# Question Answering and Summarization

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CS 421: Natural Language Processing

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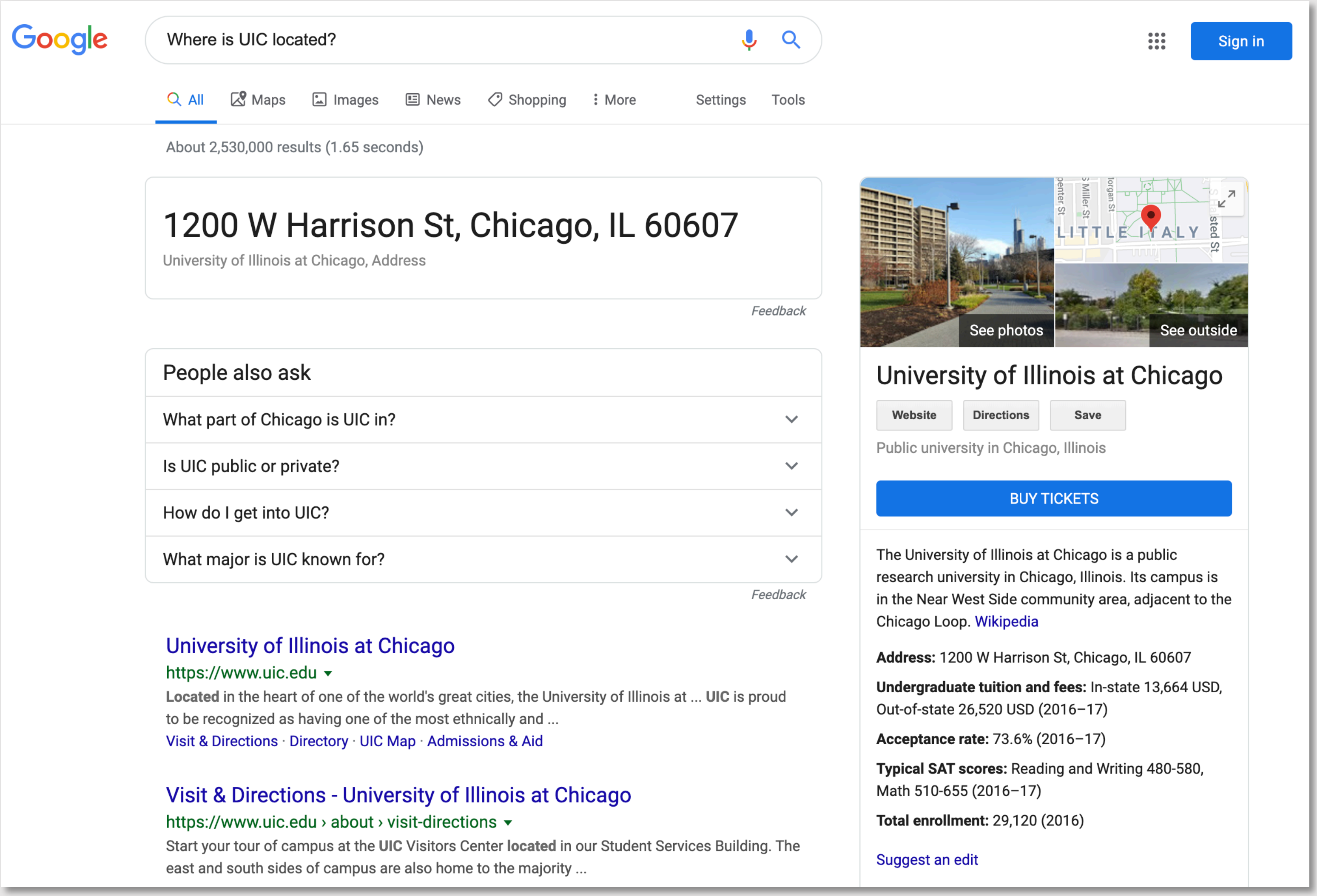
Many slides adapted from Jurafsky and Martin (https://web.stanford.edu/~jurafsky/slp3/).

# What is question answering?

- The process of **automatically retrieving** compact quantities of correct, relevant **information** in response to a user's **query**

# We use question answering systems everyday.



Where is UIC located?

About 2,530,000 results (1.65 seconds)

1200 W Harrison St, Chicago, IL 60607

University of Illinois at Chicago, Address

People also ask

- What part of Chicago is UIC in?
- Is UIC public or private?
- How do I get into UIC?
- What major is UIC known for?

University of Illinois at Chicago
https://www.uic.edu
**Located** in the heart of one of the world's great cities, the University of Illinois at ... **UIC** is proud to be recognized as having one of the most ethnically and ...
Visit & Directions · Directory · UIC Map · Admissions & Aid

Visit & Directions - University of Illinois at Chicago
https://www.uic.edu › about › visit-directions
Start your tour of campus at the **UIC** Visitors Center **located** in our Student Services Building. The east and south sides of campus are also home to the majority ...

University of Illinois at Chicago

Public university in Chicago, Illinois

The University of Illinois at Chicago is a public research university in Chicago, Illinois. Its campus is in the Near West Side community area, adjacent to the Chicago Loop. Wikipedia

**Address:** 1200 W Harrison St, Chicago, IL 60607

**Undergraduate tuition and fees:** In-state 13,664 USD, Out-of-state 26,520 USD (2016–17)

**Acceptance rate:** 73.6% (2016–17)

**Typical SAT scores:** Reading and Writing 480-580, Math 510-655 (2016–17)

**Total enrollment:** 29,120 (2016)

Suggest an edit

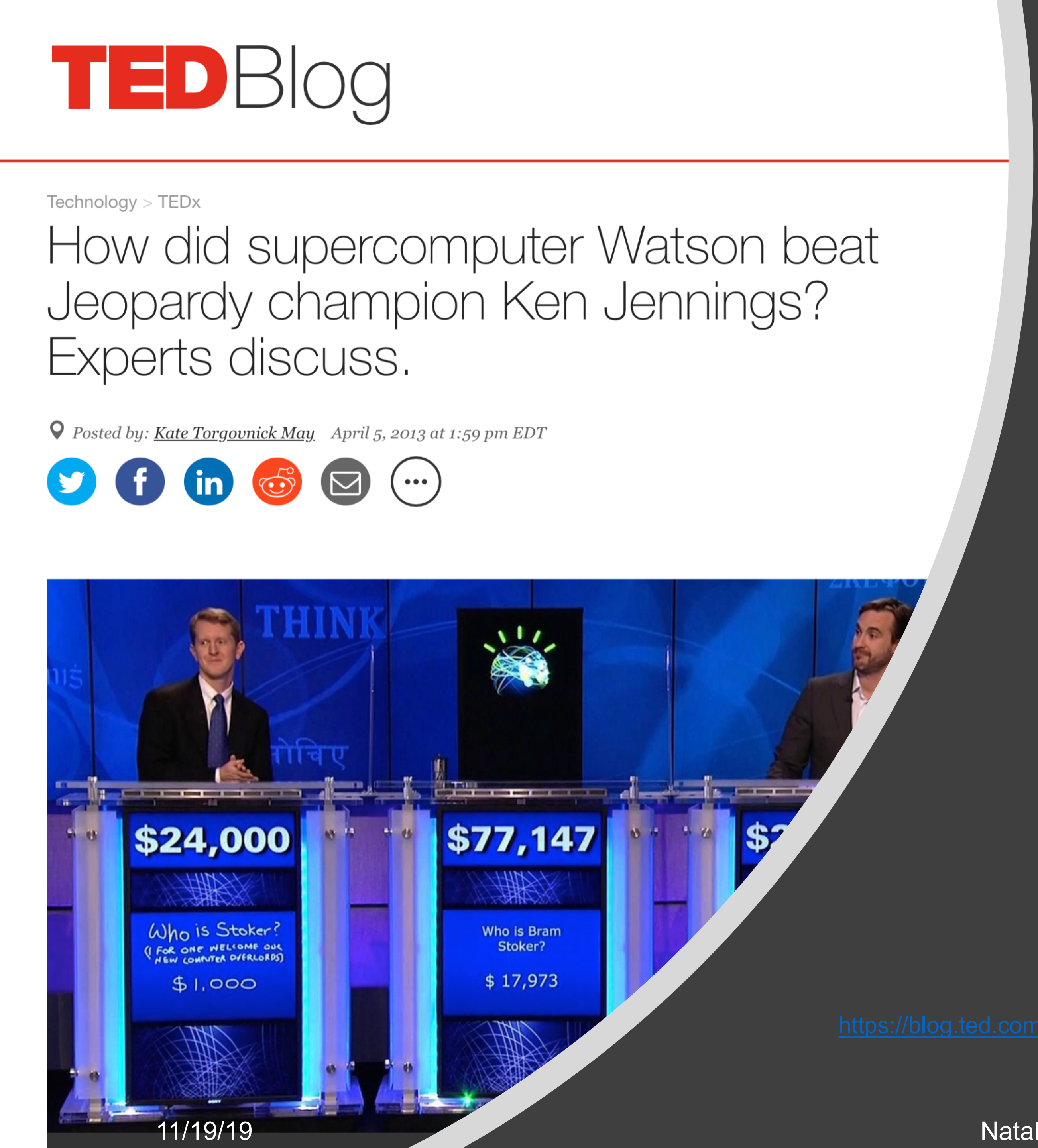
# People have been interested in question answering systems nearly as long as computers have existed.

What is the answer to the Ultimate Question Of Life, The Universe, and Everything?[1]

[1] The Hitchhiker's Guide to the Galaxy

How many games did the Yankees play in July?[1]

[1] Bert F. Green Jr., Alice K. Wolf, Carol Chomsku, and Kenneth Laughery. 1961. Baseball: An Automatic Question Answerer. Link: https://web.stanford.edu/class/linguist289/p219-green.pdf



TED Blog

Technology > TEDx

# How did supercomputer Watson beat Jeopardy champion Ken Jennings? Experts discuss.

*Posted by: Kate Torgovnick May* *April 5, 2013 at 1:59 pm EDT*

## Question answering systems have even won game shows!

https://blog.ted.com/how-did-supercomputer-watson-beat-jeopardy-champion-ken-jennings-experts-discuss/

# Question Answering Systems

- Typically focus on **factoid questions**
  - **Factoid Questions:** Questions that can be answered with simple facts expressed in short texts

When was UIC founded?

What is the average CS class size?

How far is UIC from the University of Chicago?

# Question Answering Systems

- Two major paradigms:
  - **Information retrieval-based** question answering
  - **Knowledge-based** question answering

# Information Retrieval-based Question Answering

- Relies on text from the web or from large corpora
- Given a user question:
  1. Find relevant documents and passages of text
  2. Read the retrieved documents or passages
  3. Extract an answer to the question directly from spans of text

# Knowledge-based Question Answering

- Builds a semantic representation of the user's query
  - When was UIC founded? → founded(UIC, x)
- Uses these representations to query a database of facts

# Large industrial systems are often hybrids of these two paradigms.

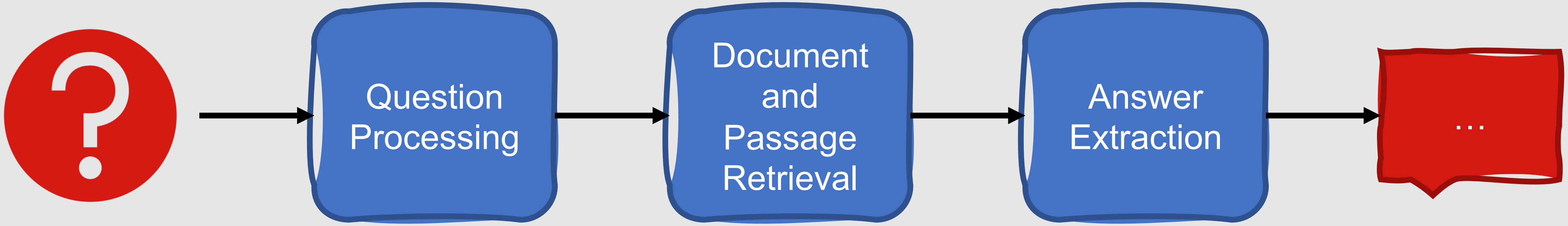
- DeepQA (the question answering system in IBM's Watson):
  - Finds candidate answers in both knowledge bases and text sources
  - Scores each candidate answer
  - Returns the highest scoring answer

# Information Retrieval-based Question Answering

Goal: Answer a user's question by finding short text segments containing the requested information

| QUESTION | ANSWER |
|---|---|
| Where is UIC located? | in Chicago, Illinois |
| What does UIC stand for? | University of Illinois at Chicago |
| Who taught CS 421 in Fall 2019? | Natalie Parde |
| How many grad students are in CS 421? | 25 |

# Information Retrieval-based Question Answering



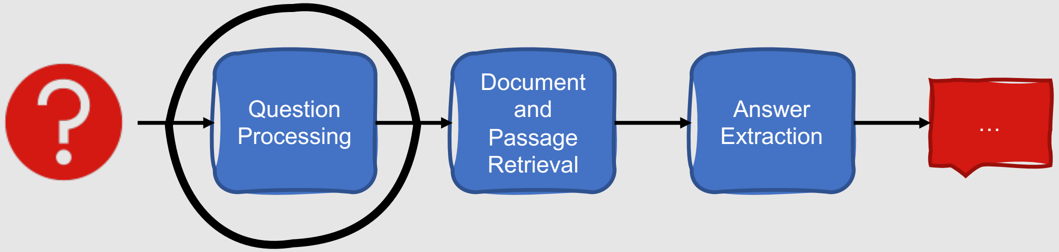
Question Processing

Document and Passage Retrieval

Answer Extraction

…

# Question Processing



- **Goal: Extract the query**
  - What keywords are needed to match relevant documents?
  - What type of entity should be in the answer (person, location, etc.)?
  - What is the focus of the question (which string of words will likely be replaced by the answer)?
  - What type of question is this (definition, math, list, etc.)?

# Question Processing

- Two most common subtasks involved in question processing:
  - Query formulation
  - Answer type detection

When was UIC's Department of Computer Science created?

**Query:** UIC Department of Computer Science created
**Answer Type:** Time

# Query Formulation

- The task of creating a query to send to an information retrieval system
  - Should contain keywords necessary to obtain relevant documents
- Simple strategy: Pass the entire question as a query
  - Only works with very large corpora (e.g., the web)
- More complex strategy for smaller corpora (e.g., corporate websites or Wikipedia): Use an IR engine to search and index documents

# Common Information Retrieval Techniques

## TF*IDF matching

- Which document has the highest cosine similarity with the query?

## Query expansion

- Add query terms in hopes of matching an answer in one of its many possible forms

## Query reformulation

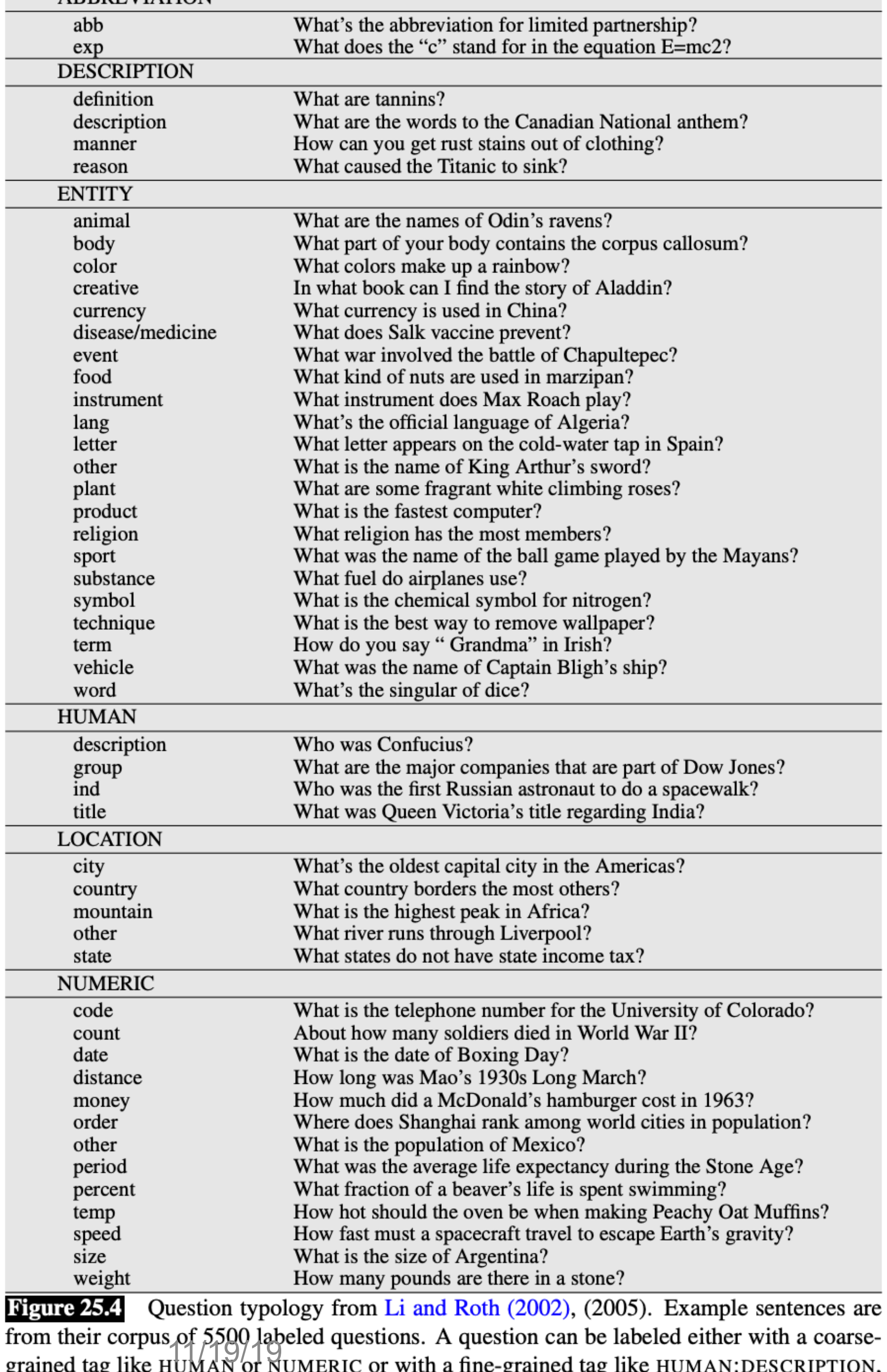
- Rephrase the question to make it look like a substring of possible answers
  - **When was UIC founded?** → **UIC was founded in**

# Answer Type Detection

- The task of determining what type of named entity is needed for the answer
  - Who was the first head of UIC’s Department of Computer Science? → PERSON
  - In what city is UIC located? → CITY
- In addition to named entity types, answers can also fall under other categories in a larger, hierarchical, answer type taxonomy
  - PERSON:INDIVIDUAL
  - PERSON:GROUP

# Answer Type Detection

- Hierarchical answer type taxonomy
  - Coarse-grained categories:
    - Abbreviation
    - Description
    - Entity
    - Human
    - Location
    - Numeric
  - Finer-grained subcategories of each



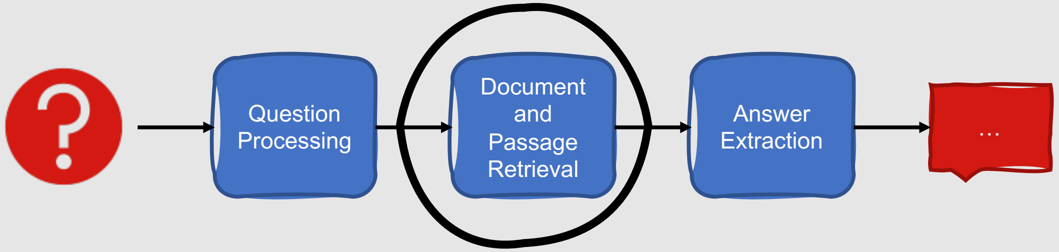
| | |
|---|---|
| ABBREVIATION | |
| abb | What's the abbreviation for limited partnership? |
| exp | What does the "c" stand for in the equation E=mc2? |
| DESCRIPTION | |
| definition | What are tannins? |
| description | What are the words to the Canadian National anthem? |
| manner | How can you get rust stains out of clothing? |
| reason | What caused the Titanic to sink? |
| ENTITY | |
| animal | What are the names of Odin's ravens? |
| body | What part of your body contains the corpus callosum? |
| color | What colors make up a rainbow? |
| creative | In what book can I find the story of Aladdin? |
| currency | What currency is used in China? |
| disease/medicine | What does Salk vaccine prevent? |
| event | What war involved the battle of Chapultepec? |
| food | What kind of nuts are used in marzipan? |
| instrument | What instrument does Max Roach play? |
| lang | What's the official language of Algeria? |
| letter | What letter appears on the cold-water tap in Spain? |
| other | What is the name of King Arthur's sword? |
| plant | What are some fragrant white climbing roses? |
| product | What is the fastest computer? |
| religion | What religion has the most members? |
| sport | What was the name of the ball game played by the Mayans? |
| substance | What fuel do airplanes use? |
| symbol | What is the chemical symbol for nitrogen? |
| technique | What is the best way to remove wallpaper? |
| term | How do you say " Grandma" in Irish? |
| vehicle | What was the name of Captain Bligh's ship? |
| word | What's the singular of dice? |
| HUMAN | |
| description | Who was Confucius? |
| group | What are the major companies that are part of Dow Jones? |
| ind | Who was the first Russian astronaut to do a spacewalk? |
| title | What was Queen Victoria's title regarding India? |
| LOCATION | |
| city | What's the oldest capital city in the Americas? |
| country | What country borders the most others? |
| mountain | What is the highest peak in Africa? |
| other | What river runs through Liverpool? |
| state | What states do not have state income tax? |
| NUMERIC | |
| code | What is the telephone number for the University of Colorado? |
| count | About how many soldiers died in World War II? |
| date | What is the date of Boxing Day? |
| distance | How long was Mao's 1930s Long March? |
| money | How much did a McDonald's hamburger cost in 1963? |
| order | Where does Shanghai rank among world cities in population? |
| other | What is the population of Mexico? |
| period | What was the average life expectancy during the Stone Age? |
| percent | What fraction of a beaver's life is spent swimming? |
| temp | How hot should the oven be when making Peachy Oat Muffins? |
| speed | How fast must a spacecraft travel to escape Earth's gravity? |
| size | What is the size of Argentina? |
| weight | How many pounds are there in a stone? |

**Figure 25.4** Question typology from Li and Roth (2002), (2005). Example sentences are from their corpus of 5500 labeled questions. A question can be labeled either with a coarse-grained tag like HUMAN or NUMERIC or with a fine-grained tag like HUMAN:DESCRIPTION,

# How are answer types detected?

- **Handwritten rules**
    - Who {is | was} the first head of ORGANIZATION → PERSON
- **Supervised machine learning**
- In general, detecting answer types like PERSON, LOCATION, and TIME is easier; detecting other types is more complex

# Document and Passage Retrieval

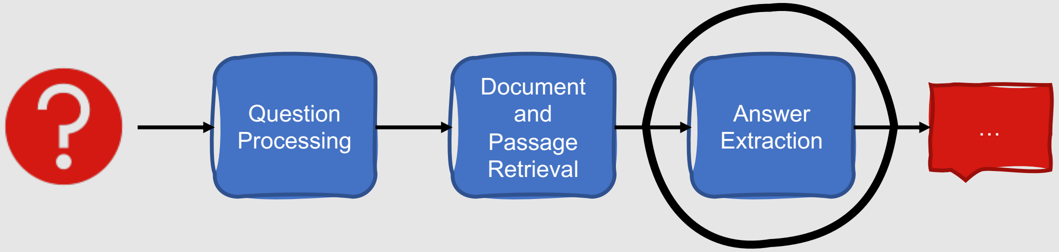


- Ranks a set of documents based on their relevance to the query
- Divides the top *n* documents into smaller passages
- Pass some or all of those passages along to the next stage

# Which passages are passed along to the next stage?

- Simplest approach: Pass along every passage from the top *n* documents to the next stage
- More sophisticated approaches:
  - Filter the passages based on whether they contain a named entity of the type specified by the question
  - Rank the passages using supervised machine learning and return the subset of highest-ranked passages

# Answer Extraction



- Extracts a specific answer from a passage
  - **Span Labeling:** Given a passage, identify the span of text which constitutes an answer

# How can we extract answers from passages?

- Simple approach: Run a named entity tagger on the candidate passage, and return whatever entity corresponds to the desired answer type
- However, the answers to many questions may not require a specific named entity type!
  - **What is natural language processing?** → **The subfield of artificial intelligence that focuses on automatically interpreting and generating natural language**
- Thus, more sophisticated answer extraction systems tend to use supervised machine learning

In what city is UIC located?

UIC, the the largest university in **Chicago**….

