A Longitudinal Study of Topic Classification on Twitter

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Abstract

Twitter represents a massively distributed information source over a kaleidoscope of topics ranging from social and political events to entertainment and sports news. While recent work has suggested that variations on standard classifiers can be effectively trained as topical filters of interest to individual users, there remain many open questions about the efficacy of such classification-based filtering approaches. For example, over a year or more after training, how well do such classifiers generalize to future novel topical content, and are such results stable across a range of topics? Furthermore, what features, feature classes, and feature attributes are most critical for long-term classifier performance? To answer these questions, we collected a corpus of over 800 million English Tweets via the Twitter streaming API during 2013 and 2014 and learned topic classifiers for 10 diverse themes ranging from social issues to celebrity deaths to the "Iran nuclear deal". The results of this long-term study of topic classifier performance provide a number of important insights, among them that (1) such classifiers can indeed generalize to novel topical content with high precision over a year or more after training, (2) simple terms and locations are the most informative feature classes (despite the intuition that hashtags may be the most topical feature class), and (3) the number of unique hashtags and tweets by a user correlates more with their informativeness than their follower or friend count. In summary, this work provides a long-term study of topic classifiers on Twitter that further justifies classification-based topical filtering approaches while providing detailed insight into the feature properties most critical for topic classifier performance.

1 Introduction

Social media sites such as Twitter present a double-edged sword for users. On one hand these sources contain a vast amount of novel and topical content that challenge traditional news media sources in terms of their timeliness and diversity. Yet on the other hand they also contain a vast amount of chatter and otherwise low-value content for most users' information needs where filtering out irrelevant content is extremely time-consuming. Previous work (Lin, Snow, and Morgan 2011; Yang et al. 2014; Magdy and Elsayed 2014) has noted this need for topic-based filtering and has adopted a range of variations on supervised classification techniques to build effective topic filters.

While these previous approaches have augmented their respective topical classifiers with extensions ranging from semi-supervised training to multiple stages of classification-based filtering to online tracking of foreground and background language model evolution, we seek to analyze the lowest common denominator of all of these methods, namely the performance of the underlying (vanilla) supervised classification paradigm. Our fundamental research questions in this paper are hence focused on a longitudinal study of the performance of such supervised topic classifiers. For example, over a year or more after training, how well do such classifiers generalize to future novel topical content, and are such results stable across a range of topics? Furthermore, what features, feature classes, and feature attributes are most critical for long-term classifier performance?

To answer these questions, we collected a corpus of over 800 million English Tweets via the Twitter streaming API during 2013 and 2014 and learned topic classifiers for 10 diverse themes ranging from social issues to celebrity deaths to the "Iran nuclear deal". We leverage ideas from (Lin, Snow, and Morgan 2011) for curating hashtags to define our 10 training topics and label tweets for supervised training; however, we also curate a disjoint set of test hashtags and *and use only these to label test data* (because training hashtags can be trivially memorized) to test true generalization performance of the topic filters to future novel content.

We empirically show that two simple and efficiently trainable methods — logistic regression and naive Bayes — generalize well to unseen future topical content (including content with no hashtags) in terms of their average precision (AP) and Precision@n for a range of n evaluated over long time-spans (typically one year or more). Furthermore, we show that terms and locations are among the most useful features — surprisingly more so than hashtags, even though hashtags were used to label the data. And perhaps even more surprisingly, the number of unique hashtags and tweets by a user correlates more with their informativeness than their follower or friend count.

In summary, this work provides a longitudinal study of Twitter topic classifiers that further justifies supervised approaches used in existing work while providing detailed insight into feature properties critical for their performance.

2 Learning Topical Social Sensors

For each Twitter topic, we want to build a binary classifier that can label a previously unseen tweet as topical (or not). To achieve this, we train the classifier on a set of topically labeled historical tweets.

More formally to define notation we will use later, given an arbitrary tweet d (a document in text classification parlance) and a set of topics $T = \{t_1, \ldots, t_K\}$, we wish to train a scoring function $f^t : D \to \mathbb{R}$ for topic $t \in T$ over a subset of labeled training tweets from $D = \{d_1, \ldots, d_N\}$. Each $d_i \in D$ has a boolean feature vector $(d_i^1, \ldots, d_i^M) \in \{0,1\}^M$. A boolean function $t : D \to \{0,1\}$ indicates whether the tweet d_i is topical (1) or not (0). In an ideal scenario, we could train for topic t so that $\forall d_i \; f^t(d_i) = t(d_i)$ — our scoring function (or more generally some threshold on it) agrees perfectly with the topic labels of all tweets.

