

An end-to-end framework for event detection in social media

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Event Detection

Event Detection: identification of items and observations that do not conform to an expected patterns or other observations.

Different types of events:



Natural disasters



Social activities



Political campaigns



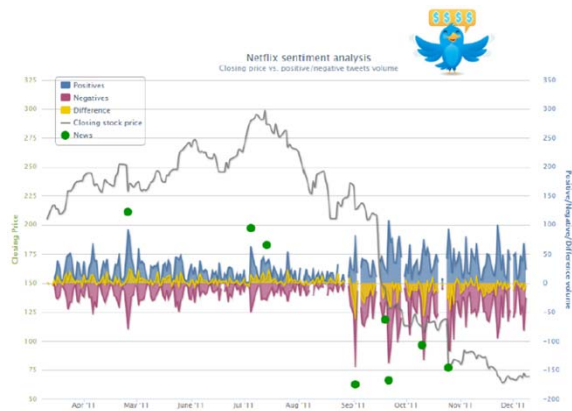
Incidents

Event Detection in Social Media

Social Media: a lot of human texts, pictures, videos

Applications of event detection:

- Predict future outcomes
- Understand a known event
- Early warning (e.g. Twitter user is faster than a BBC reporter)



Stock price vs. tweet sentiment

Topic Keywords

Obama,Vermont,wins,projects,VT
Romney,wins,Kentucky,projects,KY
Sanders,wins,Senate,Vermont,
independent,VT
Romney,wins,Indiana,IN
Romney,wins,West Virginia,WV
Romney,wins,South Carolina,SC
Obama,wins,Illinois,IL
Obama,wins,Connecticut,CT
Obama,wins,Maine,ME

Top 10 topics in US 2012 election



instant reporter

Framework for Social Media

Limitations:

- Human text has different syntactic/semantic elements (sentiment, term, topic, entity)
→ need text mining techniques
- Events are often hidden or interpreted in different ways (#followers, #burst keywords, anomalies in spatial-temporal dimensions)
→ need event detection techniques

→ **Goal:** develop an end-to-end framework for event detection in social media

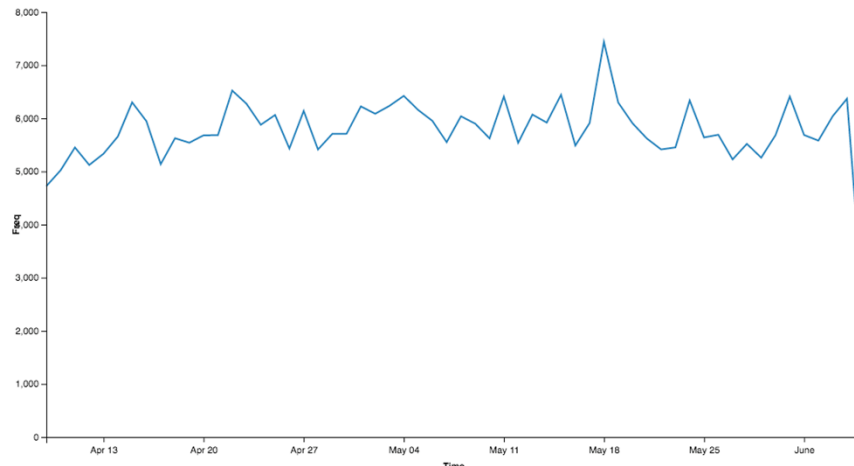
Scope:

- Target user: social media researchers for further analyses (“social good”)
- Data: Tweets from Guanajuato, a touristy city in central Mexico, collected as part of the SenseCityVity project at EPFL [1]
- Focuses: ~~Data analysis~~, machine learning, visualization

