Section 5:
Applications

Downstream adaptation of retrieval-based LMs

What are the **tasks**? **Language modeling**

The capital city of Ontario is __

Datastore

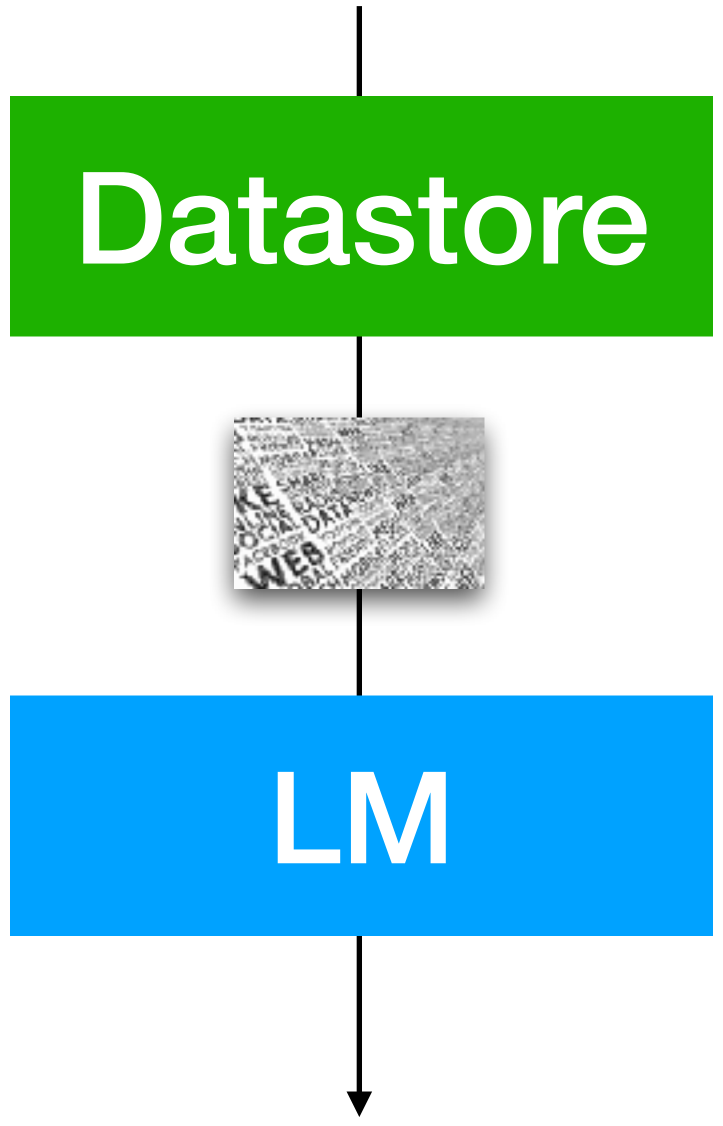
LM

Toronto, which is known for …

Downstream adaptation of retrieval-based LMs

What are the **tasks**? **Open-domain QA**

What is the capital of Ontario?



Toronto

Downstream adaptation of retrieval-based LMs

What are the **tasks**?

Fact Verification

Is the following statement true? Ottawa is the Ontario state capital.

Datastore

LM

False

A range of target tasks

Question Answering

DPR (Karpukhin et al, 2020)

RAG (Lewis et al, 2020)

REALM (Gu et al, 2020)

Many earlier retrieval-based LMs have been evaluated in the area of open-domain QA.

A range of target tasks

Question Answering

DPR (Karpukhin et al, 2020)

RAG (Lewis et al, 2020)

REALM (Gu et al, 2020)

Fact Verification

RAG (Lewis et al, 2020)

ATLAS (Izacard et al, 2022)

Evi. Generator (Asai et al, 2022)

Dialogue

BlenderBot3 (Shuster et al., 2022)

Internet-augmented generation (Komeili et a., 2022)

For a while, mainly evaluated on knowledge-intensive tasks (Lewis et al., 2020; Petroni et al., 2021)

A range of target tasks

Question Answering
DPR (Karpukhin et al, 2020)
RAG (Lewis et al, 2020)
REALM (Gu et al, 2020)

Fact Verification
RAG (Lewis et al, 2020)
ATLAS (Izacard et al, 2022)
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Dialogue
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Summarization
FLARE (Jiang et al, 2023)

Machine Translation
kNN-MT (Khandelwal et al., 2020)
TRIME-MT (Zhong et al., 2022)

Language Modeling
kNN-LM (Khandelwal et al., 2020)
TRIME (Zhong et al., 2022)
RETRO (Borgeaud et al., 2021)

NLI
kNN-Prompt (Shi et al., 2022)
NPM (Min et al., 2023)

Sentiment Analysis
kNN-Prompt (Shi et al., 2022)
NPM (Min et al., 2023)

Commonsense Reasoning
Raco (Yu et al, 2022)

More general NLU tasks

A range of target tasks

Question Answering
DPR (Karpukhin et al, 2020)

RAG (Lewis et al, 2020)

REALM (Gu et al, 2020)

Fact Verification
RAG (Lewis et al, 2020)

ATLAS (Izacard et al, 2022)

Evi. Generator (Asai et al, 2022)

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Commonsense Reasoning
Raco (Yu et al, 2022)

More generations

A range of target tasks

Question Answering
DPR (Karpukhin et al, 2020)
RAG (Lewis et al, 2020)
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NPM (Min et al., 2023)

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More classifications

Real-world applications of retrieval-based LMs

Create an itinerary for exploring Toronto over a span of two days.

Toronto is a vibrant and diverse city with many attractions and activities to suit different tastes and preferences. Here are some suggestions for creating an itinerary for exploring Toronto over two days:

- **Day 1**: Start your day with a visit to the **CN Tower**, the iconic landmark that offers panoramic views of the city and beyond [1]. You can also experience the thrill of walking on the glass floor or the EdgeWalk, the world's highest hands-free walk [1]. Next, head to the nearby **St. Lawrence Market**, one of the world's best food markets, where you can sample a variety of cuisines and local specialties [2]. After lunch, take a stroll along **Queen West**, a trendy neighborhood with eclectic shops, galleries, cafes and street art [3]. In the evening, enjoy a show at one of the many theaters or comedy clubs in the **Entertainment District**, or catch a game at the **Scotiabank Arena** if you're a sports fan.
- **Day 2**: Explore the history and culture of Toronto at the **Royal Ontario Museum**, one of the largest and most comprehensive museums in North America, featuring exhibits on art, natural history, world cultures and more [4]. Then, hop on a ferry to the **Toronto Islands**, a group of islands that offer a relaxing escape from the city, with beaches, parks, trails and amusement rides [3] [5]. You can also rent a bike or kayak to explore the islands at your own pace. For dinner, head to **Chinatown**, one of the largest and most vibrant in North America, where you can find a variety of Asian cuisines and shops [3].

I hope this helps you plan your trip to Toronto. Have fun! 😊

Learn more:

1. cntower.ca 2. travel.usnews.com 3. bing.com
4. rom.on.ca 5. tripadvisor.com

Two key questions for downstream adaptations

How can we adapt a retrieval-based LM for a task?

When should we use a retrieval-based LM?

How to adapt a retrieval-based LM for a task

What are the **tasks**?

- Open-domain QA
- Other knowledge-intensive tasks
- Sentiment analysis
- Code generation

…

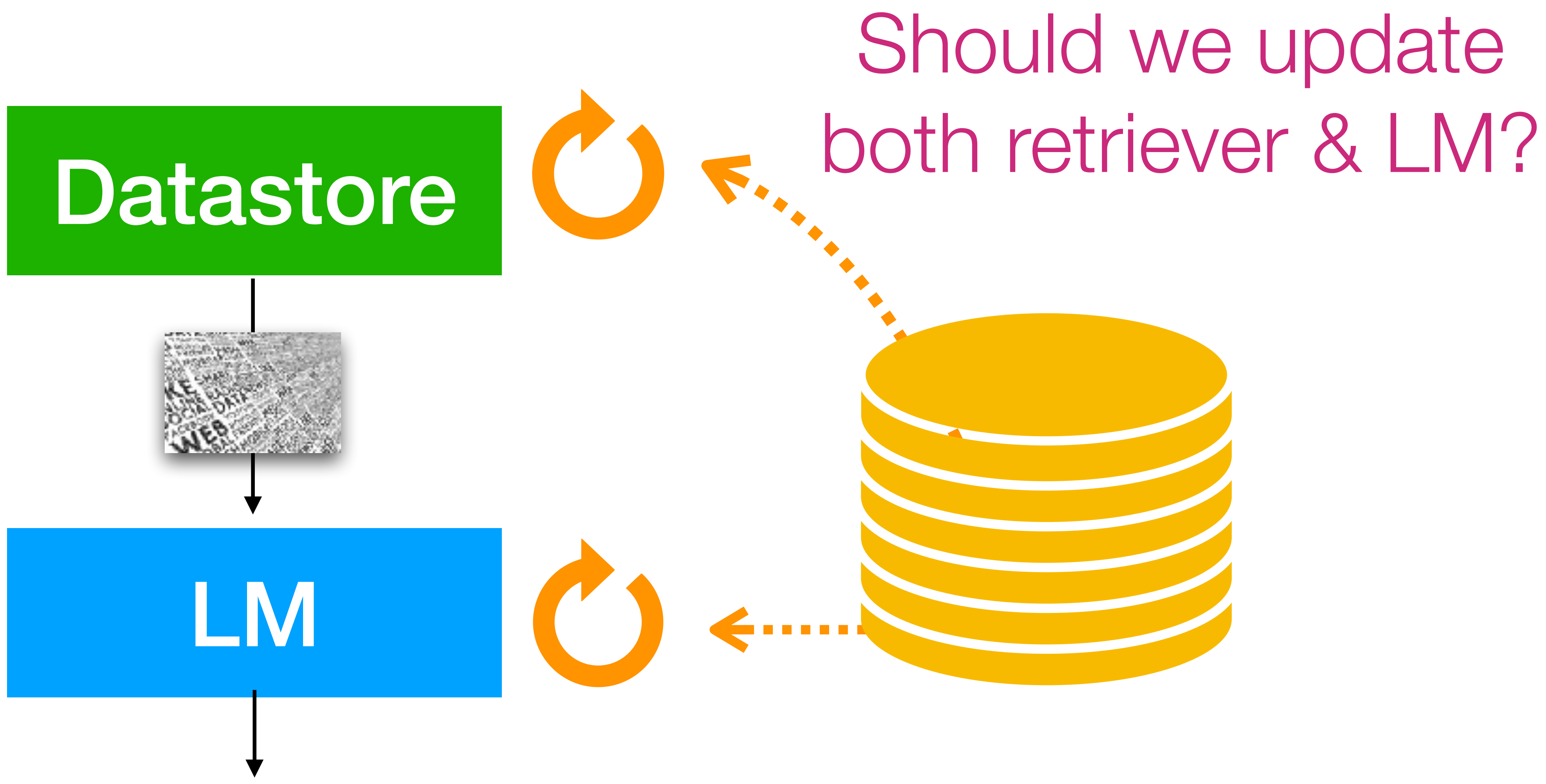
How to **adapt?**

- Supervised fine-tuning
- Reinforcement learning
- Prompting

How to adapt a retrieval-based LM for a task

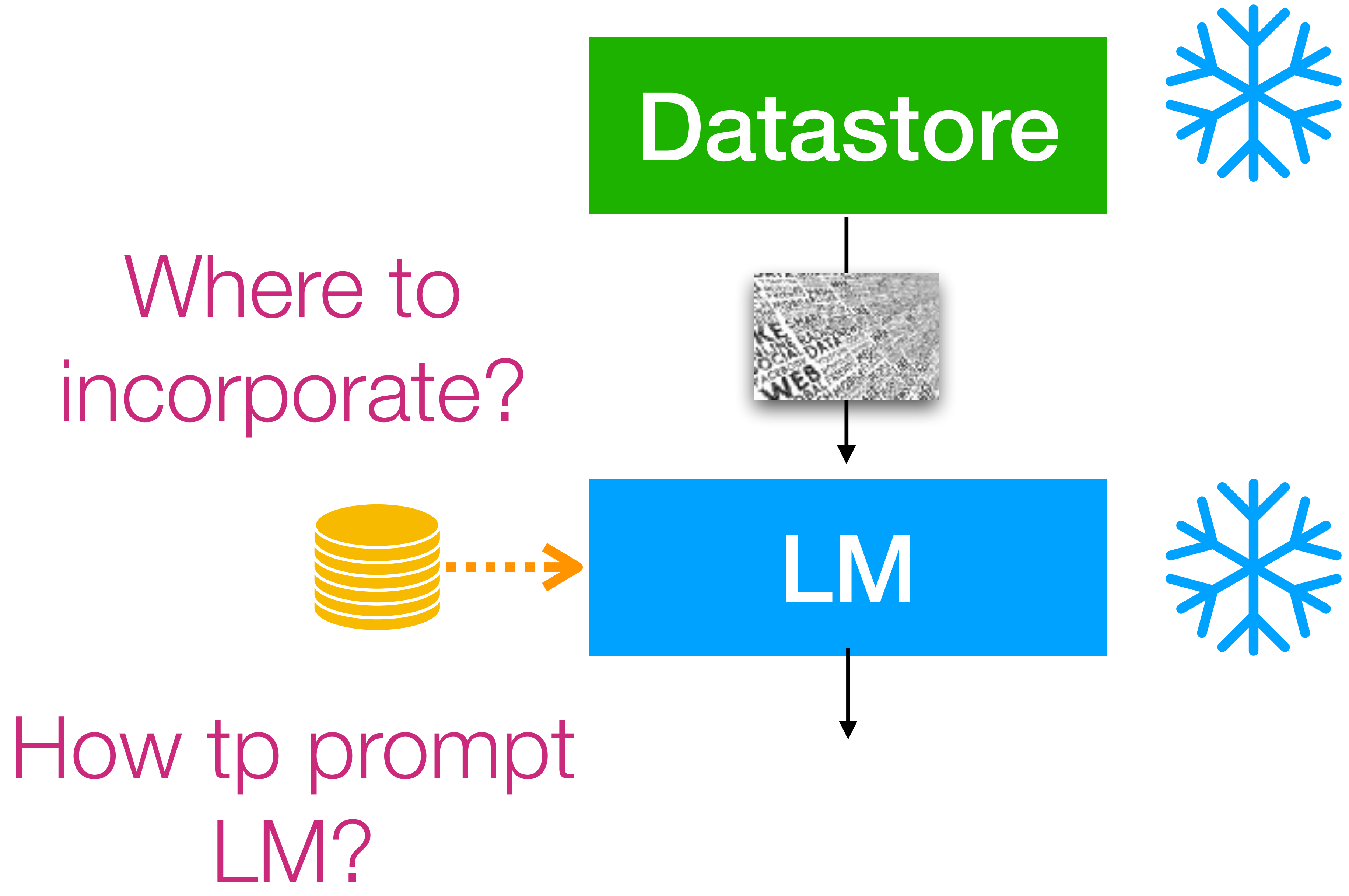
Fine-tuning (+RL)

Training LM and / or retriever
on task-data & data store



Prompting

Prompt a frozen LM with
retrieved knowledge



How to adapt a retrieval-based LM for a task

What are the **tasks**?

- Open-domain QA
- Other knowledge-intensive tasks
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…

How to **adapt?**

- Supervised fine-tuning
- Reinforcement learning
- Prompting

What is **data store?**

Wikipedia

Training data

Code documentation

When to use a retrieval-based LM

Long-tail	knowledge update	Verifiability	Parameter-efficiency	Privacy

Effectiveness of retrieval-based LMs

Long-tail | knowledge update | Verifiability | Parameter-efficiency | Privacy

Q: Is Toronto really cold during winter? → LM → Yes it is.

Effectiveness of retrieval-based LMs

Long-tail	knowledge update	Verifiability	Parameter-efficiency	Privacy

Q: Where is Toronto Zoo located? → LM → 1361A Old Finch Avenue, in Scarborough, Ontario ✗

Effectiveness of retrieval-based LMs

Long-tail | knowledge update | Verifiability | Parameter-efficiency | Privacy

Q: Where is Toronto Zoo located?

LM

Datastore

Toronto zoo Info
Location: 361A Old Finch Avenue, Toronto, Ontario
Land Area: 287 hectares

361A Old Finch Avenue, in Scarborough, Ontario

Effectiveness of retrieval-based LMs

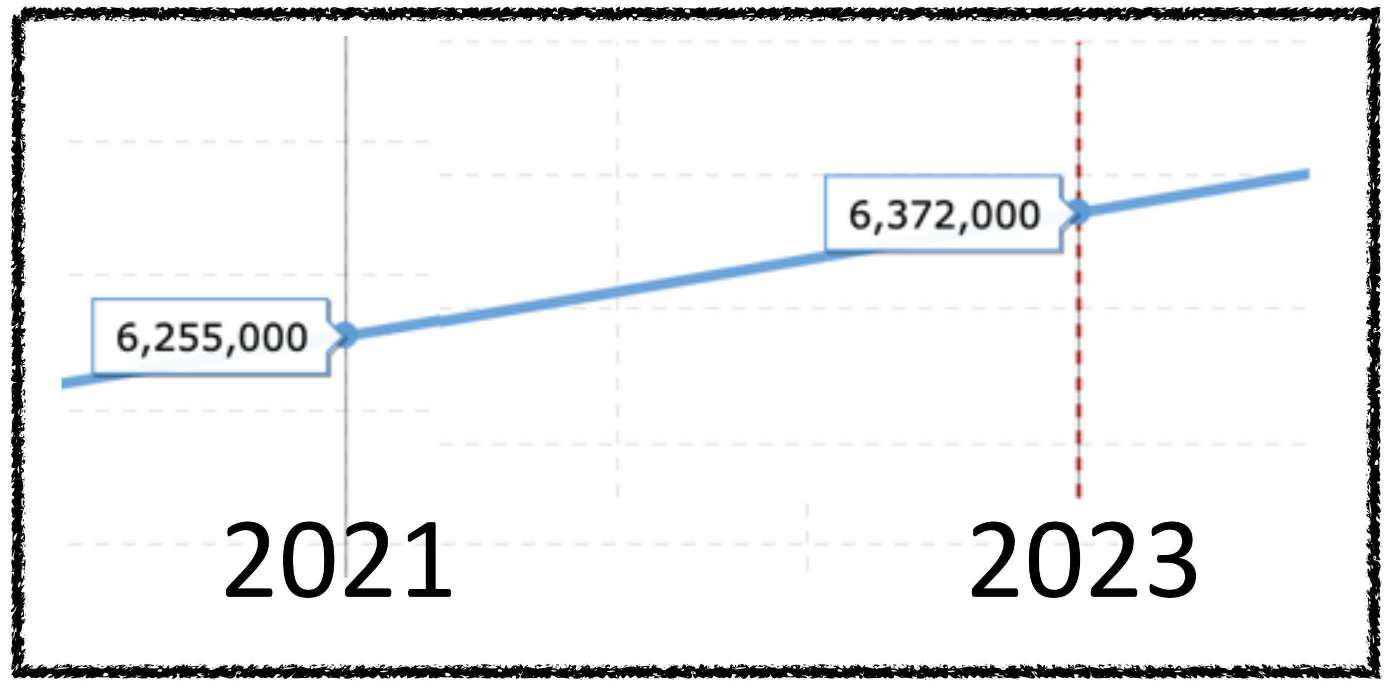
Long-tail | **Knowledge update** | Verifiability | Parameter-efficiency | Privacy

Q: What is the population of Toronto Metropolitan area in 2023?

LM

Trained on the **2021** corpus

A: 6,255,000



Effectiveness of retrieval-based LMs

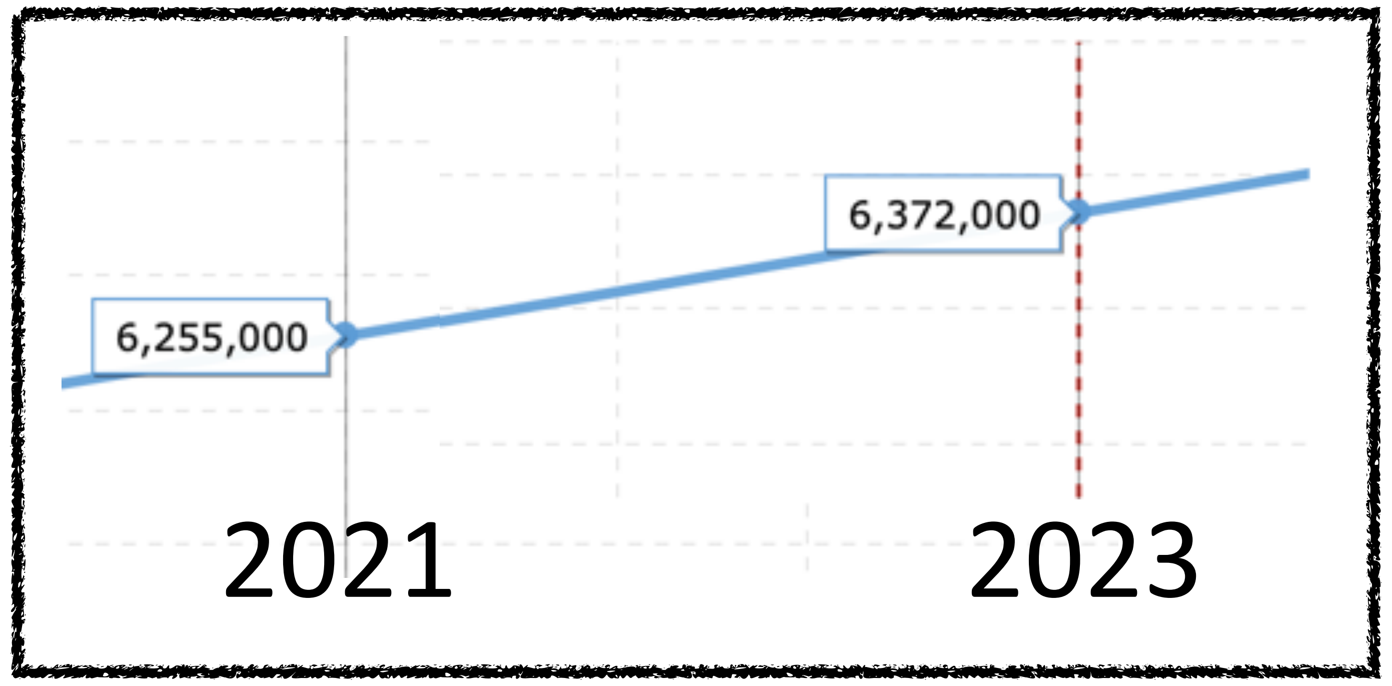
Long-tail | **Knowledge update** | Verifiability | Parameter-efficiency | Privacy

Trained on the **2021** corpus

Q: What is the population of Toronto Metropolitan area in 2023?

LM

A: 6,372,000



Collected in 2023

Datastore

Effectiveness of retrieval-based LMs

Long-tail | knowledge update | **Verifiability** | Parameter-efficiency | Privacy

Q: Where is Toronto Zoo located?

LM

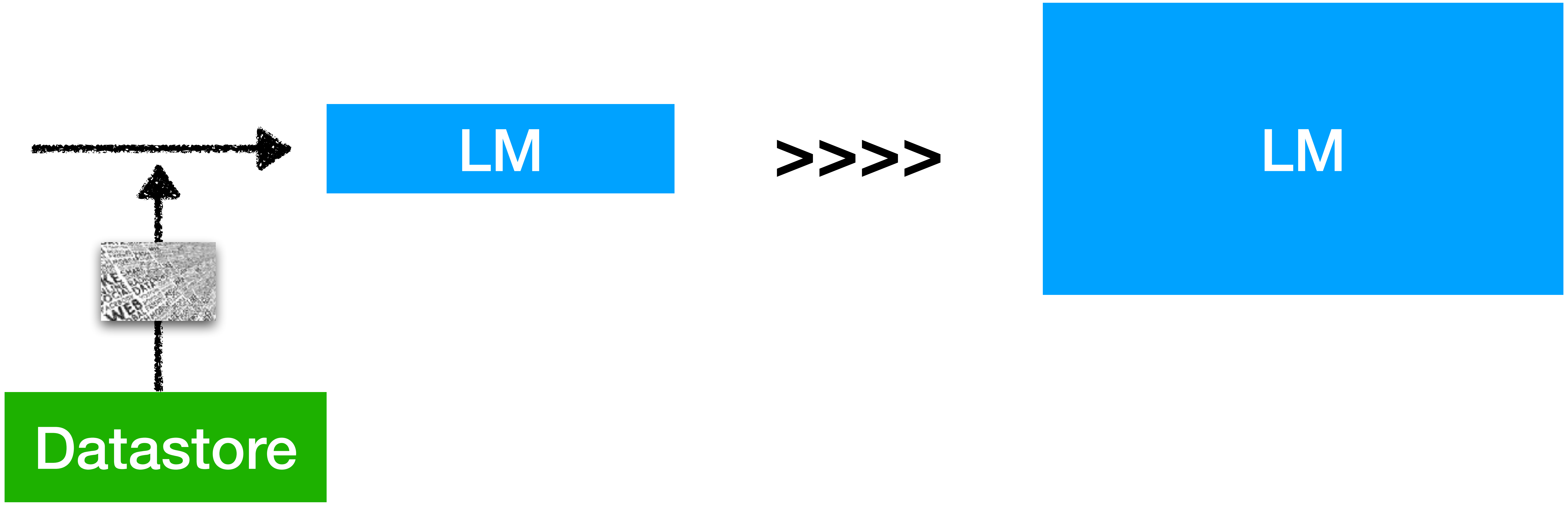
Datastore

361A Old Finch Avenue, in Scarborough, Ontario

Toronto zoo Info
Location: 361A Old Finch Avenue, Toronto, Ontario
Land Area: 287 hectares

Effectiveness of retrieval-based LMs

Long-tail | knowledge update | Verifiability | **Parameter-efficiency** | Privacy



Effectiveness of retrieval-based LMs

Long-tail | knowledge update | Verifiability | Parameter-efficiency | **Privacy**

Email: mail@alice.com

Phone: 404- → LM → **123-456**

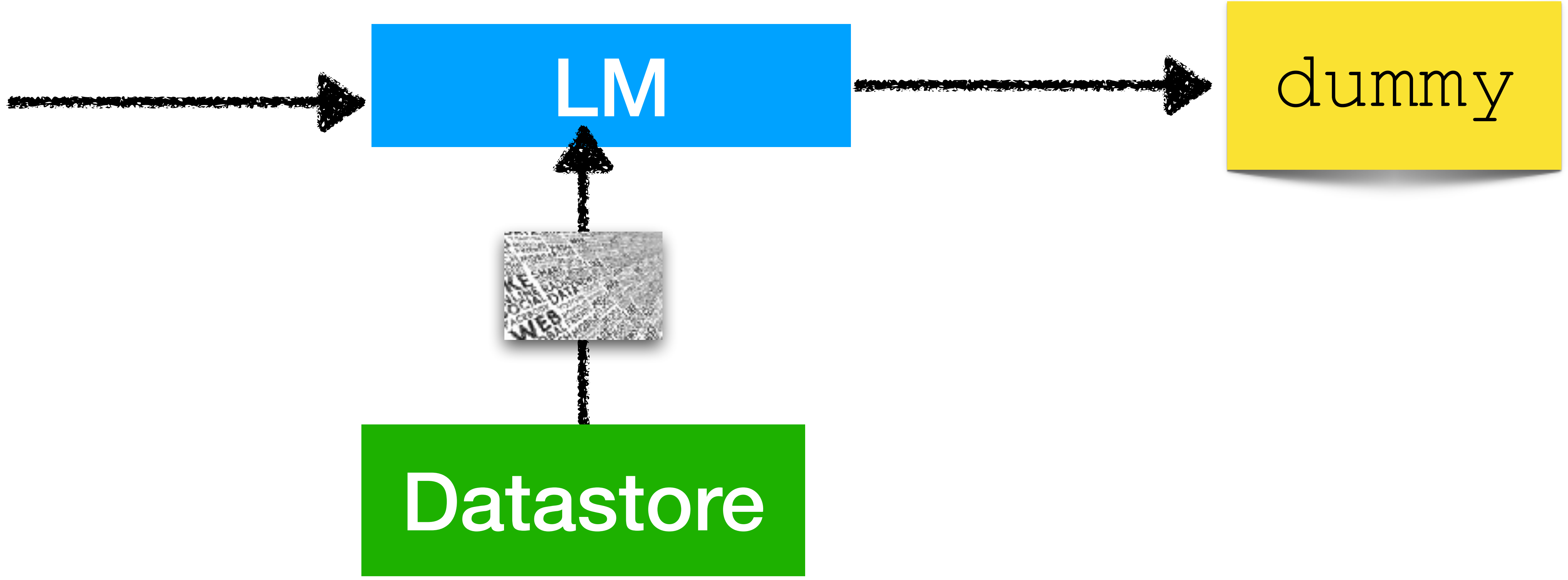
LM can leak private information included in pre-training corpora

Effectiveness of retrieval-based LMs

Long-tail | knowledge update | Verifiability | Parameter-efficiency | **Privacy**

Email: mail@alice.com

Phone: 404-



Two key questions for downstream adaptations

How can we adapt a retrieval-based LM for a task?

When should we use a retrieval-based LM?

Downstream adaptation of retrieval-based LMs

What are the **tasks**?

