Retrieval-Augmented Generation

Lara J. Martin (she/they)

https://laramartin.net/interactive-fiction-class

Slides adapted from an ACL 2023 Tutorial by Akari Asai, Sewon Min, Zexuan Zhong, & Dr. Danqi Chen

Learning Objectives

Define the Story Cloze Test and determine its place in guided story generation

Understand the reasons why RAG was created

Explore how the retrieval component interacts with the LLM in RAG

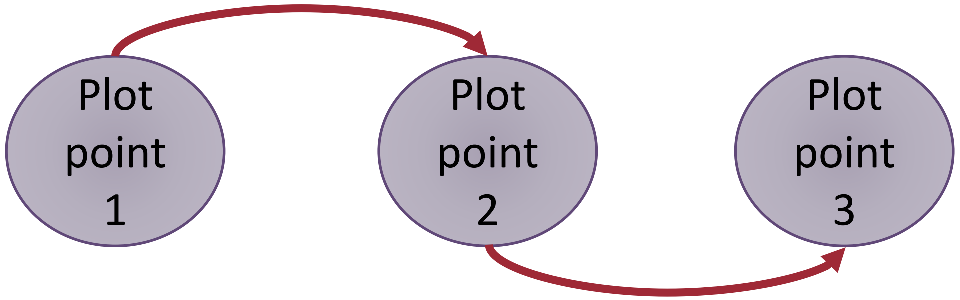
Extract implementation details from papers and find different ways RAG is implemented

Compare plot-guided generation to retrieval-augmented generation for stories

Review:
Scripts, Procedures, and Plots…oh my!

Schank & Abelson believe that everyone has scripts in their heads built from common experiences

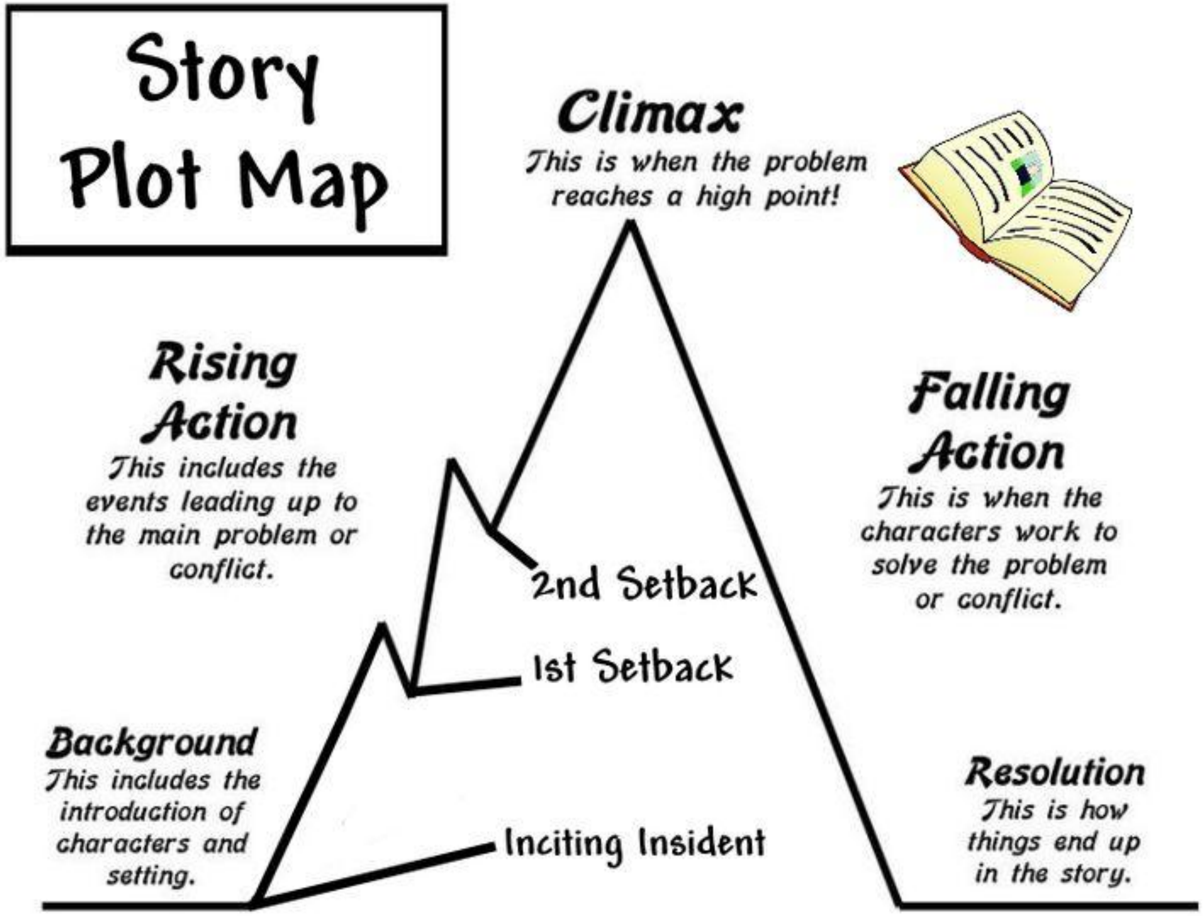
Authors often plan out **plots** before they write stories



Plot point 1

Plot point 2

Plot point 3


Story Plot Map
Climax
This is when the problem reaches a high point!
Rising Action
This includes the events leading up to the main problem or conflict.
Falling Action
This is when the characters work to solve the problem or conflict.
2nd Setback
1st Setback
Background
This includes the introduction of characters and setting.
Inciting Insident
Resolution
This is how things end up in the story.

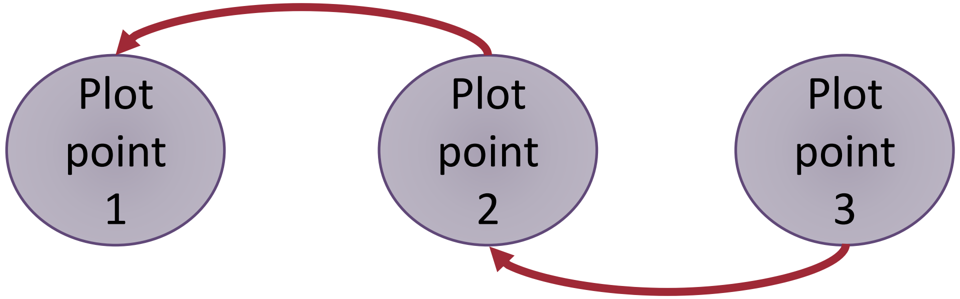
https://i.pinimg.com/736x/57/f7/03/57f703afc709080bddc2c3cfed8dd061.jpg

Review:
Scripts, Procedures, and Plots…oh my!

Schank & Abelson believe that everyone has scripts in their heads built from common experiences

Authors often plan out plots before they write stories

Stories that aren't planned out either have to "**reincorporate**"[1] ideas or the stories feel unfinished



[1] The idea of *reincorporation* is explored in the book Impro by Keith Johnstone

Review: Ways of Extracting Plot Points

Most salient keywords

Event representations

Verb-Noun Sets

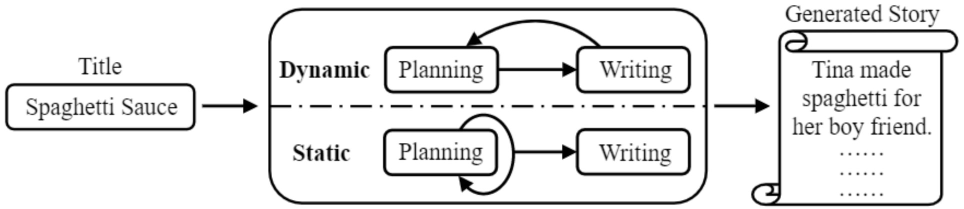
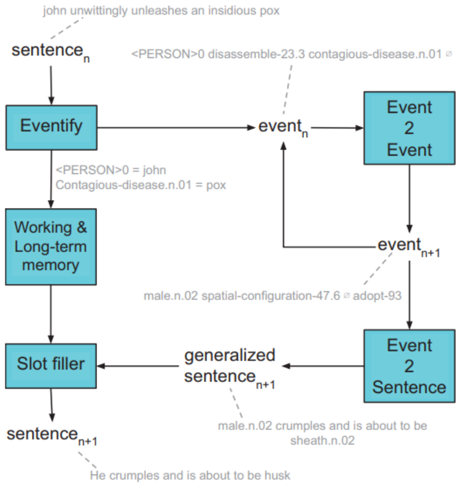
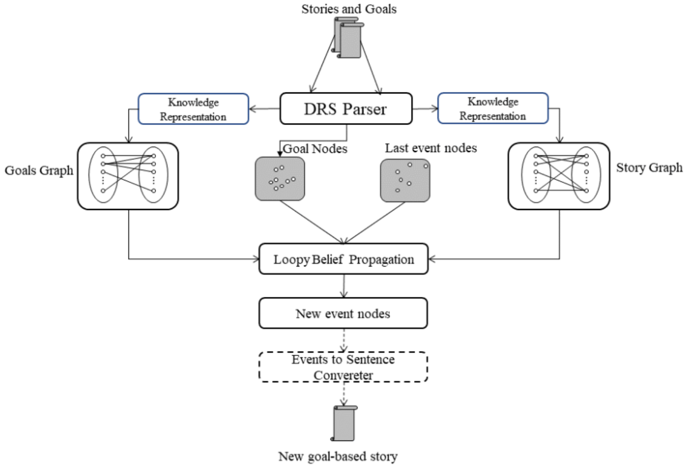


Figure 1: An overview of our system.


john unwittingly unleashes an insidious pox
sentence$_n$
<PERSON>0 disassemble-23.3 contagious-disease.n.01 ∅
Eventify
event$_n$
Event 2 Event
<PERSON>0 = john
Contagious-disease.n.01 = pox
Working & Long-term memory
event$_{n+1}$
male.n.02 spatial-configuration-47.6 ∅ adopt-93
Slot filler
generalized sentence$_{n+1}$
Event 2 Sentence
sentence$_{n+1}$
male.n.02 crumples and is about to be sheath.n.02
He crumples and is about to be husk



Review: Generating with Plot Points

Co-generated vs conditioned (prompted) with plot

Generate event & then translate to natural language

Graph algorithms (Loopy Belief Propagation)

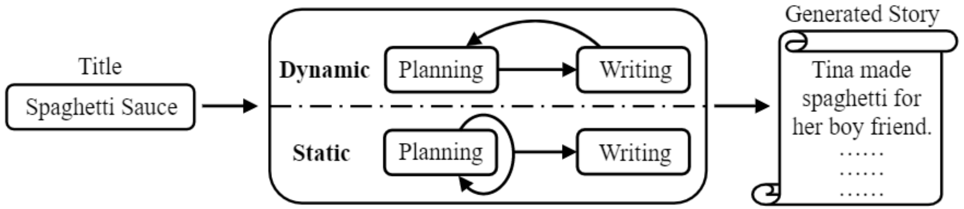
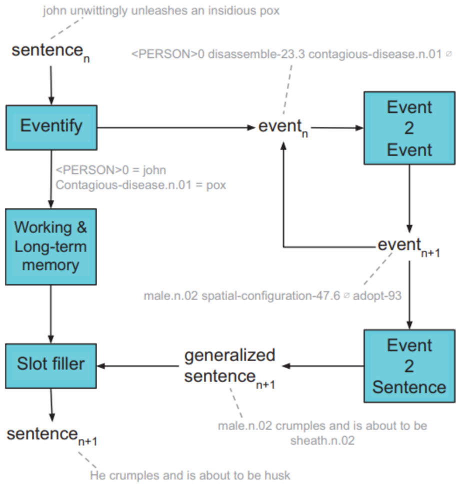
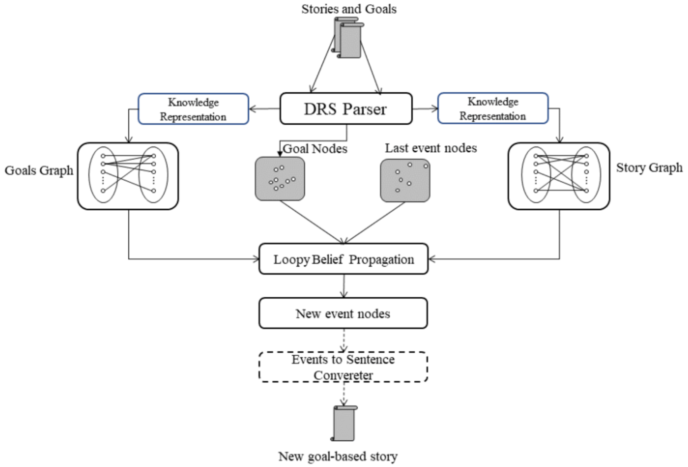


Figure 1: An overview of our system.


john unwittingly unleashes an insidious pox
sentence$_n$
<PERSON>0 disassemble-23.3 contagious-disease.n.01 ∅
Eventify
event$_n$
Event 2 Event
<PERSON>0 = john
Contagious-disease.n.01 = pox
Working & Long-term memory
event$_{n+1}$
male.n.02 spatial-configuration-47.6 ∅ adopt-93
Slot filler
generalized sentence$_{n+1}$
Event 2 Sentence
sentence$_{n+1}$
male.n.02 crumples and is about to be sheath.n.02
He crumples and is about to be husk



The Story Cloze Test

What is a Cloze Test?

