



Generative Information Retrieval

SIGIR 2024 tutorial – Sections 6 & 7

Yubao Tang^a, Ruqing Zhang^a, **Zhaochun Ren^b**, Jiafeng Guo^a and **Maarten de Rijke^c**

<https://generative-ir.github.io/>

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^a Institute of Computing Technology, Chinese Academy of Sciences & UCAS

^b Leiden University

^c University of Amsterdam

Section 6:

Applications

A range of target tasks

Fact Verification

De Cao et al. 2021, Chen et al. 2022b,
Chen et al. 2022a, Thorne et al. 2022,
Lee et al. 2023

Open Domain QA

De Cao et al. 2021, Chen et al. 2022b,
Zhou et al. 2022, Lee et al. 2023

Entity Linking

De Cao et al. 2021, Chen et al. 2022b,
Lee et al. 2023

Knowledge-intensive language tasks

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Entity Linking

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Multi-hop retrieval

Lee et al. 2022

Recommendation

Si et al. 2023, Rajput et al. 2023

Code retrieval

Naddem et al. 2022

More retrieval tasks

A range of target tasks

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Si et al. 2023, Rajput et al. 2023

Code retrieval

Naddem et al. 2022

Official site retrieval

Tang et al. 2023a

Industry retrieval tasks

How to adapt a GR model for a task?

- Docid design
- Training approach
- Inference strategy

Knowledge-intensive language tasks

Slot Filling

INPUT:
Star Trek [SEP] creator

OUTPUT:
Gene Roddenberry

PROVENANCE:
17157886-1

zsRE

Open Domain QA

INPUT:
When did Star Trek go off the air

OUTPUT:
June 3, 1969

PROVENANCE:
17157886-5

NQ

INPUT:
Which Star Trek star directed Three Men and a Baby?

OUTPUT:
Leonard Nimoy

PROVENANCE:
17157886-4, 596639-7

TQA

INPUT:
Trekanta (formerly "TrekTrax Atlanta") is an annual convention for what American science fiction media franchise?

OUTPUT:
Star Trek

PROVENANCE:
17157886-1, 28789994-6

HoPo



Knowledge source:
5.9 Million Wikipedia pages

Star Trek ¹⁷¹⁵⁷⁸⁸⁶

Star Trek is an American media franchise based on the science fiction television series created by Gene Roddenberry.¹ [...] It followed the interstellar adventures of Captain James T. Kirk (William Shatner) and his crew aboard the starship USS "Enterprise", a space exploration vessel built by the United Federation of Planets in the 23rd century.² The "Star Trek" canon includes "The Original Series", an animated series, five spin-off television series, the film franchise, and further adaptations in several media.³ [...] The original 1966-69 series featured William Shatner as Captain James T. Kirk, Leonard Nimoy⁴ as Spock, DeForest Kelley as Dr. Leonard "Bones" McCoy, James Doohan as Montgomery "Scotty" Scott, Nichelle Nichols as Uhura, George Takei as Hikaru Sulu, and Walter Koenig as Pavel Chekov. During the series' first run, it earned several nominations for the Hugo Award for Best Dramatic Presentation, and won twice. [...] NBC canceled the show after three seasons; the last original episode aired on June 3, 1969.⁵ [...]

Three Men and a Baby ⁵⁹⁶⁶³⁹

Three Men and a Baby is a 1987 American comedy film directed by Leonard Nimoy⁷ and starring Tom Selleck, Steve Guttenberg, Ted Danson and Nancy Travis. [...]

Trekanta ²⁸⁷⁸⁹⁹⁹⁴

Trekanta is an annual "Star Trek" convention based in Atlanta, Georgia that places special emphasis on fan-based events, activities, programming and productions.⁶ [...]

Dialogue

INPUT:
I am a big fan of Star Trek, the American franchise created by Gene Roddenberry. I don't know much about it. When did the first episode air?
It debuted in 1996 and aired for 3 seasons on NBC.
What is the plot of the show?

