Conversational Passage Retrieval

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October 04, 2021

(SIKS course in Advances in Information Retrieval)

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Intro - Who am I?

3rd year PhD student @ UvA (IRLab)

Topic: Conversational Search

Previously:

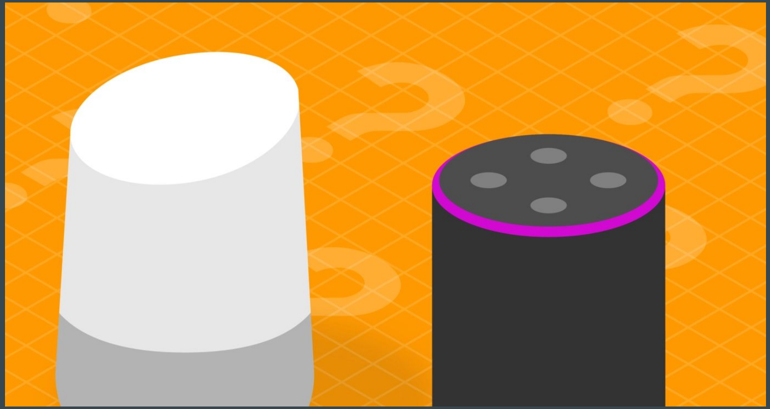
- Electrical & Computer Engineering (AuTh)
- MSc Data Science (UvA)
- Data Science @ bol.com

Conversational Search & Conv. Passage retrieval

Conversational Search

Many forms of conversations & Conv. Search:

- Conversational Question Answering [1]
- Conversations with Documents (Document-centered assistance) [2]
- Conversational Product Search [6]
- Conversational Passage Retrieval



Conversational Passage Retrieval

➔ **Given a conversation** (ie. user-system) **rank documents**/passages

Characteristics:

- Information-seeking
- Open domain
- Focus on **ranking** documents/passages
  (rather than ie. Question Answering)

Conversational Passage Retrieval

Different types (scenarios) of conversations:

- Clarifications

- Conversational Information-Seeking (CIS)

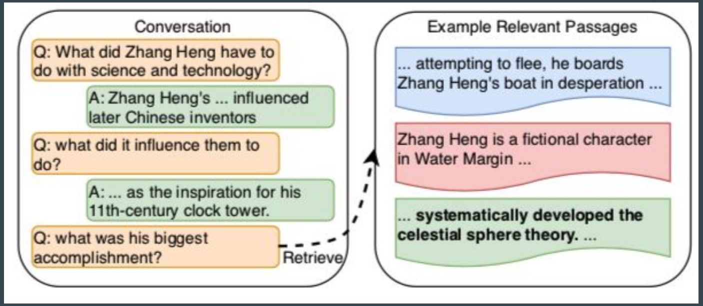
- More...

Clarification-based conversation

Conversational Passage Retrieval

Different types (scenarios) of conversations:

- Clarifications
- Conversational Information-Seeking (CIS)
- More...



Information-seeking conversation

Conversational Passage Retrieval

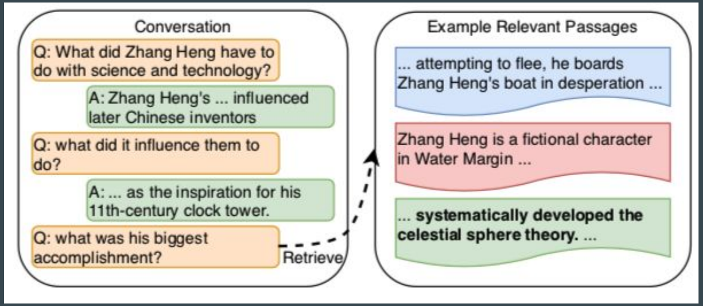
Different types (scenarios) of conversations:

- Clarifications
- Conversational Information-Seeking (CIS)
- More...

Ranking with Information Seeking Conversations

Wizard setting:

1. User continuously asks (different) questions to a system
2. System responds with a passage



CIS task

Differences: CIS vs. ConvQA

	CIS	**Conv QA**
task	passage retrieval	answer selection / generation
models	retriever	(retriever) + **reader**
	open-domain	open- or closed-domain
evaluation	ranking metrics (NDCG, MRR, P, ...)	QA metrics (F1, EM, ...)

