_i encodes contextual features, such as the previous system action, consistency between user goal and machine provided values
 - ▣ Output: a dialogue act sequence form the user
- Extrinsic evaluation for policy



Seq2Seq User Simulation (Crook and Marin, 2017)

117

- Seq2Seq trained from dialogue data
 - ▣ No labeled data
 - ▣ Trained on just human to machine conversations



User Simulator for Dialogue Evaluation Measures

118

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
- Ratio between the dialogue turns (larger is better)

Action Appropriateness

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

How NOT to Evaluate Dialog System (Liu et al., 2017)

119

<https://arxiv.org/pdf/1603.08023.pdf>

- How to evaluate the quality of the generated response ?
 - ▣ Specifically investigated for chat-bots
 - ▣ Crucial for task-oriented tasks as well

- Metrics:
 - ▣ Word overlap metrics, e.g., BLEU, METEOR, ROUGE, etc.
 - ▣ Embeddings based metrics, e.g., contextual/meaning representation between target and candidate



Dialogue Response Evaluation (Lowe et al., 2017)

120

- Problems of existing automatic evaluation
 - can be biased
 - correlate poorly with human judgements of response quality
 - using word overlap may be misleading
- Solution
 - collect a **dataset of accurate human scores** for variety of dialogue responses (e.g., coherent/un-coherent, relevant/irrelevant, etc.)
 - use this dataset to train an **automatic dialogue evaluation model** – learn to compare **the reference** to **candidate responses!**
 - Use RNN to predict scores by comparing against human scores!

Context of Conversation

Speaker A: Hey, what do you want to do tonight?

Speaker B: Why don't we go see a movie?

Model Response

Nah, let's do something active.

Reference Response

Yeah, the film about Turing looks great!

Recent Trends and Challenges

End-to-End Learning for Dialogues

Multimodality

Dialogue Breath

Dialogue Depth

Outline

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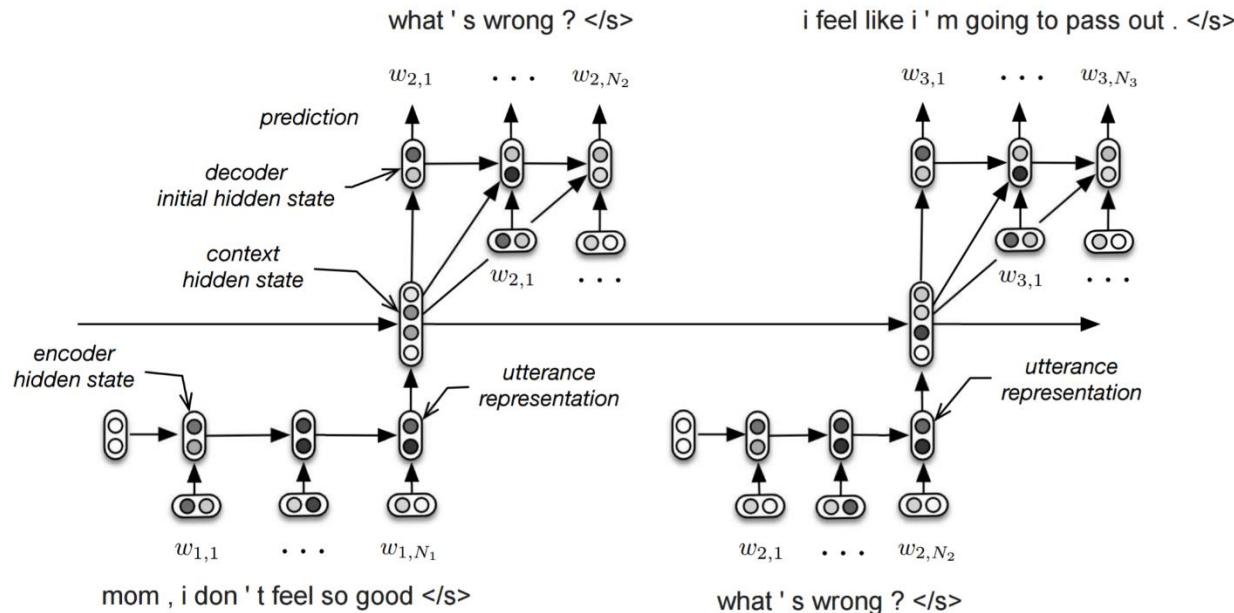
- Introduction
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 - Dialogue Policy Optimization
 - Natural Language Generation (NLG)
- Evaluation
- Recent Trends and Challenges
 - ***End-to-End Neural Dialogue System***
 - Multimodality
 - Dialogue Breath
 - Dialogue Depth

ChitChat Hierarchical Seq2Seq (Serban et al., 2016)

123

<http://www.aaai.org/ocs/index.php/AAAI/AAAI16/paper/view/11957>

- Learns to generate dialogues from offline dialogs
- No state, action, intent, slot, etc.

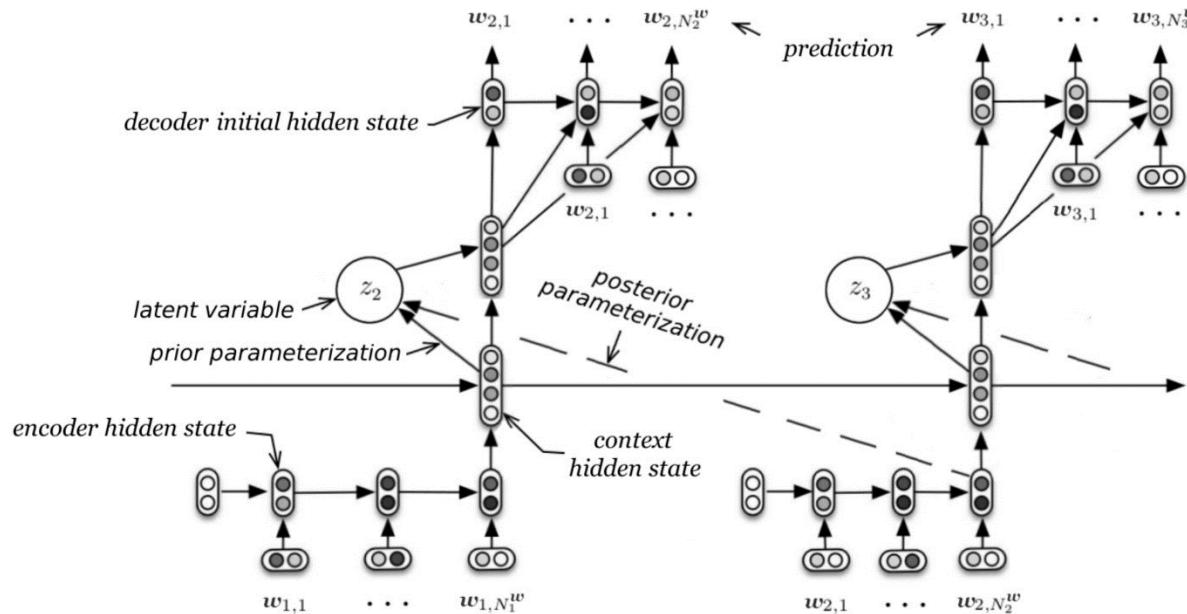


ChitChat Hierarchical Seq2Seq (Serban et.al., 2017)

124

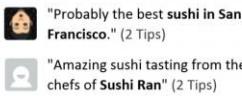
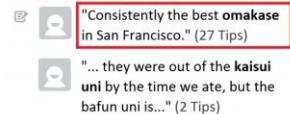
<https://arxiv.org/abs/1605.06069>

- A hierarchical seq2seq model with **Gaussian latent variable** for generating dialogues (like topic or sentiment)

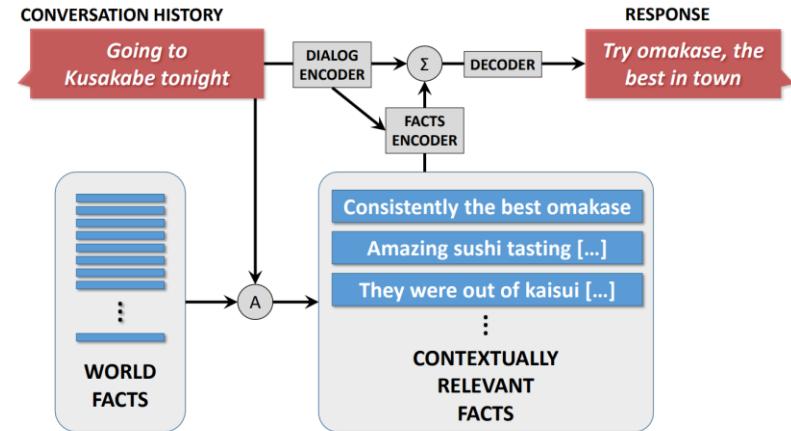


Knowledge Grounded Neural Conv. Model (Ghazvininejad et al., 2017)

125

<https://arxiv.org/abs/1702.01932>

User input: Going to Kusakabe tonight.
Neural model: Have a great time!
Human: You'll love it! Try omasake, the best in town.



