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Scalable Detection of Sentiment-Based Contradictions

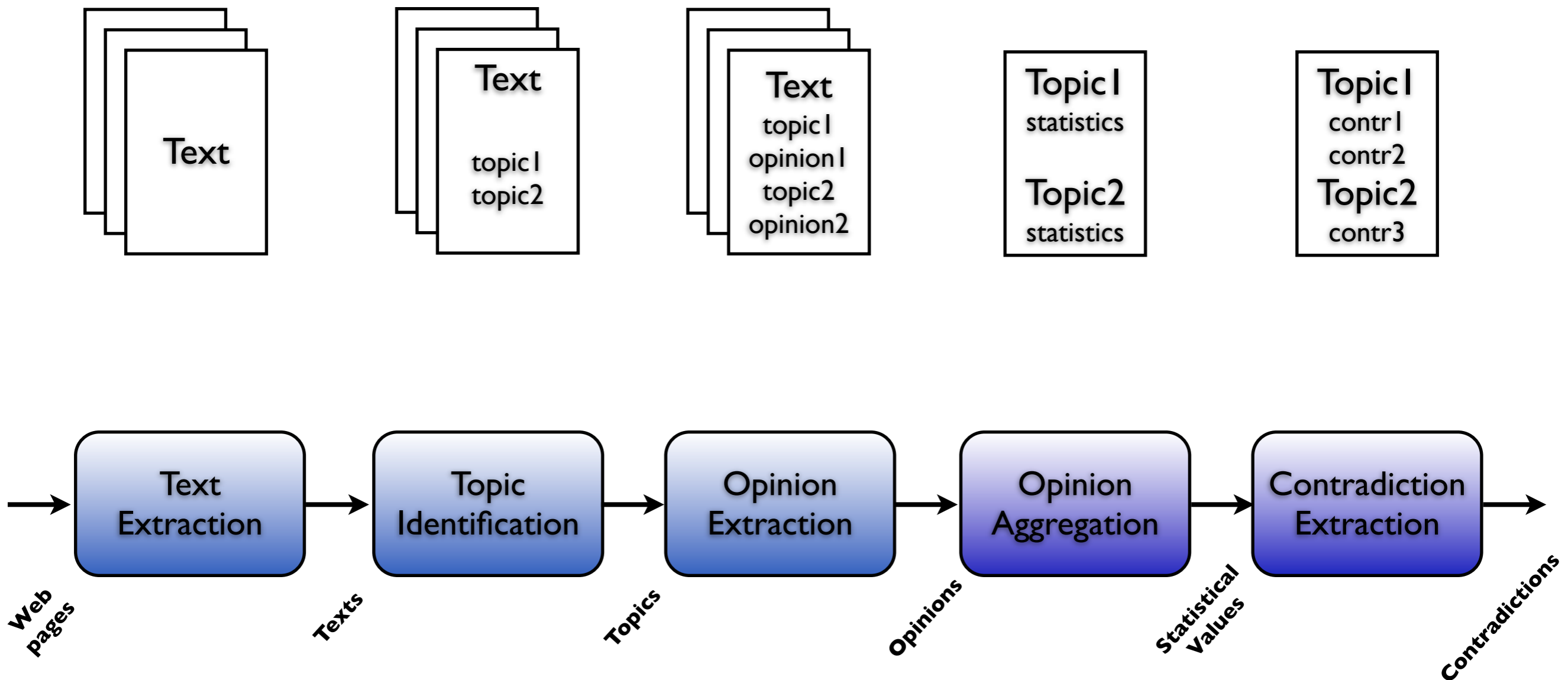
Contradictions, what are they?

- ▶ *Contradictions* in text are situations where
'two sentences are extremely unlikely to be true together'
- ▶ Contradictions may be of different types, for example:
 - antonymy: *hot - cold, light - dark, good - bad*
 - negation: *nice - not nice, i love you - i love you not*
 - mismatches: *the solar system has 8 planets - there are 9 planets*
 - sentiments**: *i like this book - this reading makes me sick*
- ▶ *Sentiment Contradictions* may occur due to:
 - diversity of views
 - change of views

Motivation

- ▶ There are many services where users publish their opinions:
blogs, wikis, forums, social networks and others
- ▶ Sentiment analysis is used to:
learn customers attitude to a product or its features
analyze people's reaction to some event
- ▶ Such problems require scalable sentiment aggregation, which is:
diversity-preserving
time-aware

