Robust and efficient frontier pipelines for complex knowledge intensive tasks in the era of LLMs

CNI Seminar series, IISC

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Knowledge Intensive Language Tasks

Efficient ⟷ **Effective**

Conversational AI

Web Search

Live fact checking

Knowledge-base Construction

Fact Checking Articles

Financial Auditing

Factual Article Generation

Indexing and Precompute

Test time Reasoning

[Hoffart et al, WWW' 16], [Fetahu et al. '16, '17]

LLM Agents as general purpose solvers

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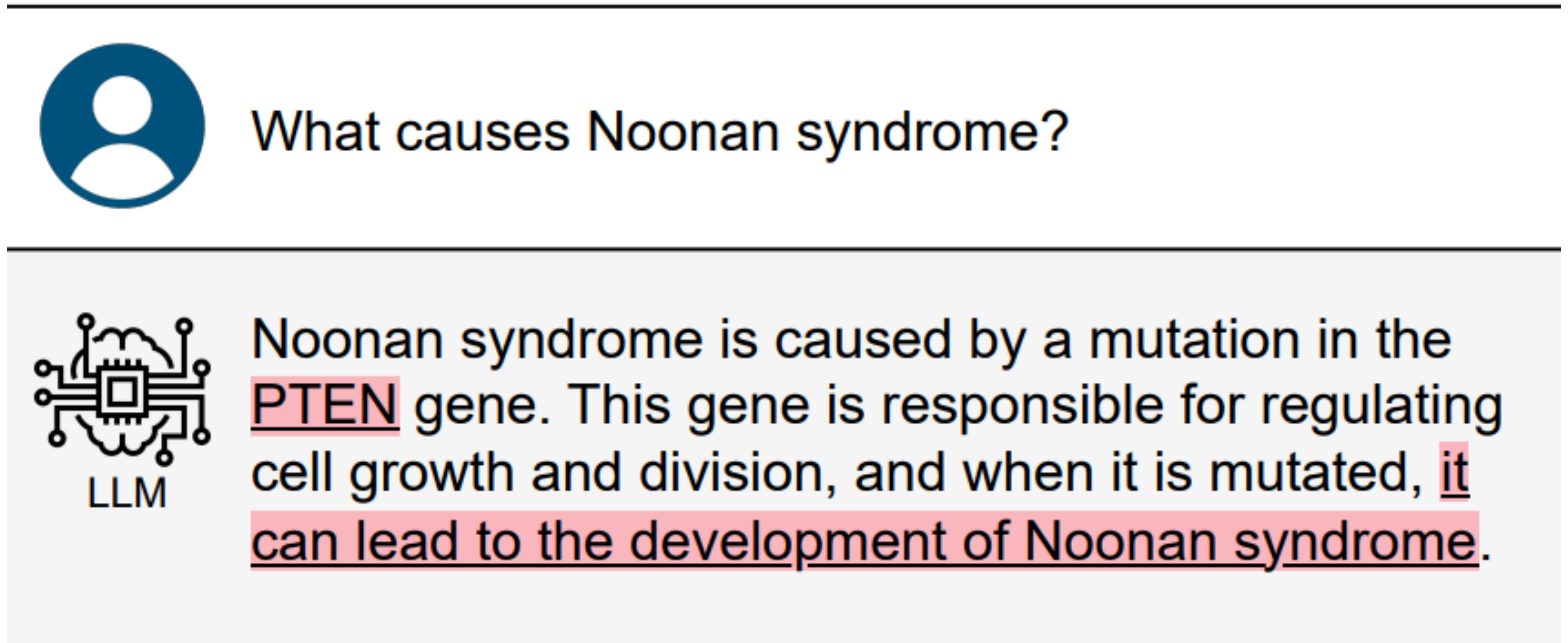
Credit: Lil'Log

Hallucination in closed book setting



Now imagine a LLM citing fake cases when a resident is preparing his report
Or a lawyer preparing his arguments

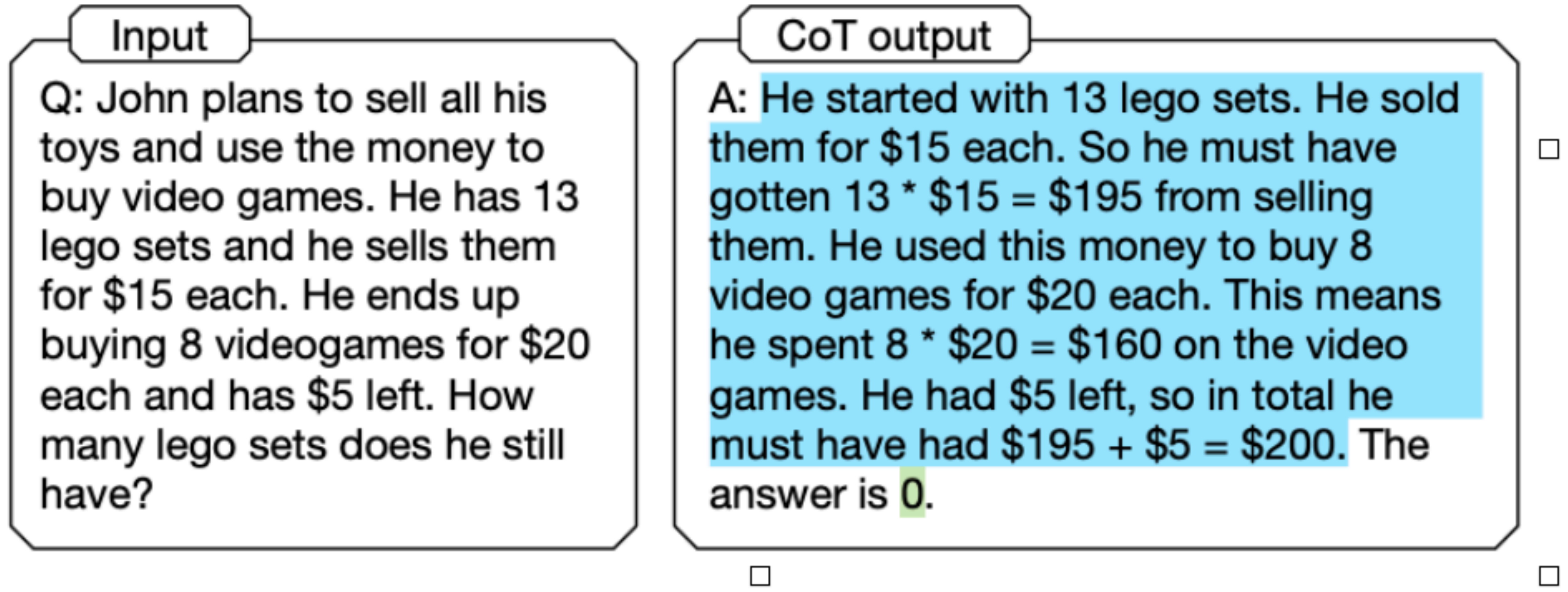
There’s no provenance even if answer is correct.

Hallucinations - catastrophic effects

How to mitigate hallucination and establish provenance?

Ask LLM to explain itself ?