OUTPUT:
William Shatner plays the role of Captain Kirk. He did a great job.

PROVENANCE:
17157886-2

WoW

Fact Checking

INPUT:
Star Trek had spin-off television series.

OUTPUT:
Supports

PROVENANCE:
17157886-3

FEV

Entity Linking

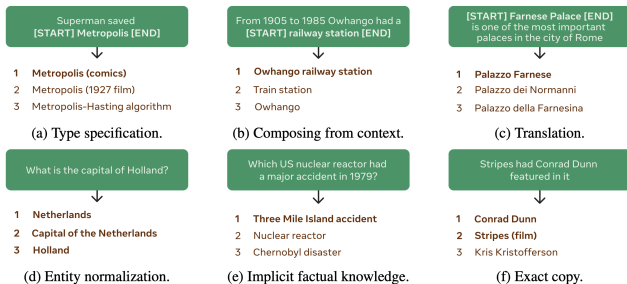
INPUT:
[...] Currently the site offers five movie collections ranging from \$149 for 10 [START_ENT] Star Trek [END_ENT] films to \$1,125 for the eclectic Movie Lovers' Collection of 75 movies. [...]

OUTPUT:
Star Trek

PROVENANCE:
17157886

CnWn

KILT example: GENRE [De Cao et al., 2021]



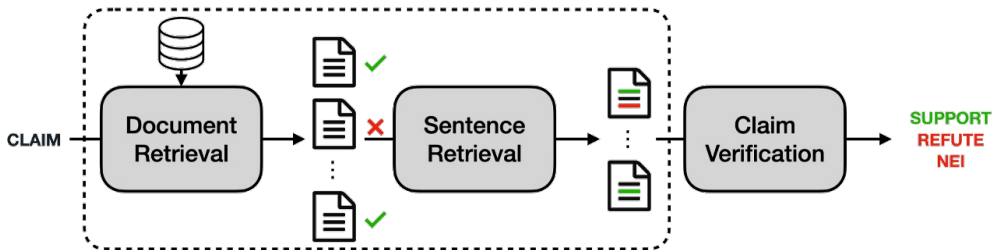
- Entity retrieval: Entity disambiguation, document retrieval, and etc
- Corpus: Wikipedia
- Input: Query
- Output: Destination/ relevant pages' title

KILT example: GENRE [De Cao et al., 2021]

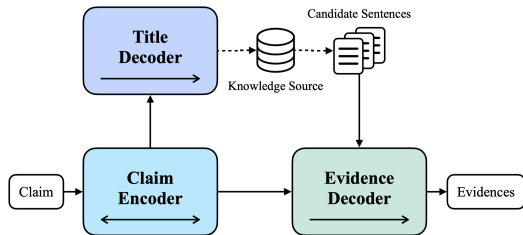
- **Docid:** Titles
- **Training:** MLE objective with document-title and query-title pairs
- **Inference:** Constrained beam search with a prefix tree

KILT example: GERE [Chen et al., 2022]

- Fact verification: Verify a claim using multiple evidential sentences from trustworthy corpora
 - Input: Claim
 - Output: Support/Refute/Not enough information



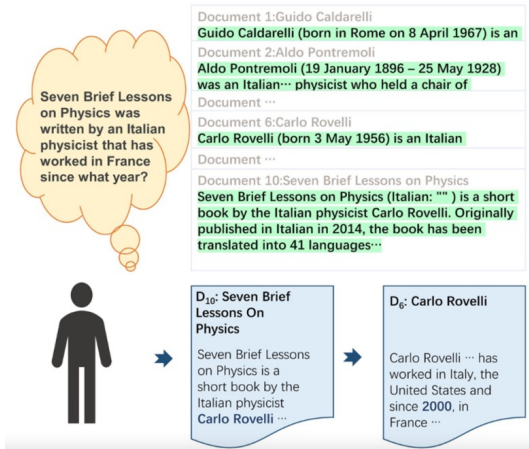
KILT example: GERE [Chen et al., 2022]



