中国科学技术大学
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Advances and Challenges in Conversational Recommender Systems: A Survey

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Conversational Recommender System (CRS), in my opinion, is

- A promising research direction.
- Providing a real-time interactive environment, making the machine more intelligent.
- An application instead of a technology. But it provides scenarios for cutting-edge technologies. E.g., reinforcement learning, debiasing, interactive recommendations, causal inference, graph neural networks, and the technologies used in NLP or CV.

❖ Introduction of this survey

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On arXiv, released in Jan 2021. *Link: https://arxiv.org/abs/2101.09459*

Advances and Challenges in Conversational Recommender Systems: A Survey

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ABSTRACT

Recommender systems exploit interaction history to estimate user preference, having been heavily used in a wide range of industry applications. However, static recommendation models are difficult to answer two important questions well due to inherent shortcomings: (a) What exactly does a user like? (b) Why does a user like an item? The shortcomings are due to the way that static models learn user preference, i.e., without explicit instructions and active feedback from users. The recent rise of conversational recommender systems (CRSs) changes this situation fundamentally. In a CRS, users and the system can dynamically communicate through natural language interactions, which provide unprecedented opportunities to explicitly obtain the exact preference of users.

Considerable efforts, spread across disparate settings and applications, have been put into developing CRSs. Existing models, technologies, and evaluation methods for CRSs are far from mature. In this paper, we provide a systematic review of the techniques used in current CRSs. We summarize the

❖ Outline

1. **Background and Motivation.**
   - Recent trends of CRSs.
   - Our definition of CRSs.
   - Framework of CRSs.
   - Difference between CRSs and (1) traditional recommendation, (2) dialogue systems, and (3) interactive recommendation.
2. **Five Important Challenges.**
3. **Promising Future Directions.**

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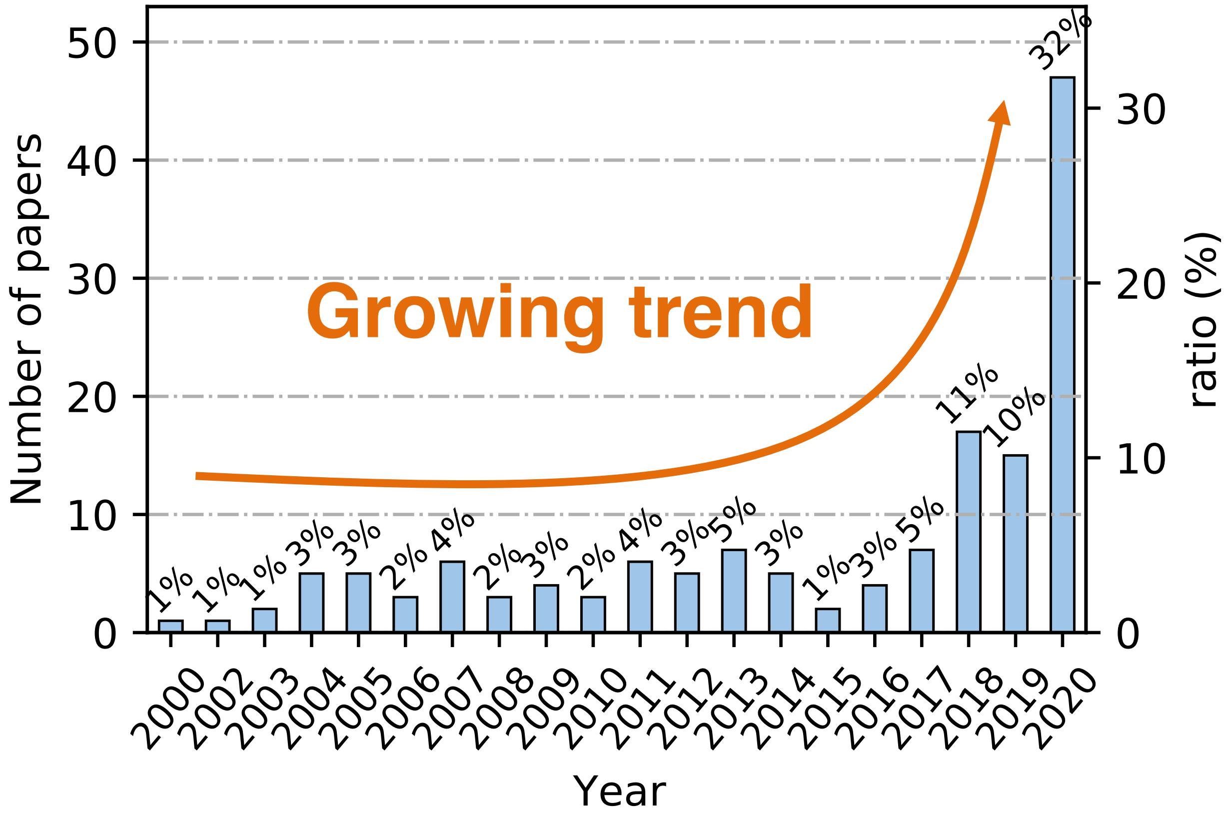
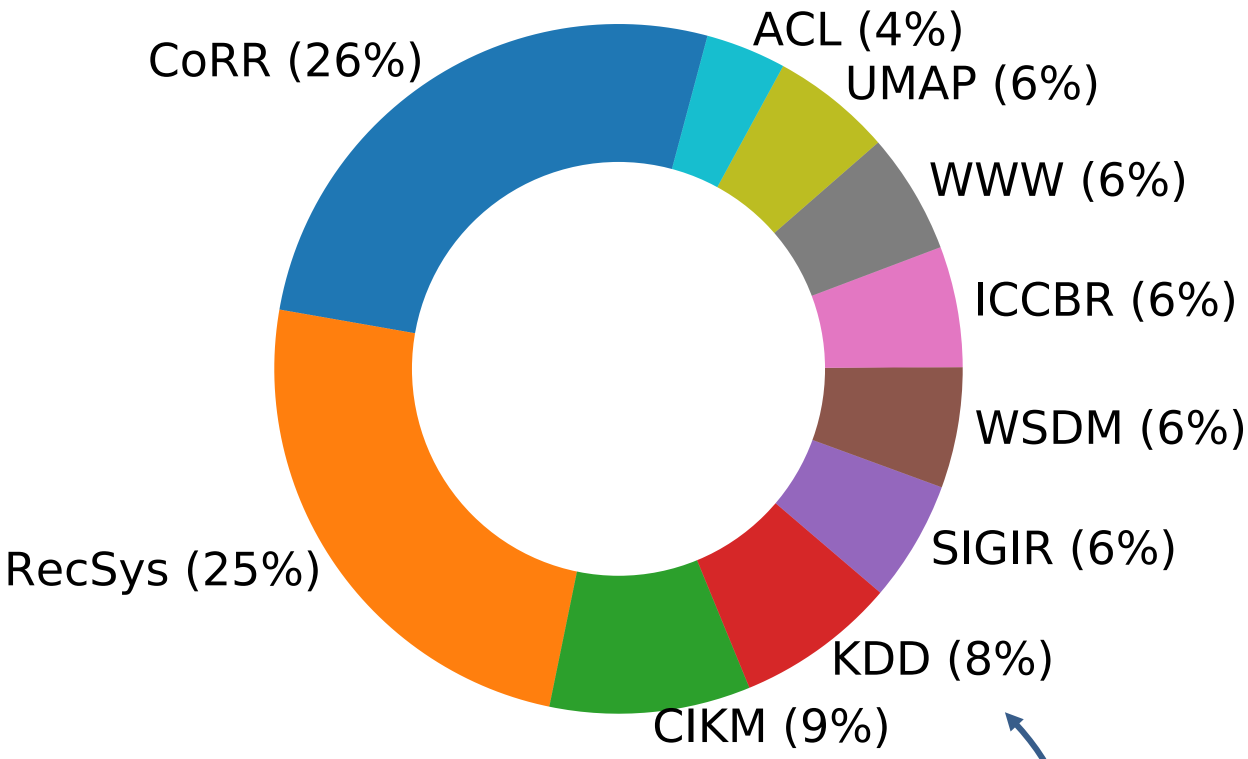
Searching results of "Conversation* Recommend*" on DBLP, * is a wildcard.

Statistics of papers w.r.t the published year.





There are 148 unique publications up to now, and we only visualize the top 10 venues in the circle chart, which contain 53 papers out of all 148 papers at all 89 venues.