A: Looking forward to trying @pizzalibretto tonight! my expectations are high.
 B: Get the rocco salad. Can you eat calamari?

A: Anyone in Chi have a dentist office they recommend? I'm never going back to [...] and would love a reco!
 B: Really looved Ora in Wicker Park.

A: I'm at California Academy of Sciences
 B: Make sure you catch the show at the Planetarium. Tickets are usually limited.

A: I'm at New Wave Cafe.
 B: Try to get to Dmitri's for dinner. Their pan fried scallops and shrimp scampi are to die for.

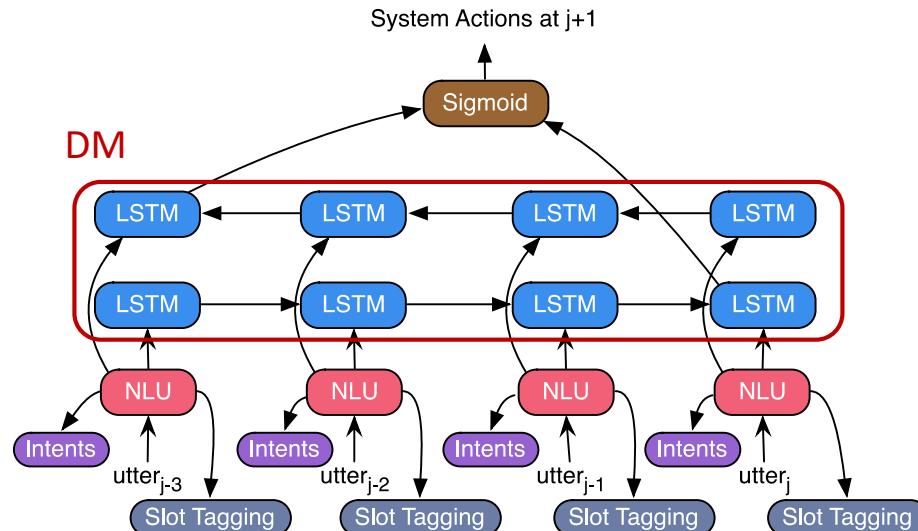
A: I just bought: [...] 4.3-inch portable GPS navigator for my wife, shh, don't tell her.
 B: I heard this brand loses battery power.

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

126

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

- Errors from DM can be propagated to NLU for *regularization + robustness*

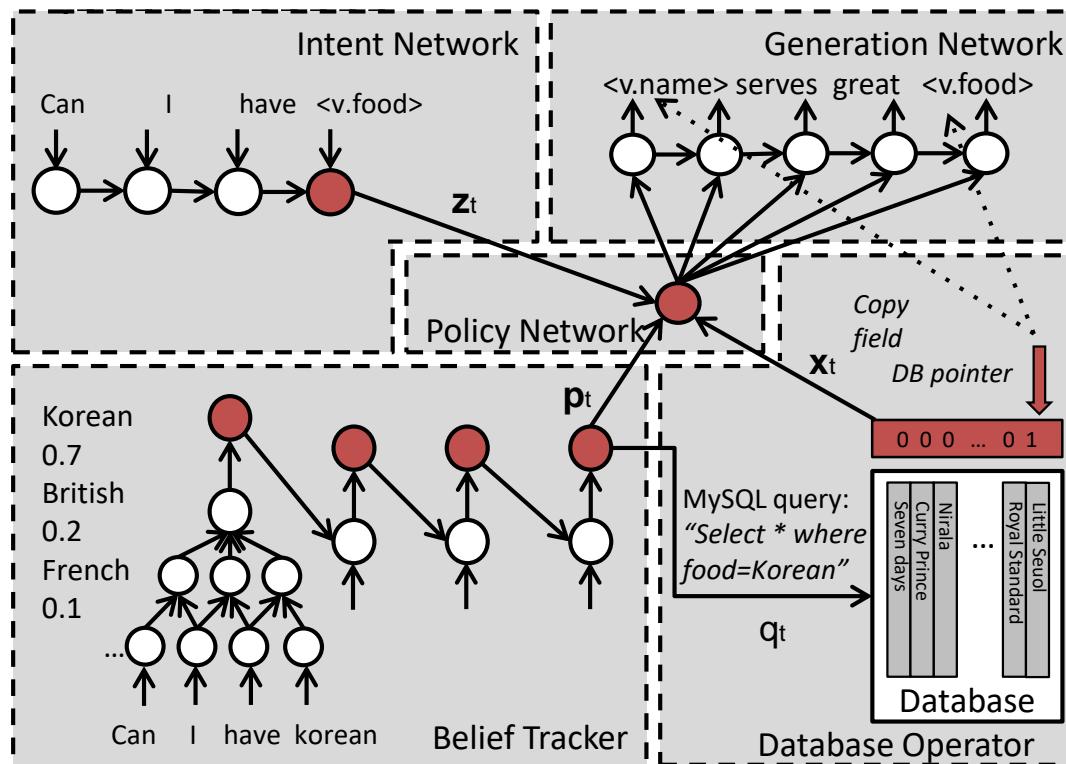


Model	DM	NLU
Baseline (CRF+SVMs)	7.7	33.1
Pipeline-BLSTM	12.0	36.4
JointModel	22.8	37.4

Both DM and NLU performance (frame accuracy) is improved

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

127

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

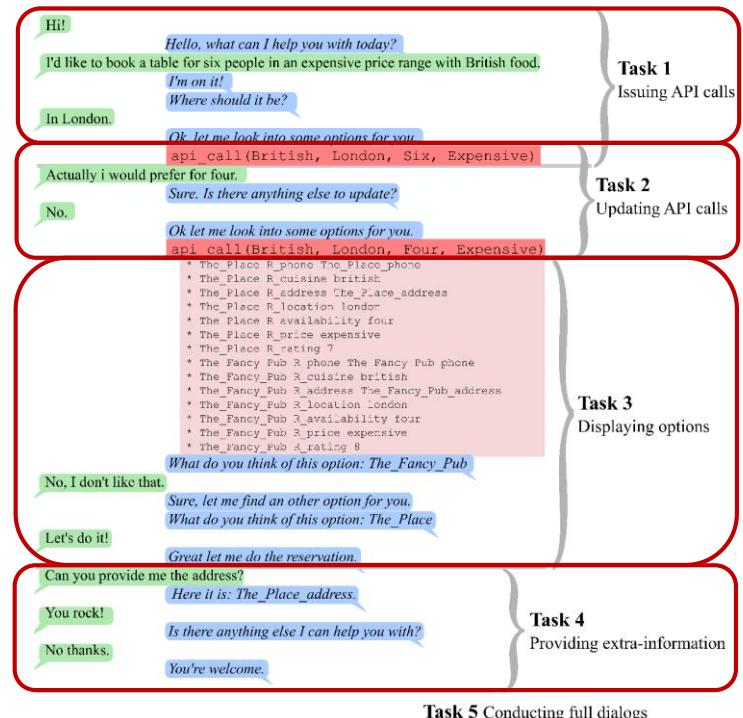
E2E MemNN for Dialogues (Bordes et al., 2016)

