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GRILL Lab

Conversational Search:
From **Fundamentals** to **Frontiers** in the **Agent** Era

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About me

Chuan Meng

- Postdoc, University of Edinburgh (since 9/2025)
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Overview

Part I: Fundamentals of Conversational Search [25 min]

- Introduction to conversational search
- Conversational search basic paradigms
- Conversational retrieval-augmented generation
- Mixed initiative
- Personalization

Part II: Emerging Topics in the Agent Era [15 min]

- Agentic search
- Agentic conversational search

Part III: Summary and Future Directions [5 min]

Part 1

Fundamentals of Conversational Search

Introduction for Conversational Search

Comparison between Conversational and Ad-hoc Search

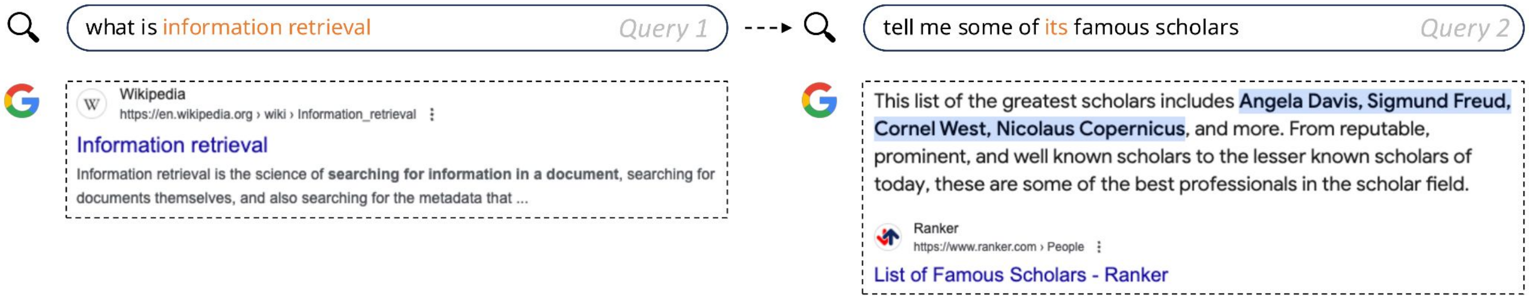
General goal: Conversational search aims to identify relevant documents to satisfy users' complex information needs through multi-turn interactions.

Conversational Search v.s. **Ad-hoc Search**:

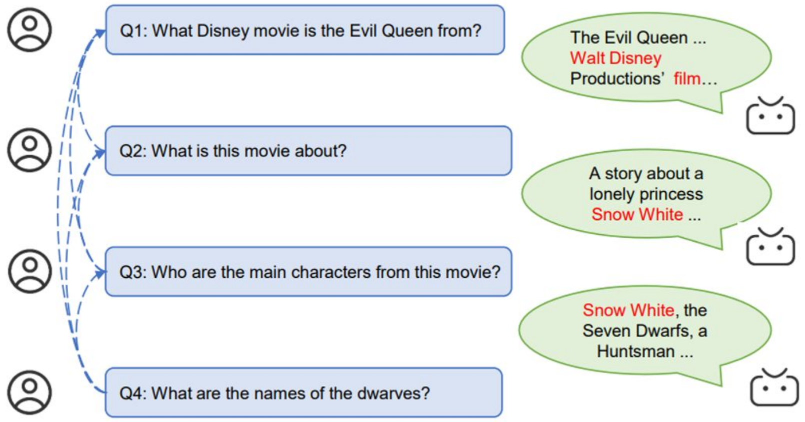
- ➢ Multi-turn interaction v.s. Single-turn search
- ➢ Natural language based query v.s. Keyword based query
- ➢ Flexible interface v.s. 10 blue links

Comparison between Conversational and Ad-hoc Search

Ad-hoc Search



Conversational Search



Why Conversational Search is Important?

- **Natural Interaction** - feel like talking to a human
- **Context Awareness** - understand follow-up queries and refine results
- **Handles Complex Queries** - support clarification, refinement, and reasoning
- **Improves User Experience:**
  - reduces the need of query reformulation
  - friendly for non-technical users
  - delivers more precise, personalized results

Introduction

User queries in conversational search

- Context-dependent query
  - Query: How many rings does he have? (what rings? who is he?)
- Ambiguous query
  - Query: What is the price of apple? (fruit or any apple products)
- Topic-Switch
  - Previous Query: When was the byzantine empire born? (Topic: History)
  - Current Query: What is its famous tourist places now? (Topic: Tourism)
- Etc.

Introduction

Conversational search systems capacity

- ➢ Context-dependent query ⇒ Understand real search intent via context modeling
- ➢ Ambiguous query ⇒ Search intent clarification (Mixed Initiatives)
- ➢ Topic-Switch ⇒ Context denoising via turn relevance/usefulness

Introduction

Conversational search systems capacity

- Understand real search intent via context modeling
  - Q1: Who is the best player in NBA so far? R1: Michael Jordan.
  - Q2: How many rings does he have?
  - ⇒ How many NBA championship rings does Michael Jordan have?
- Search intent clarification (Mixed Initiatives)
- Context denoising via turn relevance/usefulness
- Etc.

Introduction

Conversational search systems capacity

- ➢ Understand real search intent via context modeling
- ➢ Search intent clarification (Mixed Initiatives)
  - ○ What is the price of apple here?
  - ○ ⇒ Are you requesting for the price of apple fruit or any digital products from apple company?
- ➢ Context denoising via turn relevance/usefulness
- ➢ Etc.

Conversational search systems capacity

- Understand real search intent via context modeling
- Search intent clarification (Mixed Initiatives)
- Context denoising via turn relevance/usefulness
  - Q1: When was the byzantine empire born? (Relevant)
  - Q3: Which battle or event marked the fall of this empire?
  - Q5: Can you name some of major cities in Turkey? (Relevant)
  - Current Query: Were any of these cities associated with the first empire you were discussing?

Widely Used Datasets

From NLP community

- ➢ TopiOCQA [1], QReCC [2], INSCIT [3], CORAL [4], etc.

From IR community

- ➢ TREC CAsT 2019-2022 [5] and TREC iKAT 2023-2025 [6]
- ➢ OR-QuAC [7], ProCIS [8]
- ➢ Etc.