- Open-domain QA
- Other knowledge-intensive tasks
- General NLU
- Language Modeling & other generation tasks

How to **adapt?**

- **Fine-tuning**
- Reinforcement learning
- Prompting

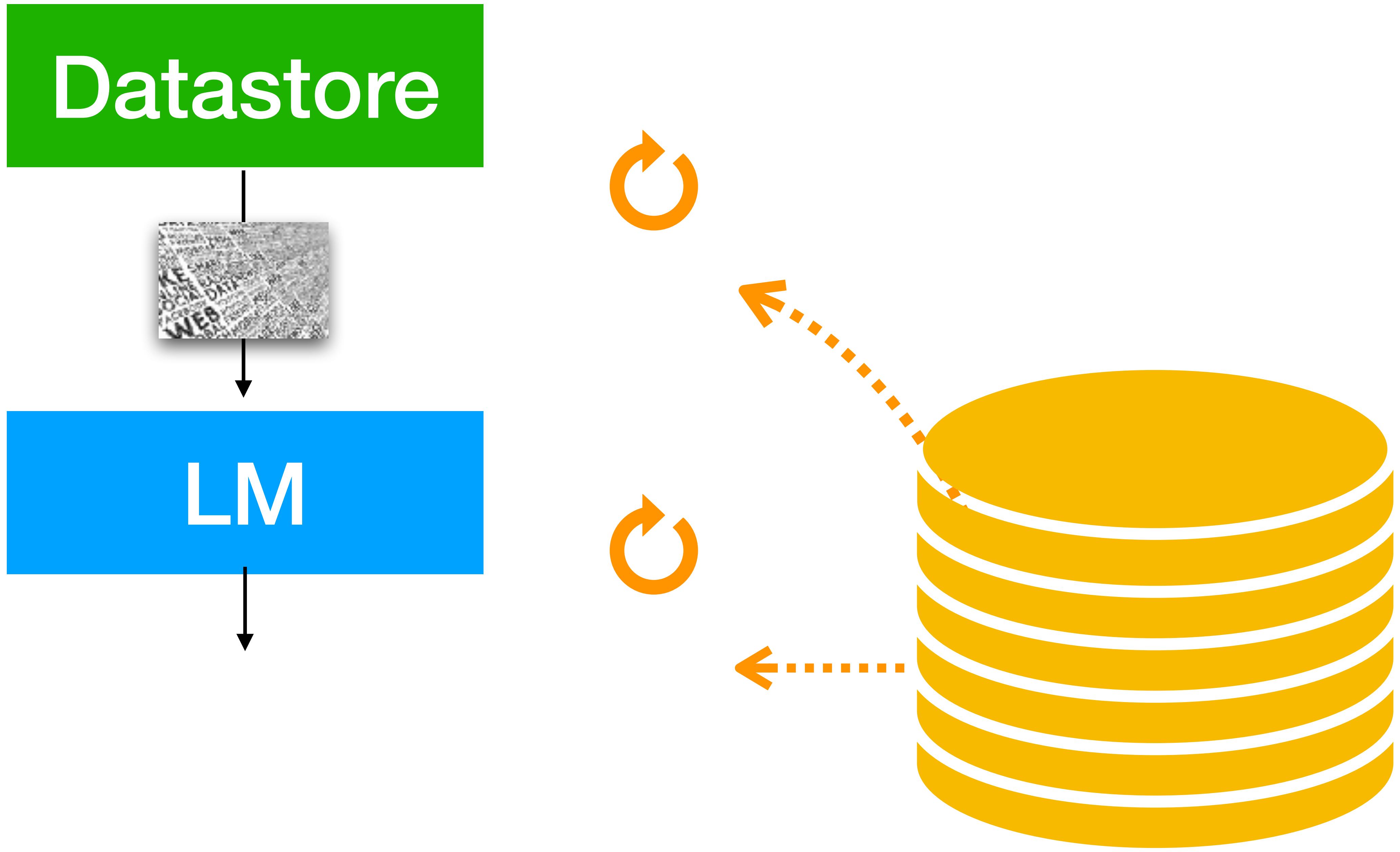
What is **data store?**

- Unlabeled Wikipedia / CC
- Web (Google / Bing Search Results)
- Training data

Adapting retrieval-based LMs for tasks

Fine-tuning

Training LM and / or retriever
on task-data & data store



Adapting retrieval-based LMs for tasks

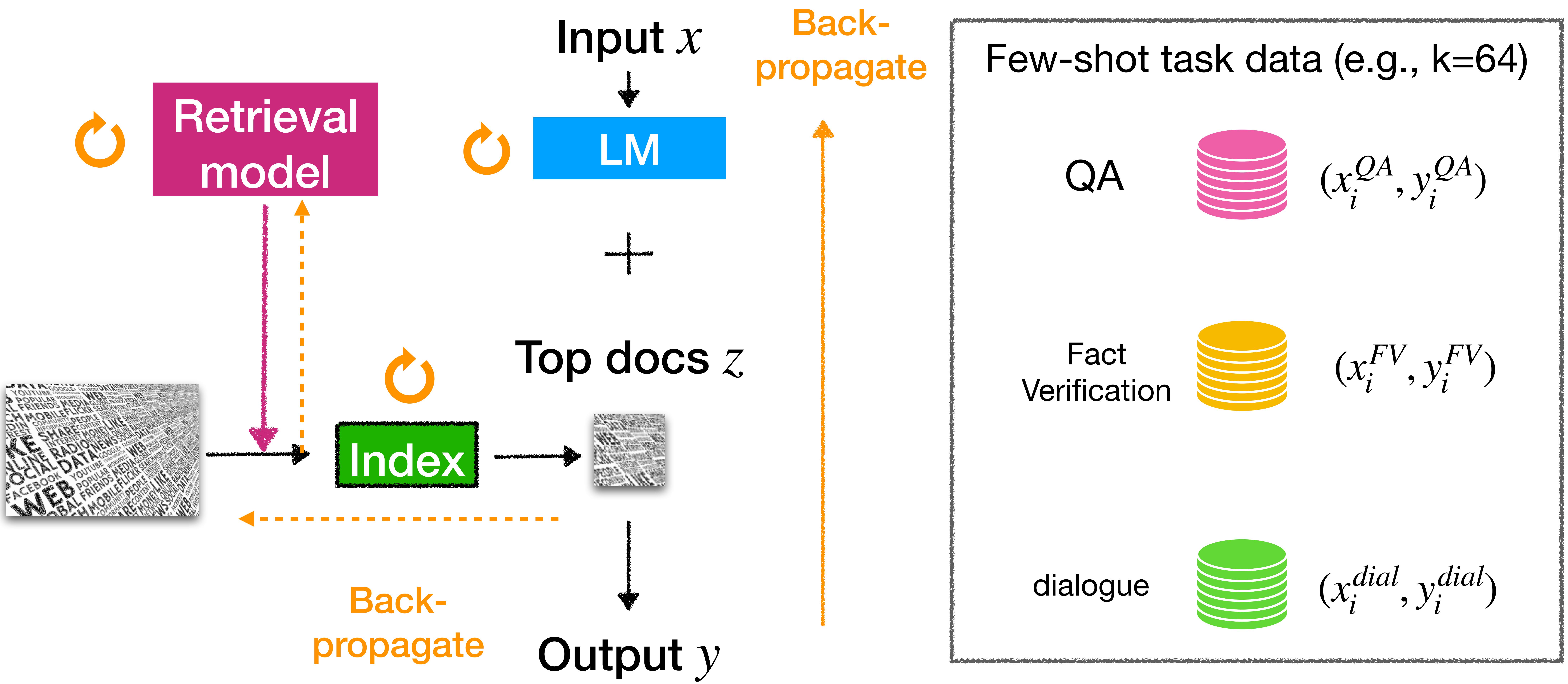
Fine-tuning

Training LM and / or retriever
on task-data & data store

Costs of retrieval-based LM training (Section 4)

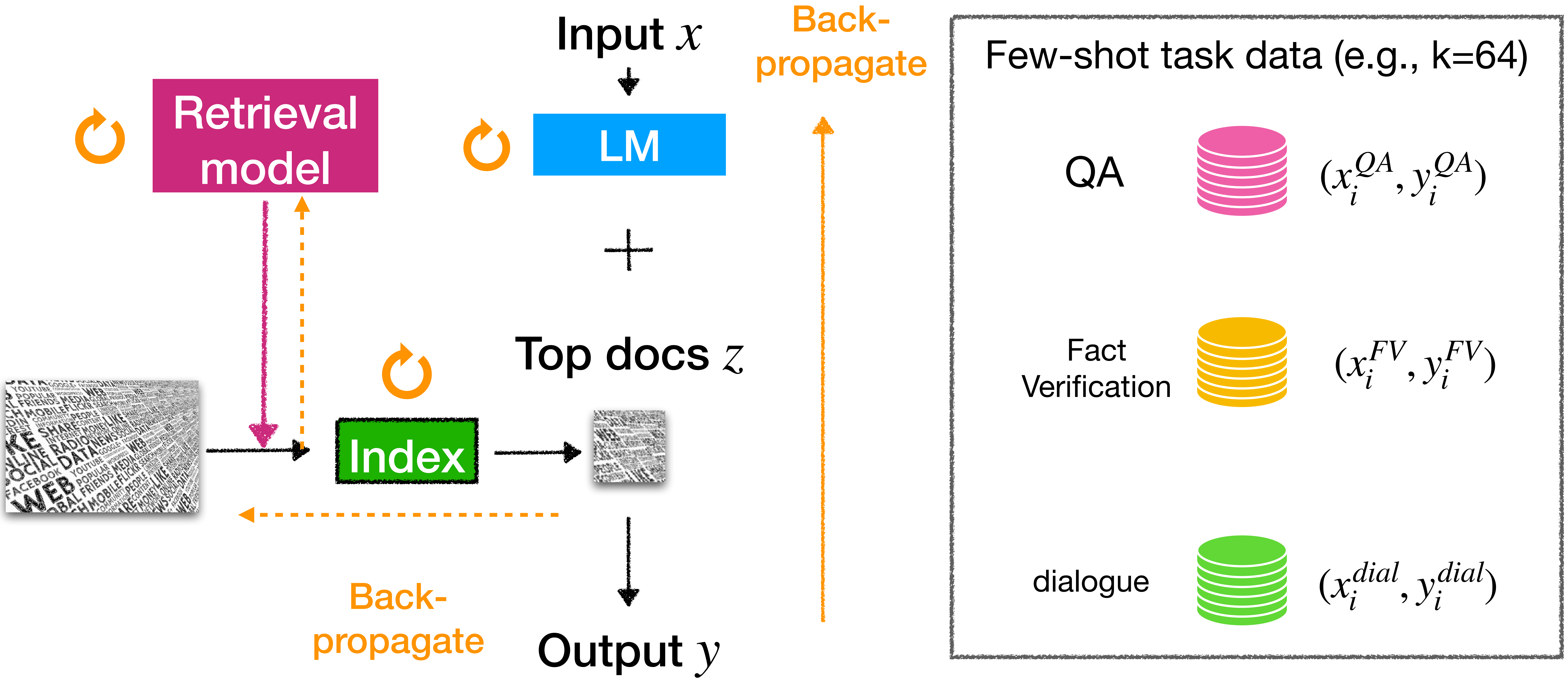
Independent training (DPR)
Asynchronous updates (REALM)
…

ATLAS (Izacard et al., 2022; Section 4)



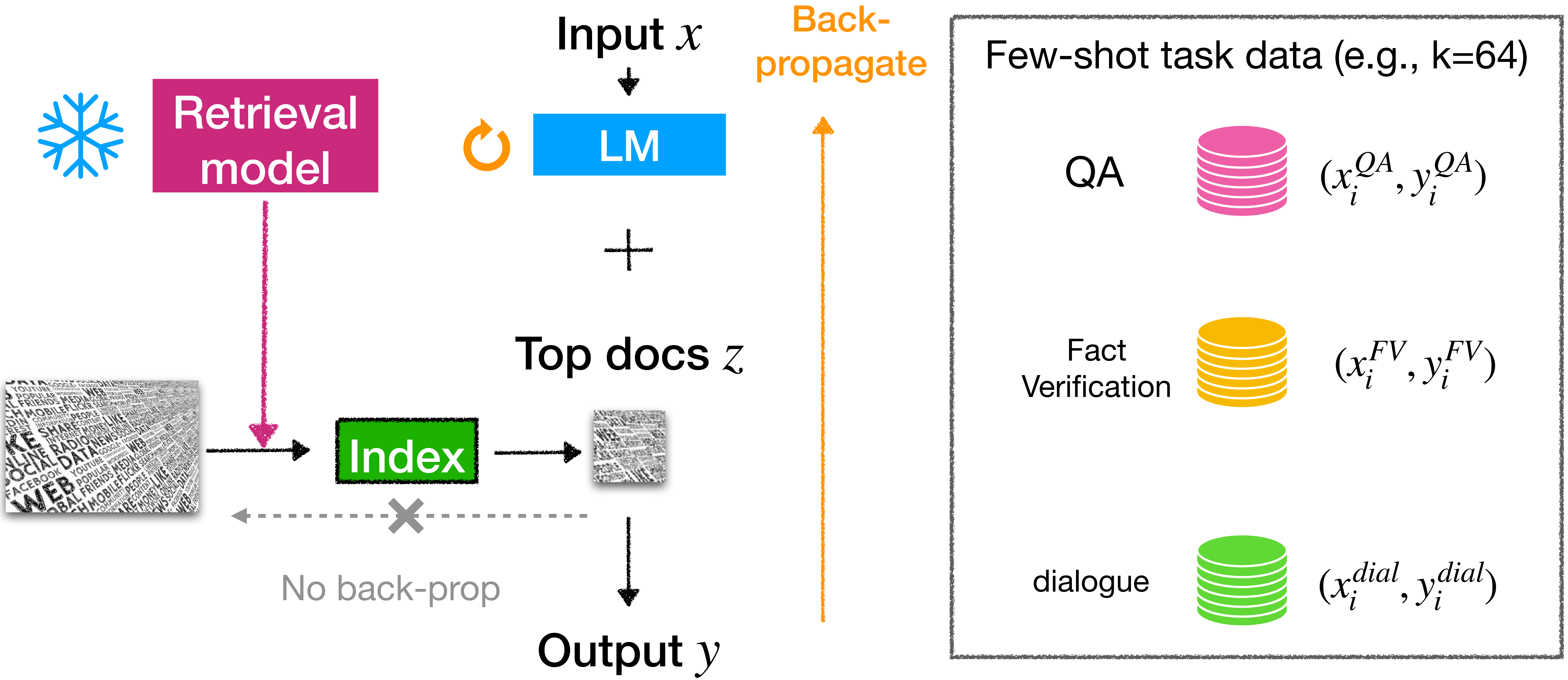
Izacard et al. 2022. “Few-shot learning with retrieval augmented language models”

ATLAS (Izacard et al., 2022; Section 4)

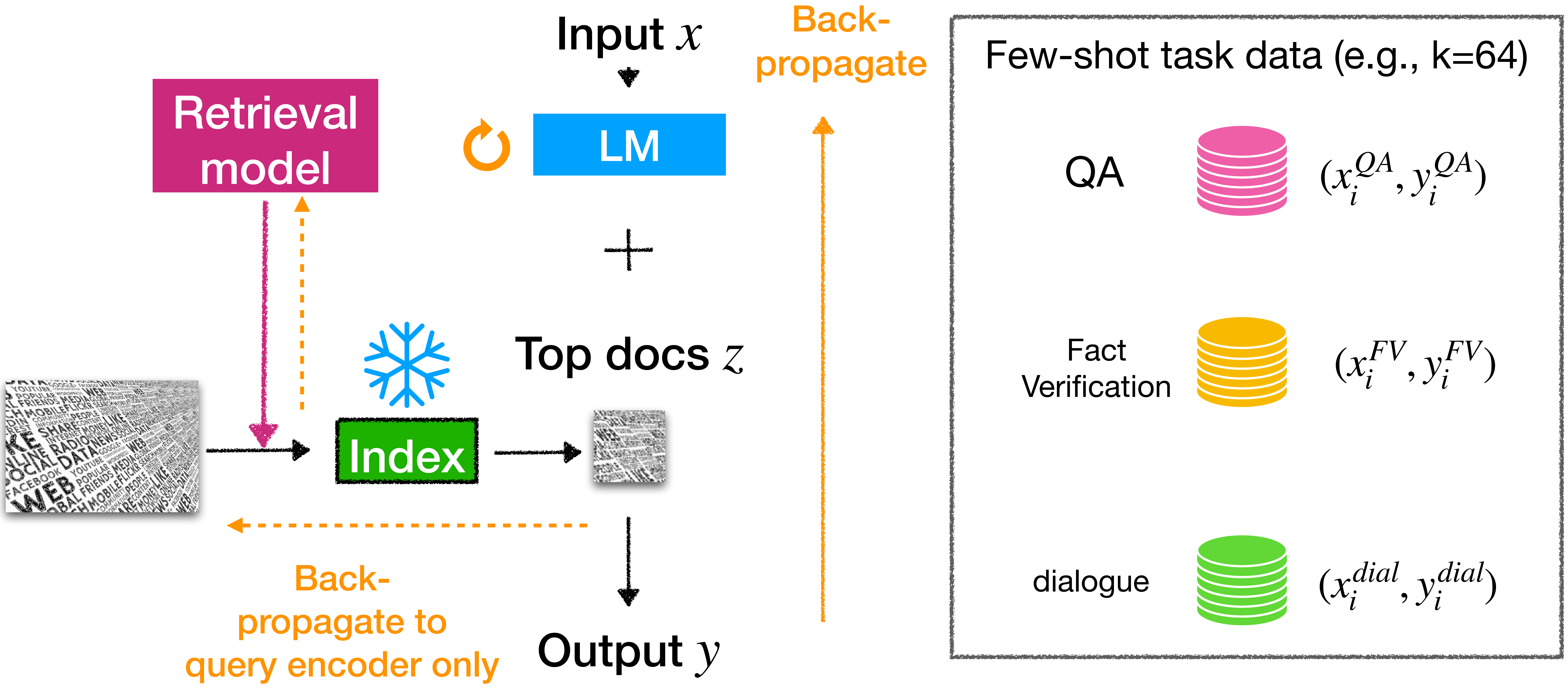


Fully updating retrieval model & index
during training expensive!

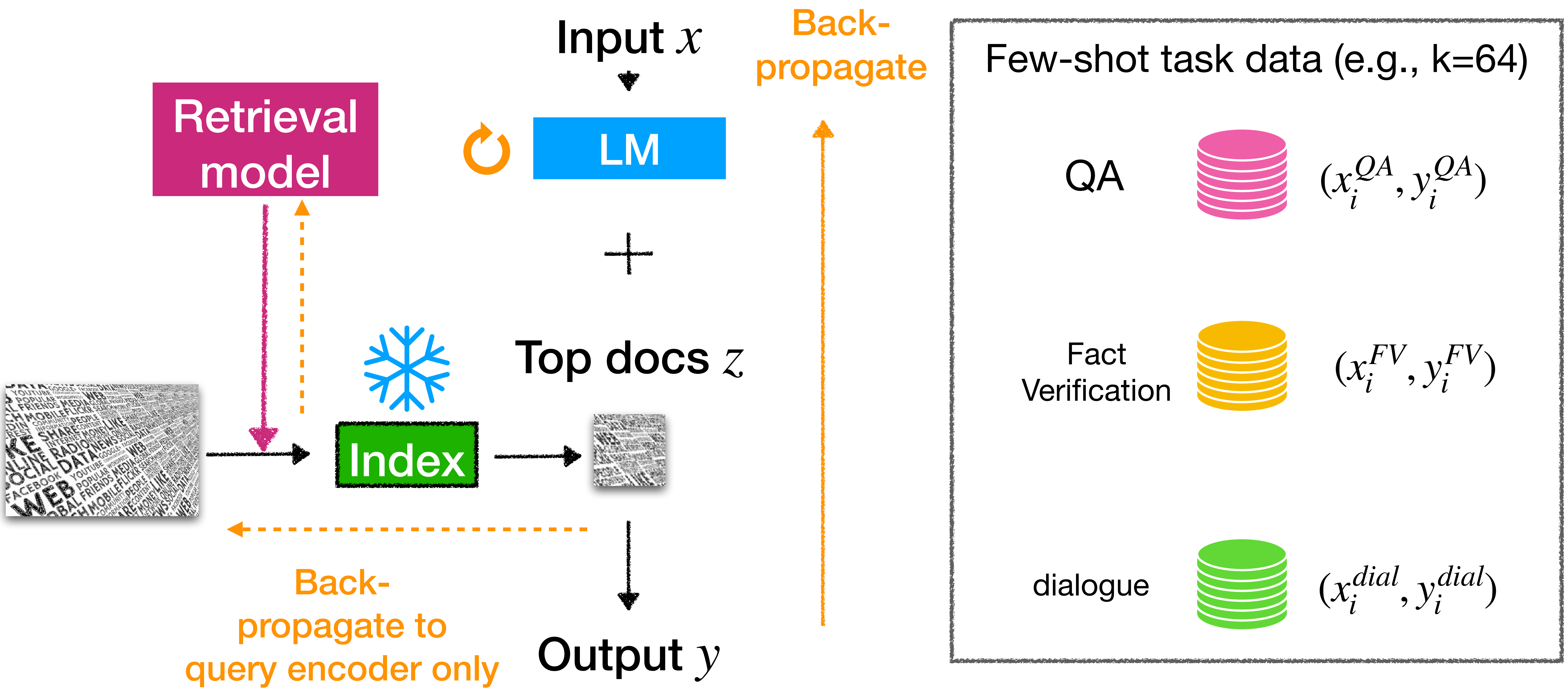
ATLAS: fixed retrieval with fine-tuned LM



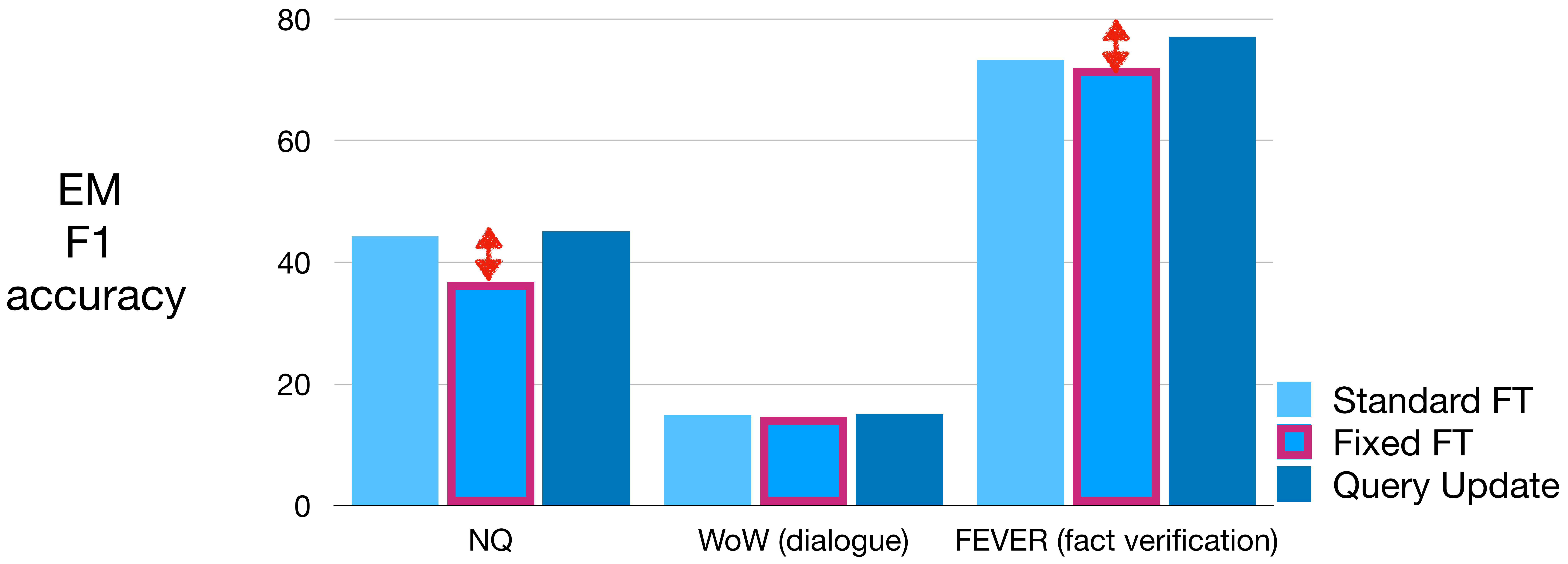
ATLAS: query-encoder only updates



ATLAS: full / transfer v.s. few dataset settings

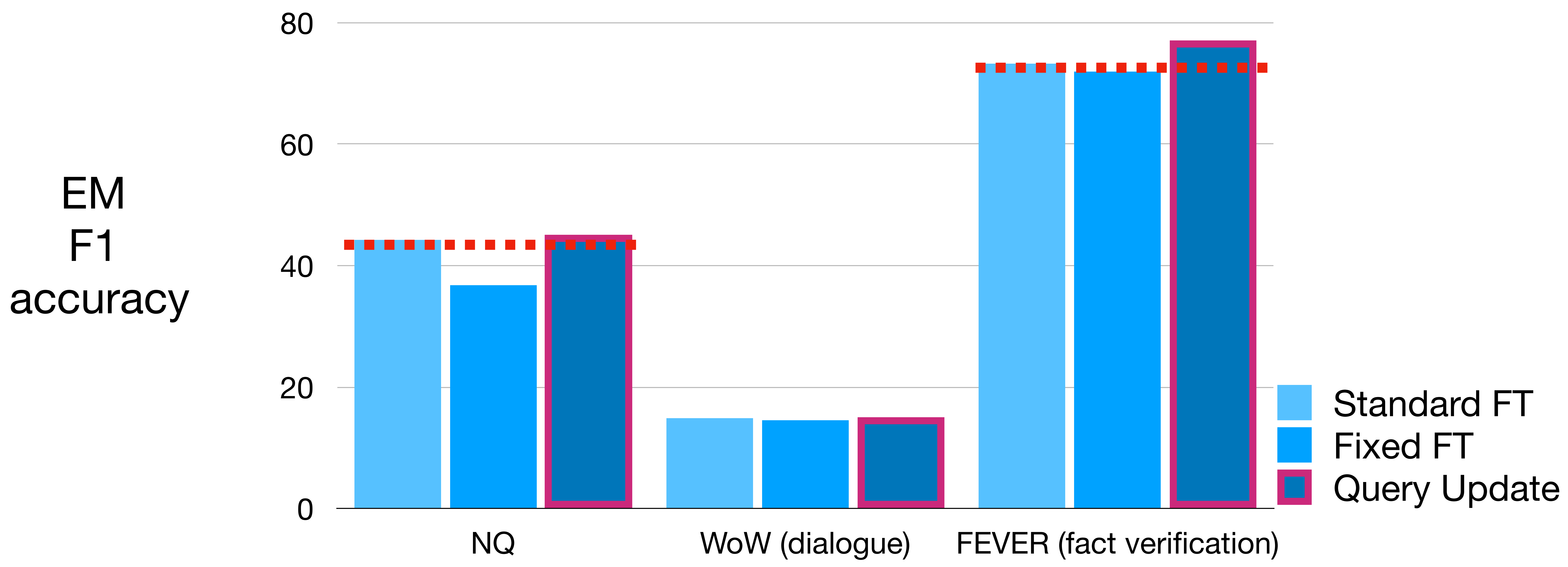


Ablations of efficient retrieval training



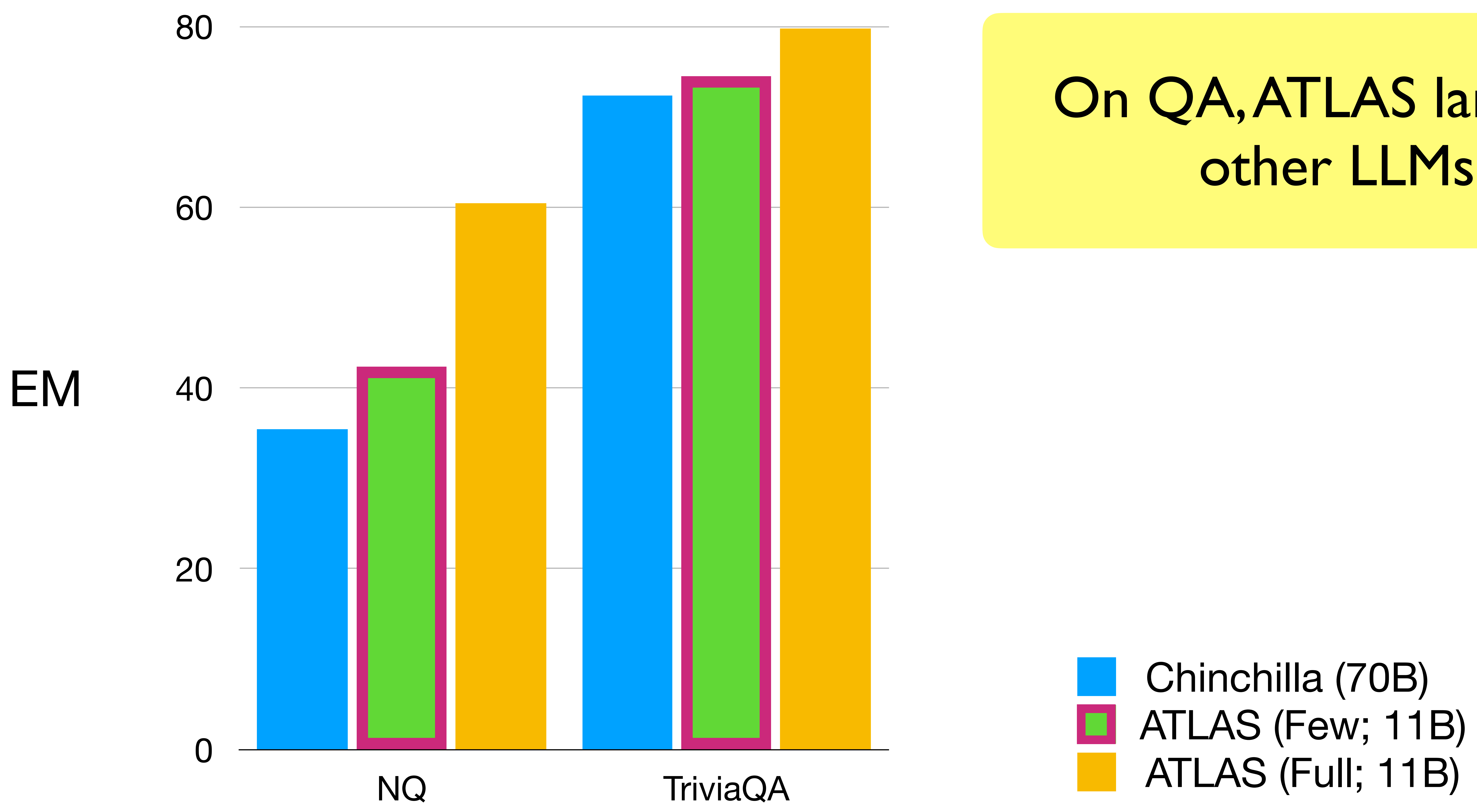
Fixed FT shows large performance drop on QA.

Ablations of efficient retrieval training



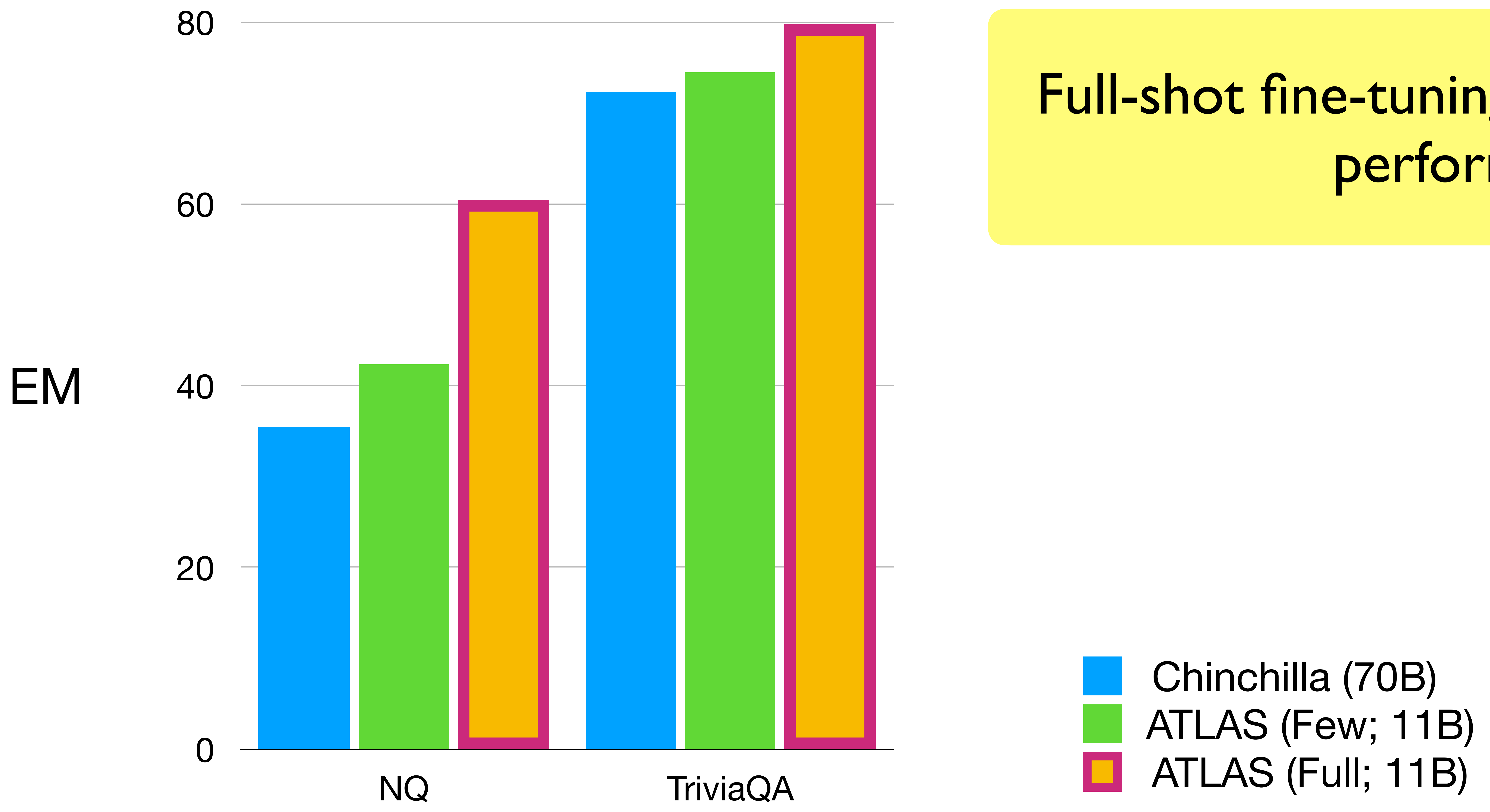
Query-side fine-tuning match or outperforms full fine-tuning

Task Results



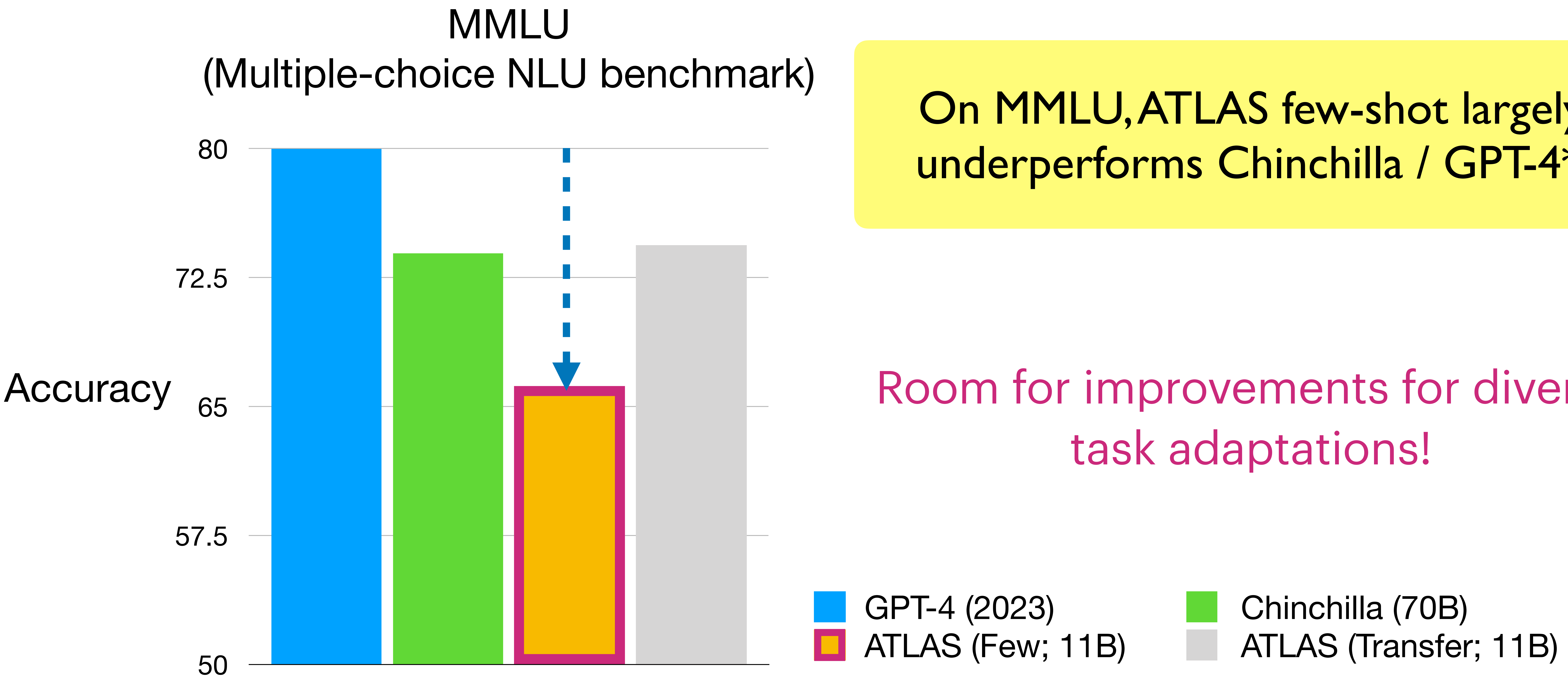
On QA, ATLAS largely outperforms other LLMs in few-shot

Task Results



Full-shot fine-tuning further improves performance

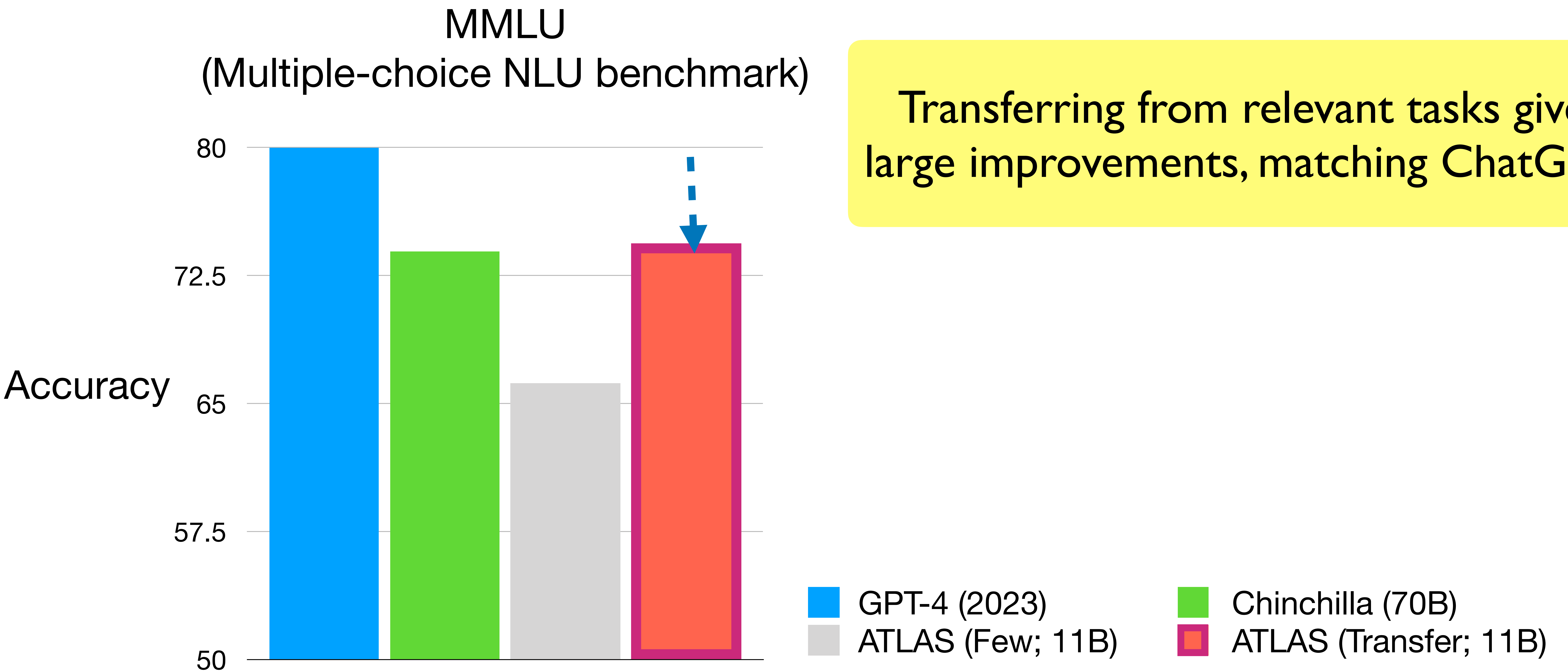
Task Results



On MMLU, ATLAS few-shot largely underperforms Chinchilla / GPT-4*.

