Question Answering – Information Retrieval – Summarization

Le Anh Cuong

Reading

- Chapter 23 [1]

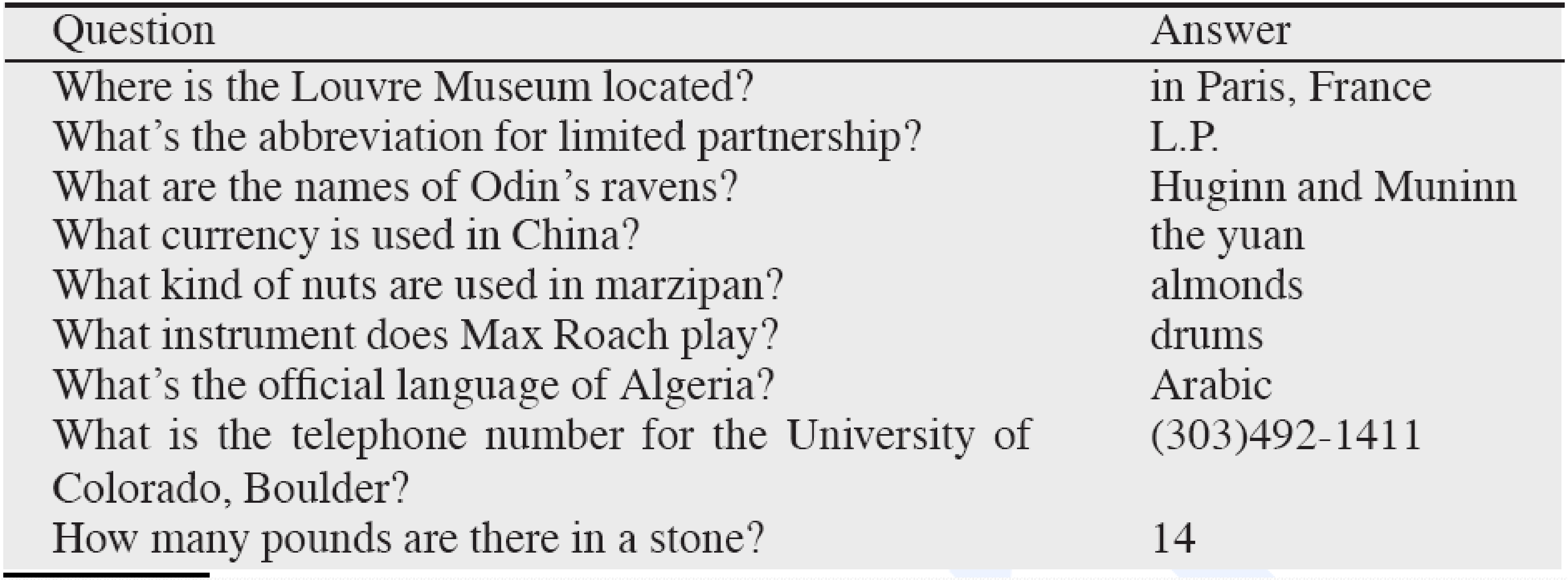
Outline

- Information retrieval
- Factoid question answering
- Single document summarization

Factoid Question Answering

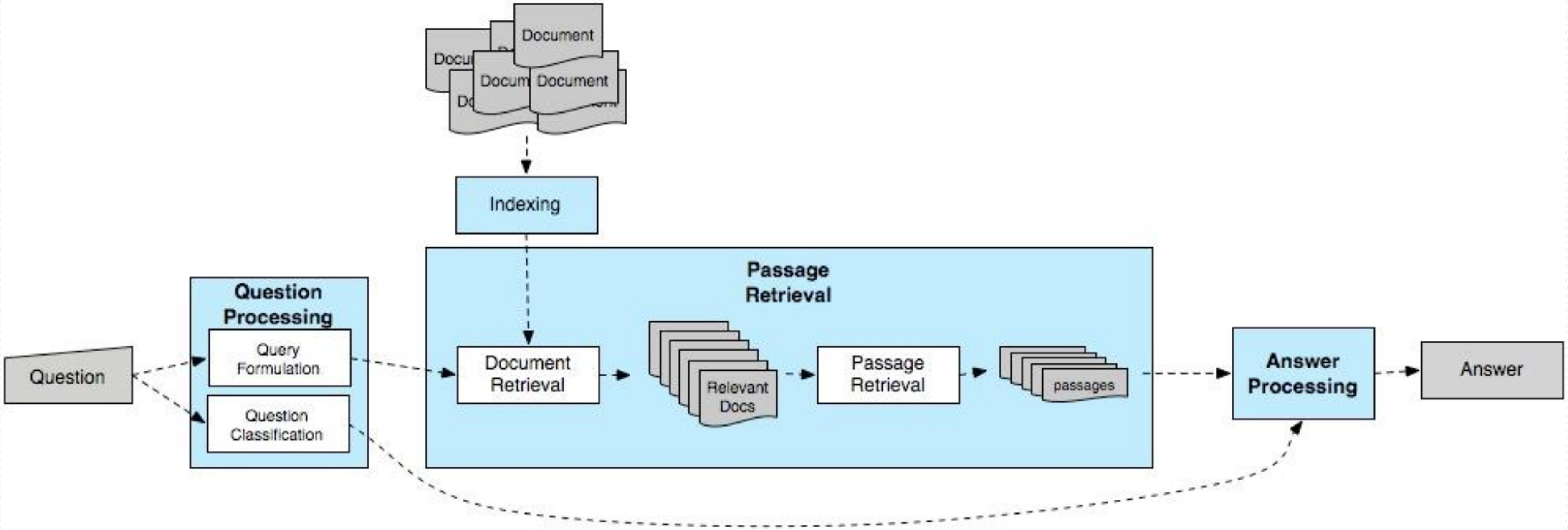
- Today
  - Introduction to Factoid QA
  - A typical full-fledged factoid QA system
  - A simpler alternative from MSR
- TREC: A Conference where many simultaneous evaluations are carried out
  - IR
  - QA

Factoid questions



Question	Answer
Where is the Louvre Museum located?	in Paris, France
What's the abbreviation for limited partnership?	L.P.
What are the names of Odin's ravens?	Huginn and Muninn
What currency is used in China?	the yuan
What kind of nuts are used in marzipan?	almonds
What instrument does Max Roach play?	drums
What's the official language of Algeria?	Arabic
What is the telephone number for the University of Colorado, Boulder?	(303)492-1411
How many pounds are there in a stone?	14