A critical bottleneck for learning targeted topical social classifiers is to achieve sufficient supervised content labeling. With data requirements often in the thousands of labels to ensure effective learning and generalization over a large candidate feature space (as found in social media), manual labeling is simply too time-consuming for many users, while crowdsourced labels are both costly and prone to misinterpretation of users' information needs. Fortuitously, hashtags have emerged in recent years as a pervasive topical proxy on social media sites — hashtags originated on IRC chat, were adopted later (and perhaps most famously) on Twitter, and now appear on other social media platforms such as Instagram, Tumblr, and Facebook. Following the approach of (Lin, Snow, and Morgan 2011), for each topic $t \in T$, we leverage a (small) set of user-curated topical hashtags H^t to efficiently provide a large number of supervised topic labels for social media content.

Next we provide a procedure for labeling data with H^t for training and validation. Following this, we proceed to train supervised classification and ranking methods to learn topical content from a large feature space (e.g., this feature space includes terms, hashtags, mentions, authors and their locations). The training process involves two steps:

1. **Temporally split train and validation using H^t:** As standard for machine learning methods, we divide our training data into train and validation sets — the latter for hyperparameter tuning to control overfitting and ensure generalization to unseen data. As a critical insight for topical generalization where we view correct classification of tweets with *previously unseen topical hashtags* as a proxy for topical generalization, we do not simply split our data temporally into train and test sets and label both with *all* hashtags in H^t. Rather, we split H^t into two disjoint sets H^t_{train} and H^t_{val} according to a time stamp t_{split} for topic t and the first usage time stamp $h_{\text{time}*}$ of each hashtag $h \in H^t$. In short, all hashtags $h \in H^t$ first used before t_{split} are used to generate positive labels in the training data and the remaining validation hashtags are used to generate positive labels in the test data.

   To achieve this effect formally, we define the following:
$$H^t_{\text{train}} = \{h | h \in H^t \wedge h_{\text{time}*} < t_{\text{split}}\},$$
$$H^t_{\text{val}} = \{h | h \in H^t \wedge h_{\text{time}*} \geq t_{\text{split}}\}.$$

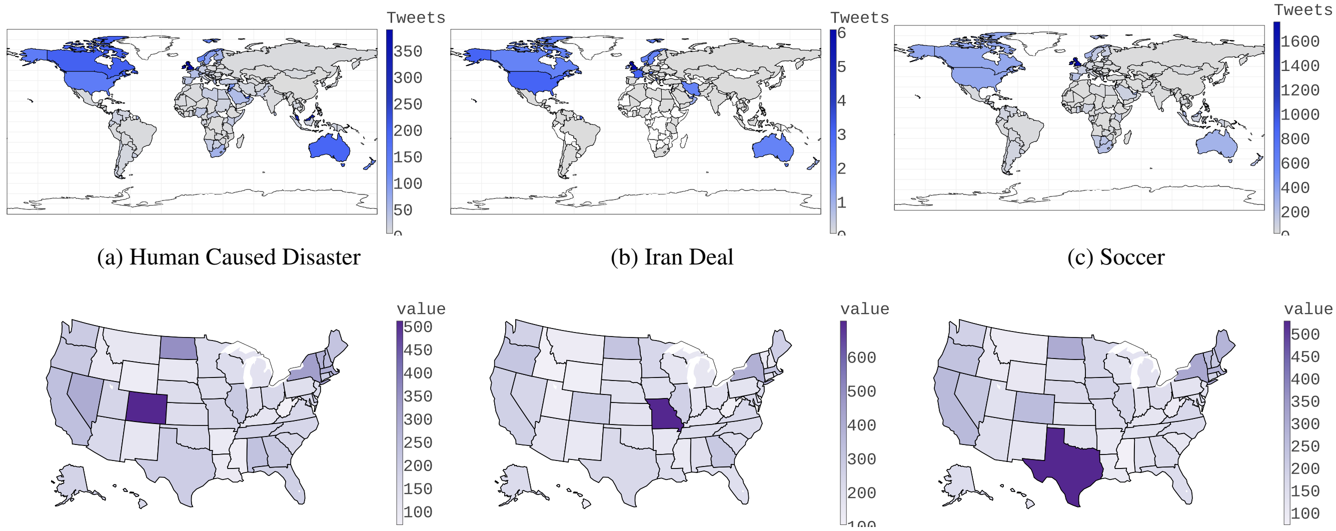
   Once we have split our hashtags into training and validation sets according to t_{split}, we next proceed to temporally split our training documents D into a training set D^t_{train} and a validation set D^t_{val} for topic t based on the posting time stamp $d_{i,\text{time}*}$ of each tweet d_i as follows:
$$D^t_{\text{train}} = \{d_i | d_i \in D \wedge d_{i,\text{time}*} < t_{\text{split}}\},$$
$$D^t_{\text{val}} = \{d_i | d_i \in D \wedge d_{i,\text{time}*} \geq t_{\text{split}}\}.$$

