딥러닝 기반 대화시스템

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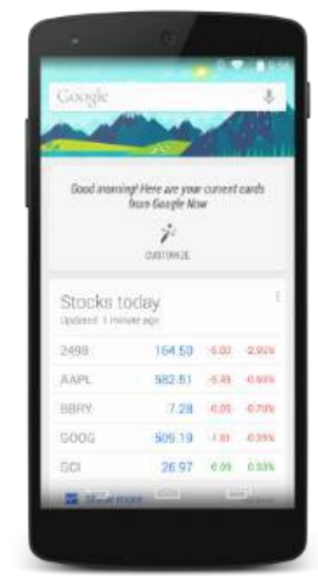
Outline

Materials are borrowed from : http://deepdialogue.miulab.tw

- Introduction
- Modular Dialogue System
  - Spoken/Natural Language Understanding (SLU/NLU)
  - Dialogue Management
    - Dialogue State Tracking (DST)
    - Dialogue Policy Optimization
  - Natural Language Generation (NLG)
- Dialogue System Evaluation
- End-to-End Neural Dialogue System

Language Empowering Intelligent Assistants

Apple Siri (2011)



Google Now (2012)
Google Assistant (2016)

Microsoft Cortana (2014)

Amazon Alexa/Echo (2014)

Google Home (2016)

Bixby

SAMSUNG Bixby (2017)

Facebook Portal (2019)

Why Natural Language?

- Global Digital Statistics (2018 January)

Total Population
7.59B

Internet Users
4.02B
7%

Active Social Media Users
3.20B
13%

Unique Mobile Users
5.14B
4%

Active Mobile Social Users
2.96B
14%

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

Spoken Dialogue System (SDS)

- 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.

Conversational Agents

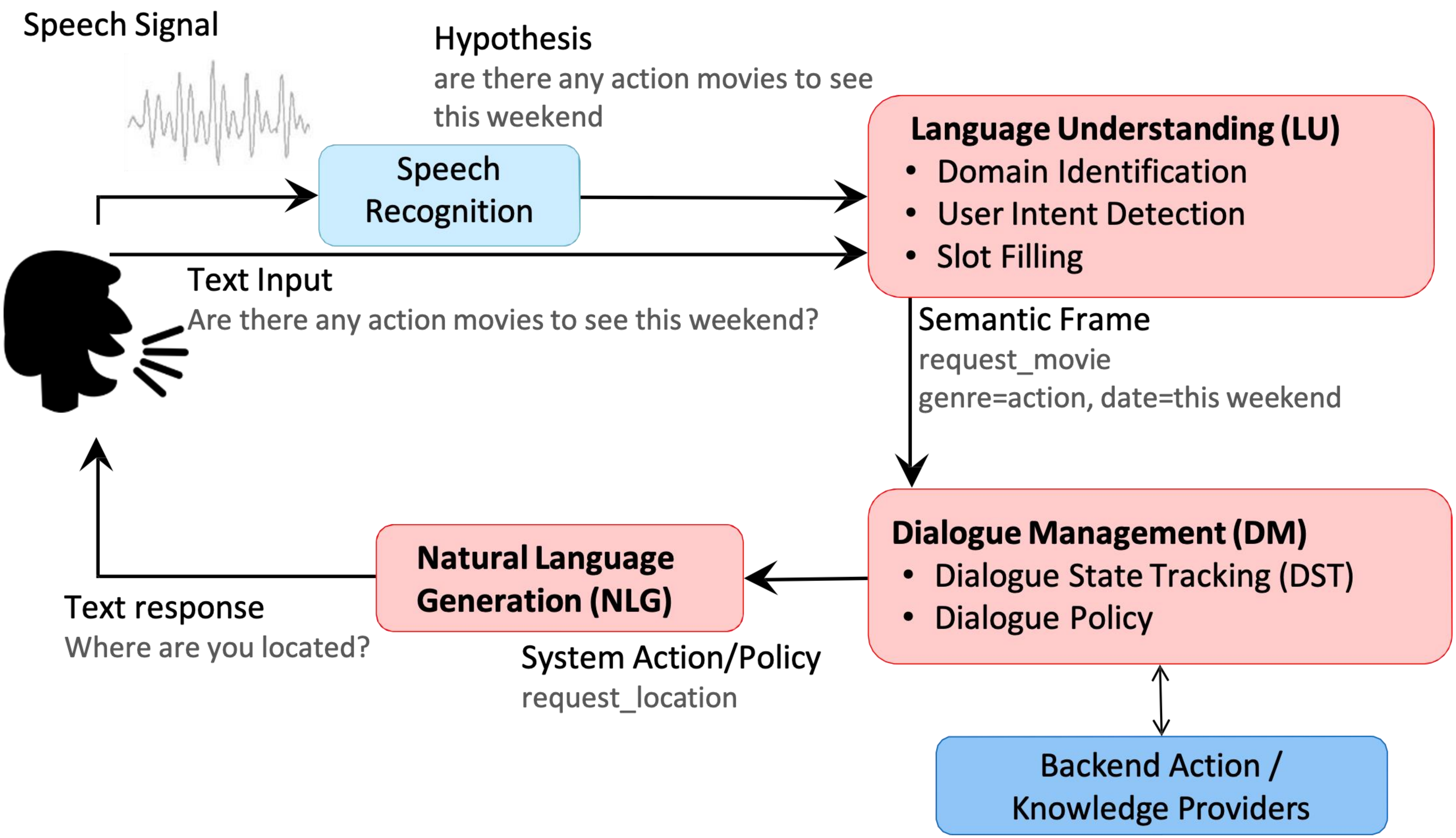
Chit-Chat

- seq2seq models
- Seq2seq with conversation contexts
- Knowledge-grounded seq2seq models

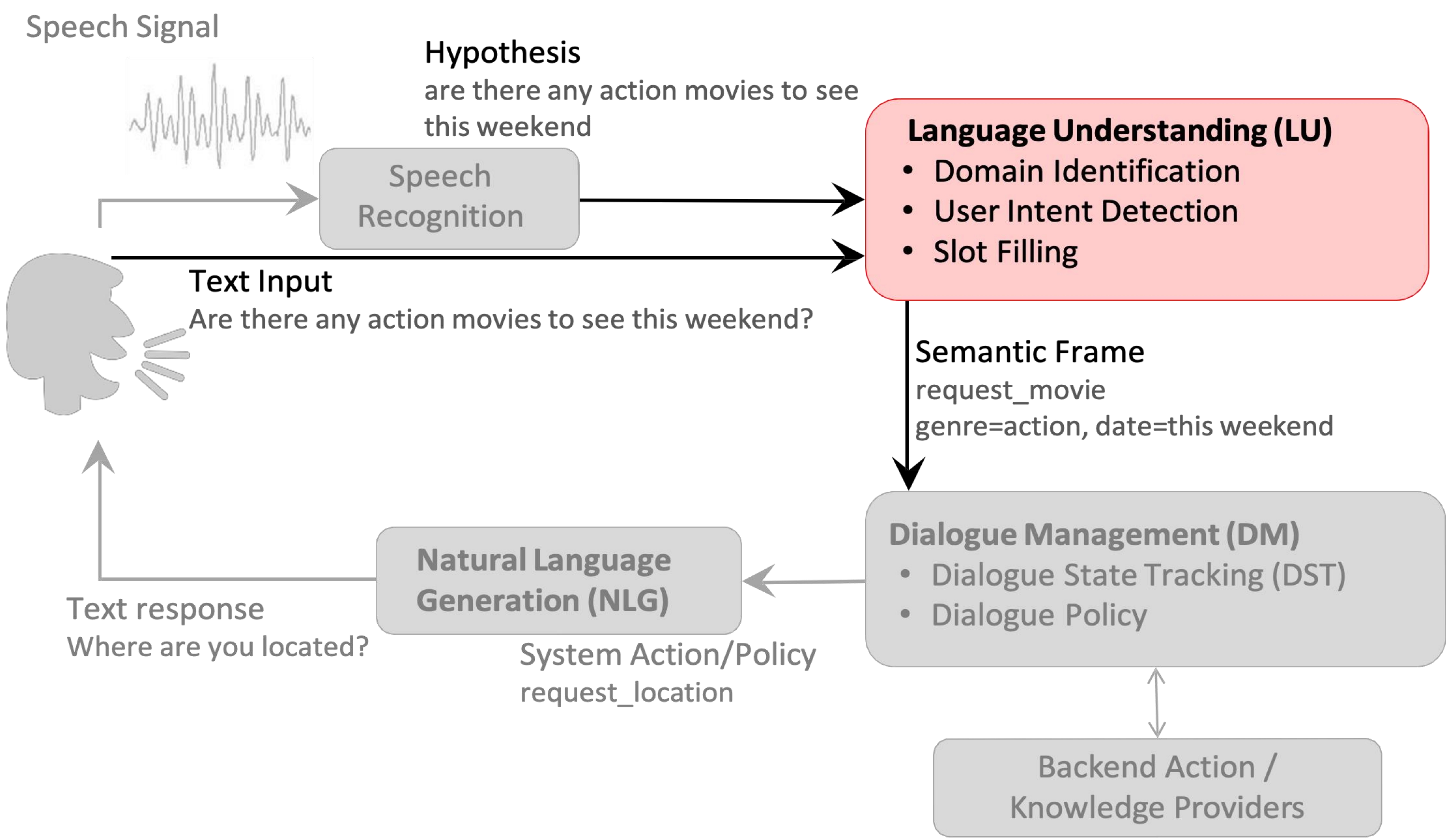
Task-Oriented

- Single-domain, system-initiative
- Multi-domain, contextual, mixed-initiative
- End-to-end learning, massively multi-domain

Task-Oriented Dialogue System (Young, 2000)



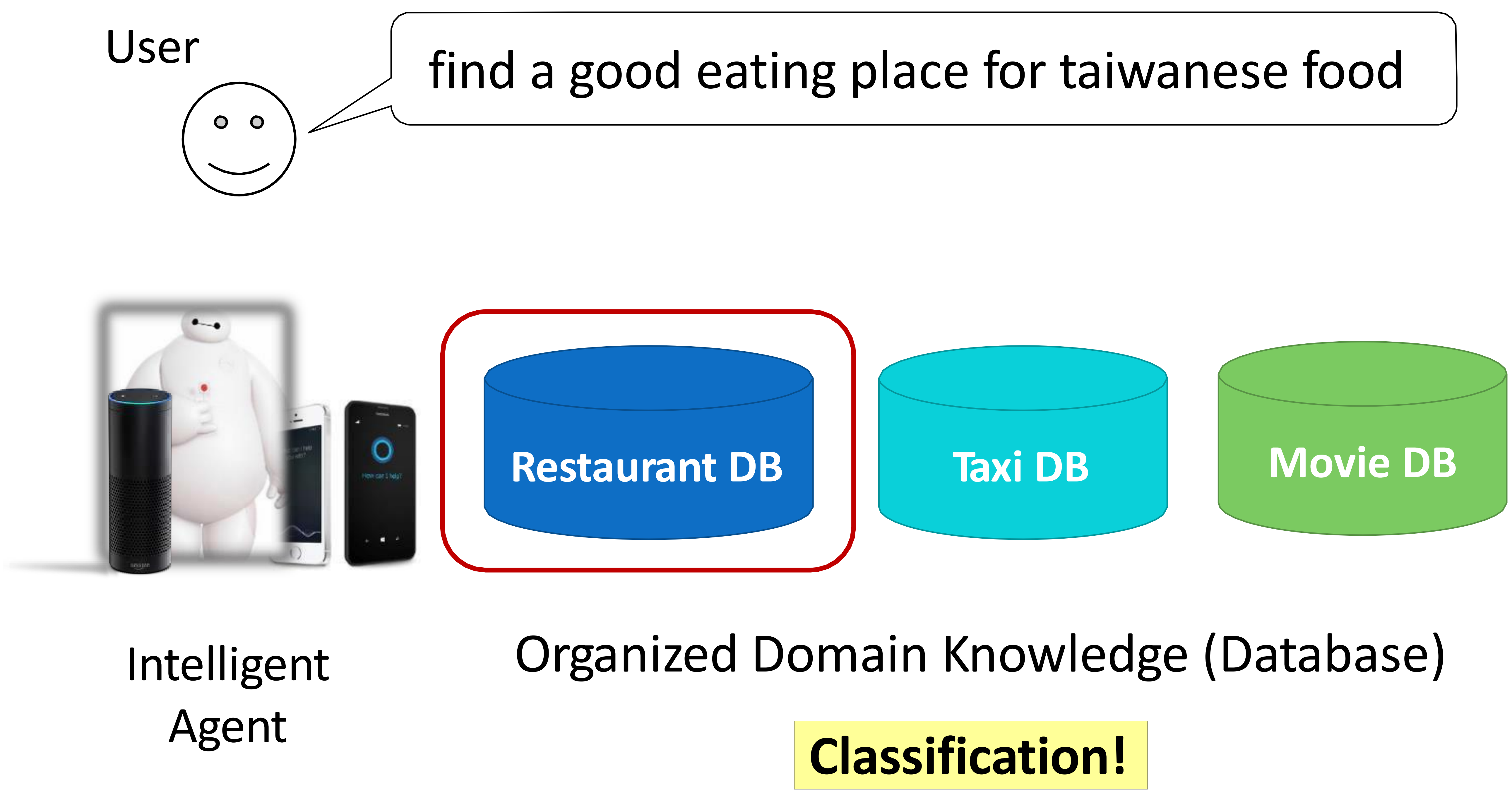
Task-Oriented Dialogue System (Young, 2000)



Language Understanding

1. Domain Identification

Requires Predefined Domain Ontology

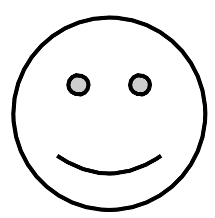


Language Understanding

2. Intent Detection

Requires Predefined Schema

User



find a good eating place for taiwanese food

Intelligent Agent

Restaurant DB

FIND_RESTAURANT
FIND_PRICE
FIND_TYPE
:

Classification!

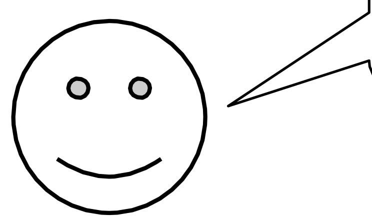
Language Understanding

3. Slot Filling

Requires Predefined Schema

O O B-rating O O O B-type O

User



find a ~~good~~ eating place for ~~taiwanese~~ food

Restaurant	Rating	Type
Rest 1	good	Taiwanese
Rest 2	bad	Thai
:	:	:

Restaurant DB

Intelligent Agent

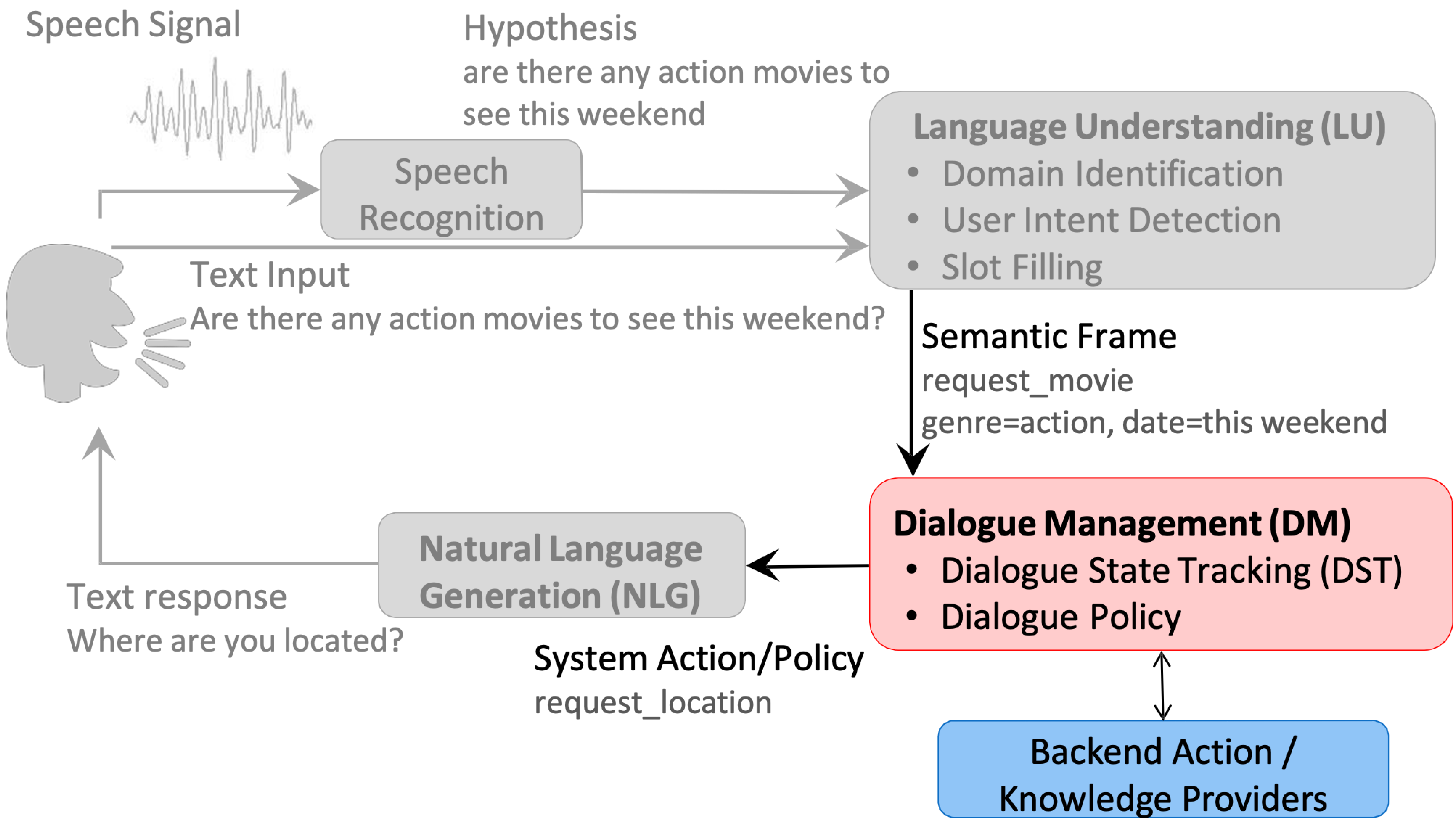
FIND_RESTAURANT
rating="good"
type="taiwanese"

Semantic Frame

SELECT restaurant { rest.rating="good" rest.type="taiwanese"
}

Sequence Labeling

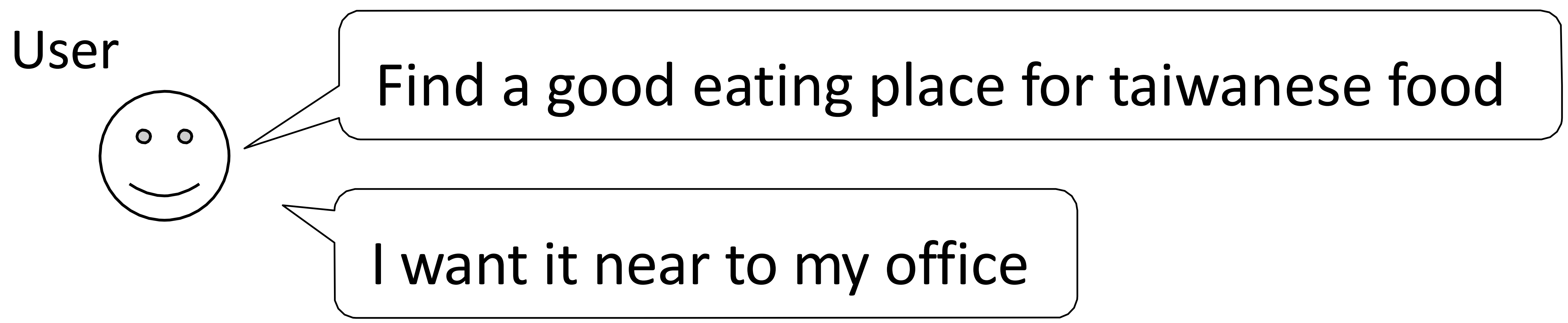
Task-Oriented Dialogue System (Young, 2000)



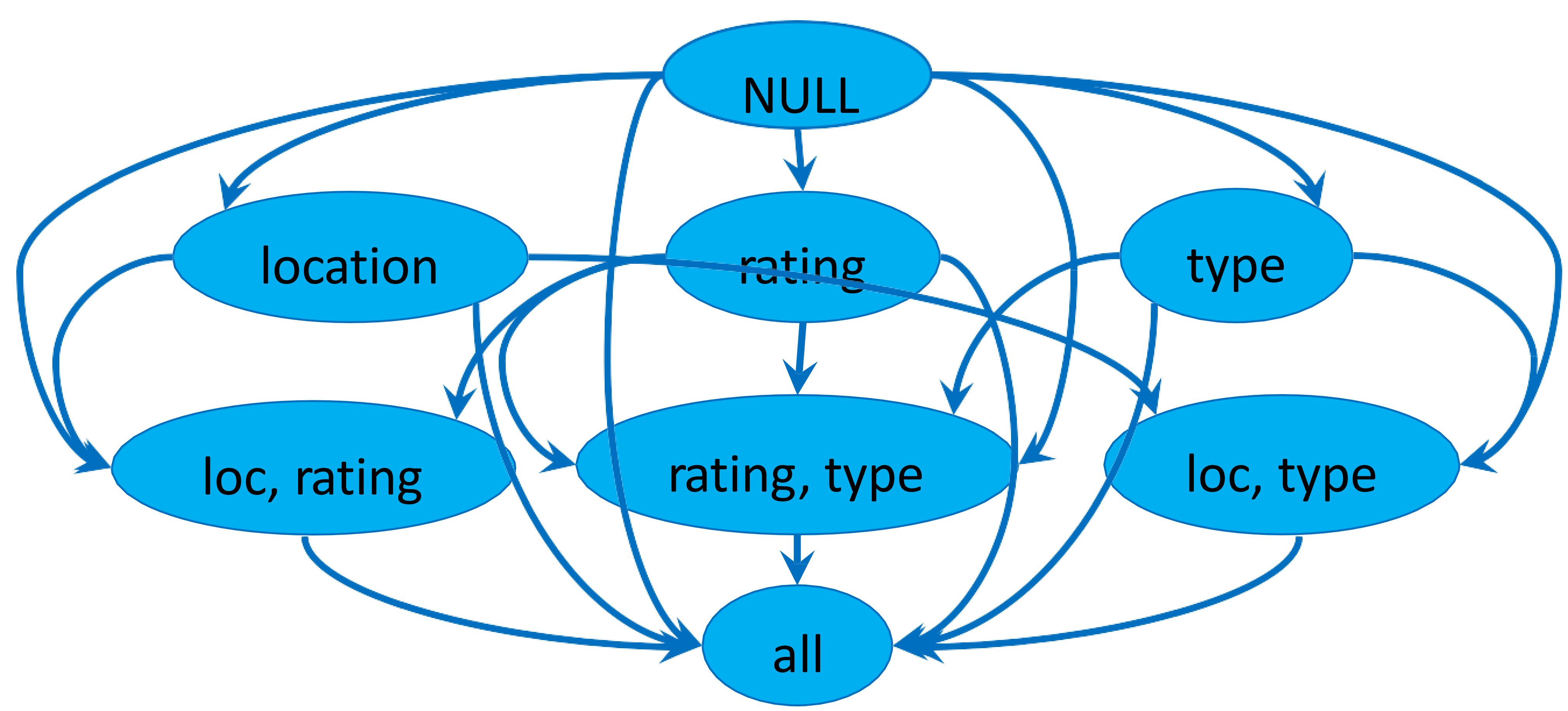
Dialogue Management

State Tracking

Requires Hand-Crafted States



Intelligent Agent

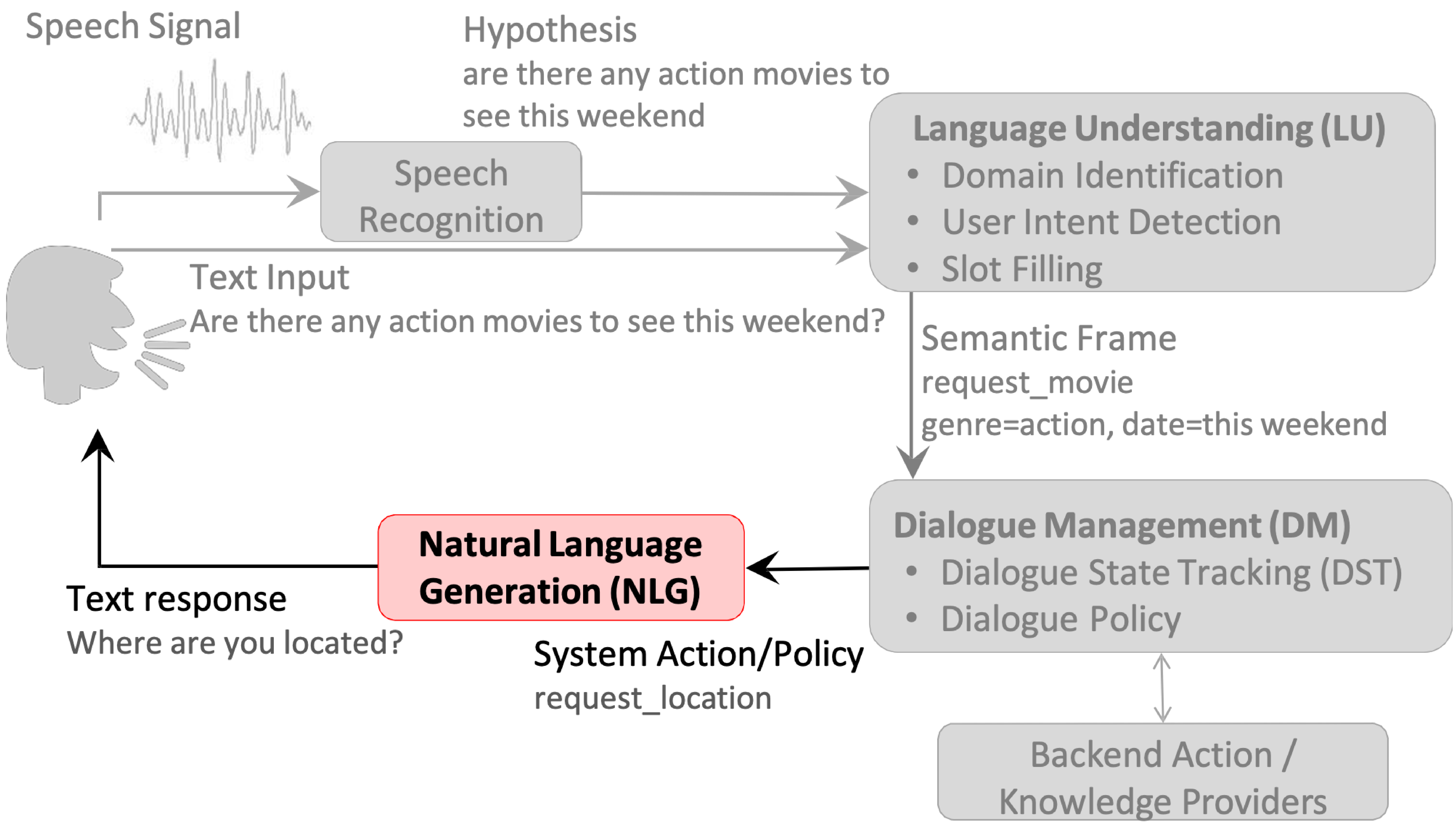


Dialogue Management

Dialogue Policy for Agent Action

- 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



Output / Natural Language Generation

- 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.

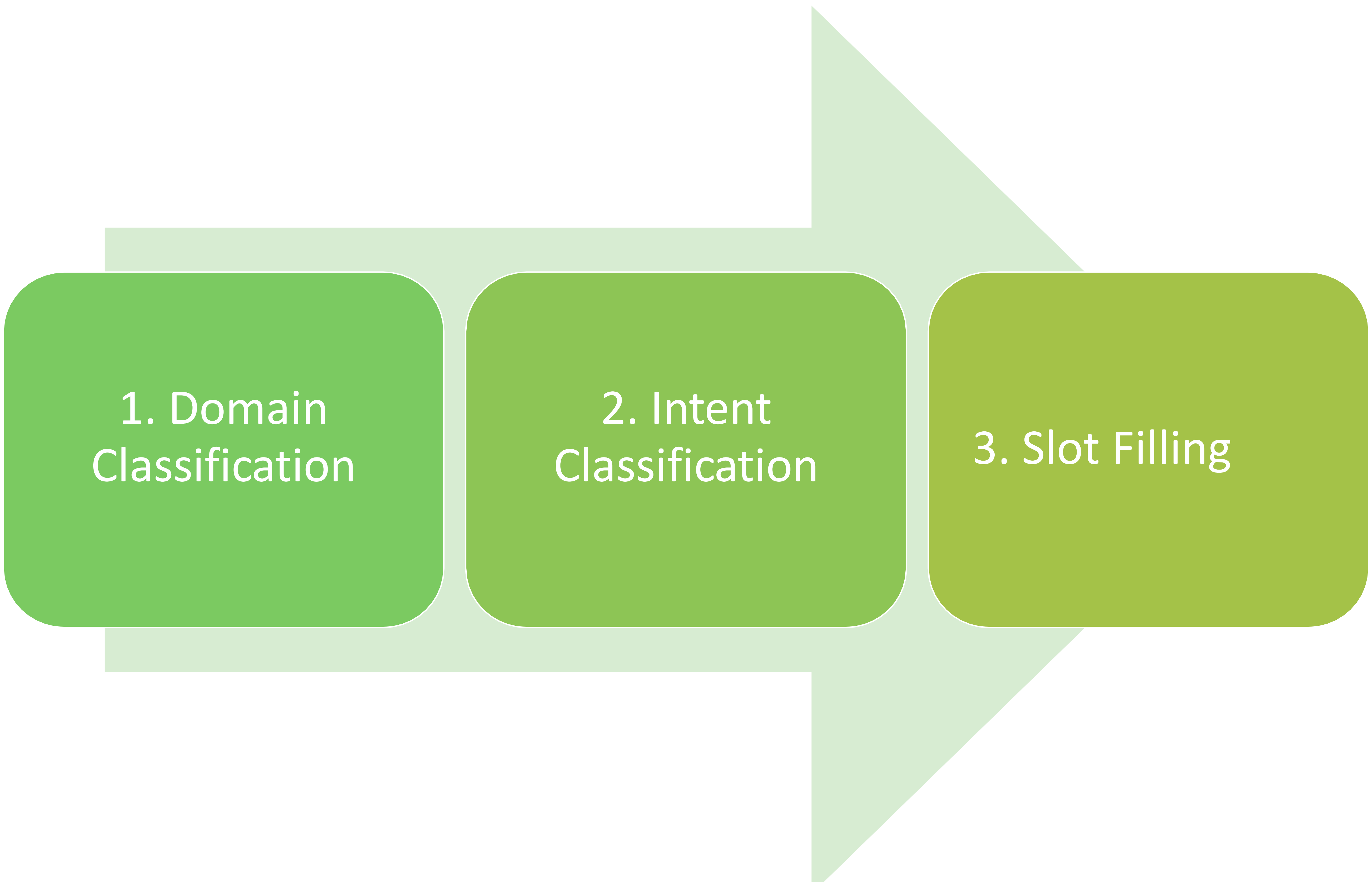
- Request(location)
    - "Where is your home?" v.s.

