

Question Answering

CSC485

Annoucement

- Last Lecture:
- Tuesday:
 - 10 – 11
 - 12 – 13

Modern QA from text

The common person's view? [From a novel]

"I like the Internet. Really, I do. Any time I need a piece of shareware or I want to find out the weather in Bogota ... I'm the first guy to get the modem humming. But as a source of information, it sucks. You got a billion pieces of data, struggling to be heard and seen and downloaded, and anything I want to know seems to get trampled underfoot in the crowd."

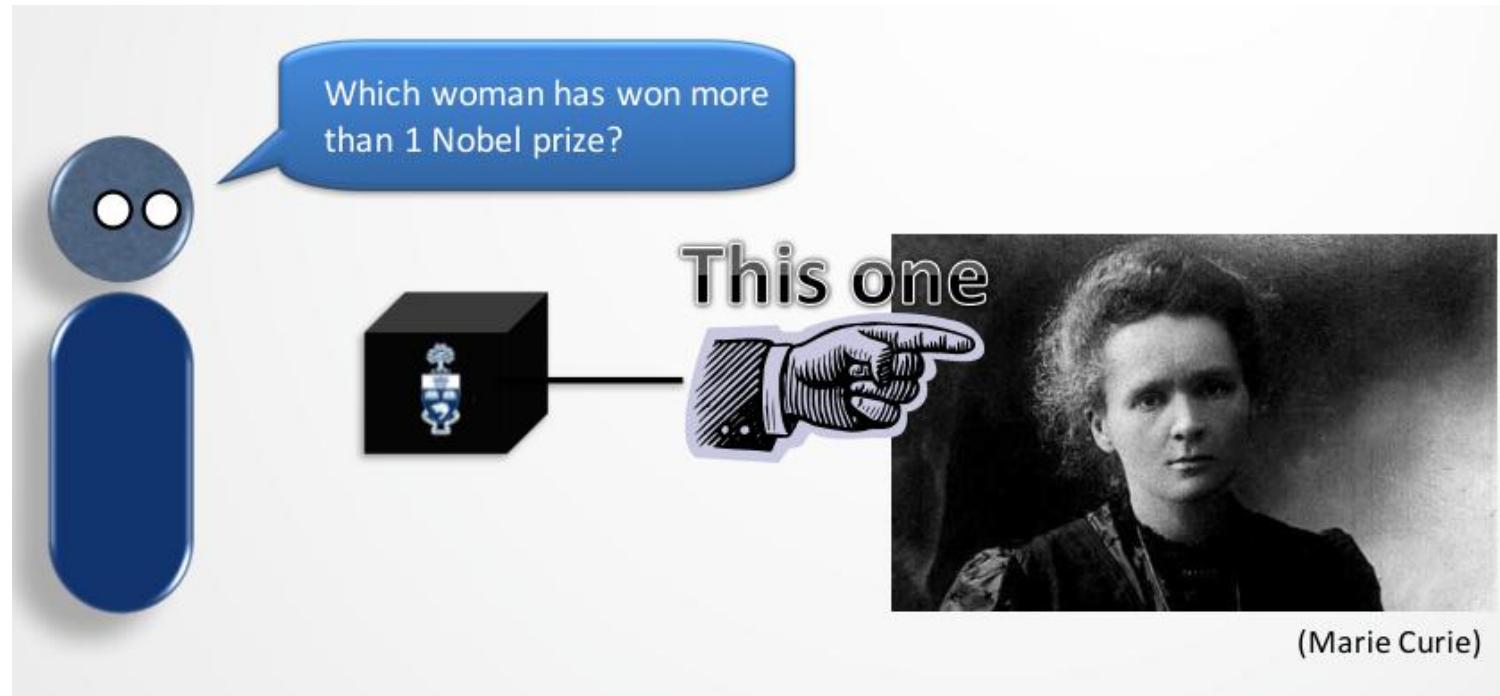
M. Marshall. The Straw Men. HarperCollins Publishers, 2002.

- An idea originating from the IR community.
- With massive collections of full-text documents, simply finding **relevant documents** is of limited use: we want **answers** from textbases.
- QA: give the user a (short) answer to their question, perhaps supported by evidence.

Outline

- Intro to QA
- QA & IR before deep learning
- QA & IR with deep learning
- RAG: QA with LLM
 - More LLM stuff: post-training & prompt-engineering.

Question Answering (QA)



- Question Answering (QA) usually involves a specific answer to a question.

Information Retrieval (IR) and QA

Google search results for "which woman has won more than 1 nobel prize?"

Search bar: which woman has won more than 1 nobel prize?

Filters: All, Images, News, Videos, Shopping, Web, Books, More, Tools

Results:

- Wikipedia - List of female Nobel laureates: Curie is also the first person and the only woman to have won multiple Nobel Prizes; in 1911, she won the Nobel Prize in Chemistry.
- Wikipedia - Nobel Prize: Multiple laureates Five people have received two Nobel Prizes. Marie Curie received the Physics Prize in 1903 for her work on radioactivity and the Chemistry ...
- Rincón educativo - The magnificent four who repeated Nobel: By Elena Sanz - The first person in history to achieve the feat of receiving a double Nobel was the Polish Marie Skłodowska Curie, laureate first in Physics and, ...
- Phys.org - The five scientists who won two Nobel prizes: Oct 5, 2022 — Marie Curie (1903, 1911) The mother of modern physics was the first woman ever to win not one, but two, Nobel prizes for her seminal ...
- The Conversation - The five scholars who won two Nobel prizes: Jul 9, 2024 — Marie Curie is the most famous of these five scholars and for good reason. The world today, as well as science in general, is different because ...
- Statista - Chart: The Nobel Prize Gender Gap

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AI Overview: Marie Curie is the only woman to have won multiple Nobel Prizes, winning the Nobel Prize in Physics in 1903 and the Nobel Prize in Chemistry in 1911.

1903: Curie won the Nobel Prize in Physics with her husband, Pierre Curie, and Henri Becquerel for their work on radioactivity.

1911: Curie won the Nobel Prize in Chemistry for discovering the elements radium and polonium.

Marie Curie: Only one woman, Marie Curie, has been honoured twice, with the Nobel Prize in Physics 1903 and the Nobel Prize in Chemistry 1911. This means that 65 women in total have been awarded the Nobel Prize between 1901 and 2024.

Nobel Prize - Nobel Prize awarded women - NobelPrize.org: The Nobel Prize and the Sveriges Riksbank Prize in Economic Sciences in Memory of Alfred Nobel have been awarded to...

One strategy is to turn QA into information retrieval (IR) and let the human complete the task.

Question Answering (QA)



A screenshot of the WolframAlpha search interface. The search query is "How much potassium is in 450,000 cubic kilometers of bananas?". The input interpretation shows the query broken down into "banana", "amount", "450 000 km³ (cubic kilometers)", and "potassium". The result is displayed as 1.5×10^{12} t (metric tons).

Knowledge-based QA



1. Build a structured semantic representation of the query.
 - Extract times, dates, locations, entities using regular expressions.
 - Fit to well-known templates.
2. Query databases with these semantics.
 - Ontologies (Wikipedia infoboxes).
 - Restaurant review databases.
 - Calendars.
 - ...

IR-based QA

Google which woman has won more than 1 nobel prize? X |

All Images News Videos Shopping Forums Web More Tools

Marie Curie

Only one woman, **Marie Curie**, has been honoured twice, with the Nobel Prize in Physics 1903 and the Nobel Prize in Chemistry 1911. This means that 65 women in total have been awarded the Nobel Prize between 1901 and 2024.



Nobel Prize
<https://www.nobelprize.org/prizes/lists/nobel-prize...> ::

[Nobel Prize awarded women - NobelPrize.org](#)

[About featured snippets](#) • [Feedback](#)

[All](#) [Images](#) [Maps](#) [Videos](#) [News](#) [Shopping](#) [Short videos](#) [More](#)[Tools](#)Results for **Paris, France** · Choose area

75001 Paris, France

Louvre Museum, Address



Wikipedia

<https://en.wikipedia.org/wiki/Louvre>

Louvre

The Louvre museum is located **inside the Louvre Palace**, in the center of Paris, adjacent to the Tuileries Gardens. The two nearest Métro stations are Louvre ...

[Louvre Palace](#) · [Louvre Pyramid](#) · [Louvre Abu Dhabi](#) · [Art museum](#)

People also ask

[Where is the Louvre located exactly?](#)[How far apart are the Louvre and Eiffel Towers?](#)[Is the Louvre where the Mona Lisa is?](#)[How much does it cost to get into the Louvre?](#)

Feedback



Le Louvre

<https://www.louvre.fr/visit/map-entrances-directions>

Map, entrances & directions - All roads lead to the Louvre

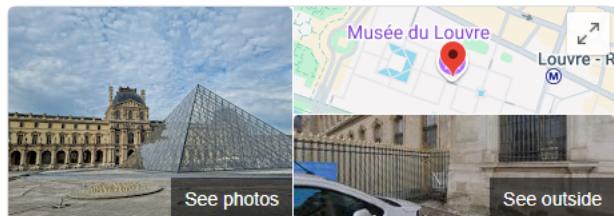
An underground car park is located at **1 Avenue du Général Lemonier**, from which you can access the museum via the Galerie du Carrousel entrance.



Britannica

<https://www.britannica.com/Visual-Arts/Painting>

Louvre | History, Collections, & Facts



Louvre Museum

[Website](#)[Directions](#)[Save](#)

4.7 ★★★★★ 325,915 Google reviews

Museum in Paris, France

[SEE TICKETS](#)

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[Louvre at Night: Explore with a Local](#)

\$125 · 5.0 ★ (1.4K)



The Louvre, or the Louvre Museum, is a national art museum in Paris, France, and one of the most famous museums in the world.

[Wikipedia](#)**Departments:** Librairie-Boutique du Musée du Louvre**Address:** 75001 Paris, France**Founded:** August 10, 1793**Hours:** Closed · Opens 9 a.m. · [More hours](#)**Director:** Laurence des Cars**Visitors:** 8.9 million (2023); Ranked 1st nationally; Ranked 1st globally**Phone:** +33 1 40 20 53 17**Subsidiary:** Louvre Conservation Center**Curator:** Marie-Laure de Rochebrune[Suggest an edit](#)

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Tools

Louvre Museum / Artworks

Mona Lisa
Leonardo da VinciVenus de Milo
Alexandros of An...Winged Victory
of SamothraceLiberty Leading
the People
Eugène DelacroixPsyche Revived
by Cupid's Kiss
Antonio CanovaThe Raft of the
Medusa
Théodore GéricaultThe Coronation
of Napoleon
Jacques-Louis D...The Wedding at
Cana
Paolo VeroneseThe Seated
ScribeThe Virgin of the
Rocks
Leonardo da VinciLa Belle
Ferronnière
Leonardo da VinciOath of the
Horatii
Jacques-Louis D...

Feedback



Paris City Vision

<https://www.pariscityvision.com> › ... › Louvre museum

Louvre artwork : top masterpieces and paintings

How can we not mention the **Mona Lisa**? The portrait assumed to be of the wife of Francesco del Giocondo is considered to be the most famous painting in the world ...

People also ask :

What is the most famous artwork in Louvre?



What are the three masterpieces of the Louvre?



What are the big 3 at the Louvre?



Where is the real Mona Lisa painting?



Feedback



Le Louvre

<https://www.louvre.fr> › explore › visitor-trails › the-lou...

The Louvre's Masterpieces - What exactly is a ...

The palace is home to some of the **world's most iconic pieces** – **paintings**, sculptures, architectural elements and **art** objects by **famous** or anonymous artists.



Louvre Museum

[Website](#)[Directions](#)[Save](#)

4.7 ★★★★☆ 325,915 Google reviews

Museum in Paris, France

[SEE TICKETS](#)

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Withlocals :

Withlocals Your Way! - Paris City Tour

\$87 · 5.0 ★ (2.2K)



The Louvre, or the Louvre Museum, is a national art museum in Paris, France, and one of the most famous museums in the world.

[Wikipedia](#)

Departments: Librairie-Boutique du Musée du Louvre



which pieces from the salon de refusés are now in the louvre



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Tools



Wikipedia
https://en.wikipedia.org/wiki/Salon_des_Refusés

Salon des Refusés

Today, by extension, salon des refusés refers to any exhibition of works rejected from a juried art show.



People also ask :

Where is the Salon Carré in the Louvre?



What happened with the works entered in the Salon of the Refused?



Which painting was included in the first Salon des Refusés Salon of the Rejected?



Does the Salon in Paris still exist?



Feedback



Artland Magazine
<https://magazine.artland.com/articles-and-features>

Contemporary Art History: The Salon Des Refusés

Discover the 1863 **Salon des** Refusés: first of a string of landmark contemporary art shows that have radically changed the course of Art History.



Le Louvre
<https://www.louvre.fr/explore/visitor-trails/the-louvre>

The Louvre's Masterpieces - What exactly is a ...

The palace is home to some of the world's most iconic **pieces** – **paintings**, **sculptures**, architectural elements and art objects by famous or anonymous artists.

