STUDYING MOOD VARIATIONS IN LONGITUDINAL TWITTER TIMELINES

APPLICATIONS TO THE DETECTION OF PSYCHOLOGICAL TRANSITIONS

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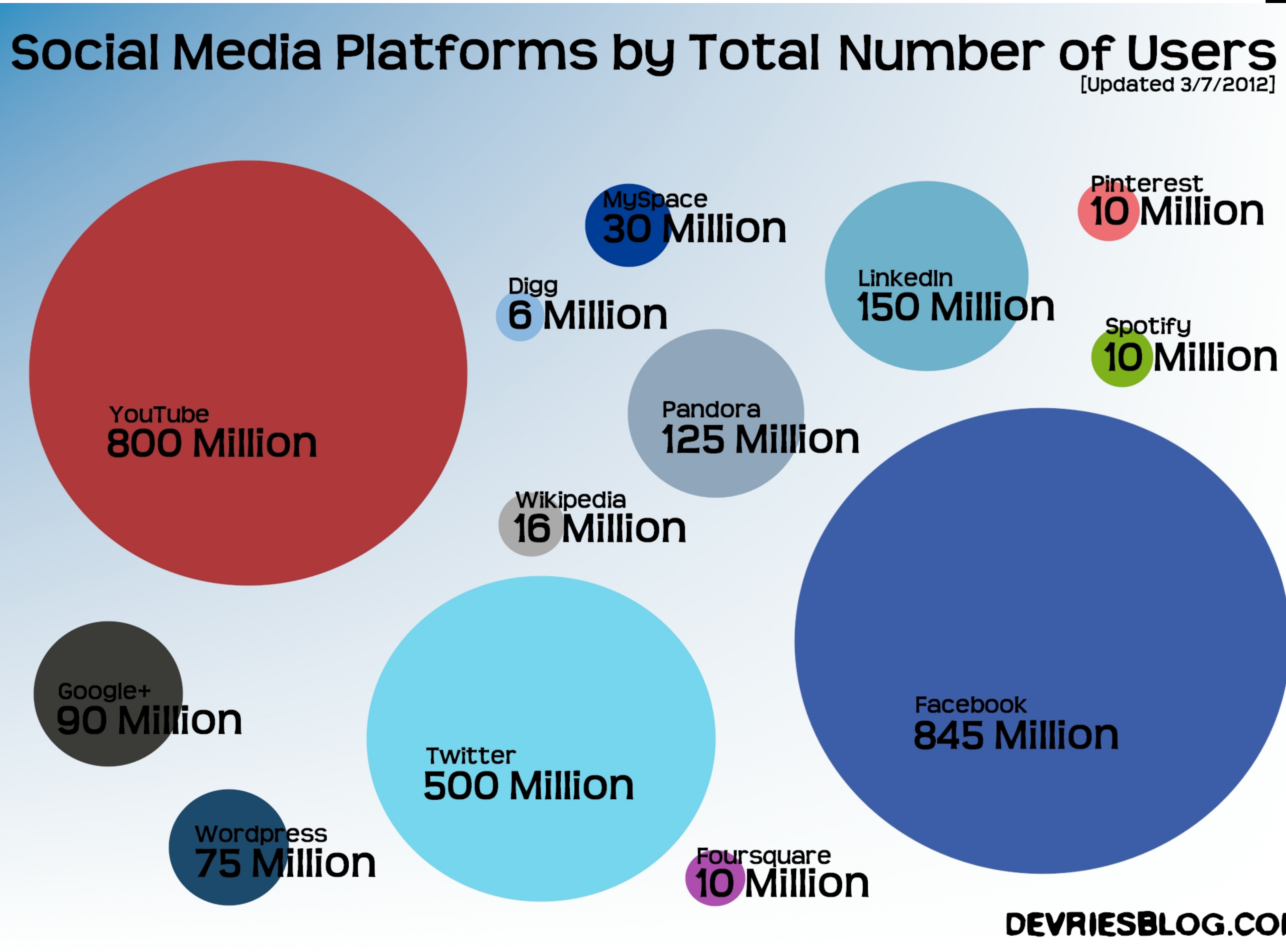
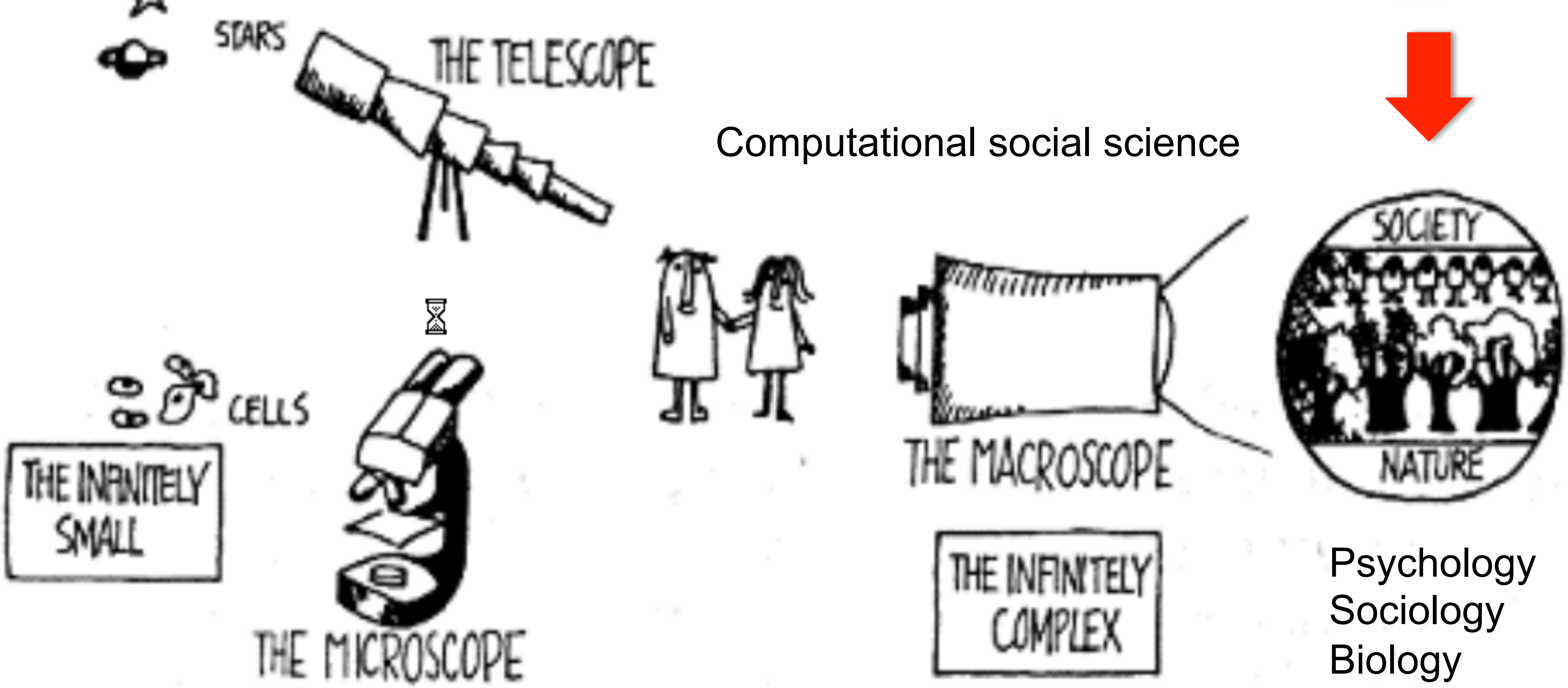

