ACL 2023 Tutorial:

Retrieval-based Language Models and Applications

Akari Asai, Sewon Min, Zexuan Zhong, Danqi Chen

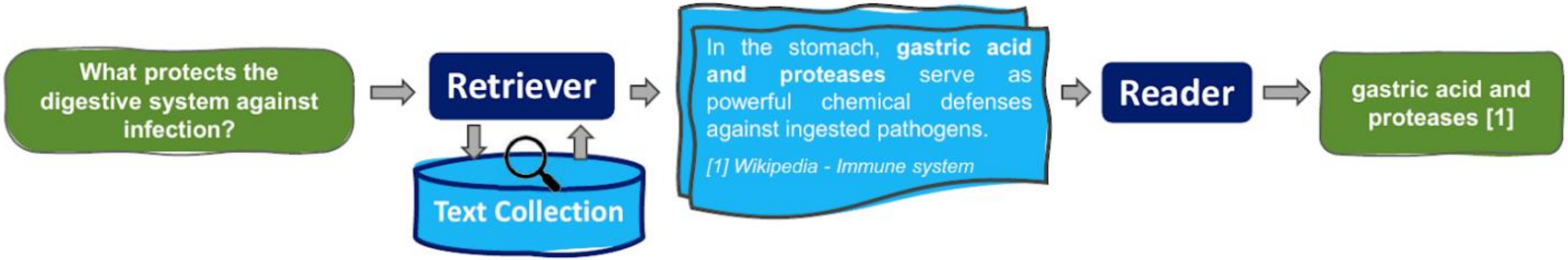
University of Washington, Princeton University

발표자: 송선영

2024/01/09

Retrieval for knowledge-intensive NLP tasks

- Representative tasks: open-domain QA, fack checking, entity linking, …



Why do retrieval-based LMs need?

1. **LLMs can't memorize all knowledge in their parameters**

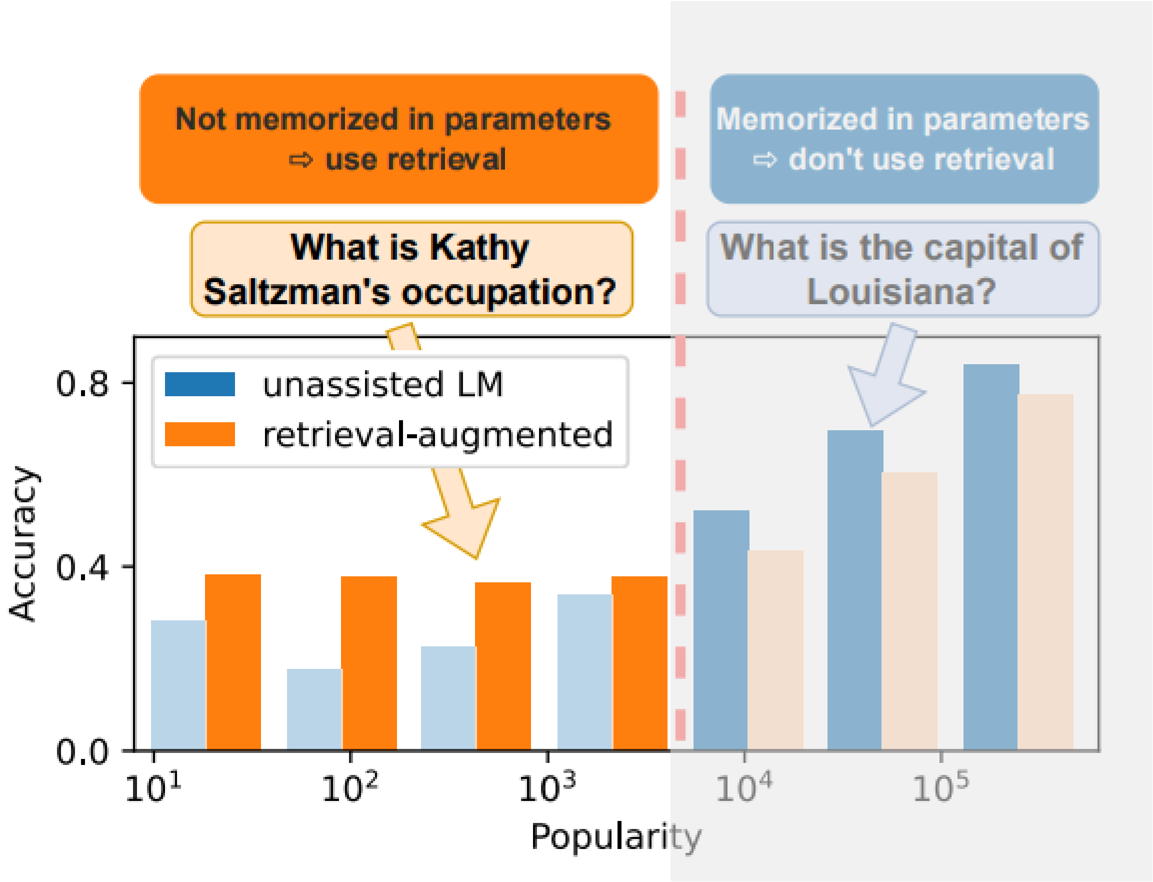
List 5 important papers authored by Geoffrey Hinton

Geoffrey Hinton is a renowned computer scientist …
Here are five important papers authored by him:

1. "**Learning Internal Representations by Error Propagation**" (with **D. E. Rumelhart** and **R. J. Williams**) - This paper, published in **1986**, ..
2. "**Deep Boltzmann Machines**" (with **R. Salakhutdinov**) - Published in **2009**, ..

