Advances and Challenges in Conversational Recommender Systems: A Survey

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problem background

- shortcoming of static recommender system:
  - (a) What exactly does a user like?
  - (b) Why does a user like an item?
- CRS
  - *A recommendation system that can elicit the dynamic preferences of users and take actions based on their current needs through real-time* ***multi-turn*** *interactions using* ***natural language****.*

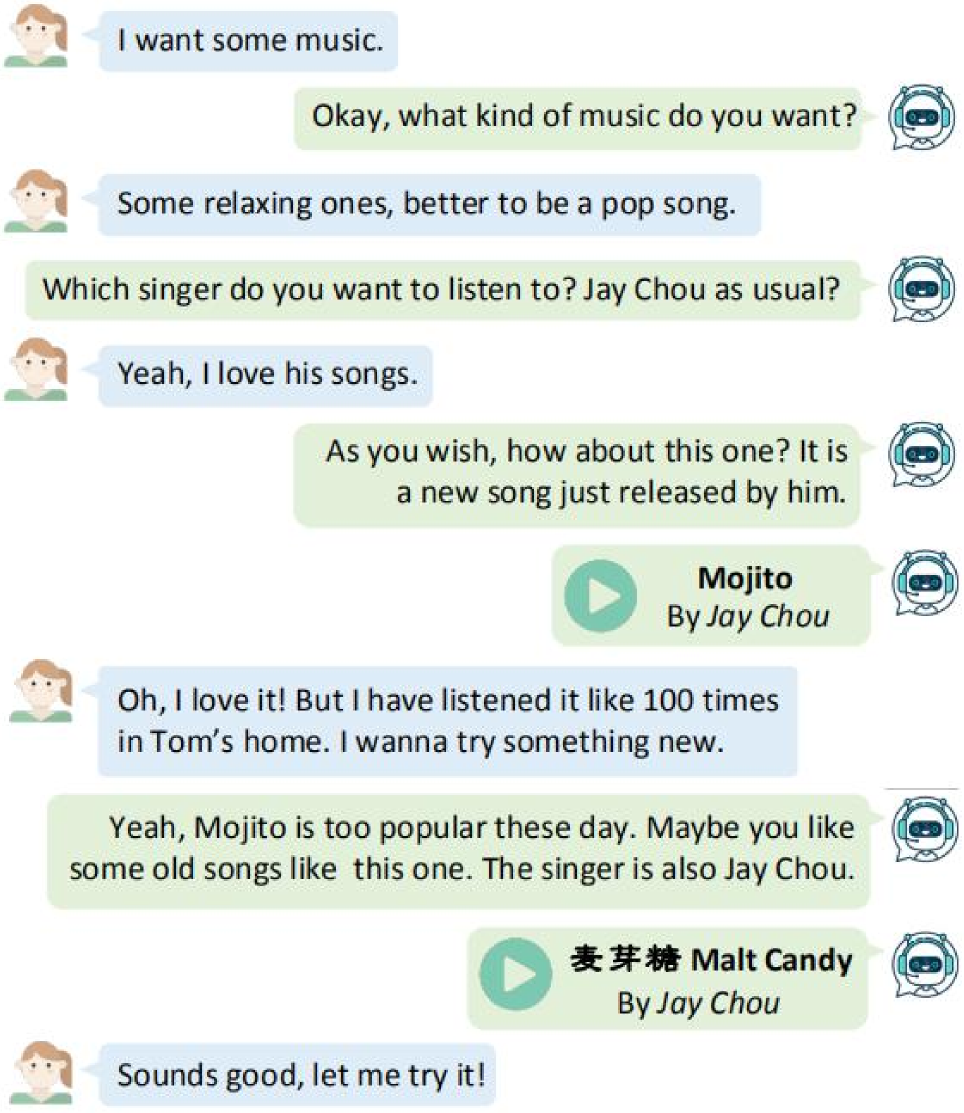


Figure 1: A toy example of a conversational recommender system in music recommendation.

Table 2: The schema based dialogue collection example. The bold utterances are written by the crowd sourcing workers via rewriting the templates to interact with the agent.

The target restaurant has the following facets.
{category: Mexican, state: AZ, city: Glendale,
price range: cheap, rating range: >=3.5}

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**

Sun et al. "Conversational Recommender System" (SIGIR' 18)

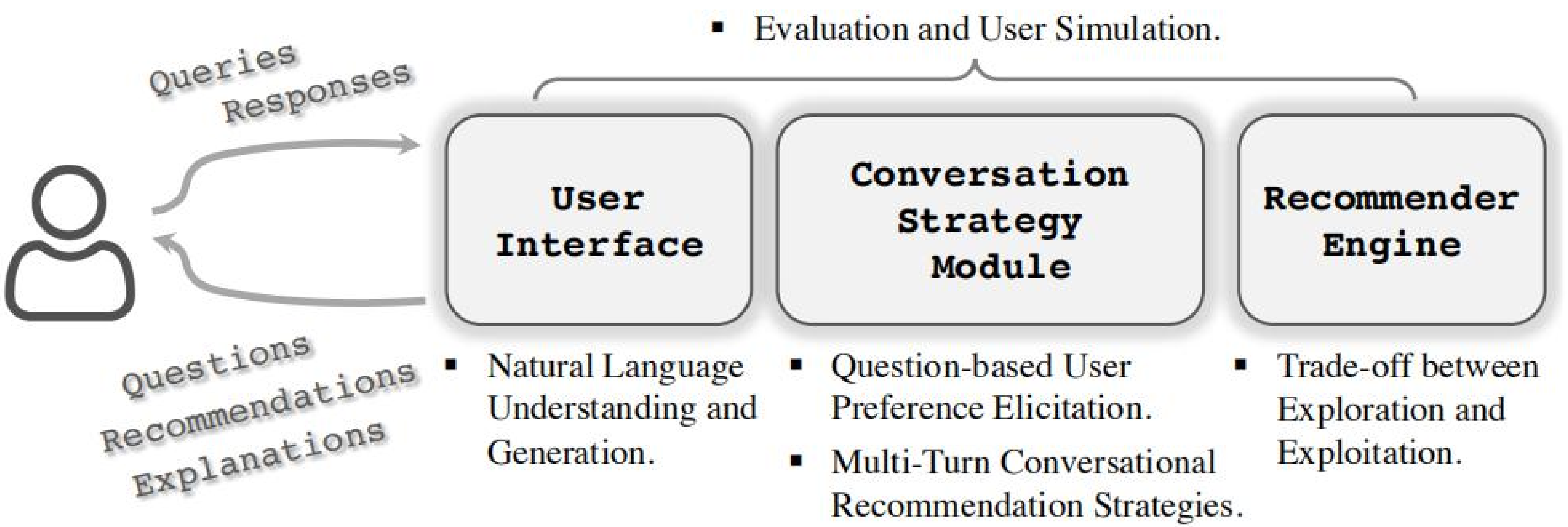


Figure 3: Illustration of the general framework of CRSs and our identified five primary challenges on the three main components.

- Question-based User Preference Elicitation
- Multi-turn Conversational Recommendation Strategies
- Natural Language Understanding and Generation
- Trade-offs between Exploration and Exploitation (E&E)
- Evaluation and User Simulation

Question-based User Preference Elicitation

- Asking about Items
  - Choice-based Methods
  - Bayesian Preference Elicitation
  - MAB-based Methods
- Asking about Attributes
  - Fitting Patterns from Historical Interaction
  - Reducing Uncertainty
    - Critiquing-based Methods
    - Reinforcement Learning-driven Methods
    - Graph-constrained Candidates

Choice-based Methods

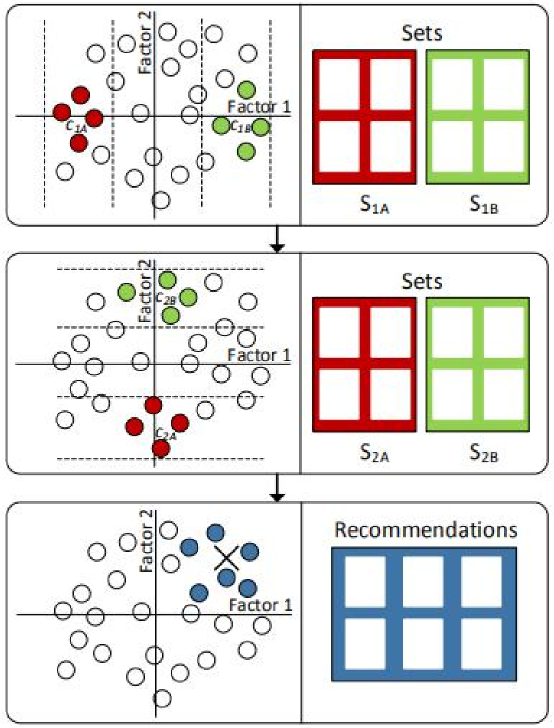


Figure 2. For each factor f taken into account, two sets of movies S_{fA} and S_{fB} are presented to the user. One set shows movies with low factor values, the other movies with high factor values. The user selects one of these sets (or indicates that he/she doesn't care). After a defined number of steps, a set of recommendations is computed.

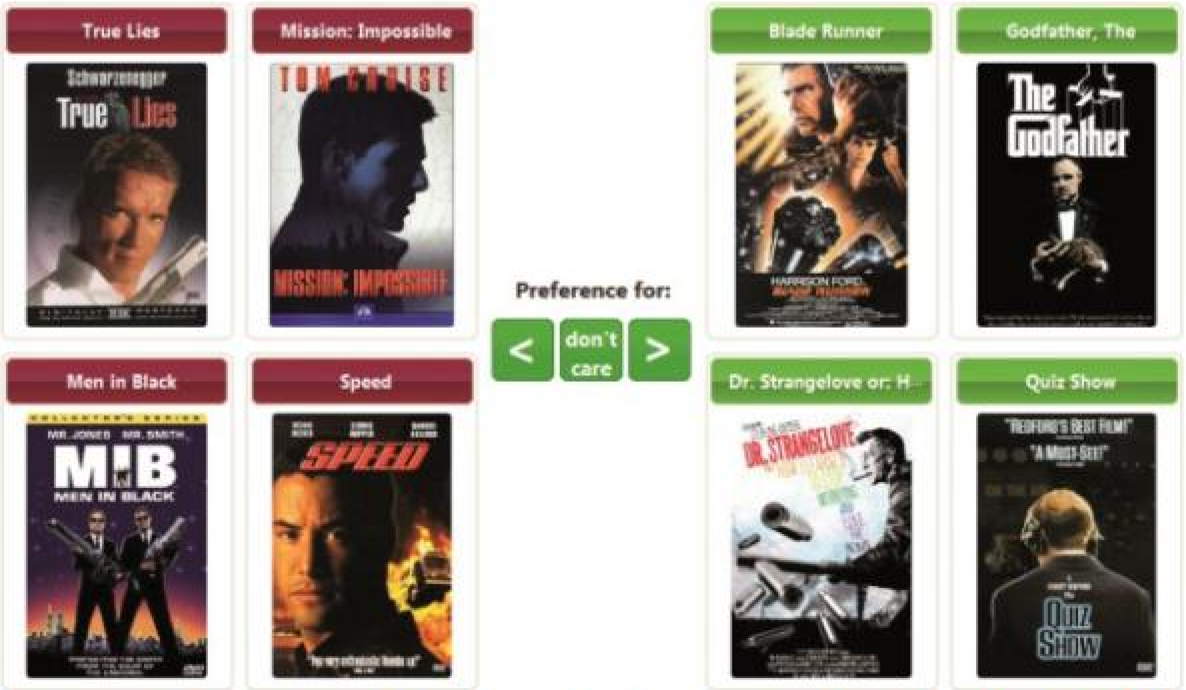


Figure 5. Screenshot showing two movie sets that differ strongly in a single factor. While the left set contains low-brow action movies, the right-hand side displays more serious movies with a rather dark mood.

Benedikt Loepp, Tim Hussein, and Jüergen Ziegler. 2014. Choice Based Preference Elicitation for Collaborative Filtering Recommender Systems. In Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI 14). 3085–3094.

Bayesian Preference Elicitation

score function: $$u\left(\mathbf{x}_j, \mathbf{u}_i\right) = \mathbf{x}_j^T \mathbf{u}_i.$$

$$\mathbb{E}\left[u\left(\mathbf{x}_j, \mathbf{u}_i\right)\right] = \int_{\mathbf{u}_i \sim \mathcal{U}^{(i)}} P(\mathbf{u}_i) u\left(\mathbf{x}_j, \mathbf{u}_i\right) d\mathbf{u}_i.$$

update: $$P(\mathbf{u}_i | q, r_i) = \frac{P\left(r_i \mid q, \mathbf{u}_i\right) P(\mathbf{u}_i)}{\int_{\mathcal{U}^{(i)}} P\left(r_i \mid q, \mathbf{u}_i\right) P(\mathbf{u}_i) d\mathbf{u}_i}$$

query strategy:

(1) a pairwise comparison query

(2) a slate query

MAB-based Methods

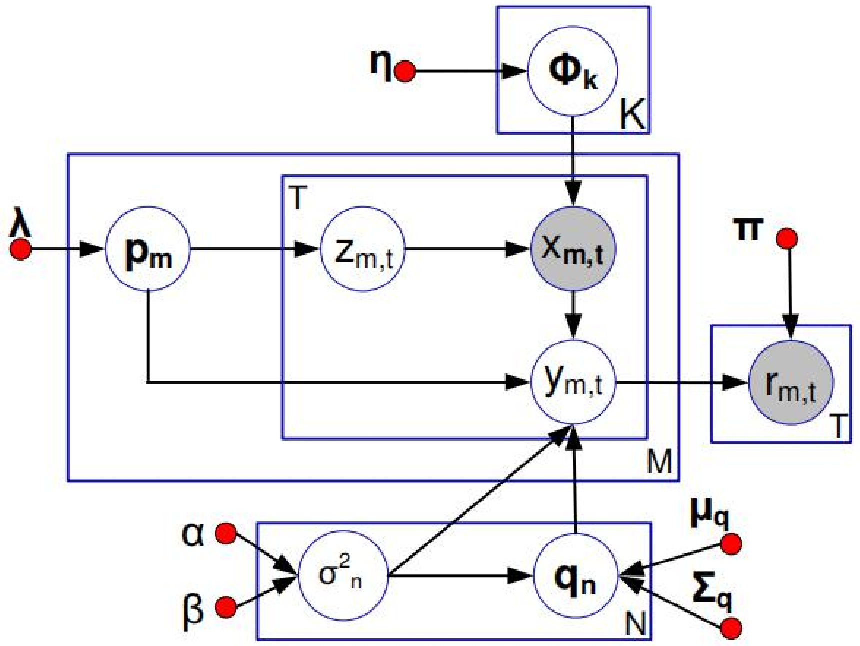


Figure 1: The graphic model for the ICTR model. Random variable is denoted as a circle. The circle with filled color denotes the observed random variable. Red dot represents a hyper parameter.