❖ 1.2 Definition of CRSs

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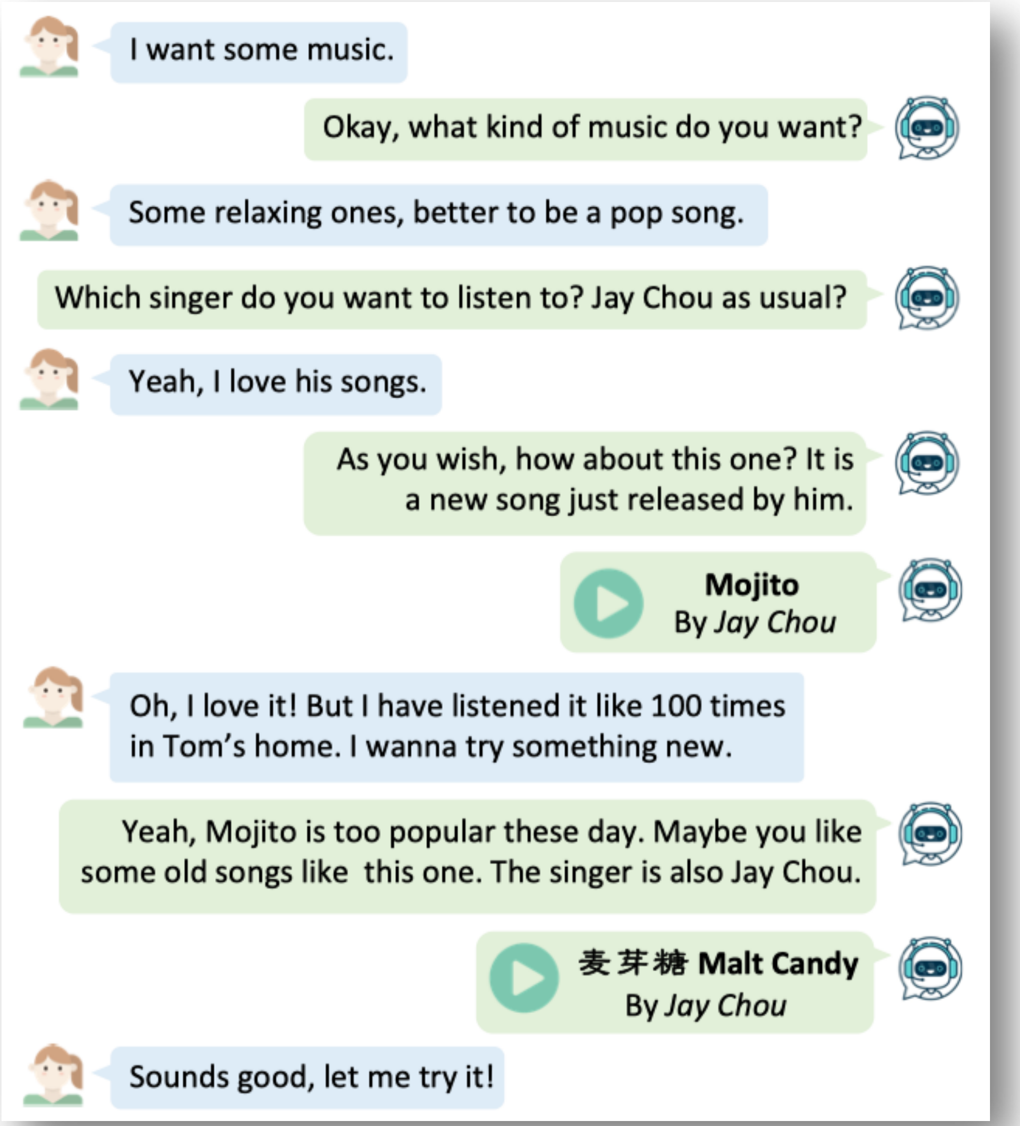

Figure: A toy example of the CRS.

Our Definition of the CRS:

"A recommendation system that can elicit the dynamic preferences of users and take actions based on their current needs through real-time multiturn interactions using natural language."

Our summarized framework of CRSs:

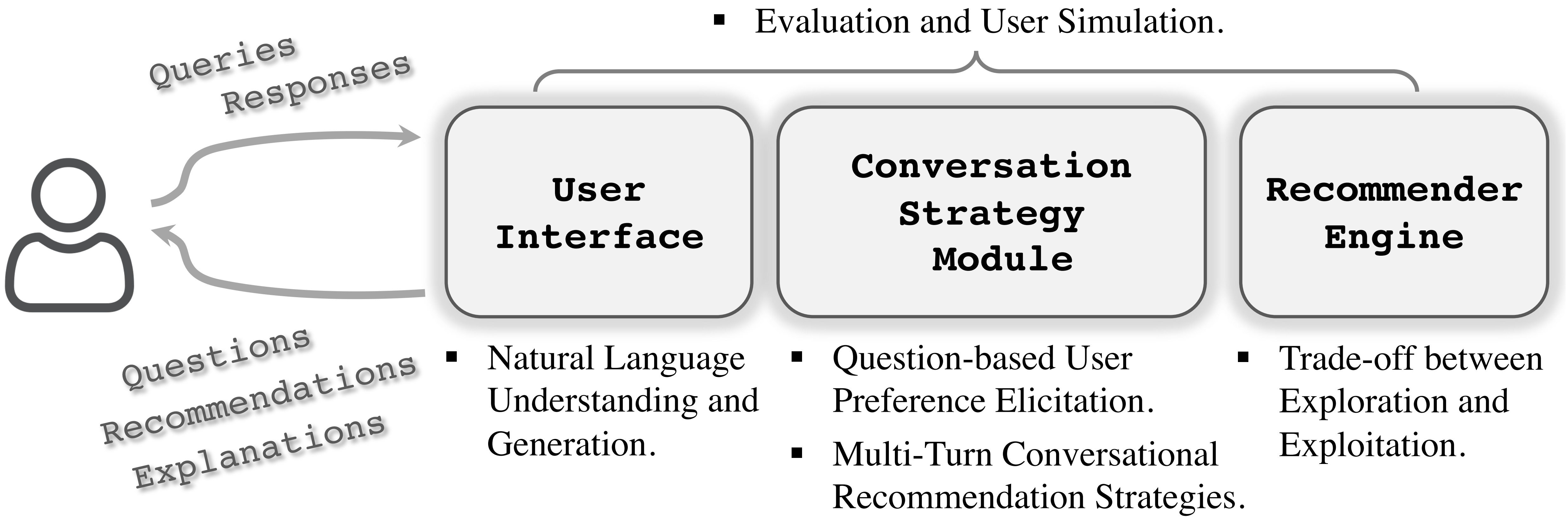

Figure: Illustration of the general framework of CRSs and our identified five primary challenges on the three main components.

Traditional recommender systems (RSs) and CRSs

- When estimating the user preference, RSs use static user-machine interaction. It has disadvantages: failure to answer two important questions:

1. What exactly does a user like? (E.g., clickbait, wrong decisions)
2. Why does a user like an item? (E.g., curious, affected by friends)

- Fortunately, CRSs resort to the dynamic interaction, which naturally addressed the two questions above.

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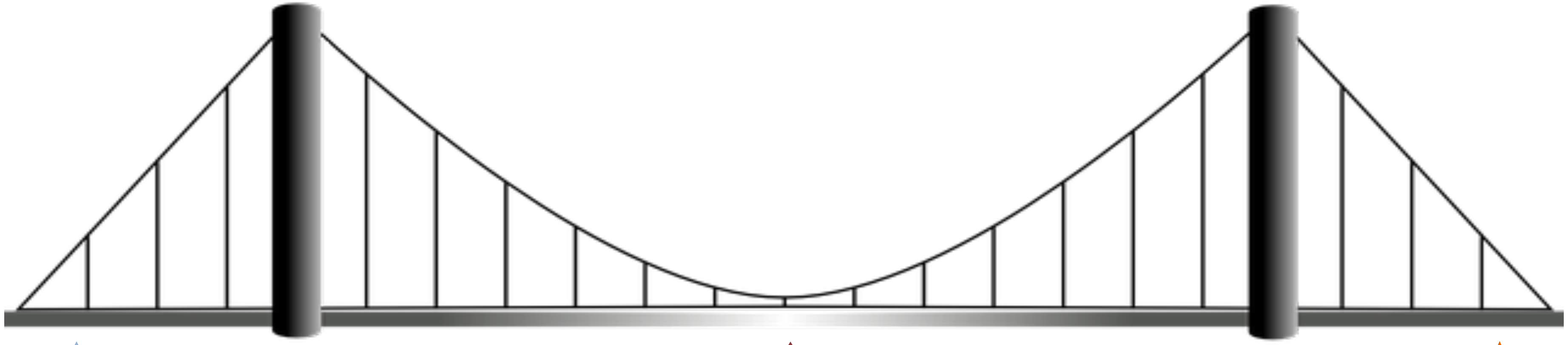
Traditional recommender systems (RSs) and CRSs

CRSs can bridge the gap between the search engines and recommender systems.



Searching:
User's Intention is clear, explicitly indicated by query

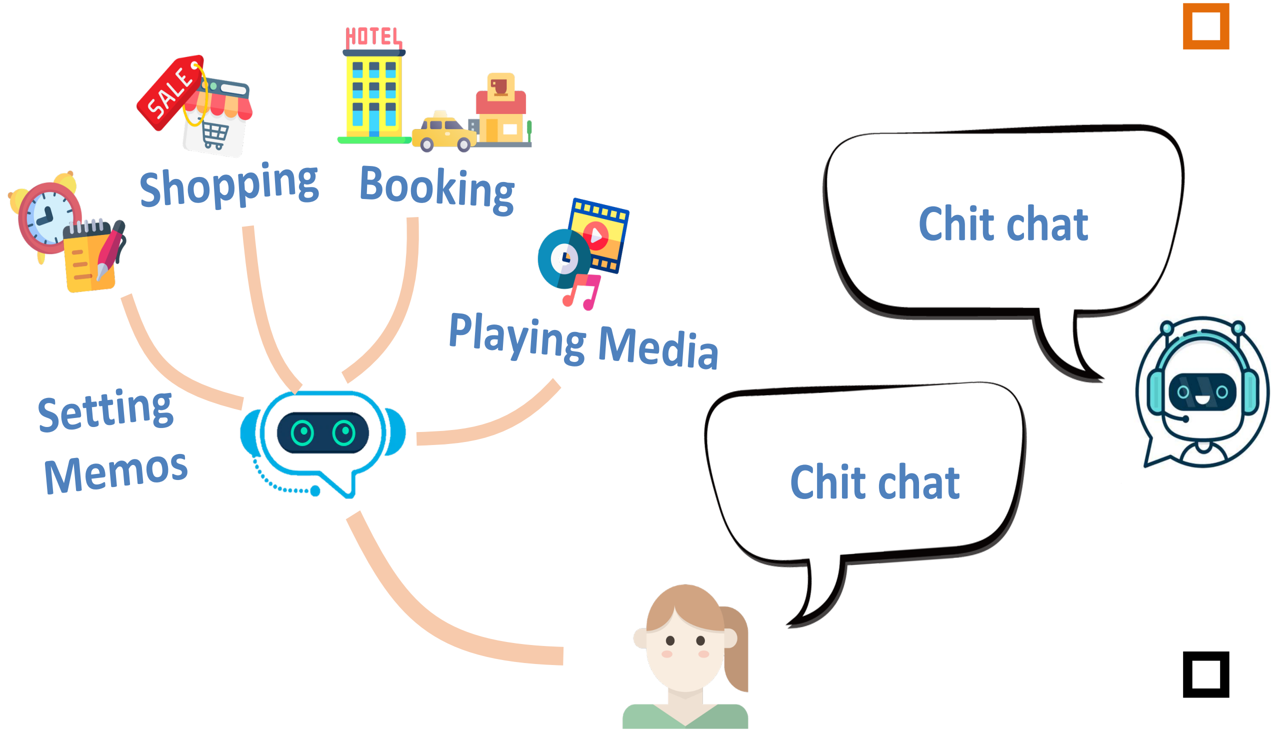
CRS:
Eliciting user preference through multi-turn conversations.
And makes confident recommendations.