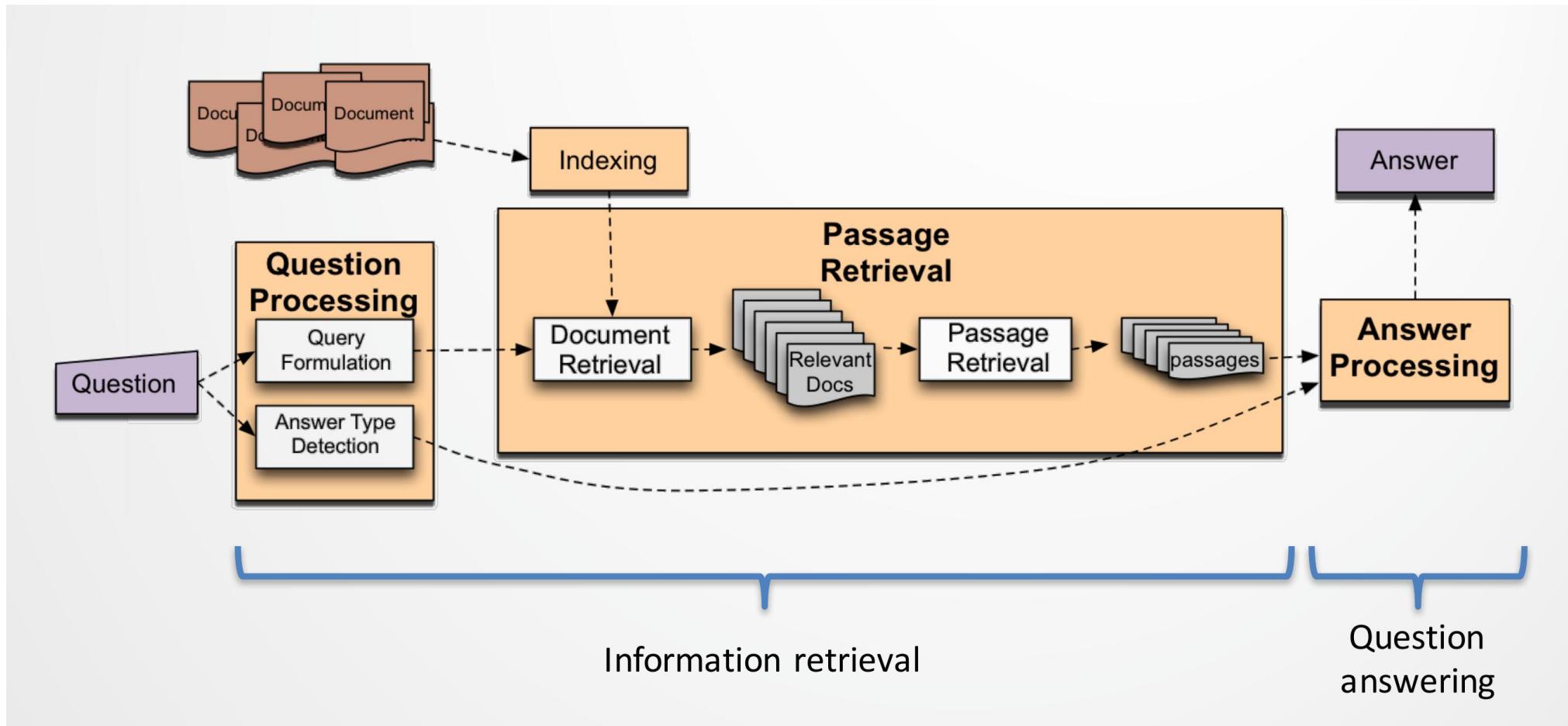


The Tour Guy
<https://thetourguy.com/france/paris/louvre>

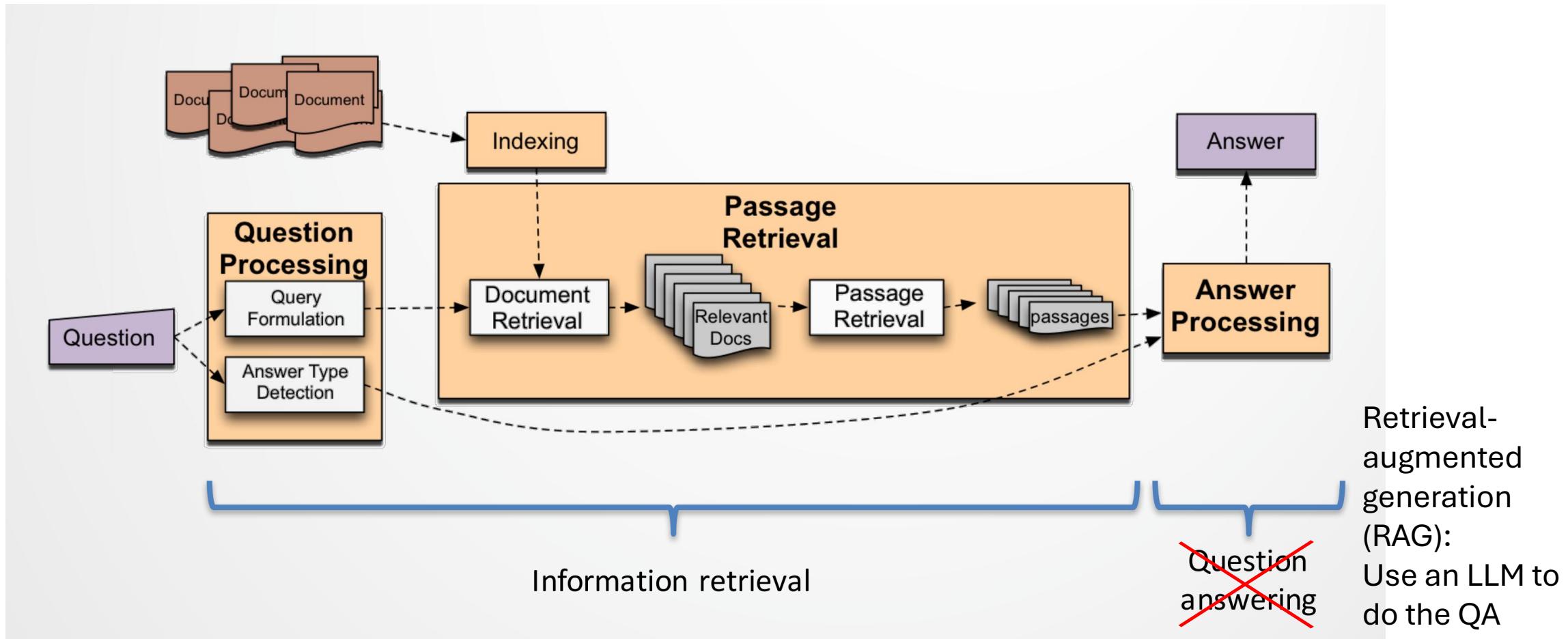
The Louvre Museum's 17 Most Important Works of Art, Paris

Oct 28, 2024 — The **Louvre** is massive. To make things easy, we've listed 17 famous **paintings** to see in the **Louvre** and explained why they're so important.

IR-based QA



IR-based QA with LLM (RAG)



Sample TREC questions

1. Who is the author of the book, "The Iron Lady: A Biography of Margaret Thatcher"?
2. What was the monetary value of the Nobel Peace Prize in 1989?
3. What does the Peugeot company manufacture?
4. How much did Mercury spend on advertising in 1993?
5. What is the name of the managing director of Apricot Computer?
6. Why did David Koresh ask the FBI for a word processor?
7. What debts did Qintex group leave?
8. What is the name of the rare neurological disease with symptoms such as: involuntary movements (tics), swearing, and incoherent vocalizations (grunts, shouts, etc.)?

Publications

Overview

Other Evaluations

Information
for Active
Participants



Frequently Asked
Questions

Tracks

Data

Past TREC
Results

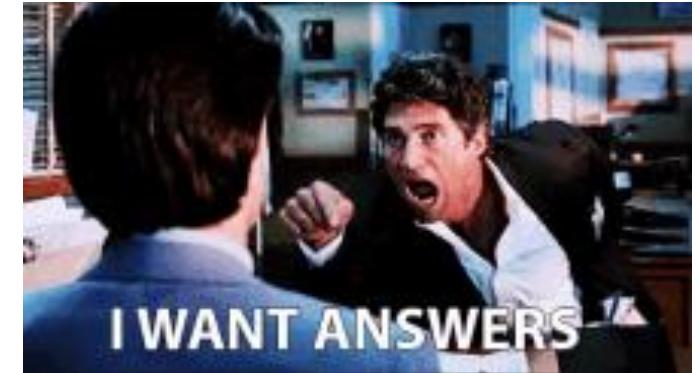
Contact
Information

Query types

- Different kinds of questions can be asked.
 - Factoid questions, e.g.,
 - *How often were the peace talks in Ireland delayed or disrupted as a result of acts of violence?*
 - Narrative (open-ended) questions, e.g.
 - *Can you tell me about contemporary interest in the Greek philosophy of stoicism?*
 - Complex/hybrid questions, e.g.,
 - *Who was involved in the Schengen agreement to eliminate border controls in Western Europe and what did they hope to accomplish?*

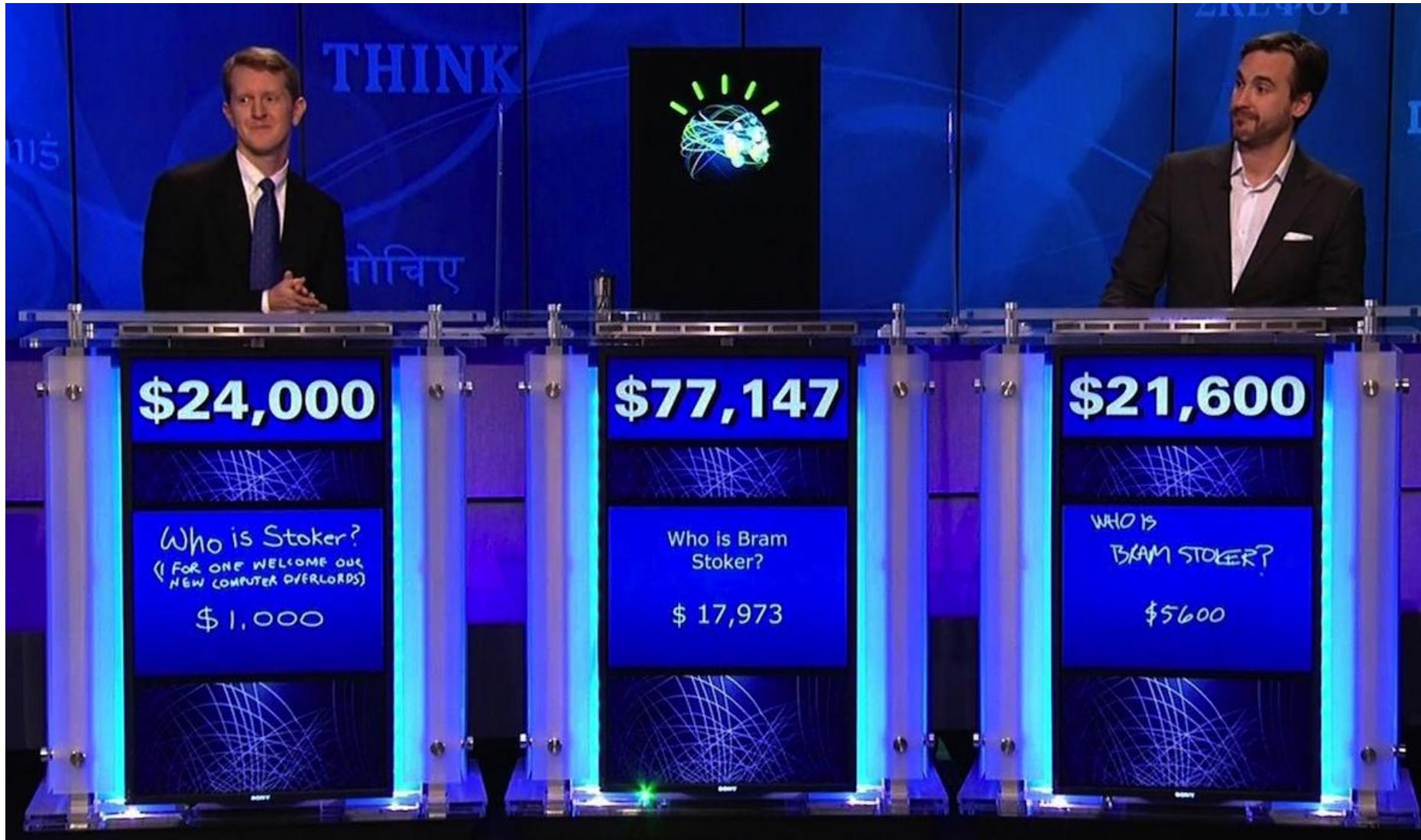
People want to ask questions...

- **Examples from AltaVista query log (late 1990s)**
 - who invented surf music?
 - how to make stink bombs
 - where are the snowdens of yesteryear?
 - which english translation of the bible is used in official catholic liturgies?
 - how to do clayart
 - how to copy psx
 - how tall is the sears tower?
- **Examples from Excite query log (12/1999)**
 - how can i find someone in texas
 - where can i find information on puritan religion?
 - what are the 7 wonders of the world
 - how can i eliminate stress
 - What vacuum cleaner does Consumers Guide recommend

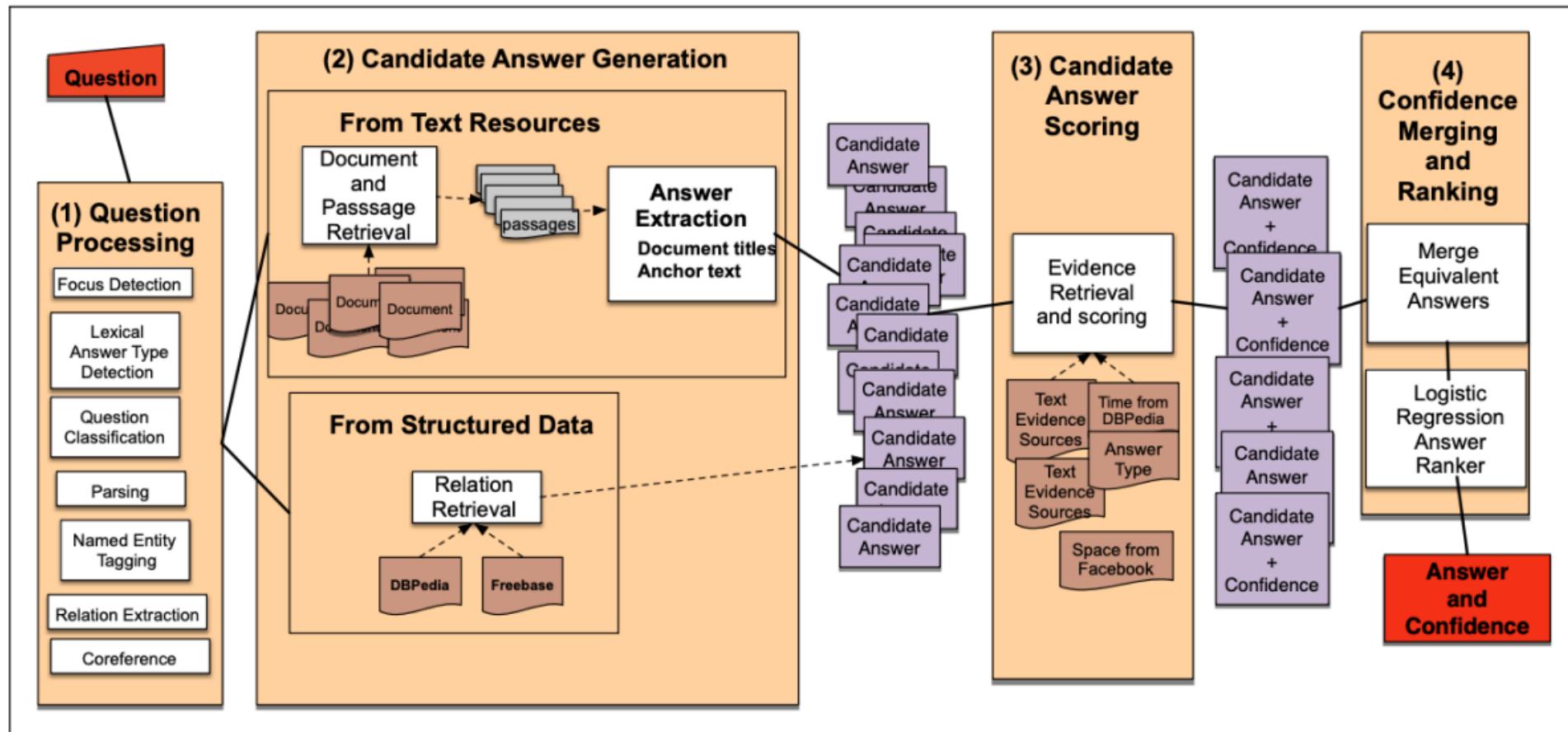


Around 10% of early query logs are QUESTIONS.

2011: IBM Watson beat Jeopardy champions



IBM Watson: Search



QA at TREC

- Question answering competition at TREC started with answering a set of 500 fact-based questions:
 - E.g., “*When was Mozart born?*”
- For the first three years systems were allowed to return 5 ranked answer snippets (50/250 bytes) to each question.
 - Mean Reciprocal Rank (MRR) scoring:
 - 1, 0.5, 0.33, 0.25, 0.2, 0 for 1, 2, 3, 4, 5, 6+ rankings
 - Mainly Named Entity answers (person, place, date, ...)
- From 2002 the systems were only allowed to return a single **exact** answer and the notion of confidence was introduced.

