Conversational Information Seeking with Dialog Systems

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Outline

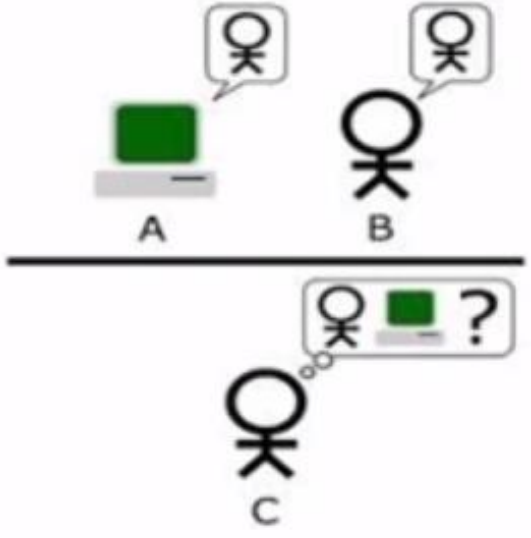
- Background of dialog systems
- Conversational information seeking
  - Task completion
  - QA + MRC
  - Knowledge grounded conversation
  - Conversational recommendation
- Future challenges

The Turing Test (1950)

《Computing Machinery and Intelligence》

"Can machines think?"

1912--1954



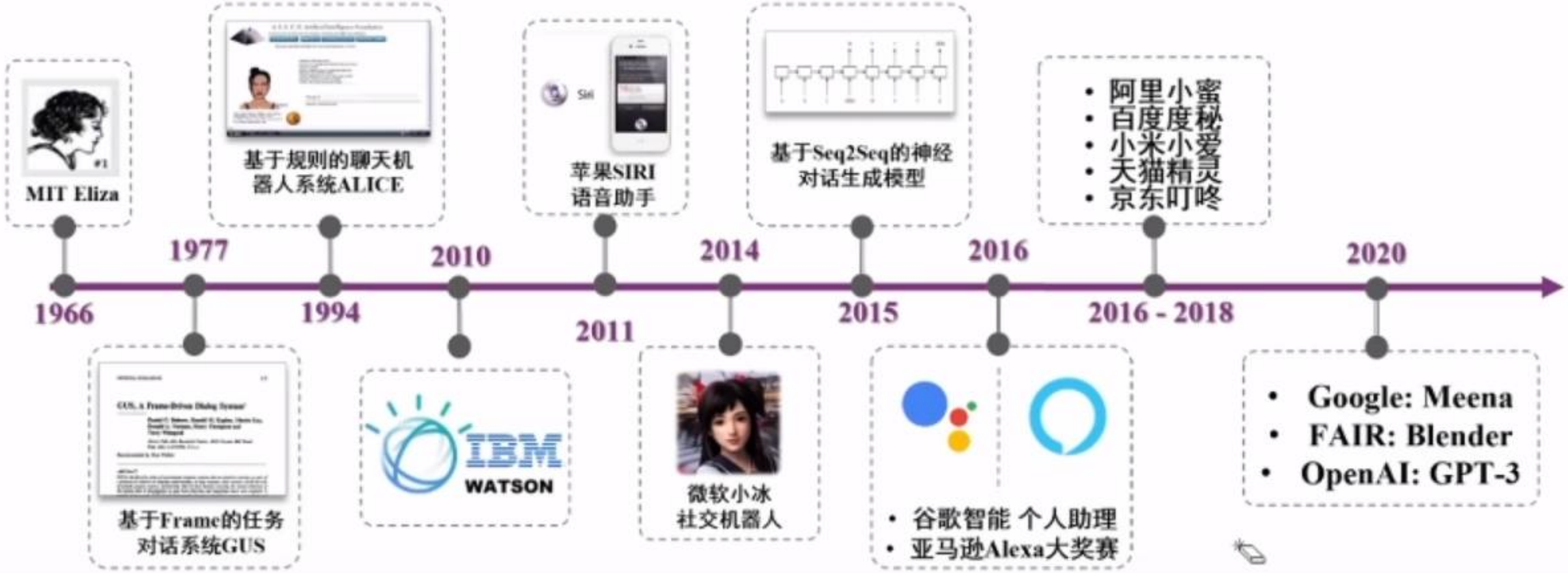
Q: Please write me a sonnet on the subject of the Forth Bridge.

A: Count me out on this one. I never could write poetry.

Q: Add 34957 to 70764.

A: (Pause about 30 seconds and then give as answer) 105621.

History of Dialog Systems



Eliza 1966

- Created by MIT professor Joseph Weizenbaum
  - **Eliza effect**

- Features
  - Hand-crafted scripts
  - keyword spotting
  - template matching

Human: Well, my boyfriend made me come here.

ELIZA: Your boyfriend made you come here?

Human: He says I'm depressed much of the time.

ELIZA: I am sorry to hear you are depressed.

Human: It's true. I'm unhappy.

ELIZA: Do you think coming here will help you not to be unhappy?

.....

Joseph Weizenbaum. 1966. ELIZA - a computer program for the study of natural language communication between man and machine. Commun. ACM 9, 1 (1966), 36–45.

Eliza 1966

pronoun reversal (key tricks): I → you, me → you

- Human: He says **I am** depressed much of the time.
- Eliza: I am sorry to hear **you are** depressed.

- Human: I need some help, that much seems certain.
- Eliza: what would it mean to you if you got some help?
  - Pattern: I need some X → What would it mean to you if you got some X?

Joseph Weizenbaum. 1966. ELIZA - a computer program for the study of natural language communication between man and machine. Commun. ACM 9, 1 (1966), 36–45.

GUS 1977-Genial Understander System

GUS: Hello. My name is GUS. I can help you plan a simple trip by air. Where do you want to go?

(1) *Client:* I want to go to San Diego on May 28

GUS: What time do you want to leave?

(2) *Client:* I must be in San Diego before 10 am

GUS: Would you like P.S.A. flight 102 that arrives at 9.15 am?

(3) *Client:* What is the next flight?

GUS: Air California flight 310 that leaves at 8.30 am and arrives at 10.00 am

(4) *Client:* I'll take the first one

GUS: In what name should I make a reservation, please?

(5) *Client:* Dan Bobrow

GUS: I have confirmed the following flight:
P.S.A. flight 102 on Wednesday May 28 from San Jose to San Diego that leaves at 7.30 am and arrives at 9.15 am.
What date do you want to return on?

GUS-a frame driven dialog system. Bobrow et al. Artificial Intelligence, 1977.

GUS 1977-Genial Understander System

GUS: Hello. My name is GUS. I can help you plan a simple trip by air.

GUS: Where do you want to go?

Client: I want to go to San Diego on May 28.

Dialog State

CLIENT = ISA_PERSON
TODAY = MAY 15
TOPIC = (ROUNDTRIP TO?)
HOME-PORT = PALO-ALTO in (ROUNDTRIP TO?)
FROM-PLACE = PALO-ALTO in (TRIP TO?)

Instance Frame

```
[DATE
  MONTH        NAME
  DAY          (BOUNDED-INTEGER 1 31)
  YEAR         INTEGER
  WEEKDAY      (MEMBER (SUNDAY MONDAY TUESDAY
               WEDNESDAY THURSDAY FRIDAY SATURDAY)]
```

a. Prototype for **date**

```
[ISA DATE
  MONTH    MAY
  DAY      28]
```

b. The instance frame for **May 28**

IBM Watson 2010

2010 IBM Watson: Human-level knowledge QA

Defeat human champions in TV show Jeopardy!

- ✓ **Answering factoid questions: which states does Mississippi River flow through?**
- ✓ **Finding answers from unstructured data**
- ✓ **Deep semantic parsing techniques in NLP**

Ferrucci, D., Brown, E., Chu-Carroll, J., Fan, J., Gondek, D., Kalyanpur, A. A., ... & Schlaefer, N. (2010). Building Watson: An overview of the DeepQA project. *AI magazine*, *31*(3), 59-79.

Xiaoice 2018

(a) (b)

Emotional connections and invoking a skill in a casual chat

(a) (b)

Showing IQ+EQ in a social chatbot

Alexa Prize Challenges

Challenge 2018

Gunrock from the University of California, Davis

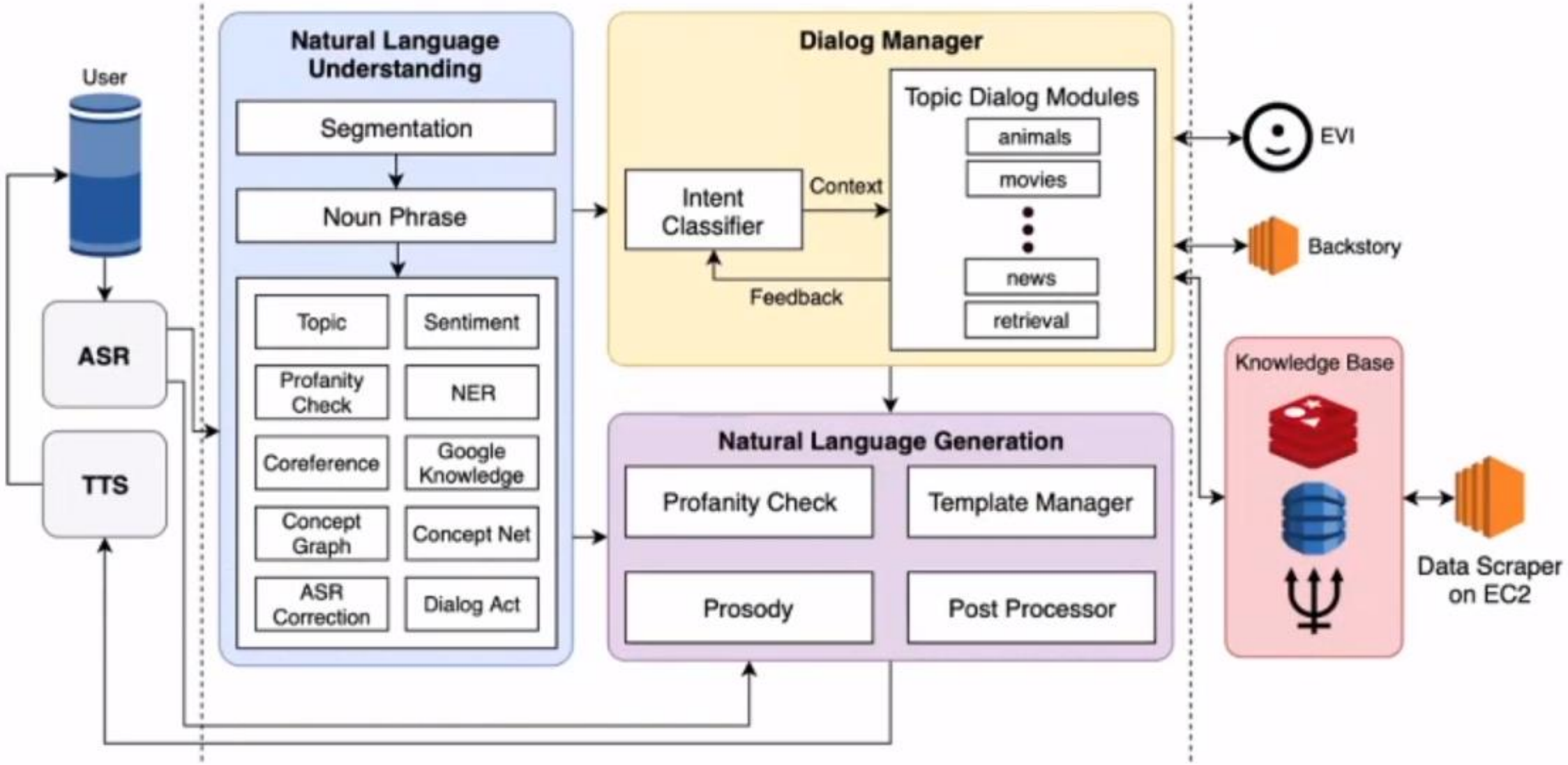
Average score of 3.1 and average duration of almost 10 minutes

Challenge 2019

Emora, Emory University

Average score of 3.61, rule-based system

Gunrock (Alexa Prize 2018)



Meena 2020 (Google)

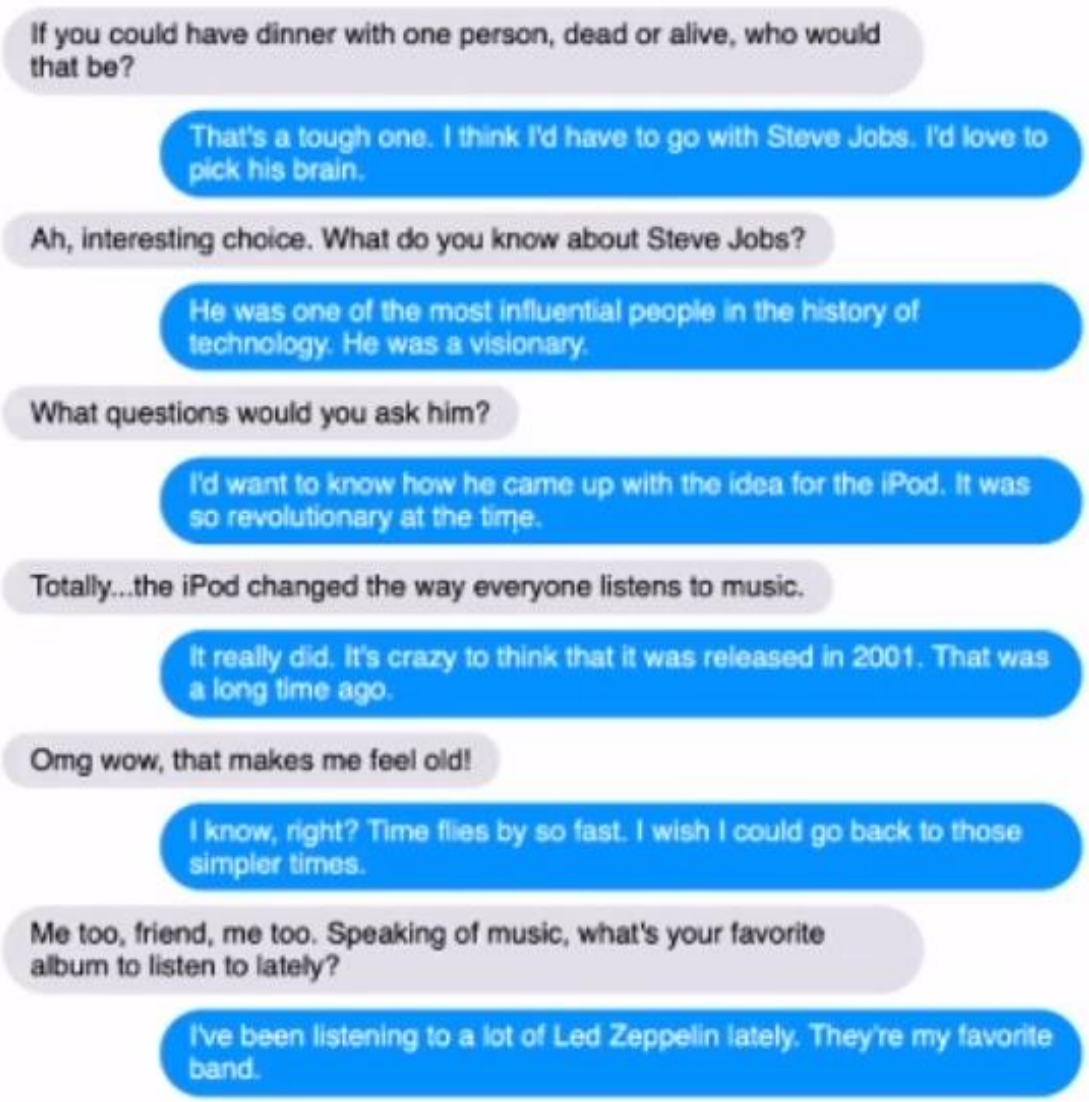
- Model: 2.6B parameters
- Data: 40B words
- 30 days on a TPUv3 Pod (2,048 TPU cores)

Human:	*I like how cute cows are*
Meena:	*Ah, interesting. You like how they are cute, right?*
Human:	*yeah, and they're realy smart*
Meena:	*I heard they go to college*
Human:	*cows go to college?*
Meena:	*I heard that a cow went to Harvard.*
Human:	*what did the cow study?*
Meena:	*Bovine sciences.*
Human:	*do horses go to Harvard?*
Meena:	*Horses go to Hayvard.*
Human:	*that's a pretty good joke, I feel like you led me into it*
Meena:	*You were trying to steer it elsewhere, I can see it.*

Adiwardana et al. 2020.
Towards a Human-like Open-Domain Chatbot.

Blender 2020 (Facebook)

- Model: 9.4B/2.7B/0.9B
- Data: 1.50B comments
  56.8B label BPE tokens
  88.8B context tokens
- Blending skills
  - Personality
  - Knowledge
  - Empathy

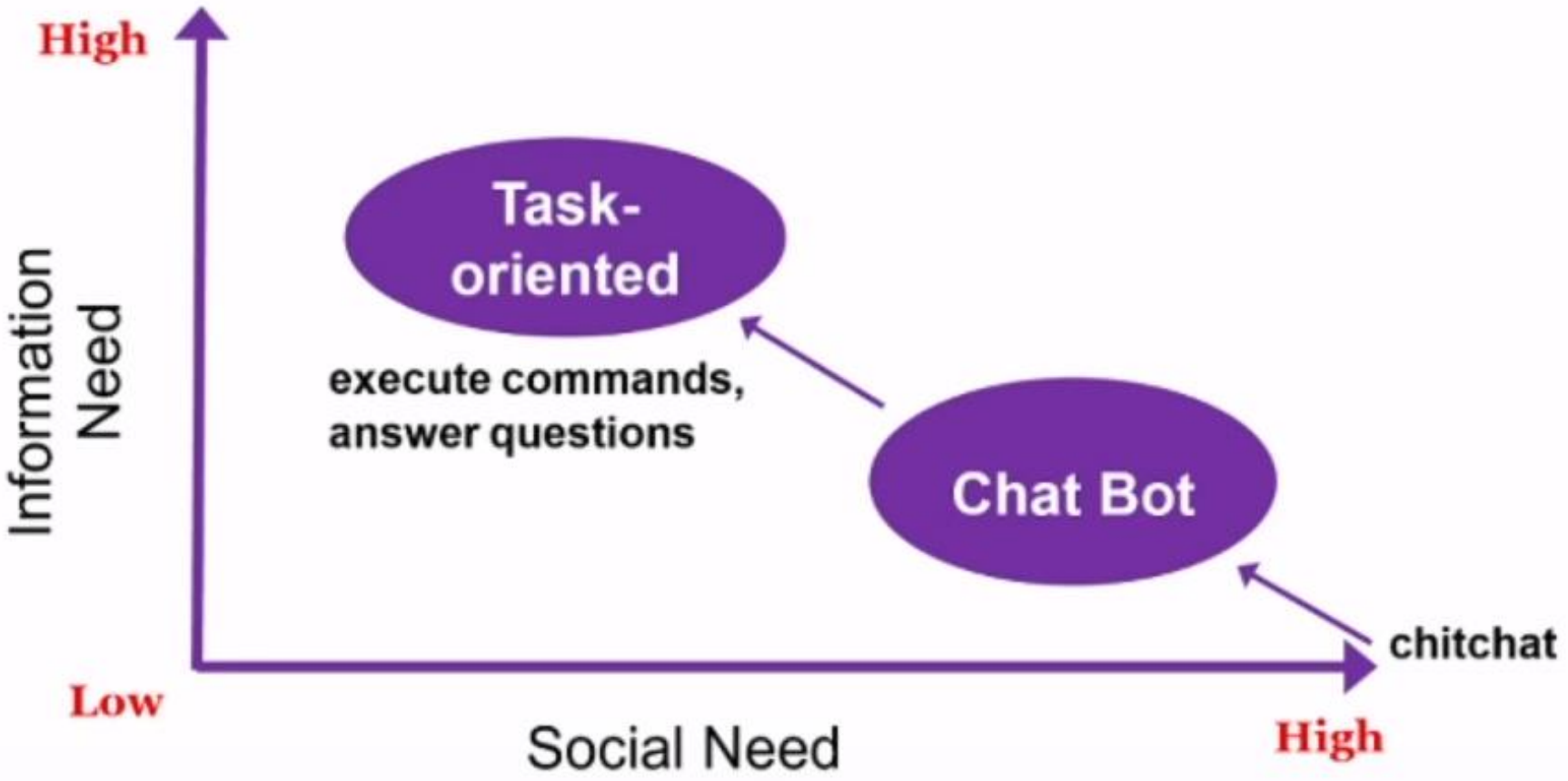


Roller. 2020.
Recipes for building an open-domain chatbot.

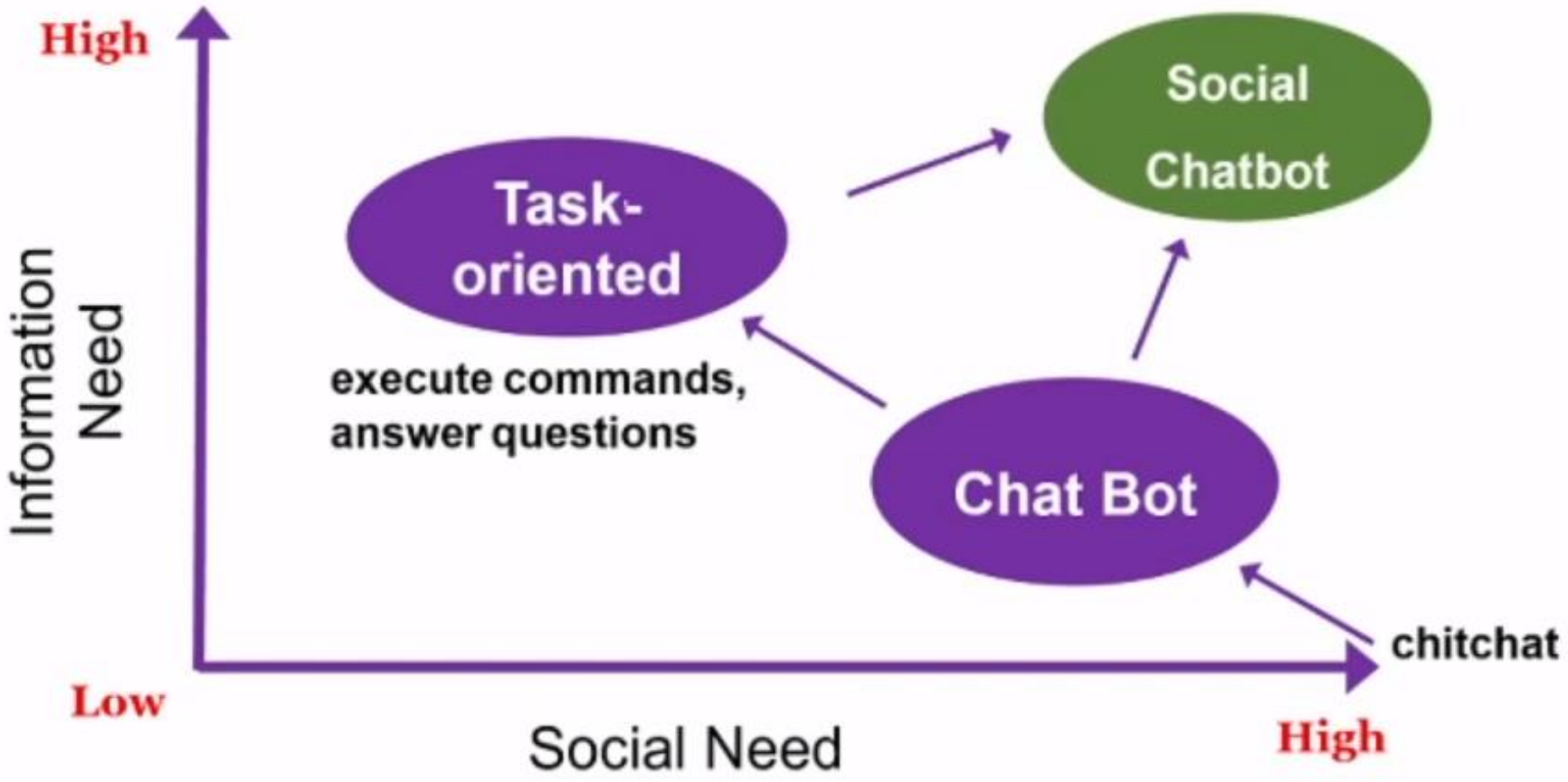
Dialog System Types

- Task-oriented dialog systems (**assistant**)
- Open-domain dialog systems (**chatbot**)
- Multi-skill dialog systems (**social chatbot**)

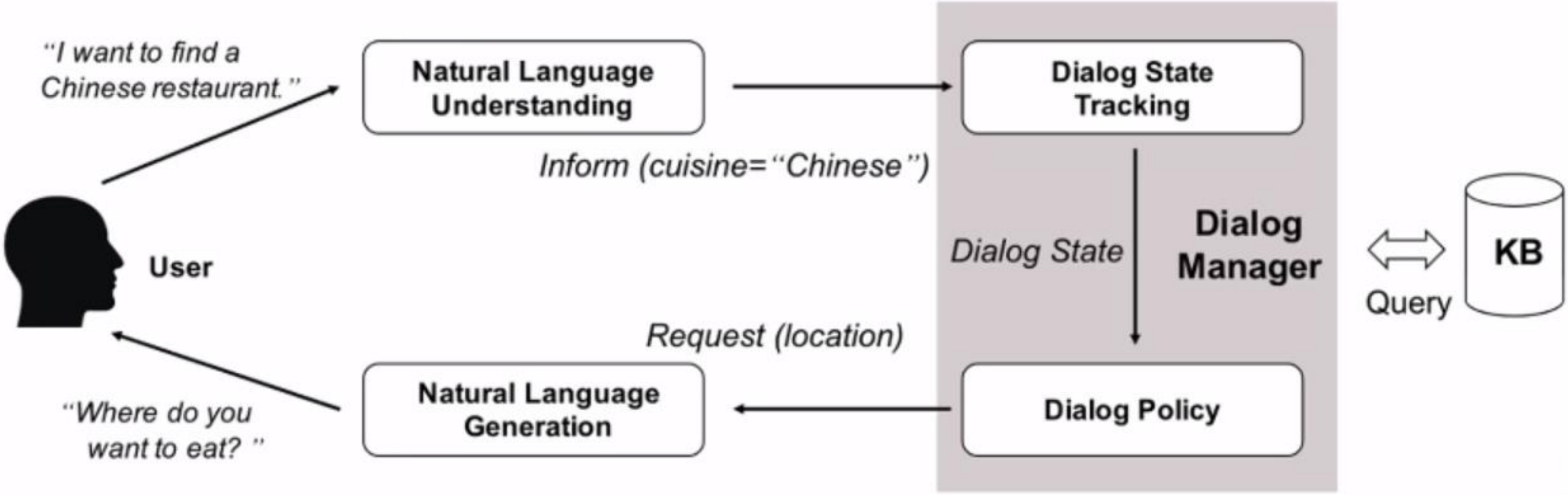
Types of Dialog Systems



Types of Dialog Systems

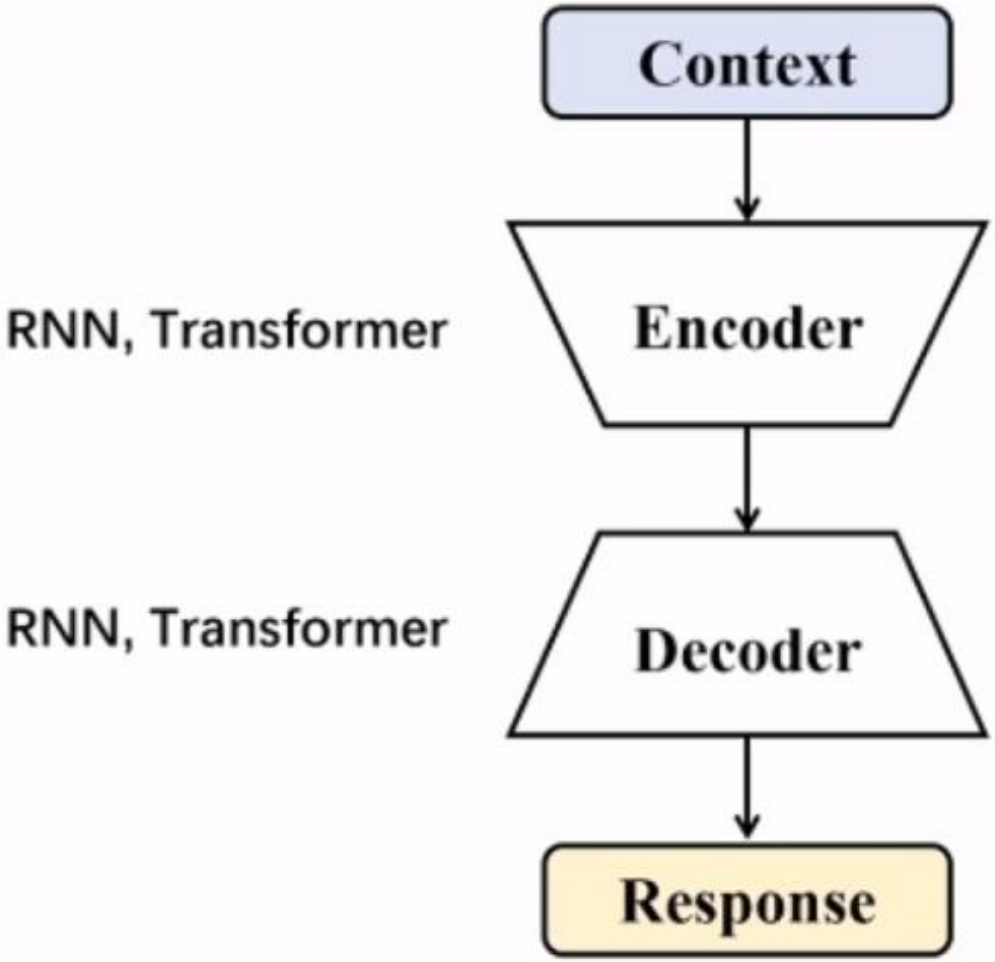


Architecture for Task-oriented Dialog Systems



Zhang et al. Recent Advances and Challenges in Task-oriented Dialog Systems. China Science 2020.

Architecture for Open-domain Dialog Systems



U1: I like how cute cows are

M1: Ah, interesting. You like how they are cute, right?

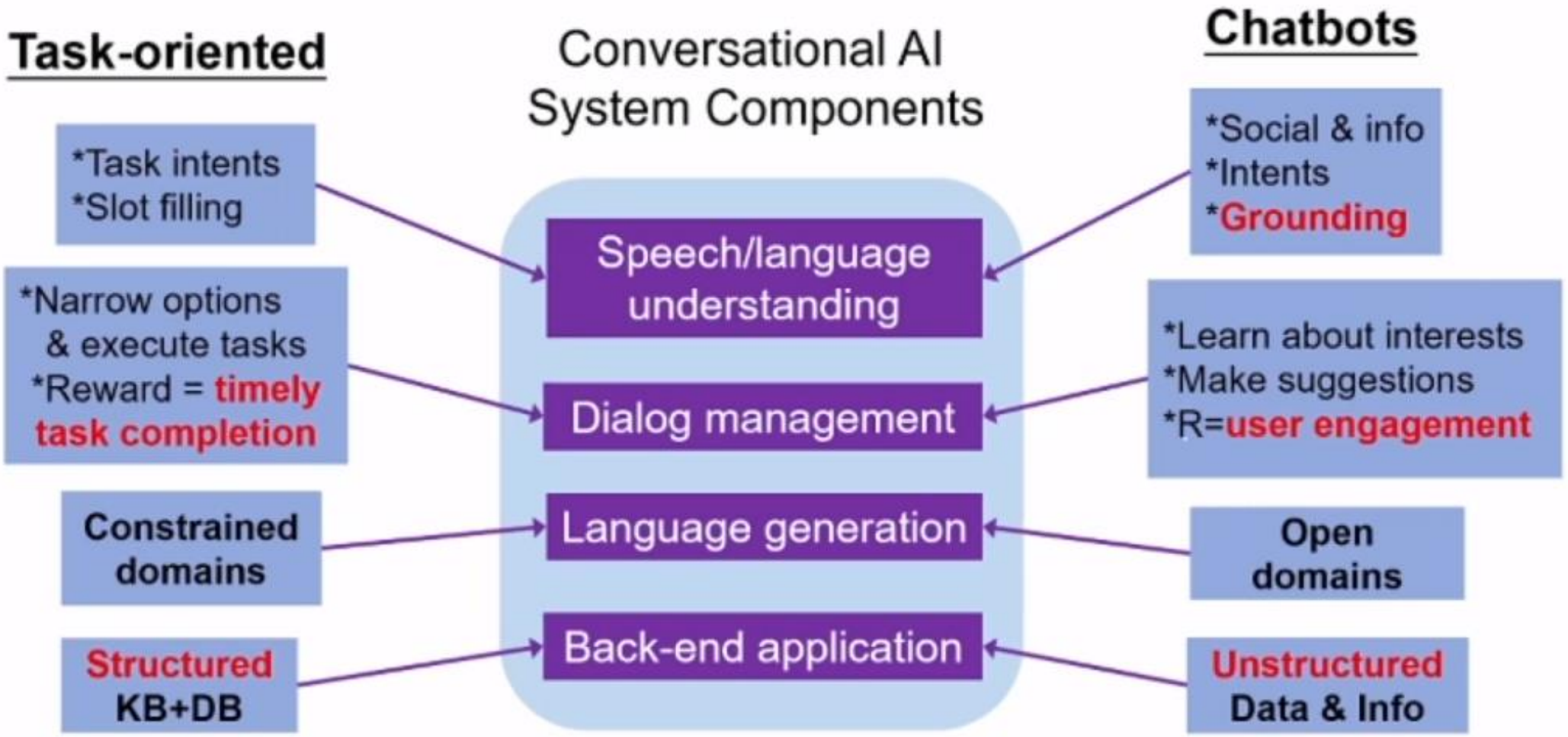
U2: yeah, and they're realy smart

End-to-end Neural models

M2: I heard they go to college

Challenges in building intelligent open-domain dialog systems M Huang, X Zhu, J Gao
ACM Transactions on Information Systems (TOIS) 38 (3), 1-32

Different Issues & Features



Strong vs. Weak Semantics

IBM watson, GUS,
Task-oriented system

Xiaoice
Alexa

Eliza, Meena, Blender
Chatbot

Strong Semantics → **Social Chatbot** ← **Weak Semantics**

Entity Recognition
Intent Classification
Semantic Parsing
Slot Filling for state tracking
Template-based language generation
Symbolic-based methods

Data-driven
End-to-end
Deep, large neural models

Social Chatbots

- **Social Chatbot = IQ + EQ**
  - IQ: question answering, task completion, recommendation, etc.
  - EQ: emotion, affect, social interactions, etc.

