An Efficiency Study for SPLADE models

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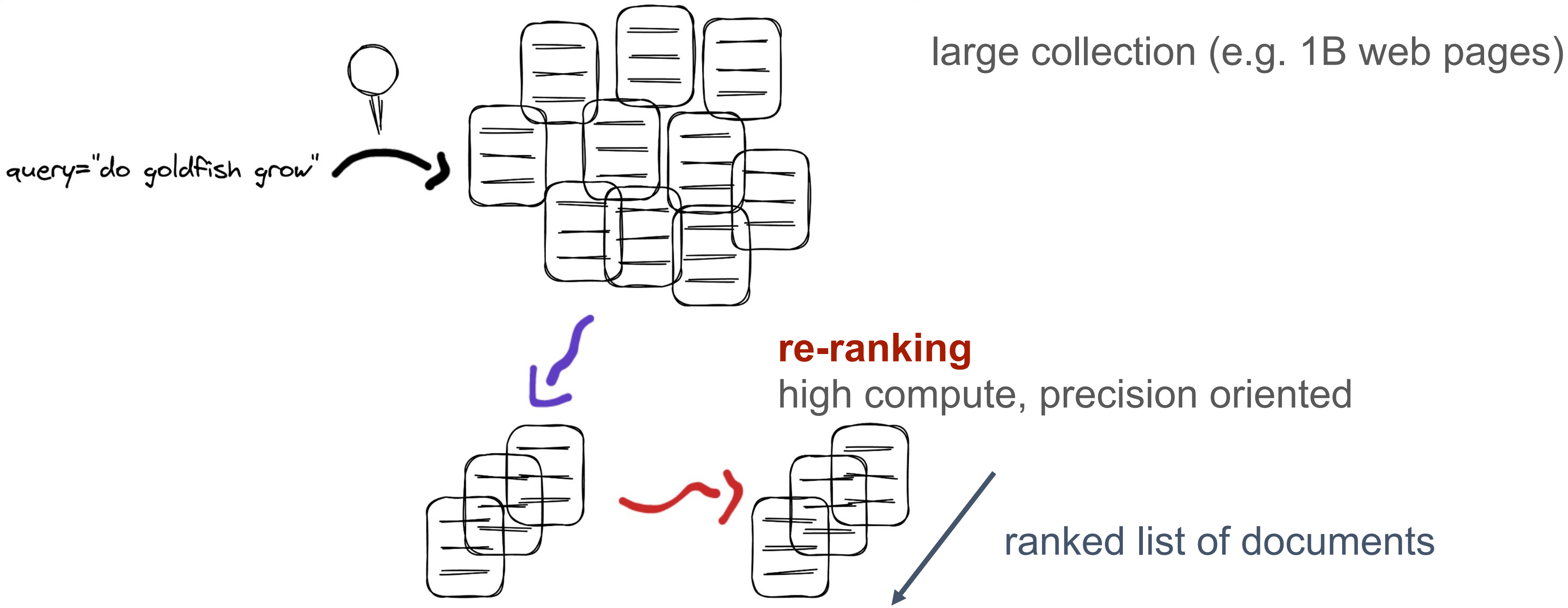
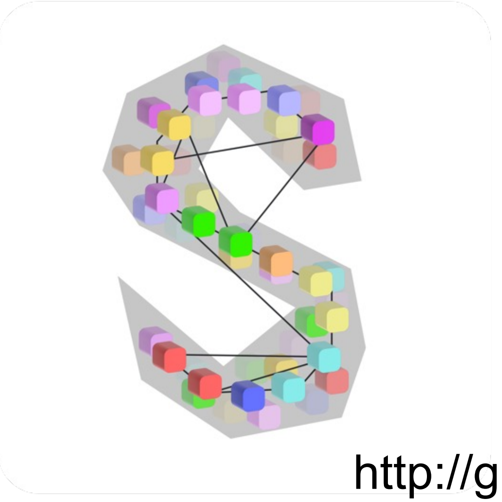
Introduction

- Goal: Study the efficiency of SPLADE models for sparse neural retrieval
  - In domain: MSMARCO passage dataset
  - Out-of-domain: 18 BEIR datasets