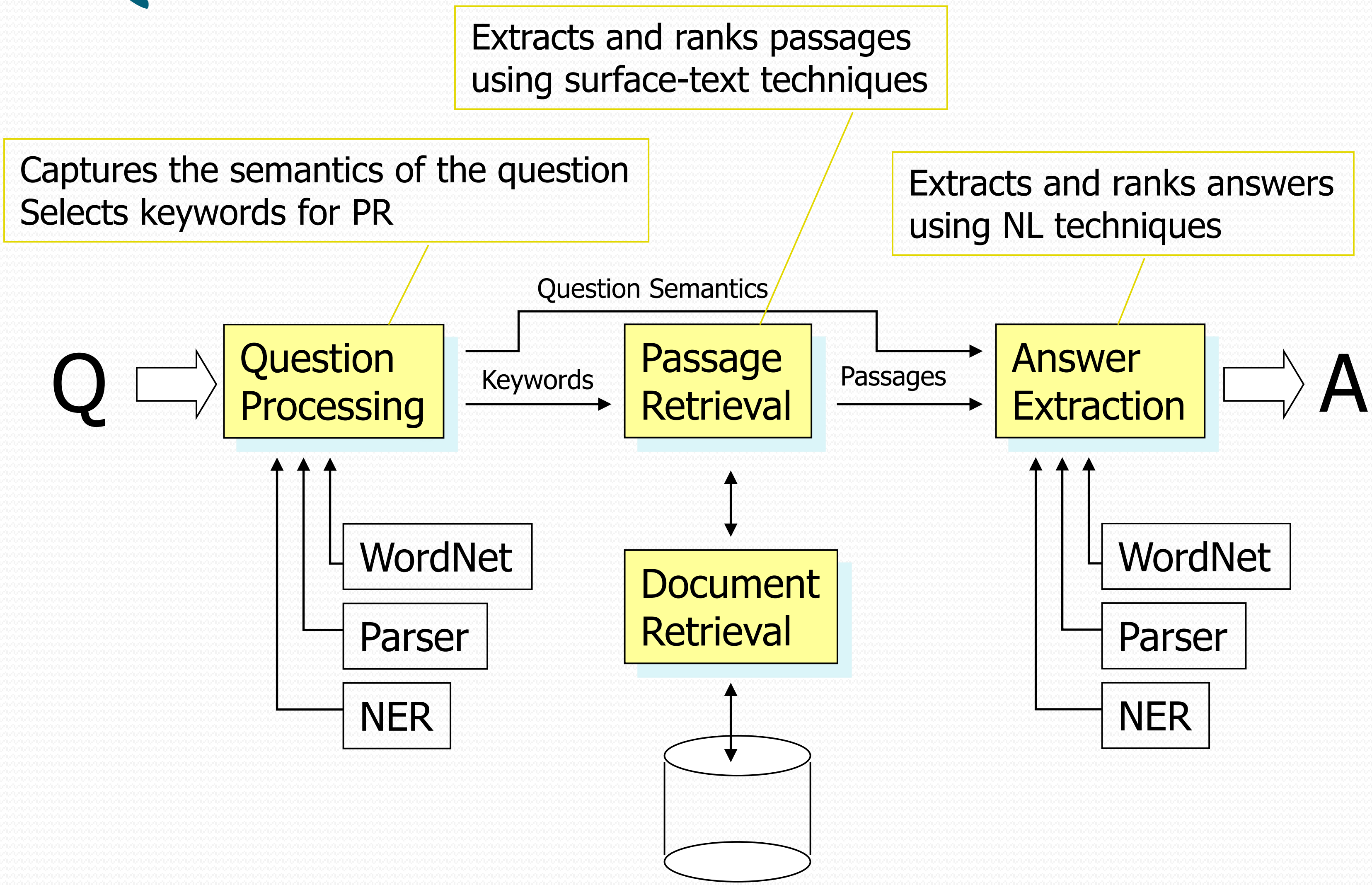
Factoid QA architecture



UT Dallas Q/A Systems

- This system contains many components used by other systems, but more complex in some ways
- Most work completed in 2001; there have been advances by this group and others since then.
- Next slides based mainly on:
  - Paşca and Harabagiu, *High-Performance Question Answering from Large Text Collections*, SIGIR'01.
  - Paşca and Harabagiu, *Answer Mining from Online Documents,* ACL'01.
  - Harabagiu, Paşca, Maiorano: *Experiments with Open-Domain Textual Question Answering.* COLING'00

QA Block Architecture



Extracts and ranks passages using surface-text techniques

Captures the semantics of the question
Selects keywords for PR

Extracts and ranks answers using NL techniques

Question Processing

- Two main tasks
  - **Question classification**: Determining the type of the answer
  - **Query formulation**: Extract keywords from the question and formulate a query

Answer Types

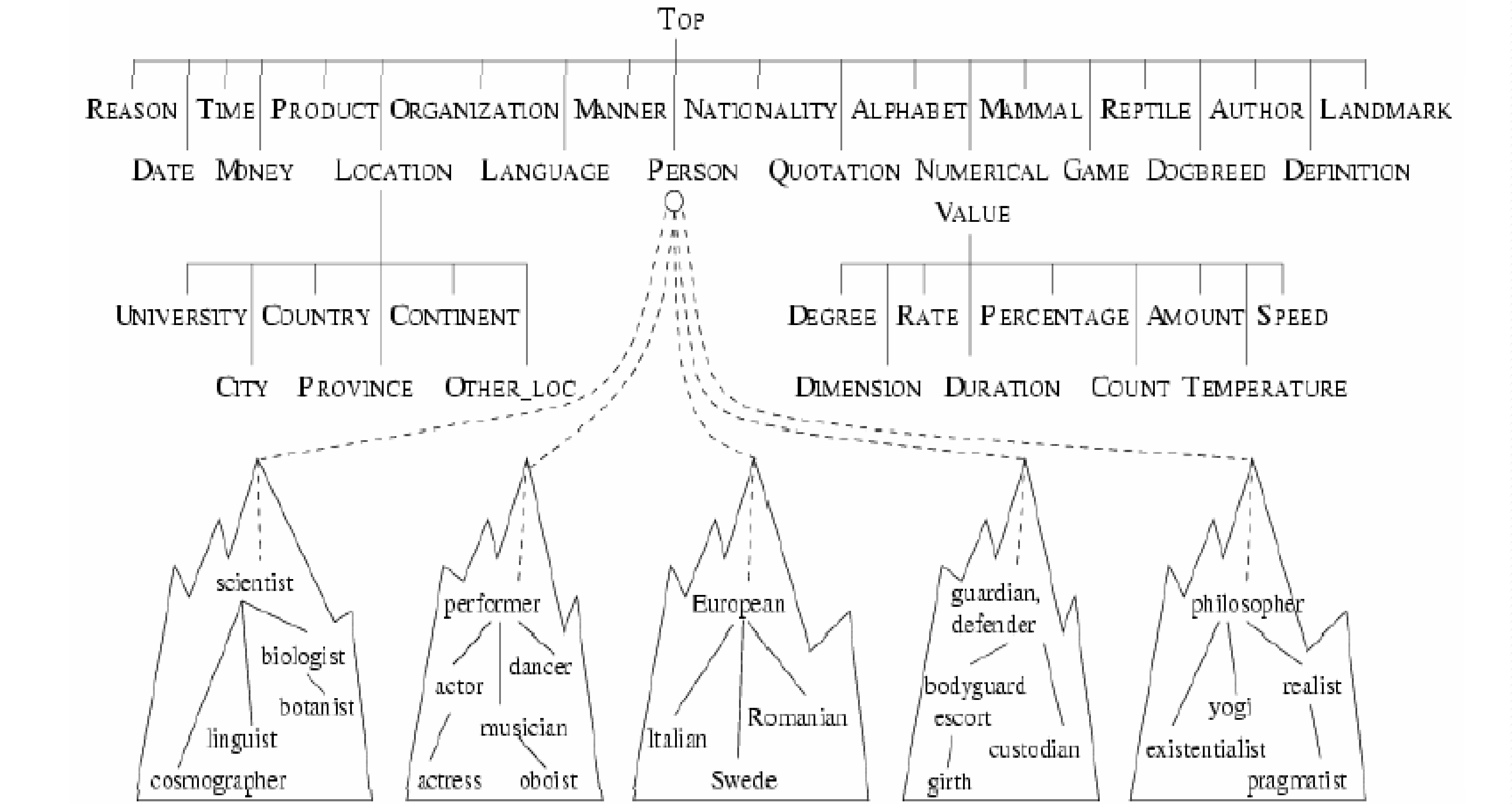
- Factoid questions…
  - Who, where, when, how many…
  - The answers fall into a limited and somewhat predictable set of categories
    - Who questions are going to be answered by…
    - Where questions…
  - Generally, systems select answer types from a set of Named Entities, augmented with other types that are relatively easy to extract

Answer Types

- Of course, it 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?