The TREC Document Collection

- Each task features a collection from a domain,
 - E.g., news articles:
 - AP newswire, 1998-2000
 - New York Times newswire, 1998-2000
 - Xinhua News Agency newswire, 1996-2000
- Usually about 1,000,000 documents in the collection. Roughly 3GB of text.
- This was once a lot of text to process entirely using advanced NLP techniques, so the systems usually consisted of an initial information retrieval phase followed by more advanced processing.
- Allowed to supplement this text with use of the web, and other knowledge bases?
- See also SQuAD (1.1 and 2.0/open).

Top Performing Systems

- Best TREC vanilla QA systems score ~60-80% !!!
- Approaches and successes have varied a fair deal
- AskMSR (2001): first wildly successful purely statistical system, stressing how much could be achieved by very simple methods with enough text (and now various copycats)

AskMSR: Shallow Approach

- *In what year did Abraham Lincoln die?*
 - Ignore hard documents and find easy ones.

Abra

***LINCOLN, ABRAHAM** was born near Hodgenville, Kentucky, on February 12, 1809. His mother died when he was nine years old, and his "angel" mother, Nancy Hanks Lincoln, died when he was ten. Lincoln attended a formal school for only a few months, but he taught himself to read and write. He moved to Illinois, in 1830 where he obtained a job as a store clerk and the local newspaper editor.

A small black and white portrait of a young Abraham Lincoln, showing him from the chest up, wearing a dark jacket over a white shirt.

Lincoln lost his attempt at the state legislature in 1834, but was elected to the state legislature in 1836. Lincoln was admitted to the bar in 1837 and began a year term in the U.S. House in 1847.

A large oil painting of Abraham Lincoln sitting in an ornate chair, resting his chin on his hand in a thoughtful pose. He is wearing a dark suit and a white shirt.

Sixteenth President
1861-1865
Married to Mary Todd Lincoln

Lincoln, 1809-1865

on February 12, 1809. In 1816, the Lincoln family moved to Indiana. Lincoln's mother died and his father married a woman he had known since she was a girl. Lincoln, who had acquired knowledge through the reading of books by himself, became a master of the law. He served without distinction in the Black Hawk War, but two years later he tried again, was successful, and became noteworthy as a witty, honest, competent circuit court judge. At which time he opposed the war with Mexico. By 1856, he had gained attention for his series of debates with Stephen A. Douglas. In the election he became a significant figure in his party. At his inauguration on March 4, seven southern states had seceded from the Union. Lincoln called for 75,000 volunteers (approximately 18,000 were accepted), for a total of 11. Lincoln immediately took action to prevent the South from leaving the Union. The Civil War would eventually be the central difference in maintaining the Union. Lincoln issued the Emancipation Proclamation which expanded the purpose of the war. After the Battle of Gettysburg, Lincoln gave his famous Gettysburg Address. The address is considered one of the greatest speeches in history. Lincoln's final speech was given at the dedication of a national cemetery in Gettysburg. Lincoln died on April 15, 1865, at Petersen's Boarding House in Washington, D.C.

Abraham Lincoln

16th President of the United States (March 4, 1861 to April 15, 1865)

Born: February 12, 1809, in Hardin County, Kentucky
Died: April 15, 1865, at Petersen's Boarding House in Washington, D.C.

"I was born February 12, 1809, in Hardin County, Kentucky. My parents were both born in Virginia, of undistinguished families, perhaps I should say. My mother, who died in my tenth year, was of a family of the name of Hanks."

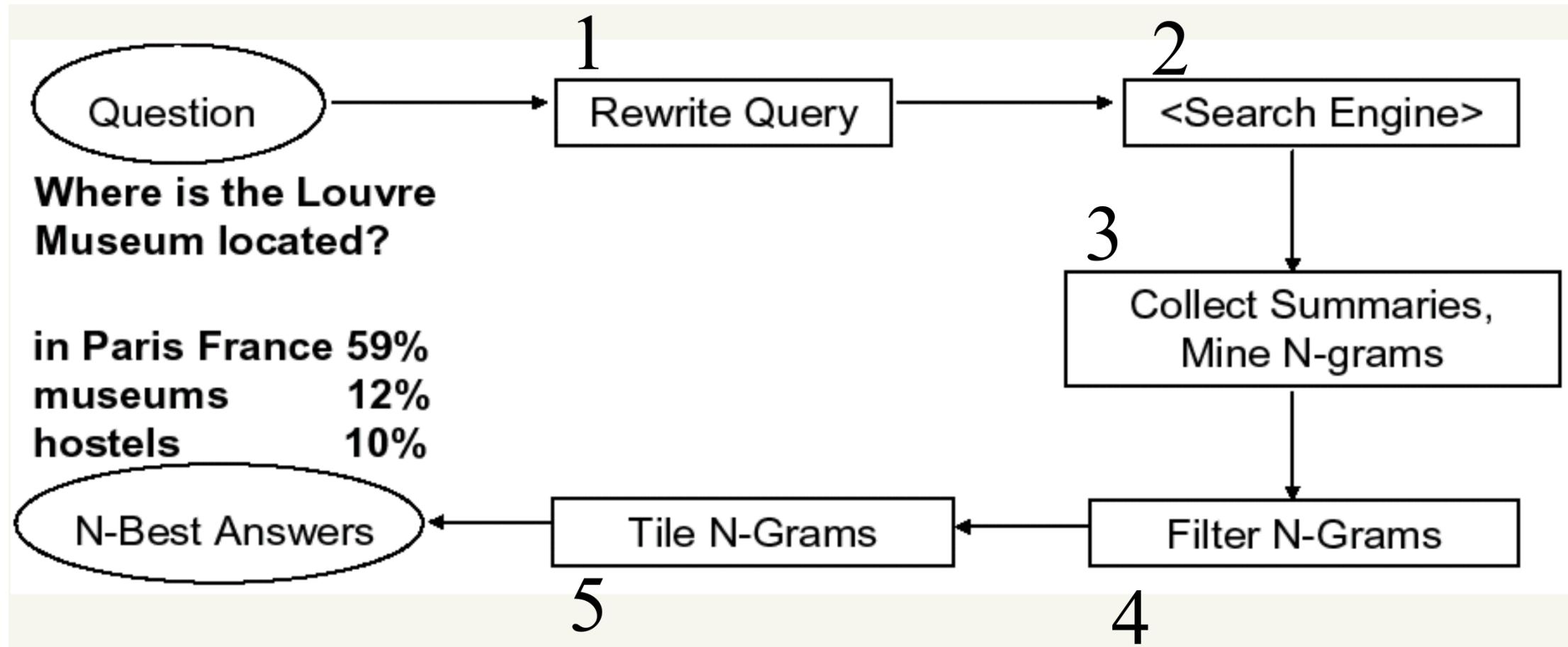
ABRAHAM LINCOLN

Sixteenth President of the United States

Born in 1809 - Died in 1865



AskMSR: Details



Step 1: Query rewriting: Answer similar to Question

- Classify question into seven categories.

- Who is/was/are/were...?
- When is/did/will/are/were ...?
- Where is/are/were ...?

1. Category-specific transformation rules.

- “Where is the Louvre Museum located”
 - “is the Louvre Museum located”
 - “the is Louvre Museum located”
 - “the Louvre is Museum located”
 - “the Louvre Museum is located”
 - “the Louvre Museum located is”

Nonsense,
but who
cares? It's
only a few
more queries
to Google.

2. Expected answer “Datatype” (eg, Date, Person, Location)

- When was the French Revolution? → DATE

3. Hand-crafted classification/rewrite/datatype rules

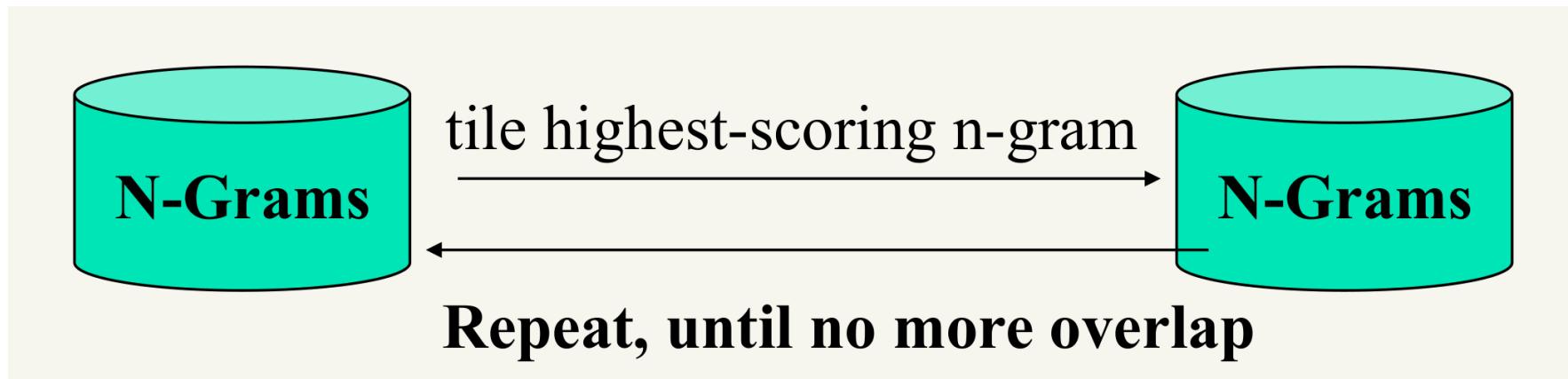
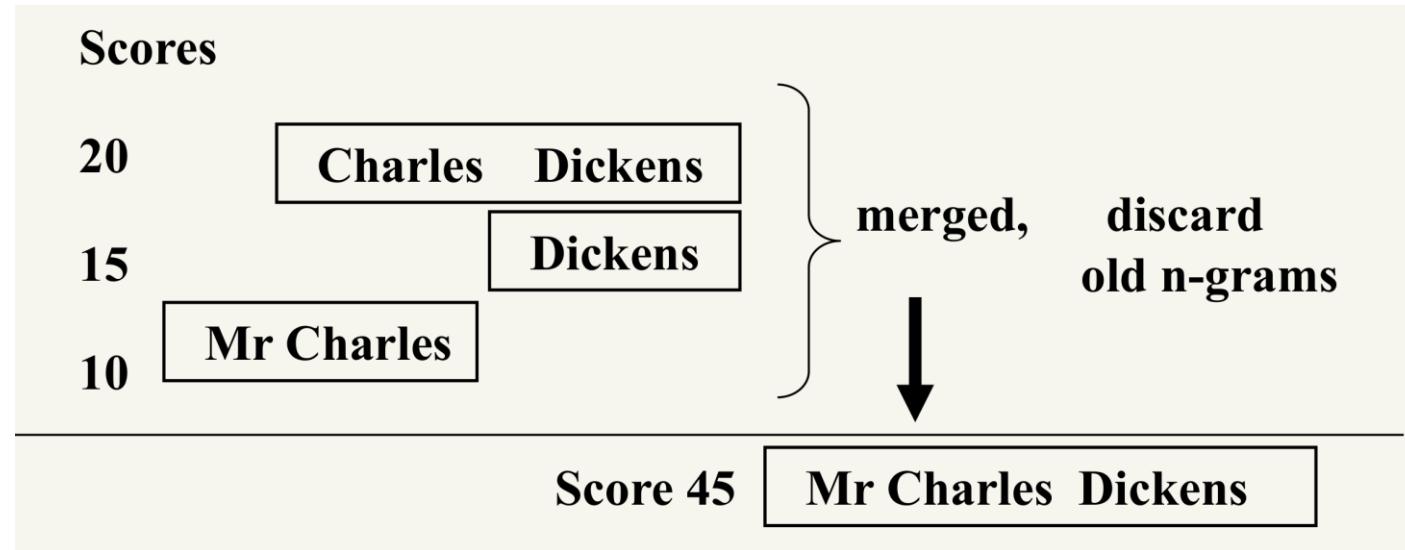
Step 3: Mining N-Grams

- Send query to search engine; use result snippets
- Enumerate all N-grams in all retrieved snippets
 - Use hash table and other fancy footwork to make this efficient
- Weight of an n-gram: occurrence count, each weighted by “reliability” (weight) of rewrite that fetched the document.
- Example: “Who created the character of Scrooge?”
 - Dickens - 117
 - Christmas Carol - 78
 - Charles Dickens - 75
 - Disney - 72
 - Carl Banks - 54
 - A Christmas - 41
 - Christmas Carol - 45
 - Uncle - 31

Step 4: Filtering N-Grams

- Each question type is associated with one or more “data-type filters” = regular expression
 - When
 - Where
 - What
 - Who
 - Boost score of n-grams that do match regexp
 - Lower score of n-grams that don’t match regexp
-
- ```
graph LR; When --> Date; Where --> Date; What --> Location; What --> Person; Who --> Location; Who --> Person;
```

# Step 5: Tiling the Answers



# Results

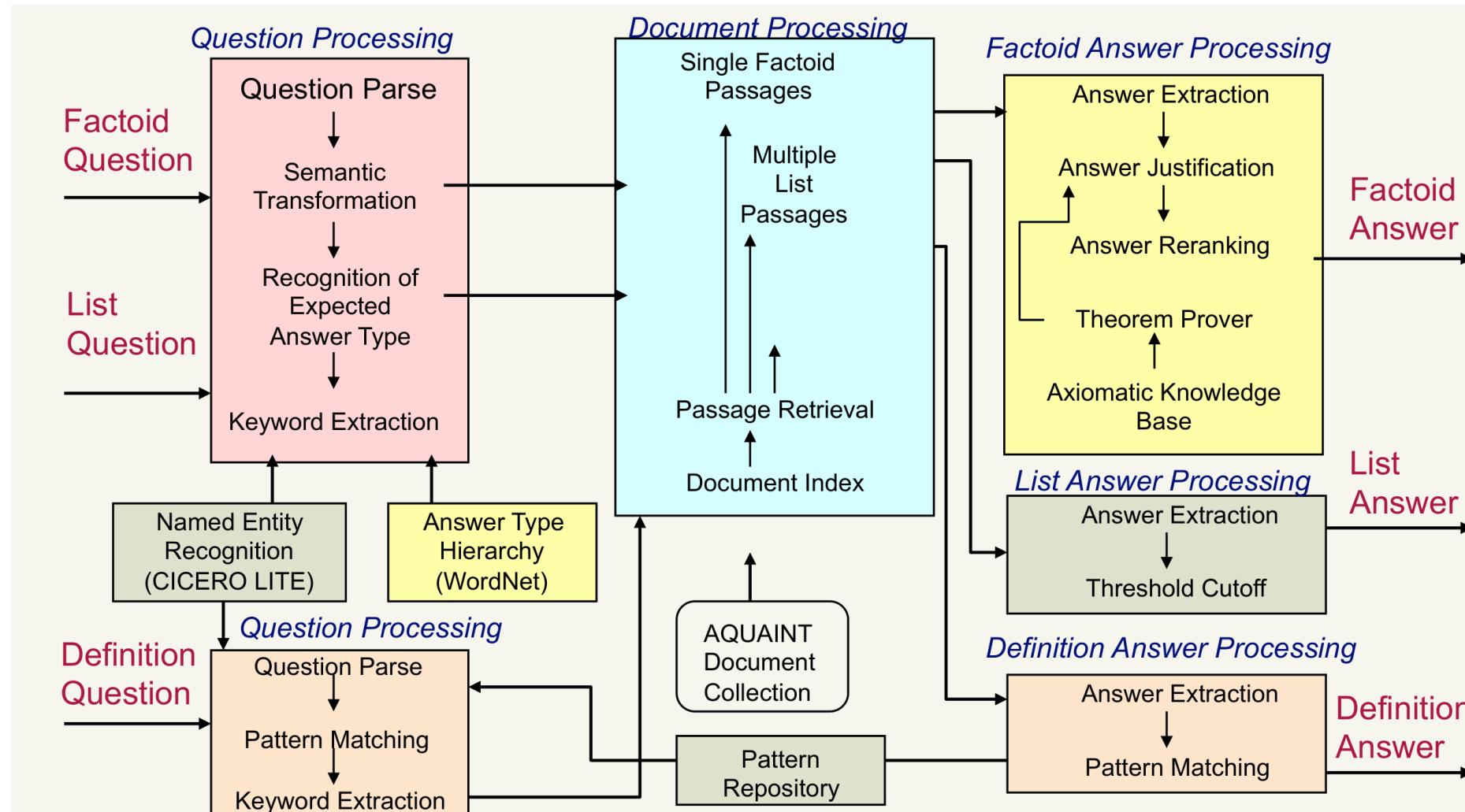
- Standard TREC contest test-bed:  
~1M documents; 900 questions.
- Doesn't do so well (but in top 9 of ~30 participants)
  - MRR = 0.262
    - Right answer ranked about #4–5 on average
    - Why? Because it relies on the enormity of the Web
- Using the Web as a whole, not just TREC's 1M documents
  - MRR = 0.42
  - On average, right answer is ranked about #2–3

