

# Learning Topical Social Sensors

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## Abstract

Twitter represents a massively distributed social sensor of a rich underlying topic space that drives its content generation. Yet Twitter content is so diverse, decentralized, and dynamic in nature, that it is hard to automatically aggregate this topical content. To address this need, we provide a novel way of learning topical social sensors on Twitter that learn from a provided set of topical hashtags and generalize to identify topical tweets with previously unseen tags. These learning social sensors leverage a variety of user-based, hashtag-based, term-based, and location-based features for distinguishing topical from non-topical tweets; we further analyze these features to understand which features are most useful and why. We further assess general global topical trends and how our learning sensors are able to follow these trends by drawing from a rich variety of sources on the Twittersphere to enable a first generation of learning social sensors for Twitter.

## Introduction

Twitter hosts lots of information, on average more than 2,200 new tweets every second. This can get up to 3 to 4 times increase during large events such as tsunami.<sup>1</sup>

- Twitter is a vast sensor of content generated by latent phenomena (e.g., flu, political sentiment, elections, environment).
- Learning topical social sensors (politicians in NY, road conditions in Toronto) – very broad topics for which its hard to manually specify a useful query.
- But there is interesting topical content and wouldn't it be cool if we could learn a social sensor for a targeted topic?
- Key insight is that hashtags are topical and can be used to bootstrap a supervised learning system that as we will show generalizes well beyond the seed hashtags.
- Conclusion is a new way to build topical real-time feeds that are otherwise difficult to do with existing Twitter tools (??).

section Learning Topical Social Sensors

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<sup>1</sup><https://blog.twitter.com/2011/the-engineering-behind-twitter-s-new-search-experience>

Start off with the questions that we want to answer in this section:

- How to evaluate, labeling (problem of no supervised labels for tweets, indirect via hashtags as topical surrogates, leads to question of hashtag curation)?

- Which classification algorithm is best / most robust for learning topical social sensors?

## Dataset Statistics

We crawled Twitter data using Twitter Streaming API for two years spanning 2013 and 2014 years. This type of crawling provides us with a very sparse set of data, roughly 1% of all tweets<sup>2</sup>. The total number of tweets collected is 829,026,458. In the context of Twitter, we consider a list of 5 features for each tweet. Each tweet has a *From*, the person who tweeted it, and a *Time* which is the date information of the tweet. It can also contain

- *Hashtag(s)*, keywords specified using # sign
- *Mention(s)*, another Twitter username being mentioned using @ sign
- *Term(s)*, uni-grams which we extract from the 140 characters of the tweet. These uni-grams are later cleaned to remove *Terms* with no meaning (total number of *Terms* before cleaning was 20,234,729)

Table 1 provides more detail statistics about each feature. For each feature, we reported the count of the feature in our dataset, in addition to maximum, average, median counts of each feature across the tweets. Lower part of the table provides these counts across user dimension meaning that for example a hashtag has been used in average by 10.08 users. Last part of the table shows the statistics for the hashtag usage of our users e.g., users have used 2 hashtags in average.

Figure ?? shows details of number of tweets per month and figure ?? shows the power law plots of tweet counts and hashtag counts for users. We chose 10 topics for our experiments. Tweets are temporally divided over 2 years to provide train and test sets. Table 2 provides samples of training hashtags and number of train hashtags, test hashtags, topical tweets for each topic. Some topics such as *HumanCausedDisaster* and *Soccor* are more general

<sup>2</sup>[http://allthingsd.com/20101110/twitter-firehose-too-intense-take-a-sip-from-the-garden-hose-or-sample-the-spritzer—](http://allthingsd.com/20101110/twitter-firehose-too-intense-take-a-sip-from-the-garden-hose-or-sample-the-spritzer/)

