Social Media & Text Analysis

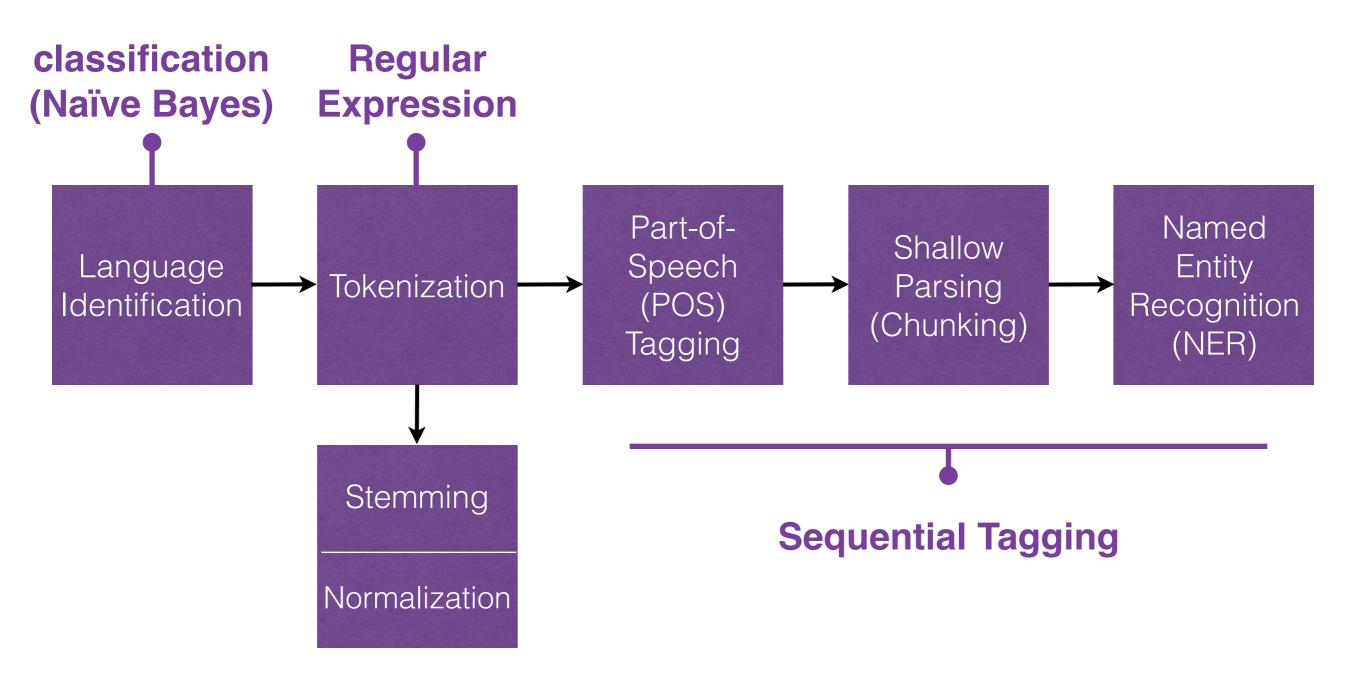
lecture 6 - Automatic Summarization for Twitter



Instructor: Wei Xu

Website: socialmedia-class.org

[Recap] NLP Pipeline



Timeline of NLP on Microblogs

- Dialogue Modeling (Ritter et al.)
- Named Entity Recog. (Ritter et al.)
- Open-Domain
 Event Extraction
 (Ritter et al.)



2010



2011



2012



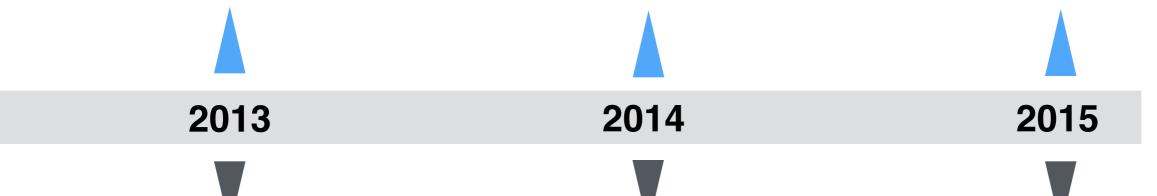
- First Story Detection (Petrovic et al.)
- Geographic Variation (Eisenstein et al.)
- POS Tagging (Gimpel et al.)
- Normalization (Han and Baldwin)
- Summarization (Liu et. al)

Censorship
 Detection

(Bamman et al.)