- Something is removed from a text; try to guess what’s missing
- Used for reading comprehension, grammar, etc. (with humans)

Narrative Cloze Test

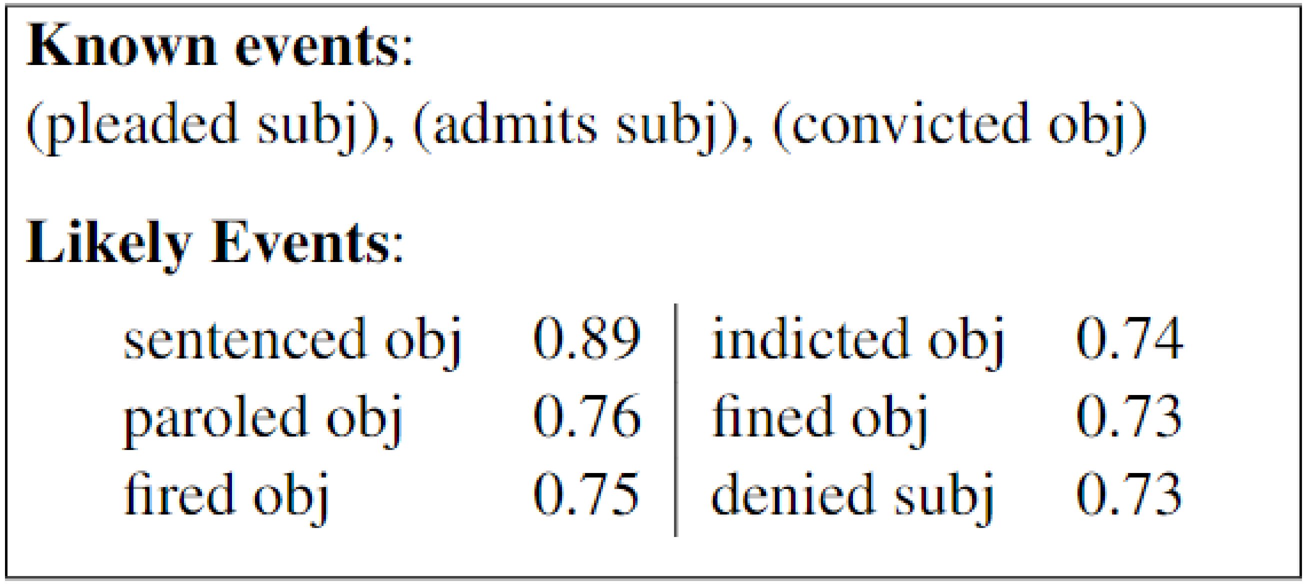
Evaluate “event relatedness”

Find which events could be missing from a narrative chain

Uses verbs only

N. Chambers and D. Jurafsky, “Unsupervised Learning of Narrative Event Chains,” in *Annual Meeting of the Association for Computational Linguistics: Human Language Technologies (ACL-HLT)*, 2008, pp. 789–797, doi: 10.1.1.143.1555.

Narrative Cloze Test



Known events:

(pleaded subj), (admits subj), (convicted obj)

Likely Events:

sentenced obj	0.89	indicted obj	0.74
paroled obj	0.76	fined obj	0.73
fired obj	0.75	denied subj	0.73

Figure 1: Three narrative events and the six most likely events to include in the same chain.

X pleaded _

X admits _

_ convicted X

N. Chambers and D. Jurafsky, “Unsupervised Learning of Narrative Event Chains,” in *Annual Meeting of the Association for Computational Linguistics: Human Language Technologies (ACL-HLT)*, 2008, pp. 789–797, doi: 10.1.1.143.1555.

Finish the story

Gina was worried the cookie dough in the tube would be gross.

She was very happy to find she was wrong.

The cookies from the tube were as good as from scratch.

Gina intended to only eat 2 cookies and save the rest.

A. Gina liked the cookies so much she ate them all in one sitting. ✓
B. Gina gave the cookies away at her church.

Mostafazadeh, N., Chambers, N., He, X., Parikh, D., Batra, D., Vanderwende, L., Kohli, P., & Allen, J. (2016). A Corpus and Cloze Evaluation for Deeper Understanding of Commonsense Stories. *Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (NAACL-HLT)*, 839–849. http://www.aclweb.org/anthology/N16-1098

Story Cloze Test

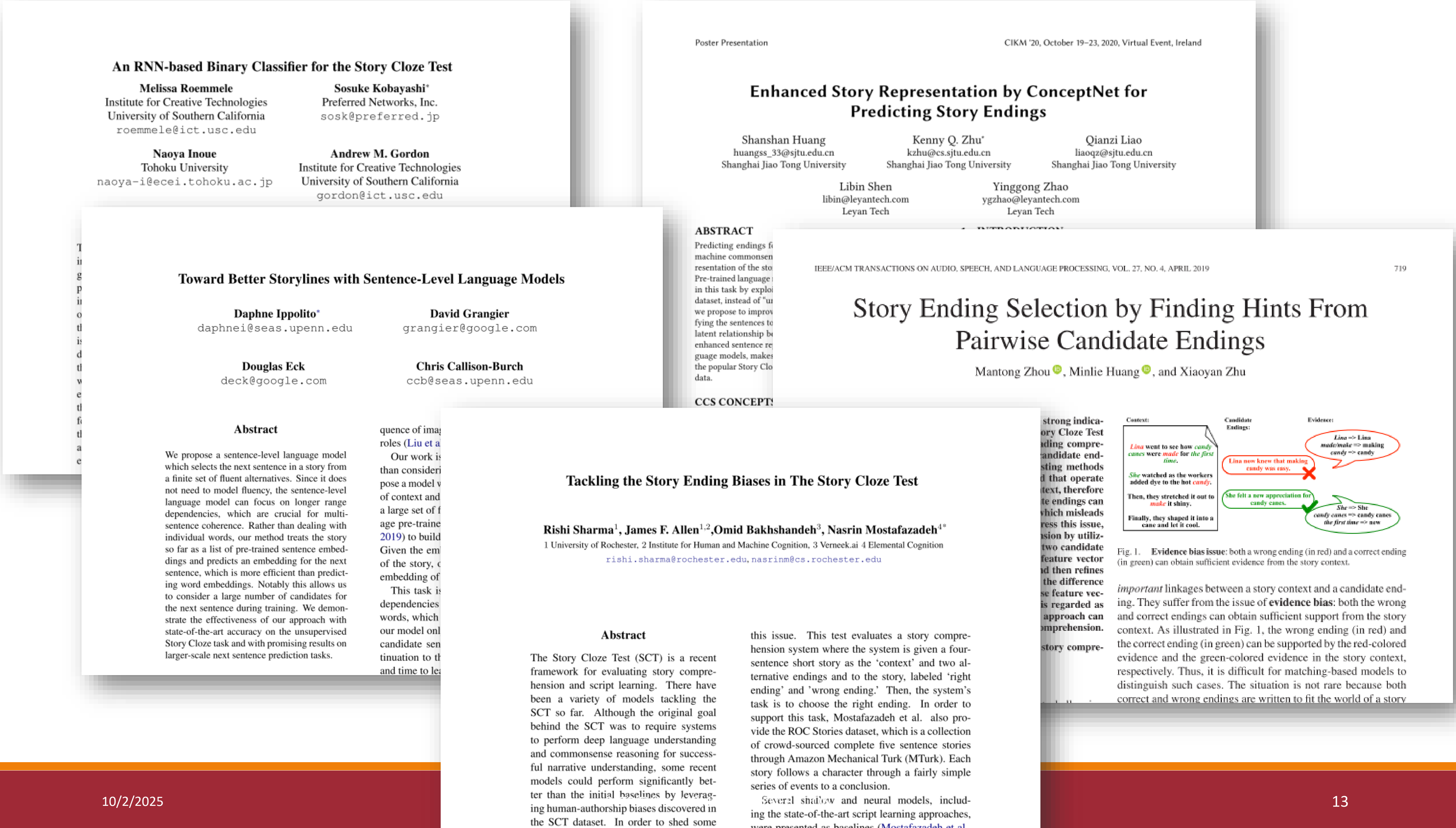
Predict/select the most likely story *ending*

- Given the first 4 sentences of the story

Full sentences

Multiple choice evaluation

Mostafazadeh, N., Chambers, N., He, X., Parikh, D., Batra, D., Vanderwende, L., Kohli, P., & Allen, J. (2016). A Corpus and Cloze Evaluation for Deeper Understanding of Commonsense Stories. *Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (NAACL-HLT)*, 839–849. http://www.aclweb.org/anthology/N16-1098



An RNN-based Binary Classifier for the Story Cloze Test

Melissa Roemmele
Institute for Creative Technologies
University of Southern California
`roemmele@ict.usc.edu`

Sosuke Kobayashi*
Preferred Networks, Inc.
`sosk@preferred.jp`

Naoya Inoue
Tohoku University
`naoya-i@ecei.tohoku.ac.jp`

Andrew M. Gordon
Institute for Creative Technologies
University of Southern California
`gordon@ict.usc.edu`

Toward Better Storylines with Sentence-Level Language Models

Daphne Ippolito*
`daphnei@seas.upenn.edu`

David Grangier
`grangier@google.com`

Douglas Eck
`deck@google.com`

Chris Callison-Burch
`ccb@seas.upenn.edu`

Abstract

We propose a sentence-level language model which selects the next sentence in a story from a finite set of fluent alternatives. Since it does not need to model fluency, the sentence-level language model can focus on longer range dependencies, which are crucial for multi-sentence coherence. Rather than dealing with individual words, our method treats the story so far as a list of pre-trained sentence embeddings and predicts an embedding for the next sentence, which is more efficient than predicting word embeddings. Notably this allows us to consider a large number of candidates for the next sentence during training. We demonstrate the effectiveness of our approach with state-of-the-art accuracy on the unsupervised Story Cloze task and with promising results on larger-scale next sentence prediction tasks.

quence of imag
roles (Liu et a
Our work is
than consideri
pose a model w
of context and
a large set of f
age pre-traine
2019) to build
Given the em
of the story, c
embedding of
This task is
dependencies
words, which
our model onl
candidate sen
tinuation to th
and time to lea

Poster Presentation CIKM '20, October 19–23, 2020, Virtual Event, Ireland

Enhanced Story Representation by ConceptNet for Predicting Story Endings

Shanshan Huang
huangss_33@sjtu.edu.cn
Shanghai Jiao Tong University

Kenny Q. Zhu*
kzhu@cs.sjtu.edu.cn
Shanghai Jiao Tong University

Qianzi Liao
liaoqz@sjtu.edu.cn
Shanghai Jiao Tong University

Libin Shen
libin@leyantech.com
Leyan Tech

Yinggong Zhao
ygzhao@leyantech.com
Leyan Tech

ABSTRACT

Predicting endings fo
machine commonsen
resentation of the sto
Pre-trained language
in this task by exploi
dataset, instead of "ur
we propose to improv
fying the sentences to
latent relationship be
enhanced sentence re
guage models, makes
the popular Story Clo
data.

CCS CONCEPTS

IEEE/ACM TRANSACTIONS ON AUDIO, SPEECH, AND LANGUAGE PROCESSING, VOL. 27, NO. 4, APRIL 2019 719

Story Ending Selection by Finding Hints From Pairwise Candidate Endings

Mantong Zhou, Minlie Huang, and Xiaoyan Zhu

strong indica-
ory Cloze Test
ding compre-
andidate end-
sting methods
d that operate
text, therefore
te endings can
which misleads
ress this issue,
nsion by utiliz-
two candidate
feature vector
d then refines
the difference
se feature vec-
is regarded as
approach can
mprehension.

story compre-

Context:
Lina went to see how candy canes were made for the first time.
She watched as the workers added dye to the hot candy.
Then, they stretched it out to make it shiny.
Finally, they shaped it into a cane and let it cool.
Candidate Endings:
Lina now knew that making candy was easy.
She felt a new appreciation for candy canes.
Evidence:
Lina => Lina
made/make => making
candy => candy
She => She
candy canes => candy canes
the first time => new

Fig. 1. **Evidence bias issue**: both a wrong ending (in red) and a correct ending (in green) can obtain sufficient evidence from the story context.

important linkages between a story context and a candidate ending. They suffer from the issue of **evidence bias**: both the wrong and correct endings can obtain sufficient support from the story context. As illustrated in Fig. 1, the wrong ending (in red) and the correct ending (in green) can be supported by the red-colored evidence and the green-colored evidence in the story context, respectively. Thus, it is difficult for matching-based models to distinguish such cases. The situation is not rare because both correct and wrong endings are written to fit the world of a story

---

Tackling the Story Ending Biases in The Story Cloze Test

Rishi Sharma[1], **James F. Allen**[1,2],**Omid Bakhshandeh**[3], **Nasrin Mostafazadeh**[4*]
1 University of Rochester, 2 Institute for Human and Machine Cognition, 3 Verneek.ai 4 Elemental Cognition
`rishi.sharma@rochester.edu`, `nasrinm@cs.rochester.edu`

Abstract

The Story Cloze Test (SCT) is a recent framework for evaluating story comprehension and script learning. There have been a variety of models tackling the SCT so far. Although the original goal behind the SCT was to require systems to perform deep language understanding and commonsense reasoning for successful narrative understanding, some recent models could perform significantly better than the initial baselines by leveraging human-authorship biases discovered in the SCT dataset. In order to shed some

this issue. This test evaluates a story comprehension system where the system is given a four-sentence short story as the 'context' and two alternative endings and to the story, labeled 'right ending' and 'wrong ending.' Then, the system's task is to choose the right ending. In order to support this task, Mostafazadeh et al. also provide the ROC Stories dataset, which is a collection of crowd-sourced complete five sentence stories through Amazon Mechanical Turk (MTurk). Each story follows a character through a fairly simple series of events to a conclusion.

