Segmentation & Wrap-up: Q-A

Ling571
Deep Processing Techniques for NLP
March 11, 2015

TextTiling (Hearst '97)

- Lexical cohesion-based segmentation
  - Boundaries at dips in cohesion score
  - Tokenization, Lexical cohesion score, Boundary ID
- Tokenization
  - White-space delimited words
  - Stopped
  - Stemmed
  - 20 words = 1 pseudo sentence

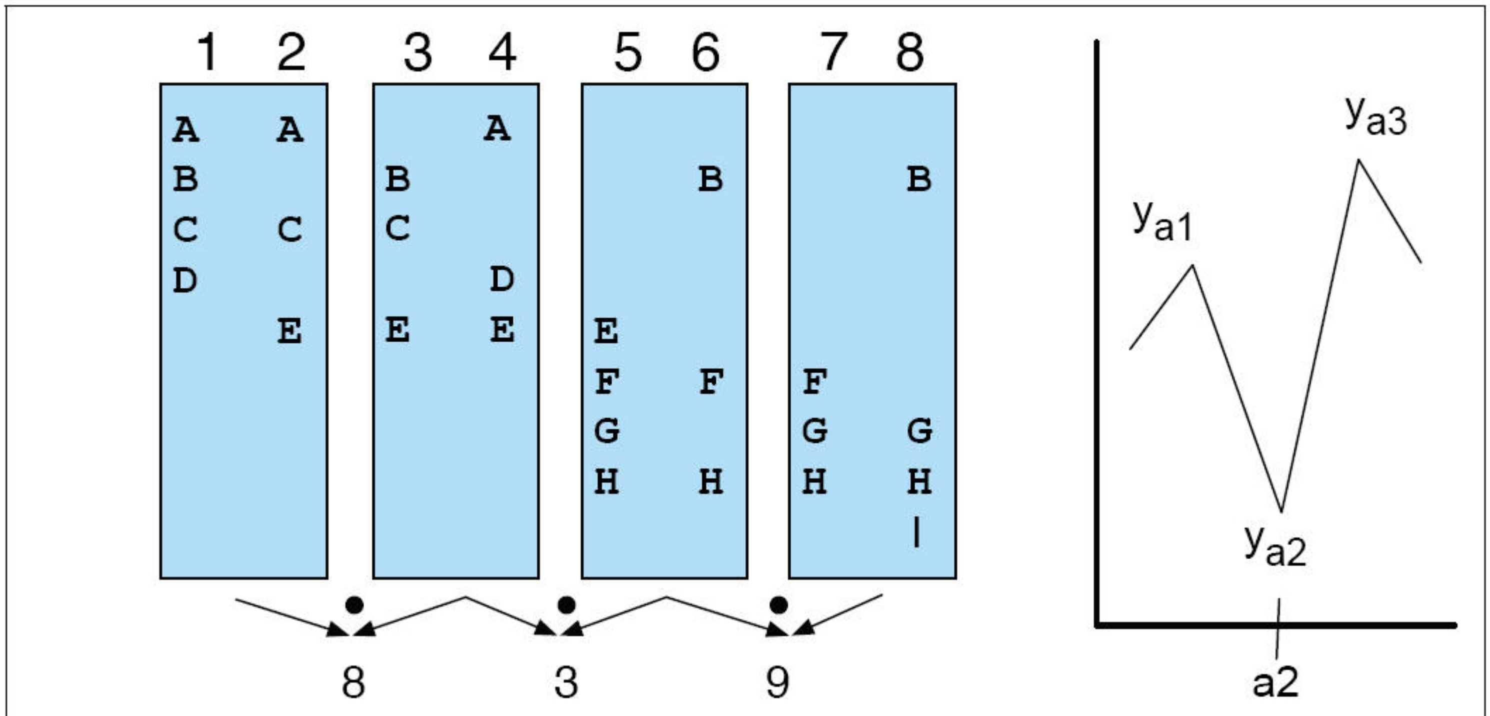
Lexical Cohesion Score

- Similarity between spans of text
  - b = 'Block' of 10 pseudo-sentences before gap
  - a = 'Block' of 10 pseudo-sentences after gap
  - How do we compute similarity?
    - Vectors and cosine similarity (again!)

$$sim_{cosine}(\vec{b},\vec{a}) = \frac{\vec{b} \bullet \vec{a}}{|\vec{b}||\vec{a}|} = \frac{\sum_{i=1}^{N} b_i \times a_i}{\sqrt{\sum_{i=1}^{N} b_i^2}\sqrt{\sum_{i=1}^{N} a_i^2}}$$

Segmentation

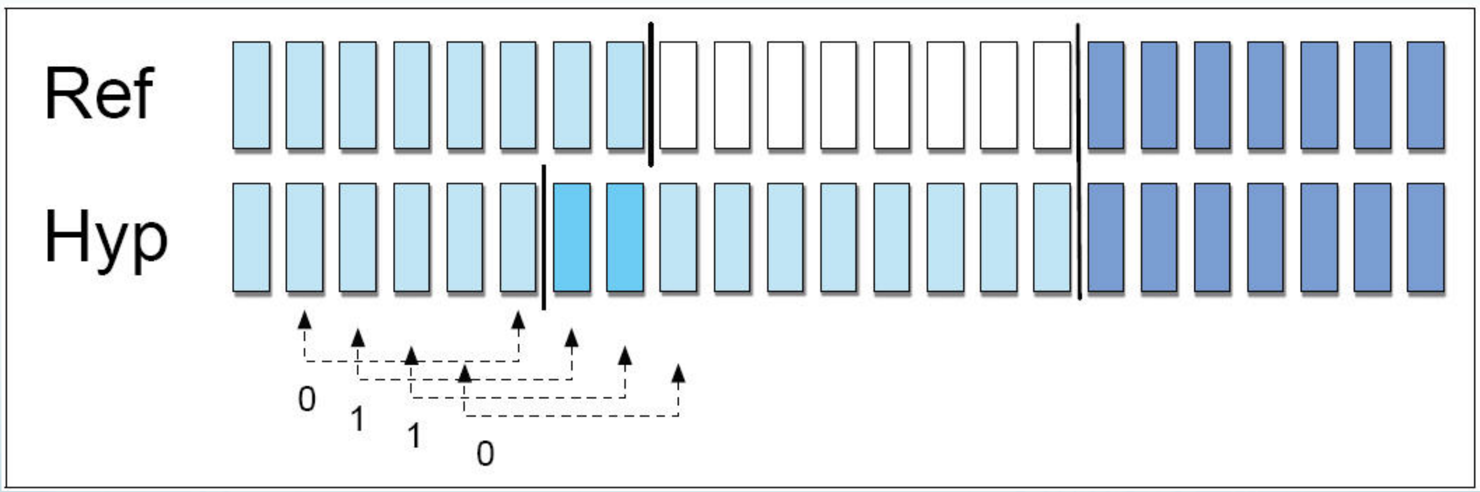
- Depth score:
  - Difference between position and adjacent peaks
  - E.g., $(y_{a1}-y_{a2})+(y_{a3}-y_{a2})$



(a) (b)

Evaluation

- How about precision/recall/F-measure?
  - Problem: No credit for near-misses
- Alternative model: WindowDiff



$$WindowDiff(ref,hyp) = \frac{1}{N-k}\sum_{i=1}^{N-k}\left(\left|b(ref_i, ref_{i+k}) - b(hyp_i, hyp_{i+k})\right| \neq 0\right)$$

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- Overall: Auto much better than random
- Issues

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- Similarity measures
  - Is raw tf the best we can do?
  - Other cues??
- Other experiments with TextTiling perform less well – Why?

