# Network Centrality Part 3 – Case Studies

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Includes material borrowed from various online sources, including slides by Lada Adamic

# Case Study 1

Measuring User Influence in Twitter: The Million Follower Fallacy, Cha et al., ICWSM 2010

### Different influence measures for OSN

- Compared different influence measures for the Twitter social network
- Network structure based:
  - In-degree (number of followers)
- Activity based:
  - Number of times a user is retweeted
  - Number of times a user is mentioned
- Two measures compared using Spearman's rank correlation coefficient

### Results of comparison

- Across all three measures, top influentials were public figures (politicians, celebrities, ...) and websites (news media sites)
- But top influentials according to indegree have low overlap with top influentials according to activity

Table 1: Spearman's rank correlation coefficients

Correlation	All	Top 10%	Top 1%
Indegree vs retweets	0.549	0.122	0.109
Indegree vs mentions	0.638	0.286	0.309
Retweets vs mentions	0.580	0.638	0.605

# Case Study 2

Understanding and Combating Link Farming in the Twitter Social Network, Ghosh et al., WWW 2012

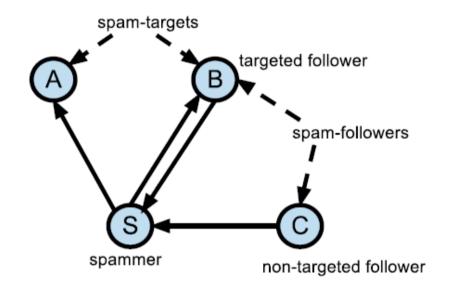
# Why link farming in Twitter?

- Twitter has become a Web within the Web
  - Vast amounts of information and real-time news
  - Twitter search becoming more and more common
  - Search engines rank users by follower-rank, Pagerank to decide whose tweets to return as search results
  - High indegree (#followers) seen as a metric of influence
- Link farming in Twitter
  - Spammers follow other users and attempt to get them to follow back

### Started by identifying spammers

- Identified 41,352 spammers in Twitter
  - Accounts suspended by Twitter
  - Had posted blacklisted URLs
- Many of the spammer accounts had high number of followers (in-degree)
  - Average in-degree for random user: 36
  - Average in-degree for spammer: 234

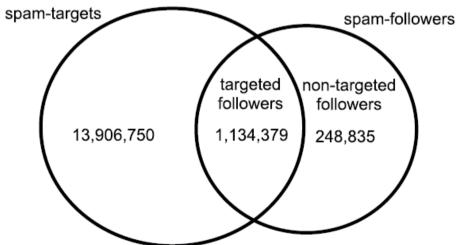
### Terminology for spammers' links



- Spam-targets: users followed by spammers
- Spam-followers: users who follow spammers
  - Targeted: spam-target and spam-follower
  - Non-targeted: follow spammers without being targeted

### Link farming by spammers

- Spammers farm links at large scale
  - Over 15 million users (27% of total) targeted by 41,352 spammers (0.08% of total)
- 1.3 million spam-followers
  - 82% are targeted → spammers get most links by reciprocation



### Who are the spam-followers?

- Non-targeted spam-followers
  - Mostly sybils / hired helps of spammers
  - Most have now been suspended by Twitter
- Targeted spam-followers
  - Ranked on the basis of number of links to spammers
  - 60% of follow-links acquired by spammers come from the top 100,000 targeted followers – LINK FARMERS
- Are the link farmers themselves spammers?





## Are link farmers themselves spammers?

- No, over 80% are real, popular, active users
- Most of them are marketers trying to promote their business or some product
- Includes some verified accounts
- Many link farmers within the top 5% users according to PageRank

# Top link-farmers: examples

Top 5 link farmers according to		
#links to spammers	Pagerank	
Larry Wentz: Internet, Affil-	Barack Obama: campaign	
iate Marketing	staff	
Judy Rey Wasserman:	Britney Spears: It's Britney	
Artist, founder		
Chris Latko: Interested in	NPR Politics: Political cover-	
tech. Will follow back	age and conversation	
Paul Merriwether: helping	UK Prime Minister: PM's of-	
others, let's talk soon	fice	
Aaron Lee: Social Media	JetBlue Airways: Follow us	
Manager	and let us help	

## Why are popular users link farming?

- Social etiquette you follow me, I follow you
- Amass social capital in the network

### Is it easy to farm links in Twitter?

- We created a Twitter account and followed some of the top targeted spam-followers
  - Followed 500 randomly selected link farmers
  - Within 3 days, 65 reciprocated by following back
  - Our account ranked within the top 9% of all users in Twitter in 3 days !!!

