Nearest Neighbour LMs

NLP: Fall 2024

Anoop Sarkar

kNN LM

IMPROVING NEURAL LANGUAGE MODELS WITH A CONTINUOUS CACHE

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https://arxiv.org/abs/1612.04426 2017

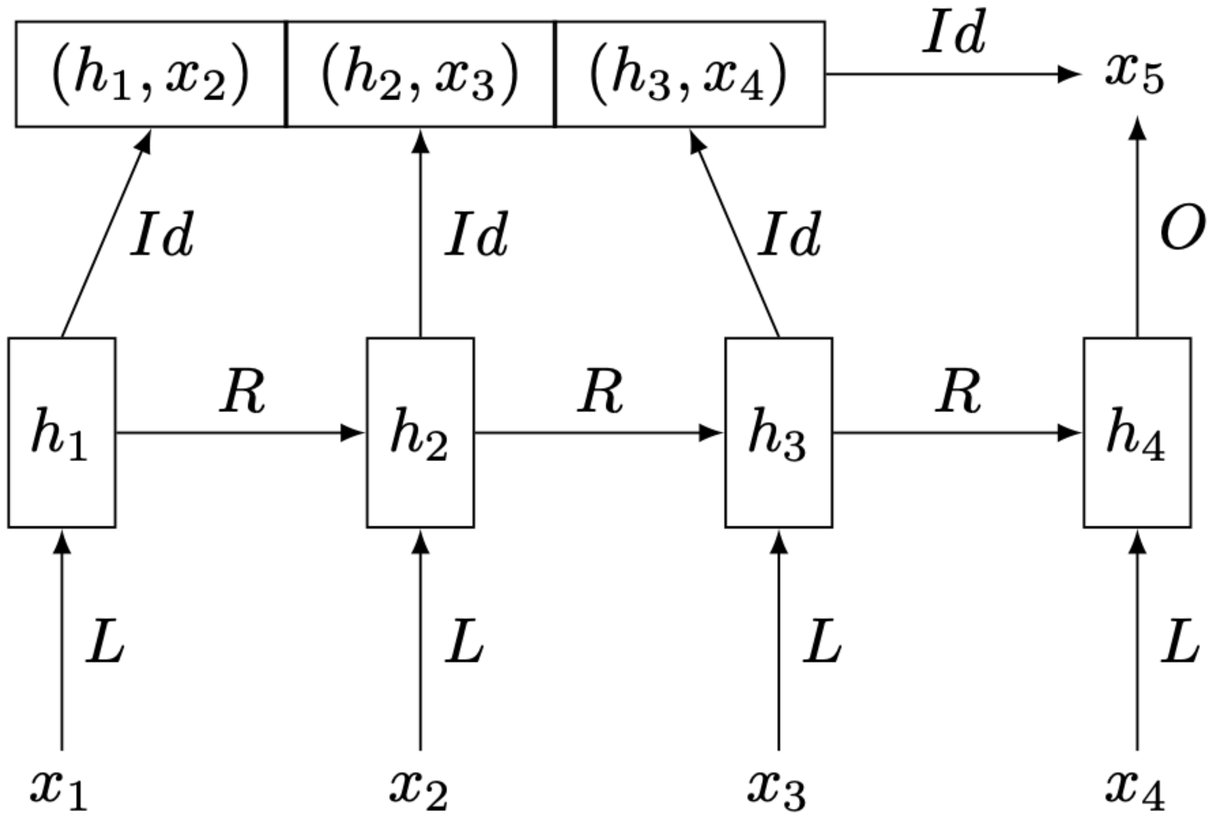

Figure 1: The neural cache stores the previous hidden states in memory cells. They are then used as keys to retrieve their corresponding word, that is the next word. There is no transformation applied to the storage during writing and reading.

$$p_{cache}(w \mid h_{1..t},\ x_{1..t}) \propto \sum_{i=1}^{t-1} \mathbb{1}_{\{w=x_{i+1}\}} \exp(\theta h_t^\top h_i)$$

GENERALIZATION THROUGH MEMORIZATION: NEAREST NEIGHBOR LANGUAGE MODELS

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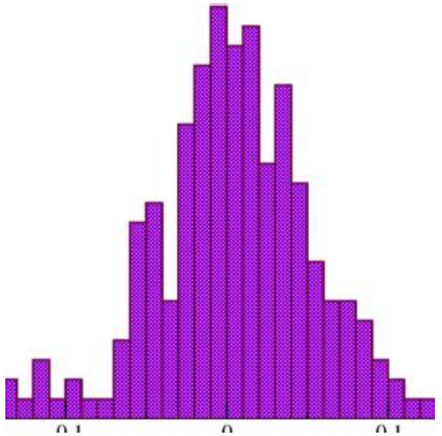
https://openreview.net/forum?id=HklBjCEKvH

Learning representations is easier than prediction

Dickens is the author of

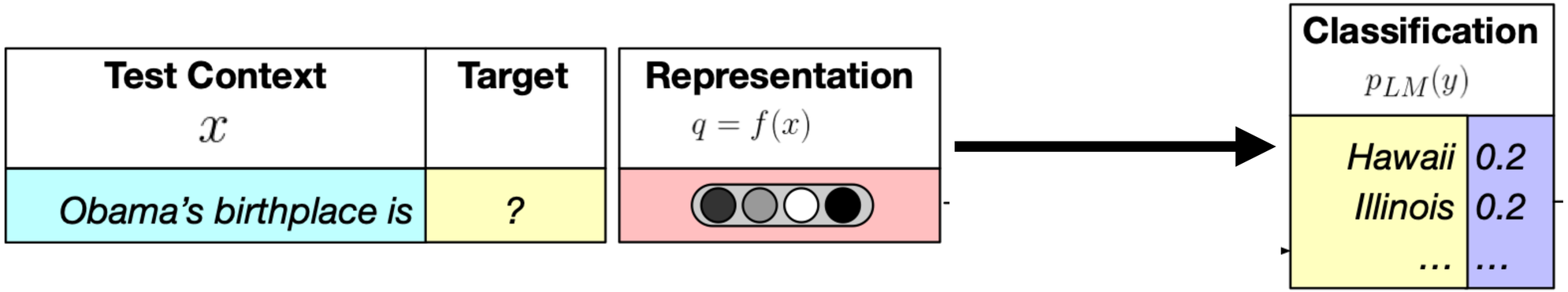
Dickens wrote

?



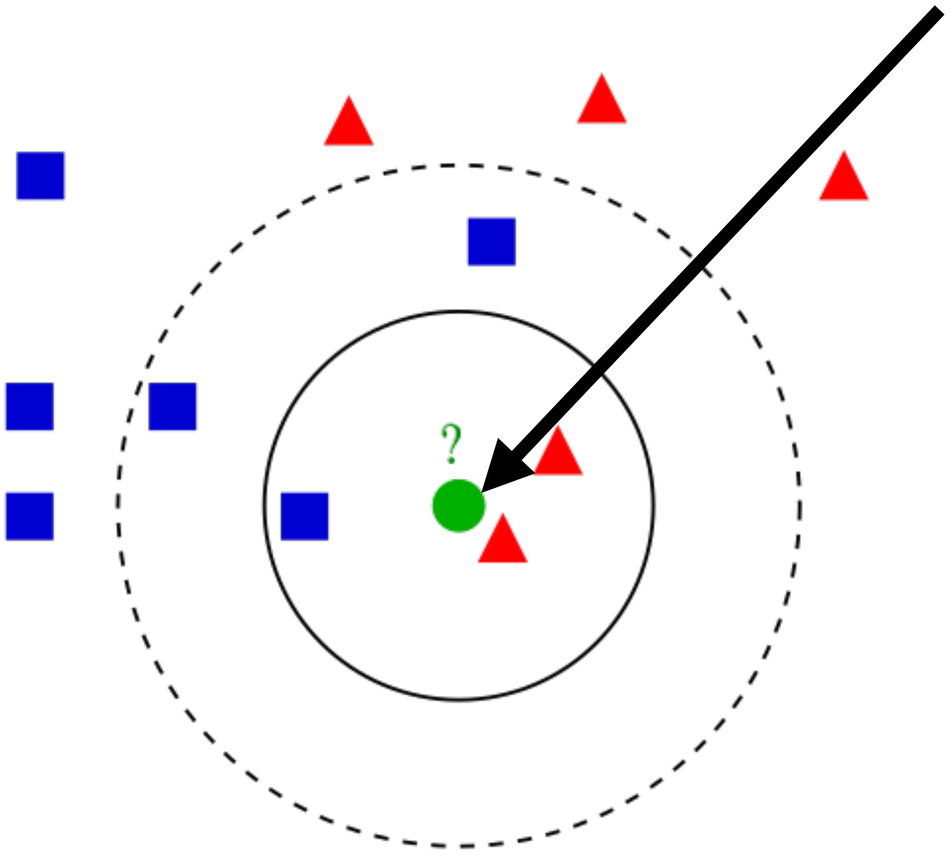
Even if you cannot predict the next token, you can predict that the distribution is identical over the vocabulary.

Standard LM prediction



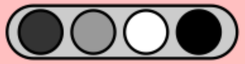
Nearest Neighbour

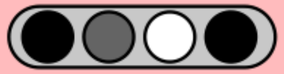
k neighbours in vector space



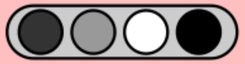
- The query vector is compared to other data vectors in the same vector space.
- Choose the class that has the most representatives inside the search perimeter.
- The search perimeter is determined by the cosine similarity of the query vector to the vectors stored in a kNN storage
- Efficient disk based kNN retrieval for very large sets of vectors is available: SCaNN, FAISS, annoy, etc.

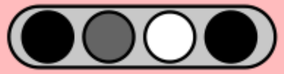
kNN LM prediction (step 1)

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

Training Contexts c_i	Targets v_i	Representations $k_i = f(c_i)$	Distances $d_i = d(q, k_i)$
Obama was senator for	*Illinois*		*4*
Barack is married to	*Michelle*		*100*
Obama was born in	*Hawaii*		*5*
...	*...*	*...*	*...*
Obama is a native of	*Hawaii*		*3*

