

Information Ordering

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Roadmap

- Information ordering
 - Ensemble of experts
 - Integrating sources of evidence
- Entity-based cohesion
 - Motivation
 - Defining the entity grid
 - Entity grid for information ordering

Integrating Ordering Preferences

- Learning Ordering Preferences
 - (Bollegala et al, 2012)
- Key idea:
 - Information ordering involves multiple influences
 - Can be viewed as soft preferences
 - Combine via multiple experts:
 - Chronology
 - Sequence probability
 - Topicality
 - Precedence/Succession

Basic Framework

- Combination of experts
- Build one expert for each of diff't preferences
 - Take a pair of sentences (a,b) and partial summary
 - Score > 0.5 if prefer a before b
 - Score < 0.5 if prefer b before a
- Learn weights for linear combination
- Use greedy algorithm to produce final order

Chronology Expert

- Implements the simple chronology model
 - If sentences from two different docs w/diff't times
 - Order by document timestamp
 - If sentences from same document
 - Order by document order
 - Otherwise, no preference

Topicality Expert

- Same motivation as Barzilay 2002
- Example:
 - The earthquake crushed cars, damaged hundreds of houses, and terrified people for hundreds of kilometers around.
 - A major earthquake measuring 7.7 on the Richter scale rocked north Chile Wednesday.
 - Authorities said two women, one aged 88 and the other 54, died when they were crushed under the collapsing walls.
- $2 > 1 > 3$

Topicality Expert

- Idea: Prefer sentence about the “current” topic
- Implementation:
 - Prefer sentence with highest similarity to sentence in summary so far
 - Similarity computation:
 - Cosine similarity b/t current & summary sentence
 - Stopwords removed; nouns, verbs lemmatized; binary

Precedence/Succession Experts

- Idea: Does current sentence look like blocks preceding/following current summary sentences in their original documents?
- Implementation:
 - For each summary sentence, compute similarity of current sentence w/most similar pre/post in original doc
 - Similarity?: cosine
- $PREF_{pre}(u,v,Q) = 0.5$ if $[Q=null]$ or $[pre(u)=pre(v)]$
- 1.0 if $[Q!=null]$ and $[pre(u)>pre(v)]$
- 0 otherwise
 - Symmetrically for post

Sketch

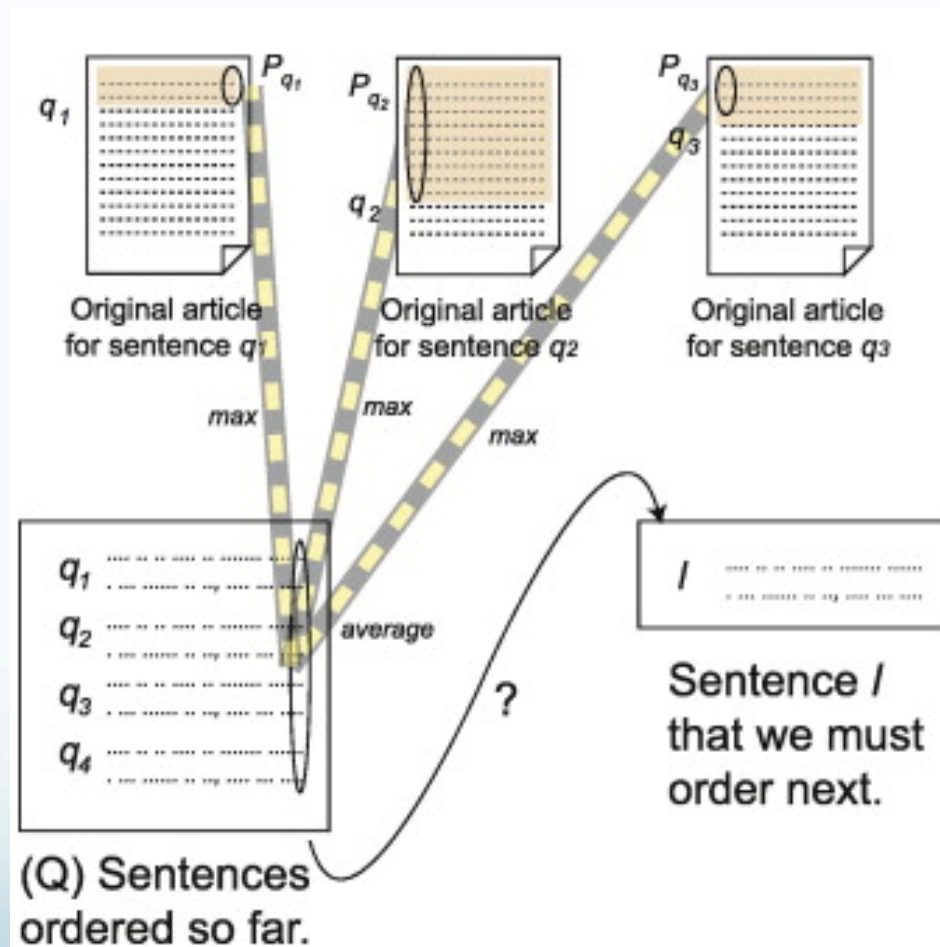


Fig. 4.

