Opinion Summarization Using Entity Features and Probabilistic Sentence Coherence Optimization

(UIUC at TAC 2008 Opinion Summarization Pilot)

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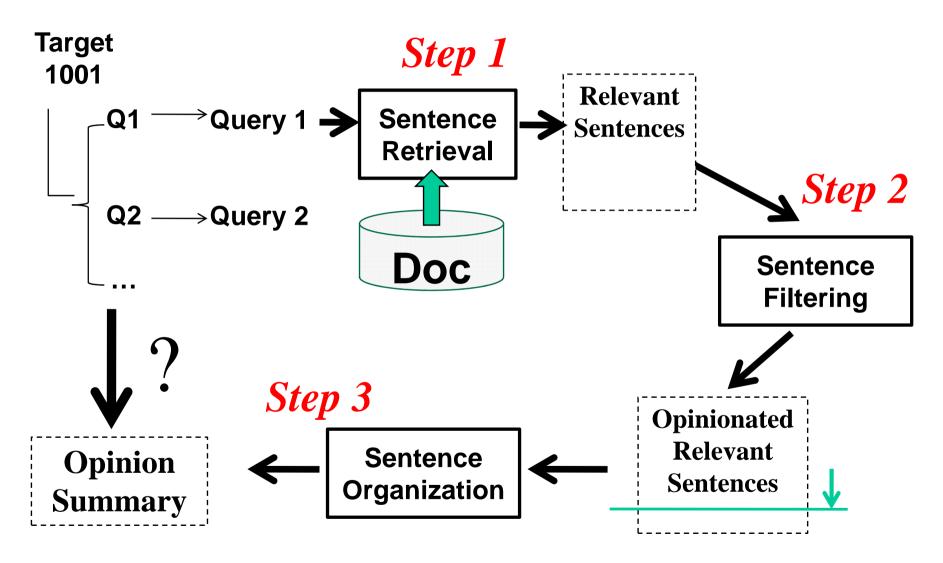
Research Questions

- 1. Can we improve sentence retrieval by assigning more weights to entity terms?
- 2. Can we optimize the coherence of a summary using a statistical coherence model?





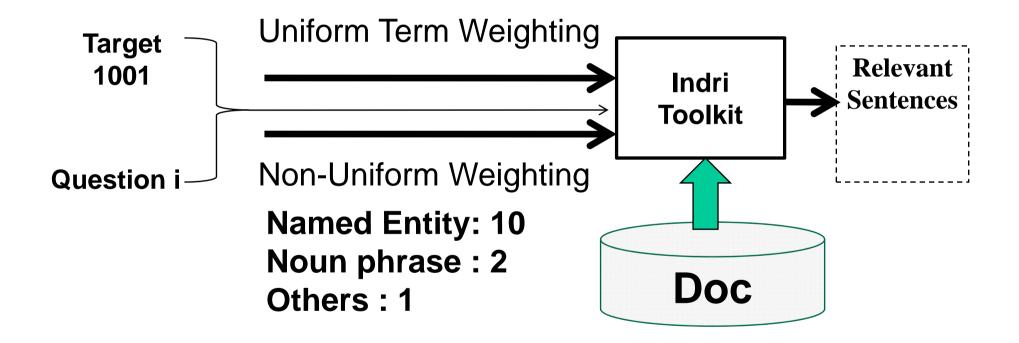
General Approach







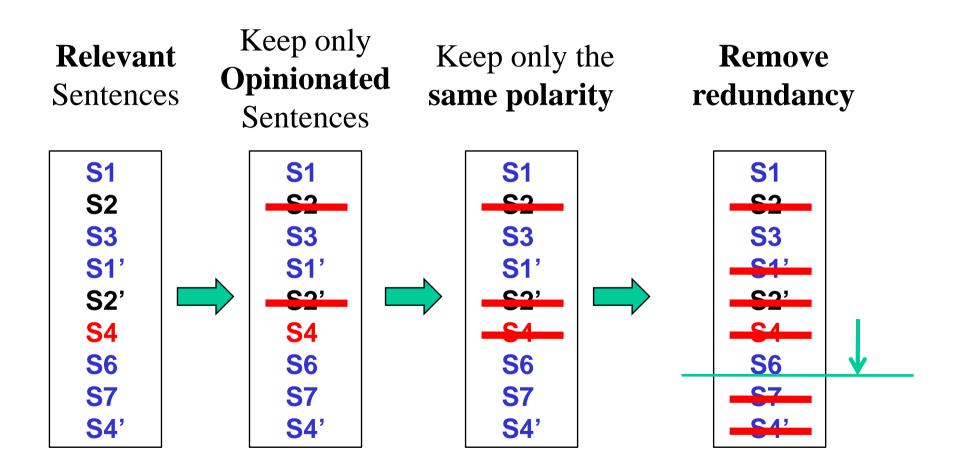
Step 1: Sentence Retrieval







Step 2: Sentence Filtering







Step 3: Summary Organization (Method 1: Polarity Ordering)

- Paragraph structure by question and polarity
- Add guiding phrase

The first question is ...
Following are positive opinions...