[1] TopiOCQA: Open-domain Conversational Question Answering with Topic Switching. Adlakha et al. TACL 2022.
[2] Open-Domain Question Answering Goes Conversational via Question Rewriting. Anantha et al. NAACL 2021.
[3] InSCIt: Information-Seeking Conversations with Mixed-Initiative Interaction. Wu et al. TACL 2023.
[4] CORAL: Benchmarking Multi-turn Conversational Retrieval-Augmentation Generation. Cheng et al. NAACL 2024.
[5] https://github.com/daltonj/treccastweb
[6] https://www.trecikat.com/
[7] Open-retrieval conversational question answering. Qu et al. SIGIR 2020.
[8] ProCIS: A benchmark for proactive retrieval in conversations. Samarinas et al. SIGIR 2024.

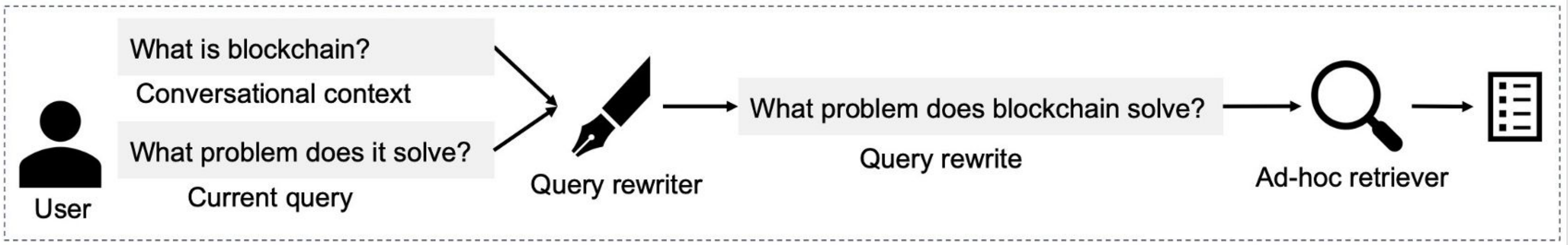
Two basic paradigms:

1. Conversational Query Rewriting
2. Conversational Dense Retrieval

Two Conversational Search Paradigms

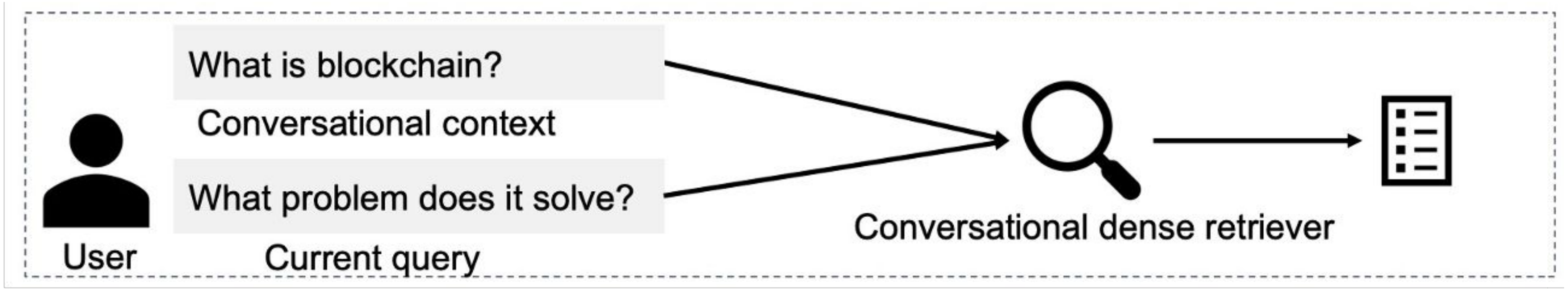
Conversational Query Rewriting (CQR)

➢ Idea: Transform a context-dependent query into an explicit rewritten query.



Conversational Dense Retrieval (CDR)

➢ Idea: Obtain a conversational dense retriever with contextual representation.



Conversational Query Rewriting

Conversational query rewriting methods in literature:

Approaches of earlier studies

- ➢ Selecting useful terms from historical context
- ➢ Rewriting context-dependent query to mimic human-rewritten one
- ➢ Leveraging search performance signals for query rewriter training

Under large language models (LLMs) era

- ➢ Prompting LLMs to directly rewrite context-dependent query
- ➢ Leverage LLMs to generate better synthetic training data

Conversational Query Rewriting

Selecting useful terms from historical context

➢ **Idea**: Context from the conversational history can be used to arrive at a better expression of the current turn query [1].

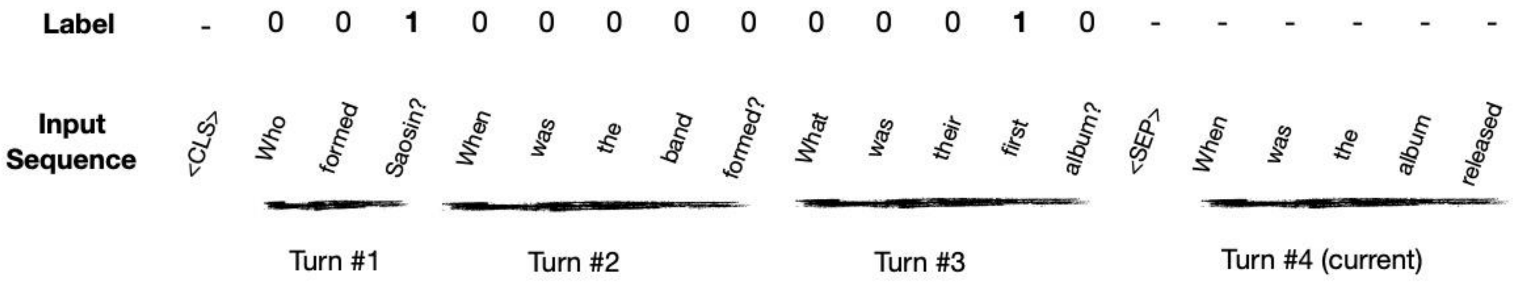
Turn	Query
1	who formed **saosin**?
2	when was the **band** founded?
3	what was their **first** album?
4	when was the album released?
	resolved: when was saosin 's first album released?
Relevant passage to turn #4: The original lineup for **Saosin**, consisting of Burchell, Shekoski, Kennedy and Green, was formed in the summer of 2003. On June 17, the **band** released their **first** commercial production, the EP Translating the Name.	

[1] Query resolution for conversational search with limited supervision. Voskarides et al. SIGIR 2020.

