RE-THINKING RE-RANKING

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Terrier

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Conduct practical research in information retrieval:

- Learned Sparse Expansion
- Search Result Evaluation using LLMs
- Document Quality Prediction
- Adaptive Re-Ranking

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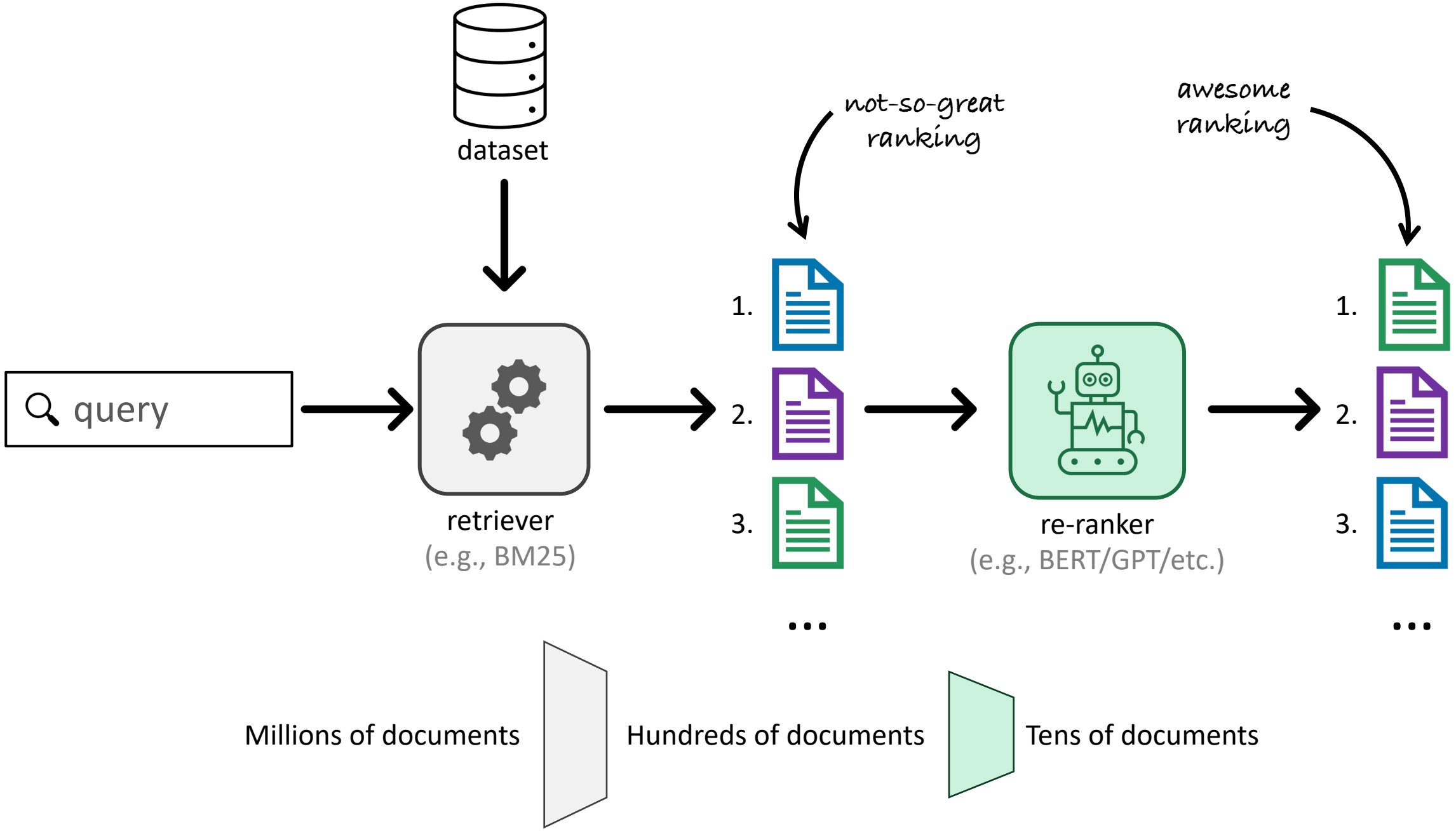
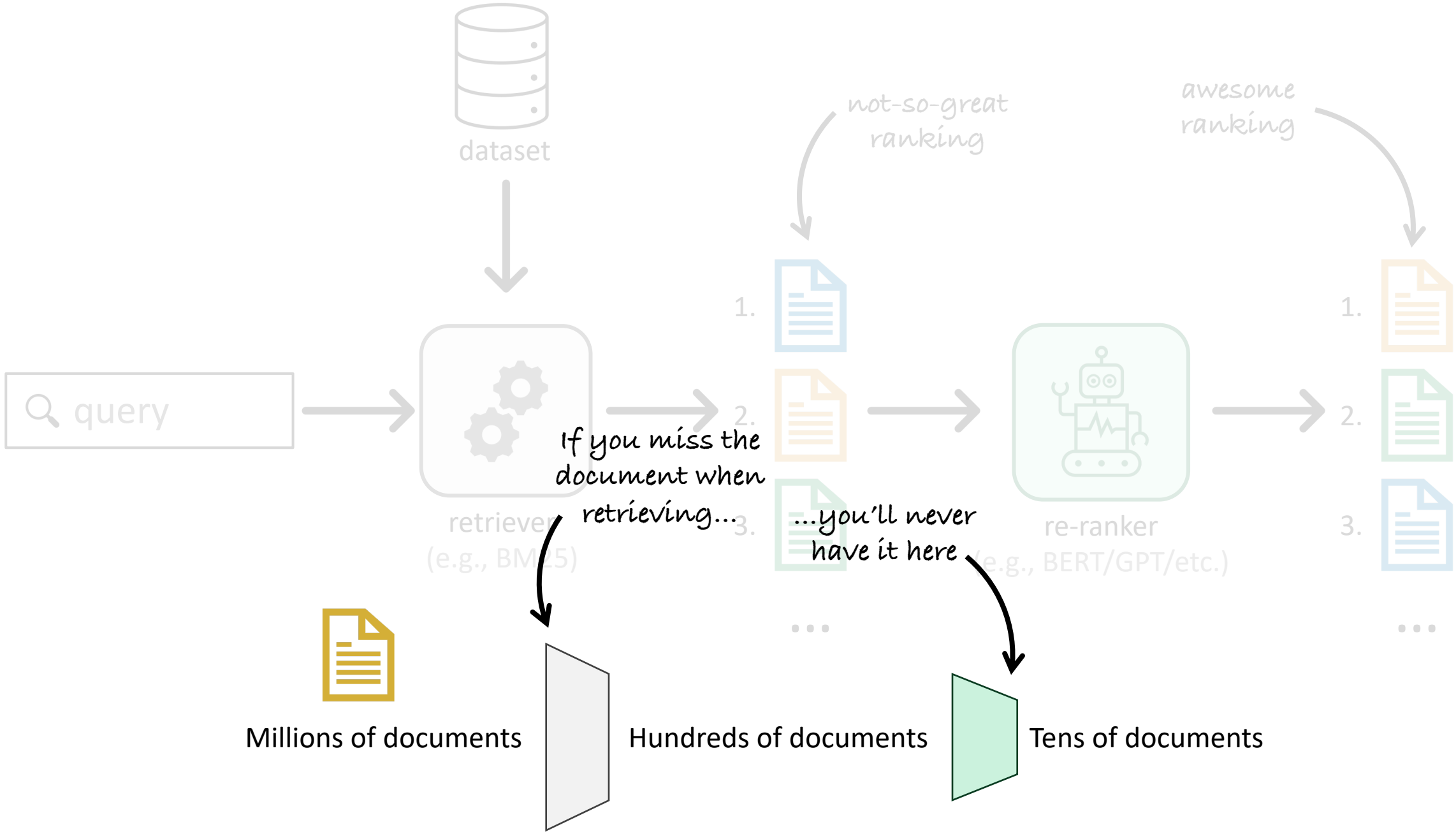
Conduct practical research in information retrieval:

- Learned Sparse Expansion
- Search Result Evaluation using LLMs
- Document Quality Prediction
- **Adaptive Re-Ranking**

What’s Re-Ranking?


dataset
not-so-great ranking
awesome ranking
query
retriever
(e.g., BM25)
1.
2.
3.
...
re-ranker
(e.g., BERT/GPT/etc.)
1.
2.
3.
...
Millions of documents
Hundreds of documents
Tens of documents


dataset
not-so-great ranking
awesome ranking
query
1.
2.
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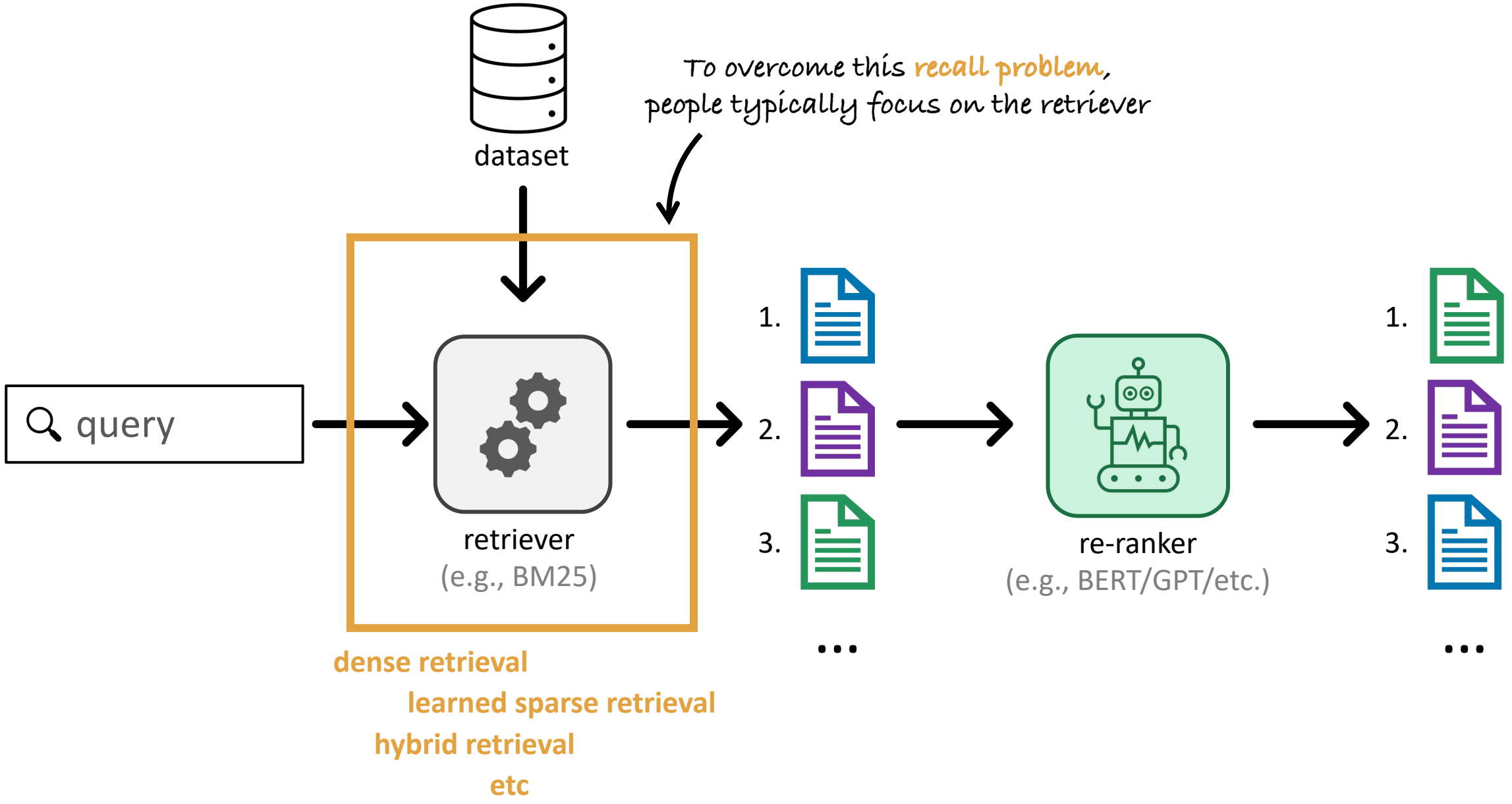
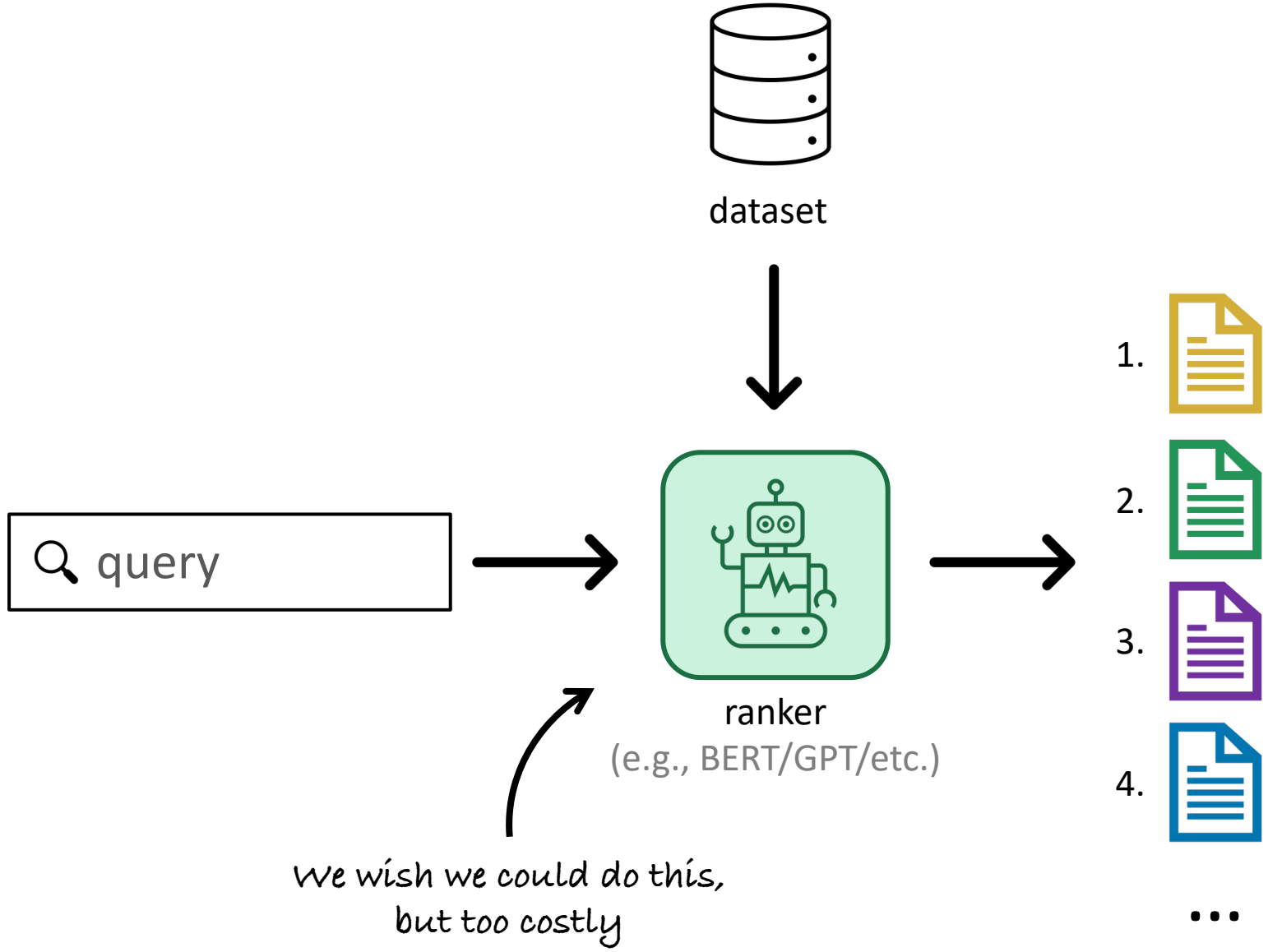
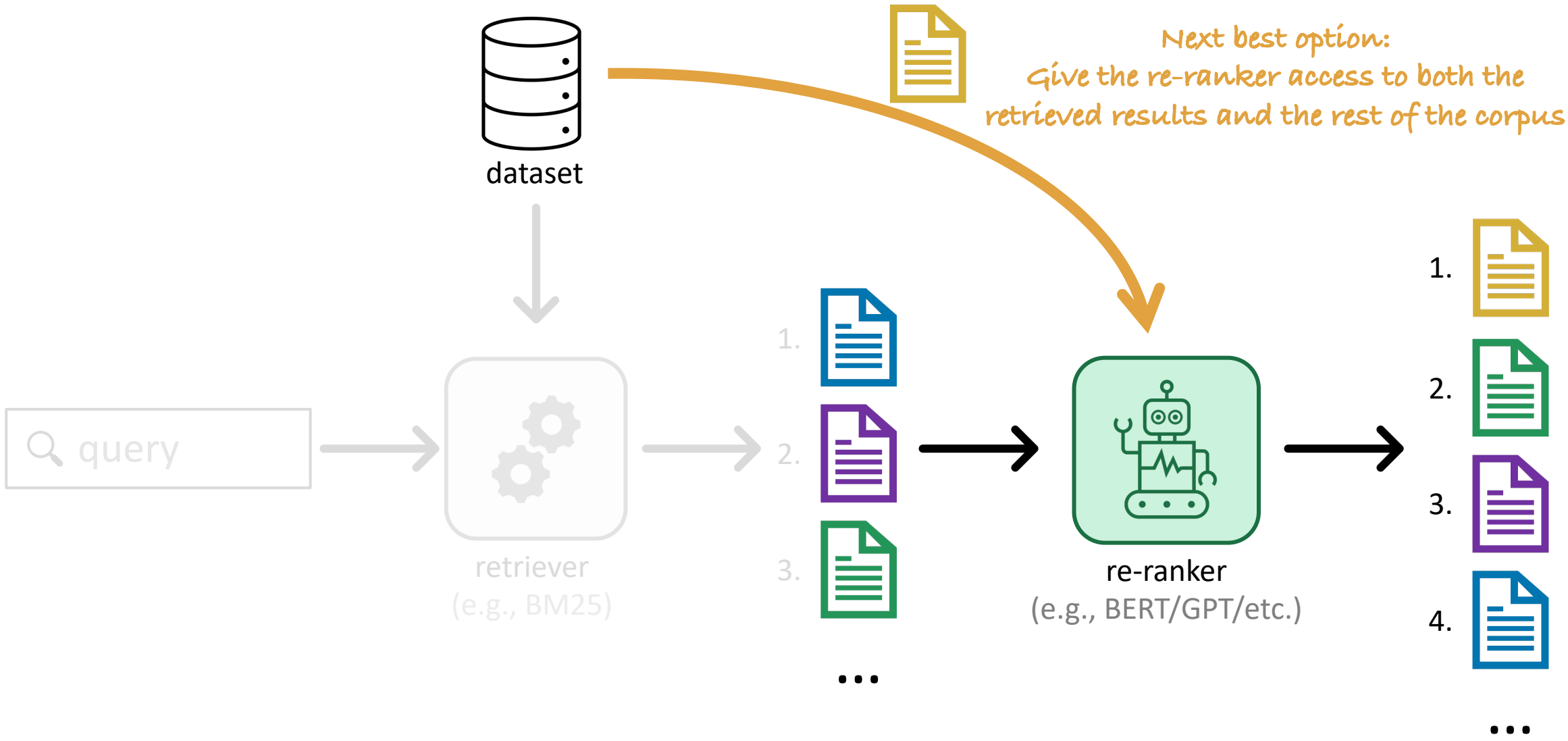
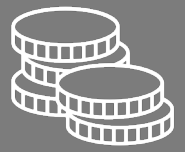
retriever
(e.g., BM25)
re-ranker
(e.g., BERT/GPT/etc.)
If you miss the document when retrieving…
…you'll never have it here
Millions of documents
Hundreds of documents
Tens of documents

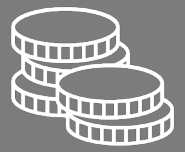

dataset
To overcome this recall problem,
people typically focus on the retriever
query
retriever
(e.g., BM25)
1.
2.
3.
...
re-ranker
(e.g., BERT/GPT/etc.)
1.
2.
3.
...
dense retrieval
learned sparse retrieval
hybrid retrieval
etc


dataset
query
ranker
(e.g., BERT/GPT/etc.)
1.
2.
3.
4.
...
We wish we could do this,
but too costly


Next best option:
Give the re-ranker access to both the retrieved results and the rest of the corpus
dataset
query
retriever
(e.g., BM25)
1.
2.
3.
...
re-ranker
(e.g., BERT/GPT/etc.)
1.
2.
3.
4.
...



I’ll show this can be done with minimal cost.



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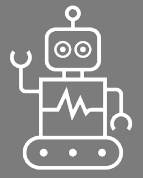
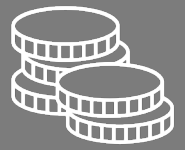


The idea can improve retrievers like ColBERT, too.



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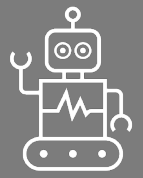


The idea can improve retrievers like ColBERT, too.

Ready-to-use with Open-Source tools!

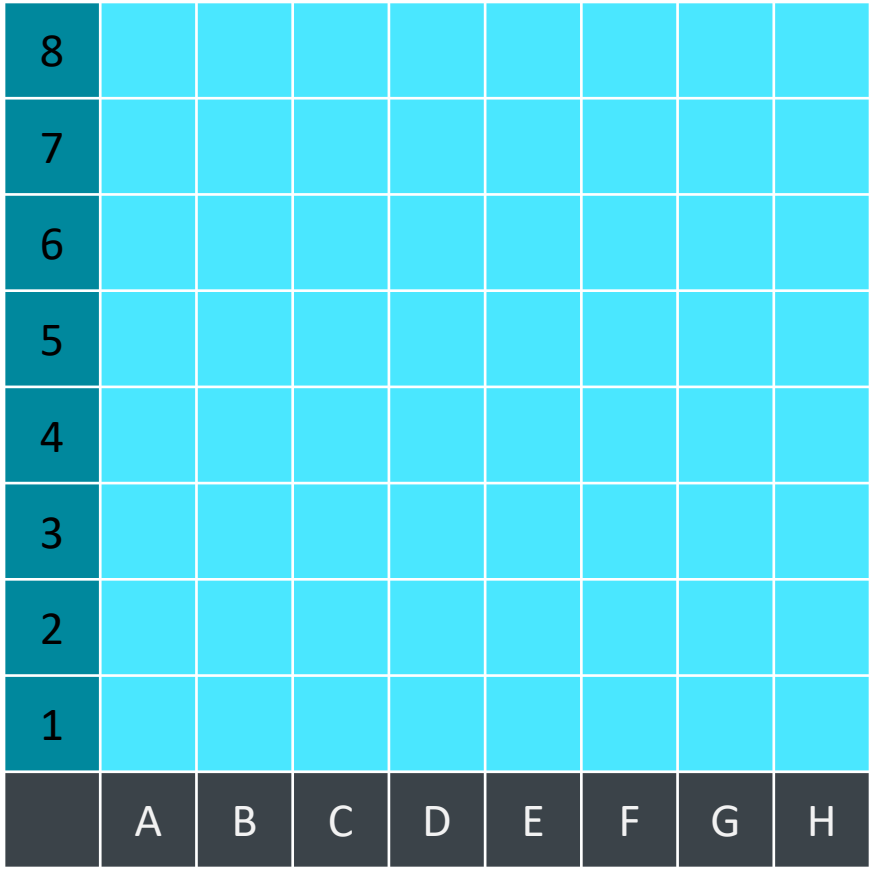
Battleship

Battleship

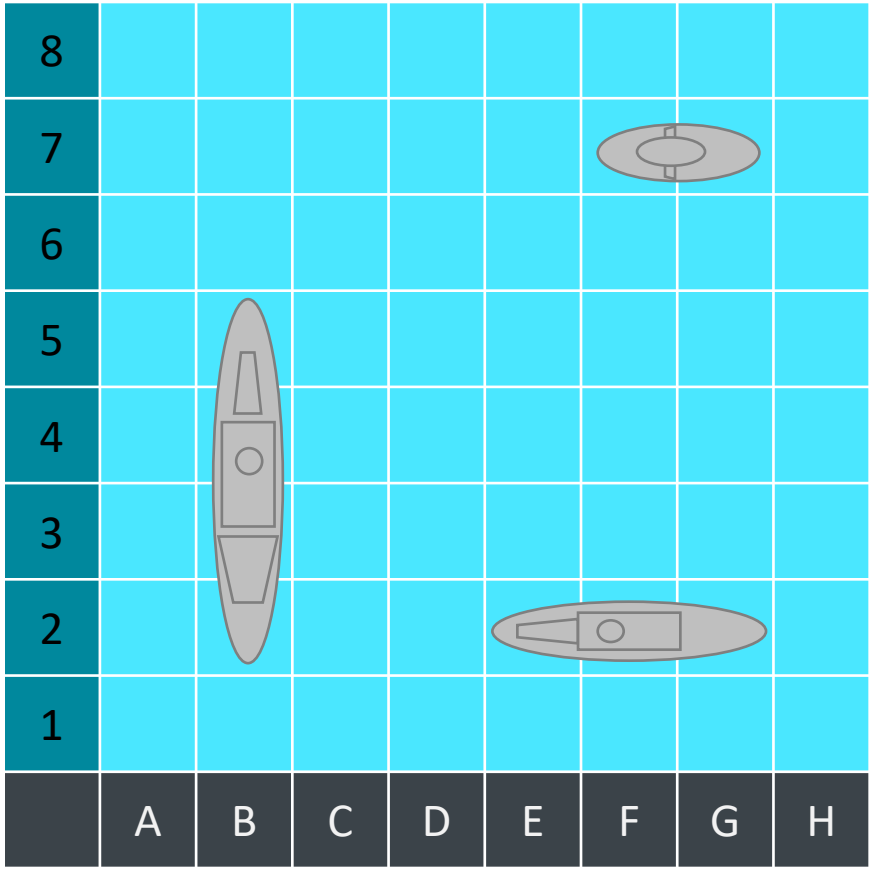
Schifferversenken

“Sink the Fleet”

Your Board

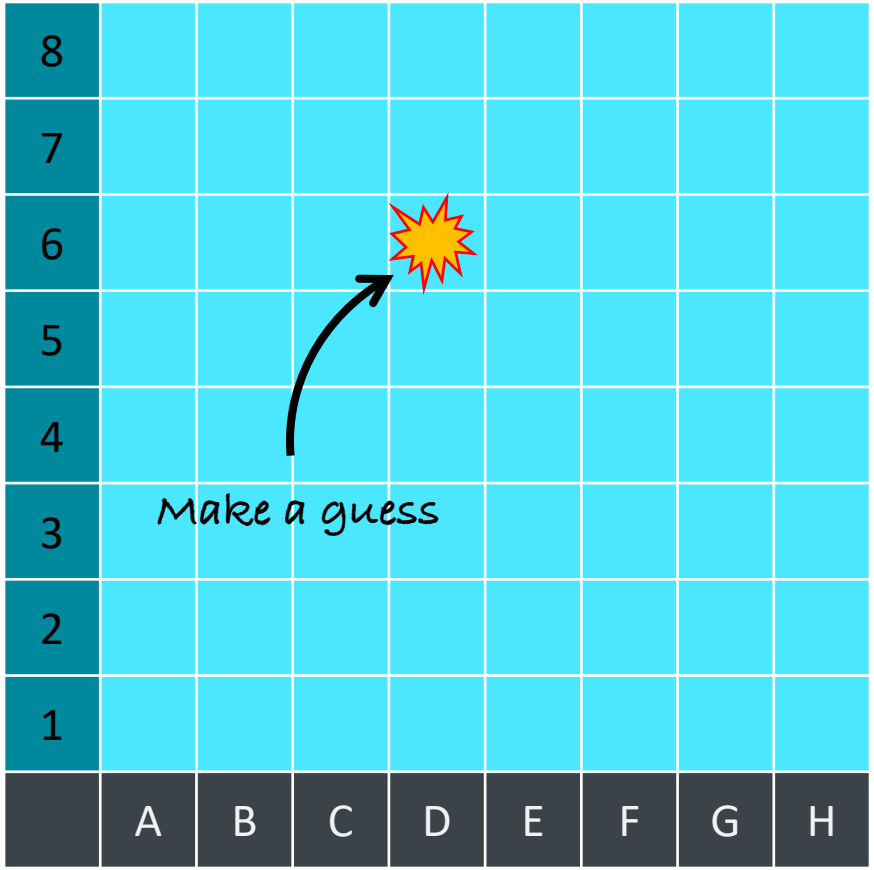


Opponent's board (Secret)



