

Five incidents, one theme:

Twitter spam as a weapon to drown voices of protest

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Motivation

- Social media solely for contacting friends
- Social media as news source
- Social media as politics
- Social media as a part of life

Incidents

Five incident over two years:

Syria April 2011 #syria

China '11 April 2011 #aiweiwei

Russia December 2011 #триумфальная

China '12 March 2012 #freetibet

Mexico May 2012 #marchaAntiEPN

Methodology: Data collection

- Twitter data from the Truthy Project (<u>http://truthy.indiana.edu/</u>)
- Varies from 1/10 to 1/15 of all tweets

 Mostly continuous, some interruptions in data collection

Methodology: Hashtag expansion

- 1. Let S = {seed hashtag} (#syria, #aiweiwei, etc)
- 2. Let T = {tweet | tweet contains a hash in S}
- 3. Let $S' = \{ top \ n \ hashtags \ in \ T \}$
- 4. If $S \neq S'$, let S = S' and goto 2
 - Stabilizes after 2-4 iterations in all cases
 - Tested with all user's tweets, did not substantially change findings

Methodology: Hashtag expansion

Syria: #syria, #bahrain, #egypt, #libya, #syria, #jan25 (Egypt), #feb14, #tahrir (Egypt), #yemen, #feb17 (Libya), #kuwait

China '11: #aiww, #aiweiwei, #cn417 (Jasmine), #5mao (5 May), #freeaiww, #freeaiweiwei, #cn424 (Jasmine), #tateaww, #cnjasmine

Russia: #чп (abbr of Чрезвычайное Происшествие, extraordinary incident), #6дек (Dec 6), #5дек (Dec 5), #выборы (elections), #митинг (meeting), #триумфальная (Triumphal Square), #победазанами (victory is ours), #5dec, #навальный (surname, likely Navalny), #ridus

Methodology: Hashtag expansion

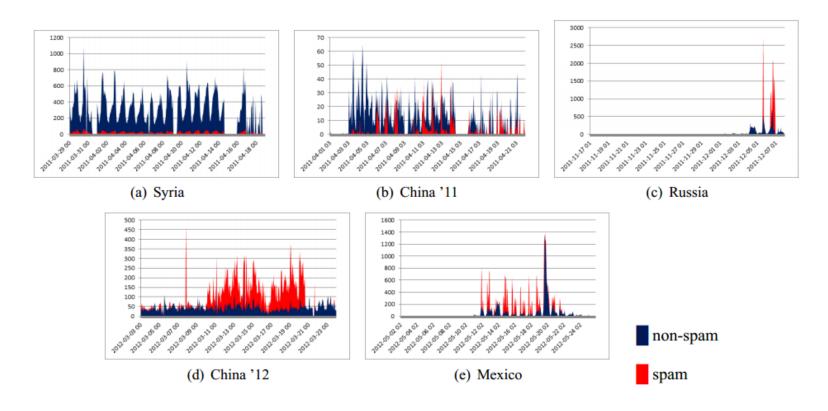
China '12: #tibet, #freetibet, #china, #monday, #西藏 (Tibet), #freetibet Free Tibet #tibet, #freetibet, #china, #monday, #西藏 (Tibet), #beijing, #shanghai, #india, #apple, #hongkong

Mexico: #marchaantiepn, #marchaantipeña, #marchamundialantiepn, #marchayosoy132 (I am 132nd to march), #votomatacopete (vote for another), #epn, #epnveracruznotequiere (no more EPN), #pr, #amlocomp (initials of competitor), #yosoy132

