Section 2:
Definition & Preliminaries

A Retrieval-based LM: Definition

A language model (LM) that uses
an external datastore at test time

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A language model (LM)

$$P(x_n \mid x_1, x_2, \cdots, x_{n-1})$$

A language model (LM)

$$P(x_n \mid x_1, x_2, \cdots, x_{n-1})$$

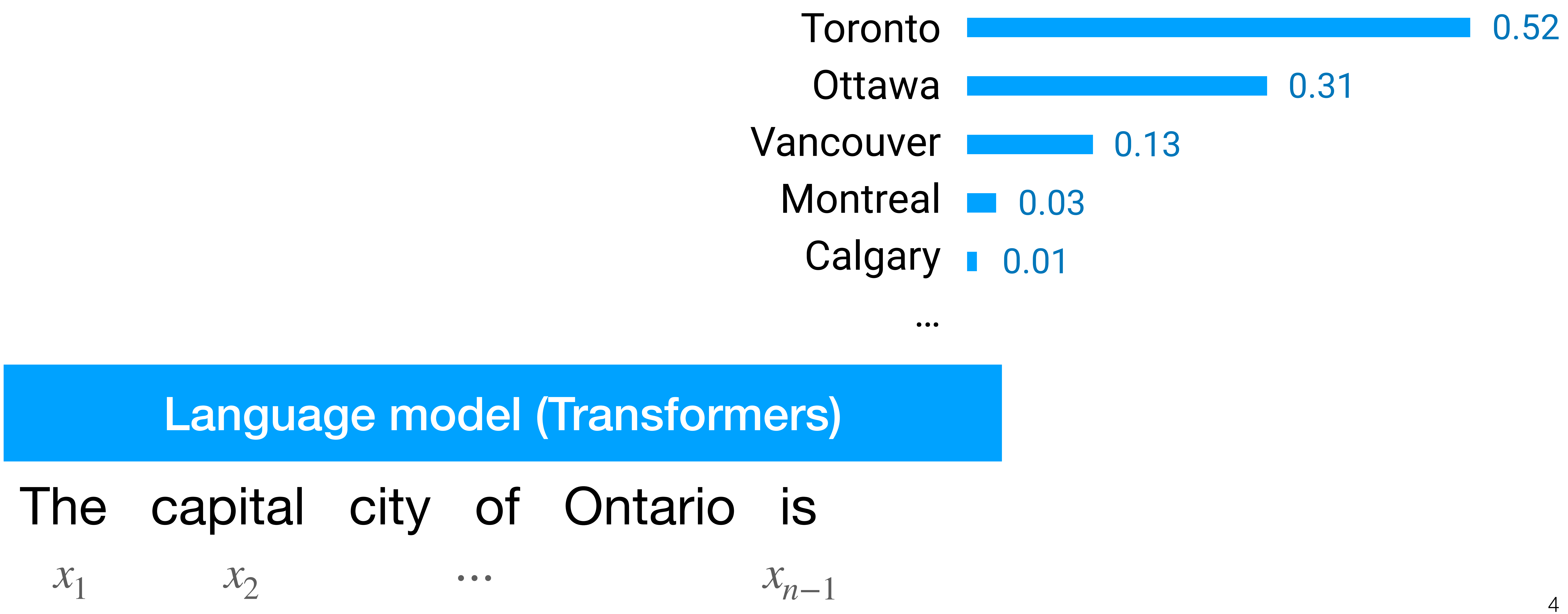
Language model (Transformers)

The capital city of Ontario is

x_1 x_2 $\cdots$ x_{n-1}

A language model (LM)

$$P(x_n \mid x_1, x_2, \cdots, x_{n-1})$$



A language model (LM): Categories

A language model (LM): Categories

Toronto

Autoregressive LM

The capital city of Ontario is ______

vs

capital Ontario

Masked LM

The ______ city of _______ is Toronto

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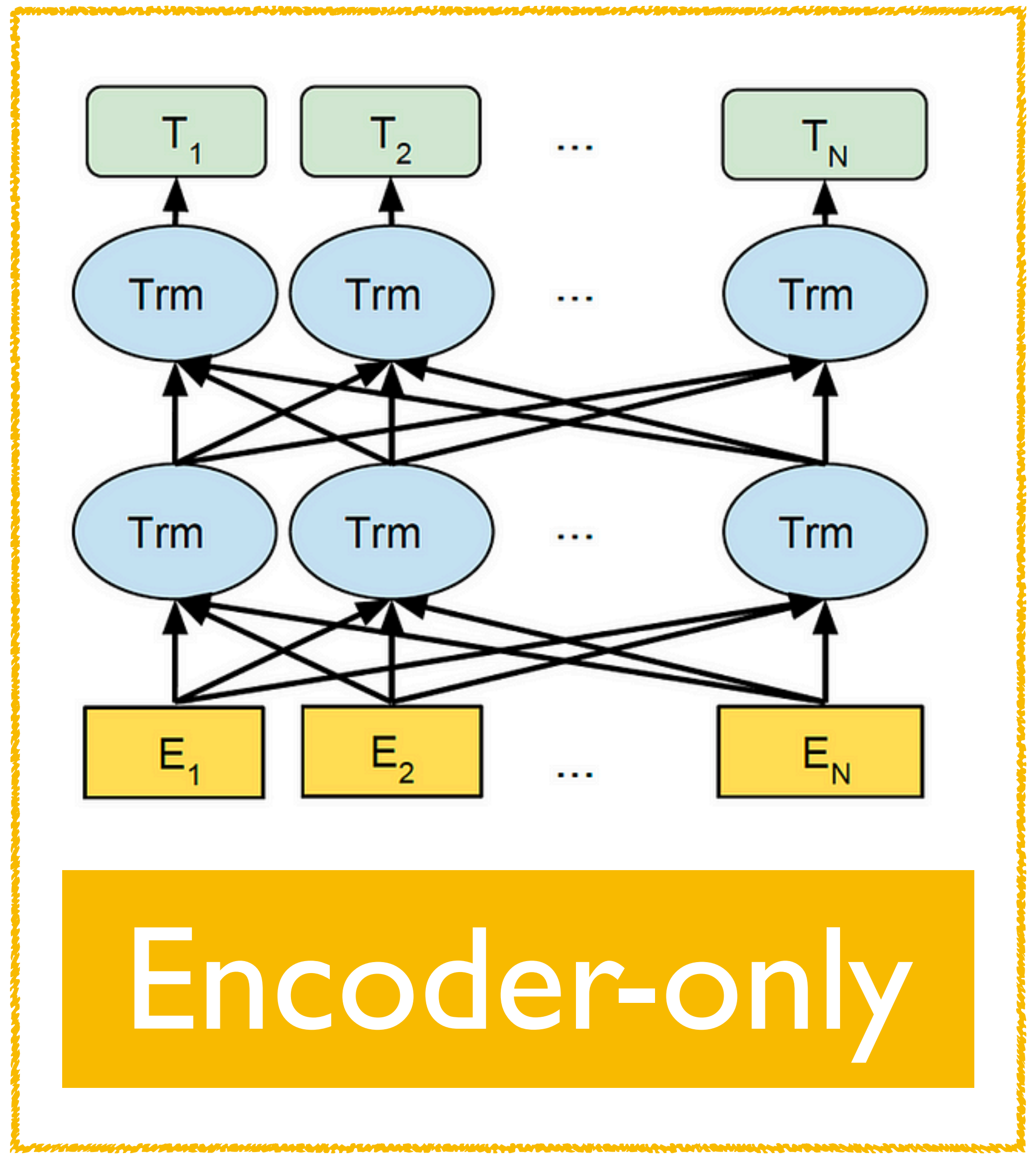

Image source: Devlin et al. 2019. "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding"

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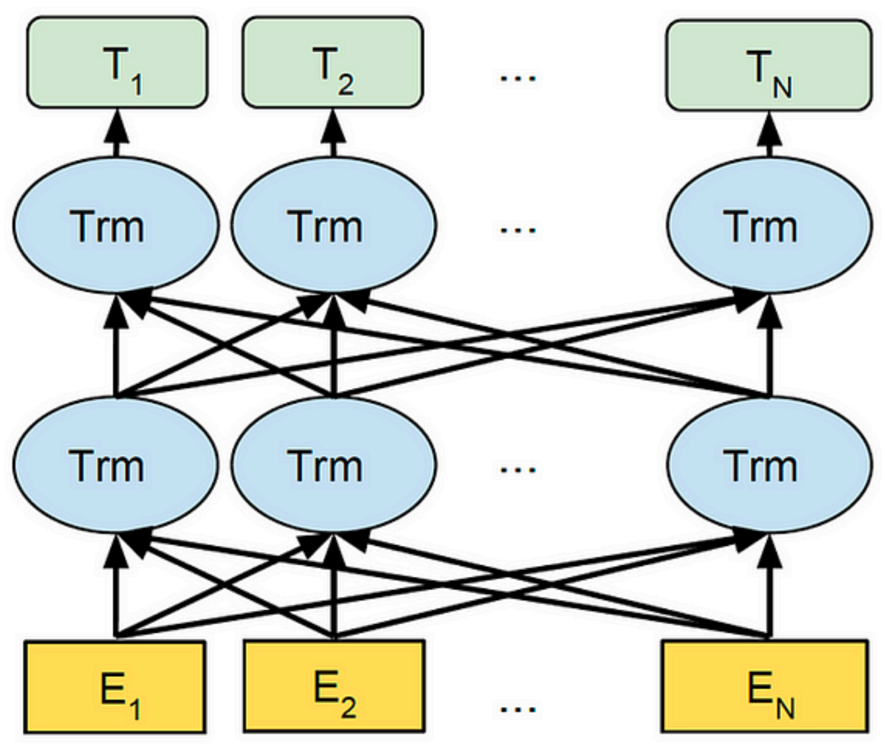
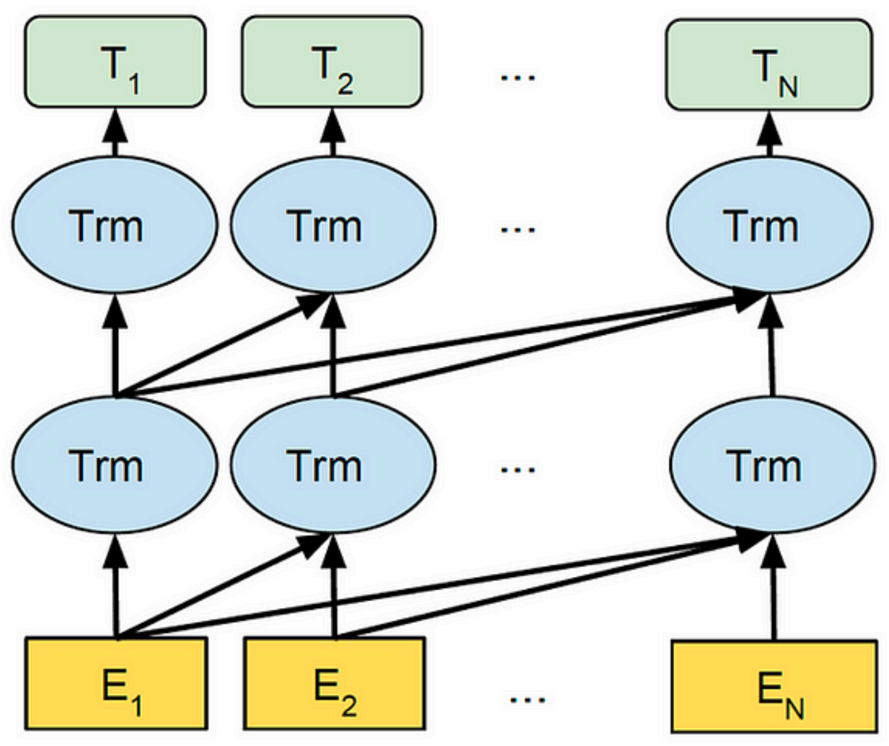


