Using social media indicators to study regional socio-economic resilience

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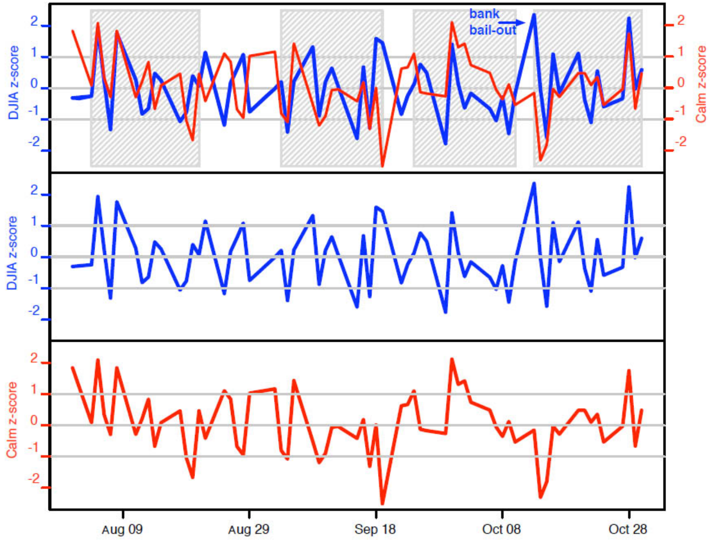
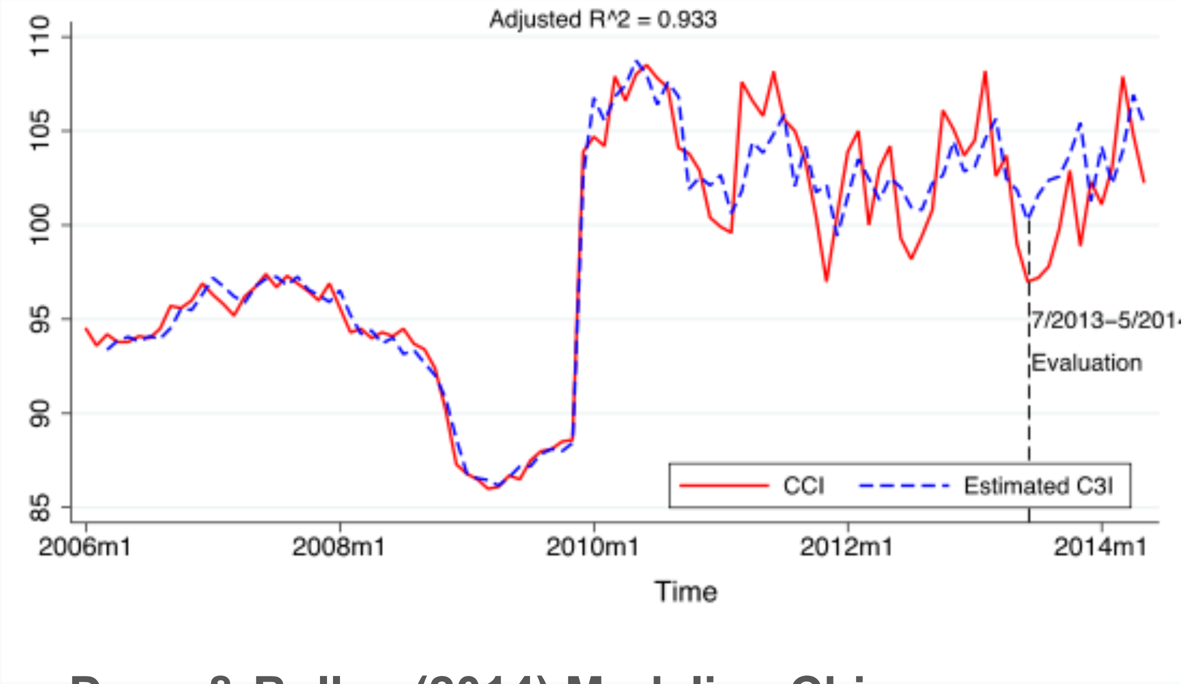
Modeling and predicting socio-economic phenomena from large-scale online data



Bollen et al (2011) Predicting market returns from social media sentiment



Dong & Bollen (2014) Modeling Chinese consumer confidence from online search data

Catch a black swan

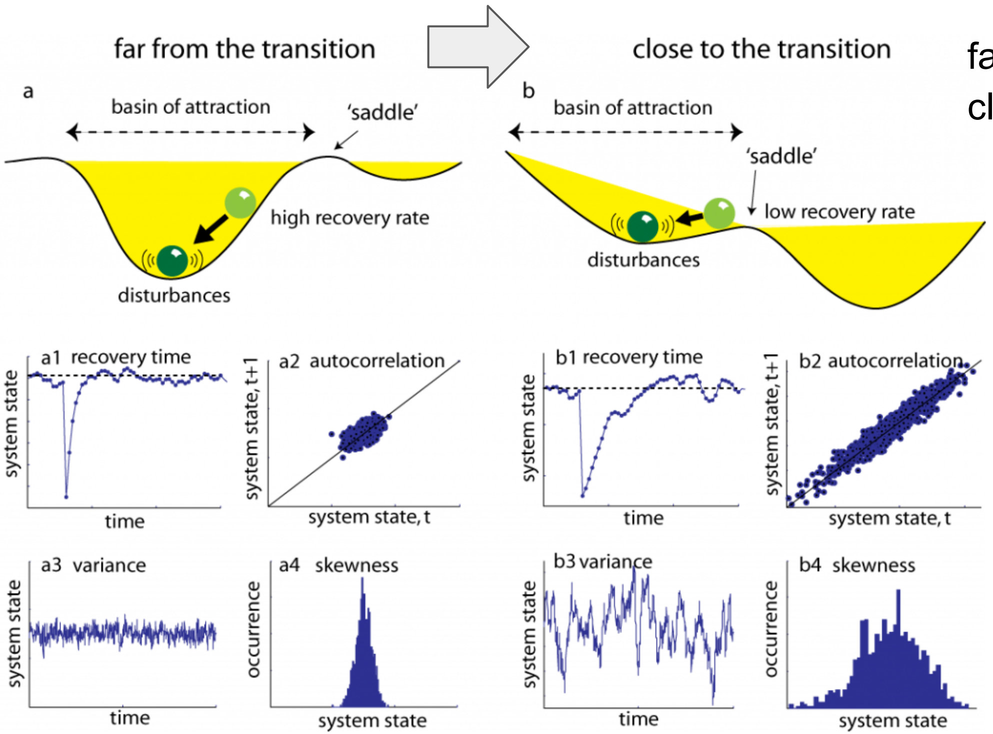
Statistical regularities of the relation between online indicators and socio-economic phenomena.