Timeline of NLP on Microblogs

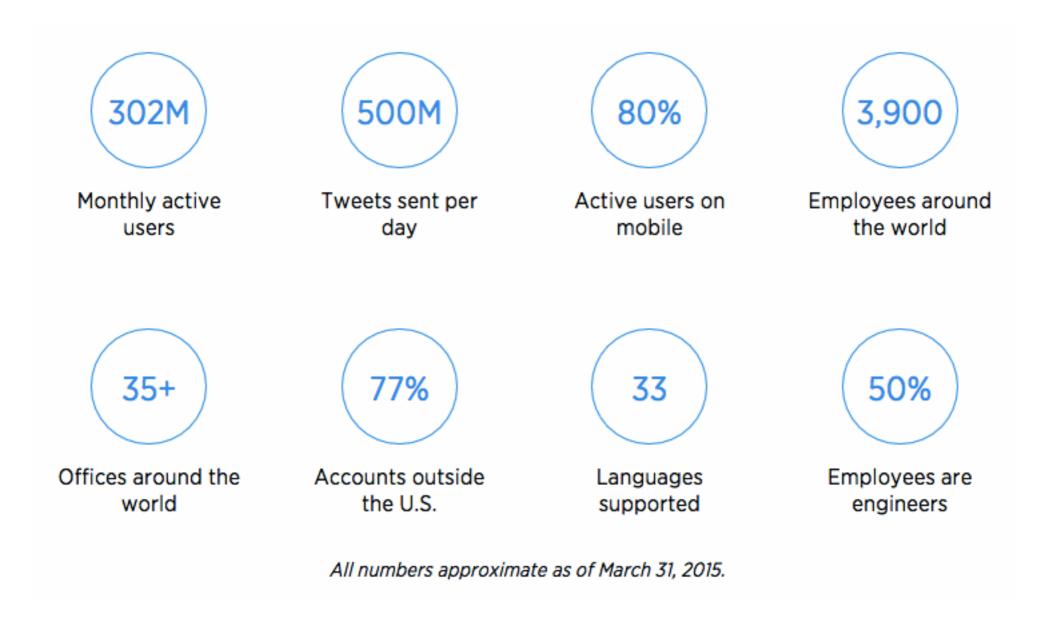
- Summarization (Xu et al.)
- Normalization Paraphrase Extraction POS
 (Xu et al.) (Cherry and Guo)



- Machine Translation (Ling et. al.)
 - POS(Owoputi et al.)

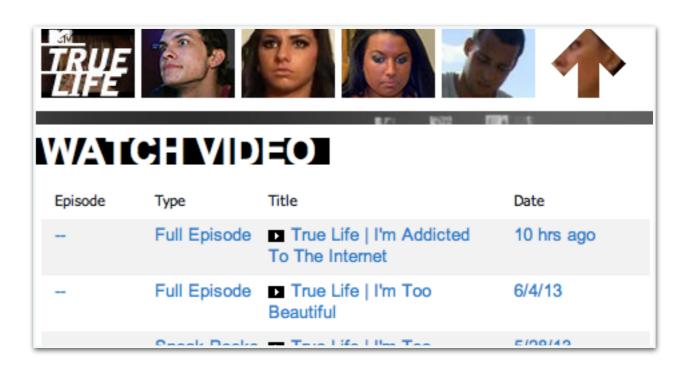
- Parsing Weibo (Wang et. al.)
- Parsing Twitter (Kong et. al.)
- Dialogue Modeling (Sordoni et al.)

Twitter Usage / Company Facts



Summarization





SUMMARY:

I'm watching true life "I'm addicted to Internet" ... while I'm on mine lol

Okay these girls on **True Life I'm Too Beautiful** are not that pretty

Summarization

 Given a (or a set) of documents, generate a short summary



Given a (large) set of topically and temporally clustered tweets, select a few representative tweets as the summary.

Previous Work

Selected Work	Size of Input	Length of Summary
Wei et al. (2012)	average 10k tweets	10 tweets
Inouye & Kalita (2011)	approximately 1500 tweets	4 tweets ❖
Rosa et al. (2011)	average 410 tweets	1, 5, 10 tweets
Liu et al. (2011)	average 1.7k tweets	about 2 or 3 tweets ★
Takamura et al. (2011)	2.8k - 5.2k tweets	26 - 41 tweets ★

- Human annotators strongly prefer different numbers of tweets in a summary for different topics.
- ★ Used the length of human reference summaries to decide the length of system outputs, which information is not available in practice.

