MUVERA:Multi-Vector Retrieval via Fixed Dimensional Encodings

APL 김주희

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1. Prerequisites

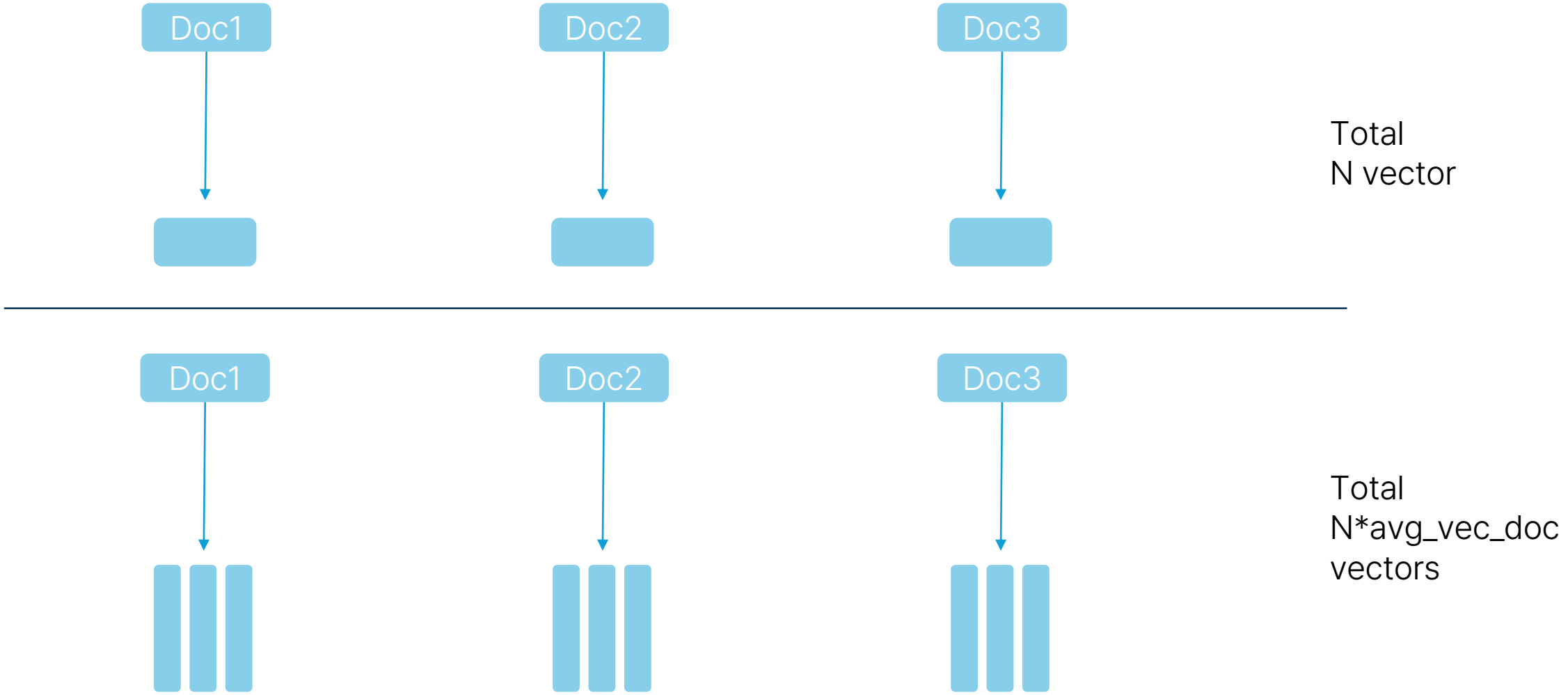
Vector database vs Vector Indexing

- **Vector DB**
  - 벡터 임베딩을 메타데이터와 함께 저장하고 관리하는 시스템
  - CRUD를 지원
  - 하이브리드 검색, 필터링, 권한 제어 등 지원
  - 예) Weaviate, Pinecone, Milvus 등
- **Vector Indexing**
  - 벡터끼리의 유사도 계산을 빠르게 하기 위한 알고리즘
  - 예) FAISS, HNSW, ScANN

2. Overview of the Paper

- **목적**
  - Multi-vector 문서 검색을 single vector 검색처럼 효율적으로 하는 것
- **Motivation**
  - 메모리 감소
  - Vector search의 CPU overhead
- **Contribution**
  - FDE (Fixed dimensional Encoding) 제안
  - 내적 기반 Chamfer 유사도 근사
  - 빠른 후보 검색 + 정확한 Reranking