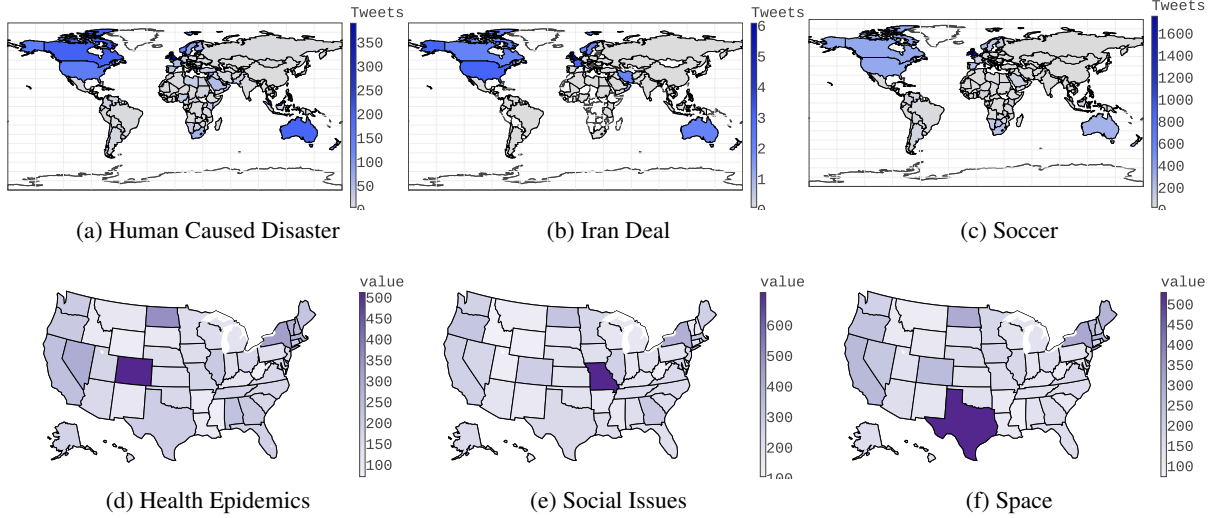


Figure 1: Choropleths of top: International map and bottom: U.S. map

Feature	Tweets				Count
	Max	Avg	Median	Max entity	
From	10,196	8.67	2	running_status	95,547,198
Hashtag	1,653,159	13.91	1	#retweet	11,183,410
Mention					411,341,569
Location					58,601
Term	2024529	7,450.58	323	the	20,234,729
Feature	Users				Count
	Max	Avg	Median	Max entity	
Hashtag	592,363	10.08	1	#retweet	
Mention	26,293	5.44	1	dimensionist	
Location	739,120	641.5	2	london	
Term	1,799,385	6,616.65	305	the	
Feature	Hashtags				Count
	Max	Avg	Median	Max entity	
From	18,167	1.62	0	daily_astrodatta	

Table 1: Feature Statistics

topics and have higher number of topical tweets while some other ones such as *IranDeal* is more specific, thus having less number of topical tweets.

Figure ?? shows distribution of tweets across different location in U.S. and international locations overall and for each topic(?).

## Experimental Methodology

How we curated hashtags: need to make up good story here. Inner-annotator agreement of 3/4.

Train/validation/test split date selection – temporally 5,1,4

Feature selection: threshold per feature 159 and 50 (just explain rationale for lower hashtag and location thresholds).

Formal notation, how do we train/test and tune hyperparameters for a generic classifier.

## Classification Algorithms

### 1. Naive Bayes

### 2. Rocchio (centroid)

### 3. Logistic Regression

All above over 1,000,000 features, \*same\* training data for all algorithms.

Not breaking down by feature type yet – that’s for the feature analysis section.

## Analysis

- Table of rows:alg, cols: MAP, P@k (k in 10,100,1000) with stderrs over all topics

- Could do a bar graph (below) each for MAP, P@100 with topics as major columns and algs as neighboring bars

- Anecdotal results for each topic – point out deficiency in our labels (a good thing, we generalized well from small hashtag set), manual evaluation of relevance for top-100 for best algorithm?

## Feature Analysis

In this section, we analyze the informativeness of each feature for learning topical tweets by looking at different characteristics for each feature in our dataset. For example, one characteristic of hashtags could be the number of the tweets that contain those hashtags. Does this have an effect on importance of the hashtag when it comes to learning topical tweets or not. In this sense, this section would bring insights to the following questions:

- What are the best features for learning social sensors, do they differ by topic? (Why?)
- For each feature type, do any attributes correlate with importance?

A famous method for measuring informativeness is Mutual Information which is a measure of amount of information one random variable contains about another random variable. In order to calculate amount of information that a feature  $f_k \in \{from, hashtag, mention, term, location\}$

Topics/Top10	NaturalDisaster	Epidemics	IranDeal	SocialIssues	LGBT	HumanCausedDisaster	CelebrityDeath	Space	Tennis	Soccer
#TrainHashtags	31	52	12	31	29	49	28	98	58	126
#TestHashtags	18	33	5	19	17	29	16	63	36	81
#TotalTopicalTweets	42,987	210,217	8,762	230,058	282,527	408,304	163,890	239,719	55,053	860,389
Sample Train Hashtags	#earthquake	#ebola	#irandeal	#policebrutality	#loveislove	#gazaundersattack	#robinwilliams	#asteroids	#usopenchampion	#worldcup
	#storm	#virus	#iranfreedom	#michaelbrown	#gaypride	#childrenofsyria	#ripmandela	#astronauts	#novakdjokovic	#lovesoccer
	#tsunami	#vaccine	#irantalk	#justice4all	#uniteblue	#iraqwar	#ripleanivers	#satellite	#wimbledon	#fifa
	#abloods	#chickenpox	#rouhani	#freetheweed	#homo	#bombthreat	#mandela	#spacecraft	#womenstennis	#realmadrid
	#hurricanekatrina	#theplague	#nuclearpower	#newnjgunlaw	#gaymarriage	#isis	#paulwalker	#telescope	#tennisnews	#beckham