   Next we define the set of positively occurring features for a document d_i formally as $D_i^+ = \{j | d_i^j = 1\}_{j=1 \ldots M}$ and note that D_i^+ may include feature IDs for the content of d_i (e.g., terms and, importantly, hashtags) as well as its meta-data (e.g., author, location). Then to label both the train and validation data sets D^t_{train} and D^t_{val}, we use the respective hashtag sets H^t_{train} and H^t_{val} for generating the topic label for a particular tweet $t(d_i) \in \{0,1\}$ as follows:
$$t(d_i) = \begin{cases} 1 : \exists_{h \in H^t_{\text{train}}} \; h \in D_i^+ \wedge d_i \in D^t_{\text{train}} \\ 1 : \exists_{h \in H^t_{\text{val}}} \; h \in D_i^+ \wedge d_i \in D^t_{\text{val}} \\ 0 : \text{otherwise} \end{cases}.$$

   The critical insight here is that we not only divide the train and validation temporally, but we also divide the hashtag labels temporally and label the validation data with an entirely disjoint set of topical labels from the training data. The purpose behind this training and validation data split and labeling is to ensure that learning hyperparameters are tuned so as to prevent overfitting and maximize generalization to unseen topical content (i.e., new hashtags). We remark that a classifier that simply memorizes training hashtags will fail to correctly classify the validation data except in cases where a tweet contains both a training and validation hashtag.

2. **Training and hyper-parameter tuning:** Once D^t_{train} and D^t_{val} have been constructed, we proceed to train our scoring function f^t on D^t_{train} and select hyperparameters to optimize Average Precision (AP) (Manning, Raghavan, and Schütze 2008) (a ranking metric) on D^t_{val}. Once the optimal f^t is found for D^t_{val}, we return it as our final learned topical scoring function f^t for topic t. Because $f^t(d_i) \in \mathbb{R}$ is a scoring function, it can be used to rank.

Analogously to train and validation data, test data is generated the same way, but we omit formal notation (identical to the above) in order to reduce clutter. Test data has its own time stamp ($> t_{\text{split}}$), its own set of temporally disjoint data, and its own set of hashtags temporally disjoint from the training and validation data; this is done in order to evaluate generalization performance of the learned classifier on future data with topical hashtags not seen during training. With train, validation, and testing data defined along with the training methodology, it remains now to empirically evaluate and analyze classifier performance, described next.



(a) Human Caused Disaster (b) Iran Deal (c) Soccer

(d) Health Epidemics (e) Social Issues (f) Space

Figure 1: Per capita tweet frequency across different international and U.S. locations for different topics. The legend provides the number of tweets per 1 Million capita.

#Unique Features

From	Hashtag	Mention	Location	Term
95,547,198	11,183,410	411,341,569	58,601	20,234,728

Feature Usage in #Tweets

Feature	Max	Avg	Median	Most frequent
From	10,196	8.67	2	running_status
Hashtag	1,653,159	13.91	1	#retweet
Mention	6,291	1.26	1	tweet_all_time
Location	10,848,224	9,562.34	130	london
Term	241,896,559	492.37	1	rt

Feature Usage by #Users

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	1	rt

Feature Using #Hashtags

From	18,167	2	0	daily_astrodata
Location	2,440,969	1,837.79	21	uk

Table 1: Feature Statistics of our $829,026,458$ tweet corpus.

3 Data Description

Now we provide details of the Twitter testbed for topical classifier learning that we evaluate in this paper. We crawled Twitter data using Twitter Streaming API for two years spanning 2013 and 2014 years. We collected more than 2.5 TB of compressed data, which contains a total number of $829,026,458$ English tweets. In the context of Twitter, we consider five feature types for each tweet. Each tweet has a *From* feature (i.e., the person who tweeted it), a possible *Location* (i.e., a string provided as meta-data), and a time stamp when it was posted. A tweet can also contain one or more of the following:

- *Hashtag*: a topical keyword specified using the # sign.
- *Mention*: a Twitter username reference using the @ sign.
- *Term*: any non-hashtag and non-mention unigrams.

We provide more detailed statistics about each feature in Table 1. For example, there are over 11 million unique hashtags, the most frequent unique hashtag occurred in over 1.6 million tweets, a hashtag has been used on average by 10.08 unique users, and authors (*From* users) have used a median value of 2 tweets.

Fig. 1 shows per capita tweet frequency across different international and U.S. locations for different topics. While English speaking countries dominate English tweets, we see that the Middle East and Malaysia additionally stand out for the topic of Human Caused Disaster (MH370 incident), Iran, U.S., and Europe for nuclear negotiations the "Iran deal", and soccer for some (English-speaking) countries where it is popular. For U.S. states, we see that Colorado stands out for health epidemics (both whooping cough and pneumonic plague), Missouri stands out for social issues (#blacklivesmatter in St. Louis), and Texas stands out for space due to NASA's presence there.