# Feature-based Answer Extraction

| | |
|---|---|
| Answer type match | •Does the candidate answer contain a phrase with the correct answer type? |
| Number of matched keywords | •How many keywords from the question are included in the candidate answer? |
| Text similarity | •What is the cosine similarity between the candidate answer and the query keywords? |
| Novelty factor | •Does the candidate answer contain a word that was not in the query? |
| Apposition features | •Is the candidate answer appositive to a phrase containing many question terms?<br>•The professor, **Natalie Parde**, is in her office making slides. |
| Punctuation location | •Is the candidate answer immediately followed by punctuation? |
| Sequences of question terms | •How long is the longest sequence of question terms in the candidate answer? |

# N-gram Tiling Answer Extraction

Relies on the redundancy of the web

Works by:

- Starting with the **text snippets returned from a web search engine**
- **Extracting all of the unigrams, bigrams, and trigrams** from each snippet
- **Weighting those n-grams**
  - Based on their frequency and the weight of the patterns that returned them
- **Scoring those n-grams** based on how well they match the predicted answer type
- **Concatenating overlapping n-grams** into longer answers
- **Adding the best concatenation to the list of candidate answers**, and removing lower-scoring candidates

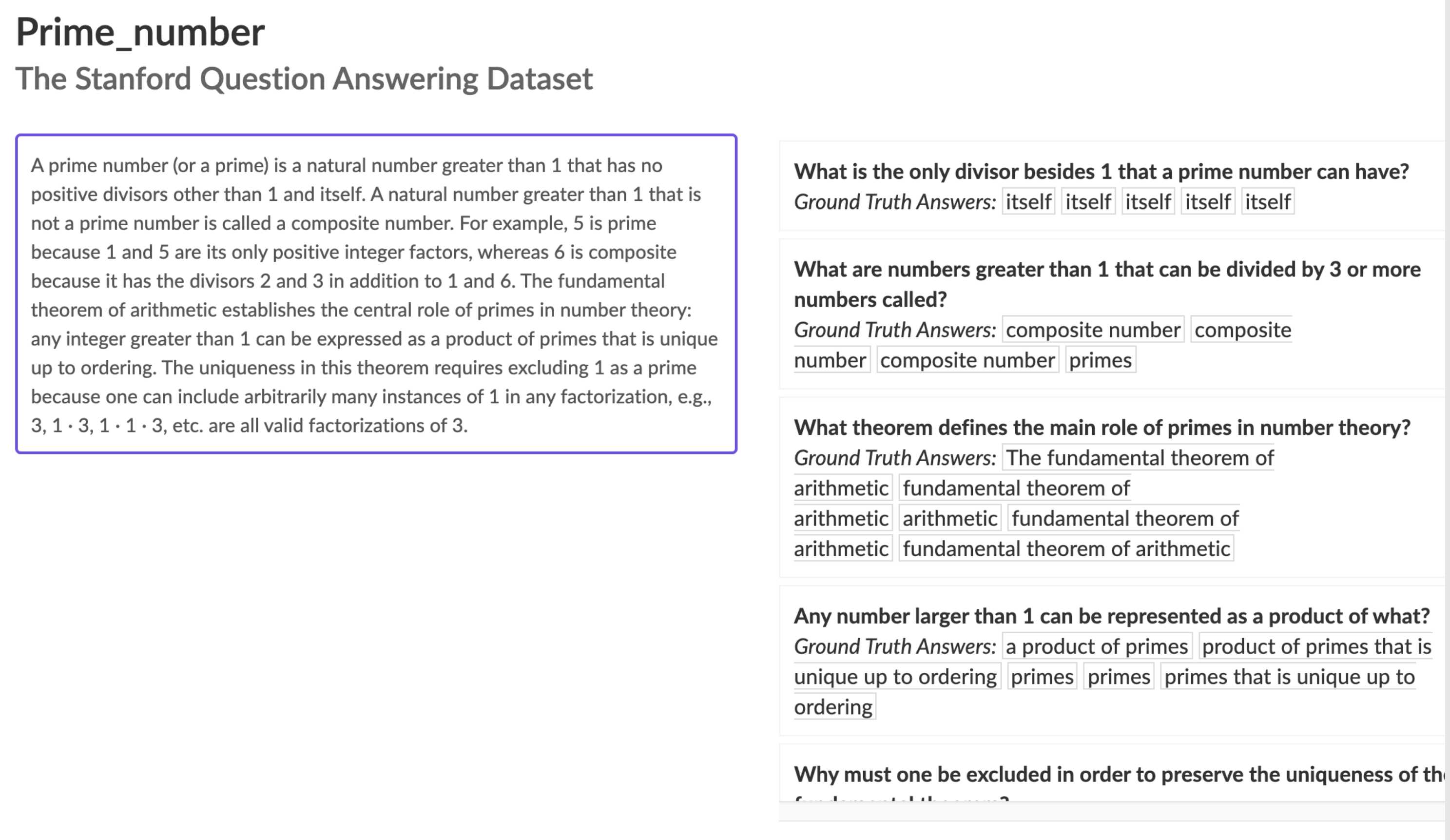
# Neural Answer Extraction

- Relies on the intuition that a question and its answer are semantically similar
- Works by:
    - Computing an embedding for the question
    - Computing an embedding for each token of the passage
    - Selecting spans from the passage whose embeddings are closest to the question embedding
- Often designed in the context of **reading comprehension**

# Reading Comprehension

- A task designed to measure natural language understanding performance
- Basic premise: Take children’s reading comprehension tests, and use them to evaluate text comprehension algorithms

# Reading Comprehension Datasets



**Prime_number**

The Stanford Question Answering Dataset

A prime number (or a prime) is a natural number greater than 1 that has no positive divisors other than 1 and itself. A natural number greater than 1 that is not a prime number is called a composite number. For example, 5 is prime because 1 and 5 are its only positive integer factors, whereas 6 is composite because it has the divisors 2 and 3 in addition to 1 and 6. The fundamental theorem of arithmetic establishes the central role of primes in number theory: any integer greater than 1 can be expressed as a product of primes that is unique up to ordering. The uniqueness in this theorem requires excluding 1 as a prime because one can include arbitrarily many instances of 1 in any factorization, e.g., 3, 1 · 3, 1 · 1 · 3, etc. are all valid factorizations of 3.

**What is the only divisor besides 1 that a prime number can have?**
*Ground Truth Answers:* itself | itself | itself | itself | itself

**What are numbers greater than 1 that can be divided by 3 or more numbers called?**
*Ground Truth Answers:* composite number | composite number | composite number | primes

**What theorem defines the main role of primes in number theory?**
*Ground Truth Answers:* The fundamental theorem of arithmetic | fundamental theorem of arithmetic | arithmetic | fundamental theorem of arithmetic | fundamental theorem of arithmetic

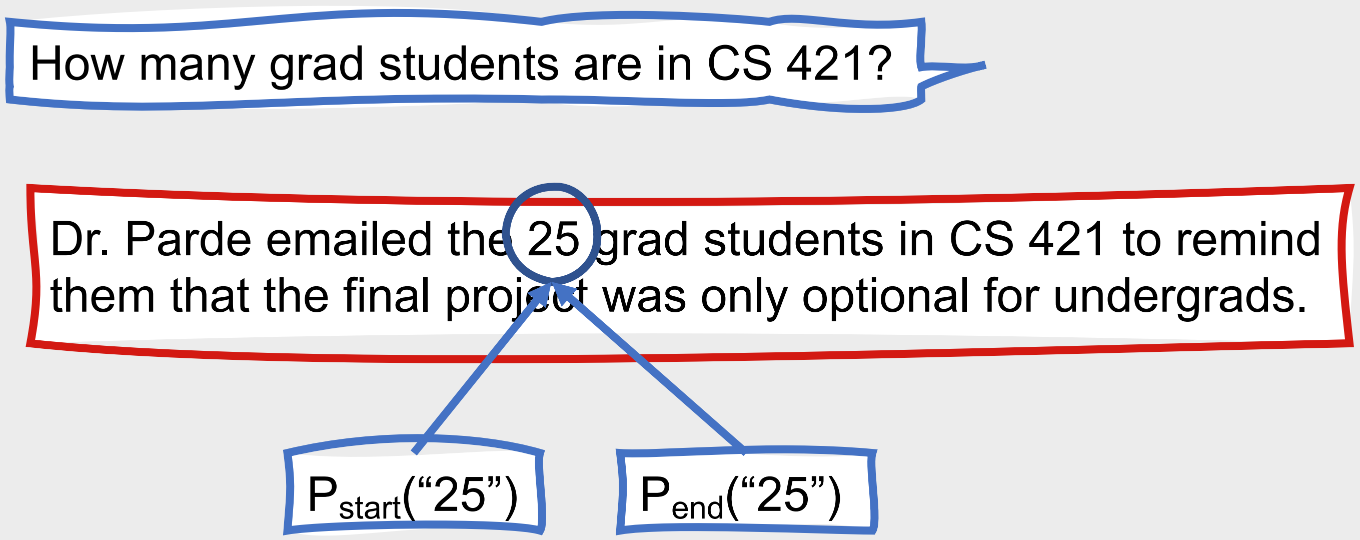
**Any number larger than 1 can be represented as a product of what?**
*Ground Truth Answers:* a product of primes | product of primes that is unique up to ordering | primes | primes | primes that is unique up to ordering

**Why must one be excluded in order to preserve the uniqueness of th**

- Stanford Question Answering Dataset (SQuAD)
  - Passages from Wikipedia
  - Associated questions
    - Many have answers that are spans from the passage
    - Some are designed to be unanswerable
  - https://rajpurkar.github.io/SQuAD-explorer/
- NewsQA Dataset
  - Question-answer pairs from CNN news articles

# Bidirectional LSTM-based Reading Comprehension

- Low-level goal: Compute, for each token, the probability that it is:
  - The start of the answer span
  - The end of the answer span



How many grad students are in CS 421?

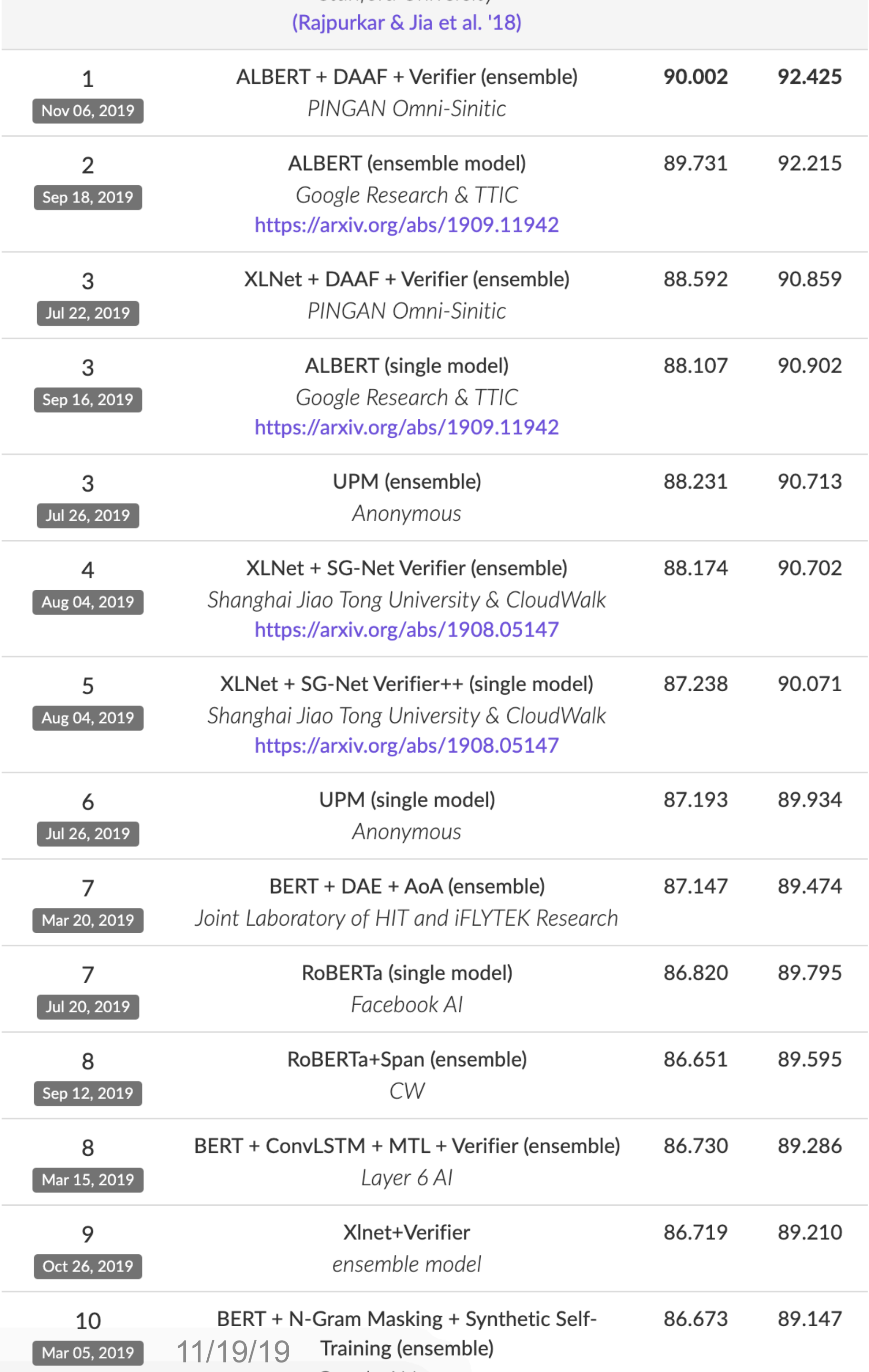
Dr. Parde emailed the 25 grad students in CS 421 to remind them that the final project was only optional for undergrads.

$P_{start}$(“25”)

$P_{end}$(“25”)

# Bidirectional LSTM-based Reading Comprehension

- Learn representations for each question and each word in a passage using bidirectional LSTMs
- Learn classifiers to predict the two probabilities for each word in the passage



(Rajpurkar & Jia et al. '18)

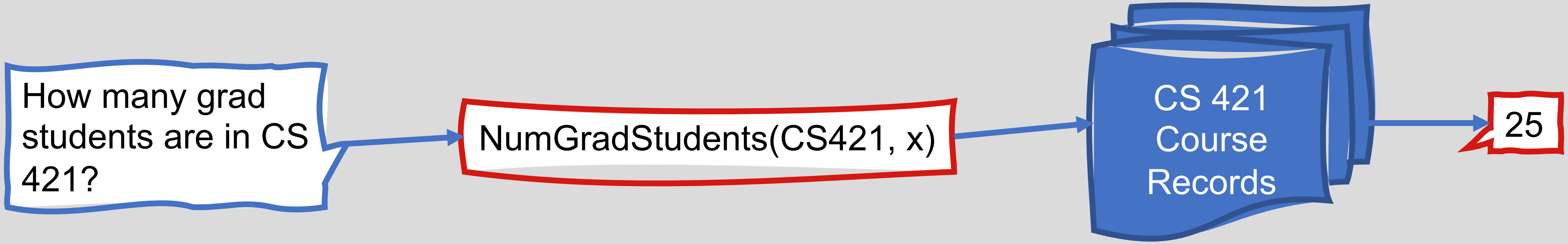
| | | | |
|---|---|---|---|
| 1<br>Nov 06, 2019 | ALBERT + DAAF + Verifier (ensemble)<br>*PINGAN Omni-Sinitic* | **90.002** | **92.425** |
| 2<br>Sep 18, 2019 | ALBERT (ensemble model)<br>*Google Research & TTIC*<br>https://arxiv.org/abs/1909.11942 | 89.731 | 92.215 |
| 3<br>Jul 22, 2019 | XLNet + DAAF + Verifier (ensemble)<br>*PINGAN Omni-Sinitic* | 88.592 | 90.859 |
| 3<br>Sep 16, 2019 | ALBERT (single model)<br>*Google Research & TTIC*<br>https://arxiv.org/abs/1909.11942 | 88.107 | 90.902 |
| 3<br>Jul 26, 2019 | UPM (ensemble)<br>*Anonymous* | 88.231 | 90.713 |
| 4<br>Aug 04, 2019 | XLNet + SG-Net Verifier (ensemble)<br>*Shanghai Jiao Tong University & CloudWalk*<br>https://arxiv.org/abs/1908.05147 | 88.174 | 90.702 |
| 5<br>Aug 04, 2019 | XLNet + SG-Net Verifier++ (single model)<br>*Shanghai Jiao Tong University & CloudWalk*<br>https://arxiv.org/abs/1908.05147 | 87.238 | 90.071 |
| 6<br>Jul 26, 2019 | UPM (single model)<br>*Anonymous* | 87.193 | 89.934 |
| 7<br>Mar 20, 2019 | BERT + DAE + AoA (ensemble)<br>*Joint Laboratory of HIT and iFLYTEK Research* | 87.147 | 89.474 |
| 7<br>Jul 20, 2019 | RoBERTa (single model)<br>*Facebook AI* | 86.820 | 89.795 |
| 8<br>Sep 12, 2019 | RoBERTa+Span (ensemble)<br>*CW* | 86.651 | 89.595 |
| 8<br>Mar 15, 2019 | BERT + ConvLSTM + MTL + Verifier (ensemble)<br>*Layer 6 AI* | 86.730 | 89.286 |
| 9<br>Oct 26, 2019 | Xlnet+Verifier<br>*ensemble model* | 86.719 | 89.210 |
| 10<br>Mar 05, 2019 | BERT + N-Gram Masking + Synthetic Self-Training (ensemble) | 86.673 | 89.147 |

# Many other neural approaches to question answering also exist!

- Many recent methods incorporate BERT embeddings
    - Contextual representations learned using Transformers

# Knowledge-based Question Answering

- Answers questions by mapping them to queries over structured databases


How many grad students are in CS 421?
NumGradStudents(CS421, x)
CS 421 Course Records
25

# How are text strings typically mapped to logical form?

- Semantic parsers
- Typically map text to:
  - Some form of predicate calculus (e.g., first-order logic)
  - Some type of query language
    - SQL
    - SPARQL
- This means that the question ends up either in the form of a database search query, or in a form that can be easily converted to one

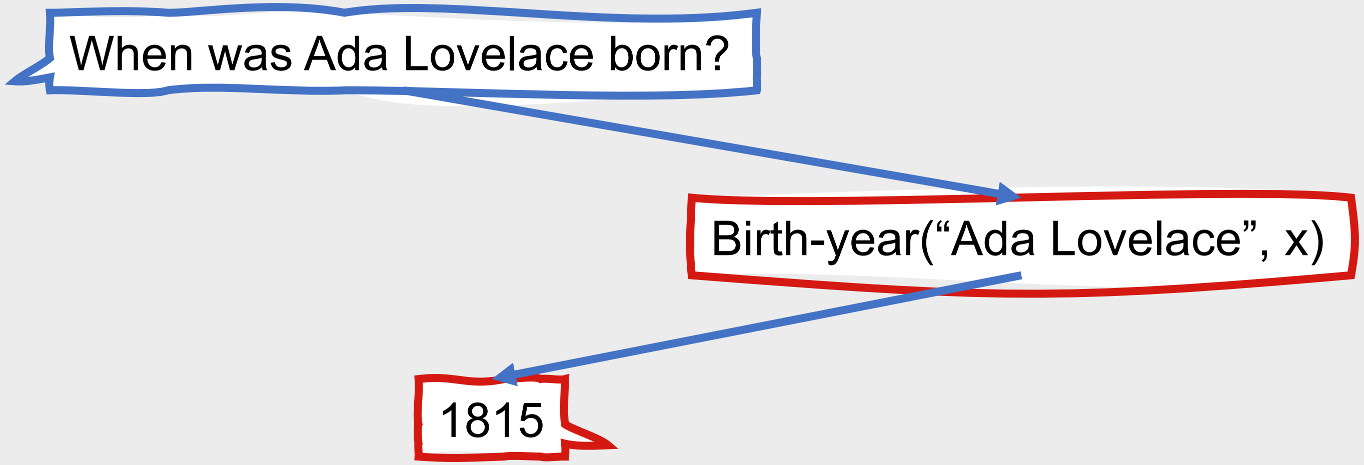
# What does the database look like?

- Differs depending on the resource
- Might be:
    - Full relational database
    - Simpler structured database
        - Sets of RDF (subject, predicate, object) triples
- Popular ontologies:
    - Wikidata: https://www.wikidata.org/wiki/Wikidata:Main_Page
    - DBpedia: https://wiki.dbpedia.org/

# Simple Knowledge-based Question Answering Task

- Answer factoid questions that ask about one of the missing arguments in a triple

| subject | predicate | object |
|---|---|---|
| Ada Lovelace | Birth-year | 1815 |



When was Ada Lovelace born?

Birth-year(“Ada Lovelace”, x)

1815

# Rule-based Methods for Knowledge-based Question Answering

Write patterns to extract frequent relations

- When .+ born → birth-year

Pros:

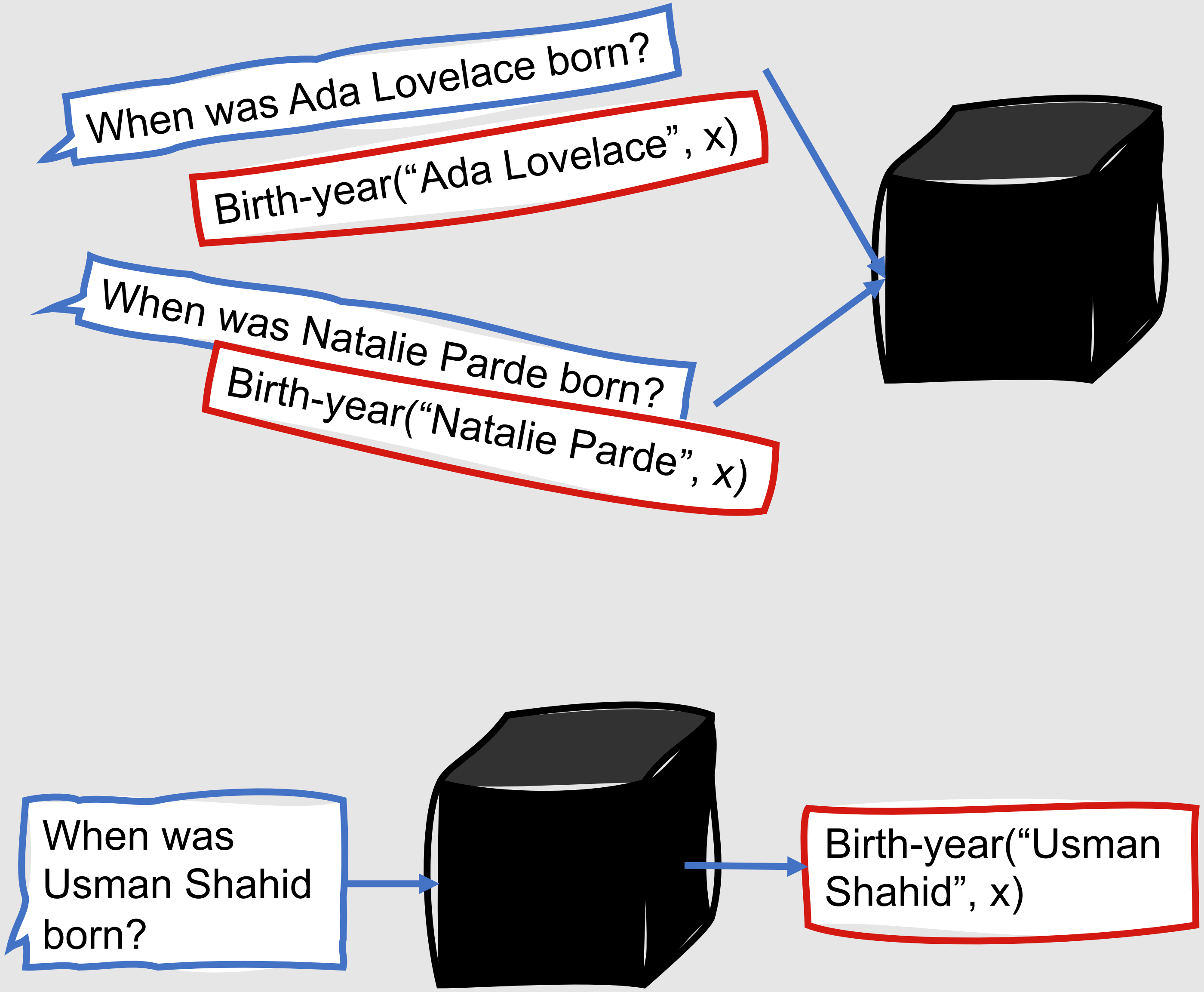
- Simple
- Precise

Cons:

- Not scalable
- Low recall

# Supervised Methods for Knowledge-based Question Answering

- Learn from pairs of training questions and their correct logical forms
- Produce a system that maps from new questions to their logical forms



When was Ada Lovelace born?
Birth-year("Ada Lovelace", x)
When was Natalie Parde born?
Birth-year("Natalie Parde", x)
When was Usman Shahid born?
Birth-year("Usman Shahid", x)

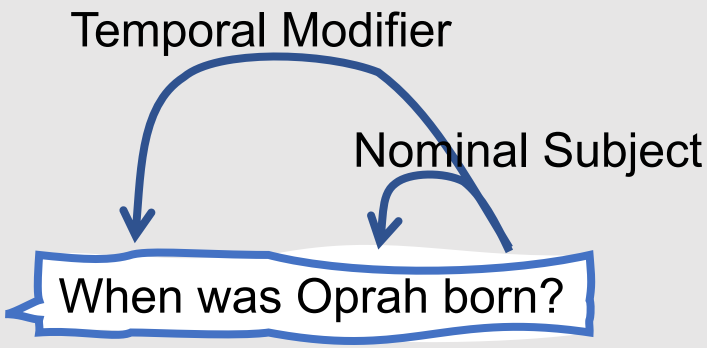
# How do most systems do this?

- First, parse the questions
- Then, align the parse trees to a logical form
- Often employ **bootstrapping**
    - Small set of rules for building the mapping
    - Small initial lexicon

# What would this look like?

When was Oprah born?