Conversational Query Rewriting

Selecting useful terms from historical context

➢ [1,2,3] train a binary classifier or selector to select useful terms in the context

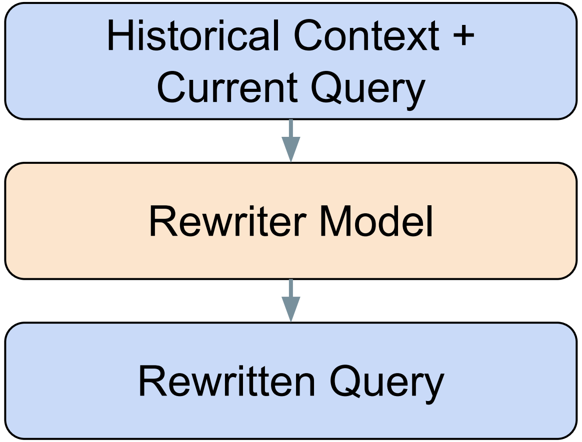


[1] Query resolution for conversational search with limited supervision. Voskarides et al. SIGIR 2020.
[2] Multi-stage conversational passage retrieval: An approach to fusing term importance estimation and neural query rewriting. Lin et al. TOIS 2021.
[3] Contextualized Query Embeddings for Conversational Search. Lin et al. EMNLP 2021.

Conversational Query Rewriting

Rewriting context-dependent query to mimic human-rewritten one

- ➢ **Idea**: [1,2,3,4] Train a generative rewriter via the pairs of context and rewrites.



Turn	Conversational Queries
Q_1	Tell me about the Bronze Age collapse.
Q_2	What is the evidence for it?
Q_3	What are some of the possible causes?
Manual Query Rewrites	
Q_2^*	What is the evidence for **the Bronze Age collapse**?
Q_3^*	... the possible causes **of the Bronze Age collapse**?

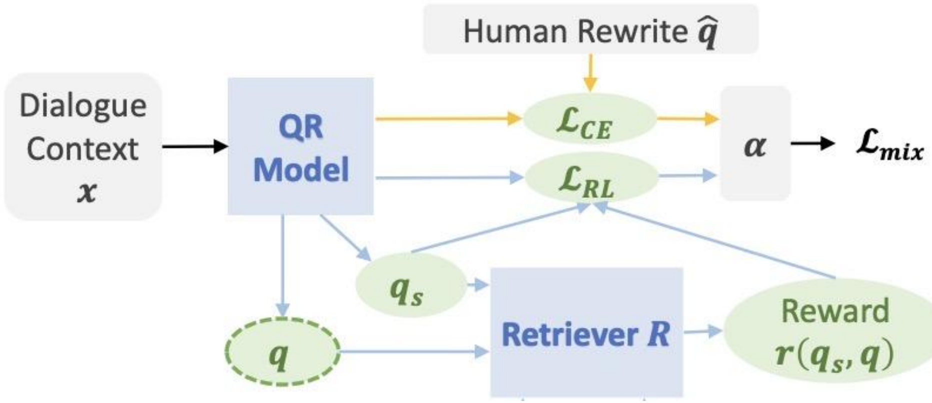
- ➢ **Cons**: rely heavily on manual labels and cannot optimize for search performance

[1] Few-shot generative conversational query rewriting. Yu et al. SIGIR 2020.
[2] Question rewriting for conversational question answering. Vakulenko et al. WSDM 2021.
[3] A Comparison of Question Rewriting Methods for Conversational Passage Retrieval. Vakulenko et al. ECIR 2021.
[4] Explicit query rewriting for conversational dense retrieval. Qian et al. EMNLP 2022.

Conversational Query Rewriting

Leveraging search task signals for rewriter model training

➢ **Approach**: The search signals could be used to train rewriters via fine-tuning [3,4] or reinforcement learning [1,2].

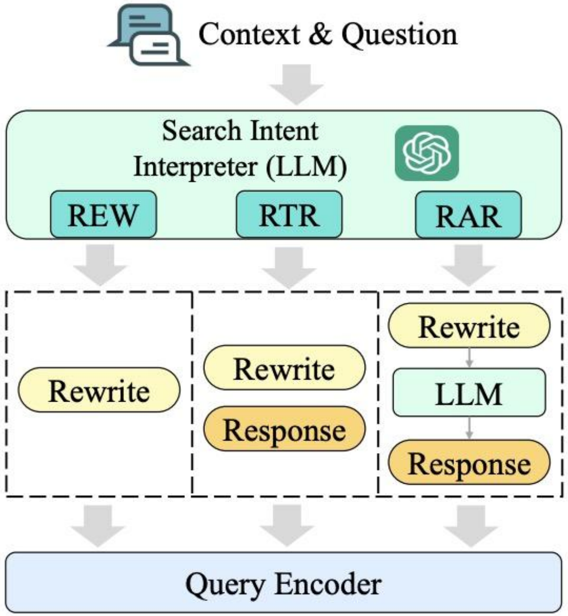


[1] CONQRR: Conversational Query Rewriting for Retrieval with Reinforcement Learning. Wu et al. EMNLP 2022.
[2] Reinforced Question Rewriting for Conversational Question Answering. Chen et al. EMNLP 2022.
[3] ConvGQR: Generative Query Reformulation for Conversational Search. Mo et al. ACL 2023.
[4] Search-Oriented Conversational Query Editing. Mao et al. ACL 2023.

Conversational Query Rewriting

Prompting LLMs to directly rewrite context-dependent query

- **Idea**: Leveraging LLMs' conversation understanding and text generation capacity to grasp users' contextual search intent [1].
- **Approach**: Design prompts [1,2,3]
  - [1] generates different types of queries and then aggregate them
- Limitation: High inference cost by calling LLMs



[1] Large Language Models Know Your Contextual Search Intent: A Prompting Framework for Conversational Search. Mao et al. EMNLP 2023.
[2] Enhancing Conversational Search: Large Language Model-Aided Informative Query Rewriting. Ye et al. EMNLP 2023.
[3] CHIQ: Contextual History Enhancement for Improving Query Rewriting in Conversational Search.. Mo et al. EMNLP 2024.

Conversational Query Rewriting

Leverage LLMs to generate better rewritten query as training signals

- ➢ **Assumption**: The human-rewritten query might be sub-optimal [1] as a search query.
- ➢ **Motivation**: Leverage small LM for query rewriting to reduce latency.
- ➢ **Idea**: Use LLMs to generate better pseudo query with qualified signal (e.g., relevance judgment [2,3], search reward [4,5]) for model training, similar to knowledge distillation from LLMs.