Summary

- Computational discourse:
  - Cohesion and Coherence in extended spans

  - Key tasks:
    - Reference resolution
      - Constraints and preferences
      - Heuristic, learning, and sieve models

    - Discourse structure modeling
      - Linear topic segmentation
    - Exploiting shallow and deep language processing

Question-Answering: Shallow & Deep Techniques for NLP

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(Examples from Dan Jurafsky)

Roadmap

- Question-Answering:
  - Definitions & Motivation
- Basic pipeline:
  - Question processing
  - Retrieval
  - Answering processing
- Shallow processing: Aranea (Lin, Brill)
- Deep processing: LCC (Moldovan, Harabagiu, et al)
- Wrap-up

Why QA?

- Grew out of information retrieval community
- Web search is great, but...
  - Sometimes you don't just want a ranked list of documents
  - Want an answer to a question!
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    - Which English translation of the bible is used in official Catholic liturgies?
    - Who invented surf music?
    - What are the seven wonders of the world?

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  - Account for 12-15% of web log queries

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  - *Who invented surf music?*
    - Rank #2 snippet:
      - Dick Dale *invented surf music*
    - Pretty good, but…

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    - The table below lists the *largest* 50 *cities in the United States* .....
  - The answer is in the document – with a calculator..

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  - "Do I need a visa to go to Japan?"
    - Result: Exact match on Yahoo! Answers

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    - 'Question mining' tries to learn paraphrases of questions to get answer

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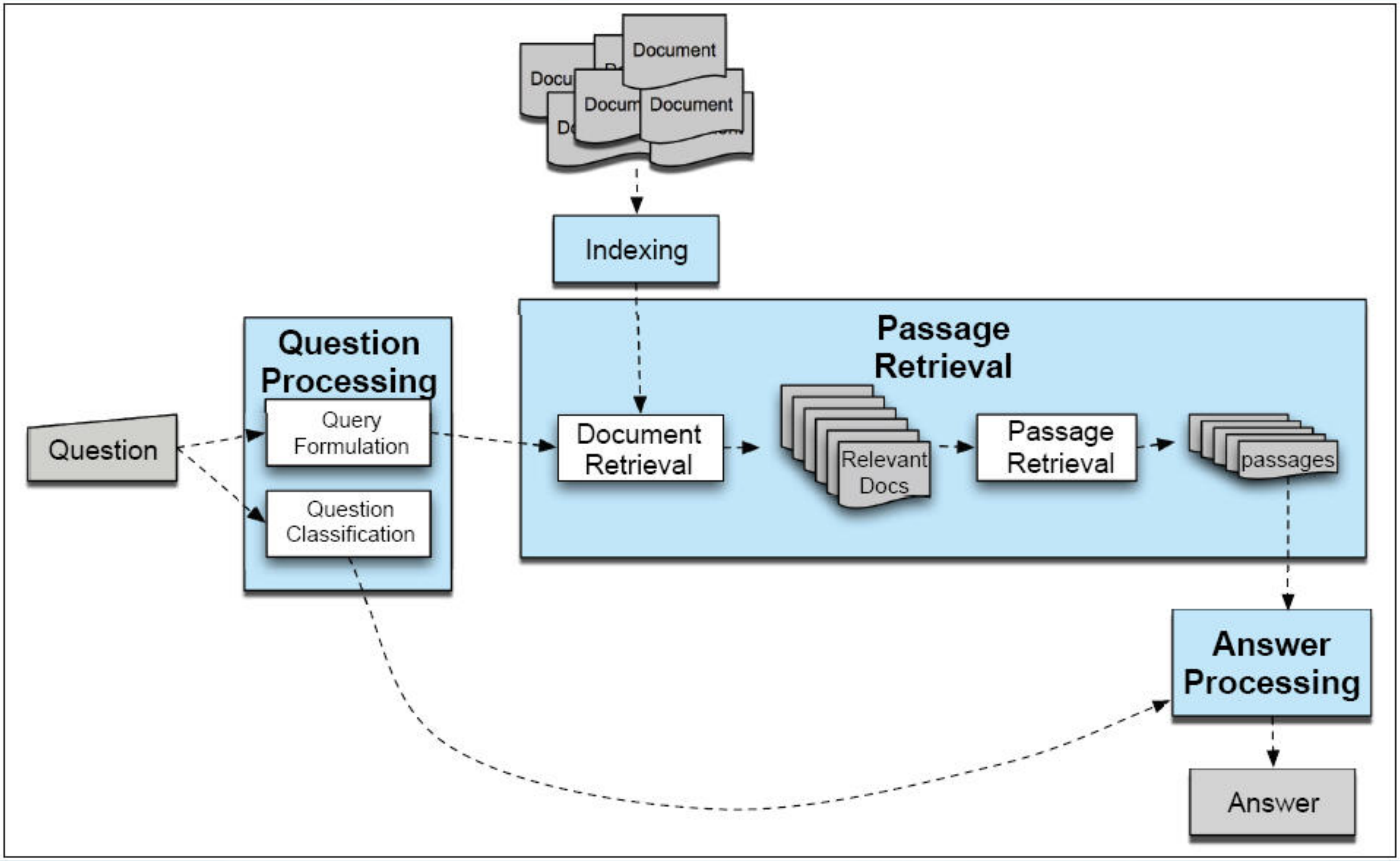
  - Also, 'machine reading'
- And, of course, Jeopardy! and Watson

Question Answering (a la TREC)

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

Basic Strategy

- Given an indexed document collection, and
- A question:
- Execute the following steps:
  - Query formulation
  - Question classification
  - Passage retrieval
  - Answer processing
  - Evaluation



Document
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Document
Indexing
Question
Question Processing
Query Formulation
Question Classification
Passage Retrieval
Document Retrieval
Relevant Docs
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passages
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  - Answer type recognition
    - Who → Person; What Canadian city → City
    - What is surf music →Definition
  - Train classifiers to recognize expected answer type
    - Using POS, NE, words, synsets, hyper/hypo-nyms

Tag	Example
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?
speed	What is the speed of the Mississippi River?
temp	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?