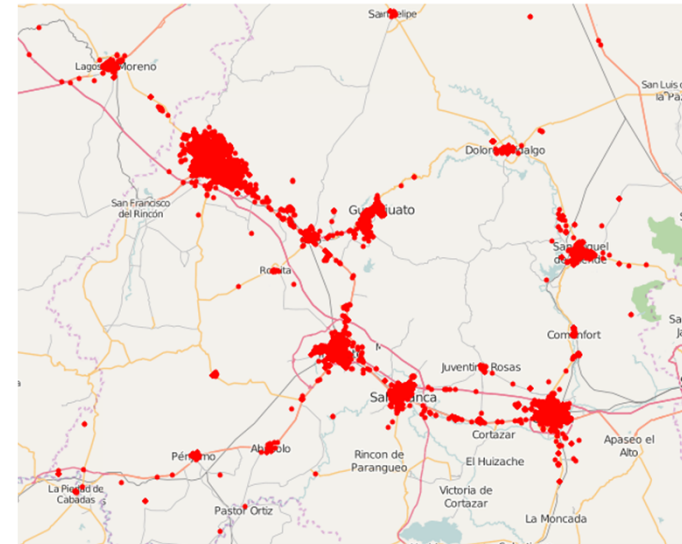
Outline

- 1. Preliminary Data Statistics**
- 2. Analytical Pipeline**
 - 2.1 Data Preparation**
 - 2.2 Syntactical Analysis**
 - 2.3 Semantic Analysis**
 - 2.4 Event Detection**
- 3. Potential Analyses**