Following are negative opinions...

The second question is ...
Following are mixed opinions...

• • •





Step 3: Summary Organization

(Method 2: Statistical Coherence Optimization)

- Coherence function: c(Si, Sj)
- Use a greedy algorithm to order sentences to maximize the total score





Probabilistic Coherence Function

(Idea similar to [Lapata 03])

$$c(s_i, s_j) = \sum_{u \in s_i, v \in s_j} \frac{p(u, v)}{|s_i| |s_j|}$$

Average coherence probability (Pointwise mutual information) over all word combinations

$$\hat{p}(u,v) = \frac{count("u \ and \ v \ in \ two \ adjacent \ sentences") + 0.001}{count(u) \cdot count(v) + 1.0}$$

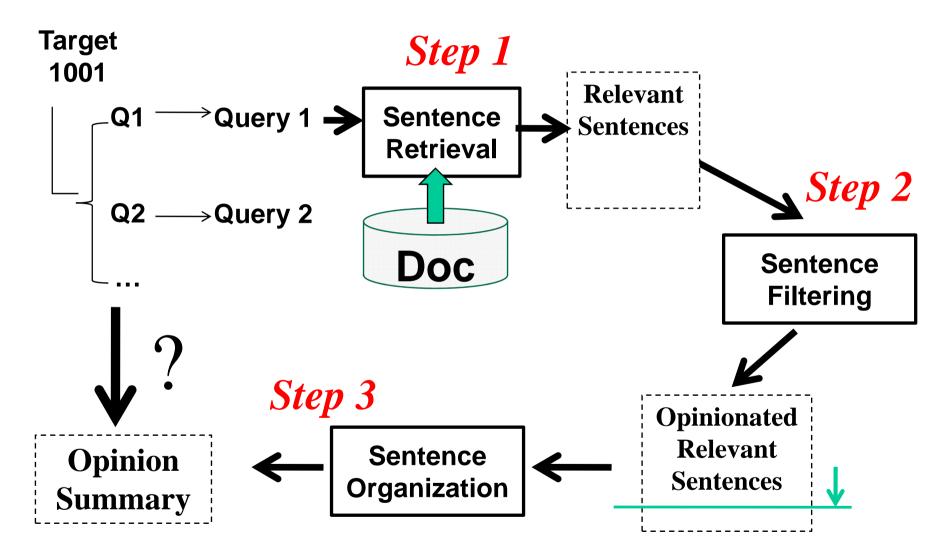