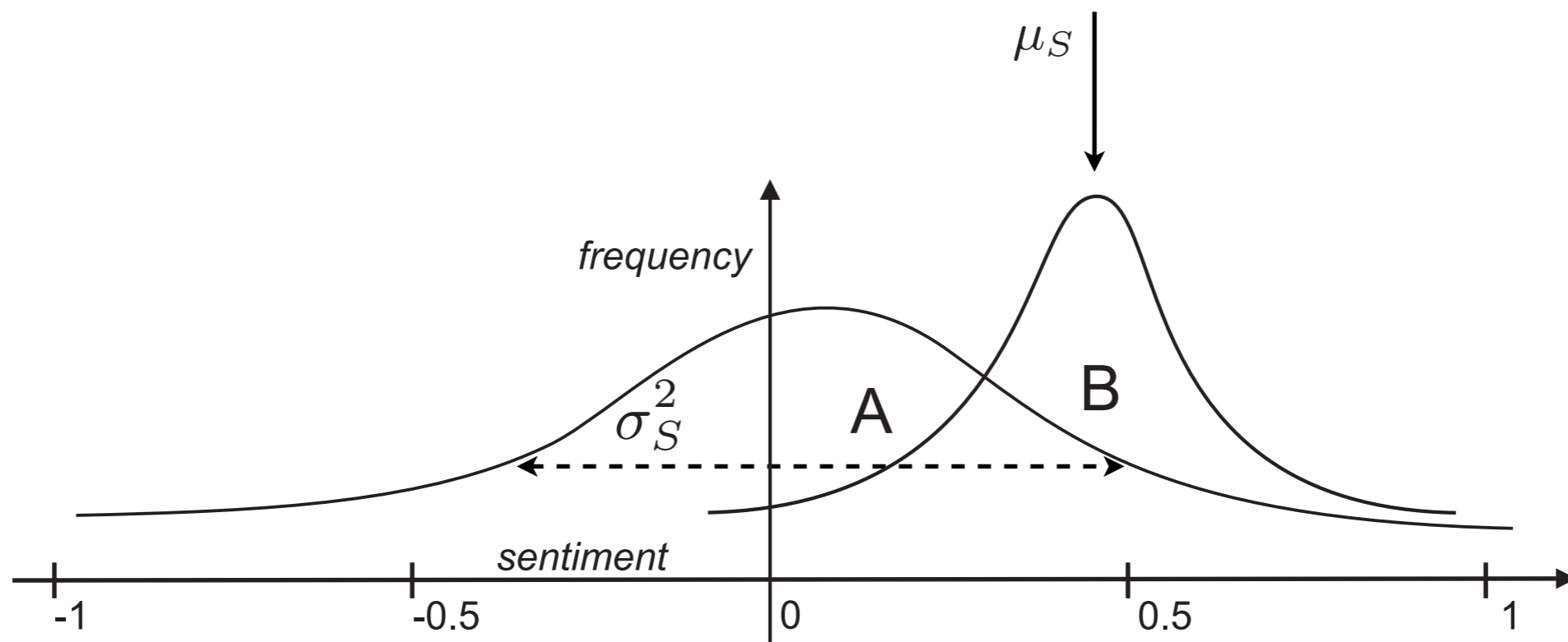
Contradiction Detection Pipeline



Formulating the Problem

- ▶ **Sentiment S** is a real number in the range $[-1,1]$, reflecting opinion polarity
- ▶ **Aggregated Sentiment μ_s** is the mean value over sentiments in the collection
- ▶ **Simultaneous Contradiction.** when two groups of documents express a very different sentiment on the same topic, *in the same time interval*.
- ▶ **Change of Sentiment.** when two groups of documents express a very different sentiment on the same topic, but *in consecutive time intervals*.

Contradiction Preserving Sentiment Aggregation



Contradiction Preserving Sentiment Aggregation

Raw Sentiments

$$S_i$$

Aggr. Sentiment

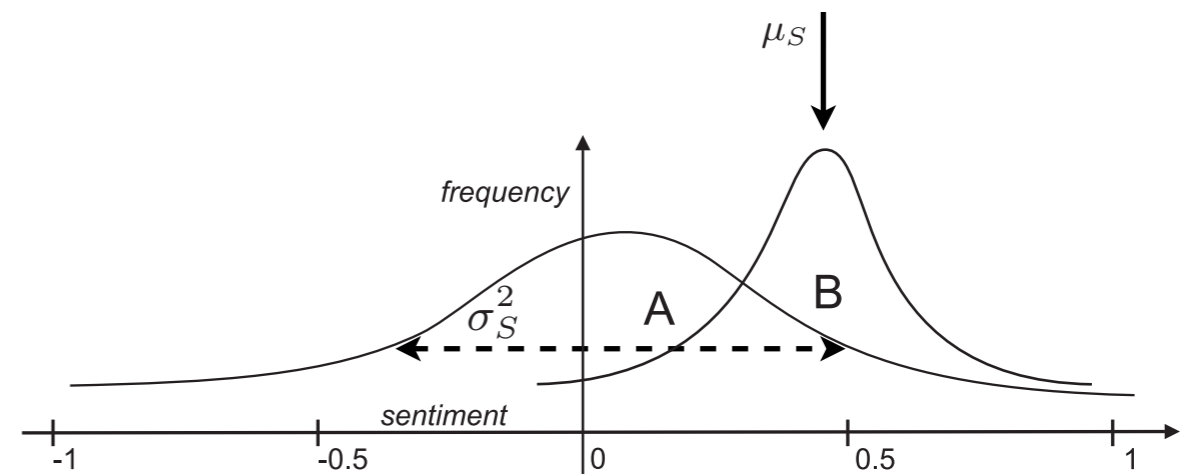
$$\mu_S = \frac{1}{n} \sum_{i=1}^n S_i$$