Recommendation:
User's Intention is unclear, implicitly revealed in history.

Interactive recommender systems (IRSs) and CRSs

- IRSs can be deemed as an early form of CRSs.
- IRSs work by repeating the following two procedure, which is stiff, inflexible, and inefficient:
  1. Making a list of recommendations.
  2. Collecting user feedback, and adjust strategies. Jump to 1.
- CRSs introduce miscellaneous types of interaction.
  - It elicits user preferences by asking questions about attributes, which is efficient.
  - It only makes recommendations when the confidence is high, which improves user experience.

Task-oriented Dialogue Systems and CRSs



(a) Task-oriented dialogue systems (b) Chatbots

Figure: Two types of dialogue systems

- Problems in dialogue systems:
  - Focusing on deep end-to-end NLP models to fit the patterns from human conversations.
  - Failure to generate new conversation; failure to produce satisfying recommendation (Jannach et al.).
- Main focus of CRSs:
  - Aiming to elicit accurate user preferences, and generate high-quality recommendations. Not focusing on language.

Dietmar Jannach and Ahtsham Manzoor. 2020. End-to-End Learning for Conversational Recommendation: A Long Way to Go? (RecSys Workshop 2020)

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1. Background and Motivation.
2. **Five Important Challenges.**
   - Question-based User Preference Elicitation.
   - Multi-turn Conversational Recommendation Strategies.
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   - Trade-offs between Exploration and Exploitation (E&E).
   - Evaluation and User Simulation.
3. Promising Future Directions.

Two kinds of questions asking methods

Asking about Items

Figure Credit: *Tong Yu, Yilin Shen, and Hongxia Jin. A Visual Dialog Augmented Interactive Recommender System. KDD' 19*

Asking about Attributes

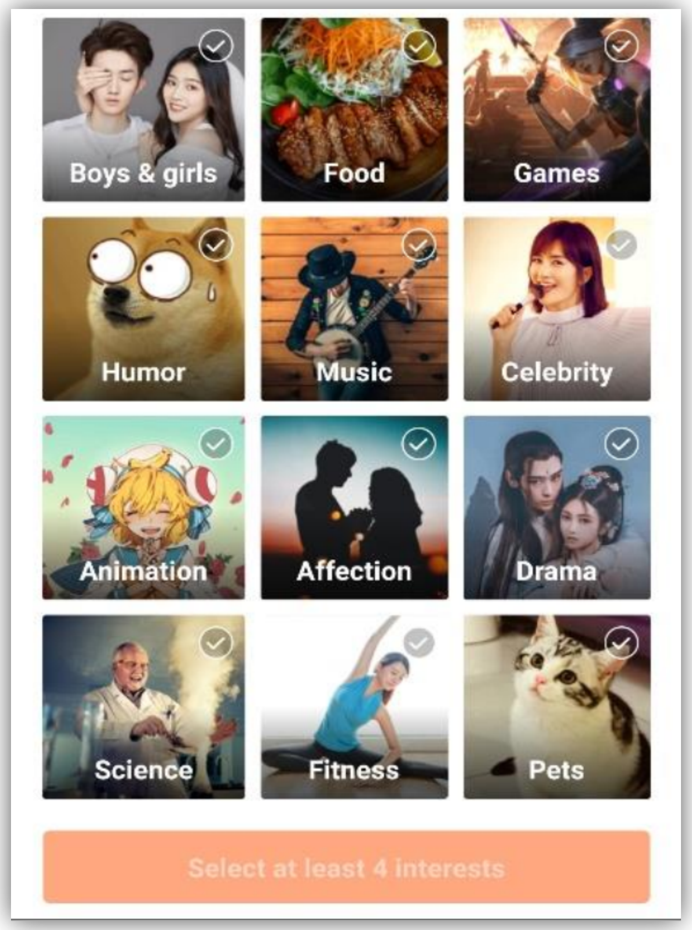

Figure Credit: *Shijun Li et al. Seamlessly Unifying Attributes and Items: Conversational Recommendation for Cold-Start Users. TOIS' 2021.*

❖ 2.1 Question-based User Preference Elicitation

Classification common CRSs w.r.t.:

- Asking mechanism
- Basic model
- Type of user feedback
- Multi-turn strategy

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]
	Exploitation & Exploration	Meta learning	Rating on the given item(s)	No	[235, 87]
	Maximal posterior user belief	Bayesian methods	Rating on the given item(s)	No	[171]
	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]
	Reducing uncertainty	Bayesian approach	Providing preferred attribute values	No	[113]
		Critiquing-based methods	Critiquing one/multiple attributes	No	[117, 155, 172, 12, 154] [135, 23, 189, 108, 107]
		Matrix factorization	Answering Yes/No for an attributes	No	[232]
	Fitting historical patterns	Sequential neural network	Providing preferred attribute values	Yes	[31, 210]
			Providing an utterance	No	[94, 25]
	Maximal reward	Reinforcement learning	Answering Yes/No for an attributes	Yes	[88, 89]
			Providing an utterance	Yes	[161, 167, 76]
				No	[141]
	Exploring graph-constrained candidates	Graph reasoning	Answering Yes/No for an attributes	Yes	[89]
			Providing an utterance	Yes	[25, 104]
				No	[225, 98]
			Providing preferred attribute values	Yes	[193]
				No	[123]

❖ 2.1 Question-based User Preference Elicitation

A classic example, in which the CRS asks the questions and generates questions based on the generated paths on the graph.

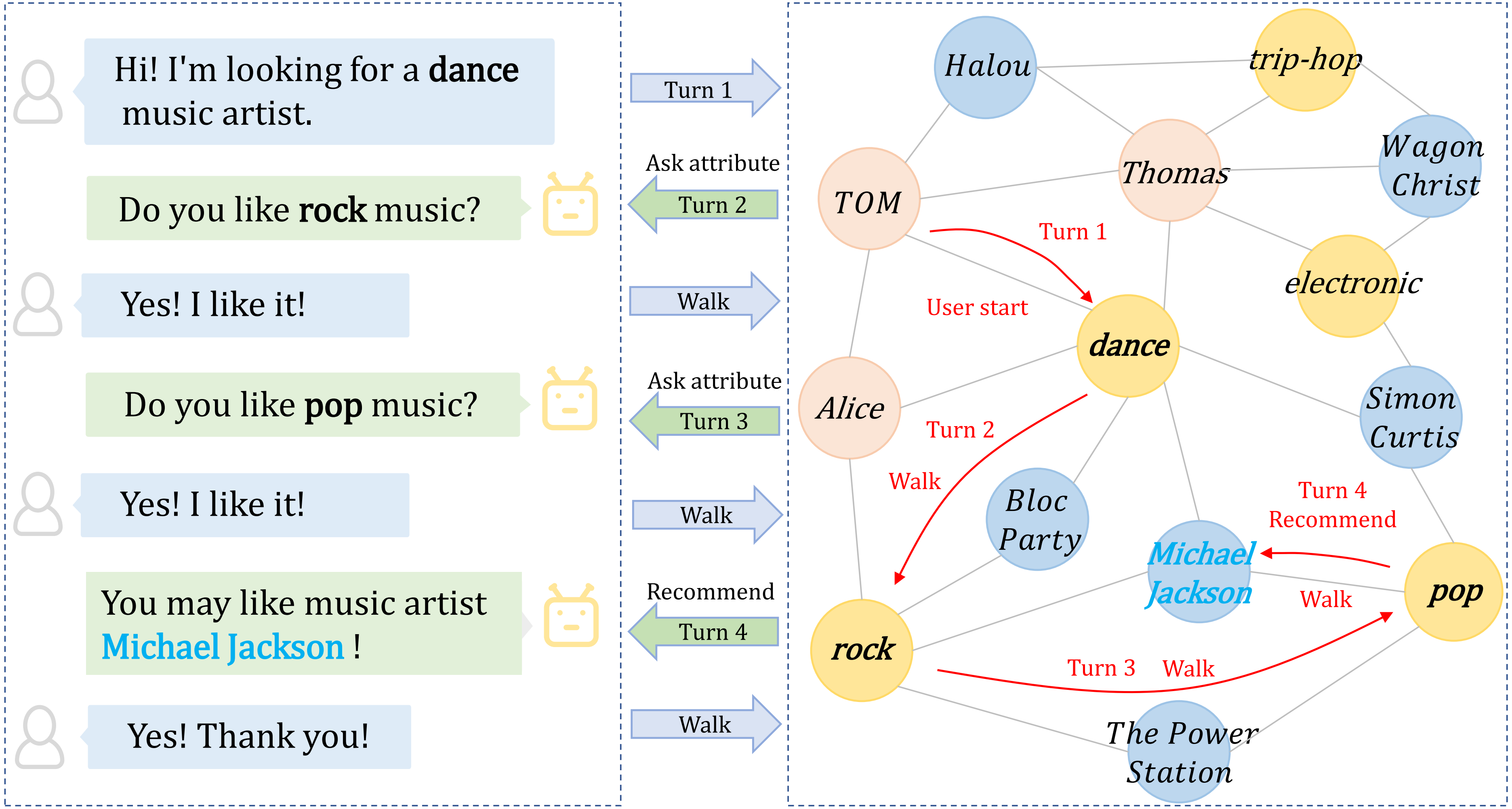

Figure Credit: Wenqiang Lei et al. Interactive Path Reasoning on Graph for Conversational Recommendation. KDD' 20

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❖ 2.2 Multi-turn Strategies

The commonly used multi-turn strategies in CRSs

Strategies of asking questions

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, 18

These studies are not related to either asking questions or elicit preference, but various strategies from a broader perspective. E.g., learn to suggest, bargain, negotiate, and persuade in conversations.

