

BMI: Bottleneck-Minimal Indexing for Generative Document Retrieval

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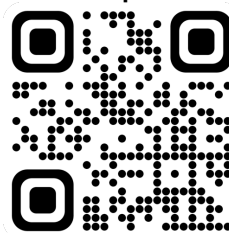
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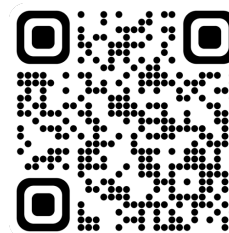
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The University of Tokyo

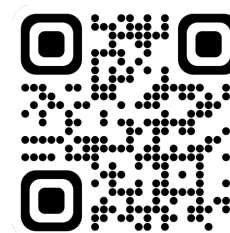
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Our lab



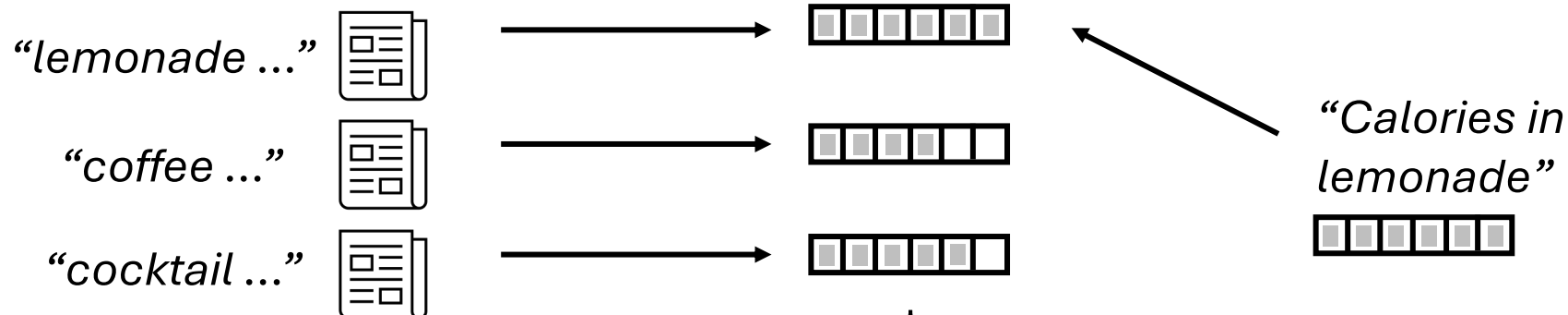
* Equal contribution

Corresponding author

Document Retrieval

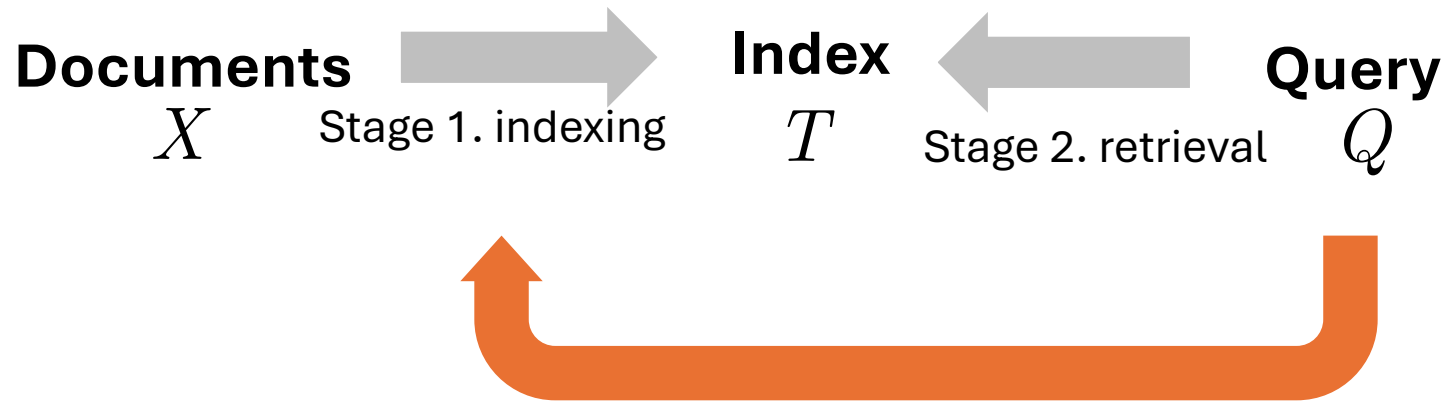


Wikipedia pages



- Boolean vectors
- TF-IDF, BM25, ...
- Semantic hashing (2009)
- BERT embedding (2018)