Topic Cluster I		
MovieId	MovieName	MovieType
32	12 Monkeys	Sci-Fi,Thriller
50	Usual Suspects	Crime,Mystery,Thriller
590	Dances with wolves	Adventure,Drama,Western
592	Batman	Action,Crime,Sci-Fi,Thriller

Topic Cluster II		
MovieId	MovieName	MovieType
344	Pet Detective	Comedy
588	Aladdin	Children,Animation,Comedy
595	Beauty and the Beast	Animation,Children,Musical
2857	Yellow Submarine	Adventure,Animation,Comedy,Musical

Qing Wang. Online Interactive Collaborative Filtering Using Multi-Armed Bandit with Dependent Arms. (TKDE'18)

- Asking about Attributes
    - Fitting Patterns from Historical Interaction
    - Reducing Uncertainty
        - Critiquing-based Methods
        - Reinforcement Learning-driven Methods
        - Graph-constrained Candidates

Fitting Patterns from Historical Interaction

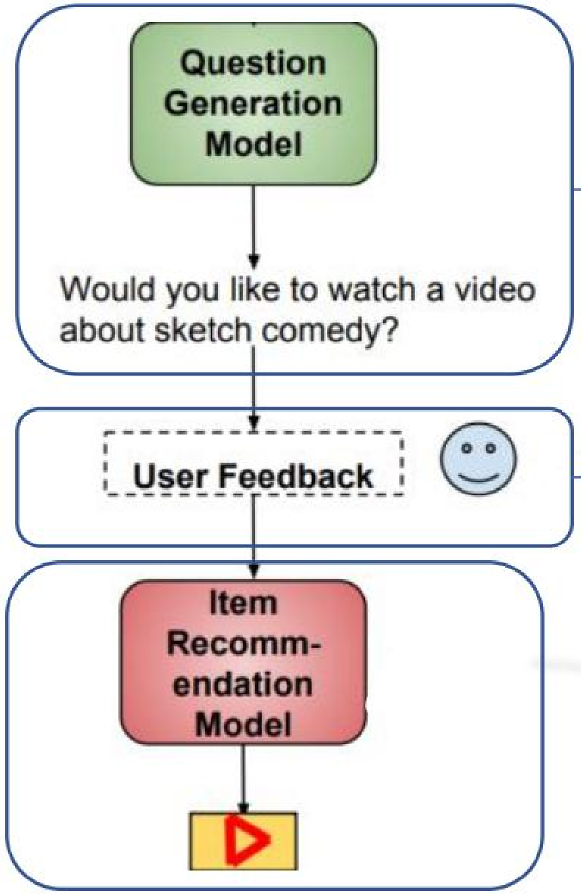


Figure 1: High-level *Q&R* overview.

Figure 2: User Onboarding UI.

Only asking question once and make one recommendation

Positive-only type of feedback (click topics)

User is prompted to choose as many topics as they like

Incorporates the user feedback to improve video recommendations

Christakopoulou et al. "Q&R: A Two-Stage Approach toward Interactive Recommendation" (KDD'18)

Fitting Patterns from Historical Interaction

Two Main Tasks

feedback

building better user profiles

i.e., predicting the sequential future (interested topic)

What to ask

step1

How to respond

step2

given the video(user interests)

i.e., predicting the video that the user be most interested in

the sequence of watch videos

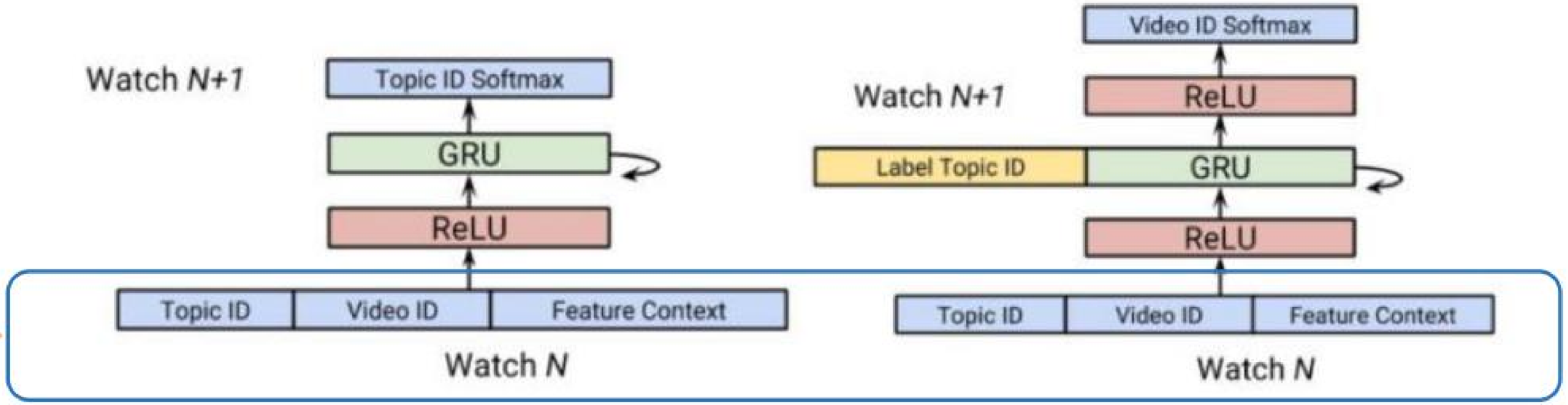


Figure 3: *Left:* Topic Prediction (Question Ranking) Model. *Right:* Post-Fusion Approach for Response Model.

Fitting Patterns from Historical Interaction

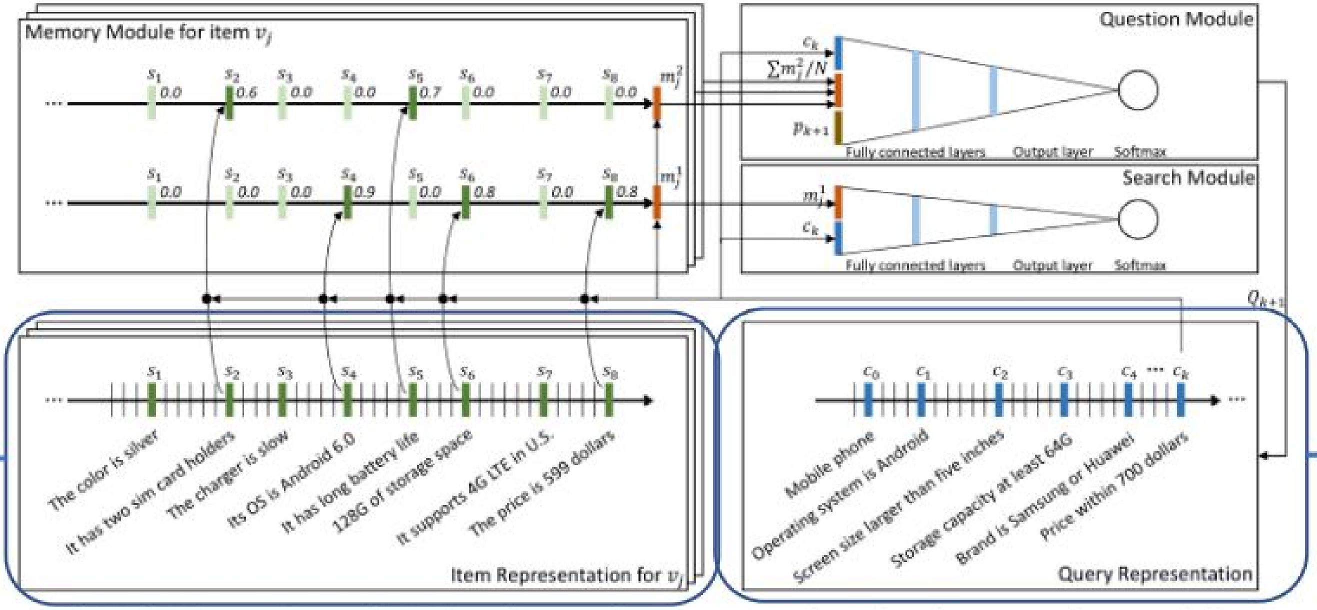


Figure 3: The Multi-Memory Network (MMN) architecture for conversational search and recommendation, including five components: query and item representations, the memory module, as well as the question and search modules.

Item Representations

- Apply a gated recurrent unit (GRU) on the text description of each item
- The hidden states of each sentence as the representation of $\boldsymbol{T}_j(s_1, s_2 \dots s_\tau)$

Query Representation

- Also a gated recurrent unit (GRU)
- Query sequence c1, c2 … is extracted in conversations

Zhang et al. “Towards Conversational Search and Recommendation: System Ask, User Respond” (CIKM‘18)

Joint optimize

Question Loss + Search (item) Loss → The Unified Architecture

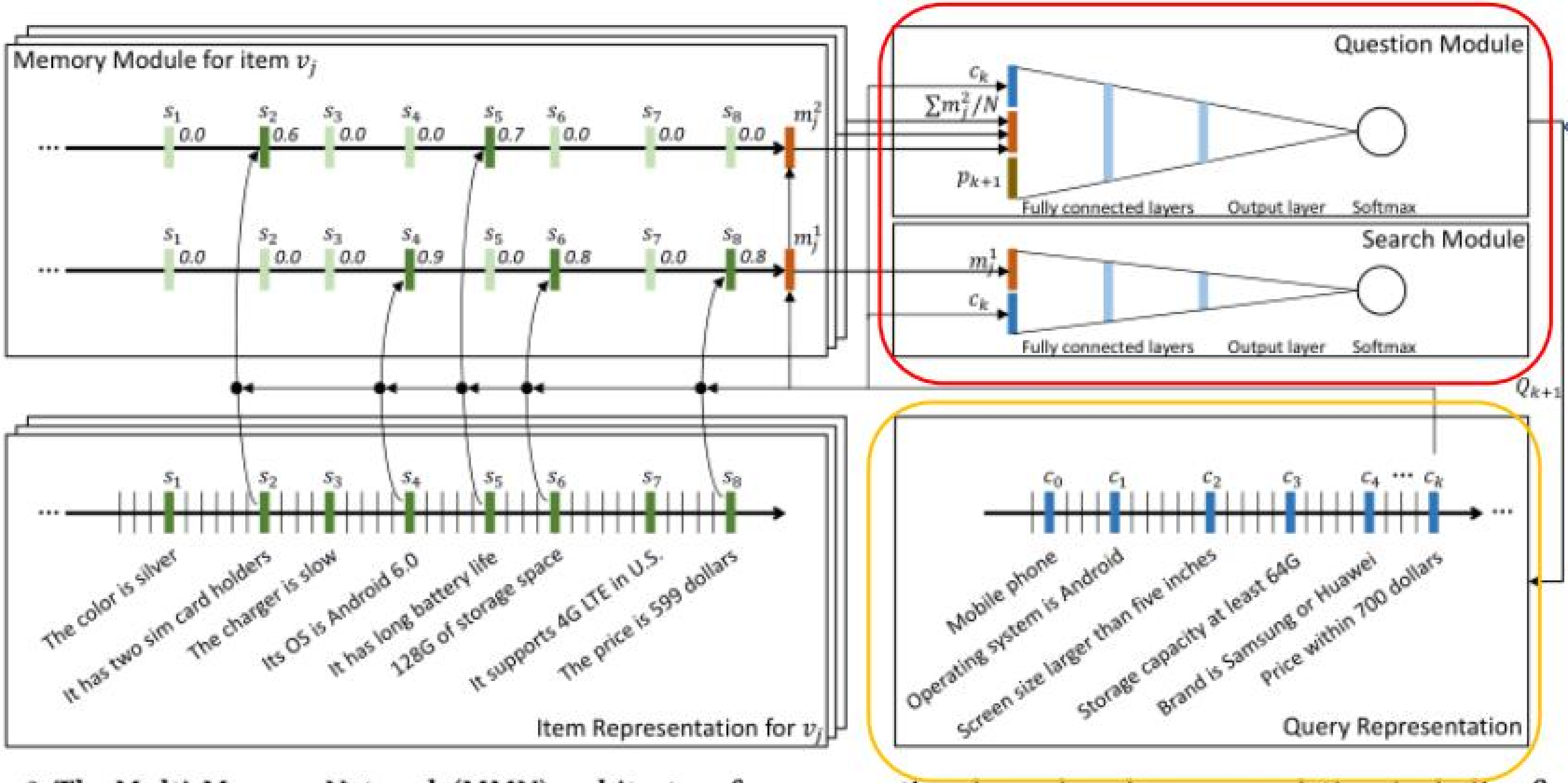


Figure 3: The Multi-Memory Network (MMN) architecture for conversational search and recommendation, including five components: query and item representations, the memory module, as well as the question and search modules.

Evaluation Criteria:

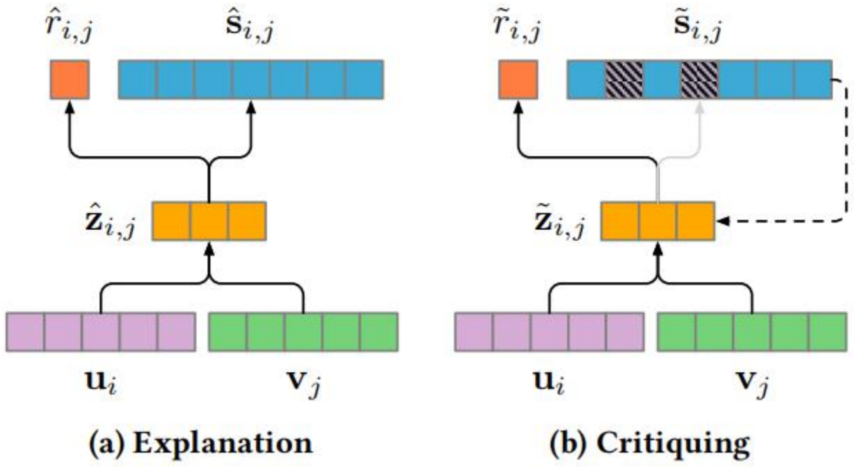
1. Query prediction
2. Item prediction (e.g., NDCG)

c_0 : constructed from the product category c

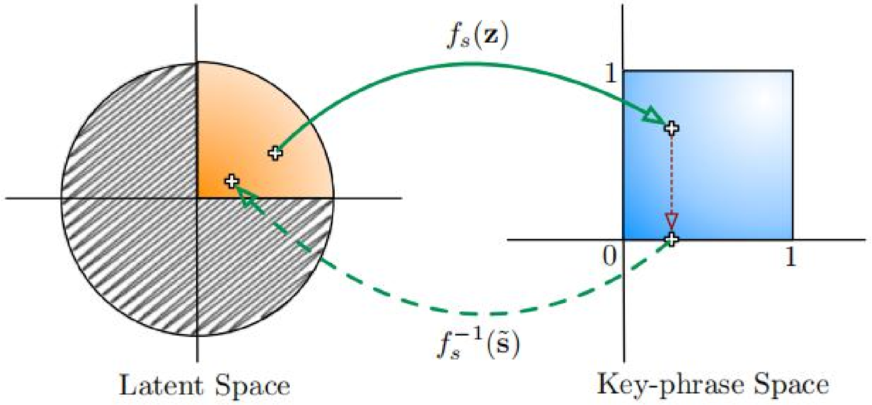
c_k : Question-answer sequence (The order mentioned in the review)

- Reducing Uncertainty
  - Critiquing-based Methods
  - Reinforcement Learning-driven Methods
  - Graph-constrained Candidates

Reducing Uncertainty—Critiquing-based Methods



Dataset	Reason Type	Keyphrases
Beer	Head	white, tan, offwhite, brown
	Malt	roasted, caramel, pale, wheat, rye
	Color	golden, copper, orange, black, yellow
	Taste	citrus, fruit, chocolate, cherry, plum
CDs&Vinyl	Genre	rock, pop, jazz, rap, hip hop, R&B
	Instrument	orchestra, drum
	Style	concert, opera
	Religious	chorus, christian, gospel



Ga Wu, Kai Luo, Scott Sanner, and Harold Soh. 2019. Deep Language-Based Critiquing for Recommender Systems. In Proceedings of the 13th ACM Conference on Recommender Systems (RecSys'19). 137–145.

