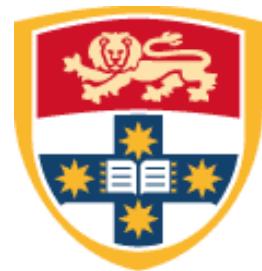




MULTIMEDIA RETRIEVAL



THE UNIVERSITY OF
SYDNEY

Week11

Semester 1, 2025

Conversational Retrieval

- Introduction
- Components
- Benchmark and evaluation
- Advance Topics
- Applications

Traditional vs Conversational

- Traditional
 - ▣ rely on keywords or short phrases
- Conversational
 - ▣ natural language dialogue interaction
 - ▣ enhancing the efficiency of information exchange and optimizing the user experience
 - ▣ Complex queries
 - ▣ Longer context



Evolution of Search System

- Key word → NLP Based → Conversational
- Examples
 - 1966: ELIZA - One of the earliest examples of a natural language processing system.
 - 2010s: Siri & Google Now - Introduction of voice-activated virtual assistants.
 - 2018: BERT - A significant advancement in natural language understanding.
 - 2020: TREC CAsT & WISE Datasets - Development of conversational search datasets.
 - 2022: ChatGPT - A breakthrough in conversational AI



Key Characteristics

- Multi-turn
- Context

what is information retrieval Query 1

 Wikipedia
https://en.wikipedia.org/wiki/Information_retrieval

Information retrieval
Information retrieval is the science of searching for information in a document, searching for documents themselves, and also searching for the metadata that ...

 **Sources**

 What is Information Retrieval? - Coveo coveo - 1	 Information retrieval - Wikipedia w_en.wikipedia - 2	 Information Retrieval: Everything You Need to Know When ... - Alooba alooba - 3
View more		

 **Answer**
Information retrieval (IR) is a crucial field within computer science and information science that focuses on the process of identifying and retrieving information from a collection of resources in response to a user's information need. This process can involve various types of data, including text documents, images, audio, and metadata.

tell me some of its famous scholars Query 2

 This list of the greatest scholars includes **Angela Davis, Sigmund Freud, Cornel West, Nicolaus Copernicus**, and more. From reputable, prominent, and well known scholars to the lesser known scholars of today, these are some of the best professionals in the scholar field.

 Ranker
<https://www.ranker.com/people>

List of Famous Scholars - Ranker

 **Sources**

 Online edition (c) 2009 Cambridge UP nlp.stanford - 1	 [PDF] The History of Information Retrieval Research clir-publications... - 2	 Information retrieval - Wikipedia w_en.wikipedia - 3
View more		

 **Answer**
Some famous scholars who have made significant contributions to the field of information retrieval include:

Early Pioneers

- **Calvin Mooers** - Coined the term "information retrieval" in 1948/1950 [1](#) [3](#).
- **Hans Peter Luhn** - Began work on mechanized punch card-based systems for searching chemical compounds in the late 1940s and published "Auto-encoding of documents for information retrieval" in 1959 [3](#).
- **Gerard Salton** - Began work on IR at Harvard in the early 1960s, later moved to Cornell. Published "Automatic Information Organization and Retrieval" in 1968 [3](#).

Influential Researchers

- **Karen Spärck Jones** - Finished her thesis "Synonymy and Semantic Classification" at Cambridge in 1964 and continued work on computational linguistics as it applies to IR [3](#).

Key Characteristics

- Multi-turn context: Handling multiple turns in a conversation to maintain context.
- Context understanding and management: Managing follow-up questions and ambiguous queries.
- Knowledge integration and reasoning: Integrating knowledge to answer complex queries.

Applications



Gemini

作业检查
语数英全科检查 秒判对错

数学练习

- 填空题
 $4 \times 6 = 24$ ✓
 $0.15 \text{ 千克} = (150) \text{ 克}$ ✓
- 口算题
 $9 - 7 = 2$ ✓
 $\frac{1}{3} - \frac{3}{4} = \frac{1}{12}$ ✓
 $3.5 + 1.6 + 2.7 = 7.8$ ✓
 $(88 - 29 + 57) \times 0 = 0$ ✓
- 计算题
 $768 \times 7 = 5402$
 768
 $\times 7$
 \hline 5402
- 解方程
 $1.2 + 3x = 4.3$
 $3x = 4.3 - 1.2$
 $3x = 3.1$
 $x = 1.03$ ✓
 $4(x + 9) = 64$
 $4x + 36 = 64$
 $4x = 28$
 $x = 7$ ✓
- 应用题
同学们参加生物兴趣小组的有48人，是参加科技兴趣小组的人数的4/7，参加这两个兴趣小组的共有多少人?
解: $48 + \frac{4}{7} \times 48 = 84$ 人
 $84 + 48 = 132$ 人
答: 参加这两个兴趣小组的同学共有132人

查看解析 ✓ 正确 □ 错误

1 2 3 4 5

User
I've just deleted some important files.
Can you help me???

Support ChatBot
Online

Support ChatBot
Don't worry! Follow this easy step-by-step tutorial to bring them back.

Watch the tutorial

Did it work?
Yes, it's working! No, I need help.

User
Yest, it's working!

Powered by ChatBot

Challenges

- Context Understanding and Management
 - ▣ follow-up questions: “Could you give more details of it?” after a previous query.
- Ambiguity and Under-Specified Queries
 - ▣ “Show me the best”
- Mixed Task and Chat Intent
 - ▣ “Hi, how are you? Can you check my order?”
- Knowledge Integration and Reasoning
 - ▣ “What is the most recent three PMs of Australia?”

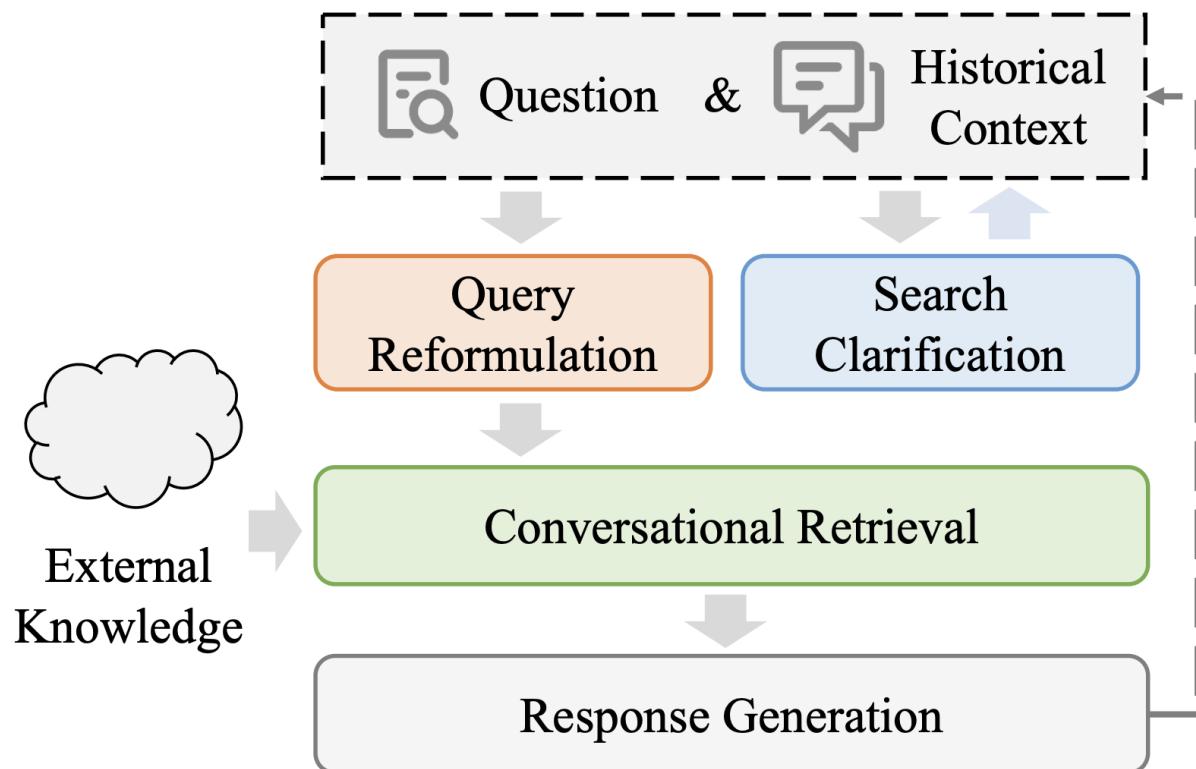
Trends

- LLM integration
- RAG
- Multimodal Conversational Search
- Domain Specific
- Personalized
- Etc...

Core Components

Core Components

□ System Architecture Overview



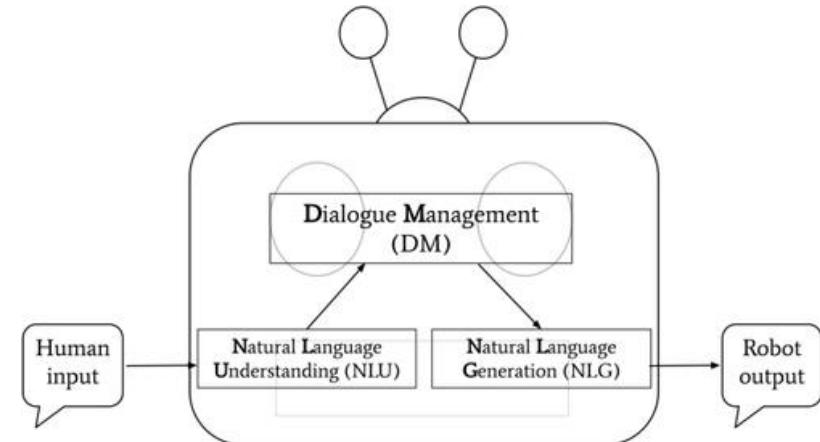
Natural Language Understanding

- Techniques
 - POS Tagging
 - Dependency Parsing
 - Semantic Parsing
 - Named Entity Recognition (NER)
 - Deep Learning based
 - RNN
 - Transformer
 - BERT
 -



Dialogue Management

- Functions
 - ▣ Dialogue State Tracking
 - ▣ Policy Management
 - ▣ Context Management
 - ▣ Error Handling and Recovery
- Techniques
 - ▣ Finite-State Machines
 - ▣ Statistical and Machine Learning Models
 - ▣ Etc.