Encoder-only



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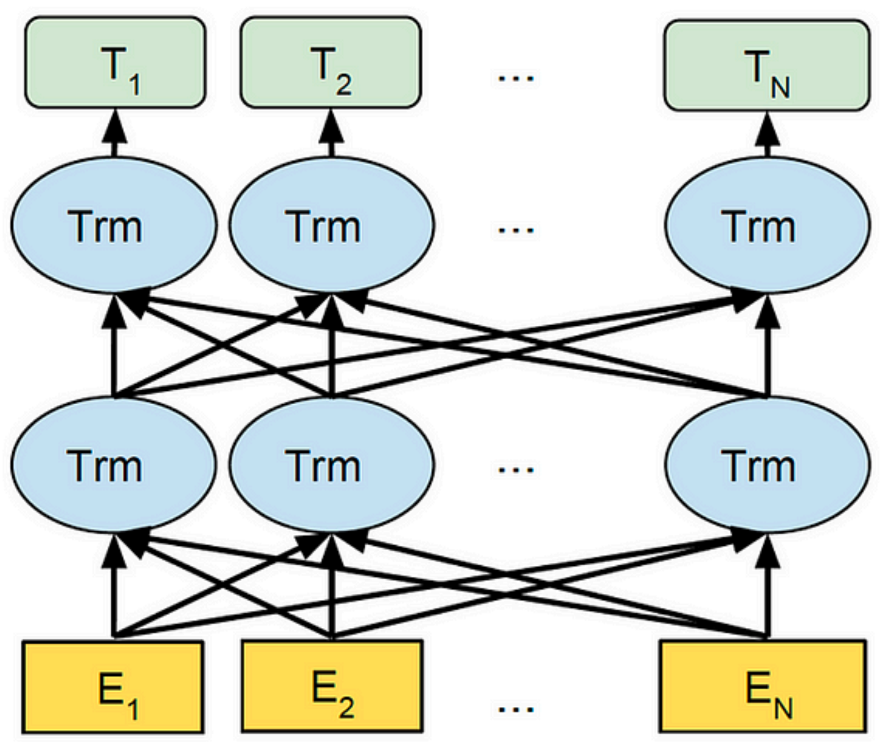

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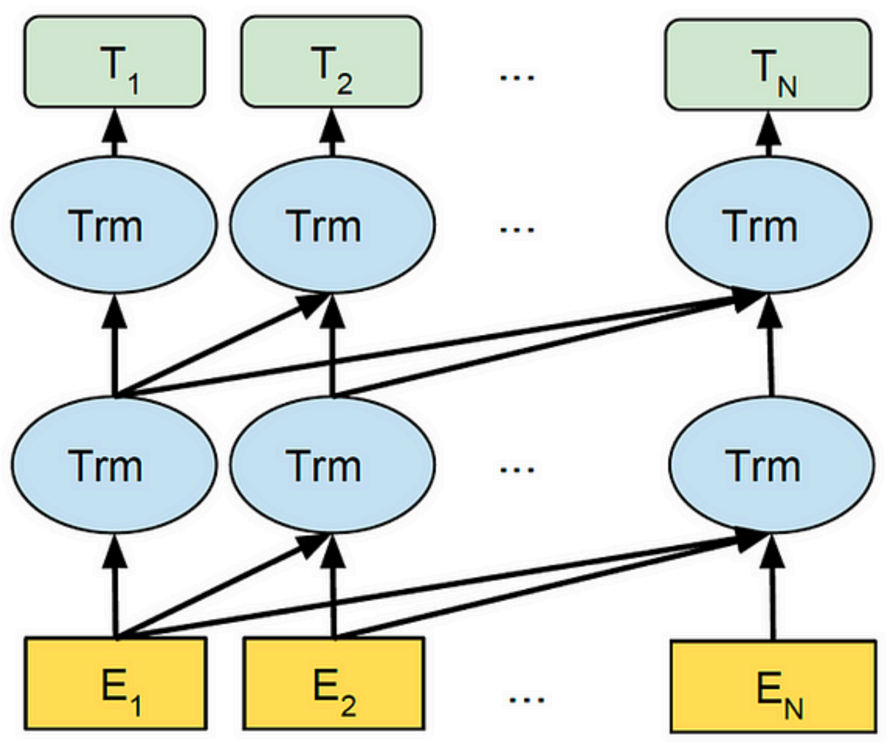

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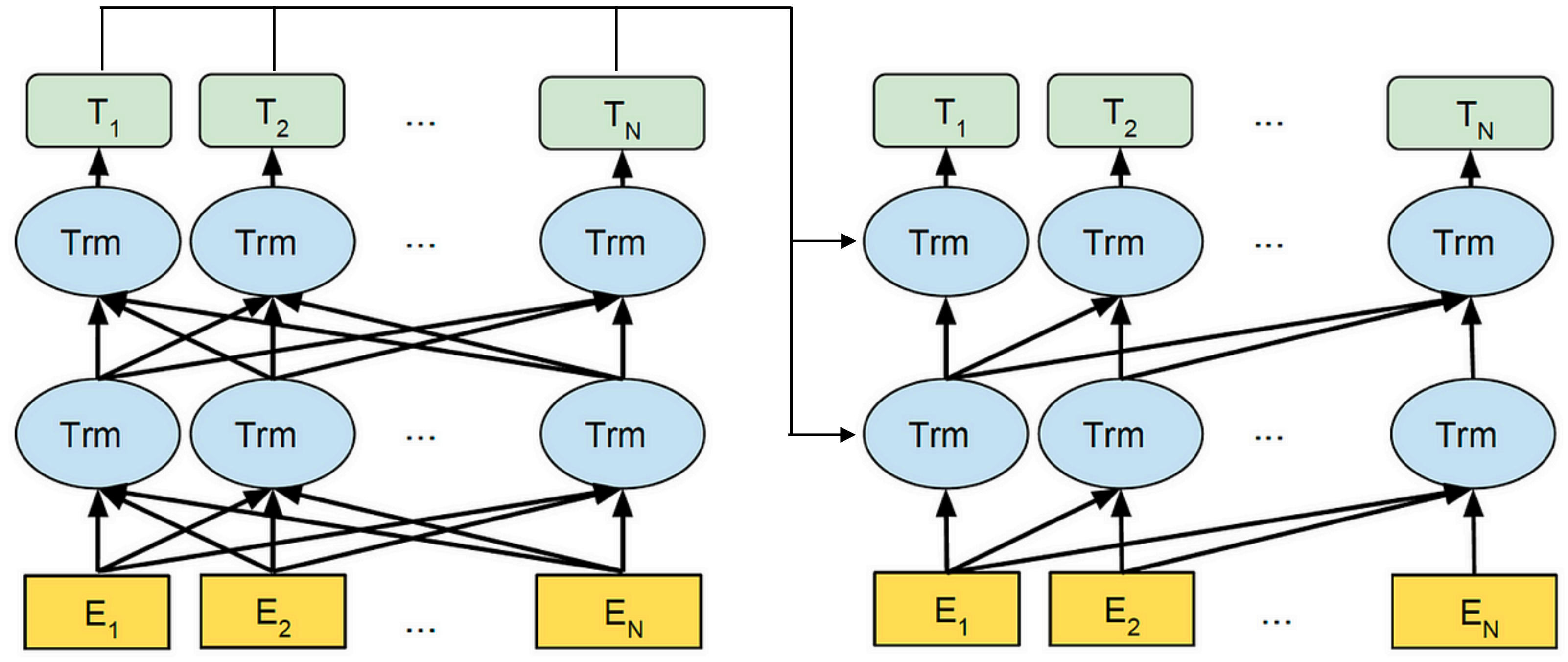

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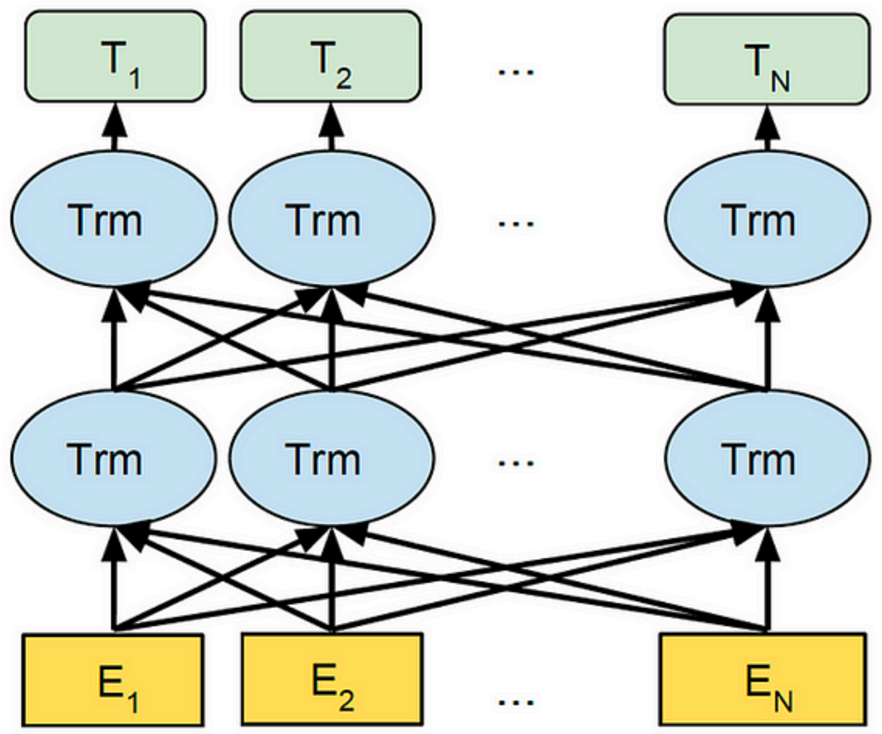