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  - Filter for correct type: answer type classification
  - Rank passages based on a trained classifier
  - Or, for web search, use result snippets

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    - Leverage large knowledge bases

Pattern	**Question**	**Answer**
<AP> such as <QP>	What is autism?	“, developmental disorders such as autism”
<QP>, a <AP>	What is a caldera?	“the Long Valley caldera, a volcanic crater 19 miles long”

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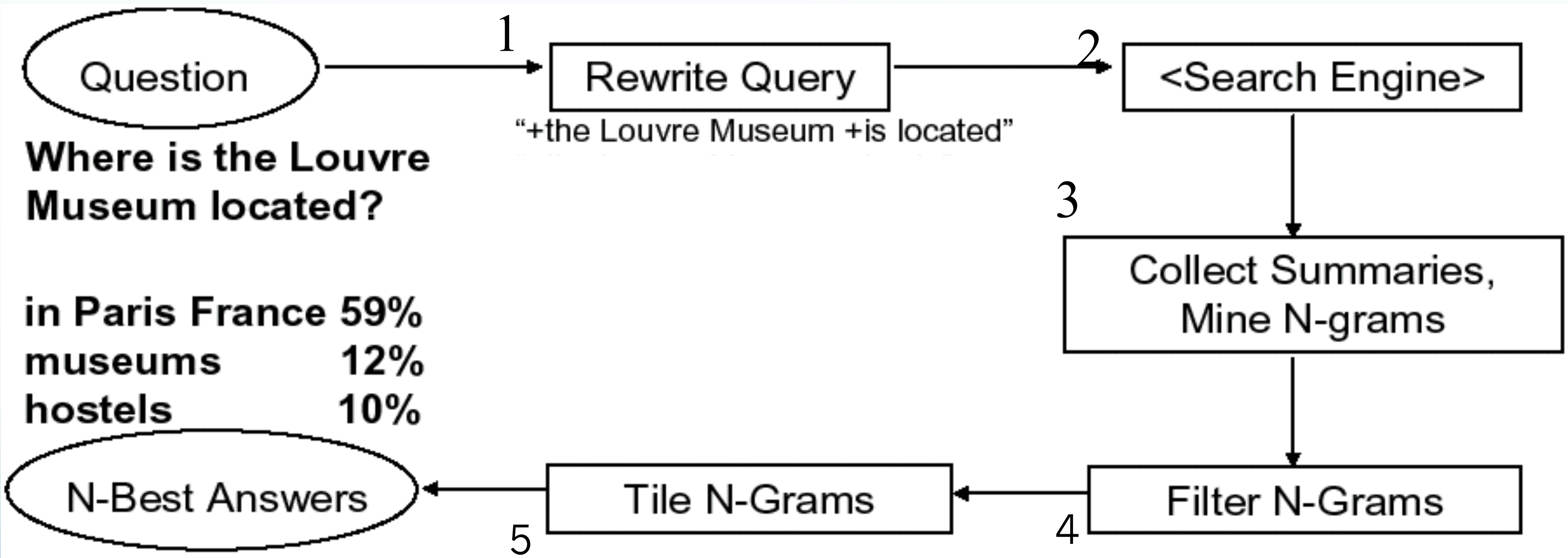
  - Measure: Mean Reciprocal Rank (MRR)
    - For each question,
      - Get reciprocal of rank of first correct answer
        - E.g. correct answer is 4 => ¼
        - None correct => 0
    - Average over all questions

$$MRR = \frac{\sum_{i=1}^{N} \frac{1}{rank_i}}{N}$$

AskMSR/Aranea (Lin, Brill)

- Shallow Processing for QA



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  - Probably 5

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      - Where is the Louvre Museum located? =>
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- Create type-specific answer type (Person, Date, Loc)

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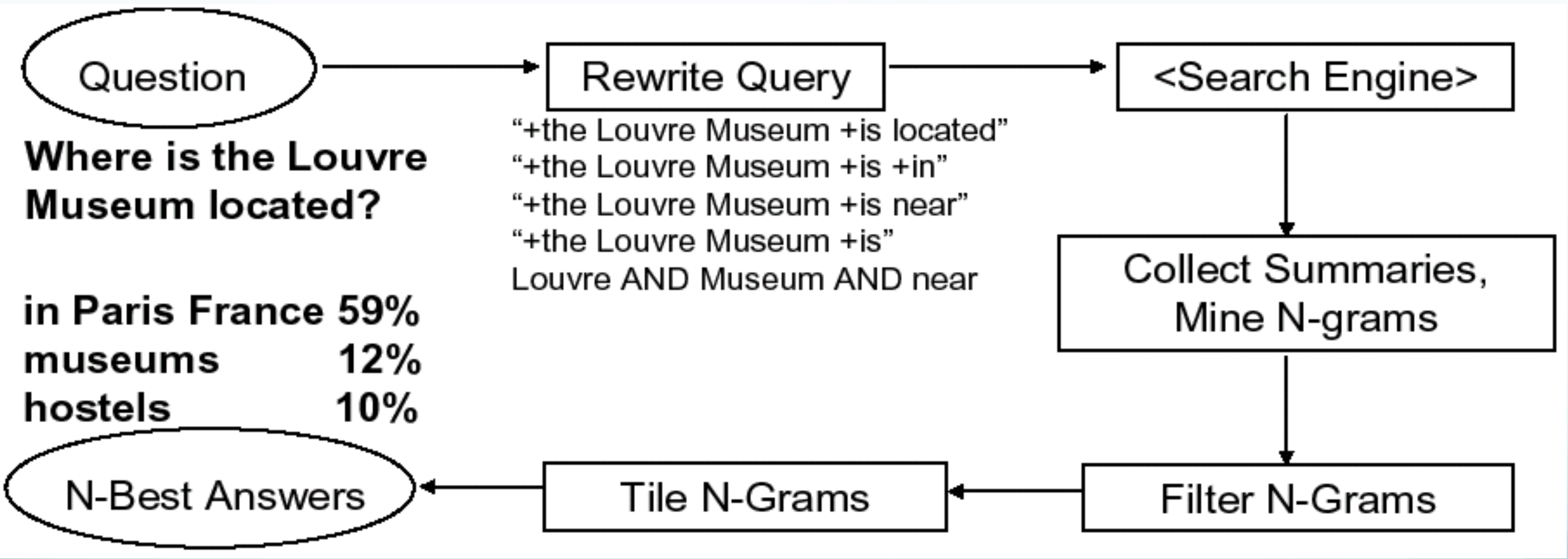
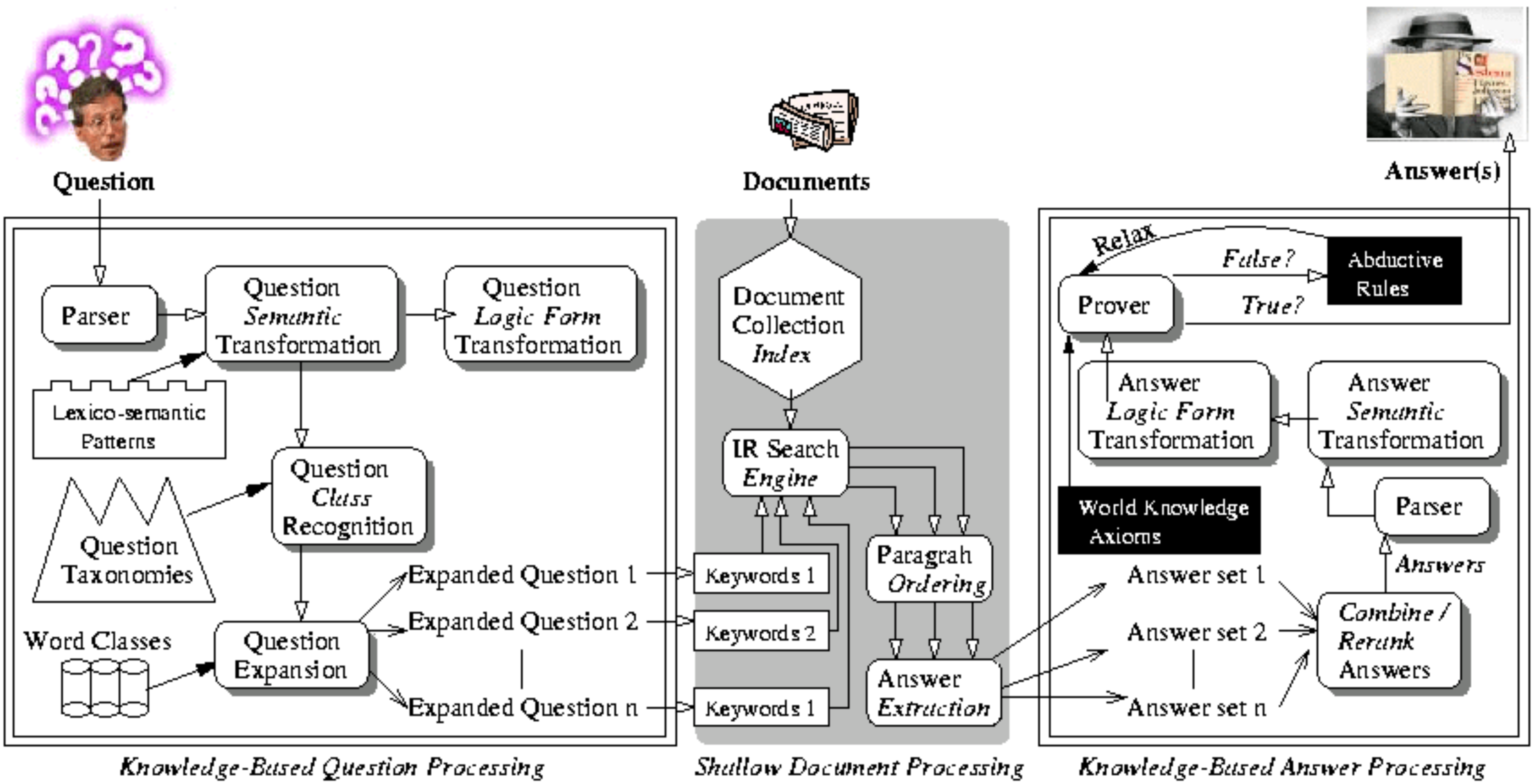
  - Concatenate n-grams into longer answers
    - E.g. Dickens, Charles Dickens, Mr. Charles ➔
      - Mr. Charles Dickens