Room for improvements for diverse task adaptations!

Task Results



Transferring from relevant tasks give large improvements, matching ChatGPT

Summary of downstream adaptations

	Target task	Adaptation method	Datastore
ATLAS (Izacard et al., 2022)	Knowledge-intensive	Fine-tuning (DS & LM)	Wikipedia | CC

Fine-tuning for QA & knowledge-intensive tasks often gives strong performance (*even in few-shot*)

Summary of downstream adaptations

	Target task	Adaptation method	Datastore
ATLAS (Izacard et al., 2022)	Knowledge-intensive	Fine-tuning (DS & LM)	Wikipedia | CC

Fine-tuning a retriever for a task matters!

Downstream adaptation of retrieval-based LMs

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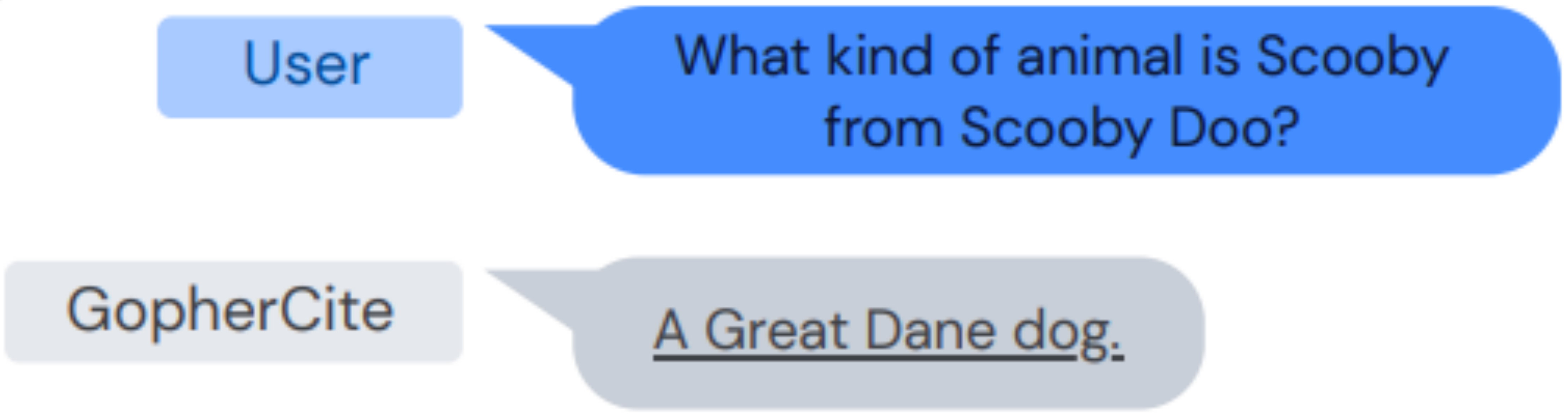
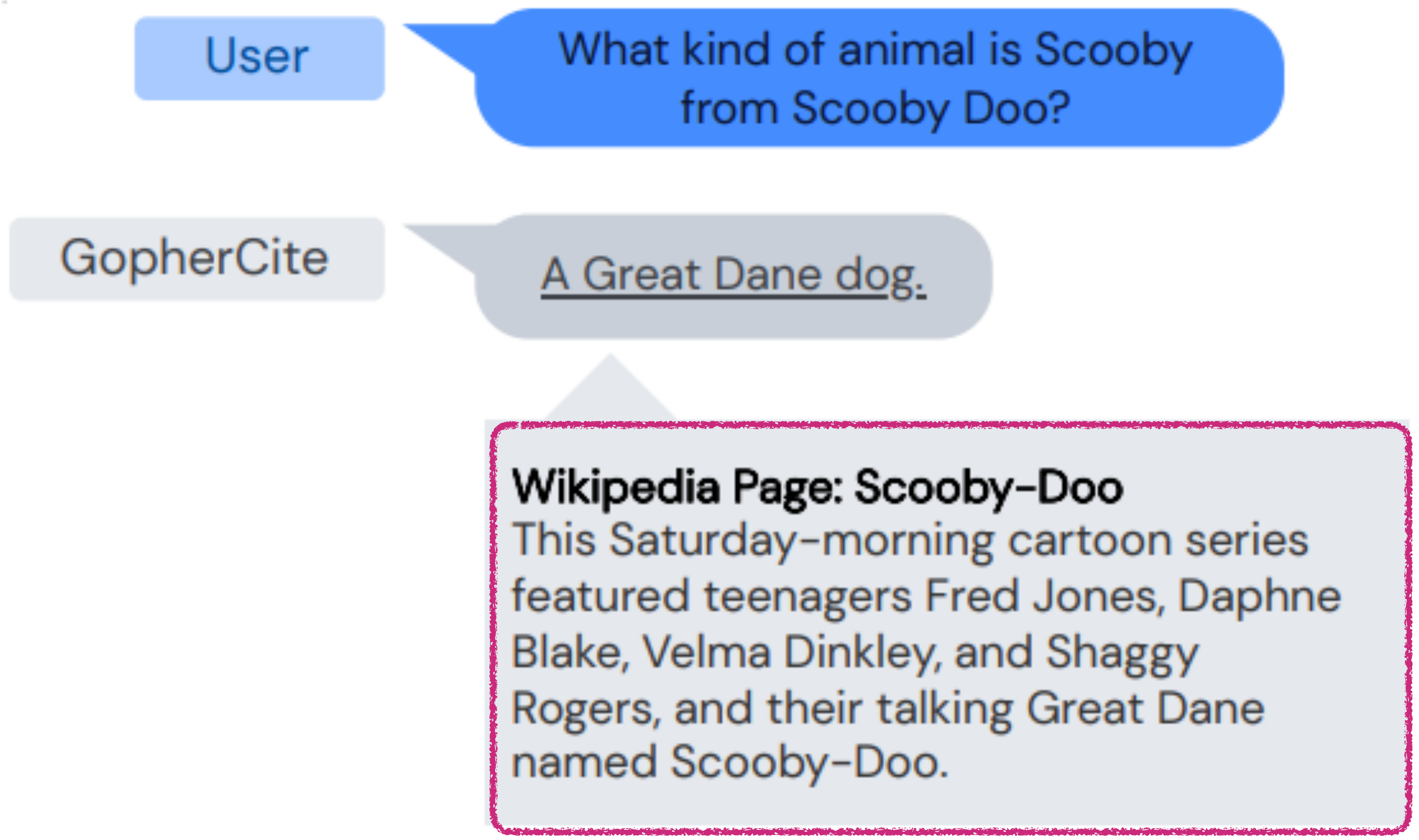
GopherCite (Menick et al., 2022)



Menick et al. 2022. “GopherCite: Teaching language models to support answers with verified quotes”

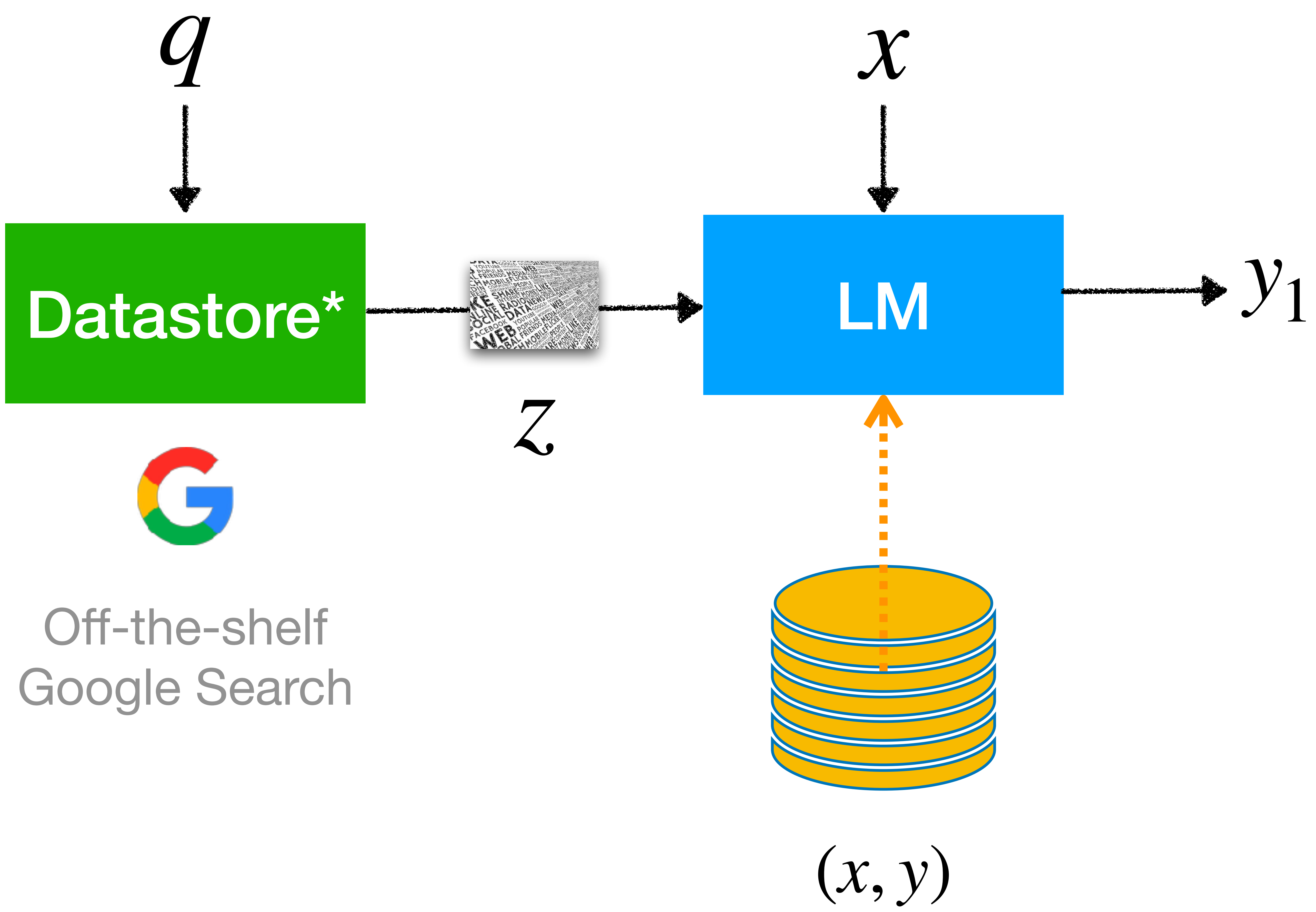
GopherCite (Menick et al., 2022)



Extract and generate a quote to support an answer

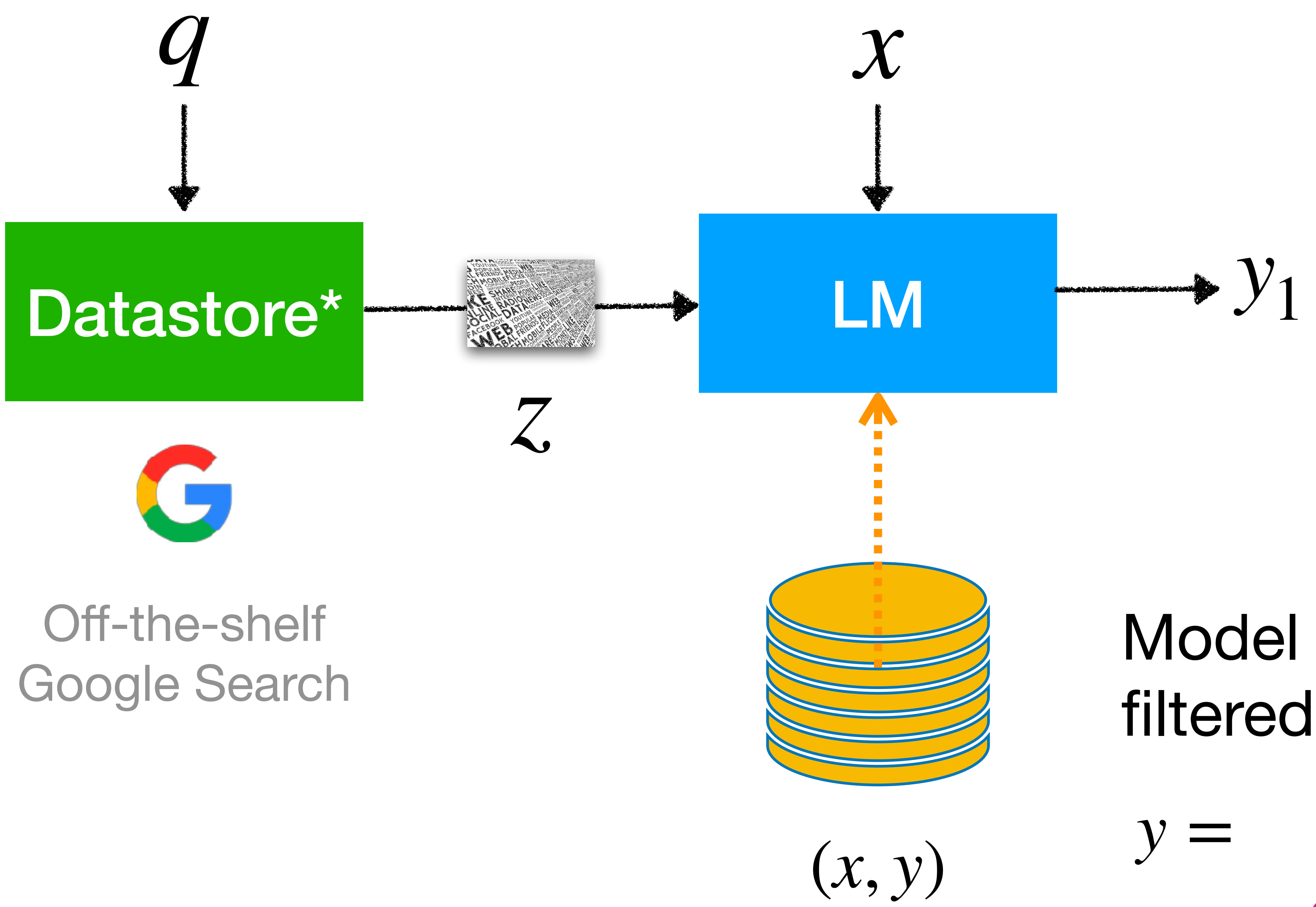
Menick et al. 2022. "GopherCite: Teaching language models to support answers with verified quotes"

GopherCite: RLHF for answering with verified quotes



Supervised fine-tuning (SFT)

GopherCite: RLHF for answering with verified quotes



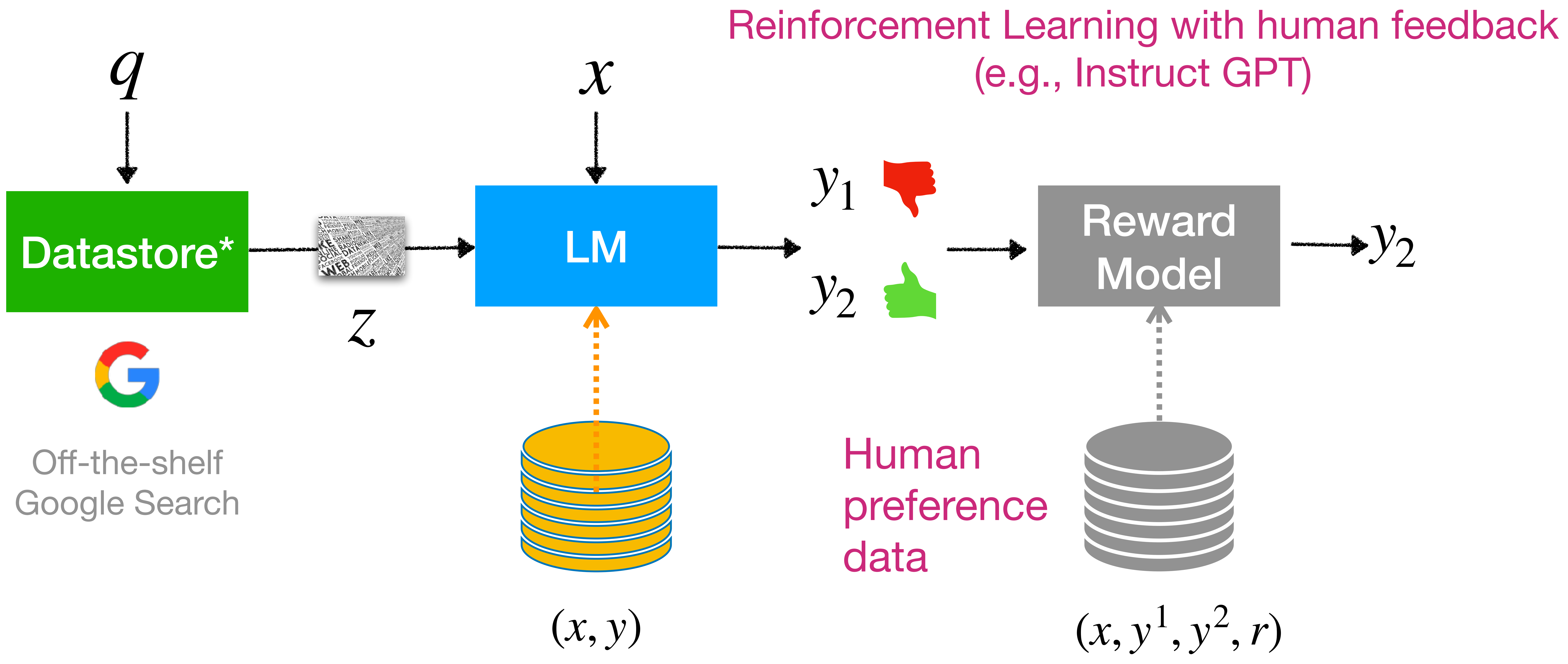
Supervised fine-tuning (SFT)

Model generated training data
filtered by human

$y =$

`%<Claim>%(Document title)%[Quote from document]%`

GopherCite: RLHF for answering with verified quotes



GopherCite: RLHF for answering with verified quotes

(x, y^1, y^2) →

Human rater

Plausible as an answer to the input

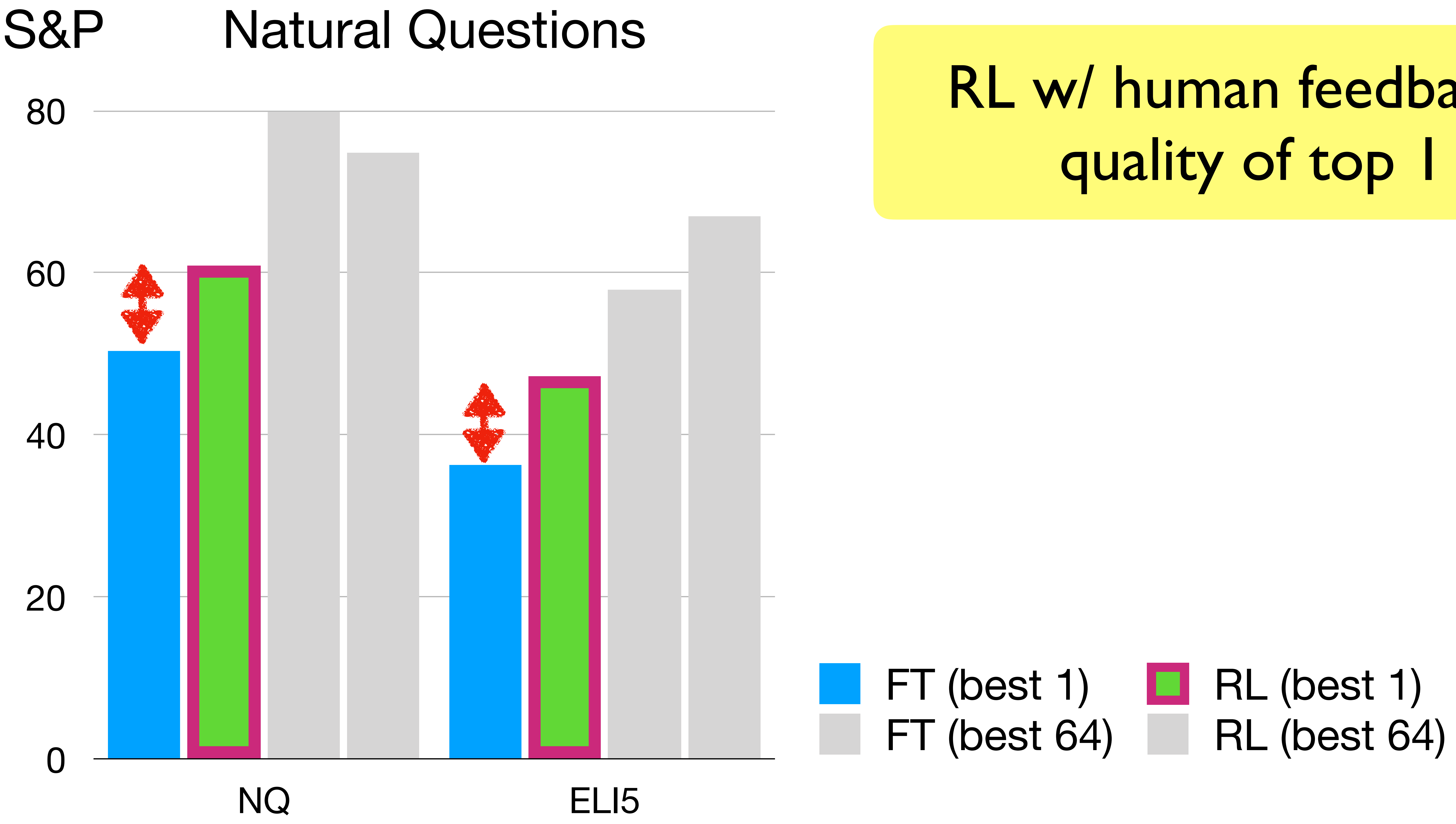
Supported by accompanying evidence

→ $r \in y_1, y_2$

33k Human preference data

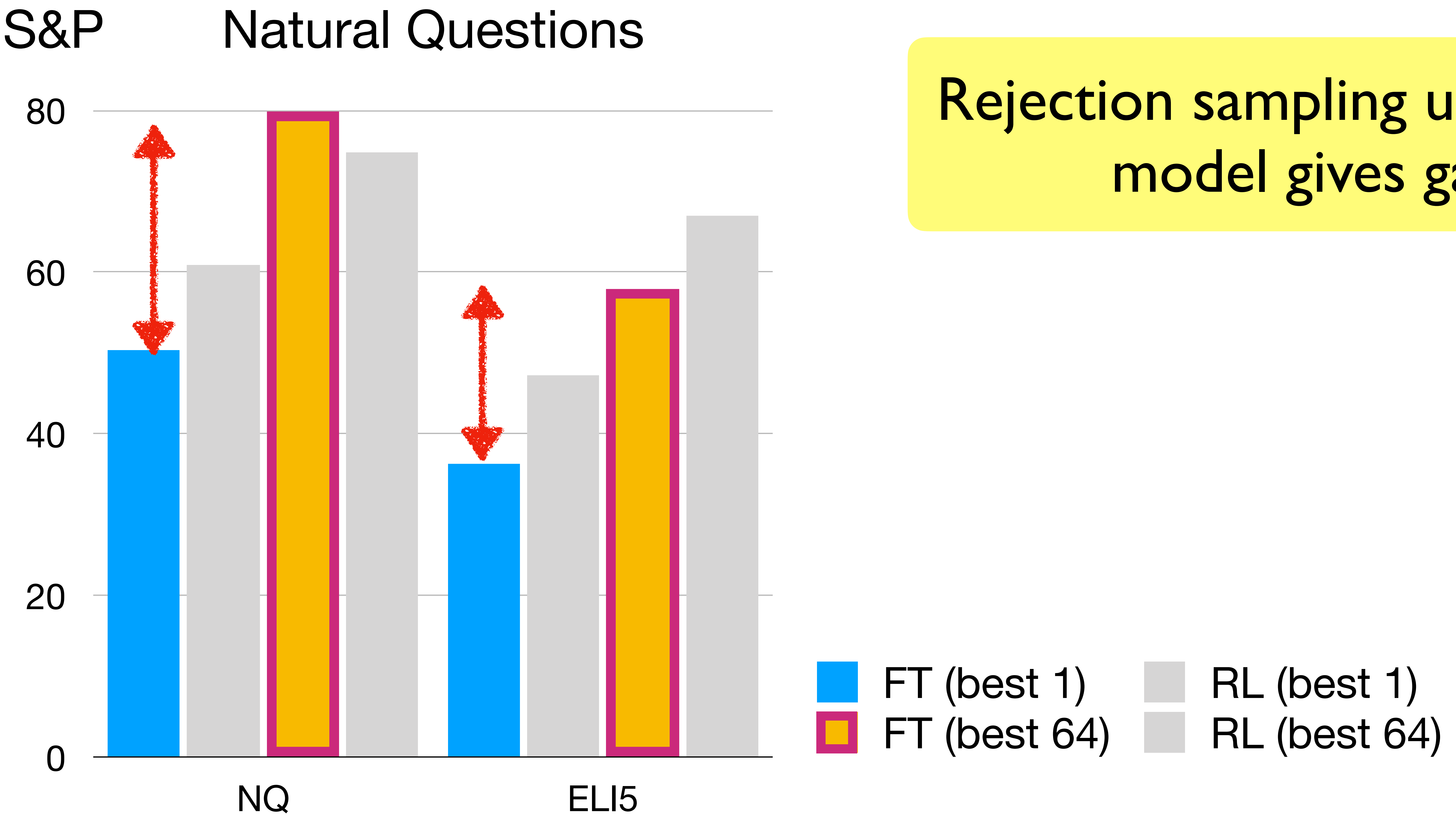
(x, y^1, y^2, r)

GopherCite: effects of RL



RL w/ human feedback improves the quality of top 1 generations

GopherCite: effects of RL



Rejection sampling using trained reward model gives gains from FT

Summary of downstream adaptations

	Target task	Adaptation method	Datastore
ATLAS (Izacard et al., 2022)	Knowledge-intensive	Fine-tuning (DS & LM)	Wikipedia | CC
GopherCite (Menick et al., 2022)	Open-domain QA, Long-form QA	Fine-tuning + RL (LM)	Google Search Results

Benefit of **fine-tuning**-based approaches

- Customizable
- Competitive w/ more data
- Require training

Summary of downstream adaptations

	Target task	Adaptation method	Datastore
ATLAS (Izacard et al., 2022)	Knowledge-intensive	Fine-tuning (DS & LM)	Wikipedia | CC
GopherCite (Menick et al., 2022), also WebGPT (Nakano et al., 2021)	Open-domain QA, Long-form QA	Fine-tuning + RL (LM)	Google Search Results

Benefit of **RL**

- Better alignment with user preferences
- Require additional data collection (preference)

Summary of downstream adaptations

	Target task	Adaptation method	Datastore
ATLAS (Izacard et al., 2022)	Knowledge-intensive	Fine-tuning (DS & LM)	Wikipedia | CC
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What if we cannot train LMs for downstream tasks?
(e.g., lack of computational resources / proprietary LM … etc)

Downstream adaptation of retrieval-based LMs

What are the **tasks**?

- Open-domain QA
- Other knowledge-intensive tasks
- General NLU
- Language Modeling & other generation tasks

How to **adapt?**

- Fine-tuning
- Reinforcement learning
- **Prompting**

What is **data store?**

- Wikipedia
- Web (Google / Bing Search Results)
- Training data

Prompting

k-shot instances (k=0, 32 … etc)

Doesn't require LM training on tasks!

