Mining Social Media

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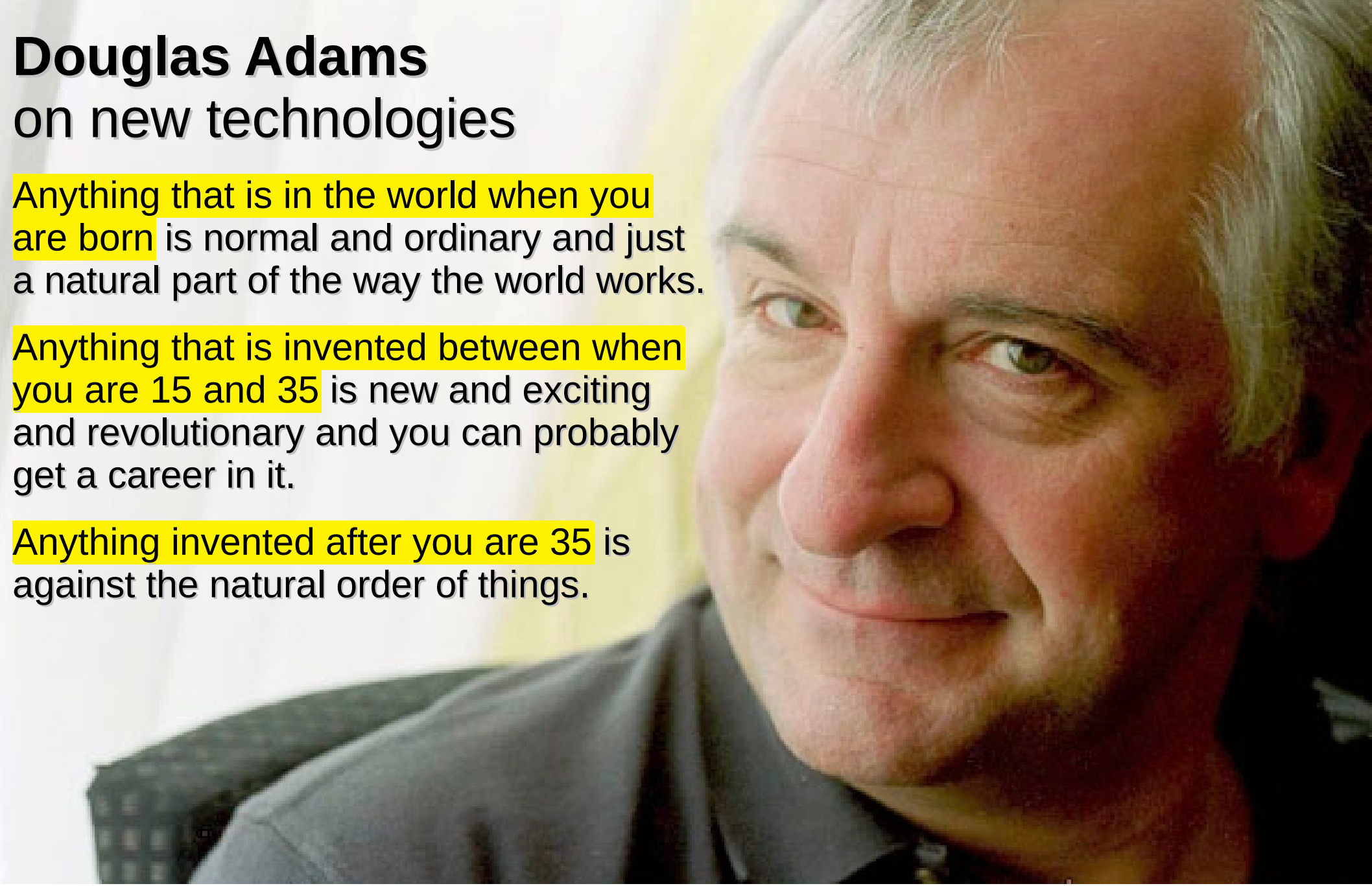
European Summer School in Information Retrieval
July 2019

Sources:
Some slides from “Twitter and the Real World” CIKM'13 Tutorial.
See also “Twitter: A Digital Socioscope” (2015) by Mejova, Weber, and Macy
Ghani et al. “Social media big data analytics: A survey” (2018).

upf. Universitat Pompeu Fabra Barcelona

Douglas Adams
on new technologies



Anything that is in the world when you are born is normal and ordinary and just a natural part of the way the world works.

Anything that is invented between when you are 15 and 35 is new and exciting and revolutionary and you can probably get a career in it.

Anything invented after you are 35 is against the natural order of things.

Definitions
Motivations
Caveats

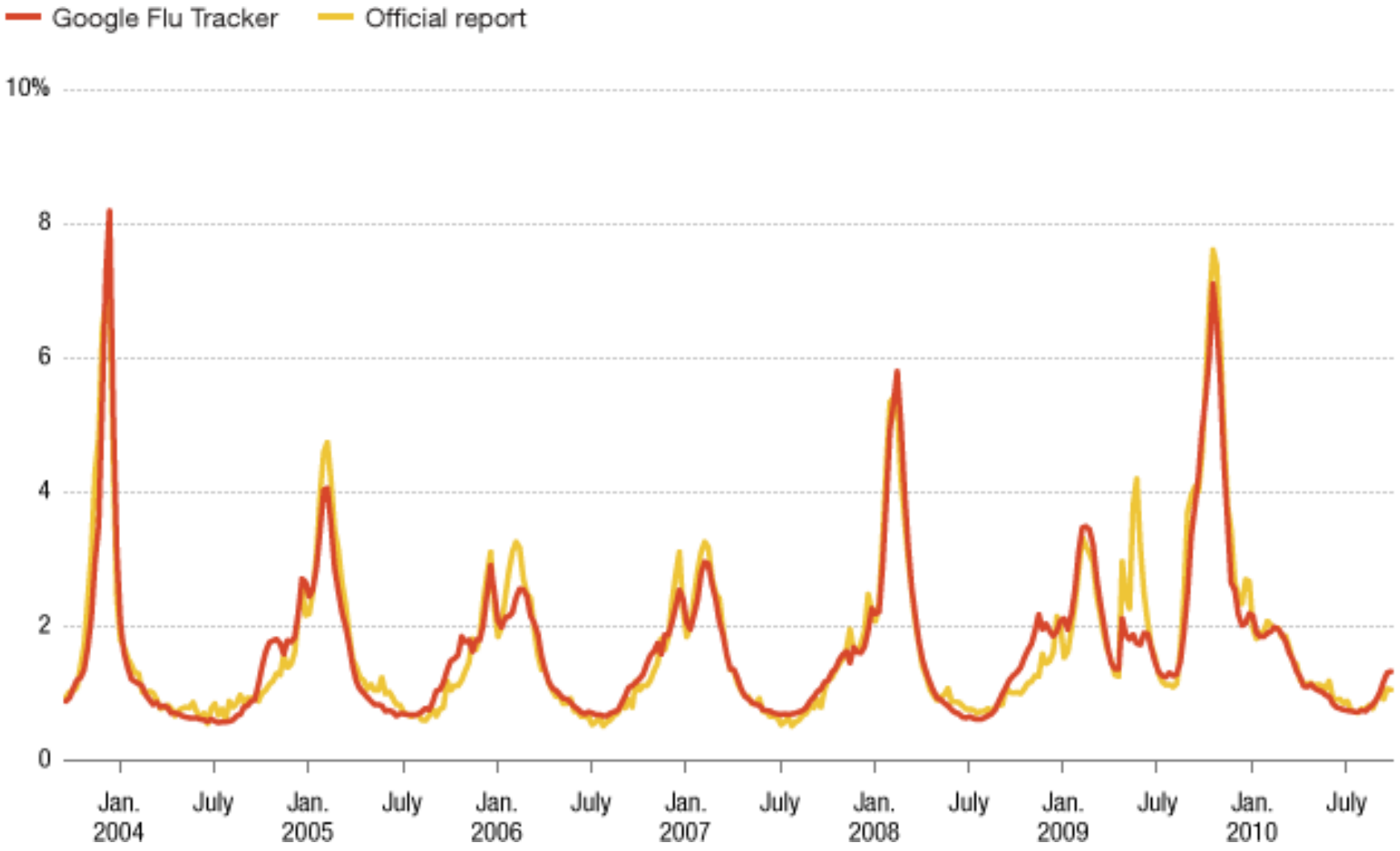
Definitions

- **Social software**
  - Software to facilitate or mediate social interactions
- **Social networking sites**
  - Sites allowing (semi-)public profiles, connections, and viewing/interacting with other people's activities [boyd & Ellison 2007]
- **User-generated content**
  - Content created by end-users of social software outside of their professional routine

Why mining social media?

- **Seen as an alternative to traditional opinion polls**
- *“What do people think about X?”*
- *“How do they feel about X?”*
  - First steps: sentiment analysis and opinion mining
- Attractive for many reasons including:
  - Lower latency (waiting time)
  - Lower cost
  - Larger population

Key example: Google Flu Trends



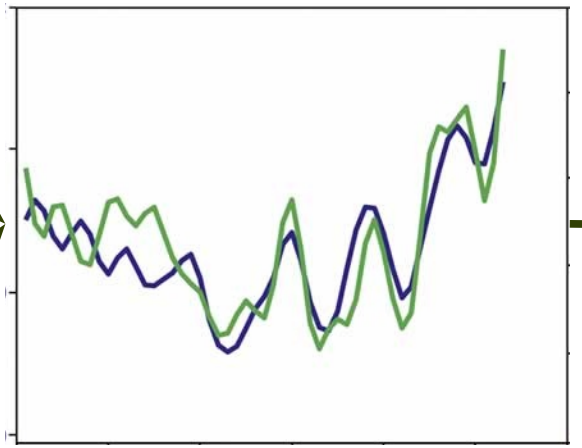
Low latency: people query symptoms before going to the doctor!

Many social media mining papers

1. Domain-specific data

2. Social media data

3. Correlation/Influence

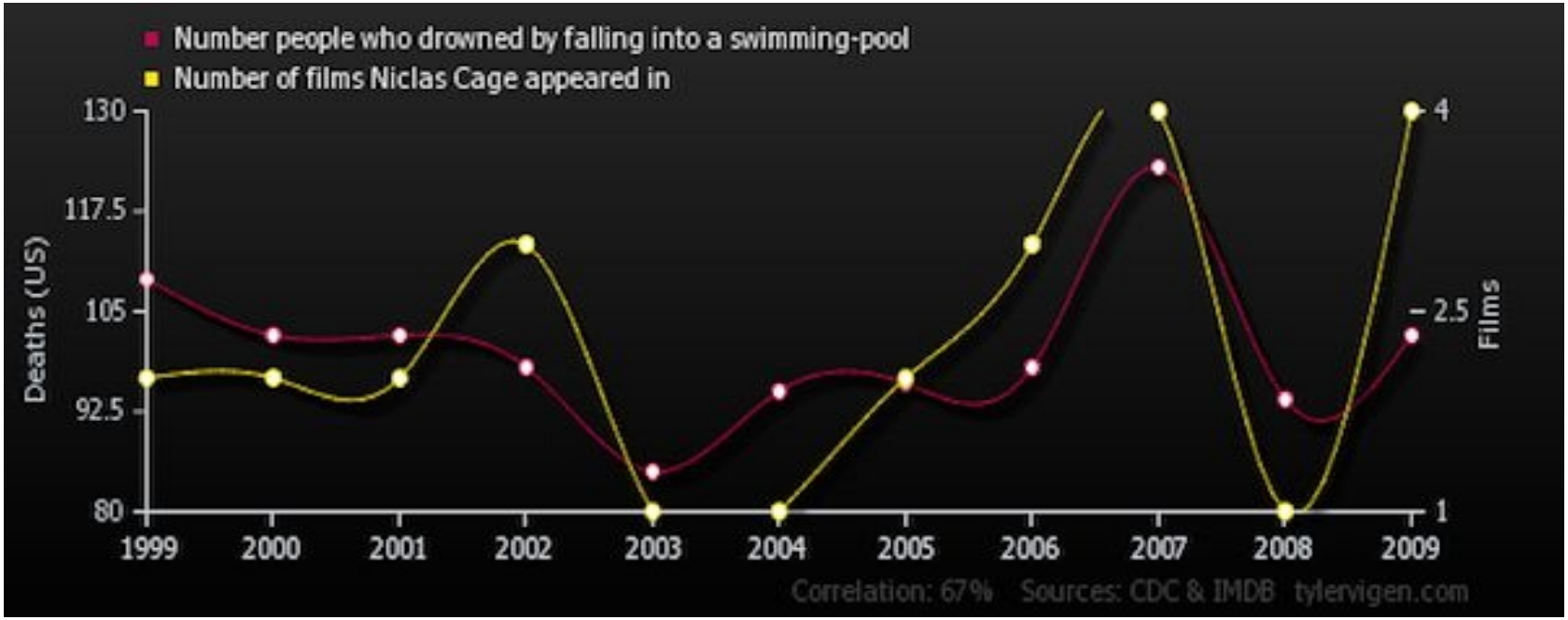


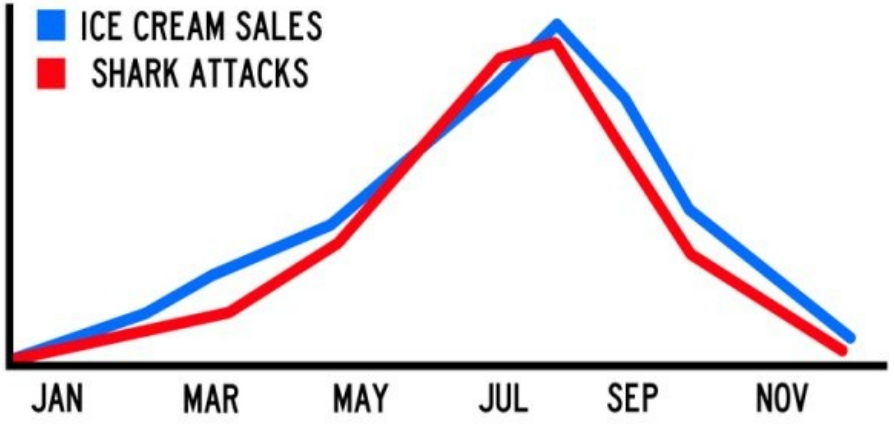
Profit?

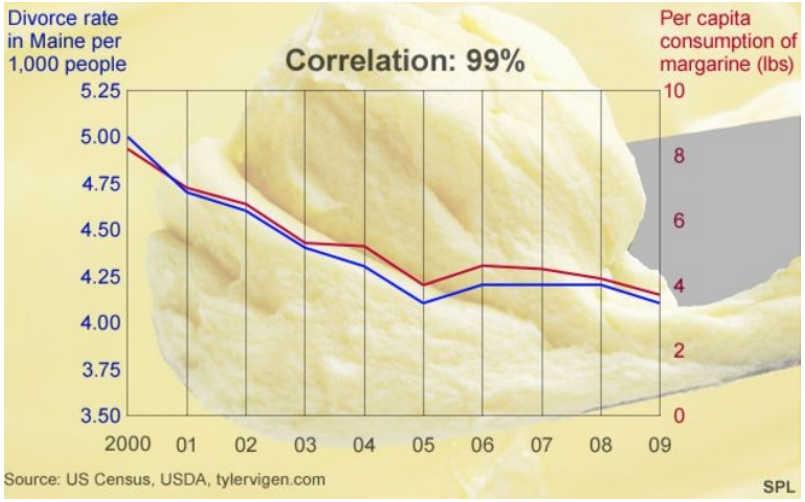
The devil is in the details

- Which domain-specific data?
  - This is not always readily available
  - Many biases can be introduced (see talk by Ricardo B.-Y.)
- Mapping social media data to a time series?
  - Geolocation of messages
  - Mapping to topics/sentiments/intents or other characteristics
  - What is the variable: Volume? Sentiment? Other?
- Measuring correlation/influence
  - Correlation (lagged); Transfer entropy
- Finding a causal mechanism

Caveat 1: correlation might be spurious







Caveat 2: correlation might be useless

- Sometimes there are much better predictors
- Social media can be used to predict box office revenue
  - But ticket sales on first weekend *almost* always determine total sales, with exceptions
    Citizen Kane (1941), Blade Runner (1982), Fight Club (1999)
- Social media can be used to detect earthquakes/floods
  - But sensors are quite dense in wealthy regions of the world

Caveat 3: the war on terror and “pink lists” (secondary use)

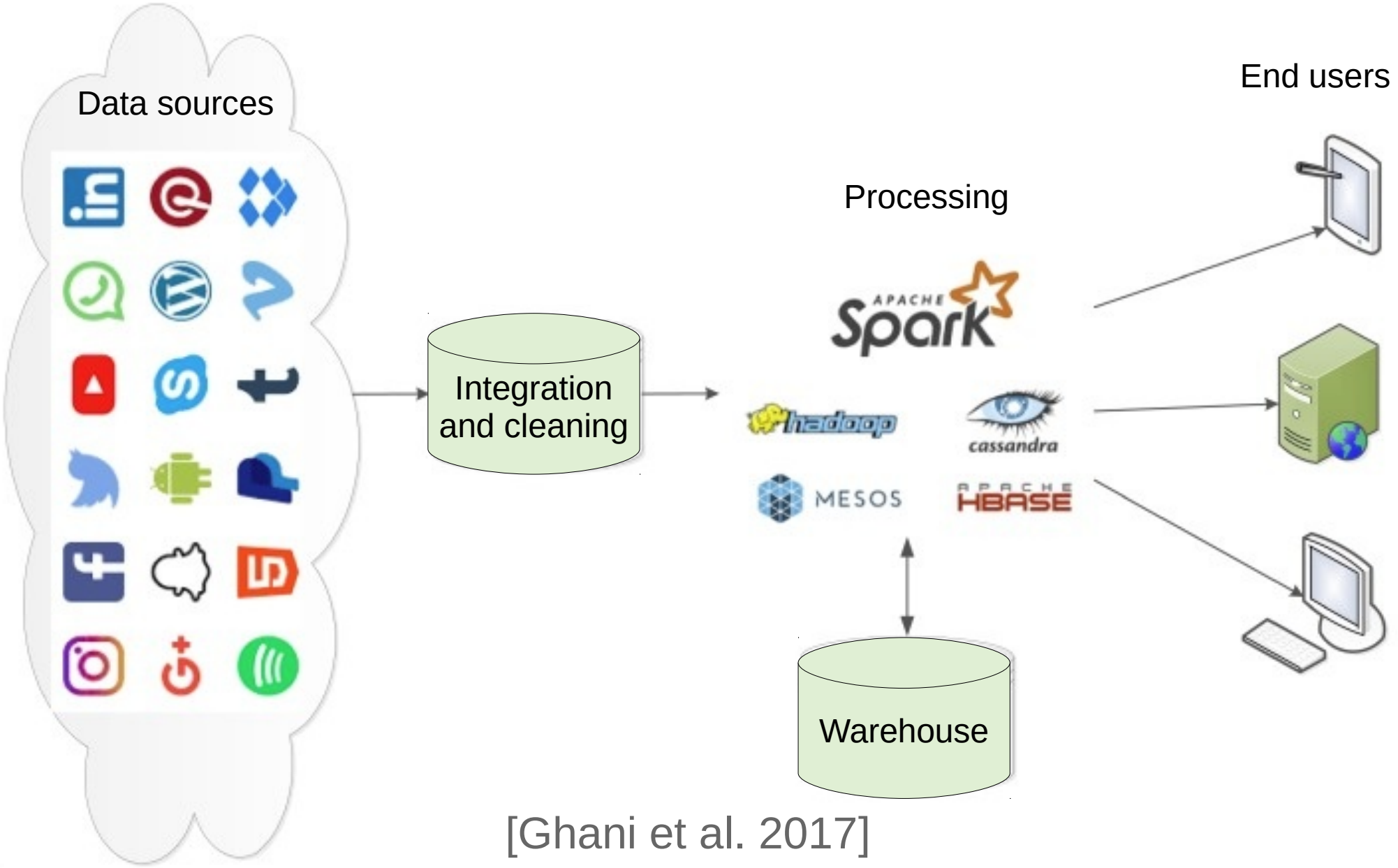
Applications
Methods
Architectures

Analysis of social media

- Most common **applications**
  - trend discovery, social media analytics, sentiment analysis, and opinion mining
- Most common **methods**
  - machine learning, particularly supervised classification and deep learning methods
- Most common **architectures** (see next slide)

