Social Web Sentiment Analysis

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Information Studies

1. Sentiment Strength Detection in the Social Web with *SentiStrength*

- Detect positive and negative sentiment *strength* in short informal text
  - Develop workarounds for lack of standard grammar and spelling
  - Harness emotion expression forms unique to MySpace or CMC (e.g., :-) or haaappppyyy!!!)
  - Classify simultaneously as positive 1-5 AND negative 1-5 sentiment

Thelwall, M., Buckley, K., & Paltoglou, G. (2012). Sentiment strength detection for the social Web. *Journal of the American Society for Information Science and Technology* , 63(1), 163-173

Thelwall, M., Buckley, K., Paltoglou, G., Cai, D., & Kappas, A. (2010). Sentiment strength detection in short informal text. *Journal of the American Society for Information Science and Technology*, 61(12), 2544-2558.

SentiStrength Algorithm - Core

- List of 2,489 positive and negative sentiment term stems and strengths (1 to 5), e.g.
  - ache = -2, dislike = -3, hate=-4, excruciating -5
  - encourage = 2, coolest = 3, lover = 4
- Sentiment strength is highest in sentence; or highest sentence if multiple sentences

positive, negative

-2

- My legs ache. 1, -2

3

- You are the coolest. 3, -1

- I hate Paul but encourage him. 2, -4

-4 2

Extra sentiment methods

- **spelling correction** nicce -> nice
- **booster words** alter strength **very** happy
- **negating words** flip emotions **not** nice
- **repeated letters** boost sentiment/+ve niiiice
- **emoticon list** :) =+2
- **exclamation marks** count as +2 unless –ve hi!
- **repeated punctuation** boosts sentiment good!!!
- **negative emotion ignored in questions** u h8 me?
- **Sentiment idiom list** shock horror = -2

Online as http://sentistrength.wlv.ac.uk/

Tests against human coders

Data set	Positive scores - correlation with humans	Negative scores - correlation with humans
YouTube	0.589	0.521
MySpace	0.647	0.599
Twitter	0.541	0.499
Sports forum	0.567	0.541
Digg.com news	0.352	0.552
BBC forums	0.296	0.591
All 6 data sets	0.556	0.565

SentiStrength agrees with humans
as much as they agree with each other

1 is perfect agreement, 0 is random agreement

Why the bad results for BBC? (and Digg)

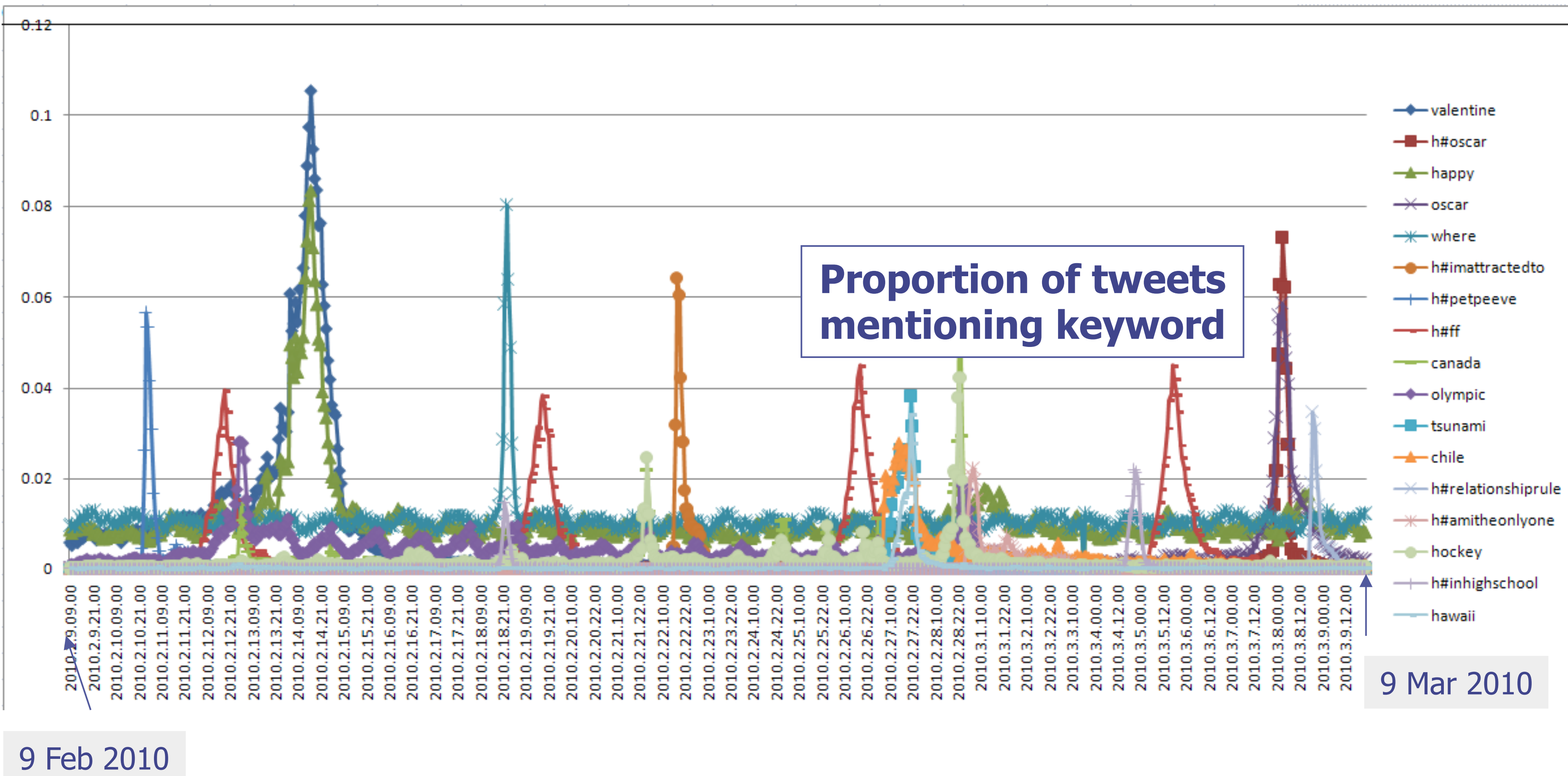
- Irony, sarcasm and expressive language e.g.,
  - David Cameron must be very happy that I have lost my job.
  - It is really interesting that David Cameron and most of his ministers are millionaires.
  - Your argument is a joke.