Social Media Platforms by Total Number of Users
[Updated 3/7/2012]
YouTube
800 Million
MySpace
30 Million
Digg
6 Million
LinkedIn
150 Million
Pinterest
10 Million
Spotify
10 Million
Pandora
125 Million
Wikipedia
16 Million
Facebook
845 Million
Google+
90 Million
Twitter
500 Million
Wordpress
75 Million
Foursquare
10 Million
DEVRIESBLOG.CO

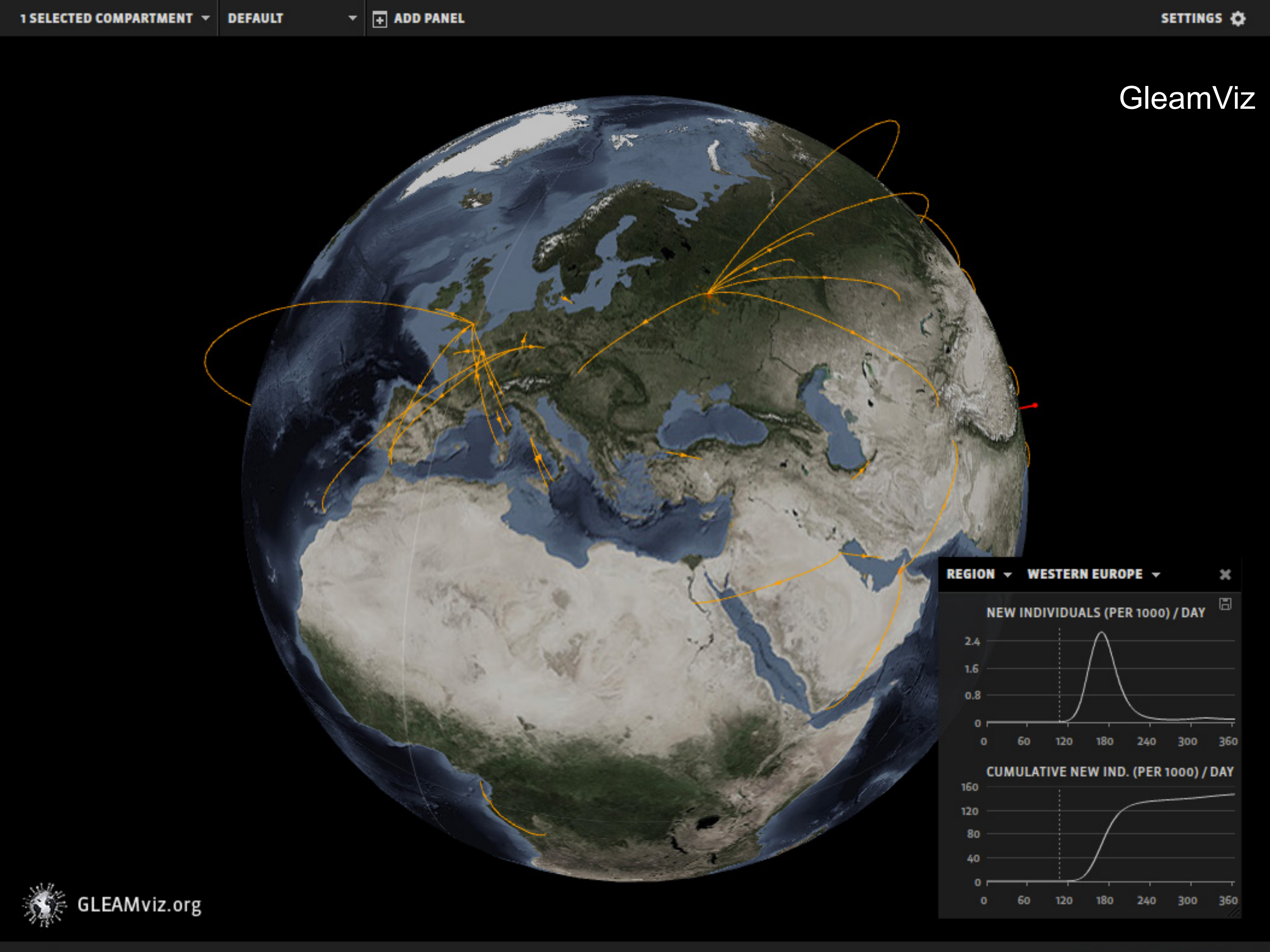
Implementing the Macroscope vision

Computational social science



Psychology
Sociology
Biology
Science

De Rosnay, J: The macroscope, Harper & Row, New York, 1979.


1 SELECTED COMPARTMENT
DEFAULT
ADD PANEL
SETTINGS
GleamViz
REGION
WESTERN EUROPE
NEW INDIVIDUALS (PER 1000) / DAY
2.4
1.6
0.8
0
0 60 120 180 240 300 360
CUMULATIVE NEW IND. (PER 1000) / DAY
160
120
80
40
0
0 60 120 180 240 300 360
GLEAMviz.org

OUR WORK: COLLECTIVE MOOD STATES

THE CROWD'S LIMBIC SYSTEM

Epictetus: "*Men are disturbed, not by things, but by the principles and notions which they form concerning things*"

Social mood:

- **Social issues: public health, unrest, …**
- **Economic issues: growth, market behavior**

But how can you determine how people feel?

OUR MACROSCOPES

Network science

Large-scale social media data

Natural language processing

Sentiment and mood analysis

This talk:

1. Social mood & stock market prediction

2. Public mood: assortativity, contagion, & eigenmoods

3. Individual mood: longitudinal analytics, mental health

SENTIMENT ANALYSIS: TOOLS

- Lexicons: ANEW (Valence, Arousal, Dominance), OpinionFinder, SentiWordnet (Wordnet)

- Machine learning approaches: classification (positive, negative, neutral)

- **Naïve Bayesian classifiers: learning from "training set" which terms mark a particular mood, classify on that basis (bag of words)**
- **Support Vector Machines (similar notion)**
- **Semantic and grammatical analysis**
- **Stanford CoreNLP Sentiment**