Unfaithful Reasoning

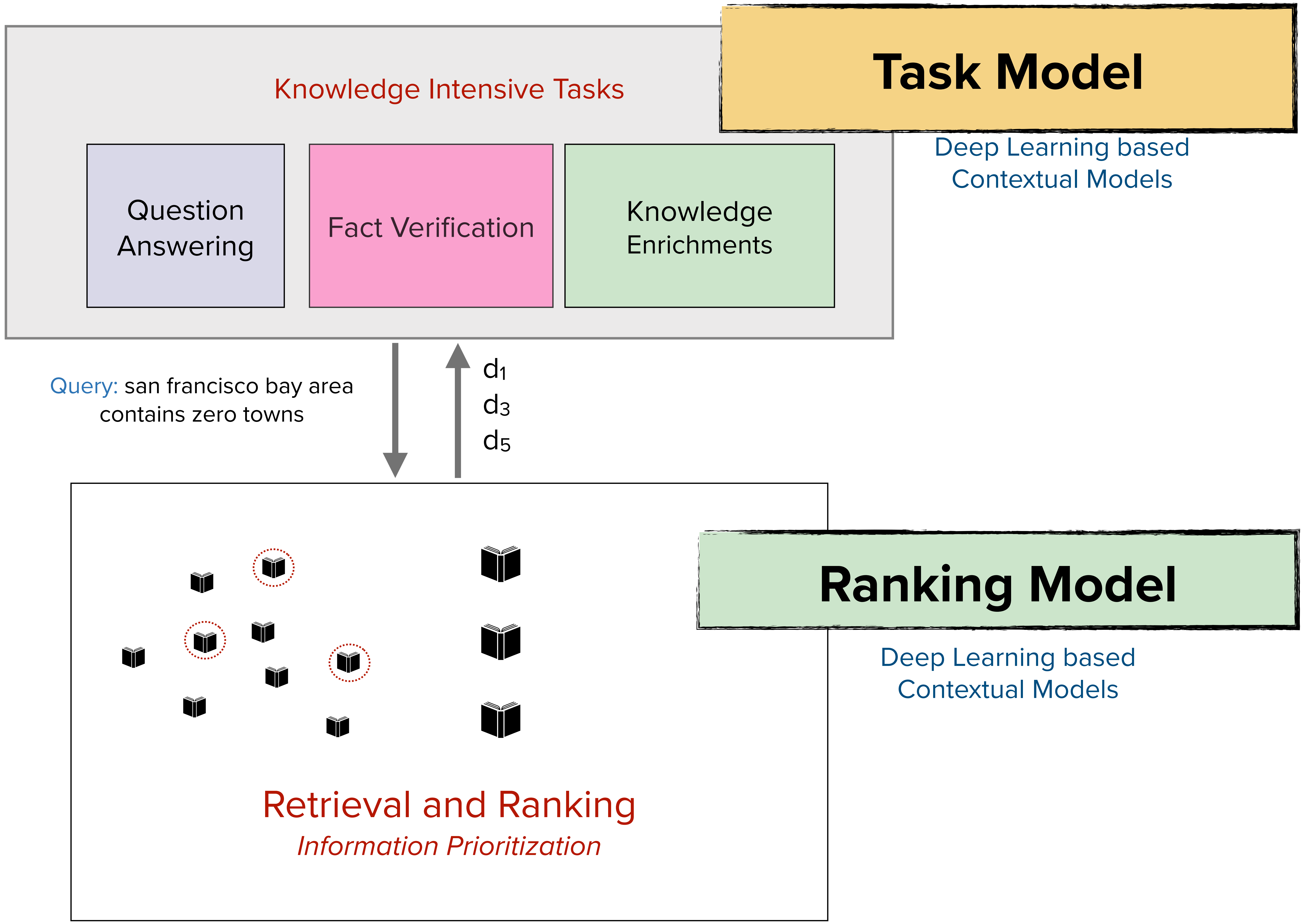


Knowledge Gaps

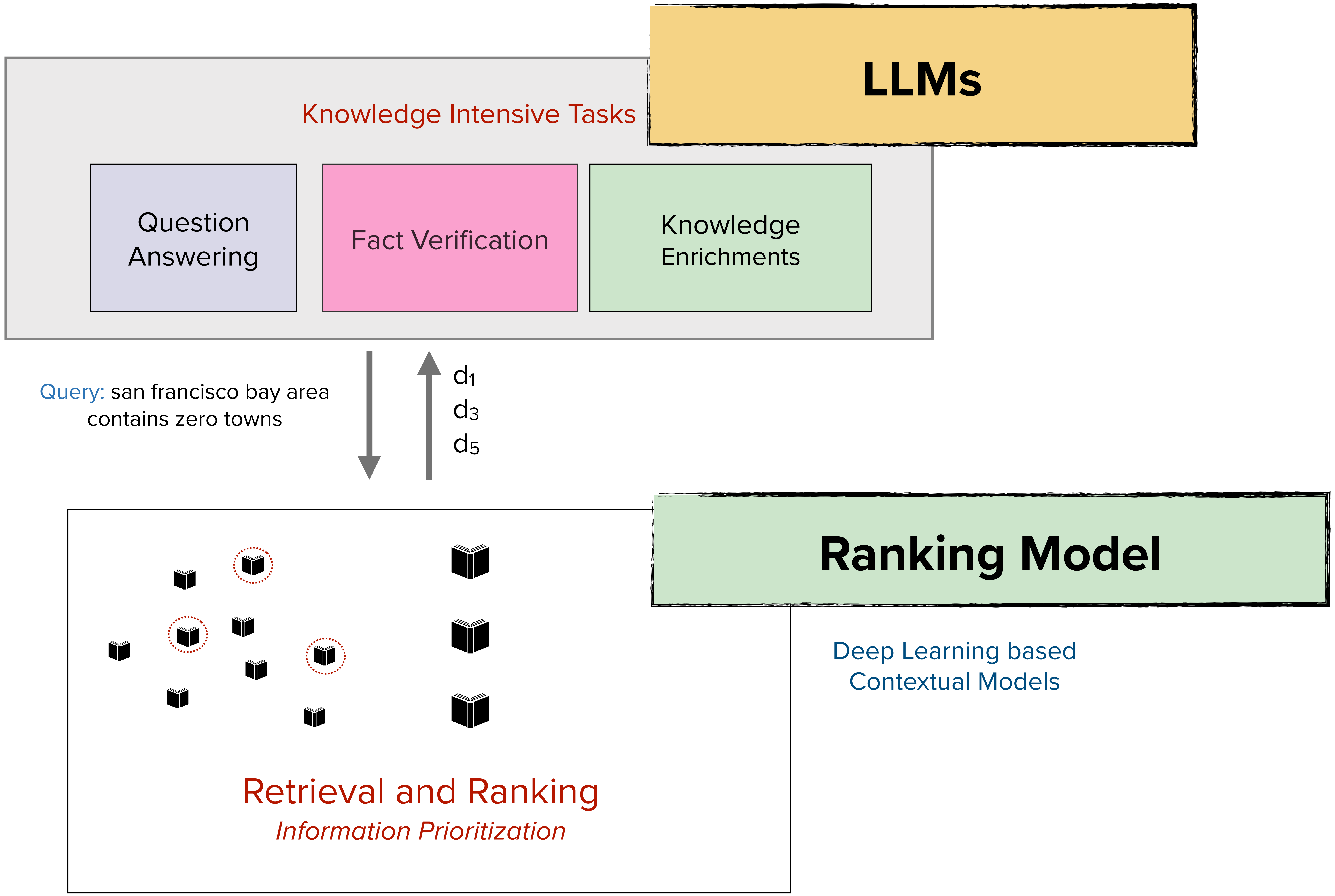
Question: What is the mouth of the river which serves as the mouth of the Bumping River?

FEW-SHOT-COT. : [Answer]: There is no river named Bumping River.

RAG to the rescue



RAG to the Rescue



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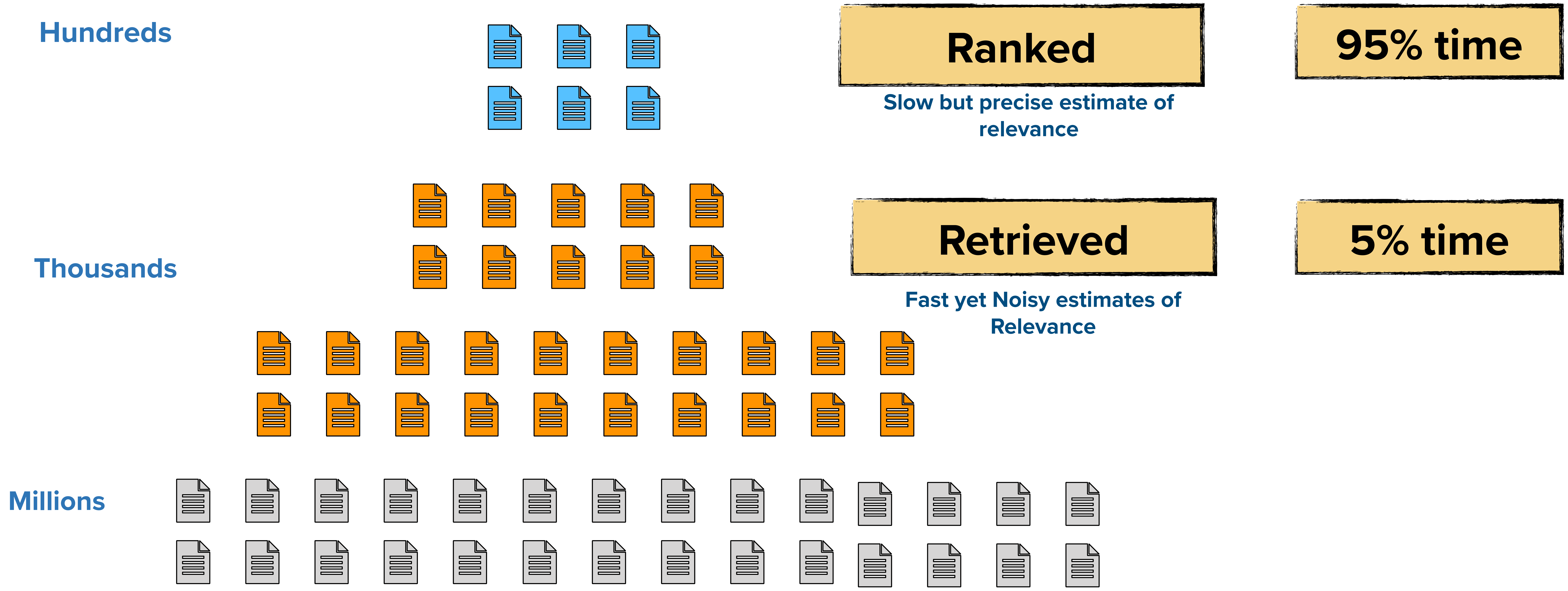
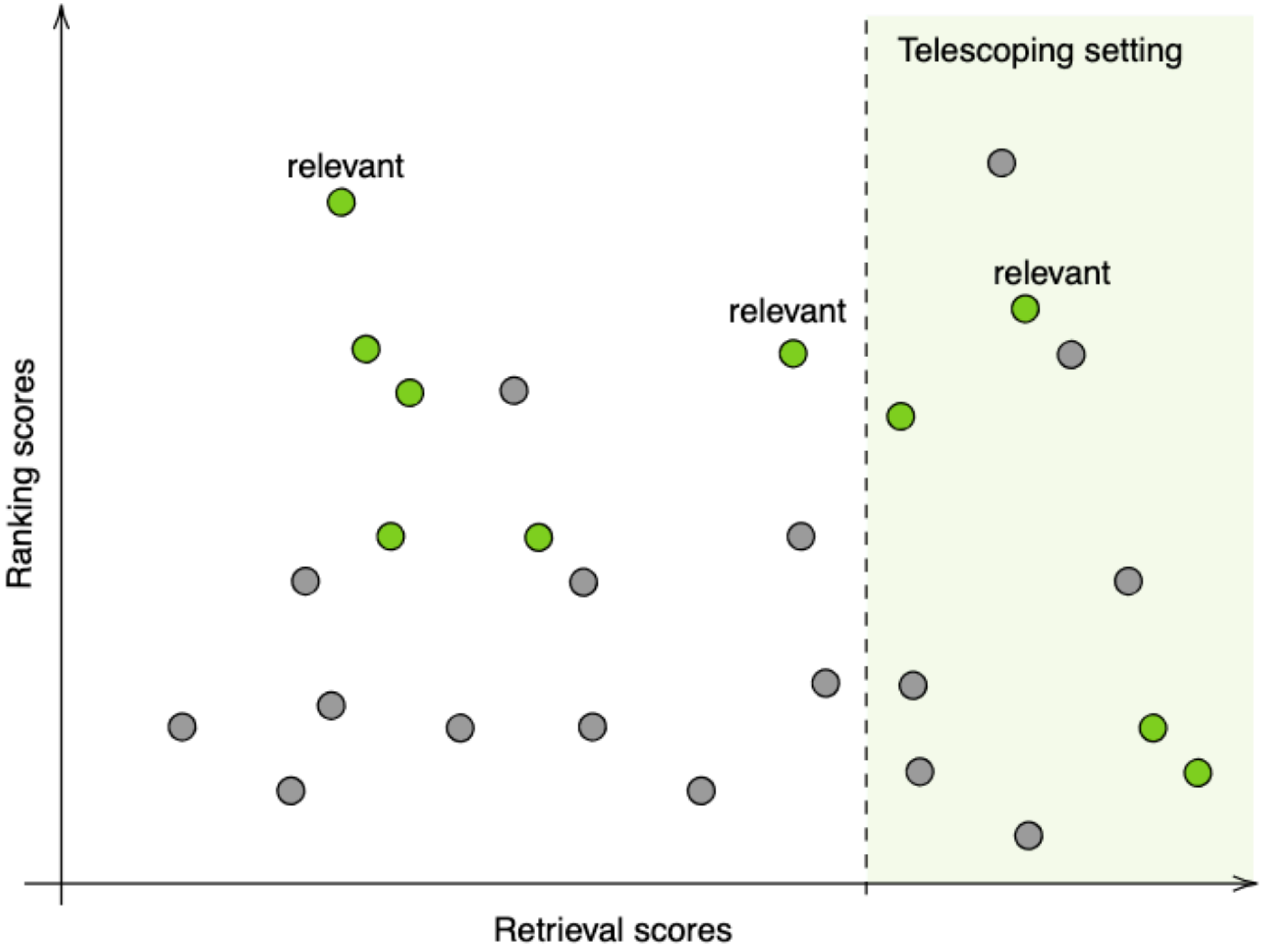
Telescoping view of retrieve-rerank pipelines