# Limitations

- In many scenarios we only have a small set of documents
  - e.g., monitoring an individuals email...
- Works best/only for trivia-style fact-based questions
- Limited/brittle repertoire of
  - question categories
  - answer data types/filters
  - query rewriting rules

# Full NLP QA: LCC (Harabagiu/Moldovan)

below is the Architecture of LCC's QA system circa 2003

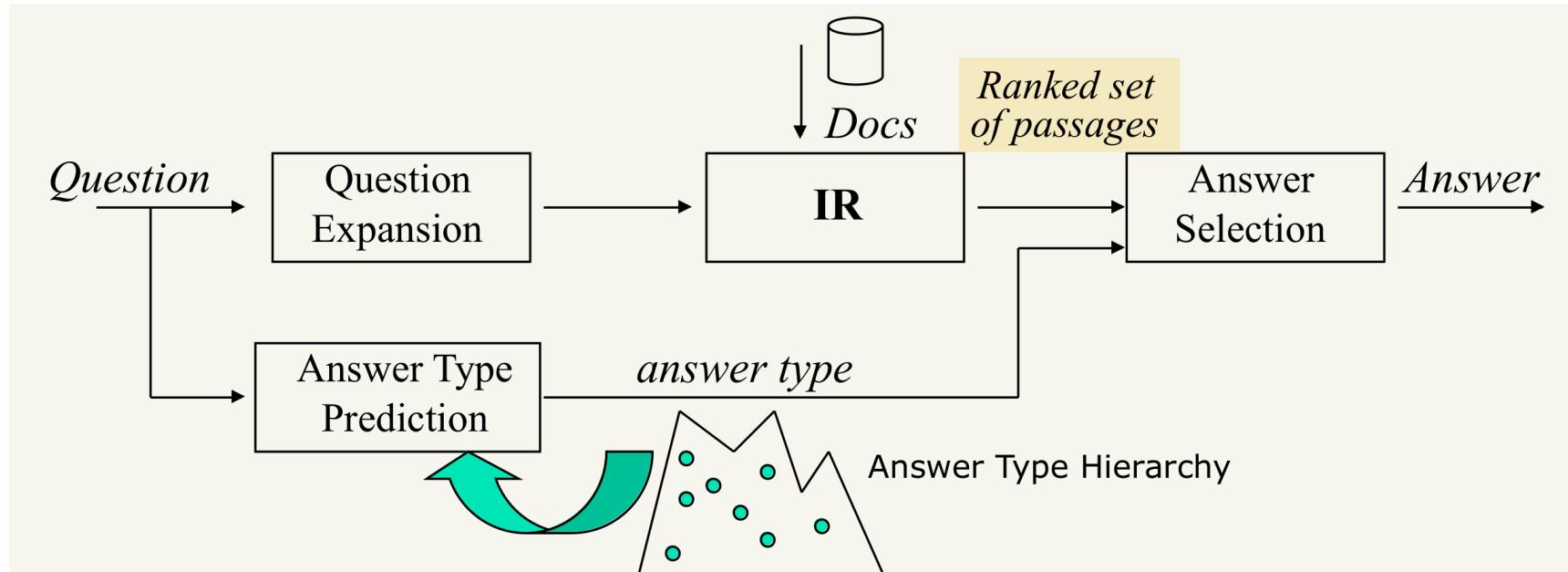


# Value from sophisticated NLP

Pasca and Harabagiu (2001)

- Good IR is needed: SMART paragraph retrieval
- Large taxonomy of question types and expected answer types is crucial
- Statistical parser used to parse questions and relevant text for answers, and to build KB
- Further value comes from deeper NLP and inferencing

# Answer types in LCC QA systems

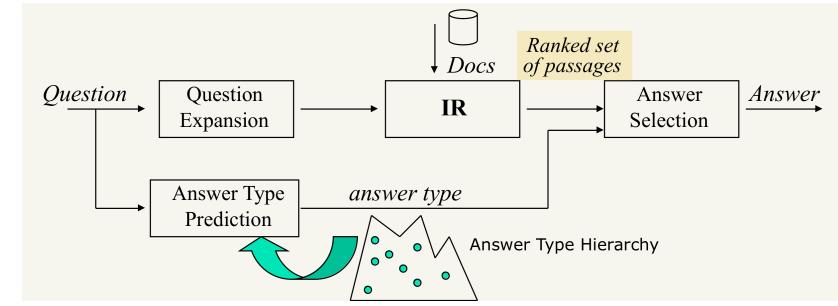


- Answer type
  - Labels questions with answer type based on a taxonomy
  - Person, location, weight, temperature, year, vehicle
  - Classifies questions (e.g. by using a maximum entropy model)

# Answer Types

- Of course, determining the answer type isn't that easy...
- **Who** questions can have organizations as answers
  - *Who sells the most hybrid cars?*
- **Which** questions can have people as answers
  - *Which president went to war with Mexico?*

# Lexical Term Extraction: Input to Information Retrieval



- Questions approximated by sets of unrelated words (lexical terms)
- Similar to bag-of-word IR models: but choose nominal non-stop words and verbs

| Question (from TREC QA track)                                       | Lexical terms                              |
|---------------------------------------------------------------------|--------------------------------------------|
| Q002: What was the monetary value of the Nobel Peace Prize in 1989? | monetary, value, Nobel, Peace, Prize, 1989 |
| Q003: What does the Peugeot company manufacture?                    | Peugeot, company, manufacture              |
| Q004: How much did Mercury spend on advertising in 1993?            | Mercury, spend, advertising, 1993          |

# Keyword Selection Algorithm

1. Select all non-stopwords in quotations
2. Select all NNP words in recognized named entities
3. Select all complex nominals with their adjectival modifiers
4. Select all other complex nominals
5. Select all nouns with adjectival modifiers
6. Select all other nouns
7. Select all verbs
8. Select the answer type word

# Passage Extraction Loop

- Passage Extraction Component
  - Extracts passages that contain all selected keywords
  - Passage size dynamic
  - Start position dynamic
- Passage quality and keyword adjustment
  - In the first iteration use the first 6 keyword selection heuristics
  - If the number of passages is lower than a threshold
    - ⇒ query is too strict
    - ⇒ drop a keyword
  - If the number of passages is higher than a threshold
    - ⇒ query is too relaxed
    - ⇒ add a keyword

# Passage Scoring

- Passage ordering is performed using a sort that involves three scores:
  - The number of words from the question that are recognized in the same sequence in the window
  - The number of words that separate the most distant keywords in the window
  - The number of unmatched keywords in the window

# Rank candidate answers in retrieved passages

Q066: Name the first private citizen to fly in space.

- Answer type: **Person**
- Text passage:

“Among them was **Christa McAuliffe**, the first private citizen to fly in space. **Karen Allen**, best known for her starring role in “Raiders of the Lost Ark”, plays **McAuliffe**. **Brian Kerwin** is featured as shuttle pilot **Mike Smith**...”
- Best candidate answer: **Christa McAuliffe**

# Extracting Answers for Factoid Questions: NER!

- In TREC 2003 the LCC QA system extracted 289 correct answers for factoid questions
- The Name Entity Recognizer was responsible for 234 of them
  - Current QA is largely based on the high accuracy recognition of a large variety of Named Entity types

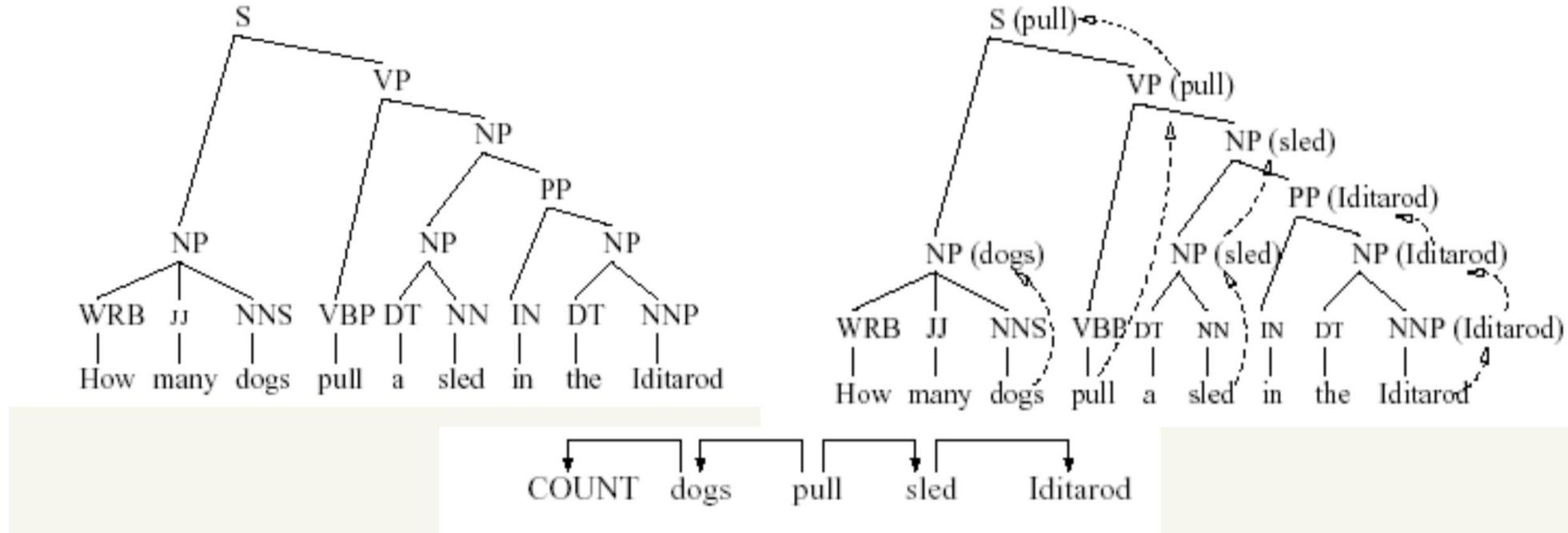
|                 |    |               |    |              |   |
|-----------------|----|---------------|----|--------------|---|
| QUANTITY        | 55 | ORGANIZATION  | 15 | PRICE        | 3 |
| NUMBER          | 45 | AUTHORED WORK | 11 | SCIENCE NAME | 2 |
| DATE            | 35 | PRODUCT       | 11 | ACRONYM      | 1 |
| PERSON          | 31 | CONTINENT     | 5  | ADDRESS      | 1 |
| COUNTRY         | 21 | PROVINCE      | 5  | ALPHABET     | 1 |
| OTHER LOCATIONS | 19 | QUOTE         | 5  | URI          | 1 |
| CITY            | 19 | UNIVERSITY    | 3  |              |   |

# Semantics and Reasoning for QA:

## Predicate-argument structure

- Q336: *When was Microsoft established?*
- This question is difficult because Microsoft tends to establish lots of things...
  - *Microsoft plans to establish manufacturing partnerships in Brazil and Mexico in May.*
- Need to be able to detect sentences in which ‘Microsoft’ is **object** of ‘establish’ or close synonym.
- Matching sentence:
  - *Microsoft Corp was founded in the US in 1975, incorporated in 1981, and established in the UK in 1982.*
- Requires analysis of sentence syntax/semantics

# Semantics and Reasoning for QA: Syntax to Logical Forms



- Syntactic analysis plus semantic => logical form
- Mapping of question and potential answer LFs to find the best match

# Abductive inference

- System attempts inference to justify an answer (often following lexical chains)
- Their inference is a kind of funny middle ground between logic and pattern matching
- But very effective: 30% improvement
  - Q: When was the internal combustion engine invented?
  - A: The first internal-combustion engine was built in 1867.
  - invent → create\_mentally → create → build

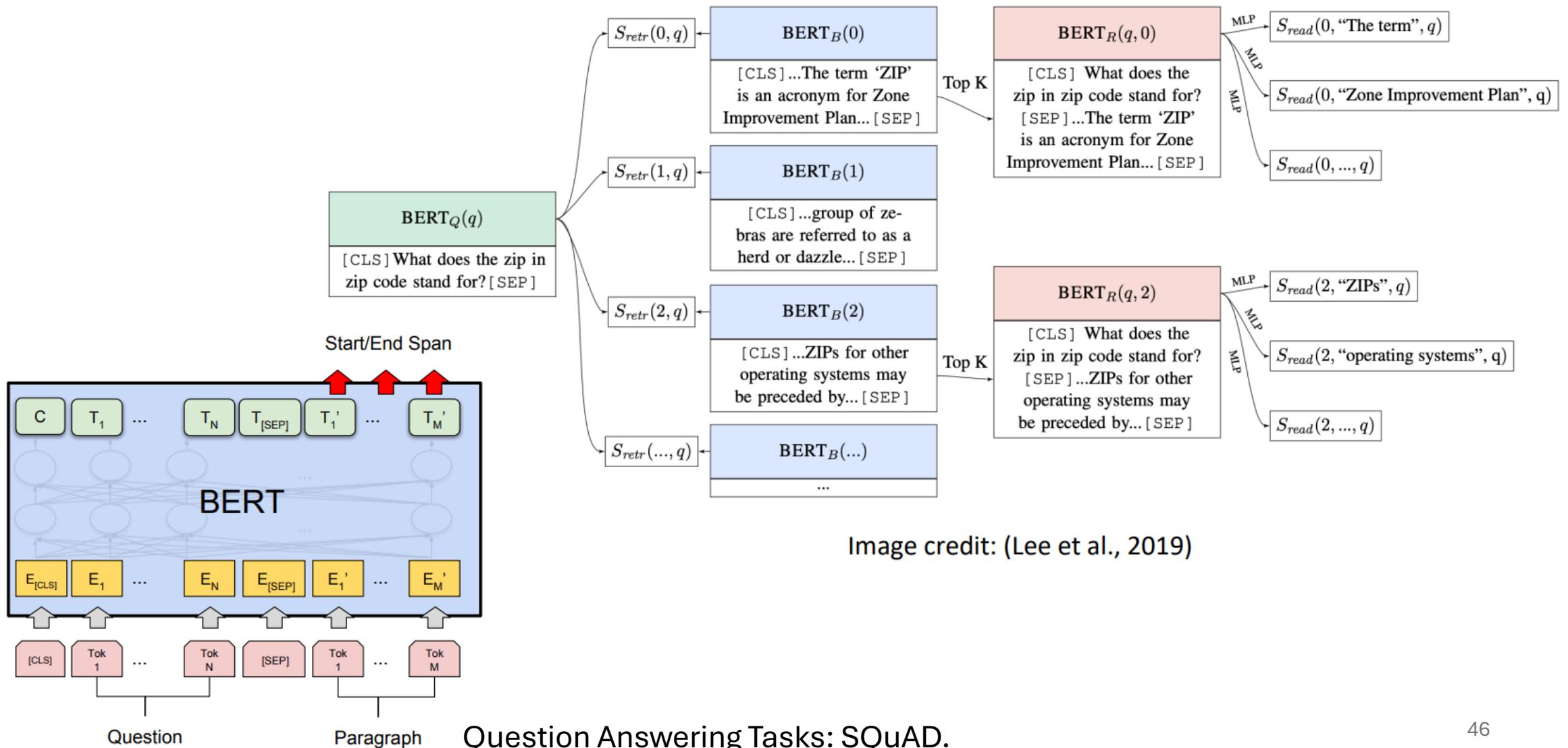
# Question Answering and Inference

- How hot does the inside of an active **volcano** get?
  - `get(TEMPERATURE, inside(volcano(active)))`
- A: “**lava** fragments belched out of the **mountain** were as hot as 300 degrees Fahrenheit”
- `fragments(X, lava, temperature(degrees(300)), belched(X, mountain))`
  - volcano IS\_A mountain
  - lava IS\_PART\_OF volcano
  - lava inside volcano
  - fragments of lava HAVE\_PROPERTIES\_OF lava
- The needed semantic information is in WordNet definitions, and was successfully translated into a form that was used for rough “proofs.”