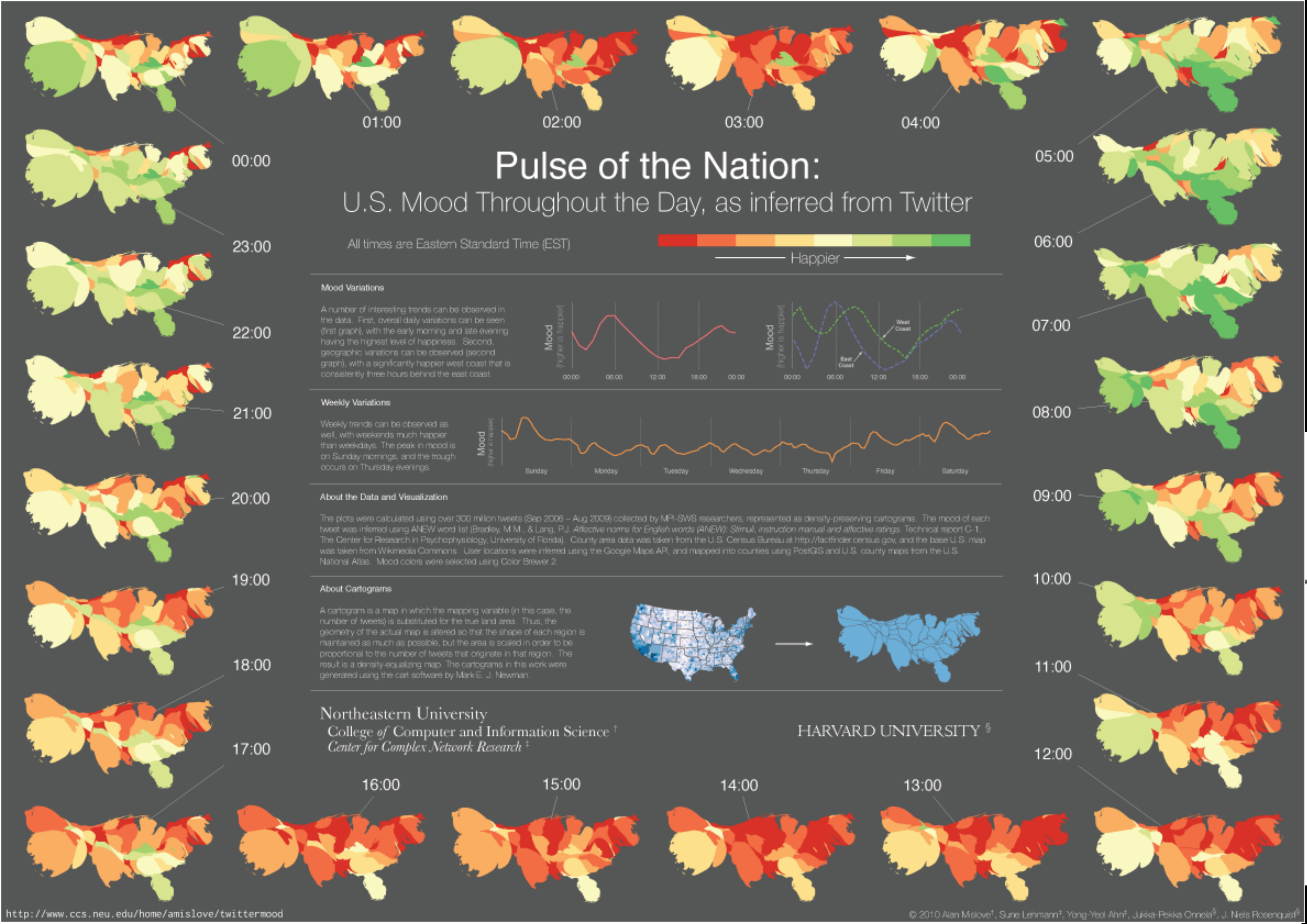
Gamon (2004), Pang (2008), Mishne (2006), Balog (2006), Gruhl (2005), Socher (2013)

Lexicon sentiment rating examples (ANEW):

*"I'm totally coveting yer seafaring ways...my **dream** is oceans of **bed**..."*
Arousal = 4.070, valence = 7.120, dominance= 6.205

*"Feeling **blue**.. hoping I feel better before **Christmas** :("*
Arousal = 5.290, valence=7.280, dominance= 5.500

See: Dodds & Danforth (2010). J Happiness 11:441–456



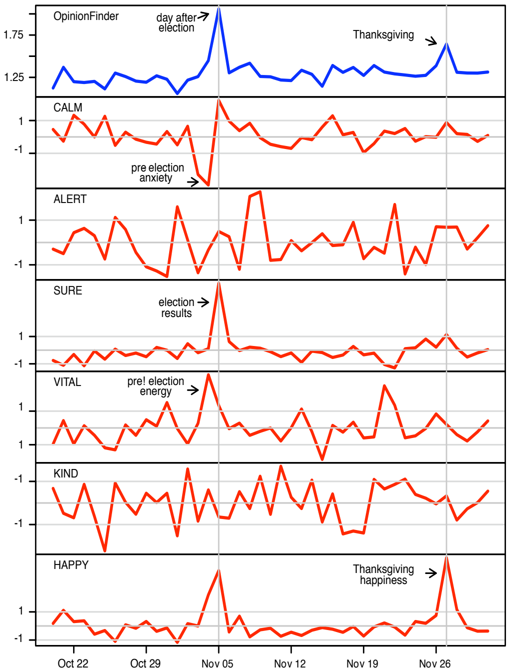
From: Dodd (2011) Temporal patterns of happiness and information in a global social network: Hedonometrics and Twitter

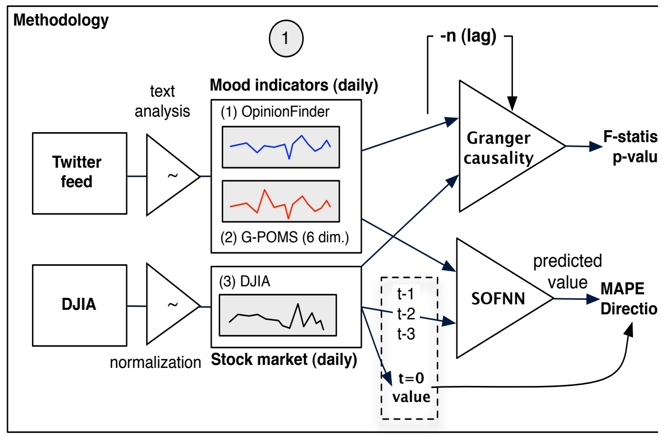
FINANCIAL MARKET PREDICTION

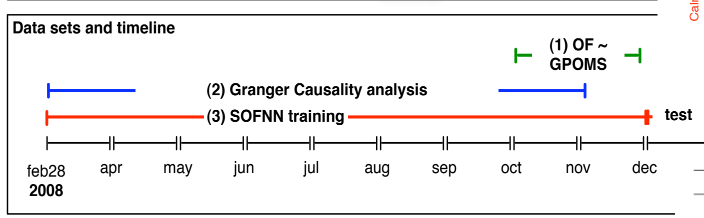
Collection of tweets: April 29, 2006 to December 20, 2008 , 2.7M users

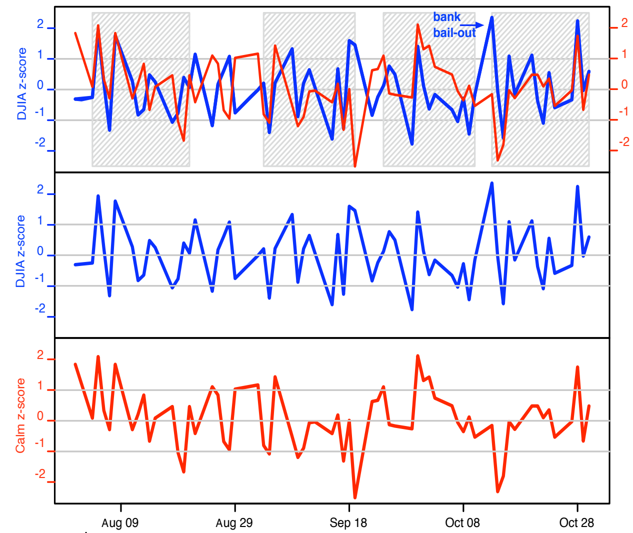
Subset: August 1, 2008 to December 2008 (9,664,952 tweets)

GPOMP: Based on Profile of Mood States, 6 dimensions of mood -- Calm, Alert, Sure, Vital, Kind, Happy.









