Retrieval-augmented language models

Slides adopted from M Iyyer, G. Neubig, C Manning and others

Bob went to the <MASK>
to get a buzz cut

BERT
(**teacher**):
24 layer
Transformer

barbershop: 54%
barber: 20%
salon: 6%
stylist: 4%
…

World knowledge is *implicitly* encoded in BERT's parameters! (e.g., that barbershops are places to get buzz cuts)

Bob went to the <MASK> to get a buzz cut

→

BERT (**teacher**): 24 layer Transformer

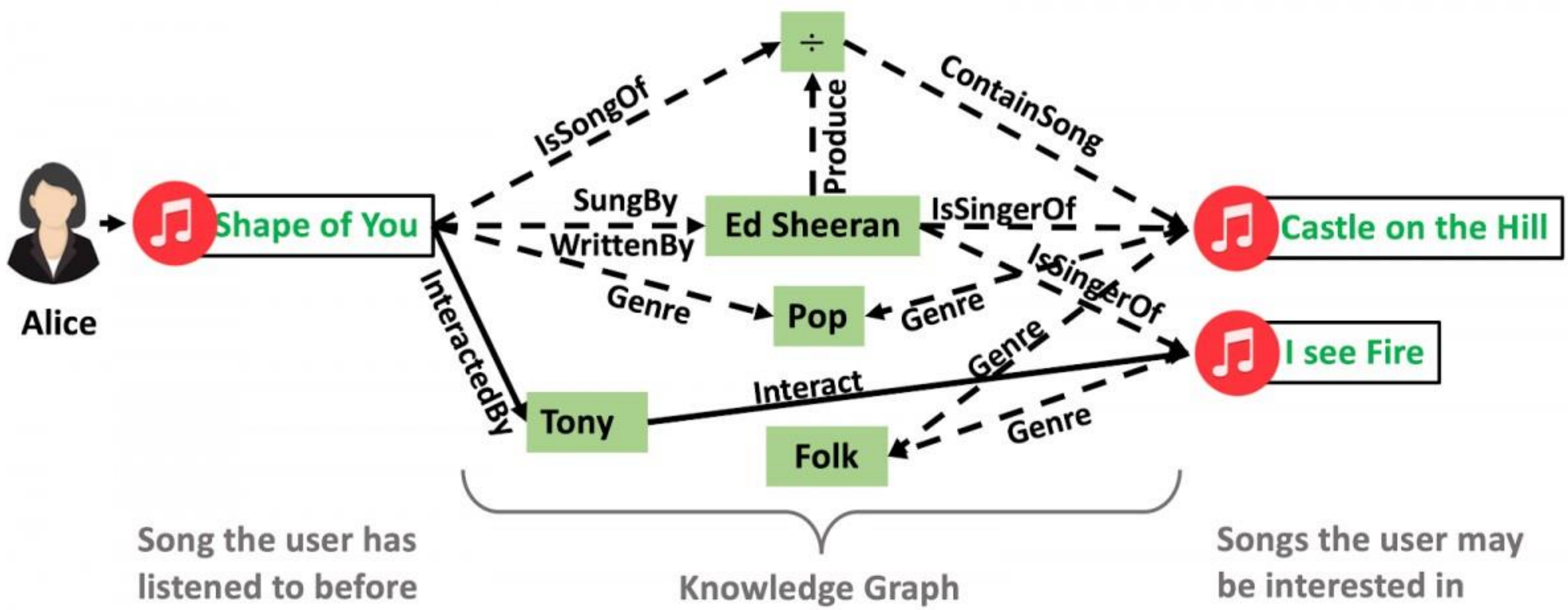
→

barbershop: 54%
barber: 20%
salon: 6%
stylist: 4%
…

In these language models, the learned world knowledge is stored *implicitly* in the parameters of the underlying neural network. This makes it difficult to determine what knowledge is stored in the network and where. Furthermore, storage space is limited by the size of the network—to capture more world knowledge, one must train ever-larger networks, which can be prohibitively slow or expensive.

Guu et al., 2020 (“REALM”)

One option: condition predictions on explicit *knowledge graphs*



Wang et al., 2019

Pros / cons

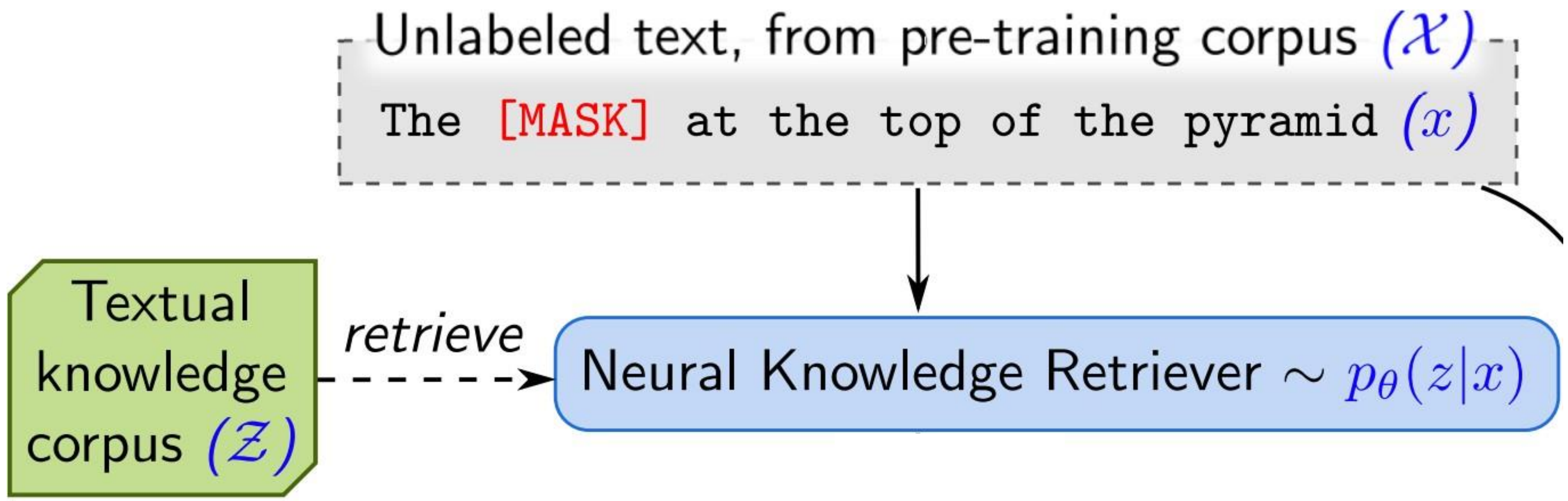
- Explicit graph structure makes KGs easy to navigate
- Knowledge graphs are expensive to produce at scale
- Automatic knowledge graph induction is an open research problem
- Knowledge graphs struggle to encode complex relations between entities