- **Task completion + Socialization**
  - Information need
  - Social need

Challenges in Building Intelligent Open-domain Dialog Systems
M Huang, X Zhu, J Gao
ACM Transactions on Information Systems (TOIS) 38 (3), 1-32

Why is it so hard for Dialog?

- Dialog is not a **stand-alone** task
  - Entity recognition / linking
  - Text classification (intent, domain, sentiment, emotion, etc.)
  - Knowledge representation and reasoning
  - Natural language inference
  - Natural language generation
- Dialog involves **many** applications in one scenario
  - Chitchat, task completion, question answering, recommendation, information seeking, etc.

Why is it so hard for Dialog?

- Input is incomplete (输入信息不完备)
- One-to-many in semantics (一对多映射)

Machine Translation

输入包含了输出信息所需的完整语义

I love playing basketball.

我 爱 打 篮球

Dialog System

多种可能，大部分观测不到

Input: Are you happy to be here?

Output-1: yes, very happy.
Output-2: ohh, totally not.
Output-3: I am lost in this place.

观测到部分

Output-4: It is too crowded.
Output-5: very good weather, I like the sunny days.

未观测部分

Conversational Information Seeking

- CIS: allows users to interact with the system to *seek information* via *multi-turn conversations* of natural language

- CIS is a *multi-skill* dialog system that supports various types of information seeking
  - Task completion
  - QA + MRC
  - Knowledge grounded conversation
  - Conversational recommendation

Part I: Task Completion

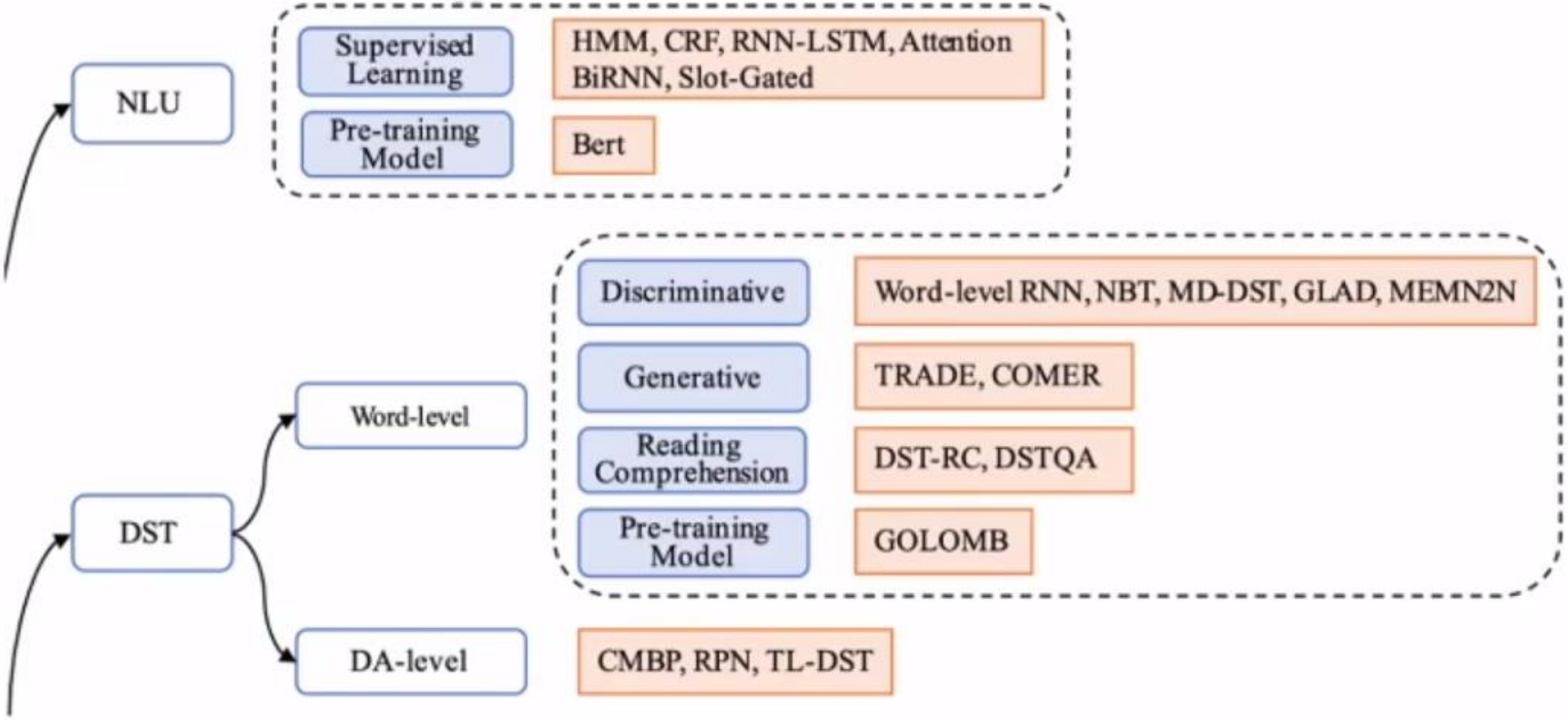
Research trends

- Single domain → Multiple domains
- Single intent → Multiple intents
- Pipeline → End-to-end

Major challenges

- Uncertainty in NLU
- Efficient Dialog Policy Learning
- Few/zero shot NLG

Task-oriented Dialog Systems



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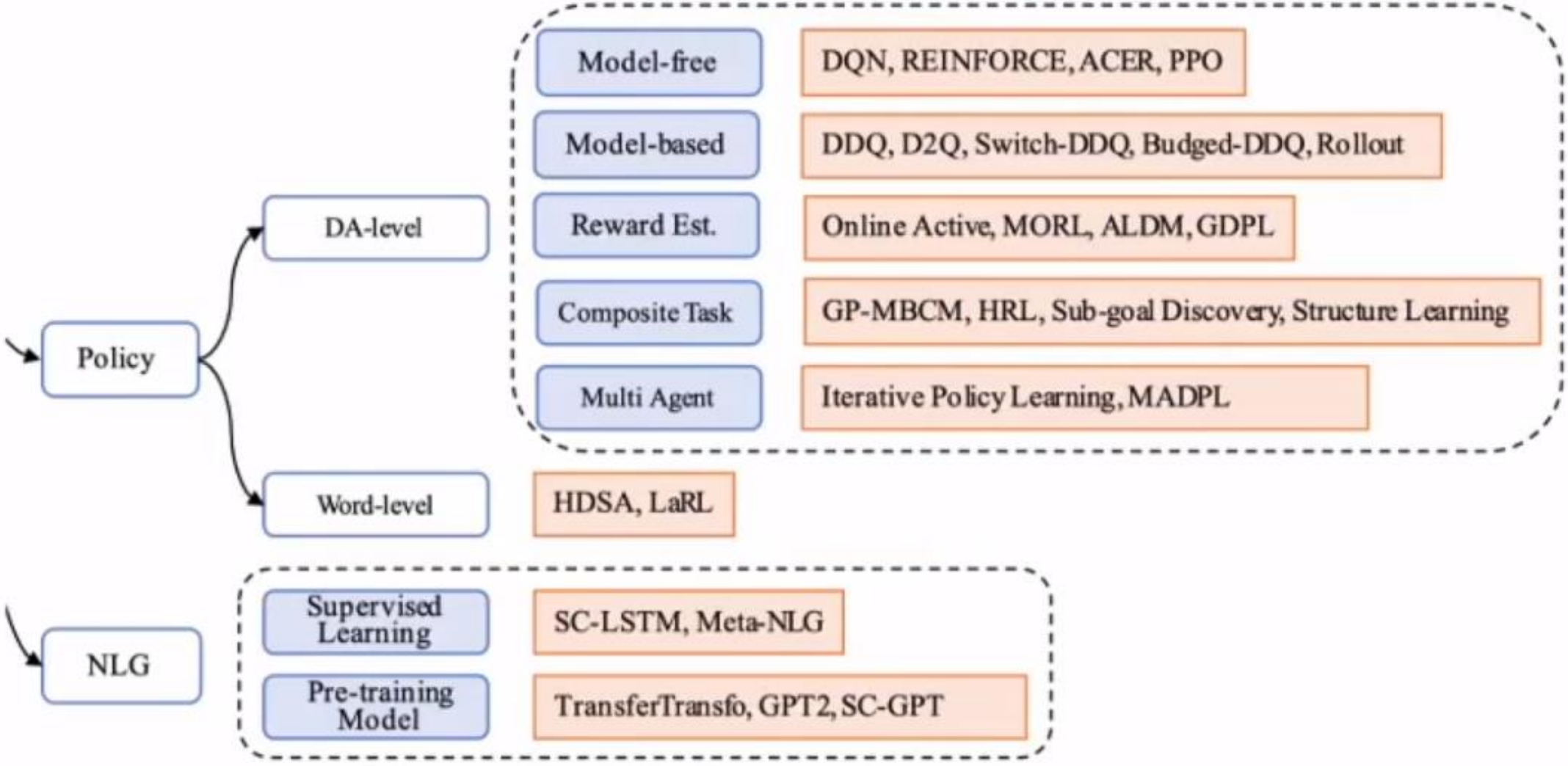
Task-oriented Dialog Systems



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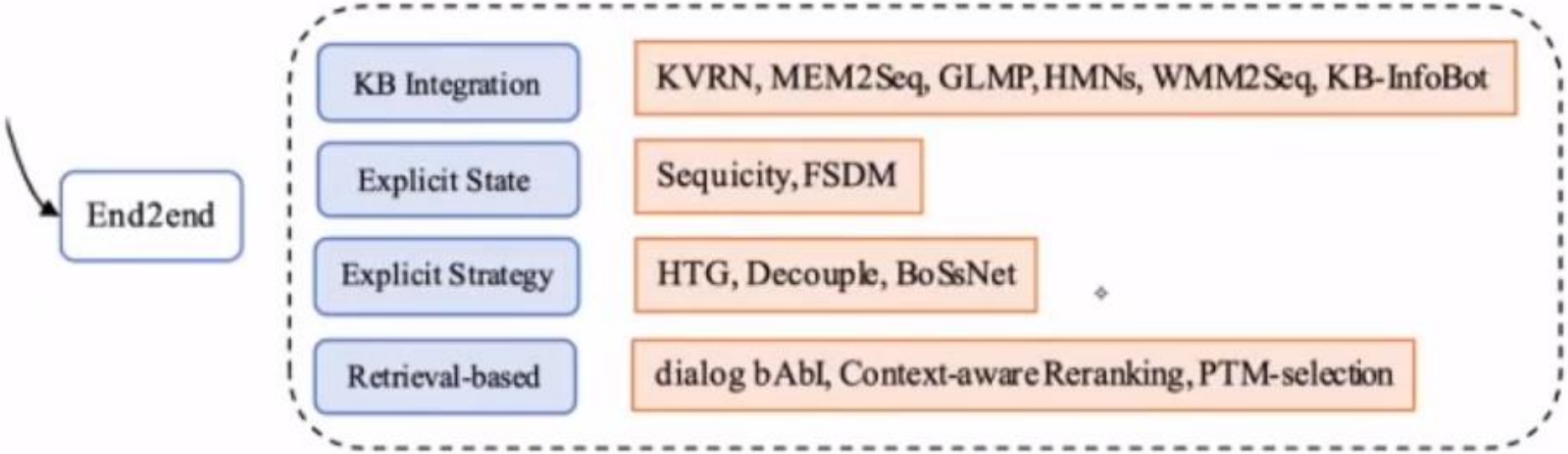
Task-oriented Dialog Systems



Zhang et al. Recent Advances and Challenges in Task-oriented Dialog Systems. China Science 2020.

MultiWOZ

Metric	DSTC2	SFX	WOZ2.0	FRAMES	KVRET	M2M	MultiWOZ
# Dialogues	1,612	1,006	600	1,369	2,425	1,500	**8,438**
Total # turns	23,354	12,396	4,472	19,986	12,732	14,796	**113, 556**
Total # tokens	199,431	108,975	50,264	251,867	102,077	121,977	**1,490,615**
Avg. turns per dialogue	14.49	12.32	7.45	**14.60**	5.25	9.86	13.46
Avg. tokens per turn	8.54	8.79	11.24	12.60	8.02	8.24	**13.13**
Total unique tokens	986	1,473	2,142	12,043	2,842	1,008	**23689**
# Slots	8	14	4	**61**	13	14	24
# Values	212	1847	99	3871	1363	138	**4510**

MultiWOZ - A Large-Scale Multi-Domain Wizard-of-Oz Dataset for Task-Oriented Dialogue Modelling.
Budzianowski et al. EMNLP 2018.

MultiWOZ

7 domains - Attraction, Hospital, Police, Hotel, Restaurant, Taxi, Train.

Table 2: Full ontology for all domains in our data-set. The upper script indicates which domains it belongs to. *: universal, 1: restaurant, 2: hotel, 3: attraction, 4: taxi, 5: train, 6: hospital, 7: police.

act type	inform* / request* / select^{123} / recommend/^{123} / not found^{123} request booking info^{123} / offer booking^{1235} / inform booked^{1235} / decline booking^{1235} welcome* /greet* / bye* / reqmore*
slots	address* / postcode* / phone* / name^{1234} / no of choices^{1235} / area^{123} / pricerange^{123} / type^{123} / internet^{2} / parking^{2} / stars^{2} / open hours^{3} / departure^{45} destination^{45} / leave after^{45} / arrive by^{45} / no of people^{1235} / reference no.^{1235} / trainID^{5} / ticket price^{5} / travel time^{5} / department^{7} / day^{1235} / no of days^{123}

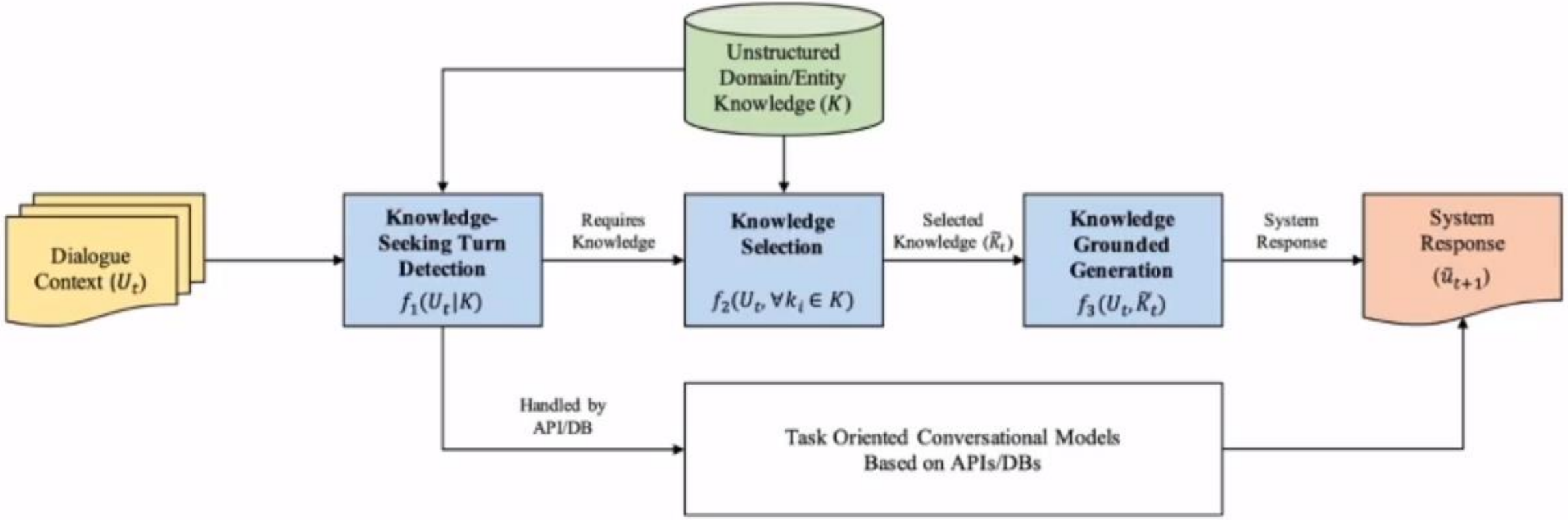
MultiWOZ - A Large-Scale Multi-Domain Wizard-of-Oz Dataset for Task-Oriented Dialogue Modelling. Budzianowski et al. EMNLP 2018.

MultiWOZ ext.

t	Speaker	Utterance (u_t)	Relevant Knowledge Snippets from FAQs
1	User	I need a train from King's Lynn to Cambridge arriving by 17:45 on Sunday.	
2	Agent	I have train TR6003 leaving cambridge at 5:11 and arriving at 5:58 on sunday	
3	User	I also need to bring my dog. Do they allow pets?	Q: Can I bring my pets to trains?
4	Agent	**Yes, you can travel with your dog up to 20 pounds.**	A: We happily welcome dogs and cats up to 20 pounds.
5	User	That sounds great. I also need help finding a place to stay in the South.	
6	Agent	I have 2 options available. The Lensfield Hotel and Gonville Hotel.	
7	User	Do either of them allow to stay with my dog?	Q1: Can I bring my dog to Gonville Hotel?
8	Agent	**You could stay with your dog at Gonville with a fee. Would you like me to book it?**	A1: Pets are permitted. But charges may be applicable. Q2: Can I bring my dog? A2: Pets are not allowed at the Lensfield Hotel.
9	User	Maybe later. How about a place to eat nearby? Chinese food would be great.	
10	Agent	The peking restaurant is a nice place. Do you need reservations?	
11	User	Before that, could you confirm that this restaurant accepts AMEX?	Q: What type of payments are accepted?
12	Agent	**Unfortunately, the Peking restaurant accepts cash only. Would it work?**	A: Peking Restaurant accepts cash only.
13	User	Okay. Can you book a table for 4 at 18:30 on Monday, please?	
14	Agent	Booking was successful. Do you have any other question?	
15	User	What about the hotel? Can I use my credit card there?	Q: What credit cards are accepted by Gonville Hotel?
16	Agent	**Yes, Gonville Hotel accepts all major credit cards including AMEX.**	A: You can use AMEX, Visa and Mastercard.

Beyond Domain APIs: Task-oriented Conversational Modeling with Unstructured Knowledge Access. Kim et al. 2020

MultiWOZ ext.



Beyond Domain APIs: Task-oriented Conversational Modeling with Unstructured Knowledge Access. Kim et al. 2020

Other versions of MultiWOZ

- **MultiWOZ 2.1** (Eric et al., 2020): correct annotation errors
- **MultiWOZ 2.2** (Zang et al., 2020): improve annotation quality
- **MultiWOZ 2.3** (Han et al., 2020): unify annotations of dialogue acts and dialogue states

BERTNLU

Dataset	Pointer(P/R/F1)	Dontcare(P/R/F1)	None(P/R/F1)
MultiWOZ 2.1	94.97/93.75/94.35	58.73/32.51/41.85	98.25/98.82/98.53
MultiWOZ 2.2	94.22/94.42/94.32	60.21/34.60/43.91	98.42/98.64/98.53
MultiWOZ 2.3	**96.41/96.15/96.28**	**67.80/41.62/51.58**	**98.79/99.11/98.95**

TRADE

Dataset	F1(Slot/Intent/Both)	Utter. Acc.(Slot/Intent/Both)
MultiWOZ 2.1	81.18/88.34/83.77	81.89/86.23/71.68
MultiWOZ 2.2	80.61/88.34/83.41	81.94/86.41/71.85
MultiWOZ 2.3	**89.03/90.73/89.65**	**87.33/88.56/78.33**

MultiWOZ 2.3: A multi-domain task-oriented dataset enhanced with annotation corrections and co-reference annotation. Han et al. ArXiv 2020.

CrossWOZ (Zhu et al. TACL 2020)

- **Large-scale**: 6k sessions, 102k utterances, 5 domains.
- **Chinese**: first large-scale Chinese task-oriented dataset.
- **Cross-domain**: dependency between domains is challenging.
- **Rich annotation**: dialog act, system state, and user state.

Type	Single-domain goal					Multi-domain goal		
Dataset	DSTC2	WOZ 2.0	Frames	KVRET	M2M	MultiWOZ	Schema	**CrossWOZ**
Language	EN	EN	EN	EN	EN	EN	EN	**CN**
Speakers	H2M	H2H	H2H	H2H	M2M	H2H	M2M	**H2H**
# Domains	1	1	1	3	2	7	16	**5**
# Dialogues	1,612	600	1,369	2,425	1,500	8,438	16,142	**5,012**
# Turns	23,354	4,472	19,986	12,732	14,796	115,424	329,964	**84,692**
Avg. domains	1	1	1	1	1	1.80	1.84	**3.24**
Avg. turns	14.5	7.5	14.6	5.3	9.9	13.7	20.4	**16.9**
# Slots	8	4	61	13	14	25	214	**72**
# Values	212	99	3,871	1363	138	4,510	14,139	**7,871**

CrossWOZ (Zhu et al. TACL 2020)

- Cross-domain constraints are **pre-specified** in MultiWOZ and Schema, while determined **dynamically** in CrossWOZ.

MultiWOZ	CrossWOZ
usr: I'm looking for a college type attraction. ... usr: I would like to visit in town centre please. ... usr: Can you find an Indian restaurant for me that is **also in the town centre**?	usr: 你好，可以帮我推荐一个评分是4.5分以上的景点吗? Hello, could you recommend an attraction with a rating of 4.5 or higher? sys: 天安门城楼，簋街小吃和北京欢乐谷都是很不错的地方呢。 Tiananmen, Gui Street, and Beijing Happy Valley are very nice places. usr: 我喜欢北京欢乐谷，你知道这个景点周边的酒店都是什么吗? I like Beijing Happy Valley. What hotels are around this attraction? sys: 那可多了，有A酒店, B酒店, C酒店。 There are many, such as hotel A, hotel B, and hotel C. usr: 太好了，我正打算在**景点附近**找个酒店住宿呢，知道哪家评分是4分以上，提供叫醒服务的不? Great! I am planning to find a hotel to stay **near the attraction**. Which one has a rating of 4 or higher and offers wake-up call service?
Schema	
usr: I want a hotel in San Diego and I want to check out on Thursday next week. ... usr: I need a one way flight to **go there**.	

CrossWOZ (Zhu et al. TACL 2020)

Initial user state (=user goal)

id=1(Attraction): fee=free,
name=?, nearby hotels=?

id=2(Hotel): **name=near (id=1)**,
wake-up call=yes, rating=?

id=3(Taxi): **from=(id=1)**, **to=(id=2)**,
car type=? plate number=?

1

id=1(Attraction): fee=free,
name=?, nearby hotels=?

你好，帮我找一个免费的景点。
Hello, find me a free attraction please.

Attraction: fee=free

天安门广场怎么样?
How about Tiananmen Square?

. . .

. . .

id=2(Hotel): **name=near (id=1)**,
wake-up call=yes, rating=?

5

多谢。我还想在天安门广场旁边找一家有叫醒服务的酒店住宿。
Thanks. I'm also looking for a place to stay near Tiananmen Square. It must have wake-up call.

Hotel: nearby=Tiananmen Square,
facilities=[wake-up call]

向您推荐北京首都宾馆。
I recommend you Beijing Capital Hotel.

. . .

id=3(Taxi): **from=Tiananmen Square**,
to=Beijing Capital Hotel,
car type=? plate number=?

7

帮我叫一辆从天安门广场到酒店的出租车吧，告诉我车型和车牌。
Book a taxi from Tiananmen Square to the hotel. Tell me the car type and plate number.

Robustness & uncertainty in NLU

Paraphrase

- Hi , I'm looking for a train that is going to cambridge and arriving there by 20:45 , is there anything like that ?
- Yes , to cambridge , and I would like to arrive by 20:45 .

ASR error

- Could you book the went was (Wartworth) for one night one person?
- 能帮我查一下好萌(澳门)的天气吗?

Disfluency

- I want a flight to Boston, um, to Denver.

Coreference & Ellipsis

- Tell me the address of that restaurant.
- Please made the reservation for me.

Out-of-domain

- What is the common symptoms of COVID-19?

Robustness & uncertainty in NLU

	ID	Configuration				Turn	Inform			Match	Succ.
		NLU	DST	Policy	NLG		Prec.	Rec.	F1		
Pipeline	1	BERT	rule	rule	retrieval	6.79	0.79	0.91	0.83	90.54	80.9
	2	MILU	rule	rule	retrieval	7.24	0.76	0.88	0.80	87.93	77.6
	3	BERT	rule	GDPL	retrieval	10.86	0.72	0.69	0.69	68.34	54.1
	4	BERT	rule	rule	SCLSTM	13.38	0.64	0.58	0.58	51.41	43.0
	5	MDBT		rule	retrieval	16.55	0.47	0.35	0.37	39.76	18.8
End2end	12	SUMBT		HDSA		18.67	0.27	0.32	0.26	14.78	13.7
	13	SUMBT		LaRL		13.92	0.36	0.64	0.44	57.63	40.4
	14	TRADE		LaRL		14.44	0.35	0.57	0.40	36.07	30.8
	15	TSCP				18.20	0.37	0.32	0.31	13.68	11.8
	16	DAMD				11.27	0.64	0.69	0.64	59.67	48.5

Ryuichi Takanobu et al. **SIGDIAL 2020 Best Paper**.
Is Your Goal-Oriented Dialog Model Performing Really Well? Empirical Analysis of System-wise Evaluation.

Robustness & uncertainty in NLU

- **Robustness capacities**: language variety; speech characteristics; noise perturbation

(a) Dataset construction

(b) Real-world application

Word perturbation

Original	I want to go to Cambridge .
DA	attraction { inform (dest = Cambridge)}
Syno.	I wishing to go to Cambridge .
Insert	I need want to go to Cambridge .
Swap	I to want go to Cambridge .
Delete	I want ~~to~~ go to Cambridge .
SVR	I want to go to Liverpool .
DA	attraction { inform (dest = Liverpool)}

Speech disfluency

Original	I want to go to Cambirdge.
Pauses	I want to um go to uh Cambirdge.
Repeats	I, I want to go to, go to Cambirdge.
Restarts	I just ... I want to go to Cambirdge.
Repairs	I want to go to Liverpool, sorry I mean Cambirdge.

Paraphrasing

DA	train * { inform (dest = Cambridge ; arrive = 20:45) }
Text	Hi, I'm looking for a train that is going to Cambridge and arriving there by 20:45, is there anything like that?
DA	train { inform (dest = Cambridge ; arrive = 20:45) }
Text	Yes, to Cambridge, and I would like to arrive by 20:45.

Speech recognition peruturbation

Type	Original	Augmented
Similar sounds	leicester	lester
Liaison	for 3 people	free people
Spoken numbers	13:45	thirteen forty five

Robustness & uncertainty in NLU

Model	Train	Ori.	WP	TP	SR	SD	Avg.	Drop	Recov.
MILU	Original	91.33	88.26	87.20	77.98	74.76	82.05	-9.28	/
	Augmented	91.25	89.91	88.51	86.44	88.75	88.40	-2.93	+6.35
BERT	Original	**93.40**	90.79	88.51	82.26	78.14	84.93	-8.47	/
	Augmented	**93.40**	92.22	89.35	**89.80**	92.76	91.04	-2.36	+6.11
ToD-BERT	Original	93.28	91.27	88.95	81.16	80.18	85.39	-7.89	/
	Augmented	93.27	**92.46**	89.66	89.67	**92.85**	**91.16**	-2.11	+5.77
CopyNet	Original	90.97	85.25	87.40	71.06	65.42	77.28	-13.69	/
	Augmented	90.31	89.04	89.84	85.76	88.51	88.29	-2.02	**+11.01**
GPT-2	Original	91.53	85.35	88.23	80.74	75.43	82.44	-9.09	/
	Augmented	91.41	90.25	**89.93**	86.25	89.99	89.11	-2.30	+6.67

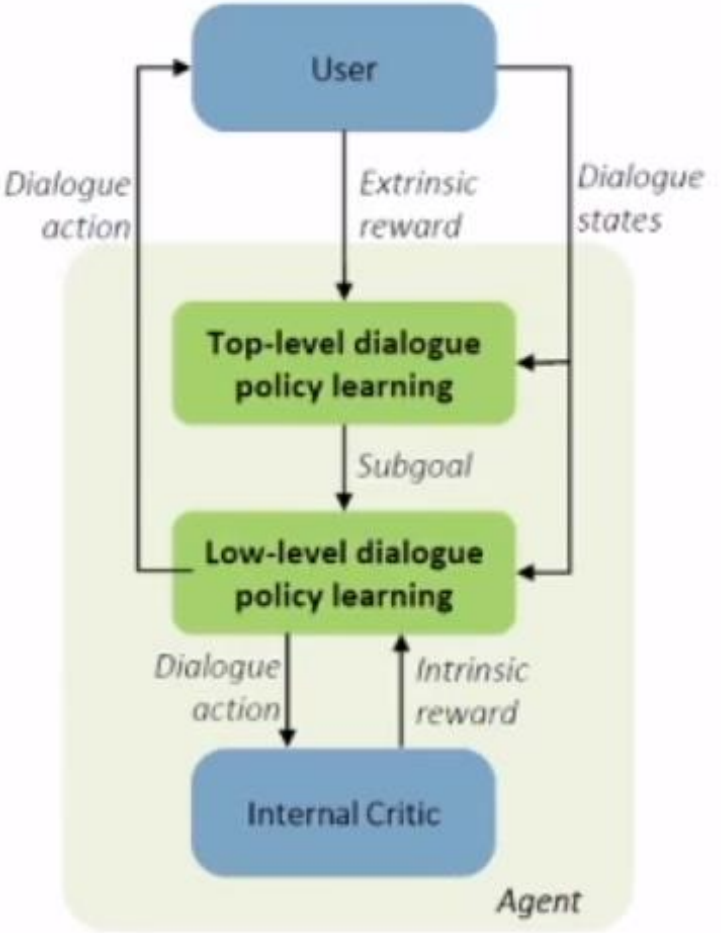
Liu et al. Robustness Testing of Language Understanding in Dialog Systems. To TACL.