Goal: identify the positions of all your opponent's ships

Your Board



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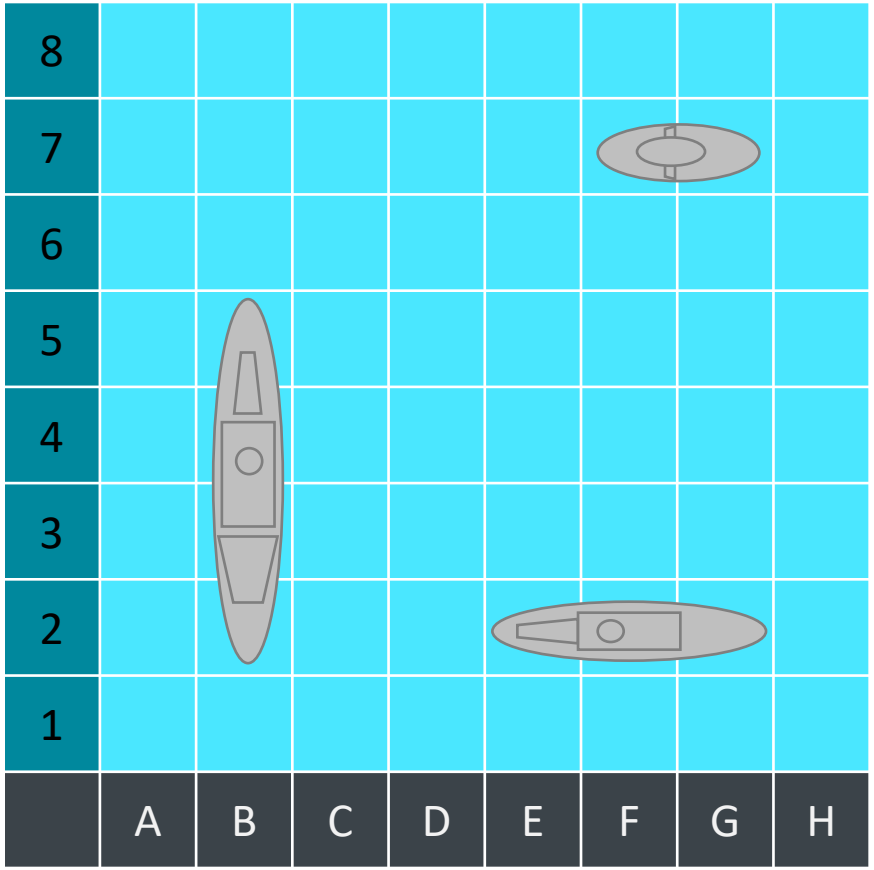
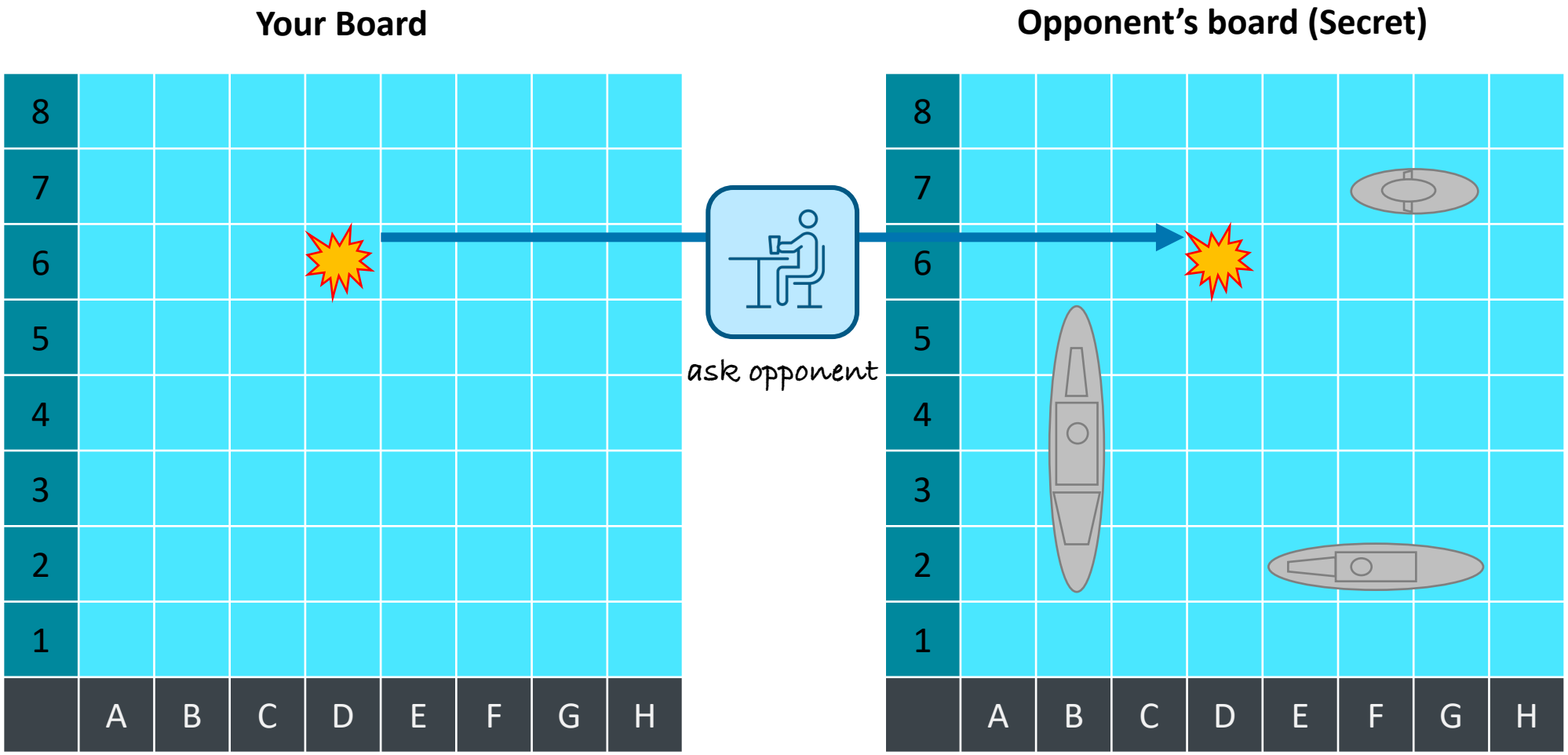
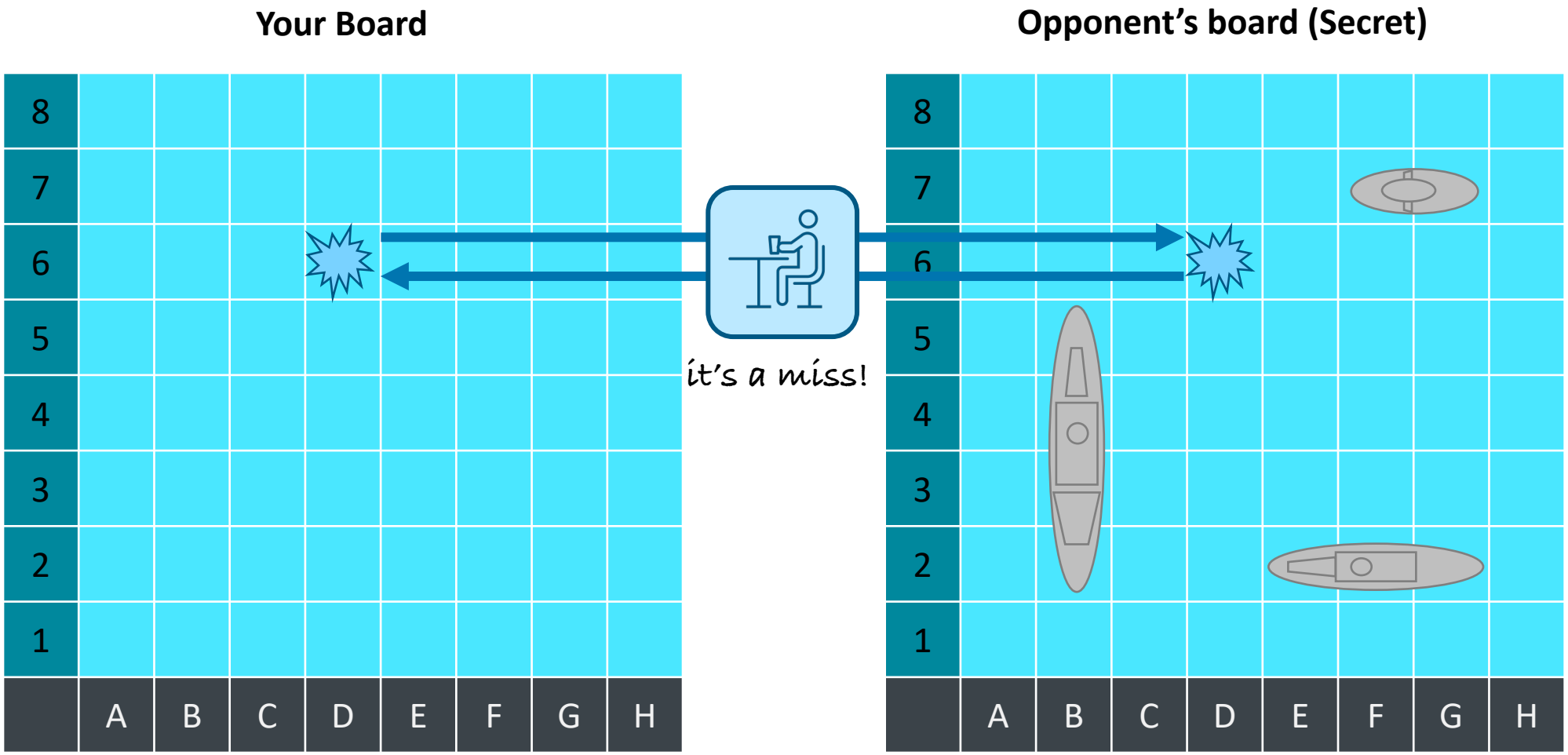
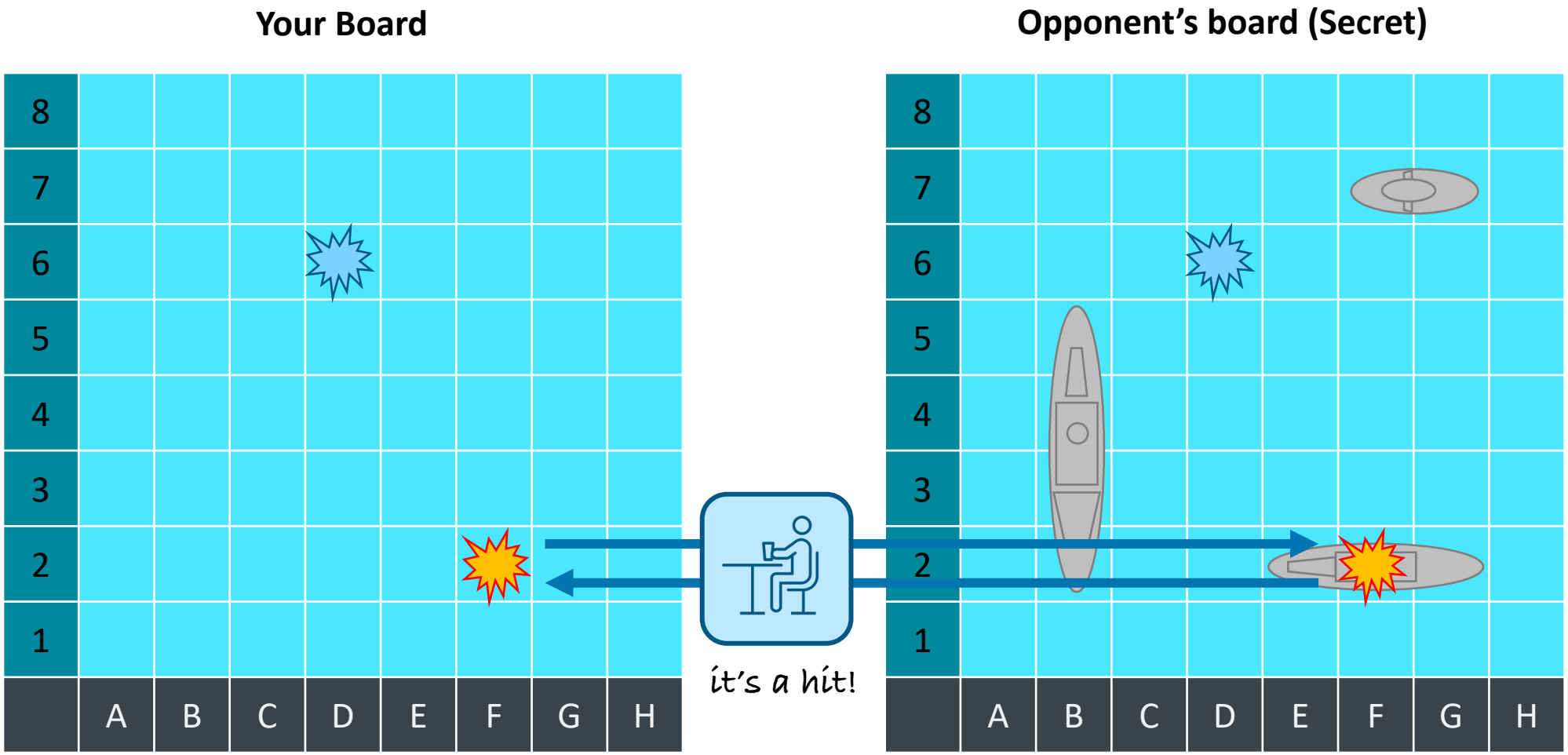
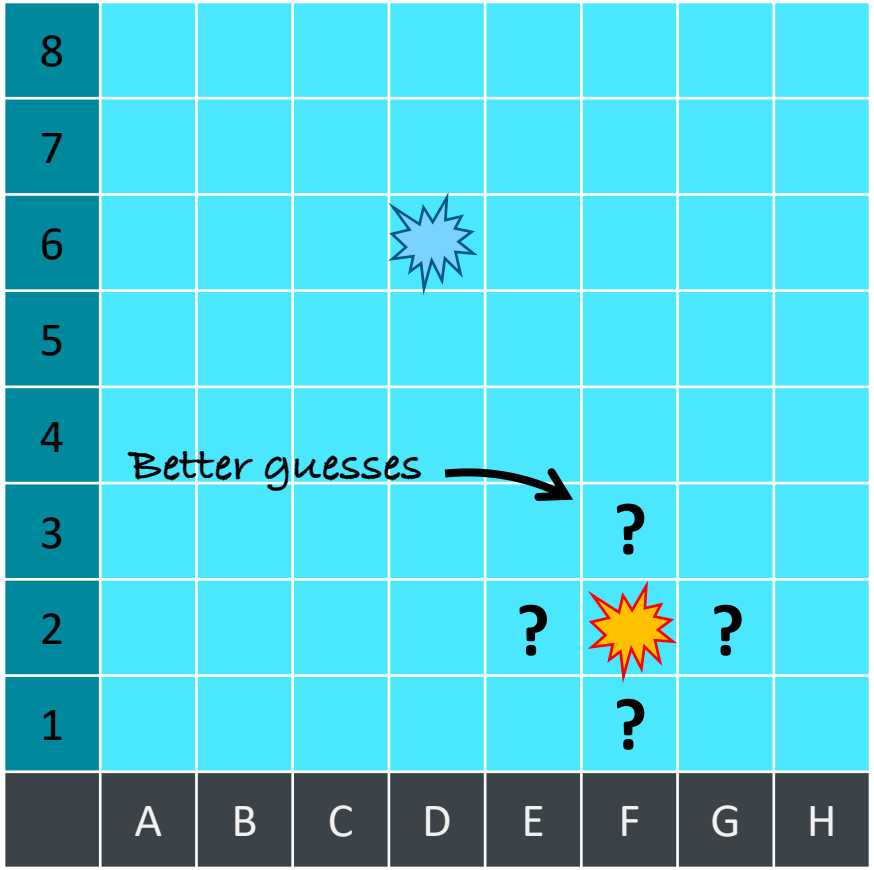



Your Board
Opponent's board (Secret)
ask opponent
8
7
6
5
4
3
2
1
A
B
C
D
E
F
G
H


Your Board
Opponent's board (Secret)
8
7
6
5
4
3
2
1
A
B
C
D
E
F
G
H
it's a miss!


Your Board
Opponent's board (Secret)
8
7
6
5
4
3
2
1
A
B
C
D
E
F
G
H
it's a hit!

Your Board



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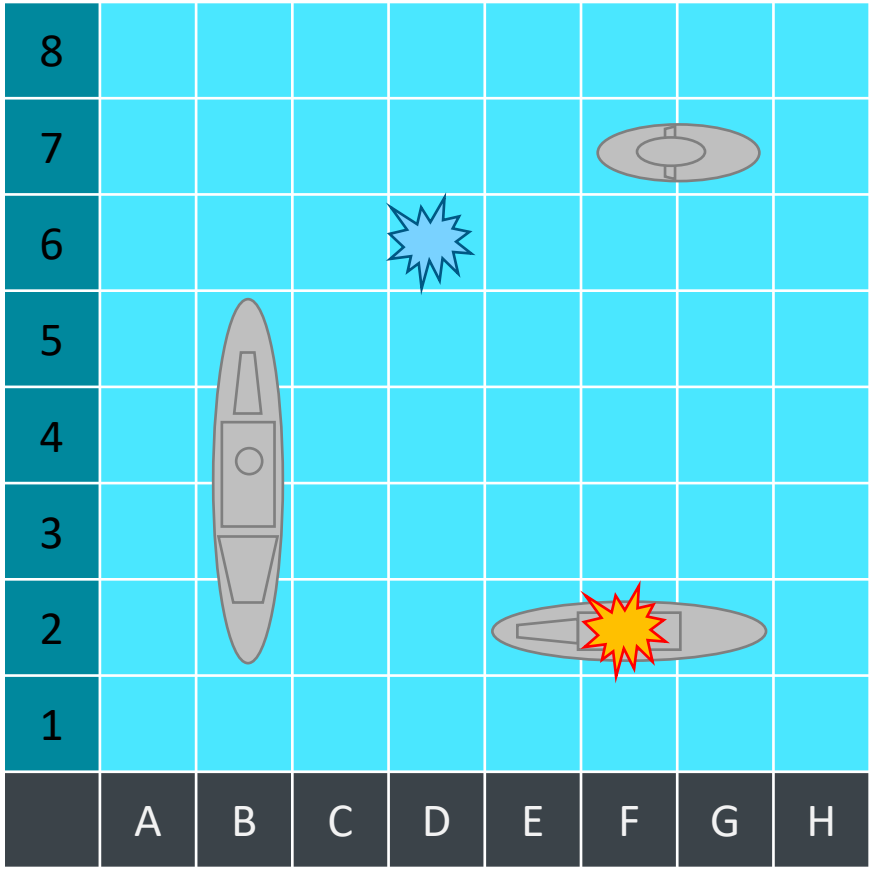
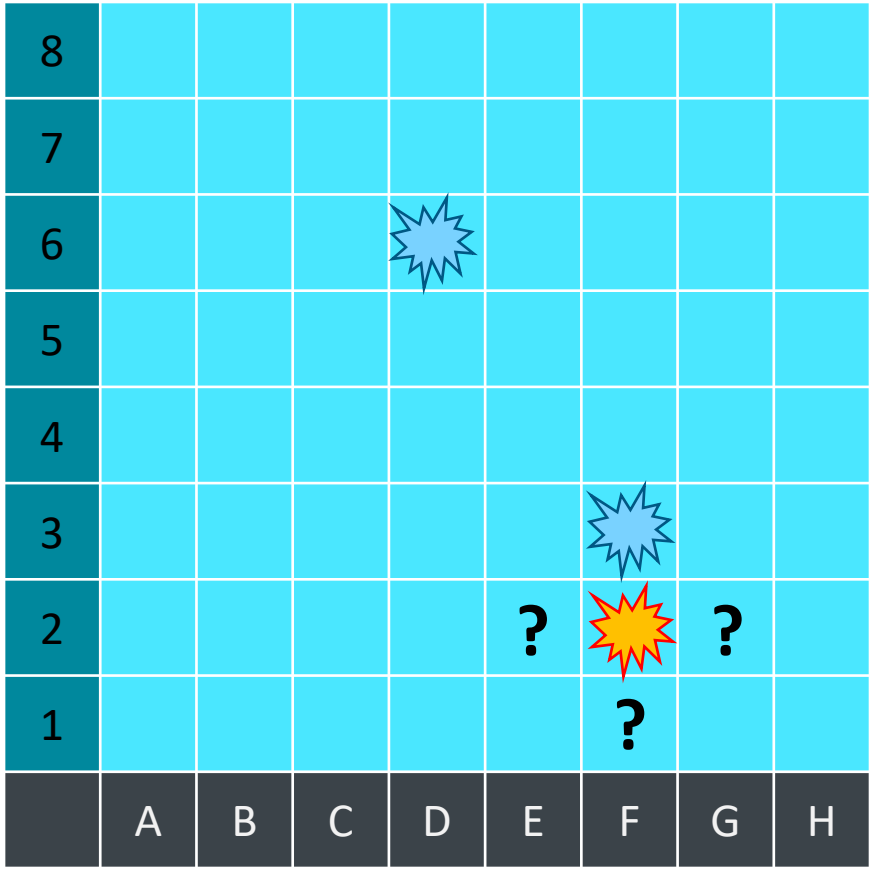


Your Board



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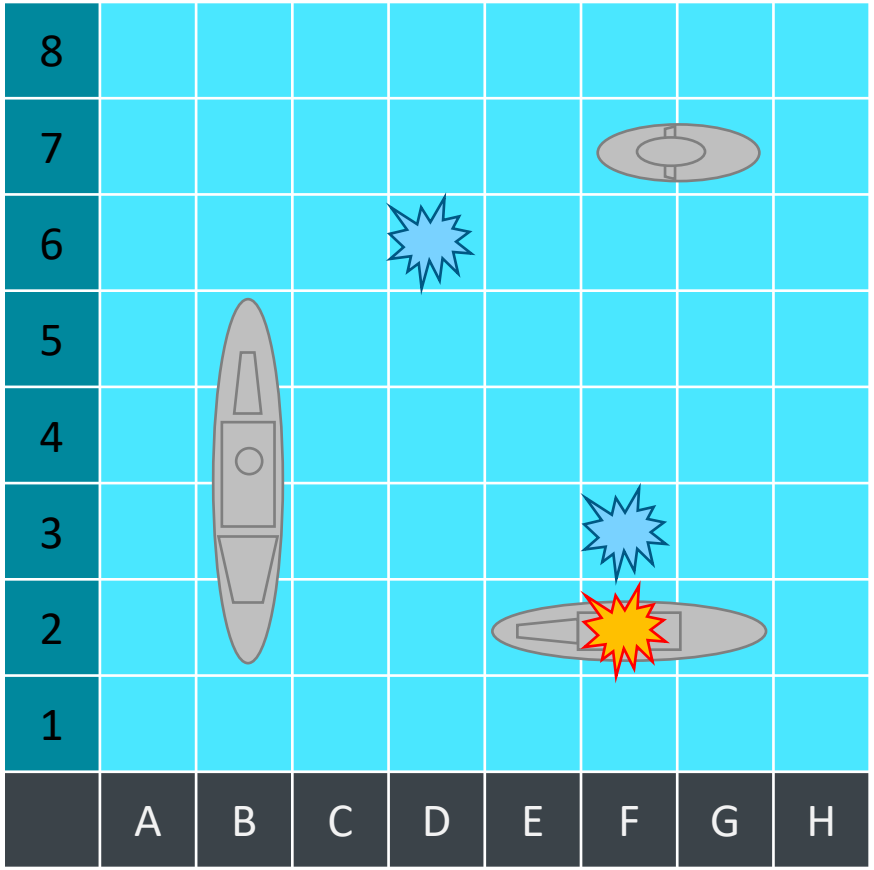
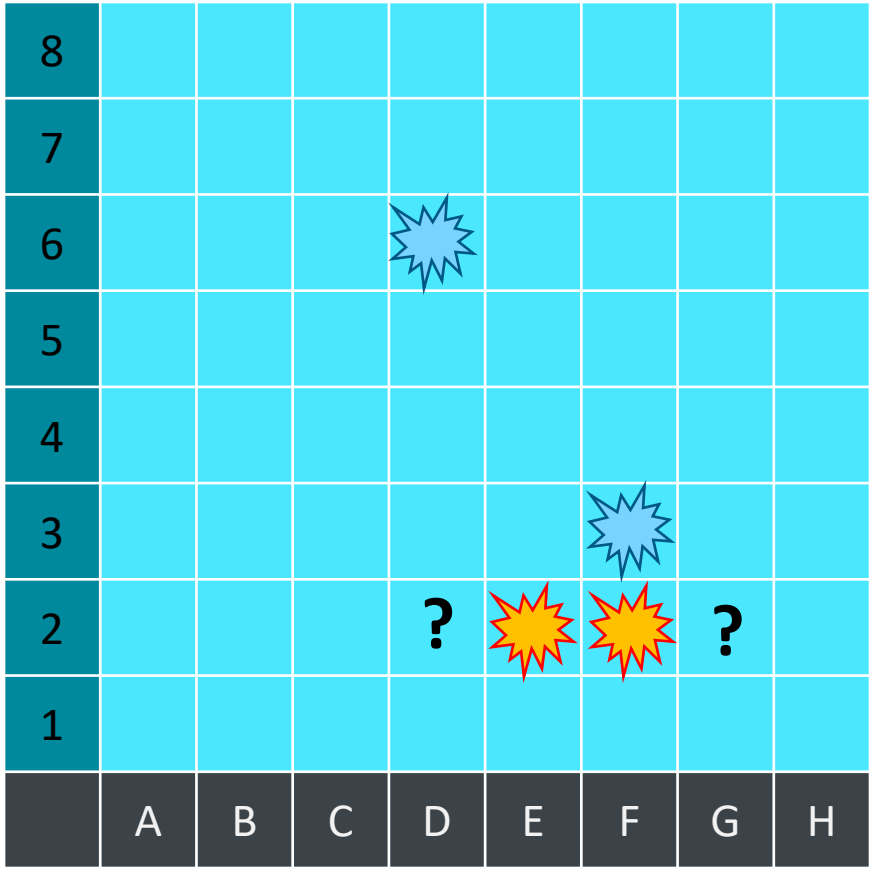