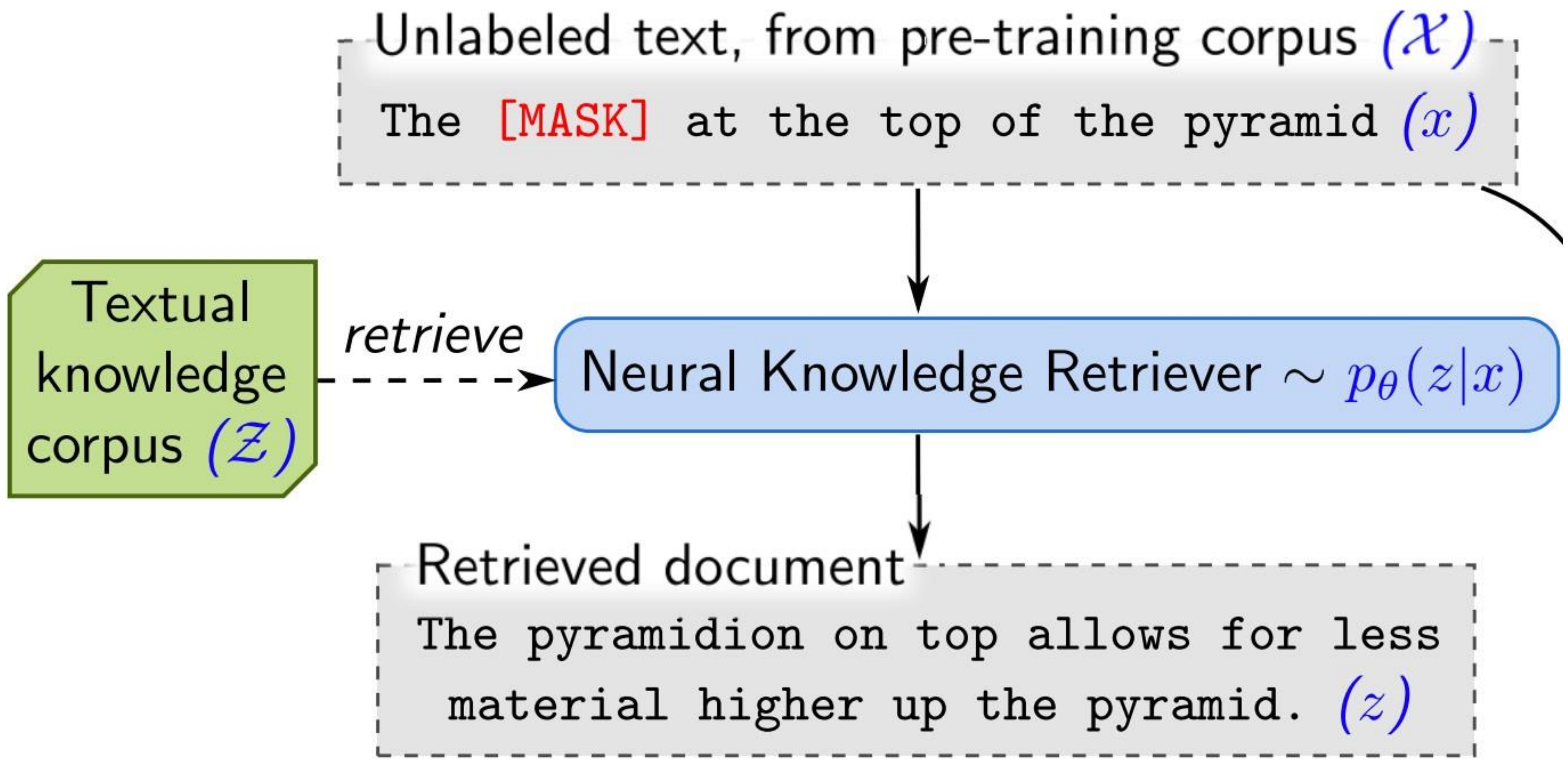
Another source of knowledge: unstructured text!