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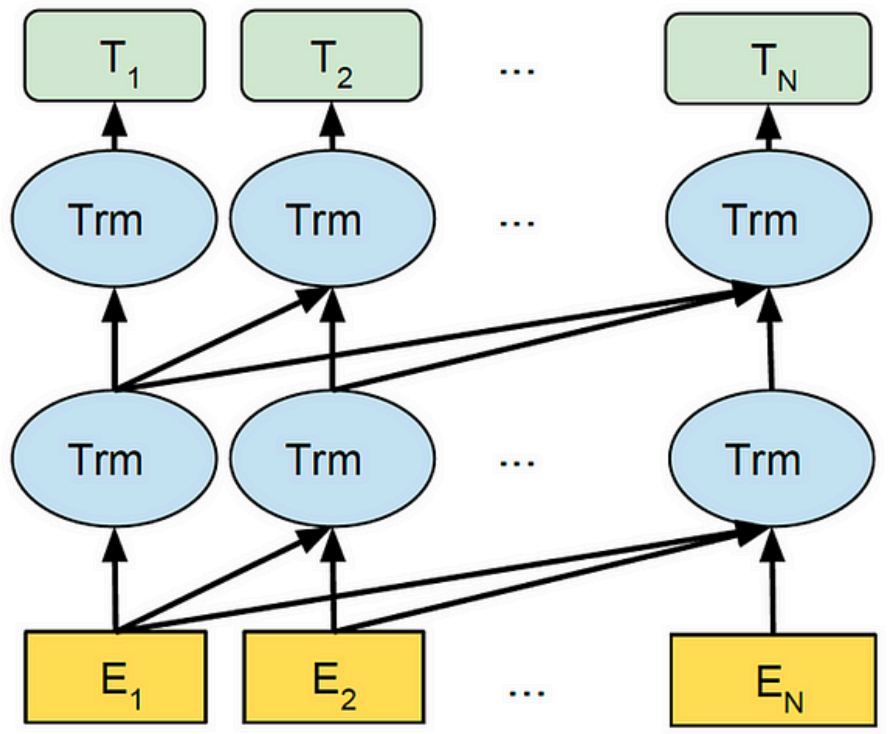

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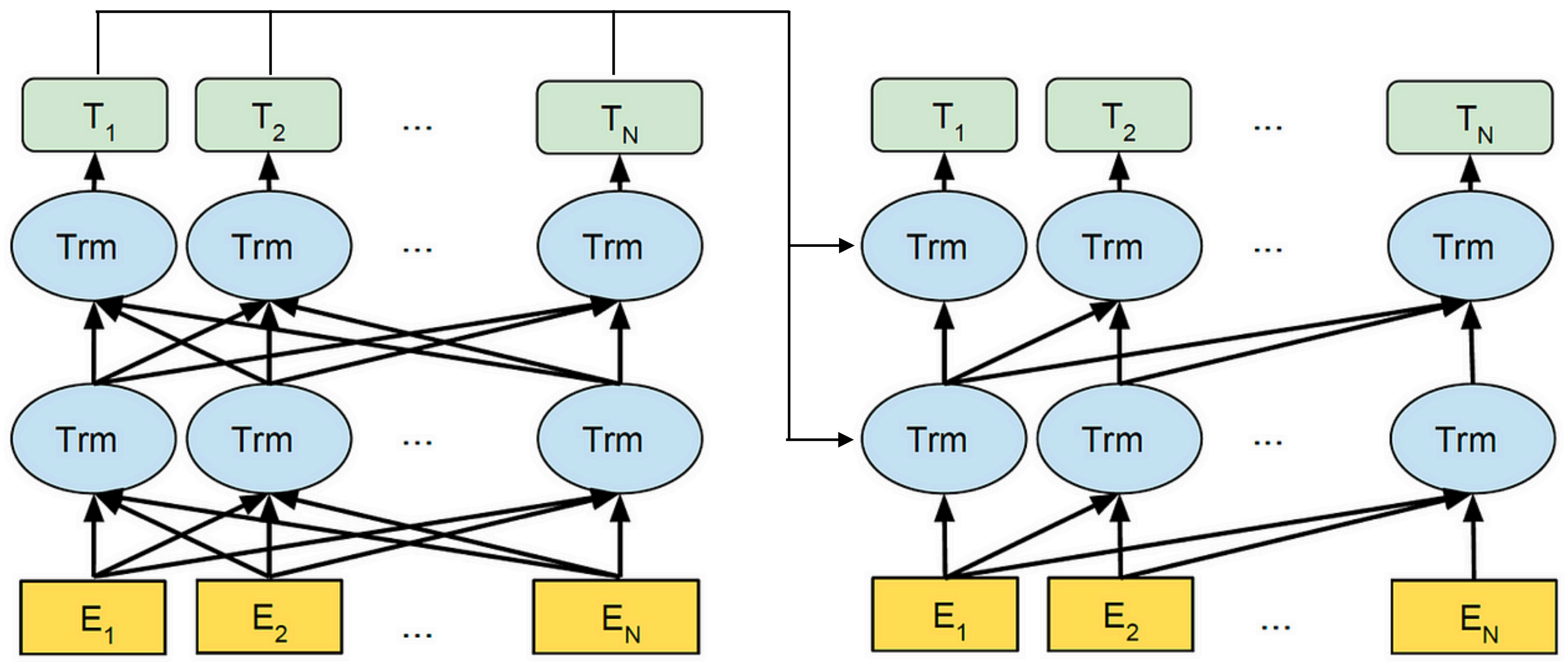

Encoder-decoder

Image source: Devlin et al. 2019. "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding"

A language model (LM): Prompting

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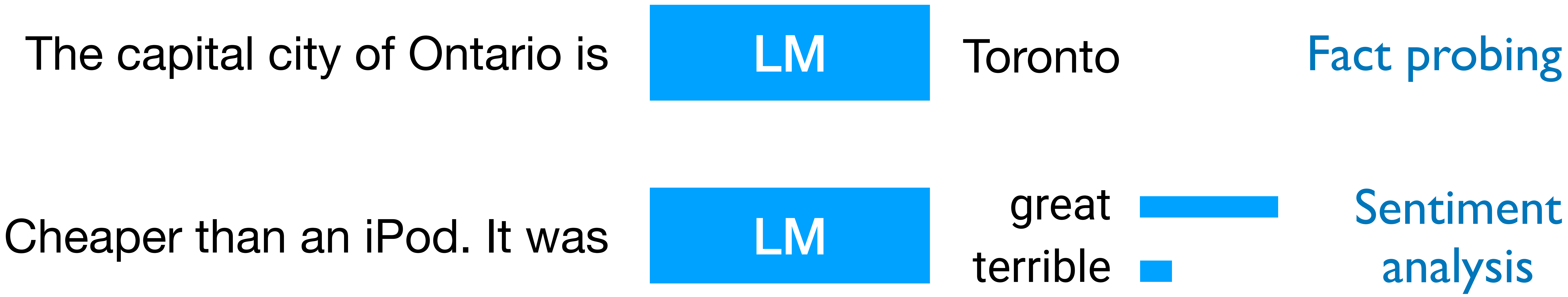
The capital city of Ontario is **LM** Toronto

Fact probing

A language model (LM): Prompting



A language model (LM): Prompting

The capital city of Ontario is → LM → Toronto — Fact probing

Cheaper than an iPod. It was → LM → great / terrible — Sentiment analysis

“Hello” in French is → LM → Bonjourno — Translation

A language model (LM): Prompting

Prompt		Output	Task
The capital city of Ontario is	LM	Toronto	Fact probing
Cheaper than an iPod. It was	LM	great terrible	Sentiment analysis
“Hello” in French is	LM	Bonjourno	Translation
I’m good at math. 5 + 8 x 12 =	LM	101	Arithmetic

A language model (LM)

Often evaluated with

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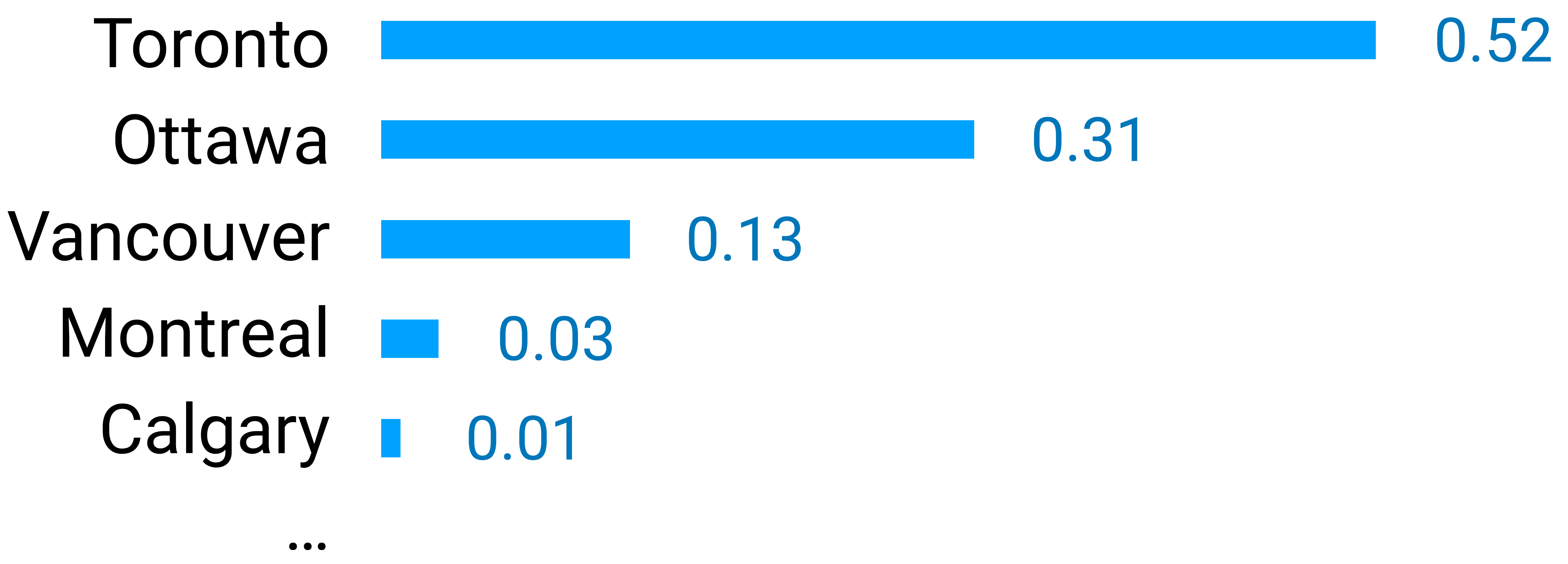
Often evaluated with