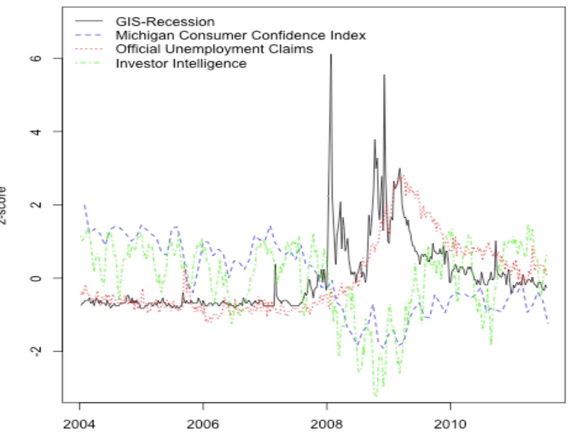
Evaluation	I_{OF}	I_0	I_1	$I_{1,2}$	$I_{1,3}$	$I_{1,4}$	$I_{1,5}$	$I_{1,6}$
MAPE (%)	1.95	1.94	1.83	2.03	2.13	2.05	1.85	**1.79**★
Direction (%)	73.3	73.3	**86.7**★	60.0	46.7	60.0	73.3	80.0

Lag	OF	Calm	Alert	Sure	Vital	Kind	Happy
1 day	**0.085**★	0.272	0.952	0.648	0.120	0.848	0.388
2 days	0.268	**0.013**★★	0.973	0.811	0.369	0.991	0.7061
3 days	0.436	**0.022**★★	0.981	0.349	0.418	0.991	0.723
4 days	0.218	**0.030**★★	0.998	0.415	0.475	0.989	0.750
5 days	0.300	**0.036**★★	0.989	0.544	0.553	0.996	0.173
6 days	0.446	**0.065**★	0.996	0.691	0.682	0.994	**0.081**★
7 days	0.620	0.157	0.999	0.381	0.713	0.999	0.150

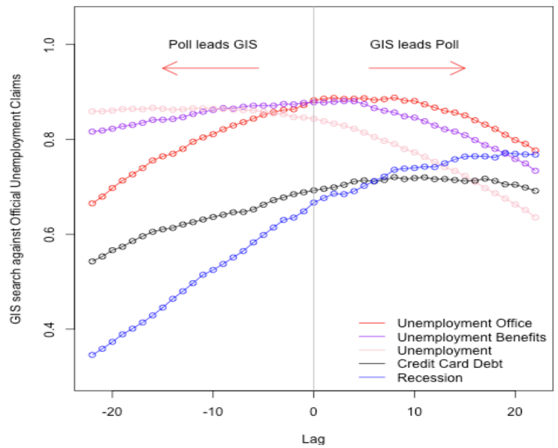
(p-value < 0.05: ★★, p-value < 0.1: ★)

Johan Bollen, Huina Mao, and Xiao-Jun Zeng. Twitter mood predicts the stock market. Journal of Computational Science, 2(1), March 2011, Pages 1-8, doi:10.1016/j.jocs.2010.12.007

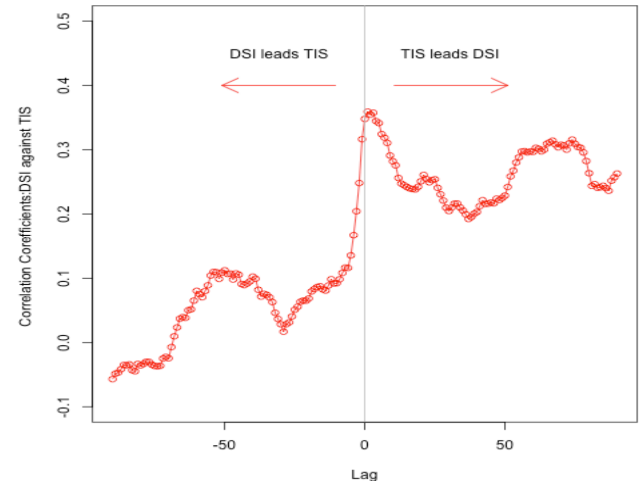
UNRAVELING PUBLIC, INVESTOR, AND COMMUNITY MOOD STATES



Google search 19 fear terms, e.g.recession”



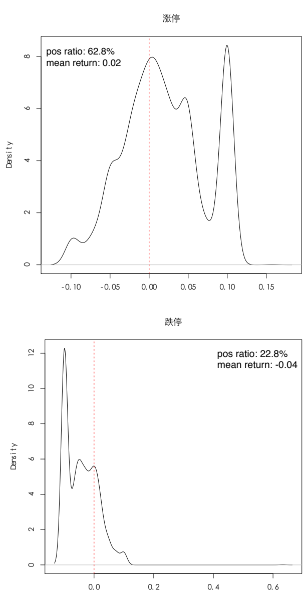
Cross-correlation US Unemployment rate vs. GIS

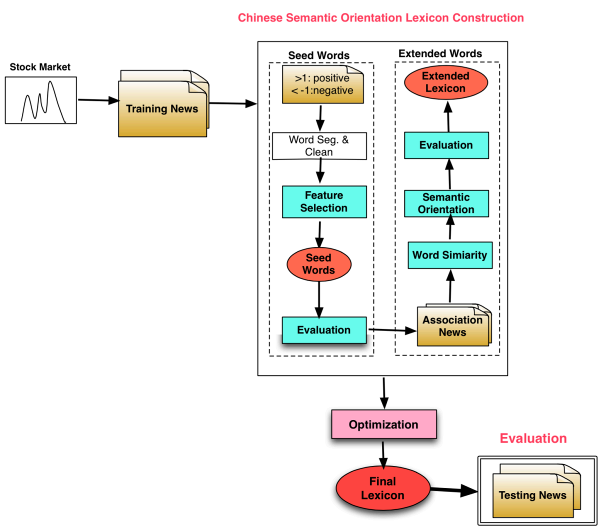


Cross-correlation DSI and Twitter Investor Sentiment

Huina Mao, Scott Counts and Johan Bollen. Computational Economic and Finance Gauges: Polls, Search, and Twitter. Meeting of the National Bureau of Economic Research - Behavioral Finance Meeting, Stanford, CA, November 5th, 2011

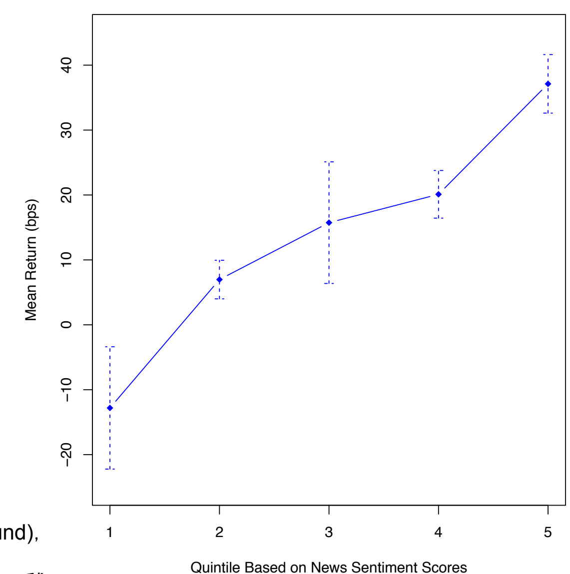
Chinese Financial Lexicon Construction (919,246 news headlines)





Positive seed words: 盈利(profit), 恢复(recover)，涨停(limit-up)，反弹(rebound), 优势(advantages) ...
Negative seed words: 跌停(limit-down)，亏(deficit)，失败(failure)，损失(loss), 稽查(inspect) ...

