Section 3:
Retrieval-based LM: Architecture

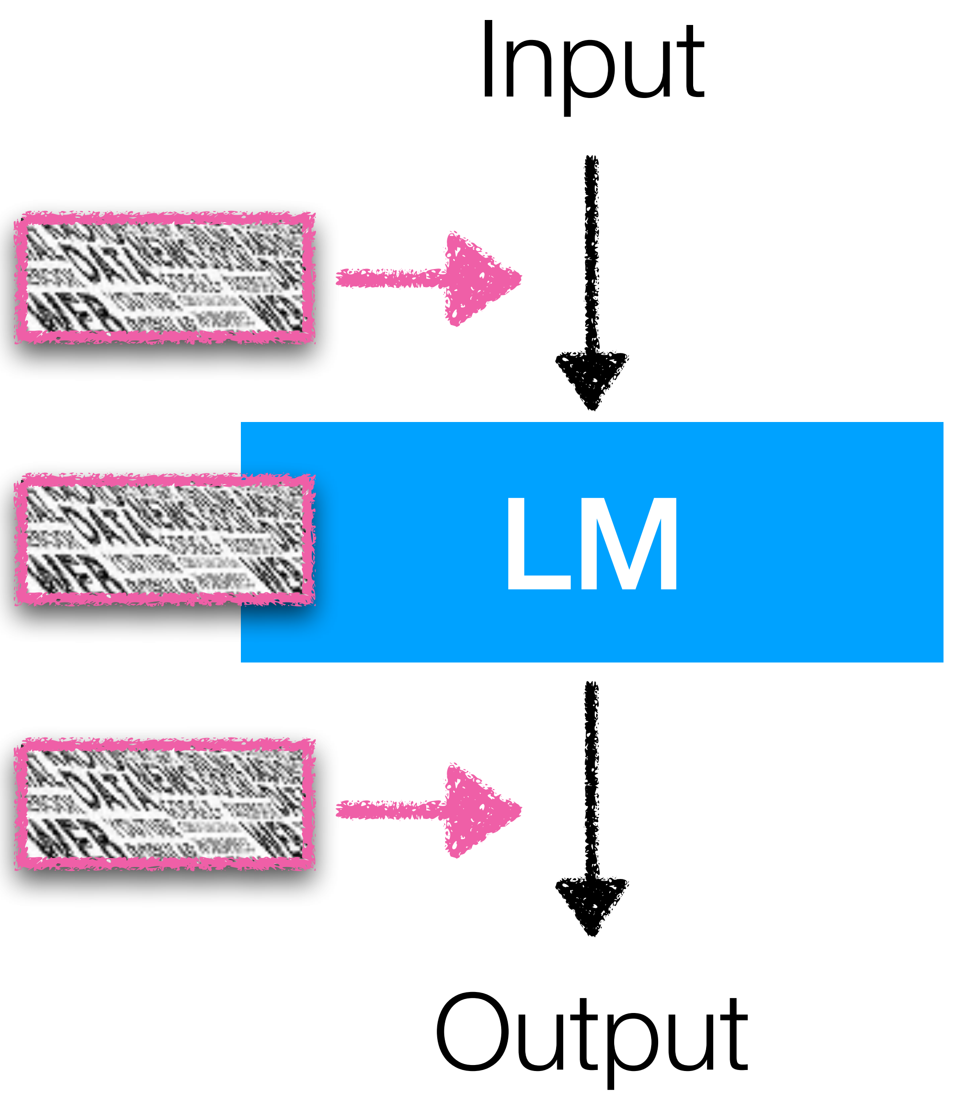
Categorization of retrieval-based LMs

What to retrieve?

Query

Text chunks (passages)?
Tokens?
Something else?

How to use retrieval?



When to retrieve?

w/ retrieval

The capital city of Ontario is Toronto.

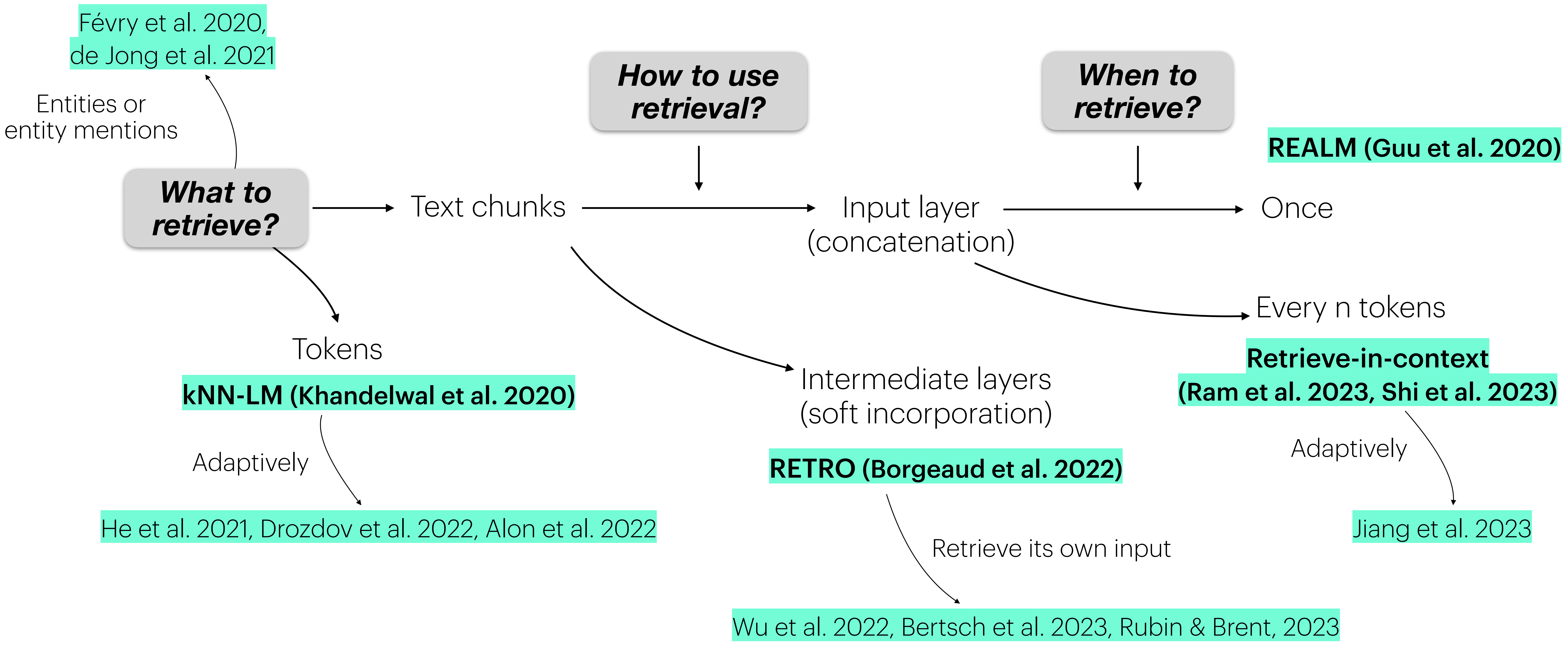
w/ retrieval w/ r w/r w/r w/ r w/r w/r

The capital city of Ontario is Toronto.

w/ retrieval w/r w/r

The capital city of Ontario is Toronto.

Roadmap

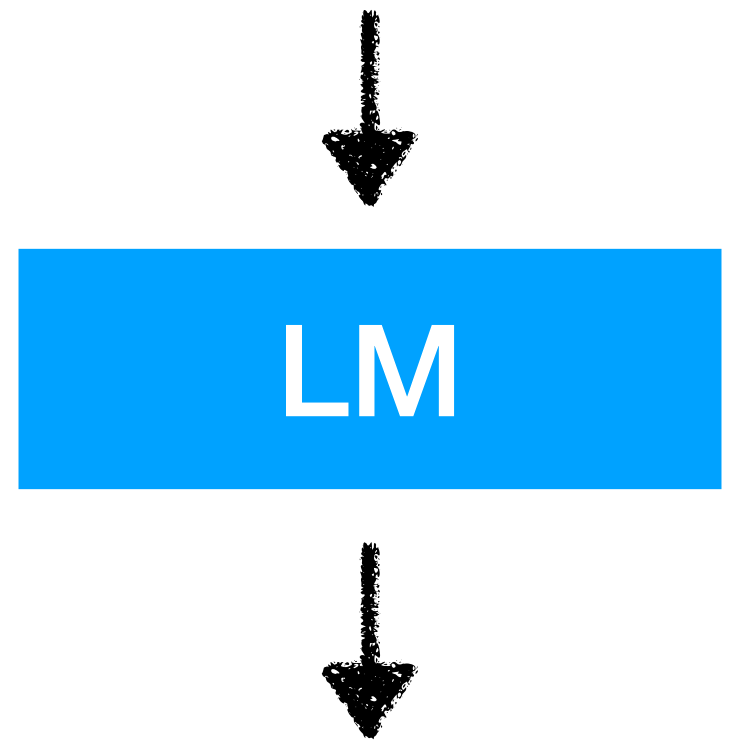


This is only about "architecture"
Section 4 will categorize & discuss "training"

REALM (Guu et al 2020)

x = World Cup 2022 was the last with 32 teams before the increase to [MASK] in 2026.

World Cup 2022 was … the increase to [MASK] in 2026.



48

Guu et al. 2020. “REALM: Retrieval-Augmented Language Model Pre-Training”

REALM (Guu et al 2020)

x = World Cup 2022 was the last with 32 teams before the increase to [MASK] in 2026.

q (=x)

Retrieval

k chunks of text (passages)

FIFA World Cup 2026 will expand to 48 teams.

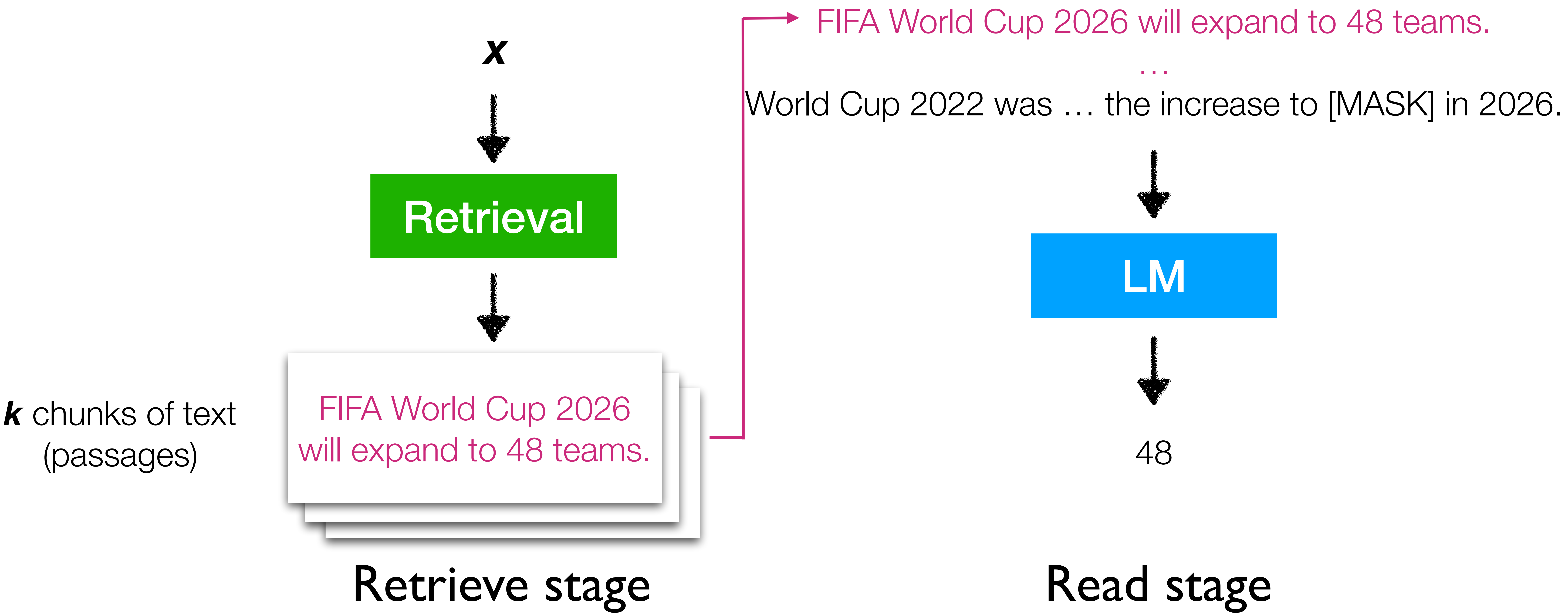
World Cup 2022 was … the increase to [MASK] in 2026.

LM

Guu et al. 2020. "REALM: Retrieval-Augmented Language Model Pre-Training"

REALM (Guu et al 2020)

x = World Cup 2022 was the last before the increase to [MASK] in the 2026 tournament.



Guu et al. 2020. “REALM: Retrieval-Augmented Language Model Pre-Training”

REALM: (I) Retrieve stage

x = World Cup 2022 was … the increase to [MASK] in 2026.

Encoder

Fast nearest neighbor search

FIFA World Cup 2026 will expand to 48 teams.

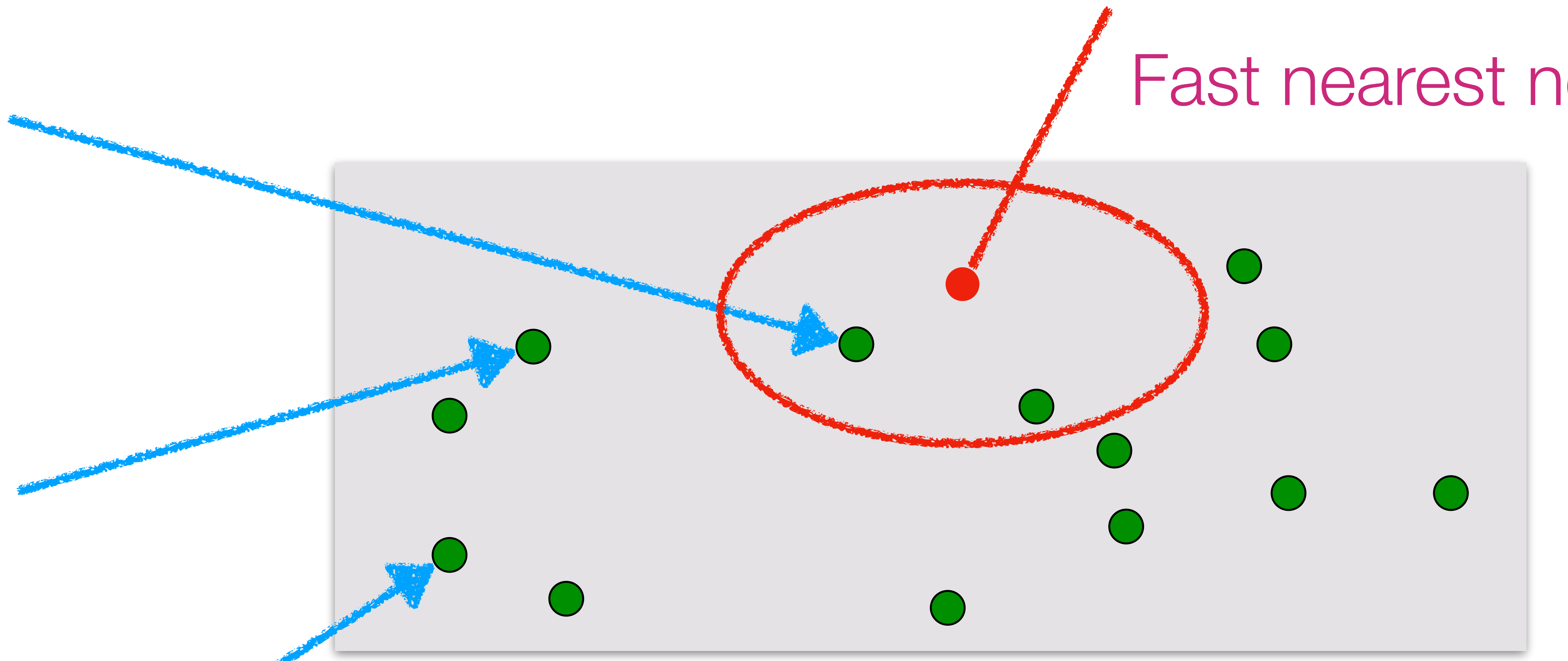
Encoder

In 2022, the 32 national teams involved in the tournament.

Encoder

Team USA celebrated after winning its match against Iran …

Encoder



$\mathbf{z} = \text{Encoder}(z)$

$\mathbf{x} = \text{Encoder}(x)$

Wikipedia
13M chunks (passages)
(called *documents* in the paper)

$$z_1, \ldots, z_k = \text{argTop-}k\,(\mathbf{x} \cdot \mathbf{z})$$

k retrieved blocks

REALM: (2) Read stage

[MASK] z_1 [SEP] x → LM → $P(y \mid x, z_1)$

[MASK] z_2 [SEP] x → LM → $P(y \mid x, z_2)$

⋮

[MASK] z_k [SEP] x → LM → $P(y \mid x, z_k)$

Weighted average

0 if not one of top k

$$\sum_{z \in \mathcal{D}} \underbrace{P(z \mid x)}_{\text{from the retrieve stage}} \underbrace{P(y \mid x, z)}_{\text{from the read stage}}$$

Need to approximate
→ Consider top k chunks only

REALM (Guu et al 2020)

What to retrieve?

- Chunks
- Tokens
- Others

How to use retrieval?

- Input layer
- Intermediate layers
- Output layer

When to retrieve?

- Once
- Every *n* tokens (*n*>1)
- Every token

REALM (Guu et al 2020)

What to retrieve?

- **Chunks** ✓
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REALM (Guu et al 2020)

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- **Chunks** ✓
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How to use retrieval?

- **Input layer** ✓
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- Output layer

When to retrieve?

- **Once** ✓
- Every *n* tokens (*n*>1)
- Every token

REALM and subsequent work

* REALM (Guu et al 2020): MLM followed by fine-tuning on open-domain QA
* DPR (Karpukhin et al 2020): Pipeline training instead of joint training, fine-tuned on open-domain QA (no explicit language modeling)
* RAG (Lewis et al 2020): “Generative” instead of “masked language modeling”, fine-tuned on open-domain QA & knowledge intensive tasks (no explicit language modeling)
* Atlas (Izcard et al 2022): Combine RAG with retrieval-based language model pre-training based on the encoder-decoder architecture (more to come in Section 4), fine-tuned on open-domain QA & other QA tasks

For a while, mainly evaluated on
knowledge-intensive tasks (e.g. open-domain QA) with fine-tuning
(more context in Section 5)

REALM and subsequent work

* REALM (Guu et al 2020): MLM followed by fine-tuning, focusing on open-domain QA
* DPR (Karpukhin et al 2020): Pipeline training instead of joint training, focusing on open-domain QA (no explicit language modeling)
* RAG (Lewis et al 2020): “Generative” instead of “masked language modeling”, focusing on open-domain QA & knowledge intensive tasks (no explicit language modeling)
* Atlas (Izcard et al 2022): Combine RAG with retrieval-based language model pre-training based on the encoder-decoder architecture (more to come in Section 4), focusing on open-domain QA & knowledge intensive tasks
* Papers that follow this approach focusing on **LM perplexity** have come out quite recently (Shi et al. 2023, Ram et al. 2023)

Ram et al. 2023. “In-Context Retrieval-Augmented Language Models”
Shi et al. 2023. “REPLUG: Retrieval-Augmented Black-Box Language Models”

Retrieval-in-context in LM

x = World Cup 2022 was the last with 32 teams, before the increase to

World Cup 2022 was the last with 32 teams, before the increase to

↓

Retrieval

↓

FIFA World Cup 2026 will expand to 48 teams.

* Can use multiple text blocks too (see the papers!)

Ram et al. 2023. “In-Context Retrieval-Augmented Language Models”
Shi et al. 2023. “REPLUG: Retrieval-Augmented Black-Box Language Models”

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World Cup 2022 was the last with 32 teams, before the increase to

↓

Retrieval

* Can use multiple text blocks too (see the papers!)

↓

FIFA World Cup 2026 will expand to 48 teams. World Cup 2022 was the last with 32 teams, before the increase to

↓

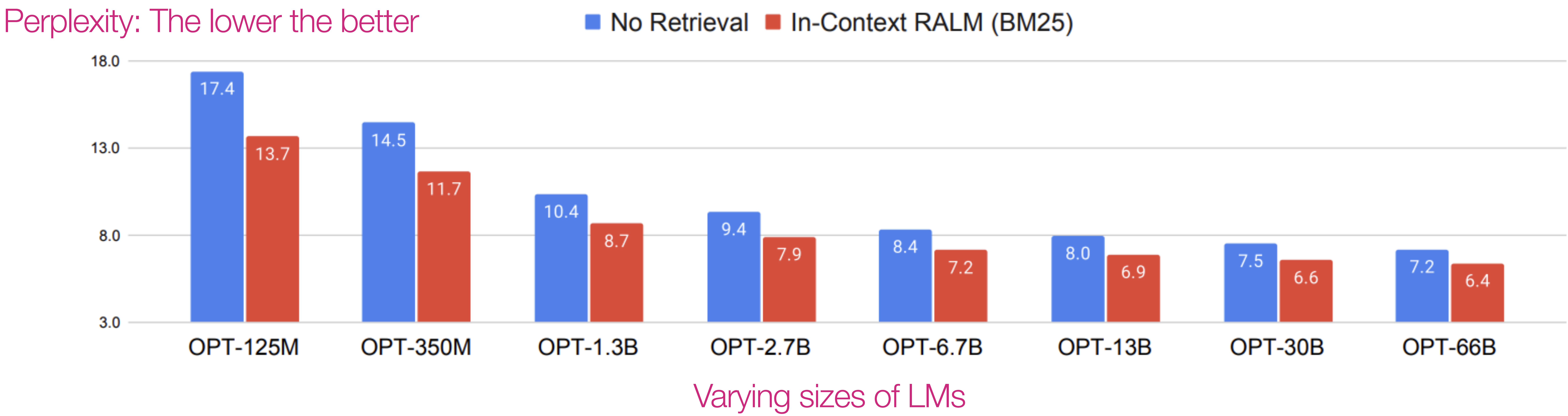
LM

↓

48 in the 2026 tournament.

Ram et al. 2023. “In-Context Retrieval-Augmented Language Models”
Shi et al. 2023. “REPLUG: Retrieval-Augmented Black-Box Language Models”

Retrieval-in-context in LM



Retrieval helps over all sizes of LMs

Graphs from Ram et al. 2023

Retrieval-in-context in LM

Is $\boldsymbol{q}=\boldsymbol{x}$ necessary?

$\boldsymbol{x}$ = Team USA celebrates after winning its match against Iran at Al Thumama Stadium in Group B play of the FIFA World Cup 2022 on Nov. 29, 2022. (..) World Cup 2022 was the last with 32 teams, before the increase to

Team USA celebrates after winning its match against Iran at Al Thumama Stadium in Group B play of the FIFA World Cup 2022 on Nov. 29, 2022. (..) World Cup 2022 was the last with 32 teams, before the increase to

Retrieval

The U.S. national team defeated Iran 1-0.

Does not cover "tokens that will come next"

Retrieval-in-context in LM

Is ***q***=***x*** necessary?

x = Team USA celebrates after winning its match against Iran at Al Thumama Stadium in Group B play of the FIFA World Cup 2022 on Nov. 29, 2022. (..) World Cup 2022 was the last with 32 teams, before the increase to

Team USA celebrates after winning its match against Iran at Al Thumama Stadium in Group B play of the FIFA World Cup 2022 on Nov. 29, 2022. (..) World Cup 2022 was the last with 32 teams, before the increase to

Retrieval

The U.S. national team defeated Iran 1-0.