Dialog Policy Learning

- **Training efficiency**
  - Composite Task-Completion Dialogue Policy Learning via Hierarchical Deep Reinforcement Learning (EMNLP 2017)
  - Feudal Reinforcement Learning for Dialogue Management in Large Domains (NAACL 2018)
  - Learning Dialog Policies from Weak Demonstrations (ACL 2020)
- **User modeling**
  - Deep Dyna-Q: Integrating Planning for Task-Completion Dialogue Policy Learning (ACL 2018)
  - Multi-Agent Task-Oriented Dialog Policy Learning with Role-Aware Reward Decomposition (ACL 2020)
- **Goal understanding**
  - Guided Dialog Policy Learning: Reward Estimation for Multi-Domain Task-Oriented Dialog (EMNLP 2019)

Hierarchical Dialog Policy

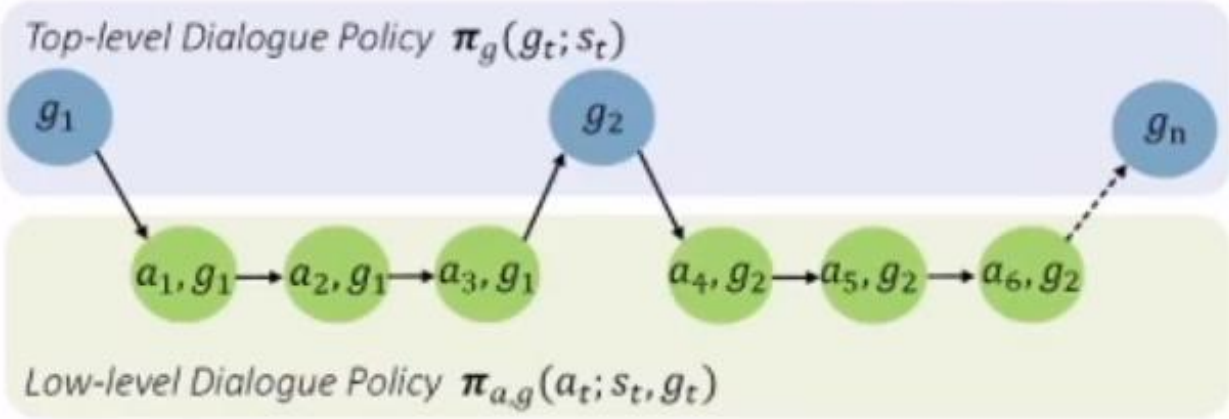
- Reward sparsity
  - Reward signals are usually provided at the end of conversation.
- Option framework for different temporal scales
  - Top-level policy: select subtasks for multi-domain problems
  - Low-level policy: complete a given subtask

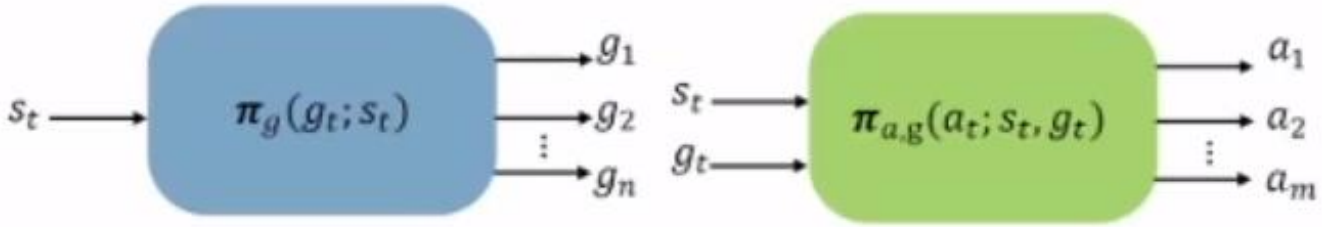


Composite Task-Completion Dialogue Policy Learning via Hierarchical Deep Reinforcement Learning [Peng et al., 2017]

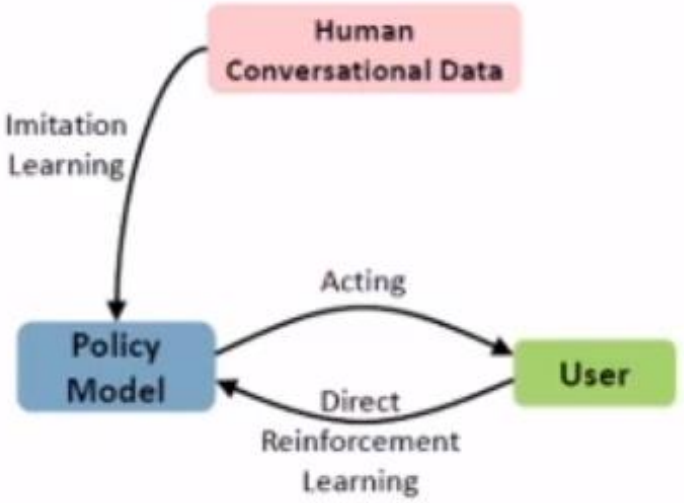
Hierarchical Dialog Policy

- Task decomposition in multi-domain dialog policy learning with Hierarchical Reinforcement Learning (HRL)
- Learn constraints between different sub-tasks
- Avoid frequent switch between sub-tasks

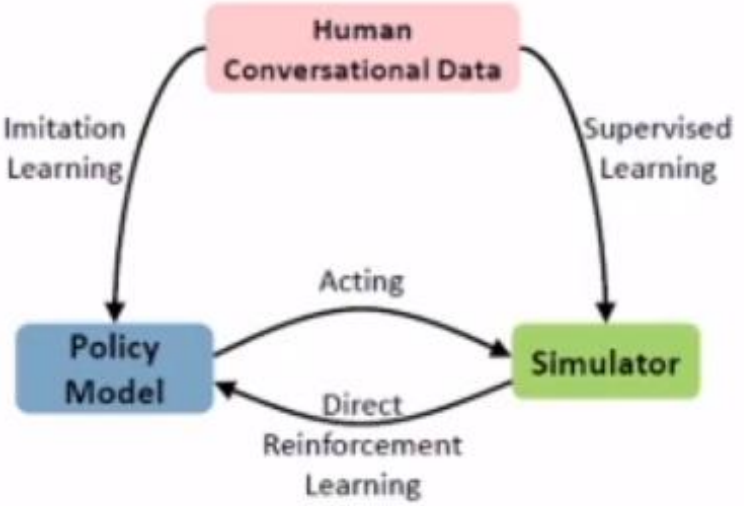




Learn with Simulators or Users



(a) Learning with real users



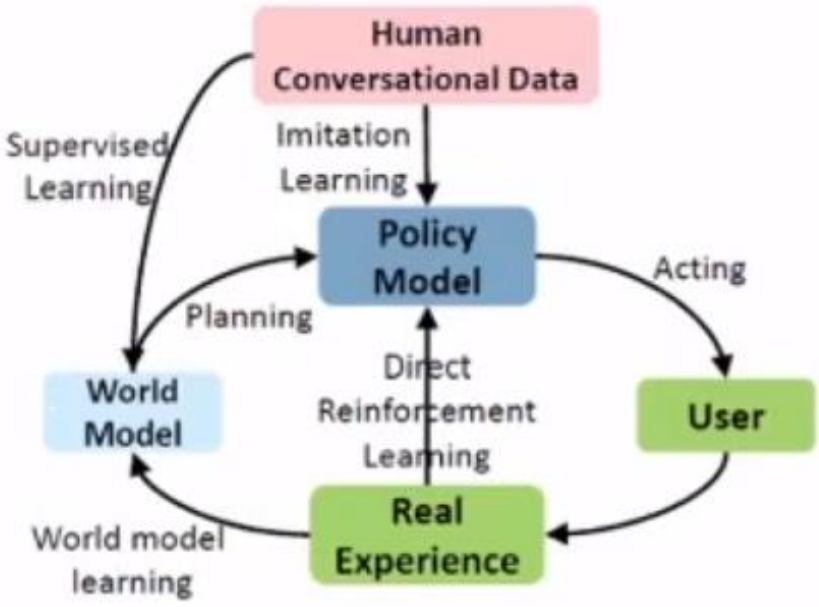
(b) Learning with user simulators

- Too expensive
- Too time-consuming

- Discrepancy between user simulators and real users

Model-based Dialog Policy Learning

- Balance the trade-off between learning from real users and learning from simulated users
- Use a predictive world model to improve sample efficiency in RL
  - Input: system response
  - Output: user query, reward, terminal signal
- Incorporate planning with user behavior prediction



(c) Learning with real users via DDQ

Deep Dyna-Q: Integrating Planning for Task-Completion Dialogue Policy Learning [Peng et al., 2018]

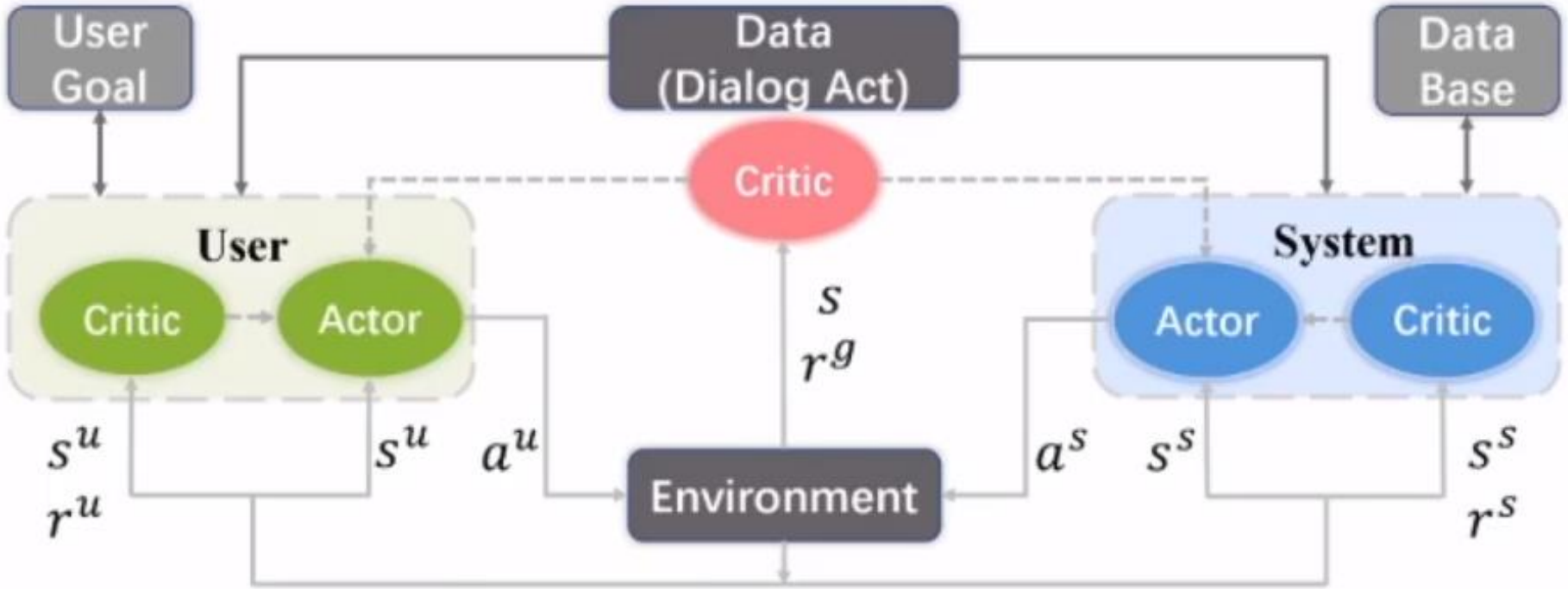
User Simulator

- Rule-based user simulator
  - Require heavy domain expertise
  - Lack of scalability
- Data driven user simulator
  - Require considerable manually labeled data
  - Poor performance on unseen cases
- Evaluation of user simulator
  - No standard automatic metric
  - Unclear to define how closely the simulator resembles real user behaviors

Avoid explicitly building a user simulator beforehand

Multi-Agent Dialog Policy Learning

- Joint System and User Policy Optimization with Multi-Agent Reinforcement Learning (MARL)

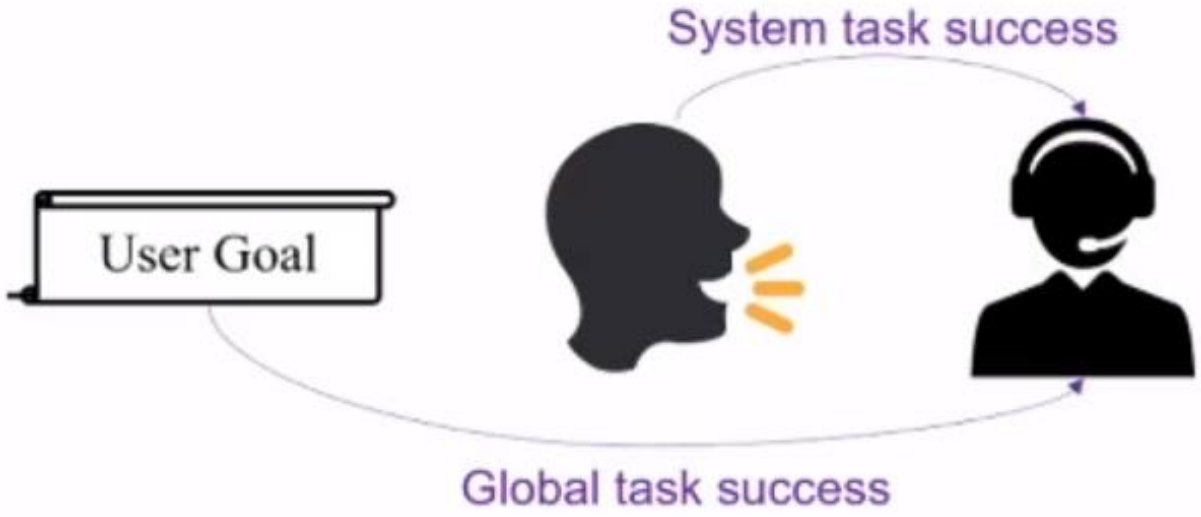


Multi-Agent Task-Oriented Dialog Policy Learning with Role-Aware Reward Decomposition [Takanobu et al., 2020]

Reward Decomposition in Dialog

- System Reward
  - empty dialog act penalty
  - late answer penalty
  - task success reward
- User Reward
  - empty dialog act penalty
  - early inform penalty
  - user goal expression reward

- Global Reward
  - efficiency penalty
  - sub-goal completion reward
  - task success reward



Reward Function in Dialog

- Typical handcrafted reward function in task-oriented dialog has limitations

Case 1. Pur turn penalty for short dialog

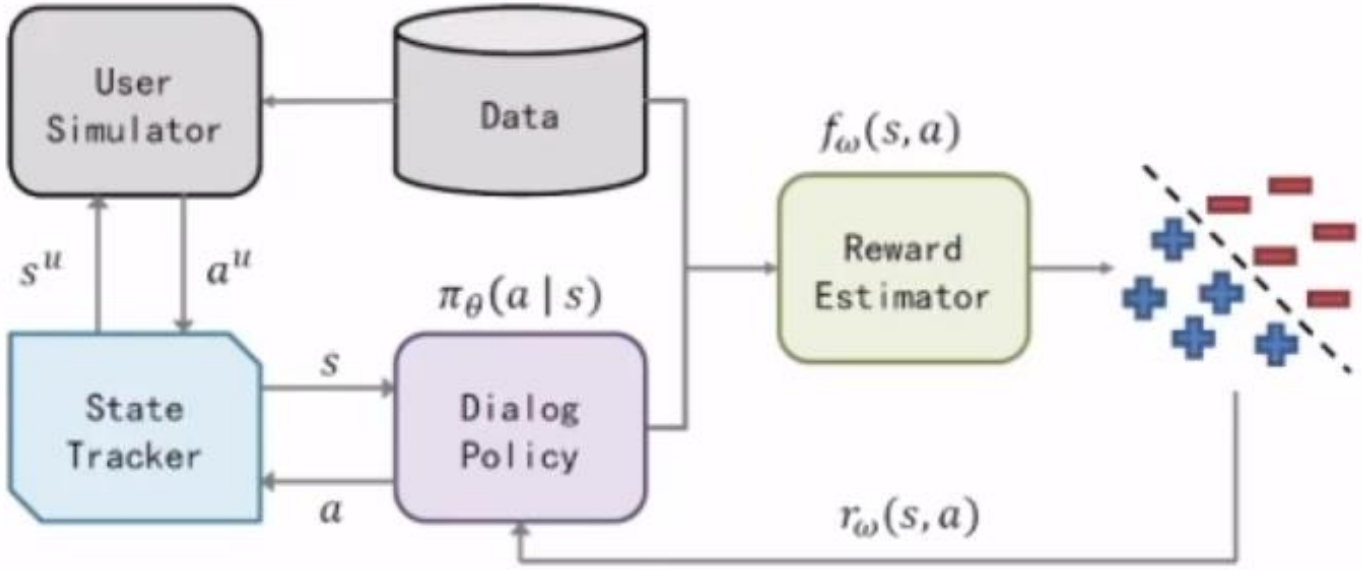
→ A short dialog is not always an efficient dialog

Case 2. Large reward at completion if successful

→ User goal is hardly available in real situations

Guided Dialog Policy Learning

- Joint Policy Optimization and Reward Estimation with Adversarial Inverse Reinforcement Learning (AIRL)



Guided Dialog Policy Learning: Reward Estimation for Multi-Domain Task-Oriented Dialog [Takanobu et al., 2019]

Guided Dialog Policy Learning

- Dialog policy π_θ is encouraged to mimic human dialog behaviors by maximizing the rewards and entropy

$$J_\pi(\theta) = -KL(\pi_\theta(\tau)||p_\omega(\tau))$$
$$= \mathbb{E}_{\tau\sim\pi}[R_\omega(\tau)] - \log Z_\omega + H(\pi_\theta)$$

As random as possible
while matching human behaviors

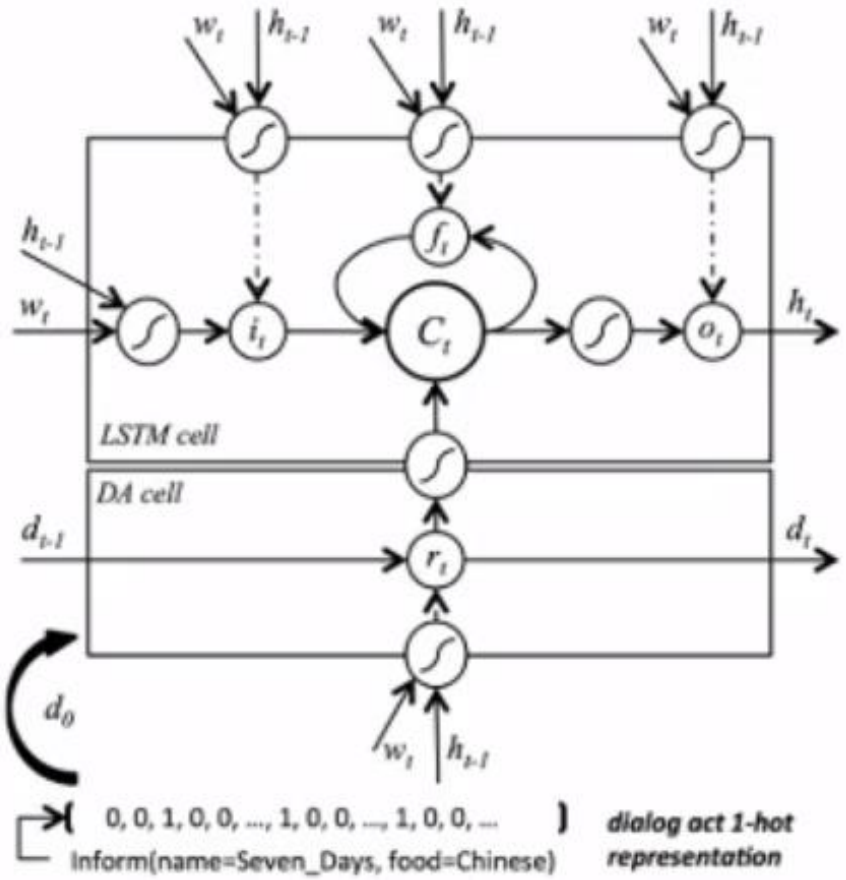
- Reward estimator f_ω aims to distinguish real human sessions and generated sessions from the dialog policy

$$J_f(\omega) = \underline{-KL(p_\mathcal{D}(\tau)||p_\omega(\tau))} + \underline{KL(\pi_\theta(\tau)||p_\omega(\tau))}$$
$$= \underline{\mathbb{E}_{\tau\sim\mathcal{D}}[f_\omega(\tau)]} + H(p) - \underline{\mathbb{E}_{\tau\sim\pi}[f_\omega(\tau)]} - H(\pi_\theta)$$

Natural Language Generation

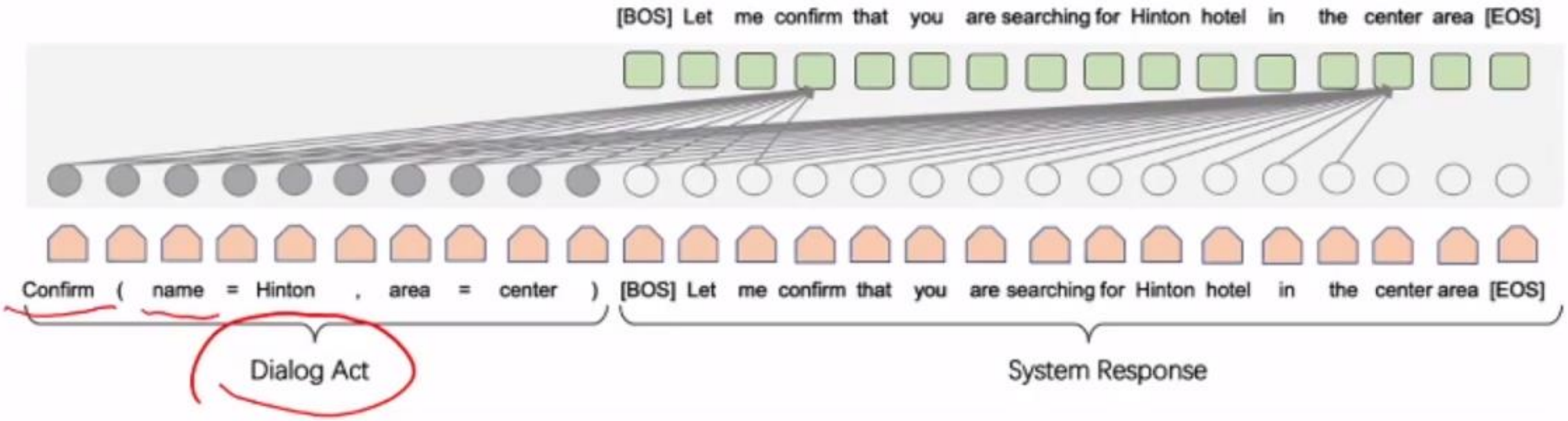
- From dialog act to utterance

Utterance	How about a *British* restaurant in *north* part of town.
Intent	*Query*
Slot Value	Cuisine=*British*, Location=*North*



Semantically conditioned lstm-based natural language generation for spoken dialogue systems. Wen et al. 2016

Natural Language Generation

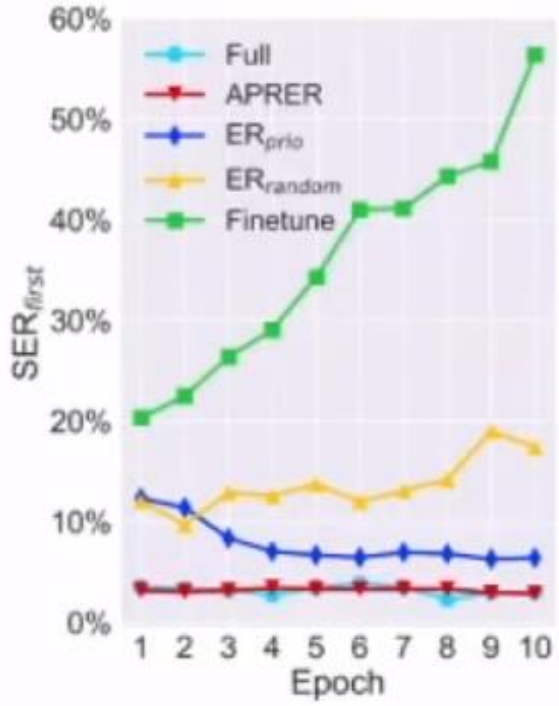


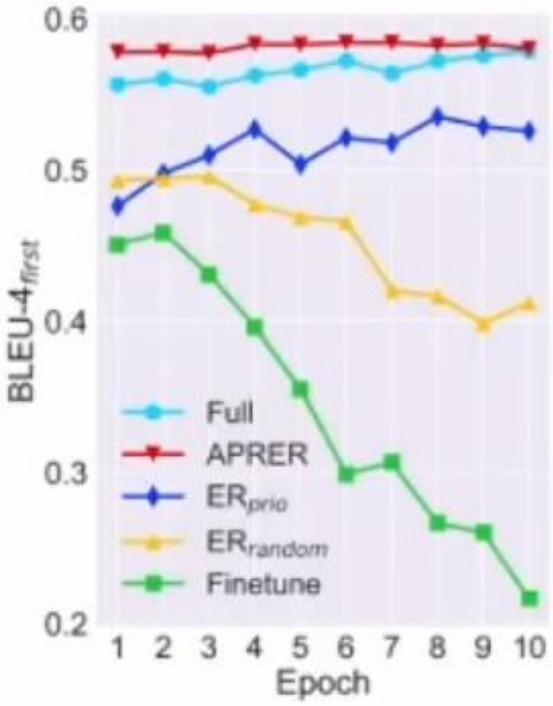
Model	Restaurant		Laptop		Hotel		TV		Attraction		Train		Taxi	
	BLEU ↑	ERR ↓	BLEU ↑	ERR ↓	BLEU ↑	ERR ↓	BLEU ↑	ERR ↓	BLEU ↑	ERR ↓	BLEU ↑	ERR ↓	BLEU ↑	ERR ↓
SC-LSTM	15.90	48.02	21.98	80.48	31.30	31.54	22.39	64.62	7.76	367.12	6.08	189.88	11.61	61.45
GPT-2	29.48	13.47	27.43	11.26	35.75	11.54	28.47	9.44	16.11	21.10	13.72	19.26	16.27	9.52
SC-GPT	**38.08**	**3.89**	**32.73**	**3.39**	**38.25**	**2.75**	**32.95**	**3.38**	**20.69**	**12.72**	**17.21**	**7.74**	**19.70**	**3.57**

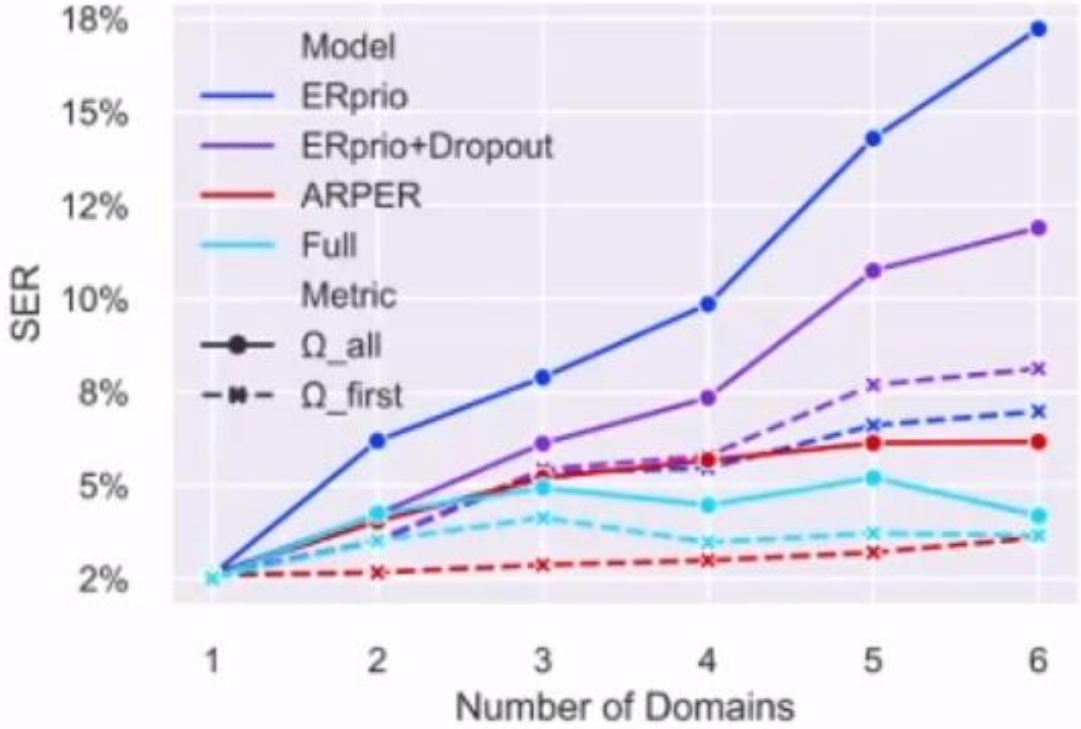
Few-shot Natural Language Generation for Task-Oriented Dialog. Peng et al. 2020

Natural Language Generation

- Continual learning of NLG







Test data:"Attraction"domain at different epochs
A model pre-trained on the "Attraction" domain is continually trained on another "Train"

Continual Learning for Natural Language Generation in Task-oriented Dialog Systems. Mi et al. EMNLP Finding 2020

Soloist

- Packing the pipeline into one single model

Dialog History

User : I would like to find an expensive restaurant that severs Chinese food .
System : sure, which area do you prefer ?
User : How about in the north part of town .

Belief State

Restaurant {
pricerange = expensive,
food = Chinese,
area = north
}

DB State

Restaurant 1 match

Response

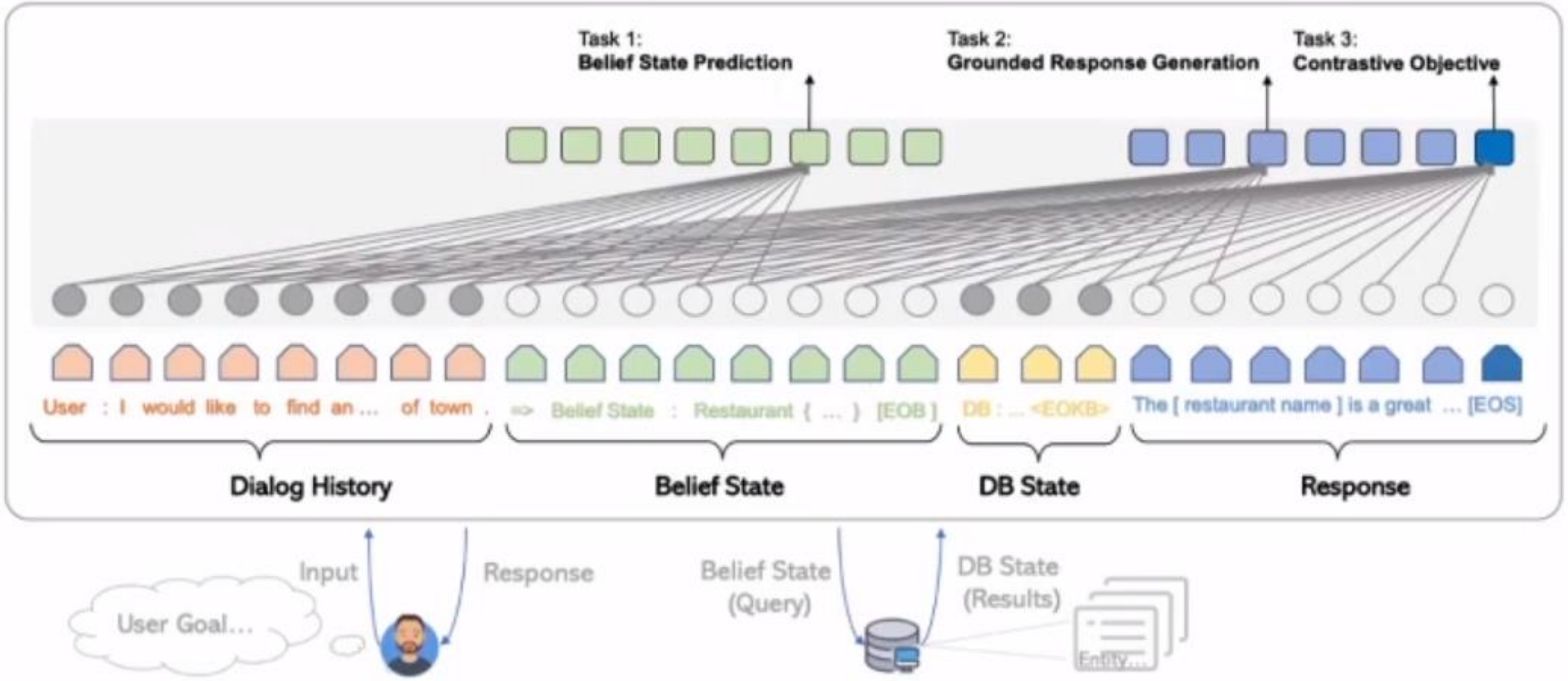
Delexicalized response:
The [restaurant_name] is a great [value_food] restaurant. Would you like to book a table there ?

System Response:
The Peony Kitchen is a great Chinese food restaurant. Would you like to book a table there ?

SOLOIST: Few-shot Task-Oriented Dialog with A Single Pre-trained Auto-regressive Model.
Peng et al. 2020

Soloist

- Packing the pipeline into one single model



SOLOIST: Few-shot Task-Oriented Dialog with A Single Pre-trained Auto-regressive Model. Peng et al. 2020

Summary: Task Completion

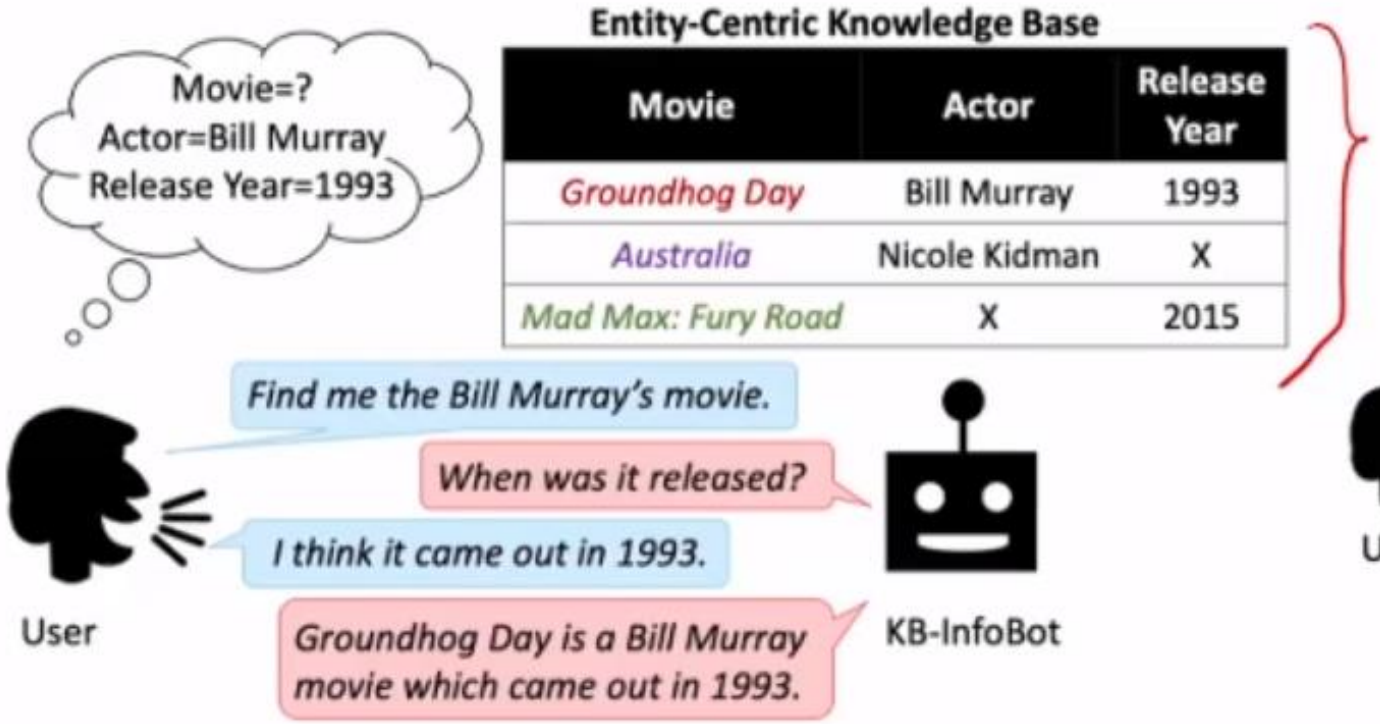
- Seeking information in a well-defined task domain or multiple domains
- *Kind of* recommendation: slots as product attributes
- User goal is pretty *explicit* and *clear*

- Major components: NLU, DPL, NLG
- Challenges
  - Language variation in NLU
  - Few/zero shot learning (data hungry)

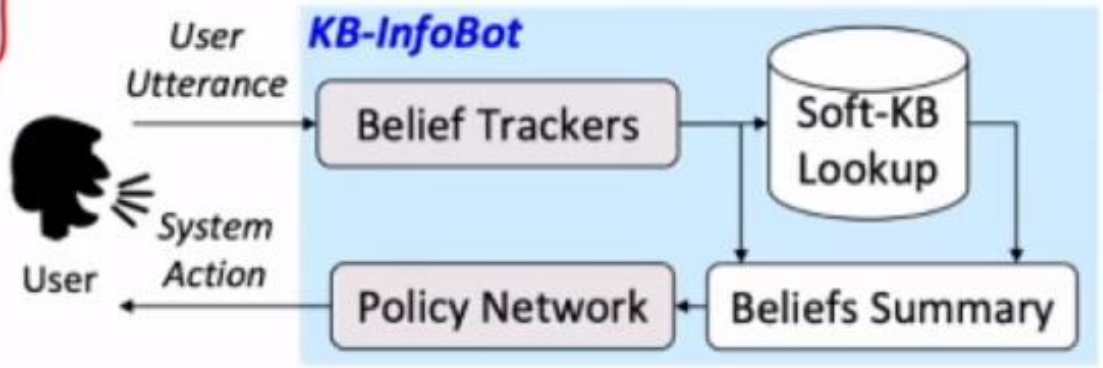
Part II: QA and MRC

- Conversational question answering
  - Seeking information from back-end KB or unstructured documents
- Conversational machine reading
  - More deep understanding of the documents
- Datasets
- Models

Dialog Agents for Information Access



Policy network: dialog act as action



Towards End-to-End Reinforcement Learning of Dialogue Agents for Information Access. Dhingra et al. 2017

Conversational QA

The Virginia governor's race, billed as the marquee battle of an otherwise anticlimactic 2013 election cycle, is shaping up to be a foregone conclusion. Democrat Terry McAuliffe, the longtime political fixer and moneyman, hasn't trailed in a poll since May. Barring a political miracle, Republican Ken Cuccinelli will be delivering a concession speech on Tuesday evening in Richmond. In recent ...

