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Context Attentive Document Ranking and Query Suggestion

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https://github.com/wasiahmad/context_attentive_ir

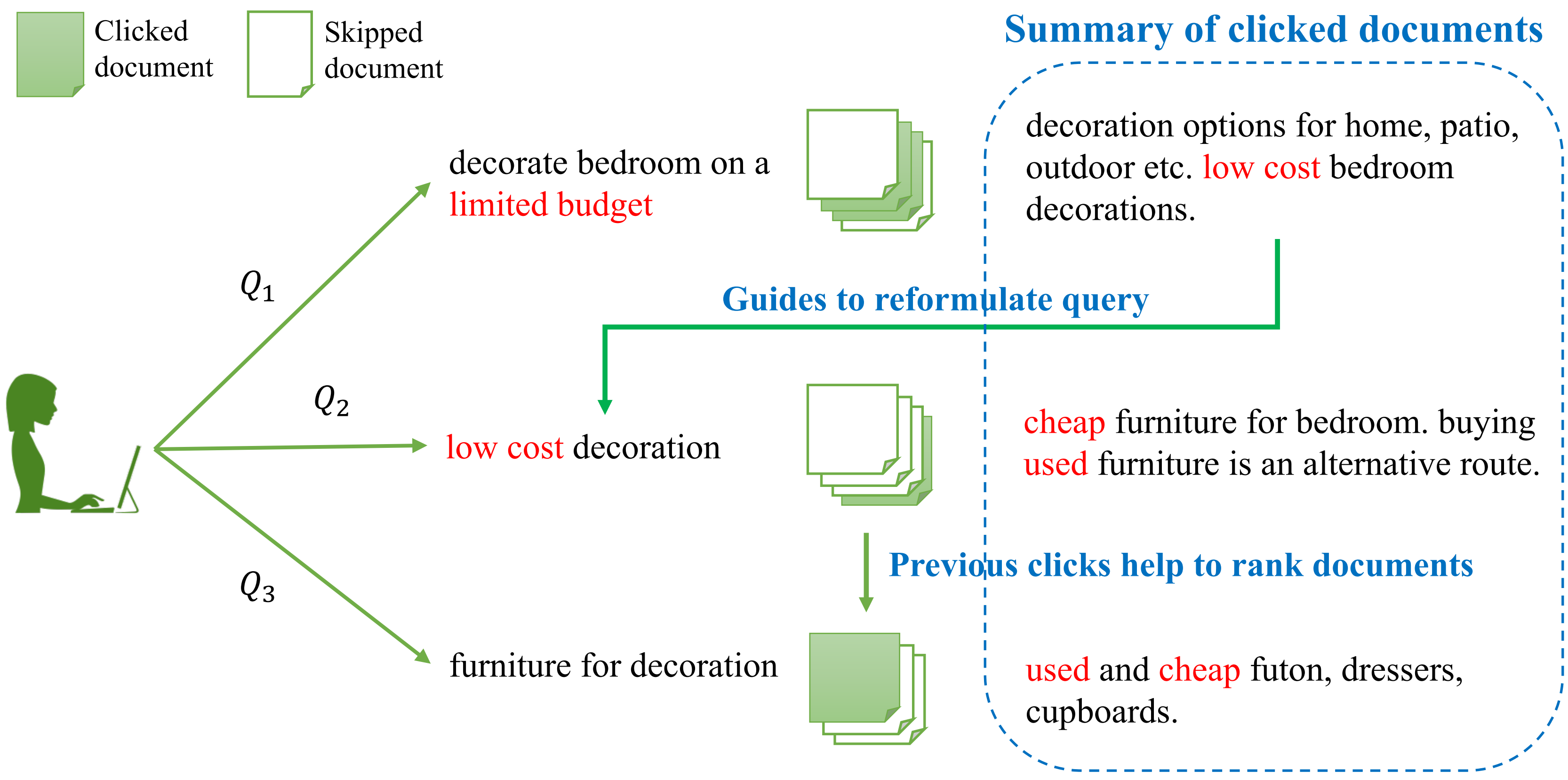
Codes will be released soon!

Search Logs Provide Rich Context to Understand Users' Search Tasks

5/29/2012	
5/29/2012 14:06:04	coney island cincinnati
5/29/2012 14:11:49	sas
5/29/2012 14:12:01	sas shoes
5/30/2012	
5/30/2012 12:12:04	exit #72 and 275 lodging
5/30/2012 12:25:19	6pm.com
5/30/2012 12:49:21	coupon for 6pm
5/31/2012	
5/31/2012 19:40:38	motel 6 locations
5/31/2012 19:45:04	hotels near coney island