Several shallow and neural models, including the state-of-the-art script learning approaches, were presented as baselines (Mostafazadeh et al.

Think Pair Share

The Story Cloze Test was created for evaluating systems’ performance on understanding stories.

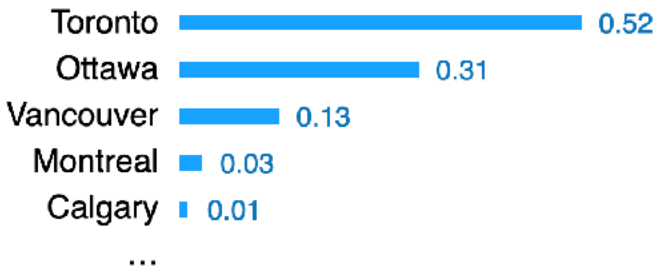
How could you use it instead for *generation*?

Retrieval-Augmented Generation

Retrieval-based language models (LMs)
Retrieval-based LMs = Retrieval + LMs

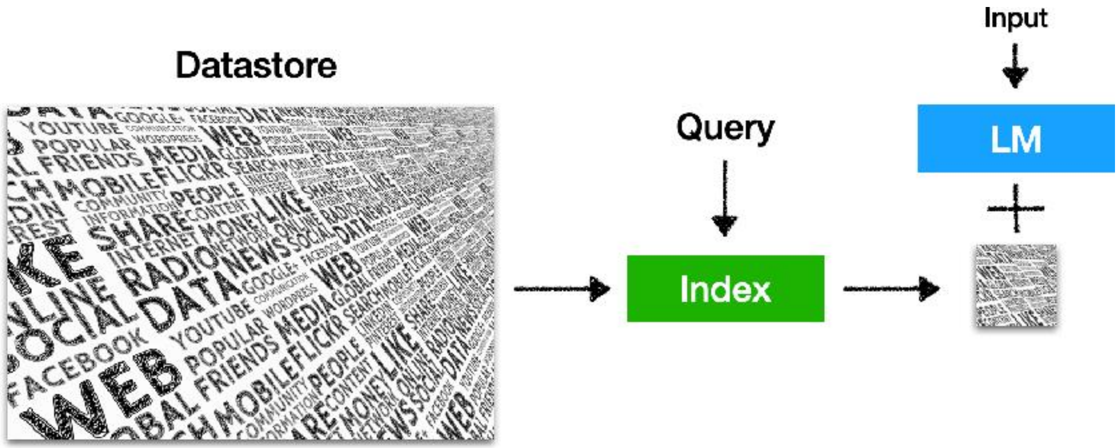
- It is a **language model** $P(x_n | x_1, x_2, \cdots, x_{n-1})$

The capital city of Ontario is ___



(can be broadly extended to masked language models or encoder-decoder models)

- It retrieves from an **external datastore** (at least during inference time)



Retrieval for knowledge-intensive NLP tasks

Representative tasks: open-domain QA, fact checking, entity linking, ..

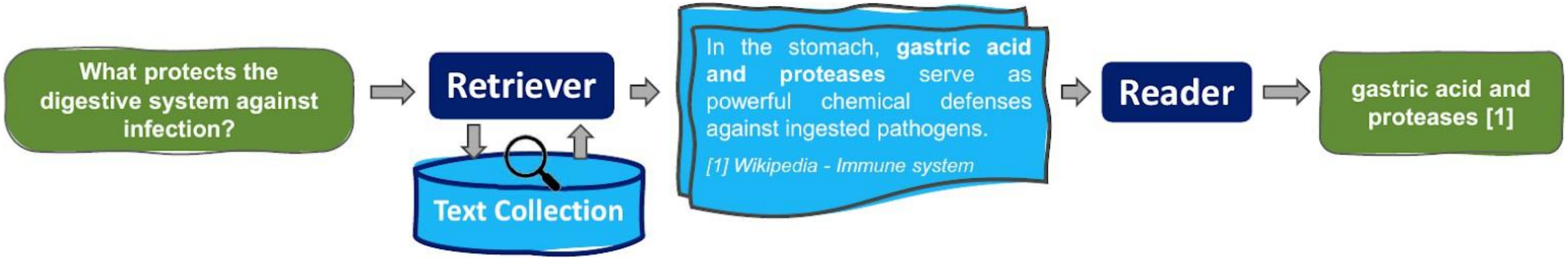

What protects the digestive system against infection?
Retriever
Text Collection
In the stomach, gastric acid and proteases serve as powerful chemical defenses against ingested pathogens.
[1] Wikipedia - Immune system
Reader
gastric acid and proteases [1]

Image: http://ai.stanford.edu/blog/retrieval-based-NLP/

Drives a lot of research on better algorithms for **dense retrieval**, e.g., **DPR** (Karpukhin et al., 2020), **ColBERT** (Khattab and Zaharia, 2020), **ANCE** (Xiong et al., 2021), **Contriever** (Izacard et al., 2022), …

Why retrieval LMs?

LLMs can’t memorize all (long-tail) knowledge in their parameters

Why retrieval-based LMs?

List 5 important papers authored by Geoffrey Hinton

ChatGPT

Geoffrey Hinton is a renowned computer scientist …
Here are five important papers authored by him:

1. "**Learning Internal Representations by Error Propagation**" (with **D. E. Rumelhart** and **R. J. Williams**) - This paper, published in **1986**, .. ✓

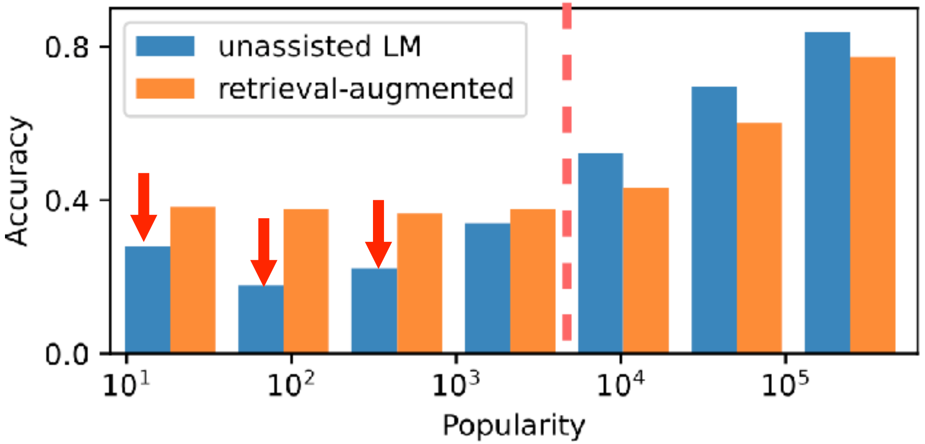
2. "**Deep Boltzmann Machines**" (with **R. Salakhutdinov**) - Published in **2009**, .. ✓

…

4. "**Deep Learning**" (with Y. Bengio and A. Courville) - Published as a book in **2016**,… ✗

5. "**Attention Is All You Need**" (with V. Vaswani, N. Shazeer, et al.) - Published in **2017**, this paper introduced the Transformer model,… ✗

What is Kathy Saltzman’s occupation?



(Mallen et al., 2023)

GPT-3 davinci-003: 20%-30% accuracy

Alex Mallen, Akari Asai, Victor Zhong, Rajarshi Das, Daniel Khashabi, and Hannaneh Hajishirzi. 2023. When Not to Trust Language Models: Investigating Effectiveness of Parametric and Non-Parametric Memories. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 9802–9822, Toronto, Canada. Association for Computational Linguistics.

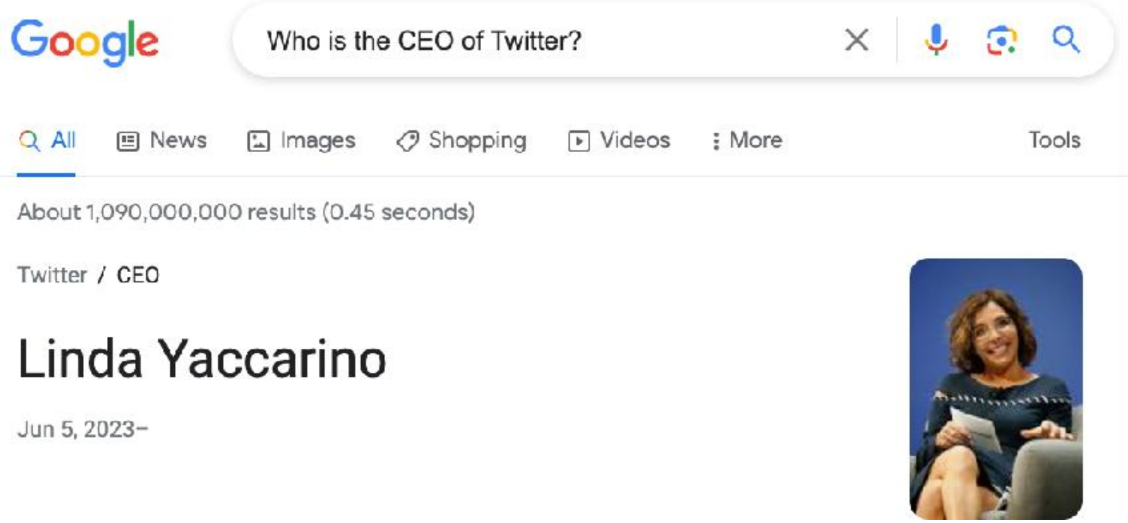
LLMs’ knowledge is easily outdated and hard to update

Why retrieval-based LMs?

Who is the CEO of Twitter?

ChatGPT

As of my **knowledge cutoff in September 2021**, the CEO of Twitter is **Jack Dorsey**….



Google

Who is the CEO of Twitter?

All | News | Images | Shopping | Videos | More | Tools

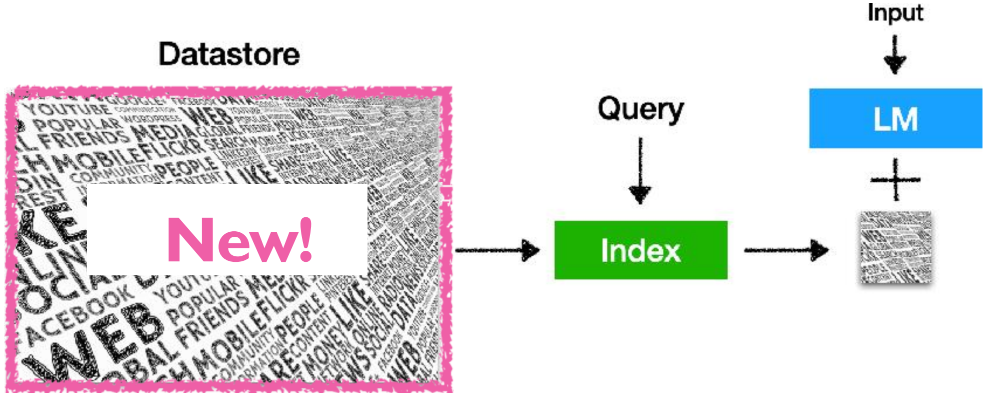
About 1,090,000,000 results (0.45 seconds)

Twitter / CEO

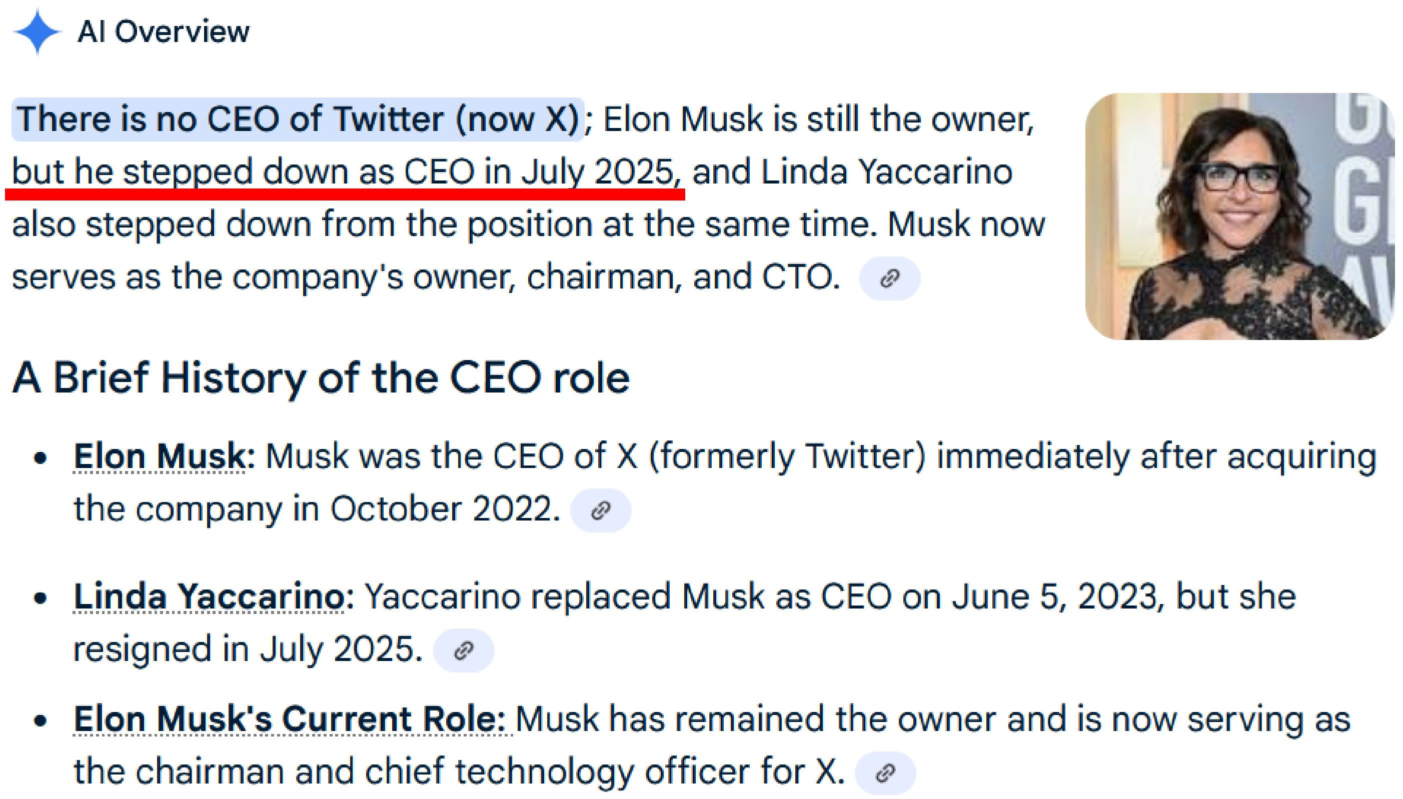
Linda Yaccarino

Jun 5, 2023–

- Existing **knowledge editing** methods are still NOT scalable (active research!)
- The datastore can be easily **updated** and **expanded** - even without retraining!