- Confirm(type="taiwanese")
    - "Did you want Taiwanese food?" v.s.

Modular Dialogue System

Spoken/Natural Language Understanding (SLU/NLU)

Language Understanding (LU)



Domain/Intent Classification

As an **utterance classification** task

- Given a collection of utterances u_i with labels c_i, $D=\{(u_1,c_1),\ldots,(u_n,c_n)\}$ 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
Restaurants
Music
Sports
…

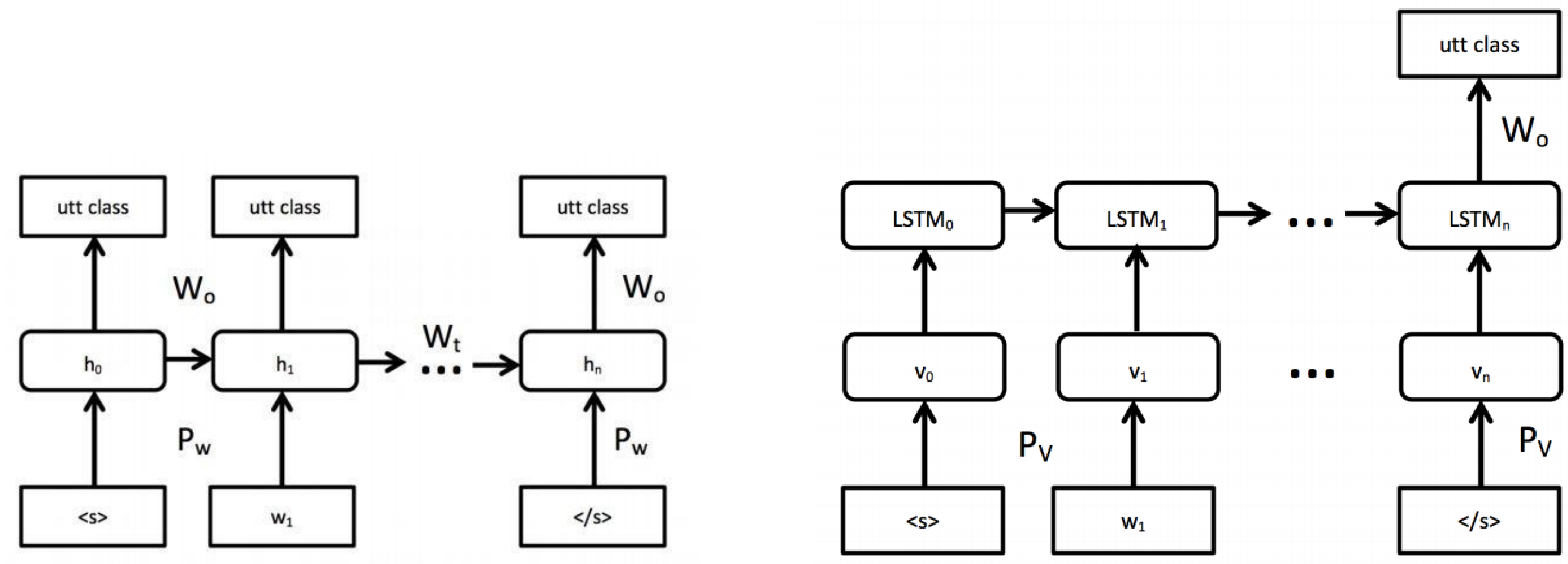
Domain

find_movie, buy_tickets find_restaurant,
find_price, book_table find_lyrics,
find_singer
…

Intent

Domain/Intent Classification (Ravuri & Stolcke, 2015)

- RNN and LSTMs for utterance classification



Intent decision after reading all words performs better

* Ravuri, Suman, and Andreas Stolcke. "Recurrent neural network and LSTM models for lexical utterance classification." Sixteenth Annual Conference of the International Speech Communication Association. 2015.

Slot Filling

As a sequence tagging task

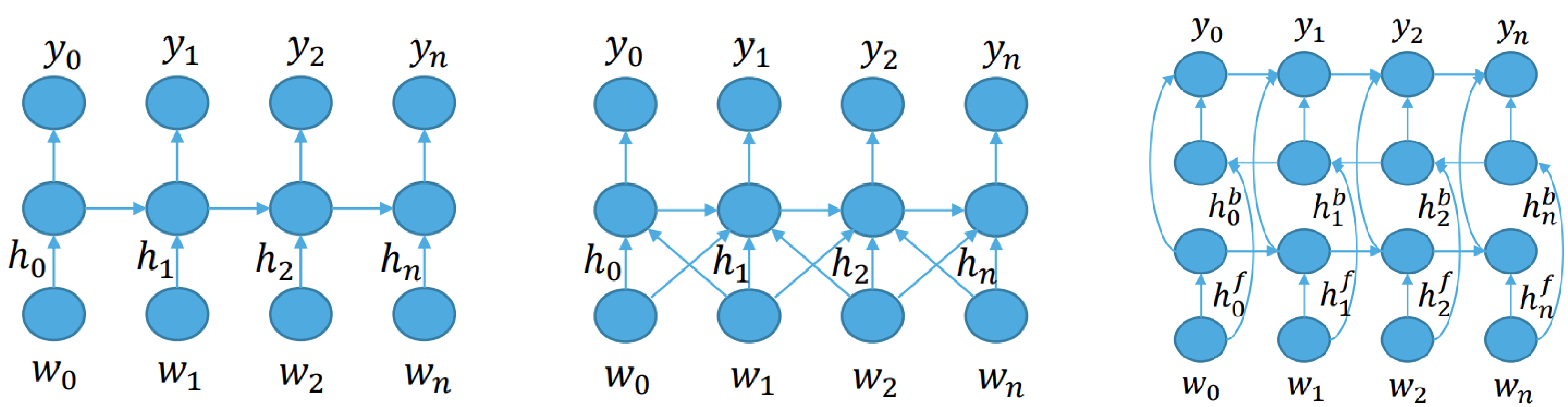
- Given a collection tagged word sequences, $S=\{((w_{1,1},w_{1,2},\ldots, w_{1,n1}), (t_{1,1},t_{1,2},\ldots,t_{1,n1})), ((w_{2,1},w_{2,2},\ldots,w_{2,n2}), (t_{2,1},t_{2,2},\ldots,t_{2,n2})) \ldots\}$ where $t_i \in M$, the goal is to estimate tags for a new word sequence.

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

Slot Tagging

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

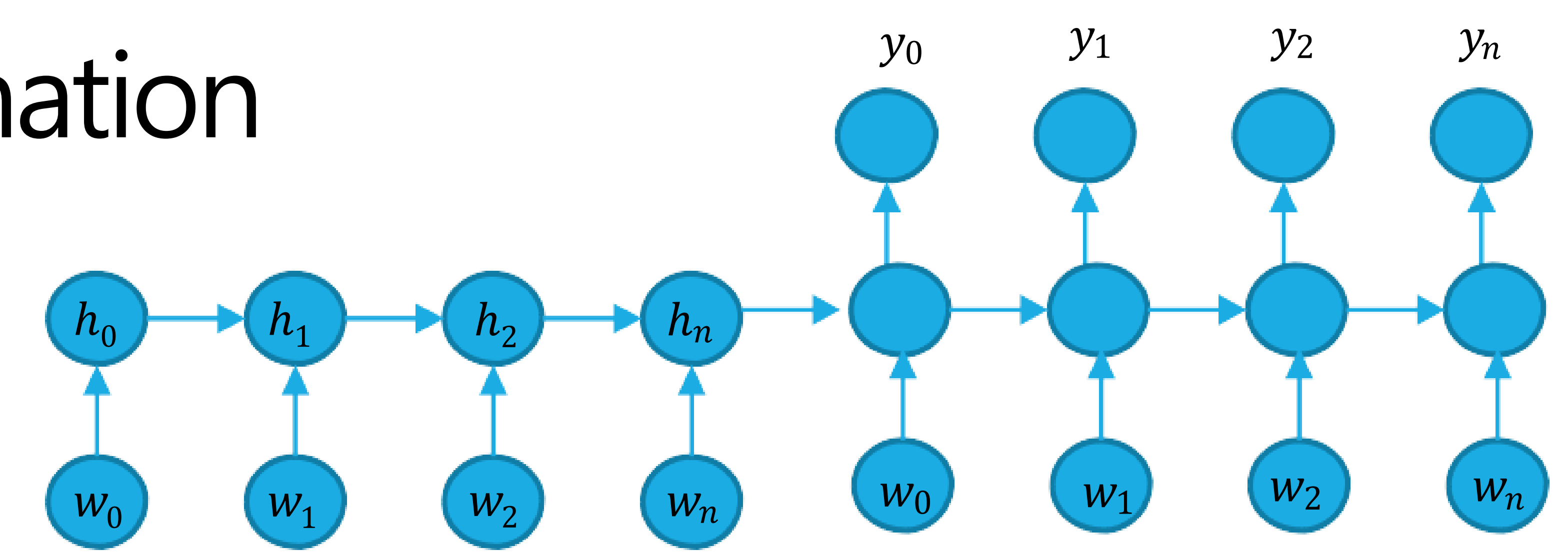


(a) LSTM (b) LSTM-LA (c) bLSTM-LA

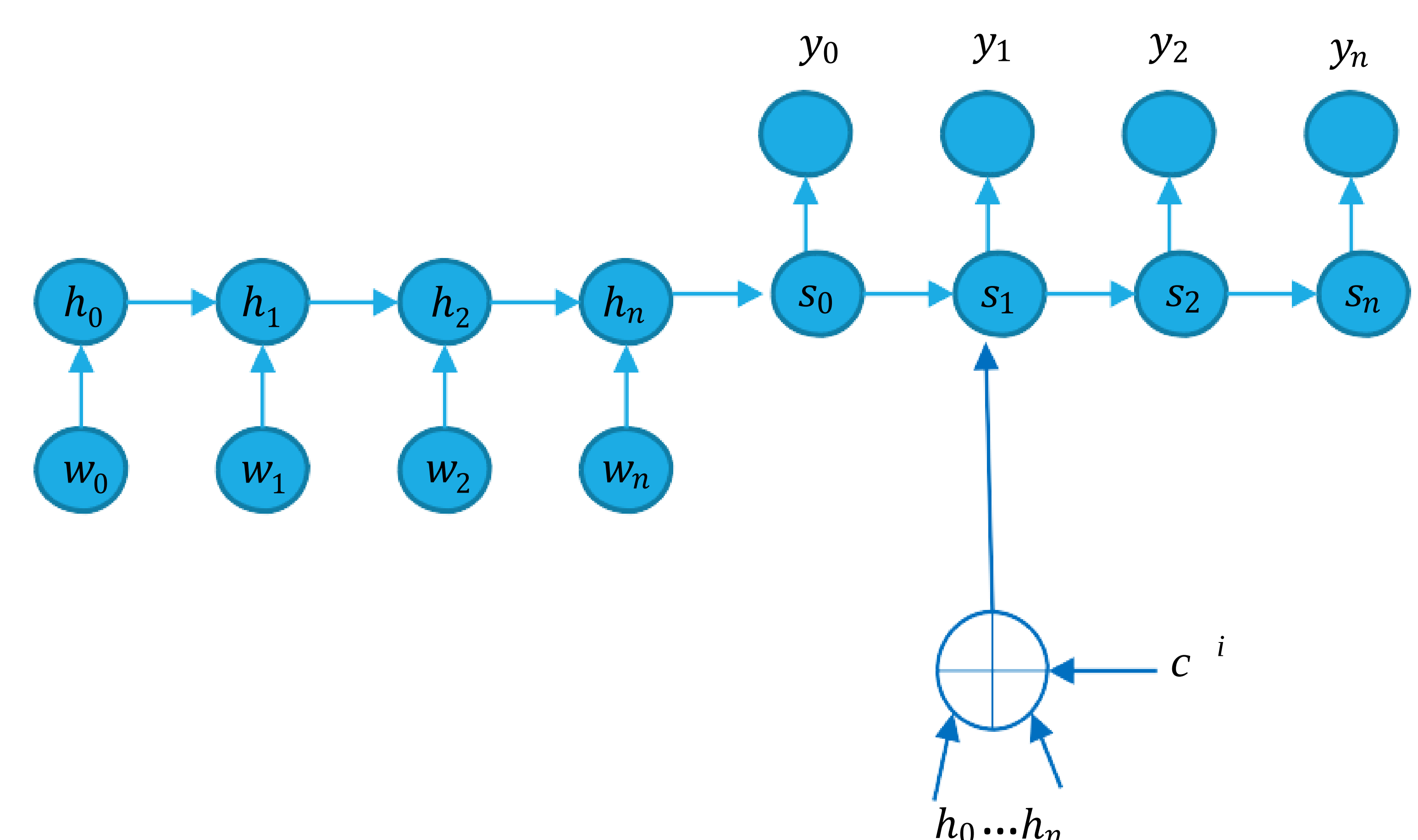
* Hakkani-Tür, Dilek, et al. "Multi-Domain Joint Semantic Frame Parsing Using Bi-Directional RNN-LSTM." Interspeech 2016.

Slot Tagging

- Encoder-decoder networks
    - Leverages sentence level information



- Attention-based encoder-decoder
    - Use of attention in the encoder-decoder network
    - Attention is estimated using a feed-forward network with input: h_t and s_t at time t

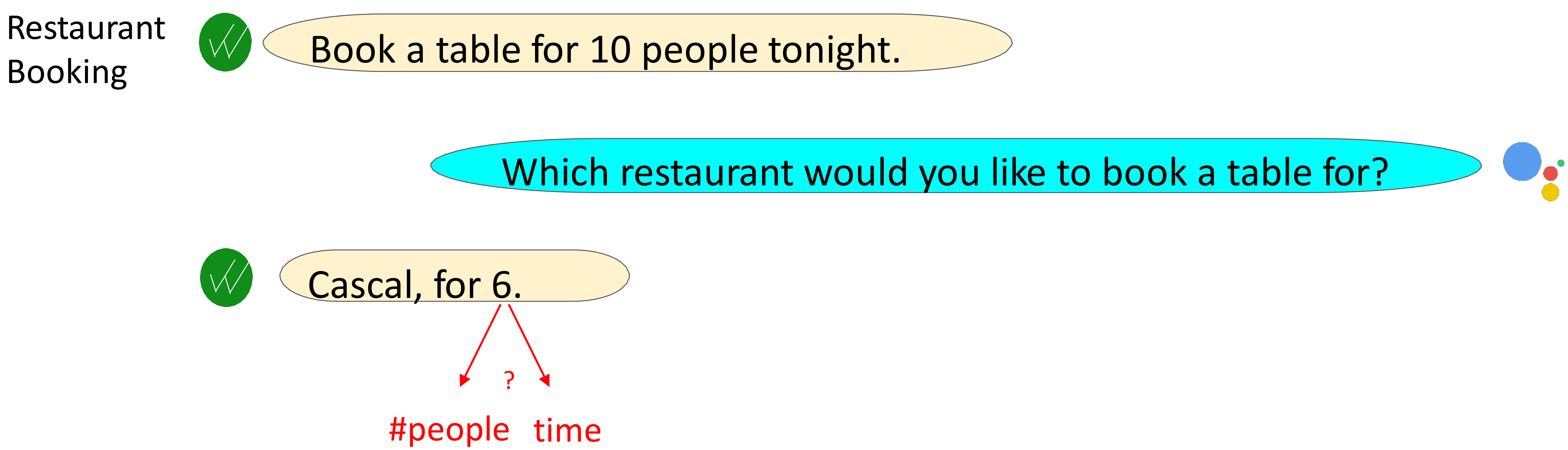


LU Evaluation

- Metrics
  - Sub-sentence-level:
    - Intent accuracy
    - Slot F1
  - Sentence-level:
    - Whole frame accuracy

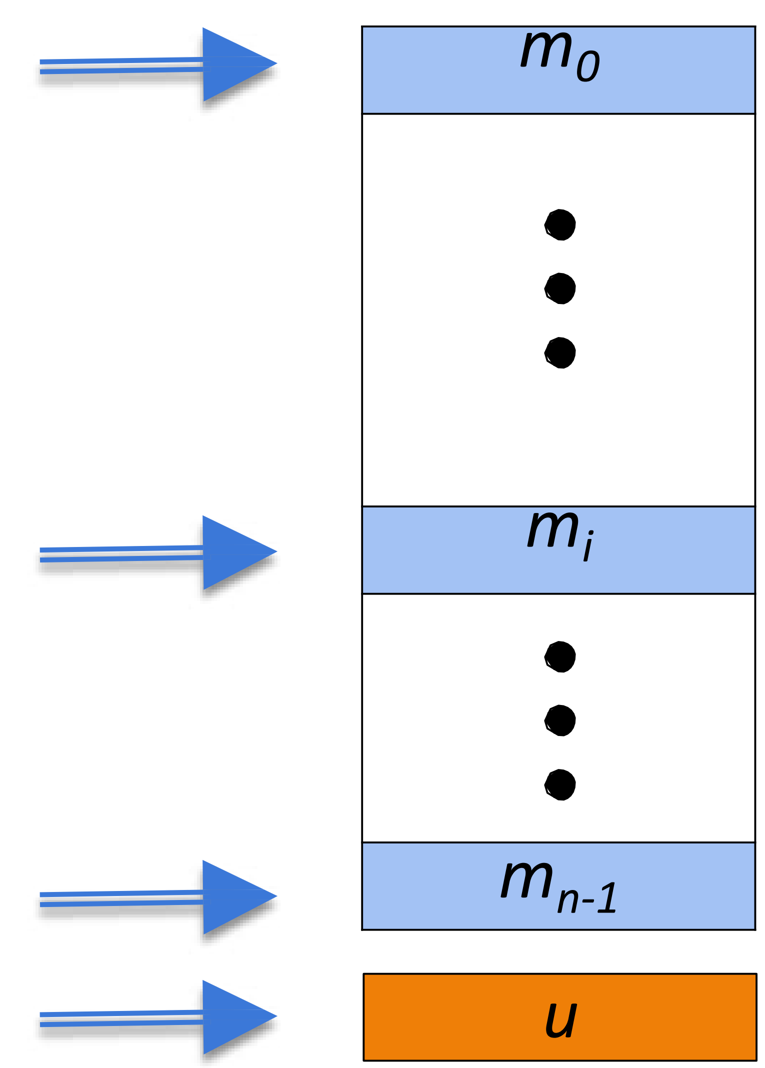
Contextual LU

- User utterances are highly ambiguous in isolation



End-to-End Memory Networks

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+, 2016[1])

1. Sentence Encoding

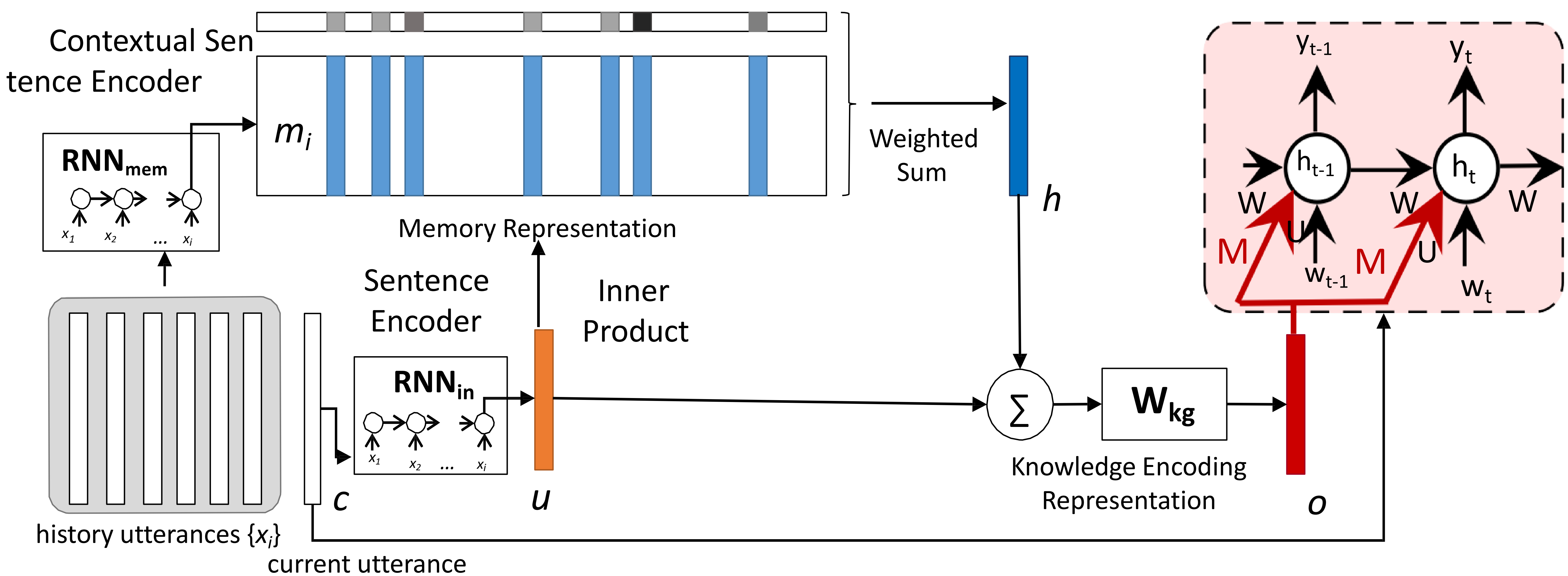
$$m_i = \mathrm{RNN}_{\mathrm{mem}}(x_i)$$
$$u = \mathrm{RNN}_{\mathrm{in}}(c)$$

2. Knowledge Attention

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

3. Knowledge Encoding

$$h = \sum_i p_i m_i \quad o = W_{\mathrm{kg}}(h + u)$$



Idea: Additionally incorporating contextual knowledge during slot tagging
→ Track dialogue states in a latent way

* Chen, Y.-N. V., Hakkani-Tur, D., Tur, G., Gao, J., and Deng, L. "End-to-end memory networks with knowledge carryover for multi-turn spoken language understanding." In Annual Meeting of the International Speech Communication Association INTERSPEECH (2016).

Analysis of Attention

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"

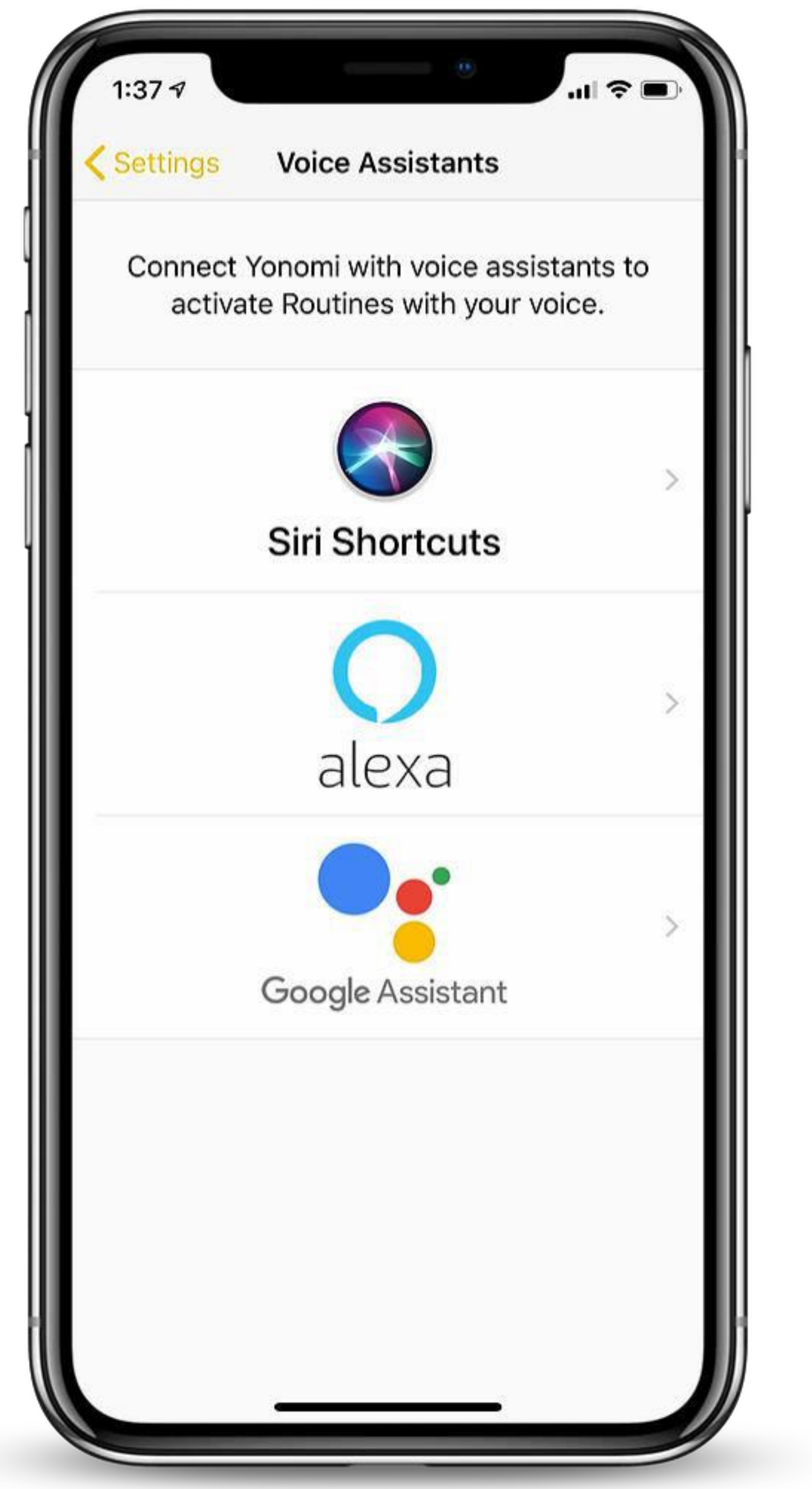
S: "okay , there is 4:10 pm , 5:40 pm and 9:20 pm" → 0.16

U: "Let's do 5:40"

Recent Advances in NLP

- Contextual Embeddings (ELMo & BERT)
  - Boost many understanding performance with **pre-trained language models**

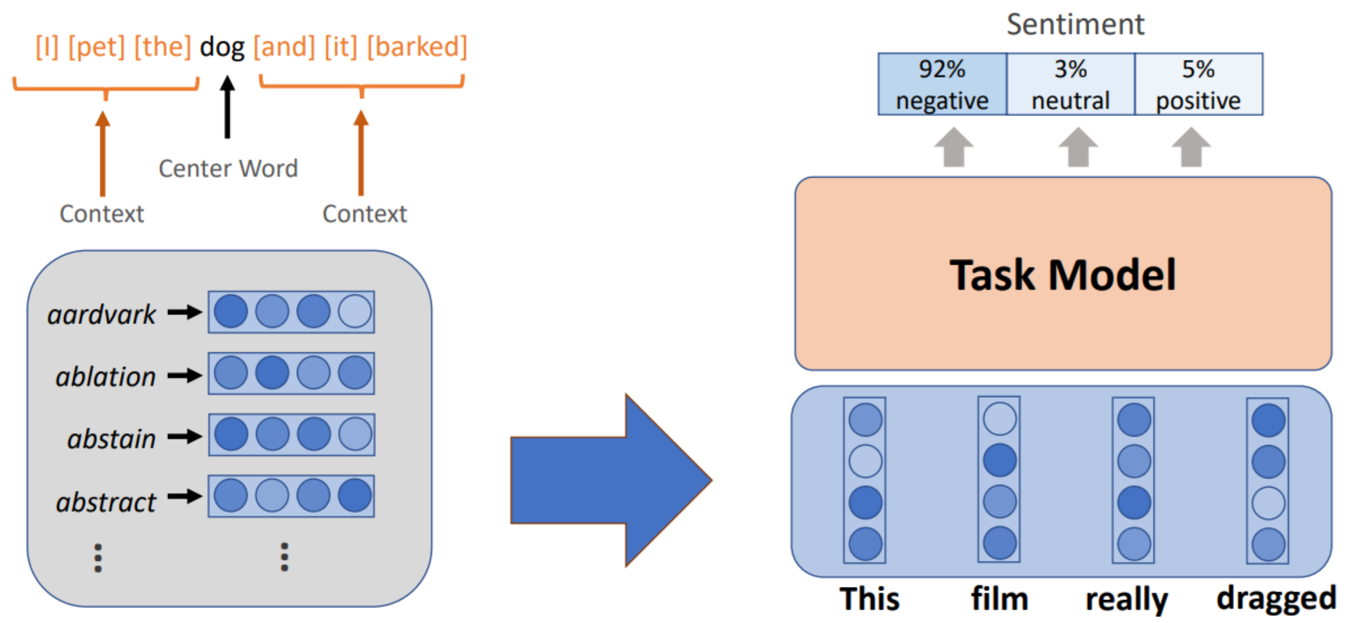
?