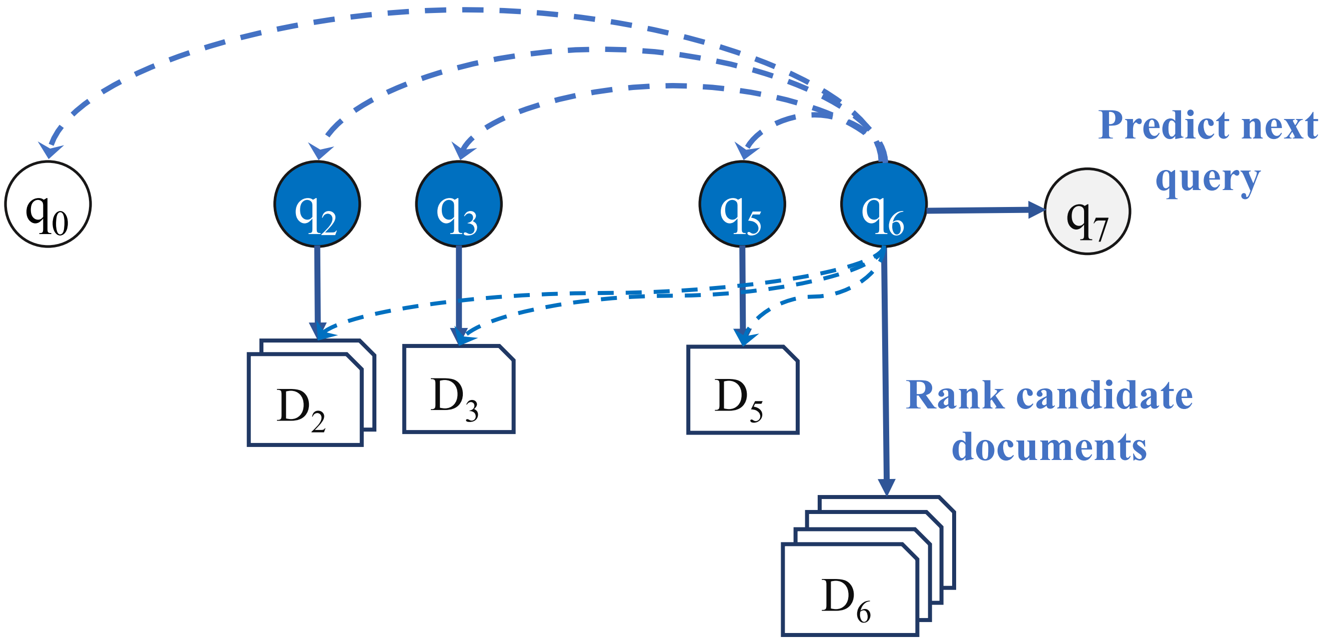
***Task**: an atomic information need that may result in one or more queries.*