Does not cover "tokens that will come next"

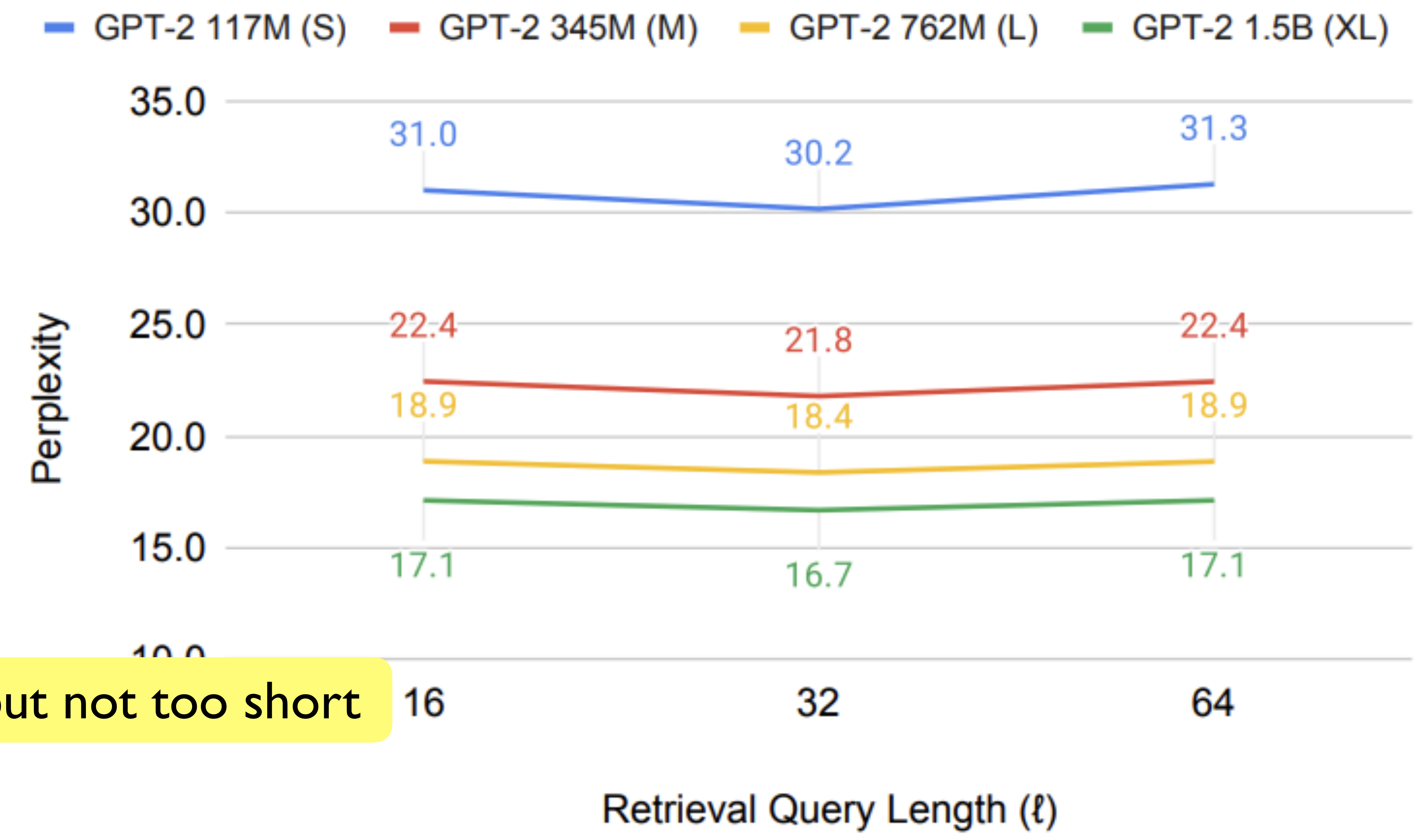
World Cup 2022 was the last with 32 teams, before the increase to

Retrieval

FIFA World Cup 2026 will expand to 48 teams.

more relevant to what will come next

Retrieval-in-context in LM



but not too short

Shorter prefix (more recent tokens) as a query helps

Graphs from Ram et al. 2023

Retrieval-in-context in LM

How frequent should retrieval be?

World Cup 2022 was the last with

↓

Retrieval

↓

The 2022 FIFA World Cup (...) 32 national teams involved in the tournament.

Retrieval-in-context in LM

How frequent should retrieval be?

World Cup 2022 was the last with

Retrieval

The 2022 FIFA World Cup (...) 32 national teams involved in the tournament. World Cup 2022 was the last with

LM

32 teams before the increase to 48 in the 2026 tournament.

explained by retrieval

not really covered

Retrieval-in-context in LM

How frequent should retrieval be?

World Cup 2022 was the last with

↓

Retrieval

↓

The 2022 FIFA World Cup (...) 32 national teams involved in the tournament. World Cup 2022 was the last with

↓

LM

↓

32 teams before the increase

Retrieval-in-context in LM

How frequent should retrieval be?

World Cup 2022 was the last with

↓

Retrieval

↓

The 2022 FIFA World Cup (...) 32 national teams involved in the tournament. World Cup 2022 was the last with

↓

LM

↓

32 teams before the increase

World Cup 2022 was the last with 32 teams before the increase

↓

Retrieval

↓

FIFA World Cup 2026 will expand to 48 teams.

Retrieval-in-context in LM

How frequent should retrieval be?

World Cup 2022 was the last with

Retrieval

The 2022 FIFA World Cup (...) 32 national teams involved in the tournament. World Cup 2022 was the last with

LM

32 teams before the increase

World Cup 2022 was the last with 32 teams before the increase

Retrieval

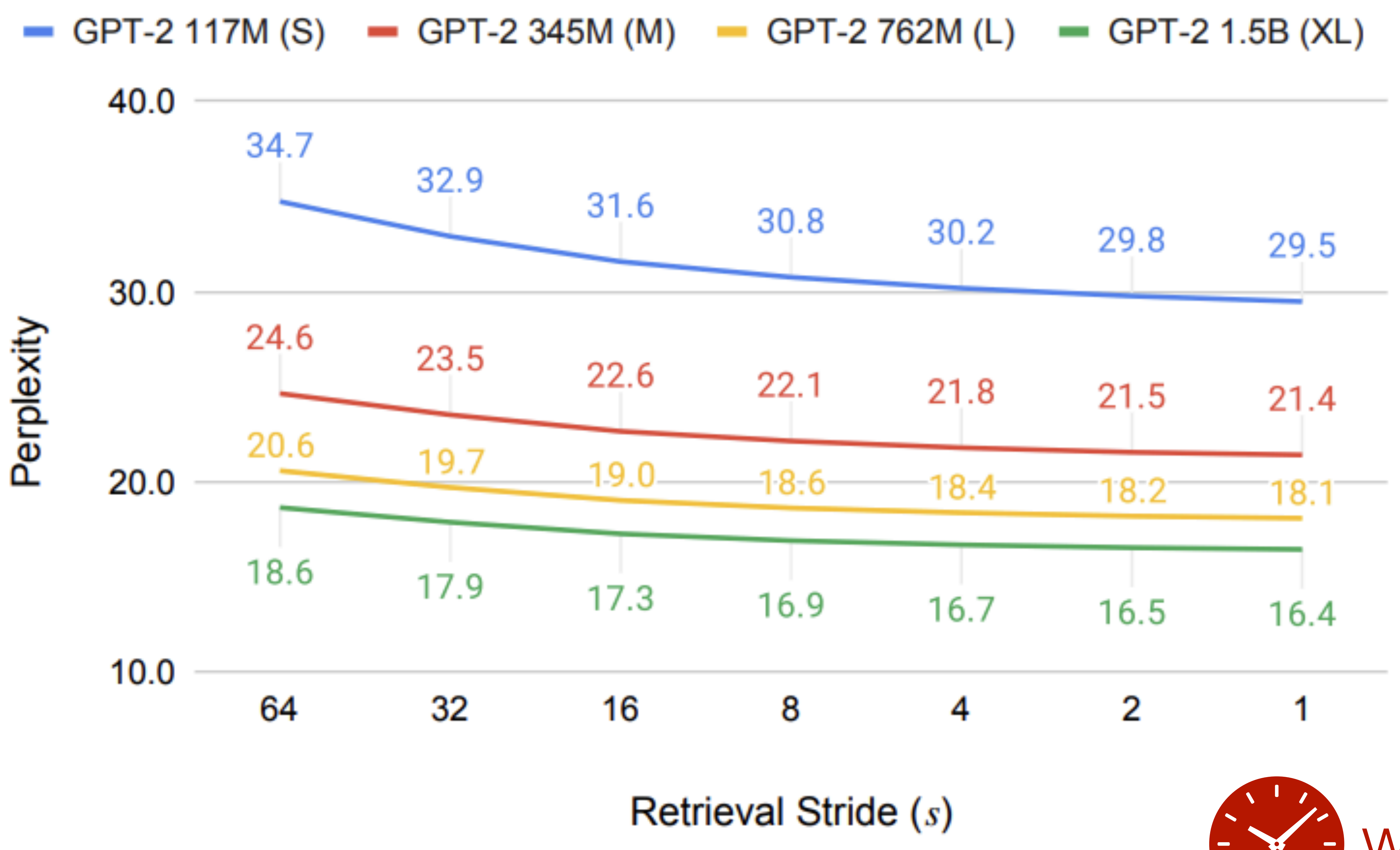
FIFA World Cup 2026 will expand to 48 teams. World Cup 2022 was the last with 32 teams, before the increase

LM

to 48 in the 2026 tournament.

Retrieval results from a new query explain them!

Retrieval-in-context in LM



with cost in inference time

Retrieving more frequently helps

Graphs from Ram et al. 2023

Retrieve-in-context LM (Shi et al 2023, Ram et al 2023)

What to retrieve?

- **Chunks** ✓
- Tokens
- Others

How to use retrieval?

- Input layer
- Intermediate layers
- Output layer

When to retrieve?

- Once
- Every n tokens (n>1)
- Every token

Retrieve-in-context LM (Shi et al 2023, Ram et al 2023)

What to retrieve?

- **Chunks** ✓
- Tokens
- Others

How to use retrieval?

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How to use retrieval?

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- Output layer

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- Once
- **Every n tokens (n>1)** ✓
- Every token

Summary

	What do retrieve?	How to use retrieval?	When to retrieve?
REALM (Guu et al 2020)	Text chunks	Input layer	Once
Retrieve-in-context LM (Shi et al 2023, Ram et al 2023)	Text chunks	Input layer	Every n tokens

Applying the same approach to LM raised new questions
which mattered less in prior work (e.g. REALM) with short inputs & short outputs

Summary

	What do retrieve?	How to use retrieval?	When to retrieve?
REALM (Guu et al 2020)	Text chunks	Input layer	Once
Retrieve-in-context LM (Shi et al 2023, Ram et al 2023)	Text chunks	Input layer	Every n tokens

can be very inefficient to retrieve <u>many</u> text chunk, <u>frequently</u>

RETRO (Borgeaud et al. 2021)

✔ Incorporation in the “intermediate layer” instead of the “input” layer
→ designed for *many* blocks, *frequently*, more *efficiently*

✔ Scale the datastore to retrieve from

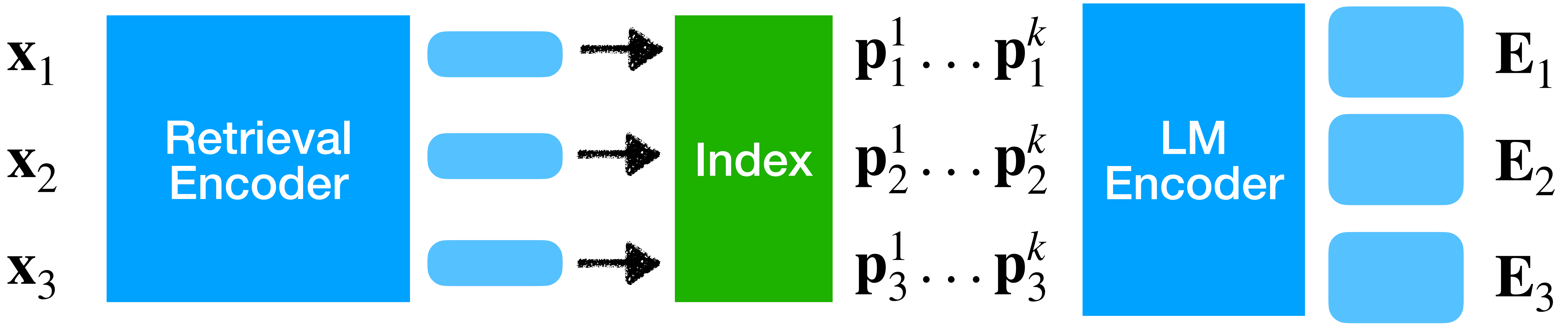
Borgeaud et al. 2021. “Improving language models by retrieving from trillions of tokens”

RETRO (Borgeaud et al. 2021)

$\boldsymbol{x}$ = World Cup 2022 was / the last with 32 teams, / before the increase to

$\mathbf{x}_1$ $\mathbf{x}_2$ $\mathbf{x}_3$

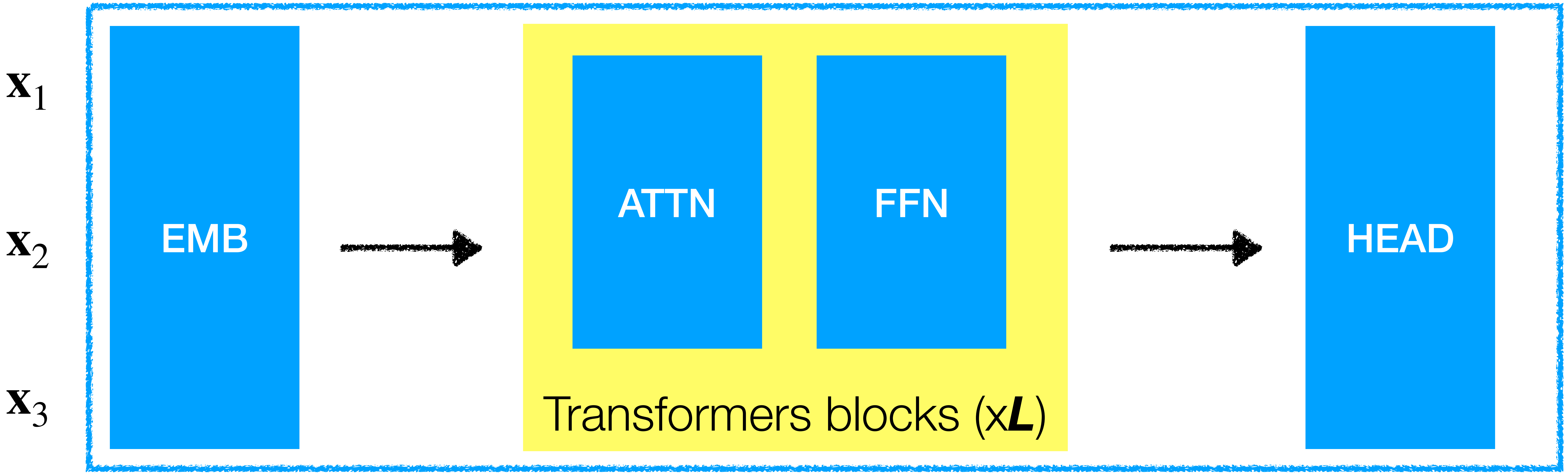
(k chunks of text per split)



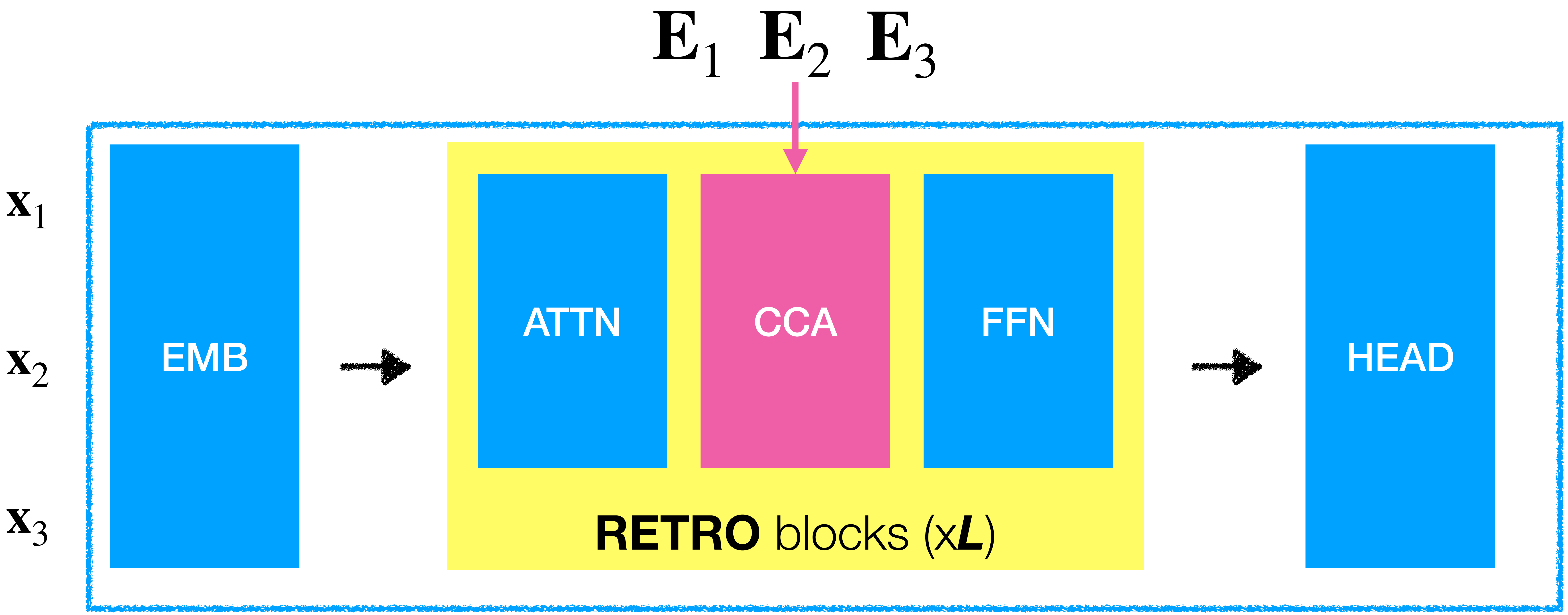
(A $r \times k \times d$ matrix)

(r = # tokens per text block)
(d = hidden dimension)
(k = # retrieved blocks per split)

Regular decoder

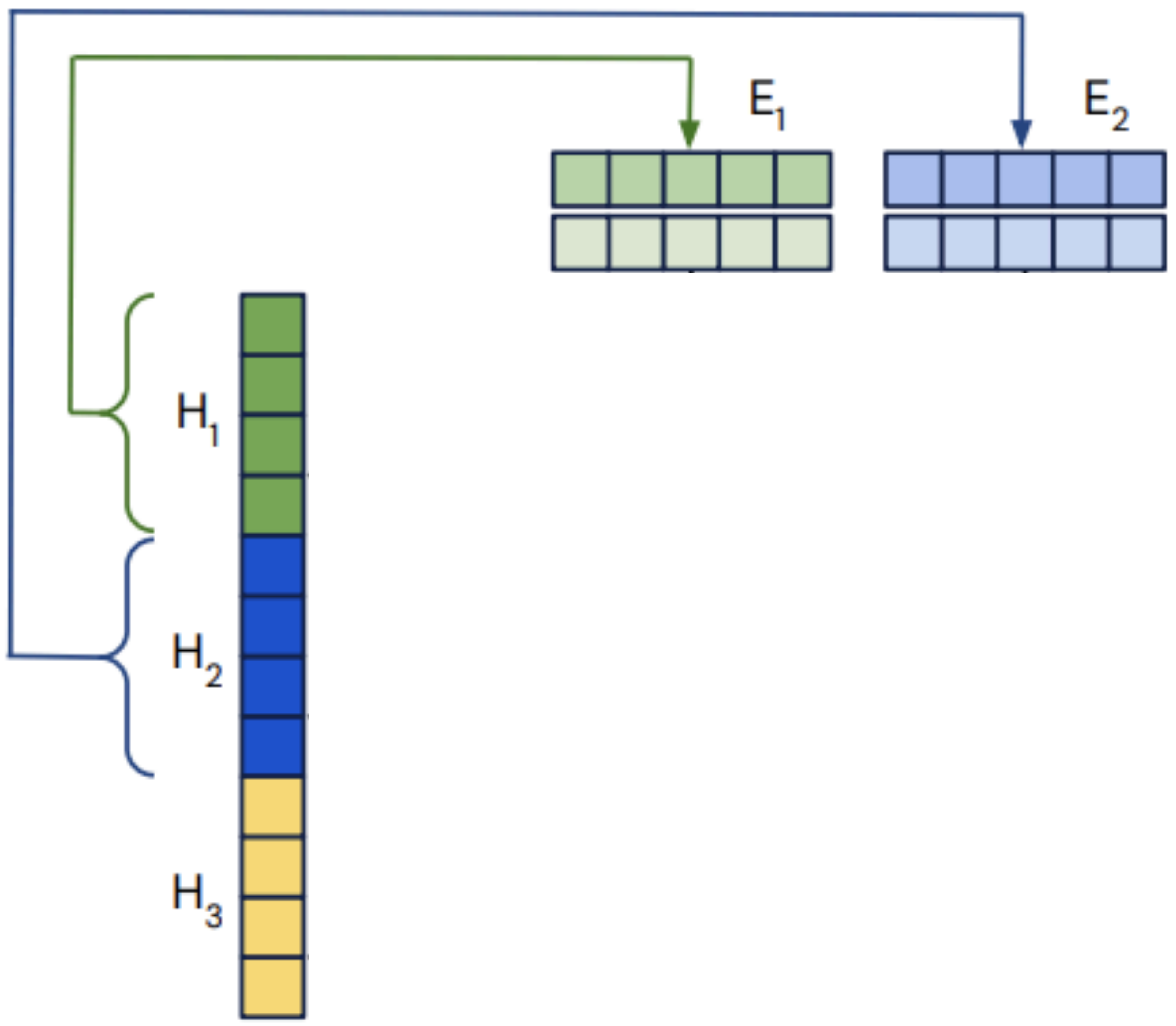


Decoder in RETRO



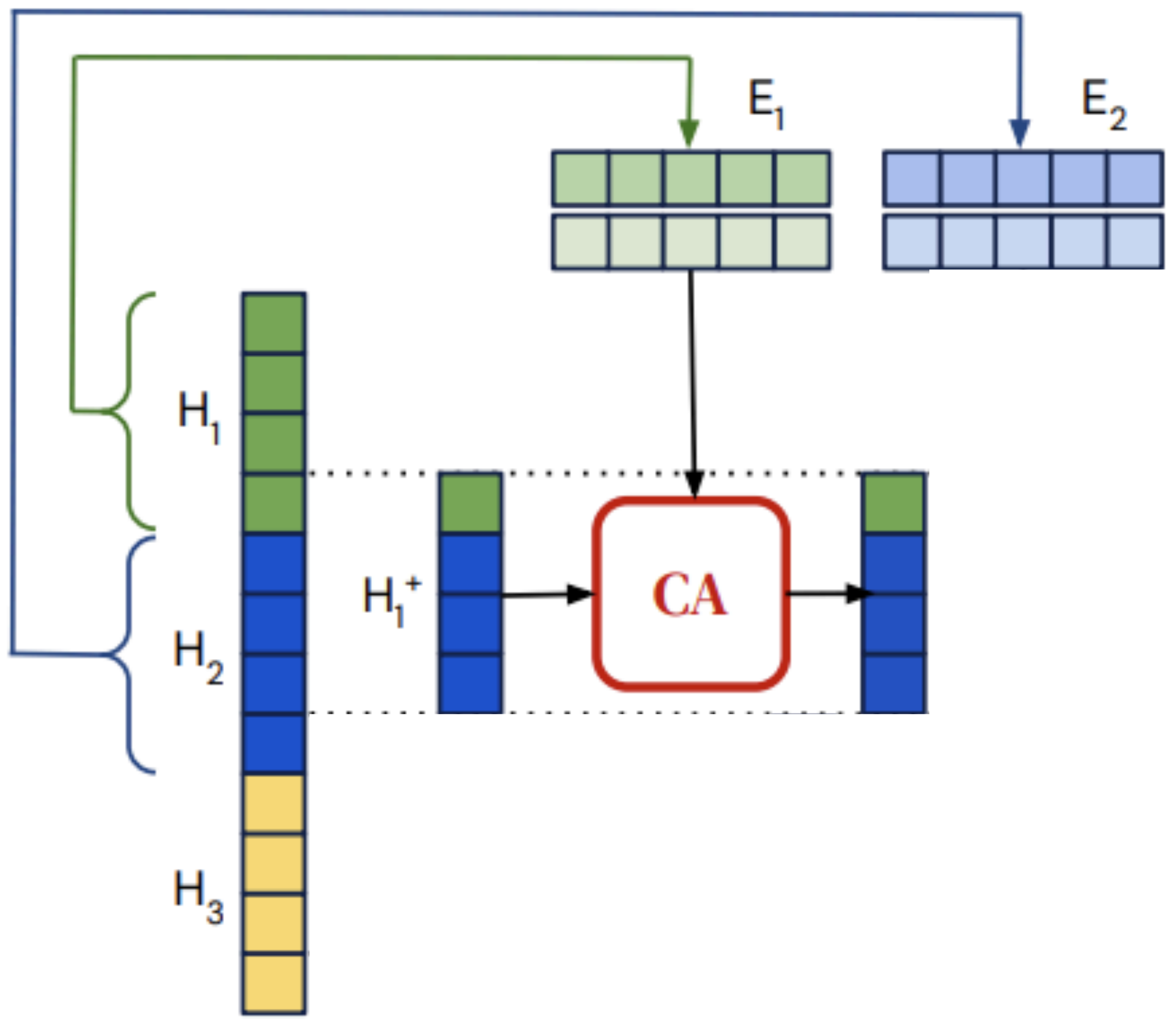
Chunked Cross Attention (CCA)

