Twitter mood predicts the stock market

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Public mood states and the markets

Do societies experience varying mood states like individuals?
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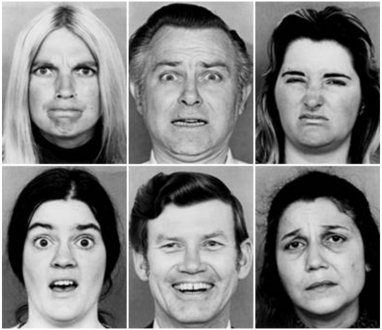

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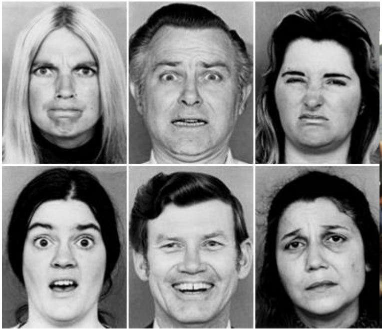

Outline

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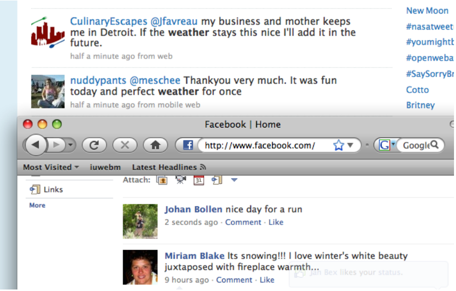
Microblogging: casu Twitter!

tweets and updates

users broadcast brief text updates to the public or to a limited group of contacts: 140 characters or less
Twitter, Facebook, Myspace

Examples

- "Our Rights from Creator (h/t @JLocke). Life, Liberty, PoH FTW! Your transgressions = FAIL. GTFO, @GeorgeIII. -HANCOCK et al."
- "at work feeling lousy"



Analyzing the chatter

Predicting the present

Mapping online traffic provides real-time information which can be mapped to real-world outcomes

Twitter – Large-scale and real-time: +70M tweets per day, +20GB of text, representative? +150M users

- Box office receipts from Twitter chatter: Asur (2010)
- Google trends: flu (verbal autopsies)
- Predicting consumer behavior from search query volume (Goel, 2010)
- Contagion of "Loneliness" and **happiness** in social networks (Cacioppo, 2010 - Bollen, 2011)

Link between sentiment, mood and behavior

Behavior is shaped not just by rational, conscious considerations

In the “real world” emotion plays a significant role in human decision-making (behavioral economics, behavioral finance, social psychology). Online? And if so, can it determine real-world consequences cf. Tunesia, economy, investment decisions, ...

- Extract indicators of individual and collective sentiment from online media feeds?
- Predict not just the present, but the future?

Mood → action → consequences → markets?

Extracting sentiment indicators from text

Happy tweets.
So...nothing quite feels like a good shower, shave and haircut...love it
My beautiful friend. i love you sweet smile and your amazing soul
i am very happy. People in Chicago loved my conference. Love you, my sweet friends
@anonymous thanks for your follow I am following you back, great group amazing people
Unhappy tweets.
She doesn't deserve the tears but i cry them anyway
I'm sick and my body decides to attack my face and make me break out!! WTF :(
I think my headphones are electrocuting me.
My mom almost killed me this morning. I don't know how much longer i can be here.

Different Approaches: Natural Language processing (n-grams) for reviews (Nasukawa, 2003), topics (Yi, 2003), Support Vector Machines: text classification (positive vs. negative) using pre-classified learning sets: Gamon (2004), Pang (2008), Blogs, web sites: mixed approaches. Mishne (2006), Balog (2006), Gruhl (2005),...

Sentiment and mood analysis is difficult for tweets

Individual tweets

- Length: 140 characters, lack of text content
- Diversity:no standardized training sets, dimensions of mood?
- Lack of topic specificity

Public mood from tweet collections and other microblog contents?

- We Feel Fine `http://www.wefeelfine.org/`
- Moodviews `http://moodviews.com`
- Myspace: Thelwall (2009), FB: United States Gross National Happiness `http://apps.facebook.com/usa_gnh/`, Michael Jackson (Kim, 2009)

What we did:

Trends in general public mood from a large-scale collection of tweets

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- Correlations to socio-economic indicators?