Clicks Further Enrich Context to Understand Users' Search Tasks



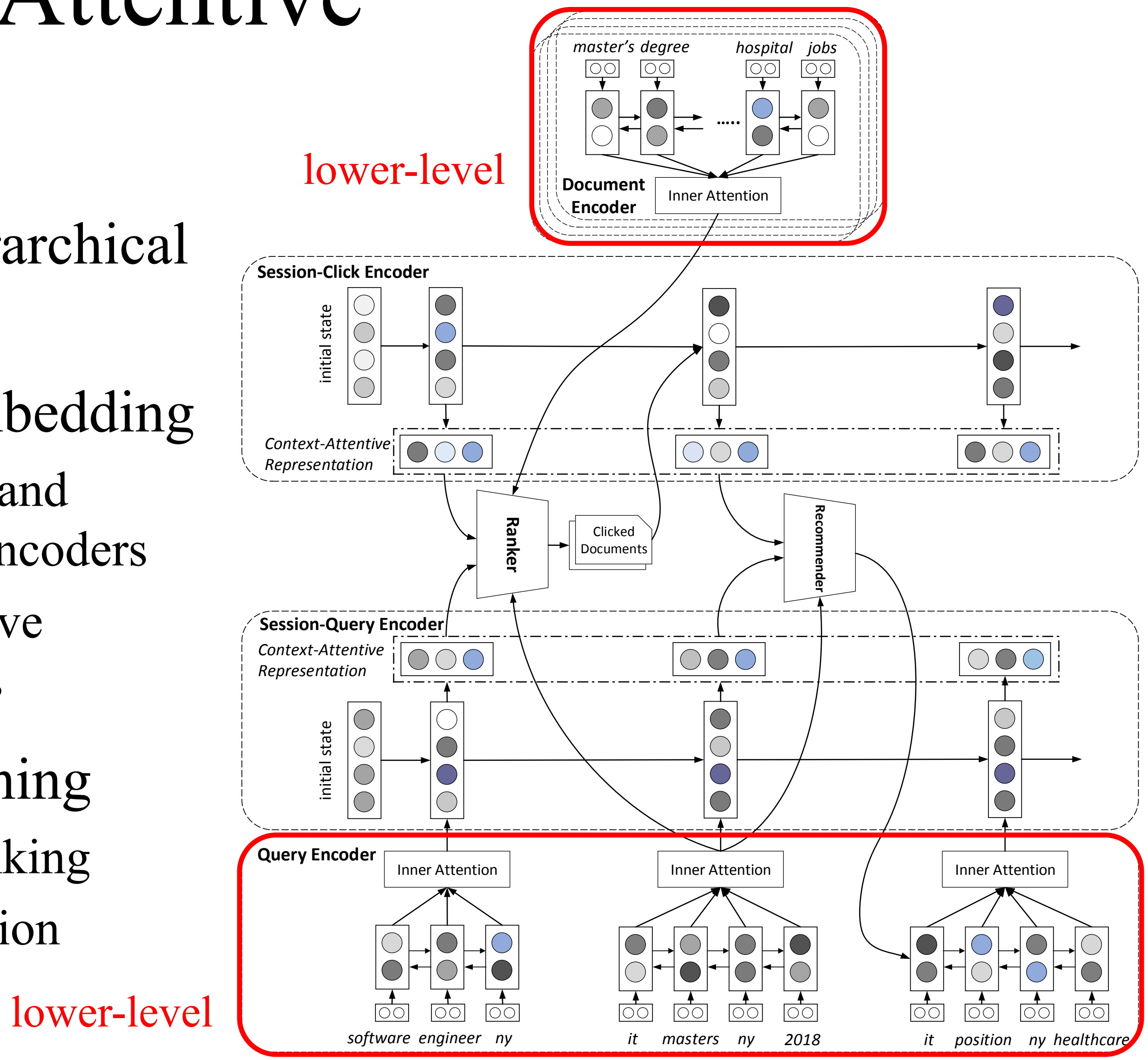
Our Proposal

- Attend on previous queries/clicks to perform retrieval tasks
- Learning to utilize context in multiple retrieval activities



A Context Attentive Solution

- A two-level hierarchical structure
- Task context embedding
    - Session-query and session-click encoders
    - Context attentive representations
- Multi-task Learning
    - Document Ranking
    - Query Suggestion



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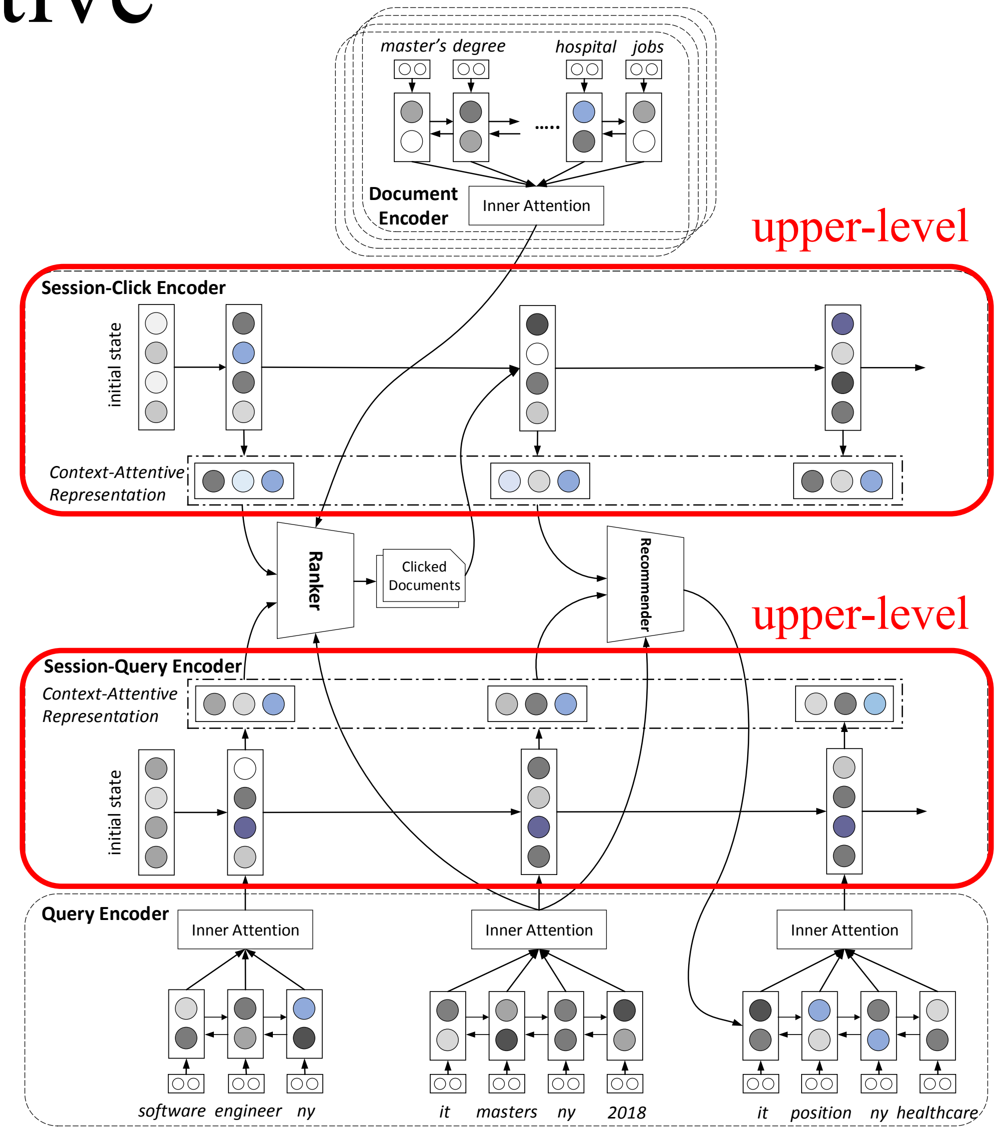