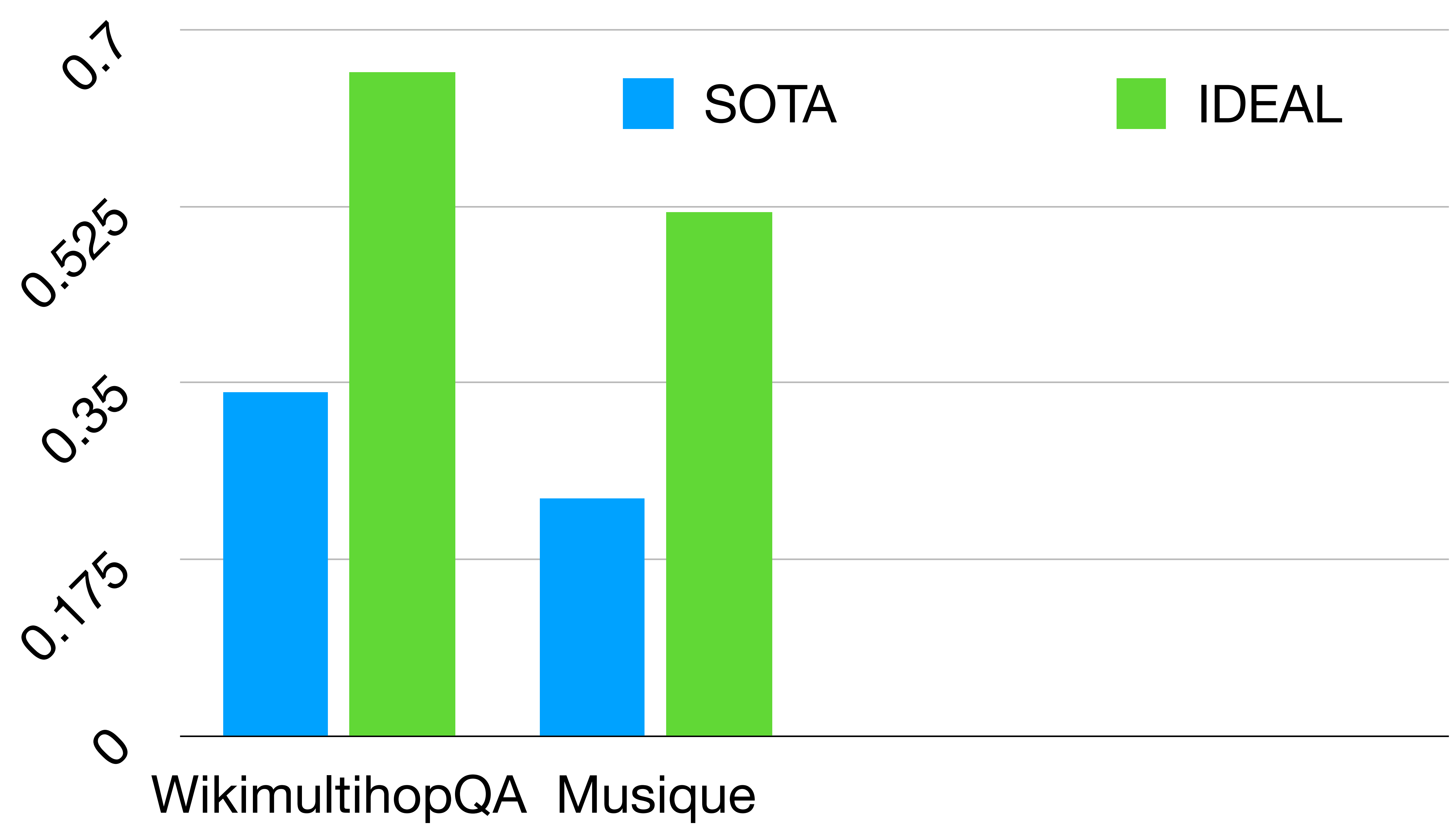
Bounded recall problem

- RAG pipelines require the most relevant document to appear within top-5 or top-10 to fit i context of most affordable LLMs.
- Classical re-ranking approaches are limited by recall of first-stage retrieval.
- How do we capture more relevant documents ?
- How do we ensure the relevant documents are ranked higher and answer the question ?

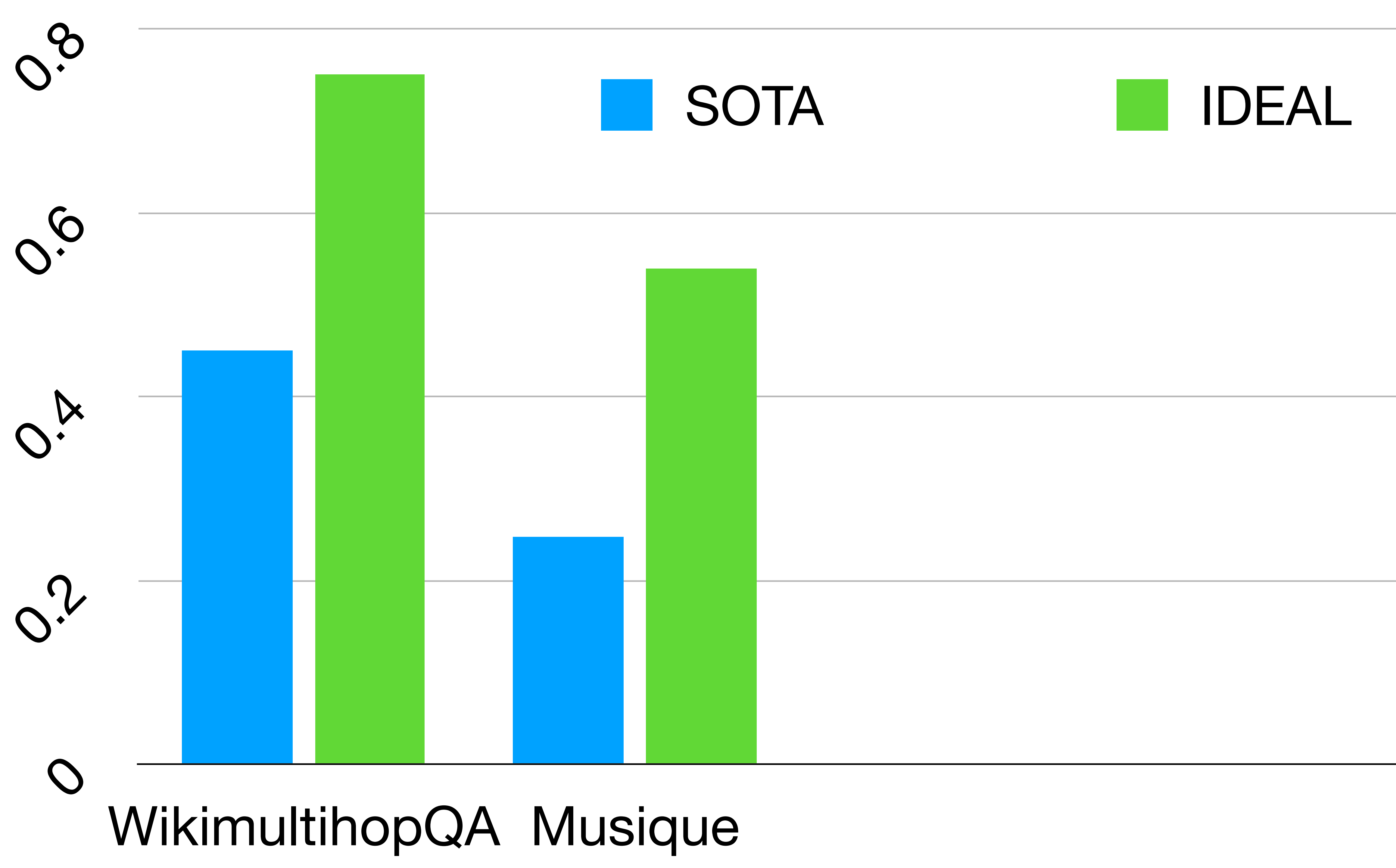


Retrieval and Reasoning Gap in complex QA

Retrieval Gap



Reasoning gap



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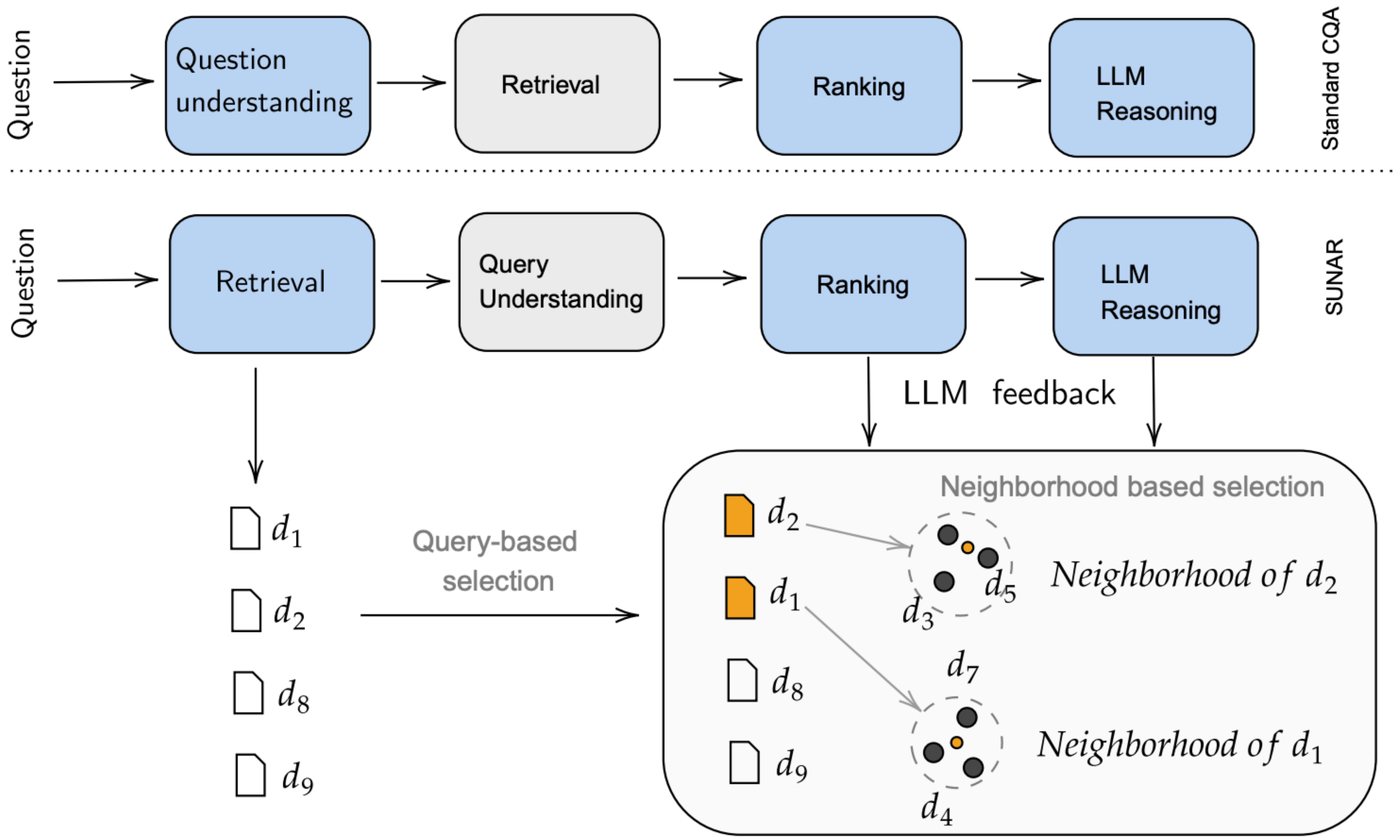
Semantic-Uncertainty based Neighborhood Aware Retrieval



Solving the Retrieval gap through LLM uncertainty based feedback

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SUNAR- Deep Dive

Algorithm 1 The SUNAR Algorithm

Input: Initial retrieved list R, batch size b, re-ranking budget c, document graph G