2. Overview of the Paper



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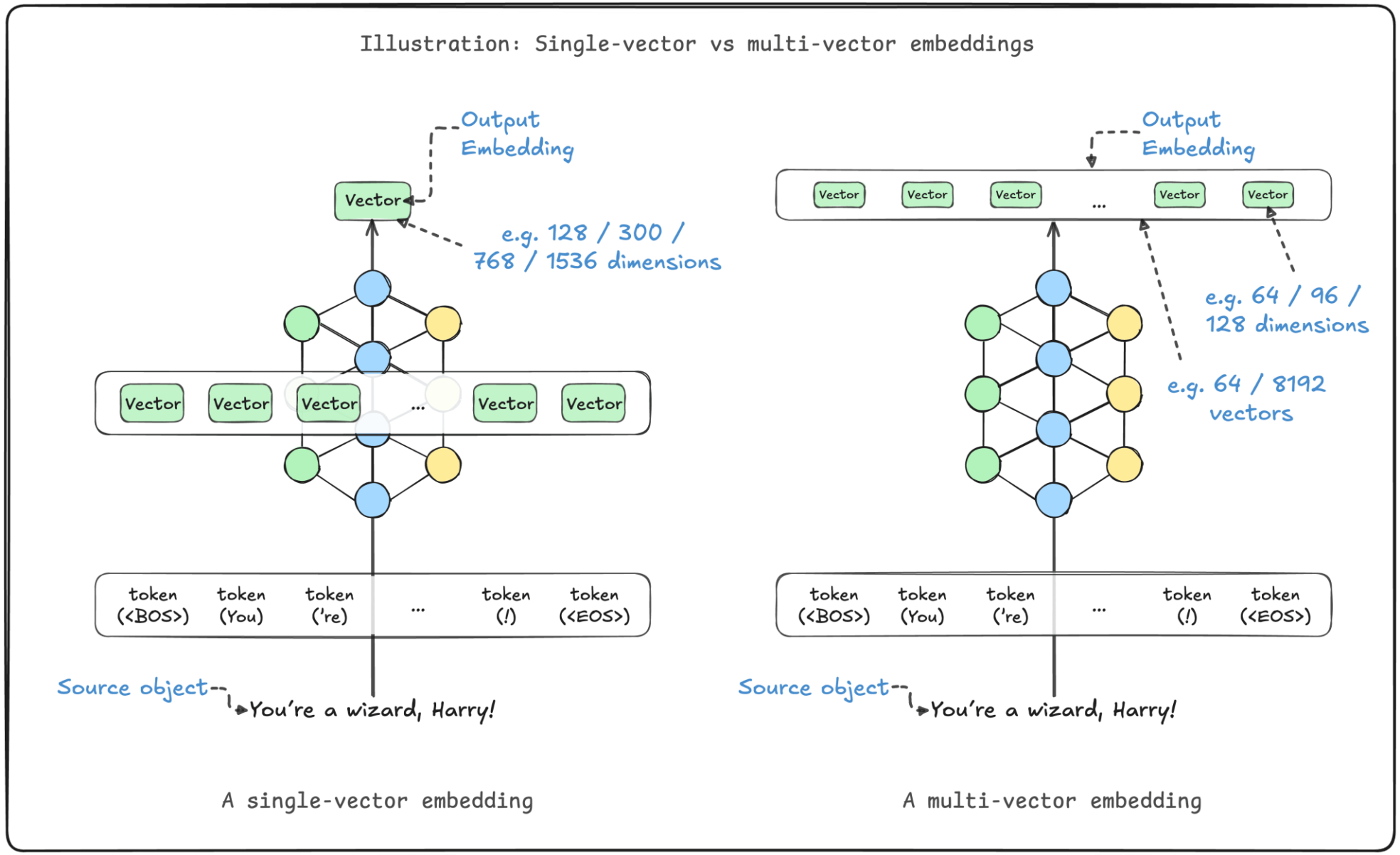


2. Overview of the Paper

- maxSim 유사도 계산
  - 문서 임베딩 D, 쿼리 임베딩 Q

$$\mathrm{sim}(D, Q) = \sum_{q \in Q} \max_{d \in D} q \cdot d$$

3. FDE

What is the FDE?