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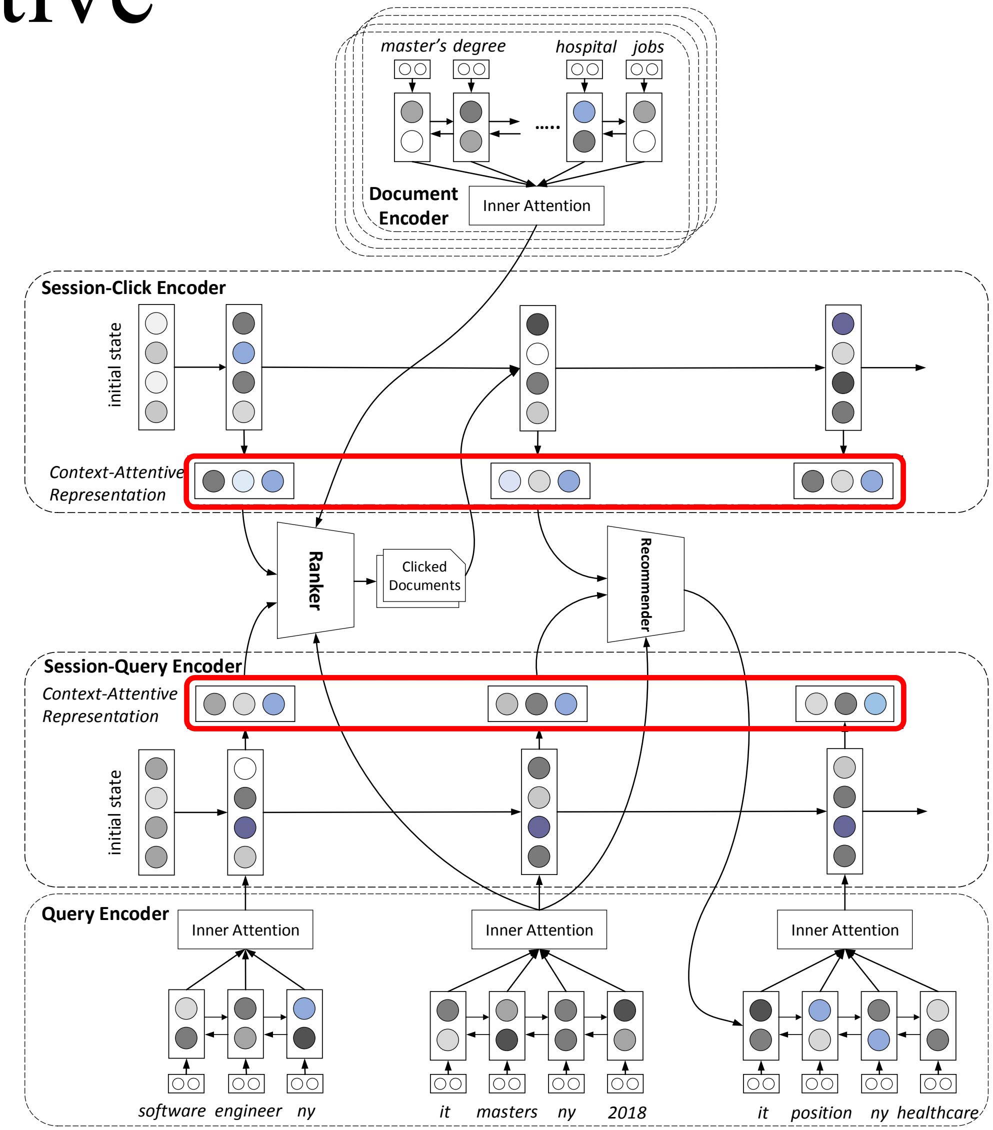