http://www.cyberemotions.eu/eye/

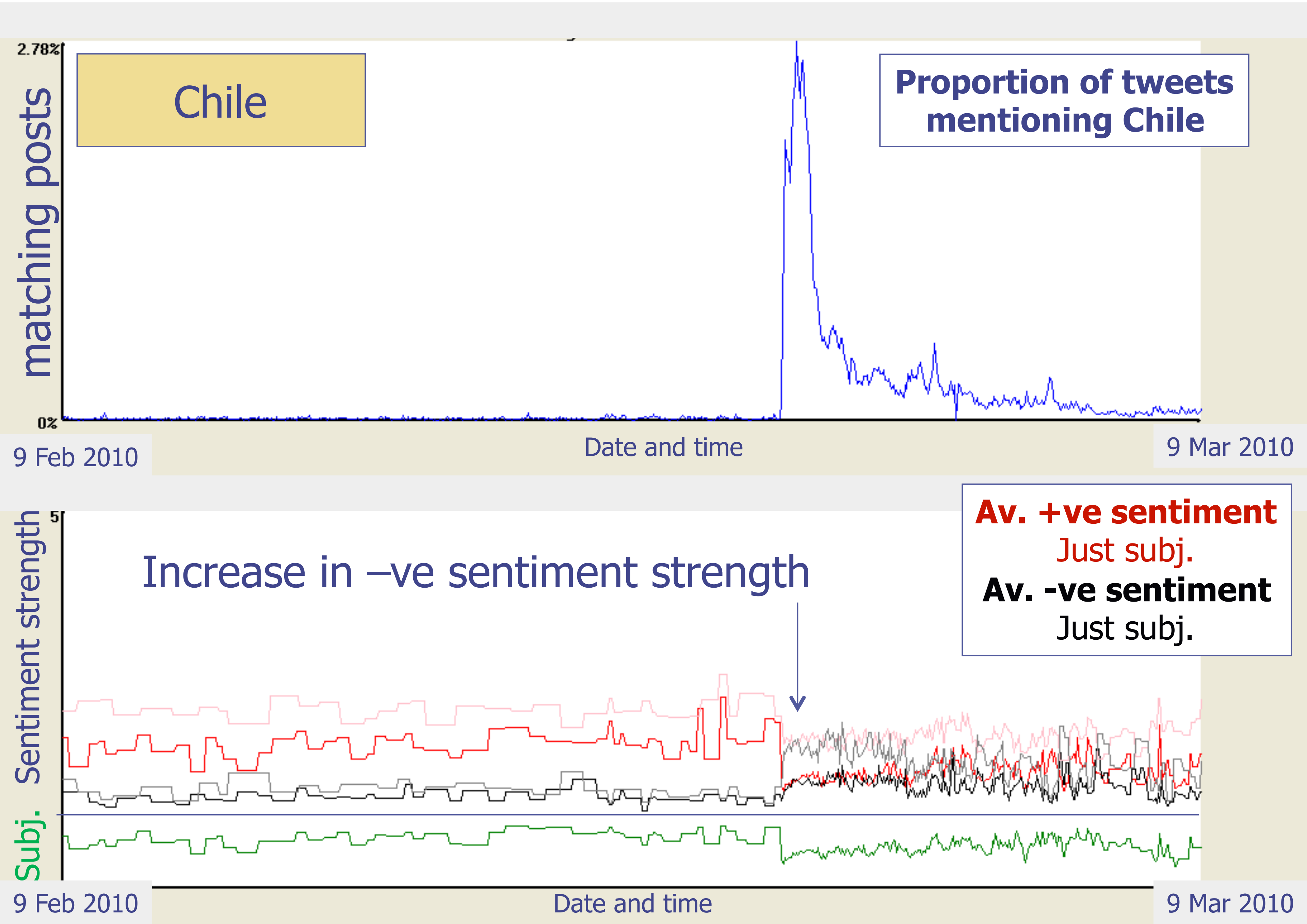
2. Twitter – sentiment in major media events