Reducing Uncertainty—Reinforcement Learning-driven Methods

We use reinforcement learning to find the best strategy.

- policy gradient method
- simple policy network (2-layer feedforward network)

- **State Vector**
- $s_{entropy}$: **The entropy of attribute is important.**
- $s_{prefrence}$: **User's preference on each attribute.**
- $s_{history}$: **Conversation history is important.**
- s_{length}: **Candidate item list length.**

Note: 3 of the 4 information come from Recommender Part

Action Space: $|\mathcal{P}| + 1$

Reward

$r_{success}$: Give the agent a big reward when it successfully recommend!

r_{ask}: Give the agent a small reward when it ask a correct attribute.

r_{quit}: Give the agent a big negative reward when the user quit (the conversation is too long)

$r_{prevent}$: Give each turn a relatively small reward to prevent the conversation goes too long.

Lei et al. "Estimation–Action–Reflection: Towards Deep Interaction Between Conversational and Recommender Systems" (WSDM'20)

Reducing Uncertainty—Graph-constrained Candidates

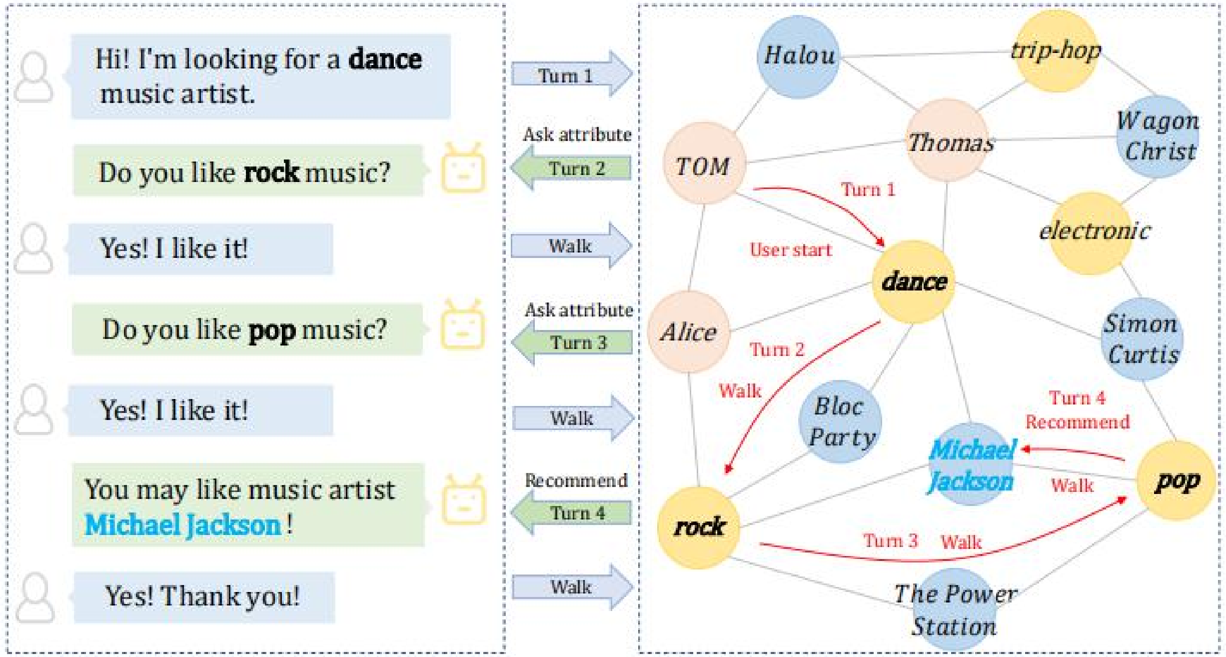
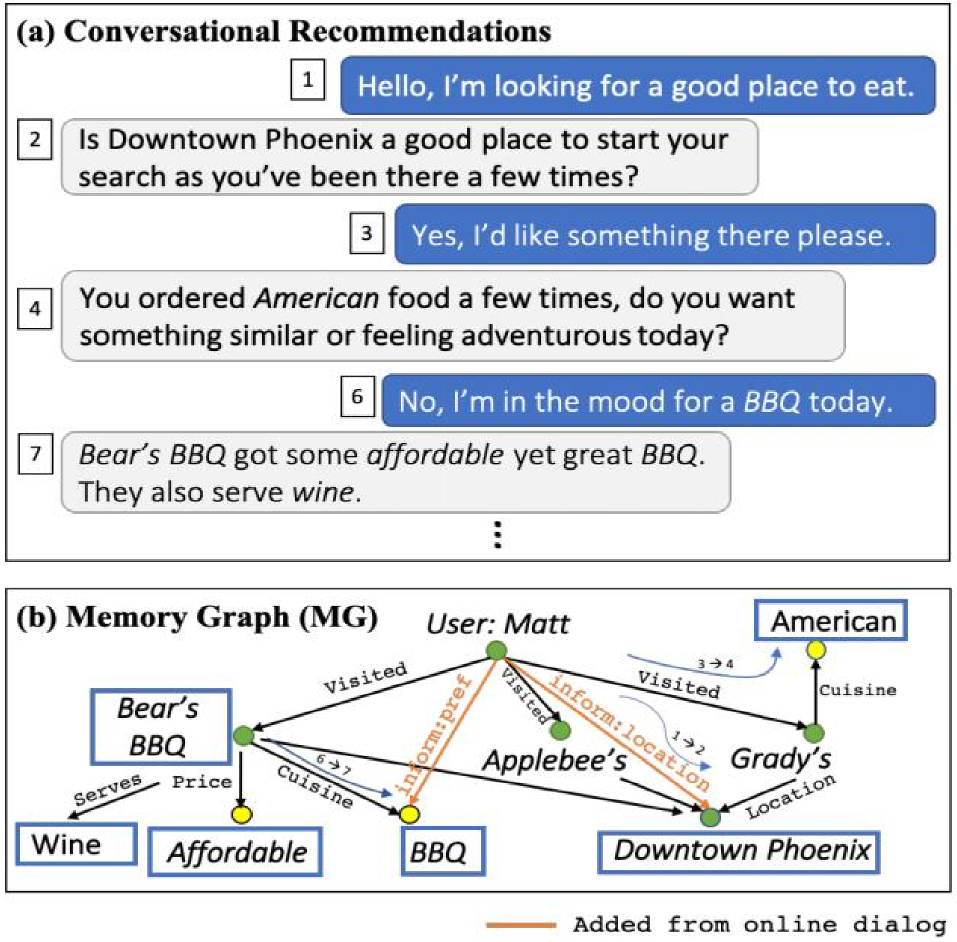


Figure 4: An illustration of interactive path reasoning in the conversational path reasoning (CPR) model. Credits: Lei et al. [89].



Wenqiang Lei. Interactive Path Reasoning on Graph for Conversational Recommendation. (KDD'20). 2073–2083.

Hu Xu. User Memory Reasoning for Conversational Recommendation. (COLING'20). 5288–5308.

Table 1

Characteristics of common CRS models in different dimensions. The strategy indicates whether the work considers an explicit strategy to control multi-turn conversations, e.g., whether to ask or recommend in the current turn.

Asking	Asking Mechanism	Basic Model	Type of User Feedback	Strategy	Publications
Items	Exploitation & Exploration	Multi-Armed bandit	Rating on the given item(s)	No	[217, 32, 220, 184, 205]
Items	Exploitation & Exploration	Meta learning	Rating on the given item(s)	No	[235, 87]
Items	Maximal posterior user belief	Bayesian methods	Rating on the given item(s)	No	[171]
Items	Reducing uncertainty	Choice-based methods	Choosing an item or a set of items	No	[105, 75, 53, 144, 140]
Attributes	Exploitation & Exploration	Multi-Armed bandit	Rating on the given attribute(s)	Yes	[209, 95]
Attributes	Reducing uncertainty	Bayesian approach	Providing preferred attribute values	No	[113]
Attributes	Reducing uncertainty	Critiquing-based methods	Critiquing one/multiple attributes	No	[117, 155, 172, 12, 154] [135, 23, 189, 108, 107]
Attributes	Reducing uncertainty	Matrix factorization	Answering Yes/No for an attributes	No	[232]
Attributes	Fitting historical patterns	Sequential neural network	Providing preferred attribute values	Yes	[31, 210]
Attributes	Fitting historical patterns	Sequential neural network	Providing an utterance	No	[94, 25]
Attributes	Maximal reward	Reinforcement learning	Answering Yes/No for an attributes	Yes	[88, 89]
Attributes	Maximal reward	Reinforcement learning	Providing an utterance	Yes	[161, 167, 76]
Attributes	Maximal reward	Reinforcement learning	Providing an utterance	No	[141]
Attributes	Exploring graph-constrained candidates	Graph reasoning	Answering Yes/No for an attributes	Yes	[89]
Attributes	Exploring graph-constrained candidates	Graph reasoning	Providing an utterance	Yes	[25, 104]
Attributes	Exploring graph-constrained candidates	Graph reasoning	Providing an utterance	No	[225, 98]
Attributes	Exploring graph-constrained candidates	Graph reasoning	Providing preferred attribute values	Yes	[193]
Attributes	Exploring graph-constrained candidates	Graph reasoning	Providing preferred attribute values	No	[123]

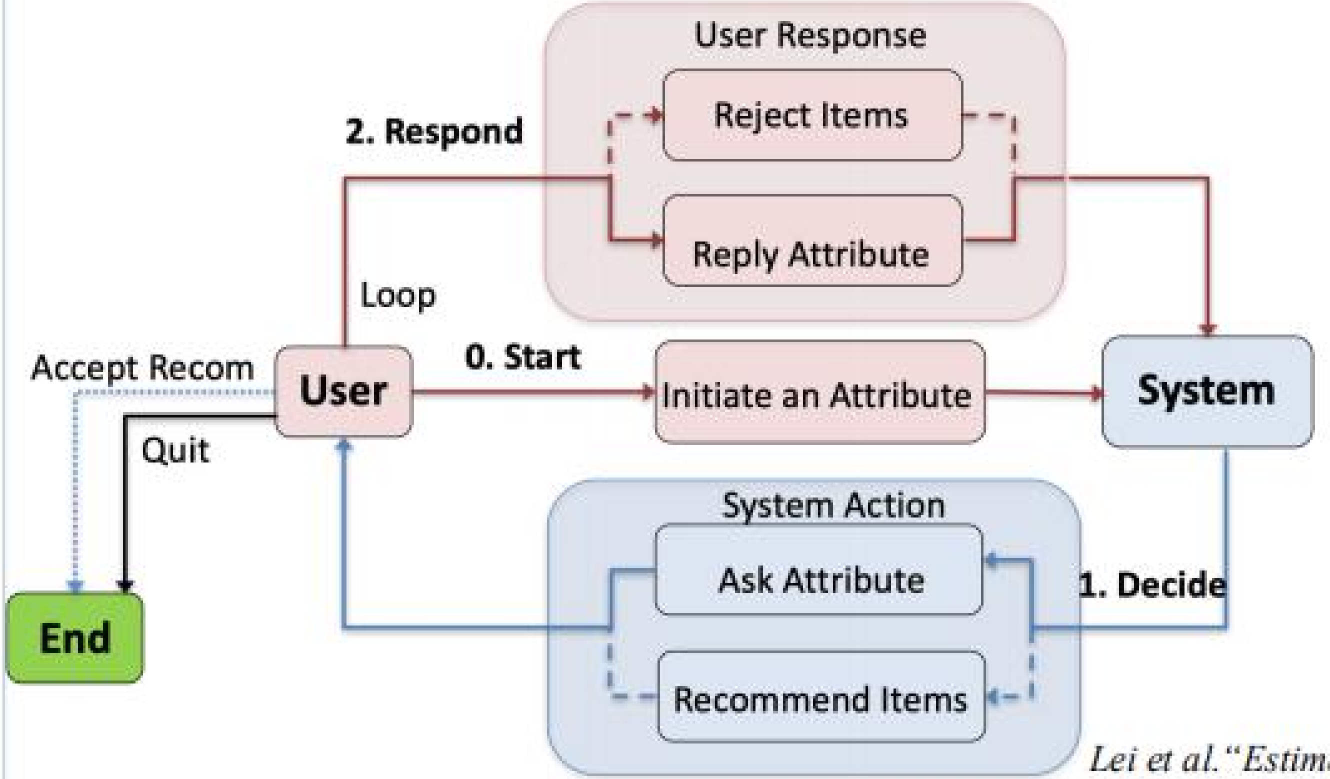
Multi-turn Conversational Strategies for CRSs

- what to ask —> when to ask (How to maintain the conversation)

- Strategies for Determining When to Ask and Recommend
- Strategies from A Broader Perspective
  - Multi-topic Learning in Conversations
  - Special Ability: Suggesting, Negotiating, and Persuading

Workflow of Multi-round Conversational Recommendation (MCR)

Objective:
Recommend desired items to user in shortest turns



- Key Research Questions

1. What item/attribute to recommend/ask?
1. Strategy to ask and recommend?
1. How to adapt to user's online feedback?

Lei et al. "Estimation–Action–Reflection: Towards Deep Interaction Between Conversational and Recommender Systems" (WSDM'20)

Scenario: single round of a conversation between a user and the system

Recommend once and break the dialogue

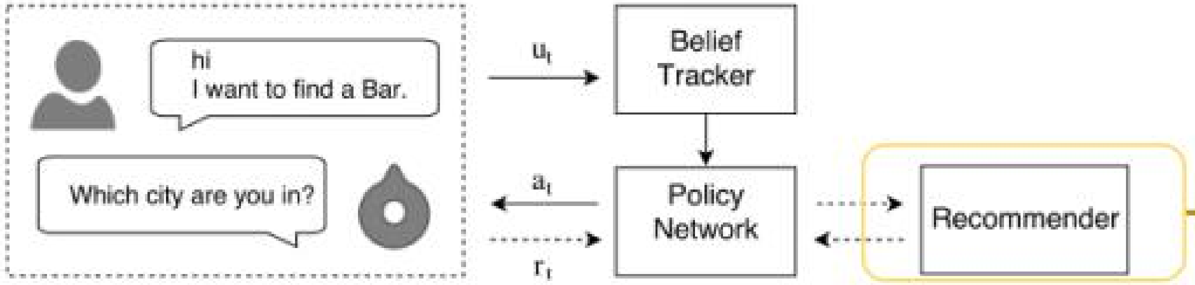


Figure 1: The conversational recommender system overview

Recommender System

- Make a recommendation only once after asking question.