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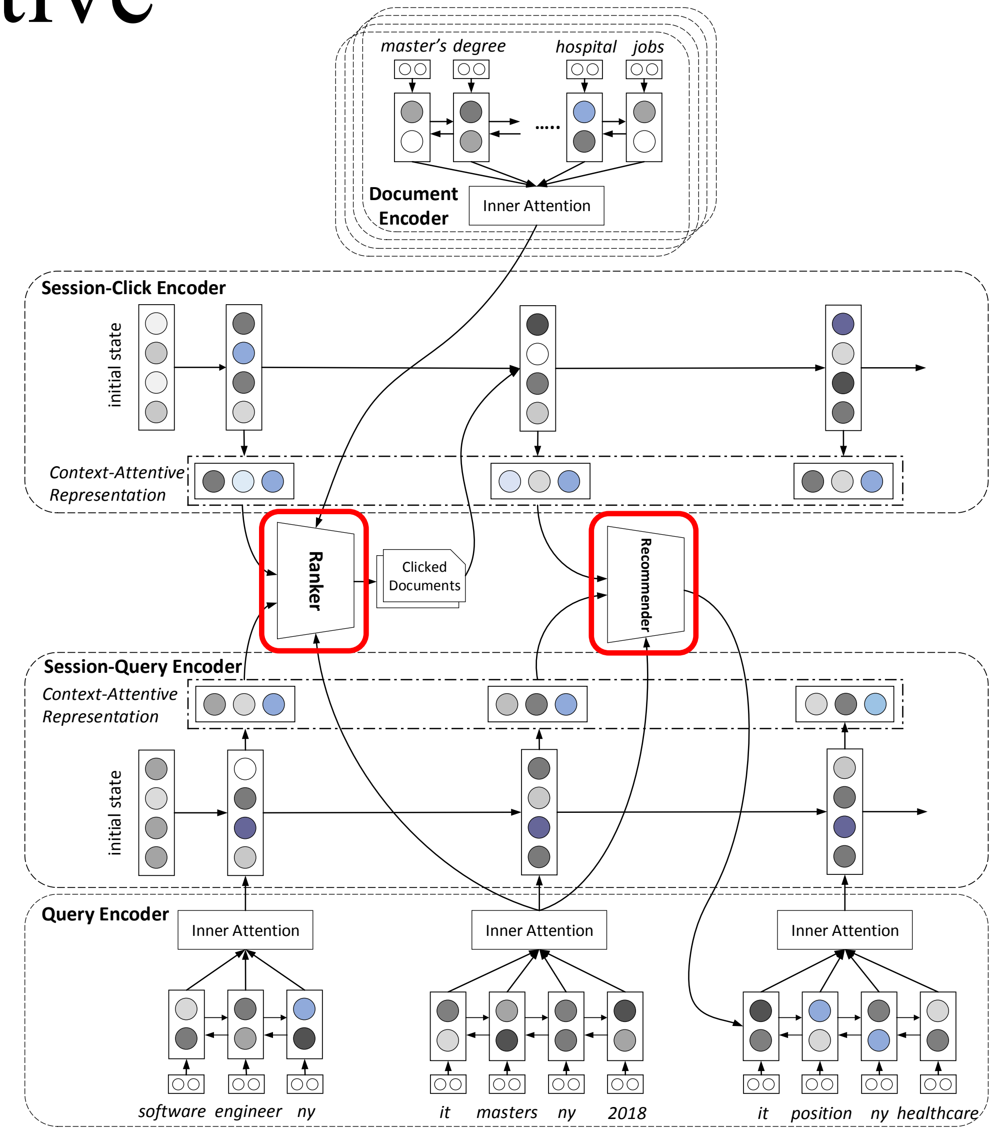


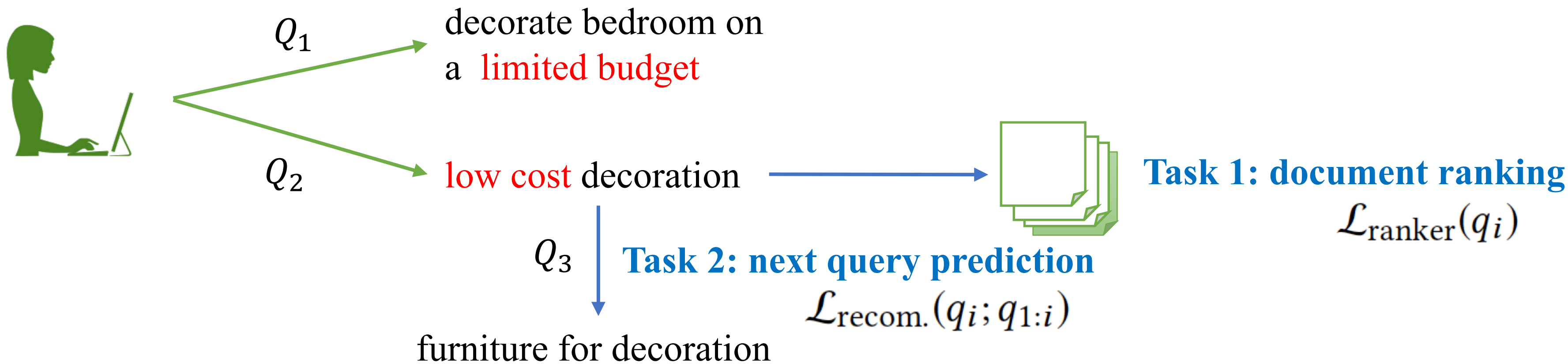
Multi-task Learning Objective

- Optimized via Regularized Multi-task Learning

Regularization

Negative log-likelihood

$$\boxed{\mathcal{L}_{R1}} + \boxed{\mathcal{L}_{R2}} + \frac{1}{N}\sum_{k=1}^{N}\sum_{q_i \in \mathcal{T}_k}\left(\boxed{\mathcal{L}_{\text{ranker}}(q_i)} + \boxed{\mathcal{L}_{\text{recom.}}(q_i; q_{1:i})}\right)$$



