Lecture 20:
CS 5306 / INFO 5306:
Crowdsourcing and Human Computation

Today at 4:15pm in Gates G01

Title: Predicting Human Visual Memory using Deep Learning

Speaker: Aditya Khosla, MIT

Used deep learning to identify what makes images memorable

(Gathered data via a game for Mturk workers)

Project Status Reports: Due Thursday

Email to your TA “mentor”

Should represent an update to your proposal:

Are you on track?

If the timetable is off, update it.

Any surprises?

What did you change?

Types of Crowdsourcing

- Overt
  - Collecting (Amazon Reviews)
  - Labor Markets (Amazon Mechanical Turk)
  - Collaborative Decisions (Prediction Markets)
  - Collaborative Creation (Wikipedia)
  - Smartest in the Crowd (Contests)
  - Games with a Purpose
- Covert / Crowd Mining
  - Web page linkage, search logs, social media, collaborative filtering
- Dark side of crowdsourcing and human intelligence
- Collective intelligence in animals

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Mining Discussion Groups

Wysocki, Peter D., Cheap Talk on the Web: The Determinants of Postings on Stock Message Boards (November 1998). University of Michigan Business School Working Paper No. 98025.

- Yahoo! Finance message boards
- Increased message postings -> next day increased volume and abnormal stock returns
- Overnight doubling of posts -> 0.18% average abnormal return

Tumarkin, Robert, and Robert F. Whitelaw. "News or noise? Internet postings and stock prices." *Financial Analysts Journal* 57.3 (2001): 41-51.

- Ragingbull.com message boards
- No connection

Antweiler, W., & Frank, M. Z. (2004). Is all that talk just noise? The information content of Internet stock message boards. *Journal of Finance*, *59*(3), 1259-1294.

- 1.5M Yahoo! Finance and Raging Bull message boards
- Increased messages -> negative return next day
- Increased disagreement -> increased trading volume
- Increased message -> increased volatility

Das, S. R., and Chen, M. Y. 2007. Yahoo! for Amazon: Sentiment extraction from small talk on the web. *Management Science* 53(9):1375–1388.

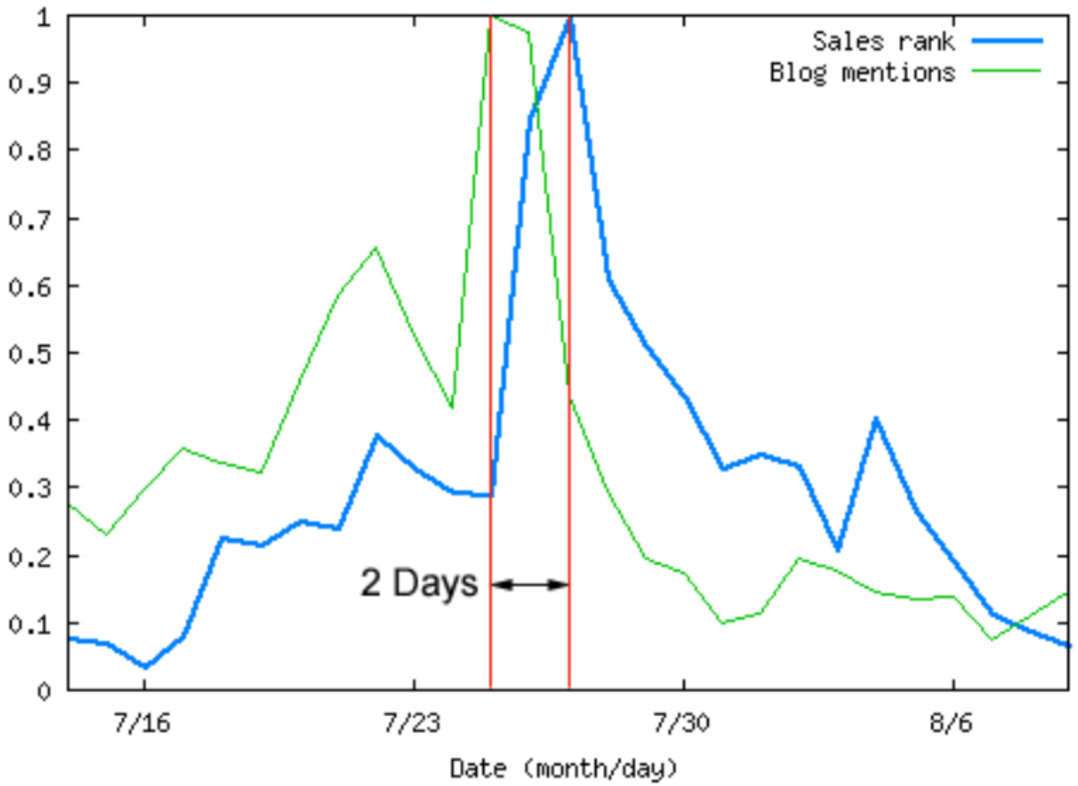
- 24 tech-sector stocks
- 2 months of message board discussions (2001) (145,000 messages)
- Assessed sentiment of each
- Predicted aggregate movement but not individual movement