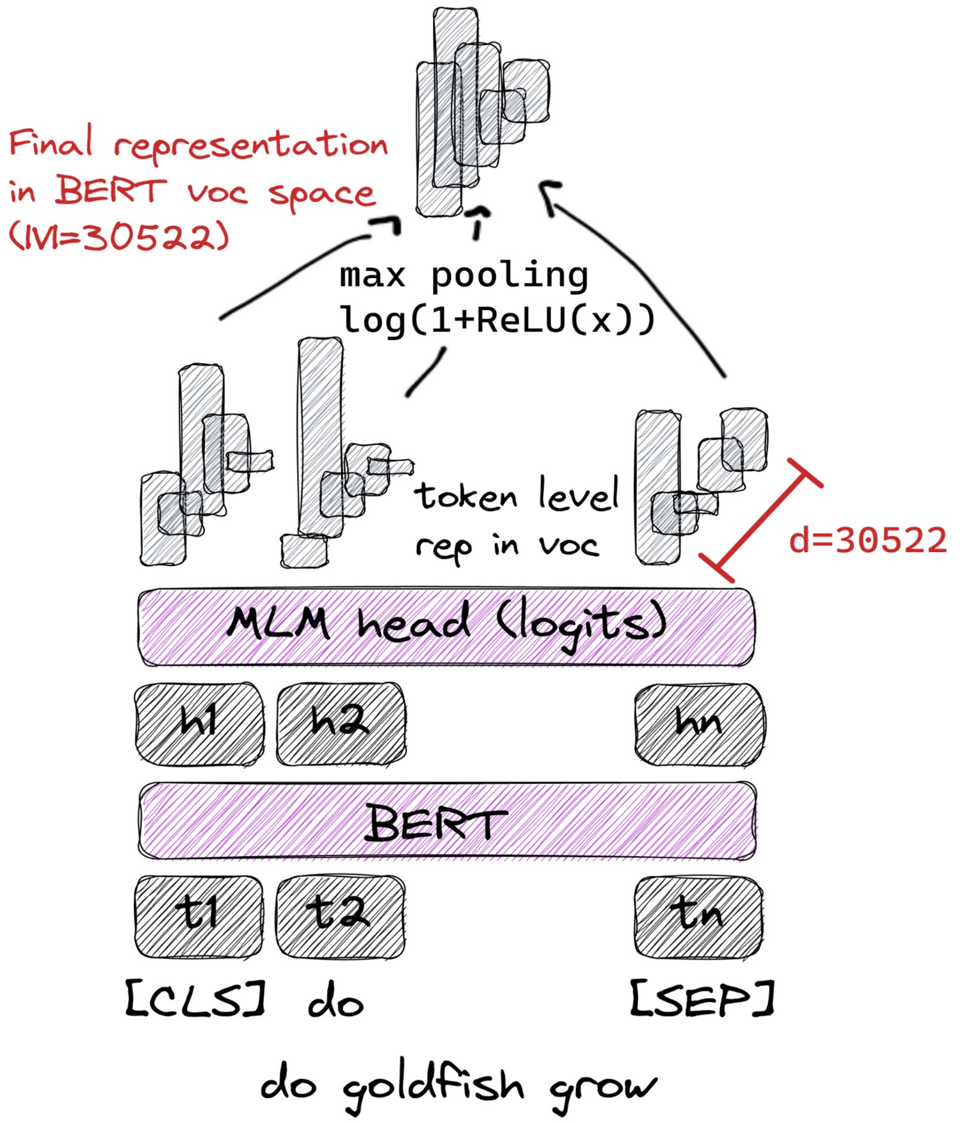


Introduction – SPLADE Recap

- Use the MLM output
  - Max pooling over each token output
  - Induce sparsity:
    - ReLU over the output
    - FLOPS [Paria et al 2020] regularization
      - Estimate number of activations in a batch
      - Proxy for total retrieval FLOPS



http://github.com/naver/splade



Motivation: Findings from Wacky Weights
Mackenzie, Trotman and Lin, 2021

Findings:

- Recent sparse models are slower than BM25
- SPLADE 50x slower on mono-thread evaluation

		Quality	Time	Space
Method		RR@10	Latency (ms)	Index Size (MB)
Anserini (Lucene): DAAT				
(1a)	BM25	0.187	40.1	661
(1b)	BM25-T5	0.277	62.8	1036
(1c)	DeepImpact	0.325	244.1	1417
(1d)	uniCOIL-T5	0.352	222.3	1313
(1e)	uniCOIL-TILDE	0.350	194.6	2067
(1f)	SPLADEv2	0.369	2140.0	4987

RQ:

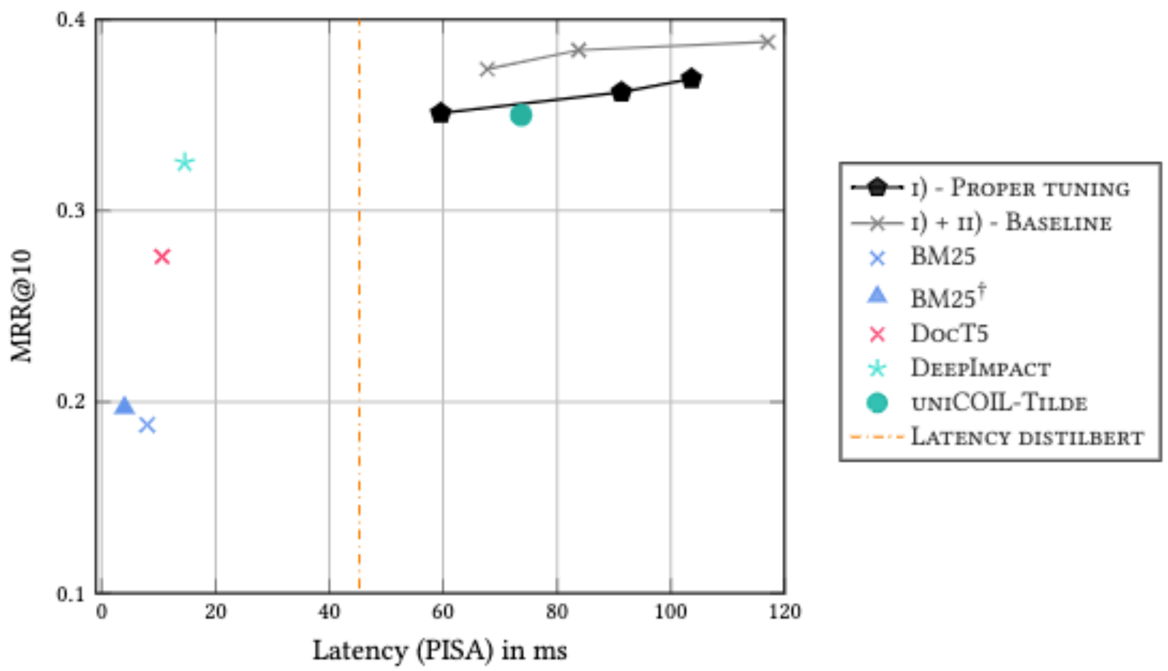
SPLADE quick as BM25?

First things first:
Is SPLADE efficient?

- <u>**Yes and No**</u>
  - **No:** It does not optimize for the same things as sparse retrieval
    - Released models are **tuned for effectiveness**, not efficiency
    - Optimized **for multi-thread retrieval** of each query
      - Measures FLOPS, not latency
  - **Yes: SPLADE is a family of models**
    - Control efficiency-effectiveness trade-off
    - Can optimize for cpu mono-thread query retrieval:
      - Focus more on query size than document size

Finding efficient SPLADE configurations

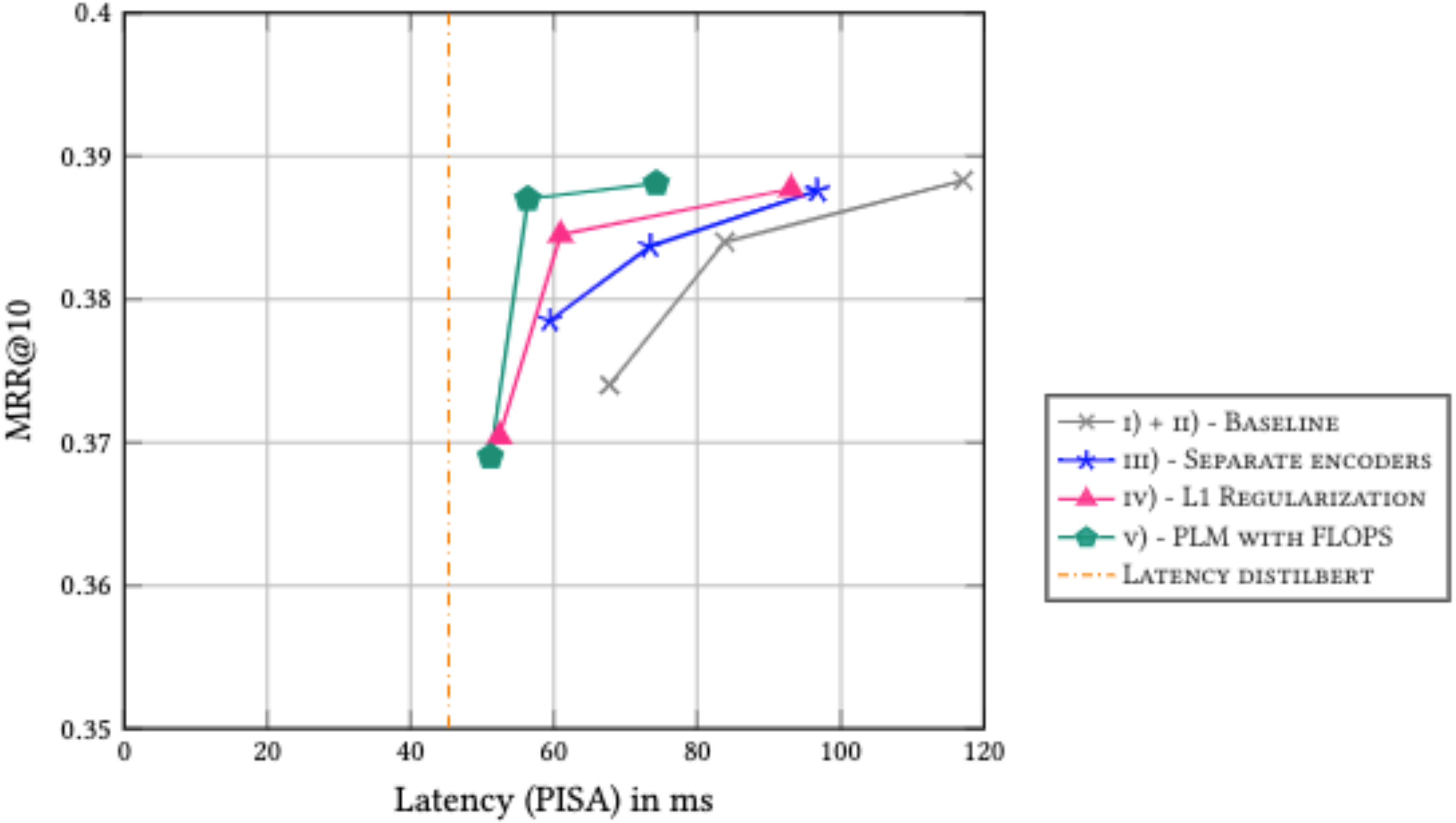
- I) Explore SPLADE family to find better configuration
  - Small, Medium and Large versions
- II) Use latest available data (better distillation)