Your Board



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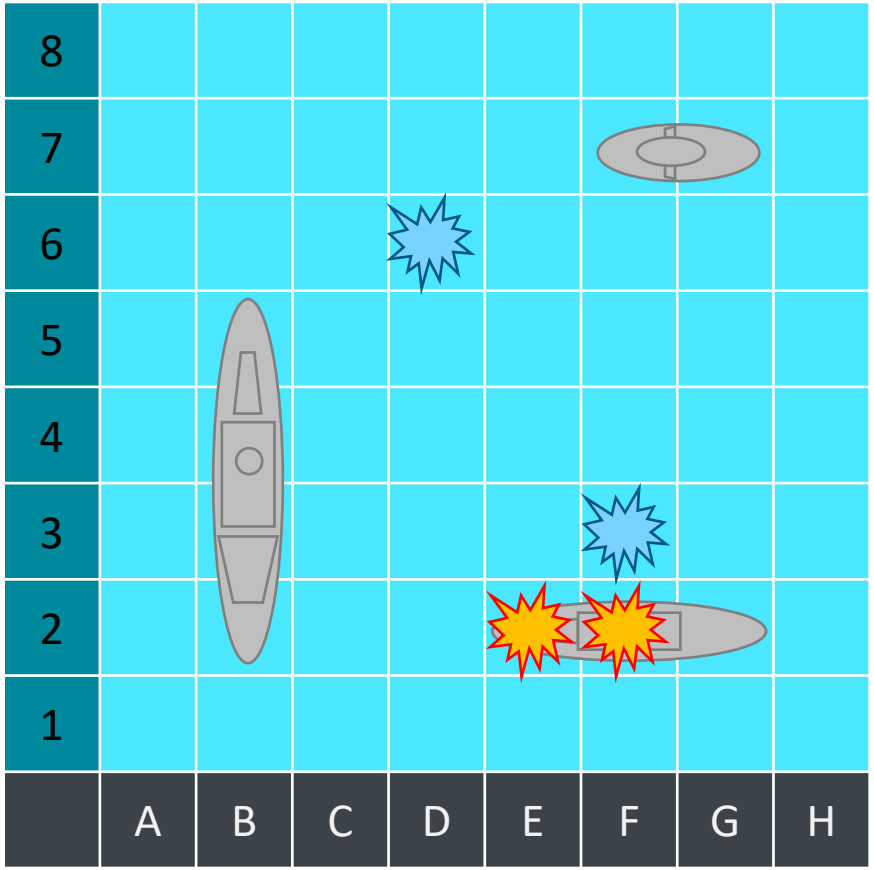
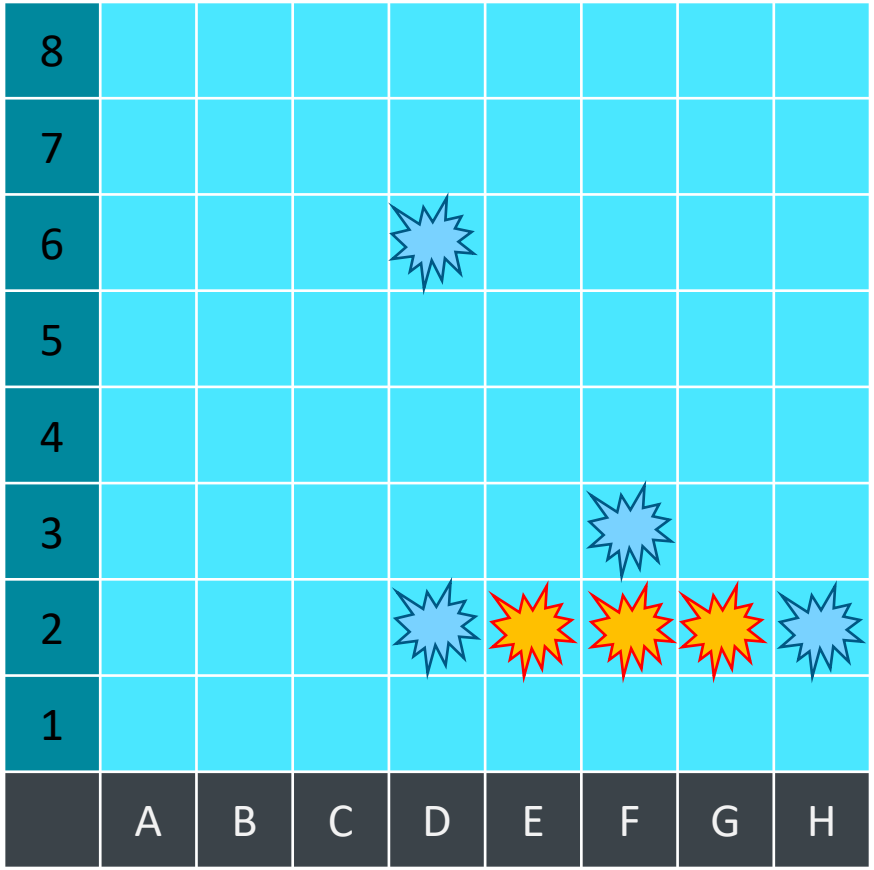


Your Board



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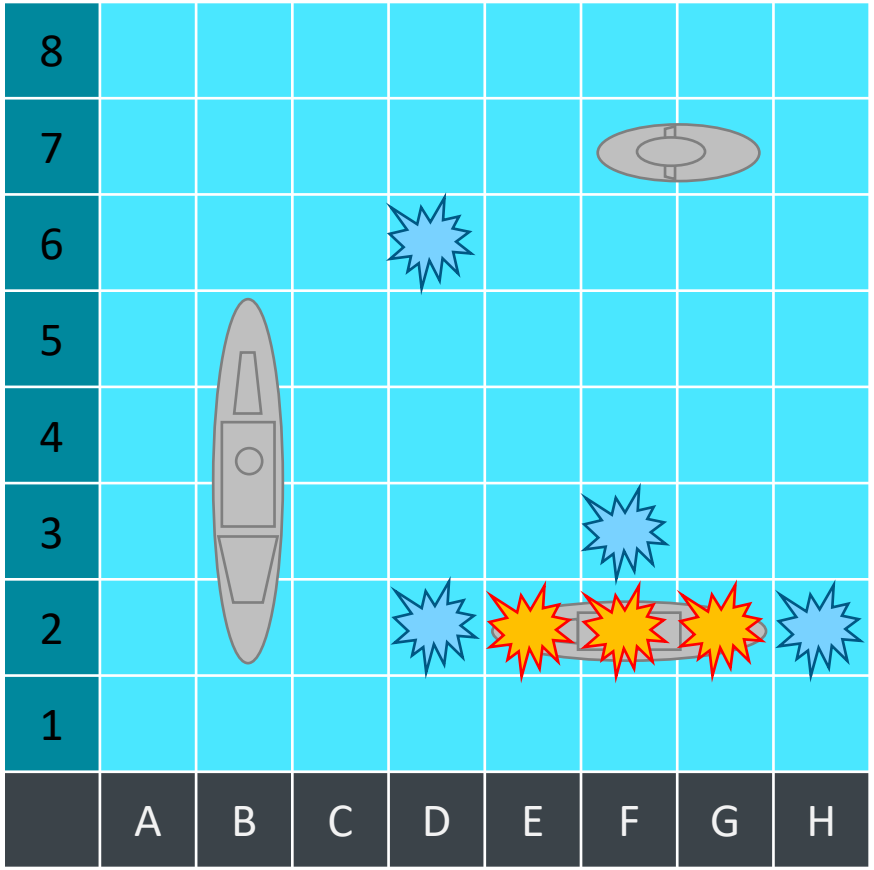
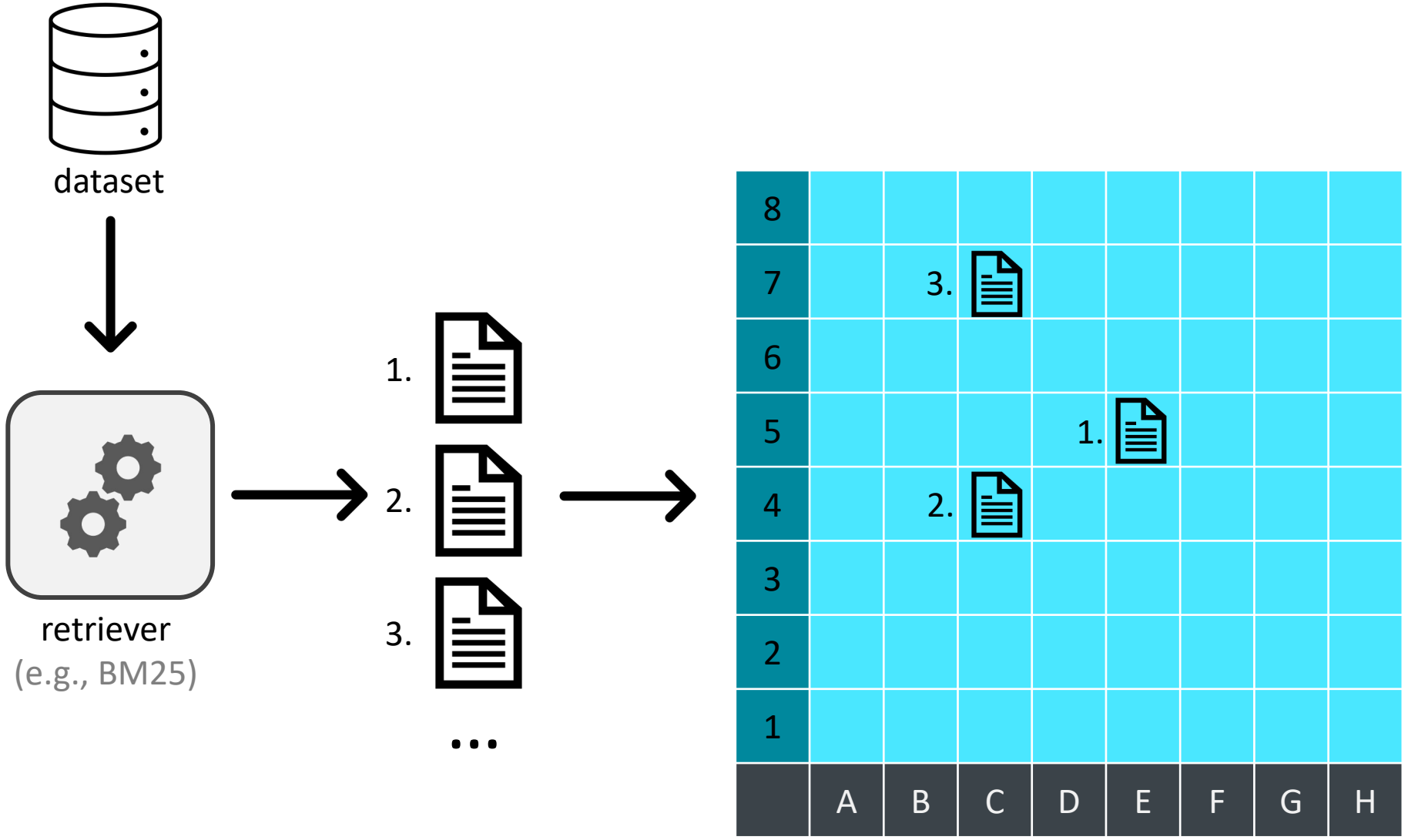


And so forth…


dataset
retriever
(e.g., BM25)
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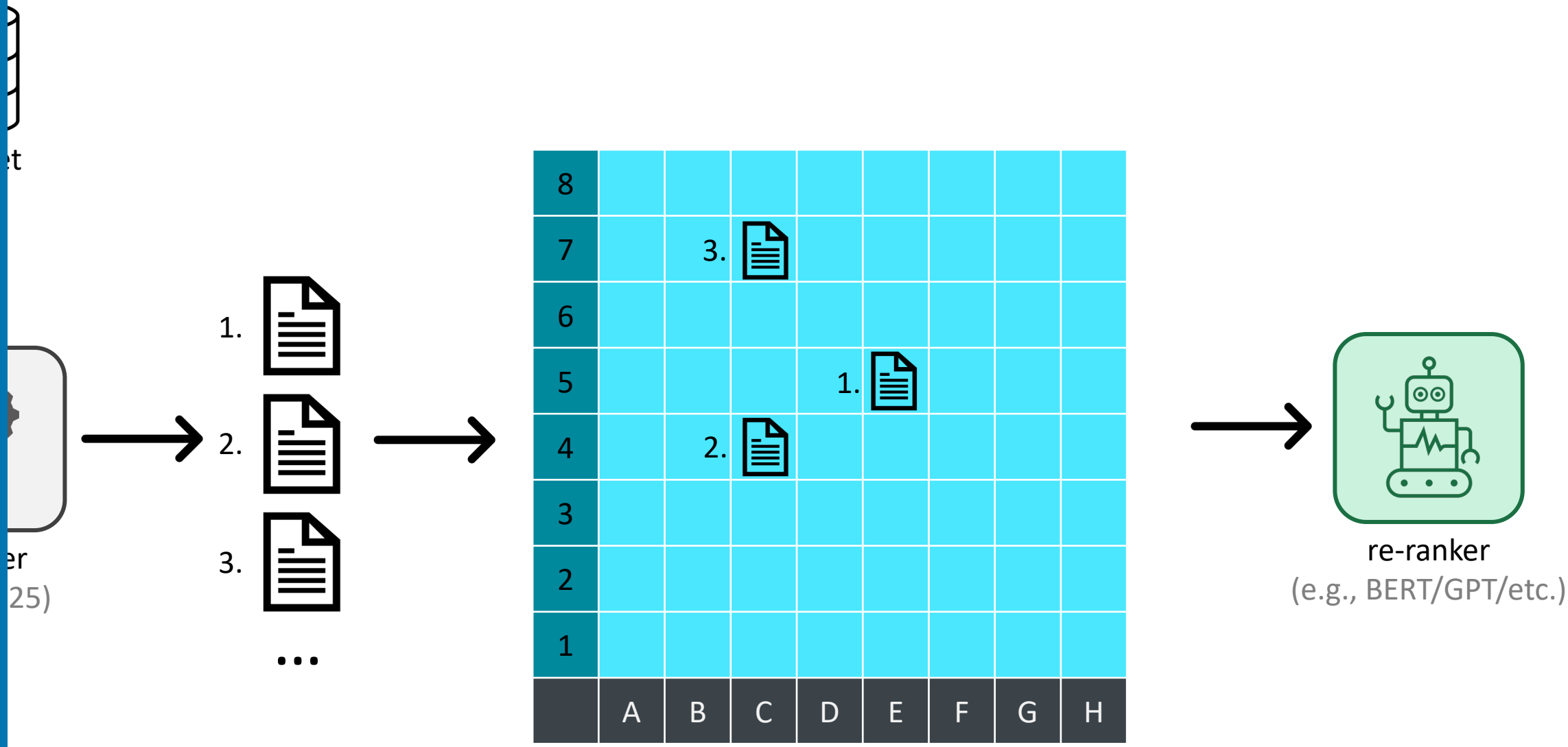
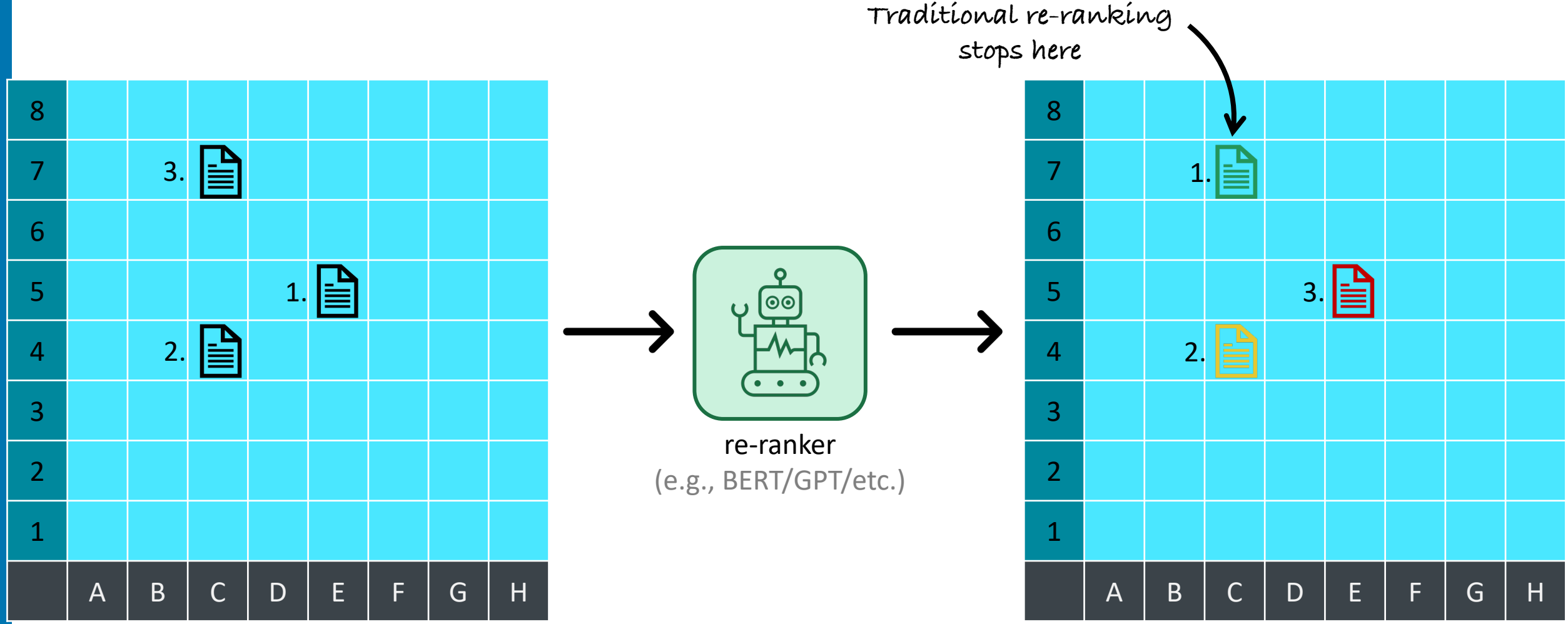
3.
1.
2.


1.
2.
3.
...
8
7
6
5
4
3
2
1
A
B
C
D
E
F
G
H
3.
1.
2.
re-ranker
(e.g., BERT/GPT/etc.)


Traditional re-ranking
stops here
8
7
6
5
4
3
2
1
A
B
C
D
E
F
G
H
3.
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2.
re-ranker
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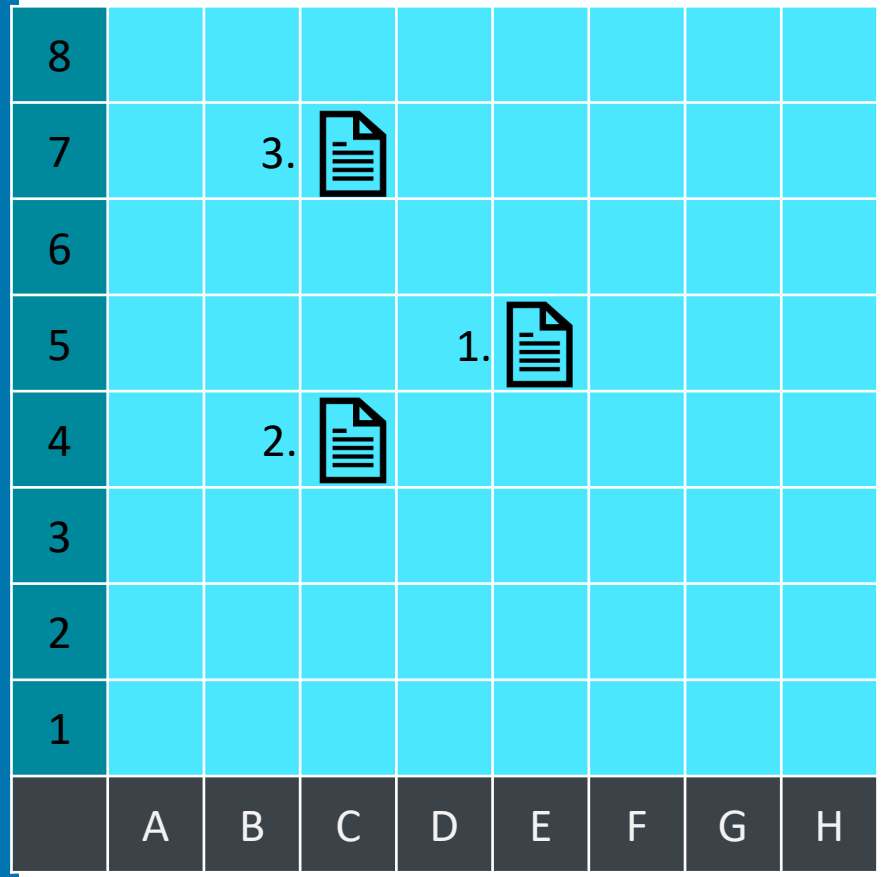
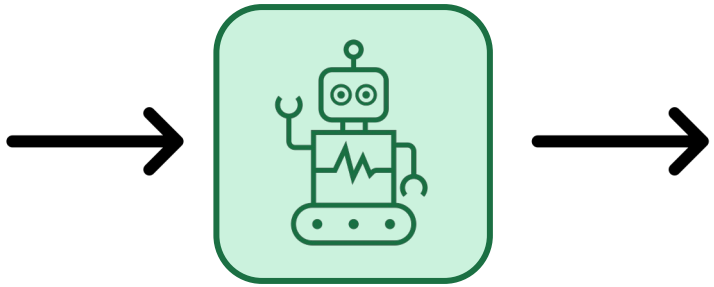
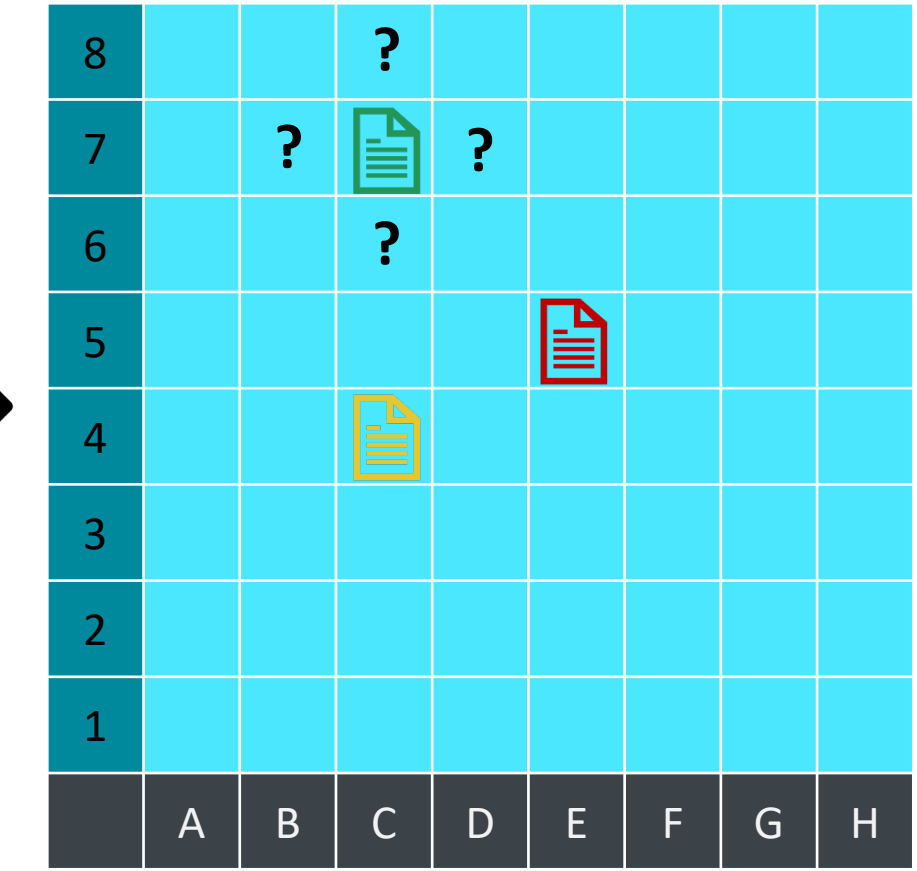
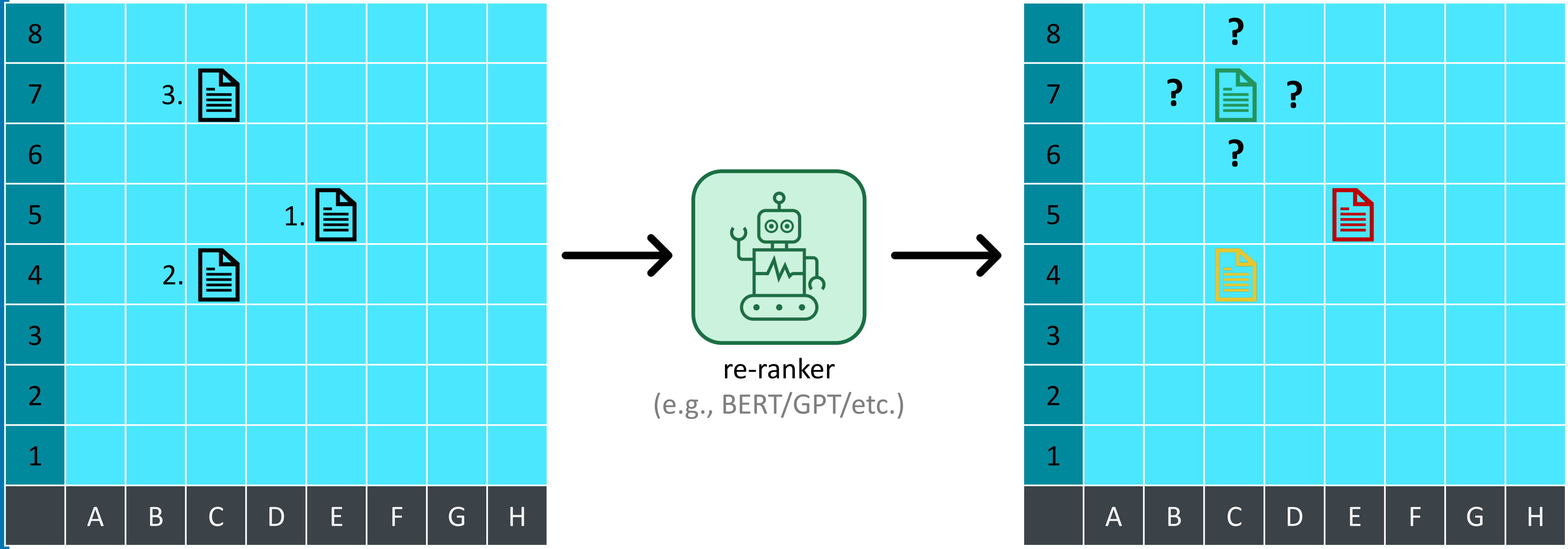




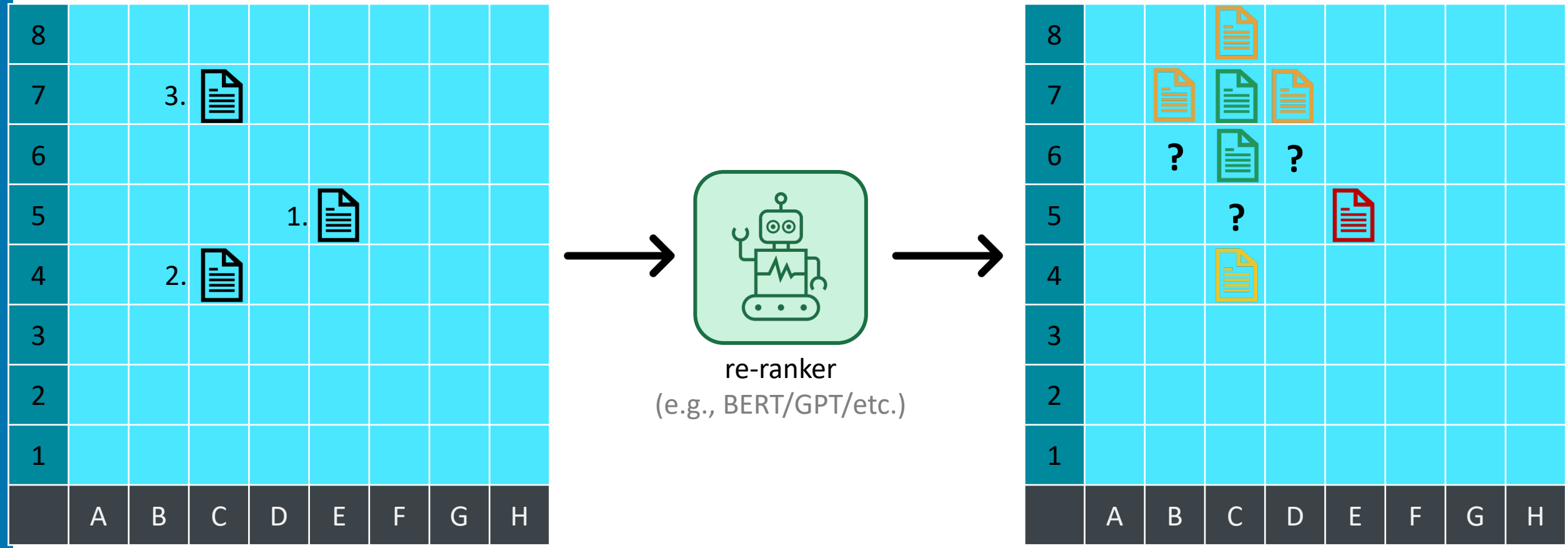
re-ranker
(e.g., BERT/GPT/etc.)