Mining Blogs

D. Gruhl, R. Guha, R. Kumar, J. Novak, and A. Tomkins, "The predictive power of online chatter." *Proceedings of the eleventh ACM SIGKDD international conference on knowledge discovery in data mining*, 2005.

- Studied mentions of books in 300,000 blogs
- Compared to 500,000 Amazon sales rank values for 2,340 books over a period of four months
- Can blog volume be used to predict sales rank?
  - Success for hand-generated queries
  - Some success for automated queries

D. Gruhl, R. Guha, R. Kumar, J. Novak, and A. Tomkins, "The predictive power of online chatter." *Proceedings of the eleventh ACM SIGKDD international conference on knowledge discovery in data mining*, 2005.



Query: Lance Armstrong OR Tour de France

Mishne, Gilad, and Natalie S. Glance. "Predicting Movie Sales from Blogger Sentiment." *AAAI Spring Symposium: Computational Approaches to Analyzing Weblogs*, 2006.

- 49 movies
- Blog entries mentioning full movie name or link to IMDB entry
- Took k words around these
- Pre-release blog volume can be used to predict income per screen
- Sentiment of posts (positive, negative, neutral) improved predictions
  - Volume of positive posts
  - Sentiment alone not enough

“Capturing global mood levels using blog posts”

G. Mishne and M. De Rijke

AAAI 2006 Spring symposium on computational approaches to analysing weblogs

G. Mishne and M. De Rijke, “Capturing global mood levels using blog posts”, *AAAI Spring Symposium: Computational Approaches to Analyzing Weblogs*, 2006.

- All public blog posts published in LiveJournal during a period of 39 days, from mid-June to early-July 2005
- 8.1M posts, 3.5M with mood (from list of 132 moods, else free text)
- Two stages:
  - Identify text features for estimating mood prevalence
  - Learning model to predict the intensity of moods
- Case studies:
  - “Drunk” and “Excited”
  - Sentiment after London terror bombings – unsuccessful

“ARSA: A sentiment-aware model for predicting sales performance using blogs”