# What would this look like?

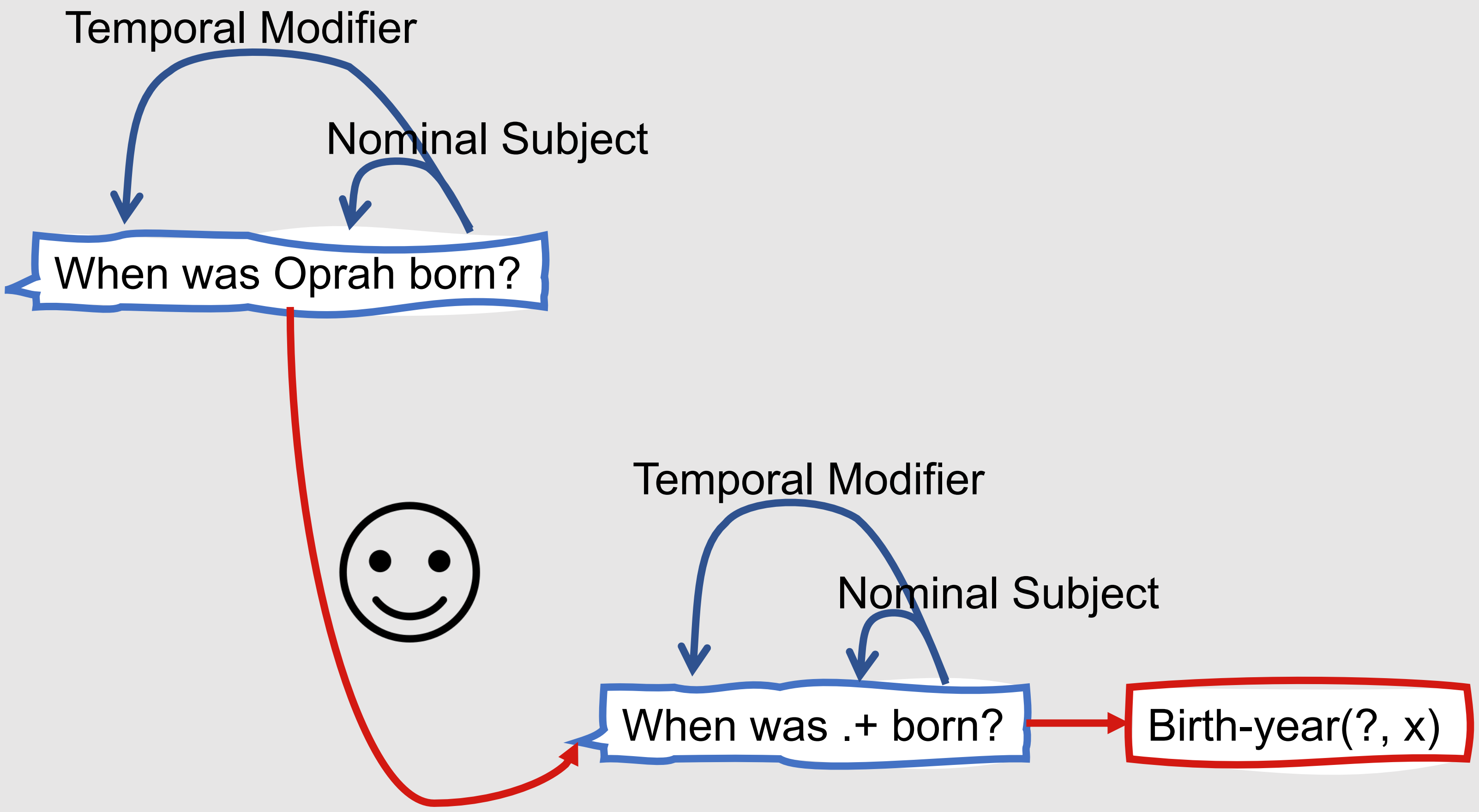


Temporal Modifier

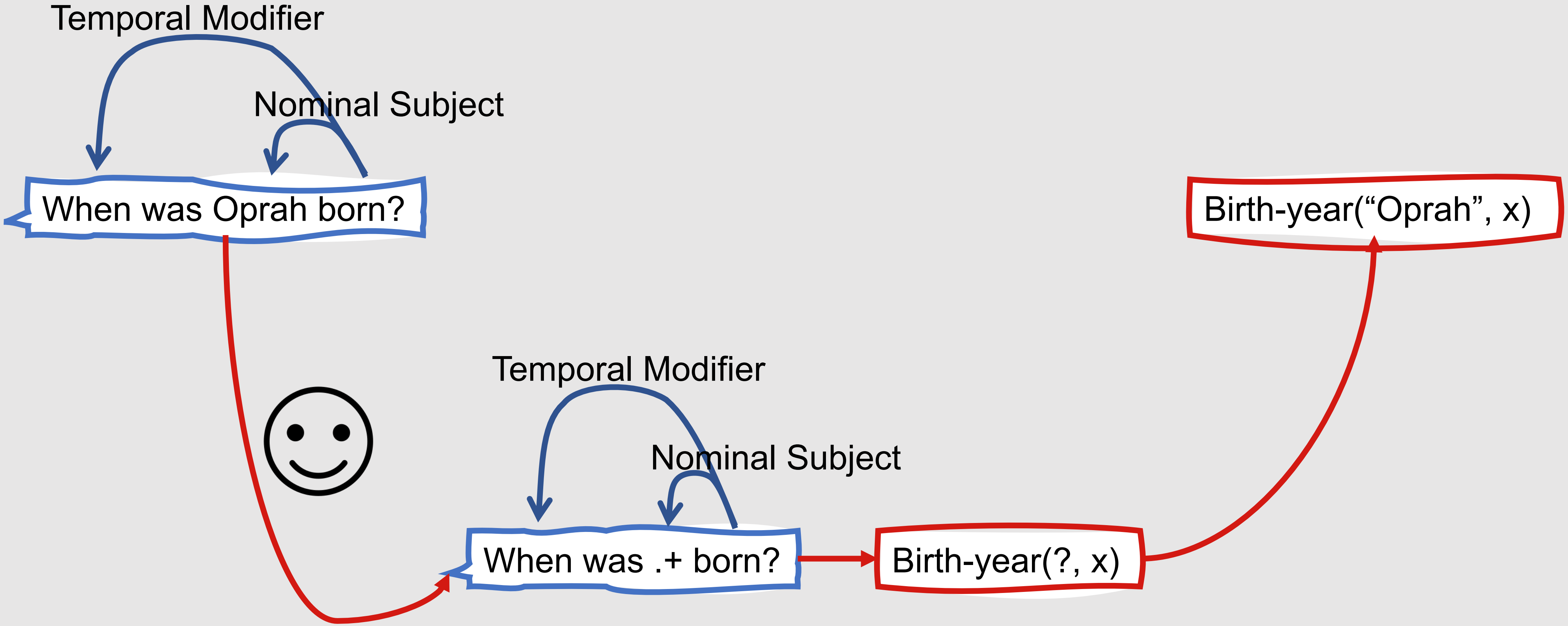
Nominal Subject

When was Oprah born?

# What would this look like?



# What would this look like?



Temporal Modifier

Nominal Subject

When was Oprah born?

☺

Temporal Modifier

Nominal Subject

When was .+ born?

Birth-year(?, x)

Birth-year(“Oprah”, x)

# Supervised approaches can be extended to handle more complex questions.

- More complex default rules can be used
- More complex logical forms can be used
- Training samples can be broken down into smaller tuples and then recombined to parse new sentences

What is the biggest state bordering Illinois?

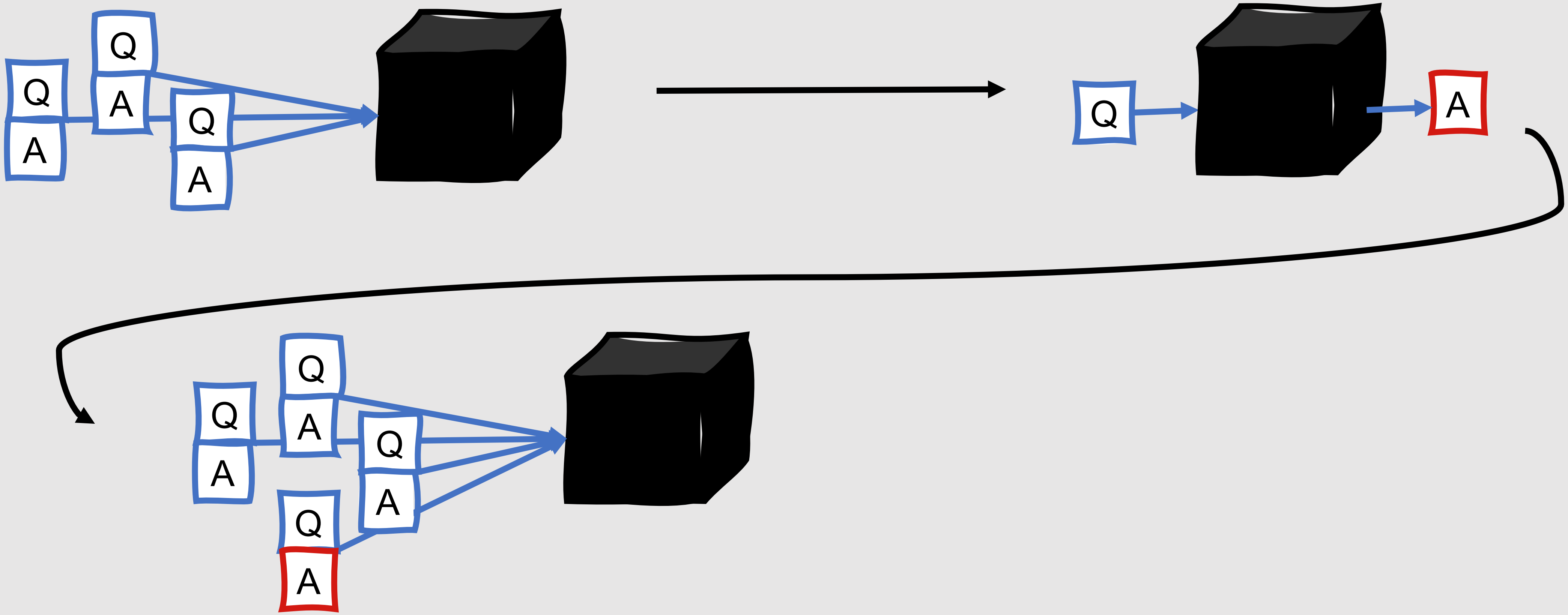
How many more undergrads are there than grad students in CS 421?

Is Chicago closer to Dallas or Denver?

# Semi-Supervised Methods for Knowledge-based Question Answering

- What is semi-supervised learning?
  - A form of machine learning that makes use of both labeled and unlabeled data for training
- Example: Bootstrapping

# Semi-Supervised Methods for Knowledge-based Question Answering



# Why used semi-supervised learning?

- Even though factoid questions may seem simple, it is difficult to build supervised datasets that comprehensively cover all of their different forms!

When was Oprah born?

What is Oprah's birth year?

What year was Oprah born?

In what year was Oprah born?

# Semi-supervised methods allow us to efficiently make use of textual redundancy.

| phrase | relation | phrase | relation | phrase | relation |
|---|---|---|---|---|---|
| Capital of | Country.capital | Capital city of | Country.capital | Become capital of | Country.capital |
| Capitol of | Country.capital | National capital of | Country.capital | Official capital of | Country.capital |
| Political capital of | Country.capital | Administrative capital of | Country.capital | Beautiful capital of | Country.capital |
| Capitol city of | Country.capital | Remain capital of | Country.capital | Make capital of | Country.capital |
| Political center of | Country.capital | Bustling capital of | Country.capital | Capital city in | Country.capital |
| Cosmopolitan capital of | Country.capital | Move its capital to | Country.capital | Modern capital of | Country.capital |
| Federal capital of | Country.capital | Beautiful capital city of | Country.capital | Administrative capital city of | Country.capital |

# Combining Information Sources

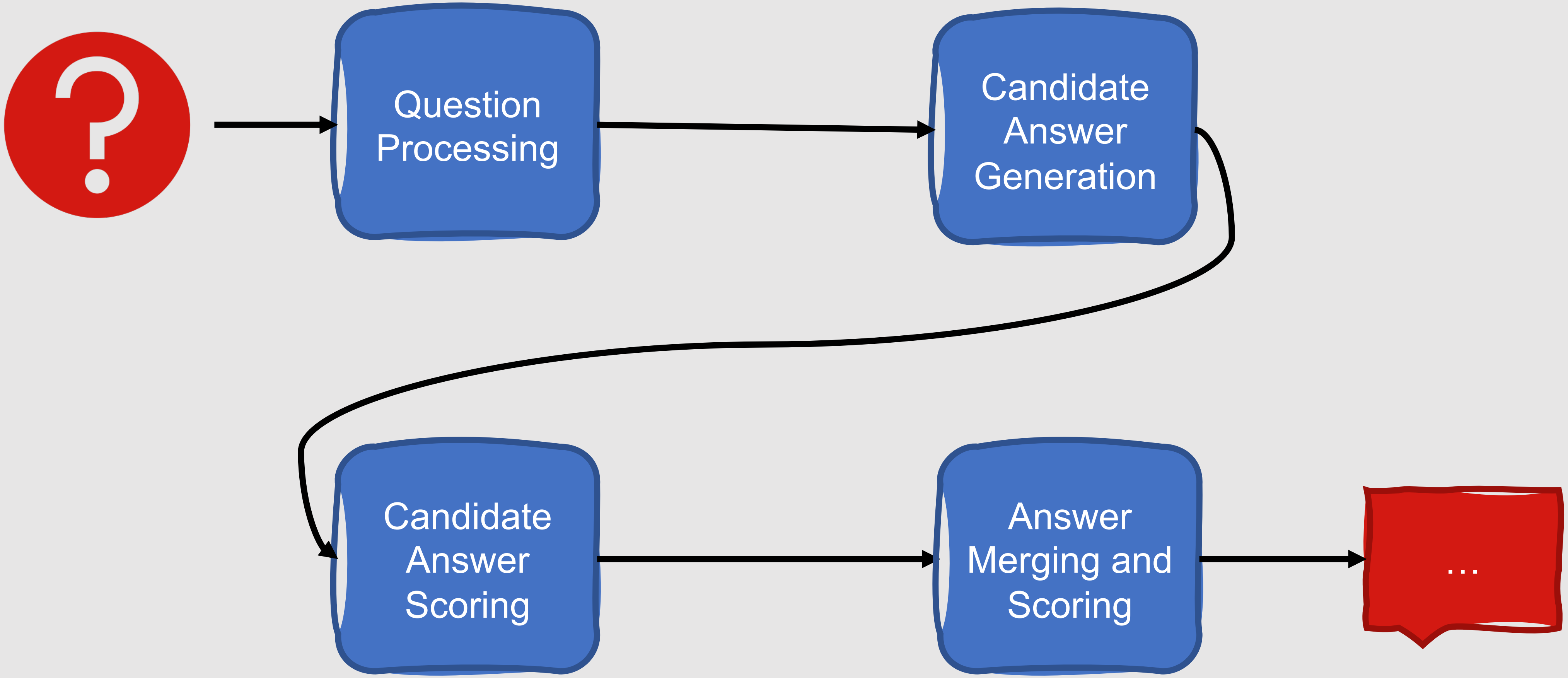
Remember …there’s no need to limit a system to using *only* text-based or *only* knowledge-based methods!

Many high-performing systems combine these two information sources

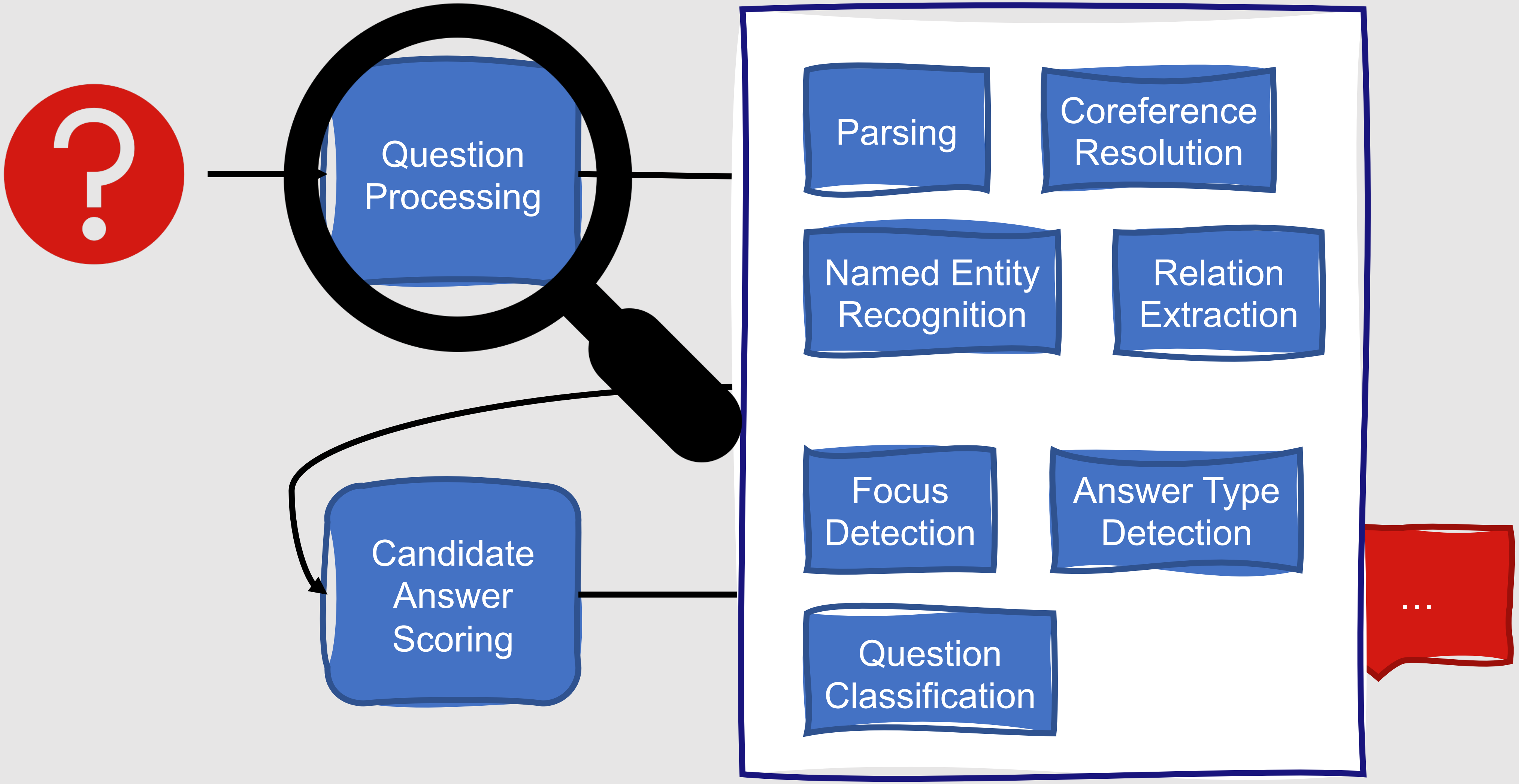
# Case Example: DeepQA

- Question answering component of Watson
- Four stages:
  1. **Question processing**
  2. **Candidate answer generation**
  3. **Candidate answer scoring**
  4. **Answer merging and scoring**

# Case Example: DeepQA



# Stage 1: Question Preprocessing


Question Processing

Candidate Answer Scoring

Parsing

Coreference Resolution

Named Entity Recognition

Relation Extraction

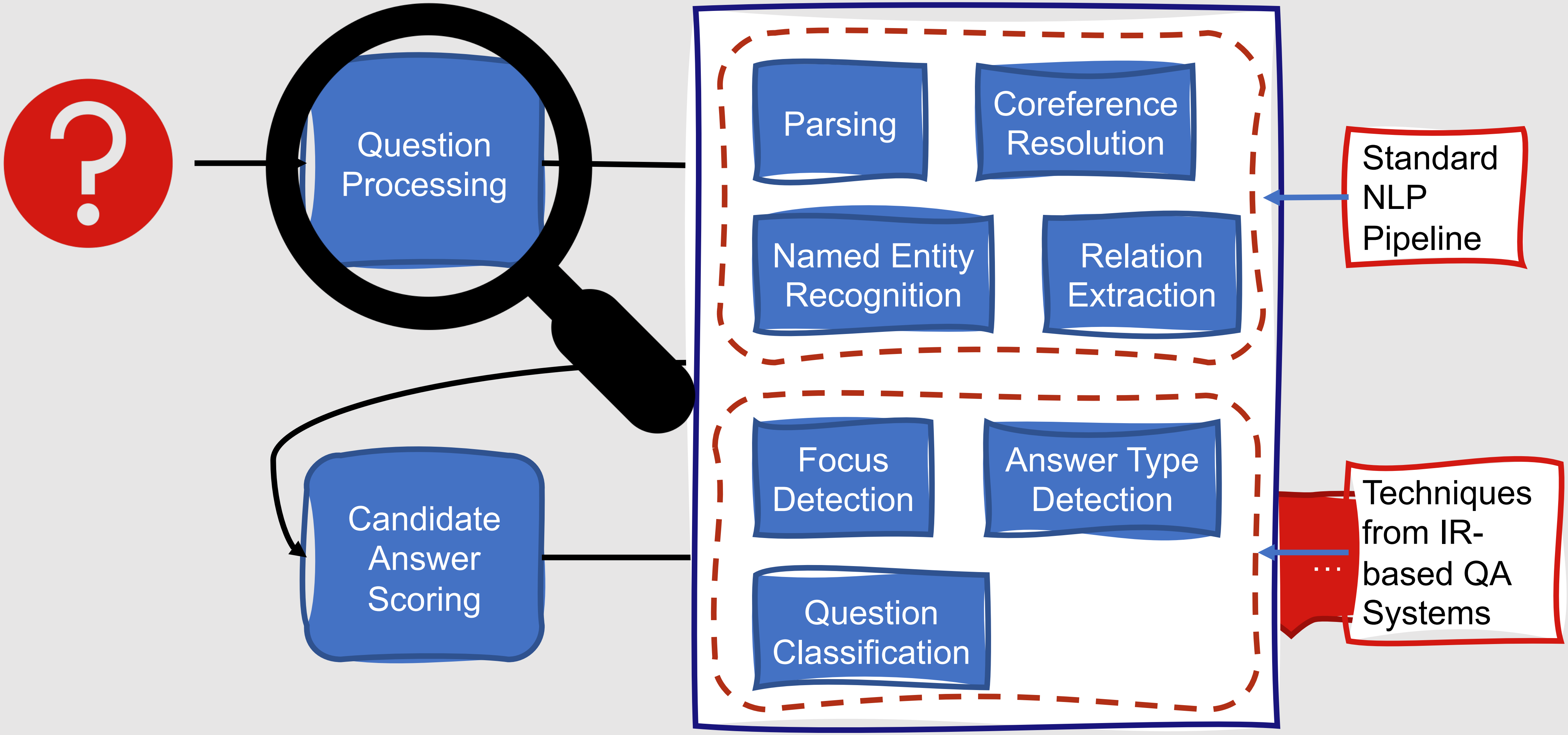
Focus Detection

Answer Type Detection

Question Classification

…

# Stage 1: Question Preprocessing



Question Processing

Candidate Answer Scoring

Parsing

Coreference Resolution

Named Entity Recognition

Relation Extraction

Focus Detection

Answer Type Detection

Question Classification

Standard NLP Pipeline

Techniques from IR-based QA Systems

# Stage 1: Question Preprocessing

**Jeopardy! Example:**
A new play based on this Sir Arthur Conan Doyle canine classic opened on the London stage in 2007.

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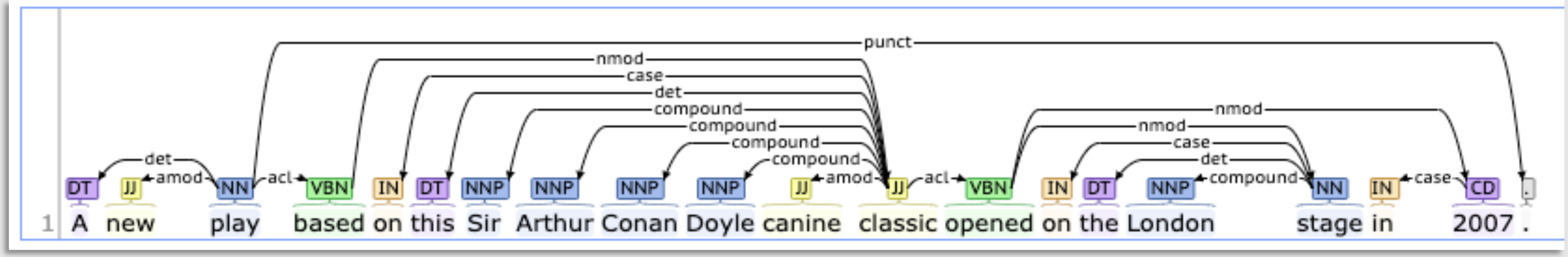

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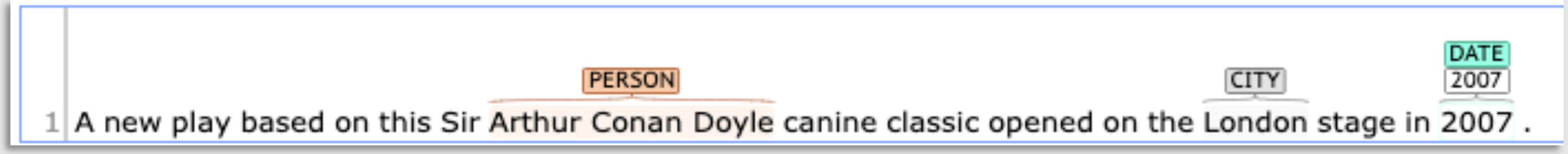
1 A new play based on this Sir Arthur Conan Doyle canine classic opened on the London stage in 2007 .



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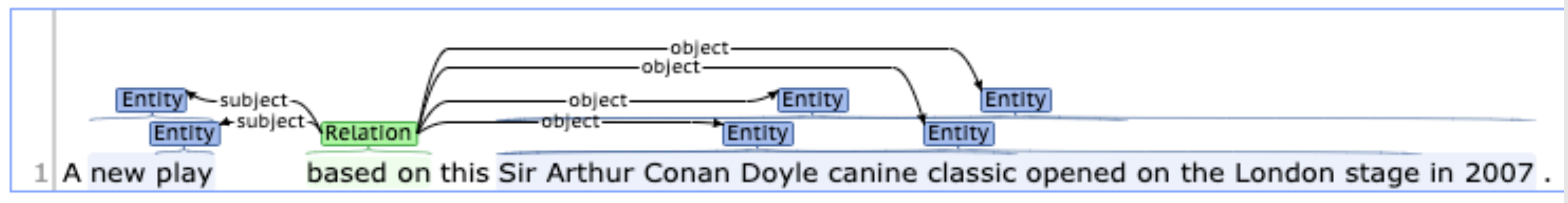
1 A new play based on this Sir Arthur Conan Doyle canine classic opened on the London stage in 2007 .



object
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subject
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Entity
1 A new play based on this Sir Arthur Conan Doyle canine classic opened on the London stage in 2007 .