Output: Re-Ranked pool R^+

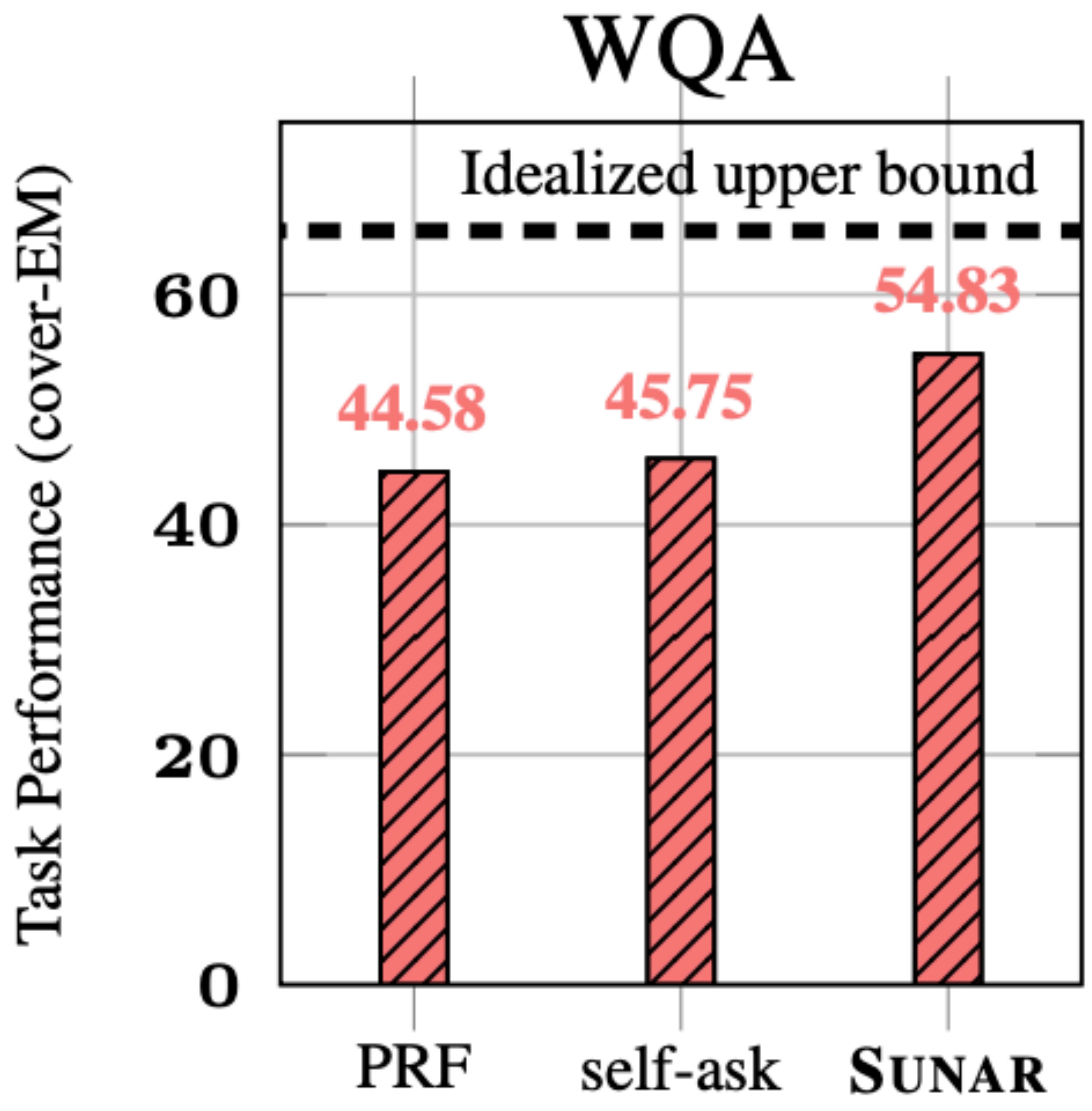
$R^+ \leftarrow \emptyset$ ▷ Re-Ranking results
$C \leftarrow R$ ▷ Re-ranking pool
$N \leftarrow \emptyset$ ▷ Neighbor pool
do
  $B \leftarrow \text{SCORE}(\text{top } b \text{ from } P\text{, subject to } c)$
  $\{sa_1 \ldots sa_m\} \leftarrow \phi(\mathbb{P}_{LLM}(sq_1, B))$
  $\{ac_1 .. ac_s\} \leftarrow \sigma(sa_1 .. sa_m)$ ▷ Clustering

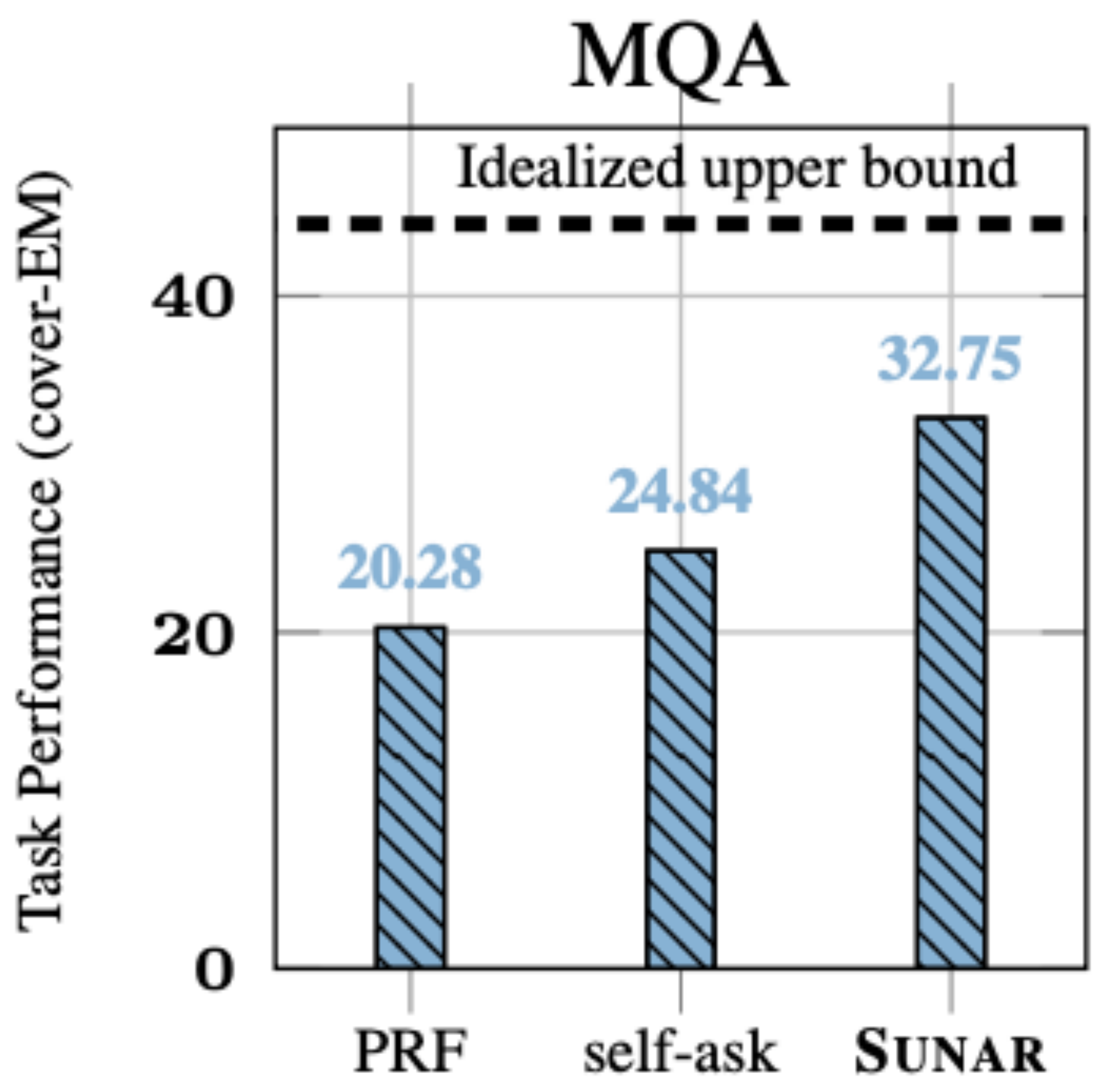
  $B \leftarrow \text{RESCORE}(B, 1/s)$ ▷ Rescore batch
  $R^+ \leftarrow R^+ \cup B$ ▷ Add batch to results

  // Discard Batches
  $R \leftarrow R \setminus B$
  $N \leftarrow N \setminus B$
  $N \leftarrow N \cup (\text{NEIGHBOURS}(B, G) \setminus R^+)$

  //Alternate R and N
  $C \leftarrow \begin{cases} R & \text{if } C = F \\ N & \text{if } C = N \end{cases}$
while $|R^+| < c$

Bridging retrieval gap and downstream reasoning enhancement





Outperforms existing state-of-the-art approaches & LLM agnostic

Method	MQA	WQA
Methods (w/o query understanding)		
ZERO-SHOT-COT (Kojima et al., 2023)	8.62	30.42
FEW-SHOT-COT (Wei et al., 2023)	15.02	32.83
FEW-SHOT-COT +PRF (Li et al., 2022)	16.69	35.55
SUNAR$_R$ (ours)	21.32	40.96
Methods (w/ query understanding)		
Self-RAG (Asai et al., 2024)	17.80	35.25
ReAct (Yao et al., 2023)	21.41	43.25
DecomP (Khot et al., 2023)	21.01	44.08
SearChain (Xu et al., 2024)	21.72	44.42
SELF-ASK +PRF (Li et al., 2022)	20.28	44.58
SELF-ASK (Press et al., 2023)	24.84	45.75
NAR (w/ query understanding) (ours)		
SUNAR$_R$	28.11	47.67
SUNAR	**32.75** †	**54.83**†
Golden Evidence (Ideal Upper Bound)		
FEW-SHOT-COT	44.28	65.55

Method	MQA	WQA
gpt-40-mini		
SELF-ASK	26.76	37.33
SUNAR	**32.19**	**48.16**
Llama 3.1 (8B)		
SELF-ASK	5.43	25.83
SUNAR	**13.82**	**39.52**
Mistral v0.2 (7B)		
SELF-ASK	7.84	27.72
SUNAR	**26.12**	**40.23**

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SUNAR helps tackle hallucination and knowledge gaps

Method	Evidences
Question	**Where was the director of film Ronnie Rocket born?** [Dataset: **WQA**]
SELF-ASK	[Evidence 1]: This is a list of film series by director. [Evidence 2]: This is a list of notable directors in motion picture and television arts. [Final Answer]: Unknown
SUNAR (ours)	[Evidence 1]: Ronnie Rocket is an unfinished film project written by David Lynch, who also intended [. . .]. [Evidence 2]: David Keith Lynch was born in Missoula, Montana, on January 20, 1946. His father [. . .] . [Final Answer]: Missoula, Montana
Question	**Who did the screenwriter for Good Will Hunting play in Dazed and Confused?** [Dataset: **MQA**]
SELF-ASK	[Evidence 1]: Damon begins working alongside his younger brother, Stefan Salvatore, to resist greater[. . .]. [Evidence 2]: Damon Salvatore is a fictional character in The Vampire Diaries. He is portrayed by Ian Somerhalder in the television. [Final Answer]: Damon Salvatore
SUNAR (ours)	[Evidence 1]: Damon and Ben Affleck wrote G̈ood Will Hunting(̈1997), a screenplay[. . .]. [Evidence 2]: Benjamin Affleck- Boldt(born August 15, 1972) is an American actor . He later appeared in the independent coming- of- age comedyD̈azed and Confused as Fred O'Bannion [. . .]" [Final Answer]: Fred O'Bannion