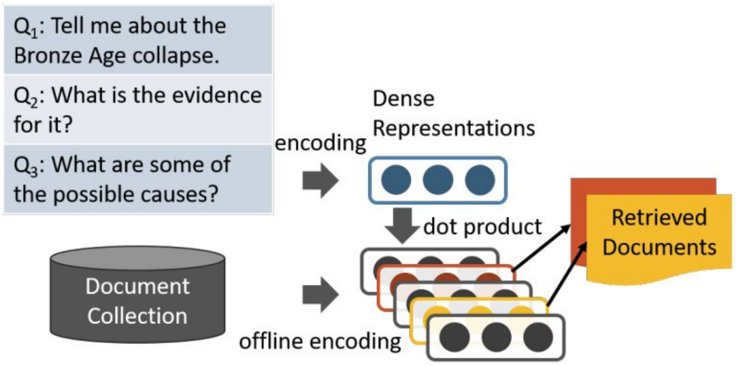
[1] ConvGQR: Generative Query Reformulation for Conversational Search. Mo et al. ACL 2023.
[2] IterCQR: Iterative Conversational Query Reformulation without Human Supervision. Jang et al. NAACL 2023.
[3] CHIQ: Contextual History Enhancement for Improving Query Rewriting in Conversational Search.. Mo et al. EMNLP 2024.
[4] ADACQR: Enhancing Query Reformulation for Conversational Search via Sparse and Dense Retrieval Alignment. Lai et al. COLING 2024.
[5] Adaptive Query Rewriting: Aligning Rewriters through Marginal Probability of Conversational Answers. Zhang et al. EMNLP 2024.

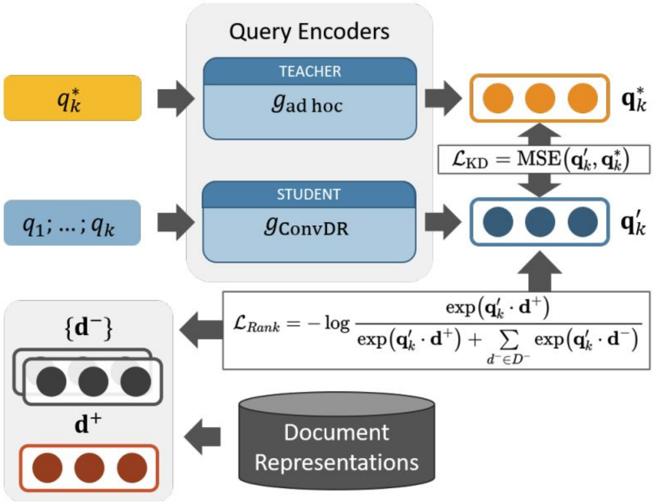
Q & A

Conversational Dense Retrieval

Teacher-student framework

- [1] learns a student query encoder (fed with raw conversational query) to mimic the embeddings from a teacher encoder (self-contained human rewritten queries



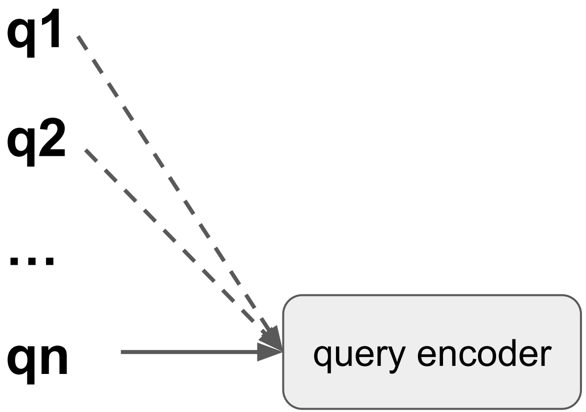


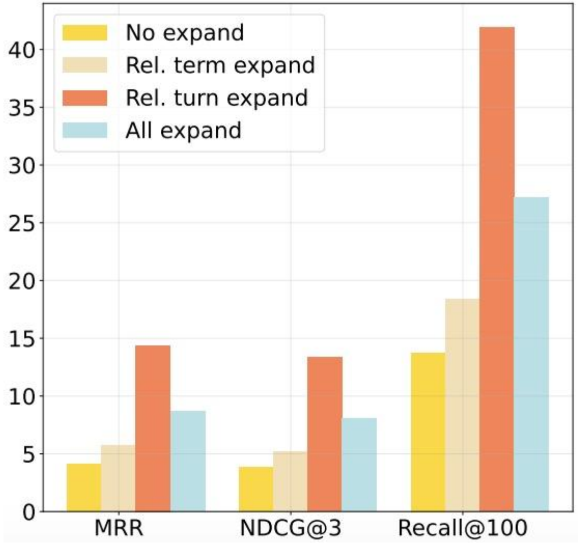
[1] Few-Shot Conversational Dense Retrieval. Yu et al. SIGIR 2021.

Conversational Dense Retrieval

Context denoising

- ➢ [1,2] conducts pseudo labeling for the context based on the impact on retrieval results of a candidate turn or term, which is used to expand the query.
- ➢ Example: If $Score(q_n) < Score(q_n * q_i)$, we assume q_i is relevant to q_n.





[1] Learning to relate to previous turns in conversational search. Mo et al. SIGKDD 2023.
[2] History-aware conversational dense retrieval.. Mo et al. ACL 2024.

Summary

Conversational query rewriting

- ➢ **Pros**: Can re-use any existing retrievers and has good interpretability with explicit rewritten query.
- ➢ **Cons**: Cannot directly optimize for ranking performance; and the rewriter model training rely on available annotations as supervision signals.

Conversational dense retrieval

- ➢ **Pros**: Direct optimize with conversational session to obtain representation in an end-to-end way
- ➢ **Cons**: Data scarcity problem and de-noising requirement for the input context.

Conversational retrieval-augmented generation

Conversational retrieval-augmented generation

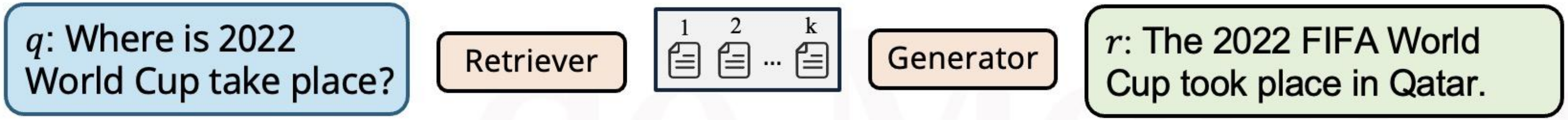
Conversational retrieval-augmented generation (RAG)

- ➢ Single turn RAG v.s. Conversational (Multi-turn) RAG
- ➢ Leveraging historical information for conversational RAG

Conversational retrieval-augmented generation

Single turn RAG [1]

- ➢ **Trend**: LLMs can direct reply users' question with their parametric knowledge.
- ➢ **Challenge**:
  - ○ LLMs often generate plausible but factually incorrect text (hallucination)
  - ○ LLMs' internal knowledge can be out-of-date
- ➢ **Goal**: Incorporate the retrieved up-to-date information for generation.
- ➢ **Paradigm**: Generate response for a query on top of retrieved information.