### The problem with link farming

- Existence of a set of users from whom social links (hence social influence) can be farmed easily
- Spammers easily gain links from popular users
- Increases the PageRank of spammers as well
- Leads to increases spam in Twitter search results

# Combating link farming in Twitter

- Key challenges
  - Real, popular users engaged in link farming
  - Detecting and suspending spammers alone will not help
- Discourage users from following others carelessly
  - Penalize users for following someone bad lower the influence scores of users who follow spammers

### **CollusionRank**

- Identify a seed set of known spammers
- In PageRank style
  - Negatively bias initial scores towards the known spammers
  - Iteratively penalize users who follow spammers, or those who follow spam-followers



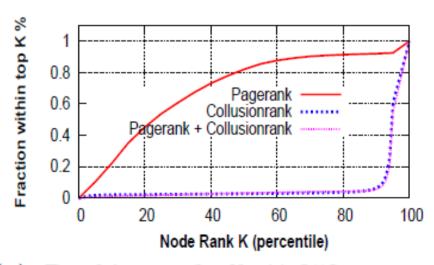
### **CollusionRank**

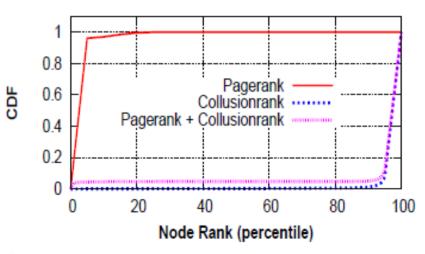
```
Input: network, G; set of known spammers, S; decay factor for
   biased Pagerank, \alpha
Output: Collusionrank scores, c
   initialize score vector d for all nodes n in G
                        d(n) \leftarrow \begin{cases} \frac{-1}{|S|} & \text{if } n \in S \\ 0 & \text{otherwise} \end{cases}
   /* compute Collusionrank scores */
   c \leftarrow d
   while c not converged do
      for all nodes n in G do
         tmp \leftarrow \sum_{nbr \in followings(n)} \frac{c \, (nbr)}{|followers \, (nbr)|}
         c(n) \leftarrow \alpha \times tmp + (1 - \alpha) \times d(n)
      end for
   end while
   return c
```



### How effective is CollusionRank?

- Compare ranks of spammers and link farmers
  - PageRank
  - CollusionRank
  - PageRank + CollusionRank



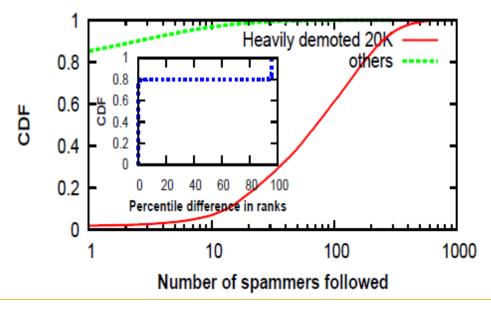


mers

(a) Rankings of all 41,352 spam- (b) Rankings of Top 100,000 capitalists

### Pagerank + Collusionrank

- Selectively penalizes spammers & link-farmers
  - Out of top 100K according to Pagerank, 20K demoted heavily, rest 80% not affected much (inset)
  - The heavily demoted 20K follow many more spammers than the rest (main figure)



# Case Study 3

Cognos: Crowdsourcing Search for Topic Experts in Microblogs, Ghosh et al., SIGIR 2012

### Topical search on Twitter

- Twitter has emerged as an important source of information & real-time news
  - Most common search in Twitter: search for trending topics and breaking news
- Topical search
  - Identifying topical attributes / expertise of users
  - Searching for topical experts
  - Searching for information on specific topics

### Prior approaches to find topic experts

### Research studies

- Pal et. al. (WSDM 2011) uses 15 features from tweets, network, to identify topical experts
- Weng et. al. (WSDM 2010) uses ML approach

### Application systems

- Twitter Who To Follow (WTF), Wefollow, ...
- Methodology not fully public, but reported to utilize several features

# Prior approaches use features extracted from

- User profiles
  - Screen-name, bio, ...
- Tweets posted by a user
  - Hashtags, others retweeting a given user, ...
- Social graph of a user
  - #followers, PageRank, ...