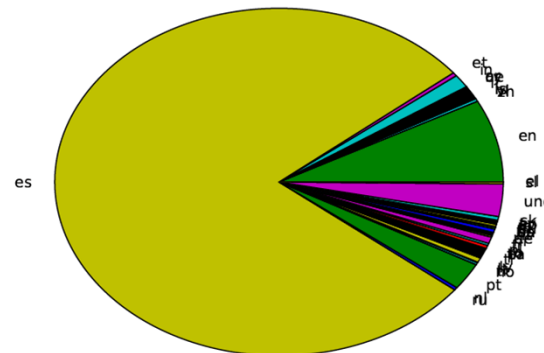
1. Preliminary Data Statistics



Tweet Count (~6K/day)
09/04/2014 -> 05/06/2014

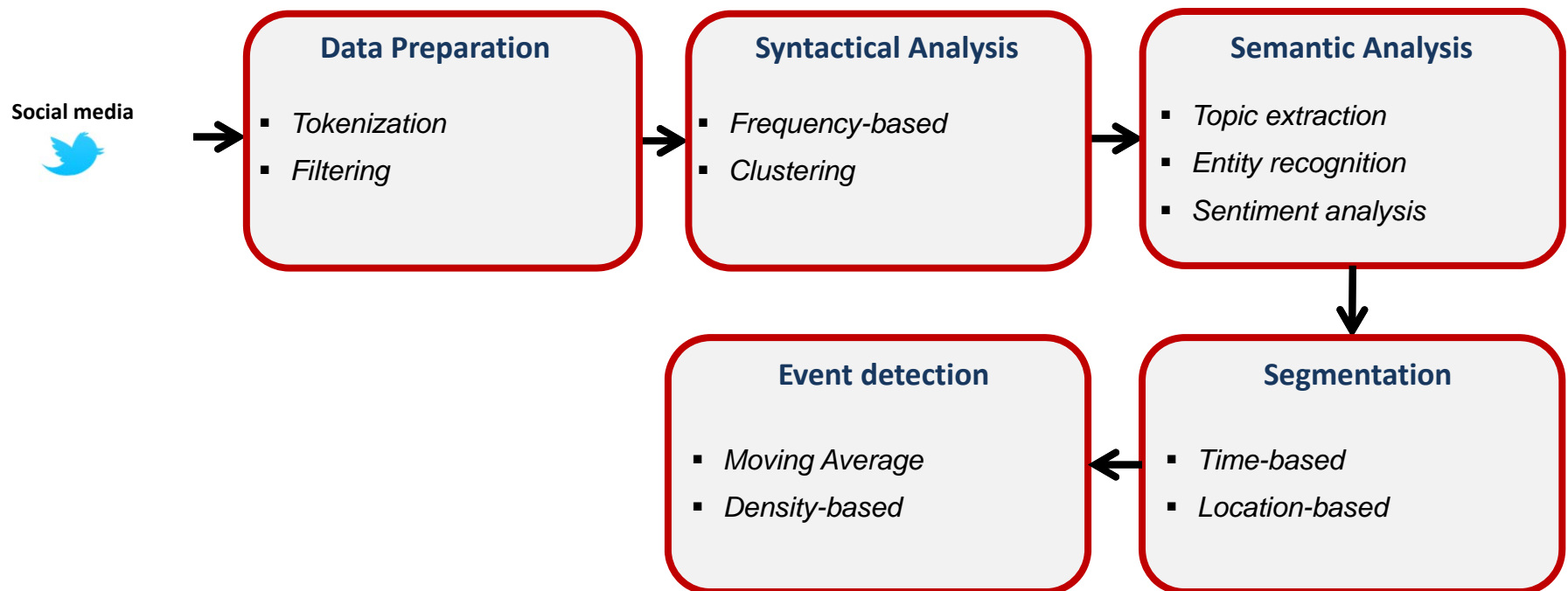


Geographic Distribution



Language Distribution (en = 7.7%, es = 78.52%, total=334836)

2. Analytical Pipeline



- Emoticons: eyes [:=;], nose [oO\~]?, mouth [D\)\)\(\)\^\/OpP]

- HTML tags: <[^>]+>
- @-mentions: (?:@[\\w_]+)
- #hashtags: (?:\\#+[\\w_]+[\\w'_-]*[\\w_]+)
- #numbers: (?:((?:\\d+,?)+(?:\\.?\\d+)?)?)
- #words with - and ' : (?:[a-z][a-z'\\-_]+[a-z])
- #other words: (?:[\\w_]+)
- #anything else: (?:\\S)

- stop words (NLTK English corpus), punctuation, special characters

- n-grams (NLTK library): keep phrases of 2,3, etc. words
- hashtag_only: keep only hashtag

Data Preparation: Example

Input

@KunderaQuotes you're my favorite writer ♥️

Everything that kills me makes me feel alive
<http://t.co/ifdqOkCPou>

My queen looks incredible, love her more than
anything #katyperry #iheartradio @ Reality
<http://t.co/jrxEiHxMOa>