Dialogue Management

□ Finite-State Machines

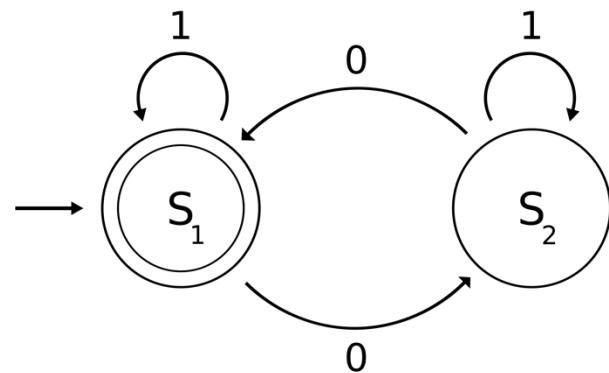
- ▣ States: stages
- ▣ Transitions: rules
- ▣ Actions: response

□ Pros

- ▣ **Predictability**
- ▣ Simplicity

□ Cons

- ▣ Not flexible
- ▣ Not scalable



Dialogue Management

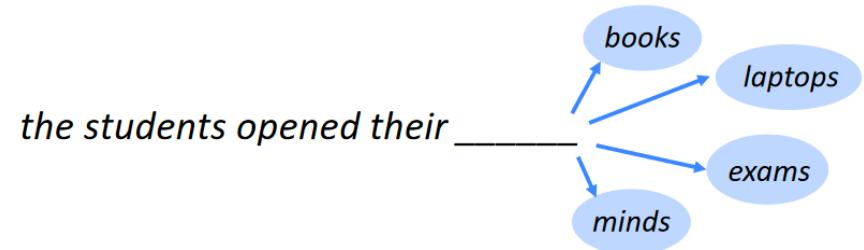
- Machine learning models
 - Dialogue State Tracking
 - current state
 - LSTM/RNN
 - Policy Learning
 - determines the system's next action based on the current dialogue state
 - Deep Reinforcement Learning
 - End-to-End Neural Models
 - Seq2Seq
 - Transformer-Based Models
 - BERT
 - GPT

Enhancing Dialogue Management

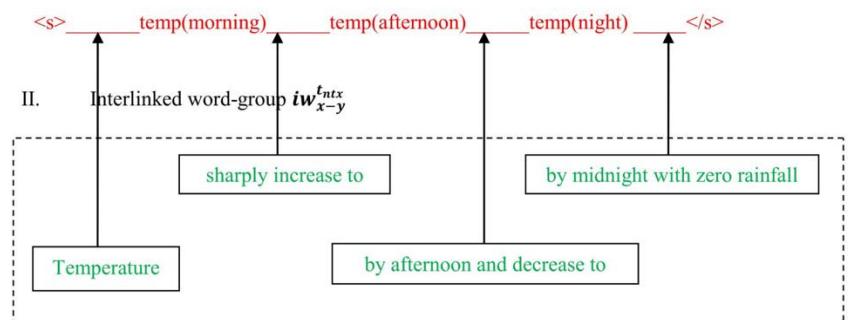
- Contextual Embeddings
 - ▣ Capture contextual information
- Hierarchical Models
 - ▣ Utterance-level and dialogue-level
- Transfer Learning
 - ▣ pre-trained, fine tuning

Natural Language Generation(NLG)

- Template-Based NLG
 - ▣ Easy
 - ▣ Rigid
- Statistical NLG
 - ▣ Scalability
 - ▣ Data Dependency
- Neural NLG



I. Attributes' name sequence $s_{t_{ntx}}$ for t_{ntx} (note: no match found on 'rainfall' attribute value)



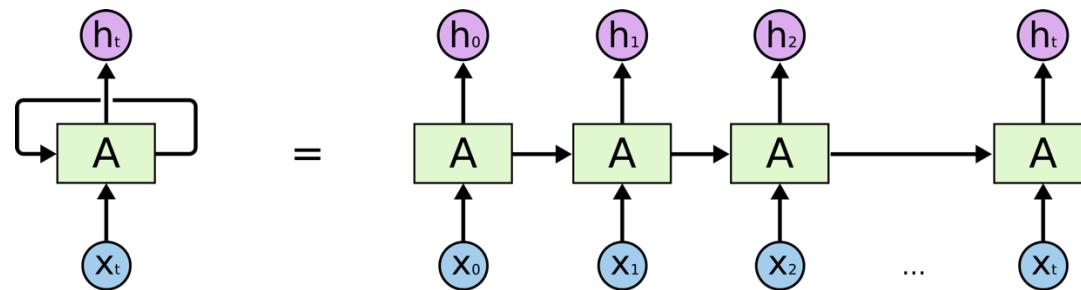
Natural Language Generation(NLG)

- Neural NLG
 - Recurrent Neural Network, LSTM
 - Transformer
 - Encoder-decoder

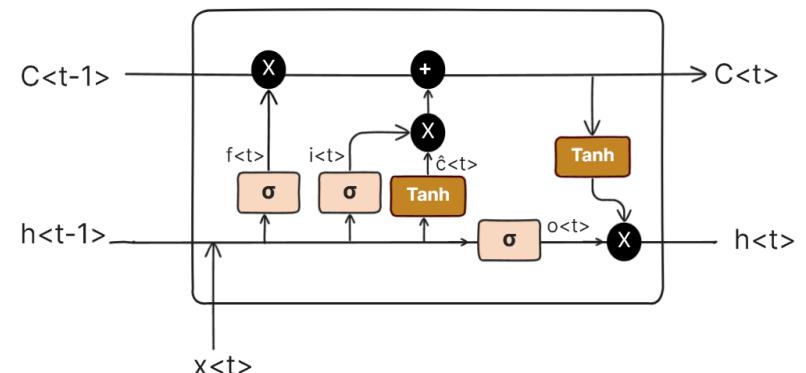
Natural Language Generation(NLG)

□ Neural NLG

□ LSTM

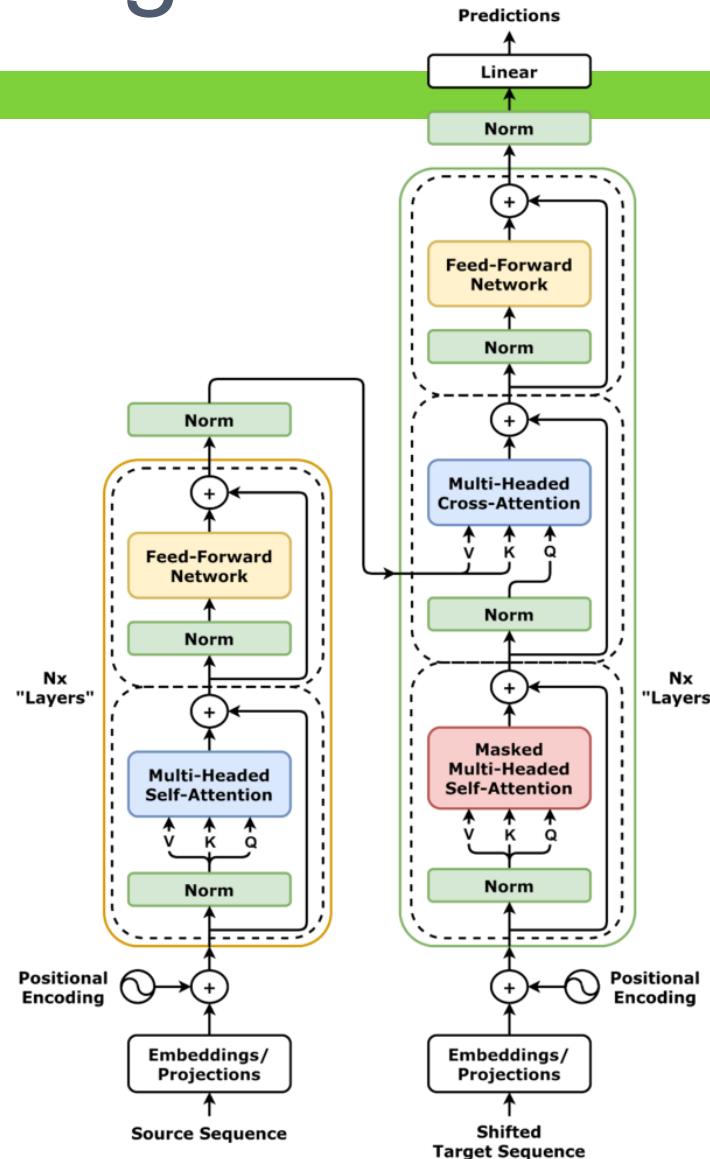


LSTM Architecture



Natural Language Generation(NLG)

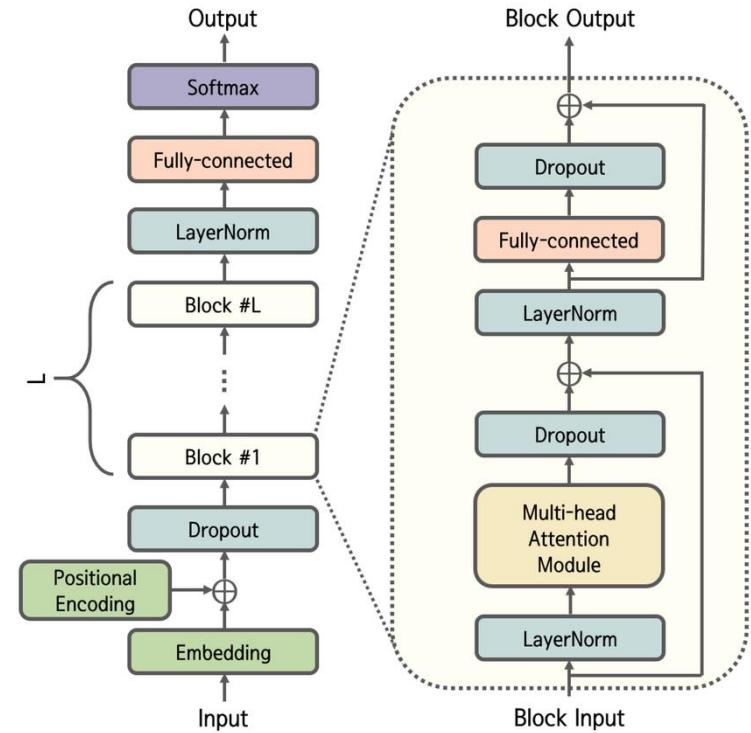
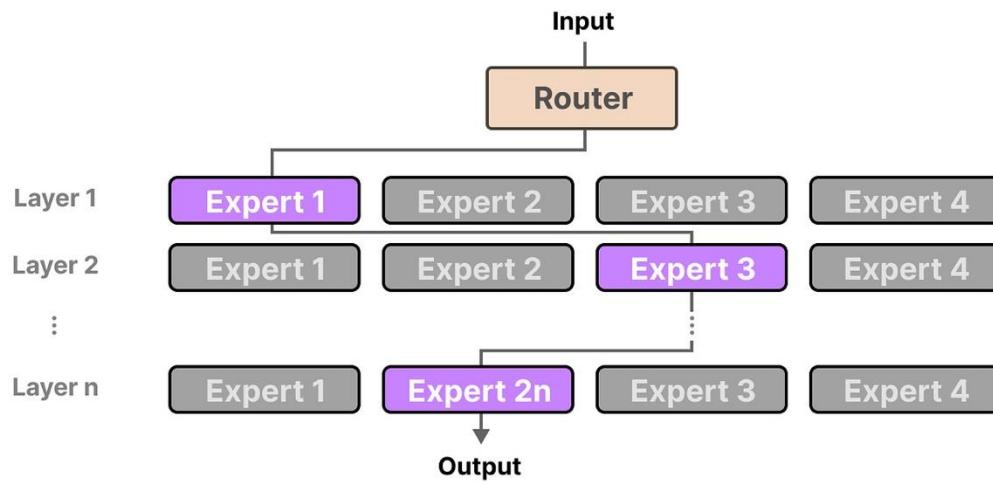
- Neural NLG
 - Transformer



Natural Language Generation(NLG)

□ Neural NLG

- GPT
- MoE



Natural Language Generation(NLG)