SumBasic

Intuition:

words occurring frequently in the documents occur with higher probability in the human summaries than words occurring less frequently

SumBasic

 a very simple but strong summarization algorithm [Nenkova and Vanderwende, 2005]

Intuition:

words occurring frequently in the documents occur with higher probability in the human summaries than words occurring less frequently

SumBasic

Step 1: computes the probability of each word w:

$$P(w) = \frac{n(w)}{\sum_{i} w_{i}}$$

• Step 2: computes the salience score of each sentence S:

$$Score(S) = \sum_{w \in S} \frac{P(w)}{|\{w \mid w \in S\}|}$$

- Step 3: pick the highest scored sentence into summary
- Step 4: for each word in sentences chosen at step 3, update their probability:

$$P_{new}(w) = P_{old}(w) \cdot P_{old}(w)$$

Step 5: repeat Step 2~4 until reach desired length of summary

Varied-length Summary

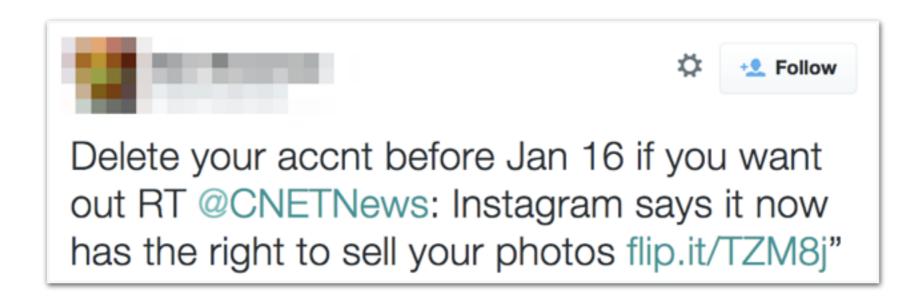
- For a set of topically clustered tweets, amount of information varies greatly:
 - from very repetitive to very discrete
 - e.g.

album release of a less notable singer vs.

album release of a famous/controversy singer

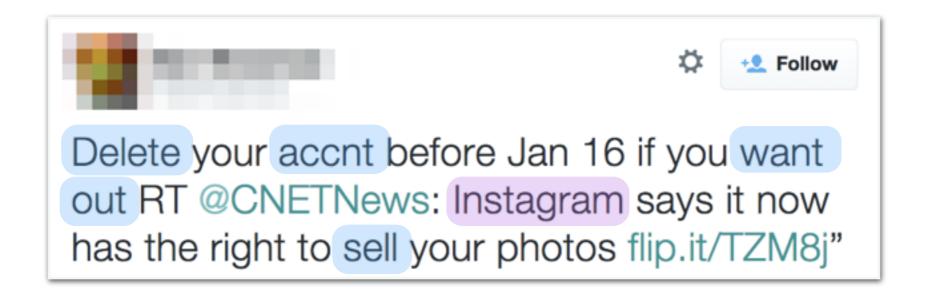
Information Extraction (IE)

- Named Entity [Ritter et al. 2011]
- Event Phrases [Ritter et al. 2012]



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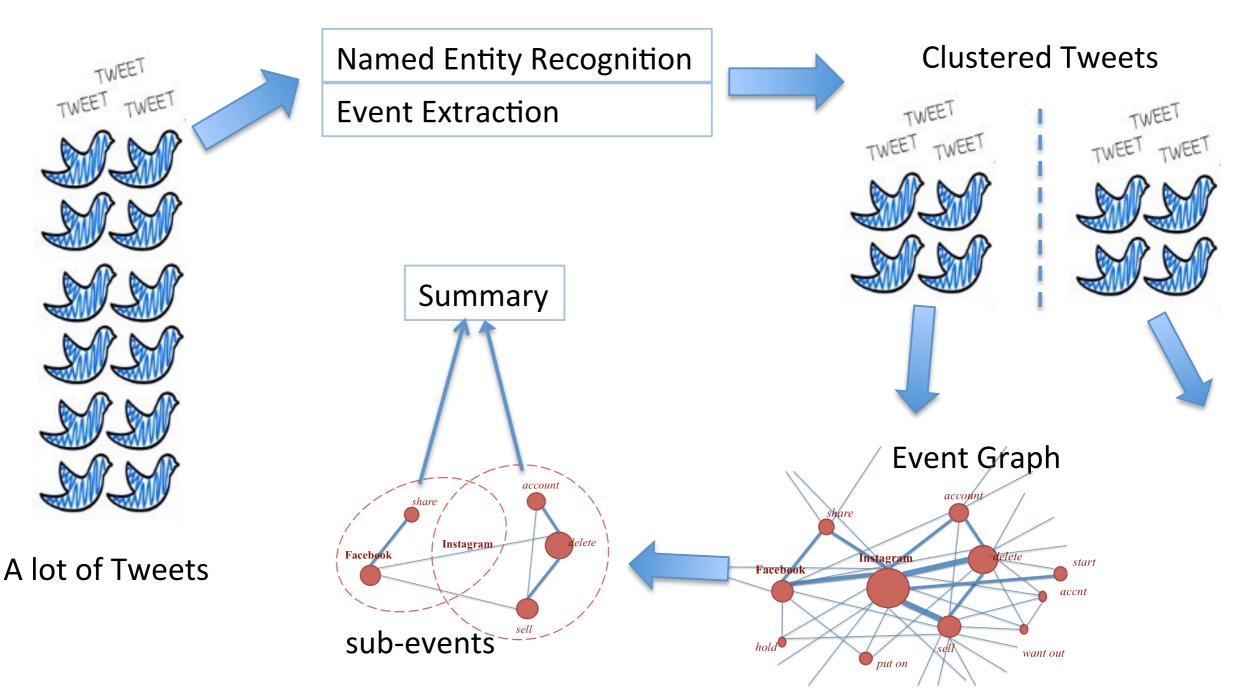


Research Questions

- What is the perfect length of multi-tweet summary?
- Will IE help summarization on Twitter?
 - noisy text: performance of IE?
 - short context: still need in-depth event analysis?
 - redundant: is word enough?