Q: who Is the US president
A: Joe Biden
##
Q: What is the capital of US?
A: Washington DC.
##

Training instances (demonstrations)

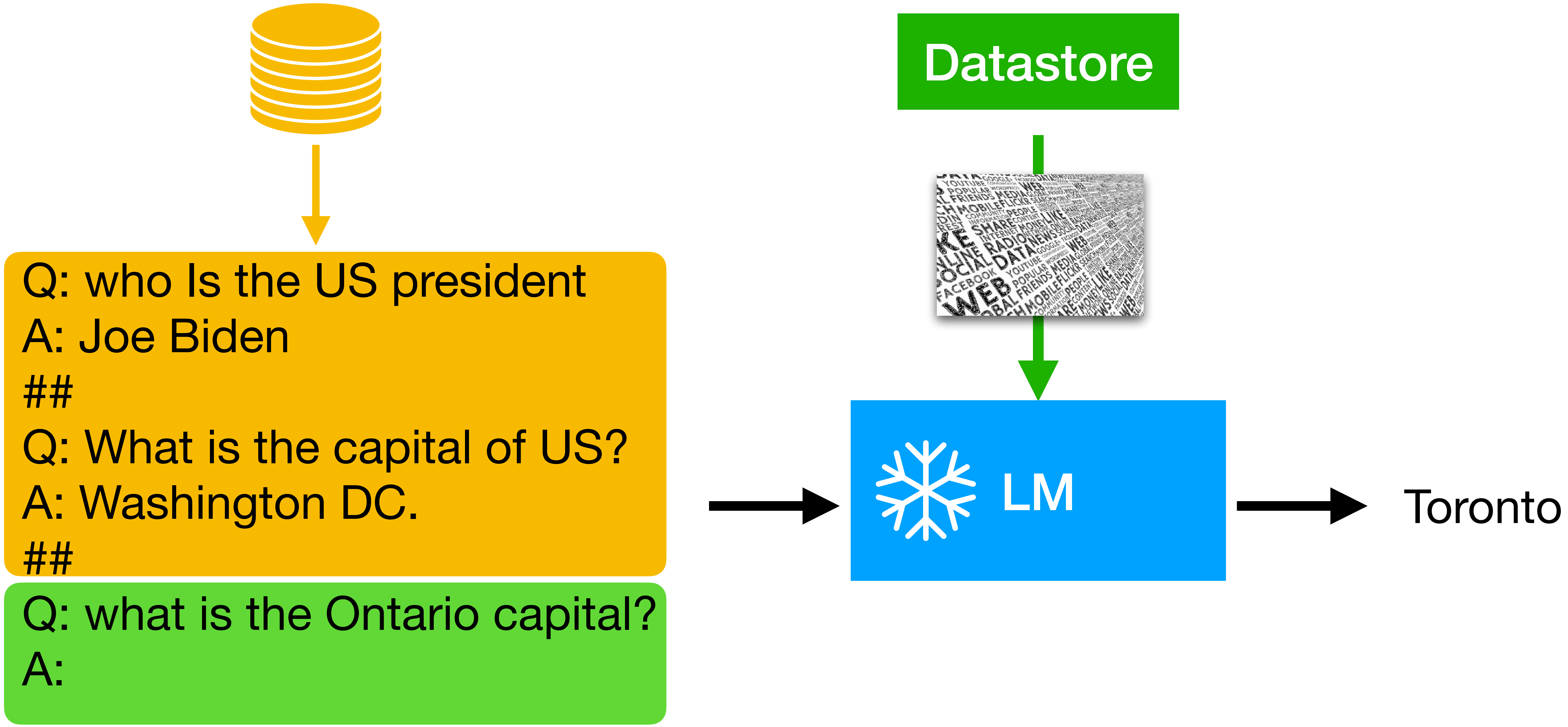
Q: what is the Ontario capital?
A:

Toronto

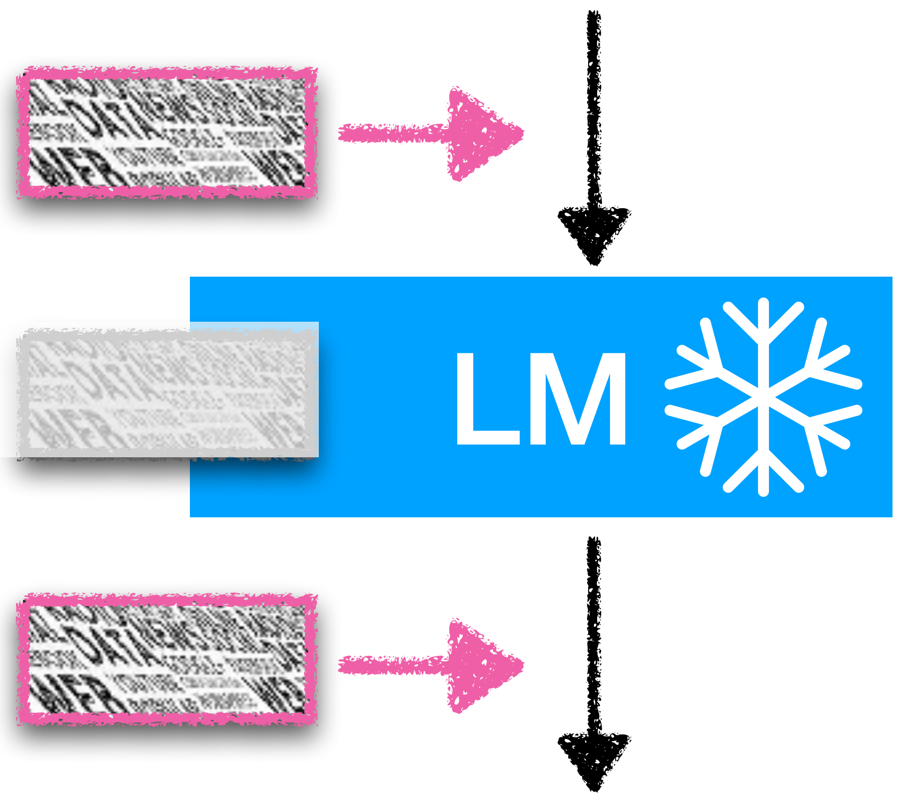
Test instances

Retrieval-based prompting

k-shot instances (k=0, 32 … etc)



Design choice of retrieval-based Prompting

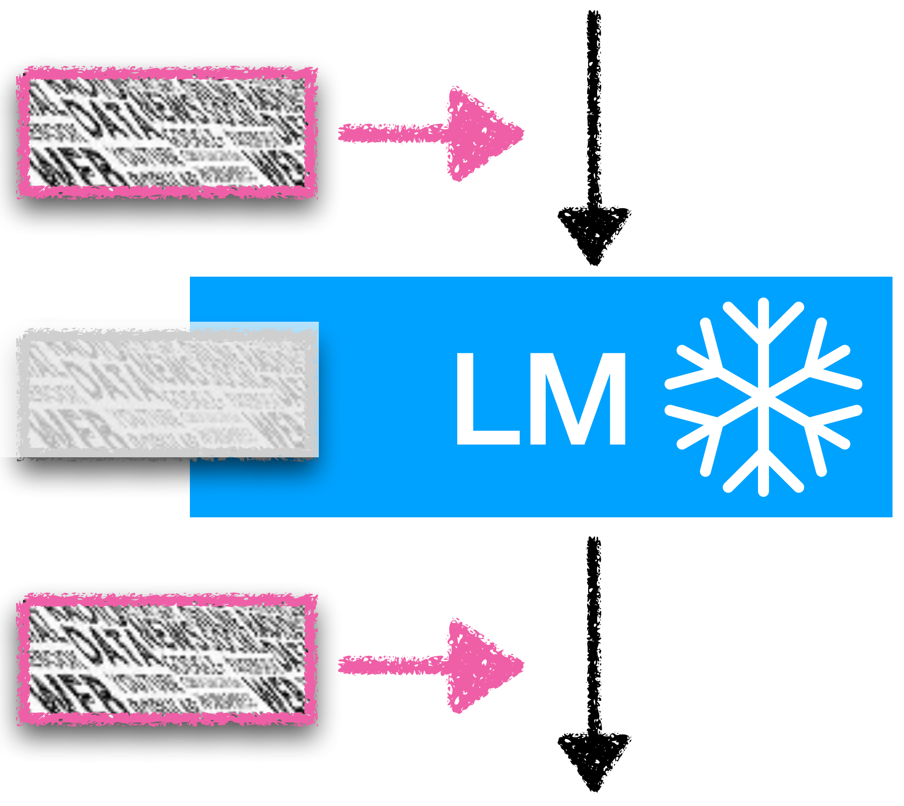


Input space:
Incorporate retrieved context in input space

Intermediate layers:
N/A

Output space:
Interpolate token probability distributions in output space

Design choice of retrieval-based Prompting



Input space:
Incorporate retrieved context in input space

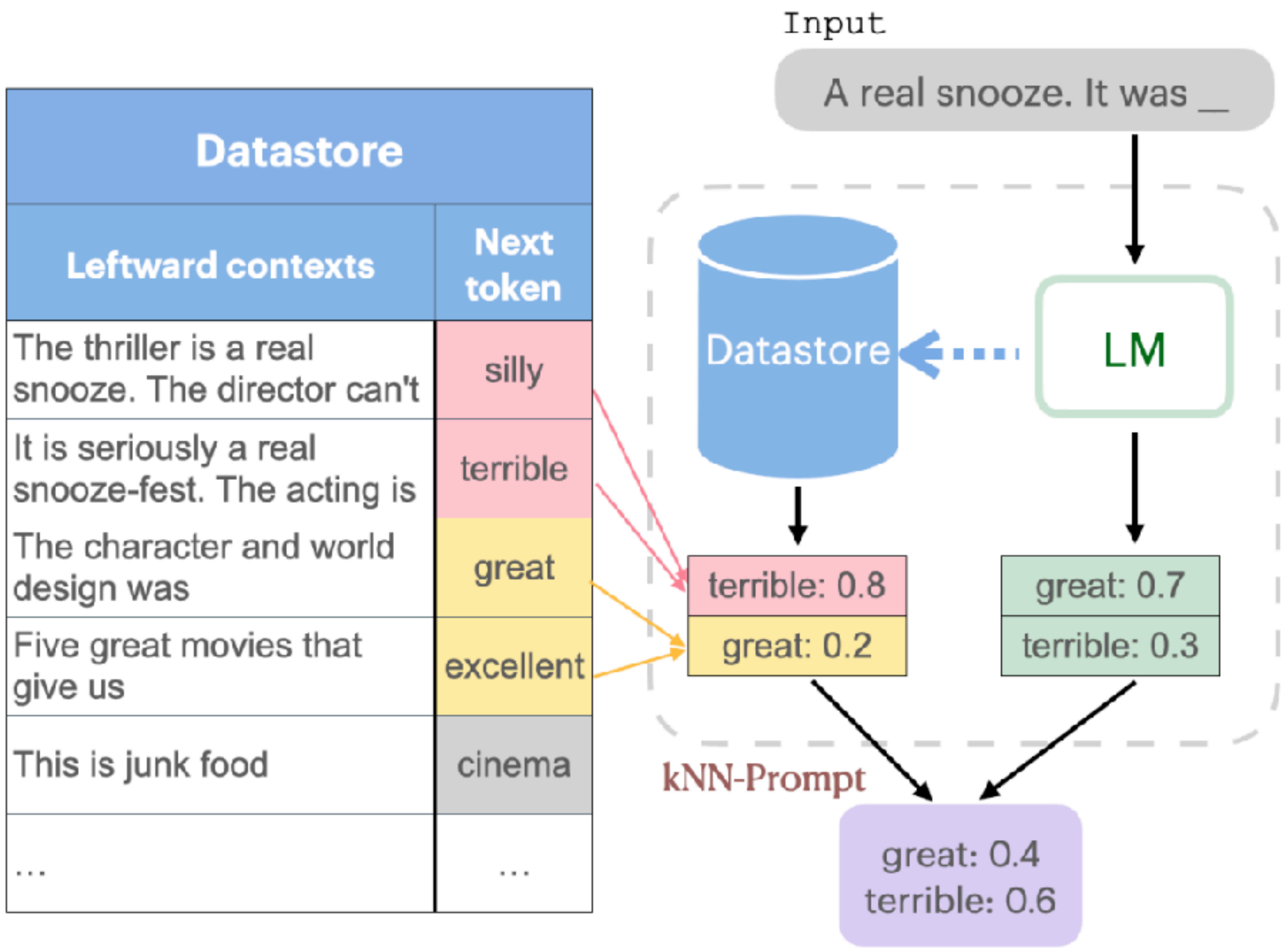
Intermediate layers:
N/A

Output space:
Interpolate token probability distributions in output space

Extending kNN-LM for downstream tasks

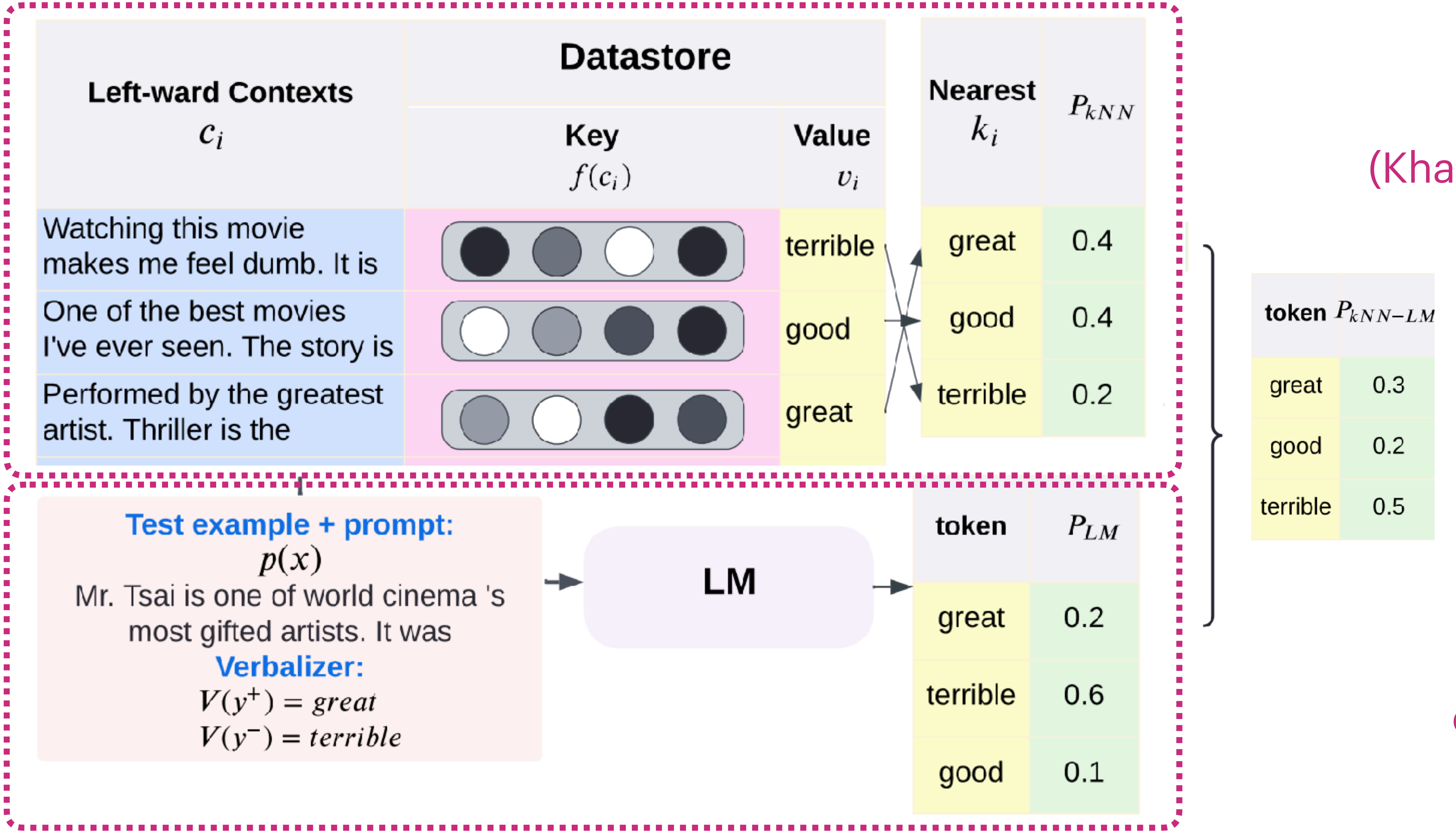
kNN-prompt (Shi et al., 2022)

kNN LM with fuzzy verbalizers
for zero-/few-shot **classification**



Shi et al. 2022. “Nearest Neighbor Zero-shot Inference”

kNN-prompt (Shi et al., 2022)

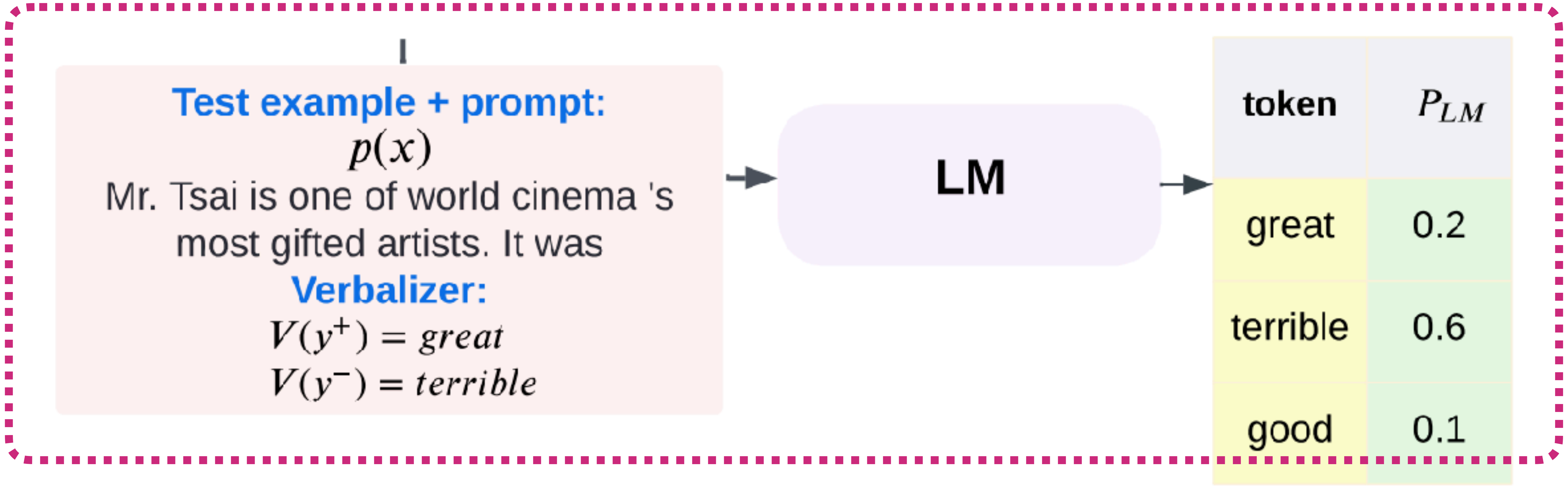


kNN-LM
(Khandelwal et al., 2020

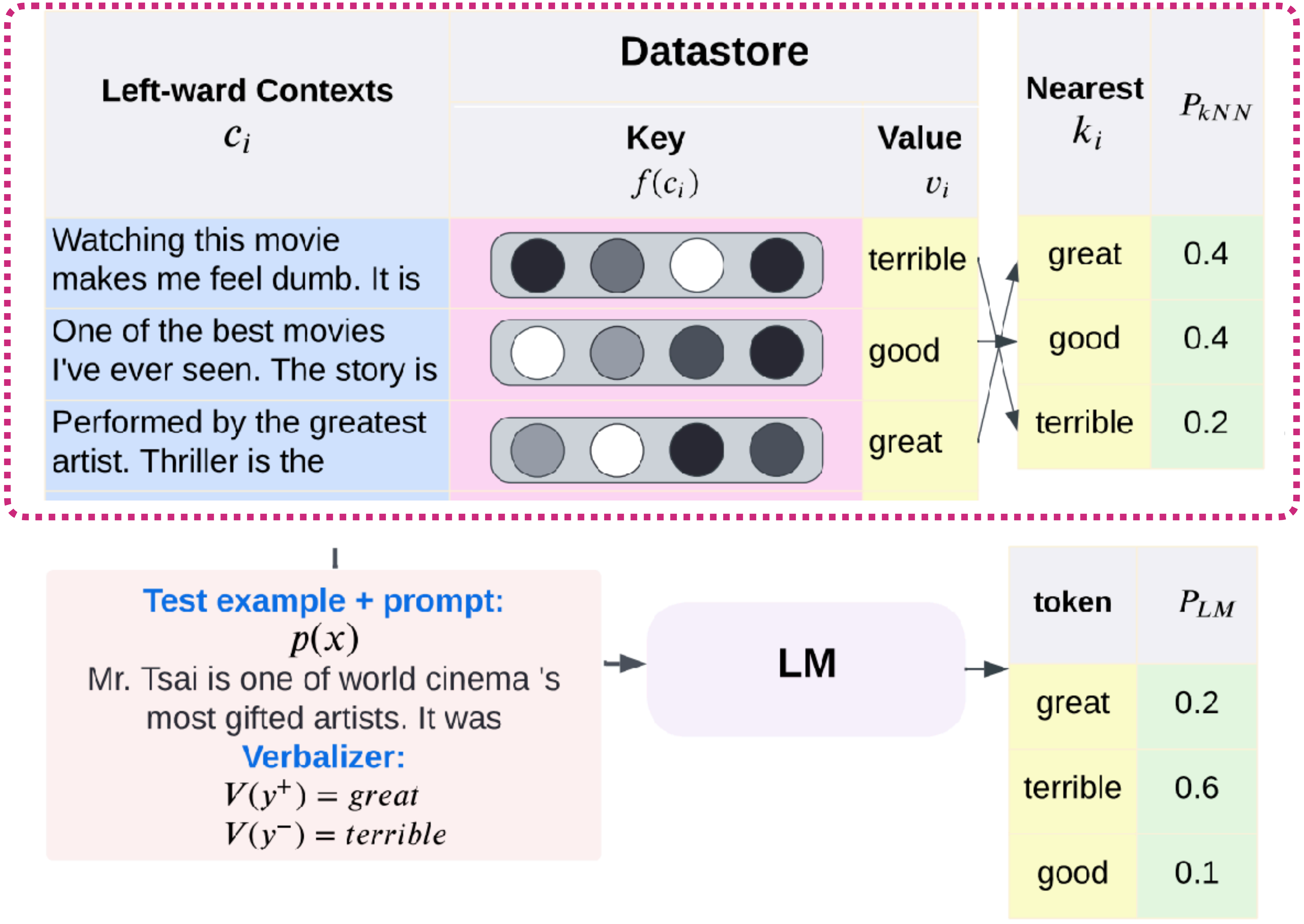
The kNN token distributions are quite sparse

kNN-prompt (Shi et al., 2022)

LM predicts next token

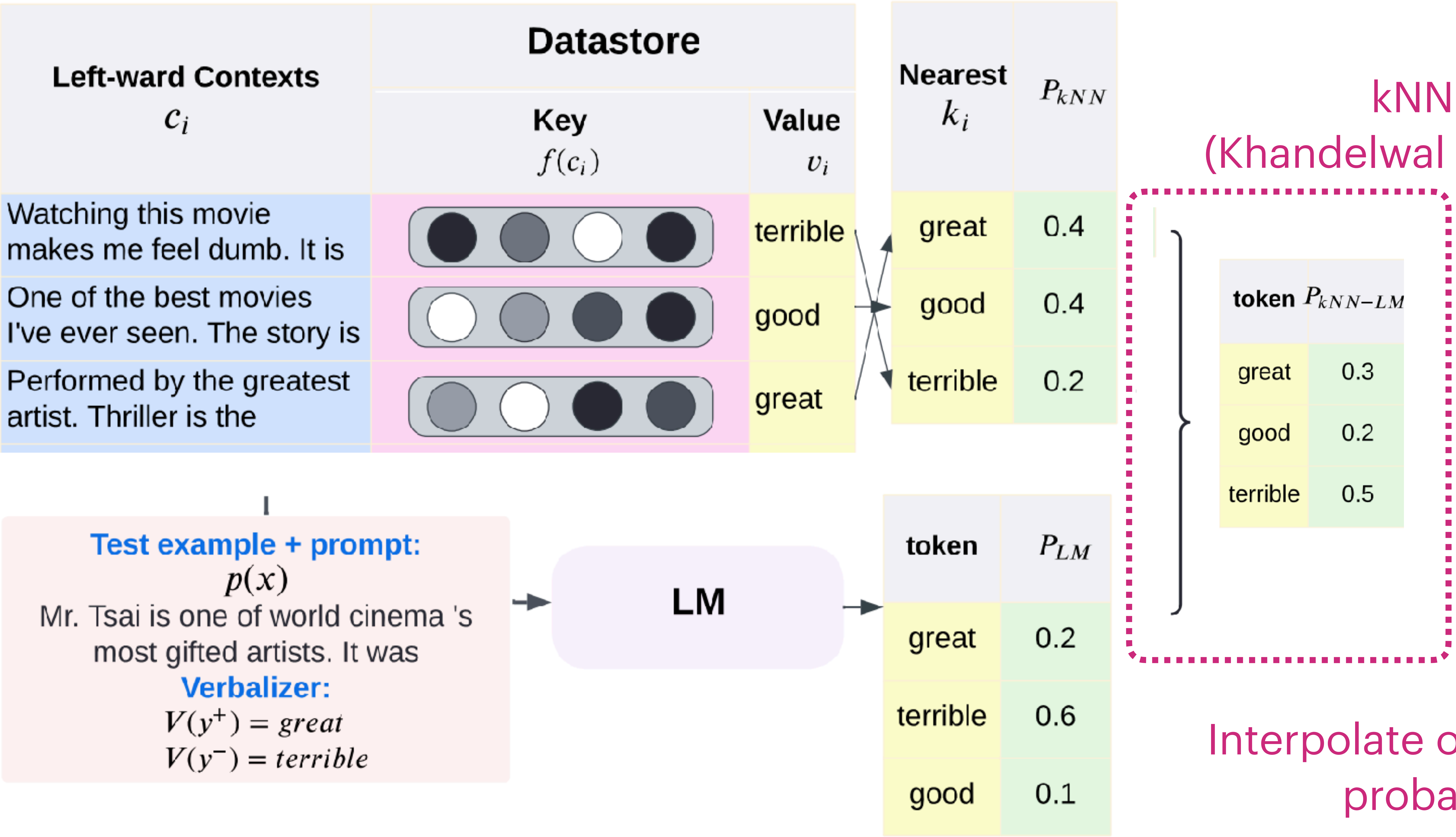


kNN-prompt (Shi et al., 2022)



kNN predicts next tokens

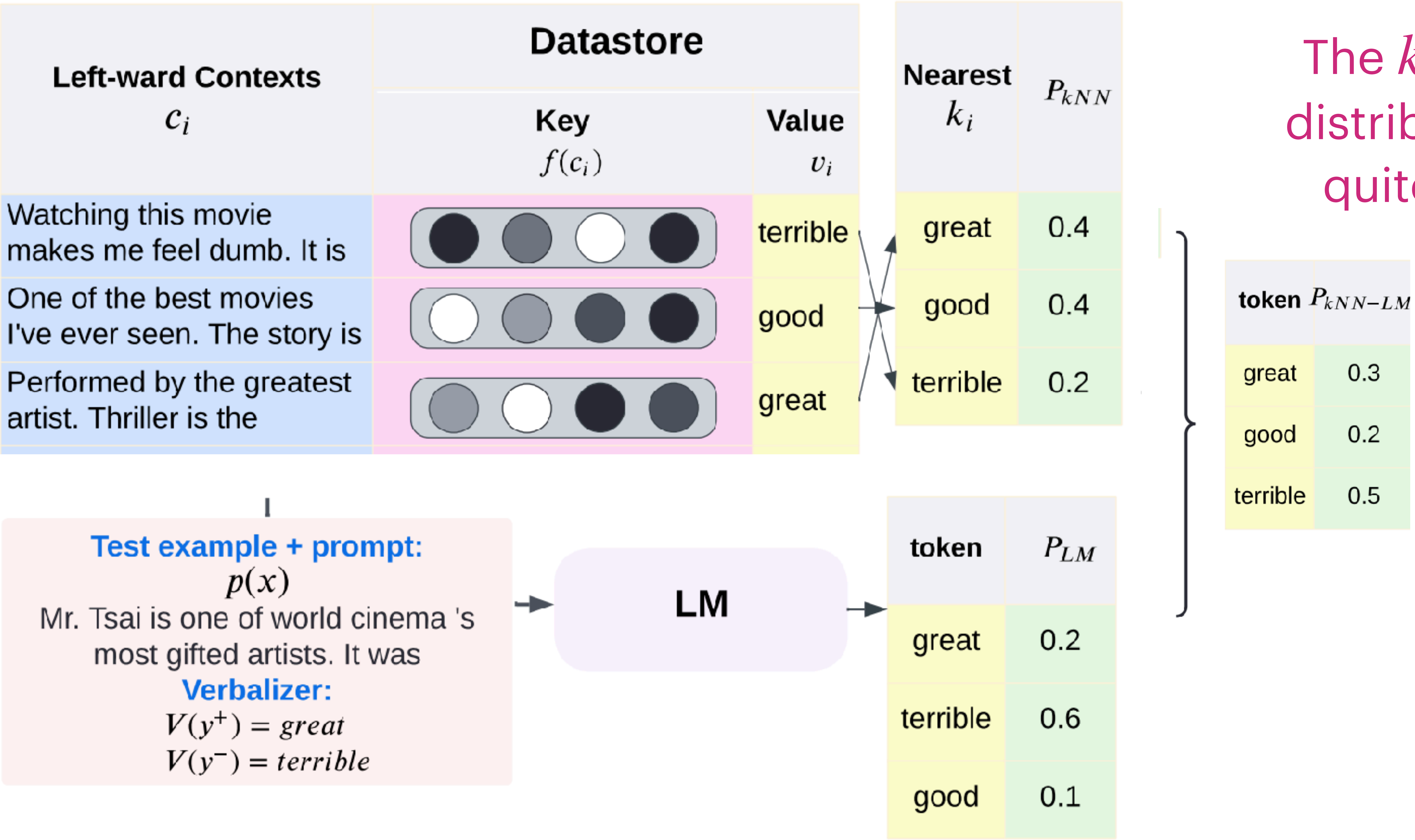
kNN-prompt (Shi et al., 2022)



kNN-LM
(Khandelwal et al., 2020)

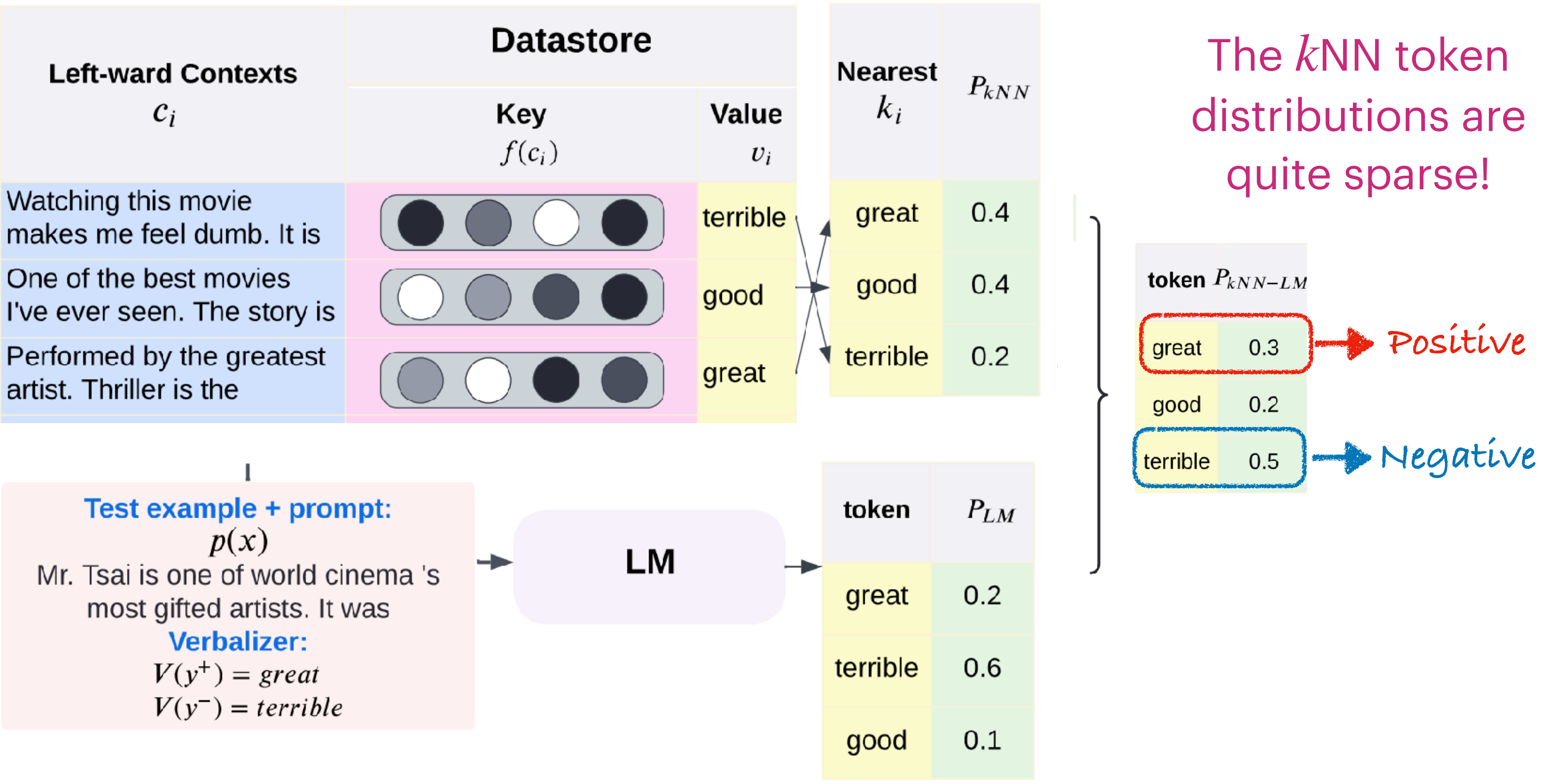
Interpolate output token probability

kNN-prompt (Shi et al., 2022)



The kNN token distributions are quite sparse!

kNN-prompt (Shi et al., 2022)