❑ Neural NLG

❑ Pros

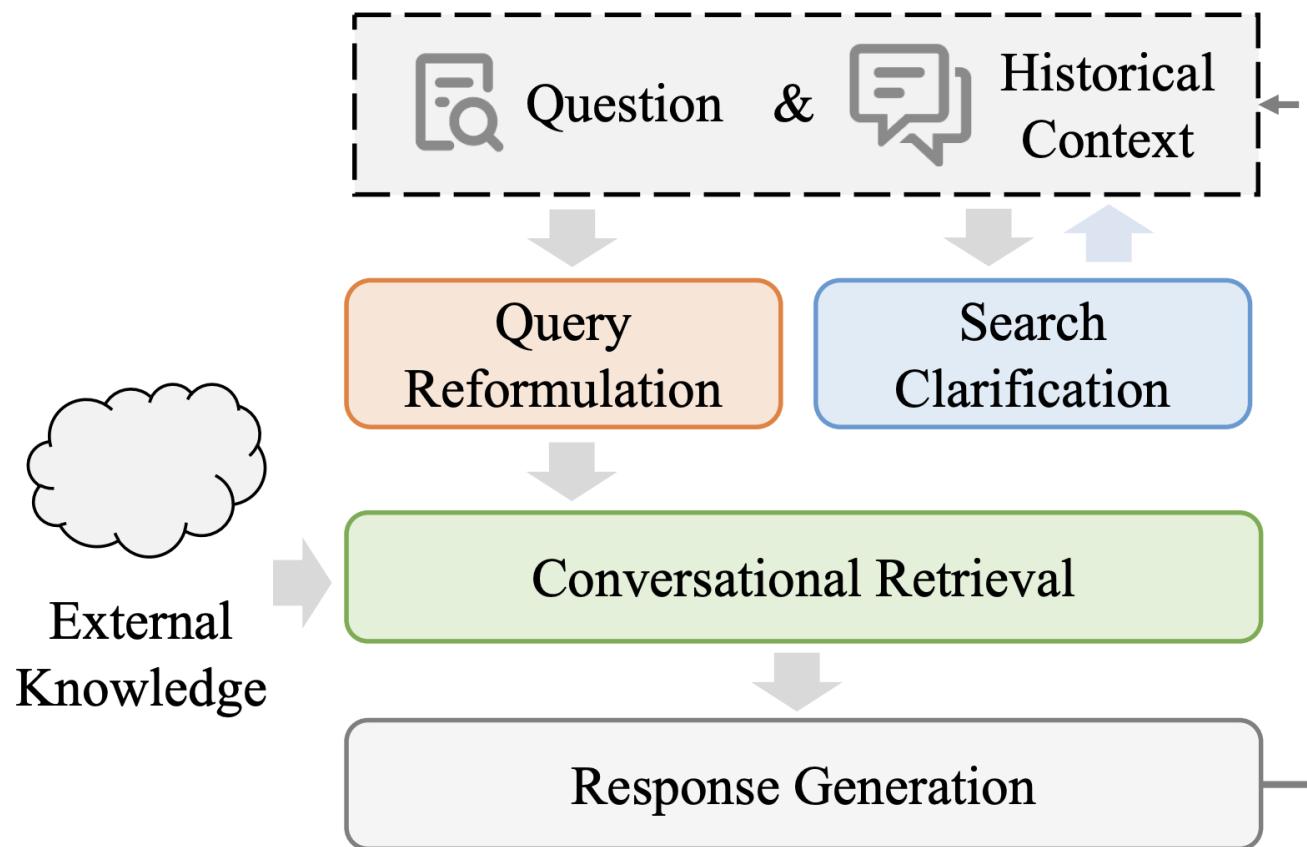
- Very powerful
- Adaptability

❑ Cons

- Expensive
- Bias



System Architecture Overview



Query Reformulation

- Reformulating the initial user search query
- Initial query can be:
 - ▣ Vague
 - ▣ Incomplete
- Challenges
 - ▣ Anaphora
 - semantics rely on previous context
 - ▣ Ellipsis
 - omission

Anaphora and Ellipsis



What were the key outcomes of the climate summit?

The main outcomes were ambitious emission targets and increased renewable energy funding.



How much funding (was committed to renewable energy)?

Ellipsis

Several countries pledged billions, with a focus on solar and wind projects.



Anaphora



Did it (the summit) addresses international cooperation?

Yes, but there were concerns, especially from developing countries.



Query Reformulation Techniques

- Query Expansion
 - ▣ Adding related terms
- Query Rewriting
 - ▣ Paraphrasing the query
- Hybrid Approaches

Query Expansion

- Traditional query logs
 - expand the current query turn from different resources
 - Expert annotate relationships
 - OR
 - AND
 - NEAR/SAME
 -

TABLE I. SEMANTIC RELATIONS PROVIDED BY THE QUERY LOGS

Semantic Relations	Definition	Example	Code
co-occurrence relation	X and Y	(scan) and (tooth)	CR
synonym relation	X or Y	(drill) or (burr)	SR
proximity relation	X near Y	(tool) near (gear)	PR
proximity relation	X same Y	(plastic) same (ring)	PR
proximity relation	X with Y	(drive) with (pin)	PR
proximity relation	X adj Y	(foot) adj (pedal)	PR

W. Tannebaum and A. Rauber, "Acquiring lexical knowledge from query logs for query expansion in patent searching," in Sixth IEEE International Conference on Semantic Computing, ICSC 2012, Palermo, Italy, September 19-21, 2012. IEEE Computer Society, 2012, pp. 336–338.



Query Expansion

- Heuristic with linguistic features
 - part-of-speech tagging
 - dependency parsing
 - coreference resolution

W. Tannebaum and A. Rauber, "Acquiring lexical knowledge from query logs for query expansion in patent searching," in Sixth IEEE International Conference on Semantic Computing, ICSC 2012, Palermo, Italy, September 19-21, 2012. IEEE Computer Society, 2012, pp. 336–338.

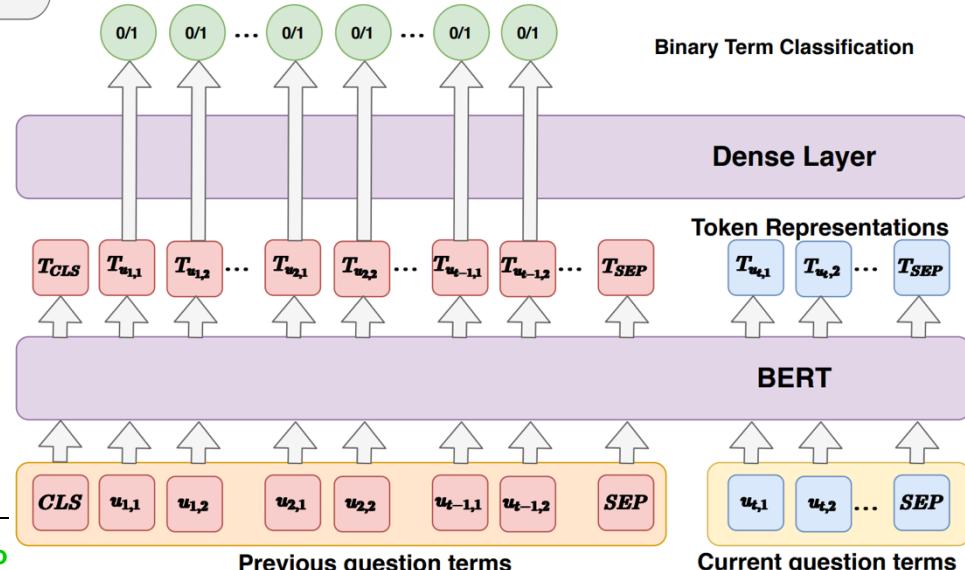
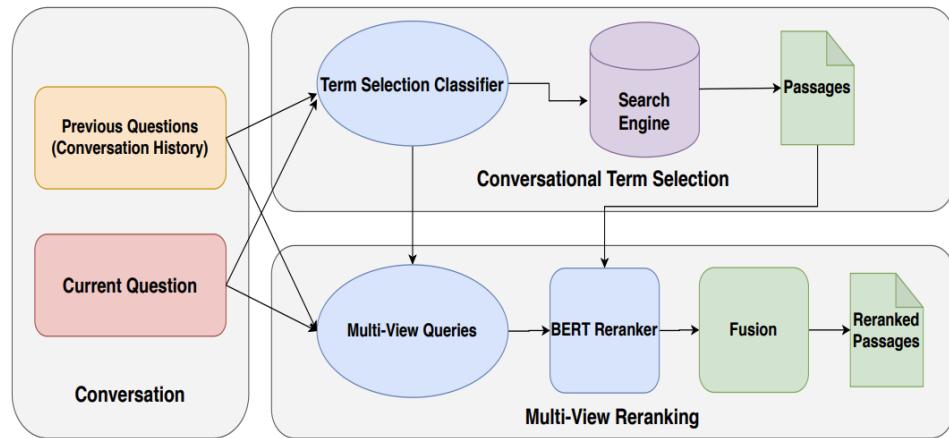


Query Expansion

- As a binary classification task
 - terms in the query context are labeled as relevant or irrelevant
 - The relevant terms are then appended to the original query as expansion

Query Expansion

□ Pseudo relevance feedback (PRF)

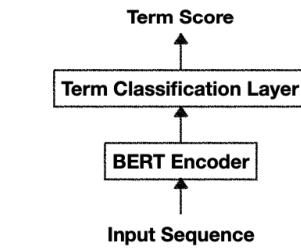


V. Kumar and J. Callan, "Making information seeking easier: An improved pipeline for conversational search," in Findings of the Association for Computational Linguistics: EMNLP 2020,



Query Expansion

□ QuReTeC (Query Resolution by Term Classification),



Label	-	0	0	1	0	0	0	0	0	0	0	1	0	-	-	-	-	-	-	
Input Sequence	<CLS>	Who	formed	SaoisIn?	When	was	the	band	formed?	What	was	their	first	album?	<SEP>	When	was	the	album	released

(a) QuReTeC model architecture.

(b) Example input sequence and gold standard term labels (1: relevant, 0: non-relevant) for QuReTeC.

pseudo labels are readily available and can be inferred from user-system interactions.

Query Expansion

- ❑ Not relying on human labeling for model training
- ❑ Challenge: distinguishing the usefulness of the expansion terms

Query Rewriting

- transform context-dependent **queries** into stand-alone ones conditioned on the previous **conversational context**
 - ▣ What is the laptop's price → What is the Apple laptop's price
- Techniques
 - ▣ Rules-based
 - ▣ Supervised Learning-Based Rewriting
 - ▣ reinforcement learning related
 - ▣ LLM
 - ▣ Hybrid Approaches



Query Rewriting Rules-based

□ Pros

- High Precision
- Interpretable

□ Cons

- No scalability
- Rule engineering

Q_6	What causes throat cancer ?
Q_7	What is the first sign of it?
Q_8	Is it the same as esophageal cancer ?
Q_9	What's the difference in <u>their</u> symptoms?

Oracle What's the difference in **throat cancer** and **esophageal cancer's** symptoms?

Output What's the difference between **throat cancer** and **esophageal cancer**?

Q_1	What are the types of pork ribs ?
Q_2	What are baby backs?
Q_3	What are the differences with spareribs?
Q_4	What are ways to cook them?
Q_5	How <u>about</u> on the bbq?

Oracle How do you cook **pork ribs** on the bbq?

Output How about on the bbq?



Supervised Learning-Based Rewriting

- Training a sequence-to-sequence model
 - ▣ Input: user initial query
 - ▣ Output: desired query rewritten
- Pros
 - ▣ Handling complex linguistic patterns
 - ▣ Adaptations
- Cons
 - ▣ Data dependent
 - ▣ Interpretation is hard



Reinforcement Learning-Based Rewriting

Implementation:

Initial Model:

- Start with a pre-trained query rewriting model.

Reward Function:

- Define a reward based on retrieval metrics, such as the relevance of retrieved documents.

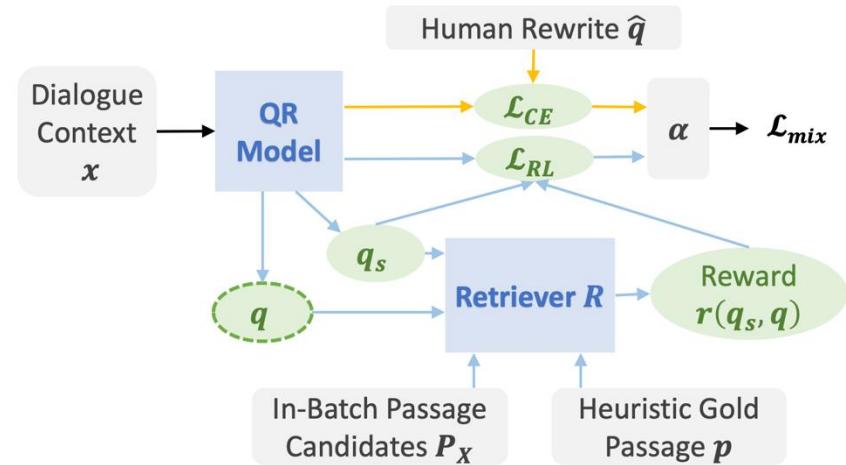
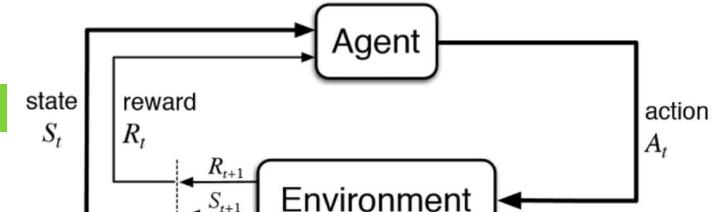
Training: Use reinforcement learning to fine-tune the model, maximizing the defined reward.