Answer Type Taxonomy

- Contains ~9000 concepts reflecting expected answer types
- Merges named entities with the WordNet hierarchy



Answer Type Detection

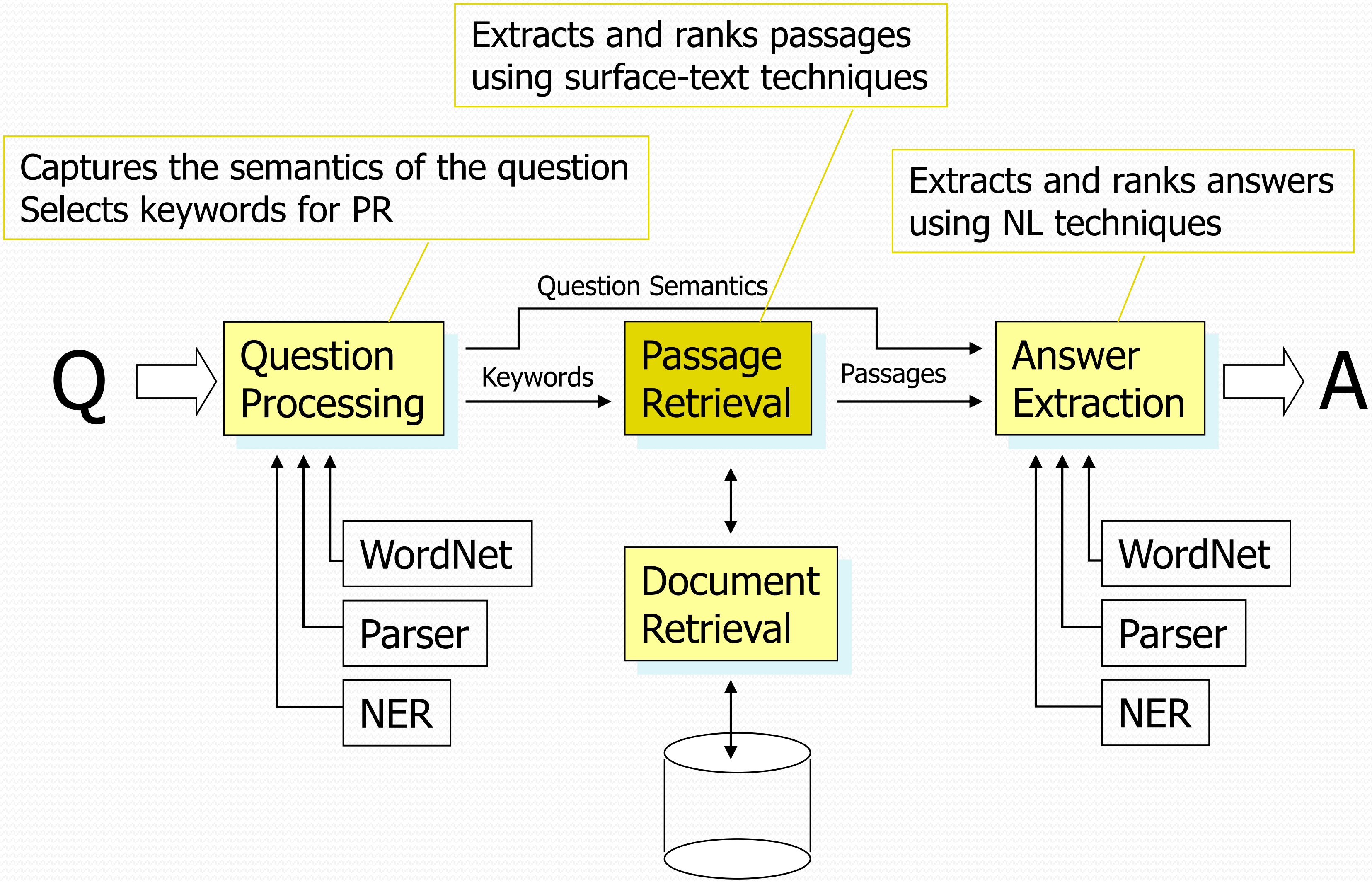
- Most systems use a combination of hand-crafted rules and supervised machine learning to determine the right answer type for a question.
- But how do we use the answer type?

Query Formulation: Lexical Terms Extraction

- Questions approximated by sets of unrelated words (lexical terms)
- Similar to bag-of-word IR models

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**
Q003: What does the Peugeot company manufacture?	**Peugeot, company, manufacture**
Q004: How much did Mercury spend on advertising in 1993?	**Mercury, spend, advertising, 1993**
Q005: What is the name of the managing director of Apricot Computer?	**name, managing, director, Apricot, Computer**

Passage Retrieval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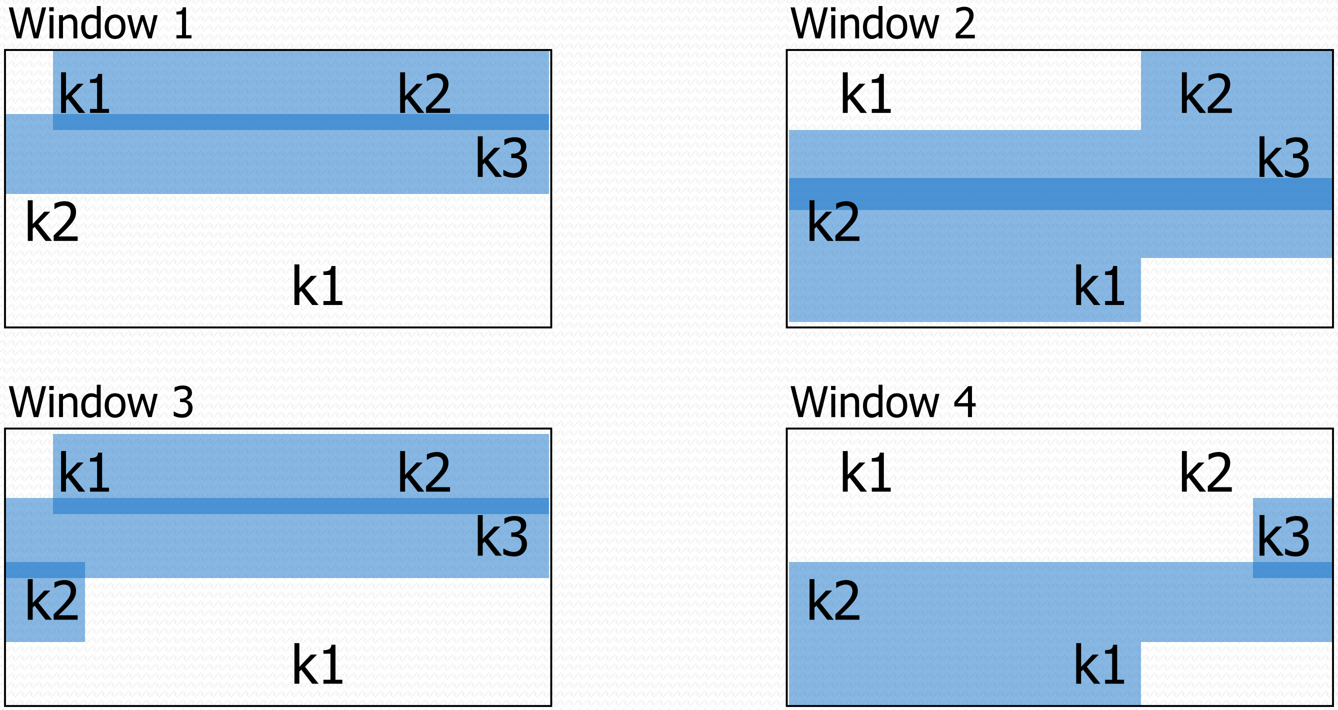
Question Semantics
Q
Question Processing
Keywords
Passage Retrieval
Passages
Answer Extraction
A
WordNet
Parser
NER
Document Retrieval
WordNet
Parser
NER