Adaptive Re-Ranking leverages the information gained from high-scoring documents to find ones missed by the retriever.

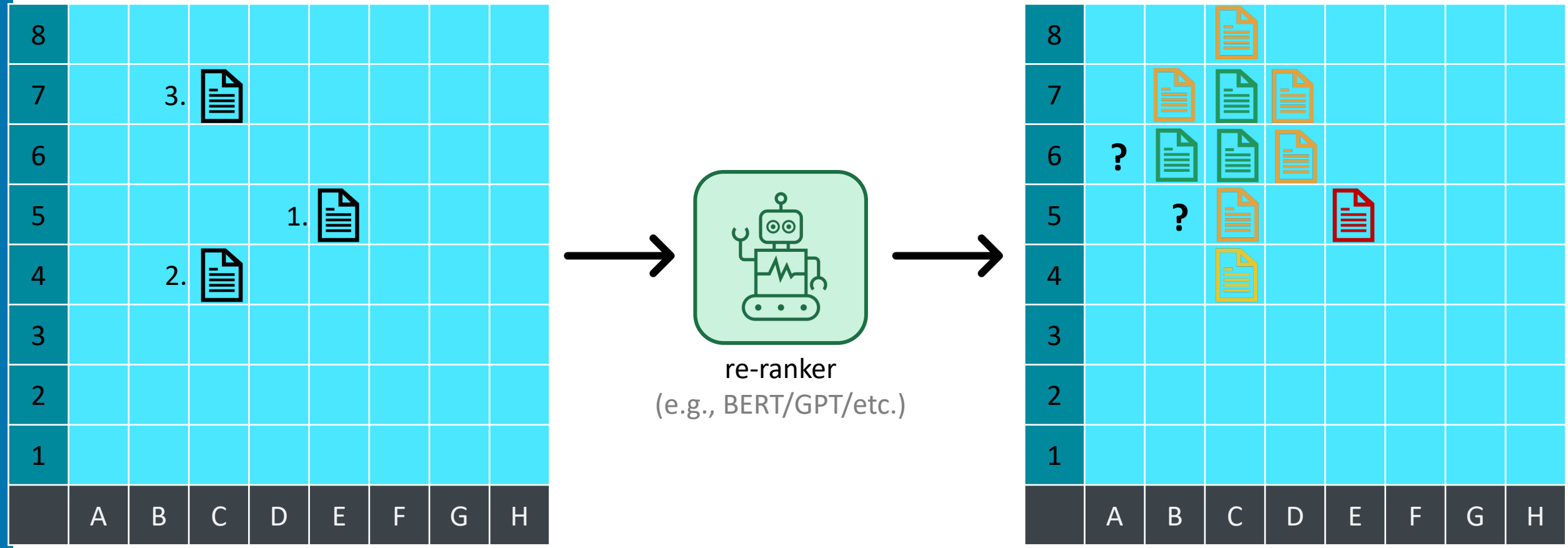


Adaptive Re-Ranking leverages the information gained from high-scoring documents to find ones missed by the retriever.



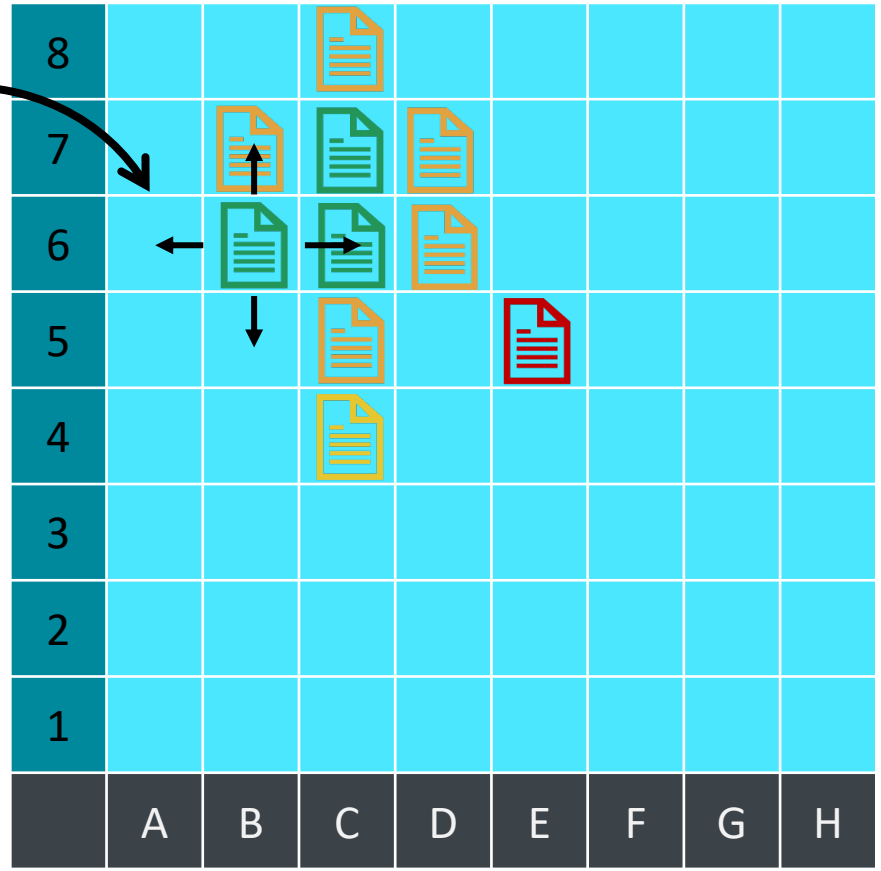
And so forth…

Adaptive Re-Ranking leverages the information gained from high-scoring documents to find ones missed by the retriever.

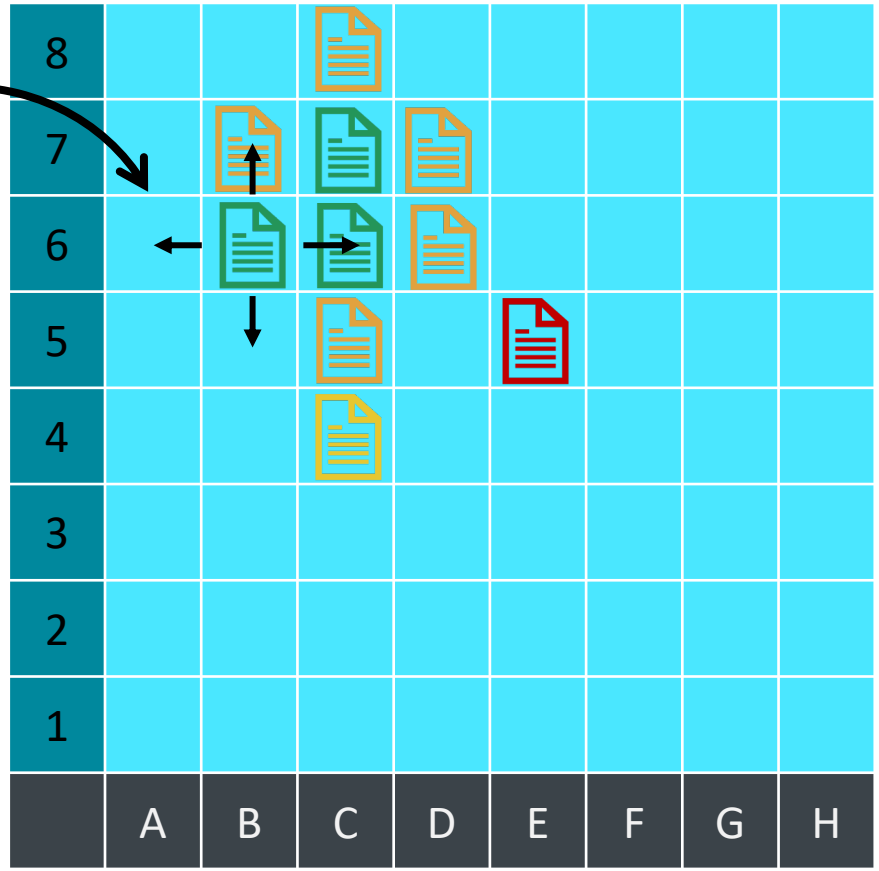


And so forth…

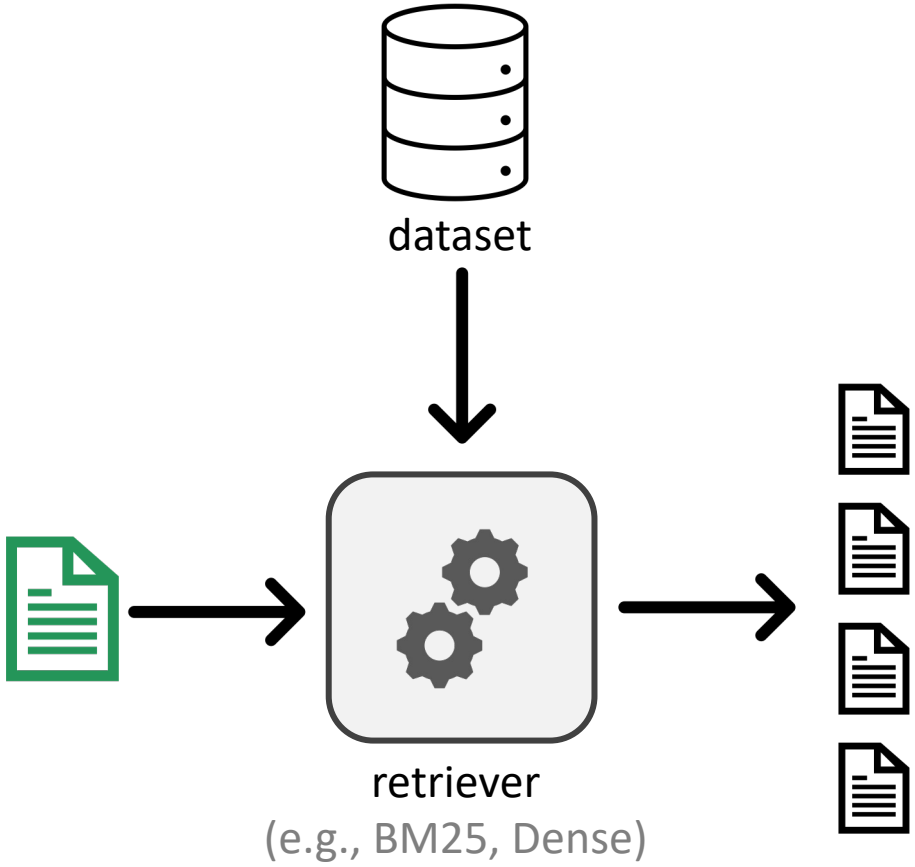
How to decide which documents to check?



How to decide which documents to check?



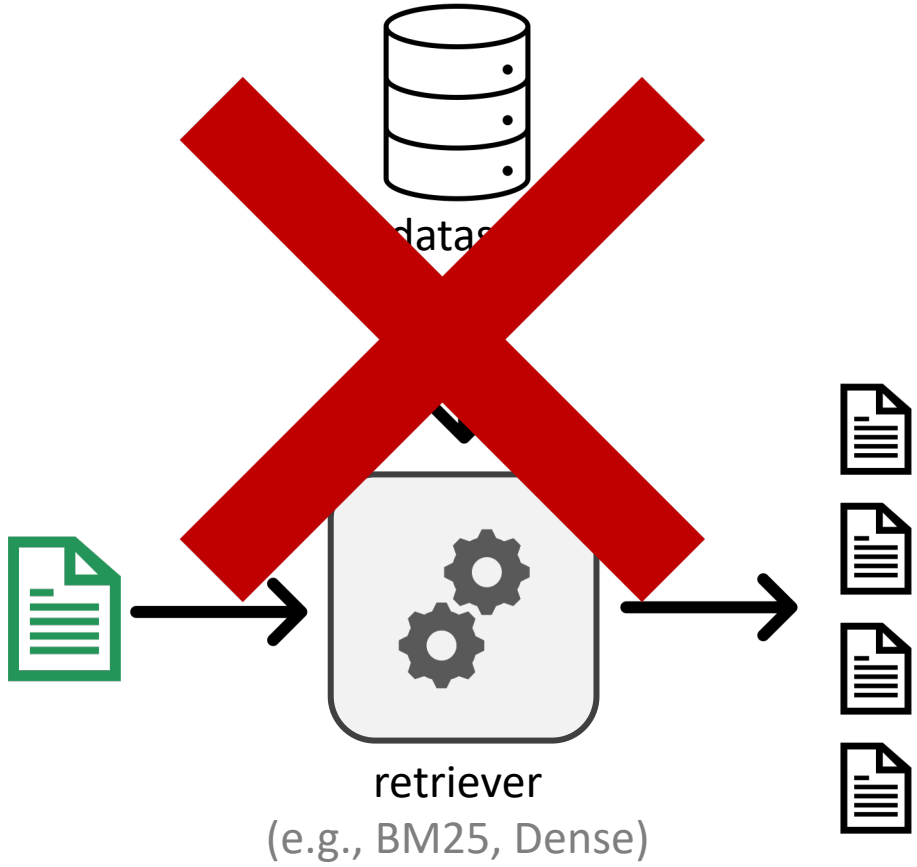
We could issue the document as a query to the engine and take the top *k* results.



Really slow!

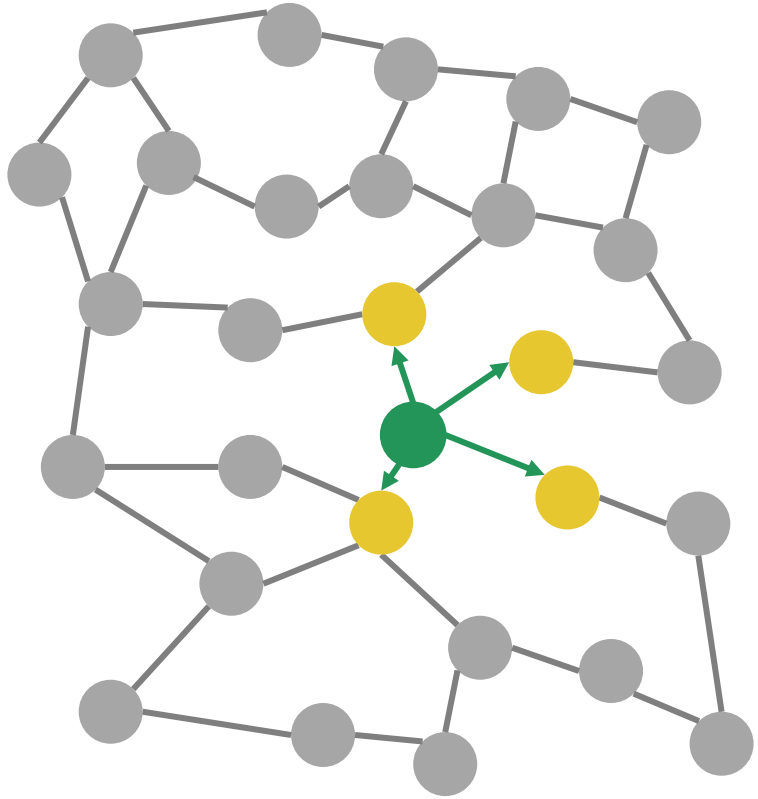
Right idea, bad execution.

We could issue the document as a query to the engine and take the top *k* results.



Better: Use the KNN graph we already have for HNSW search.

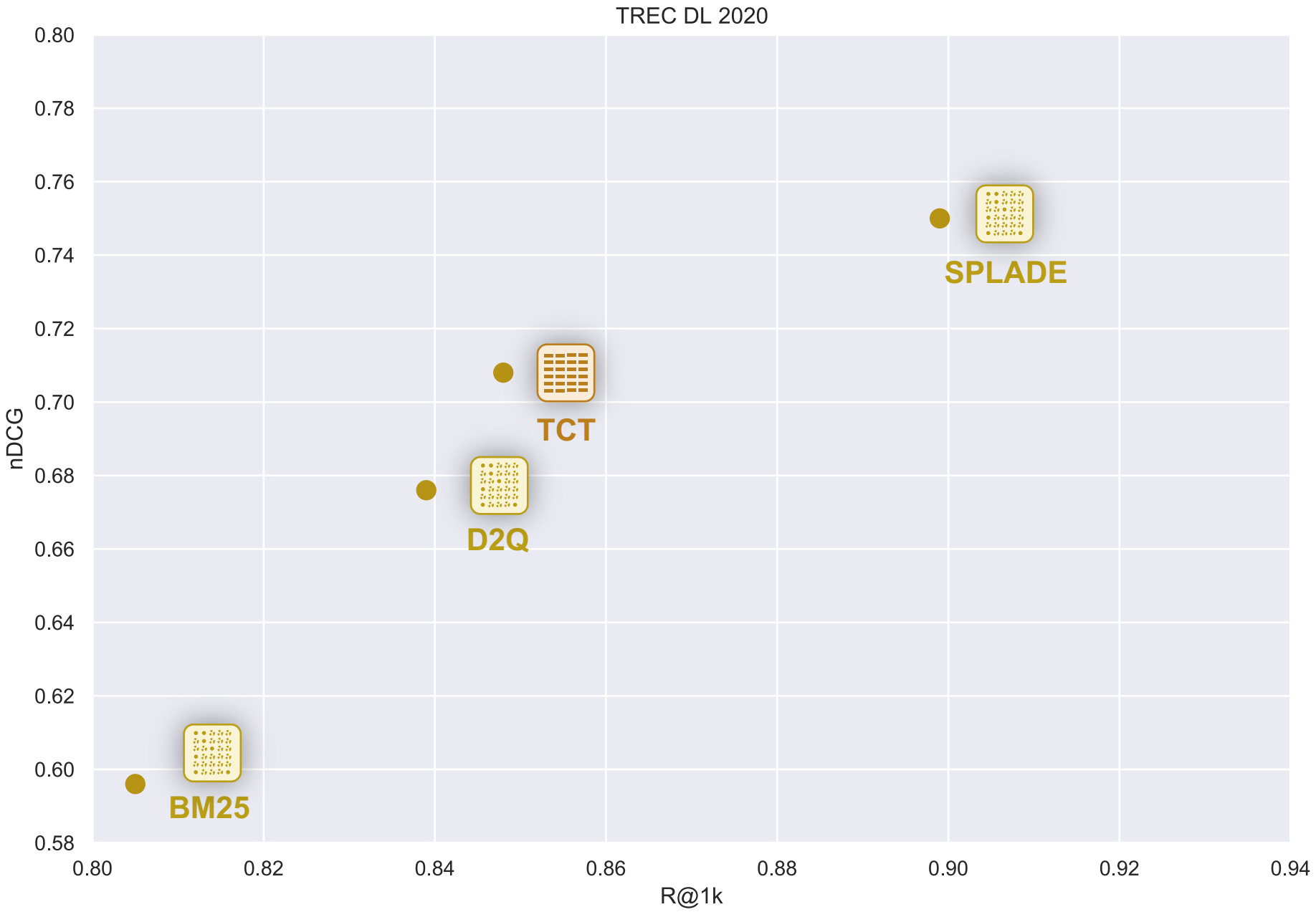
- Establishes proximity
- Fast lookups
- Constructed offline

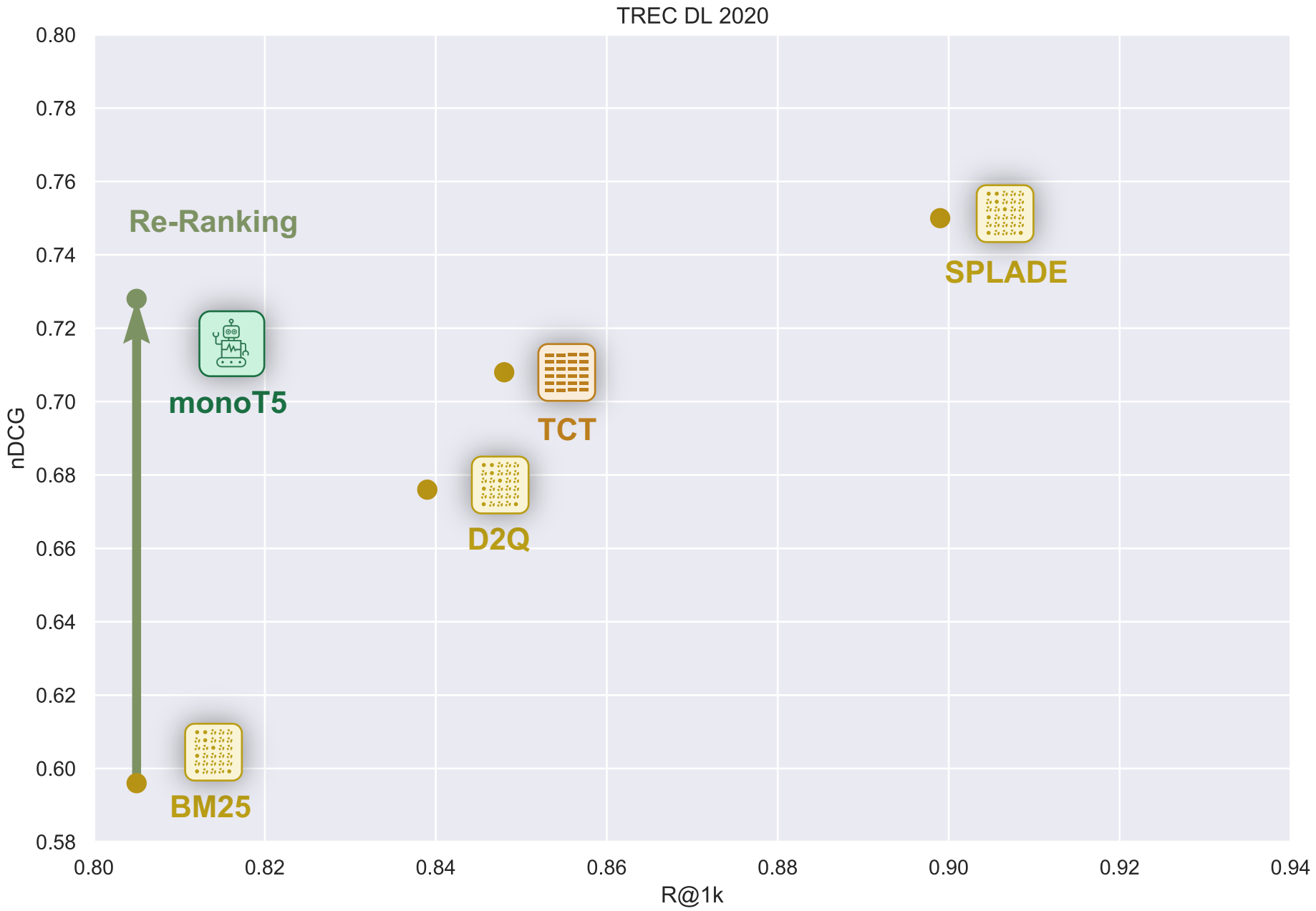


Alright, so how well does this *adaptive* re-ranking strategy work?

A few technical bits…

- We fix the re-ranking “budget” (number of docs to score) across all pipelines.
- In adaptive setting, we take half from first-stage ranker and half from graph.
- Measure nDCG (overall ranking quality) and Recall (% of relevant docs retrieved).
- Test on a variety of re-ranking pipelines.


TREC DL 2020
nDCG
R@1k
0.80
0.78
0.76
0.74
0.72
0.70
0.68
0.66
0.64
0.62
0.60
0.58
0.80
0.82
0.84
0.86
0.88
0.90
0.92
0.94
SPLADE
TCT
D2Q
BM25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0.64
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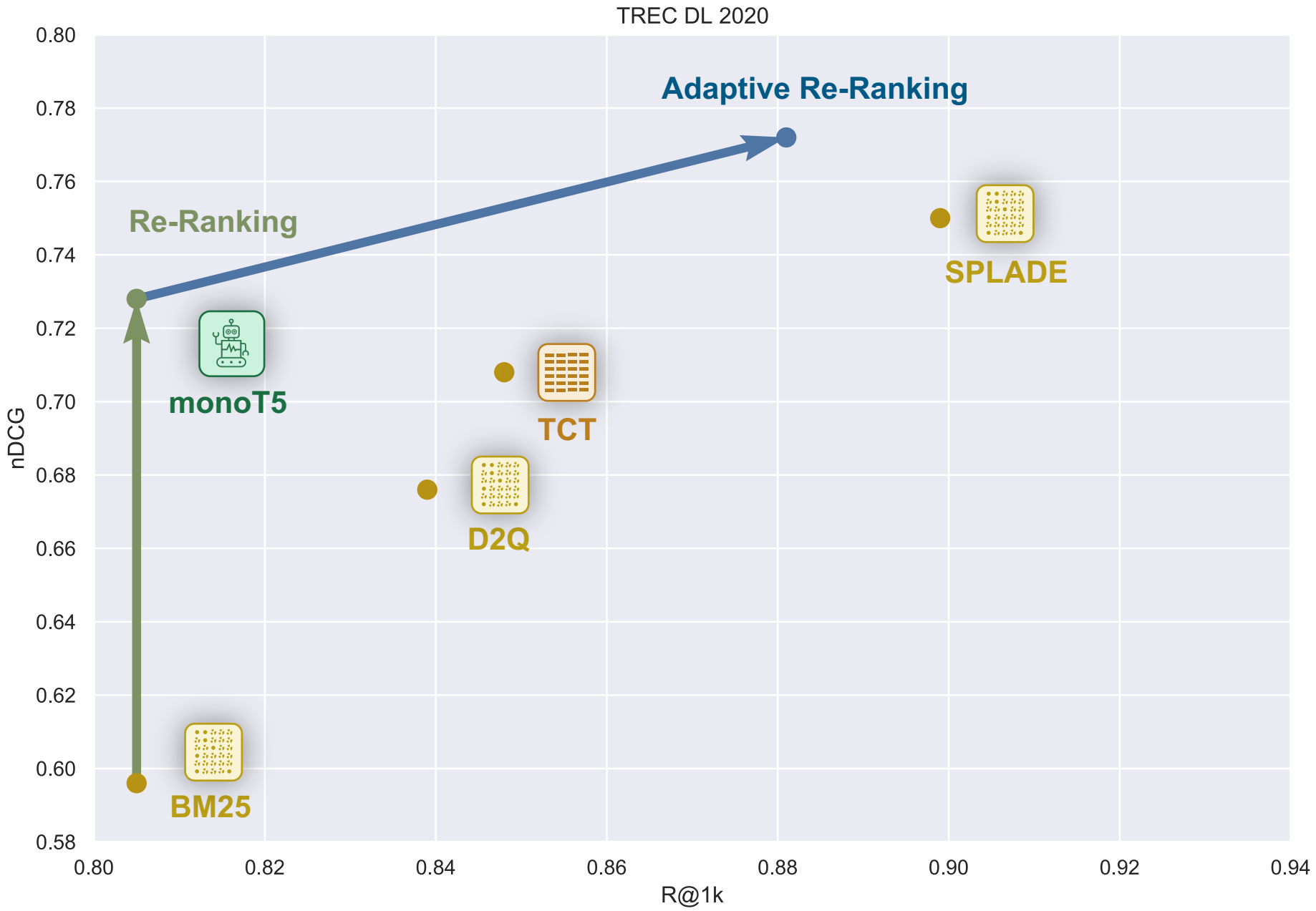
0.60
0.58
0.80
0.82
0.84
0.86
0.88
0.90
0.92
0.94
Re-Ranking
monoT5
BM25
TCT
D2Q
SPLADE