Pros

- Align with end-task
- Adaption

Cons

- Reward dependent
- Computationally expensive.



Large Language Model (LLM)-Based Rewriting

- Feed the prompt and the current conversational query into the LLM to generate a rewritten query.
- Pros
 - ▣ adaptability
 - ▣ No need for fine-tuning
- Cons
 - ▣ Prompt quality is very important
 - ▣ Hard to control



Hybrid Approaches Rewriting

- Combine different methods
- E.g.
 - ▣ Two step method
 - Enhance conversation history with LLM
 - Generate search query with LLMs
 - Example
 - Dialogue Context:
 - User: “Tell me about the Great Wall.”
 - User: “When was it built?”
 - Enhanced History: “Tell me about the Great Wall of China.”
 - Rewritten Query: “When was the Great Wall of China built?”
 - Pros
 - ▣ Great results.
 - Cons
 - ▣ Complexity



Search Clarification

The image displays a grid of search interface snippets, each showing a user query and a system response, often involving multiple rounds of clarification.

- Row 1:**
 - User: I want to see universal animal cuts reviews.
Bot: Would you like to see the lowest reviews for universal animal cuts? (Icon: Robot)
 - User: No, I want to read testimonials of universal animal cuts nutritional supplements.
Bot: Did universal animal cuts work for you? (Icon: Robot)
- Row 2:**
 - Search for "watches":** User: watches
Bot: Which watch brand are you looking for?
Options: Casio, Lorex, Omega (highlighted), IWC, Fossil
 - Search for "volcano":** User: volcano
Bot: Which "volcano" do you mean?
Options: the movie, park, hawaii
- Row 3:**
 - Search for "nike shoes":** User: nike shoes
Bot: Who are you shopping for?
Options: women, men, girls (highlighted), boys
 - Search for "vista, ca":** User: vista, ca
Bot: What do you want to know about the city?
Options: population, home sale, zip code (highlighted), weather
- Row 4:**
 - Search for "Midori":** User: What languages are used to create the source code of Midori?
Bot: When you say the source code language used in the program Midori, are you referring to web browser Midori or the operating system Midori?
User: I mean the first one.
Bot: C (Icon: Document)
 - Search for "Ubuntu":** User: How to configure path or set environment variables for installation?
Bot: I'm aiming to install ape, a simple code for pseudopotential generation. I'm having this error message while running ./configure <error message>. So I have the library but the program installation isn't finding it.
User: What version of Ubuntu do you have?
User: I want to install ape in Ubuntu 14.04 LTS
- Row 5:**
 - Search for "jacket":** User: Hi, I would like to buy a jacket
Bot: Which color do you like?
Options: White, Black (highlighted), Others
 - Search for "bird":** User: Saw a little black bird with black eyes.
Bot: What is the bill length of the bird: shorter, similar, or longer than head?
User: Shorter than head.
Bot: Is the bird underpart orange? (Icon: Question)

Search Clarification

- User Query: “Tell me about Mercury.”
- System Clarification: “Do you mean Mercury the planet, the element, or the Roman god?”
- Importance:
 - ▣ Disambiguating Queries: Clarifying vague or ambiguous terms.
 - ▣ Understanding User Intent: Gaining deeper insights into what the user is seeking.
 - ▣ Enhancing User Satisfaction: Providing more accurate and relevant results by aligning with the user’s true intent.

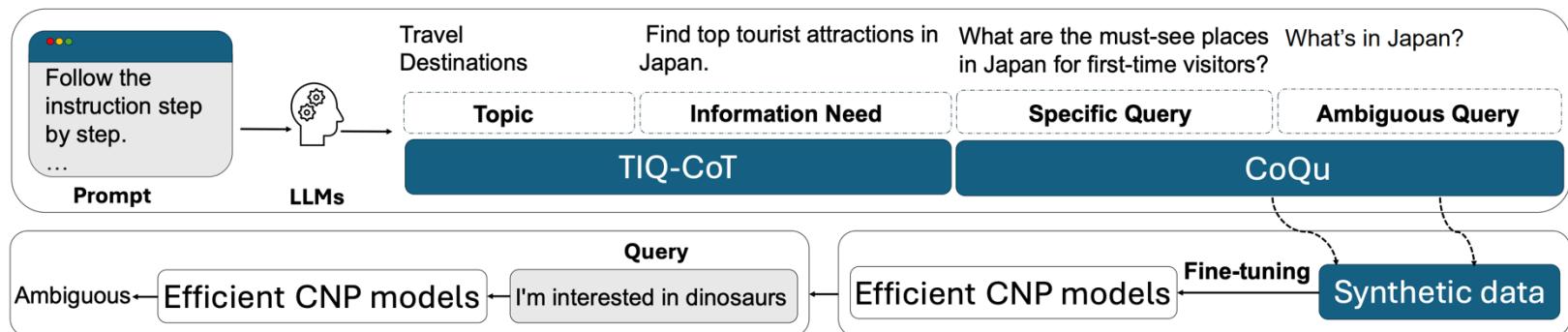


Techniques Search Clarification

- Clarification Need Prediction (CNP)
- Clarifying Question Generation
- Clarification Question Ranking
- Mixed-Initiative Strategies
- Multi-Turn Multi-Modal Clarification

Techniques Search Clarification

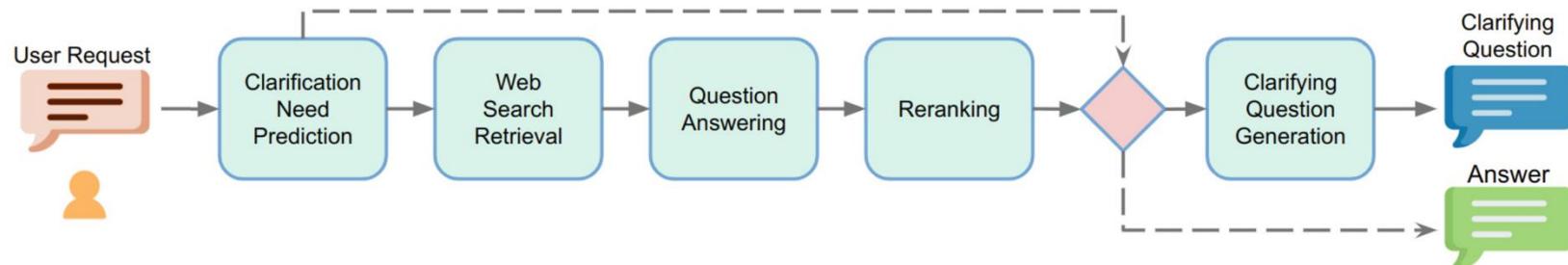
- Clarification Need Prediction (CNP)
 - Determine whether a user's query requires a clarifying question before proceeding with information retrieval



Lu, L., Meng, C., Ravenda, F., Aliannejadi, M., & Crestani, F. (2025, April). Zero-shot and efficient clarification need prediction in conversational search. In *European Conference on Information Retrieval* (pp. 389-404). Cham: Springer Nature Switzerland.

Techniques Search Clarification

- Clarifying Question Generation
 - Automatically generate questions that help disambiguate or refine the user's information need.



Zamani, H., Dumais, S., Craswell, N., Bennett, P., & Lueck, G. (2020, April). Generating clarifying questions for information retrieval. In *Proceedings of the web conference 2020* (pp. 418-428).

Techniques Search Clarification

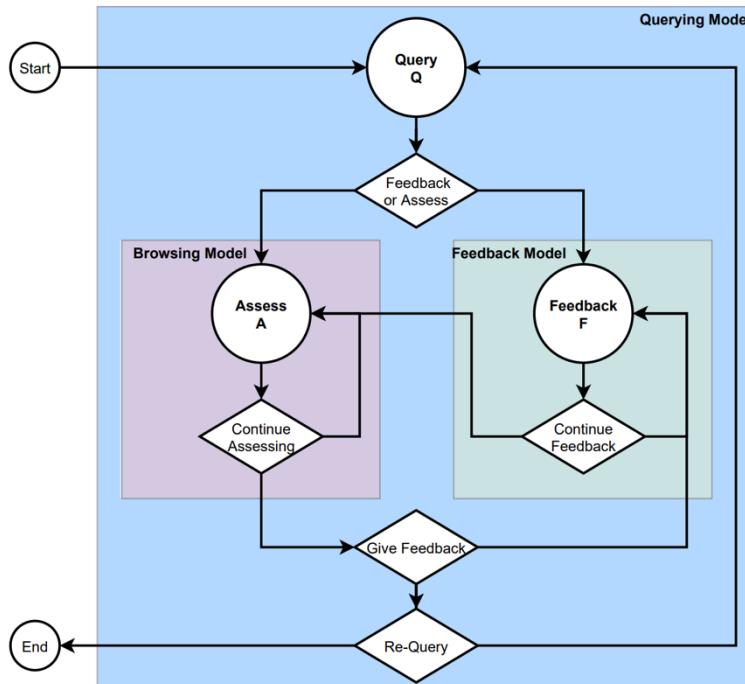
- Clarification Question Ranking
 - Rank multiple candidate clarifying questions to select the most effective one for user interaction.
 - leverages document-based features, such as entity recognition and topic modeling (e.g., LDA), to generate facets representing different aspects of the query.

Sekulić, I., Aliannejadi, M., & Crestani, F. (2022, April). Exploiting document-based features for clarification in conversational search. In *European Conference on Information Retrieval* (pp. 413-427). Cham: Springer International Publishing.

Techniques Search Clarification

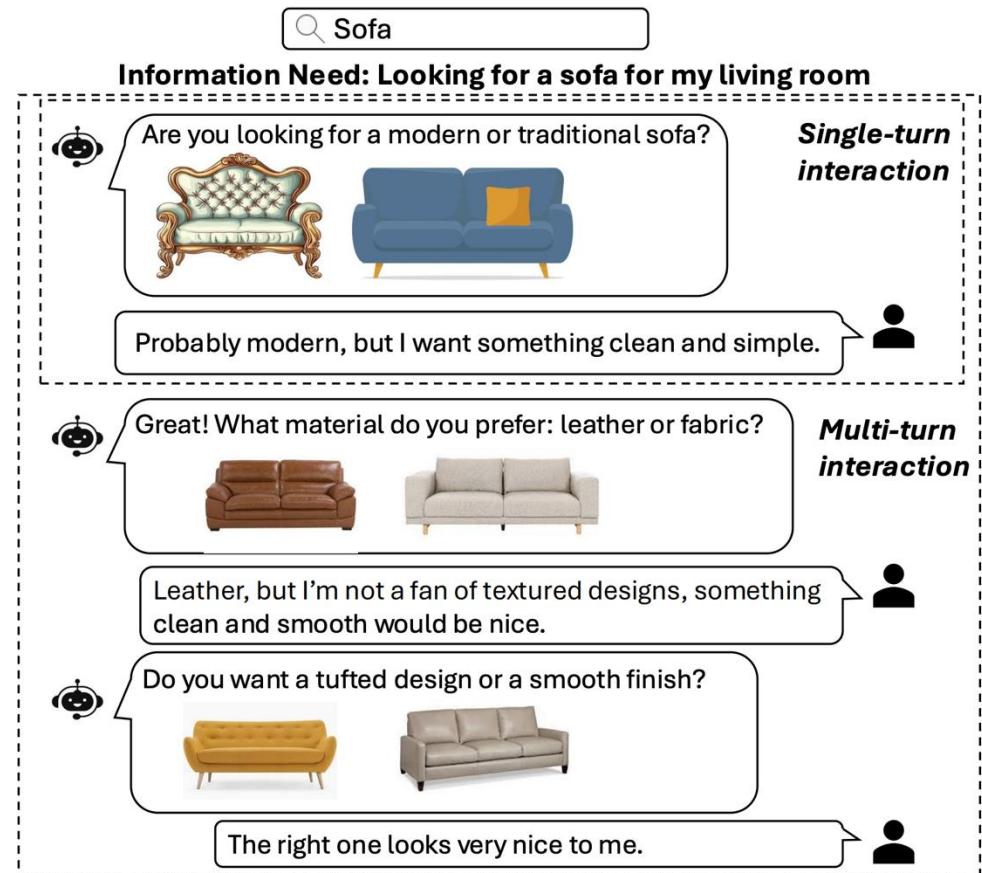
□ Mixed-Initiative Strategies

- when and how to ask clarifying questions during a conversation.