…

4. "**Deep Learning**" (with Y. Bengio and A. Courville) - Published as a book in **2016**,…
5. "**Attention Is All You Need**" (with V. Vaswani, N. Shazeer, et al.) - Published in **2017**, this paper introduced the Transformer model,…



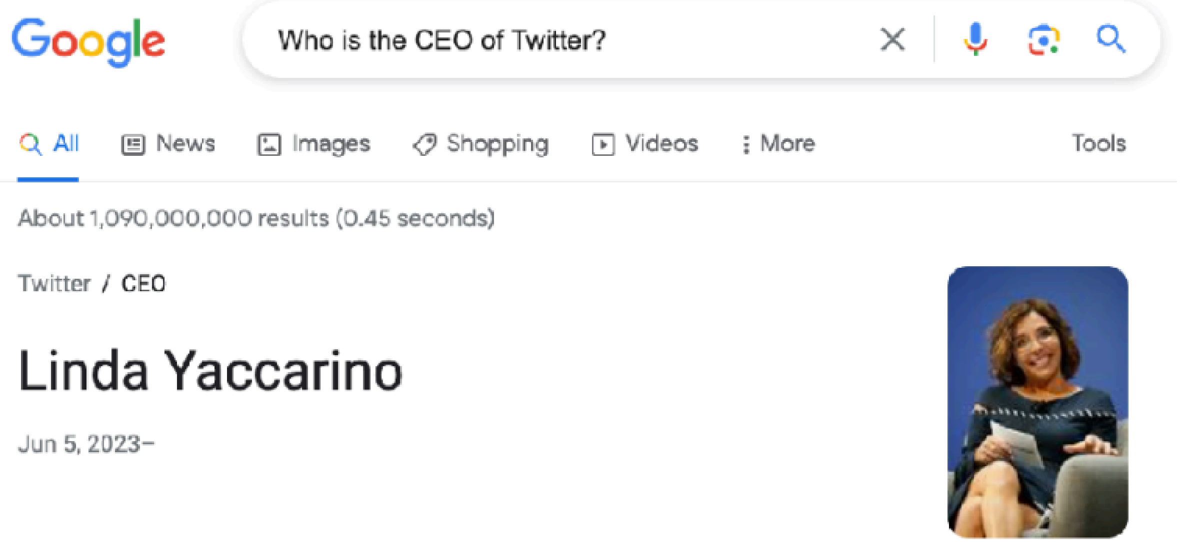
Why do retrieval-based LMs need?

2. LLMs' knowledge is easily outdated and hard to update

Who is the CEO of Twitter?

ChatGPT

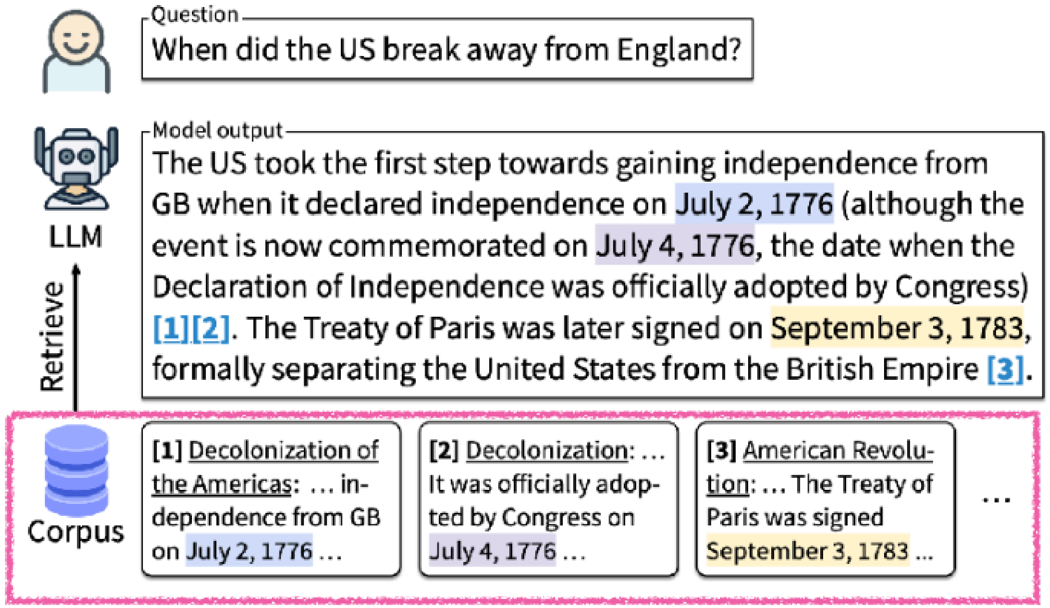
As of my **knowledge cutoff in September 2021**, the CEO of Twitter is **Jack Dorsey**….