Table 2: Test/Train Hashtag samples and statistics

Method	Metric	Tennis	Space	Soccer	IranDeal	HumanCausedDisaster	CelebrityDeath	SocialIssues	NaturalDisaster	Epidemics	LGBT	Mean±Std
LR	MAP	0.918	0.870	0.827	0.811	0.761	0.719	0.498	0.338	0.329	0.165	0.623±0.19
NB	MAP	0.908	0.897	0.731	0.824	0.785	0.748	0.623	0.267	0.178	0.092	0.605±0.22
Rocchio	MAP	0.690	0.221	0.899	0.584	0.481	0.253	0.393	0.210	0.255	0.089	0.407±0.18
RankSVM	MAP	0.702	0.840	0.674	0.586	0.603	0.469	0.370	0.248	0.136	0.082	0.471±0.18
LR	P@10	1.000	0.000	0.200	0.700	0.600	0.000	0.100	0.200	0.300	0.500	0.360±0.24
NB	P@10	1.000	0.900	0.700	0.600	0.600	0.700	1.000	0.100	0.400	0.100	0.610±0.23
Rocchio	P@10	0.800	0.000	1.000	0.900	0.000	0.000	0.000	0.500	0.500	0.100	0.380±0.29
RankSVM	P@10	1.000	0.800	0.600	0.800	0.400	0.300	0.000	0.100	0.000	0.200	0.420±0.26
LR	P@100	0.950	0.580	0.650	0.870	0.620	0.490	0.640	0.690	0.790	0.210	0.649±0.15
NB	P@100	0.980	0.850	0.600	0.880	0.750	0.860	0.730	0.230	0.090	0.190	0.616±0.23
Rocchio	P@100	0.980	0.000	1.000	0.690	0.170	0.000	0.280	0.170	0.680	0.120	0.409±0.28
RankSVM	P@100	0.730	0.720	0.310	0.700	0.880	0.440	0.480	0.340	0.020	0.100	0.472±0.20
LR	P@1000	0.963	0.954	0.816	0.218	0.899	0.833	0.215	0.192	0.343	0.071	0.550±0.26
NB	P@1000	0.954	0.954	0.716	0.218	0.904	0.881	0.215	0.195	0.141	0.060	0.524±0.28
Rocchio	P@1000	0.604	0.000	0.925	0.218	0.359	0.000	0.215	0.167	0.144	0.065	0.270±0.21
RankSVM	P@1000	0.799	0.922	0.764	0.218	0.525	0.547	0.215	0.173	0.154	0.064	0.438±0.22

Table 3: Different learning methods results on topics with hyper-parameter tuning based on MAP

provides w.r.t  $t_i \in \{NaturalDisaster, Epidemics, \dots\}$ , mutual information is defined as:

$$I(t_i, f_k) = \sum_{t_i \in \{true, false\}} \sum_{f_k \in \{true, false\}} p(f_k, t_i) \log \left( \frac{p(f_k, t_i)}{p(f_k)p(t_i)} \right) \quad (1)$$

Higher values for this metric indicates more informative features for the specified topic.

First, we provide mutual information values for each feature across different topics shown by boxplots in figure ??, and average values of mutual information for each feature vs different topics shown in table 2. The last column in table 2 shows average mutual information for the feature with the standard error range provided. We make a few observations from the analysis of Table 2:

- Term features provide more information for all of the topics on average which shows the importance of uni-grams when it comes to selection of topical tweet.
- From and mention features are the least informative features for all of the topics.
- Location and Hashtag feature provide second and third most informative features respectively.
- A few topics such as irandeal and tennis are less sensitive to selection of a specific features.
- Location feature provides more information regarding HumanCausedDisaster, LGBT, and Soccer topics.