128

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

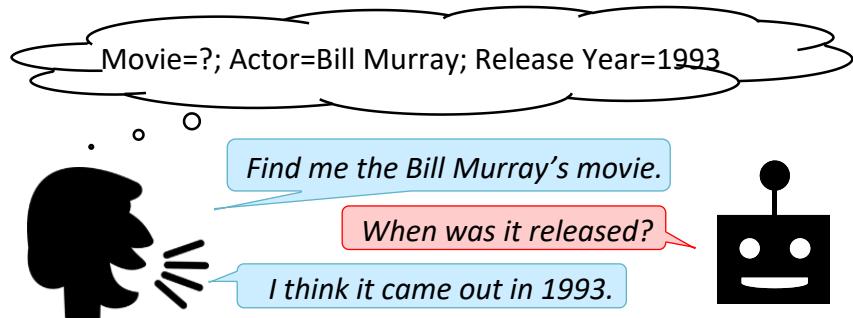
- Split dialogue system actions into subtasks
 - API issuing
 - API updating
 - Option displaying
 - Information informing

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)

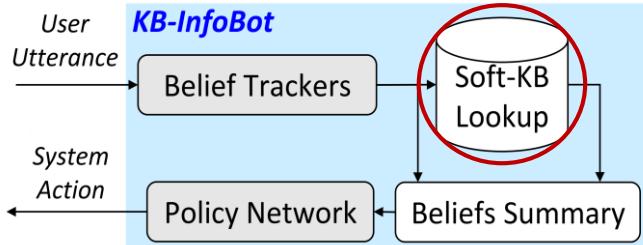


E2E RL-Based KB-InfoBot (Dhingra et al., 2017)

129

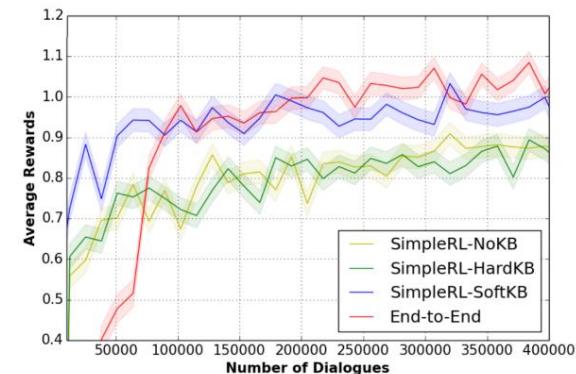
<http://www.aclweb.org/anthology/P/P17/P17-1045.pdf>


User: *Groundhog Day is a Bill Murray movie which came out in 1993.*



Entity-Centric Knowledge Base

Movie	Actor	Release Year
<i>Groundhog Day</i>	Bill Murray	1993
<i>Australia</i>	Nicole Kidman	X
<i>Mad Max: Fury Road</i>	X	2015



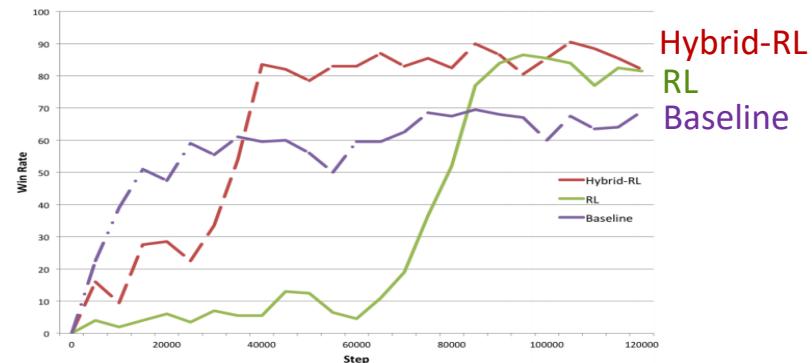
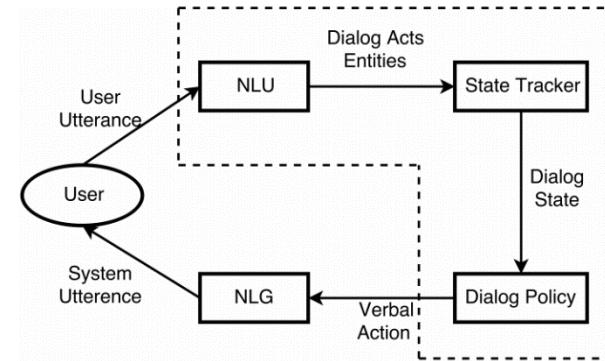
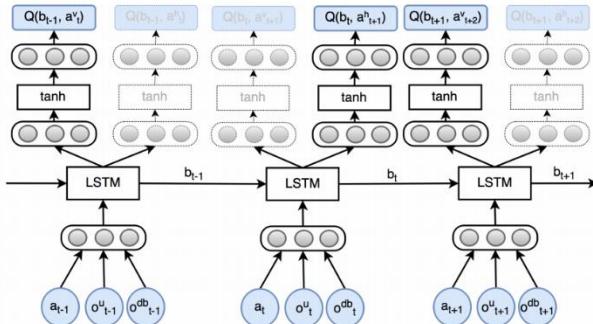
Idea: differentiable database for propagating the gradients

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

130

<http://www.aclweb.org/anthology/W/W16/W16-36.pdf>

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

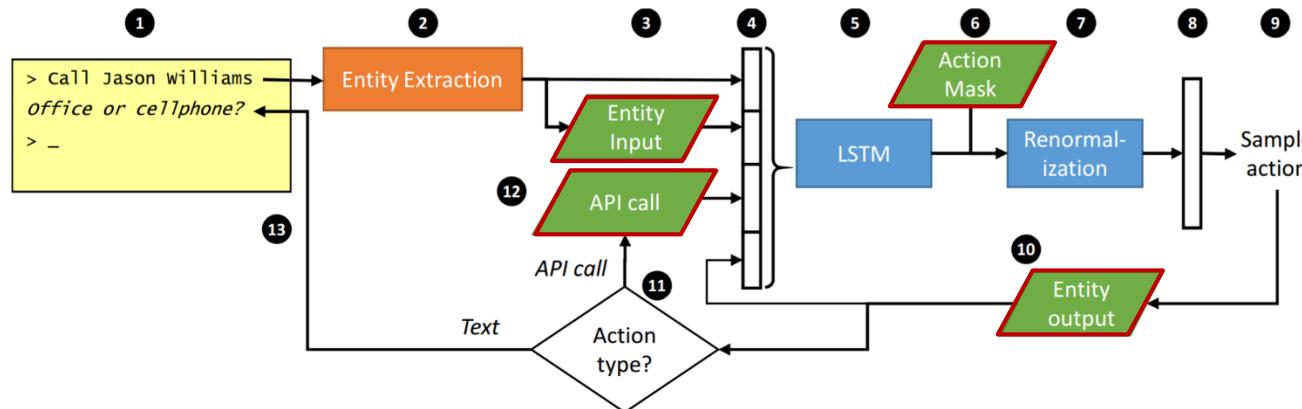


E2E LSTM-Based Dialogue Control (Williams and Zweig, 2016)