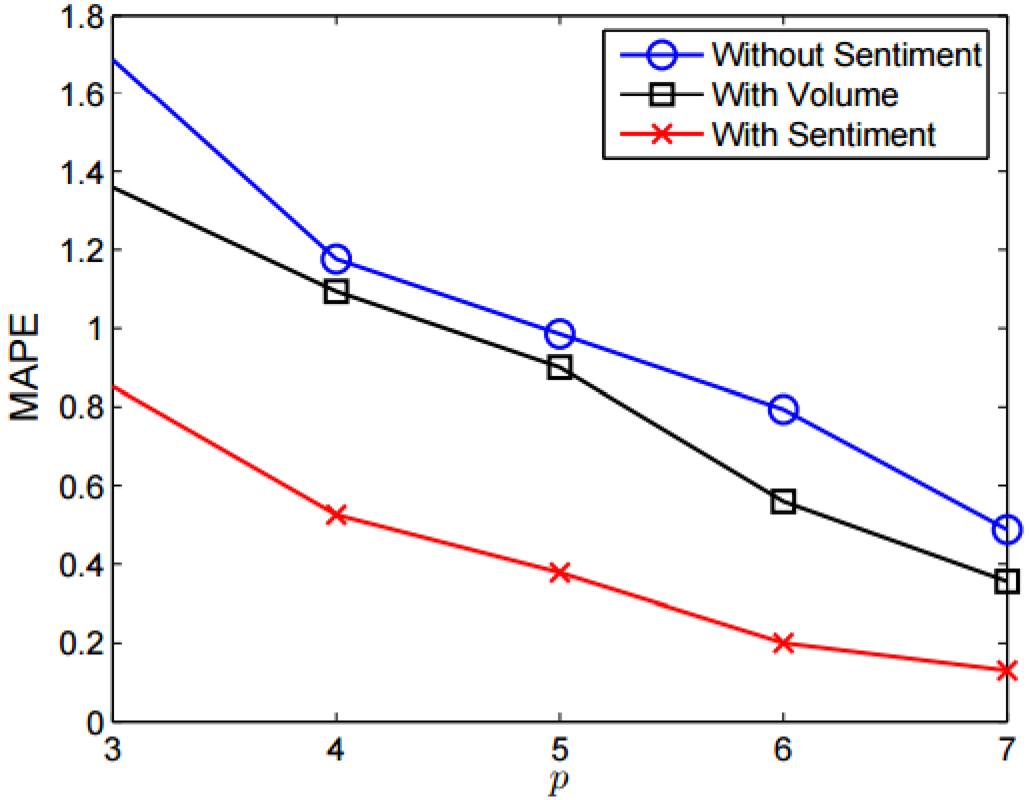
Y. Liu, X. Huang, A. An, and X. Yu

Proceedings of the 30th annual international ACM SIGIR conference on Research and development in information retrieval, 2007

Y. Liu, X. Huang, A. An, and X. Yu, “ARSA: A sentiment-aware model for predicting sales performance using blogs”, *Proceedings of the 30th annual international ACM SIGIR conference on Research and development in information retrieval*, 2007

- Studied mentions of movies in blogs
- 45046 blog entries that comment on 30 different movies
- Performed sentiment analysis on blog entries