Indexing for Document Retrieval

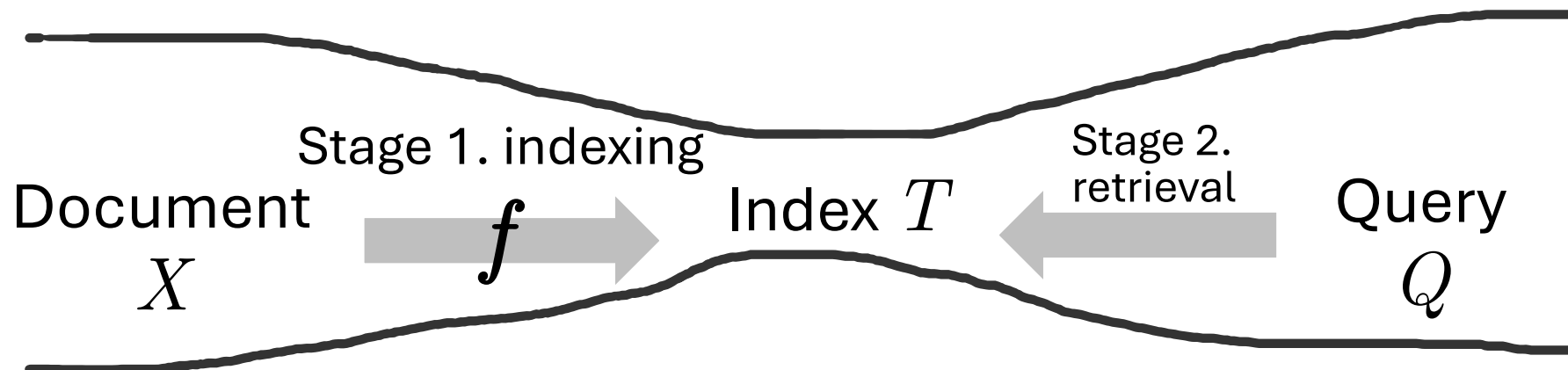


A long-existing idea: **Queries Q should be incorporated** in indexing

But how?

It lacks a theoretical guide.

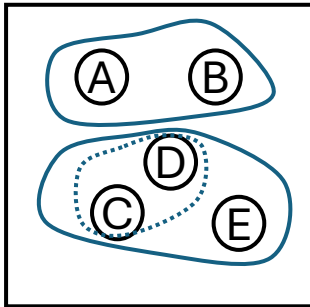
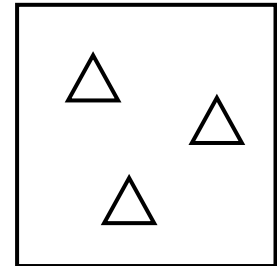
This Work: An Information Bottleneck Model ^[1] for Generative Document Retrieval (GDR explained in the next page)



- Retrieval as “data transmission” from query Q to document X .
- Index T as the “*bottleneck*”.

Optimal indexing $f^*: X \mapsto T$ should be
bottleneck-minimal.

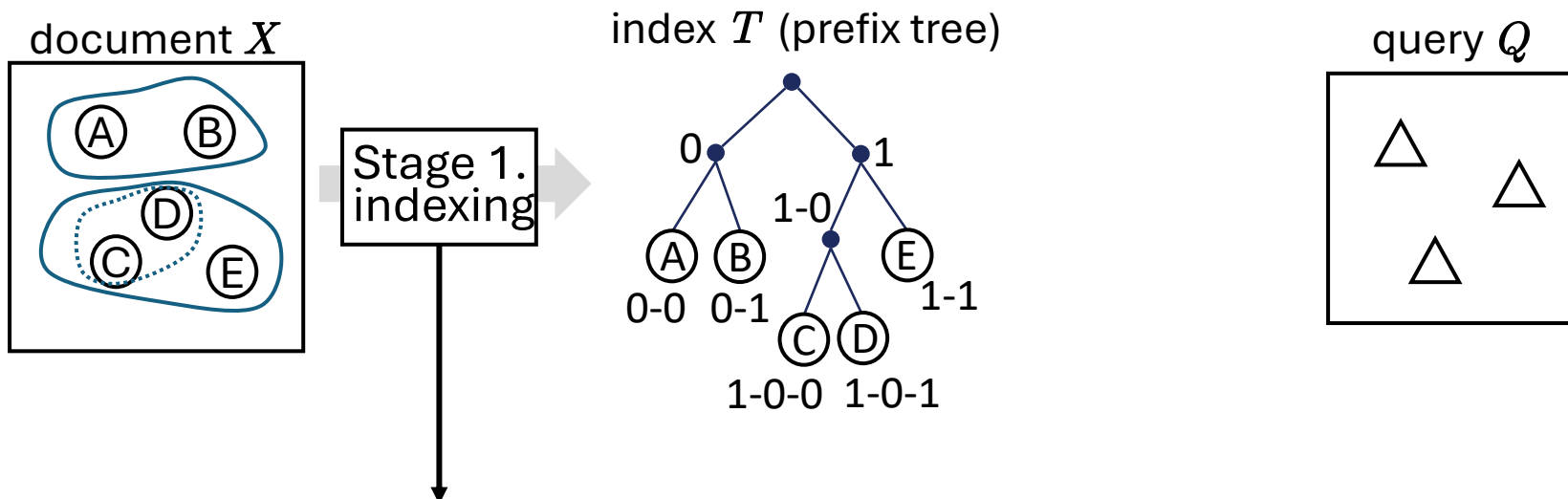
Generative Document Retrieval (GDR)^[2,3]