Example Redux



Deep Processing Technique for QA

- LCC, PowerAnswer, Qanda (Moldovan, Harabagiu, et al)



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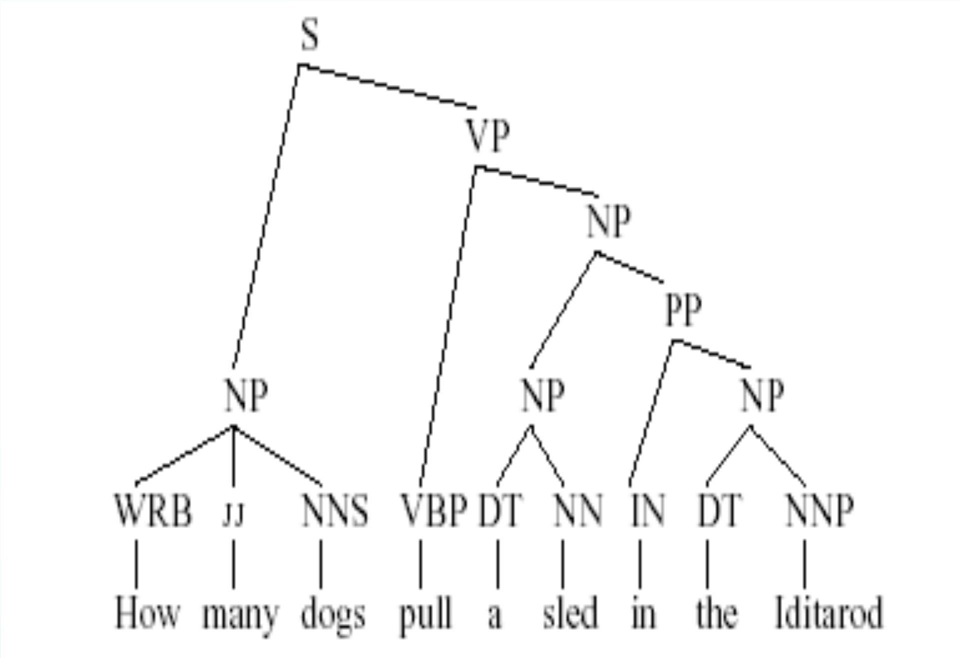
- Coreference resolution links entity references
- Translate to full logical form
  - As close as possible to syntax

Syntax to Logical Form



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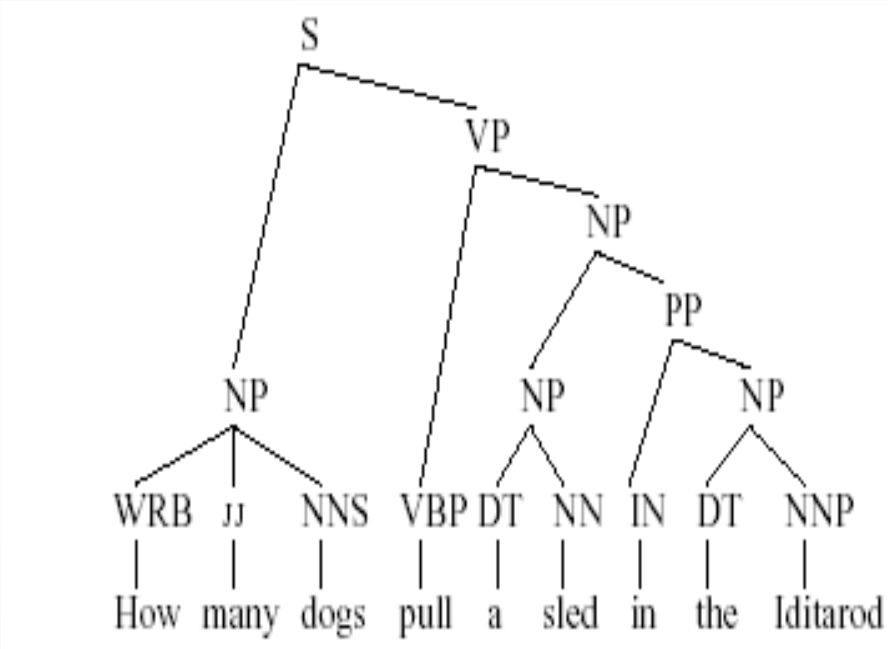