Y. Liu, X. Huang, A. An, and X. Yu, “ARSA: A sentiment-aware model for predicting sales performance using blogs”, *Proceedings of the 30th annual international ACM SIGIR conference on Research and development in information retrieval*, 2007



E. Gilbert and K. Karahalios, “Widespread worry and the stock market”, *Proceedings of the International Conference on Weblogs and Social Media,* 2010

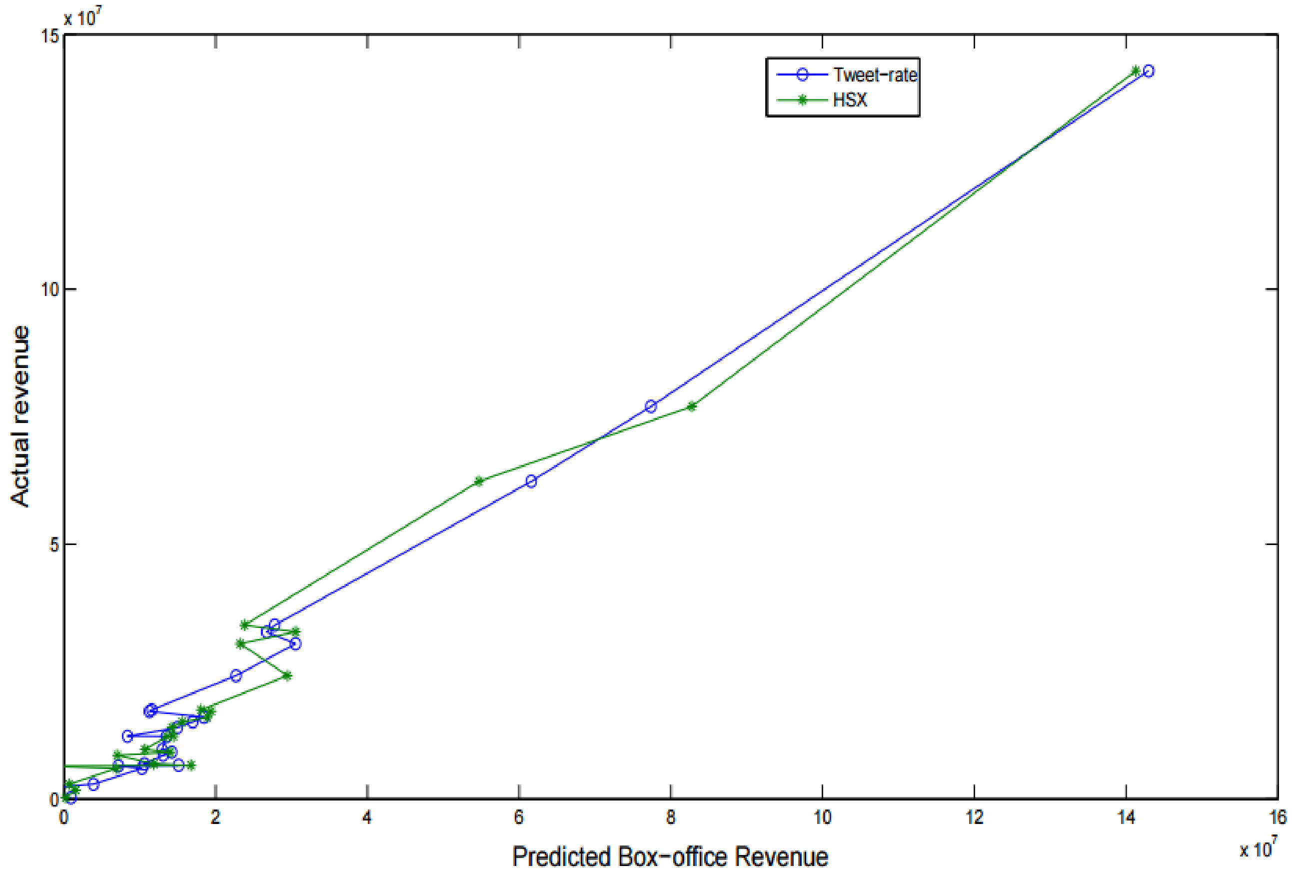
- Estimate anxiety, worry and fear from a dataset of over 20 million posts made on the site LiveJournal
- increases in expressions of anxiety, evidenced by computationally-identified linguistic features, predict downward pressure on the S&P 500 index