- Sorting features based on their average mean value across different topics results in the following order:

1. Term
2. Location
3. Hashtag
4. Mention
5. From

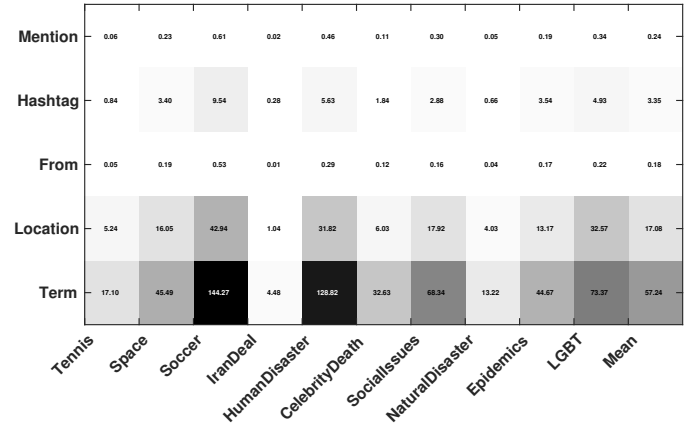


Figure 2: Average MI for different features vs. Topics, last two column show mean value and stderr across all topics

It is important to note that due to very large amount of Term features, they were cleaned based on their frequency (having at least frequency value of 100).