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

- Passages are scored based on keyword windows
  - For example, if a question has a set of keywords: {k1, k2, k3, k4}, and in a passage k1 and k2 are matched twice, k3 is matched once, and k4 is not matched, the following windows are built:



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

Answer Extraction

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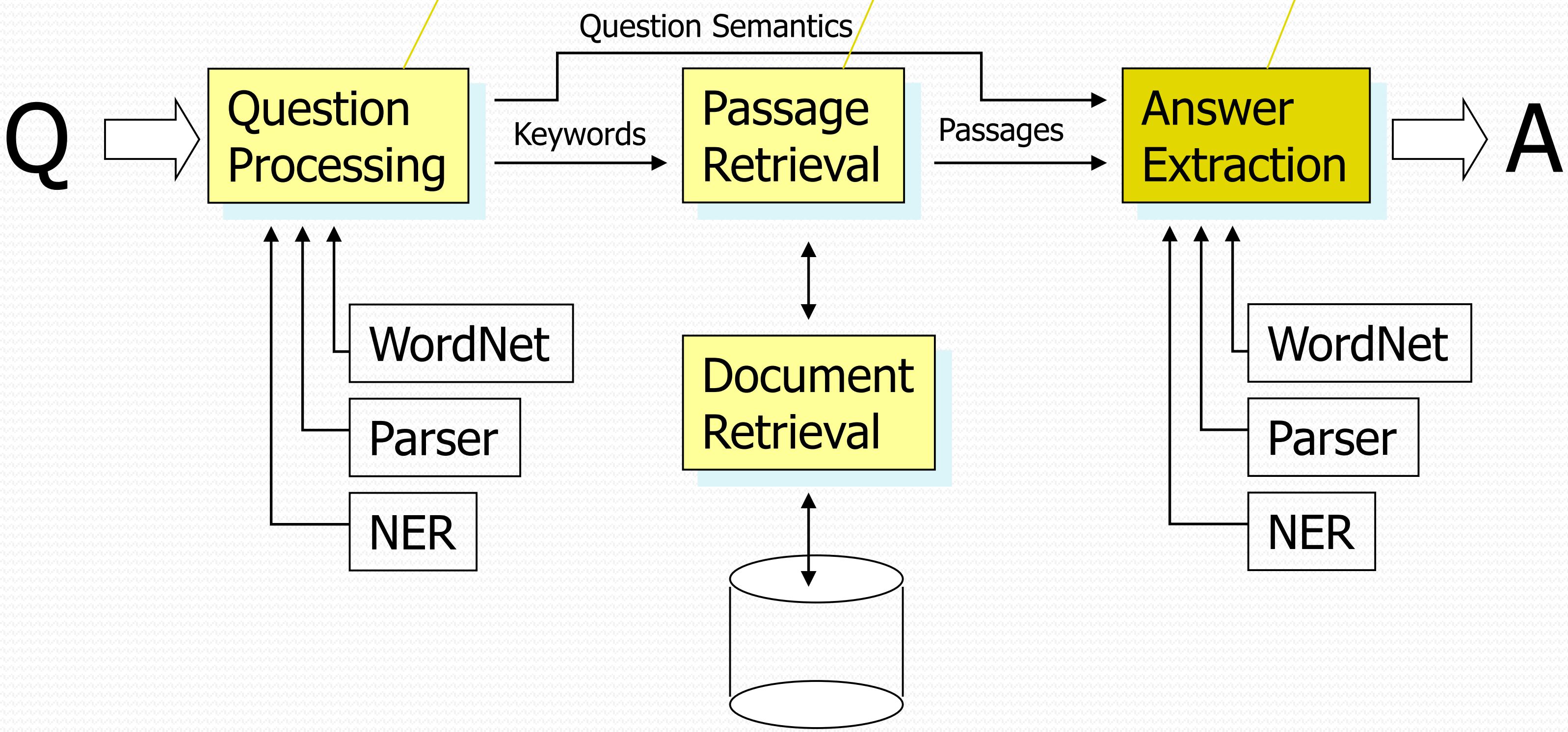

Ranking Candidate Answers

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..."

Ranking Candidate Answers

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

Features for Answer Ranking

- Number of question terms matched in the answer passage
- Number of question terms matched in the same phrase as the candidate answer
- Number of question terms matched in the same sentence as the candidate answer
- Flag set to 1 if the candidate answer is followed by a punctuation sign
- Number of question terms matched, separated from the candidate answer by at most three words and one comma
- Number of terms occurring in the same order in the answer passage as in the question
- Average distance from candidate answer to question term matches

SIGIR ‘01

Other Methods? Other Questions?

- When was Barack Obama born?
- Where was George Bush born?
- What college did John McCain attend?
- When did John F Kennedy die?

How does IE figure in?

Some examples

- Q: What is the population of Venezuela?
  - Patterns (with Precision score):
    - 0.60 <NAME> ' s <C-QUANTITY> population
    - 0.37 of <NAME> ' s <C-QUANTITY> people
    - 0.33 <C-QUANTITY> people in <NAME>
    - 0.28 <NAME> has <C-QUANTITY> people
- 3.2 Q: What is the population of New York?
    - S1. The mayor is held in high regards by the 8 million New Yorkers.
    - S2. The mayor is held in high regards by the two New Yorkers.

Where to find the answer?

- Wikipedia, WordNet often more reliable

- Wikipedia:
  - Q: What is the Milky Way?
    - Candidate 1: outer regions
    - Candidate 2: the galaxy that contains the Earth

- WordNet
    - Wordnet: Milky Way—the galaxy containing the solar system

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An Online QA System

- http://tangra.si.umich.edu/clair/NSIR/html/nsir.cgi

Is the Web Different?