BUT, many socio-technical systems undergo rapid, difficult to predict, and infrequent transitions:

- Economic collapse
- Community collapse
- Social order collapse

=> may be more important to predict than overall dynamics

Early warning indicators of critical transitions



far from transition = High resilience = fast recovery

close to transition = low resilience = slow recovery

Early warning indicators:

- Increasing auto-correlation
- Variance

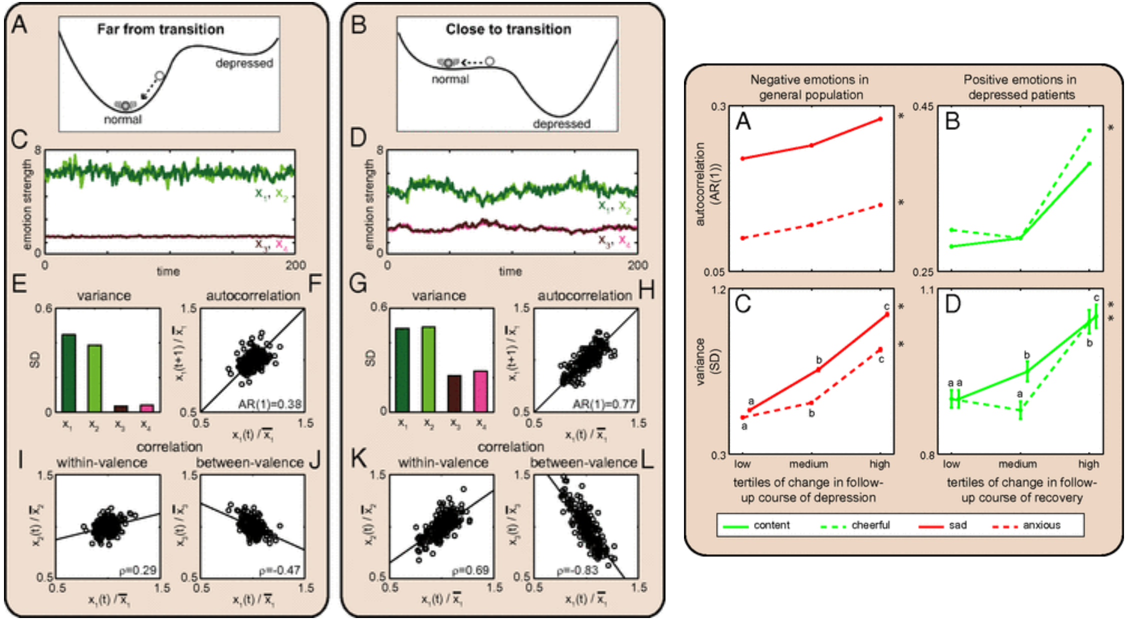
Quantitative early warning indicators from longitudinal dynamics of system parameters

http://www.early-warning-signals.org/

Scheffer et al (2012) Anticipating Critical Transitions. Science, 338(6105):344-348

Our approach

1. **Large-scale social media data**
2. Temporal patterns that express **social and economic resilience for a region**
3. **Early warning indicators** of potential transition



Van de Leemput et al (2014) **Critical slowing down as early warning for the onset and termination of depression.** PNAS January 7, 2014 111 (1) 87-92

Data and Processing

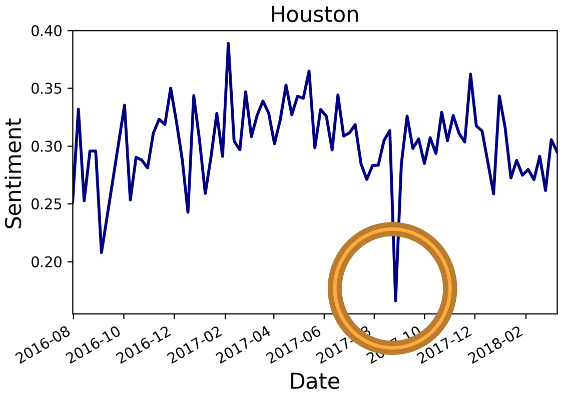
Twitter data
random 10%
daily

Indiana University
Network institute

Lon/Lat

Content
analysis

Time
stamp



Regional
early warning
indicators

"favorited": false,

"text": "One of my favorite Tony Gillian\u0027s!! #SexyVillian #MichealDrucker #MCM #MCE #tonygoldwyn @… https://t.co/I3lxtyMRYZ",

"created_at": "Mon Aug 01 17:15:45 -0400 2016",

"user_id_str": "77403942",

"user_screen_name": "Gladiator6082",

"retweet_count": 0,

"retweeted": false,

"source": "\u003ca href\u003d\"http://instagram.com\" rel\u003d\"nofollow\"\u003eInstagram\u003c/a\u003e",

"id_str": "760222511644680193",

"entities": {
"hashtags": [...],
"urls": [...],
},

"coordinates": {
"type": "Point",
"coordinates": [
-85.8445,
31.3275
]
},

"user": {...},

"place": {...}

CONTENT

TIME STAMP

GEO-LOCATION

VADER - *V*alence ***A***ware ***D***ictionary and s***E***ntiment ***R***easoner

- Best performer in large-scale benchmark (Ribeiro et al, 2016)
- Crowd-coursed valence lexicon (7,516 terms)
- 5 grammatical and syntactical rules geared towards social media

1. **Punctuation** (!) modifies intensity: “great” vs. “great**!!!!”**
2. **Capitalization** (all caps): “great” vs **“GREAT”**
3. **Degree Modifiers** (adjectives/ adverbs): “That was **really** great”
4. **Contrastive Conjunction** (but): “That was fun **but** I didn’t like it”
5. **Trigram** analysis to find negation: “That was not that great”