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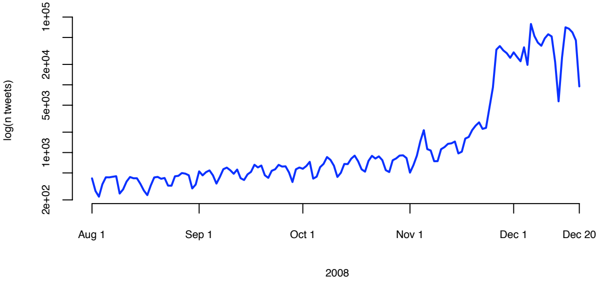
Data sets

Collection of tweets:

- April 29, 2006 to December 20, 2008
- 2.7M users
- **Subset**: August 1, 2008 to December 2008 - 9,664,952 tweets



Each tweet:

ID	date-time	type	text
1	2008-11-28 02:35:48	web	Getting ready for Black Friday. Sleeping out at Circuit City or Walmart not sure which. So cold out.
2	2008-11-28 02:35:48	web	@anonymous I didn't know I had an uncle named Bob :-P I am going to be checking out the new Flip sometime soon
	...		

GPOMS: mood assessment tool

Definition

Uses model derived from existing psychometric instrument (40 years of practice). Maps the content of Tweet to 6 dimensions of human mood. Uses "ancient magic" (just kidding).

composed/anxious : calm

clearheaded/confused : alert

confident/unsure: sure

energetic/tired: vital

agreeable/hostile: kind

elated/depressed: happy

Tool built "in-house", beyond mere term matching, learns from the web, lots of behind the scenes processing, continuous development.

Tweet:

I am so not bored. way too busy! I feel really great!

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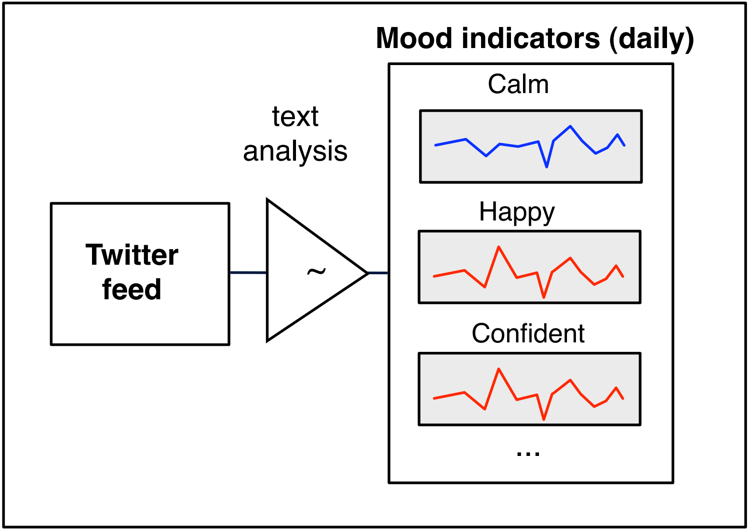
I am so not bored. way too busy! I feel really great!

$$\begin{array}{l} \text{composed/anxious} \\ \text{clearheaded/confused} \\ \text{confident/unsure} \\ \text{energetic/tired} \\ \text{agreeable/hostile} \\ \text{elated/depressed} \end{array} \quad \begin{pmatrix} 0.01725 \\ 0.05125 \\ 0.725625 \\ 0.666625 \\ 0.361 \\ 0.53175 \end{pmatrix}$$