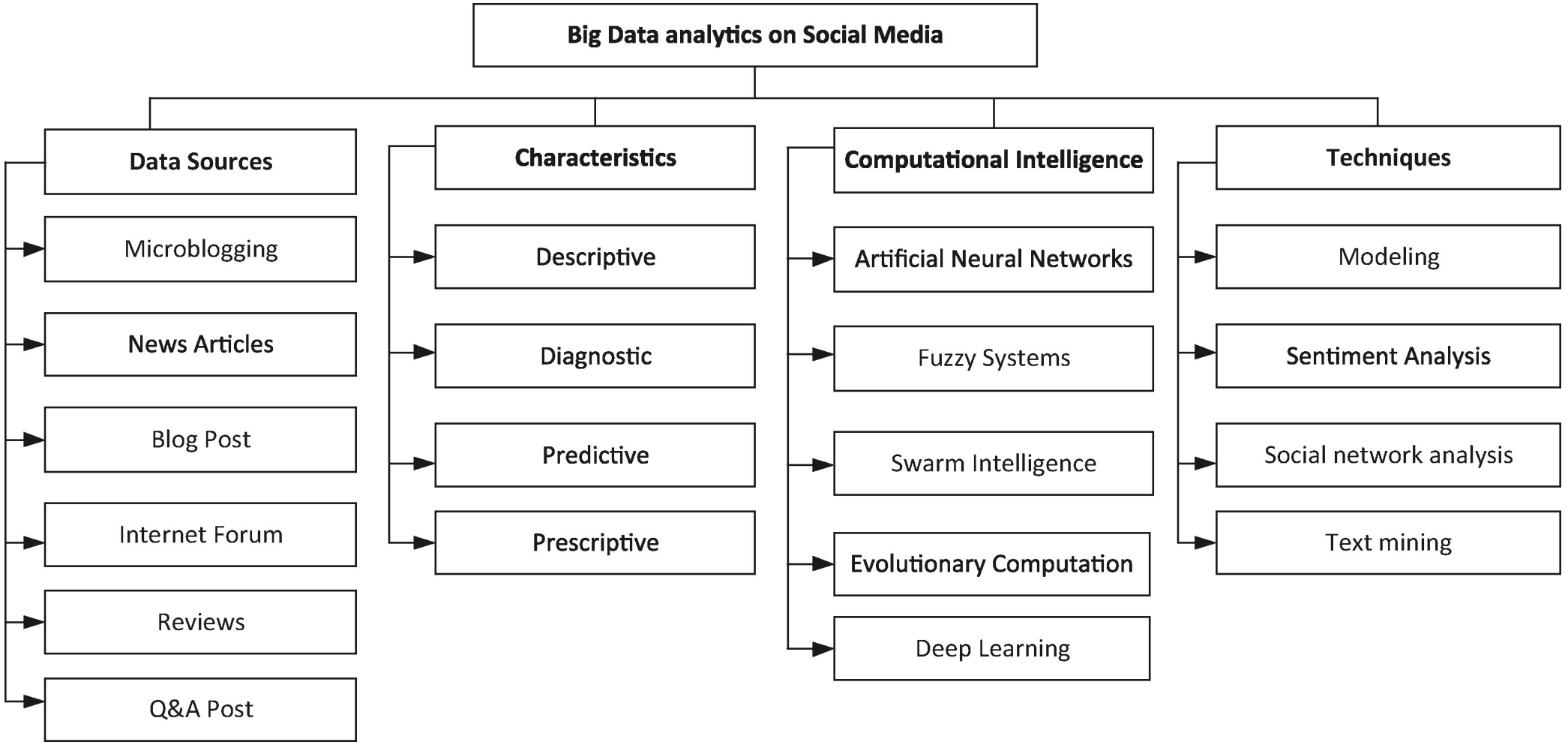
[Ghani et al. 2017]

Architectures for SM analysis



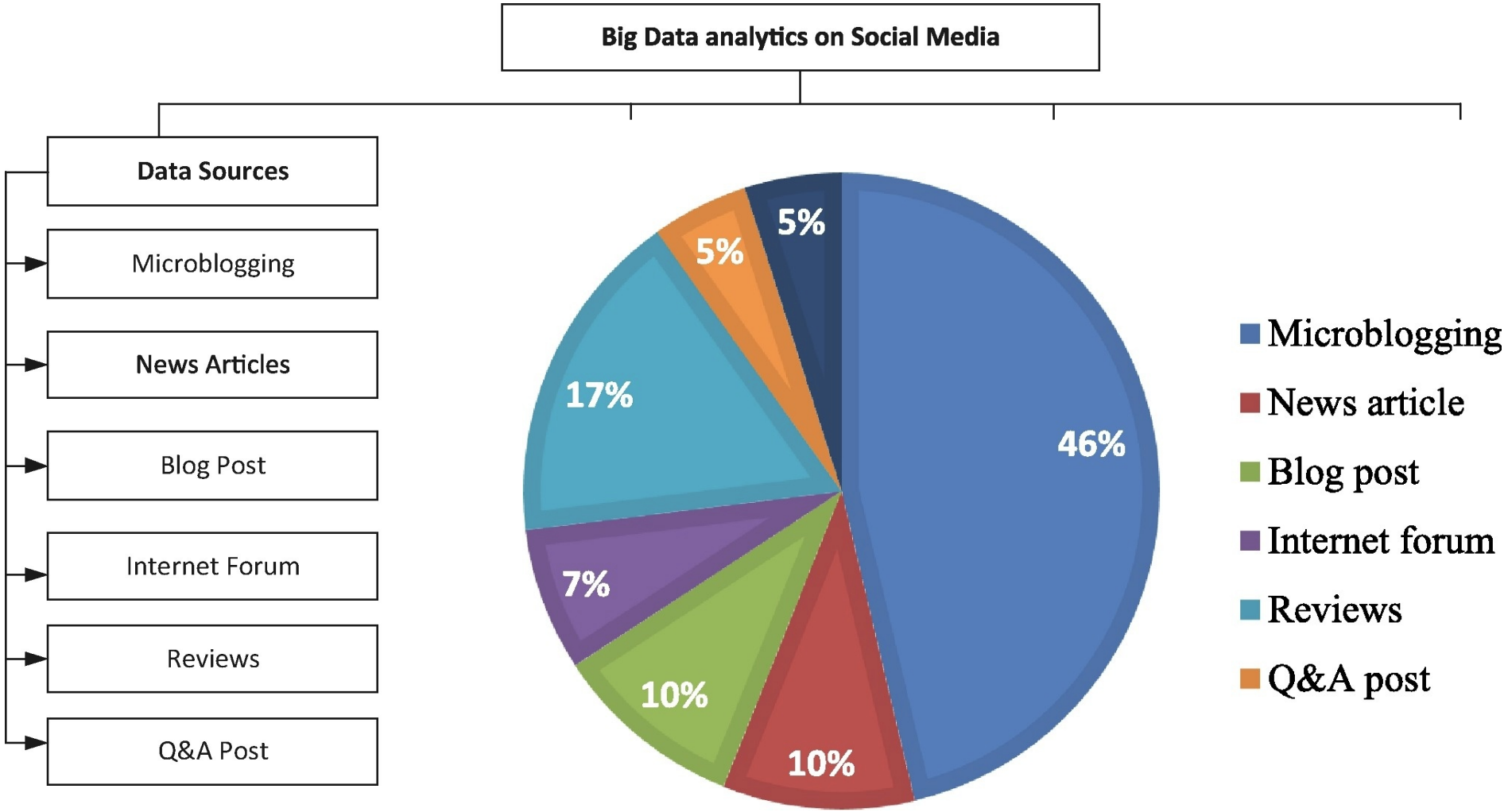
[Ghani et al. 2017]

Elements of SM analytics

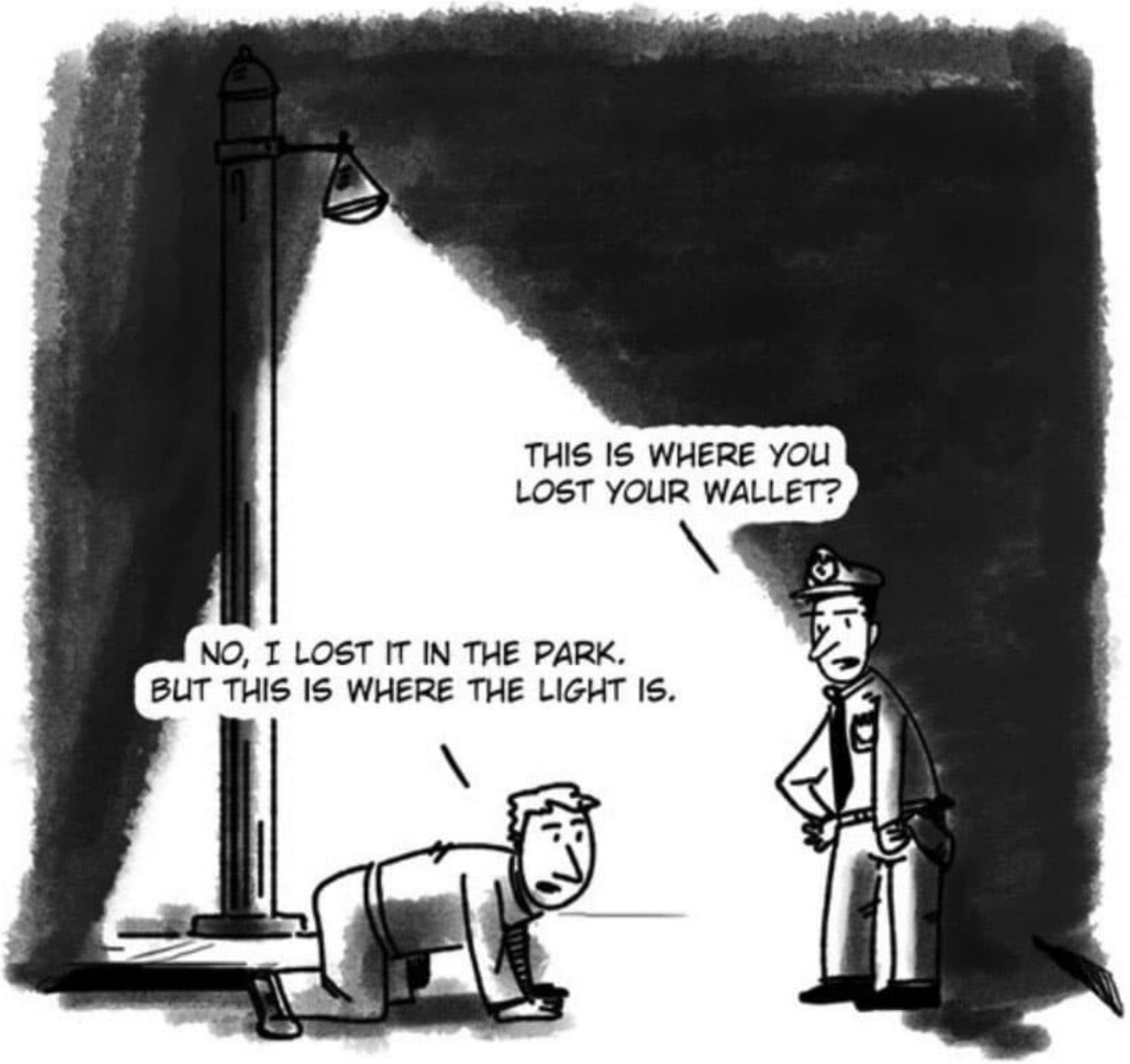


[Ghani et al. 2017]

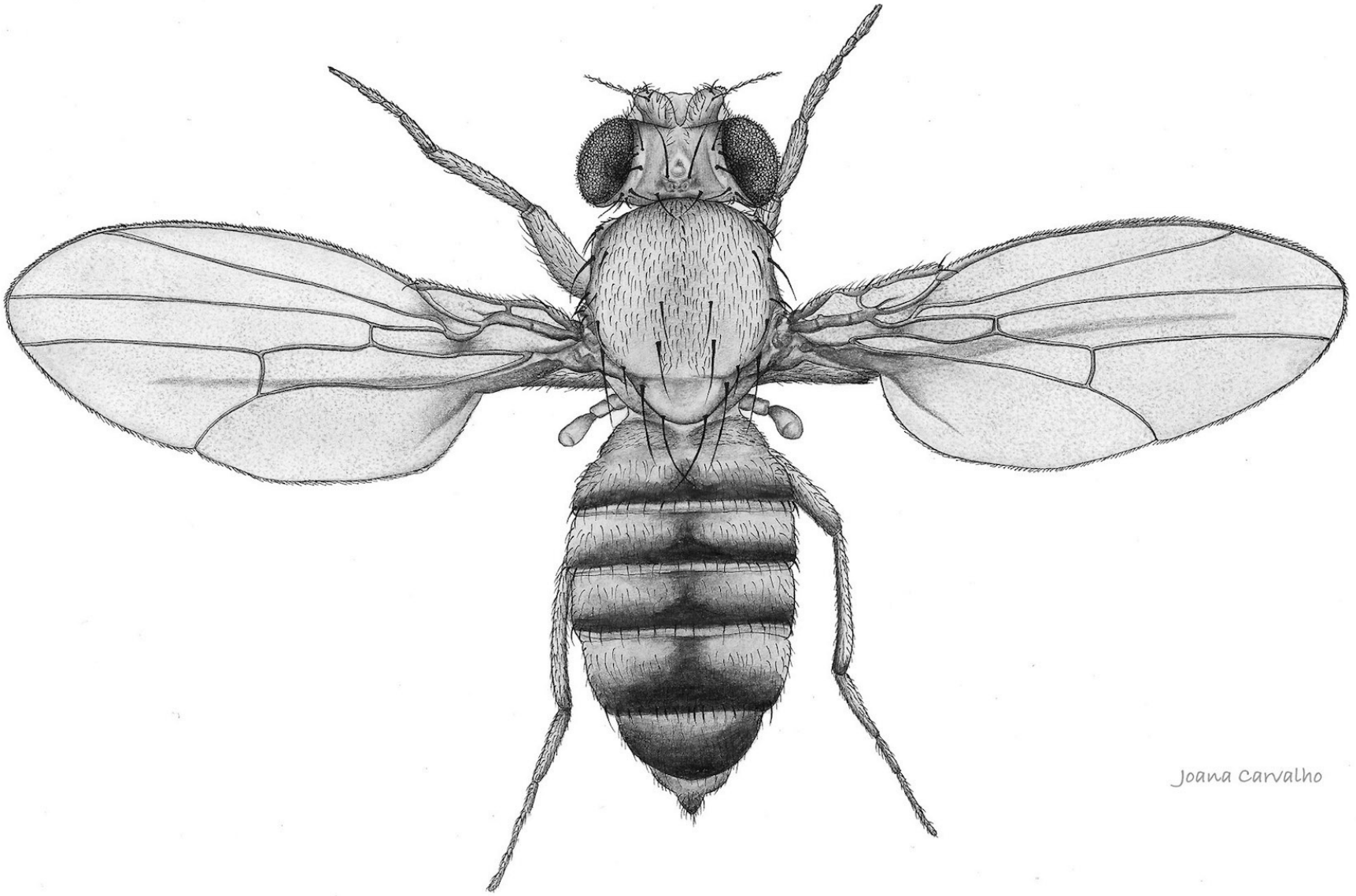
Data sources



[Ghani et al. 2017]


THIS IS WHERE YOU LOST YOUR WALLET?
NO, I LOST IT IN THE PARK. BUT THIS IS WHERE THE LIGHT IS.

Twitter = *Drosophila melanogaster*



Tufekci, Z. (2014). Big questions for social media big data: Representativeness, validity and other methodological pitfalls. In Proc. ICWSM.

Types of SM analysis

- **Descriptive**
  - Observe and report on what happens
- **Diagnostic**
  - Explain why something happens
- **Predictive**
  - Predict what will continue happening or happen
- **Prescriptive**
  - Indicate what should happen to achieve an outcome

[Ghani et al. 2017]

Common techniques

- **Modeling user behavior**
  - capturing, understanding, describing, ...
- **Sentiment analysis**
  - positive, neutral, negative, …
- **Social network analysis**
  - clusters, centrality, anomaly detection, ...
- **Text mining methods**
  - extraction, summarization, classification, …
- **Natural experiment methods / observational studies**
  - difference-in-differences, regression discontinuity, matching, ...