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Online Relevance Estimation

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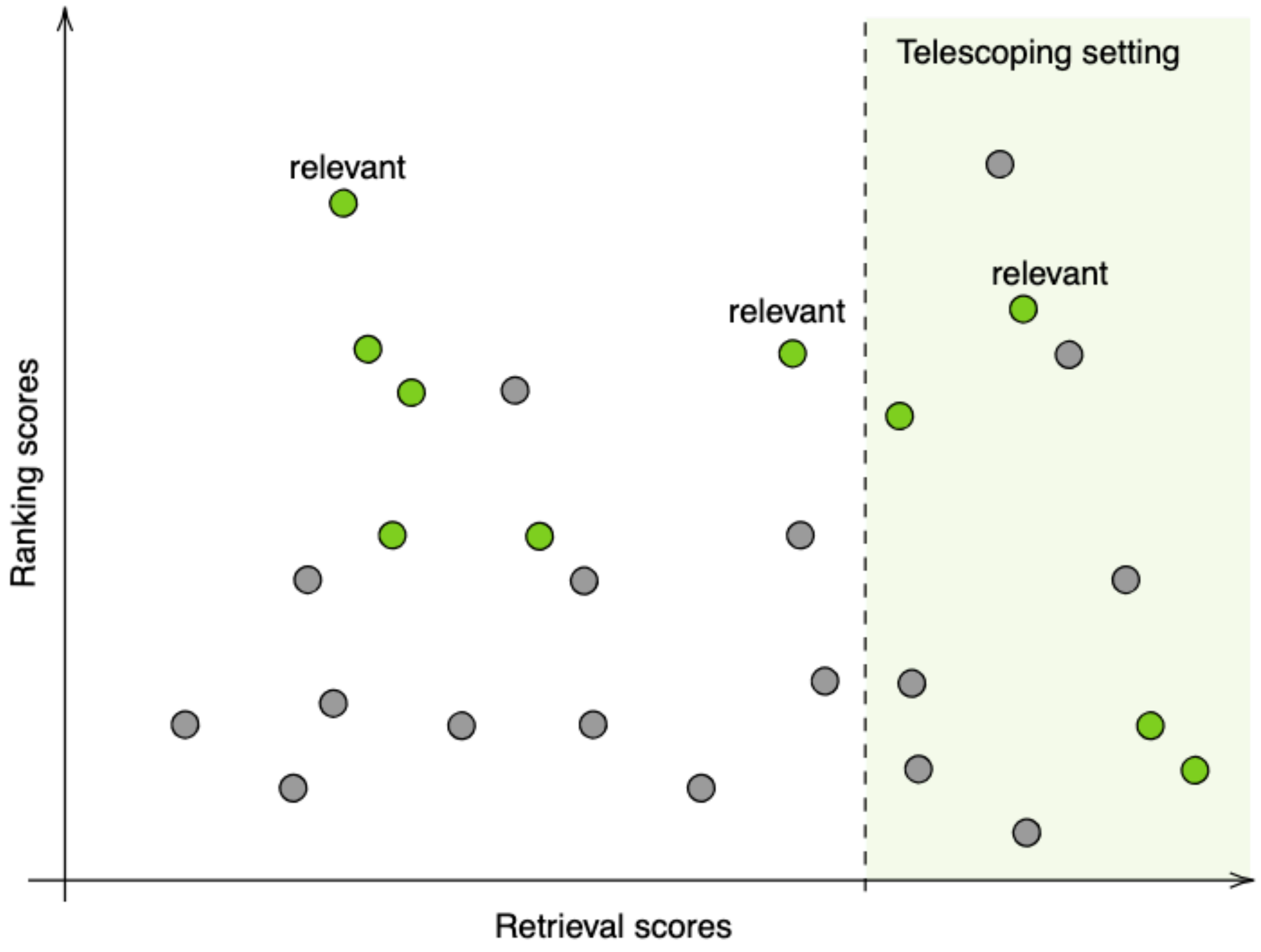
Telescoping systems and drawbacks



- Telescoping approaches involve progressive filtering of documents through less-precise retrieval methods

- Key is capturing relevant documents with low retrieval scores that current approaches ignore.

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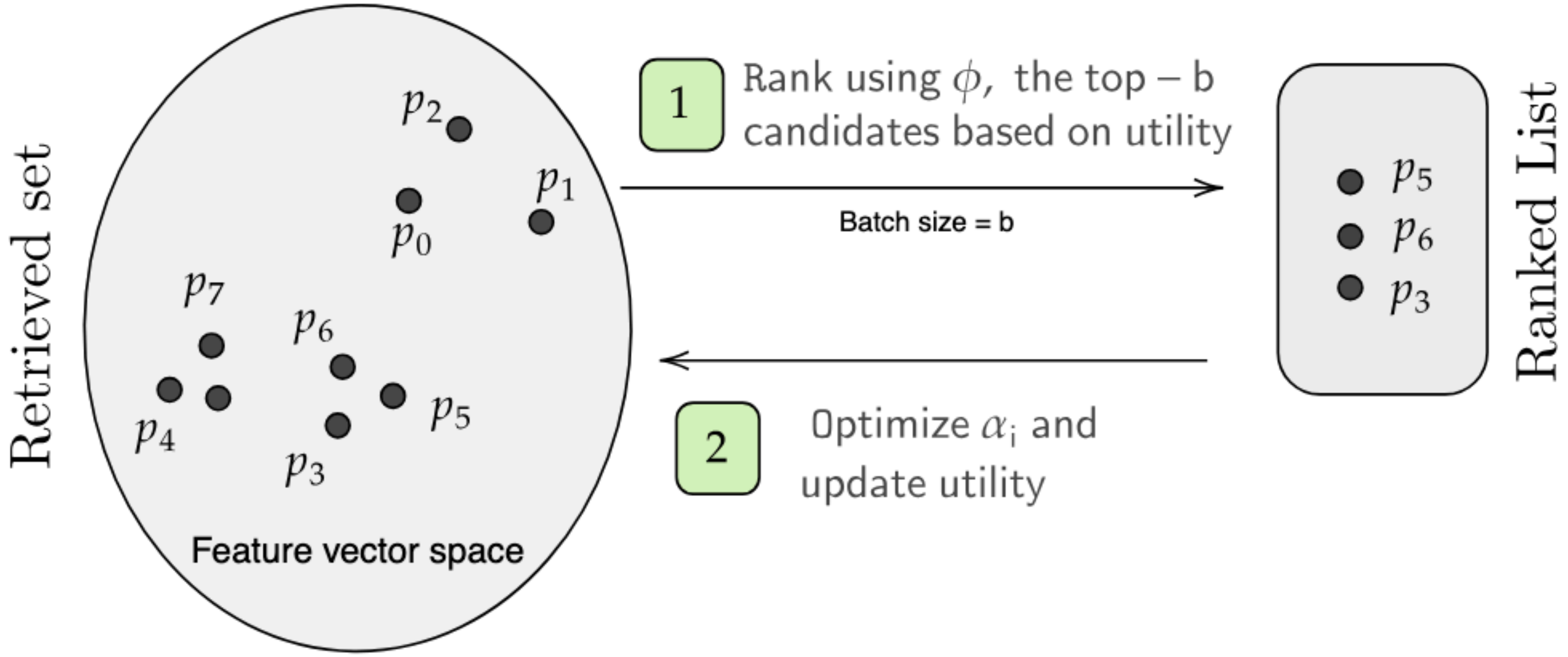
Online Relevance Estimation