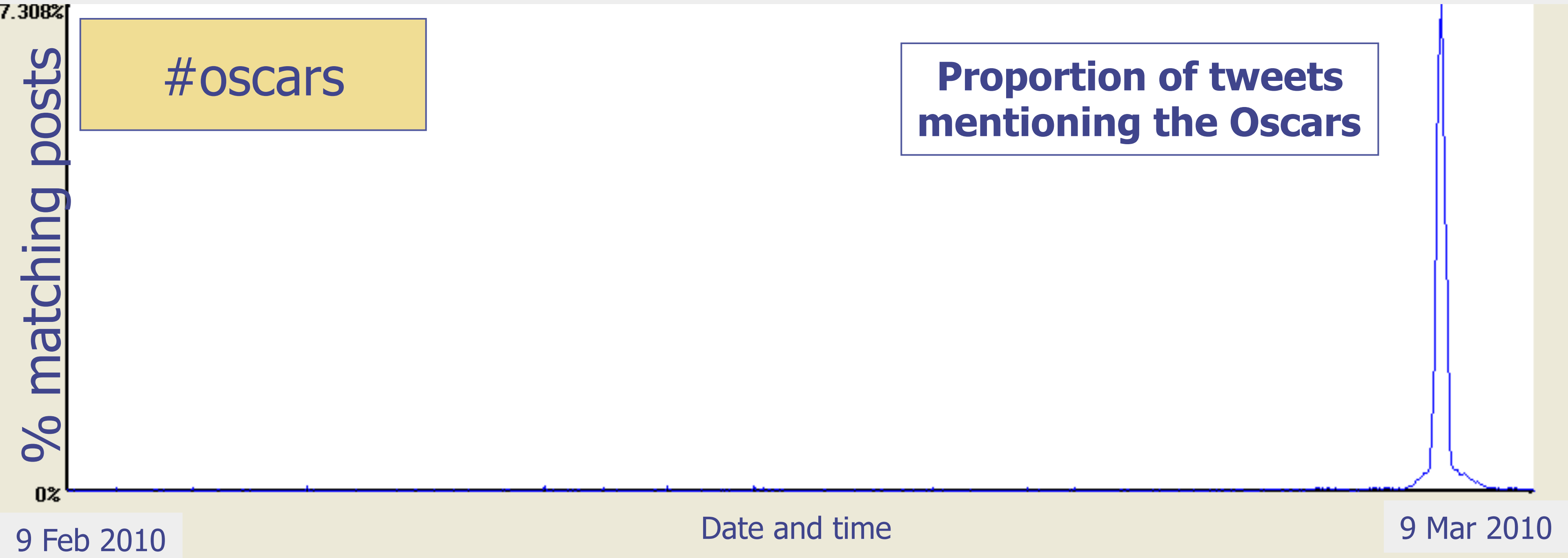
- Analysis of a corpus of 1 month of English Twitter posts (35 Million, from 2.7M accounts)
- Automatic detection of spikes (events)
- Assessment of whether sentiment changes during major media events