4 Empirical Evaluation

With the formal definition of learning topical classifiers provided in Sec. 2 and the overview of our data in Sec. 3, we proceed to outline our experimental methodology on our Twitter corpus. We manually curated a broad thematic range of 10 topics shown in the top row of Table 2 by annotating

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

Table 2: Test/Train Hashtag samples and statistics.

	Threshold	**#Unique Values**
From	159	361,789
Hashtag	159	184,702
Mention	159	244,478
Location	50	57,767
Term	50	317,846
Features (CF)	-	1,166,582

Table 3: Cutoff threshold and corresponding number of unique values of candidate features *CF* for learning.

hashtag sets H^t for each topic $t \in T$. We used 4 independent annotators to query the Twitter search API to identify candidate hashtags for each topic, requiring an inner-annotator agreement of 3 annotators to permit a hashtag to be assigned to a topic set. Per topic, hashtags were split into train and test sets according to their first usage time stamp roughly according to a 3/5 to 2/5 proportion (the test interval spanned between 9-14 months). The train set was further temporally subdivided into train and validation hashtag sets according to a 5/6 to 1/6 proportion. We show a variety of statistics and five sample hashtags per topic in Table 2. Here we can see that different topics had varying prevalence in the data with *Soccer* being the most tweeted topic and *IranDeal* being the least tweeted according to our curated hashtags.

As noted in Sec. 3, positively occurring features D_i^+ in our d_i may include *From*, *Mention*, *Location*, *Term*, and *Hashtag* features. Because we have a total of $538,365,507$ unique features in our Twitter corpus, it is critical to pare this down to a size amenable for efficient learning and robust to overfitting. To this end, we thresholded all features according to the frequencies listed in Table 3. The rationale in our thresholding was initially that all features should have the same frequency cutoff in order to achieve roughly 1 million features. However, in initial experimentation, we found that a high threshold pruned a large number of informative terms and locations. To this end, we lowered the threshold for terms and locations noting that even at these adjusted thresholds, we still have more authors than terms. We also removed common English stopwords which further reduced the unique term count. Overall, we end up with $1,166,582$ candidate features (*CF*) for learning topical classifiers.

Supervised Learning Algorithms

With our labeled training and validation datasets defined in Sec. 2 and our candidate feature set *CF* defined previously, we proceed to apply different probabilistic classification and ranking algorithms to generate a score function f^t for learning topical classifiers as defined in Sec. 2. In this paper, we experiment with the following four state-of-the-art supervised classification and ranking methods:

1. **Logistic Regression** using LibLinear (Fan et al. 2008)
2. **Bernoulli Naïve Bayes** (McCallum and Nigam 1998)
3. **Rocchio** (Manning, Raghavan, and Schütze 2008) (a centroid-based classifier)
4. **RankSVM** (Lee and Lin 2014)

As outlined in Sec 2, tuning of hyperparameters on a validation dataset is critical. In our experiments, we tune the following hyperparameters:

- *Logistic Regression*: L_2 regularization constant C is tuned for $C \in \{1E-12, 1E-11, ..., 1E+11, 1E+12\}$.
- *Naïve Bayes*: Dirichlet prior α is tuned for $\alpha \in \{1E-20, 1E-15, 1E-8, 1E-3, 1E-1, 1\}$.
- *All Classfiers*: The number of top features M selected based on their Mutual Information is tuned for $M \in \{1E2, 1E3, 1E4, 1E5, 1166582 \text{ (all features) }\}$.

We remark that many algorithms such as Naive Bayes and Rocchio performed better with feature selection and hence we used feature selection for all algorithms (where it is possible to select all features). Hyperparameter tuning is done via exhaustive grid search and using the Average Precision (AP) (Manning, Raghavan, and Schütze 2008) ranking metric to select the best scoring function f^t on the validation data. Once found, f^t can be applied to any tweet d_i to provide a score $f^t(d_i)$ used to *rank* tweets in the test data.

Performance Analysis

While our training data is provided as supervised class labels, we remark that topical classifiers are targeted towards individual users who will naturally be inclined to *examine only the highest ranked tweets*. Hence we believe ranking metrics represent the best performance measures for the intended use case of this work. While RankSVM naturally produces a ranking, all classifiers are score-based, which also allows them to provide a natural ranking of the test data that we evaluate via the following ranking metrics:

- **AP:** Average precision over the ranked list; the mean over all topics provides mean AP (mAP).
- **P@k:** Precision at k for $k \in \{10, 100, 1000\}$.