Techniques Search Clarification

- Multi-Turn Multi-Modal Clarification
 - multiple turns and multiple modalities(images/text)

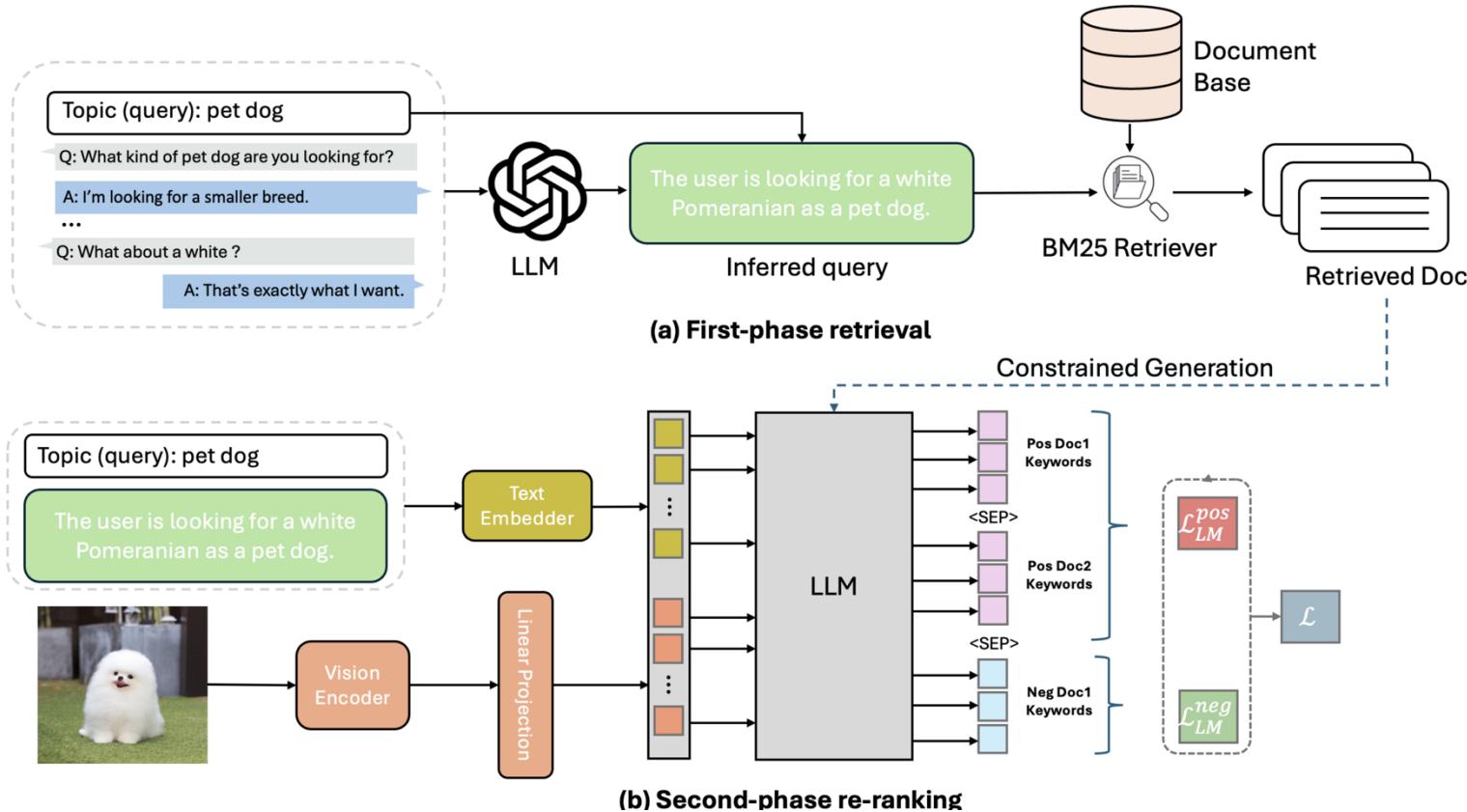


Ramezan, K., Bavandpour, A. A., Yuan, Y., Siro, C., & Aliannejadi, M. (2025). Multi-Turn Multi-Modal Question Clarification for Enhanced Conversational Understanding. *arXiv preprint arXiv:2502.11442*.

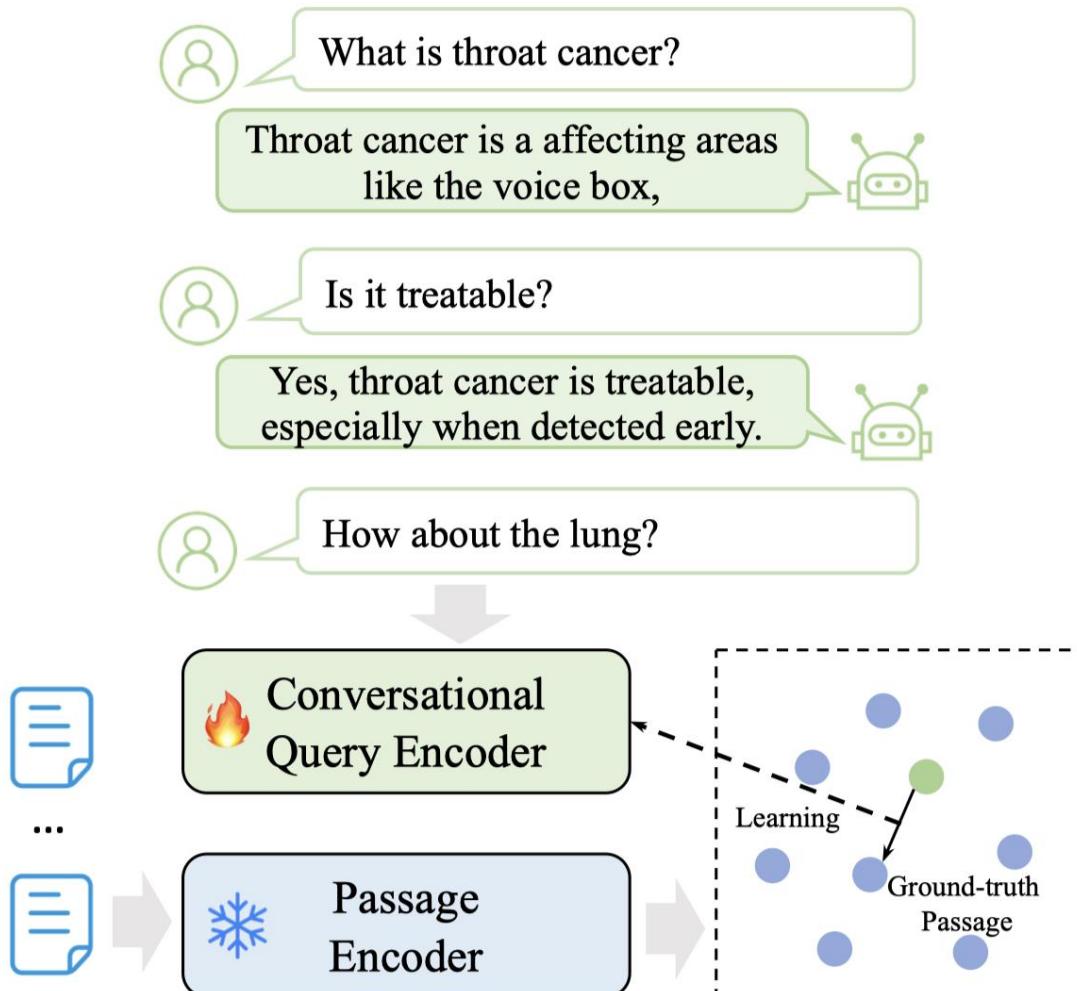


Techniques Search Clarification

□ Multi-Turn Multi-Modal Clarification



CONVERSATIONAL RETRIEVAL

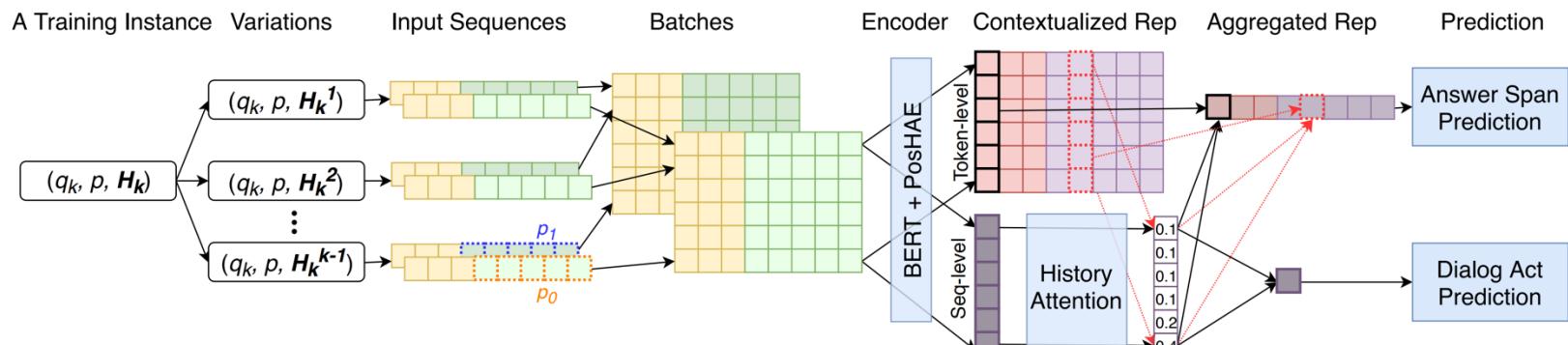


CONVERSATIONAL RETRIEVAL

- Conversation/Context Modelling
- Context Denoising
- Data Augmentation
- Re-ranking