"A Preliminary Study of Tweet Summarization using Information Extraction" in LASM (2014)

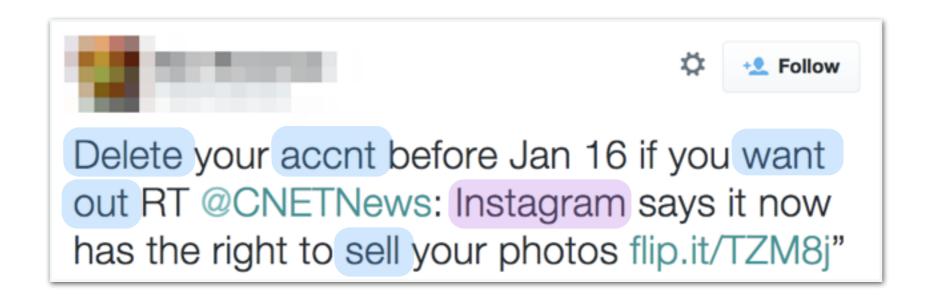
System Overflow

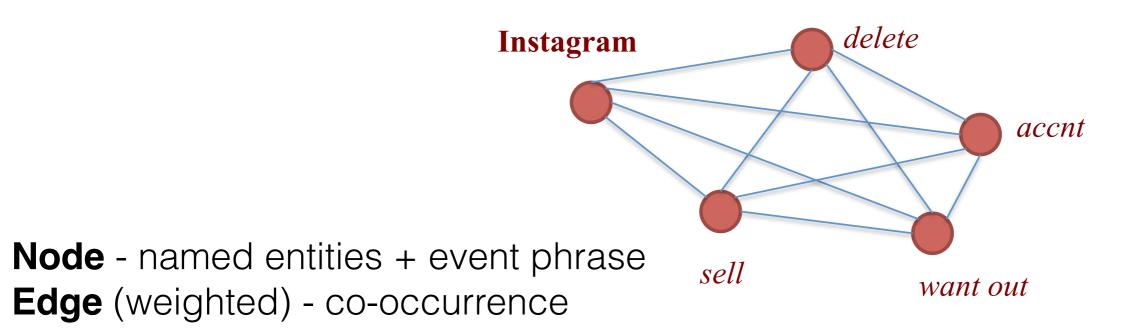


Wei Xu, Alan Ritter, Ralph Grishman.

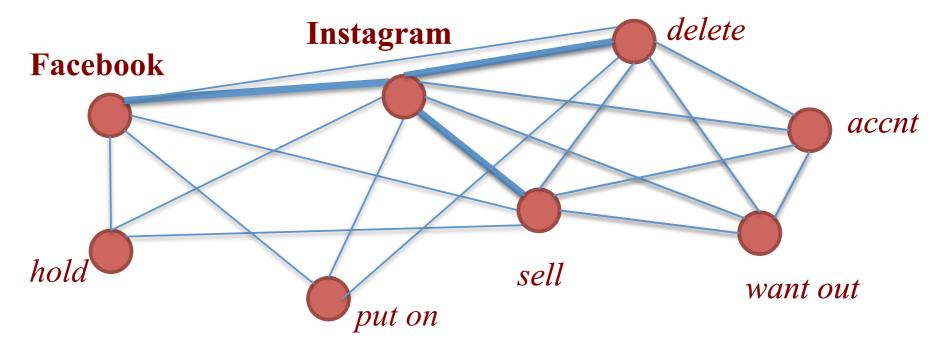
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Event Graph