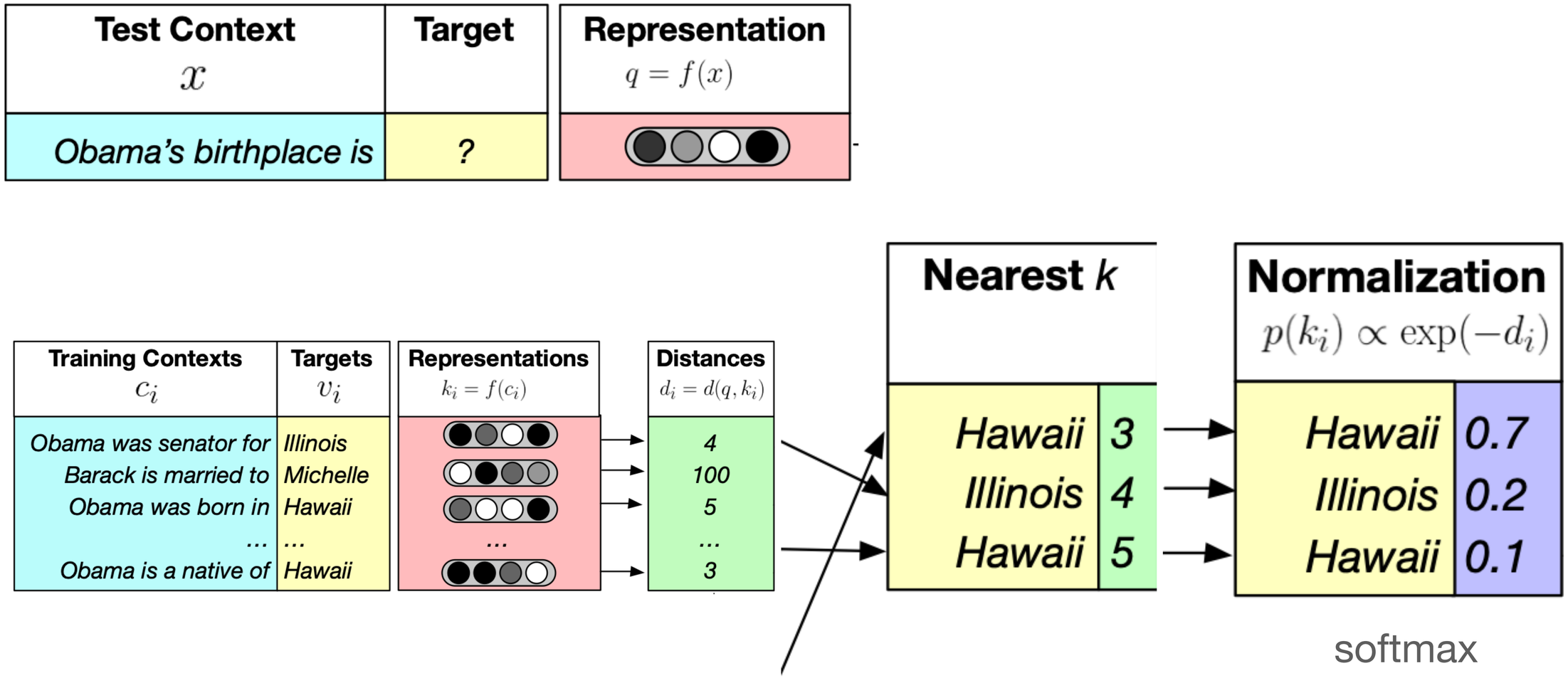
kNN LM prediction (step 2)

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

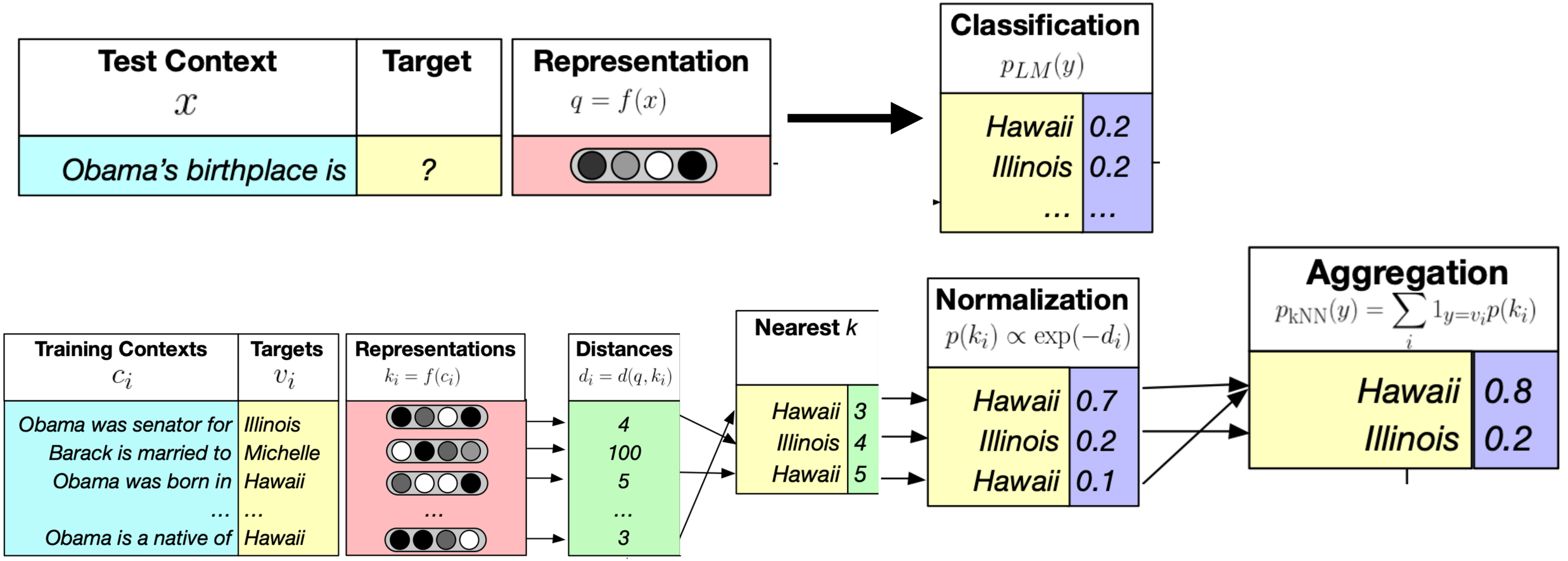
Training Contexts c_i	Targets v_i	Representations $k_i = f(c_i)$	Distances $d_i = d(q, k_i)$
Obama was senator for	*Illinois*		*4*
Barack is married to	*Michelle*		*100*
Obama was born in	*Hawaii*		*5*
...	*...*	*...*	*...*
Obama is a native of	*Hawaii*		*3*

Nearest *k*	
Hawaii	*3*
Illinois	*4*
Hawaii	*5*

kNN LM prediction (step 3)



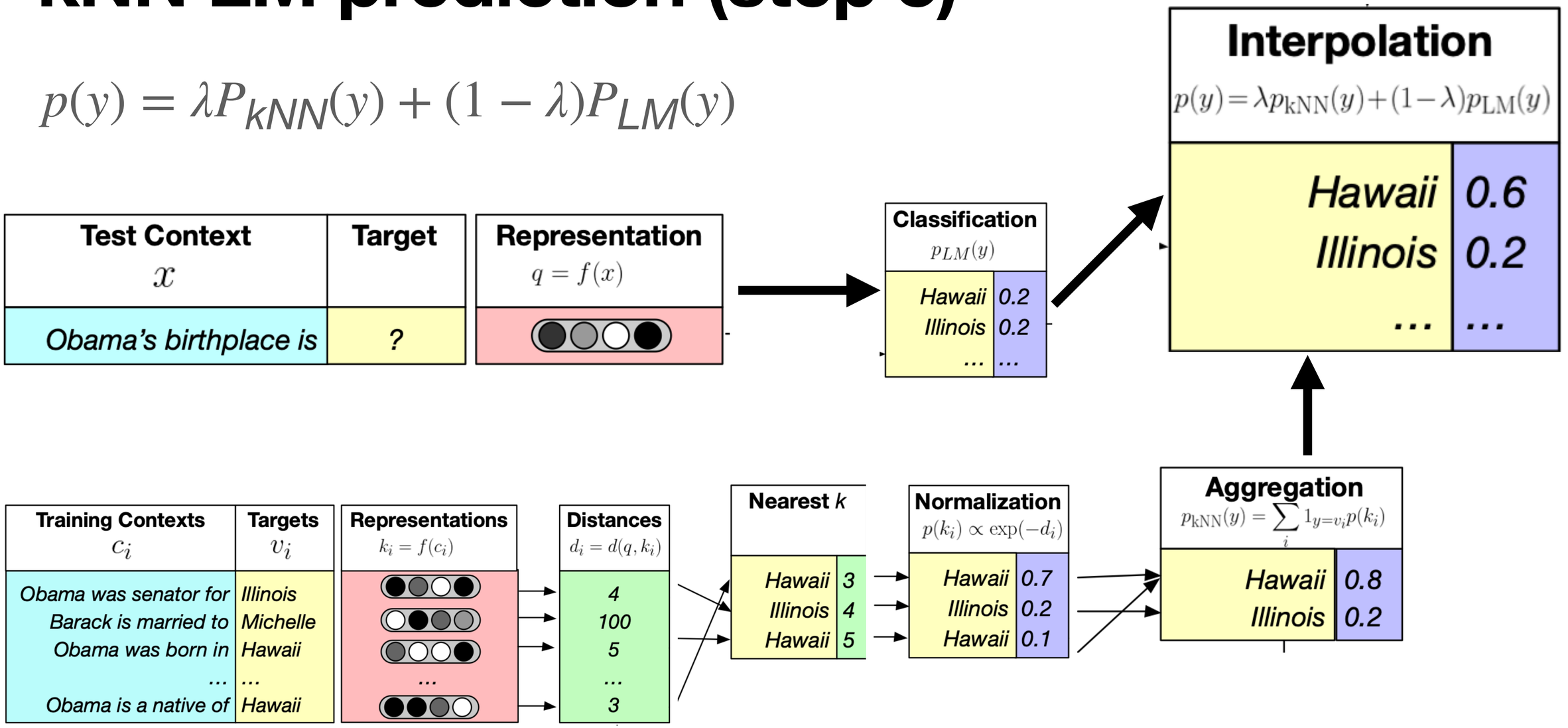
kNN LM prediction (step 4)



$$P_{kNN}(y) \approx \sum_{k_i, v_i \in \mathcal{N}} 1_{y=v_i} \exp(-d(k_i, f(x)))$$

kNN LM prediction (step 5)

$$p(y) = \lambda P_{kNN}(y) + (1 - \lambda) P_{LM}(y)$$



Best representation for $f(c)$?

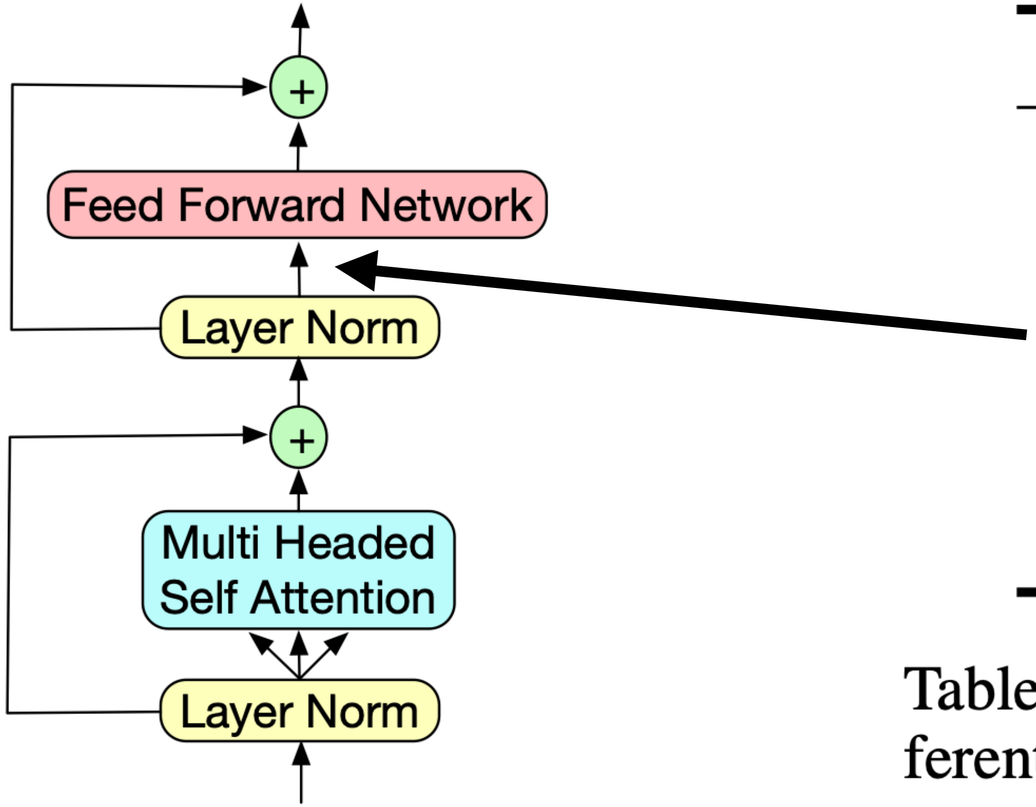


Figure 3: Transformer LM layer.