While P@10 may be a more standard retrieval metric for tasks such as ad-hoc web search, we remark that the short

		Tennis	Space	Soccer	IranDeal	HumanDisaster	CelebrityDeath	SocialIssues	NaturalDisaster	Epidemics	LGBT	Mean
LR	**AP**	**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	**AP**	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	**AP**	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	**AP**	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 4: Performance of topical classifier learning algorithms across metrics and topics with the mean performance over all topics shown in the right column. The best performance per metric is shown in bold.

Tennis	**Space**
✓rt @espntennis: shock city. darcis drops rafa in straight sets. first time nadal loses in first rd of a. major...	✗rt @jaredleto: rt @30secondstomars: icymi: mars performing a cover of @rihanna's #stay on australia's @trip...
✓@ESPNTennis: Shock city. Darcis drops Rafa in straight sets. First time Nadal loses in first rd of a...	✗voting mars @30secondstomars @jaredleto @shannonleto @tomofromearth xobest group http://t.co/dls...
✓@ESPNTennis: Djokovic ousts the last American man standing @Wimbledon, beating Reynolds 7-6...	✗rt @jaredleto_com: show everyone how much you are proud of @30secondstomars !#mtvhottest 30 seconds to...
✓Nadal's a legend. After 3 years; Definitely He's gonna be the best of all the time. Unbelievable perf...	✗rt @30secondstomars: missed the big news? mars touring with @linkinpark + special guests @afi this summer...
✓@calvy70 @ESPNTennis @Wimbledon I see, thanks for the info and enjoy #Wimbledon2014	✗rt @30secondstomars: to the right,to the left,we will fightto the death.go #intothewildonvyrt with mars, starting...
Soccer	**IranDeal**
✗rt @tomm_dogg: #thingstodobeforeearthends spend all my money.	✓rt @iran_policy: @vidalquadras:@isjcommittee has investigated 10 major subjects of irans controversial #nuc...
★@mancityonlineco nice performance	✓rt @iran_policy: @vidalquadras:@isjcommittee has investigated 10 major subjects of irans controversial #nuc...
★rt @indykaila: podolski: "let's see what happens in the winter. the fact is that i'm not happy with it, th...	✗rt @negarmortazavi: thank you @hassanrouhani for retweeting. let's hope for a day when no iranian fears retur...
★rt @indykaila: wenger: "i don't believe match-fixing is a problem in england." #afc	✗rt @iran_policy: iran: details of savage attack on political prisoners in evin prison http://t.co/xdzuakqdiv #iran...
✗@indykaila you never got back to me about tennis this week	✓rt @iran_policy: chairman ros-lehtinen speaking on us commitment 2 protect camp liberty residents. #iranhr...
HumanDisaster	**CelebrityDeath**
✓rt @baselsyrian: there'Ve been peaceful people in #homs not terrorists! #assad,enemy of #humanity...	★rt @sawubona_chris: today is my birthday & also the day my hero @nelsonmandela has died. lets never...
✓what a helpless father, he can do nothing under #assad's siege!#speakup4syrianchildren http://t.co/vg...	★rt @nelsonmandela: death is something inevitable.when a man has done what he considers to be his duty to...
★exclusive: us formally requested #un investigation; russia pressured #assad to no avail;chain of evidence...	★rt @nelsonmandela: la muerte es algo inevitable.cuando un hombre ha hecho lo que considera que es su...
★#save_aleppo from #assadwarcrimes#save_aleppo from #civilians -targeted shelling of #assad regime...	✗#jacques #kallis: a phenomenal cricketing giant of all time - #cricket #history #southafrica http://t.co/ms5p...
✓rt @canine_rights: why does the #un allow this to continue? rt@tintin1957 help raise awareness of the...	✗@sudesh1304 south africa has the most beautiful babies....so diverse,so unique...so god!! lol #durban #southa...
SocialIssues	**NaturalDisaster**
★the us doesn't actually borrow is the thing. i believe in a creationist theory of the us dollar @usanationdebt...	✗us execution in #oklahoma : not cruel and unusual? maybe just barbaric, inhumane and reminiscent of the...
★rt @2anow: according to @njsenatepres women's rights do not include this poor nj mother's right to defend...	✗#haiti #politics - the haiti-dominican crisis - i agree with how martelly is handling the situation: i totally... http...
★rt @2anow: confiscation ? how many carry permits are in the senate and assembly? give us ours or turn ...	★rt @soilhaiti: a new reforestation effort in #haiti. local compost, anyone? http://t.co/xpad0rqbjk @richardbran...
★rt @2anow: vote with your wallet against #guncontrolforest city enterprises does not support the #2a http...	✗mes cousins jamais ns hantent les nuits de duvalier #haiti #duvalier
★@2anow @momsdemand @jstines3 they dont have a plan for that,which is why they should never be allow...	✓tony burgener of @swisssolidarity says you can't compare the disaster response in #haiti with the response to...
Epidemics	**LGBT**
✓rt @who: fourteen of the susp. & conf. ebola cases in #conakry, #guinea, are health care workers, of...	★rt @jackmcoldcuts: @lunaticrex @fingersmalloy @toddkincannon @theanonliberal anthony kennedy just wro...
✗@who who can afford also been cover in government health insurance [with universal health coverage]	✗@toddkincannon your personal account, your interest. separate from your business.
✓#ebolaoutbreak this health crisis..unparalleled in modern times, @who dir. aylward - requires $1 billion ...	✗why would you report someone as spam if he is not spam? @illygirlbrea @toddkincannon
✗rt @medsin: @who are conducting a survey on the social determinants of health in medical teaching. fill...	✗rt @t3h_arch3r: @toddkincannon thanks for your tl having the female realbrother. between them is 600 lbs....
✗augmentation vertigineuse de 57,4% en 1 an des actes islamophobes en france, dit le collectif contre l'is...	✗@toddkincannon who us dick trickle.