document X query Q 

[2] Cao et al. Auto-regressive entity retrieval. ICLR 2021.

[3] Tay et al. Transformer memory as a differentiable search index. NeurIPS 2022.

Generative Document Retrieval (GDR)

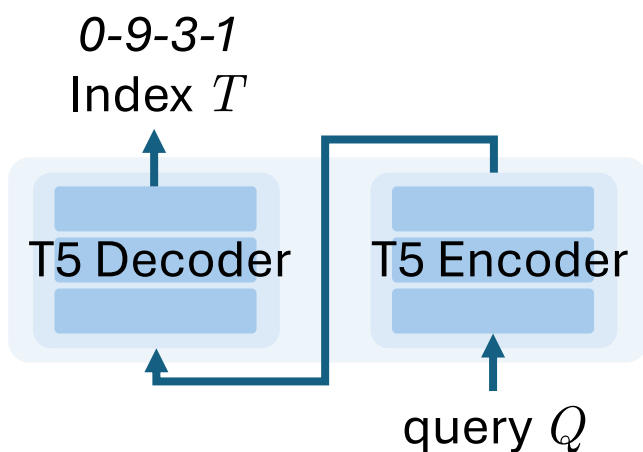
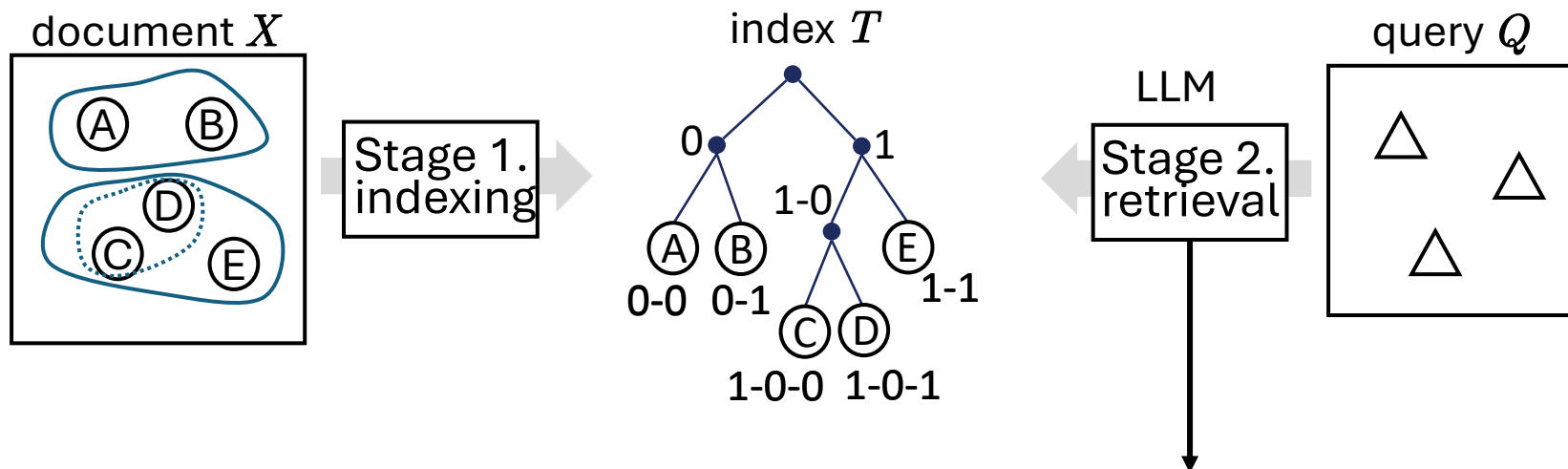


Stage 1.