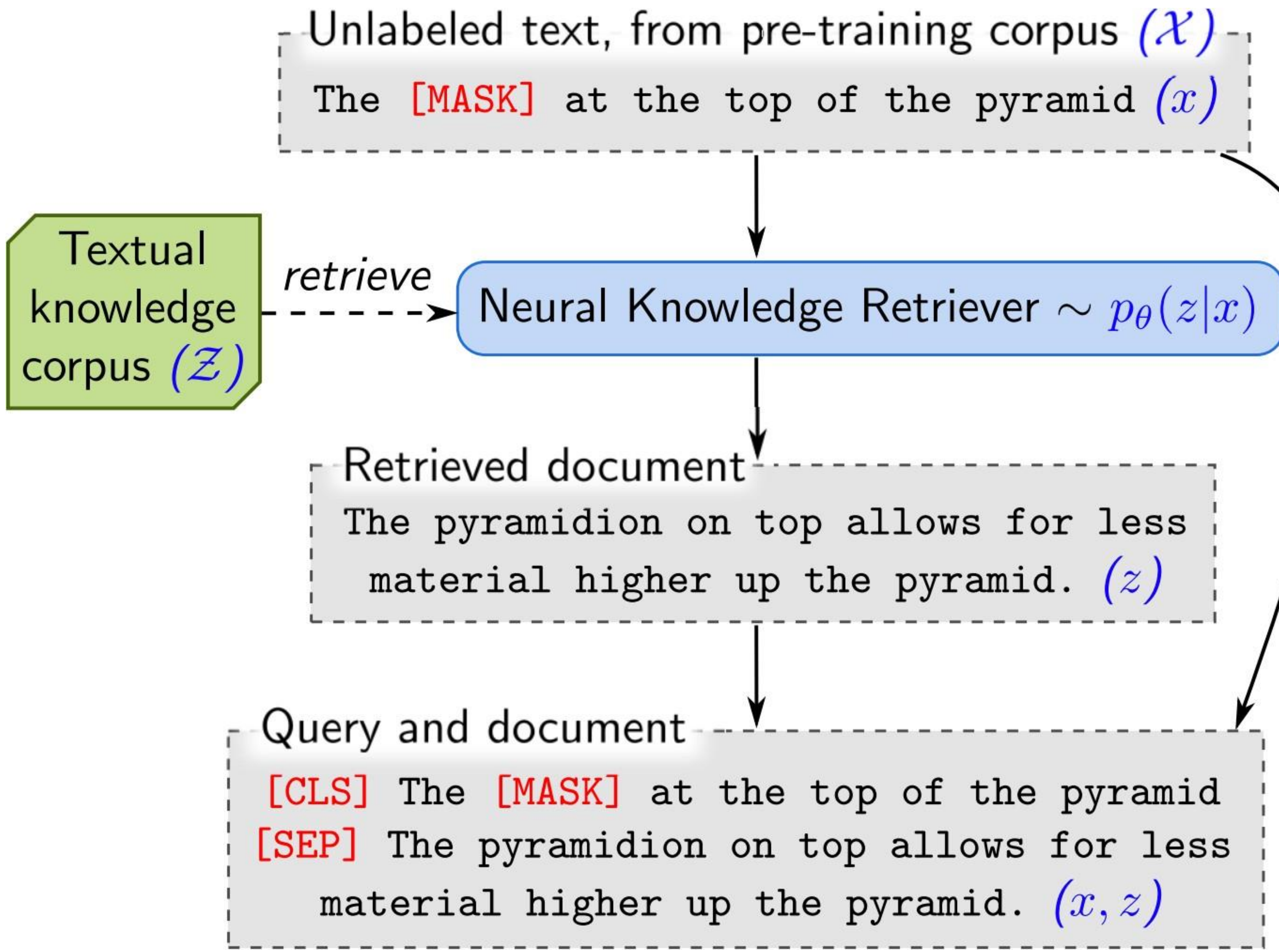
- Readily available at scale, requires no processing
- We have powerful methods of encoding semantics (e.g., BERT)
- However, these methods don’t really work with larger units of text (e.g., books)
- Extracting relevant information from unstructured text is more difficult than it is with KGs

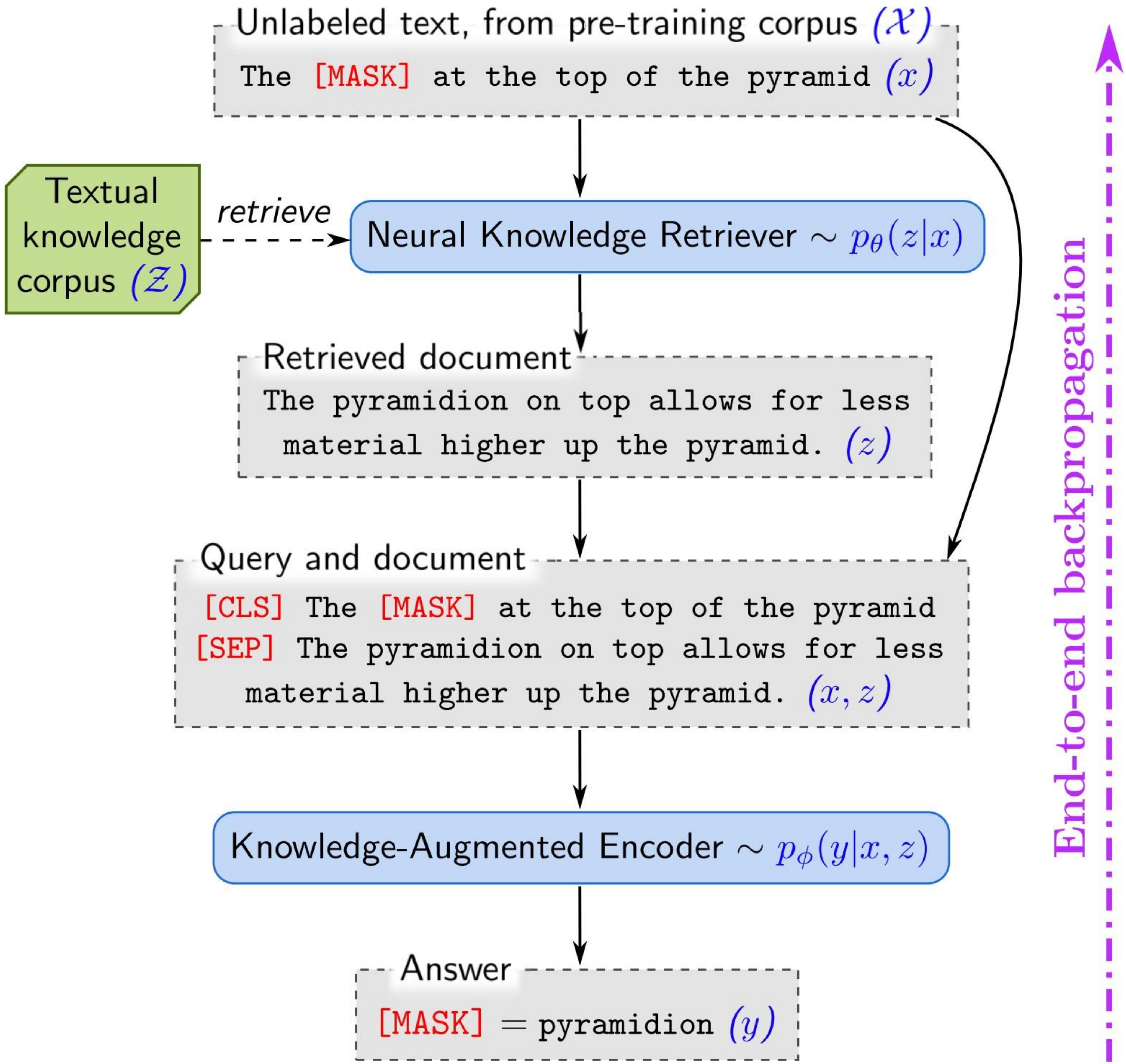
Unlabeled text, from pre-training corpus $(\mathcal{X})$