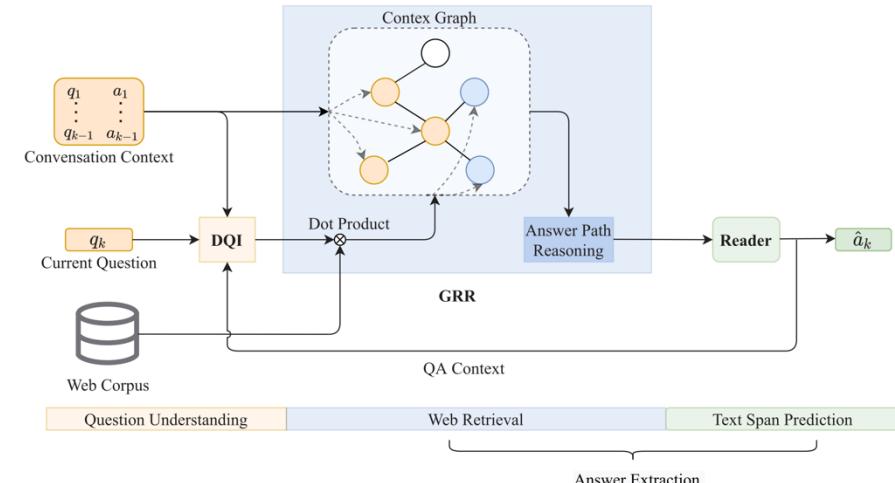
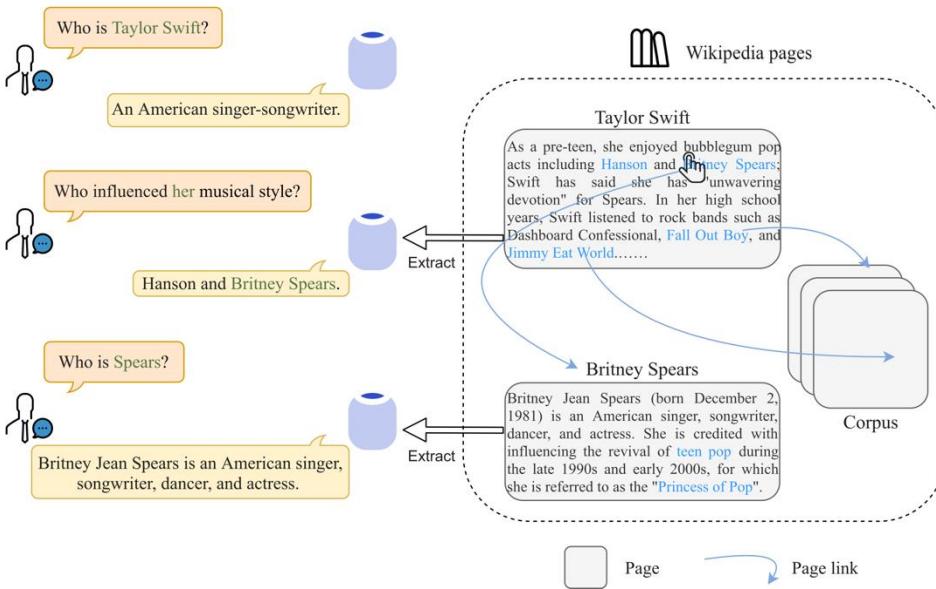
CONVERSATIONAL RETRIEVAL

□ Conversation/Context Modelling

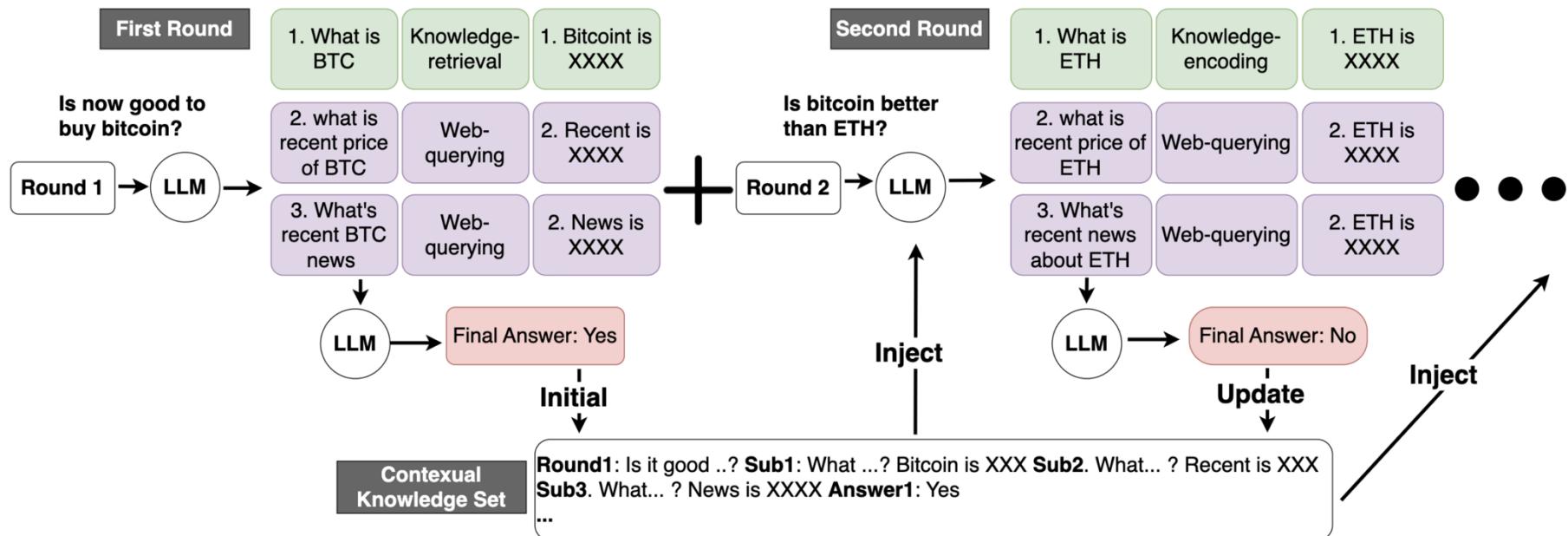


CONVERSATIONAL RETRIEVAL

□ Conversation/Context Modelling



CONVERSATIONAL RETRIEVAL



CONVERSATIONAL RETRIEVAL

□ Context Denoising

□ Why

- not all historical query turns are relevant
- concatenating all historical context → noisy
- Enhanced Query Understanding

□ How

■ Implicit

- Curriculum Contrastive Context Denoising (COTED)

■ Explicit

- History-Aware Conversational Dense Retrieval (HAConvDR)

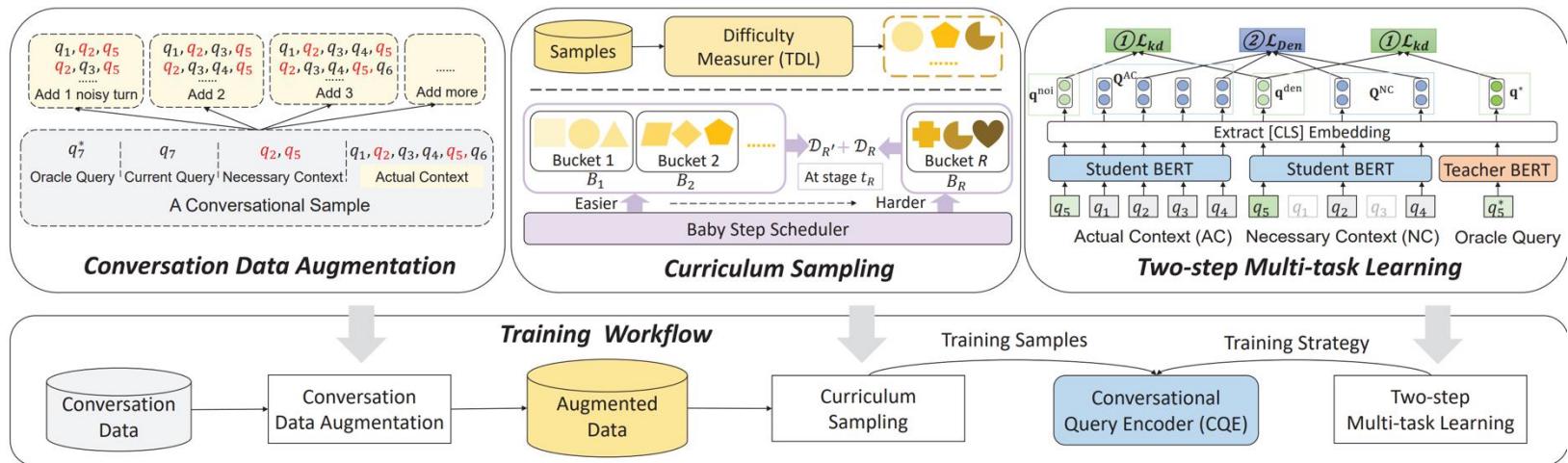


Context Denoising

- COTED
 - ▣ curriculum learning
 - ▣ contrastive learning
 - ▣ relevant vs irrelevant context
 - ▣ trained on augmented conversational data
 - noise is systematically introduced
 - contrastive learning

Context Denoising

COTED

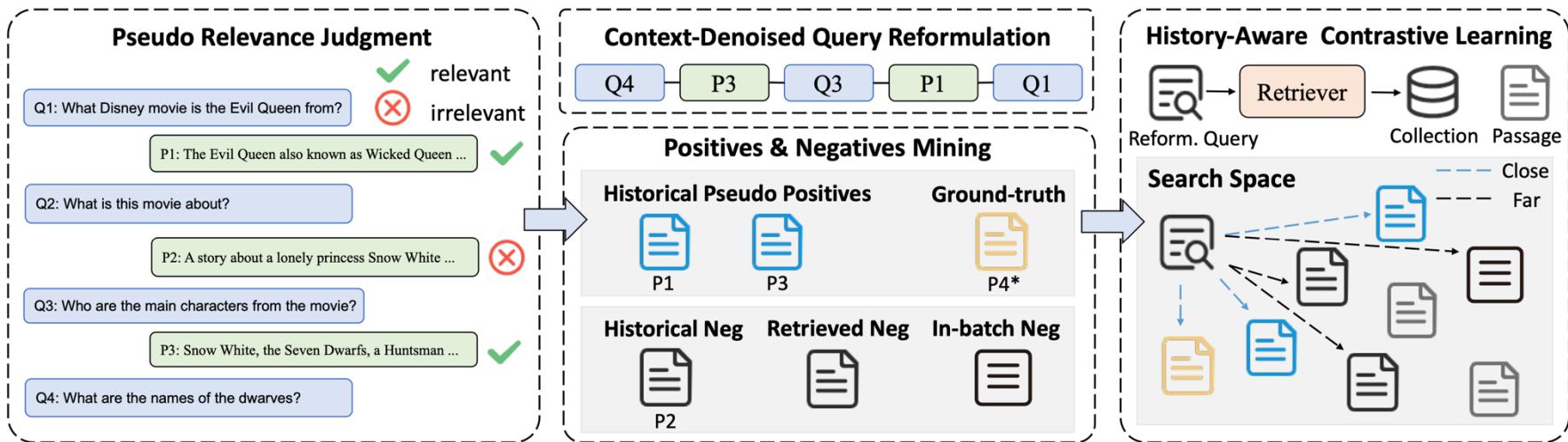


Context Denoising

- HAConvDR
 - integrates context-denoised query reformulation
 - mining of supervision signals based on the impact of historical turns

Context Denoising

□ HAConvDR



CONVERSATIONAL RETRIEVAL

- Data Augmentation
 - ▣ Performance relies heavily on large-scale datasets
 - ▣ abundant annotations not available
- How
 - ▣ relevance judgment generation
 - ▣ contrastive sample generation
 - ▣ conversation session generation

Data Augmentation

- Relevance Judgment Generation
 - manual relevance judgments are expensive
 - pseudo-relevance labels based on the pseudo relevance feedback
 - Use LLMs as instructors

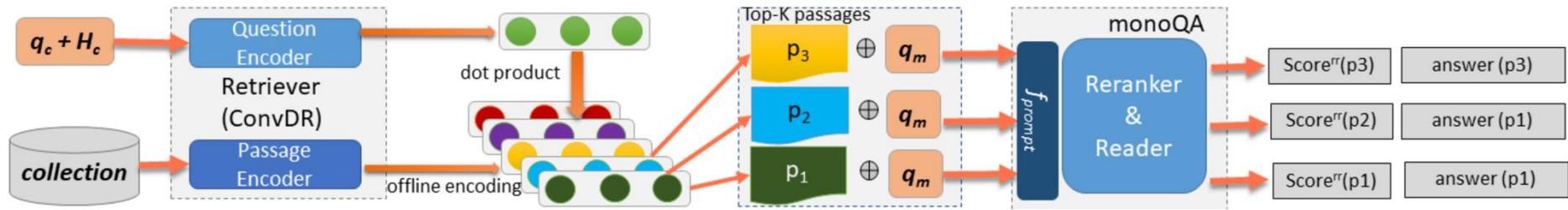
Data Augmentation

- contrastive sample generation
 - challenging to obtain enough high-quality session-level search data
 - transforming readily available web search sessions into conversational search sessions