Table 5: Top tweets for each topic from *Logistic Regression* method results, marked with ✗as irrelevant, ✓as relevant and labeled as topical, and ★as relevant but labeled as non-topical (a false negative).

length of tweets relative to web documents makes it more plausible to look at a much larger number of tweets, hence the reason for also evaluating P@100 and P@1000.

Table 4 evaluates these metrics for each topic. *Logistic Regression* is the best performing method on average except for $P@10$. We conjecture the reason is that *Naïve Bayes* tends to select fewer features for training, which allows it to achieve higher precision over the top-10 at the expense of lower $P@100$ and $P@1000$. These results suggest that in general both *Logistic Regression* and *Naïve Bayes* make for effective topical learners with *Naïve Bayes* useful for its efficiency compared to its overall performance. *Notably, trained classifiers outperform RankSVM on the ranking task thus justifying the use of trained topic classifiers for ranking.*

To provide more insight into the general performance of our learning topical classifier framework, we provide the top five tweets for each topic according to *Logistic Regression* in Table 5. We've annotated tweets with symbols as follows:

- ✓: the tweet was labeled topical by our test hashtag set.
- ★: the tweet was determined to be topical through manual evaluation even though it did not contain a hashtag in our curated hashtag set (*this corresponds to a false negative due to non-exhaustive labeling of the data*).

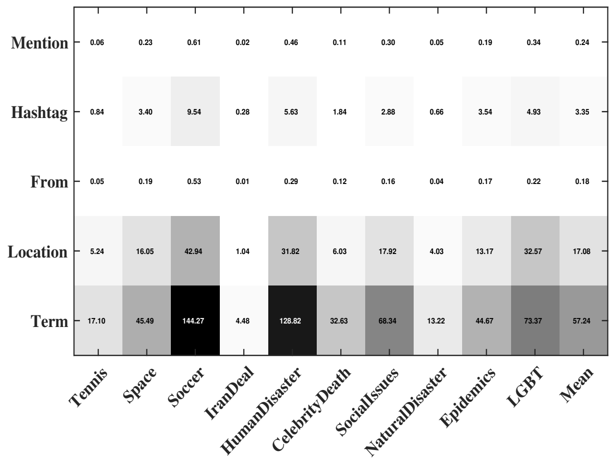


Figure 2: Matrix of mean Mutual Information values for different feature types vs. topics. The last column as average of mean values across all topics. All values should be multiplied by $1E+10$.)

- ✗: the tweet was not topical.

In general, we remark that our topical classifier based on logistic regression performs even better than the quantitative results in Table 4 would indicate: many of the highly ranked tweets are false negatives — *they are actually relevant*. Furthermore, even though we use hashtags to label our training, validation, and testing data, our topical classifier has highly (and correctly) ranked topical tweets that *do not contain hashtags*, indicating strong generalization properties from a relatively small set of curated topical hashtags.

5 Feature Analysis

In this section, we analyze the informativeness of our defined features in Sec 3 and the effect of their attributes on learning targeted topical classifiers. To this end, our goal in this section is to answer the following questions:

- What are the best features for learning classifiers and do they differ by topic?
- For each feature type, do any attributes correlate with importance?