Sentiment Variance

$$\sigma_S^2 = \frac{1}{n} \sum_{i=1}^n (S_i - \mu_S)^2$$

Contradiction

$$C = \frac{\vartheta \cdot \sigma_S^2}{\vartheta + (\mu_S)^2} W$$



- ▶ We calculate contradiction by combining Aggr. Sentiment and Sentiment Variance.
- ▶ If Aggregated Sentiment close to 0, the contradiction is high.
- ▶ The larger the variance, the higher the contradiction.

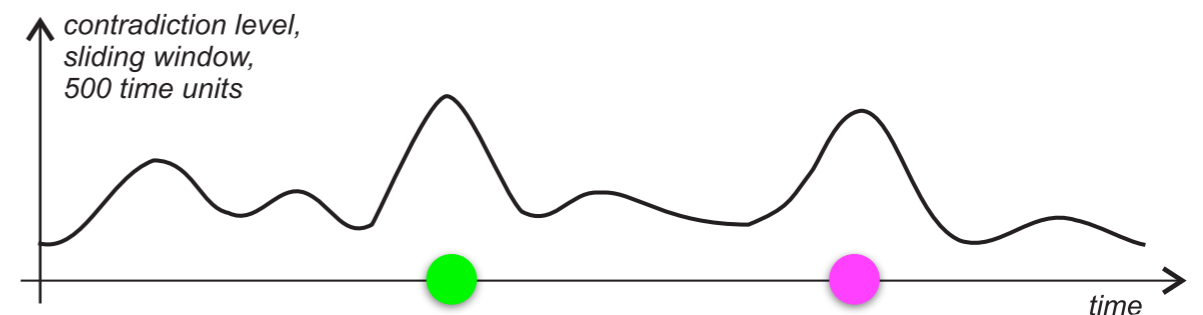
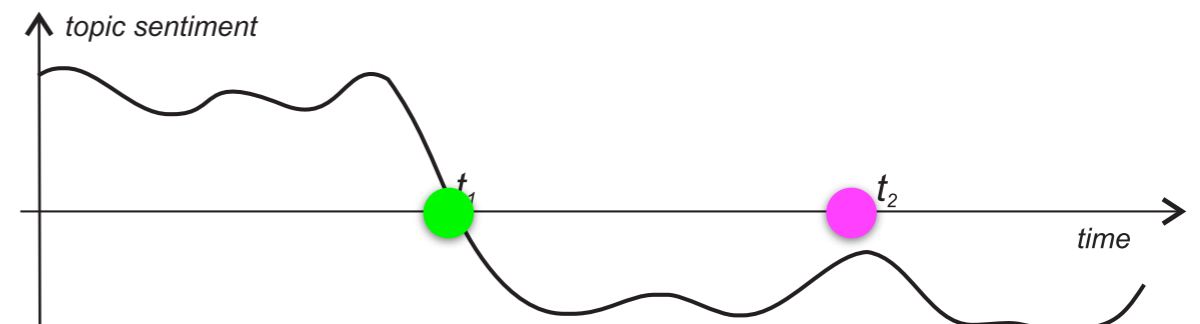
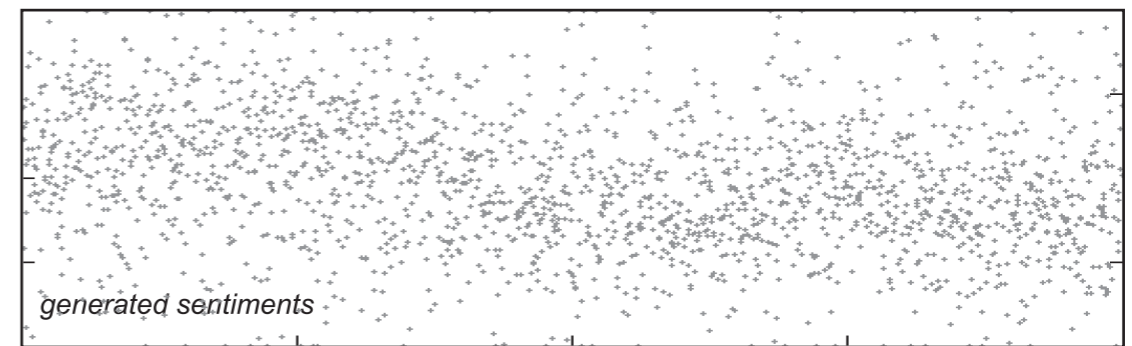
Contradiction Time Series

We generated time series of raw sentiments with half of them being gaussian noise

We can see an aggregated sentiment, which is first positive and later changes to negative

On the contradiction series we get peaks of contradiction only at the time points t_1 and t_2

They correspond either to simultaneous contradiction (t_2) or to change of sentiment (t_1) and can be distinguished by change of signs of μ_s just before and just after peak points.