Actually Google AI gets it wrong too…



There is no CEO of Twitter (now X); Elon Musk is still the owner, but he stepped down as CEO in July 2025, and Linda Yaccarino also stepped down from the position at the same time. Musk now serves as the company's owner, chairman, and CTO.

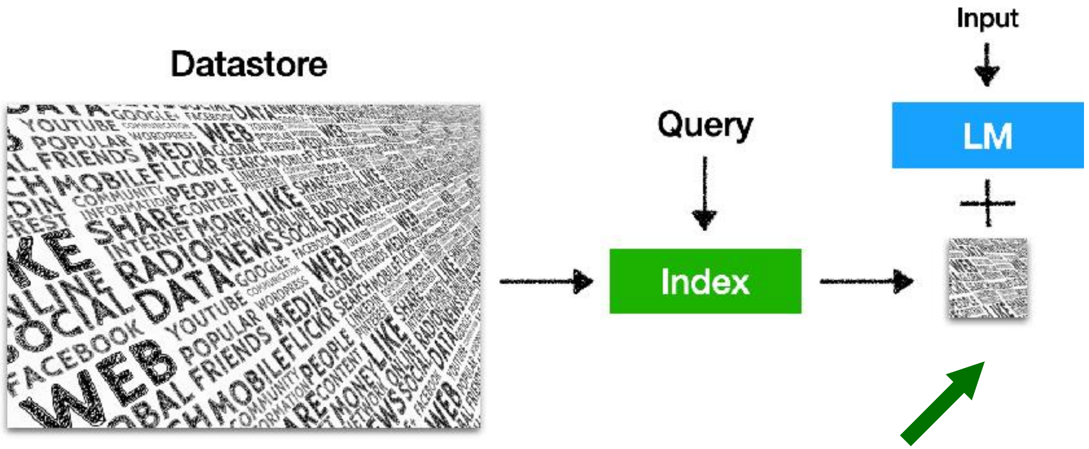
A Brief History of the CEO role

- **Elon Musk:** Musk was the CEO of X (formerly Twitter) immediately after acquiring the company in October 2022.
- **Linda Yaccarino:** Yaccarino replaced Musk as CEO on June 5, 2023, but she resigned in July 2025.
- **Elon Musk's Current Role:** Musk has remained the owner and is now serving as the chairman and chief technology officer for X.

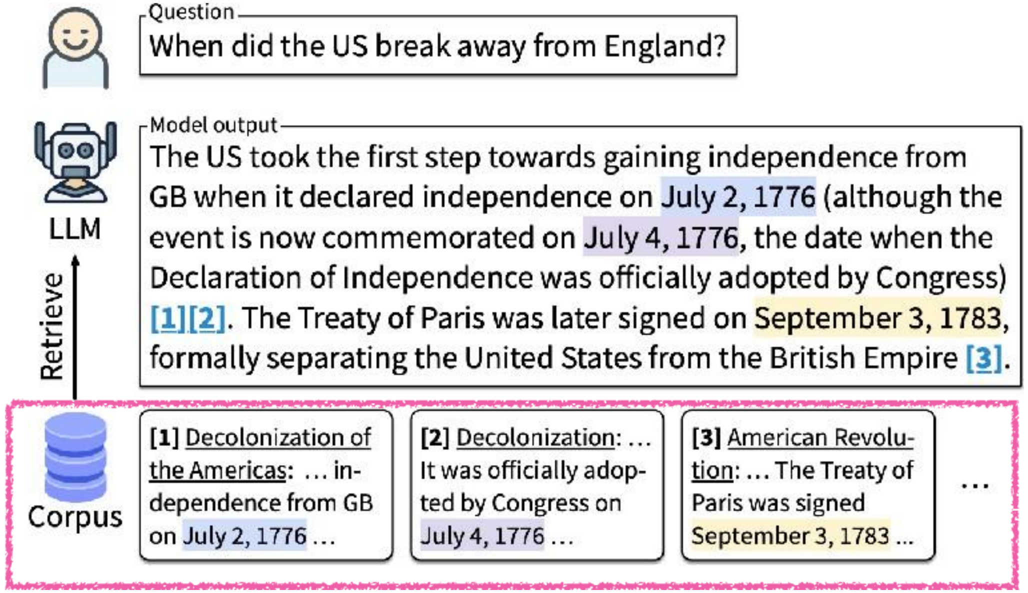
LLMs' output is challenging to interpret and verify

Why retrieval-based LMs?

Generating text with citations



Can **trace knowledge source** from retrieval results - better **interpretability** & **control**



When did the US break away from England?

The US took the first step towards gaining independence from GB when it declared independence on July 2, 1776 (although the event is now commemorated on July 4, 1776, the date when the Declaration of Independence was officially adopted by Congress) [1][2]. The Treaty of Paris was later signed on September 3, 1783, formally separating the United States from the British Empire [3].

[1] Decolonization of the Americas: … independence from GB on July 2, 1776 …

[2] Decolonization: … It was officially adopted by Congress on July 4, 1776 …

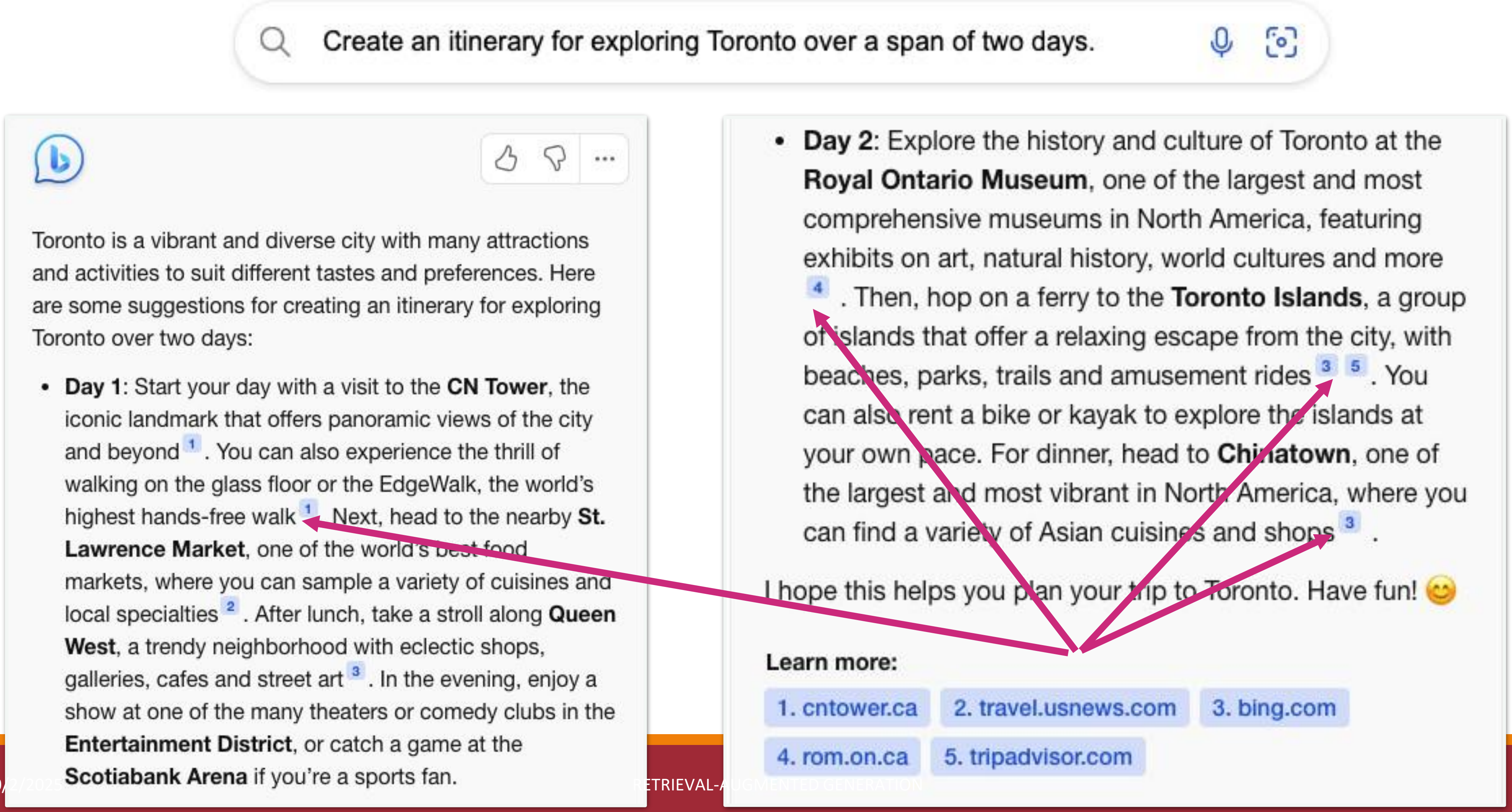
[3] American Revolution: … The Treaty of Paris was signed September 3, 1783 …

…

(Nakano et al. 2021; Menick et al., 2022; Gao et al., 2023)

LLMs’ output is challenging to interpret and verify

Why 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].

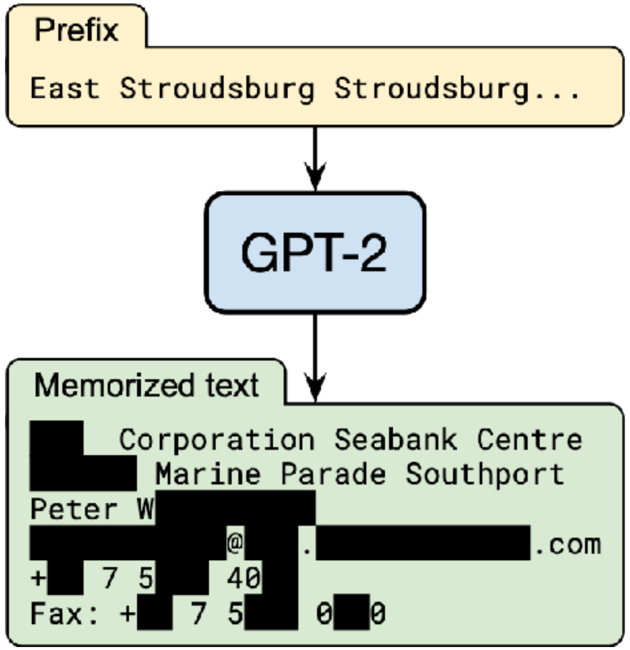
I hope this helps you plan your trip to Toronto. Have fun! 😊

Learn more:

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

LLMs are shown to easily leak private training data

Why retrieval-based LMs?



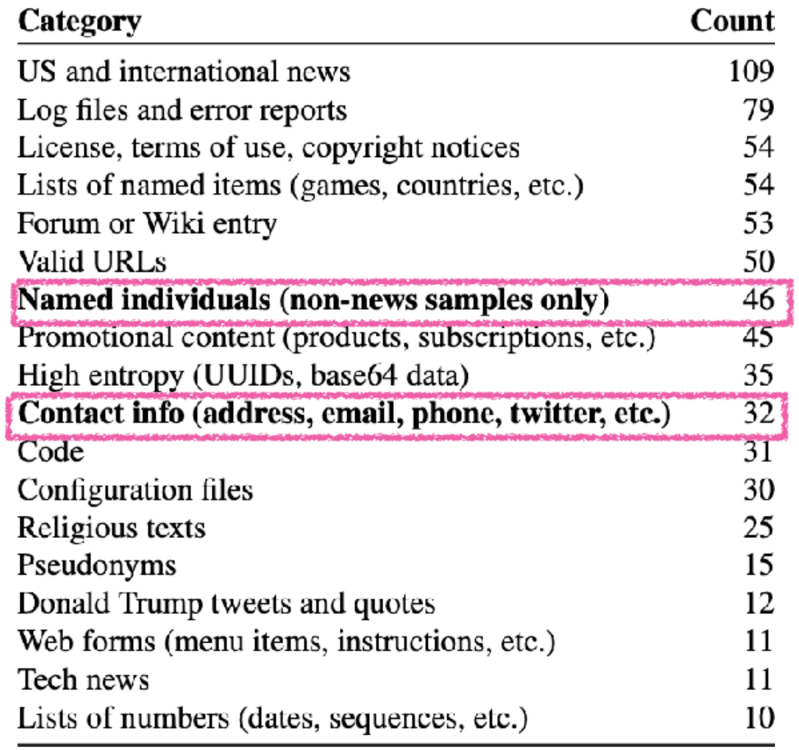
Prefix

East Stroudsburg Stroudsburg...