Sun et al. "Conversational Recommender System" (SIGIR'18)

• CRM - Method

Decisions based only on the belief tracker

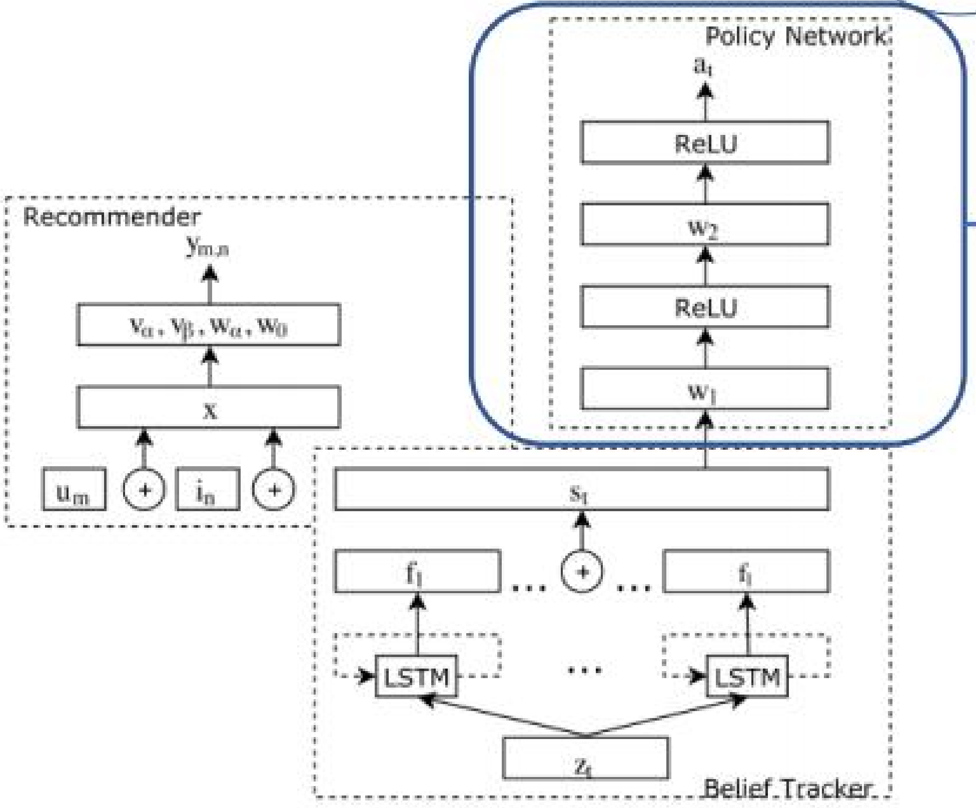


Figure 2: The structure of the proposed conversational recommender model. The bottom part is the belief tracker, the top left part is the recommendation model, and the top right part is the deep policy network.

Sun et al. "Conversational Recommender System"(SIGIR' 18)

Deep Policy Network

- **State:** $s_t = \{\mathbf{f}_1 \oplus \mathbf{f}_2 \ldots \oplus \mathbf{f}_l\}.$

  Description of the conversation context

- **Action:** $\{a_1, a_2, \ldots, a_l\}$, request the value of a facet; a_{rec}, make a personalized recommendation

- **Reward:** benefit/penalty the agent gets from interacting with its environment

- **Policy:** $\pi(a_t|s_t)$, two fully connected layers as the policy network

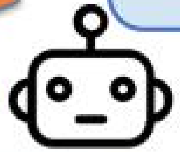
Adopt the policy gradient method of reinforcement learning

Sun et al. "Conversational Recommender System" (SIGIR'18)

• CRM - Evaluation

User Simulation

Yelp (the restaurants and food data)



Item Name: "*Small Italy Restaurant*"
Item Attributes: [Italian, San Diego, California, cheap, rating>=3.5]

(city="Italian", category="San Diego")

I'm looking for Italian food in San Diego.

Which state are you in?

I'm in California. *(state="CA")*

Which price range do you like?

Low price *(price_range="cheap")*

What rating range do you want?

3.5 or higher. *(rating_range>="3.5")*

Do you want "Small Italy Restaurant"?

thank you!

Evaluation Metrics

Evaluation Matrices:

- SR @ k (Success rate at k-th turn)
- AT (Average Turns)

$$SR = \frac{\#sucessful\,dialogues}{\#dialogues} \cdot 100\%$$

$$AT = \overline{dialogue\ length}.$$

Sun et al. "Conversational Recommender System" (SIGIR'18)

Table 1: Dataset statistics.

Dataset	#users	#items	#interactions	#attributes
Yelp	27,675	70,311	1,368,606	590
LastFM	1,801	7,432	76,693	33

Item Name: "*Small Italy Restaurant*"
Item Attributes: [Pizza, Nightlife, Wine, Jazz]

Lei et al. "Estimation–Action–Reflection: Towards Deep Interaction Between Conversational and Recommender Systems" (WSDM'20)

We use **reinforcement learning** to find the best strategy.

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Lei et al. "Estimation–Action–Reflection: Towards Deep Interaction Between Conversational and Recommender Systems" (WSDM'20)

Method: How to Adapt to User's Online Feedback? (Reflection stage)

Solution: We treat the recently rejected 10 items as negative samples to re-train the recommender, to adjust the estimation of user preference.

$$L_{ref} = \sum_{(u,v,v')\in\mathcal{D}_4} -\ln\sigma\left(\hat{y}(u,v,\mathcal{P}_u) - \hat{y}(u,v',\mathcal{P}_u)\right) + \lambda_\Theta\|\Theta\|^2$$

Notation	Meaning
$\mathcal{V}^t$	Recently rejected item set.
$\mathcal{D}_4 \coloneqq \{(u,v,v') \mid v' \in \mathcal{V}_u^+ \wedge v' \in \mathcal{V}^t\}$	Paired sample for online update.

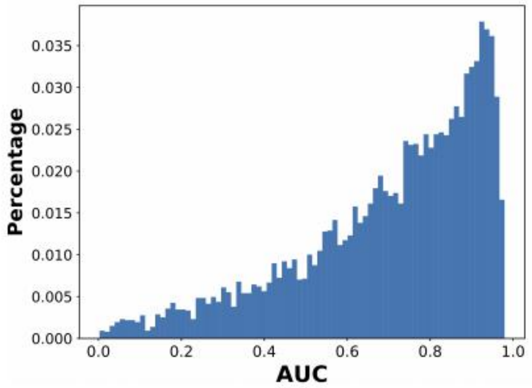


Figure 3: Percentage of bad updates w.r.t. the offline model's AUC on the users on Yelp (RQ4).

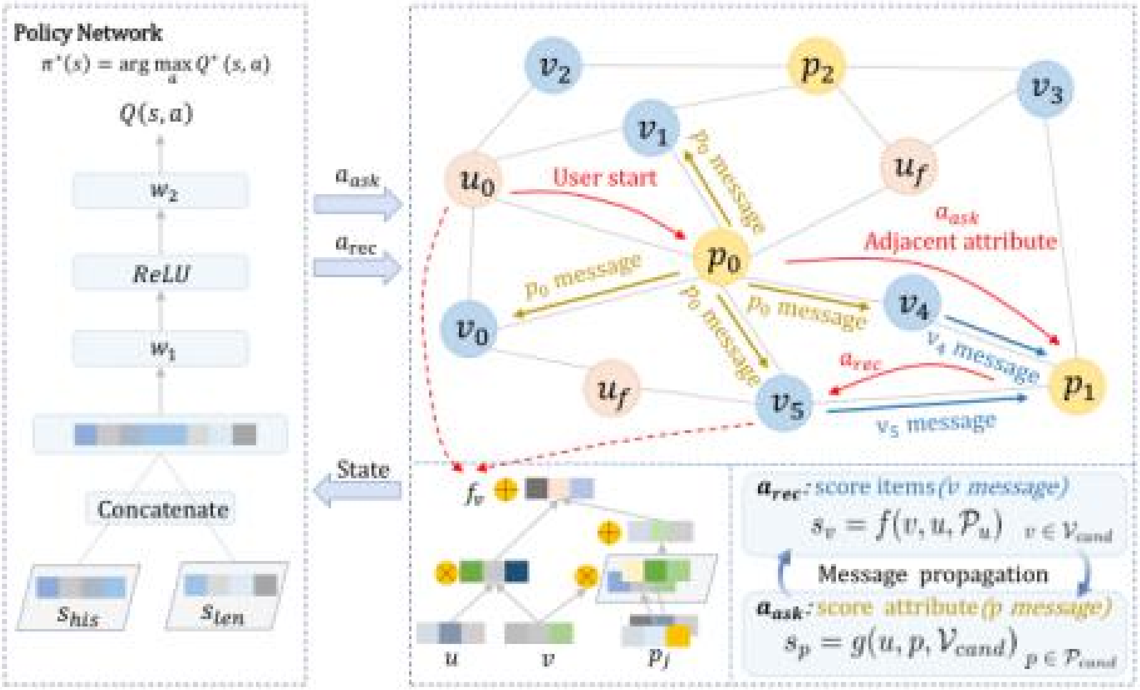


Figure 2: CPR framework overview. It starts from the user u_0 and walks over adjacent attributes, forming a path (the red arrows) and eventually leading to the desired item. The policy network (left side) determines whether to ask an attribute or recommend items in a turn. Two reasoning functions f and g score attributes and items, respectively.

CPR Framework

- **Assuming**
  - Current path $P = p_0, p_1, p_2, \ldots, p_t$
  - u: user v: item p: attribute
  - $\mathcal{P}_u$: user's preferred attributes
  - $\mathcal{V}_{cand}$: candidate items
- **Reasoning**
  - Score items to recommend (v message):

$$s_v = f(v, u, \mathcal{P}_u)$$

  - Score attribute to ask (p message):

$$s_p = g(u, p, \mathcal{V}_{cand})$$

- **Consultation**
  - Policy network (choose to ask or rec)
- **Transition**
  - Extended path

$$P = p_0, p_1, p_2 \ldots p_t\, p_{t+1}$$

  - Update candidate item /attribute set ($\mathcal{V}_{cand}/\mathcal{P}_{cand}$)

$$f(v, u, \mathcal{P}_u) = \mathbf{u}^T \mathbf{v} + \sum_{p \in \mathcal{P}_u} \mathbf{v}^T \mathbf{p}$$

$$g(u, p, \mathcal{V}_{cand}) = -\mathrm{prob}(p) \cdot \log_2(\mathrm{prob}(p)),$$

$$\mathrm{prob}(p) = \frac{\sum_{v \in \mathcal{V}_{cand} \cap \mathcal{V}_p} \sigma(s_v)}{\sum_{v \in \mathcal{V}_{cand}} \sigma(s_v)}$$

- Strategies from A Broader Perspective
    - Multi-topic Learning in Conversations
    - Special Ability: Suggesting, Negotiating, and Persuading

Multi-topic Learning in Conversations

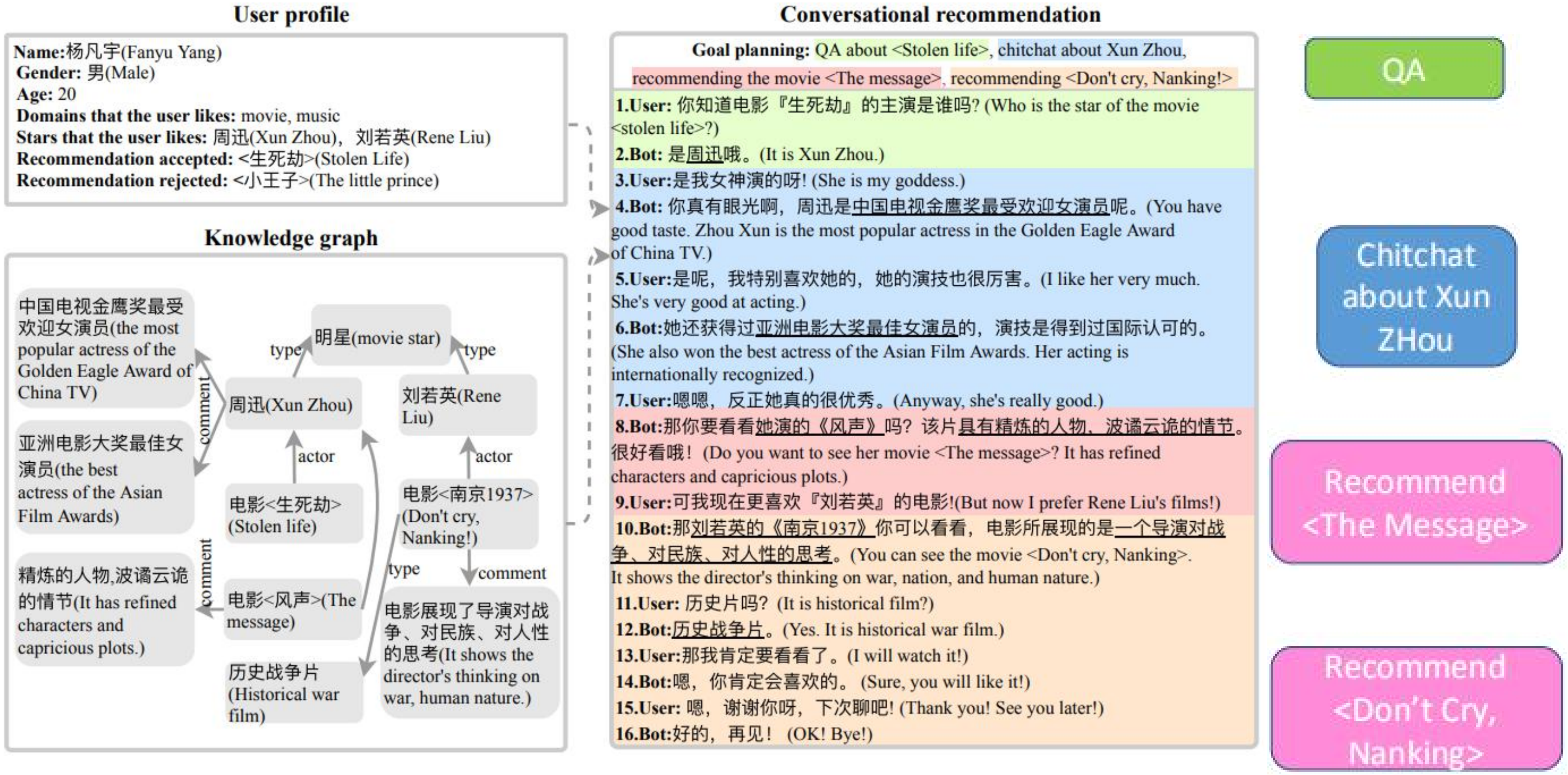


Figure 1: A sample of conversational recommendation over multi-type dialogs. The whole dialog is grounded on knowledge graph and a goal sequence, while the goal sequence is planned by the bot with consideration of user's interests and topic transition naturalness. Each goal specifies a dialog type and a dialog topic (an entity). We use different colors to indicate different goals and use underline to indicate knowledge texts.