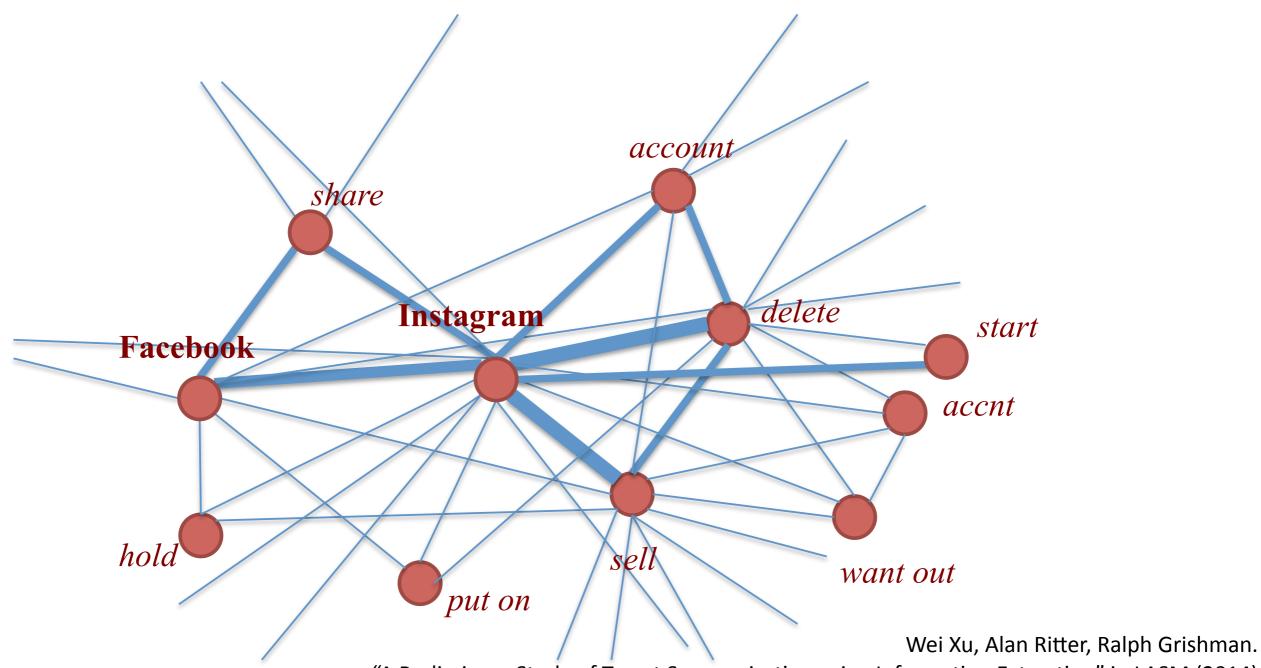
Event Graph



Wei Xu, Alan Ritter, Ralph Grishman.

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Event Graph



PageRank

- a graph-based ranking algorithm
- a trademark of Google
- Idea: web surfing / random walk
 - The importance of a webpage is defined recursively and depends on the number and importance of all webpages that link to it.
- also used for local graph partitioning

PageRank

Salience score of nodes:

$$Score(u) = (1 - d) + d \times \sum_{v \in Adj(u)} \frac{Score(v)}{|Adj(v)|}$$

adjacent nodes

- directed graph
- iterate towards converge
- initial rank of node does not matter
- only edges matter
- total weight of the graph stays the same

PageRank → Event Rank

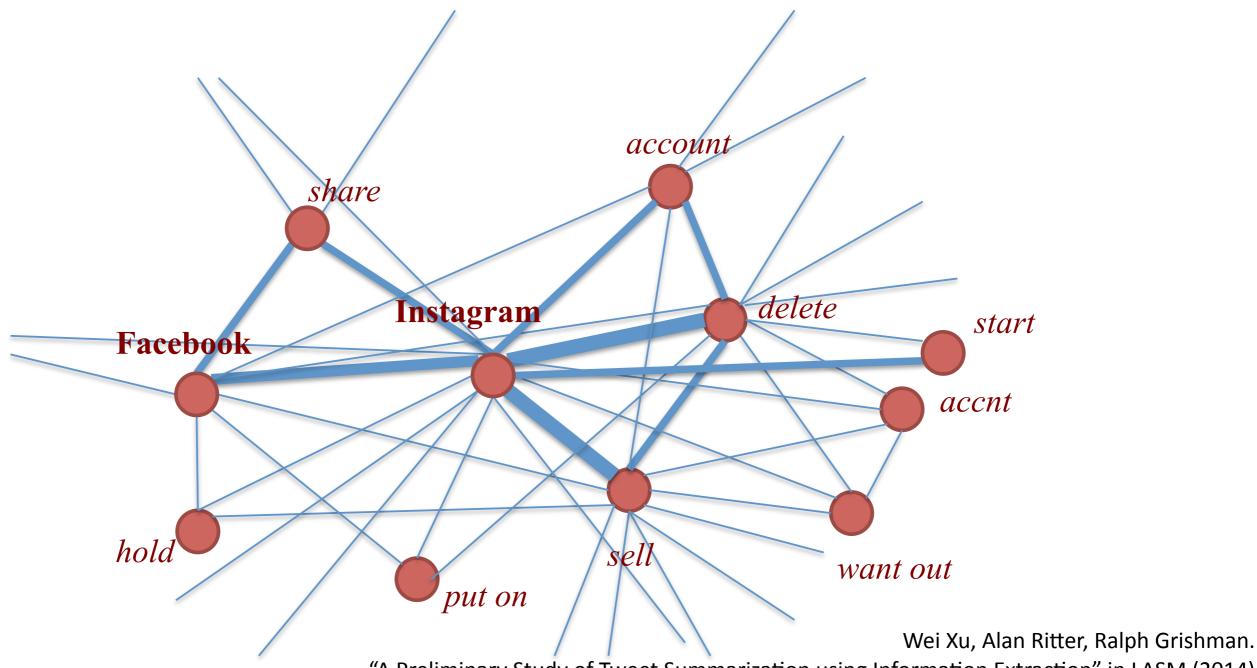
Salience score of nodes:

$$Score(u) = (1-d) + d \times \sum_{v \in Adj(u)} \frac{e_{uv} \times Score(v)}{\sum_{w \in Adj(v)} e_{vw}}$$
- undirected graph

adjacent nodes

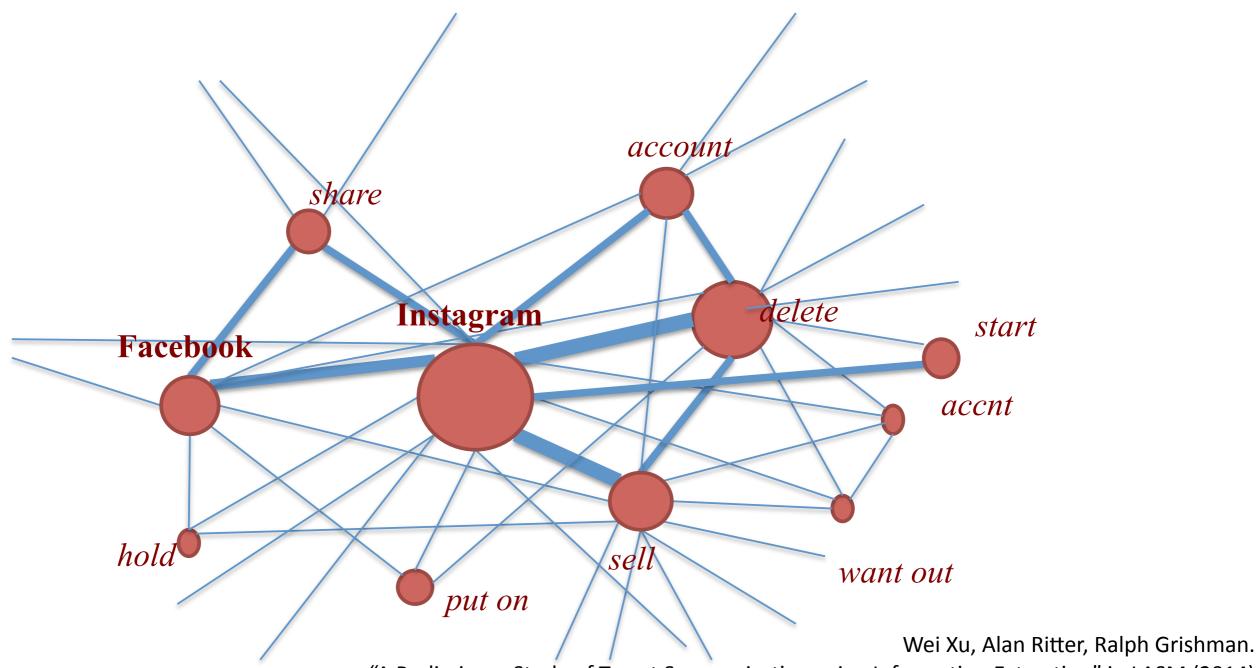
- iterate towards converge
- initial rank of node does not matter
- only edges and their weights matter
- total weight of the graph stays the same

Graph Ranking



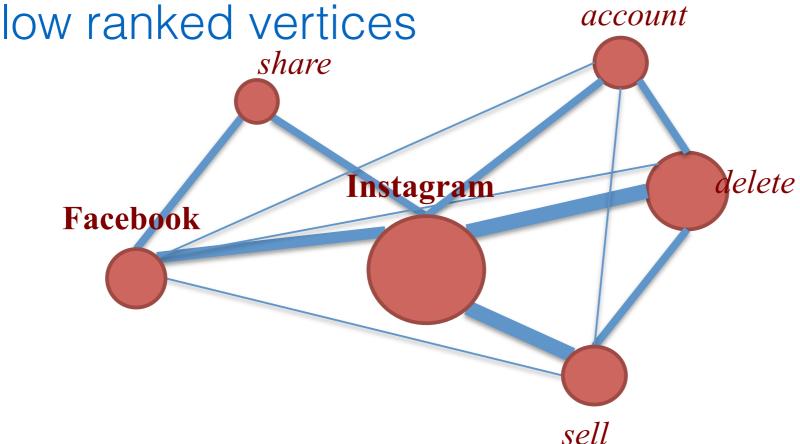
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Graph Ranking