### Problems with prior approaches

- User profiles screen-name, bio, ...
  - Bio often does not give meaningful information
  - Information in users profiles mostly unvetted
- Tweets posted by a user
  - Tweets mostly contain day-to-day conversation
- □ Social graph of a user − #followers, PageRank
  - Does not provide topical information

### We proposed

- Use crowdsourcing
  - How does the Twitter crowd describe a user?
  - Social annotations
- Crowdsourced information collected using a feature called Twitter Lists



### Pete Cashmore

#### @mashable NYC / SF

Breaking social media, tech and digital news and analysis from Mashable.com, the top resource and guide for all things web. Updates from @mashable staff.

http://mashable.com

Tweets

Favorites

Following \*

Followers

Lists ~

#### mashable's lists



#### @mashable/news

A curated list of news organization's Twitter accounts.



#### @mashable/tech

Experts and sources to keep up with the latest in tech.



#### @mashable/design

Tweets and tips from designers.



#### @mashable/food

Love food? Here are chef's, cooks and others in food to follow.



#### @mashable/celebrity

Celebrities on Twitter.



#### @mashable/journalism

Journalists interested in the future of news media.



#### @mashable/music

Musicians on Twitter.



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Lists 3



nytimes The New York Times 📀

Where the Conversation Begins. Follow breaking news, NYTimes.com home page articles, special features and more.

#### mashable's lists



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A curated list of news organization's Twitter accounts.



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#### @mashable/music

Musicians on Twitter.



#### **BBCNews** BBC News

The latest stories, features and updates from BBC News



#### WSJ Wall Street Journal

Breaking news, investigative reporting, business coverage and features from The Wall Street Journal.



#### cnnbrk CNN Breaking News 📀

CNN.com is among the world's leaders in online news and information delivery.



#### @mashable/celebrity

Celebrities on Twitter.





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A curated list of news organization's Twitter accounts.



#### 101Cookbooks 101 Cookbooks

Heidi Swanson from 101Cookbooks.com - Healthy, vegetarian recipes made from natural foods and seasonal produce.



#### @mashable/tech

Experts and sources to keep up with the latest in tech.



#### epicurious epicurious

Written by Tanya Steel and the Epicurious editorial staff



#### @mashable/design

Tweets and tips from designers.



#### **LATimesfood** LA Times Food

News, recipes + reviews from the LA Times Food staff, test kitchen + Daily Dish blog, by @renelynch.



#### @mashable/food

Love food? Here are chef's, cooks and others in food to follow



#### TylerFlorence Tyler Florence

Chef, Restaurateur, Wine Maker, Cookbook Writer, Shop Keep, Product Designer, Dad.



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Celebrities on Twitter.



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Journalists interested in the future of news media.



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Musicians on Twitter.

### Using Lists to infer topics for users

- If U is an expert / authority in a certain topic
  - U likely to be included in several Lists
  - List names / descriptions provide valuable semantic cues to the topics of expertise of U











### Mining Lists to infer expertise

#### ashton kutcher 📀

@aplusk

**Movies TV** by Patty Holmes 59 members

Hollywood by mpc2000 1 members

**Stars** by Nadine Schultz *Meine Lieblingsstars*4 members

**Entertainment** by Al Royce 54 members

Celebrities by Ben Elcomb
142 members

**Celebs** by KING5 Photog Jim 126 members

**Hollywood** by Praesidian 17 members

- Collect Lists containing a given user U
- Merge List meta-data to get a 'topic document' T<sub>U</sub> for U
- Identify U's topics from T<sub>U</sub>
  - Basic IR techniques: case-folding, remove domain-specific stopwords
  - Extract nouns and adjectives using partof-speech tagger
  - Topics for U: the extracted words along with their frequencies

### Mining Lists to infer expertise

















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### **Dataset**

- Crawled the List-data for all users in our Twitter dataset, in November 2011
- 1.3 million users are included in 10 or more Lists
  - Includes a large majority of the most popular users
  - Our studies focus on this set of users

### Topics inferred from Lists



politics, senator, congress, government, republicans, lowa, gop, conservative



Claire McCaskill 
@clairecmc Missouri/ Washington DC
http://twitter.com/clairecmc

politics, senate, government, congress, democrats, Missouri, progressive, women



#### The Linux Foundation

@linuxfoundation San Francisco, CA

A nonprofit consortium dedicated to fostering the growth of

http://www.linux-foundation.org/

linux, tech, open, software, libre, gnu, computer, developer, ubuntu, unix

# Evaluating the List-based methodology

- Are the inferred topics (i) accurate (ii) informative?
- Evaluated using feedback through a user-survey
- More than 93% evaluators judged the topics to be both accurate and informative
  - The few negative judgments were a result of subjectivity

### Lists work better than other features



### ashton kutcher

@aplusk

I make stuff, actually I make up stuff, stories mostly, collaborations of thoughts, dreams, and actions. Thats me.