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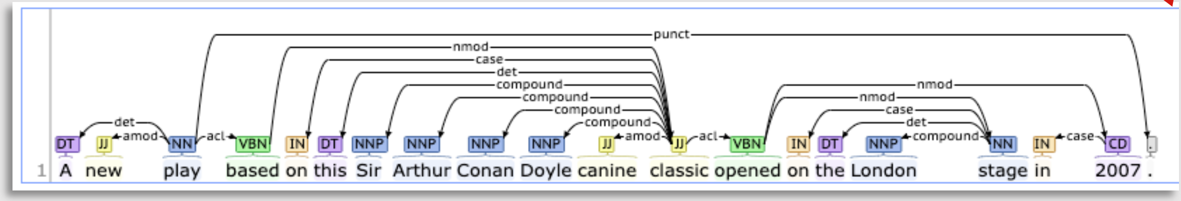

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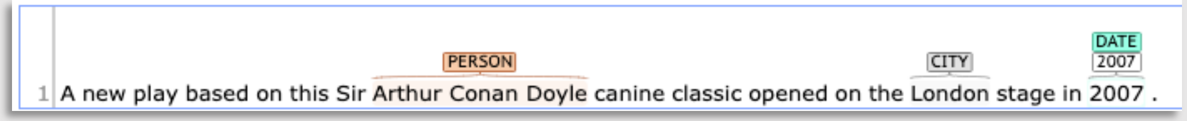

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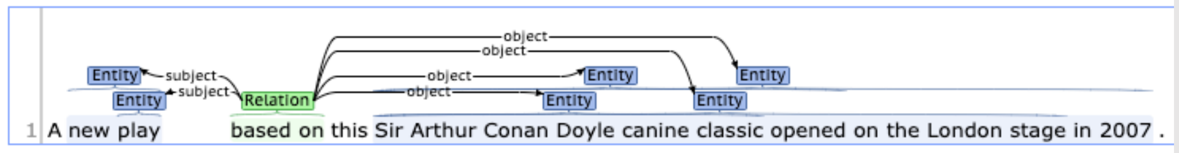

1 A new play based on this Sir Arthur Conan Doyle canine classic opened on the London stage in 2007 .

**Focus Detection:** Which part of the question co-refers with the answer?

Extracted using handwritten rules in DeepQA

# Stage 1: Question Preprocessing

**Jeopardy! Example:**
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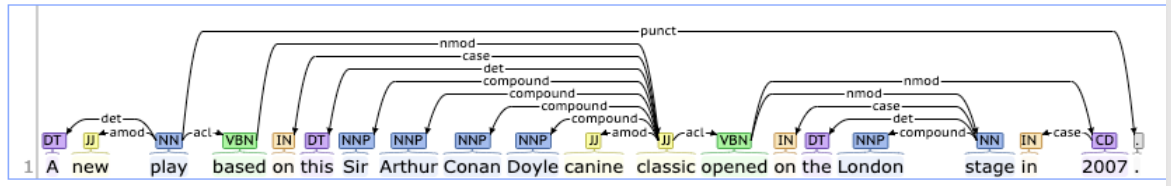

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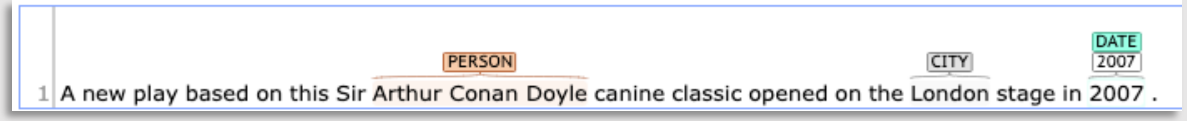

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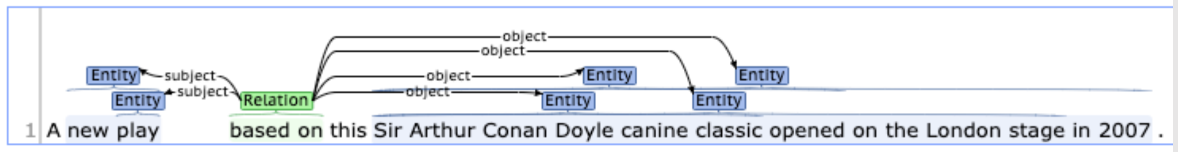


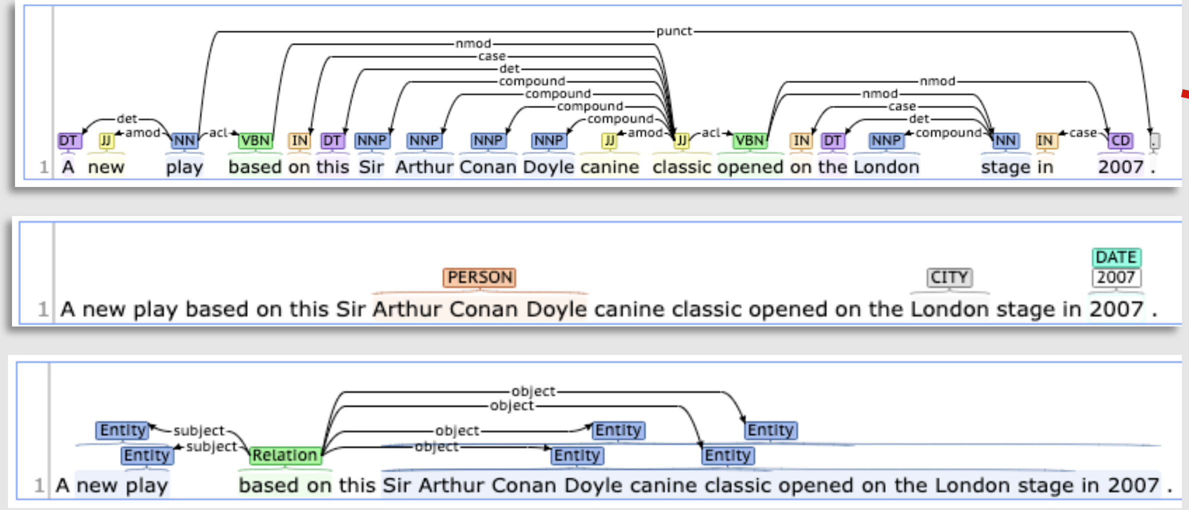
1 A new play based on this Sir Arthur Conan Doyle canine classic opened on the London stage in 2007 .

**Answer Type Detection:** Which word tells us about the semantic type of answer to expect?

DeepQA extracts roughly 5000 possible answer types (some questions may take multiple answer types), using a rule-based approach

# Stage 1: Question Preprocessing

**Jeopardy! Example:**
A new play based on **this Sir Arthur Conan Doyle canine** **classic** opened on the London stage in 2007.



punct
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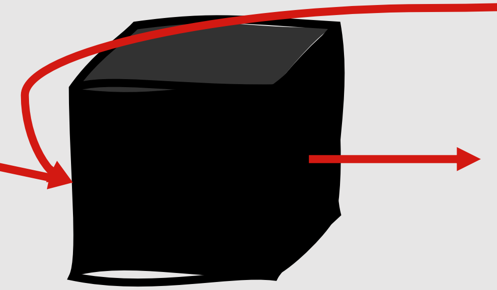
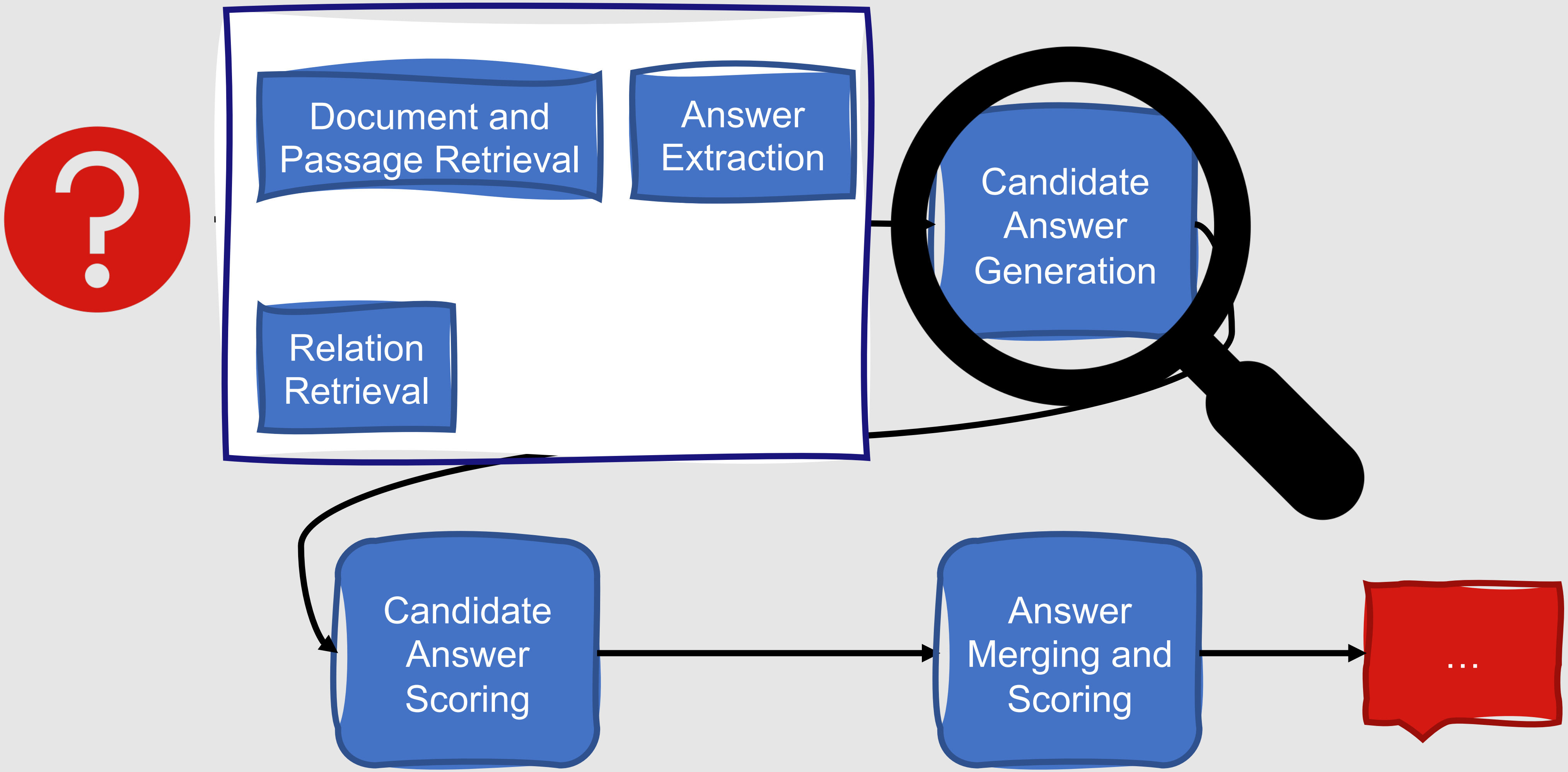


Definition

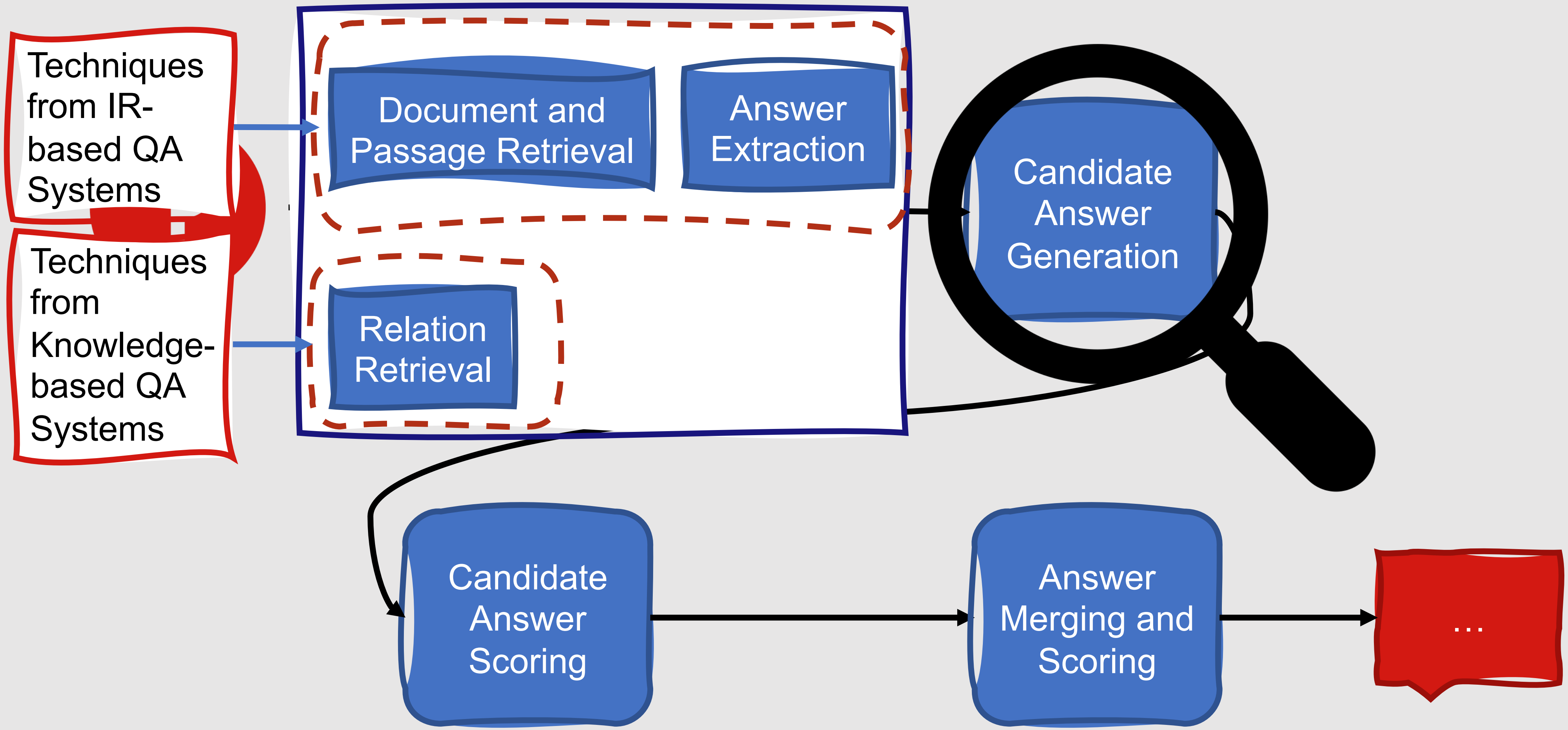
**Question Classification:** What type of question is this (multiple choice, fill-in-the-blank, definition, etc.)?

Generally done using pattern-matching regular expressions over words or parse trees

# Stage 2: Candidate Answer Generation


?
Document and Passage Retrieval
Answer Extraction
Relation Retrieval
Candidate Answer Generation
Candidate Answer Scoring
Answer Merging and Scoring
…

# Stage 2: Candidate Answer Generation



Techniques from IR-based QA Systems

Techniques from Knowledge-based QA Systems

Document and Passage Retrieval

Answer Extraction

Relation Retrieval

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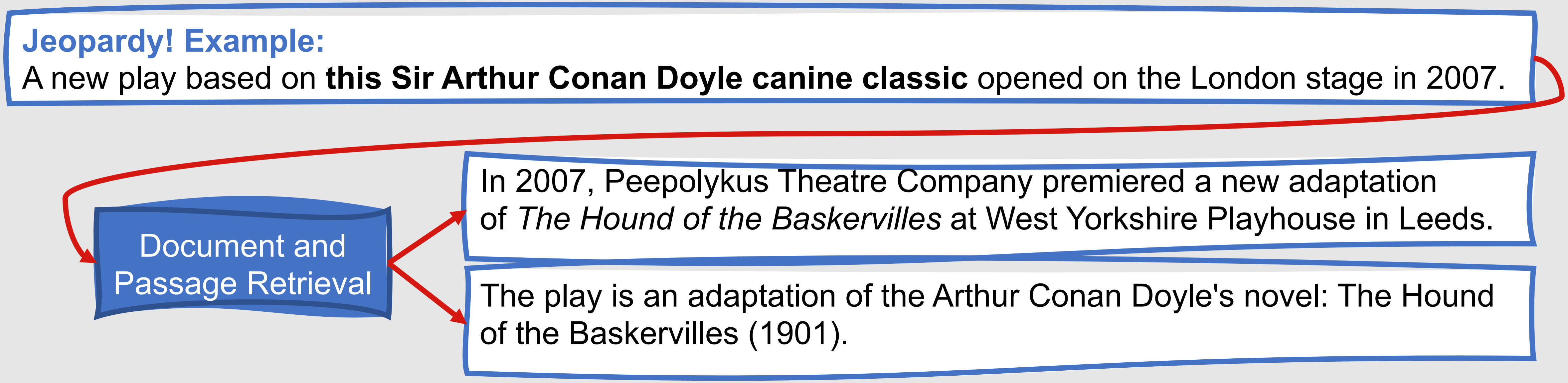


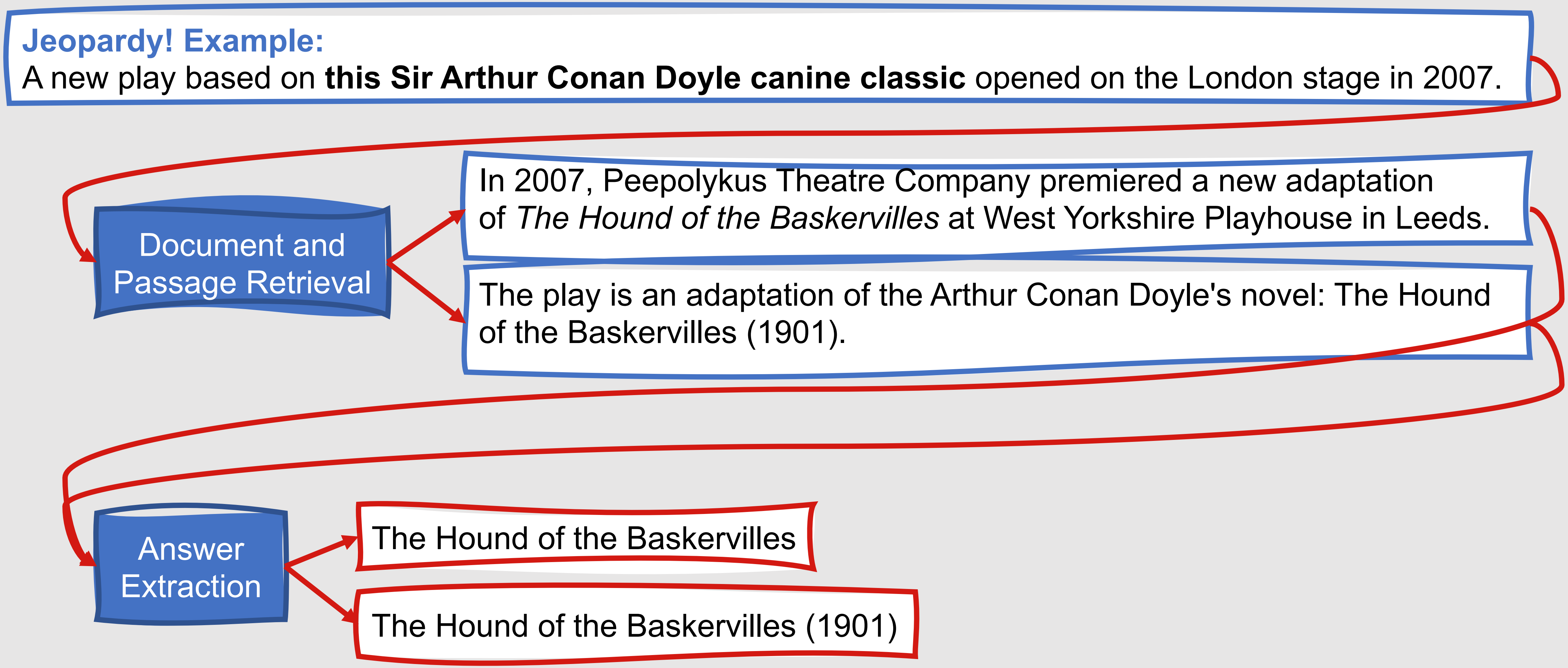
**Jeopardy! Example:**
A new play based on **this Sir Arthur Conan Doyle canine classic** opened on the London stage in 2007.

Document and Passage Retrieval

In 2007, Peepolykus Theatre Company premiered a new adaptation of *The Hound of the Baskervilles* at West Yorkshire Playhouse in Leeds.

The play is an adaptation of the Arthur Conan Doyle's novel: The Hound of the Baskervilles (1901).

# Stage 2: Candidate Answer Generation



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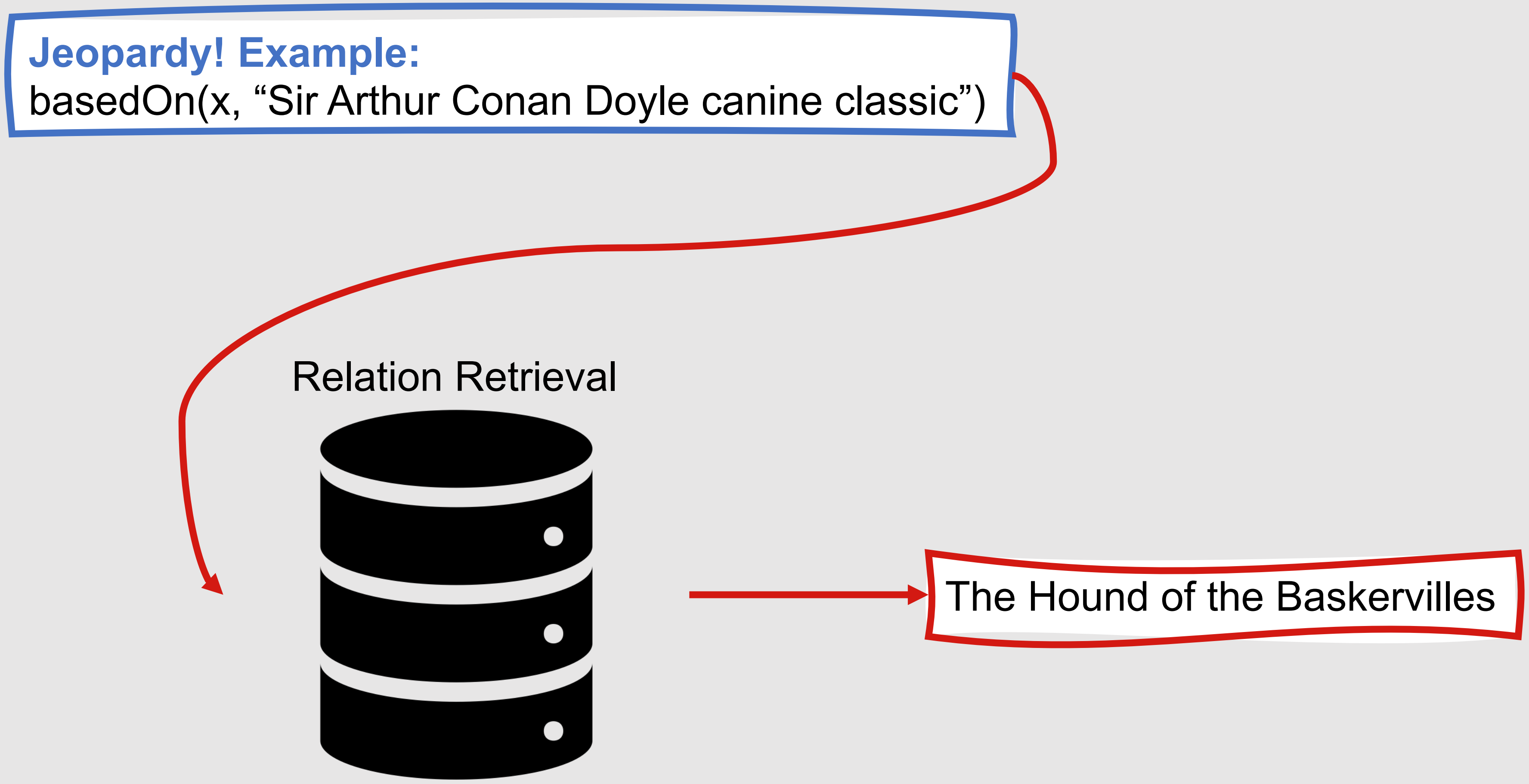
Answer Extraction

The Hound of the Baskervilles

The Hound of the Baskervilles (1901)

# Stage 2: Candidate Answer Generation

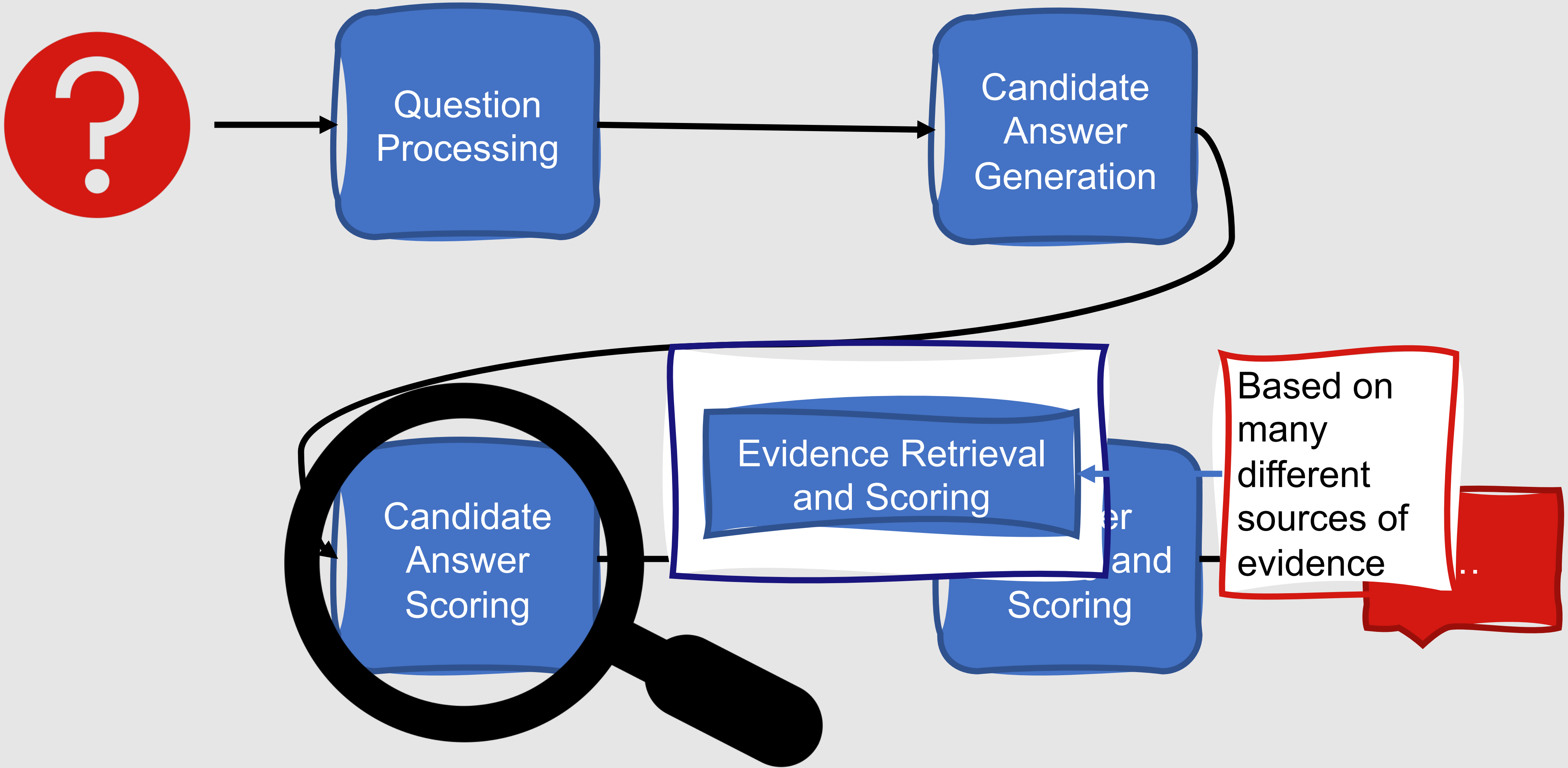


**Jeopardy! Example:**
basedOn(x, “Sir Arthur Conan Doyle canine classic”)

Relation Retrieval

The Hound of the Baskervilles

# Stage 3: Candidate Answer Scoring


Question Processing
Candidate Answer Generation
Evidence Retrieval and Scoring
Candidate Answer Scoring
er and Scoring
Based on many different sources of evidence
..