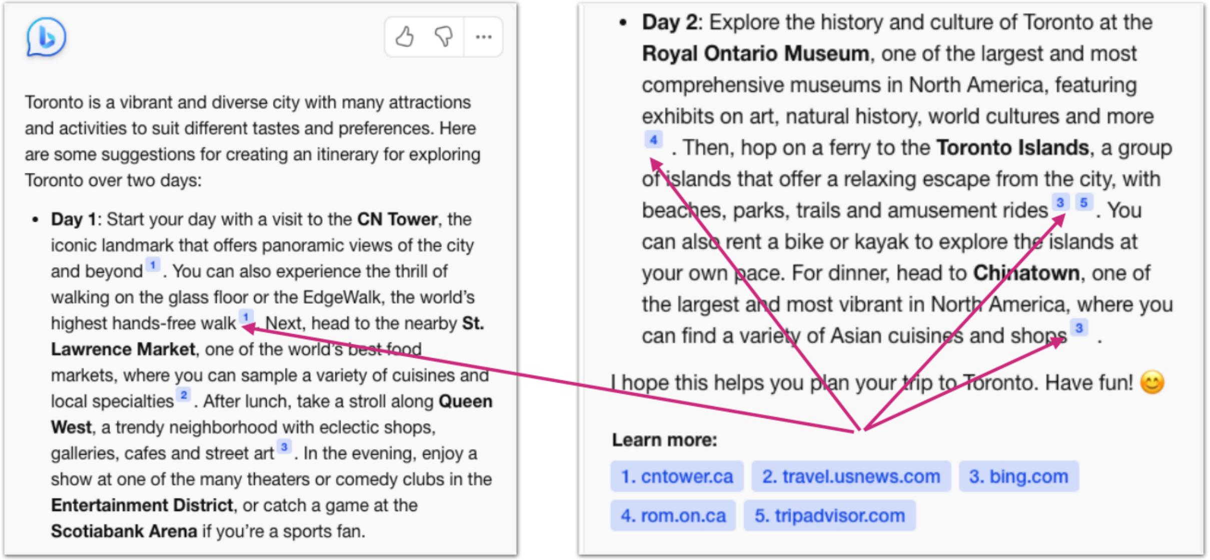


Why do retrieval-based LMs need?

3. LLMs' output is challenging to interpret and verify

→ **Solution**: Generating text with citations

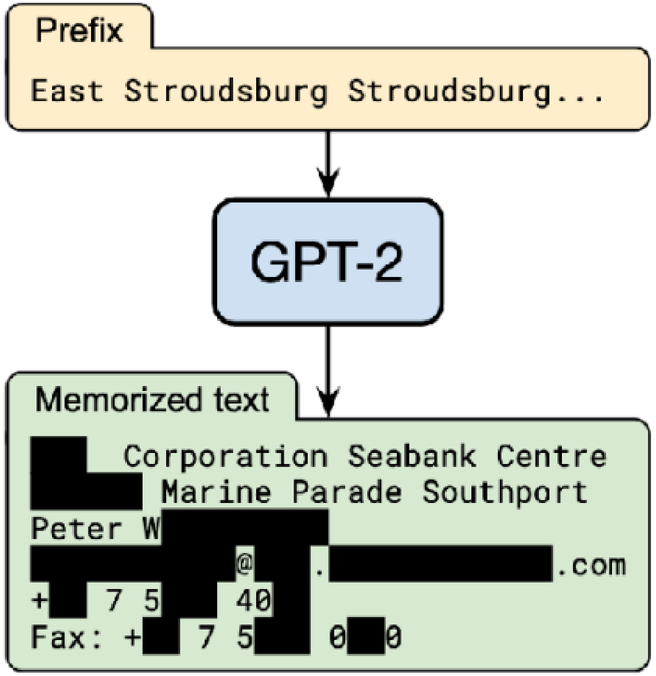




Why do retrieval-based LMs need?

4. LLMs are shown to easily leak private training data
    - Private data: address email, phone number, …

  → **Solution**: Individualization on private data by storing it in the datastore

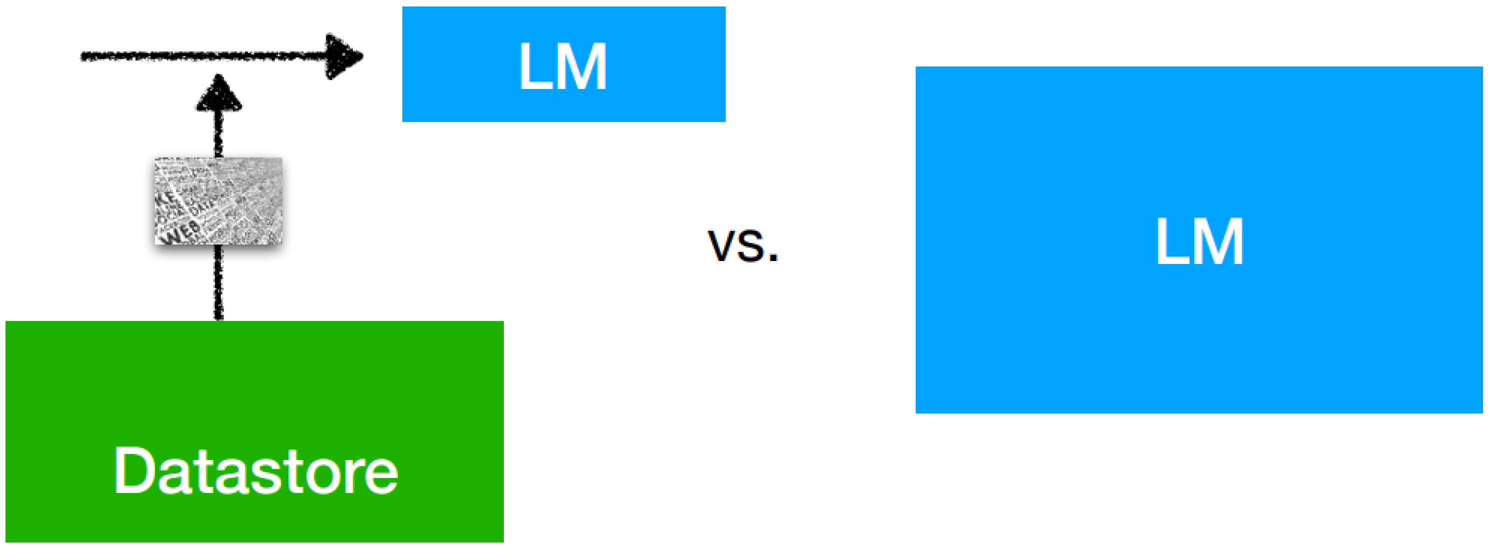


Why do retrieval-based LMs need?