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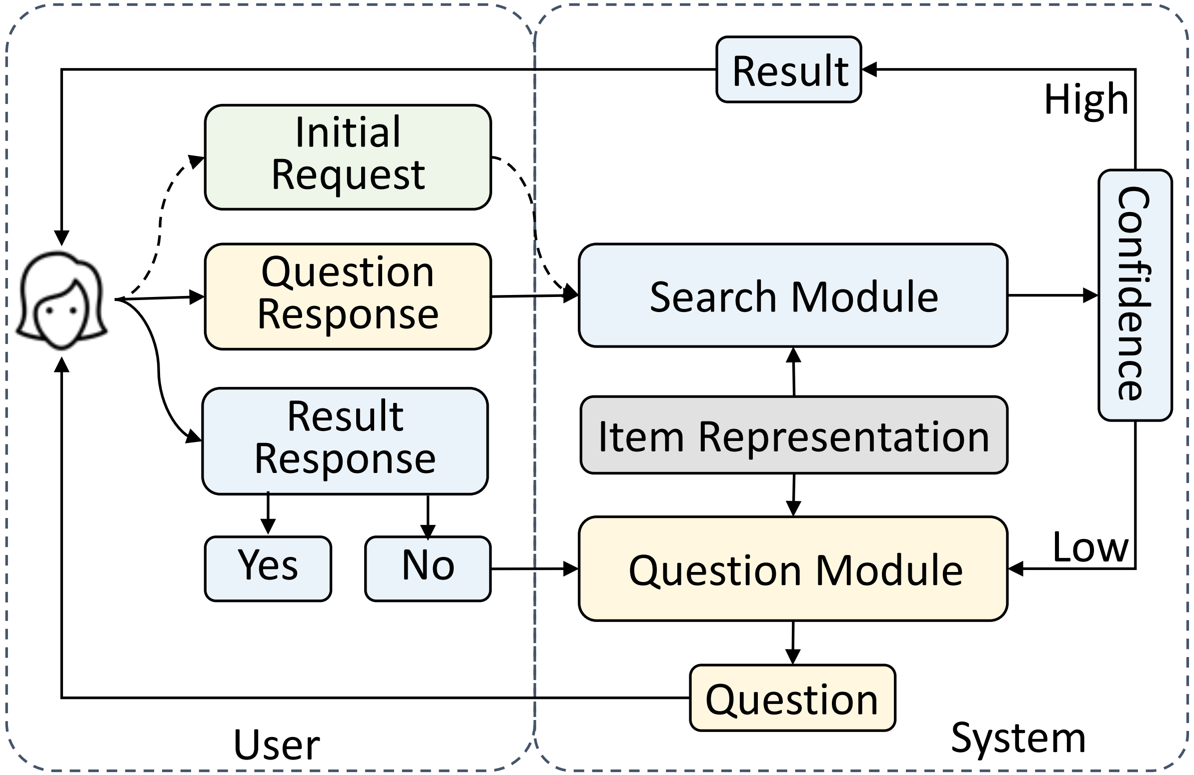
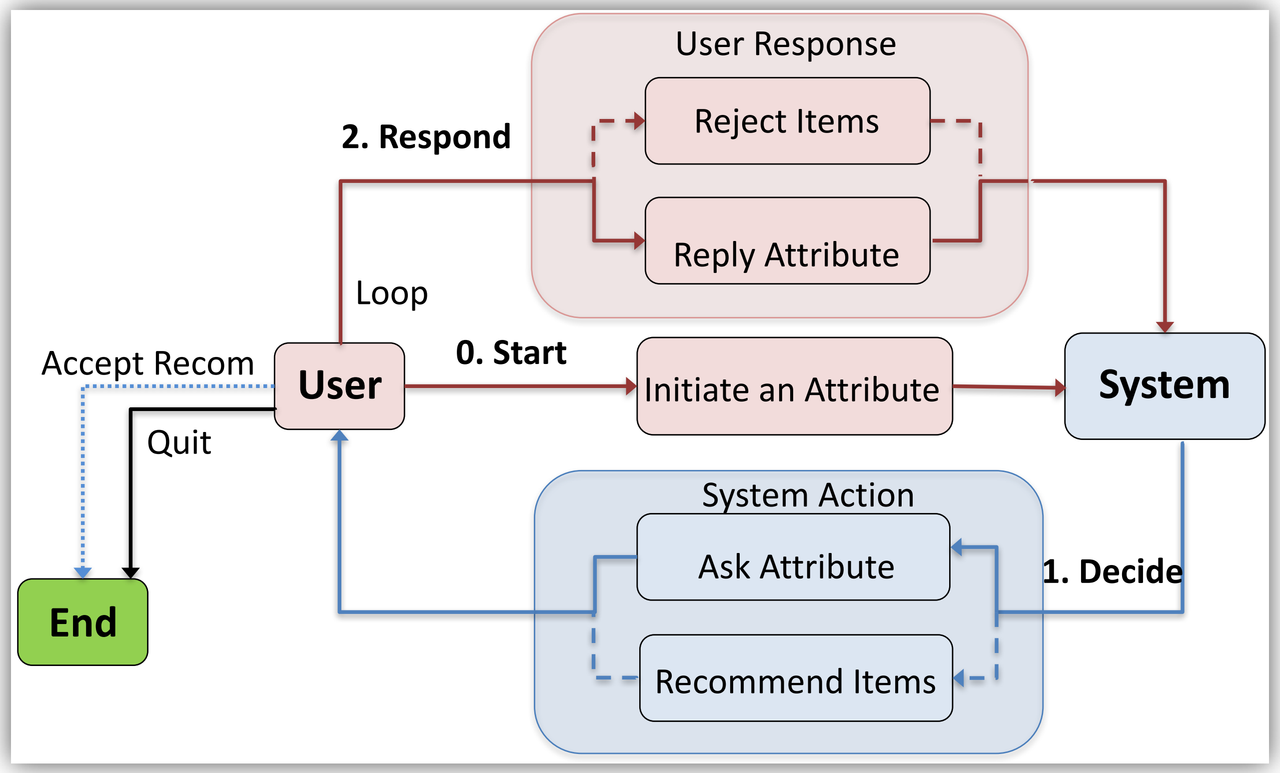
Two exemplary CRS workflows

They are similar in the design but **different in implementation**.





Implemented by memory network (Supervised Learning)

Implemented by reinforcement learning

Figure Credit: *Yongfeng Zhang et al. Towards Conversational Search and Recommendation: System Ask, User Respond. CIKM' 18*

Figure Credit: *Wenqiang Lei et al. Estimation-Action-Reflection: Towards Deep Interaction Between Conversational and Recommender Systems. WSDM' 20.*

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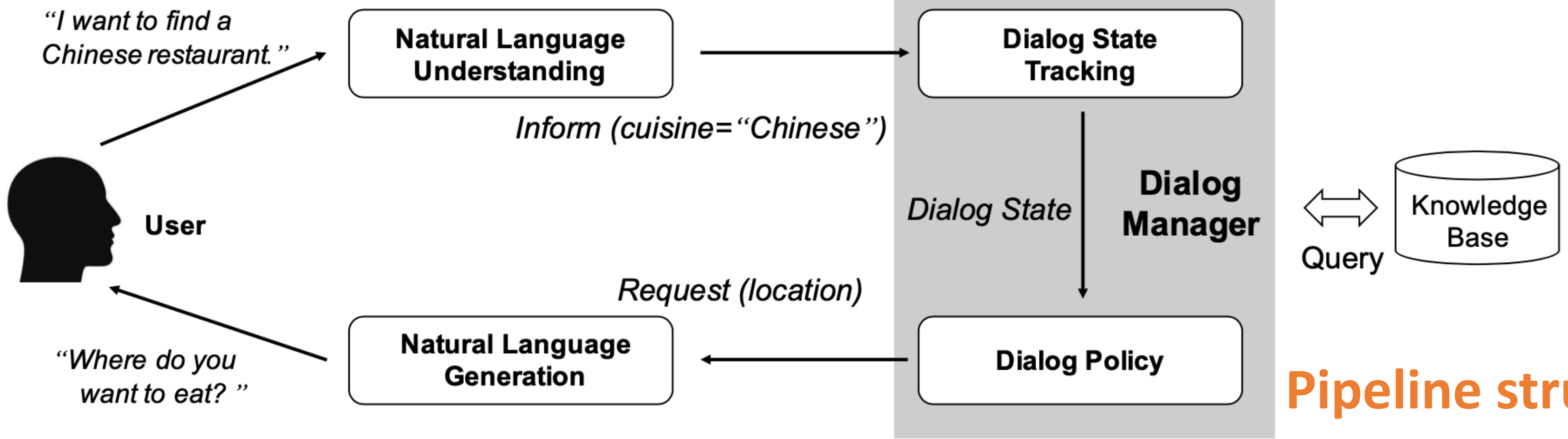
Mechanisms of language understanding and response generation in CRSs.