- chit-chat
- task oriented dialogs
- recommendation
- question answering

Zeming Liu, Haifeng Wang, Zheng-Yu Niu, Hua Wu, Wanxiang Che, and Ting Liu. 2020. Towards Conversational Recommendation over Multi-Type Dialogs. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics (ACL'20). 1036–1049.

Multi-topic Learning in Conversations

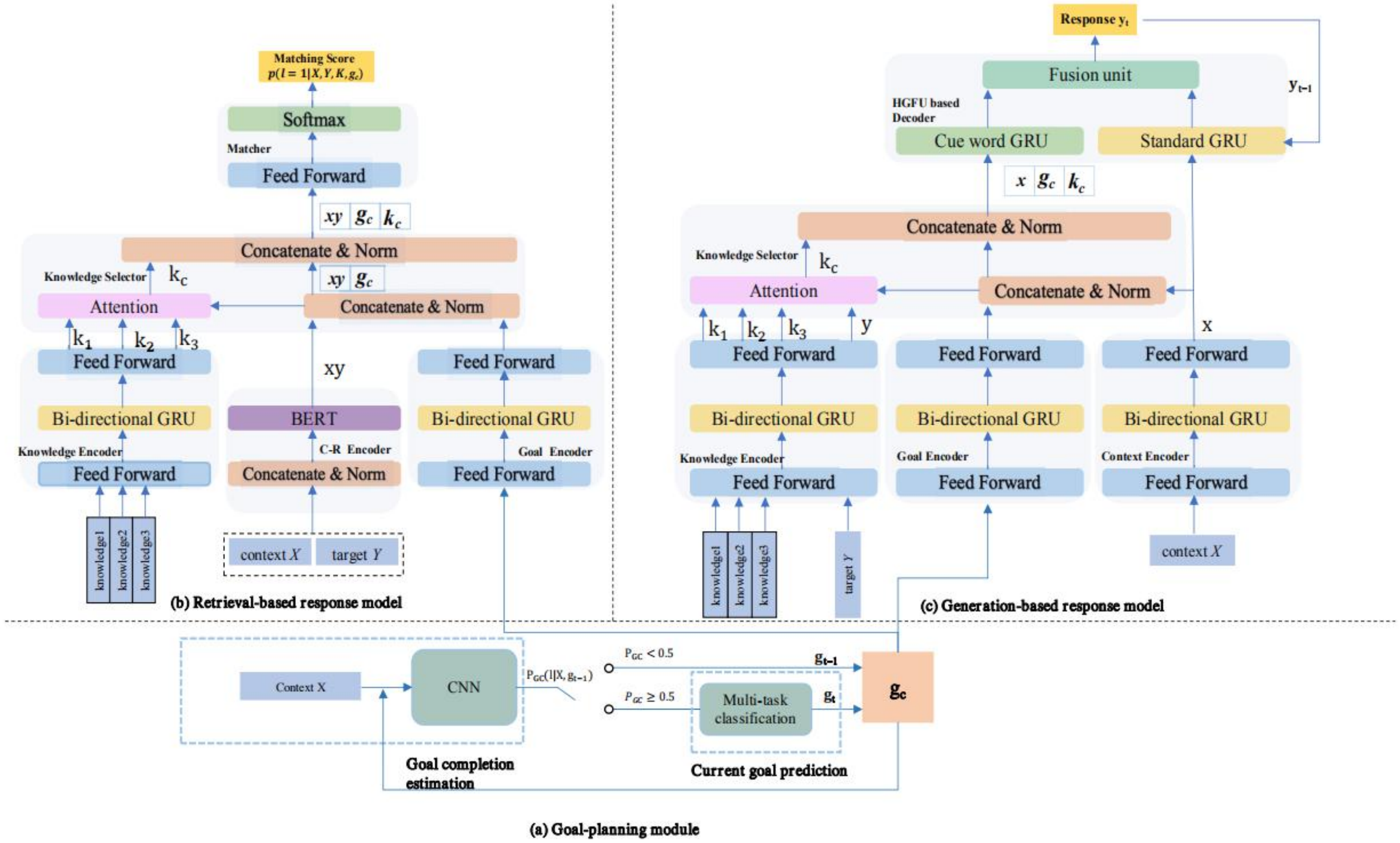
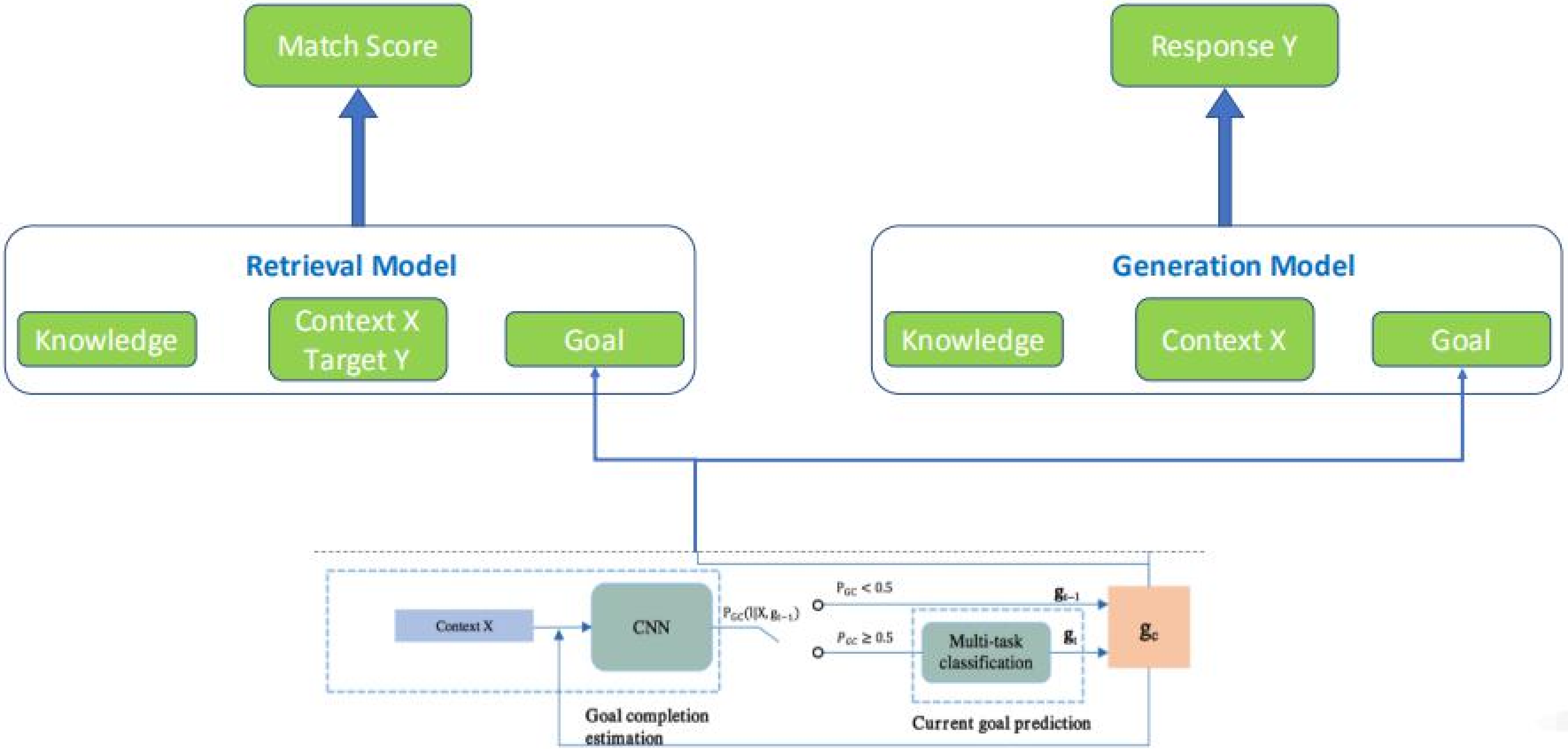


Figure 3: The architecture of our multi-goal driven conversation generation framework (denoted as **MGCG**).

Kun Zhou, Yuanhang Zhou, Wayne Xin Zhao, Xiaoke Wang, and Ji-Rong Wen. 2020. Towards Topic-Guided Conversational Recommender System. In Proceedings of the 28th International Conference on Computational Linguistics (COLING'2020).

Multi-topic Learning in Conversations



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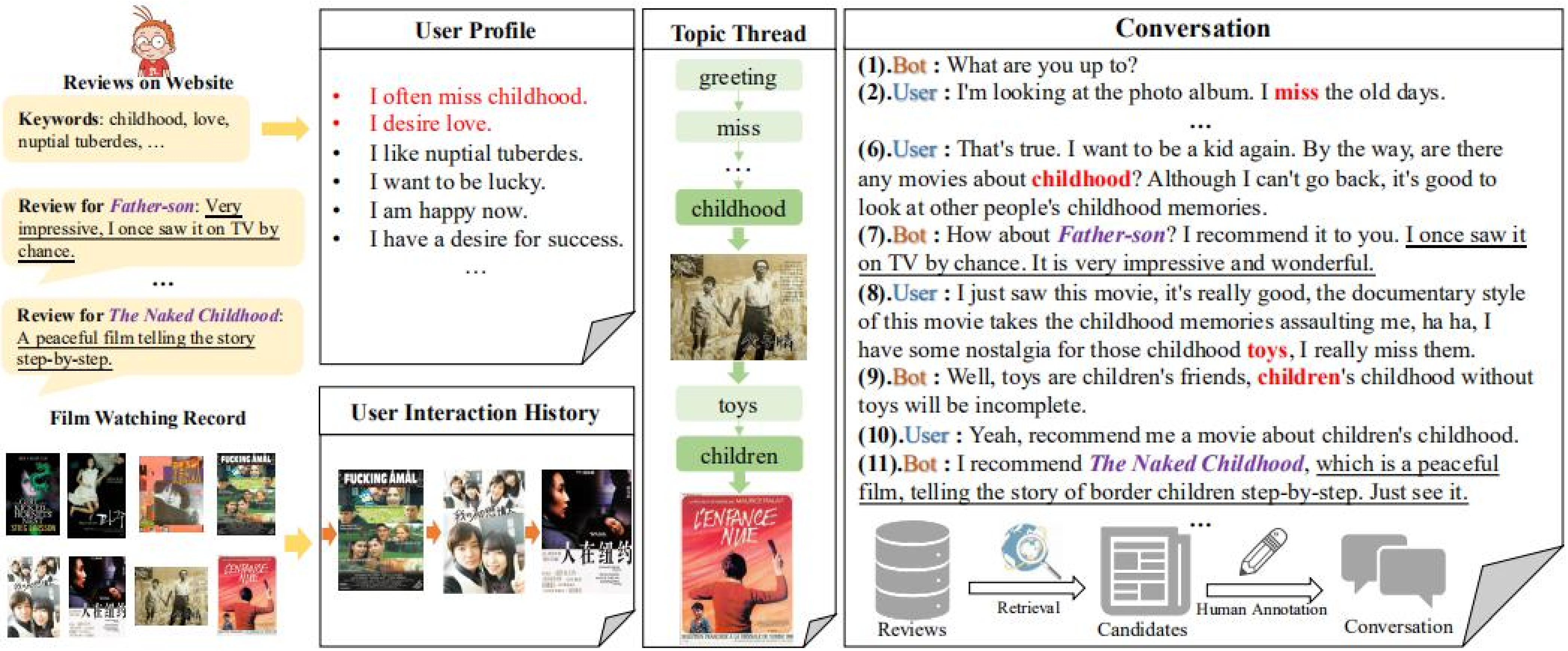


Figure 1: An illustrative example for TG-ReDial dataset. We utilize real data to construct the recommended movies, topic threads, user profiles and utterances. Other user-related information (*e.g.*, historical interaction records) is also available in our dataset.

Kun Zhou, Yuanhang Zhou, Wayne Xin Zhao, Xiaoke Wang, and Ji-Rong Wen. 2020. Towards Topic-Guided Conversational Recommender System. (COLING'2020).

Special Ability: Suggesting, Negotiating, and Persuading

conversational question suggestion

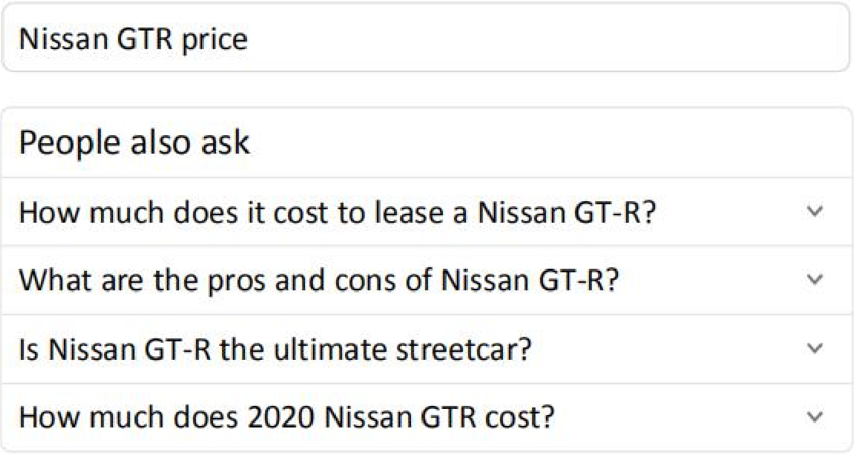


Figure 1: A Conversational Question Suggestion Example.

