Late interaction beyond ColBERT

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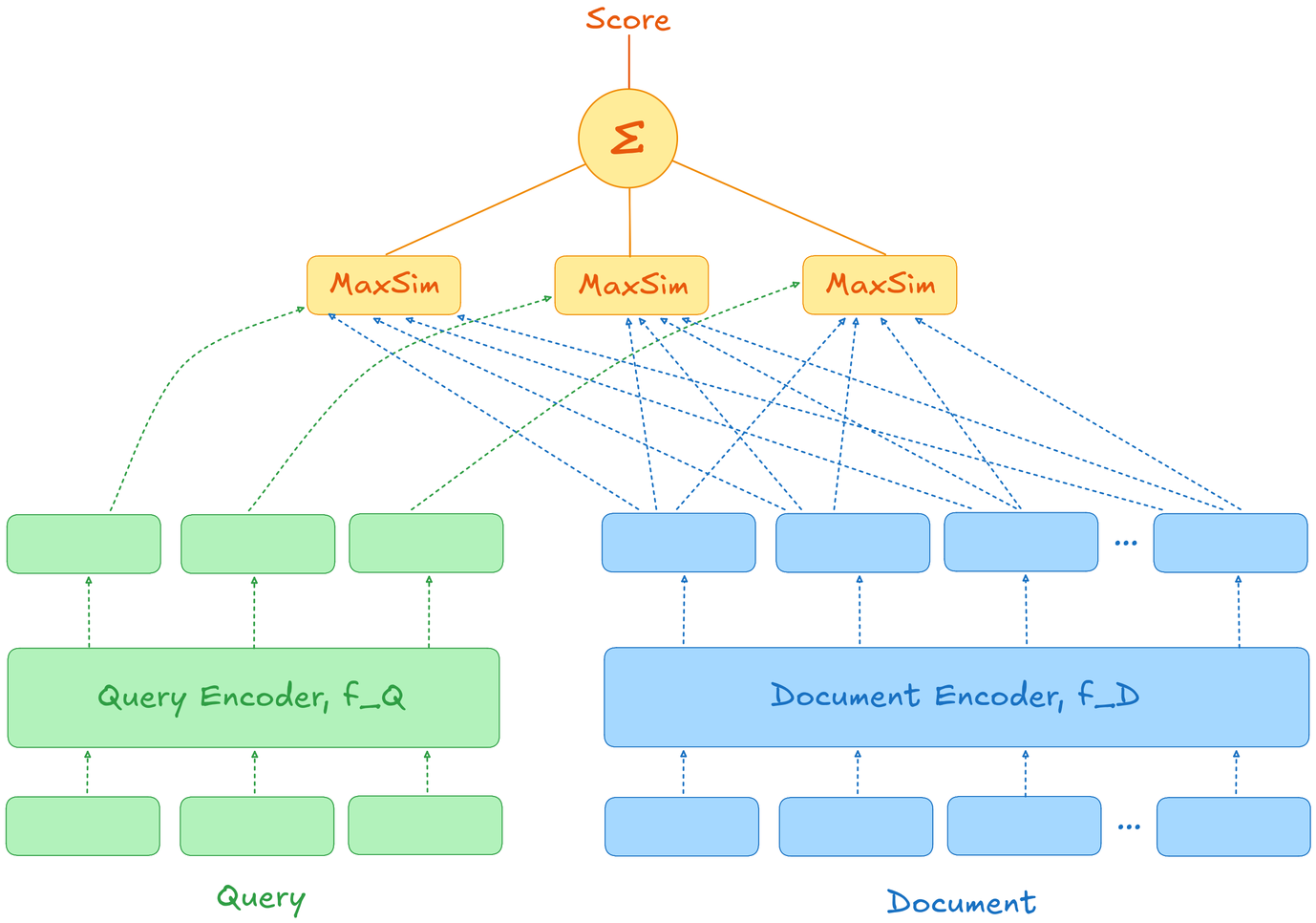
github.com/joein/vector-search-course

ColBERT recap

- Late interaction is a retrieval paradigm where queries and documents are encoded independently, but their token-level interactions are computed only at search time to recover fine-grained relevance signals.
- ColBERT is the first model to publicly formalise Late Interaction and demonstrate that it can be used in ANN
- Relevance is computed using *MaxSim operator*, matching each query token to its most similar document token
- ColBERT produces a 128 dim vector for each of the tokens
- Might provide a better recall than representation based models, as well as be faster than full interaction models like cross-encoders
- Though, the authors claims that ColBERT can be a first-stage retrieval, the actual usage might be tricky and expensive
- The authors propose a multistage IVFPQ pipeline that first prefetches candidates by retrieving documents whose token embeddings are closest to each query token, and then reranks this candidate set using the original vectors.
- Despite ANN algorithms can operate on ColBERT vectors, the sheer number of token-level embeddings makes index construction computationally intensive, regardless of the underlying ANN algorithm.