Mining Tweets

S. Asur and B. A. Huberman, “Predicting the future with social media”, *Proceedings of the ACM Conference on Web Intelligence*, 2010

- Movie tweet rate can be use to predict box office revenues before movie opens
- Sentiment of tweets can improve this after movie release
  - Applied machine learning to label tweets as positive, negative, or neutral
  - Training data labeled using Amazon Mechanical Turk
- Better than prediction market (Hollywood Stock Exchange)

S. Asur and B. A. Huberman, “Predicting the future with social media”, *Proceedings of the ACM Conference on Web Intelligence*, 2010



B. O’Connor, R. Balasubramanyan, B. R. Routledge, and N. A. Smith. From Tweets to polls: Linking text sentiment to public opinion time series. In International AAAI Conference on Weblogs and Social Media, Washington, D.C., 2010.

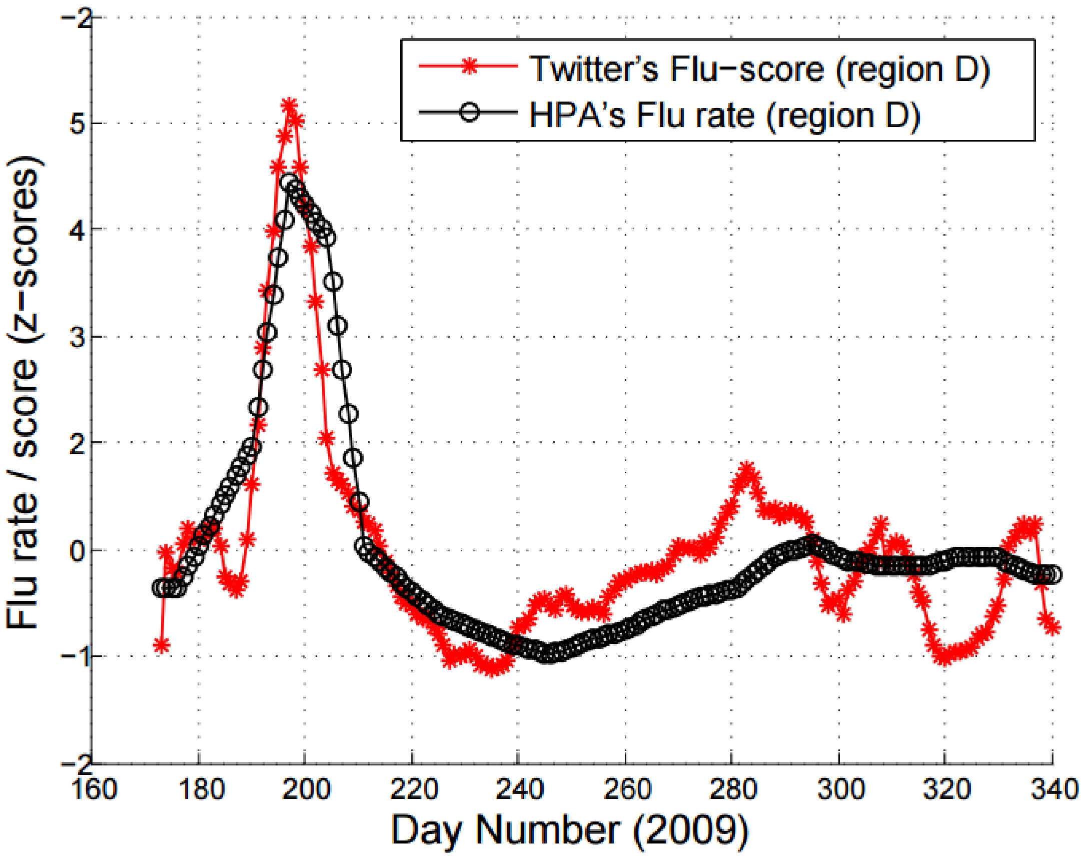
- Consumer confidence: “economy”, “job”, and “jobs”
- Presidential approval: “obama”
- Elections: “obama” and “mccain”
- Frequency of 2800 positive/negative words

Culotta, A. Towards detecting influenza epidemics by analyzing twitter messages. In *Proceedings of the First Workshop on Social Media Analytics*, ACM, 115–122, 2010

- 500,000 tweets over 10 weeks
- Learned classifier to filter tweets
- 0.78 correlation with CDC data

Lampos, Vasileios, and Nello Cristianini. "Tracking the flu pandemic by monitoring the social web." *Cognitive Information Processing (CIP), 2010 2nd International Workshop on*. IEEE, 2010.

- 4M tweets over 50 weeks



Paul, Michael J., and Mark Dredze. "You are what you Tweet: Analyzing Twitter for public health." *ICWSM* 20 (2011).

- 2B tweets
- 1.5M relevant tweets
- Used to:
  - Track illnesses over times (syndromic surveillance)
  - Measuring behavioral risk factors
  - Localizing illnesses by geographic region
  - Analyzing symptoms and medication usage