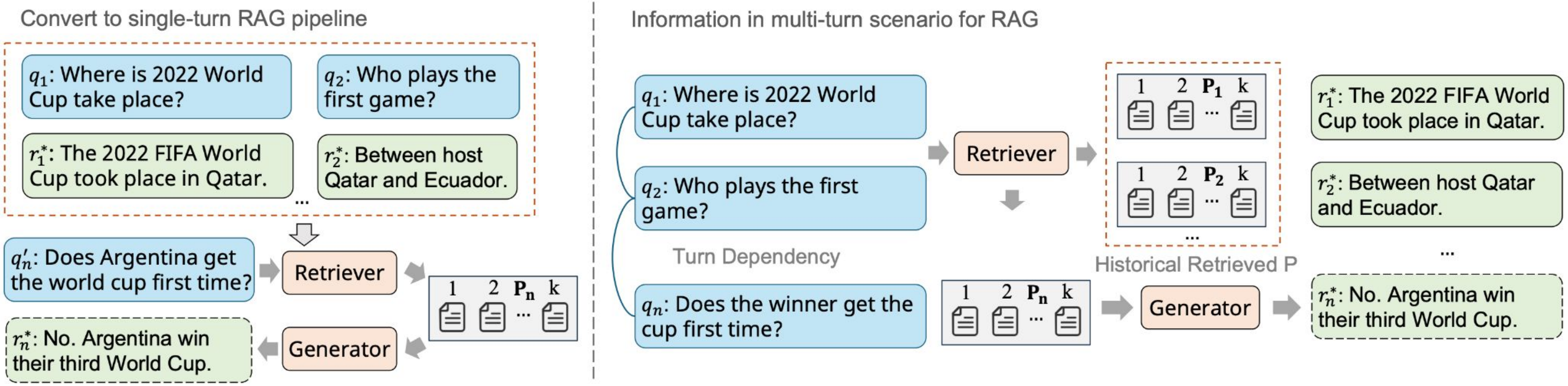


[1] Retrieval-augmented generation for knowledge-intensive nlp tasks. Lewis et al. NIPS 2020.

Conversational retrieval-augmented generation

Single turn RAG [1] v.s. Conversational (Multi-turn) RAG [2]

- ➢ **Feature**: More available information beyond query-response pairs.
- ➢ **Existing paradigm**: Convert multi-turn into single-turn
- ➢ **Question**: Could we improve the system performance by multi-turn information?



[1] Retrieval-augmented generation for knowledge-intensive nlp tasks. Lewis et al. NIPS 2020.
[2] CORAL: Benchmarking Multi-turn Conversational Retrieval-Augmentation Generation. Cheng et al. NAACL 2024.

Conversational retrieval-augmented generation

Conversational retrieval-augmented generation (RAG)

➢ Leveraging historical information for conversational RAG

- **Idea**: The historical information (not limited to query-response pairs) could enhance the effectiveness [1,3], efficiency [2], and truthfulness [1] of the current turn RAG.

[1] CORAL: Benchmarking Multi-turn Conversational Retrieval-Augmentation Generation. Cheng et al. NAACL 2024.
[2] Learning When to Retrieve, What to Rewrite, and How to Respond in Conversational QA. Roy et al. EMNLP 2024.
[3] Conv-CoA: Improving Open-domain Question Answering in Large Language Models via Conversational Chain-of-Action. Pan 2024.

Leveraging Historical Information for conversational RAG

- ➢ **Effectiveness** and **truthfulness** in conversational RAG
  - [1] proposes a conversational RAG benchmark with passage retrieval, response generation, and citation labeling grounding on passage IDs.

Question3: Who received the Governors Award and why were they chosen?
Response3: The Governors Award was presented to Tyler Perry and the Perry Foundation "in recognition of their unparalleled contributions to shaping the television medium" and for their "inclusion, engagement, employment and other philanthropic initiatives".[65233][65234] The award was moved to the main telecast from its usual presentation at the Creative Arts Emmys.[65235]
Golden Retrieval Passage IDs: 65233, 65234, 65235
Golden Rewrite: Who received the Governors Award at the 72nd Primetime Emmy Awards and for what reasons?
URL: `https://en.wikipedia.org/wiki/72nd_Primetime_Emmy_Awards`

...

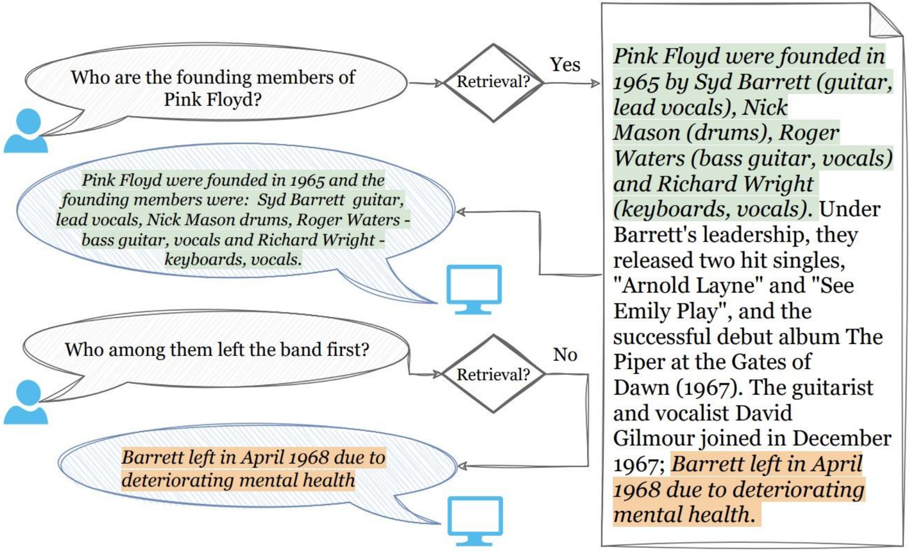
Question10: Who performed during the in Memoriam Segment, and which notable figures were mentioned?
Response10: The annual in Memoriam Segment featured H.E.R. performing "Nothing Compares 2 U" on piano and electric guitar .[65284][65285]...
Golden Retrieval Passage IDs: 65284, 65285, 65286, 65287
Golden Rewrite: Who performed during the in Memoriam Segment at the 72nd Primetime Emmy Awards, and which notable figures were mentioned?
URL: `https://en.wikipedia.org/wiki/72nd_Primetime_Emmy_Awards`

[1] CORAL: Benchmarking Multi-turn Conversational Retrieval-Augmentation Generation. Cheng et al. NAACL 2024.