- 여러 벡터로 표현된 문서를 고정된 하나의 벡터로 변환
- 클러스터링 + 차원 축소 + 반복을 통해 하나의 벡터로 압축
- 내적으로 chamfer 유사도 근사 가능

3. FDE

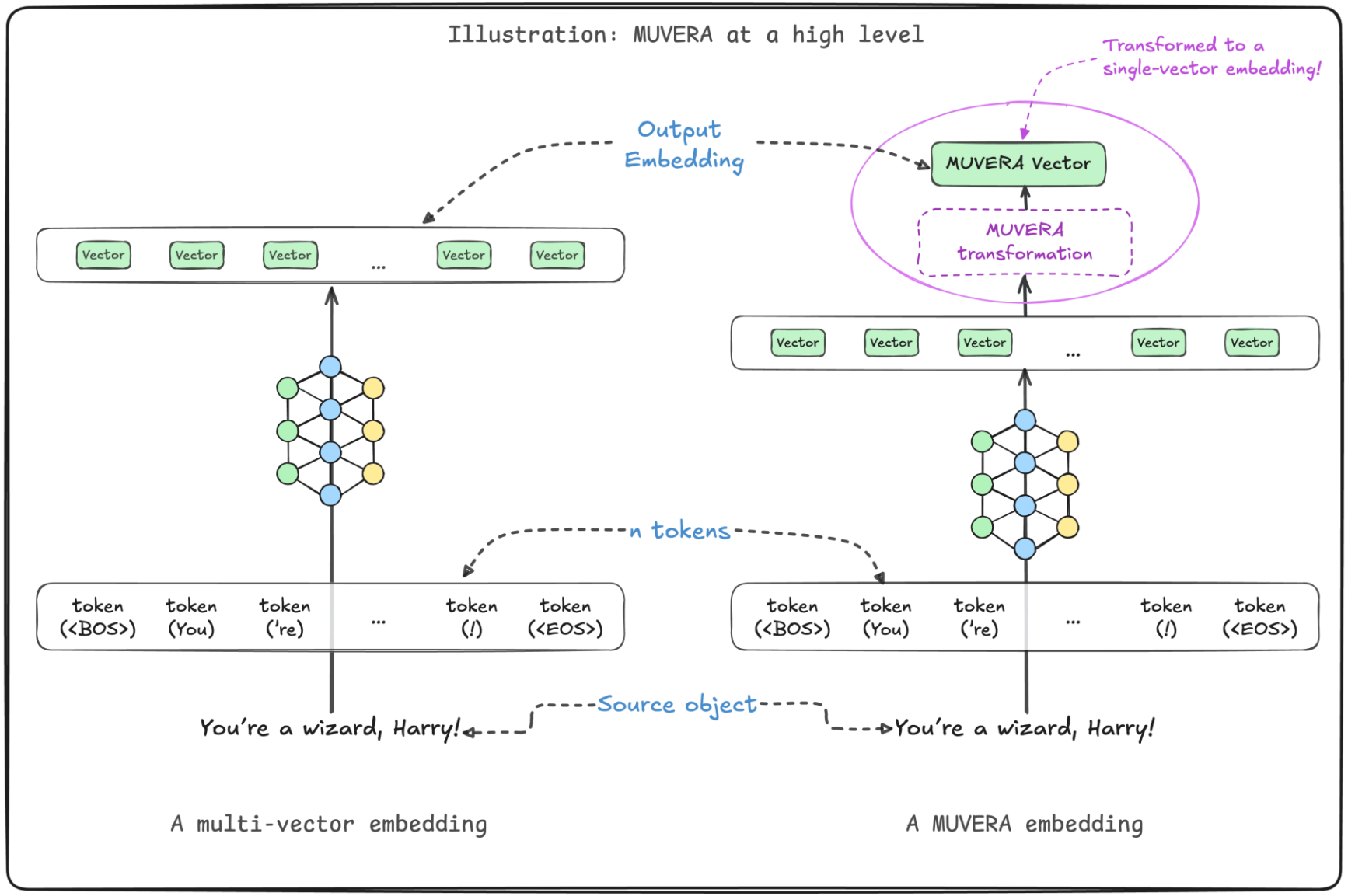


Illustration: MUVERA at a high level
Transformed to a single-vector embedding!
Output Embedding
MUVERA Vector
MUVERA transformation
Vector
Vector
Vector
...
Vector
Vector
n tokens
token (<BOS>)
token (You)
token ('re)
...
token (!)
token (<EOS>)
Source object
You're a wizard, Harry!
You're a wizard, Harry!
A multi-vector embedding
A MUVERA embedding

3. FDE

Key Idea

- Multi-vector embedding D
- Single-vector embedding d_single

$$encode(x_{multi}) \Longrightarrow x_{single}$$
$$x \in D, Q$$

$$maxSim(D, Q) \approx d_{single} \cdot q_{single}$$
$$where$$
$$d_{single} = encode(D) \wedge q_{single} = encode(Q)$$