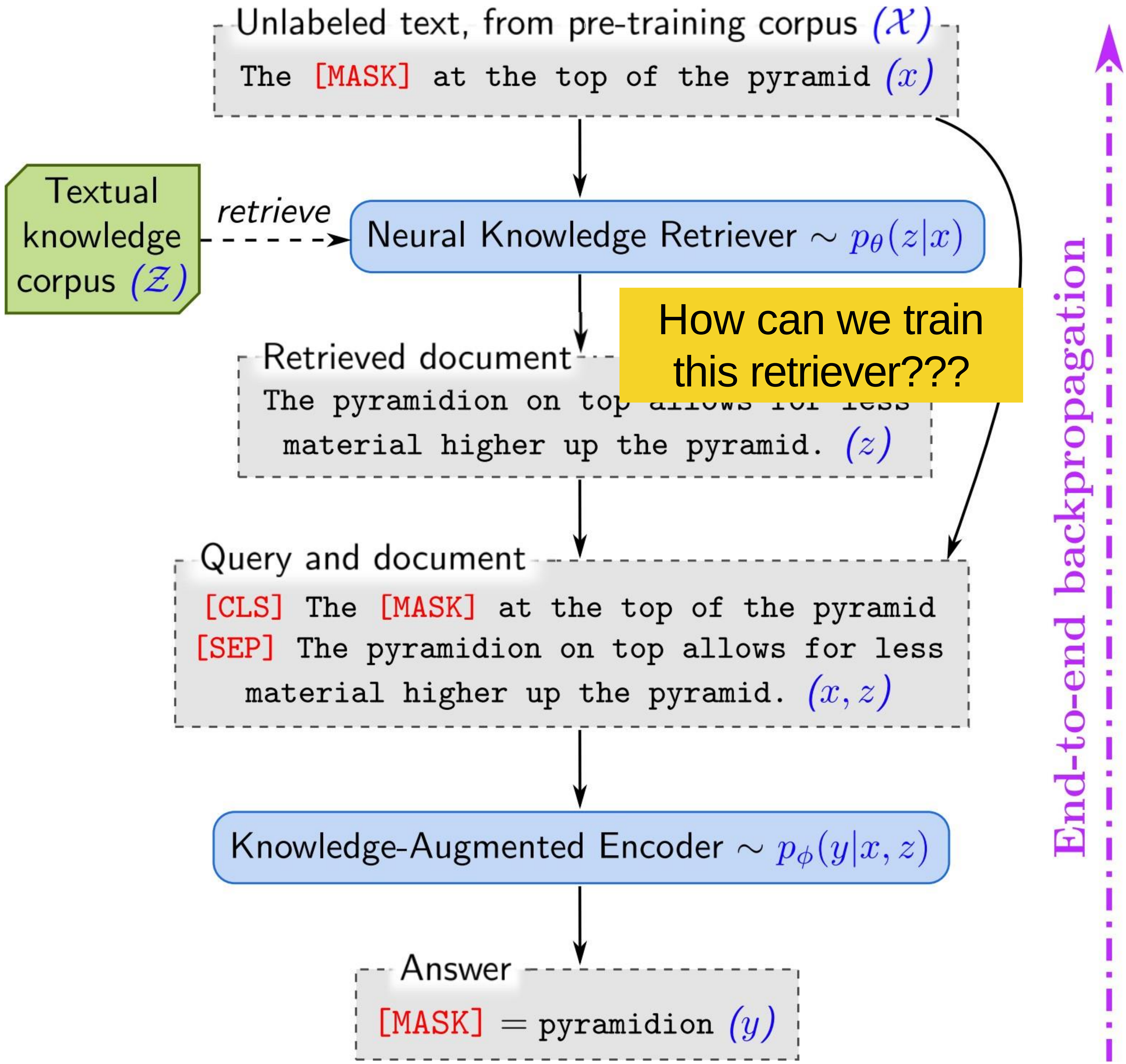
`The [MASK] at the top of the pyramid` (x)


Unlabeled text, from pre-training corpus $(\mathcal{X})$
The [MASK] at the top of the pyramid (x)
Textual knowledge corpus $(\mathcal{Z})$
retrieve
Neural Knowledge Retriever $\sim p_\theta(z|x)$


Unlabeled text, from pre-training corpus $(\mathcal{X})$
The [MASK] at the top of the pyramid (x)
Textual knowledge corpus $(\mathcal{Z})$
retrieve
Neural Knowledge Retriever $\sim p_\theta(z|x)$
Retrieved document
The pyramidion on top allows for less material higher up the pyramid. (z)


Unlabeled text, from pre-training corpus $(\mathcal{X})$
The [MASK] at the top of the pyramid (x)
Textual knowledge corpus $(\mathcal{Z})$
retrieve
Neural Knowledge Retriever $\sim p_\theta(z|x)$
Retrieved document
The pyramidion on top allows for less material higher up the pyramid. (z)
Query and document
[CLS] The [MASK] at the top of the pyramid [SEP] The pyramidion on top allows for less material higher up the pyramid. (x, z)


Unlabeled text, from pre-training corpus $(\mathcal{X})$
The [MASK] at the top of the pyramid (x)
Textual knowledge corpus $(\mathcal{Z})$
retrieve
Neural Knowledge Retriever $\sim p_\theta(z|x)$
Retrieved document
The pyramidion on top allows for less material higher up the pyramid. (z)
Query and document
[CLS] The [MASK] at the top of the pyramid [SEP] The pyramidion on top allows for less material higher up the pyramid. (x, z)
Knowledge-Augmented Encoder $\sim p_\phi(y|x, z)$
Answer
[MASK] = pyramidion (y)
End-to-end backpropagation



Unlabeled text, from pre-training corpus $(\mathcal{X})$
The [MASK] at the top of the pyramid (x)
Textual knowledge corpus $(\mathcal{Z})$
retrieve
Neural Knowledge Retriever $\sim p_\theta(z|x)$
Retrieved document
The pyramidion on top allows for less material higher up the pyramid. (z)
How can we train this retriever???
Query and document
[CLS] The [MASK] at the top of the pyramid [SEP] The pyramidion on top allows for less material higher up the pyramid. (x, z)
Knowledge-Augmented Encoder $\sim p_\phi(y|x, z)$
Answer
[MASK] = pyramidion (y)
End-to-end backpropagation