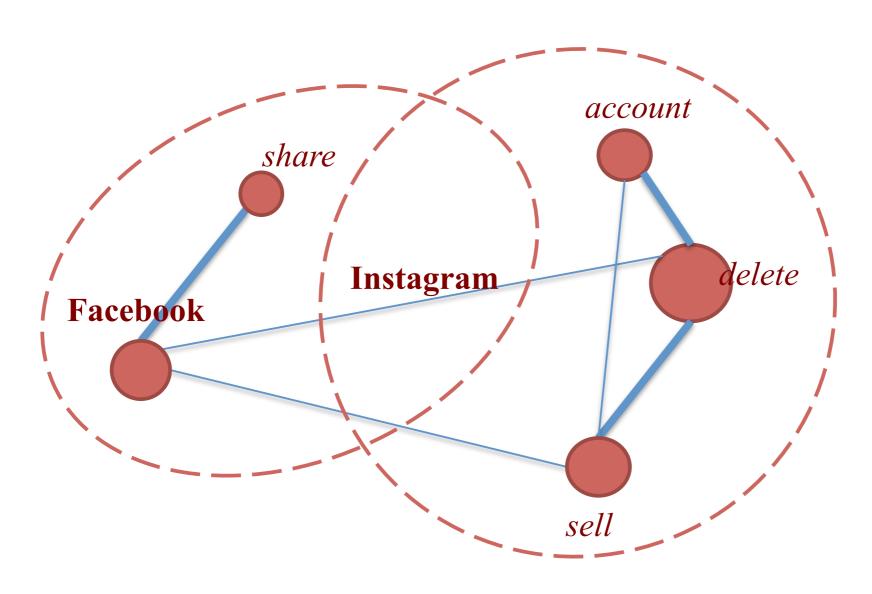


Graph Partitioning

 local graph partitioning by PageRank [Andersen et al., 2006]: a good partition of the graph can be obtained by separating high ranked vertices from