4. How FDE is Constructed

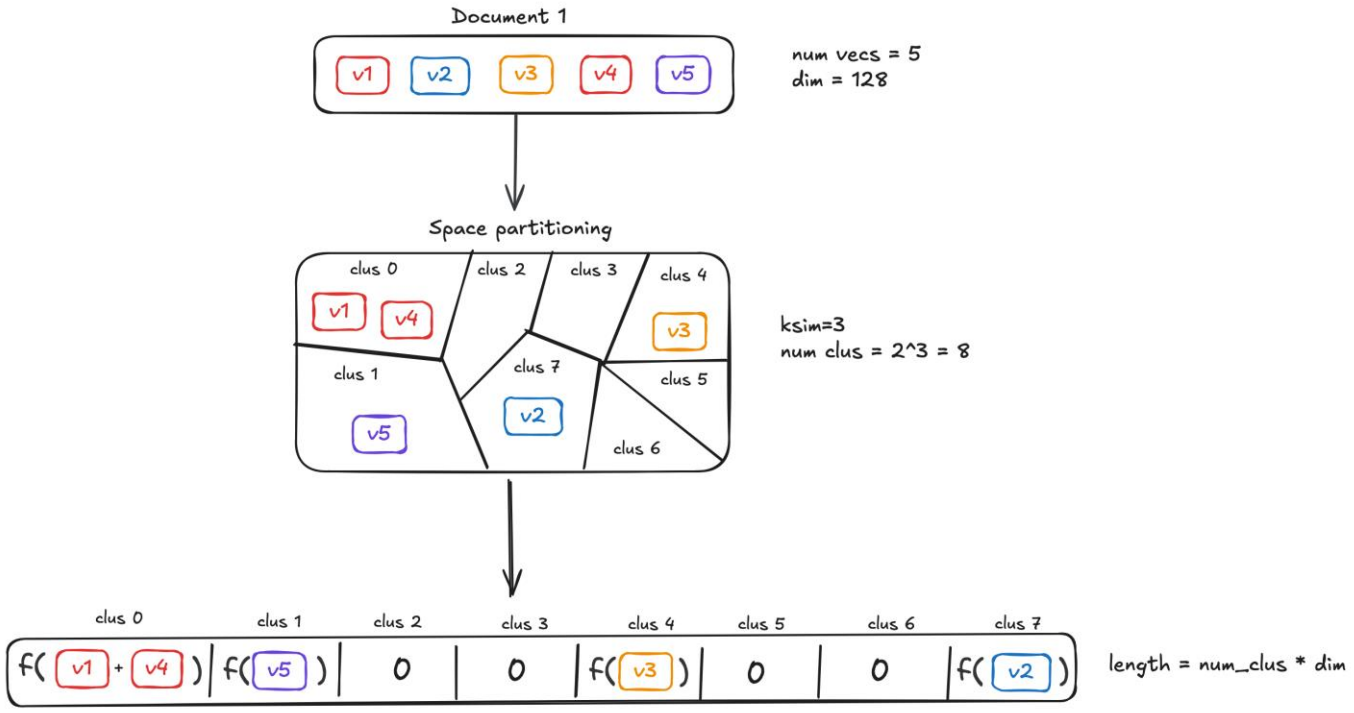
Four Steps

1. Space partitioning
2. Dimensionality reduction
3. Multiple repetitions
4. Final Projection

4. How FDE is Constructed

Space Partitioning

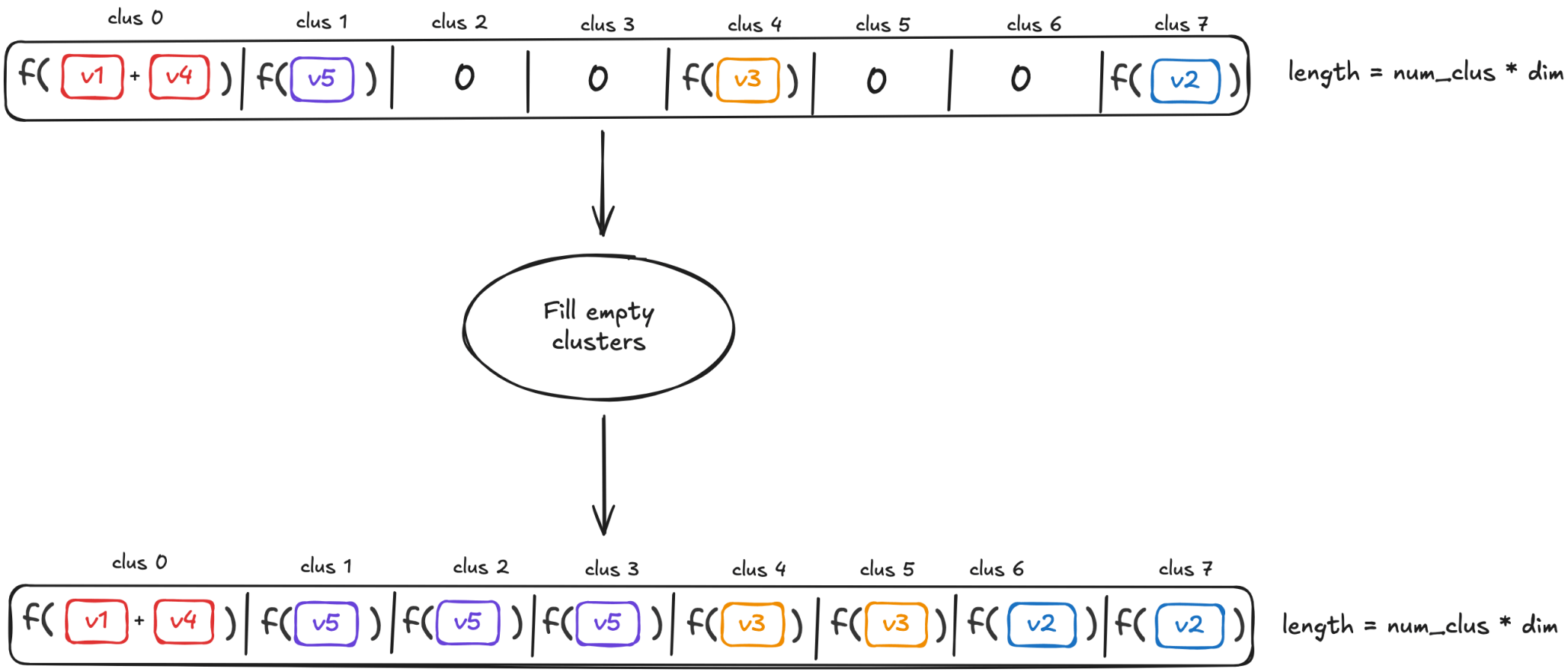
- **SimHash로 벡터 공간을 B개의 클러스터로 분할**
  - 함수 φ(x) 를 알 수 있다면 k번째 클러스터로 들어갈 수 있음
  - 이 때, 클러스터 k는 총 B개 중 하나이므로 k ∈ {1, 2, ..., B} 로 표현 가능
  - g1, . . . , gksim ∈ Rd , and set φ(x) = (1(⟨g1, x⟩ > 0), . . . , 1(⟨gksim , x⟩ > 0)), where 1(·) ∈ {0, 1} is the indicator function



4. How FDE is Constructed

Space Partitioning

- Fill empty cluster



4. How FDE is Constructed

Space Partitioning

- **최종 단일 벡터**