Conversational retrieval-augmented generation (RAG)

➢ Leveraging historical information for **efficient** conversational RAG

- **Idea:** Reducing the system latency by judging whether the required passages have already been retrieved in history before calling retriever for searching [1].
- **Challenge**: When to retrieve?



[1] Learning When to Retrieve, What to Rewrite, and How to Respond in Conversational QA. Roy et al. EMNLP 2024.

Generating Response in Conversational Search

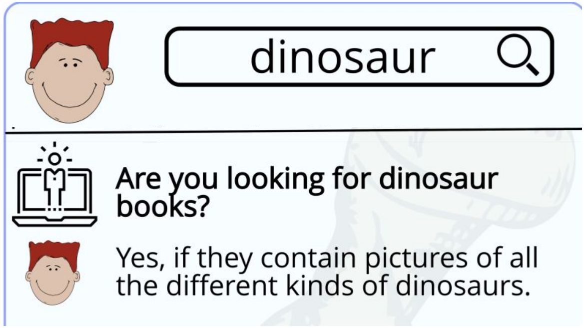
Summary:

- **Conclusion**: The useful information from historical turns can improve system performance from different perspectives.
- **Key Challenge**: Identify the useful information from super noisy history.
- **Open questions**:
  - How to better leverage historical information for conversational RAG?
  - How to make the system more efficient with large models?
  - How to evaluate the generated response (in conversational scenario)?

Mixed Initiative

Mixed Initiative

- What is mixed initiative?
  - User and system can both take the initiative at different times in a conversation [1]
  - System can take initiative to ask clarifying questions, elicit user preferences, ask for feedback, provide suggestions
  - User satisfaction has been reported to increase when prompted with system-initiatives, e.g., clarifications [2]



[1] Radlinski et al. A Theoretical Framework for Conversational Search. CHIIR 2017.
[2] Kiesel et al. Toward voice query clarification. SIGIR 2018.

Mixed Initiative

- Clarifying question selection
  - [1] releases the Qulac dataset, where each query is associated with a set of human-generated questions
    - Retrieve a set of questions for a given query, and then select the best question by a BERT-based model (NeuQS)
    - Adding selected question improves document retrieval quality
  - [2] releases a larger dataset, ClariQ

Method	**Qulac-T Dataset**				
	MRR	P@1	nDCG@1	nDCG@5	nDCG@20
OriginalQuery	0.2715	0.1842	0.1381	0.1451	0.1470
σ-QPP	0.3570	0.2548	0.1960	0.1938	0.1812
LambdaMART	0.3558	0.2537	0.1945	0.1940	0.1796
RankNet	0.3573	0.2562	0.1979	0.1943	0.1804
NeuQS	**0.3625***	**0.2664***	**0.2064***	**0.2013***	**0.1862***
WorstQuestion	0.2479	0.1451	0.1075	0.1402	0.1483
BestQuestion	0.4673	0.3815	0.3031	0.2410	0.2077

[1] Aliannejadi et al. Asking Clarifying Questions in Open-Domain Information-Seeking Conversations. SIGIR 2019.
[2] Aliannejadi et al. Building and Evaluating Open-Domain Dialogue Corpora with Clarifying Questions. EMNLP 2021.

Mixed Initiative

- Clarifying question generation
  - Selecting clarifying questions from a human-generated question set does not generalize well in real-world scenarios; training data is scarce
  - [1] learns to generate clarifying questions
    - Mine question templates from query reformulation data from Bing
    - Generate training data by selecting and filling out question templates
    - Train a sequence-to-sequence model on the data

(1) What do you want to know about QUERY?
(2) What do you want to know about this QUERY_ENTITY_TYPE?
(3) What ASPECT_ENTITY_TYPE are you looking for?
(4) Whom are you looking for?
(5) Who are you shopping for?

[1] Zamani et al. Generating Clarifying Questions for Information Retrieval. WWW 2020.

Mixed Initiative

- Clarifying question generation
  - [1,2] use LLMs with better capabilities
    - Apply few-shot [1,2] and chain-of-thought (CoT) prompting [1,2] to improve performance

Few-shot w/ CoT: Given a query, answer the question or ask a clarifying question. The response should start with "The answer is" or "The clarifying question is".

Question: Who played michael myers in rob zombie's movie?
Output: In Rob Zombie's "Halloween" films, the role of Michael Myers was primarily played by Tyler Mane. Mane portrayed the iconic horror character in both Rob Zombie's "Halloween" (2007) and its sequel, "Halloween II" (2009). Therefore, the question is not ambiguous. The answer is Tyler Mane.

Question: Give me some Mother's Day gift ideas.
Output: there could be underlying ambiguities depending on the interests of the specific mother in question, the budget, and the giver's relationship to the mother. Without this context, a broad range of ideas could be considered appropriate. Therefore, the question is ambiguous. The clarifying question is: What are the interests or hobbies of the mother, and is there a particular budget range for the gift?

Question: <Question>

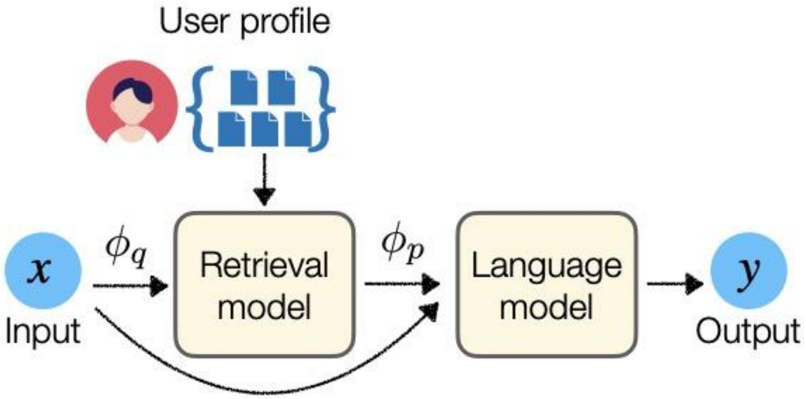
[1] Zhang et al. CLAMBER: A Benchmark of Identifying and Clarifying Ambiguous Information Needs in Large Language Models. ACL 2024.
[2] Deng et al. Prompting and Evaluating Large Language Models for Proactive Dialogues: Clarification, Target-guided, and Non-collaboration. EMNLP 2023.