Los Angeles, California http://www.facebook.com/Ashton

**Profile bio** 

love, daily, people, time, GUI, movie, video, life, happy, game, cool

Most common words from tweets

celeb, actor, famous, movie, stars, comedy, music, Hollywood, pop culture

Most common words from Lists

### Who-is-who service

- Developed a Who-is-Who service for Twitter
  - Shows word-cloud for major topics for a given user
  - http://twitter-app.mpisws.org/who-is-who/



ladamic : Lada Adamic

Associate Professor, School of Information (+ Complex Systems and EECS), University of Michigan

complexity sna organizations network science big news si media icwsm information networks education ph students analysis tech techies coursera research social umsi academics computer sci course faculty school data

### Search system for topic experts

- Given a query (topic)
  - Identify users related to the topic using Lists
  - Rank identified users

# Ranking experts

- Used a ranking scheme solely based on Lists
- Two components of ranking user U w.r.t. query Q
  - Relevance of user to query cover density ranking between topic document T<sub>U</sub> of user and Q
  - Popularity of user number of Lists including the user

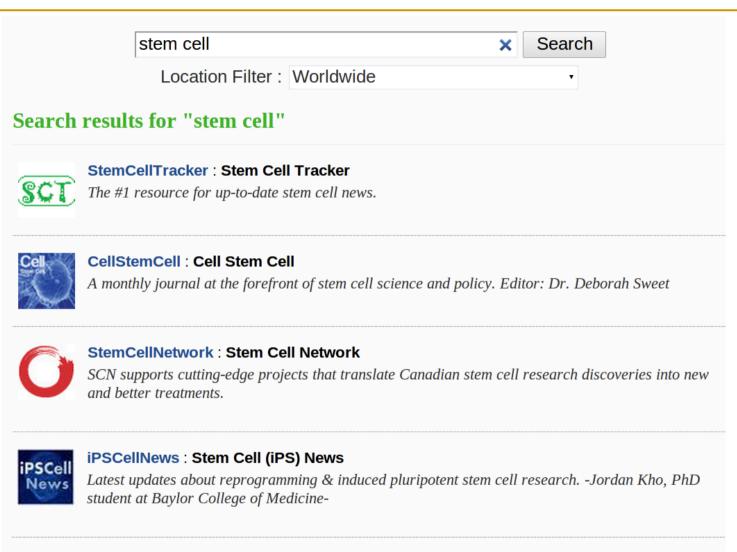
Topic relevance( $T_U$ , Q) × log(#Lists including U)

### Search system for topic experts

Cognos, a search system for topic experts

http://twitter-app.mpi-sws.org/whom-to-follow/





Cognos results for "stem cell"



#### ATStemCell: All Things Stem Cell

Blog discusses stem cells in multifaceted manner: history, apps, probs, news, & more. Run by PhD stem cell grad student/science writer- Need something written?

## User-evaluation of Cognos

#### Please rate the top 10 results for "science news"



bbcscitech: BBC SciTech



Set up by @mario, supported by backstage.bbc.co.uk



Reuters Science: Reuters Science News



From newly charted astronomical anomalies at the far reaches of the universe to the rise of nanotechnology, nobody covers science like Reuters.com.



newscientist: New Scientist



New Scientist is the world's leading science and technology weekly



NatGeo: National Geographic



Since 1888, we've traveled the Earth, sharing its amazing stories with new generations. Official Twitter account of National Geographic.



science: science



Science news from ScienceNewsBlog.com.