Table 1: Examples of Query-Question Suggestion Pairs and their Usefulness Labels.

Query	Question Suggestion	Gold Label
used washer and dry	Can I store a washer and dryer in the garage ?	Misses Intent
best questions to ask interviewer	What should I ask in an interview ?	Dup. w/ Q
medicaid expansion	Did Florida accept Medicaid expansion ?	Too Specific
verizon yahoo purchase	Who bought out Yahoo ?	Prequel
jaundice in newborns	How to tell if your newborn has jaundice ?	Dup. w/ Ans.
jonestown massacre	What was in the Kool-Aid at Jonestown ?	Useful
affirmative action	Who does affirmative action benefit ?	Useful
best hair clippers	What clippers do barbers use ?	Useful

Corbin Rosset, Chenyan Xiong, Xia Song, Daniel Campos, Nick Craswell, Saurabh Tiwary, and Paul Bennett. 2020. Leading Conversational Search by Suggesting Useful Questions. In Proceedings of The Web Conference 2020 (WWW'20). 1160–1170.

Summary

Table 2
The commonly used multi-turn strategies in CRSs.

Main Mechanism	Asking Method	When to ask and recommend	Determining X and Y	Publications
Asking questions	Explicit	Asking 1 turn; recommending 1 turn	Fixed	[31, 205]
		Asking X turn(s); recommending 1 turn	Fixed	[232]
			Adaptive	[161]
		Asking X turn(s); recommending Y turn(s)	Adaptive	[88, 89, 95, 194]
	Implicit	Contained in natural language	Adaptive	[94, 25, 225, 227]
Leading diverse topics or explore special abilities				[104, 227, 143, 90, 186]

Dialogue Understanding and Generation in CRSs

- Dialogue Understanding
  - Slot Filling
  - Intentions and Sentiment Learning
- Response Generation
  - Generating Proper Utterances in Natural Language
    - Retrieval-based Methods
    - Generation-based Methods
  - Incorporating Recommendation-oriented Information

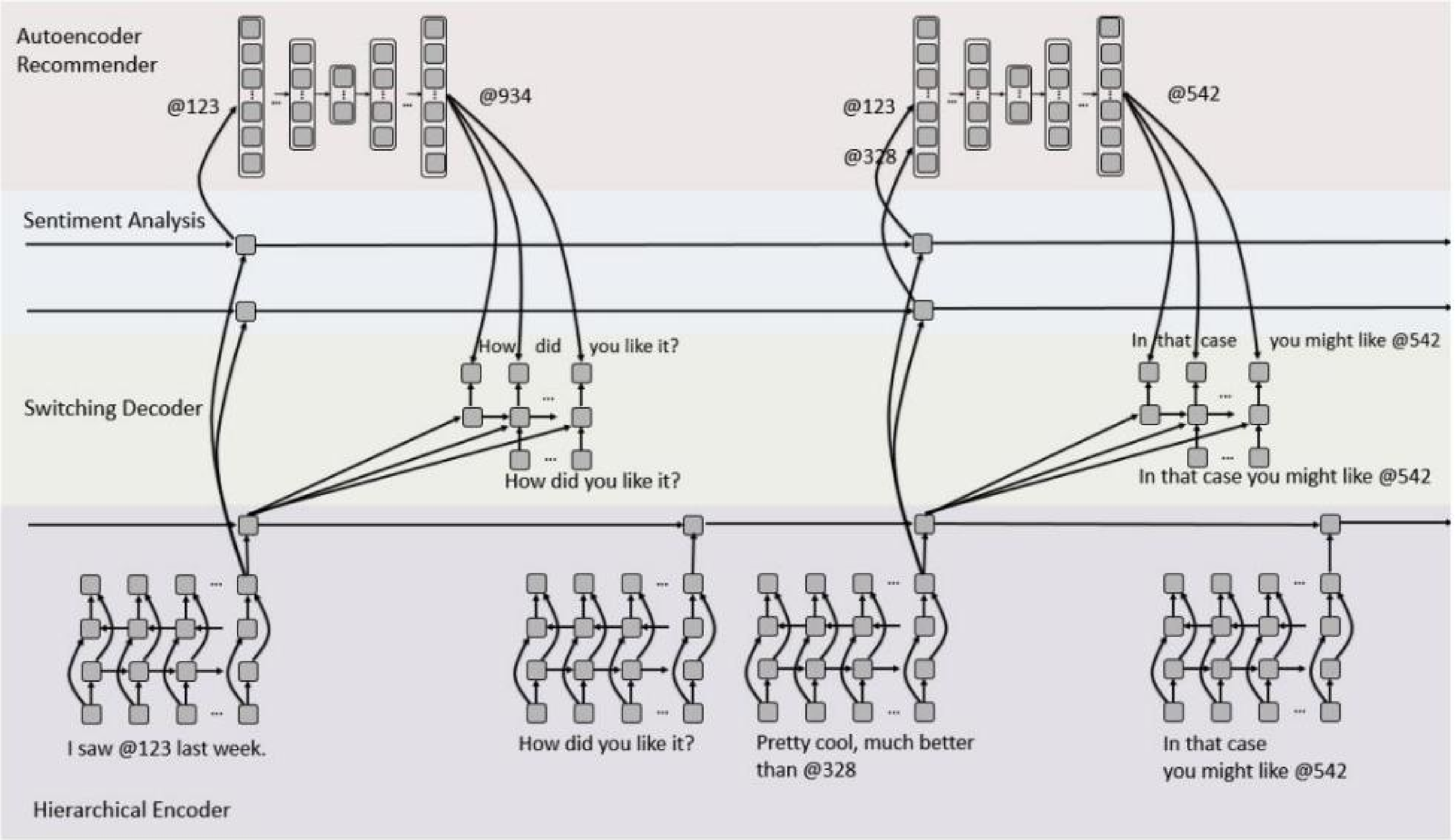
Dialogue Understanding-Intentions and Sentiment Learning

3
Recommender

2
Sentiment Analysis

4
Switching Decoder

1
Encoder



Raymond Li, Samira Ebrahimi Kahou, Hannes Schulz, Vincent Michalski, Laurent Charlin, and Chris Pal. 2018. Towards Deep Conversational Recommendations. In Proceedings of the 32nd International Conference on Neural Information Processing Systems (NeurIPS '18). 9748–9758.

	Recommendation	Search and Genre	Conversational Recommendation
User input	Critters (1986) → NeverEnding Story, The (1984) → Power Rangers (1995) → Turbo: A Power Rangers Movie (1997)→	**search** "[...] and there's the music in the movie: the songs Tarantino chose for his masterpiece fit their respective scenes so perfectly that most of those pieces of music." **genre** "drama, thriller"	"90's film with great soundtrack.[...] I thought Power Rangers in 1995 and then Turbo in 1997 were masterpieces of cinema, mind you [..] I'm looking for movies from that era with great music. Dramas, thrillers, road movies, adventure... Any genre (except too much romantic) will do ."
System output	Pulp Fiction (1994)	Pulp Fiction (1994)	You should see Pulp Fiction, Rock Star, [...]
Task type	probing	probing	downstream
Knowledge	collaborative	content	content and collaborative

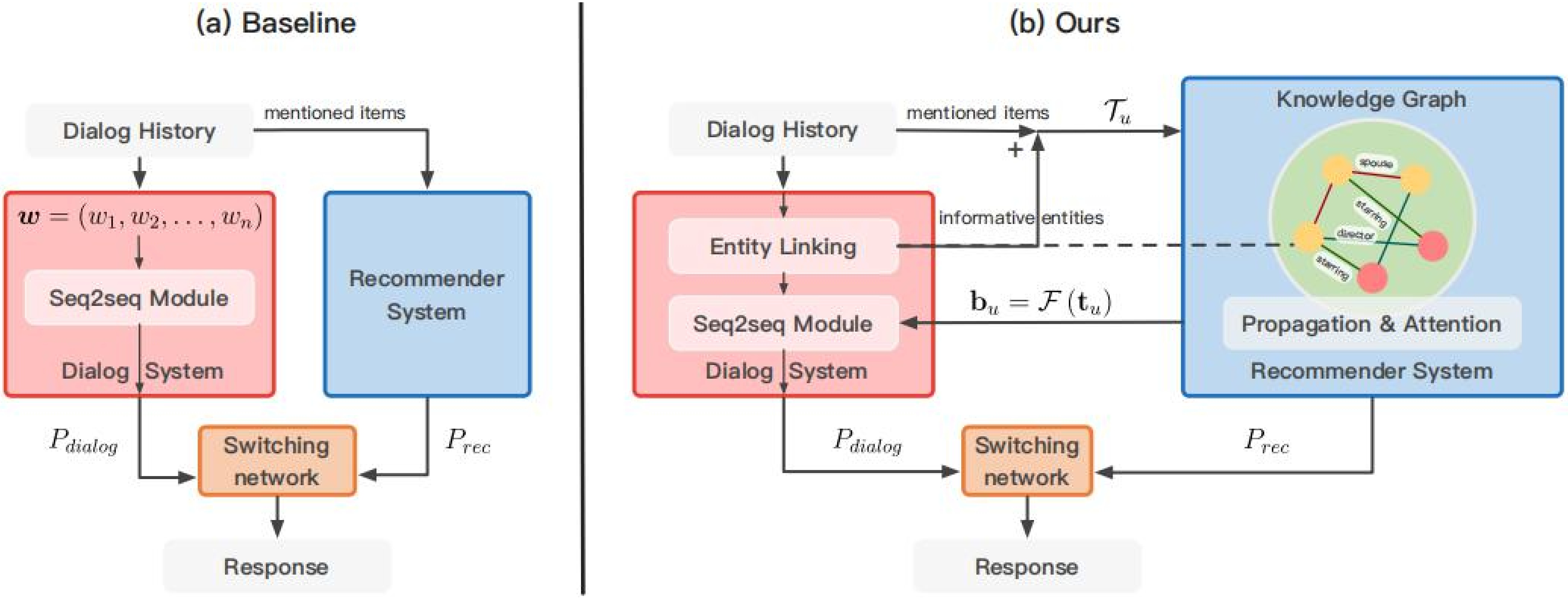
Type	Prediction	Task	Prompt Examples	Labels
MLM	Token	Genre	TP-NoTitle: *"It is a movie of the [MASK] genre."*	crime
			TP-Title:*"Pulp Fiction is a [MASK] movie."*	crime
			TP-TitleGenre:*"Pulp Fiction is a movie of the [MASK] genre ."*	crime
			TP-NoTitle:*"It is a book of the [MASK] genre."*	comic
			TP-Title:*"Palestine by Joe Sacco is a [MASK] book."*	comic
			TP-TitleGenre:*"Palestine by Joe Sacco is a book of the [MASK] genre."*	comic
SIM	IsSimilar	Recommendation	*{("The Hobbit", "Lord of the Rings"), ("The Hobbit", "Twilight")}*	{1, 0}
		Search	*{("The book is not about the murder [...]", "The Brothers Karamazov"), ("It gives a brilliant picture of three bright young people [...]", "The Brothers Karamazov.")}*	{1, 0}
NSP	IsNext	Recommendation	*{ "If you liked The Hobbit, [SEP] you will also like Lord of the Rings", "If You liked The Hobbit, [SEP] you will also like Twilight"}*	{1, 0}
		Search	*{ "The book is not about the murder [...] [SEP] The Brothers Karamazov.", "It gives a brilliant picture of three bright young people [...] [SEP] The Brothers Karamazov. "}*	{1, 0}

Gustavo Penha and Claudia Hauff. 2020. What Does BERT Know about Books, Movies and Music? Probing BERT for Conversational Recommendation. In Fourteenth ACM Conference on Recommender Systems (RecSys '20). 388–397.

Response Generation-
Generating Proper Utterances in Natural Language

- Retrieval-based Methods
- Generation-based Methods

Incorporating Recommendation-oriented Information



Qibin Chen, Junyang Lin, Yichang Zhang, Ming Ding, Yukuo Cen,Hongxia Yang, and Jie Tang. 2019. Towards Knowledge-Based Recommender Dialog System. (EMNLP-IJCNLP'2019). 1803–1813.

Improving Conversational Recommender Systems via Knowledge Graph based Semantic Fusion

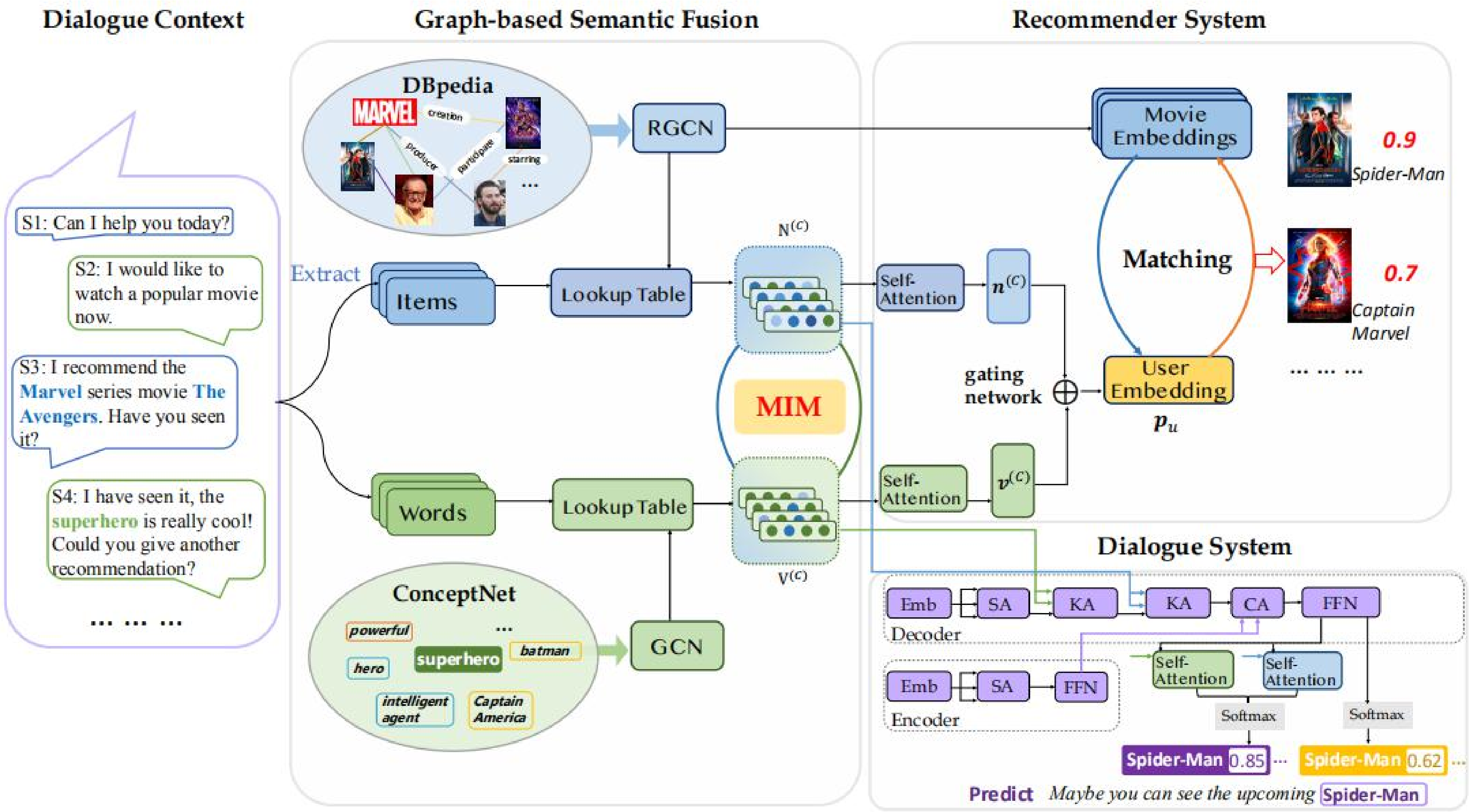


Figure 1: The overview of our model with a movie recommendation scenario. Here,"SA", "KA", and "CA" denotes *self-attention*, *KG-based attention* and *context-based attention*, respectively.