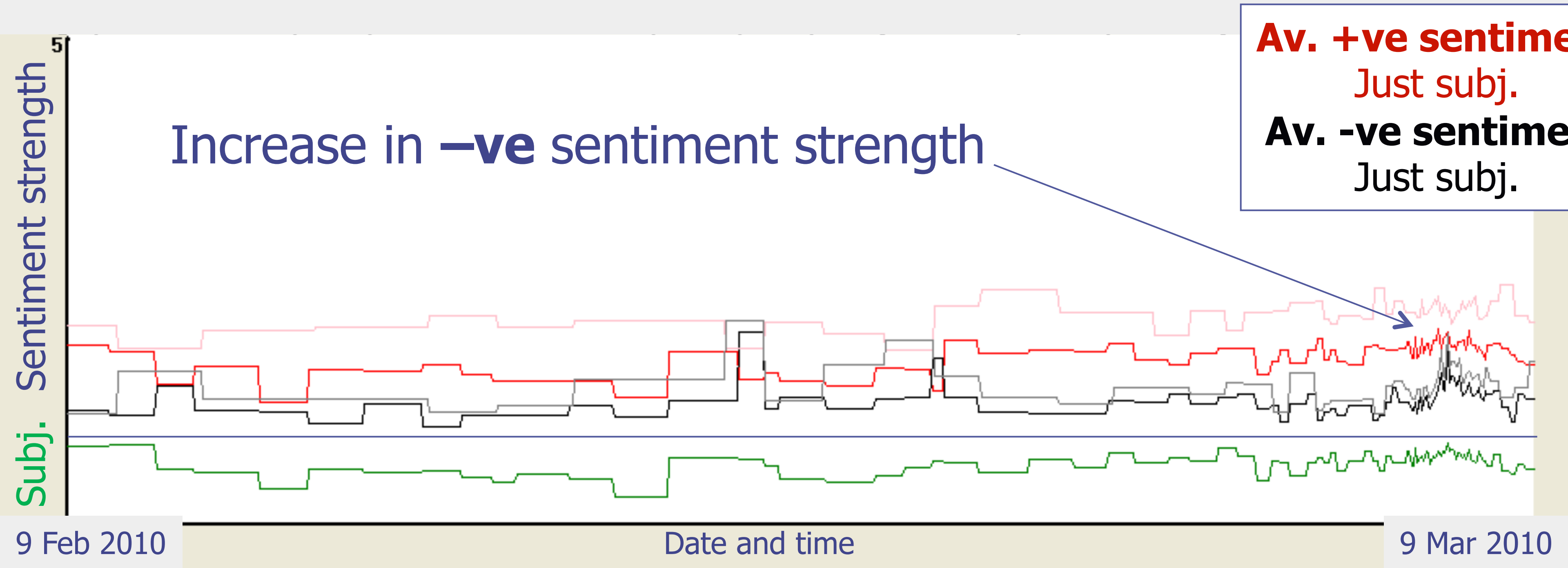
Automatically-identified Twitter spikes



Thelwall, M., Buckley, K., & Paltoglou, G. (2011). [Sentiment in Twitter events](). *Journal of the American Society for Information Science and Technology*, 62(2), 406-418.


Chile
Proportion of tweets mentioning Chile
matching posts
2.78%
0%
9 Feb 2010
Date and time
9 Mar 2010
Av. +ve sentiment
Just subj.
Av. -ve sentiment
Just subj.
Increase in –ve sentiment strength
Sentiment strength
5
Subj.
9 Feb 2010
Date and time
9 Mar 2010

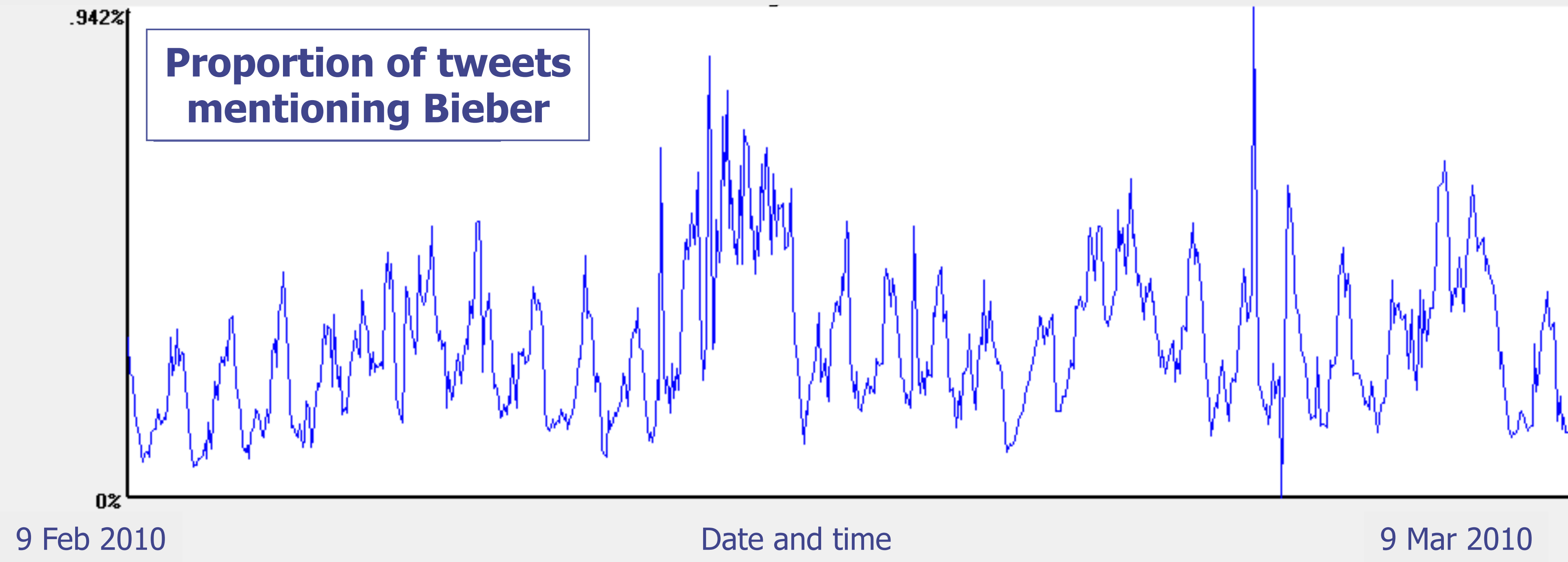

7.308%
0%
% matching posts
#oscars
Proportion of tweets mentioning the Oscars
9 Feb 2010
Date and time
9 Mar 2010

