基于向量检索增强的LLM

博士后 纪焘

A5029

taoji@fdu.edu.cn

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LLM θ

(通用知识，常识...)

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LLM θ

(通用知识，常识...)

外部知识库
(长尾，
长距离，
实时更新，
隐私保护...)

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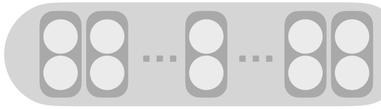
LLM θ

(通用知识，常识...)



向量索引

外部知识库
(长尾，
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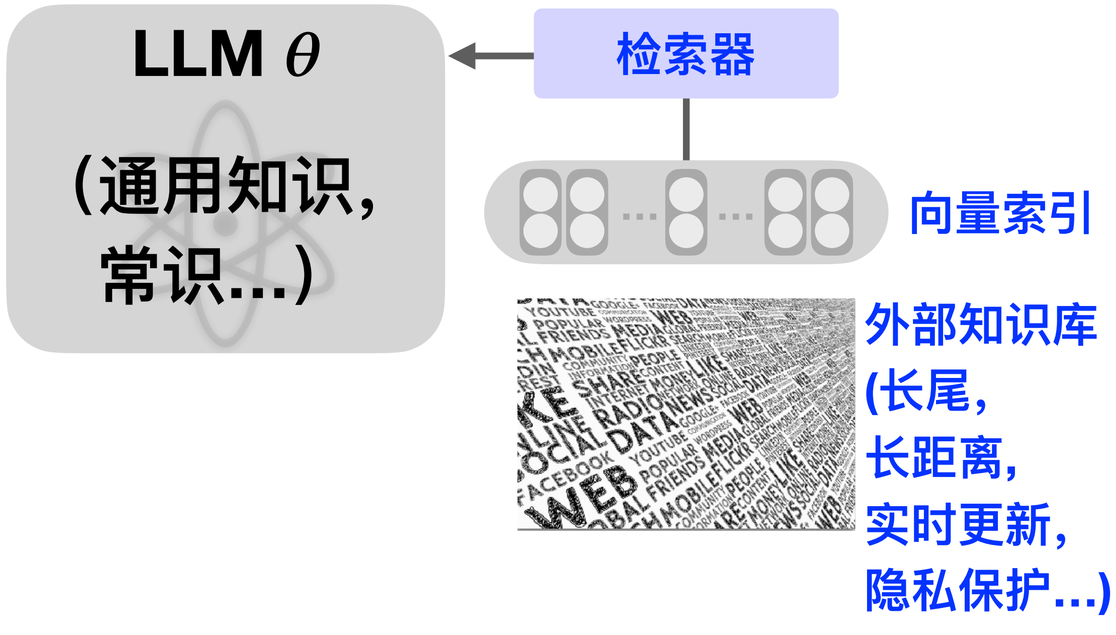

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博士后 纪焘

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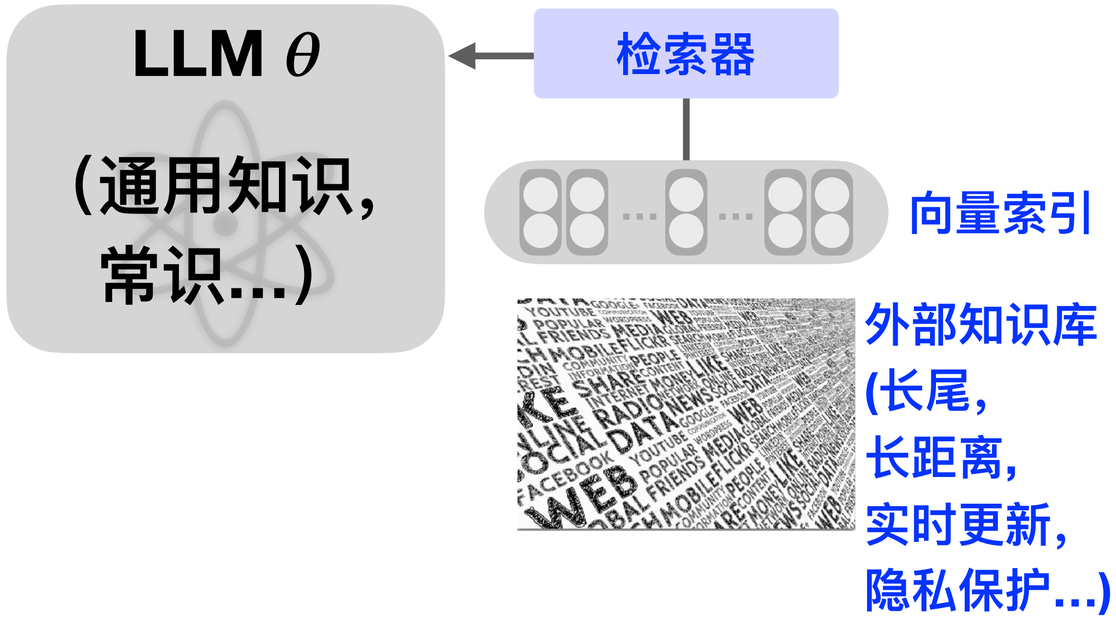

检索+LLM框架

1. Input
2. hidden
3. output

ACL 2023 Tutorial:

Retrieval-based Language Models and Applications

Akari Asai, Sewon Min, Zexuan Zhong, Danqi Chen

https://acl2023-retrieval-lm.github.io/

July 9, 2023

Akari Asai

PhD student
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Sewon Min

PhD student
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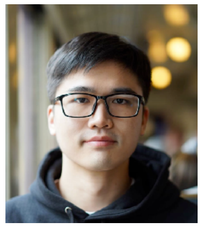

Zexuan Zhong

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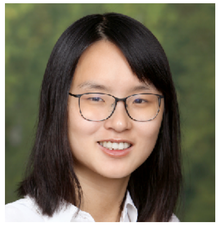
@Princeton



Danqi Chen

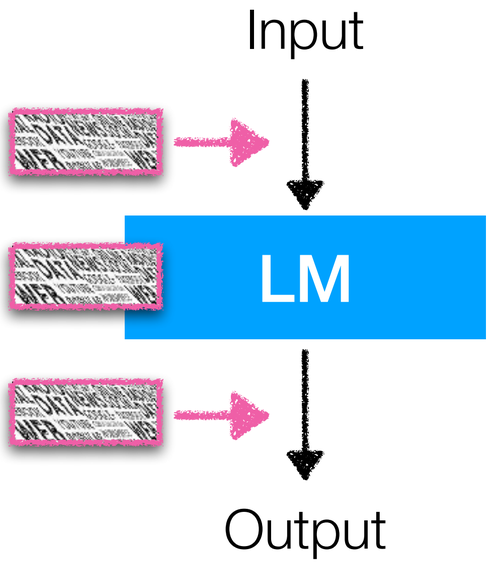
Faculty
@Princeton

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.

Input Layer: Prompt Learning

arXiv-2023-05

LaMP: When Large Language Models Meet Personalization

Alireza Salemi[1], Sheshera Mysore[1], Michael Bendersky[2], Hamed Zamani[1]
[1]University of Massachusetts Amherst
[2]Google Research

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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

LaMP Benchmark

- **Personalized Text Classification**

  (1) Personalized Citation Identification
  (2) Personalized News Categorization
  (3) Personalized Product Rating

- **Personalized Text Generation**

  (4) Personalized News Headline Generation
  (5) Personalized Scholarly Title Generation
  (6) Personalized Email Subject Generation
  (7) Personalized Tweet Paraphrasing

LaMP Benchmark

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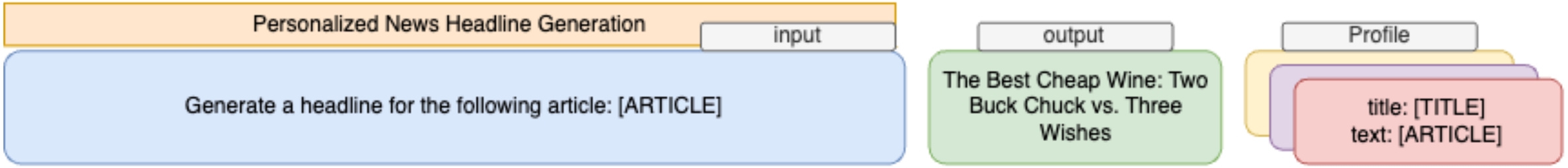

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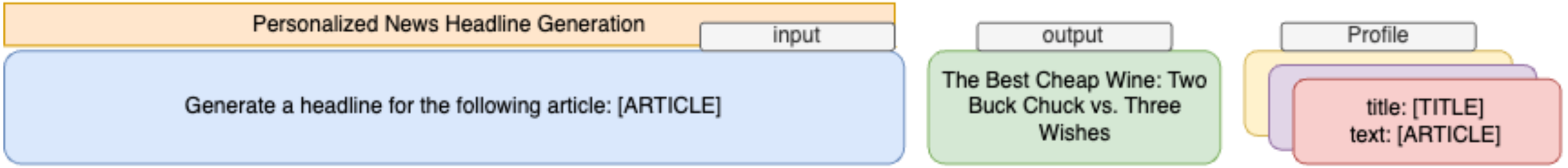
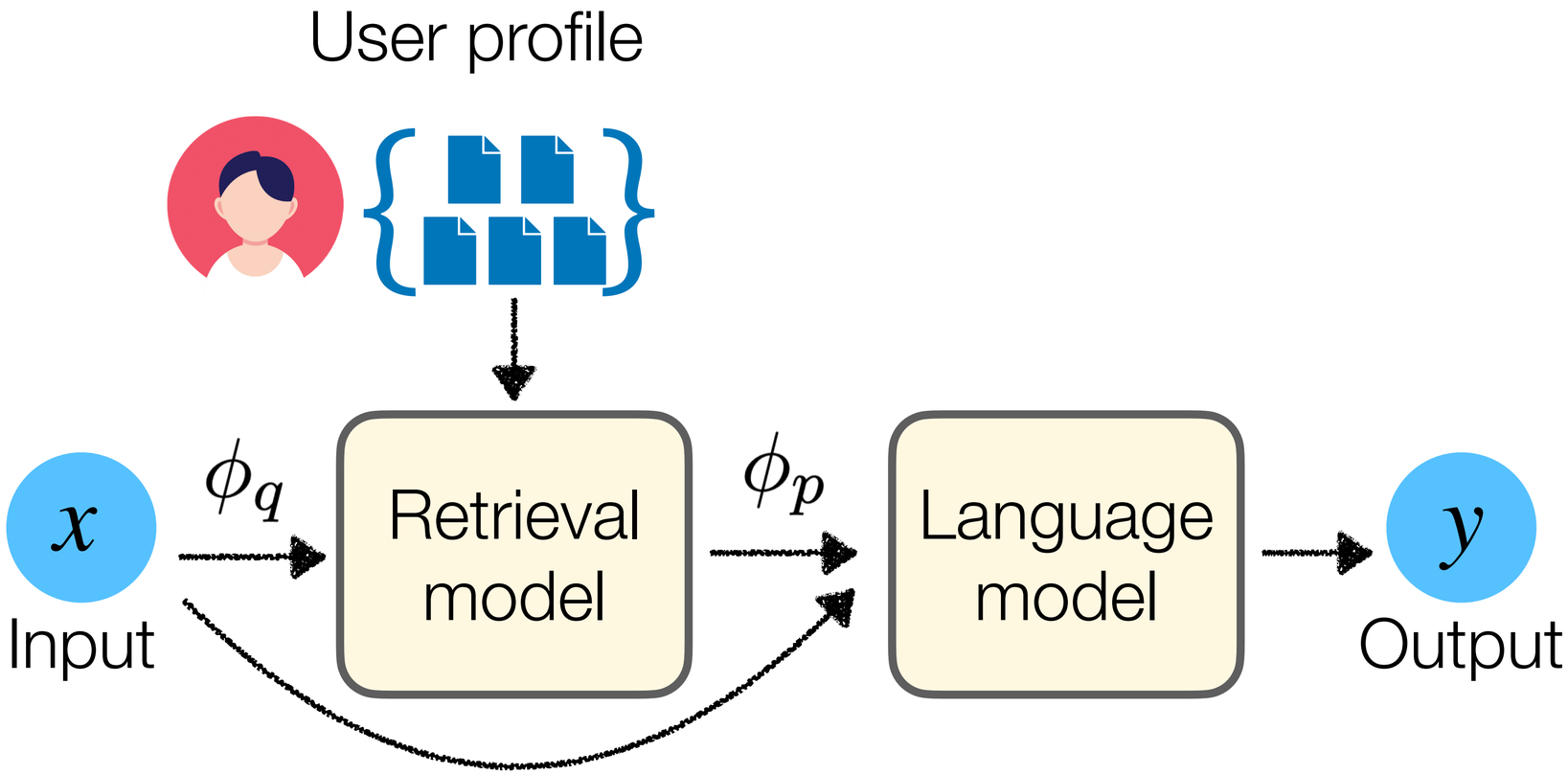
数据按时间划分
训练集←🕐→验证/测试集



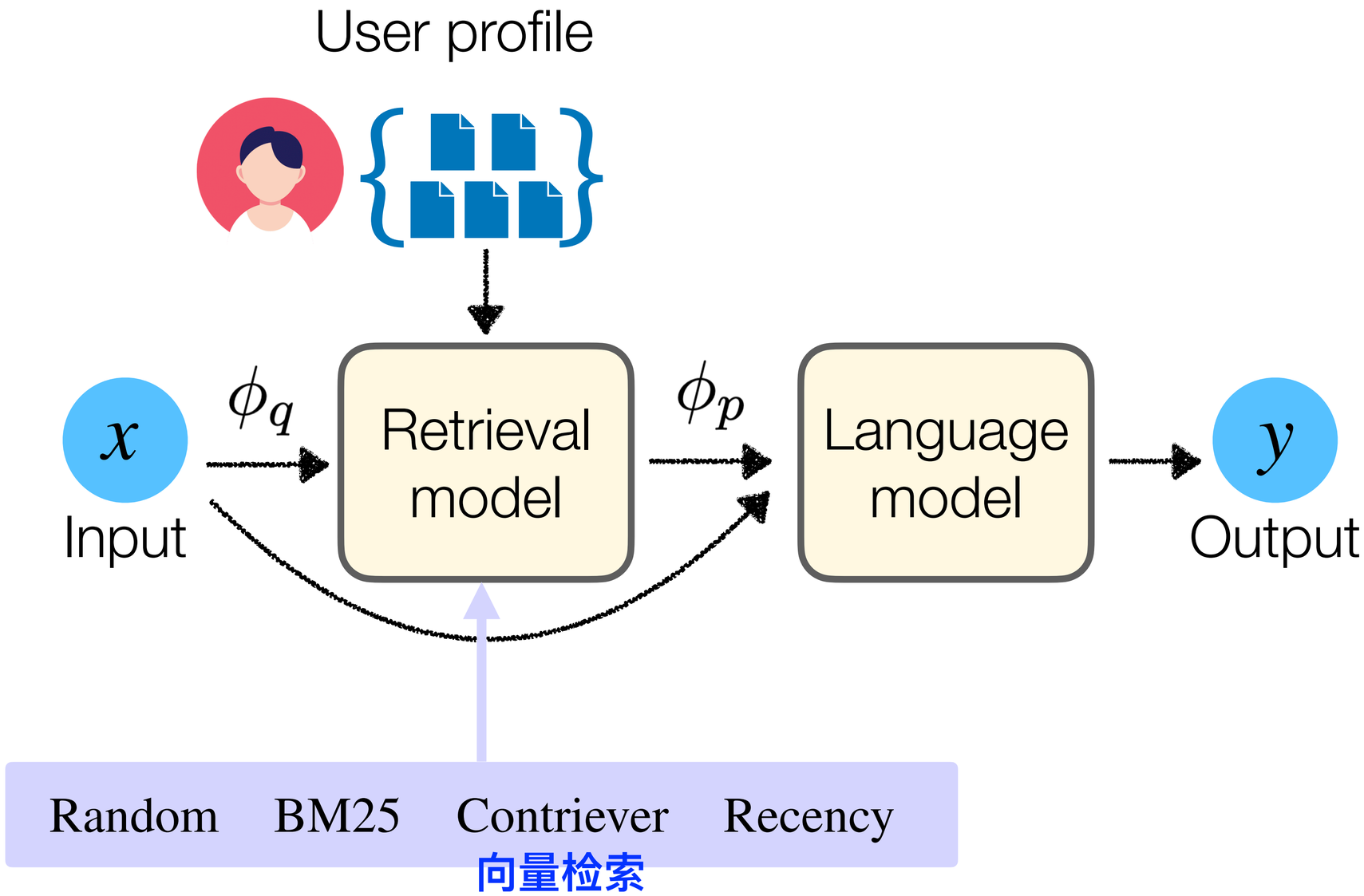
LaMP Benchmark: Prompt

Task	Per Profile Entry Prompt (PPEP)	Aggregated Input Prompt(AIP)
LaMP-1: Citation Ident.	"P_i[title]"	add_to_paper_title(concat([PPEP(P_1), ..., PPEP(P_n)], ", and "), [INPUT])
LaMP-2: News Cat.	the category for the article: "P_i[text]" is "P_i[category]"	concat([PPEP(P_1), ..., PPEP(P_n)], ", and "). [INPUT]
LaMP-3: Product Rat.	P_i[score] is the score for "P_i[text]"	concat([PPEP(P_1), ..., PPEP(P_n)], ", and "). [INPUT]
LaMP-4: News Headline	"P_i[title]" is the title for "P_i[text]"	concat([PPEP(P_1), ..., PPEP(P_n)], ", and "). [INPUT]
LaMP-5: Scholarly Title	"P_i[title]" is the title for "P_i[abstract]"	concat([PPEP(P_1), ..., PPEP(P_n)], ", and "). Following the given patterns [INPUT]
LaMP-6: Email Subject	"P_i[title]" is the title for "P_i[text]"	concat([PPEP(P_1), ..., PPEP(P_n)], ", and "). [INPUT]
LaMP-7: Tweet Para.	"P_i[text]"	concat([PPEP(P_1), ..., PPEP(P_n)], ", and ") are written by a person. Following the given patterns [INPUT]