Aggregating daily tweets into a mood time series



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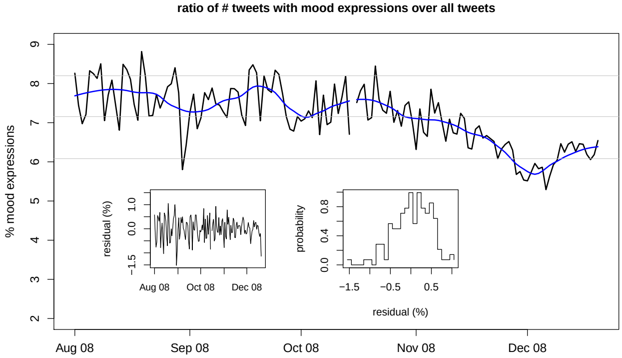
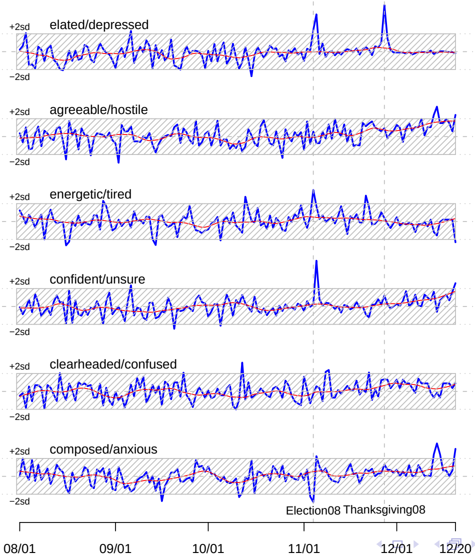
Ratio of emotional tweets, over time.

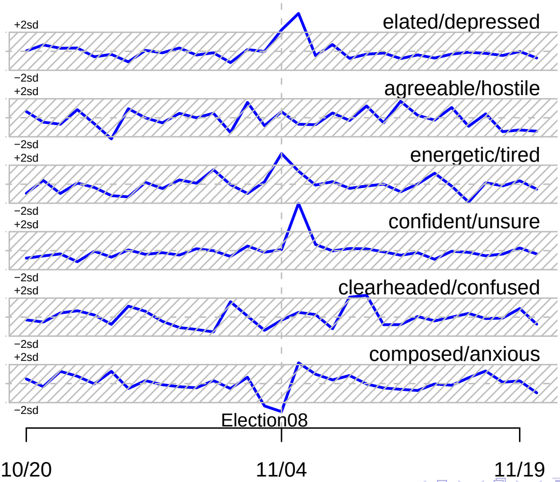


Ratio of tweets containing mood expressions vs. all tweets on a given day, including residuals from trendline.

Public mood trends: overview



Case study 1: November 4th, 2008 - the presidential election



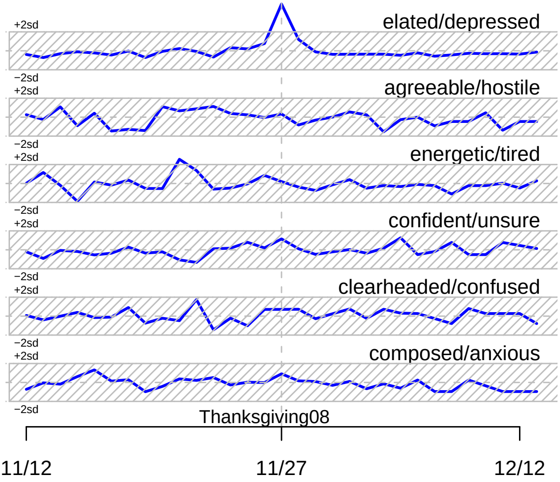
TFIDF scoring of tweet terms

2008 U.S. Presidential Election

Nov 03	Nov 04	Nov 05
robocal	poll	histori
business	plumber	won
voter	result	barack
cleanser	absente	prop
grandmoth	ballot	speech
russert	turnout	result
socialist	barack	president-elect
halloween	citizen	hologram
acknowledg	joe	victori
race	thoughtfulli	ecstat

Table: Top 10 TF-IDF ranking terms 1 day before, on and 1 day after election day.