- In TREC (and most commercial applications), retrieval is performed against a smallish closed collection of texts.
- The diversity/creativity in how people express themselves necessitates all that work to bring the question and the answer texts together.
- But…

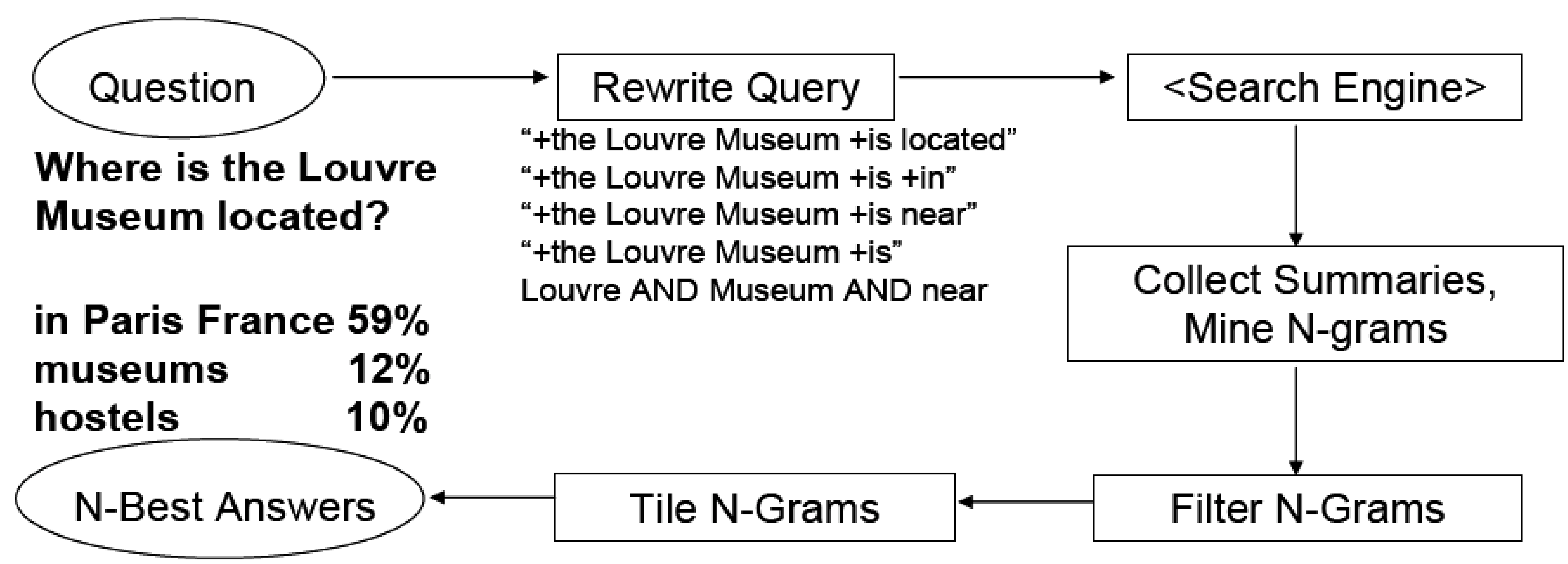
The Web is Different

- On the Web popular factoids are likely to be expressed in a gazzilion different ways.
- At least a few of which will likely match the way the question was asked.
- So why not just grep (or agrep) the Web using all or pieces of the original question.

AskMSR

- Process the question by…
  - Simple rewrite rules to rewriting the original question into a statement
    - Involves detecting the answer type
- Get some results
- Extract answers of the right type based on
  - How often they occur

AskMSR



Question

Where is the Louvre Museum located?

Rewrite Query

“+the Louvre Museum +is located”
“+the Louvre Museum +is +in”
“+the Louvre Museum +is near”
“+the Louvre Museum +is”
Louvre AND Museum AND near

<Search Engine>

Collect Summaries, Mine N-grams

Filter N-Grams

Tile N-Grams

N-Best Answers

in Paris France	59%
museums	12%
hostels	10%

Step 1: Rewrite the questions

- Intuition: The user’s question is often syntactically quite close to sentences that contain the answer
  - Where is the Louvre Museum located?
    - The Louvre Museum is located in ***Paris***
  - Who created the character of Scrooge?
    - ***Charles Dickens*** created the character of Scrooge.

Query rewriting

Classify question into seven categories

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

a. Hand-crafted category-specific transformation rules

e.g.: For *where* questions, move 'is' to all possible locations

Look to the right of the query terms for the answer.

"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"

Step 2: Query search engine

- Send all rewrites to a Web search engine
- Retrieve top N answers (100-200)
- For speed, rely just on search engine's "snippets", not the full text of the actual document

Step 3: Gathering N-Grams

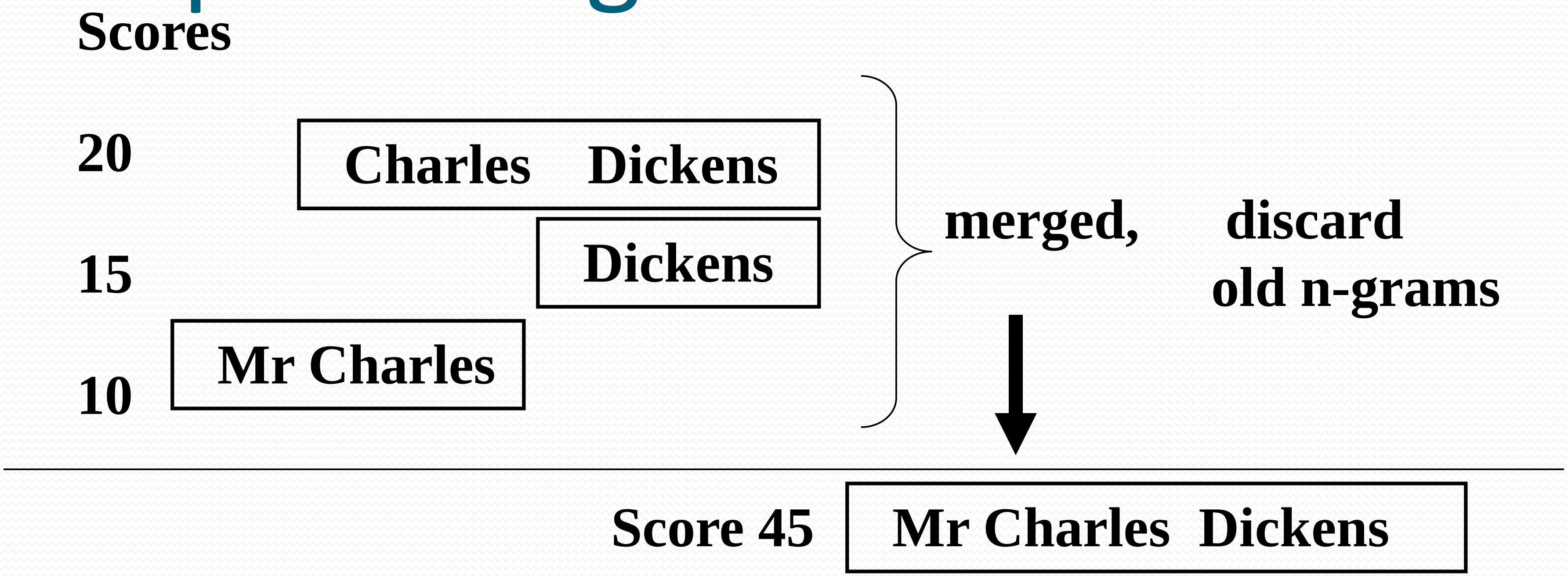
- Enumerate all N-grams (N=1,2,3) in all retrieved snippets
- Weight of an n-gram: occurrence count, each weighted by "reliability" (weight) of rewrite rule that fetched the document
  - Example: "Who created the character of Scrooge?"