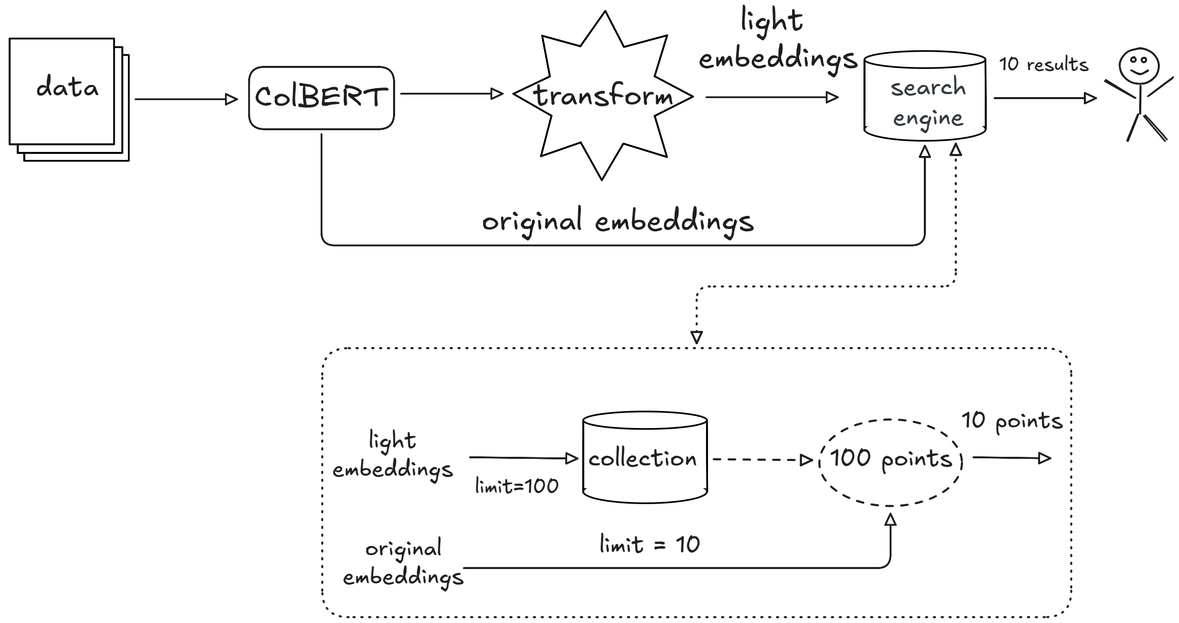


ColBERT is slow for retrieval

How to actually search with late interaction?

- As the authors proposed, the practical way for retrieving with ColBERT is to build a multistage pipeline
- The first stage prefetches a large set of candidates, whilst ColBERT narrows it down
- There are several ways to implement the first stage, some of them are:

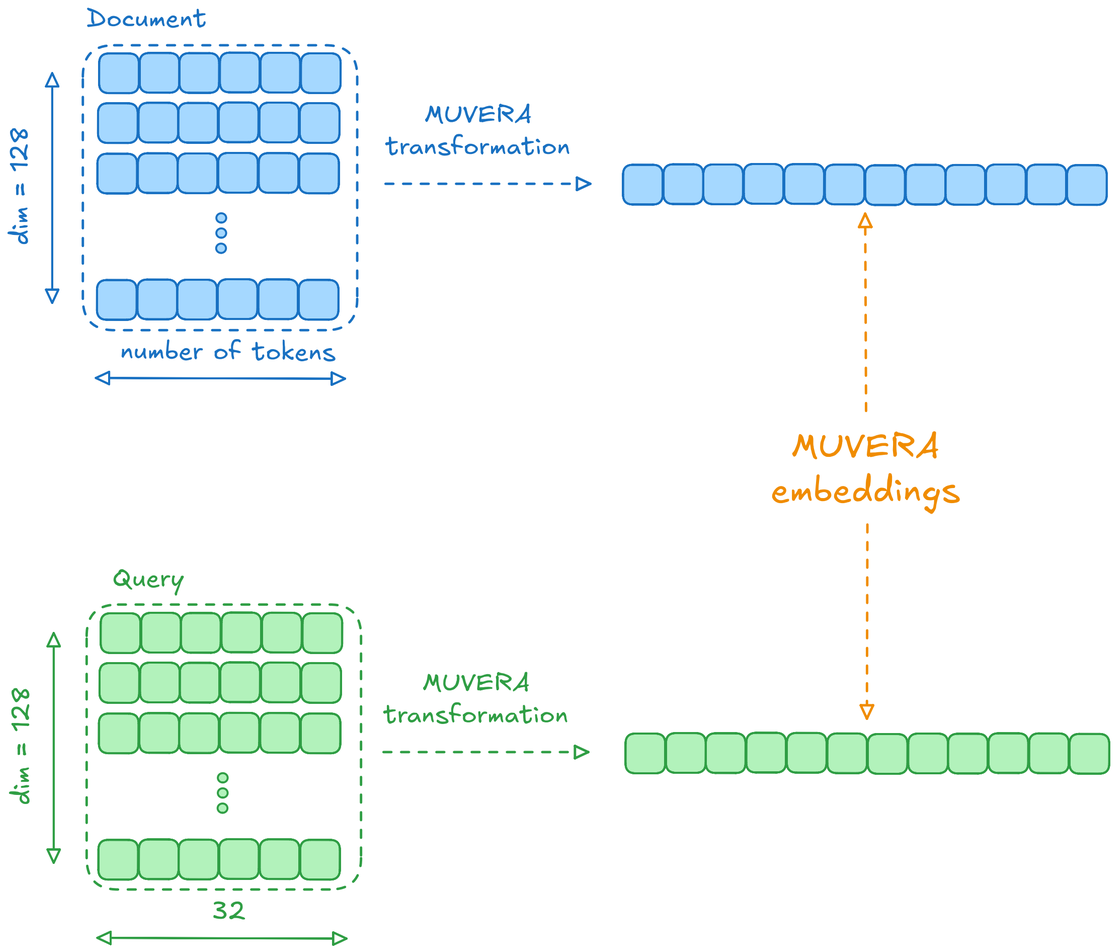
  1) use a different model to select a pool of candidates
  2) create heuristics like looking for the documents closest to each of the query tokens independently
  3) use ColBERT vectors transformation methods