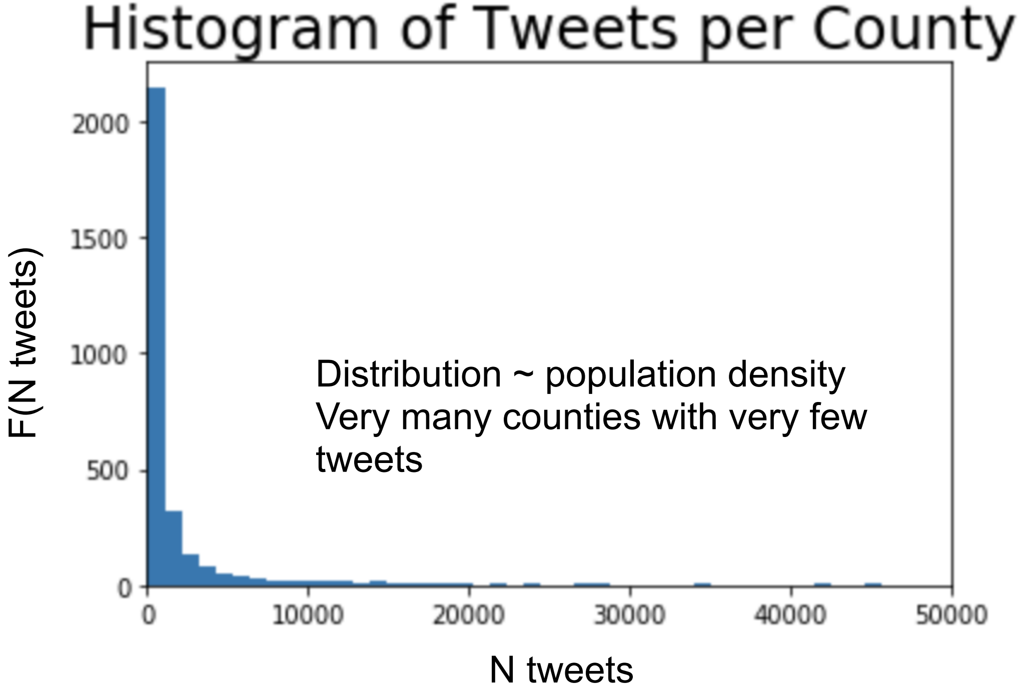
“Johan is smart, handsome, and funny.”
- Neg: 0.0, Neu: 0.254, Pos: 0.746
- **Compound: +0.8316**

“Today SUX!”
- Neg: 0.779, Neu: 0.221, Pos: 0.0
- Compound: -0.5461

C.J. Hutto and Eric Gilbert (2014) VADER: A Parsimonious Rule-based Model for Sentiment Analysis of Social Media Text. In ICWSM-14. Ann Arbor, MI, June 2014.

Our data

- 3,221 US counties (US Census Bureau 2010)
- 11,063,495 total tweets
- Mean 3434.8 Tweets/county
- 19 month period

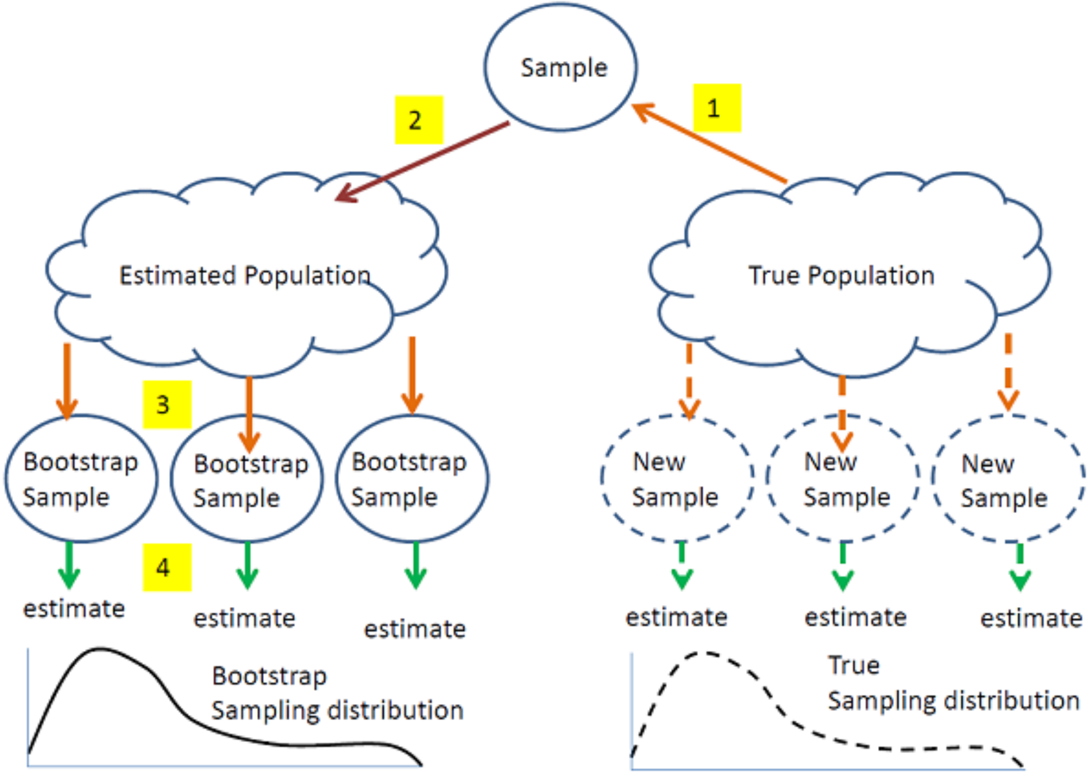


Most counties will few tweets, increasing uncertainty of our estimate of “average sentiment” at time t

Bootstrapping time series

Rationale: Twitter posts at irregular intervals, so different samples for each time window. Uncertainty estimated mean/ time?