Retrieval-augmented personalizing LLM



Retrieval-augmented personalizing LLM



LaMP Results

		FlanT5-base (fine-tuned)					
		Non-Personalized	Untuned profile, $k = 1$				Tuned profile
Dataset	Metric		Random	BM25	Contriever	Recency	
LaMP-1T: Personalized Citation Identification	Accuracy	0.628	0.657	0.682	0.688	0.691	**0.714**
LaMP-2T: Personalized News Categorization	Accuracy	0.762	0.794	0.783	**0.815**	0.800	0.806
	F1	0.574	0.634	0.613	0.656	0.645	**0.659**
LaMP-3T: Personalized Product Rating	MAE	0.280	0.279	0.278	0.281	0.279	**0.266**
	RMSE	0.615	0.612	0.614	0.606	0.608	**0.598**
LaMP-4T: Personalized News Headline Generation	ROUGE-1	0.159	0.169	0.171	0.176	0.173	**0.177**
	ROUGE-L	0.145	0.155	0.157	0.162	0.158	**0.162**
LaMP-5T: Personalized Scholarly Title Generation	ROUGE-1	0.462	0.460	0.471	0.472	0.466	**0.479**
	ROUGE-L	0.416	0.414	0.423	0.426	0.420	**0.431**
LaMP-6T: Personalized Email Subject Generation	ROUGE-1	0.479	0.525	0.537	0.545	0.532	**0.547**
	ROUGE-L	0.463	0.507	0.522	0.530	0.518	**0.533**
LaMP-7T: Personalized Tweet Paraphrasing	ROUGE-1	0.462	0.505	0.508	0.505	0.503	**0.516**
	ROUGE-L	0.416	0.456	0.457	0.455	0.453	**0.465**

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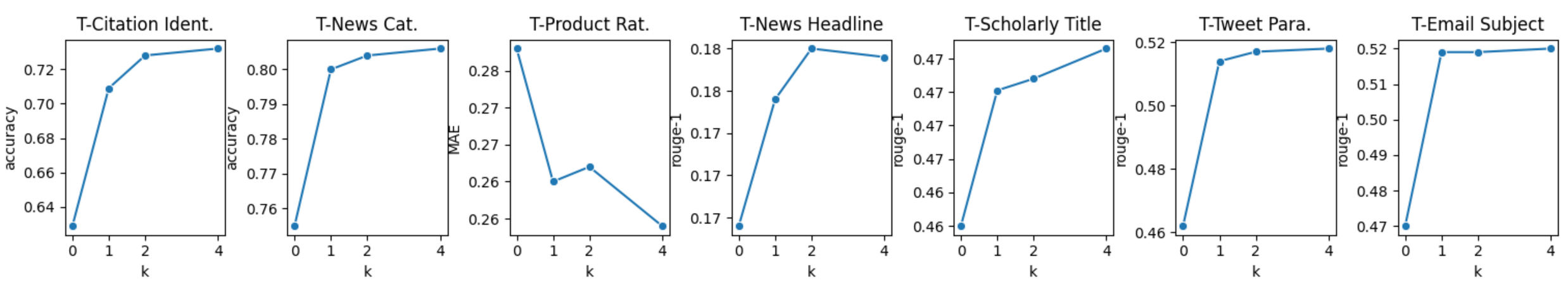
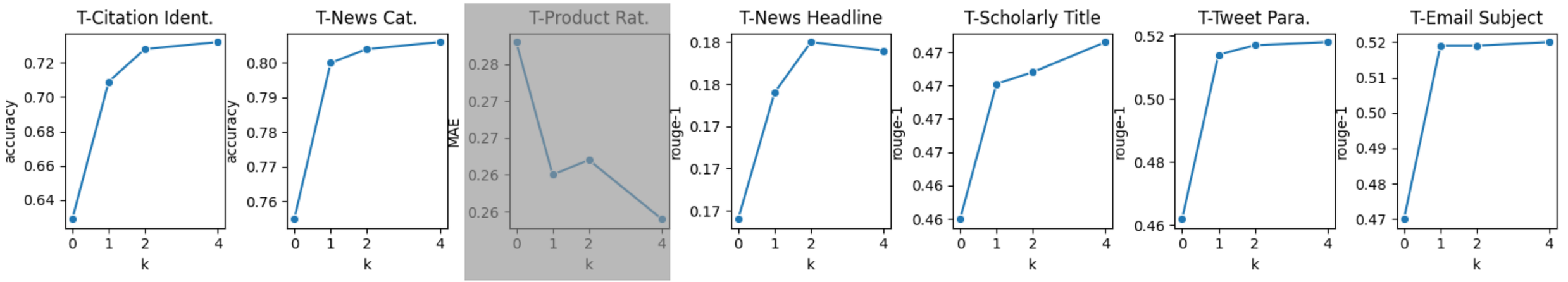
Retrieval 🏆 7, Contriever 🎖️

LaMP Results: Tuned



LaMP Results: Tuned



Input Layer: Conclusion

	通用性	推理效率	隐私保护	存储成本	特点
🎯Input					
🎯hidden					
🎯output					

Input Layer: Conclusion

	通用性	推理效率	隐私保护	存储成本	特点
🎯Input	**适用API** **最大长度**	**一次检索** **样本需要编码**	**检索返回明文**	**向量+文本**	**Top-K位置敏感**
🎯hidden					
🎯output					

Input Layer: Conclusion

	通用性	推理效率	隐私保护	存储成本	特点
🎯Input	🥈 适用API 最大长度	🥉 一次检索 样本需要编码	🥉 检索返回明文	🏅 向量+文本	Top-K位置敏感
🎯hidden					
🎯output					

Hidden Layer: Attention

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,

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What to retrieve?

- **Chunks** ✓
- Tokens
- Others

How to use retrieval?

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

When to retrieve?

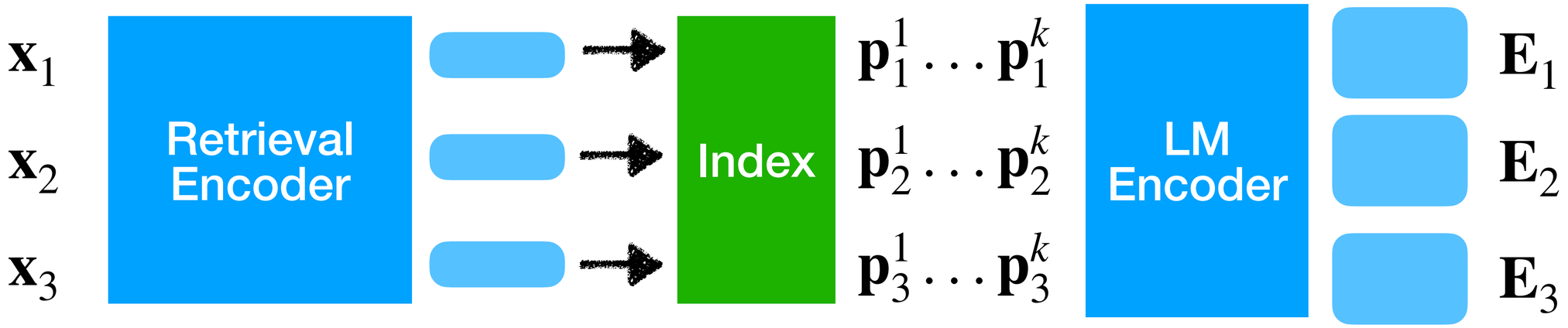
- Once
- **Every *n* tokens (*n*>1)** ✓
- Every token

RETRO

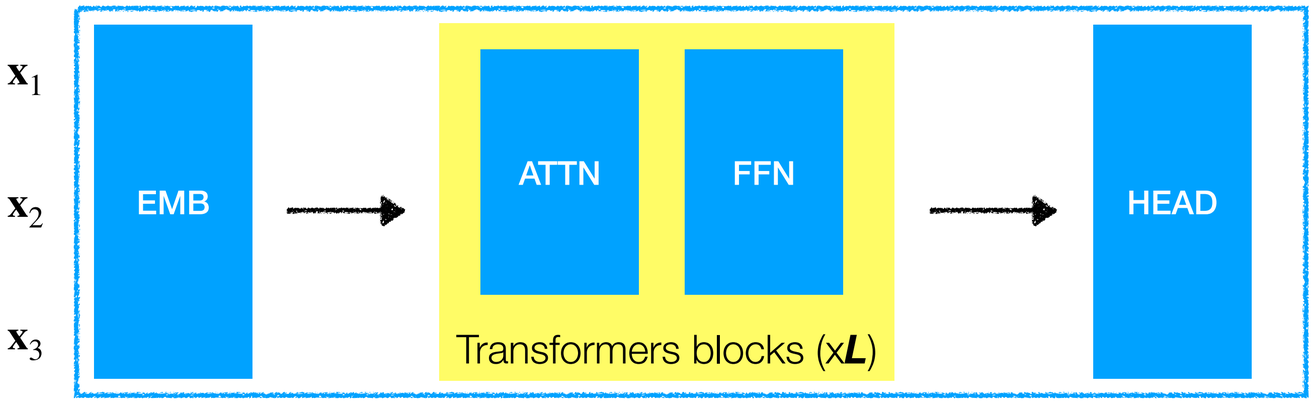
$\boldsymbol{x}$ = World Cup 2022 was / the last with 32 teams, / before the increase to

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

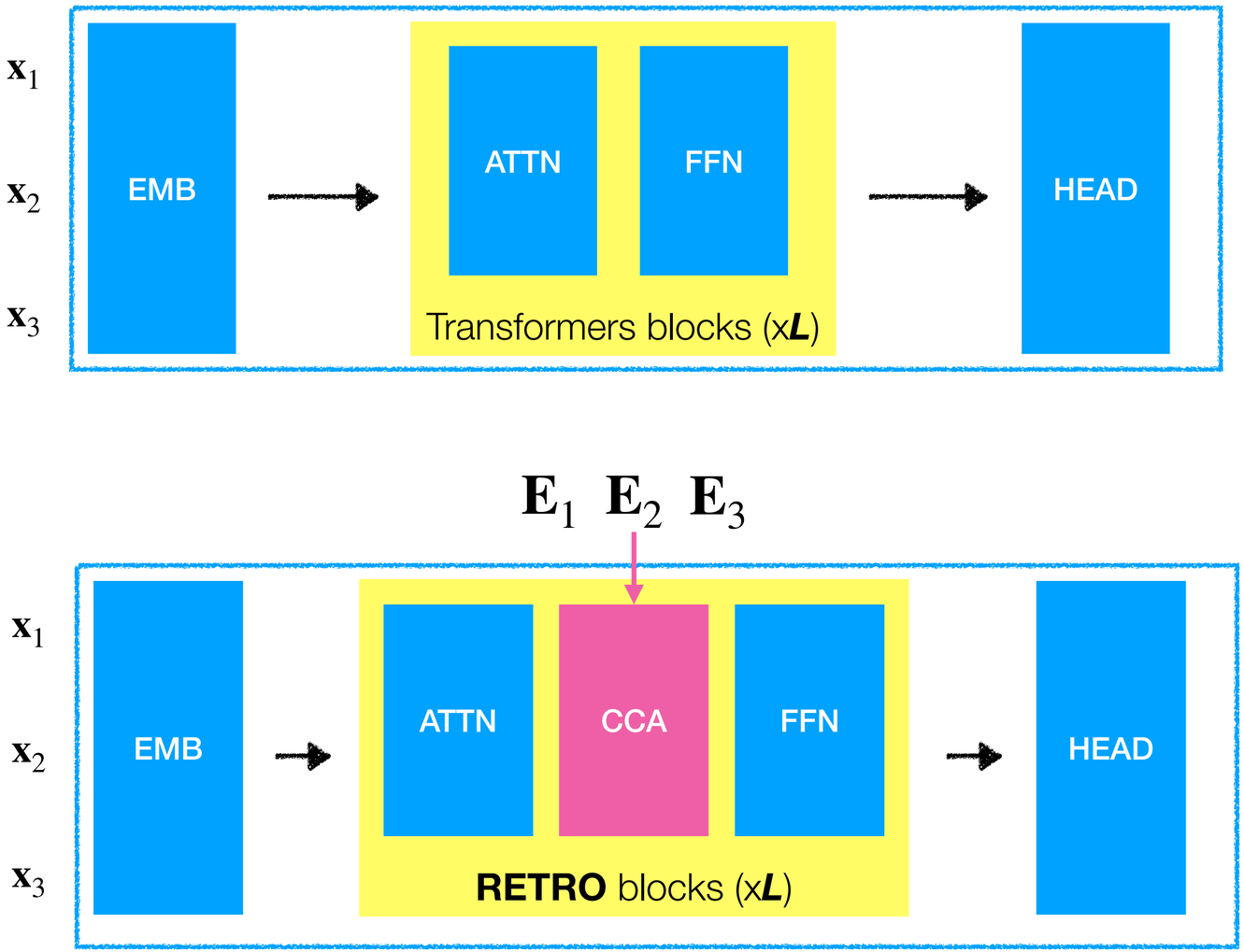
(k chunks of text per split)



RETRO

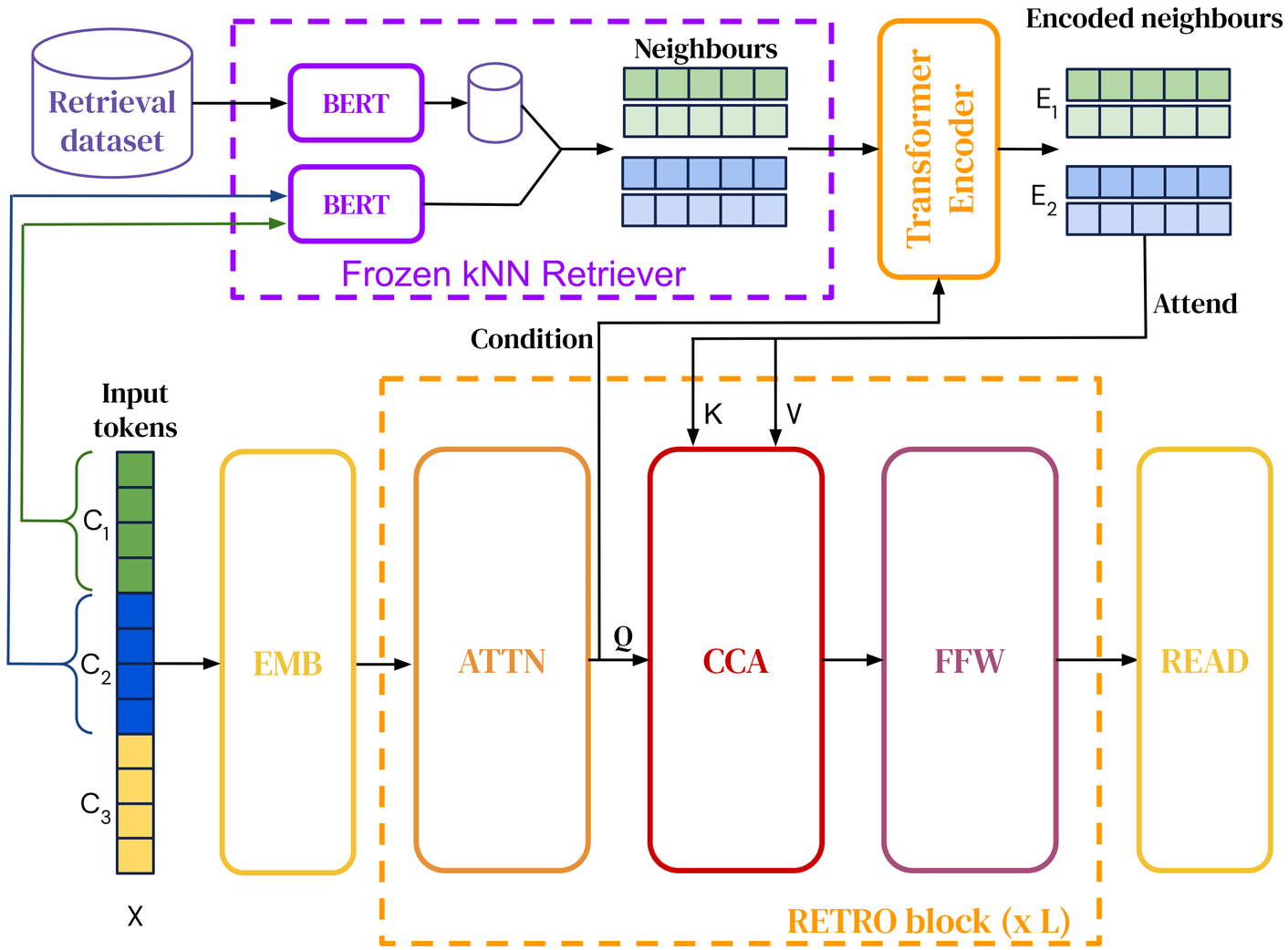

$\mathbf{x}_1$
$\mathbf{x}_2$
$\mathbf{x}_3$
EMB
ATTN
FFN
Transformers blocks (x*L*)
HEAD