REALM decomposes $p(y \mid x)$ into two steps: *retrieve*, then *predict*. Given an input x, we first retrieve possibly helpful documents z from a knowledge corpus $\mathcal{Z}$. We model this as a sample from the distribution $p(z \mid x)$. Then, we condition on both the retrieved z and the original input x to generate the output y—modeled as $p(y \mid z, x)$. To obtain the overall likelihood of generating y, we treat z as a latent variable and marginalize over all possible documents z, yielding

$$p(y \mid x) = \sum_{z \in \mathcal{Z}} p(y \mid z, x)\, p(z \mid x)$$

REALM decomposes $p(y \mid x)$ into two steps: *retrieve*, then *predict*. Given an input x, we first retrieve possibly helpful documents z from a knowledge corpus $\mathcal{Z}$. We model this as a sample from the distribution $p(z \mid x)$. Then, we condition on both the retrieved z and the original input x to generate the output y—modeled as $p(y \mid z, x)$. To obtain the overall likelihood of generating y, we treat z as a latent variable and marginalize over all possible documents z, yielding

Knowledge-augmented encoder

$$p(y \mid x) = \sum_{z \in \mathcal{Z}} p(y \mid z, x)\, p(z \mid x)$$

Neural knowledge retriever

Knowledge Retriever The retriever is defined using a dense inner product model:

$$p(z \mid x) = \frac{\exp f(x, z)}{\sum_{z'} \exp f(x, z')},$$
$$f(x, z) = \texttt{Embed}_{\texttt{input}}(x)^\top \texttt{Embed}_{\texttt{doc}}(z),$$

where $\texttt{Embed}_{\texttt{input}}$ and $\texttt{Embed}_{\texttt{doc}}$ are embedding functions that map x and z respectively to d-dimensional vectors. The *relevance score* $f(x, z)$ between x and z is defined as the inner product of the vector embeddings. The retrieval distribution is the softmax over all relevance scores.

Embed function is just BERT!

$$\mathtt{join}_{\mathtt{BERT}}(x) = \texttt{[CLS]}\, x\, \texttt{[SEP]}$$

$$\mathtt{join}_{\mathtt{BERT}}(x_1, x_2) = \texttt{[CLS]}\, x_1\, \texttt{[SEP]}\, x_2\, \texttt{[SEP]}$$

$$\mathtt{Embed}_{\mathtt{input}}(x) = \mathbf{W}_{\mathtt{input}} \mathrm{BERT}_{\mathrm{CLS}}(\mathtt{join}_{\mathtt{BERT}}(x))$$

$$\mathtt{Embed}_{\mathtt{doc}}(z) = \mathbf{W}_{\mathtt{doc}} \mathrm{BERT}_{\mathrm{CLS}}(\mathtt{join}_{\mathtt{BERT}}(z_{\text{title}}, z_{\text{body}}))$$

Knowledge-Augmented Encoder Given an input x and a retrieved document z, the knowledge-augmented encoder defines $p(y \mid z, x)$. We join x and z into a single sequence that we feed into a Transformer (distinct from the one used in the retriever).

$$p(y \mid z, x) = \prod_{j=1}^{J_x} p(y_j \mid z, x)$$

$$p(y_j \mid z, x) \propto \exp\left(w_j^\top \mathtt{BERT}_{\mathtt{MASK}(j)}(\mathtt{join}_{\mathtt{BERT}}(x, z_{\text{body}}))\right)$$

where $\mathtt{BERT}_{\mathtt{MASK}(j)}$ denotes the Transformer output vector corresponding to the j^{th} masked token, J_x is the total number of [MASK] tokens in x, and w_j is a learned word embedding for token y_j.

Isn't training the retriever extremely expensive?

The key computational challenge is that the marginal probability $p(y \mid x) = \sum_{z \in \mathcal{Z}} p(y \mid x, z)\, p(z \mid x)$ involves a summation over all documents z in the knowledge corpus $\mathcal{Z}$. We approximate this by instead summing over the top k documents with highest probability under $p(z \mid x)$—this is reasonable if most documents have near zero probability.

Imagine if your knowledge corpus was every article in Wikipedia… this would be super expensive without the approximation

Maximum inner product search (MIPS)

- Algorithms that *approximately* find the top-*k* documents

- Scales *sub-linearly* with the number of documents (both time and storage)
  - Shrivastava and Li, 2014 (“Asymmetric LSH…”)

- Requires precomputing the BERT embedding of every document in the knowledge corpus and then building an index over the embeddings

Evaluation on *open-domain QA*

- Unlike SQuAD-style QA, in open-domain QA we are only given a question, not a supporting document that is guaranteed to contain the answer
- Open-domain QA generally has a large *retrieval* component, since the answer to any given question could occur anywhere in a large collection of documents

Name	Architectures	Pre-training	NQ (79k/4k)	WQ (3k/2k)	CT (1k /1k)	# params
BERT-Baseline (Lee et al., 2019)	Sparse Retr.+Transformer	BERT	26.5	17.7	21.3	110m
T5 (base) (Roberts et al., 2020)	Transformer Seq2Seq	T5 (Multitask)	27.0	29.1	-	223m
T5 (large) (Roberts et al., 2020)	Transformer Seq2Seq	T5 (Multitask)	29.8	32.2	-	738m
T5 (11b) (Roberts et al., 2020)	Transformer Seq2Seq	T5 (Multitask)	34.5	37.4	-	11318m
DrQA (Chen et al., 2017)	Sparse Retr.+DocReader	N/A	-	20.7	25.7	34m
HardEM (Min et al., 2019a)	Sparse Retr.+Transformer	BERT	28.1	-	-	110m
GraphRetriever (Min et al., 2019b)	GraphRetriever+Transformer	BERT	31.8	31.6	-	110m
PathRetriever (Asai et al., 2019)	PathRetriever+Transformer	MLM	32.6	-	-	110m
ORQA (Lee et al., 2019)	Dense Retr.+Transformer	ICT+BERT	33.3	36.4	30.1	330m
Ours ($\mathcal{X}$ = Wikipedia, $\mathcal{Z}$ = Wikipedia)	Dense Retr.+Transformer	REALM	39.2	40.2	**46.8**	330m
Ours ($\mathcal{X}$ = CC-News, $\mathcal{Z}$ = Wikipedia)	Dense Retr.+Transformer	REALM	**40.4**	**40.7**	42.9	330m