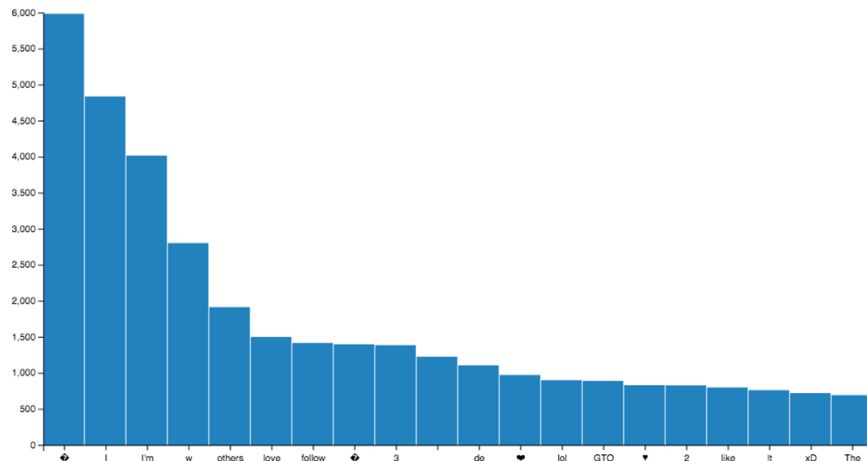
Output

you're my favorite writer

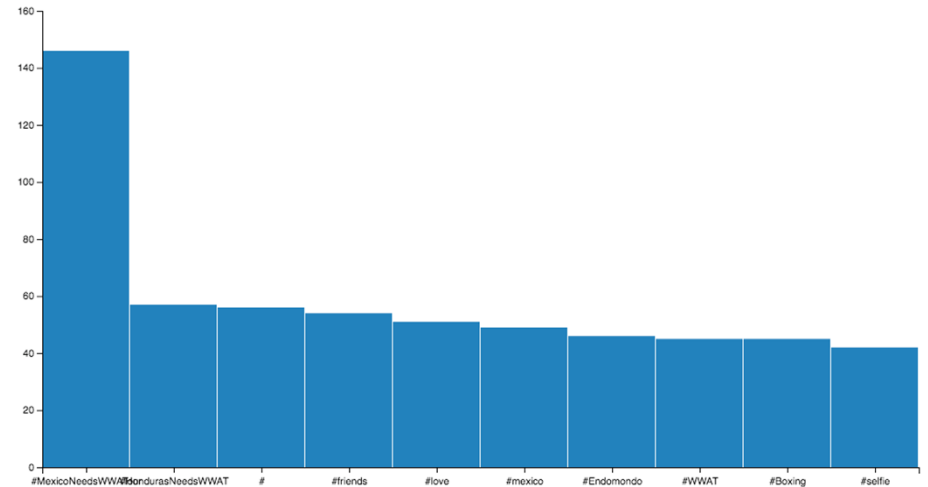
Everything kills makes feel alive

My queen looks
incredible love anything

2.2. Syntactical Analysis



Top 20-terms (love, follow, like)



Top-10 hashtags (#WWAT, #Boxing, #Endomondo)

1.00	0.33	0.33	0.67	0.33
0.17	1.00	0.33	0.33	0.33
0.20	0.40	1.00	0.80	0.40
0.33	0.33	0.67	1.00	0.50
0.25	0.50	0.50	0.75	1.00

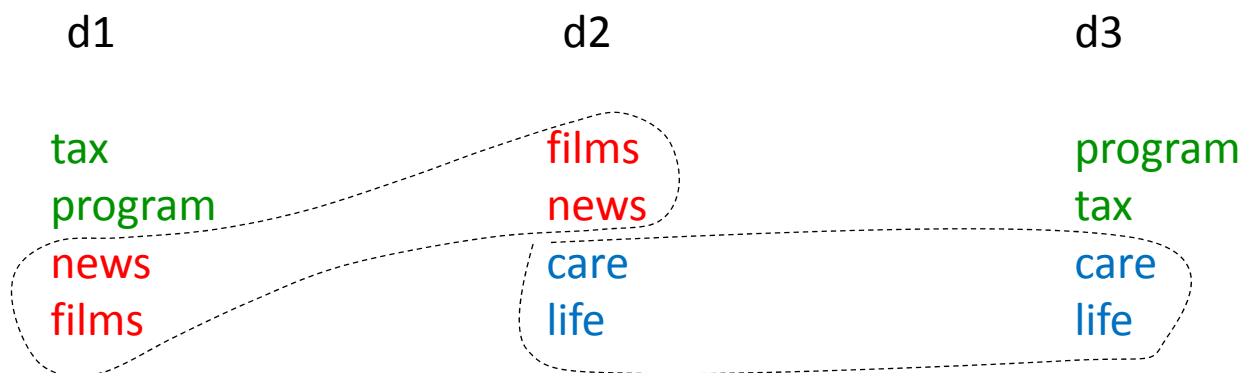
(#birthday, #katyperry)
 (#friends, #selfie)
 (#mexico, #sanmigueldeallende)

Co-occurrence

2.3. Semantic analysis: topic (Latent Dirichlet Allocation)

Input: tweets (bags of terms) + **tf/idf** (term frequency)