Pre-train language models

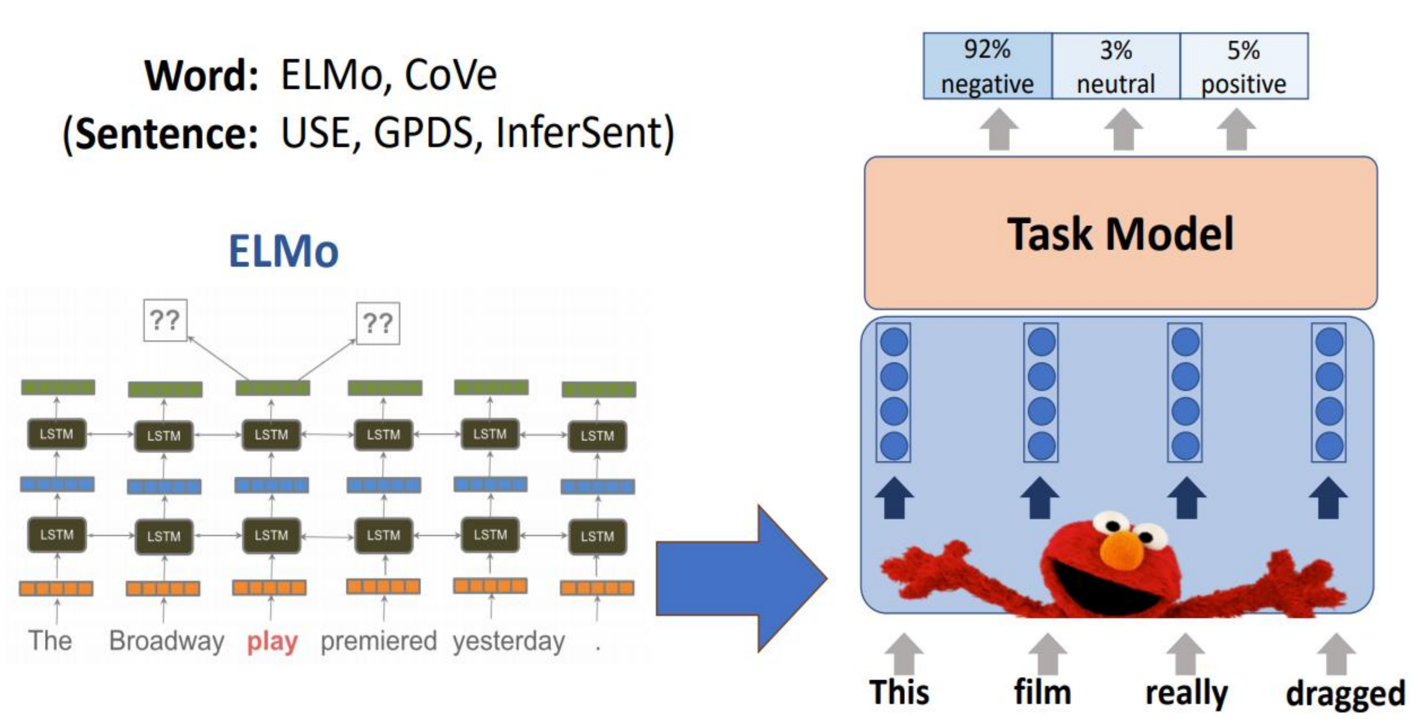
Feature-based

Word Embedding(2013)
word2vec/Glove/Fasttext



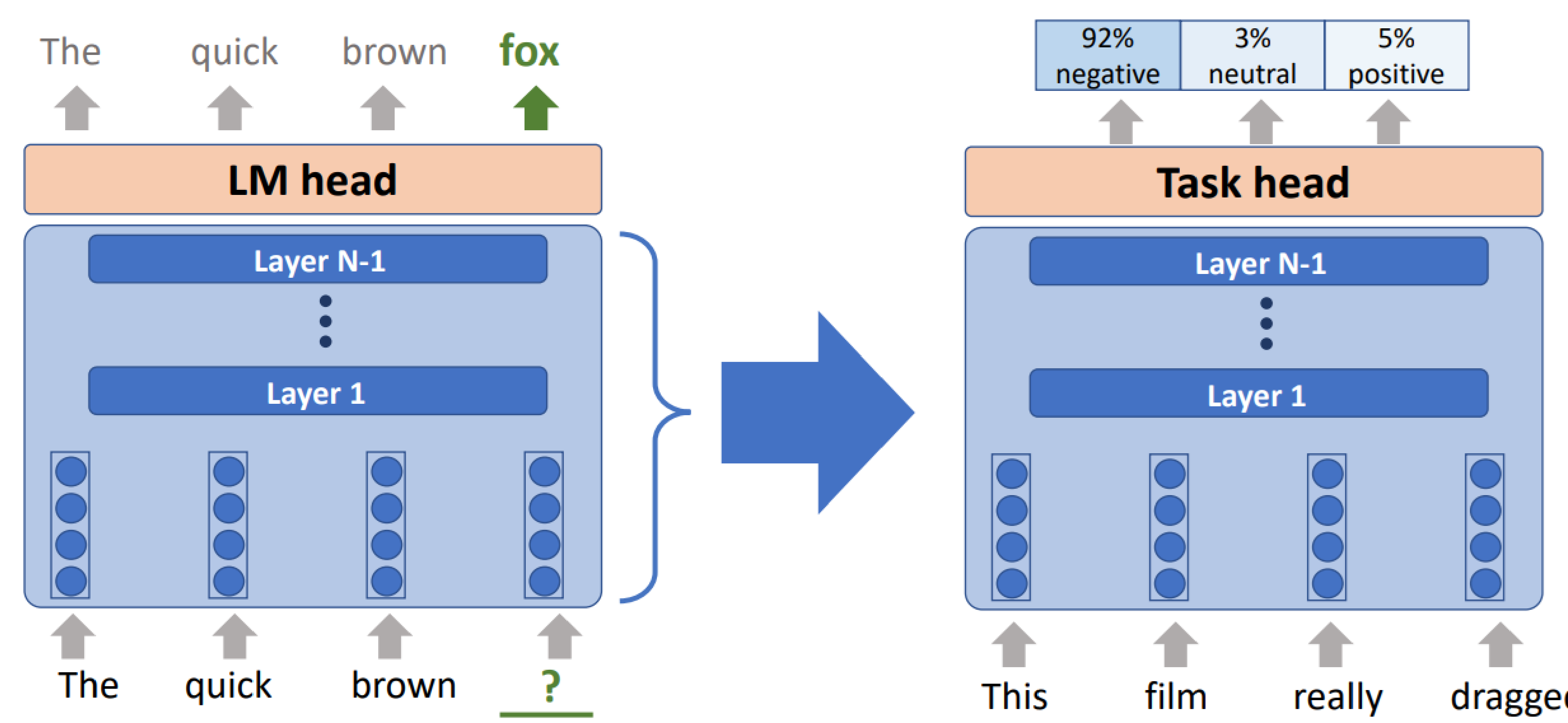
Contextual Embedding
ELMo/Cove

Word: ELMo, CoVe
(**Sentence:** USE, GPDS, InferSent)



Fine-tuning based

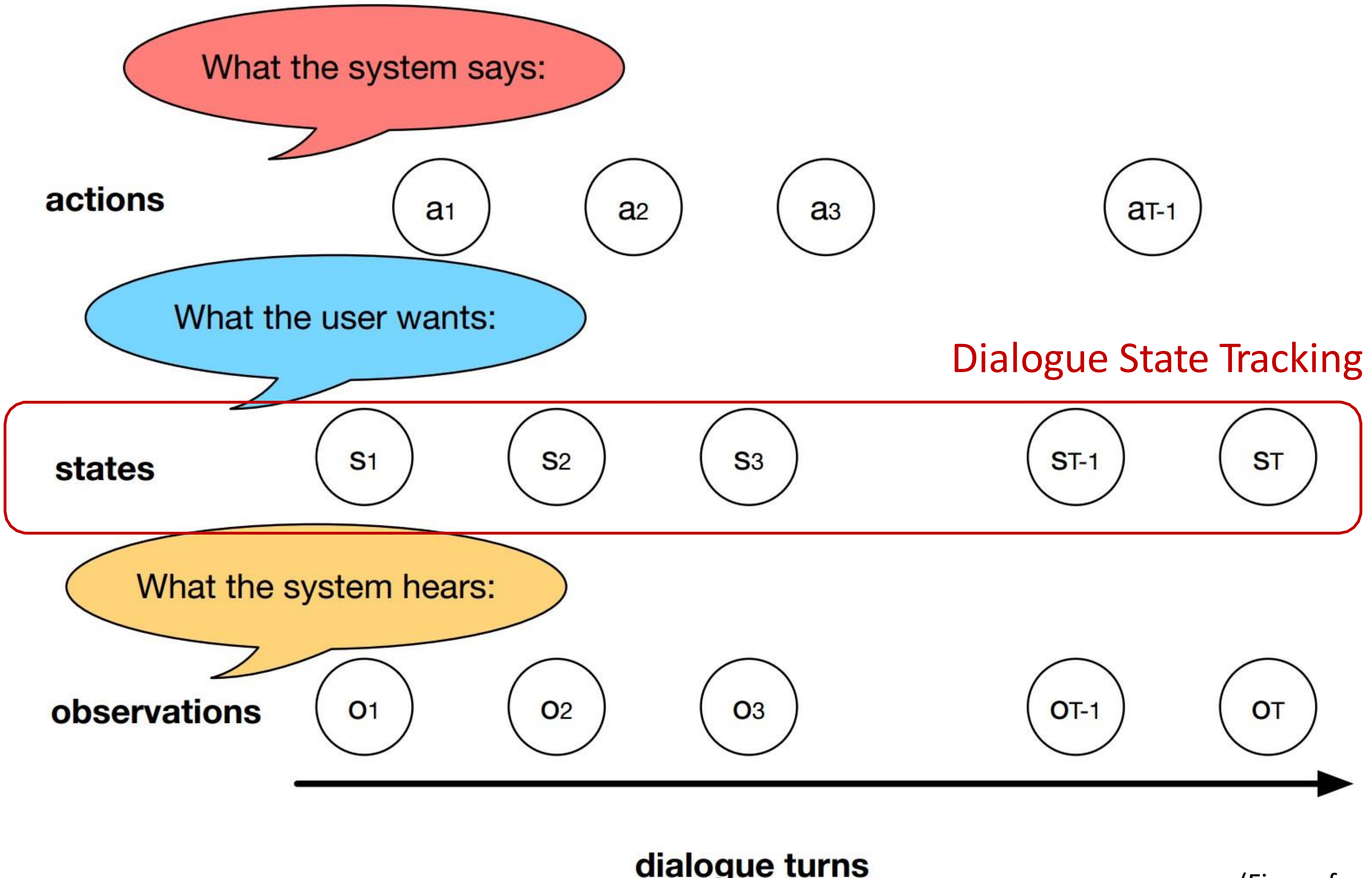
OpenAI GPT, Google BERT



Modular Dialogue System

Dialogue Management – Dialogue State Tracking (DST)

Dialogue State Tracking (DST)



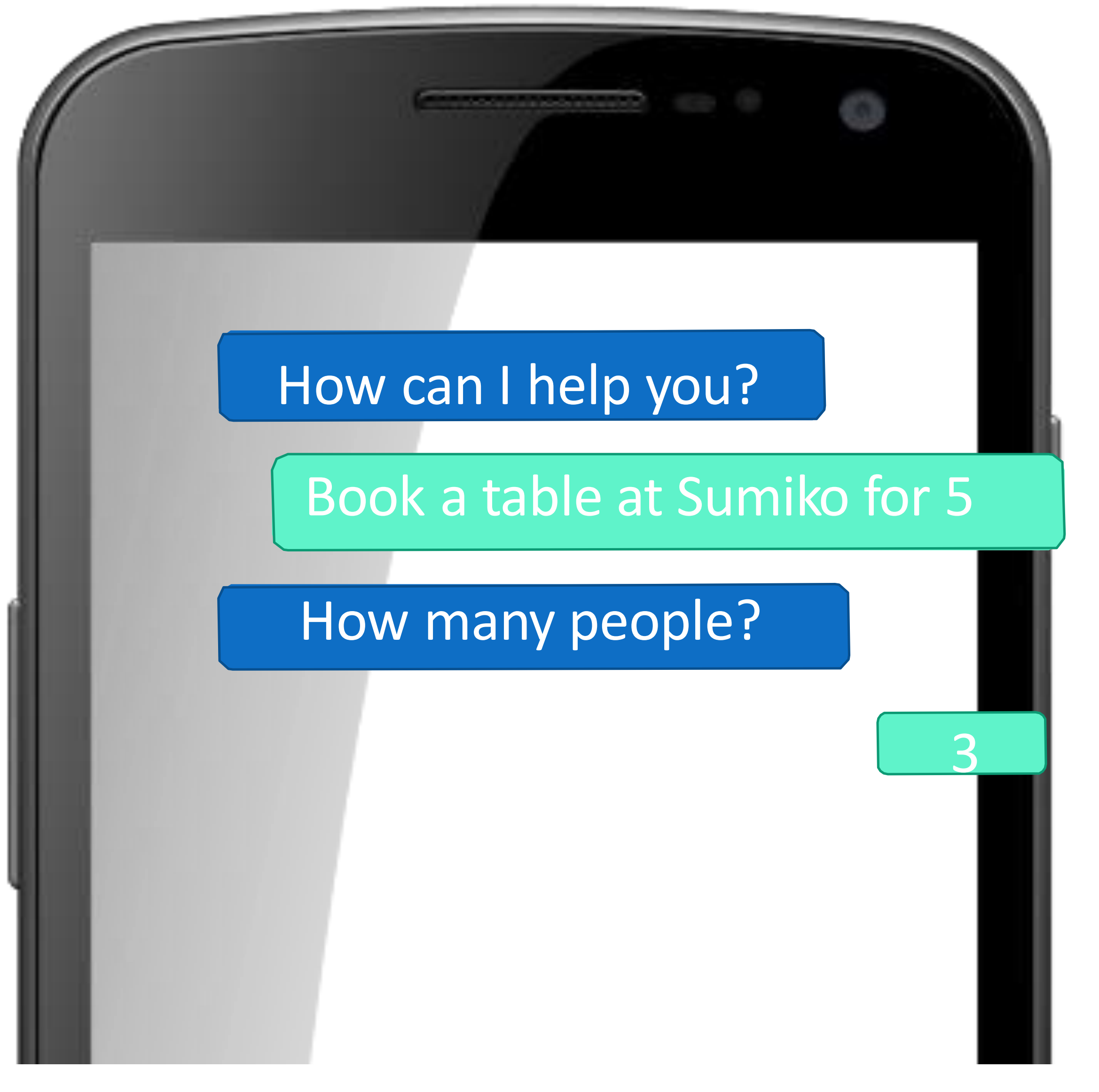
(Figure from Gašić)

Dialogue State Tracking (DST)

- 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

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

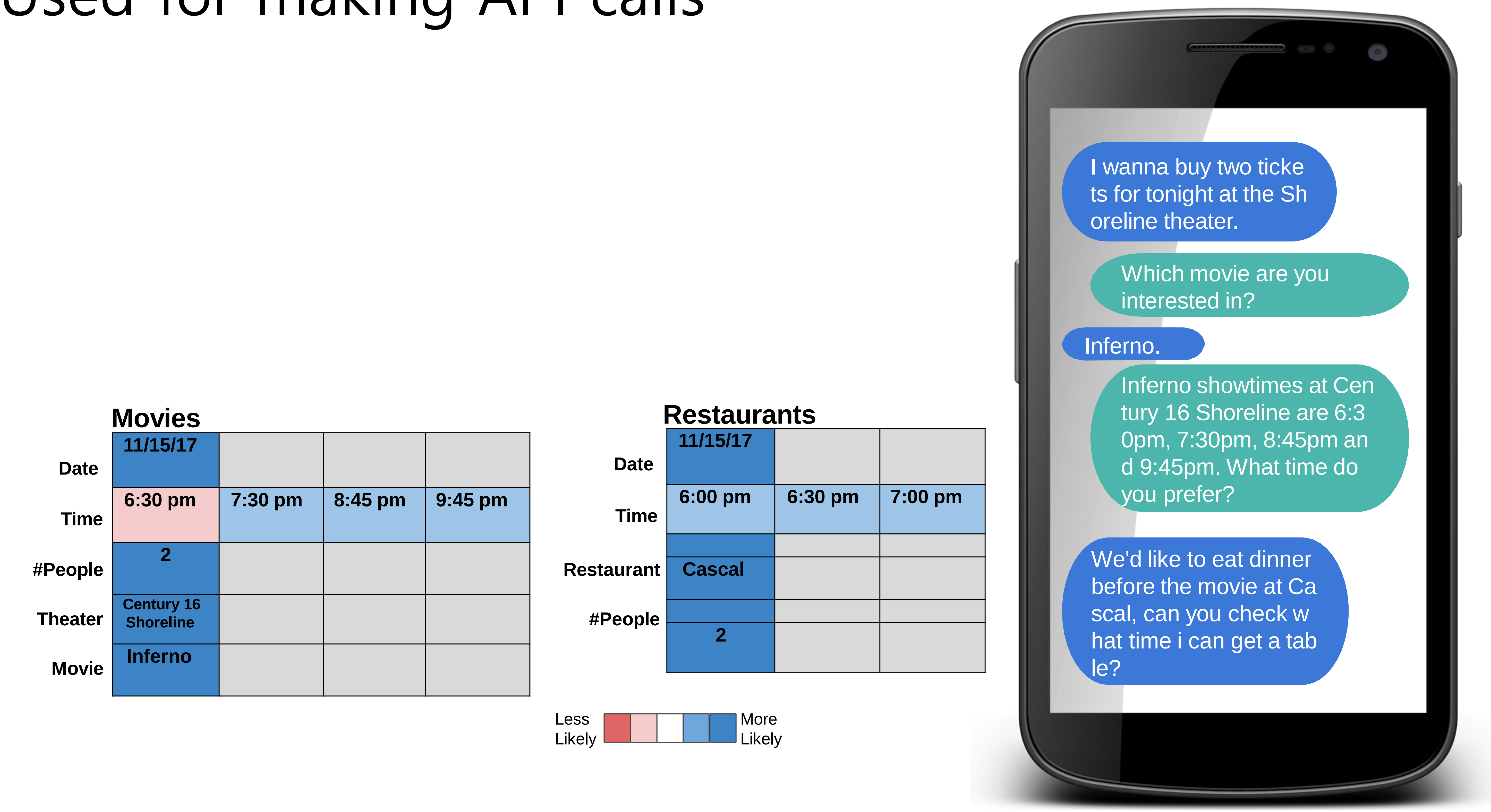
Movies

Date	11/15/17			
Time	6 pm	7 pm	8 pm	9 pm
#People	2			
Theater	Century 16 Shoreline			
Movie	Inferno			

Less Likely — More Likely

Multi-Domain Dialogue State Tracking

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



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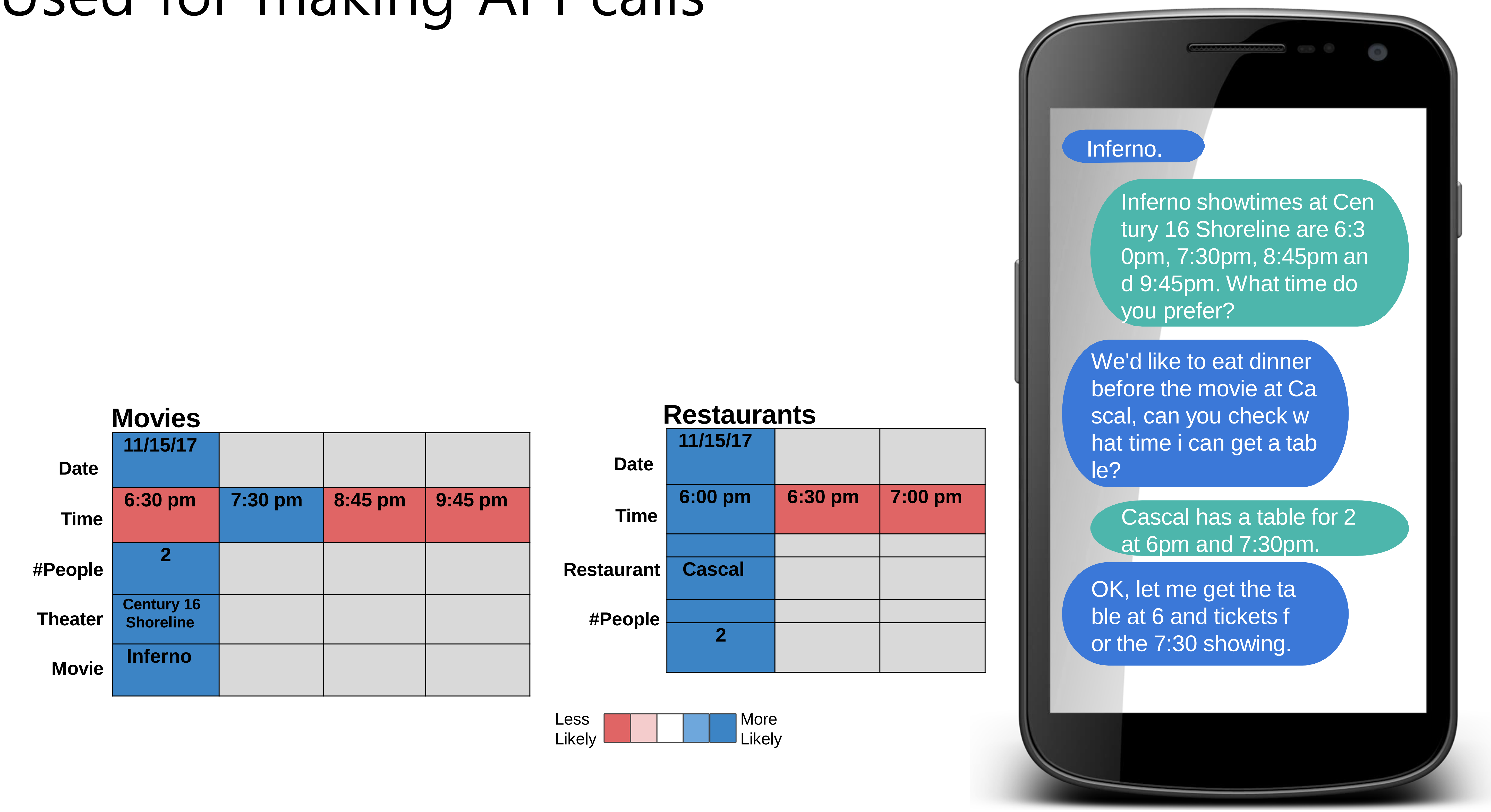
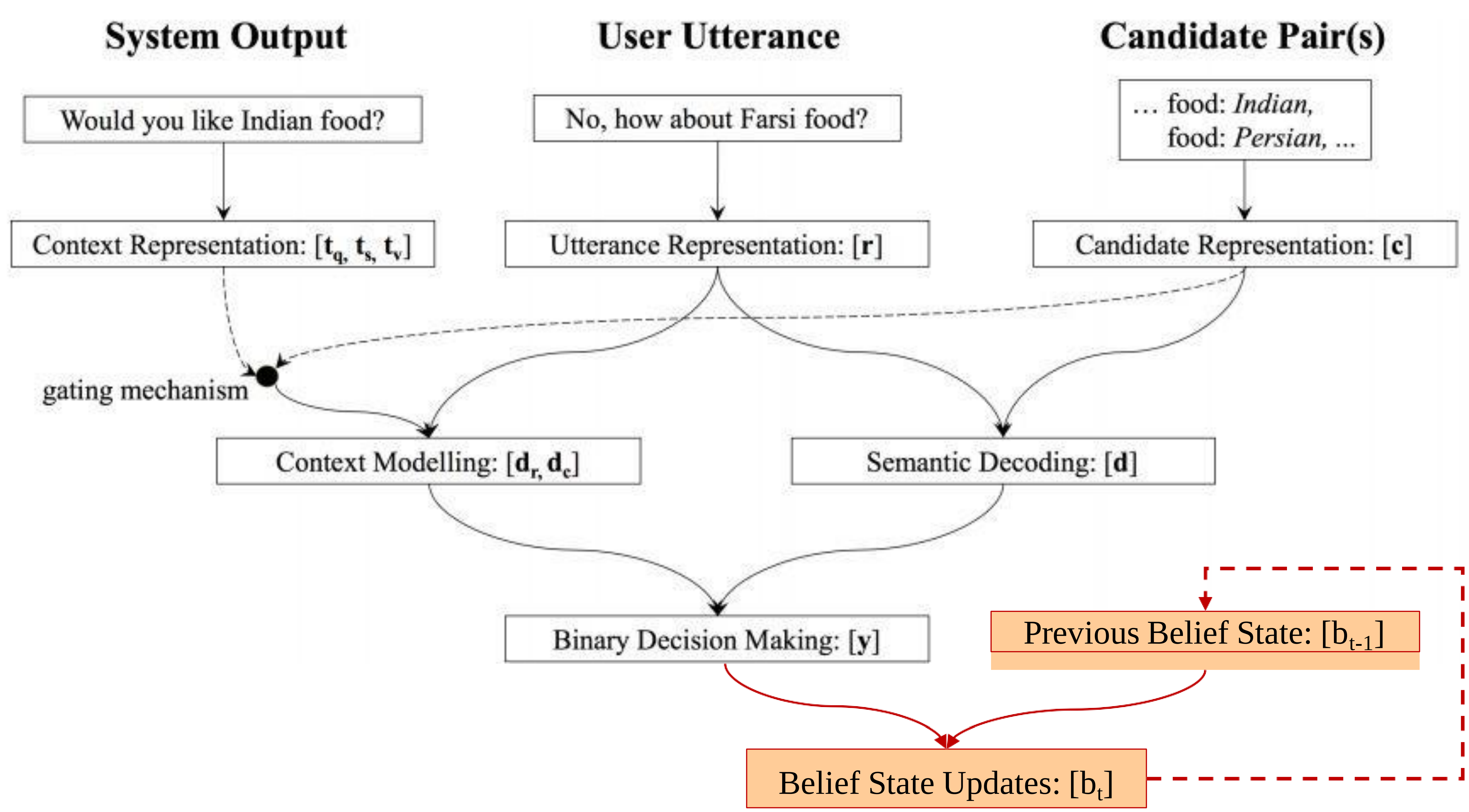


Neural Belief Tracker (Mrkšić+, 2016)

- Candidate pairs are considered



* Mrkšić, Nikola, et al. "Neural Belief Tracker: Data-Driven Dialogue State Tracking." ACL 2017.