MUVERA

Multivector Retrieval Algorithm

- Goal: Compress a multi-vector representation into a single fixed-dimensional encoding (FDE).
- Document and queries contain variable numbers of token embeddings, so we need a uniform format.
- How it works:
  - Partitions the token-embedding space into a fixed number of regions via SimHash (LSH with random hyperplanes)
  - Aggregates token vectors within each region, producing a structured, fixed-layout representation
  - Concatenating outputs from multiple independent projections, forming a rich fixed dimensional encoding (FDE).
- SimHash assigns each token vector to one of 2^{k_sim} clusters using only hyperplane sign tests, enabling fast, consistent clustering across all documents and queries.



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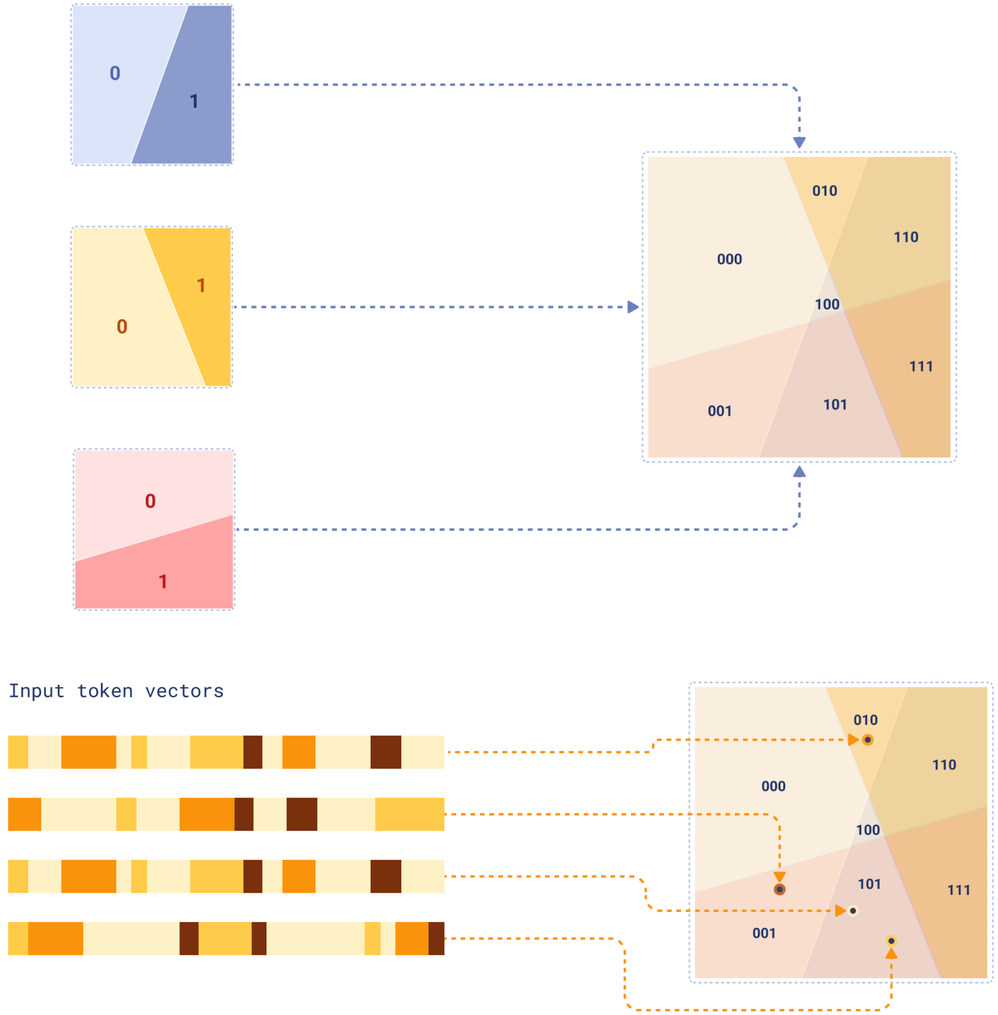
SimHash recap

SimHash is an LSH technique that maps vectors to binary codes using random hyperplanes

How it works:

- Sample k_{sim} random hyperplanes (normal vectors drawn from a standard normal distribution)
- Each hyperplane splits the space into 2 halves, together forming 2^{k_sim} regions
- For a token vector x, compute $sign(x \cdot h_i)$ for every hyperplane h_i
- The sequence of signs forms a k_{sim}-bit binary code
- Interpret this binary code as an integer → this becomes the cluster ID.



MUVERA: Making multi-vectors more performant

MUVERA

Fixed Dimensional Encoding

Once token vectors are assigned to SimHash clusters, MUVERA aggregates them differently for documents and queries.