Sentiment analysis:

Valence and Arousal

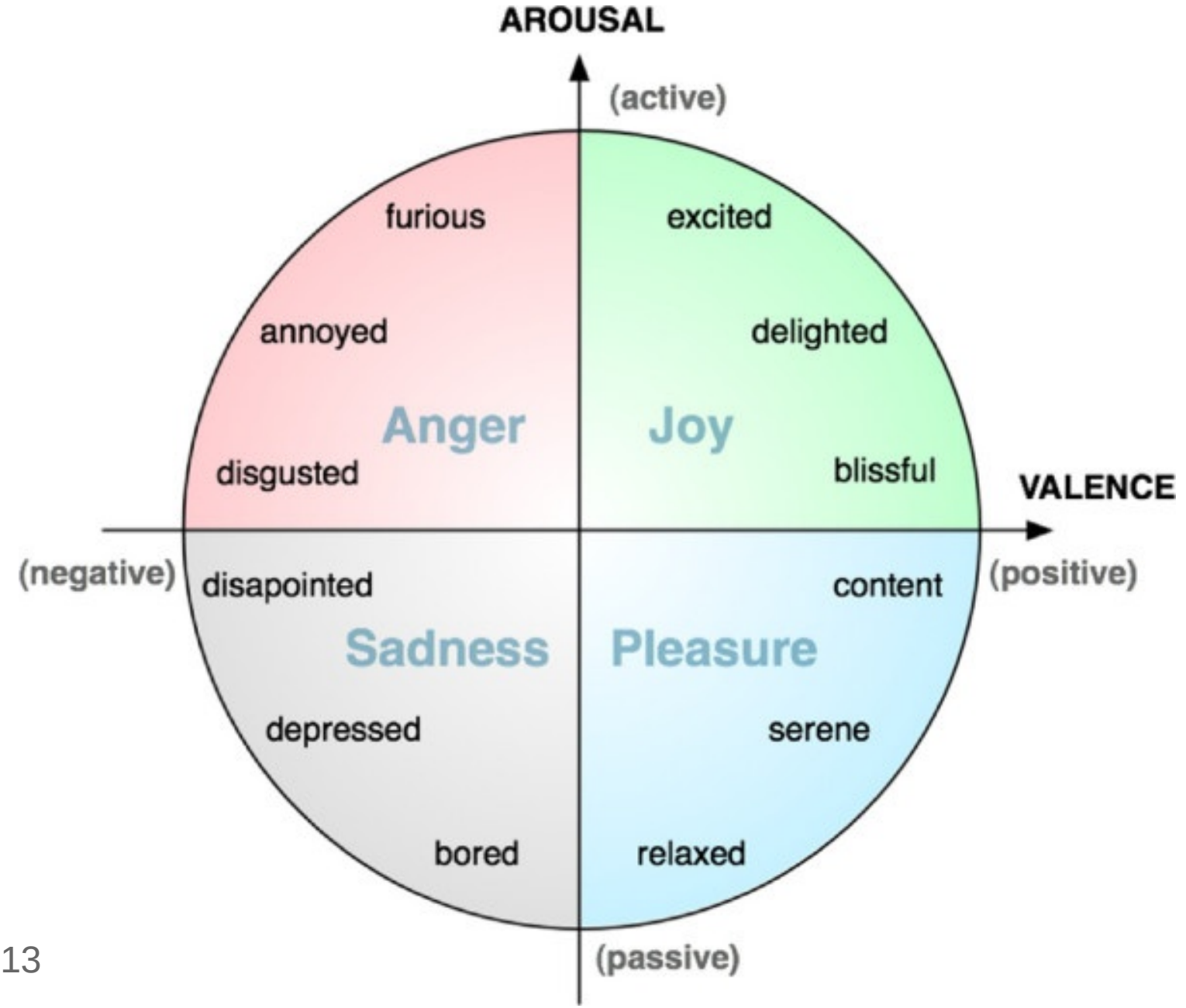
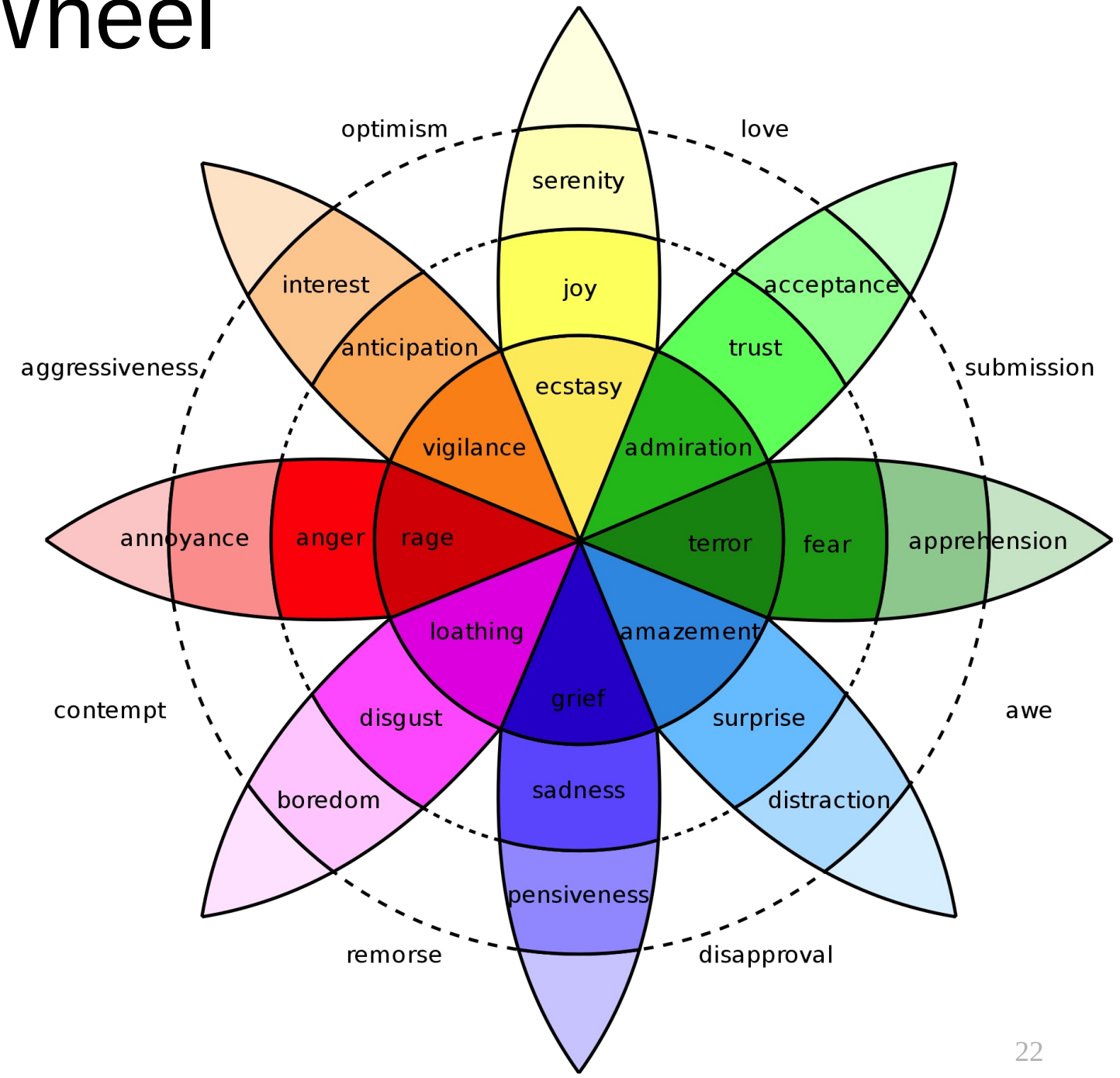


Figure: Yazdani et al. 2013

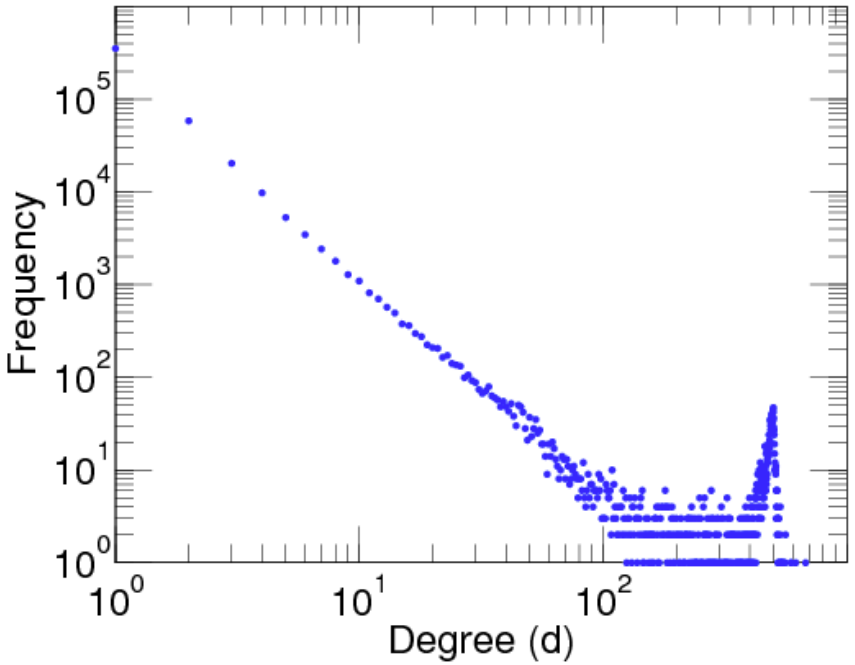
Sentiment analysis:
Plutchik's Wheel



Network analysis 1/2

social networks are scale-free networks

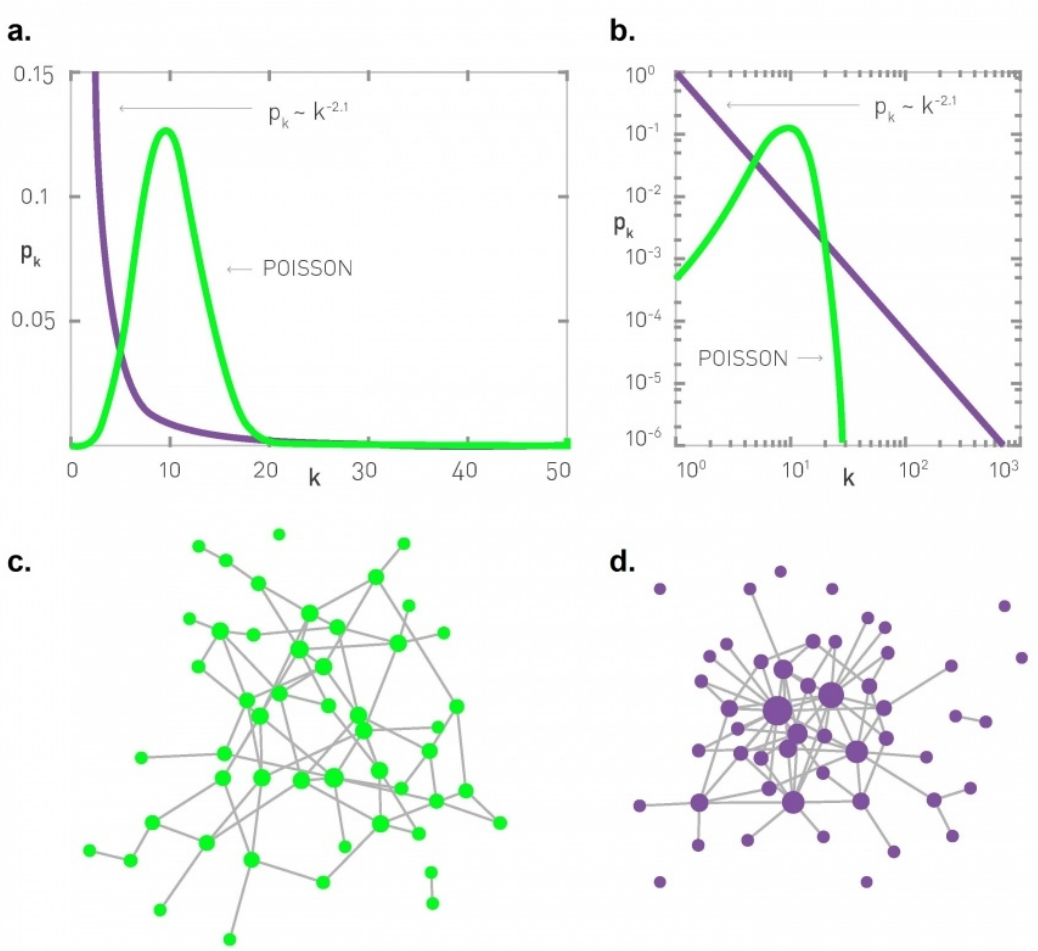
Twitter [De Choudhury et al. 2010]



Random (Erdős–Rényi model)

vs.

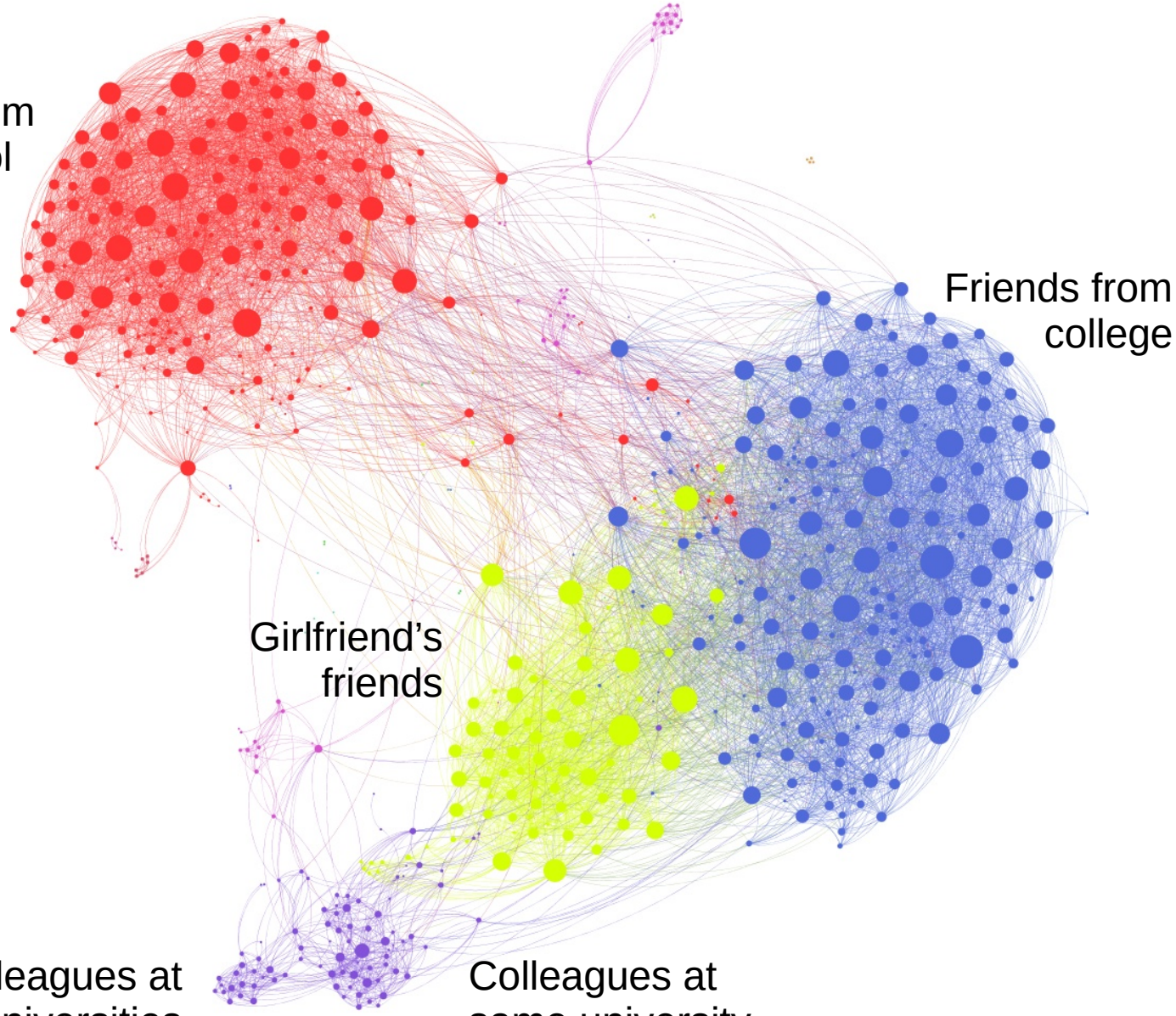
Scale-free (Barabási-Albert model)



Similar phenomena are observed with other measures of *centrality*

Network analysis 2/2

social networks have community structure



The ego network of Brendan G. on Facebook [2012]

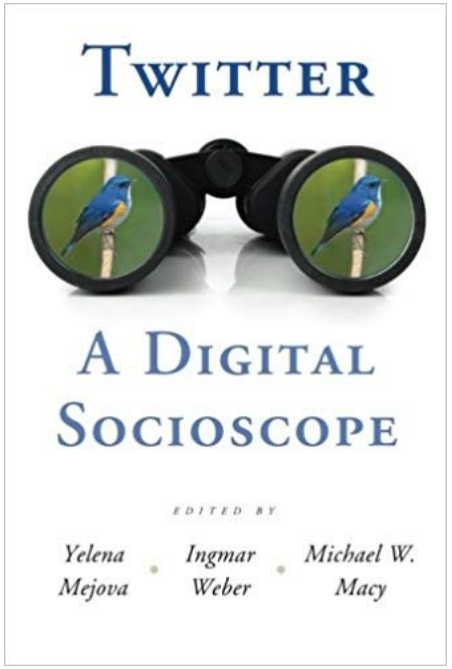
Examples

ICWSM-2019

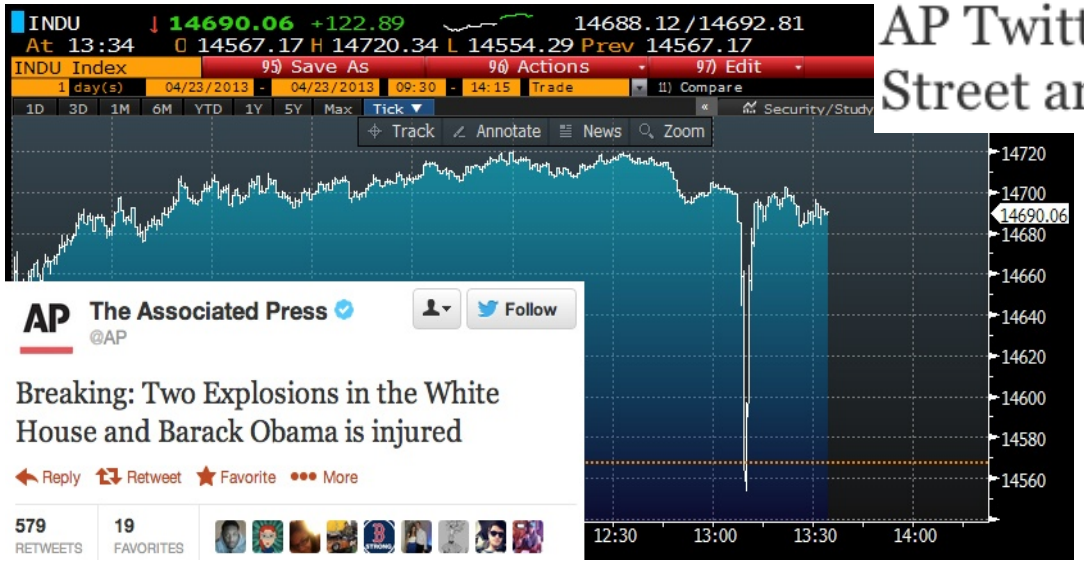
Tag cloud of titles of accepted papers

Typical social media mining topics

- **Economics**: marketing, stock market, ...
- **Politics**: elections, demonstrations, ...
- **Public health**: epidemics, ...
- **Smart cities**: transportation, pollution, ...
- **Disasters** and **mass convergence** events



When Twitter sneezes, the stock market gets the flu ...



