Using Text to Predict the Real World

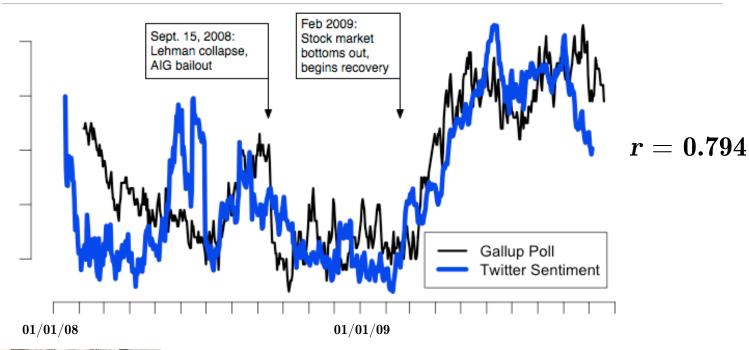
#textworld

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^{*}Joint work with Ramnath Balasubramanyan, Dipanjan Das, Jacob Eisenstein, Kevin Gimpel, Mahesh Joshi, Shimon Kogan, Dimitry Levin, Brendan O'Connor, Bryan Routledge, Jacob Sagi, Eric Xing.

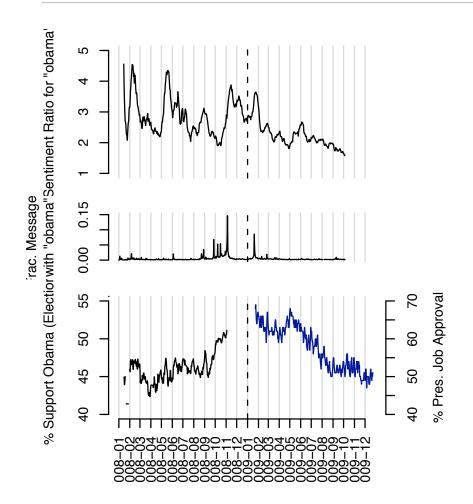
jobs on Twitter





O'Connor, B.; Balasubramanyan, R.; Routledge, B. R.; Smith, N. A. 2010. From tweets to polls: linking text sentiment to public opinion time series. *Proc. ICWSM* pp. 122-129.

obama on Twitter





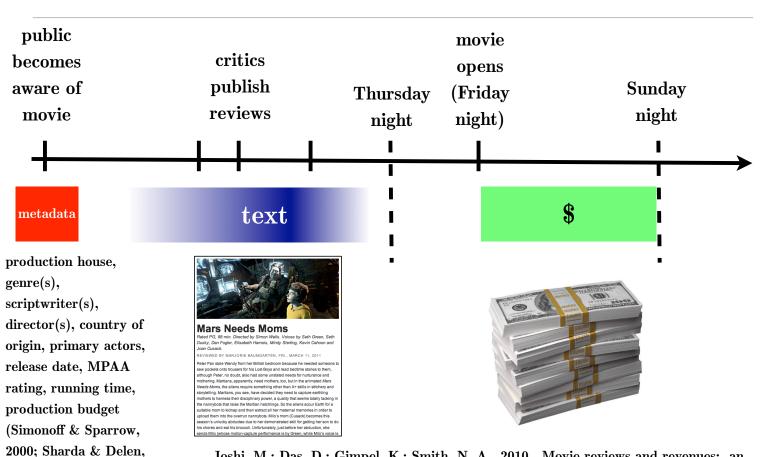
 $egin{aligned} r = 0.725 \ ext{(approval)} \end{aligned}$

O'Connor, B.; Balasubramanyan, R.; Routledge, B. R.; Smith, N. A. 2010. From tweets to polls: linking text sentiment to public opinion time series. *Proc. ICWSM* pp. 122-129.

Conjecture

Text,
written by everyday people
in large volumes,
or by specialized experts,
can tell us about the social world.

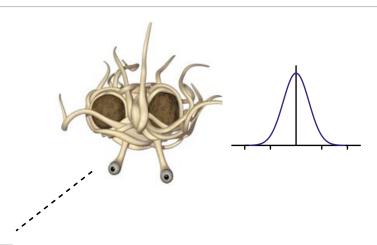
An Example: Movie Reviews & Revenue



2006)

Joshi, M.; Das, D.; Gimpel, K.; Smith, N. A. 2010. Movie reviews and revenues: an experiment in text regression. $Proc.\ NAACL\ pp.\ 293-296.$

Model





Mars Needs Moms

Rated PG, 88 min. Directed by Simon Wells. Voices by Seth Green, Seth Dusky, Dan Fogler, Elisabeth Hamois, Mindy Sterling, Kevin Cahoon and Joan Cusack.