Chunked Cross Attention



Outputs from the previous layer H

Chunked Cross Attention



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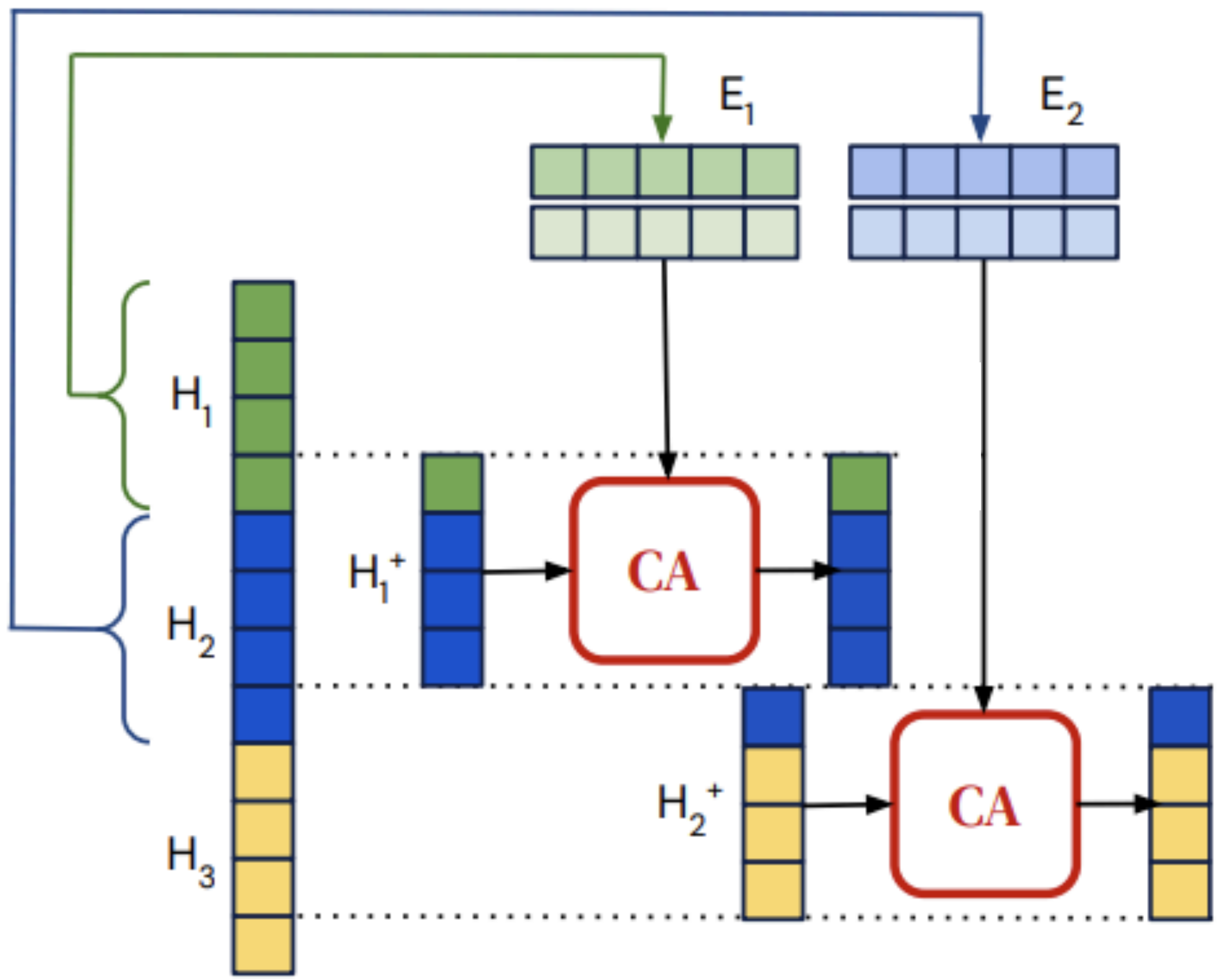

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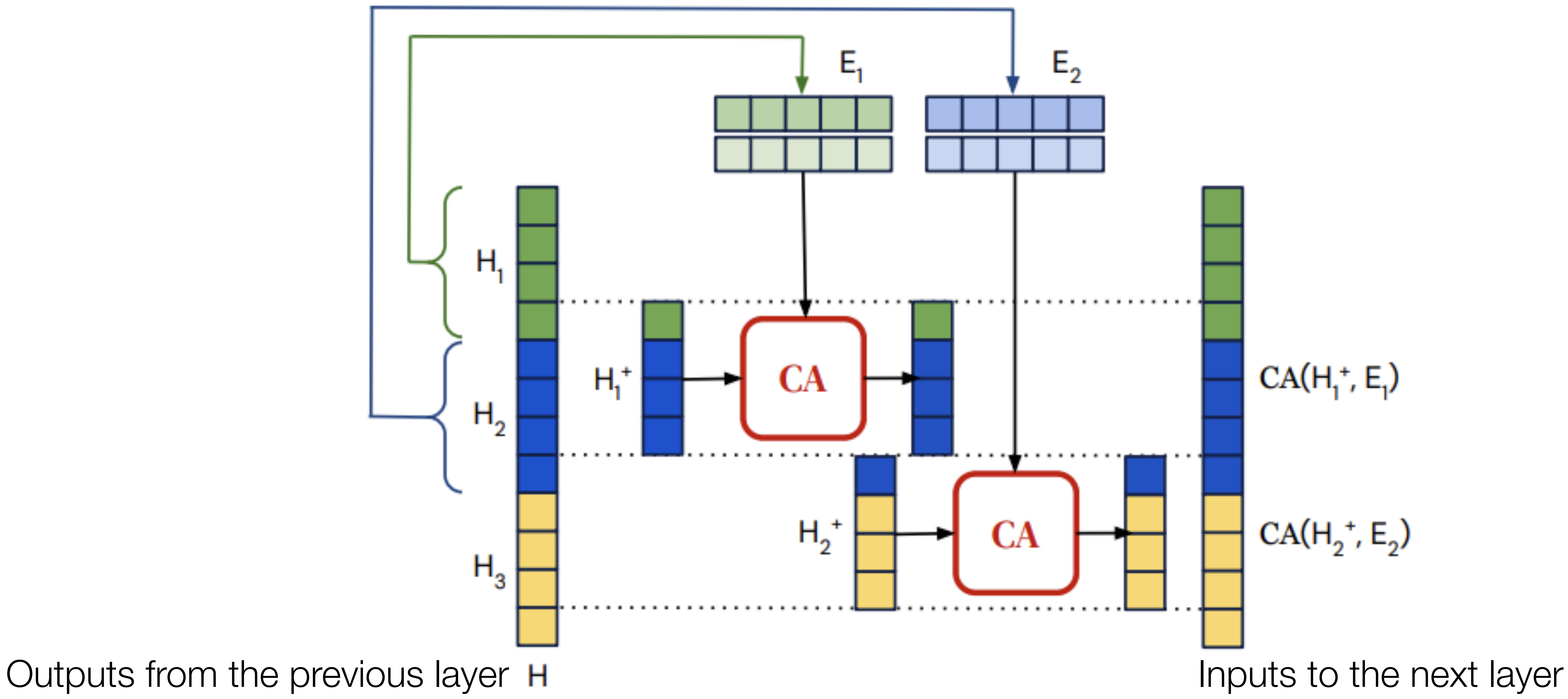

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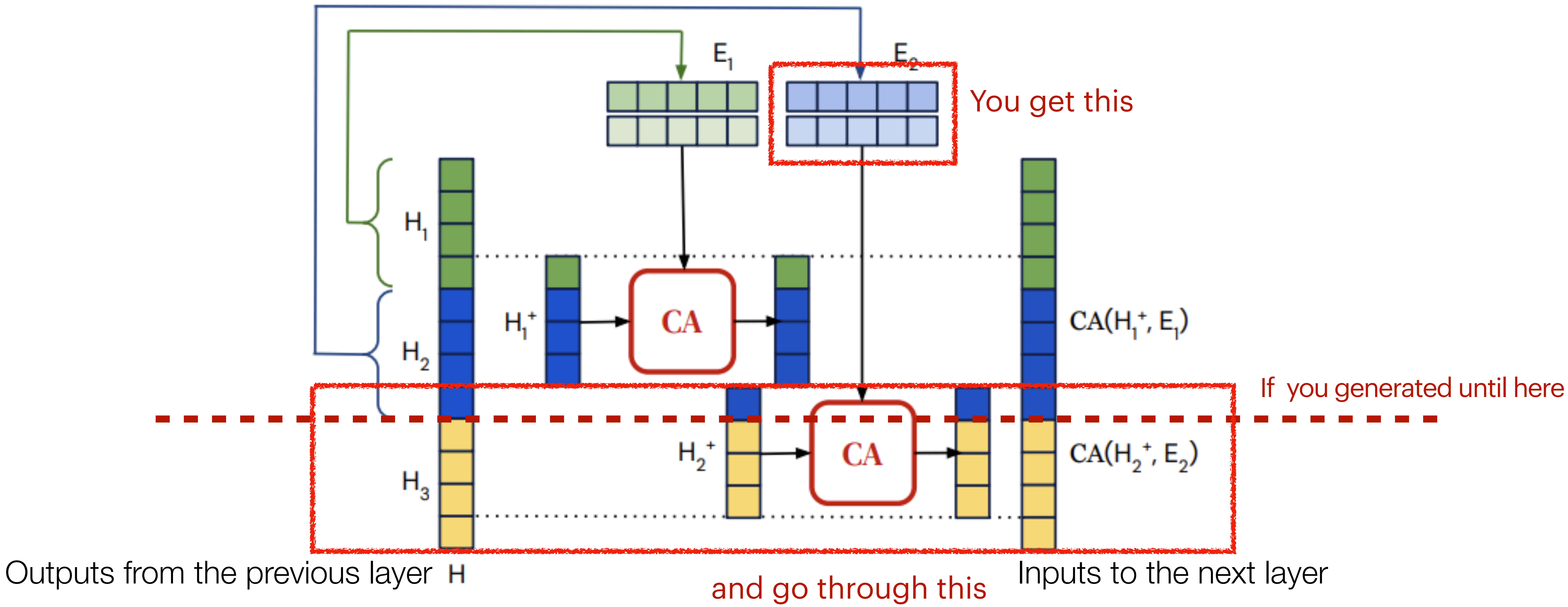
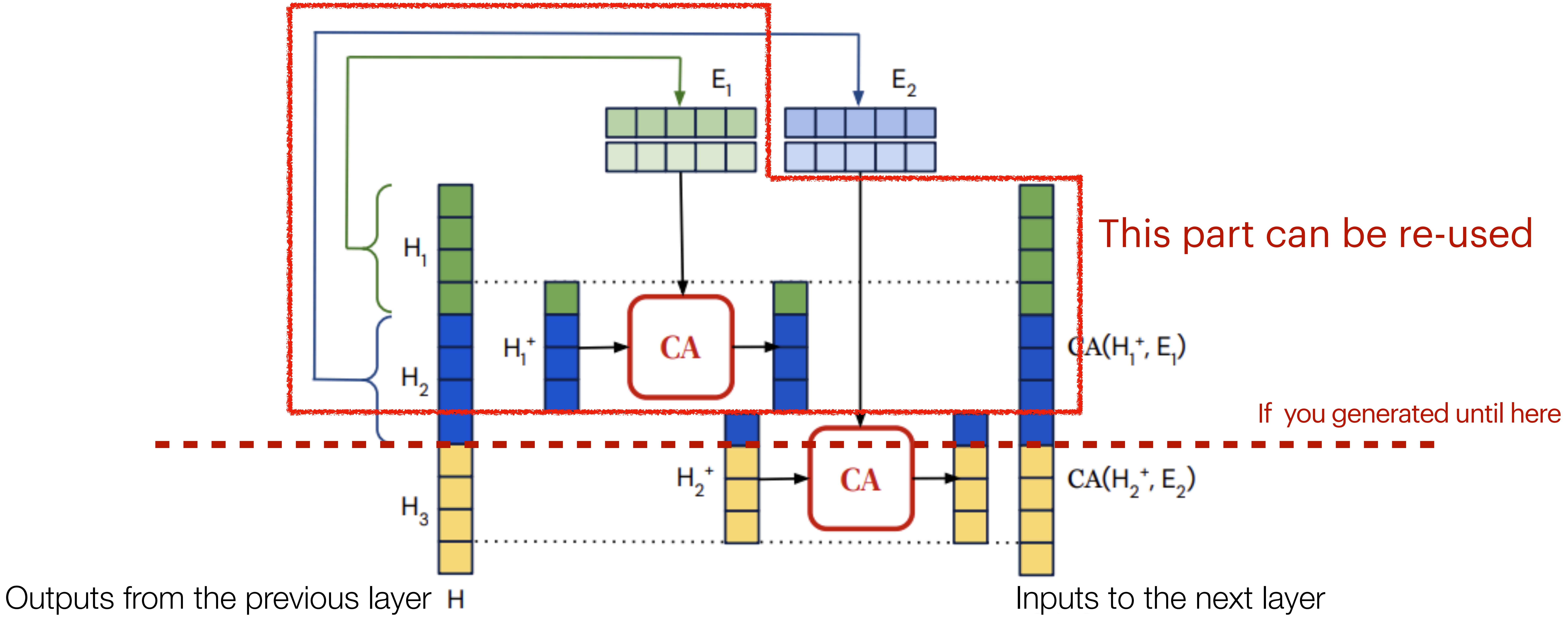


✔ Cross-attention can be computed in parallel

Chunked Cross Attention



✔ Cross-attention can be computed in parallel

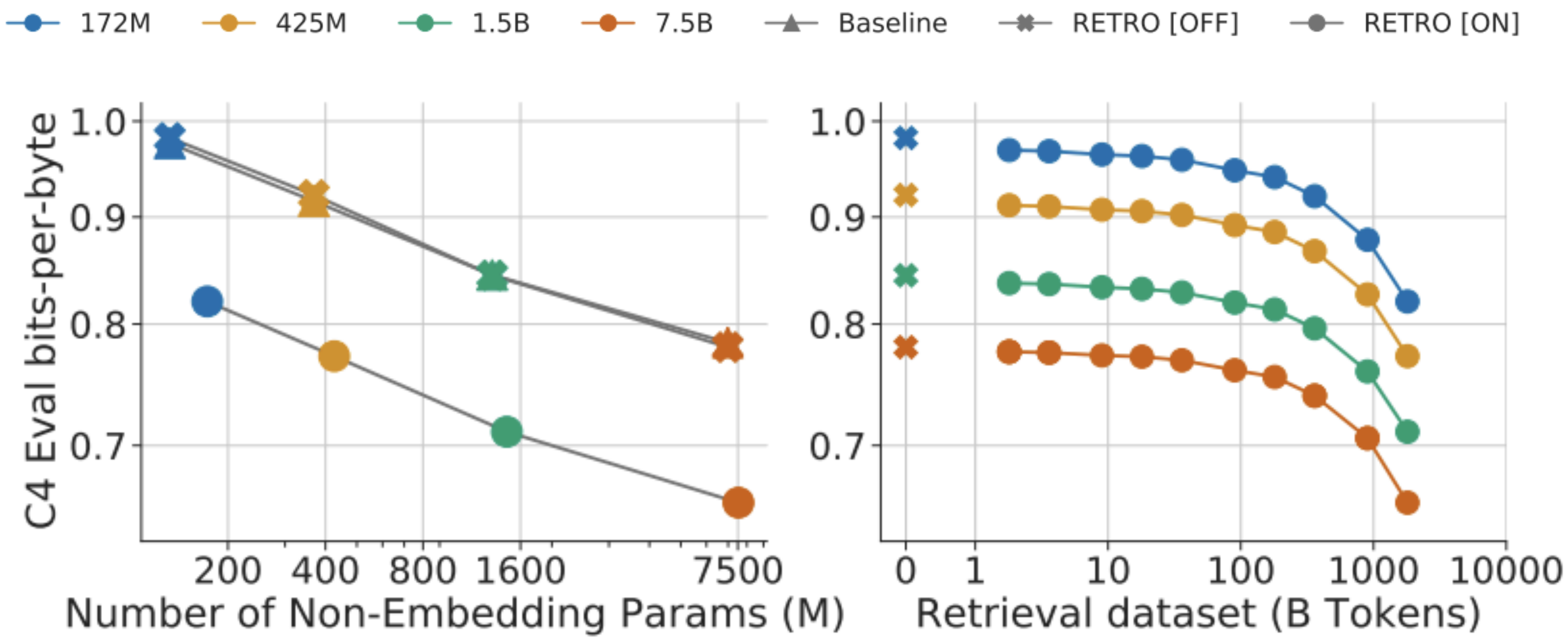
Results

Perplexity: The lower the better

Model	Retrieval Set	#Database tokens	#Database keys	Valid	Test
Adaptive Inputs (Baevski and Auli, 2019)	-	-	-	17.96	18.65
SPALM (Yogatama et al., 2021)	Wikipedia	3B	3B	17.20	17.60
*k*NN-LM (Khandelwal et al., 2020)	Wikipedia	3B	3B	16.06	16.12
Megatron (Shoeybi et al., 2019)	-	-	-	-	10.81
Baseline transformer (ours)	-	-	-	21.53	22.96
*k*NN-LM (ours)	Wikipedia	4B	4B	18.52	19.54
RETRO	Wikipedia	4B	0.06B	18.46	18.97
RETRO	C4	174B	2.9B	12.87	10.23
RETRO	MassiveText (1%)	18B	0.8B	18.92	20.33
RETRO	MassiveText (10%)	179B	4B	13.54	14.95
RETRO	MassiveText (100%)	1792B	28B	**3.21**	**3.92**

Significant improvements by retrieving from 1.8 trillion tokens

Results



Gains are constant with model scale

The larger datastore is, the better

RETRO (Borgeaud et al. 2021)

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RETRO (Borgeaud et al. 2021)	Text chunks	Intermediate layers	Every n tokens

👍 Can use many blocks, more frequently, more efficiently

👎 Additional complexity; Can't be used without training (more in section 4)

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What else?

kNN-LM (Khandelwal et al. 2020)

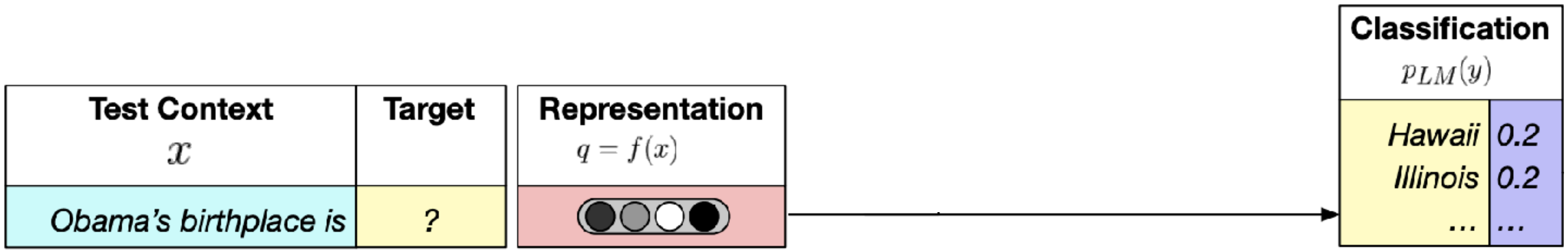
- ✓ A different way of using retrieval, where the LM outputs a nonparametric distribution over every token in the data.
- ✓ Can be seen as an incorporation in the “output” layer

Khandelwal et al. 2020. “Generalization through Memorization: Nearest Neighbor Language Models”

kNN-LM (Khandelwal et al. 2020)

Test Context x	Target
Obama's birthplace is	?

kNN-LM (Khandelwal et al. 2020)



kNN-LM (Khandelwal et al. 2020)

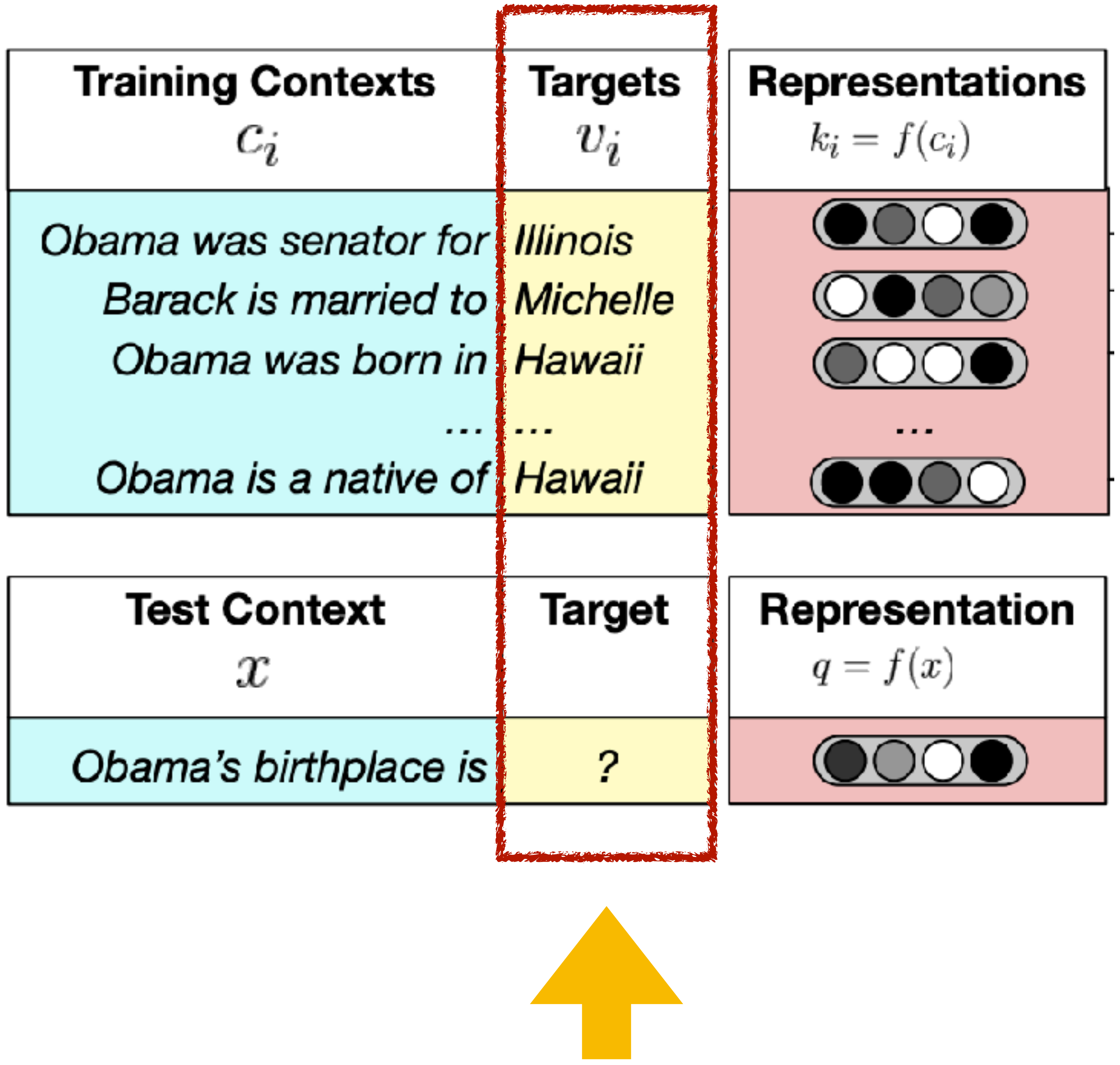
The size of the datastore = # of tokens in the corpus (>1B)

Training Contexts c_i	Targets v_i
Obama was senator for	*Illinois*
Barack is married to	*Michelle*
Obama was born in	*Hawaii*
...	...
Obama is a native of	*Hawaii*

... Obama was senator for Illinois from 1997 to 2005, ... Barack is Married to Michelle and their first daughter, ... Obama was born in Hawaii, and graduated from Columbia University. ... Obama is a native of Hawaii, ...