Hierarchical clustering applied to document vectors. [2-3]

- Good Intuition but lacks theoretical support.

Generative Document Retrieval (GDR)

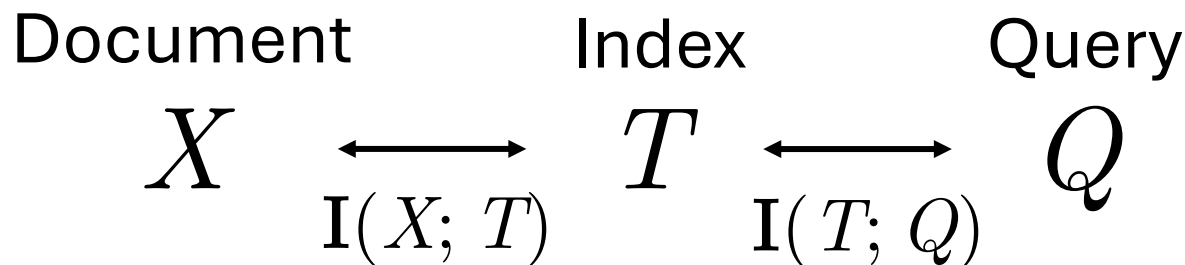


"Calories in lemonade."

Stage 2. Train a language model to "translate" a query into index. (i.e., generate the index digit by digit)

Promising, but limited by the model's *finite* and often *insufficient* size.

Information Bottleneck (IB) Model for GDR



IB studies the *tradeoff* by the Lagrangian:

$$L[p(T|X), \beta] = I(X; T) - \beta I(T; Q) \quad \beta \geq 0$$

assuming Markov chain $T \leftrightarrow X \leftrightarrow Q$

Why is this *tradeoff* essential for GDR ?

Why is this *tradeoff* essential for GDR ?

Document

X

Index

T

Query

Q

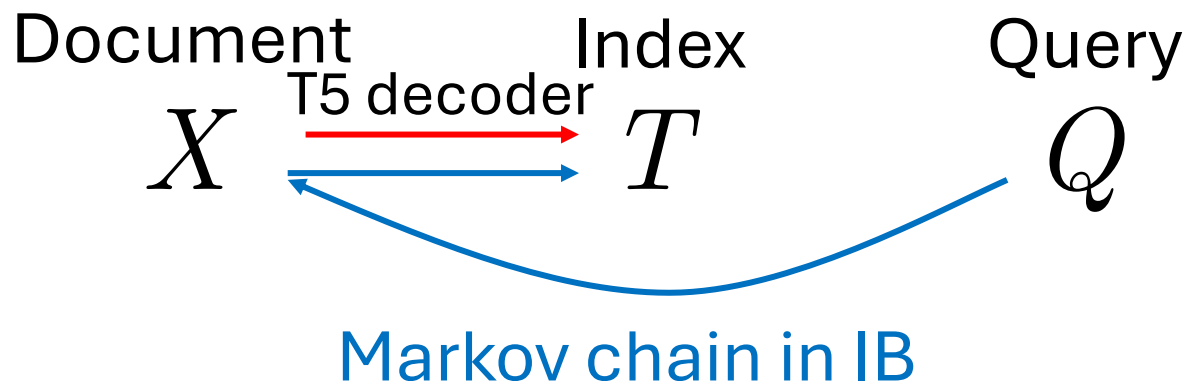
←
Retrieve by
generation

Performance

$I(T; Q)$

Maximal
retrieval accuracy

Why is this *tradeoff* essential for GDR ?



Cost of Memory

$$I(X; T)$$

How many bits the language model must "*memorize*" per document

Performance

$$I(T; Q)$$

Maximal retrieval accuracy

Tradeoff: Model Size v.s. Retrieval Performance

minimize

$$L[p(T|X), \beta] = \mathbf{I}(X; T) - \beta \mathbf{I}(T; Q)$$

Model size **Performance**

Tradeoff: Model Size v.s. Retrieval Performance

minimize

$$L[p(T|X), \beta] = \mathbf{I}(X; T) - \beta \mathbf{I}(T; Q)$$

Model size (T5) **Performance**

Optimal indexing achieves:

highest accuracy for a specific model size, or

Tradeoff: Model Size v.s. Retrieval Performance

minimize

$$L[p(T|X), \beta] = \mathbf{I}(X; T) - \beta \mathbf{I}(T; Q)$$

Model size (T5) **Performance**

Optimal indexing achieves:

smallest model size for a given accuracy

Tradeoff: Model Size v.s. Retrieval Performance

minimize

$$L[p(T|X), \beta] = \mathbf{I}(X; T) - \beta \mathbf{I}(T; Q)$$

Model size (T5) **Performance**

Such optimal indexing under a **limited model-size budgets** is called the ***bottleneck-minimal indexing*** (next page),

NOT the case when a model can be infinitely-large (**unlimited model size**), e.g., a maximum inner-product search model.