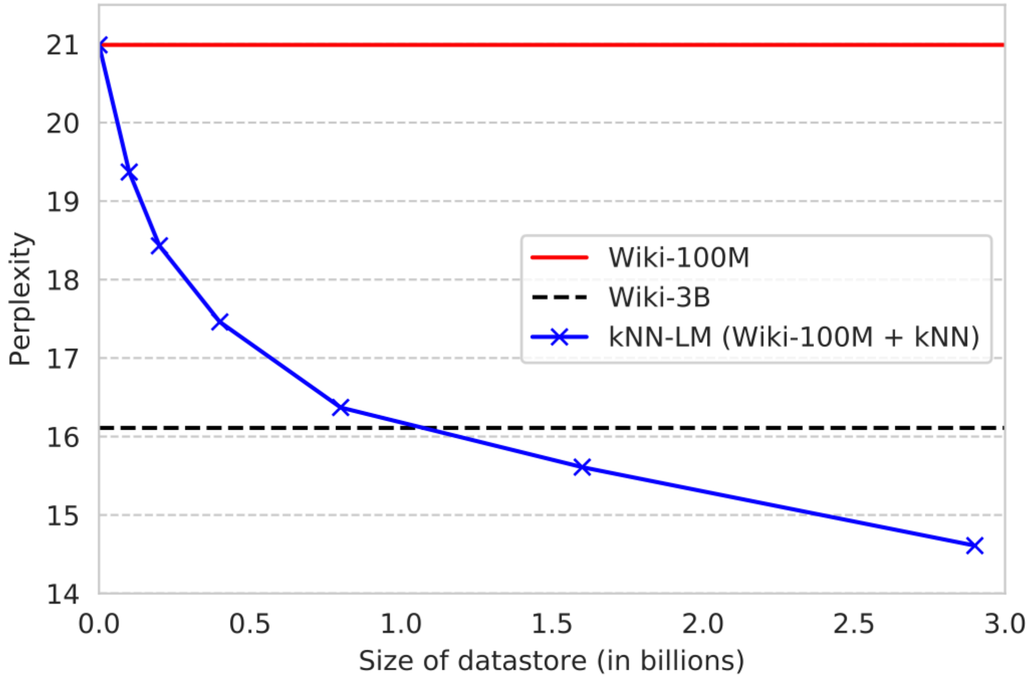
Key Type	Dev ppl. (↓)
No datastore	17.96
Model output	17.07
Model output layer normalized	17.01
FFN input after layer norm	**16.06**
FFN input before layer norm	17.06
MHSA input after layer norm	16.76
MHSA input before layer norm	17.14

Table 5: WIKITEXT-103 validation results using different states from the final layer of the LM as the representation function $f(\cdot)$ for keys and queries. We retrieve k=1024 neighbors and λ is tuned for each.

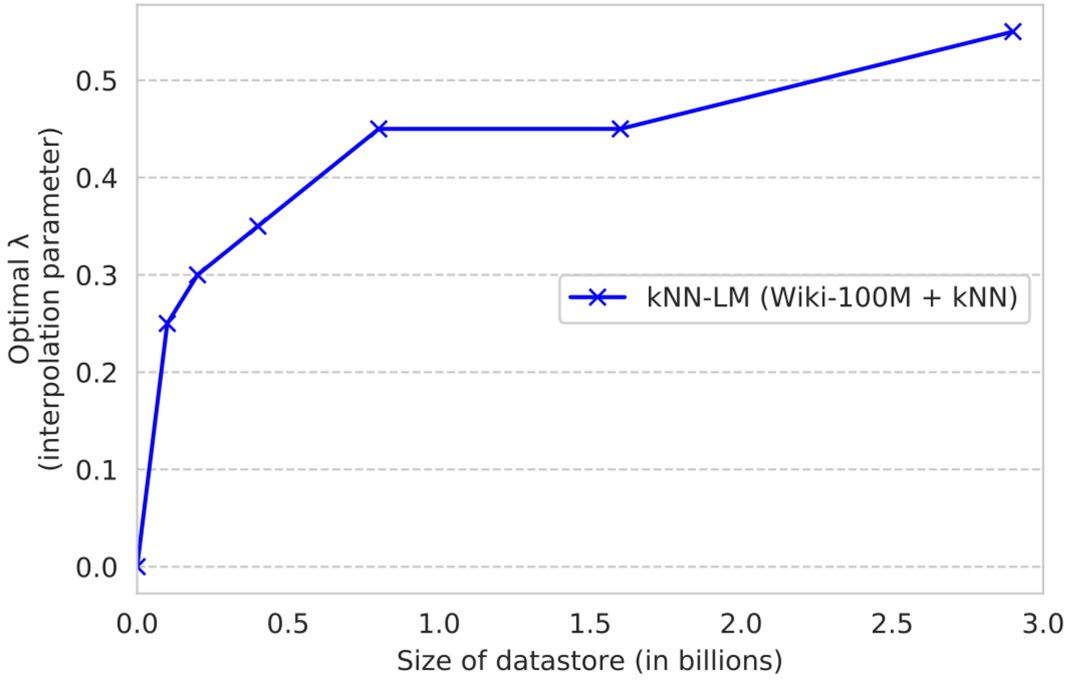
Output of FFN focuses on prediction; attention output focuses on representation

Model	Perplexity (↓) Dev	Test	# Trainable Params
Baevski & Auli (2019)	17.96	18.65	247M
+Transformer-XL (Dai et al., 2019)	-	18.30	257M
+Phrase Induction (Luo et al., 2019)	-	17.40	257M
Base LM (Baevski & Auli, 2019)	17.96	18.65	247M
+kNN-LM	**16.06**	**16.12**	247M
+Continuous Cache (Grave et al., 2017c)	17.67	18.27	247M
+kNN-LM + Continuous Cache	**15.81**	**15.79**	247M

Table 1: Performance on WIKITEXT-103. The kNN-LM substantially outperforms existing work. Gains are additive with the related but orthogonal continuous cache, allowing us to improve the base model by almost 3 perplexity points with no additional training. We report the median of three random seeds.



(a) Effect of datastore size on perplexities.



(b) Tuned values of λ for different datastore sizes.

Figure 2: Varying the size of the datastore. (a) Increasing the datastore size monotonically improves performance, and has not saturated even at about 3B tokens. A kNN-LM trained on 100M tokens with a datastore of 1.6B tokens already outperforms the LM trained on all 3B tokens. (b) The optimal value of λ increases with the size of the datastore.

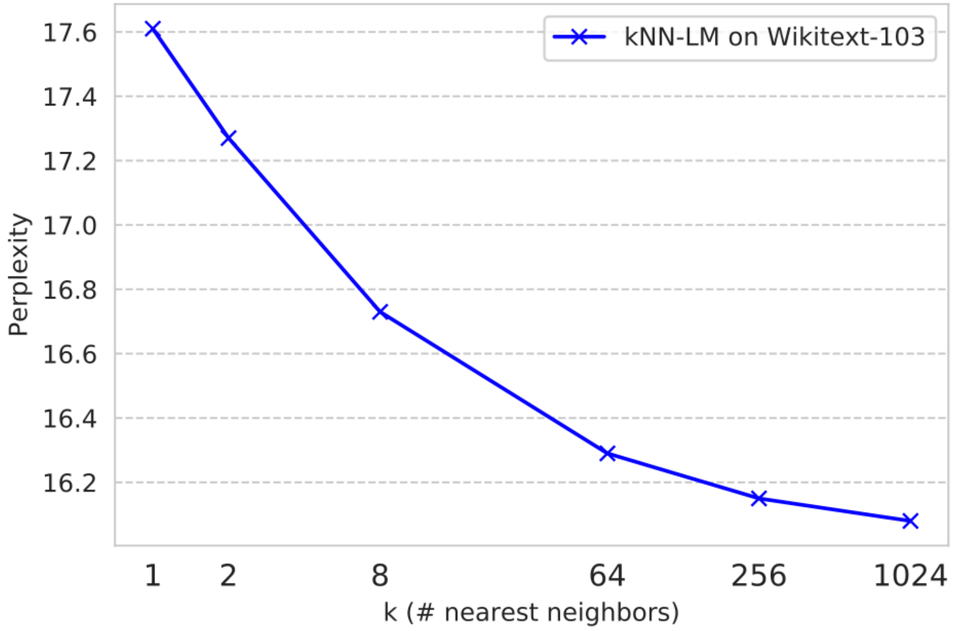


Figure 4: Effect of the number of nearest neighbors returned per word on WIKITEXT-103 (validation set). Returning more entries from the datastore monotonically improves performance.

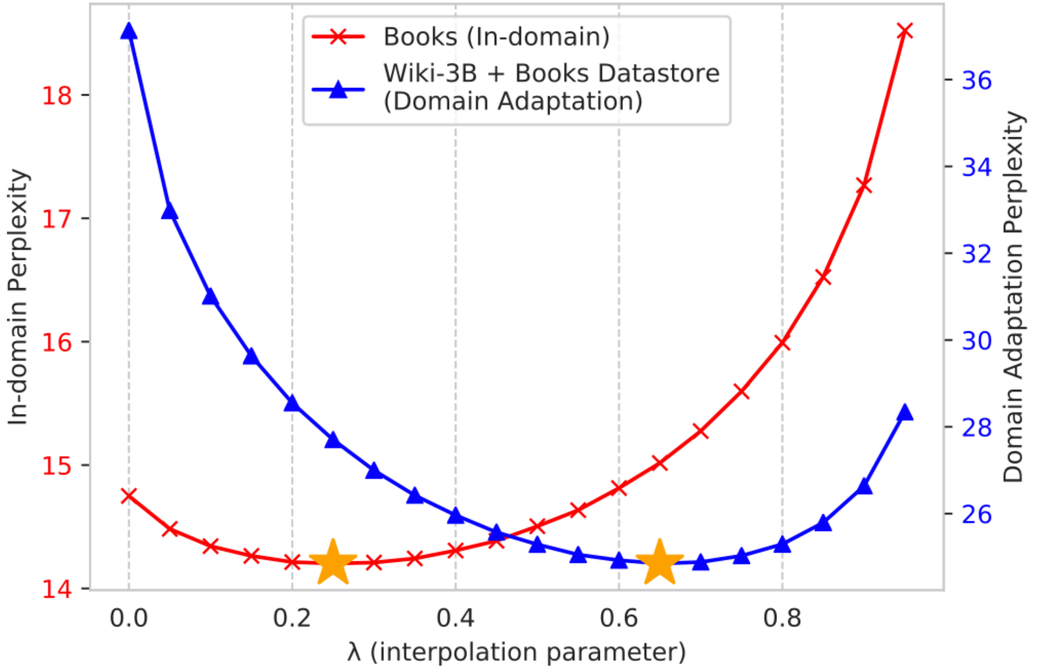


Figure 5: Effect of interpolation parameter λ on in-domain (left y-axis) and out-of-domain (right y-axis) validation set performances. More weight on p_{kNN} improves domain adaptation.