- Bootstrap Twitter sample for each time period by randomly sampling with replacement
- 95% CIs expresses uncertainty



Face validity

Testing our regional sentiment signal for three cities

- **Florida (Sep 2017)**
- **Houston (Aug 2017)**
- **Puerto Rico (Sep 2017)**

Significant sentiment change in areas when afflicted by hurricane

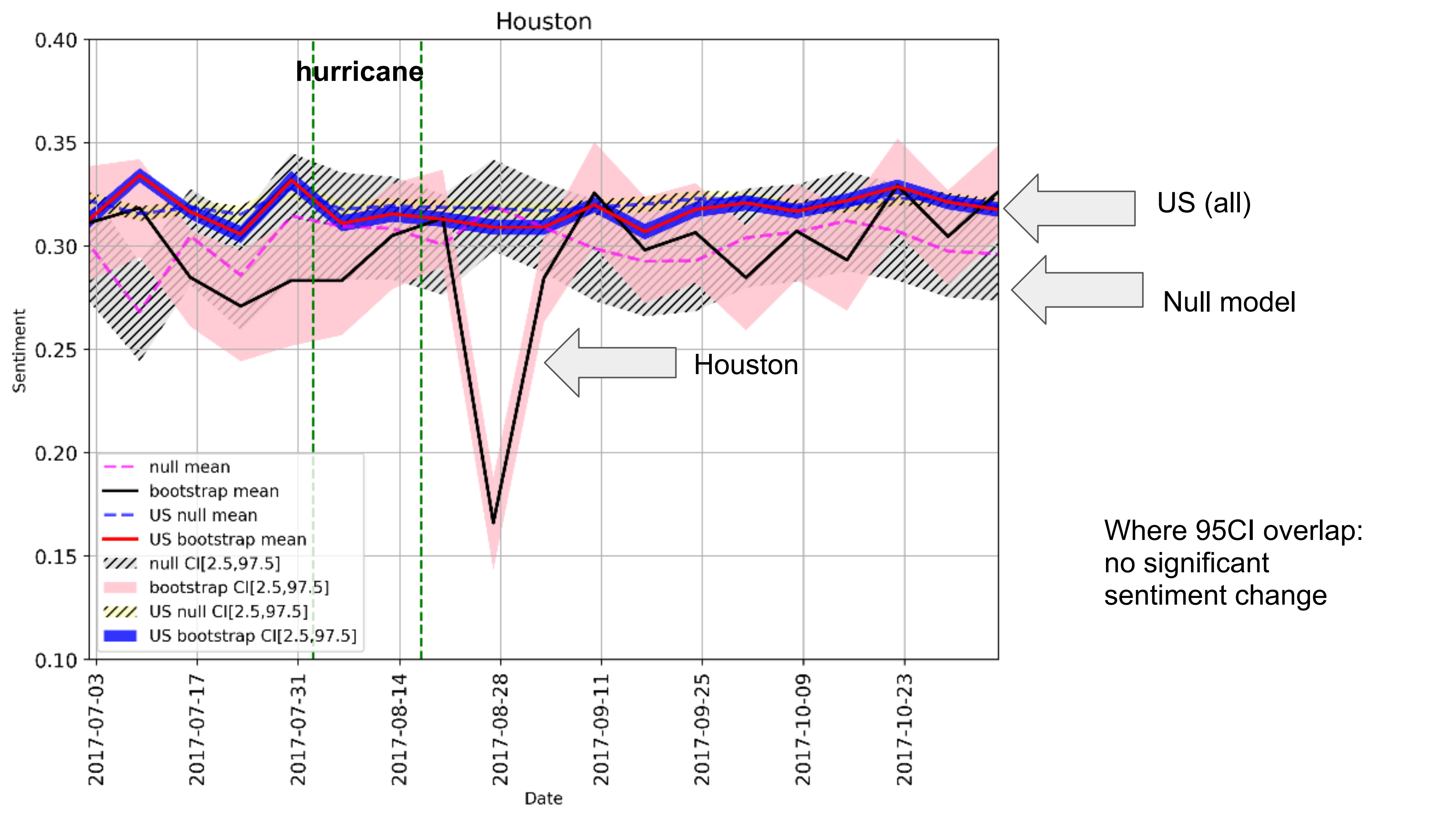
AND, counter-factual: no sentiment change in unaffected areas?

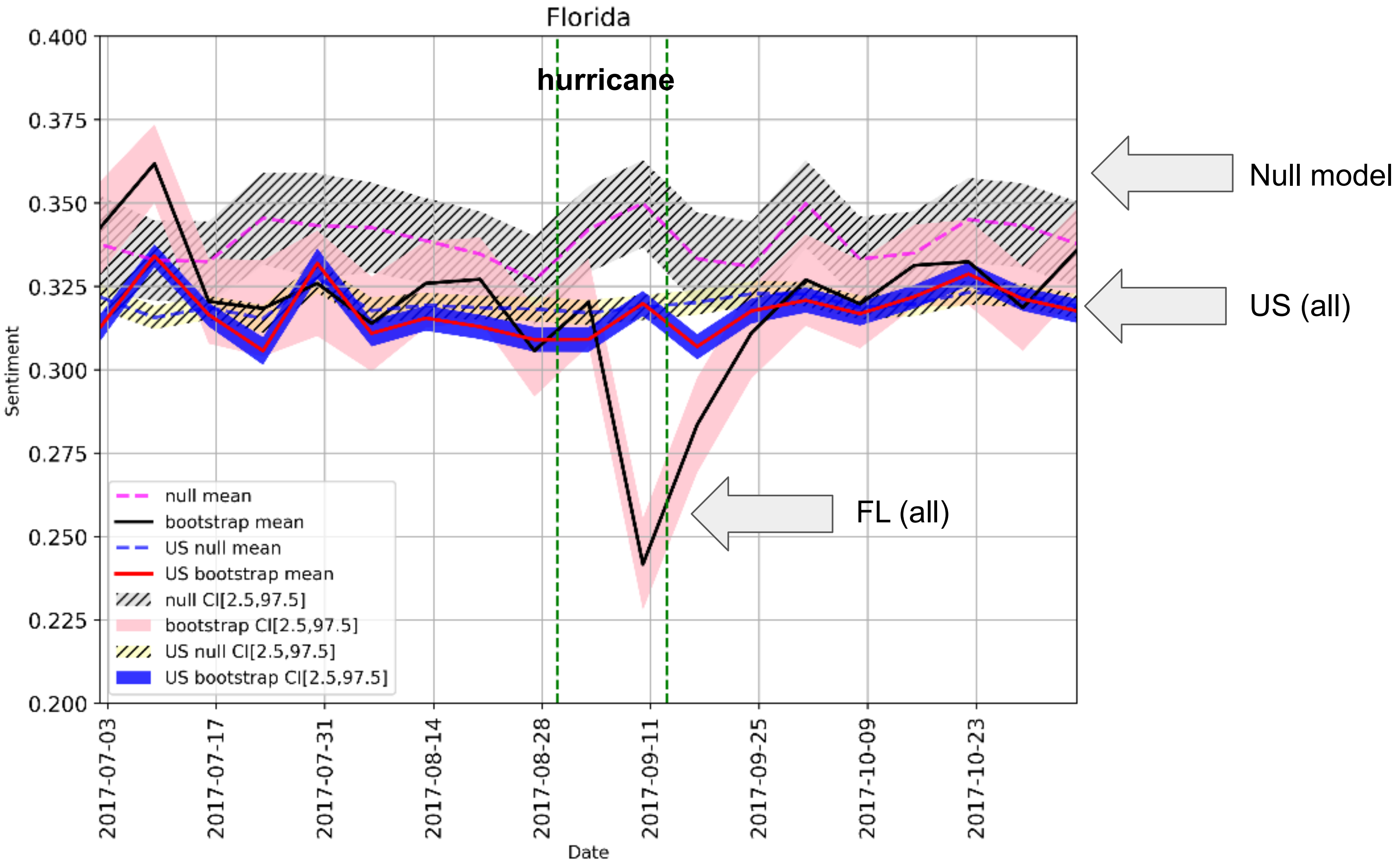
Compare sentiment levels at time t to appropriate null-models for same time t:

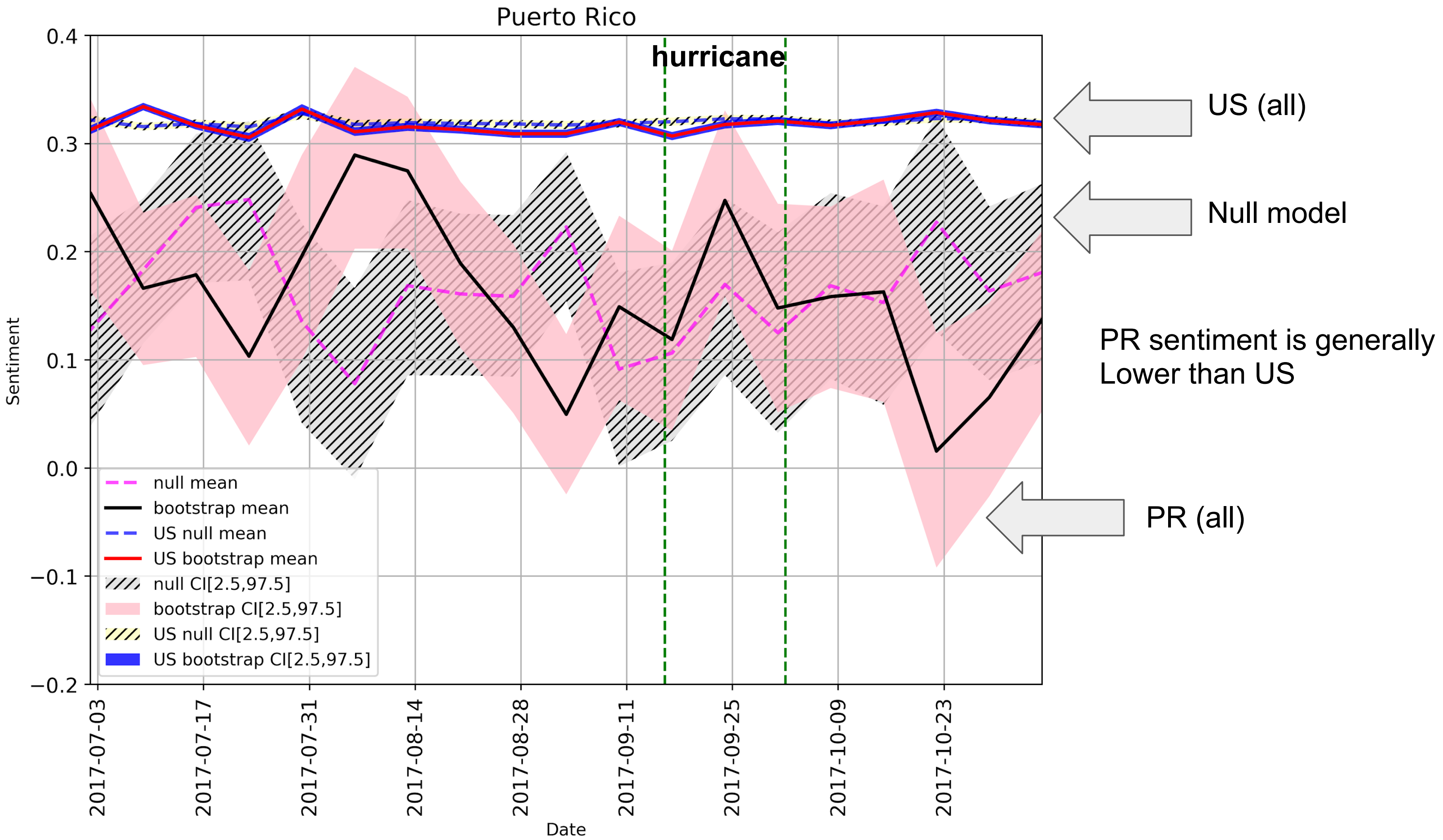
(1) bootstrap sentiment time series to estimate 95% CI (N=10,000)
(2) US baseline (all counties)
(3) Null-model: random selection of tweets with same ”day of week distribution”