To answer these questions, we use Mutual Information (MI) (Manning, Raghavan, and Schütze 2008) as our primary metric for feature evaluation. Mutual Information is a general method for measuring the amount of information one random variable contains about another random variable and is used to select predictive features in machine learning. To calculate the amount of information that each feature $j \in \{From \cup Hashtag \cup Mention \cup Term \cup Location\}$ provides w.r.t. each topic label $t \in \{NaturalDisaster, Epidemics, ...\}$, Mutual Information is formally defined as

$$I(j,t) = \sum_{t \in \{0,1\}} \sum_{j \in \{0,1\}} p(j,t) \log\left(\frac{p(j,t)}{p(j)p(t)}\right),$$

with marginal probabilities of topic $p(t)$ and feature $p(j)$ occurrence and joint probability $p(t,j)$ computed over the sample space of all tweets, where higher values for this metric indicate more informative features j for the topic t.

In order to answer the first question regarding the best features for learning topical classifiers, we provide the mean Mutual Information values for each feature across different topics in Fig. 2. The last column in Fig. 2 shows the average of the mean Mutual Information for each feature type. From analysis of Table 2, we can make a set of observations:

- The *Term* and *Location* features are the most informative features on average.
- The Location feature provides the highest MI regarding the topics of *HumanDisaster*, *LBGT*, and *Soccer* indicating a lot of content in these topics is heavily localized.
- Looking at the overall average values, the order of informativeness of feature types appears to be the following: *Term*, *Location*, *Hashtag*, *Mention*, *From*.

To further analyze the relationship between the informativeness of feature types and topics, we refer to the box plots of Fig. 3. Here we see the quartiles and outliers of the distribution rather than just the average of the MI values in order to ensure the mean MI values were not misleading our interpretations. Overall, the story is the same: term and location features dominate in terms of MI followed by the other less informative features. Furthermore, two observations are apparent: (1) terms have more outliers indicating that *the most useful individual features may be terms*, and (2) the topic has little impact on which feature is most important indicating *stability of feature type informativeness over topics*.

As anecdotal evidence to inspect which features are most informative, we refer to Table 6, which displays the top five feature instances for each feature type and topic. Among many remarkable insights in this table, one key aspect we note is that the *terms appear to be the most generic* (and hence most generalizable) features, providing strong intuition as to why these features figure so prominently in terms of their informativeness. The top *locations are also highly relevant to most topics* indicating the overall importance of these tweet features for identifying topical tweets.

In order to answer the second question on whether any attributes correlate with importance for each feature, we provide two types of analysis. The first analysis shown in Fig. 4 analyzes the distributions of Mutual Information values for features when binned by the magnitude of various attributes of those features, outlined as follows:

- **From** vs.
  - *Favorite count:* # of tweets user has favorited.
  - *Followers count:* # of users who follow user.
  - *Friends count:* # of users followed by user.
  - *Hashtag count:* # of hashtags used by user.
  - *Tweet count:* # of tweets from user.
- **Hashtag** vs.
  - *Tweet count:* # of tweets using hashtag.
  - *User count:* # of users using hashtag.
- **Location** vs. *User count:* # of users using location.
- **Mention** vs. *Tweet count:* # of tweets using mention.

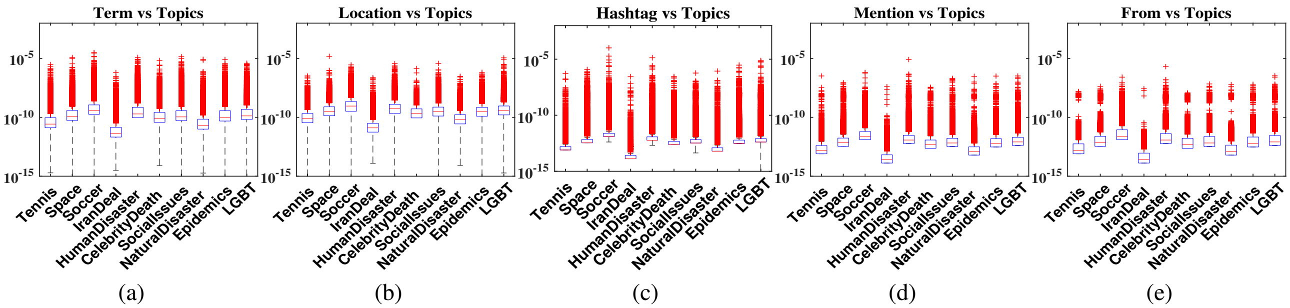


Figure 3: Box plots of Mutual Information values (y-axis) per feature type across topics (x-axis labels).