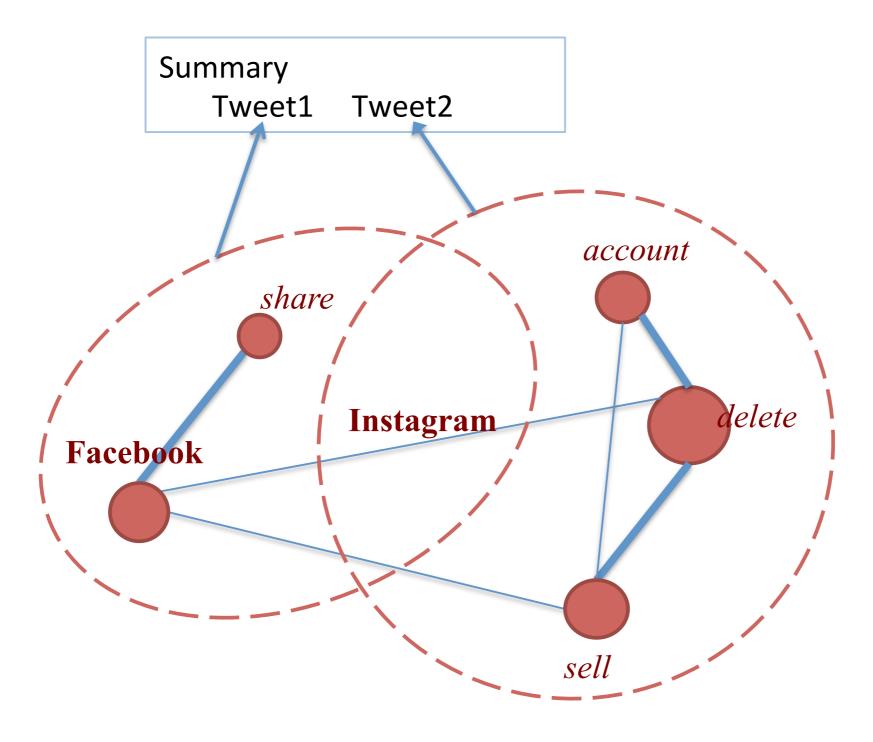


Graph Partitioning



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Graph Partitioning



Example Event Graph

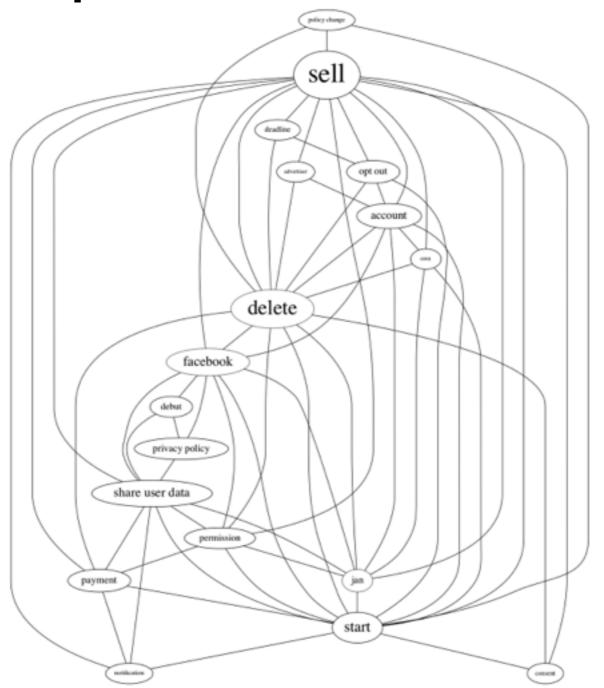


Figure 3: Event graph of 'Instagram - 1/16/2013', an example of event cluster with a single but complex focus

Wei Xu, Alan Ritter, Ralph Grishman.

Example Summary

	EventRank	- So Instagram can sell your pictures to advertisers without u knowing
	(Flexible)	starting January 16th I'm bout to delete my instagram!
		- Instagram debuts new privacy policy, set to share user data with Face-
		book beginning January 16
Instagram		- Instagram will have the rights to sell your photos to Advertisers as of
1/16/2013		jan 16
	SumBasic	- Over for Instagram on January 16th
		- Instagram says it now has the right to sell your photos unless you delete
		your account by January 16th http://t.co/tsjic6yA

Example Event Graph

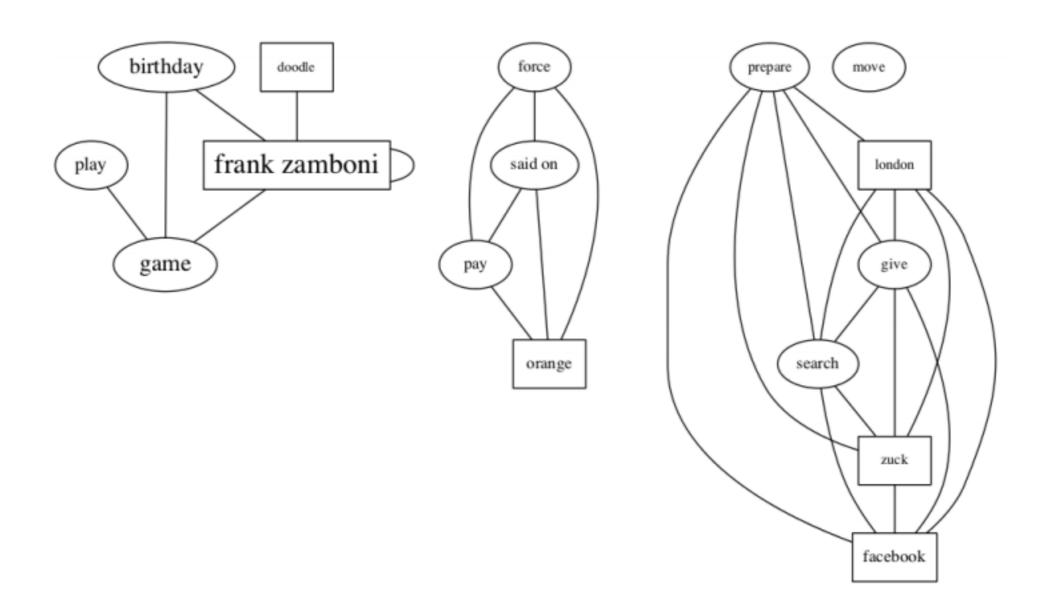


Figure 2: Event graph of 'Google - 1/16/2013', an example of event cluster with multiple focuses

Example Summary

		- Google 's home page is a Zamboni game in celebration of Frank Zam-
		boni 's birthday January 16 #GameOn
	EventRank	- Today social, Tomorrow Google! Facebook Has Publicly Redefined
	(Flexible)	Itself As A Search Company http://t.co/dAevB2V0 via @sai
Google		- Orange says has it has forced Google to pay for traffic . The Head of
1/16/2013		the Orange said on Wednesday it had http://t.co/dOqAHhWi
		- Tomorrow's Google doodle is going to be a Zamboni! I may have to
		take a vacation day.
	SumBasic	- the game on google today reminds me of hockey #tooexcited #saturday
		- The fact that I was soooo involved in that google doodle game says
		something about this Wednesday #TGIW You should try it!

[Recap]Research Questions

- What is the perfect length of multi-tweet summary?
- Will IE help summarization on Twitter?
 - noisy text: performance of IE?
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 - redundant: is word enough?

Research Questions

- What is the perfect length of multi-tweet summary?
 variable length
- Will IE help summarization on Twitter?
 - noisy text: performance of IE?
 summary is more readable and newsworthy
 - short context: still need in-depth event analysis?
 self-contained (no coref.) → better event graph
 - redundant: is word enough?
 unbalanced event graph → easier partitioning

Thank You!



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