Su	M	T	W	Th	F	S
20	22	30	30	35	45	59

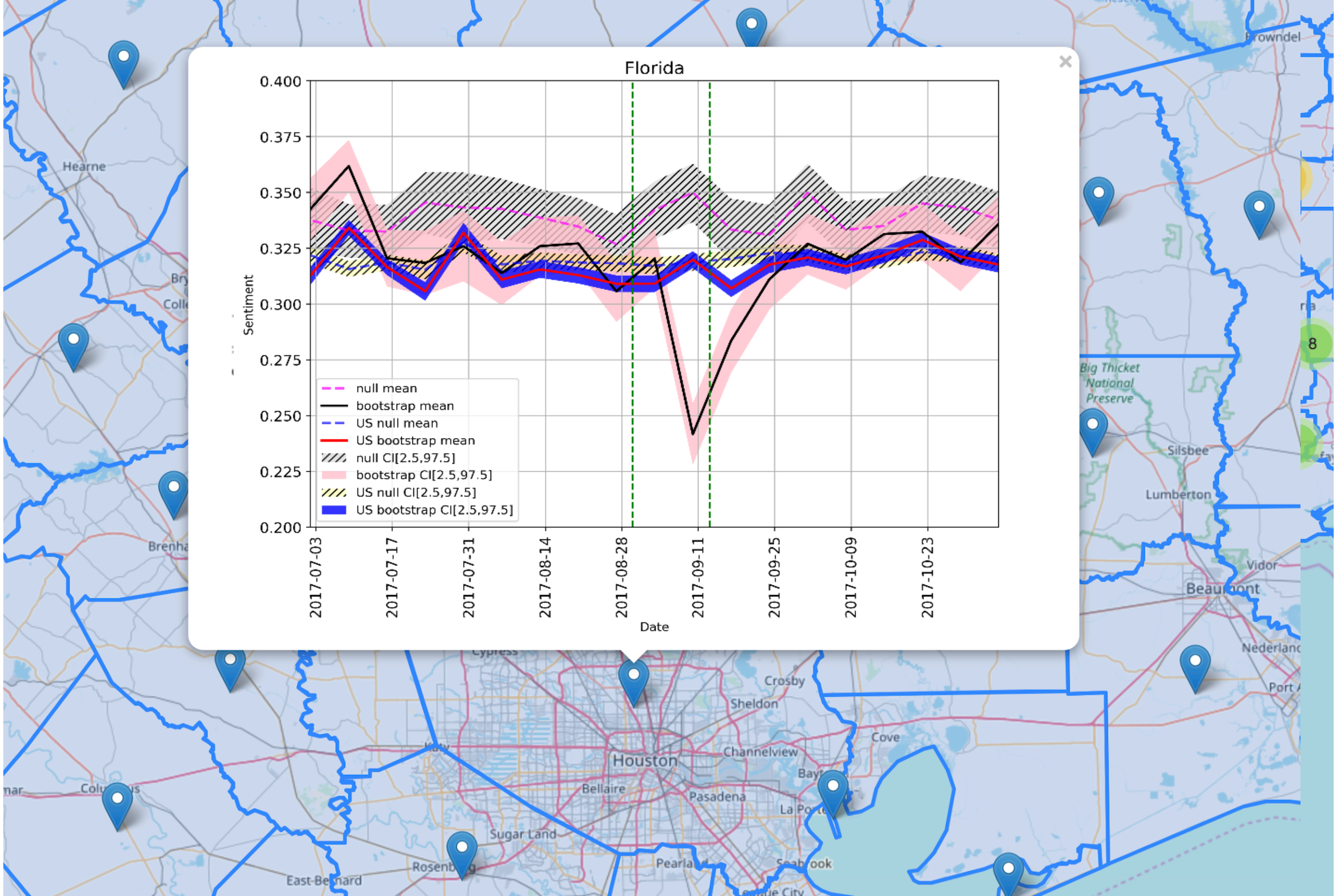
Null-model follows same distribution to mitigate weekly cycles


Houston
hurricane
US (all)
Null model
Houston
Sentiment
Date
0.40
0.35
0.30
0.25
0.20
0.15
0.10
2017-07-03
2017-07-17
2017-07-31
2017-08-14
2017-08-28
2017-09-11
2017-09-25
2017-10-09
2017-10-23
null mean
bootstrap mean
US null mean
US bootstrap mean
null CI[2.5,97.5]
bootstrap CI[2.5,97.5]
US null CI[2.5,97.5]
US bootstrap CI[2.5,97.5]
Where 95CI overlap:
no significant
sentiment change


Florida
hurricane
0.400
0.375
0.350
0.325
0.300
0.275
0.250
0.225
0.200
Sentiment
2017-07-03
2017-07-17
2017-07-31
2017-08-14
2017-08-28
2017-09-11
2017-09-25
2017-10-09
2017-10-23
Date
null mean
bootstrap mean
US null mean
US bootstrap mean
null CI[2.5,97.5]
bootstrap CI[2.5,97.5]
US null CI[2.5,97.5]
US bootstrap CI[2.5,97.5]
Null model
US (all)
FL (all)



Puerto Rico
hurricane
Sentiment
Date
0.4
0.3
0.2
0.1
0.0
−0.1
−0.2
2017-07-03
2017-07-17
2017-07-31
2017-08-14
2017-08-28
2017-09-11
2017-09-25
2017-10-09
2017-10-23
null mean
bootstrap mean
US null mean
US bootstrap mean
null CI[2.5,97.5]
bootstrap CI[2.5,97.5]
US null CI[2.5,97.5]
US bootstrap CI[2.5,97.5]
US (all)
Null model
PR sentiment is generally
Lower than US
PR (all)


Florida
0.400
0.375
0.350
0.325
0.300
0.275
0.250
0.225
0.200
Sentiment
2017-07-03
2017-07-17
2017-07-31
2017-08-14
2017-08-28
2017-09-11
2017-09-25
2017-10-09
2017-10-23
Date
null mean
bootstrap mean
US null mean
US bootstrap mean
null CI[2.5,97.5]
bootstrap CI[2.5,97.5]
US null CI[2.5,97.5]
US bootstrap CI[2.5,97.5]
Hearne
Big Thicket
National
Preserve
Silsbee
Lumberton
Vidor
Crosby
Sheldon
Cove
Channelview
Houston
Bellaire
Pasadena
Sugar Land
East Bernard
8