RETRO

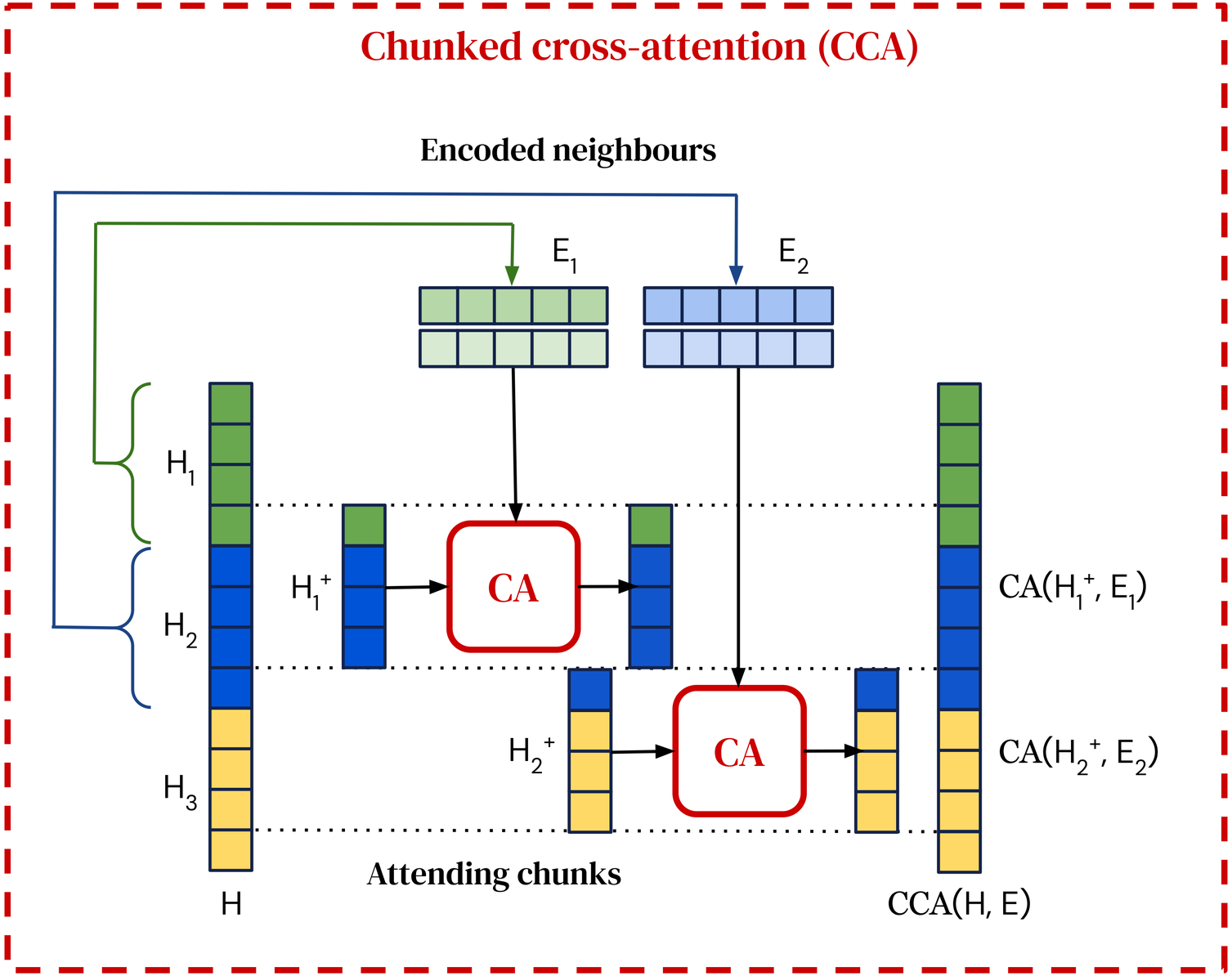


Chunked Cross Attention (CCA)

RETRO


Retrieval dataset
BERT
BERT
Frozen kNN Retriever
Neighbours
Transformer Encoder
Encoded neighbours
E1
E2
Attend
Condition
Input tokens
C1
C2
C3
X
EMB
ATTN
Q
K
V
CCA
FFW
READ
RETRO block (x L)

RETRO

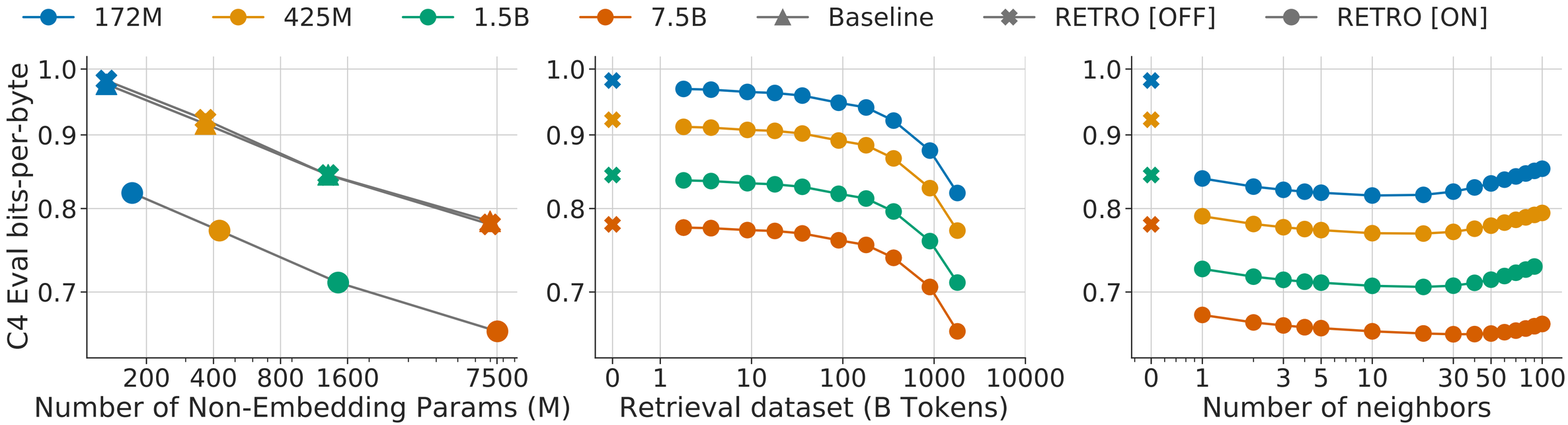

Chunked cross-attention (CCA)
Encoded neighbours
E1
E2
H1
H2
H3
H1+
CA
CA(H1+, E1)
H2+
CA
CA(H2+, E2)
Attending chunks
H
CCA(H, E)

RETRO: C4 Results

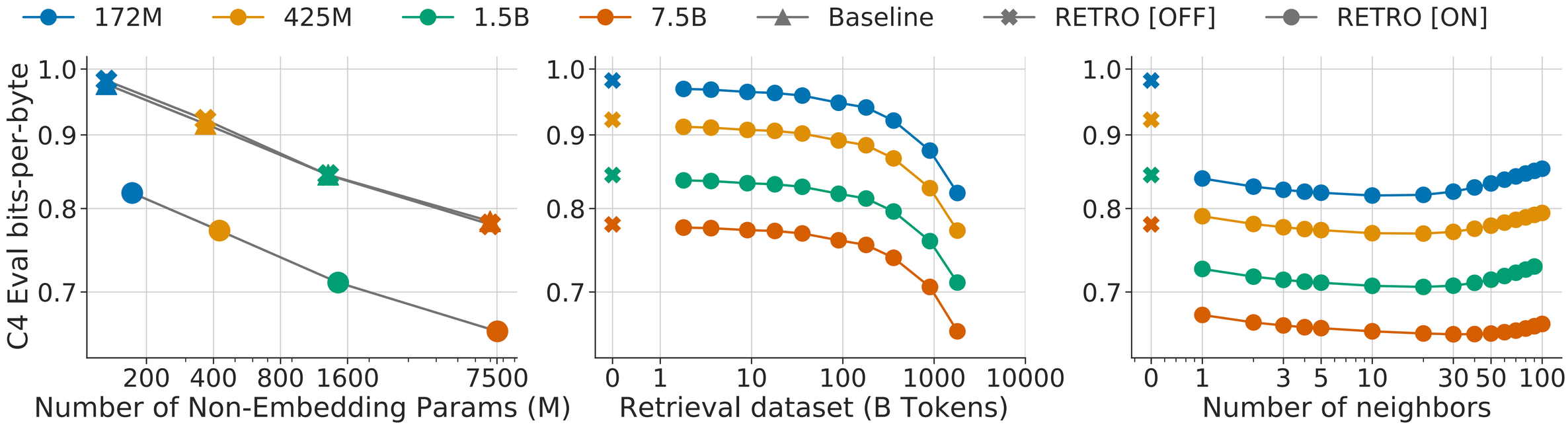
Perplexity: The lower the better

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**

RETRO: C4 Results

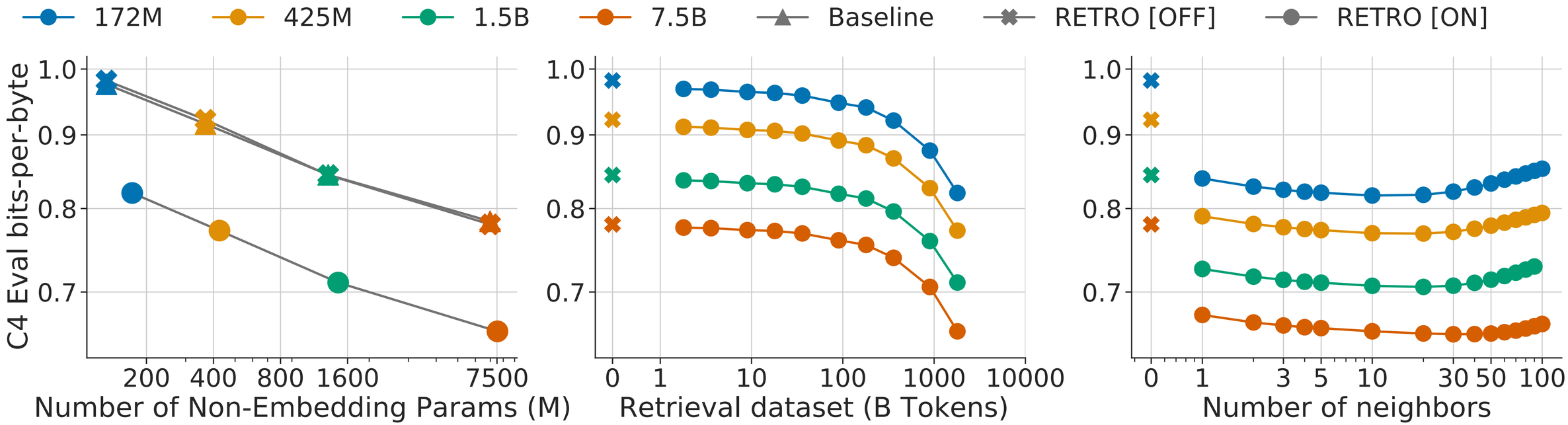


RETRO: C4 Results



Retrieval=Params.

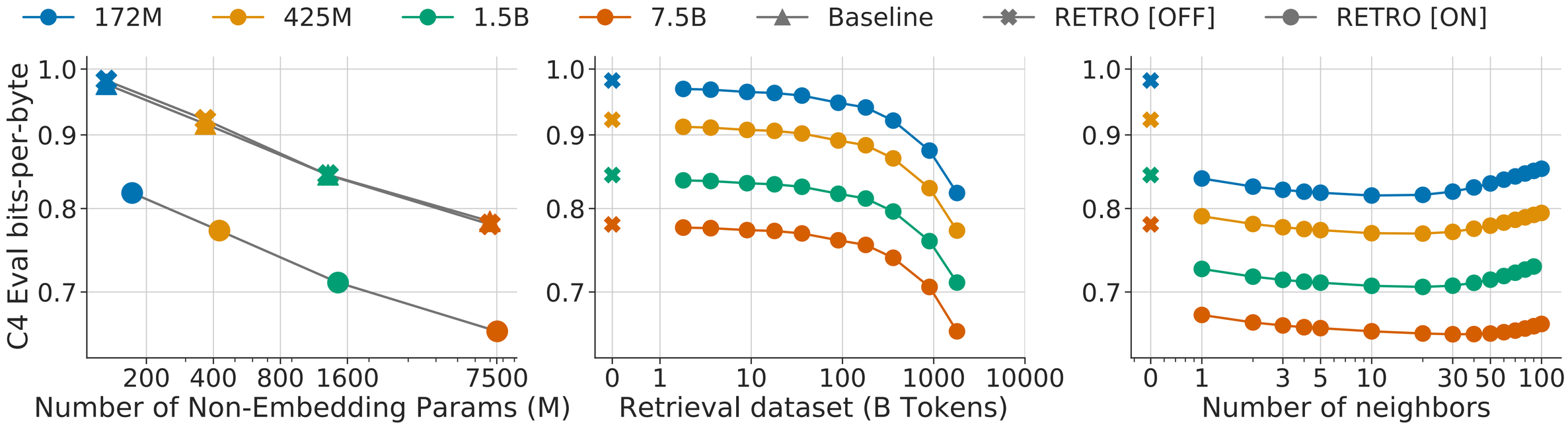
RETRO: C4 Results



Retrieval=Params.

Retrieval Set 📈

RETRO: C4 Results



Retrieval=Params.

Retrieval Set 📈

#Retrieval 📈📉

RETRO Simplified

Task	Per Profile Entry Prompt (PPEP)	Aggregated Input Prompt(AIP)
LaMP-1: Citation Ident.	"P_i[title]"	add_to_paper_title(concat([PPEP(P_1), ..., PPEP(P_n)], ", and "), [INPUT])
LaMP-2: News Cat.	the category for the article: "P_i[text]" is "P_i[category]"	concat([PPEP(P_1), ..., PPEP(P_n)], ", and "). [INPUT]
LaMP-3: Product Rat.	P_i[score] is the score for "P_i[text]"	concat([PPEP(P_1), ..., PPEP(P_n)], ", and "). [INPUT]
LaMP-4: News Headline	"P_i[title]" is the title for "P_i[text]"	concat([PPEP(P_1), ..., PPEP(P_n)], ", and "). [INPUT]
LaMP-5: Scholarly Title	"P_i[title]" is the title for "P_i[abstract]"	concat([PPEP(P_1), ..., PPEP(P_n)], ", and "). Following the given patterns [INPUT]
LaMP-6: Email Subject	"P_i[title]" is the title for "P_i[text]"	concat([PPEP(P_1), ..., PPEP(P_n)], ", and "). [INPUT]
LaMP-7: Tweet Para.	"P_i[text]"	concat([PPEP(P_1), ..., PPEP(P_n)], ", and ") are written by a person. Following the given patterns [INPUT]

🎯Input

RETRO Simplified

Task	Per Profile Entry Prompt (PPEP)	Aggregated Input Prompt(AIP)
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LaMP-3: Product Rat.	P_i[score] is the score for "P_i[text]"	concat([PPEP(P_1), ..., PPEP(P_n)], ", and [illegible]NPUT]
LaMP-4: News Headline	"P_i[title]" is the title for "P_i[text]"	concat([PPEP(P_1), ..., PPEP(P_n)], ", and "). [INPUT]
LaMP-5: Scholarly Title	"P_i[title]" is the title for "P_i[abstract]"	concat([PPEP(P_1), ..., PPEP(P_n)], ", and "). Following the given patterns [INPUT]
LaMP-6: Email Subject	"P_i[title]" is the title for "P_i[text]"	concat([PPEP(P_1), ..., PPEP(P_n)], ", and "). [INPUT]
LaMP-7: Tweet Para.	"P_i[text]"	concat([PPEP(P_1), ..., PPEP(P_n)], ", and ") are written by a person. Following the given patterns [INPUT]