Most CRSs are based on templates, since the focus is the recommendation, not the language.

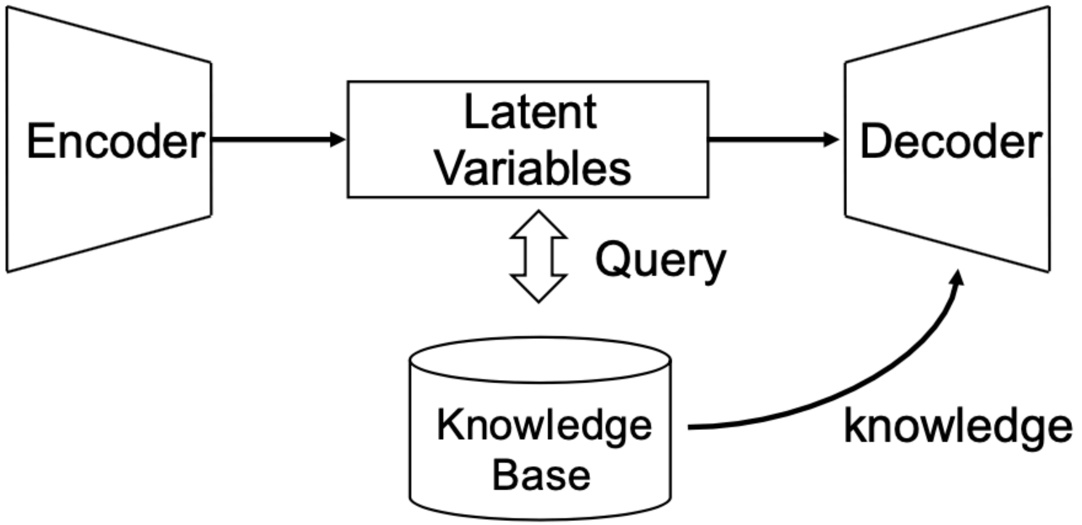
Forms of Input & Output	Publications
Pre-annotated Input & Template-based Output	[217, 232, 105, 210, 161], [32, 31, 88, 89, 95]
Raw Language Input & Natural Language Generation	[141, 94, 25], [225, 111, 104]

❖ 2.3 Natural Language Understanding and Generation

- **Two philosophies of handling raw language in dialogue systems**



Pipeline structure



End-to-end structure

Figure Credit: *Zhang et al. Recent Advances and Challenges in Task-oriented Dialog Systems (Science China' 20)*

A classic CRS with end-to-end structure.

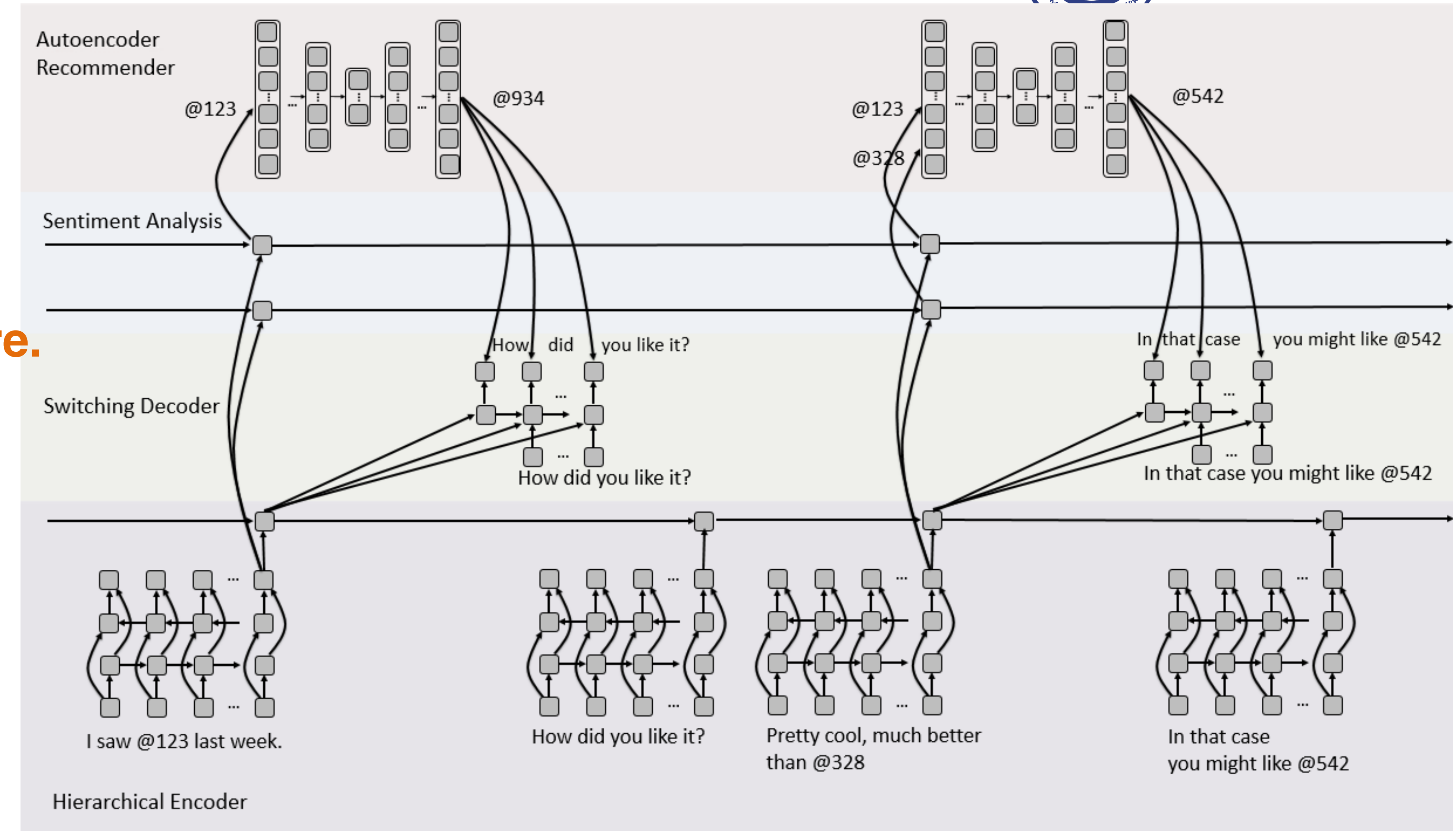


Figure Credit: *Jianfeng Gao, et al. Neural Approaches to Conversational AI: Question Answering, Task-oriented Dialogues and Social Chatbots. Now Foundations and Trends.*

❖ 2.3 Natural Language Understanding and Generation

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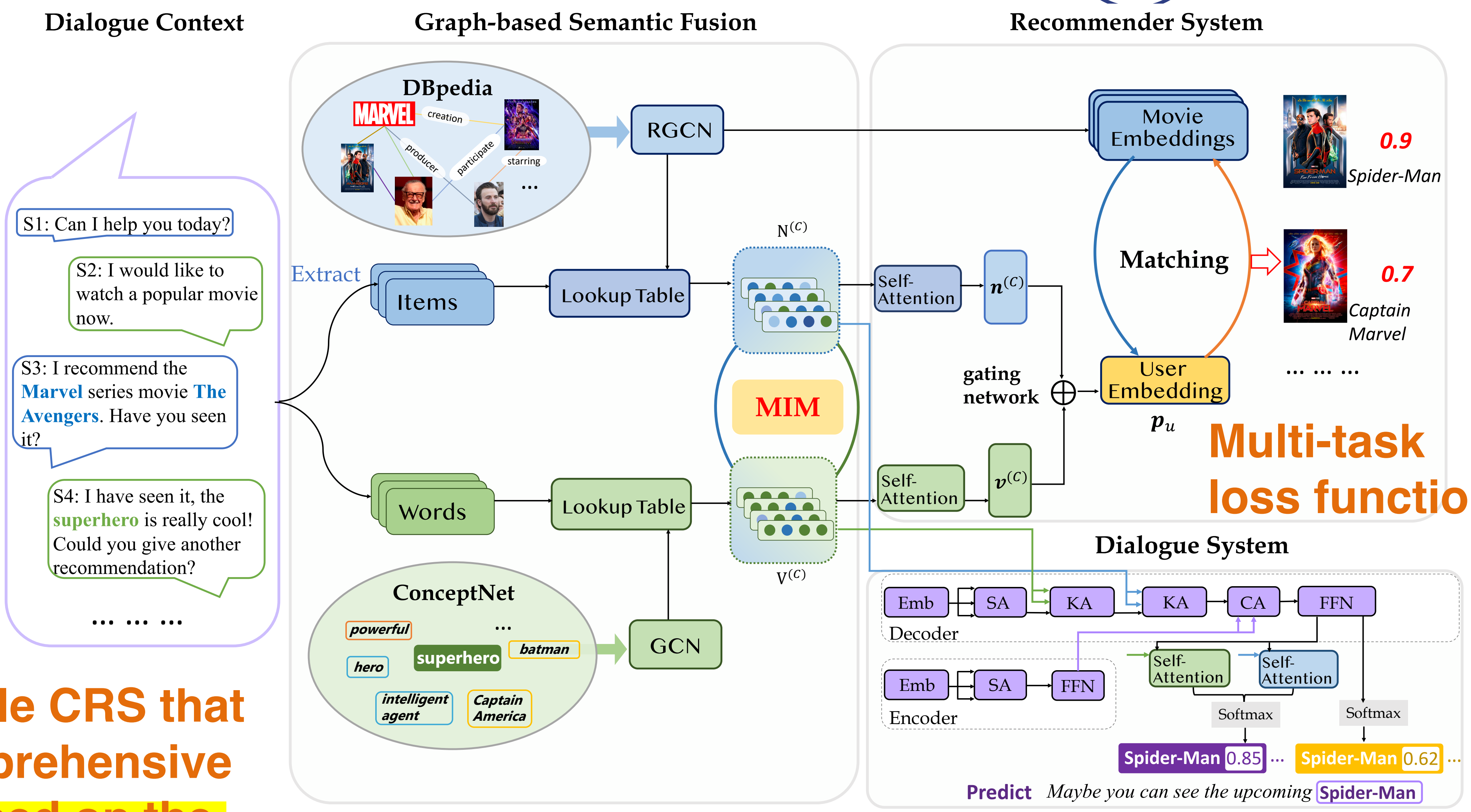