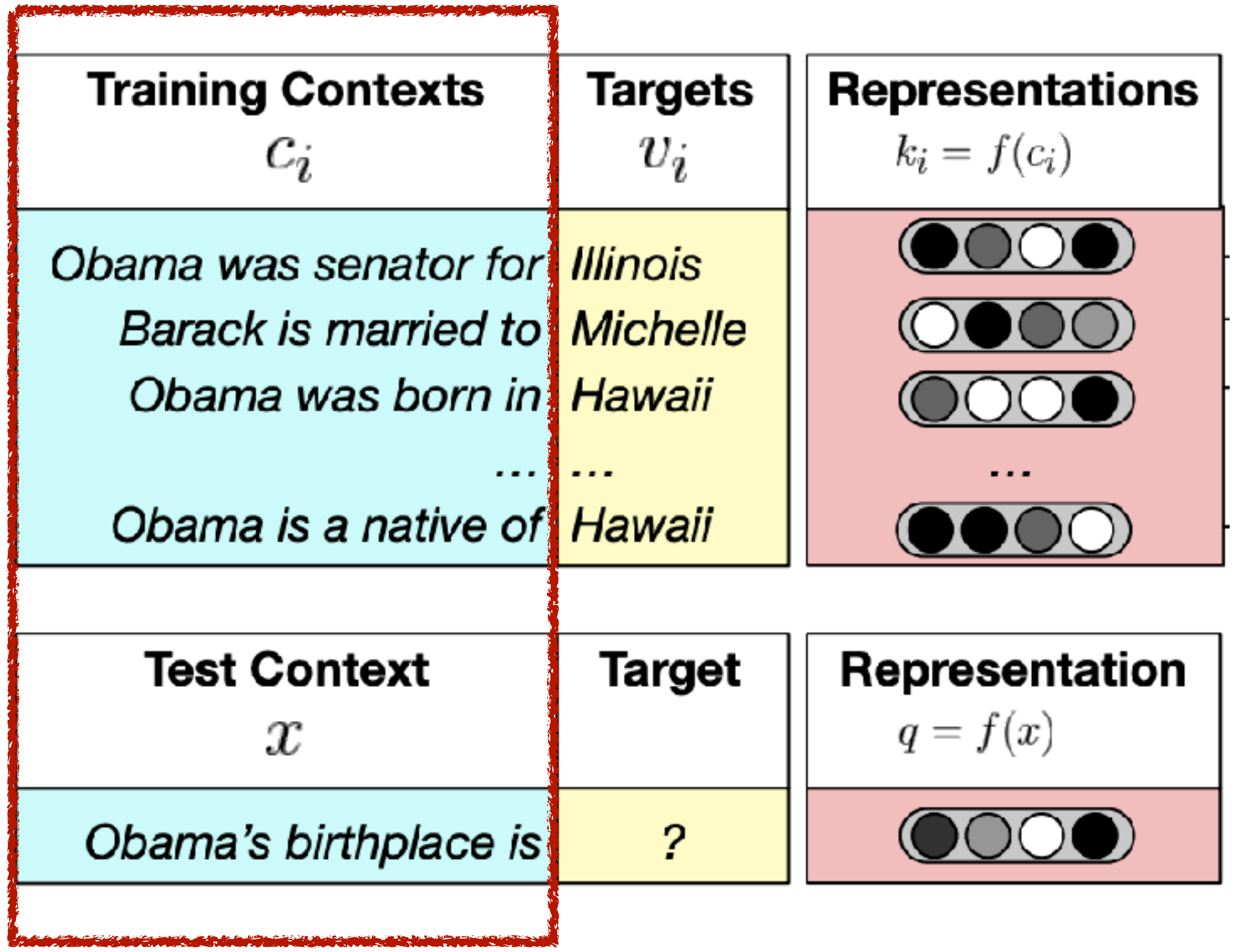
Test Context x	Target	Representation $q = f(x)$
Obama's birthplace is	*?*	

kNN-LM (Khandelwal et al. 2020)



Which tokens <u>in a datastore</u> are close to the next token?

kNN-LM (Khandelwal et al. 2020)

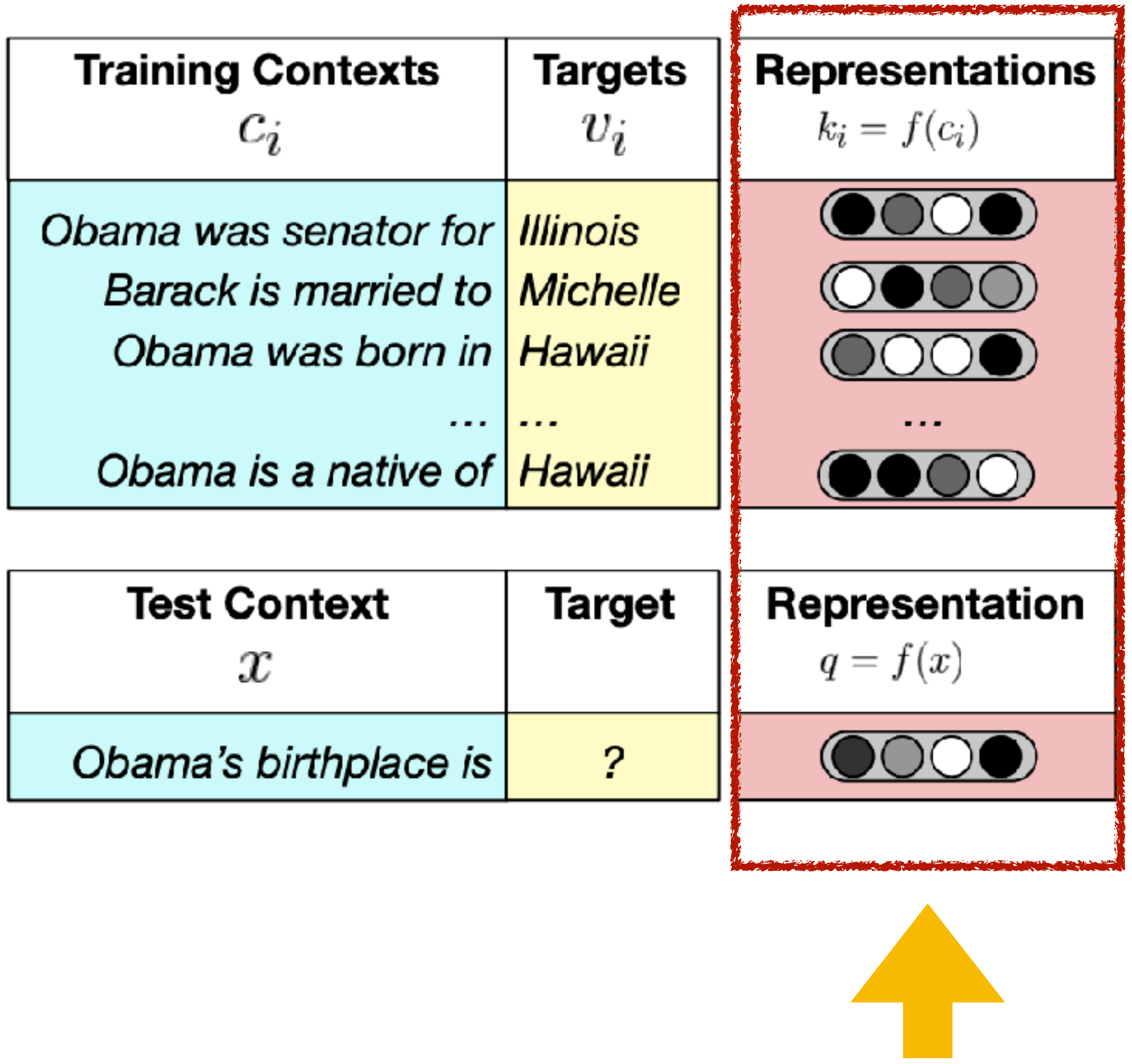


Which tokens <u>in a datastore</u> are close to the next token?

=

Which prefixes in a datastore are close to the prefix we have?

kNN-LM (Khandelwal et al. 2020)



Which tokens <u>in a datastore</u> are close to the next token?

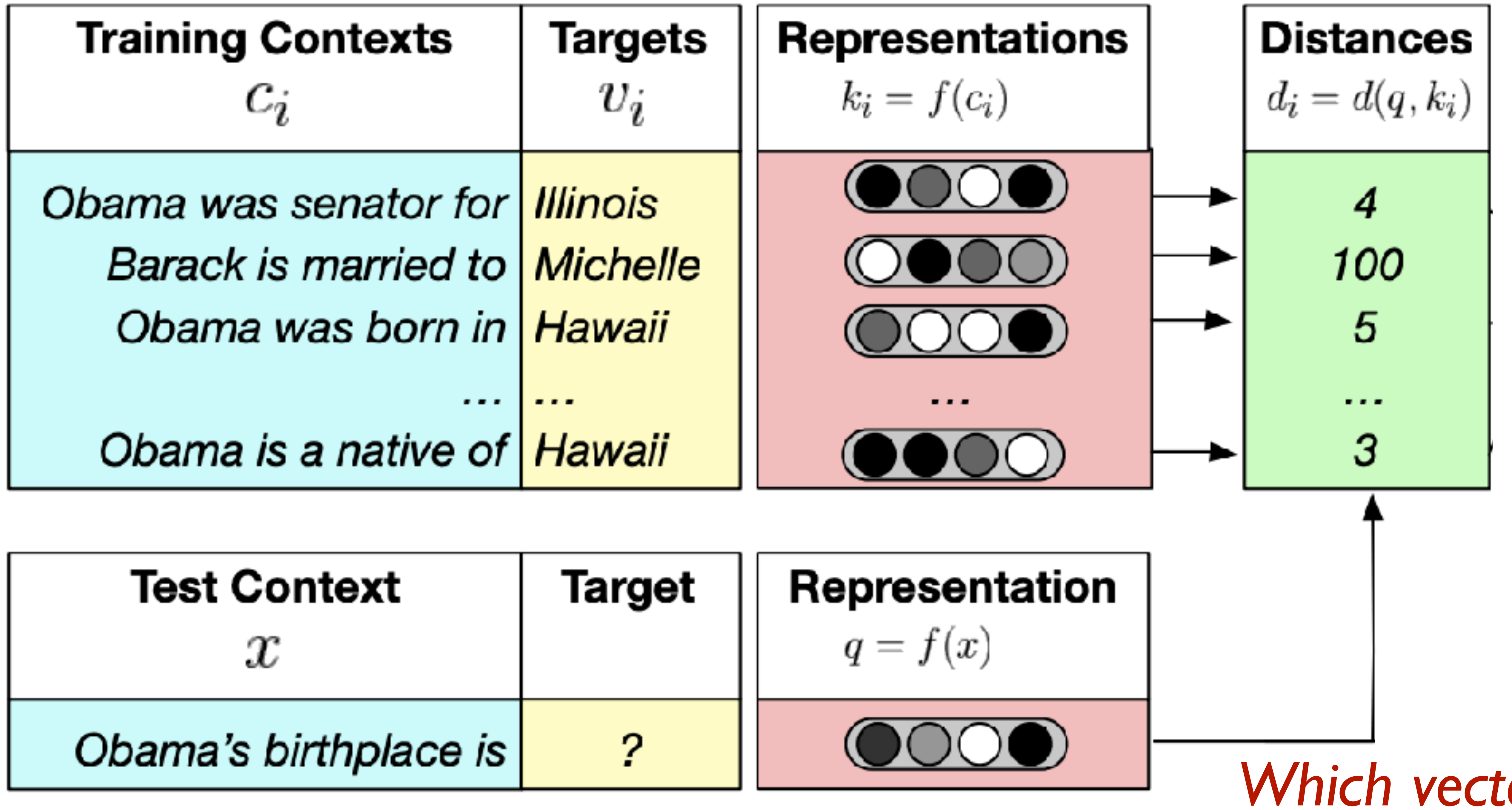
=

Which prefixes in a datastore are close to the prefix we have?

=

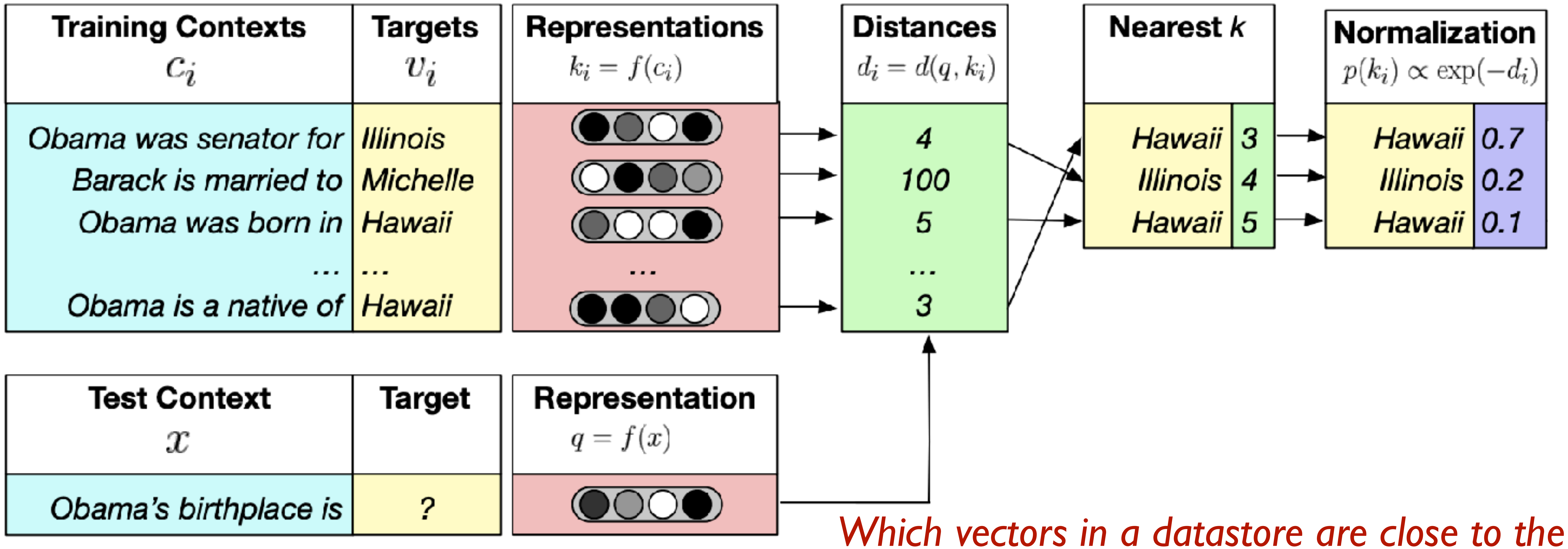
Which vectors in a datastore are close to the vector we have?

kNN-LM (Khandelwal et al. 2020)



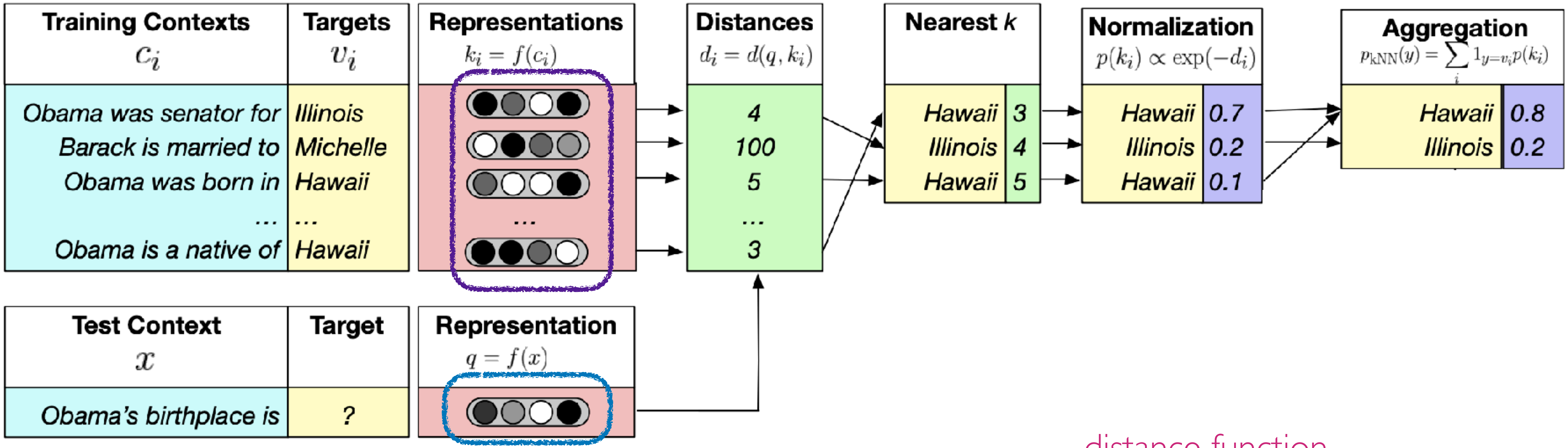
Which vectors in a datastore are close to the vector we have?

kNN-LM (Khandelwal et al. 2020)



Which vectors in a datastore are close to the vector we have?

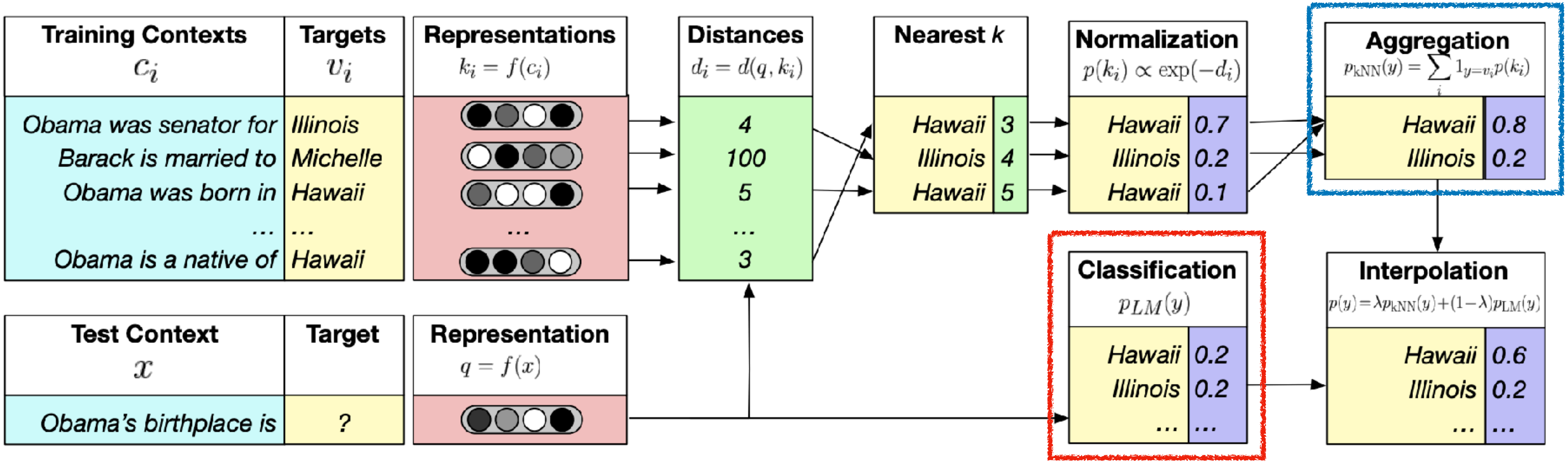
kNN-LM (Khandelwal et al. 2020)



distance function

$$P_{k\text{NN}}(y \mid x) \propto \sum_{(k,v)\in\mathcal{D}} \mathbb{1}[v = y]\,\text{sim}(k, x) \qquad \text{sim}(k, x) = \exp\left(-d(\text{Enc}(k), \text{Enc}(x))\right)$$

kNN-LM (Khandelwal et al. 2020)



λ: hyperparameter

$$P_{k\text{NN-LM}}(y \mid x) = (1-\lambda) P_{\text{LM}}(y \mid x) + \lambda P_{k\text{NN}}(y \mid x)$$

Later work, e.g., NPM (Min et al. 2023) removed interpolation (more in Section 4)

kNN-LM - why?

Training contexts	Targets
10/10, would buy this	*cheap*
Item delivered broken. Very	*cheap*
To check the version of PyTorch, you can use	*torch*
You are permitted to bring a	*torch*
A group of infections … one of the	*torch*

kNN-LM - why?

Training contexts	Targets
10/10, would buy this	***cheap***
Item delivered broken. Very	***cheap***
To check the version of PyTorch, you can use	*torch*
You are permitted to bring a	*torch*
A group of infections … one of the	*torch*


kNN-LM - why?

Training contexts	Targets
10/10, would buy this	***cheap***
Item delivered broken. Very	***cheap***
To check the version of PyTorch, you can use	*torch*
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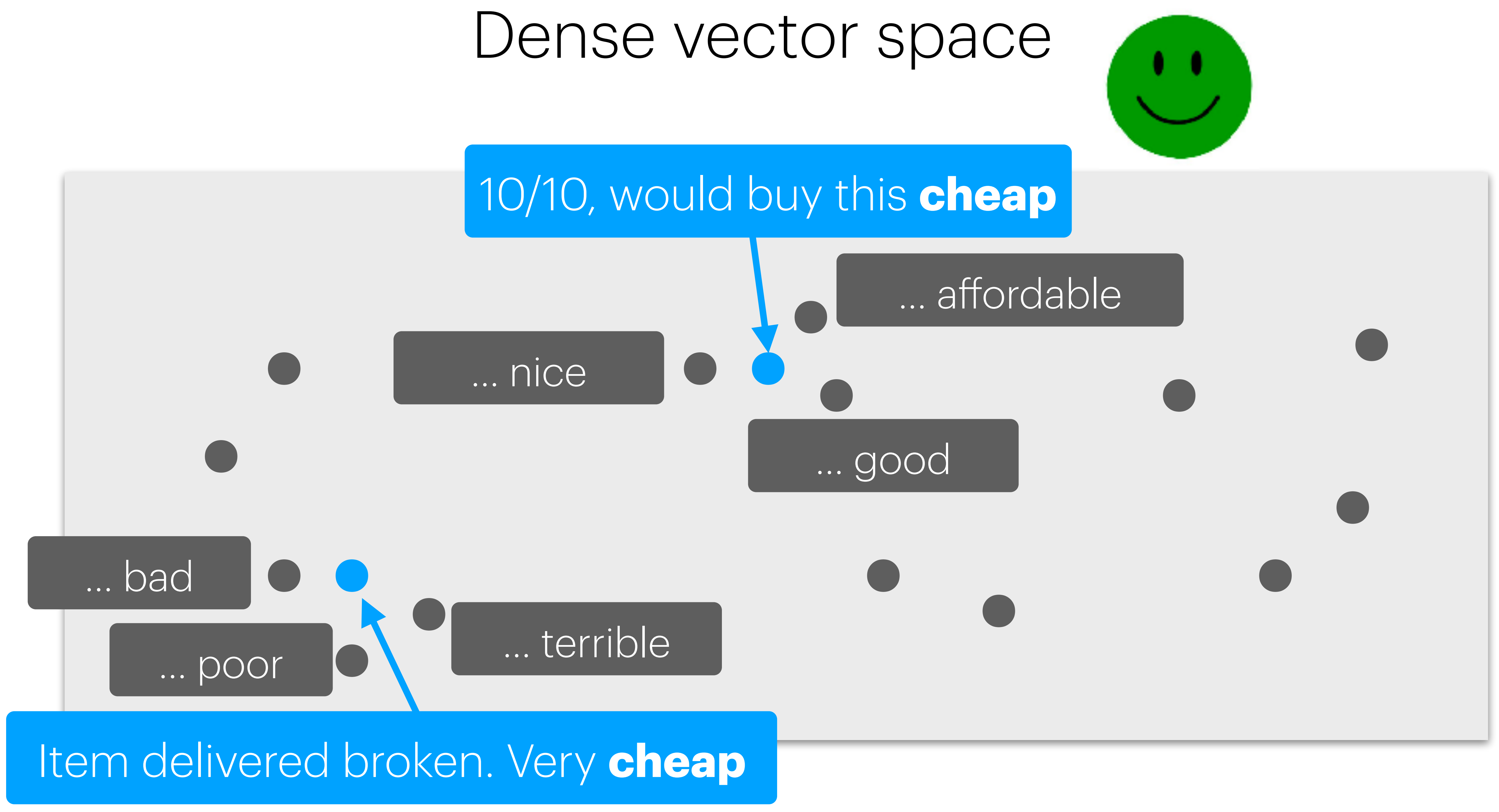

kNN-LM - why?

Training contexts	Targets
10/10, would buy this	*cheap*
Item delivered broken. Very	*cheap*
To check the version of PyTorch, you can use	*torch*
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kNN-LM - why?