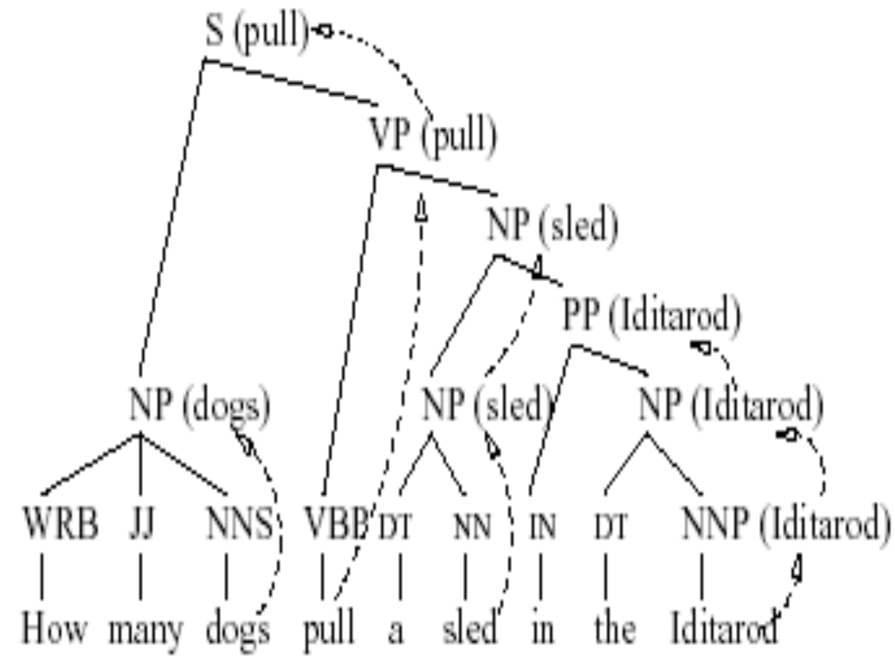

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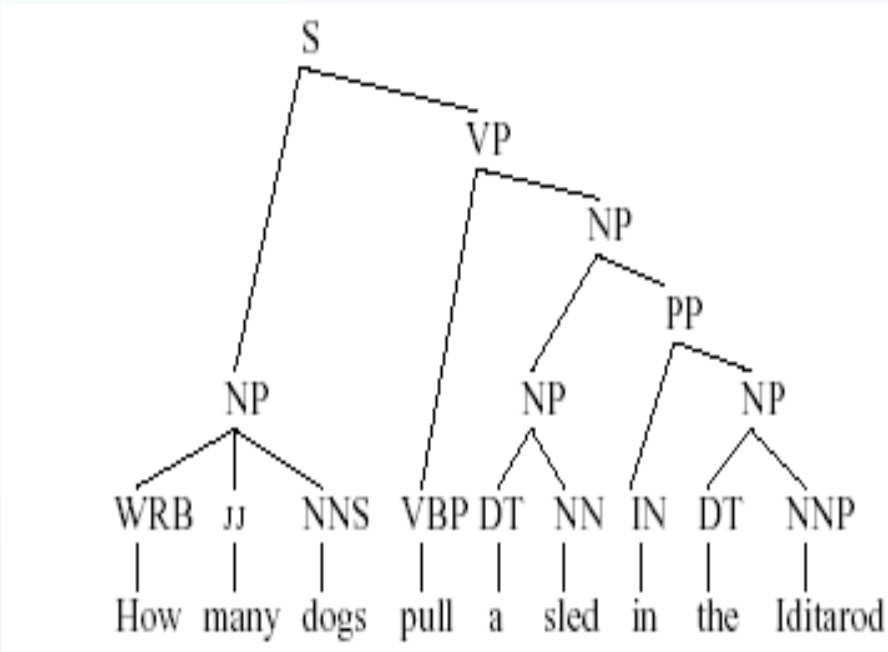

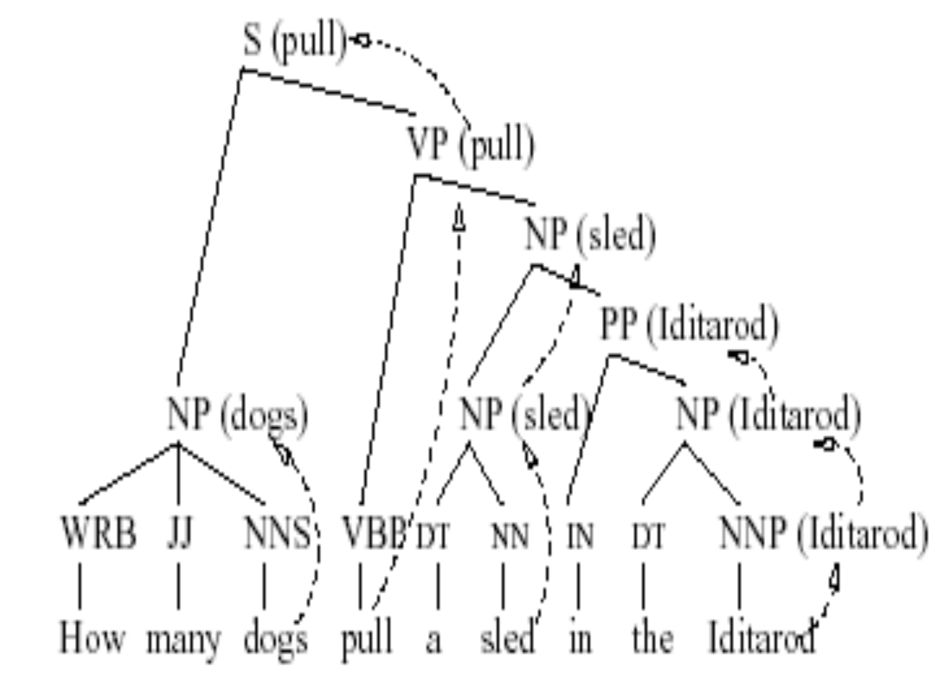

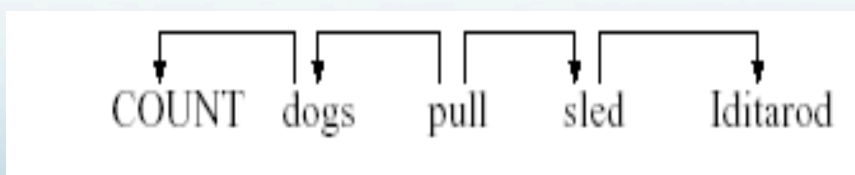

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- Perform abductive reasoning
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  - Yields 30% improvement in accuracy!