REVIEWED BY MARJORIE BAUMGARTEN, FRI., MARCH 11, 2011

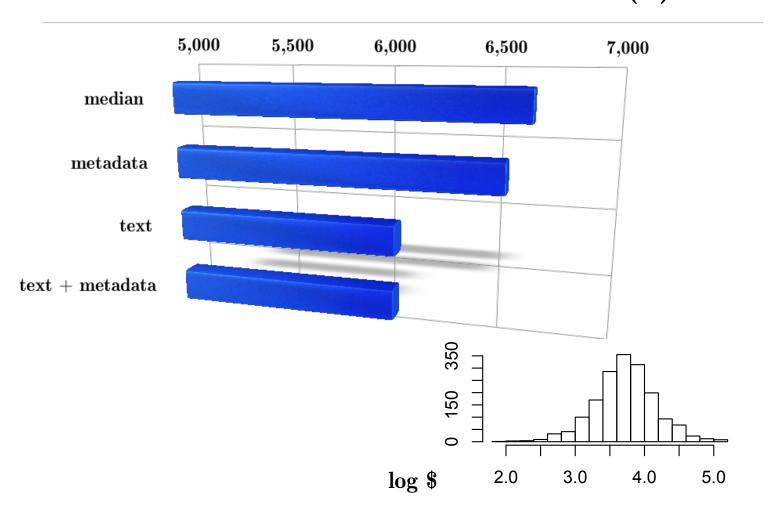
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Experiment

- **♦** 1,718 films from 2005-9:
 - 7,000 reviews (up to 7 reviews per movie)
 - Metadata from metacritic.com and the-numbers.com
 - Opening weekend gross and number of screens (the-numbers.com)
- **♦** Train the probabilistic model (elastic net linear regression) on movies from 2005-8.
- ♦ Evaluate on movies from 2009.
- Data available at www.ark.cs.cmu.edu

Mean Absolute Error Per Screen (\$)



Features (\$M)

rating	$\mathbf{p}\mathbf{g}$	+0.085	
	adult	-0.236	
	rate r	-0.364	
sequels	this series	+13.925	
	the franchise	+5.112	
	the sequel	+4.224	
people	will smith	+2.560	
	brittany	+1.128	
	^ producer brian	+0.486	

genre	testosterone	+1.945
	comedy for	+1.143
	a horror	+0.595
	documentary	-0.037
	independent	-0.127
sent.	best parts of	+1.462
	smart enough	+1.449
	a good thing	+1.117
	shame \$	-0.098
	bogeyman	-0.689
plot	torso	+9.054
	vehicle in	+5.827
	superhero \$	+2.020

Also ... of the art, and cgi, shrek movies, voldemort, blockbuster, anticipation, summer movie; cannes is bad.

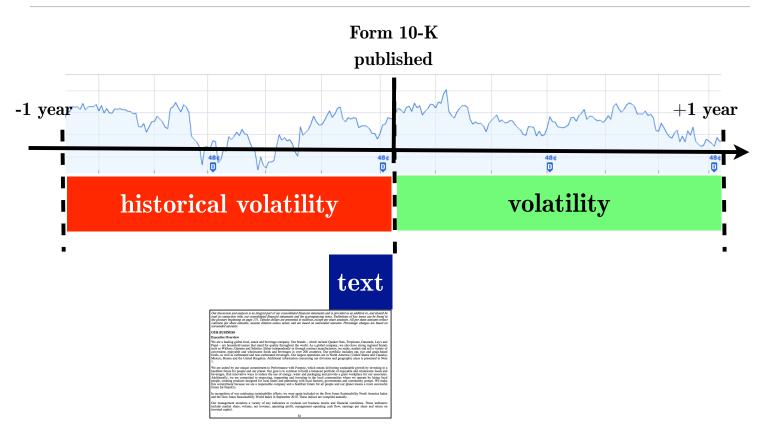
Discussion

- **♦** Can we do it on Twitter?
 - Yes! See Asur & Huberman (2010).
- **♦** Was that sentiment analysis?
 - Sort of, but "sentiment" was measured in revenue.
 - And standard linguistic preprocessing didn't really help us.