<p><b>Tennis</b></p> <ul style="list-style-type: none"> <li>✓ rt @spennits: shock city, darcis drops rafa in straight sets, first time nadal loses in first rd of a. major in career. #espwimbledon #w</li> <li>✓ rt @spennits: shock city, darcis drops rafa in straight sets, first time nadal loses in first rd of a. major in career. #espwimbledon #w</li> <li>✓ rt @spennits: shock city, darcis drops rafa in straight sets, first time nadal loses in first rd of a. major in career. #espwimbledon #w</li> <li>✓ rt @spennits: shock city, darcis drops rafa in straight sets, first time nadal loses in first rd of a. major in career. #espwimbledon #w</li> <li>✓ rt @spennits: shock city, darcis drops rafa in straight sets, first time nadal loses in first rd of a. major in career. #espwimbledon #w</li> </ul> <p><b>Source</b></p> <ul style="list-style-type: none"> <li>✱ @troom_dopg: #thingstodobeforetheends spend all my money.</li> <li>✱ #mancityonline nice performance</li> <li>✱ rt @indykala: podolski: "let's see what happens in the winter, the fact is that i'm not happy with it, that's clear." #arsenal</li> <li>✱ rt @indykala: wenger: "i don't believe match-fixing is a problem in england." #afc</li> <li>✱ @indykala you never get back to me about texts this week</li> </ul> <p><b>HumanCausedDisaster</b></p> <ul style="list-style-type: none"> <li>✓ rt @bushlamb: there've been peaceful people in rhomes not terrorists! #assad.enemy of #humanity destroyed it. #eyehonors #withyriaa htp:</li> <li>✓ what a helpless father, he can do nothing under #hassad's siege #assadku4yrianchidhah http://rt.cvo.g3c3byehw#hassad #yriawaricams2014</li> <li>✱ exclusive: u formally requested #un investigation; russia pressured #assad to no avail;chance of evidence proof hard http://rt.cvo.500s2zrdw</li> <li>✱ #savealeppo from #assadwaricams2wae_aleppo from #civilians 'targeted shelling' of #assad regime#yriaa #aleppo http://rt.cvo.3dfk3dtpsl</li> <li>✓ rt @canein.rights: why does the #un allow this to continue? #rt(intin1957 help raise awareness of the suffering in #yriawaricams2014</li> </ul> <p><b>LocalIssues</b></p> <ul style="list-style-type: none"> <li>✱ #what we need: actually better is the thing i believe in a christianist theory of the us dollar @nosatonedict @nationaldeb</li> <li>✱ #Zanov: according to @jnsenatepressers women's rights do not include this poor m'r mother's right to defend herself http://rt.cvo.zshnqsh6 #</li> <li>✱ rt @Zanov: confication ? how many carry permits are in the senate and assembly? g've us our turn them in. @senatorcormier @lougreenw</li> <li>✱ #Zanov: vote with your wallet against #guncontrolforest city enterprises does not support the #2a http://rt.cvo.tpkok3berm7tas #frcot</li> <li>✱ #Zanov @momdemand @jstices3 they don't have a plan for that... which is why they should never be allowed to take our guns</li> </ul> <p><b>Epidemics</b></p> <ul style="list-style-type: none"> <li>✓ rt @who: fourteen of the spox. &amp;amp; con. ebola cases in #conakry, #guinea, are health care workers, of which 11 died #isebolakia</li> <li>✱ #who who can afford also to care in government health facilities [with universal health coverage]</li> <li>✱ #ebolabreakth this health crisis, unparalleled in modern times, @who dir, aywale - requires \$1 billion to stem http://rt.cvo.tqzghy3d3d</li> <li>✱ rt @medcin: #who are conducting a survey on the social determinants of health in medical teaching, fill the survey in at http://rt.cvo.359x</li> <li>✱ #augmentation vertigineuse de 57,4 € en 1 an des actes islamophobes en france, dit le collectif contre l'islamophobie http://rt.cvo.2gohcegi5</li> </ul>	<p><b>Space</b></p> <ul style="list-style-type: none"> <li>✱ rt @jaredtello: rt @30secondstomars: icym: mars performing a cover of @rihanna's #stay on australia's @triplemmh - video. http://rt.cvo.4q</li> <li>✱ #xoving mars @30secondstomars @jaredtello @shannonleah @tomofearth xobest group http://rt.cvo.4ds0zovjnf</li> <li>✱ rt @jaredtello.com: space everyone how much are you proud of @30secondstomars #muthottest 30 seconds to mars http://rt.cvo.bxyrni4657</li> <li>✱ rt @30secondstomars: missed the big news? mars touring with @linkpark + special guests @if this summer! http://rt.cvo.3ec5m9pwwd</li> <li>✱ rt @30secondstomars: to the right! to the left! we will fighto the deathgo @tntothedwldownyt to mars, starting weekly, now 30. it's</li> </ul> <p><b>Israel</b></p> <ul style="list-style-type: none"> <li>✓ rt @iran.poliv: @vidalquadrax @ijcomittee has investigated 10 major subjects of irans controversial #nuclear program #iranatlankienna</li> <li>✓ rt @iran.poliv: @vidalquadrax @ijcomittee has investigated 10 major subjects of irans controversial #nuclear program #iranatlankienna</li> <li>✱ rt @negarmotazavi: thank you @hassansouhani for retweeting. let's hope for a day when no iranian feels returning to their homeland. http://rt.cvo.4iran.poliv: iran: details of savage attack on political prisoners in evin prison http://rt.cvo.zduakgqlv #iran #humanrights</li> <li>✓ rt @iran.poliv: chairman rosh-lehinen speaking on us commitment 2 protect camp liberty residents. #iranvrahiolities http://rt.cvo.1g6dx3.1zru</li> </ul> <p><b>Celebrity Death</b></p> <ul style="list-style-type: none"> <li>✱ rt @bushlamb: charis: today is my birthday #amc also the day the hero @nelsonmaddala has died. lets never forget what he taught us. forgiveness i</li> <li>✱ rt @nelsonmaddala: death is something inevitable when a man has done what he considers to be his duty to his people.#karthiay his country,he can re</li> <li>✱ rt @nelsonmaddala: la muerte es algo inevitable.cuando un hombre ha hecho lo que considera que es su deber para con su gente y su pas.pued</li> <li>✱ #jacques #kallis: a phenomenal cricketing giant of all time...#cricket #history #bouthafrica http://rt.cvo.m5pmw9q4</li> <li>✱ #sudehi 304 south africa has the most beautiful babies... so diverse, so unique... so god!! no #durban #southafrica</li> </ul> <p><b>NaturalDisaster</b></p> <ul style="list-style-type: none"> <li>✱ #what we need in #akabakoma: not cruel and unusual? maybe just barbaric, inhuman and reminiscent of the dark ages?</li> <li>✱ #what #philippines: the haiti-dominican crisis i agree with how marately is handling the situation. i totally. http://rt.cvo.3pwwsax</li> <li>✱ rt @soilhai: a new reforestation effort in #haiti, local compact, anyone? http://rt.cvo.psd4rqrqk #richardbranson @clintonfdu @virginiunite</li> <li>✱ #mes coussins jamaïis n'ontent les nuits de duvalier #haiti #duvalier</li> <li>✱ #tony burgerer of @swissolidarity says you can't compare the disaster response in #haiti with the response to #huyain in #philippines @fheid</li> </ul> <p><b>LGBT</b></p> <ul style="list-style-type: none"> <li>✱ rt @jackmcdoucks: @lunaticxer @fingersmally @toddicknacion @theanonliberal anthony kennedy just wrote opinion granting legal protection to cupcake kippers</li> <li>✱ #toddicknacion your personal account, your interest, separate from your business.</li> <li>✱ #why would you report someone as spam if he is not spam? @lylyibya @toddicknacion</li> <li>✱ rt @3h.ackch3r: @toddicknacion thanks for your t!d having the female realbrother. between them it's 600 lbs, 104 iq points, and a lot of hate.</li> <li>✱ @toddicknacion who us dick trickle.</li> </ul>
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**For each feature type, do any attributes correlate with importance?** In order to give a better sense of what features are better for each topic, we provided top-5 features for each topic in table 5. It can be observed how different locations, hashtags, or terms showed as the top features based on mutual information are actually in relation with the specific topic.

