

Content Selection: Supervision & Discourse

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Systems & Applications
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Roadmap

- Content selection
 - Supervised content selection
 - Analysis & Regression with rich features
- Discourse structure
 - Models of discourse structure
 - Structure and relations for summarization

Supervised Word Selection

- RegSumm:
 - Improving the Estimation of Word Importance for News Multi-Document Summarization (Hong & Nenkova, '14)
- Key ideas:
 - Supervised method for word selection
 - Diverse, rich feature set: unsupervised measures, POS, NER, position, etc
 - Identification of common “important” words via side corpus of news articles and human summaries

Basic Approach

- Learn keyword importance
 - Contrasts with unsupervised selection, learning sentences
- Train regression over large number of possible features
 - Supervision over *words*
 - Did document word appear in summary or not?
- Greedy sentence selection:
 - Highest scoring sentences: average word weight
 - Do not add if ≥ 0.5 cosine similarity w/any curr sents

Features I

- Unsupervised measures:
 - Used as binary features given some threshold
- Word probability: $\text{count}(w)/N$
 - Computed over input cluster
- Log likelihood ratio: Gigaword as background corpus
- Markov Random Walk (MRW):
 - Graphical model approach similar to LexRank
 - Nodes: words
 - Edges: # syntactic dependencies b/t wds in sentences
 - Weights via PageRank algorithm

Features II

- “Global” word importance:
 - Question: Are there words which are intrinsically likely to show up in (news) summaries?
- Approach:
 - Build language models on NYT corpus of articles+summs
 - One model on articles, one model on summaries
 - Measures: $\Pr_A(w)$, $\Pr_A(w) \cdot \Pr_G(w)$, $\Pr_A(w) / \Pr_G(w)$
 - $KL(A || G) = \Pr_A(w) * \ln (\Pr_A(w) / \Pr_G(w))$
 - $KL(G || A) = \Pr_G(w) * \ln (\Pr_G(w) / \Pr_A(w))$
 - Binary features: top-k or bottom-k features

Features III

- Adaptations of common features:
 - Word position as proportion of document [0,1]
 - Earliest first, latest last, average, average first
 - Word type: POS, NER
 - Emphasizes NNS, NN, capitalization; ORG, PERS, LOC
- MPQA and LIWC features:
 - MPQA: sentiment, subjectivity terms
 - Strong sentiment likely or not? NOT
 - LIWC: words for 64 categories: +: death, anger, money
 - Neg: pron, neg, fn words, swear, adverbs, etc

Assessment: Words

- Select N highest ranked keywords via regression
- Compute F-measure over words in summaries
 - G_i : i = # of summaries in which word appears

G_i	#words	PROB	LLR	MRW	REGBASIC	REGSUM
G_1	80	43.6	37.9	38.9	39.9	45.7
G_1	100	44.3	38.7	39.2	41.0	46.5
G_1	120	44.6	38.5	39.2	40.9	46.4
G_2	30	47.8	44.0	42.4	47.4	50.2
G_2	35	47.1	43.3	42.1	47.0	49.5
G_2	40	46.5	42.4	41.8	46.4	49.2

Assessment: Summaries

- Compare summarization w/ROUGE-1,2,4

Basic
Systems

System	R-1	R-2	R-4
PROB	35.14	8.17	1.06
LLR	34.60	7.56	0.83
MRW	35.78	8.15	0.99
REGBASIC	37.56	9.28	1.49
KL	37.97	8.53	1.26
PEER-65	37.62	8.96	1.51
SUBMOD	39.18	9.35	1.39
DPP	39.79	9.62	1.57
REGSUM	38.57	9.75	1.60

State of
The Art
Systems

Text Coherence

- Cohesion – repetition, etc – does not imply coherence
- Coherence relations:
 - Possible meaning relations between utts in discourse
 - Examples:
 - **Result:** Infer state of S_0 cause state in S_1
 - The Tin Woodman was caught in the rain. His joints rusted.
 - **Explanation:** Infer state in S_1 causes state in S_0
 - 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