Another Example: Financial Disclosures

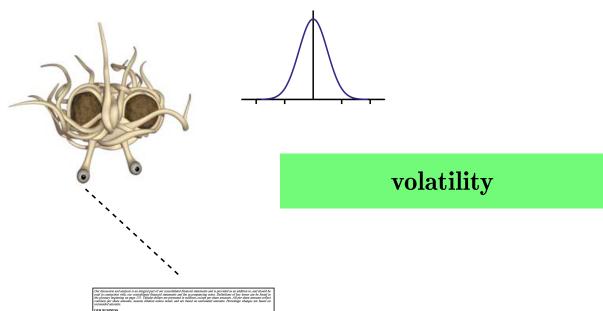
- **♦** The SEC mandates that publicly traded firms report to their shareholders.
 - Form 10-K, section 7: "Management's Discussion and Analysis," a disclosure about risk.
- **♦** Does the text in an MD&A predict return volatility?
 - We're not predicting returns, which would require finding new information (hard).

Disclosures and Volatility



Kogan, S.; Levin, D.; Routledge, B. R.; Sagi, J. S.; Smith, N. A. 2009. Predicting risk from financial reports with regression. *Proc. NAACL* pp. 272-280.

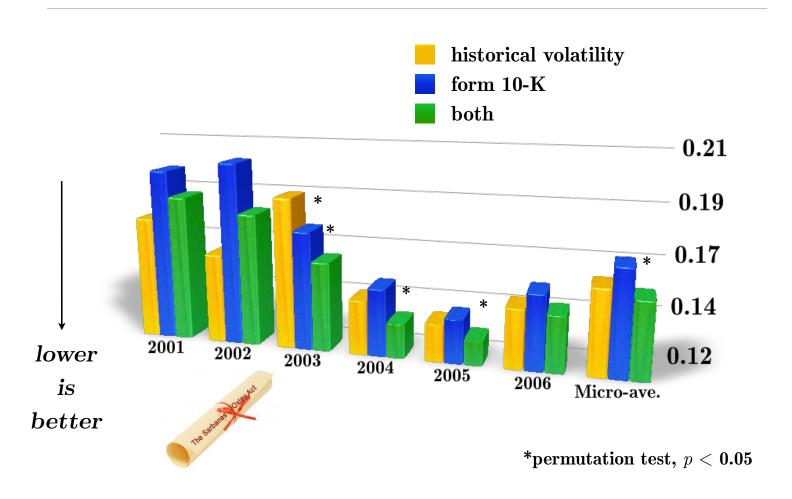
Model



Data

- **◆ 26,806 10-K** reports from 1996-2006 (sec.gov)
 - Section 7 automatically extracted (noisy)
 - Volatility in the previous year and the following year (Center for Research in Security Prices: U.S. Stocks Databases)
- ♦ Data available at www.ark.cs.cmu.edu

MSE of Log-Volatility



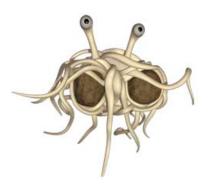
Dominant Weights (2000-4)

loss	0.025	net income	-0.021
net loss	0.017	rate	-0.017
year #	0.016	properties	-0.014
expenses	0.015	dividends	-0.013
going concern	0.014	lower interest	-0.012
a going	0.013	critical accounting	-0.012
administrative	0.013	insurance	-0.011
personnel	0.013	distributions	-0.011

high volatility terms low volatility terms

More Examples

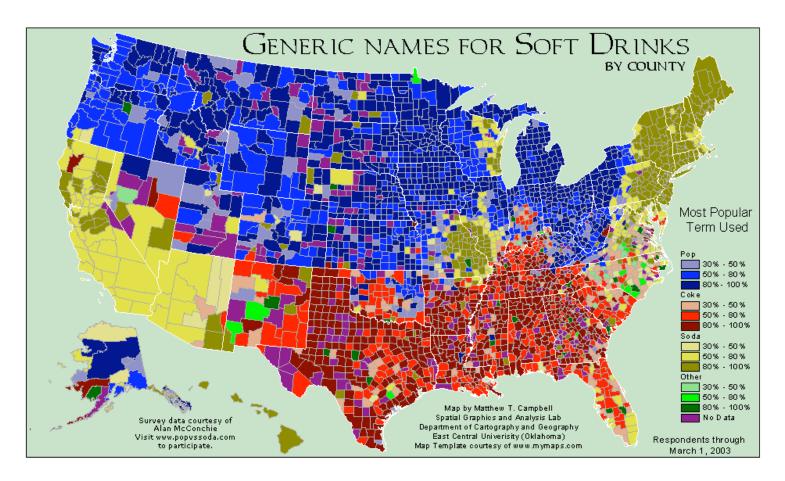
- ♦ Will a political blog post attract a high volume of comments?
- ♦ Will a piece of legislation get a long debate, a partisan vote, success?
- ♦ Will a scientific article be heavily downloaded, cited?