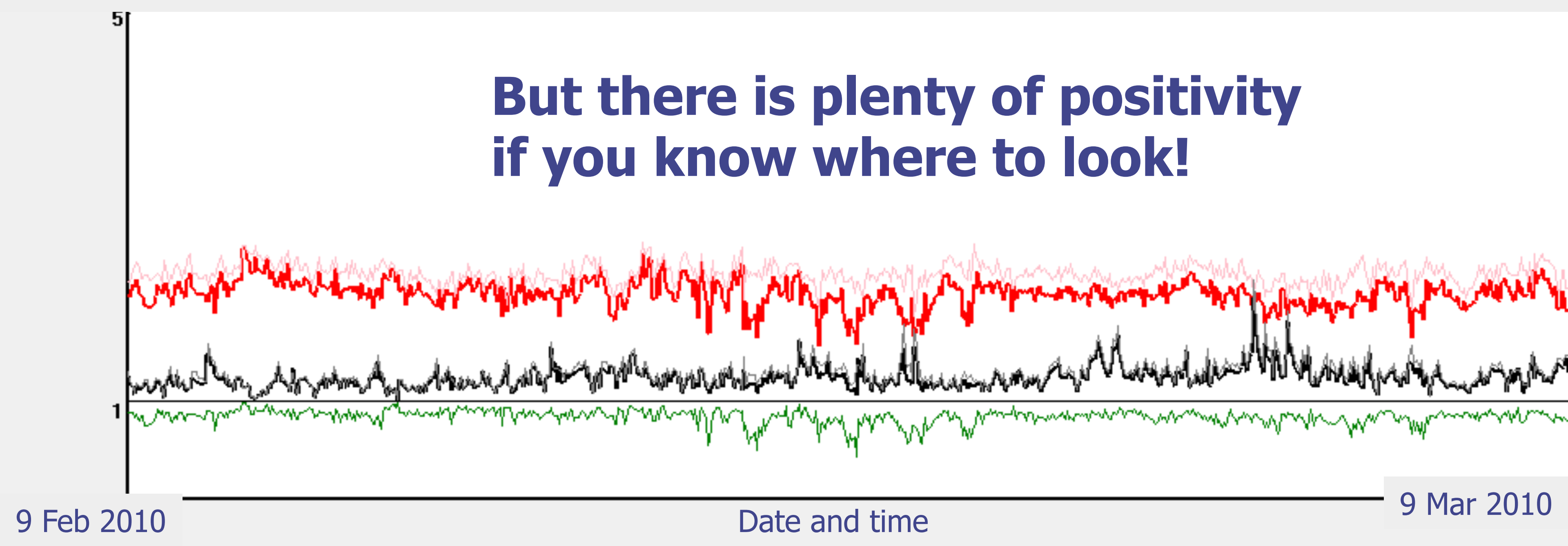

5
Sentiment strength
Subj.
Increase in –ve sentiment strength
Av. +ve sentime
Just subj.
Av. -ve sentime
Just subj.
9 Feb 2010
Date and time
9 Mar 2010

Sentiment and spikes

- Statistical analysis of top 30 events:
  - Strong evidence that *higher volume hours have stronger negative sentiment than lower volume hours*
  - *No evidence* that higher volume hours have different *positive* sentiment strength than lower volume hours

=> Spikes are typified by *small* increases in *negativity*


.942%
Proportion of tweets mentioning Bieber
0%
9 Feb 2010
Date and time
9 Mar 2010


5
But there is plenty of positivity if you know where to look!
1
9 Feb 2010
Date and time
9 Mar 2010

3. YouTube Video *comments*

- 1000 comm. per video via *Webometric Analyst* (or the YouTube API)
- Good source of social web text data
- Analysis of all comments on a pseudo-random sample of 35,347 videos with < 1000 comments

THAT'S RIGHT.