AP Twitter hack causes panic on Wall Street and sends Dow plunging

During those three minutes, the "fake tweet erased $136 billion in equity market value,"
- Bloomberg News

http://www.washingtonpost.com/blogs/worldviews/wp/2013/04/23/syrian-hackers-claim-ap-hack-that-tipped-stock-market-by-136-billion-is-it-terrorism/

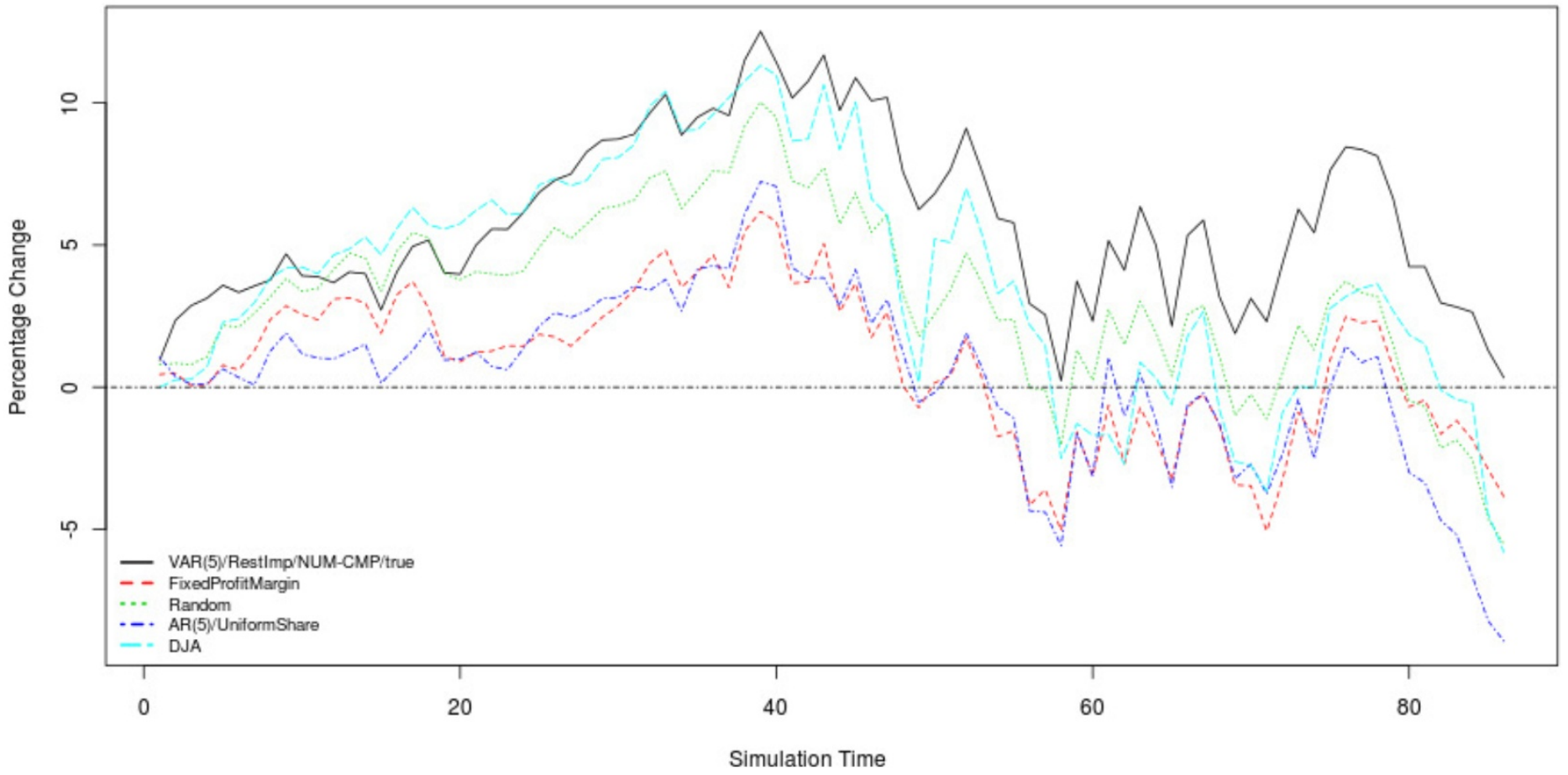
Twitter Death Rumor Leads to Spike in Oil Prices

http://mashable.com/2012/08/07/twitter-rumor-oil-price/

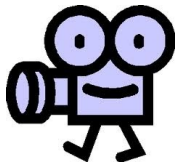
Netflix CEO's Facebook Post Triggered SEC Wells Notice

http://www.cnbc.com/id/100289227

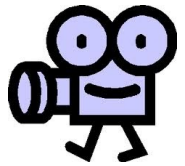
Trading stock using social media



http://dx.doi.org/10.1145/2124295.2124358

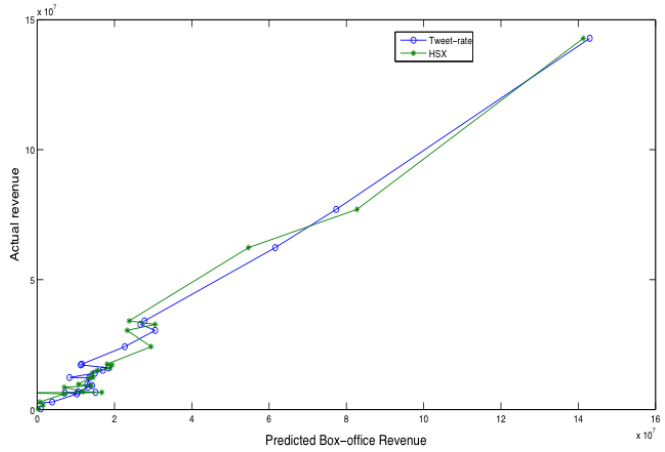


Movies!

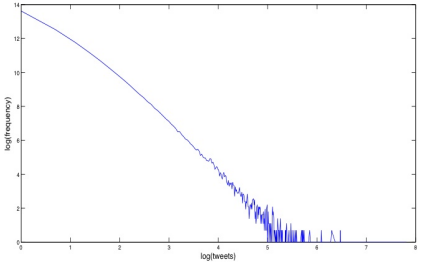


- 2.89 million tweets
- 24 movies (manually compiled keywords)

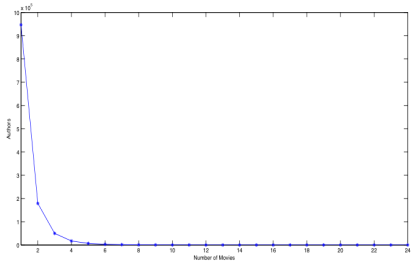
Correlation
(tweet volume vs. box office gross revenue) **= 0.90**



predicted vs actual box office scores



authors to tweets



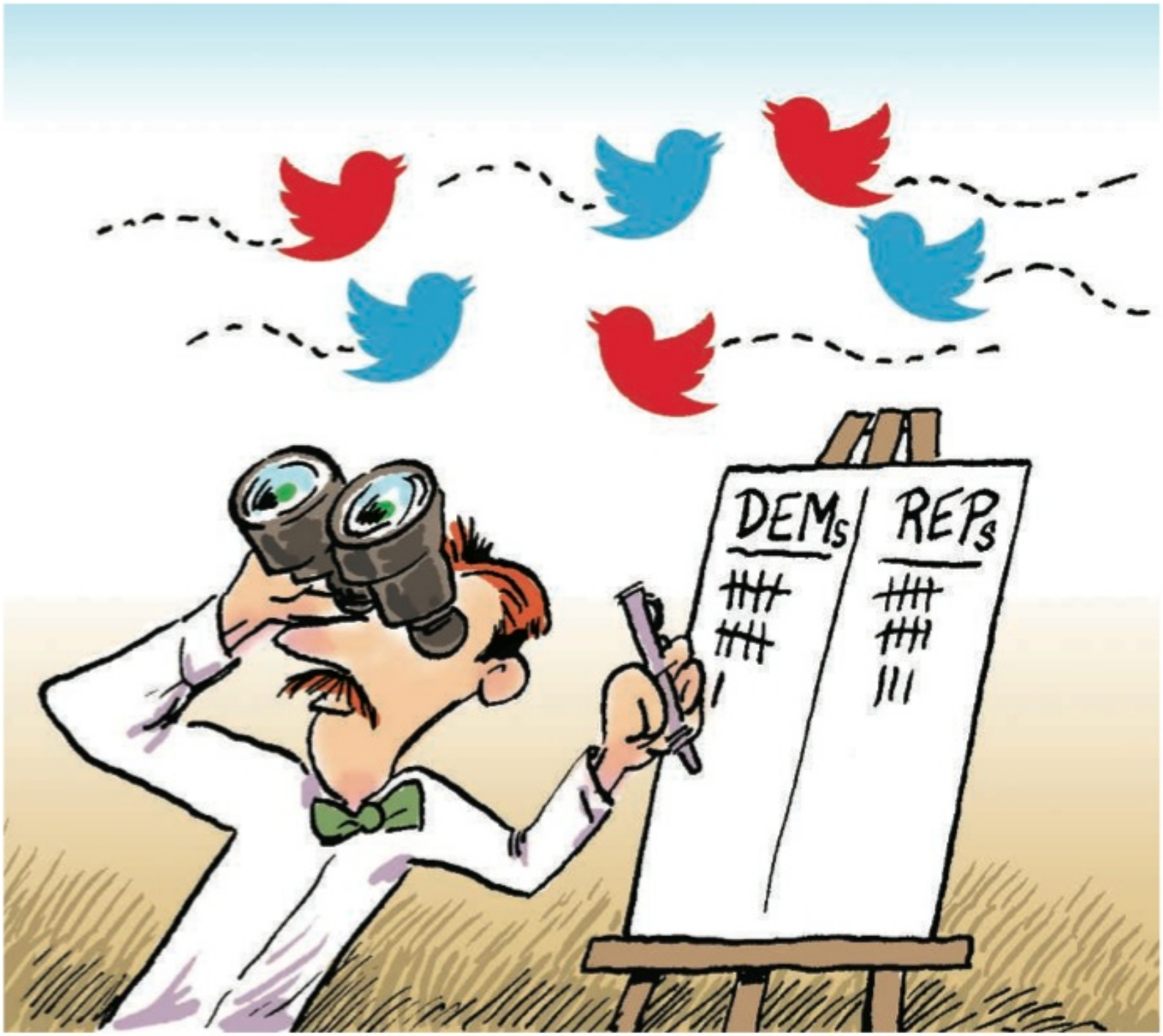
authors to movies

linear regression using previous week's tweets to predict weekend box office gross:

	Adj R^2
Average Tweet-rate	0.80
Tweet-rate time series	0.93
Tweet-rate time series + theater count	**0.973**
HSX time series + theater count	0.965

DEMOCRAT
≃ left

REPUBLICAN
≃ right

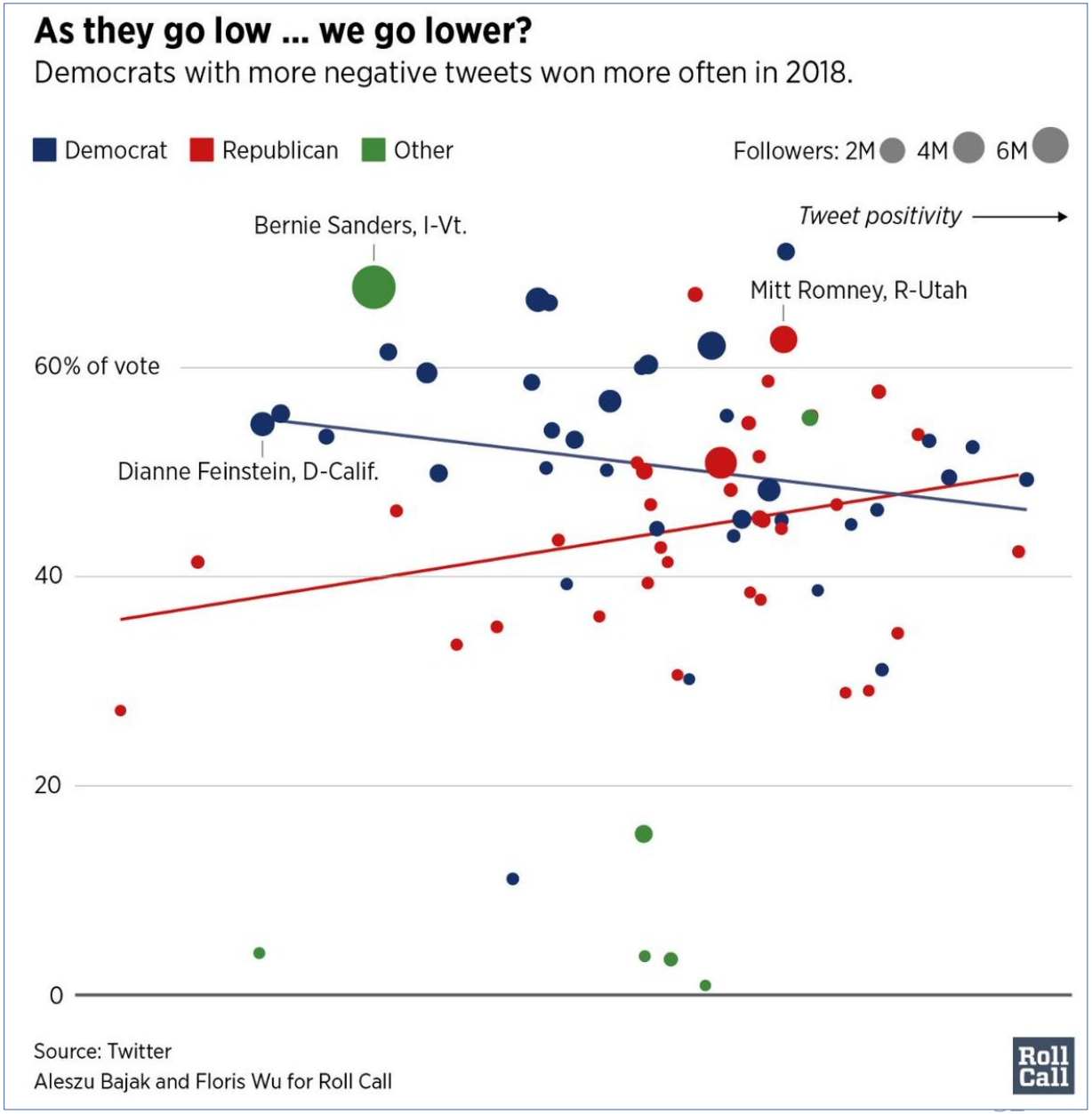


US Democrats vs US Republicans

- Studies based on volume and sentiment of postings
- Automated with tools from social media monitoring companies

- Claims often overstretched by journalists, authors, or both

Tip: understate results for journalists, they will exaggerate them anyway



(Not) predicting election results

- A method of prediction should be an algorithm finalized **before** the election
  - specify data collection, cleaning, analysis, interpretation…
- Data from social media are fundamentally different than data from natural phenomena
  - people change their behavior next time around
  - spammers & activists will try to take advantage
- From a testable theory on *why* and *when* it predicts (avoid self-deception!)
- (maybe) Learn from professional pollsters
  - tweet ≠ user
  - user ≠ eligible voter
  - eligible voter ≠ voter

Predict political stance

Results using an SVM

Features	Conf. matrix	Accuracy
Full-Text	$\begin{bmatrix} 266 & 107 \\ 75 & 431 \end{bmatrix}$	79.2%
Hashtags	$\begin{bmatrix} 331 & 42 \\ 41 & 465 \end{bmatrix}$	90.8%
Clusters	$\begin{bmatrix} 367 & 6 \\ 38 & 468 \end{bmatrix}$	94.9%
Clusters + Tags	$\begin{bmatrix} 366 & 7 \\ 38 & 468 \end{bmatrix}$	94.9%

network-based method

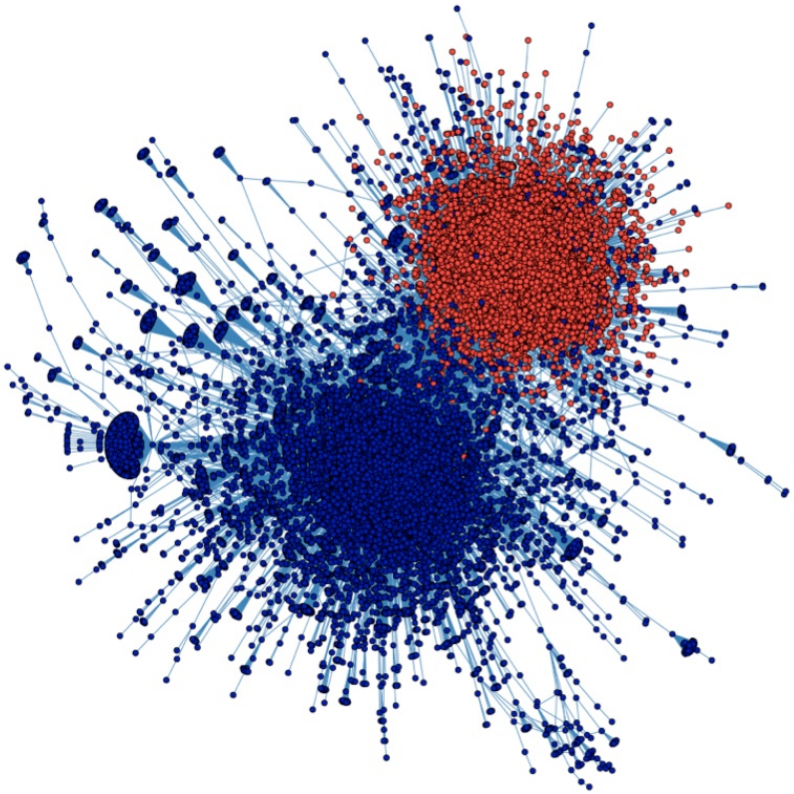
Conover, Gonçalves, Ratkiewicz, Flammini, Menczer @ SocialCom (2011)

Network-based methods

- Label propagation
  - Random initialization of labels
  - Update according to majority label among neighbors, break ties arbitrarily
- Use known node labels to determine which cluster means what

Network	Min	Max	Mean
Mention	0.80	1.0	0.89
Retweet	0.94	0.98	0.96

Adjusted Rand Index for 100 label propagation runs on political data



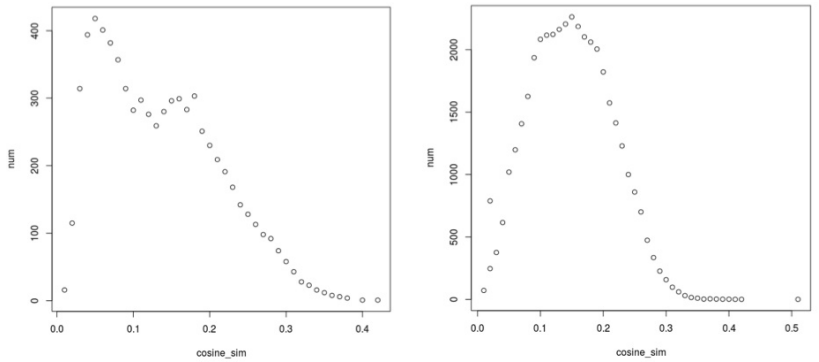
retweet network

Clusters $\begin{bmatrix} 367 & 6 \\ 38 & 468 \end{bmatrix}$ 94.9%

class assignment by cluster majority

Secular vs Islamist

hashtag cosine user-user similarity

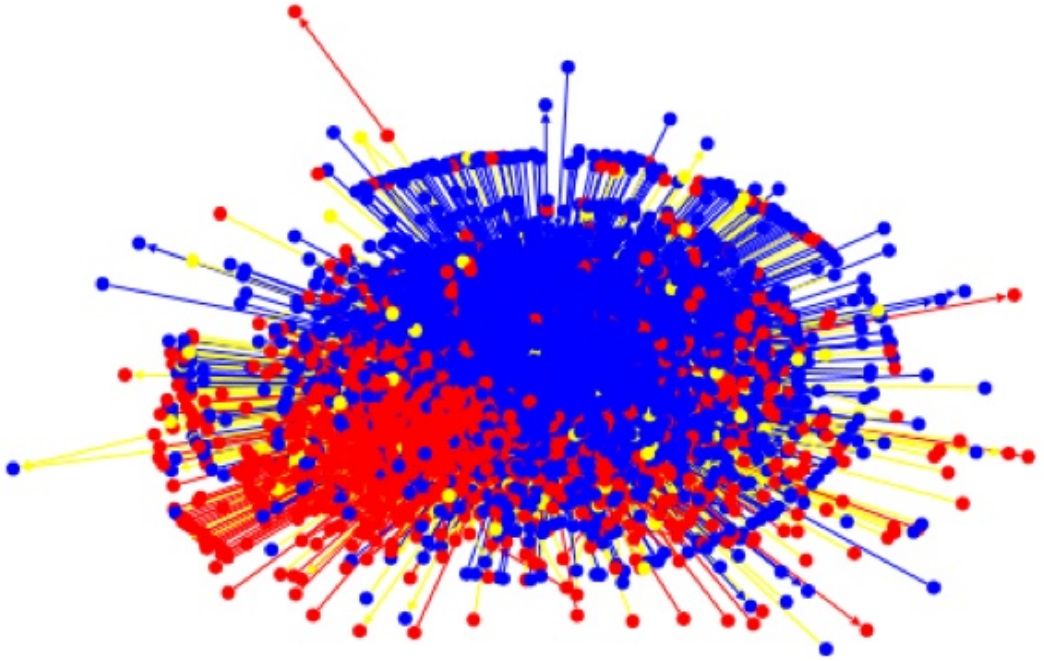


Islamist

average: 0.16
median: 0.11

Secularist

average: 0.16
median: 0.21



Islamist, Secular, intra-ideology

the closer to Islamist, use of

–religious terms *increases*

–charity-related terms *increases*

–derogatory terms *decreases*

Weber, Garimella, Batayneh @ ASONAM (2013)