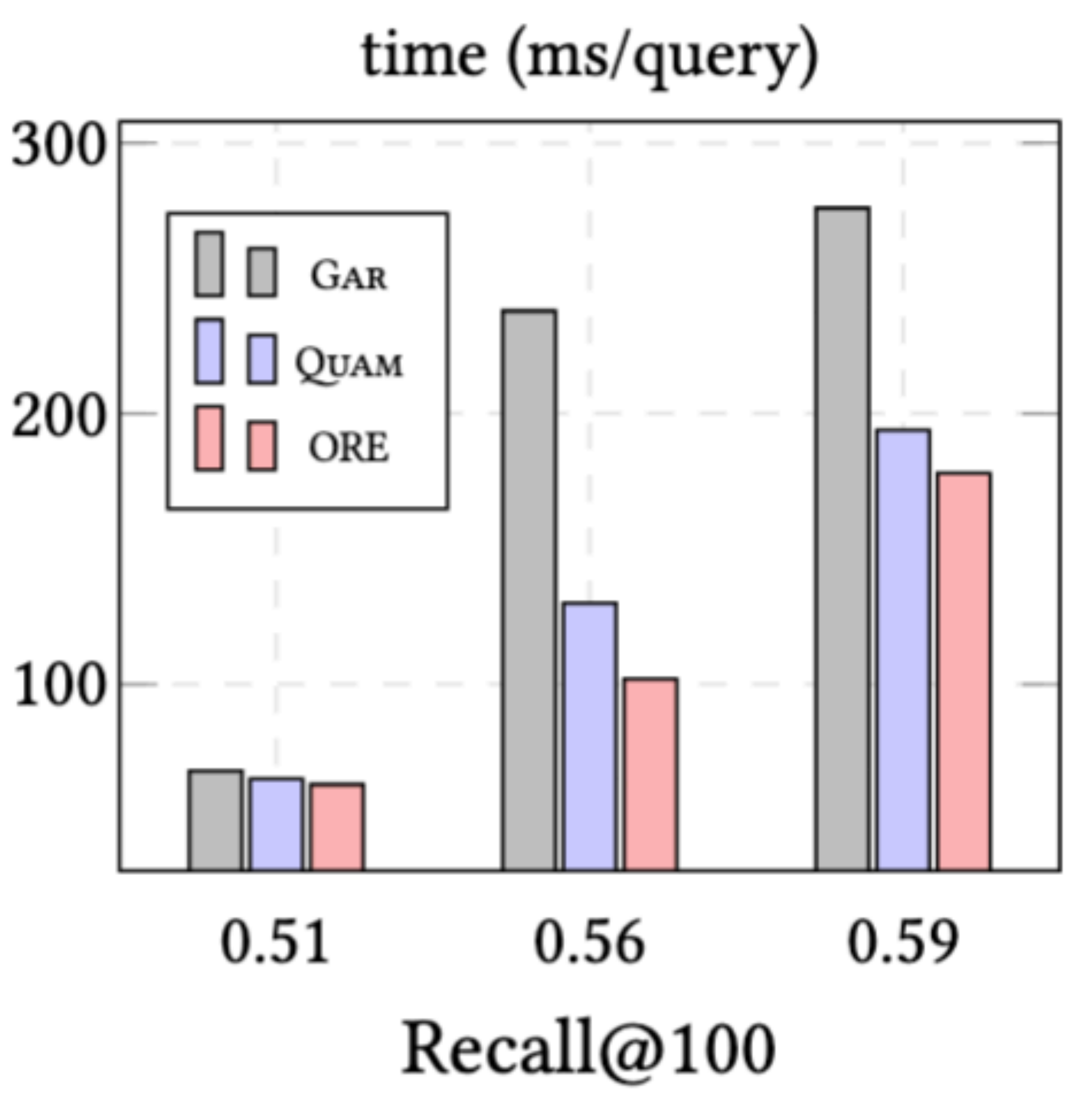


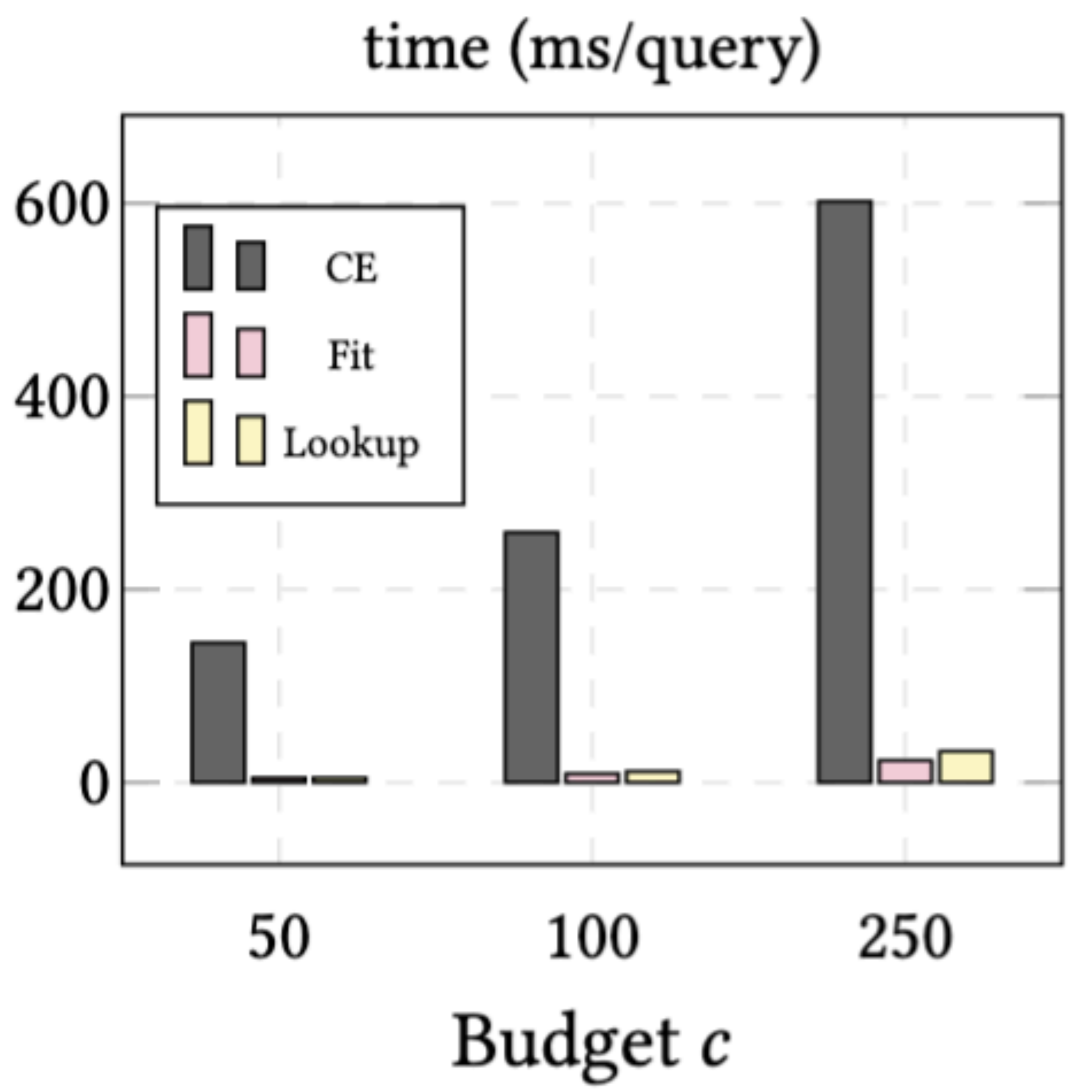
Features are flexible

Feature	Notation	Taxonomy	Source		Description
			Offline	Online	
x_1	$BM25(q, d)$	Q2DAff		✓	Lexical similarity between query and document.
x_2	$TCT(q, d)$	Q2DAff		✓	Semantic similarity between query and document.
x_3	$RM3(q', d)$	D2DAff		✓	Lexical similarity between expanded query using RM3 and document.
x_4	$BM25(d, d')$	D2DAff	✓		Lexical similarity between pair of documents.
x_5	$TCT(d, d')$	D2DAff	✓		Semantic similarity between pair of documents.
x_6	$\textsc{Laff}(d, d')$	D2DAff	✓		Learnt affinity or similarity between pair of documents [34].

Latency and Computational Efficiency

ORE offers 2x-7x speedup over SOTA based on ranker employed





The online estimation component takes **10x** less time than ranker calls

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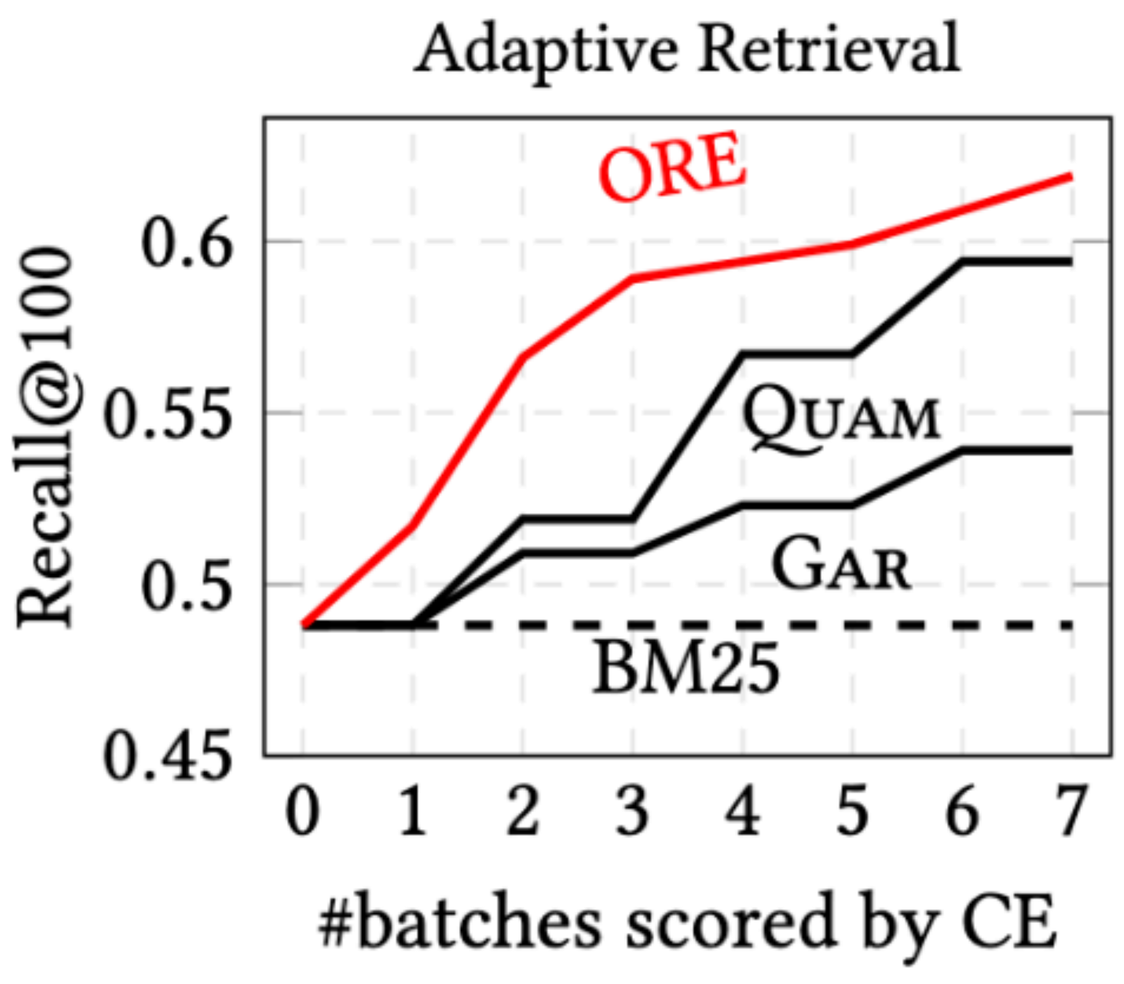
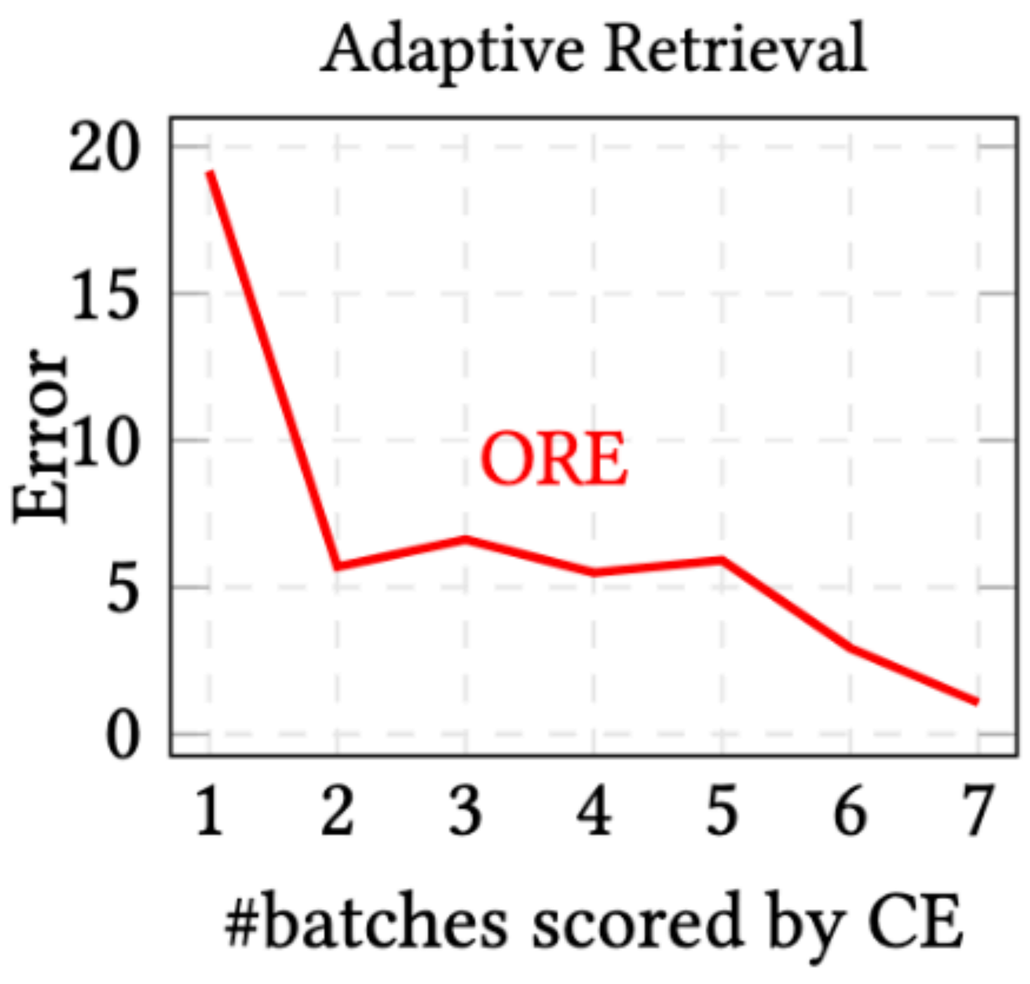
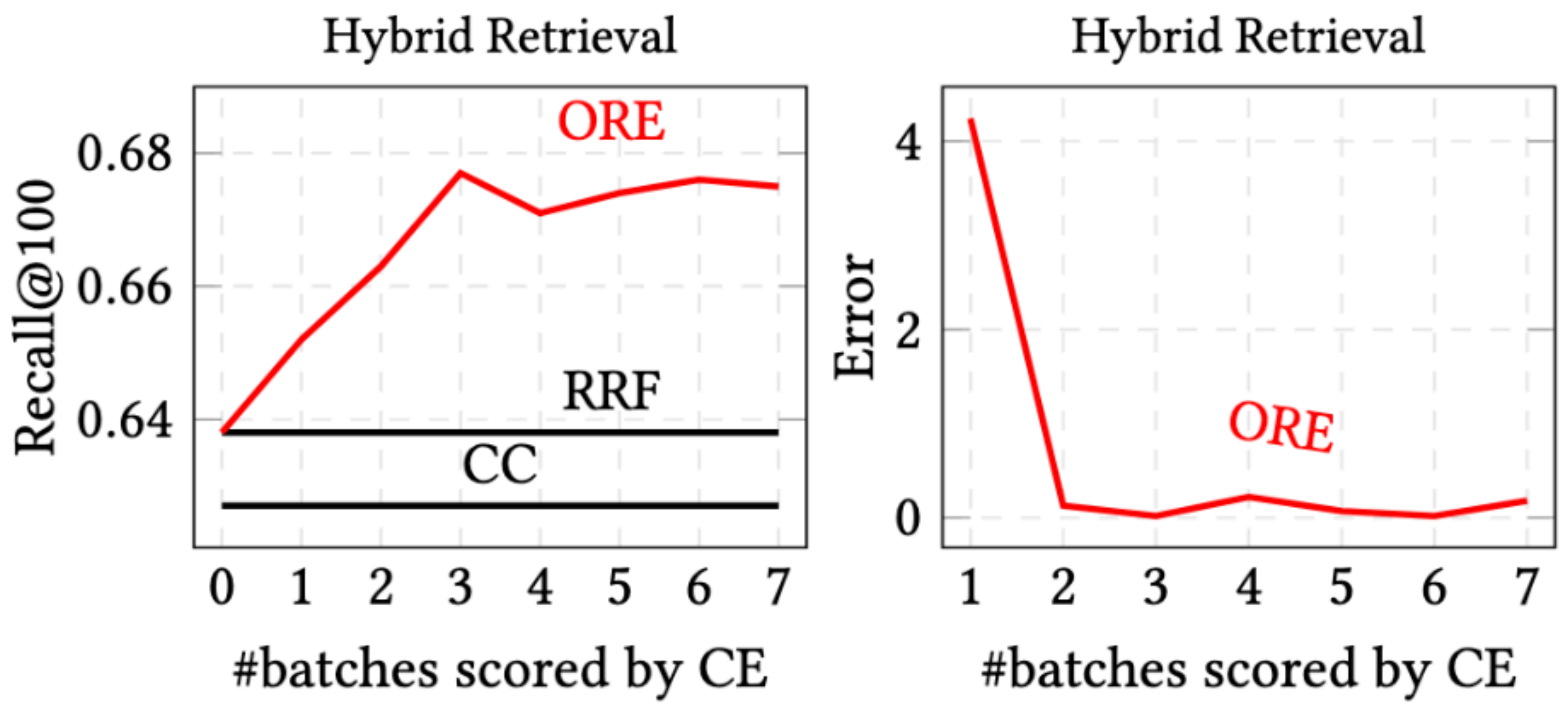
Sample Efficiency of ORE