TREC DL 2020
Adaptive Re-Ranking
Re-Ranking
SPLADE
monoT5
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D2Q
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nDCG
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0.80
0.78
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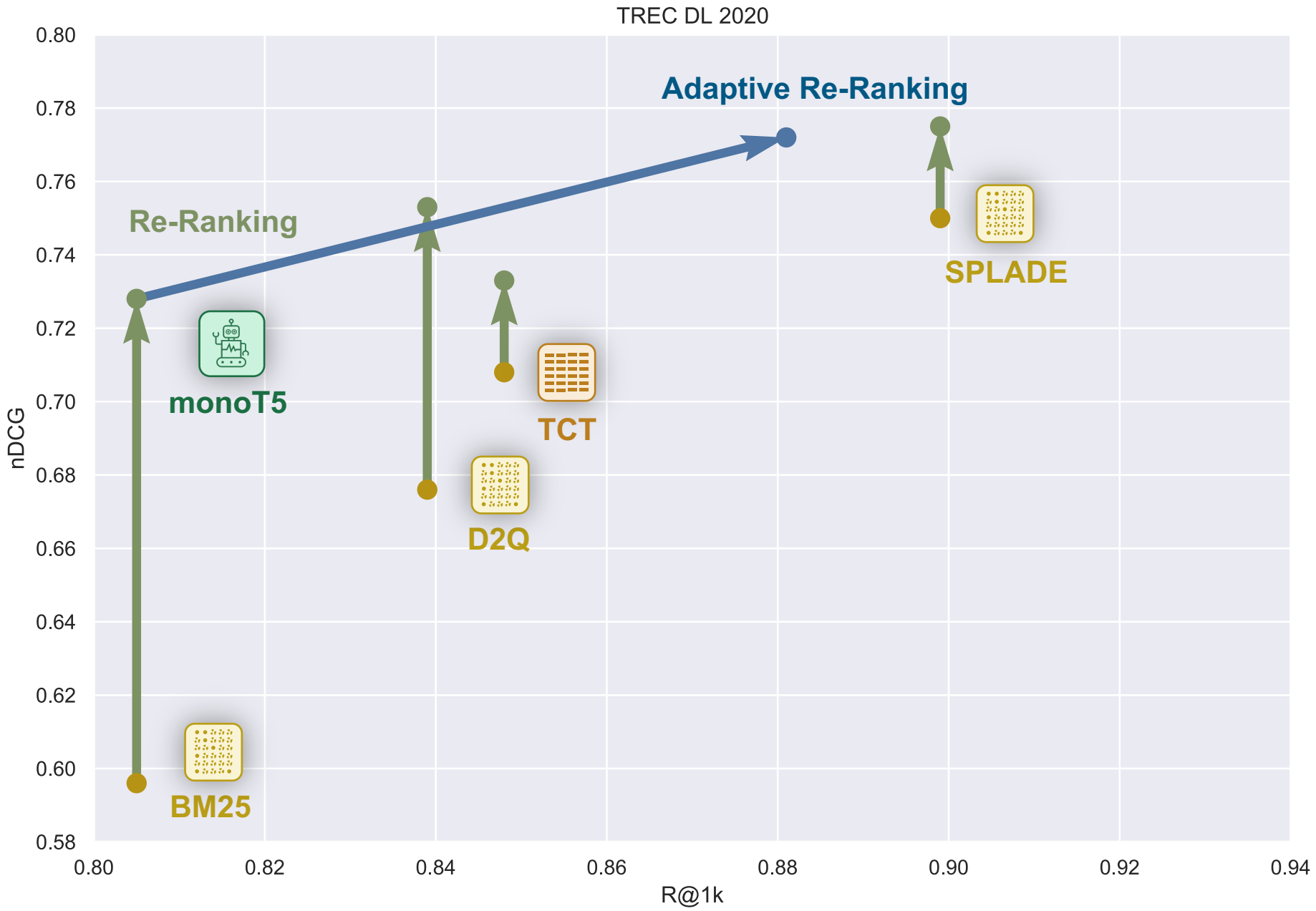
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Adaptive Re-Ranking
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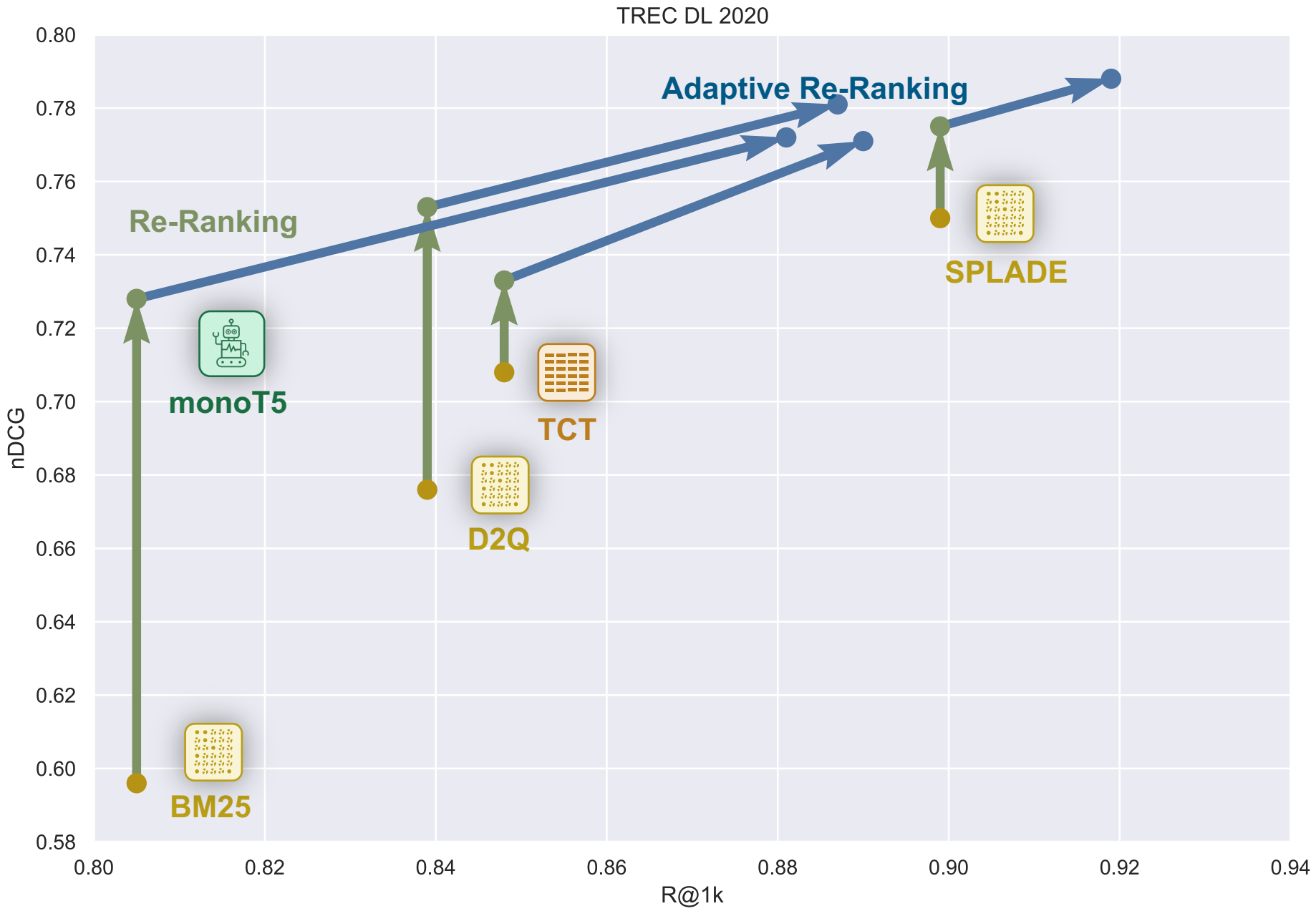

TREC DL 2020
nDCG
R@1k
0.80
0.78
0.76
0.74
0.72
0.70
0.68
0.66
0.64
0.62
0.60
0.58
0.80
0.82
0.84
0.86
0.88
0.90
0.92
0.94
Adaptive Re-Ranking
Re-Ranking
monoT5
TCT
SPLADE
D2Q
BM25

Sean MacAvaney
@macavaney

I ❤️ cross-encoders! Awesome to see another one from Cohere

A quick test showing it turbocharged when using Graph-based Adaptive Reranking :)

```
dataset = pt.get_dataset('irds:msmarco-passage/trec-dl-2019/judged')

pt.Experiment(
  [
    bm25,
    bm25 >> cohere_rerank,
    bm25 >> GAR(cohere_rerank, graph, num_results=100),
  ],
  dataset.get_topics(),
  dataset.get_qrels(),
  [nDCG@10, nDCG, R(rel=2)@100]
)

#                 name  nDCG@10   nDCG  R(rel=2)@100
#                 BM25    0.499  0.459         0.497
#       BM25 >> Rerank    0.708  0.523         0.497
#  BM25 >> GAR(Rerank)    0.753  0.604         0.609
```

ALT

In summary

Nearest neighbor graph exploration helps re-rankers

Focusing on the neighbors of the top scored documents helps prioritize the documents that are most likely to be relevant

Other findings

- Even works when no relevant documents returned by the first stage
- Ineffective when there are lots of duplicate documents (lesson learned from TREC DL 2022)
- Robust to various measures of document similarity (semantic or lexical)
- Room to improve by finding smarter ways to prioritize (but might be costly)

Conference Paper:

MacAvaney, Tonellotto, Macdonald. Adaptive Re-Ranking with a Corpus Graph. CIKM 2022.

Retrievers

Adaptive Re-Ranking involved **two** strategies:

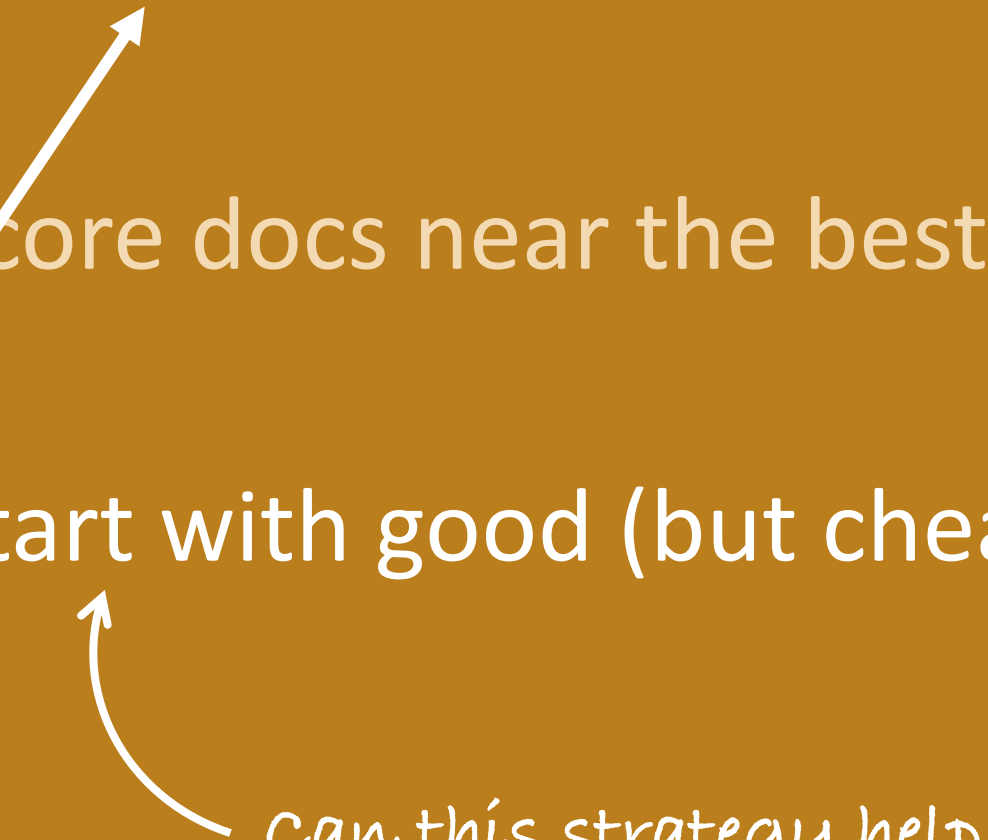
1. Score docs near the best ones found so far.

Adaptive Re-Ranking involved **two** strategies:

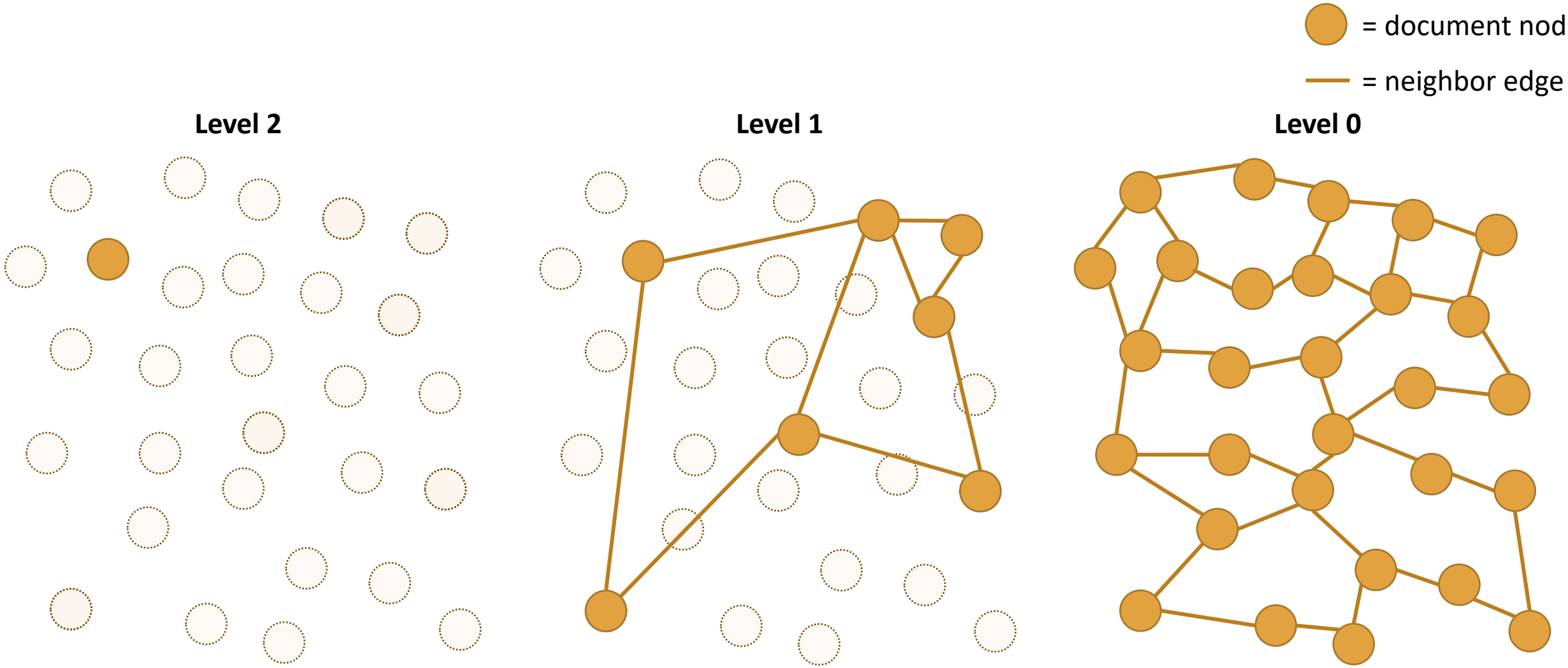
1 Score docs near the best ones found so far.

Adaptive **Re-Ranking** involved **two** strategies:

1. Score docs near the best ones found so far.
2. Start with good (but cheap) guesses.



Can this strategy help dense retrievers?



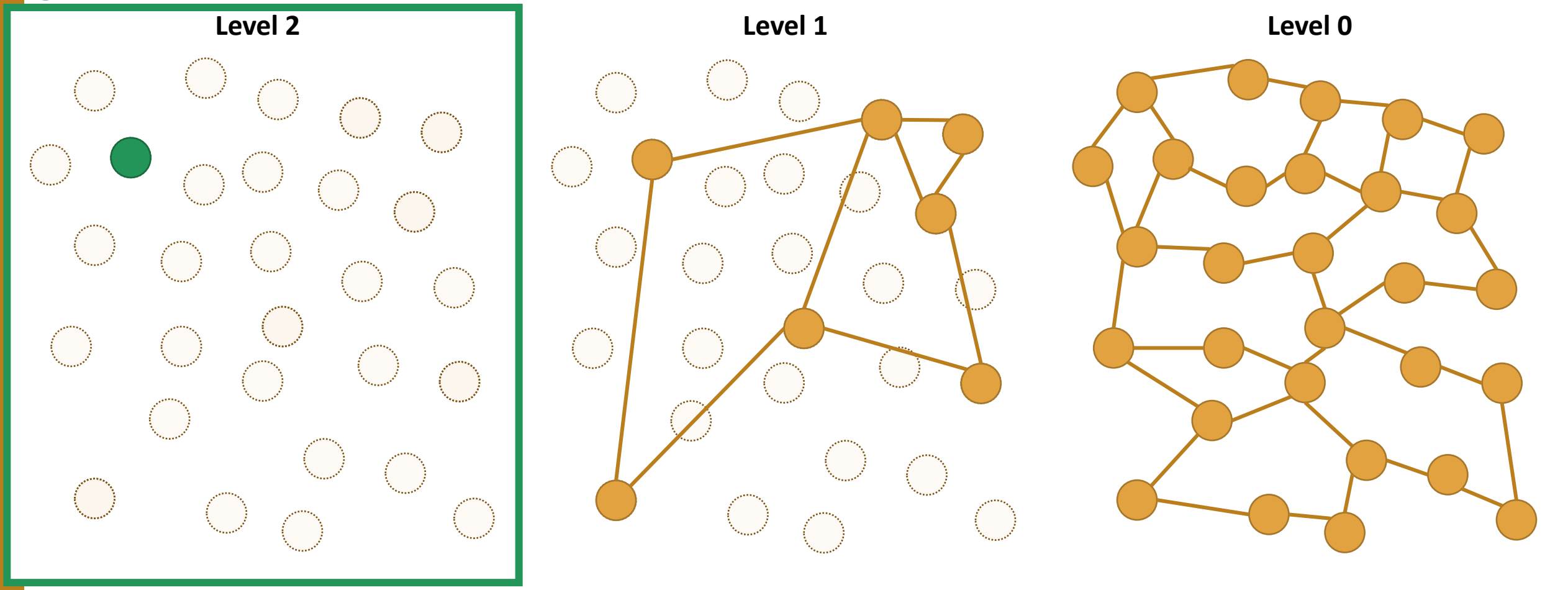
HNSW: Score random nodes to narrow in on the best ones.

= top document

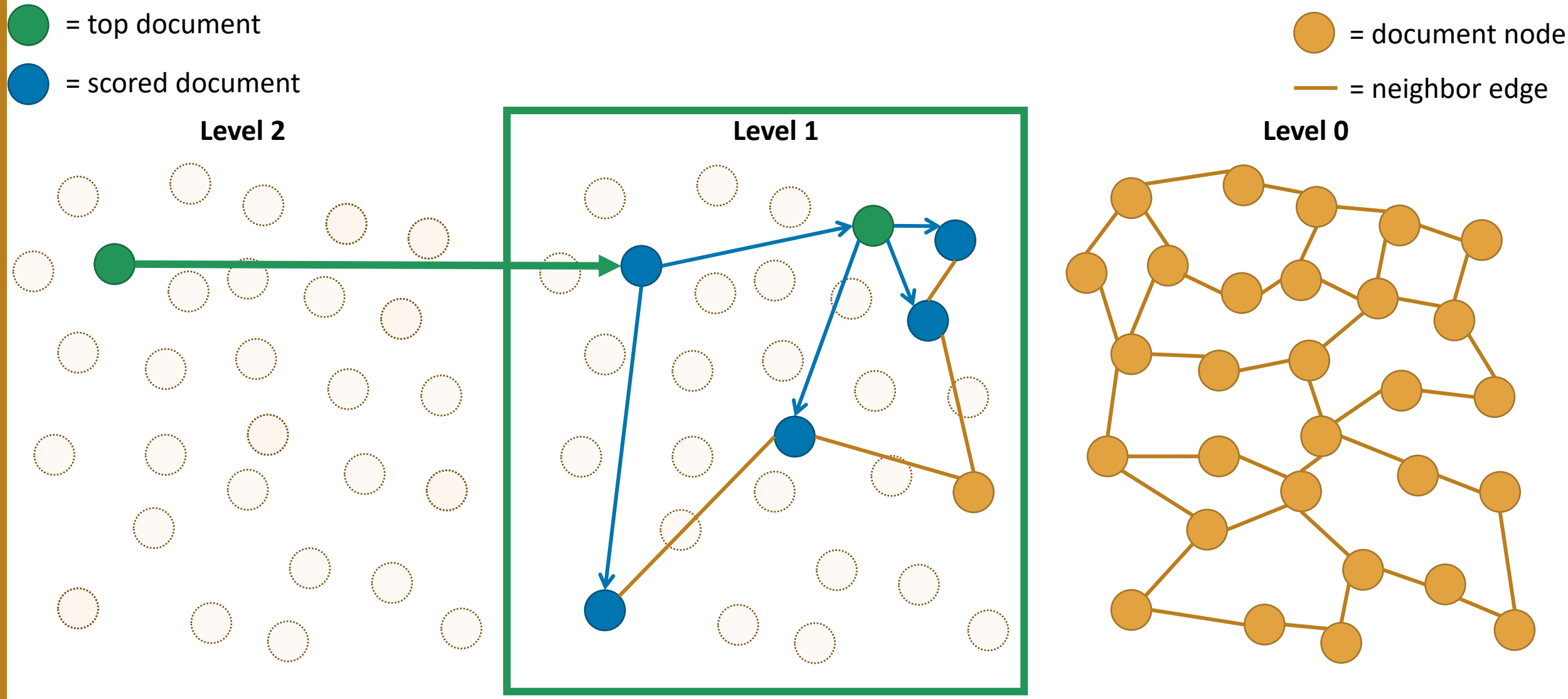
= scored document

= document node

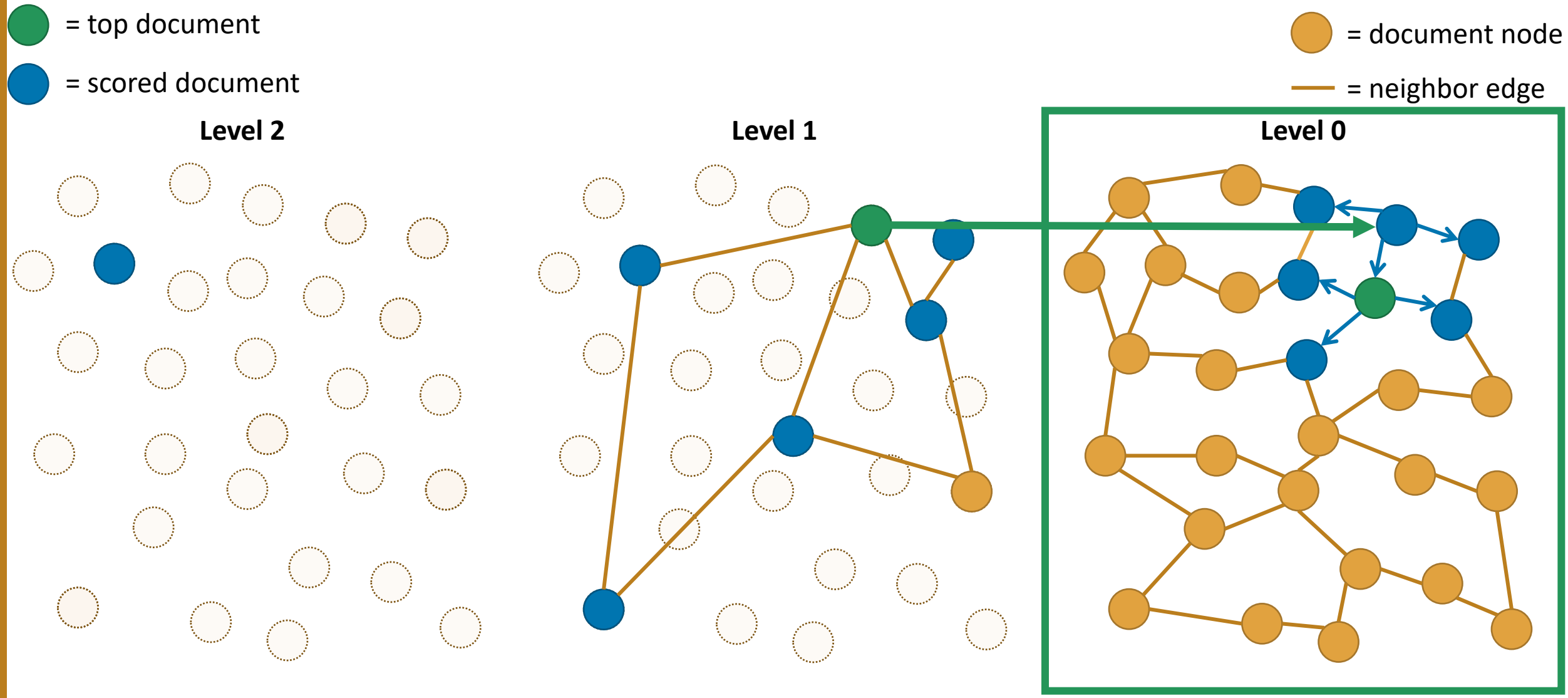
= neighbor edge



HNSW: Score random nodes to narrow in on the best ones.



HNSW: Score random nodes to narrow in on the best ones.