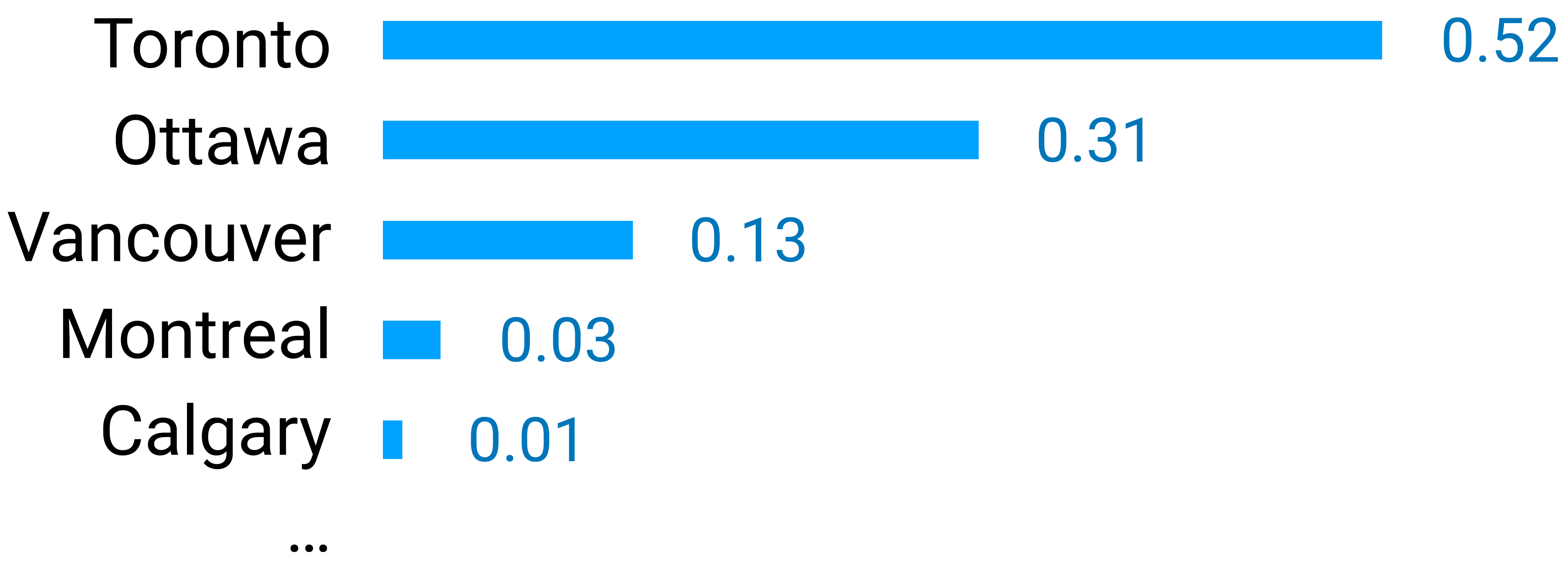


$$-\log(0.52) = 0.284$$

Perplexity

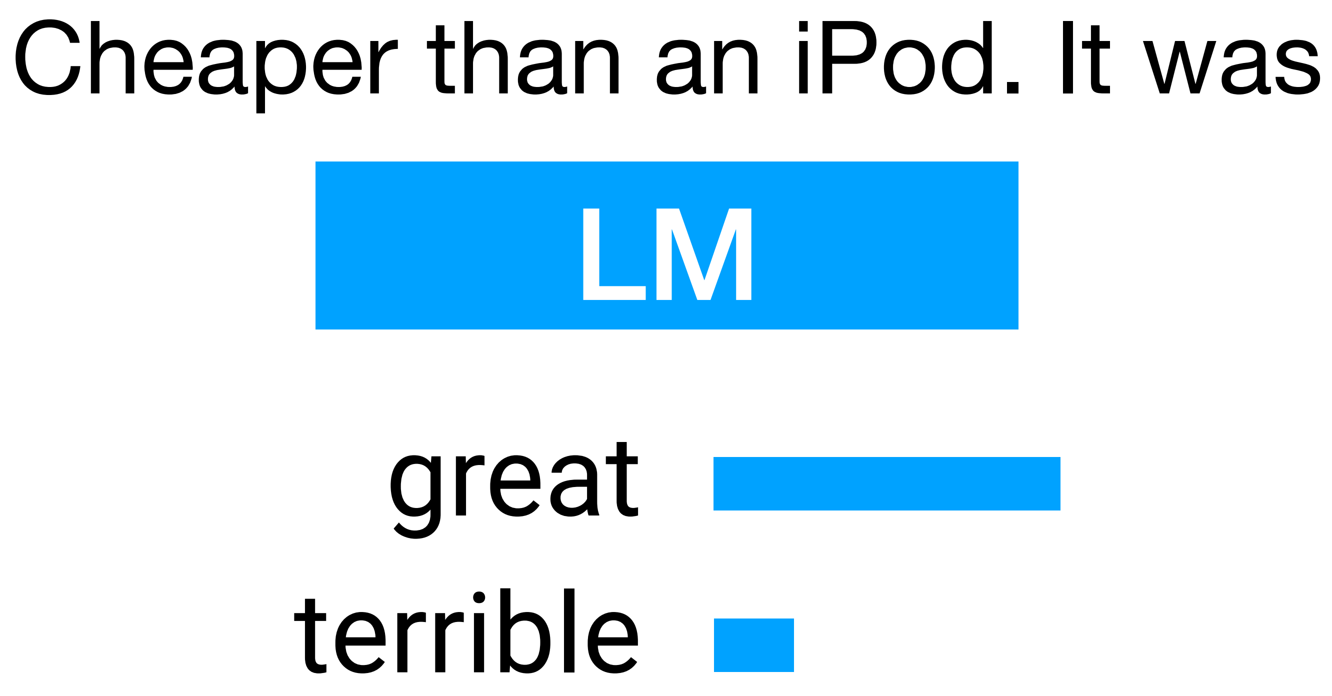
A language model (LM)

Often evaluated with



$$-\log(0.52) = 0.284$$

Perplexity



Prediction: positive ✓

Downstream accuracy

(Zero-shot or few-shot in-context learning, or fine-tuning)

(More in Section 5)