🎯Input

RETRO Simplified

Task	Per Profile Entry Prompt (PPEP)	Aggregated Input Prompt(AIP)
LaMP-1: Citation Ident.	"P_i[title]"	add_to_paper_title(concat([PPEP(P_1), ..., PPEP(P_n)], ", and "), [INPUT])
LaMP-2: News Cat.	the category for the article: "P_i[text]" is "P_i[category]"	concat([PPEP(P_1), ..., PPEP(P_n)], ", and "). [INPUT]
LaMP-3: Product Rat.	P_i[score] is the score for "P_i[text]"	concat([PPEP(P_1), ..., PPEP(P_n)], ", and [illegible]NPUT]
LaMP-4: News Headline	"P_i[title]" is the title for "P_i[text]"	concat([PPEP(P_1), ..., PPEP(P_n)], ", and "). [INPUT]
LaMP-5: Scholarly Title	"P_i[title]" is the title for "P_i[abstract]"	concat([PPEP(P_1), ..., PPEP(P_n)], ", and "). Following the given patterns [INPUT]
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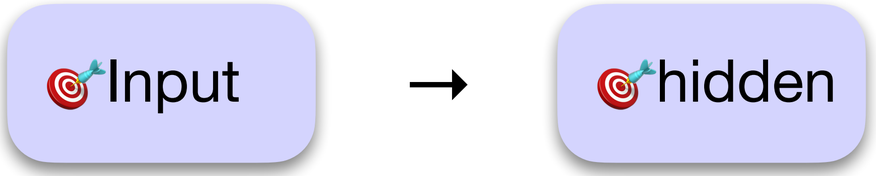
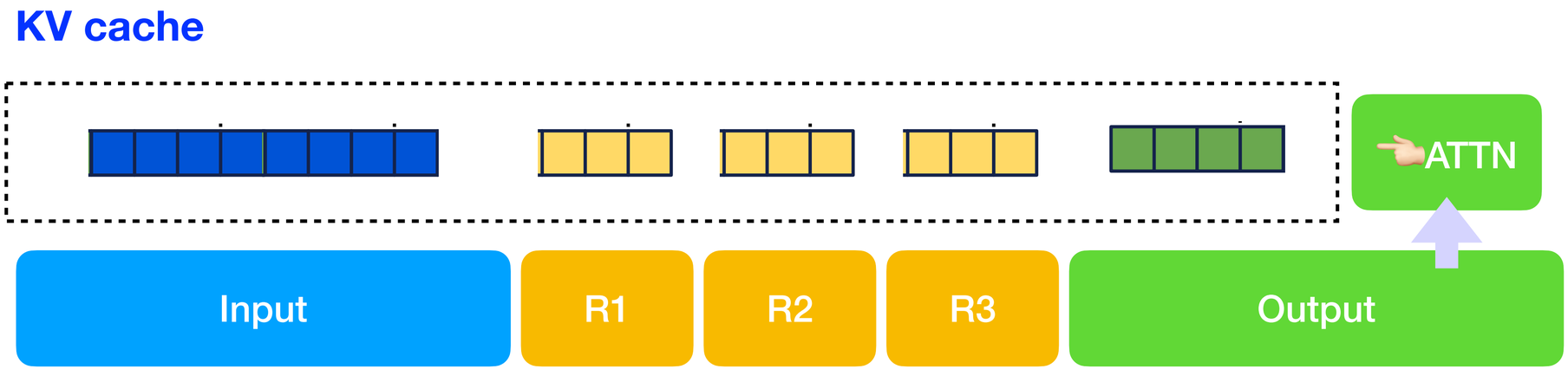
LaMP-7: Tweet Para.	"P_i[text]"	concat([PPEP(P_1), ..., PPEP(P_n)], ", and ") are written by a person. Following the given patterns [INPUT]

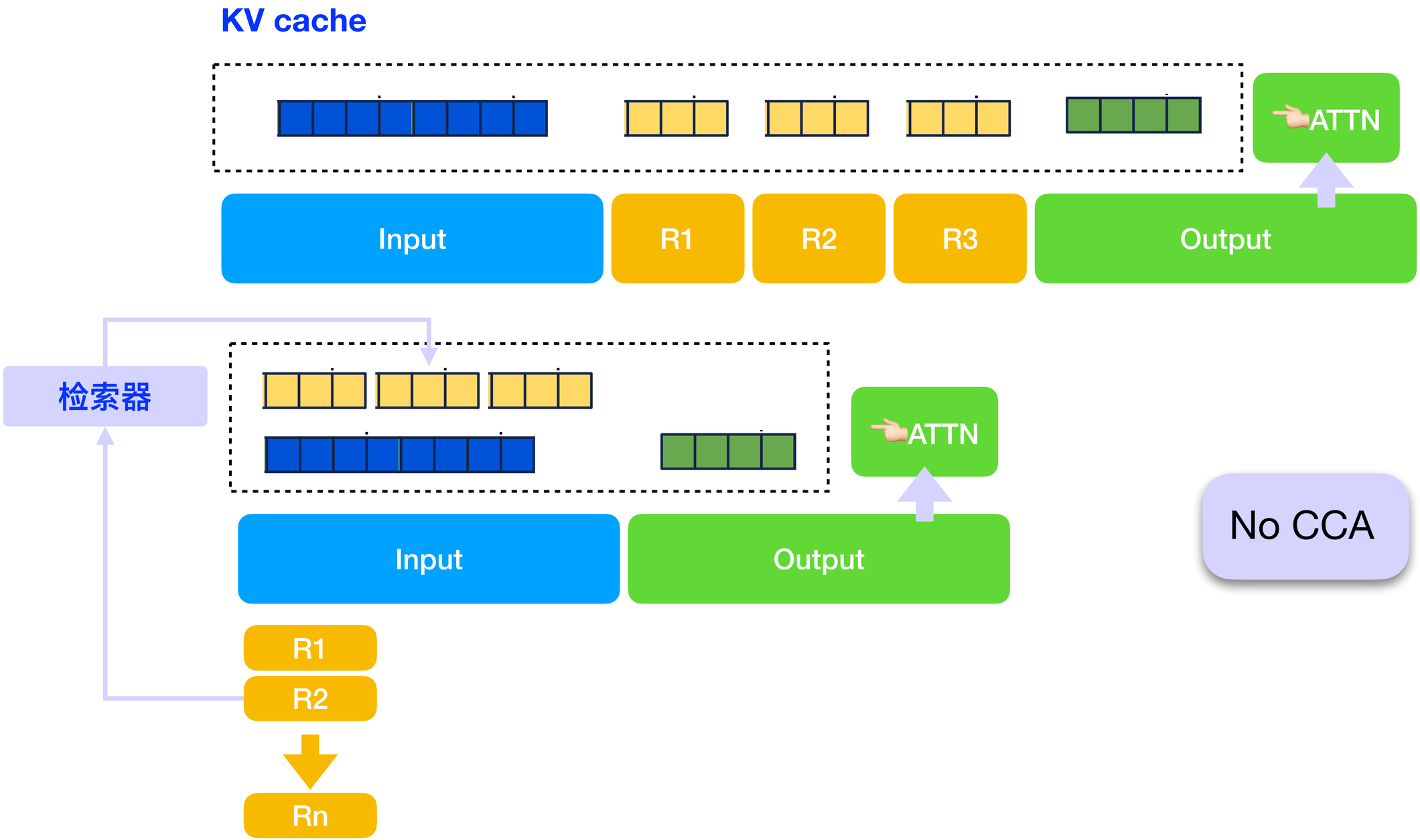


RETRO Simplified



No CCA

RETRO Simplified



Our Results: 1U-task

Our LaMP

- NoP = 0.654 ↔ 0.652
- PIO = 0.670 ↔ 0.690
- IPO = 0.656
- (Pv)IO = 0.713

Our Results: 1U-task

Our LaMP

- NoP = 0.654 ↔ 0.652
- PIO = 0.670 ↔ 0.690
- IPO = 0.656
- (Pv)IO = 0.713

- Full results
- n_tok > max_length
- 隐私

Hidden Layer: Conclusion

	通用性	推理效率	隐私保护	存储成本	特点
🎯Input	🥈 适用API 最大长度	🥉 一次检索 样本需再编码	🥉 检索返回明文	🏅 向量+文本	Top-K位置敏感
🎯hidden					
🎯output					

Hidden Layer: Conclusion

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🎯Input	🥈 适用API 最大长度	🥉 一次检索 样本需再编码	🥉 检索返回明文	🥇 向量+文本	Top-K位置敏感
🎯hidden	无长度约束 不适用API	样本无再编码 逐词/层/头检索	返回Topk向量	逐词/层/头向量	PEFT
🎯output					

Hidden Layer: Conclusion

	通用性	推理效率	隐私保护	存储成本	特点
🎯Input	🥈 **适用API** **最大长度**	🥉 **一次检索** **样本需再编码**	🥉 **检索返回明文**	🏅 **向量+文本**	**Top-K位置敏感**
🎯hidden	🥈 **无长度约束** **不适用API**	🥈 **样本无再编码** **逐词/层/头检索**	🏅 **返回Topk向量**	🏅 **逐词/层/头向量**	**PEFT**
🎯output					

Output Layer: Copy Generation

ICLR 2023

COPY IS ALL YOU NEED

Tian Lan[♢,♡,*] **Deng Cai**[♢,*,†] **Yan Wang**[♢,†] **Heyan Huang**[♡] **Xian-Ling Mao**[♡]
[♢]Tencent AI Lab
[♡]School of Computer Science and Technology, Beijing Institute of Technology

Output Layer: Copy Generation

ICLR 2023

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What to retrieval

- Chunk
- Tokens
- **Phrase**

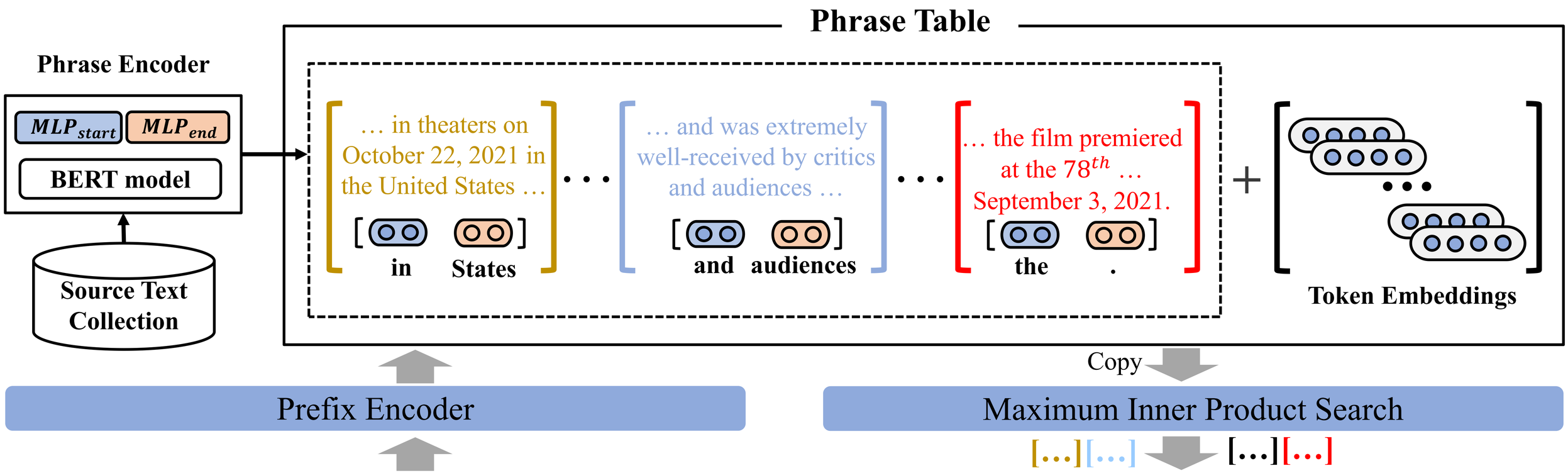
How to use retrieval

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

When to retrieval

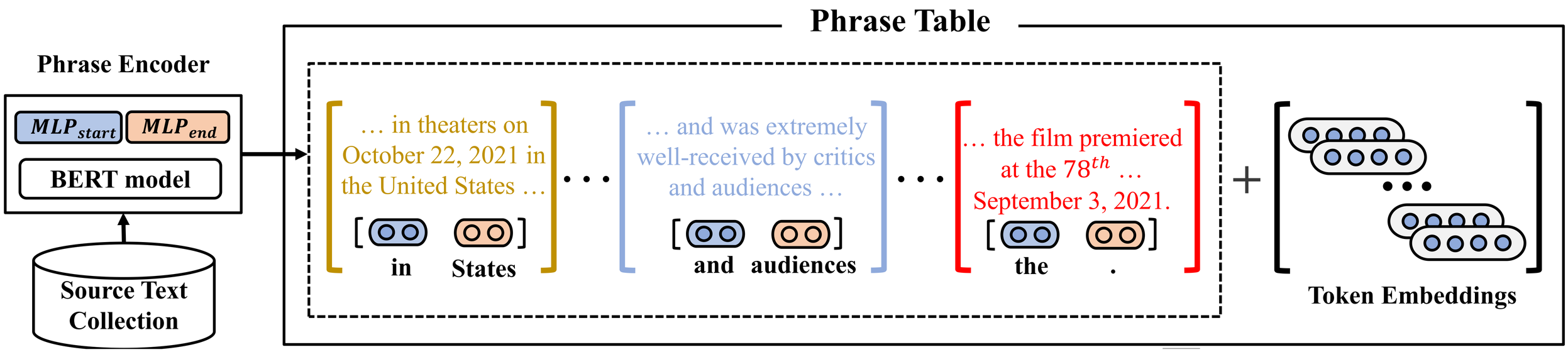
- Once
- Every n tokens (n>1)
- Every token
- **Adaptive**

Method

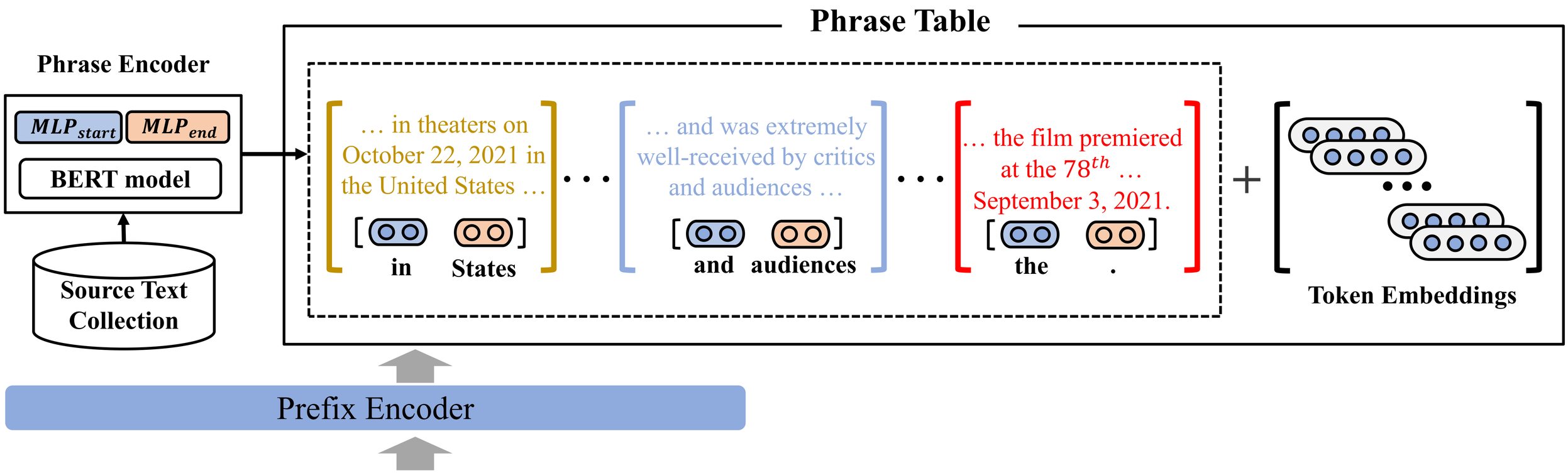


The Dune film was released [in theaters on October 22, 2021 in the United States] [and was extremely well-received by critics and audiences] **[Before] [that] [,]** [the film premiered at the 78^{th} International Film Festival on September 3, 2021.]