Experiments

Data Source

- AOL search log – 13 weeks search log of ~650k users
  - Background set – 5 weeks
  - Training set – 6 weeks
  - Validation and Test set – 2 weeks
- Aggregation of candidate documents for ranking
  - Candidates are sampled from the top 1000 documents retrieved by BM25 from a pool of 1M documents
- Task Segmentation
  - Averaging the query term vectors → Query embedding
  - Consecutive queries* with cosine similarity > 0.5

* within 30 mins interval

Data Statistics

- Only the document titles are utilized in the experiments

Dataset Split	Train	Validation	Test
# Task	219,748	34,090	29,369
# Query	566,967	88,021	76,159
Average Task Length	2.58	2.58	2.59
Average Query Length	2.86	2.85	2.90
Average Document Length	7.27	7.29	7.08
Average # Click per Query	1.08	1.08	1.11

Evaluation Metrics and Baselines

- Document Ranking
  - Metrics – MAP, MRR, NDCG@k (where k=1,3,10)
  - Baselines – BM25, QL, FixInt, DSSM, DUET, MNSRF etc.

- Query Suggestion
  - Metrics – MRR, F1, BLEU-k (where k=1,2,3,4)
  - Baselines – HRED-qs, Seq2seq+Attn, MNSRF etc.

MRR – assesses discrimination ability, rank a list of candidate queries that might follow a given query

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F1, BLEU-k – assesses generation ability, measures overlapping between the generated query term sequence and ground-truth sequence.

Evaluation on Document Ranking

- *Vocabulary gap limits the performance*
- *Do not utilize any search context information*

Model	MAP	MRR	NDCG		
			@1	@3	@10
Traditional IR-models					
BM25	0.230	0.206	0.206	0.269	0.319
QL	0.195	0.166	0.166	0.213	0.276
Single-task Learning					
CDSSM	0.313	0.341	0.205	0.252	0.373
DUET	0.479	0.490	0.332	0.462	0.546
Match Tensor	0.481	0.501	0.345	0.472	0.555
Multi-task Learning					
M-NSRF	0.491	0.502	0.348	0.474	0.557
M-Match Tensor	0.505	0.518	0.368	0.491	0.567
CARS	**0.531**	**0.542**	**0.391**	**0.517**	**0.596**

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Evaluation on Document Ranking

+ *Jointly learns ranking and suggestion*
– *Utilizes query history but no click history*

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Evaluation on Query Suggestion

Model	MRR	F1	BLEU			
			1	2	3	4
Single-task Learning						
Seq2seq	0.422	0.077	8.5	0.0	0.0	0.0
Seq2seq + Attn.	0.596	0.555	52.5	30.7	18.8	11.4
HRED-qs	0.576	0.522	48.8	26.3	15.3	9.2
Multi-task Learning						
M-Match Tensor	0.551	0.458	41.5	20.6	11.5	7.0
M-NSRF	0.582	0.522	49.7	26.7	16.0	9.9
CARS	**0.614**	**0.589**	**55.6**	**36.2**	**25.6**	**19.1**

Do not utilize any context

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Do not utilize click history

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+ *Utilizes both in-task query and click history*

Ablation Study

- Modeling search context is beneficial
- Joint learning of related retrieval tasks results in improvements

CARS Variant	NDCG			BLEU	
	@1	@3	@10	1	2
CARS	0.391	0.517	0.596	55.6	36.2
CARS w/o Attn.	0.387*	0.515*	0.594*	48.6*	26.1*
Ablation on search context					
w/o Session Query	0.379	0.505	0.586	33.7*	14.2*
w/o Session Click	0.356	0.485	0.568	48.2*	25.6*
Ablation on joint learning					
w/o Recommender	0.379	0.505	0.585	-	-
w/o Ranker	-	-	-	55.9	36.9

∗ indicates that the attention in the query recommender

Ablation Study

- Modeling search context is beneficial
- Joint learning of related retrieval tasks results in improvements

Performance drops

CARS Variant	NDCG @1	NDCG @3	NDCG @10	BLEU 1	BLEU 2
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w/o Ranker	-	-	-	55.9	36.9