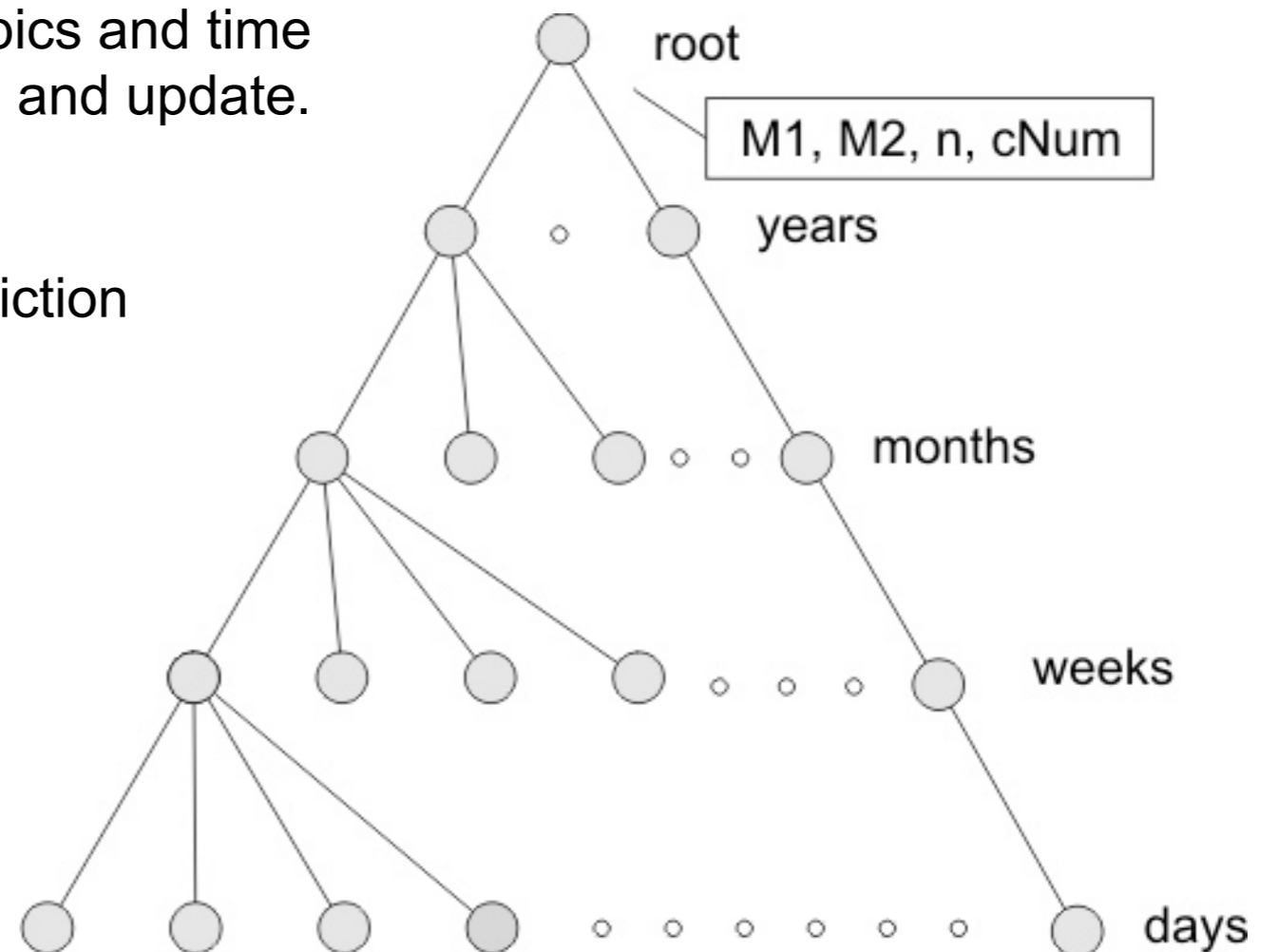
Contradiction Time Series Storage - TimeTree

We need a scalability on the number of topics and time interval length, yet the efficiency of access and update.

We need to analyze time series of contradiction level using different granularities online.

Smaller time windows allow us to detect more simultaneous contradiction.

Larger ones reveal opposite opinions, which are sparse across time.