Method


Phrase Table
Phrase Encoder
MLP_{start}
MLP_{end}
BERT model
Source Text Collection
… in theaters on October 22, 2021 in the United States …
in
States
… and was extremely well-received by critics and audiences …
and
audiences
… the film premiered at the 78^{th} … September 3, 2021.
the
.
Token Embeddings

Method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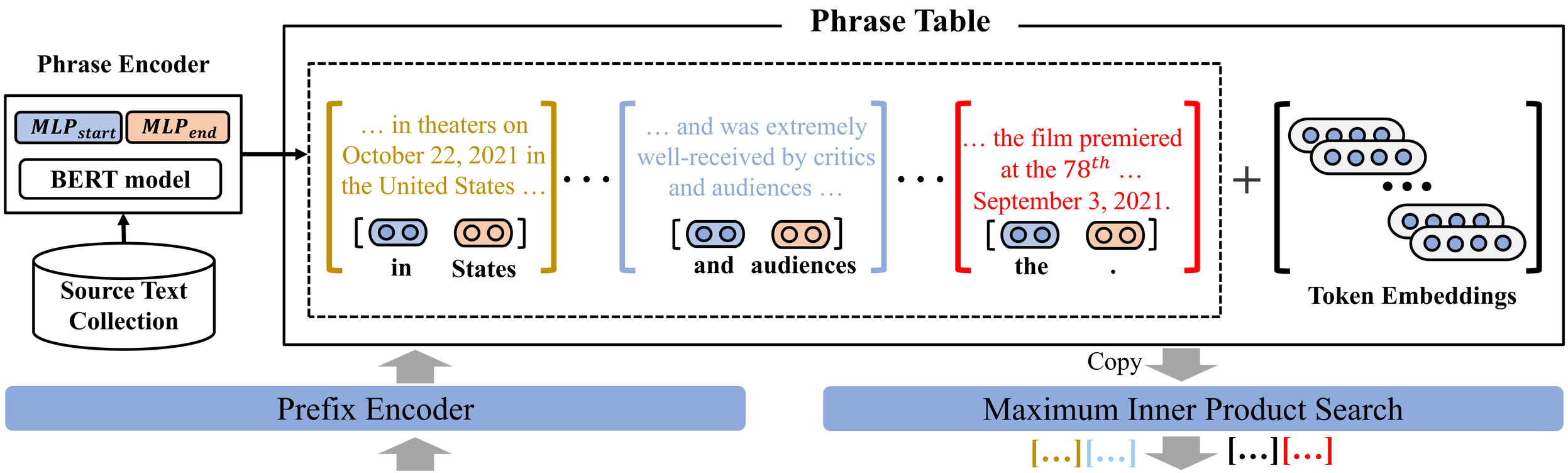
the
.
Token Embeddings
Prefix Encoder
The Dune film was released

Method



The Dune film was released [in theaters on October 22, 2021 in the United States]

Finetuned Phrase Encoder

Phrase Table → LM Vocabulary

Method

- phrase怎么获得？ 传统分词算法→最大前向算法
- 动态词表size？50257 + 950942（k=1024）
- 训练目标？🤔

Method

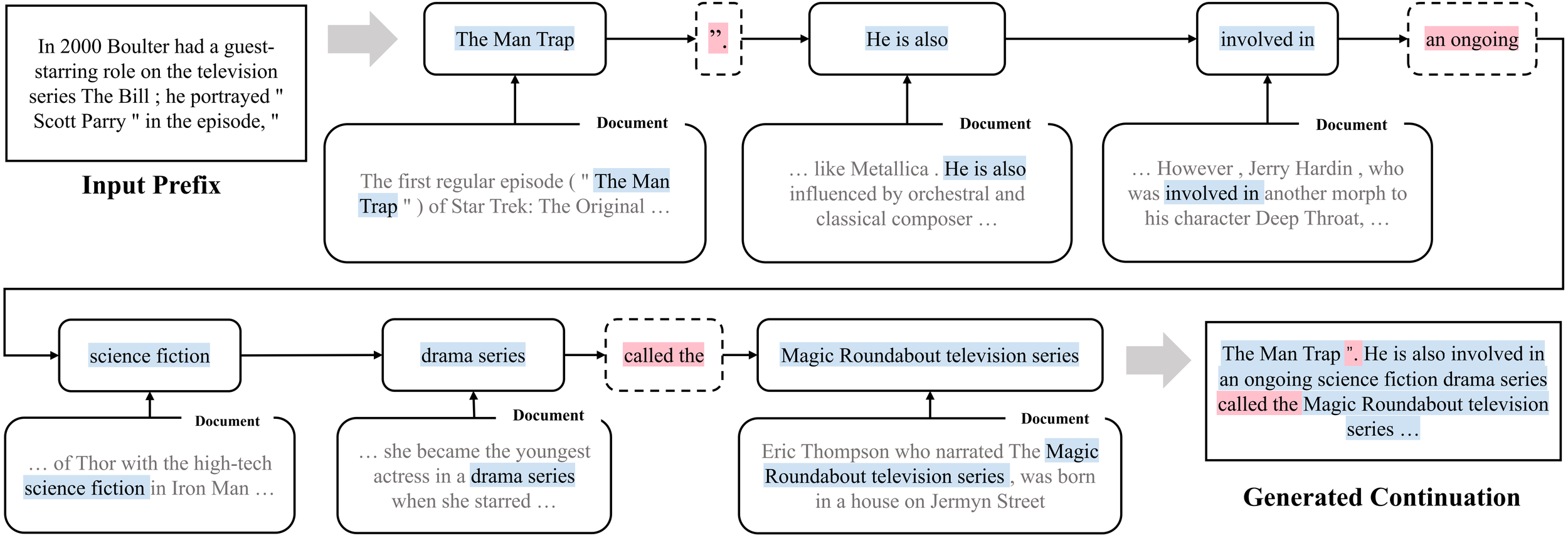
- phrase怎么获得？ 传统分词算法→最大前向算法
- 动态词表size？50257 + 950942（k=1024）
- 训练目标？🤔

$$\mathcal{L}_p = -\frac{1}{n}\sum_{k=1}^{n}\log\frac{\exp(q_k \cdot p_k)}{\sum_{p\in\mathcal{P}_k}\exp(q_k \cdot p_p) + \sum_{w\in V}\exp(q_k \cdot v_w)}$$

$$\mathcal{L}_t = -\frac{1}{m}\sum_{i=1}^{m}\log\frac{\exp(q_i, v_{D_i})}{\sum_{w\in V}\exp(q_i, v_w)}$$

$$\mathcal{L} = \mathcal{L}_p + \mathcal{L}_t$$

Method


In 2000 Boulter had a guest-starring role on the television series The Bill ; he portrayed " Scott Parry " in the episode, "
Input Prefix
The Man Trap
".
He is also
involved in
an ongoing
Document
The first regular episode (" The Man Trap ") of Star Trek: The Original …
Document
… like Metallica . He is also influenced by orchestral and classical composer …
Document
… However , Jerry Hardin , who was involved in another morph to his character Deep Throat, …
science fiction
drama series
called the
Magic Roundabout television series
Document
… of Thor with the high-tech science fiction in Iron Man …
Document
… she became the youngest actress in a drama series when she starred …
Document
Eric Thompson who narrated The Magic Roundabout television series , was born in a house on Jermyn Street
The Man Trap ". He is also involved in an ongoing science fiction drama series called the Magic Roundabout television series …
Generated Continuation

WikiText103 Results

Model	Decoding	MAUVE↑	Rep-2↓	Rep-3↓	Rep-4 ↓	Diversity↑	Latency (s)↓
Transformer	greedy	19.87	43.56	38.55	35.5	22.37	1.32
	nucleus	23.43	5.10	1.33	0.50	93.22	1.48
kNN-LM	greedy	19.92	43.79	38.76	35.69	22.13	10.36
	nucleus	22.50	**3.33**	**0.69**	**0.21**	**95.8**	10.42
RETRO	greedy	21.19	44.65	39.63	36.6	21.19	4.39
	nucleus	22.86	6.21	1.93	0.86	91.19	4.51
CoG	greedy	26.01	28.14	23.80	21.40	43.03	**1.29**
	nucleus	**26.14**	7.31	2.66	1.28	89.07	1.54

WikiText103 Results

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CoG🏆MAUVE or greedy dec.

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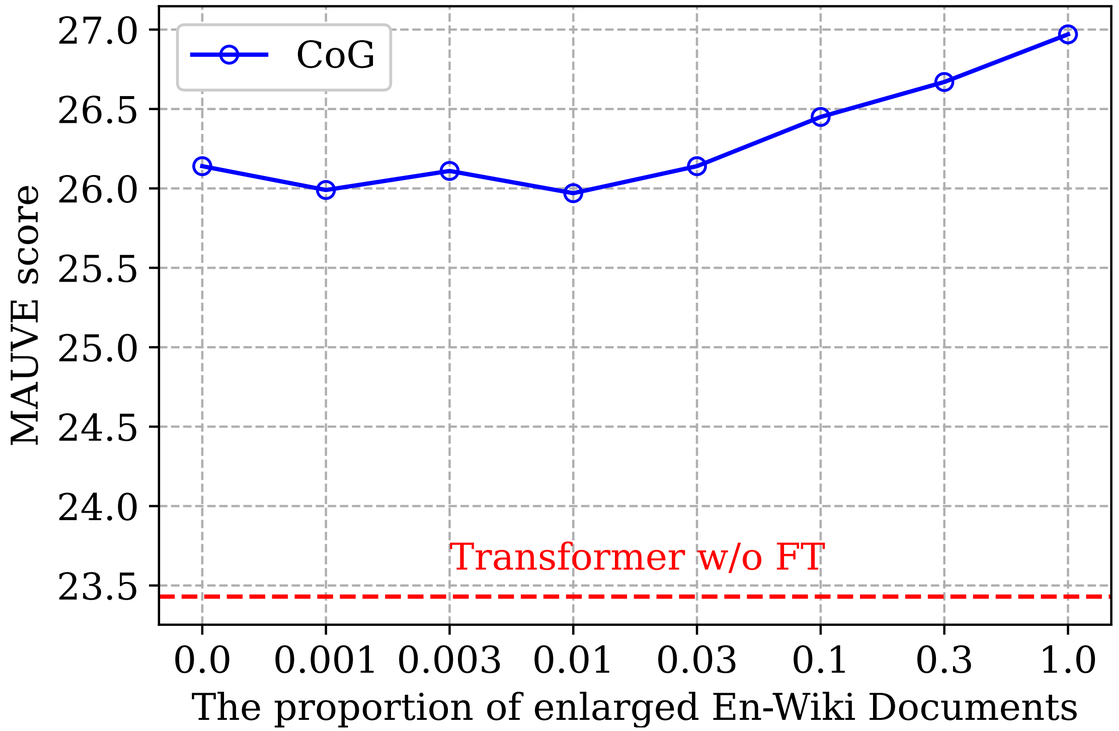
Law-MT Results

Model	Decoding	MAUVE ↑	Diversity ↑
Transformer w/o FT	greedy	19.87	22.37
	nucleus	23.43	93.22
Transformer w/ FT	greedy	20.21	19.62
	nucleus	21.31	92.92
kNN-LM	greedy	23.21	20.33
	nucleus	23.39	**96.37**
RETRO	greedy	19.75	21.15
	nucleus	22.87	91.09
CoG	greedy	24.68	40.45
	nucleus	**26.97**	90.00



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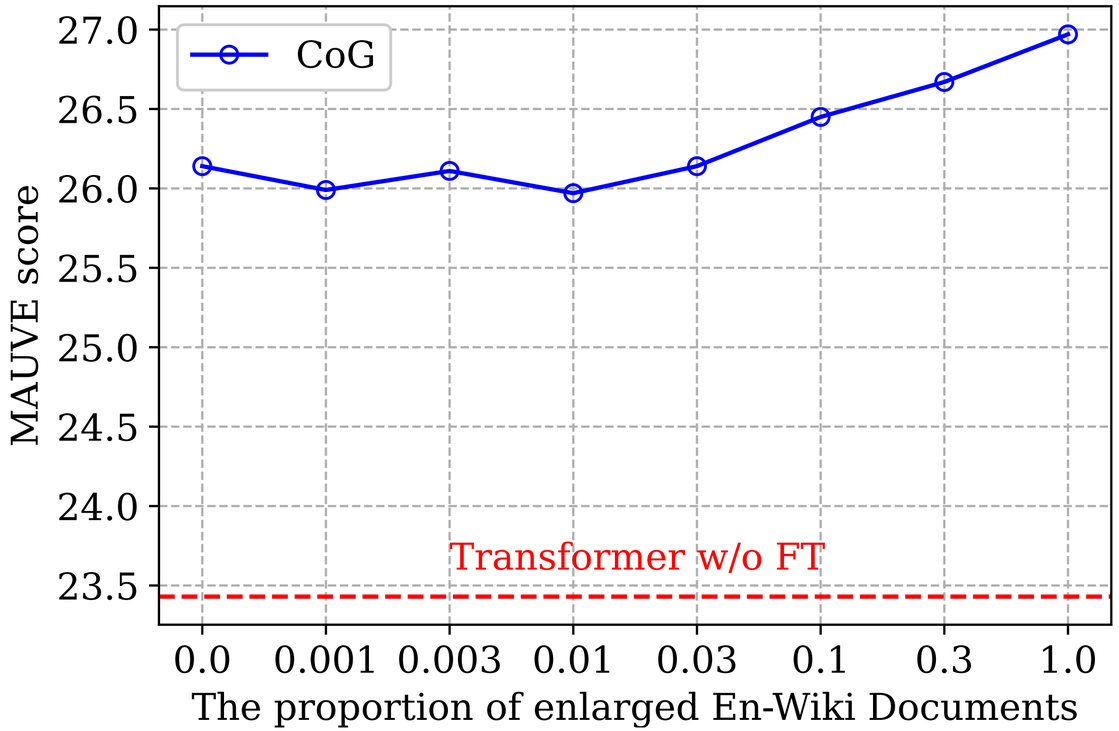

#phrase 📈

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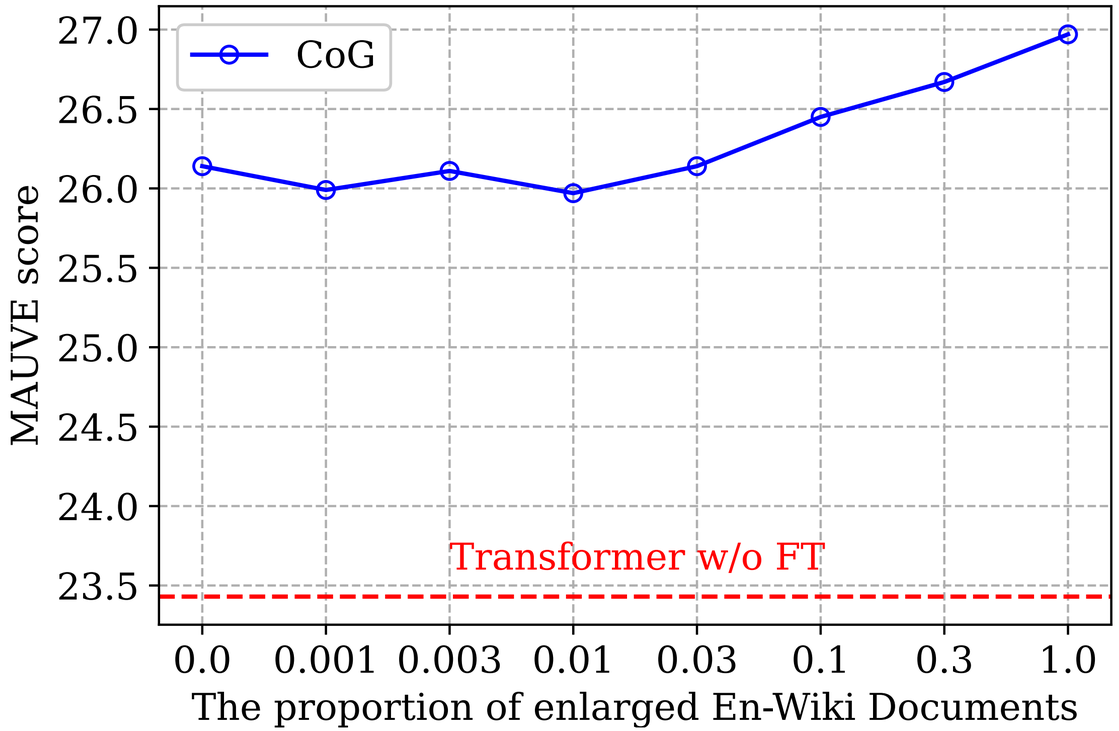

🤦‍♀️BERT ↔️ GPT

Humen Evaluation

Comparison	Better	No Prefer.	Worse
CoG vs. Transformer	**48%**	24%	28%

Comparison	Better	No Prefer.	Worse
CoG vs. Transformer w/ FT	**52%**	12%	36%

Inference Speed

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Output Layer: Conclusion

	通用性	推理效率	隐私保护	存储成本	特点
🎯Input	🥈 **适用API** **最大长度**	🥉 **一次检索** **样本需再编码**	🥉 **检索返回明文**	🏅 **向量+文本**	**Top-K位置敏感**
🎯hidden	🥈 **无长度约束** **不适用API**	🥈 **样本无再编码** **逐词/层/头检索**	🏅 **返回Topk向量**	🥈 **逐词/层/头向量**	**PEFT**
🎯output					