Our contribution

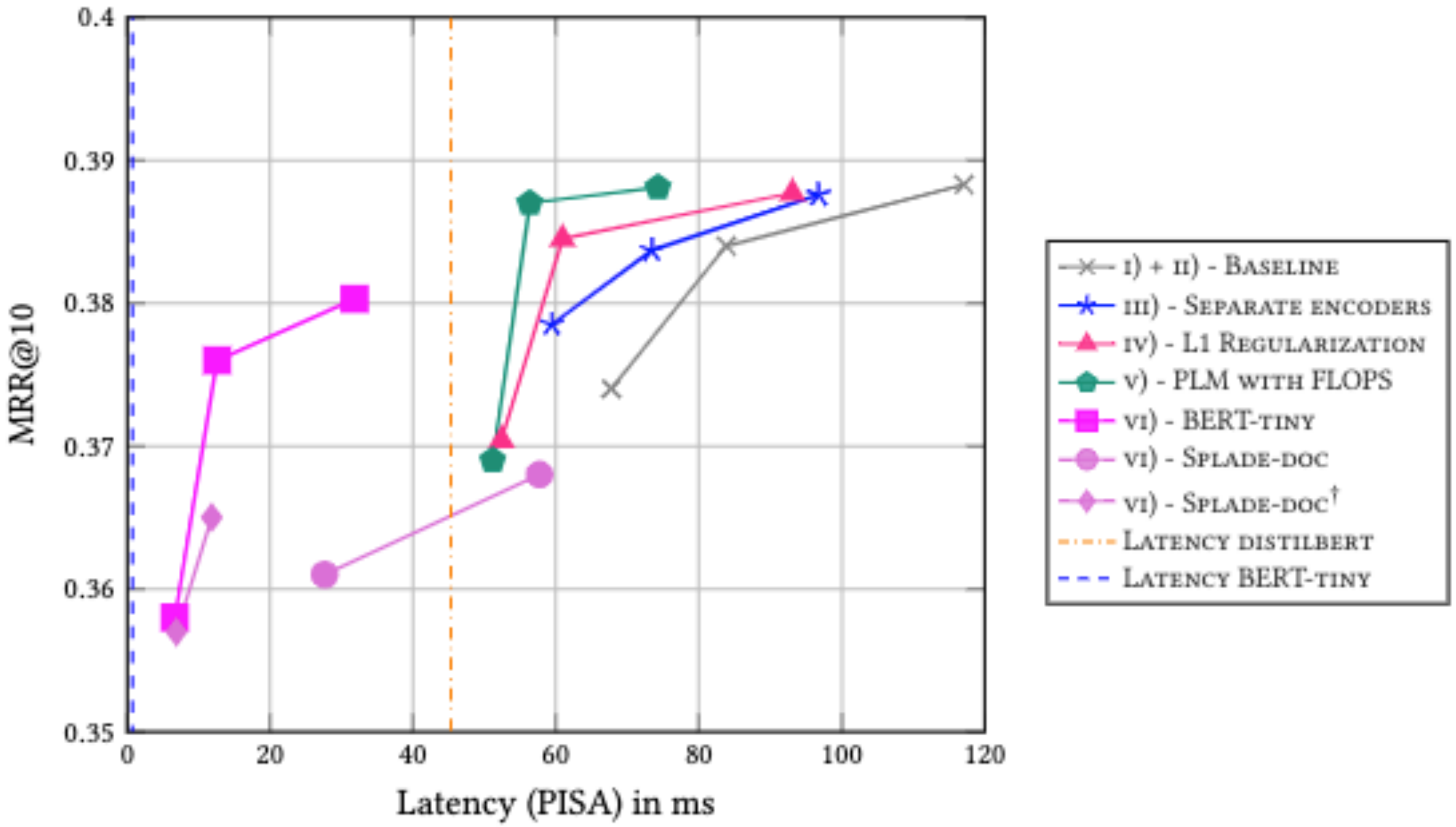
- Can we go further than those adjustments?
  - **III) Separating encoders**
    - Traditional SPLADE makes no difference between query and document
    - Hard for the model to learn that sparsities may be different
  - IV) **Using L1 regularization instead of FLOPS on queries**
    - FLOPS is optimized for generating balanced indexes
    - Queries need to be small, but don't need to be balanced
  - V) **Unsupervised FLOPS+MLM training**
    - Improves the state of the network before pretraining
    - Network already knows output should be sparse