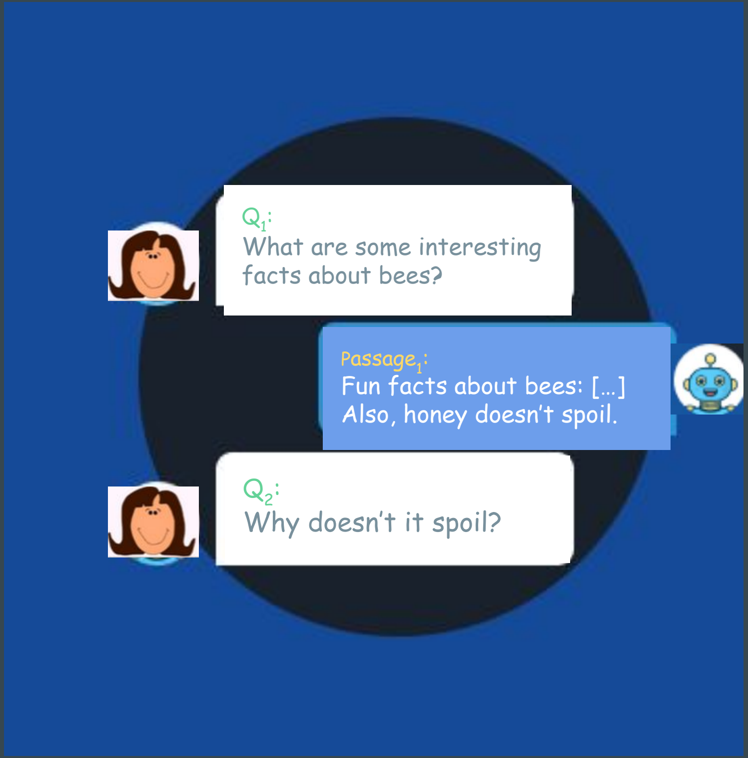
Comparison: CIS vs. Conv QA

Competitions/Datasets for CIS

1. Trec Conversational Assistant Track (CAsT) [2019-2021] [7]

	2019	2020/21
Next question depends on:	- Previous user questions (Q_1 , Q_2, … , Q_{X-1})	- Previous user questions (Q_1 , Q_2, … , Q_{X-1}) - Previous answer passages (P_1 , P_2, … , P_{X-1})

Task differences (per year)



CAsT 2020 example

Competitions/Datasets for CIS

2. OrQuaC

- **synthetic** data from QA pairs

- All relevant passages of a conversation come from 1 wikipedia article (dataset bias?)

Pipeline methods for CIS

- CAsT-19
  - QuReTeC
  - Few-shot Query Rewriting
  - An overview

- CAsT-20
  - h2oloo submission

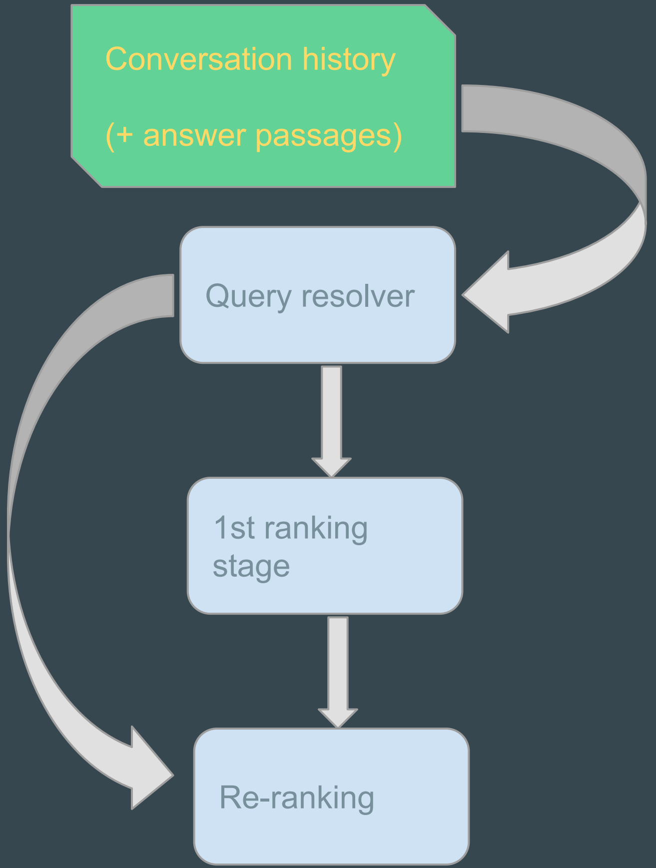
Pipeline methods

Focus on **query resolution/rewriting:**

- **Make the query** (last user utterance) → **self-contained**

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?

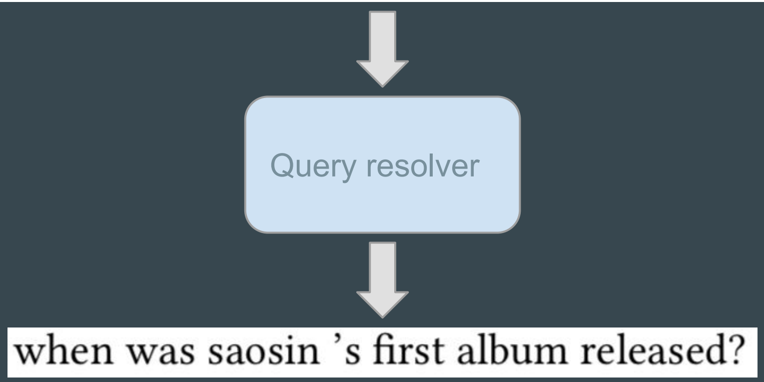
Cast-19 example



Conv. Passage Retrieval Pipeline (inference)

Query resolution / rewriting

Turn	Query
1	who formed **saosin**?
2	when was the **band** founded?
3	what was their **first** album?
4	when was the album released?