Multi-task loss function

Another example CRS that considers comprehensive information based on the deep dialogue system

Figure Credit: Kun Zhou, et al. Improving Conversational Recommender Systems via Knowledge Graph based Semantic Fusion. KDD' 20

- **Problems** in existing CRSs based on dialogue systems:
  - Focusing on deep end-to-end NLP models to fit the patterns from human conversations.
  - Failure to generate new conversation;
  - Failure to produce satisfying recommendation (Jannach et al.).

  Source: *Dietmar Jannach and Ahtsham Manzoor. 2020. End-to-End Learning for Conversational Recommendation: A Long Way to Go? (RecSys Workshop 2020)*

- However, it is worthy of trying, since natural language have the advantages:
  - Flexible.
  - Natural for users.

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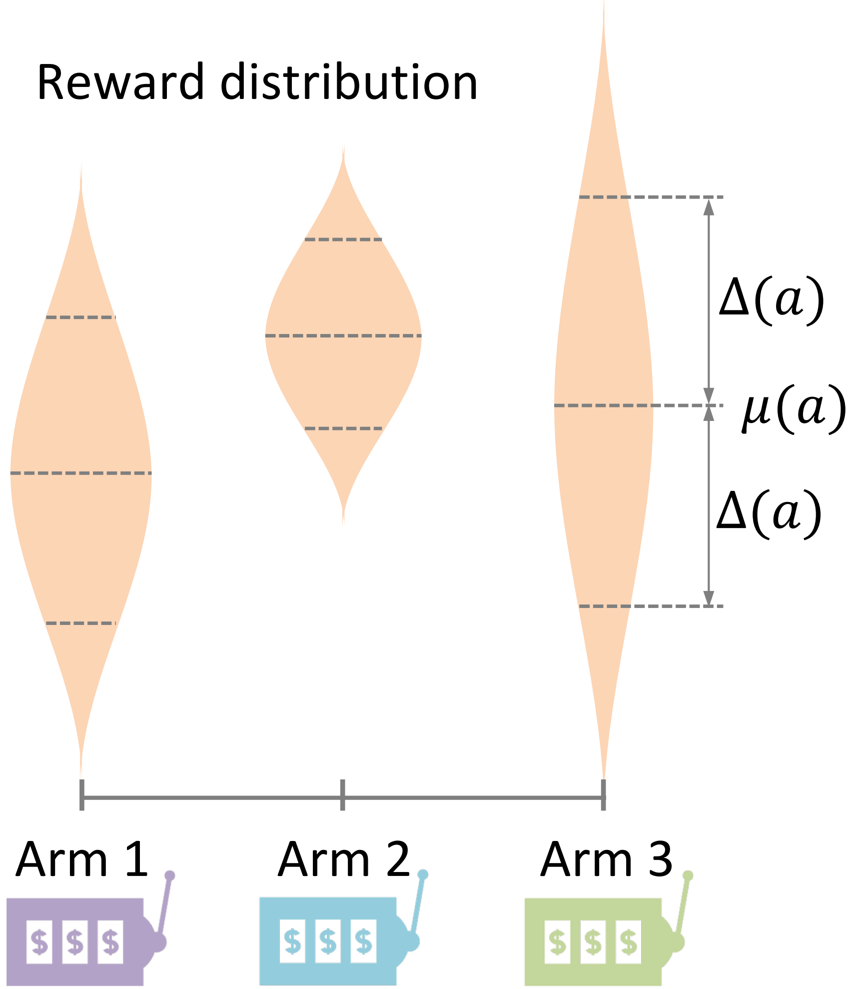
Multi-armed Bandit problem: A gambler needs to decide which arm to pull to get the maximal reward.



He can only estimate the statistics, e.g., the mean $\mu(a)$ and uncertainty $\Delta(a)$ of each arm by doing experiments.

❖ 2.4 E&E Tradeoff

Exploration (Learning)		Exploitation (Earning)
✓ Take some risk to collect information about unknown options	⟺ Trade-off	✓ Takes advantage of the best option that is known.

Multi-armed bandit example: which arm to select next?

#(Successes) / #(Trials)

Arm 1	Arm 2	Arm 3	Arm 4	…
2/5	0/1	3/8	1/3	…

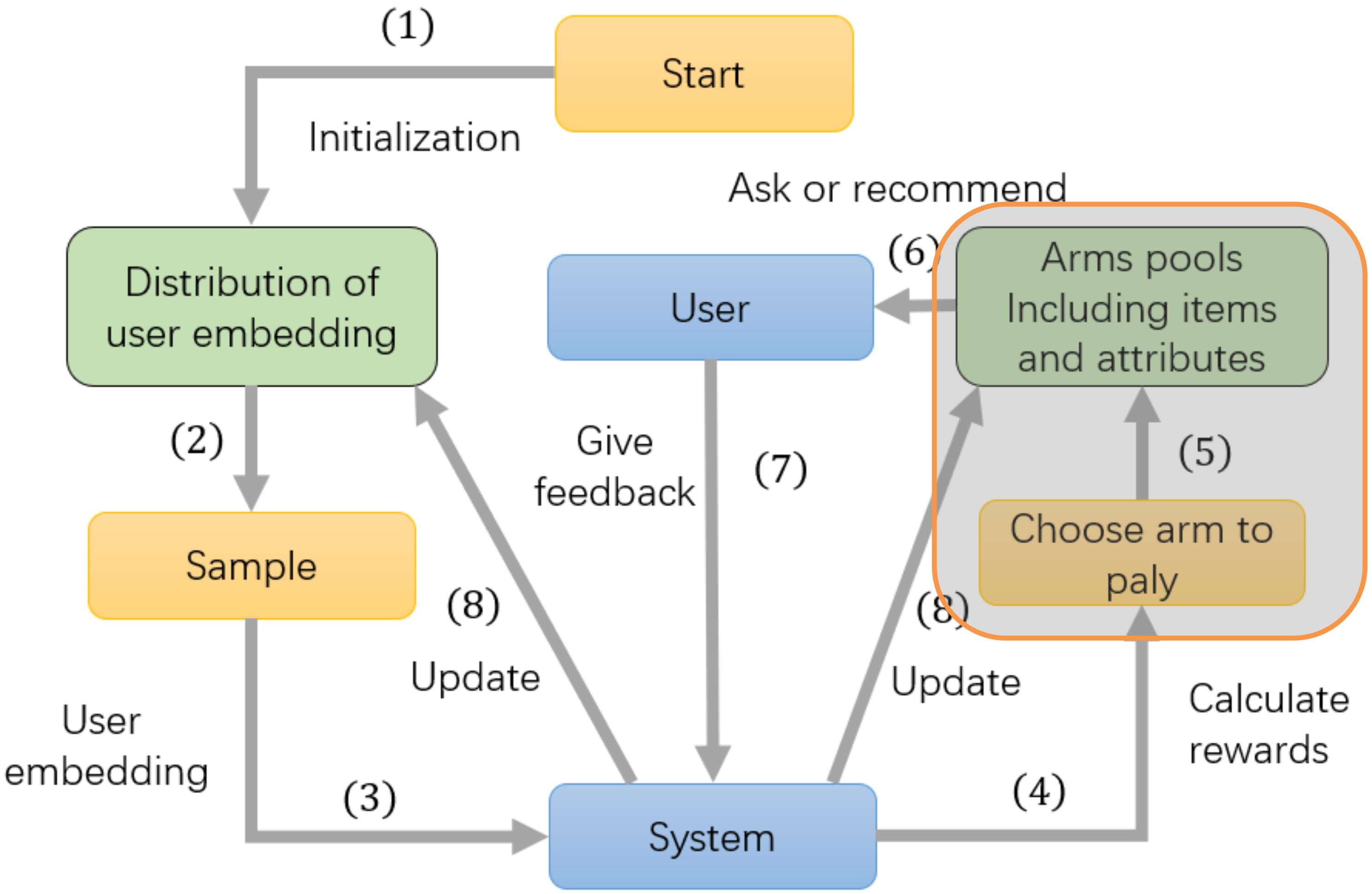
Common intuitive ideas:

- **Greedy:** trivial exploit-only strategy
- **Random:** trivial explore-only strategy
- **Epsilon-Greedy:** combining Greedy and Random.
- **Max-Variance**: only exploring w.r.t. uncertainty.