# Stage 3: Candidate Answer Scoring

The Hound of the Baskervilles

The Hound of the Baskervilles

The Hound of the Baskervilles (1901)

# Stage 3: Candidate Answer Scoring

The Hound of the Baskervilles

The Hound of the Baskervilles

The Hound of the Baskervilles (1901)

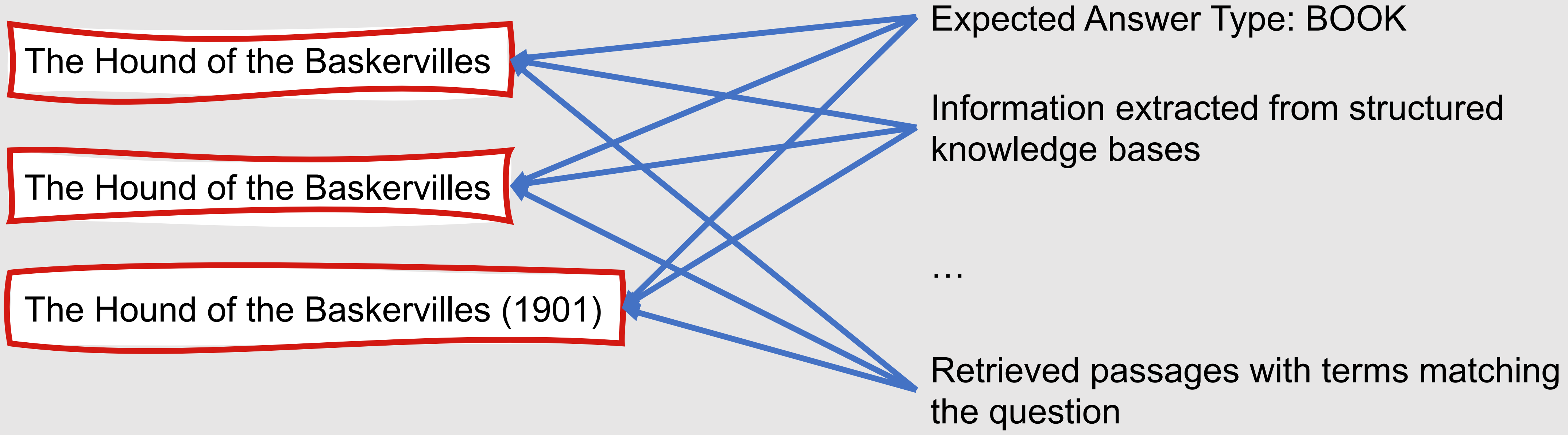
Expected Answer Type: BOOK

Information extracted from structured knowledge bases

…

Retrieved passages with terms matching the question

# Stage 3: Candidate Answer Scoring



The Hound of the Baskervilles

The Hound of the Baskervilles

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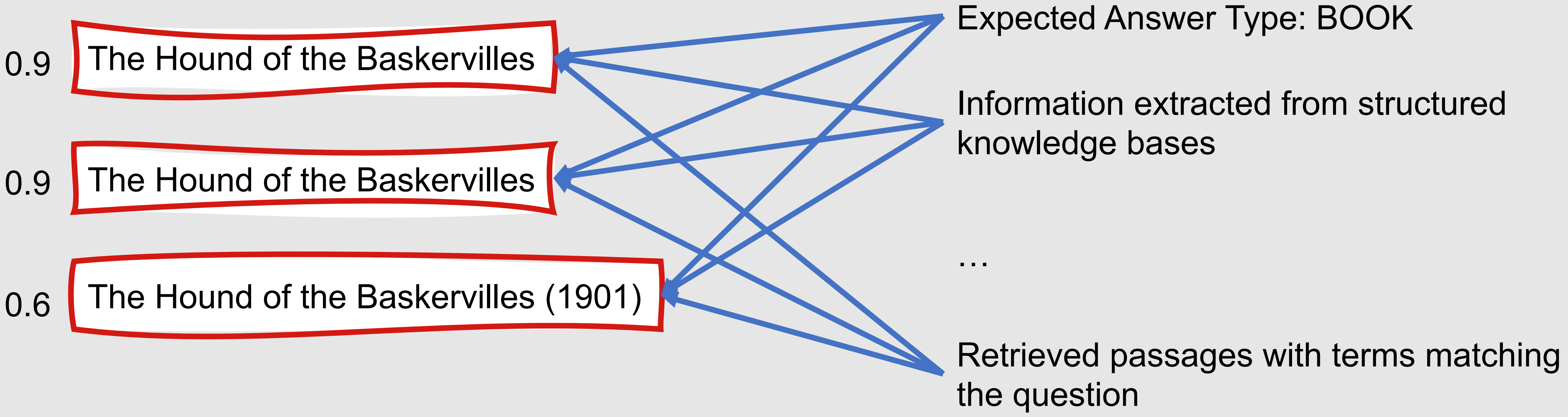
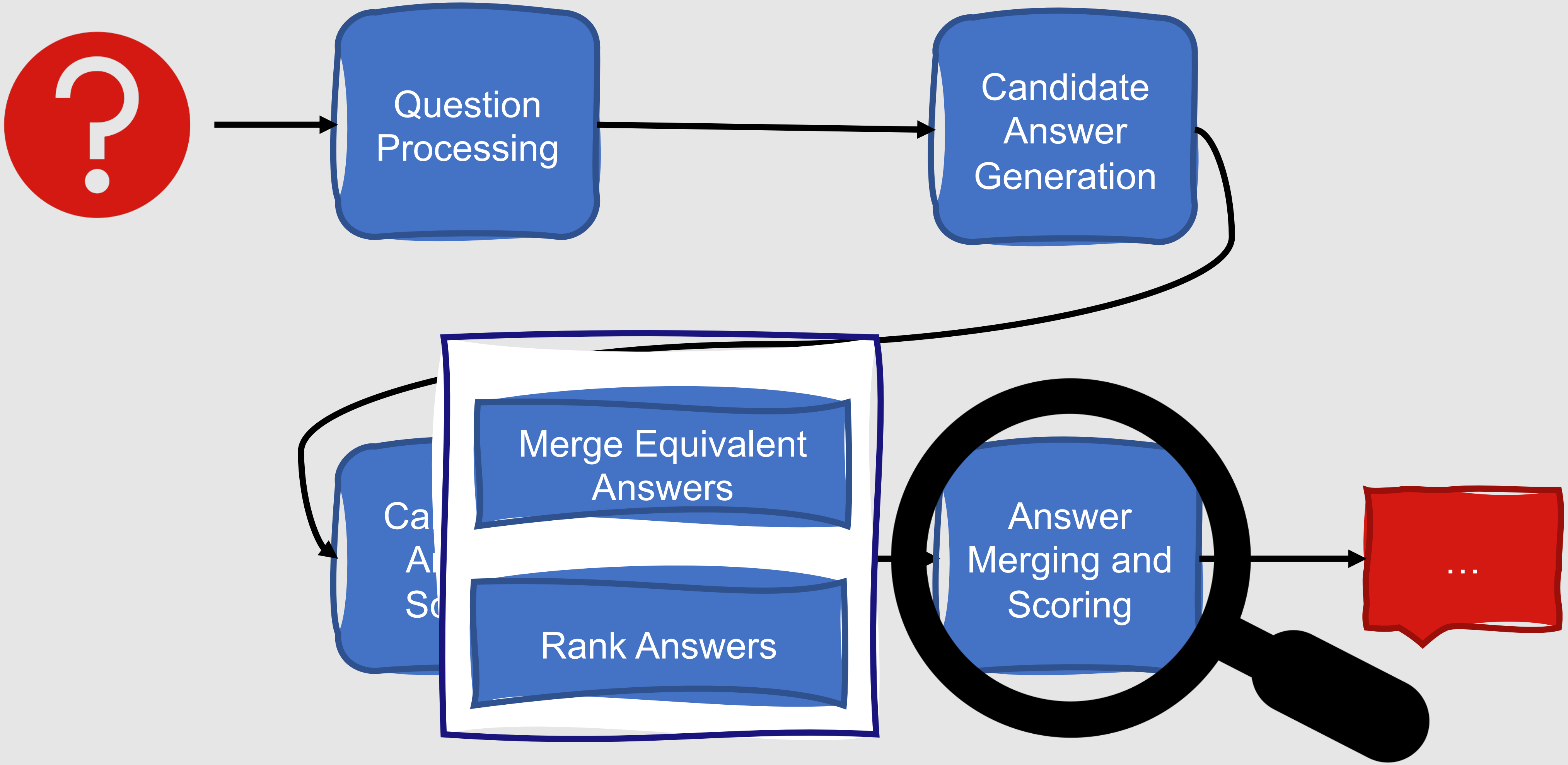
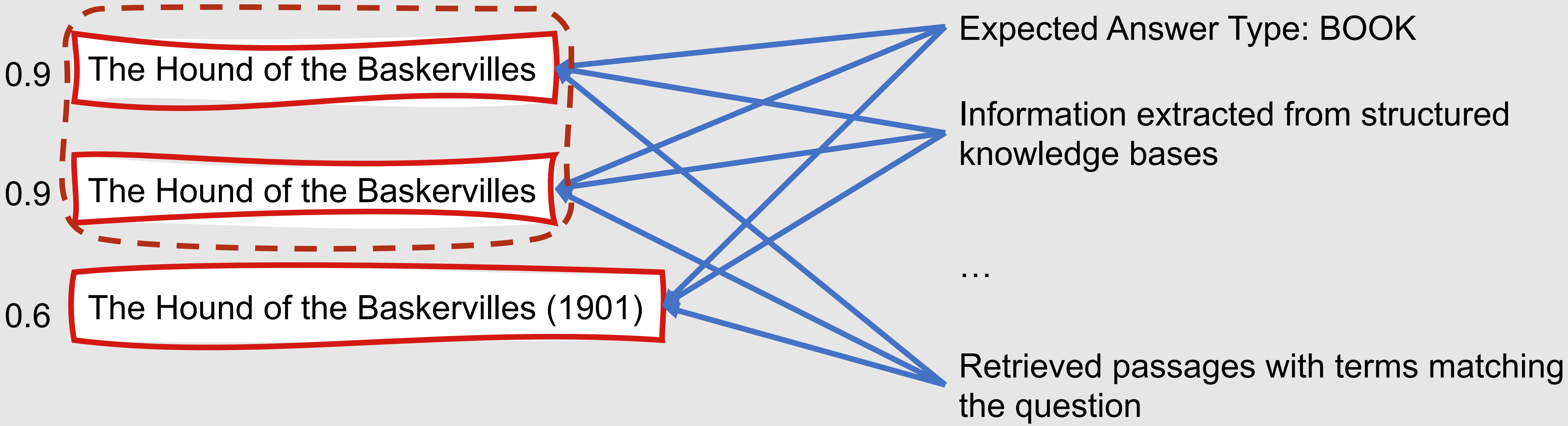

0.9
The Hound of the Baskervilles
0.9
The Hound of the Baskervilles
0.6
The Hound of the Baskervilles (1901)
Expected Answer Type: BOOK
Information extracted from structured knowledge bases
…
Retrieved passages with terms matching the question

# Stage 4: Answer Merging and Scoring



# Stage 4: Answer Merging and Scoring



0.9 The Hound of the Baskervilles

0.9 The Hound of the Baskervilles

0.6 The Hound of the Baskervilles (1901)

Expected Answer Type: BOOK

Information extracted from structured knowledge bases

…

Retrieved passages with terms matching the question

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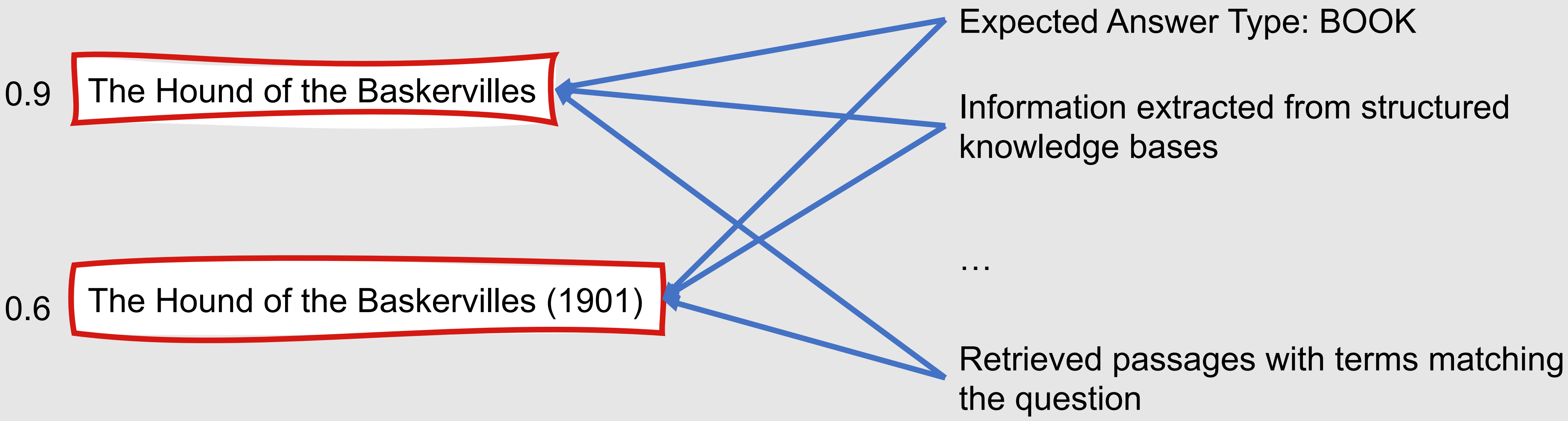
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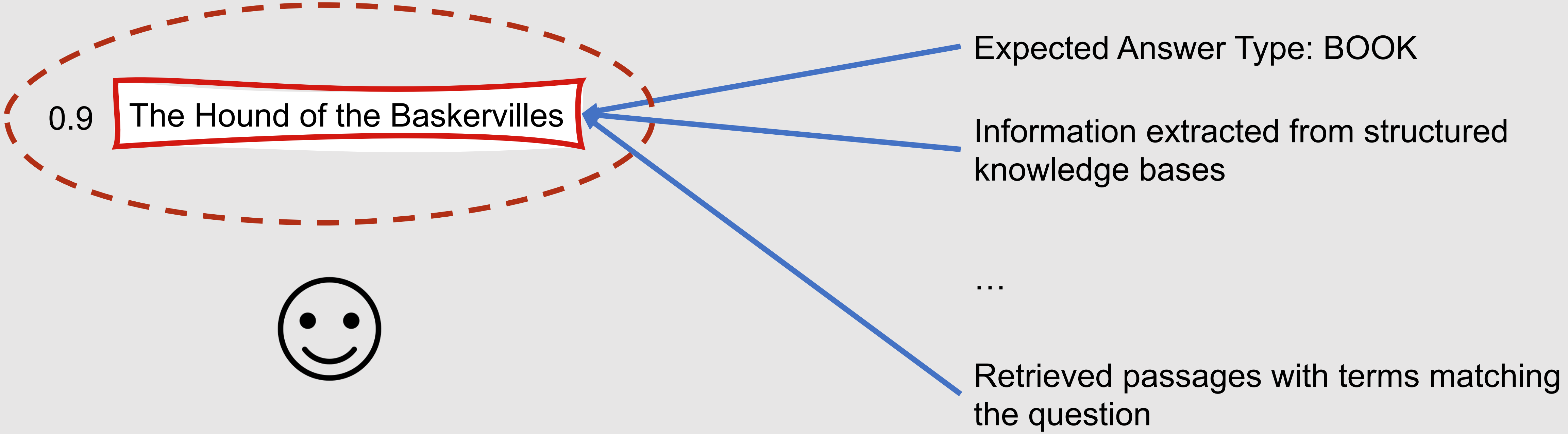


0.9 The Hound of the Baskervilles

Expected Answer Type: BOOK

Information extracted from structured knowledge bases

…

Retrieved passages with terms matching the question

☺

# Watson is just one of many question answering architectures!

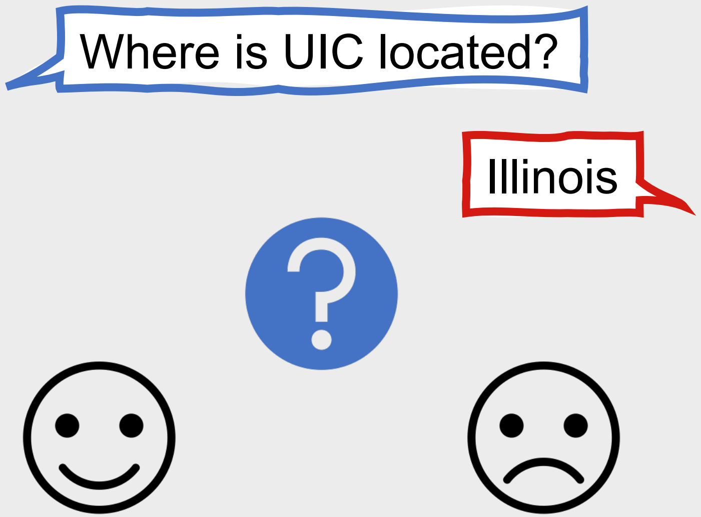
- Most high-performing QA systems will follow the same intuition:
  - Propose a large number of candidate answers using both IR-based and knowledge-based techniques
  - Develop a variety of IR-based and knowledge-based features to score the candidates

# Summary: Question Answering (Part 1)

- **Question answering** is the process of automatically retrieving short spans of correct, relevant information in response to a user's **query**
- Most question answering systems focus on **factoid** questions
- There are two major types of question answering systems:
  - **Information retrieval-based**
  - **Knowledge-based**
- These two types of question answering systems are often combined, as seen in Watson's DeepQA architecture

# How are question answering systems evaluated?

- Common metric for factoid question answering: **Mean Reciprocal Rank**
  - Assumes that gold standard answers are available for test questions
  - Assumes that systems return a short ranked list of answers



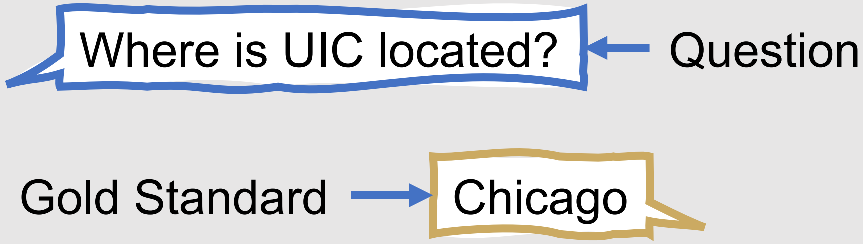
Where is UIC located?

Illinois

# Mean Reciprocal Rank

- Scores each question according to the reciprocal of the rank of the first correct answer
    - Highest ranked correct answer is ranked fourth → reciprocal rank = ¼
- Assigns a score of 0 to questions with no correct answers returned
- System's overall score is the average of all individual question scores
    - $\mathrm{MRR} = \frac{1}{N}\sum_{i=1}^{N} \text{s.t. } _{rank_i \neq 0} \frac{1}{rank_i}$

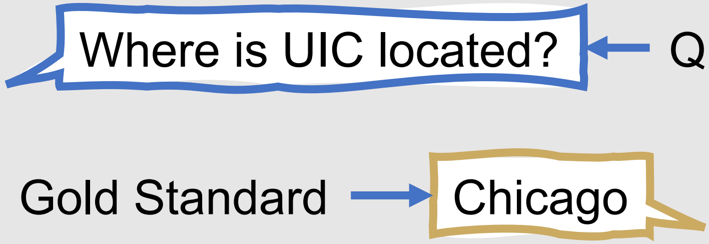
# Mean Reciprocal Rank



Where is UIC located? ← Question

Gold Standard → Chicago

# Mean Reciprocal Rank

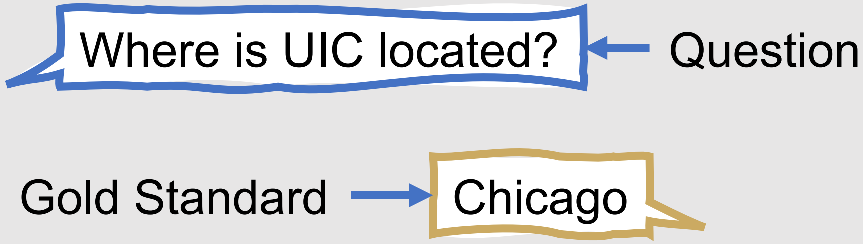


Where is UIC located? ← Question

Gold Standard → Chicago

| Prediction | Rank |
|---|---|
| Illinois | 1 |
| West Loop | 2 |
| Chicago | 3 |
| Little Italy | 4 |

# Mean Reciprocal Rank



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Gold Standard

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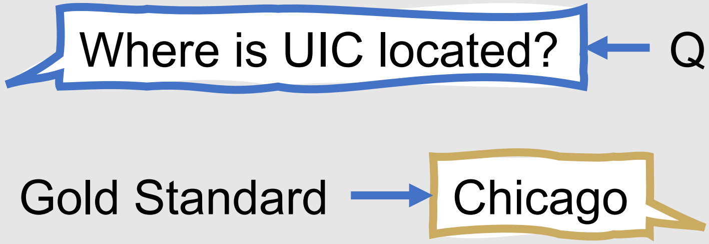

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Question

Gold Standard

Chicago

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| Illinois | 1 |
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Reciprocal
Rank = 1/3

# Mean Reciprocal Rank

Where is UIC located? ← Question

Gold Standard → Chicago

| Prediction | Rank |
|---|---|
| Illinois | 1 |
| West Loop | 2 |
| Chicago | 3 |
| Little Italy | 4 |

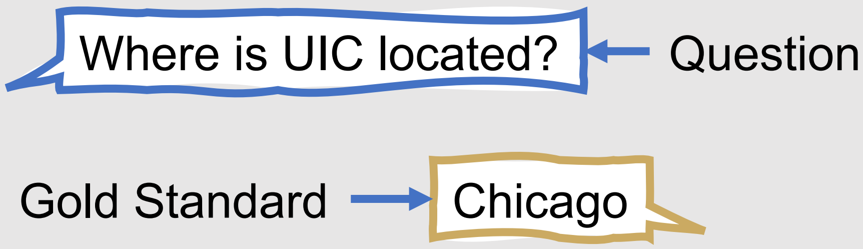
Reciprocal
Rank = 1/3

Who is the head of UIC's Department of Computer Science? ← Question

Gold Standard → Robert Sloan

| Prediction | Rank |
|---|---|
| Peter Nelson | 1 |
| Robert Sloan | 2 |
| Natalie Parde | 3 |
| Usman Shahid | 4 |

# Mean Reciprocal Rank



Where is UIC located?

Question

Gold Standard

Chicago

| Prediction | Rank |
|---|---|
| Illinois | 1 |
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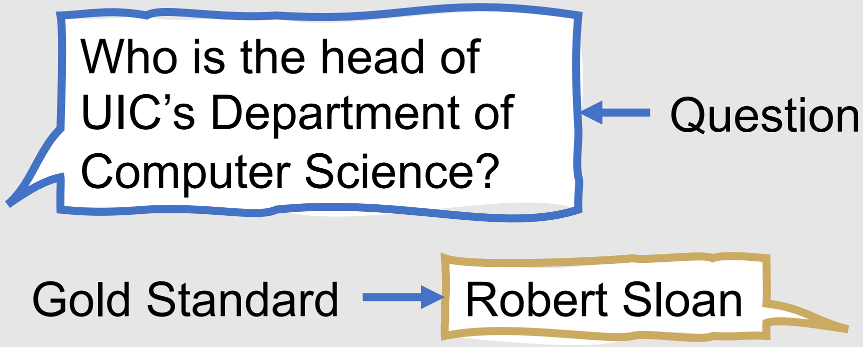
Reciprocal
Rank = 1/3



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Question

Gold Standard

Robert Sloan

| Prediction | Rank |
|---|---|
| Peter Nelson | 1 |
| Robert Sloan | 2 |
| Natalie Parde | 3 |
| Usman Shahid | 4 |

Reciprocal
Rank = 1/2

# Mean Reciprocal Rank

Where is UIC located? ← Question

Gold Standard → Chicago

| Prediction | Rank |
|---|---|
| Illinois | 1 |
| West Loop | 2 |
| Chicago | 3 |
| Little Italy | 4 |

Reciprocal Rank = 1/3

Who is the head of UIC's Department of Computer Science? ← Question

Gold Standard → Robert Sloan

| Prediction | Rank |
|---|---|
| Peter Nelson | 1 |
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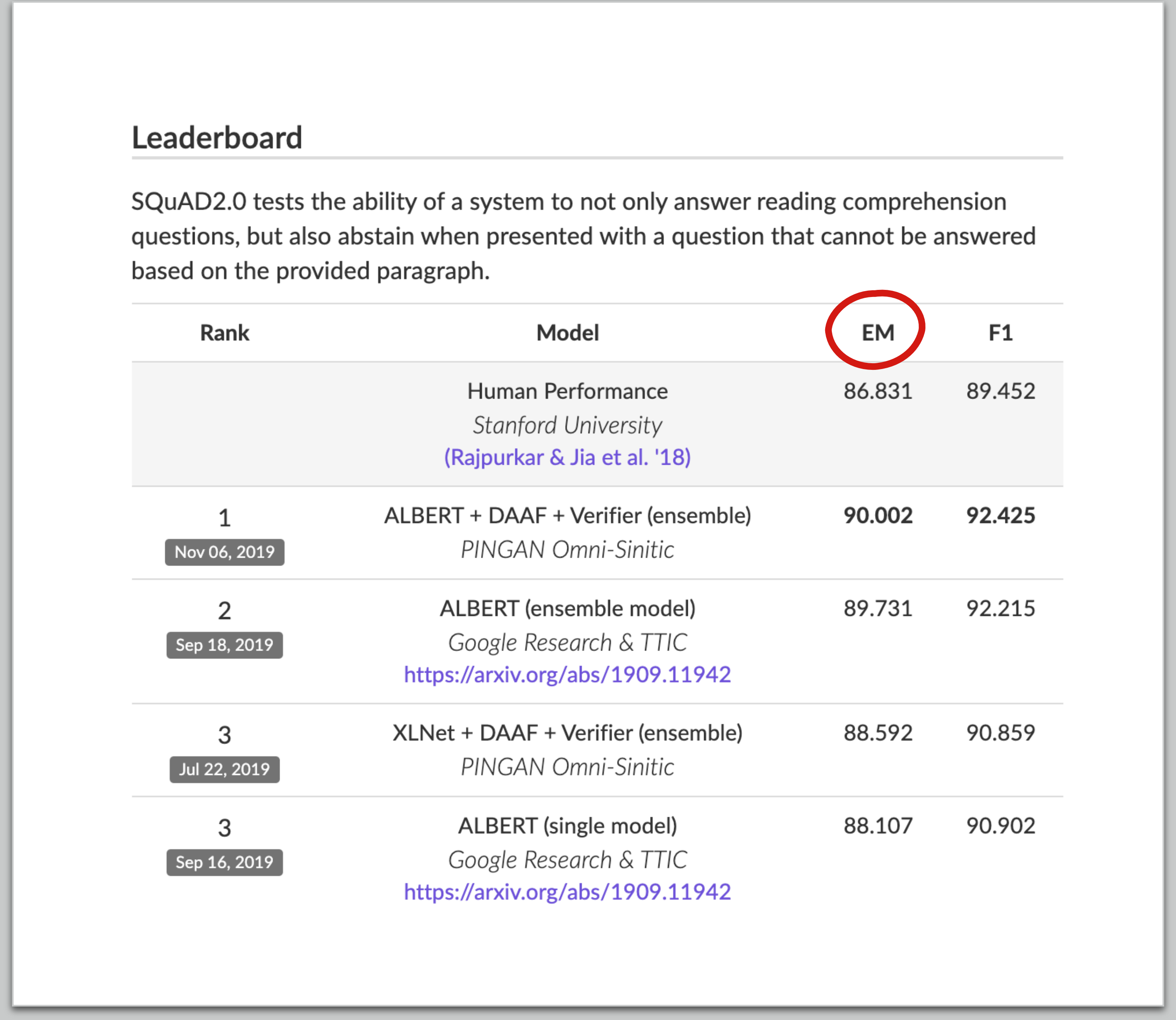
Reciprocal Rank = 1/2

$$\text{MRR} = \frac{\frac{1}{3}+\frac{1}{2}}{2} = 0.417$$

# Other Evaluation Metrics for Question Answering Systems

- **Exact Match**
  - Remove punctuation and articles
  - Compute the percentage of predicted answers that match the gold standard answer exactly