Contradiction Time Series Queries

We have the following types of queries:

- ▶ Adaptive-threshold queries

output nodes $C > \rho \cdot C_{\text{parent}}$

- ▶ Fixed-threshold queries

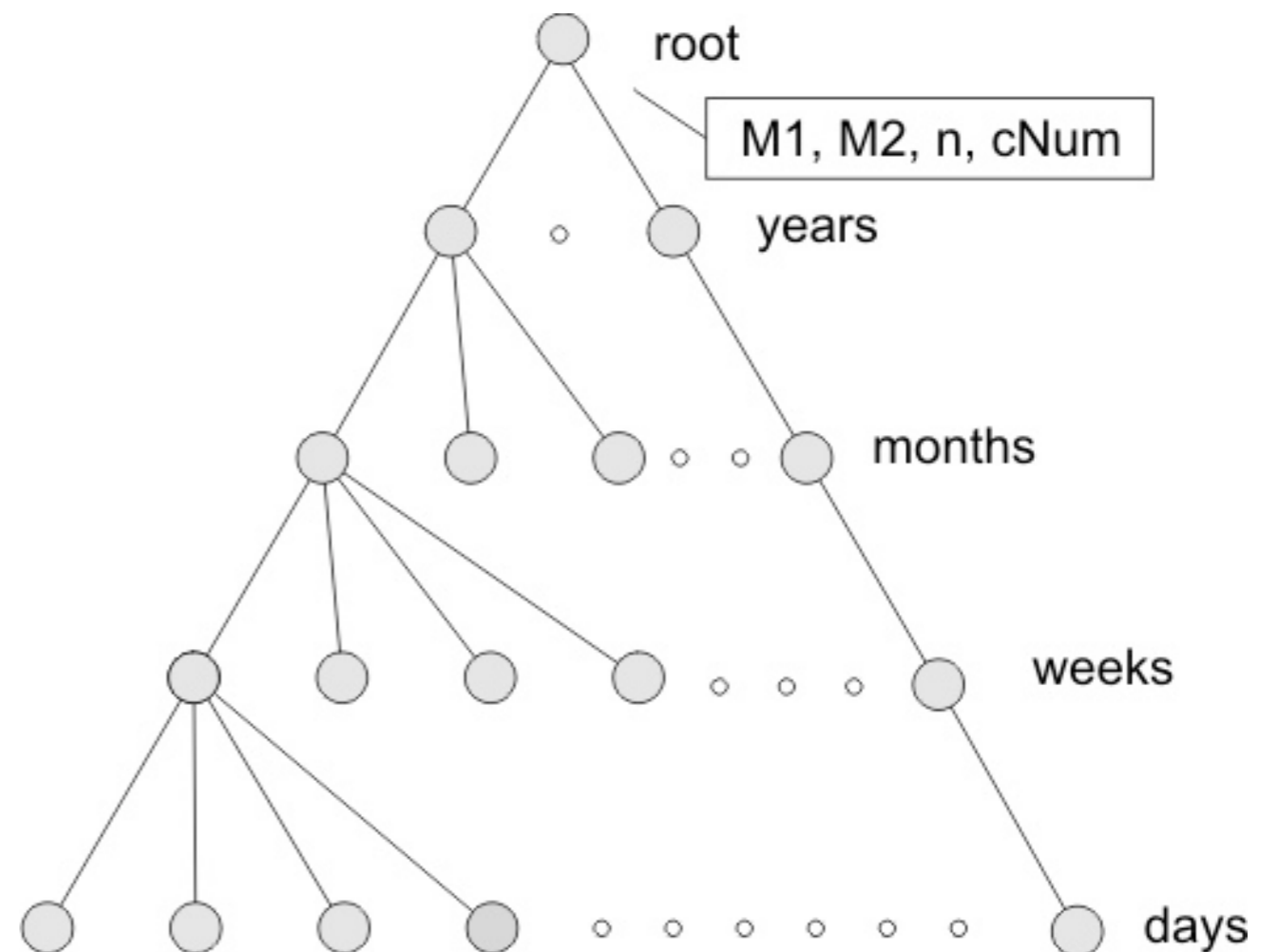
output nodes $C > \rho$

- ▶ Single-topic retrieval

topic is specified

- ▶ All-topic retrieval

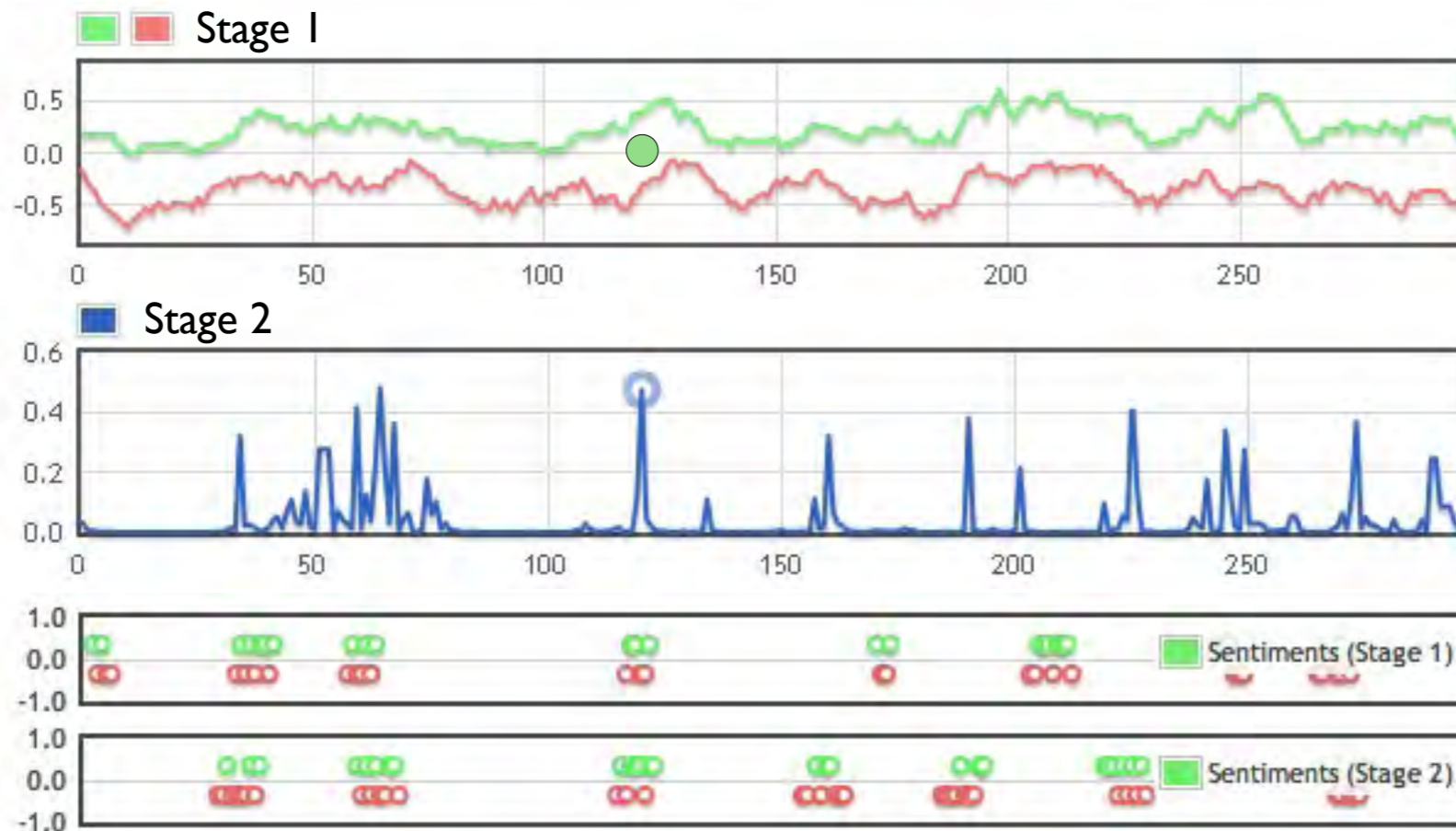
retrieve all



Usefulness Evaluation - Setup

- ▶ We applied our algorithms to a range of data sets:
 - drug reviews collected from the DrugRatingz.com website
 - comments to YouTube videos from L3S
 - comments on postings from Slashdot.com
- ▶ User evaluation was performed in two independent stages, during each step we asked users to find sentiment contradictions:
 - in the first stage, by looking at trends of positive and negative sentiments
 - in the second stage, by providing a plot of the contradiction level
- ▶ We measured time and number of clicks, needed to find one contradiction
$$\Delta T = T_2/T_1 \quad \Delta N = N_2/N_1 \quad \textit{smaller is better}$$
- ▶ We also asked users to evaluate the effectiveness of each approach
$$\Delta D = D_2/D_1 \quad \textit{each value was in the range [1-5], larger is better}$$
- ▶ Precision was calculated as a fraction of clicks, finding contradiction
$$\Delta P = P_2/P_1 \quad P_1 = N_1/N_c \quad P_2 = N_2/N_c \quad \textit{larger is better}$$
- ▶ Then, we compared their improvements for each dataset

Usefulness Evaluation - Workflow



Just say "NO" ladies! My ARNP prescribed it and three months later: headaches 24/7, hair l ...

I have been taking Yaz for 2 1/2 years, it has been very effective in preventing pregnancy ...

The three months I took Yaz were probably the three worst months of my life. I tried Yaz a ...

I am almost 19 years old and Yaz was the first birth control I have ever been on. I am cur ...

Ladies, you MUST take a Vitamin B supplement with Yaz! (I take B-

I was on yasmine for one year and things were fine. My doctor switched me to yaz and I dec ...

I am with most of the other woman on how awful Yaz has made me feel. I am also taking Lexa ...