Data Augmentation

- Contrastive Sample Generation
 - ▣ As search systems under conversational scenarios are not yet widely implemented
 - ▣ transforming readily available web search sessions into conversational search sessions,
 - ▣ LLMs to create additional conversational session data to enhance the diversity and volume of training data through two approaches: dialogue-level session generation, which creates entire sessions based on a given topic, and querylevel augmentation, which rephrases existing queries to express the same intent in various ways

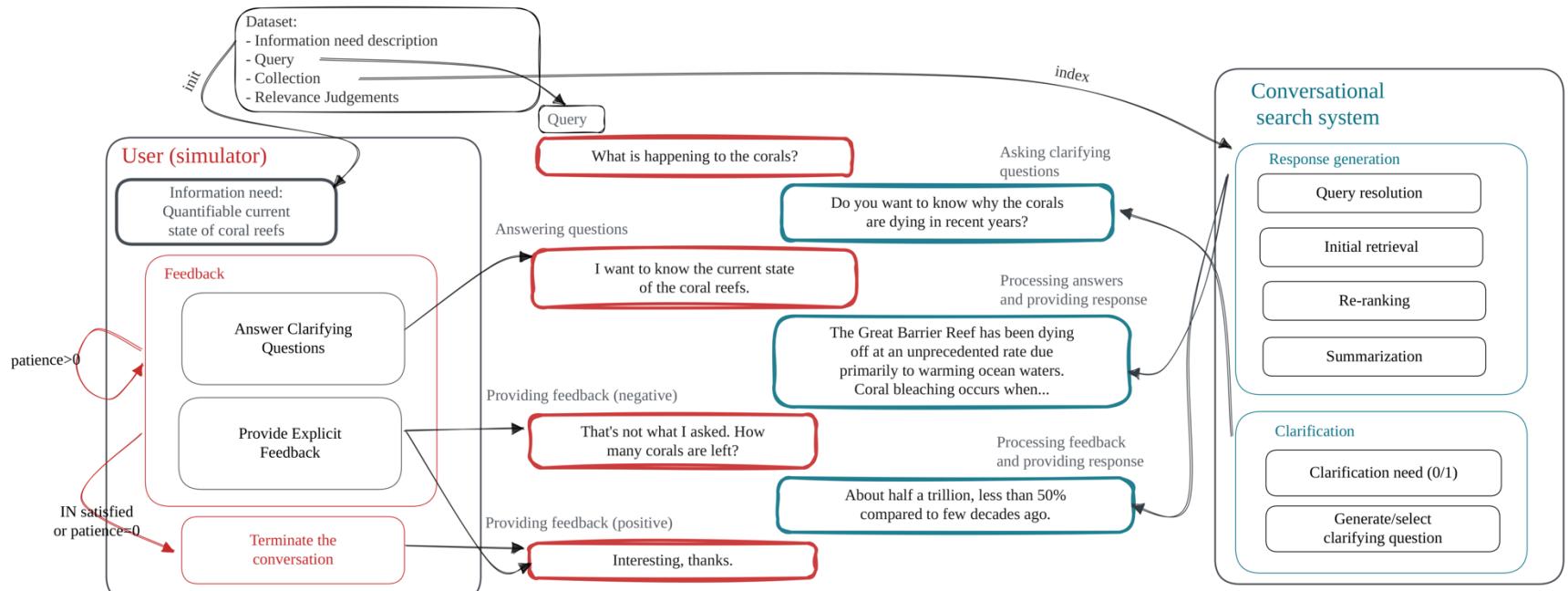
Re-ranking



S. Kongyoung, C. Macdonald, and I. Ounis, "monoqa: Multi-task learning of reranking and answer extraction for open-retrieval conversational question answering," in Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing, EMNLP 2022



Re-ranking



P. Owoicho, I. Sekulic, M. Aliannejadi, J. Dalton, and F. Crestani, "Exploiting simulated user feedback for conversational search: Ranking, rewriting, and beyond," CoRR,

Generation



Question



Historical Conversations



Historical Context Utilization:

- Previous search results utilization.
- Long context input handling.

Context Dependency Modeling:

- Selecting relevant conversational segments for generation purpose.



Returning a User-Centric and Reliable Response



Response Generation and Knowledge Attribution:

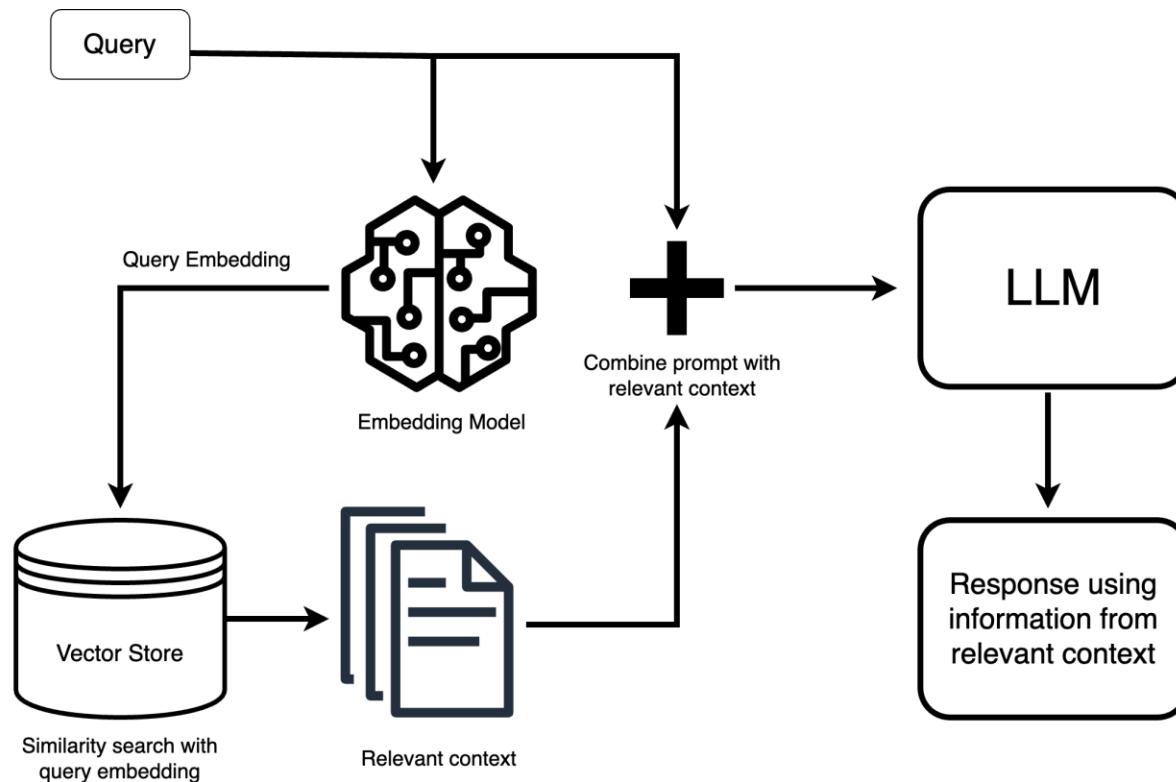
- Attribution in/after generation.
- Multi-turn knowledge attribution.
- User intent and target prediction.
- System decision making.

Generation

- LLMs plays a part
- retrieval-augmented generation (RAG)
 - single-turn

Generation

□ RAG



Generation

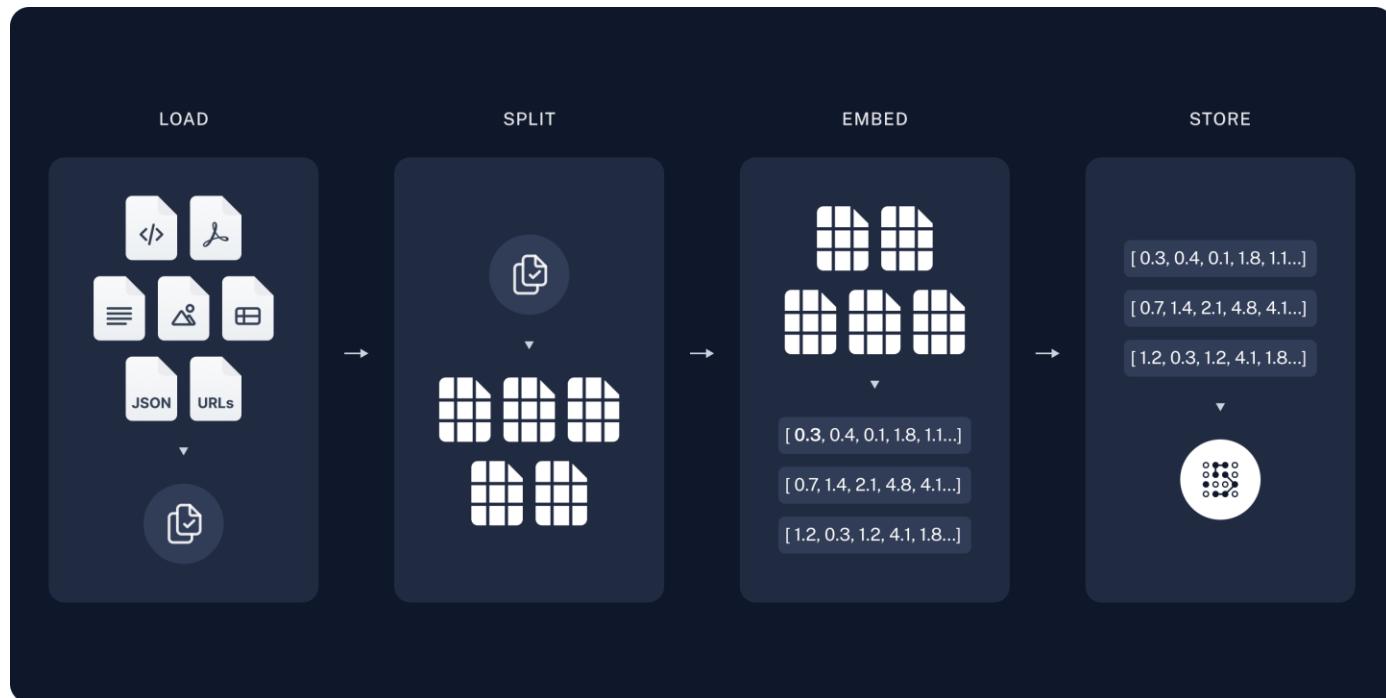
- Benefits of RAG
 - ▣ Enhanced Accuracy
 - ▣ Reduced Hallucinations
 - ▣ Domain Adaptability
 - ▣ Cost Efficiency

Generation

- RAG
 - The RAG process involves several key steps:
 - Query Input
 - Retrieval
 - Augmentation
 - Generation