Query resolution/rewriting

Inference pipeline (ranking)

Methods for query resolution:

I. Lexical methods (text)
   A. Query Resolution by Term Classification (QuReTeC) [8]
   B. Few-shot generative conversational query rewriting [9]
   C. h2oloo system (T5-based) [12]

II. Dense methods (embedding space)
   A. Few-shot conversational query rewriting [9]

Query Resolution by Term Classification (QuReTeC)

QuReTeC [8] approach

Key idea:

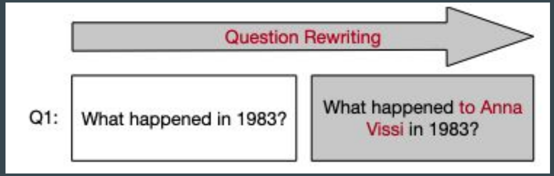
Query resolution as Term Classification
(of relevant history terms)

turn #	Question
$turn_1$	who formed **saosin**?
$turn_2$	when was the **band** founded?
$turn_3$	what was their **first** album?
$turn_4$	when was the album released?
resolution	when was the album released? **first saosin band**

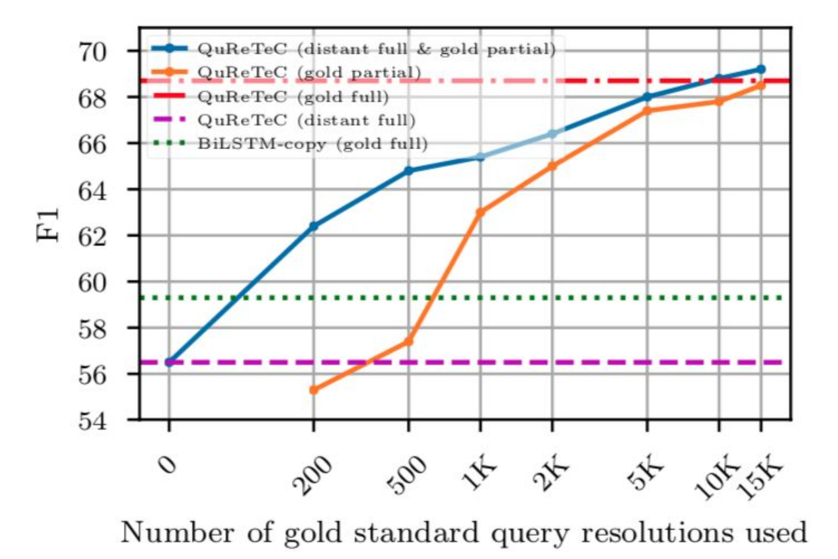
Query resolution by QuReTeC

Query Resolution by Term Classification (QuReTeC) [8]

training approaches:

Supervision	Labels	
Full	human resolutions (CAsT & CANARD)	
Weak	Distant supervision (from relevant passages)	Relevant terms are found in a relevant document

Query Resolution by Term Classification (QuReTeC) [8]



performance wrt. # of training examples

- ➔ **Good performance** with combination of

  human + distant supervision labels

- ➔ **Few human annotations needed**

Few-shot generative conversational query rewriting

Few-shot generative conversational query rewriting [9]

Key idea:

Try to address resolution by solving correferences & omissions

- ➢ Full rewriting (instead of adding salient terms)
- ➢ model: GPT-2

turn #	Question
$turn_1$	What causes throat cancer?
$turn_2$	What is the first sign of it?
$turn_3$	Is it the same as esophageal cancer?
$turn_4$	What's the difference in their symptoms?
resolution	What's the difference ***between*** throat cancer and esophageal cancer symptoms?

Query resolution by FSGCQR [9]

FS G CQR [9]: Training

Construct synthetic rewrite data

- ➔ Given a search session log:

  $\{query_1, query_2, ..., query_k\}$

- ➔ Use "QuerySimplifier" to simulate conversation (corrupt last query):

  $\{query_1, query_2, ..., query_k\} \rightarrow query_k^*$

- ➔ Teach rewriter to **reconstruct self-contained query**

  $\{query_1, query_2, ..., query_k^*\} \rightarrow query_k$

turn #	Session log
$turn_1$	who formed saosin?
$turn_2$	when was **the saosin band** founded?
$turn_2^*$	when was **their** band founded?