E&E-based methods adopted in IRSs (interactive RSs) and CRSs

	Mechanism	Publications
MAB in IRSs	Linear UCB considering item features	[92]
	Considering diversity of recommendation	[137, 103, 40]
	Cascading bandits providing reliable negative samples	[84, 231]
	Leveraging social information	[205]
	Combining offline data and online bandit signals	[145]
	Considering pseudo-rewards for arms without feedback	[30]
	Considering dependency among arms	[180]
	Considering exploration overheads	[198]
MAB in CRSs	Traditional bandit methods in CRSs	[32]
	Conversational upper confidence bound	[209]
	Conversational thompson sampling	[95]
	Cascading bandits augmented by visual dialogues	[205]
Meta learning for CRSs	Learning to learn the recommendation model	[87, 235, 188]

An exemplar CRS that uses contextual bandit model.



The core idea:

There are N+M arms (actions).

Each arm corresponds to either:

(1) asking a question out of N questions, or

(2) making a recommendation out of M.

The model will decide.

Figure Credit: *Shijun Li et al. Seamlessly Unifying Attributes and Items: Conversational Recommendation for Cold-Start Users. TOIS' 2021.*

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❖ 2.5 Evaluation and User Simulation

Two kinds of Evaluation metrics:

- **Turn-level Evaluation**
  - Evaluation of Recommendation: RMSE, MSE, recall, precision, F1-score, Hit, NDCG, MAP, MRR
  - Evaluation of Dialogue Generation: BLEU, Rouge

- **Conversation-level Evaluation:**
  - AT (Average turn), the lower the better as the system should achieve the goal as soon as possible.
  - SR@*k* (success rate at *k*-th turn), the higher the better.

User simulation:

- Motivation: since the real-time interaction between the machine and user is:
  - Very slow, very sparse, hard to collect.
  - Hurting user experience when the user does not like the recommended items.

- Therefore, a natural solution is to simulate fake users.

❖ 2.5 Evaluation and User Simulation

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Methods of user simulation:

- **Using direct interaction history of users**
  - Similar to traditional recommendation.
  - Disadvantage: Very sparse.
- **Estimating user preferences on all items in advance**
  - Solved the missing data problem
  - Disadvantage: May introduce estimating error
- **Extracting from user reviews**
  - Explicitly mentions attributes, which can reflect the personalized opinions of the user on this item.
  - Disadvantage: Hard to distinguish user sentiment
- **Imitating human conversational corpora**
  - Used in the dialogue system-driven CRSs
  - Disadvantage: non-transparent and hard to interpret

❖ 2.5 Evaluation and User Simulation

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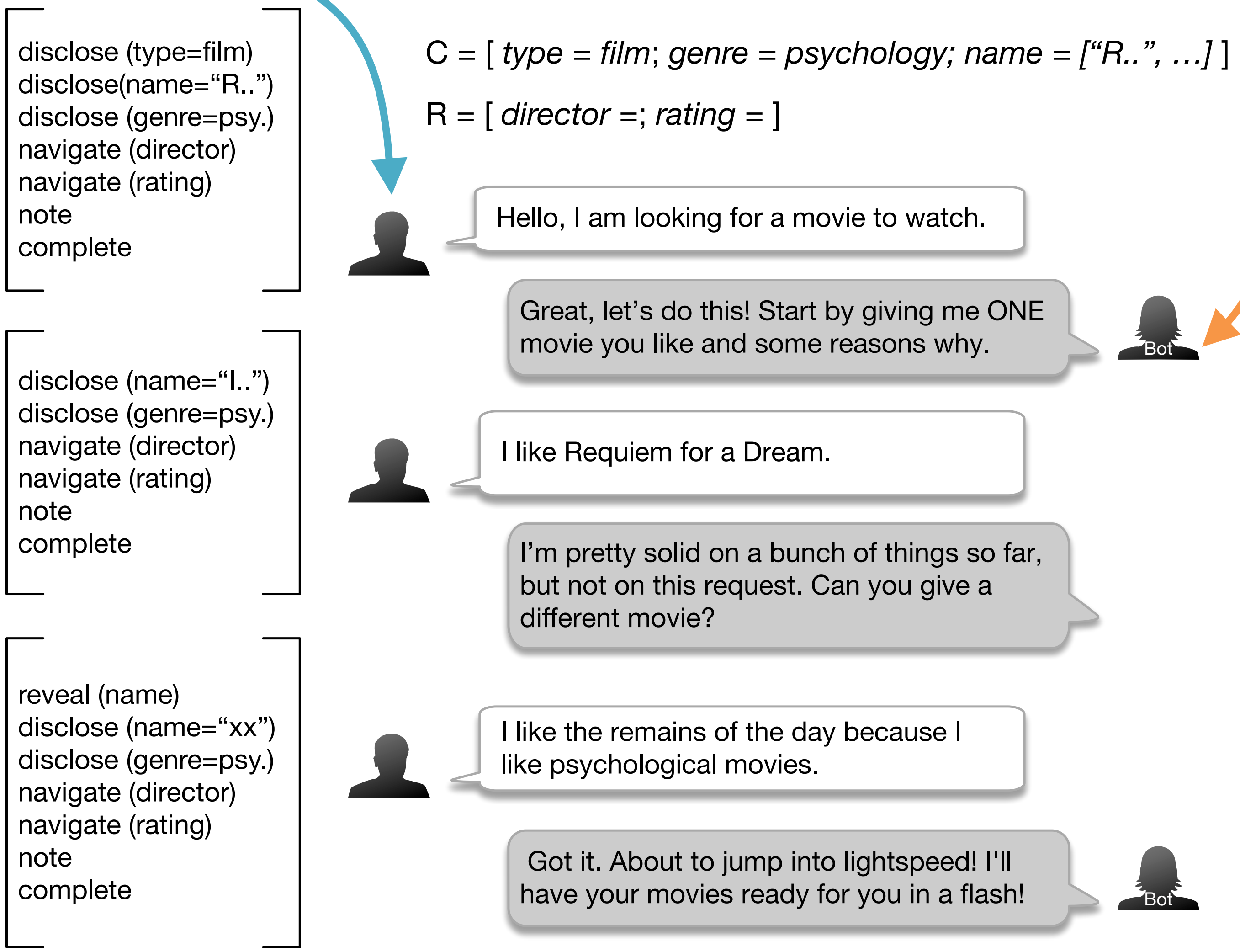
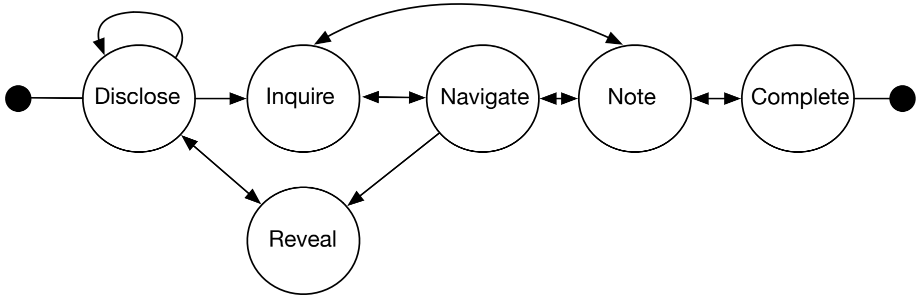
Simulated user

CRS

Stack-like simulation strategy





Defined state transition rule

Figure Credit: *Shuo Zhang and Krisztian Balog. Evaluating Conversational Recommender Systems via User Simulation. KDD' 20*

❖ 2.5 Evaluation and User Simulation

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Datasets:

Simulated from traditional RS data (without dialogues)

Collected with dialogue data

Dataset	#Dialogs	#Turns	Dialogue Type	Domains	Dialogue Resource	Related
MovieLens [7]	Depended on the dialogue simulation process			Movie	From item ratings	[217, 10 [87, 69,
LastFM [7]				Music	From item ratings	[88, 89,
Yelp				Restaurant	From item ratings	[161, 88
Amazon [116]				E-commerce	From item ratings	[210, 47 [189, 10
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,
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]