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- The needed semantic information is in WordNet definitions, and was successfully translated into a form that was used for rough 'proofs'

A Victory for Deep Processing

Run Tag	Score	#	%	Inexact	Prec	Recall
LCCmain2002	0.856	415	83.0	8	0.578	0.804
exactanswer	0.691	271	54.2	12	0.222	0.848
pris2002	0.610	290	58.0	17	0.241	0.891
IRST02D1	0.589	192	38.4	17	0.167	0.217
IBMPQSQACYC	0.588	179	35.8	9	0.196	0.630
uwmtB3	0.512	184	36.8	20	0.000	0.000
BBN2002C	0.499	142	28.4	18	0.182	0.087
isi02	0.498	149	29.8	15	0.385	0.109
limsiQalir2	0.497	133	26.6	11	0.188	0.196
ali2002b	0.496	181	36.2	15	0.156	0.848
ibmsqa02c	0.455	145	29.0	44	0.224	0.239
FDUT11QA1	0.434	124	24.8	6	0.139	0.957
aranea02a	0.433	152	30.4	36	0.235	0.174
nuslamp2002	0.396	105	21.0	17	0.000	0.000

Aranea: 0.30 on TREC data; 0.42 on TREC queries w/full web

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- Trends:
  - Systems continue to make greater use of
    - Web resources: Wikipedia, answer repositories
    - Machine learning!!!!

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- Shallow processing techniques have dominated many areas
  - IR, QA, MT, WSD, etc
    - More computationally tractable, fewer required resources

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  - Create richer computational models of natural language
    - Closer to language understanding
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  - IR, QA, MT, WSD, etc
    - More computationally tractable, fewer required resources
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Summary

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- Deep processing techniques experiencing resurgence
  - Some big wins – e.g. QA
  - Improved resources: treebanks (syn/disc, Framenet, Propbank)
  - Improved learning algorithms: structured learners,…
  - Increased computation: cloud resources, Grid, etc

Notes

- Last assignment posted – Due March 18

- Course evaluation web page posted:
  - Please respond!

- THANK YOU!

Text Coherence

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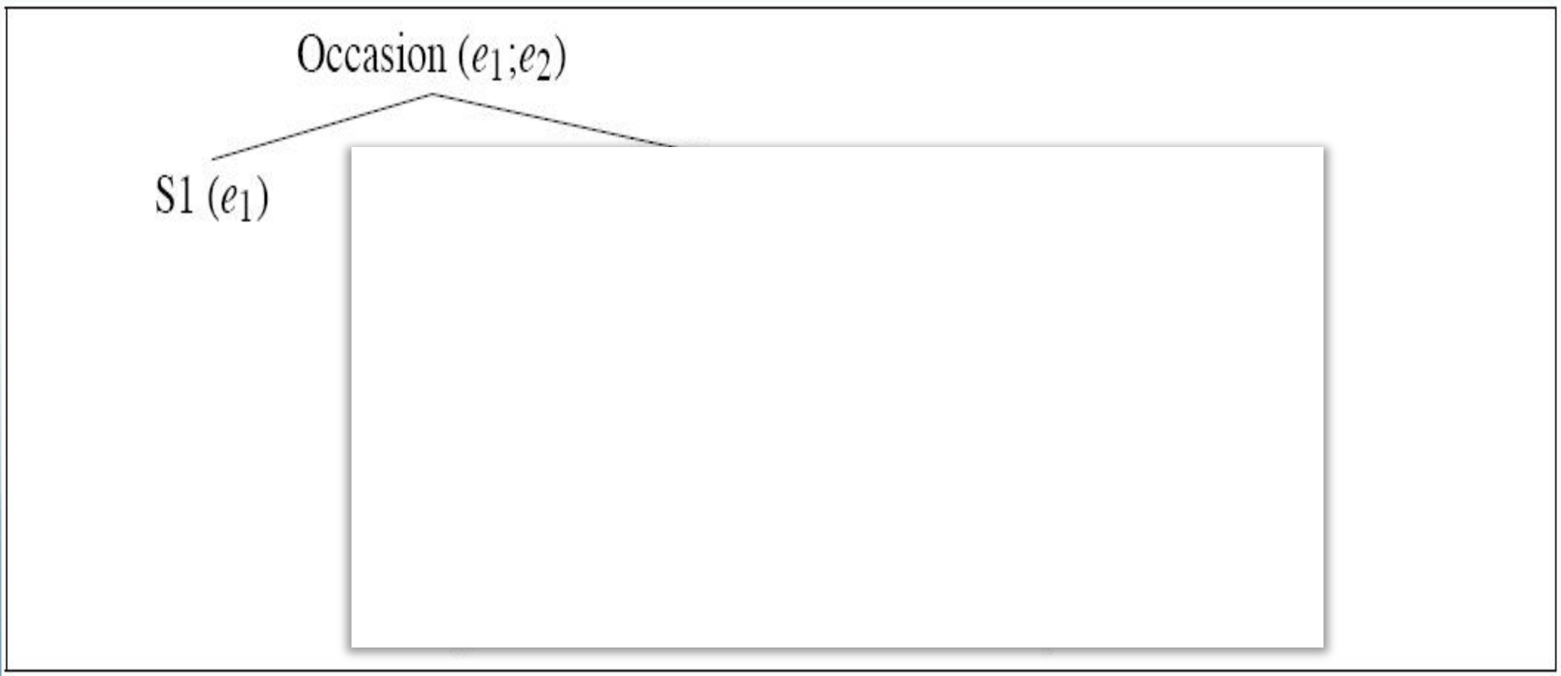
      - John hid Bill's car keys. He was drunk.
    - **Elaboration**: Infer same prop. from S_0 and S_1.
      - Dorothy was from Kansas. She lived in the great Kansas prairie.
  - Pair of locally coherent clauses: discourse segment

Coherence Analysis

S1: John went to the bank to deposit his paycheck.
S2: He then took a train to Bill’s car dealership.
S3: He needed to buy a car.
S4: The company he works now isn’t near any public transportation.
S5: He also wanted to talk to Bill about their softball league.