QuerySimplifier ($turn_2 \longrightarrow turn_2^*$)

FS G CQR [9]: "Conversational" Query corruption

QuerySimplifiers used:

A. **Rule-based**, from discourse phainomena:
   a. Correference *(he, it, …)*
   b. Omission

B. **Self-learn**
   a. few-shot GPT-2 corruptor from manual annotations

turn #	Question
$turn_1$	who formed saosin?
$turn_2$	when was the saosin band founded?
$turn_2^*$	when was their band founded?

Conversational Query simulation

FS G CQR [9]: Results

Method	BLEU-2	NDCG@3	QA-ROUGE
CAsT Queries			
Original	0.659	0.304	0.231
AllenNLP Coref w/o sw	–	0.314	–
AllenNLP Coref w/ sw	0.750	0.437	0.278
Oracle	1.000	0.544	0.314
Zero-Shot Rewriter			
GPT-2 Raw	0.112	0.124	0.196
MARCO Raw	0.380	0.172	0.183
Rule-Based	**0.755**	**0.437**	0.266
Few-Shot Rewriter			
Rule-Based + CV w/o PLM	0.178	0.065	0.151
Self-Learn	0.750	0.435	0.263
CV	0.793	0.467	0.280
Rule-Based + CV	**0.809**	**0.492**	**0.291**
Self-Learn + CV	0.804	0.491	**0.291**

Performance of zero- and few-shot rewriters [9]

- zero-shot: *(query corruption)*
  - substantial improvement over other zero-shot baselines
  - close to AllenNLP correference resolution (not zero-shot)
- few-shot *(query corruption + finetune)*
  - fine-tuning (CV) helps (+12%)
  - rule-based vs self-learn: on par
  - close to oracle (human resolutions)

Query Rewriters:
A comparison (so far)

Which resolution method works best ?

- Classification *[QuReTeC]*
- Rewriting *[FS query rewriting / others]*

Query Rewriters: A comparison

QR Method	Recall@1000	NDCG@3		ROUGE-1		
	Initial	Initial	Reranked	P	R	F
Original	0.417	0.131	0.266	0.92	0.76	0.82
Transformer++ Q	0.743	0.265	**0.525**	**0.96**	0.88	**0.91**
Self-Learn Q	0.725	0.261	0.513	0.93	0.89	0.90
Rule-Based Q	0.717	0.248	0.487	0.94	0.89	0.91
QuReTeC Q	**0.768**	**0.296**	0.500	0.89	**0.90**	0.89

CAsT-19 results (from [9])

Common retrieval & rerank pipeline: **BM25 + BERT**

- @ retrieval:
  - best rewrite: QuReTeC
- @ re-ranking:
  - best rewrite: Transformer++

What is a good resolution?

- Should it be **human-readable**?
- **human resolution =? oracle**
- Rouge-**Precision** vs. Rouge-**Recall** ?
- Depends on pipeline component
  - ie. **Retrieval vs. Reranker**
  - ie. **BERT vs. T5**

Such issues affect **robustness of pipeline systems**

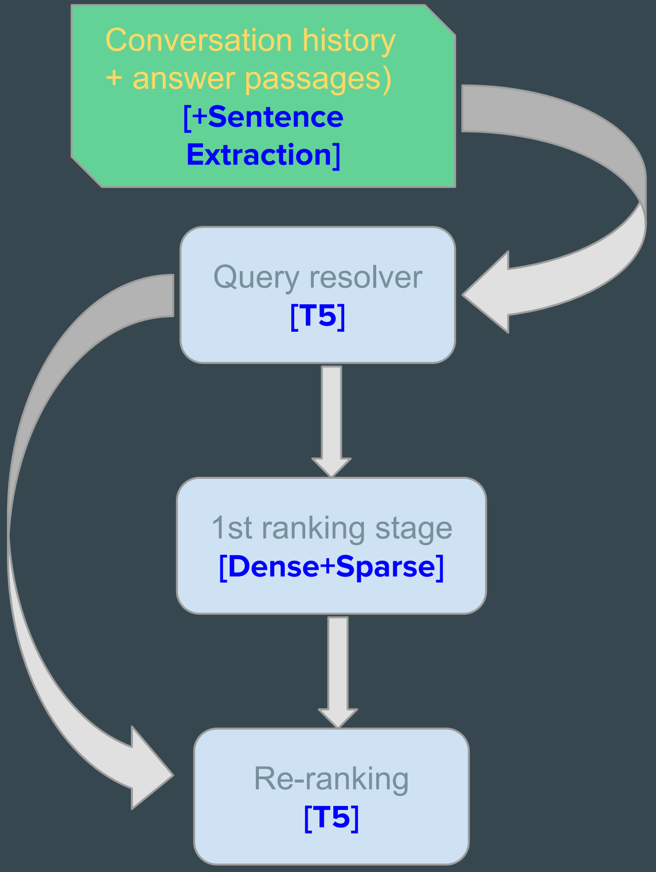
h2oloo trec-cast participation

h2oloo (Waterloo) system [12]