  - 문서에서 클러스터별 vector d_k 만들기
  - 쿼리 벡터는 합만 구함
  - D1부터 db까지 이어붙여 하나의 벡터로 만듦

$$d_k = \frac{1}{|D_k|} \sum_{d \in D, \phi(d)=k} d \qquad q_k = \sum_{q \in Q, \phi(q)=k} q$$

$$d_{\text{single}} = [d_1, d_2, \ldots, d_B]$$

4. How FDE is Constructed

Dimensionality Redcution & Multiple repetitions

- D_k를 줄이기
  - S∈R d proj ×dim :±1로 구성된 랜덤 행렬(JL 렘마 근거)
  - D_proj: 축소하고 싶은 목표 차원 예)16, 32
  - $\psi(dk)$: 압축된 d_k 벡터

$$\psi(d_k) = \frac{1}{\sqrt{d_{\text{proj}}}} \cdot S \cdot d_k$$

$$d_{\text{single}} = [\psi(d_1), \psi(d_2), \ldots, \psi(d_B)]$$

5. Strengths of MUVERA

- 기존 Multi-vector 방식보다 훨씬 빠른 검색 속도 제공
- Dot product 기반이라 GPU최적화가 가능함
- 다양한 벡터 수와 구조에 유연하게 대응할 수 있음