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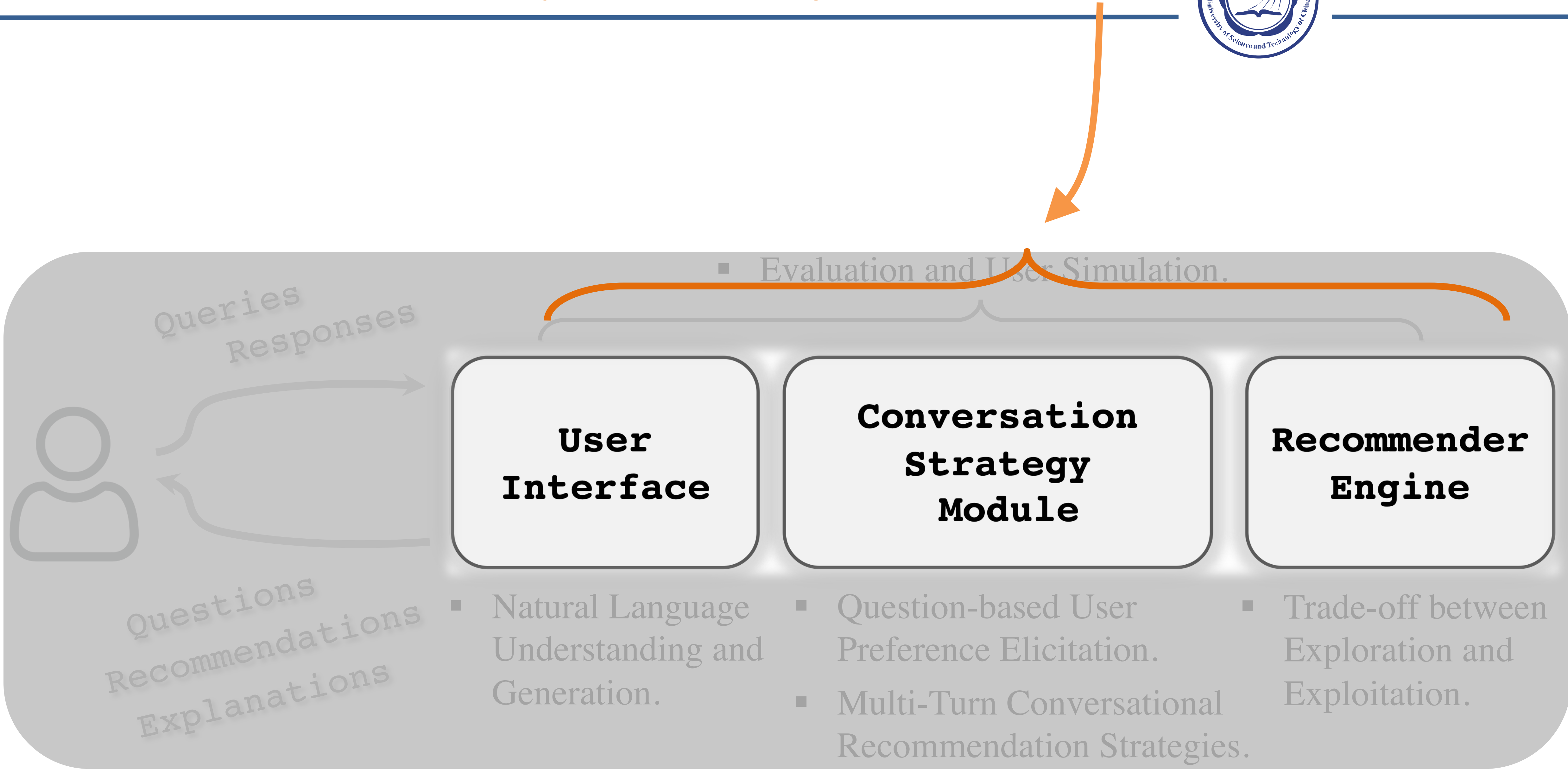
❖ Future direction: Jointly Optimizing Three Tasks



❖ Future direction: Bias and Debiasing in CRSs

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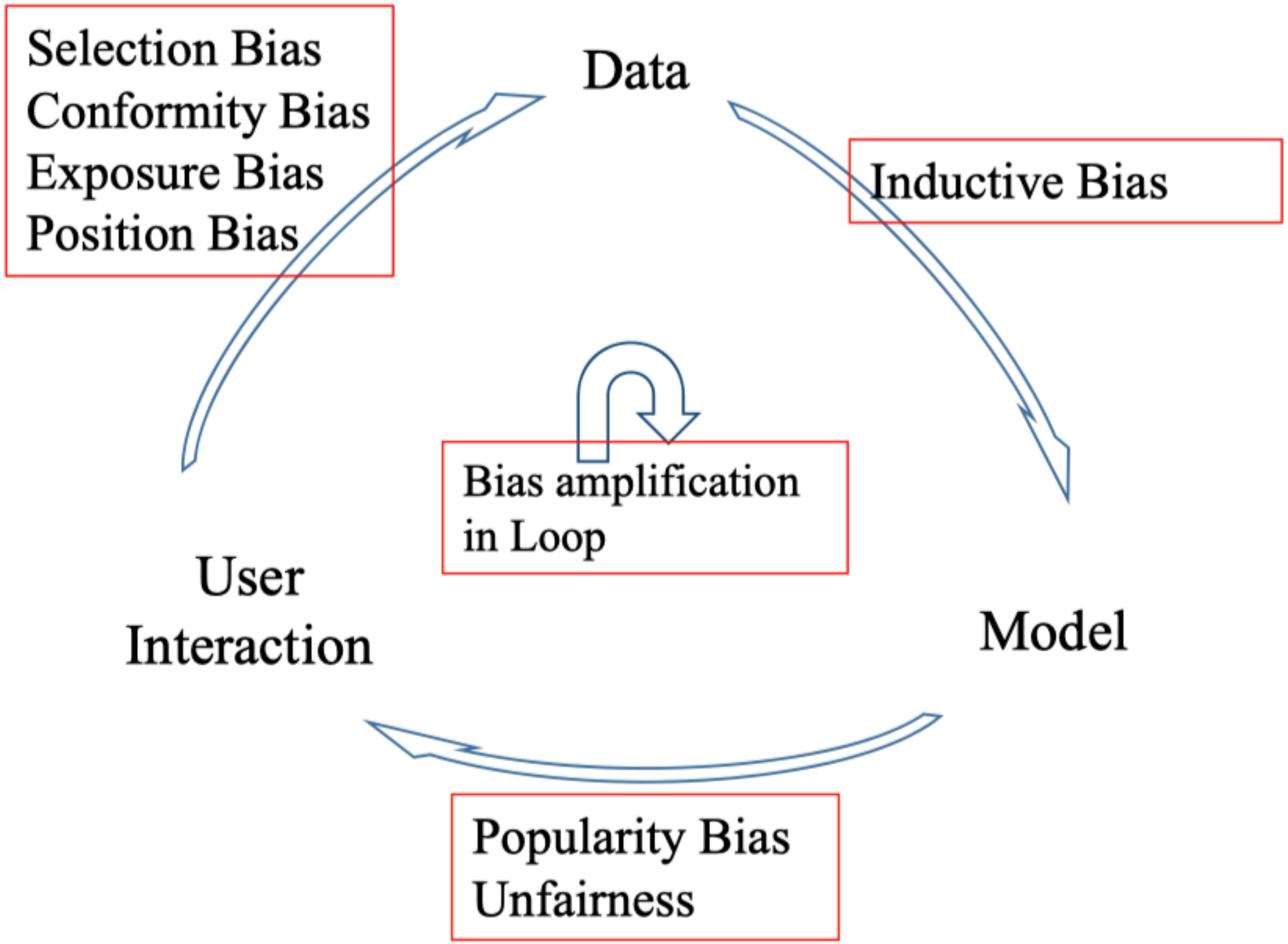
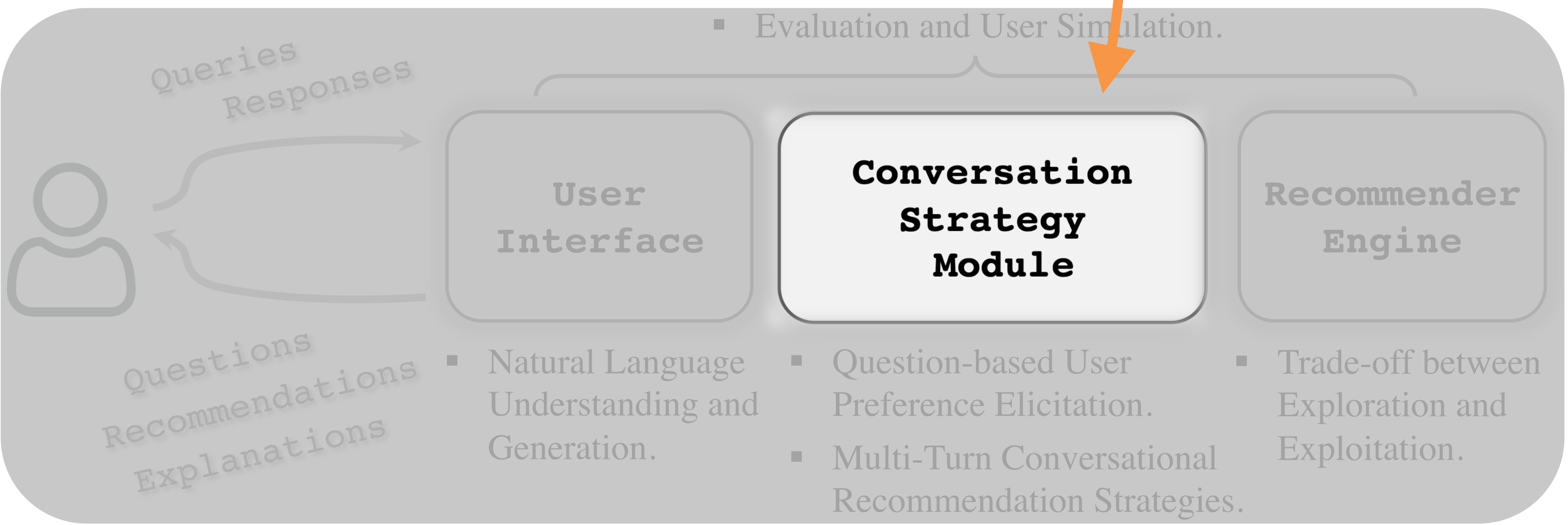


Figure Credit: *Jiawei Chen, Hande Dong, Xiang Wang, Fuli Feng, Meng Wang, and Xiangnan He. 2020. Bias and Debias in Recommender System: A Survey and Future Directions. arXiv preprint*

❖ Future direction: Sophisticated Strategies

- How to handle negative feedback?
- How to design the reward function based on the feedback?
- How to do E&E in sparse interaction?



❖ Future direction: Knowledge Enrichment

- To import word-level, concept-level knowledge graph
- To import visual, sound modality

❖ Future direction: Better Evaluation and User Simulation

- ☐ How to simulate reliable users?

Thanks

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