Performance drops

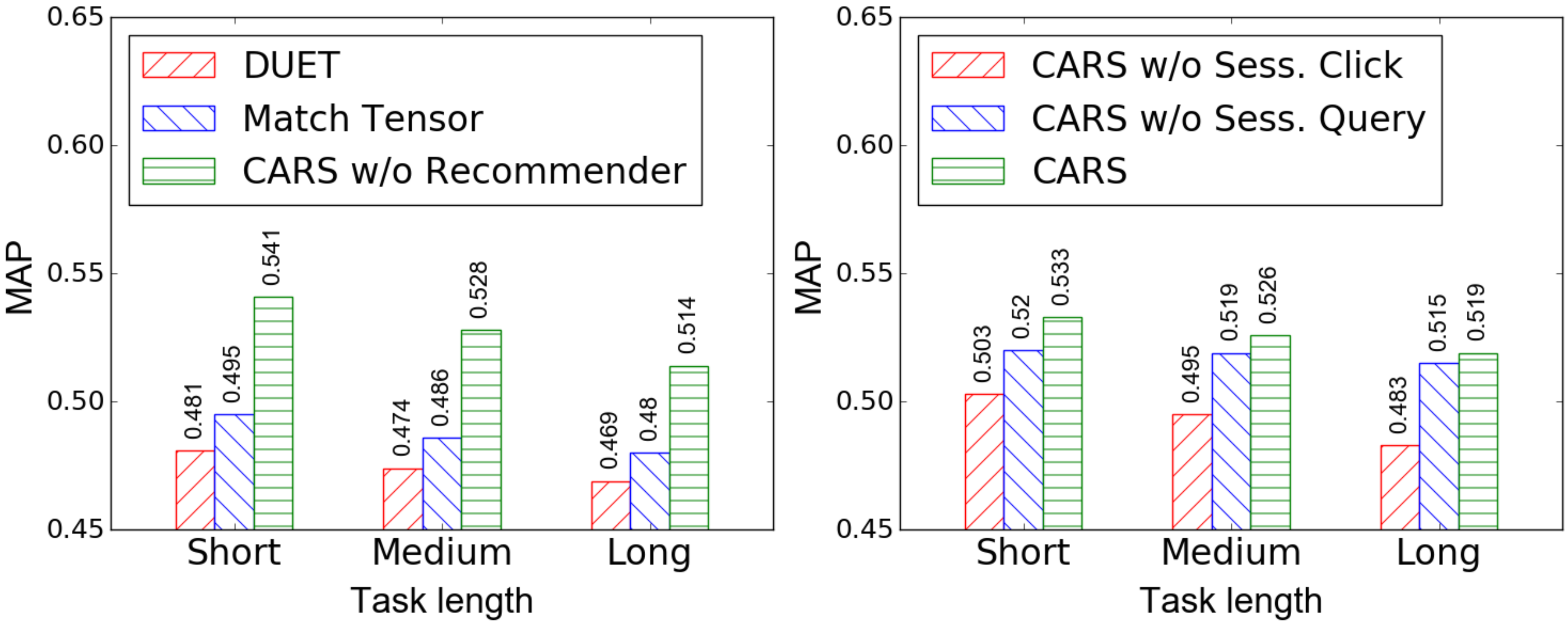
Performance increases

∗ indicates that the attention in the query recommender

Short tasks (with 2 queries)
Medium tasks (with 3–4 queries)
Long tasks (with 5+ queries)

Effect of Context Modeling

Hypothesis – longer tasks are intrinsically more difficult.