131

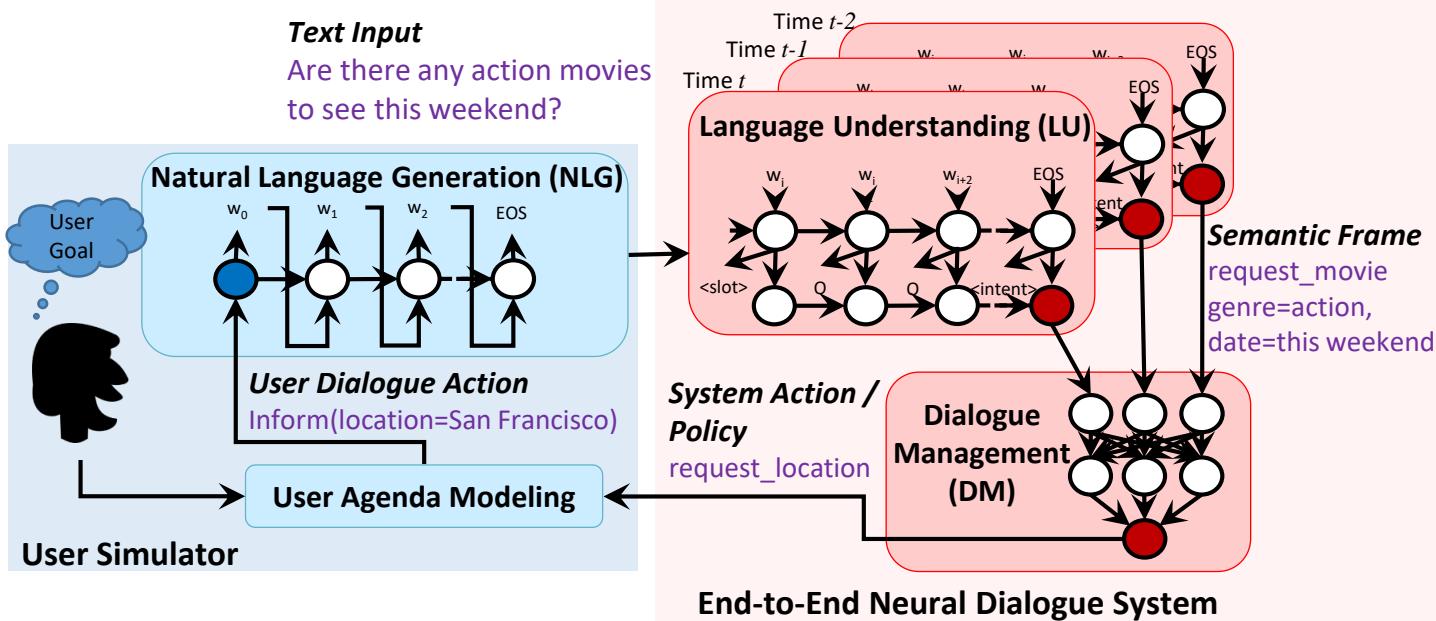
<https://arxiv.org/abs/1606.01269>

- 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)

132

<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)

133

<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!

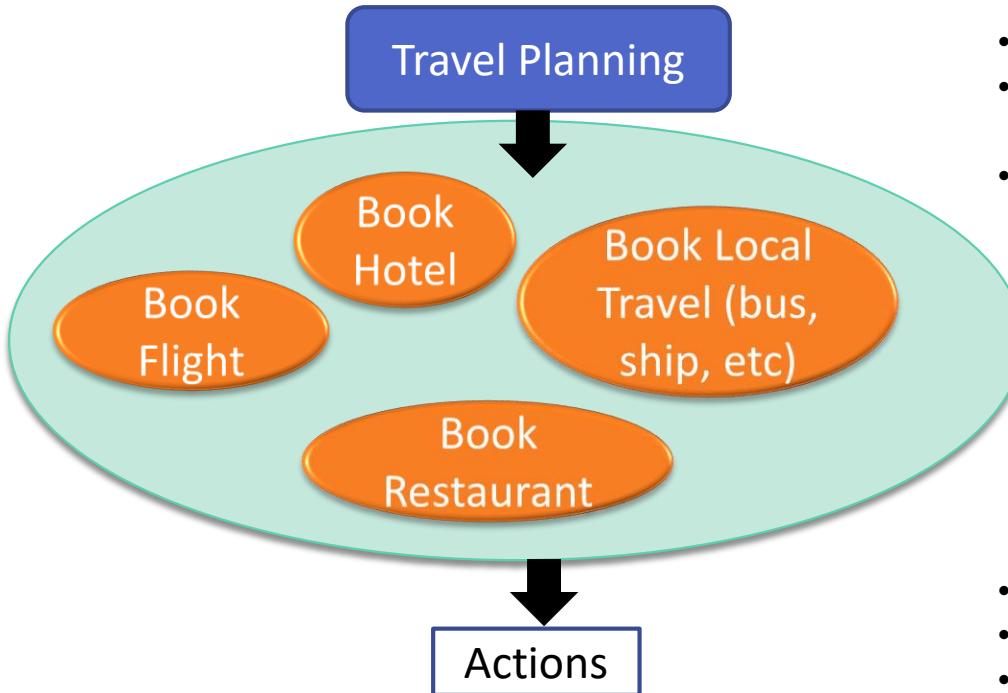


The system can learn how to efficiently interact with users for task completion

Hierarchical RL for Composite Tasks (Peng et al., 2017)

134

Peng et.al., EMNLP 2017

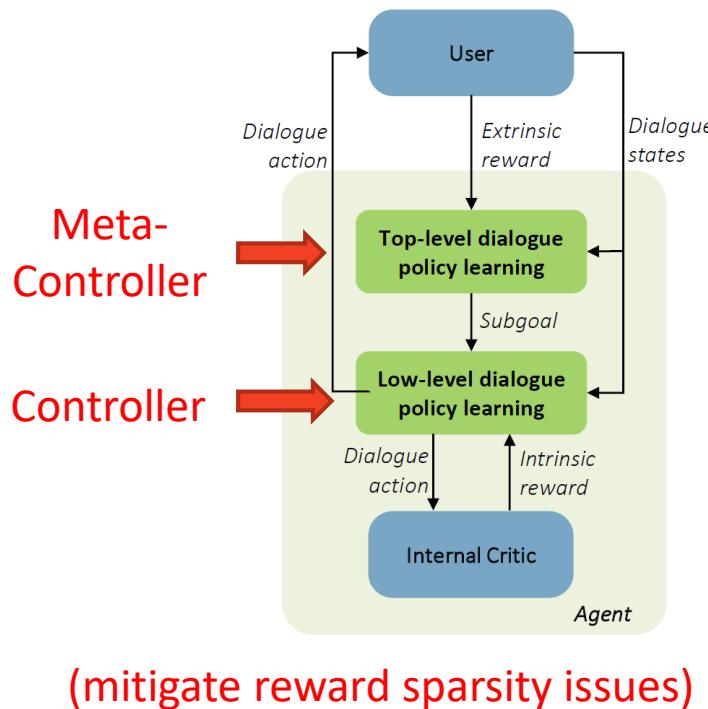
<https://arxiv.org/abs/1704.03084>

- Set of tasks that need to be fulfilled collectively!
 - Build a dialog manager that satisfies **cross-subtask constraints (slot constraints)**
 - Temporally constructed goals
-
- $\text{hotel_check_in_time} > \text{departure_flight_time}$
 - $\# \text{flight_tickets} = \# \text{people checking in the hotel}$
 - $\text{hotel_check_out_time} < \text{return_flight_time}$,

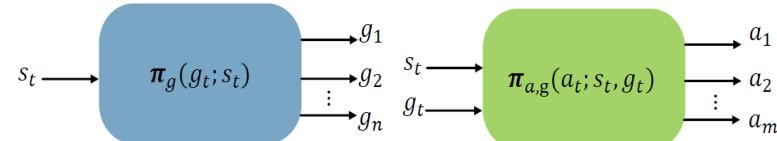
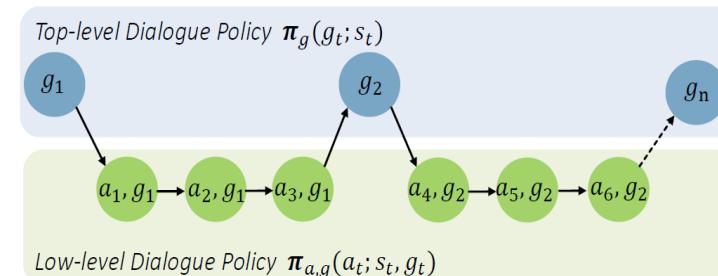
Hierarchical RL for Composite Tasks (Peng et al., 2017)

