

Content Selection: Supervision & Discourse

Ling573
Systems & Applications
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Roadmap

- Content selection
 - Supervised content selection
 - Analysis & Regression with rich features
 - “CLASSY”: HMM methods
 - 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

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

CLASSY

- “Clustering, Linguistics and Statistics for Summarization Yield”
 - Conroy et al. 2000-2011
- Highlights:
 - High performing system
 - Often rank 1 in DUC/TAC, commonly used comparison
 - Topic signature-type system (LLR)
 - HMM-based content selection
 - Redundancy handling

Using LLR for Weighting

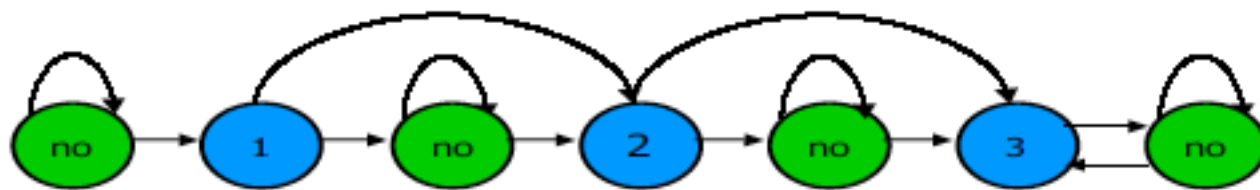
- Compute weight for all cluster terms
 - $\text{weight}(w_i) = 1$ if $-2\log \lambda > 10$, 0 o.w.
- Use that to compute sentence weights

$$\text{weight}(s_i) = \sum_{w \in s_i} \frac{\text{weight}(w)}{|\{w | w \in s_i\}|}$$

- How do we use the weights?
 - One option: directly rank sentences for extraction
- LLR-based systems historically perform well
 - Better than $\text{tf} \cdot \text{idf}$ generally

HMM Sentence Selection

- CLASSY strategy: Use LLR as feature in HMM
- How does HMM map to summarization?
 - Key idea:
 - Two classes of states: summary, non-summary
 - Feature(s)?: $\log(\#sig+1)$ (tried: length, position,..)
 - Lower cased, white-space tokenized (a-z), stopped
 - Topology:



- Select sentences with highest posterior (in “summary”)

Matrix-based Selection

- Redundancy minimizing selection
- Create term x sentence matrix
 - If term in sentence, weight is nonzero
- Loop:
 - Select highest scoring sentence
 - Based on Euclidean norm
 - Subtract those components from remaining sentences
 - Until enough sentences
- Effect: selects highly ranked but different sentences
 - Relatively insensitive to weighting schemes

Combining Approaches

- Both HMM and Matrix method select sentences
- Can combine to further improve
- Approach:
 - Use HMM method to compute sentence scores
 - (e.g. rather than just weight based)
 - Incorporates context information, prior states
 - Loop:
 - Select highest scoring sentence
 - Update matrix scores
 - Exclude those with too low matrix scores
 - Until enough sentences are found

Other Linguistic Processing

- Sentence manipulation (before selection):
 - Remove uninteresting phrases based on POS tagging
 - Gerund clauses, restr. rel. appos, attrib, lead adverbs
- Coreference handling (Serif system)
 - Created coref chains initially
 - Replace all mentions with longest mention (# caps)
 - Used only for sentence selection

Outcomes

- HMM, Matrix: both effective, better combined
- Linguistic pre-processing improves
 - Best ROUGE-1, ROUGE-2 in DUC
- Coref handling improves:
 - Best ROUGE-3, ROUGE-4; 2nd ROUGE-2

Discourse Structure for Content Selection

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

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

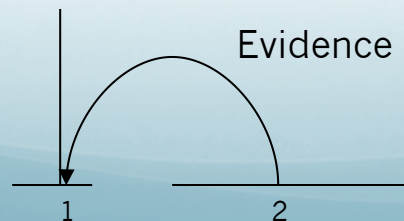
Components of RST

- 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

RST Relations

- Evidence
 - The program really works. (N)
 - I entered all my info and it matched my results. (S)