(a)



(b)



Impressive Performance Gains

Dataset	Pipeline	$c = 50$		$c = 100$	
		nDCG@c	Recall@c	nDCG@c	Recall@c
DL21	**Hybrid**				
	RRF»MonoT5 [R]	0.576	0.401	0.558	0.520
	CC»MonoT5 [C]	0.584	0.419	0.569	0.545
	ORE	^{R}**0.604**	^{R}**0.444**	^{RC}**0.609**	^{RC}**0.609**
	Adaptive				
	BM25»MonoT5 [B]	0.436	0.242	0.433	0.331
	w/ GAR$_{BM25}$ [G]	0.457	0.290	0.465	0.414
	w/ QUAM$_{BM25}$ [Q]	0.478	0.310	**0.499**	0.454
	w/ ORE$_{BM25}$	$^{GQ}_{B}$**0.503**	$^{GQ}_{B}$**0.364**	$_{B}$0.481	$^{G}_{B}$**0.463**
	w/ GAR$_{TCT}$ [G]	0.502	0.331	**0.520**	0.489
	w/ QUAM$_{TCT}$ [Q]	0.491	0.311	0.518	0.477
	w/ ORE$_{TCT}$	$^{GQ}_{B}$**0.532**	$^{GQ}_{B}$**0.406**	$_{B}$0.512	$_{B}$**0.502**
DL22	**Hybrid**				
	RRF»MonoT5 [R]	0.452	0.260	0.430	0.341
	CC»MonoT5 [C]	0.459	0.278	0.433	0.362
	ORE	^{RC}**0.481**	^{R}**0.297**	^{RC}**0.459**	^{RC}**0.389**
	Adaptive				
	BM25»MonoT5 [B]	0.290	0.115	0.275	0.164
	w/ GAR$_{BM25}$ [G]	0.287	0.121	0.290	0.191
	w/ QUAM$_{BM25}$ [Q]	**0.308**	0.135	**0.303**	**0.196**
	w/ ORE$_{BM25}$	**0.292**	**0.137**	0.284	0.195
	w/ GAR$_{TCT}$ [G]	0.329	0.157	**0.348**	0.256
	w/ QUAM$_{TCT}$ [Q]	0.329	0.155	0.334	0.237
	w/ ORE$_{TCT}$	$^{GQ}_{B}$**0.364**	$^{GQ}_{B}$**0.206**	$_{B}$0.342	$_{B}$**0.260**

The Retrieval Gap

The Reasoning Gap

Numerical and Compositional Reasoning

Claim: Repealing the sales tax on boats in Rhode Island has spawned 2,000 companies, 7,000 jobs and close to $2 billion a year in sales activity

How many companies where there before the tax ?

Numerical and Compositional Reasoning

Claim: Repealing the sales tax on boats in Rhode Island has spawned 2,000 companies, 7,000 jobs and close to $2 billion a year in sales activity

How many jobs
where there
before the tax ?

Numerical and Compositional Reasoning

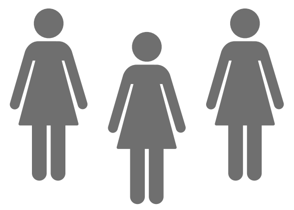
Claim: Repealing the sales tax on boats in Rhode Island has spawned 2,000 companies, 7,000 jobs and close to $2 billion a year in sales activity

What was the annual sales there before the tax ?

Numerical and Compositional Reasoning

Claim: Repealing the sales tax on boats in Rhode Island has spawned 2,000 companies, 7,000 jobs and close to $2 billion a year in sales activity

Need More than Prompting LLMs



Rationales or Explanations

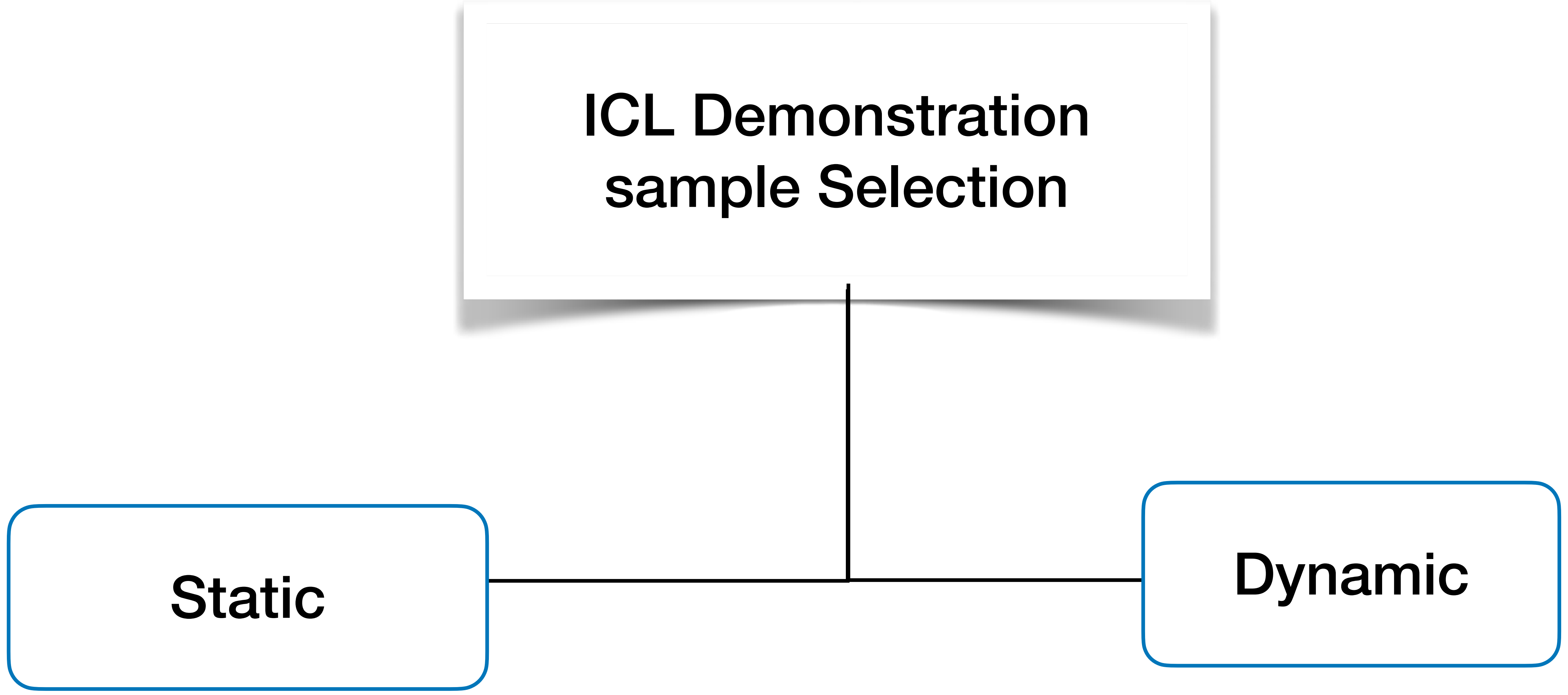
Need to compose abilities required to solve the task

Could be achieved through fine-tuning on required abilities.
Result: Smaller 1M param models outperform larger 1B param models

Or skill composition through In-Context Learning

Vishwanath, Setty & Anand, [SIGIR '24]

Demonstration Samples is all you need ?



FinQA Prompt

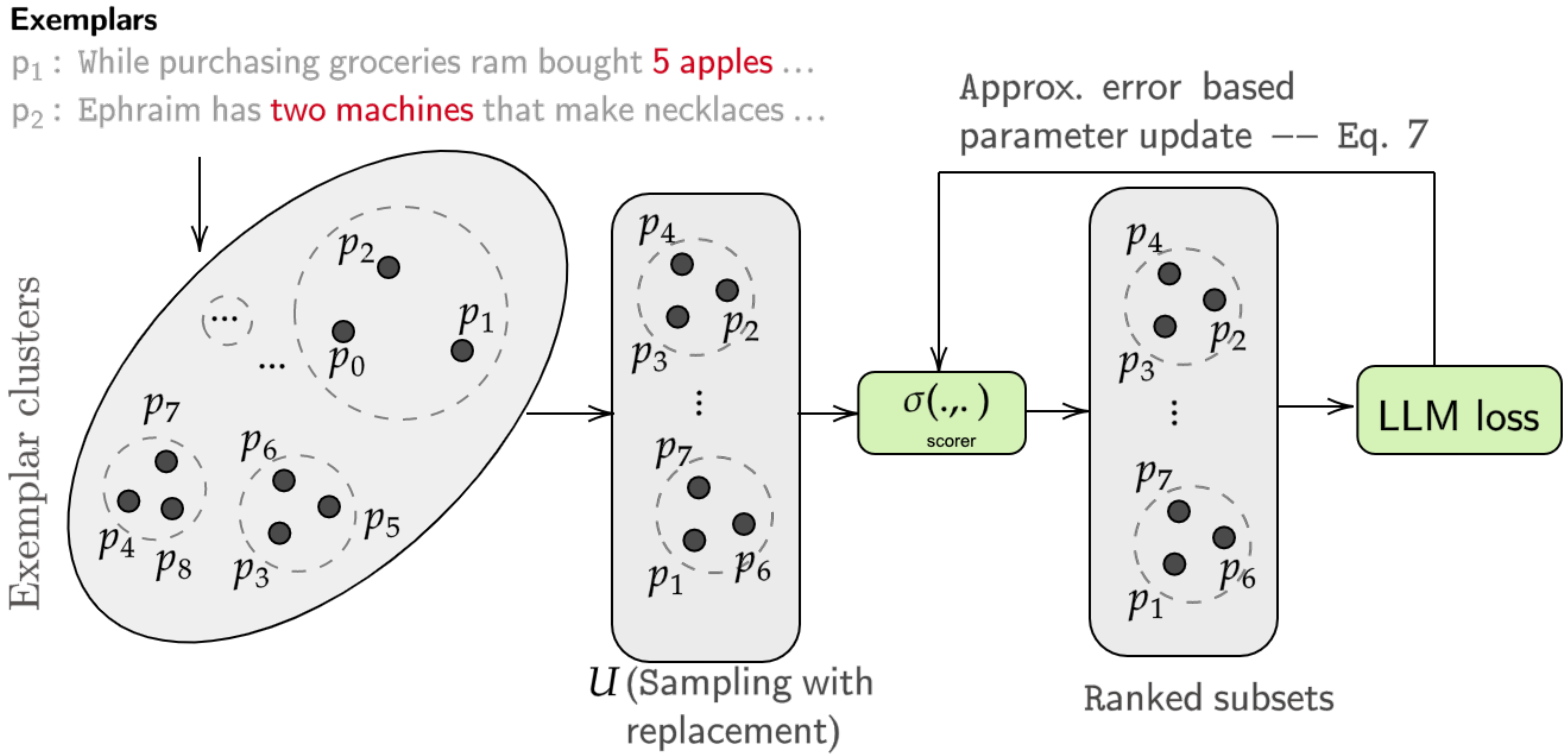
Instruction:`You are a helpful, respectful and honest assistant helping to solve math word problems or tasks requiring reasoning or math, using the information from given table and text.`

Exemplars :

Read the following table, and then answer the question:
[Table]: Year | 2016 | 2015 | 2014 |
share-based compensation expense | 30809 | 21056 | 29793 |
income tax benefit | 9879 | 6907 | 7126 |
[Question]: *how much percent did the income tax benefit increase from 2014 to 2016?*
[Explanation]: $x0 = (9879 - 7126)$,
ans=($x0/7126$)
[Answer]: The answer is increased 38.6%
...
...