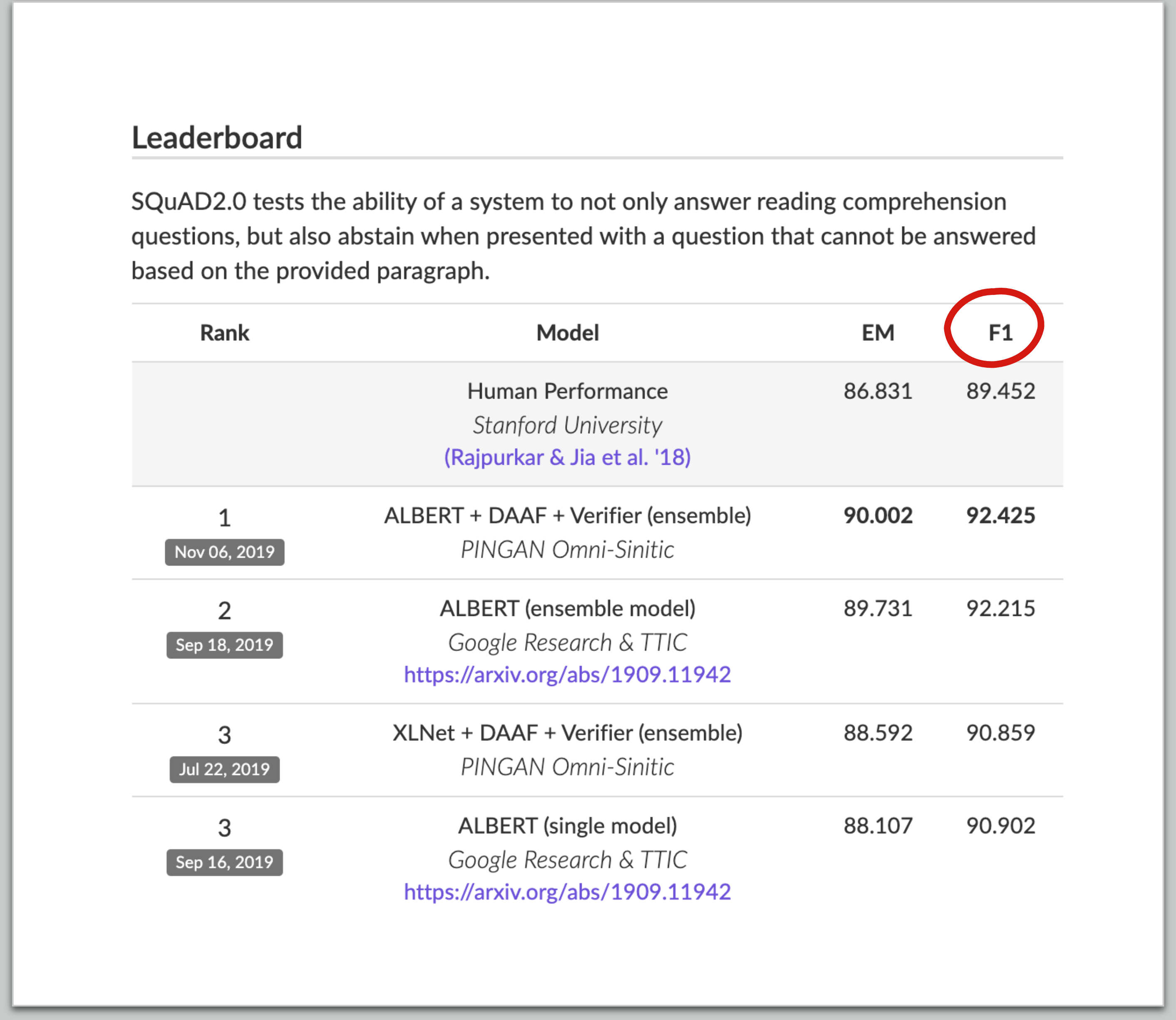
## Leaderboard

SQuAD2.0 tests the ability of a system to not only answer reading comprehension questions, but also abstain when presented with a question that cannot be answered based on the provided paragraph.

| Rank | Model | EM | F1 |
|---|---|---|---|
| | Human Performance<br>*Stanford University*<br>(Rajpurkar & Jia et al. '18) | 86.831 | 89.452 |
| 1<br>Nov 06, 2019 | ALBERT + DAAF + Verifier (ensemble)<br>*PINGAN Omni-Sinitic* | **90.002** | **92.425** |
| 2<br>Sep 18, 2019 | ALBERT (ensemble model)<br>*Google Research & TTIC*<br>https://arxiv.org/abs/1909.11942 | 89.731 | 92.215 |
| 3<br>Jul 22, 2019 | XLNet + DAAF + Verifier (ensemble)<br>*PINGAN Omni-Sinitic* | 88.592 | 90.859 |
| 3<br>Sep 16, 2019 | ALBERT (single model)<br>*Google Research & TTIC*<br>https://arxiv.org/abs/1909.11942 | 88.107 | 90.902 |

# Other Evaluation Metrics for Question Answering Systems

- **$F_1$ Score**
  - Remove punctuation and articles
  - Treat the predicted and gold standard answers as bags of tokens
  - True positives: Tokens that exist in both the gold standard and predicted answers
  - Average $F_1$ over all questions



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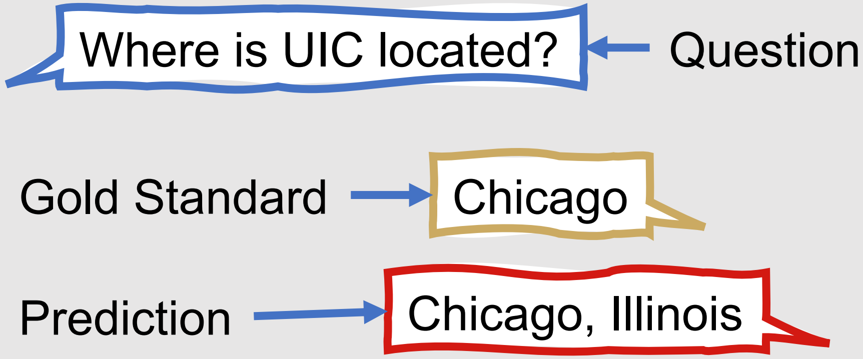
# Computing $F_1$ for Question Answering Systems



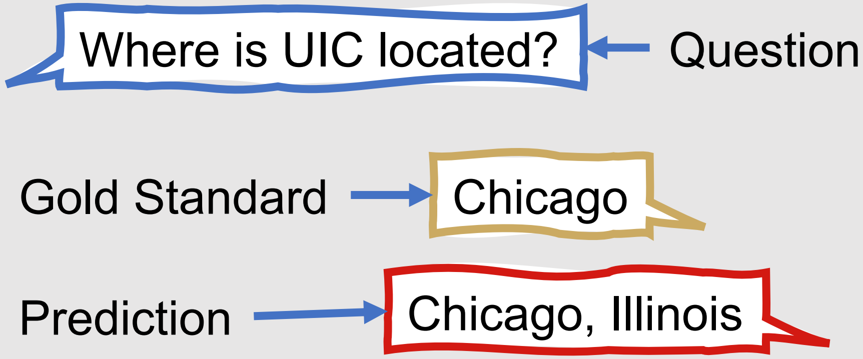
Where is UIC located? ← Question

Gold Standard → Chicago

Prediction → Chicago, Illinois

| | Actual True | Actual False |
|---|---|---|
| Predicted True | | |
| Predicted False | | |

# Computing $F_1$ for Question Answering Systems



Where is UIC located? ← Question

Gold Standard → Chicago

Prediction → Chicago, Illinois

| | Actual True | Actual False |
|---|---|---|
| Predicted True | 1 | 1 |
| Predicted False | 0 | |

# Computing $F_1$ for Question Answering Systems

Where is UIC located? ← Question

Gold Standard → Chicago

Prediction → Chicago, Illinois

| | Actual True | Actual False |
|---|---|---|
| **Predicted True** | 1 | 1 |
| **Predicted False** | 0 | |

Precision = $\frac{TP}{TP+FP} = \frac{1}{1+1}$ = 0.5

Recall = $\frac{TP}{TP+FN} = \frac{1}{1+0}$ = 1

$F_1$ = $\frac{2*P*R}{P+R} = \frac{2*0.5*1}{0.5+1}$ = 0.67

# More Question Answering Datasets

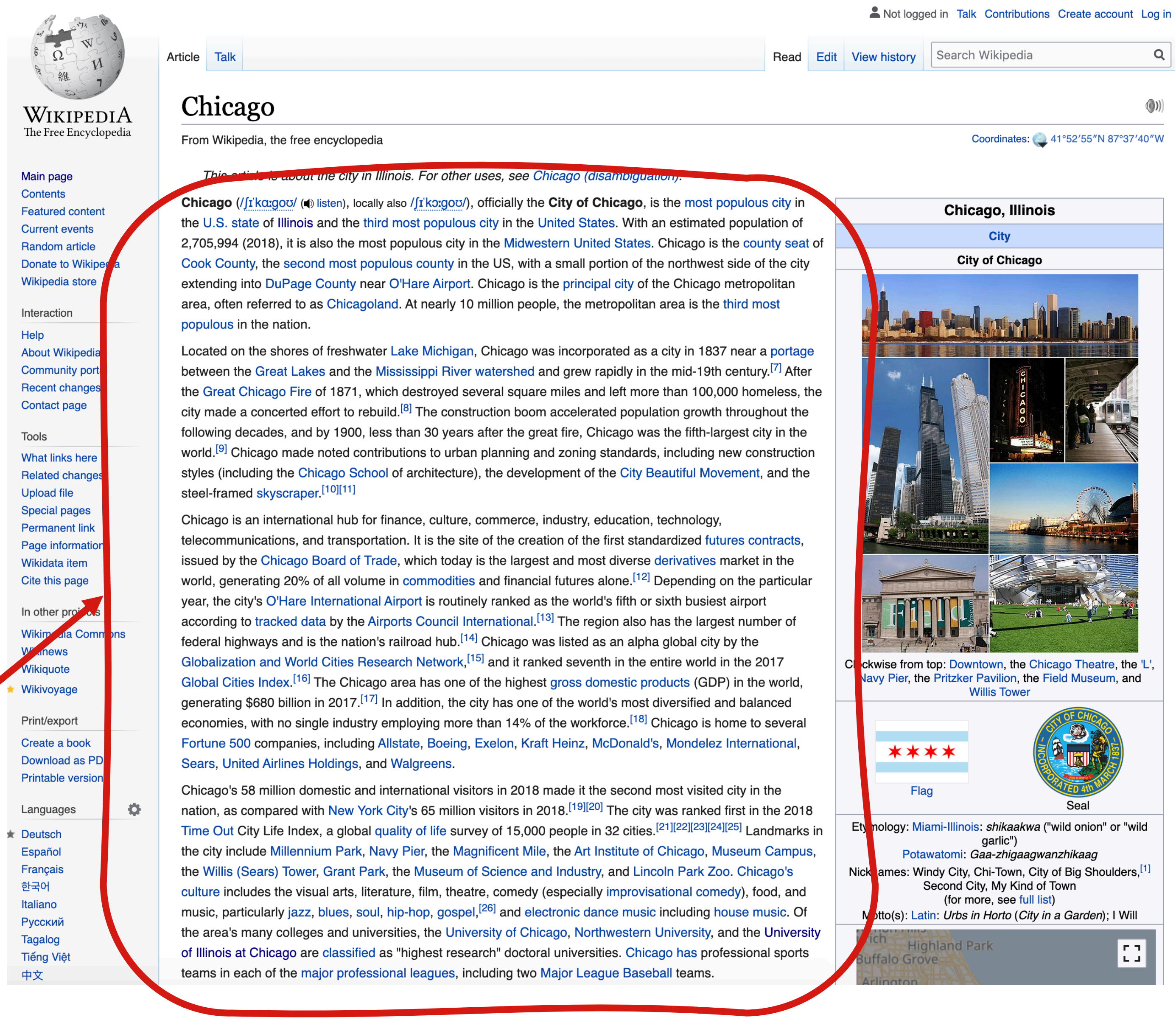
| | |
|---|---|
| TREC QA Dataset | https://trec.nist.gov/data/qa.html |
| TriviaQA Dataset | https://nlp.cs.washington.edu/triviaqa/ |
| WebQuestions Dataset | https://worksheets.codalab.org/worksheets/0xba659fe363cb46e7a505c5b6a774dc8a |
| NarrativeQA Dataset | https://github.com/deepmind/narrativeqa |
| Question Answering in Context Dataset | https://quac.ai/ |
| MCTest Dataset | https://github.com/mcobzarenco/mctest/tree/master/data/MCTest |
| AI2 Reasoning Challenge | http://data.allenai.org/arc/ |

# What is text summarization?

- The process of **automatically extracting the most important information** from a text to create an abridged version of it

# Summarization

Chicago is one of the largest cities in the United States. It is located in Illinois, and is bordered by Lake Michigan. It is an international cultural, financial, and transportation hub.



## Chicago

From Wikipedia, the free encyclopedia

Coordinates: 41°52′55″N 87°37′40″W

*This article is about the city in Illinois. For other uses, see Chicago (disambiguation).*

**Chicago** (/ʃɪˈkɑːɡoʊ/ listen), locally also /ʃɪˈkɔːɡoʊ/), officially the **City of Chicago**, is the most populous city in the U.S. state of Illinois and the third most populous city in the United States. With an estimated population of 2,705,994 (2018), it is also the most populous city in the Midwestern United States. Chicago is the county seat of Cook County, the second most populous county in the US, with a small portion of the northwest side of the city extending into DuPage County near O'Hare Airport. Chicago is the principal city of the Chicago metropolitan area, often referred to as Chicagoland. At nearly 10 million people, the metropolitan area is the third most populous in the nation.

Located on the shores of freshwater Lake Michigan, Chicago was incorporated as a city in 1837 near a portage between the Great Lakes and the Mississippi River watershed and grew rapidly in the mid-19th century.[7] After the Great Chicago Fire of 1871, which destroyed several square miles and left more than 100,000 homeless, the city made a concerted effort to rebuild.[8] The construction boom accelerated population growth throughout the following decades, and by 1900, less than 30 years after the great fire, Chicago was the fifth-largest city in the world.[9] Chicago made noted contributions to urban planning and zoning standards, including new construction styles (including the Chicago School of architecture), the development of the City Beautiful Movement, and the steel-framed skyscraper.[10][11]

Chicago is an international hub for finance, culture, commerce, industry, education, technology, telecommunications, and transportation. It is the site of the creation of the first standardized futures contracts, issued by the Chicago Board of Trade, which today is the largest and most diverse derivatives market in the world, generating 20% of all volume in commodities and financial futures alone.[12] Depending on the particular year, the city's O'Hare International Airport is routinely ranked as the world's fifth or sixth busiest airport according to tracked data by the Airports Council International.[13] The region also has the largest number of federal highways and is the nation's railroad hub.[14] Chicago was listed as an alpha global city by the Globalization and World Cities Research Network,[15] and it ranked seventh in the entire world in the 2017 Global Cities Index.[16] The Chicago area has one of the highest gross domestic products (GDP) in the world, generating $680 billion in 2017.[17] In addition, the city has one of the world's most diversified and balanced economies, with no single industry employing more than 14% of the workforce.[18] Chicago is home to several Fortune 500 companies, including Allstate, Boeing, Exelon, Kraft Heinz, McDonald's, Mondelez International, Sears, United Airlines Holdings, and Walgreens.

Chicago's 58 million domestic and international visitors in 2018 made it the second most visited city in the nation, as compared with New York City's 65 million visitors in 2018.[19][20] The city was ranked first in the 2018 Time Out City Life Index, a global quality of life survey of 15,000 people in 32 cities.[21][22][23][24][25] Landmarks in the city include Millennium Park, Navy Pier, the Magnificent Mile, the Art Institute of Chicago, Museum Campus, the Willis (Sears) Tower, Grant Park, the Museum of Science and Industry, and Lincoln Park Zoo. Chicago's culture includes the visual arts, literature, film, theatre, comedy (especially improvisational comedy), food, and music, particularly jazz, blues, soul, hip-hop, gospel,[26] and electronic dance music including house music. Of the area's many colleges and universities, the University of Chicago, Northwestern University, and the University of Illinois at Chicago are classified as "highest research" doctoral universities. Chicago has professional sports teams in each of the major professional leagues, including two Major League Baseball teams.

**Chicago, Illinois**

City

**City of Chicago**

Clockwise from top: Downtown, the Chicago Theatre, the 'L', Navy Pier, the Pritzker Pavilion, the Field Museum, and Willis Tower

Flag

Seal

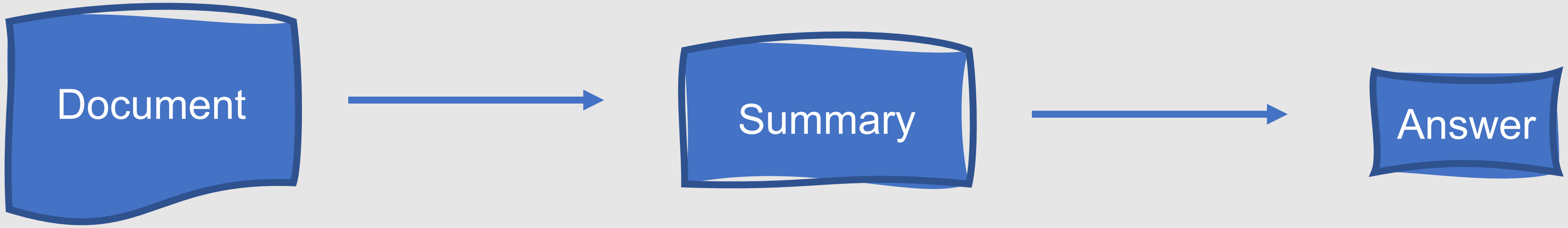
Etymology: Miami-Illinois: *shikaakwa* ("wild onion" or "wild garlic")
Potawatomi: *Gaa-zhigaagwanzhikaag*

Nicknames: Windy City, Chi-Town, City of Big Shoulders,[1] Second City, My Kind of Town
(for more, see full list)

Motto(s): Latin: *Urbs in Horto* (*City in a Garden*); I Will

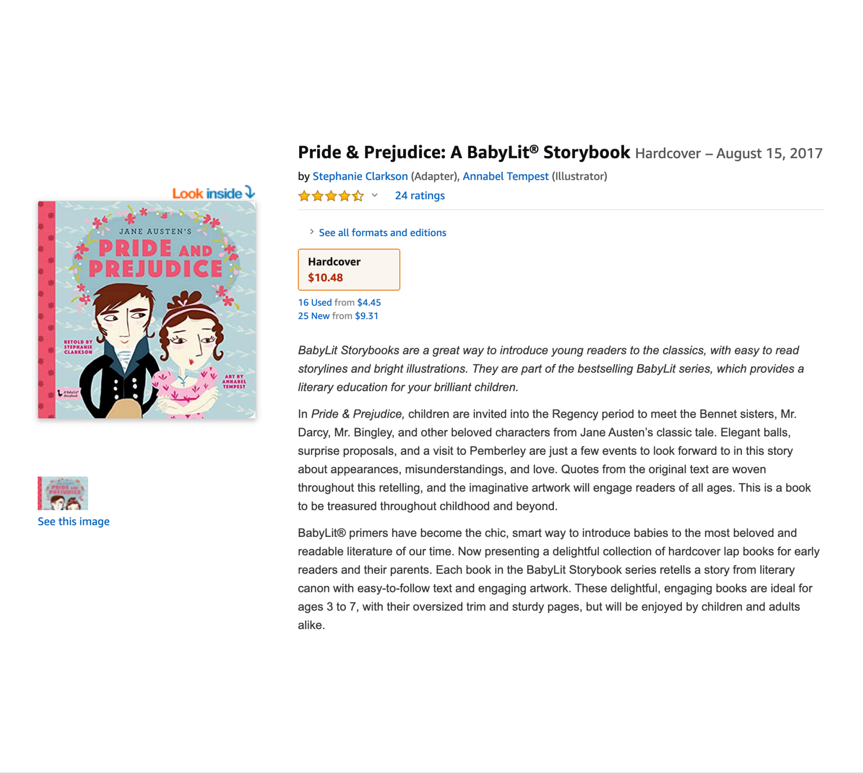
# Summarization

- Summaries are shorter than the full documents returned using information retrieval algorithms
- Summaries are longer than the short answer phrases returned by question answering systems



# Summaries in the Real World

- Document outlines
- Abstracts for academic articles
- News article headlines
- Website snippets on search results pages
- Meeting minutes
- “Child-friendly” versions of text



**Pride & Prejudice: A BabyLit® Storybook** Hardcover – August 15, 2017

by Stephanie Clarkson (Adapter), Annabel Tempest (Illustrator)

24 ratings

See all formats and editions

Hardcover
$10.48

16 Used from $4.45
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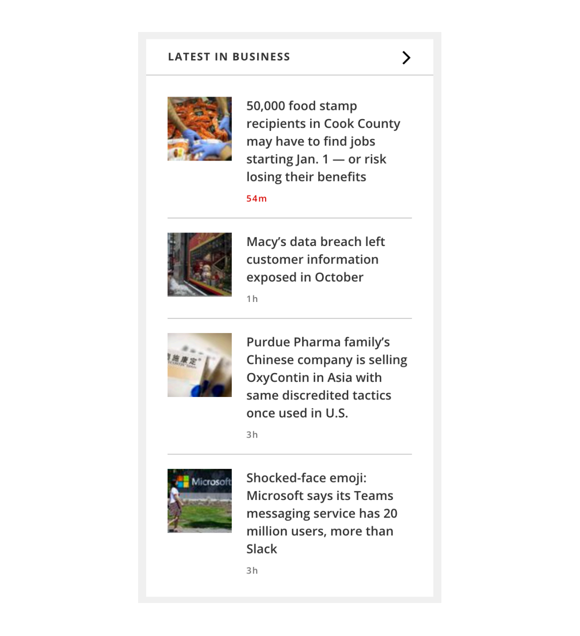
*BabyLit Storybooks are a great way to introduce young readers to the classics, with easy to read storylines and bright illustrations. They are part of the bestselling BabyLit series, which provides a literary education for your brilliant children.*

In *Pride & Prejudice*, children are invited into the Regency period to meet the Bennet sisters, Mr. Darcy, Mr. Bingley, and other beloved characters from Jane Austen’s classic tale. Elegant balls, surprise proposals, and a visit to Pemberley are just a few events to look forward to in this story about appearances, misunderstandings, and love. Quotes from the original text are woven throughout this retelling, and the imaginative artwork will engage readers of all ages. This is a book to be treasured throughout childhood and beyond.

BabyLit® primers have become the chic, smart way to introduce babies to the most beloved and readable literature of our time. Now presenting a delightful collection of hardcover lap books for early readers and their parents. Each book in the BabyLit Storybook series retells a story from literary canon with easy-to-follow text and engaging artwork. These delightful, engaging books are ideal for ages 3 to 7, with their oversized trim and sturdy pages, but will be enjoyed by children and adults alike.



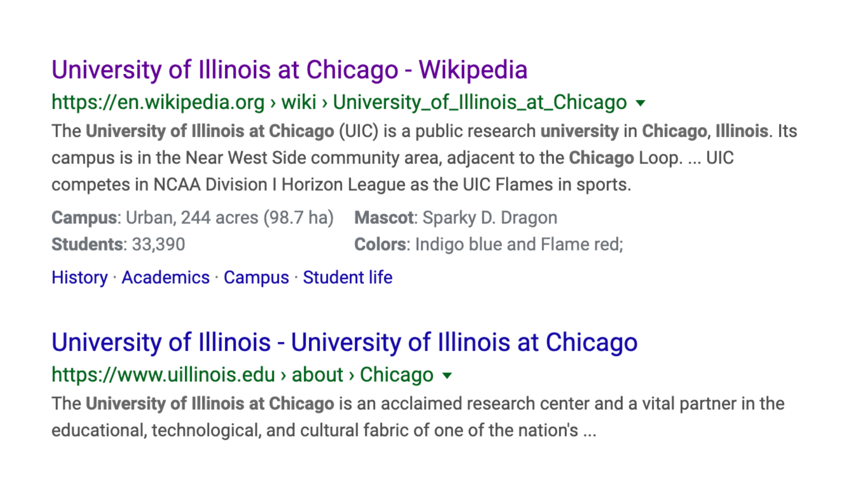
LATEST IN BUSINESS

50,000 food stamp recipients in Cook County may have to find jobs starting Jan. 1 — or risk losing their benefits
54m

Macy’s data breach left customer information exposed in October
1h

Purdue Pharma family’s Chinese company is selling OxyContin in Asia with same discredited tactics once used in U.S.
3h

Shocked-face emoji: Microsoft says its Teams messaging service has 20 million users, more than Slack
3h



University of Illinois at Chicago - Wikipedia
https://en.wikipedia.org › wiki › University_of_Illinois_at_Chicago ▾
The **University of Illinois at Chicago** (UIC) is a public research **university** in **Chicago, Illinois**. Its campus is in the Near West Side community area, adjacent to the **Chicago** Loop. ... UIC competes in NCAA Division I Horizon League as the UIC Flames in sports.