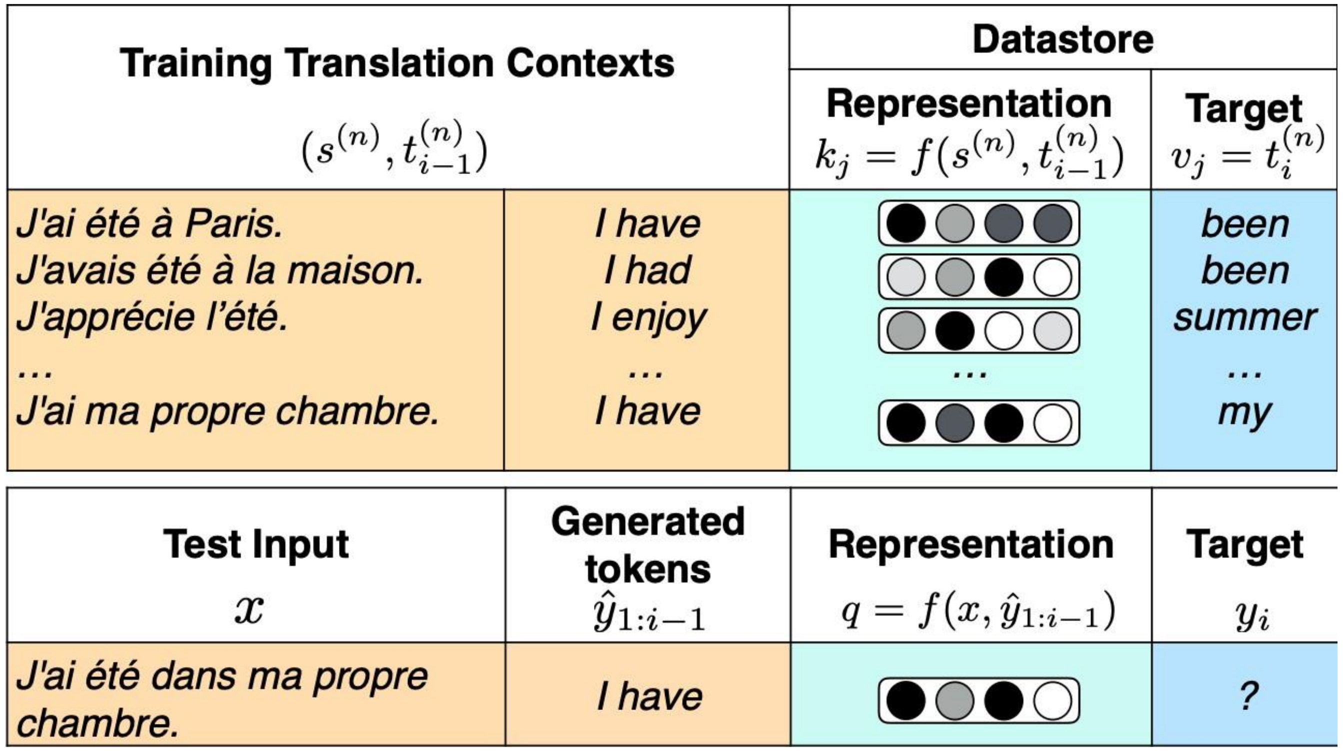
Can retrieval-augmented LMs improve other tasks?

Nearest-neighbor machine translation

Test Input x	**Generated tokens** $\hat{y}_{1:i-1}$	**Representation** $q = f(x, \hat{y}_{1:i-1})$	**Target** y_i
J'ai été dans ma propre chambre.	*I have*		*?*