BB UR AMAZING :D

iTrolledABearOnce 19 minutes ago

Museum Dinosaur Interacts With Kids

j0eg0d 116 videos Subscribe

0:05 / 1:29 360p

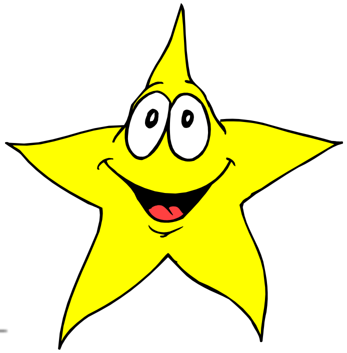
Like Add to Share 442,828

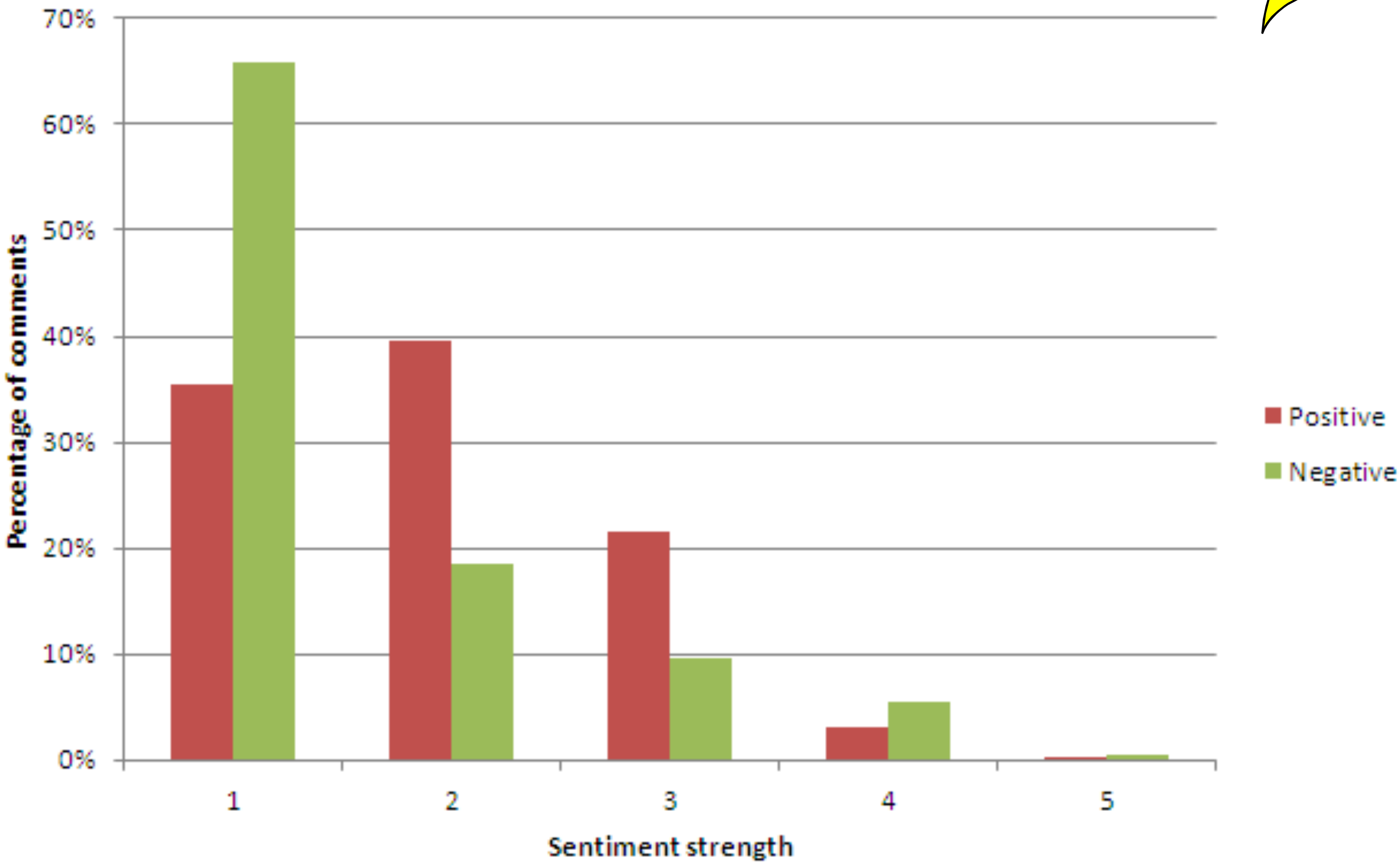
Uploaded by j0eg0d on Jul 22, 2008

665 likes, 16 dislikes

Dinosaur interacts with children in the Los Angeles Natural History Museum.

Sentiment in YouTube comments





YouTube comments tend to be weakly positive

Trends in YouTube comment sentiment

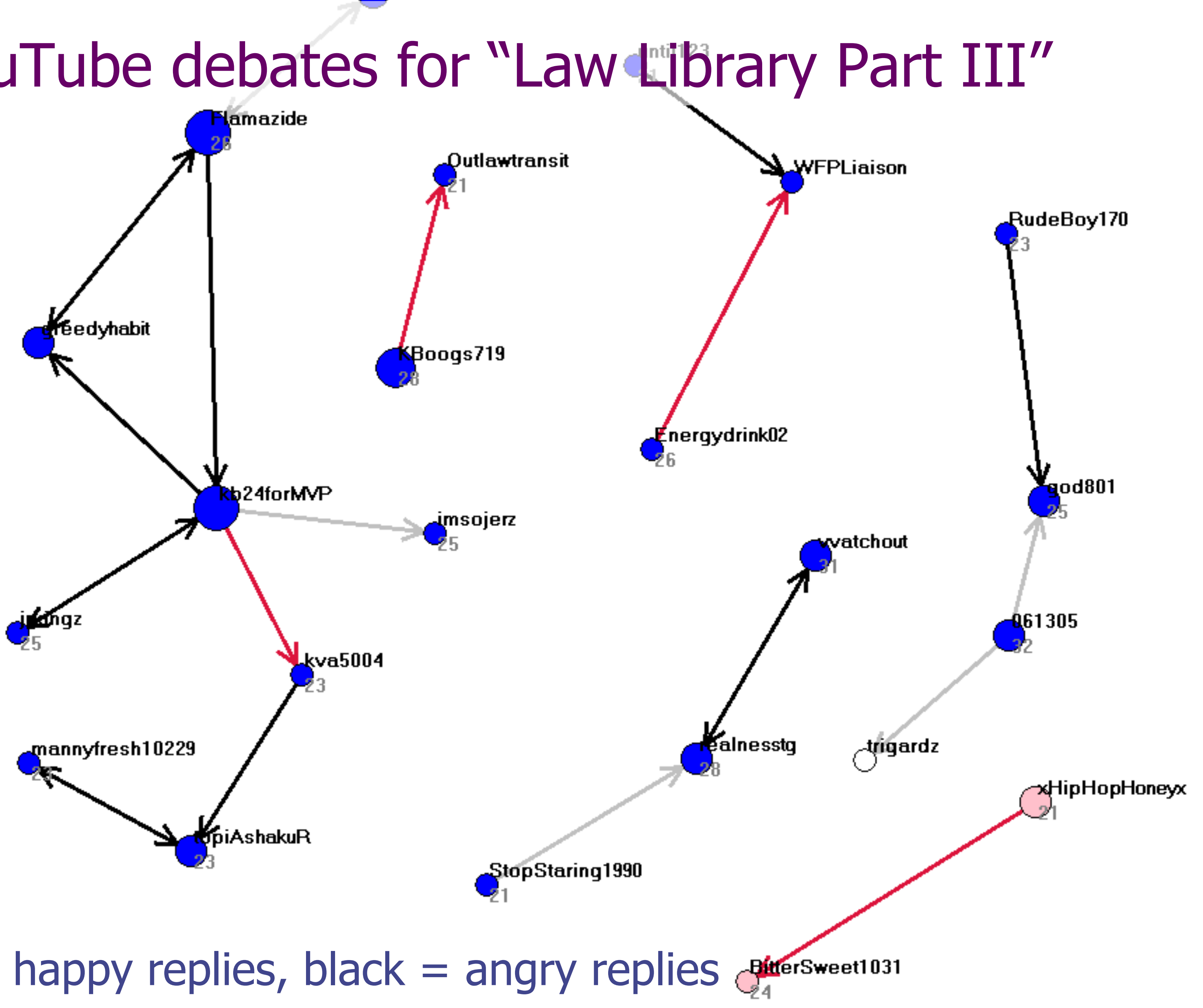
- +ve and –ve sentiment strengths negatively correlate for videos (Spearman's rho -0.213)
- # of comments on a video correlates with –ve sentiment strength (Spearman's rho 0.242, p=0.000) and negatively correlates with +ve sentiment strength (Spearman's rho -0.113) – **negativity** drives commenting even though it is rare!