## Related Works

gory, clustering-based methods, focuses on the hypothesis that trends are topical and topics are defined by the collection of relevant content; hence trends can be detected by clustered content (Petrović, Osborne, and Lavrenko 2010; Ishikawa et al. 2012; Phuvipadawat and Murata 2010; Becker, Naaman, and Gravano 2011; O'Connor, Krieger, and Ahn 2010; Weng and Lee 2011). With more focus on machine learning methods, (Wei et al. 2015) proposed a graphical model to discover latent events clustered in the spatial, temporal and lexical dimensions, while (Yamamoto and Satoh 2015) focused on the task of multi-label classification of tweets into living aspects such as eating. The second category, term-based methods focuses on the hypothesis that topics can be detected by focusing on temporal patterns of terms/keywords independent of the content of documents (Mathioudakis and Koudas 2010; Cui et al. 2012; Zhao et al. 2011; Nichols, Mahmud, and Drews 2012). The third category, query-based methods, focuses on the hypothesis that trending topics can be detected by measuring user defined criteria (Albakour, Macdonald, and Ounis 2013; Sakaki et al. 2012). The fourth category, network Structure-based method, focuses on the hypothesis that trending topics can be detected by studying the network structure of users (Budak, Agrawal, and El Abbadi 2011). The final category, hybrid method of (Diplaris et al. 2012) introduced concept of Dynamic Social Containers in this work to take advantage of aggregation of mining both the structure, content, and multimedia data to index and provide personalized, context-aware search. In this work, the authors defined social sensor as analyzing the dynamic and massive amount of information provided by user with the purpose of extracting unbiased trending topics and events in addition to using social connections for recommendation.

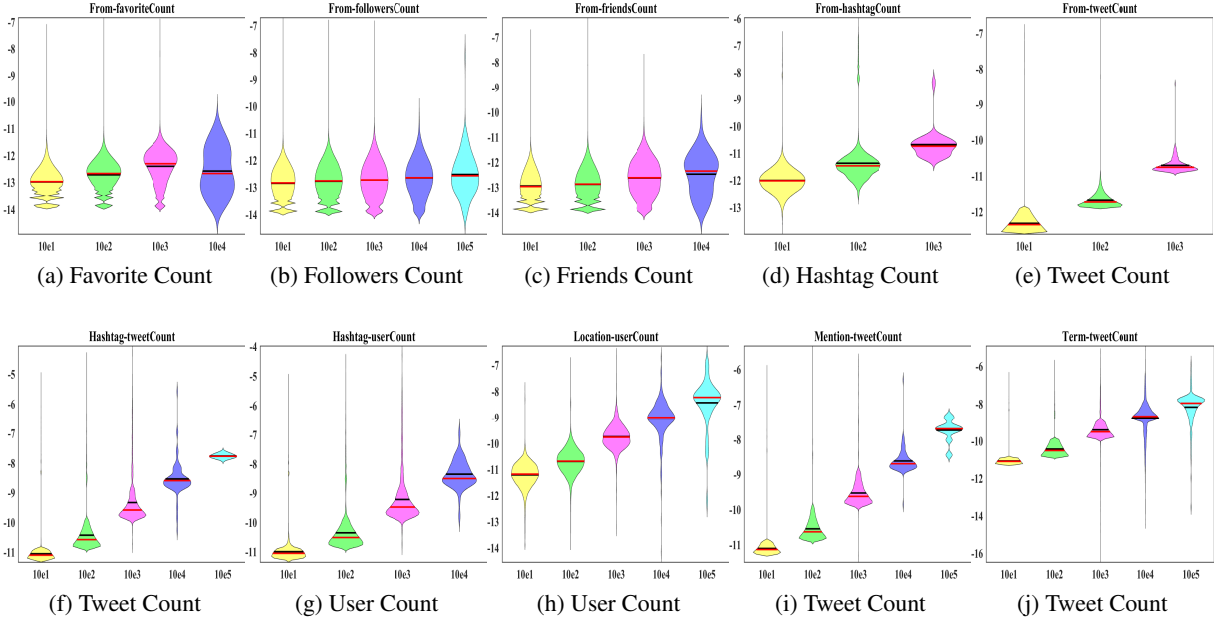


Figure 3: ViolinPlots for feature attributes counts vs. MI. Top row shows attributes {favoriteCount, followerCount, friendCount, hashtagCount, tweetCount} for *From* feature. Bottom row shows attributes tweetCount and/or userCount for *Hashtag*, *Location*, *Mention*, and *Term* features.