135

Peng et.al., EMNLP 2017

<https://arxiv.org/abs/1704.03084>

- The dialog model makes decisions over two levels: *meta-controller and controller*
- The *agent* learns these policies simultaneously
 - the policy of optimal sequence of goals to follow $\pi_g(g_t, s_t; \theta_1)$
 - Policy $\pi_{a,g}(a_t, g_t, s_t; \theta_2)$ for each sub-goal g_t



Outline

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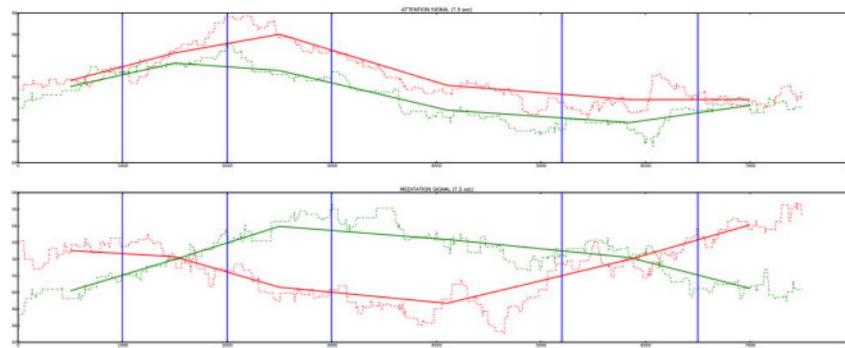
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 - Natural Language Generation (NLG)
- Recent Trends and Challenges
 - End-to-End Neural Dialogue System
 - **Multimodality**
 - Dialogue Breath
 - Dialogue Depth

Brain Signal for Understanding

137

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

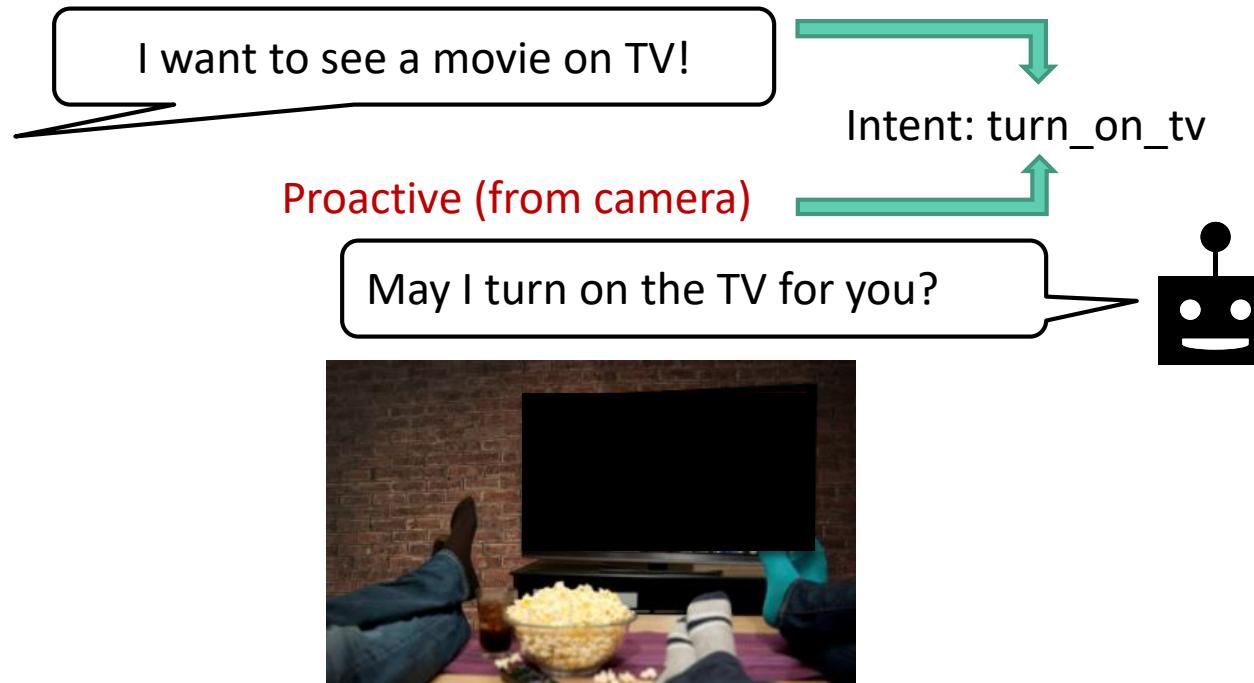
- Misunderstanding detection by brain signal
 - Green: listen to the correct answer
 - Red: listen to the wrong answer



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

Video for Intent Understanding

138



Proactively understanding user intent to initiate the dialogues.

App Behavior for Understanding

139

<http://dl.acm.org/citation.cfm?id=2820781>

- Task: user intent prediction
- Challenge: language ambiguity



① User preference

- ✓ Some people prefer “Message” to “Email”
- ✓ Some people prefer “Ping” to “Text”

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.

Video Highlight Prediction Using Audience Chat Reactions

140

Fu et.al., EMNLP 2017

<https://arxiv.org/pdf/1707.08559.pdf>

NALCS1 Videos 91 Clips Collections Events Followers 459,073 ... Follow

Chat Replay

- Cursecut3r : RYU STAT
- Shijiazhuang : haHAA
- Ich860504 : Where is Meteos
- TSM_Kibitz : Cass no boots haHAA
- ceofetas : =___=
- Pitamus : RHESTAT???
- colossushest : WHO'S BETTER INORI OR METEOS
- Ceramic_Llama : <message deleted>
- WHIPsering : NA CS
- bik0 : Ryu
- anomuuu : @momom3,
- memeoji : ONLY METEOS CAN FIX THIS
- completely_serious : <message deleted>
- AlejandroKisaragi : <message deleted>
- Colluder : @G2_S7_World_Champs, NICE MEME M8 xD LUL
- mikishark242 : DAISY ME ROLLING
- monkz007 : CS LUL
- DonutEatingBear : HADOKEN!