Results: Improvements add up

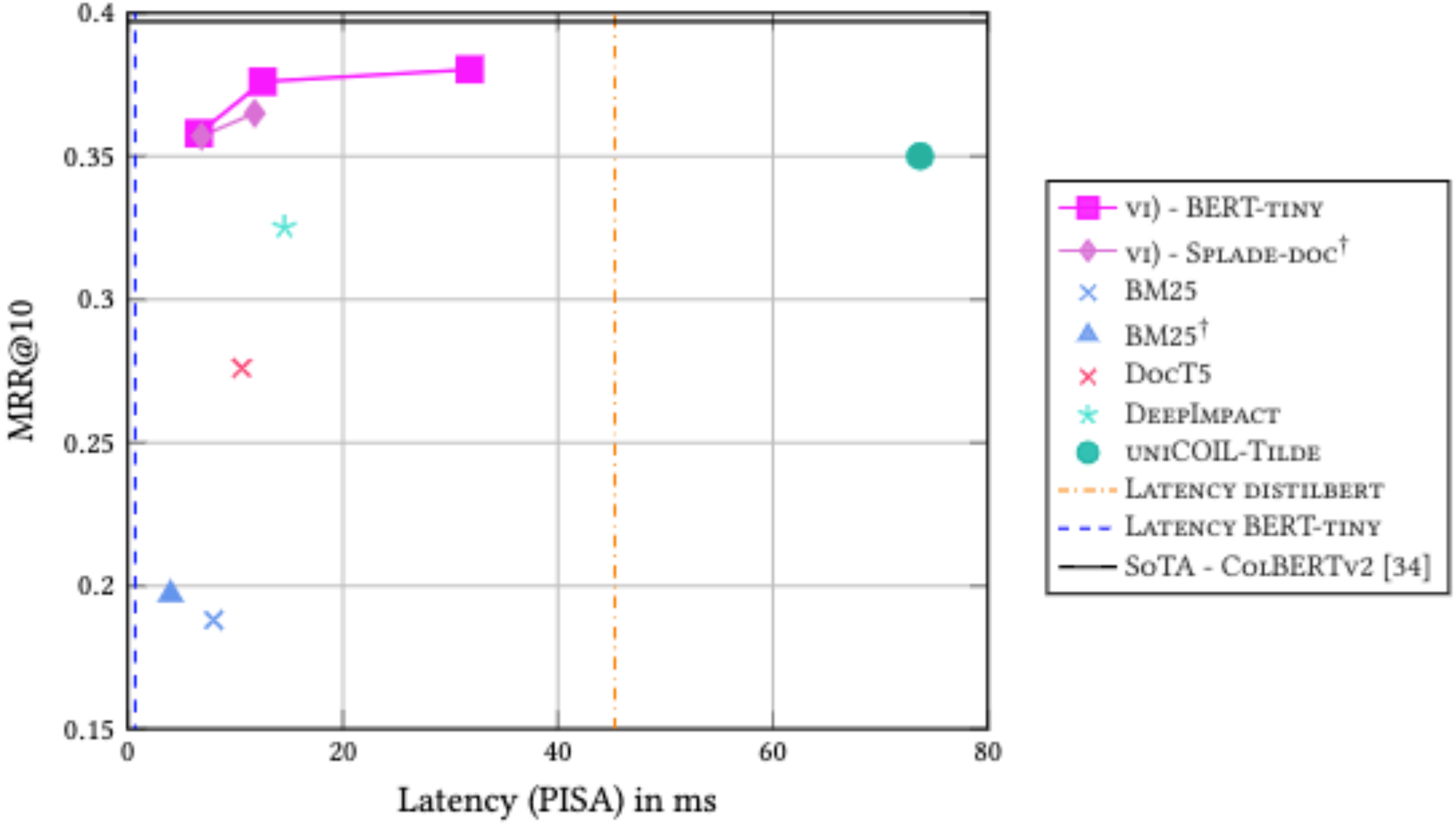


VI) Reducing query encoder latency

- VI-BT) Using a smaller query encoder (BERT-Tiny)
  - Reduces the query encoder latency to almost 0 (43 ms -> 0.7ms)
- VI-SD) SPLADE doc
  - No encoding
  - *: without stop words