5. LLMs are *large* and expensive to train and run

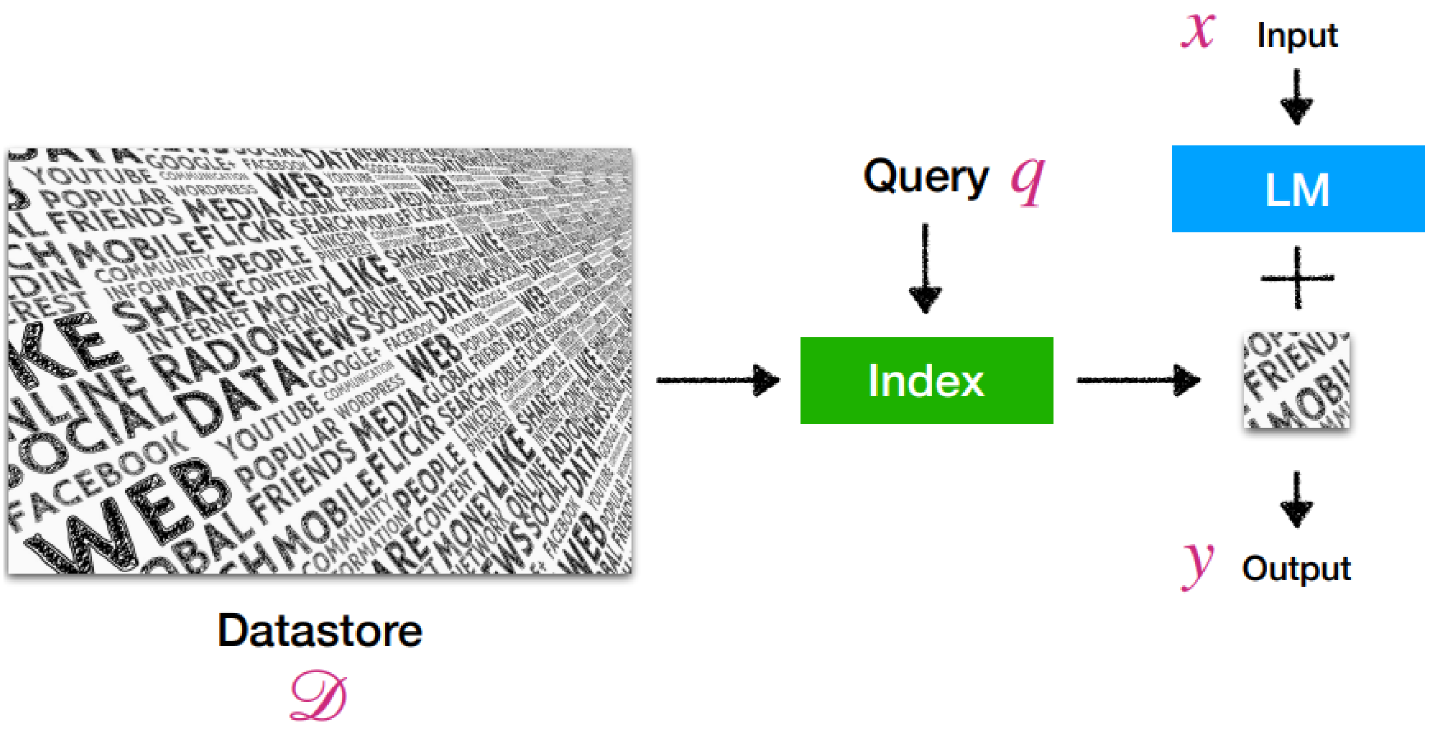
→ **Solution**: to directly access a large external database

- Improving Language Models by Retrieving from Trillions of Tokens (RETRO) (Borgeaud, Sebastian, et al. PMLR, 2022)
- RETRO obatins comparable performance to GPT-3 and Jurassic-1 on the Pile, despite using 25x fewer parameters



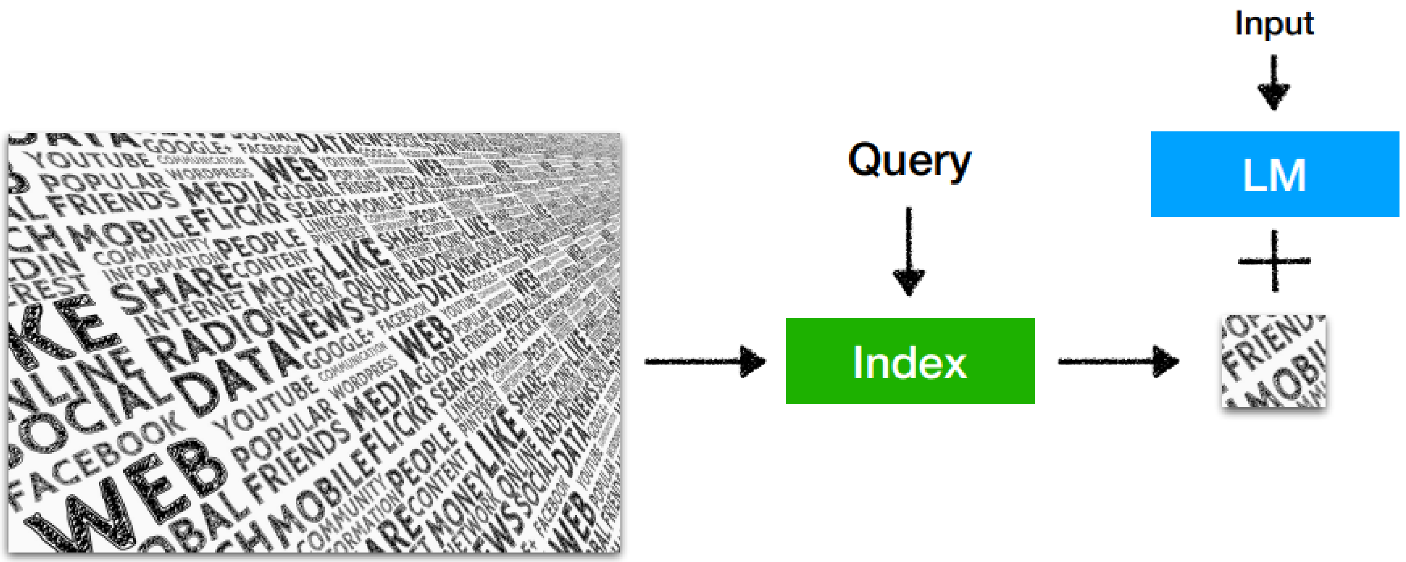
What is a Retrieval-based LM?