Test Input : Read the following table, and then answer the question: Table: Question:
Explanation: [INS] Answer: [INS]

Smart Exploration and Exploitation for ICL Exemplars



Loss Modeling (Approximation) for efficient selection

Subset of k Exemplars ($S \subseteq \mathcal{S}$)

Loss modelling function;
Approximating $L(S, \mathcal{V})$

$$\overbrace{\sigma(\vec{\alpha}, S) = \frac{1}{m} \sum_{j=1}^{m} \sum_{i=1}^{n} \alpha_i (x_i \in S) E_{ij}} \tag{1}$$

ith exemplars contribution, low if important exemplar

Any transformer based encoder

$$E_{ij} = \frac{\phi(x_i)^T \phi(u_j)}{\|\phi(x_i)\| \|\phi(u_j)\|}$$

ith exemplar, $x_i \in S$

ith validation sample, $u_i \in \mathcal{V}$

Efficient Estimation of parameters

Update parameters to reduce approximation error

set of l subsets at timestep t with lowest validation loss

Validation Set

$$\mathcal{L}(\vec{\alpha}; U_t, V_t) = \sum_{S \in U_t} (L(S, \mathcal{V}) - \sigma(\vec{\alpha}, S))^2 + \sum_{S' \sim V_t} (L(S', \mathcal{V}) - \sigma(\vec{\alpha}, S'))^2$$

Remaining subsets; $V_t \leftarrow \mathcal{U} \setminus U_t$, where $\mathcal{U} \subset \mathcal{S}$

Negative samples from high-loss set V_t

Estimating loss here involves LLM calls and equivalent to arm pulling

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Summary

Algorithm 1: EXPLORA

Input: $\mathcal{U} \subseteq \mathcal{S}$: $\triangleright$ Initial exemplar subsets
Initialize: $U_0 \leftarrow$ set of random l subsets from $\mathcal{U}$
  $t \leftarrow 0$
  $\vec{\alpha} \leftarrow \mathcal{N}(0, 1)$ $\triangleright$ Sampling from a gaussian
while $t < T$ **do**
  Let $V_t \leftarrow \mathcal{U} \setminus U_t$
  $\vec{\alpha_t} \leftarrow \min_{\vec{\alpha}} \mathcal{L}(\vec{\alpha}, U_t, V_t)$ $\triangleright$ Eq. in previous slide
  $S_t^* = \arg\min_{S \in V_t} \sigma(\vec{\alpha_t}, S)$ $\triangleright$ Lowest loss subset
  $\tilde{S}_t = \arg\max_{S \in U_t} \sigma(\vec{\alpha_t}, S)$ $\triangleright$ Highest loss subset
  if $\sigma(\vec{\alpha_t}, S_t^*) < \sigma(\vec{\alpha_t}, \tilde{S}_t)$ **then**
    $U_t \leftarrow U_t \setminus \{\tilde{S}_t\}$ $\triangleright$ Remove $\tilde{S}_t$
    $U_{t+1} \leftarrow U_t \cup \{S_t^*\}$ $\triangleright$ add S_t^*
  end
  $t \leftarrow t + 1$
end
Output: U_T;Set of l subsets from $\mathcal{U}$ which have the lowest validation loss

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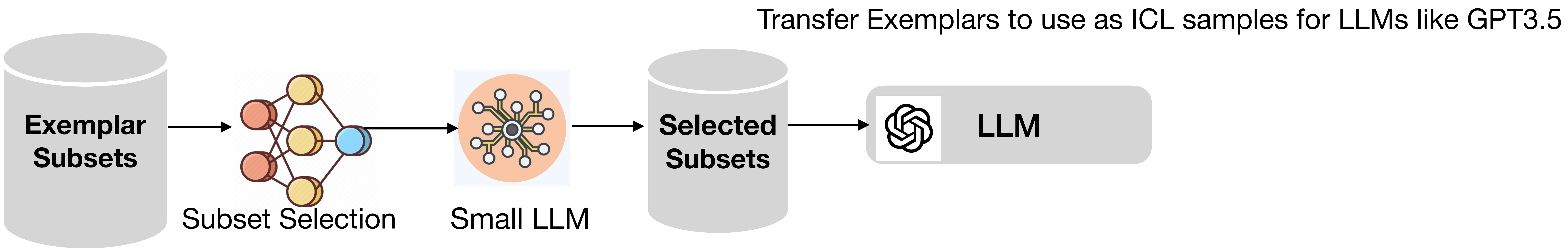
Tune and Transfer



EXPLORA is Robust (Low Variance across test samples)

Datasets	**GSM**	**Aqua**	**Tab**	**Fin**
Zero-Shot COT	±5.18	±7.08	±1.84	±4.50
Few-Shot COT	±4.48	±12.03	±1.66	±4.76
KNN	±3.76	±5.49	±1.27	±4.17
MMR	±4.00	±10.53	±1.68	±6.10
Graph Cut	±6.38	±8.18	±2.03	±5.29
Facility Location	±4.23	±6.71	±1.74	±4.94
LENS	±5.04	±6.67	±1.72	±5.81
EXPLORA	±**3.39**	±**4.93**	±1.45	±**3.41**

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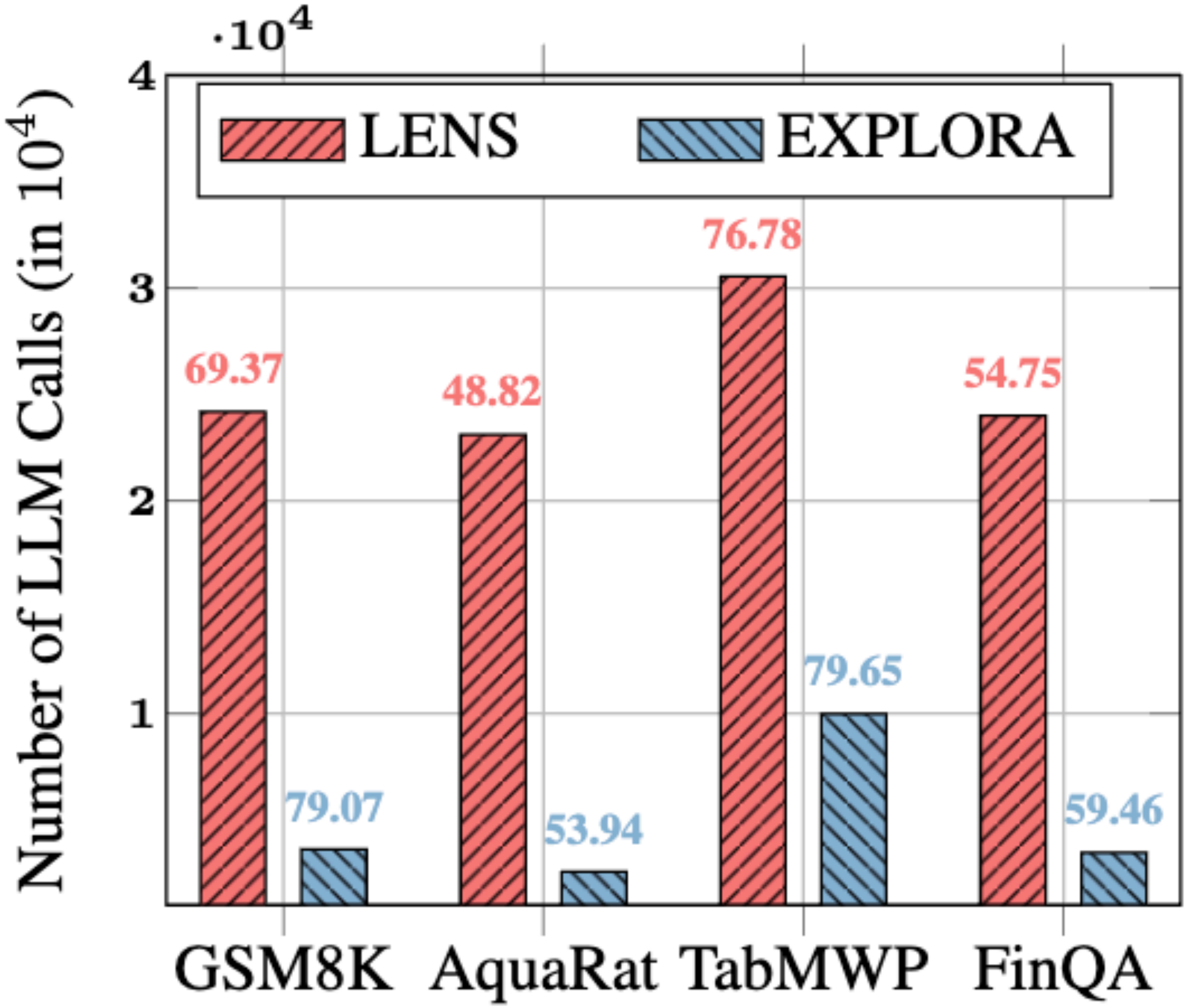
EXPLORA is Resource Efficient



Results Transfers Well (L for Llama and M for Mistral)

Method	T	GSM	Aqua	Tab	Fin
EXP	L	79.07	53.94	79.65	54.66
	M	77.86	53.54	77.41	59.46
EXP+SC	L	85.82	63.78	86.76	61.16
	M	86.35	63.39	85.52	64.52
EXP+KNN+SC	L	85.89	64.17	85.74	63.64
	M	85.14	62.20	86.29	65.12
EXP+MMR+SC	L	86.20	62.99	87.81	64.60
	M	86.13	63.78	86.96	64.60

Prompts are transferred from Llama or Mistral to GPT3.5-turbo

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A Recap

- Efficiency and Effectiveness are critical for practical robust RAG pipelines.
- Telescoping systems are limited in efficiency and suffer from Recall Boundedness.
- LLMs are still limited in reasoning.
- Test Time scaling for Retrieval is central to robust pipelines for complex knowledge intensive tasks.
- Careful selection of exemplars help in transferring abilities to LLMs through ICL.

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Conclusion - Research Vision

- End-End Test Time Reasoning (TTR) has huge scope.
  - How do we incorporate Reasoning feedback (LLM) to improve retrieval
  - How can retrieval improve reasoning.
  - How to do this efficiently?

- How can we do this in a scalable manner ?

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