Testing



OTHER RESULTS

Eric Gilbert et al (2010) Widespread Worry and the Stock Market. Proceedings of ICWSM, May, Washington DC – available at: http://comp.social.gatech.edu/papers/icwsm10.worry.gilbert.pdf

Timm O. Sprenger and Isabell Welpe (2010). Tweets and Trades: The Information Content of Stock Microblogs (November 1, 2010). Available at SSRN: http://ssrn.com/abstract=1702854

Huina Mao, Scott Counts, Johan Bollen (2011) Predicting Financial Markets: Comparing Survey, News, Twitter and Search Engine Data. http://arxiv.org/abs/1112.1051

Tobias Preis, Helen Susannah Moat & H. Eugene Stanley (2013). Quantifying Trading Behavior in Financial Markets Using Google Trends, Scientific Reports 3 (1684) doi: 10.1038/srep01684

Sul (2014) Trading on Twitter. HICCS'47, Hawaii, January 2014
Computational models of consumer confidence from large-scale online attention data: crowd-sourcing econometrics.

Dong, X and Bollen, J. (2015) Computational models of consumer confidence from large-scale online attention data: crowd-sourcing econometrics. PLoS One, In press.

BUT, WHERE DOES ONLINE COLLECTIVE MOOD COME FROM?

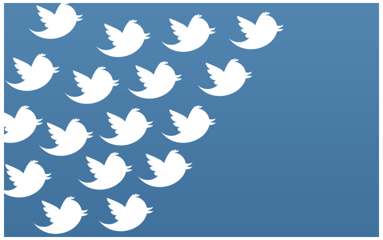
Measuring and averaging individual mood states =

- not really "collective" mood… sum of individual text sentiment
- Collective mood ~ emergent phenomenon, endogenous response, function of social network, response to drivers "internal" to community
- Median or average mood !~ variance, uncertainty, communities, language

Very active research area:

- Use of epidemiological models to model mood contagion (Ferrara et al)
- Agent-based models (Garcia, 2012)
- Role of homophily, preferential attachment, contagion, socio-economic factors, modeling uncertainty and community effects (our present work)

ROLE OF HOMOPHILY IN COLLECTIVE MOOD



"birds of a feather" in social networks:

McPherson, M., Smith-Lovin, L., & Cook, J. M. (2001). "Birds of a Feather: Homophily in Social Networks". Annual Review of Sociology. 27:415–444.

- **Homophily:** tendency of individuals to associate with those of similar age, sex, religion, race, etc.
- **Heterophily:** associating with opposite or contrary features
- **Distinction:** Homophily vs features that it applies to.

Also referred to as *Assortativity*, cf. Newman, M. E. J. (2002). Assortative mixing in networks. Phys. Rev. Lett., 89, 208701/1–4.

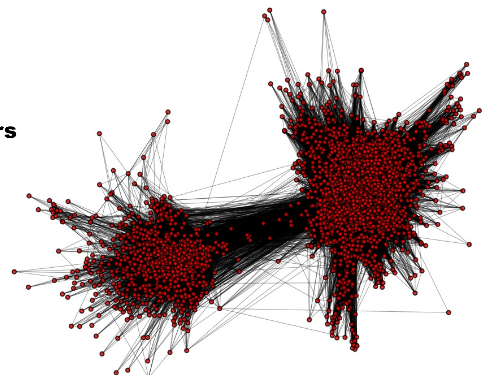
Note: homophily != contagion

Aral, S., Muchnik, L., & Sundararajan, A. (2009). Distinguishing influence-based contagion from homophily-driven diffusion in dynamic networks. Proceedings of the National Academy of Sciences of the United States of America, 106(51), 21544–9. doi:10.1073/pnas.0908800106

TWITTER MOOD ASSORTATIVITY

Nov. 20, 2008 to May 29, 2009, 4,844,430 user timelines, 129M tweets

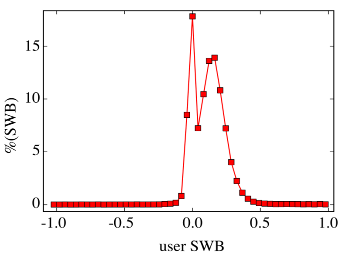
Network parameter	Value
Nodes	102,009 users
Edges	2,361,547
Density	0.000454
Diameter	14
Avg. Degree:	46.300
Avg. Clustering Coefficient	0.262

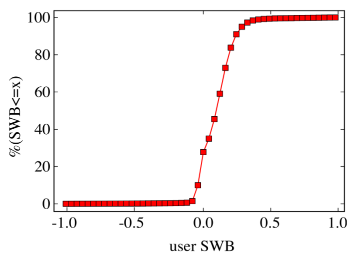


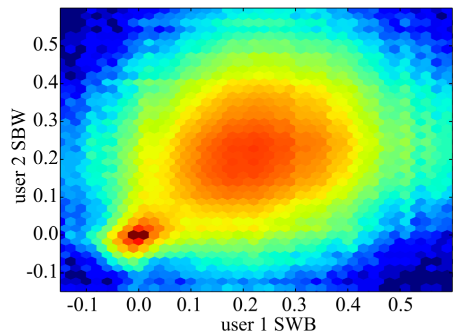
Longitudinal "Subjective Well-being"

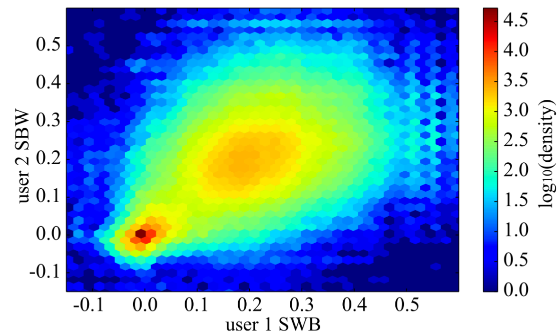
$$\mathcal{S}(u) = \frac{N_p(u) - N_n(u)}{N_p(u) + N_n(u)}$$

PAIRWISE SWB ASSORTATIVITY

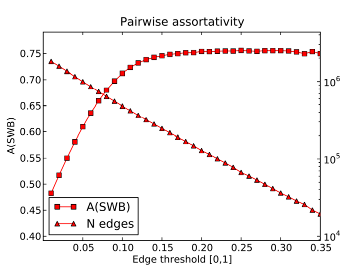


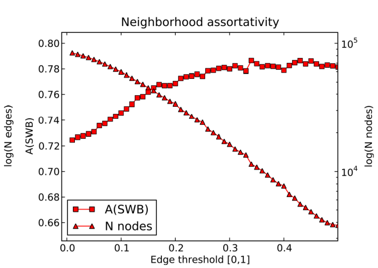


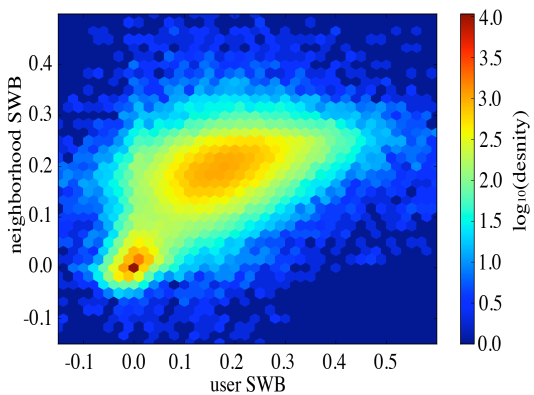


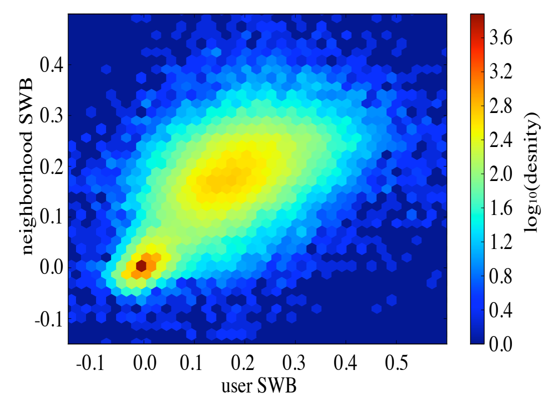


NEIGHBORHOOD SWB ASSORTATIVITY









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RECENT WORK

Two lines of research:

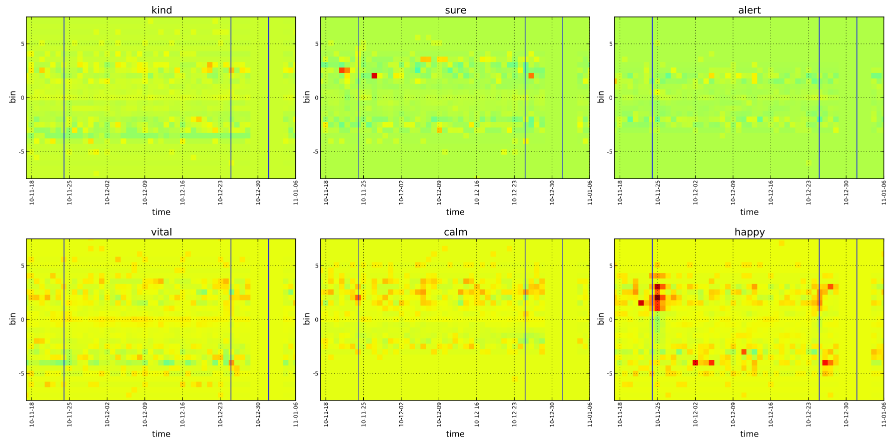
1) **Study spectrum of mood states**
    1) **Collective: "Eigenmoods"**
    2) **Individual: longitudinal timeline analysis**
2) **Applications to personal well-being and health**
    1) **Detecting mental health issues: depression features**
    2) **Critical transitions, early warning indicators**

EIGENMOODS

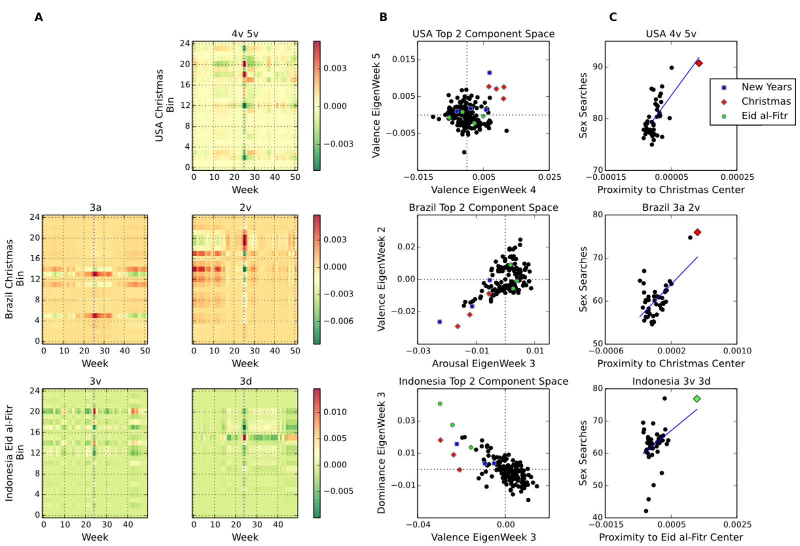
WITH LUIS ROCHA, IAN WOODS, JOAN SA, & PEDRO VARELA

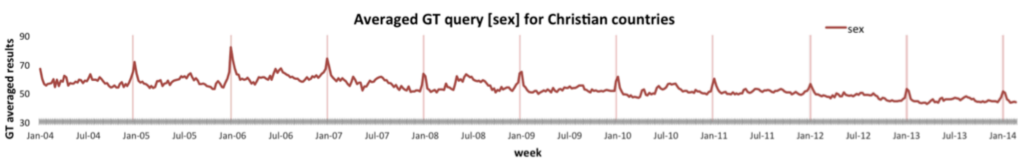
Average sentiment: language model x word sentiment value
Remove language effect, and find “eigenmood”.
Singular Value Decompositions of Mood Bin x time matrix:

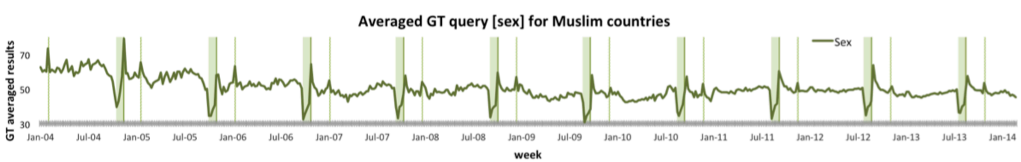
- Decompose mood bin x time matrix: $M = U\Sigma V^t$
- Approximate without first singular value (language model)

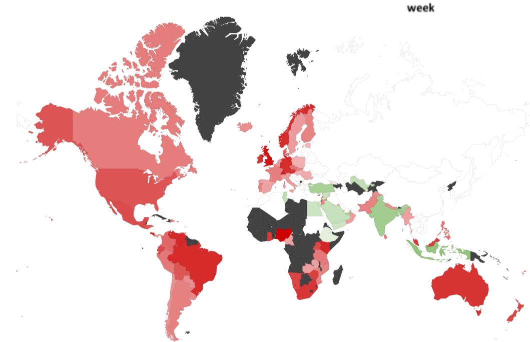


Interesting correlations to social phenomena, for example Google sex searches, birth rates, and public eigenmoods





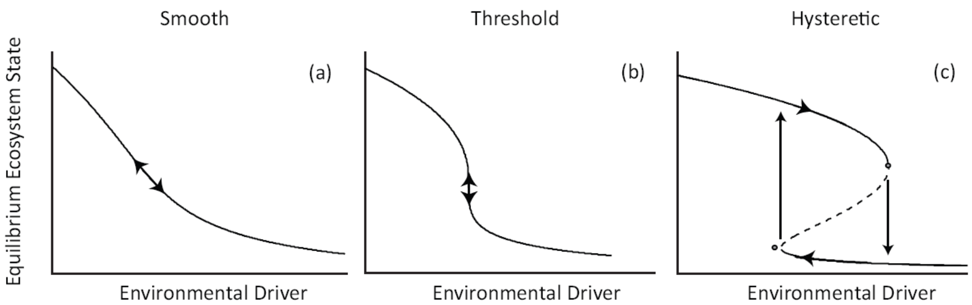




Sex searches during xmas week

CRITICAL TRANSITIONS IN MENTAL HEALTH

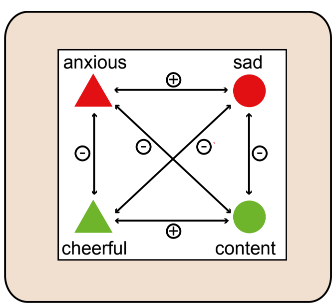
Ingrid van de Leemput et al.