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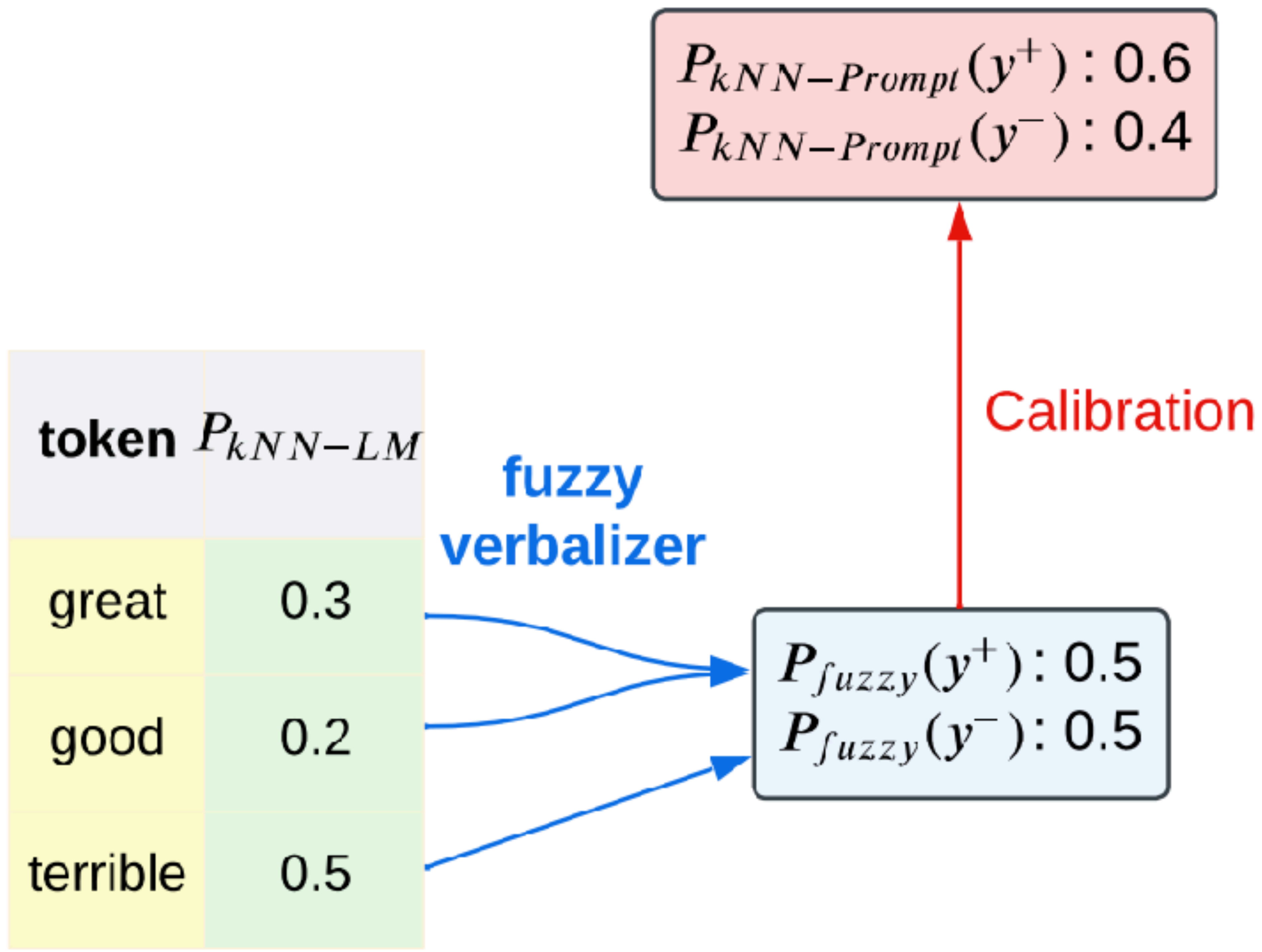
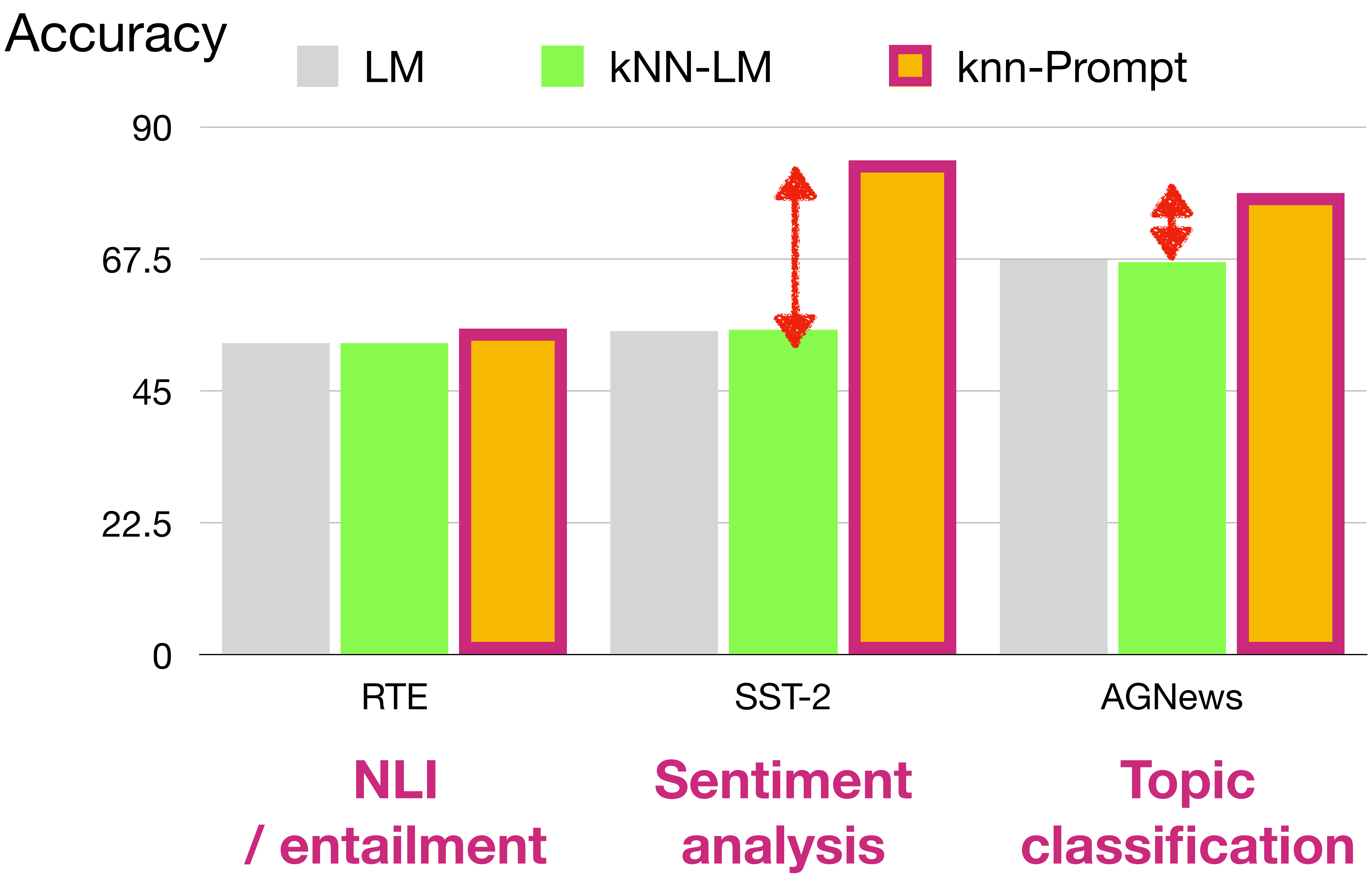


Fuzzy verbalizer maps token probability to target class labels

$$P_{FV}(y \mid x) \propto \sum_{v_i \in \mathcal{N}(v)} P(v_i \mid p(\mathbf{x}))$$

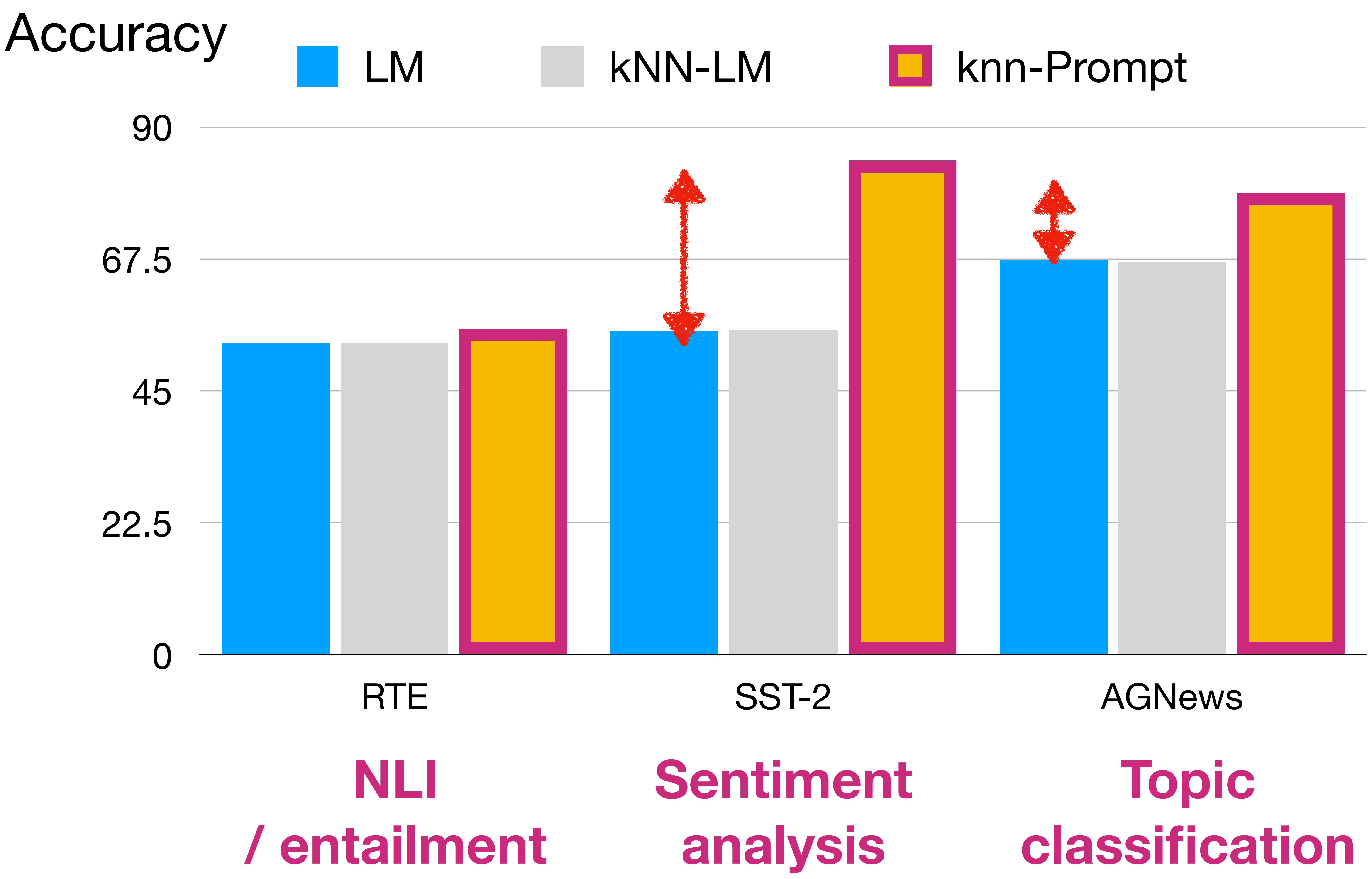
Find similar tokens using GloVe & ConceptNet

Results on diverse classification tasks



Significant gains from kNN-LM

Results on diverse classification tasks



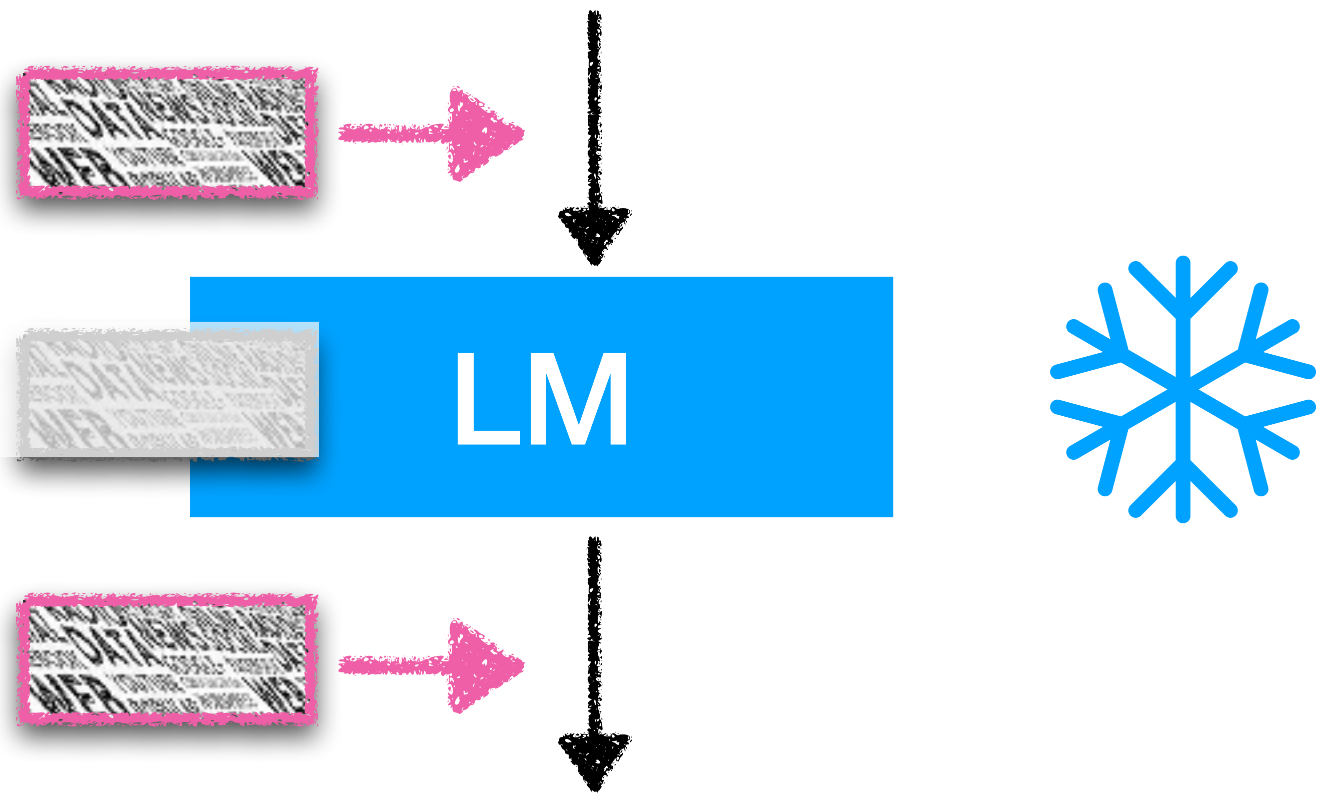
kNN prompt largely outperforms vanilla LM in zero-shot classification

Summary of downstream adaptations

	Target task	Adaptation method	Datastore
ATLAS (Izacard et al., 2022)	Knowledge-intensive	Fine-tuning (DS & LM)	Wikipedia | CC
GopherCite (Menick et al., 2022)	Open-domain QA, Long-form QA	Fine-tuning + RL (LM)	Google Search Results
kNN Prompt (Shi et al., 2022)	Classification	Prompting (output)	Wikipedia | CC

Retrieval-based LMs are effective in general NLU tasks!

Retrieval-based Prompting

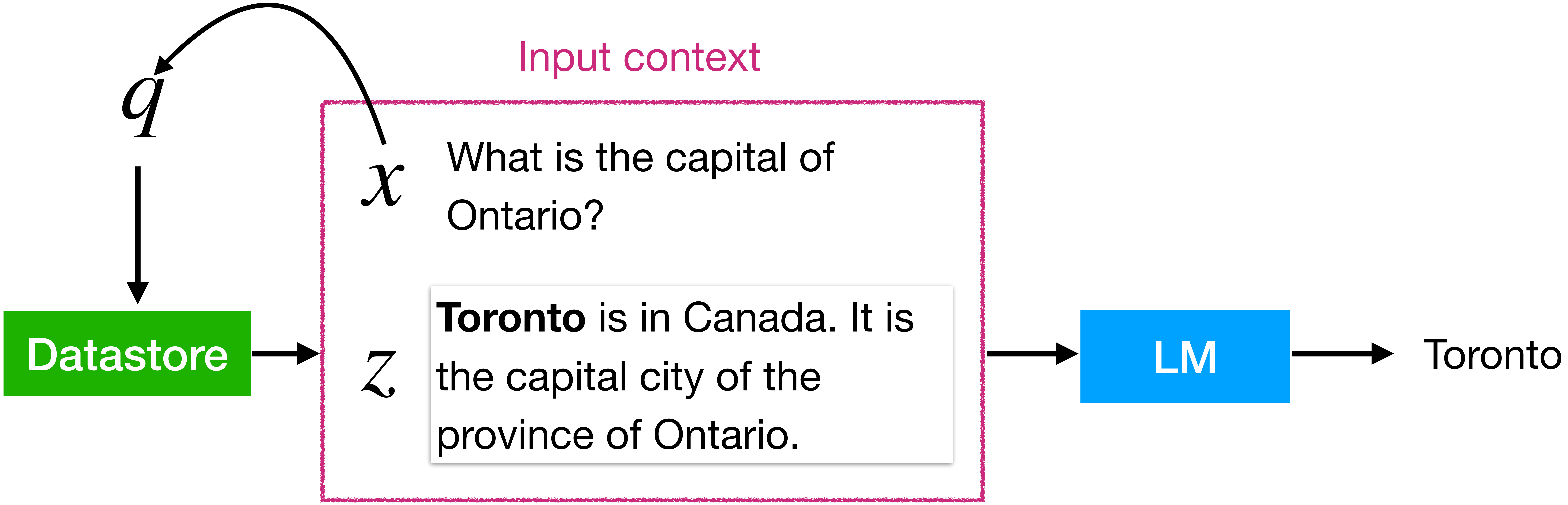


Input space:
Incorporate retrieved context in input space

Intermediate layers:
N/A

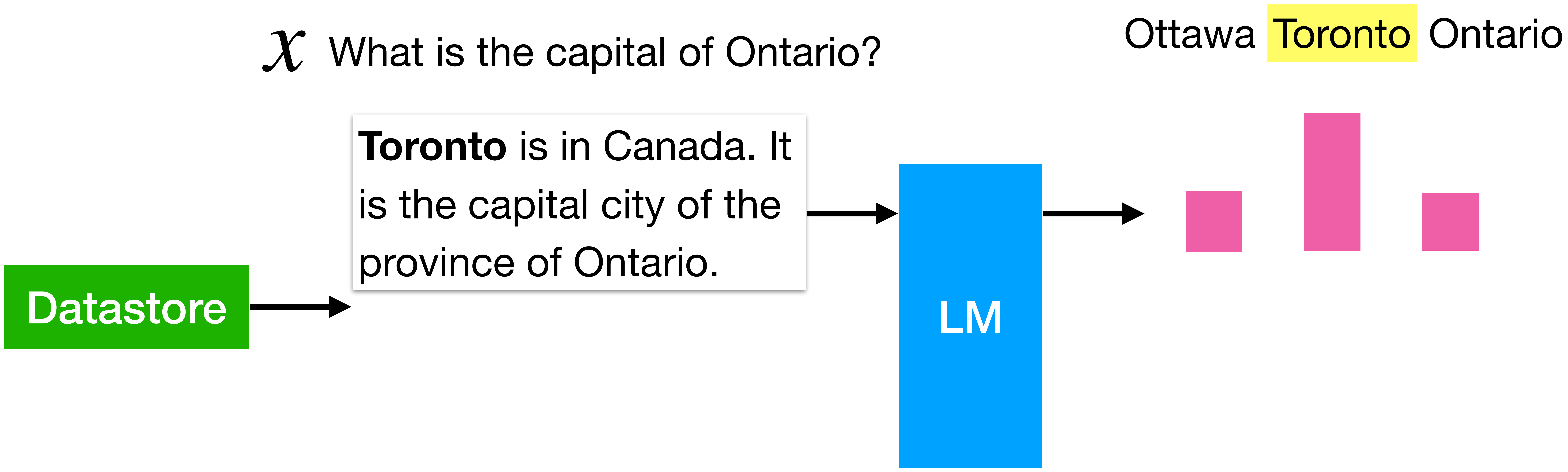
Output space:
Interpolate token probability distributions in output space

Retrieval-in-context

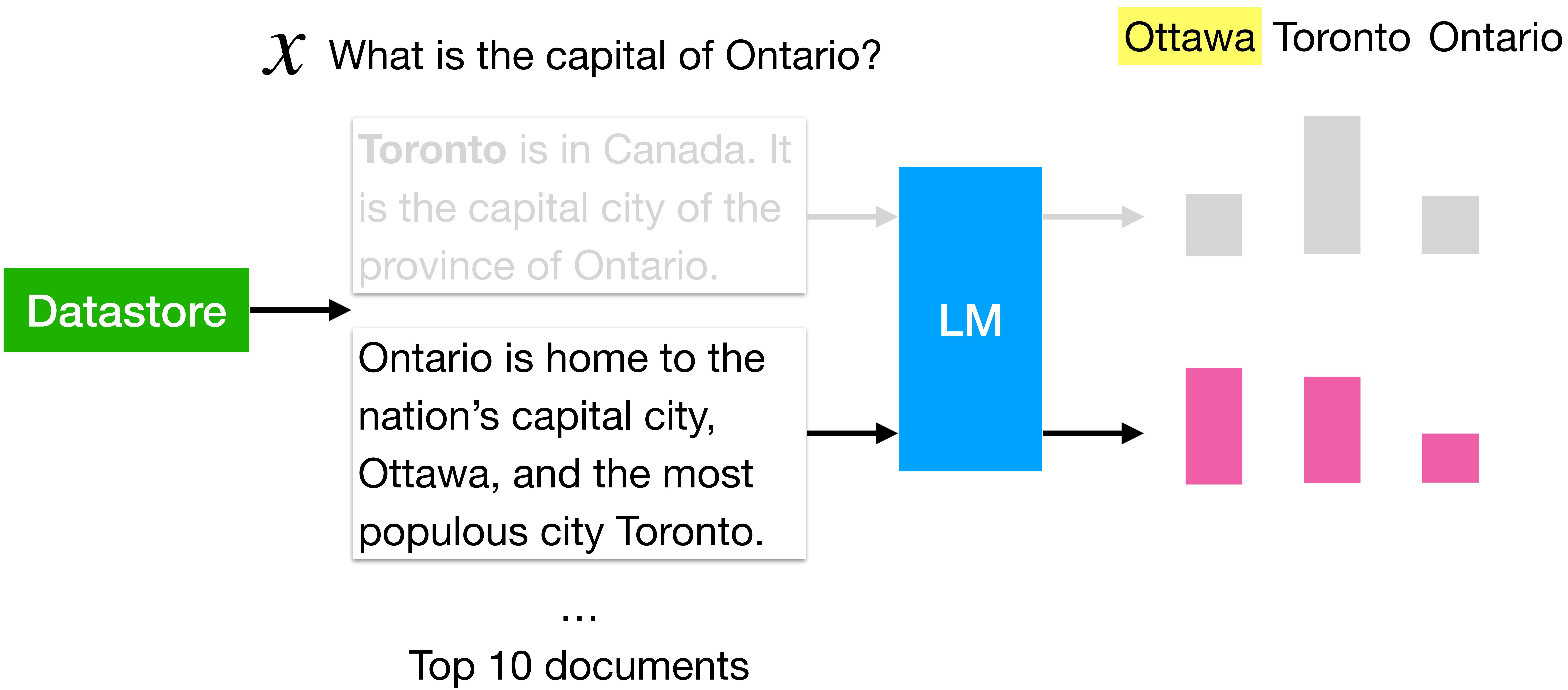


(Shi et al., 2023; Ram et al., 2022; Mallen et al., 2022; Yu et al., 2022; Press et al., 2022; *inter alia*)

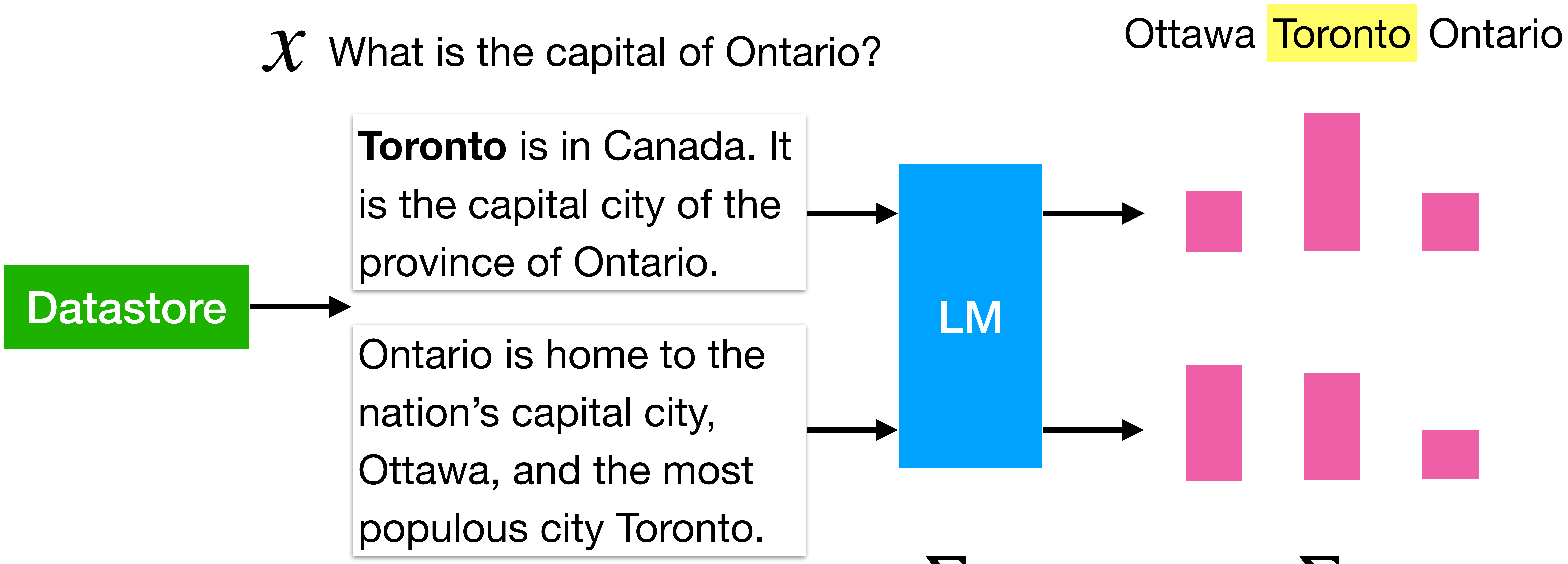
REPLUG (Shi et al., 2023; Section 3&4)



REPLUG (Shi et al., 2023; Section 3&4)



REPLUG (Shi et al., 2023; Section 3&4)

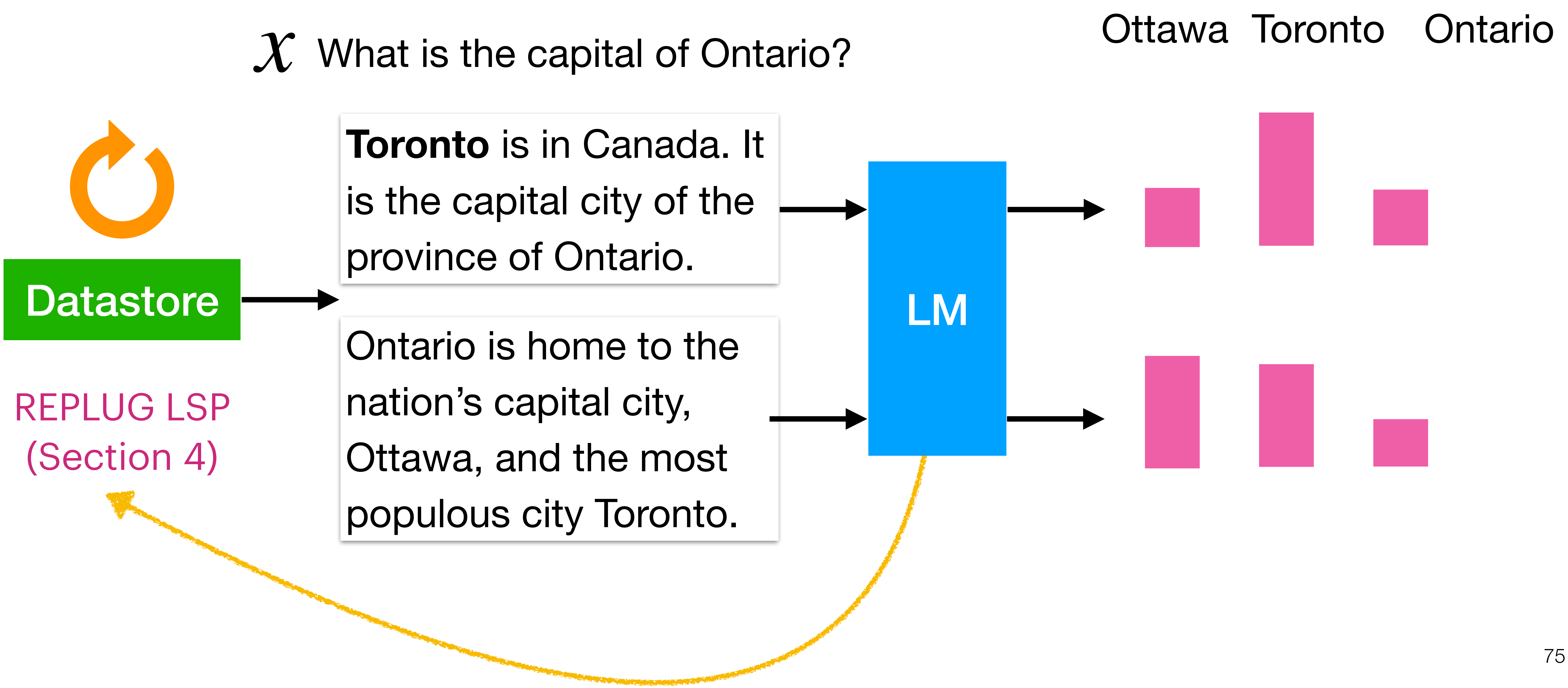


...

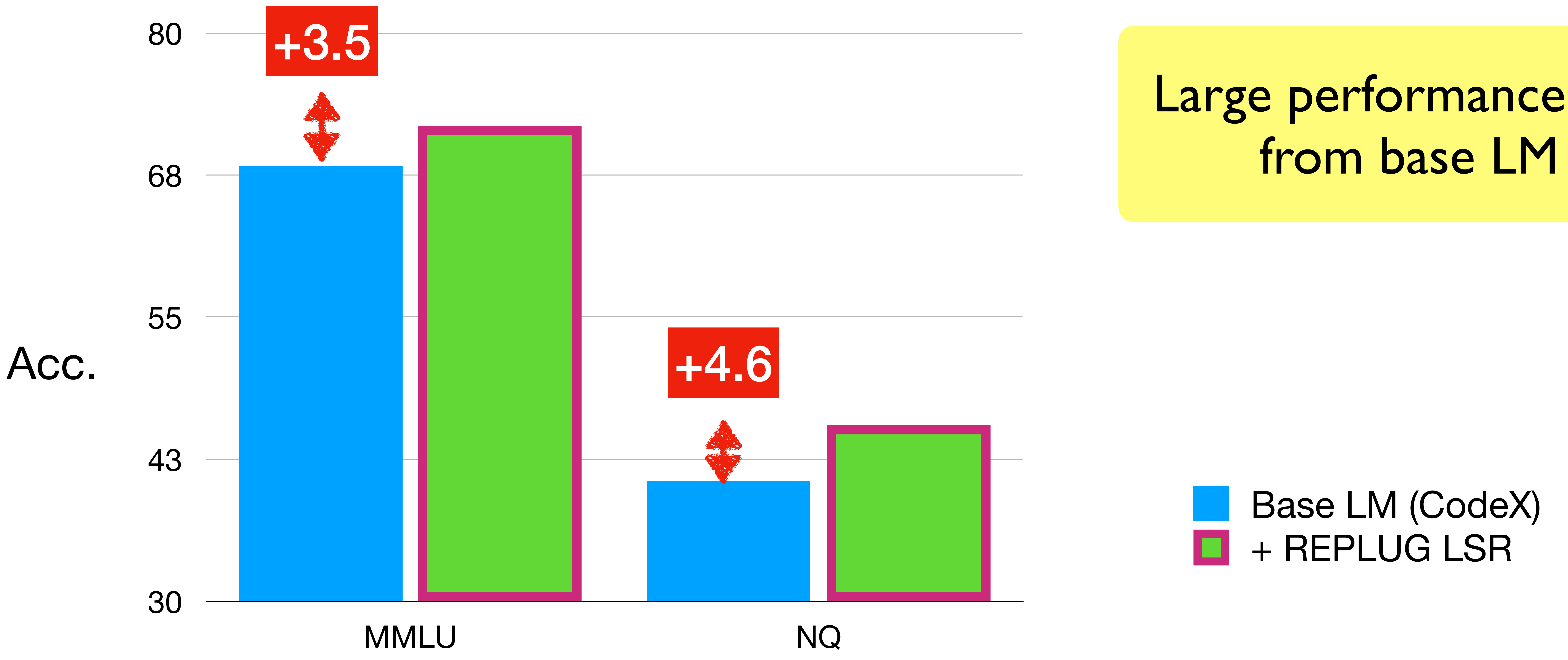
Top 10 documents

$$\sum_i p(\text{Toronto} \mid x, p_i) > \sum_i p(\text{Ottawa} \mid x, p_i)$$

REPLUG (Shi et al., 2023; Section 3&4)