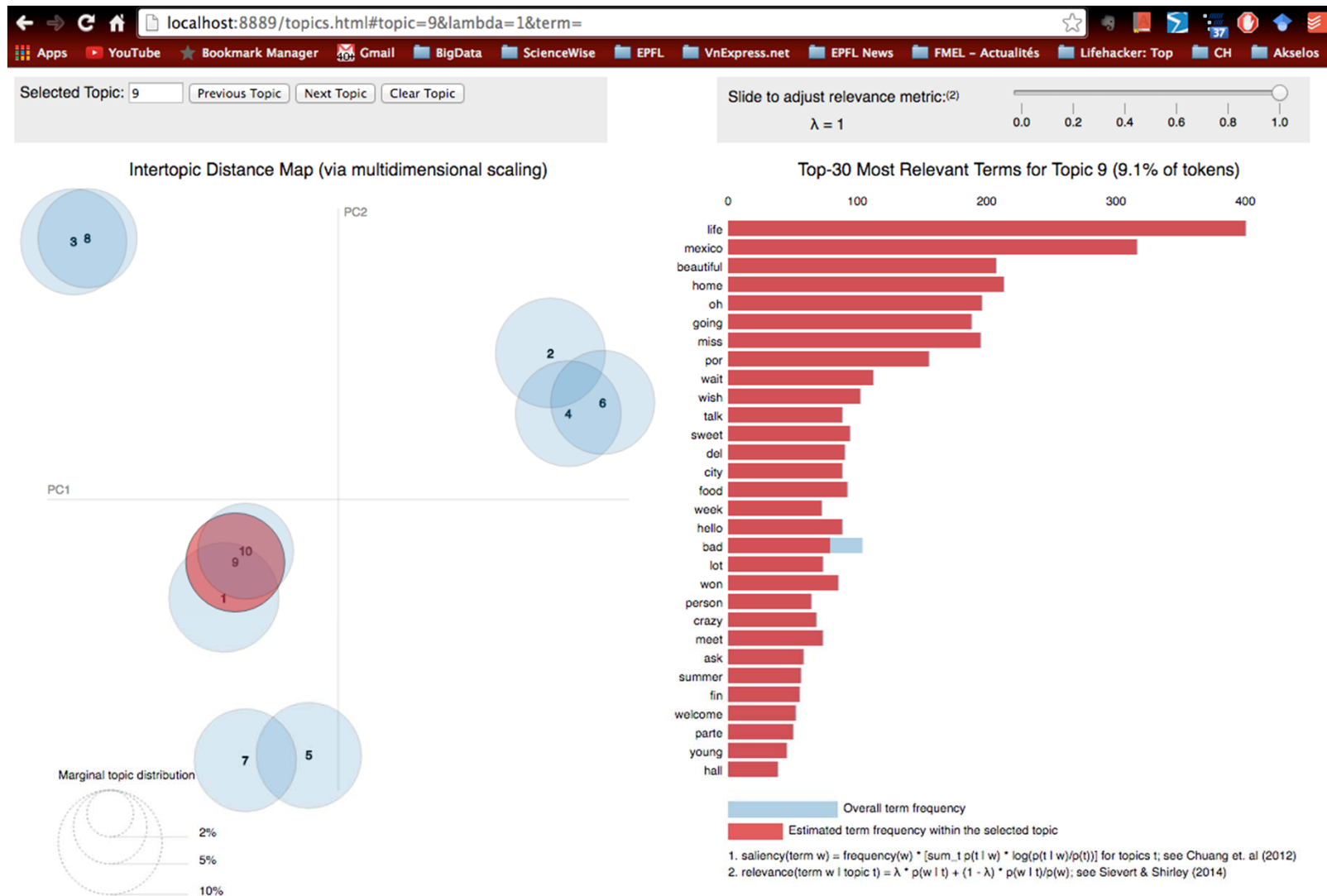
Output: 'clusters' of **co-occurring** words



Limitations:

- Sensitive to parameter K (#topics) → Hierarchical topic models [4] (non-parametric)
- Sensitive to short text → Twitter-LDA [5,6] (assumption: each tweet has 1 topic)

Topic modeling: user interface



Topic distance: Jensen-Shannon divergence with multidimensional downscale to 2 [10]

Semantic analysis: sentiment

Polarity (semantic orientation): user opinion in the text (positive, neutral, negative)

- Simple unsupervised method: co-occurrences with pre-defined positive/negative words (English lexicon [2])
- Supervised method: Python NLTK, Stanford classifiers

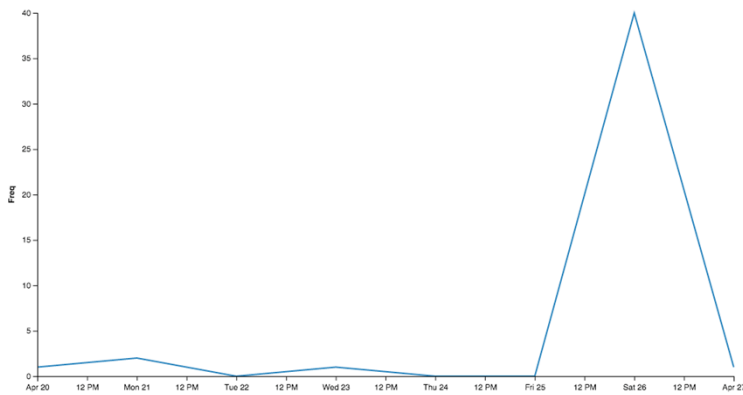
Term	Polarity
birthday	80.34
goodness	53.35
photograph	0
forecast	0
cigarettes	-40.39
bitch	-114.36