A Retrieval-based LM: Definition

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Typical LMs

The capital city of Ontario is **Toronto**

LM

Training time

The capital city of Ontario is _____

LM

Test time

Retrieval-based LMs

The capital city of Ontario is **Toronto**

LM

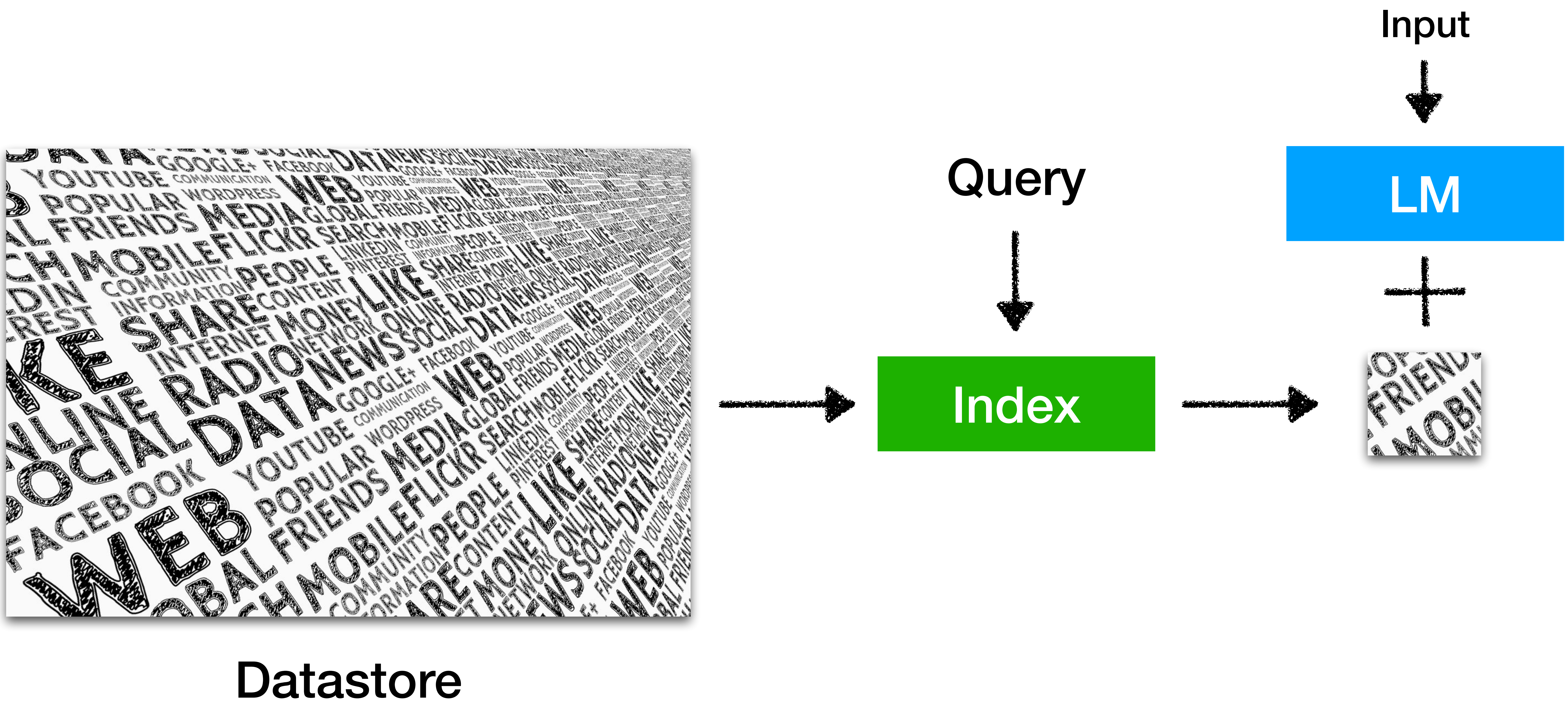
Training time

The capital city of Ontario is _____

LM

Test time

Inference



Inference: Datastore

Input

Query

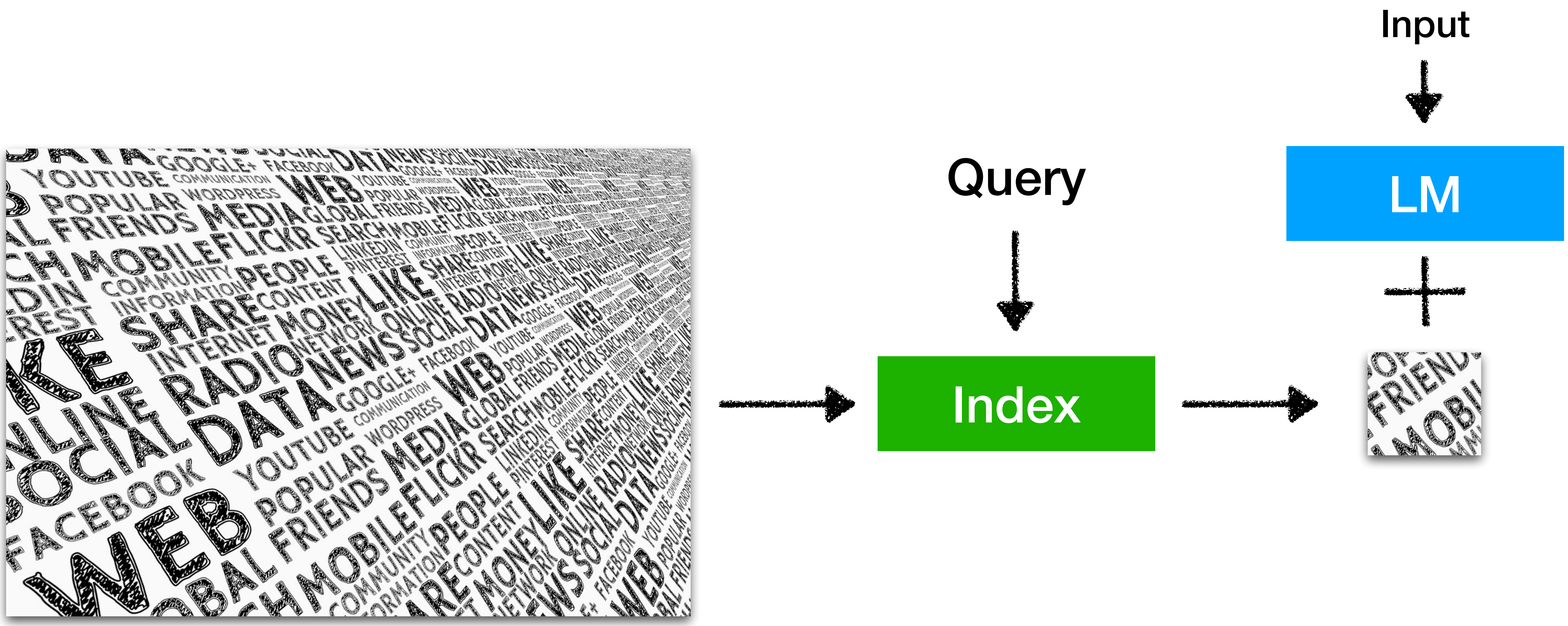
LM

Index

Datastore

Raw text corpus

Inference: Datastore

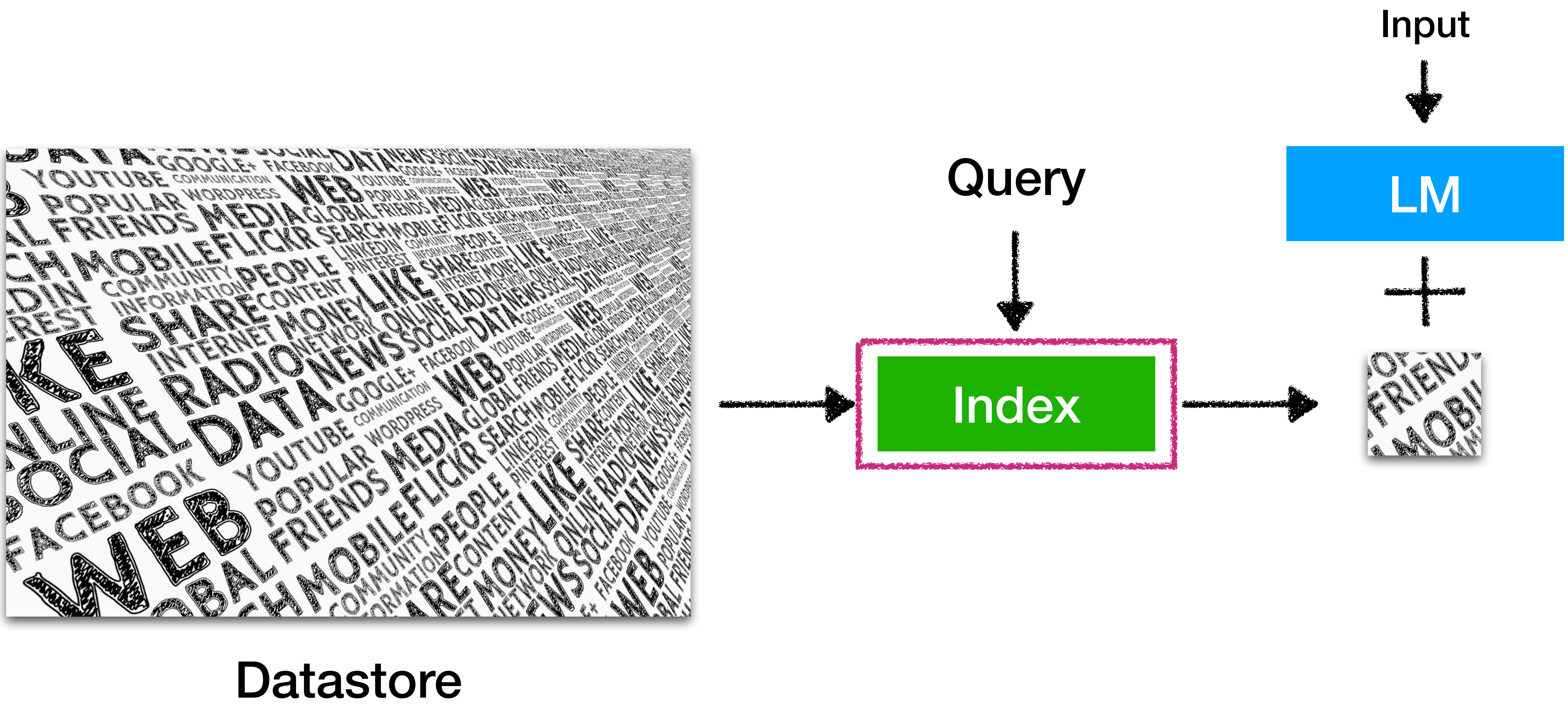


Datastore

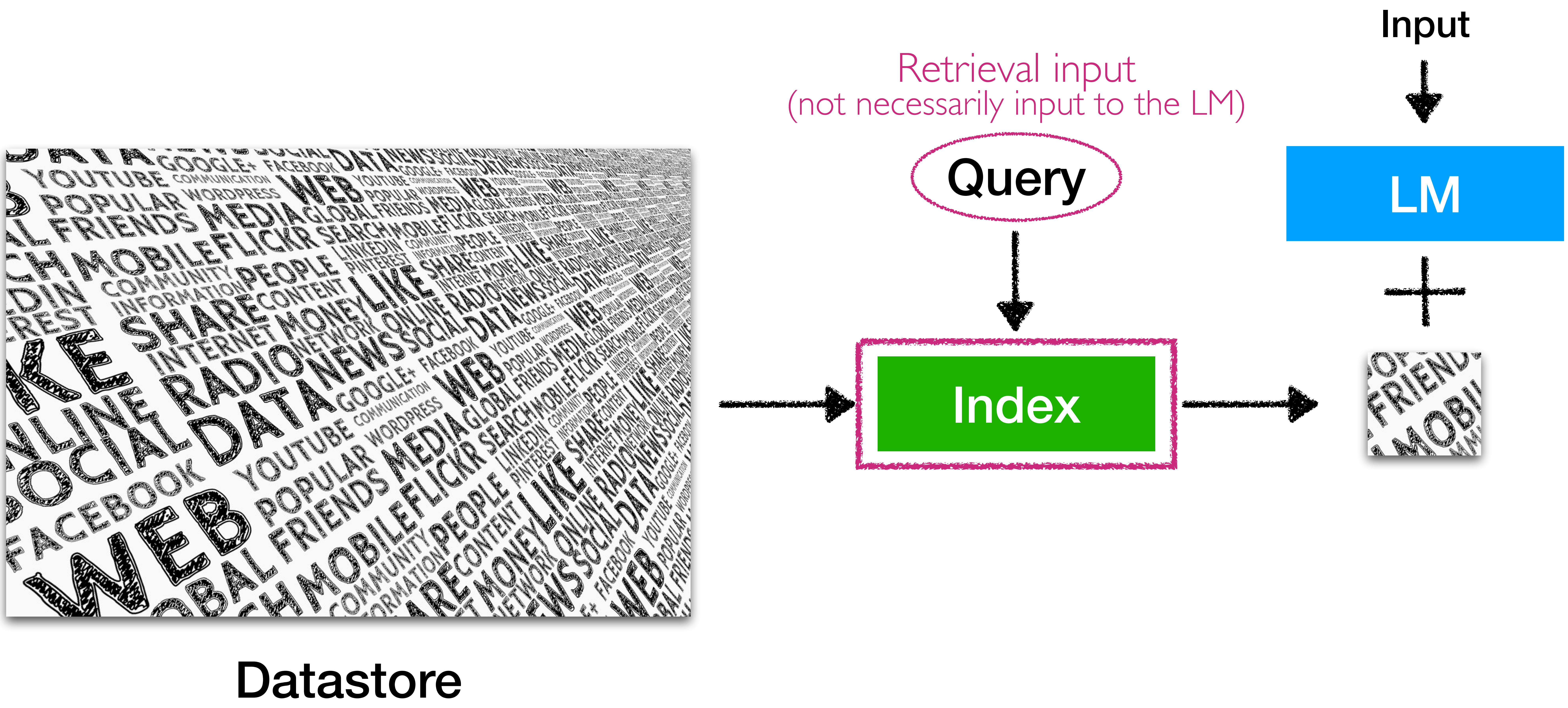
Raw text corpus

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

Inference: Index

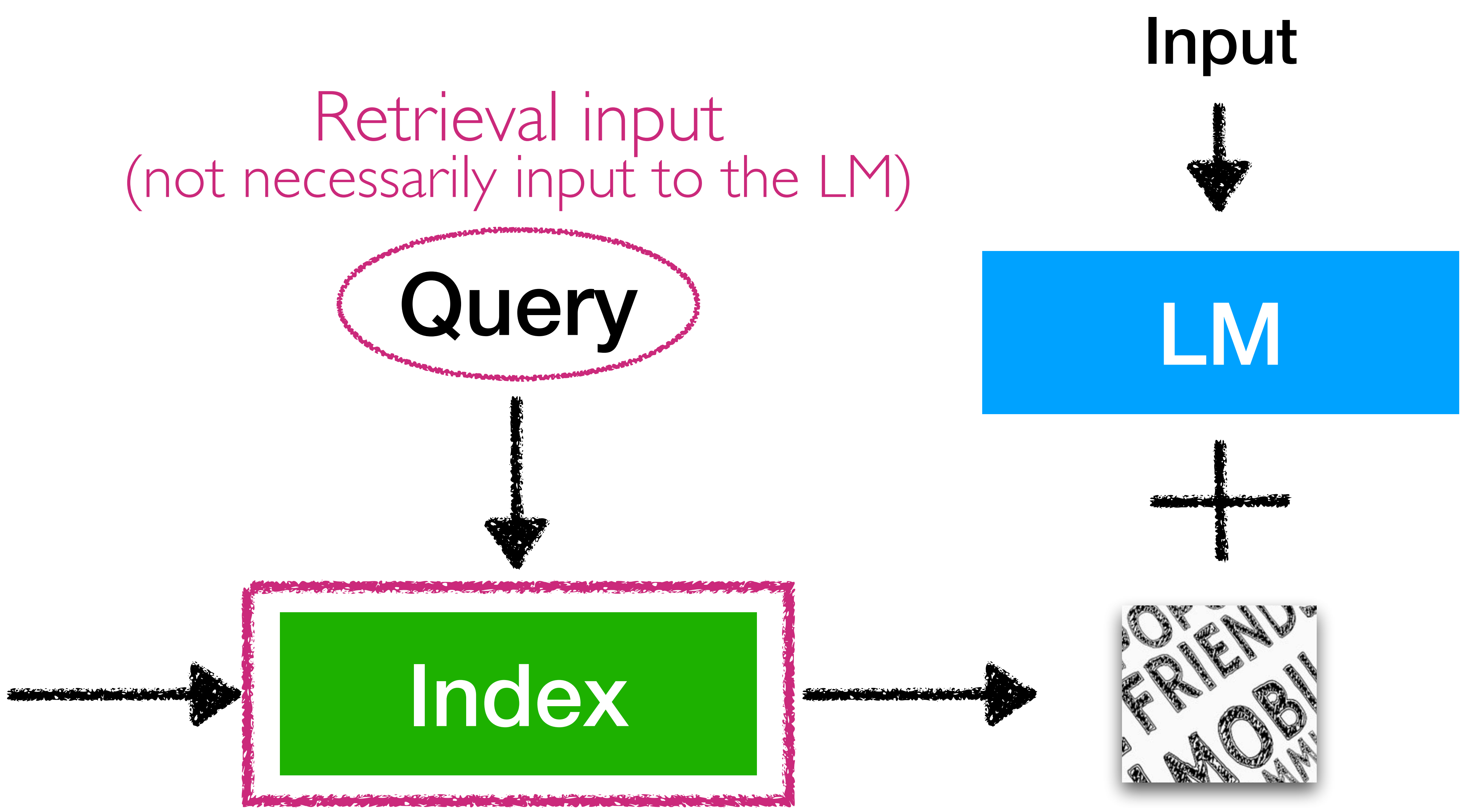


Inference: Index



Inference: Index

Datastore



Find a small subset of elements in a datastore that are the most similar to the query

Inference: Index

Goal: find a small subset of elements in a datastore that are the most similar to the query

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sim: a similarity score between two pieces of text

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sim: a similarity score between two pieces of text

Example

$$\text{sim}(i,j) = \text{tf}_{i,j} \times \log \frac{N}{\text{df}_i}$$

$\text{tf}_{i,j}$: # of occurrences of i in j

N: # of total docs

df_i: # of docs containing i

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Example

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

Encoder: Maps the text into an h-dimensional vector

Inference: Index

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Example

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