More data without training

Train LM on data; Store kNN on larger dataset

- Train LM on 100M token dataset, then run on 3B token dataset to store context vectors in kNN store
- Use kNN-LM to predict next token
- Surprisingly kNN-LM (100M + 3B) does better than LM trained on 3B token dataset
- "retrieving nearest neighbors from the corpus outperforms training on it"
- "rather than training language models on ever larger datasets, we can use smaller datasets to learn representations and augment them with kNN-LM over a large corpus"

Test Context ($p_{\text{kNN}} = 0.998$, $p_{\text{LM}} = 0.124$)	**Test Target**
it was organised by New Zealand international player Joseph Warbrick, promoted by civil servant Thomas Eyton, and managed by James Scott, a publican. The Natives were the first New Zealand team to perform a haka, and also the first to wear all black. They played 107 rugby matches during the tour, as well as a small number of Victorian Rules football and association football matches in Australia. Having made a significant impact on the...	development

Training Set Context	**Training Set Target**	**Context Probability**
As the captain and instigator of the 1888-89 Natives – the first New Zealand team to tour the British Isles – Warbrick had a lasting impact on the...	development	0.998
promoted to a new first grade competition which started in 1900. Glebe immediately made a big impact on the...	district	0.00012
centuries, few were as large as other players managed. However, others contend that his impact on the...	game	0.000034
Nearly every game in the main series has either an anime or manga adaptation, or both. The series has had a significant impact on the...	development	0.00000092

Test Context ($p_{\text{kNN}} = 0.995, p_{\text{LM}} = 0.025$)	**Test Target**
For Australians and New Zealanders the Gallipoli campaign came to symbolise an important milestone in the emergence of both nations as independent actors on the world stage and the development of a sense of national identity. Today, the date of the initial landings, 25 April, is known as Anzac Day in Australia and New Zealand and every year thousands of people gather at memorials in both nations, as well as Turkey, to...	honour

Training Set Context	**Training Set Target**	**Context Probability**
Despite this, for Australians and New Zealanders the Gallipoli campaign has come to symbolise an important milestone in the emergence of both nations as independent actors on the world stage and the development of a sense of national identity. Today, the date of the initial landings, 25 April, is a public holiday known as Anzac Day in Australia and New Zealand and every year thousands of people gather at memorials in both nations, and indeed in Turkey, to ...	honour	0.995
On the anniversary date of his death, every year since 1997, thousands of people gather at his home in Memphis to...	celebrate	0.0086
Twenty-five years after Marseille's death, fighter pilot veterans of World War II gathered to...	honour	0.0000041

Test Context ($p_{\text{kNN}} = 0.959$, $p_{\text{LM}} = 0.503$)	**Test Target**
U2 do what they're best at, slipping into epic rock mode, playing music made for the arena". In two other local newspaper reviews, critics praised the song's inclusion in a sequence of greatest hits. For the PopMart Tour of 1997–...	1998

Training Set Context	**Training Set Target**	**Context Probability**
Following their original intent, "Sunday Bloody Sunday" was not played during any of the forty-seven shows on the Lovetown Tour in 1989. The song reappeared for a brief period during the Zoo TV Tour, and late during the second half of PopMart Tour (1997–...	1998	0.936
They are 6 times Champions and they won the Challenge Cup in 1938, and have experienced two previous stretches in the Super League, 1997–...	2002	0.0071
About $40 million ($61.4 million in 2018 dollars) was spent on the property acquisition. After weather-related construction delays due to the El Nino season of the winter of 1997–...	1998	0.0015
This made it the highest-rated season of The X-Files to air as well as the highest rated Fox program for the 1997–...	98	0.00000048

RETRO

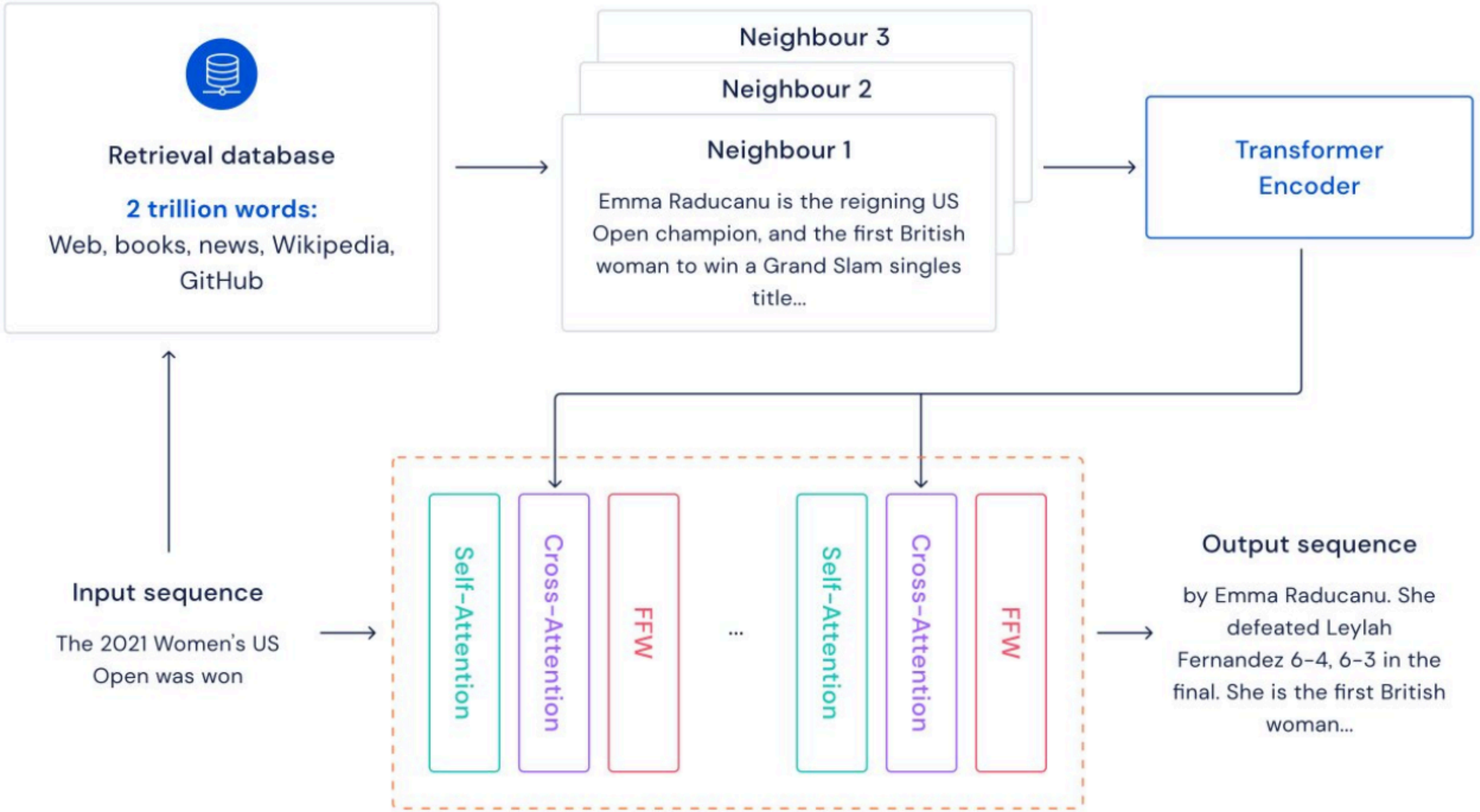
DeepMind

Improving language models by retrieving from trillions of tokens

Sebastian Borgeaud[†], Arthur Mensch[†], Jordan Hoffmann[†], Trevor Cai, Eliza Rutherford, Katie Millican, George van den Driessche, Jean-Baptiste Lespiau, Bogdan Damoc, Aidan Clark, Diego de Las Casas, Aurelia Guy, Jacob Menick, Roman Ring, Tom Hennigan, Saffron Huang, Loren Maggiore, Chris Jones, Albin Cassirer, Andy Brock, Michela Paganini, Geoffrey Irving, Oriol Vinyals, Simon Osindero, Karen Simonyan, Jack W. Rae[‡], Erich Elsen[‡] and Laurent Sifre[†,‡]