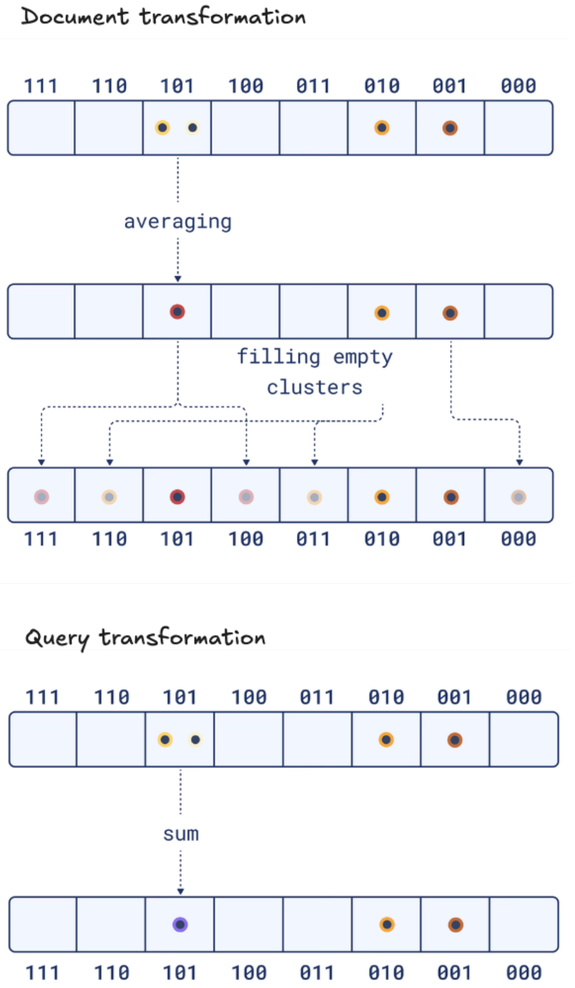
Document aggregation:

- For each cluster, compute the centroid (mean) of all assigned vectors
- If a cluster is empty, fill it using the a vector from the nearest non-empty cluster (not centroid) (nearest = smallest Hamming distance between cluster IDs)

Output: 2^{k_sim} vectors, each of dimension *dim*

Query aggregation:

- For each cluster, compute the sum of assigned vectors (not the mean). Larger cluster → larger magnitudes → reflects query term frequency.
- Do not fill empty clusters: Queries are short → empty cluster are expected. Filling them would add artificial terms and distort the scoring.



MUVERA: Making multi-vectors more performant

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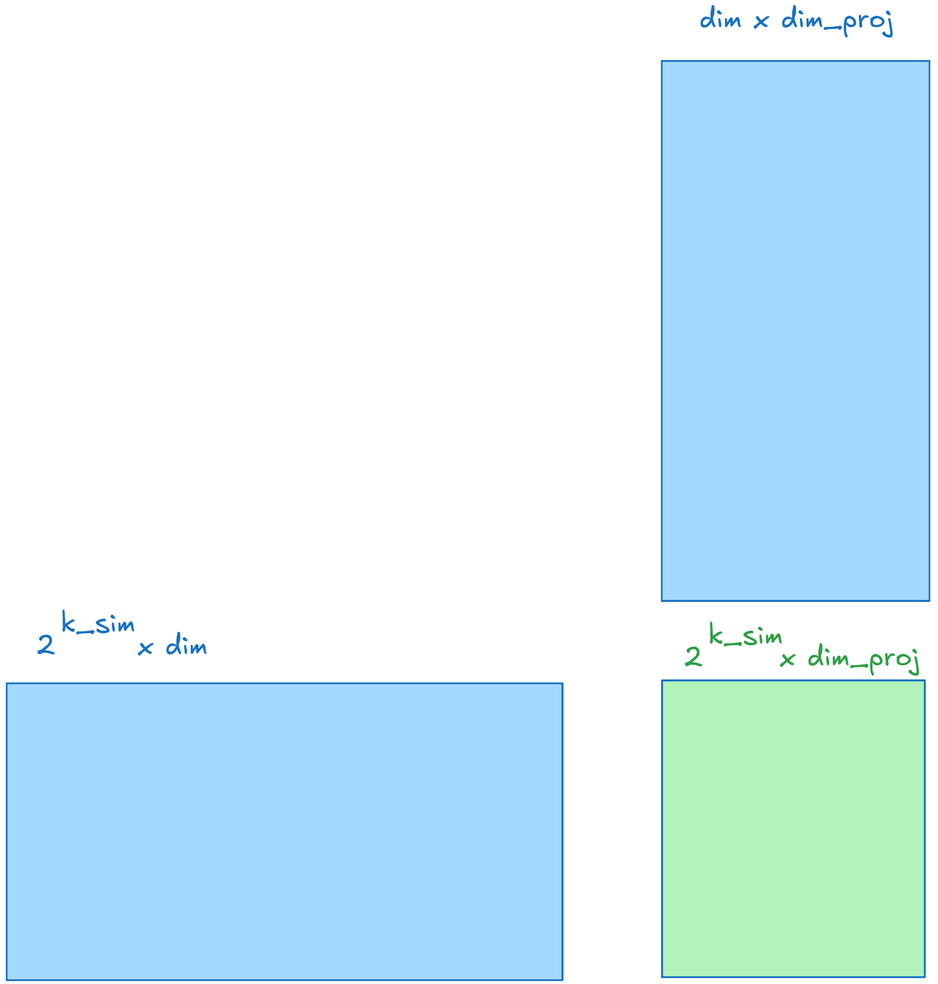
Dimensionality reduction through Random Projection