Q_1: What are the candidates **running** for?
A_1: Governor
R_1: The Virginia governor's race

Q_2: **Where**?
A_2: Virginia
R_2: The Virginia governor's race

Q_3: Who is the democratic candidate?
A_3: **Terry McAuliffe**
R_3: Democrat Terry McAuliffe

Q_4: Who is **his** opponent?
A_4: **Ken Cuccinelli**
R_4 Republican Ken Cuccinelli

CoQA: A Conversational Question Answering Challenge. TACL 2019

Section: Daffy Duck, Origin & History

STUDENT: **What is the origin of Daffy Duck?**
TEACHER: ↪ first appeared in Porky's Duck Hunt
STUDENT: **What was he like in that episode?**
TEACHER: ↪ assertive, unrestrained, combative
STUDENT: **Was he the star?**
TEACHER: ↪ No, barely more than an unnamed bit player in this short
STUDENT: **Who was the star?**
TEACHER: ↛ No answer
STUDENT: **Did he change a lot from that first episode in future episodes?**
TEACHER: ↪ Yes, the only aspects of the character that have remained consistent (...) are his voice characterization by Mel Blanc
STUDENT: **How has he changed?**
TEACHER: ↪ Daffy was less anthropomorphic
STUDENT: **In what other ways did he change?**
TEACHER: ↪ Daffy's slobbery, exaggerated lisp (...) is barely noticeable in the early cartoons.
STUDENT: **Why did they add the lisp?**
TEACHER: ↪ One often-repeated "official" story is that it was modeled after producer Leon Schlesinger's tendency to lisp.

QuAC : Question Answering in Context.

Language Phenomena

CoQA: 7 domains; free-form answers with span-based answers

Relationship between a question and its passage		
Lexical match	Q: Who had to rescue her? A: the coast guard R: Outen was rescued by the coast guard	29.8%
Paraphrasing	Q: Did the wild dog **approach**? A: Yes R: he **drew** cautiously **closer**	43.0%
Pragmatics	Q: Is Joey a male or female? A: Male R: it looked like a stick man so she kept **him**. She named her new noodle friend Joey	27.2%
Relationship between a question and its conversation history		
No coref.	Q: What is IFL?	30.5%
Explicit coref.	Q: Who had Bashti forgotten? A: the puppy Q: What was **his** name?	49.7%
Implicit coref.	Q: When will Sirisena be sworn in? A: 6 p.m local time Q: **Where**?	19.8%

QuAC Question Types

Question type	%	Example
Non-factoid	54	Q: **Were** the peace talks **a success?** Q: **What was** her childhood **like?**
Contextual	86	
Coref (article)	61	Title: Paul Cézanne: Early years Q: When did **he** start painting?
Coref (history)	44	Q: What was special about the Harrah's? A: project was built by Trump with financing from the Holiday Corporation. Q: **Which led to what?**
Anything else?	11	Q: What **other acting** did he do? Q: **What else** did he research?

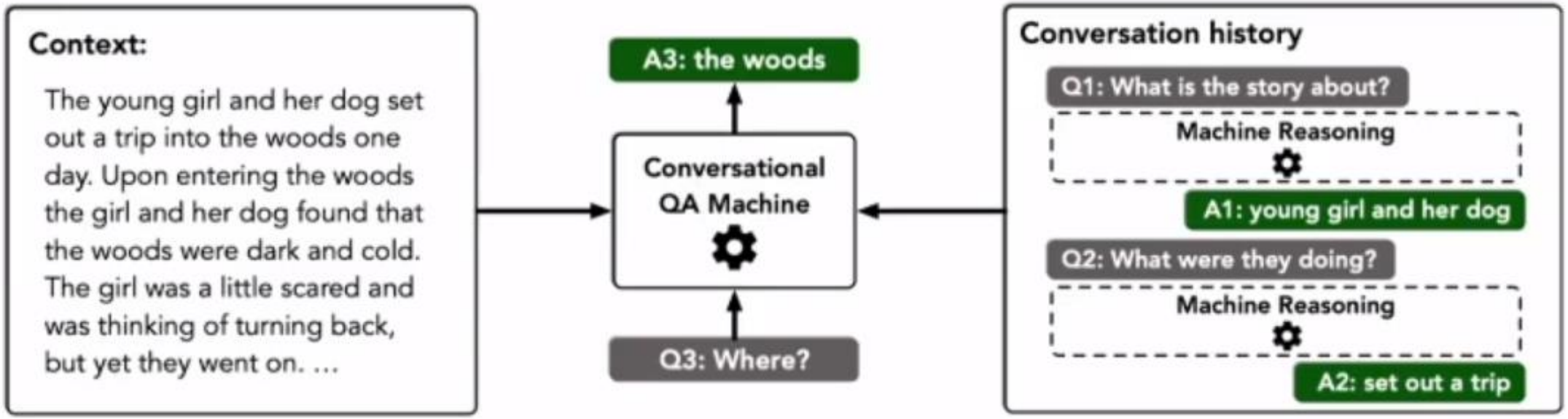
Dialog behaviors in conversational QA

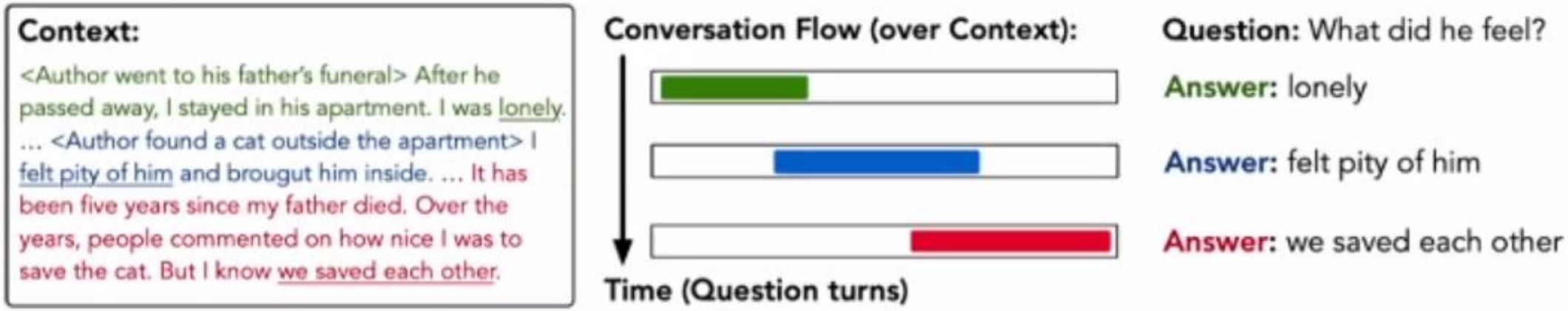
- **Topic shift**: a question about sth. previous discussed
- **Drill down**: a request for more info about a topic being discussed
- **Topic return**: asking about a topic again after being shifted
- **Clarification**: reformulating a question
- **Definition:** asking what is meant by a term

Dataset	Topic Shift	Drill Down	Return to Topic	Clarification Question	Definition Question	Sentence Coverage	Total Questions
CoQA	21.6	72.0	2.9	0.0	0.7	63.3	722
QuAC	35.4	55.3	5.6	0.7	3.0	28.4	302

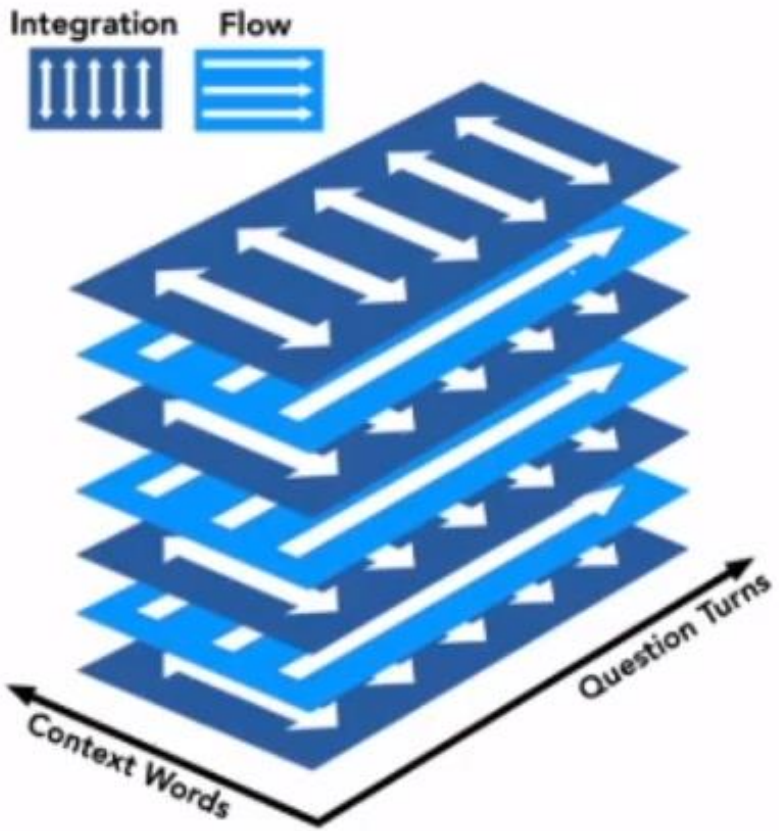
A Qualitative Comparison of CoQA, SQuAD 2.0 and QuAC. Yatskar et al. 2019

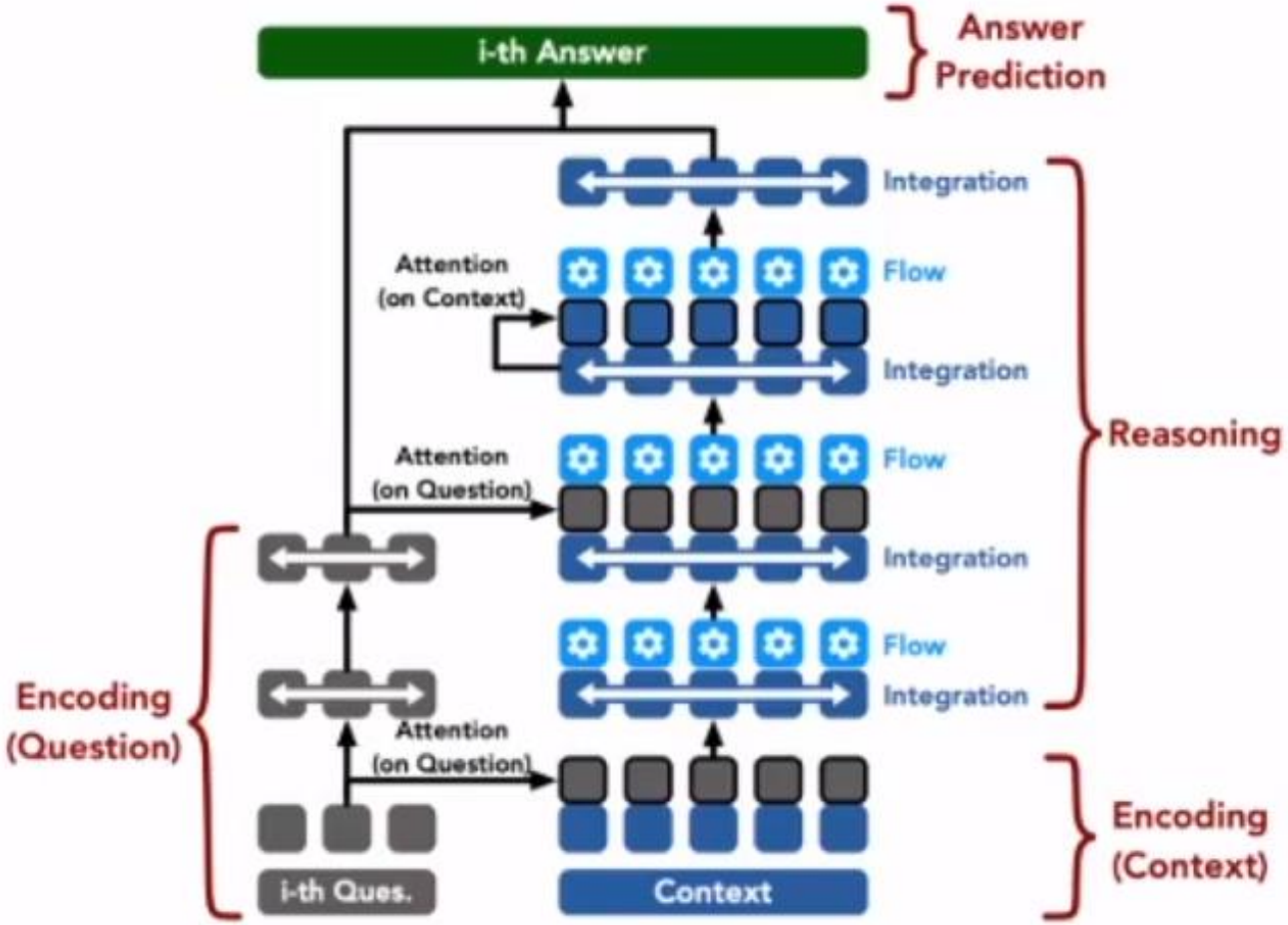
FlowQA


Context:
The young girl and her dog set out a trip into the woods one day. Upon entering the woods the girl and her dog found that the woods were dark and cold. The girl was a little scared and was thinking of turning back, but yet they went on. …
A3: the woods
Conversational QA Machine
Q3: Where?
Conversation history
Q1: What is the story about?
Machine Reasoning
A1: young girl and her dog
Q2: What were they doing?
Machine Reasoning
A2: set out a trip


Context:
<Author went to his father's funeral> After he passed away, I stayed in his apartment. I was lonely. … <Author found a cat outside the apartment> I felt pity of him and brougut him inside. … It has been five years since my father died. Over the years, people commented on how nice I was to save the cat. But I know we saved each other.
Conversation Flow (over Context):
Time (Question turns)
Question: What did he feel?
Answer: lonely
Answer: felt pity of him
Answer: we saved each other

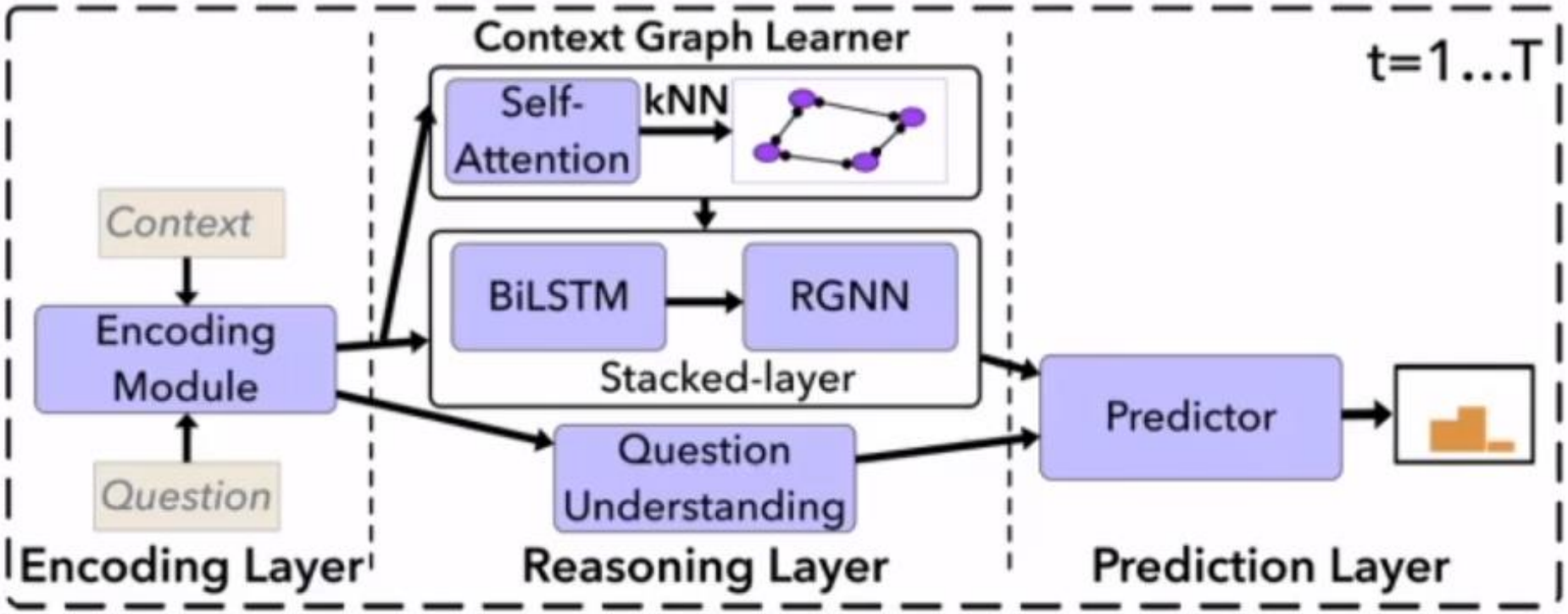
FlowQA





Flowqa: Grasping flow in history for conversational machine comprehension. Huang et al. 2018

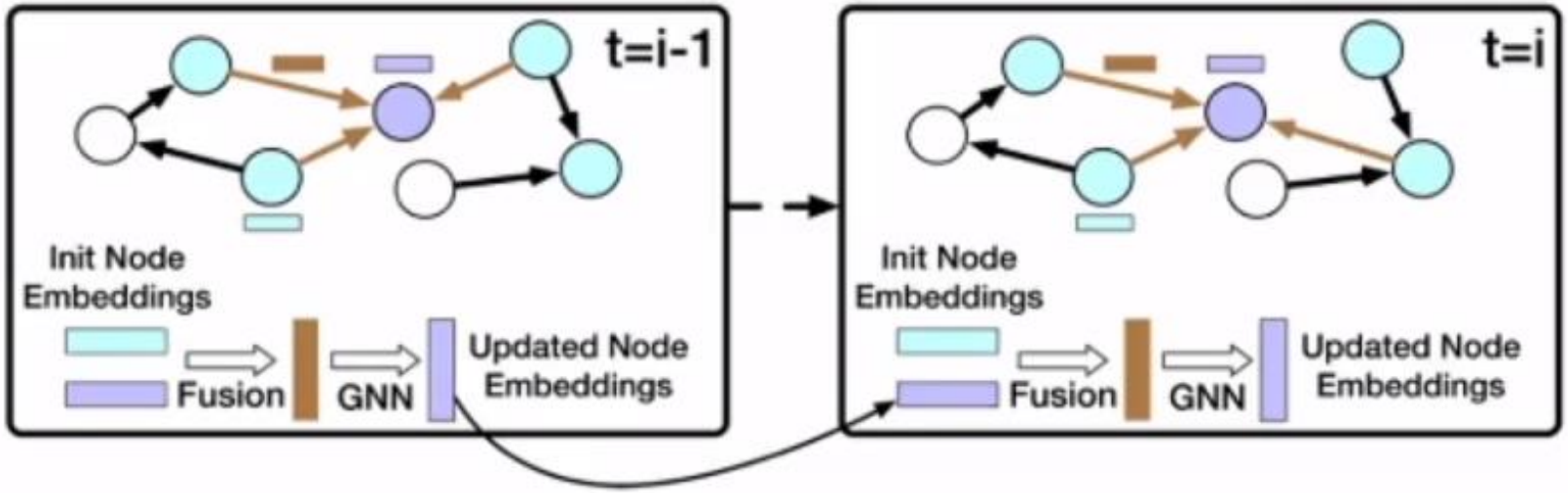
GraphQA



GraphFlow: Exploiting Conversation Flow with Graph Neural Networks for Conversational Machine Comprehension. Chen et al. IJCAI 2020

GraphQA

Recurrent Graph Neural Network



$$\mathbf{A}^{(i)} = (\mathbf{W}_C^{(i)} \odot \mathbf{u})^T \mathbf{W}_C^{(i)}$$

$$\widetilde{\mathbf{A}}^{(i)} = \mathrm{softmax}(\mathrm{topk}(\mathbf{A}^{(i)}))$$

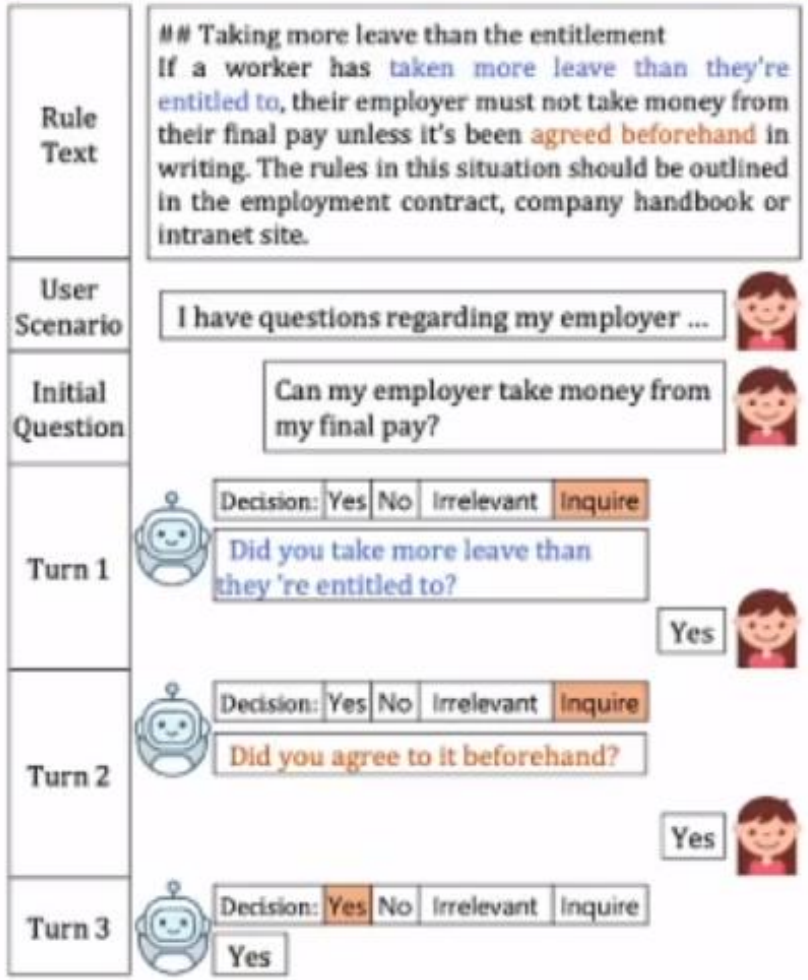
$$\bar{\mathbf{C}}^{(i)} = \mathrm{GNN}(\mathrm{Fuse}(\mathbf{C}^{(i)}, \bar{\mathbf{C}}^{(i-1)}), \widetilde{\mathbf{A}}^{(i)})$$

$$\mathrm{Fuse}(\mathbf{a}, \mathbf{b}) = \mathbf{z} * \mathbf{a} + (1 - \mathbf{z}) * \mathbf{b}$$

$$\mathbf{z} = \sigma(\mathbf{W}_z[\mathbf{a}; \mathbf{b}; \mathbf{a} * \mathbf{b}; \mathbf{a} - \mathbf{b}] + \mathbf{b}_z)$$

Conversational MRC

Doc2Dial: a Framework for Dialogue Composition Grounded in Business Documents. Feng et al.



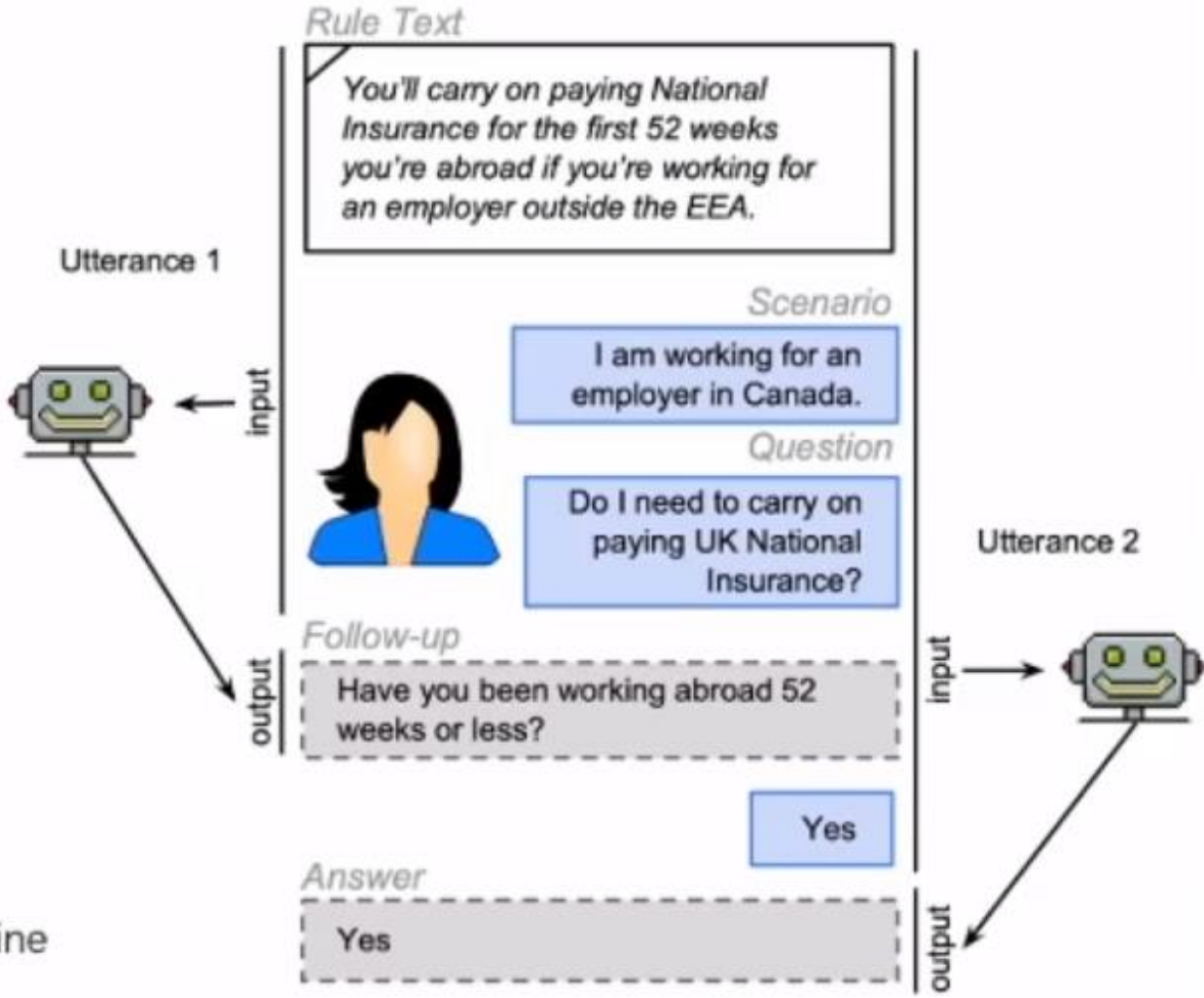
Explicit Memory Tracker with Coarse-to-Fine Reasoning for Conversational Machine Reading. Gao et al.

Differences to CoQA

- Not locating literal answer in the context
- Contains a recipe to derive an answer together with the reader's background knowledge
  - Interpretation of rules
  - Application of background knowledge
- Procedural texts

ShARC: Shaping Answers with Rules through Conversation

- Support rule text
- Scenario (personal background)
- Current question
- Dialog history
- Predict:
  - y ∈ {YES, NO, IRRELEVANT} ∪ Q



Interpretation of Natural Language Rules Conversational Machine Reading. EMNLP 2018

Challenges

- Interpreting rules
  - Identifying the follow-up questions within the rule text
  - Deciding the logical structure of the rule (disjunction vs. conjunction vs. conjunction of disjunctions)

Interpretation of Natural Language Rules in Conversational Machine Reading. EMNLP 2018

Challenges

	Question	Rule Text	
In-line Conditions	Do these benefits apply to me?	These are benefits that apply to individuals who have earned enough Social Security credits and are at least age 62.	39%
Conjunctions	Could I qualify for Letting Relief?	If you qualify for Private Residence Relief and have a chargeable gain, you may also qualify for Letting Relief. This means youll pay less or no tax.	18%
Disjunctions	Can I get deported?	The United States may deport foreign nationals who participate in criminal acts, are a threat to public safety, or violate their visa.	41%
Understanding Questioner Role	Am I eligible?	The borrower must qualify for the portion of the loan used to purchase or refinance a home. Borrowers are not required to qualify on the portion of the loan used for making energy-efficient upgrades.	10%
Negations	Will I get the National Minimum Wage?	You wont get the National Minimum Wage or National Living Wage if youre work shadowing	15%

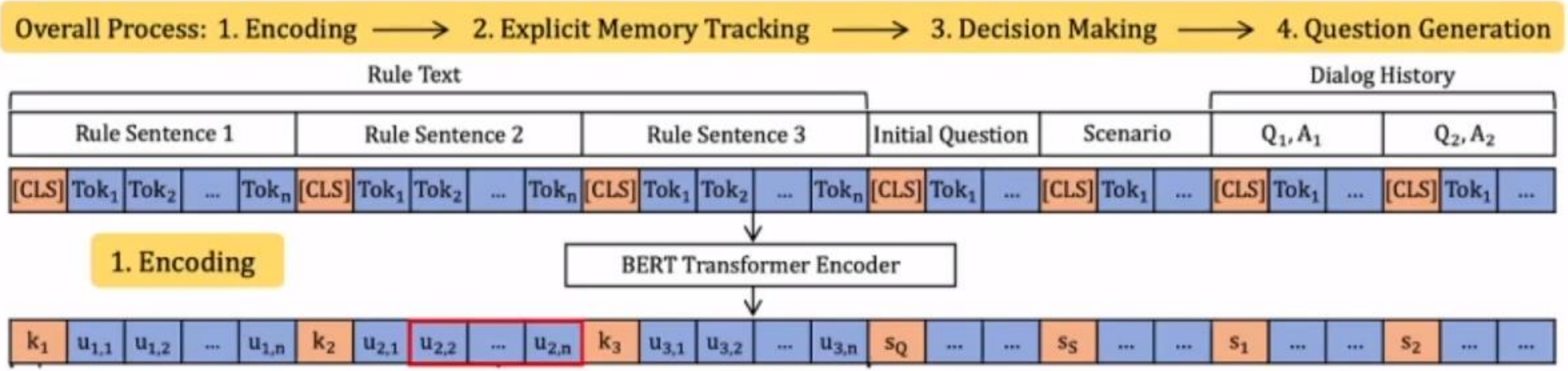
Interpretation of Natural Language Rules in Conversational Machine Reading. EMNLP 2018

Challenges

- Interpreting scenarios (multi-sentence entailment)
  - Numerical reasoning
  - Temporal reasoning
  - Implication (common sense and external knowledge)

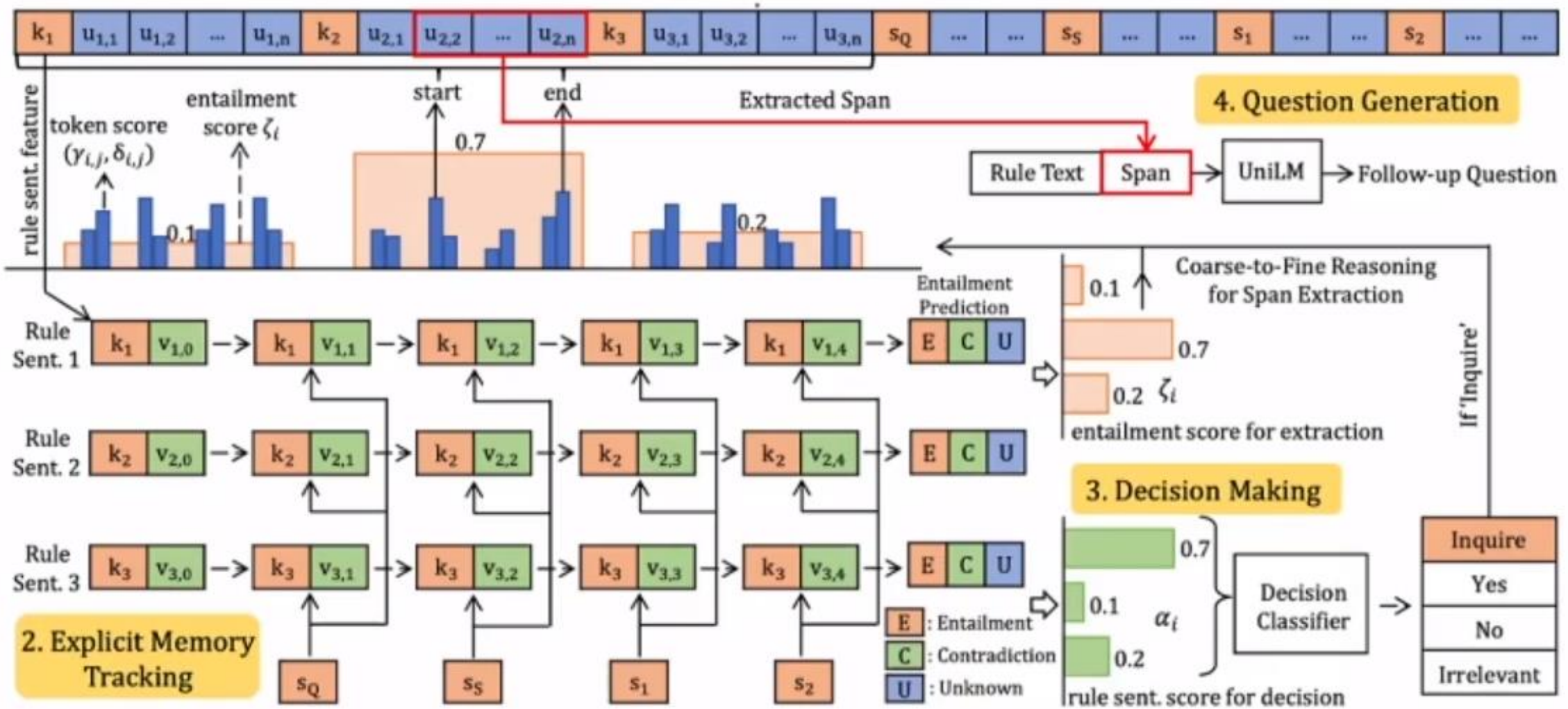
Interpretation of Natural Language Rules in Conversational Machine Reading. EMNLP 2018

EMT (Explicit Memory Tracker)



Explicit Memory Tracker with Coarse-to-Fine Reasoning for Conversational Machine Reading. Gao et al.