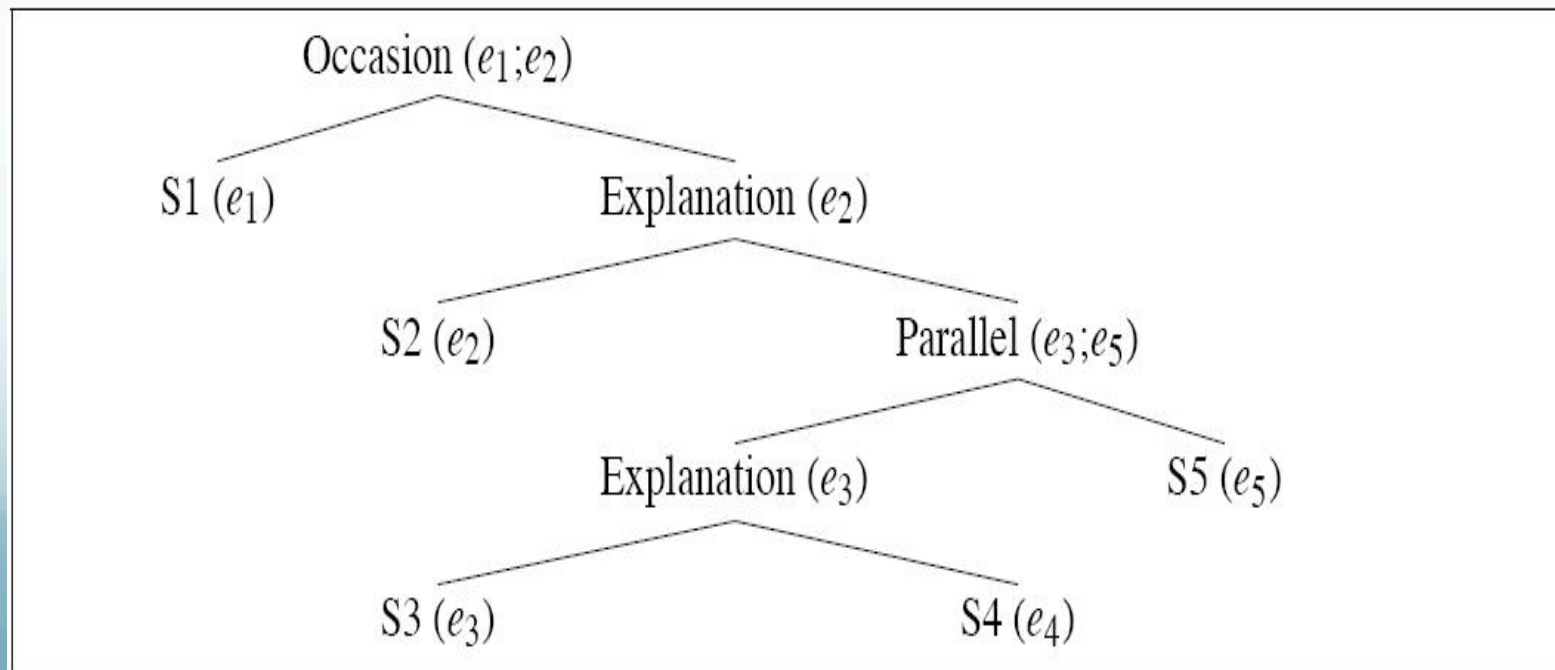
S1: John went to the bank to deposit his paycheck.

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.



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
 - Units: Elementary discourse units (EDUs), e.g. clauses
- Schemas:
 - Grammar of legal relations between text spans
 - Define possible RST text structures
 - Most common: N + S, others involve two or more nuclei
- Structures:
 - Using clause units, complete, connected, unique, adjacent

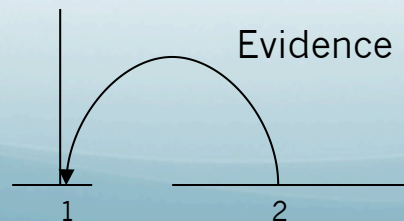
RST Relations

- 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
- Captured in:
 - RST treebank: corpus of WSJ articles with analysis
 - RST parsers: Marcu, Peng and Hirst 2014