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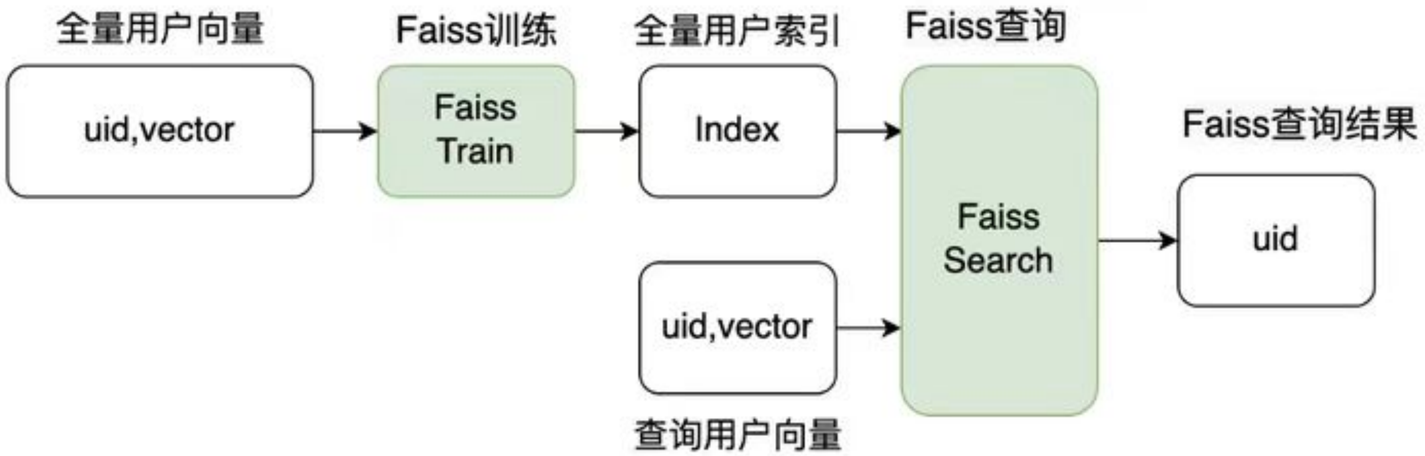
	通用性	推理效率	隐私保护	存储成本	特点
🎯Input	🥈 **适用API** 最大长度	🥉 **一次检索** 样本需再编码	🥉 检索返回明文	🏅 **向量+文本**	Top-K位置敏感
🎯hidden	🥈 **无长度约束** 不适用API	🥈 **样本无再编码** 逐词/层/头检索	🏅 **返回Topk向量**	🥈 逐词/层/头向量	PEFT
🎯output	**只需输出层**	**样本无再编码** **缩短长度**	**返回Topk向量**	**向量+文本**	拷贝→引用/解释

Output Layer: Conclusion

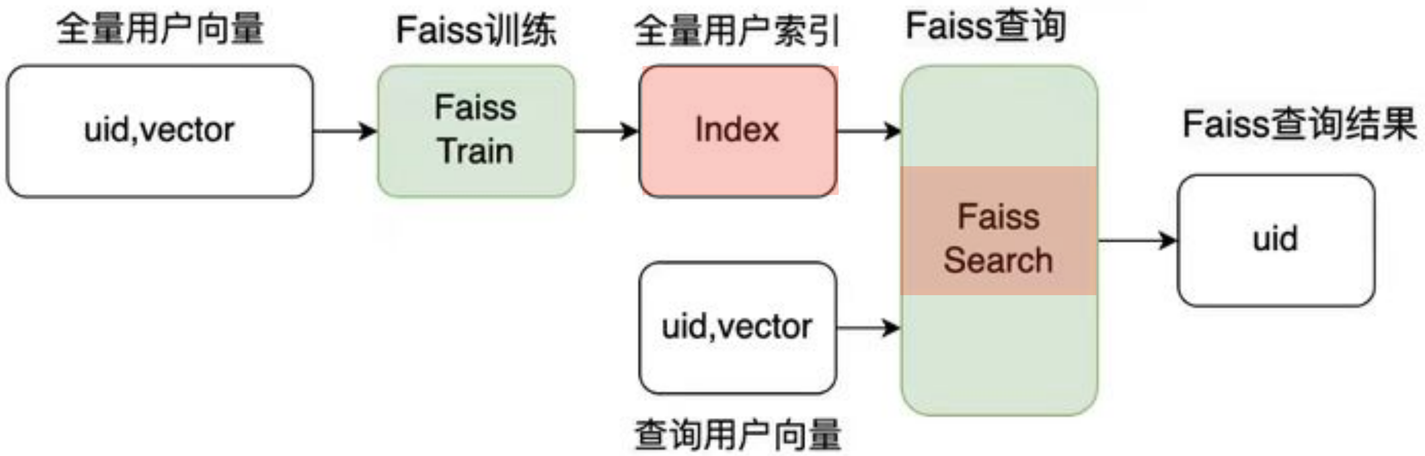
	通用性	推理效率	隐私保护	存储成本	特点
🎯Input	🥈 **适用API** 最大长度	🥉 **一次检索** 样本需再编码	🥉 检索返回明文	🥇 **向量+文本**	Top-K位置敏感
🎯hidden	🥈 **无长度约束** 不适用API	🥈 **样本无再编码** 逐词/层/头检索	🥇 **返回Topk向量**	🥈 逐词/层/头向量	PEFT
🎯output	🥇 **只需输出层**	🥇 **样本无再编码** **缩短长度**	🥇 **返回Topk向量**	🥇 **向量+文本**	拷贝→引用/解释

Q & A

Faiss


全量用户向量
uid,vector
Faiss训练
Faiss
Train
全量用户索引
Index
Faiss查询
Faiss
Search
Faiss查询结果
uid
uid,vector
查询用户向量

Faiss


全量用户向量
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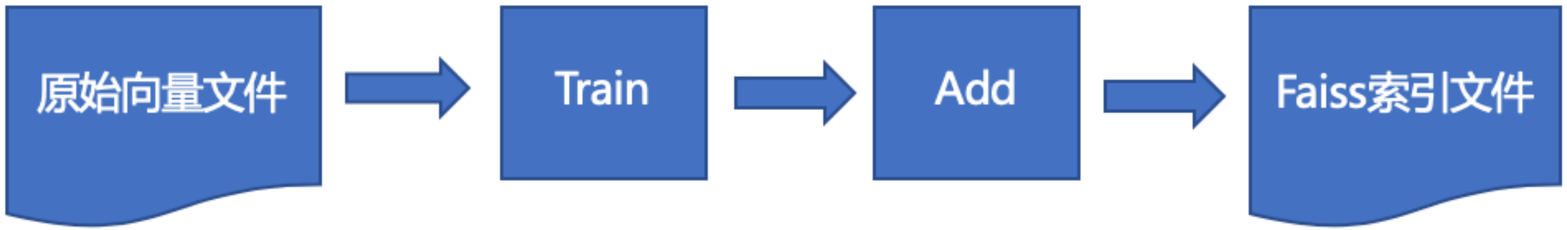
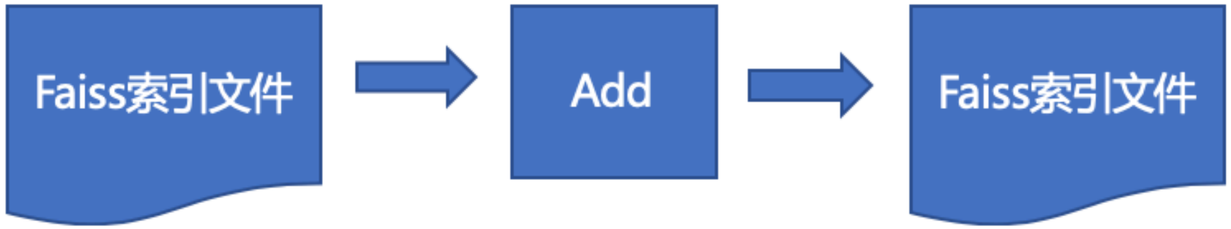
全量用户索引
Index
Faiss查询
Faiss
Search
Faiss查询结果
uid
uid,vector
查询用户向量

Faiss

全量构建索引：



增量构建索引：



Search: Dist

原生支持

- INNER_PRODUCT
- L1, L2, …, Lp
- Canberra
- BrayCurtis
- JensenShannon

可转换

- Cosine similarity
- Mahalanobis

Faiss: 暴力查询IndexFlatL2

Faiss: 查询优化IndexIVFFlat

🎯聚类→减少查询数量（c+n/c, nprobe）

Faiss: 查询优化IndexIVFFlat

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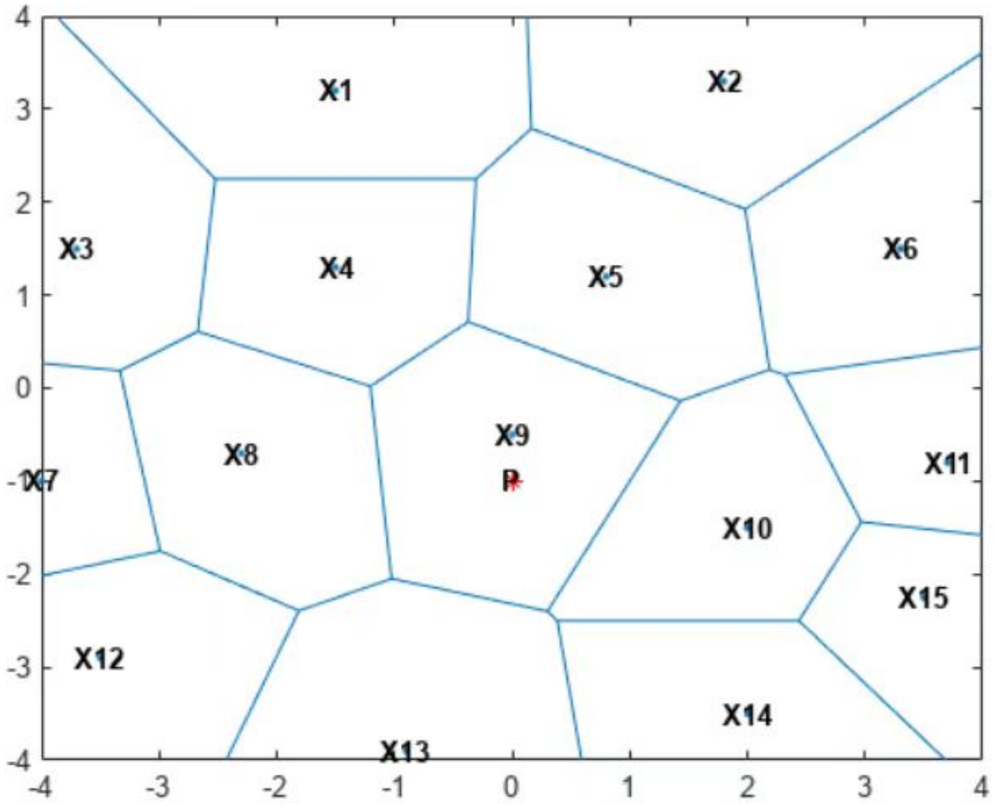
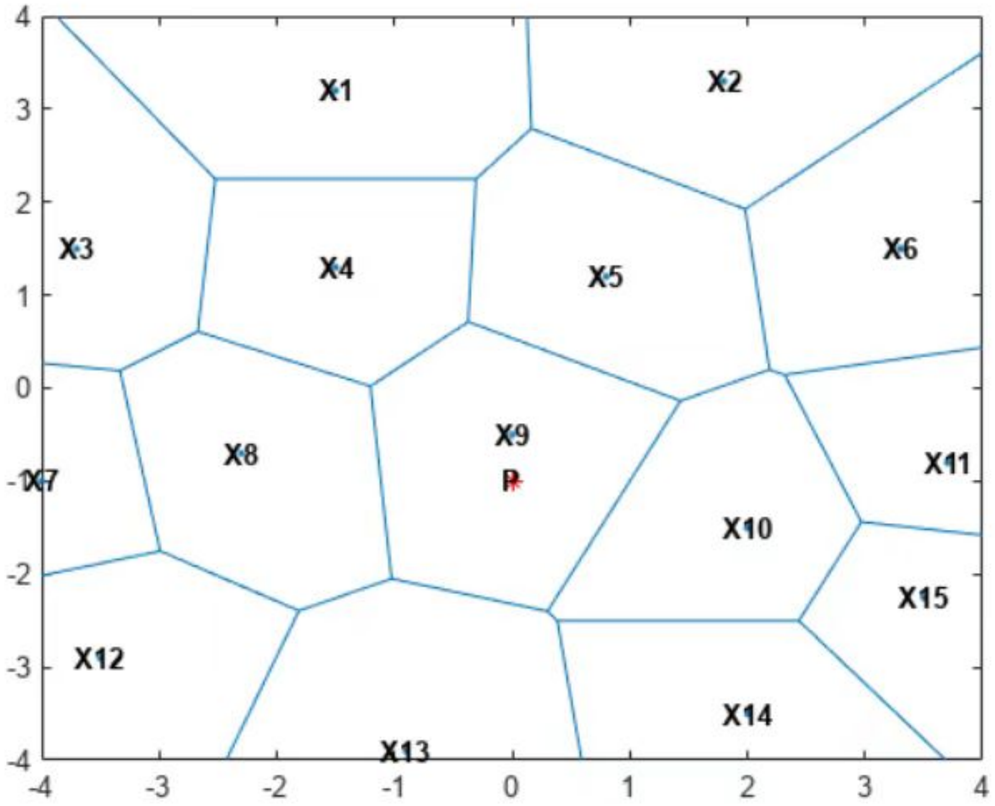


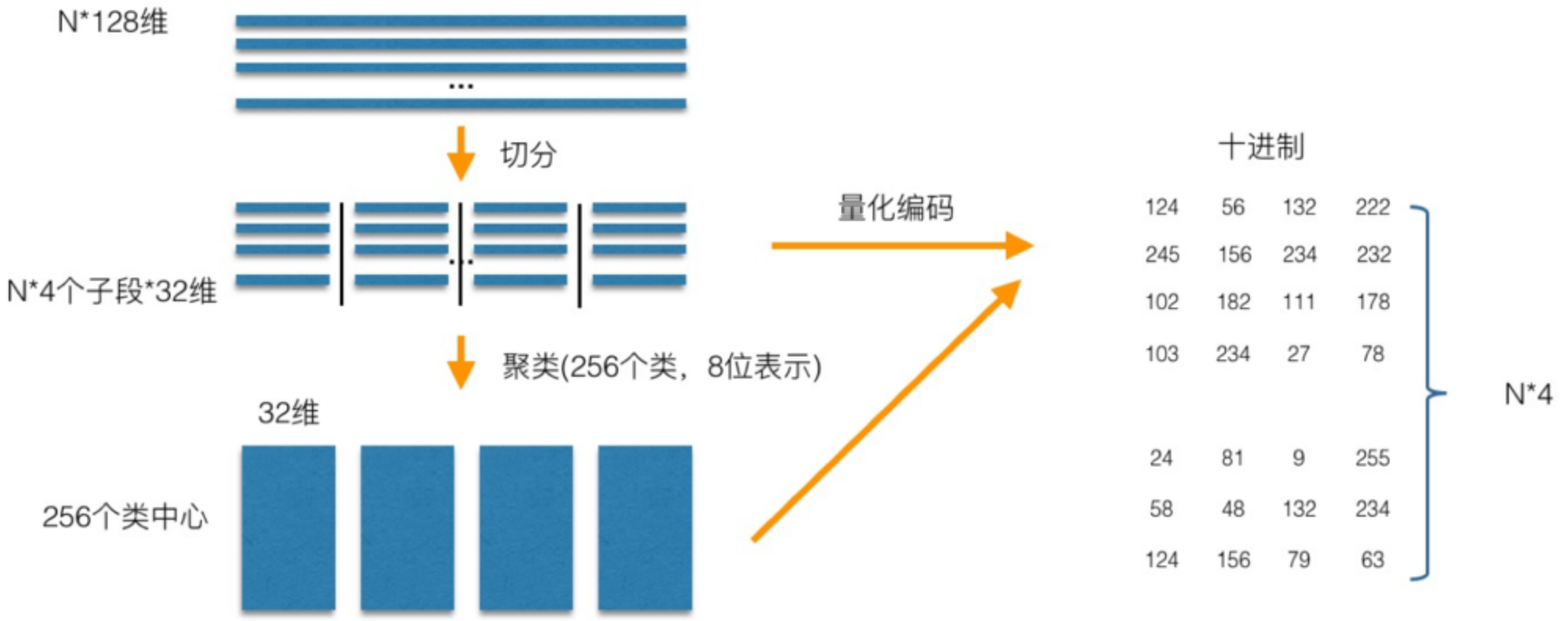
Faiss: 查询优化IndexIVFFlat

🎯聚类→减少查询数量（c+n/c, nprobe）



[4*sqrt(N), 16*sqrt(N)] → [30K, 256K]