Usefulness Evaluation - Results

Dataset	Topic name	Size	ΔD	ΔT	ΔN	P_1	P_2	ΔP
Drug Ratingz	Ambien	60	1.50	0.60	0.88	0.70	0.81	1.20
	Yaz	300	1.58	0.93	0.78	0.75	0.95	1.32
Slashdot	Int. control	159	1.17	0.89	0.58	0.37	0.63	2.14
YouTube	Zune HD	472	2.07	0.68	0.62	0.36	0.61	2.09
Average			1.58	0.77	0.72	0.55	0.75	1.69

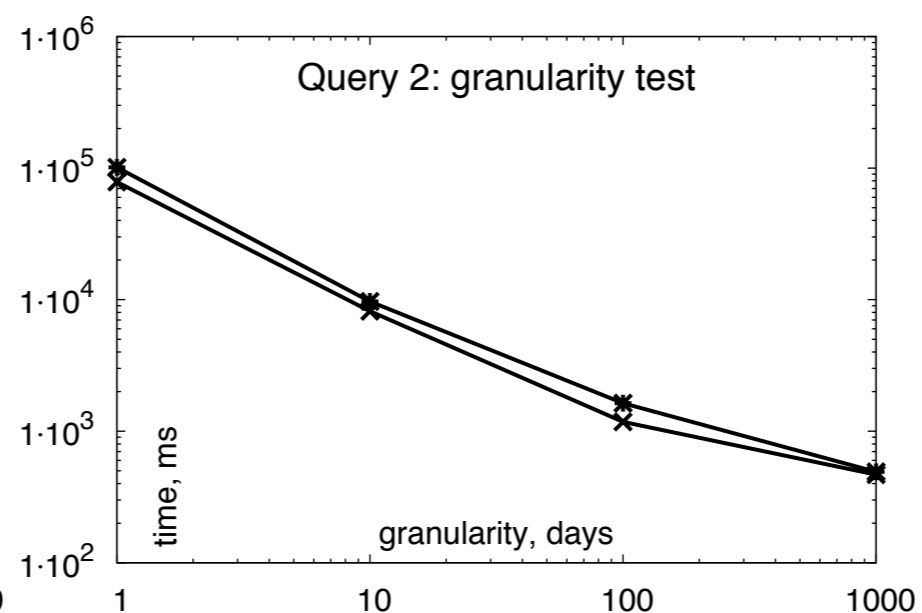
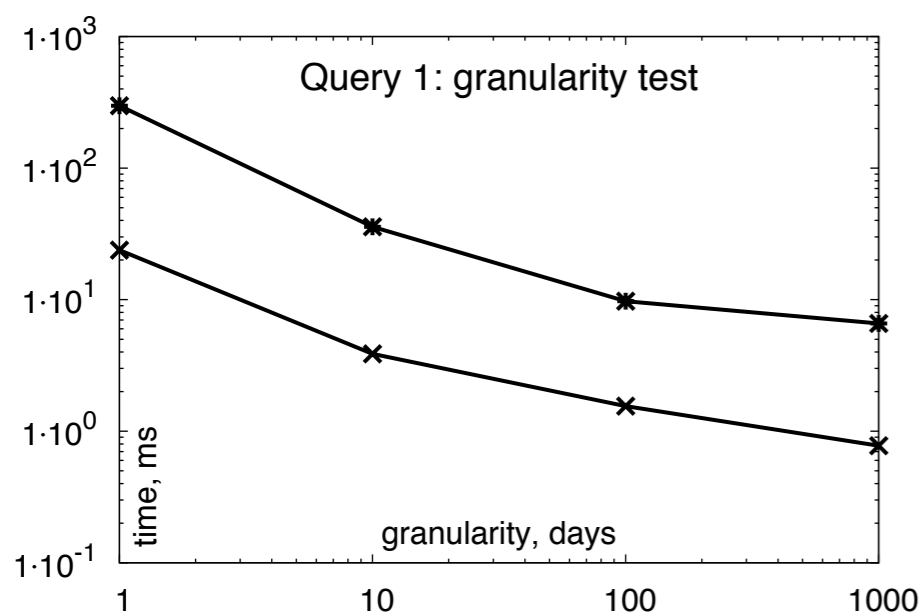
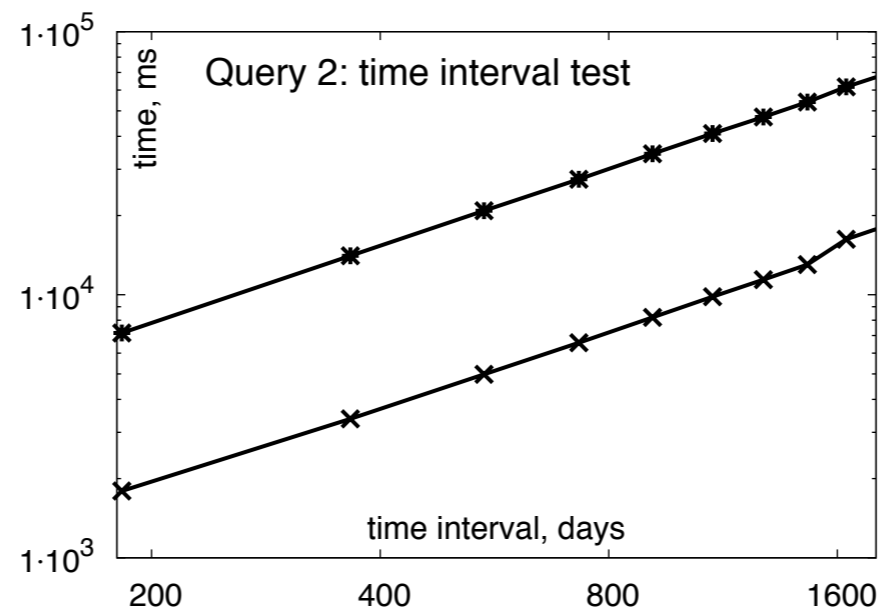
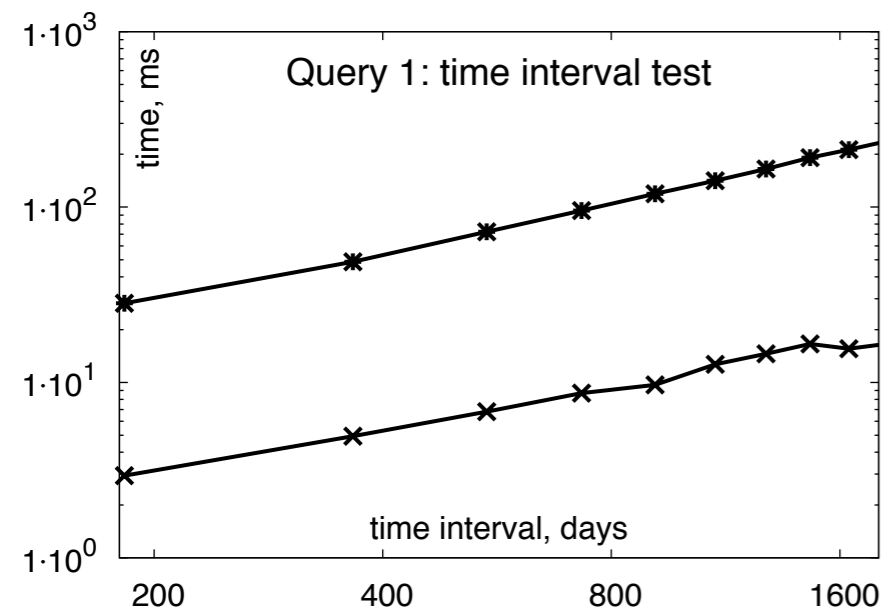
- ▶ Stage 2 (based on contradictions) has showed improvement on all measures
- ▶ The largest improvement in precision was achieved for Slashdot and YouTube
- ▶ Time improvement was small for a dataset with many contradictions (Yaz), but it was large for dataset with infrequent contradictions (Ambien)
- ▶ In all cases, our tool allowed to reduce the search space (number of clicks)