Comparison with SoTA sparse on in-domain data (MSMARCO)

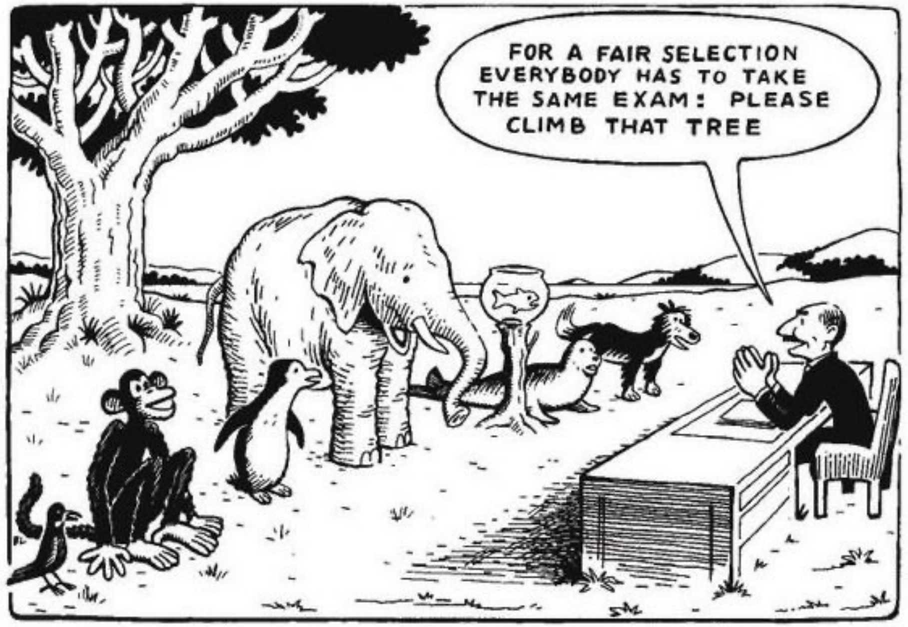


Comparison on OOD (BEIR)

Method	Latency	MSMARCO	TREC19	BEIR	BEIR*
Baselines					
BM25†	**4**	19.7	50.6	43.0	-
DocT5 [36]	11	27.6	64.2	44.1	-
SPLADEv2-distil [10]	691	36.8	**72.9**	**47.0**§	**49.3**
Proposed models					
VI) BT-SPLADE-S	*7*	35.8	67.2	39.2	45.9
VI) BT-SPLADE-M	13	*37.6*	69.4	42.1	47.1
VI) BT-SPLADE-L	32	**38.0**	*70.3*	*44.5*	*48.0*

BEIR* creates an ensemble with BM25 to non BM25-baselines
Latency increases by 4 ms

Comparison with dense models
How to?

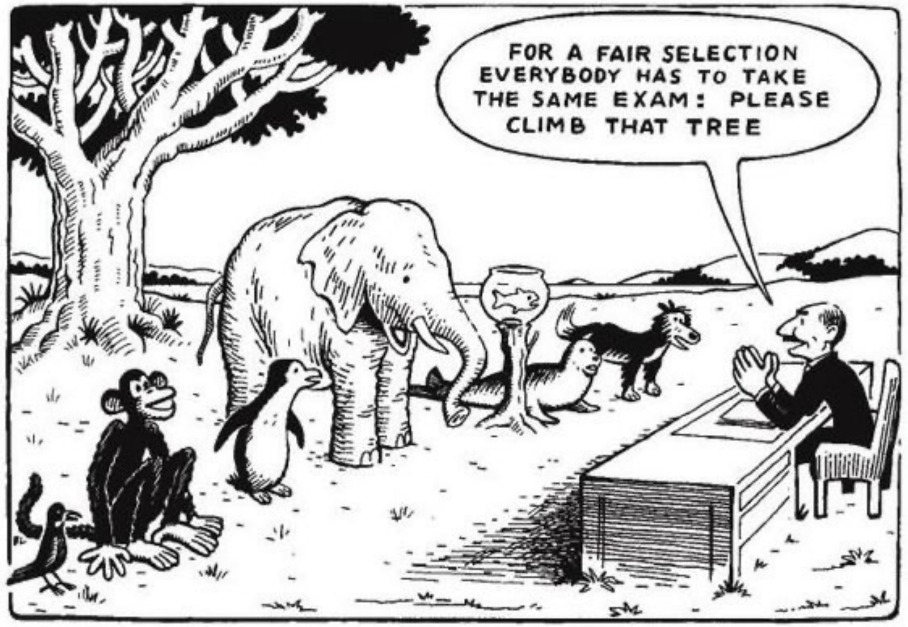


- Not exactly sure how to do it fairly
  - Different software makes for different benchmark
    - Comparing PISA/Anserini/JASS vs NMSlib/FAISS ?
    - Example: How to be sure that all of them are warmed up correctly/fairly?