Training contexts	Targets
10/10, would buy this	*cheap*
Item delivered broken. Very	*cheap*
To check the version of PyTorch, you can use	*torch*
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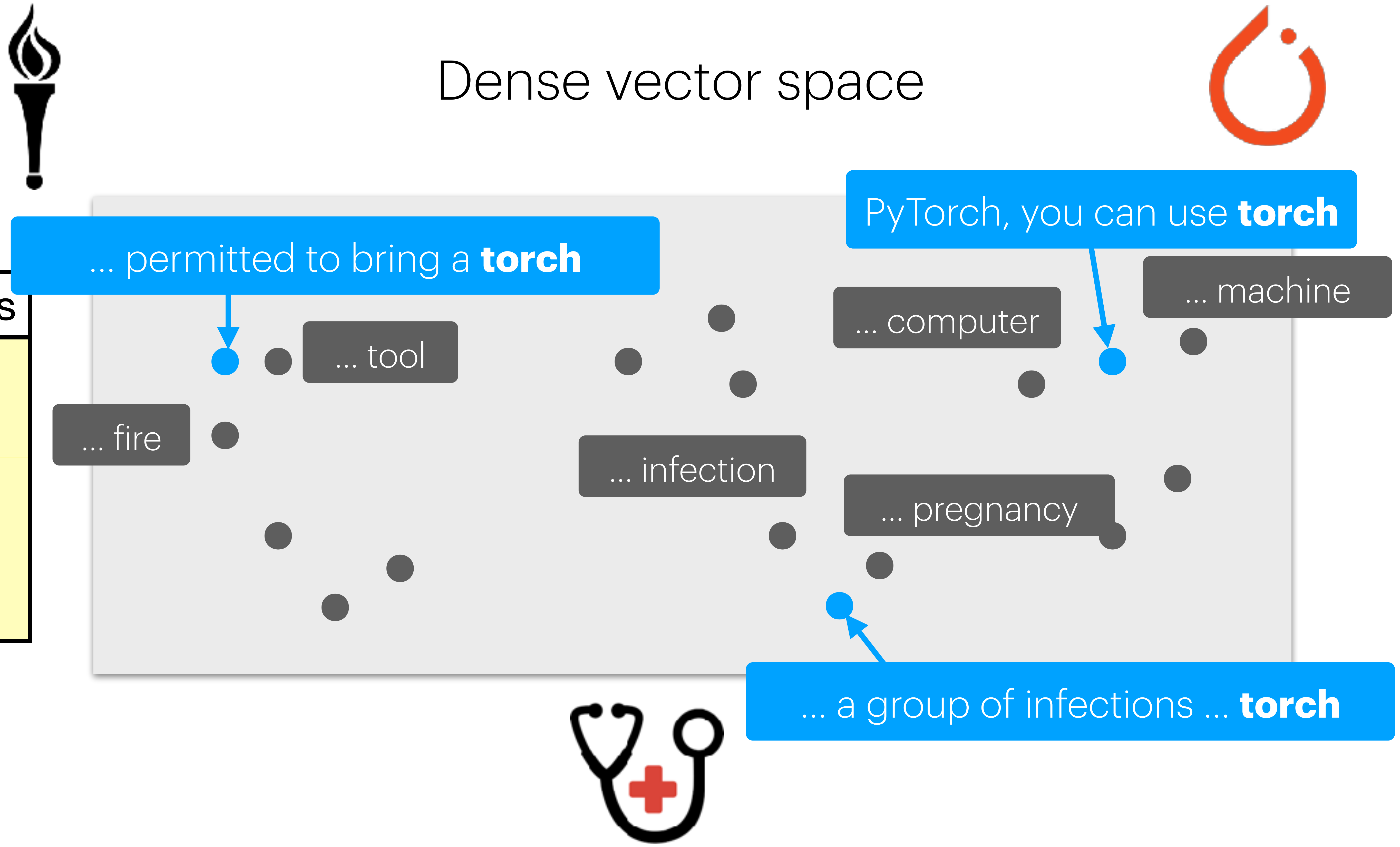
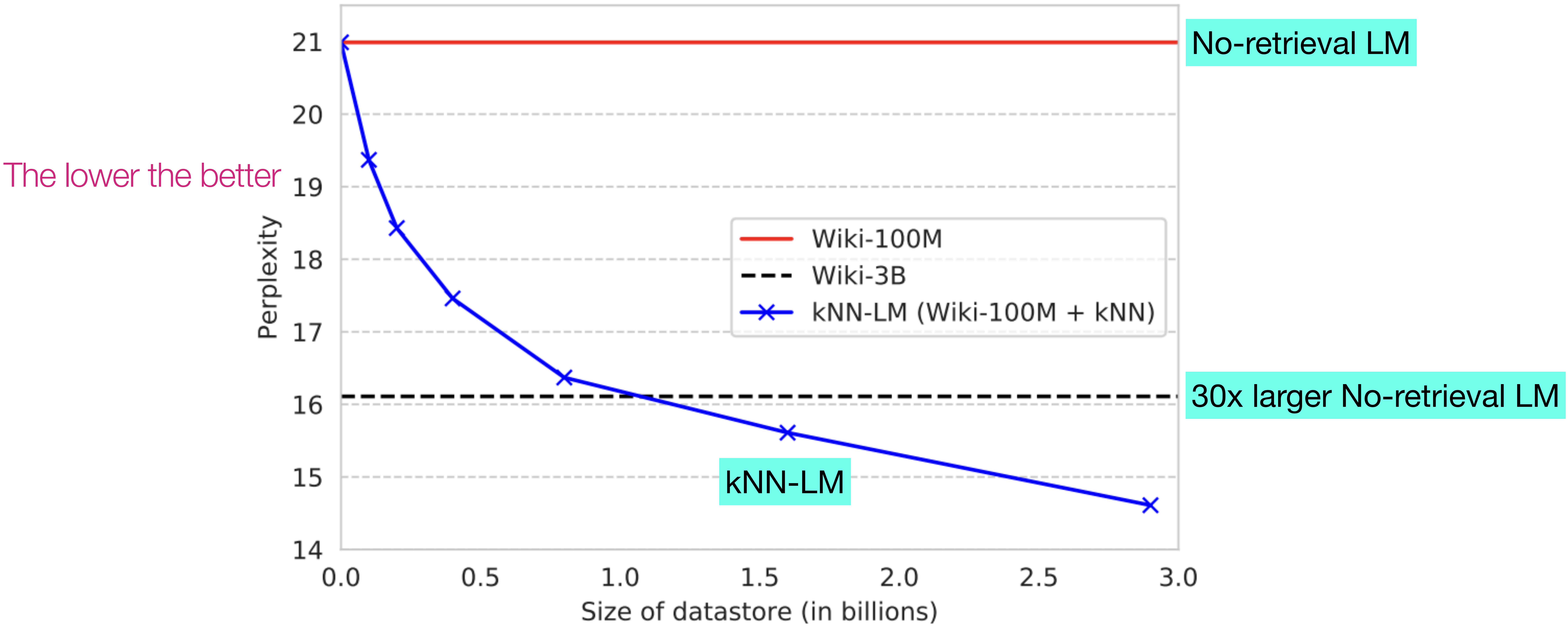


kNN-LM - results

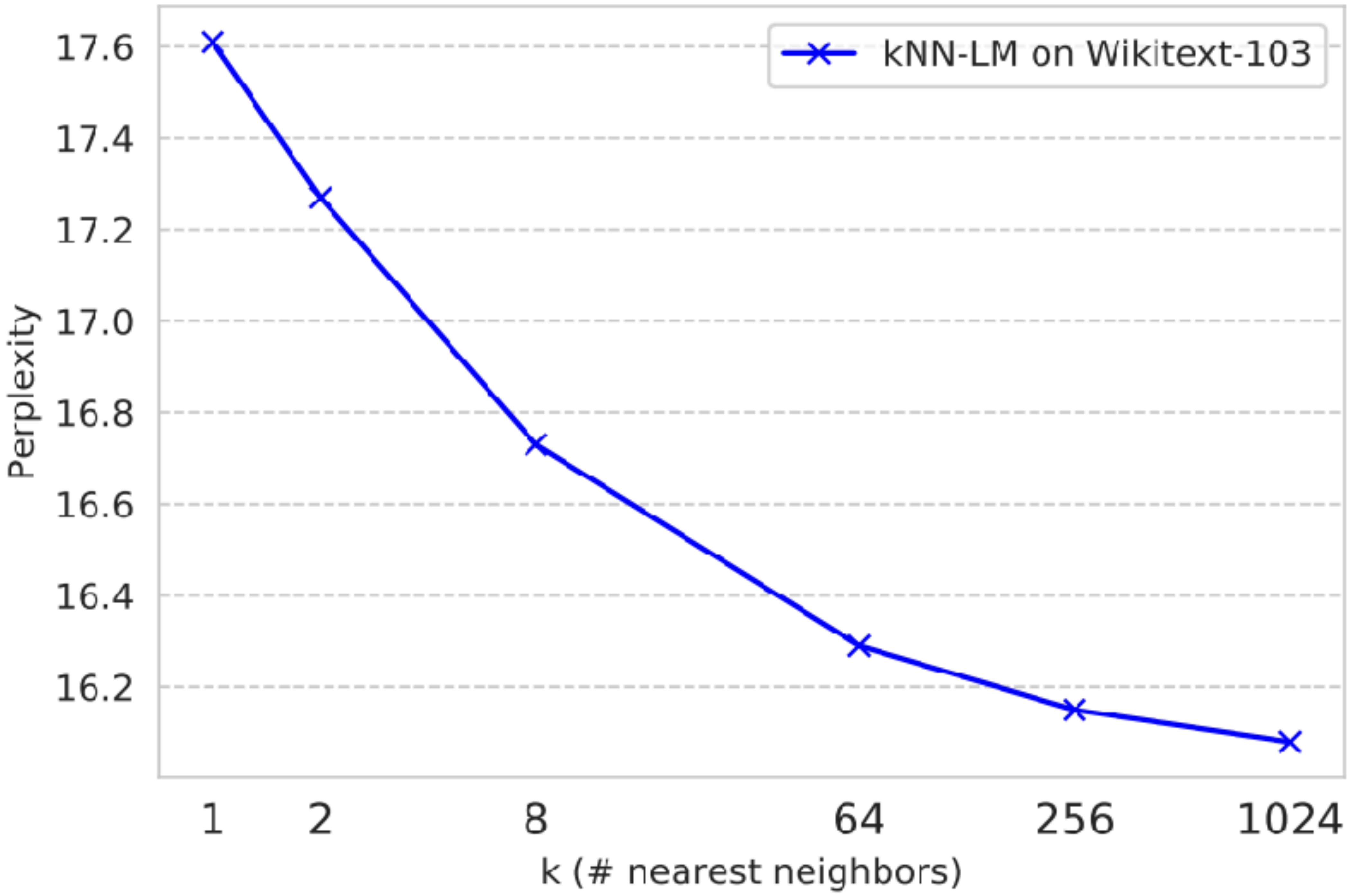


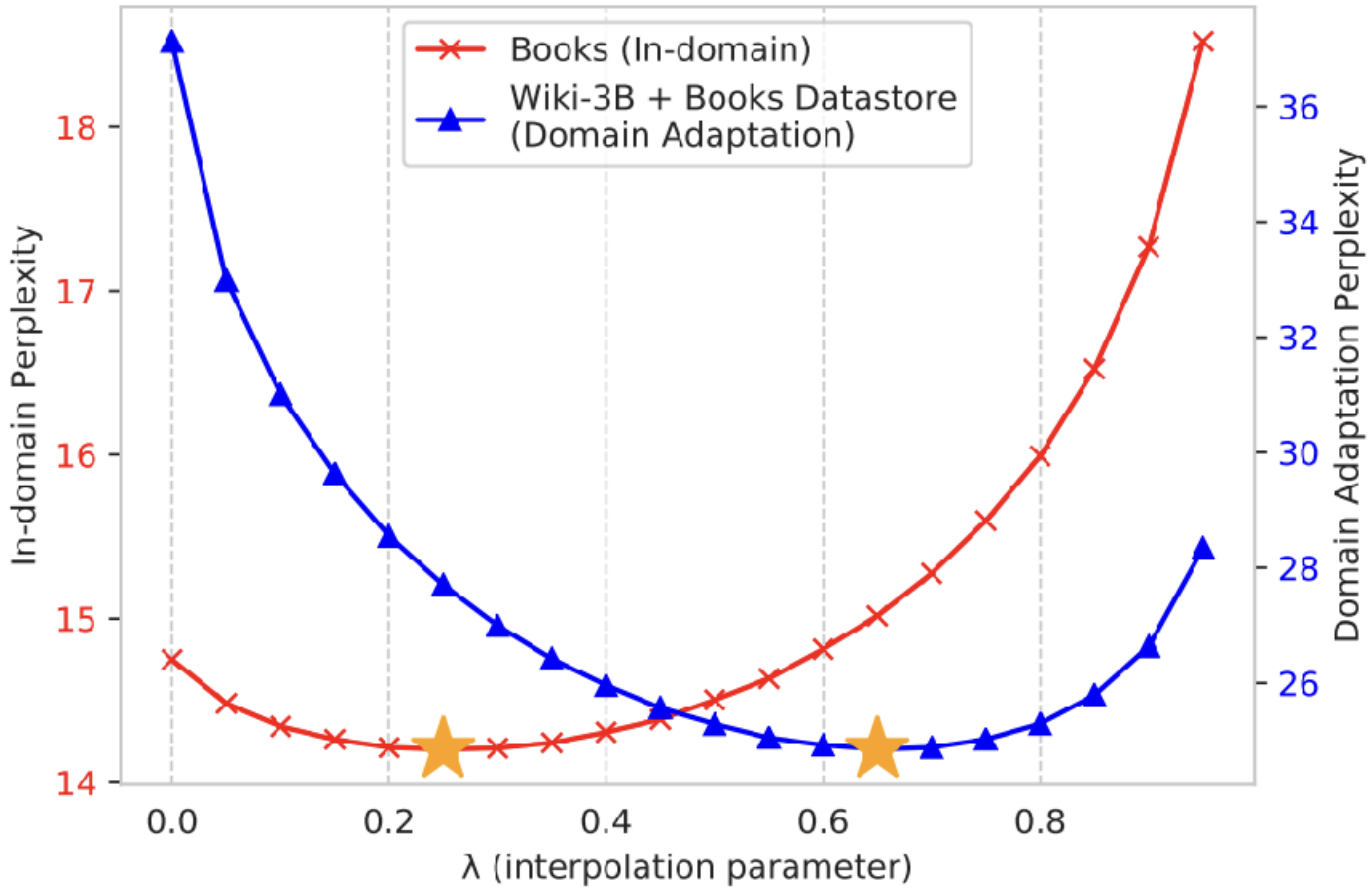
Outperforms no-retrieval LM

Better with bigger datastore

kNN-L

Can use in-domain datastore
even if parameters were not trained in-domain





Better with
bigger ***k***

Helps more
out-of-domain

kNN-LM (Khandelwal et al. 2020)

What to retrieve?

- Chunks
- Tokens
- Others

How to use retrieval?

- Input layer
- Intermediate layers
- Output layer

When to retrieve?

- Once
- Every n tokens (n>1)
- Every token

kNN-LM (Khandelwal et al. 2020)

What to retrieve?

- Chunks
- **Tokens** ✓
- Others

How to use retrieval?

- Input layer
- Intermediate layers
- Output layer

When to retrieve?

- Once
- Every *n* tokens (*n*>1)
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kNN-LM (Khandelwal et al. 2020)

What to retrieve?

- Chunks
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- Others

How to use retrieval?

- Input layer
- Intermediate layers
- **Output layer**

When to retrieve?

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- Every *n* tokens (*n*>1)
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kNN-LM (Khandelwal et al. 2020)

What to retrieve?

- Chunks
- **Tokens** ✓
- Others

How to use retrieval?

- Input layer
- Intermediate layers
- **Output layer** ✓

When to retrieve?

- Once
- Every *n* tokens (*n*>1)
- **Every token** ✓

Summary

	What do retrieve?	How to use retrieval?	When to retrieve?
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RETRO (Borgeaud et al. 2021)	Text chunks	Intermediate layers	Every n tokens
kNN-LM (Khandelwal et al. 2020)	Tokens	Output layer	Every token

More fine-grained; Can be better at rare patterns & out-of-domain
Can be very efficient (as long as kNN search is fast)

(Wikipedia) 13M vs. 4B

Datastore is expensive in space: given the same data, # text chunks vs. # tokens
No cross attention between input and retrieval results

Extensions

	What do retrieve?	How to use retrieval?	When to retrieve?
REALM (Guu et al 2020)	Text chunks	Input layer	Once
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kNN-LM (Khandelwal et al. 2020)	Tokens	Output layer	Every token

It's fixed! Can we do adaptively?

Adaptive retrieval for efficiency

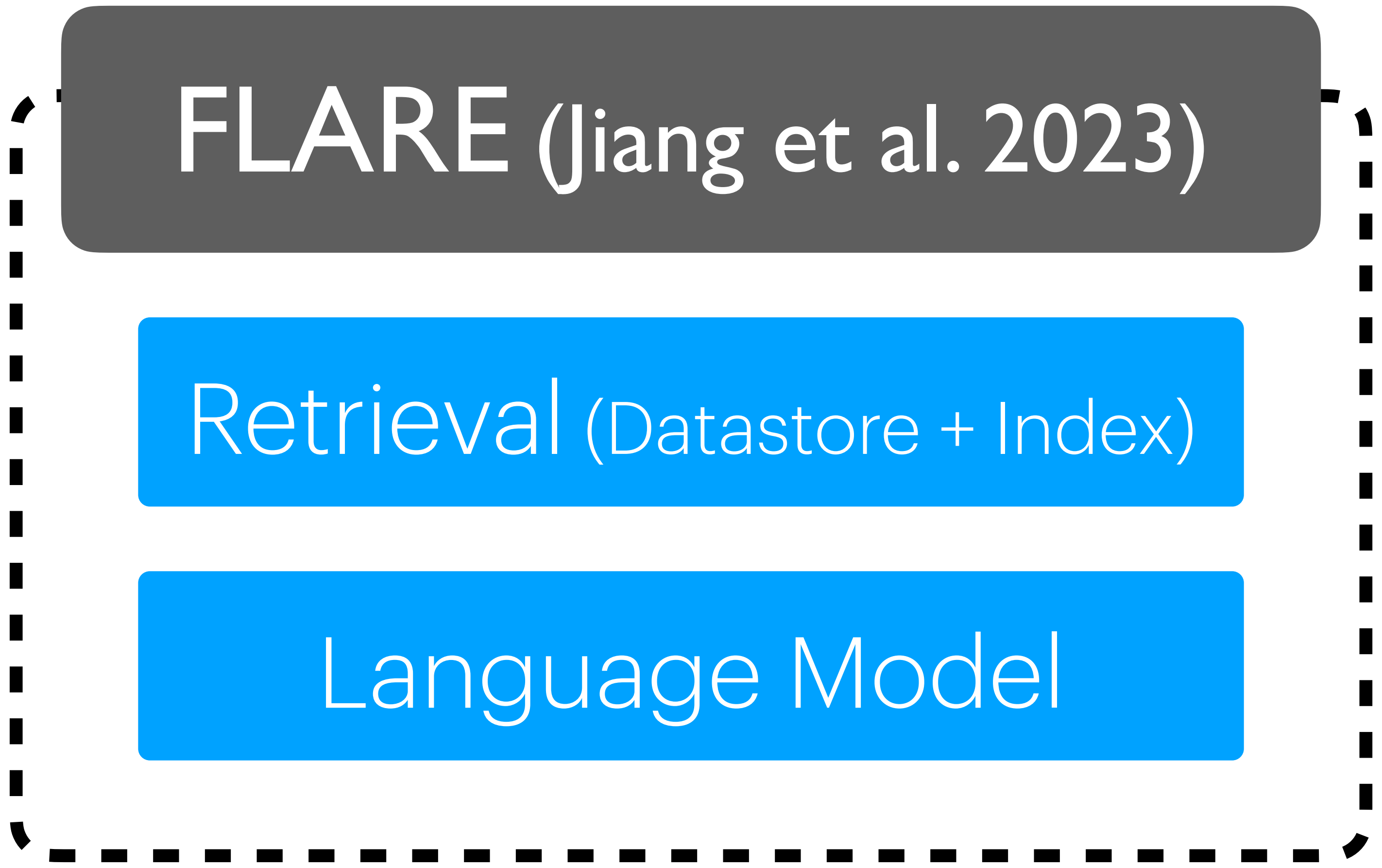
Adaptive retrieval of text chunks
(following retrieve-in-context)

Adaptive retrieval of tokens
(following kNN-LM)

Adaptive retrieval of *chunks*

- Judge necessity

Input: Generate a summary about Joe Biden.



Jiang et al. “Active Retrieval Augmented Generation”

Adaptive retrieval of *chunks*

- Judge necessity

FLARE (Jiang et al. 2023)

Retrieval (Datastore + Index)

Language Model

Input: Generate a summary about Joe Biden.

Joe Biden (born November 20, 1942) is the 46th president of the United States.

I am confident!

Jiang et al. "Active Retrieval Augmented Generation"

Adaptive retrieval of *chunks*

- *Judge necessity*

FLARE (Jiang et al. 2023)

Retrieval (Datastore + Index)

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Joe Biden (born November 20, 1942) is the 46th president of the United States.

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Adaptive retrieval of *chunks*

- *Judge necessity*

FLARE (Jiang et al. 2023)

Retrieval (Datastore + Index)

Language Model

Input: Generate a summary about Joe Biden.

Joe Biden (born November 20, 1942) is the 46th president of the United States. Joe Biden attended **the University of Pennsylvania**, where he earned **a law degree**.

Unsure…

Jiang et al. "Active Retrieval Augmented Generation"

Adaptive retrieval of *chunks*

- *Judge necessity*

FLARE (Jiang et al. 2023)

Retrieval (Datastore + Index)

Language Model

Input: Generate a summary about Joe Biden.

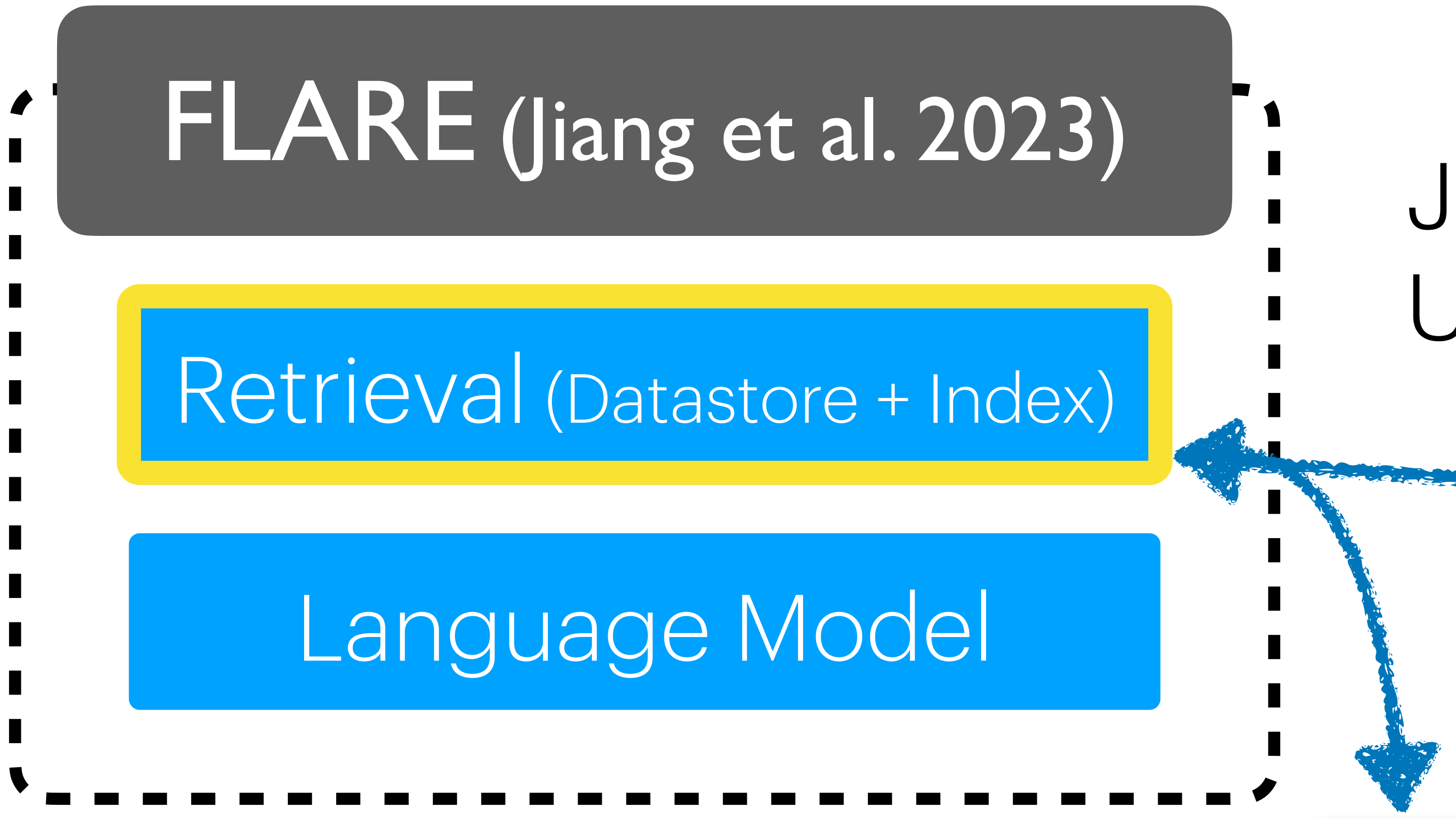
Joe Biden (born November 20, 1942) is the 46th president of the United States. Joe Biden attended **[mask]**, where he earned **[mask]**.