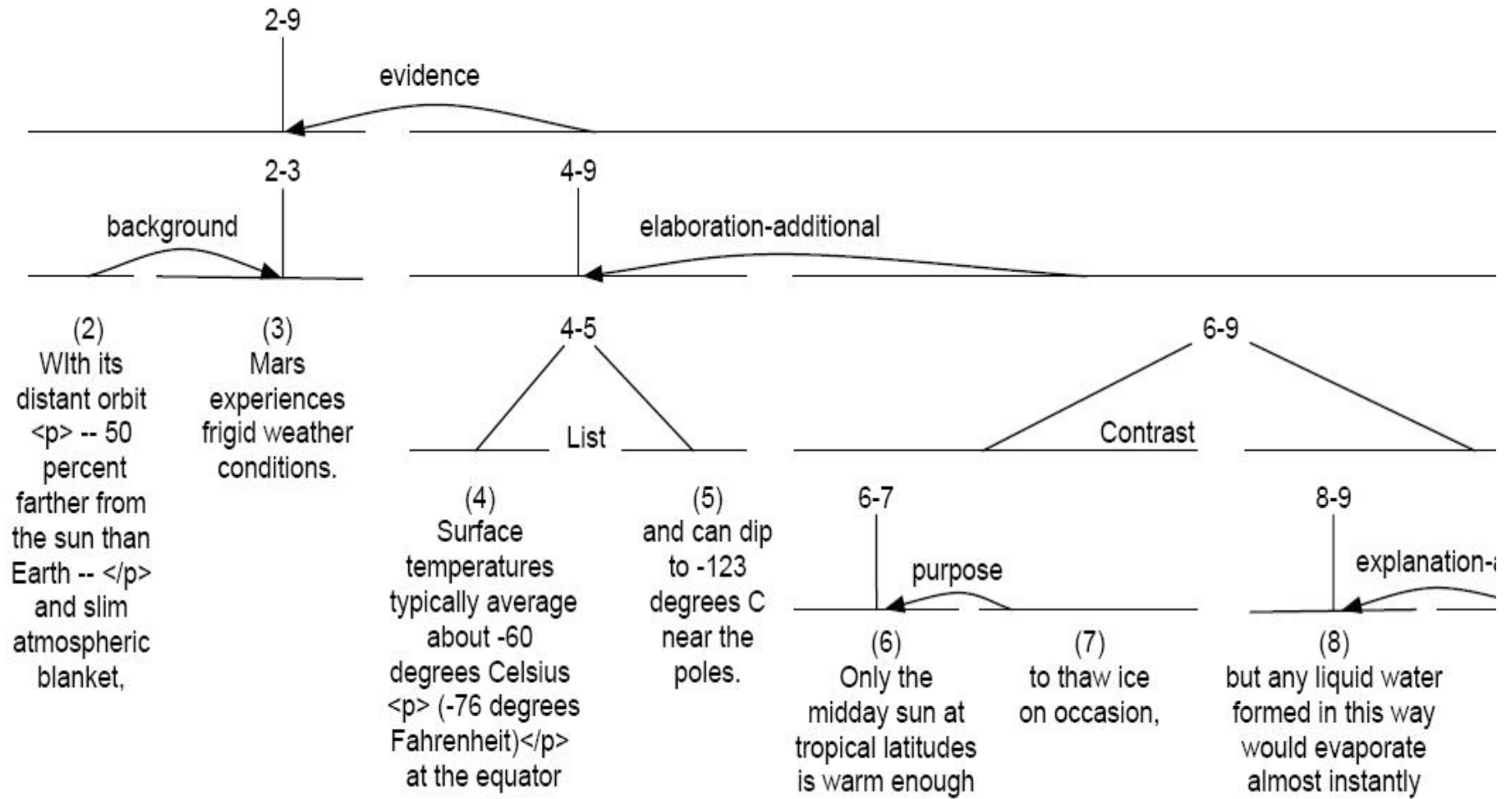
RST Relations

- 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



Title
(1)
Mars



GraphBank

- Alternative discourse structure model
 - Wolf & Gibson, 2005
- Key difference:
 - Analysis of text need not be tree-structure, like RST
 - Can be arbitrary graph, allowing crossing dependency
- Similar relations among spans (clauses)
 - Slightly different inventory