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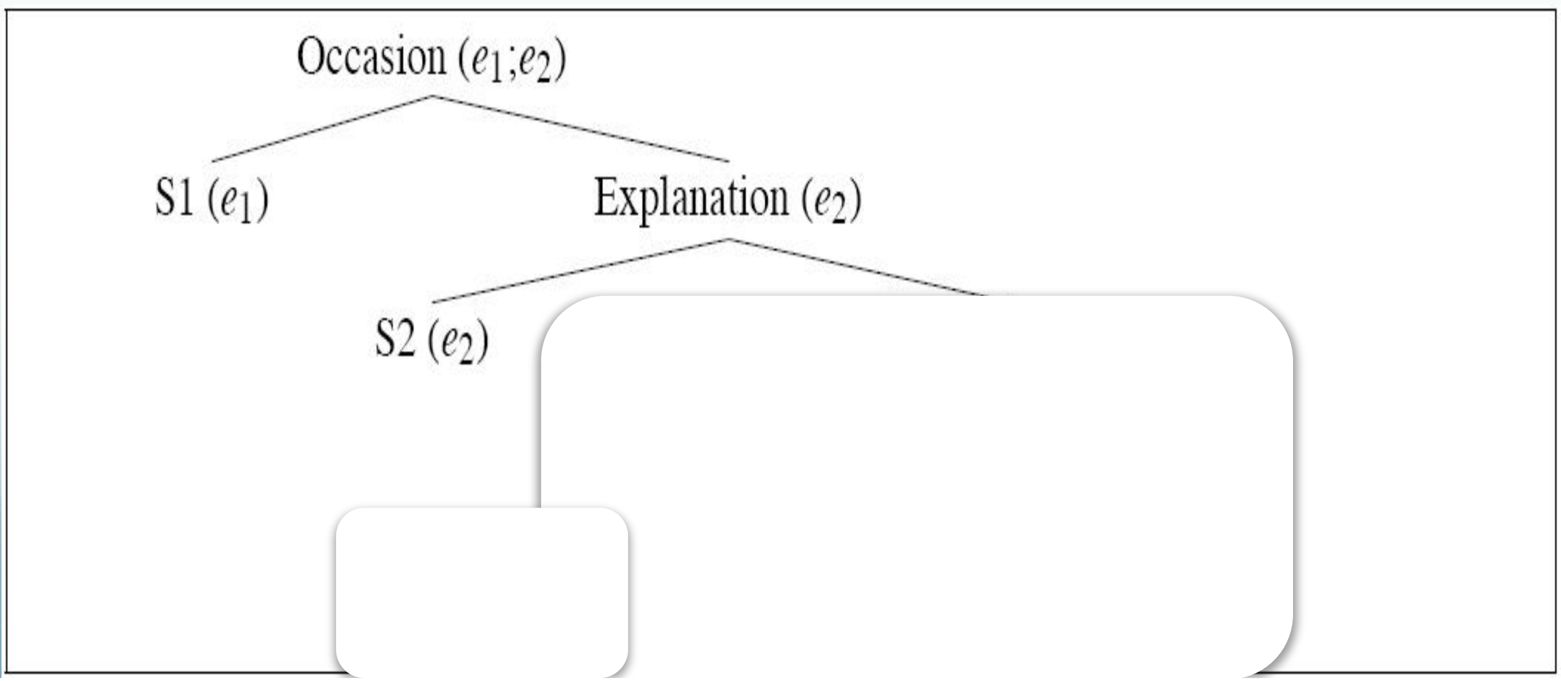

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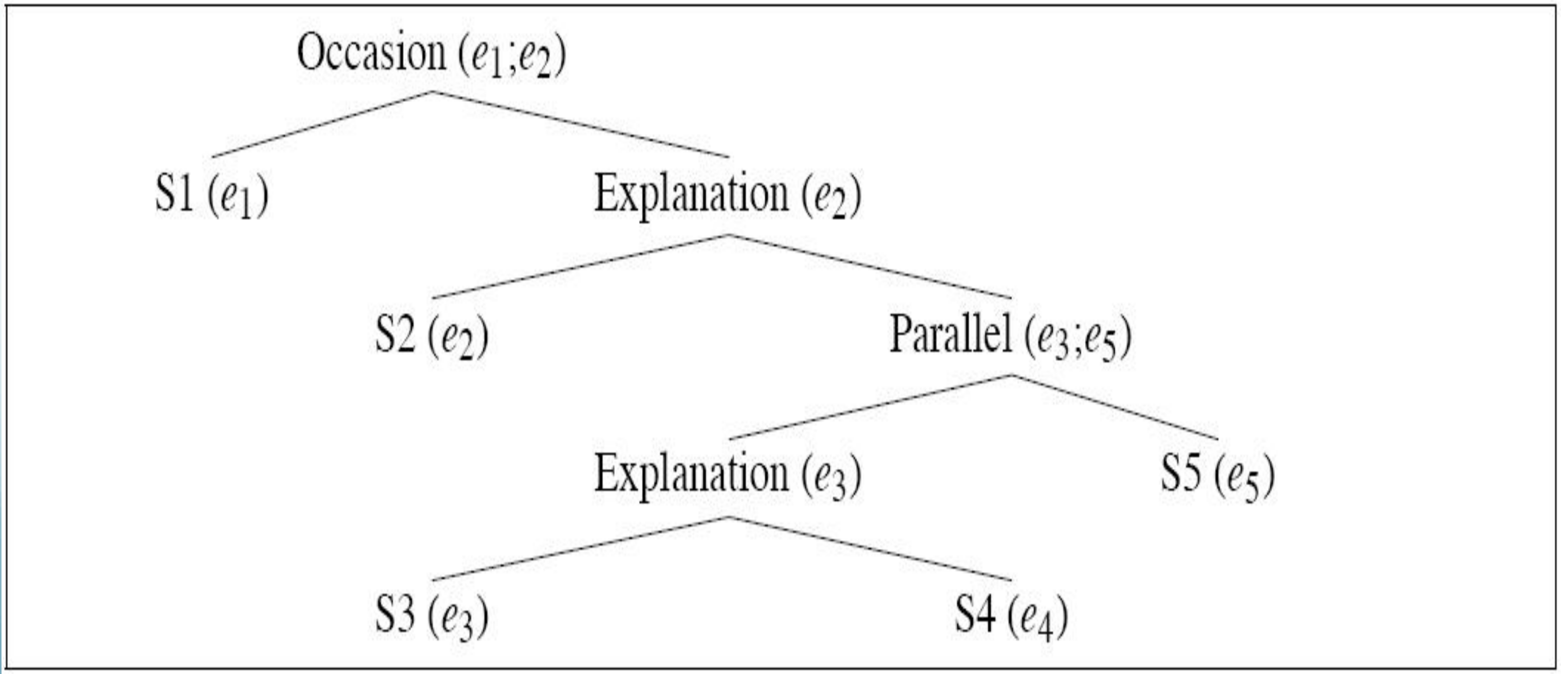

Rhetorical Structure Theory

- Mann & Thompson (1987)
- Goal: Identify hierarchical structure of text
  - Cover wide range of TEXT types
    - Language contrasts
  - Relational propositions (intentions)
- Derives from functional relations b/t clauses

Components of RST

- Relations:
  - Hold b/t two text spans, nucleus and satellite
    - Nucleus core element, satellite peripheral
    - Constraints on each, between
    - Effect: why the author wrote this

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    - Most common: N + S, others involve two or more nuclei
- Structures:
  - Using clause units, complete, connected, unique, adjacent