  - Different optimizations
    - Approximate KNN (Dense) vs KNN (Sparse)
    - “Uniform” Latency (Dense) vs “Variable” Latency (Sparse)
    - Mono-cpu (Latency) vs Multi-cpu/gpu (QPS)
    - Keep index small (IVF, PISA) vs Precompute and store everything (HNSW)

Comparison with dense models
How to?

OPEN QUESTION
Take results with a grain of salt



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Latency

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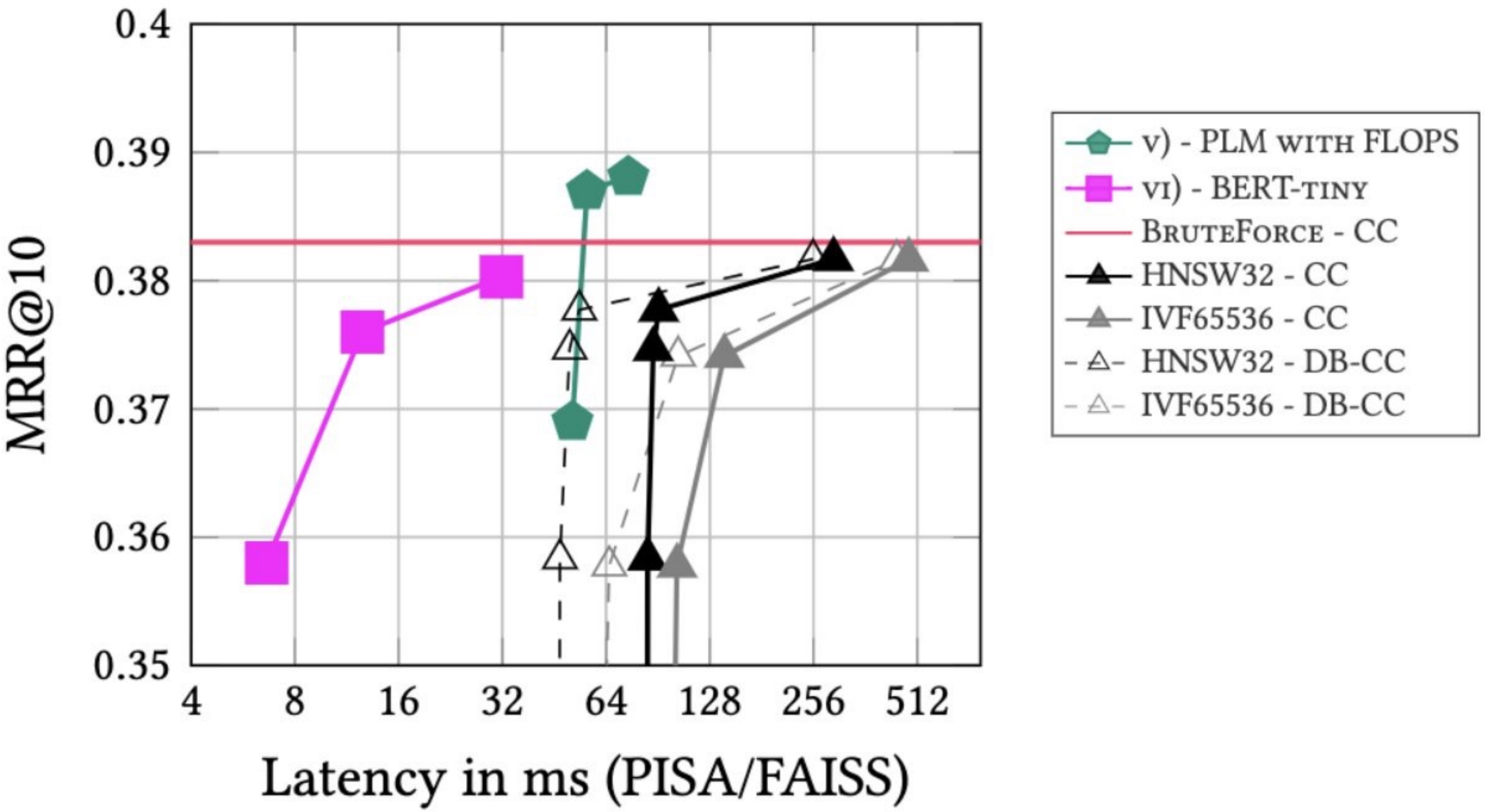