Dialog State Tracking Challenge (DSTC)

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

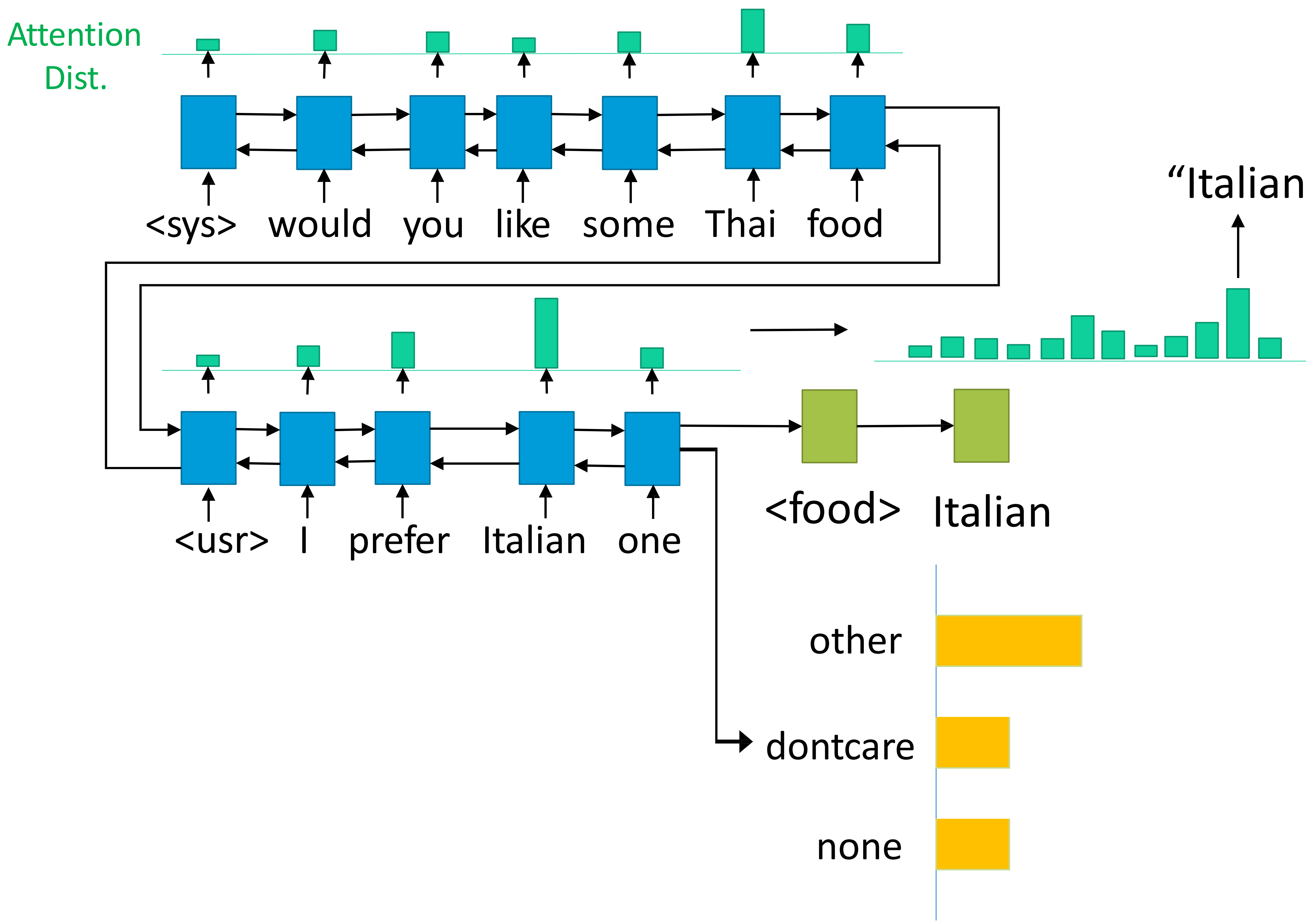
(Williams et al. 2013, Henderson et al. 2014, Henderson et al. 2014, Kim et al. 2016, Kim et al. 2016)

DST Evaluation

- 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

DST – Handling Unknown Values (Xu & Hu, 2018)

- Issue: fixed value sets in DST

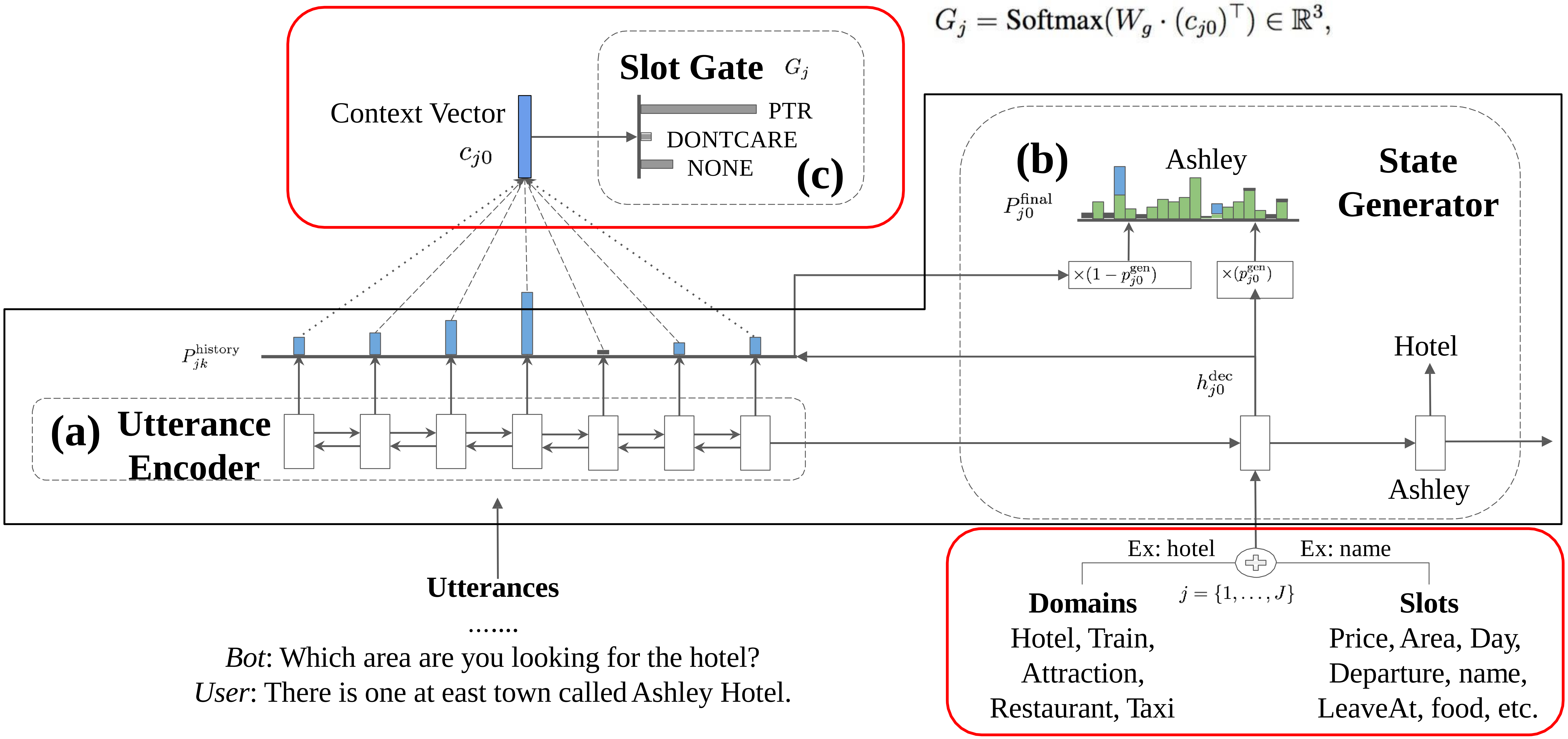


Pointer networks for generating unknown values

* Xu, Puyang, and Qi Hu. "An End-to-end Approach for Handling Unknown Slot Values in Dialogue State Tracking." ACL 2018.

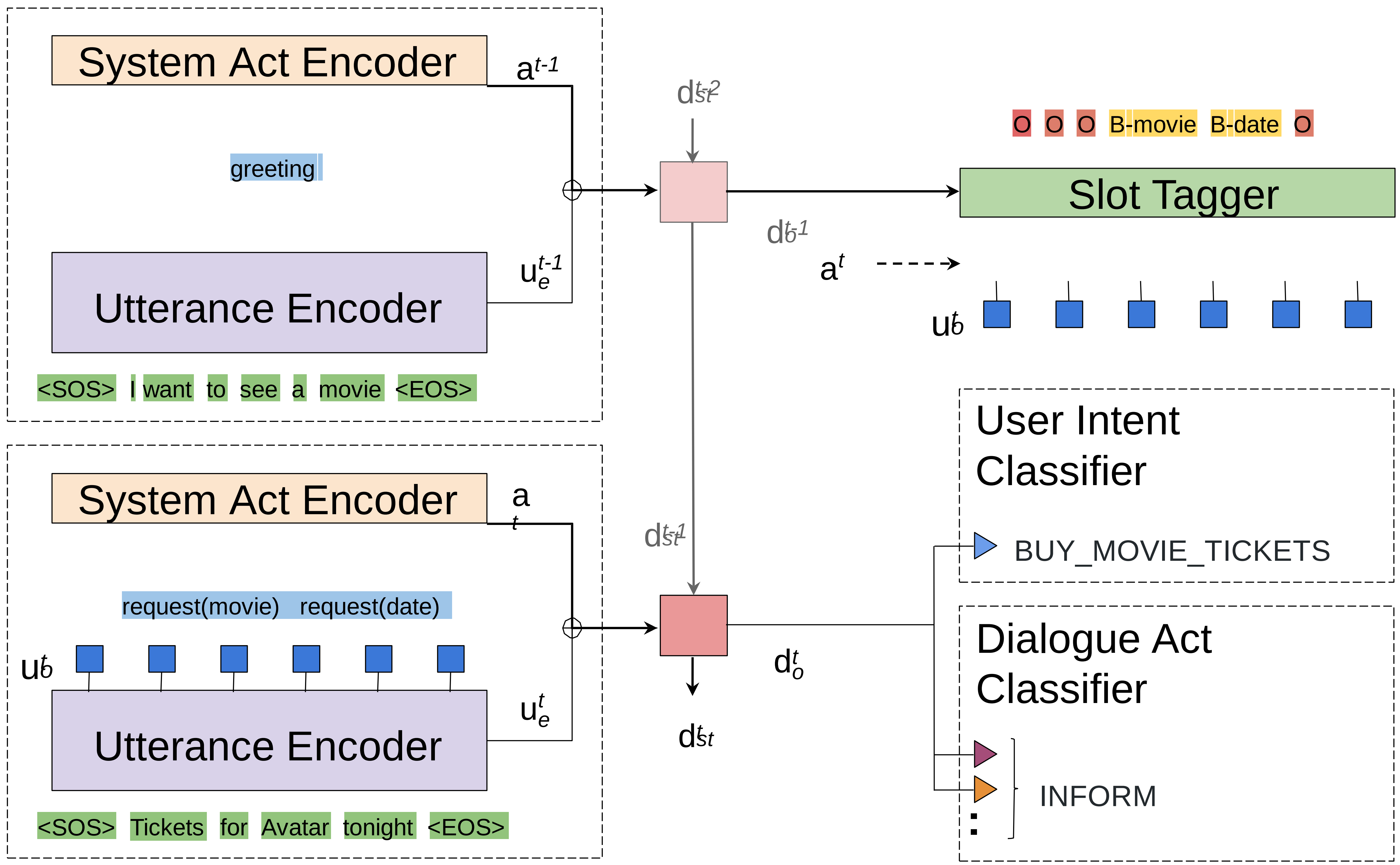
TRADE: Transferable DST (Wu+, 2019)

$$G_j = \text{Softmax}(W_g \cdot (c_{j0})^\top) \in \mathbb{R}^3,$$



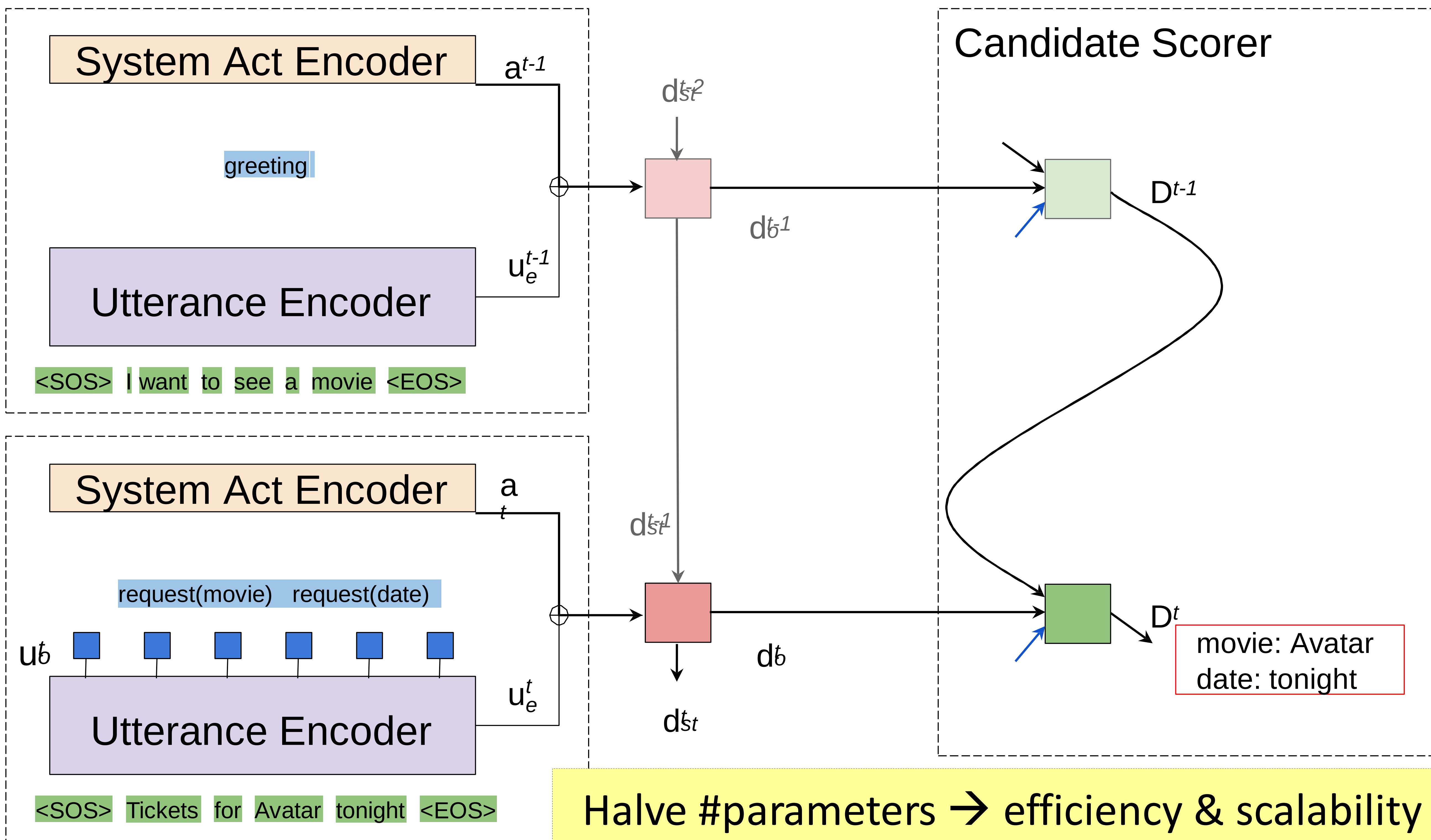
* Wu, Chien-Sheng, et al. "Transferable Multi-Domain State Generator for Task-Oriented Dialogue Systems." ACL 2019.

Joint NLU and DST (Gupta+, 2018)



* Rastogi, Abhinav, Raghav Gupta, and Dilek Hakkani-Tur. "Multi-task Learning for Joint Language Understanding and Dialogue State Tracking." Proceedings of the 19th Annual SIGdial Meeting on Discourse and Dialogue. 2018.

Joint NLU and DST (Gupta+, 2018)



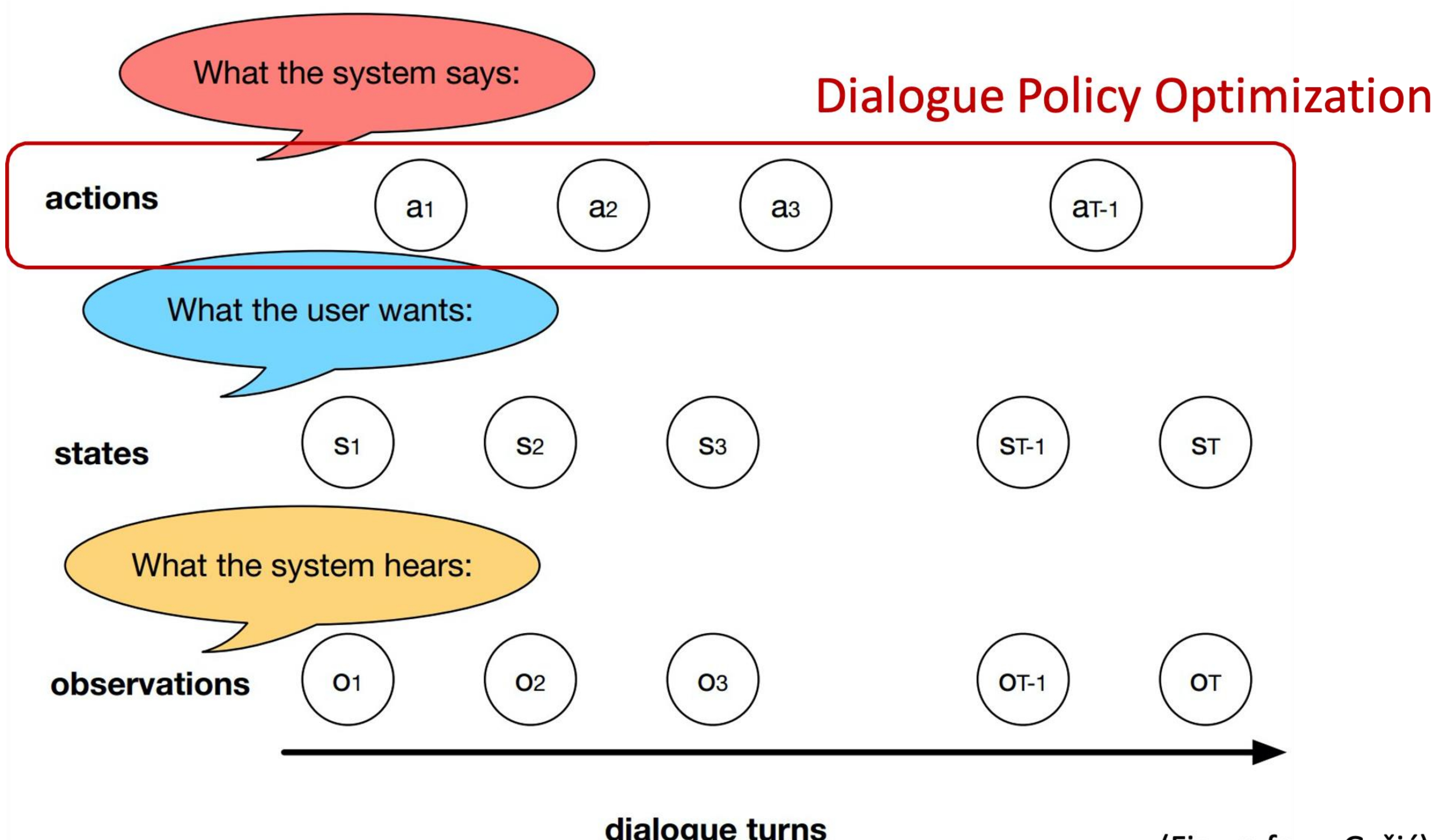
Halve #parameters → efficiency & scalability

* Rastogi, Abhinav, Raghav Gupta, and Dilek Hakkani-Tur. "Multi-task Learning for Joint Language Understanding and Dialogue State Tracking." Proceedings of the 19th Annual SIGdial Meeting on Discourse and Dialogue. 2018.

Modular Dialogue System

Dialogue Management – Dialogue Policy Optimization

Elements of Dialogue Management

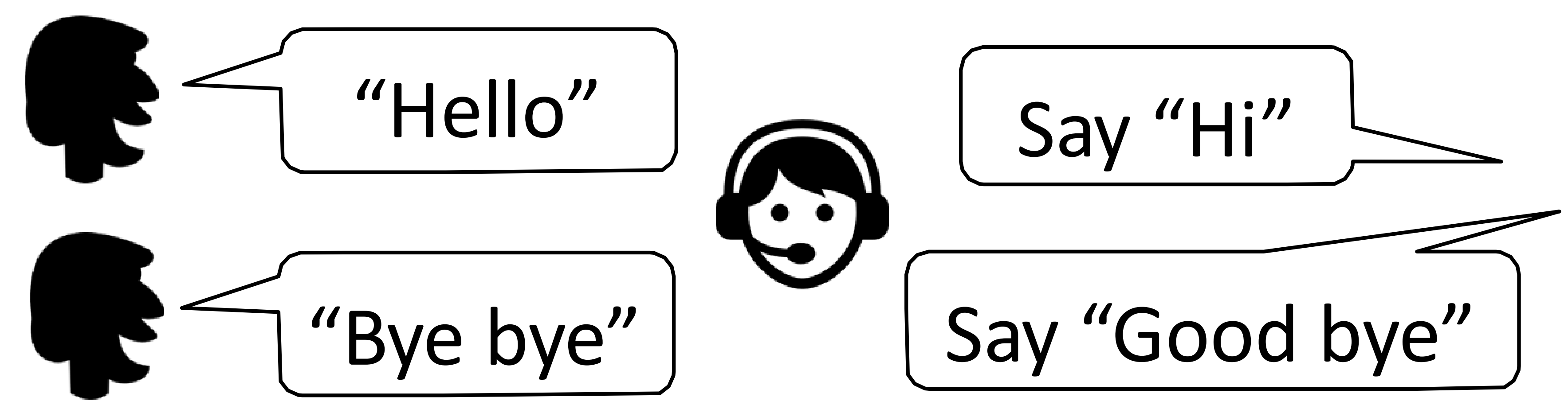


(Figure from Gašić)

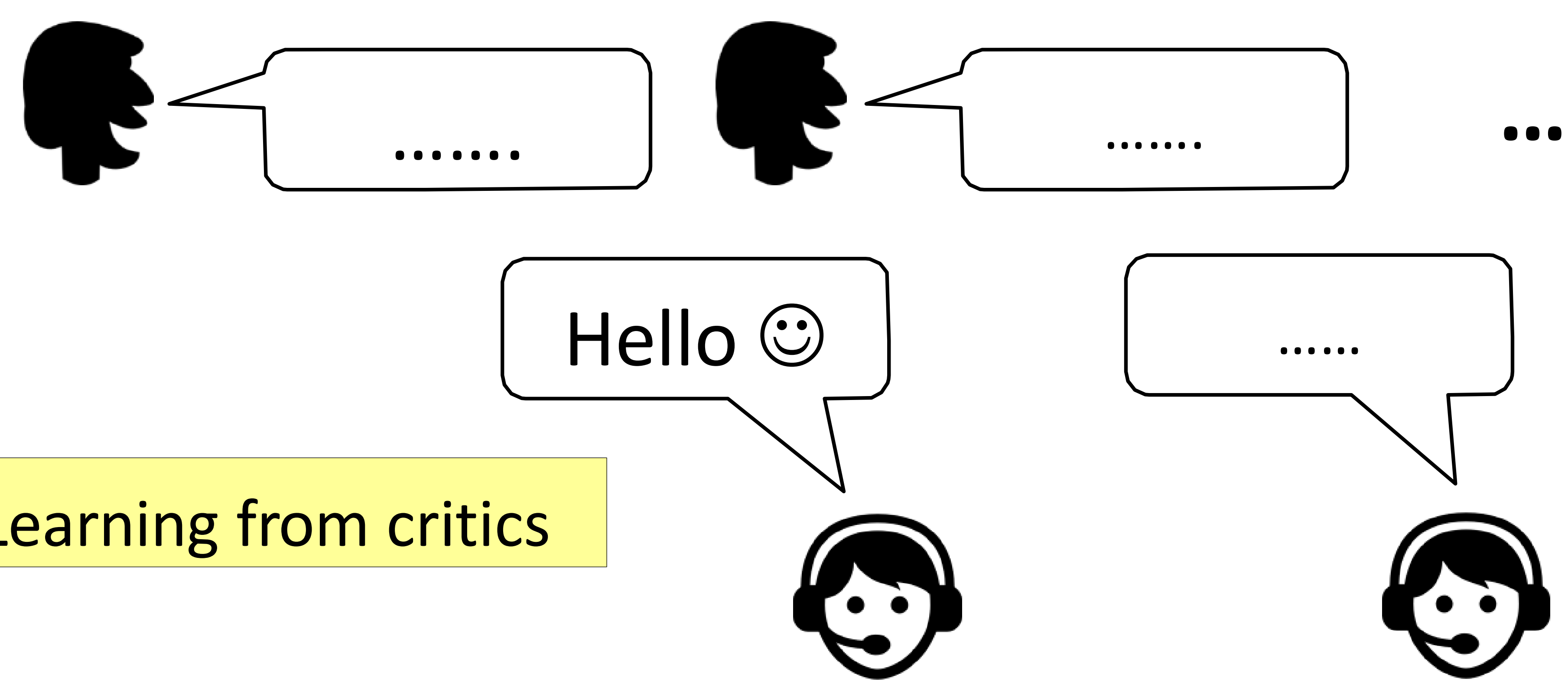
Supervised vs. Reinforcement

- Supervised

Learning from teacher



- Reinforcement

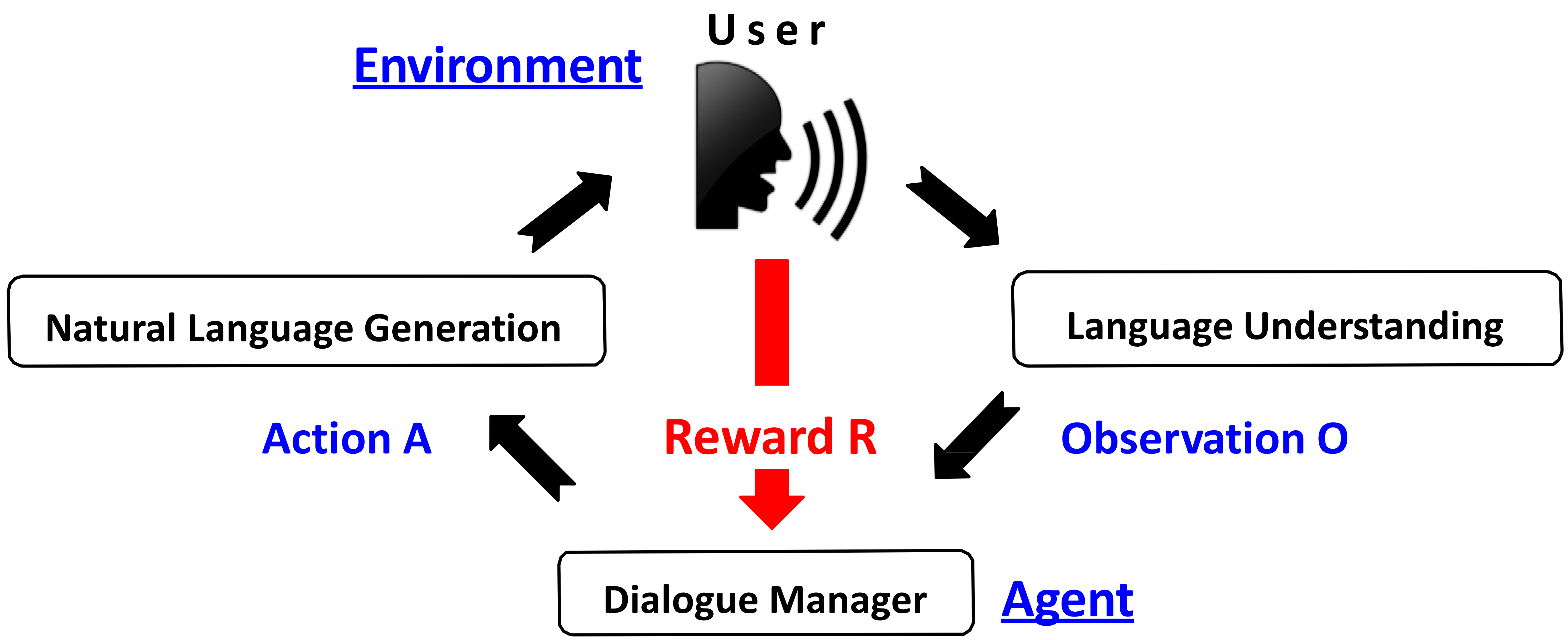


Learning from critics

Bad

Dialogue Policy Optimization

- Dialogue management in a RL framework



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

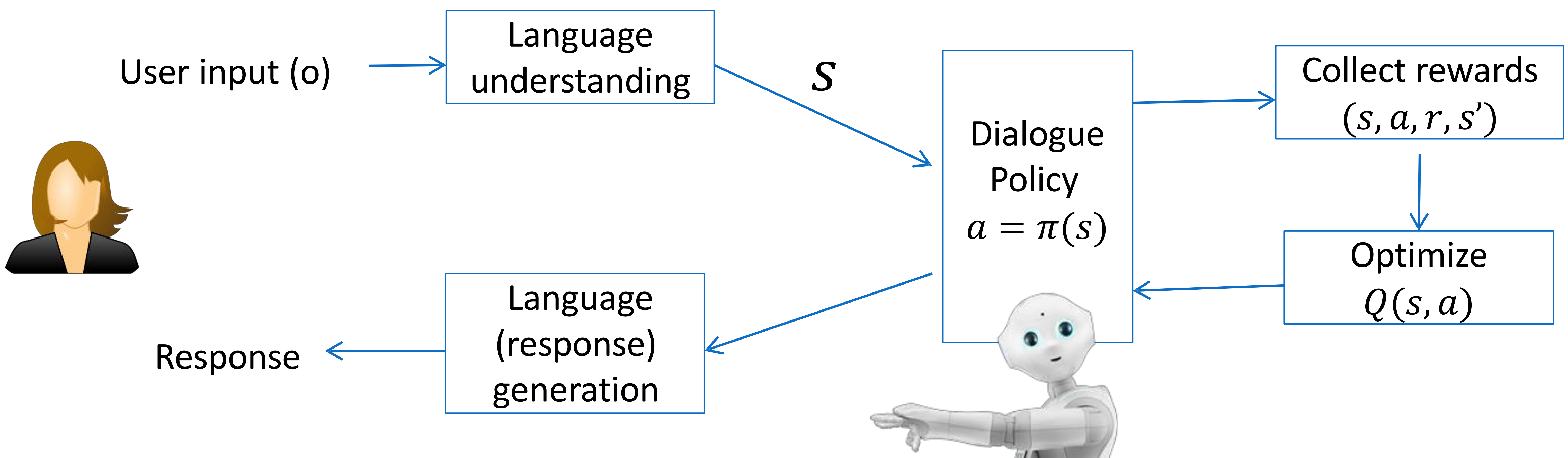
Reward for RL ≅ Evaluation for System

- 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

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

RL for Dialogue Policy Optimization

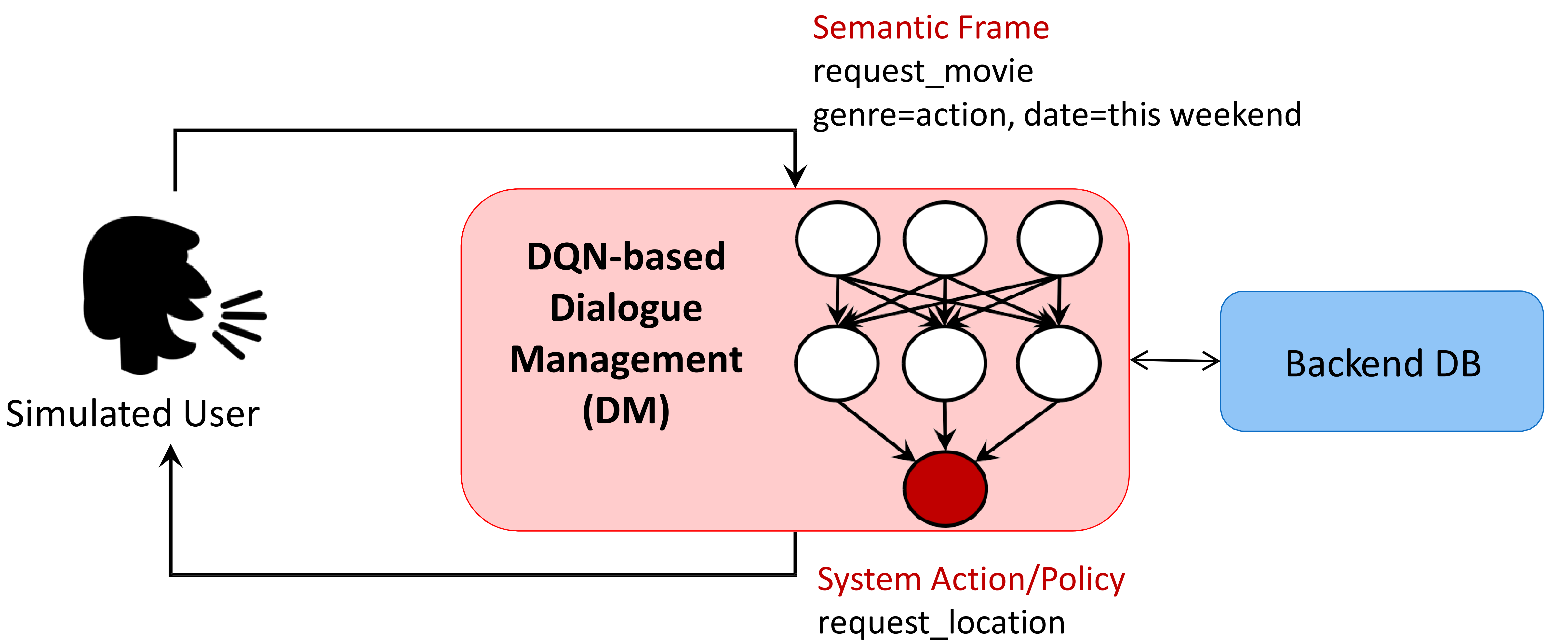


Type of Bots	State	Action	Reward
Social ChatBots	Chat history	System Response	# of turns maximized; Intrinsically motivated reward
InfoBots (interactive Q/A)	User current question + Context	Answers to current question	Relevance of answer; # of turns minimized
Task-Completion Bots	User current input +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

Neural Dialogue Manager (Li et al., 2017)

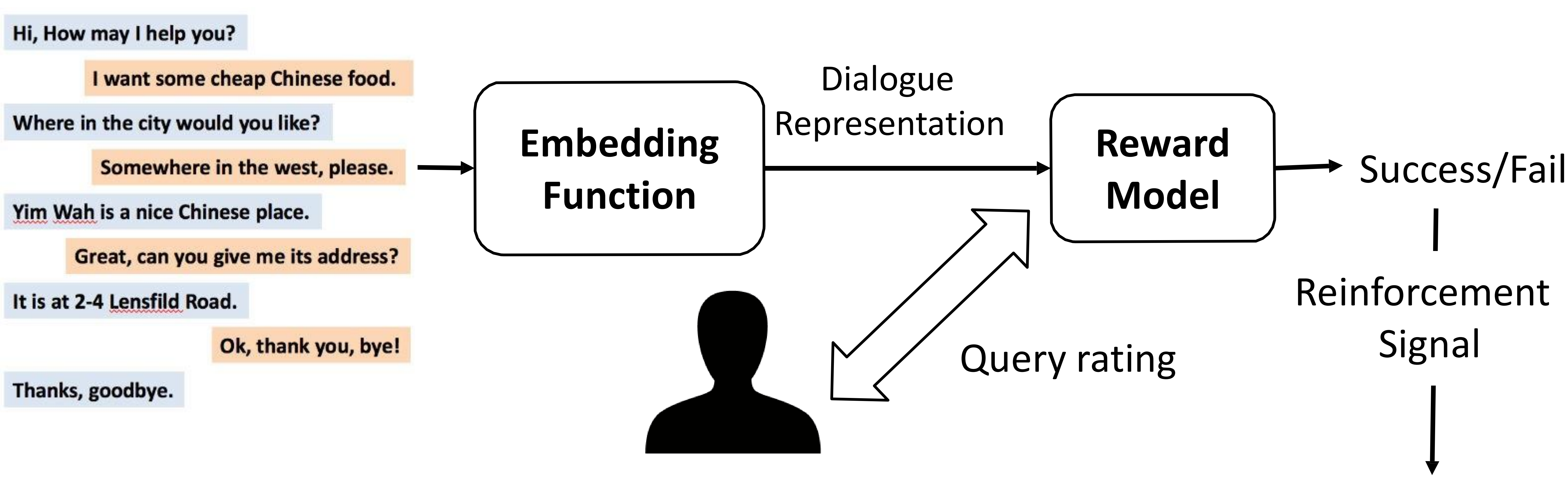
- Deep Q-network for training DM policy
  - Input: current semantic frame observation, database returned results
  - Output: system action



* Li, Xiujun, et al. "End-to-End Task-Completion Neural Dialogue Systems." ACL 2017.