Jiang et al. "Active Retrieval Augmented Generation"

Adaptive retrieval of *chunks*

- *Judge necessity*

Input: Generate a summary about Joe Biden.



Joe Biden (born November 20, 1942) is the 46th president of the United States. Joe Biden attended **[mask]**, where he earned **[mask]**.

Unsure...

Joe Biden

At the University of Delaware in Newark, Biden ... earned a Bachelor of Arts degree in 1965 with a double major in history and political science.

Jiang et al. "Active Retrieval Augmented Generation"

Adaptive retrieval of *chunks*

- Judge necessity

FLARE (Jiang et al. 2023)

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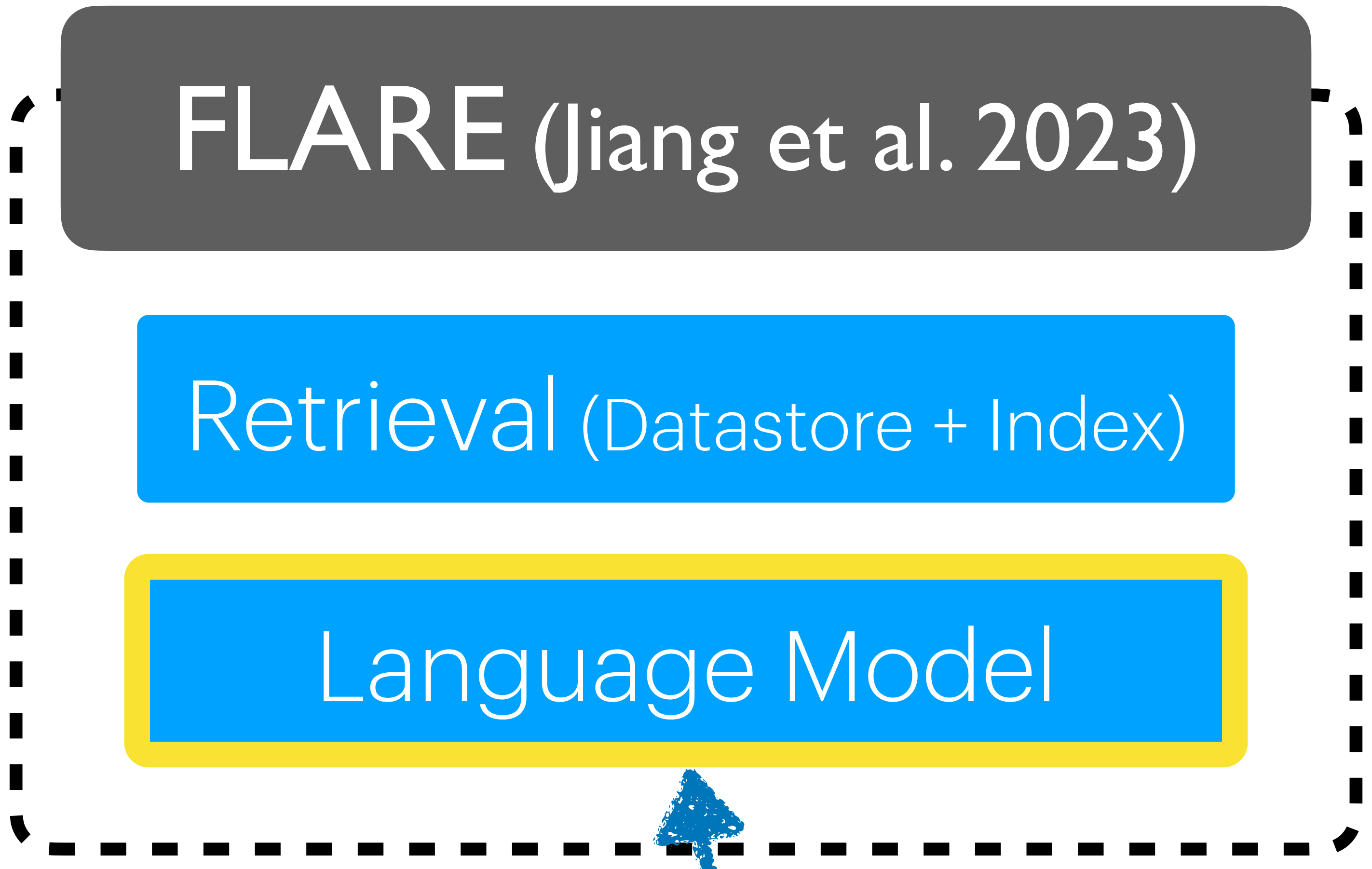

Input: Generate a summary about Joe Biden.

Joe Biden (born November 20, 1942) is the 46th president of the United States. ~~Joe Biden attended **[mask]**, where he earned **[mask]**.~~ He graduated from the University of Delaware in 1965 with a Bachelor of Arts in history and political science.

Joe Biden
At the University of Delaware in Newark, Biden … earned a Bachelor of Arts degree in 1965 with a double major in history and political science.

Jiang et al. "Active Retrieval Augmented Generation"

Adaptive retrieval of *tokens*

- Judge necessity

retrieve retrieve retrieve retrieve retrieve retrieve retrieve

Joe Biden graduated from the University of Delaware .

retrieve LM LM retrieve retrieve retrieve LM

Joe Biden graduated from the University of Delaware .

$$P_{k\mathrm{NN-LM}}(y \mid x) = \underline{(1 - \lambda(x))}P_{\mathrm{LM}}(y \mid x) + \underline{\lambda(x)}P_{k\mathrm{NN}}(y \mid x)$$

*A function of the input **x***

$\rightarrow \ \lambda = 0 \quad$ *if* $\ \lambda < \gamma$

He et al. 2021. "Efficient Nearest Neighbor Language Models"

Adaptive retrieval of *tokens*

- Use local info

Training contexts	Targets
At	*the*
At the	*University*
At the Universty	*of*
At the University of	*Delaware*
At the University of Delaware	*in*
At the University of Delaware in	*Newark*

Joe Biden graduated from

Alon et al. 2022. “Neuro-Symbolic Language Modeling with Automaton-augmented Retrieval”

Adaptive retrieval of *tokens*

- Use local info

Training contexts	Targets
At	*the*
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At the University of Delaware	*in*
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retrieve

Joe Biden graduated from the

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retrieve retrieve

Joe Biden graduated from the University

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retrieve retrieve retrieve

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retrieve

Joe Biden graduated from the

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Training contexts	Targets
At	*the*
At the	*University*
At the Universty	*of*
At the University of	*Delaware*
At the University of Delaware	*in*
At the University of Delaware in	*Newark*

pointer

retrieve pointer

Joe Biden graduated from the University

Alon et al. 2022. “Neuro-Symbolic Language Modeling with Automaton-augmented Retrieval”

Adaptive retrieval of *tokens*

- Use local info

Training contexts	Targets
At	*the*
At the	*University*
At the Universty	*of*
At the University of	*Delaware*
At the University of Delaware	*in*
At the University of Delaware in	*Newark*

pointer

retrieve pointer pointer

Joe Biden graduated from the University of

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Adaptive retrieval of *tokens*

- Use local info

Training contexts	Targets
At	*the*
At the	*University*
At the Universty	*of*
At the University of	*Delaware*
At the University of Delaware	*in*
At the University of Delaware in	*Newark*

pointer

retrieve pointer pointer pointer

Joe Biden graduated from the University of Delaware.

Retrieve once, and save other searches!

Alon et al. 2022. "Neuro-Symbolic Language Modeling with Automaton-augmented Retrieval"

Summary

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FLARE (Jiang et al. 2023)	Text chunks	Input layer	Every n tokens ***(adaptive)***
Adaptive kNN-LM (He et al 2021, Alon et al 2022, etc)	Tokens	Output layer	Every n tokens ***(adaptive)***

More efficient

Decision may not always be optimal

Soft adaptive instead of hard adaptive (Drozdov et al. 2022 & more)**:**

More expressivity, Better performance

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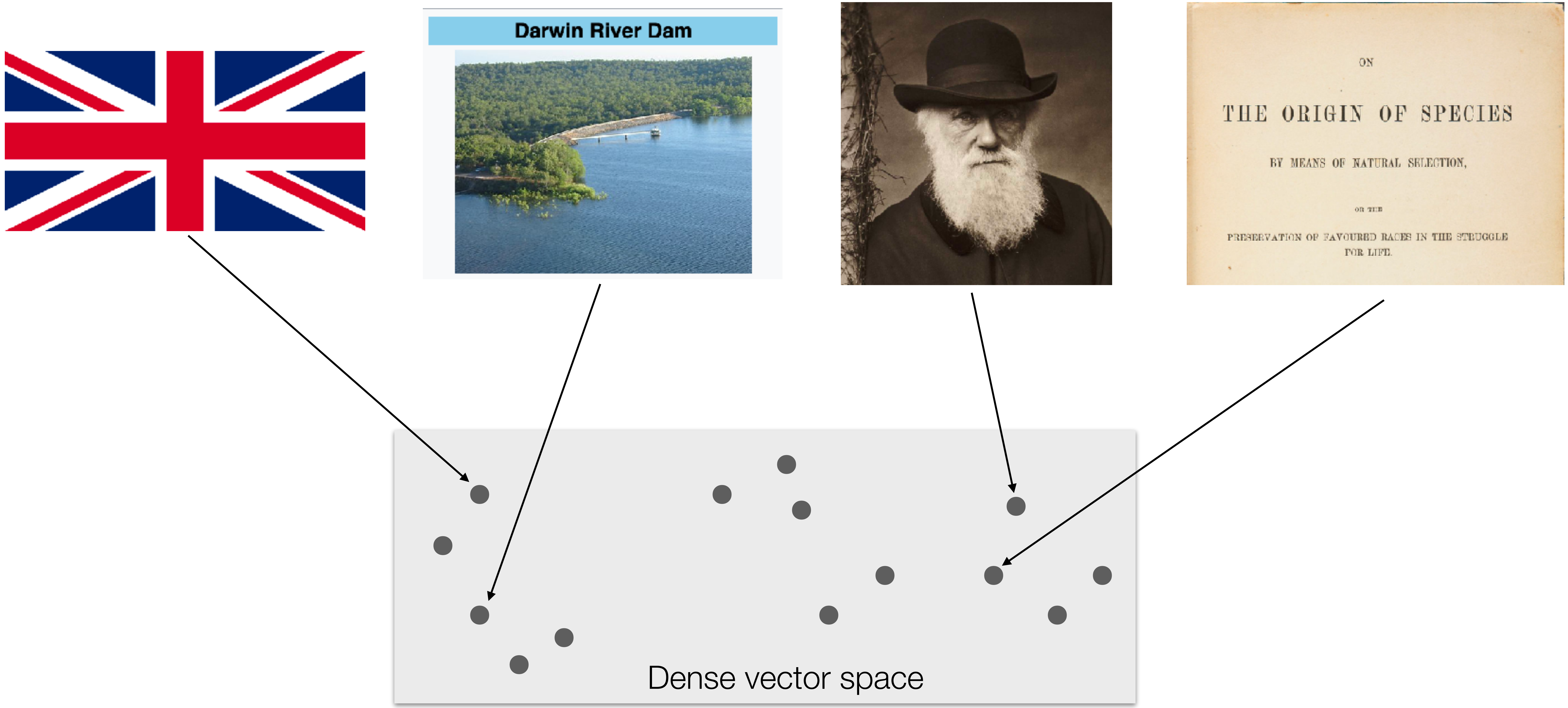
What else beyond text chunks and tokens?

Entities as Experts (Fevry et al. 2020)



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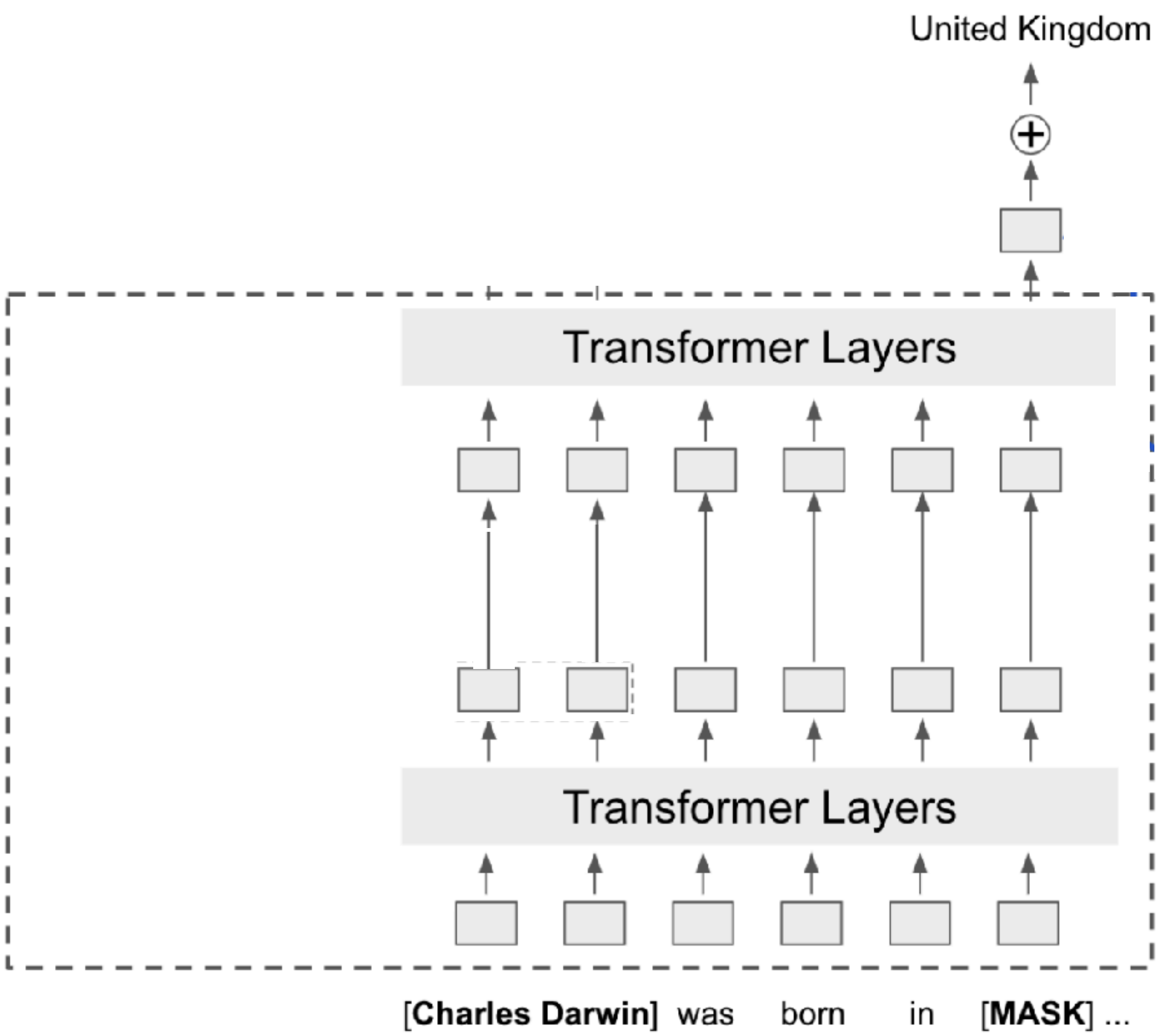
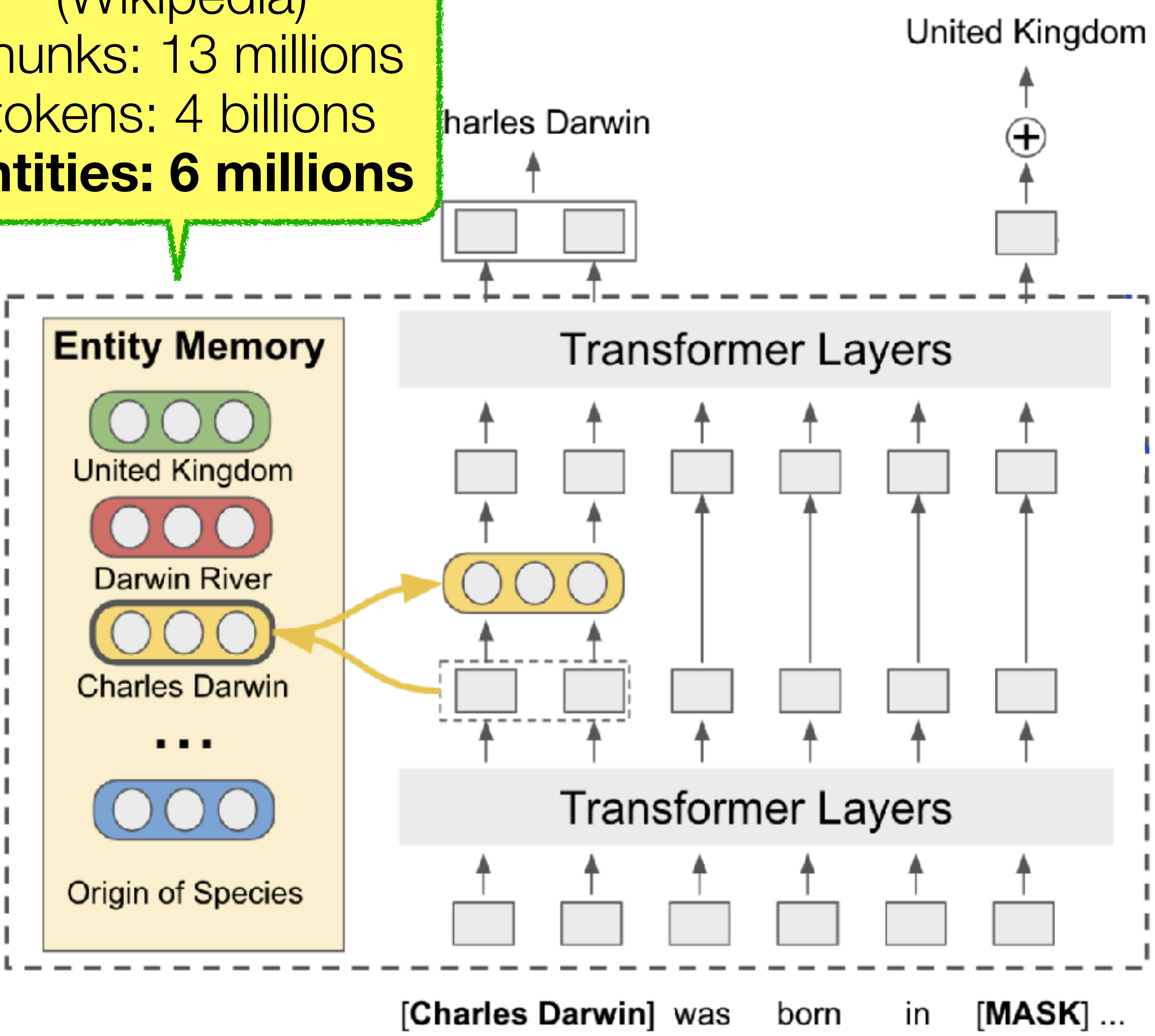


Fevry et al. 2020. “Entities as Experts: Sparse Memory Access with Entity Supervision”

Entities as Experts (Fevry et al. 2020)

(Wikipedia)
chunks: 13 millions
tokens: 4 billions
entities: 6 millions



Need text with entity detected

Need entity linker

Fevry et al. 2020. "Entities as Experts: Sparse Memory Access with Entity Supervision"

Mention Memory (de Jong et al. 2022)

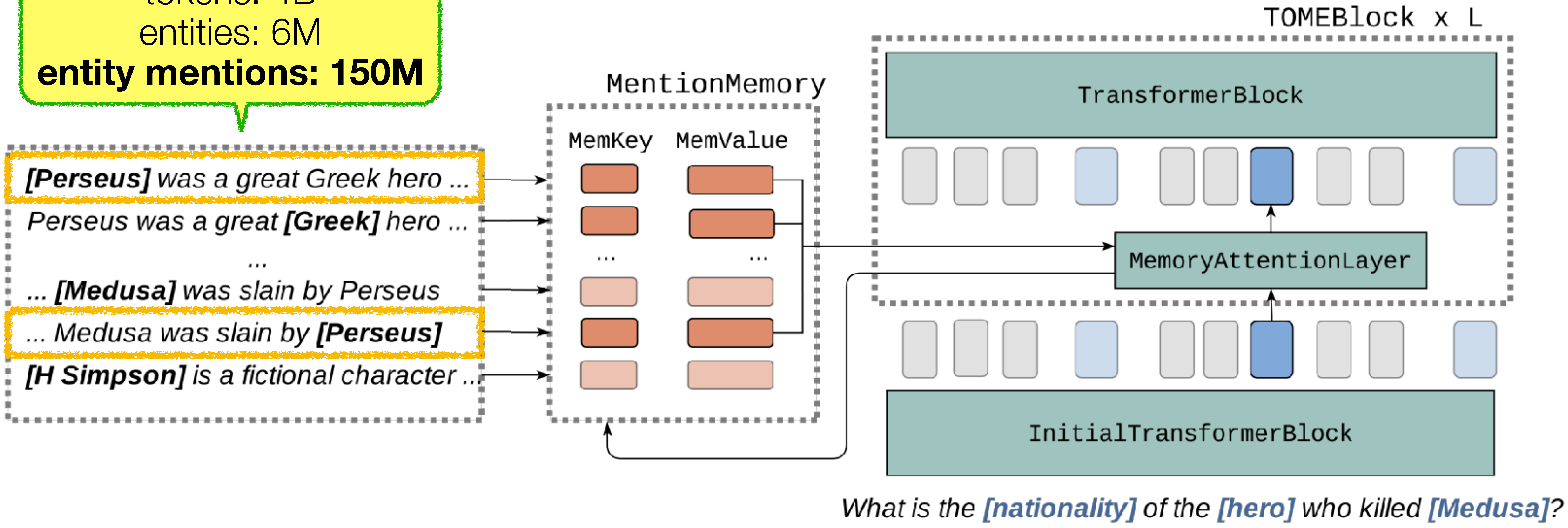
One vector per entity → One vector per entity *mention*

de Jong et al. 2022. "Mention Memory:
incorporating textual knowledge into Transformers through entity mention attention"

Mention Memory (de Jong et al. 2022)

(Wikipedia)
chunks: 13M
tokens: 4B
entities: 6M
entity mentions: 150M

per entity → One vector per entity *mention*



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Most effective for entity-centric tasks & space-efficient

Additional entity detection required

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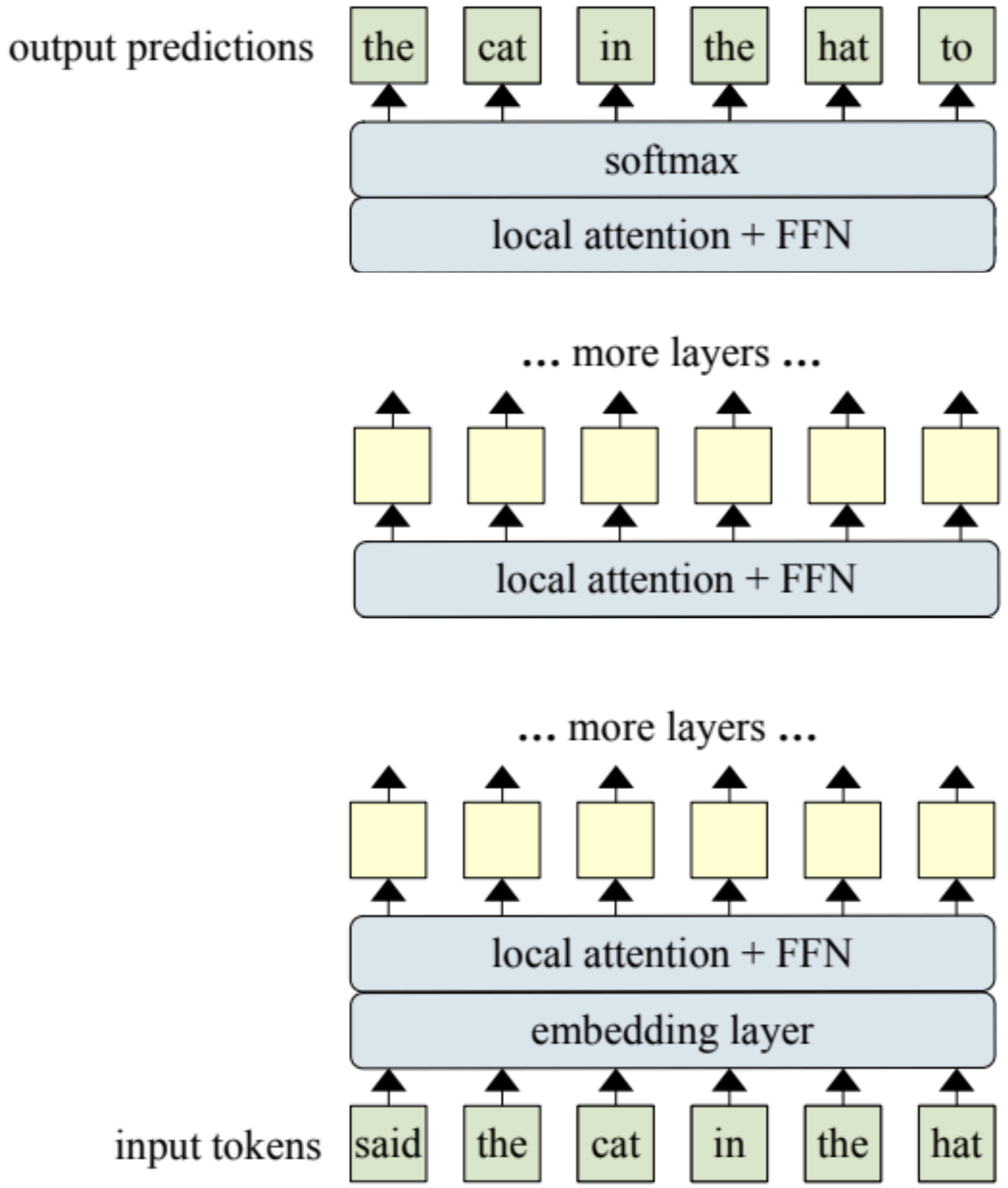
All models retrieve from the external text

What else can we do with these models?