NA LCS Playoffs: Phoenix1 vs. Team Dignitas • 5 days ago
League of Legends

2017 NA LCS SPRING PLAYOFFS

0 DIG 4 3 P1 0

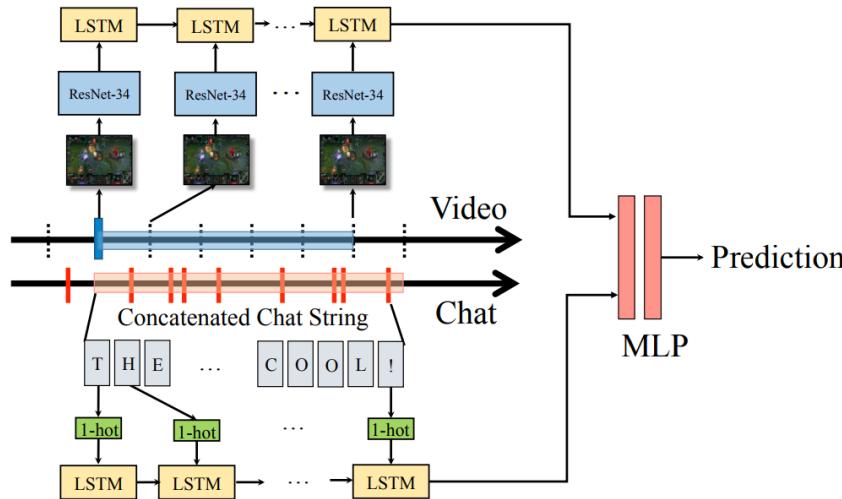
21,634 Share



Video Highlight Prediction Using Audience Chat Reactions

141

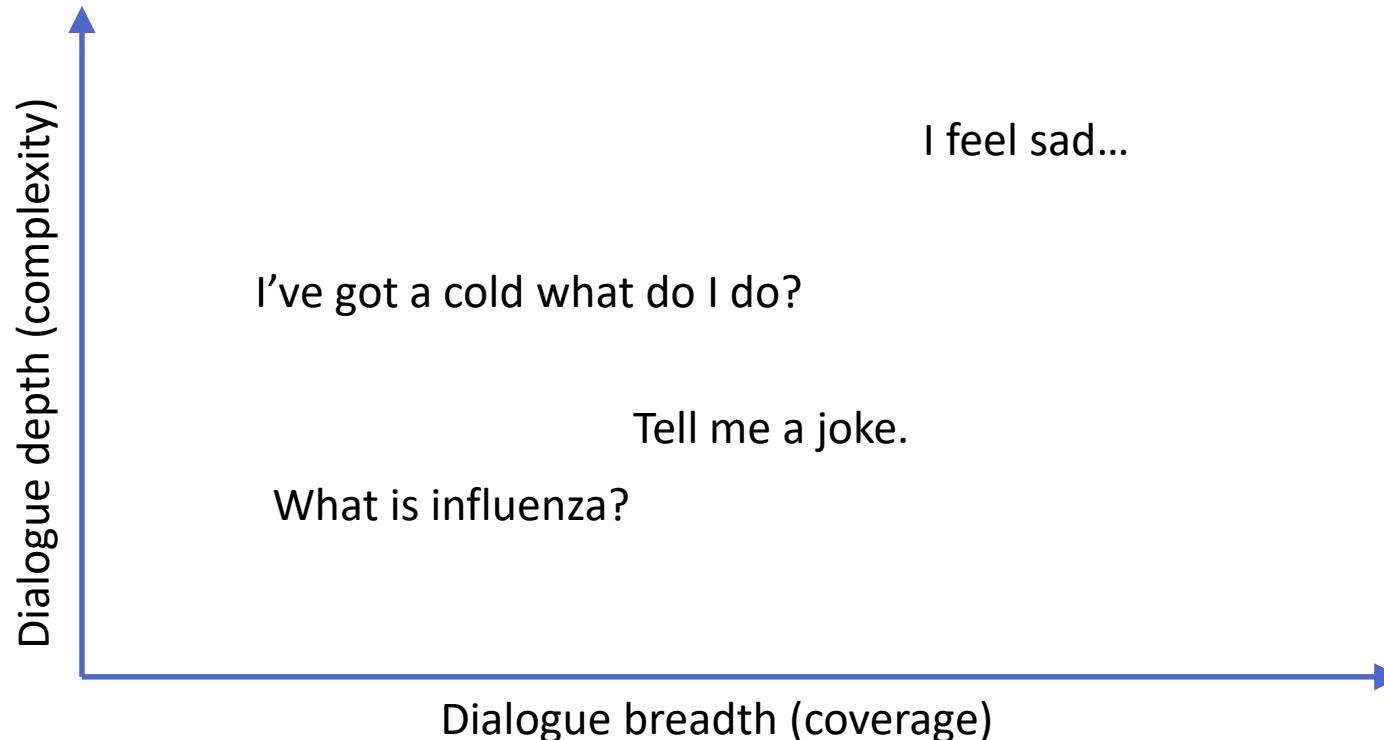
Fu et.al., EMNLP 2017

<https://arxiv.org/pdf/1707.08559.pdf>

- Goal: predict highlight from the video
- Input : multi-modal and multi-lingual (real time text commentary from fans)
- Output: tag if a frame part of a highlight or not

Evolution Roadmap

142



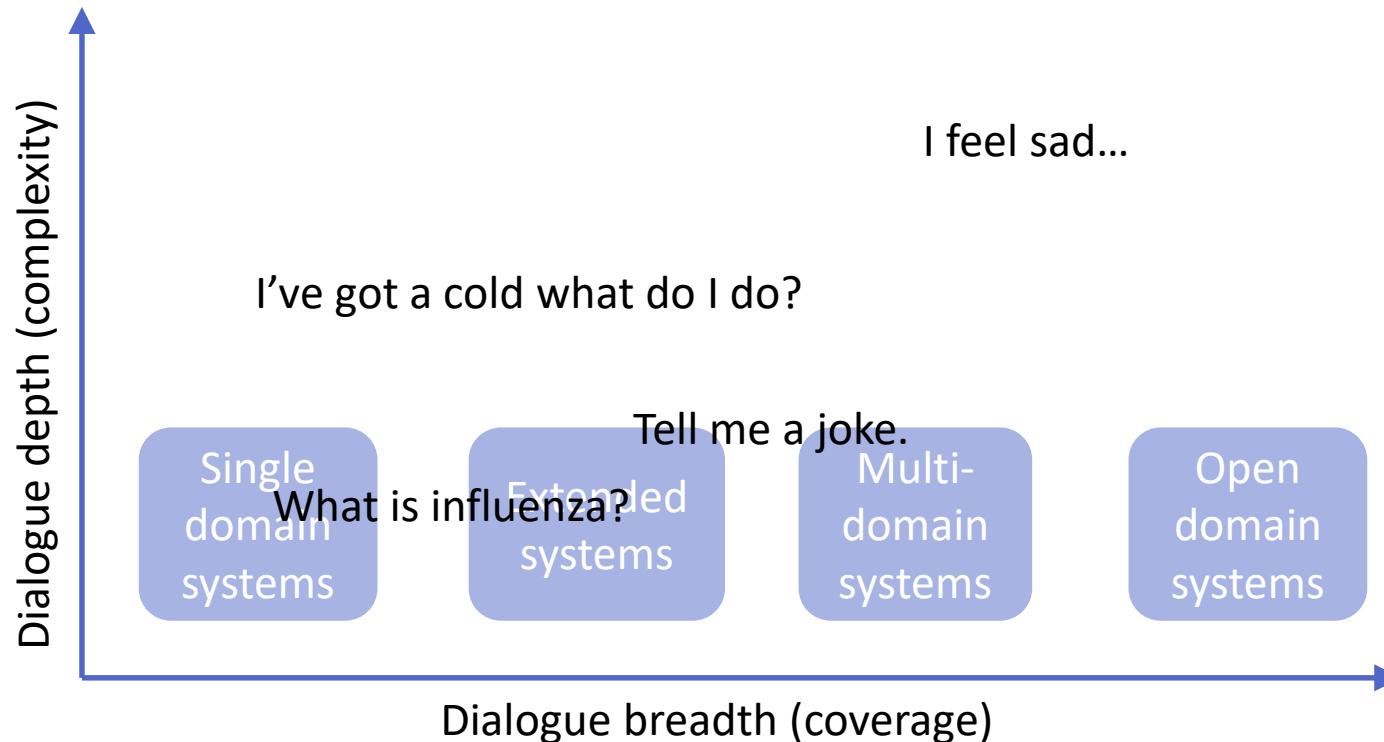
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 - ***Dialogue Breath***
 - Dialogue Depth

Evolution Roadmap

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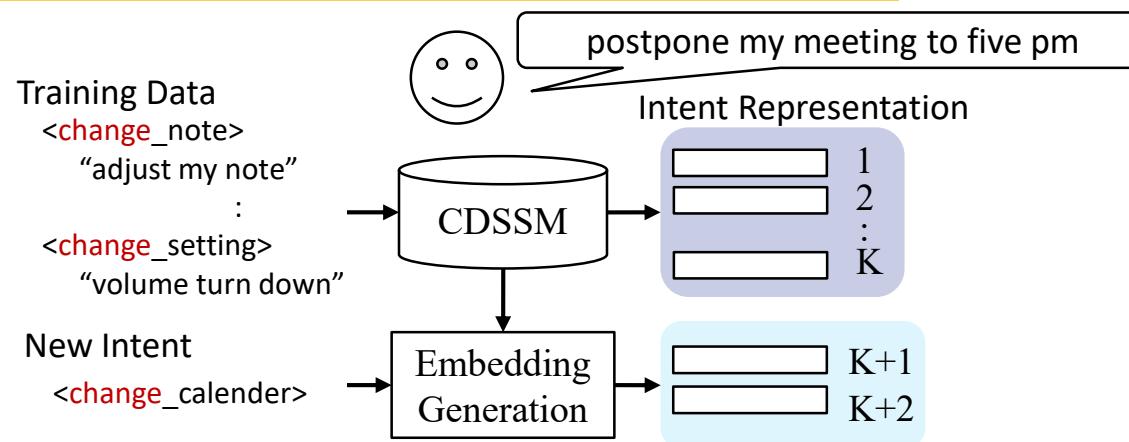


Intent Expansion (Chen et al., 2016)

145

<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



The dialogue act representations can be automatically learned for other domains

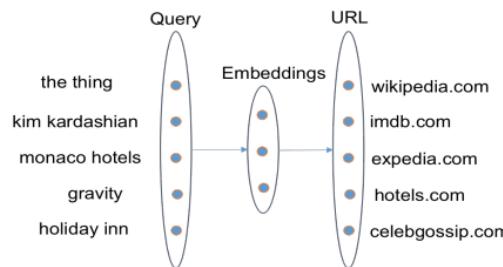
Zero-Shot Learning (Daupin et al., 2016)

146

<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.