**Campus**: Urban, 244 acres (98.7 ha)    **Mascot**: Sparky D. Dragon
**Students**: 33,390    **Colors**: Indigo blue and Flame red;

History · Academics · Campus · Student life

University of Illinois - University of Illinois at Chicago
https://www.uillinois.edu › about › Chicago ▾
The **University of Illinois at Chicago** is an acclaimed research center and a vital partner in the educational, technological, and cultural fabric of one of the nation's ...

**BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding**

**Jacob Devlin  Ming-Wei Chang  Kenton Lee  Kristina Toutanova**
Google AI Language
{jacobdevlin,mingweichang,kentonl,kristout}@google.com

**Abstract**

We introduce a new language representation model called **BERT**, which stands for **B**idirectional **E**ncoder **R**epresentations from **T**ransformers. Unlike recent language representation models (Peters et al., 2018a; Radford et al., 2018), BERT is designed to pretrain deep bidirectional representations from unlabeled text by jointly conditioning on both left and right context in all layers. As a result, the pre-trained BERT model can be fine-tuned with just one additional output layer to create state-of-the-art models for a wide range of tasks, such as question answering and language inference, without substantial task-specific architecture modifications.

BERT is conceptually simple and empirically powerful. It obtains new state-of-the-art results on eleven natural language processing tasks, including pushing the GLUE score to 80.5% (7.7% point absolute improvement), MultiNLI accuracy to 86.7% (4.6% absolute improvement), SQuAD v1.1 question answering Test F1 to 93.2 (1.5 point absolute improvement) and SQuAD v2.0 Test F1 to 83.1 (5.1 point absolute improvement).

**1 Introduction**

Language model pre-training has been shown to be effective for improving many natural language processing tasks (Dai and Le, 2015; Peters et al., 2018a; Radford et al., 2018; Howard and Ruder, 2018). These include sentence-level tasks such as natural language inference (Bowman et al., 2015; Williams et al., 2018) and paraphrasing (Dolan and Brockett, 2005), which aim to predict the relationships between sentences by analyzing them holistically, as well as token-level tasks such as named entity recognition and question answering, where models are required to produce fine-grained output at the token level (Tjong Kim Sang and De Meulder, 2003; Rajpurkar et al., 2016).

There are two existing strategies for applying pre-trained language representations to downstream tasks: *feature-based* and *fine-tuning*. The feature-based approach, such as ELMo (Peters et al., 2018a), uses task-specific architectures that include the pre-trained representations as additional features. The fine-tuning approach, such as the Generative Pre-trained Transformer (OpenAI GPT) (Radford et al., 2018), introduces minimal task-specific parameters, and is trained on the downstream tasks by simply fine-tuning *all* pretrained parameters. The two approaches share the same objective function during pre-training, where they use unidirectional language models to learn general language representations.

We argue that current techniques restrict the power of the pre-trained representations, especially for the fine-tuning approaches. The major limitation is that standard language models are unidirectional, and this limits the choice of architectures that can be used during pre-training. For example, in OpenAI GPT, the authors use a left-to-right architecture, where every token can only attend to previous tokens in the self-attention layers of the Transformer (Vaswani et al., 2017). Such restrictions are sub-optimal for sentence-level tasks, and could be very harmful when applying fine-tuning based approaches to token-level tasks such as question answering, where it is crucial to incorporate context from both directions.

In this paper, we improve the fine-tuning based approaches by proposing BERT: **B**idirectional **E**ncoder **R**epresentations from **T**ransformers. BERT alleviates the previously mentioned unidirectionality constraint by using a “masked language model” (MLM) pre-training objective, inspired by the Cloze task (Taylor, 1953). The masked language model randomly masks some of the tokens from the input, and the objective is to predict the original vocabulary id of the masked

# Types of Summarization

## Number of documents summarized

- Single-document summarization
- Multiple-document summarization

## Nature of the summary

- Generic summarization
- Query-focused summarization

# Single-Document Summarization

- Given a single document, produce a summary
- Best for situations where the end goal is to characterize the content of a single document
- Example use cases:
  - Generating a headline for a news article
  - Producing an outline for a document

# Multiple-Document Summarization

- Given a group of documents, produce a summary
- Best for situations when content from multiple sources needs to be synthesized
- Example use cases:
  - Summarizing a series of news stories covering the same event
  - Reviewing a cluster of similar prior work in a research area

# Generic vs. Query-focused Summarization

## Generic Summaries

- Provide the important information in a document
- Do not consider a specific user or a specific information need

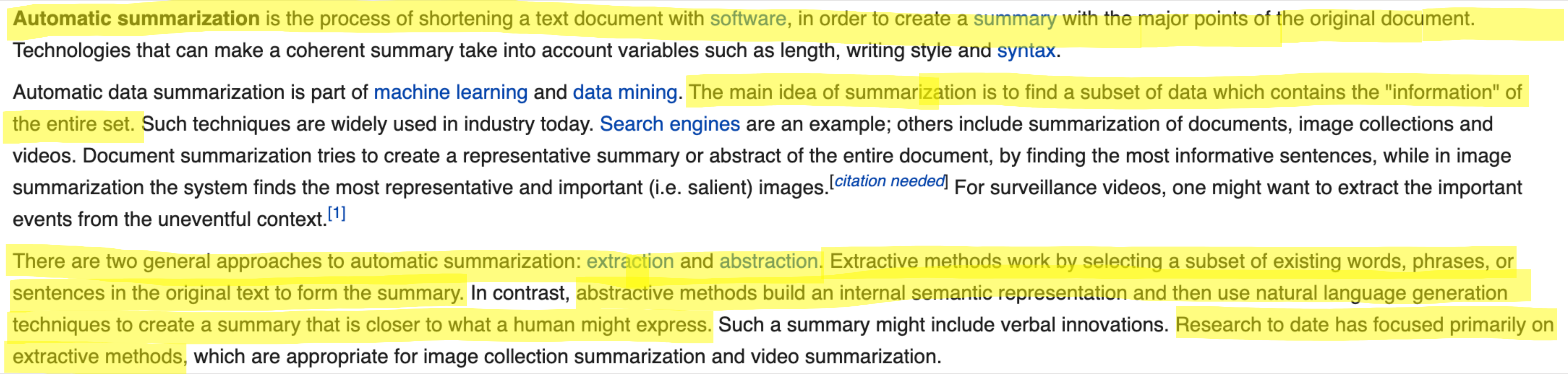
## Query-focused Summaries

- Provide a specific set of information in response to a user's query
- Can be viewed as a longer, non-factoid answer to a question

# Text Summarization Paradigms

Extractive Summarization

Abstractive Summarization



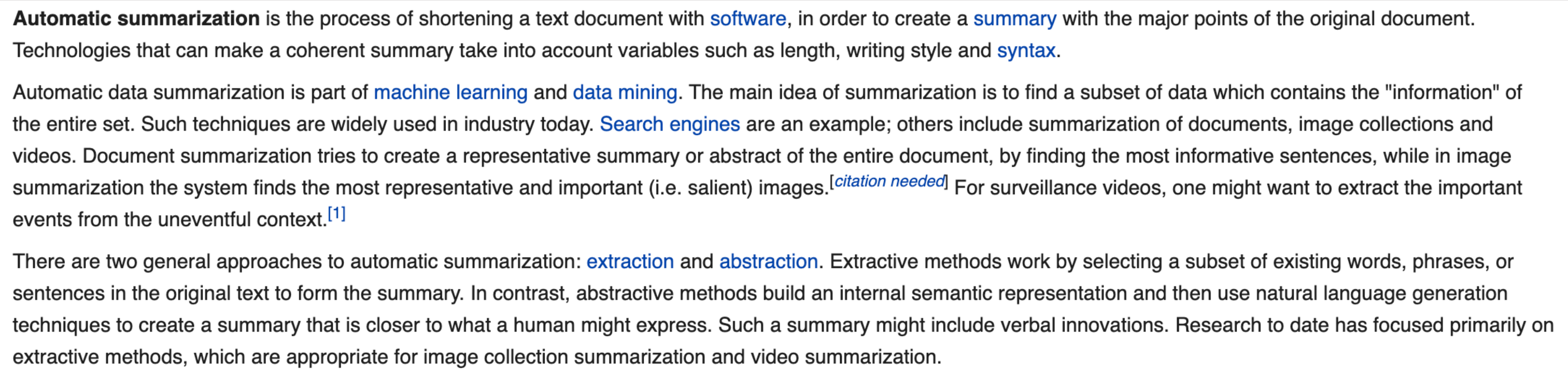
**Automatic summarization** is the process of shortening a text document with software, in order to create a summary with the major points of the original document. Technologies that can make a coherent summary take into account variables such as length, writing style and syntax.

Automatic data summarization is part of machine learning and data mining. The main idea of summarization is to find a subset of data which contains the "information" of the entire set. Such techniques are widely used in industry today. Search engines are an example; others include summarization of documents, image collections and videos. Document summarization tries to create a representative summary or abstract of the entire document, by finding the most informative sentences, while in image summarization the system finds the most representative and important (i.e. salient) images.[citation needed] For surveillance videos, one might want to extract the important events from the uneventful context.[1]

There are two general approaches to automatic summarization: extraction and abstraction. Extractive methods work by selecting a subset of existing words, phrases, or sentences in the original text to form the summary. In contrast, abstractive methods build an internal semantic representation and then use natural language generation techniques to create a summary that is closer to what a human might express. Such a summary might include verbal innovations. Research to date has focused primarily on extractive methods, which are appropriate for image collection summarization and video summarization.

# Extractive Summarization

- Simplest form of text summarization
- Extract phrases or sentences from the source document(s) and combine them



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Automatic summarization is the process of transforming a full text document into a concise summary containing the same key information. The two general approaches to automatic summarization are extraction and abstraction. Extractive methods select subsets of text from the original document to form the summary, whereas abstractive methods generate new text that conveys the same core content. Most research to date has focused on extractive summarization.

# Abstractive Summarization

- Much more complex
- Summarizes the underlying content in the text using different words
- Key goal in recent research is to move toward better abstractive summarization techniques

# In general, summarization approaches need to focus on three main problems.

- **Content Selection**
  - What information should be selected from the document(s) being summarized?
- **Information Ordering**
  - How should the extracted information be ordered?
- **Sentence Realization**
  - What changes need to be made to the resulting summary to ensure that it is grammatically correct and natural-sounding?

# Single-Document Summarization

Key focus:

- Content selection
- Sentence realization

Information ordering is often unnecessary!

- Original order from the source document can be used

# How is content selected?

- Classification task
  - Predict whether each sentence in a document is **important** or **unimportant**
- This can be done using either **supervised** or **unsupervised** methods

# Unsupervised Content Selection

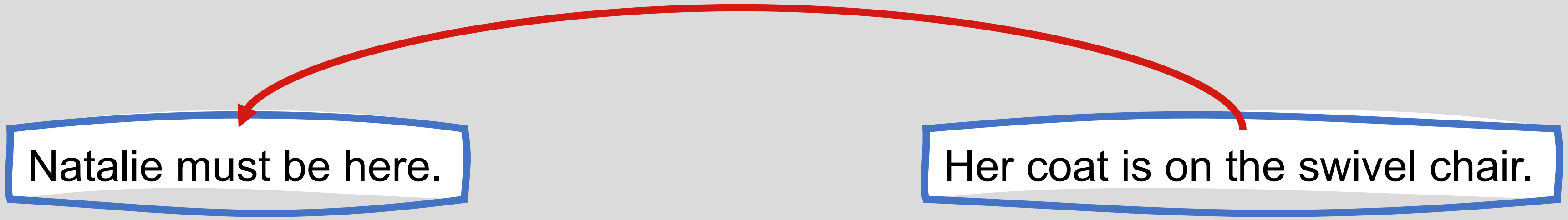
- Often determine whether sentences are informative based on different **characteristics of their individual words**
- Sometimes detect **representative sentences** by computing each sentence's similarity with all other sentences in the document
- Sometimes rely on **rhetorical parsing**
  - **Rhetorical Parsing:** Identifying a hierarchical **discourse structure** for a passage of text

# Rhetorical Structure Theory

- Text organization model
- Based on a set of 23 **rhetorical relations** that can hold between spans of text within a discourse
- Most relations are between two spans:
  - **Nucleus**
    - More central to the writer’s purpose
    - Interpretable independently
  - **Satellite**
    - Less central to the writer’s purpose
    - Only interpretable with respect to the nucleus

# Rhetorical Structure Theory

- Relations are **asymmetric**
  - Represented graphically with arrows pointing from the satellite to the nucleus
- Relations are defined by a **set of constraints** on the nucleus and satellite
- Constraints are based on:
  - **Goals and beliefs** of the writer and reader
  - **Effect** on the reader



# Common RST Relations

### Elaboration

- Satellite gives further information about the content of the nucleus

### Attribution

- Satellite gives the source of attribution for an instance of reported speech in the nucleus

### Contrast

- Two or more nuclei contrast along some important dimension

### List

- A series of nuclei is given, without contrast or explicit comparison

# Common RST Relations

### Elaboration

- Satellite gives further information about the content of the nucleus

### Attribution

- Satellite gives the s of reported speech

Natalie told the class not to come on November 28th, **reminding them that it would be Thanksgiving**.

### Contrast

- Two or more nuclei contrast along some important dimension

### List

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# Common RST Relations

## Elaboration

- Satellite gives further information about the content of the nucleus

## Attribution

- Satellite gives the source of attribution for an instance of reported speech in the nucleus

## Contrast

- Two or more nuc
dimension

**Natalie pointed out that her students preferred to work the day before the deadline.**

## List

- A series of nuclei is given, without contrast or explicit comparison

# Common RST Relations

### Elaboration

- Satellite gives further information about the content of the nucleus

### Attribution

- Satellite gives the source of attribution for an instance of reported speech in the nucleus

### Contrast

- Two or more nuclei contrast along some important dimension

### List

- A series of nuc comparison

**Outside was freezing**, but **inside was uncomfortably warm**.

# Common RST Relations

## Elaboration

- Satellite gives further information about the content of the nucleus

## Attribution

- Satellite gives the source of attribution for an instance of reported speech in the nucleus

## Contrast

- Two or mor
  dimension

**In the fall, Natalie taught CS 421**; **in the spring, Natalie taught CS 521**.

## List

- A series of nuclei is given, without contrast or explicit comparison

# RST relations can be hierarchically organized into discourse trees.

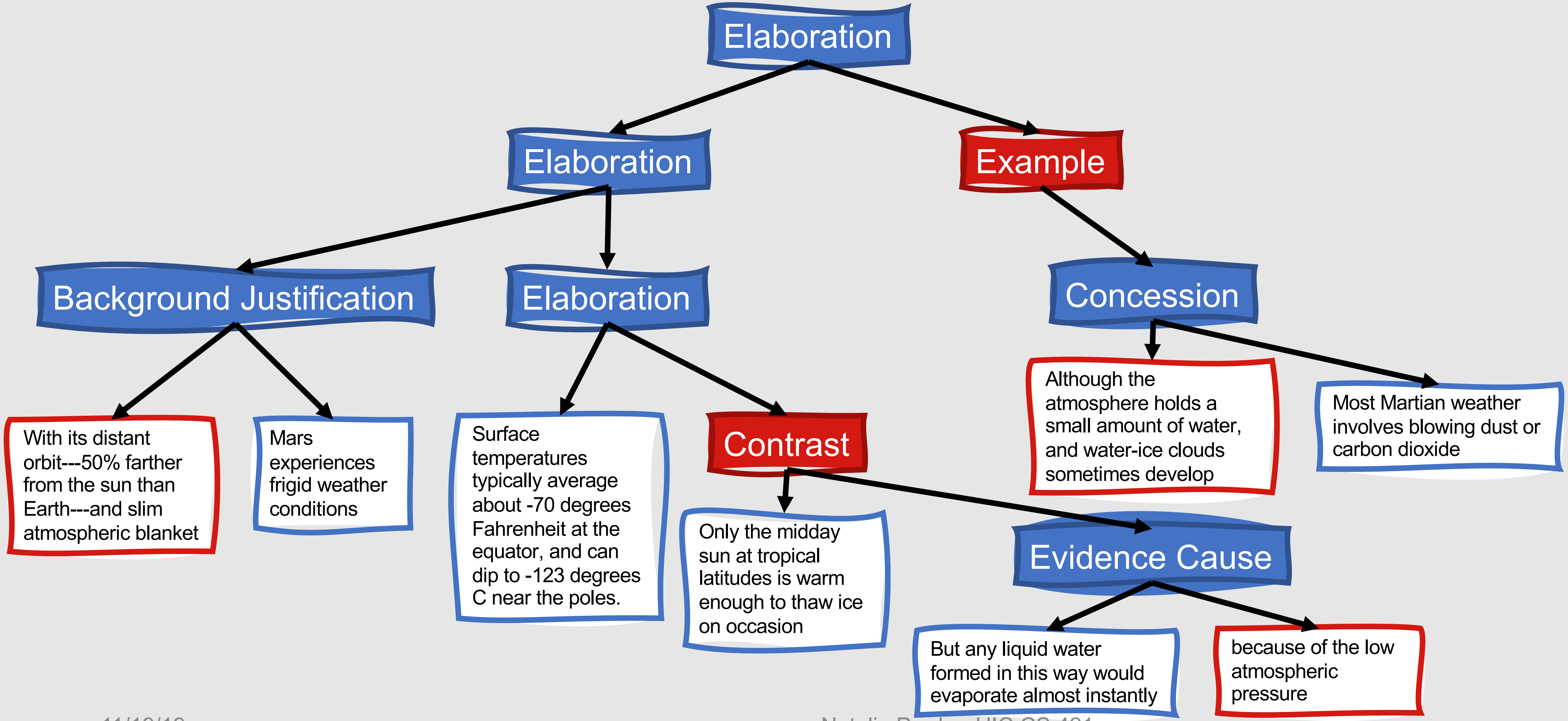
- This structure can in turn be used to determine which information to extract for a summary
- Simple strategy:
  - Keep nuclei
  - Discard satellites

# Summarization based on Rhetorical Parsing

With its distant orbit-–50% farther from the sun than Earth-–and slim atmospheric blanket, Mars experiences frigid weather conditions.  Surface temperatures typically average about -70 degrees Fahrenheit at the equator, and can dip to -123 degrees C near the poles.

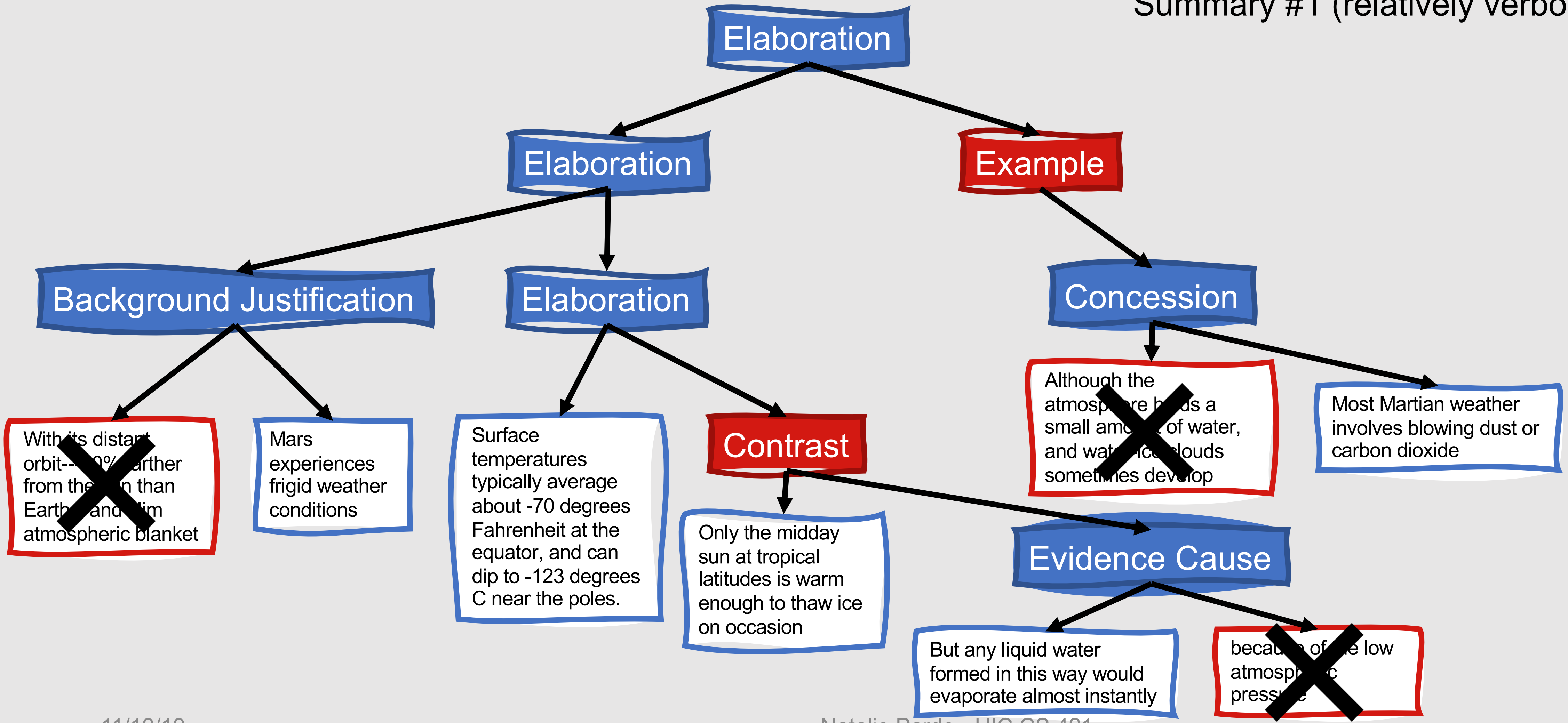
Only the midday sun at tropical latitudes is warm enough to thaw ice on occasion, but any liquid water formed in this way would evaporate almost instantly because of the low atmospheric pressure. Although the atmosphere holds a small amount of water, and water-ice clouds sometimes develop, most Martian weather involves blowing dust or carbon dioxide.

# Summarization based on Rhetorical Parsing


Elaboration
Elaboration
Example
Background Justification
Elaboration
Concession
With its distant orbit---50% farther from the sun than Earth---and slim atmospheric blanket
Mars experiences frigid weather conditions
Surface temperatures typically average about -70 degrees Fahrenheit at the equator, and can dip to -123 degrees C near the poles.
Contrast
Although the atmosphere holds a small amount of water, and water-ice clouds sometimes develop
Most Martian weather involves blowing dust or carbon dioxide
Only the midday sun at tropical latitudes is warm enough to thaw ice on occasion
Evidence Cause
But any liquid water formed in this way would evaporate almost instantly
because of the low atmospheric pressure

# Summarization based on Rhetorical Parsing

Summary #1 (relatively verbose)



Elaboration

Elaboration

Example

Background Justification

Elaboration

Concession

~~With its distant orbit--50% farther from the sun than Earth--and slim atmospheric blanket~~

Mars experiences frigid weather conditions

Surface temperatures typically average about -70 degrees Fahrenheit at the equator, and can dip to -123 degrees C near the poles.