GPT-2

Memorized text

[redacted] Corporation Seabank Centre
[redacted] Marine Parade Southport
Peter W[redacted]
[redacted]@[redacted].[redacted].com
+[redacted] 7 5[redacted] 40[redacted]
Fax: +[redacted] 7 5[redacted] 0[redacted]0



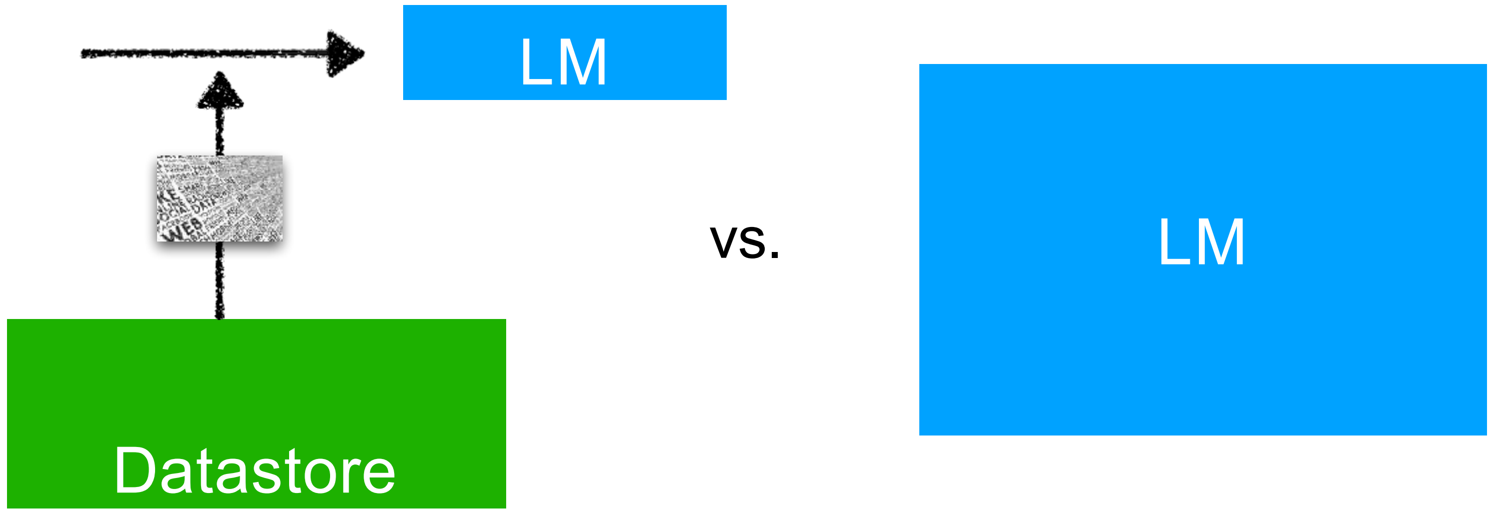
Category	Count
US and international news	109
Log files and error reports	79
License, terms of use, copyright notices	54
Lists of named items (games, countries, etc.)	54
Forum or Wiki entry	53
Valid URLs	50
Named individuals (non-news samples only)	46
Promotional content (products, subscriptions, etc.)	45
High entropy (UUIDs, base64 data)	35
Contact info (address, email, phone, twitter, etc.)	32
Code	31
Configuration files	30
Religious texts	25
Pseudonyms	15
Donald Trump tweets and quotes	12
Web forms (menu items, instructions, etc.)	11
Tech news	11
Lists of numbers (dates, sequences, etc.)	10

Individualization on private data by storing it in the datastore

Carlini, N., *et al.* (2020). Extracting Training Data from Large Language Models. https://arxiv.org/abs/2012.07805

LLMs are *large* and expensive to train and run

Why retrieval-based LMs?


LM

Datastore

vs.

LM

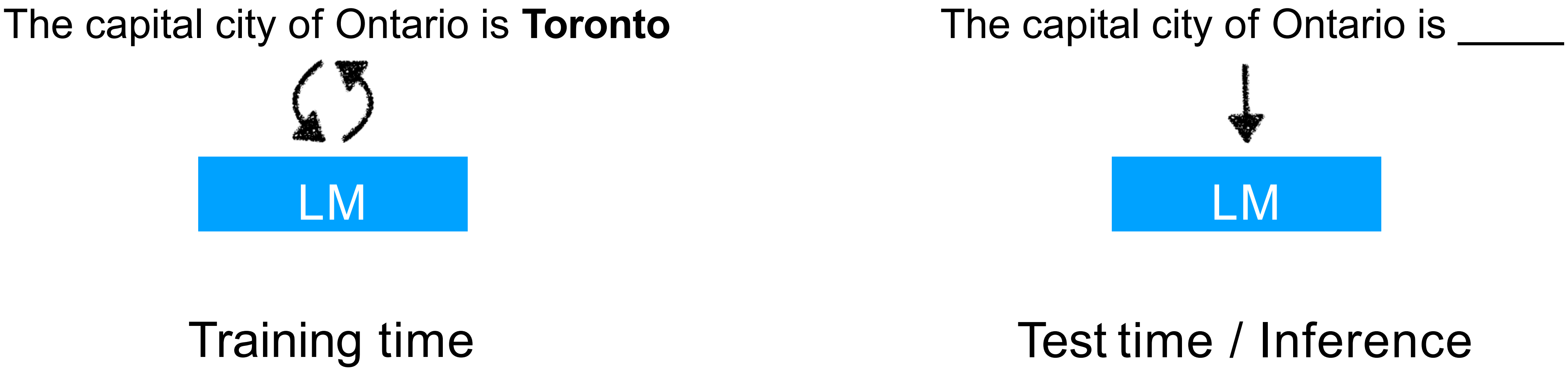
Long-term goal: can we possibly reduce the **training** and **inference costs,** and scale down the size of LLMs?

e.g., RETRO (Borgeaud et al., 2021): “obtains comparable performance to GPT-3 on the Pile, despite using **25x fewer parameters**”