Faiss: 存储/计算优化IndexPQ



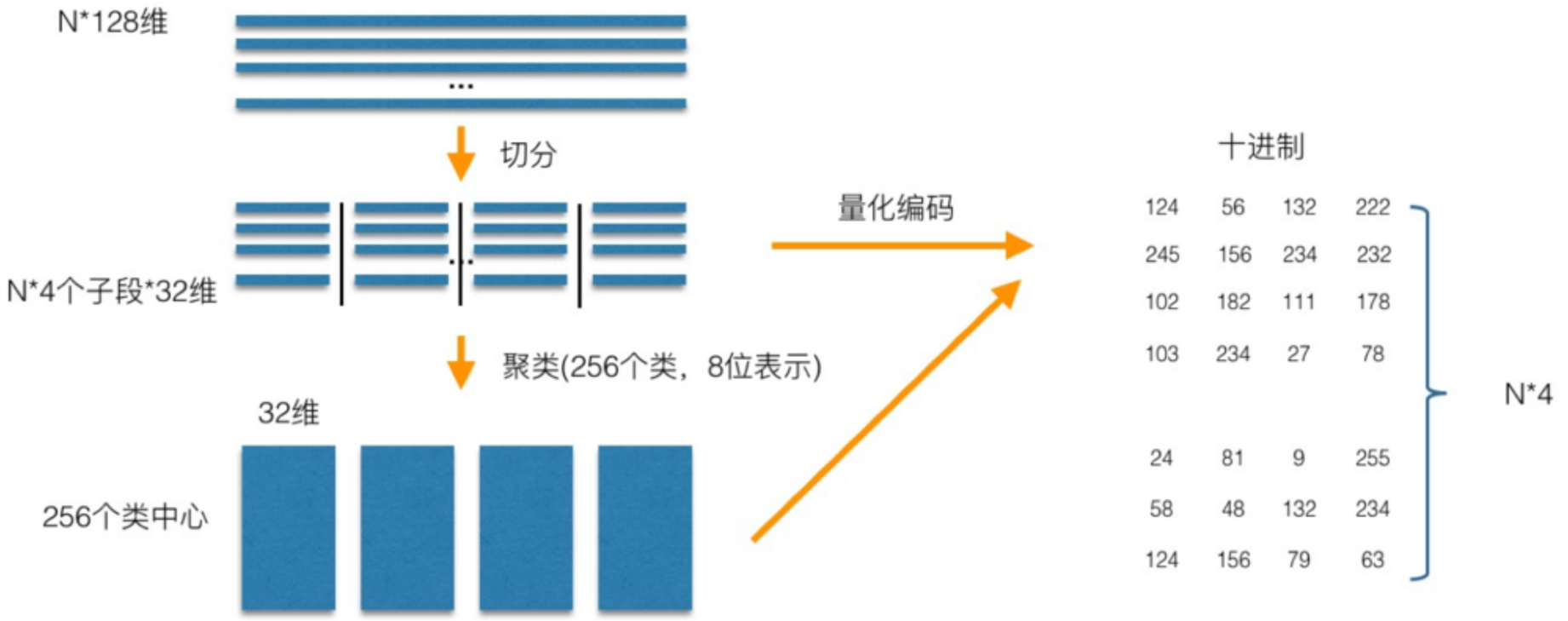
PQ

4x256次128维向量距离计算；

暴力

N次128维向量距离计算。

Faiss: 存储/计算优化IndexPQ



PQ

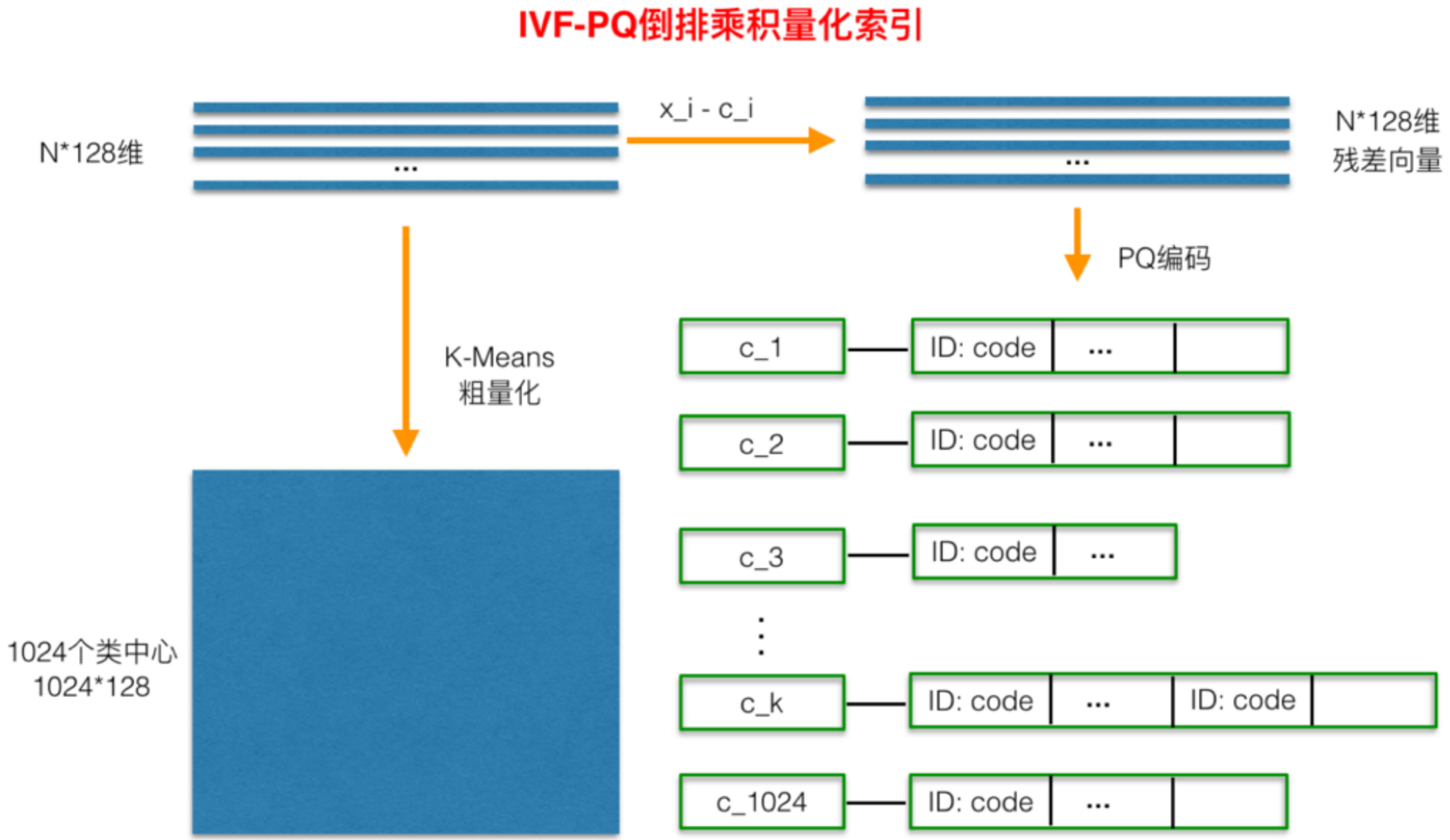
4x256次128维向量距离计算；

暴力

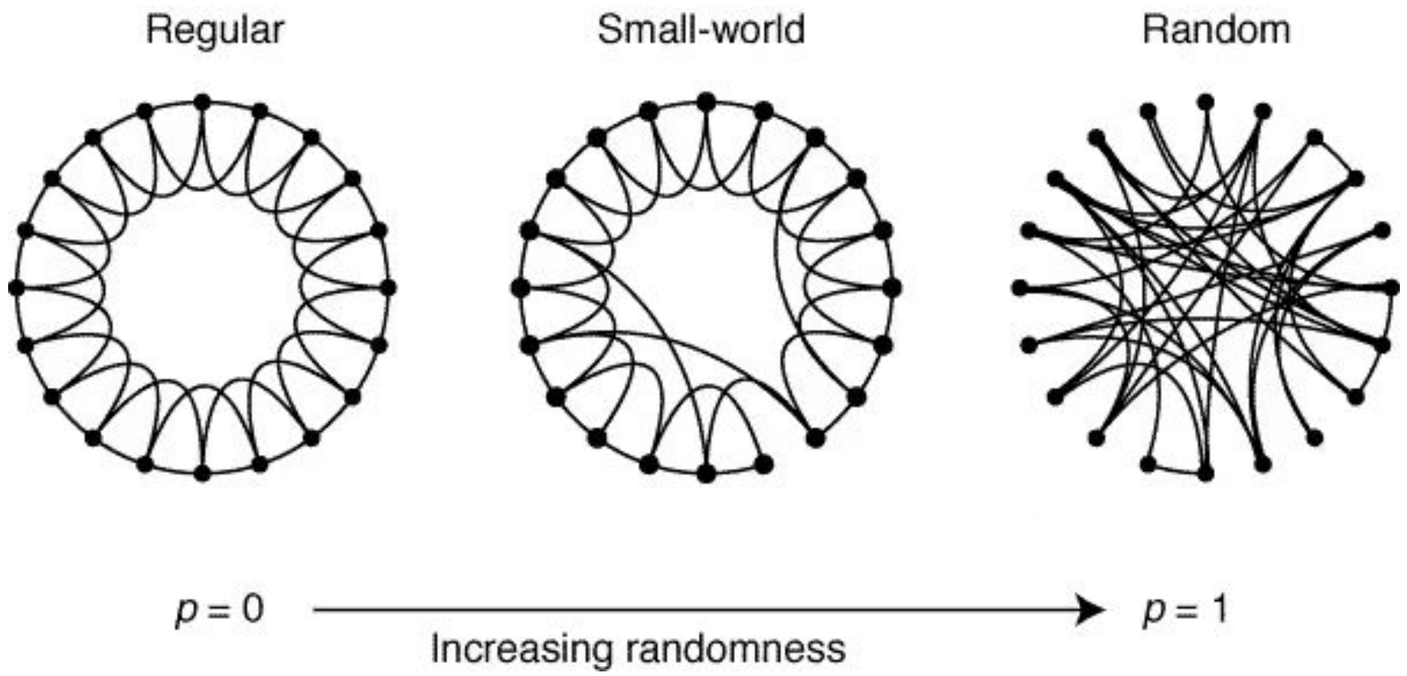
N次128维向量距离计算。

M = 64

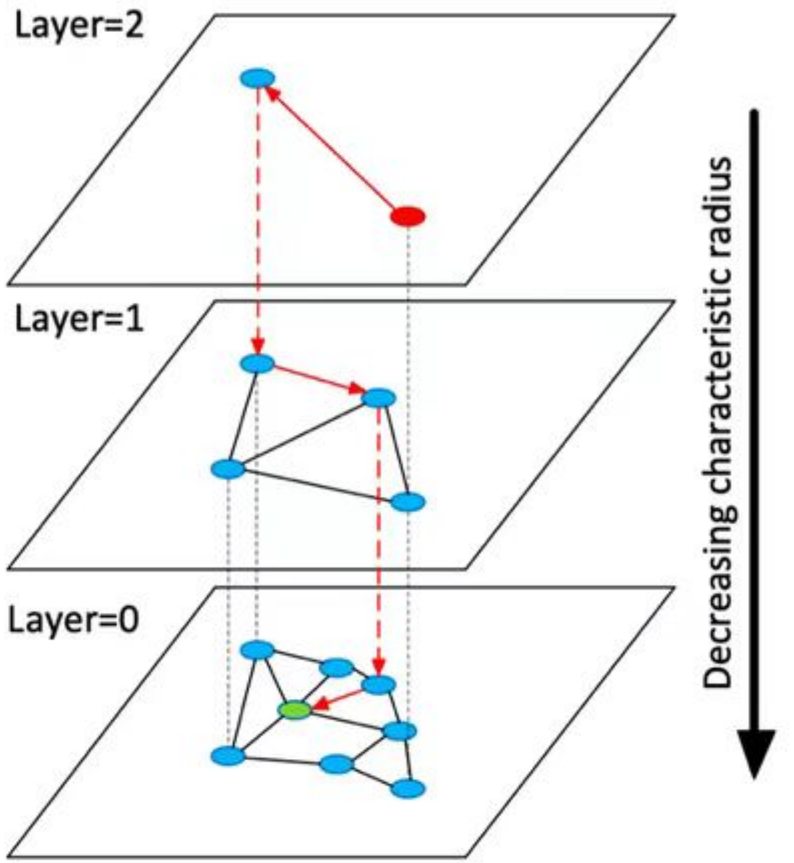
Faiss:存询优化IndexIVFPQ



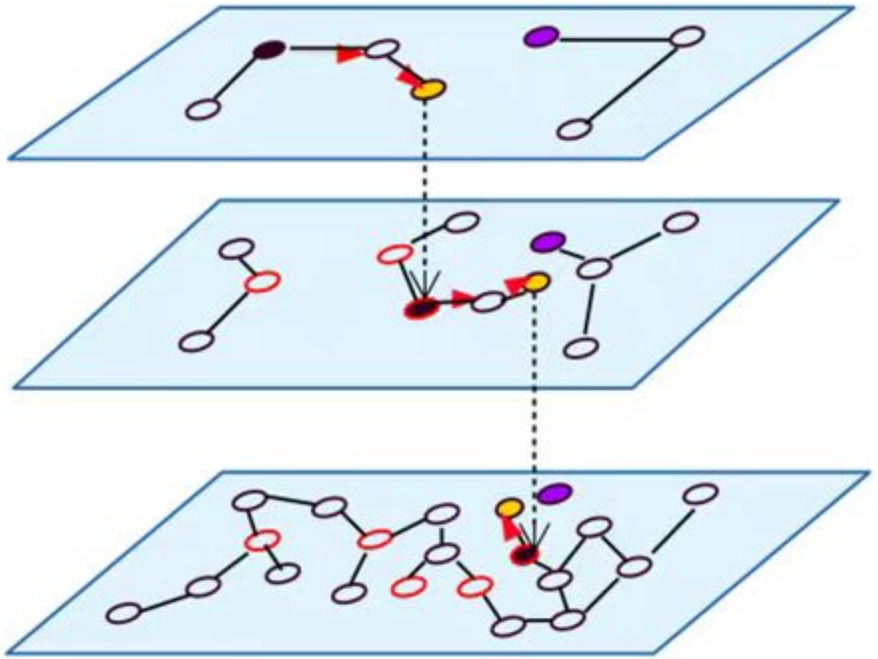
Faiss: 图索引IndexHNSWFlat



Faiss: 图索引IndexHNSWFlat



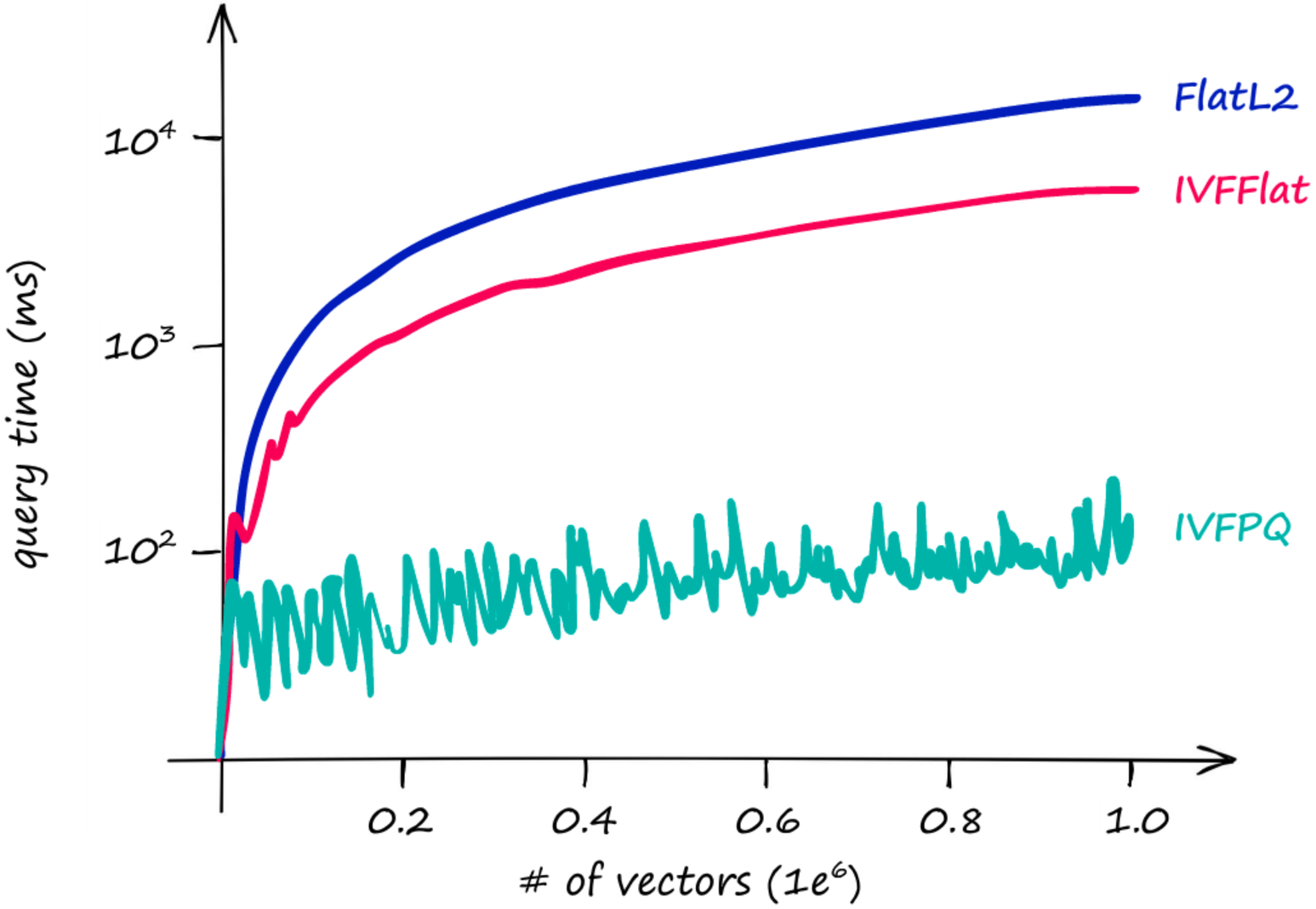
Faiss: 图索引IndexHNSWFlat



Faiss: PQ vs HNSW

特性	OPQ	HNSW
内存占用	小	大
召回率	较高	高
数据动态增删	灵活	不易

Faiss:存询优化IndexIVFPQ@GPU



1e5 query

Faiss:存询优化IndexIVFPQ@M1CPU

Index	Memory (MB)	Query Time (ms)	Recall	Notes
Flat	~500	18	1.0	适用于查询时间要求不高的小数据集
IVF	~520	1 - 9	0.7 - 0.95	一个扩展性比较高的方案
LSH	20 - 600	1.7 - 30	0.4 - 0.85	对于低维向量最好的方案
HNSW	600 - 1600	0.6 - 2.1	0.5 - 0.95	适用于对于精度和速度要求高的场景，但是费内存

d=128，N=1M，k=10

Retrieval Cost

Retrieval Cost

Retrieval n vectors → Add m tokens

Retrieval Cost

Retrieval n vectors → Add m tokens

params	dimension	n heads	n layers
6.7B	4096	32	32
13.0B	5120	40	40
32.5B	6656	52	60
65.2B	8192	64	80