- Retrieval-based LM is a language model (LM) that uses an external datastore at test time



Inference

1. Datastore
   - consists of raw text corpus
   - It's very large-scale consisting of at least billions or tillion tokens



Datastore

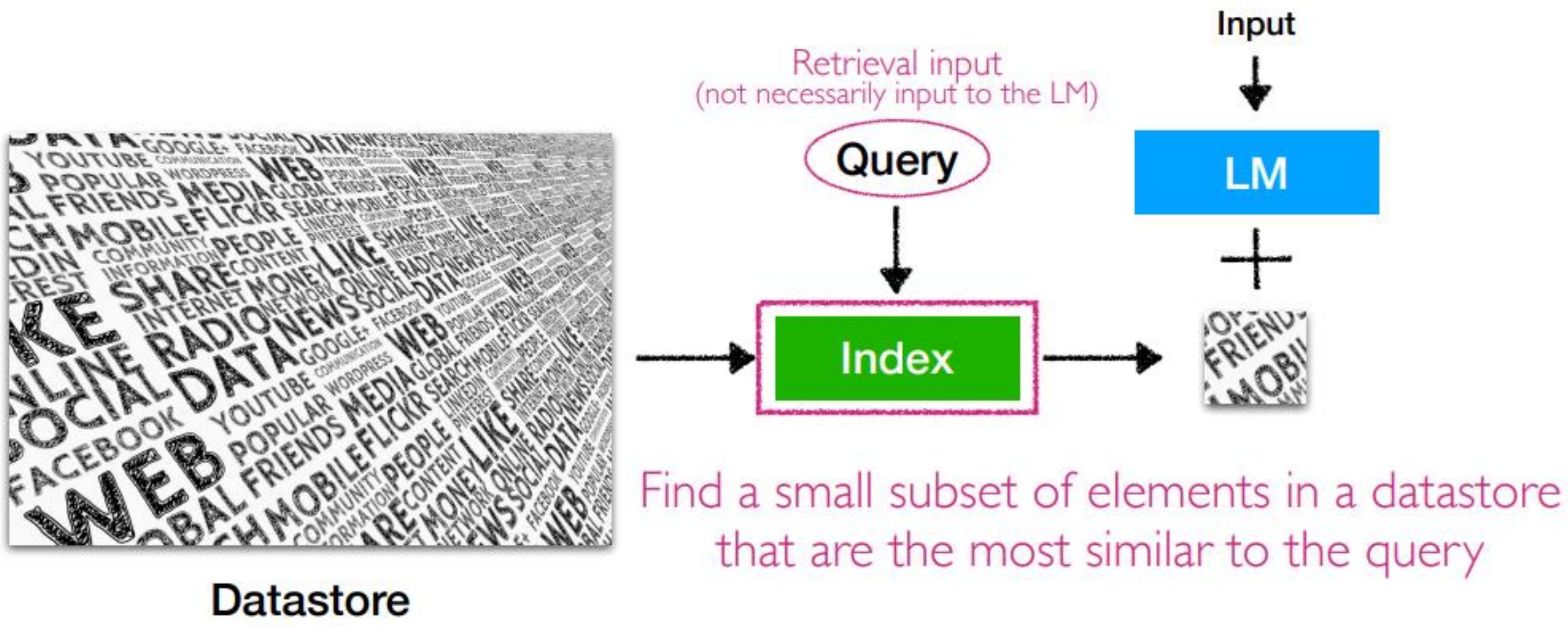
Raw text corpus

At least billions~trillions of tokens
Not labeled datasets
Not structured data (knowledge bases)

Inference

2. Index

    - Input: query
    - Output: a small subset of elements in a datastore that are the most similar to the query



Inference

2. Index
   - **Similarity score** is a score that represent how similar two pieces of text is in semantically
     - **TF-IDF**

Example $$\mathrm{sim}(i,j) = \underbrace{\mathrm{tf}_{i,j}}_{\text{\# of occurrences of } i \text{ in } j} \times \log \frac{\overbrace{N}^{\text{\# of total docs}}}{\underbrace{\mathrm{df}_i}_{\text{\# of docs containing } i}}$$