Key ideas:

1. use more **advanced models**
   a. **T5** *(rewriter + re-ranker)*
   b. **Hybrid Dense + Sparse** *retriever*

2. **Incorporating previous answer passages : Sentence Extraction**
   a. long input causes **performance degradation** (language models)
   b. Time **efficiency**

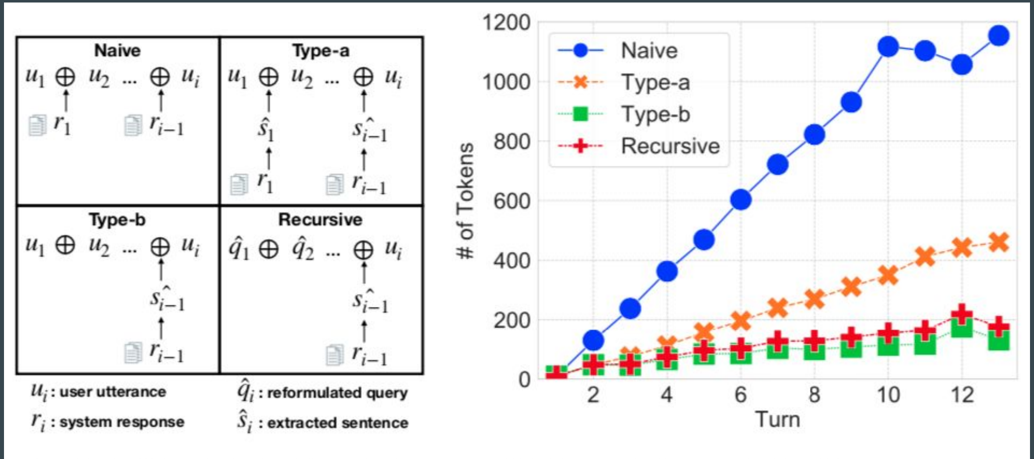


Conv. Passage Retrieval Pipeline
(inference)

h2oloo [12]: Handling previous answers

Extraction method	Canonical answer representation in query
Naive	Concatenate all previous answers
Type-a	Concatenate all extracted sentences
Type-b	Concatenate **last** extracted sentence
Recursive	Concatenate **previous query reformulations** + **last** extracted sentence

Query reformulation methods



(a) Query reformulation inference types (b) Average # of tokens input to T5 by turn depth
Figure 1: The comparison of different query reformulation methods

Query reformulation methods & lengths

h2oloo [12]: Experimental results

Query reformulation		Retrieval (dense+sparse)			Re-ranking (T5-3B)	
Model(T5)	Inference	R@1000	MAP	NDCG@3	MAP	NDCG@3
-	-	0.840	0.324	0.463	0.459	0.613
base	Query-only	0.668	0.225	0.343	0.330	0.452
base	Type-b	0.661	0.216	0.337	-	-
base	Recursive	0.684	0.220	0.328	-	-
large	Query-only	0.696	0.238	0.360	-	-
large	Type-a	0.708	0.239	0.364	-	-
large	Type-b	0.697	0.238	0.358	0.345	0.480
large	Recursive	**0.724**	**0.250**	**0.367**	**0.363**	**0.494**

Experimental results

- @ retrieval:
  - Reformulation roughly matters with T5-LARGE
- @ re-ranking:
  - T5-BASE + QUERY-ONLY: quite good already
  - [T5 BASE ⟶ T5 LARGE] + [QUERY-ONLY ⟶ TYPE-B]: +5%

h2oloo [12]: Experimental results

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Experimental results

- model **size** matters
- sentence extraction **?**

- @ retrieval:
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  - T5-BASE + QUERY-ONLY: quite good already
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Neural methods for CIS

Few-shot Conversational Dense Passage Retrieval [11]

First e2e Dense Retrieval architecture for Conv Passage retrieval:

Query resolution + retrieval: directly on the dense space

- backbone ranker: ANCE

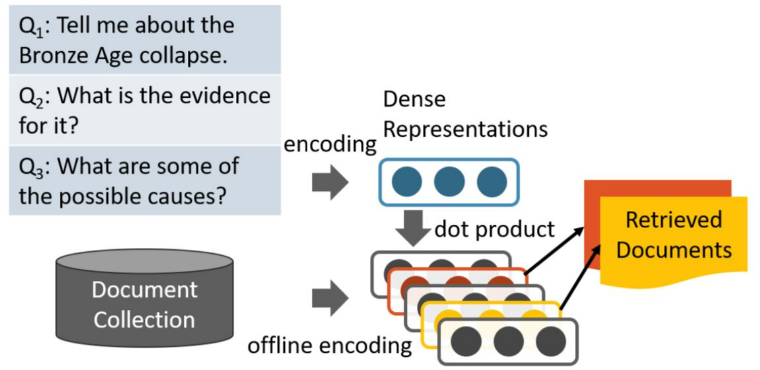


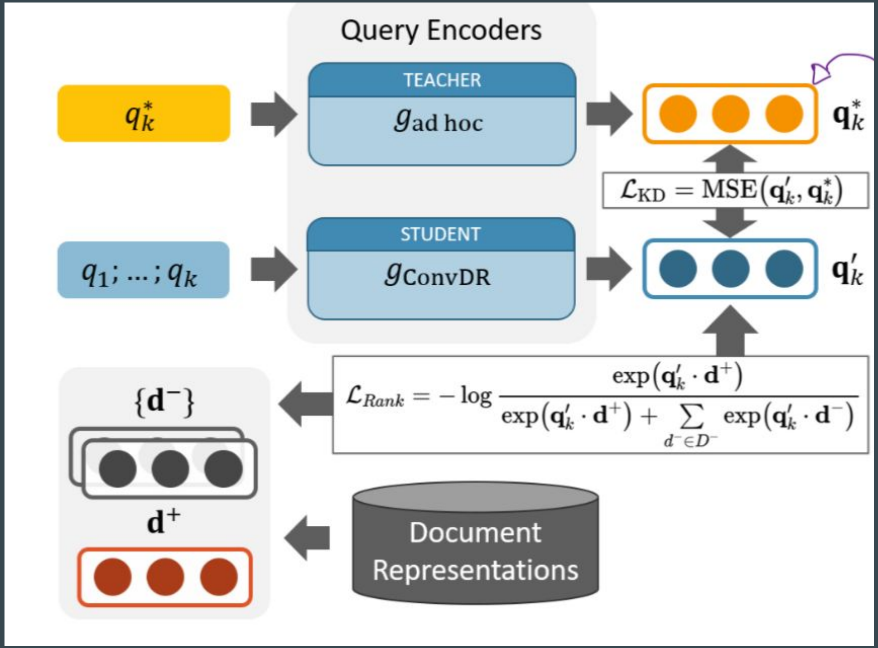
Figure 1: An illustration of Conversational Dense Retrieval. The conversational queries are contextually embedded and matched with documents via dense retrieval.

Inference (FS Conv DPR [11])

F.S. Conv.DPR [11]: Resolution in dense space

To resolve the query in the dense space:

➔ **Teacher-student network** that "pushes" the representation of the conversation to be close to the resolved query

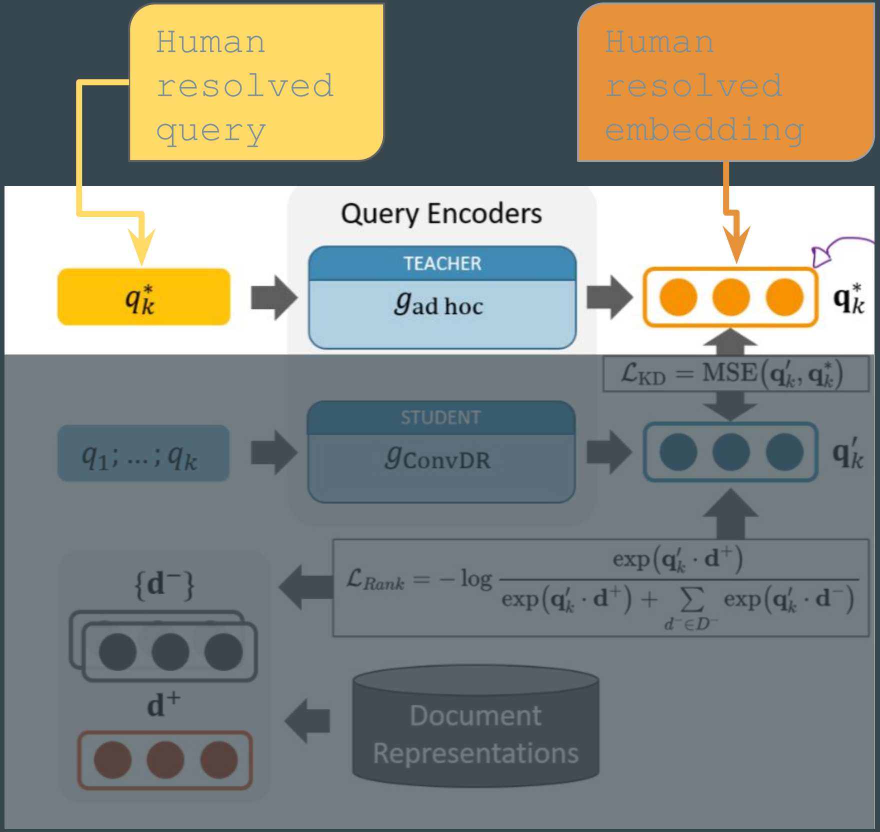


Training (FS Conv DPR [11])

F.S. Conv.DPR [11] : Training

➔ **Teacher:** produces "ideal" embedding (based on resolution)