Comparison with dense models
QPS

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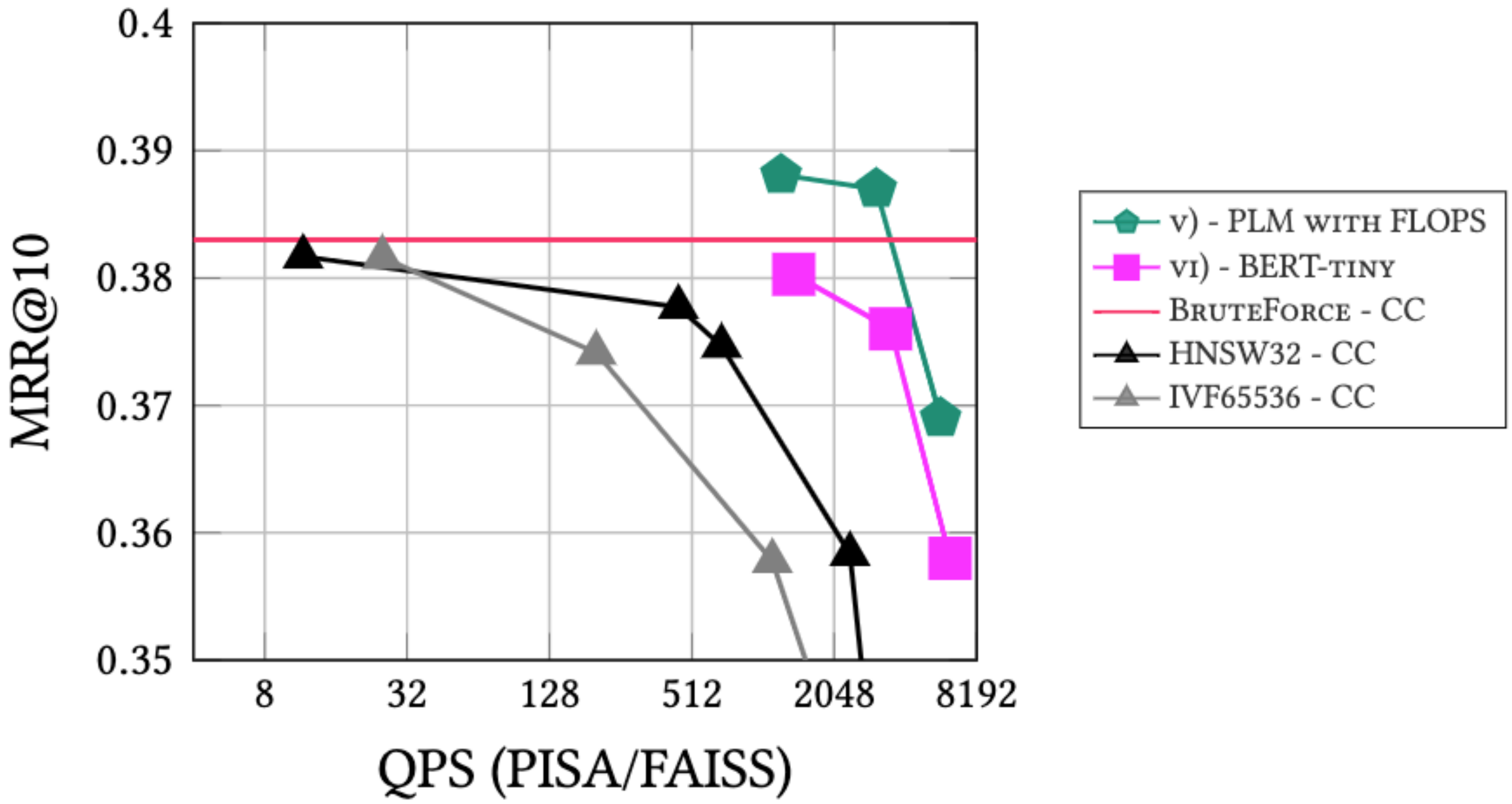

Conclusion

SPLADE can be efficient and VI) BT-Medium is the first method to concurrently:

- Only 2x the cost of BM25 (or 4 times of BM25 without stop words)
- Comparable to ColBERTv2 on MSMARCO (<10% loss of MRR@10)
- Comparable to SPLADEv2 on BEIR (<5% loss of NDCG@10)

Code: https://github.com/naver/splade
Indexes: https://github.com/naver/splade/tree/main/efficient_splade_pisa
HuggingFace weights: https://huggingface.co/naver

Improving other sparse methods

- Kinda unfair comparison with them as well
- Distillation and hyperparameter search can easily be added to both
- Better PLM initialization as well
  - MLM+Flops? Contriever? CoCondenser?
- Removing stop words from queries could also be important
- Is there a way to benchmark all this?