Exposure of Chinese tourists to protests in Hong Kong

- **Study group**
  Chinese who traveled to Hong Kong before the protests started
- **Control**
  returned to China 36 to 6 days before the protests started
- **Treatment**
  returned after the protests, and hence possibly witnessed them

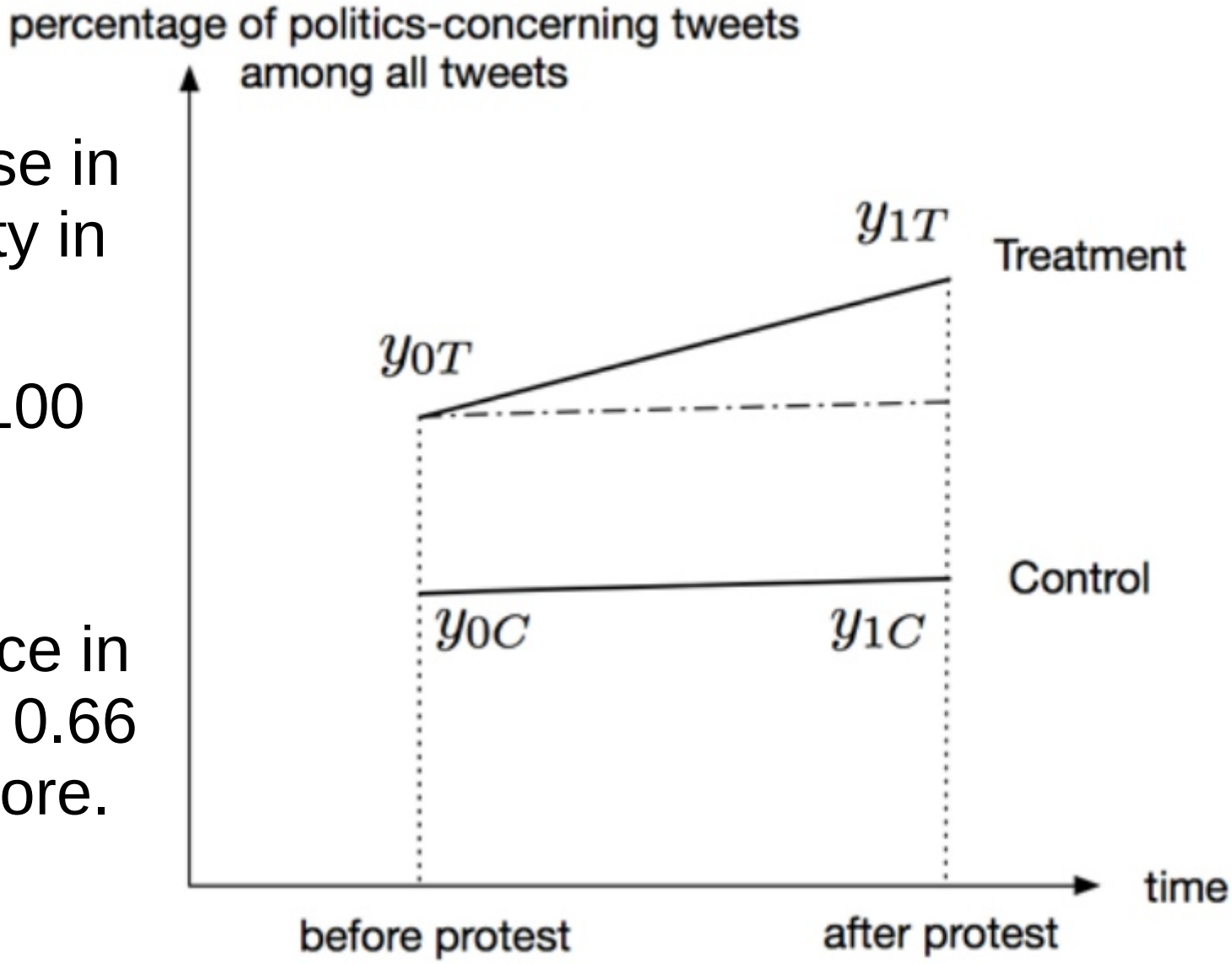
[Zhang 2015]

Treatment vs matched control group

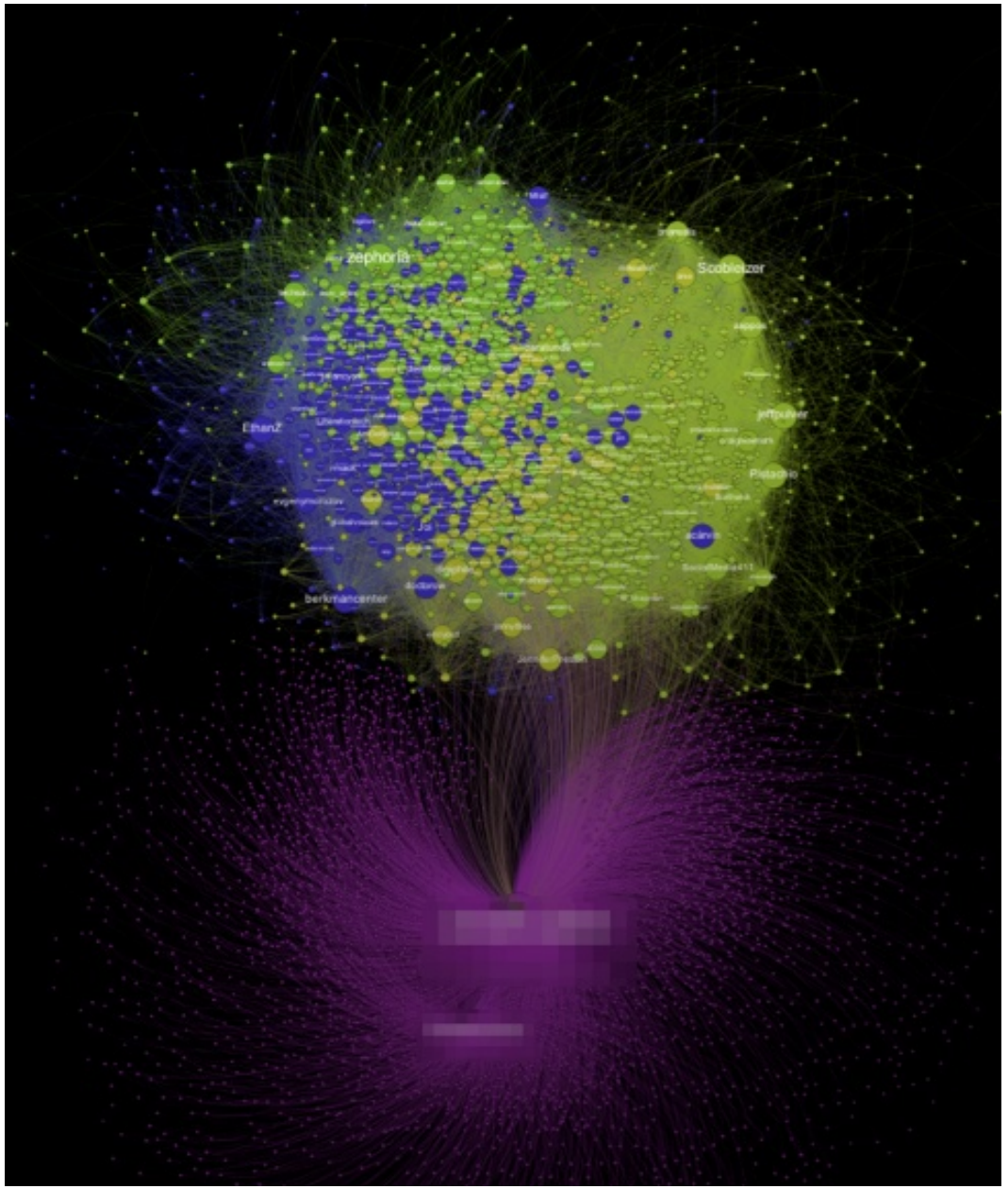
	T	C	C_{match}
Size	355	10169	710
Mean number of posts	787.30	726.96	772.13
Mean number of check-in	68.36	72.02	64.09
Gender=Male	108	3283	222
Female	176	6154	418
M/F Ratio	61.36%	53.35%	53.11%
Not Self-labelled	49	742	70
Education=College and beyond	108	3849	231
Not Self-labelled	225	6320	479
Age $<$ 25	68	1806	129
$\geq$25	8	163	14
Not Self-labelled	257	8200	567

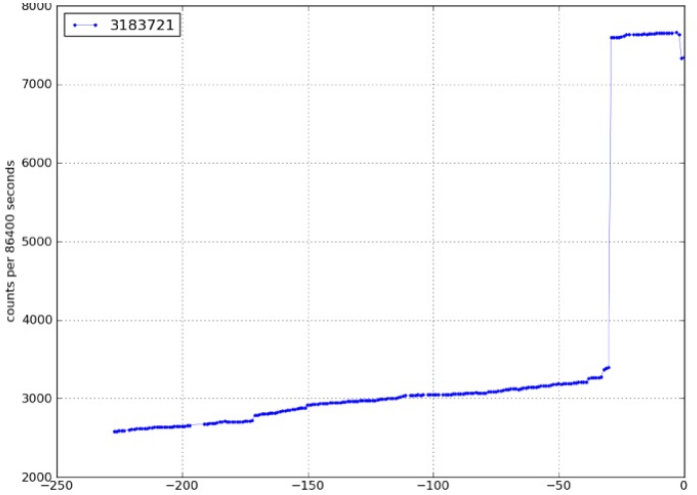
Difference-in-differences

- Found increase in political activity in Weibo
- Before: 1.66/100 posts were political posts
- After: difference in differences of 0.66 posts: 75% more.



4K followers x $5





Faster organic followers acquisition after paid followers acquisition

Fake Friends with [Real Benefits]
by Gilad Lotan

Political Spam ("Truthy")

Classifier	Resampling?	Accuracy	AUC
AdaBoost	No	92.6%	0.91
AdaBoost	Yes	96.4%	0.99
SVM	No	88.3%	0.77
SVM	Yes	95.6%	0.95

Ratkiewicz, J., Conover, M. D., Meiss, M., Gonçalves, B., Flammini, A., & Menczer, F. M. (2011, July). Detecting and tracking political abuse in social media. In Fifth international AAAI conference on weblogs and social media.

Truthiness is a quality characterizing a "truth" that a person making an argument or assertion claims to know intuitively "from the gut" or because it "feels right" without regard to evidence, logic, intellectual examination, or facts.

`nodes`	Number of nodes
`edges`	Number of edges
`mean_k`	Mean degree
`mean_s`	Mean strength
`mean_w`	Mean edge weight in largest connected component
`max_k(i,o)`	Maximum (in,out)-degree
`max_k(i,o)_user`	User with max. (in,out)-degree
`max_s(i,o)`	Maximum (in,out)-strength
`max_s(i,o)_user`	User with max. (in,out)-strength
`std_k(i,o)`	Std. dev. of (in,out)-degree
`std_s(i,o)`	Std. dev. of (in,out)-strength
`skew_k(i,o)`	Skew of (in,out)-degree distribution
`skew_s(i,o)`	Skew of (in,out)-strength distribution
`mean_cc`	Mean size of connected components
`max_cc`	Size of largest connected component
`entry_nodes`	Number of unique injections
`num_truthy`	Number of times 'truthy' button was clicked
sentiment scores	Six GPOMS sentiment dimensions

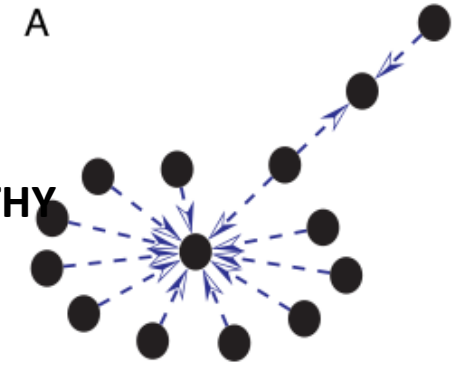
Social bots distort the 2016 U.S. Presidential election online discussion

Bot specific statistics	*Top 50K users (exact)*
# Bot-generated tweets	2,330,252 (18.45%)
# Human-generated tweets	10,303,251 (81.55%)
# Bots	7,183 (14.4%)
# Humans	40,163 (80.3%)
# Unknown	2,654 (5.3%)

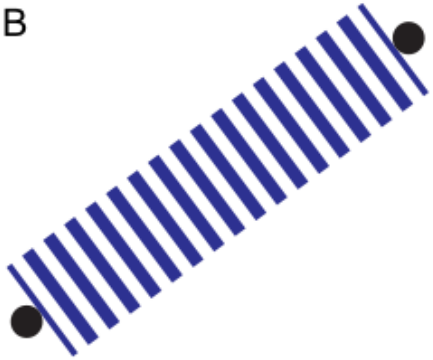
Bessi, Alessandro, and Emilio Ferrara. "Social bots distort the 2016 US Presidential election online discussion." First Monday 21.11-7 (2016).

(Ab)normal linking patterns

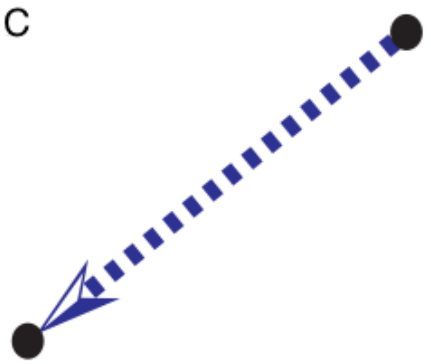
TRUTHY



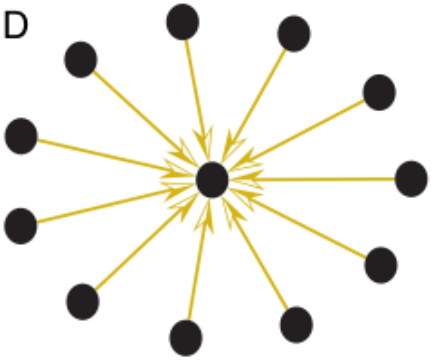
#ampat



@PeaceKaren_25 &
@HopeMarie_25

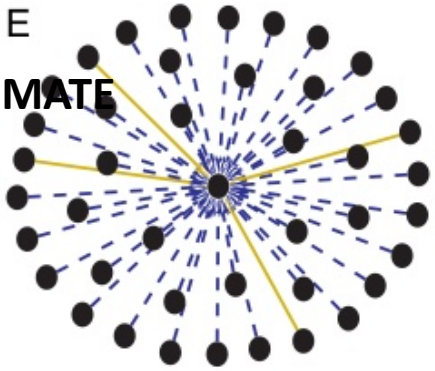


gopleader.gov

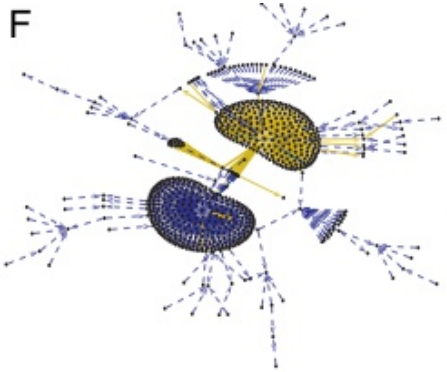


Chris Coons

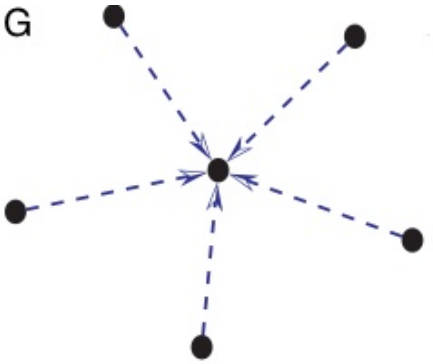
LEGITIMATE



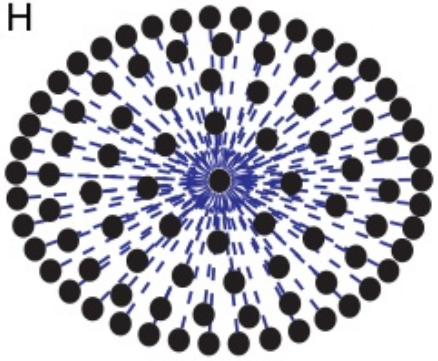
#Truthy



@senjohnmccain



on.cnn.com/aVMu5y



“Obama said…”

Lifestyle and health at scale

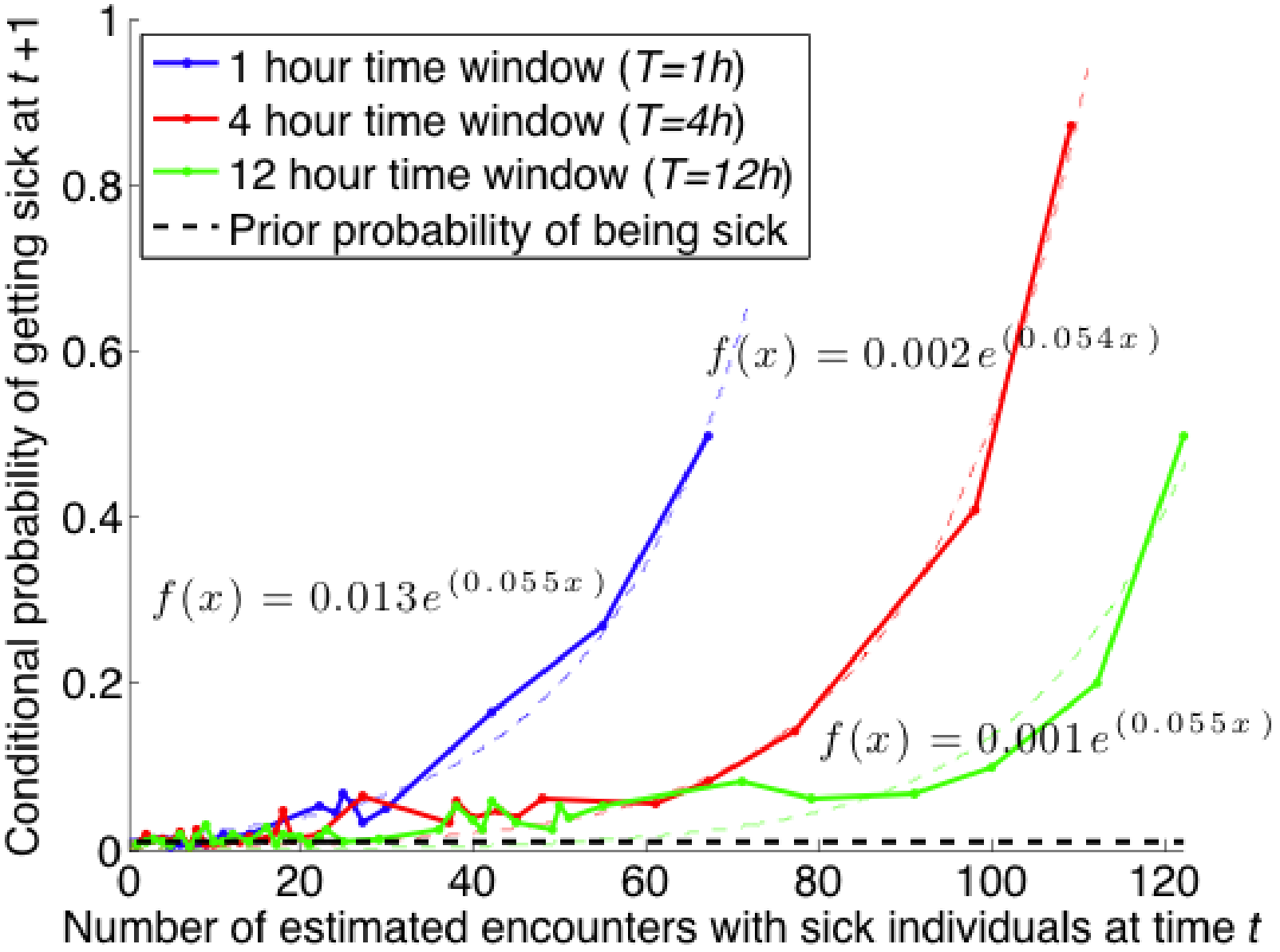
Sadilek et al.
WSDM 2013

Example features

Positive Features		Negative Features	
Feature	**Weight**	**Feature**	**Weight**
sick	0.9579	sick of	−0.4005
headache	0.5249	you	−0.3662
flu	0.5051	lol	−0.3017
fever	0.3879	love	−0.1753
feel	0.3451	i feel your	−0.1416
coughing	0.2917	so sick of	−0.0887
being sick	0.1919	bieber fever	−0.1026
better	0.1988	smoking	−0.0980
being	0.1943	i'm sick of	−0.0894
stomach	0.1703	pressure	−0.0837
and my	0.1687	massage	−0.0726
infection	0.1686	i love	−0.0719
morning	0.1647	pregnant	−0.0639