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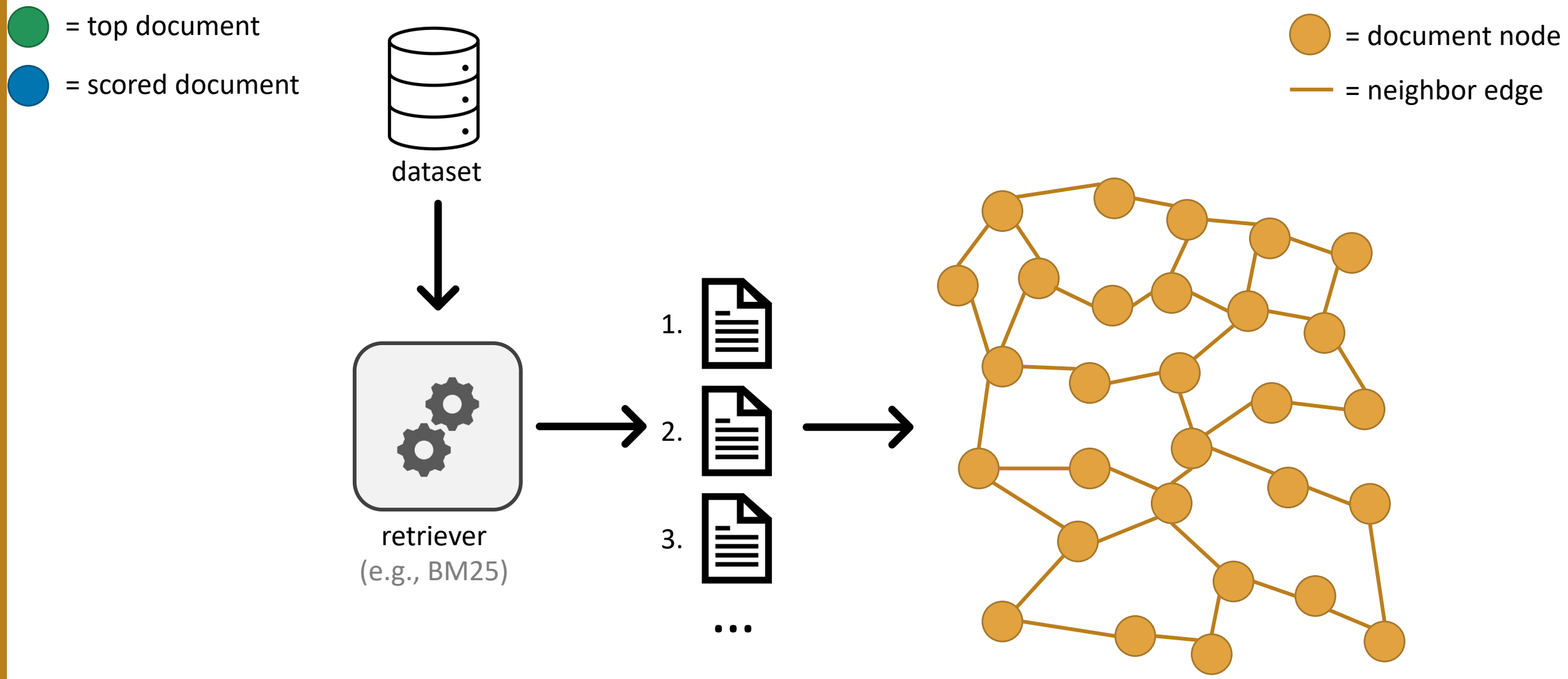
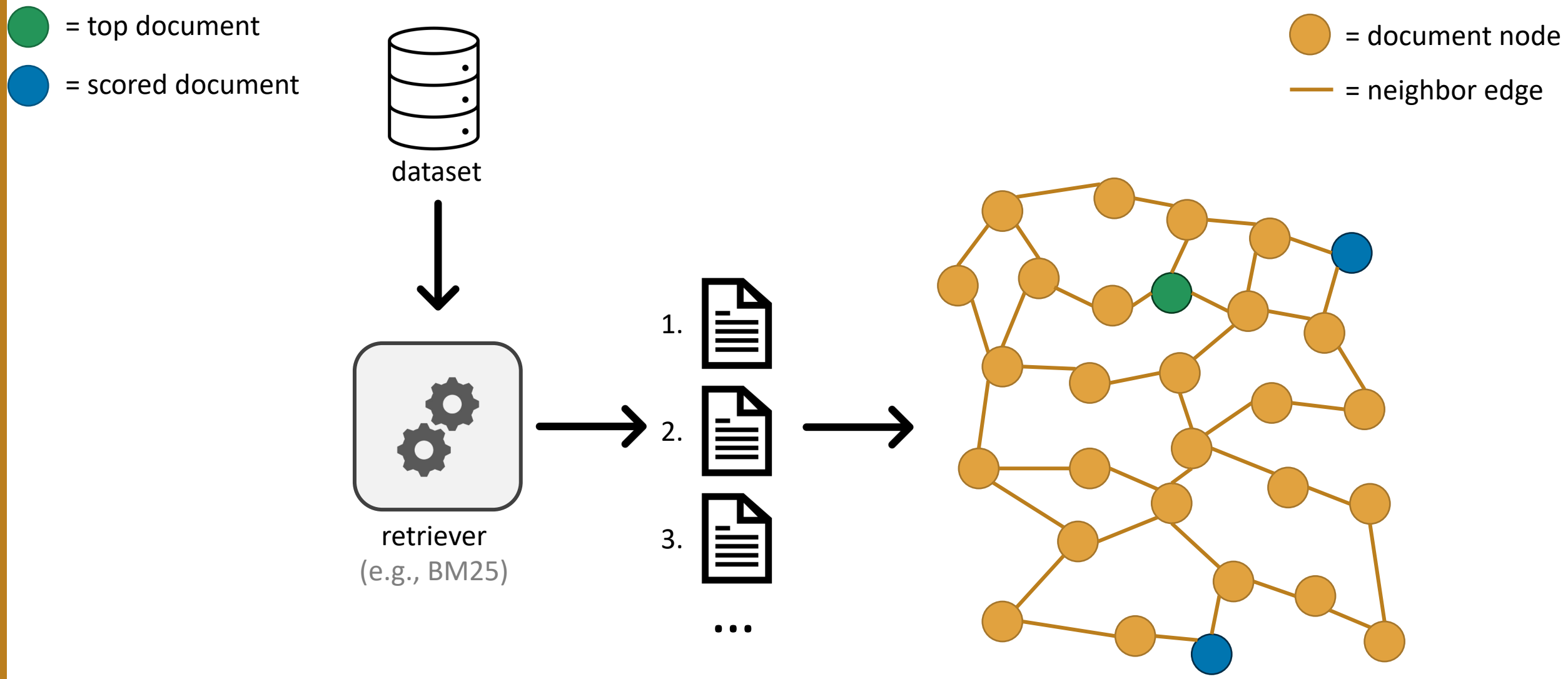


LADR (Lexically-Accelerated Dense Retrieval):
Use lexical search to seed dense retrieval.



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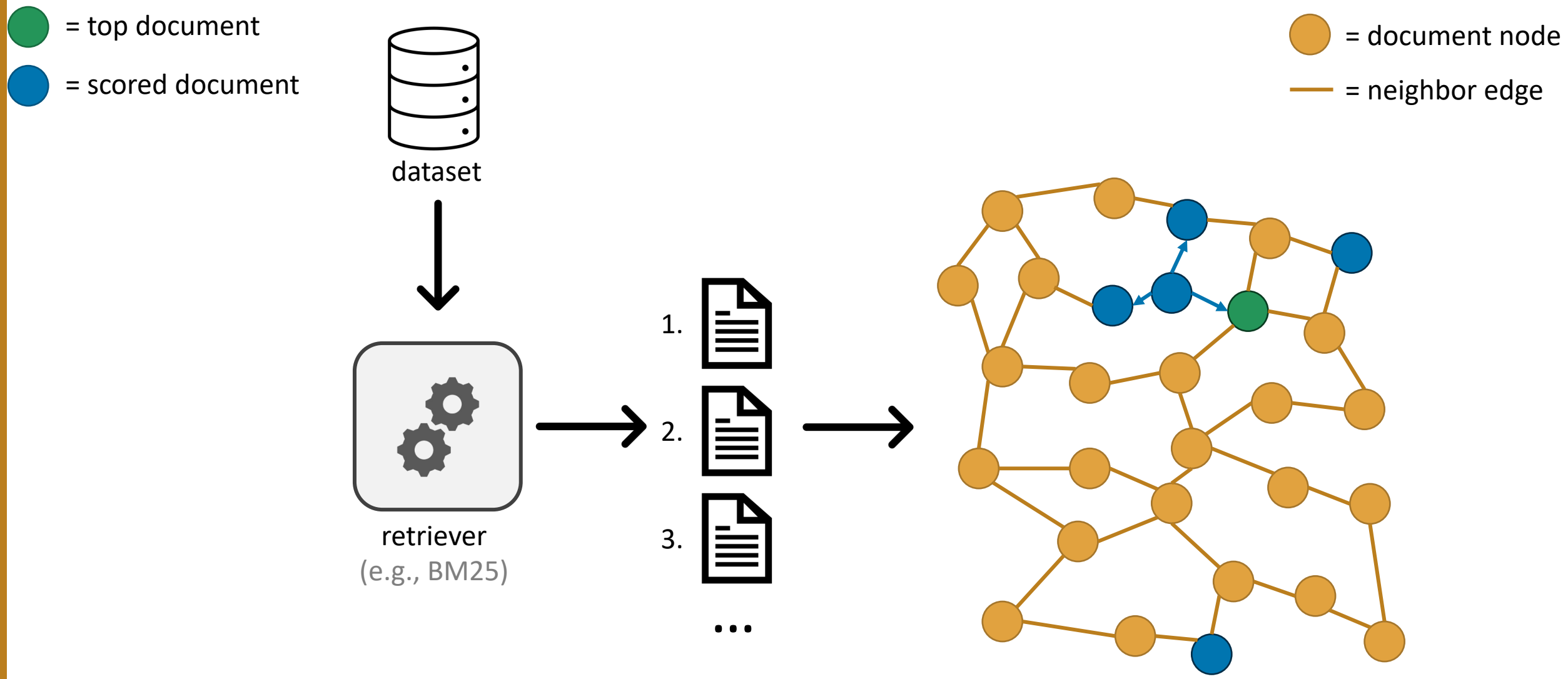

LADR (Lexically-Accelerated Dense Retrieval):
Use lexical search to seed dense retrieval.

= top document

= scored document

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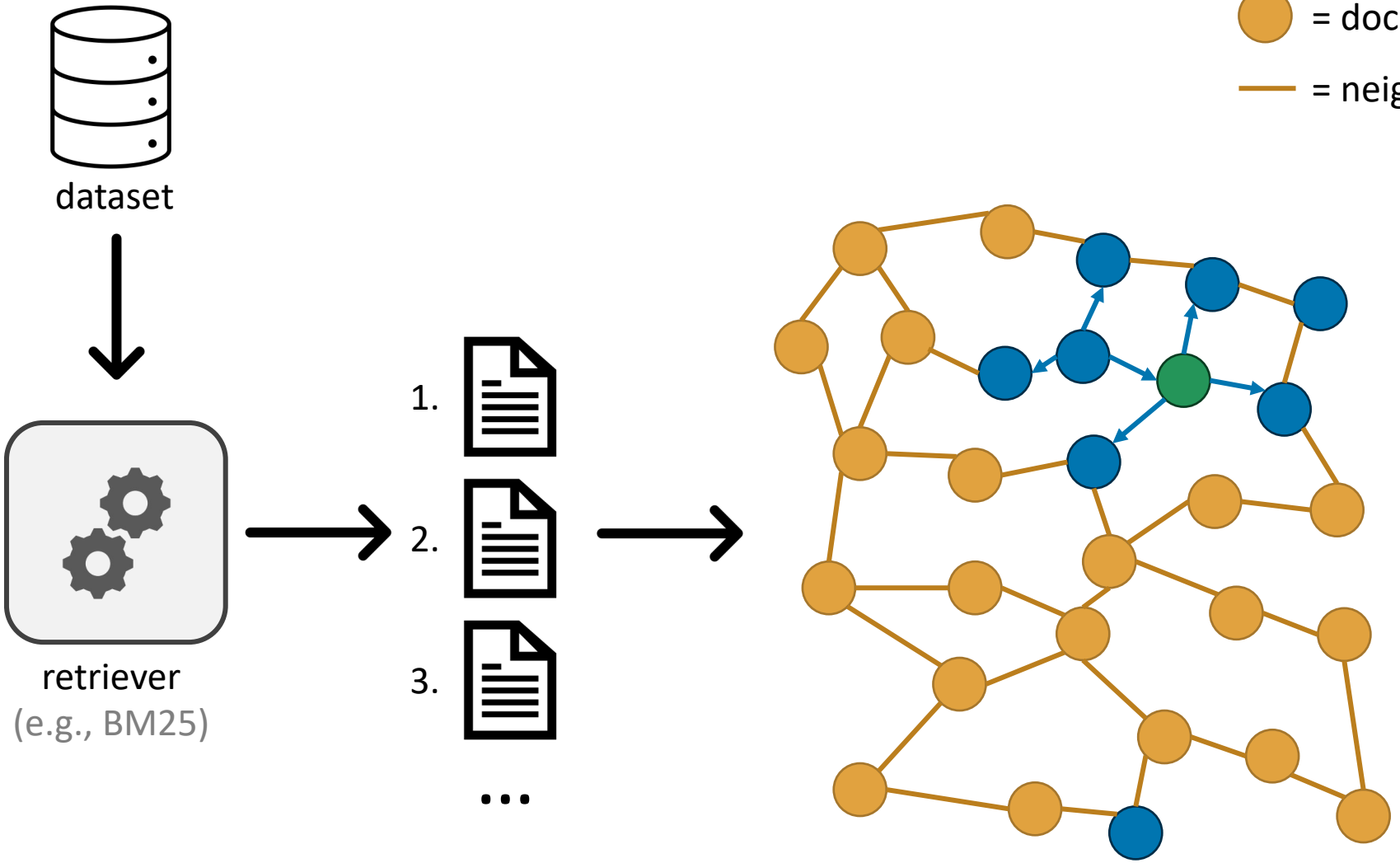
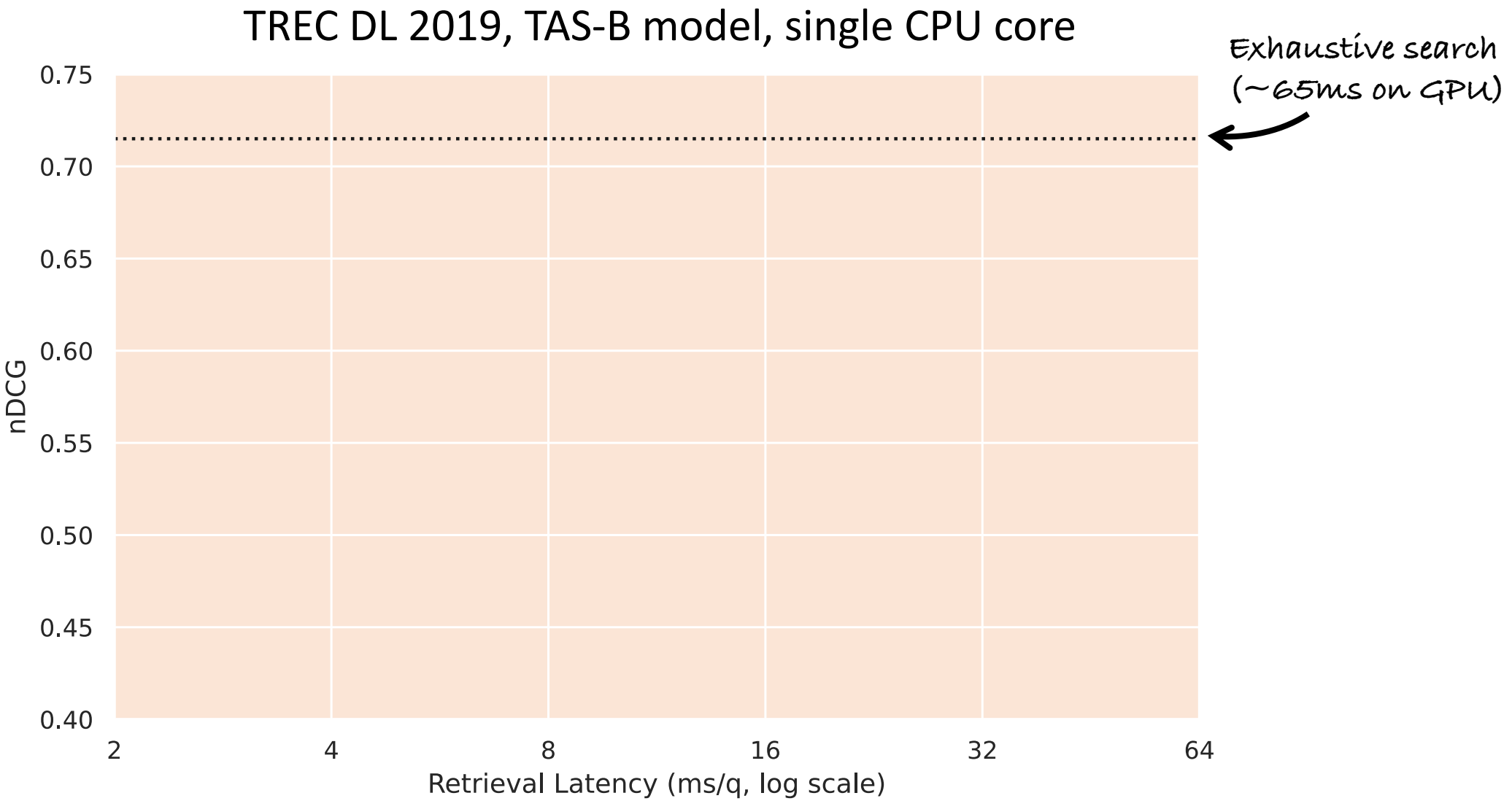
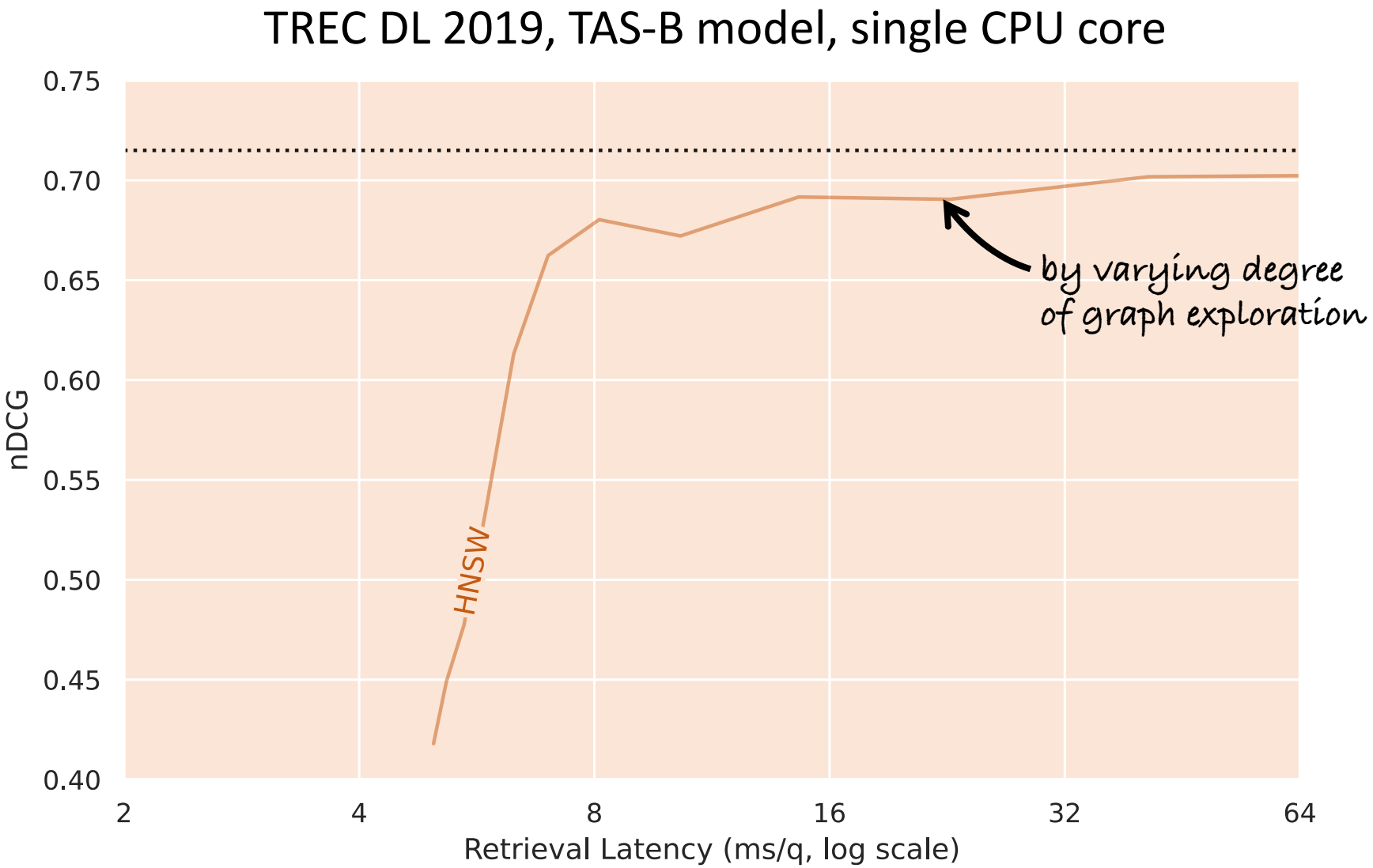
= neighbor edge



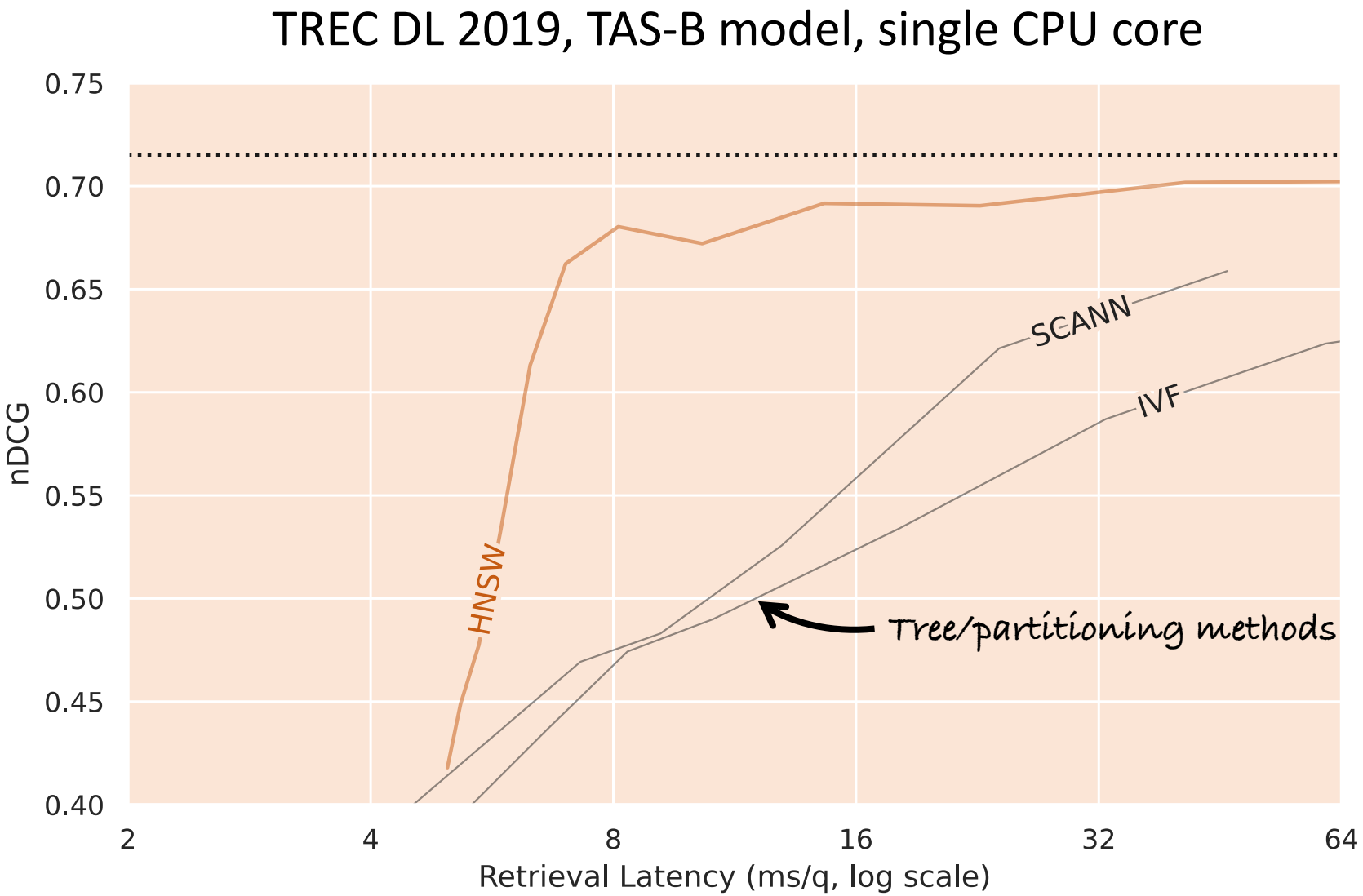
Iterate…

How well does it work?

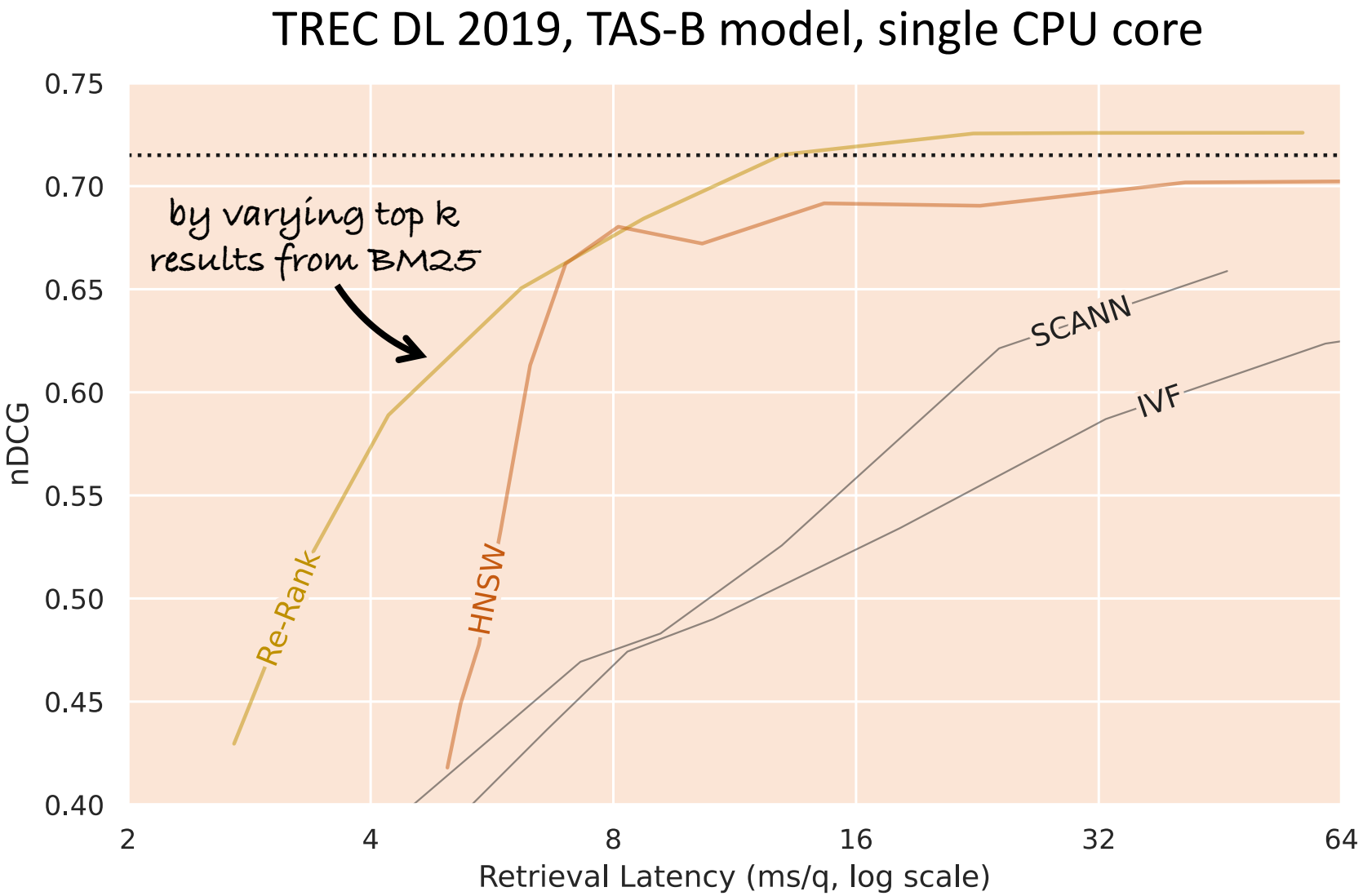

TREC DL 2019, TAS-B model, single CPU core
Exhaustive search
(~65ms on GPU)
0.75
0.70
0.65
0.60
0.55
0.50
0.45
0.40
nDCG
2
4
8
16
32
64
Retrieval Latency (ms/q, log scale)