Generation

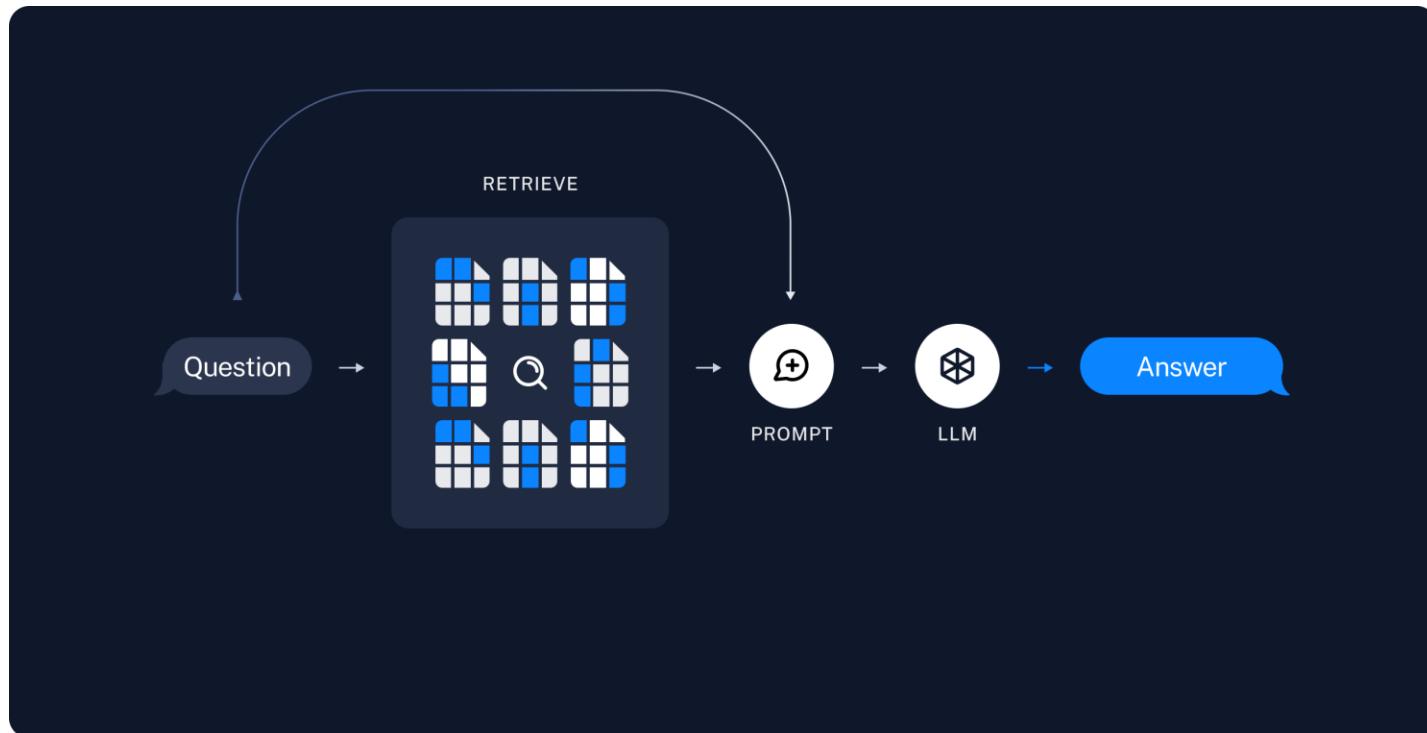
- ❑ RAG
- ❑ Indexing



Generation

❑ RAG

❑ Retrieval and generation



Generation

- Utilization of Historical Search Results
 - ▣ Integrate search results from previous turns -> improve current turn of RAG
 - increasing the recall
 - Diversified search
 - ▣ Selecting the useful information and avoiding injecting additional noise
 - ▣ Still open
 - ▣ Challenge
 - long context input
 - identifying the utilization of historical search results.
 - relevance/usefulness

Generation

- Context Dependency Modeling
 - ▣ Why
 - better understanding users' search intents
 - ▣ How
 - Concatenate history with input
 - Other complicated

Generation

- Conversational Knowledge Attribution
 - Aka citation labeling
 - associate the output content with knowledge source
 - How
 - Parallel with generation
 - After generation

Generation

- Conversational Knowledge Attribution
 - Parallel with generation
 - directly generates citations
 - After generation
 - use natural language inference (NLI) models
 - calculate relevance between response and evidence

Domain-specific and User-centric

- Complexity
 - ▣ Knowledge are different in different domain
 - Table, graphs, multi-modal
 - ▣ Cover intended utilization by real users
 - ▣ User-centric perspective
 - dataset construction
 - evaluation criteria
 - Intergrate user profile

Domain-specific

- multi-domain/task
 - ▣ search cross-domain information for sharing by reasoning over the conversational history
 - ▣ Unable to when targeting a specific domain
- Domain-specific models
 - ▣ Medical
 - ▣ Financial
 - ▣ Legal
 - ▣ Other

Domain-specific and User-centric

 (a) Medical Domain

My child has a fever, and his cough is getting worse with a runny nose. He has already been taking traditional Chinese medicine for a few days.

Based on your description, your child may be experiencing a fever and cough due to a respiratory infection. I recommend considering oral Western medicine for treatment.

My child's fever has not gone down, and I am very worried.

What is the child's temperature?

Last night it was 38.5°C, and during the day it was 38°C.

If the temperature exceeds 38.5°C, it is recommended to take antipyretic medication; for temperatures below 38.5°C, you can try physical cooling methods.

 (b) Financial Domain

How is the option price calculated?

The price of an option is calculated using the Black-Scholes Model, which determines the price based on factors such as the expiration time of the option, the price of the underlying asset, the strike price, the risk-free interest rate, and the volatility of the underlying asset. These factors allow for the computation of a fair market price through mathematical methods.

Could you share the rules for trading options?

When an investor purchases an option, they pay a fee known as the option premium. The rules of option trading include steps for buying and selling options, as well as details regarding the expiration date and strike price of the option. Investors who buy options pay an option premium at the time of purchase...On the other hand, investors who sell options must secure a corresponding margin to ensure they can fulfill their obligations at expiration...

 (c) Legal Domain

If a couple divorces due to one partner's gambling, can the gambler be left with nothing?

Based on the situation you provided, if a couple divorces due to one partner's gambling, the other party may, according to Article 1092 of the Civil Code, request the court to allocate a reduced share or no share of the assets associated with gambling... Has the other party in your scenario committed such a significant fault?

One of the spouses is definitely at fault here.

In such cases, the court may take into account the fault of the spouse when dividing assets. If the gambling is deemed to have caused significant financial damage or distress...

 (d) Multi-Modal Domain

Hello, I'm very interested in this bronze artifact on display. Can you provide more information?

Of course! Would you like to know about its historical context or its artistic features?

I'd like to know about its historical background.

This bronze artifact is an early Western Zhou dynasty piece, dated to around the 11th century BC. I can show you a detailed high-resolution image to help you examine these decorations more closely.



Medical Specific

- extract relevant medical concepts from retrieved information

 (a) Medical Domain

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Medical Specific

- Challenges
 - ▣ Scarcity of Expert-Annotated Data
 - ▣ Poor Correlation Between Automatic Metrics and Human Judgments
 - ▣ Domain Complexity and Knowledge Sensitivity
 - ▣ Lack of Standardization

Medical Specific

- Opportunities
 - ▣ LLM-Assisted Annotation
 - ▣ Creating Benchmarks with Diverse Judgments
 - ▣ Few-shot and Prompting Techniques
 - ▣ **Cross-domain Transfer Learning**
 - ▣ **Interactive & Real-time Evaluation**
 - ▣ Collaborative Platforms for Crowdsourcing Expert Feedback



Finance Specific

- Challenges
 - **Hallucination and Reliability**
 - Domain-Specific Adaptation
 - **Computational and Ethical Constraints**
 - **Realtime-ness**

Finance Specific

- Opportunities
 - Specialization for Financial Tasks
 - Multimodal Financial Analysis
 - Retrieval-Augmented Generation (RAG)
 - Autonomous Financial Agents

Legal Specific

- Challenges:
 - ▣ Legal Feature Alignment: Not all content in a case is important—legal facts and legal issues are the key factors for relevance.
 - ▣ Legal Context Preservation: Truncating or segmenting legal texts leads to loss of holistic context, especially since legal cases can span thousands of words.

User-centric

□ personalized search

First dialogue session

User

Hi, I am looking to make dinner.

Assistant

What sort of dishes do you normally like to eat?

User

I am a **vegetarian** and [...]

Assistant

Great! Based on your preferences, I would recommend [...]

Preference memory

Category	Attribute
diet_requirements	Vegetarian
...	...

Subsequent dialogue session

Hi, please can you help me with some lunch recipes?

⋮

How about this chickpea curry?
<https://recipe/chickpea-curry>

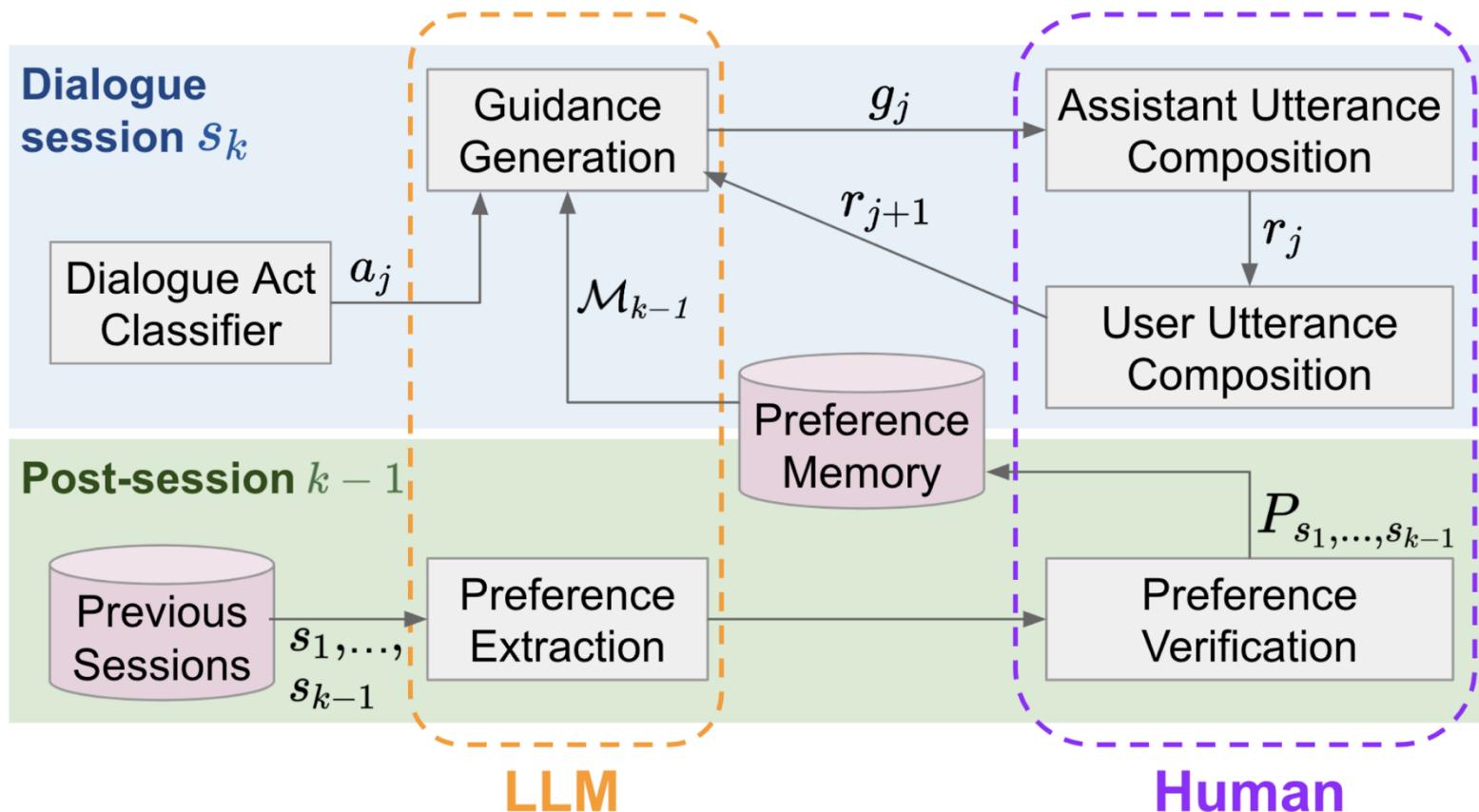
 Chickpea curry

🕒 Prep: 15 mins
Cook: 25 mins

Gluten-free 🌱 Vegan 🥑 Vegetarian

I love spicy food and I was happy you **remembered I am a vegetarian**.

User-centric



Limitations of Conversational Search

- Data Resources
- Domain-Specific IR
- Faithfulness

Evaluation

- Types
 - ▣ Retrieval-based Evaluation
 - P R F1
 - ▣ Generation-based Evaluation
 - BLEU ROUGE ...

Evaluation

- Limitations
 - ▣ Conversational-Originated Evaluation
 - ▣ Retrieval Effectiveness Evaluation
 - ▣ Mixed-initiative Evaluation

Take away

- Introduced conversational search in very high level.
- Showed key techniques related to conversational search
- Covered core components and features
- Covered evaluation