- With small SimHash codes (k_{sim}=4 or 5 - we get only 16 or 32 clusters), a single projection may be too coarse. To increase expressiveness, MUVERA repeats the clustering-and-aggregation process r_reps times, each with independent random hyperplanes.
- Example (dim=128, k_{sim} =4): $FDE = 16 \cdot 128 = 2048$; After r_reps: $20 \cdot 2048 = 40960$
- Sizes like 40960 are probably too large for efficient ANN search
- To keep the FDE compact, each cluster vector is projected using a random {-1, +1} matrix of shape (dim, dim_{proj}) and applying a scaling factor of $\frac{1}{\sqrt{dim_{proj}}}$
- The resulting FDE dim_{fde} is then $r\_reps \cdot 2^{k\_sim} \cdot dim_{proj}$
- The original paper suggests applying an additional random projection to the final FDE to further reduce its dimensionality, however, it's an optional step.



MUVERA

Benchmark

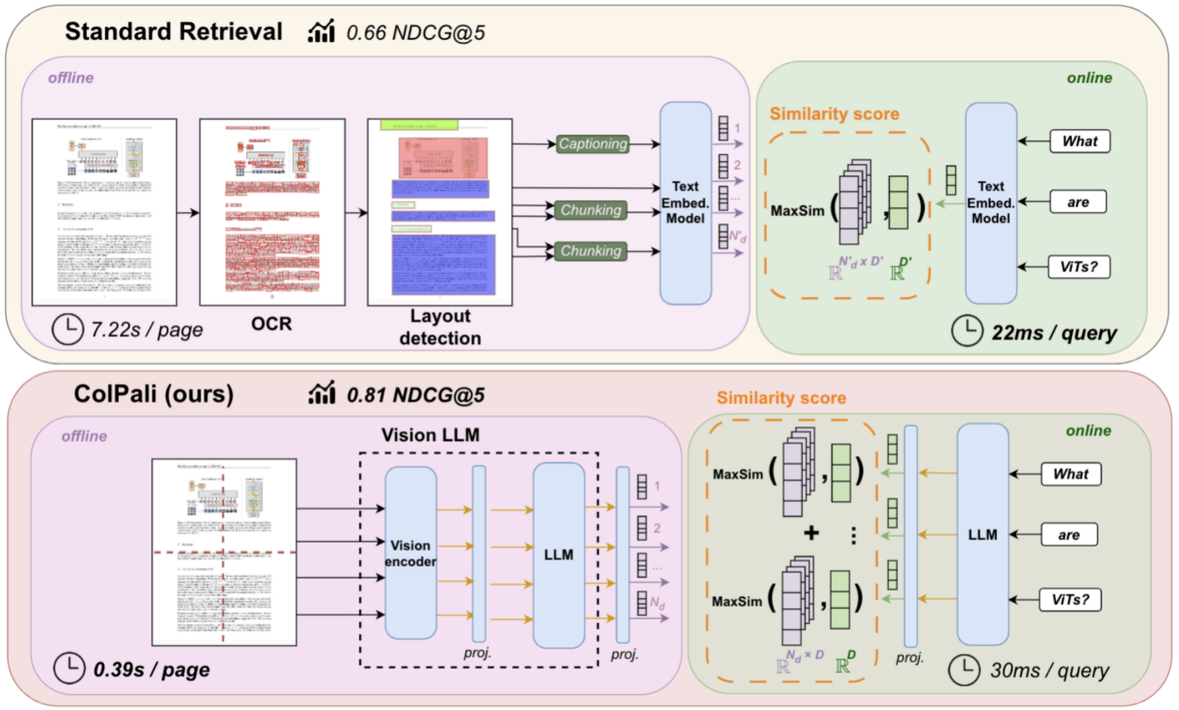
- Evaluation on BEIR / NFCorpus using ColBERTv2 as the multi-vector baseline.
- MUVERA configuration: $k_{sim} = 5$, $dim_{proj} = 16$, $r\_reps = 20$
- The results show that MUVERA-only search trades some accuracy for speed, achieving about 70% of the full multi-vector performance.
- Multistage pipeline recovers nearly all the original performance while maintaining the efficiency benefits for the initial search phase.
- MUVERA-only search is approximately 8x faster than full multi-vector search, while the hybrid approach with reranking still achieves about 7x speed improvement while maintaining nearly identical search quality.

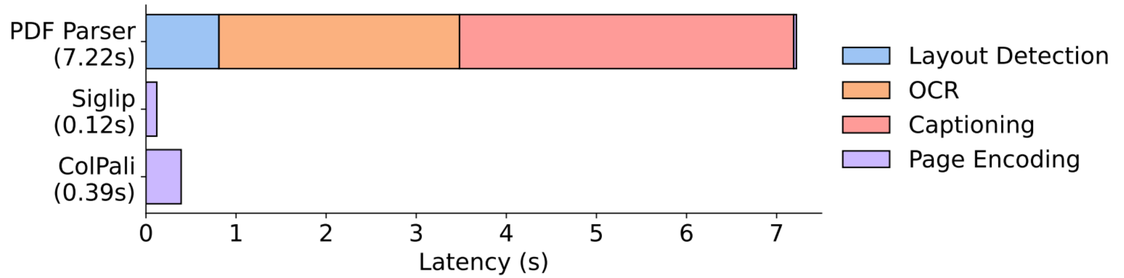
Approach	NDCG@1	NDCG@5	NDCG@10	Average search time
Full multi-vector (ColBERT)	0.478	0.387	0.347	1.27
MUVERA-only	0.319	0.267	0.242	0.15
MUVERA + reranking	0.475	0.383	0.343	0.18