Train with original document

$$P(u,v) = (2+0.001)/(3*4+1.0)$$





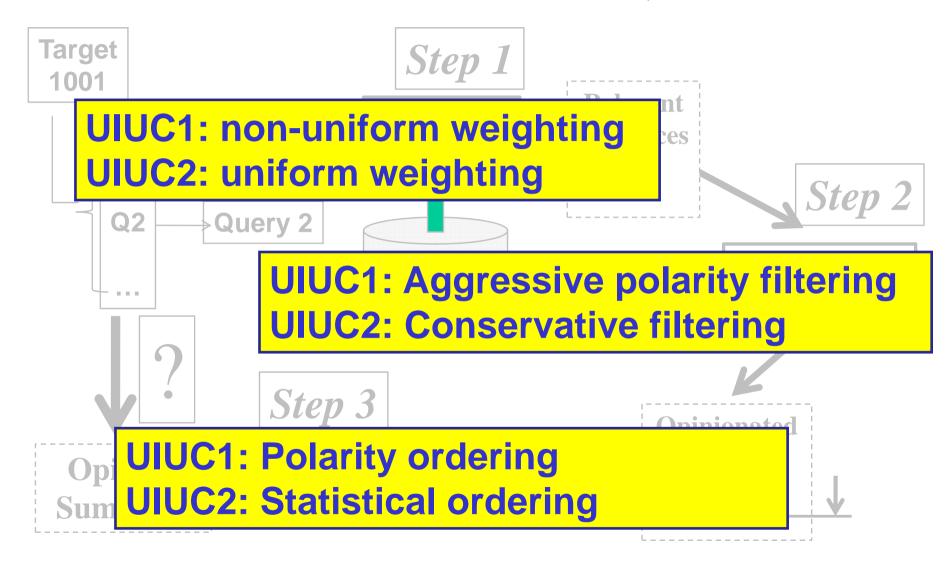
General Approach







Submissions: UIUC1, UIUC2







Evaluation

Rank among runs without answer-snippet

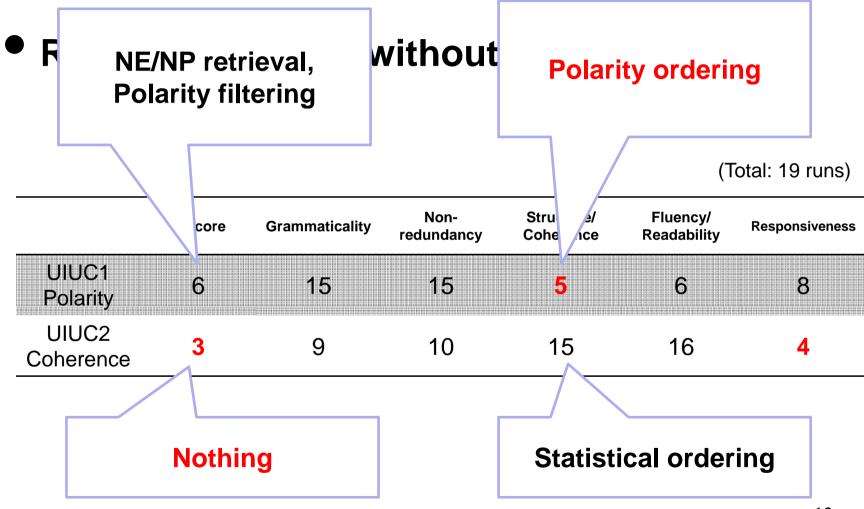
(Total: 19 runs)

	F-Score	Grammaticality	Non- redundancy	Structure/ Coherence	Fluency/ Readability	Responsiveness
UIUC1 Polarity	6	15	15	5	6	8
UIUC2 Coherence	3	9	10	15	16	4





Evaluation

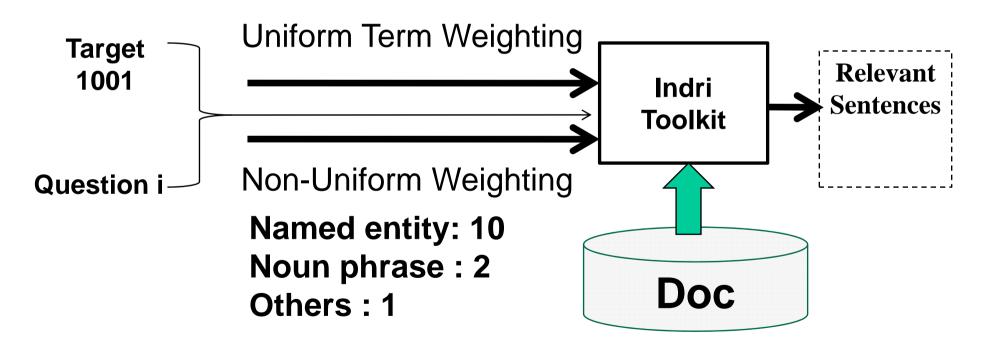






Evaluation of Named EntityWeighting

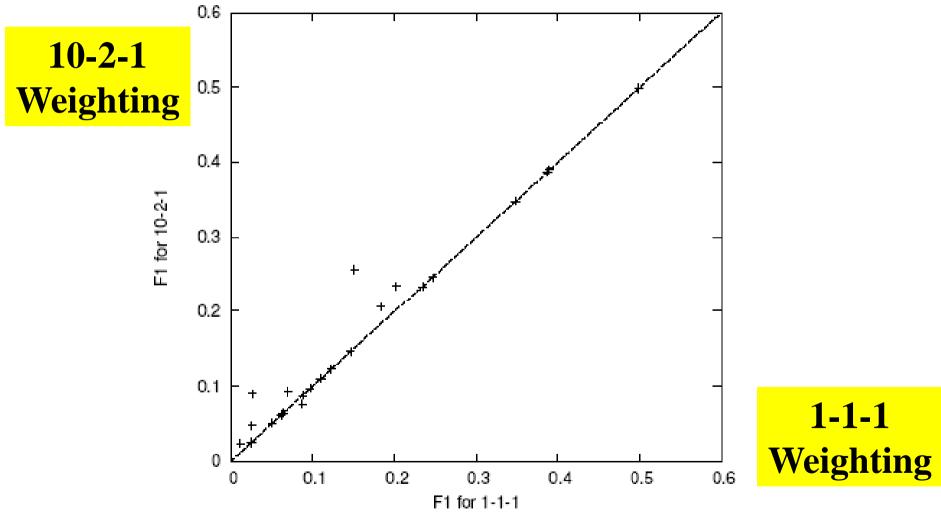
Assume a sentence is relevant iff similarity(sentence, nugget description) > threshold