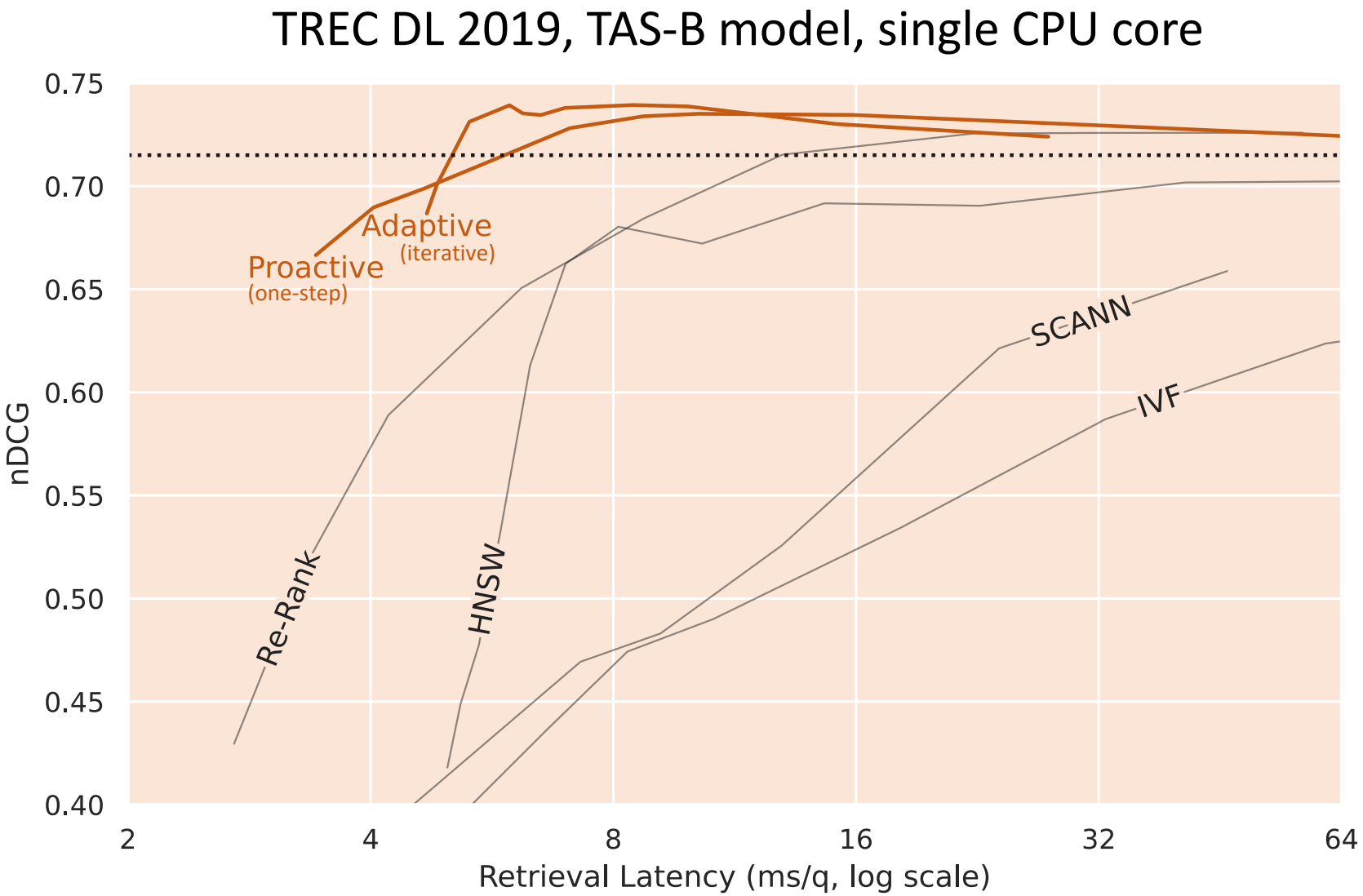


* FAISS implementation



* FAISS implementation


TREC DL 2019, TAS-B model, single CPU core
0.75
0.70
0.65
0.60
0.55
0.50
0.45
0.40
nDCG
by varying top k
results from BM25
Re-Rank
HNSW
SCANN
IVF
2
4
8
16
32
64
Retrieval Latency (ms/q, log scale)


TREC DL 2019, TAS-B model, single CPU core
0.75
0.70
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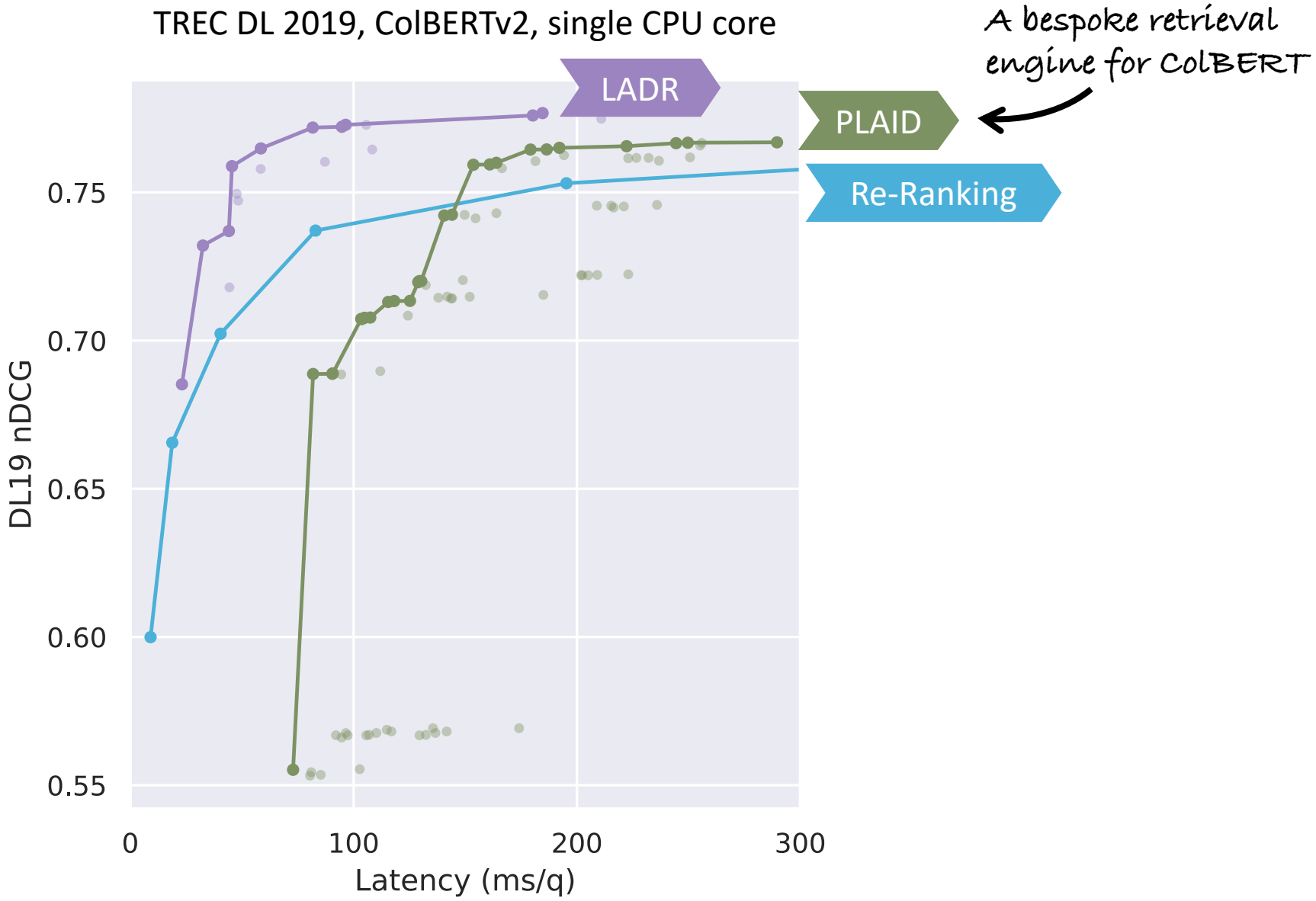
0.60
0.55
0.50
0.45
0.40
nDCG
Proactive
(one-step)
Adaptive
(iterative)
Re-Rank
HNSW
SCANN
IVF
2
4
8
16
32
64
Retrieval Latency (ms/q, log scale)


TREC DL 2019, ColBERTv2, single CPU core
A bespoke retrieval engine for ColBERT
LADR
PLAID
Re-Ranking
DL19 nDCG
0.75
0.70
0.65
0.60
0.55
0
100
200
300
Latency (ms/q)

In summary

Adaptive Re-Ranking improves **retrievers** too!

Both single-vector and multi-vector dense retrieval.

Other findings

- Clear trade-offs between the model parameters and efficiency/effectiveness
- Works across a variety of dense retrieval models and standard benchmarks
- Works with approximate NN graph, and even graphs constructed from other models

Conference Papers:

Kulkarni, MacAvaney, Goharian, Frieder. Lexically-Accelerated Dense Retrieval. SIGIR 2023.
MacAvaney, Tonellotto. A Reproducibility Study of PLAID. SIGIR 2024. [Best Paper Runner-Up]

Open Source!

Adaptive Re-Ranking and LADR in PyTerrier

```python
import pyterrier as pt
from pyterrier_t5 import MonoT5
from pyterrier_pisa import PisaIndex
from pyterrier_adaptive import GAR, CorpusGraph

bm25 = PisaIndex('my_index.pisa').bm25()
reranker = MonoT5()
graph = CorpusGraph.load('my_index.graph')

pipeline = bm25 >> GAR(reranker, graph)
```

```python
from pyterrier_dr import FlexIndex
from pyterrier_pisa import PisaIndex

sparse = PisaIndex('my_index.pisa').bm25()
dense = PisaIndex('my_index.flex').ladr()

ladr = sparse.bm25() >> dense.ladr()
```

https://github.com/terrierteam/pyterrier_dr
https://github.com/terrierteam/pyterrier_adaptive

Adaptive Re-Ranking using the `rerankers` package

```python
from rerankers import Reranker

reranker = Reranker(...)

adaptive_reranker = GAR(reranker.as_pyterrier_transformer(), graph)
```

Currently on my fork here: https://github.com/seanmacavaney/rerankers, pull request coming soon :)

We’re also working on adding LADR to Lucene:

Seeding HNSW Search #13634

Open **seanmacavaney** opened this issue on Aug 6 · 2 comments

seanmacavaney commented on Aug 6

Description

In some vector search cases, users may already know some documents that are likely related to a query. Let's support seeding HNSW's scoring stage with these documents, rather than using HNSW's hierarchical stage.

An example use case is hybrid search, where both a traditional and vector search are performed. The top results from the traditional search are likely reasonable seeds for the vector search. Even when not performing hybrid search, traditional matching can often be faster than traversing the hierarchy, which can be used to speed up the vector search process (up to 2x faster for the same effectiveness), as was demonstrated in this article (full disclosure: I'm an author of the article).

This enhancement proposes adding a `seed` query, alongside the existing `filter` query, to the KNN query classes. The results of this query will be fed into `HnswGraphSearcher`, and ultimately replace the graph entry points here. If the seed query fails (e.g., keywords do not match any documents), the approach will fall back onto the existing hierarchical search process.

Pull request to follow.

🎉 1

`AbstractKnnVectorQuery.seed`

Thanks to my collaborators!

Craig Macdonald
University of Glasgow

Nicola Tonellotto
University of Pisa

Hrishikesh Kulkarni
Georgetown University

Nazli Goharian
Georgetown University

Ophir Frieder
Georgetown University

RE-THINKING RE-RANKING

Sean MacAvaney
University of Glasgow

Presented at:
Haystack EU 2024

Terrier

University of Glasgow

extra slides

Search Strategy	Effectiveness	Query Efficiency	Index Efficiency	Storage Costs
Sparse	Low	High	High	Low
Dense	High	Low	Low	High

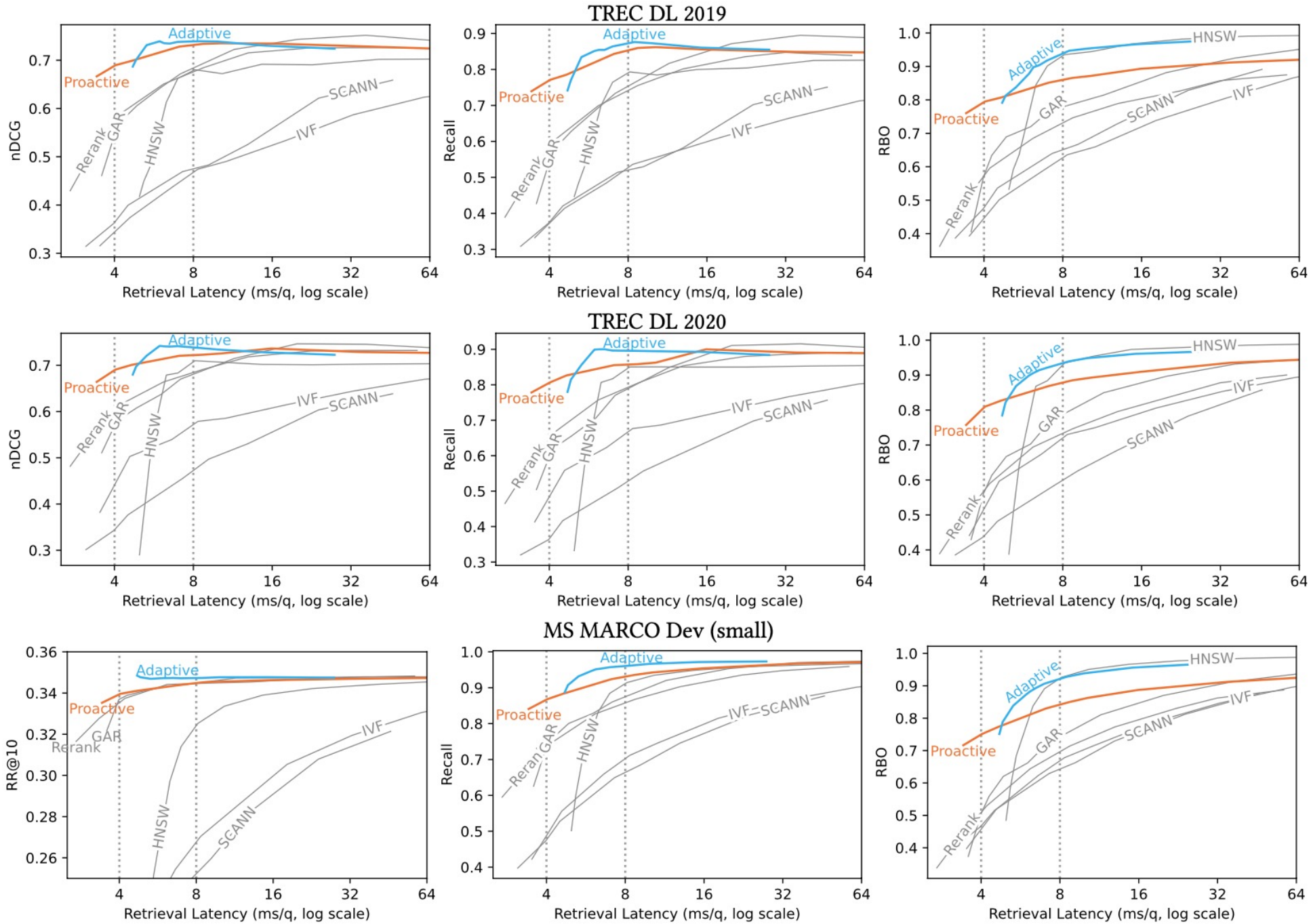
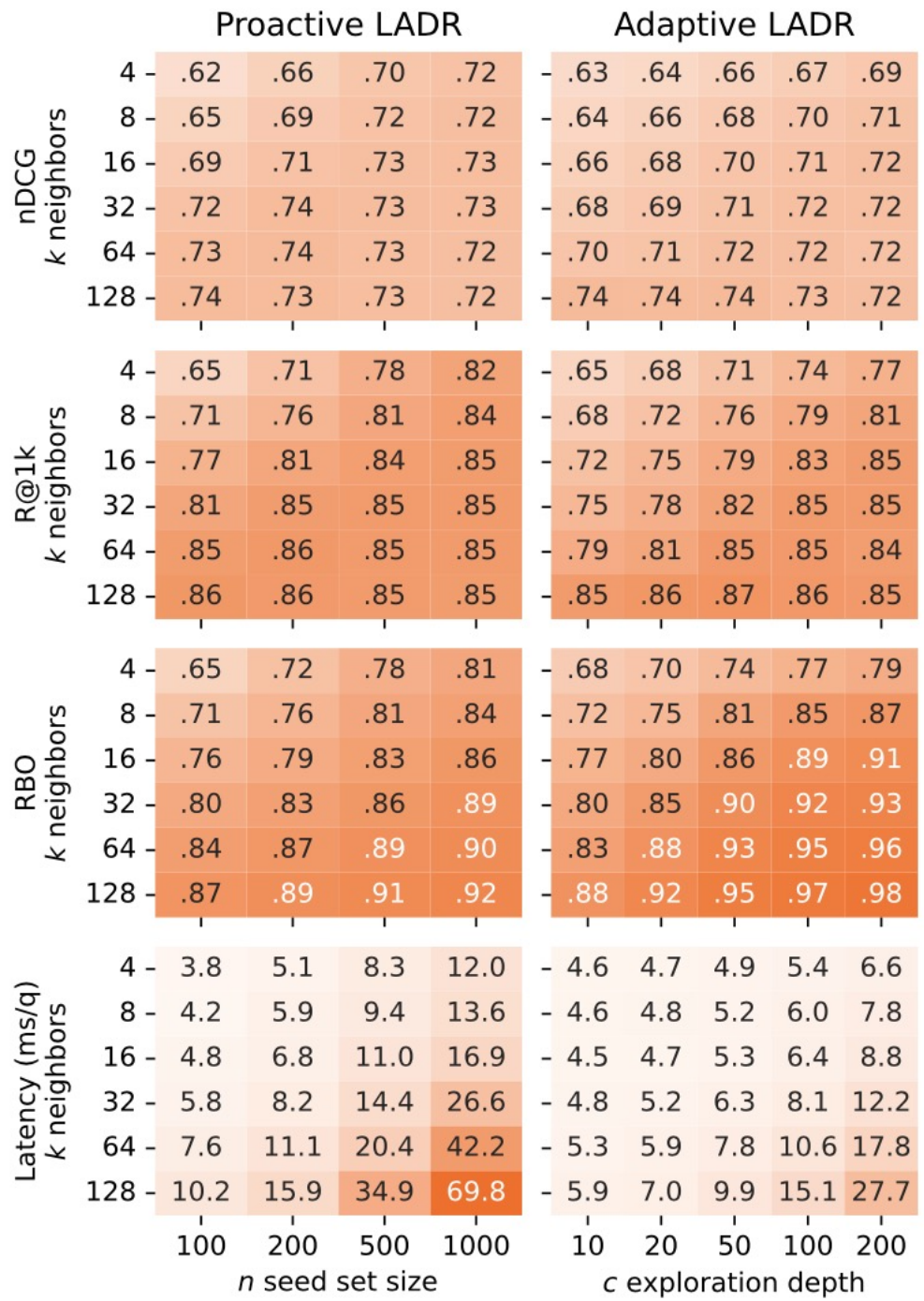


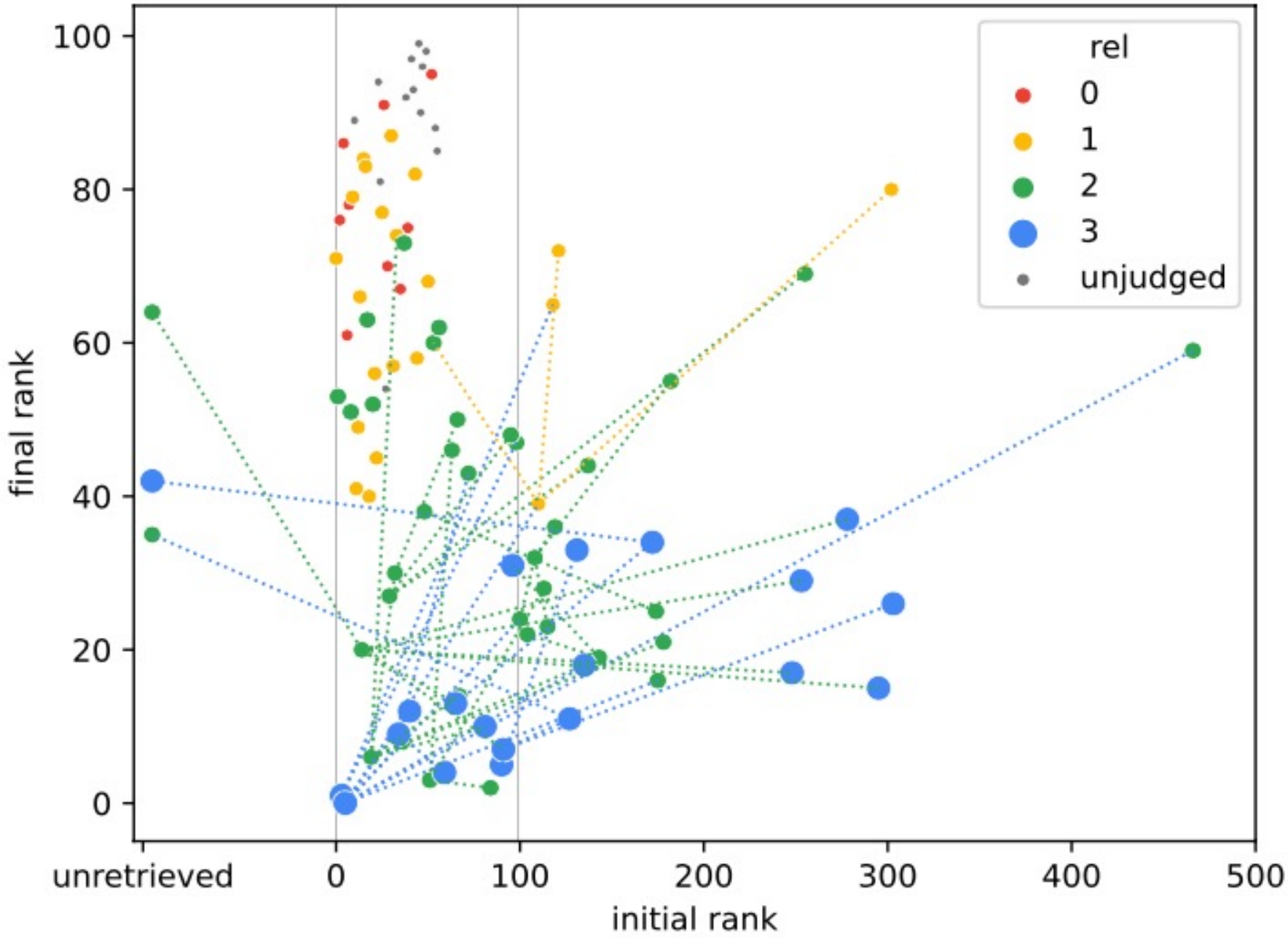
Figure 3: Performance of LADR over TAS-B and baselines across various operational points.

Method	DL19 ~4ms		DL19 ~8ms		DL20 ~4ms		DL20 ~8ms		Dev (sm) ~4ms		Dev (sm) ~8ms	
	nDCG	R@1k	nDCG	R@1k	nDCG	R@1k	nDCG	R@1k	RR@10	R@1k	RR@10	R@1k
TAS-B (Exh.)	0.715	0.842	0.715	0.842	0.713	0.875	0.713	0.875	0.347	0.978	0.347	0.978
IVF [I]	0.374	0.414	0.474	0.536	0.503	0.559	0.579	0.677	0.217	0.556	0.270	0.712
ScaNN [S]	0.475	0.519	0.537	0.598	0.476	0.527	0.553	0.641	0.254	0.669	0.292	0.774
HNSW [H]	-	-	0.614	0.707	-	-	0.699	0.836	-	-	0.310	0.872
GAR [G]	0.543	0.540	0.688	0.755	0.568	0.594	0.684	0.796	0.337	0.732	0.345	0.876
Re-Ranking [R]	0.589	0.605	0.684	0.755	0.615	0.667	0.691	0.805	0.337	0.748	0.345	0.868
Proactive LADR	$^{IS}_{GR}$**0.690**	$^{IS}_{GR}$**0.771**	$^{ISH}_{GR}$0.730	$^{ISH}_{GR}$0.850	$^{IS}_{GR}$**0.691**	$^{IS}_{GR}$**0.807**	$^{IS}_{GR}$0.722	$^{IS}_{GR}$0.857	^{IS}**0.340**	$^{IS}_{GR}$**0.868**	^{ISH}0.345	$^{ISH}_{GR}$0.932
Adaptive LADR	-	-	$^{ISH}_{GR}$**0.738**	$^{ISH}_{GR}$**0.872**	-	-	$^{ISH}_{GR}$**0.739**	$^{ISH}_{GR}$**0.900**	-	-	$^{ISH}_{GR}$**0.347**	$^{ISH}_{GR}$**0.960**
RetroMAE (Exh.)	0.699	0.806	0.699	0.806	0.701	0.839	0.701	0.839	0.375	0.981	0.375	0.981
IVF [I]	0.226	0.225	0.346	0.358	0.272	0.263	0.372	0.375	0.157	0.381	0.221	0.541
ScaNN [S]	0.468	0.502	0.525	0.588	0.486	0.509	0.555	0.606	0.275	0.665	0.312	0.769
HNSW [H]	-	-	0.630	0.720	-	-	0.673	0.798	-	-	0.338	0.874
GAR [G]	0.559	0.553	0.696	0.763	0.578	0.604	0.692	0.789	**0.357**	0.750	0.368	0.890
Re-Ranking [R]	0.594	0.605	0.685	0.755	0.622	0.667	0.696	0.805	0.355	0.748	0.369	0.868
Proactive LADR	$^{IS}_{GR}$**0.691**	$^{IS}_{GR}$**0.765**	$^{ISH}_{GR}$0.733	$^{ISH}_{GR}$0.844	$^{IS}_{GR}$**0.702**	$^{IS}_{GR}$**0.811**	$^{ISH}_{G}$0.723	$^{IS}_{G}$0.846	^{IS}0.356	$^{IS}_{GR}$**0.864**	^{ISH}0.368	$^{ISH}_{GR}$0.938
Adaptive LADR	-	-	$^{ISH}_{R}$**0.740**	$^{ISH}_{GR}$**0.866**	-	-	$^{ISH}_{G}$**0.731**	$^{ISH}_{GR}$**0.879**	-	-	$^{ISH}_{GR}$**0.374**	$^{ISH}_{GR}$**0.973**
TCT-HNP (Exh.)	0.708	0.830	0.708	0.830	0.689	0.848	0.689	0.848	0.359	0.970	0.359	0.970
IVF [I]	0.340	0.366	0.437	0.469	0.369	0.383	0.470	0.522	0.219	0.527	0.276	0.687
ScaNN [S]	0.378	0.410	0.444	0.496	0.355	0.376	0.427	0.459	0.215	0.522	0.253	0.632
HNSW [H]	-	-	0.625	0.721	-	-	0.634	0.762	-	-	0.315	0.853
GAR [G]	0.546	0.547	0.687	0.755	0.569	0.598	0.678	0.797	0.342	0.733	0.354	0.878
Re-Ranking [R]	0.586	0.605	0.679	0.755	0.614	0.667	0.685	0.805	0.342	0.748	0.353	0.868
Proactive LADR	$^{IS}_{GR}$**0.680**	$^{IS}_{GR}$**0.747**	$^{ISH}_{GR}$0.719	$^{ISH}_{GR}$0.827	$^{IS}_{GR}$**0.682**	$^{IS}_{GR}$**0.803**	$^{ISH}_{G}$0.709	^{ISH}0.841	$^{IS}_{G}$**0.346**	$^{IS}_{GR}$**0.856**	^{ISH}0.354	$^{ISH}_{GR}$0.927
Adaptive LADR	-	-	^{ISH}**0.729**	$^{ISH}_{GR}$**0.848**	-	-	$^{ISH}_{GR}$**0.721**	$^{ISH}_{GR}$**0.878**	-	-	$^{ISH}_{GR}$**0.359**	$^{ISH}_{GR}$**0.962**
ANCE (Exh.)	0.617	0.755	0.617	0.755	0.634	0.777	0.634	0.777	0.330	0.957	0.330	0.957
IVF [I]	0.358	0.395	0.441	0.500	0.407	0.437	0.498	0.549	0.212	0.530	0.268	0.703
ScaNN [S]	0.374	0.405	0.433	0.488	0.440	0.495	0.535	0.614	0.262	0.691	0.287	0.783
HNSW [H]	-	-	0.606	0.737	-	-	0.635	0.790	-	-	0.311	0.897
GAR [G]	0.527	0.540	0.648	0.750	0.568	0.622	0.655	0.794	**0.326**	0.751	0.329	0.888
Re-Ranking [R]	0.578	0.605	0.653	0.755	0.602	0.667	**0.674**	0.805	0.325	0.748	**0.333**	0.868
Proactive LADR	$^{IS}_{GR}$**0.645**	$^{IS}_{GR}$**0.751**	^{IS}0.657	^{ISH}0.800	$^{IS}_{GR}$**0.660**	$^{IS}_{GR}$**0.807**	^{IS}0.666	^{IS}0.822	^{IS}0.321	$^{IS}_{GR}$**0.872**	^{ISH}0.327	$^{ISH}_{GR}$0.932
Adaptive LADR	-	-	^{ISH}**0.665**	^{ISH}**0.820**	-	-	^{ISH}0.665	^{IS}**0.830**	-	-	^{ISH}0.329	$^{ISH}_{GR}$**0.959**