All authors from DeepMind, [†]Equal contributions, [‡]Equal senior authorship

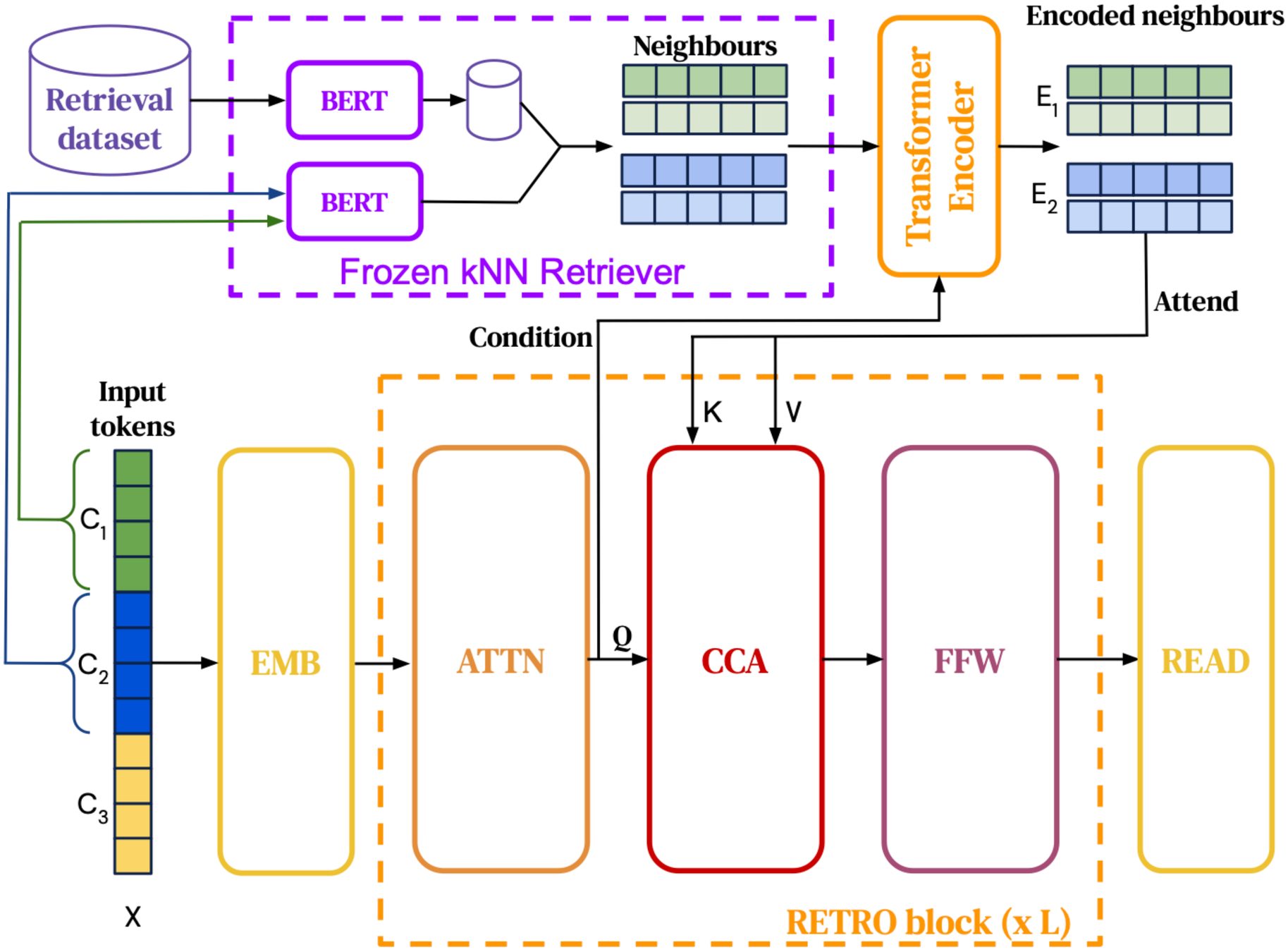
https://arxiv.org/abs/2112.04426

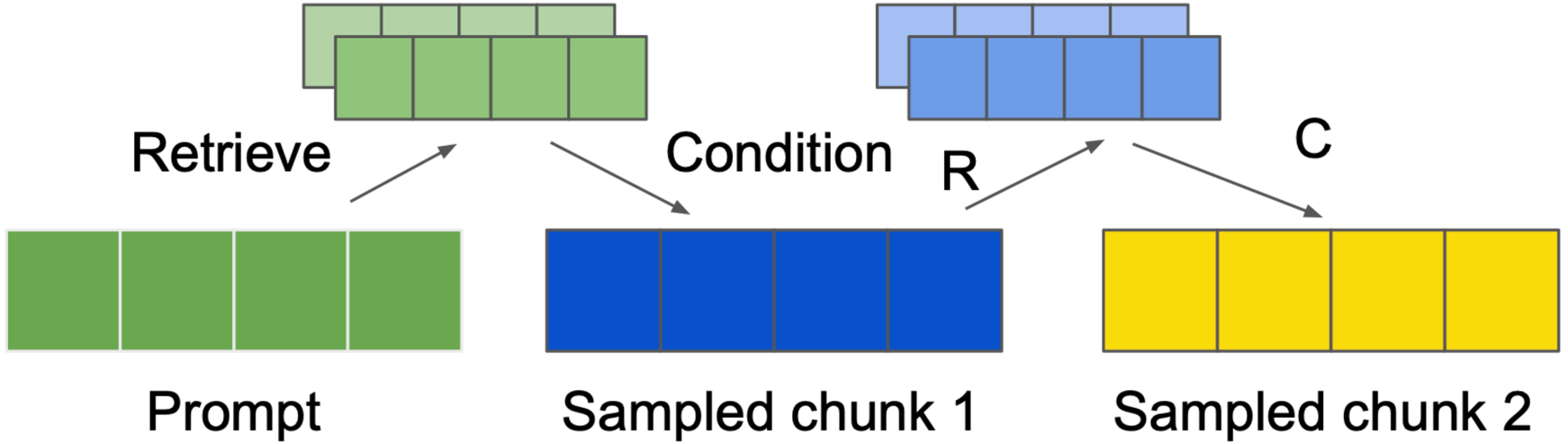


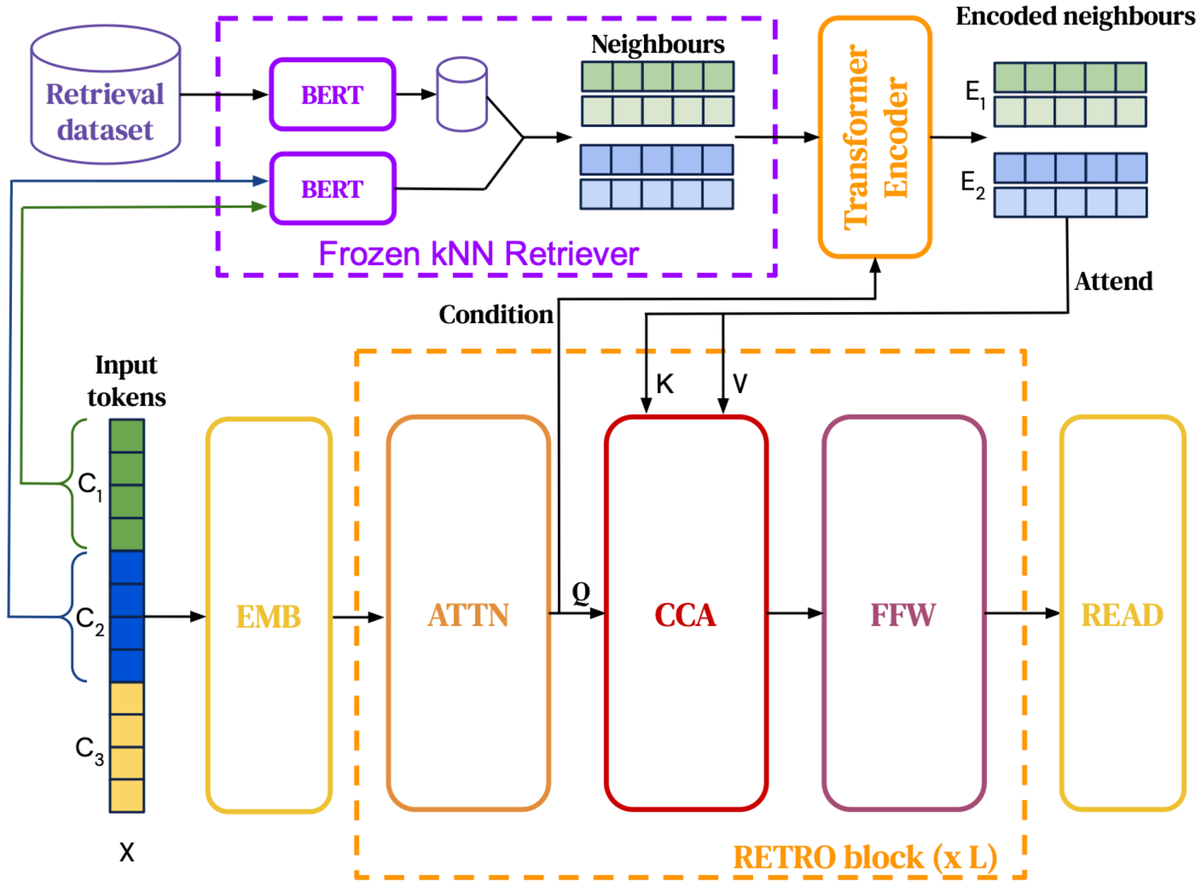
https://www.deepmind.com/blog/improving-language-models-by-retrieving-from-trillions-of-tokens

Table 3 | **Comparison of RETRO with existing retrieval approaches.**

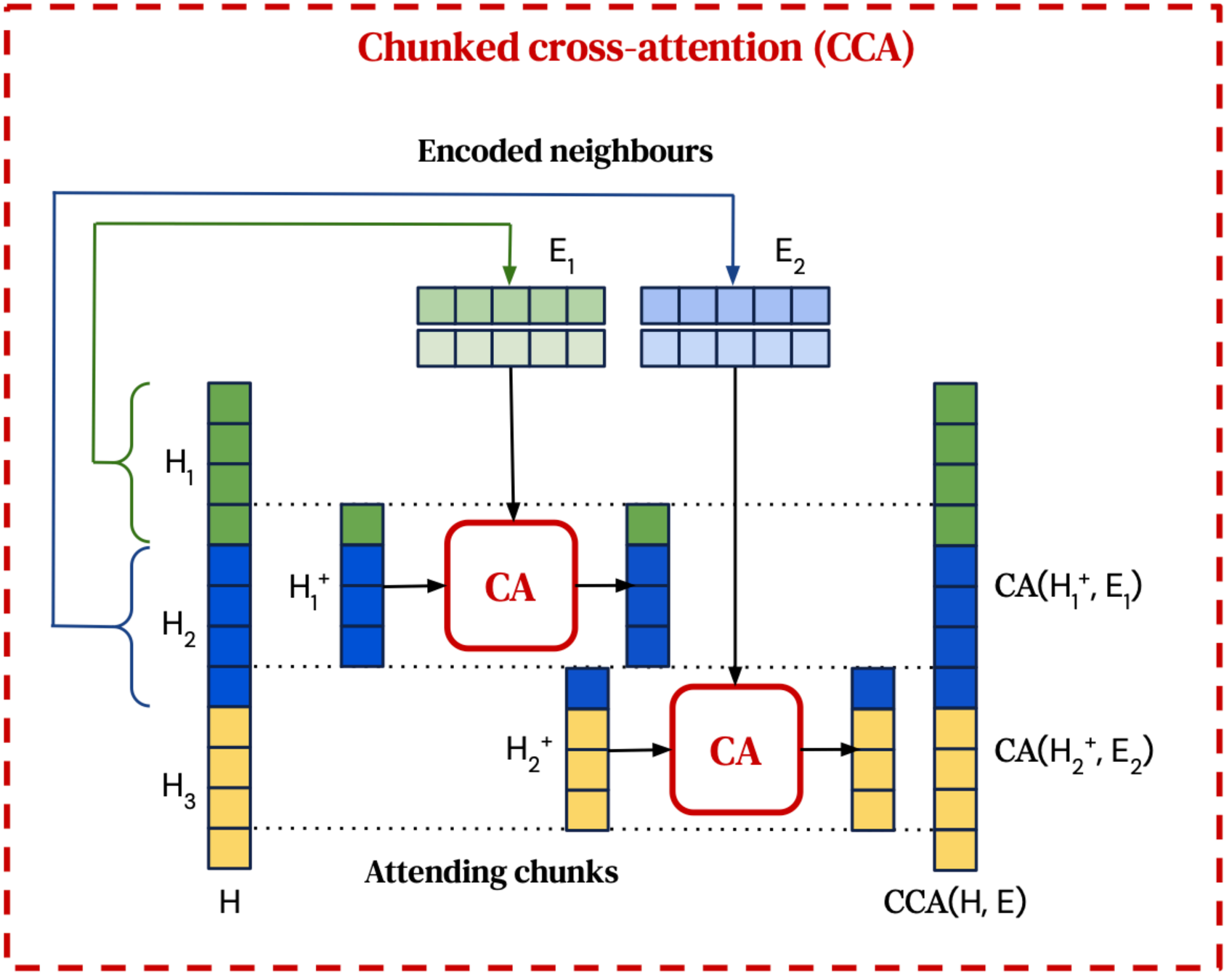
	# Retrieval tokens	Granularity	Retriever training	Retrieval integration
Continuous Cache	$\mathcal{O}(10^3)$	Token	Frozen (LSTM)	Add to probs
kNN-LM	$\mathcal{O}(10^9)$	Token	Frozen (Transformer)	Add to probs
SPALM	$\mathcal{O}(10^9)$	Token	Frozen (Transformer)	Gated logits
DPR	$\mathcal{O}(10^9)$	Prompt	Contrastive proxy	Extractive QA
REALM	$\mathcal{O}(10^9)$	Prompt	End-to-End	Prepend to prompt
RAG	$\mathcal{O}(10^9)$	Prompt	Fine-tuned DPR	Cross-attention
FID	$\mathcal{O}(10^9)$	Prompt	Frozen DPR	Cross-attention
EMDR^2	$\mathcal{O}(10^9)$	Prompt	End-to-End (EM)	Cross-attention
RETRO (ours)	$\mathcal{O}(\mathbf{10^{12}})$	**Chunk**	**Frozen (BERT)**	**Chunked cross-attention**


Retrieval dataset
BERT
BERT
Frozen kNN Retriever
Neighbours
Transformer Encoder
Encoded neighbours
E_1
E_2
Attend
Condition
Input tokens
C_1
C_2
C_3
X
EMB
ATTN
Q
K
V
CCA
FFW
READ
RETRO block (x L)