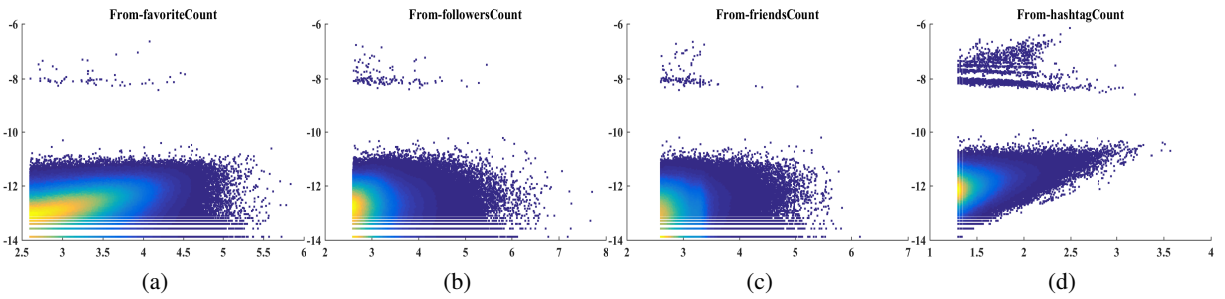


Figure 4: DensityPlots for feature attributes counts vs. MI. (a-d) show attributes {favoriteCount, followerCount, friendCount, hashtagCount} for *From* feature

Topics/Top10	NaturalDisaster	Epidemics	IranDeal	SocialIssues	LGBT	HumanCausedDisaster	CelebrityDeath	Space	Tennis	Soccer
From	earthquake_wo	changedecopine	mazandara	nsingerdebt	eph4_15	ydukozyf	nmandelaquotes	daily_astrodata	tracktennisnews	losangelessrh
From	earthalerts	drdaveanddee	hhadi119	debtadvisork	mgdauber	syriatweeten	boiknox	freesolarleads	tennis_result	shoetale
From	seelites	joimmentotetwk	140iran	debt_protect	stevendickinson	tintin1957	jacanews	houston_jobs	i_roger_federer	sport_agent
From	globalfloodnews	followebola	setarehgan	negativeequityf	lileensvf1	sirajsol	ewnreporter	star_wars_gifts	tennislessnow	books_you_want
From	gcmcdrought	localnursejobs	akgharshabaneh	dolphin_ls	truckerbooman	rt3syria	paulretweet	lenautilus	kamranisbest	makeupbella
Hashtag	earthquake	health	iran	ferguson	tcot	syria	rip	science	wimbledon	lfc
Hashtag	haiyan	uniteblue	irantalks	mikebrown	p2	gaza	riprobinwilliams	starwars	usopen	worldcup
Hashtag	storm	ebola	rouhani	ericgarner	pjnet	isis	ripcoreymonteith	houston	tennis	arsenal
Hashtag	tornado	healthcare	iranian	blacklivesmatter	uniteblue	israel	mandela	sun	nadal	worldcup2014
Hashtag	prayforthephilippines	depression	no2rouhani	fergusondecision	teaparty	mh370	nelsonmandela	sxsw	wimbledon2014	halamadrid
Location	philippines	usa	tehran	st.louis	usa	malaysia	southafrica	germany	london	liverpool
Location	ca	ncusa	u.s.a	mo	bordentown	palestine	johannesburg	roodepoort	uk	manchester
Location	india	garlandtx	nederland	usa	newjersey	syria	capetown	houston	india	london
Location	newdelhi	oh-sandiego	iran	dc	sweethomealabama!	israel	pretoria	austin	pakistan	nigeria
Location	newzealand	washington	globalcitizen	washington	aurora	london	durban	tx	islamabad	india
Mention	oxfamgb	foxtamedia	4freedominiran	deray	jjauthor	ifalasteen	nelsonmandela	bizarro_chile	wimbledon	lfc
Mention	weatherchannel	obi_obadike	iran_policy	natedrug	2anow	revolutionsyria	realpaulwalker	nasa	usopen	arsenal
Mention	redcross	who	hassanrouhani	antoniofrench	govchristie	drbasselabuward	robinwilliams	j_ksen	andy_murray	realmadriden
Mention	twcbreaking	obadike1	un	bipartisanism	a5h0ka	mogaza	rememberrobin	jaredleto	serenawilliams	ussoccer
Mention	abc7	c25kfree	statedept	theanonmessage	barackobama	palestinianism	tweetlikegiris	30secondstomars	esptennis	mcfc
Term	philippines	health	iran	police	obama	israel	robin	cnblue	murray	madrid
Term	donate	ebola	regime	protesters	gun	gaza	williams	movistar	tennis	goal
Term	typhoon	acrx	nuclear	officer	rights	israeli	nelson	enero	federer	cup
Term	affected	medical	iranian	protest	america	killed	mandela	imperdible	djokovic	manchester
Term	relief	virus	resistance	cops	gop	children	cory	greet	nadal	match

Table 5: Top 5 features for each topic based on Mutual Information

However, trending topics detection methods are not targeted. Our method differs from trending topic detection methods in that we are focusing on a set of topics that cannot necessarily be detected using bursts. Thus, trending topics detection methods are of limited relevance to the work presented hereinafter.