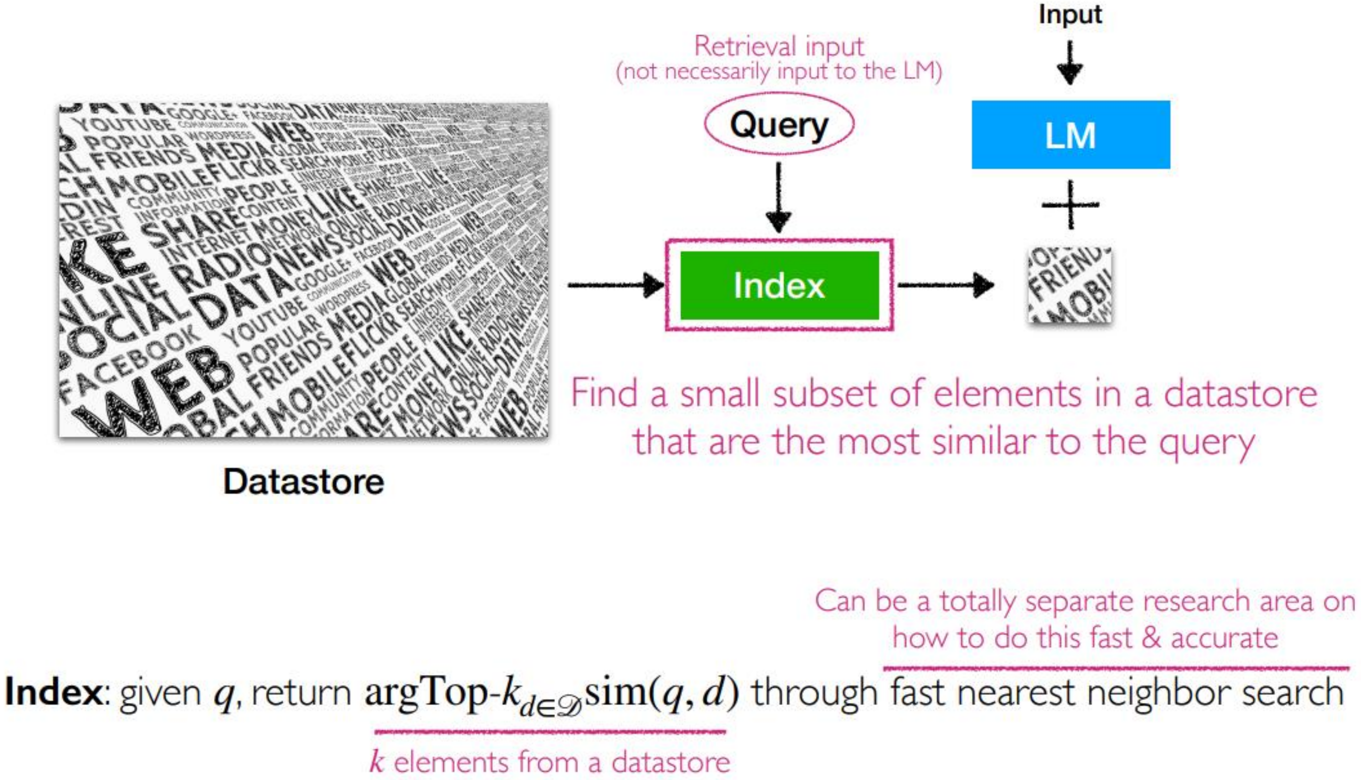
     - **Mapping the text into the dense vector**
       - Using the neural encoder
       - The similarity score would be an inner product between these two vectors