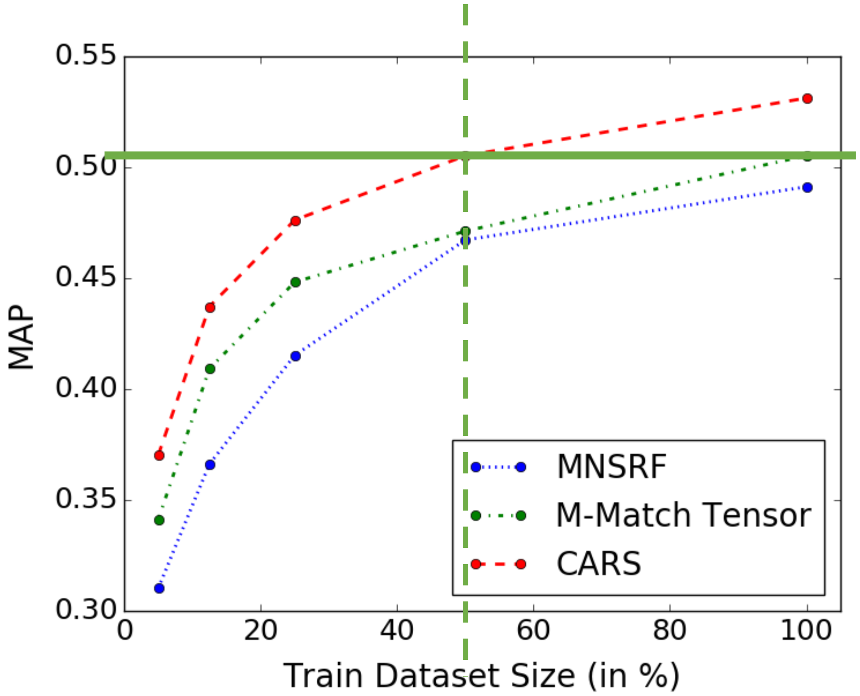


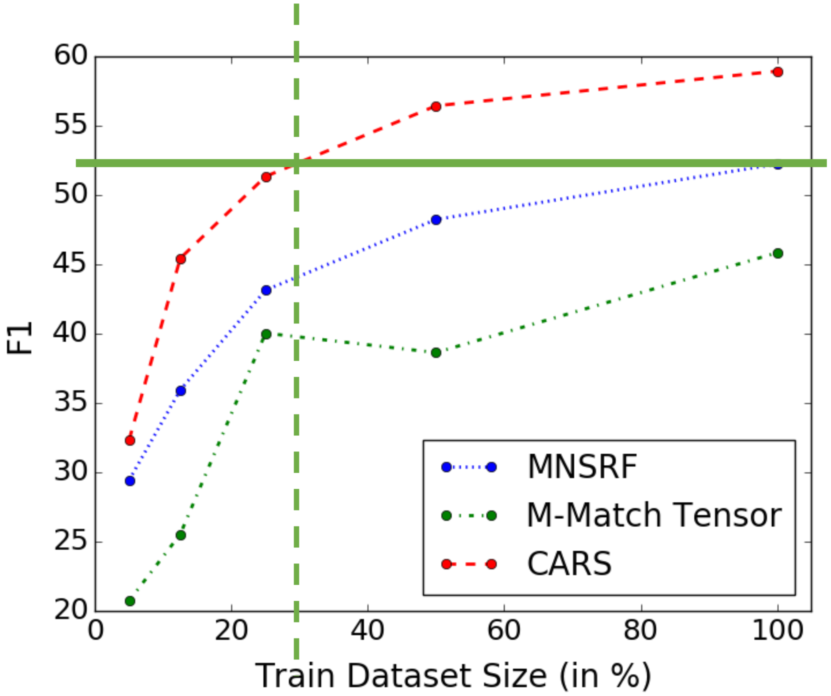
Effect of Context Modeling

- Context information helps more on short/medium tasks
- Longer tasks are intrinsically more difficult.

Sample Complexity

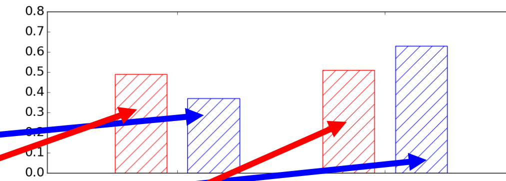
In terms of #parameters, CARS > MNSRF > M-Match Tensor



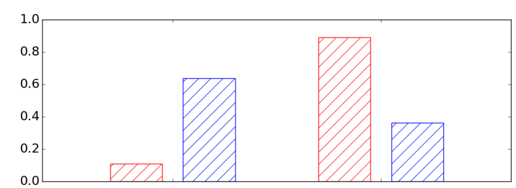


Case Analysis

How in-task previous queries and clicks impact predicting the next query and click for it?



Q1: **abortion** at **home**	Q2: **consequences** of **abortion** in future pregnancy	Q3: **abortion** laws in los **angeles**
D1. **private clinic** caring doctors and staff free consultations call us now D2. **not** every **pregnancy** is planned and sometimes a pregnancy is unwanted ✓D3. **natural home** remedies for abortion in early pregnancy ✓D4. **carrying** out an **abortion** at home is even more complex D5. have you come across unwanted **pregnancy** do you want natural **miscarriage**	D1. the effect of **pregnancy termination** on future reproduction ncbi ✓D2. **how** an **abortion** affects your chance of getting pregnant again D3. does **having** an abortion affect your future **fertility** D4. **abortion** does it affect **subsequent** pregnancies mayo clinic ✓D5. **medical abortion** won't affect future pregnancies abc news	



Conclusion & Future Works

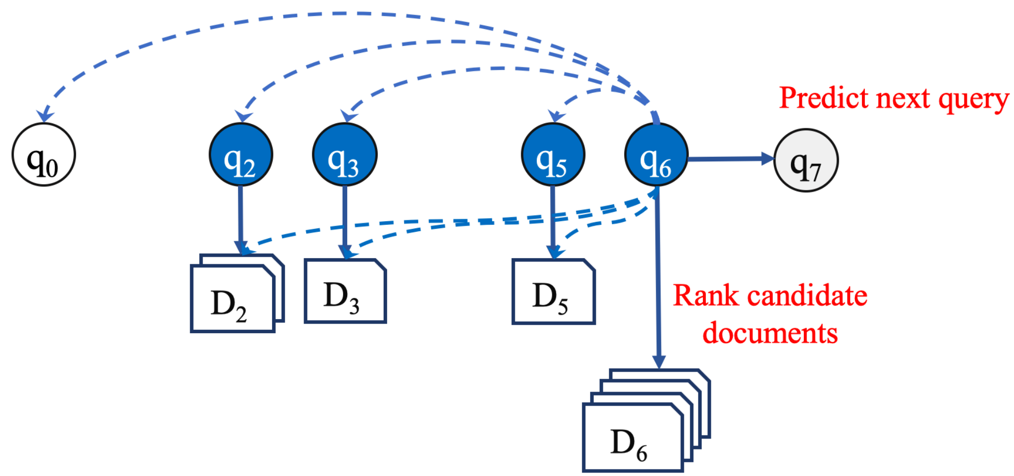
- A task-based approach of learning search context
  - Exploiting users' on-task search query and click sequence
  - Jointly optimized on two companion retrieval tasks

- Future works
  - Modeling across-task relatedness, e.g., users' long-term search interest
  - Apply to any scenario where a user sequentially interacts with a system

https://github.com/wasiahmad/context_attentive_ir

Codes will be released soon!

***In-task Context*: a richer way to understand users' search intent**



Thank You!

Q&A