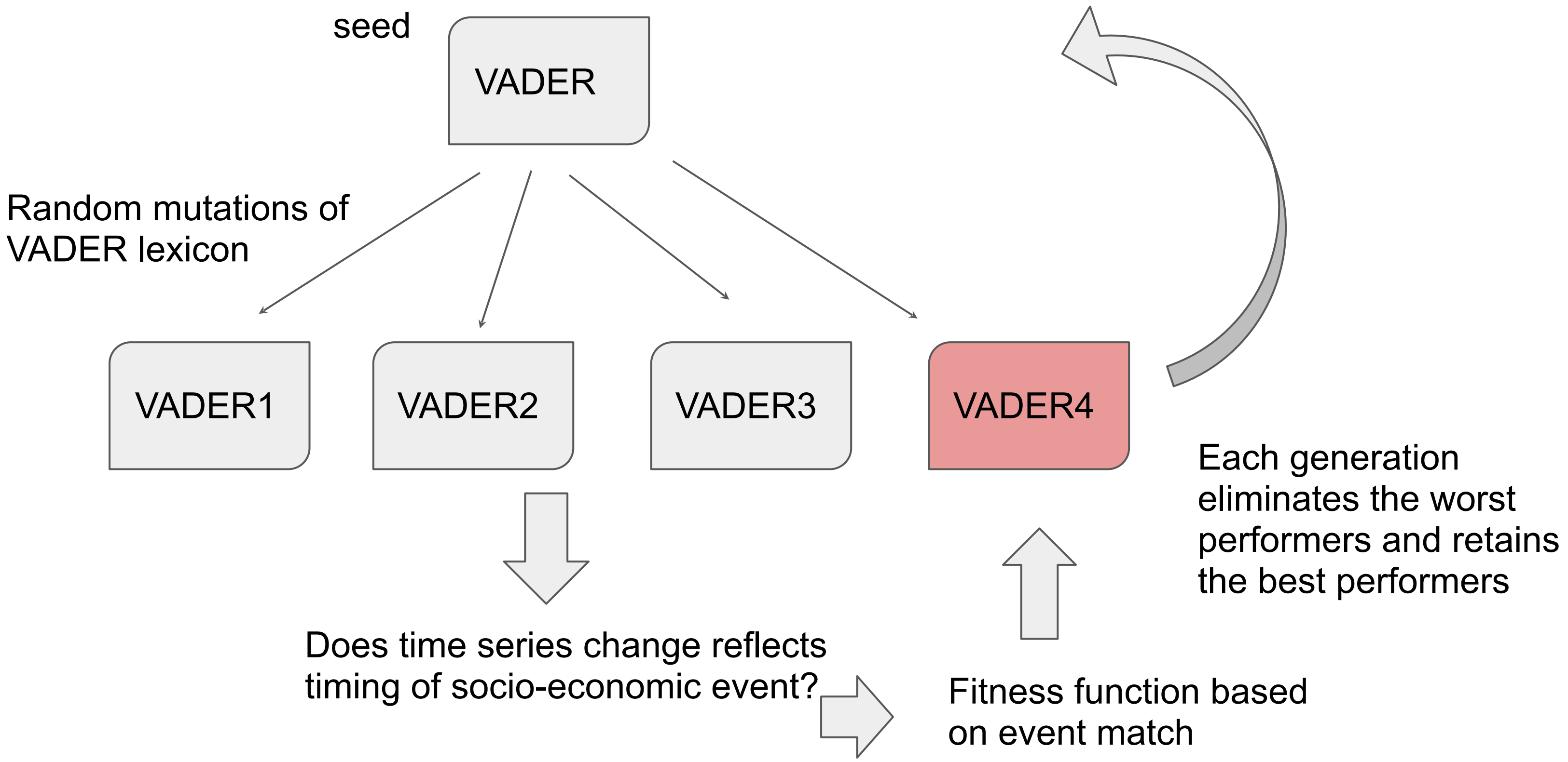
Beyond valence

Valence is very broad category of sentiment, but how about...

- Culture and collective personality
- Specific socio-economic trends, e.g. unrest, dissatisfaction, apprehension, confidence

General approach:

- Pick specific event with **ground truth of event occurrence at given time t**, e.g Ferguson unrest
- “Breed” a NLP tool whose lexicon is specifically suited to generate the most specific signal with respect to the occurrence of that socio-economic phenomenon in time


seed
VADER
Random mutations of
VADER lexicon
VADER1
VADER2
VADER3
VADER4
Each generation
eliminates the worst
performers and retains
the best performers
Does time series change reflects
timing of socio-economic event?
Fitness function based
on event match