A Different Kind of Prediction

- ♦ So far, we've looked at what people have written, and made predictions about future measurements.
- ♦ Next, we'll consider how text reveals context.

Language Variation



Quantitative Study of Language Variation

- **♦** Strong tradition:
 - dialectology (Labov et al., 2006)
 - sociolinguistics (Labov, 1966; Tagliamonte, 2006)

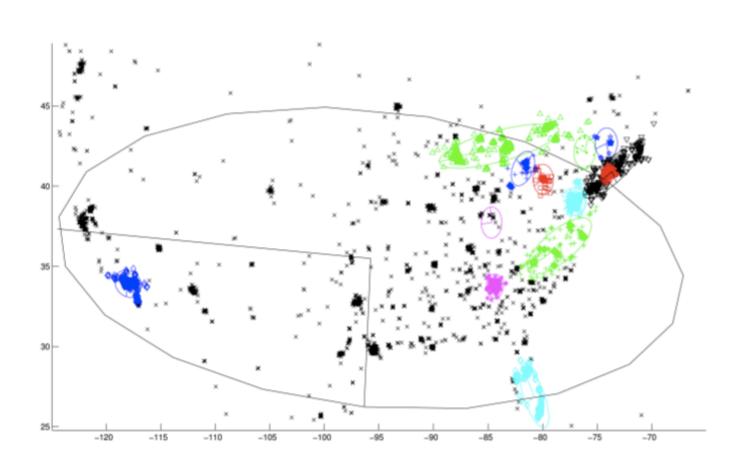
Data

- **♦** 380,000 geo-tagged tweets from one week in March 2010
 - 9,500 authors in (roughly) the United States
 - Informal: 25% of the most common words are not in standard dictionaries
 - ullet Conversational: more than 50% of messages mention another user
- → Data available at www.ark.cs.cmu.edu

Eisenstein, J.; O'Connor, B.; Smith, N. A.; Xing, E. P. 2010. A latent variable model for geographic lexical variation. *Proc. EMNLP* pp. 1277-1287.

Model (Part 1)

Gaussian Mixtures over Tweet Locations



Model (Part 2)

- ♦ What will you talk about (topics)?
- **♦** Pick words on those topic.
- **♦** Tweet.



Model

- **♦** We can combine the two FSM myths:
 - Generate location and text.
 - ullet Each topic gets corrupted in each region.

Topic: Food





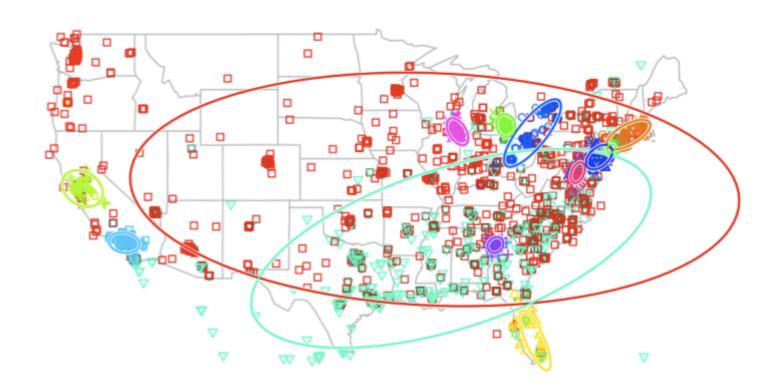
dinner delicious snack tasty



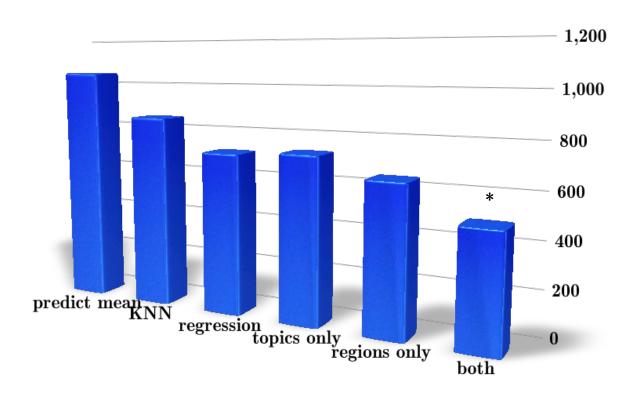




Regions from Text Content



Location Prediction (Error in km)