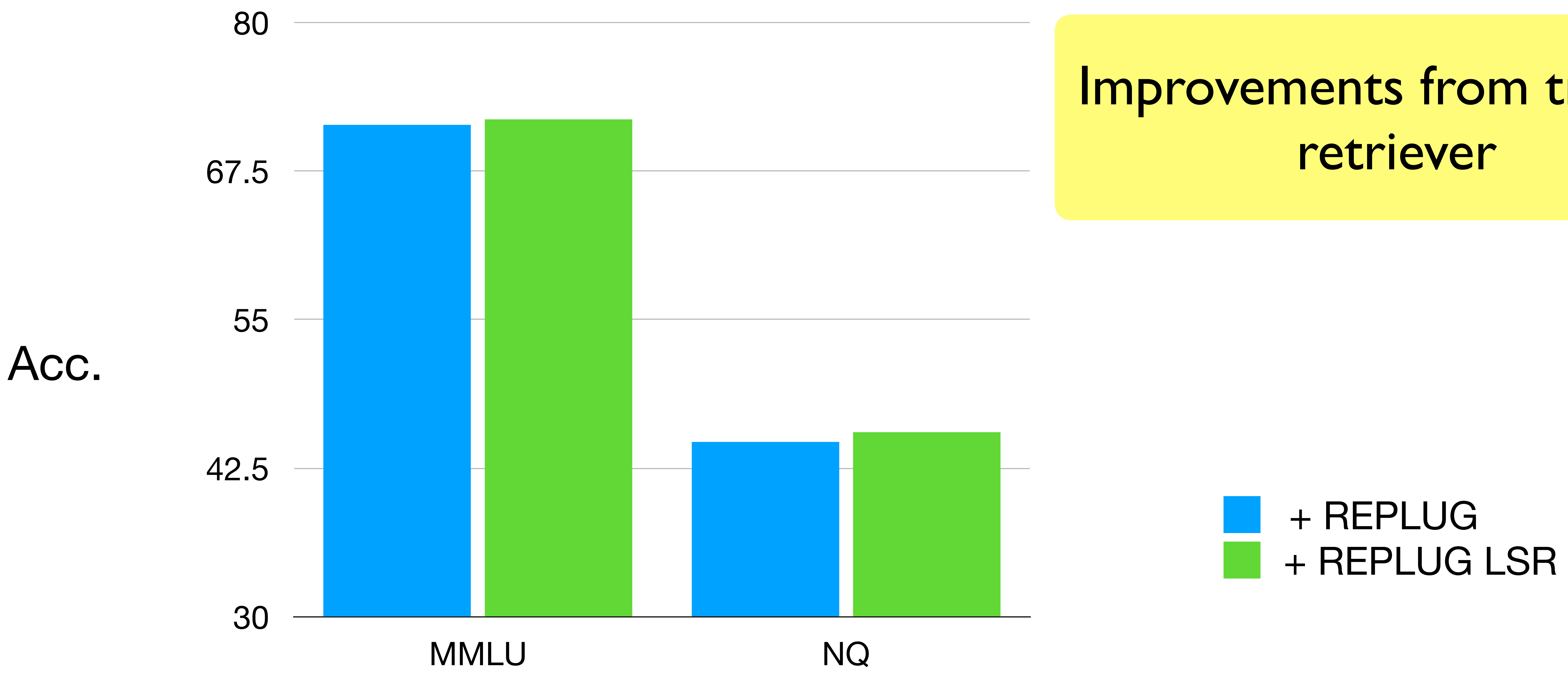


REPLUG: results on QA & MMLU



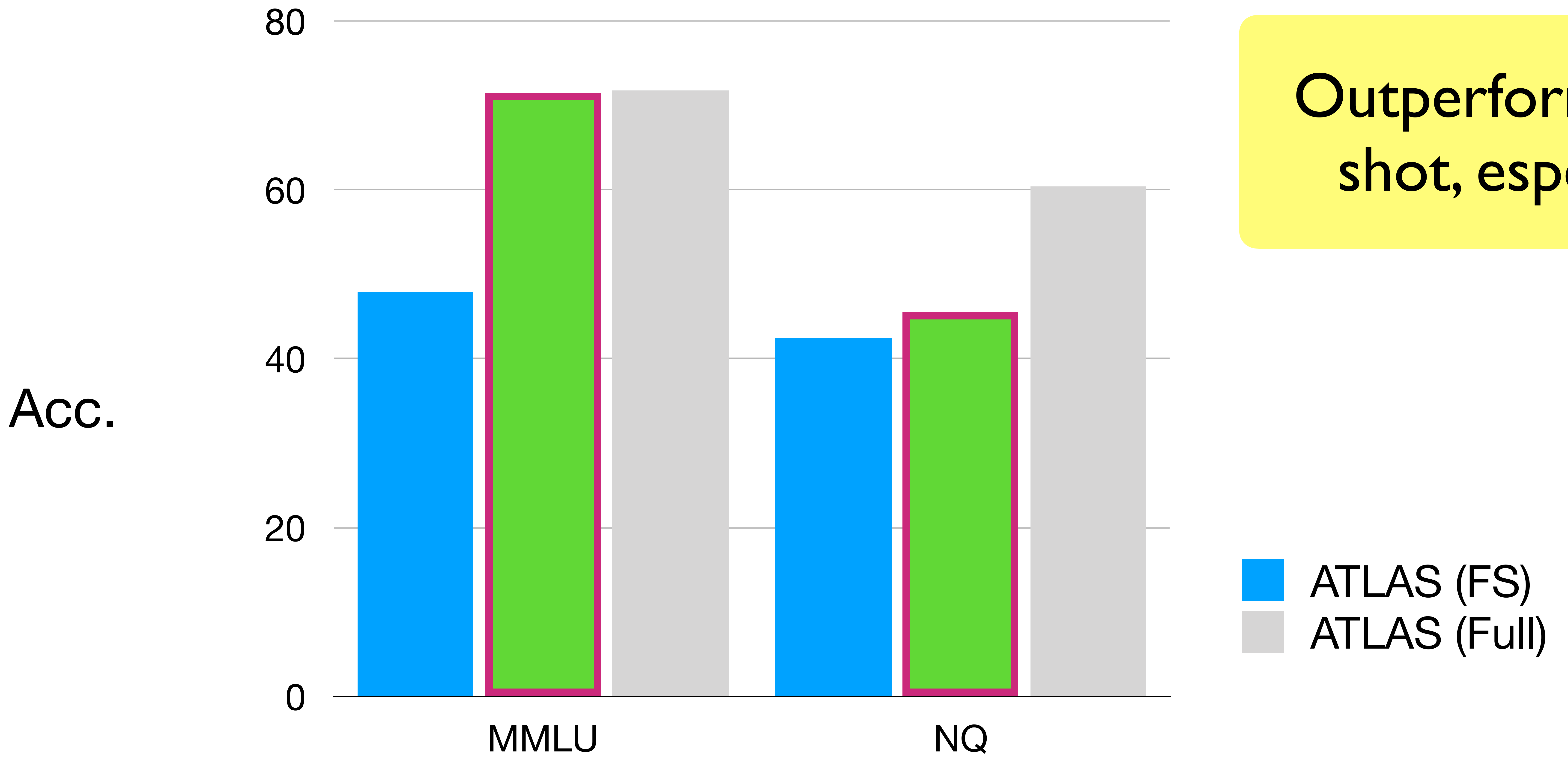
Large performance gain from base LM

REPLUG ablations of retriever training



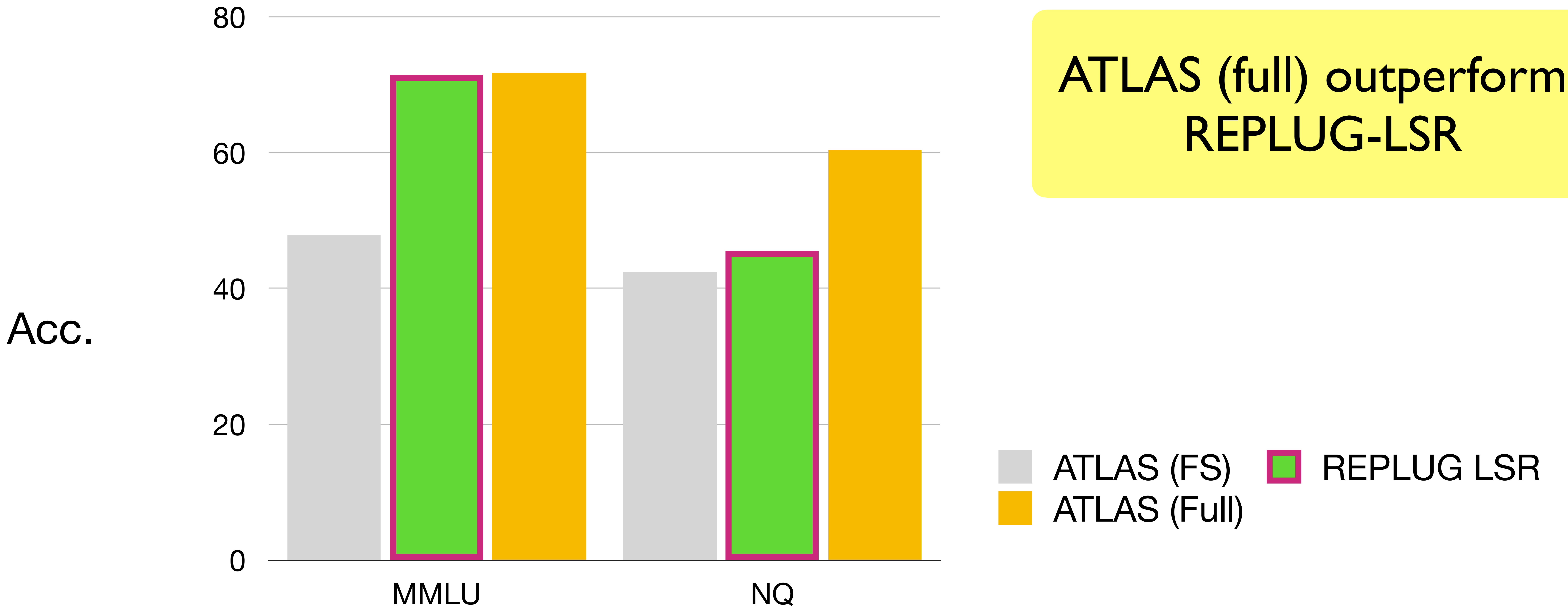
Improvements from training retriever

REPLUG: comparison with ATLAS



Outperforms ATLAS in few-shot, especially in MMLU

REPLUG: comparison with ATLAS



ATLAS (full) outperforms REPLUG-LSR

Summary of downstream adaptations

	Target task	Adaptation method	Datastore
ATLAS (Izacard et al., 2022)	Knowledge-intensive	Fine-tuning (DS & LM)	Wikipedia | CC
GopherCite (Menick et al., 2022)	Open-domain QA, Long-form QA	Fine-tuning + RL (LM)	Google Search Results
kNN Prompt (Shi et al., 2022)	Classification	Prompting (output)	Wikipedia | CC
REPLUG (Shi et al., 2023)	Knowledge-intensive	Prompting (input)	Wikipedia | CC

Benefit of **retrieval-based** prompting

No training & strong performance

Hard to control, underperforming full FT model

Summary of downstream adaptations

	Target task	Adaptation method	Datastore
ATLAS (Izacard et al., 2022)	Knowledge-intensive	Fine-tuning (DS & LM)	Wikipedia | CC
GopherCite (Menick et al., 2022)	Open-domain QA, Long-form QA	Fine-tuning + RL (LM)	Google Search Results
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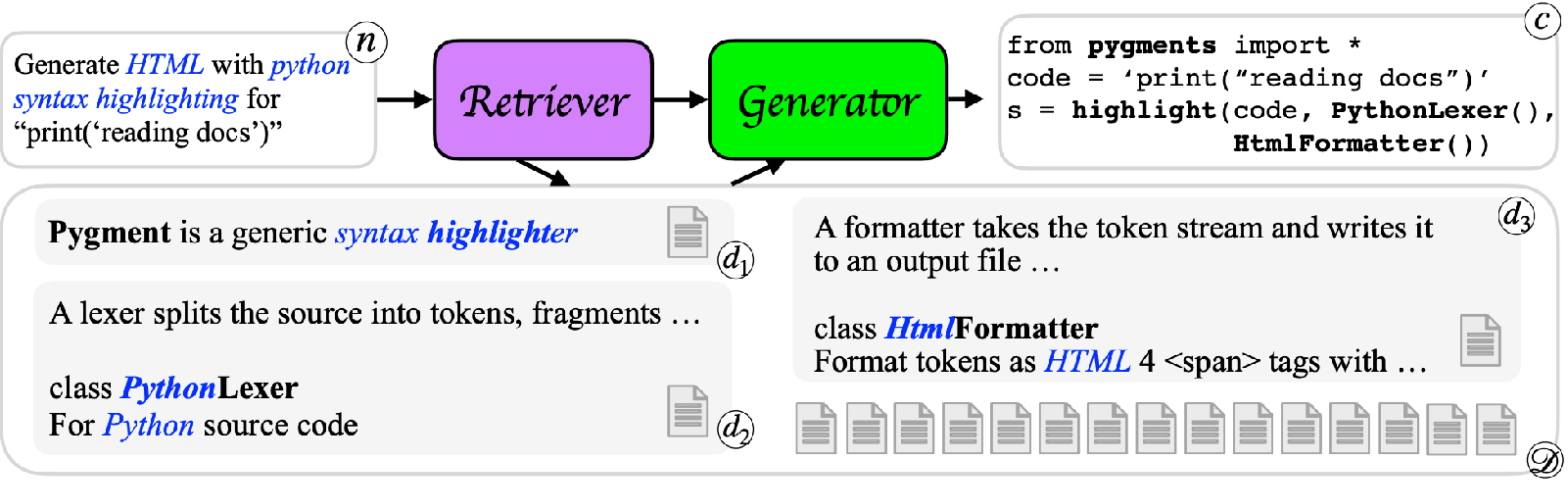
REPLUG (Shi et al., 2023)	Knowledge-intensive	Prompting (input)	Wikipedia | CC

What can be other types of datastores?

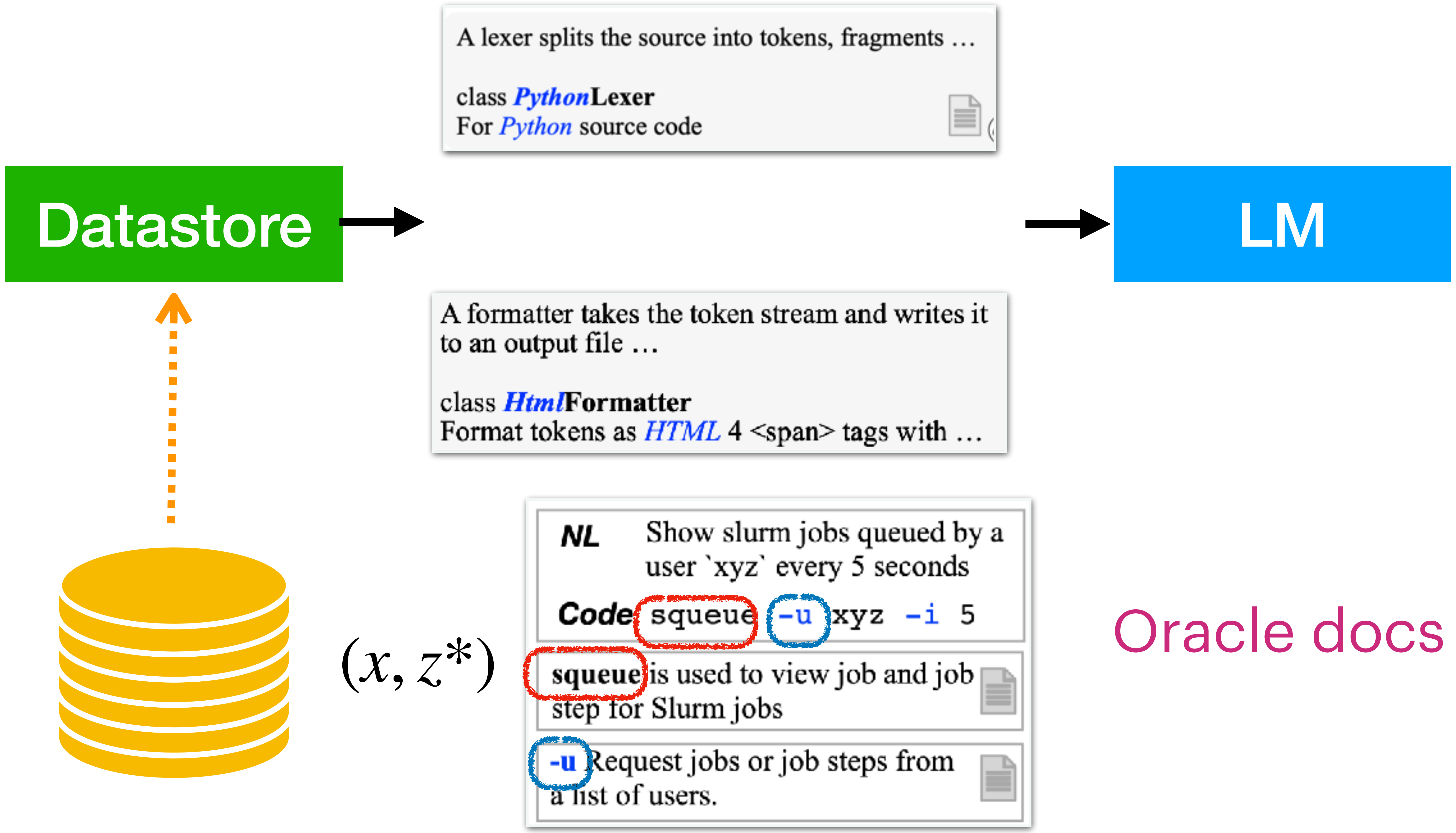
DocPrompting (Zhou et al., 2023)



Retrieve **code documentations** about related functions

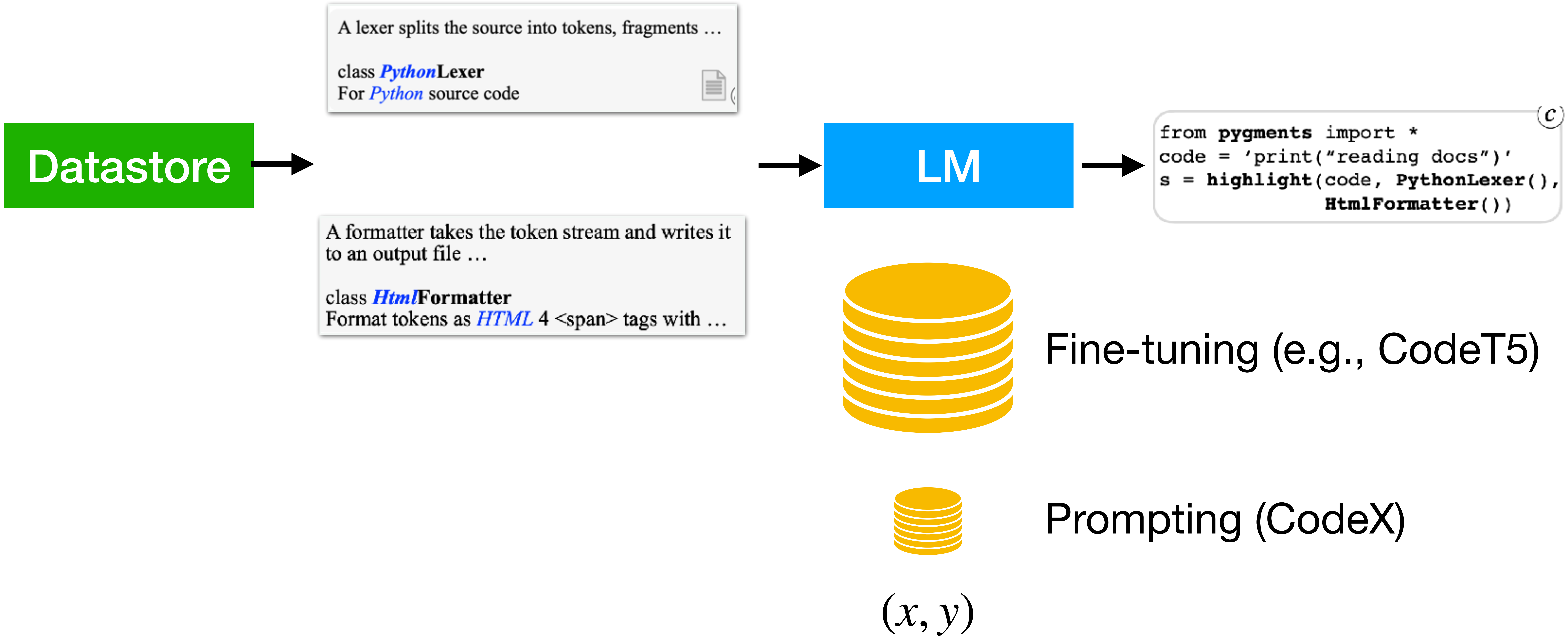
Zhou et al. 2023. "DocPrompting: Generating the Codes by Retrieving the Docs"

DocPrompting (Zhou et al., 2023)

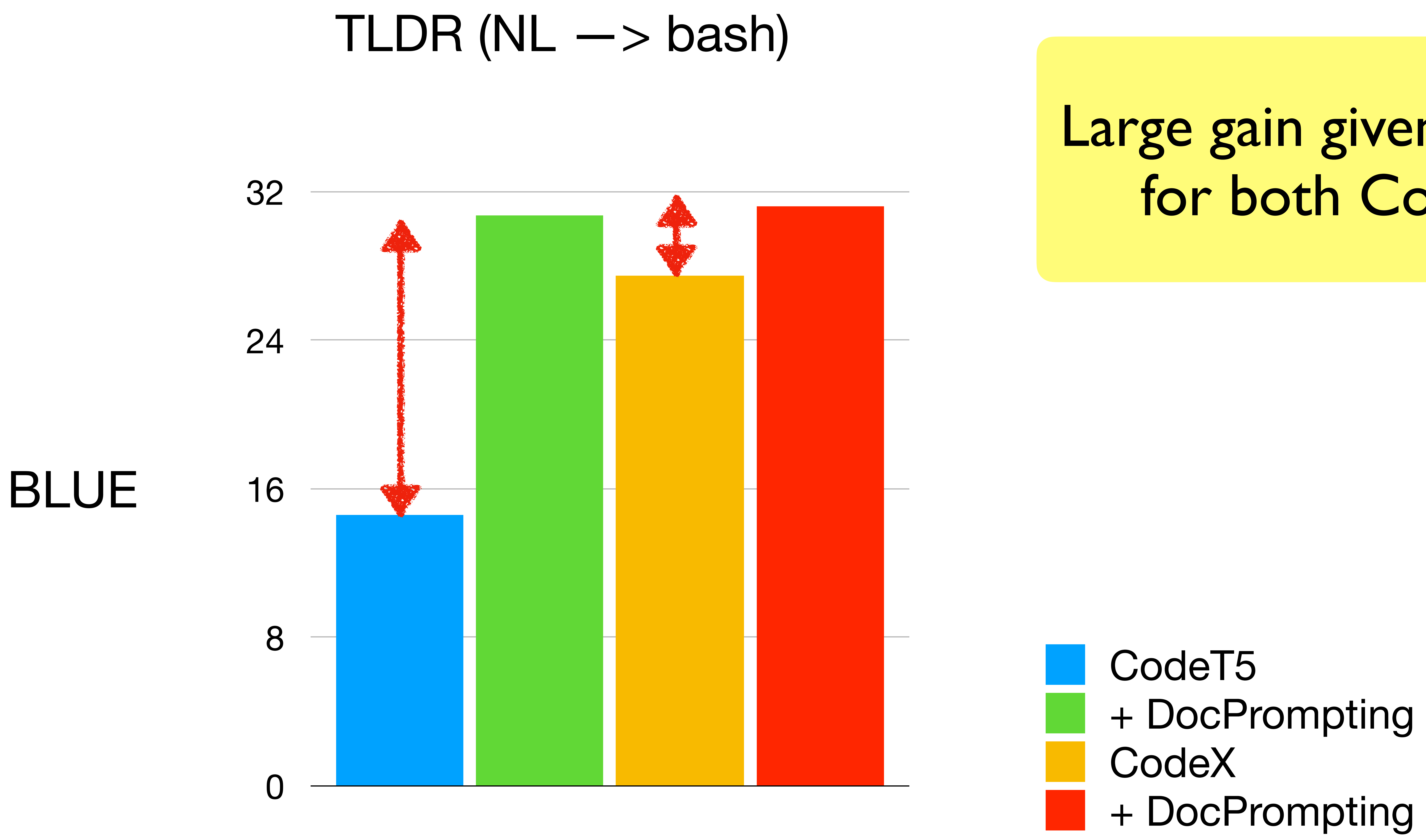


Oracle docs retrieved by simple text matching

DocPrompting (Zhou et al., 2023)

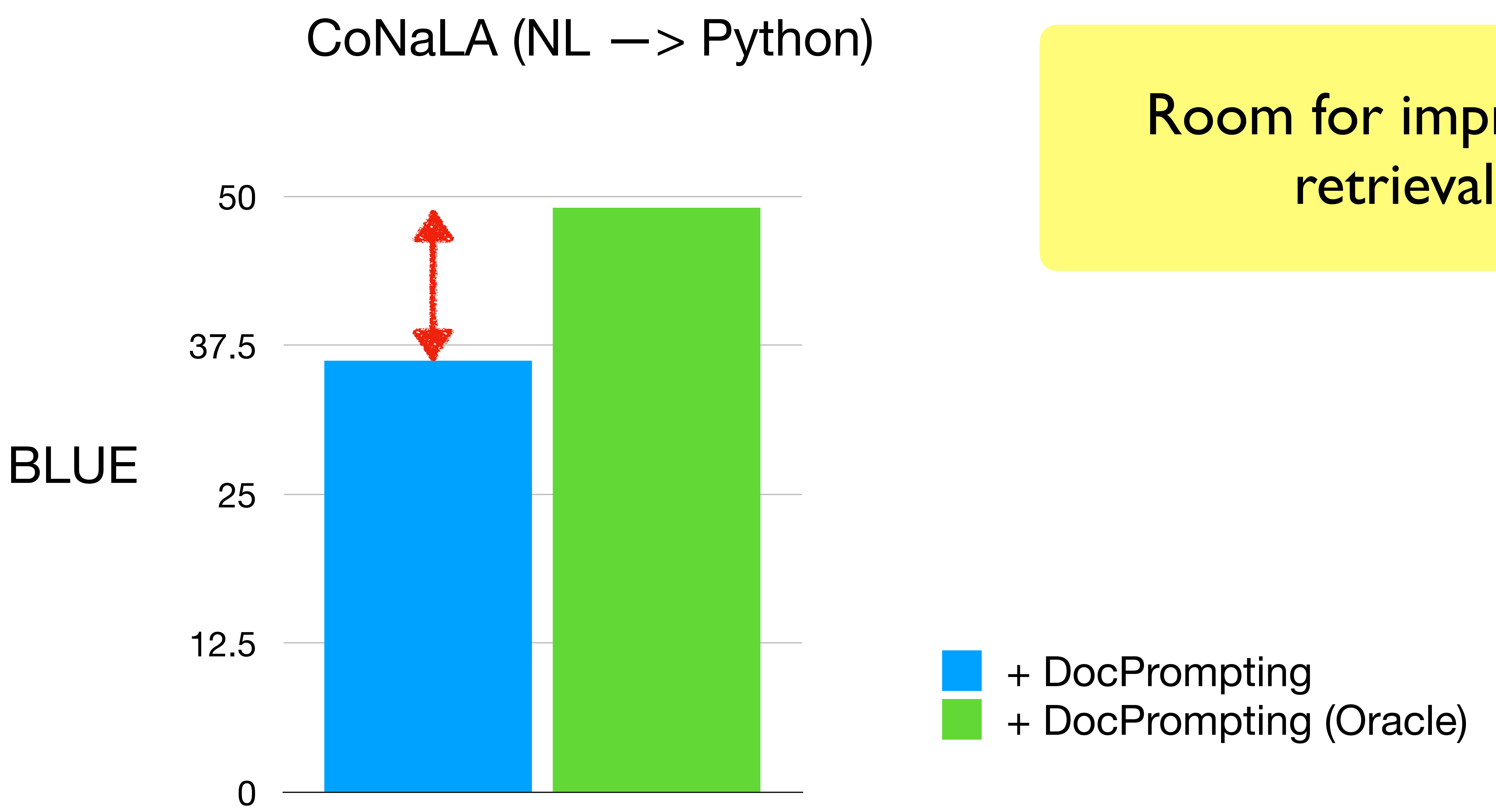


DocPrompting (Zhou et al., 2023)



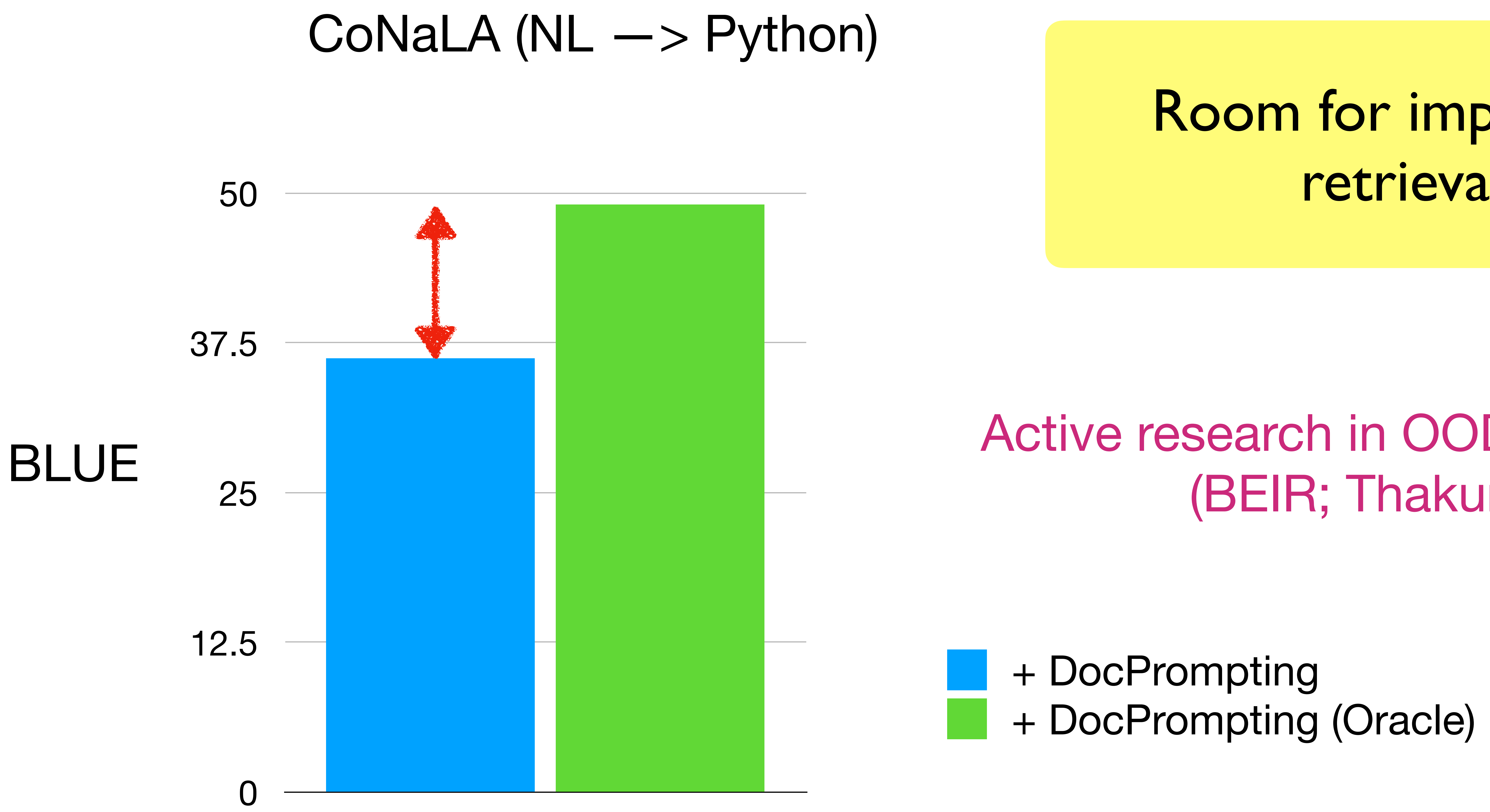
Large gain given by DocPrompting for both CodeT5 & CodeX

DocPrompting (Zhou et al., 2023)



Room for improvement for retrieval model

DocPrompting (Zhou et al., 2023)



Room for improvement for retrieval model

Active research in OOD / Zero-shot retrieval!
(BEIR; Thakur et al., 2021)

Summary of downstream adaptations

	Target task	Adaptation method	Datastore
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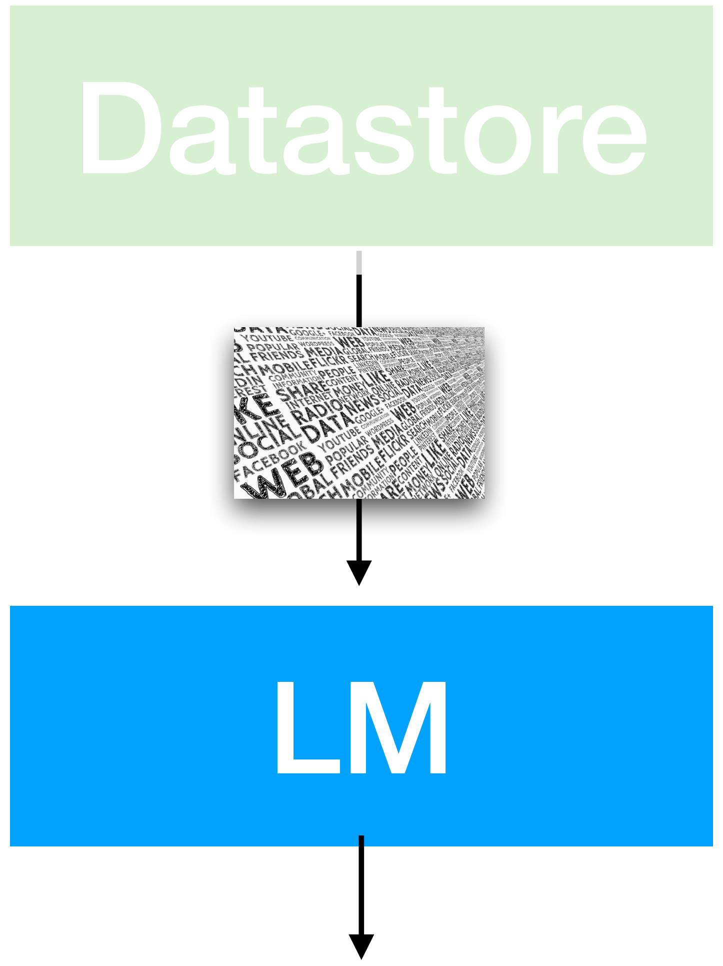
GopherCite (Menick et al., 2022)	Open-domain QA, Long-form QA	Fine-tuning + RL (LM)	Google Search Results
kNN Prompt (Shi et al., 2022)	Classification	Prompting (output)	Wikipedia | CC
REPLUG (Shi et al., 2023)	Knowledge-intensive	Prompting (input)	Wikipedia | CC
DocPrompting (Zhou et al., 2023)	Code Generation	Fine-tuning (DS & LM), Prompting (Input)	Code documentations

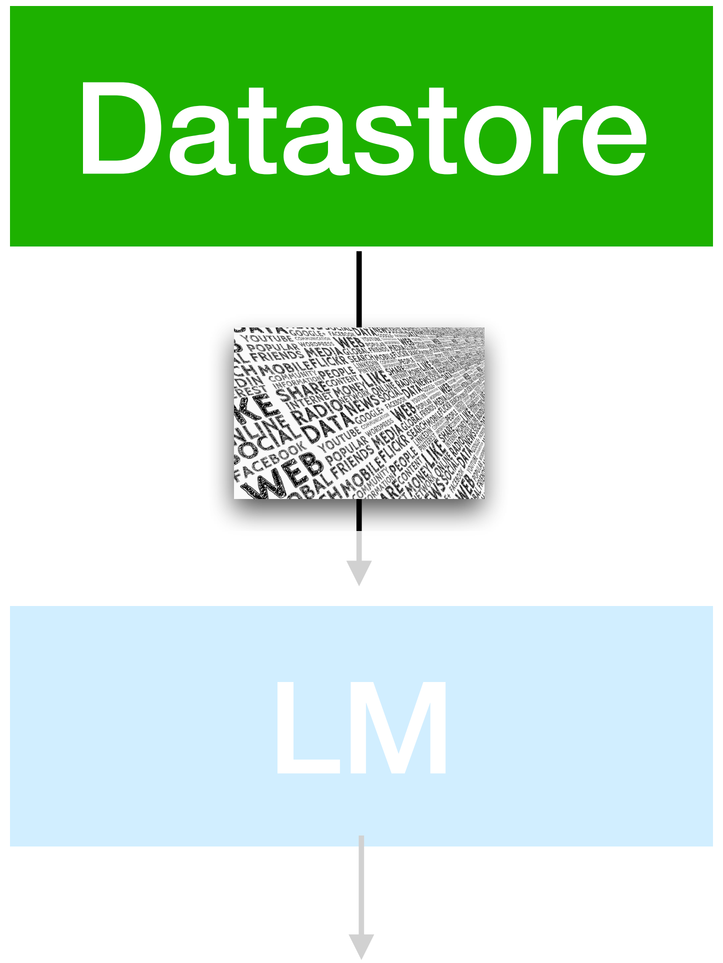
How to adapt a retrieval-based LM for a task



Retrieval-based prompting is competitive

Fine-tuning (+ RL) often show comparable / better performance & is more customizable

How to adapt a retrieval-based LM for a task



Training a retriever on downstream tasks helps both fine-tuning and prompting

Datastore can be diverse (also in Section 6) while challenges remain in OOD retrieval

Two key questions for downstream adaptations

How can we adapt a retrieval-based LM for a task?