MUVERA: Making multi-vectors more performant

Search your documents

- Traditional document retrieval in RAG/search systems relies on text extraction (OCR, layout detection) → text embedding pipelines
- These pipelines can be slow and complex, involving OCR, layout reconstruction, chunking
- Visually rich documents (PDFs with tables, figures, layouts) often lose important cues when converted to plain text
- ColPali proposes a vision-centred approach: embed the document page as an image, capturing text, layout, and visuals in a single model

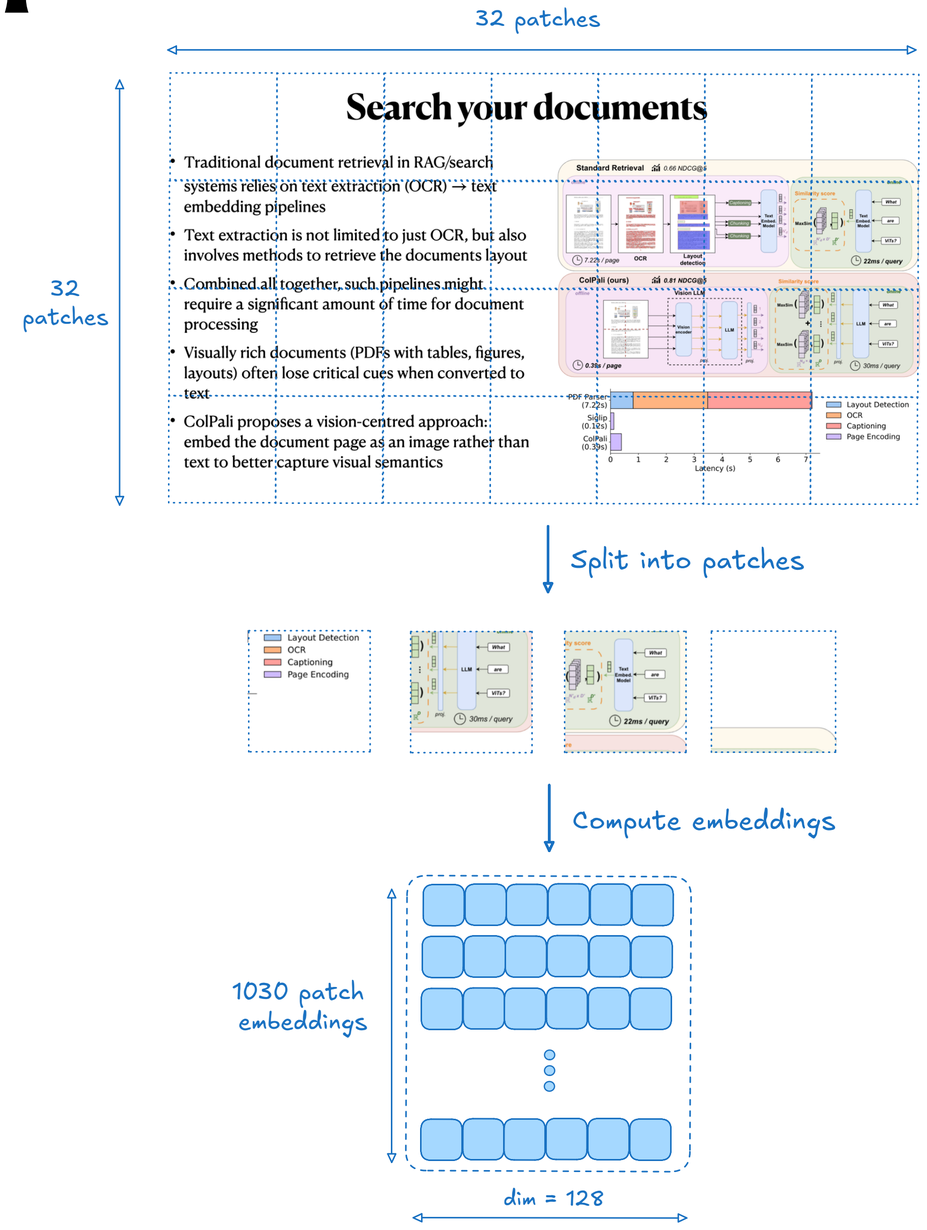




ColPali: Efficient Document Retrieval With Visual Language Models

ColPali

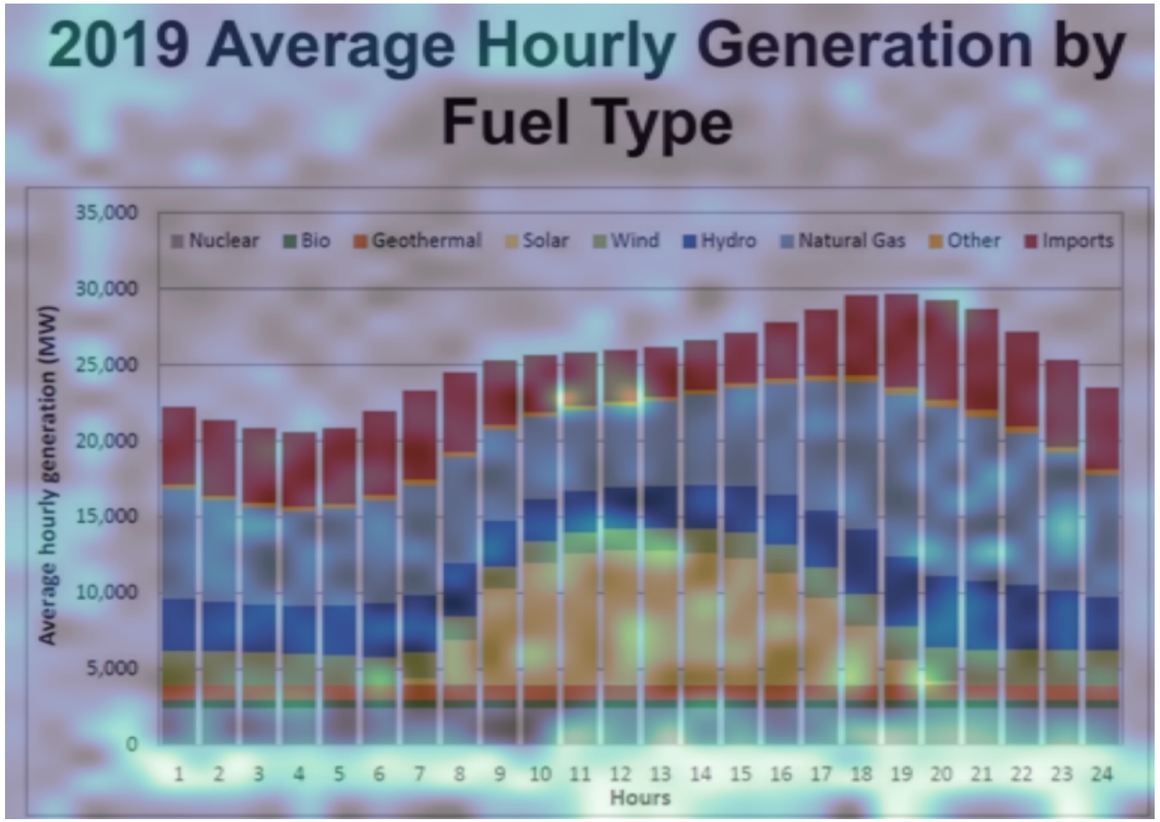
- ColPali uses a VLM (e.g., PaliGemma-3B) to generate multi-vector embeddings from document page images
- Each page is split into 32x32=1024 image patches; the model also uses a small number of prefix tokens (e.g., *<bos>Describe the image.)* for instruction/context.
- The VLM computes embeddings for all patch tokens and prefix tokens, producing ~1030 vectors per page
- Inspired by ColBERT, ColPali uses late interaction: each query vector matches its most similar document vector via MaxSim, and these scores are summed
- This setup replaces OCR + layout parsing + text embedding with a single image → embedding step in the retrieval pipeline



ColPali

Benefits & Performance

- ColPali outperforms text-centric retrievers on benchmarks like ViDoRe (visual document retrieval)
- Document preprocessing is faster than OCR & others
- It improves recall on documents where layout and visual structure matter
- Offers good interpretability via heatmaps
- However, generated multi-vectors have a large memory footprint and expensive to index
- As with ColBERT, building ANN indexes over thousands of vectors per document can be slow, so it's natural to use a multi-stage pipeline where a cheaper model prefetches candidates