# Not all problems are solved by these

- Where do lobsters like to live?
  - on a Canadian airline
- Where are zebras most likely found?
  - near dumps
  - in the dictionary
- Why can't ostriches fly?
  - Because of American economic sanctions
- What's the population of Mexico?
  - Three
- What can trigger an allergic reaction?
  - ..something that can **trigger** an allergic reaction

# Question answering in deep learning era



# SQuAD: Stanford question answering dataset

---

- 100k annotated (passage, question, answer) triples
  - Large-scale supervised datasets are also a key ingredient for training effective neural models for reading comprehension!
- Passages are selected from English Wikipedia, usually 100~150 words.
- Questions are crowd-sourced.
- Each answer is a short segment of text (or span) in the passage.
  - This is a limitation— not all the questions can be answered in this way!
- SQuAD was for years the most popular reading comprehension dataset; it is “almost solved” today (though the underlying task is not,) and the state-of-the-art exceeds the estimated human performance.
- SQuAD 2.0: some questions can’t be answered.

In meteorology, precipitation is any product of the condensation of atmospheric water vapor that falls under **gravity**. The main forms of precipitation include drizzle, rain, sleet, snow, **graupel** and hail... Precipitation forms as smaller droplets coalesce via collision with other rain drops or ice crystals **within a cloud**. Short, intense periods of rain in scattered locations are called “showers”.

What causes precipitation to fall?  
**gravity**

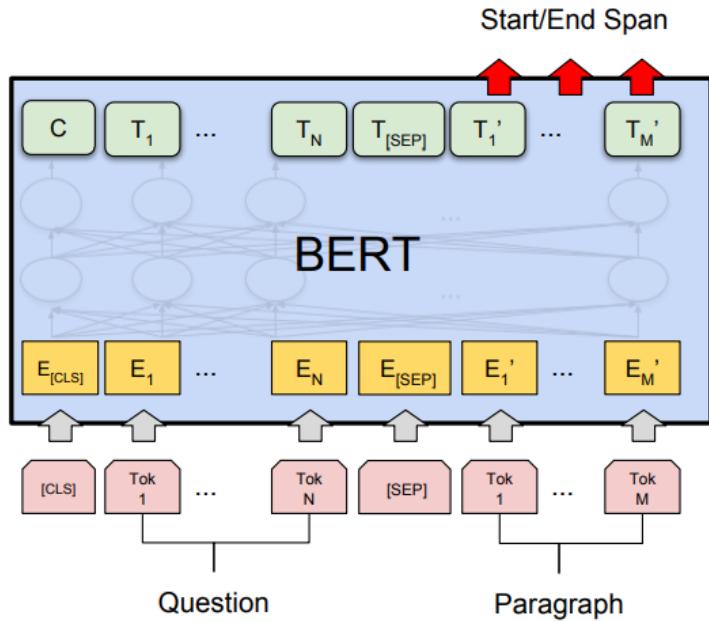
What is another main form of precipitation besides drizzle, rain, snow, sleet and hail?  
**graupel**

Where do water droplets collide with ice crystals to form precipitation?  
**within a cloud**

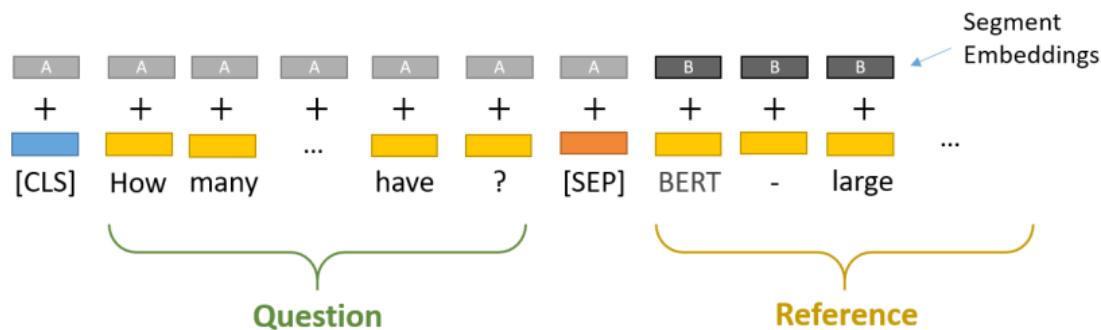
---

<https://rajpurkar.github.io/SQuAD-explorer/>

# BERT for Reading Comprehension



- This simplified version of QA aka **Reading Comprehension**.
  - (Passage, Question)  $\Rightarrow$  Answer



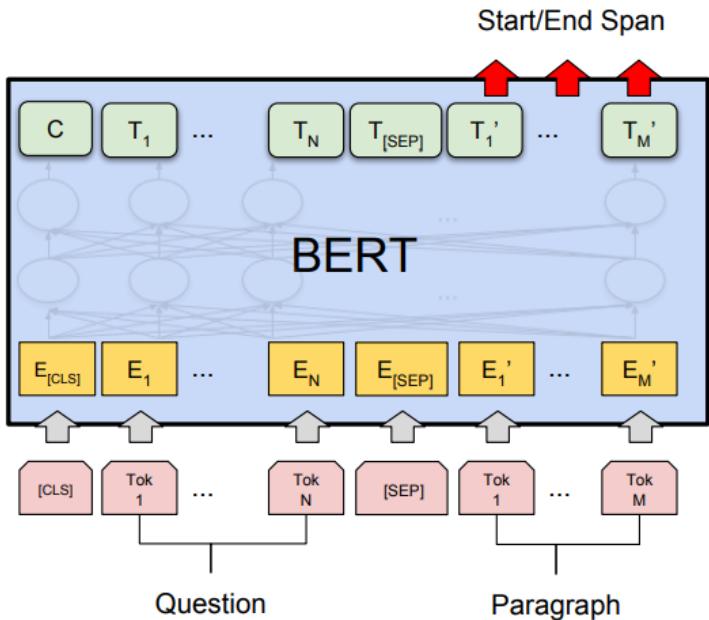
$$p_{\text{start}}(i) = \text{softmax}(\mathbf{W}_s \mathbf{h}_i)$$

$$p_{\text{end}}(i) = \text{softmax}(\mathbf{W}_e \mathbf{h}_i)$$

**Question:** How many parameters does BERT-large have?

**Reference Text:** BERT-large is really big... it has 24 layers and an embedding size of 1,024, for a total of 340M parameters! Altogether it is 1.34GB, so expect it to take a couple minutes to download to your Colab instance.

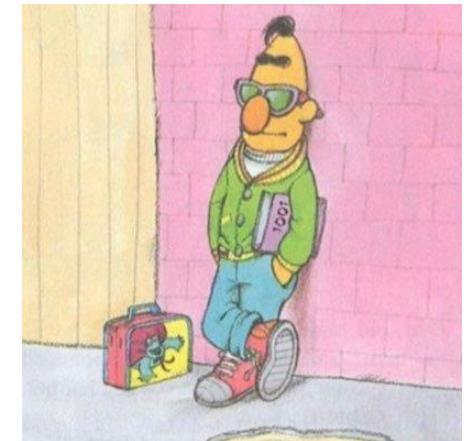
# BERT for Reading Comprehension



$$p_{\text{start}}(i) = \text{softmax}(\mathbf{W}_s \mathbf{h}_i)$$

$$p_{\text{end}}(i) = \text{softmax}(\mathbf{W}_e \mathbf{h}_i)$$

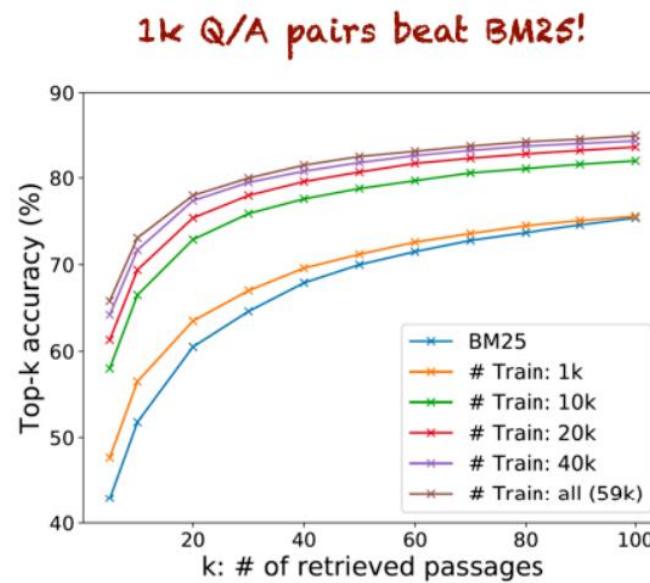
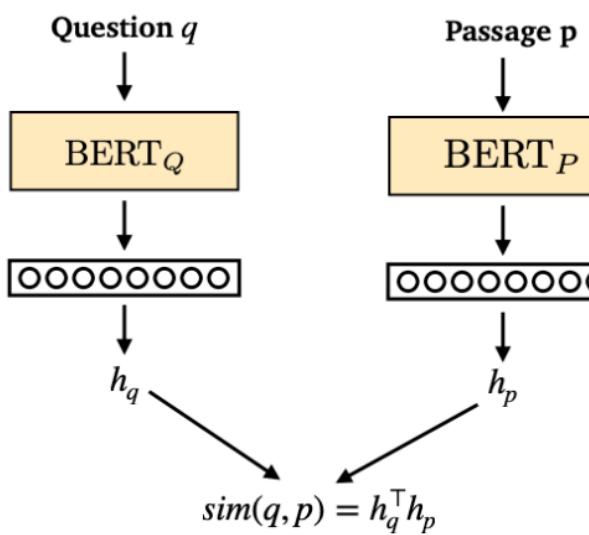
- This simplified version of QA aka **Reading Comprehension**.
  - (Passage, Question)  $\Rightarrow$  Answer



|                   | F1    | EM    |
|-------------------|-------|-------|
| Human performance | 91.2* | 82.3* |
| BiDAF             | 77.3  | 67.7  |
| BERT-base         | 88.5  | 80.8  |
| BERT-large        | 90.9  | 84.1  |
| XLNet             | 94.5  | 89.0  |
| RoBERTa           | 94.6  | 88.9  |
| ALBERT            | 94.8  | 89.3  |

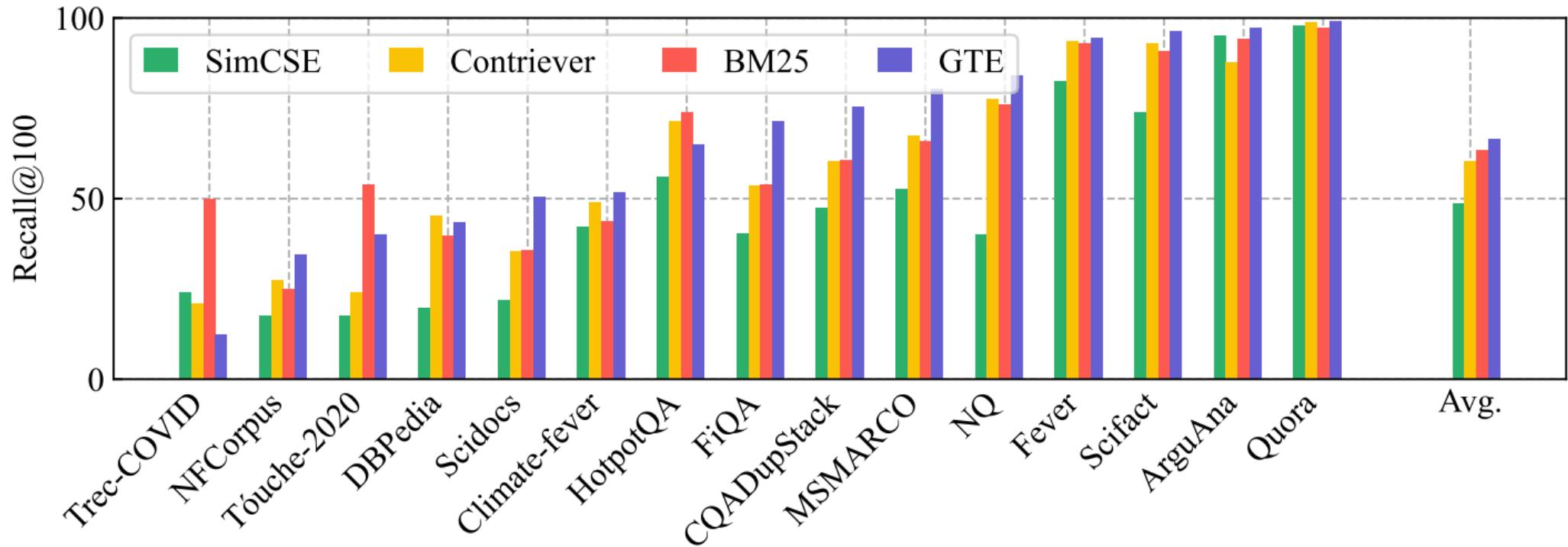
# BERT for IR

- Dense passage retrieval (DPR)
  - We can also just train the retriever using question-answer pairs!



- Trainable retriever (using BERT) largely outperforms traditional IR retrieval models.

# Improvements



- GTE: general-purpose text embedding
  - Multi-stage contrastive learning.
  - Recall SBERT, SimCSE.

# Retrieval-Augmented Generation (RAG)

- Sounds fancy, but actually very simple.
- RAG:
  - Step 1: retrieve N documents using some IR algorithm.
  - Step 2: write the augmented query.

Context information is below.

-----

{context\_str}

-----

Given the context information and not  
prior knowledge, answer the query.