Effectiveness of Entity Weighting







Polarity Module

 Polarity module performance evaluation on the sentiment corpus. [Hu&Liu 04, Hu&Liu 04b]

(Unit: # of sentence)

Classification result	Positive	Negative	
NonOpinionated	1063	598	
Positive	1363	371	
Negative	383	412	
Mixed	296	210	
Total	3105	1591	
Exact Match	1363/3105=0.44	412/1591=0.26	
	(1363+412)/(3105+1591)= <mark>0.38</mark>		
Exact Opposite	383/3105=0.12	371/1591=0.23	
	(383+371)/(3105	5+1591)= <mark>0.16</mark>	
		15	





Coherence optimization

Evaluation methods

- Basic assumption
 - the sentence order of original document is coherent
- Among given target documents,
 use 70% as training set, 30% as test set.
- Measurement: strict pair matching
 - # of correct sentence pair / # of total adjacent sentence pair





Probabilistic Coherence Function

$$c(s_{i}, s_{j}) = \sum_{u \in s_{i}, v \in s_{j}} \frac{p(u, v)}{|s_{i}| |s_{j}|}$$

 $c(s_i, s_j) = \sum_{u \in s_i, v \in s_j} \frac{p(u, v)}{|s_i| |s_j|}$ Average coherence probability over all word combinations

Point-wise Mutual information with smoothing

$$\hat{p}(u,v) = \frac{count("u \ and \ v \ in \ two \ adjacent \ sentences") + 0.001}{count(u) \cdot count(v) + 1.0}$$

Strict joint probability

$$\hat{p}(u,v) = \frac{count("u \ and \ v \ in \ two \ adjacent \ sentences") + 1}{"total \ count \ of \ word \ pairs" + (dictionary \ size)^2}$$





Probabilistic Coherence Function

Mutual information

$$\hat{p}(u,v) = p(u,v)\log(\frac{p(u,v)}{p(u)p(v)}) + p(not u,v)\log(\frac{p(not u,v)}{p(not u)p(v)})$$

$$+ p(u,not v)\log(\frac{p(u,not v)}{p(u)p(not v)}) + p(not u,not v)\log(\frac{p(not u,not v)}{p(not u)p(not v)})$$
where,

$$p(u,v) = \frac{c(u,v) + 0.25}{N+1}, p(not u,v) = \frac{c(not u,v) + 0.25}{N+1},$$
$$p(not u,v) = \frac{c(u,not v) + 0.25}{N+1}, p(not u,not v) = \frac{c(not u,not v) + 0.25}{N+1},$$

N = c(u,v)+c(not u, v)+c(u, not v)+c(not u, not v)For unseen pairs, p(u,v)=0.5*MIN(seen pairs in training)





Coherence optimization test

Selection of training words	Strict Joint Probability	Mutual Information	Pointwise Mutual Information
No Omission	0.022259	0.041651	0.056063
Omitted stopwords	0.031389	0.054554	0.057119
Omitted frequent words (counts > 33) (counts > 11) (counts > 6) (counts > 2)	0.031389 0.027013 0.020448 0.019769	0.051460 0.045725 0.032219 0.022259	0.049498 0.046103 0.034785 0.021882
Omitted rare words (counts < 33) (counts < 14) (counts < 6) (counts < 2)	0.022259 0.022033 0.021203 0.022259	0.032898 0.032823 0.037048 0.041802	0.044065 0.049045 0.054931 0.056591

Pointwise mutual information effectively penalize common words



Coherence optimization test

Top ranked p(u,v) of strict joint probability

u	V	p(u,v)
the	the	1.75E-003
to	the	1.22E-003
the	to	1.21E-003
the	of	1.14E-003
the	and	1.14E-003
of	the	1.13E-003
and	the	1.12E-003
a	the	1.06E-003
the	a	1.06E-003

A lot of stopwords are top-ranked.





Coherence optimization test

Selection of training words	Coherence score
Baseline: random order	0.01586
Strict Joint Probability	0.04308
Mutual Information	0.041651
Pointwise Mutual Information (UIUC2)	0.056063
Omitted stopwords	0.057119
Omitted non-stopwords	0.020750
Omitted 95% least frequent words (counts < 33):	0.044065
Omitted 90% least frequent words (counts < 14):	0.049045
Omitted 80% least frequent words (counts < 6):	0.054931
Omitted 60% least frequent words (counts < 2):	0.056591

- Pointwise Mutual information was better than joint probability and normal mutual information.
- Eliminating common words, very rare words improved performance





Conclusions

- Limited improvement in retrieval performance using named entity and noun phrase
- Need for a good polarity classification module
- Possibility on the improvement of statistical sentence ordering module with different coherence function and word selection



Thank you

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