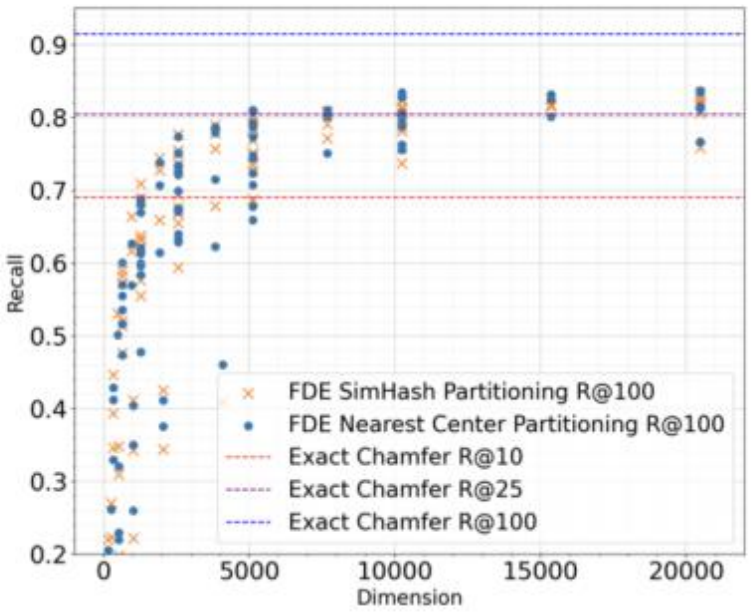
6. Limitation of MUVERA

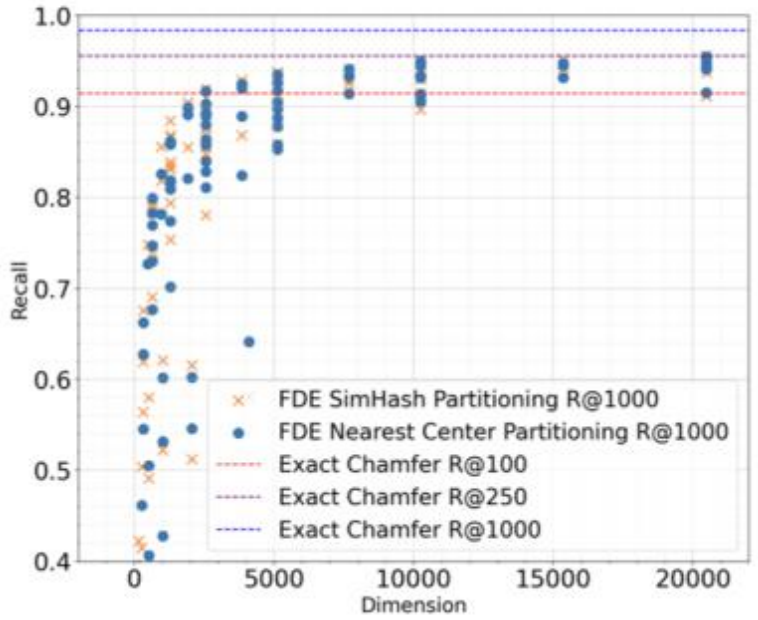
- 근사 방식이기 때문에 정확도 손실 가능성 존재
- 하이퍼파라미터 설정이 복잡함
- 빈 클러스터 보정이 완벽하지 않음
- 일부 데이터셋에서 다른 방식보다 성능이 낮음

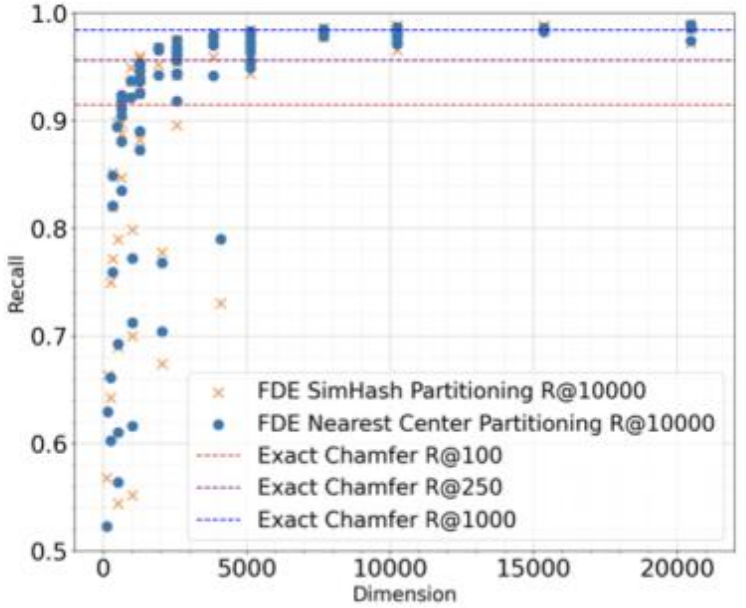
7. Experimental Results

- **비교 대상**
  - MaxSim (Chamfer): 정확하지만 느림
  - PLAID: 빠른 multi-vector 근사 방법
  - Dense Retrieval: single-vector만 쓰는 방식
- **데이터셋**
  - BEIR (MS MARCO, NQ, TREC-COVID 등 다수)
  - LoTTE (Long-form QA)
  - MS MARCO (웹검색 쿼리 기반)
- **평가지표**
  - Recall@k
  - 검색 속도 (query per second)
  - 메모리 사용량