Kun Zhou, Wayne Xin Zhao, Shuqing Bian, Yuanhang Zhou, Ji Rong Wen, and Jingsong Yu. 2020. Improving Conversational Recommender Systems via Knowledge Graph based Semantic Fusion. (SIGKDD' 20). 1006–1014.

Bridging the Gap between Conversational Reasoning and Interactive Recommendation

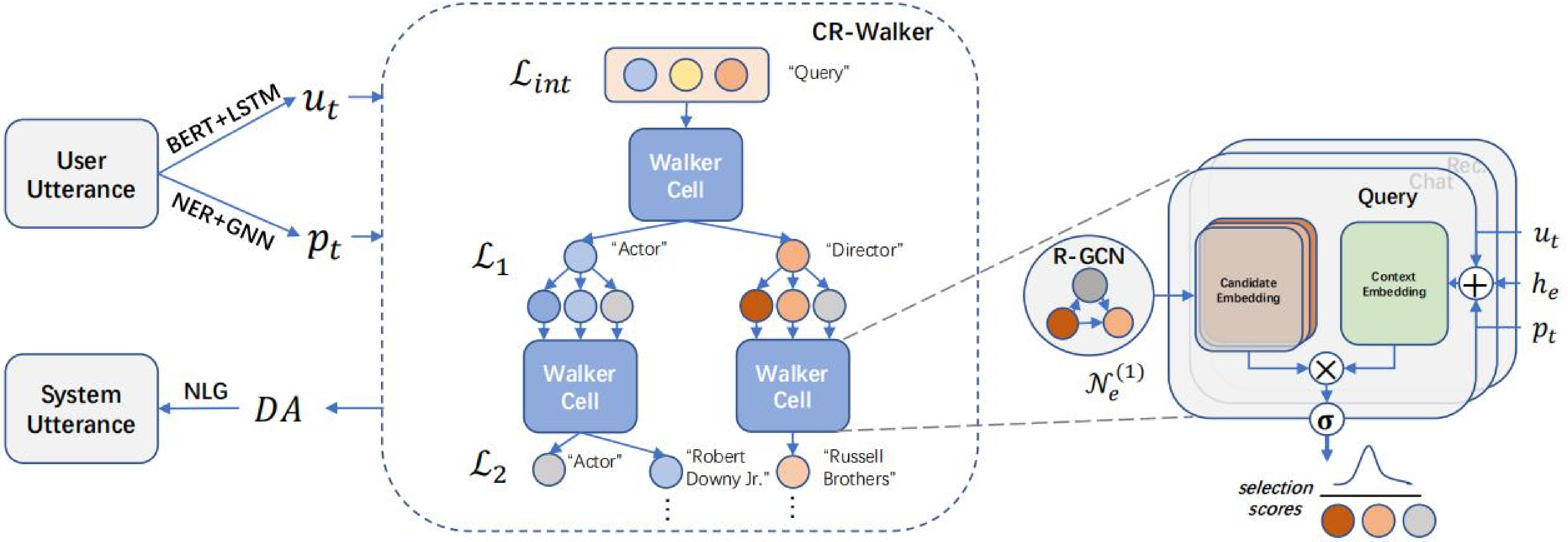


Figure 3: Left: Illustration of the overall architecture for our model. The graph walker performs tree-structured reasoning on the knowledge graph, which is then transformed into dialog acts. Right: Detailed structure for a single walker cell. A walker cell calculates the similarity between the entities on a graph and the context embedding that integrates current utterance embedding and user portrait. The selection process of each entity is learned by logistic regression to enable multiple selections.

Wenchang Ma, Ryuichi Takanobu, Minghao Tu, and Minlie Huang.2020. Bridging the Gap between Conversational Reasoning and Interactive Recommendation. arXiv preprint arXiv:2010.10333(2020).

Towards Explainable Conversational Recommendation

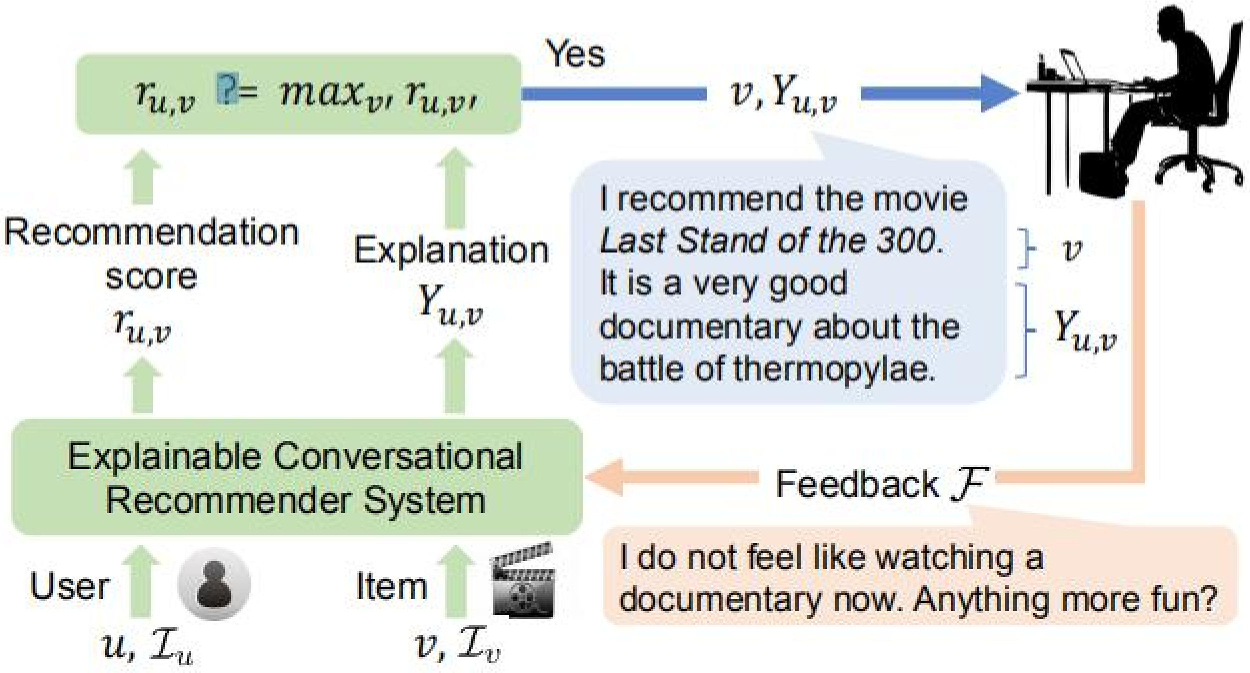


Figure 2: Pipeline of explainable conversational recommendation.

Zhongxia Chen, Xiting Wang, Xing Xie, Mehul Parsana, Akshay Soni, Xiang Ao, and Enhong Chen. 2020. Towards Explainable Conversational Recommendation. In Proceedings of the 29th International Joint Conference on Artificial Intelligence, IJCAI '20. 2994–3000.

Towards Explainable Conversational Recommendation

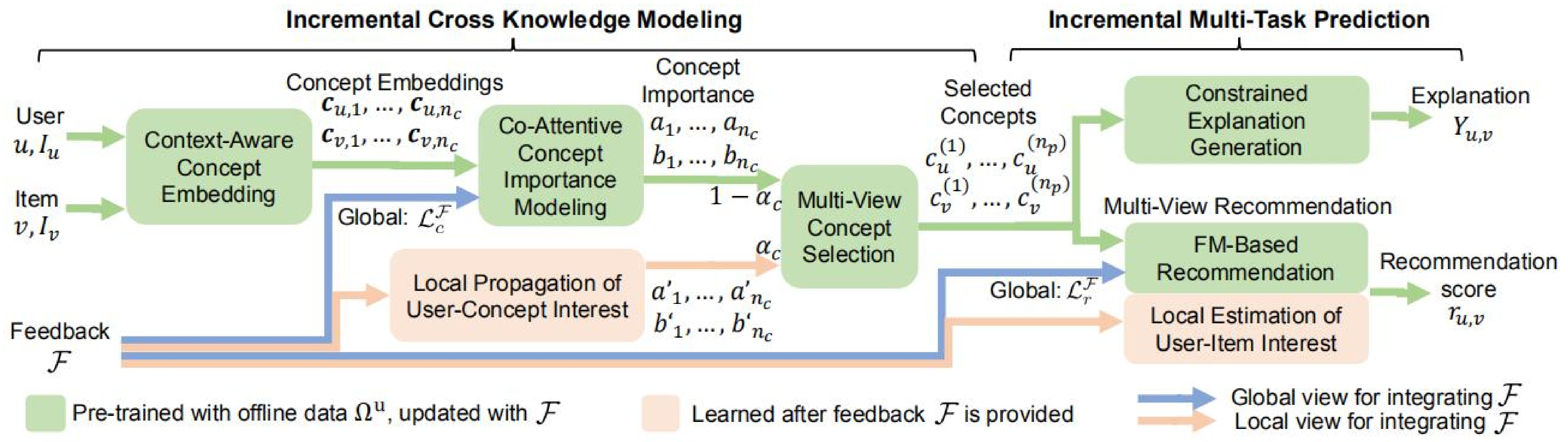


Figure 3: Our incremental multi-task learning framework for explainable conversational recommendation (ECR)

Zhongxia Chen, Xiting Wang, Xing Xie, Mehul Parsana, Akshay Soni, Xiang Ao, and Enhong Chen. 2020. Towards Explainable Conversational Recommendation. In Proceedings of the 29th International Joint Conference on Artificial Intelligence, IJCAI '20. 2994–3000.

Summary

Table 3
Mechanisms of language understanding and generation in CRSs.

Forms of Input & Output	Publications
Pre-annotated Input & Template-based Output	[217, 232, 105, 210, 161], [32, 31, 88, 89, 95]
Raw Language Input & Natural Language Generation	[141, 94, 25], [225, 111, 104]

Exploration-Exploitation Trade-offs

- Multi-Armed Bandits In Recommendation
  - Introduction to Multi-Armed Bandits
  - Recommendation via MAB-based Methods
- Multi-Armed Bandits in CRSs
- Meta Learning for CRSs

Evaluation and User Simulation

- Datasets and Tools
- Turn-level Evaluation
  - Evaluation of Language Generation
  - Evaluation of Recommendation
    - Rating-based Metrics
    - Ranking-based Metrics
- Conversation-level Evaluation
  - Online User Test
  - User Simulation
    - Using Direct Interaction History of Users
    - Estimating User Preferences on All Items
    - Extracting Information from User Reviews
    - Imitating Humans' Conversational Corpora

Datasets and Tools

Table 5
Statistics of datasets commonly used in CRSs.