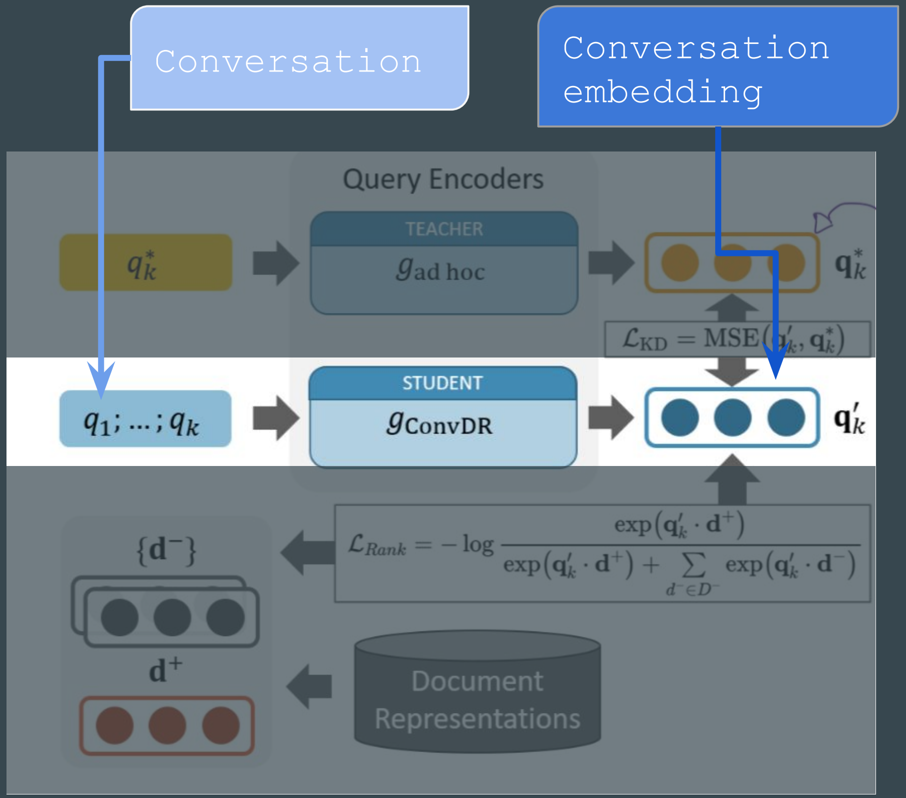
➔ Teacher: pre-trained **ANCE ranker**



Training (FS Conv DPR [11])

F.S. Conv.DPR [11]: Training

→ **Student:** produces embedding from conversation

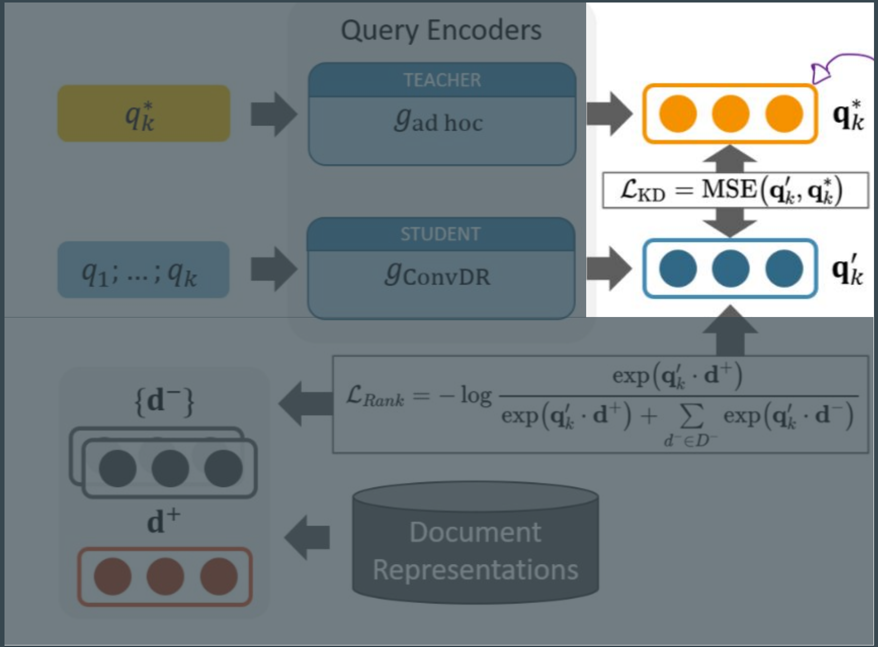


Training (FS Conv DPR [11])