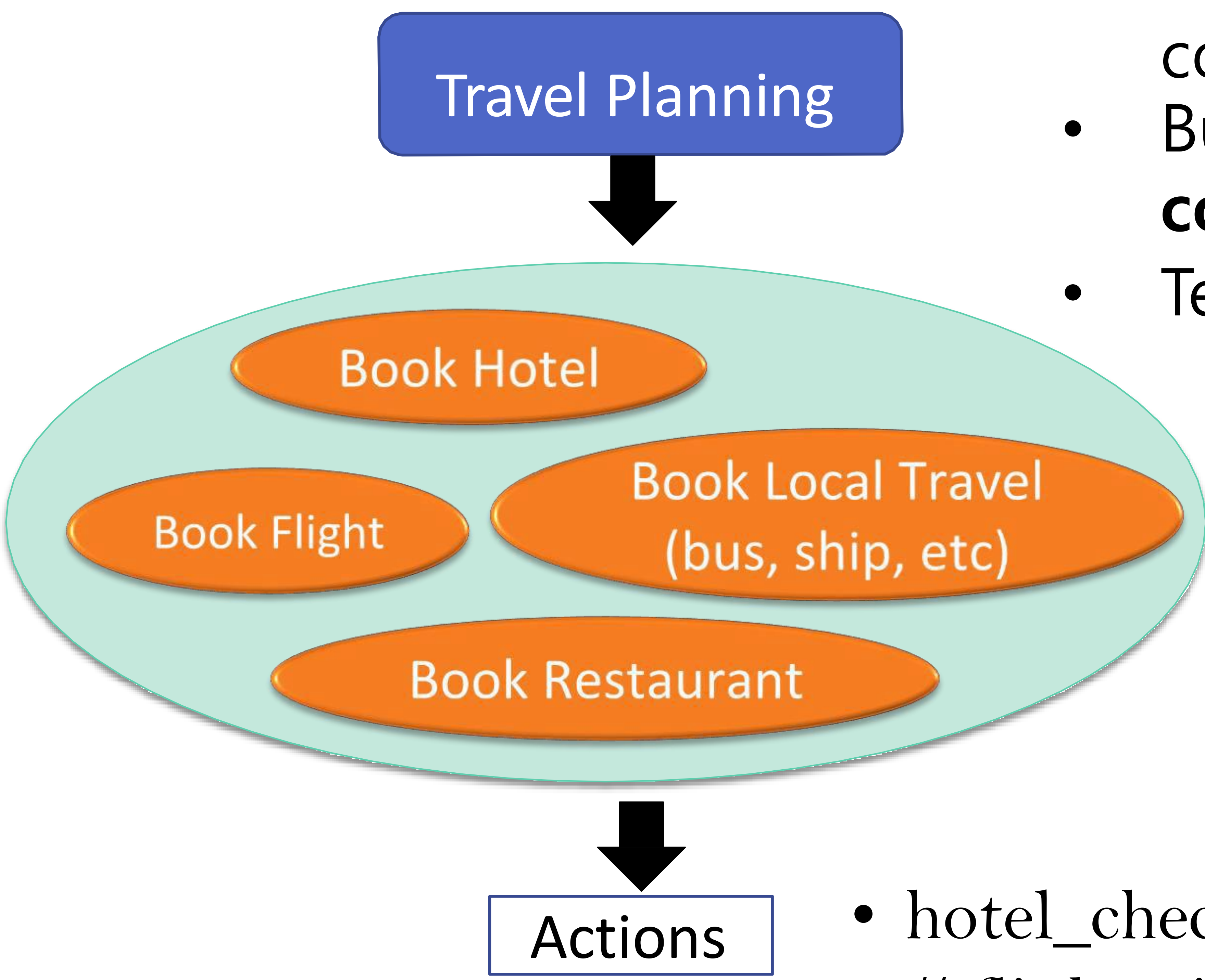
Online Training (Su+, 2015; Su+, 2016)

- 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



* Su, Pei-Hao, et al. "Reward Shaping with Recurrent Neural Networks for Speeding up On-Line Policy Learning in Spoken Dialogue Systems." Proceedings of the 16th Annual Meeting of the Special Interest Group on Discourse and Dialogue. 2015.
* Su, Pei-Hao, et al. "On-line Active Reward Learning for Policy Optimisation in Spoken Dialogue Systems." ACL 2016.

Multi-Domain – Hierarchical RL (Peng+, 2017)



- Set of tasks that need to be fulfilled collectively!
- Build a DM for **cross-subtask constraints** (**slot constraints**)
- Temporally constructed goals

- hotel_check_in_time > departure_flight_time
- # flight_tickets = #people checking in the hotel
- hotel_check_out_time< return_flight_time,

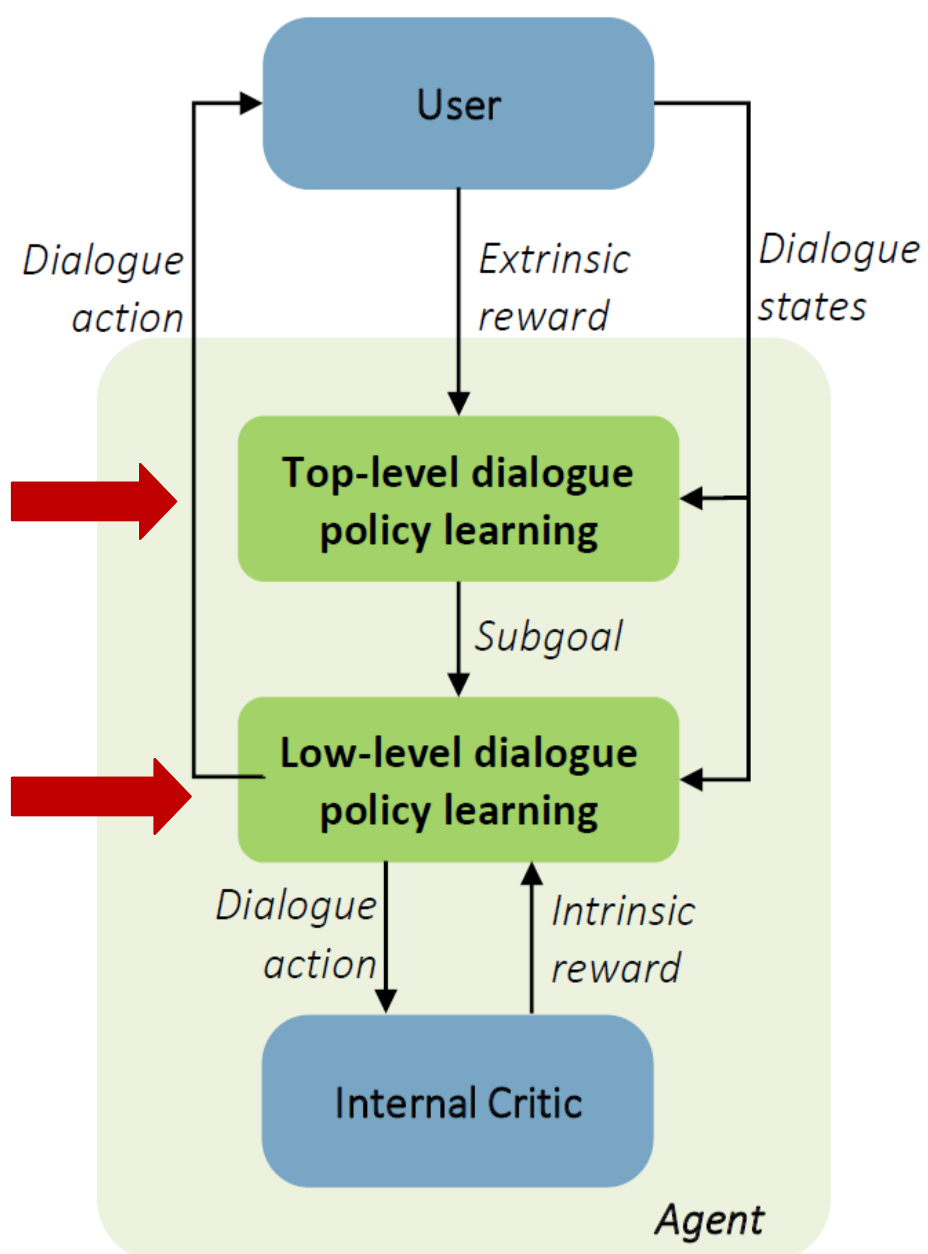
* Peng, Baolin, et al. "Composite Task-Completion Dialogue Policy Learning via Hierarchical Deep Reinforcement Learning." EMNLP 2017.

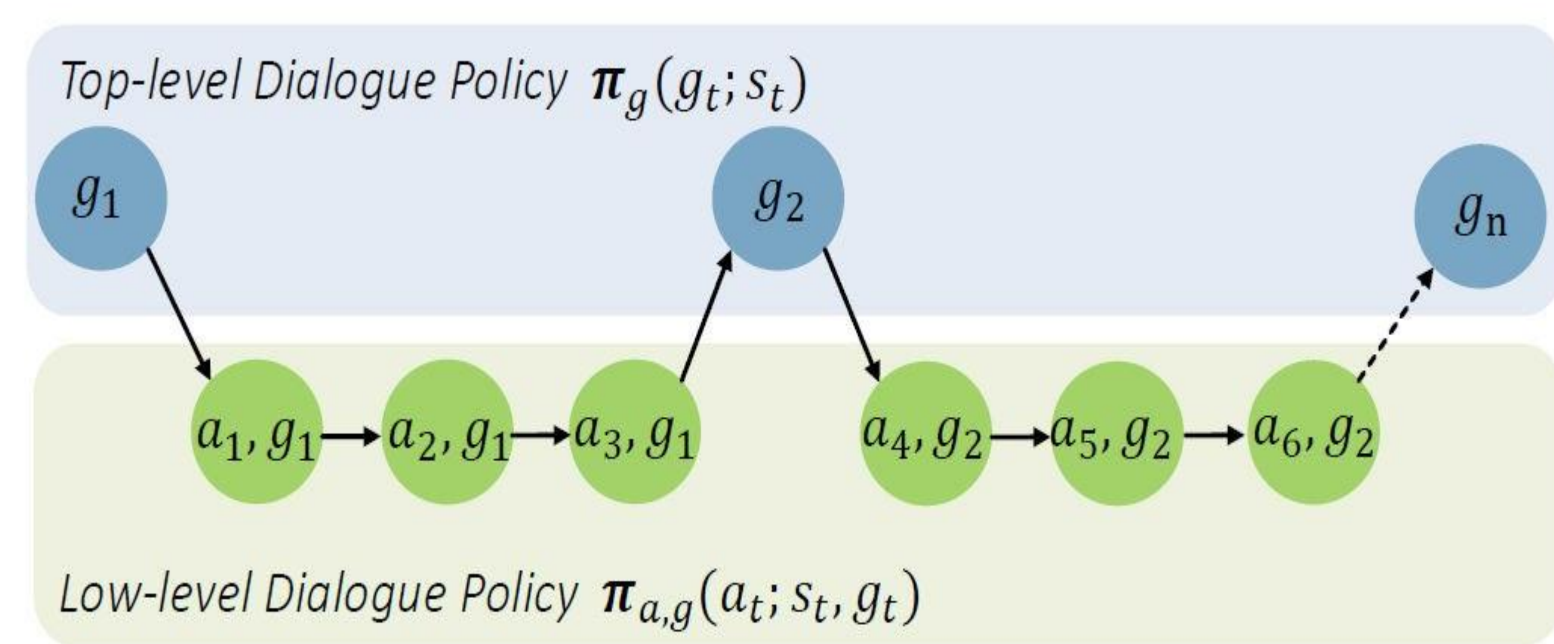
Multi-Domain – Hierarchical RL (Peng+, 2017)

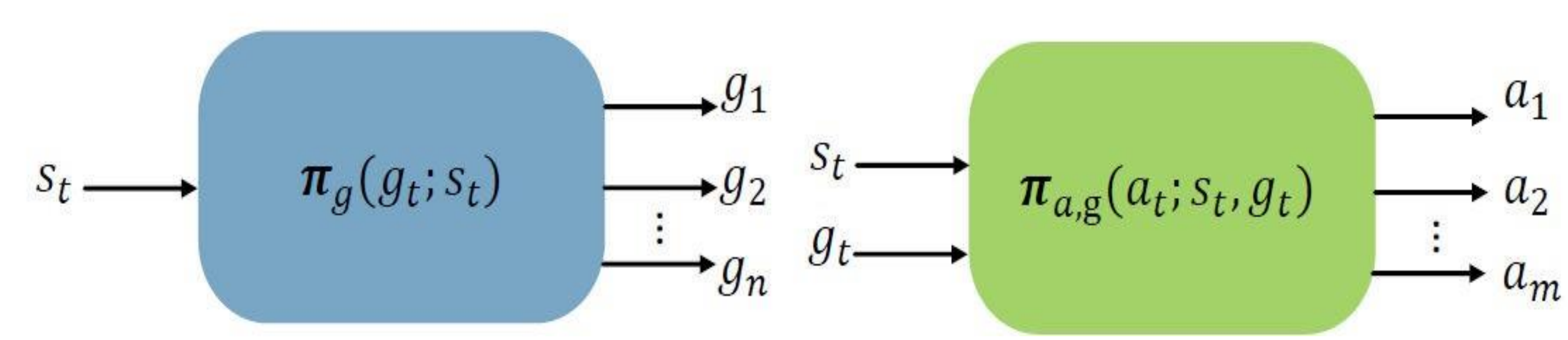
- Model makes decisions over two levels: *meta-controller & controller*
- The *agent* learns these policies simultaneously
  - the policy of optimal sequence of goals to follow $\pi_g(g_t, s_t; \theta_1)$
  - Policy $\pi_{a,g}(a_t, g_t, s_t; \theta)$ for each sub-goal g_t

Meta-Controller

Controller





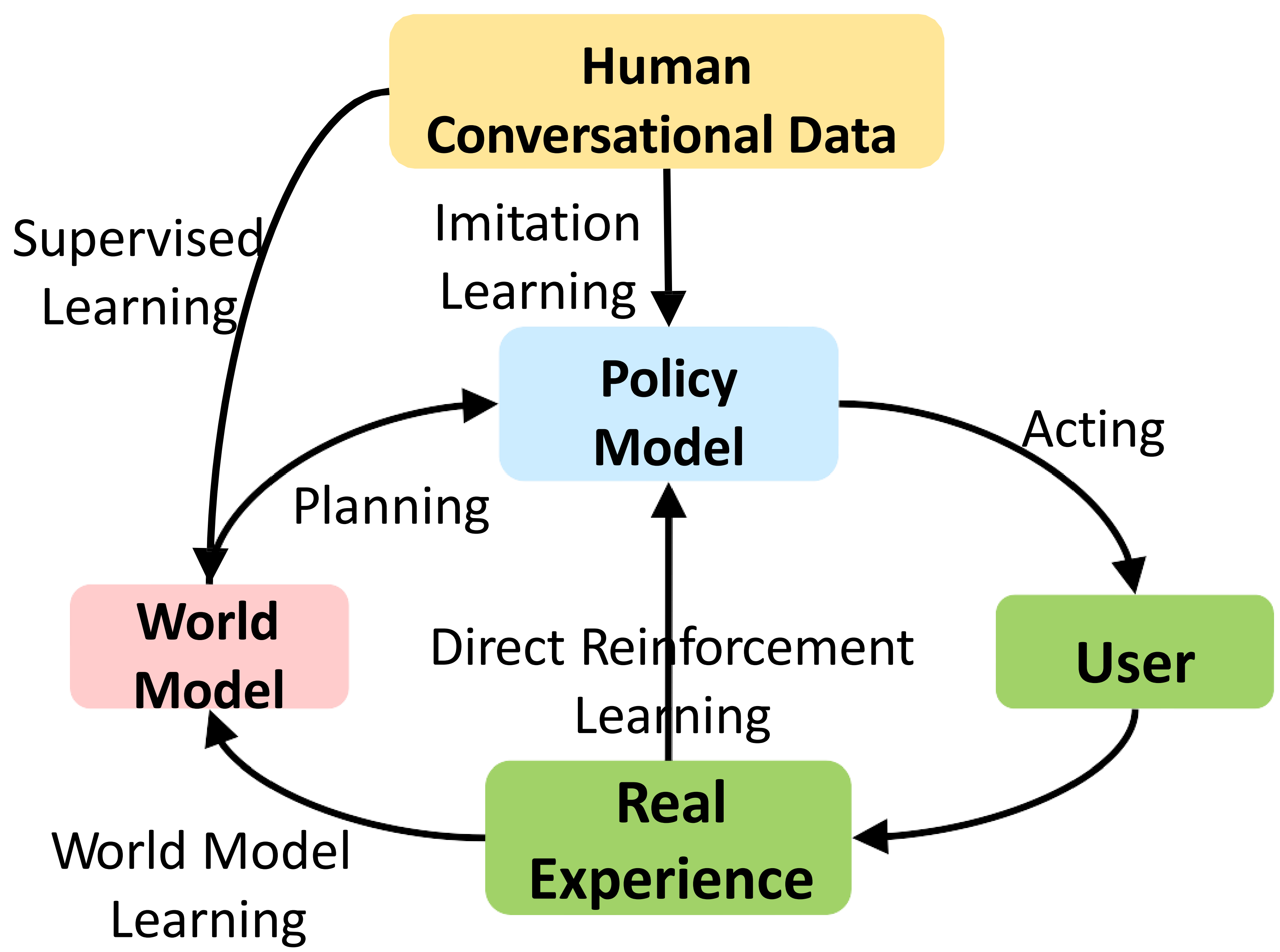


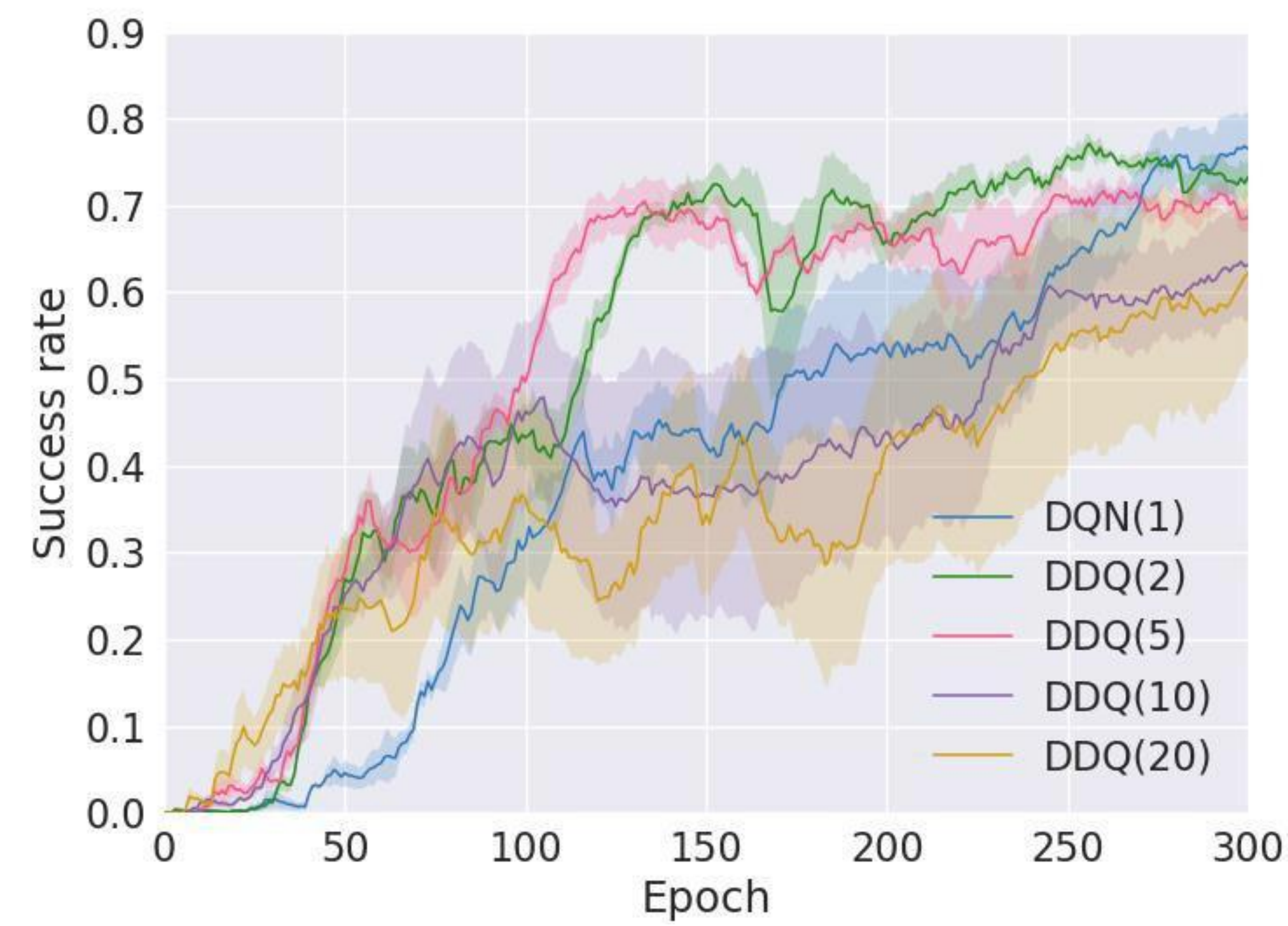
(mitigate reward sparsity issues)

* Peng, Baolin, et al. "Composite Task-Completion Dialogue Policy Learning via Hierarchical Deep Reinforcement Learning." EMNLP 2017.

Planning – Deep Dyna-Q (Peng+, 2018)

- Idea: learning with real users with planning



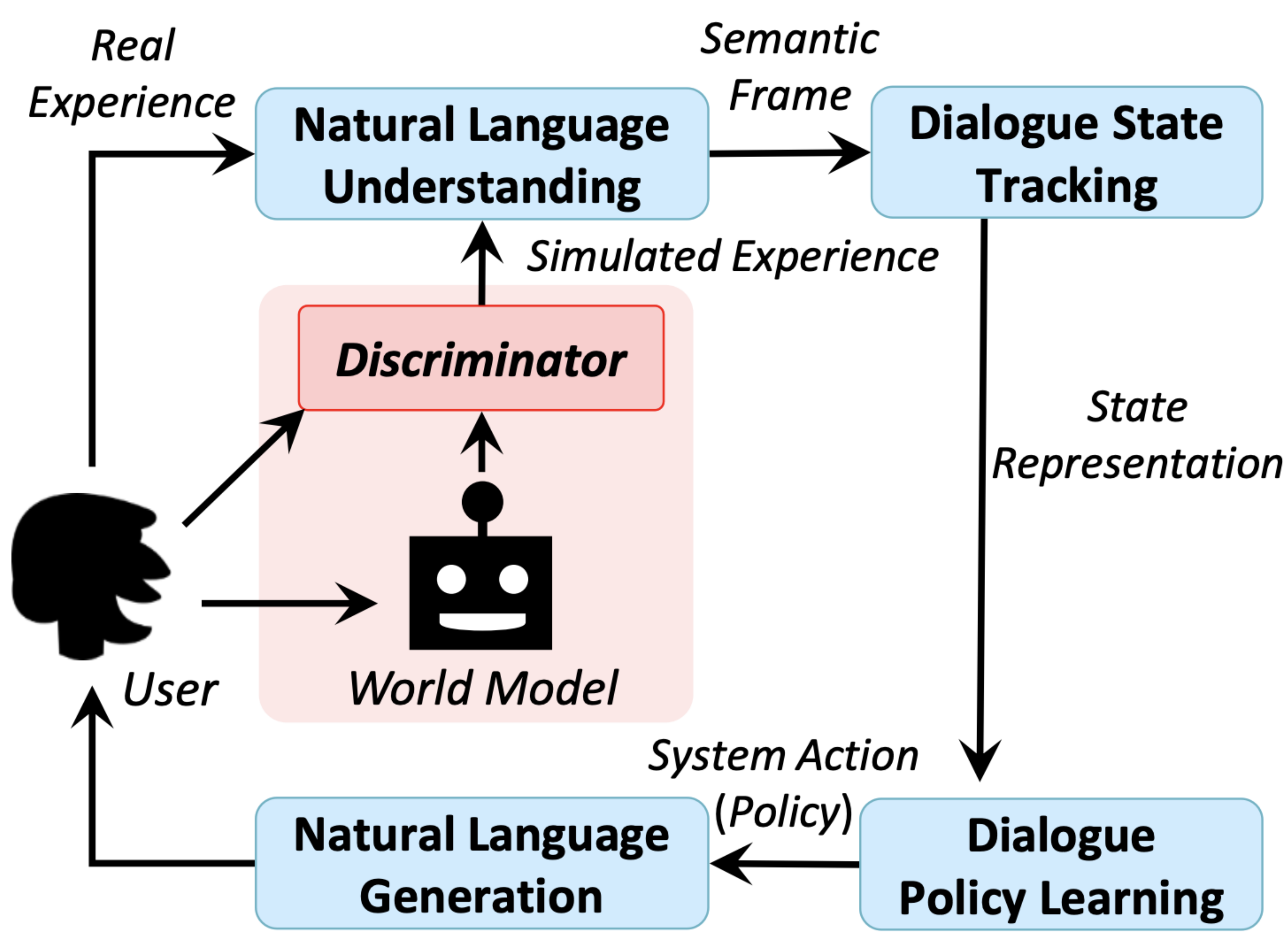


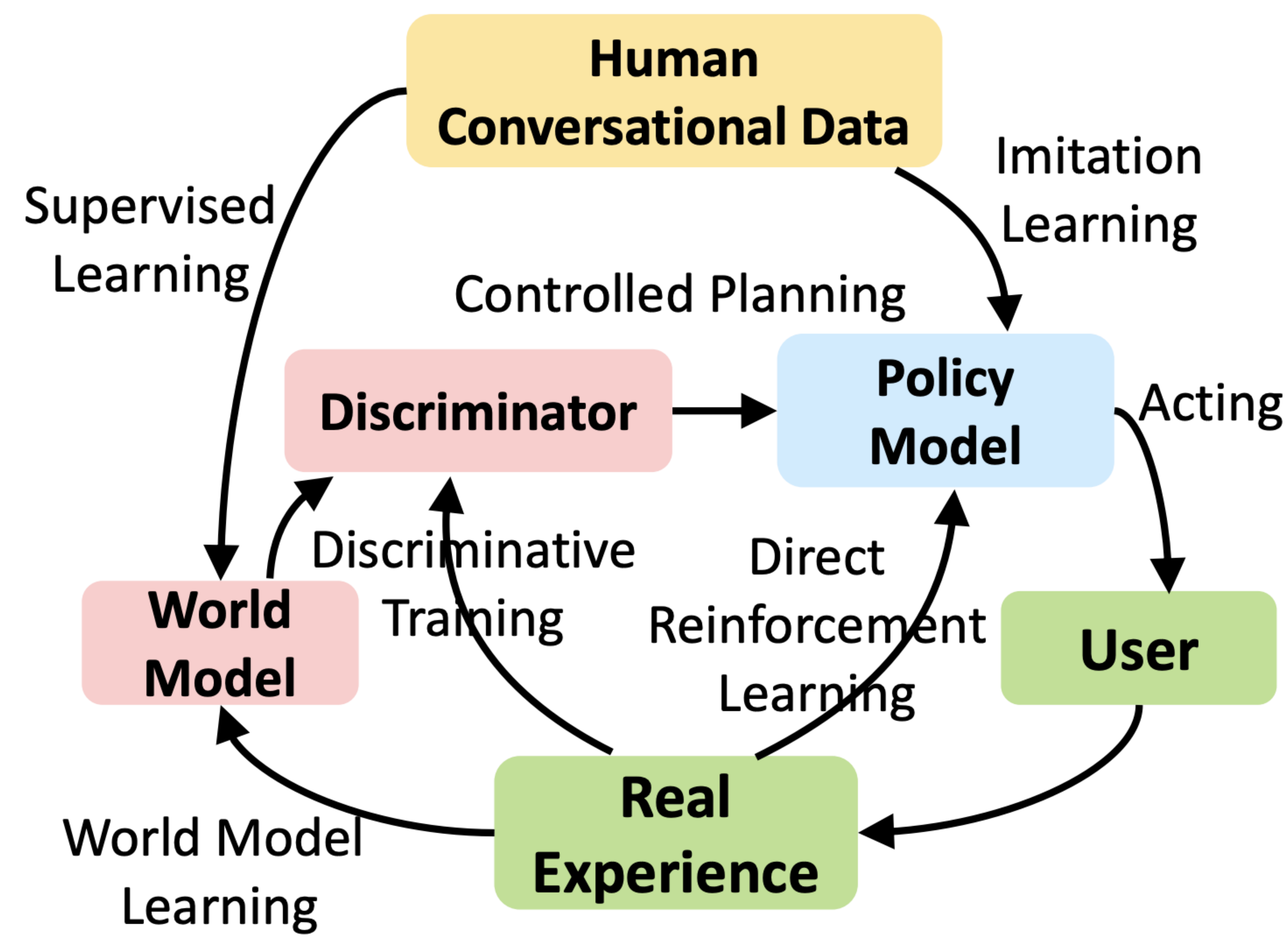
Policy learning suffers from the poor quality of fake experiences

* Peng, Baolin, et al. "Deep Dyna-Q: Integrating Planning for Task-Completion Dialogue Policy Learning." ACL 2018.