A Retrieval-based LM: Definition

A language model (LM) that uses
an external datastore at test time

Typical LMs



The capital city of Ontario is **Toronto**

Training time

The capital city of Ontario is _____

Test time / Inference

Retrieval-based LMs

The capital city of Ontario is **Toronto**

LM

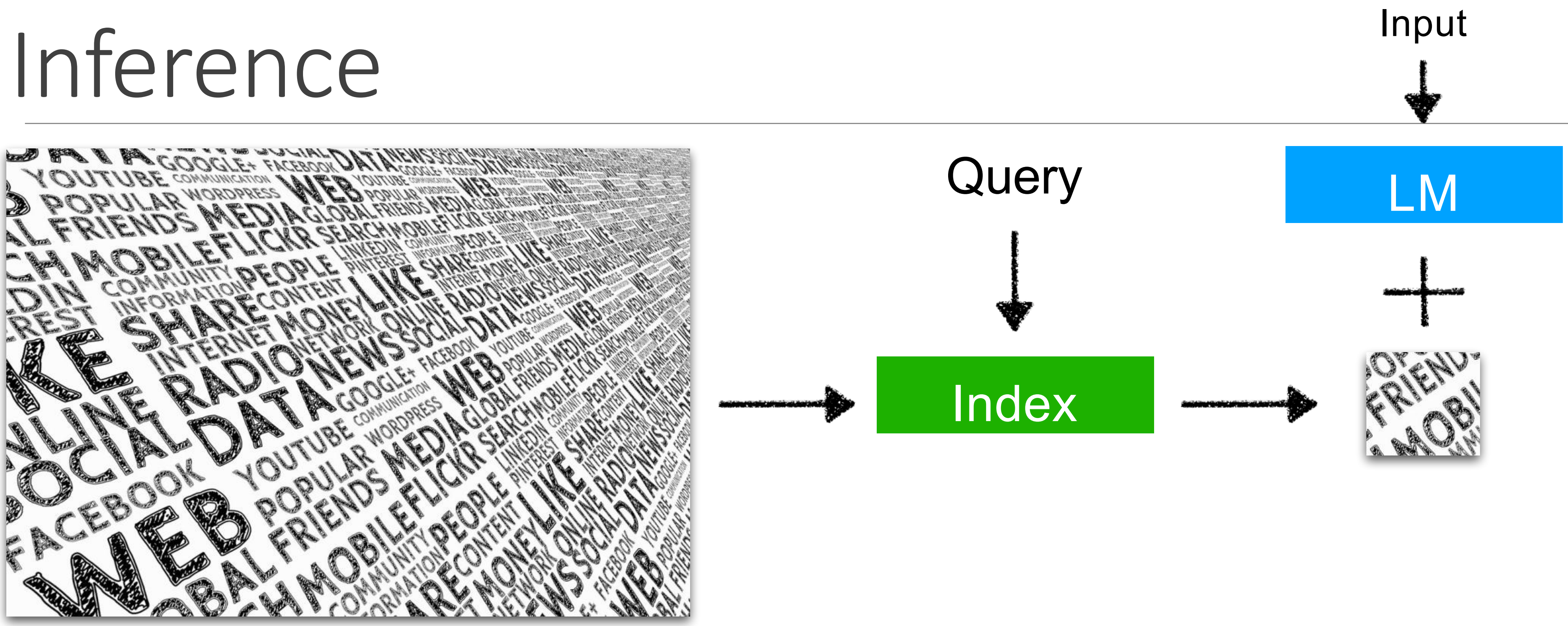
Training time

The capital city of Ontario is _____

LM

Test time / Inference

Inference



Input

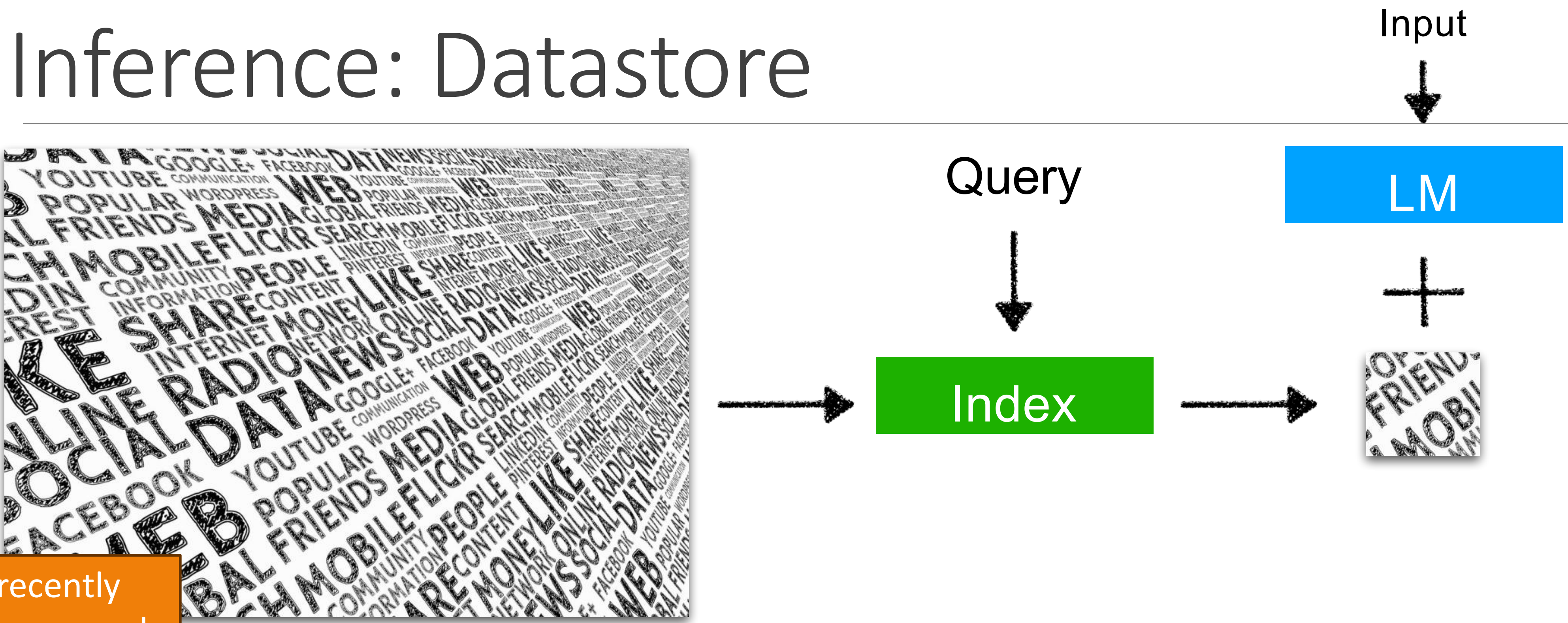
Query

LM

Index

Datastore

Inference: Datastore



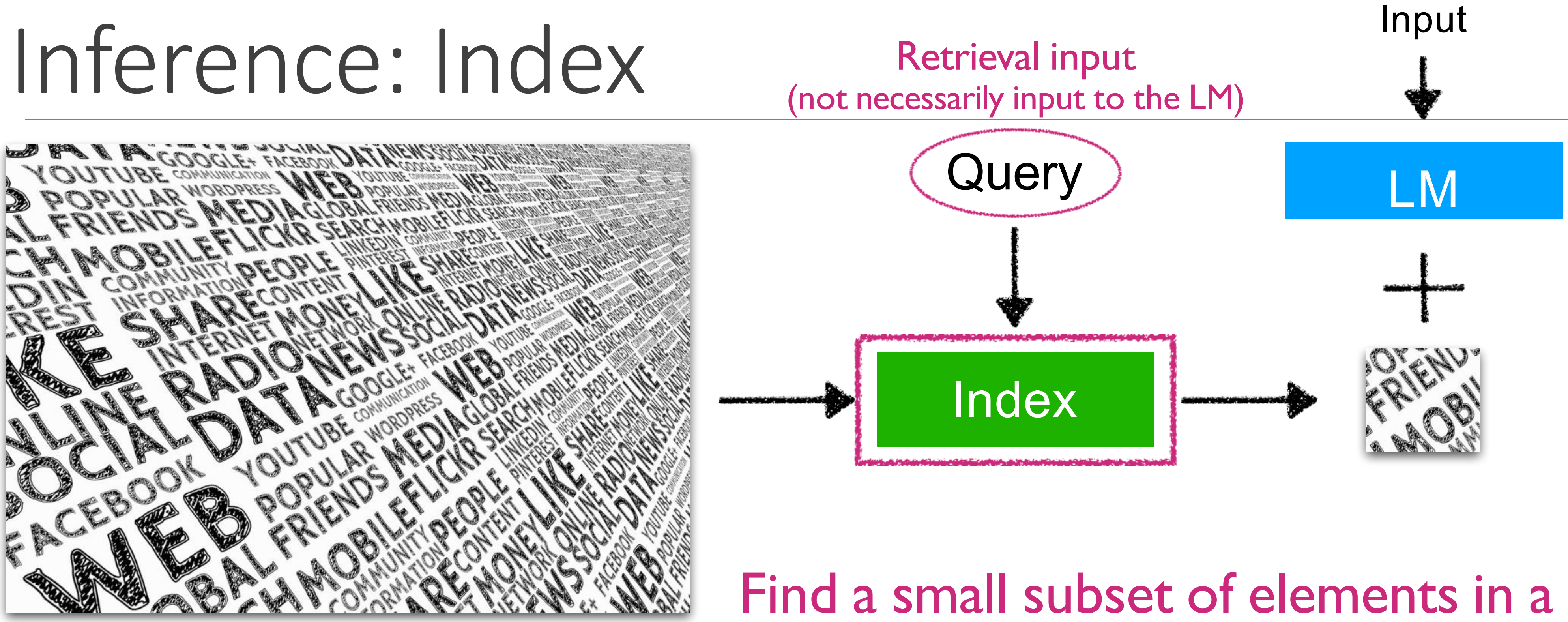
More recently people **have** used structured data

Datastore

Raw text corpus

At least billions~trillions of tokens
Not labeled datasets
Not structured data (knowledge bases)

Inference: Index



Input

Retrieval input
(not necessarily input to the LM)

Query

LM

Index

+

Datastore

Find a small subset of elements in a datastore that are the most similar to the query

Inference: Index

Goal: find a small subset of elements in a datastore that are the most similar to the query

sim: a similarity score between two pieces of text

Inference: Index

Goal: find a small subset of elements in a datastore that are the most similar to the query

sim: a similarity score between two pieces of text

Example

$$\mathrm{sim}(i,j) = \boxed{\mathrm{tf}_{i,j}} \times \log \frac{\boxed{N}}{\boxed{\mathrm{df}_i}}$$

# of total docs

# of docs containing

# of occurrences of in j

Example

$$\mathrm{sim}(i,j) = \underline{\mathrm{Encoder}(i)} \cdot \underline{\mathrm{Encoder}(j)}$$

Maps the text into an -dimensional vector

Remember cosine similarity from our discussion of word embeddings

$$\frac{\vec{a} \cdot \vec{b}}{|\vec{a}|\,|\vec{b}|}$$

Inference: Index

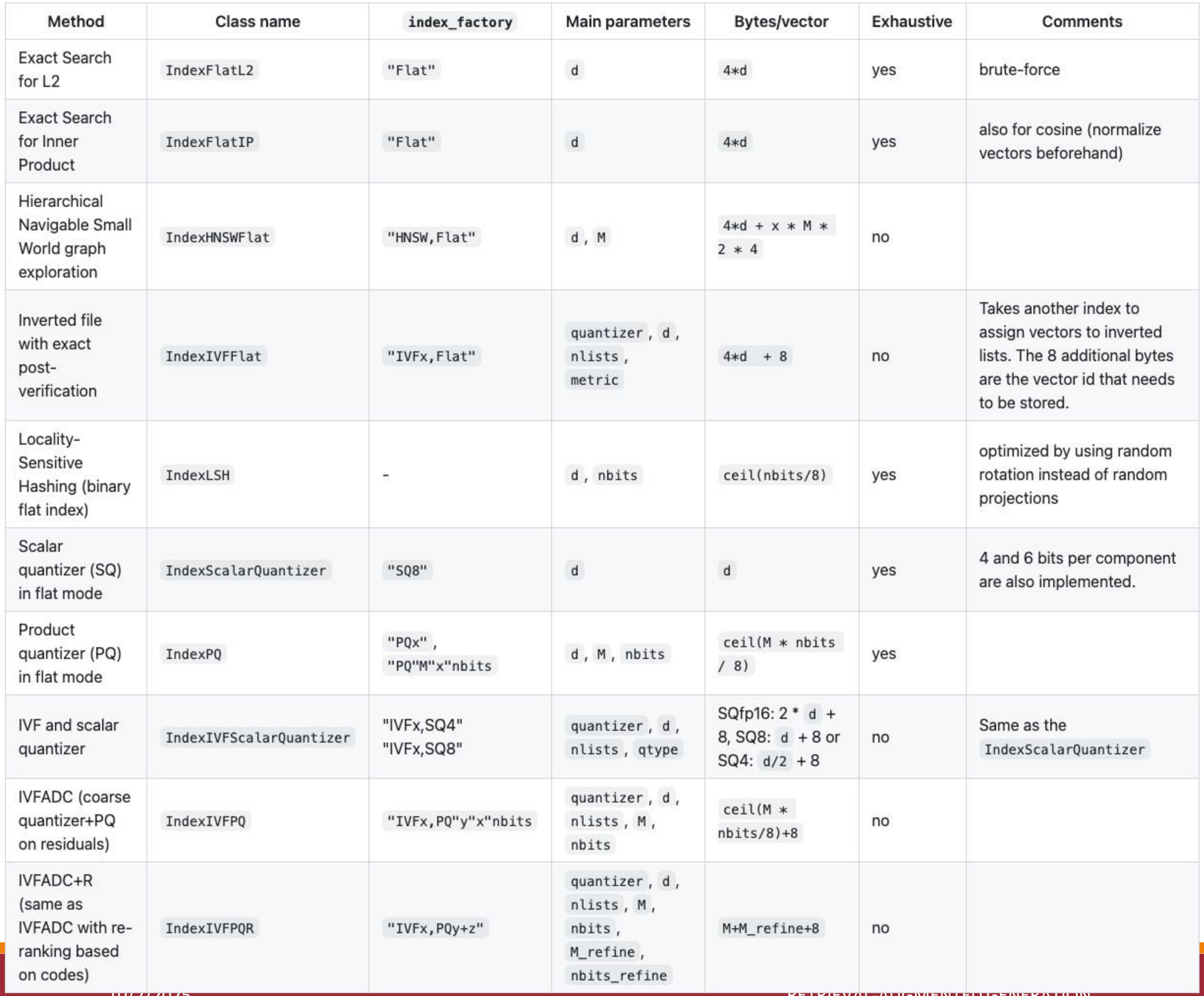
Goal: find a small subset of elements in a datastore that are the most similar to the query

sim: a similarity score between two pieces of text

Can be a totally separate research area on how to do this fast & accurate

Index: given q, return $\underbrace{\text{argTop-}k_{d \in \mathcal{D}}\text{sim}(q, d)}_{k \text{ elements from a datastore}}$ through fast nearest neighbor search

Software: FAISS, Distributed FAISS, SCaNN, etc…



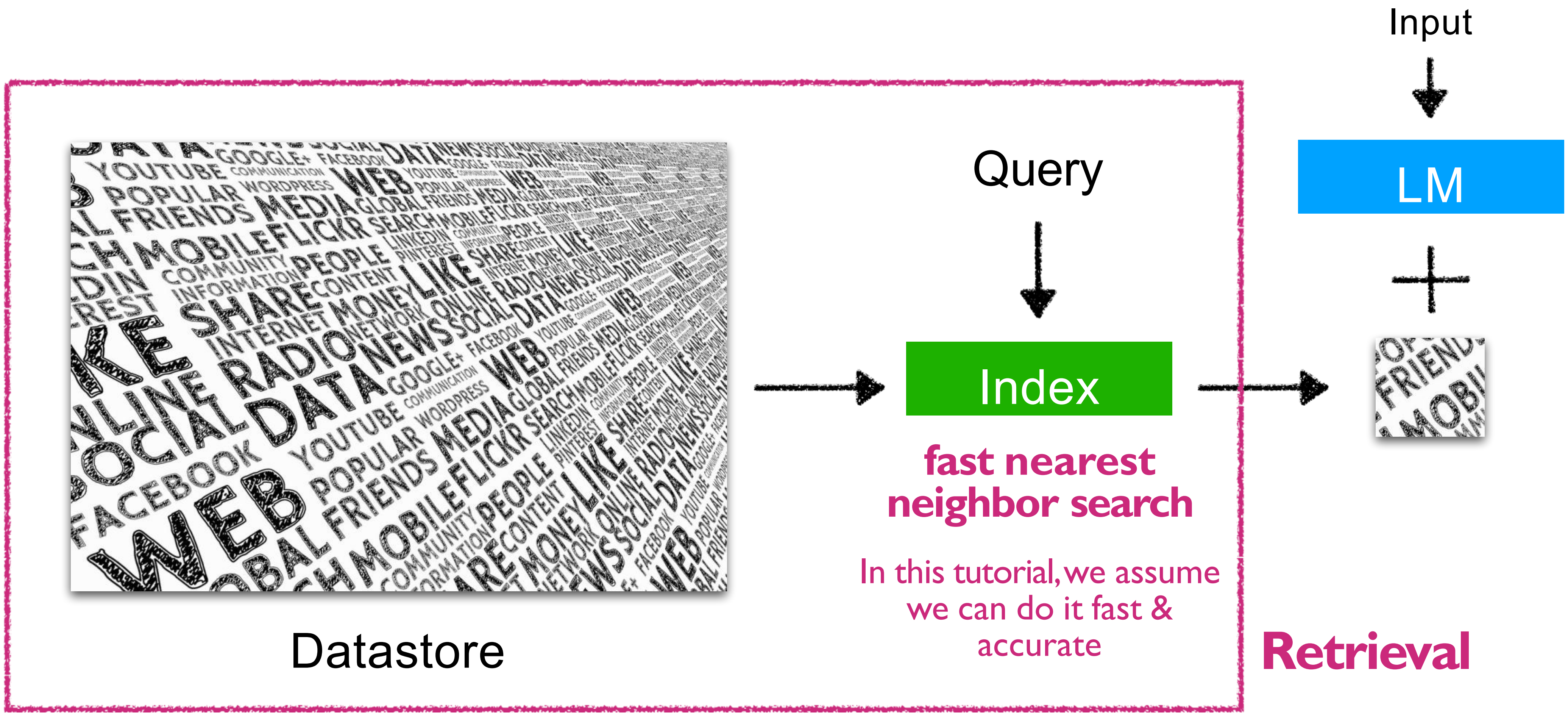
Method	Class name	`index_factory`	Main parameters	Bytes/vector	Exhaustive	Comments
Exact Search for L2	`IndexFlatL2`	`"Flat"`	`d`	`4*d`	yes	brute-force
Exact Search for Inner Product	`IndexFlatIP`	`"Flat"`	`d`	`4*d`	yes	also for cosine (normalize vectors beforehand)
Hierarchical Navigable Small World graph exploration	`IndexHNSWFlat`	`"HNSW,Flat"`	`d`, `M`	`4*d + x * M * 2 * 4`	no	
Inverted file with exact post-verification	`IndexIVFFlat`	`"IVFx,Flat"`	`quantizer`, `d`, `nlists`, `metric`	`4*d` + 8	no	Takes another index to assign vectors to inverted lists. The 8 additional bytes are the vector id that needs to be stored.
Locality-Sensitive Hashing (binary flat index)	`IndexLSH`	-	`d`, `nbits`	`ceil(nbits/8)`	yes	optimized by using random rotation instead of random projections
Scalar quantizer (SQ) in flat mode	`IndexScalarQuantizer`	`"SQ8"`	`d`	`d`	yes	4 and 6 bits per component are also implemented.
Product quantizer (PQ) in flat mode	`IndexPQ`	`"PQx"`, `"PQ"M"x"nbits`	`d`, `M`, `nbits`	`ceil(M * nbits / 8)`	yes	
IVF and scalar quantizer	`IndexIVFScalarQuantizer`	"IVFx,SQ4" "IVFx,SQ8"	`quantizer`, `d`, `nlists`, `qtype`	SQfp16: 2 * `d` + 8, SQ8: `d` + 8 or SQ4: `d/2` + 8	no	Same as the `IndexScalarQuantizer`
IVFADC (coarse quantizer+PQ on residuals)	`IndexIVFPQ`	`"IVFx,PQ"y"x"nbits`	`quantizer`, `d`, `nlists`, `M`, `nbits`	`ceil(M * nbits/8)+8`	no	
IVFADC+R (same as IVFADC with re-ranking based on codes)	`IndexIVFPQR`	`"IVFx,PQy+z"`	`quantizer`, `d`, `nlists`, `M`, `nbits`, `M_refine`, `nbits_refine`	`M+M_refine+8`	no	