Query: {query\_str}

Answer:

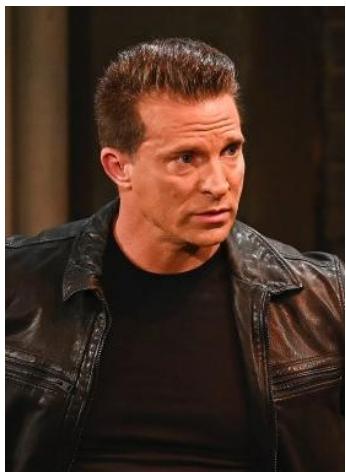
Prompt templates:

[https://github.com/  
run-llama/llama\\_index](https://github.com/run-llama/llama_index)

- Step 3: Profit.

# Distraction in RAG

- Distraction:
  - When a piece of irrelevant context is provided, the model generates an incorrect response.



Q: Who is the actor playing Jason on general hospital?

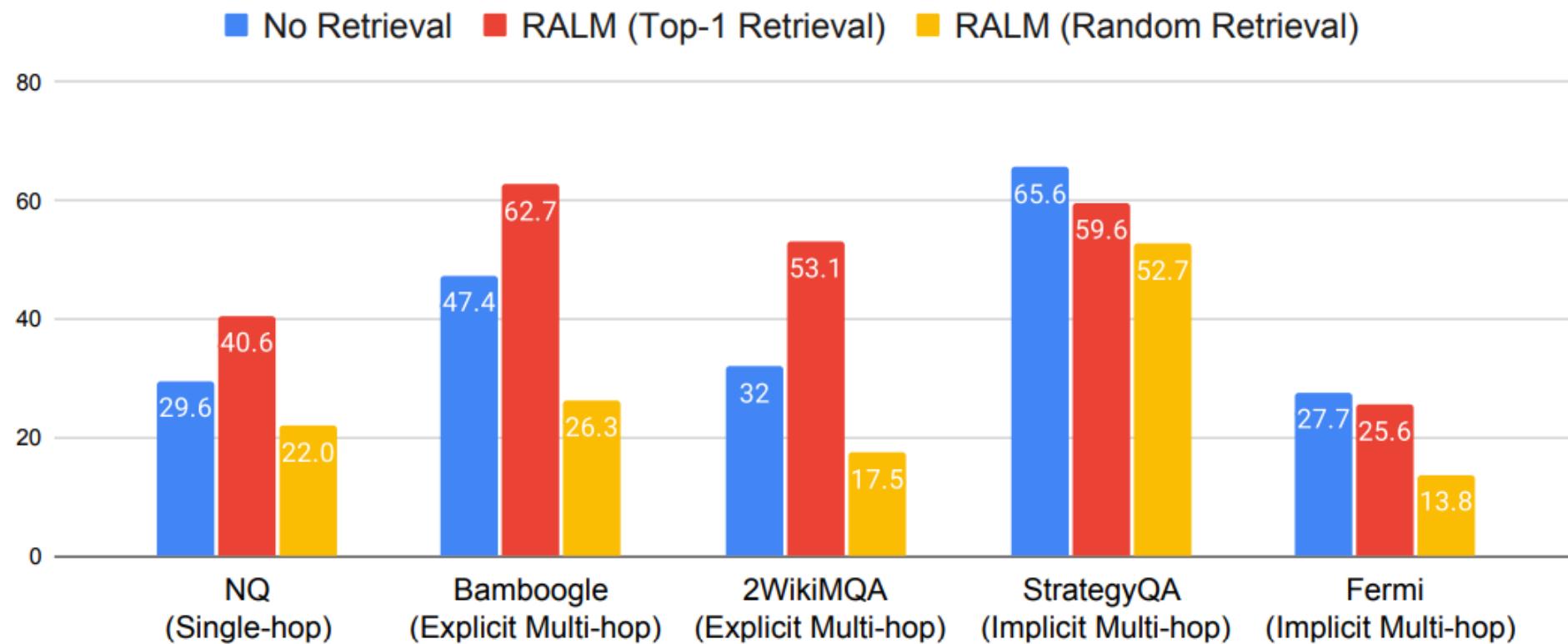
Large Language Model (no retrieval) The answer is: Steve Burton

Retrieval Augmented Language Model E: Jason Gerhardt (born April 21, 1974) is an American actor. He is known for playing the role of Cooper Barrett in General Hospital and Zack Kilmer in Mistresses. The answer is: Jason Gerhardt



- **Relevant** refers to whether the correct answer is in the prompt or not.

# Distraction in RAG



# Solution #1: Use NLI to filter irrelevant context

- Review: NLI models
  - Premise:
    - *If you help the needy, God will reward you.*
  - Hypotheses:
    - *Giving money to a poor man has good consequences.*
    - *Giving money to a poor man has no consequences.*
    - *Giving money to a poor man will make you a better person.*
- NLI against distraction:
  - Remove context sentence if it contradicts the question.

Entailment  
Contradiction  
Neutral

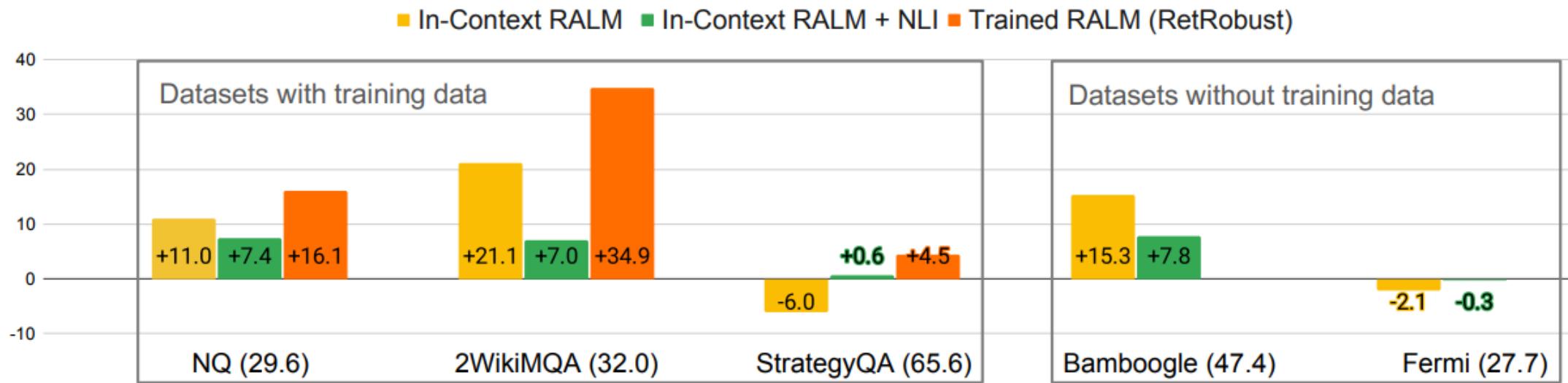
# Solution #2: Finetuning

- Fine-tune the LM with:
  - Both relevant and irrelevant contexts

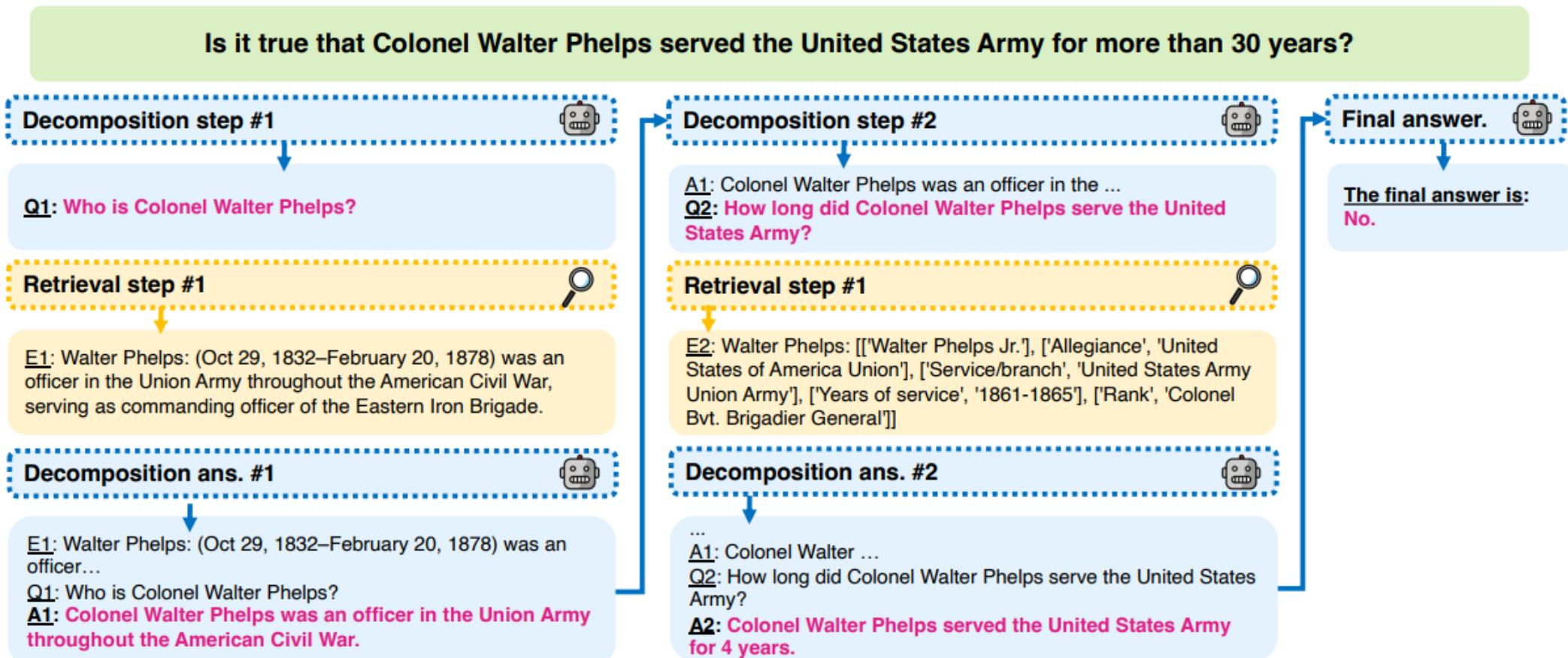
Q: Who is the actor playing Jason on general hospital?

|                                                                                                                                                                                                                                                                                                                                               |                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                |
|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| <b>Large Language Model (no retrieval)</b> <br><div style="border: 2px dotted blue; padding: 5px; background-color: #e0f2e0;"><u>The answer is: Steve Burton</u></div>  | <b>Retrieval Augmented Language Model</b> <br><div style="border: 2px dotted blue; padding: 5px; background-color: #e0f2e0;"><p>E: Jason Gerhardt (born April 21, 1974) is an American actor. He is known for playing the role of Cooper Barrett in General Hospital and Zack Kilmer in Mistresses.</p><p><u>The answer is: Jason Gerhardt</u> Steve Burton</p></div>  |
|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|

# Distraction in RAG: Mitigation Result



# Solution #3: Interleaving decomposition

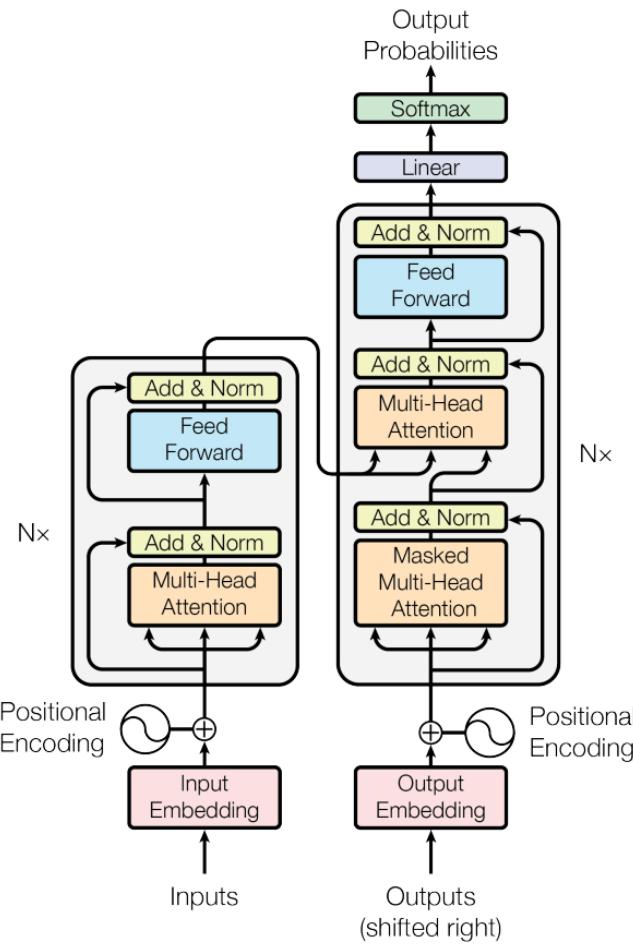


# Prompt Engineering

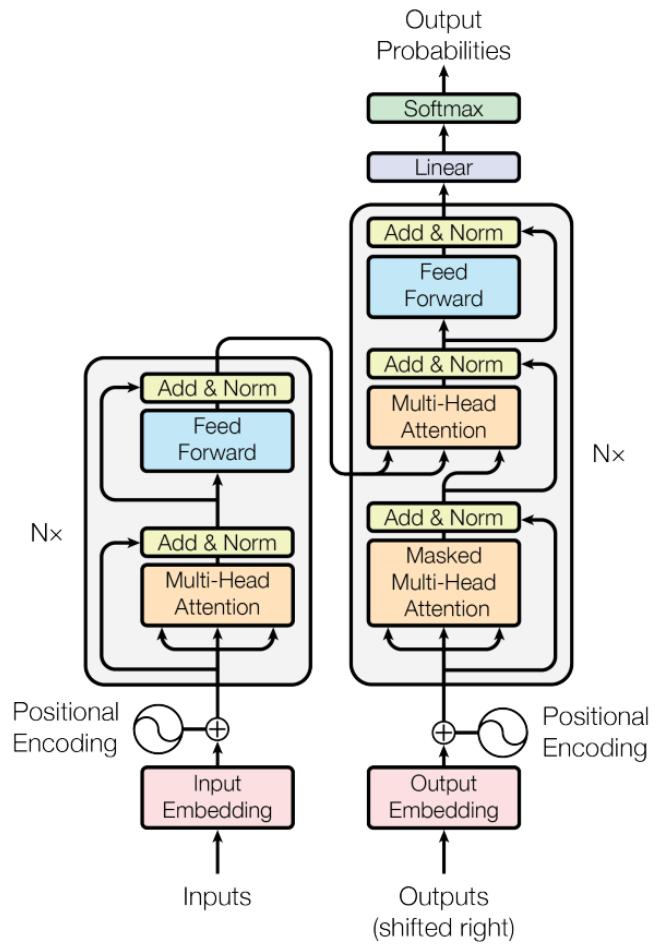
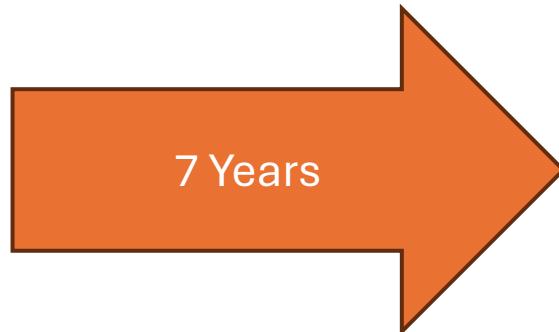
We will return to interleaving decomposition soon



# LLM Architecture Development Progress



Vaswani et al. (2017)  
Attention is All You Need



LLaMA 3.1 (2024)  
GPT-4 (2024)

...