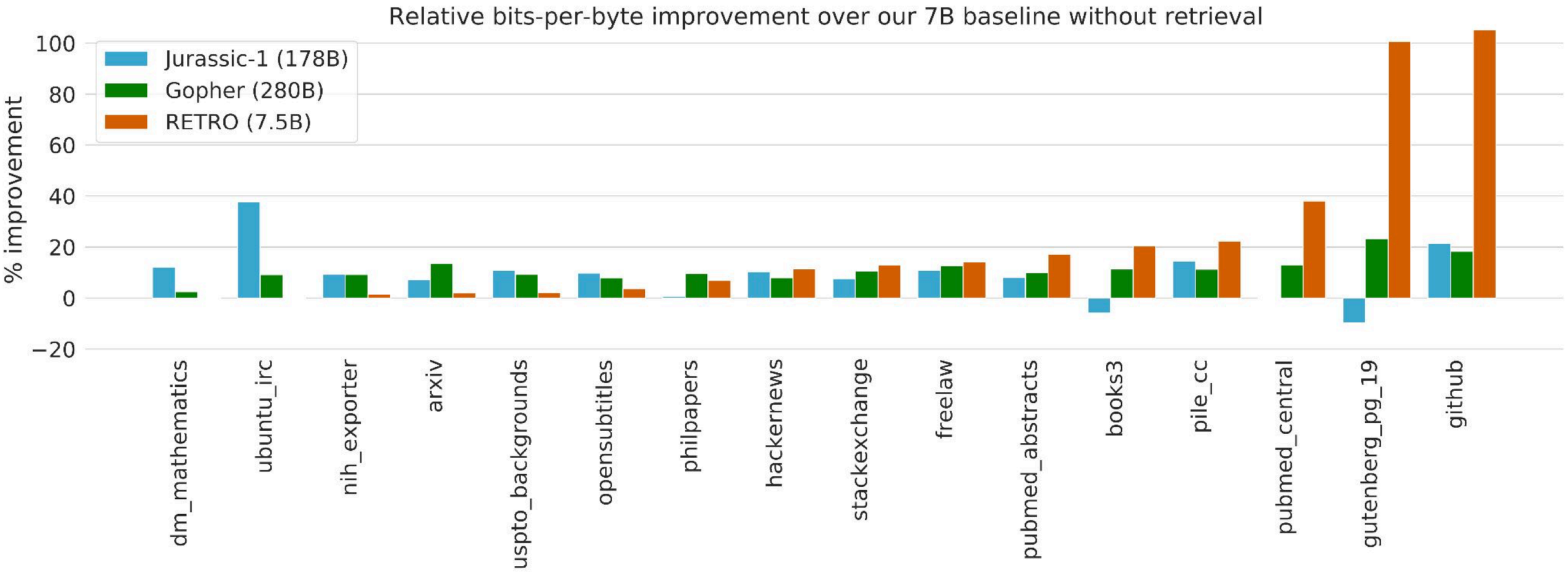




https://icml.cc/media/icml-2022/Slides/17480_uuemO20.pdf


Chunked cross-attention (CCA)
Encoded neighbours
E1
E2
H1
H2
H3
H
H1+
CA
H2+
CA
CA(H1+, E1)
CA(H2+, E2)
Attending chunks
CCA(H, E)

Language modelling: The Pile



https://icml.cc/media/icml-2022/Slides/17480_uuemO20.pdf

Gao et al. 2020. The Pile: An 800GB Dataset of Diverse Text for Language Modeling

RETRO Takeaways

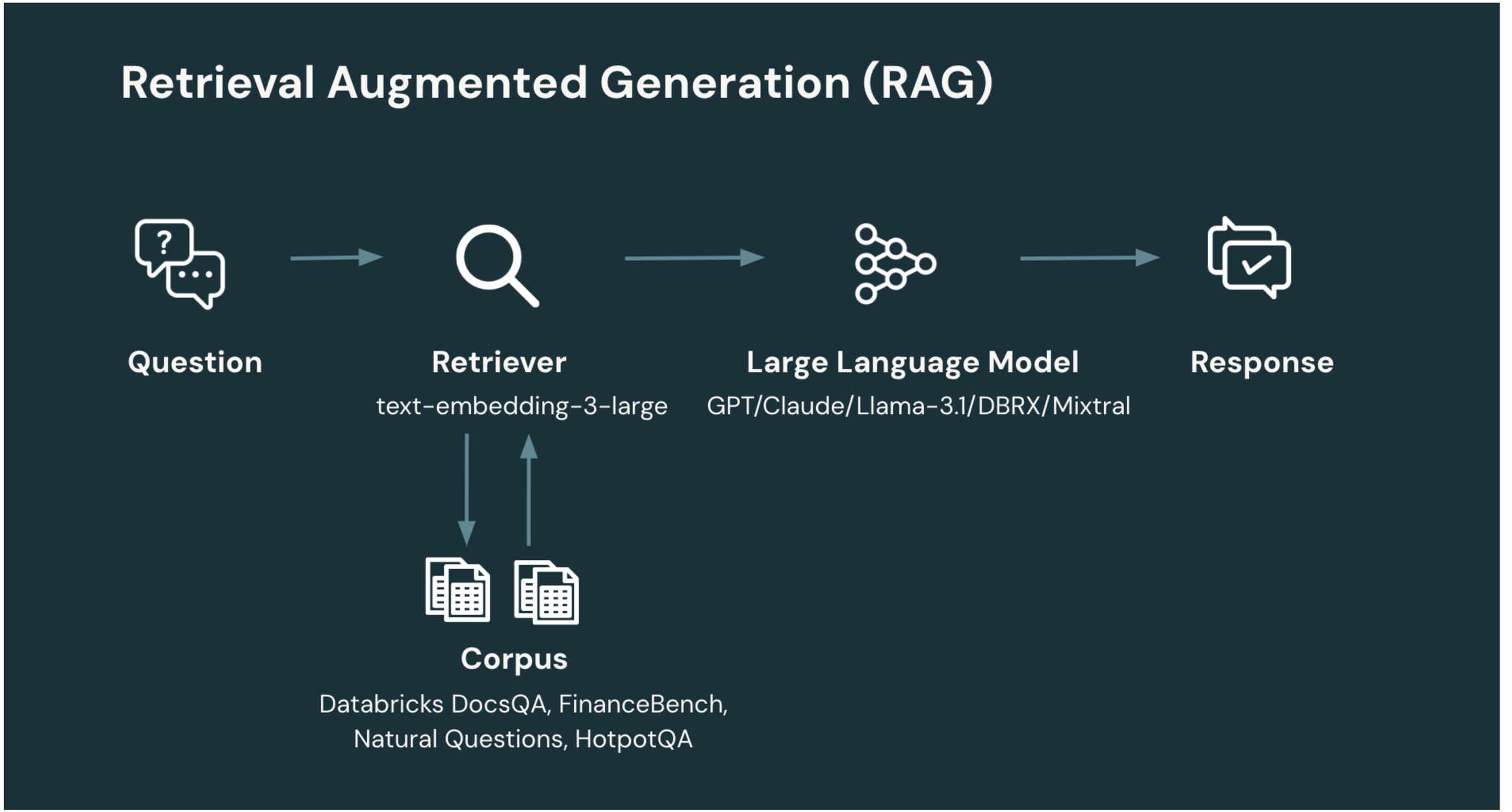
- RETRO is a general architecture, that is fully autoregressive and enables large scale retrieval
- Adding a 2T token database yields a performance improvement that's constant with model size: Similar performance to models with 10x more parameters on the Pile
- Consistent performance across benchmarks
  - Retrieval does exploit train-test leakage more than standard language models
  - But performance also improves on held-out tokens
- Future work on few-shot evaluation

https://icml.cc/media/icml-2022/Slides/17480_uuemO20.pdf

Retrieval Augmented Generation

NLP: Fall 2024

Anoop Sarkar



https://www.databricks.com/blog/long-context-rag-performance-llms

Hallucinations

Questions for Blade Runner (subset)
Ridley Scott directed which films?
What year was the movie Blade Runner released?
Who is the writer of the film Blade Runner?
Which films can be described by dystopian?
Which movies was Philip K. Dick the writer of?
Can you describe movie Blade Runner in a few words?

Problem:

The LLM can hallucinate (incorrectly generate) items of information like the year or book titles

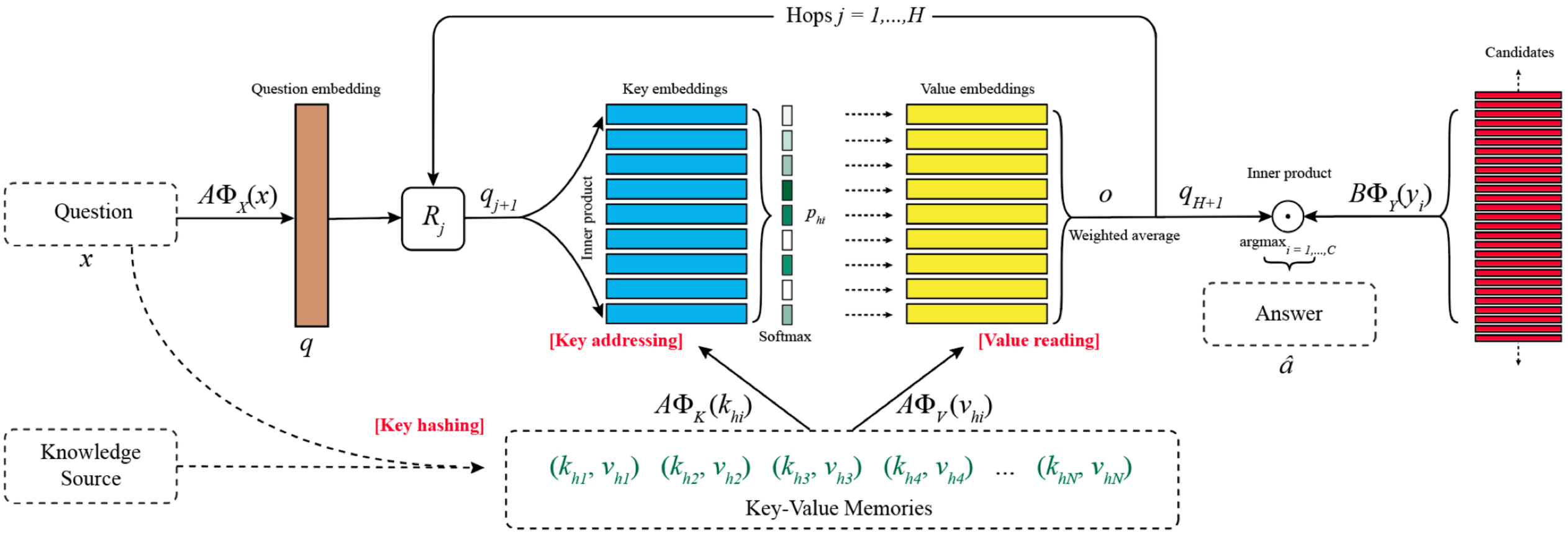
WikiMovies

Doc: Wikipedia Article for Blade Runner (partially shown)

Blade Runner is a 1982 American neo-noir dystopian science fiction film directed by Ridley Scott and starring Harrison Ford, Rutger Hauer, Sean Young, and Edward James Olmos. The screenplay, written by Hampton Fancher and David Peoples, is a modified film adaptation of the 1968 novel "Do Androids Dream of Electric Sheep?" by Philip K. Dick. The film depicts a dystopian Los Angeles in November 2019 in which genetically engineered replicants, which are visually indistinguishable from adult humans, are manufactured by the powerful Tyrell Corporation as well as by other "mega-corporations" around the world. Their use on Earth is banned and replicants are exclusively used for dangerous, menial, or leisure work on off-world colonies. Replicants who defy the ban and return to Earth are hunted down and "retired" by special police operatives known as "Blade Runners". . . .

WikiMovies

KB entries for Blade Runner (subset)
Blade Runner *directed_by* Ridley Scott
Blade Runner *written_by* Philip K. Dick, Hampton Fancher
Blade Runner *starred_actors* Harrison Ford, Sean Young, . . .
Blade Runner *release_year* 1982
Blade Runner *has_tags* dystopian, noir, police, androids, . . .
IE entries for Blade Runner (subset)
Blade Runner, Ridley Scott *directed* dystopian, science fiction, film
Hampton Fancher *written* Blade Runner
Blade Runner *starred* Harrison Ford, Rutger Hauer, Sean Young. . .
Blade Runner *labelled* 1982 neo noir
special police, Blade *retired* Blade Runner
Blade Runner, special police *known* Blade



https://aclanthology.org/D16-1147.pdf

Document Retrieval QA

https://aclanthology.org/P17-1171.pdf

Open-domain QA

SQuAD, TREC, WebQuestions, WikiMovies

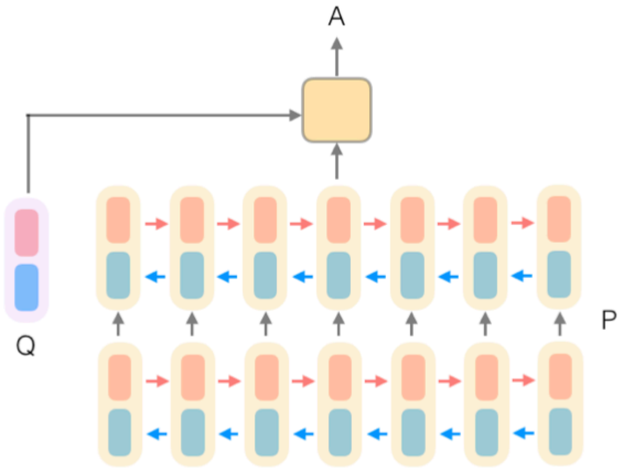
Q: How many of Warsaw's inhabitants spoke Polish in 1933?