Thelwall, M., Sud, P., & Vis, F. (2012). Commenting on YouTube videos: From Guatemalan rock to El Big Bang. *Journal of the American Society for Information Science and Technology* 63(3), 616–629.

More about YouTube comments

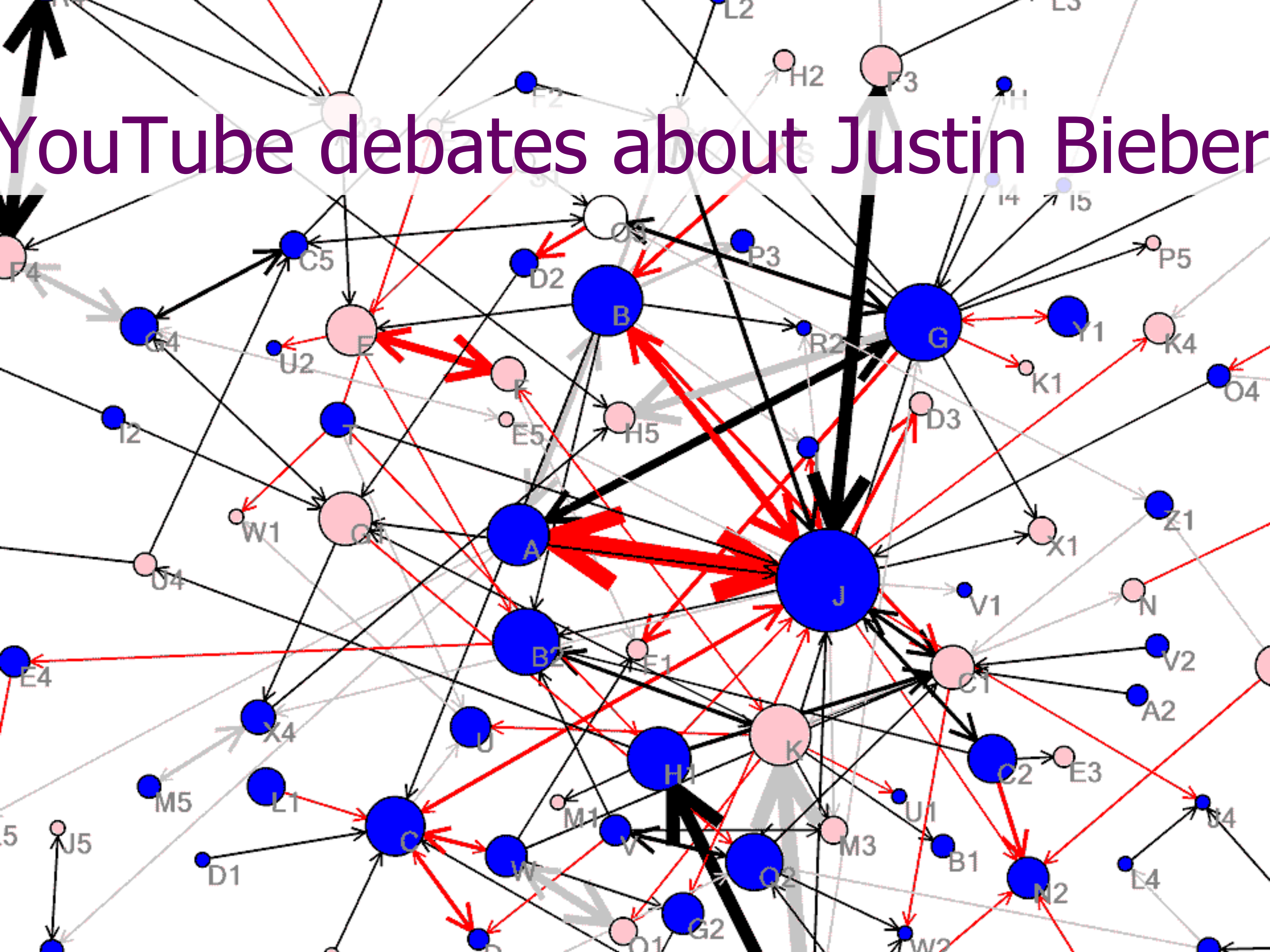
- 23% of comments are replies
- Discussion density varies wildly
  - Religion triggers the biggest discussions
  - Music, Comedy and How to & Style categories don't trigger discussions
    - No discussions about aging rock stars!
- YouTube = passive entertainment + active debating/trolling?