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Multi-hop retrieval [Lee et al., 2022]

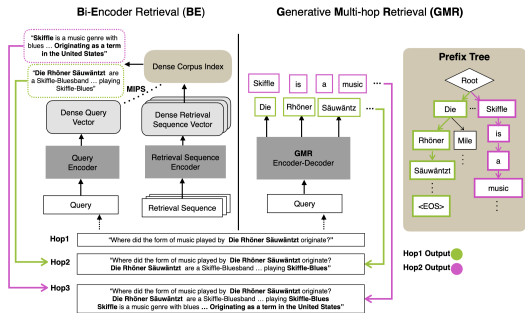
Image source: Memory enhances ChatGPT performance in multi-hop QA



- Multi-hop retrieval
 - One needs to retrieve multiple documents that together provide sufficient evidence to answer the query
 - Previously retrieved items are appended to the query while iterating through multiple hops

"Generative multi-hop retrieval". Lee et al. [2022]

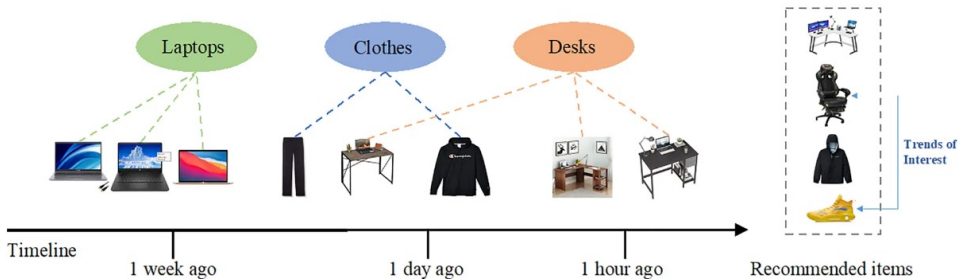
Multi-hop retrieval [Lee et al., 2022]



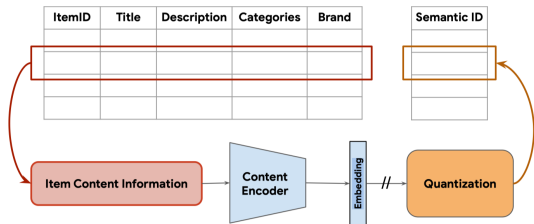
- **Docid:** Word-based answer
- **Jointly training:**
 - **Indexing:** Randomly select the first m words of the document as input and predict the remaining words with MLE
 - **Retrieval:** Learn pseudo query-answer pairs with MLE
- **Inference:** Constrained beam search with a prefix tree

Item recommendation [Rajput et al., 2023]

- Sequential recommendation: Help users discover content of interest; ubiquitous in various recommendation domains
 - Input: User history
 - Output: Next item docid

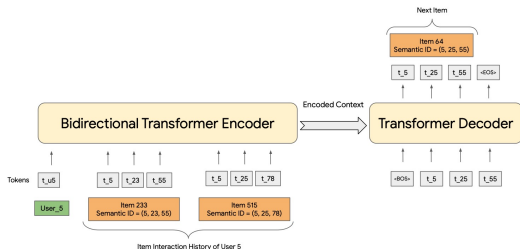


Item recommendation [Rajput et al., 2023]



- **Docid:** Product quantization strings
- **Docid training:** Train a residual-quantized variational autoencoder model with a docid reconstruction loss and a multi-stage quantization loss

Item recommendation [Rajput et al., 2023]



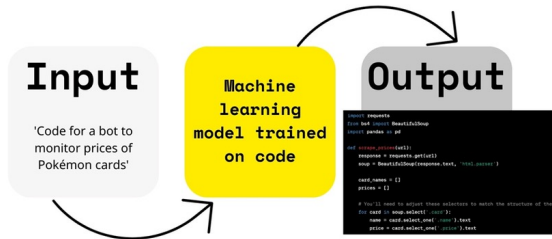
- **Recommendation training**

- Construct item sequences for every user by sorting chronologically the items they have interacted with
- Given item sequences, the model is to predict the next item with MLE