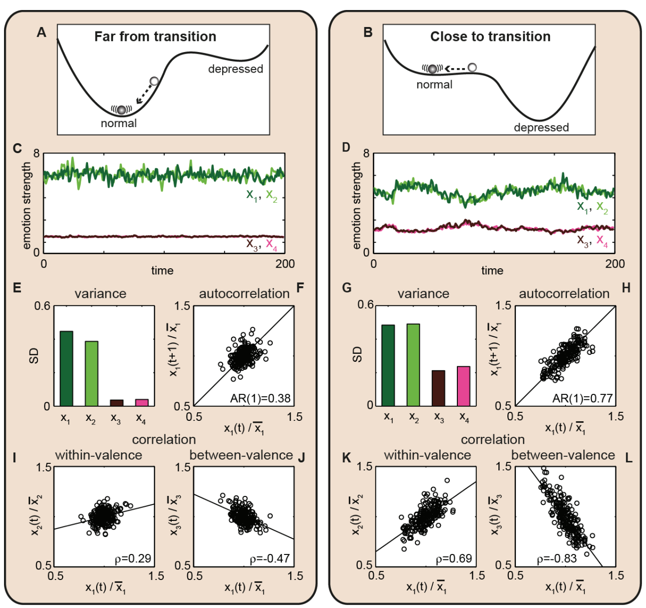


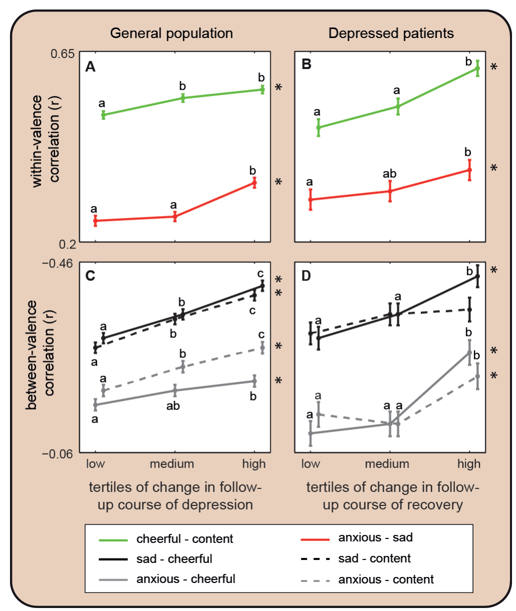
Observed in complex systems in biology and physics. Preceded by early warning signals: critical slowing down, increased variance

Applications to mental health: modeling depression as a critical transition in mood dynamics

2 populations: (1) not depressed (n=535), depressed (n=93). 6 consecutive days, 10 times a day (7:30 - 22:30). Monitoring of follow-up course depressive symptoms







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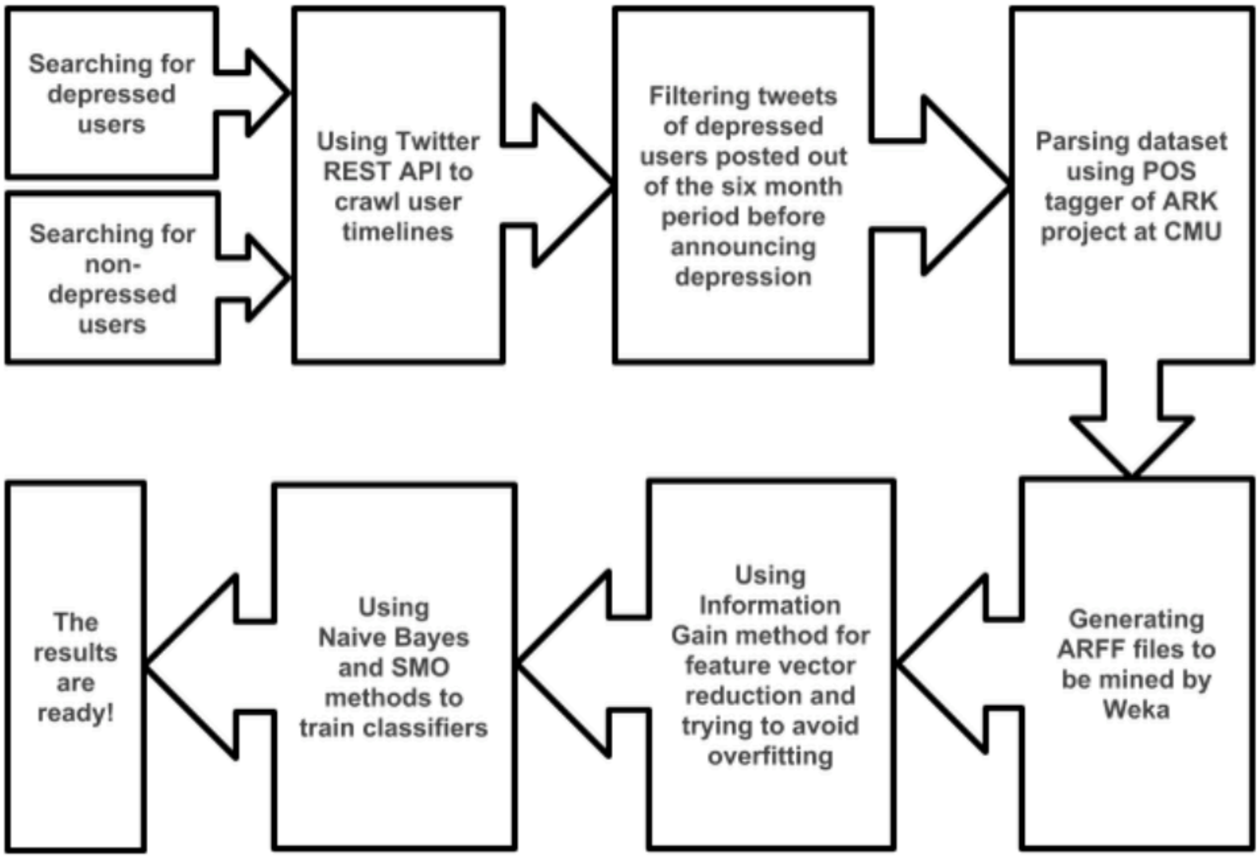
Van de Leemput et al (2014), PNAS 111(1) Critical slowing down as early warning for the onset and termination of depression

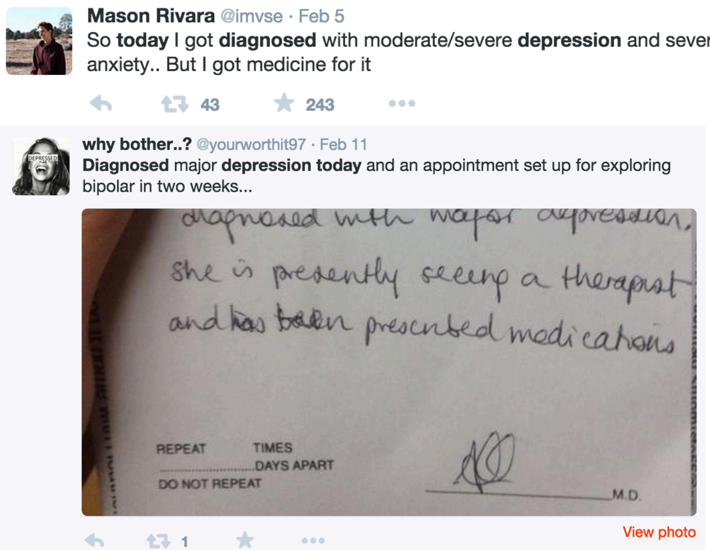
DEPRESSION With Ali Varamesh, Ingrid van de Leemput