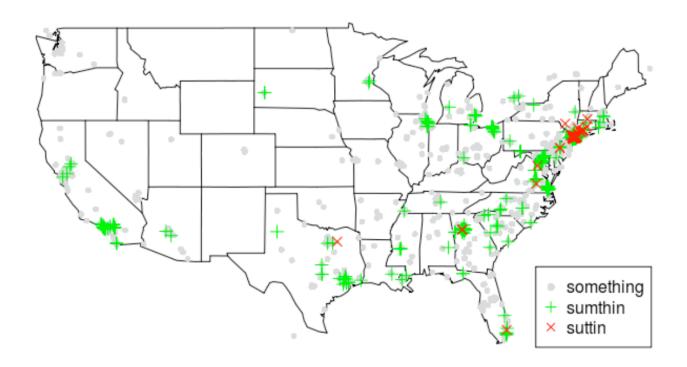


*Wilcoxon-Mann-Whitney, p < 0.01

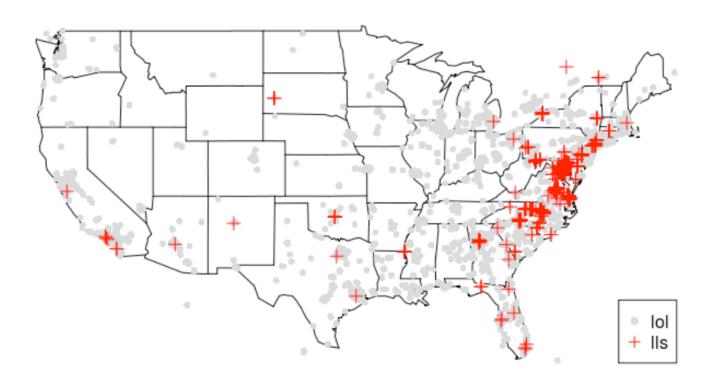
Qualitative Results

- **♦** Geographically-linked proper names are in the right places boston, knicks, bieber
- **♦** Some words reflect local prominence tacos, cab
- ◆ Geographically distinctive slang hella (Bucholtz et al., 2007), fasho, coo/koo, ;p
- ♦ Spanish words in regions with more Spanish speakers ese, pues, papi, nada

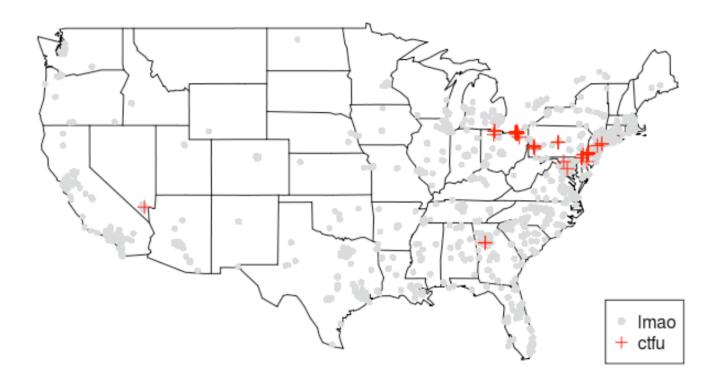
${\bf something/sumthin/suttin}$



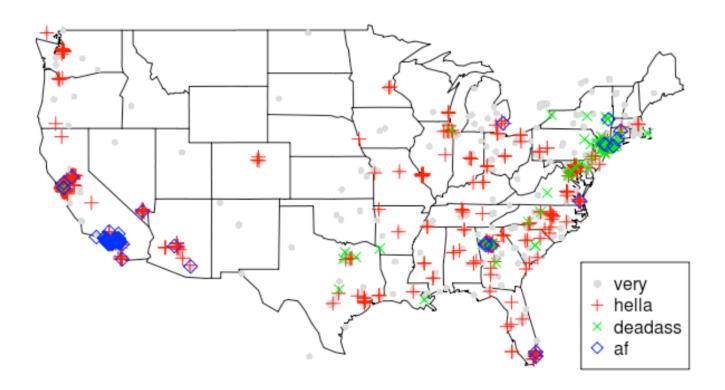
lol/lls



lmao/ctfu



Intensifiers



Ongoing Work

- **♦** From location to demographics*
- **♦** Languages other than American Twitter English
- **♦** Language change over time

^{*}Eisenstein, J.; Smith, N. A.; Xing, E. P. 2011. Discovering sociolinguistic associations with structured sparsity. *Proc. ACL* (to appear).

Key Messages

- **♦** Text is data.
 - It carries useful information about the social world.
 - Models based on text can "talk to us."
 - We are just beginning to figure out how to extract quantitative, social information from text data.
- → If you want to study/exploit language, look at the data.
 - Statistical modeling is a powerful tool.