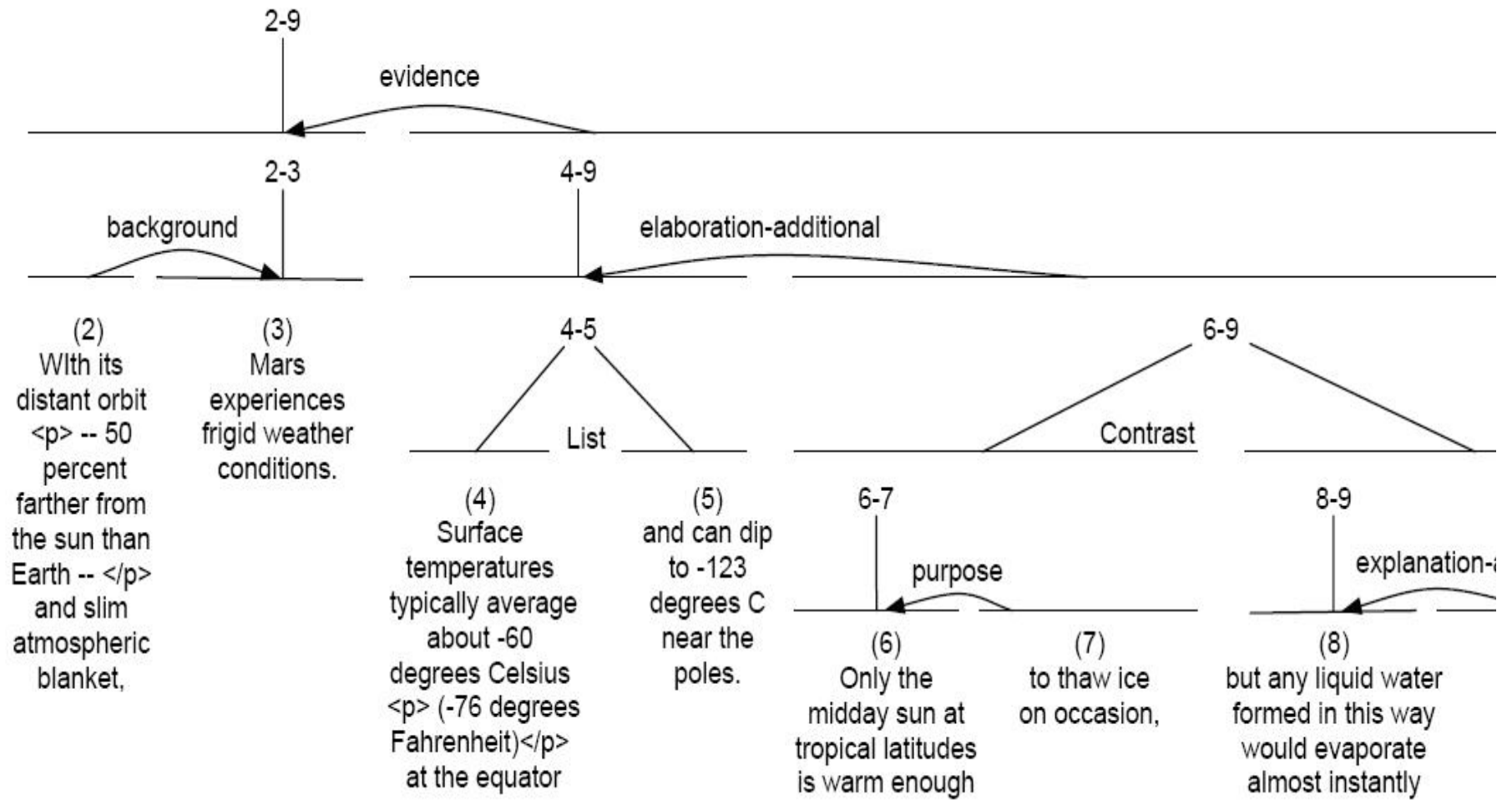
Relation Name:	Evidence
Constraints on N:	R might not believe N to a degree satisfactory to W
Constraints on S:	R believes S or will find it credible
Constraints on N+S:	R's comprehending S increases R's belief of N
Effects:	R's belief of N is increased



RST Relations

- Core of RST
 - RST analysis requires building tree of relations
 - Relations include:
 - Circumstance, Solutionhood, Elaboration. Background, Enablement, Motivation, Evidence, etc
- Captured in:
 - RST treebank: corpus of WSJ articles with analysis
 - RST parsers: Marcu, Peng and Hirst 2014

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