Detect linguistic features of Depression in online social media users

DEPRESSION

With Ali Varamesh, Ingrid van de Leemput



Query: "**I was diagnosed with depression today**"

Class	Users	Tweets	avg#tweets/user
Depressed	42	124,015	2,952
Non-Depressed	73	150,775	2,065

Feature extraction: Twitter Part-of-Speech Tagger from ARK project at CMU
24 different POS tags and about 25,448 tokens
User feature vectors: number of times a token or POS tag is used in a user's timeline divided by the total number of user's tweets.
Based on OneR test removal of "diagnosis" and "depression"

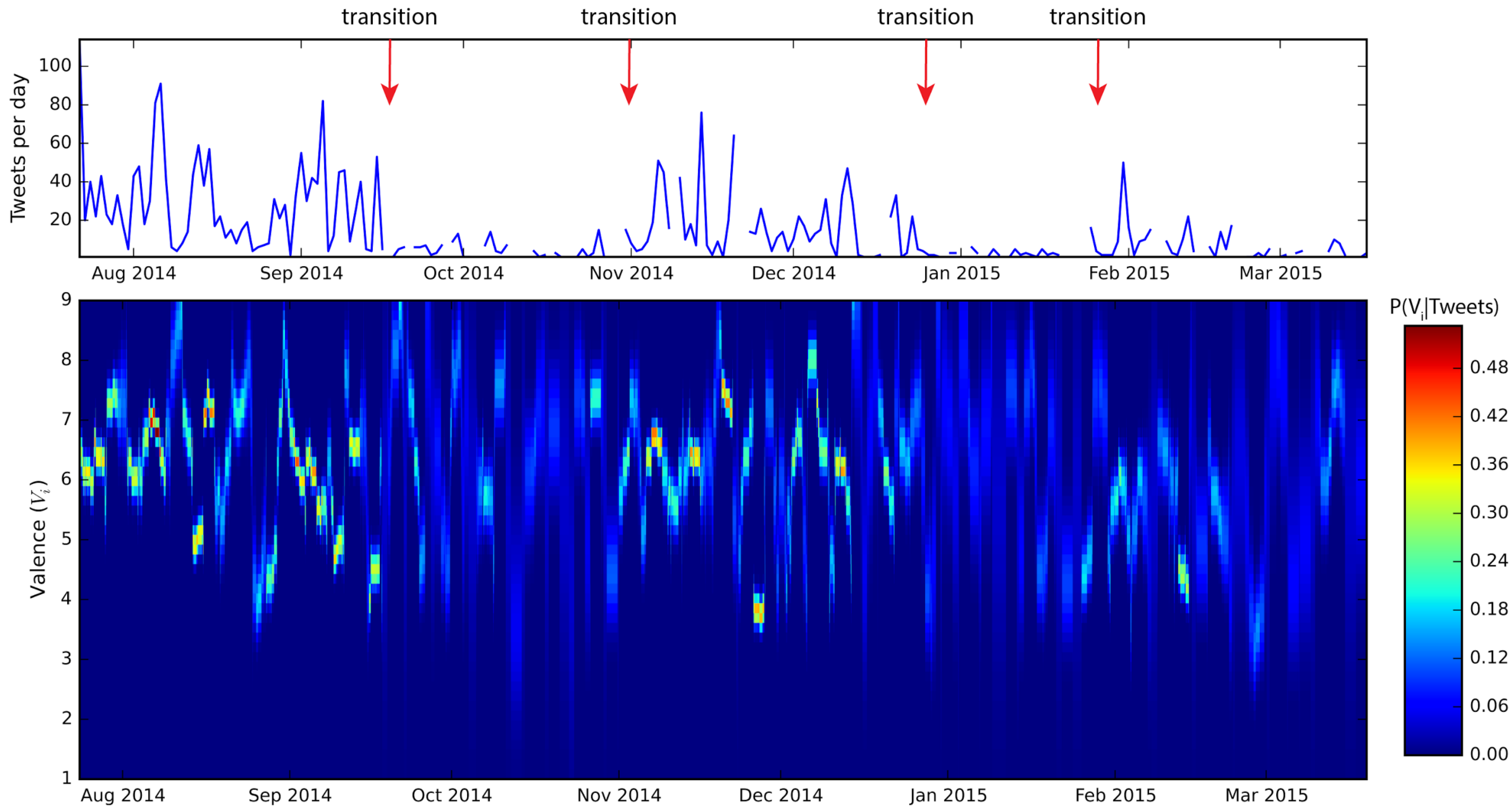
Rank	Feature	Info. Gain	Rank	Feature	Info.n Gain
1	awards	0.1755	14	ugh	0.1287
2	gross	0.1616	15	pokemon	0.1283
3	massive	0.1518	16	figured	0.1283
4	hope	0.145	17	oops	0.127
5	casually	0.1443	18	deserved	0.165
6	congratulations	0.1443	19	thankful	0.1264
7	guess	0.1432	20	changes	0.1245
8	my	0.1432	21	will	0.1234
9	maybe	0.1382	22	treat	0.1211
10	oh	0.1382	23	laundry	0.1196
11	gosh	0.1356	24	pick	0.1196
12	holy	0.1356	25	considering	0.1196
13	memories	0.1296	26	chores	0.1194

Classification Method	Precision	Recall	F-Measure	ROC Area
ZeroR (Baseline)	0.425	0.652	0.514	0.474
Naive Bayes	0.991	0.991	0.991	1.0
SMO	0.974	0.973	0.973	0.962

LONGITUDINAL MOOD DATA CRITICAL TRANSITIONS

Ingrid van de Leemput, Marten Scheffer, Luis Rocha, Rion Correia

- About 700,000 timelines of individual Twitter users: June 2010 to June 2013
- Use of ANEW lexicon (13k terms: Valence, Arousal, Dominance), CRR U. Gent
- “I was diagnosed with depression today”



Bayesian updating using ANEW lexicon and Google n-grams as prior, with likelihood P(D|M) from lexicon distribution.

CONCLUSION

Growth of "social" data is likely to be most significant in "ego"-related data vs. network data pur sang:

- **significant longitudinal data since advent of social media 8 years ago**
- **Increasing use of personal monitoring devices**
- **Increasing focus on personal, well-being related data**

Tremendous opportunities in:

- medicine, public health, forecasting, and possibly intervention strategies to prevent "hysteresis".

- Study relations between individual features vs. network topology.

COLLABORATORS

Luis Rocha (IU)

Marten Scheffer (IU)

Huina Mao (ORNL)

Rion Coreia (IU)

Ian Woods (IU)

Ali Varamesh (IU)

Ingrid van de Leemput (U. Wageningen)

READINGS

Bollen J, Mao H, Zeng XJ (2011) Twitter mood predicts the stock market. Journal of Computational Science 2: 1–8. doi: 10.1016/j.jocs.2010.12.007.(featured on CNBC, CNN International and Bloomberg News!)

Johan Bollen, Bruno Gonçalves, Guangchen Ruan & Huina Mao (2011). Happiness is assortative in online social networks. Artificial Life, Summer - 17(3), 237-251 arxiv:1103.0784, doi:10.1162/artl_a_00034)

Huina Mao, Scott Counts, Johan Bollen (2011) Predicting Financial Markets: Comparing Survey, News, Twitter and Search Engine Data - http://arxiv.org/abs/1112.1051

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Huina Mao, Alberto Pepe, and Johan Bollen (2010). Structure and evolution of mood contagion in the Twitter social network. Proceedings of the International Sunbelt Social Network Conference XXX, Riva del Garda, Italy, July 2010

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