Dataset	#Dialogs	#Turns	Dialogue Type	Domains	Dialogue Resource	Related Publications
MovieLens [7]	Depended on the dialogue simulation process			Movie	From item ratings	[217, 105, 171, 235], [87, 69, 69, 55]
LastFM [7]				Music	From item ratings	[88, 89, 226]
Yelp				Restaurant	From item ratings	[161, 88, 89]
Amazon [116]				E-commerce	From item ratings	[210, 47, 232, 132], [189, 108, 107]
TG-ReDial [227]	10,000	129,392	Rec., chichat	Movie, Multi topics	From item rating, and enhanced by multi topics	[227]
DuRecDial [104]	10,190	155,477	Rec., QA, etc.	Movie, restaurant, etc.	Generated by workers	[104]
Facebook_Rec [41]	1M	6M	Rec.	Movie	From item ratings	[41]
OpenDialKG [123]	15,673	91,209	Rec. chitchat	Movie, Book, Sport, etc.	Generated by workers	[123]
ReDial [94]	10,006	182,150	Rec., chitchat	Movie	Generated by workers	[94, 25, 225, 111]
COOKIE [47]	No given	11,638,418	Rec.	E-commerce	From user activities and item meta data	[47]
MGConvRex [193]	7.6K+	73K	Rec.	Restaurant	Generated by workers	[193]
GoRecDial [76, 111]	9,125	170,904	Rec.	Movie	Generated by workers	[76]
INSPIRED [56]	1,001	35,811	Rec.	Movie	Generated by workers	[56]

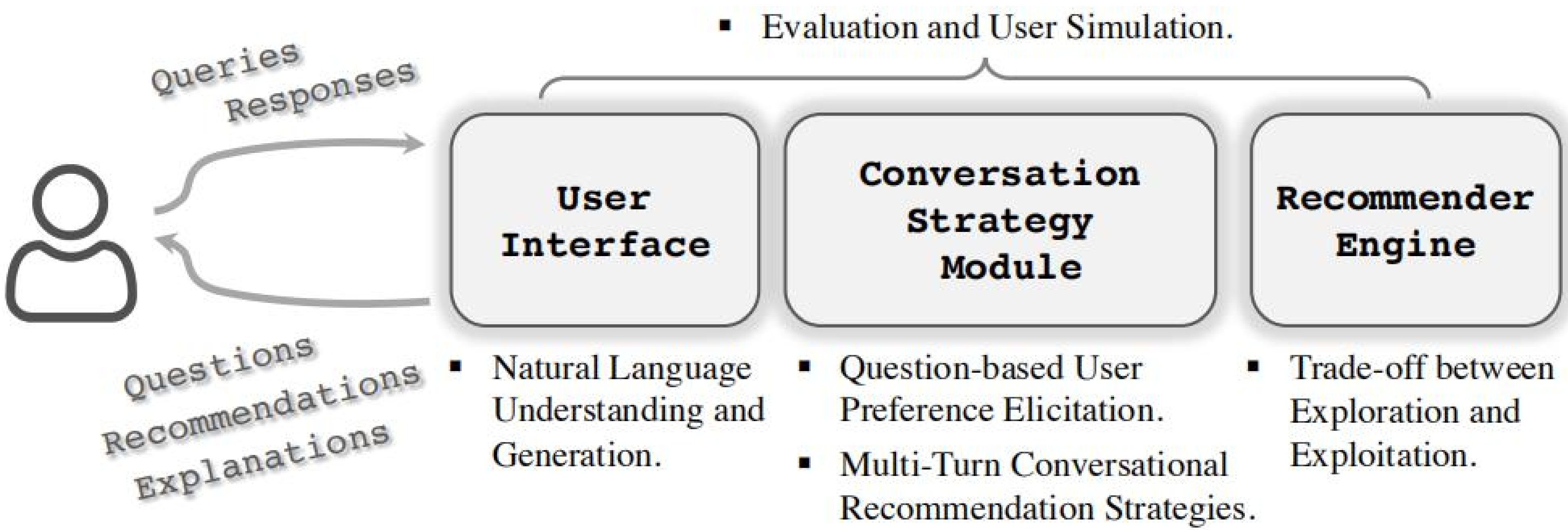


Figure 3: Illustration of the general framework of CRSs and our identified five primary challenges on the three main components.

https://github.com/RUCAIBox/CRSLab

https://link.zhihu.com/?target=https%3A//arxiv.org/pdf/2101.00939.pdf

Turn-level Evaluation

- Evaluation of Language Generation:

  BLUE, ROUGE, fluency, consistency, readability, informativeness
- Evaluation of Recommendation
  - Rating-based Metrics

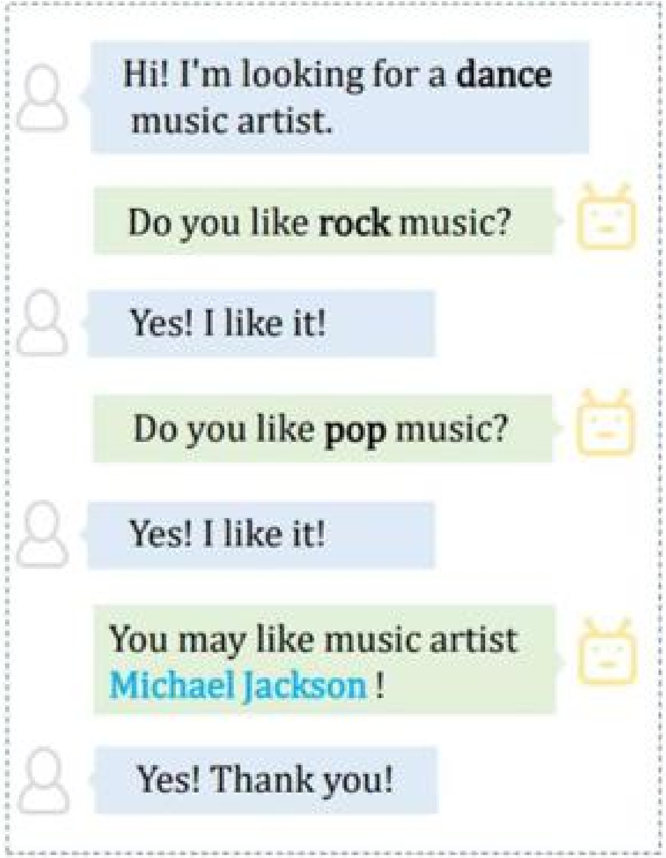
    MSE, RMSE
  - Ranking-based Metrics

    hits, precision, recall, F1-score, Mean Reciprocal Rank (MRR), Mean Average Precision (MAP), and Normalized Discounted Cumulative Gain (NDCG)

Conversation-level Evaluation

- Online User Test
- User Simulation
    - Using Direct Interaction History of Users
    - Estimating User Preferences on All Items
    - Extracting Information from User Reviews
    - Imitating Humans' Conversational Corpora

Using Direct Interaction History of Users



Estimating User Preferences on All Items

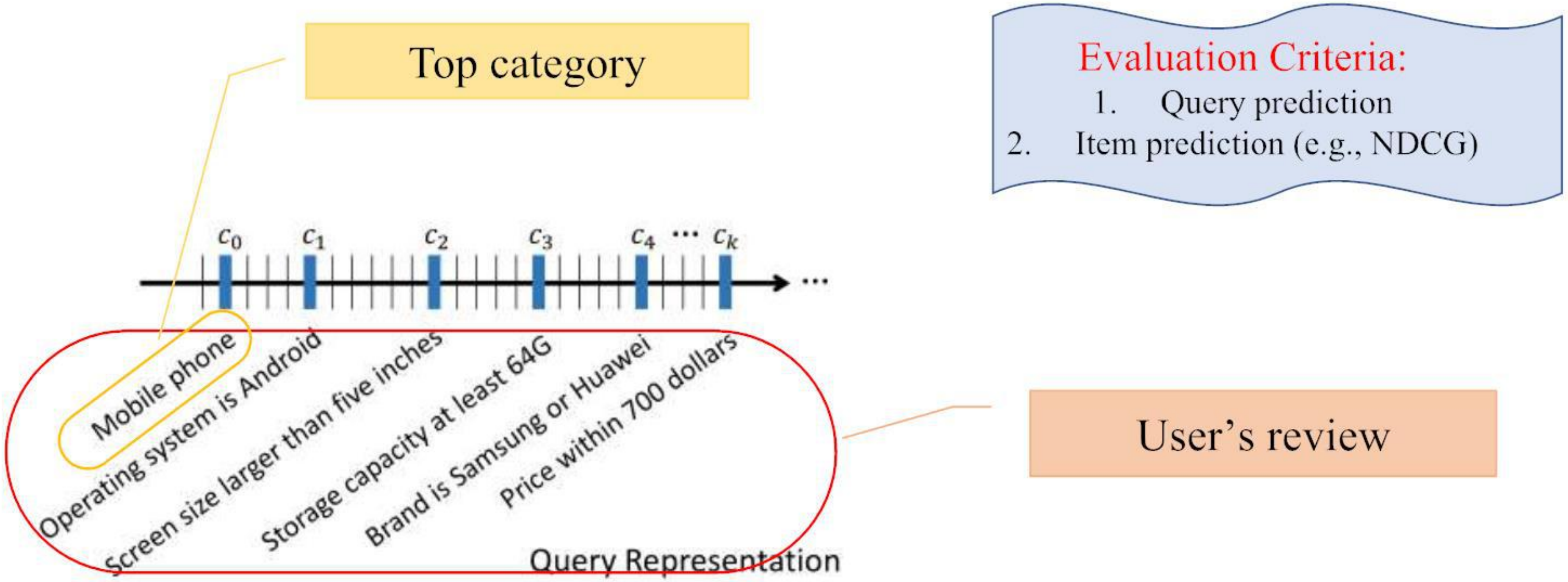
- Motivation： obtain the user preferences on all items in advance
- matrix factorization model+noise[1]
- ridge regression[2]

[1] Konstantina Christakopoulou, Filip Radlinski, and Katja Hofmann.2016. Towards Conversational Recommender Systems. In Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD ’16). 815–824.

[2] Xiaoying Zhang, Hong Xie, Hang Li, and John C.S. Lui. 2020. Conversational Contextual Bandit: Algorithm and Application. In Proceedings of The Web Conference (WWW ’20). 662–672.

Extracting Information from User Reviews

- **SAUR - Evaluation**



Imitating Humans' Conversational Corpora

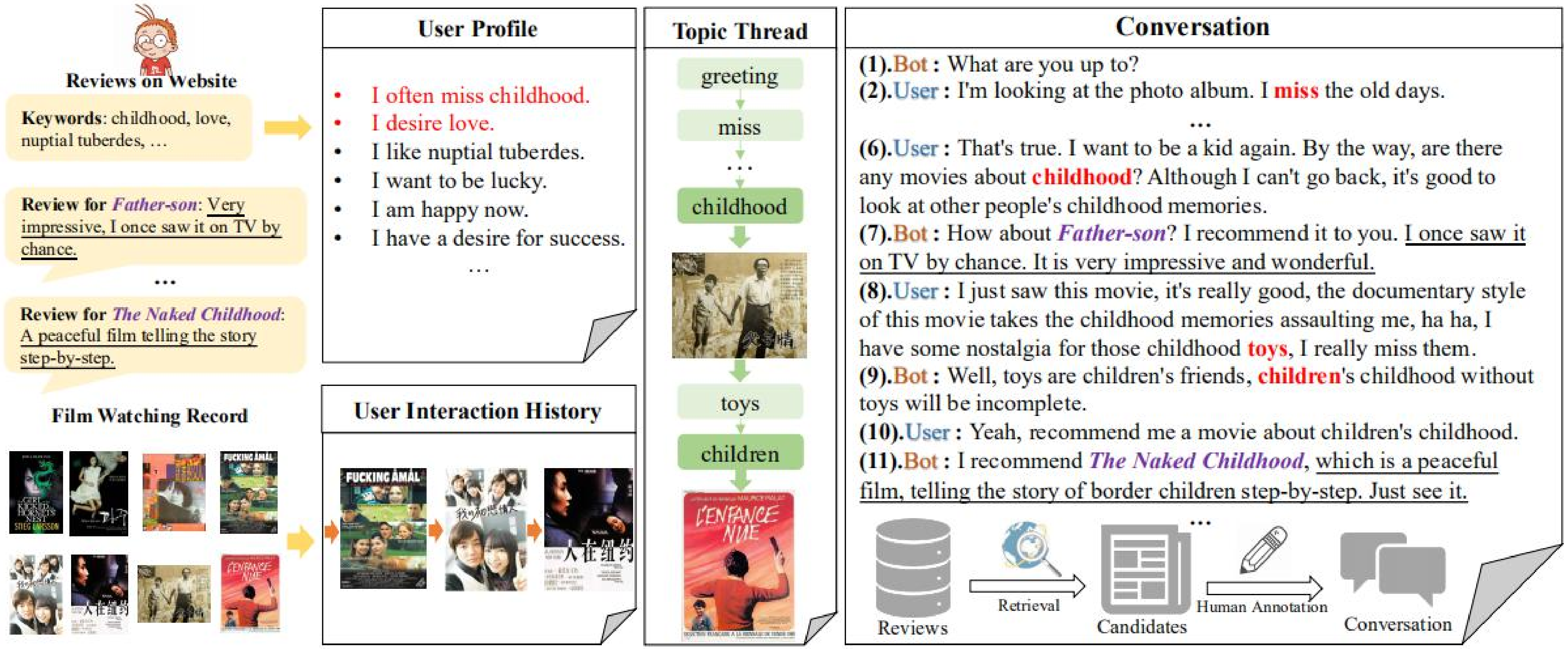


Figure 1: An illustrative example for TG-ReDial dataset. We utilize real data to construct the recommended movies, topic threads, user profiles and utterances. Other user-related information (*e.g.*, historical interaction records) is also available in our dataset.

summary

- Using Direct Interaction History of Users
- Estimating User Preferences on All Items
- Extracting Information from User Reviews
- Imitating Humans' Conversational Corpora

Future Directions and Opportunities

- Jointly Optimizing Three Tasks
- Bias and Debiasing
- Sophisticated Multi-turn Conversation Strategies
- Knowledge Enrichment
- Better Evaluation and User Simulation

Conclusion

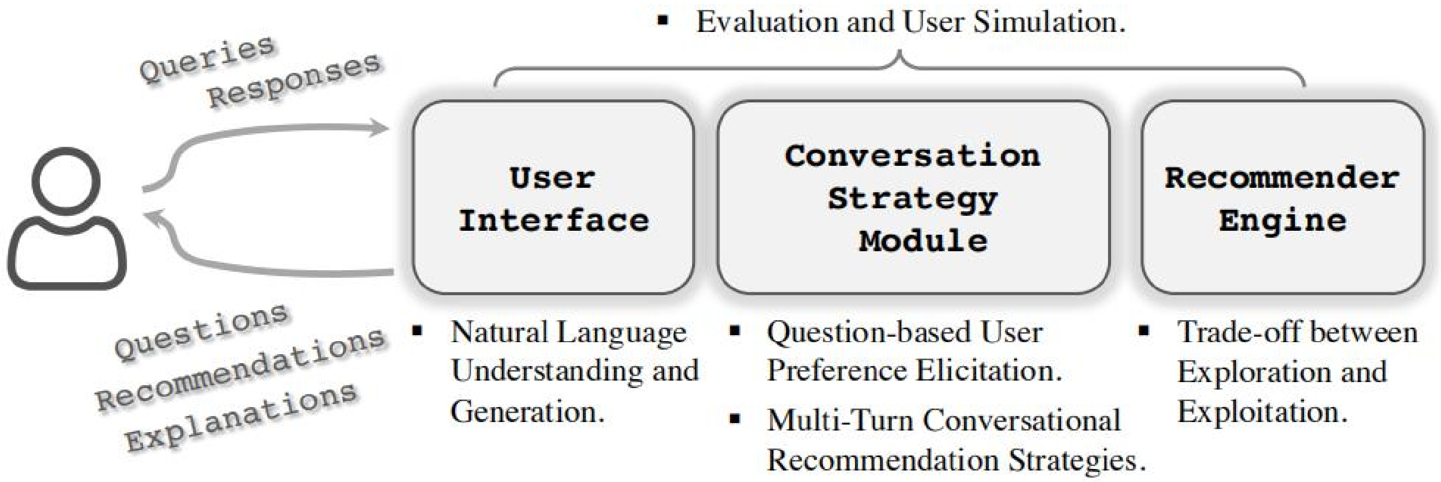


Figure 3: Illustration of the general framework of CRSs and our identified five primary challenges on the three main components.

- Question-based User Preference Elicitation
- Multi-turn Conversational Recommendation Strategies
- Natural Language Understanding and Generation
- Trade-offs between Exploration and Exploitation (E&E)
- Evaluation and User Simulation