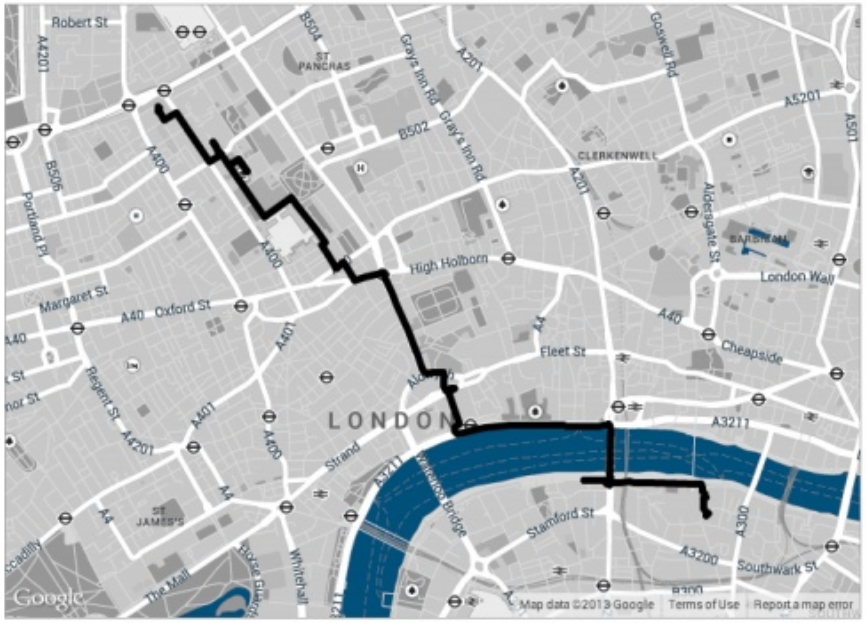
Positively and negatively weighted significant features.

Probability of being sick increases with closeness to sick people



Examples in “smart cities”

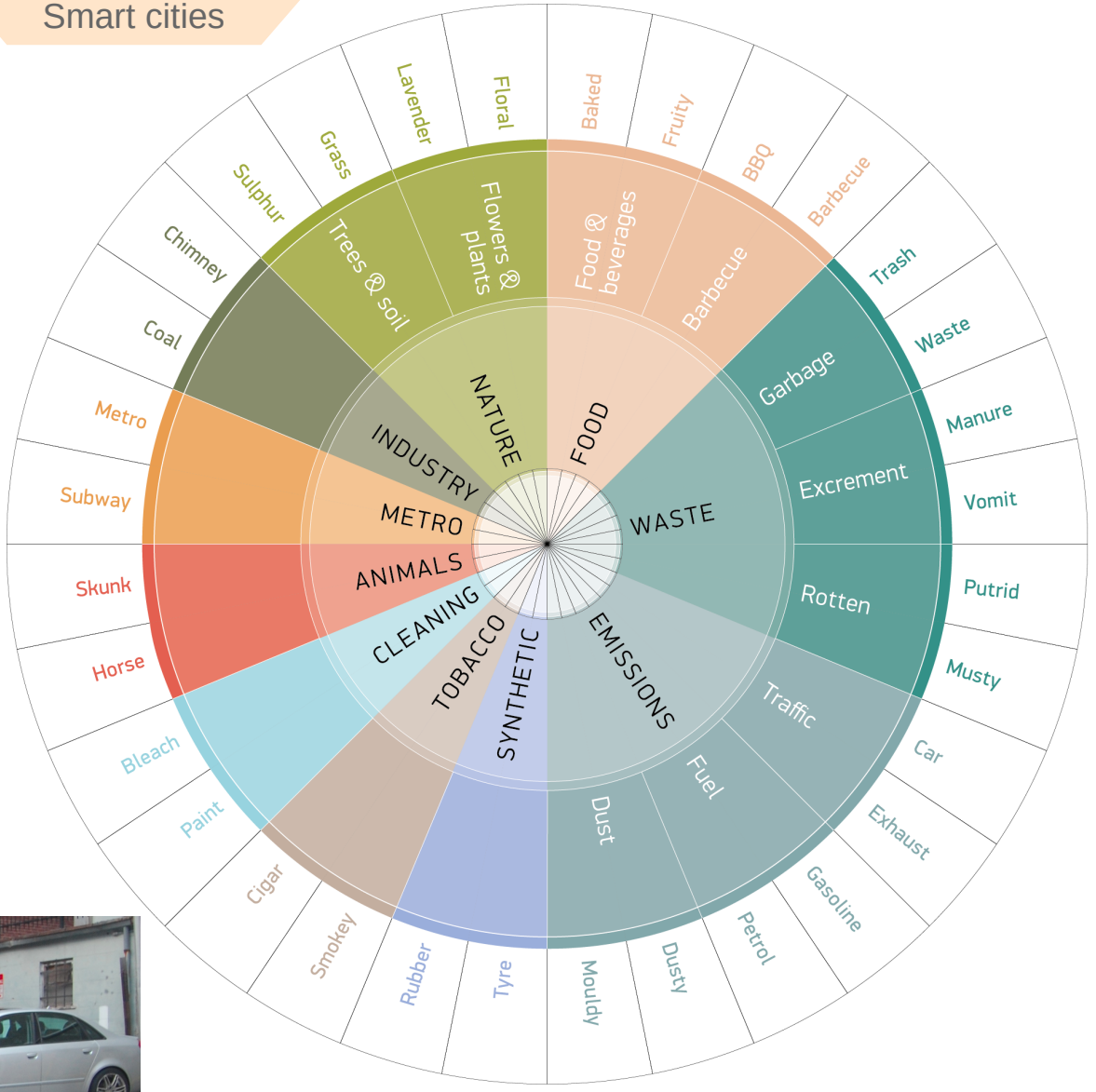
- Data-driven neighborhood boundaries
- Data-driven residential/commercial zones
- Tourism and beauty



(a) Shortest

(b) Beauty

Smell maps

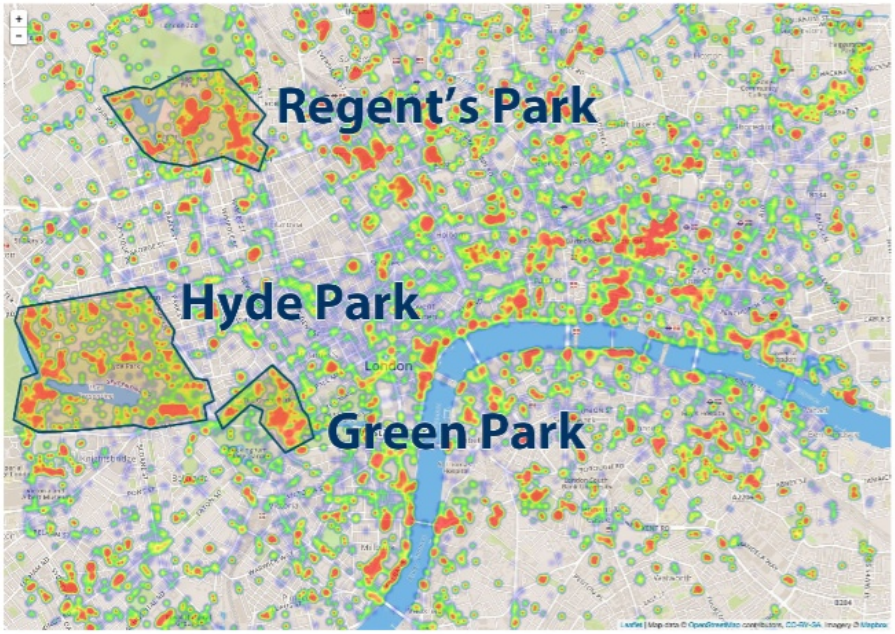


Urban Smellscape Aroma Wheel
(depicting background and episodic aromas only)
Aiello, L., McLean, K, Quercia, D, Schifanella, R, 2015

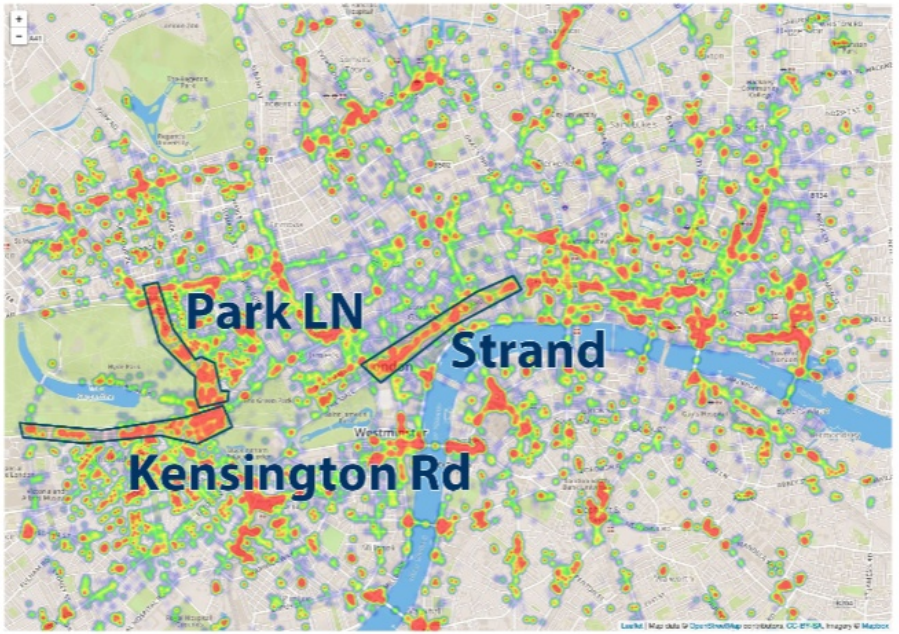
Smells and tags
Data: Instagram and Twitter

- Compute P(smell|tags) for places where both
  - a set of tagged photos and
  - a set of smell annotations

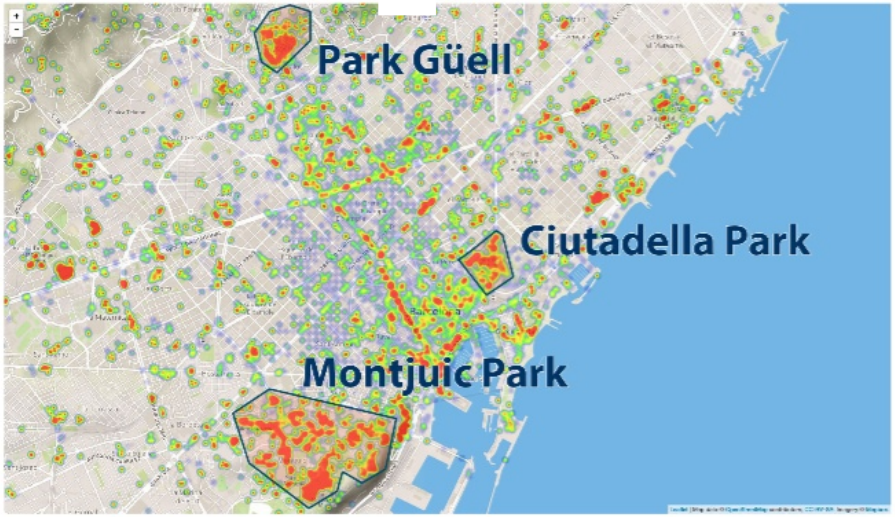
  … have been observed
- Supervised learning approach



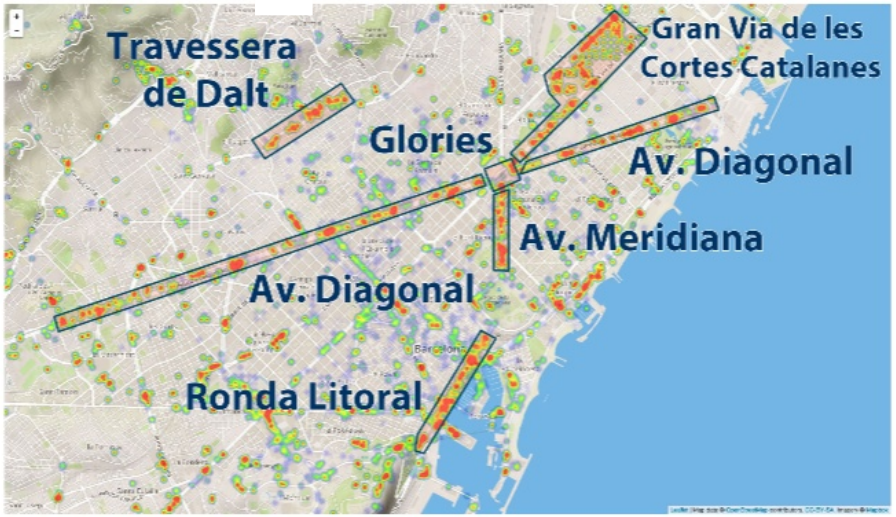
London, nature



London, emissions



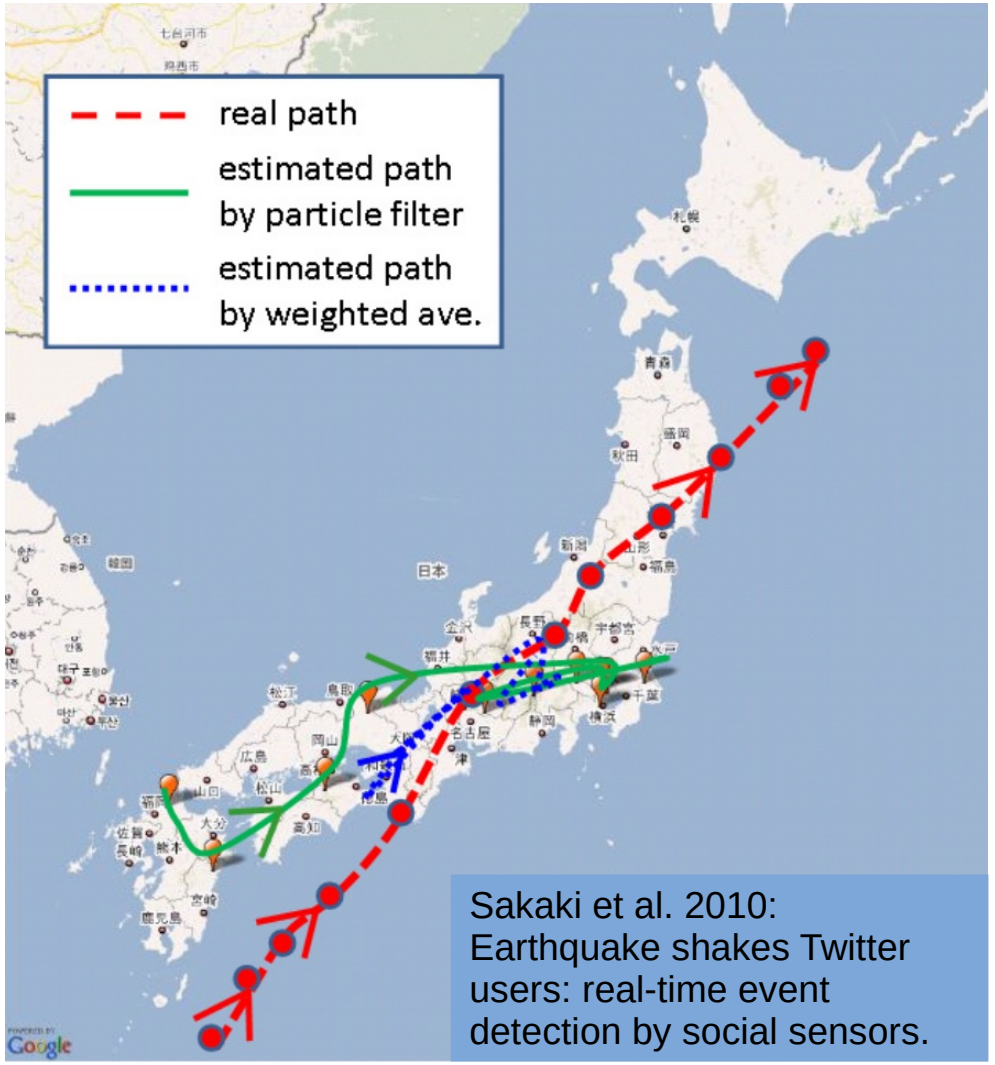
Barcelona, nature



Barcelona, emissions

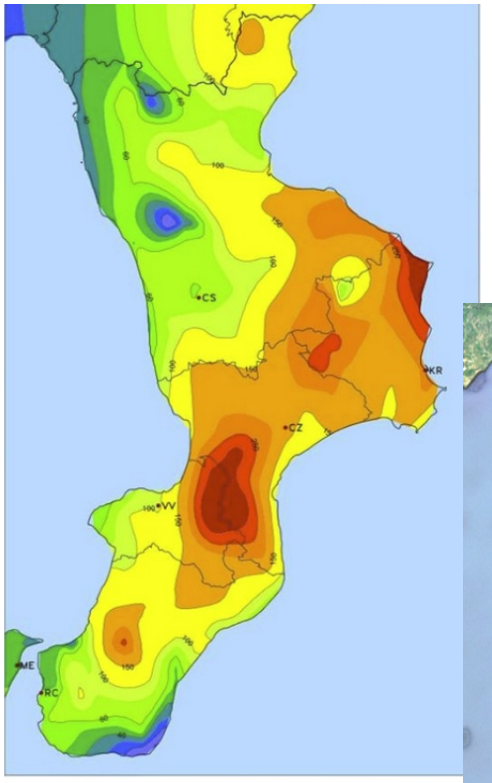
http://researchswinger.org/smellymaps/

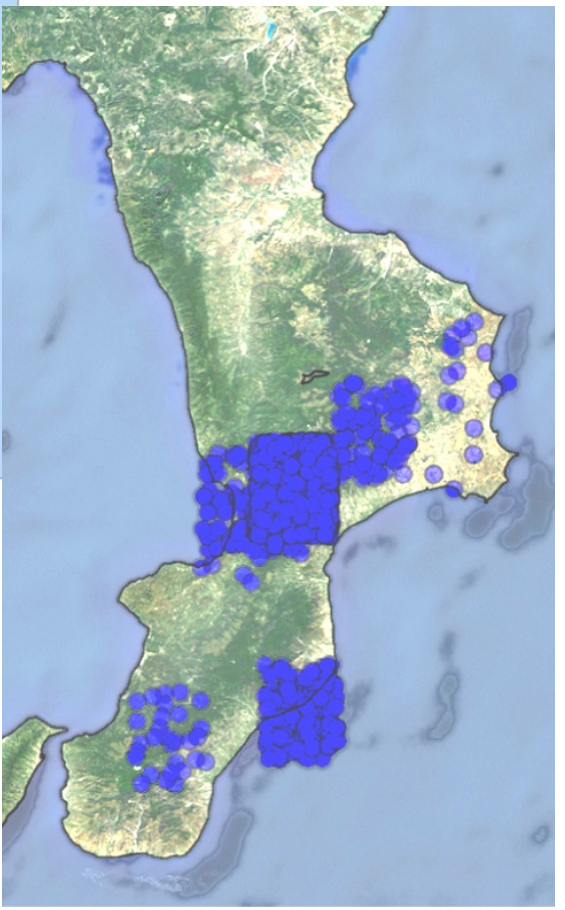
Typhoon trajectory



Sakaki et al. 2010: Earthquake shakes Twitter users: real-time event detection by social sensors.