Exact Search

Approximate Search
(Relatively easy to scale to ~1B elements)

More info: https://github.com/facebookresearch/faiss/wiki

Inference: Search



Datastore

Query

Index

fast nearest neighbor search

In this tutorial, we assume we can do it fast & accurate

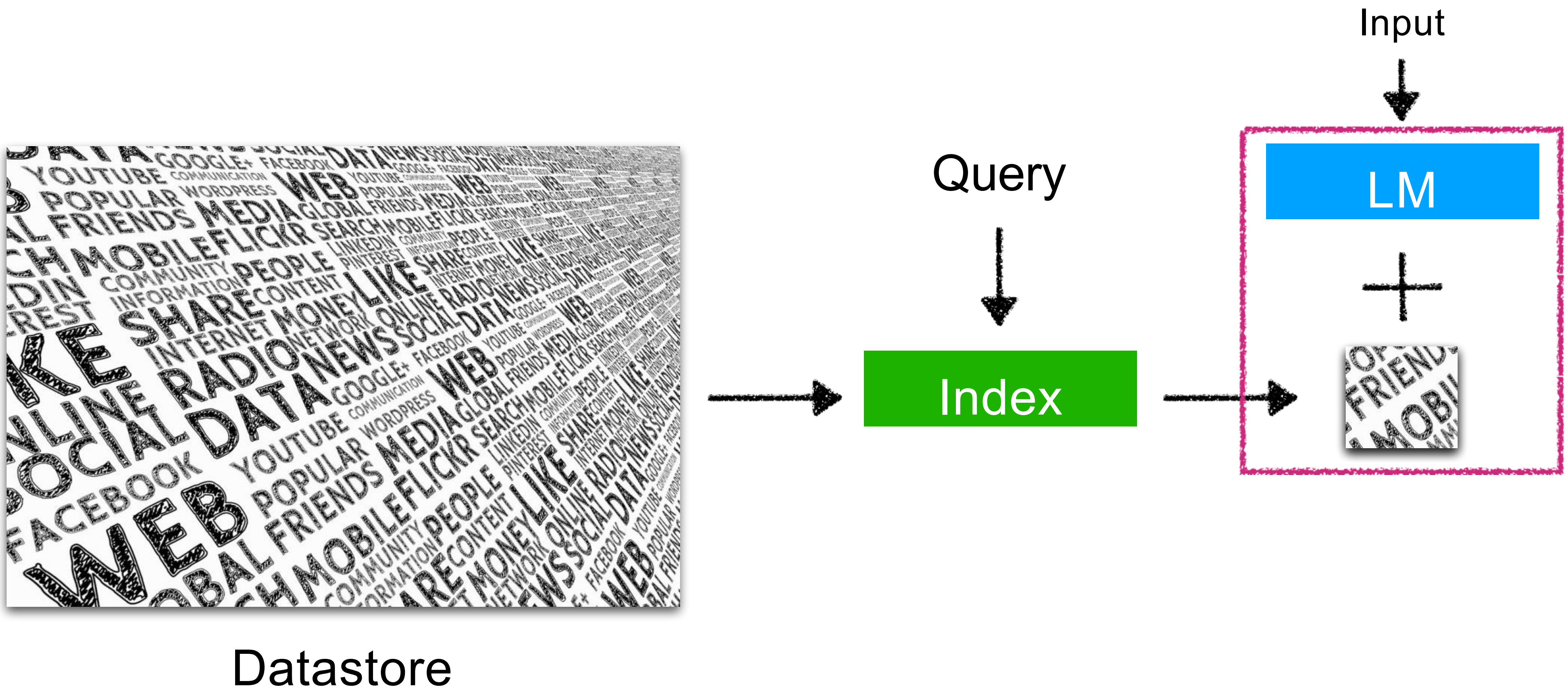
Input

LM

+

Retrieval

Inference: Search



Input

Query

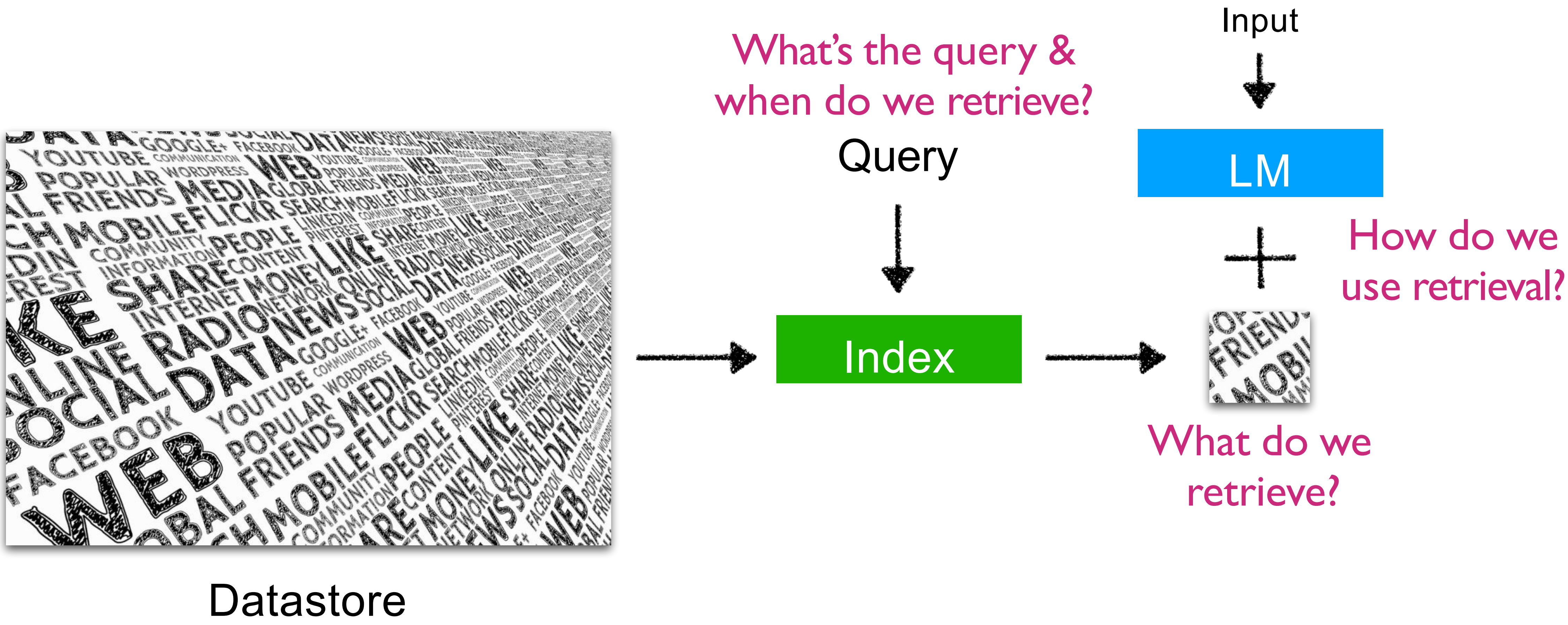
LM

+

Index

Datastore

Variations of RAG



What's the query &
when do we retrieve?

Query

Input

LM

How do we
use retrieval?

Index

Datastore

What do we
retrieve?

Variations of RAG

What to retrieve?

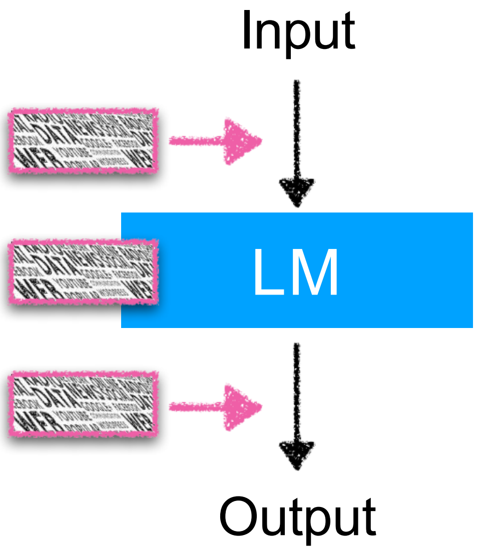
Query

Text chunks (passages)?

Tokens?

Something else?

How to use retrieval?

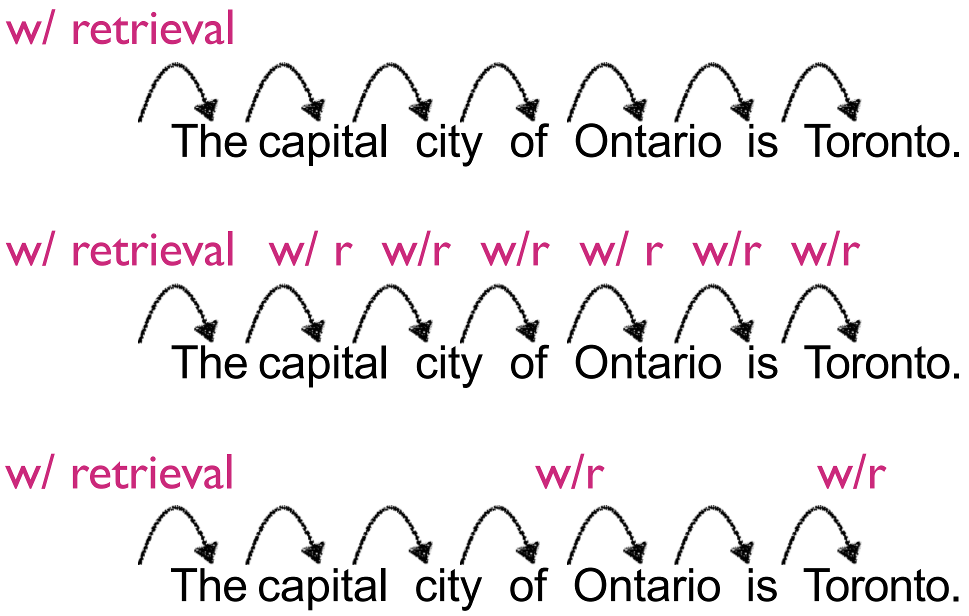


Input

LM

Output

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.

In-Class Activity

This is also an exercise for reading academic papers to look for specific details

Skim the paper assigned to you

In your paper, find the answers to these questions

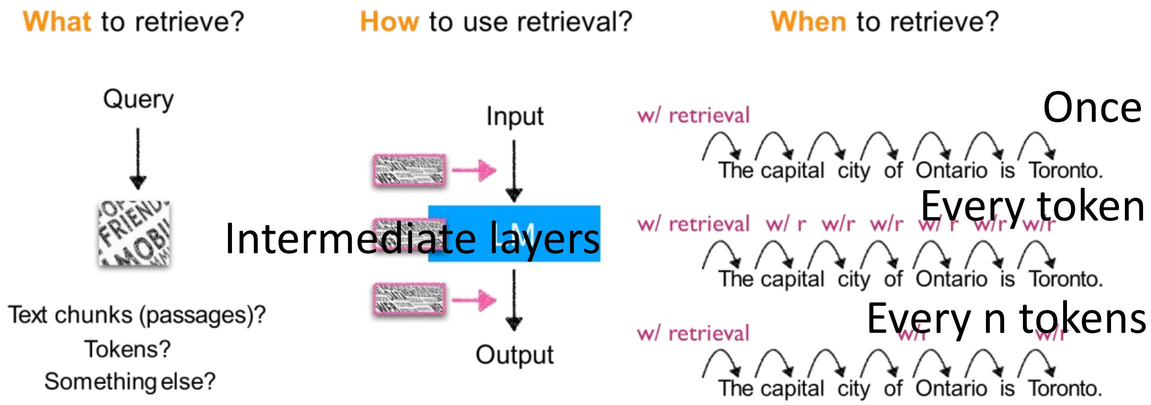
What to retrieve?

How to use retrieval?

When to retrieve?

Share what you learned with your table

Don't submit anything this time!