This Work: Bottleneck-Minimal Indexing

Our proposed definition of BMI:

An indexing function $f: X \mapsto T$ is called an BMI if it maximizes the likelihood function $p(\text{dataset} | f)$

$$\begin{aligned}
 f^* &= \operatorname{argmax}_f \prod_{\text{doc } x} p^*(X=x | T=f(x)) \\
 &= \operatorname{argmax}_f \prod_{\text{doc } x} \frac{p^*(T=f(x) | X=x)}{p^*(f(x))} \overset{\text{constant}}{p(x)} \\
 &= \operatorname{argmin}_f \sum_{\text{doc } x} \text{KL}[p(Q|x) \parallel p(Q|f(x))]
 \end{aligned}$$

How we acquire f^*

Assume $p(Q|x)$ and $p(Q|f(x))$ to be Gaussian

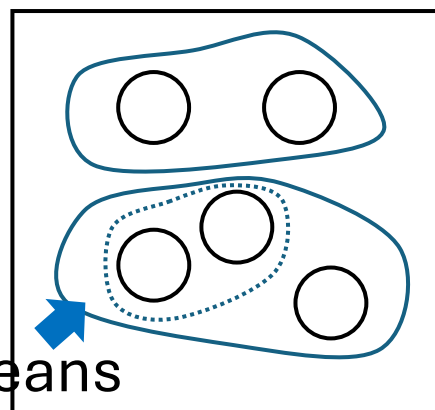
$$f^* = \operatorname{argmin}_f \sum_{\text{doc } x} \left\| \mathbb{E}[\underbrace{p(Q|x)}_{\substack{\text{center vector of Gaussian} \\ \text{Estimated with a} \\ \text{doc2query}^{[4]} \text{ model}}}] - \mathbb{E}[Q|f(x)] \right\|^2$$

Essentially, we applying k-means clustering to query center vectors $\{\mathbb{E}[p(Q|x)]\}$ instead of document vectors $\{x\}$.

How we acquire f^*

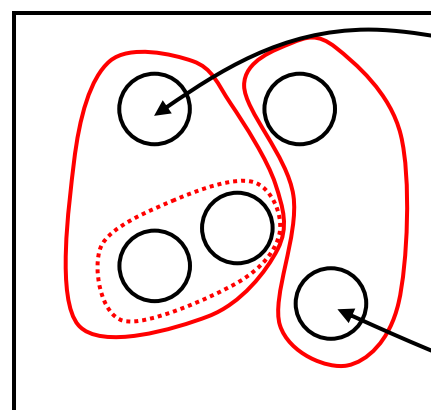
Previous method [2-3]

Document X

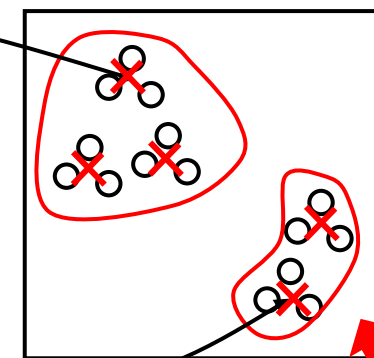


Our method

Document X



Query Q



Doc2query [4]