Flood risks

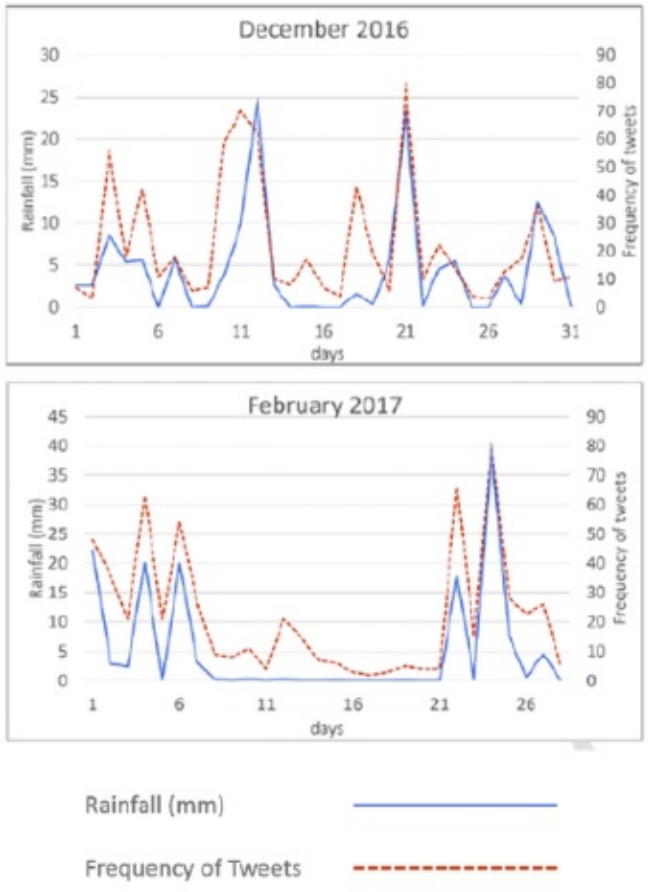


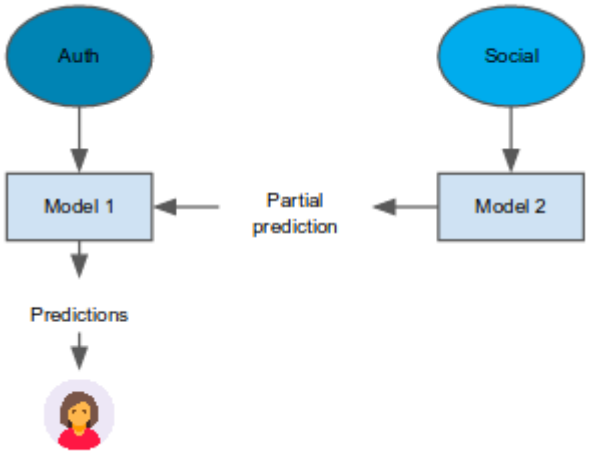


Lorini et al. 2019: Integrating Social Media into a Pan-European Flood Awareness System. Best paper award at ISCRAM.

From data points to the “Big Picture”

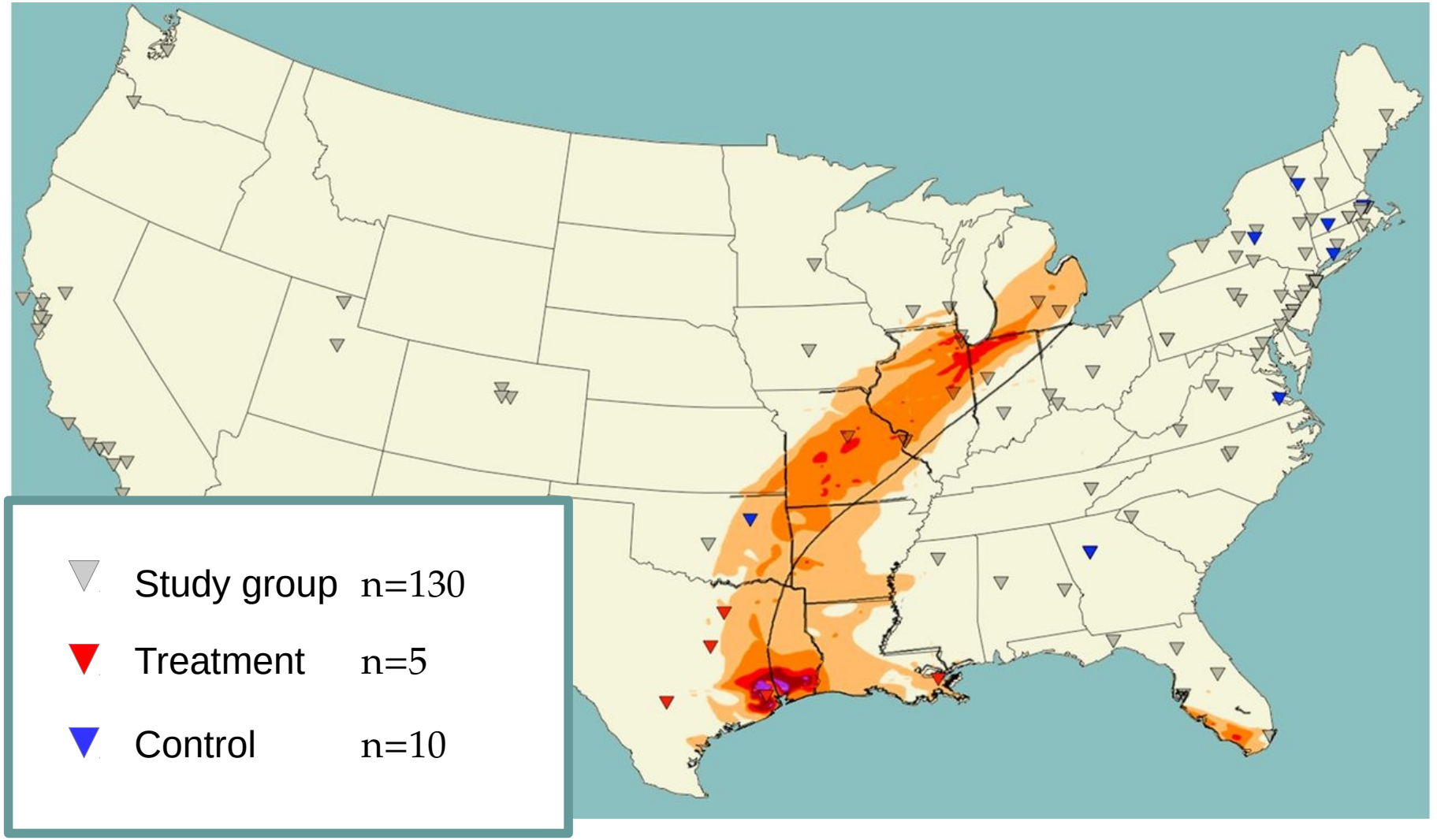
- Based on geocoded tweets (<2% of total) filtered to select those having keywords related to rain ("*chuva*" in Portuguese).
- Used to estimate rainfall (supervised setting), which is then fed into the flood risk prediction model





[Restrepo-Estrada et al. 2018]

The effect of a hurricane in online social networks



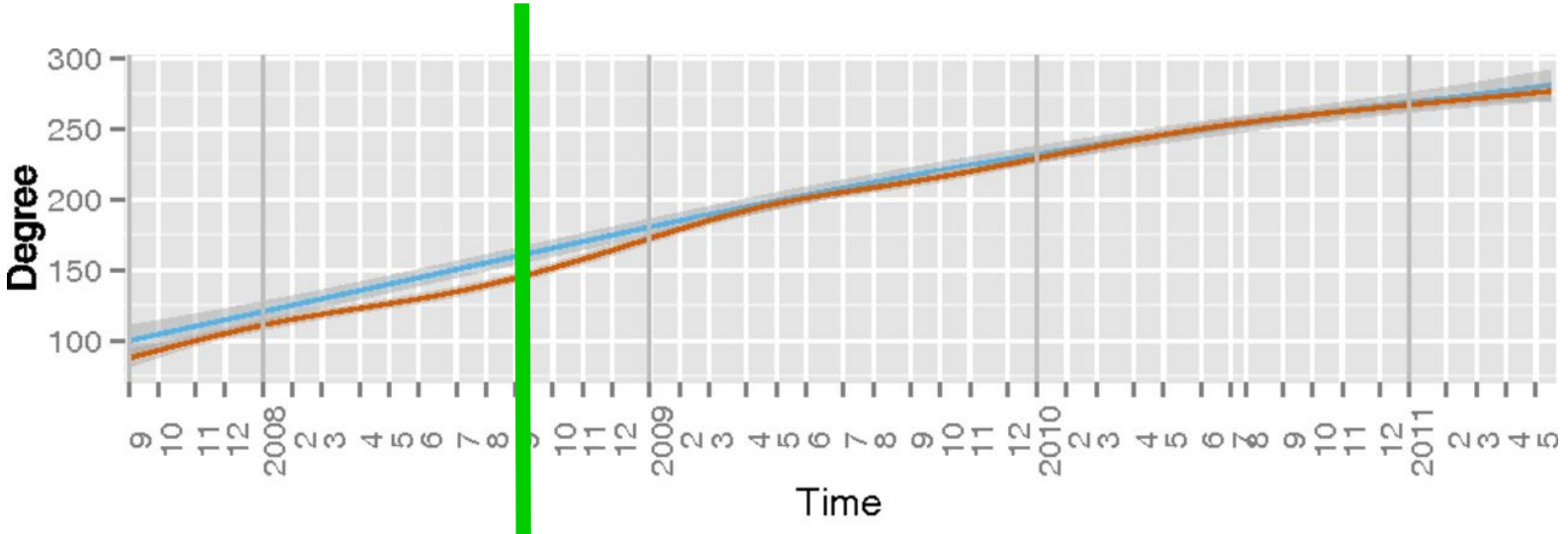
Phan, Tuan Q., and Edoardo M. Airoldi. "A natural experiment of social network formation and dynamics." Proceedings of the National Academy of Sciences 112.21 (2015): 6595-6600.

Matching design: selection of control group

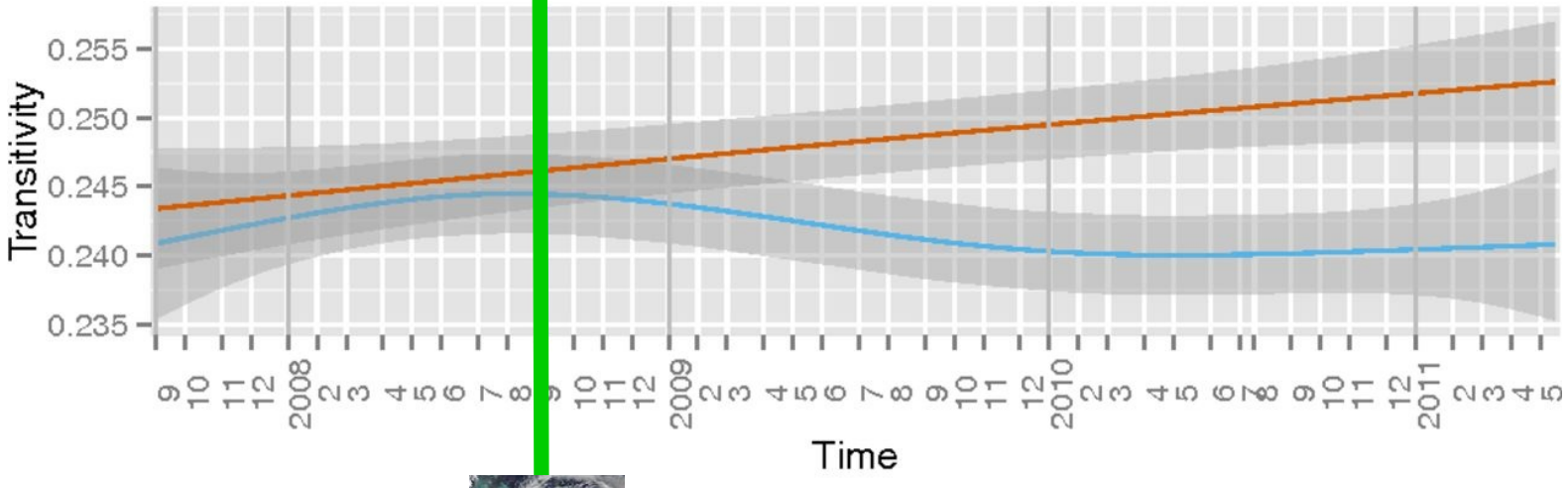
- Facebook posts from 1.5M students in 130 universities
- Matched 5 affected with 10 unaffected:
  - Similar: size, college ranking according to USNews, whether these colleges are public or private institutions, tuition fees, and other regional factors

Universities	No. of Users
Affected universities	
Baylor University	8,462
Rice University	2,355
Southern Methodist University	4,324
Trinity University	1,882
Tulane University	4,505
Unaffected universities	
Colgate University	2,359
The College of William and Mary	4,446
Georgia Institute of Technology	8,703
Middlebury College	2,374
Smith University	1,874
Tufts University	4,337
University of Pennsylvania	8,644
University of Tulsa	1,877
University of Utah	4,296
Yale University	4,519

Results (red=treatment, blue=control)



Both undergo densification



Treatment has larger clustering coefficient (more triangles)

Beyond matching on specific attributes:

Propensity matching

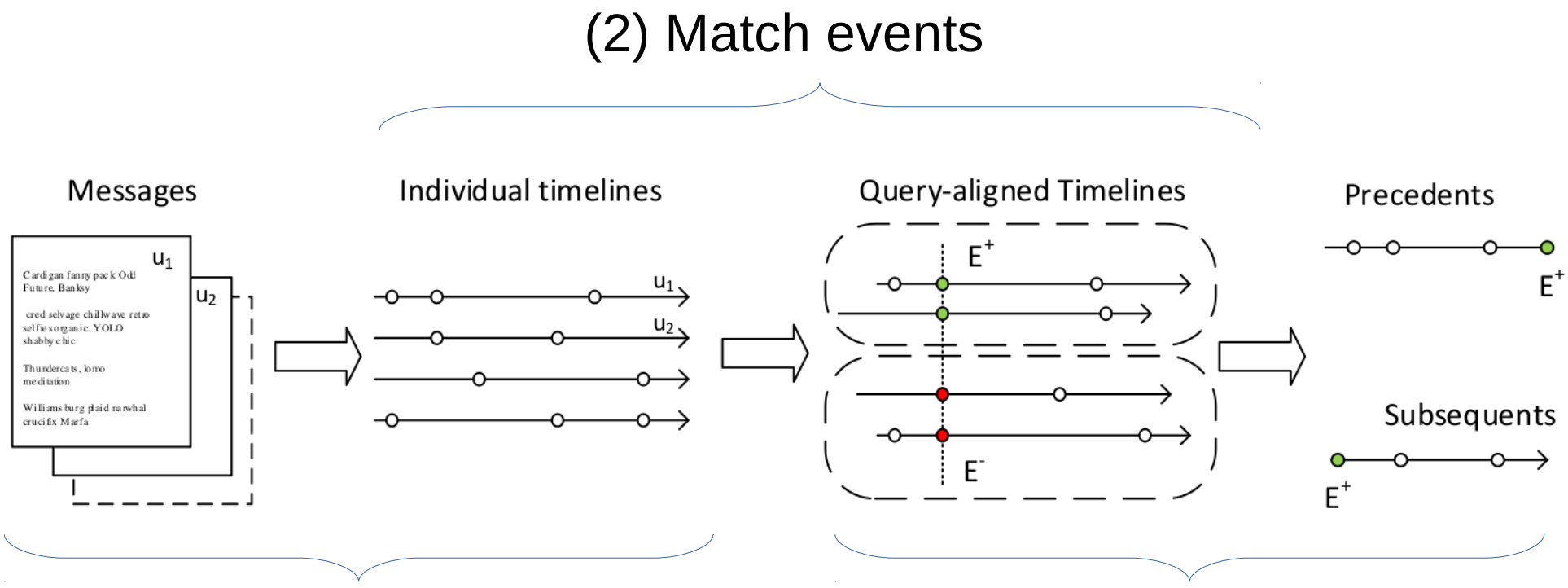
Alexandra Olteanu, Onur Varol, and Emre Kıcıman, Towards an Open-Domain Framework for Distilling the Outcomes of Personal Experiences from Social Media Timelines, in International Conference on Web and Social Media (ICWSM), AAAI - Association for the Advancement of Artificial Intelligence, 17 May 2016. [link]

Idea: create a system to extract **Situation → Action → Outcomes** from social media

T_1: “I got a kitten! We named her Versace :-)”

T_2: “No sleep because the damn kitten is nuts!”

Basic operations



Many sub-problems

- Identification of experiential messages
- Timestamping event occurrences
- Recognition and canonicalization events
- Identification of precedent and subsequent events
- Identification of positive and negative valence of events

Experiential messages classifier

Based on 10k labeled tweets.

26% of tweets mention personal experiences

8% mention goals/desires

66% are news/3rd person or other tweets

Personal Experiences	Other (news, 3rd person, etc.)
Just completed a 15.72km run with @RunKeeper. Check it out! <URL> #RunKeeper	New campaign to protect children from second hand smoke launched <URL>
Just to set the mood I brought some Marvin Gaye and Chardonnay	Whoa. The kid from Cincinnati just suffered a horrible injury. Not good.
Lacrosse is so much fun why didn't I start earlier lol	@Bob I hear you.
Oh yeah guys we got a new puppy	@Charlie did you enjoy your night at the club?