Encoder: Maps the text into an h-dimensional vector

An entire field of study on how to get (or learn) the similarity function better

(We'll see some in Section 4)

Inference: Index

Goal: find a small subset of elements in a datastore
that are the most similar to the query

sim: a similarity score between two pieces of text

Index: given q, return $\mathrm{argTop}\text{-}k_{d \in \mathcal{D}} \mathrm{sim}(q, d)$ through fast nearest neighbor search

Inference: Index

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k elements from a datastore

Inference: Index

Goal: find a small subset of elements in a datastore
that are the most similar to the query

sim: a similarity score between two pieces of text

Can be a totally separate research area on
how to do this fast & accurate

Index: given q, return $\text{argTop-}k_{d \in \mathcal{D}} \text{sim}(q, d)$ through fast nearest neighbor search

k elements from a datastore

Software: FAISS, Distributed FAISS, SCaNN, etc…

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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	

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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
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Exact Search

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Exact Search

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

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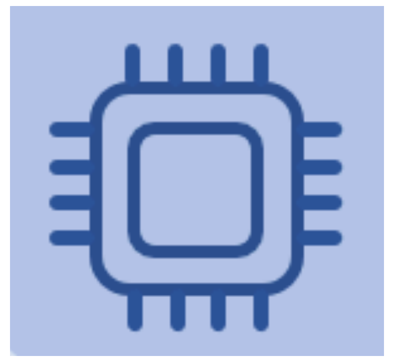
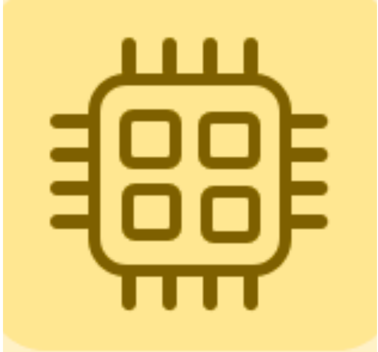
Exact Search





CPU vs. GPU

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

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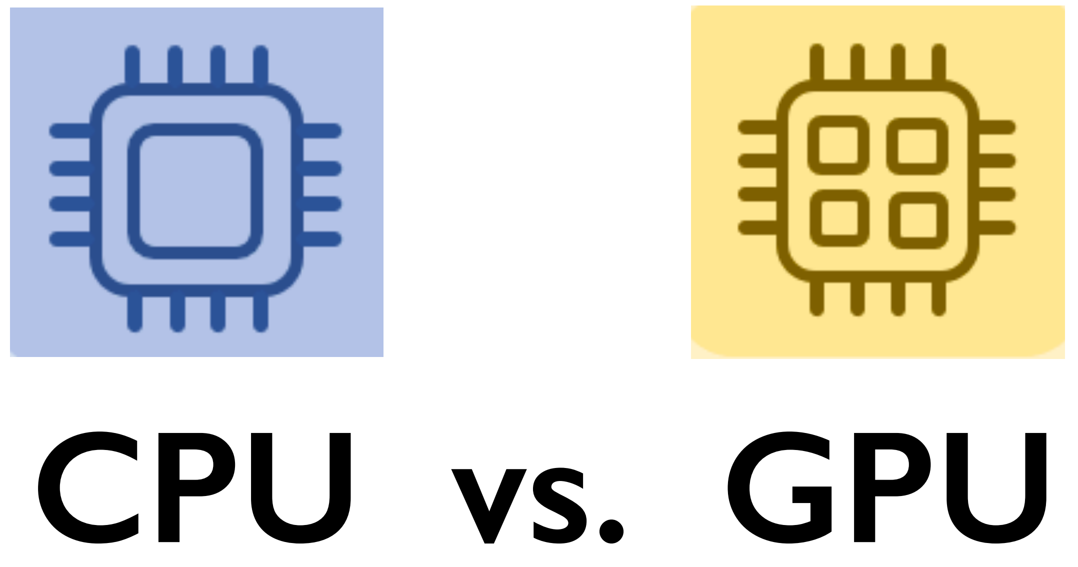
Exact Search