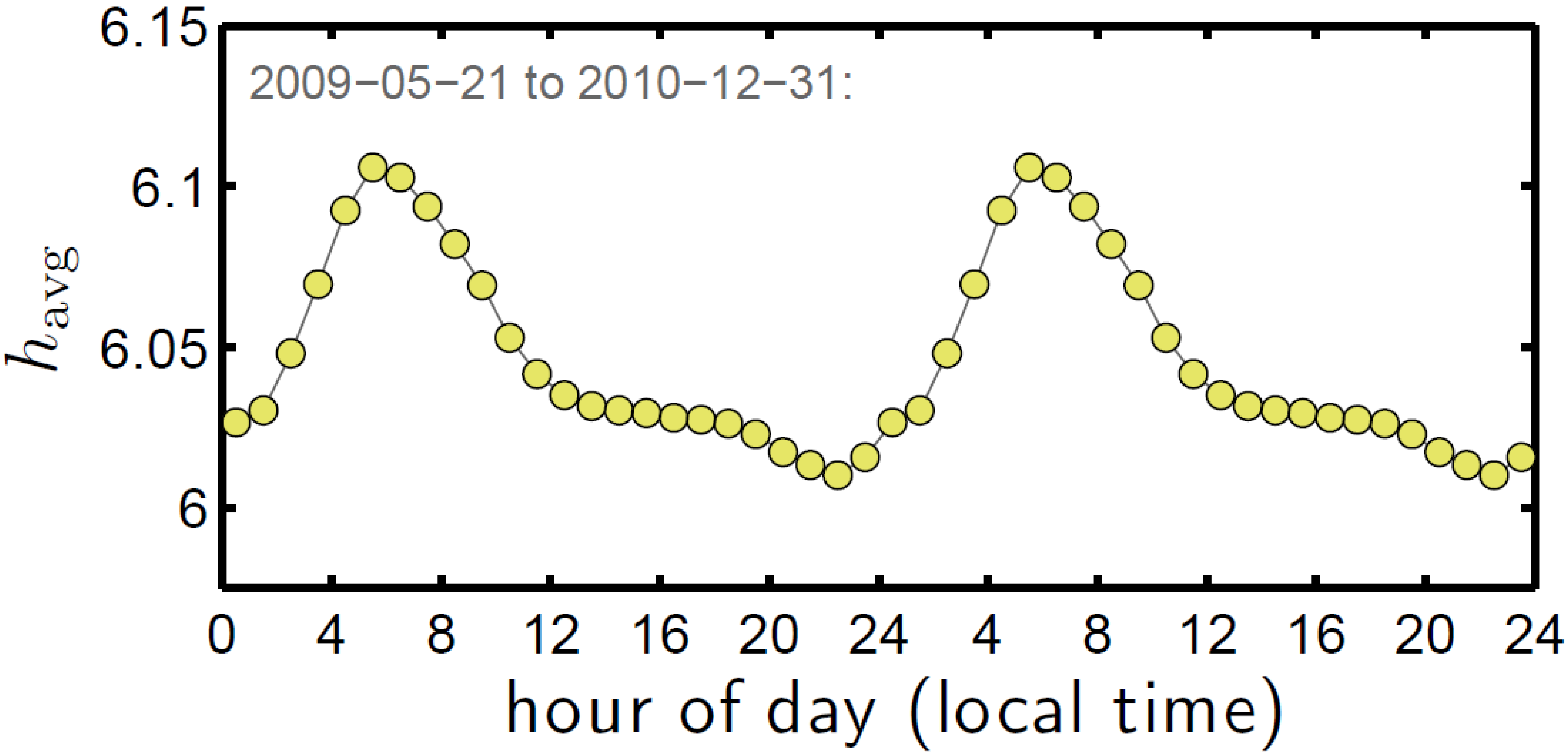
J. Bollen, H. Mao, and X. Zeng, "Twitter mood predicts the stock market", *Journal of Computational Science*, 2011

- Uses two different methods for assessing the mood of tweets about stocks
- Some have effect in changes in DJIA closing values

P.S. Dodds, K.D. Harris, I. M. Kloumann, C. A. Bliss, and C. M. Danforth, "Temporal patterns of happiness and information in a global social network: Hedonometrics and Twitter", *PLoS 1,* December 2011

- Used Twitter: 4.6 billion tweets, 46 billion words, 63 million users, 33 months
- Tracked "happiness" of over 100,000 words (assessed via Amazon Mechanical Turk) by location, day, time of year, etc.

P.S. Dodds, K.D. Harris, I. M. Kloumann, C. A. Bliss, and C. M. Danforth, "Temporal patterns of happiness and information in a global social network: Hedonometrics and Twitter", *PLoS 1,* December 2011