When should we use a retrieval-based LM?

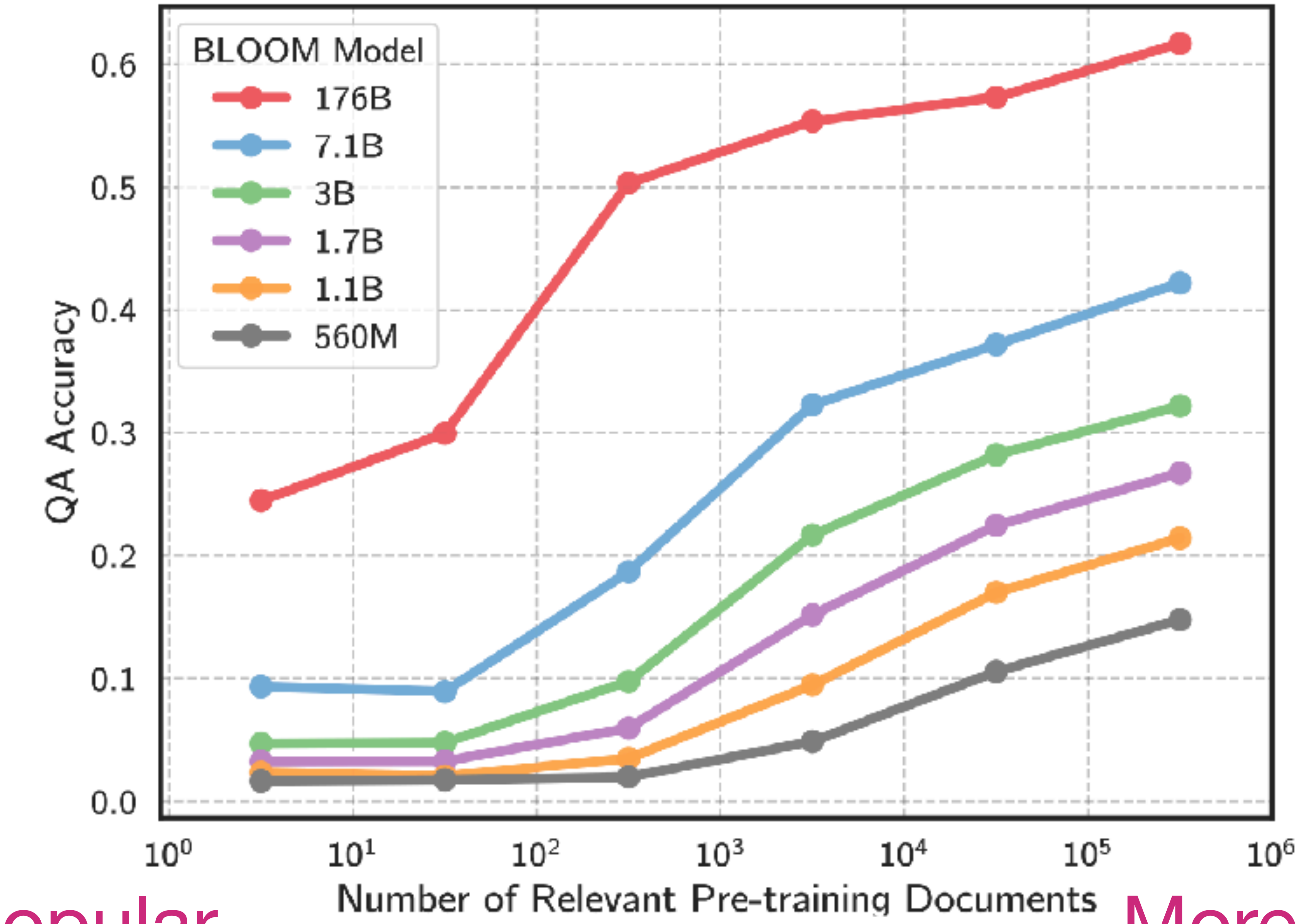
When to use a retrieval-based LM

- Long-tail
- knowledge update
- Verifiability
- Parameter-efficiency
- Privacy

Key effectiveness in downstream tasks

Long-tail

LLMs often struggle in long **tail / less frequent entities**



<— less popular

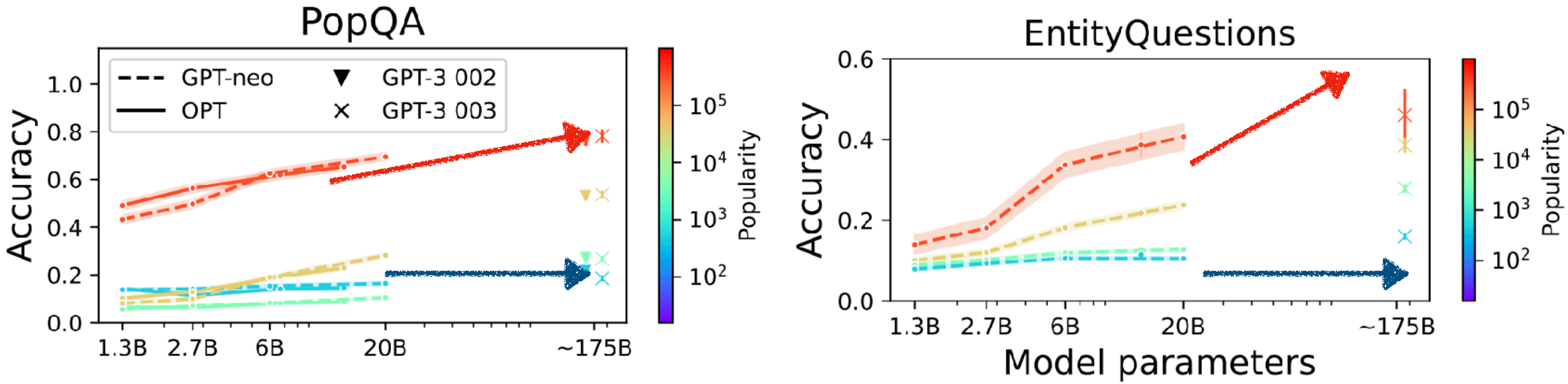
More popular —>

Kandpal et al. 2023. "Large language models struggle to learn long-tail knowledge"

Key effectiveness in downstream tasks

Long-tail

Scaling LLMs only helps for **popular knowledge;** for long tail, scaling gives marginal performance improvements

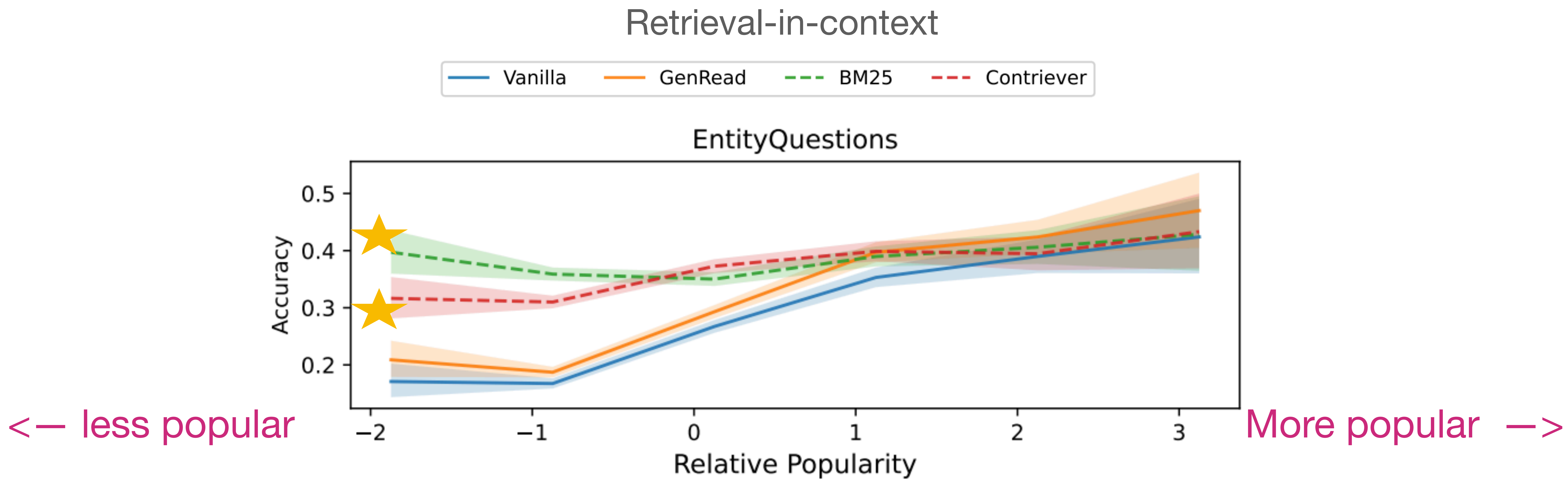


Mallen* and Asai* et al. 2023. "When Not to Trust Language Models: Investigating Effectiveness of Parametric and Non-Parametric Memories"

Key effectiveness in downstream tasks

Long-tail

Retrieval gives large performance gain in such **long-tail**



Mallen* and Asai* et al. 2023. "When Not to Trust Language Models: Investigating Effectiveness of Parametric and Non-Parametric Memories"

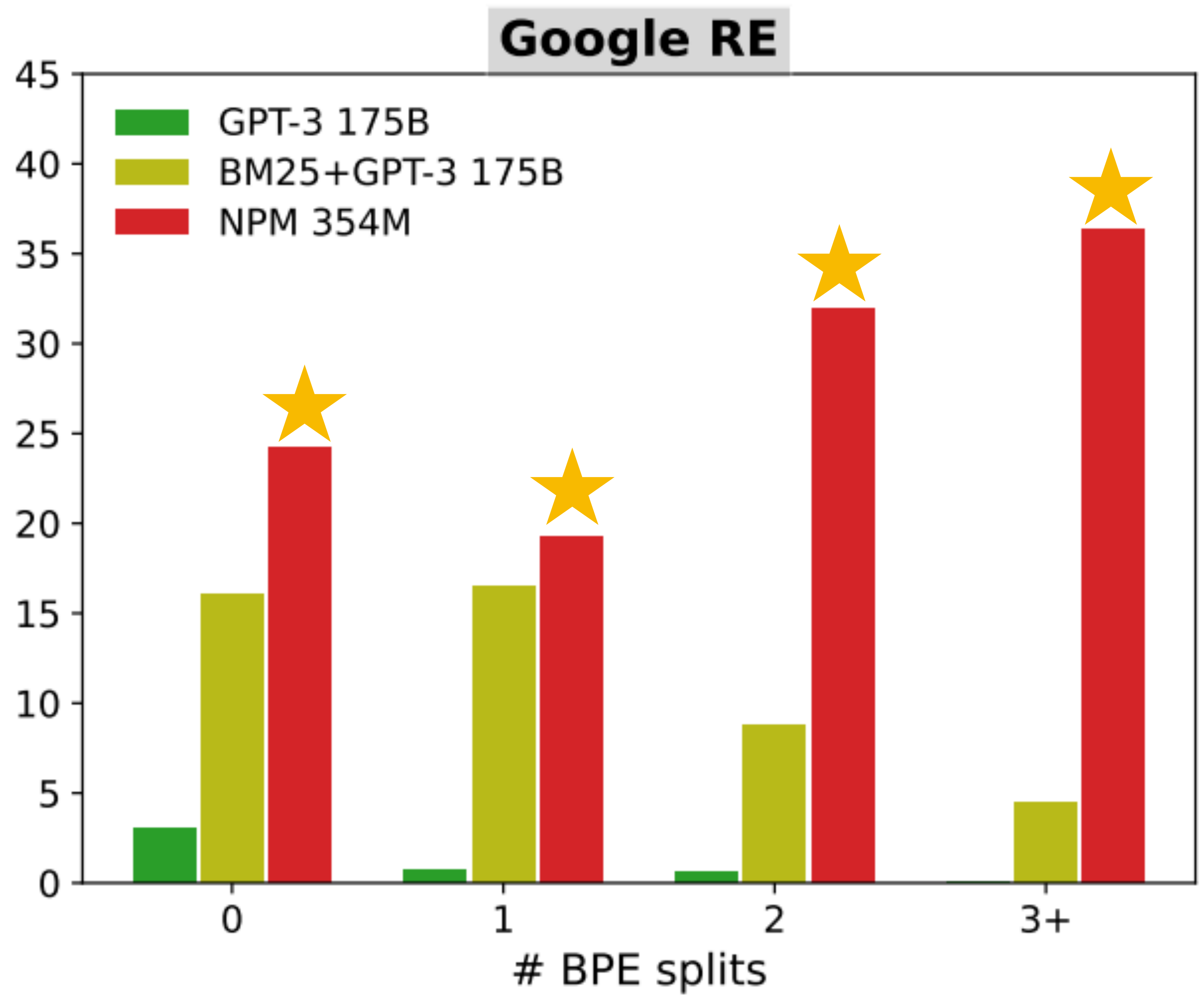
Key effectiveness in downstream tasks

Long-tail

Retrieval gives large performance gain in such **long-tail**

Output space
(e.g., kNN, NPM)

<— more popular



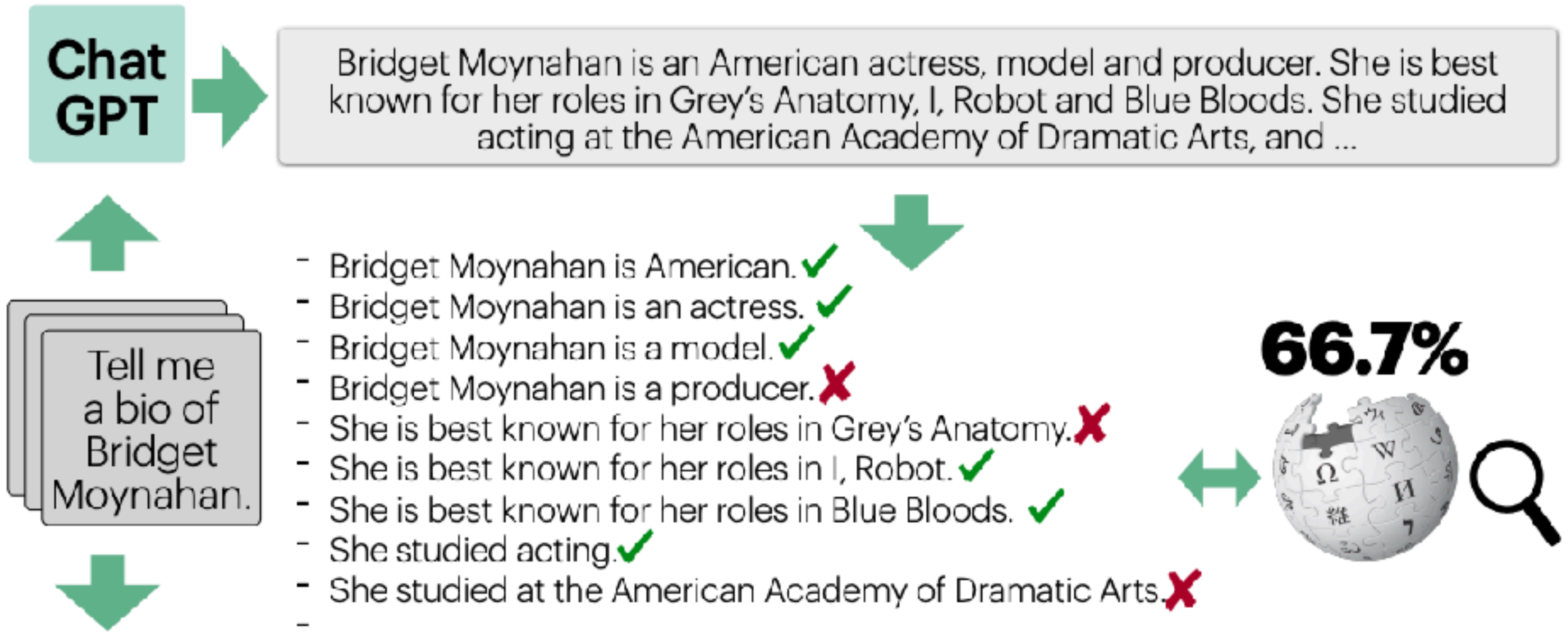
Less popular —>

Min et al. 2023. "Nonparametric Masked Language Modeling"

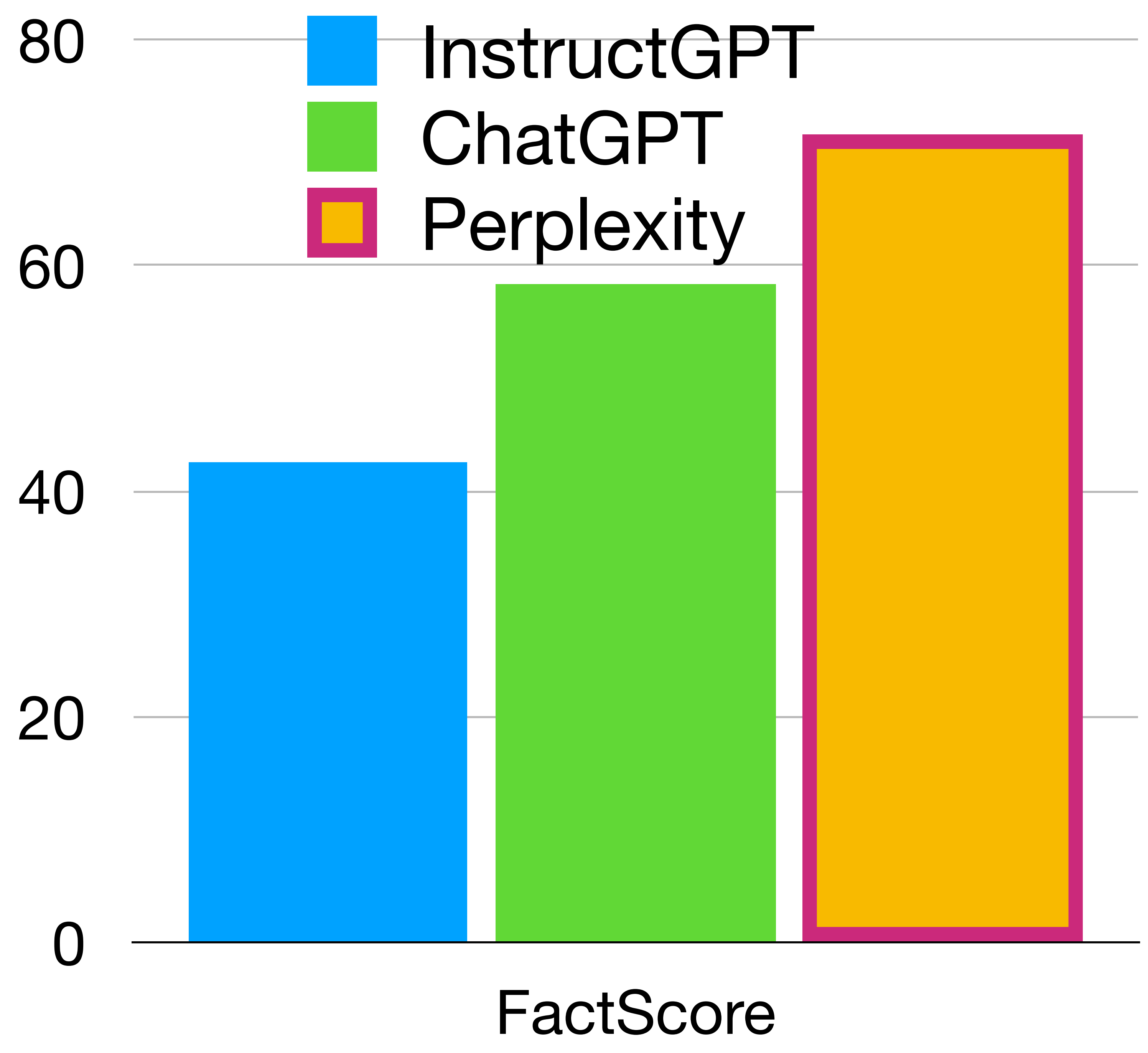
Key effectiveness in downstream tasks

Long-tail

Largely reduce hallucinations in **long-form generations**



FactScore



Min et al. 2023. "FActScore: Fine-grained Atomic Evaluation of Factual Precision in Long Form Text Generation"

Key effectiveness in downstream tasks

Update

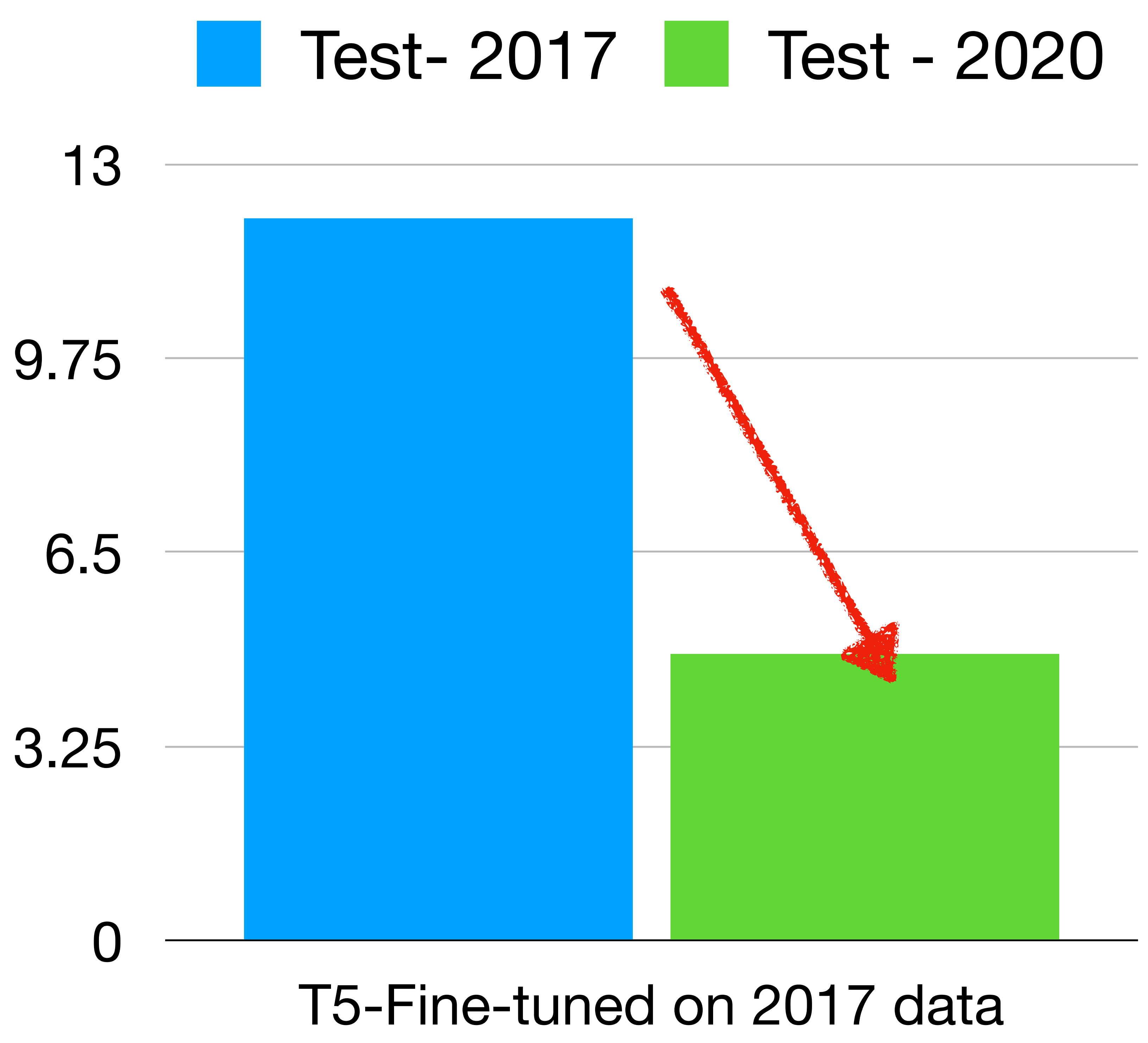
Standard LLMs needs to be **trained again** to adapt to evolving world knowledge

Temp LAMA

2012	Cristiano Ronaldo plays for _X_.	Real Madrid
2019	Cristiano Ronaldo plays for _X_.	Juventus FC

Huge performance drop when test knowledge needs to be updated

Izacard et al. 2022. “Few-shot learning with retrieval augmented language models”



Key effectiveness in downstream tasks

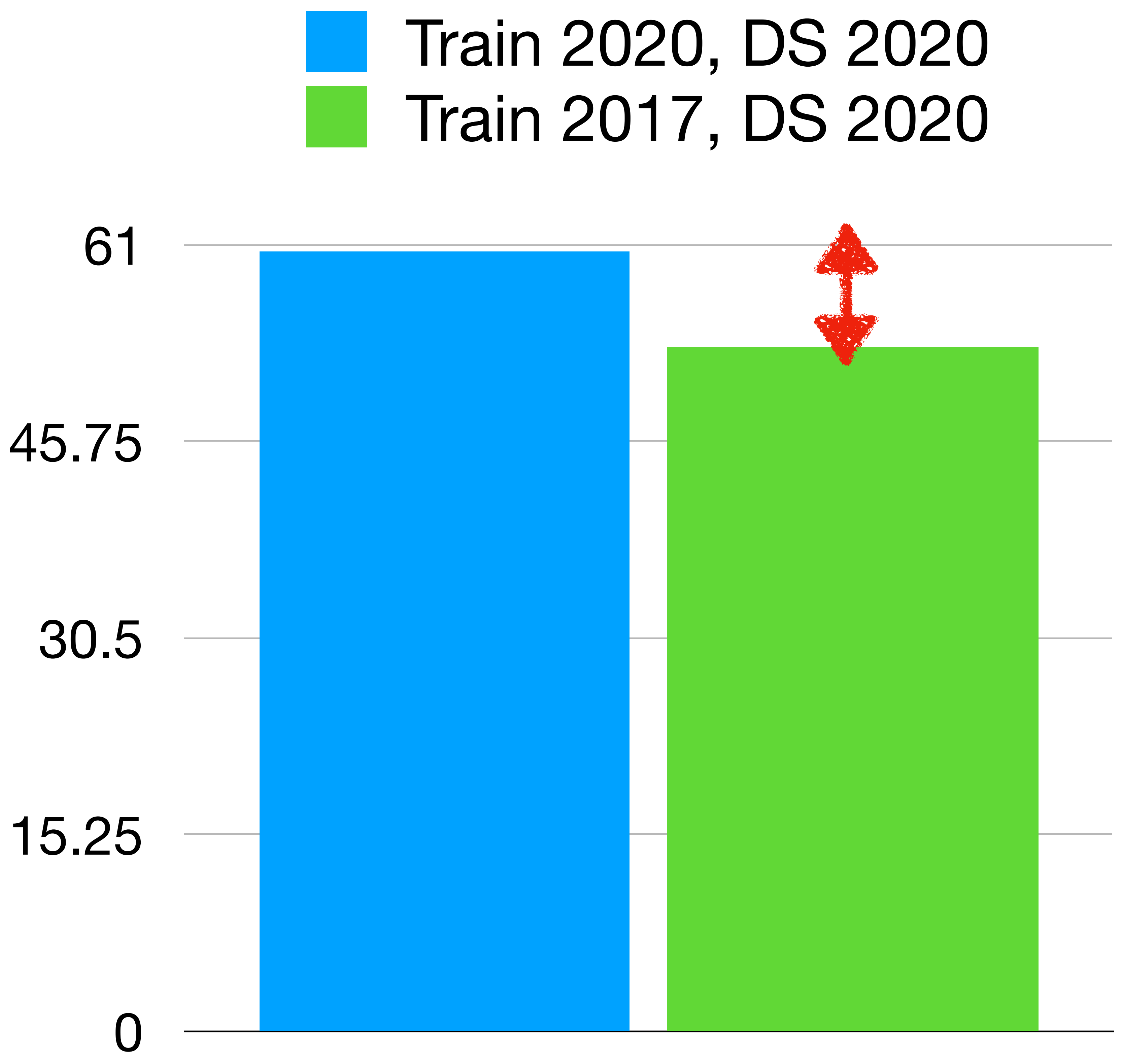
Update

Swapping the knowledge corpus to **accommodate temporal changes** without additional training.