Robust Planning – Discriminative Deep Dyna-Q (Su+, 2018)

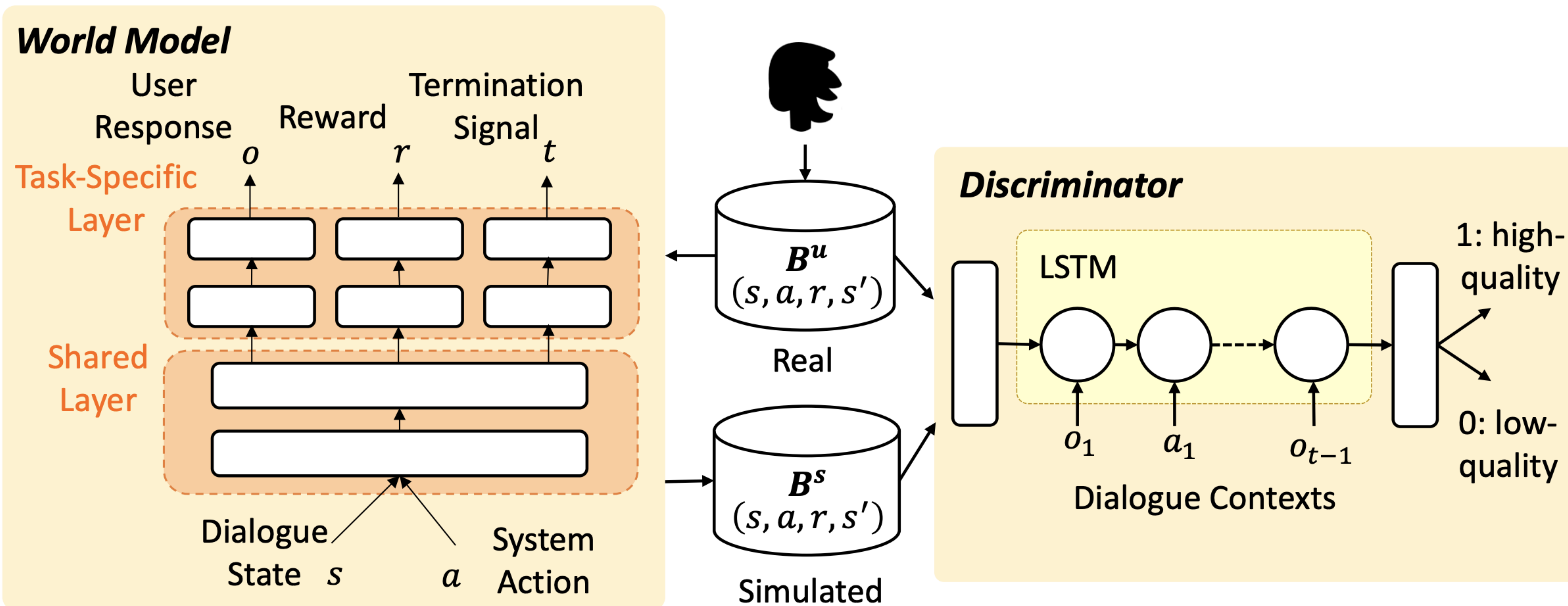
- Idea: add a discriminator to filter out the bad experiences





* Su, Shang-Yu, et al. "Discriminative Deep Dyna-Q: Robust Planning for Dialogue Policy Learning." EMNLP 2018.

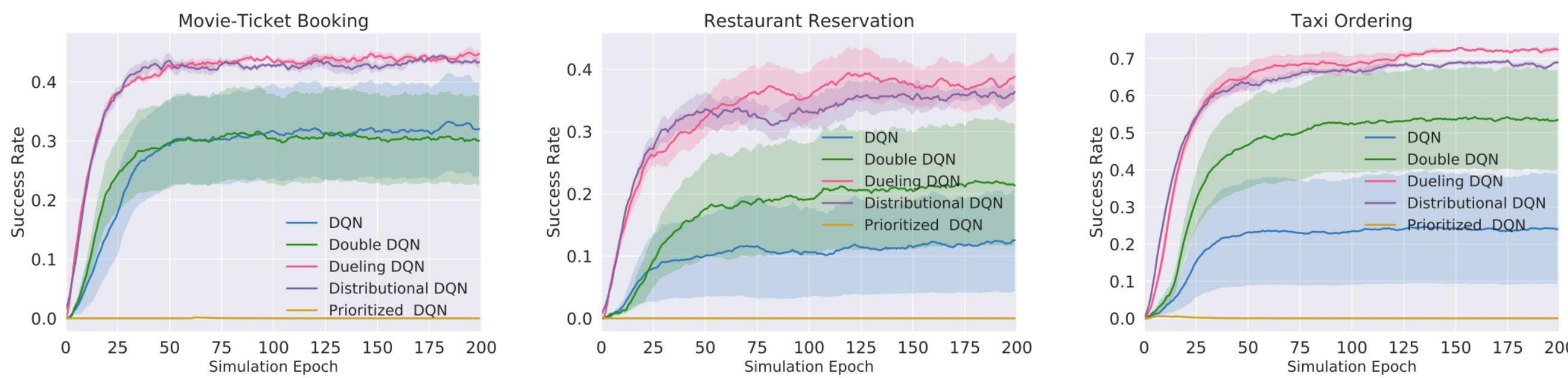
Robust Planning – Discriminative Deep Dyna-Q (Su+, 2018)



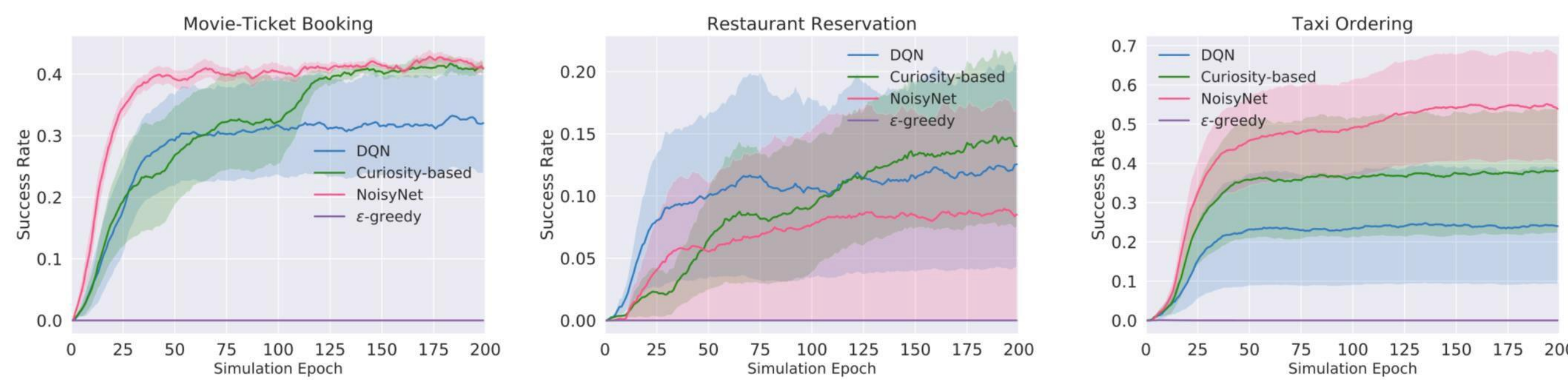
* Su, Shang-Yu, et al. "Discriminative Deep Dyna-Q: Robust Planning for Dialogue Policy Learning." EMNLP 2018.

Investigating RL in Dialogues (Wang and Chen, 2019)

- Variants of DQN



- Exploration strategies



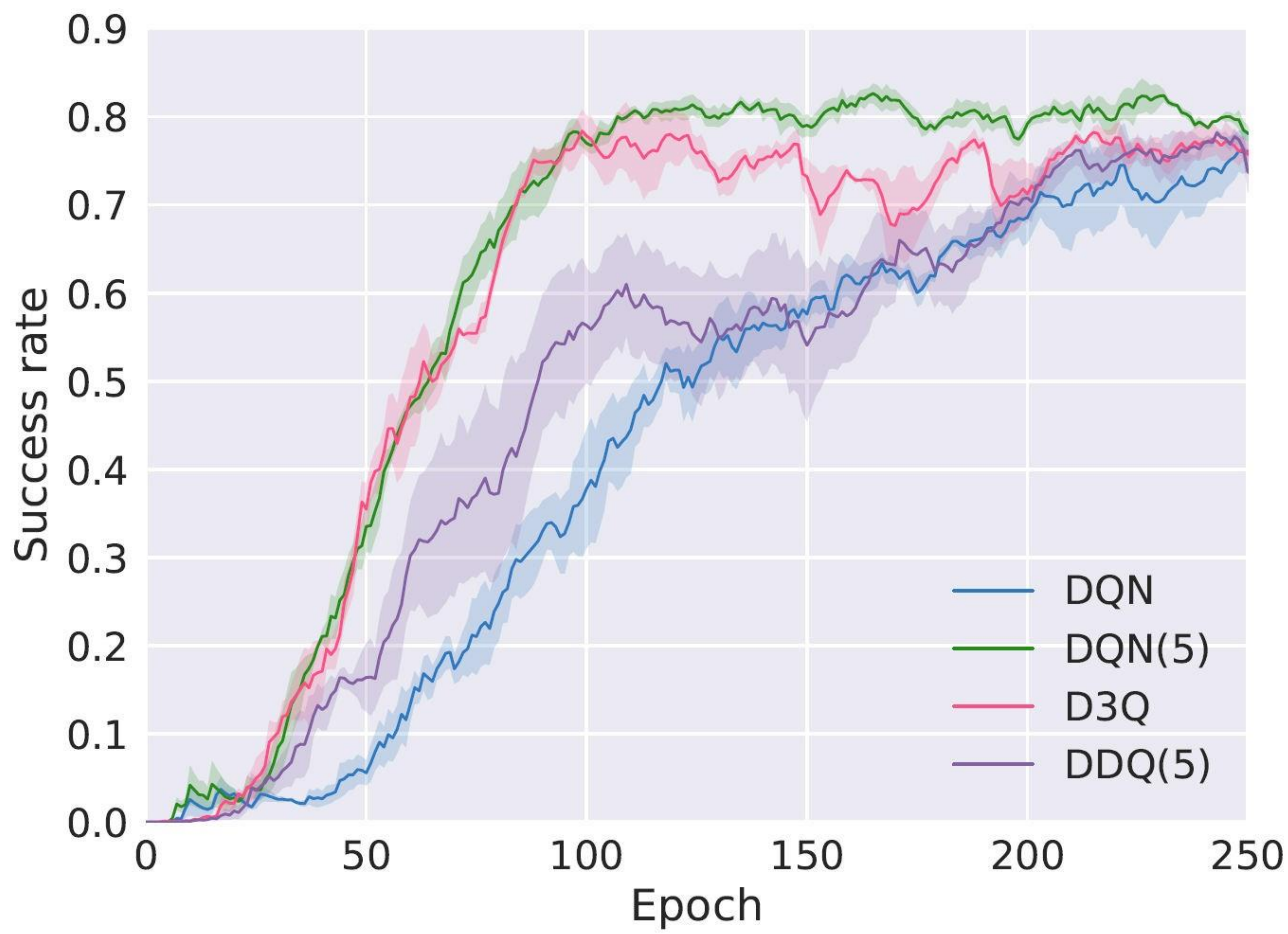
Models better for games may not fit dialogue environments, and different domains have diverse properties

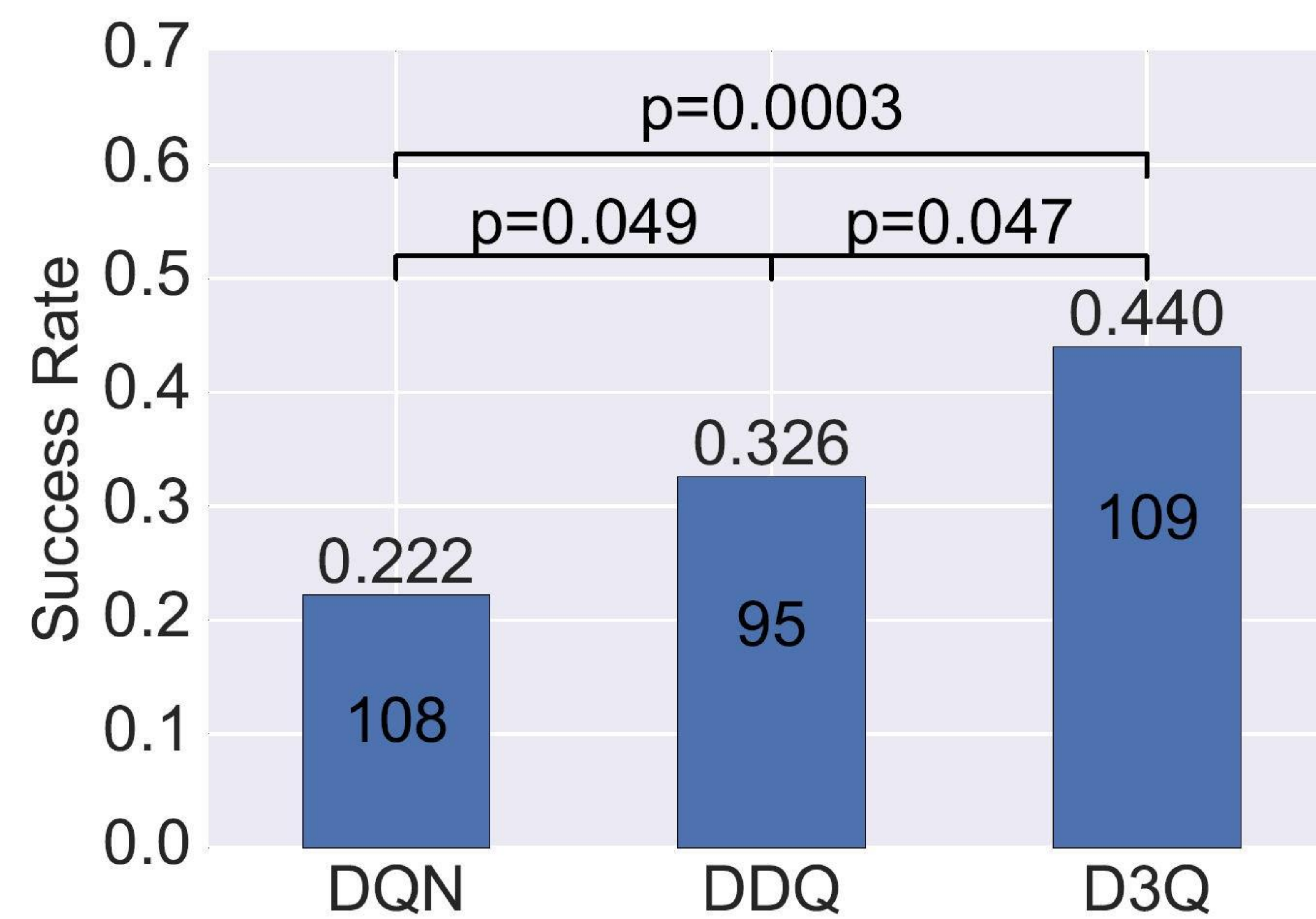
* Li, Xiujun, et al. "Investigation of language understanding impact for reinforcement learning based dialogue systems." arXiv preprint (2017).

Dialogue Management Evaluation

- Metrics
  - Turn-level evaluation:
    - System action accuracy
  - Dialogue-level evaluation:
    - Task success rate
    - Reward

Robust Planning – Discriminative Deep Dyna-Q (Su+, 2018)





The policy learning is more robust and shows the improvement in human evaluation

* Su, Shang-Yu, et al. "Discriminative Deep Dyna-Q: Robust Planning for Dialogue Policy Learning." EMNLP 2018.

Modular Dialogue System

Natural Language Generation (NLG)

RL-Based DM Challenge

☐ SLT 2018 Microsoft Dialogue Challenge:
End-to-End Task-Completion Dialogue Systems

- Domain 1: Movie-ticket booking
- Domain 2: Restaurant reservation
- Domain 3: Taxi ordering

☐ DSTC8 Multi-domain Task Completion

- Traveling (hotel, flight, etc.)

Natural Language Generation (NLG)

- Mapping dialogue acts into natural language

inform(name=Seven_Days, foodtype=Chinese)

Seven Days is a nice Chinese restaurant

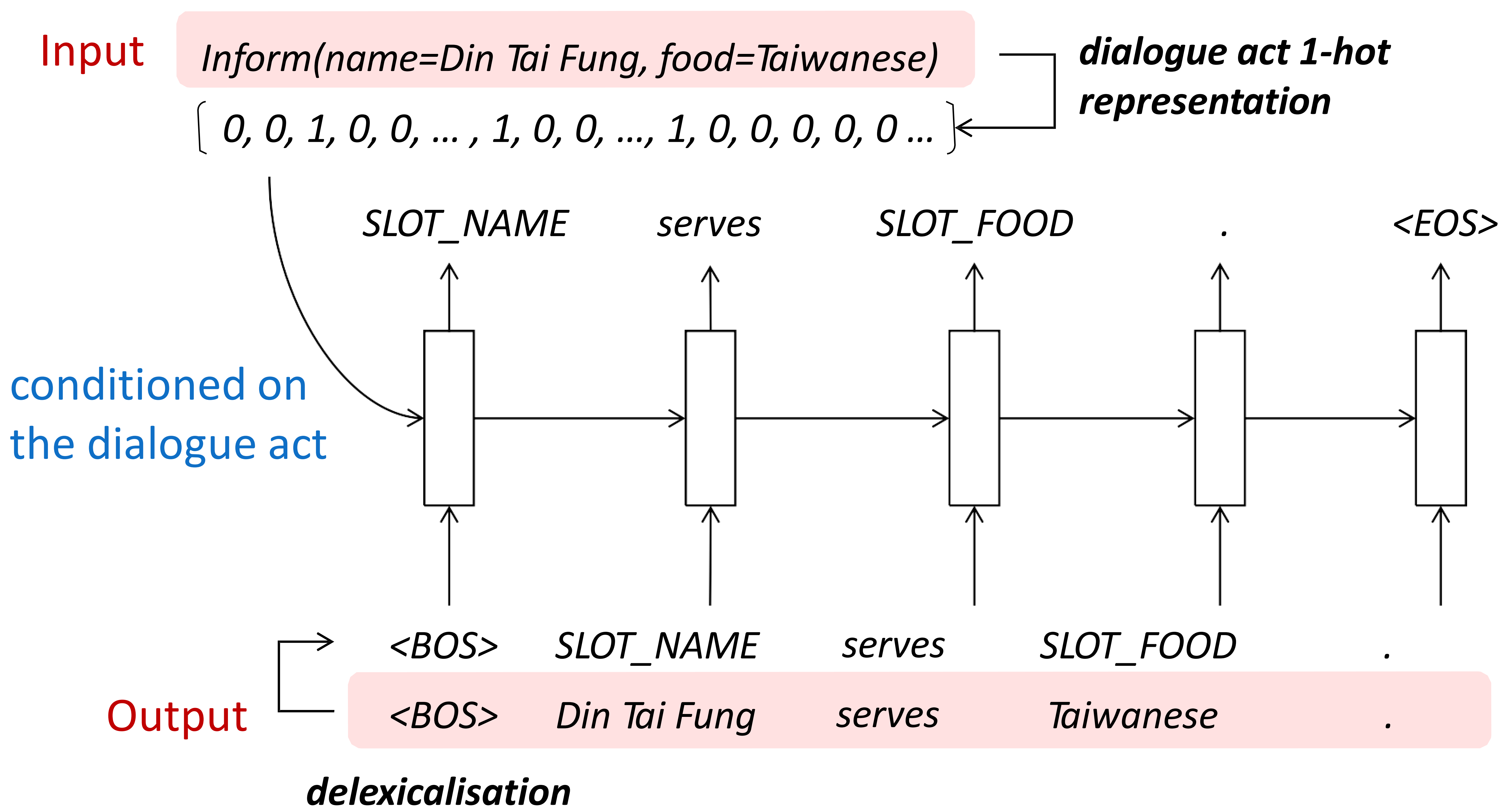
Template-Based NLG

- ☐ 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=$V)	"Do you want somewhere in the ΨV?"
confirm(food=$V)	"Do you want a ΨV restaurant?"
confirm(food=$V,area=$W)	"Do you want a ΨV restaurant in the ΨW."

Pros: simple, error-free, easy to control
Cons: time-consuming, poor scalability

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

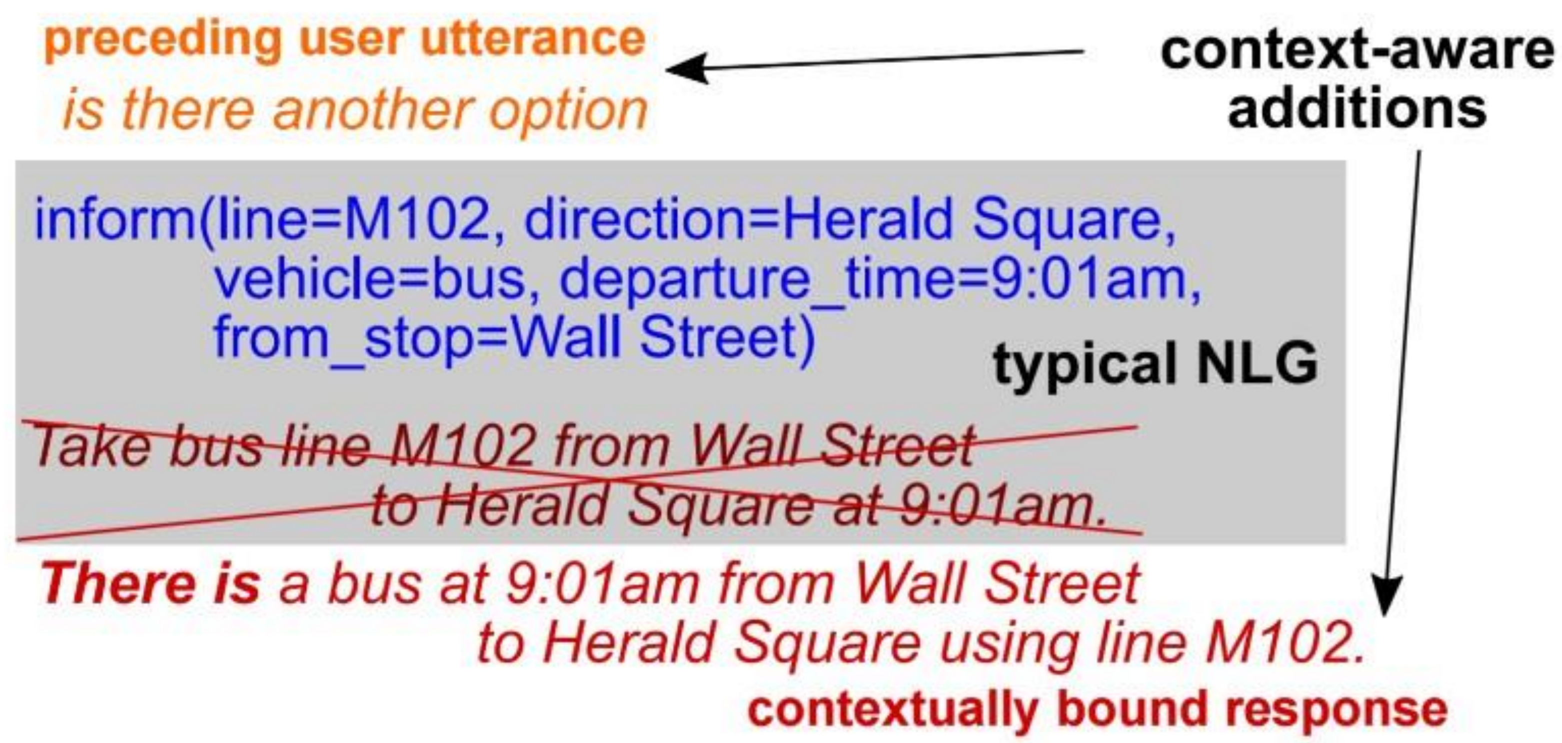


* Wen, Tsung-Hsien, et al. "Stochastic Language Generation in Dialogue using Recurrent Neural Networks with Convolutional Sentence Reranking." Proceedings of the 16th Annual Meeting of the Special Interest Group on Discourse and Dialogue. 2015.

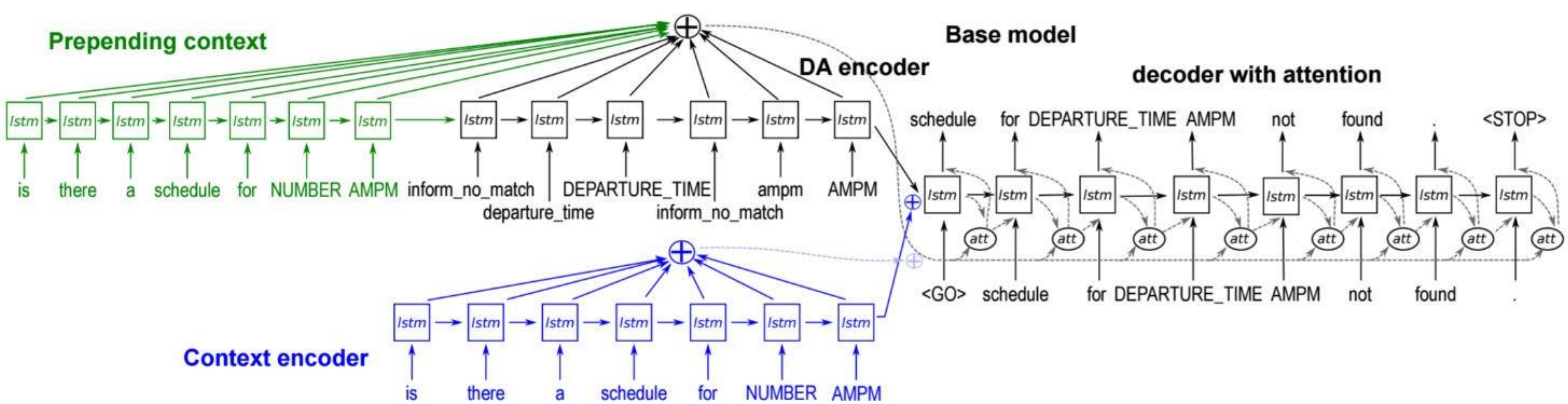
Contextual NLG (Dušek and Jurčíček, 2016)

☐ **Goal**: adapting users' way of speaking, providing context-aware responses

- Context encoder



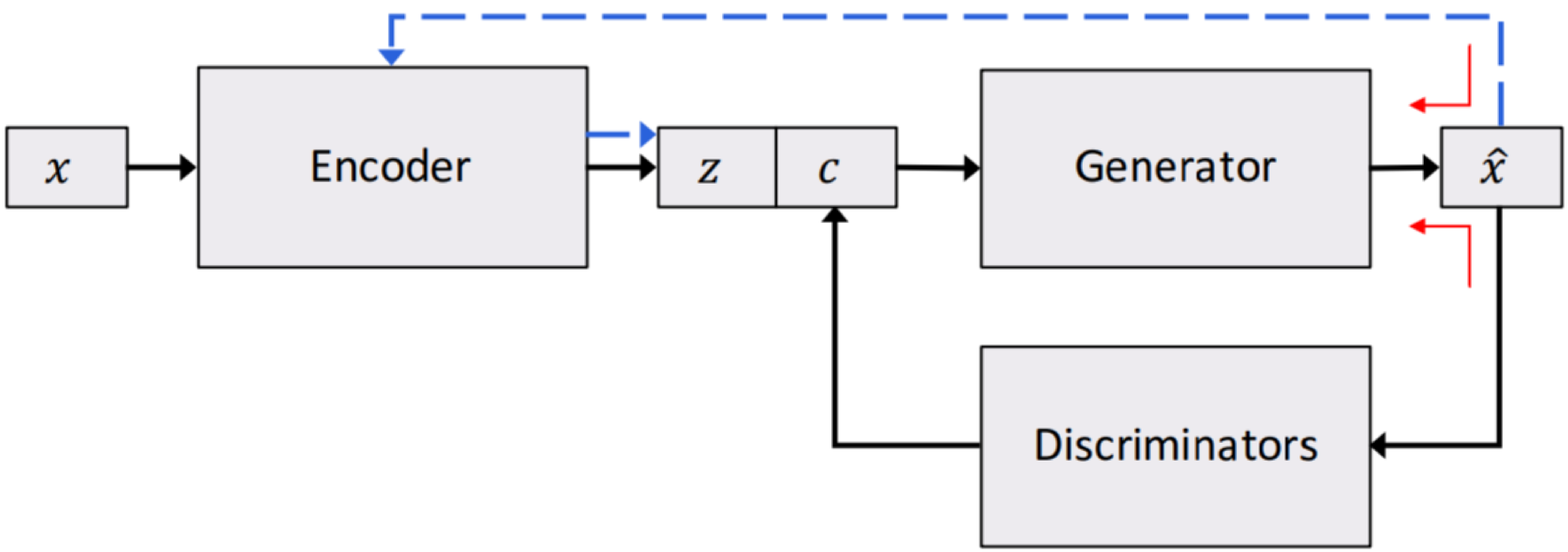
- Seq2Seq model



* Dušek, Ondřej, and Filip Jurcicek. "A Context-aware Natural Language Generator for Dialogue Systems." Proceedings of the 17th Annual Meeting of the Special Interest Group on Discourse and Dialogue. 2016.