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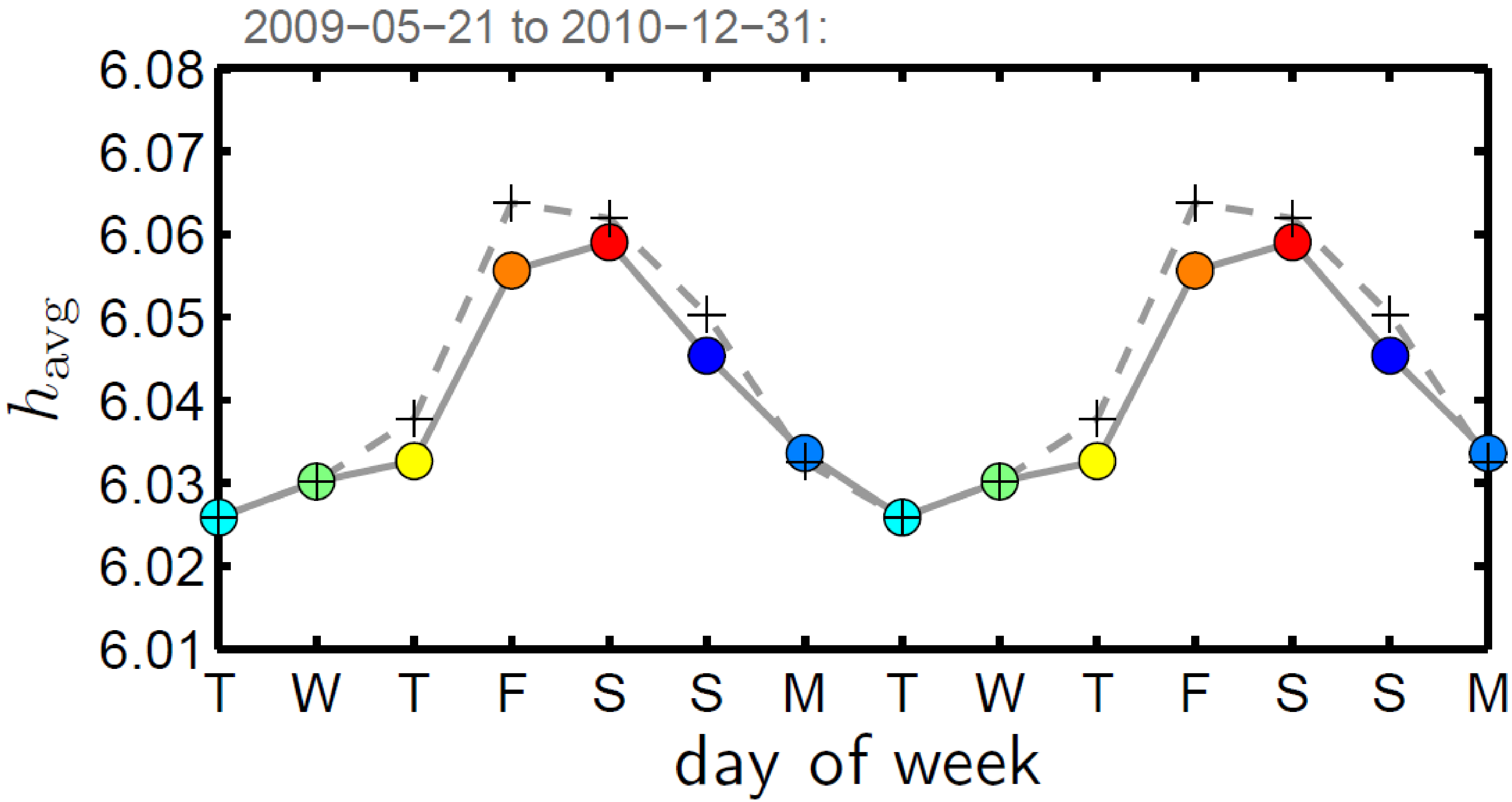