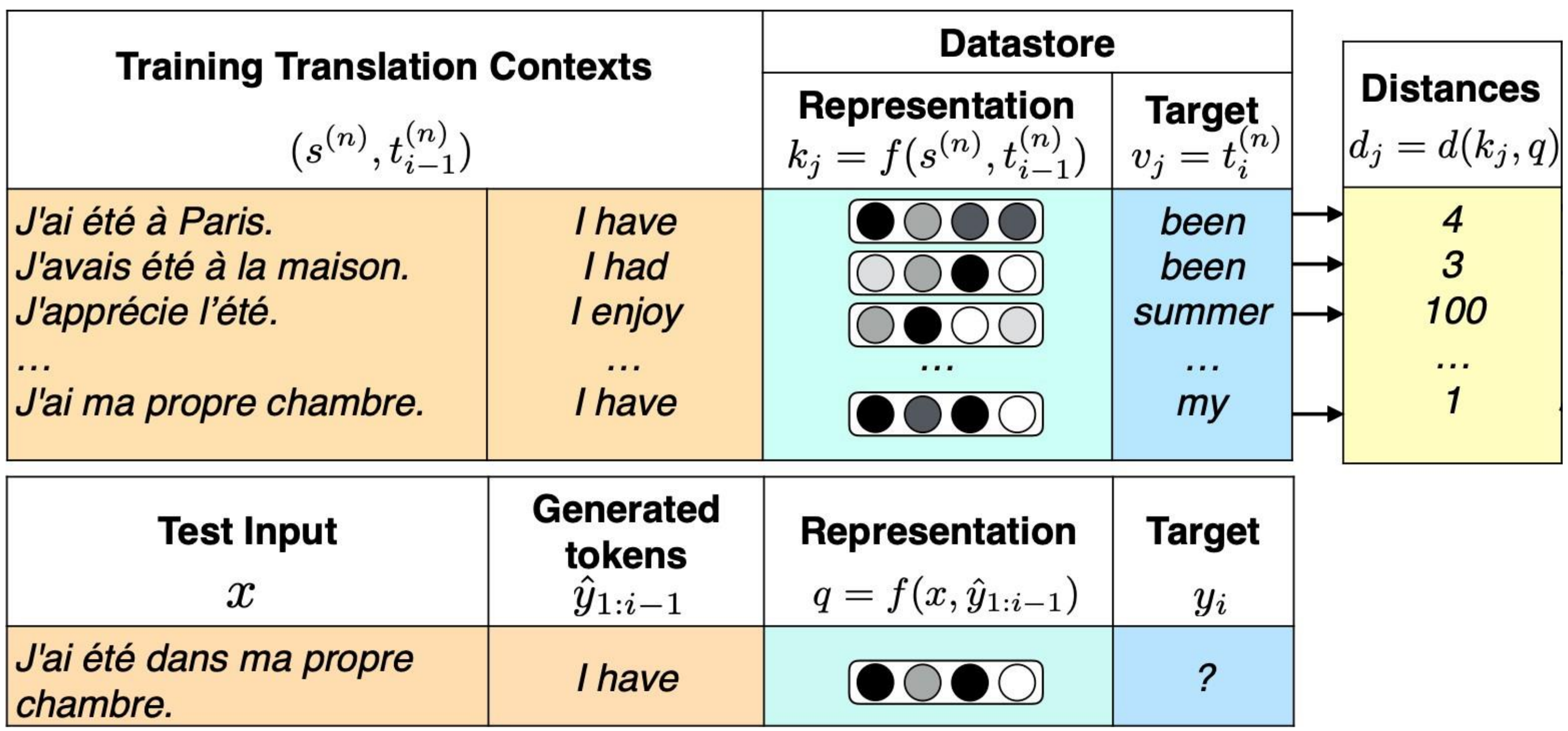
Khandelwal et al., 2020

Nearest-neighbor machine translation



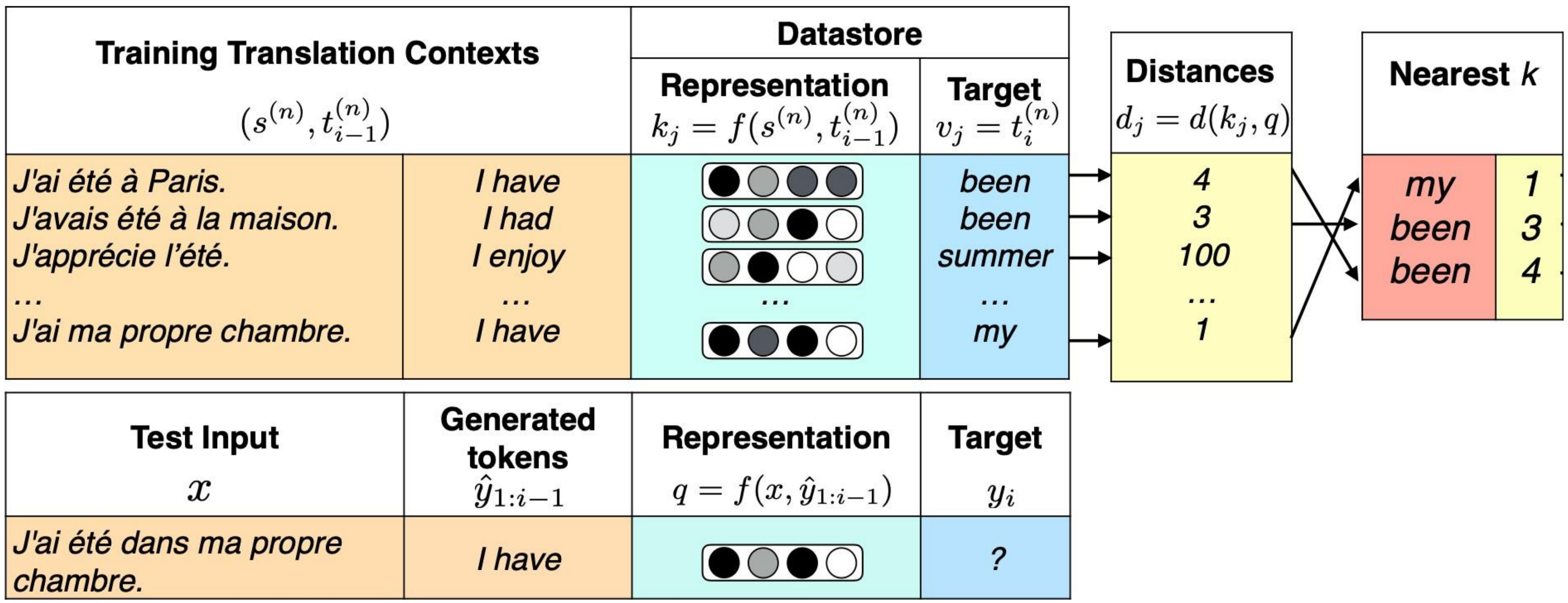
Khandelwal et al., 2020

Nearest-neighbor machine translation



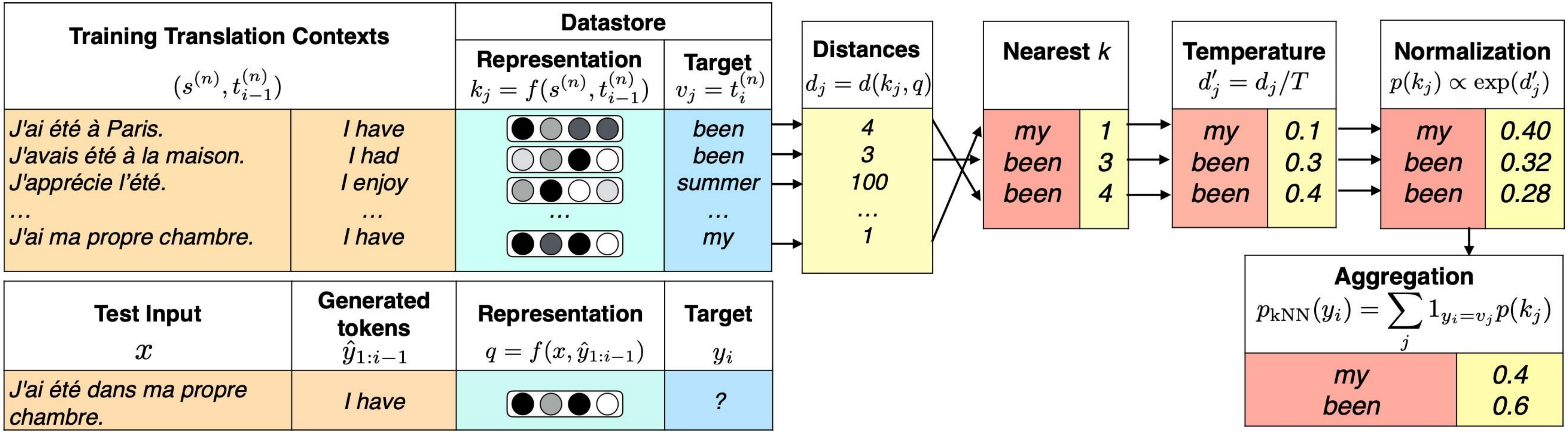
Khandelwal et al., 2020

Nearest-neighbor machine translation



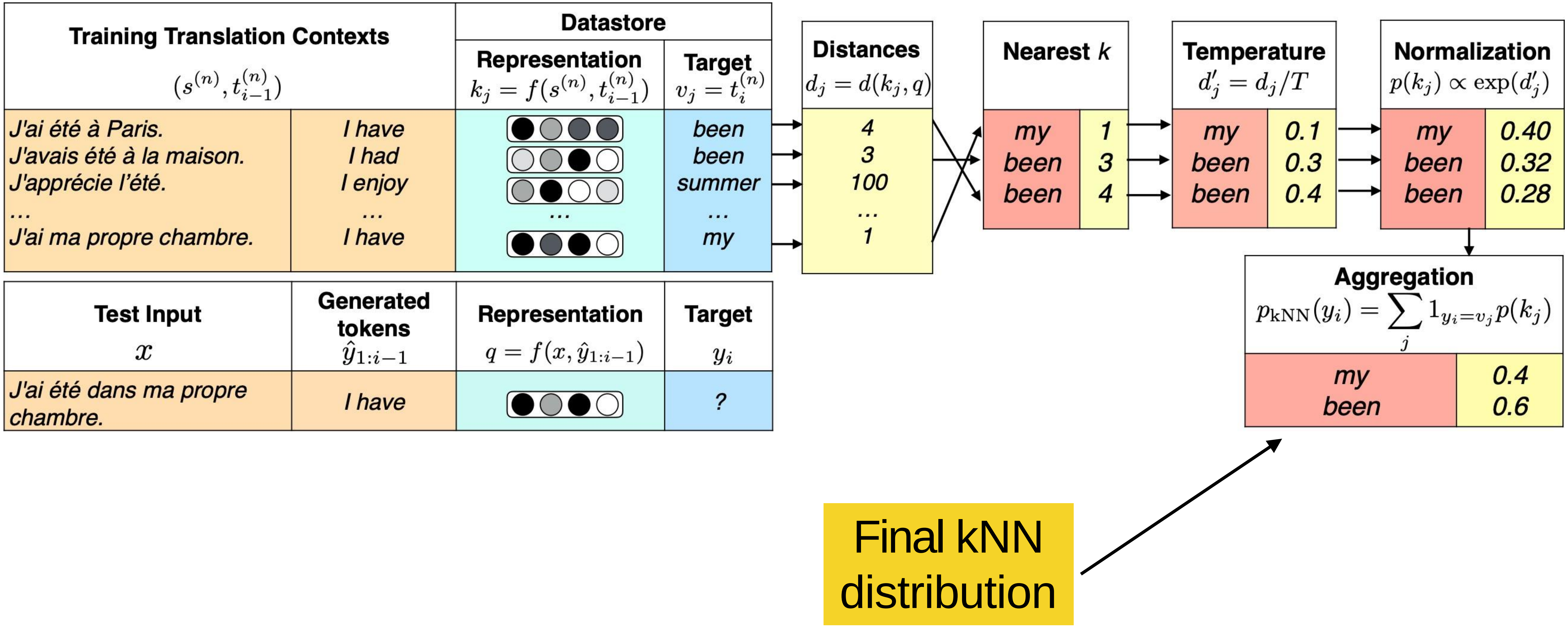
Khandelwal et al., 2020

Nearest-neighbor machine translation



Khandelwal et al., 2020

Nearest-neighbor machine translation



Khandelwal et al., 2020

Interpolate between kNN prediction and decoder's actual prediction

$$p(y_i|x, \hat{y}_{1:i-1}) = \lambda\, p_{\mathrm{kNN}}(y_i|x, \hat{y}_{1:i-1}) + (1-\lambda)\, p_{\mathrm{MT}}(y_i|x, \hat{y}_{1:i-1})$$

Final kNN distribution

Decoder's predicted distribution

Khandelwal et al., 2020

Unlike REALM, this approach doesn’t require any training! It retrieves the kNNs via L2 distance using a fast kNN library (FAISS)

This is quite expensive!