Methodology: Incident sizes

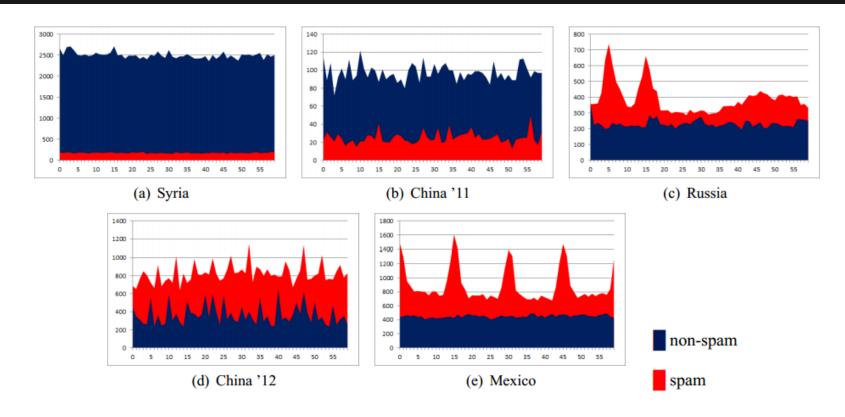
Incident	Tweets	Accounts	Comments
Syria	1,540,000 non-spam 107,000 spam	157,000 non-spam 3,000 spam	Most overall tweets Smallest % spam tweets
China '11	58,000 non-spam 15,000 spam	3,950 non-spam 550 spam	Smallest attack Relatively low % spam
Russia	151,000 non-spam 338,000 spam	12,000 non-spam 25,000 spam	Highest % spam Highest number of spam accounts
China '12	227,000 non-spam 600,000 spam	10,00 non-spam 1,700 spam	Highest % spam Fewer + high volume spam accounts
Mexico	306,000 non-spam 498,000 spam	28,800 non-spam 3,200 spam	High % spam Fewer + high volume spam accounts

Analysis of tweets: Daily tweet volume



- China'11, Russia, and Mexico show definite spikes of activity
- Syria, China '11, and China '12 are more sustained

Analysis of tweets: Timing of tweets



- Russia and Mexico show automated (cron related?) spikes
- Diurnal activity (not pictured) generally matches that of normal usage

Analysis of tweets: Tweet meta content

Incident	URLs (spam / non-spam)		Mentions (spam / non-spam)		Retweets (spam / non-spam)	
Syria	41.0%	96.4%	59.1%	60.4%	44.2%	45.2%
China '11	58.8%	36.2%	69.7%	68.3%	3.3%	29.8%
Russia	2.8%	36.8%	4.2%	54.6%	3.1%	35.8%
China '12	60.6%	64.5%	81.3%	36.4%	0.2%	13.7%
Mexico	1.0%	32.8%	1.9%	80.7%	1.6%	68.9%

- Spam with URLs is often product placement; (unrelated) news stories
- Spam has significantly fewer retweets (other than in Syria)
- Number of mentions is a good indicator, but could go either way

Analysis of tweets: Most common content

rt, #bahrain, #egypt, #libya, the, in, #syria, to, فى (in), of

Syria

Spam:

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Non-spam:
                          rt, #egypt, #bahrain, #libya, the, in, #syria, في (in), to, ن, (of)
                          #aiww, rt, #5mao (May 5), #cn417, 艾未未的童话涉嫌抄袭 (headline about Ai Weiwei), url_1, #cn424, url_2, #aiweiwei, #china
China '11
                 Spam:
                          rt, #aiww, #aiweiwei, #cn417, ai, @aiww, #freeaiww, #5mao, the, #freeaiweiwei
            Non-spam:
                          на (on), #победазанами (victory is ours), не (no), #чп, и (and), #выборы (elections), в (in), #бдек (Dec. 6), я (I), площади (areas)
   Russia
                 Spam:
            Non-spam:
                          #выборы, rt, в, на, #чп, и, не (not), за (for), с (with), #митинг (meeting)
                          #tibet, #freetibet, @degewa, @tibet, #西藏 (#tibet), #degewa, #china, and, @sfchoi8964, #315
China '12
                 Spam:
                          #china, #tibet, rt, in, #beijing, #shanghai, the, to, #hongkong, #freetibet
            Non-spam:
  Mexico
                 Spam:
                          #marchaantiepn, marcha (march), la (the), de (of), anti, epn (initials), i, rt, #marchaantipeña, marchaantiepn
                          #marchaantiepn, la, rt, de, a, en (in), no, el (the), que (that), v (and)
            Non-spam:
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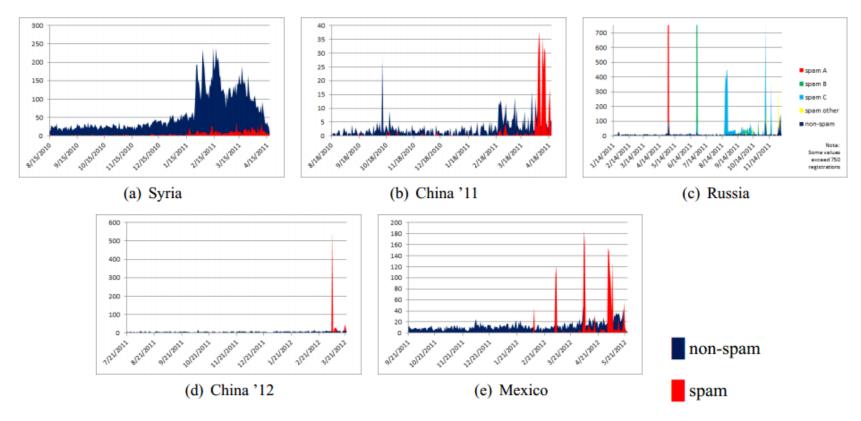
- Hashtags expected, because that's how data was collected
- China '11: Two specific URLs (for products) appeared in many spam tweets
- Russia: Stop words are much more common in non-spam Retweet indicators are not common in spam
- China'12: Spammers often targeted a small set of users with mentions

Analysis of tweets: Tweet recipients

Incident	@non-spam	@spam	neither
Syria	4.7%	78.3%	17.0%
China '11	1.1%	21.5%	77.5%
Russia	10.7%	63.8%	25.4%
China '12	0.7%	75.0%	24.3%
Mexico	4.8%	51.6%	43.6%

- @non-spam / @spam are people that tweeted at least once in the incident
- Each incident shows spammers creating internal social mention networks
- China '11 and Mexico were connecting to other people

Analysis of accounts: Registration



- All but Syria have registration blocks
- Russian blocks each have their own username patterns

Analysis of accounts: Usernames

- Syria Often end in numbers, patterns less common zuhair77, GC814, walidraafat, ToQiiiZ, GeorgiaKillick0, libyana1702, Bahraini61, ScottsdaleReb, Updates2424
- China '11 Often end in numbers, patterns less common cnjs2, cnjs5, cnjs10, cnjs11, cnjs12, cxbenben113, dabenben222, huashengdun111, huashengdun203
- Russia Most are {name} or {initial} {name}; vary by registration block SScheglov, SSchelkachev, SSchelkonogov, SSchelokov, SSchemilov, SScherbakov, SShabalin, SShabarshin
- China '12 Most are {name}{name}{random/number}, max length
 LanelleL4nelle6, LanieSl1dek1103, LarondaGuererro, LatanyaZummoMNS, LatarshaWeed181,
 LauraHelgerm1nV
- Mexico Most are {name}{name}{number}, max length
 AnaAvil58972814, AnaAvil76571383, AnaLope95971326, AnaRive02382949, AnaSuar79305176,
 AnaSuar83449134

Analysis of accounts: Default profile and image

	Default profile		Default image	
Incident	spam	non-spam	spam	non-spam
Syria	46.2%	42.9%	9.4%	6.0%
China '11	89.4%	51.2%	12.3%	12.6%
Russia	57.8%	34.7%	7.8%	11.1%
China '12	95.1%	47.8%	59.0%	11.8%
Mexico	1.7%	27.0%	0.6%	3.0%

- Earlier incidents show higher defaults among spam accounts
- Mexico reverses this trend

Summary of findings

- Spam often shows a distinct spiking pattern
- There can be indications of scheduled activity; however diurnal patterns were matched
- Non-spam tweets use more stop words; Chinese language analysis is difficult
- URLs, mentions, and retweets vary between spam and nonspam but not consistently
- Spam accounts are registered in blocks with generated usernames
- Default accounts are a good indicator of spammers in older incidents

Obligatory question slide