Penn Discourse Treebank

- PDTB (Prasad et al, 2008)
 - “Theory-neutral” discourse model
 - No stipulation of overall structure, identifies local rels
- Two types of annotation:
 - Explicit: triggered by lexical markers (‘but’) b/t spans
 - Arg2: syntactically bound to discourse connective, ow Arg1
 - Implicit: Adjacent sentences assumed related
 - Arg1: first sentence in sequence
- Senses/Relations:
 - Comparison, Contingency, Expansion, Temporal
 - Broken down into finer-grained senses too

Discourse & Summarization

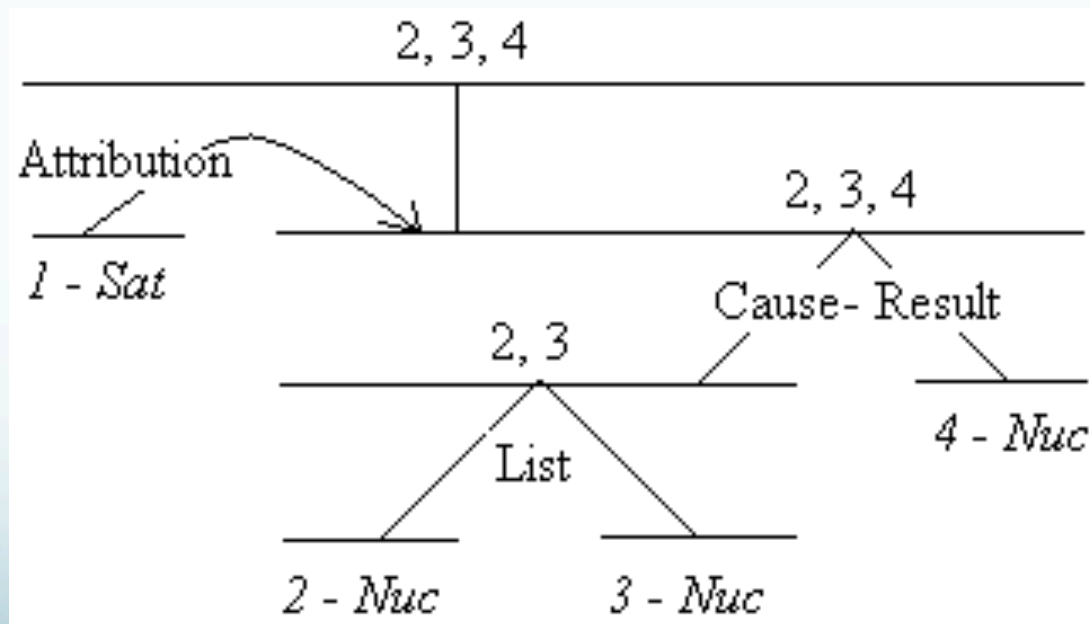
- Intuitively, discourse should be useful
 - Selection, ordering, realization
- Selection:
 - Sense: some relations more important
 - E.g. cause vs elaboration
 - Structure: some information more core
 - Nucleus vs satellite, promotion, centrality
- Compare these, contrast with lexical info
 - Louis et al, 2010

Framework

- Association with extractive summary sentences
 - Statistical analysis
 - Chi-squared (categorical), t-test (continuous)
- Classification:
 - Logistic regression
 - Different ensembles of features
 - Classification F-measure
 - ROUGE over summary sentences

Discourse Structure Example

- 1. [Mr. Watkins said] 2. [volume on Interprovincial's system is down about 2% since January] 3. [and is expected to fall further,] 4. [making expansion unnecessary until perhaps the mid-1990s.]



RST Parsing

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

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- Assign coherence relations between spans

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