EMT (Explicit Memory Tracker)



Summary: QA and MRC

- Seeking information from structured KB or unstructured documents

- Background understanding
  - Unstructured information
  - Reasoning required
- Context (question + history) understanding
  - Coreferences, ellipsis

Part III: knowledge grounded conversation

- Why knowledge grounding
- Tasks + datasets
- Major research problems:
  - Knowledge representation
  - Knowledge selection
  - Generation with knowledge
- Notable models

Grounding to Knowledge

"The photographer asked me to do a "Napoleon" for the camera."

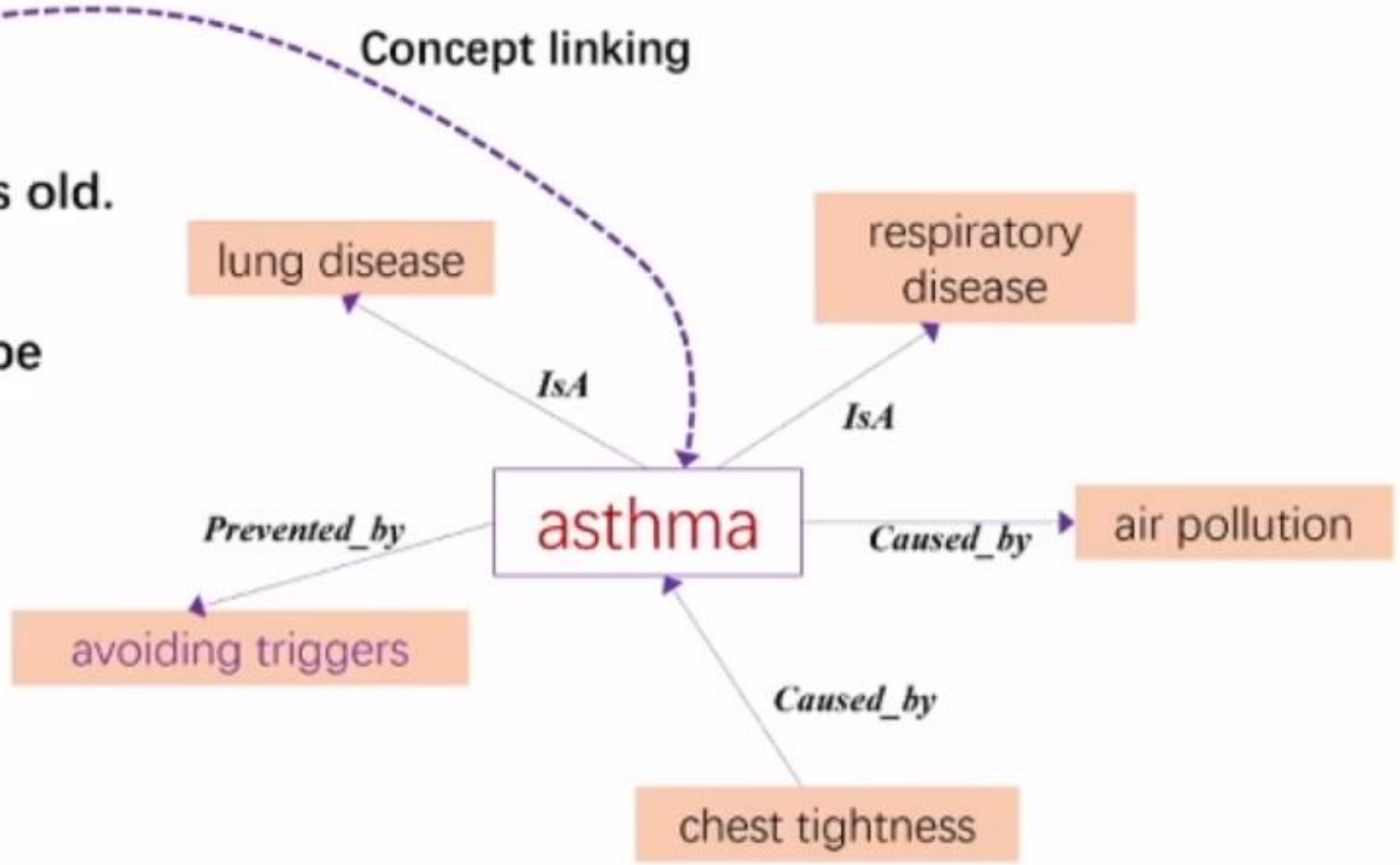
pose

Bender and Koller. Climbing towards NLU: On Meaning, Form, and Understanding in the Age of Data. ACL 2020. Best theme paper.

Grounding to Knowledge

Post: I have an asthma since three years old.

Response: I am sorry to hear that. Maybe avoiding triggers can prevent asthma attacks.



Zhou et al. Commonsense Knowledge Aware Conversation Generation with Graph Attention.
IJCAI-ECAI 2018 distinguished paper

Knowledge Grounding

- Knowledge provides ***kind of*** understanding
- ***Contentful*** generation: aligning generation to knowledge

- **World facts:** entities, relations, (Jobs –founder – Apple)

- **Commonsense knowledge** consists of facts about the everyday world, that all humans are expected to know
  - Lemons are sour
  - Tree has leafs
  - Dog has four legs

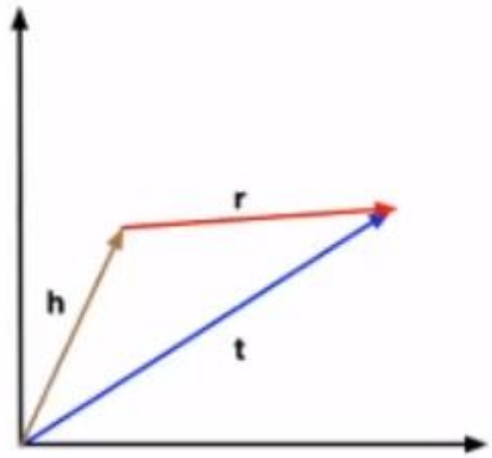
Research Problems

- Knowledge representation
- Knowledge selection
- Knowledge aware generation

- Structured vs. unstructured knowledge

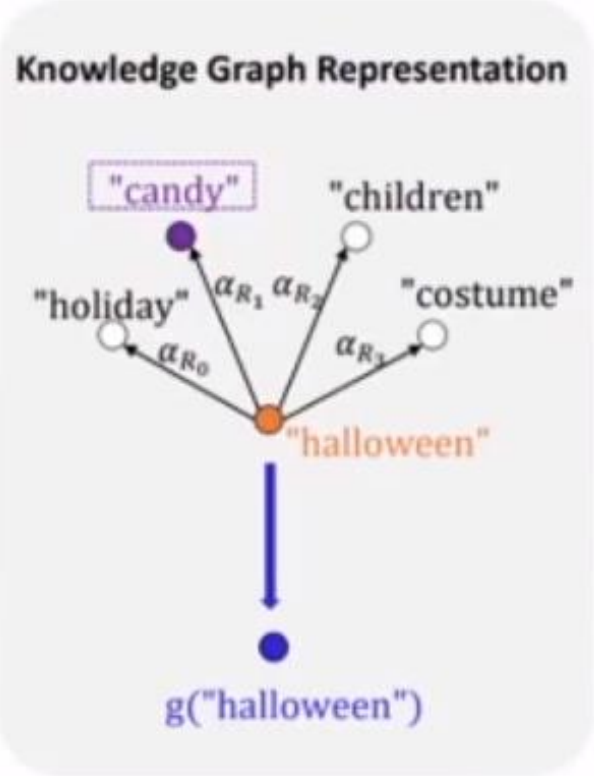
Knowledge Representation

- Translation-based (TransE, H, R, G etc.)
- Graph Neural Networks
- Graph Attention Networks



$$\boldsymbol{H}' = f(\hat{\boldsymbol{A}}\boldsymbol{H}\boldsymbol{W})$$

$$\boldsymbol{h}'_v = f\Big(\sum_{r\in R}\sum_{u\in\mathcal{N}_r(v)}\frac{1}{c_{v,r}}\boldsymbol{W}_r\boldsymbol{h}_u + \boldsymbol{W}_s\boldsymbol{h}_v\Big)$$



Knowledge Representation

CMU DOG [191]	30 movies' Wikipedia page	Crowd source	English	4,112 dialogs 31.6 turns per dialog 10.8 words per turn	Knowledge-grounded
Holl-E [86]	921 movies	Crowd source	English	9,071 dialogs 10.0 turns per dialog 15.3 words per turn	Knowledge-grounded
Wizard of Wikipedia [25]	1,365 Wikipedia articles	Crowd source	English	22,311 dialogs 9.0 turns per dialog	Knowledge-grounded
Grounded Response Generation DSTC7 [104]	Web articles	Reddit	English	32.7K dialog-document pairs 2.8M utterances 17M document sentences	Knowledge-grounded
Topical-Chat [40]	8 domains, e.g., politics, fashion	Crowd source	English	11,319 dialogs 22 turns per dialog 19.8 words per turn	Knowledge-grounded
OpenDialKG [87]	Movie, book, sports, music	Crowd source	English	15,673 dialogs 91,209 turns	Knowledge-grounded
DuConv [156]	Films and film stars	Crowd source	Chinese	29,858 dialogs 9.1 turns per dialog 10.6 words per turn	Knowledge-grounded/Proactivity modeling
DyKgChat [17]	2 TV series	TV series	Chinese English	1,247/3,092 dialogs[2] 13.8/18.7 turns per dialog[2]	Knowledge-grounded

Wizard of Wikipedia (Dinan et al. 2018)

- Expert-apprentice mode: expert has full access to the knowledge
- 1365 topics, each linked to Wikipedia
- Large-scale, more than 20,000 dialogs

Table 1: Dataset statistics of the Wizard of Wikipedia task.

Wizard of Wikipedia Task	Train	Valid	Test Seen	Test Unseen
Number of Utterances	166,787	17,715	8,715	8,782
Number of Dialogues	18,430	1,948	965	968
Number of Topics	1,247	599	533	58
Average Turns per Dialogue	9.0	9.1	9.0	9.1
Knowledge Database	5.4M articles		93M sentences	

Wizard of Wikipedia (Dinan et al. 2018)

Topic:	Ice cream
Wizard:	I just love ice cream. I love the types with fruits and flavours. Do you like ice cream?
Apprentice:	I love Ice cream as much as any one. I especially like Gelato, foreign ice cream!
Knowledge	Ice cream is a sweetened frozen food typically eaten as a snack or dessert.. . . It is usually made from dairy products, such as milk and cream, and . . . . . . Bacon ice cream (or bacon-and-egg ice cream) is an ice cream generally created by adding bacon to egg custard and freezing the mixture.
Wizard:	Me too. There are some strange combinations though, have you heard of bacon ice cream? where they add bacon and even egg custard to the freezing mixture!
Apprentice:	Surprisingly bacon ice cream doesn't surprise me. That doesn't sound appealing to me, but perhaps it could be delicious. . .

Towards Exploiting Background Knowledge for Building Conversation Systems (EMNLP 2018)

Plot

... The lab works on spiders and has even managed to create new species of spiders through genetic manipulation. While Peter is taking photographs of Mary Jane for the school newspaper, one of these new spiders lands on his hand and bites him Peter comes home feeling ill and immediately goes to bed. ...

Review

... I thoroughly enjoyed "Spider-Man" which I saw in a screening. I thought the movie was very engrossing. Director Sam Raimi kept the action quotient high, but also emphasized the human element of the story. Tobey was brilliant as a gawky teenager...

Movie: Spider-Man

Speaker 1(N): Which is your favourite character?

Speaker 2(C): My favorite character was Tobey Maguire.

Speaker 1(N): I thought he did an excellent job as peter parker, I didn't see what it was that turned him into Spider-Man though.

Speaker 2(P): Well this happens while Peter is taking photographs of Mary Jane for the school newspaper, one of these new spiders lands on his hand and bites him.

Speaker 1 (N): I see. I was very excited to see this film and it did not disappoint!

Speaker 2(R): I agree, I thoroughly enjoyed "Spider-Man"

Speaker 1(N): I loved that they stayed true to the comic.

Speaker 2(C): Yeah, it was a really great comic book adaptation

Speaker 1(N): The movie is a great life lesson on balancing power.

Speaker 2(F): That is my most favorite line in the movie, "With great power comes great responsibility."

Comments

... Crazy attention to detail. My favorite character was Tobey Maguire. I can't get over the "I'm gonna kill you dead" line. It was too heavily reliant on constant light-hearted humor. However the constant joking around kinda bogged it down for me. A really great comic book adaptation. ....

Fact Table

Awards	Golden Trailer Awards 2002
Taglines	With great power comes great responsibility. Get Ready For Spidey !
Similar Movies	Iron Man Spider-Man 2

Topical-Chat (Gopalakrishnan et al. 2019)

- Rich configurations of data collection (Asymmetric + symmetric)
- 8 topics, 300 entities
- 11,319 dialogs, 22 turns per dialog

Topic	Budget
Fashion	20
Politics	25
Books	33
Sports	35
General Entertainment	38
Music	39
Science & Technology	44
Movies	66
Total	300

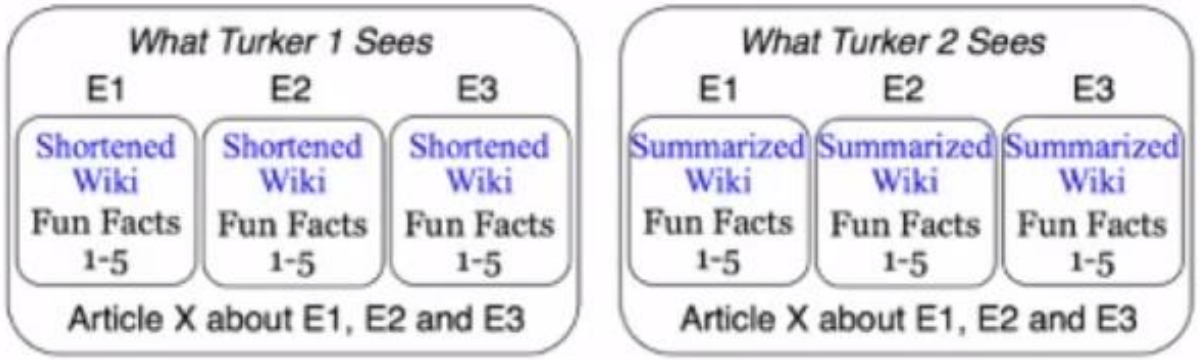


Figure 3: *Reading sets for Turkers 1 and 2 in Config B*

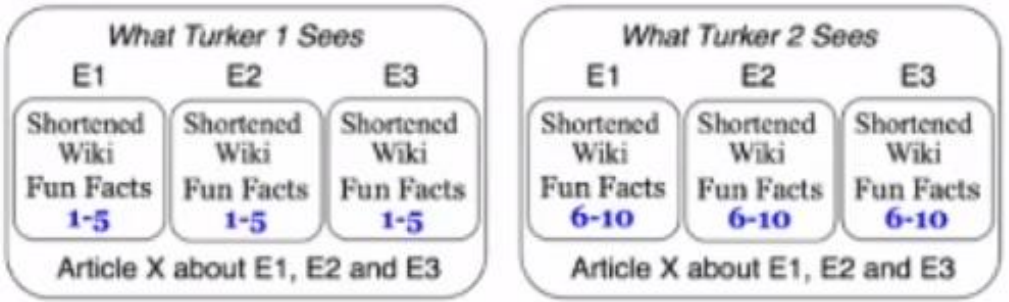


Figure 2: *Reading sets for Turkers 1 and 2 in Config A*

Topical-Chat (Gopalakrishnan et al. 2019)

config: B

agent_1: Hello. how are you
agent_2: Hello, I'm great thank you. Do you like animals?
agent_1: Yes, I love Animals.
agent_2: Me too. Did you know there are over 20 quintillion animals on the planet?
agent_1: No. I didnt. That is really something.
agent_2: I agree. Animals develop white patches on their foreheads when they are domesticated.
agent_1: That is interesting. I wonder why that is?
agent_2: Not too sure. I saw Germany gives animals constitutional rights.
agent_1: Yes. I had heard that too. I think that is a good thing.
agent_2: I think so too. Hiccups are a holdover from early evolution when land animals had both gills and lungs.

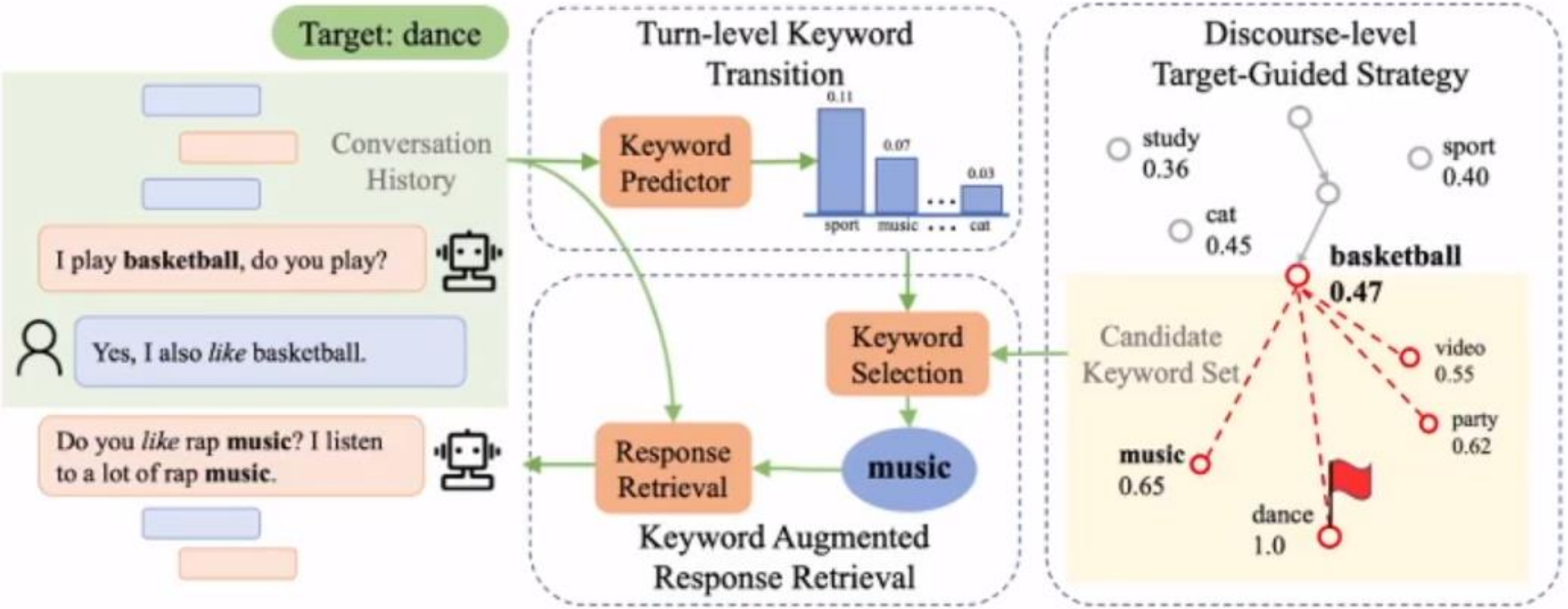
KDConv (Zhou et al. ACL2020)

User A: 知道《飞得更高》这首歌吗?
User B: 知道呀，这首歌入选了中歌榜中国年度最受华人欢迎十大金曲。
User A: 具体的发行时间你记得吗?
User B: 记得，是在 2005 年 3 月 19 日。
User A: 我觉得这首歌算是汪峰的经典之曲。
User B: 我也那么认为，编曲填词都由他自己完成，真的算是经典之作了。

Target Guided Conversation

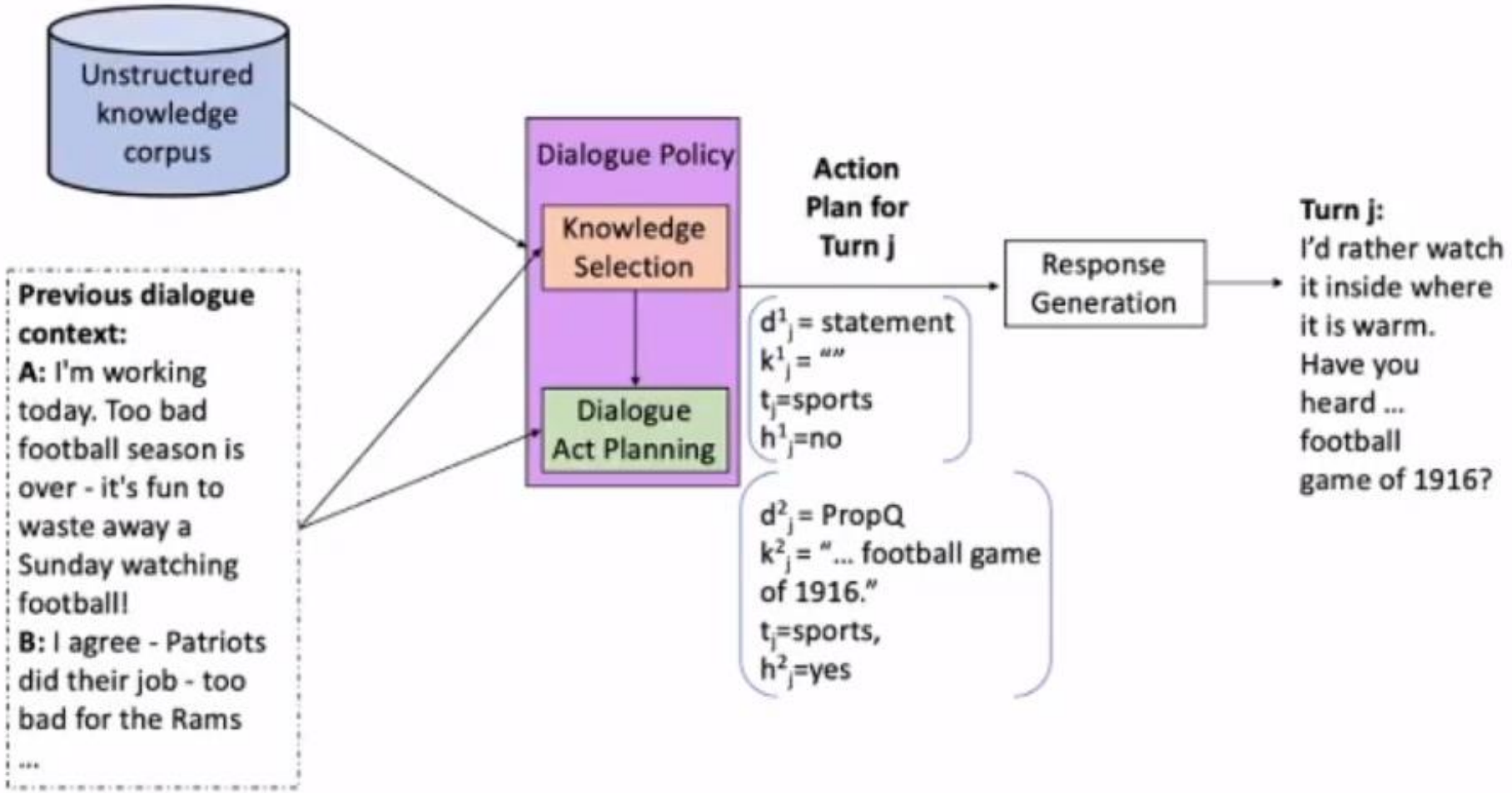
Keyword prediction: PMI, Neural-based, Hybrid kernel-based

Smooth transition



Target-Guided Open-Domain Conversation. Tang et al. ACL 2019

Dialog Act Planning



Policy-Driven Neural Response Generation for Knowledge-Grounded Dialogue Systems. Hedayatnia et al.

Dialog Act Planning

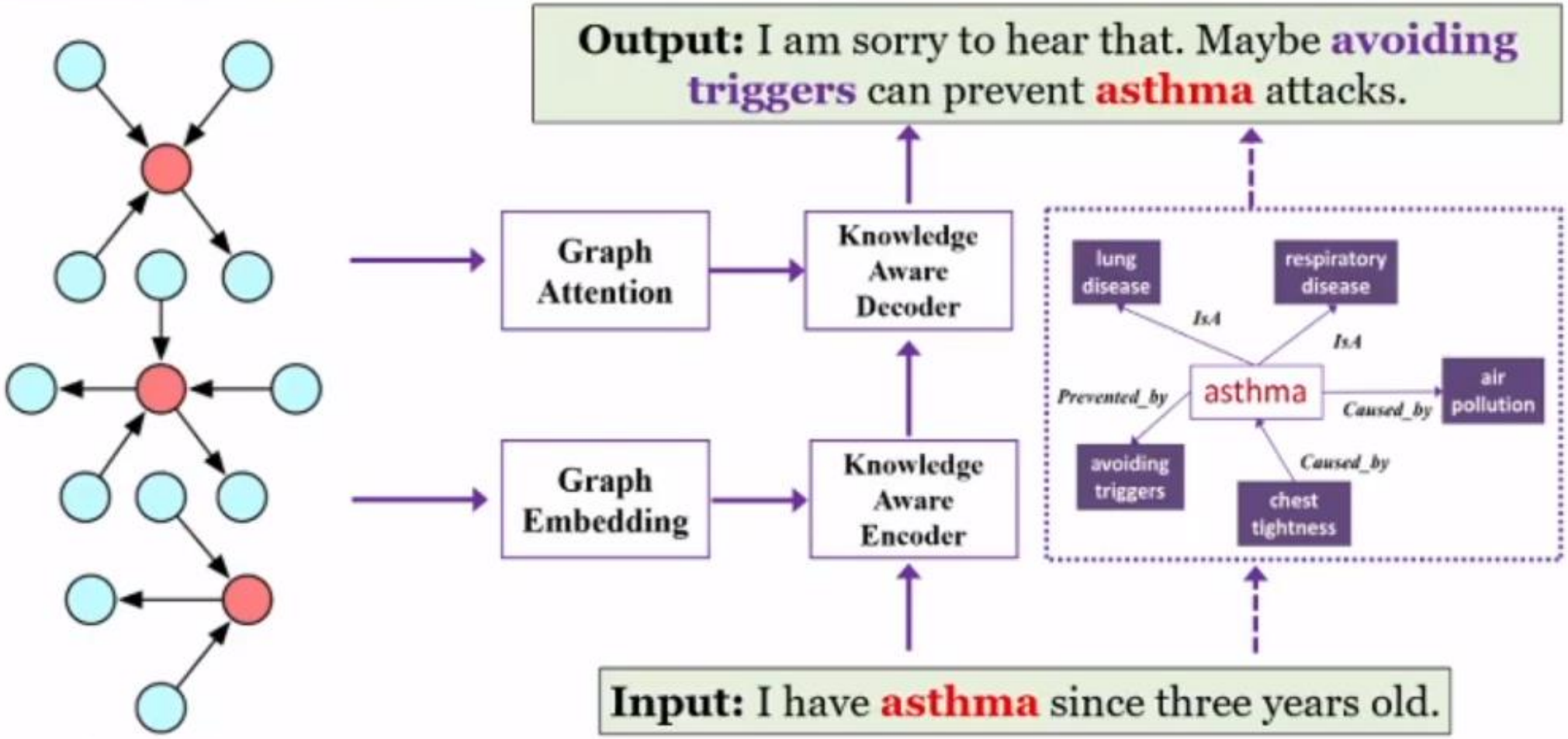
Authors	Knowledge modality	Grounding method	Issues focused	Models
Zhou et al. [190]	Knowledge graph	Retrieval	Knowledge-aware generation	Seq2Seq+Graph Attention
Ghazvininejad et al. [36]	Unstructured text	Retrieval	Knowledge-aware generation	Memory Networks
Zhu et al. [196]	Knowledge base	Retrieval	Knowledge-aware generation	Seq2Seq+ Knowledge Retriever
Liu et al. [74]	Knowledge base	Retrieval	Knowledge-aware generation	HRED+ Knowledge Retriever
Qin et al. [104]	Unstructured text	QA	Knowledge-aware generation	SAN + Generator
Chen and Lee [17]	Knowledge graph	Multi-hop reasoning	Knoweldge-aware generation +Zero-shot adaptation	Seq2Seq+ Multi-hop Reasoning
Dinan et al. [25]	Unstructured text	Retrieval	Knowledge-aware generation	Transformer
Gopalakrishnan et al. [40]	Unstructured text	Retrieval	Knowledge-aware generation	Transformer
Moghe et al. [86]	Unstructured text+ Fact table	Grounding label	Knowledge-aware generation	HRED/GTTP/BiDAF
Moon et al. [87]	Knowledge graph	Grounding label	Knowledge selection	KG path decoder
Wu et al. [156]	Unstructured text+ Knowledge graph	Grounding label	Proactive conversation	BERT/PostKS
Zhou et al. [191]	Unstructured text	Grounding label	Knowledge-aware generation	Seq2Seq
Lian et al. [68]	Unstructured text	Grounding label	Knowledge selection	PostKS
Liu et al. [77]	Unstructured text+ Knowledge graph	QA+Grounding label	Knowledge selection	RL+BiDAF
Ren et al. [110]	Unstructured text	Grounding label	Knowledge selection	BiDAF+GTTP
Zhang et al. [178]	Unstructured text	Grounding label	Knowledge selection	BiDAF+Seq2Seq
Li et al. [67]	Unstructured text	Grounding label	Knowledge-aware generation	Incremental Transformer+ Two-pass Decoder

Challenges in building intelligent open-domain dialog systems M Huang, X Zhu, J Gao
ACM Transactions on Information Systems (TOIS) 38 (3), 1-32

Knowledge Selection

- Matching-based
- Single-step selection
- Sequential selection
  - RL based
  - Sequential latent selection

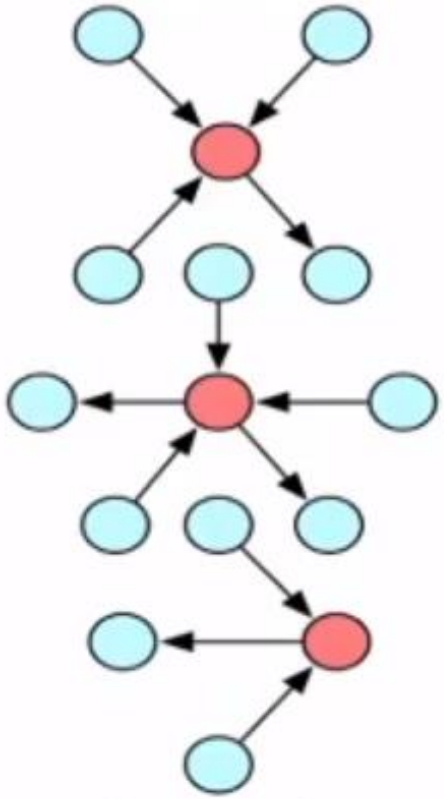
Knowledge-grounded Dialog (CCM)

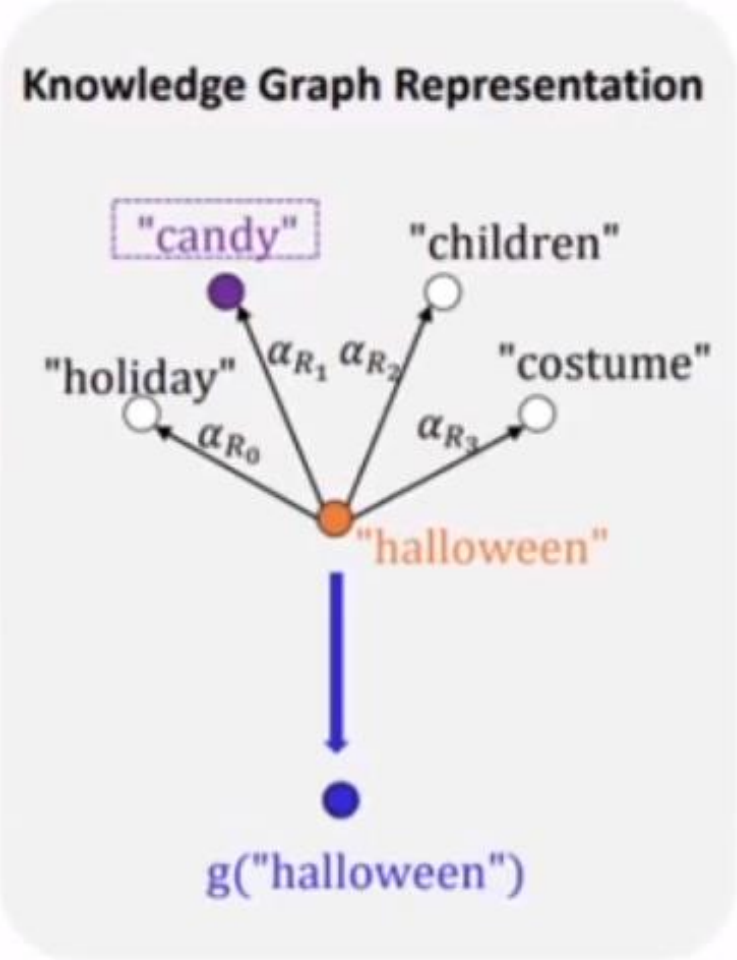


Hao Zhou, Tom Yang, Minlie Huang, Haizhou Zhao, Jingfang Xu, Xiaoyan Zhu.
Commonsense Knowledge Aware Conversation Generation with Graph Attention. **IJCAI-ECAI 2018, distinguished paper**.