Controlled Text Generation (Hu et al., 2017)

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



* Hu, Zhiting, et al. "Toward controlled generation of text." ICML 2017.

NLG Evaluation

- 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 System Evaluation

Dialogue System Evaluation

☐ Dialogue model evaluation

- Crowd sourcing
- User simulator

☐ Response generator evaluation

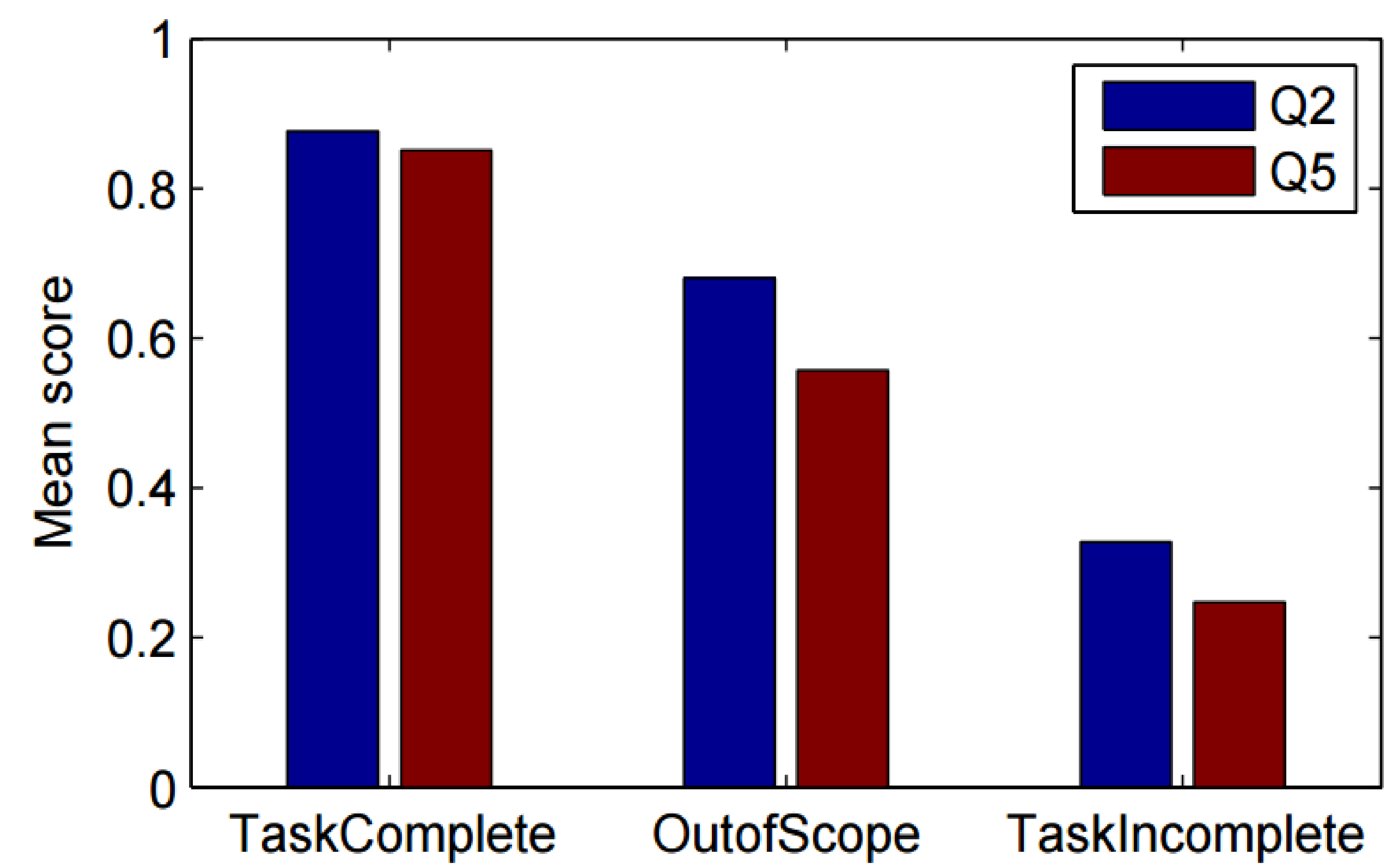
- Word overlap metrics
- Embedding based metrics

Crowdsourcing for System Evaluation (Yang+, 2013)

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

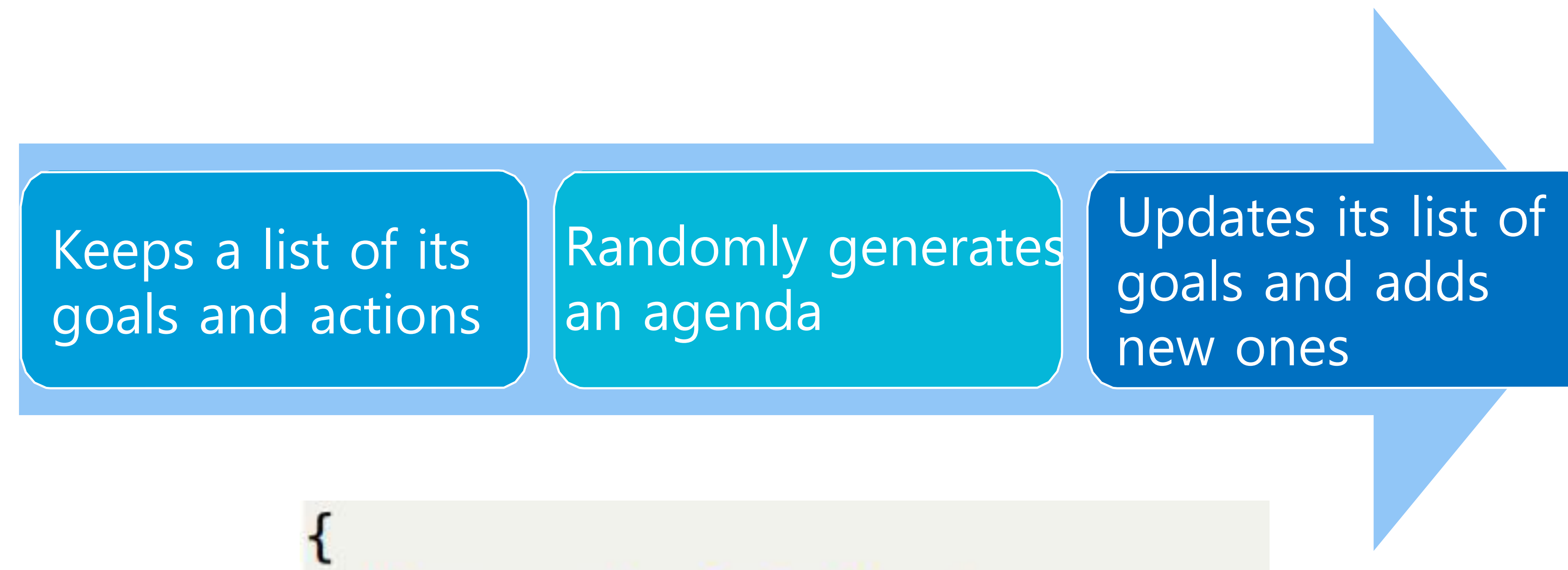
Q1	**Do you think you understand from the dialog what the user wanted?**
Opt	1) No clue 2) A little bit 3) Somewhat 4) Mostly 5) Entirely
Aim	*elicit the Worker's confidence in his/her ratings.*
Q2	**Do you think the system is successful in providing the information that the user wanted?**
Opt	1) Entirely 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.*



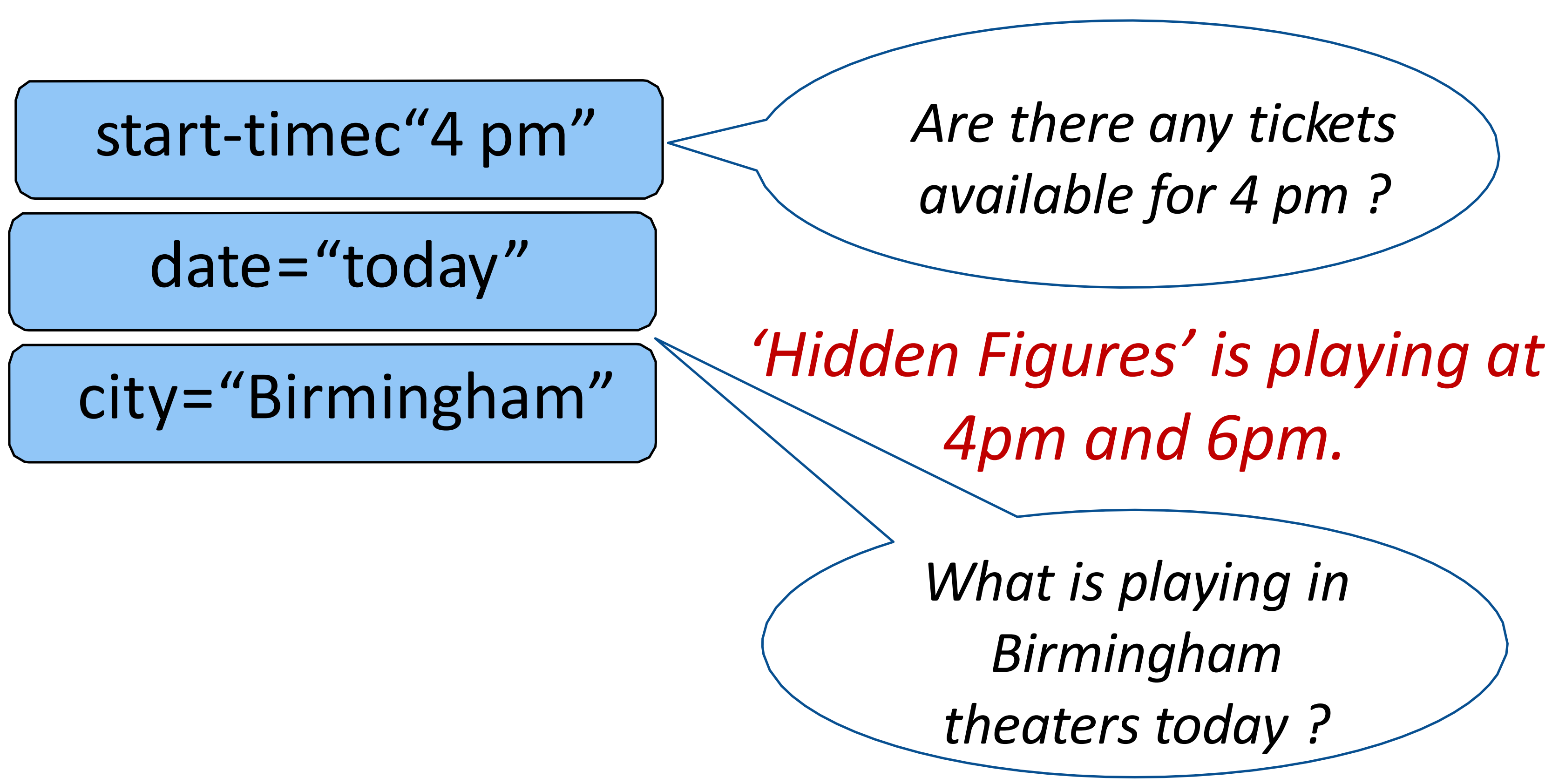
* Yang, Zhaojun, Gina-Anne Levow, and Helen M. Meng. "Crowdsourcing for spoken dialog systems evaluation.", Crowdsourcing for Speech Processing: Applications to Data Collection, Transcription and Assessment (2013): 217-240.

User Simulation

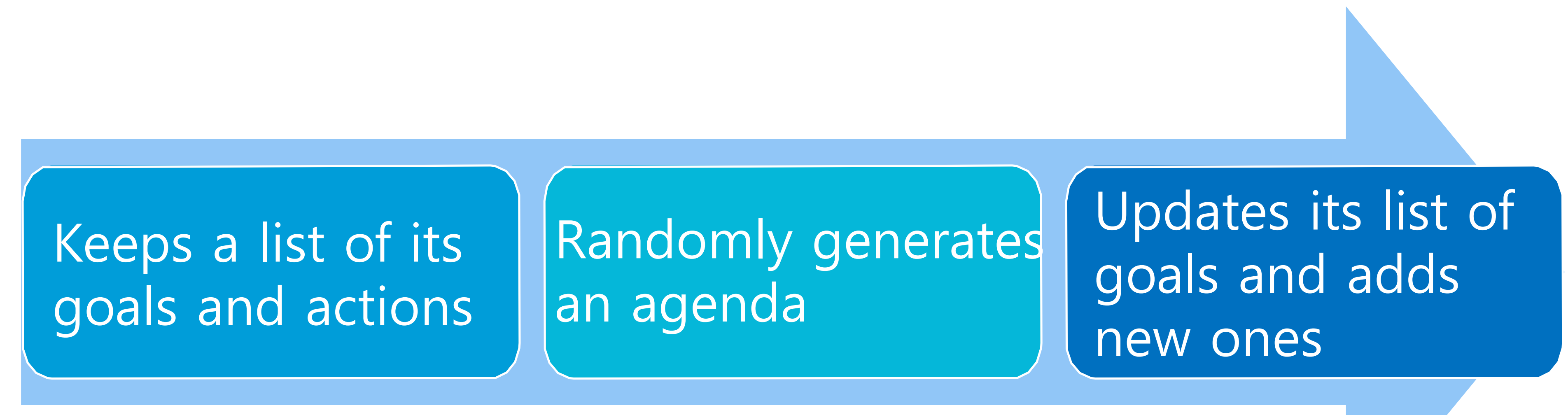
- First, generate a user goal.
- The user goal contains:
  - Dialog act
  - Inform slots
  - Request slots



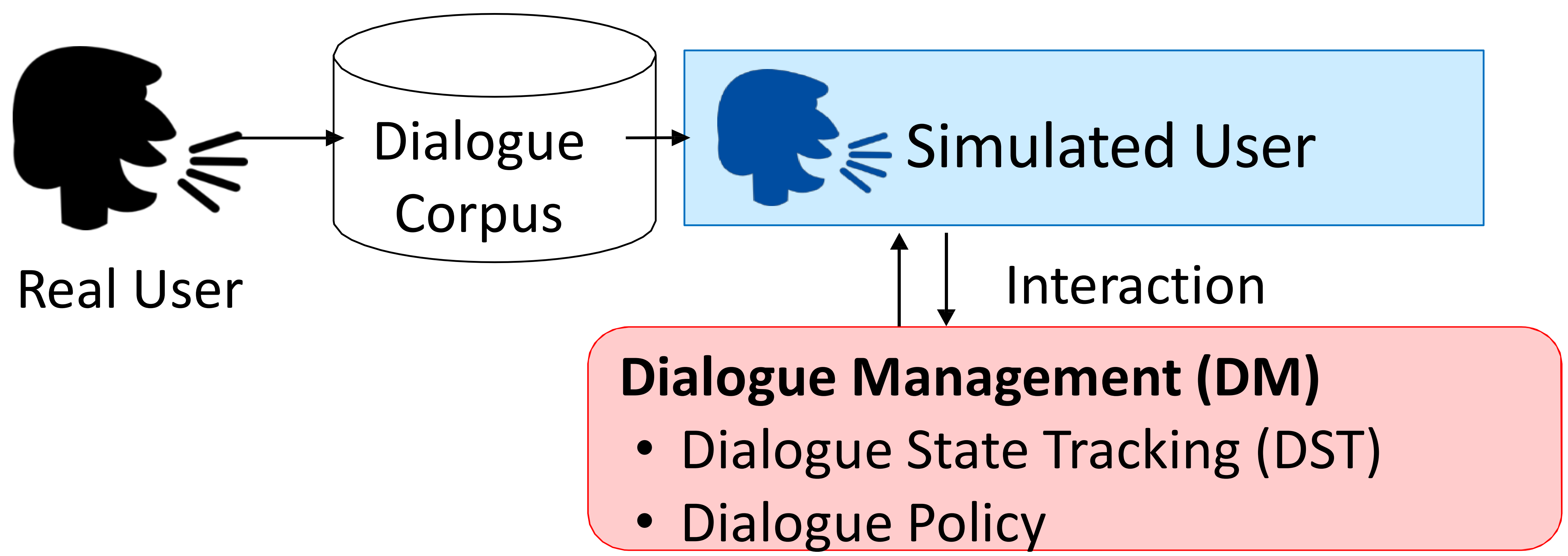

```
{
  "request_slots": {
    "ticket": "UNK",
    "theater": "UNK"
  },
  "diaact": "request",
  "inform_slots": {
    "city": "birmingham",
    "numberofpeople": "2",
    "state": "al",
    "starttime": "4 pm",
    "date": "today",
    "moviename": "deadpool"
  }
}
```

User Simulation



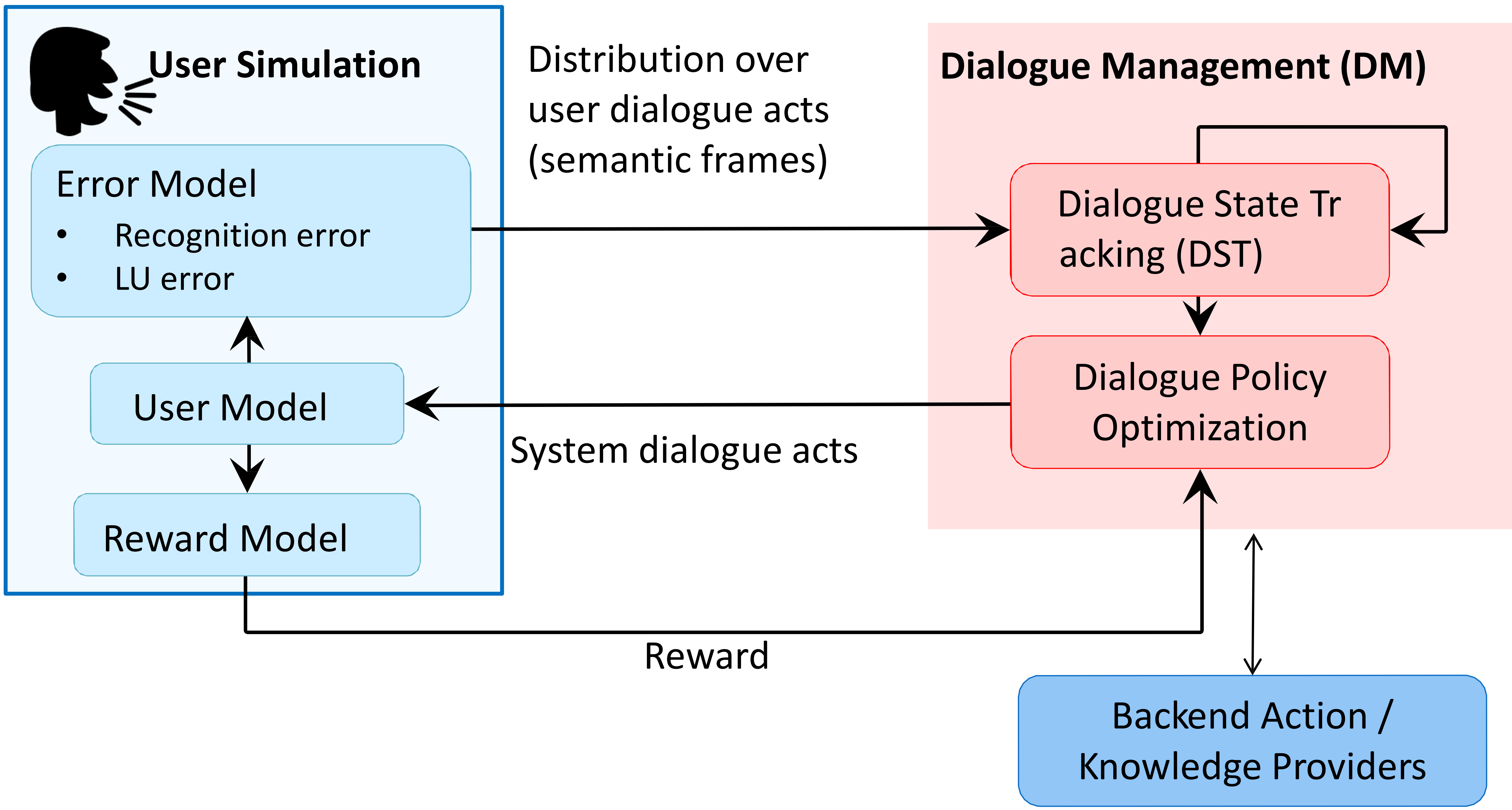
☐ Goal: generate natural and reasonable conversations to enable reinforcement learning for exploring the policy space



☐ Approach

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

Elements of User Simulation



The error model enables the system to maintain the robustness

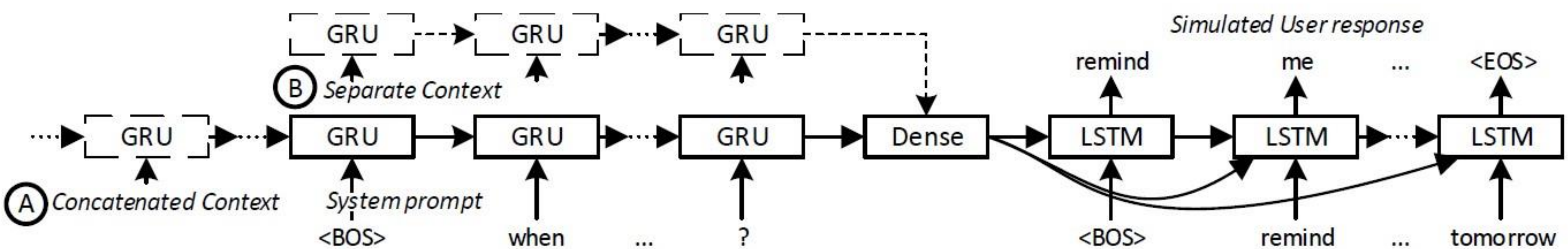
Learning-Based User Simulators

- 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)

Seq2Seq User Simulation (Crook and Marin, 2017)

☐ Seq2Seq trained from dialogue data

- No labeled data
- Trained on just human to machine conversations



* Crook, Paul, and Alex Marin. "Sequence to Sequence Modeling for User Simulation in Dialog Systems." Interspeech 2017.

User Simulator for Dialogue Evaluation Measures

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

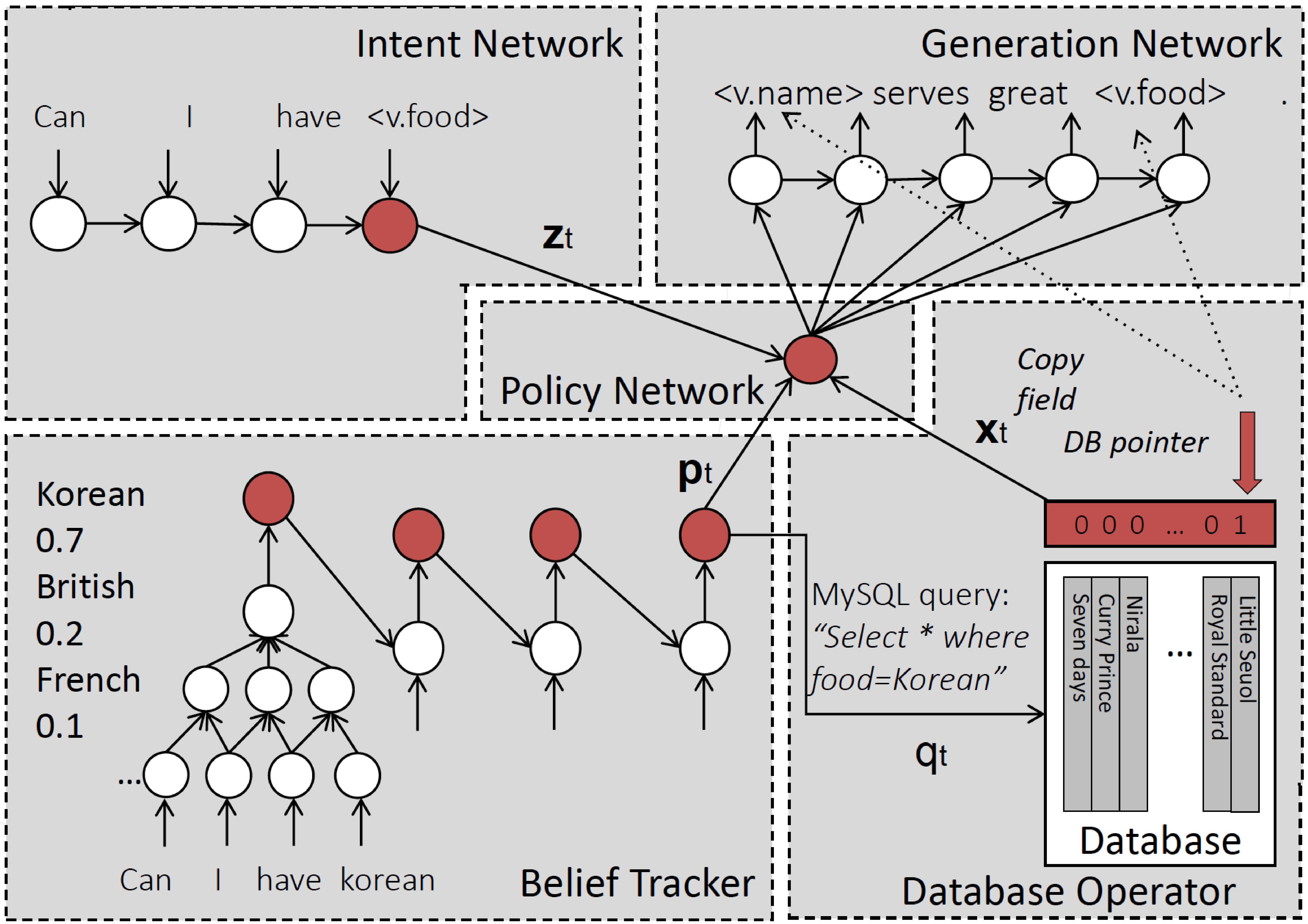
- Number of dialogue turns
- Ratio between the dialogue turns (larger is better)

Action Appropriateness

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

End-to-End Neural Dialogue System

E2E Supervised Dialogue System (Wen et al., 2017)



* Wen, Tsung-Hsien, et al. "A Network-based End-to-End Trainable Task-oriented Dialogue System." Proceedings of the 15th Conference of the European Chapter of the Association for Computational Linguistics: Volume 1, Long Papers. 2017

E2E MemNN for Dialogues (Bordes et al., 2017)