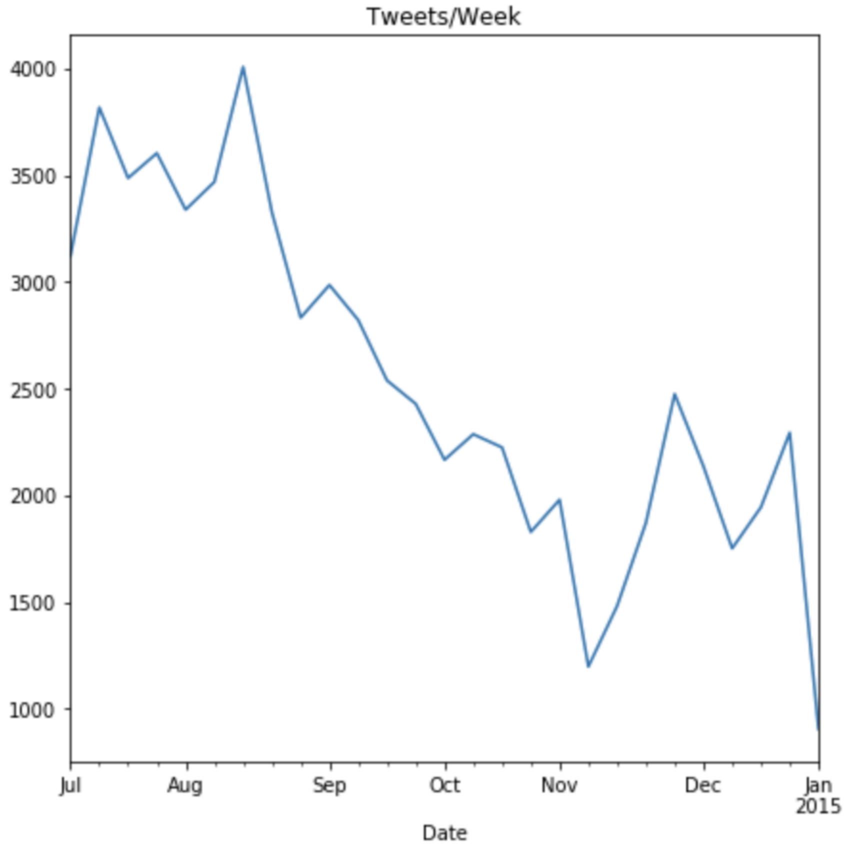
Breeding a “social unrest” indicator

Ferguson MO riots in 2016

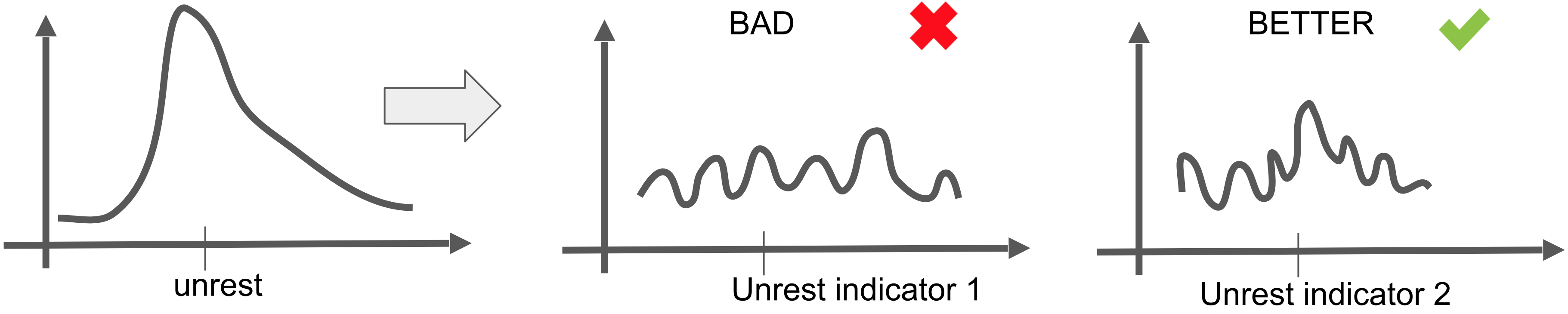
- All tweets in St. Louis county from July - December 2016
- N = 68,333 Tweets
- Mean weekly resamples
- Sentiment converted to Z-scores

$$z = \frac{x - \mu}{\sigma}$$

N

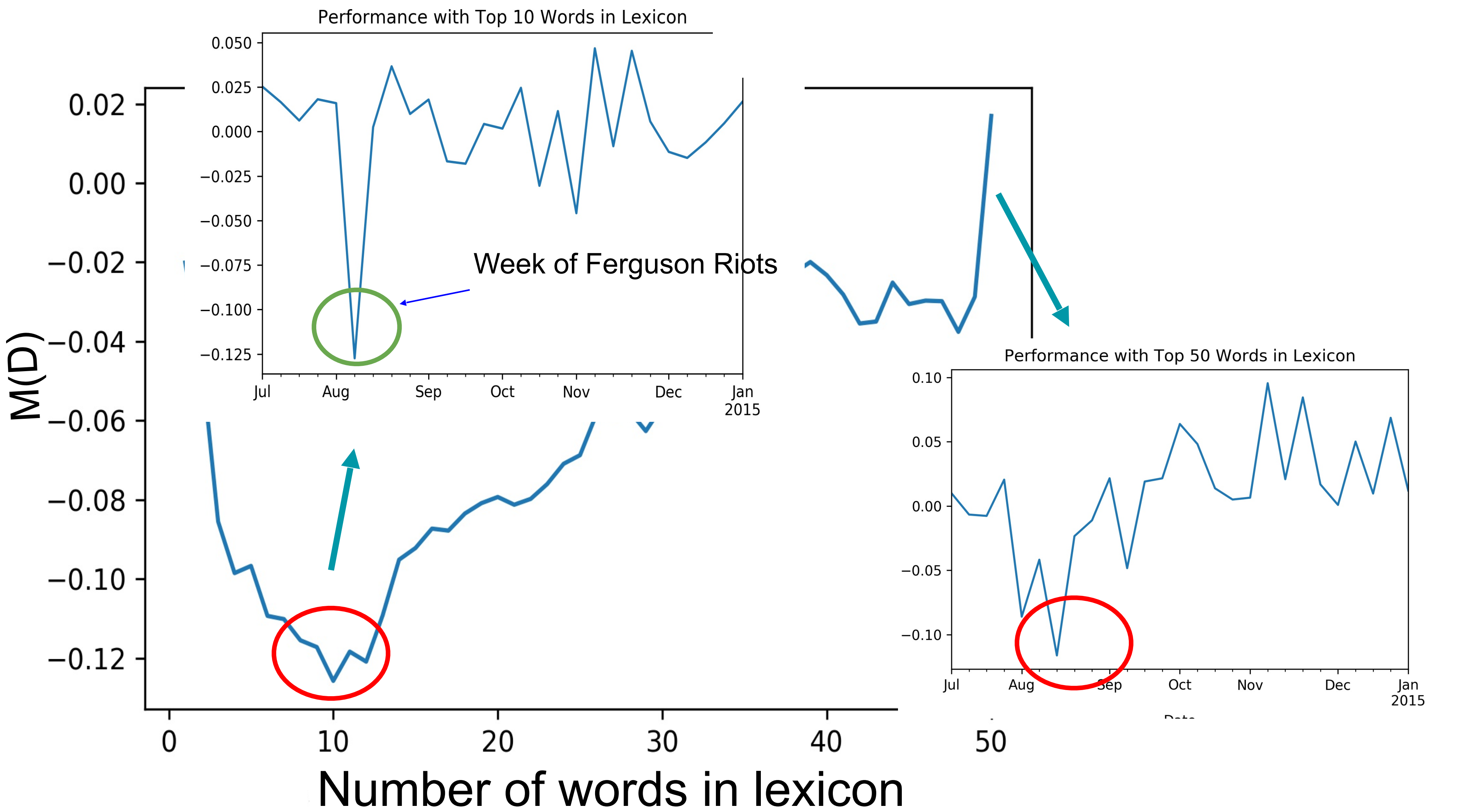


Fitness: does our indicator respond to social unrest?



$$M(D) = \mathcal{H} + \min(D.z) + \frac{|\arg\min_{D.w} D.z - D.w_R|}{|D.w_F - D.w_R|}$$

Binned Entropy (specificity) + Max value (response magnitude) + Ratio of distance from unrest of minimum value compared to the farthest difference



Performance with Top 10 Words in Lexicon
Week of Ferguson Riots
Performance with Top 50 Words in Lexicon
M(D)
Number of words in lexicon

Continuing work

We have the time series! Now:

- Train sentiment analyzer for recognition of other “black swans”: riots, emergencies, disasters, economic cycles
- Detection of critical transitions: early warning indicators?
- Contribution to EDA indicator of regional social and economic resilience

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