Example $$\mathrm{sim}(i,j) = \mathrm{Encoder}(i) \cdot \mathrm{Encoder}(j)$$

Maps the text into an h-dimensional vector

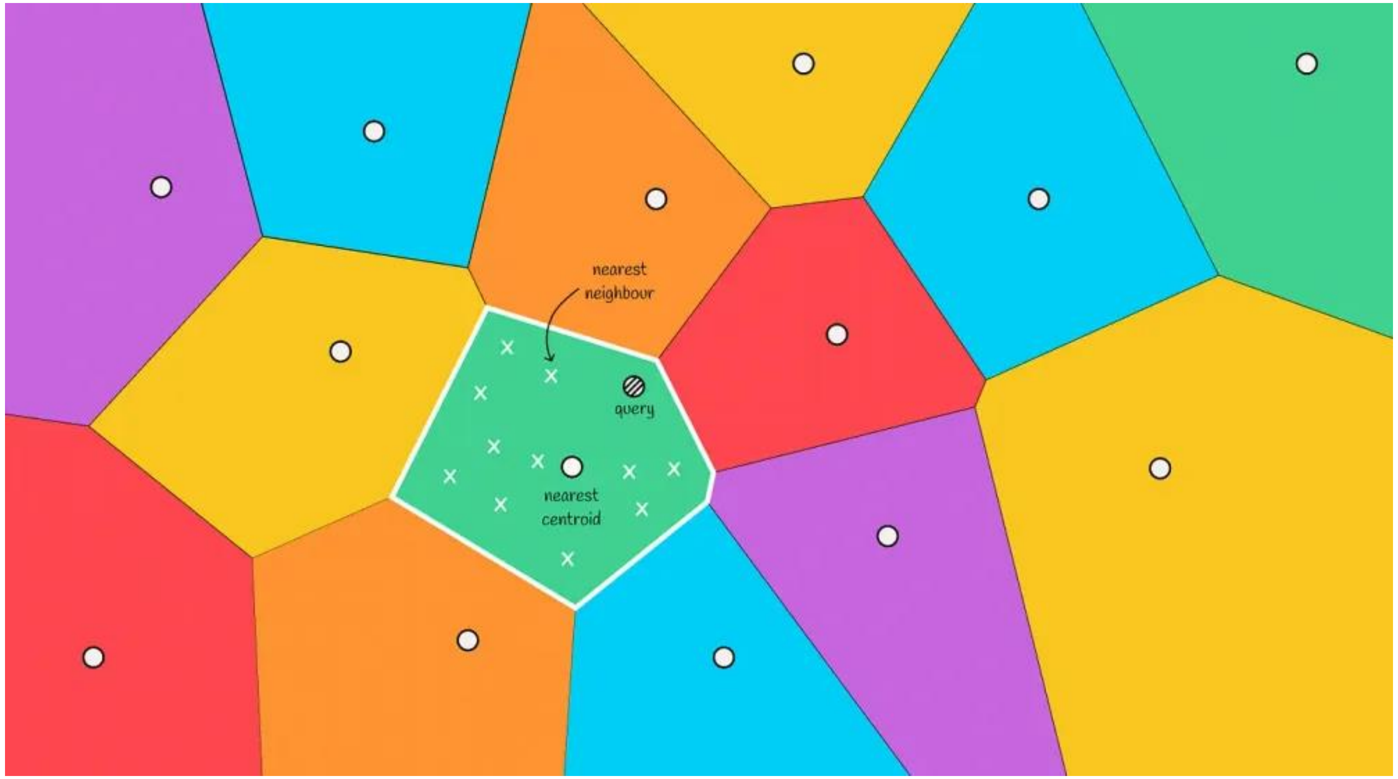
Inference

2. Index
   - Input: query
   - Output: a small subset of elements in a datastore that are the most similar to the query



Inference

2. Index
    - FAISS (Facebook AI Similarity Search)
        - Facebook AI 연구팀에서 만든 벡터 클러스터링 및 similarity search library



Inference

2. Index

- FAISS (Facebook AI Similarity Search)

```
!pip install faiss
```

```
import faiss
import torch

database_size = 100000
num_queries = 1
dimension = 10

db_vector = np.random.random((database_size, dimension)).astype('float32')
query_vector = np.random.random((num_queries, dimension)).astype('float32')

# Build an index와 index에 벡터 더하기
faiss_index = faiss.IndexFlatL2(dimension)
faiss_index.add(db_vector)
```

```
k = 4 # k-th nearest
Distance, Index = faiss_index.search(db_vector[:5], k)
print(f'Index:\n {Index}\n')
print(f'Distance:\n {Distance}')
```

```
Index:
 [[    0 97535 93445 39043]
 [    1 90328 71553 22453]
 [    2  4693  9260 97107]
 [    3 85724 90148   789]
 [    4 10436 75005 68128]]

Distance:
 [[0.         0.09631573 0.12315865 0.14702493]
 [0.         0.11033922 0.12349739 0.1381162 ]
 [0.         0.08538684 0.09451801 0.0999269 ]
 [0.         0.09128504 0.09506419 0.12409284]
 [0.         0.11630931 0.1257291  0.13669585]]
```

```
Distance, Index = faiss_index.search(query_vector, k)
print(f'Index:\n {Index}\n')
print(f'Distance:\n {Distance}')
```

```
Index:
 [[40365 14002 12745 83120]]

Distance:
 [[0.07748464 0.0808847  0.08550636 0.10243338]]
```

Inference

2. Index

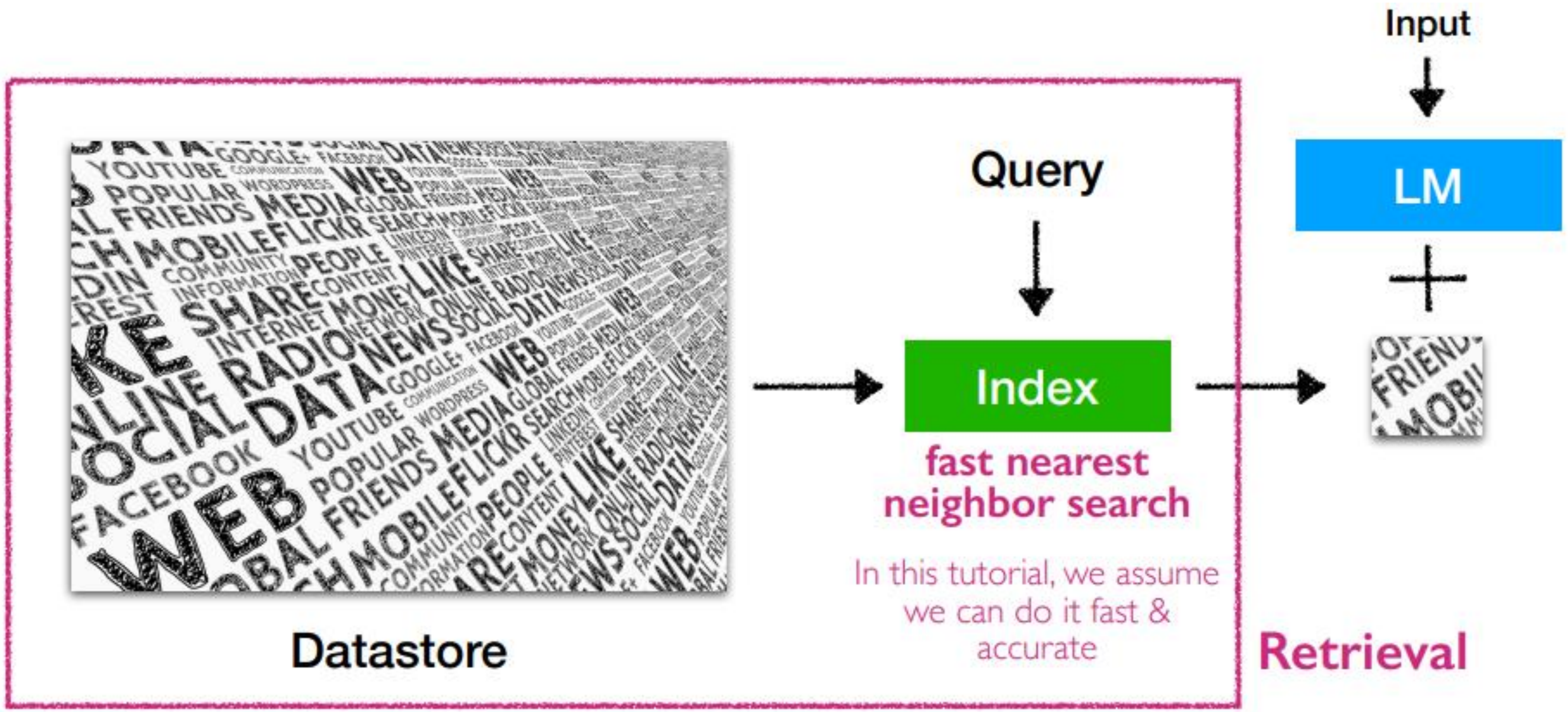
Method	Class name	`index_factory`	Main parameters	Bytes/vector	Exhaustive	Comments
Exact Search for L2	`IndexFlatL2`	`"Flat"`	`d`	`4*d`	yes	brute-force
Exact Search for Inner Product	`IndexFlatIP`	`"Flat"`	`d`	`4*d`	yes	also for cosine (normalize vectors beforehand)
Hierarchical Navigable Small World graph exploration	`IndexHNSWFlat`	`"HNSW,Flat"`	`d`, `M`	`4*d + x * M * 2 * 4`	no	
Inverted file with exact post-verification	`IndexIVFFlat`	`"IVFx,Flat"`	`quantizer`, `d`, `nlists`, `metric`	`4*d + 8`	no	Takes another index to assign vectors to inverted lists. The 8 additional bytes are the vector id that needs to be stored.
Locality-Sensitive Hashing (binary flat index)	`IndexLSH`	-	`d`, `nbits`	`ceil(nbits/8)`	yes	optimized by using random rotation instead of random projections
Scalar quantizer (SQ) in flat mode	`IndexScalarQuantizer`	`"SQ8"`	`d`	`d`	yes	4 and 6 bits per component are also implemented.
Product quantizer (PQ) in flat mode	`IndexPQ`	`"PQx"`, `"PQ"M"x"nbits`	`d`, `M`, `nbits`	`ceil(M * nbits / 8)`	yes	
IVF and scalar quantizer	`IndexIVFScalarQuantizer`	"IVFx,SQ4" "IVFx,SQ8"	`quantizer`, `d`, `nlists`, `qtype`	SQfp16: 2 * `d` + 8, SQ8: `d` + 8 or SQ4: `d/2` + 8	no	Same as the `IndexScalarQuantizer`
IVFADC (coarse quantizer+PQ on residuals)	`IndexIVFPQ`	`"IVFx,PQ"y"x"nbits`	`quantizer`, `d`, `nlists`, `M`, `nbits`	`ceil(M * nbits/8)+8`	no	
IVFADC+R (same as IVFADC with re-ranking based on codes)	`IndexIVFPQR`	`"IVFx,PQy+z"`	`quantizer`, `d`, `nlists`, `M`, `nbits`, `M_refine`, `nbits_refine`	`M+M_refine+8`	no	