Contrast

~~Although the atmosphere holds a small amount of water, and water-ice clouds sometimes develop~~

Most Martian weather involves blowing dust or carbon dioxide

Only the midday sun at tropical latitudes is warm enough to thaw ice on occasion

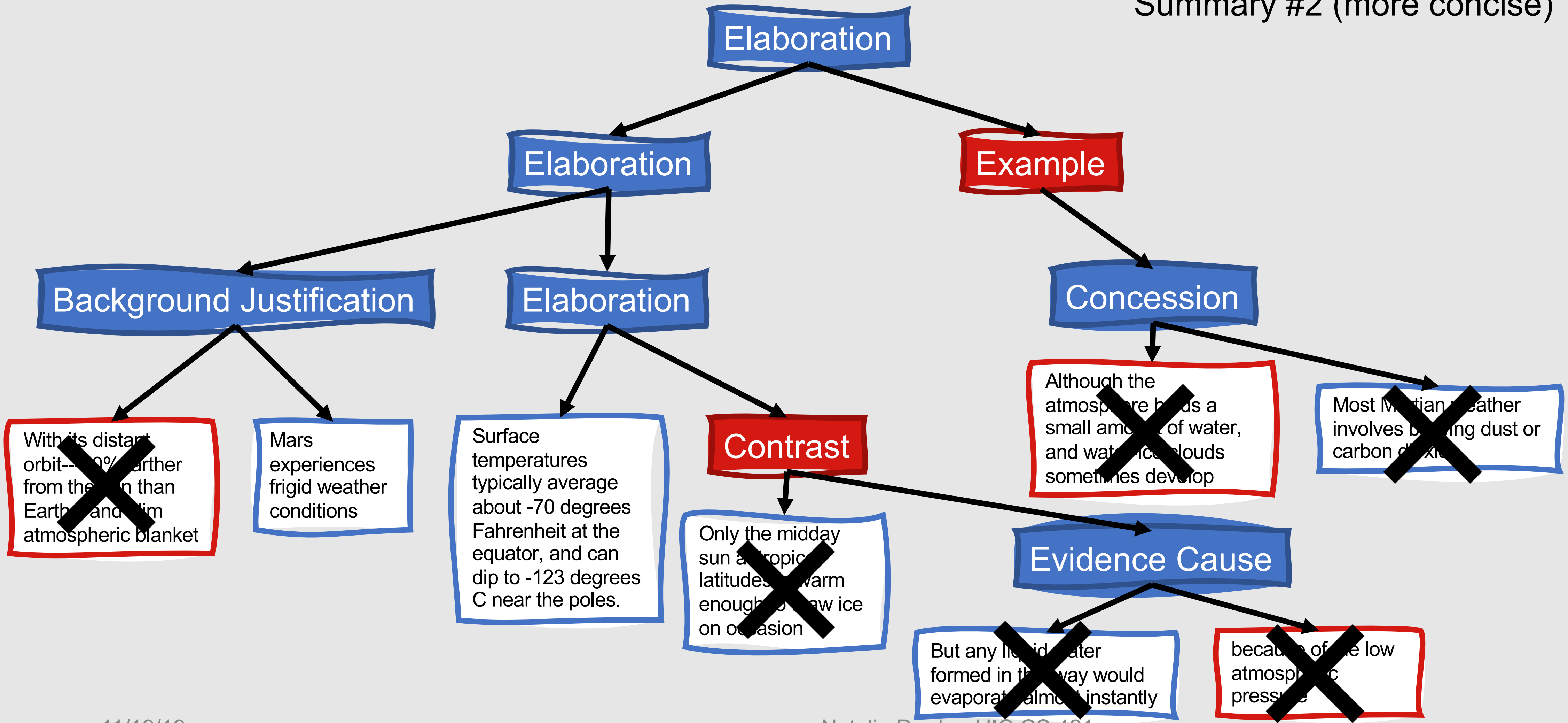
Evidence Cause

But any liquid water formed in this way would evaporate almost instantly

~~because of the low atmospheric pressure~~

# Summarization based on Rhetorical Parsing

Summary #2 (more concise)



Elaboration

Elaboration

Example

Background Justification

Elaboration

Concession

~~With its distant orbit--50% farther from the sun than Earth--and slim atmospheric blanket~~

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~~Although the atmosphere holds a small amount of water, and water-ice clouds sometimes develop~~

~~Most Martian weather involves blowing dust or carbon dioxide~~

~~Only the midday sun at tropical latitudes is warm enough to thaw ice on occasion~~

Evidence Cause

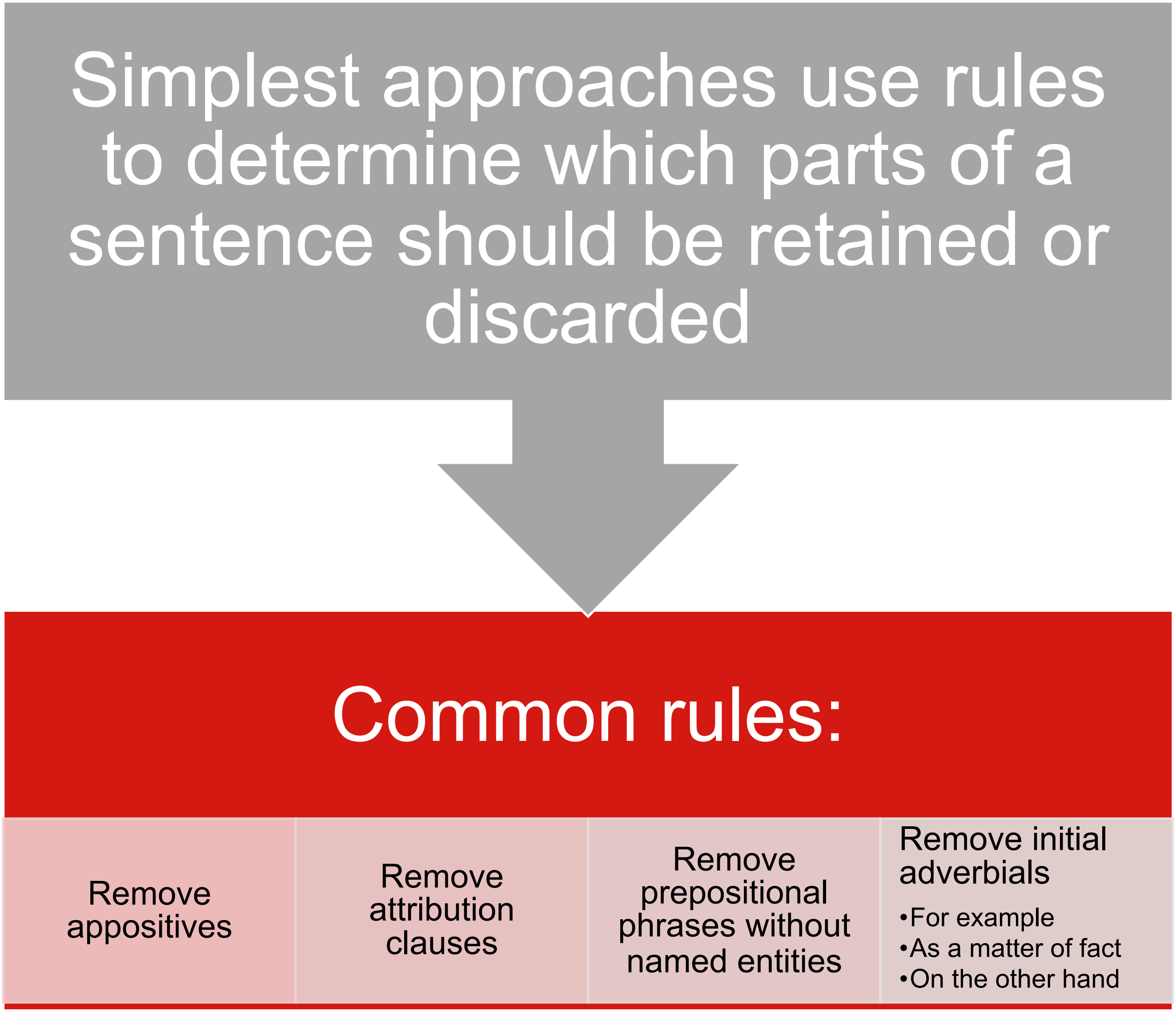
~~But any liquid water formed in this way would evaporate almost instantly~~

~~because of the low atmospheric pressure~~

# Supervised Content Selection

- **Supervised machine learning**
  - Train a model based on various characteristics of the data to predict whether individual sentences should be included in a summary
- Requires that an **alignment** is found between source and summary content during the training phase
- Common training corpora:
  - Academic articles and their abstracts
  - Wikipedia and Simple Wikipedia (https://simple.wikipedia.org/wiki/Main_Page) articles

# Sentence Simplification



Simplest approaches use rules to determine which parts of a sentence should be retained or discarded

Common rules:

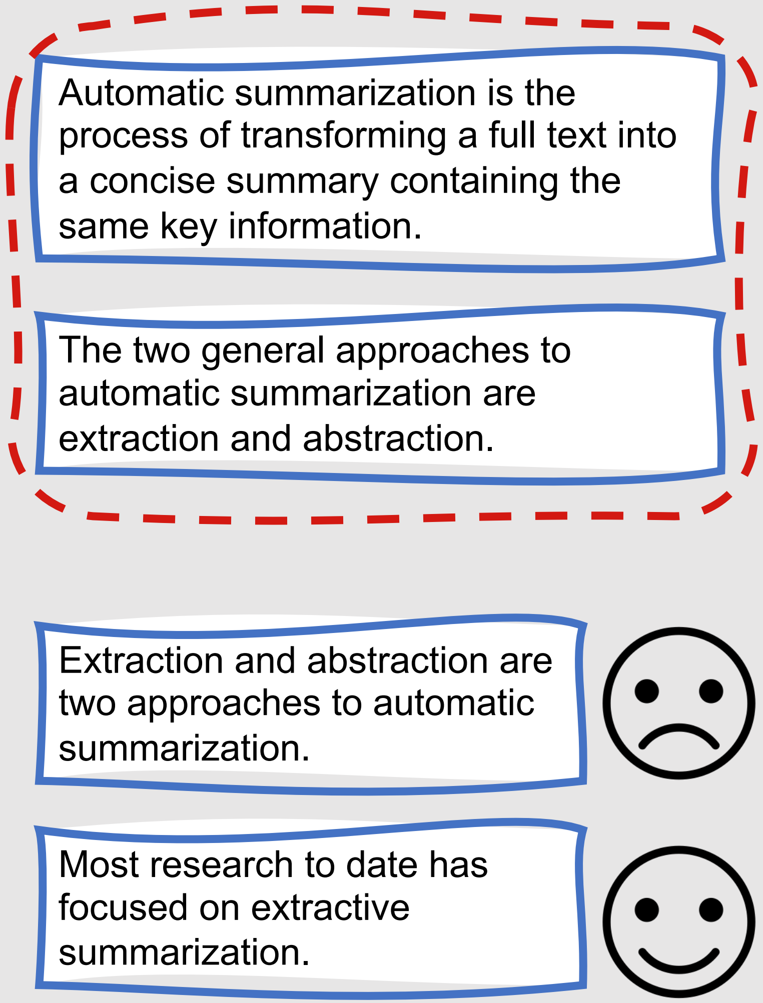
- Remove appositives
- Remove attribution clauses
- Remove prepositional phrases without named entities
- Remove initial adverbials
  - For example
  - As a matter of fact
  - On the other hand

# Multiple-Document Summarization

- Requires **content selection** and **sentence realization** techniques, just like with single-document summarization
- Additionally, **information ordering** is important!

# How is content selected in multi-document summarization tasks?

- Main difference: Greater risk of selecting **redundant information**
- The most important sentences in individual documents may overlap substantially with one another
  - We don't want a summary to consist of sets of identical sentences!
- How to address this?
  - Penalize sentences that are similar to those that have already been extracted into a summary



Automatic summarization is the process of transforming a full text into a concise summary containing the same key information.

The two general approaches to automatic summarization are extraction and abstraction.

Extraction and abstraction are two approaches to automatic summarization. ☹

Most research to date has focused on extractive summarization. ☺

# Information Ordering

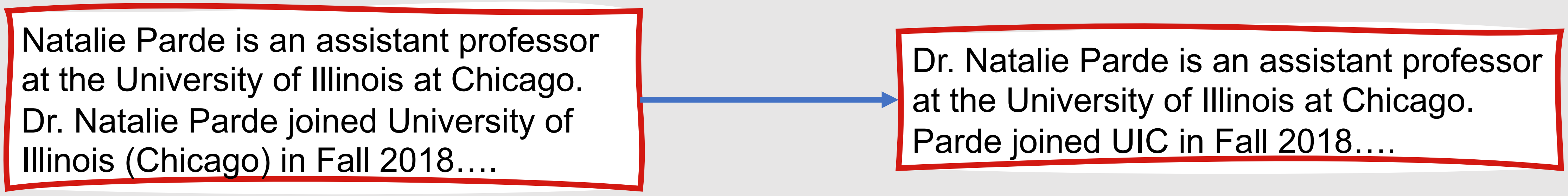
- One option: **Chronological order**
  - Can only be used if each sentence can be mapped to some location on a timeline
- However, placing sentences from multiple documents in chronological order can result in summaries with **low cohesion**
  - Summaries can seem like a collection of jumbled sentences rather than a unified block of text

# Information Ordering

- Most important factor: **Coherence**
  - Is the information presented in a logical, consistent order?
- Simple way to maximize coherence:
  - Check the cosine similarity between each pair of sentences
  - Order the sentences in a way that maximizes the average cosine similarity between neighboring sentences
- Although good approximation approaches exist, finding an optimal order of sentences is challenging
  - Technically an **NP-complete** problem (Cohen et al., 1999)

# Sentence Realization

- In multi-document summarization, entity names may need to be normalized
- Can be addressed by:
  - Applying **coreference resolution** to the summary
  - Extracting all possible names for each entity
  - Selecting one for the first mention, and a shorter one for all subsequent mentions



Natalie Parde is an assistant professor at the University of Illinois at Chicago. Dr. Natalie Parde joined University of Illinois (Chicago) in Fall 2018….

Dr. Natalie Parde is an assistant professor at the University of Illinois at Chicago. Parde joined UIC in Fall 2018….

# Query-Focused Summarization

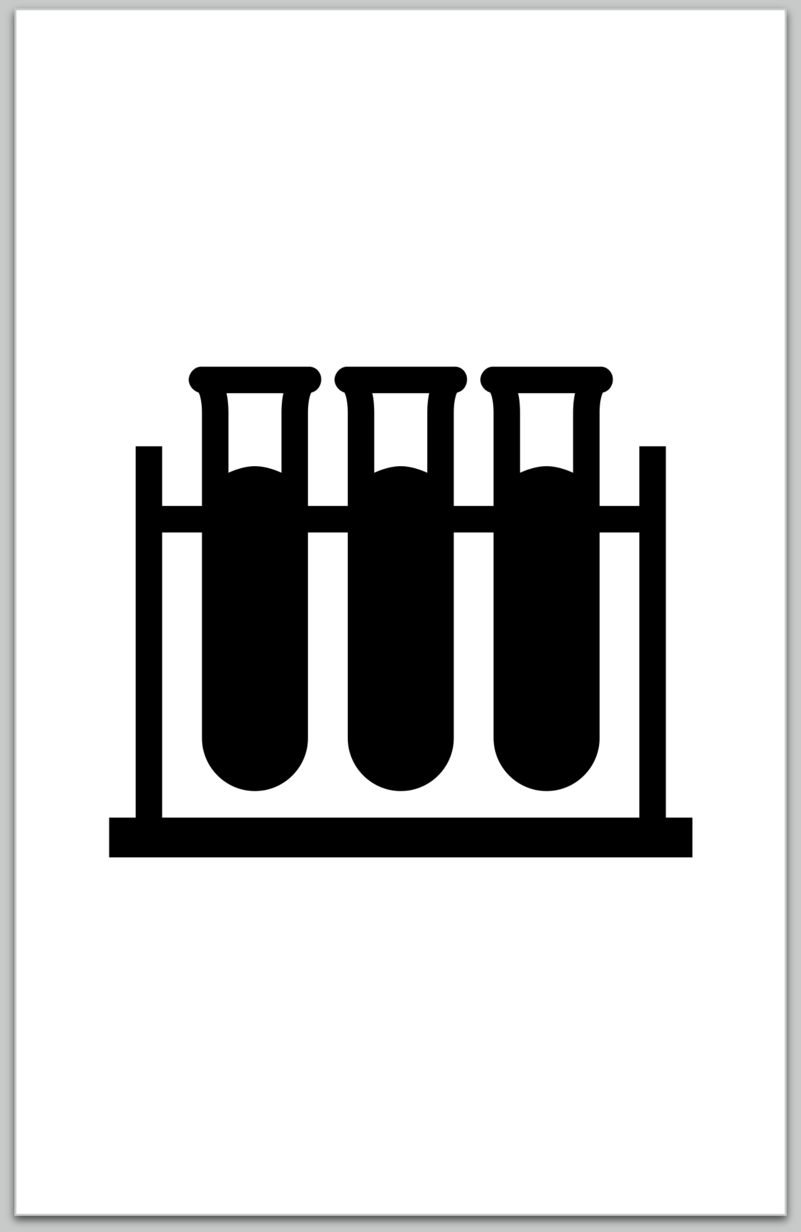
- Main difference from general summarization: Produced summary needs to **be relevant** to a user's question
- Thus, query-focused summarization may be viewed as a **long-form question answering** task

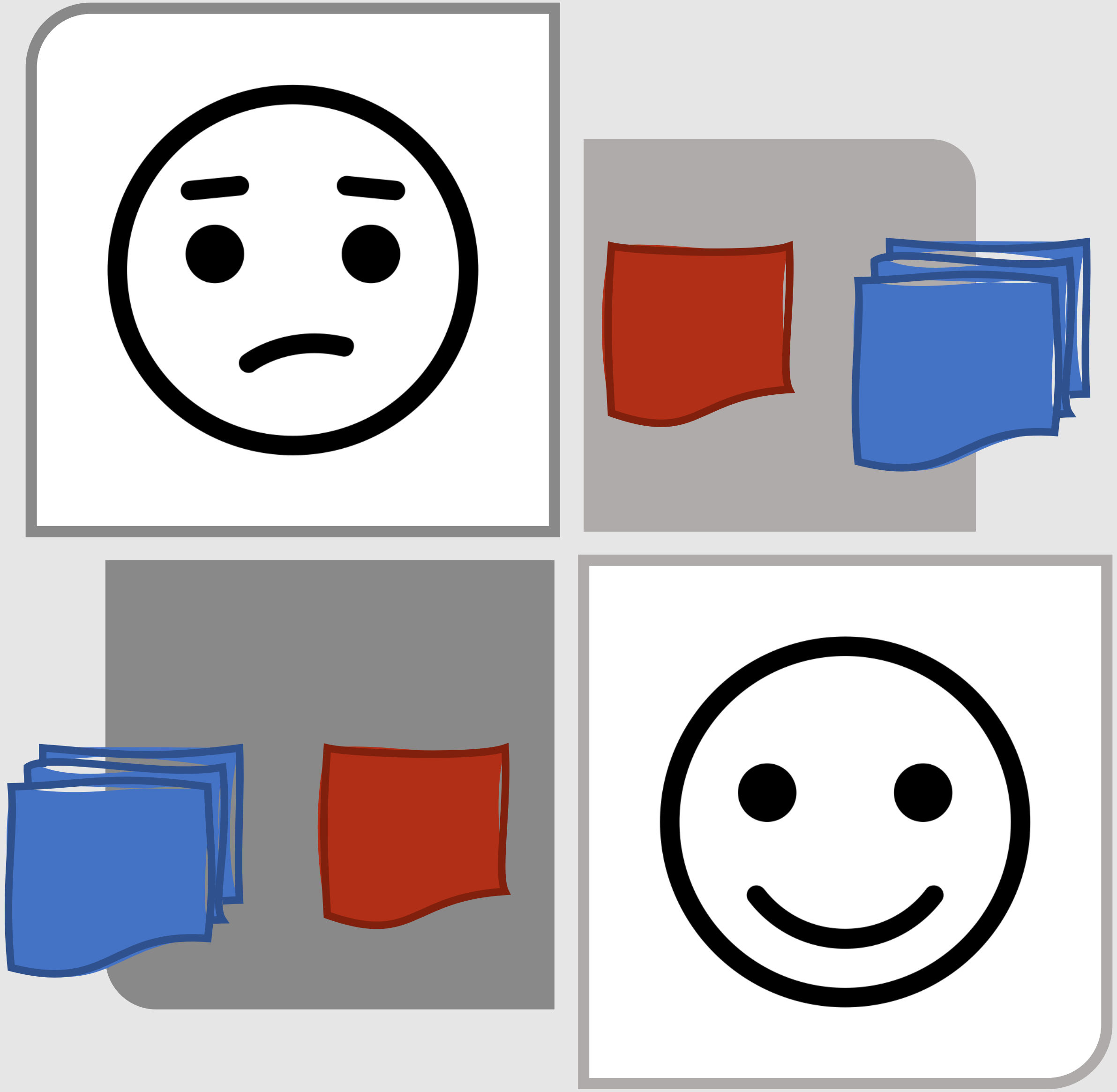
# How can we modify general summarization methods for query-focused settings?

- When ranking sentences during content selection, **require a minimum amount of overlap with the query**
- **Add the cosine similarity with the query as a feature** for supervised content selection approaches
- Domain-specific approaches can **incorporate external knowledge about what factors are likely to interest people**
  - People asking biographical questions are likely to want to know about birth date, education, and nationality
  - People asking medical questions are likely to want to know symptoms, interventions, and outcomes

# How do we determine the quality of our summarization approaches?

- Extrinsic methods
- Intrinsic methods





# Extrinsic Evaluation

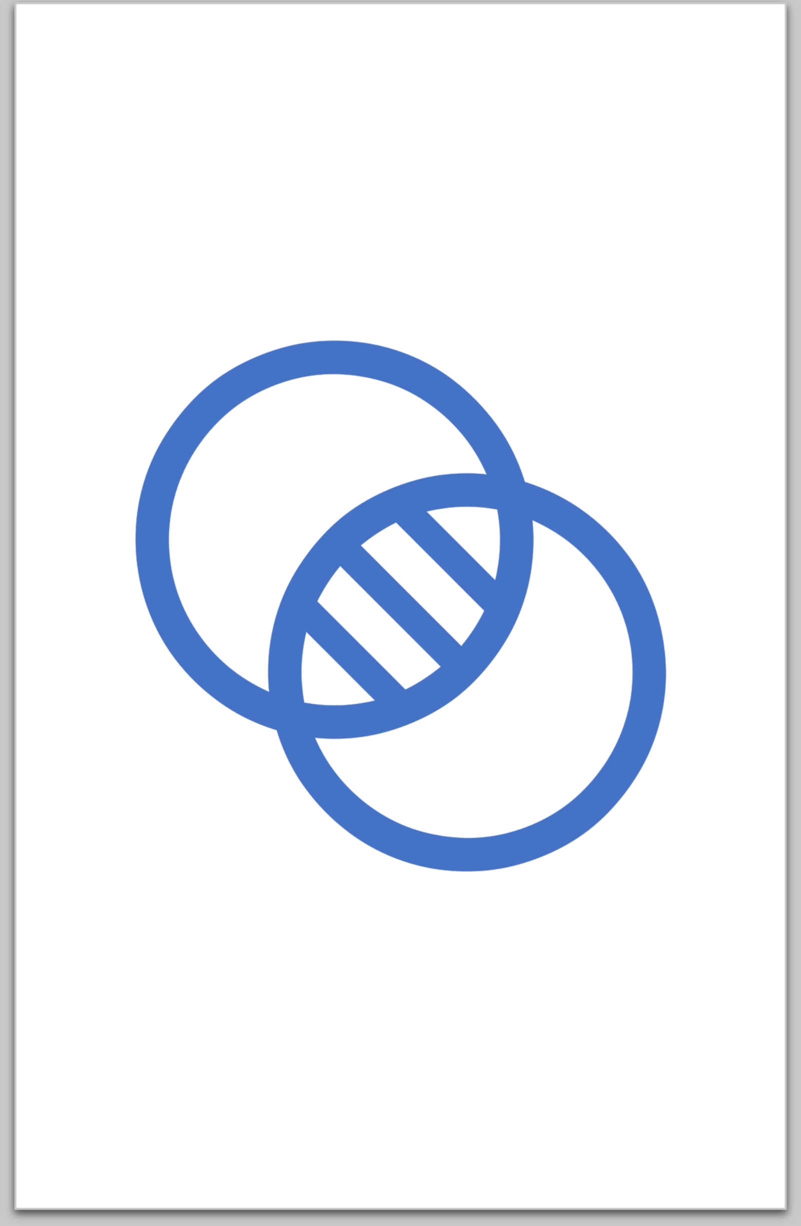
- Give automatically-generated summaries to humans to use while performing some task
- Evaluate their performance at the task relative to others using manually-generated summaries

# Intrinsic Evaluation

- Recall-Oriented Understudy for Gisting Evaluation (**ROUGE**)
- Automatically scores a machine-generated candidate summary by measuring its **n-gram overlap with human-generated reference summaries**

# Recall-Oriented Understudy for Gisting Evaluation (ROUGE)

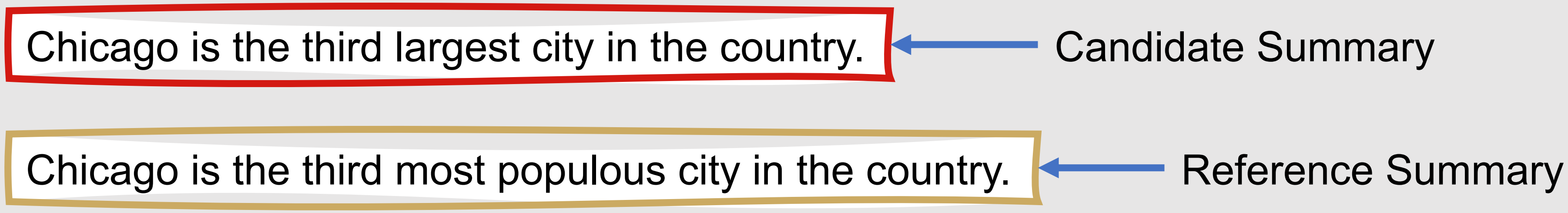
- **Fixed n-gram length**
  - ROUGE-1 uses unigram overlap
  - ROUGE-2 uses bigram overlap
  - ROUGE-4 uses four-gram overlap
- Can be viewed as a form of **n-gram recall**



# Computing ROUGE Scores

- Extract all n-grams from the candidate summary
- Extract all n-grams from the reference summary
- Find the intersection of the two lists
  - You can view these as true positives
- Divide the number of n-grams in the intersection (TP) by the total number of n-grams in the reference summary
- Formal equation:
  - $\mathrm{ROUGE{-}N} = \frac{\sum_{S\in\{ReferenceSummaries\}}\sum_{gram_s\in S} Count_{match}(gram_s)}{\sum_{S\in\{ReferenceSummaries\}}\sum_{gram_s\in S} Count(gram_s)}$

# Example: Computing ROUGE-2



Chicago is the third largest city in the country.

Candidate Summary

Chicago is the third most populous city in the country.

Reference Summary

# Example: Computing ROUGE-2

Chicago is the third largest city in the country. ← Candidate Summary

Chicago is the third most populous city in the country. ← Reference Summary

| |
|---|
| Chicago is |
| is the |
| the third |
| third largest |
| largest city |
| city in |
| in the |
| the country. |

| |
|---|
| Chicago is |
| is the |
| the third |
| third most |
| most populous |
| populous city |
| city in |
| in the |
| the country. |

# Example: Computing ROUGE-2

Chicago is the third largest city in the country. ← Candidate Summary

Chicago is the third most populous city in the country. ← Reference Summary

- Chicago is
- is the
- the third
- third largest
- largest city
- city in
- in the
- the country.

∩

- Chicago is
- is the
- the third
- third most
- most populous
- populous city
- city in
- in the
- the country.

=

- Chicago is
- is the
- the third
- city in
- in the
- the country.

# Example: Computing ROUGE-2

Chicago is the third largest city in the country. ← Candidate Summary

Chicago is the third most populous city in the country. ← Reference Summary

| |
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=

| |
|---|
| Chicago is |
| is the |
| the third |
| city in |
| in the |
| the country. |

ROUGE-2 = 6/9 = .67

# Many variations of ROUGE exist!

## ROUGE-L

- Longest common subsequence between the candidate and reference summaries

## ROUGE-S

- Allows skip bigrams (any pair of words in their sentence order)

## ROUGE-SU

- Uses both skip bigrams and unigrams

# ROUGE isn’t perfect….

- Measuring word overlap is only one (relatively poor) way to measure the similarity between a candidate and reference sentence
- Plus, human summarizers tend to disagree about which sentences to include in a summary, even with one another

# Other Evaluation Metrics

Some metrics instead check the overlap between **summary content units (SCUs)** in candidate and reference sentences

- **Summary Content Unit:** Semantic units that roughly correspond to propositions or coherent pieces of propositions

However, identifying SCUs can be a very difficult task in itself

# Baselines for Comparison

## Random sentences

- Choose N random sentences from the full document to use as the summary

## Leading sentences

- Choose the first N sentences from the full document to use as the summary

## The leading sentences baseline is surprisingly strong!

- People tend to put the most important information early in a document

# Summary: Question Answering and Summarization

- Question answering systems are often evaluated using **mean reciprocal rank**
  - Scores each question according to the reciprocal of the rank of the first correct answer
- Other common evaluation metrics are **exact match** and **$F_1$**
- **Text summarization** is the process of extracting the most important content from a text and presenting it in a concise, coherent manner
- Text summarization can be:
  - Performed on **one or more documents**
  - **Abstractive** or **extractive**
- Summaries can be **generic** or **query-focused**
- The three key processes involved in summarization are:
  - **Content selection**
  - **Information ordering**
  - **Sentence realization**
- Content selection is sometimes performed using **rhetorical parsing**
- Text summarization techniques are usually evaluated using **ROUGE**