Computational Cost While kNN-MT does not add trainable model parameters, it does add some computational overhead. The primary cost of building the datastore is a single forward pass over all examples in the datastore, which is a fraction of the cost for training on the same examples for one epoch. During inference, retrieving 64 keys from a datastore containing billions of items results in a generation speed that is two orders of magnitude slower than the base MT system.

But also increases translation quality!

	de-en	ru-en	zh-en	ja-en	fi-en	lt-en	de-fr	de-cs	en-cs
Test set sizes	2,000	2,000	2,000	993	1,996	1,000	1,701	1,997	2,000
Base MT	34.45	36.42	24.23	12.79	25.92	29.59	32.75	21.15	22.78
+kNN-MT	**35.74**	**37.83**	**27.51**	13.14	26.55	29.98	**33.68**	21.62	**23.76**
Datastore Size	5.56B	3.80B	1.19B	360M	318M	168M	4.21B	696M	533M

	en-de	en-ru	en-zh	en-ja	en-fi	en-lt	fr-de	cs-de	Avg.
Test set sizes	1,997	1,997	1,997	1,000	1,997	998	1,701	1,997	-
Base MT	36.47	26.28	30.22	21.35	21.37	17.41	26.04	22.78	26.00
+kNN-MT	**39.49**	**27.91**	**33.63**	**23.23**	22.20	18.25	**27.81**	23.55	**27.40**
Datastore Size	6.50B	4.23B	1.13B	433M	375M	204M	3.98B	689M	-