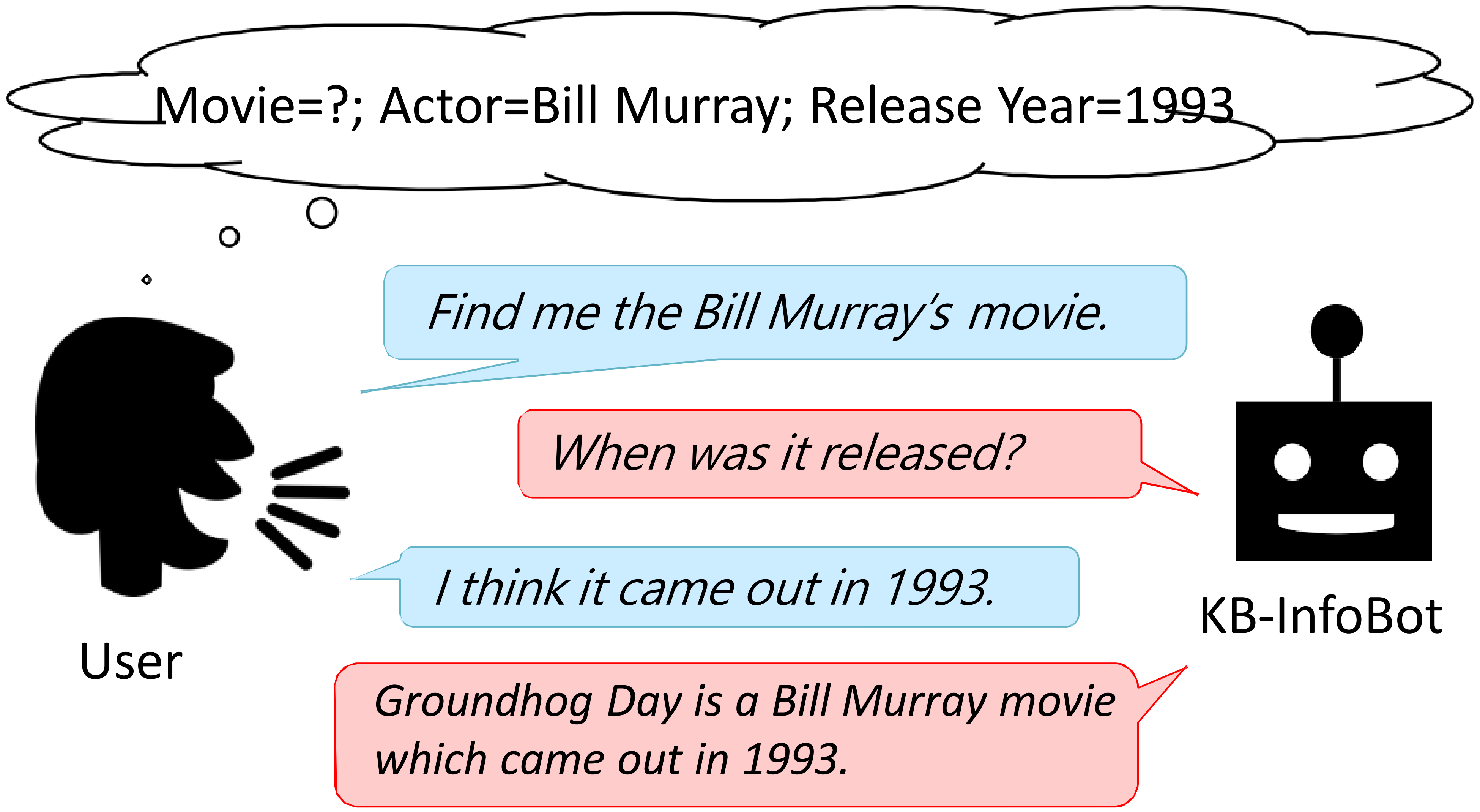
- Split dialogue system actions into subtasks
  - API issuing
  - API updating
  - Option displaying
  - Information informing

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)

Task 5 Conducting full dialogs

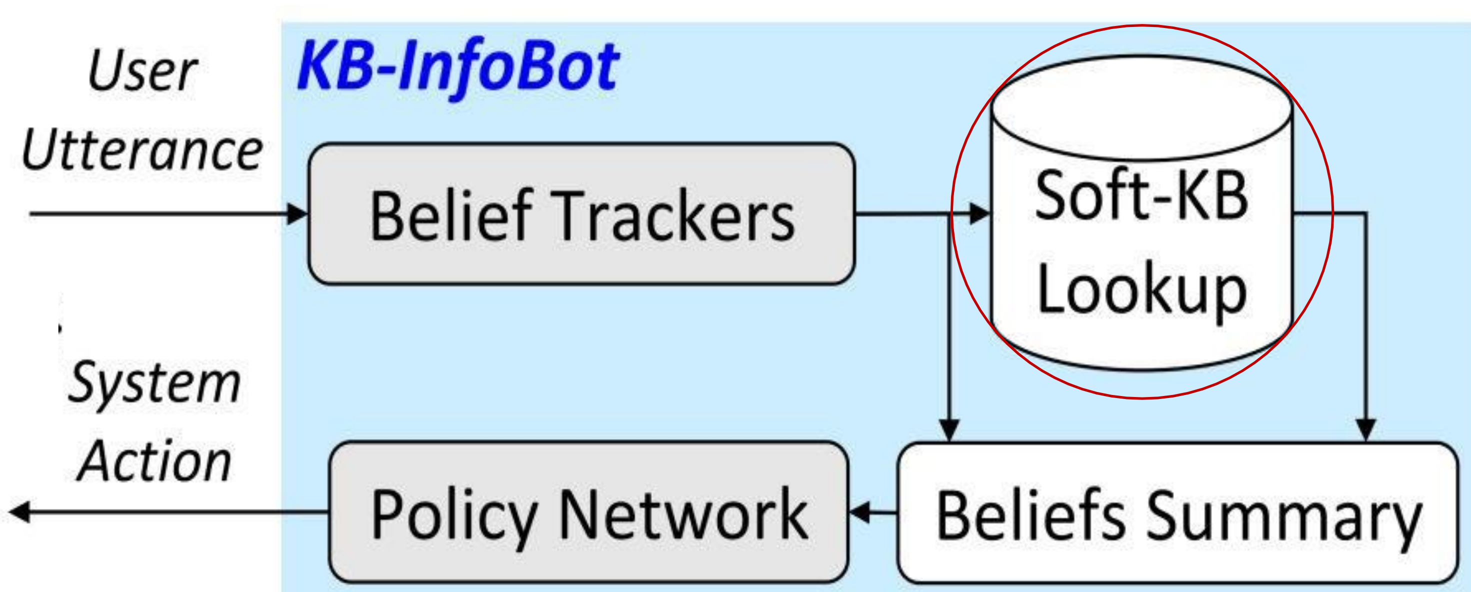
* Bordes, Antoine, Y-Lan Boureau, and Jason Weston. "Learning end-to-end goal-oriented dialog." ICLR 2017.

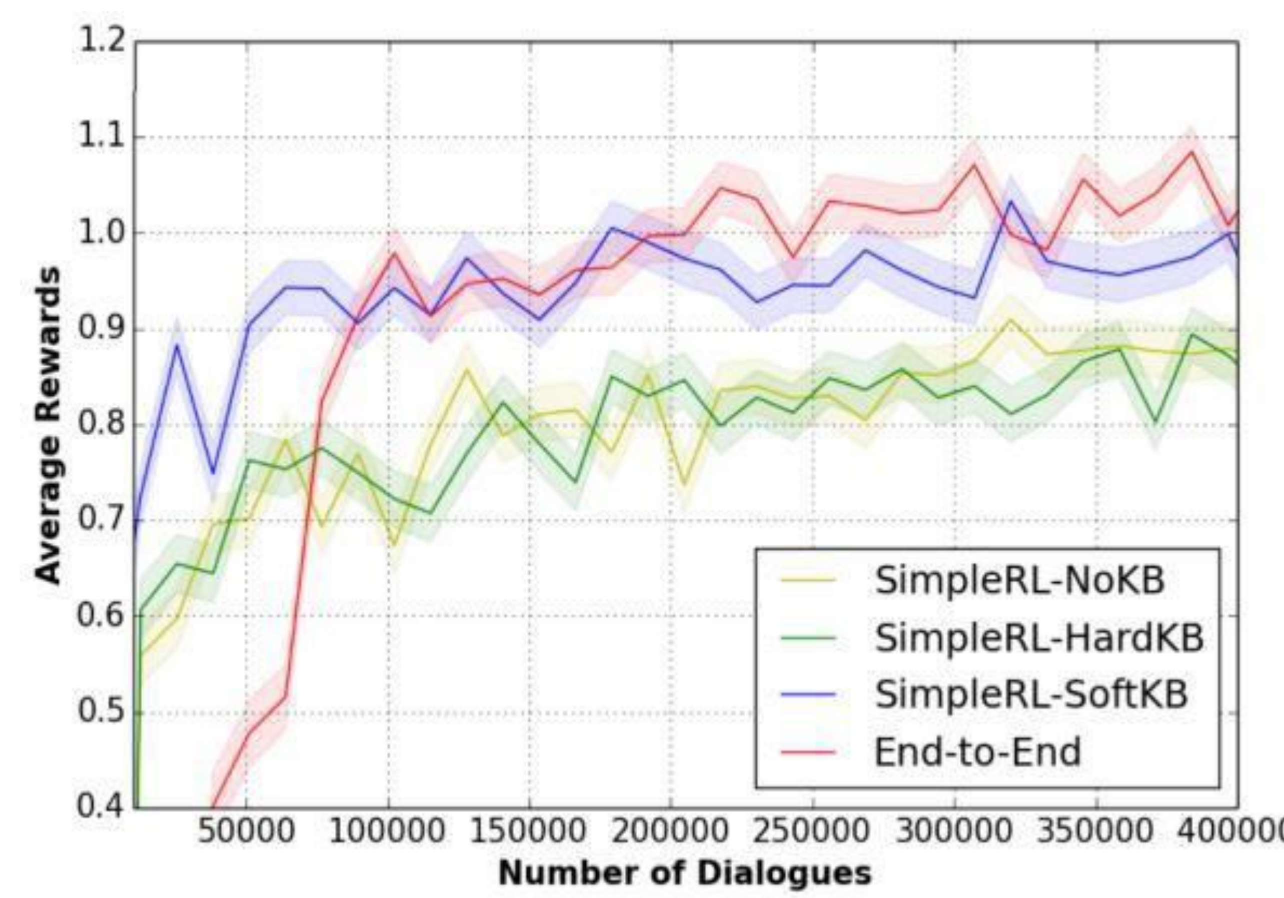
E2E RL-Based KB-InfoBot (Dhingra et al., 2017)



Entity-Centric Knowledge Base

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





Idea: differentiable database for propagating the gradients

* Dhingra, Bhuwan, et al. "Towards End-to-End Reinforcement Learning of Dialogue Agents for Information Access." ACL 2017.

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

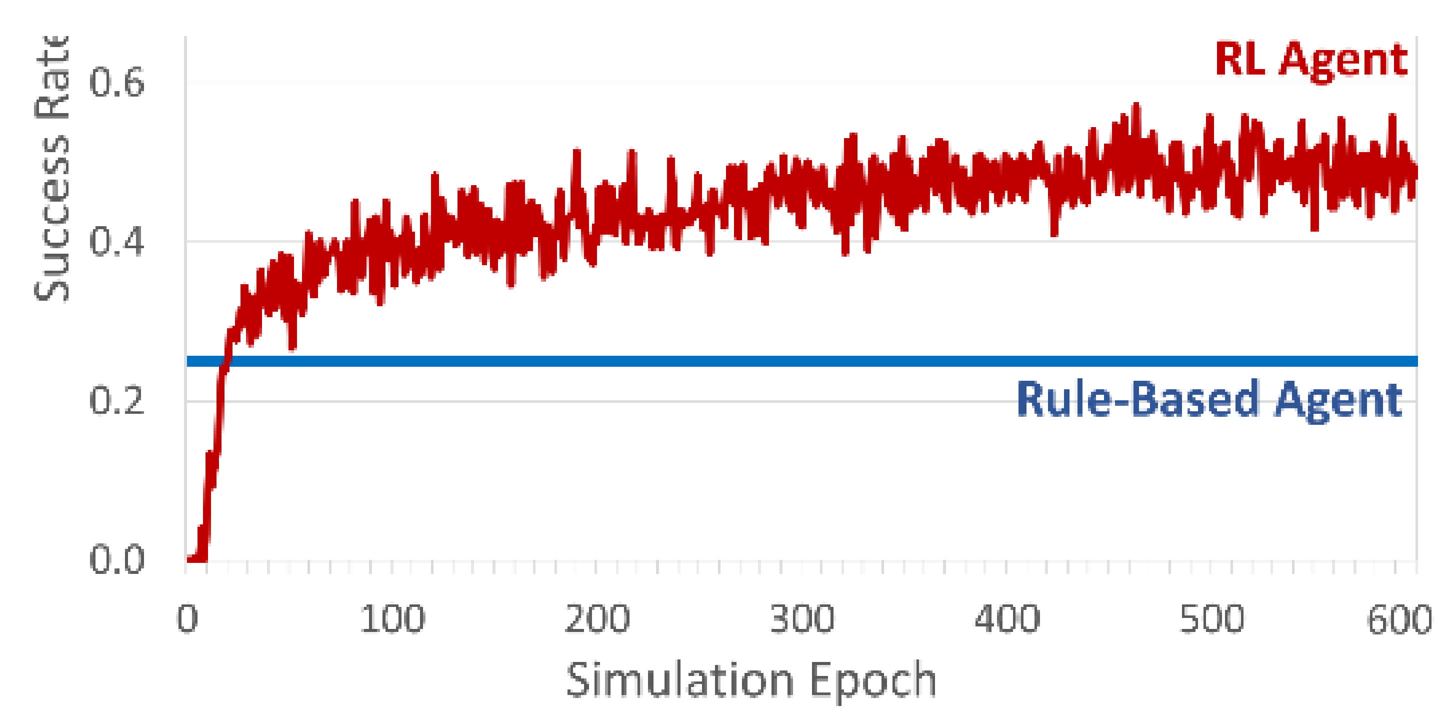
- User goal: ***Two tickets for "the witch" tomorrow 9:30 PM at regal meridian 16, Seattle.***

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

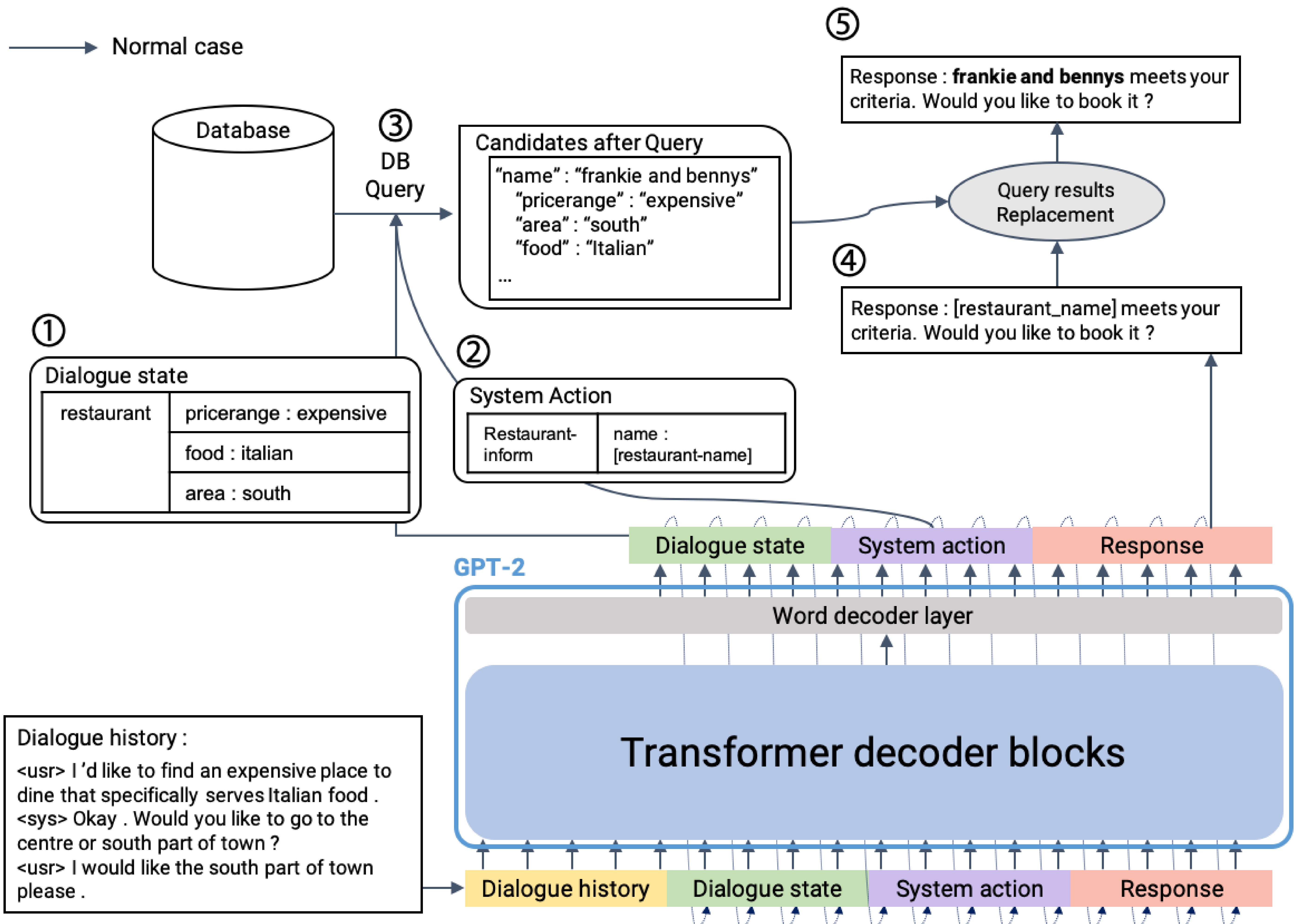
User: Can I get 2 tickets for the witch?
Agent: What date would you like to see it?
User: Tomorrow
Agent: Which theater do you prefer?
User: Regal meridian 16
Agent: What is your location?
User: Seattle
Agent: What time would you like to see it?
User: 9:30 pm.
Agent: Great - I was able to purchase 2 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

* Li, Xiujun, et al. "End-to-End Task-Completion Neural Dialogue Systems." *Proceedings of the Eighth International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*. 2017.

End-to-End Neural Pipeline (Ham & Lee et al., 2020)

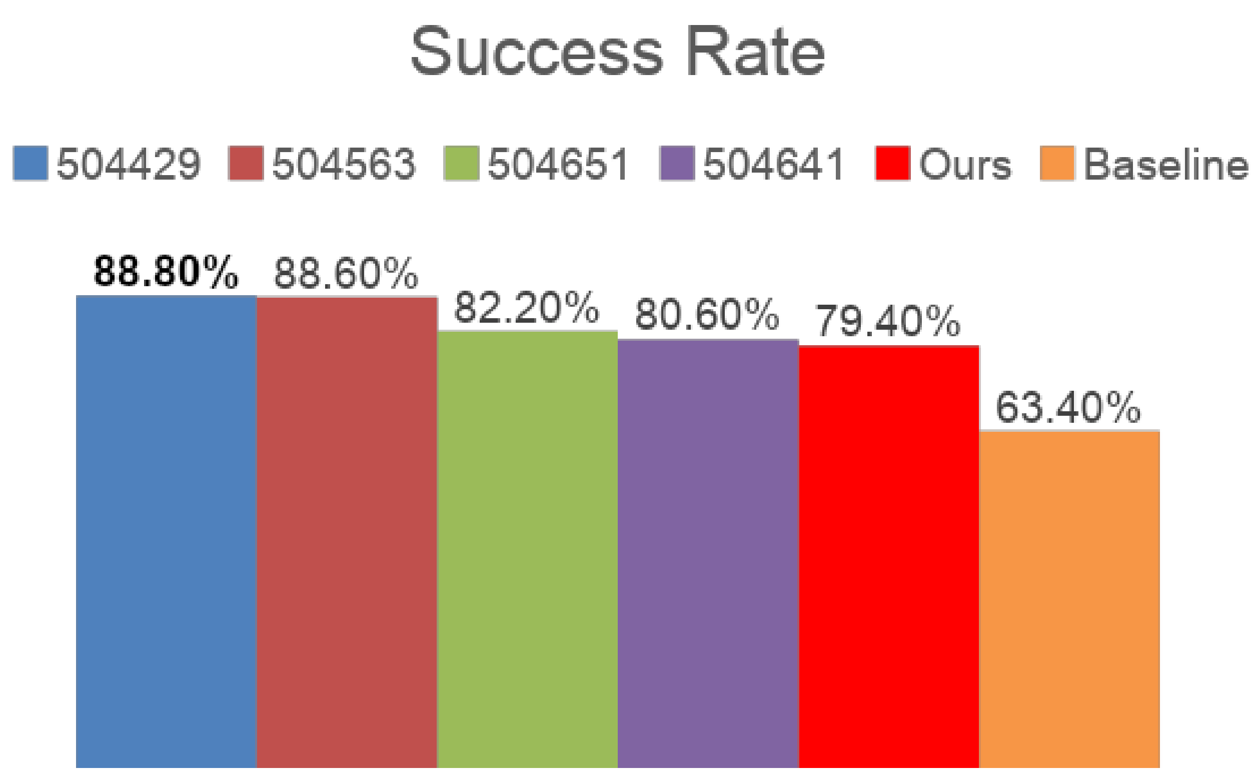


Idea: Integrate Pipelined Architecture into single GPT-2

* Donghoon Ham*, Jeong-Gwan Lee*, Youngsoo Jang, and Kee-Eung Kim. 2020. End-to-End Neural Pipeline for Goal-Oriented Dialogue System using GPT-2. ACL 2020

End-to-End Neural Pipeline (Ham & Lee et al., 2020)

Automatic Evaluation



Limitation of automatic evaluation

- Unnatural user simulator response

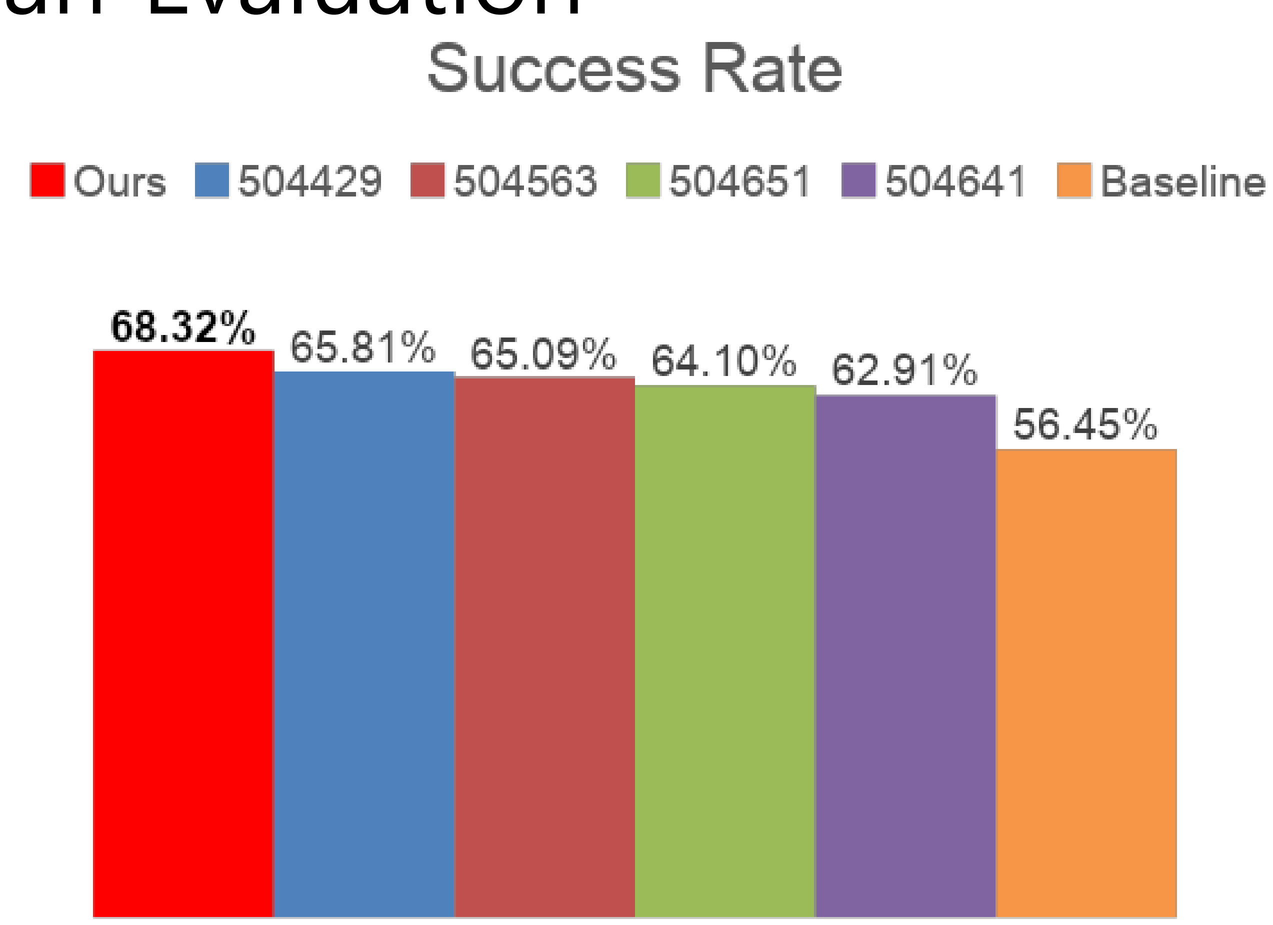
  System utterance: I have several. What area of town would you like?
  User utterance: I 'd like to be in the **don't care** please .

- Misunderstanding

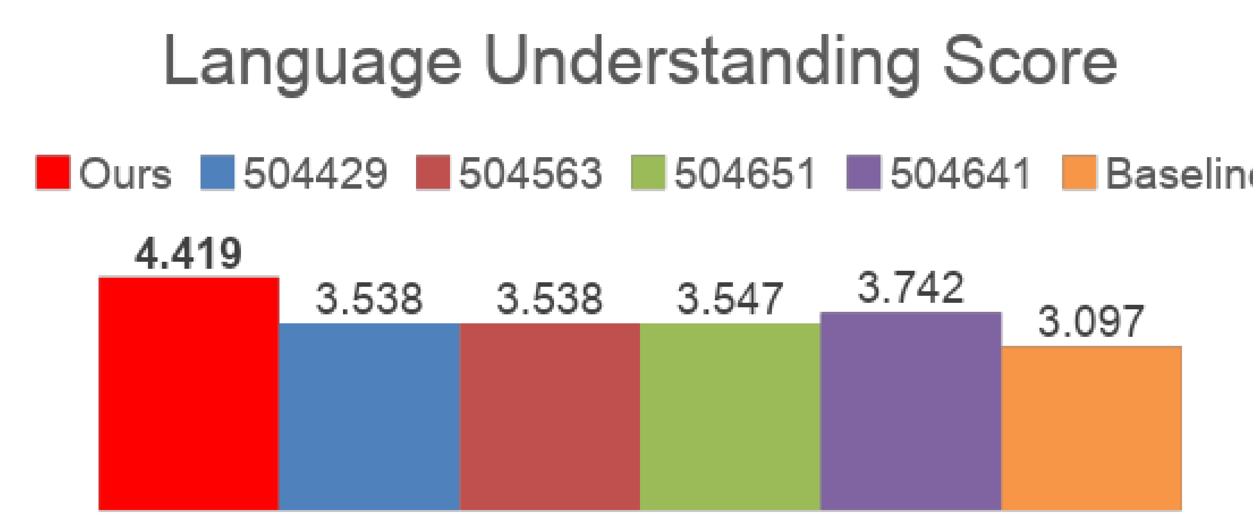
  User utterance: Does that have free parking ?
  System utterance: **Yes, they have free parking.**

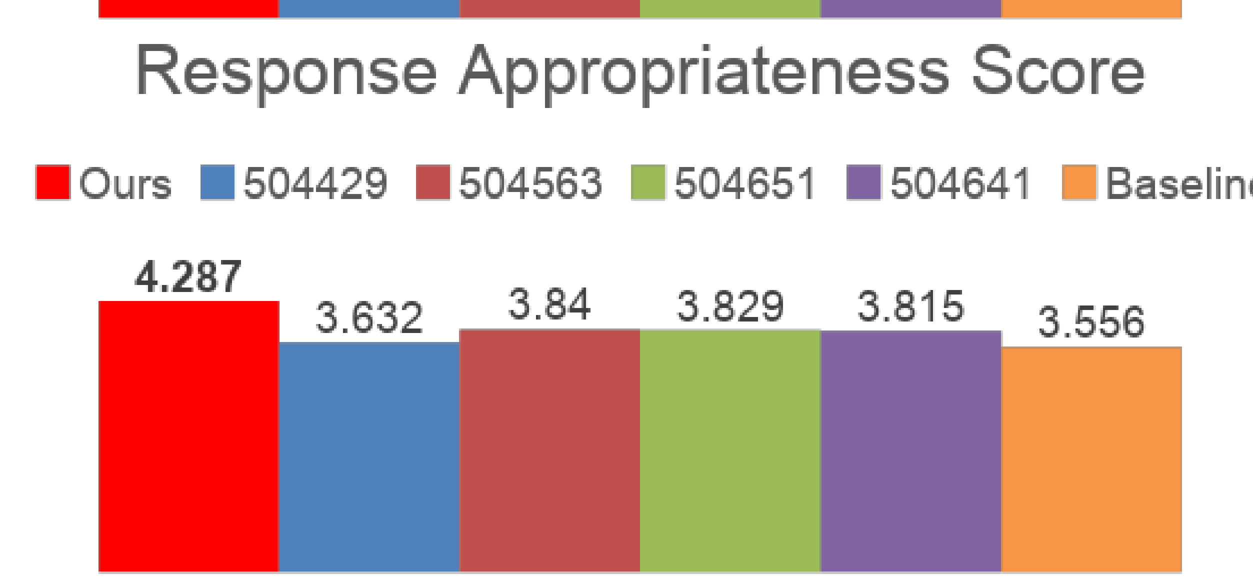
```
sys_act = self.nlu_model.parse(input, context)
print(sys_act)
<class 'dict'>: {'Hotel-Inform': [['Parking', 'none']]}
```

Human Evaluation



ConvLab & Challenge Leaderboard (https://convlab.github.io)





* Donghoon Ham*, Jeong-Gwan Lee*, Youngsoo Jang, and Kee-Eung Kim. 2020. End-to-End Neural Pipeline for Goal-Oriented Dialogue System using GPT-2. ACL 2020

Dialogue Challenge

- DSTC: Dialog System Technology Challenge

Challenge	Track	Theme
DSTC6	Track 1	End-to-End Goal-Oriented Dialog Learning
	Track 2	End-to-End Conversation Modeling
	Track 3	Dialogue Breakdown Detection
DSTC7	Track 1	Sentence Selection
	Track 2	Sentence Generation
	Track 3	AVSD: **A**udio **V**isual **S**cene-aware **D**ialog
DSTC8	Track 1	Multi-domain Task Completion
	Track 2	NOESIS II: Predicting Responses
	Track 3	Audio Visual Scene-Aware Dialog
	Track 4	Schema-Guided State Tracking

- SLT 2018 Microsoft Dialogue Challenge: End-to-End Task-Completion Dialogue Systems
- The Conversation Intelligence Challenge: ConvAI2 - PersonaChat

Summarized Challenges

- Human-machine interface is a hot topic but several components must be integrated!
- Accuracy and robustness of each component
- Fast domain adaptation with scarse data + re-use of rules/knowledge
- Handling reasoning / common sense understanding
- User modeling for personalization
- Complex-cascade systems requires high accuracy for working good as a whole

Conclusions

- 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