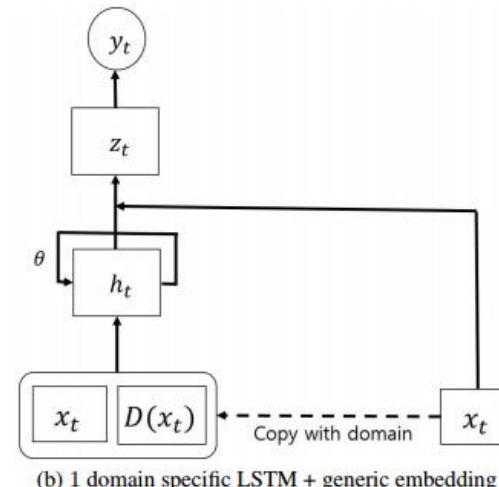
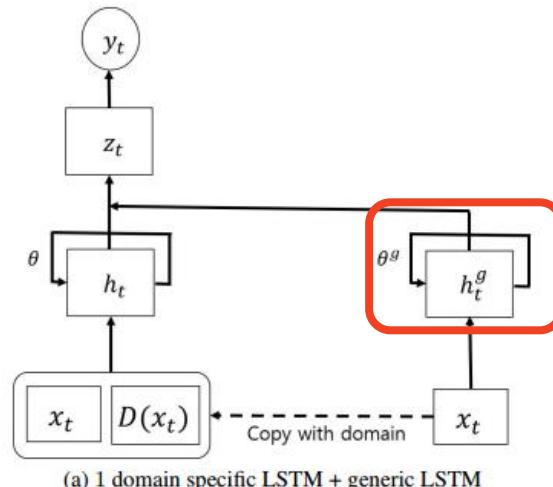
- The semantic features are the last hidden layer of the DNN
- Use Zero-Shot Discriminative embedding model combines H with the minimization of entropy of a zero-shot classifier

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

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<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

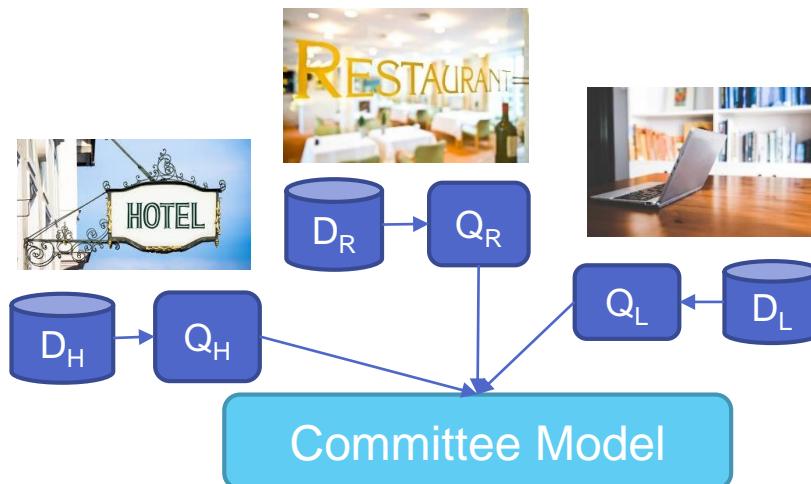


Policy for Domain Adaptation (Gašić et al., 2015)

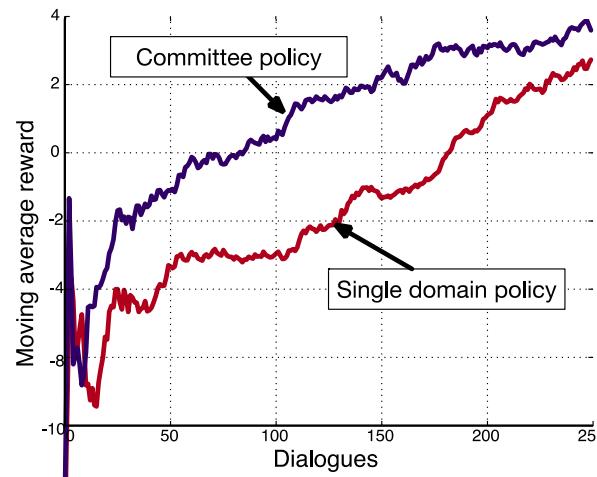
148

<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



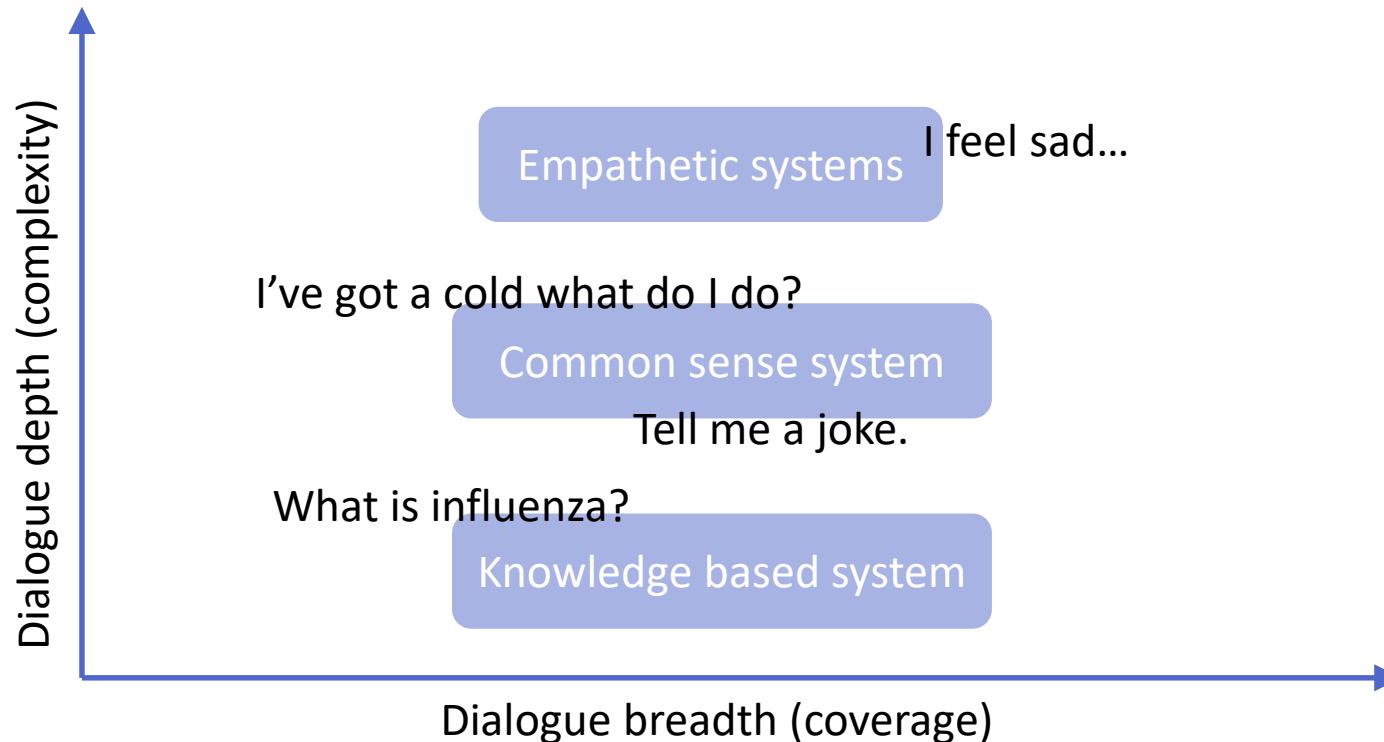
Outline

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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)
- Recent Trends and Challenges
 - End-to-End Neural Dialogue System
 - Multimodality
 - Dialogue Breath
 - **Dialogue Depth**