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

More info: https://github.com/facebookresearch/faiss/wiki

Inference: Search

Datastore

Query

Index

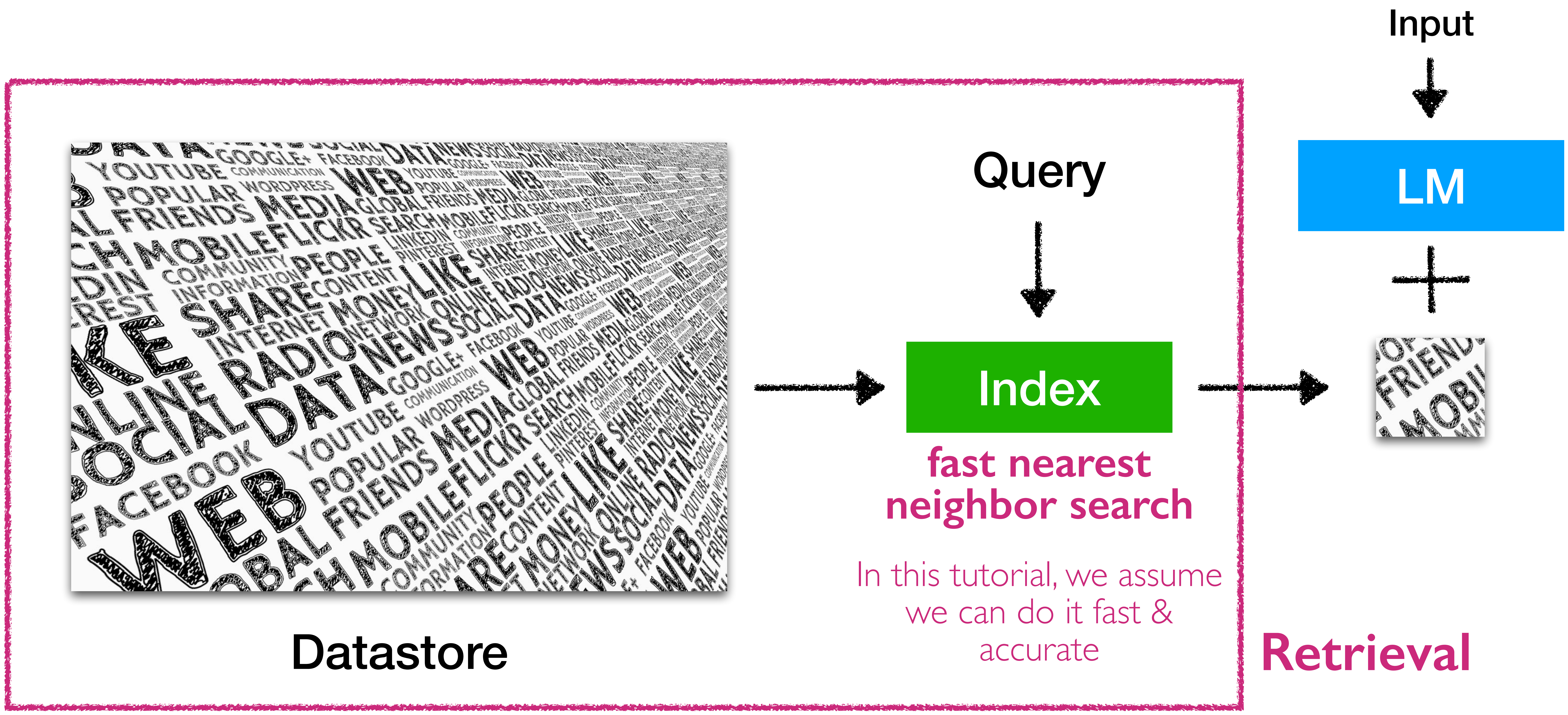
fast nearest neighbor search

In this tutorial, we assume we can do it fast & accurate

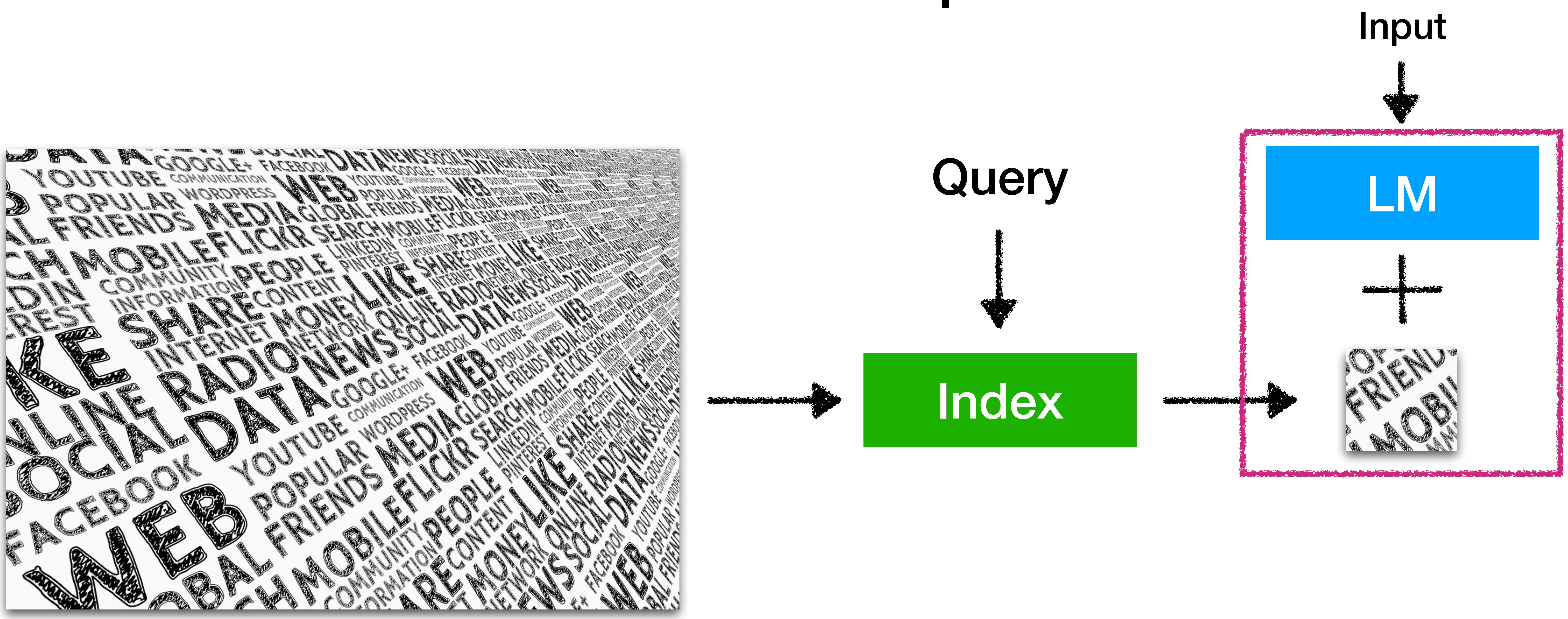
Input

LM

Inference: Search

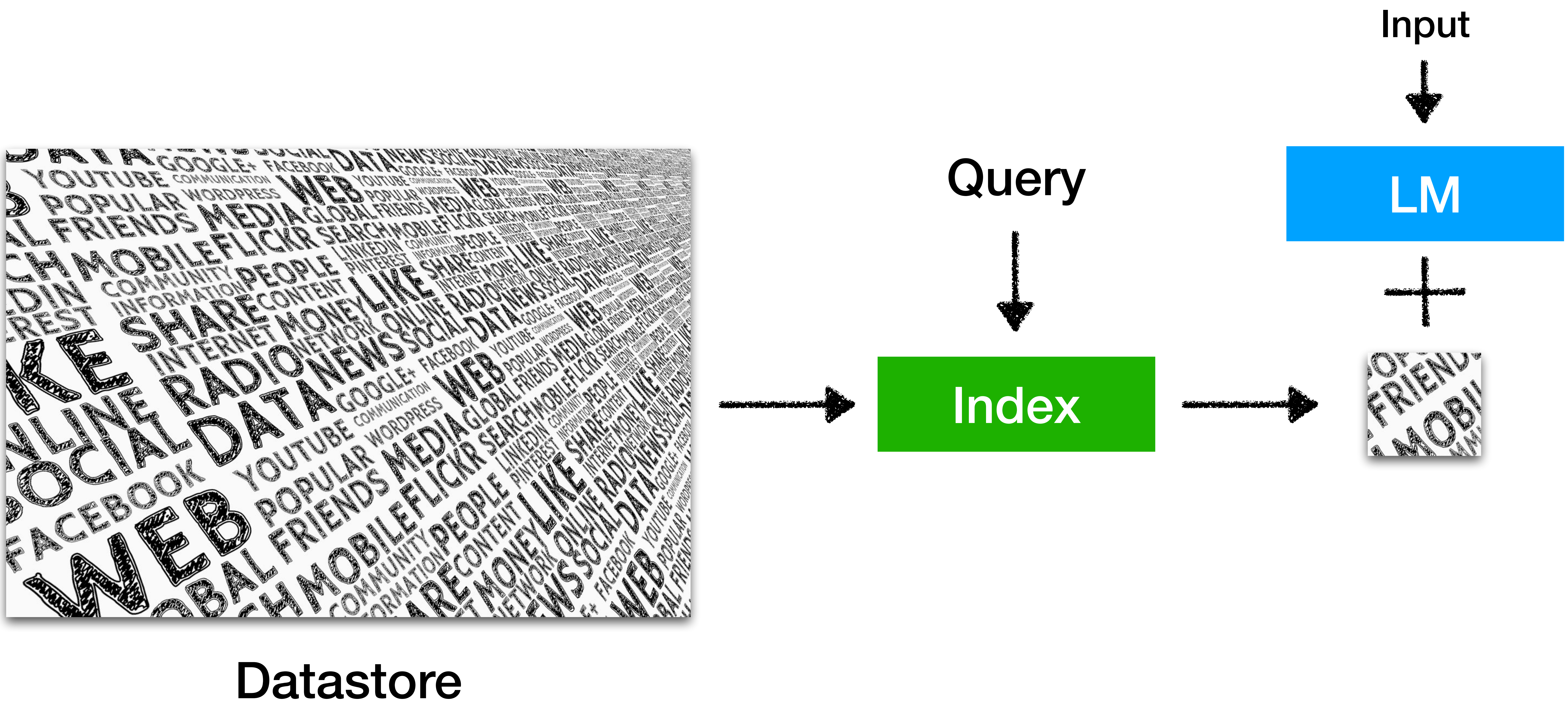