Scalability Evaluation - Experimental Setup

- ▶ Synthetic dataset contained randomly generated sentiments for 1,000 topics
- ▶ We generated sets of 25 single-topic and all-topics queries
- ▶ In queries we used granularities and topics drawn uniformly at random
- ▶ We measured the time needed to execute these queries against the database as a function of the time interval, and the granularity of the time windows.
- ▶ We report results for both the fixed threshold and the adaptive threshold.

```
select c1.topic_id, c1.timeBegin, c1.timeEnd from contradictions c1
join contradictions c2 on c1.topic_id = c2.topic_id and c2.granularity = c1.granularity + 1 and
c1.timeBegin is between c2.timeBegin and c2.timeEnd
where c1.contradiction ≥ c2.contradiction * @threshold and c1.granularity = @window and
(c1.timeBegin is between startDate and endDate or c1.timeEnd is between startDate and endDate);
```


Scalability Evaluation - Results



- ▶ Linearly scales on the length of time series
- ▶ Fixed threshold shows lower answering time
- ▶ Increasing granularity makes answering faster
- ▶ All-Topic queries approx. by two orders slower

dbms adaptive —*— dbms fixed —x—

Related Work - Contradiction Analysis

- ▶ Contradictions were initially defined as textual inference and analyzed using linguistic technologies:

(De Marneffe et al., 2008; Harabagui et al., 2006).

- ▶ Contradictions can be distinguished on a large scale by calculating the entropy or clustering accuracy:

(Choudhury et.al., 2008; Varlamis et.al., 2008).

- ▶ Contradictions can also be analyzed using visual inspection of opposite sentiments:

(Chen et al., 2006; Liu et.al., 2005).

- ▶ Contradictive sentiments can be useful sources for opinion summarization:

(Kim and Zhai, 2009; Paul et.al., 2010).



Thanks for your attention!