The second overarching group of works focuses on detection of a specific targeted topic, such as a disaster or epidemic. In a predictive study by (Kryvasheyeu et al. 2014), the authors studied the network of users and focused on choosing the best groups of users in order to achieve lead-times i.e. faster detection of disastrous event (following the concept of "friendship paradox" (Feld 1991)<sup>3</sup>). (Sakaki, Okazaki, and Matsuo 2013) used SVM classifier to detect earthquakes and employed a location estimation method such as Kalman Filtering for localizing it. The authors detected the occurrence of earthquakes through extracted statistical features e.g., the number and position of words in a tweet, keyword features and word context features from tweets.

Whereas the above works addressed exploiting the detection of crisis events, the following works focused on descriptive studies on disaster. The studies discuss the behavior of Twitter users during a crisis (Vieweg et al. 2010; Cheong and Cheong 2011; Starbird and Palen 2010) and do not address exploiting detection of crisis events. The studies investigated the use of social media during a crisis in order to identify information propagation properties, the social behavior of users (their retweeting behavior), information contributing to situational awareness, and the active players in communicating information. The behavioral information gleaned from these studies is exploited in this work to aid in the development of social sensors for detection of topics.

To detect health epidemics, researchers used content-

<sup>3</sup>On average, most people have fewer friends than their friends have

based and/or structure-based methods. The content-based methods of (Culotta 2010) and (Aramaki, Maskawa, and Morita 2011) identified influenza-related tweets and correlated these tweets to United States Center for Disease Control (CDC) statistics on influenza, such as the infection and incubation rate. As for methodology, both works extracted bag-of-words as features, while the former employed single and multiple linear regression showing that multiple linear regression works better, while the latter employed SVM. Results indicated a high correlation between their estimation of influenza cases in early stages of an epidemic, and statistics from the CDC and Japan's Infection Disease Surveillance Center. The other approach to early detection of contagious outbreaks is to use structure-based methods, (García-Herranz et al. 2012) designed a sensor based on the friendship paradox concept for early detection of contagious outbreaks. In this regard, García-Herranz et al. provided a method for choosing sensor groups from friends of random sets of users to find more central individuals in order to enforce early detection. The central assumption made in this work is that a sensor group represents more central individuals, and individuals at the center of a network are more likely to become infected than randomly-chosen members of the population. As a result, (García-Herranz et al. 2012) argued that this selection process of sensor groups helps in the early detection of outbreaks.

On the other hand, hybrid method of (Sadilek, Kautz, and Silenzio 2012), exploited tweet content and the structural information of a user's network. The authors employed a semi supervised approach to learn a SVM classifier, using n-grams as features in order to detect ill individuals. Using co-location and friendship, the authors estimated the probability of physical interaction between healthy and sick people. This enabled them to study the effect of these two factors of social activity (co-location for contact network and friendship for social ties) on public health.

The limitations of these studies centers on the fact that the

proposed methods are only valid for detecting a single topic. These methods used a primitive methods for curating the data e.g., querying keyword earthquake. In addition, there is no discussion within these works on how these methods can be generalized for other topics.

Another set of studies have moved towards creating more generalizable methods. Using a dataset of 55,000 news articles and 121,000 tweets, (Krestel et al. 2015) compared four different methods of language model, topic model, logistic regression, and boosting, to evaluate recommended tweets for a given news article.. (Yan, Lapata, and Li 2012; Chen et al. 2012) also focused on tweet recommendation. Their methods considered the users twitter profile, including tweet and retweet history, and social relations as features. Coupled with tweet popularity, the methods are able to generate tweet recommendations. With the purpose of photo recommendation on social media websites, (Chiarandini et al. 2013) analyzed the user logs of pageviews, navigation patterns between photostreams. The authors used collaborative filtering method and built a stream transition graph to analyze common stream topic transitions to this end.

On retweet prediction, (Can, Oktay, and Manmatha 2013; Xu and Yang 2012; Petrovic, Osborne, and Lavrenko 2011) used classification-based approaches using tweet-based and author-based features. However, (Can, Oktay, and Manmatha 2013) took advantage of visual cues from images linked in the tweets, and (Xu and Yang 2012) employed social-based features in addition to tweet author-based features. Different from the other two works, (Xu and Yang 2012) performed the analysis from the perspective of individual users. (Petrovic, Osborne, and Lavrenko 2011) worked on retweet prediction of real-time tweeting with online learning algorithms and claimed that performance is dominated by social features, but that tweet features add a substantial boost. These studies showed that temporal features have a stronger effect on messages with low and medium volume of retweets compared to highly popular messages, and user activity features can further improve the performance marginally.

## Conclusions

conclusion

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