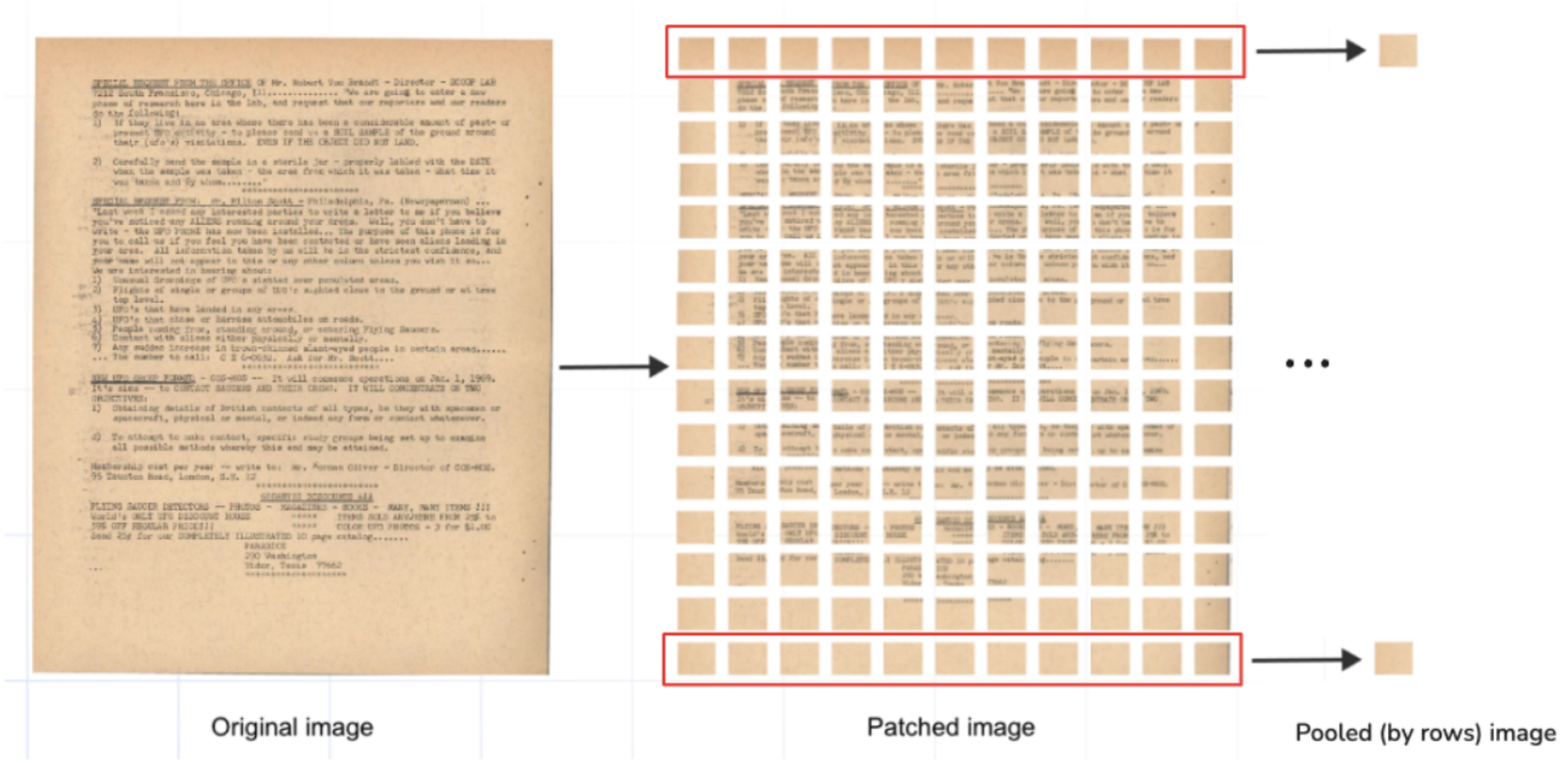
Query: "Which hour of the day had the highest overall electricity generation in 2019?"

ColPali: Efficient Document Retrieval With Visual Language Models

ColPali

Multistage pipeline

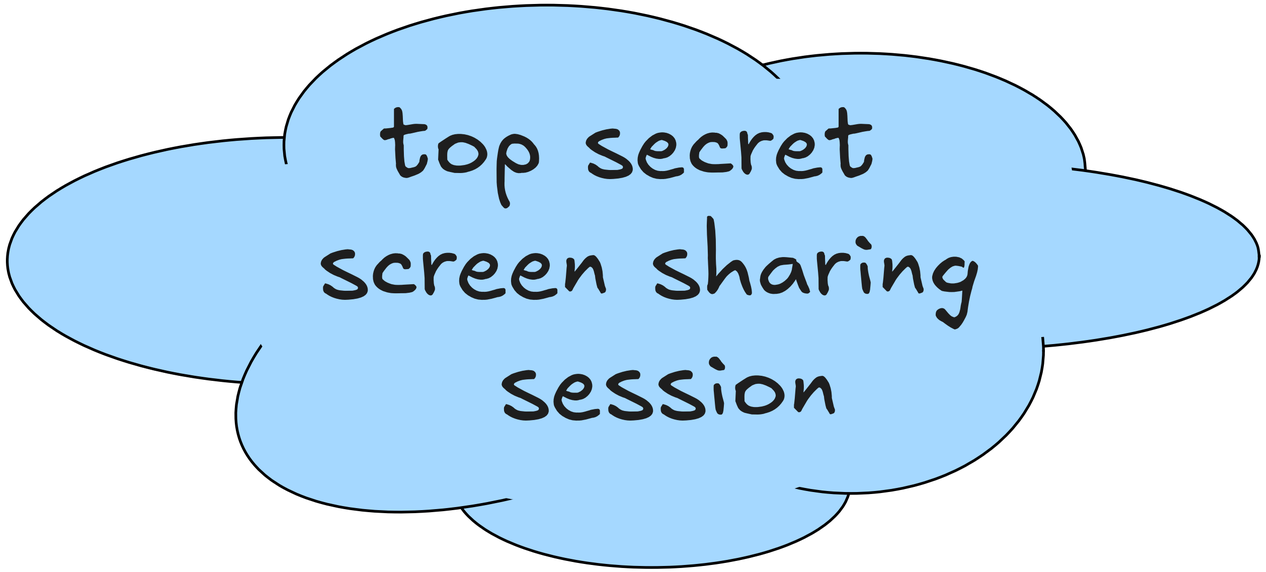
- As it was said, ColPali produces 1030 vectors per page
- Building an ANN index like HNSW on these vectors is expensive: with *ef_construct=100*, the total number of vector comparisons would be *1030*1030*100 =106 090 000* per page
- There are few alternative vision-based models that could serve as a cheaper first-stage retriever for this exact task, so a natural direction is to compress ColPali's own representations
- A practical approach is to pool ColPali embeddings by rows or by columns of the original document.
- Mean pooling reduces the number of vectors by a factor of 32, while maintaining high recall



PDF retrieval at scale

Demo in Qdrant

- We didn’t have enough time for the demo last time, let’s do it now



Questions?