<https://github.com/meta-llama/llama3/blob/main/llama/model.py>

```
class TransformerBlock(nn.Module):
 def __init__(self, layer_id: int, args: ModelArgs):
 super().__init__()
 self.n_heads = args.n_heads
 self.dim = args.dim
 self.head_dim = args.dim // args.n_heads
 self.attention = Attention(args)
 self.feed_forward = FeedForward(
 dim=args.dim,
 hidden_dim=4 * args.dim,
 multiple_of=args.multiple_of,
 ffn_dim_multiplier=args.ffn_dim_multiplier,
)
 self.layer_id = layer_id
 self.attention_norm = RMSNorm(args.dim, eps=args.norm_eps)
 self.ffn_norm = RMSNorm(args.dim, eps=args.norm_eps)

 def forward(
 self,
 x: torch.Tensor,
 start_pos: int,
 freqs_cis: torch.Tensor,
 mask: Optional[torch.Tensor],
):
 h = x + self.attention(self.attention_norm(x), start_pos, freqs_cis, mask)
 out = h + self.feed_forward(self.ffn_norm(h))
 return out
```

Large Language Model  
Introducing Meta Llama 3: The most capable  
openly available LLM to date  
April 18, 2024



Architectural Changes



Post-training

# Limits of prompting for harder tasks?

- Some tasks seem too hard for even large LMs to learn through prompting alone.
- Especially tasks involving richer, multi-step reasoning.

$$19583 + 29534 = 49117$$

$$98394 + 49384 = 147778$$

$$29382 + 12347 = 41729$$

$$93847 + 39299 = ?$$

**Improvement:** change the prompt!

# Chain-of-thought

## Standard Prompting

Model Input

Q: Roger has 5 tennis balls. He buys 2 more cans of tennis balls. Each can has 3 tennis balls. How many tennis balls does he have now?

A: The answer is 11.

Q: The cafeteria had 23 apples. If they used 20 to make lunch and bought 6 more, how many apples do they have?

Model Output

A: The answer is 27. 

## Chain-of-Thought Prompting

Model Input

Q: Roger has 5 tennis balls. He buys 2 more cans of tennis balls. Each can has 3 tennis balls. How many tennis balls does he have now?

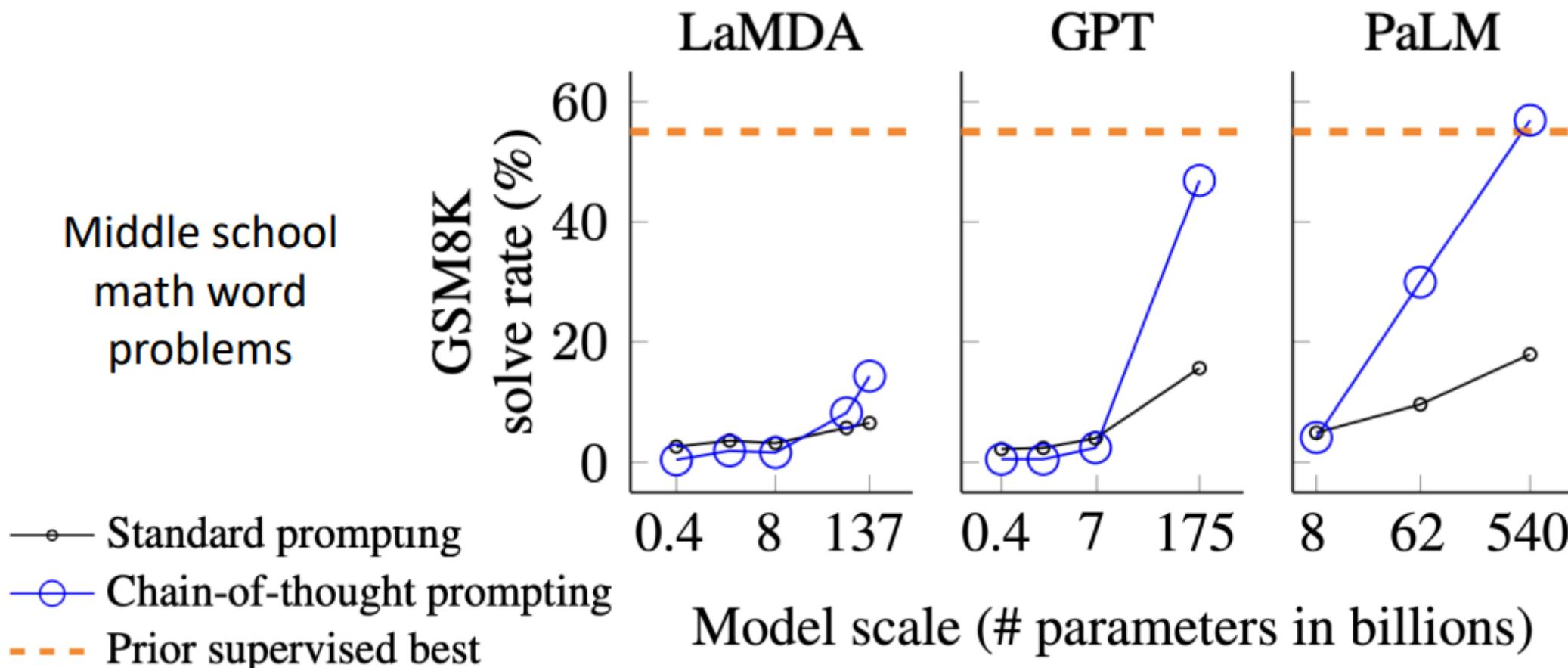
A: Roger started with 5 balls. 2 cans of 3 tennis balls each is 6 tennis balls.  $5 + 6 = 11$ . The answer is 11.

Q: The cafeteria had 23 apples. If they used 20 to make lunch and bought 6 more, how many apples do they have?

Model Output

A: The cafeteria had 23 apples originally. They used 20 to make lunch. So they had  $23 - 20 = 3$ . They bought 6 more apples, so they have  $3 + 6 = 9$ . The answer is 9. 

# Chain-of-thought



# Chain-of-thought

## Model Input

Q: Roger has 5 tennis balls. He buys 2 more cans of tennis balls. Each can has 3 tennis balls. How many tennis balls does he have now?

A: Roger started with 5 balls. 2 cans of 3 tennis balls each is 6 tennis balls.  $5 + 6 = 11$ . The answer is 11.

Q: The cafeteria had 23 apples. If they used 20 to make lunch and bought 6 more, how many apples do they have?

## Model Output

A: The cafeteria had 23 apples originally. They used 20 to make lunch. So they had  $23 - 20 = 3$ . They bought 6 more apples, so they have  $3 + 6 = 9$ . The answer is 9. ✓

**Do we even need examples of reasoning?  
Can we just ask the model to reason through things?**

# Chain-of-thought

## Model Input

Q: Roger has 5 tennis balls. He buys 2 more cans of tennis balls. Each can has 3 tennis balls. How many tennis balls does he have now?

A: Roger started with 5 balls. 2 cans of 3 tennis balls each is 6 tennis balls.  $5 + 6 = 11$ . The answer is 11.

Q: The cafeteria had 23 apples. If they used 20 to make lunch and bought 6 more, how many apples do they have?

## Model Output

A: The cafeteria had 23 apples originally. They used 20 to make lunch. So they had  $23 - 20 = 3$ . They bought 6 more apples, so they have  $3 + 6 = 9$ . The answer is 9. 

Q: A juggler can juggle 16 balls. Half of the balls are golf balls, and half of the golf balls are blue. How many blue golf balls are there?

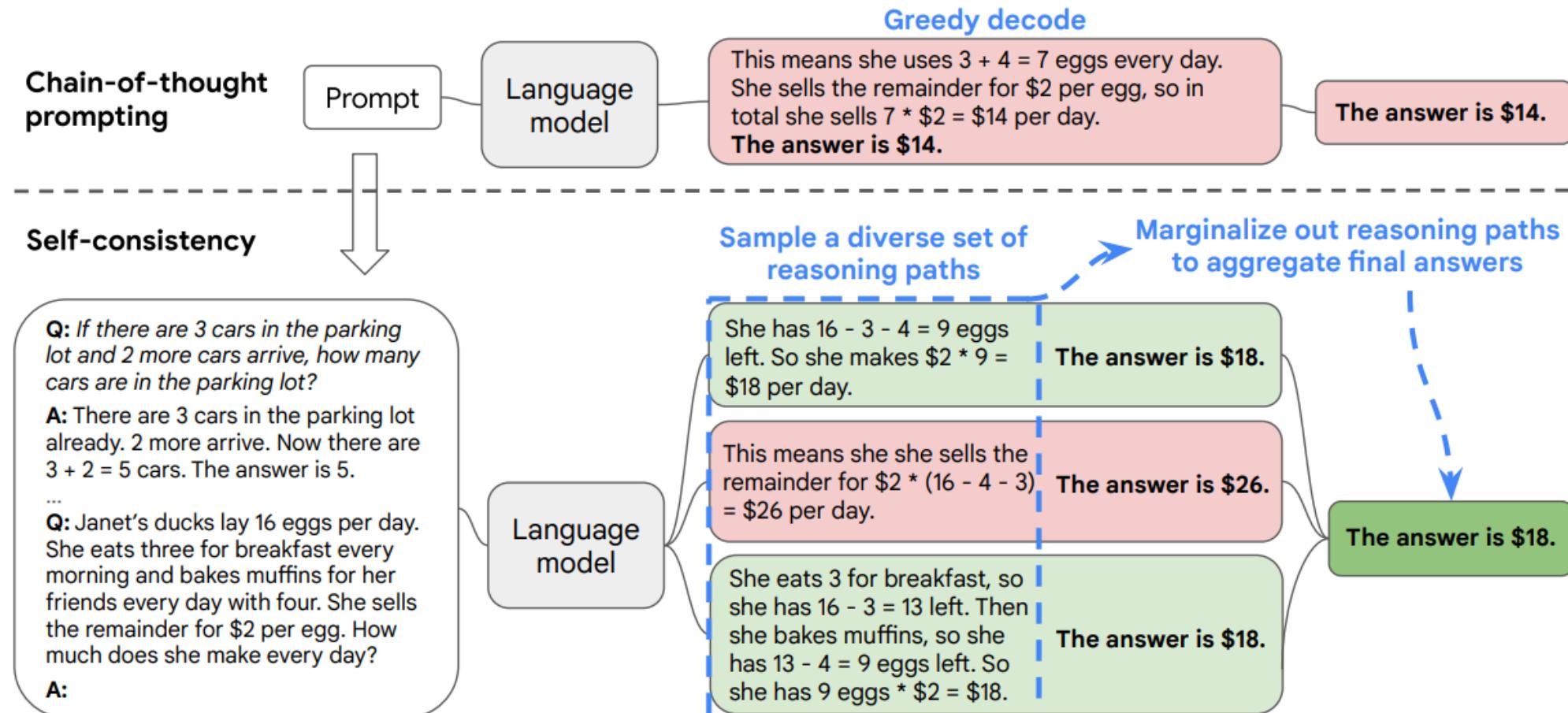
A: **Let's think step by step.** There are 16 balls in total. Half of the balls are golf balls. That means there are 8 golf balls. Half of the golf balls are blue. That means there are 4 blue golf balls. 

# Zero-shot CoT prompting

|                                                | MultiArith                            | GSM8K       |
|------------------------------------------------|---------------------------------------|-------------|
| <b>Zero-Shot</b>                               | <b>17.7</b>                           | <b>10.4</b> |
| Few-Shot (2 samples)                           | 33.7                                  | 15.6        |
| Few-Shot (8 samples)                           | 33.8                                  | 15.6        |
| <b>Zero-Shot-CoT</b>                           | <b>Greatly outperforms zero-shot!</b> | <b>78.7</b> |
| Few-Shot-CoT (2 samples)                       | 84.8                                  | 41.3        |
| Few-Shot-CoT (4 samples : First) (*1)          | 89.2                                  | -           |
| Few-Shot-CoT (4 samples : Second) (*1)         | 90.5                                  | -           |
| Few-Shot-CoT (8 samples)                       | 93.0                                  | 48.7        |
| <b>Zero-Plus-Few-Shot-CoT (8 samples) (*2)</b> | <b>Manual CoT still better</b>        | <b>92.8</b> |
|                                                |                                       | <b>51.5</b> |

# CoT with “Self-consistency”

- Replace greedy decoding with an ensemble of samples...
- Main idea: correct reasoning processes have greater agreement than incorrect processes.



# CoT with “Self-consistency”

|                                | GSM8K          | MultiArith     | AQuA           | SVAMP          | CSQA           | ARC-c          |
|--------------------------------|----------------|----------------|----------------|----------------|----------------|----------------|
| Greedy decode                  | 56.5           | 94.7           | 35.8           | 79.0           | 79.0           | 85.2           |
| Weighted avg (unnormalized)    | $56.3 \pm 0.0$ | $90.5 \pm 0.0$ | $35.8 \pm 0.0$ | $73.0 \pm 0.0$ | $74.8 \pm 0.0$ | $82.3 \pm 0.0$ |
| Weighted avg (normalized)      | $22.1 \pm 0.0$ | $59.7 \pm 0.0$ | $15.7 \pm 0.0$ | $40.5 \pm 0.0$ | $52.1 \pm 0.0$ | $51.7 \pm 0.0$ |
| Weighted sum (unnormalized)    | $59.9 \pm 0.0$ | $92.2 \pm 0.0$ | $38.2 \pm 0.0$ | $76.2 \pm 0.0$ | $76.2 \pm 0.0$ | $83.5 \pm 0.0$ |
| Weighted sum (normalized)      | $74.1 \pm 0.0$ | $99.3 \pm 0.0$ | $48.0 \pm 0.0$ | $86.8 \pm 0.0$ | $80.7 \pm 0.0$ | $88.7 \pm 0.0$ |
| Unweighted sum (majority vote) | $74.4 \pm 0.1$ | $99.3 \pm 0.0$ | $48.3 \pm 0.5$ | $86.6 \pm 0.1$ | $80.7 \pm 0.1$ | $88.7 \pm 0.1$ |

Table 1: Accuracy comparison of different answer aggregation strategies on PaLM-540B.