Polarity	#Documents
positive	1894
negative	8279
neutral	15617

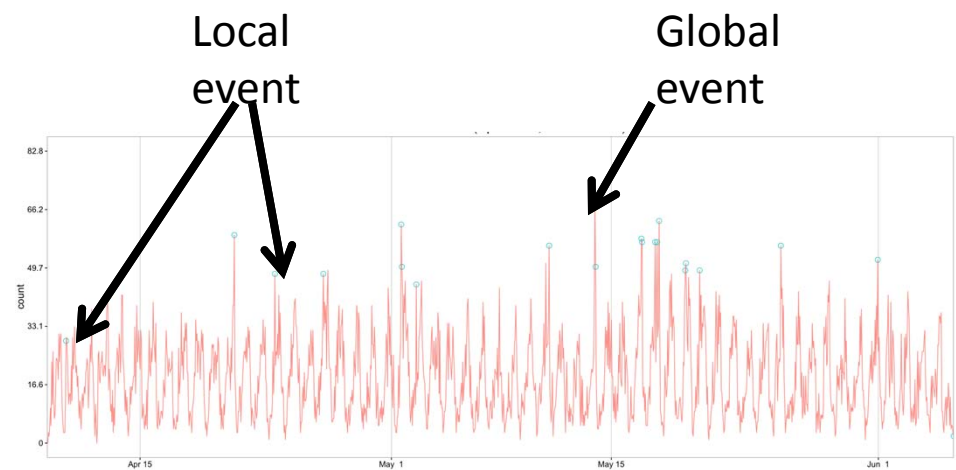
2.4. Event Detection

Event: different definitions

- Time-based: burst period of #topics
 - Manual observation
 - Automatic techniques [3]: moving average, box-and-whisker



Hashtag '#WWAT'



#Topics per tweet

Interactive UI

- Choose different algorithms
- Click and observe important tweets of that event

Moving Average



Box And Whisker



Event Detection (cont'd)

Event: different definitions

- Time-based: burst period of #topics
- Location-based: areas with high-density of #topics (tentative)
 - Step 1: Gridded topic counts (count unique tweets of given topic in an area using Twitter coordinates)
 - Step 2: Locate high-density areas



Conclusions

Take-home messages:

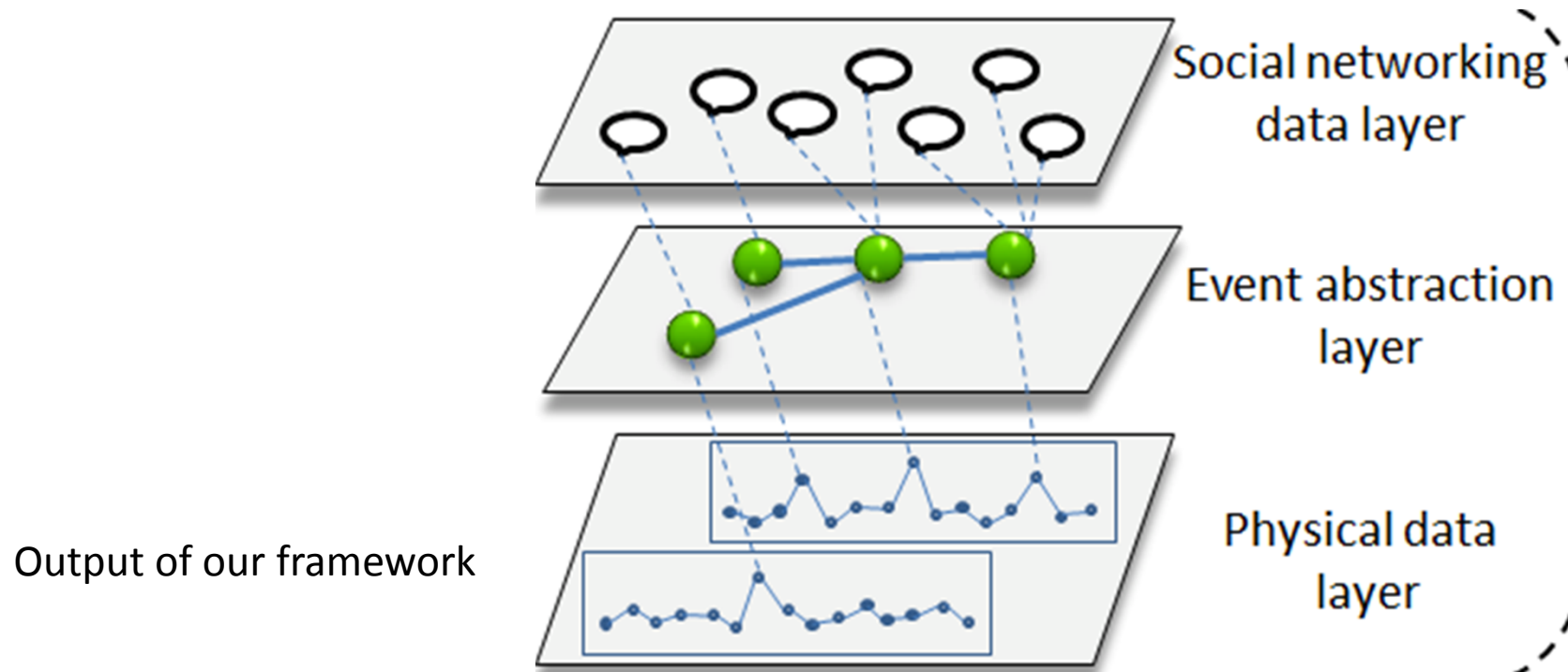
- An end-to-end and unified framework for event detection in social media (Twitter)
- <https://github.com/tamlhp/csm>

Limitations:

- Only a prototype
- English only (7.7% of Guanajuato data)

Future Work

1. Streaming version for Twitter API (online topic modeling [7], online event detection [8])
2. Complex event processing:
 - Aggregate small events into a complex event → more understanding
 - Techniques: formulation, abstraction, matching [9]



References

- [1] <http://www.idiap.ch/project/sensecityvity/>
- [2] <https://www.cs.uic.edu/~liub/FBS/sentiment-analysis.html#lexicon>
- [3] http://videolectures.net/icwsm2011_lee_detection/
- [4] <http://www.cse.ust.hk/~lzhang/teach/6931a/slides/3.HTM.pdf>
- [5] <http://users.cecs.anu.edu.au/~ssanner/Papers/sigir13.pdf>
- [6] Zhao, Wayne Xin, et al. "Comparing twitter and traditional media using topic models." *European Conference on Information Retrieval*. Springer Berlin Heidelberg, 2011.
- [7] Wang, Yu, Eugene Agichtein, and Michele Benzi. "TM-LDA: efficient online modeling of latent topic transitions in social media." *Proceedings of the 18th ACM SIGKDD international conference on Knowledge discovery and data mining*. ACM, 2012.
- [8] Abdelhaq, Hamed, Christian Sengstock, and Michael Gertz. "Eventtweet: Online localized event detection from twitter." *Proceedings of the VLDB Endowment* 6.12 (2013): 1326-1329.
- [9] Cameron, Mark A., et al. "Emergency situation awareness from twitter for crisis management." *Proceedings of the 21st International Conference on World Wide Web*. ACM, 2012.
- [10] <https://cran.r-project.org/web/packages/LDAvis/vignettes/details.pdf>

Demos

```
python -m SimpleHTTPServer 8889
```

http://localhost:8889/test.en.term_freq.html

http://localhost:8889/test.en.count_time_chart.html

http://localhost:8889/test.en.topic_time_chart.html

http://localhost:8889/test.en.term_freq.html

http://localhost:8889/test.count_time_chart.html

<http://localhost:8889/test.en.geo.html>

<http://localhost:8889/topics.html>

THANK YOU