K-means

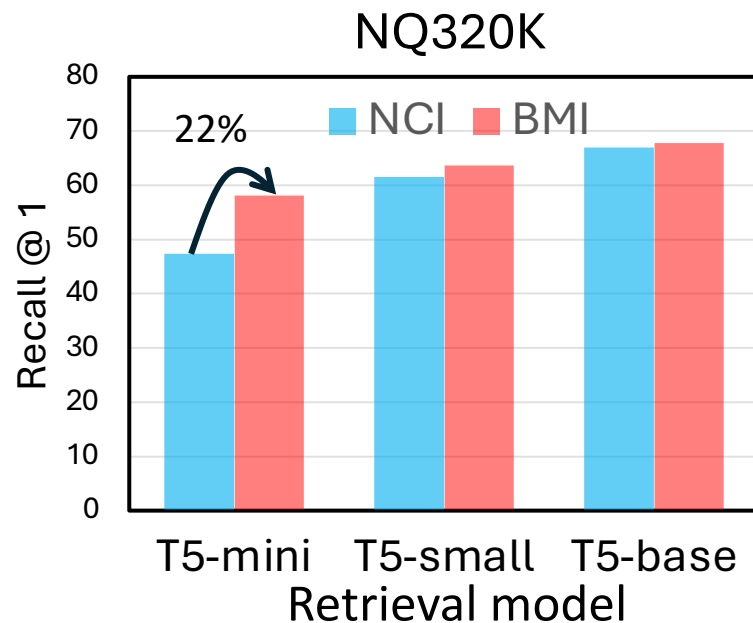
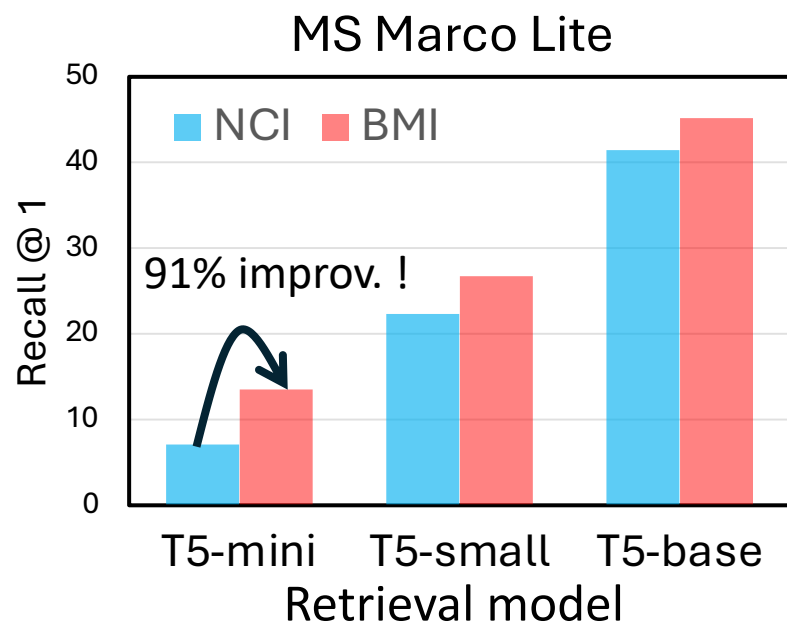
Essentially, we applying k-means clustering to query center vectors $\{E[p(Q|x)]\}$ instead of document vectors $\{x\}$.

[2] Cao et al. Auto-regressive entity retrieval. ICLR 2021.

[3] Tay et al. Transformer memory as a differentiable search index. NeurIPS 2022.

[4] Nogueira and Jimmy Lin. From doc2query to docTTTTTquery (2019).

Retrieval Accuracy



BMI organize indexing “knowledge” in a much more efficient way than previous GDR methods [2-3] when model size is insufficient, which is common in real-world applications.

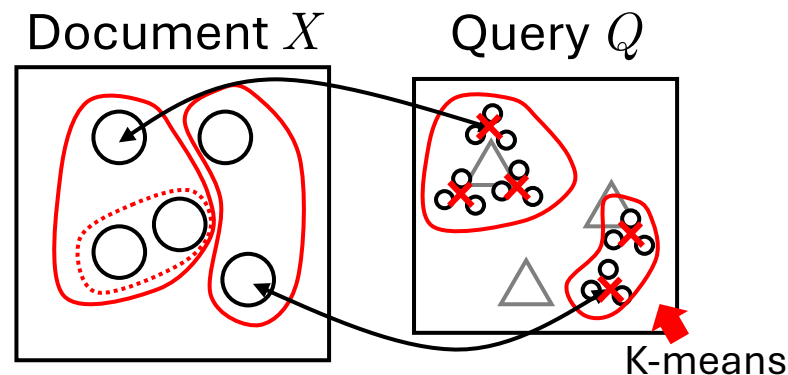
Takeaway

Bottleneck-minimal indexing: an optimal indexing principle under a limited model-size budget.

$$L[p(T|X), \beta] = \mathbf{I}(X; T) - \beta \mathbf{I}(T; Q)$$

Model size **Performance**

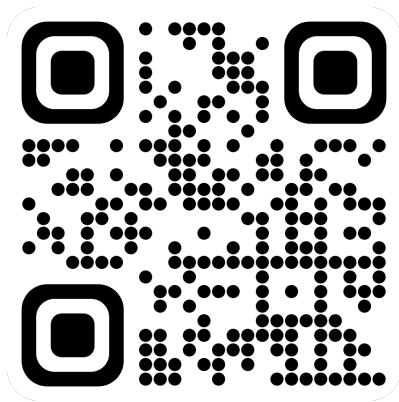
In GDR, better to watch queries rather than documents.