NASA: NASA



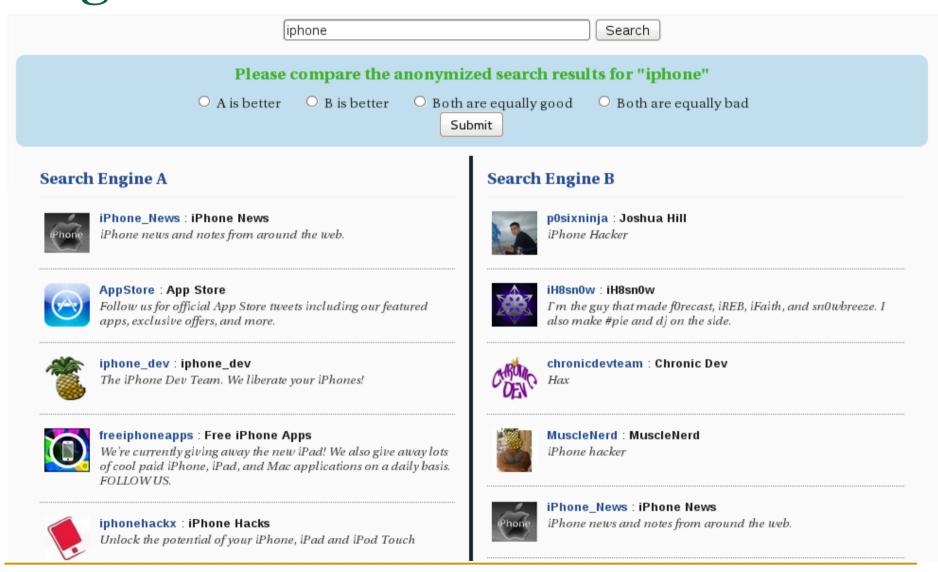
# Sample queries for evaluation

Enter your query	Search
Location Filter : Worldwide	<u>-</u>
Sample Queries	
News: politics sports entertainment science technology business	
Journalists: politics sports entertainment science technology business	
Politics: conservative news liberal politicians USA / German / Brasilian / Indian politicians	
Sports: F1 baseball soccer poker tennis NFL NBA Bundesliga	LA Lakers
Entertainment: celebrities movie reviews theater music	
Hobbies: hiking cooking chefs traveling photography	
Lifestyle: wine dining book clubs health fashion	
Science: biology astronomy computer science complex networks	
Technology: iPhone mac linux cloud computing	
Business: markets finance energy	

#### Evaluation results

- Overall 2136 relevance judgments
  - 1680 said relevant (78.7%)
- Large amount of subjectivity in evaluations
  - Same result for same query received both relevant and non-relevant judgments
  - E.g., for query "cloud computing", Werner Vogels got
     4 relevant judgments, 6 non-relevant judgments

### Cognos vs. Twitter Who-To-Follow



## Cognos vs. Twitter Who-To-Follow

- Considering 27 distinct queries asked at least twice
- Judgment by majority voting
- Cognos judged better on 12 queries
  - Computer science, Linux, Mac, Apple, Ipad, Internet,
     Windows phone, photography, political journalist, ...
- Twitter Who-To-Follow judged better on 11 queries
  - Music, Sachin Tendulkar, Anjelina Jolie, Harry Potter, metallica, cloud computing, IIT Kharagpur, ...

## Results for query music

music Search

#### De-anonymized search results for "music"

#### Search Engine A: Our results



katyperry : Katy Perry

i kissed a girl AND diddled her skittle.



ladygaga Lady Gaga

mother mons†er



taylorswift13 taylorswift13



jtimberlake : Justin Timberlake

Official Justin Timberlake Twitter.



Pink : P!nk

it`s all happening

#### **Search Engine B: Twitter results**



iTunesMusic : iTunes Music

Official music updates for the U.S. iTunes Store including new releases, pre-orders, iTunes LP, exclusive offers and more.



guardianmusic : Guardian music

Squashing music into 140 characters since 2008



yahoo\_music : Yahoo! Music

The official Twitter account of Yahoo! Music. We tweet about music news, concerts, performances, videos, and all the things that make us yode!



SonyMusicGlobal : Sony Music Global

The home of Sony Music on Twitter!



CountryMusic : Country Music Associ

Official Tweet of the Country Music Association (CMA) managed by @bennett49r & @chappedman.

### Scalability problem

- Twitter now has around 500 million users
- 740K new users join daily
- How to keep the system up-to-date by discovering newly joining experts?
- Twitter restricts crawling through API
  - Brute-force crawl of all users is infeasible

### Solution

- Only 1.1% users are listed 10 or more times
  - If experts can be identified efficiently, possible to crawle
     their Lists
- Used hubs to identify authorities / experts
  - Hubs users who selectively List many experts
  - Identify hubs using HITS, crawl Lists created by top hubs
  - □ 50% of users listed by top 2% hubs listed 10 or more times

Details in paper