Case study 2: November 27th, 2008 - Thanksgiving

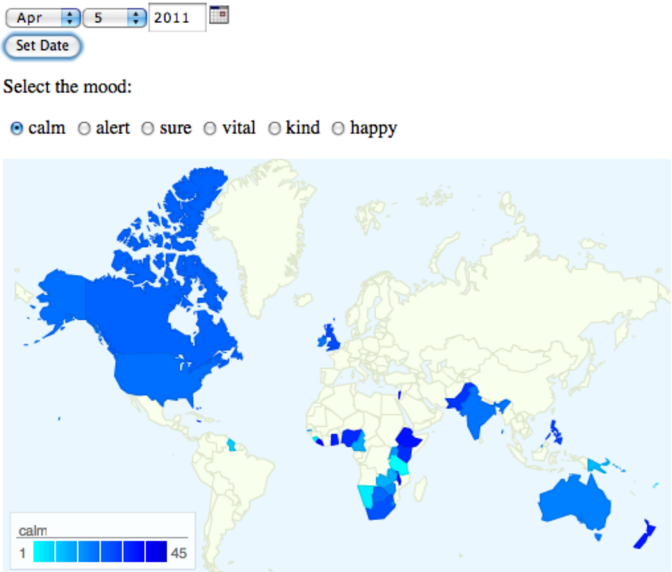


Long-term changes in public mood: statistical significance

Mood dimension	Period 1	Period 2	p-value
Agreeable/Hostile	08/01-20	12/01-20	0.0001338
	Mean 1=	Mean 2=	Difference
	-0.007sd	1.286sd	1.292sd
Confident/Unsure	08/01-20	12/01-20	0.002381
	Mean 1=	Mean 2=	Difference
	-0.120sd	0.785sd	0.905sd
Composed/Anxious	08/01-20	12/01-20	0.0272
	Mean 1=	Mean 2=	Difference
	0.162	0.897	0.736

Table: T-tests to compare mood levels in two 20-day periods (August 1-20 and December 1-20, 2008) show statistically significant elevated z-scores for Agreeable, Confident and Composed mood.

TerraMood:World Mood Analysis from Twitter



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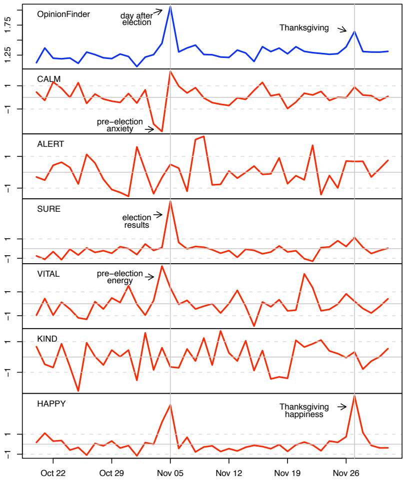
Comparison to existing sentiment tracking tools: OpinionFinder

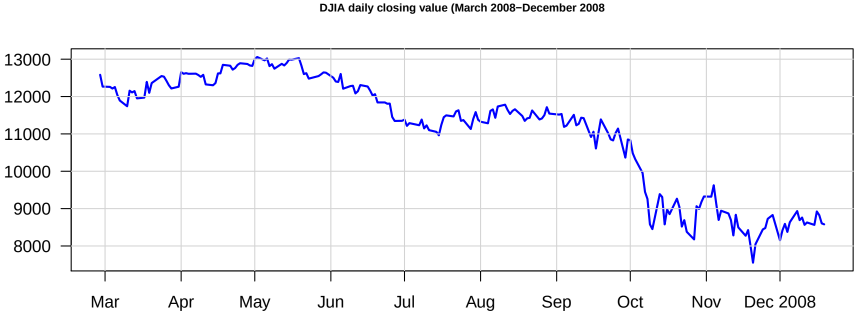


http://www.cs.pitt.edu/mpqa/
Theresa Wilson, Janyce Wiebe, and Paul Hoffmann (2005). Recognizing Contextual Polarity in Phrase-Level Sentiment Analysis. Proc. of HLT-EMNLP-2005.

Table: Multiple Regression Results for OpinionFinder vs. GPOMS dimensions.