Q & A

Personalization

Personalization

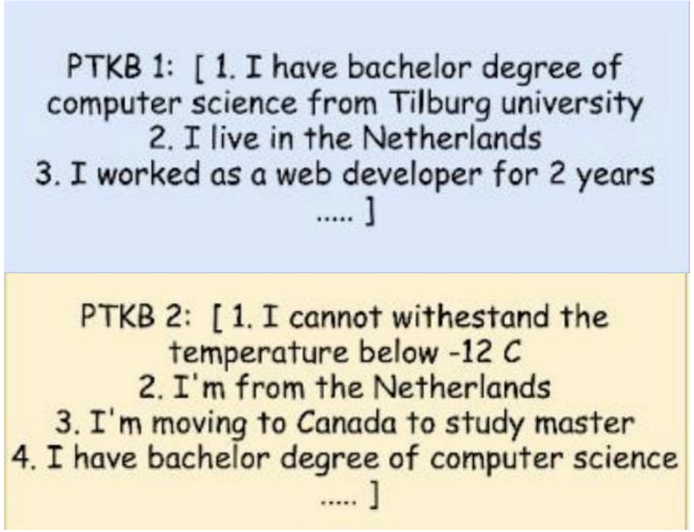
- **Goal**: Satisfy users' complex information needs based on **users' profiles and preference** through multi-turn interactions.
- **Assumption**: The same query turn from different users may correspond to different search intents, thus yielding different results.
- **User information**: Profile, historical preference, click/interactive behaviour.
- **General Paradigm**:

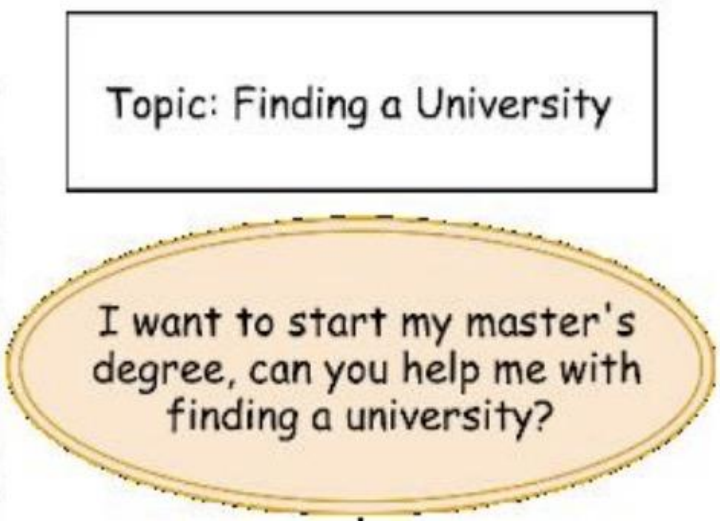


Personalization

Incorporating explicit user profile into query rewriting

- ➢ User profile in natural language as Personal Text Knowledge Base (PTKB) [1,2]
- ➢ **Sub-task**: (1) PTKB selection, (2) Personalized retrieval in conversations.





[1] TREC iKAT 2023: The Interactive Knowledge Assistance Track Overview. Aliannejadi et al. TREC 2023.
[2] Conversational Gold: Evaluating Personalized Conversational Search System using Gold Nuggets. Abbasiantaeb et al. SIGIR 2025.

Personalization

Incorporating explicit user profile into query rewriting

- **Idea**: Determine the relevant pieces from user profile for each query turn and incorporate the selected information into query rewriting as user modeling.
- **Key challenge**: Not all turns require personalization (using user profile).
  - Do I need a visa to travel to Egypt? (Require user information)
  - What are the prices of Egyptian E-visa and on-arrival visa. (Not require)

Incorporating explicit user profile into query rewriting

➢ **Observation [1]**: using personal info at a wrong time or using all historical turns will both hurt the performance compared to without personalized query rewriting.

Model	Method	MRR	N@3	N@5	MAP
Evaluate on the whole test set (176 turns)					
BM25	None	**44.35**†	**21.22**†	**20.68**†	**8.91**
	Use all	40.36	19.19	18.84	8.28
	Human	41.65	19.66	19.46	8.82
	Automatic	40.29	19.12	18.87	8.58
	LLM-STR	41.53	18.96	18.09	8.37
	LLM-SAR	36.04	17.48	16.87	8.02

[1] How to Leverage Personal Textual Knowledge for Personalized Conversational Information Retrieval. Mo et al. CIKM 2024.

Q & A

Part 2

Emerging Topics in the Agent Era

Agentic search

Agentic Search

- What is an “agent”?
  - An agent is an autonomous entity that makes decisions and takes actions on users’ behalf [1,2]
  - The idea of agents traces back to the 1950s with the emergence of symbolic AI [1]

- Typical capabilities of agents [3]
  - Planning
  - Tool use
  - Memory
  - Reflection and refinement
  - Multi-agent collaboration

[1] Shah et al. Agents Are Not Enough. arXiv 2024.
[2] Meng et al. Optimizing Agentic Workflows for Information Access. University of Amsterdam 2025.
[3] White et al. Information Access in the Era of Generative AI. Springer 2025.

Agentic Search

- Agentic search
  - good at handling multi-hop, reasoning-intensive queries
    - e.g., What type of profession does Chris Jericho and Gary Barlow have in common?
  - Reason-Act-Reflection (ReAct): multi rounds of reasoning and search invocations [1,2]
  - Use RL for training

Answer the given question. You must conduct reasoning inside <think> and </think> first every time you get new information. After reasoning, if you find you lack some knowledge, you can call a search engine by <search> query </search>, and it will return the top searched results between <information> and </information>. You can search as many times as you want. If you find no further external knowledge needed, you can directly provide the answer inside <answer> and </answer> without detailed illustrations. For example, <answer> xxx </answer>. Question: question.

[1] Jin et al. Search-R1: Training LLMs to Reason and Leverage Search Engines with Reinforcement Learning. COLM 2025.
[2] Song et al. R1-Searcher: Incentivizing the Search Capability in LLMs via Reinforcement Learning. arXiv 2025.

Agentic Search

- Agentic search example

Question: What type of profession does Chris Jericho and Gary Barlow have in common?