Graph Attention (GAT)

Graph attention





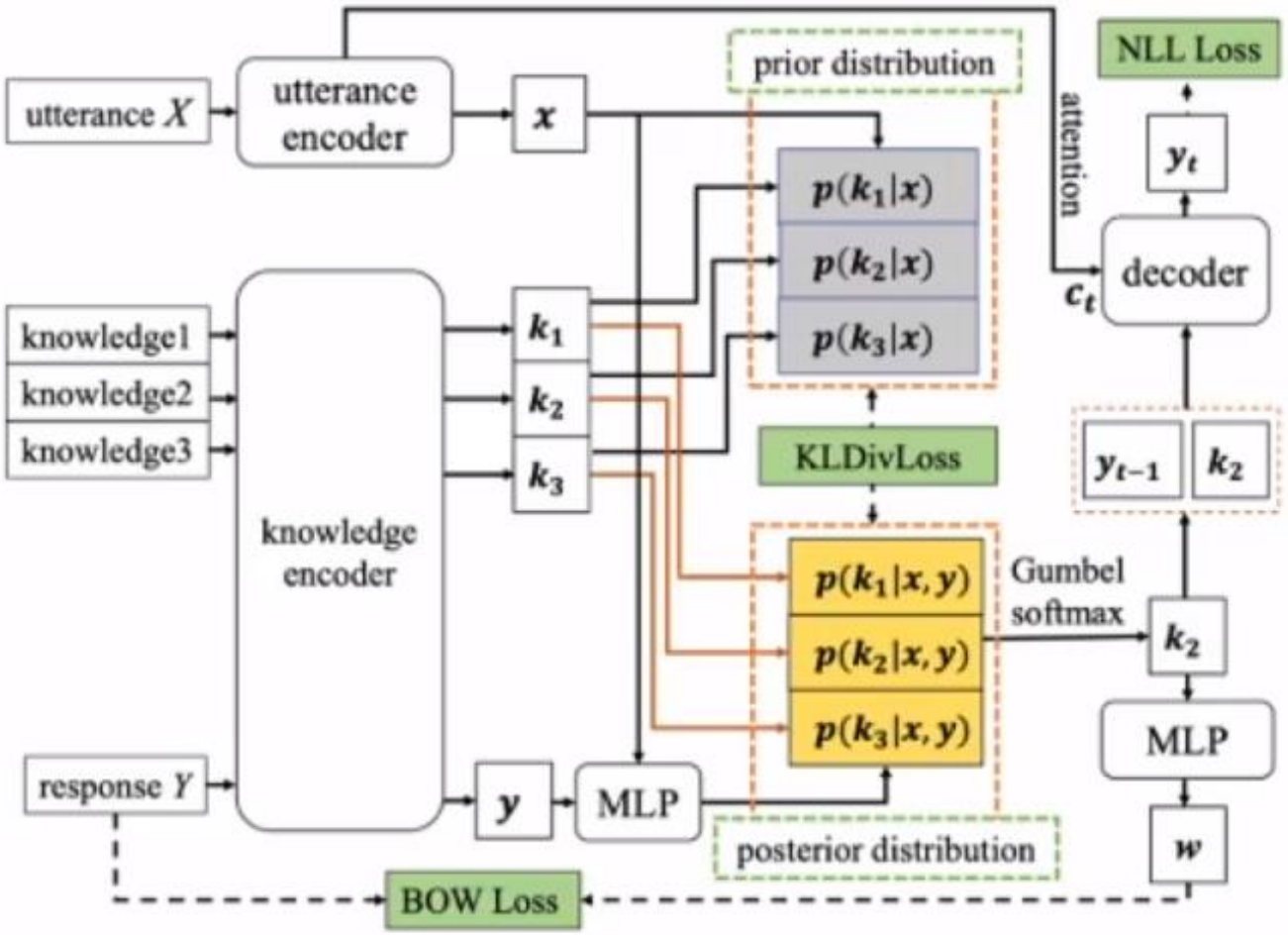
h/t: head/tail entity vectors

$$\mathbf{g}(x) = \sum_{i=1}^{N_x} \alpha_{R_i} [\mathbf{h}_i; \mathbf{t}_i],$$

$$\alpha_{R_i} = \frac{e^{\beta_{R_i}}}{\sum_{j=1}^{N_x} e^{\beta_{R_j}}},$$

$$\beta_{R_i} = (\mathbf{W_r r}_i)^{\mathrm{T}} \, tanh(\mathbf{W_h h}_i + \mathbf{W_t t}_i),$$

Single-step Selection (Lian et al. 2019)



$$\mathcal{L}_{KL}(\theta) = \sum_{i=1}^{N} p(\mathbf{k} = \mathbf{k}_i|\mathbf{x}, \mathbf{y}) \log \frac{p(\mathbf{k} = \mathbf{k}_i|\mathbf{x}, \mathbf{y})}{p(\mathbf{k} = \mathbf{k}_i|\mathbf{x})}$$

$$\mathcal{L}_{NLL}(\theta) = -\mathbf{E}_{\mathbf{k}_i \sim \mathbf{p}(\mathbf{k}|\mathbf{x},\mathbf{y})} \sum_{t=1}^{m} \log p(y_t|y_{<t}, \mathbf{x}, \mathbf{k}_i)$$

$$\mathcal{L}_{BOW}(\theta) = -\mathbf{E}_{\mathbf{k}_i \sim \mathbf{p}(\mathbf{k}|\mathbf{x},\mathbf{y})} \sum_{t=1}^{m} \log p(y_t|\mathbf{k}_i)$$

$$\mathcal{L}(\theta) = \mathcal{L}_{KL}(\theta) + \mathcal{L}_{NLL}(\theta) + \mathcal{L}_{BOW}(\theta)$$

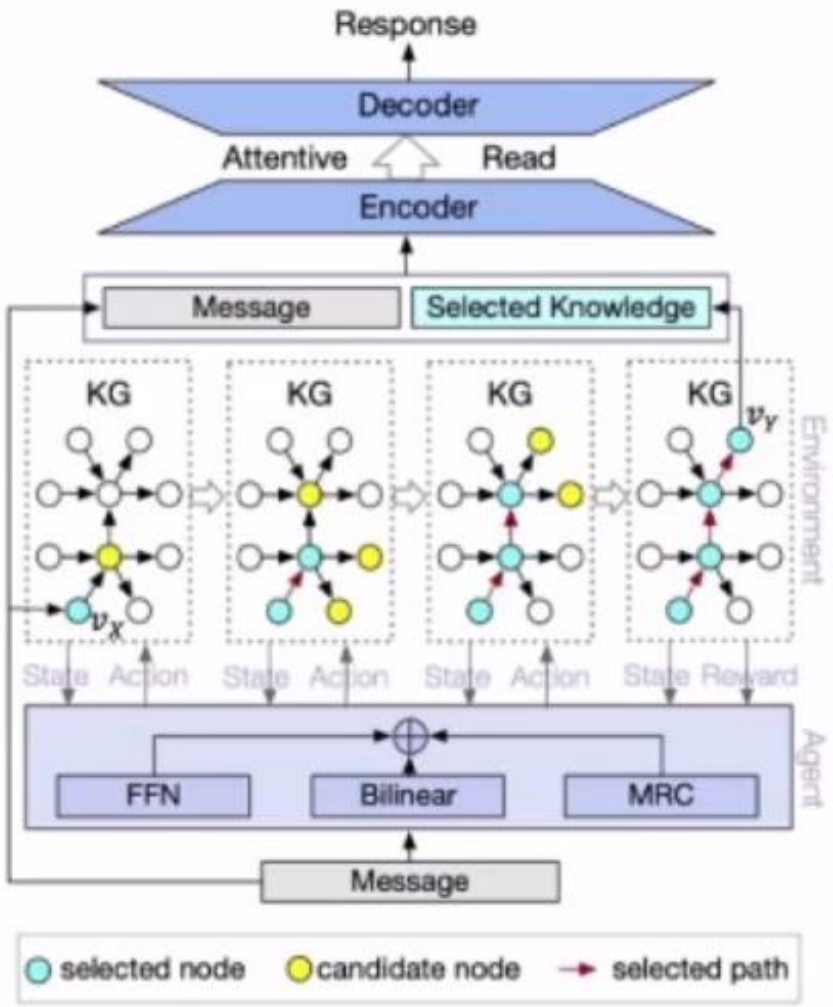
RL-based (Liu et al. ACL2019)

- Knowledge selection as RL in Graph
  - Entity graph augmented with sentences

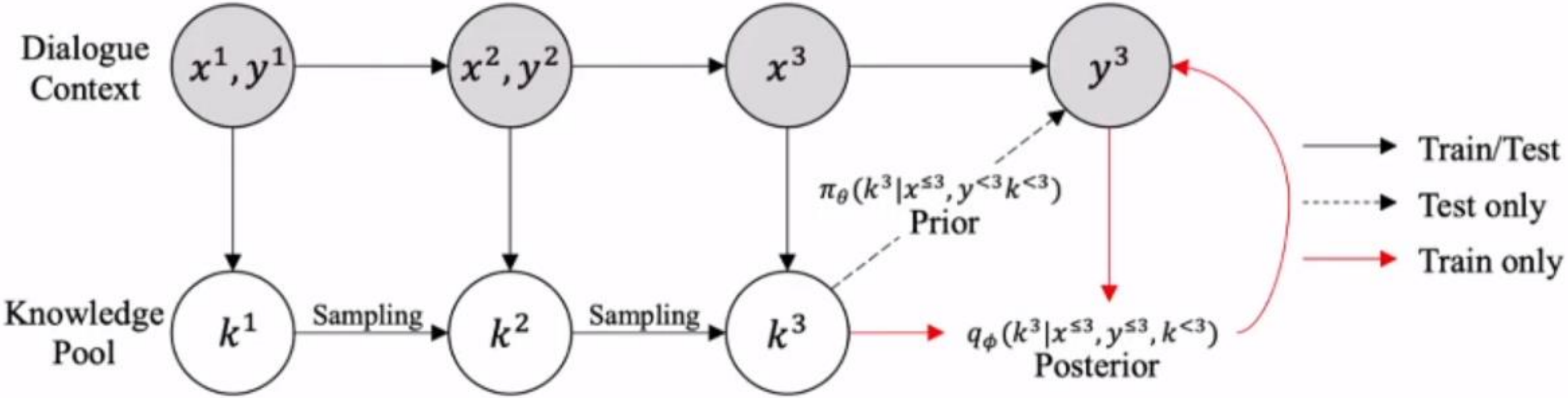
$$v_Y = \arg\max_{v} P_{KS}(v|v_X, \mathcal{G}, X).$$

- Knowledge aware dialog generation given a predicted entity

$$P_{RG}(Y|X, v_Y) = \prod_{t=1}^{n} P(y_t|y_{<t}, X, v_Y).$$



Sequential Latent Selection



$$\pi_\theta(\mathbf{k}^t|\mathbf{x}^{\leq t}, \mathbf{y}^{<t}, \mathbf{k}_s^{\leq t-1}) = \text{softmax}(\mathbf{q}_{prior}^t[\mathbf{h}_k^{t,1}, ..., \mathbf{h}_k^{t,L}]^\top) \in \mathbb{R}^L$$

$$q_\phi(\mathbf{k}^t|\mathbf{x}^{\leq t}, \mathbf{y}^{\leq t}, \mathbf{k}_s^{\leq t-1}) = \text{softmax}(\mathbf{q}_{post}^t[\mathbf{h}_k^{t,1}, ..., \mathbf{h}_k^{t,L}]^\top) \in \mathbb{R}^L,$$

$$\mathbf{q}_{prior}^t = \mathbf{W}_{prior}([\mathbf{d}_{xy}^{t-1}; \mathbf{h}_x^t; \text{GRU}_{hist}(\mathbf{d}_k^{t-2}, \mathbf{h}_k^{t-1,s})]),$$

$$\mathbf{q}_{post}^t = \mathbf{W}_{post}([\mathbf{d}_{xy}^t; \text{GRU}_{hist}(\mathbf{d}_k^{t-2}, \mathbf{h}_k^{t-1,s})]),$$

Sequential latent knowledge selection for knowledge-grounded dialog. Kim et al. ICLR 2020

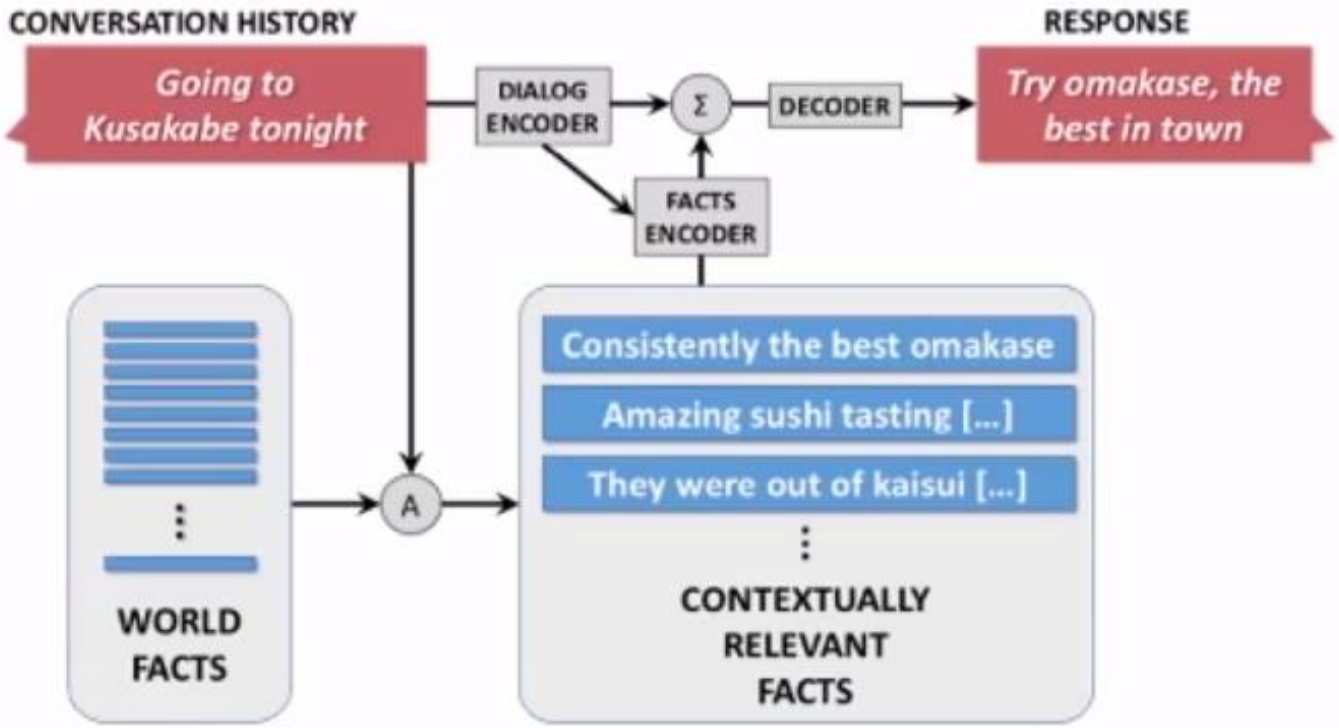
Knowledge aware Generation

- Memory-based
- Copy mechanism
- Knowledge-enhanced pretraining

A Knowledge-Grounded Neural Conversation Model (arXiv 2017)

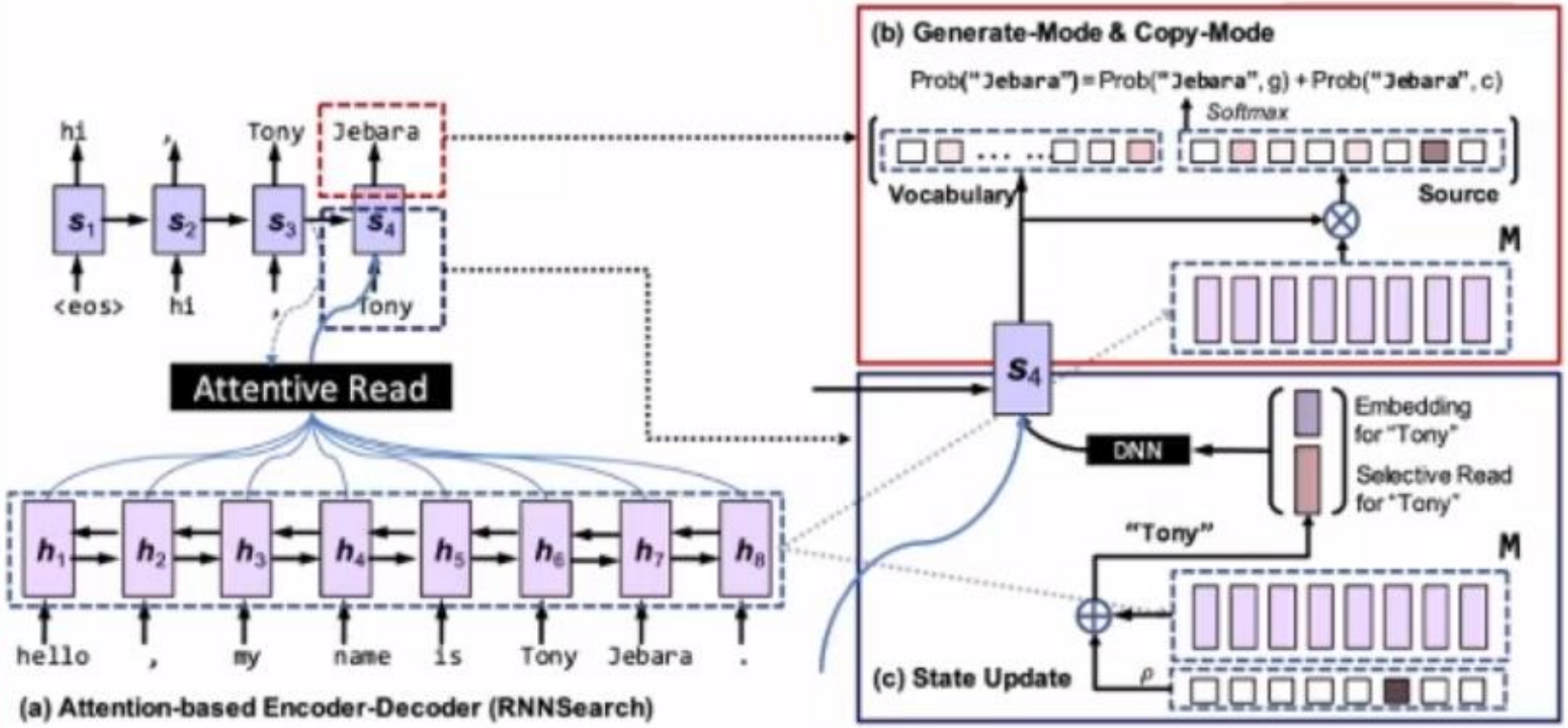
- ✓ Facts: relevant posts retrieved using IR methods
- ✓ Unstructured, may be of low-quality

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



Ghazvininejad, Marjan, et al. "A knowledge-grounded neural conversation model." *arXiv preprint arXiv:1702.01932* (2017).

Copy Mechanism



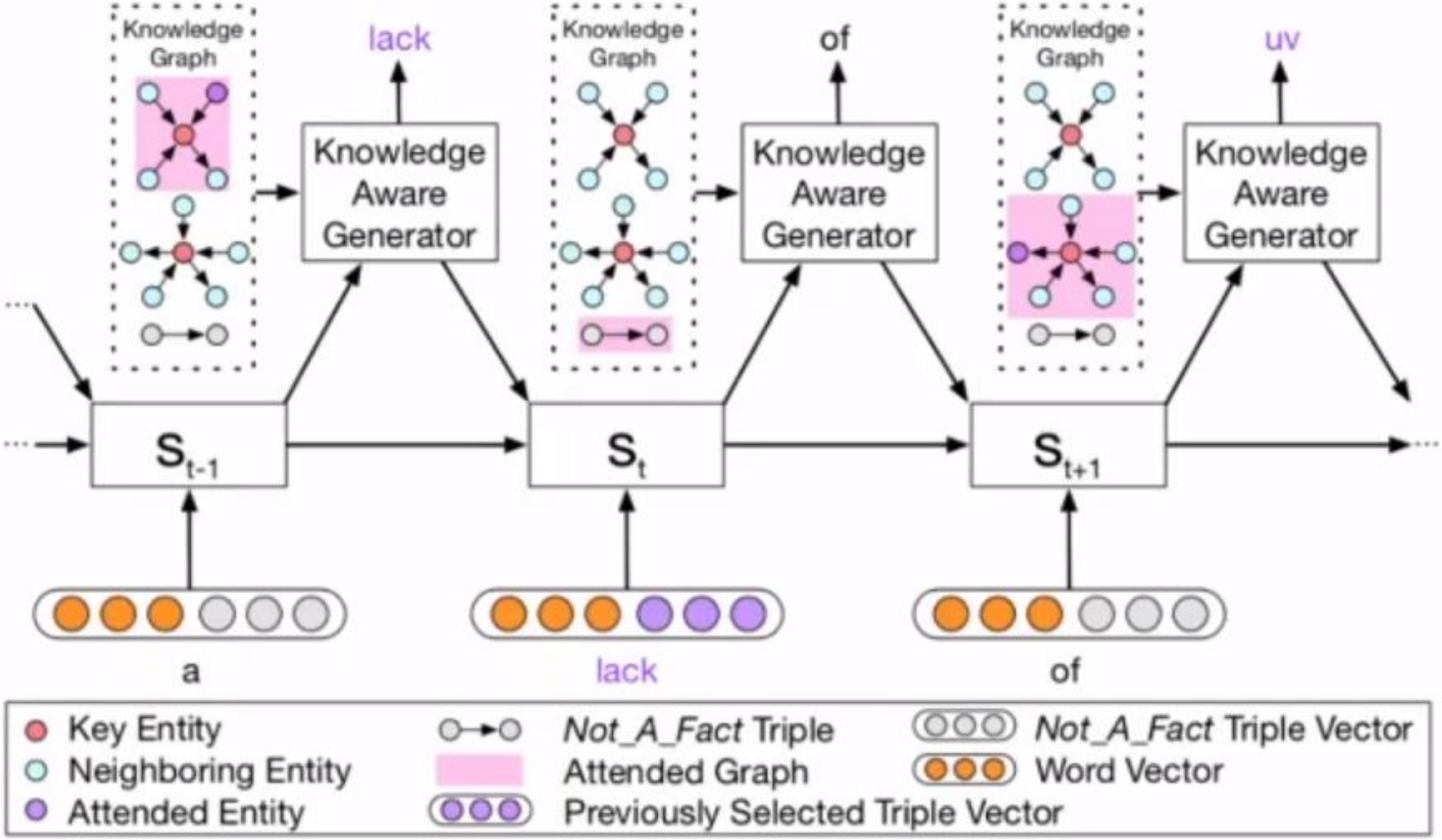
$$p(y_t|\mathbf{s}_t, y_{t-1}, \mathbf{c}_t, \mathbf{M}) = p(y_t, \mathsf{g}|\mathbf{s}_t, y_{t-1}, \mathbf{c}_t, \mathbf{M}) + p(y_t, \mathsf{c}|\mathbf{s}_t, y_{t-1}, \mathbf{c}_t, \mathbf{M})$$

$$p(y_t, \mathsf{g}|\cdot) = \begin{cases} \frac{1}{Z} e^{\psi_g(y_t)}, & y_t \in \mathcal{V} \\ 0, & y_t \in \mathcal{X} \cap \bar{\mathcal{V}} \\ \frac{1}{Z} e^{\psi_g(\mathrm{UNK})} & y_t \notin \mathcal{V} \cup \mathcal{X} \end{cases}$$

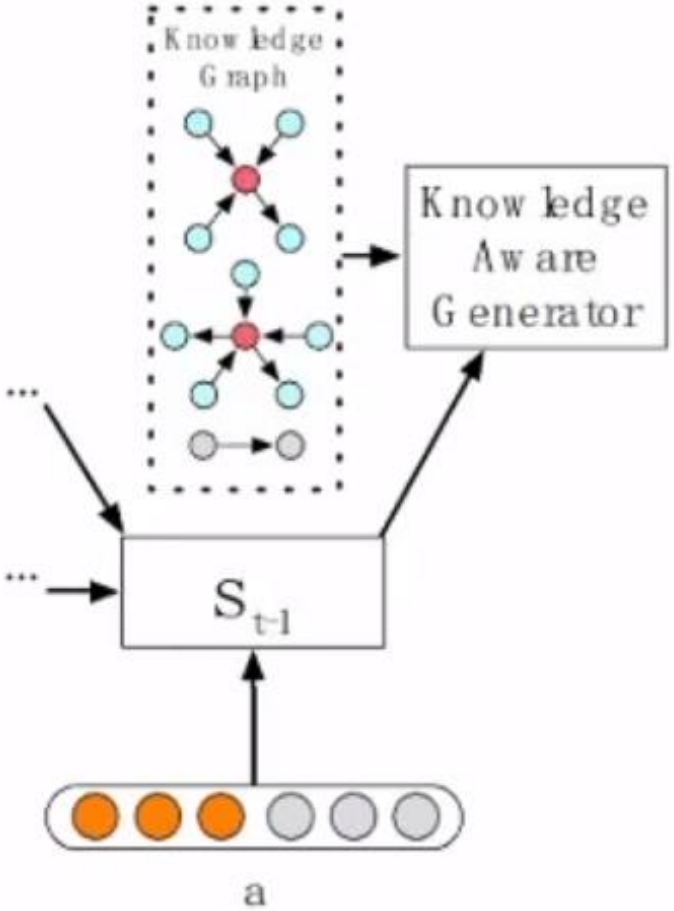
$$p(y_t, \mathsf{c}|\cdot) = \begin{cases} \frac{1}{Z} \sum_{j:x_j=y_t} e^{\psi_c(x_j)}, & y_t \in \mathcal{X} \\ 0 & \text{otherwise} \end{cases}$$

Jiatao Gu, Zhengdong Lu, Hang Li, Victor O.K. Li. Incorporating Copying Mechanism in Sequence-to-Sequence Learning. ACL, 2016.

Copy-based (CCM)



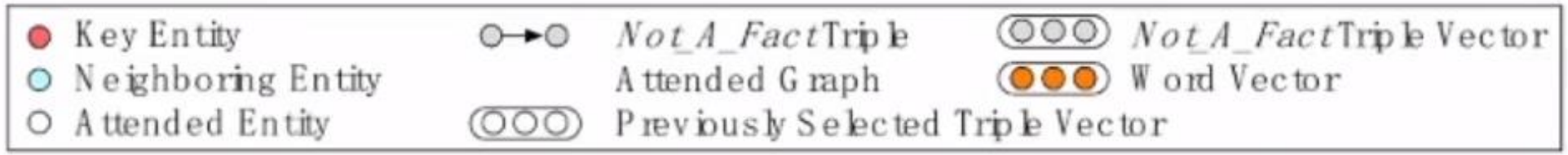
Commonsense Knowledge in Chatbots



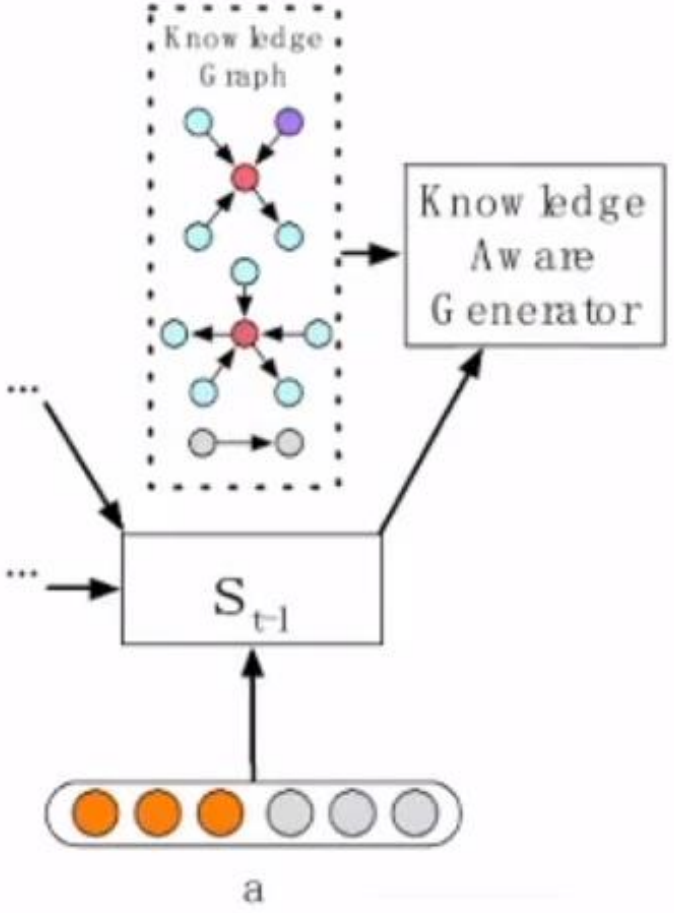
$$\boldsymbol{c}_t^g = \sum_{i=1}^{N_G} \alpha_{ti}^g \boldsymbol{g}_i,$$

$$\alpha_{ti}^g = \frac{\exp(\beta_{ti}^g)}{\sum_{j=1}^{N_G} \exp(\beta_{tj}^g)},$$

$$\beta_{ti}^g = \boldsymbol{V}_b^\top \tanh(\mathbf{W_b} \boldsymbol{s}_t + \mathbf{U_b} \boldsymbol{g}_i),$$