7. Experimental Results







7. Experimental Results

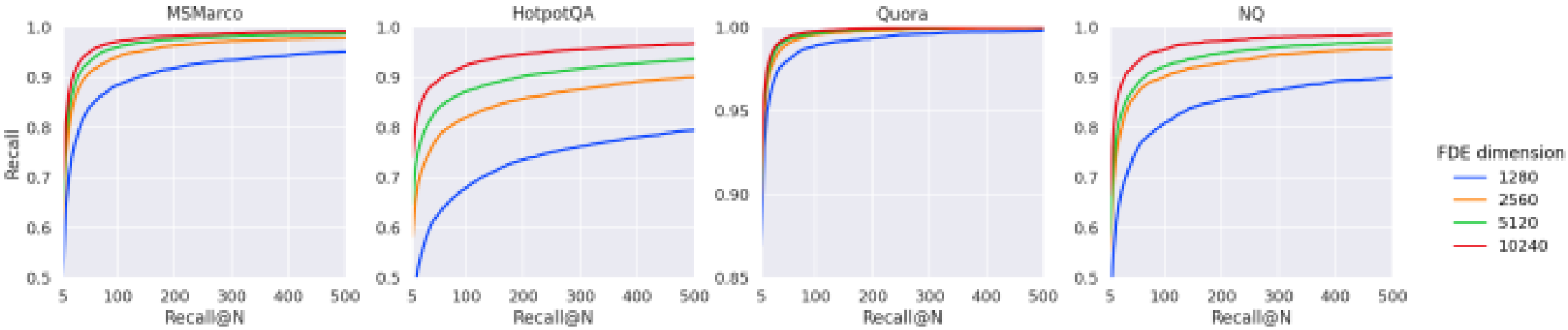


Figure 4: Comparison of FDE recall versus brute-force search over Chamfer similarity.

7. Experimental Results

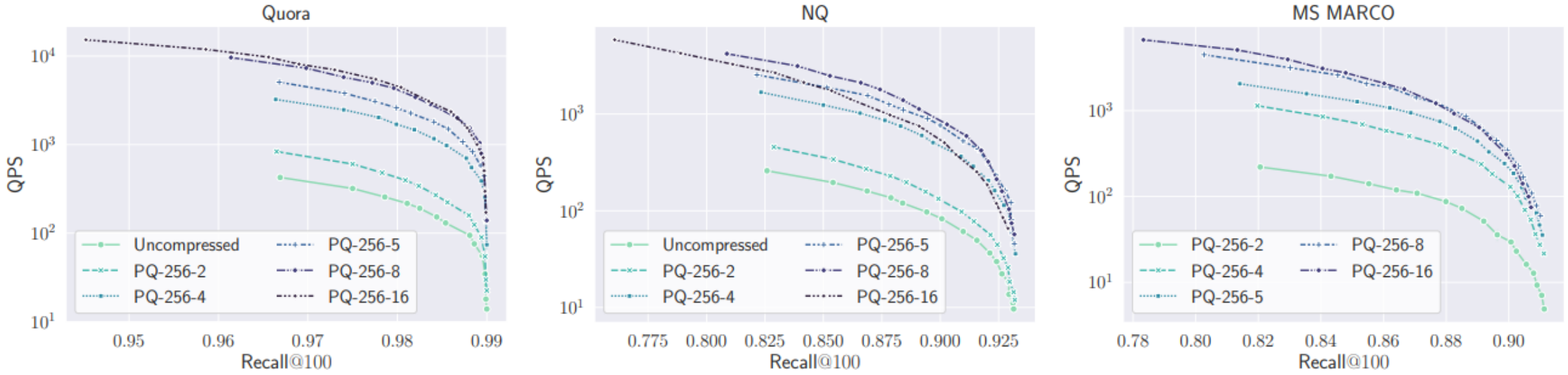


Figure 6: Plots showing the QPS vs. Recall@100 for MUVERA on a subset of the BEIR datasets. The different curves are obtained by using different PQ methods on 10240-dimensional FDEs.