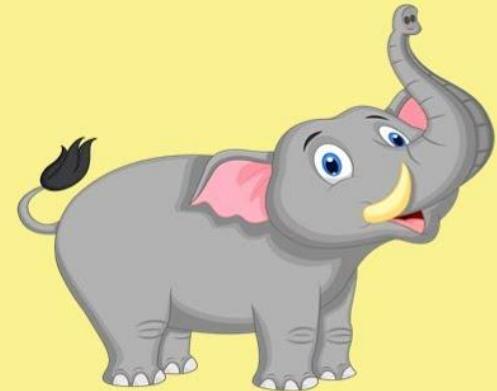
|                                     | GSM8K                            | MultiArith                       | SVAMP                            | ARC-e                            | ARC-c                            |
|-------------------------------------|----------------------------------|----------------------------------|----------------------------------|----------------------------------|----------------------------------|
| CoT (Wei et al., 2022)              | 17.1                             | 51.8                             | 38.9                             | 75.3                             | 55.1                             |
| Ensemble (3 sets of prompts)        | $18.6 \pm 0.5$                   | $57.1 \pm 0.7$                   | $42.1 \pm 0.6$                   | $76.6 \pm 0.1$                   | $57.0 \pm 0.2$                   |
| Ensemble (40 prompt permutations)   | $19.2 \pm 0.1$                   | $60.9 \pm 0.2$                   | $42.7 \pm 0.1$                   | $76.9 \pm 0.1$                   | $57.0 \pm 0.1$                   |
| Self-Consistency (40 sampled paths) | <b><math>27.7 \pm 0.2</math></b> | <b><math>75.7 \pm 0.3</math></b> | <b><math>53.3 \pm 0.2</math></b> | <b><math>79.3 \pm 0.3</math></b> | <b><math>59.8 \pm 0.2</math></b> |

Out-performs  
regular CoT on a  
variety of  
benchmarks

Self-consistency is  
doing more than  
simple ensembling

# Least-to-Most prompting

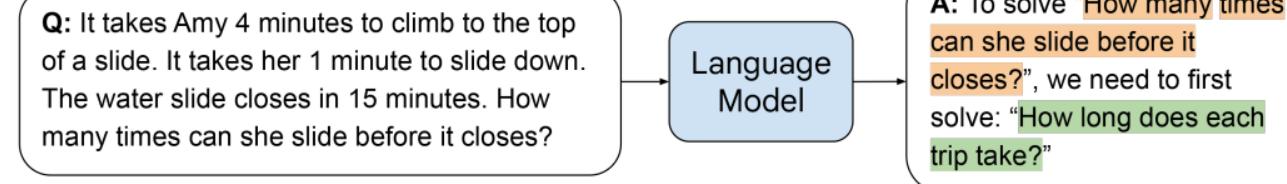
How do you put an elephant  
into a refrigerator in 3  
steps?



# Least-to-Most prompting

- **Idea:** decompose a problem into smaller ones.

## Stage 1: Decompose Question into Subquestions



# Least-to-Most prompting

- **Idea:** decompose a problem into smaller ones.

## Stage 1: Decompose Question into Subquestions

Q: It takes Amy 4 minutes to climb to the top of a slide. It takes her 1 minute to slide down. The water slide closes in 15 minutes. How many times can she slide before it closes?

Language Model

A: To solve "How many times can she slide before it closes?", we need to first solve: "How long does each trip take?"

## Stage 2: Sequentially Solve Subquestions

It takes Amy 4 minutes to climb to the top of a slide. It takes her 1 minute to slide down. The slide closes in 15 minutes.

Q: How long does each trip take?

Language Model

A: It takes Amy 4 minutes to climb and 1 minute to slide down.  $4 + 1 = 5$ . So each trip takes 5 minutes.

Append model answer to Subquestion 1

It takes Amy 4 minutes to climb to the top of a slide. It takes her 1 minute to slide down. The slide closes in 15 minutes.

Q: How long does each trip take?

A: It takes Amy 4 minutes to climb and 1 minute to slide down.  $4 + 1 = 5$ . So each trip takes 5 minutes.

Q: How many times can she slide before it closes?

Language Model

A: The water slide closes in 15 minutes. Each trip takes 5 minutes. So Amy can slide  $15 \div 5 = 3$  times before it closes.

Subquestion 2

# Least-to-Most prompting for Math Reasoning

Q: Elsa has 5 apples. Anna has 2 more apples than Elsa. How many apples do they have together?

A: Anna has 2 more apples than Elsa, so Anna has  $2 + 5 = 7$  apples. Elsa and Anna have  $5 + 7 = 12$  apples together. The answer is 12.

Standard CoT prompting

Q: Elsa has 5 apples. Anna has 2 more apples than Elsa. How many apples do they have together?

A: Let's break down this problem: 1. How many apples does Anna have? 2. How many apples do Elsa and Anna have together?

1. Anna has 2 more apples than Elsa. So Anna has  $2 + 5 = 7$  apples.

2. Elsa and Anna have  $5 + 7 = 12$  apples together.

Least-to-most prompting

Q: {question}

A: Let's break down this problem:

---

The answer is:

# Least-to-Most prompting for Math Reasoning

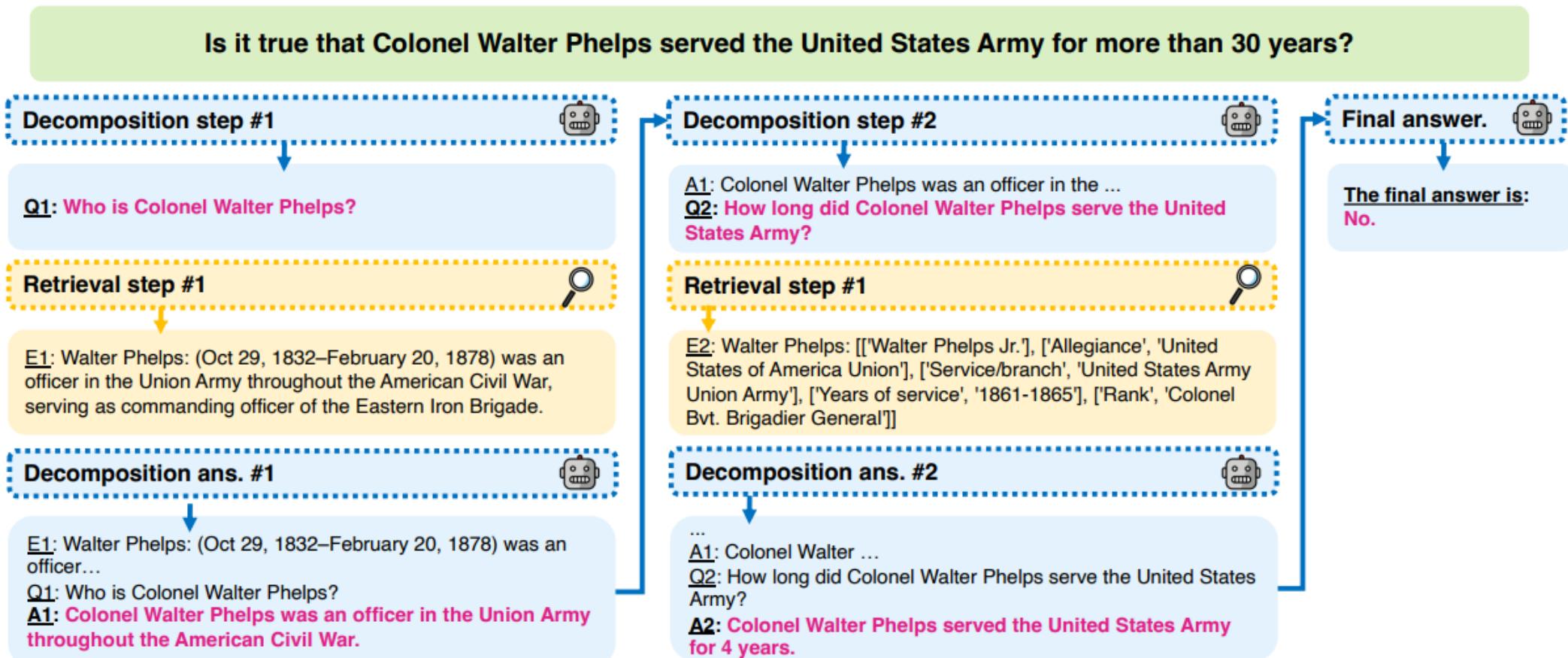
| Accuracy by Steps (GSM8K) | All          | 2 Steps      | 3 Steps      | 4 steps      | $\geq$ 5 steps |
|---------------------------|--------------|--------------|--------------|--------------|----------------|
| Least-to-Most             | <b>62.39</b> | 74.53        | <b>68.91</b> | <b>59.73</b> | <b>45.23</b>   |
| Chain-of-Thought          | 60.87        | <b>76.68</b> | 67.29        | 59.39        | 39.07          |

Generalizes to more #steps than in-context example!

| Prompting method            | Accuracy                  |
|-----------------------------|---------------------------|
| Zero-Shot                   | 16.38                     |
| Standard prompting          | 17.06 <sup>3</sup>        |
| Chain-of-Thought (original) | 61.18                     |
| Chain-of-Thought (1-shot)   | 60.88                     |
| Least-to-Most (1-shot)      | 62.39                     |
| Chain-of-Thought (best)     | <b>68.61</b> <sup>3</sup> |
| Least-to-Most (best)        | 68.01                     |

But with enough prompt engineering, CoT  $\approx$  Least-to-Most

# Solution #3: Interleaving decomposition



# Solution #3: Interleaving decomposition SelfAsk

## Direct Prompting

GPT-3

Question: Who lived longer, Theodor Haecker or Harry Vaughan Watkins?

Answer: Harry Vaughan Watkins.

Question: Who was president of the U.S. when superconductivity was discovered?

Answer: Franklin D. Roosevelt 

## Chain of Thought

GPT-3

Question: Who lived longer, Theodor Haecker or Harry Vaughan Watkins?

Answer: Theodor Haecker was 65 years old when he died. Harry Vaughan Watkins was 69 years old when he died.

So the final answer (the name of the person) is: Harry Vaughan Watkins.

Question: Who was president of the U.S. when superconductivity was discovered?

Answer: Superconductivity was discovered in 1911 by Heike Kamerlingh Onnes. Woodrow Wilson was president of the United States from 1913 to 1921. So the final answer (the name of the president) is: Woodrow Wilson. 

## Self-Ask

GPT-3

Question: Who lived longer, Theodor Haecker or Harry Vaughan Watkins?

Are follow up questions needed here: Yes.

Follow up: How old was Theodor Haecker when he died?

Intermediate answer: Theodor Haecker was 65 years old when he died.

Follow up: How old was Harry Vaughan Watkins when he died?

Intermediate answer: Harry Vaughan Watkins was 69 years old when he died.

So the final answer is: Harry Vaughan Watkins

Question: Who was president of the U.S. when superconductivity was discovered?

Are follow up questions needed here: Yes.

Follow up: When was superconductivity discovered?

Intermediate answer: Superconductivity was discovered in 1911.

Follow up: Who was president of the U.S. in 1911?

Intermediate answer: William Howard Taft.

So the final answer is: William Howard Taft. 

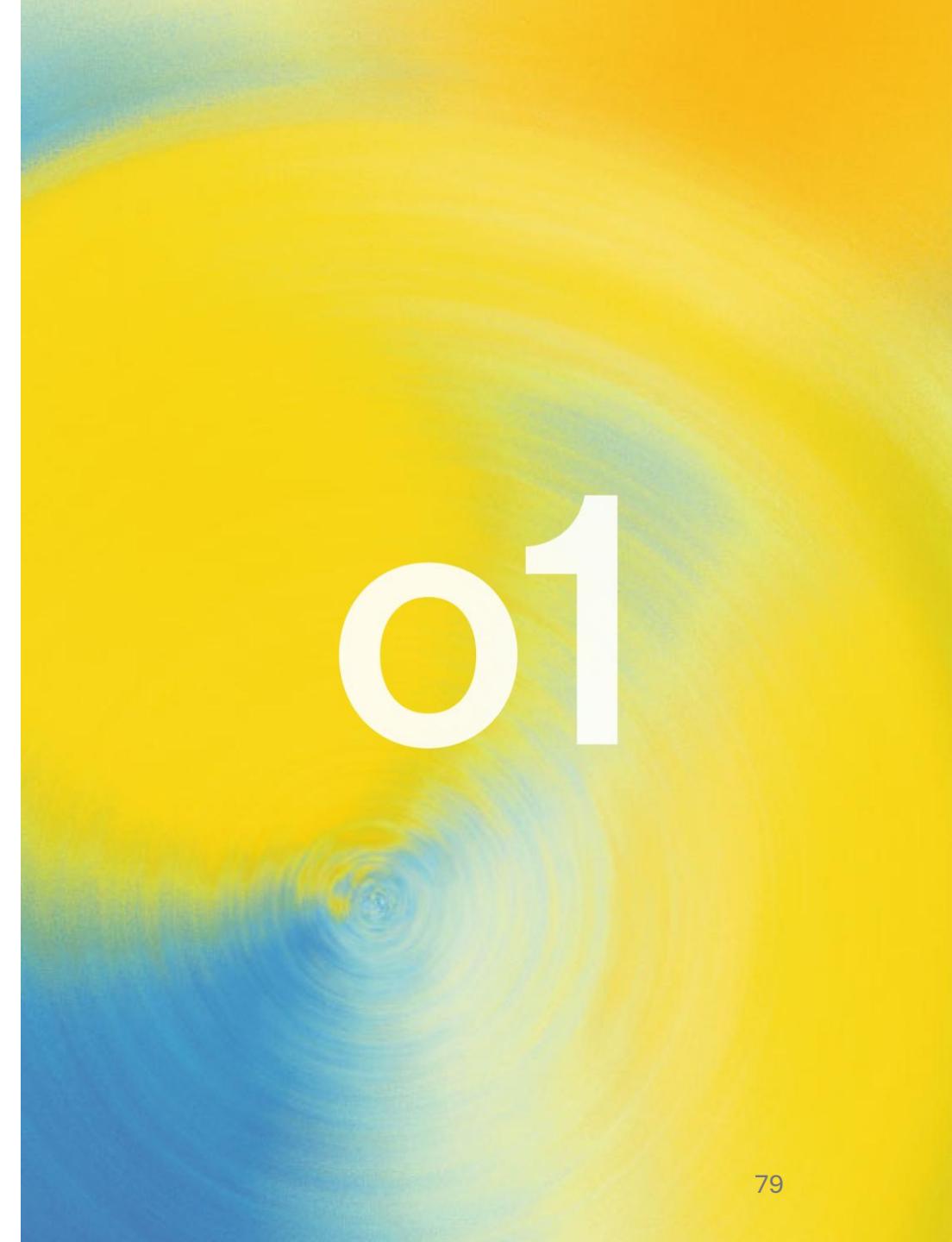
# Solution #3: Interleaving decomposition SelfAsk

|                    | Bamb.       | 2Wiki.      | Musique     |
|--------------------|-------------|-------------|-------------|
| Direct prompting   | 17.6        | 25.4        | 5.6         |
| Chain of Thought   | 46.4        | 29.8        | 12.6        |
| Search             | 0.0         | 2.2         | 1.5         |
| Search + postproc. | -           | 26.3        | 6.5         |
| Self-ask           | 57.6        | 30.0        | 13.8        |
| Self-ask + Search  | <b>60.0</b> | <b>40.1</b> | <b>15.2</b> |

|               | 2Wiki.      |            | Musique     |            |
|---------------|-------------|------------|-------------|------------|
|               | Acc. ↑      | # Toks ↓   | Acc. ↑      | # Toks ↓   |
| Least-to-Most | 29.0        | 844        | <b>16.8</b> | 1020       |
| Self-ask      | <b>35.5</b> | <b>569</b> | <b>16.3</b> | <b>663</b> |

# ChatGPT-o1

- We know very little about how exactly it is built.
- OpenAI released very little about its implementation details.
- But we have an idea:
  - Chain-of-thought
  - Use reinforcement learning (similar to RLHF) to improve the CoT process.



# Last Quiz

- Which of the following is not a prompt engineering technique?
  - A. Adding retrieved context or examples to a prompt
  - B. Using specific instructions in the prompt
  - C. Changing the programming language used to implement the model
  - D. Asking for outputs with the “thinking process”

May You  
Live In  
Interesting  
Times

BIENNALE ARTE  
2019

11.05–24.11  
VENEZIA  
GIARDINI/ARSENALE