Event identification

I got a new kitten and he has blue eyes and stripes and I need a good name but nothing that's normal

Kıcıman, Emre, and Matthew Richardson. "Towards decision support and goal achievement: Identifying action-outcome relationships from social media." KDD 2015. [link]

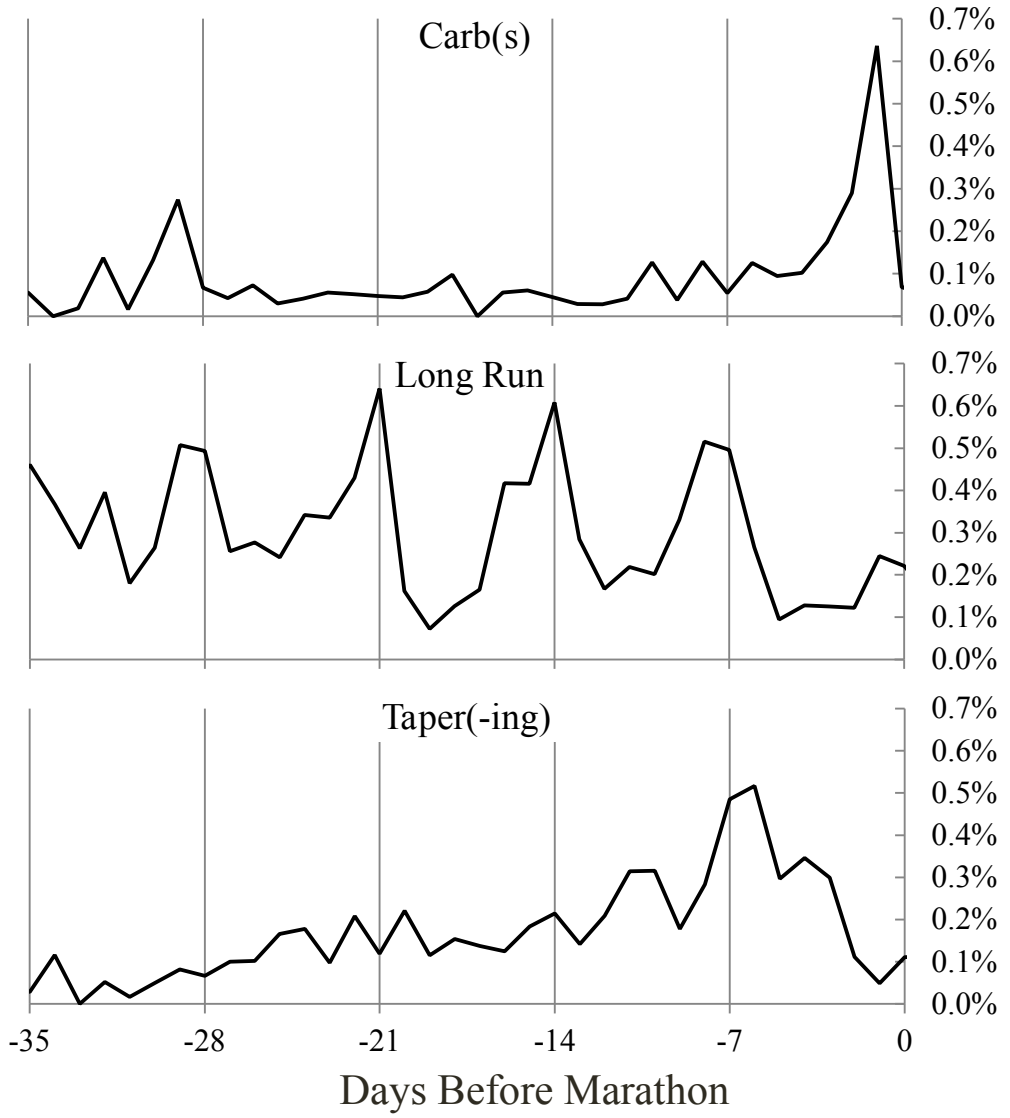
- I got a new kitten == *got a cat, got a new cat, …*
- he has blue eyes
- stripes
- but nothing that's normal
- I need a good name

Example subsequents

	Event	Example	PosNeg
Pros	cat named	We just got a cat and named it Versace	0.70
	I've got a cat	I've got a kitten asleep on my lap, and my heart has softened.	0.67
	Love my new kitten	I love my new kitten	0.88
Cons	Ran upstairs	But I ran upstairs and fell and now my head hurts	0.20
	Damn kitten	… no sleep because the damn kitten kept going nuts…	0.22
	Cat is literally	My cat is literally the devil	0.31

Example precedents

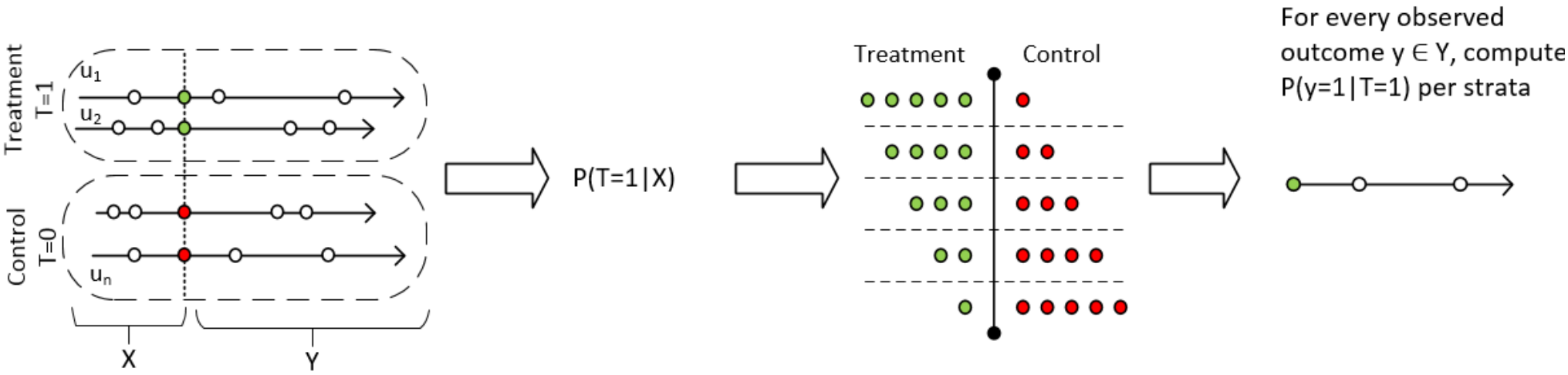
- Event: “personal record” in marathon



Propensity matching explained

- You got a kitten
- According to what's known about your past, your probability of getting a kitten was x
- You will be matched with someone whose probability of getting a kitten was also x
  - But who did not get a kitten
- Every strata has a different unbalance
  - Which is predictable

Propensity matching



Features of a user are all of their past events

PS Estimator trained w/average perceptron learning algorithm; extracted timelines are training data.

Decile stratification

Matching design

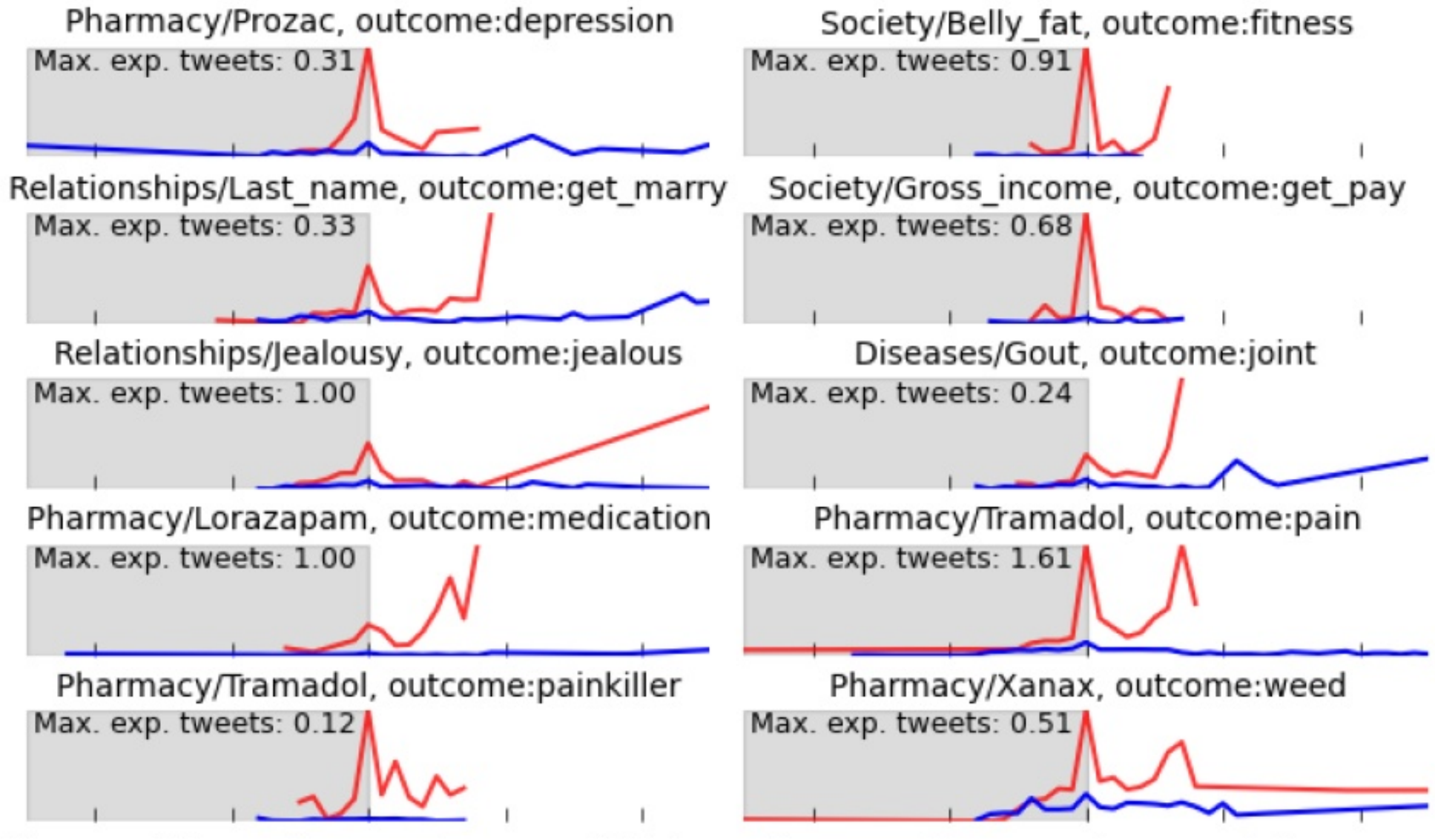
- 39 situations in 9 groups
- Outcome is binary variable
- Average effect

P(outcome|T) - P(outcome|C)

Category		Event	Treatment Users	Treatment Msgs
Business	Construct. and Maintenan.	Building stairs	24	8.3K
		Cleaning countertops	8	3.7K
		Installing a garbage disposal	29	8.2K
		Painting the deck	592	164K
	Financial Services	Owning a good credit card	2291	920K
		Paying credit card debts	414	233K
		Buying life insurance	1881	561K
		Having pension	2344	796K
		Incorporating one's business	28	9.1K
	Investing	Becoming a broker	855	355K
		Investing money	23981	9.8M
		Total	32447	12.8M
Health	Diseases	Having high blood pressure	5279	1.9M
		Having gout	364	118K
		Having high cholesterol	1384	522K
		Having kidney stone	727	259K
		Having high triglycerides lev.	27	12K
	Mental	Suffering from depression	25207	10.5M
		Suffering from OCD	11429	4.8M
		Being a sociopath	1491	676K
		Being a psychopath	2895	1.3M
		Suffering from anxiety	53983	22.6M
		Suffering from bipolar disord.	13723	6.3M
	Pharmacy	Taking Prozac	617	222K
		Taking Lorazepam	47	19.4K
		Taking Promethazine	242	118K
		Taking Tramadol	397	161K
		Taking Xanax	3300	1.4M
		Total	121112	50.9M
Society	Issues	Losing belly fat	93	24.8K
		Increasing gross income	135	93.2K
	Law	Getting divorced	2717	1.2M
		Becoming a notary	65	22.7K
		Applying for social security	6172	2.3M
		Filing for bankruptcy	921	347K
		Having a living trust	18	7.5K
	Relationsh.	Finding true love	1885	654K
		Recovering after adultery	9	4.4K
		Filing divorce	422	178K
		Dealing with jealousy issues	789	370K
		Changing last name	1019	403K
		Total	14245	5.7M

Example: having high triglycerides level

Outcome	Count	Absolute Increase	Z-Score
Your_risk	46	24.8%	18.12
Statin	48	23.1%	17.69
Lower	120	35.9%	17.18
Cardiovascular	54	23.0%	16.72
Healthy_diet	55	19.3%	16.54
Fatty_acid	29	18.3%	16.37
Help_prevent	73	26.9%	16.01
Risk_factor	33	18.3%	15.55
Fish_oil	48	24.4%	15.42
inflammation	78	25.1%	15.30


Pharmacy/Prozac, outcome:depression
Max. exp. tweets: 0.31
Society/Belly_fat, outcome:fitness
Max. exp. tweets: 0.91
Relationships/Last_name, outcome:get_marry
Max. exp. tweets: 0.33
Society/Gross_income, outcome:get_pay
Max. exp. tweets: 0.68
Relationships/Jealousy, outcome:jealous
Max. exp. tweets: 1.00
Diseases/Gout, outcome:joint
Max. exp. tweets: 0.24
Pharmacy/Lorazapam, outcome:medication
Max. exp. tweets: 1.00
Pharmacy/Tramadol, outcome:pain
Max. exp. tweets: 1.61
Pharmacy/Tramadol, outcome:painkiller
Max. exp. tweets: 0.12
Pharmacy/Xanax, outcome:weed
Max. exp. tweets: 0.51
Treatment
Control

Example Treatments and Outcomes
(paraphrased for anonymity)

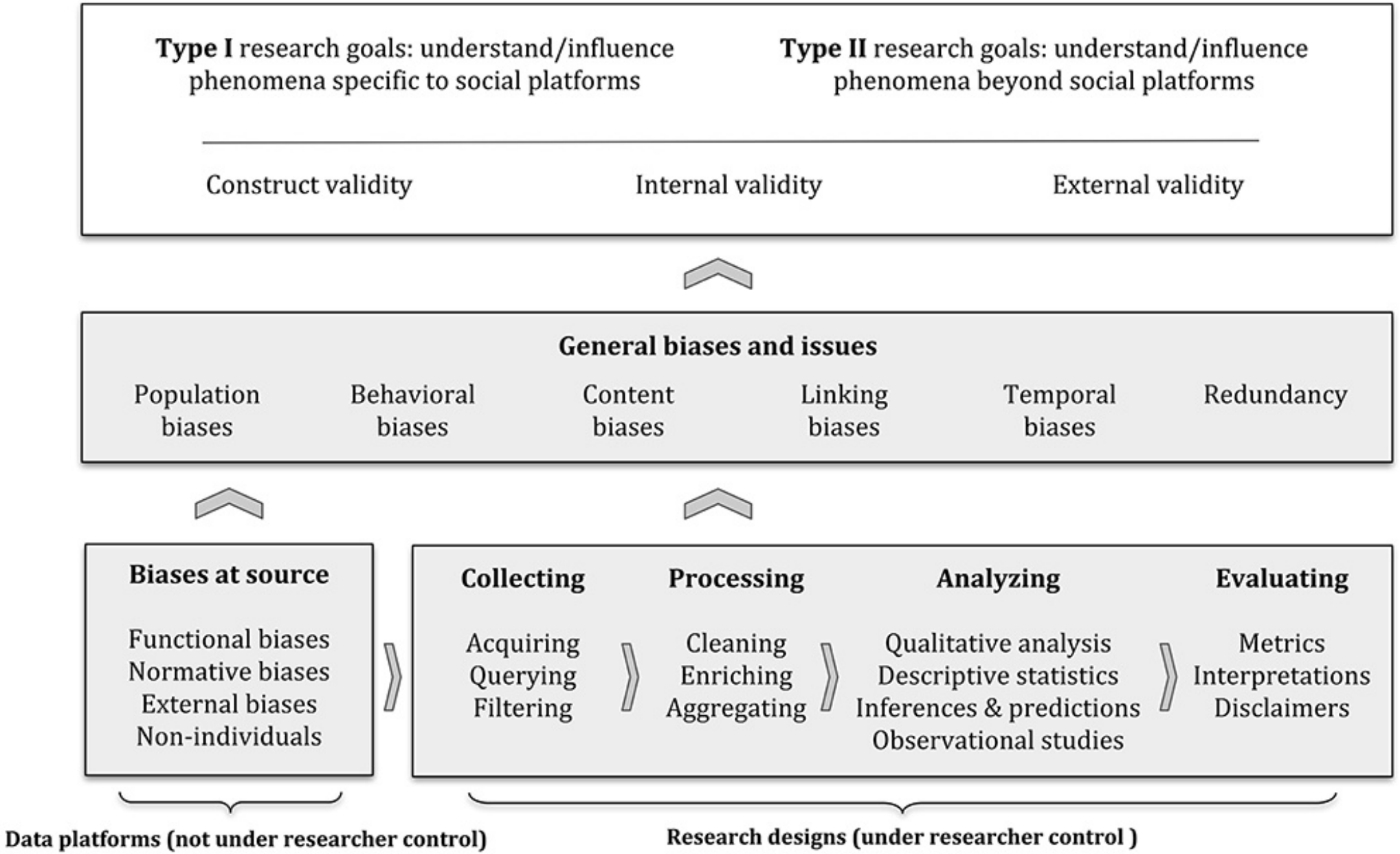
Treatment	Example tweet	Outcome	Example tweet
Dealing with jealousy issues	*ironically, u ask why I have jealousy issues*	wake up	*@user I need u to wake up because im bored*
Suffering from depression	*if u think depression is eccentric or cute u can have mine bc i dont wanna deal with it*	thoughts	*hate small talks, dont talk abt weather, tell me what keeps u up at night, ur thoughts abt dying*
Suffering from depression	*if u think depression is eccentric or cute u can have mine bc i dont wanna deal with it*	self harm	*@user dont self harm, remember yr worth so much better, u dont deserve this pain, stay safe*
Suffering from anxiety	*if hadnt spent years dealing with anxiety, I wouldnt have my sense of humor*	yelling	*dont have any anger issues at all, im really happy when yelling at people*
Paying credit card debts	*seriously, my soul was deep hurt when I paid that credit card bill*	apartment	*Im checking some apartments in NYC lol*
Having high blood pressure	*@user but I do have really high blood pressure!*	stress	*had a heart mri and the news are as good as they can be. much stress is now removed from my life*
Having gout	*@user I know I have gout...*	uric	*is the increase in uric acid production in blood, forming crystals and depositing them in joints*

Labeling by non-experts (Mechanical Turk workers)

Further reading: observational studies and propensity matching

Biases, biases all the way

Credit: Sam Hollingsworth



Olteanu, Alexandra and Castillo, Carlos and Diaz, Fernando and Kiciman, Emre (2019) Social Data: Biases, Methodological Pitfalls, and Ethical Boundaries. Frontiers in Big Data 2:13. doi: 10.3389/fdata.2019.00013

Take-home messages

Best practices: social media mining

- **Interdisciplinary work**
  - Mixed methods: qualitative and quantitative
  - Robust to different settings, metrics, datasets
  - Aware that there are biases, biases all the way
- **Good applied research**
  - Is well-grounded in the literature of the domain
  - Has a measurable impact in the problem domain

Practical advice: social media research

This is a very crowded area

- Stand out with a completely new problem, a new dataset, and a deeper grounding on a problem domain
- Be the data you want to see in the world

Become learned in your problem domain

- Commit to cross-disciplinary research or don't do it
- Talk to many experts on the problems you're trying to address; learn their language; read key books
- They'll dislike your results and/or jump to high-level conclusions that don't follow your low-level observations, probably both; listen and be patient