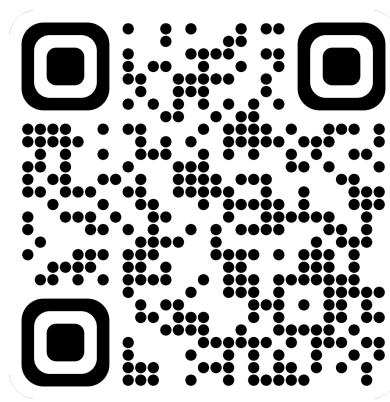
Information-bottleneck theory worked well to explain how knowledge like indexing can be organized efficiently.

Thank you for listening!

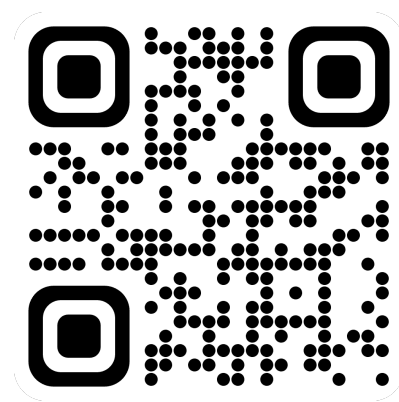
Paper



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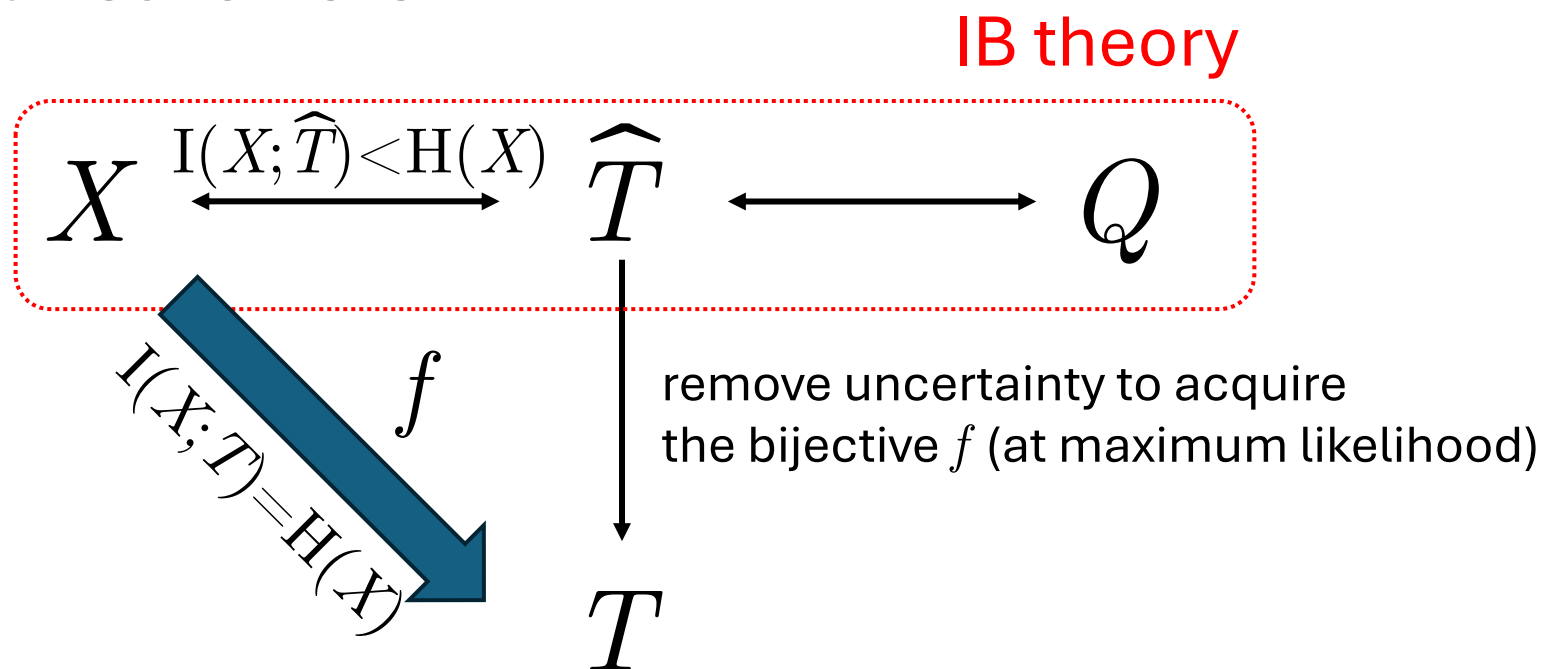
Our lab



As f is bijective, isn't $I(X; T)$ constant ?