Inference: Incorporation

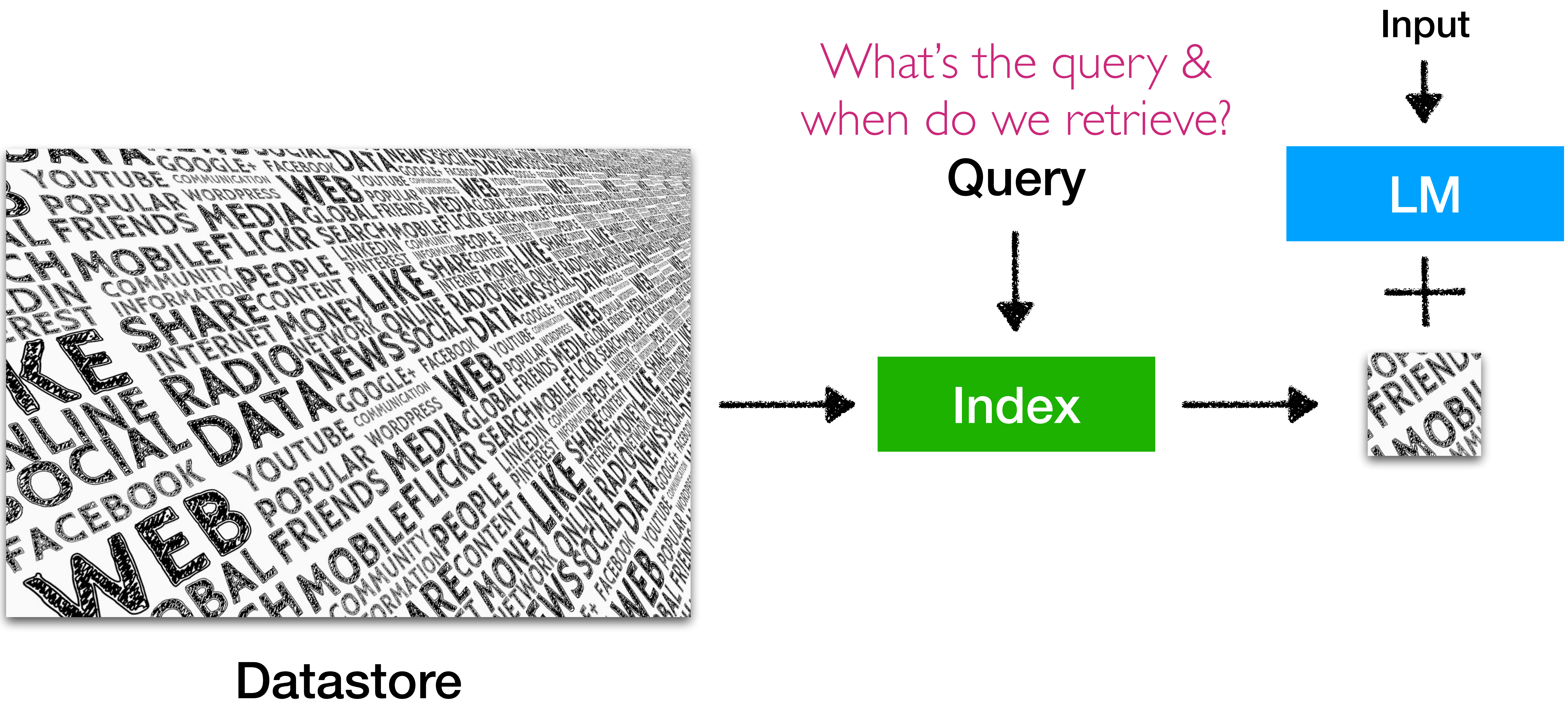


Datastore

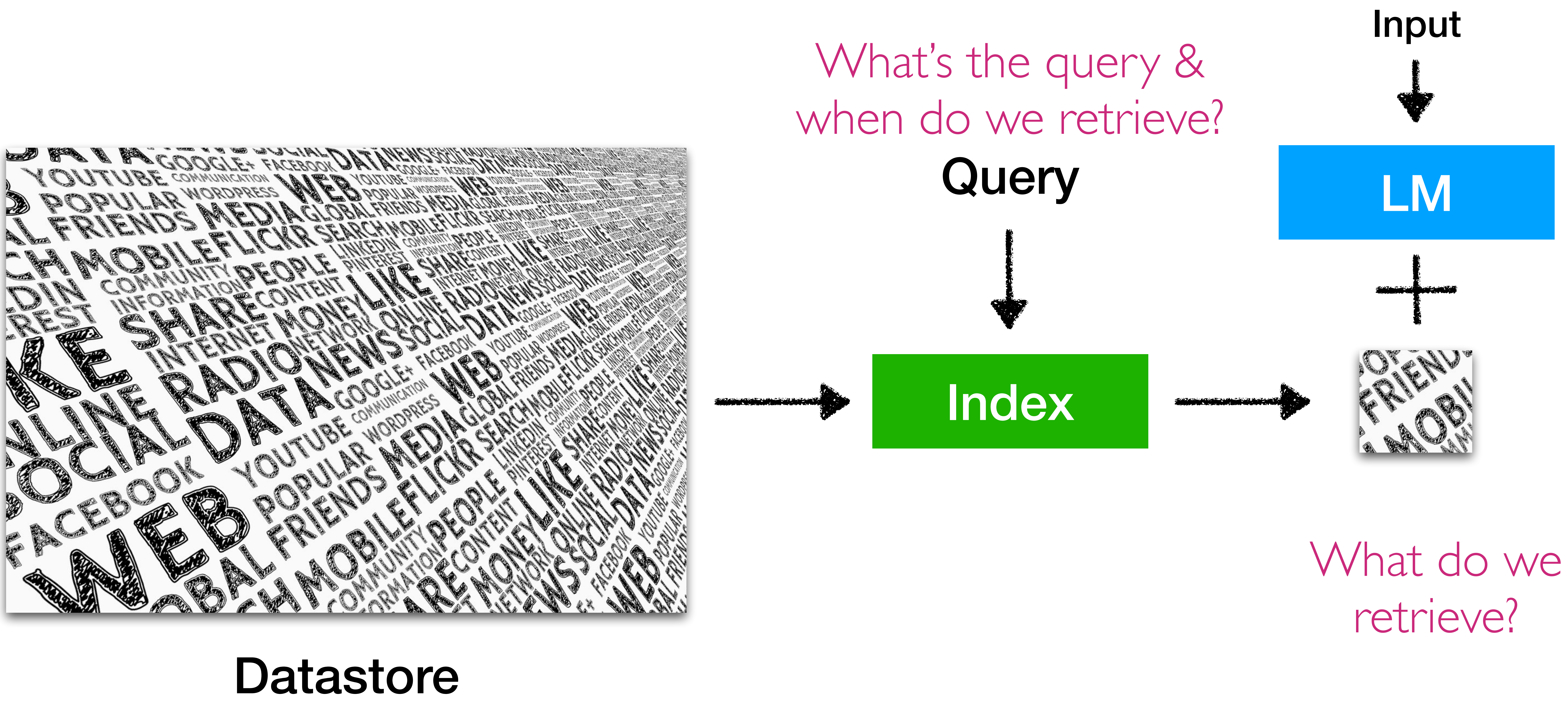
Questions to answer



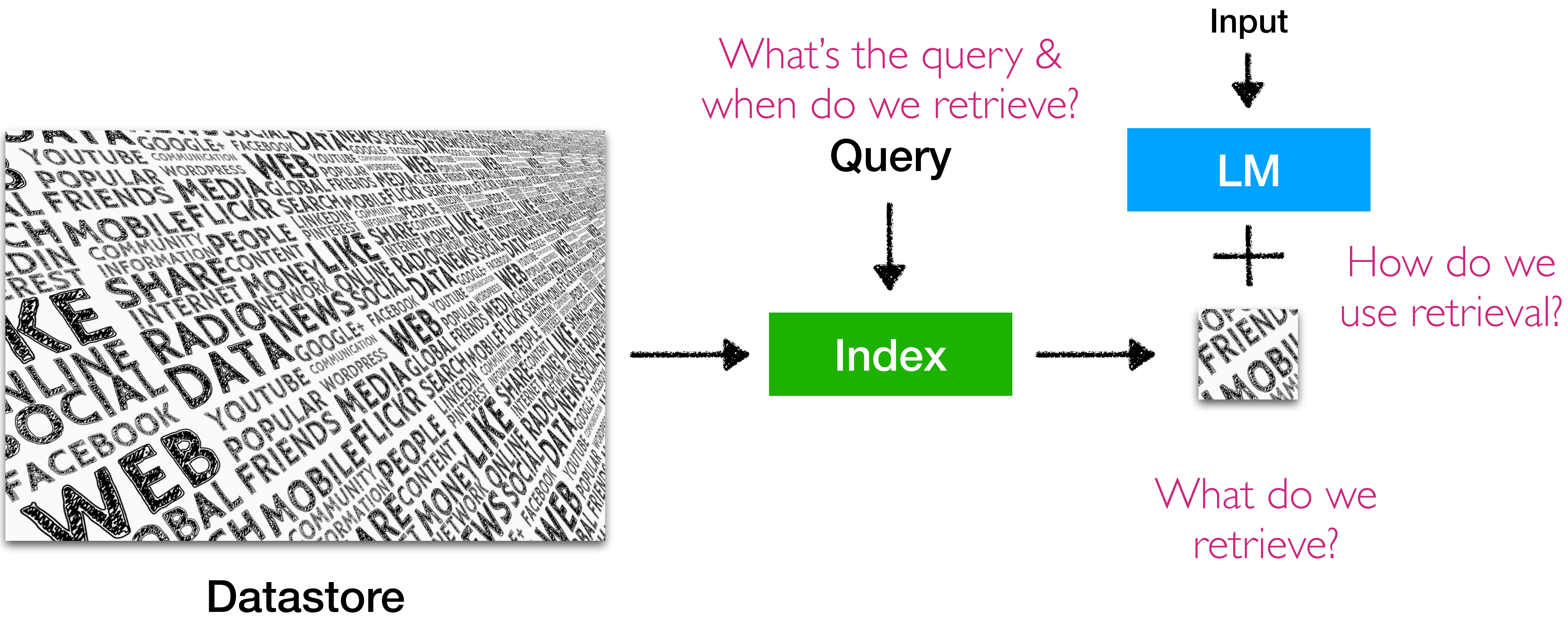
Questions to answer



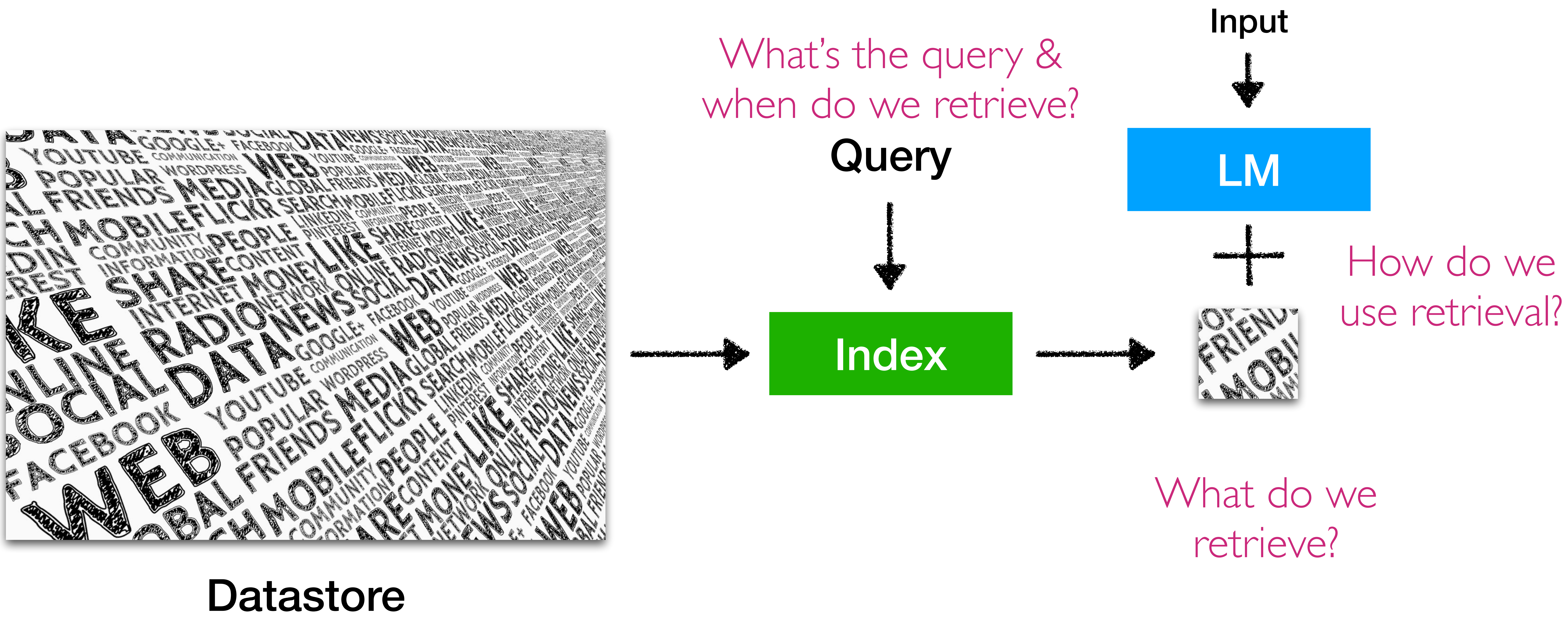
Questions to answer



Questions to answer



Questions to answer



We'll answer these questions in Section 3!

Notations