Ground Truth: musician

SEARCH-R1:

<think> I need to find the type of profession that Chris Jericho and Gary Barlow have in common. I'll search for it. </think>
<search> Chris Jericho and Gary Barlow profession </search>
<information> Doc 2(Title: ”Chris Jericho”) ””Do You Wanna Start a War”” (2014) and ””Judas”” (2017) are comprised entirely or predominantly of original compositions. He has also appeared on numerous TV shows over the years, having competed in the 2011 season of ””Dancing With the Stars””, lasting until the sixth week. Prior to that, Jericho hosted the ABC game show ””Downfall”” and the Revolver Golden Gods Awards. Christopher Keith Irvine was born on November 9, 1970, in Manhasset, New York, but grew up in Winnipeg. His father, ice hockey player Ted Irvine, had been playing for the New York Rangers at the time of his birth. ... </information>

<think> I found out that Chris Jericho is a professional wrestler, musician, author, and actor. Now I need to find if Gary Barlow has any of these professions in common. </think>
<search> Gary Barlow profession </search>
<information> Doc 1(Title: ”Gary Barlow”) hits, twelve number one singles and seven number one albums with Take That. Barlow has received six Ivor Novello Awards from the British Academy of Songwriters, Composers and Authors, including the award for Outstanding Services to British Music. He has sold over 50 million records worldwide. Barlow was born on 20 January 1971 in Frodsham, Cheshire, the second son of Colin (died 15 October 2009) and Marjorie Barlow. In Barlow's autobiography, he relates that his love of music began at an early age, and calls himself ””one of those kids that's forever dancing in front of the TV looking at ... </information>

<think> I found out that Gary Barlow is a singer, songwriter, musician, and record producer. Now I need to find if there is a common profession between Chris Jericho and Gary Barlow. </think>
<search> common profession of Chris Jericho and Gary Barlow </search>
<information> Doc 1(Title: ”Gary Barlow”) Gary Barlow Gary Barlow (born 20 January 1971) is an English singer, songwriter, musician and record producer. He is best known as the lead singer of the British pop group Take That. Barlow also served as head judge of ””The X Factor UK”” in 2011, 2012 and 2013 and ””Let It Shine”” in 2017. Barlow is one of Britain's most successful songwriters, having written fourteen number one singles and twenty-four top 10 hits. As a solo artist he has had three number one singles, six top 10 singles and two number one albums, and has additionally had seventeen top 5 ... </information>

<think> I found out that Gary Barlow is a singer, songwriter, musician, and record producer. Now I need to find if Chris Jericho has any of these professions in common. </think>
<search> Chris Jericho profession </search>
<information> Doc 1(Title: ”Chris Jericho”) Chris Jericho Christopher Keith Irvine (born November 9, 1970), better known by the ring name Chris Jericho, is an American-born professional wrestler, musician, author and actor. He currently wrestles for New Japan Pro-Wrestling (NJPW) where he is the current IWGP Intercontinental Champion in his first reign. Jericho also makes sporadic appearances for WWE on the SmackDown brand, with whom he has worked since 1999. Within professional wrestling, he is known for his over-the-top, rock star persona. Jericho is regarded as one of the greatest professional wrestlers of all time. During the 1990s, Jericho performed for the American organizations Extreme Championship ... </information>

<think> I found out that Chris Jericho is a professional wrestler, musician, author, and actor. Now I can compare it to Gary Barlow's professions. I found out that Gary Barlow is a singer, songwriter, musician, and record producer. The common profession between Chris Jericho and Gary Barlow is musician. </think>
<answer> musician </answer>

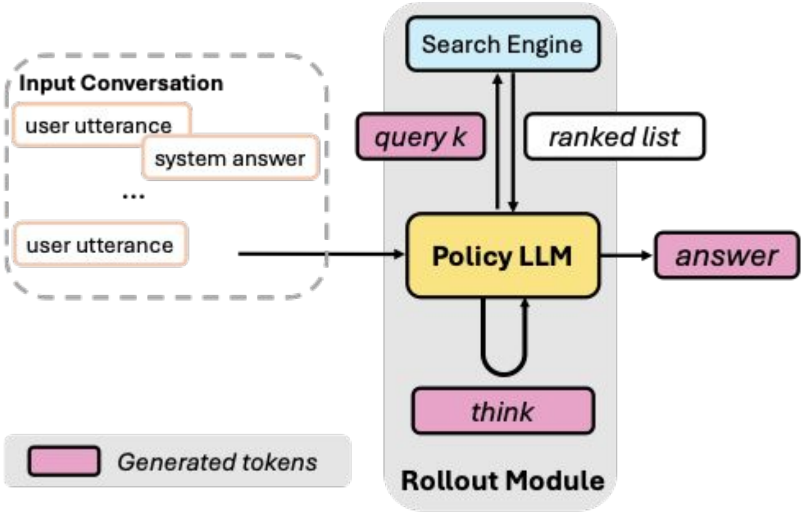
Agentic Conversational Search

Agentic Conversational Search

- [1,2] develop agentic conversational search systems that can do multi-rounds of reasoning and search
  - query formulation (<search>...</search>) is more challenging [1]

```
You are a helpful assistant tasked with
answering a user query. Your primary goal is
to generate a complete and informative answer.
If the query is ambiguous or refers to
earlier context (e.g., pronouns or ellipsis),
use the conversation history provided below
to resolve it.
- Always perform your reasoning inside <think>
...</think>.
- If external information is needed, use
<search>your query</search>.
- Retrieved documents will appear between
<information>...</information>.
- You may issue multiple search queries if
needed.
- Once you have enough information, provide a
complete answer within <answer>...</answer>.

Conversation context: {context_block}
User query: {last_user_utterance}
```



[1] Lupart et al. ChatR1: Reinforcement Learning for Conversational Reasoning and Retrieval Augmented Question Answering. arXiv 2025.
[2] Mo et al. Agentic Conversational Search with Contextualized Reasoning via Reinforcement Learning. arXiv 2026.

Part III: Summary and Future Directions

Conclusions and future directions

- We revisited key tasks and concepts in conversational search:
  - The core concepts of conversational search
  - Conversational search basic paradigms
  - Conversational RAG
  - Mixed-initiative interactions
  - Personalization
- We explored emerging topics in the era of agents:
  - Agantic search
  - Agentic conversational search

Conclusions and future directions

- Future directions
  - Agentic related
    - Efficiency & scalability, running on device
    - Personalization, memory, context management
    - Human-AI collaboration
    - Explainability, transparency & trustworthiness
  - Broader applicability
    - Multilingual and Multimodal scenarios
    - Domain-specific scenarios (financial, legal, medical, etc.)

Thank you!

Q & A