WIKIPEDIA
The Free Encyclopedia

Document Retriever

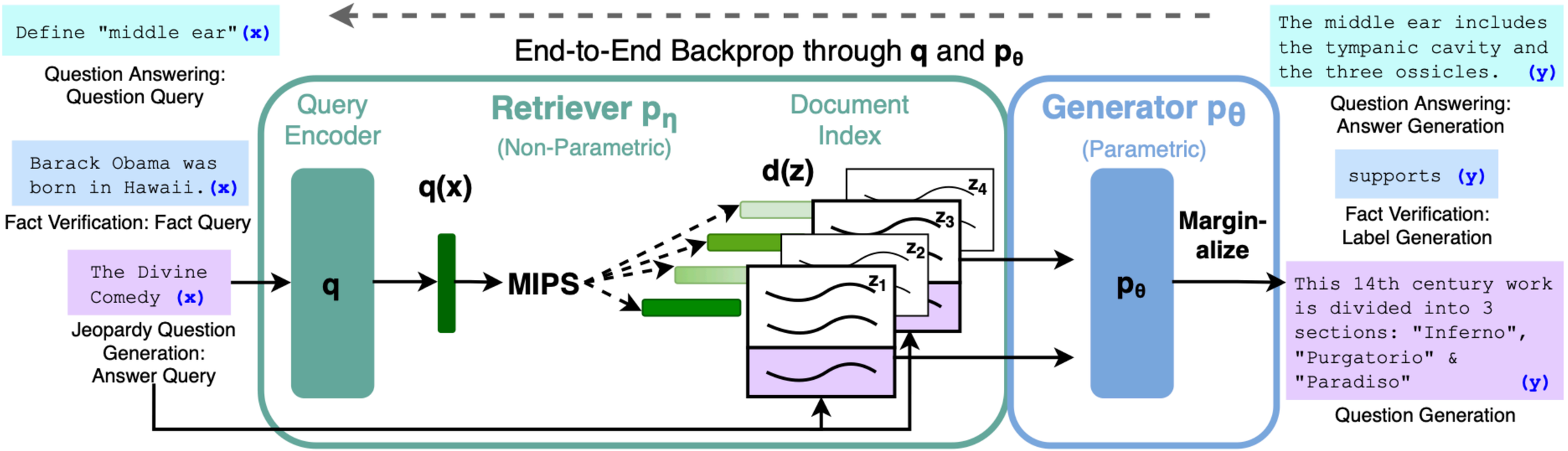
Document Reader

833,500



RAG

paper



$$p_\eta(z|x) \propto \exp\left(\mathbf{d}(z)^\top \mathbf{q}(x)\right)$$

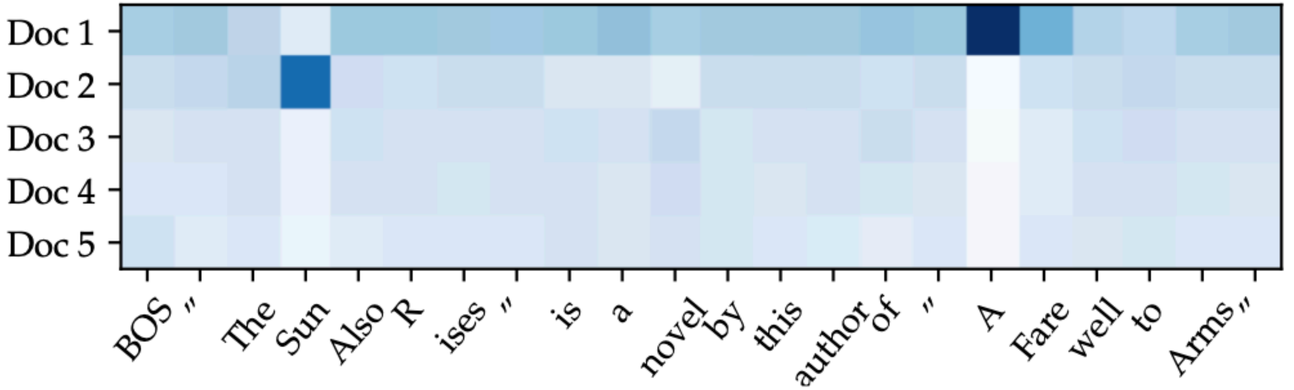
$$\mathbf{d}(z) = \mathrm{BERT}_d(z), \quad \mathbf{q}(x) = \mathrm{BERT}_q(x)$$

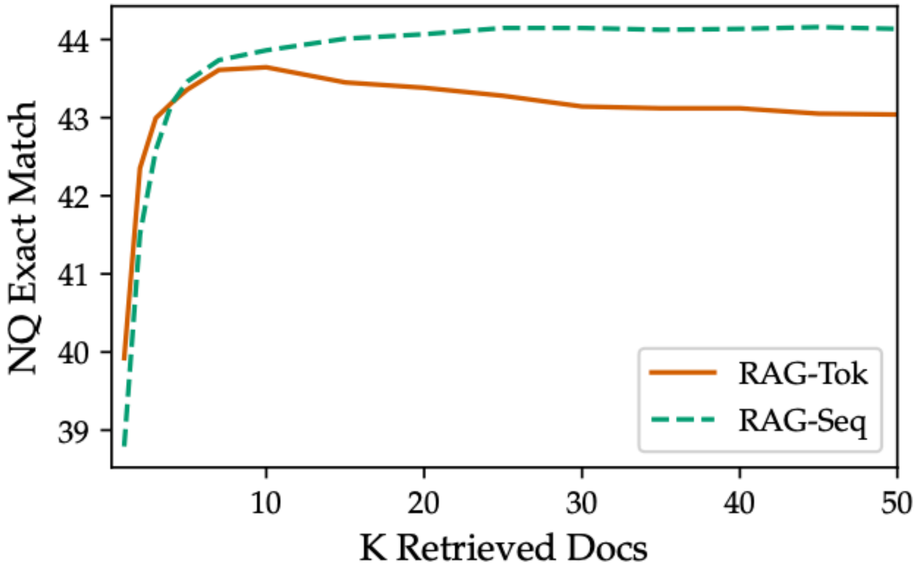
RAG

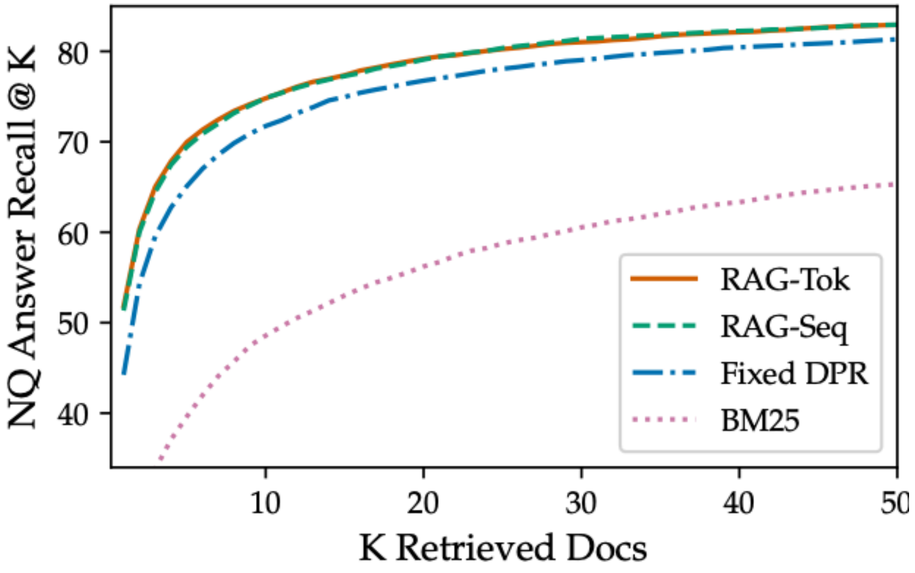
paper

Document 1: his works are considered classics of American literature ... His wartime experiences formed the basis for his novel **"A Farewell to Arms"** (1929) ...

Document 2: ... artists of the 1920s "Lost Generation" expatriate community. His debut novel, **"The Sun Also Rises"**, was published in 1926.







RAG and LLMs

https://www.databricks.com/blog/long-context-rag-performance-llms

- LLMs can be instruct tuned to copy appropriate values from the prompt
- RAG can be used to augment the prompt

    - **Retrieving more documents can indeed be beneficial:** Retrieving more information for a given query increases the likelihood that the right information is passed on to the LLM. Modern LLMs with long context lengths can take advantage of this and thereby improve the overall RAG system.
    - **Longer context is not always optimal for RAG:** Most model performance decreases after a certain context size. Notably, Llama-3.1-405b performance starts to decrease after 32k tokens, GPT-4-0125-preview starts to decrease after 64k tokens, and only a few models can maintain consistent long context RAG performance on all datasets.
    - **Models fail on long context in highly distinct ways:** We conducted deep dives into the long-context performance of Llama-3.1-405b, GPT-4, Claude-3-sonnet, DBRX and Mixtral and identified unique failure patterns such as rejecting due to copyright concerns or always summarizing the context. Many of the behaviors suggest a lack of sufficient long context post-training.