7. Experimental Results

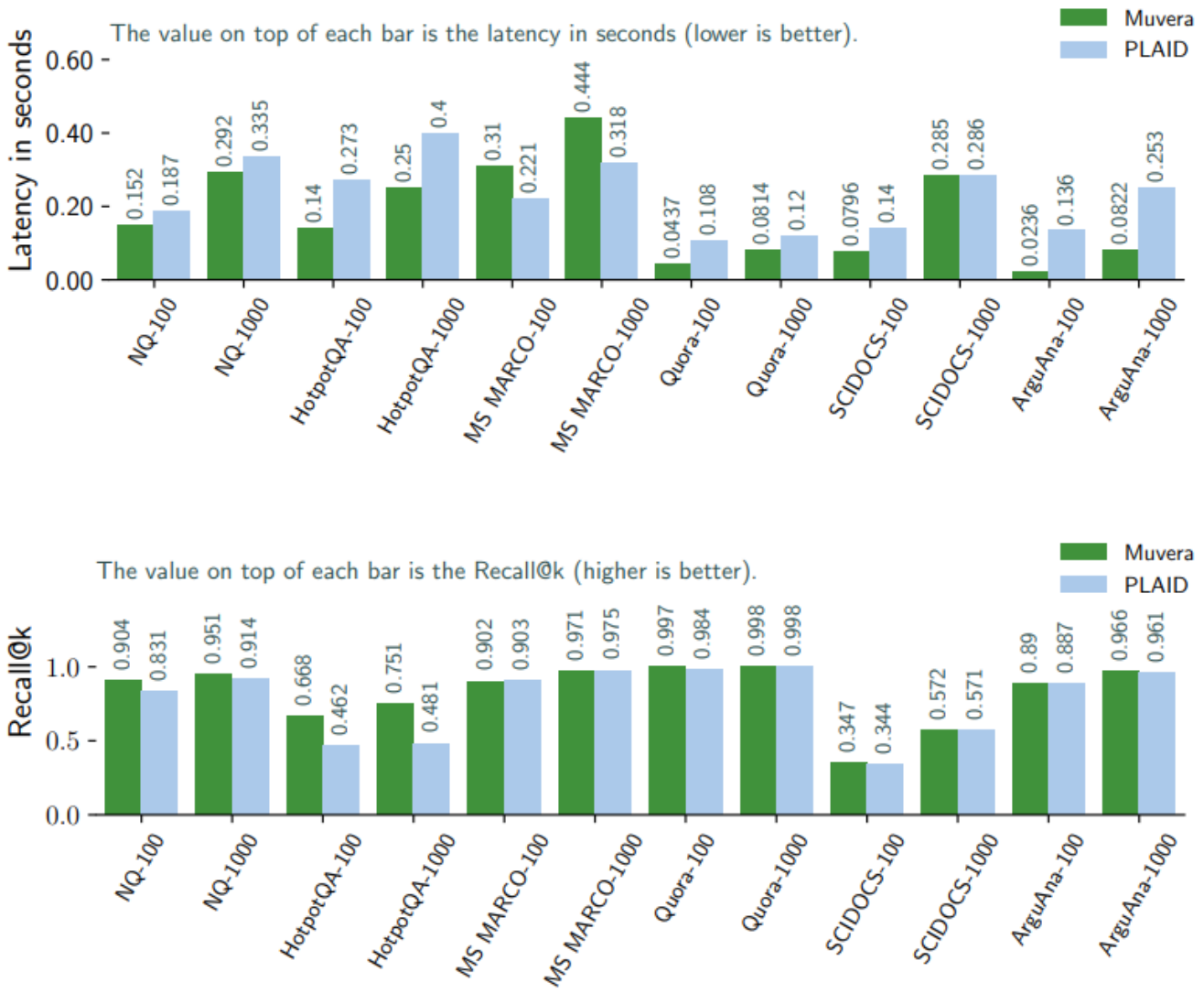


Figure 7: Bar plots showing the latency and Recall@k of MUVERA vs PLAID on a subset of the BEIR datasets. The x-tick labels are formatted as dataset-k, i.e., optimizing for Recall@k on the given dataset.

8. Conclusion

- MUVERA는 효율성과 정확도의 균형을 맞춘 최신 vector 검색 방식
- 실무 적용 시 튜닝이 필요하지만 가치가 충분함
- 하이브리드 방식 등으로 향후 발전 가능성이 있음

9. Experimental

- Dataset: https://huggingface.co/datasets/google-research-datasets/go_emotions
- 실험 구성: muvera의 ksim, dproj, reps를 다르게 설정하여 메모리와 속도를 실험