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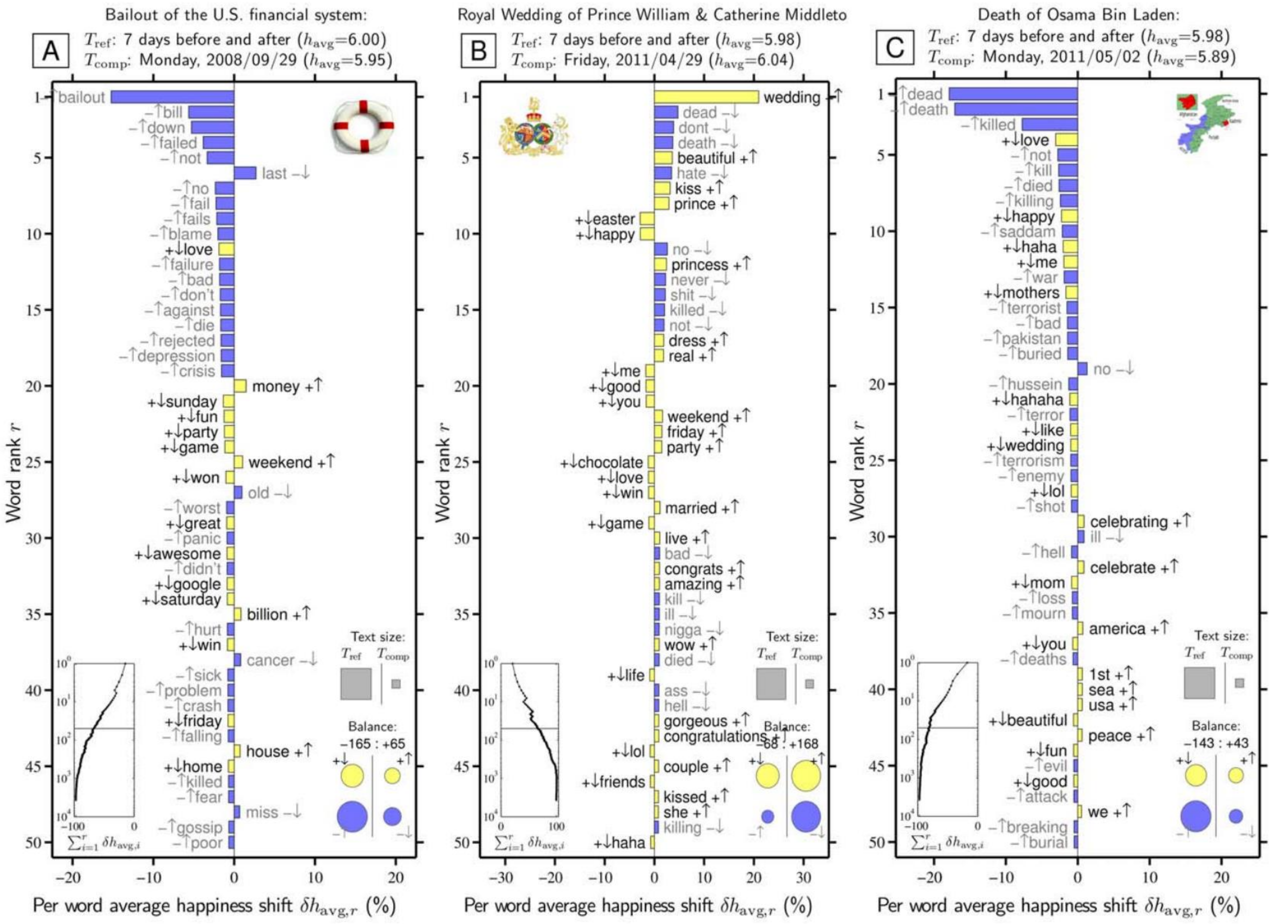

Further Applications in Medicine

- Signorini, A., Segre, A. M., and Polgreen, P. M. The use of Twitter to track levels of disease activity and public concern in the U.S. during the influenza a H1N1 pandemic. PLoS ONE 6, 5 (May 2011), e19467.
- De Choudhury, M., Gamon, M., Counts, S., and Horvitz, E. Predicting depression via social media. In ICWSM (2013). 9. Dredze, M. How social media will change public health. IEEE Intelligent Systems 27, 4 (2012), 81–84.
- Hanson, C. L., Burton, S. H., Giraud-Carrier, C., West, J. H., Barnes, M. D., and Hansen, B. Tweaking and tweeting: Exploring twitter for nonmedical use of a psychostimulant drug (adderall) among college students. Journal of Medical Internet Research 15, 4 (Apr. 2013), e62.
- Jamison-Powell, S., Linehan, C., Daley, L., Garbett, A., and Lawson, S. ”I can’t get no sleep”: discussing #insomnia on Twitter. In CHI, ACM (New York, NY, USA, 2012), 1501–1510.
- Wang S1, Paul MJ, Dredze M., “Social Media as a Sensor of Air Quality and Public Response in China”, *J Med Internet Res*. 2015 Mar 26
- Richard Sloane, Orod Osanlou, David Lewis, Danushka Bollegala, Simon Maskell, & Munir Pirmohamed, “Social media and pharmacovigilance: A review of the opportunities and challenges”, *British Journal of Clinical Pharmacology*, 3 July 2015

Further Applications

- Kamath, Radhika and Prabhu, Srikanth and Shenoy, Manjula K and Akshay, M J, “Mining Social Media to Find Criminal Behavior- A Survey”, *2nd International Conference on on Computational Methods in Engineering and Health Sciences*, 2015.

Further Applications in Medicine

Social Media Mining Template

- What data to use
  - Examples:
    - Tweets mentioning name of movie
    - Blog posts with mood annotation
- What aspects of data to measure
  - Examples:
    - Volume of tweets, posts
    - Sentiment of tweets, posts
      - Use machine learning