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 expressions for answer types
- Boost score of n-grams that match the expected answer type.
- Lower score of n-grams that don’t match.
- For example
  - The filter for
    - How many dogs pull a sled in the Iditarod?
  - prefers a number
  - So disprefer candidate n-grams like
    - Dog race, run, Alaskan, dog racing
  - Prefer canddiate n-grams like
    - Pool of 16 dogs

Step 5: Tiling the Answers



Scores

20 Charles Dickens

15 Dickens

10 Mr Charles

merged, discard old n-grams

Score 45 Mr Charles Dickens

Evaluation

- Evaluation of this kind of system is usually based on some kind of TREC-like metric.
- In Q/A the most frequent metric is
  - Mean reciprocal rank

    You're allowed to return N answers. Your score is based on 1/Rank of the first right answer.

    Averaged over all the questions you answer.

Results

- Standard TREC contest test-bed (TREC 2001): 1M documents; 900 questions
  - Technique does ok, not great (would have placed in top 9 of ~30 participants)
    - MRR = 0.507
  - But with access to the Web… They do much better, would have come in second on TREC 2001
    - Be suspicious of any after the bake-off is over metrics

Harder Questions

- A more interesting task is one where the answers are fluid and depend on the fusion of material from disparate texts over time.
  - Who is Condoleezza Rice?
  - Who is Stephen Harper?
  - Why did San Francisco have to hand-count ballots in the last election?

Harder Questions: Query-Based Summarization

- Much of the work has focused on getting the answer from multiple documents
  - Do web search and use snippets (each as a document)
  - Do question-answering from many documents and merge together the answers you get from multiple sources
    - Like multi-document summarization – you want new information and want to avoid redundant information
  - Use “templates” for each type of question – e.g., definition, biography, medicine
    - Use information extraction techniques to find answer.

Information Retrieval

- Basic assumption: meanings of documents can be captured by analyzing (counting) the words that occur in them.

- This is known as the bag of words approach.

Inverted Index

- The fundamental operation we need is the ability to map from words to documents in a collection that contain those words
- An inverted index is just a list of words along with the document ids of the documents that contain them
  - `Dog: 1,2,8,100,119,210,400`
  - `Dog: 1:4,7:11,13:15,17`

Stop Lists and Stemming

- IR systems use them

- Stop List
  - List of frequent largely content-free words that are not stored in the index (of, the, a, etc)
  - The primary benefit is in the reduction of the size of the inverted index

- Stemming
  - Are dog and dogs separate entries or are they collapsed to dog?

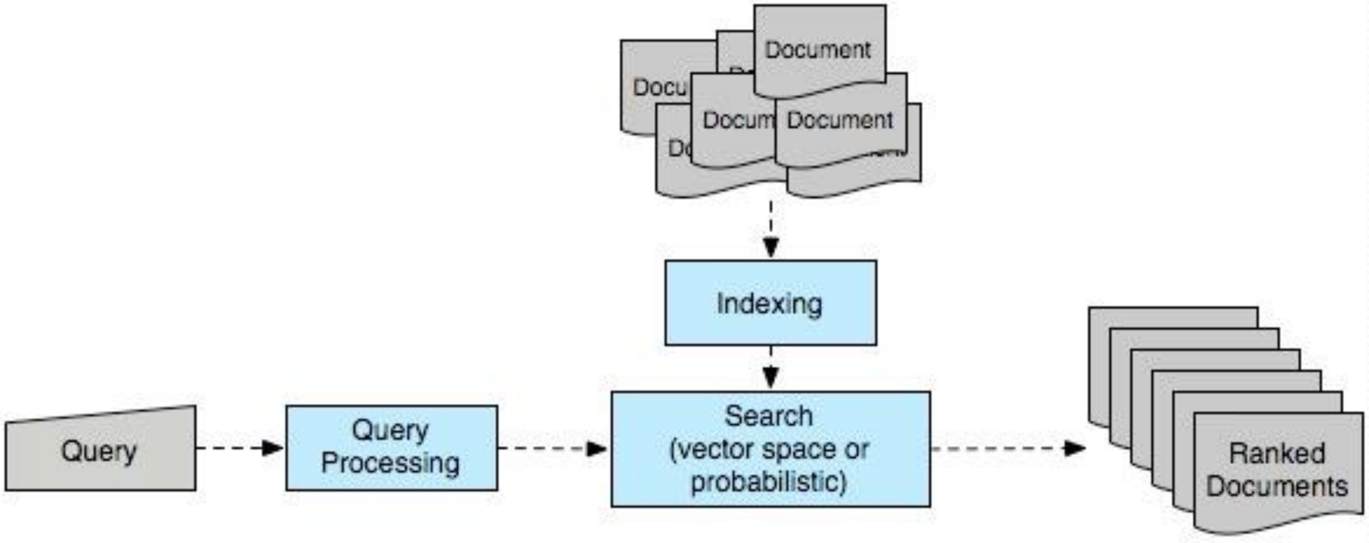
Phrases

- Google et al allow users to perform phrasal searches “big red dog”.
  - Hint: they don’t grep the collection
  - Add locational information to the index
    - `dog: 1{104}, 2{10}, etc`
    - `red: 1{103},…`
    - `big: 1{102},…`
  - Phrasal searches can operate incrementally by piecing the phrases together.

Ranked Retrieval

- The inverted index is just the start
- Given a query we want to know how relevant all the documents in the collection are to that query

Ad hoc retrieval



Vector Space Model

- In the vector space model, both documents and queries are represented as vectors of numbers.
- The numbers are derived from the words that occur in the collection

Representation

- Start with bit vectors

$$\vec{d_j} = (t_1, t_2, t_3, \ldots t_N)$$

- This says that there are N word types in the collection and that the representation of a document consists of a 1 for each corresponding word type that occurs in the document.
- We can compare two docs or a query and a doc by summing the bits they have in common

$$sim(\vec{q}_k, \vec{d}_j) = \sum_{i=1}^{N} t_{i,k} \times t_{i,j}$$

Term Weighting

- Bit vector idea treats all terms that occur in the query and the document equally.

- Its better to give the more important terms greater weight.
  - Why?
  - How would we decide what is more important?

Term Weighting

- Two measures are used
  - Local weight
    - How important is this term to the meaning of this document
    - Usually based on the frequency of the term in the document
  - Global weight
    - How well does this term discriminate among the documents in the collection
    - The more documents a term occurs in the less important it is; The fewer the better.

Term Weights

- Local weights
  - Generally, some function of the frequency of terms in documents is used
- Global weights
  - The standard technique is known as inverse document frequency

$$idf_i = \log\left(\frac{N}{n_i}\right)$$

N= number of documents; ni = number of documents with term i

TFxIDF Weighting

- To get the weight for a term in a document, multiply the term’s frequency derived weight by its inverse document frequency.