Exact Search

Approximate Search
(Relatively easy to scale to ~1B elements)

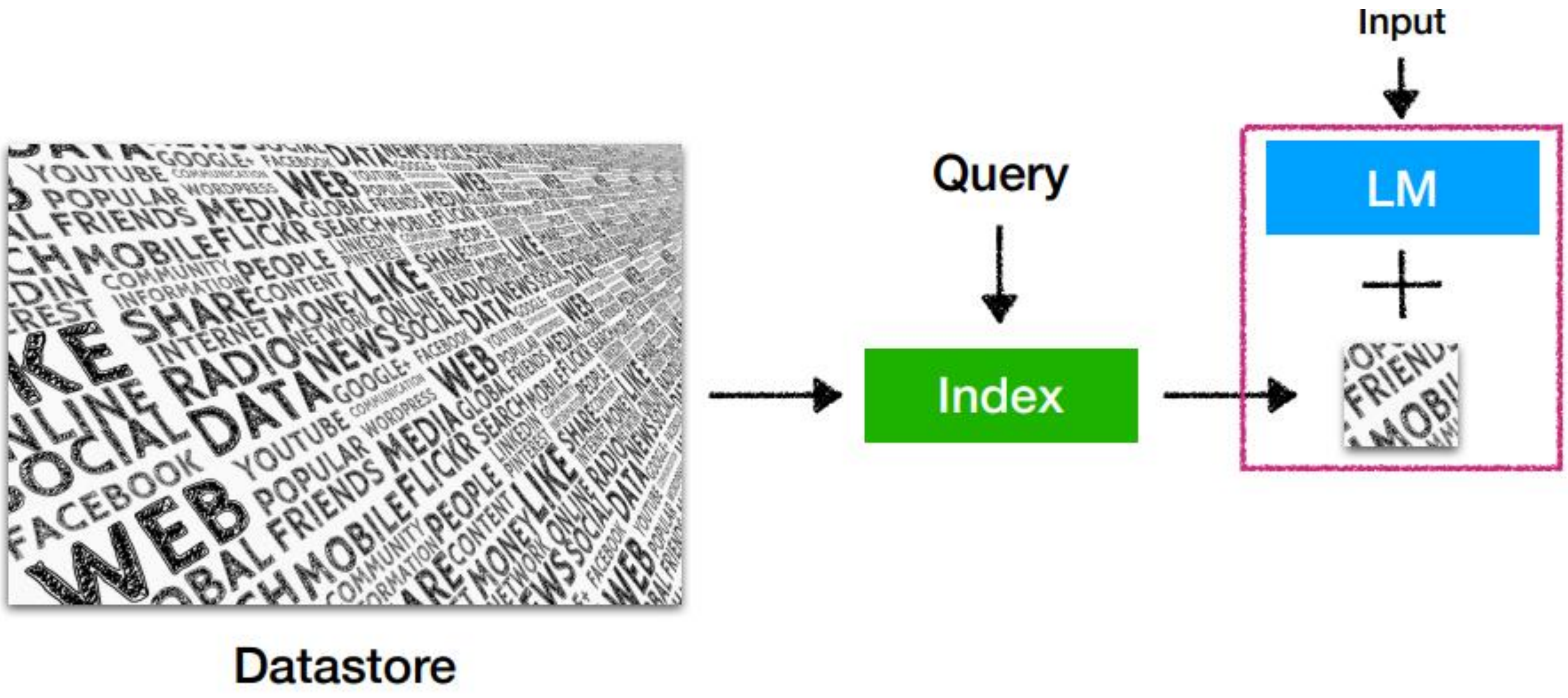
Inference

3. Search
    - Retrieval system is a combination of datastore and the index



Inference

3. Search
   - After obtaining retrieval results, incorporate it into the language model and make the final prediction



Thank You

감사합니다.