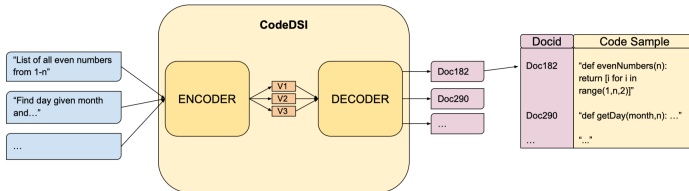
- **Inference:** Beam search

Code retrieval [Nadeem et al., 2022]

- Code retrieval: A model takes natural language queries as input and, in turn, relevant code samples from a database are returned
 - Input: Query
 - Output: Relevant code samples



Code retrieval [Nadeem et al., 2022]



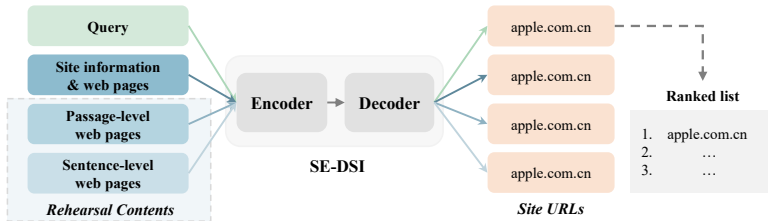
- **Docid:** Naively structured strings/ semantically structured strings
- **Training:** Standard indexing loss with code-docid pairs and retrieval loss with query-docid pairs
- **Inference:** Beam search

Official site retrieval [Tang et al., 2023]



- Official sites: Web pages that have been operated by universities, departments, or other administrative units

Official site retrieval [Tang et al., 2023]



- **Docid:** Unique site URLs
- **Jointly training:**
 - Indexing: Learn site information (site name/ site domain/ ICP record) - docid pairs, web pages-docid pairs, and important web pages-docid pairs with MLE
 - Retrieval: Learn query - docid pairs with MLE
- **Inference:** Constrained beam search with a prefix tree

Overall performance

Tasks (Datasets)	GR method & DR baseline	Retrieval performance	Memory cost	Inference time
KILT (Wikipedia)	GENRE	83.6 RP ✓	2.1 GB ✓	-
	DPR+BERT	72.9 RP	70.9GB	-
Fact Verification- Document retrieval (FEVER)	GERE	84.3 P ✓	-	5.35ms ✓
	RAG	62.17 P	-	13.89ms
Multi-hop retrieval (EntailTree & HotpotQA)	GMR	52.5 F1 ✓	2.95 GB ✓	-
	ST5	16.9 F1	15.81GB	-
Sequential recommendation (Sports and Outdoors)	TIGER	1.81 nDCG@5 ✓	-	-
	S ³ -Rec	1.61 nDCG@5	-	-
Code retrieval (CodeSearchNet)	CodeDSI	90.4 Acc ✓	-	-
	CodeBERT	89.8 Acc	-	-
Official site retrieval (Industry online data)	SE-DSI	+42.4 R@20 ✓	-31 times ✓	-2.5 times ✓
	DualEnc	-	-	-

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The performance of current GR methods can only compete with part of dense retrieval baselines, but still falls short compared to full-ranking methods

Applications: limitations

- The current performance of GR can only be compared to the **index-retrieval** stage of certain dense retrieval methods
- Generalizing to **ultra-large-scale corpora** remains a challenge
- How to adapt to the significant **dynamic** changes in large-scale corpora for **online** applications

Section 7: Challenges & Opportunities

- **Definition & preliminaries**
- **Generative retrieval: docid design**
 - Single docids: number-based and word-based identifiers
 - Multiple docids: single type and diverse types
- **Generative retrieval: training approaches**
 - Stationary scenarios: supervised learning and pre-training
 - Dynamic scenarios
- **Generative retrieval: inference strategies**
 - Single docids: constrained greedy search, constrained beam search and FM-index
 - Multiple docids: aggregation functions
- **Generative retrieval: applications**