Back to Similarity

- We were counting bits to get similarity

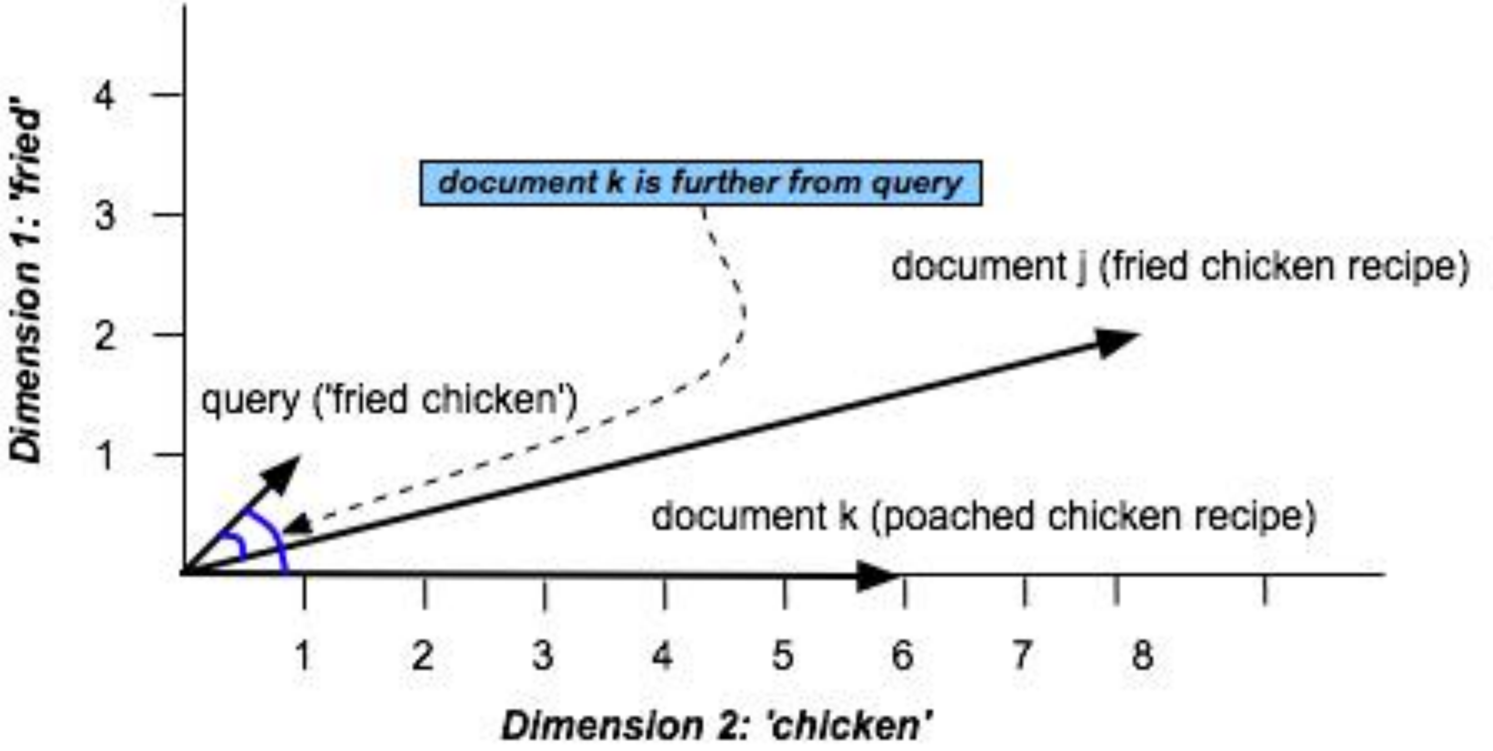
$$sim(\vec{q}_k, \vec{d}_j) = \sum_{i=1}^{N} t_{i,k} \times t_{i,j}$$

- Now we have weights

$$sim(\vec{q}_k, \vec{d}_j) = \sum_{i=1}^{N} w_{i,k} \times w_{i,j}$$

- But that favors long documents over shorter ones

Similarity in Space (Vector Space Model)


document k is further from query
document j (fried chicken recipe)
query ('fried chicken')
document k (poached chicken recipe)
Dimension 1: 'fried'
4
3
2
1
1
2
3
4
5
6
7
8
Dimension 2: 'chicken'

Similarity

- View the document as a vector from the origin to a point in the space, rather than as the point.
- In this view it’s the direction the vector is pointing that matters rather than the exact position
- We can capture this by normalizing the comparison to factor out the length of the vectors

Similarity

- The cosine measure

$$sim(qk, dj) = \frac{\sum_{i=1}^{N} w_{i,k} \times w_{i,j}}{\sqrt{\sum_{i=1}^{N} w^{2}_{i,k}} \times \sqrt{\sum_{i=1}^{N} w^{2}_{i,j}}}$$

Ad Hoc Retrieval

1. Take a user's query and find all the documents that contain any of the terms in the query
2. Convert the query to a vector using the same weighting scheme that was used to represent the documents
3. Compute the cosine between the query vector and all the candidate documents and sort

Text Summarization: News and Beyond

Kathleen McKeown
Department of Computer Science
Columbia University

What is Summarization?

- Data as input (database, software trace, expert system), text summary as output
- Text as input (one or more articles), paragraph summary as output
- Multimedia in input or output
- Summaries must convey maximal information in minimal space

Types of Summaries

- Informative vs. Indicative
  - Replacing a document vs. describing the contents of a document
- Extractive vs. Generative (abstractive)
  - Choosing bits of the source vs. generating something new
- Single document vs. Multi Document
- Generic vs. user-focused

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Questions (from Sparck Jones)

- Should we take the reader into account and how?
- “Similarly, the notion of a basic summary, i.e., one reflective of the source, makes hidden fact assumptions, for example that the subject knowledge of the output’s readers will be on a par with that of the readers for whom the source was intended. (p. 5)”
- Is the state of the art sufficiently mature to allow summarization from intermediate representations and still allow robust processing of domain independent material?

Single-Document Summarization Stages

1. **Content Selection:** Choose units (sentences?) to extract from the document

2. **Information Ordering:** Choose an order in which to place these sentences in the summary

3. **Sentence Realization:** Clean-up the sentences, e.g., by removing non-essential phrases, by fusing multiple sentences, by fixing problems of coherence

Foundations of Summarization – Luhn; Edmunson

- Text as input
- Single document
- Content selection
- Methods
  - Sentence selection
  - Criteria

Sentence extraction

- Sparck Jones:
- `what you see is what you get’, some of what is on view in the source text is transferred to constitute the summary

Luhn 58

- Summarization as sentence extraction
  - Example

- Term frequency determines sentence importance
  - TF*IDF
  - Stop word filtering
  - Similar words count as one
  - Cluster of frequent words indicates a good sentence

TF*IDF

- Intuition: Important terms are those that are frequent in this document but not frequent across all documents

Term Weights

- Local weights
  - Generally, some function of the frequency of terms in documents is used
- Global weights
  - The standard technique is known as inverse document frequency

$$idf_i = \log\left(\frac{N}{n_i}\right)$$

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TFxIDF Weighting

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TF*IDF

Edmunson 69

Sentence extraction using 4 weighted features:

- Cue words ("In this paper..", "The worst thing was ..")
- Title and heading words
- Sentence location
- Frequent key words