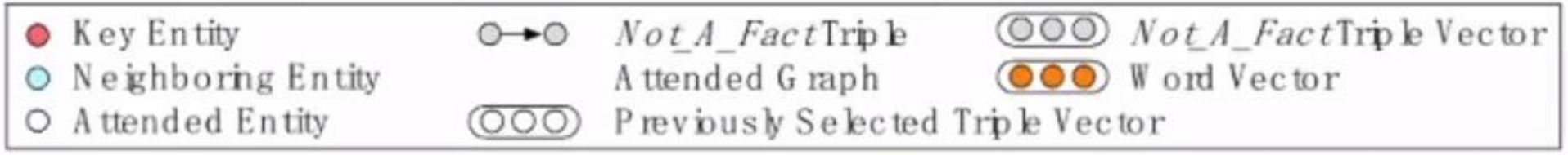
Commonsense Knowledge in Chatbots



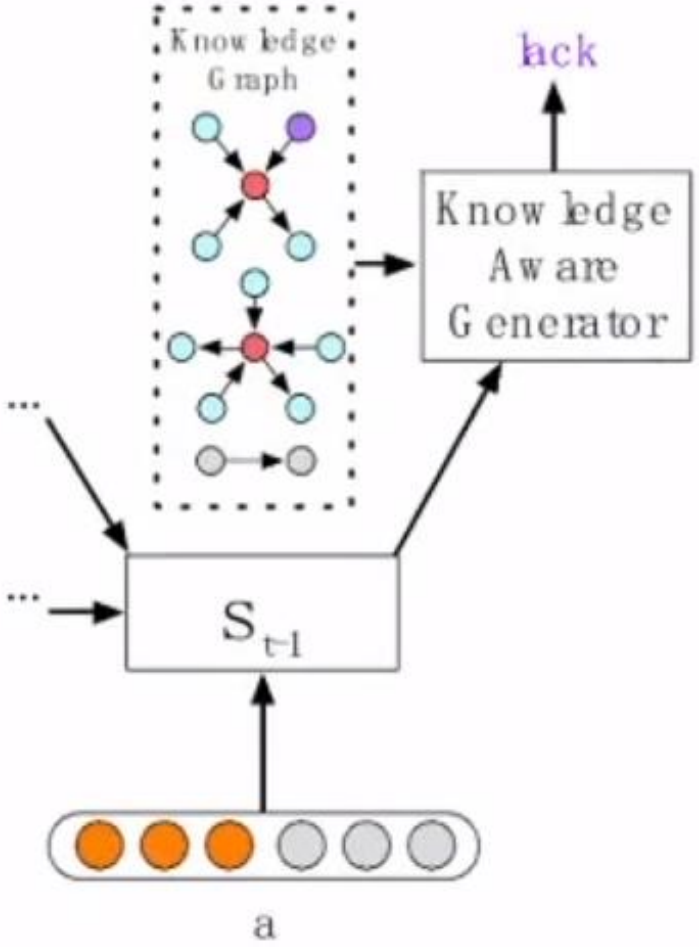
$$\boldsymbol{c}_t^k = \sum_{i=1}^{N_G} \sum_{j=1}^{N_{g_i}} \alpha_{ti}^g \alpha_{tj}^k \boldsymbol{k}_j,$$

$$\alpha_{tj}^k = \frac{\exp(\beta_{tj}^k)}{\sum_{n=1}^{N_{g_i}} \exp(\beta_{tn}^k)},$$

$$\beta_{tj}^k = \boldsymbol{k}_j^\top \mathbf{W}_\mathbf{c} \boldsymbol{s}_t,$$

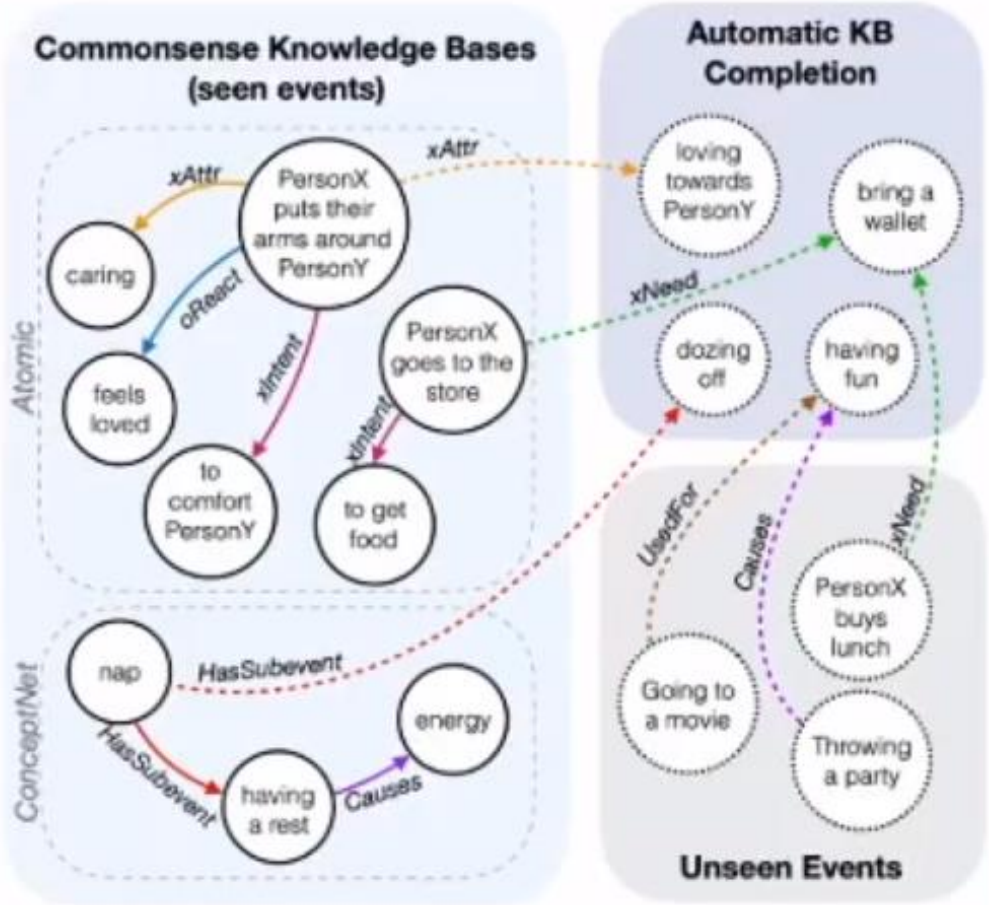


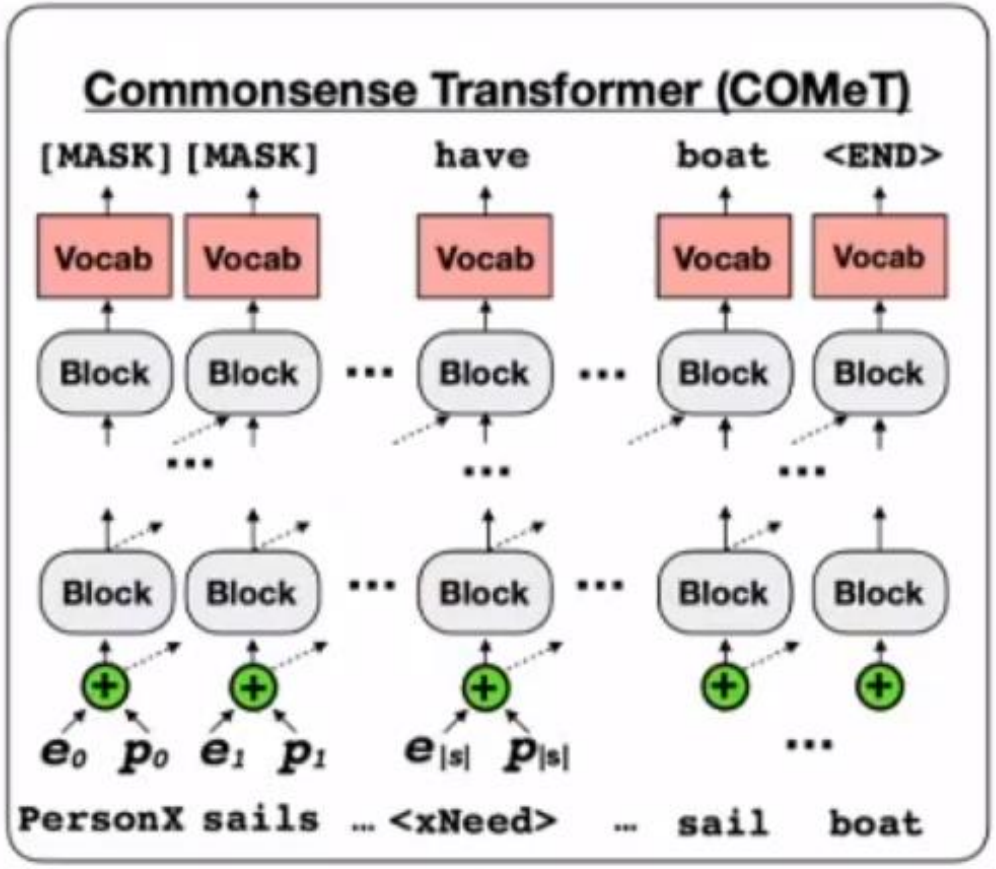
Commonsense Knowledge in Chatbots



$$
\begin{aligned}
\boldsymbol{a}_t &= [\boldsymbol{s}_t; \boldsymbol{c}_t; \boldsymbol{c}_t^g; \boldsymbol{c}_t^k], \\
\gamma_t &= \text{sigmoid}(\mathbf{V_o}^\top \boldsymbol{a}_t), \\
P_c(y_t = w_c) &= \text{softmax}(\mathbf{W_o} \boldsymbol{a}_t), \\
P_e(y_t = w_e) &= \alpha_{ti}^g \alpha_{tj}^k, \\
y_t \sim \boldsymbol{o}_t = P(y_t) &= \begin{bmatrix} (1-\gamma_t) P_g(y_t = w_c) \\ \gamma_t P_e(y_t = w_e) \end{bmatrix},
\end{aligned}
$$

Knowledge-enhanced post training





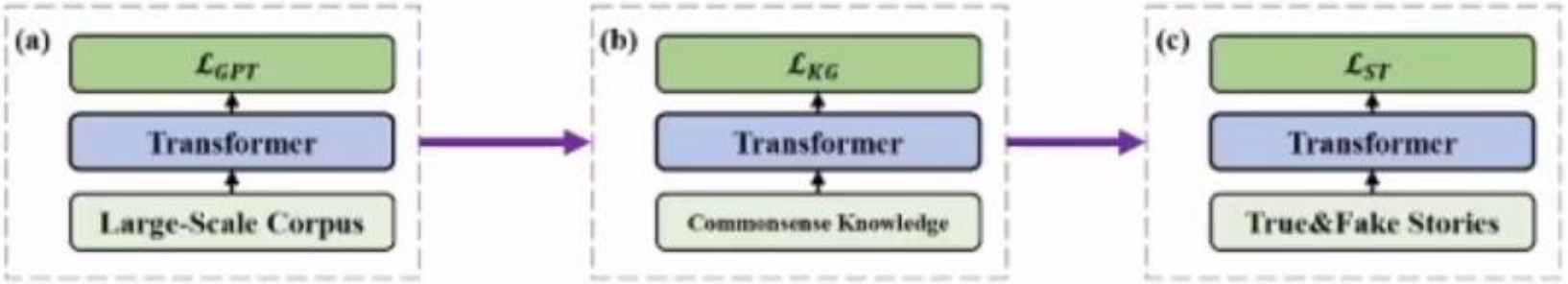
(c)

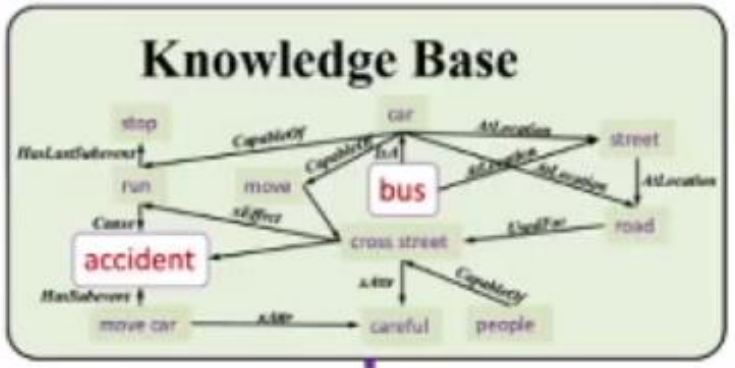
Bosselute et al. 2019. COMET : Commonsense Transformers for Automatic Knowledge Graph Construction.

Knowledge-enhanced post training

- Story generation, explanation generation, etc.
- ConceptNet, COMet

Knowledge Base	Original Triples	Examples of Transformed Sentences
ConceptNet	(basketball player, **HasProperty**, tall) (telephone, **UsedFor**, communication)	basketball player **has property** tall. telephone **is used for** communication.
ATOMIC	(PersonX dates for years, **oEffect**, continue dating) (PersonX cooks spaghetti, **xIntent**, to eat)	PersonX dates for years. **PersonY will** continue dating. PersonX cooks spaghetti. **PersonX wants** to eat.





bus *is a* car.

bus *is at* street.

cross street *causes* accident.

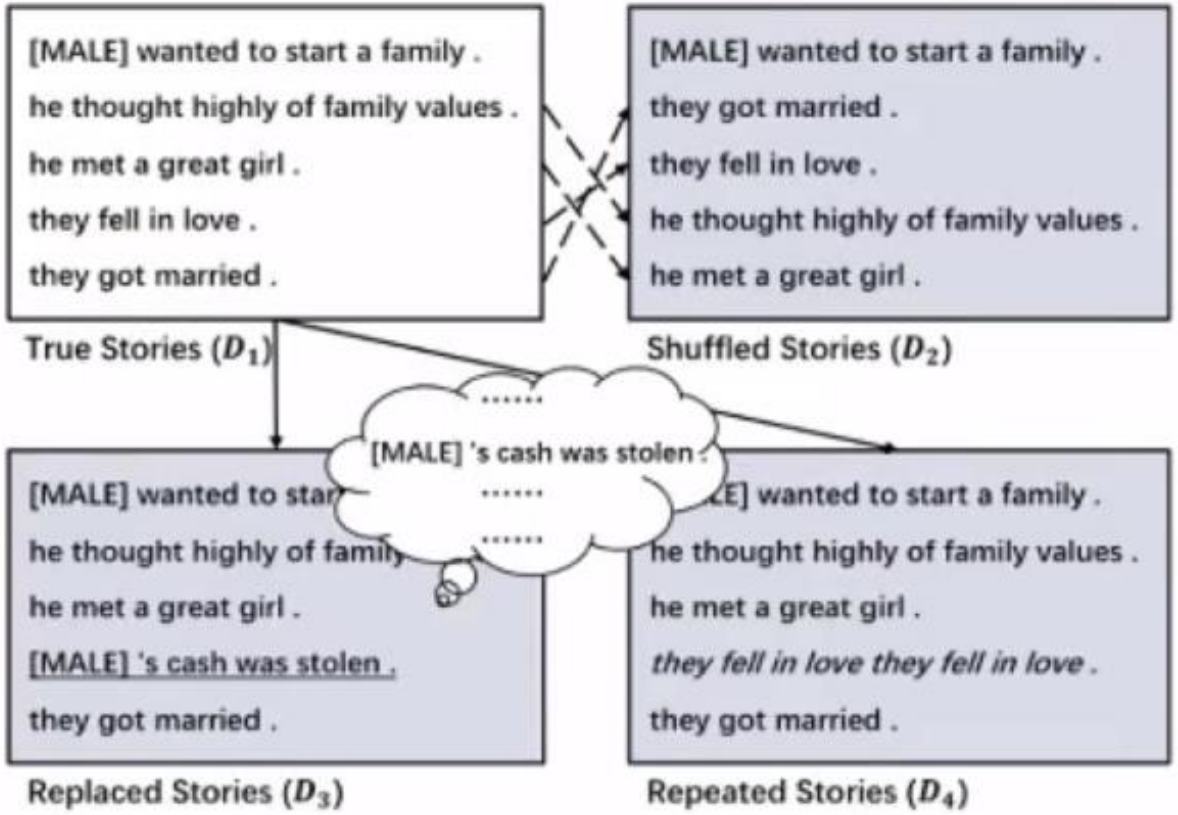
PersonX cross street. ***PersonX should be*** careful.

.....

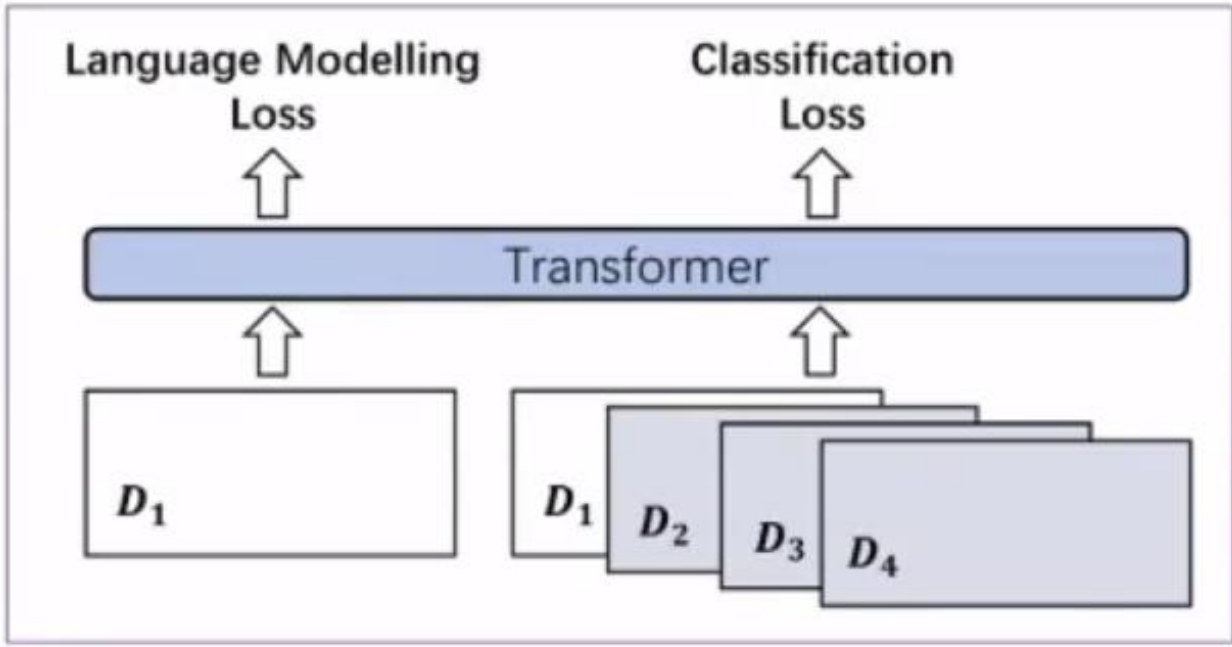
Guan et al. A Knowledge-Enhanced Pretraining Model for Commonsense Story Generation. TACL 2020.

Knowledge-enhanced post training

- Self-supervised learning



Multi-task learning



Guan et al. A Knowledge-Enhanced Pretraining Model for Commonsense Story Generation. TACL 2020.

Knowledge-enhanced post training

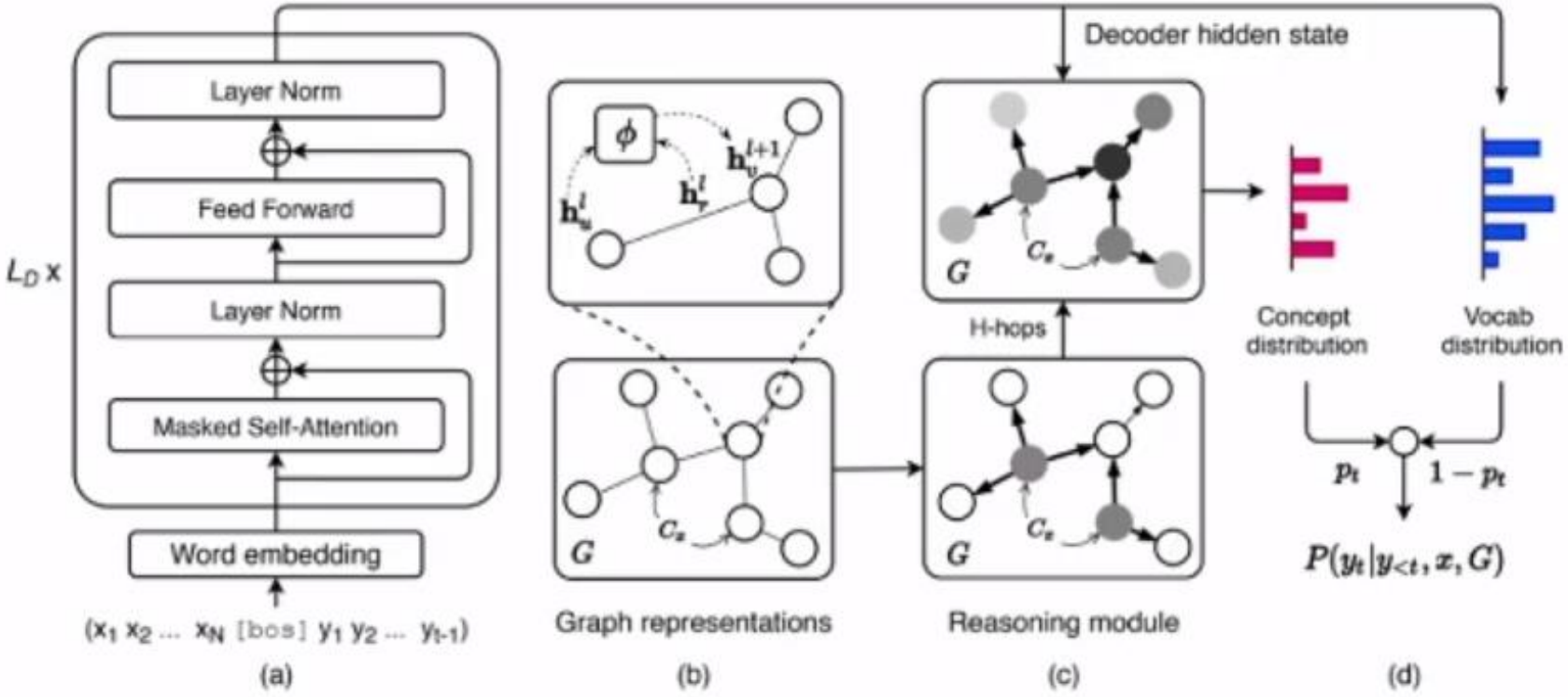
- Manual evaluation of generation quality

Models	Grammaticality				Logicality			
	Win (%)	Lose (%)	Tie (%)	κ	Win (%)	Lose (%)	Tie (%)	κ
Ours vs. Fusion	50.0**	27.0	23.0	0.421	57.0**	28.0	15.0	0.455
Ours vs. DSRL	58.0**	24.0	18.0	0.441	58.0**	29.0	12.0	0.475
Ours vs. GPT-2 (Scratch)	54.0**	24.5	21.5	0.385	54.0**	26.0	20.0	0.304
Ours vs. GPT-2 (Pretrain)	52.0**	31.5	16.5	0.483	56.5**	32.5	11.0	0.493
Ours vs. GPT-2 (Fine-tune)	42.0**	28.0	30.0	0.344	51.0**	27.5	21.5	0.371
Ours vs. Ours w/o Pretrain	51.0**	31.0	18.0	0.378	56.0**	28.0	16.0	0.375
Ours vs. Ours w/o Knowledge	46.0**	23.0	21.0	0.289	48.0**	29.0	23.0	0.314
Ours vs. Ours w/o Multi-task	37.5	31.0	31.5	0.313	48.5**	25.5	26.0	0.297

Guan et al. A Knowledge-Enhanced Pretraining Model for Commonsense Story Generation. TACL 2020.

Explicit control on generation

- Explicitly **construct the commonsense knowledge graph** associated with input text
- **Conduct multi-hop reasoning with graph neural network**



Ji et al. Language Generation with Multi-Hop Reasoning on Commonsense Knowledge Graph. EMNLP 2020.

Explicit control on generation

Generation from the graph + from context:

$$P(y_t|\boldsymbol{y}_{<t}, \boldsymbol{x}, G) = g_{t+N} \cdot \boxed{P(c_{t+N}|\boldsymbol{s}_{<t+N}, G)} + (1 - g_{t+N}) \cdot \boxed{P(s_{t+N}|\boldsymbol{s}_{<t+N})}, \quad (13)$$

From graph

From context

Generation from the graph:

$$P(c_t|\boldsymbol{s}_{<t}, G) = \mathbf{softmax}_{v \in V}(ns(v)),$$

Evidence score propagation over graph:

$$ns(v) = \underset{(u,r) \in \mathcal{N}_{in}(v)}{f} \Big(\gamma \cdot ns(u) + R(u, r, v)\Big),$$

Explicit control on generation

Generation from the graph:

$$P(c_t|\boldsymbol{s}_{<t}, G) = \text{softmax}_{v\in V}(ns(v)),$$

Evidence score propagation over graph:

$$ns(v) = \underset{(u,r)\in\mathcal{N}_{in}(v)}{f}\Big(\gamma\cdot ns(u)+R(u,r,v)\Big),$$

Alignment btw text and graph representations:

$$R(u,r,v) = \sigma(\boldsymbol{h}_{u,r,v}^{\mathrm{T}}\mathbf{W}_{sim}\boldsymbol{h}_t^{L_D}),$$

$$\boldsymbol{h}_{u,r,v} = [\boldsymbol{h}_u^{L_G}; \boldsymbol{h}_r^{L_G}; \boldsymbol{h}_v^{L_G}].$$

Transformer Networks (GPT)

$$\boldsymbol{h}_t^0 = \boldsymbol{e}_t + \boldsymbol{p}_t,$$

$$\boldsymbol{h}_t^l = \texttt{T_block}(\mathbf{H}_{\leq t}^{l-1}), l \in [1, L_D]$$

$$P(s_t|\boldsymbol{s}_{<t}) = \text{softmax}(\mathbf{W}_{LM}\boldsymbol{h}_t^{L_D} + \boldsymbol{b})$$

Graph Neural Network

$$\boldsymbol{o}_v^l = \frac{1}{|\mathcal{N}(v)|}\sum_{(u,r)\in\mathcal{N}(v)}\mathbf{W}_N^l\phi(\boldsymbol{h}_u^l, \boldsymbol{h}_r^l),$$

$$\boldsymbol{h}_v^{l+1} = \text{ReLU}\Big(\boldsymbol{o}_v^l + \mathbf{W}_S^l\boldsymbol{h}_v^l\Big),$$

$$\boldsymbol{h}_r^{l+1} = \mathbf{W}_R^l\boldsymbol{h}_r^l.$$

Explicit control on generation

Story ending generation

Models	BLEU-1/2	Distinct-2/3
Seq2Seq	19.1 / 5.5	0.181 / 0.360
IE+GA	20.8 / 6.4	0.140 / 0.280
WriterForcing	16.5 / 3.7	0.335 / 0.584
GPT2-FT	25.5 / 10.2	0.304 / 0.505
GPT2-OMCS-FT	25.5 / 10.4	0.352 / 0.589
GRF	**26.1 / 11.0**	**0.378 / 0.622**

Explanation generation Abductive NLG

Models	EG				αNLG			
	BLEU-4	METEOR	ROUGE-L	CIDEr	BLEU-4	METEOR	ROUGE-L	CIDEr
Seq2Seq	6.09	24.94	26.37	32.37	2.37	14.76	22.03	29.09
COMeT-Txt-GPT2	N/A	N/A	N/A	N/A	2.73†	18.32†	24.39†	32.78†
COMeT-Emb-GPT2	N/A	N/A	N/A	N/A	3.66†	19.53†	24.92†	32.67†
GPT2-FT	15.63	38.76	37.32	77.09	9.80	25.82	32.90	57.52
GPT2-OMCS-FT	15.55	38.28	37.53	75.60	9.62	25.83	32.88	57.50
GRF	**17.19**	**39.15**	**38.10**	**81.71**	**11.62**	**27.76**	**34.62**	**63.76**

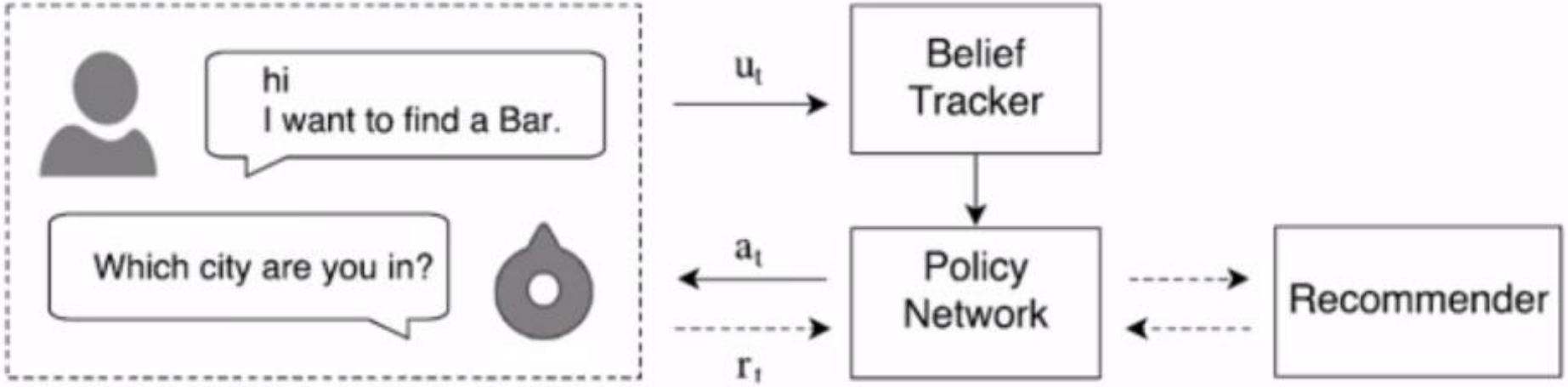
Ji et al. Language Generation with Multi-Hop Reasoning on Commonsense Knowledge Graph. EMNLP 2020.

Summary: Knowledge-grounded Conversation

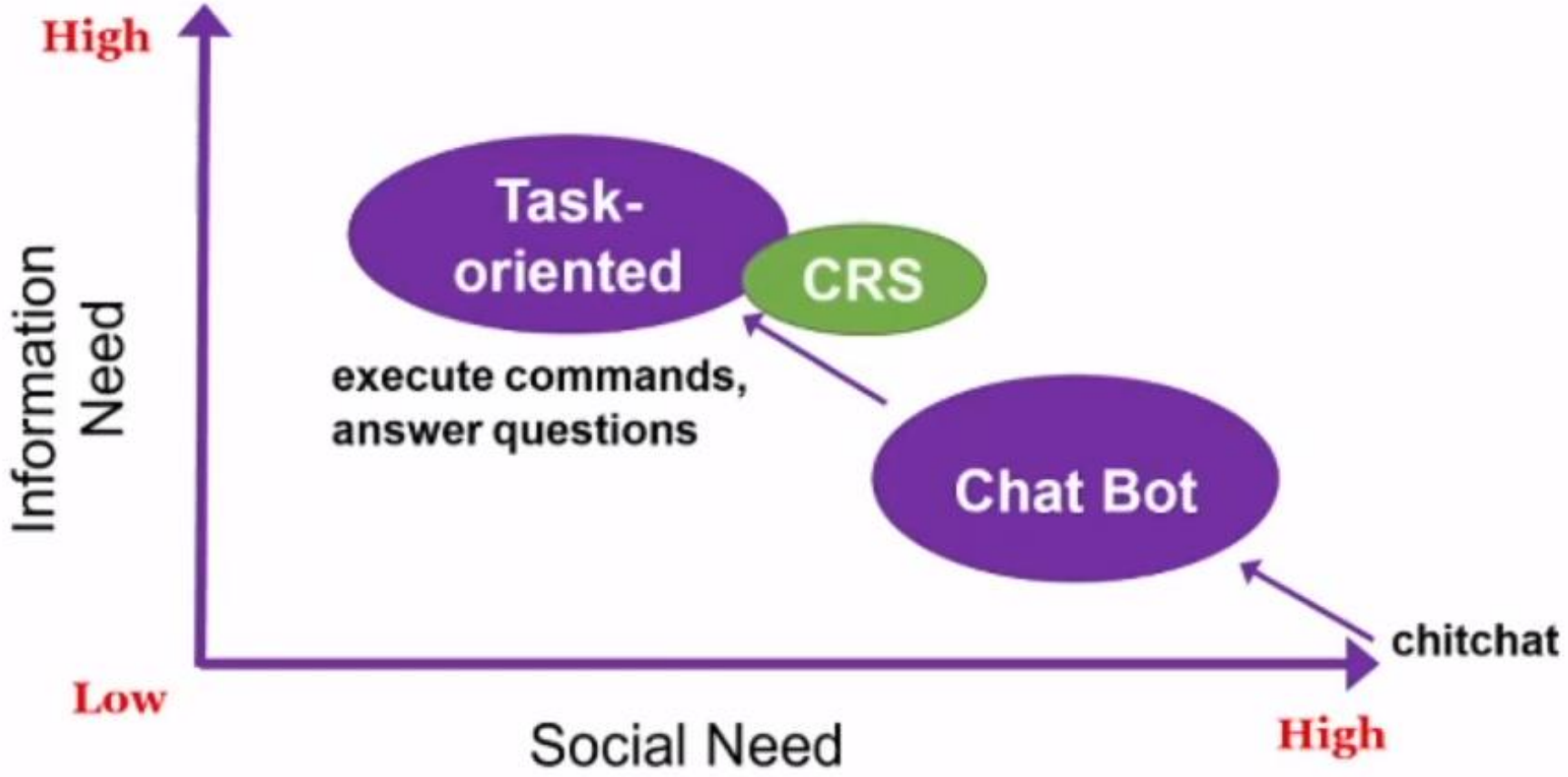
- Seeking information from structured KB or unstructured documents in very casual interactions
  - Injecting knowledge in conversations *naturally* and *coherently*
- Key issues: knowledge representation, selection, know-aware generation
- Challenges: topic/knowledge planning, controllability

Part IV: Recommendation

- A Conversational Recommender System (CRS) is a software system that supports its users in achieving recommendation-related goals through a multi-turn dialog
- Three roles: exploring user preferences, making conversational interactions, recommending items



Types of Dialog Systems



Challenge of CRS

- UIU: user intent understanding

Intent Name	Intent Description
Initiate Conversation	Start a dialogue with the system.
Chit-chat	Utterances unrelated to the recommendation goal.
Provide Preferences	Share preferences with the system.
Revise Preferences	Revise previously stated preferences.
Ask for Recommendation	Obtain system suggestions.
Obtain Explanation	Learn more about why something was recommende
Obtain Details	Ask about more details of a recommended object.
Feedback on Recommendation	Give feedback on the provided recommendation(s).
Restart	Restart the dialogue.
Accept Recommendation	Accept one of the recommendations.
Quit	Terminate the conversation.

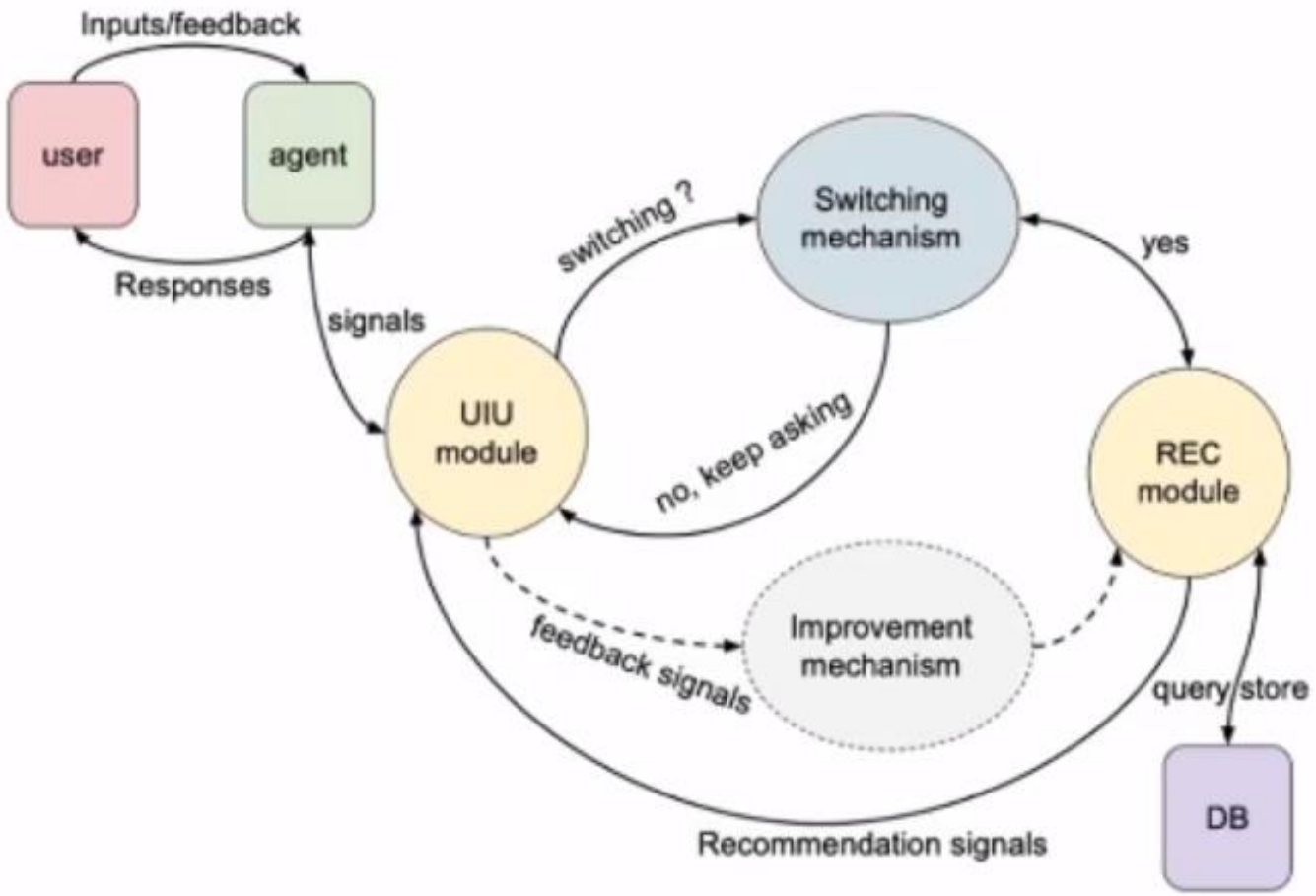
A Survey on Conversational Recommender Systems. Jannach et al.