Temp LAMA

2012	Cristiano Ronaldo plays for _X_.	Real Madrid
2019	Cristiano Ronaldo plays for _X_.	Juventus FC

Swapping test datastore only retains strong performance

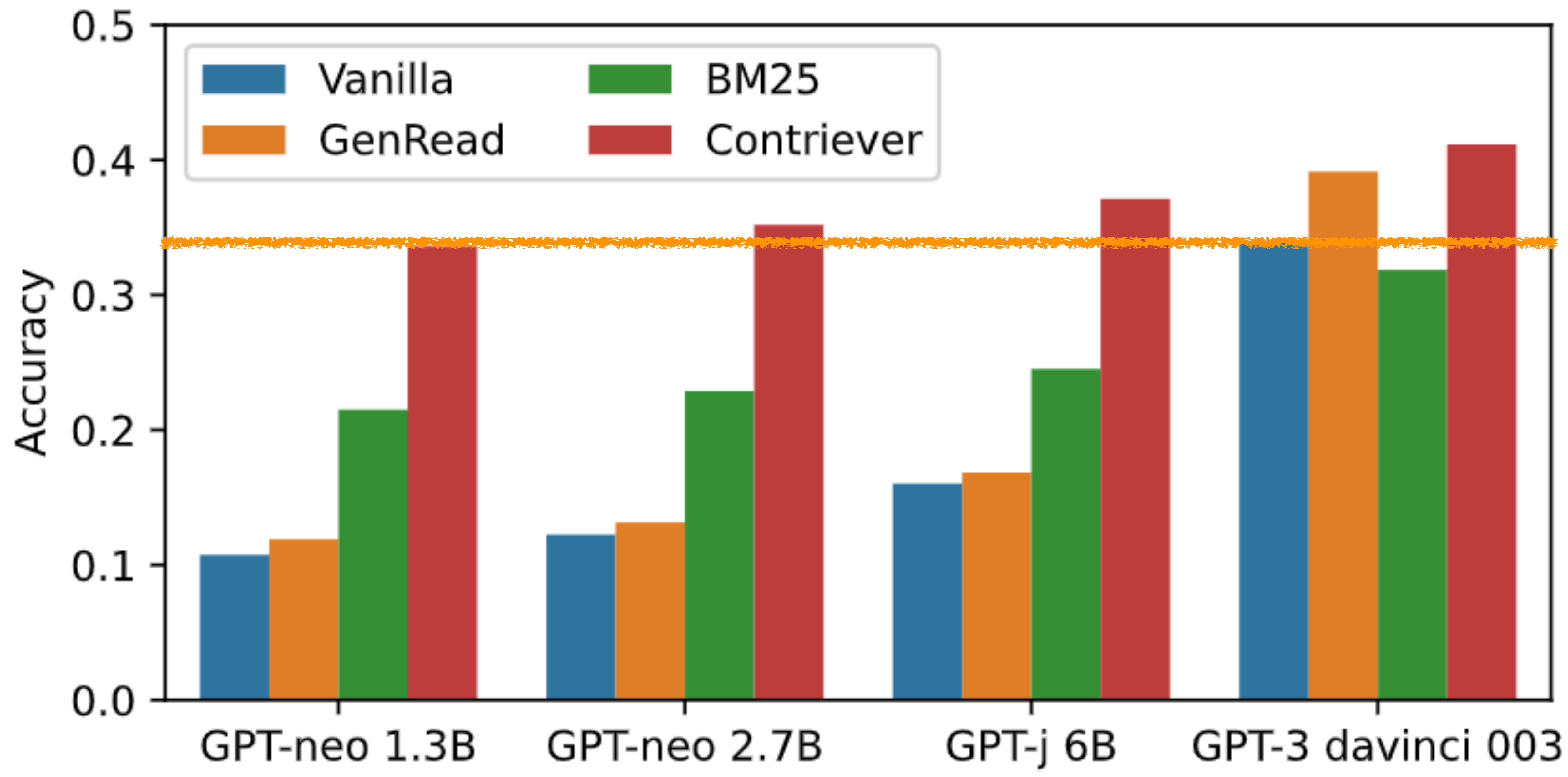


Key effectiveness in downstream tasks

Parameter-efficiency

Much smaller LMs with retrieval can outperforms much larger LMs in *knowledge-intensive tasks.*

Retrieval + GPT Neo 1.3B outperforms vanilla GPT3 on QA



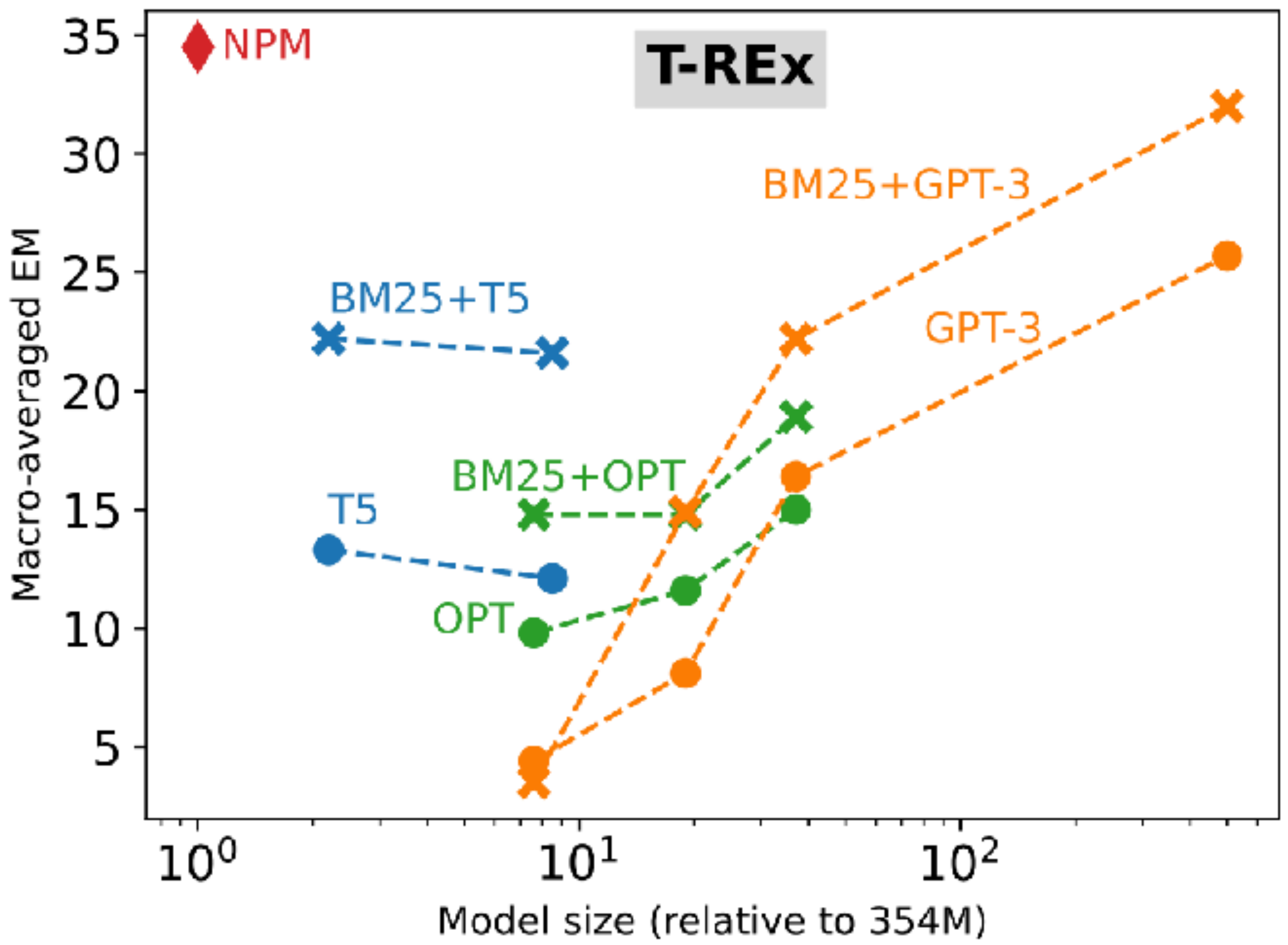
Mallen* and Asai* et al. 2023. "When Not to Trust Language Models: Investigating Effectiveness of Parametric and Non-Parametric Memories"

Key effectiveness in downstream tasks

Parameter-efficiency

Much smaller LMs with retrieval can outperforms much larger LMs in *knowledge-intensive tasks.*

T-Rex AVCDH is owned by [MASK]



NPM (354 M) outperforms GPT-3 (175B) on T-Rex.

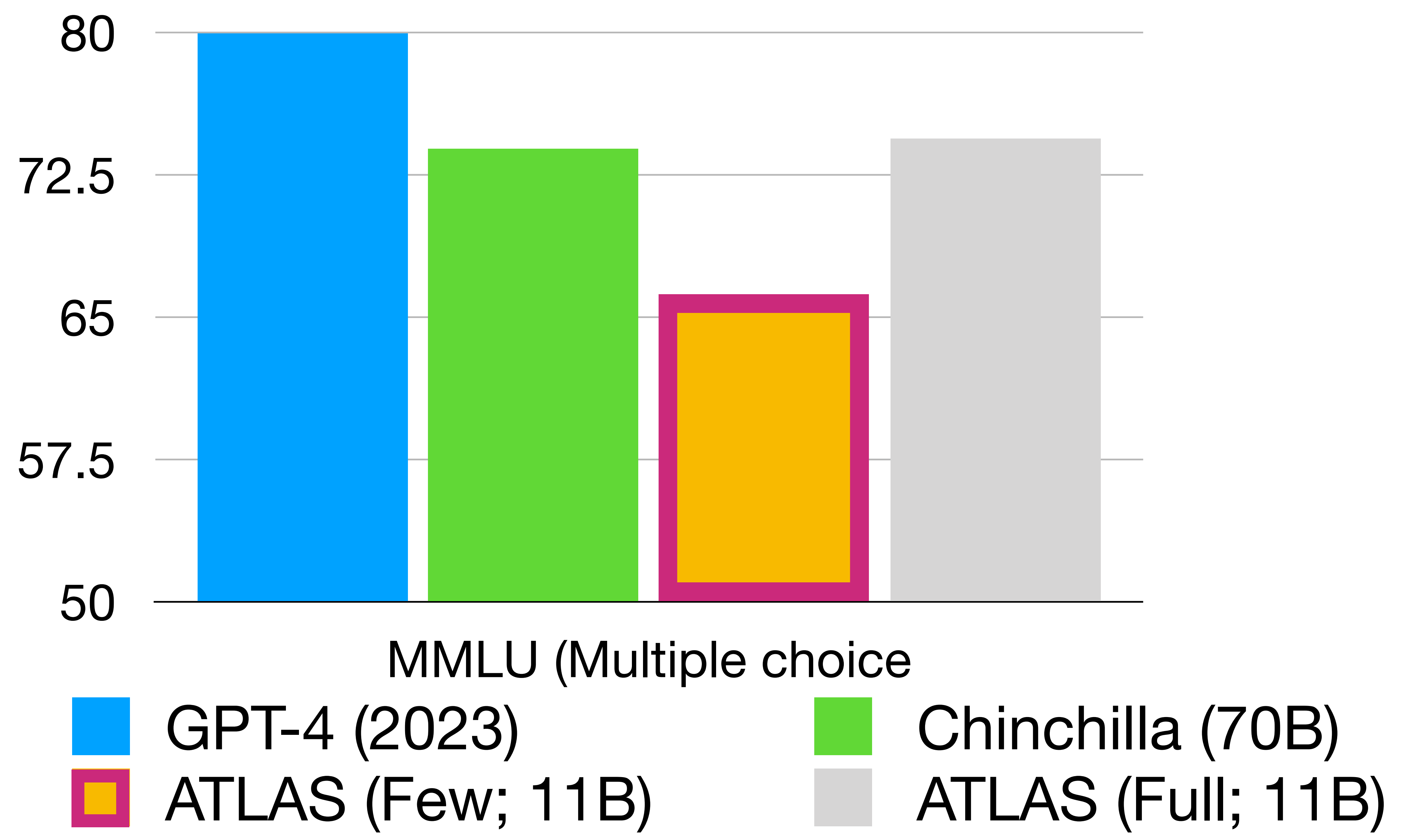
Min et al. 2023. “Nonparametric Masked Language Modeling”

Key effectiveness in downstream tasks

Parameter-efficiency

Much smaller LMs with retrieval can outperforms much larger LMs in *knowledge-intensive tasks.*

Room for improvements for diverse task adaptations!



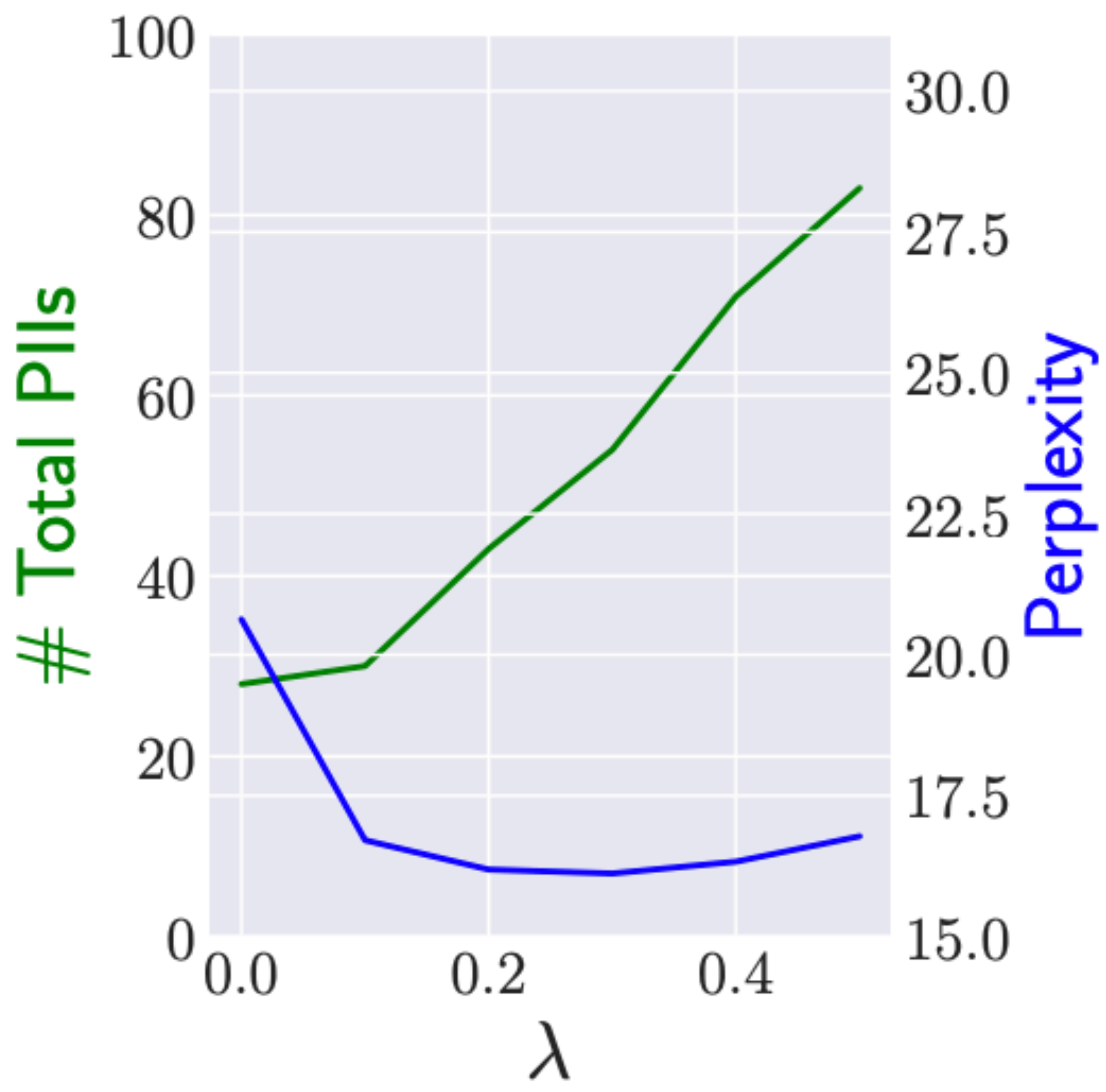
Izacard et al. 2022. "Few-shot learning with retrieval augmented language models"

Key effectiveness in downstream tasks

Privacy

Retrieval-based LMs enable us to mitigate privacy risks.

Higher, more risk



Lower, better generation

Huang et al. 2023. "Privacy Implications of Retrieval-Based Language Models"

Key effectiveness in downstream tasks

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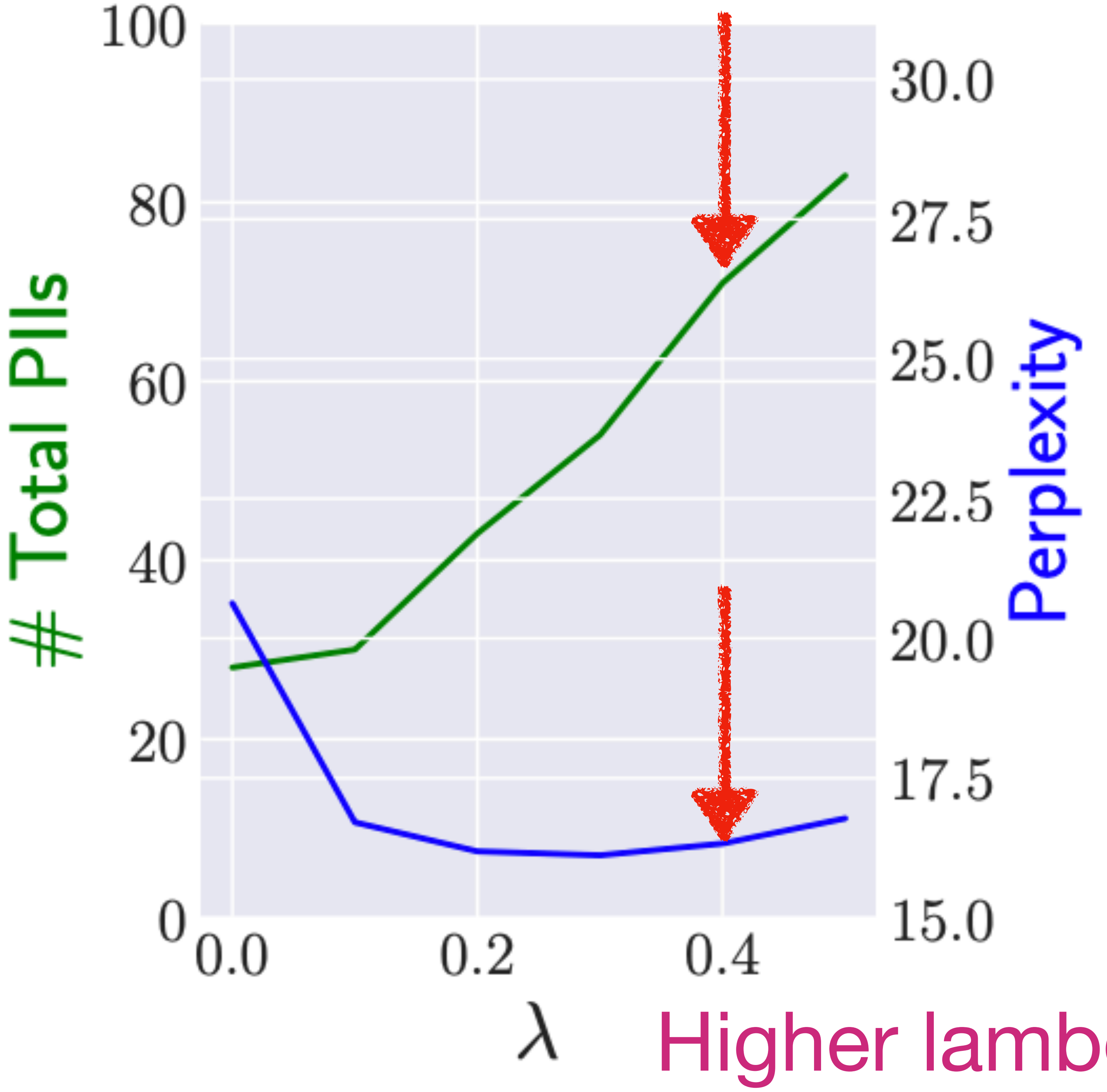
Higher, more risk



Lower, better generation

Higher lambda —> better performance, more PIIS

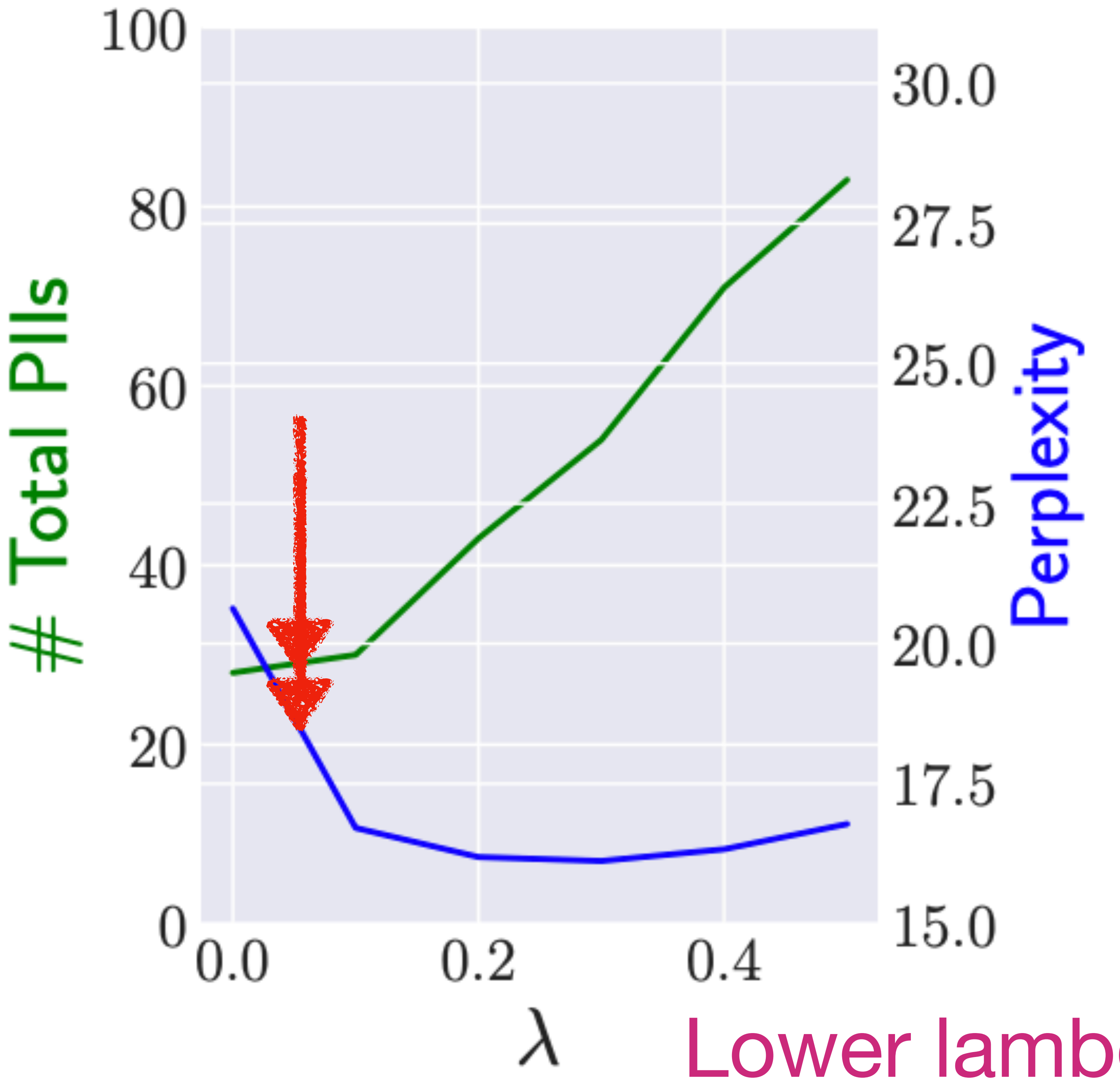
Huang et al. 2023. “Privacy Implications of Retrieval-Based Language Models”

Key effectiveness in downstream tasks

Privacy

Retrieval-based LMs enable us to mitigate privacy risks.

Higher, more risk



Lower, better generation

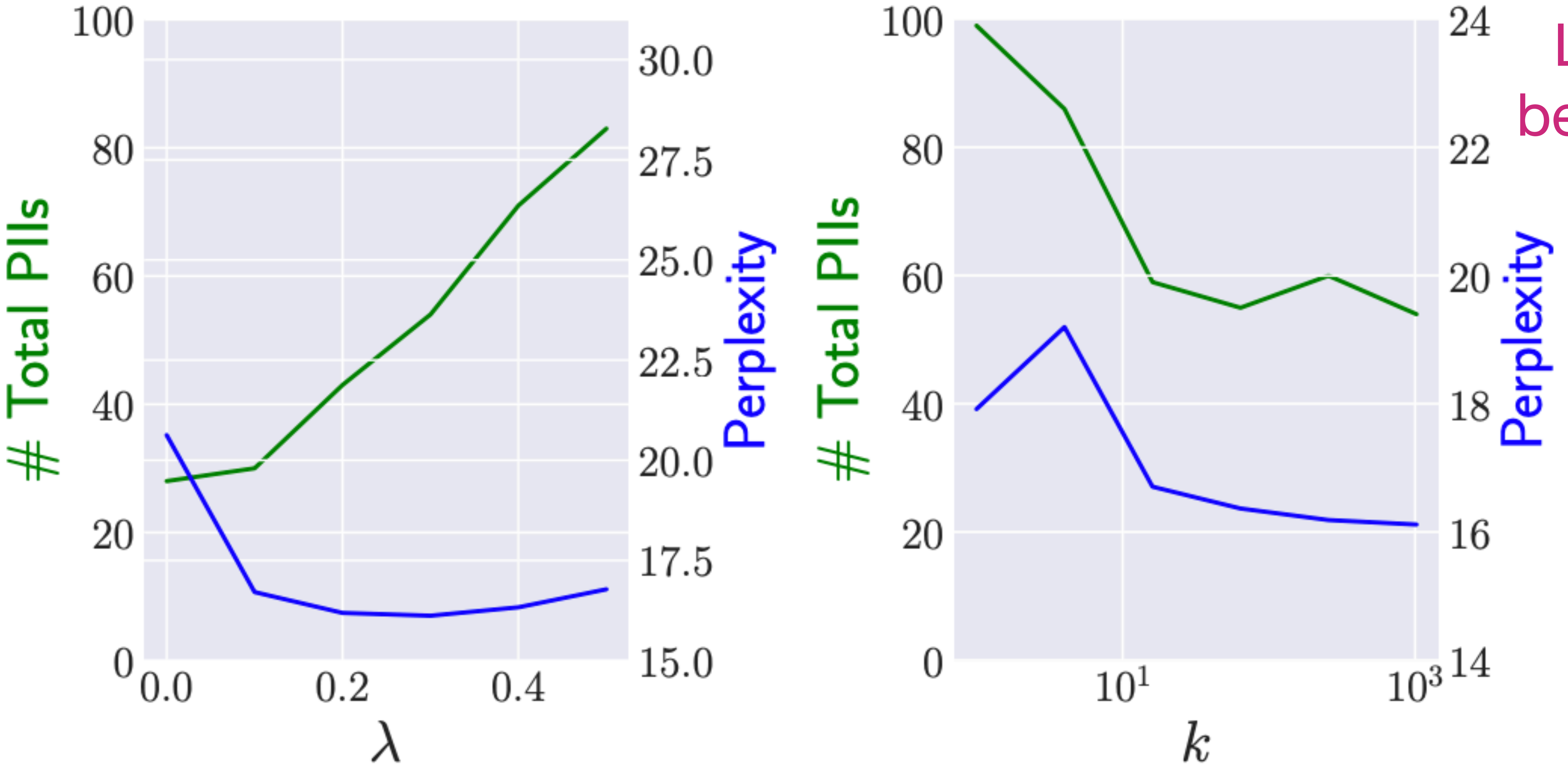
Lower lambda —> worse performance, less PIIS

Huang et al. 2023. “Privacy Implications of Retrieval-Based Language Models”

Key effectiveness in downstream tasks

Privacy

Retrieval-based LMs enable us to mitigate privacy risks.



Larger k for better trade off

Huang et al. 2023. "Privacy Implications of Retrieval-Based Language Models"

Key effectiveness in downstream tasks

Verifiability

Human and model can reliably assess the **factuality of the generations** using the retrieved evidence.

Why is it sometimes hard to eat after not eating for a while?

175B best-of-64

There are several reasons why not eating for long periods of time can make you lose your appetite. One is that not eating triggers the same response as starvation, adrenaline drives a process called lipolysis, which is the process your body undertakes when it wants to break down your fat reserves for energy, and also prevents you from burning through your muscle[1][3]. Another reason is that not eating means your body doesn't get the sugars it needs to operate properly, which causes a process called gluconeogenesis[2]. Also, leptin levels can rapidly decline in the fasted state[4], which may cause an increase in appetite.

1. Why Don't You Feel Hungry After Not Eating For a Long Time? – Neuro (getneuro.com)
2. Why Don't You Feel Hungry After Not Eating For a Long Time? – Neuro (getneuro.com)
3. Why Don't You Feel Hungry After Not Eating For a Long Time? – Neuro (getneuro.com)
4. Fasting may change the body's hunger response - here's what to do about it - Diabetes (www.diabetes.co.uk)

Nakano et al. 2021. "WebGPT: Browser-assisted question-answering with human feedback"

Attributions: AttributedQA (Bohnet et al., 2022)

Expected Model Output

$$g(x) = (a, c)$$

Q: The population of Toronto is _

LM

6,255,000

Answer:

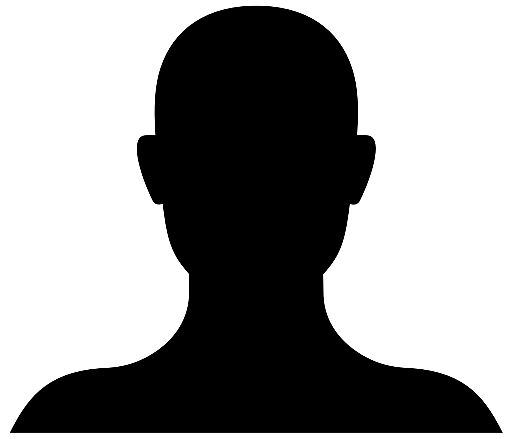
Datastore

Attribution: The current metro area population of Toronto in **2021** is 6,255,000.

Bohnet et al. 2022. "Attributed Question Answering: Evaluation and Modeling for Attributed Large Language Models"

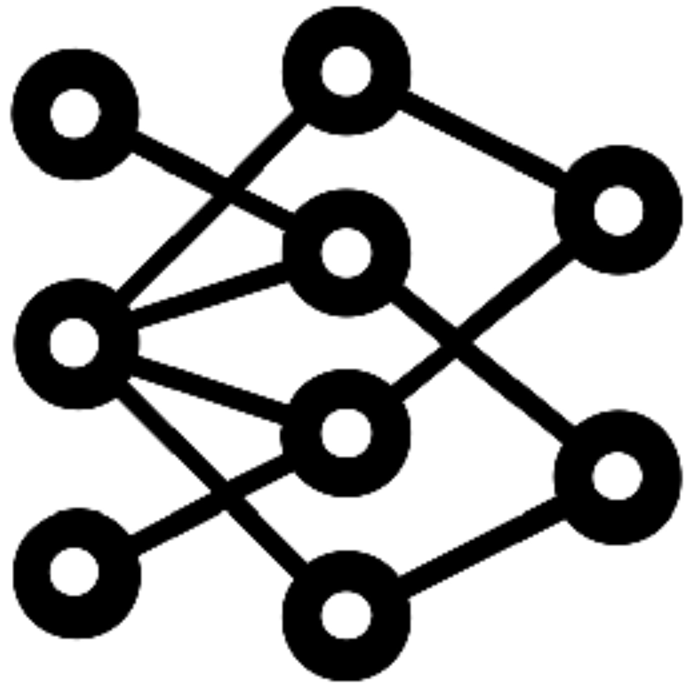
Attributions: AttributedQA (Bohnet et al., 2022)

Human Evaluation
(AIS)



1. Are all (a,c) interpretable?
2. Is any information in a supported by c?

Automatic Evaluation
(Auto AIS)



NLI model

$$E^{\mathsf{A}}[g] = \frac{1}{n}\sum_{i=1}^{n} \texttt{AutoAIS}(x_i, g(x_i))$$

AttributedQA (Bohnet et al., 2022)

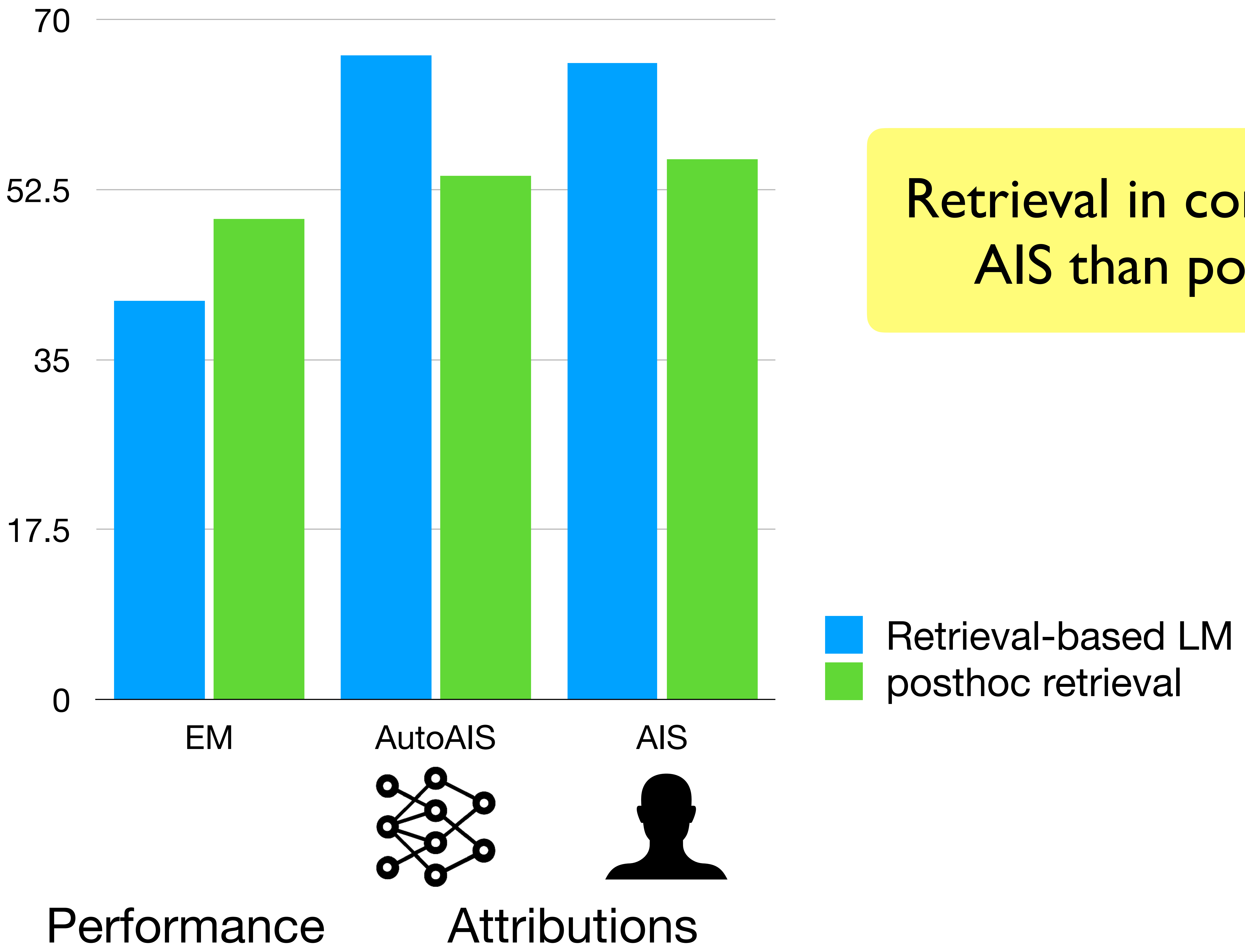
Retrieval-based LMs

Datastore → **Evidence:** The current metro area population of Toronto in 2023 is 6,372,000. → LM → **6,372,000**

Post-hoc retrieval

LM → **6,372,000** → Datastore → **Attribution:** The current metro area population of Toronto in **2021** is 6,255,000.

AttributedQA (Bohnet et al., 2022)



Retrieval in context yields higher AIS than post-hoc retrieval

When to use a retrieval-based LM

Long-tail

knowledge update

Verifiability

Parameter-efficiency

Privacy

Out of domain adaptations
(Shi et al., 2022; Zheng et al., 2021)

and many others!!

Shi et al. 2022. “Nearest Neighbor Zero-shot Inference”

Zhang et al. 2021. “Non-Parametric Unsupervised Domain Adaptation for Neural Machine Translation”