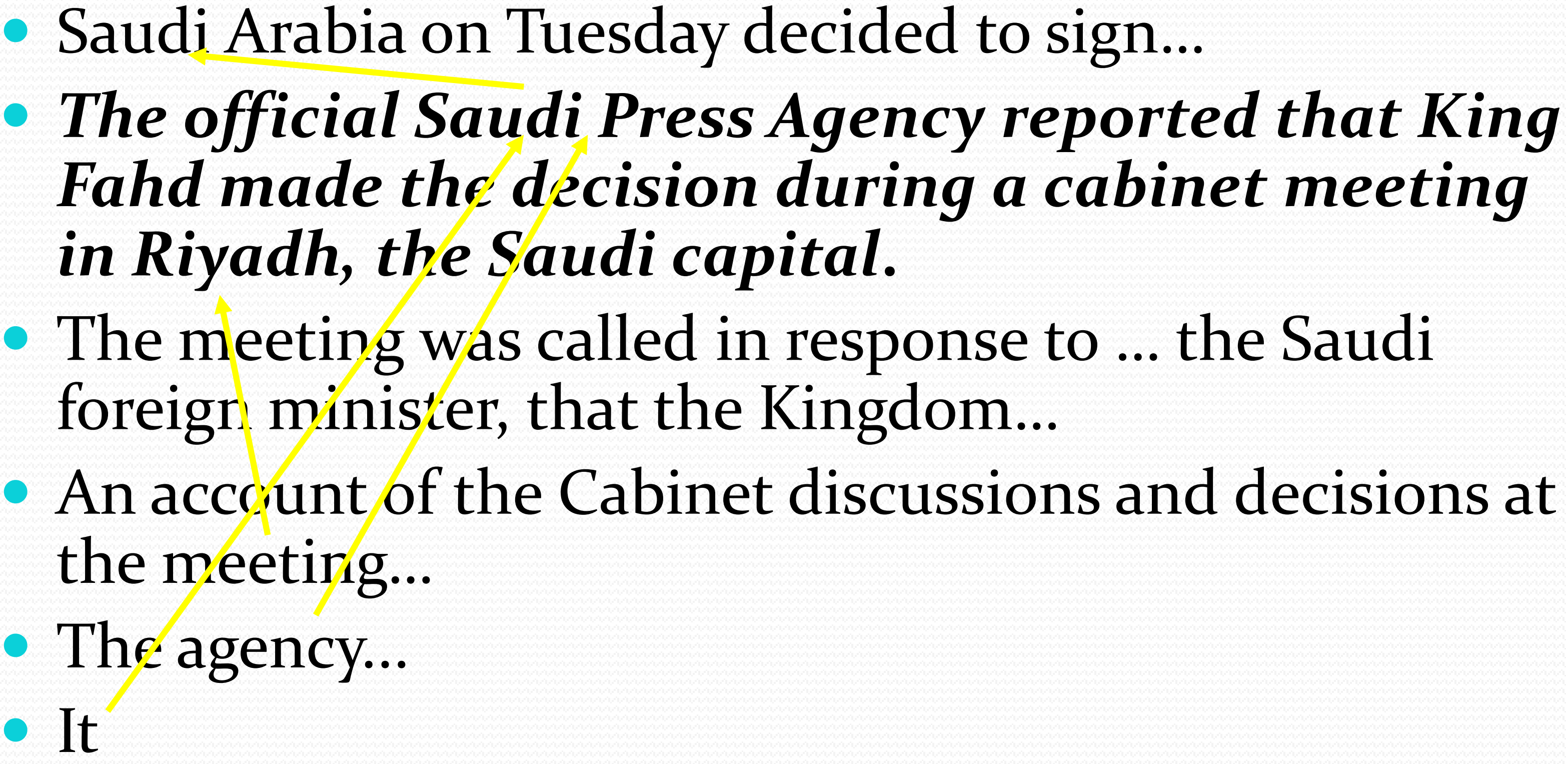
Sentence extraction variants

- Lexical Chains
  - Barzilay and Elhadad
  - Silber and McCoy
- Discourse coherence
  - Baldwin
- Topic signatures
  - Lin and Hovy

Lexical Chains

- “Dr.Kenny has invented an anesthetic machine. This device controls the rate at which an anesthetic is pumped into the blood.“
- “Dr.Kenny has invented an anesthetic machine. The doctor spent two years on this research.“
- Algorithm: Measure strength of a chain by its length and its homogeneity
  - Select the first sentence from each strong chain until length limit reached
- Semantics needed?

Discourse Coherence



- Saudi Arabia on Tuesday decided to sign…
- ***The official Saudi Press Agency reported that King Fahd made the decision during a cabinet meeting in Riyadh, the Saudi capital.***
- The meeting was called in response to … the Saudi foreign minister, that the Kingdom…
- An account of the Cabinet discussions and decisions at the meeting…
- The agency…
- It

Topic Signature Words

- Uses the log ratio test to find words that are highly descriptive of the input
- the log-likelihood ratio test provides a way of setting a threshold to divide all words in the input into either descriptive or not
  - the probability of a word in the input is the same as in the background
  - the word has a different, higher probability, in the input than in the background
- Binomial distribution used to compute the ratio of the two likelihoods
- The sentences containing the highest proportion of topic signatures are extracted.

Summarization as a Noisy Channel Model

- Summary/text pairs
- Machine learning model
- Identify which features help most

Julian Kupiec SIGIR 95
Paper Abstract

- To summarize is to reduce in complexity, and hence in length while retaining some of the essential qualities of the original.
- This paper focusses on document extracts, a particular kind of computed document summary.
- Document extracts consisting of roughly 20% of the original can be as informative as the full text of a document, which suggests that even shorter extracts may be useful indicative summaries.
- The trends in our results are in agreement with those of Edmundson who used a subjectively weighted combination of features as opposed to training the feature weights with a corpus.
- We have developed a trainable summarization program that is grounded in a sound statistical framework.

Statistical Classification Framework

- A training set of documents with hand-selected abstracts
  - Engineering Information Co provides technical article abstracts
  - 188 document/summary pairs
  - 21 journal articles
- Bayesian classifier estimates probability of a given sentence appearing in abstract
  - Direct matches (79%)
  - Direct Joins (3%)
  - Incomplete matches (4%)
  - Incomplete joins (5%)
- New extracts generated by ranking document sentences according to this probability

Features

- Sentence length cutoff
- Fixed phrase feature (26 indicator phrases)
- Paragraph feature
  - First 10 paragraphs and last 5
  - Is sentence paragraph-initial, paragraph-final, paragraph medial
- Thematic word feature
  - Most frequent content words in document
- Upper case Word Feature
  - Proper names are important

Evaluation

- Precision and recall
- Strict match has 83% upper bound
  - Trained summarizer: 35% correct
- Limit to the fraction of matchable sentences
  - Trained summarizer: 42% correct
- Best feature combination
  - Paragraph, fixed phrase, sentence length
  - Thematic and Uppercase Word give slight decrease in performance

Questions (from Sparck Jones)

- Should we take the reader into account and how?
- "Similarly, the notion of a basic summary, i.e., one reflective of the source, makes hidden fact assumptions, for example that the subject knowledge of the output's readers will be on a par with that of the readers for whom the source was intended. (p. 5)"
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