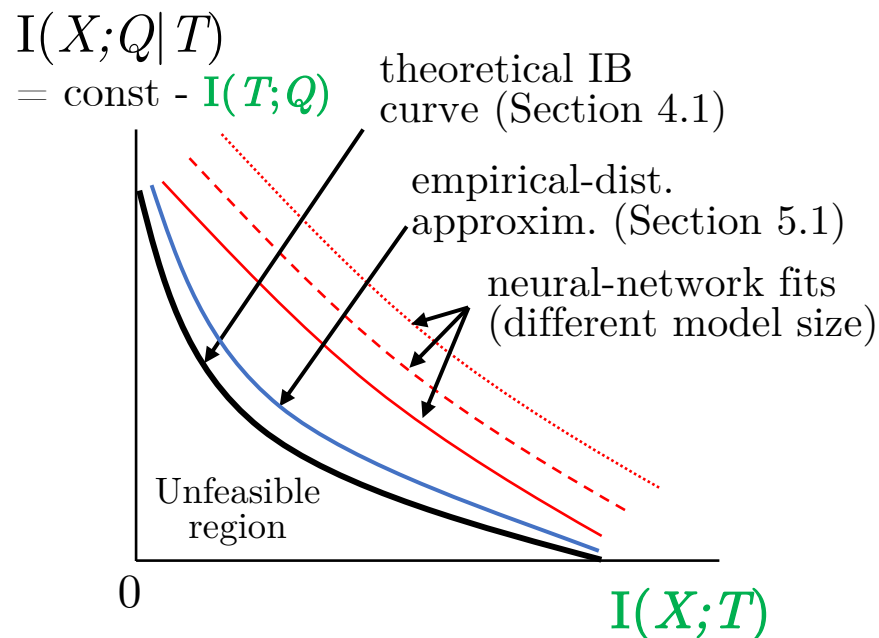
We reused T for two different variables T and \hat{T} for simpler presentation.

The full scheme is:



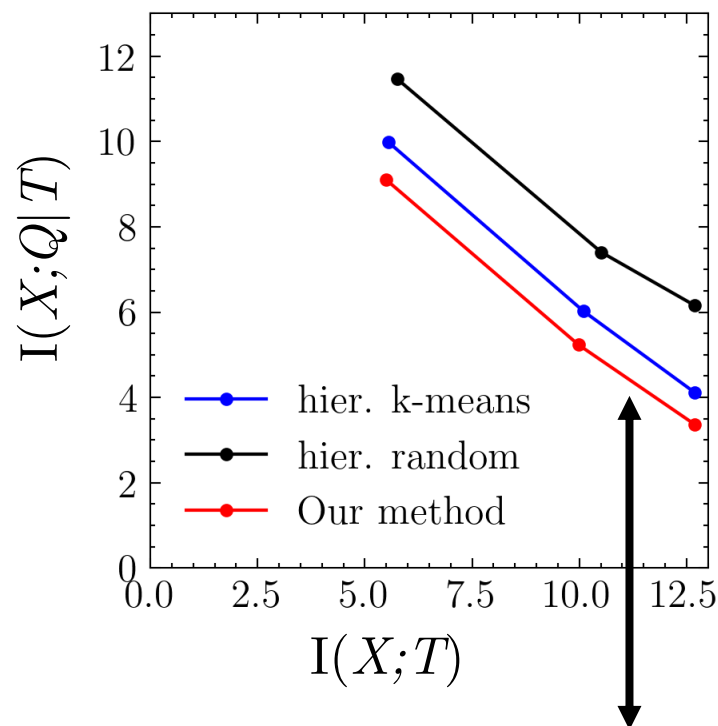
Theoretical & Empirical IB Curves

Theoretical IB curve



IB theory: balance between $I(X;T)$ and $I(T;Q)$

Empirical IB curve



Our method is closer to the theoretical IB curve.

Datasets & Settings

	NQ320K	MS Marco Lite
# Documents	109,739	138,457
# Queries (train)	307,373	183,947
# Queries (test)	7,830	2,792

Used docT5query (base) ^[5] for query generation.

Retrieval model training: used the implementation of NCI ^[3]

The change from NCI ^[3] is only the indexing $f: X \mapsto T$