Precedence expert.

Probabilistic Sequence

- Intuition:
 - Probability of summary is the probability of sequence of sentences in it, assumed Markov
 - $P(\text{summary}) = \prod P(S_i | S_{i-1})$
- Issue:
 - Sparsity: will we actually see identical pairs in training?
- Repeatedly backoff:
 - To N, V pairs in ordered sentences
 - To backoff smoothing + Katz

Results & Weights

- Trained weighting using a boosting method
- Combined:
 - Learning approach significantly outperforms random, prob
 - Somewhat better than raw chronology

Expert	Weight
Succession	0.44
Chronology	0.33
Precedence	0.20
Topic	0.016
Prob. Seq.	0.00004

Observations

- Nice ideas:
 - Combining multiple sources of ordering preference
 - Weight-based integration
- Issues:
 - Sparseness everywhere
 - Ubiquitous word-level cosine similarity
 - Probabilistic models
 - Score handling

Entity-Centric Cohesion

- Continuing to talk about same thing(s) lends cohesion to discourse
- Incorporated variously in discourse models
 - Lexical chains: Link mentions across sentences
 - Fewer lexical chains crossing → shift in topic
 - Salience hierarchies, information structure
 - Subject > Object > Indirect > Oblique >
 - Centering model of coreference
 - Combines grammatical role preference with
 - Preference for types of reference/focus transitions

Entity-Based Ordering

- Idea:
 - Leverage patterns of entity (re)mentions
- Intuition:
 - Captures local relations b/t sentences, entities
 - Models cohesion of evolving story
- Pros:
 - Largely delexicalized
 - Less sensitive to domain/topic than other models
 - Can exploit state-of-the-art syntax, coreference tools

Entity Grid

- Need compact representation of:
 - Mentions, grammatical roles, transitions
 - Across sentences
- Entity grid model:
 - Rows: sentences
 - Columns: entities
 - Values: grammatical role of mention in sentence
 - Roles: (S)ubject, (O)bject, X (other), __ (no mention)
 - Multiple mentions: Take highest

	Department	Trial	Microsoft	Evidence	Competitors	Markets	Products	Brands	Case	Netscape	Software	Tactics	Government	Suit	Earnings	
1	s	O	S	X	O	-	-	-	-	-	-	-	-	-	-	1
2	-	-	O	-	-	X	S	O	-	-	-	-	-	-	-	2
3	-	-	S	O	-	-	-	-	S	O	O	-	-	-	-	3
4	-	-	S	-	-	-	-	-	-	-	-	S	-	-	-	4
5	-	-	-	-	-	-	-	-	-	-	-	-	S	O	-	5
6	-	X	S	-	-	-	-	-	-	-	-	-	-	-	O	6

- 1 [The Justice Department]_s is conducting an [anti-trust trial]_o against [Microsoft Corp.]_x with [evidence]_x that [the company]_s is increasingly attempting to crush [competitors]_o.
- 2 [Microsoft]_o is accused of trying to forcefully buy into [markets]_x where [its own products]_s are not competitive enough to unseat [established brands]_o.
- 3 [The case]_s revolves around [evidence]_o of [Microsoft]_s aggressively pressuring [Netscape]_o into merging [browser software]_o.
- 4 [Microsoft]_s claims [its tactics]_s are commonplace and good economically.
- 5 [The government]_s may file [a civil suit]_o ruling that [conspiracy]_s to curb [competition]_o through [collusion]_x is [a violation of the Sherman Act]_o.
- 6 [Microsoft]_s continues to show [increased earnings]_o despite [the trial]_x.

Grids → Features

- Intuitions:
 - Some columns dense: focus of text (e.g. MS)
 - Likely to take certain roles: e.g. S, O
 - Others sparse: likely other roles (x)
 - Local transitions reflect structure, topic shifts
- Local entity transitions: $\{s, o, x, _ \}^n$
 - Continuous column subsequences (role n-grams?)
 - Compute probability of sequence over grid:
 - $\frac{\# \text{ occurrences of that type}}{\# \text{ of occurrences of that len}}$

Vector Representation

- Document vector:
 - Length: # of transition types
 - Values: Probabilities of each transition type

	SS	SO	SX	S-	OS	OO	OX	O-	XS	XO	XX	X-	-S	-O	-X	--
d_1	.01	.01	0	.08	.01	0	0	.09	0	0	0	.03	.05	.07	.03	.59
d_2	.02	.01	.01	.02	0	.07	0	.02	.14	.14	.06	.04	.03	.07	0.1	.36
d_3	.02	0	0	.03	.09	0	.09	.06	0	0	0	.05	.03	.07	.17	.39

- Can vary by transition types:
 - E.g. most frequent; all transitions of some length, etc