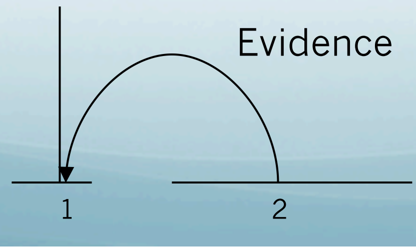
RST Relations

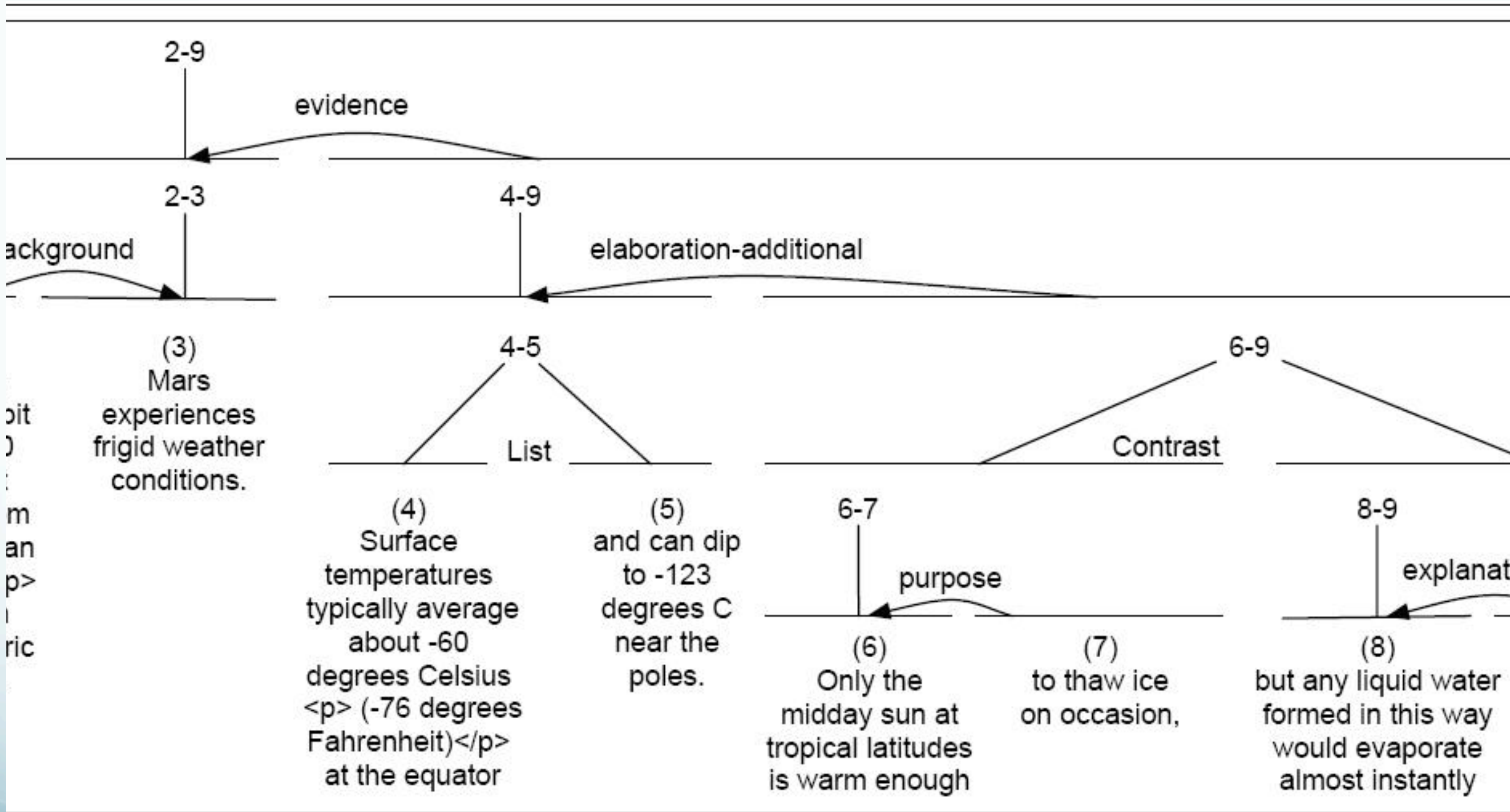
- Core of RST
  - RST analysis requires building tree of relations
  - Circumstance, Solutionhood, Elaboration. Background, Enablement, Motivation, Evidence, Justify, Vol. Cause, Non-Vol. Cause, Vol. Result, Non-Vol. Result, Purpose, Antithesis, Concession, Condition, Otherwise, Interpretation, Evaluation, Restatement, Summary, Sequence, Contrast

RST Relations

- Evidence
  - Effect: Evidence (Satellite) increases R's belief in Nucleus
    - The program really works. (N)
    - I entered all my info and it matched my results. (S)

Relation Name:	Evidence
Constraints on N:	R might not believe N to a degree satisfactory to W
Constraints on S:	R believes S or will find it credible
Constraints on N+S:	R's comprehending S increases R's belief of N
Effects:	R's belief of N is increased





2-9
evidence
2-3
4-9
ackground
elaboration-additional
(3)
Mars
experiences
frigid weather
conditions.
4-5
6-9
List
Contrast
(4)
Surface
temperatures
typically average
about -60
degrees Celsius
<p> (-76 degrees
Fahrenheit)</p>
at the equator
(5)
and can dip
to -123
degrees C
near the
poles.
6-7
purpose
(6)
Only the
midday sun at
tropical latitudes
is warm enough
(7)
to thaw ice
on occasion,
8-9
(8)
but any liquid water
formed in this way
would evaporate
almost instantly

RST Parsing

- Learn and apply classifiers for
  - Segmentation and parsing of discourse

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RST Parsing

- Learn and apply classifiers for
  - Segmentation and parsing of discourse
- Assign coherence relations between spans
- Create a representation over whole text => parse
- Discourse structure
  - RST trees
    - Fine-grained, hierarchical structure
      - Clause-based units

Identifying Segments & Relations

- Key source of information:

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  - Cue phrases
    - Aka discourse markers, cue words, clue words
    - Although, but, for example, however, yet, with, and....
      - John hid Bill's keys **because** he was drunk.
- Issues:

Identifying Segments & Relations

- Key source of information:
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    - Although, but, for example, however, yet, with, and....
      - John hid Bill's keys **because** he was drunk.
- Issues:
  - Ambiguity: discourse vs sentential use
      - **With** its distant orbit, Mars exhibits frigid weather.
      - We can see Mars **with** a telescope.
  - Ambiguity: cue multiple discourse relations
    - Because: CAUSE/EVIDENCE; But: CONTRAST/ CONCESSION

Cue Phrases

- Last issue:
  - Insufficient:

Cue Phrases

- Last issue:
  - Insufficient:
    - Not all relations marked by cue phrases
    - Only 15-25% of relations marked by cues

Learning Discourse Parsing

- Train classifiers for:
  - Segmentation
  - Coherence relation assignment
  - Discourse structure assignment
    - Shift-reduce parser transitions

- Use range of features:
  - Cue phrases
  - Lexical/punctuation in context
  - Syntactic parses

Evaluation

- Segmentation:
  - Good: 96%
    - Better than frequency or punctuation baseline
- Discourse structure:
  - Okay: 61% span, relation structure
- Relation identification: poor

Issues

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  - Difficult to achieve

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    - Significant disagreement among labelers

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- Goal: Single tree-shaped analysis of all text
  - Difficult to achieve
    - Significant ambiguity
    - Significant disagreement among labelers
    - Relation recognition is difficult
      - Some clear “signals”, I.e. although
      - Not mandatory, only 25%