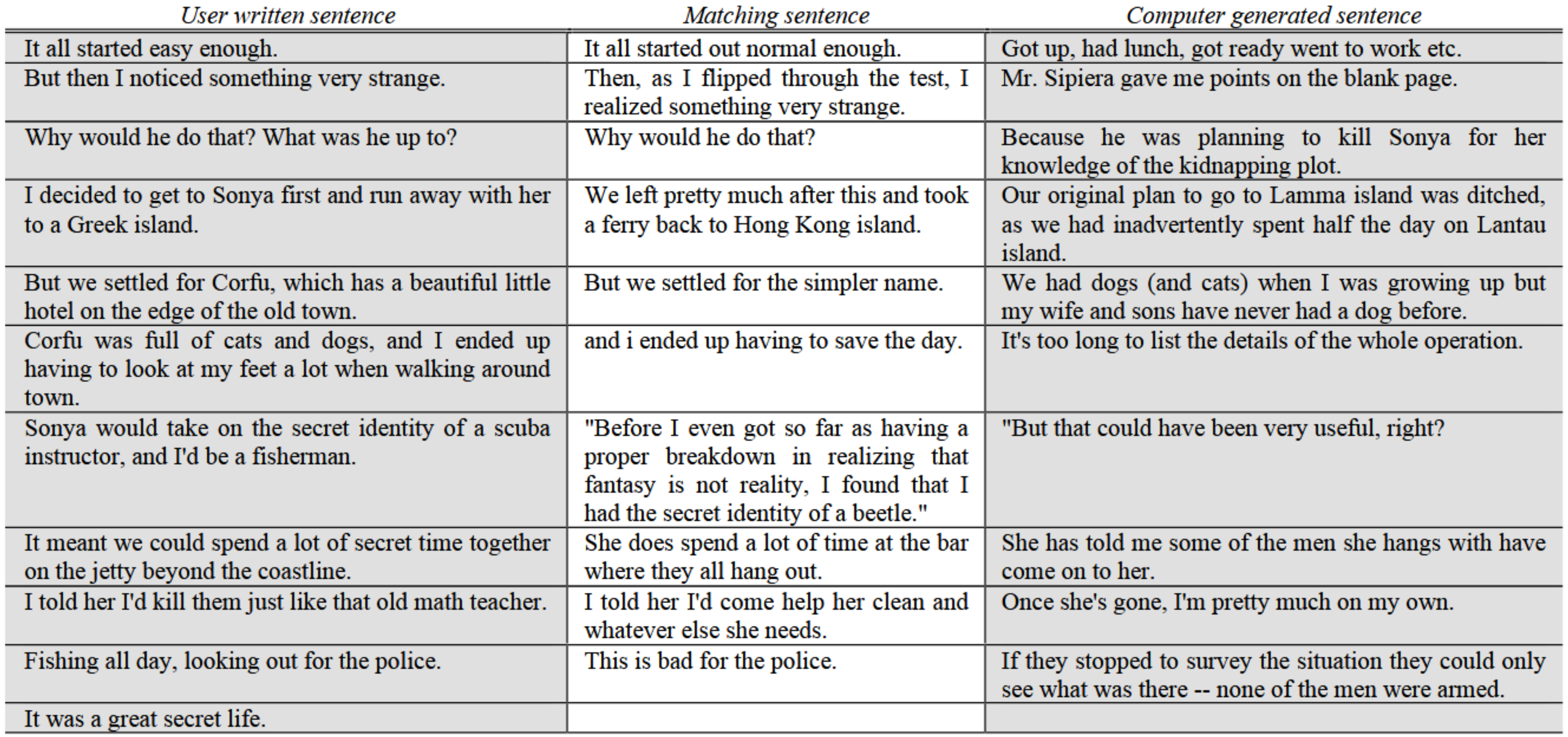


Answers

	What do retrieve?	How to use retrieval?	When to retrieve?
REALM (Guu et al 2020)	Text chunks	Input layer	Once
RETRO (Borgeaud et al. 2022)	Text chunks	Intermediate layers	Every n tokens
kNN-LM (Khandelwal et al. 2020)	Tokens	Output layer	Every token
FLARE (Jiang et al. 2023)	Text chunks	Input layer	Every n tokens (adaptive)

All models retrieve from the external text

Say Anything (2009)

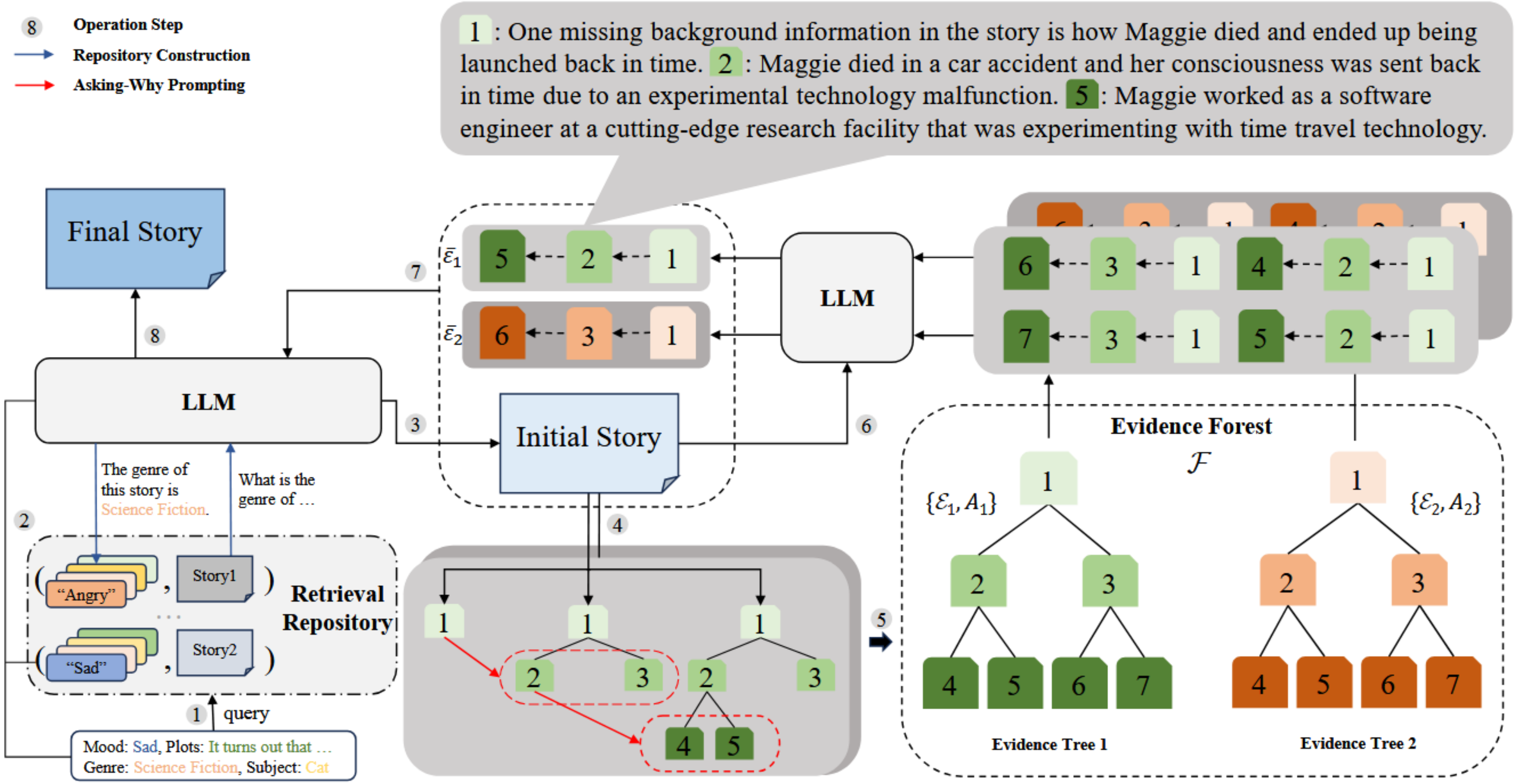


User written sentence	*Matching sentence*	*Computer generated sentence*
It all started easy enough.	It all started out normal enough.	Got up, had lunch, got ready went to work etc.
But then I noticed something very strange.	Then, as I flipped through the test, I realized something very strange.	Mr. Sipiera gave me points on the blank page.
Why would he do that? What was he up to?	Why would he do that?	Because he was planning to kill Sonya for her knowledge of the kidnapping plot.
I decided to get to Sonya first and run away with her to a Greek island.	We left pretty much after this and took a ferry back to Hong Kong island.	Our original plan to go to Lamma island was ditched, as we had inadvertently spent half the day on Lantau island.
But we settled for Corfu, which has a beautiful little hotel on the edge of the old town.	But we settled for the simpler name.	We had dogs (and cats) when I was growing up but my wife and sons have never had a dog before.
Corfu was full of cats and dogs, and I ended up having to look at my feet a lot when walking around town.	and i ended up having to save the day.	It's too long to list the details of the whole operation.
Sonya would take on the secret identity of a scuba instructor, and I'd be a fisherman.	"Before I even got so far as having a proper breakdown in realizing that fantasy is not reality, I found that I had the secret identity of a beetle."	"But that could have been very useful, right?
It meant we could spend a lot of secret time together on the jetty beyond the coastline.	She does spend a lot of time at the bar where they all hang out.	She has told me some of the men she hangs with have come on to her.
I told her I'd kill them just like that old math teacher.	I told her I'd come help her clean and whatever else she needs.	Once she's gone, I'm pretty much on my own.
Fishing all day, looking out for the police.	This is bad for the police.	If they stopped to survey the situation they could only see what was there -- none of the men were armed.
It was a great secret life.		

Before neural methods, retrieval was used for generating stories

Swanson, R. and Gordon, A. (2009) Open Domain Collaborative Storytelling With Say Anything. Third International Conference on Weblogs and Social Media, San Jose, CA, May 17-20, 2009.

GROVE (2023)



1 : One missing background information in the story is how Maggie died and ended up being launched back in time. 2 : Maggie died in a car accident and her consciousness was sent back in time due to an experimental technology malfunction. 5 : Maggie worked as a software engineer at a cutting-edge research facility that was experimenting with time travel technology.

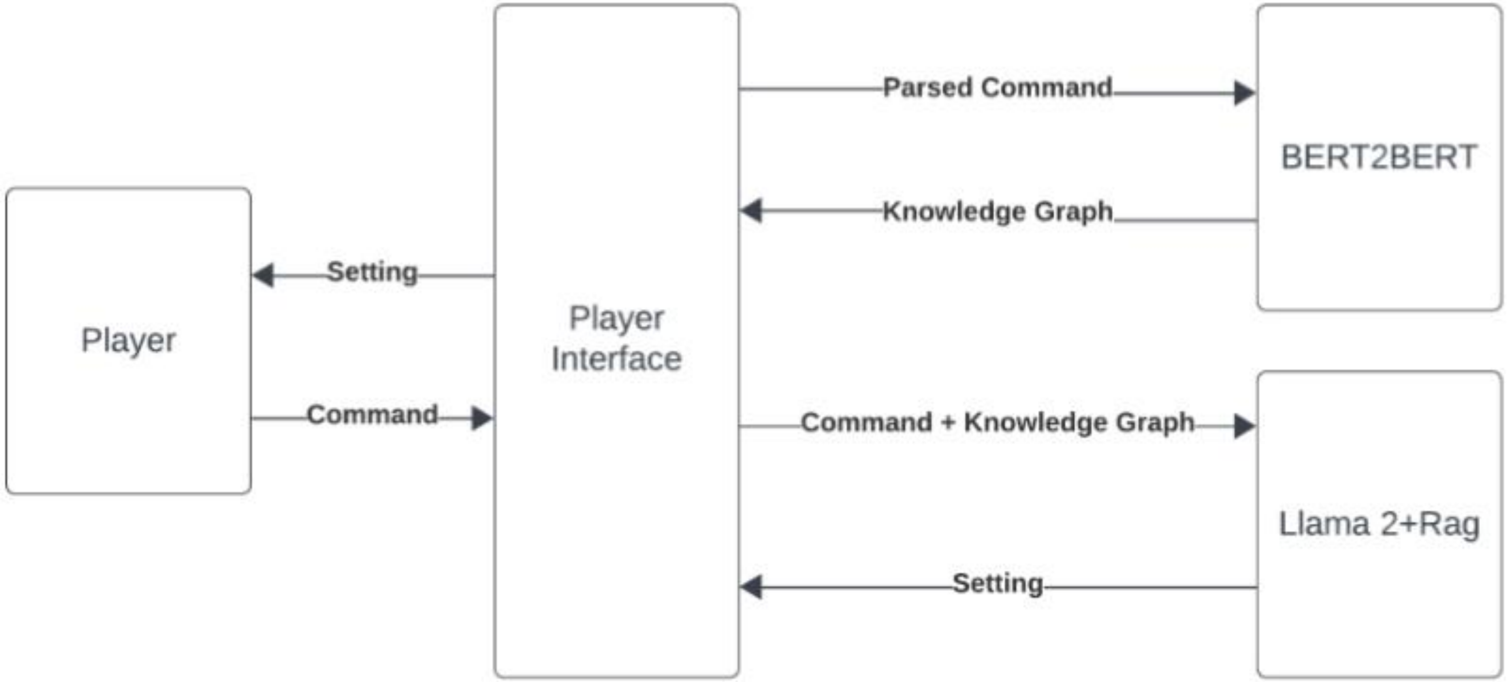
The genre of this story is Science Fiction.

What is the genre of …

Mood: Sad, Plots: It turns out that …
Genre: Science Fiction, Subject: Cat

Zhihua Wen, Zhiliang Tian, Wei Wu, Yuxin Yang, Yanqi Shi, Zhen Huang, and Dongsheng Li. 2023. GROVE: A Retrieval-augmented Complex Story Generation Framework with A Forest of Evidence. In *Findings of the Association for Computational Linguistics: EMNLP 2023*, pages 3980–3998, Singapore. Association for Computational Linguistics.

BERALL (2024) (to be presented on Tuesday)



Rachel Chambers, Naomi Tack, Eliot Pearson, Lara J. Martin, Francis Ferraro, BERALL: Generating Retrieval-augmented State-based Interactive Fiction Games. Wordplay Workshop 2024.