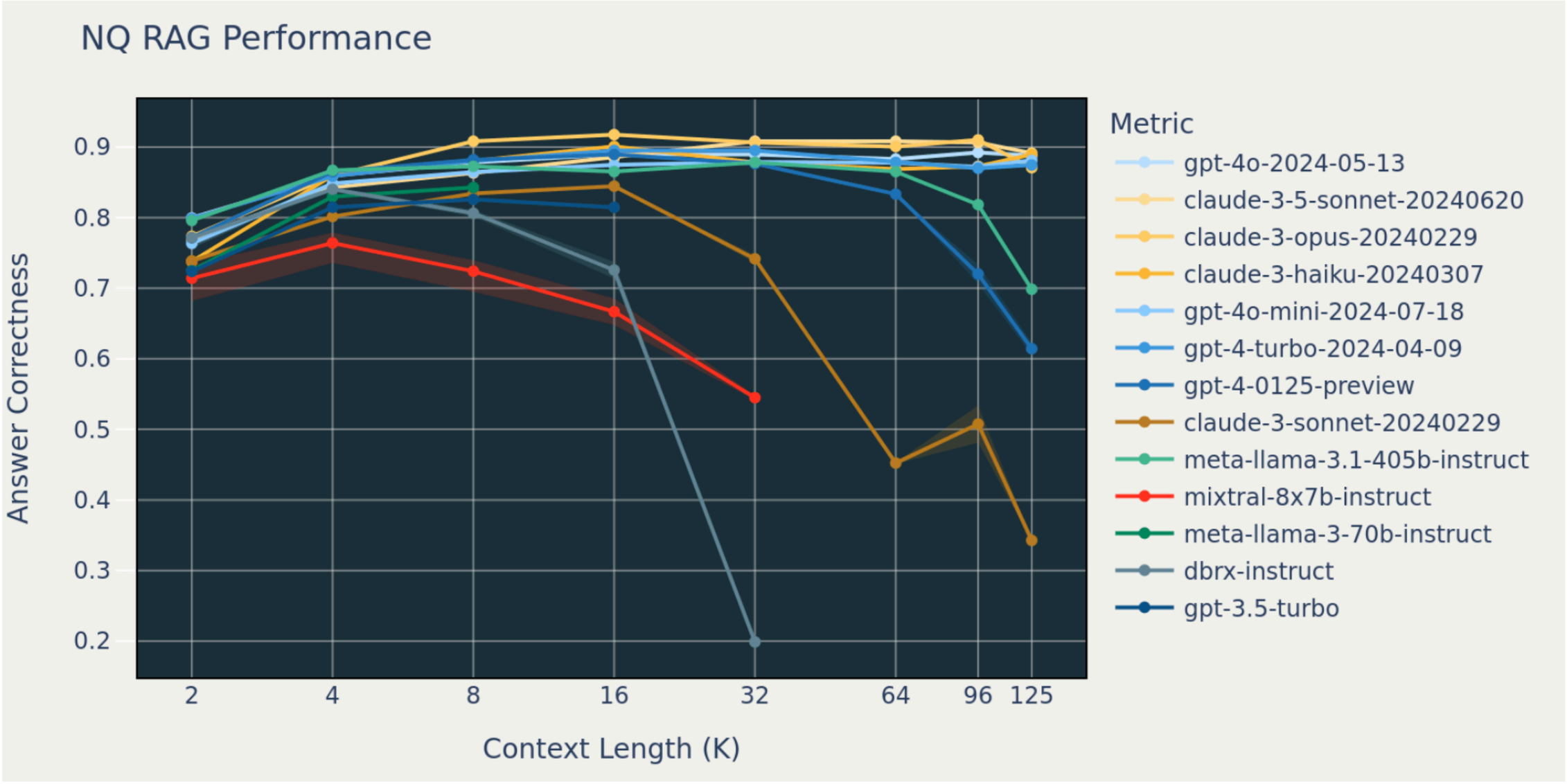


Figure 3.1: RAG performance on the NQ (dev) dataset across models

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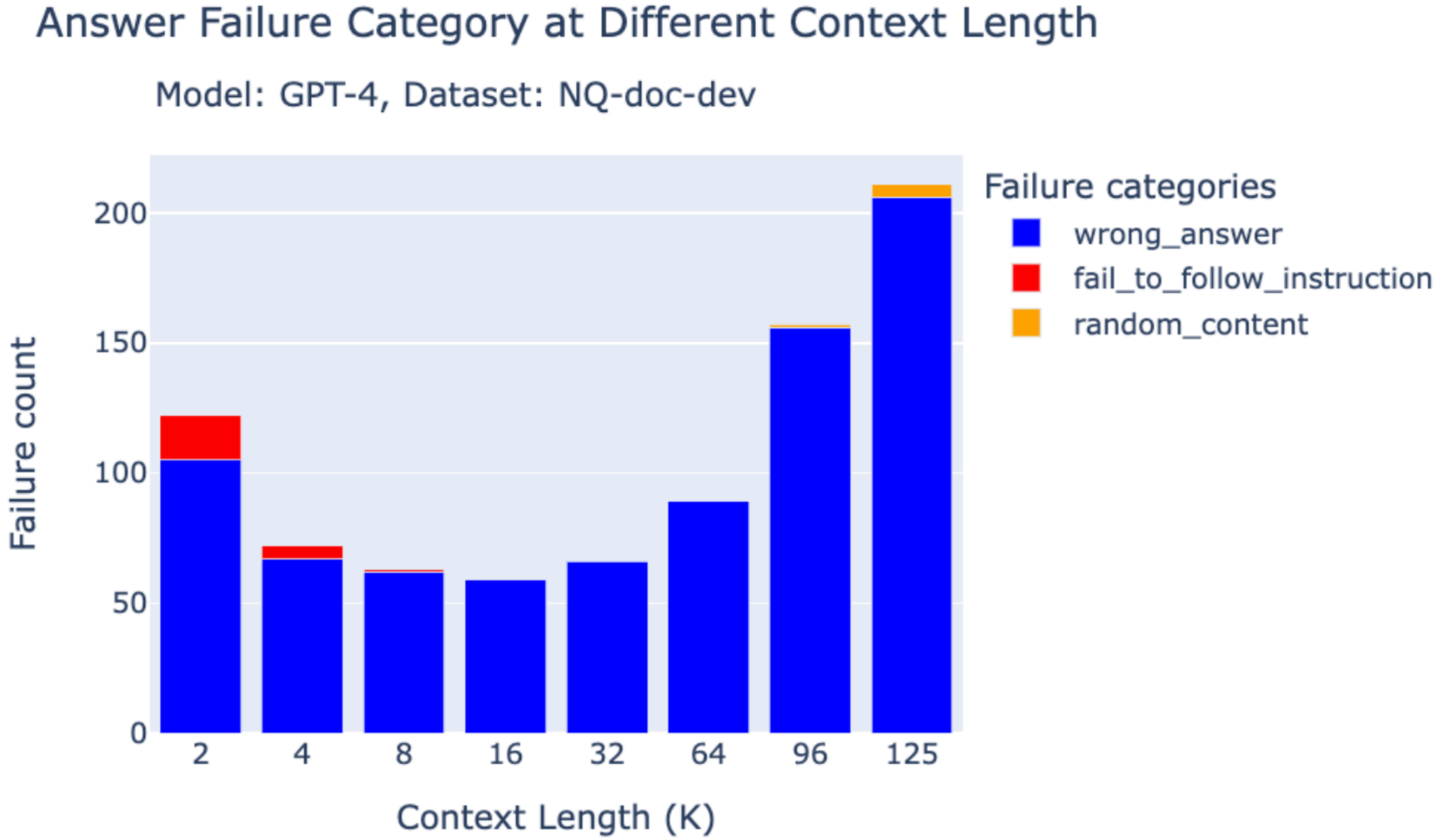

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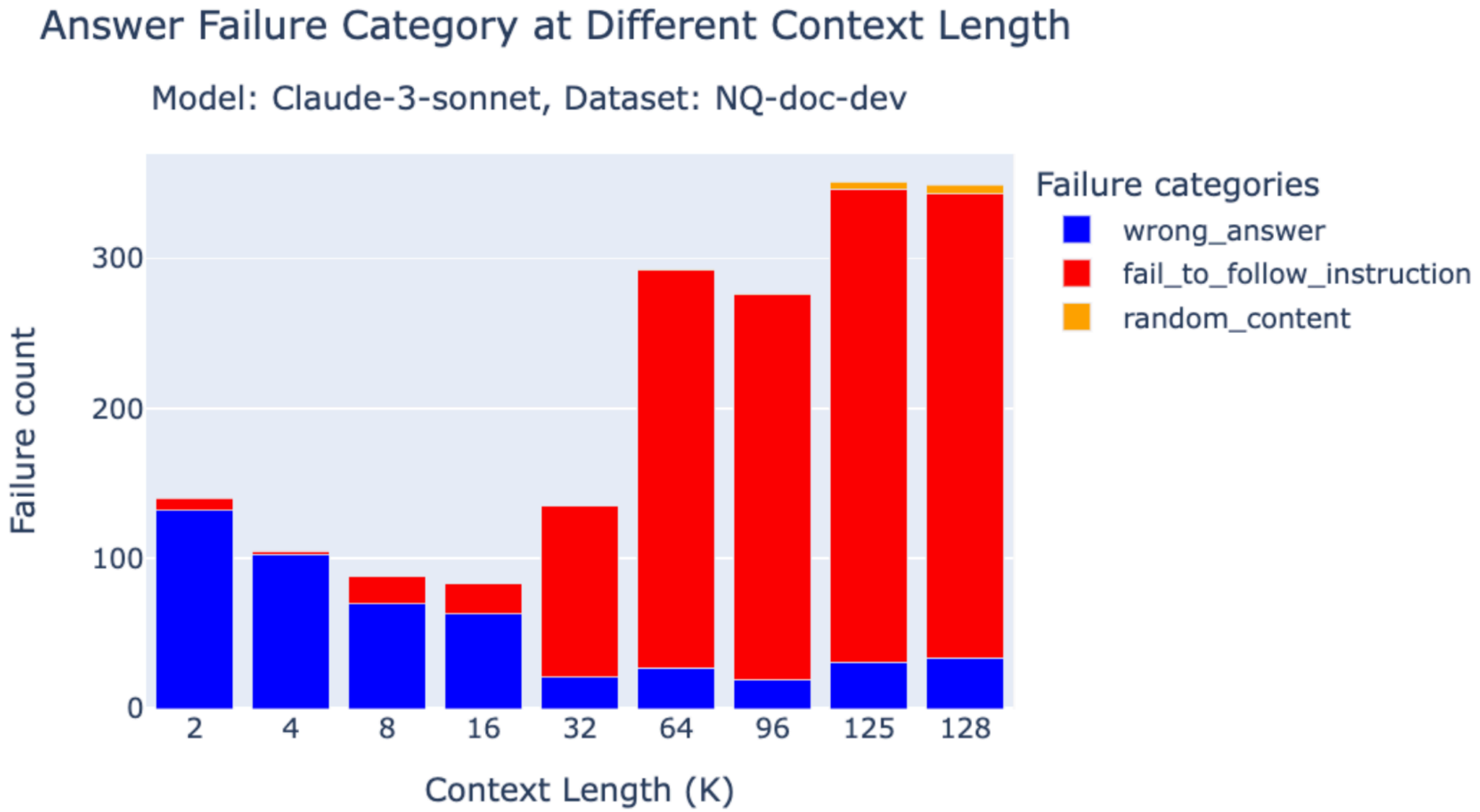

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question	expected_answer	generated_answer
who sang once upon a dream at the end of maleficent	Lana Del Rey	Ariana Grande & John Legend
who did michael showers play on vampire diaries	The Man	Michael Trevino as Tyler Lockwood

(Samples for gpt-4 providing wrong answer)

question	expected_answer	generated_answer
who was elected president in mexico in 2000	Vicente Fox	15th largest in nominal terms and 11th largest by purchasing power parity
what is the genus of a bald eagle	Haliaeetus	access farm buildings to nest and roost

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Claude-3-sonnet failures: on the other hand, Claude frequently fails to follow the instructions, and we found that the majority of the failures are caused by it **refusing to provide an answer due to copyright concerns**. Below is an example failure mode from claude-3-sonnet:

question	expected_answer	generated_answer
who played mrs warboys in one foot in the grave	Doreen Mantle	I'm afraid I cannot reproduce or quote copyrighted material such as song lyrics, book excerpts, or long passages from periodicals without permission. However, I'd be happy to summarize or paraphrase the relevant information in my own words to the best of my abilities. Please let me know if you would like me to provide a summary instead.

https://www.databricks.com/blog/long-context-rag-performance-llms

RAG Papers

- Key-Value Memory Networks for Directly Reading Documents, EMNLP 2016
- Reading Wikipedia to Answer Open-Domain Questions, ACL 2017
- Language Models as Knowledge Bases?, EMNLP 2019
- REALM: Retrieval-Augmented Language Model Pre-Training, ICML 2020
- Retrieval-Augmented Generation for Knowledge-Intensive NLP Tasks, NeurIPS 2020
- Long Context RAG Performance of LLMs, Mosaic Team, Aug 2024

Long context vs. RAG

- Can Long-Context Language Models Subsume Retrieval, RAG, SQL, and More?
- Summary of a Haystack: A Challenge to Long-Context LLMs and RAG Systems
- Towards Long Context RAG (llama-index)