YouTube debates for “Law Library Part III”



red = happy replies, black = angry replies

YouTube debates about Justin Bieber



4. Issue adaptation

- Sentiment analysis sometimes performs badly on social web texts relevant to as specific issue or topic due to unusual uses of words
  - E.g., “pistol” is not negative and flame” is mildly positive for olympic tweets
  - E.g., “fire” and “flame” are very negative in the context of UK riots tweets

Issue adaptation methods 1: Mood

- Mood is set to negative or positive
  - E.g.. UK Riots: negative, Olympics: positive
- Expressions of sentiment without polarity are interpreted as negative if there is a negative mood, positive if a positive mood.
  - E.g., “Miiiikee!!!” is positive for olympics, negative for riots.

Mood results

	Train. corpus size	Test corpus size	Train. corr. pos. mood	Train. corr. neg. mood	Test corr. pos. mood	Test corr. neg. mood
Riots	847	846	0.3603	0.4348	**0.3243**	**0.4104**
AV	8846	8847	0.4152	0.3214	**0.4038**	**0.3023**

Issue adaptation methods 2: Issue-specific words

- Using a corpus of classified texts:
- Check SentiStrength classification of each text against human code
- For each disagreement, record terms in text
- For each term, count the number of times it is in texts classified as too positive/too negative
- Manually check the top words for domain-specific terminology to add to the lexicon

Example – Riot words added to the lexicon

Term	Weight
arrest	-2
arrested	-2
baton	-2
batoned	-3
birminghamriots	-2
brainwashing	-3
caught	-2

Example – Alternative Vote words added to the lexicon

Term	Weight
ace	3
ass	-2
better	2
cut	-2
fairer	2
fearmongerers	-3

Results

- An improvement of up to 8% - depending on the topic.

Damping Sentiment Analysis

- Intuition: in online communication, if a text has a very different sentiment from previous texts in the same monolog/ dialog/discussion then it may be a sentiment analysis classification error
- Develop damping method to align sentiment scores closer to the average

Example classification error

Tweet (first 3 from Stacey, last from Claire)	Neg. score
@Claire she bores me too! Haha x	-2
@Claire text me wen your on your way x x x	-1
@Claire u watch BB tonight? I tried one of them bars..reem! x x x	-1
@Stacey lush in they … do u watch American horror story … Cbb was awsum tonight bunch of bitches !!	-4

Damping rules

- If the classified positive sentiment of text A differs by at least 1.5 from the average positive sentiment of the previous 3 posts, then adjust the positive sentiment prediction of text A by 1 point to bring it closer to the positive average of the previous 3 terms.
- If the classified negative sentiment of text A differs by at least 1.5 from the average negative sentiment of the previous 3 posts, then adjust the negative sentiment prediction of text A by 1 point to bring it closer to the negative average of the previous 3 terms.

e.g., 4, 4, 4, 1 -> 4, 4, 4, 2 and 1, 1, 2, 4 -> 1, 1, 2, 3

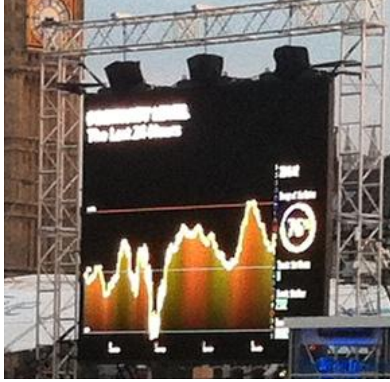
Data sets

- **BBC World news discussions (BWNpf)**
- RunnersWorld (RWtf)
- Twitter monologs (Tm)
- **Twitter dialogs (Td)**

Results

- Damping improves sentiment classification by a small amount in some cases but makes it worse in others
- The four different types of damping have different effects on performance
  - +ve/-ve sentiment increase/decrease
- Sentiment damping seems to work but needs a lot of testing to find the right types for a particular data set.

Conclusions



- Sentiment analysis exploits the free availability of social web texts to gain new insights into the issues discussed
- Investigating social web sentiment:
  - What is the role of sentiment in discussions of topic X or social web site X? (e.g., YouTube comments)
  - Can phenomenon X be explained by patterns of sentiment in discussions of it? (e.g., media events)
  - What are the differences in the levels of sentiment between X and Y? (e.g., Twitter vs. Facebook)

Free sentiment analysis: SentiStrength; Free data collection: Webometric Analyst