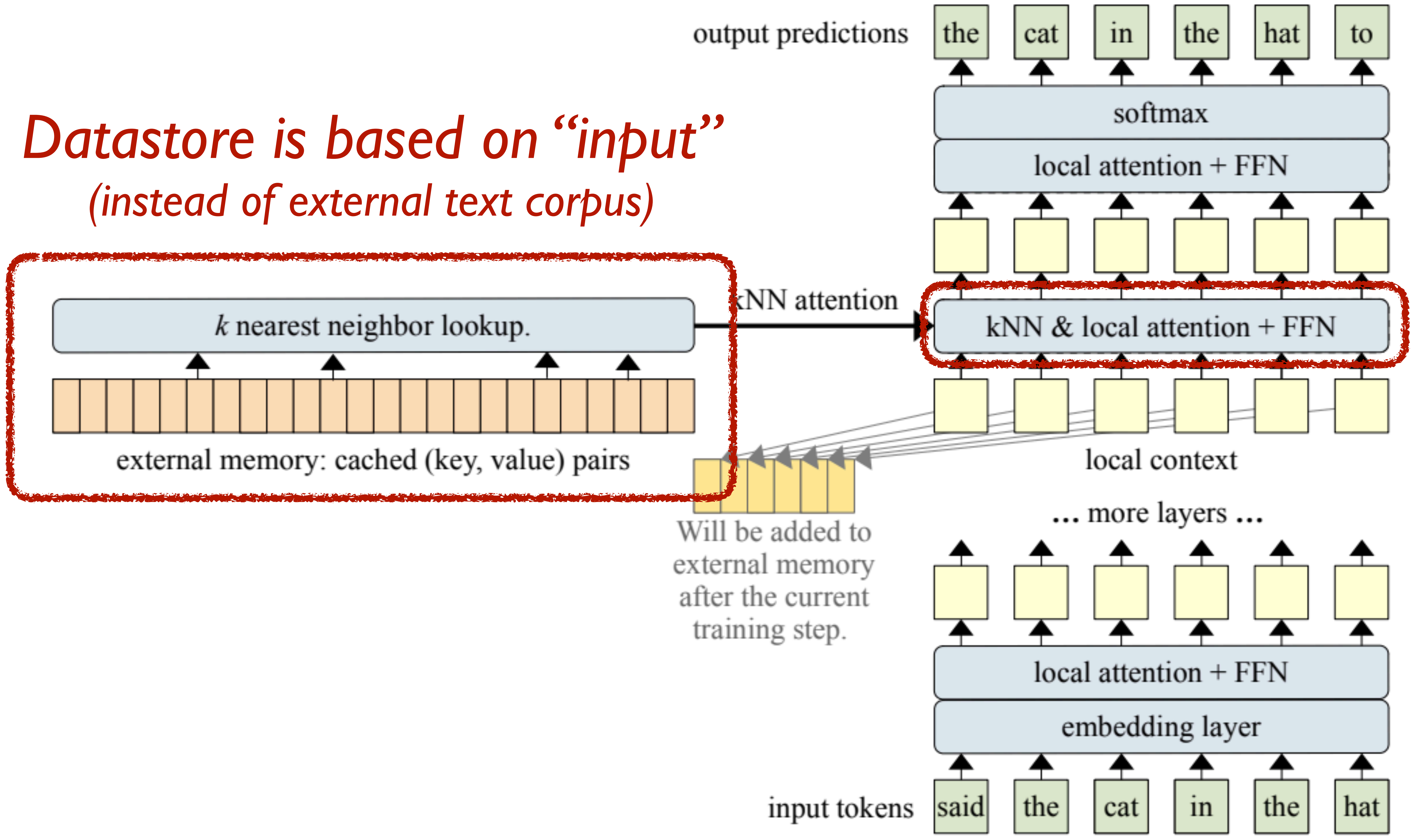
Retrieval for long-range LM



Wu et al. 2022. Memorizing Transformers **(Figure source)**
Bertsch et al. 2023. Unlimiformer: Long-Range Transformers with Unlimited Length Input
Rubin & Berant. 2023. Long-range Language Modeling with Self-retrieval

Retrieval for long-range LM

Datastore is based on "input"
(instead of external text corpus)



kNN search incorporated in the attention layer

Wu et al. 2022. Memorizing Transformers **(Figure source)**
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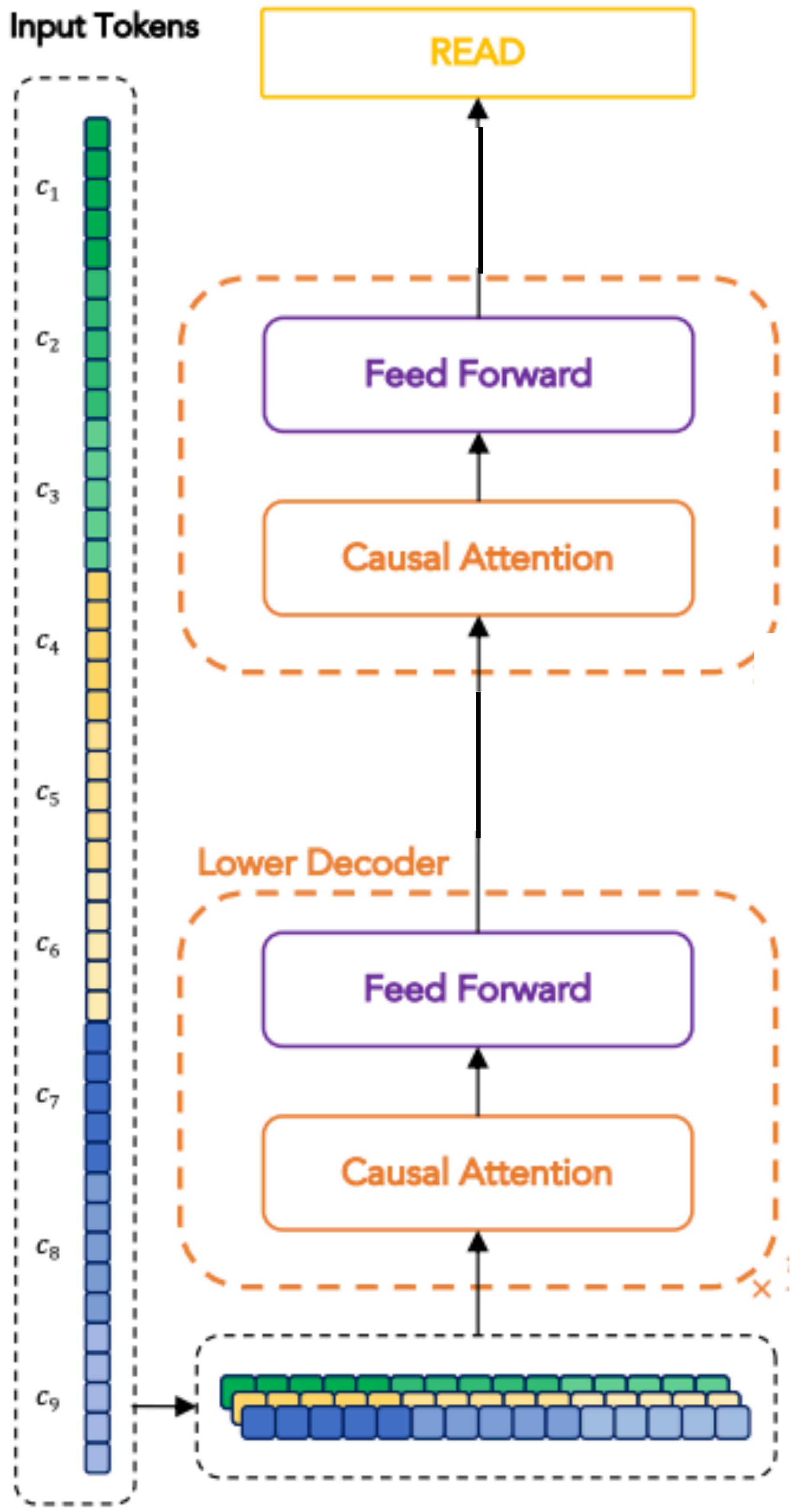
Retrieval for long-range LM



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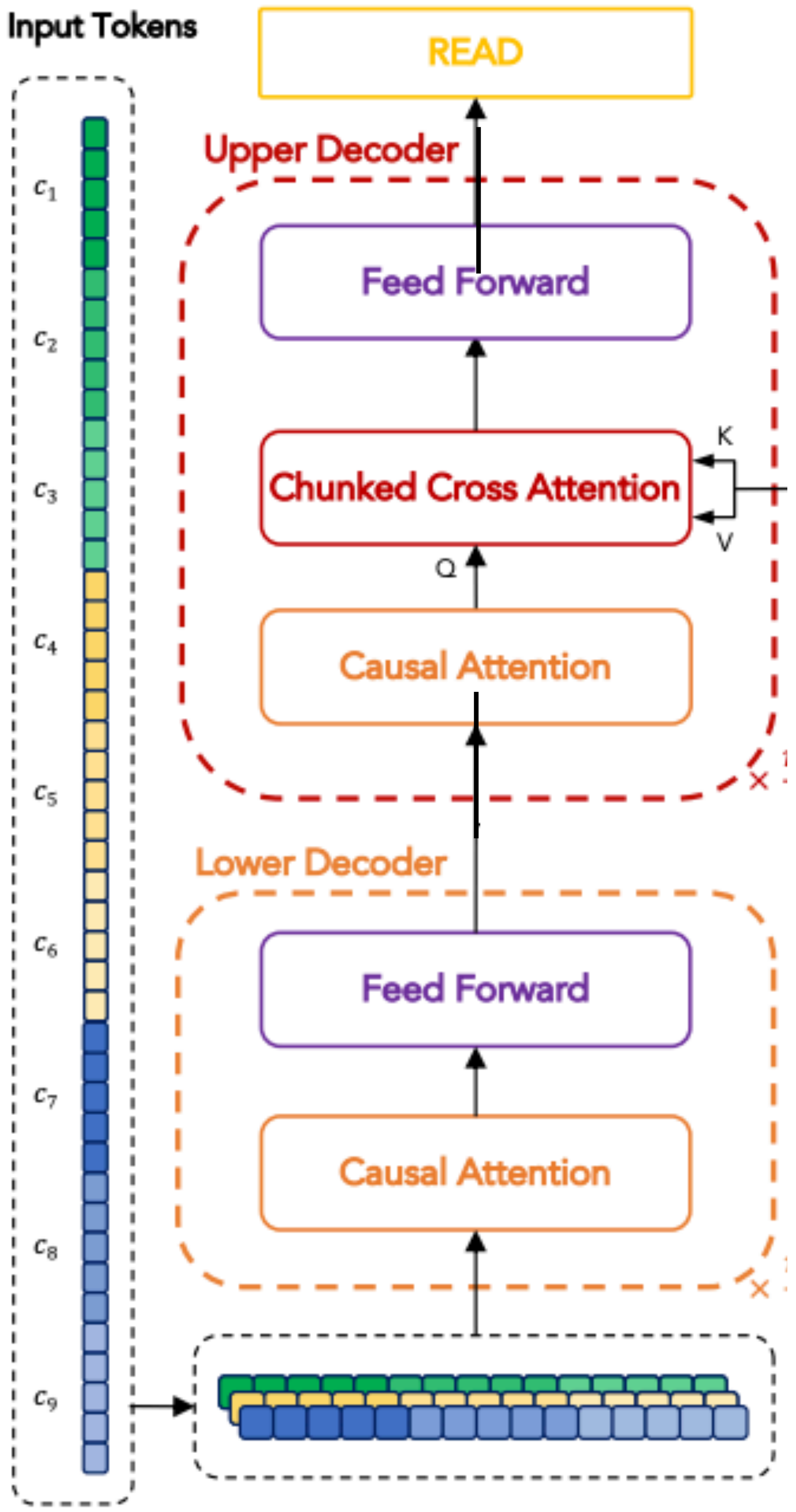
Retrieval for long-range LM



Chunked Cross Attention

Wu et al. 2022. Memorizing Transformers
Bertsch et al. 2023. Unlimiformer: Long-Range Transformers with Unlimited Length Input
Rubin & Berant. 2023. Long-range Language Modeling with Self-retrieval **(Figure source)**

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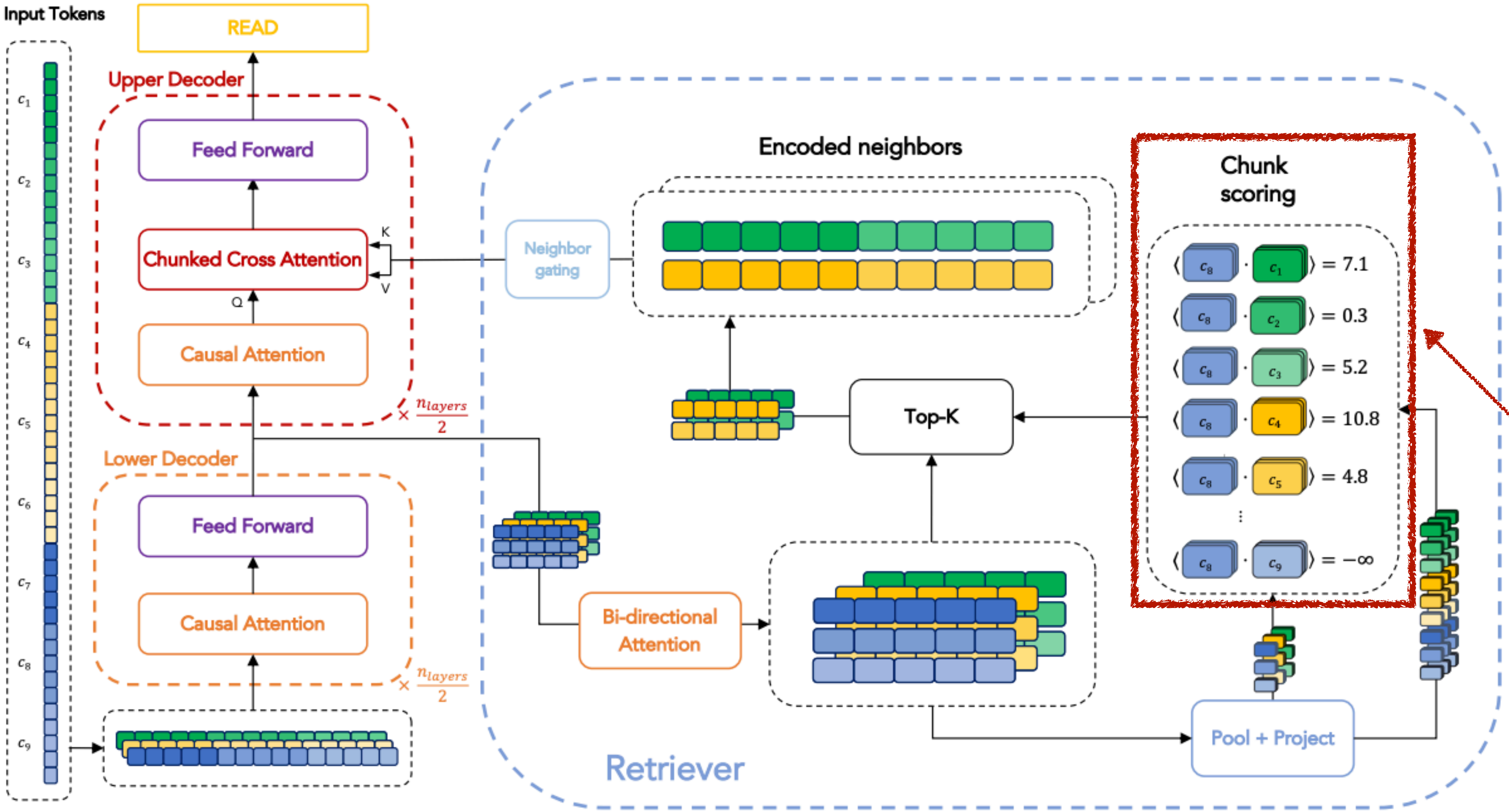

Every chunk is assigned a similarity score

Wu et al. 2022. Memorizing Transformers
Bertsch et al. 2023. Unlimiformer: Long-Range Transformers with Unlimited Length Input
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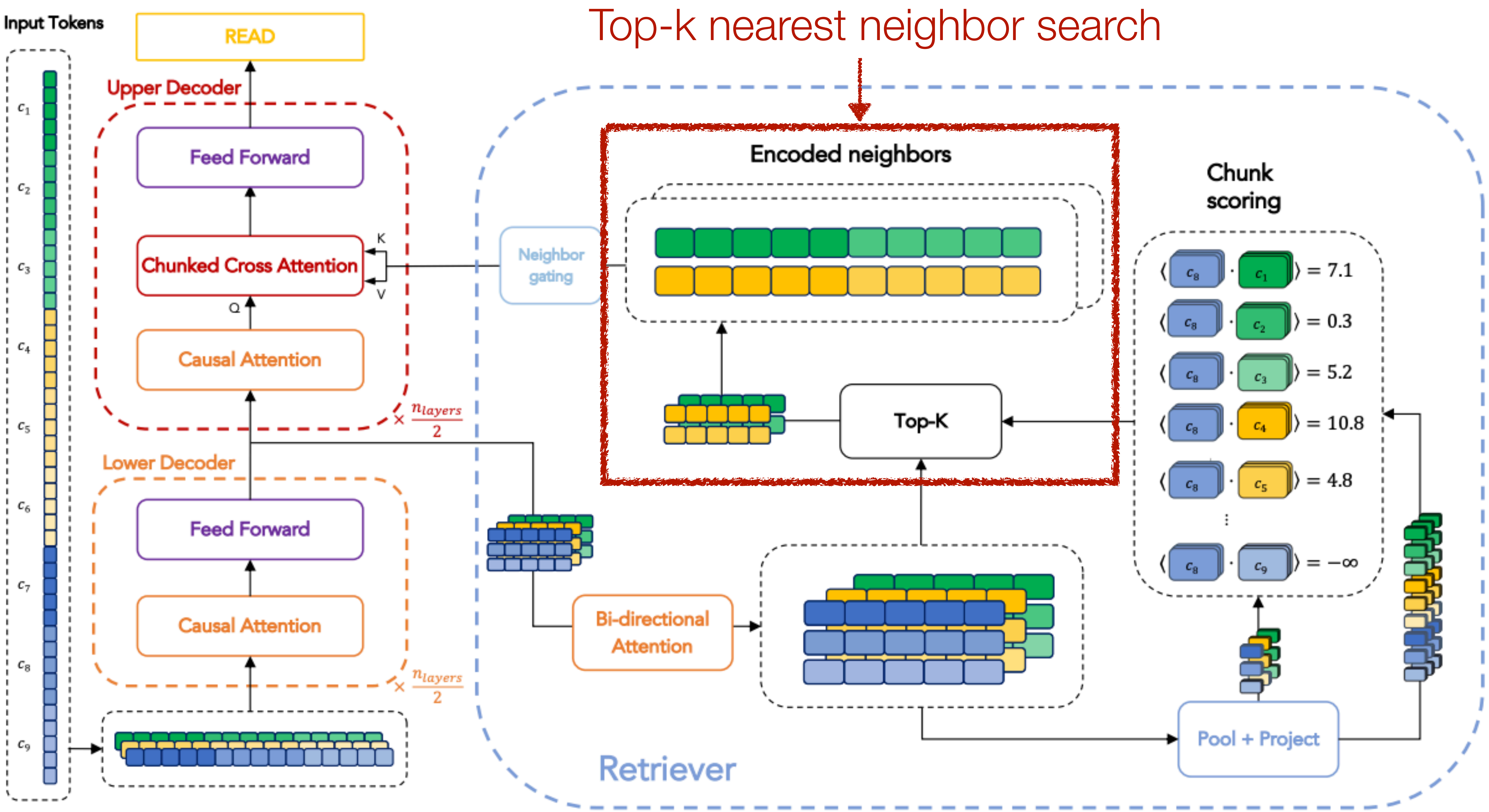

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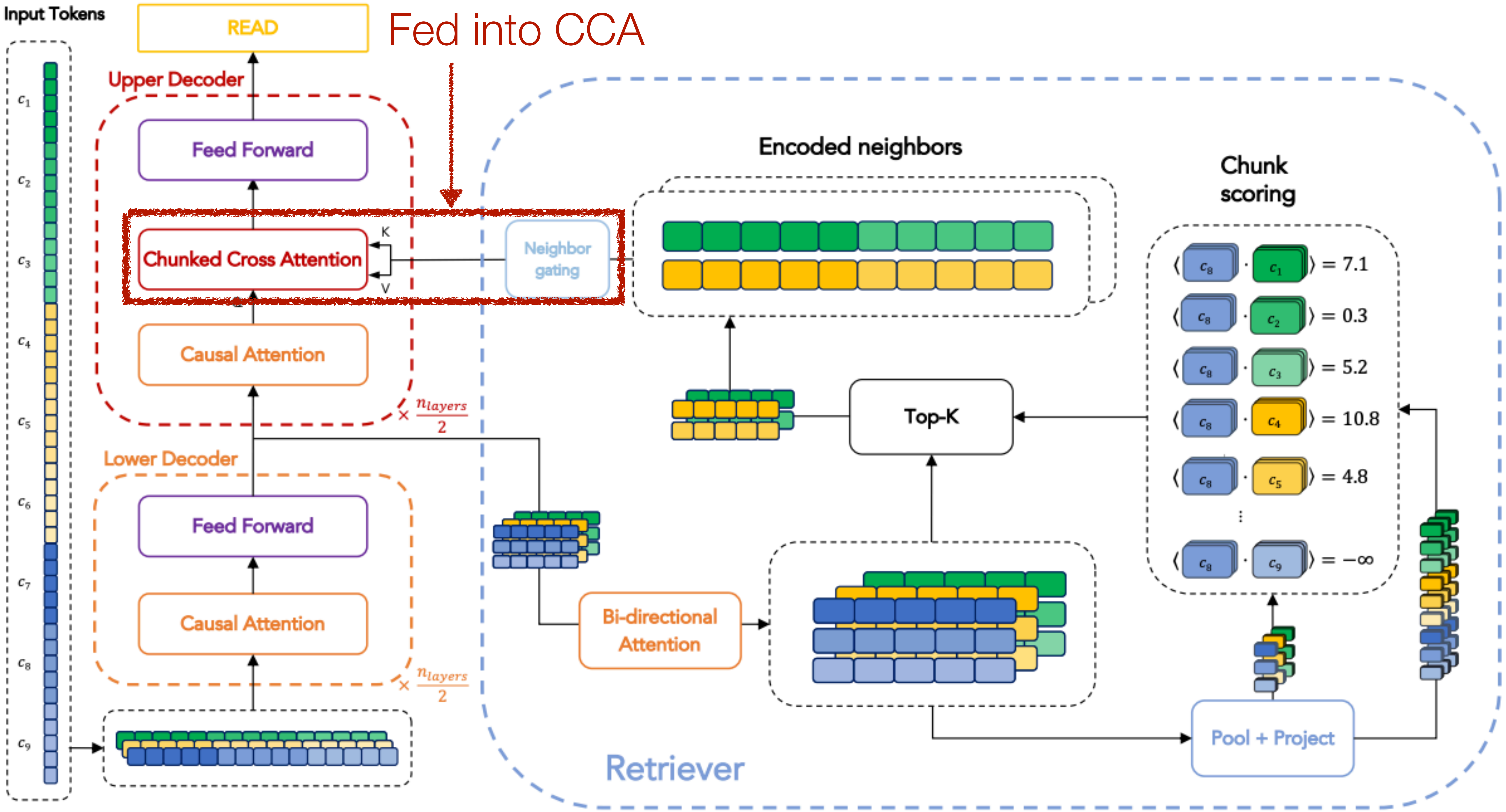
Retrieval for long-range LM