F.S. Conv.DPR [11] : Training

➔ **Knowledge Distillation loss** L_{KD} **:**

Teaching the student to **produce "good embeddings" from conversation**

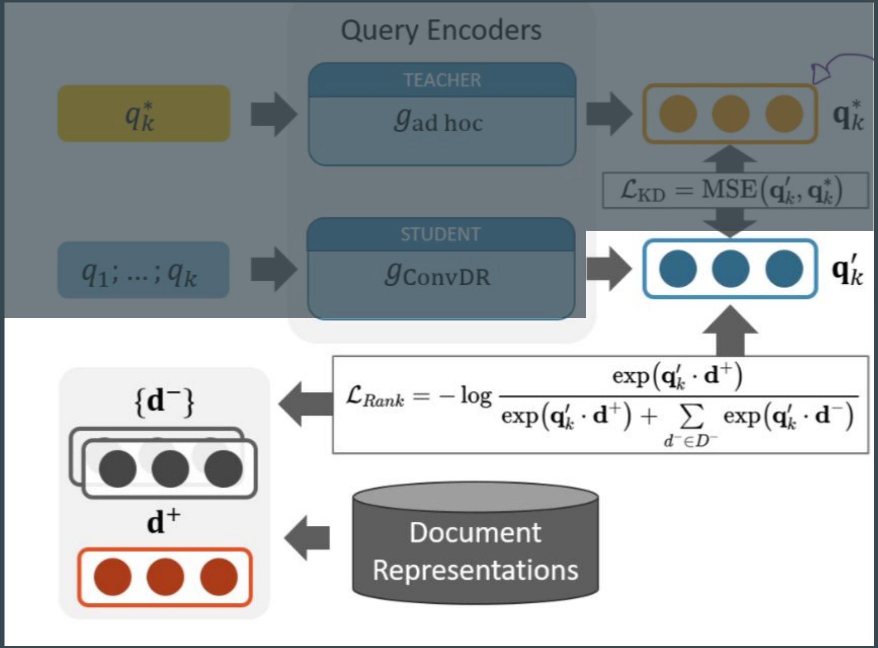


Training (FS Conv DPR [11])

F.S. Conv.DPR [11] : Training

➔ **Ranking loss** L_{Rank} **:**

Further fine-tuning of ranker in this task (Negative log likelihood)



Training (FS Conv DPR [11])

Which loss is more important?

- L_{Rank}
- L_{KD}

Ranking vs. Knowledge Distillation losses

Method	CAsT 2019		OR-QuAC	
	NDCG@3	W/T/L	MRR@5	W/T/L
First Stage Retrieval Only				
ConvDR (Zero-Shot)	0.202	13/30/57	0.568	24/61/16
ConvDR (KD)	**0.466**	38/39/24	0.519	19/63/18
ConvDR (Rank)	0.084	3/19/78	0.588	29/52/19
ConvDR (Multi-Task)	0.157	12/19/69	**0.616**	30/56/14

Ablation study ([11])

- ➔ **CAsT 19:** Fine-tuning w/o knowledge distillation fails
  - ◆ Few-shot setting
- ➔ **OR-QuAC:** Ranking loss is useful
  - ◆ why?
    - # training data?
    - dataset bias: all relevant passages from Wikipedia article

F.S. Conv.DPR [11] : Initial retrieval results

Ranker	MRR	NDCG @ 3
QuReTeC + BM25	-	0.17
FS Conv QR + BM25	-	0.15
FS Conv DPR	**0.50**	**0.34**
Human queries + BM25	0.45	0.30
Human queries + ANCE	**0.59**	**0.42**

Cast-20: First-stage Ranking Results

- ➔ largely outperforms other query rewriting methods when BM25 is the ranker
- ➔ w.r.t. **oracles** (human resolutions):
  - ◆ +15% wrt. BM25
  - ◆ -20% wrt. **ANCE** oracle

F.S. Conv.DPR [11] : Re-ranking results

Ranker	MRR	NDCG @ 3
QuReTeC + BERT		
h2oloo (T5-based)	**0.62**	**0.49**
FS Conv QR + BERT	-	0.34
FS Conv DPR + BERT	**0.54**	**0.39**
Human queries + BM25 + BERT	0.63	0.47
Human queries + ANCE + BERT	0.66	0.48

Cast-20: Re-ranking Results

$$\mathbf{H}_0(q_k, d) = \mathrm{BERT}([\mathrm{CLS}] \circ q_1 \circ \ldots [\mathrm{SEP}] \circ q_k \circ [\mathrm{SEP}] \circ d \circ [\mathrm{SEP}]),$$

Re-ranking method

- After **re-ranking**, improvements fade away
  - **ANCE 1st stage ranking** vs … **reranking**
- Waterloo's T5-based pipeline outperforms all approaches, even human!
- What's a fair evaluation?

Conclusions

- Discussed various methods for Conv Passage Retrieval
  - lexical vs. neural
- Evaluation varies on various ranking components
  - what's a **fair comparison**?
- Open problems:
  - Handling **previous answers / long context**
  - **Robustness** to pipeline changes
  - Training in **few-shot** setting?
  - **other types of conversations**?

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