Information retrieval in the era of language models

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- Encode the **global information** in corpus; optimize in an **end-to-end way**
- The semantic-level **association** extending beyond mere signal-level matching

Information retrieval in the era of language models

- Encode the **global information** in corpus; optimize in an **end-to-end way**
- The semantic-level **association** extending beyond mere signal-level matching
- Constraint decoding over **thousand-level vocabulary**
- Internal index which **eliminates** large-scale external index

Cons of generative retrieval: Scalability

- Large-scale real-word corpus
 - Current research can generalize from corpora of hundreds of thousands to millions
 - How to accurately memorize vast amounts of complex data?

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- Highly dynamic corpora
 - Document addition, removal and updates
 - How to keep such GR models up-to-date?
 - How to learn on new data without forgetting old ones?

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- Multi-modal/granularity/language search tasks
 - Different search tasks leverage very different indexes
 - How to unify different search tasks into a single generative form?
 - How to capture task specifications while obtaining the shared knowledge?

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 - Different search tasks leverage very different indexes
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 - How to capture task specifications while obtaining the shared knowledge?
- Combining GR with retrieval-augmented generation (RAG)
 - How to integrate GR with RAG to enhance the effectiveness of both?

Cons of generative retrieval: Controllability

For a failure issue, it is often unclear what modeling knobs one should turn to fix the model's behavior

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- Interpretability
 - Black-box neural models
 - How to provide credible explanation for the retrieval process and results?

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For a failure issue, it is often unclear what modeling knobs one should turn to fix the model's behavior

- **Interpretability**
 - Black-box neural models
 - How to provide credible explanation for the retrieval process and results?
- **Debuggable**
 - Attribution analysis: how to conduct causal traceability analysis on the causes, key links and other factors of specific search results?
 - Model editing: how to accurately and conveniently modify training data or tune hyperparameters in the loss function?

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 - Attribution analysis: how to conduct causal traceability analysis on the causes, key links and other factors of specific search results?
 - Model editing: how to accurately and conveniently modify training data or tune hyperparameters in the loss function?
- **Robustness**
 - When a new technique enters into the real-world application, it is critical to know not only how it works in average, but also how would it behave in abnormal situations

Cons of generative retrieval: User-centered

Searching is a **socially** and **contextually** situated activity with diverse set of goals and needs for support that must not be boiled down to a combination of text matching and text generating algorithms [[Shah and Bender, 2022](#)]

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- Human information seeking behavior
- Transparency
- Provenance
- Accountability

Cons of generative retrieval: Performance

The current performance of GR can only be compared to the **index-retrieval** stage of traditional methods, and it has **not yet** achieved the additional improvement provided by **re-ranking**

So much to do ...

- **Closed-book:** The language model is the only source of knowledge leveraged during generation, e.g.,
 - Capturing document ids in the language models
 - Language models as retrieval agents via prompting
- **Open-book:** The language model can draw on external memory prior to, during and after generation, e.g.,
 - Retrieve-augmented generation of answers
 - Tool-augmented generation of answers

So much to do ...

Cater for long-term effects

- How to combine the short-term **relevance** goal with long-term goals such as diversity

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Cater for **long-term effects**

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Address needs of **interactive environments**

- Interactive systems must operate under high degrees of uncertainty
 - User feedback, non-stationarity, exogenous factor, user preferences, ...

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- Interactive systems must operate under high degrees of uncertainty
 - User feedback, non-stationarity, exogenous factor, user preferences, ...

Searching/recommending **slates of items**

- Interface of many search/recommendation platforms requires showing combinations of results to users on the same page
- Different combinations may lead to different short vs. long-term outcomes
- Problem thus becomes combinatorial in nature, intractable for most applications

Sharing more than code

- Models
- ...

Reducing compute resources

So much to do ...

Re-invent information retrieval in the age of large language models!

Q & A

Thank you for joining us today!

All materials are available at

<https://TheWebConf2024-generative-IR.github.io>

References

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