Evolution Roadmap

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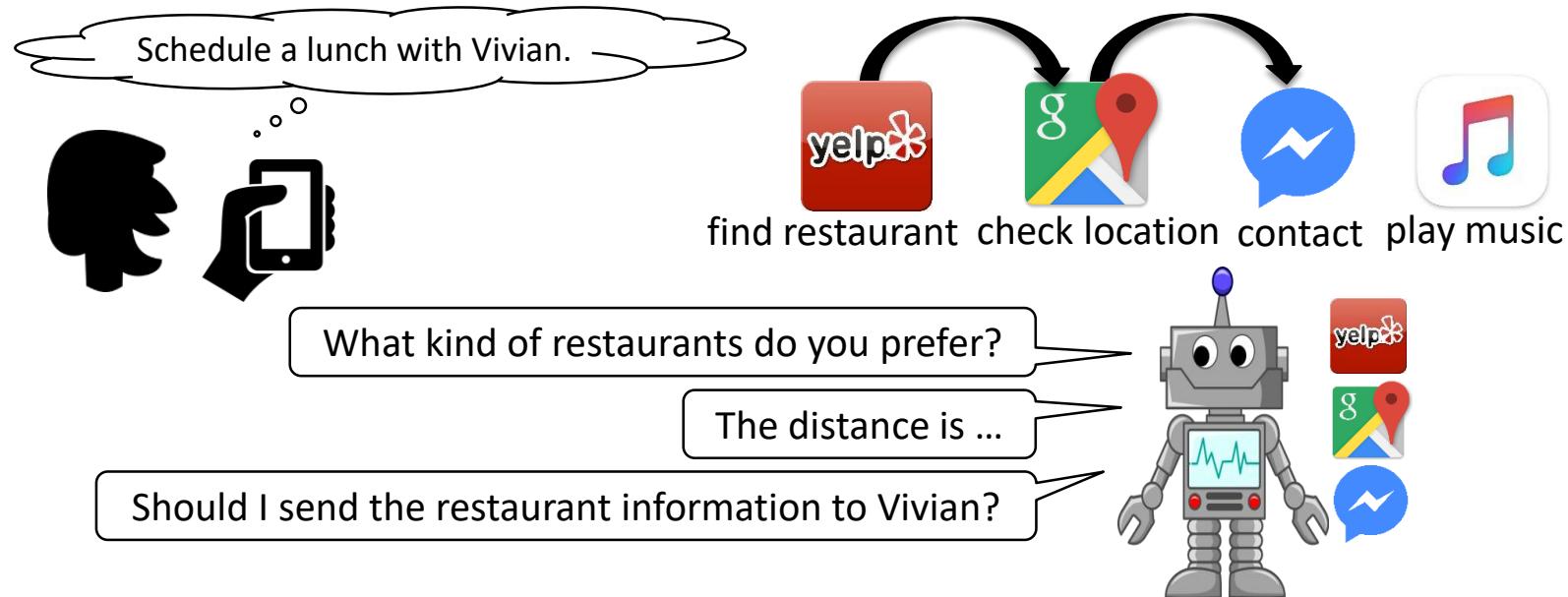


High-Level Intention for Dialogue Planning (Sun et al., 2016)

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<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



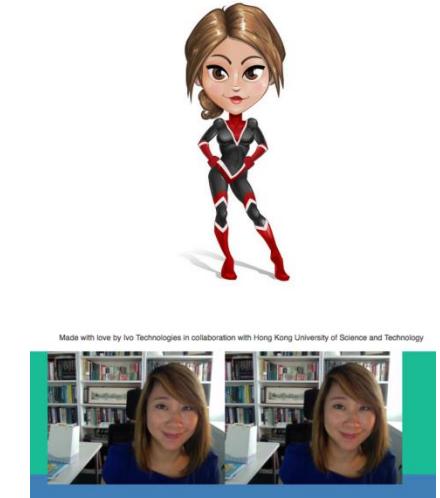
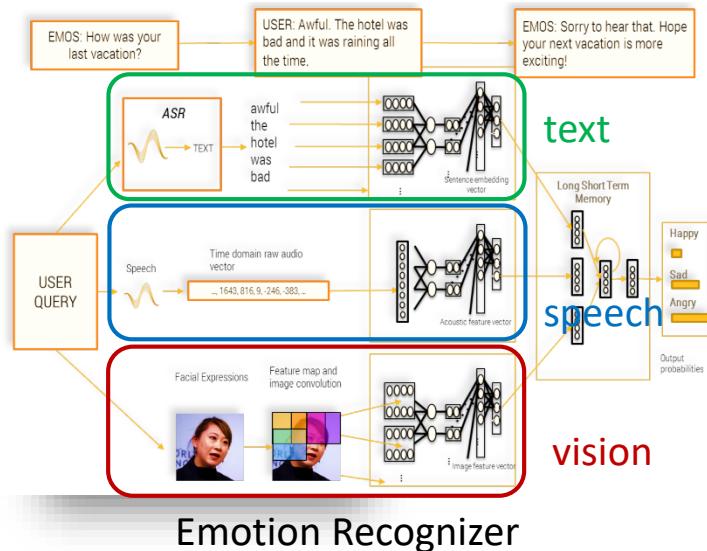
Users can interact via high-level descriptions and the system learns how to plan the dialogues

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

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<https://arxiv.org/abs/1605.04072>**Zara** - The Empathetic Supergirl

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



```
Face recognition output
{
  "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"
}
```

(index):1728
(index):1729

Visual Object Discovery through Dialogues (Vries et al., 2017)

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<https://arxiv.org/pdf/1611.08481.pdf>

- Recognize objects using “Guess What?” game
- Includes “spatial”, “visual”, “object taxonomy” and “interaction”



- Is it a person? **No**
Is it an item being worn or held? **Yes**
Is it a snowboard? **Yes**
Is it the red one? **No**
Is it the one being held by the person in blue? **Yes**



- Is it a cow? **Yes**
Is it the big cow in the middle? **No**
Is the cow on the left? **No**
On the right ? **Yes**
First cow near us? **Yes**

Conclusion

Summarized Challenges

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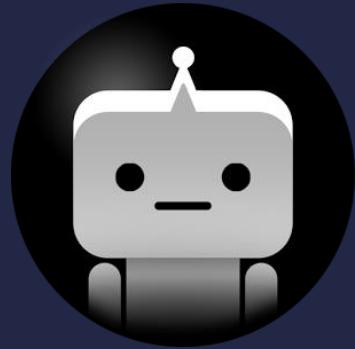
- 
- Human-machine interfaces is a hot topic but several components must be integrated!
 - Most state-of-the-art technologies are based on DNN
 - Requires huge amounts of labeled data
 - Several frameworks/models are available
 - Fast domain adaptation with scarce data + re-use of rules/knowledge
 - Handling reasoning
 - Data collection and analysis from un-structured data
 - Complex-cascade systems requires high accuracy for working good as a whole

Brief Conclusions

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- Introduce recent deep learning methods used in dialogue models
- Highlight main components of dialogue systems and new deep learning architectures used for these components
- Talk about challenges and new avenues for current state-of-the-art research
- Provide all materials online!

<http://deepdialogue.miulab.tw>



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