Proactive LADR
Adaptive LADR
nDCG
k neighbors
4 .62 .66 .70 .72 .63 .64 .66 .67 .69
8 .65 .69 .72 .72 .64 .66 .68 .70 .71
16 .69 .71 .73 .73 .66 .68 .70 .71 .72
32 .72 .74 .73 .73 .68 .69 .71 .72 .72
64 .73 .74 .73 .72 .70 .71 .72 .72 .72
128 .74 .73 .73 .72 .74 .74 .74 .73 .72
R@1k
k neighbors
4 .65 .71 .78 .82 .65 .68 .71 .74 .77
8 .71 .76 .81 .84 .68 .72 .76 .79 .81
16 .77 .81 .84 .85 .72 .75 .79 .83 .85
32 .81 .85 .85 .85 .75 .78 .82 .85 .85
64 .85 .86 .85 .85 .79 .81 .85 .85 .84
128 .86 .86 .85 .85 .85 .86 .87 .86 .85
RBO
k neighbors
4 .65 .72 .78 .81 .68 .70 .74 .77 .79
8 .71 .76 .81 .84 .72 .75 .81 .85 .87
16 .76 .79 .83 .86 .77 .80 .86 .89 .91
32 .80 .83 .86 .89 .80 .85 .90 .92 .93
64 .84 .87 .89 .90 .83 .88 .93 .95 .96
128 .87 .89 .91 .92 .88 .92 .95 .97 .98
Latency (ms/q)
k neighbors
4 3.8 5.1 8.3 12.0 4.6 4.7 4.9 5.4 6.6
8 4.2 5.9 9.4 13.6 4.6 4.8 5.2 6.0 7.8
16 4.8 6.8 11.0 16.9 4.5 4.7 5.3 6.4 8.8
32 5.8 8.2 14.4 26.6 4.8 5.2 6.3 8.1 12.2
64 7.6 11.1 20.4 42.2 5.3 5.9 7.8 10.6 17.8
128 10.2 15.9 34.9 69.8 5.9 7.0 9.9 15.1 27.7
100 200 500 1000
n seed set size
10 20 50 100 200
c exploration depth

	DL19		DL20		Dev (sm)	
Graph	nDCG	R@1k	nDCG	R@1k	RR@10	R@1k
Proactive LADR						
Exact	0.730	**0.850**	**0.722**	**0.857**	**0.345**	**0.932**
Approx.	$^{=}$0.731	0.845	$^{=}$0.720	0.849	*0.343	*0.916
BM25	$^{=}$**0.732**	0.835	$^{=}$0.720	0.853	*0.339	*0.883
Adaptive LADR						
Exact	0.738	**0.872**	0.739	**0.900**	**0.347**	0.960
Approx.	$^{=}$0.736	0.861	$^{=}$0.737	$^{=}$**0.900**	$^{=}$**0.347**	***0.966**
BM25	**0.743**	0.859	$^{=}$**0.742**	**0.900**	*0.345	*0.933

	DL19 (valid.) $c = 100$			DL19 (valid.) $c = 1000$			DL20 (test) $c = 100$			DL20 (test) $c = 1000$		
Pipeline	nDCG	MAP	R@1k	nDCG	MAP	R@1k	nDCG	MAP	R@1k	nDCG	MAP	R@1k
BM25»MonoT5-base	0.665	0.417	0.755	0.699	0.483	0.755	0.672	0.421	0.805	0.711	0.498	0.805
w/ GAR_{BM25}	* 0.697	* 0.456	* 0.786	0.727	0.490	* 0.827	* 0.695	0.439	* 0.823	* 0.743	**0.501**	* 0.874
w/ GAR_{TCT}	***0.722**	***0.491**	***0.800**	***0.743**	**0.511**	***0.839**	***0.714**	***0.472**	***0.831**	***0.749**	**0.501**	***0.892**
BM25»MonoT5-3b	0.667	0.418	0.755	0.700	0.489	0.755	0.678	0.442	0.805	0.728	0.534	0.805
w/ GAR_{BM25}	* 0.693	0.454	* 0.790	* 0.741	0.517	* 0.831	* 0.715	* 0.469	* 0.829	* 0.772	0.556	* 0.881
w/ GAR_{TCT}	***0.715**	***0.484**	***0.806**	***0.746**	**0.522**	***0.846**	***0.735**	***0.512**	***0.837**	***0.787**	***0.564**	***0.899**
BM25»ColBERT	0.663	0.409	0.755	0.681	0.458	0.755	0.667	0.421	0.805	0.697	0.469	0.805
w/ GAR_{BM25}	* 0.690	* 0.442	* 0.783	* 0.720	0.480	* 0.825	* 0.695	* 0.446	* 0.823	* 0.732	0.479	* 0.870
w/ GAR_{TCT}	***0.716**	***0.475**	***0.798**	***0.727**	**0.482**	***0.841**	***0.707**	***0.463**	***0.829**	***0.740**	**0.481**	***0.887**
TCT»MonoT5-base	0.708	0.472	0.830	0.704	0.473	0.830	0.698	0.488	0.848	0.693	0.471	0.848
w/ GAR_{BM25}	***0.728**	**0.484**	**0.852**	***0.733**	**0.480**	***0.883**	***0.719**	***0.501**	**0.861**	***0.719**	**0.473**	***0.881**
w/ GAR_{TCT}	0.722	0.481	0.847	* 0.724	0.474	0.866	* 0.712	0.494	0.856	* 0.710	0.471	0.871
TCT»MonoT5-3b	0.720	0.498	0.830	0.725	0.513	0.830	0.723	0.534	0.848	0.733	0.544	0.848
w/ GAR_{BM25}	***0.748**	***0.521**	***0.857**	***0.759**	**0.521**	***0.885**	***0.743**	**0.546**	***0.864**	***0.771**	***0.555**	***0.890**
w/ GAR_{TCT}	* 0.742	* 0.517	0.849	* 0.749	0.516	* 0.868	* 0.741	* 0.545	* 0.861	* 0.759	0.551	* 0.880
TCT»ColBERT	0.708	0.464	0.830	0.701	0.452	0.830	0.698	0.476	0.848	0.697	0.470	0.848
w/ GAR_{BM25}	***0.729**	***0.480**	**0.853**	***0.727**	**0.459**	**0.876**	***0.715**	**0.485**	**0.857**	***0.722**	***0.477**	***0.877**
w/ GAR_{TCT}	* 0.722	0.474	0.845	* 0.715	0.452	0.852	* 0.711	* 0.484	***0.857**	* 0.713	0.473	0.864
D2Q»MonoT5-base	0.736	0.503	0.830	0.747	0.531	0.830	0.726	0.499	0.839	0.731	**0.508**	0.839
w/ GAR_{BM25}	* 0.748	0.506	0.848	0.757	0.519	***0.880**	* 0.734	0.497	* 0.847	**0.748**	0.504	* 0.880
w/ GAR_{TCT}	***0.760**	***0.528**	**0.850**	***0.766**	**0.533**	* 0.879	**0.740**	**0.508**	***0.856**	**0.748**	0.499	***0.895**
D2Q»MonoT5-3b	0.737	0.506	0.830	0.751	0.542	0.830	0.738	0.531	0.839	0.753	0.557	0.839
w/ GAR_{BM25}	0.744	0.512	* 0.850	**0.772**	**0.549**	***0.880**	* 0.751	0.535	* 0.852	* 0.781	0.561	* 0.887
w/ GAR_{TCT}	**0.755**	**0.524**	***0.857**	0.769	0.544	***0.880**	***0.764**	**0.550**	***0.860**	***0.790**	**0.565**	***0.905**
D2Q»ColBERT	0.724	0.475	0.830	0.733	0.501	0.830	0.718	0.483	0.839	0.717	0.479	0.839
w/ GAR_{BM25}	0.734	0.484	0.845	**0.753**	**0.505**	* 0.876	* 0.731	0.487	* 0.849	* 0.737	0.482	* 0.872
w/ GAR_{TCT}	***0.744**	***0.496**	**0.849**	* 0.752	0.503	***0.878**	***0.735**	**0.488**	***0.856**	***0.746**	**0.485**	***0.893**
SPLADE»MonoT5-base	0.750	0.506	0.872	0.737	**0.487**	0.872	0.748	0.505	0.899	0.731	**0.480**	0.899
w/ GAR_{BM25}	***0.762**	0.509	**0.888**	**0.745**	**0.487**	**0.893**	***0.757**	**0.509**	0.902	**0.737**	0.479	**0.909**
w/ GAR_{TCT}	* 0.759	**0.512**	0.878	0.737	0.481	0.875	0.751	0.506	**0.903**	0.734	0.475	0.908
SPLADE»MonoT5-3b	0.761	0.526	0.872	0.764	**0.533**	0.872	0.774	0.559	0.899	0.775	0.560	0.899
w/ GAR_{BM25}	***0.775**	0.532	***0.891**	**0.774**	**0.533**	**0.896**	***0.780**	0.559	0.903	***0.788**	**0.562**	***0.919**
w/ GAR_{TCT}	* 0.773	**0.539**	0.884	0.769	0.531	0.881	***0.780**	**0.561**	**0.905**	0.783	0.559	0.910
SPLADE»ColBERT	0.741	0.479	0.872	0.727	**0.456**	0.872	0.747	0.495	0.899	0.733	0.474	0.899
w/ GAR_{BM25}	***0.753**	**0.490**	**0.885**	**0.730**	**0.456**	**0.875**	***0.755**	**0.501**	0.902	***0.742**	***0.477**	**0.914**
w/ GAR_{TCT}	* 0.750	0.489	0.876	0.727	0.455	0.868	* 0.752	0.500	**0.903**	0.740	* 0.476	0.911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initial rank
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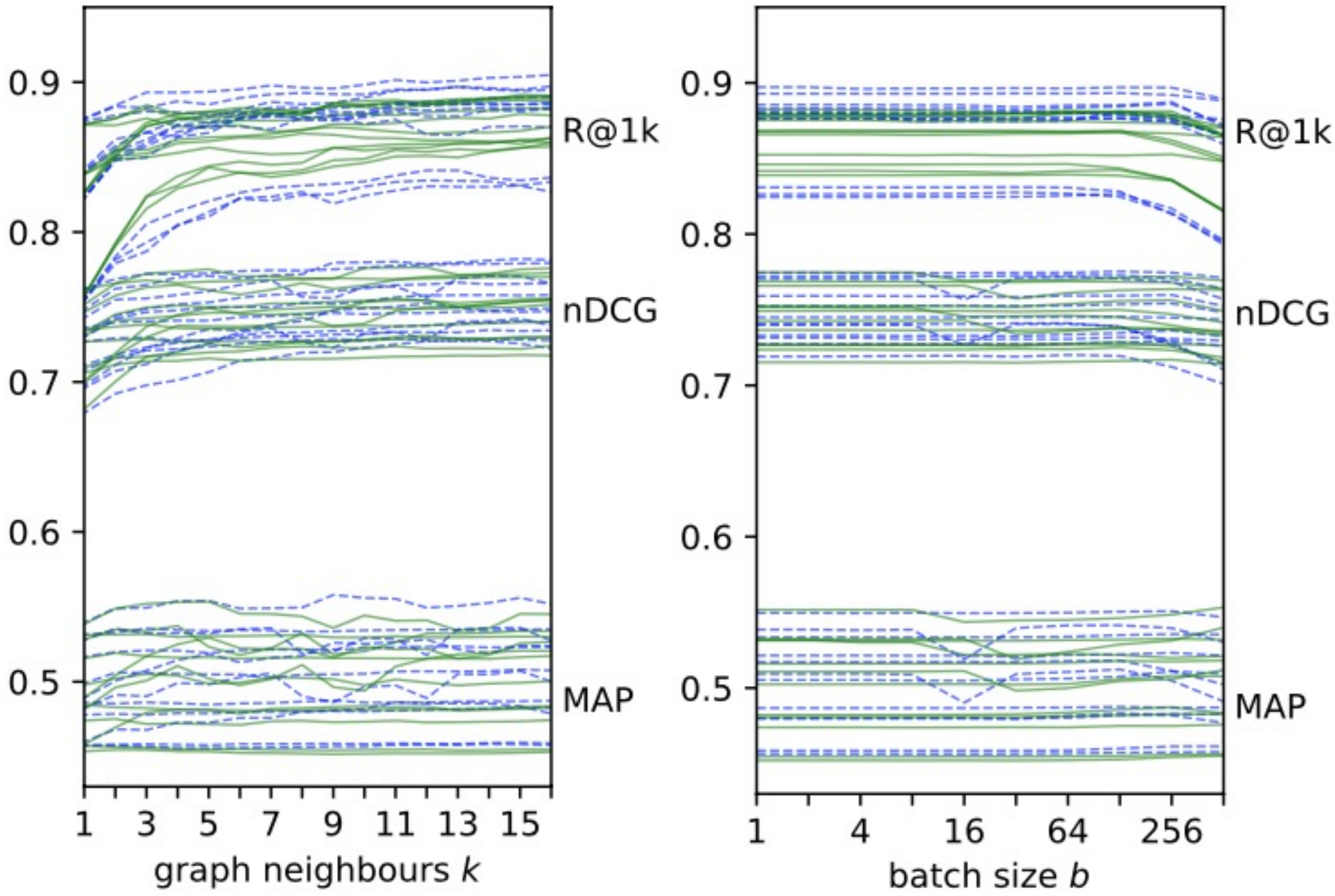
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0.6
0.5
R@1k
nDCG
MAP
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graph neighbours k
0.9
0.8
0.7
0.6
0.5
R@1k
nDCG
MAP
1 4 16 64 256
batch size b

	GAR$_{TCT}$		MonoT5-base
c	$b = 16$	$b = 64$	Scoring
100	2.68 ± 0.02	0.57 ± 0.01	267.06 ± 6.12
250	8.10 ± 0.05	4.34 ± 0.01	652.30 ± 7.53
500	17.38 ± 0.07	13.66 ± 0.02	1, 362.14 ± 5.27
750	26.96 ± 0.12	22.29 ± 0.07	2, 047.20 ± 6.71
1000	37.37 ± 0.07	30.82 ± 0.04	2, 631.75 ± 6.28

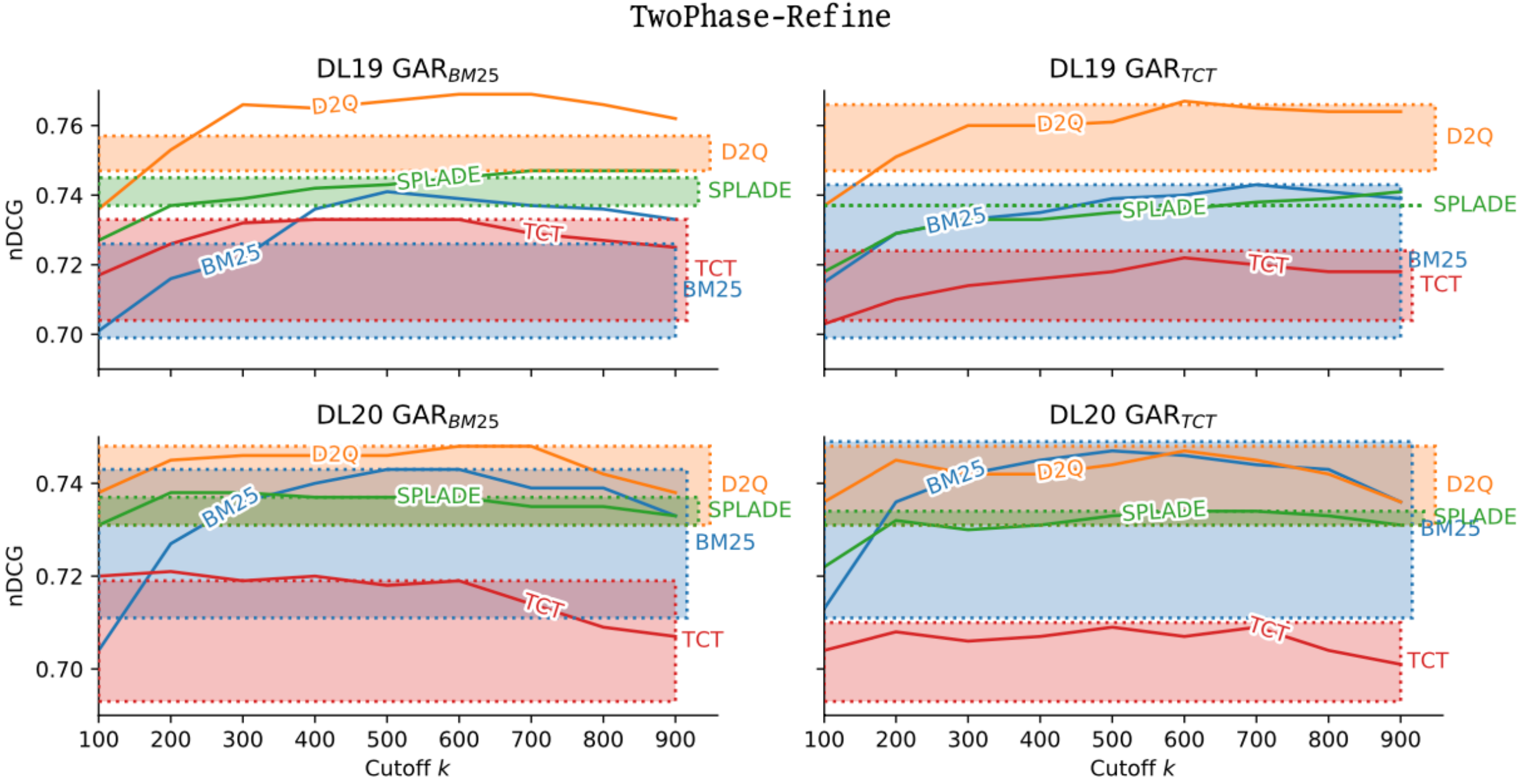
Table 6: Intra-List Similarity (ILS) among retrieved relevant documents. Since the set of retrieved documents does not change using typical Re-Ranking (RR), each value in this column is only listed once. ILS scores that are statistically equivalent to the RR setting are indicated with * (procedure described in Section 6.5).

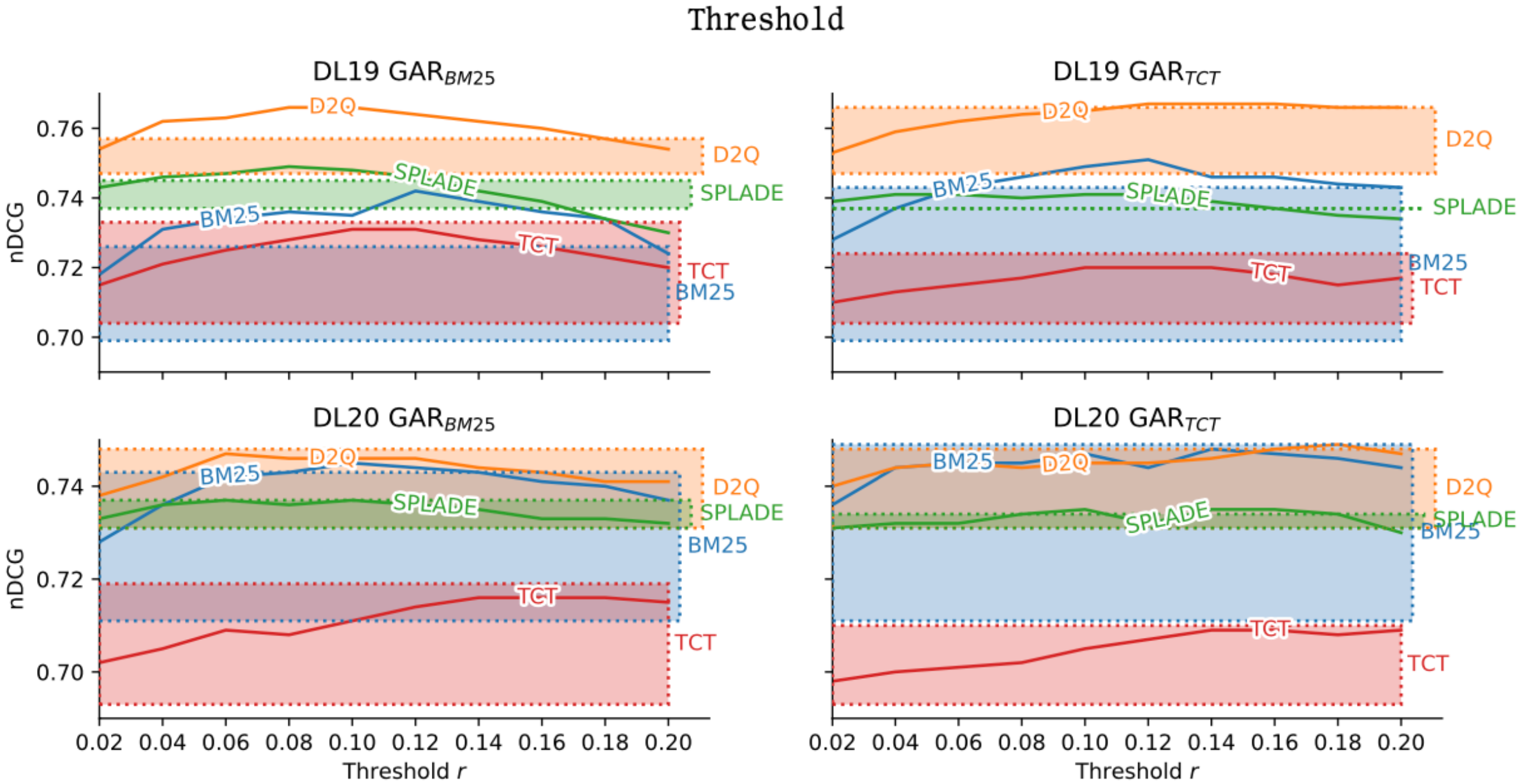
		GAR_{BM25}		GAR_{TCT}	
Pipeline	RR	c=100	c=1k	c=100	c=1k
BM25»MonoT5-base	0.947	* 0.946	* 0.946	* 0.947	* 0.946
BM25»MonoT5-3b		* 0.946	* 0.946	* 0.946	* 0.946
BM25»ColBERT		* 0.946	* 0.946	* 0.947	* 0.946
TCT»MonoT5-base	0.969	* 0.969	* 0.968	* 0.969	* 0.969
TCT»MonoT5-3b		* 0.969	* 0.968	* 0.969	* 0.969
TCT»ColBERT		* 0.969	* 0.969	* 0.969	* 0.969
D2Q»MonoT5-base	0.969	* 0.968	* 0.968	* 0.969	* 0.968
D2Q»MonoT5-3b		* 0.968	* 0.968	* 0.968	* 0.968
D2Q»ColBERT		* 0.968	* 0.968	* 0.969	* 0.968
SPLADE»MonoT5-base	0.969	* 0.968	* 0.968	* 0.969	* 0.969
SPLADE»MonoT5-3b		* 0.968	* 0.968	* 0.968	* 0.969
SPLADE»ColBERT		* 0.968	* 0.969	* 0.969	* 0.969

		TREC DL 2019 (dev)				TREC DL 2020 (test)			
		GAR_{bm25}		GAR_{tct}		GAR_{bm25}		GAR_{tct}	
Pipeline	Agent	nDCG	R@1k	nDCG	R@1k	nDCG	R@1k	nDCG	R@1k
BM25»MonoT5	Non-Adaptive	0.699	0.755	0.699	0.755	0.711	0.805	0.711	0.805
	Oracle	0.747	0.804	0.786	0.853	0.748	0.791	0.768	0.828
	Alternate	0.726	^{N}0.827	^{NO}0.743	^{N}0.839	^{N}0.743	^{NO}**0.874**	^{N}**0.749**	^{N}**0.892**
	TwoPhase-Fixed	^{N}0.729	^{N}0.815	^{NO}0.740	^{N}0.836	^{N}0.732	^{NA}0.838	^{N}0.742	^{NA}0.858
	TwoPhase-Refine	^{N}0.741	^{N}0.826	^{NO}0.743	^{N}0.841	^{N}0.743	^{NO}0.871	^{NA}0.744	^{NA}0.879
	Threshold	^{N}**0.742**	^{N}**0.829**	^{NOA}**0.751**	^{N}**0.849**	^{N}**0.744**	^{NO}**0.874**	^{N}0.744	^{NA}0.874
	Greedy	0.723	^{N}0.823	^{NO}0.737	^{N}0.839	^{N}0.743	^{NO}0.868	^{N}0.744	^{N}0.882
TCT»MonoT5	Non-Adaptive	0.704	0.830	0.704	0.830	0.693	0.848	0.693	0.848
	Oracle	0.793	0.891	0.766	0.846	0.762	0.874	0.754	0.861
	Alternate	^{NO}**0.733**	^{N}0.883	^{NO}0.724	^{N}0.866	^{NO}**0.719**	^{N}0.881	^{NO}**0.710**	^{N}**0.871**
	TwoPhase-Fixed	^{NO}**0.733**	^{N}0.874	^{NO}0.719	^{N}0.857	^{NO}0.717	^{N}0.877	^{NO}**0.710**	^{N}0.868
	TwoPhase-Refine	^{NO}**0.733**	^{N}0.882	^{NO}0.722	0.859	^{NO}**0.719**	^{N}**0.883**	^{NOA}0.707	^{A}0.866
	Threshold	^{NO}0.731	^{N}**0.886**	^{NO}0.720	^{N}0.866	^{NOA}0.711	0.871	^{NOA}0.705	0.862
	Greedy	^{NO}0.731	^{N}0.881	^{NO}**0.725**	^{N}**0.871**	^{NOA}0.713	^{N}0.873	^{NO}0.708	^{N}0.868
D2Q»MonoT5	Non-Adaptive	0.747	0.830	0.747	0.830	0.731	0.839	0.731	0.839
	Oracle	0.797	0.867	0.798	0.867	0.791	0.884	0.793	0.889
	Alternate	0.757	^{N}**0.880**	^{NO}0.766	^{N}**0.879**	^{NO}**0.748**	^{N}**0.880**	^{O}**0.748**	^{N}**0.895**
	TwoPhase-Fixed	^{N}0.765	^{N}0.866	^{NO}0.765	^{N}0.870	^{NO}**0.748**	^{NA}0.867	^{O}0.745	^{NA}0.870
	TwoPhase-Refine	^{N}**0.769**	^{N}0.875	^{N}**0.767**	^{N}0.878	^{NO}**0.748**	^{N}0.877	^{O}0.747	^{N}0.892
	Threshold	^{N}0.766	^{N}0.876	^{NO}**0.767**	^{N}0.877	^{O}0.746	^{NA}0.874	^{O}0.745	^{N}0.881
	Greedy	0.754	^{N}0.874	^{O}0.757	^{N}0.873	^{O}0.744	^{N}0.878	^{O}**0.748**	^{N}0.894
SPLADE»MonoT5	Non-Adaptive	0.737	0.872	0.737	0.872	0.731	0.899	0.731	0.899
	Oracle	0.807	0.898	0.783	0.859	0.777	0.886	0.781	0.899
	Alternate	^{O}0.745	0.893	^{O}0.737	0.875	^{O}0.737	**0.909**	^{O}0.734	**0.908**
	TwoPhase-Fixed	^{O}0.763	0.863	**0.764**	0.869	**0.748**	^{A}0.868	^{O}0.742	^{NA}0.867
	TwoPhase-Refine	^{O}**0.769**	0.875	**0.764**	0.870	^{O}**0.748**	0.877	^{O}0.736	^{A}0.869
	Threshold	^{O}0.766	0.871	0.759	0.857	^{O}0.746	0.874	^{O}**0.744**	^{NA}0.865
	Greedy	^{NO}0.747	^{N}**0.895**	^{O}0.740	**0.882**	^{O}0.734	0.903	^{O}0.734	0.906

Table 1

Re-ranking performance on TREC Deep Learning 2019 and 2020 using various agents. The best-performing (non-oracle) agent in section is listed in bold. Significant differences compared to the Non-Adaptive, Oracle, and `Adaptive` systems are marked with ^{NOA}, respectively (paired t-test, $p < 0.05$).


TwoPhase-Refine
DL19 GAR$_{BM25}$
DL19 GAR$_{TCT}$
DL20 GAR$_{BM25}$
DL20 GAR$_{TCT}$
nDCG
Cutoff k
D2Q
SPLADE
BM25
TCT
0.70
0.72
0.74
0.76
100
200
300
400
500
600
700
800
900


Threshold
DL19 GAR$_{BM25}$
DL19 GAR$_{TCT}$
DL20 GAR$_{BM25}$
DL20 GAR$_{TCT}$
nDCG
0.76
0.74
0.72
0.70
D2Q
SPLADE
BM25
TCT
0.02 0.04 0.06 0.08 0.10 0.12 0.14 0.16 0.18 0.20
Threshold r