Retrieval Cost: Llama-13B

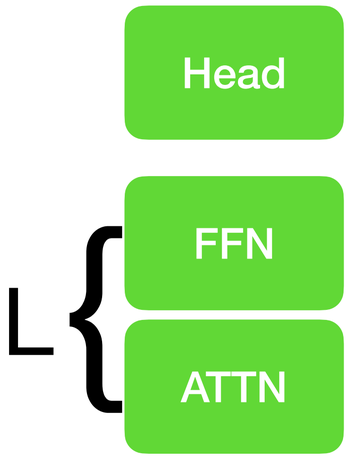
Retrieval n vectors → Add m tokens

Input = 1024, add 1 token

Retrieval Cost: Llama-13B

Retrieval n vectors → Add m tokens

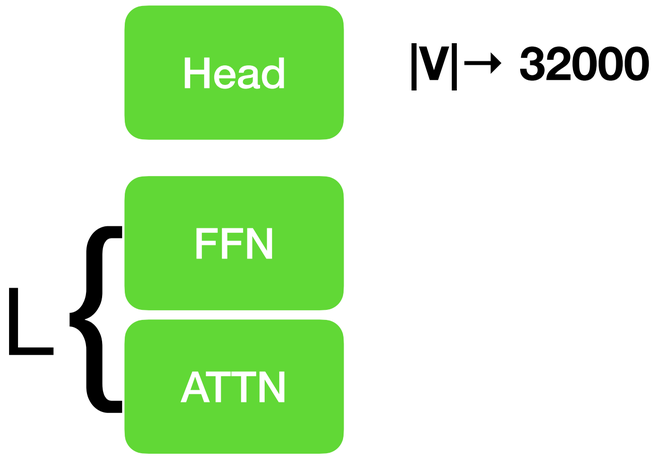
Input = 1024, add 1 token



Retrieval Cost: Llama-13B

Retrieval n vectors → Add m tokens

Input = 1024, add 1 token



Retrieval Cost: Llama-13B

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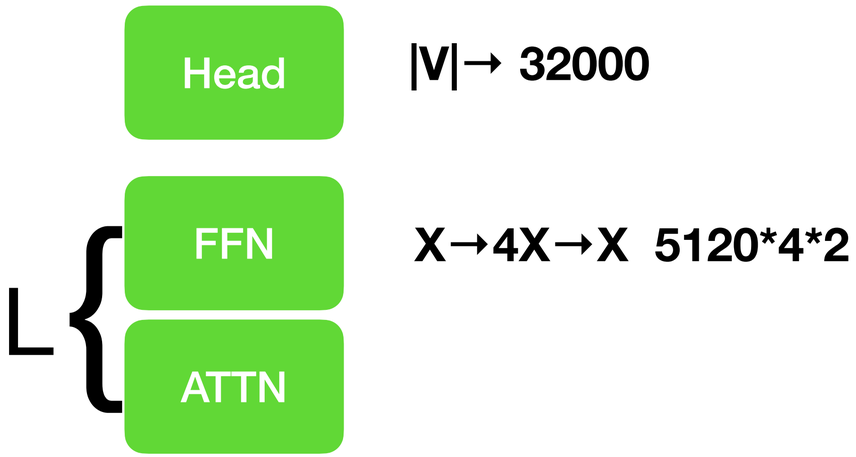

Retrieval Cost: Llama-13B

Retrieval n vectors → Add m tokens

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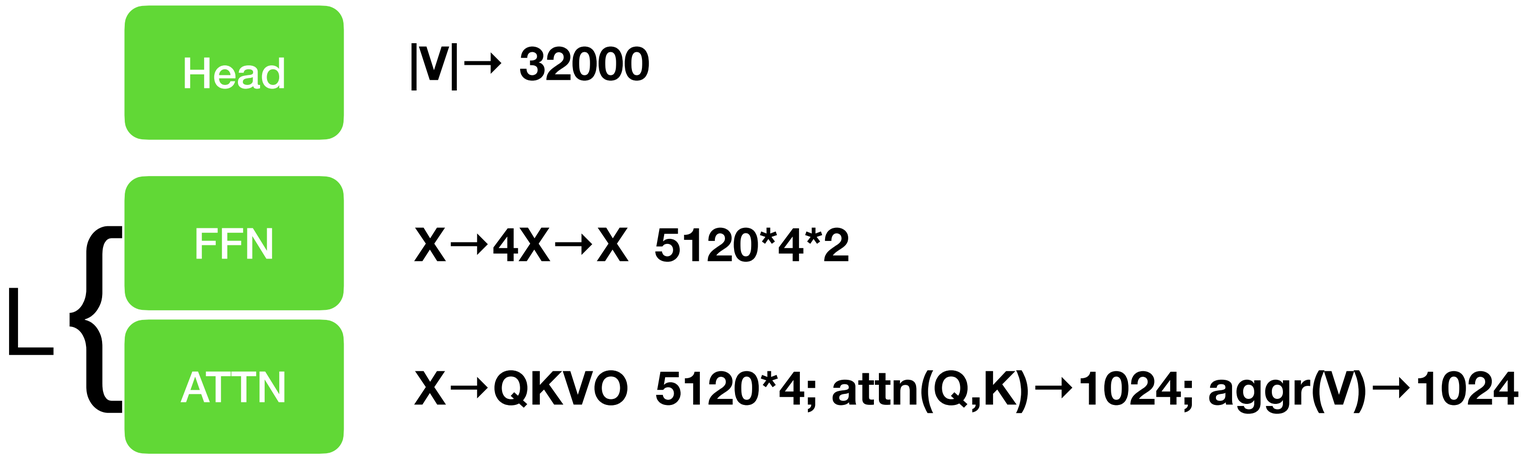


Retrieval Cost: Llama-13B

Retrieval n vectors → Add m tokens

Input = 1024, add 1 token

Head — **|V|→ 32000**

L { FFN — **X→4X→X 5120*4*2**

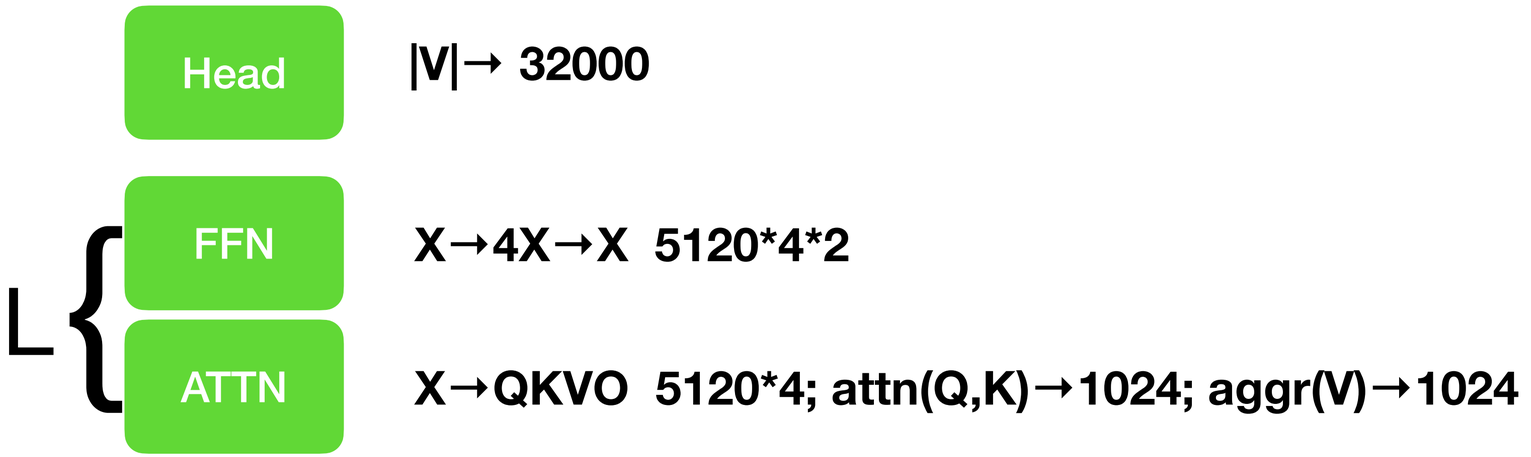
L { ATTN — **X→QKVO 5120*4; attn(Q,K)→1024; aggr(V)→1024**

> 2571520

Retrieval Cost: Llama-13B

Retrieval n vectors → Add m tokens

Input = 1024, add 1 token



> 2571520

- CoG: 动态词表size？ 50257 + 950942（k=1024）
- 检索3个token等于长度上增加1个token

Retrieval Cost: Llama-13B

Retrieval n vectors → Add m tokens

Input = 1024, add 1 token

Head

|V|→ 32000

L{

FFN

X→4X→X 5120*4*2

MoE 👉 向量近似检索

ATTN

X→QKVO 5120*4; attn(Q,K)→1024; aggr(V)→1024

> 2571520

- CoG: 动态词表size？ 50257 + 950942（k=1024）
- 检索3个token等于长度上增加1个token

Similarity

检索负例🤔　向量距离远→负例?

条件检索：C-STS

Similarity

检索负例🤔 向量距离远→负例?

条件检索：C-STS

C-STS: Conditional Semantic Textual Similarity

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Vishvak Murahari[1] **Victoria Graf**[1] **Tanmay Rajpurohit**[3]
Ashwin Kalyan[2] **Danqi Chen**[1] **Karthik Narasimhan**[1]

[1]Princeton University [2]The Allen Institute for AI [3]Georgia Tech
asd@cs.princeton.edu

Similarity

检索负例🤔 向量距离远→负例?

条件检索：C-STS

C-STS: Conditional Semantic Textual Similarity

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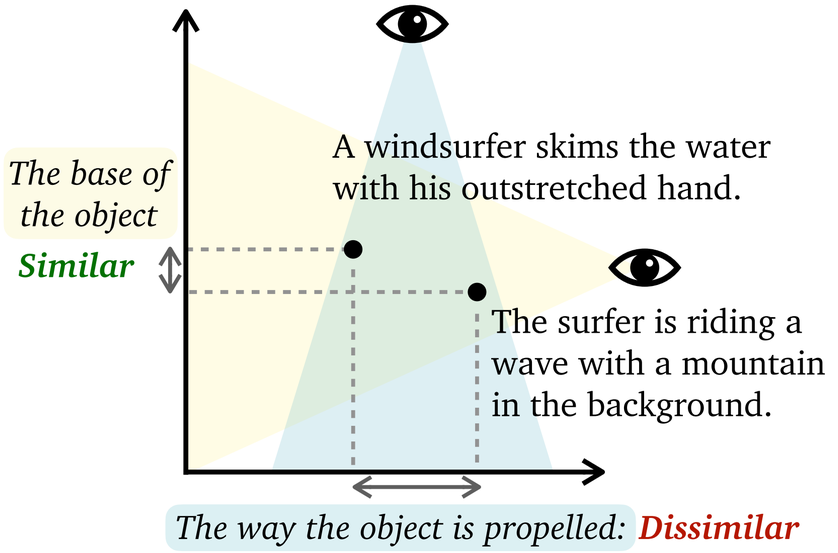

基于向量检索增强的LLM

博士后 纪焘

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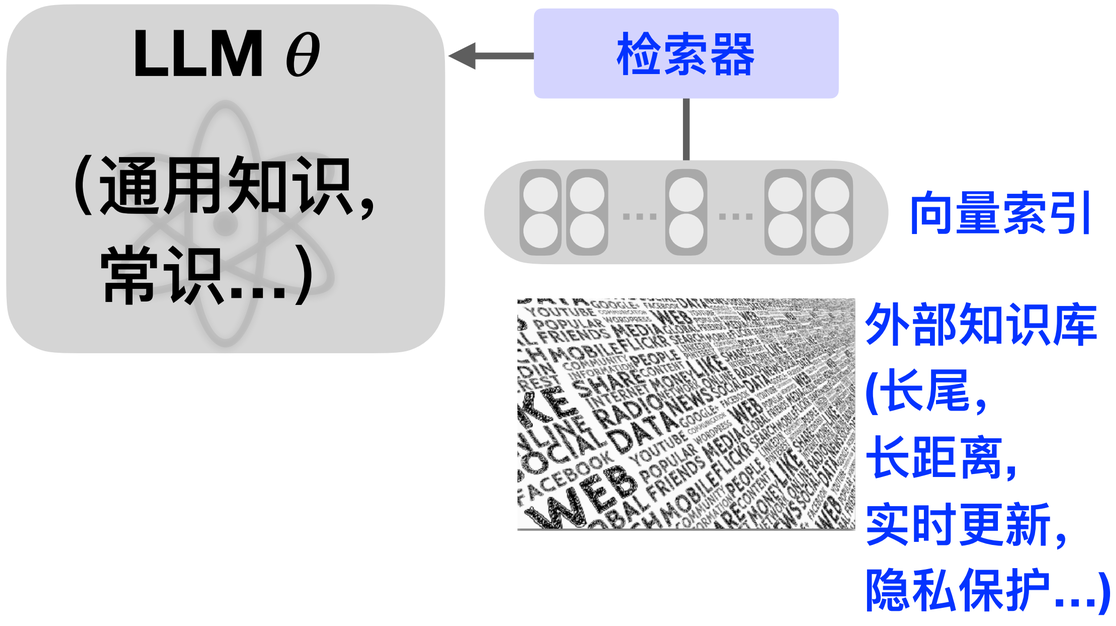
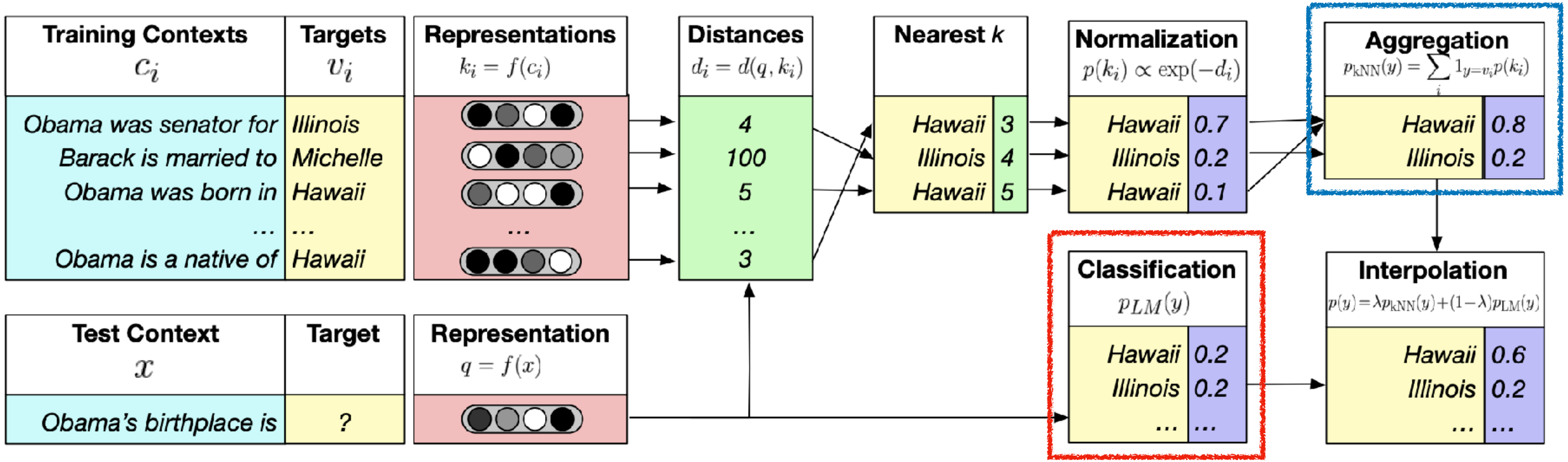


检索+LLM框架

1. Input
2. hidden
3. output

KNN-LM



λ: hyperparameter

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