Parameters	Coeff.	Std.Err.	t	p
Calm (X_1)	1.731	1.348	1.284	0.20460
Alert (X_2)	0.199	2.319	0.086	0.932
Sure (X_3)	3.897	0.613	6.356	**4.25e-08** ⋆⋆
Vital (X_4)	1.763	0.595	2.965	0.004⋆
Kind (X_5)	1.687	1.377	1.226	0.226
Happy (X_6)	2.770	0.578	4.790	**1.30e-05** ⋆⋆
Summary	Residual Std.Err	Adj.R^2	$F_{6,55}$	p
	0.078	0.683	22.93	2.382e-13

Comparison to DJIA



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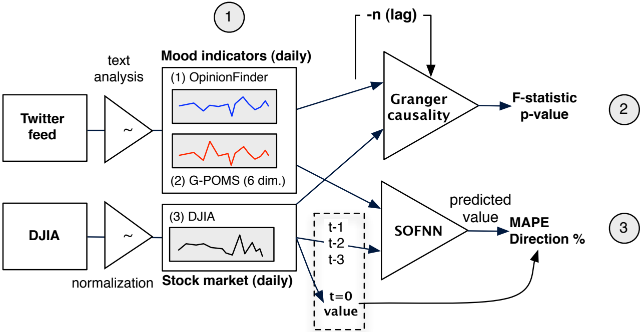

Figure: Methodological diagram outlining use of Granger causality analysis and Self-Organizing Fuzzy Neural Network to predict daily DJIA values from (1) past DJIA values at $t-1, t-2, t-3$, and various permutations of Twitter mood values (OpinionFinder and GPOMS).

bivariate-causal analysis: DJIA vs. public mood

Table: Calm (X_1), Alert (X_2),Sure (X_3), Vital (X_4), Kind (X_5), Happy (X_6)

lag	X_{OF}	X_1	X_2	X_3	X_4	X_5	X_6
1	0.703	**0.080***	0.521	0.422	0.679	0.712	0.300
2	0.633	**0.004****	0.777	0.828	0.996	0.935	0.697
3	0.928	**0.009****	0.920	0.563	0.897	0.995	0.652
4	0.657	**0.03****	0.54	0.61	0.87	0.78	0.68
5	0.235	**0.053***	0.753	0.703	0.246	0.837	**0.05***

Calm vs. DJIA

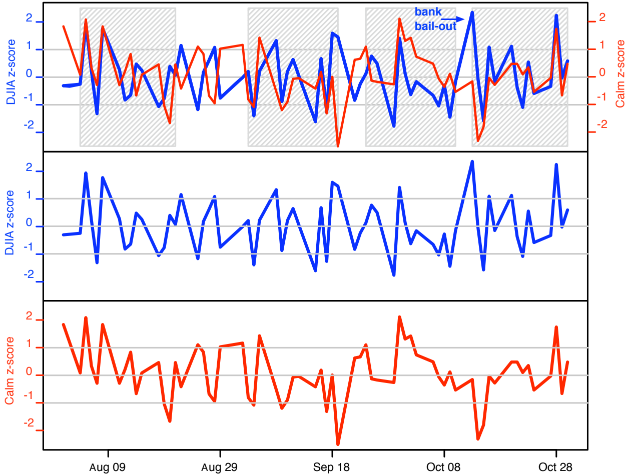
bank
bail-out
DJIA z-score
Calm z-score
2
1
0
-1
-2
Aug 09
Aug 29
Sep 18
Oct 08
Oct 28

Table: DJIA Daily Prediction Using SOFNN

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

Citation:

Johan Bollen, Huina Mao, and Xiao-Jun Zeng. Twitter mood predicts the stock market. Journal of Computational Science, 2010, http://arxiv.org/abs/1010.3003.

When we meet Socionomics

- Socionomics:**Changes in social mood precede – and even cause – shifts in the stock market, cultural trends and more.**
- Robert Prechter:**Financial/Economic dichotomy; Social mood is the engine of social action;**
  Investor moods,generated endogenously and shared via the hearding impulse, motivate aggregate stock market values and trends.
- John Casti: **Events don't matter, but Mood matters**

Other names we got to be familar with:

Dave Allman, Wayne Parker, John Nofsinger, Ken Olson, Matt Lampert, etc.

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  - Predictive power?
  - Research front: growing support

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  - Time scales matter! Emotion $<$ hours, days but mood $>$ several months.
- Future research:
  - Causal relation between mood/emotion and markets?
  - Interactions with news, topics, chatter?
  - Differences between traders, economists and the "public"?

References

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THANK YOU!

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