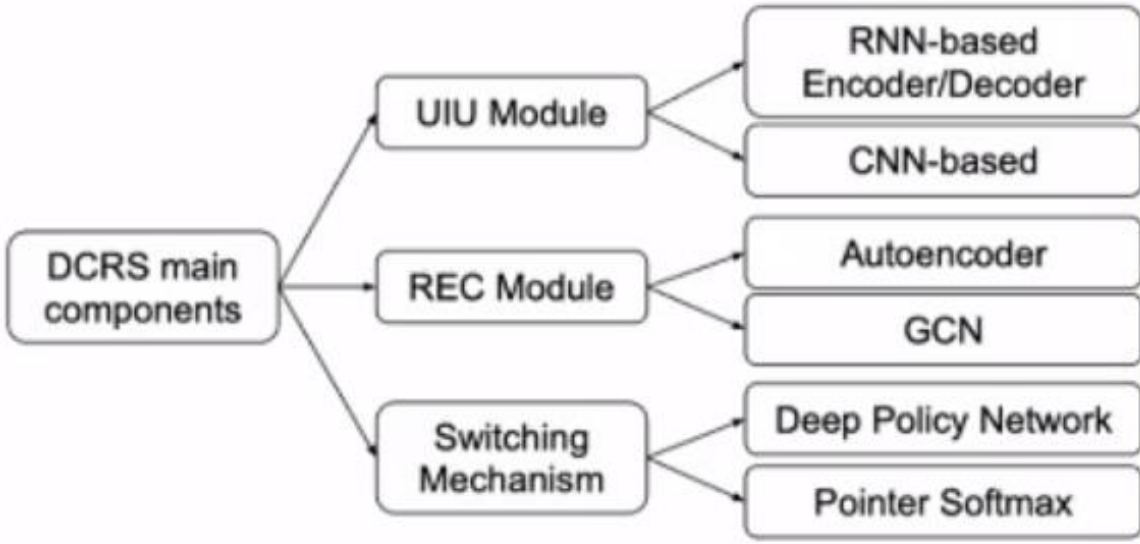
Deep Conversational Recommender System: A New Frontier for Goal-Oriented Dialogue Systems. Tran et al.

Challenge of CRS

- UIU: user intent understanding
- Dialog Policy
  - Exploring user preferences
  - Giving recommendation
- Recommendation and Generation

Procedure of CRS





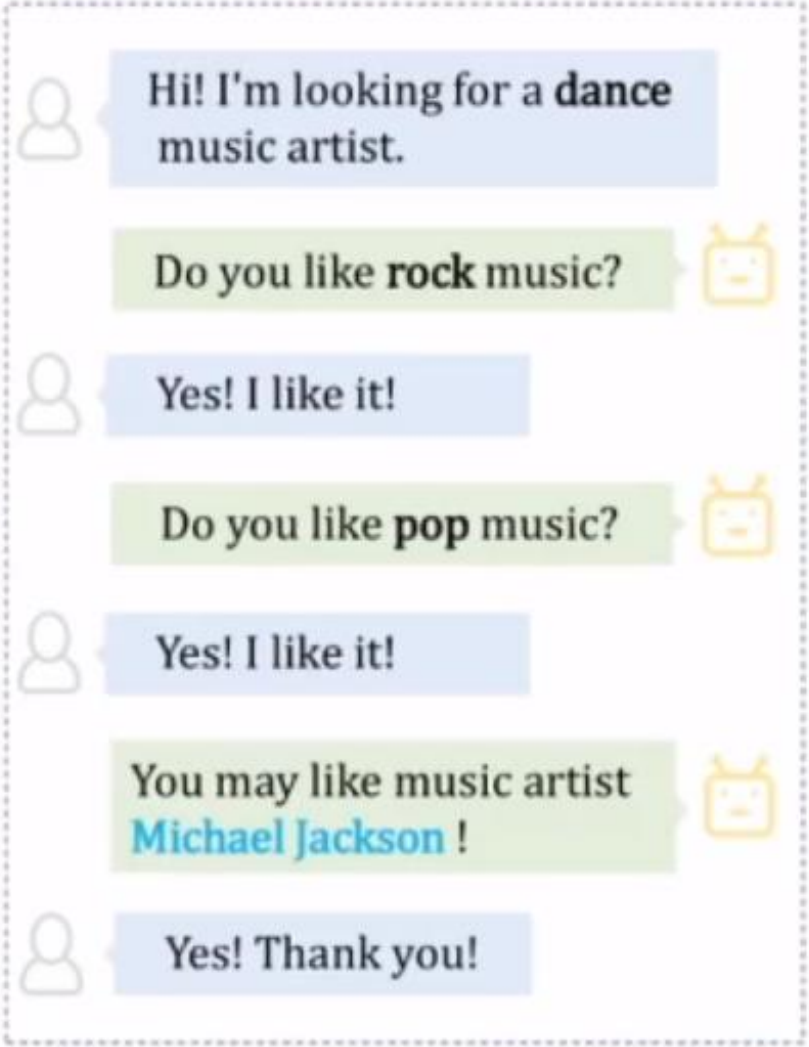
Deep Conversational Recommender System: A New Frontier for Goal-Oriented Dialogue Systems. Tran et al.

Types of CRS

- Recommendation-biased
  - Ask questions about user preference **over pre-defined slots/attributes** to select items for recommendation
  - Clear, controllable but constrained user interaction
- Dialog-biased
  - Have more freedom to influence how the dialog continues and make recommendation **using free text**
  - Natural, flexible but suffered from existing limitations in NLP

Example: R-based CRS

User: inform(city="Glendale", category="Mexican")
User Write: **I'm looking for Mexican food in Glendale.**
Agent: Which state are you in?
User: inform(state="AZ")
User Write: **I'm in Arizona.**
Agent: Which price range do you like?
User: inform(price_range="cheap")
User Write: **Low price.**
Agent: What rating range do you want?
User: inform(rating_range>="3.5")
User Write: **3.5 or higher**
Agent: <make recommendations>
User: thanks()
User Write: **thank you**



Conversational Recommender System [Sun and Zhang, 2018]

Example: D-based CRS

User: I am looking for recommendation!

Agent: What kinds of movies do you like?

User: I like thriller movies and filmed around 1990

Agent: How about this movie? [Recommend "Out of Sight"]

Agent: I recommend this because it's filmed on 19s and crime movie. You may like it!

User: [Accept recommendation] I like the film by George Cooney because he is my favorite actor!

Recommendation as a Communication Game: Self-Supervised Bot-Play for Goal-oriented Dialogue [Kang, et al., 2019]

D-based CRS

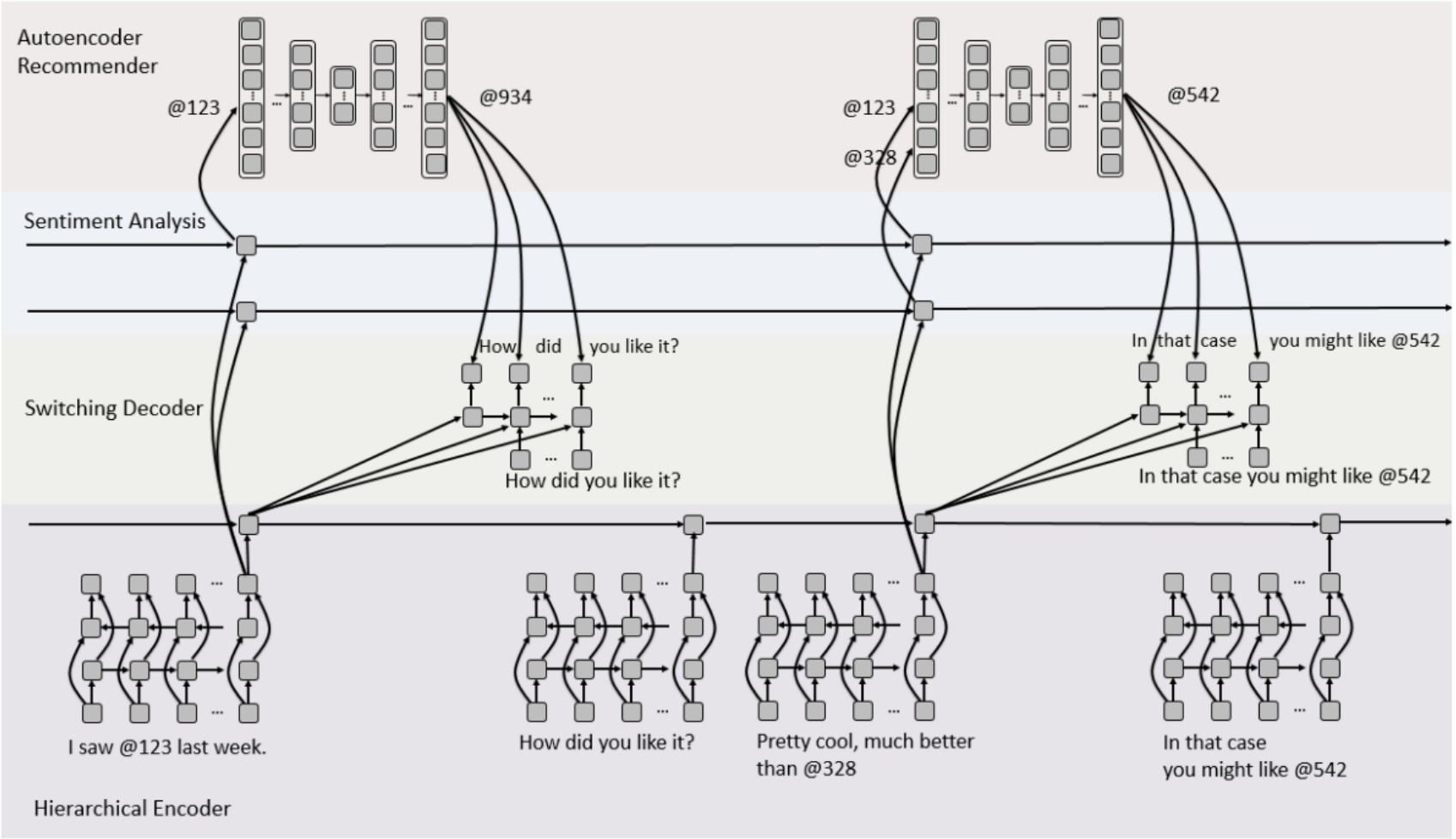


Figure 1: Our proposed model for conversational recommendations.

Towards Deep Conversational Recommendations. NIPS 2018

D-based CRS

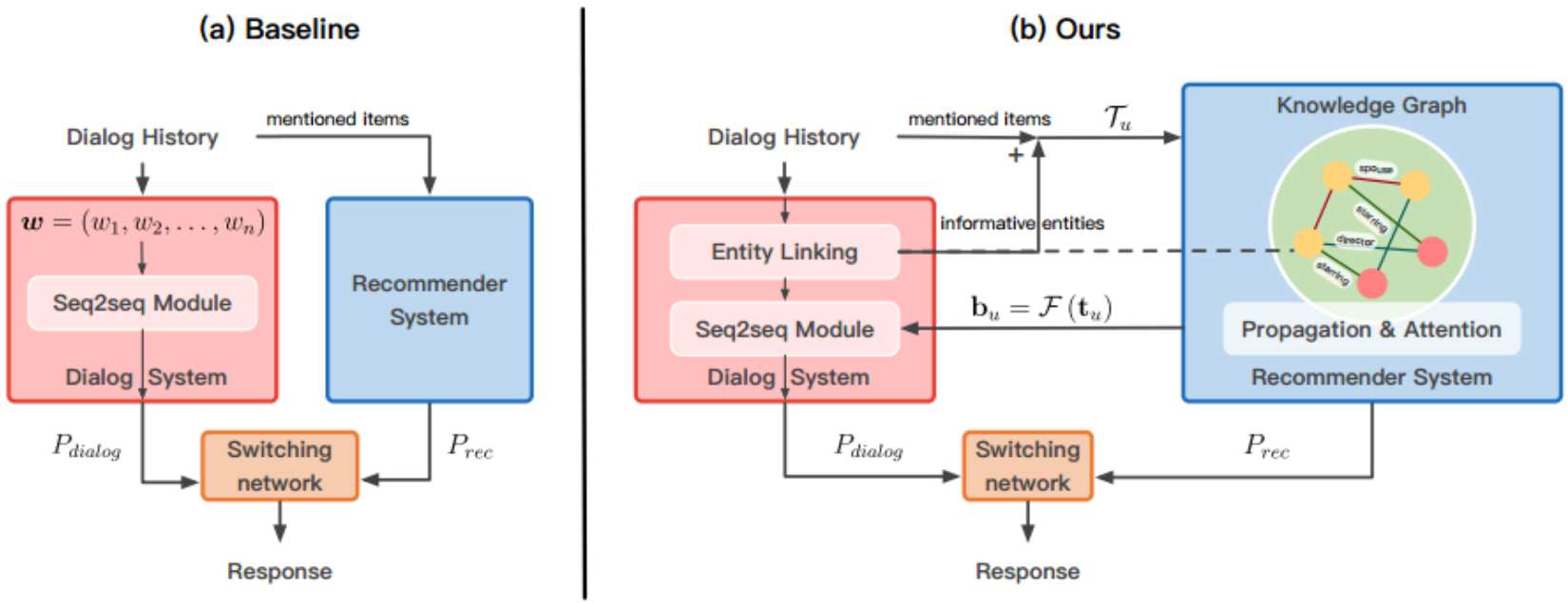


Figure 1: **Comparative illustration on modules of the existing baseline framework and our proposed KBRD framework.** (a) The connection between the recommender system and the dialog system in the baseline framework is weak. The dialog system takes the plain text of the dialog history as input and the recommender only considers mentioned items in the dialog. (b) Our framework enables interaction between the two systems. First, informative entities are linked to an external knowledge graph and sent to the recommender besides items. They are propagated on the KG via a relational graph convolutional network, enriching the representation of user interest. Second, the knowledge-enhanced user representation is sent back to the dialog system in the form of vocabulary bias, enabling it to generate responses that are consistent with the user's interest.

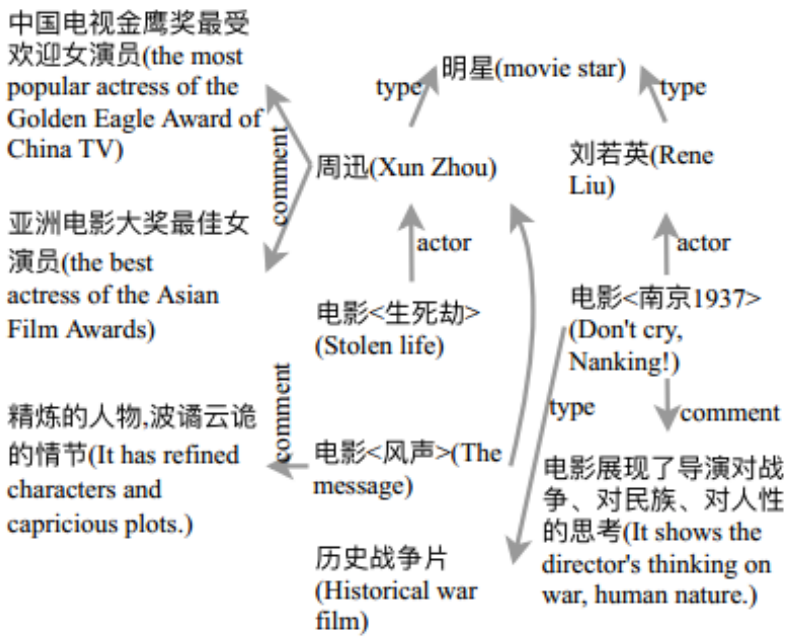
$$P_{\text{dialog}} = \text{softmax}\left(Wo + b + b_u\right)$$

Towards Knowledge-Based Recommender Dialog System. EMNLP 2019

User profile

Name:杨凡宇(Fanyu Yang)
Gender: 男(Male)
Age: 20
Domains that the user likes: movie, music
Stars that the user likes: 周迅(Xun Zhou)，刘若英(Rene Liu)
Recommendation accepted: <生死劫>(Stolen Life)
Recommendation rejected: <小王子>(The little prince)

Knowledge graph



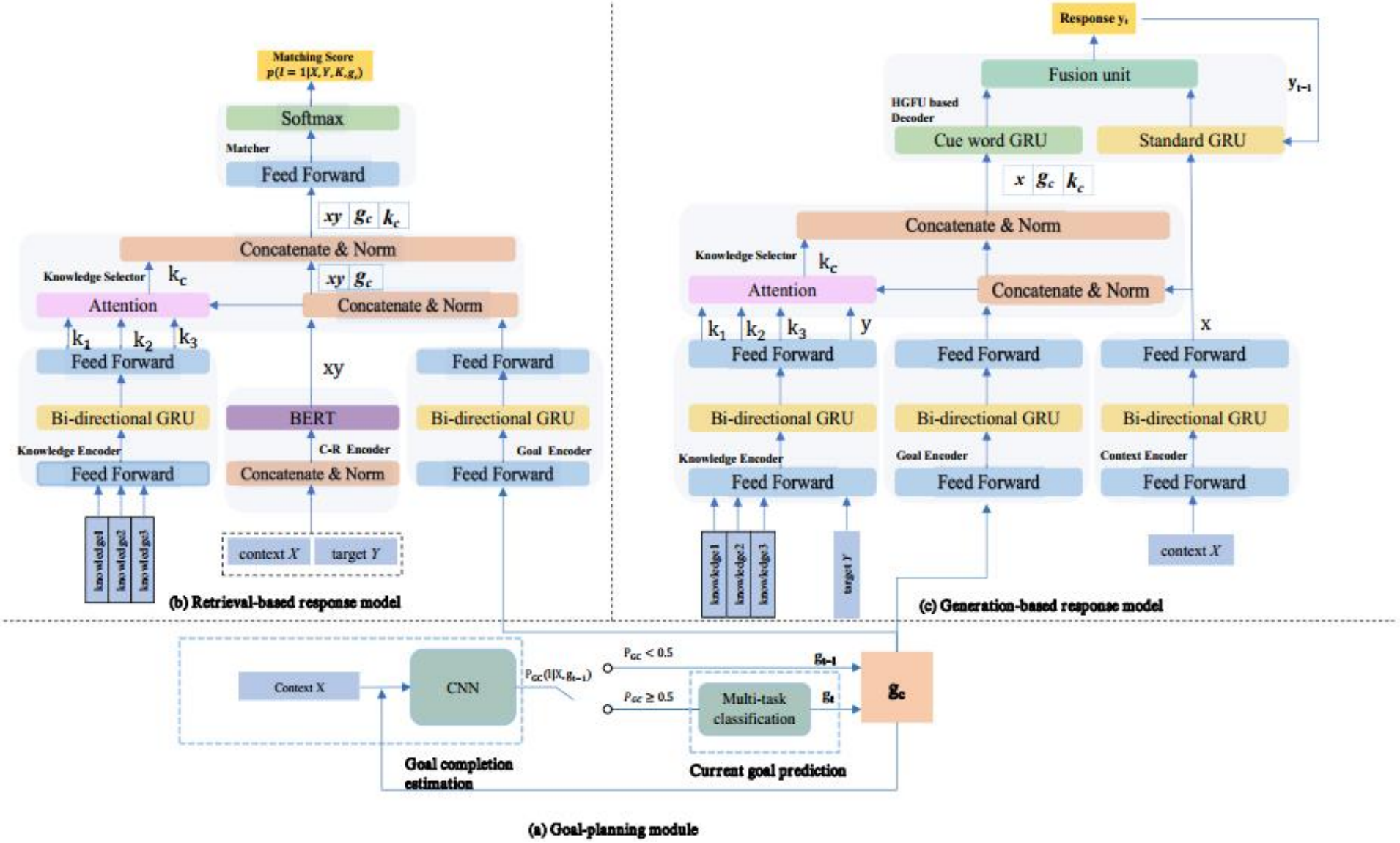
Conversational recommendation

Goal planning: QA about <Stolen life>, chitchat about Xun Zhou, recommending the movie <The message>, recommending <Don't cry, Nanking!>

1.User: 你知道电影『生死劫』的主演是谁吗? (Who is the star of the movie <stolen life>?)
2.Bot: 是周迅哦。(It is Xun Zhou.)
3.User:是我女神演的呀! (She is my goddess.)
4.Bot: 你真有眼光啊，周迅是中国电视金鹰奖最受欢迎女演员呢。(You have good taste. Zhou Xun is the most popular actress in the Golden Eagle Award of China TV.)
5.User:是呢，我特别喜欢她的，她的演技也很厉害。(I like her very much. She's very good at acting.)
6.Bot:她还获得过亚洲电影大奖最佳女演员的，演技是得到过国际认可的。(She also won the best actress of the Asian Film Awards. Her acting is internationally recognized.)
7.User:嗯嗯，反正她真的很优秀。(Anyway, she's really good.)
8.Bot:那你要看看她演的《风声》吗？该片具有精炼的人物，波谲云诡的情节。很好看哦！(Do you want to see her movie <The message>? It has refined characters and capricious plots.)
9.User:可我现在更喜欢『刘若英』的电影!(But now I prefer Rene Liu's films!)
10.Bot:那刘若英的《南京1937》你可以看看，电影所展现的是一个导演对战争、对民族、对人性的思考。(You can see the movie <Don't cry, Nanking>. It shows the director's thinking on war, nation, and human nature.)
11.User: 历史片吗？(It is historical film?)
12.Bot:历史战争片。(Yes. It is historical war film.)
13.User:那我肯定要看看了。(I will watch it!)
14.Bot:嗯，你肯定会喜欢的。(Sure, you will like it!)
15.User: 嗯，谢谢你呀，下次聊吧! (Thank you! See you later!)
16.Bot:好的，再见！(OK! Bye!)

Towards Conversational Recommendation over Multi-Type Dialogs. ACL2020

A multi-goal driven conversation generation framework (MGCG)

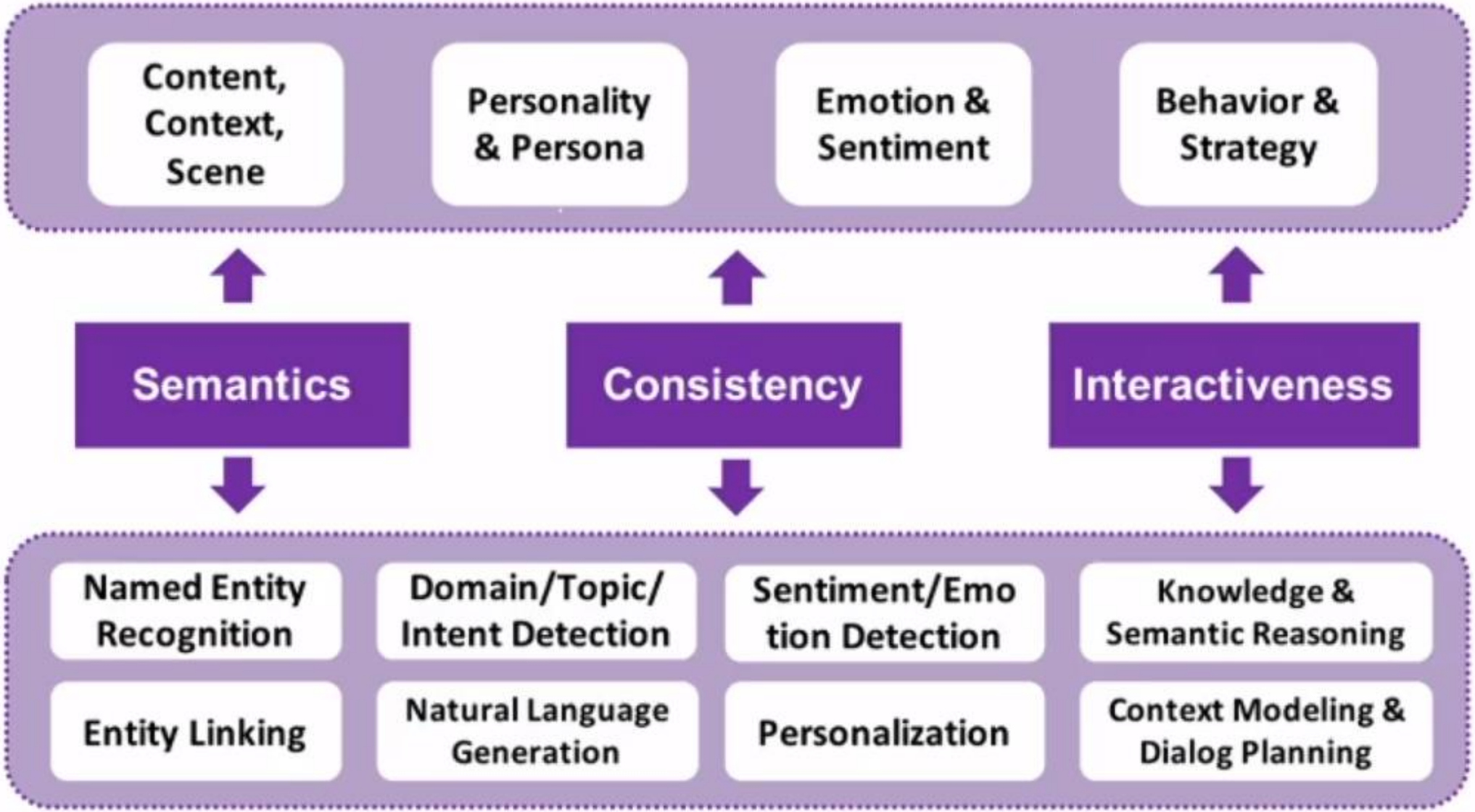


Towards Conversational Recommendation over Multi-Type Dialogs. ACL2020

Future: where to go?

- Robustness and uncertainty
- Huge data, huge model?

Challenges in Socialbots



Future: robustness & uncertainty

Uncertainty in natural language generation

- Avoid generating offensive language
- Avoid morality and ethics issues

[P1:] greetings and salutations my friend
[P2:] hi how are you doing?
[P1:] i'm well. enjoying some r r from the navy station
[P2:] i love to cook. do you cook?
[P1:] i do on occasion. i love to read more though.
[P2:] **reading the menu doesnt count**

Case from: "Build it Break it Fix it for Dialogue Safety: Robustness from Adversarial Human Attack"

Challenges and Issues

Human: What's your favorite band?

Meena: Avenged sevenfold.

Human: Ooh, that's a good answer! What's your least favorite band?

Meena: Avenged sevenfold.

Human: Oh, i thought you liked Avenged sevenfold?

Meena: Yeah. That's my favorite band.

From: Gary Marcus. Then next decades in AI: the four steps towards robust artificial intelligence. 2020.

Challenges and Issues

Human: What are some of your new year resolutions?

Meena: Lose 60 pounds Learn Cantonese Learn French

Human: Don't you think, that's pretty far fetched? :P

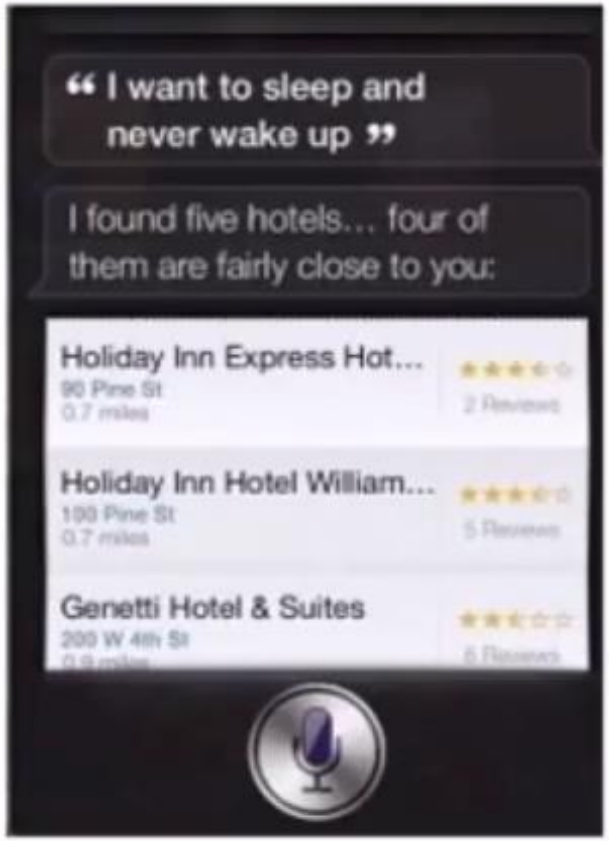
Meena: Not really. I'm currently down 35 pounds, I can already speak Cantonese to a basic level, and I'm already learning French in school.

Human: Wao! That's impressive!

Meena: I'm learning French on the side, it's really easy for me since I'm a native Cantonese speaker.

From: Gary Marcus. Then next decades in AI: the four steps towards robust artificial intelligence. 2020.

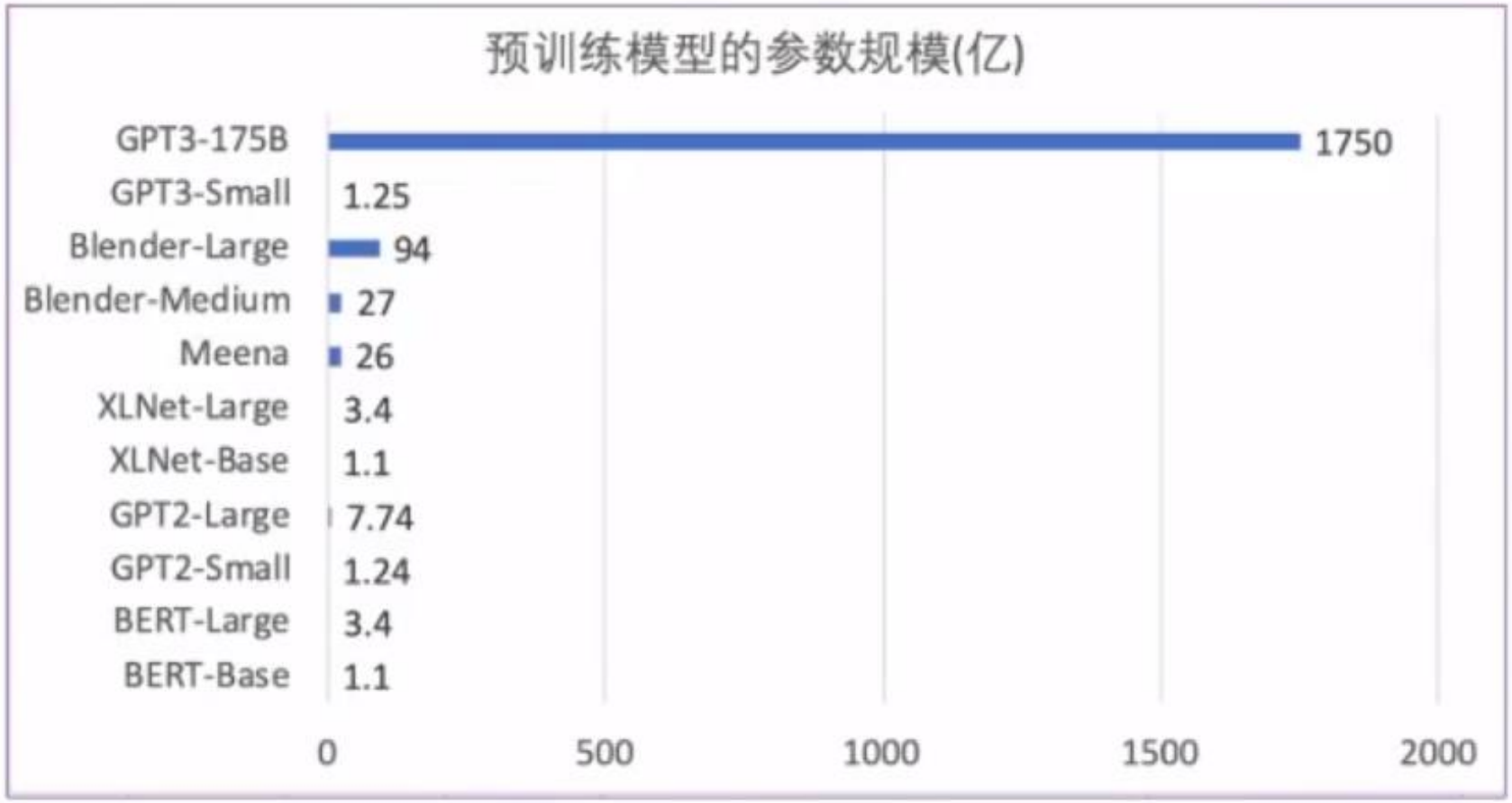
Challenges and Issues



Serious ethic problems!

Picture from Prof. Frank Rudzicz, University of Toronto

Future: data & model Size



训练数据

GPT3	**500B tokens;** Common Crawl (410B), WebText2 (19B), Books1 (12B), Books2 (55B), Wikipedia (3B)
Blender	Reddit (1.5B comments, 56.8B BPE tokens, 88.8B context tokens)
Meena	**40B words**, social media
XLNet	**130GB** Book, ClueWeb, Common Crawl
GPT2	WebText (8M documents, 40GB text)
BERT	**3.3B words;** BookCorpus, English Wikipedia

Huge model + huge data + huge compute

- Size matters!
- Extremely compute and resource consuming!
- **What is the future?**

	Model	Size	Data Scale	Training Time using a single V100 GPU
OpenAI	GPT	110M	4GB	3 days
Google	BERT	330M	16GB	50 days
OpenAI	GPT-2	1.5B	40GB	200 days
Facebook	RoBERTa	330M	160GB	3 years
Google	T5	11B	800GB	66 years
OpenAI	GPT-3	175B	2TB	355 years

Our recent papers

- Challenges in Building Intelligent Open-domain Dialog Systems. ACM Transactions on Information Systems 2020.
- A Pre-training Based Personalized Dialogue Generation Model with Persona-sparse Data. AAAI 2020
- KdConv: A Chinese Multi-domain Dialogue Dataset Towards Multi-turn Knowledge-driven Conversation. ACL 2020
- A Large-scale Chinese Short-text Conversation Dataset. NLPCC 2020, Best Student Paper
- Is Your Goal-Oriented Dialog Model Performing Really Well? Empirical Analysis of System-wise Evaluation. SIGDIAL 2020, Best Paper
- ConvLab-2: An Open-Source Toolkit for Building, Evaluating, and Diagnosing Dialogue Systems. ACL 2020 demo track
- Multi-Agent Task-Oriented Dialog Policy Learning with Role-Aware Reward Decomposition. ACL 2020
- Out-of-domain Detection for Natural Language Understanding in Dialog Systems. IEEE/ACM Trans. Audio, Speech, and Language Processing 2020
- CrossWOZ: A Large-Scale Chinese Cross-Domain Task-Oriented Dialogue Dataset. TACL 2020

More is on http://coai.cs.tsinghua.edu.cn/hml

Thanks for your attention

- Recruiting post-docs, engineers, PhDs, & interns

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