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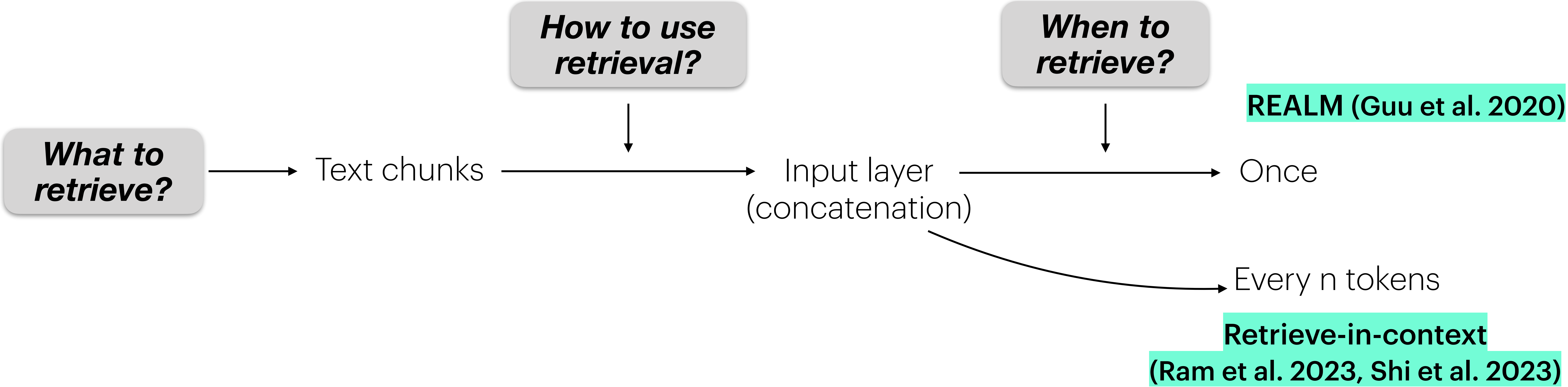
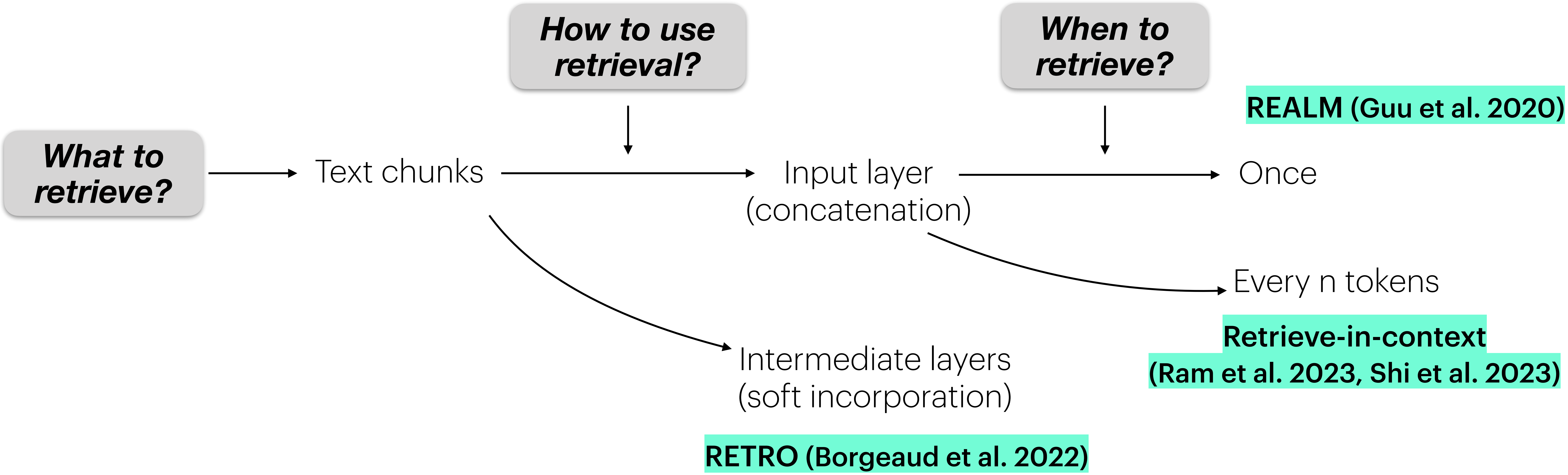
Entities as Experts (Fevry et al. 2020), Mention Memory (de Jong et al. 2022)	Entities or entity mentions	Intermediate layers	Every entity mentions
Wu et al. 2022, Bertsch et al. 2023, Rubin & Berant. 2023	Text chunks ***from the input***	Intermediate layers	Once or every n tokens

Wrapping up



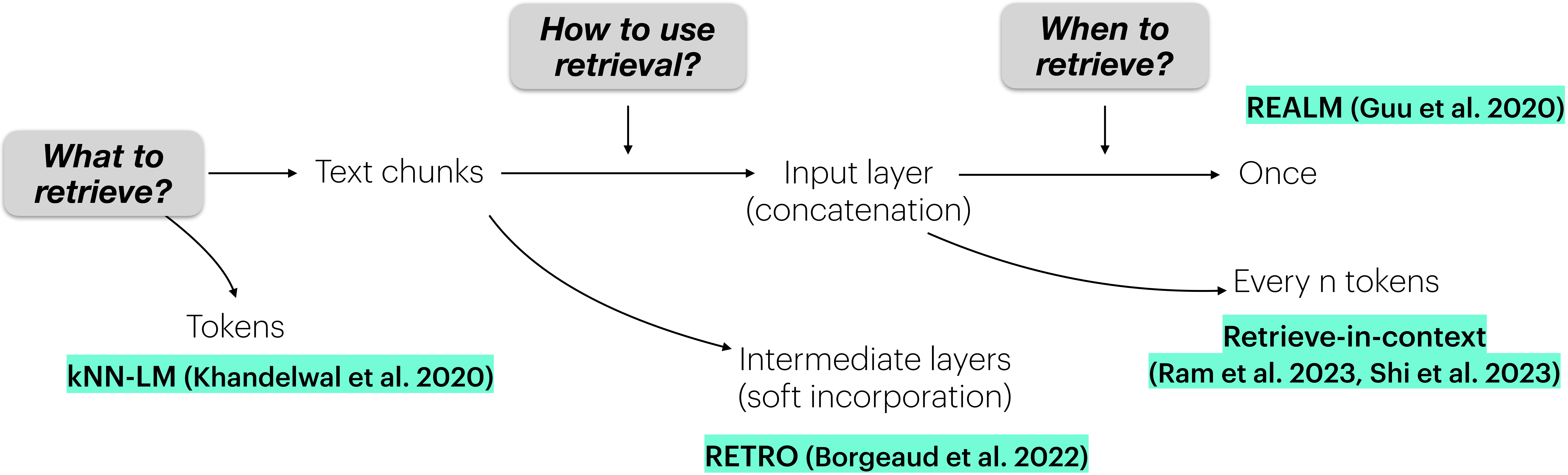
More frequent retrieval = better in performance, but slower

Wrapping up



- Input layer: Simple but can be slower
- Intermediate layers: More complex (need training) but can be designed to be more efficient

Wrapping up



- Text blocks: Datastore can be space-efficient, more computation
- Tokens: More fine-grained, compute-efficient, but datastore can be space-expensive

Wrapping up

What to retrieve? → Text chunks → Input layer (concatenation) → Once

How to use retrieval?

When to retrieve?

REALM (Guu et al. 2020)

Tokens

kNN-LM (Khandelwal et al. 2020)

Adaptively

He et al. 2021, Alon et al. 2022

Intermediate layers (soft incorporation)

RETRO (Borgeaud et al. 2022)

Every n tokens

Retrieve-in-context
(Ram et al. 2023, Shi et al. 2023)

Adaptively

Jiang et al. 2023

Adaptive retrieval can improve efficiency

Wrapping up

Févry et al. 2020,
de Jong et al. 2021

Entities or
entity mentions

What to retrieve?

Text chunks

How to use retrieval?

Input layer
(concatenation)

When to retrieve?

REALM (Guu et al. 2020)

Once

Every n tokens

Retrieve-in-context
(Ram et al. 2023, Shi et al. 2023)

Adaptively

Jiang et al. 2023

Tokens

kNN-LM (Khandelwal et al. 2020)

Adaptively

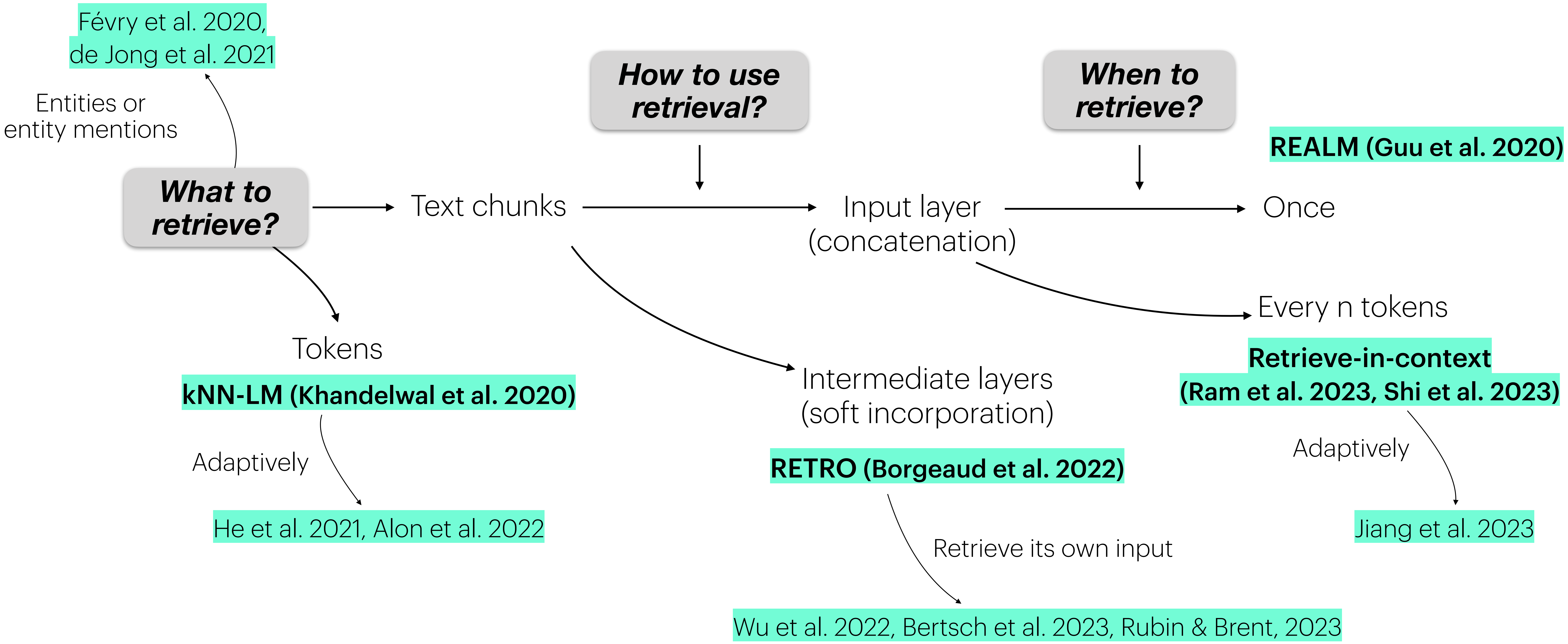
He et al. 2021, Alon et al. 2022

Intermediate layers
(soft incorporation)

RETRO (Borgeaud et al. 2022)

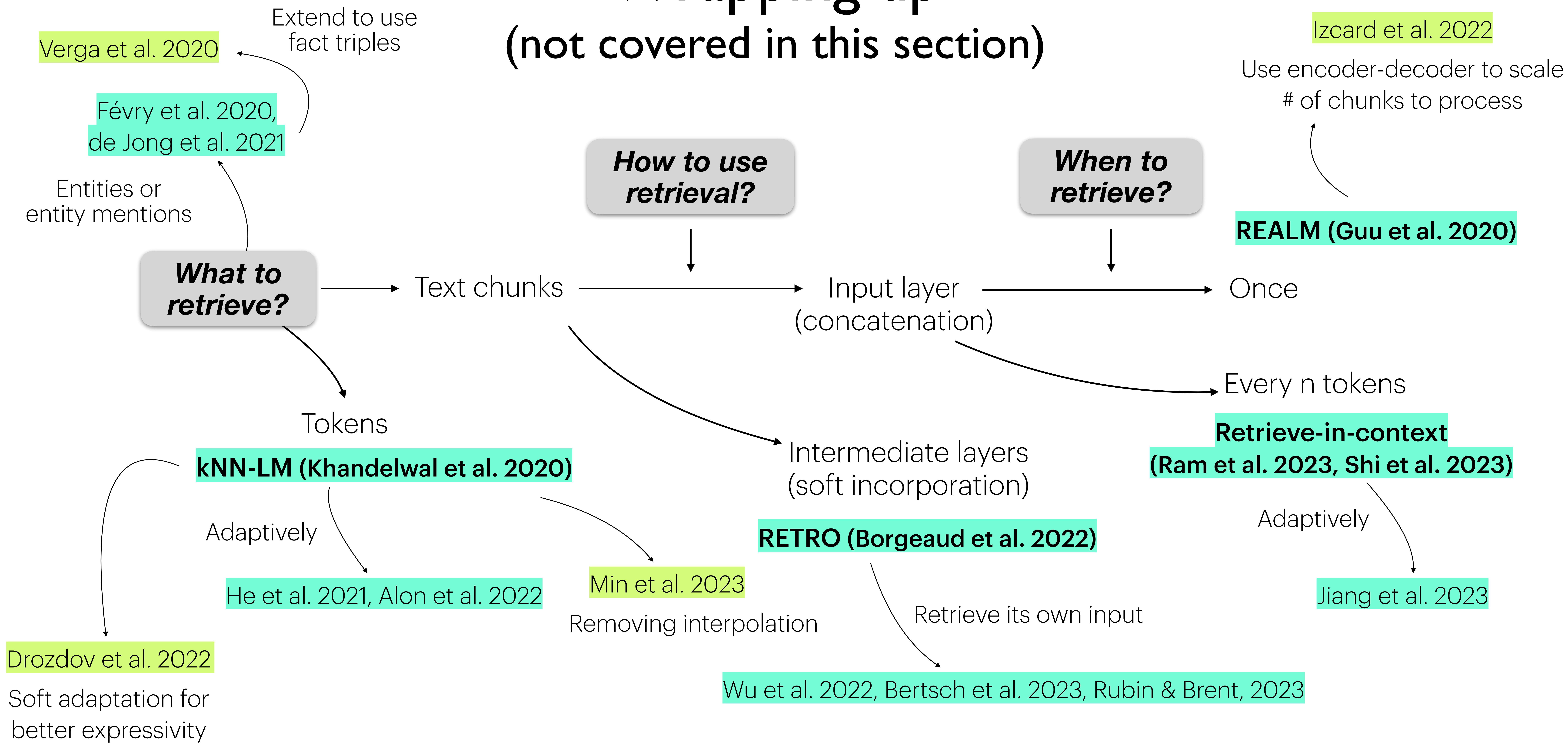
Entities or entity mentions instead of every token or chunk

Wrapping up

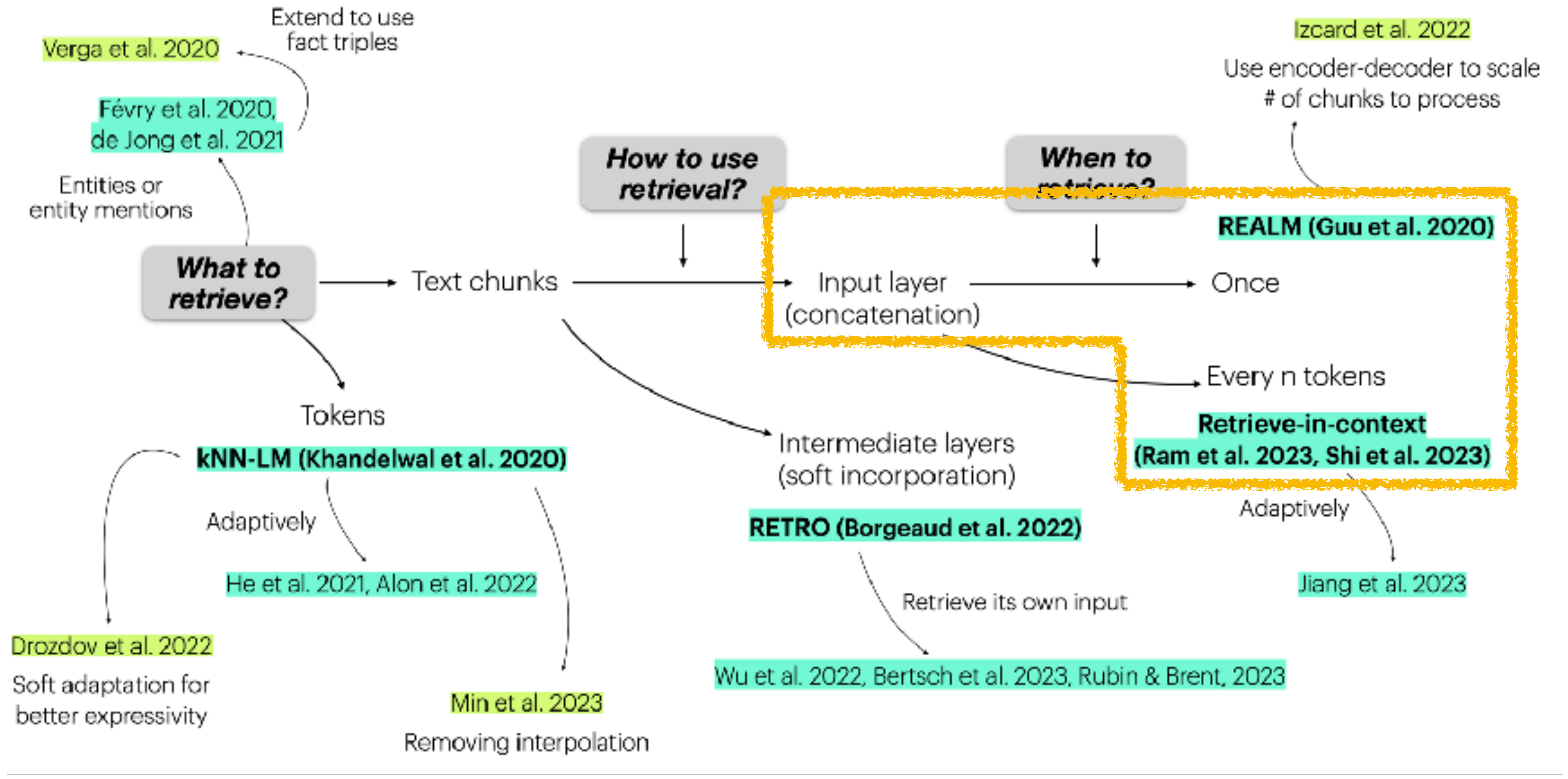


We can use a similar approach for long-sequence modeling

Wrapping up
(not covered in this section)



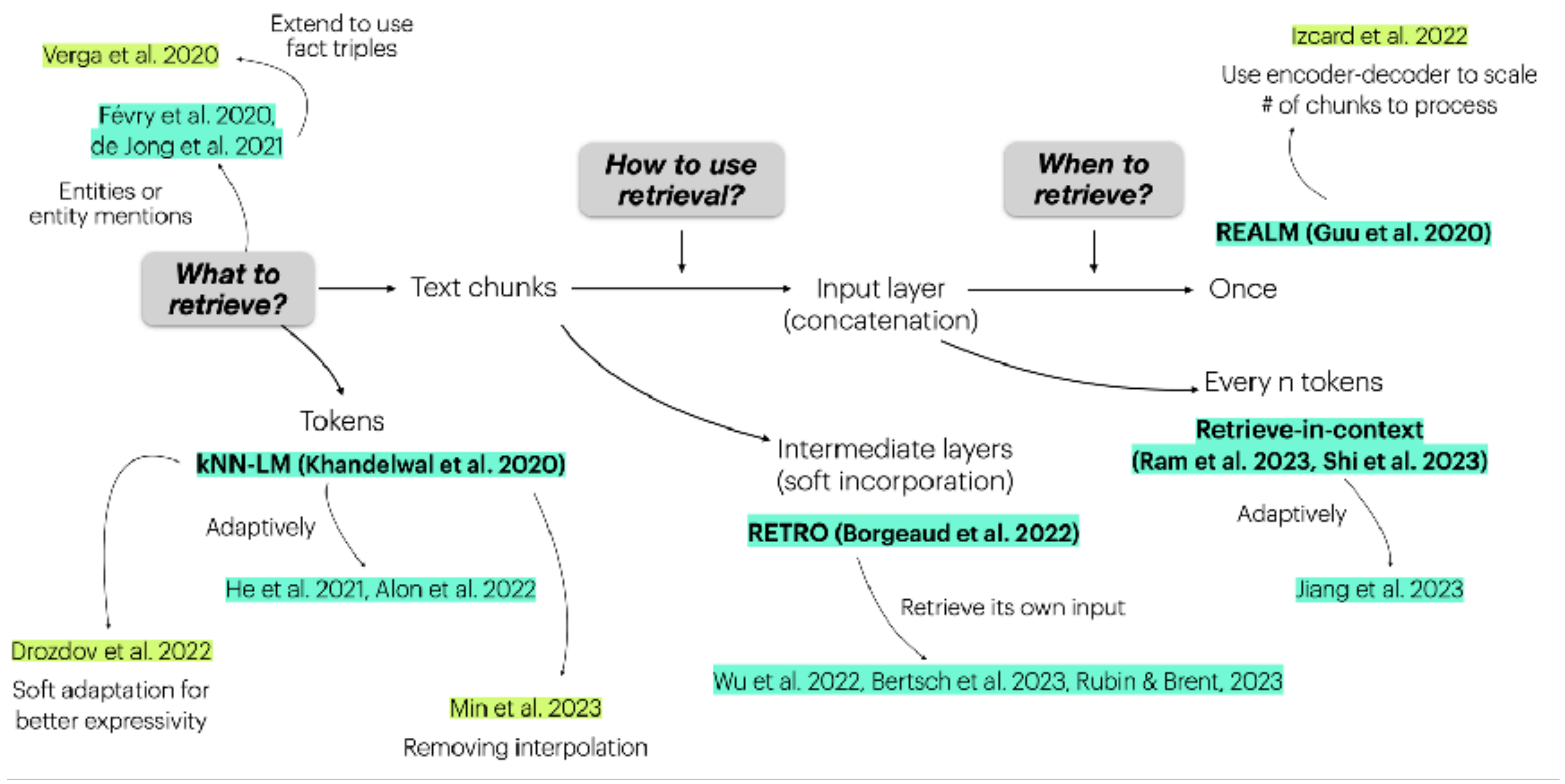
Wrapping up



Perplexity WebGPT YOU Chat GPT Extension

Still largely under-explored!

Wrapping up



We didn't cover anything about training → **Section 4**!

We briefly saw some results but not extensively on downstream tasks → **Section 5**!