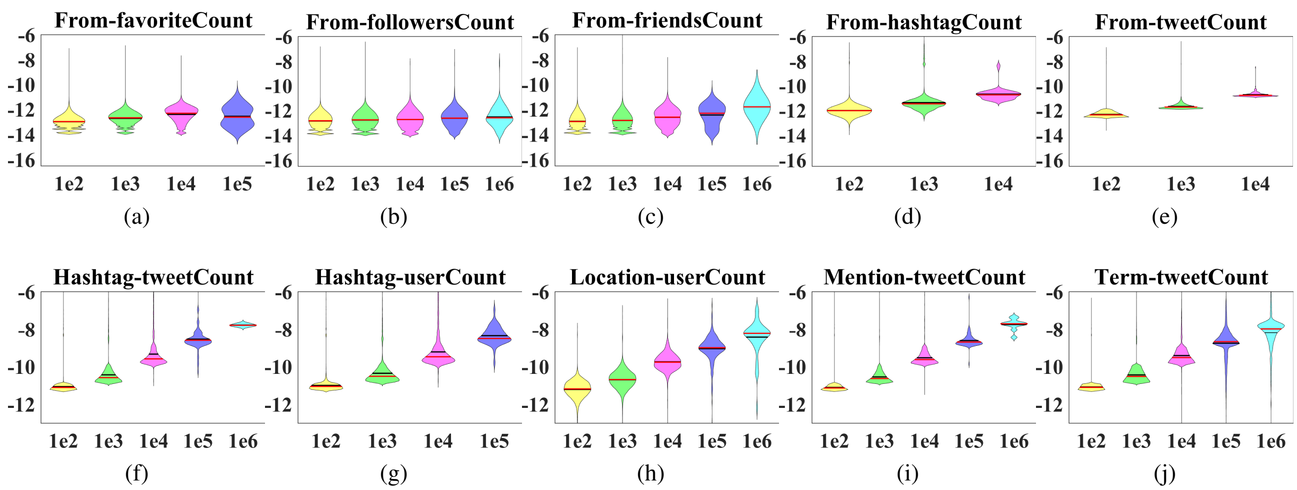


Figure 4: Violin plots for the distribution of Mutual Information values (y-axis) of different features as a function of their attribute values (binned on x-axis). Plots (a-e) respectively show attributes {favoriteCount, followerCount, friendCount, hashtagCount, tweetCount} for *From* feature. Plots (f-j) respectively show attributes tweetCount and userCount for *Hashtag*, userCount for *Location* feature, tweetCount for *Mention* and *Term* features.

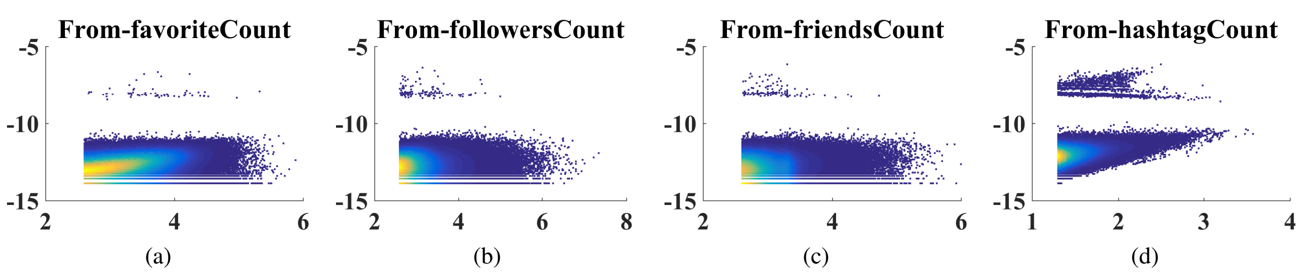


Figure 5: Density plots for the frequency values of feature attributes (y-axis) vs. Mutual Information (x-axis). Plots (a-d) respectively show attributes {favoriteCount, followerCount, friendCount, hashtagCount} for the *From* feature.

Topics/Top10	**NaturalDisaster**	**Epidemics**	**IranDeal**	**SocialIssues**	**LBGT**	**HumanDisaster**	**CelebrityDeath**	**Space**	**Tennis**	**Soccer**
From	earthquake_wo	changedecopine	mazandara	nsingerdebtpaid	eph4_15	ydumozyf	nmandelaquotes	daily_astrodata	tracktennisnews	losangelessrh
From	earthalerts	drdaveanddee	hhadi119	debtadvisoruk	mgdauber	syriatweeten	boiknox	freesolarleads	tennis_result	shoetale
From	seelites	joinmentornetwk	140iran	debt_protect	stevendickinson	tintin1957	jacanews	houston__jobs	i_roger_federer	sport__agent
From	globalfloodnews	followebola	setarehgan	negativeequityf	lileensvf1	sirajsol	ewnreporter	star_wars_gifts	tennislessonnow	books_you_want
From	gcmcdrought	localnursejobs	akhgarshabaneh	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	ripcorymonteith	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	foxtramedia	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	espntennis	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 6: The top 5 features for each feature type and topic based on Mutual Information.

- **Term** vs. *Tweet count:* # of tweets using term.

As we can see in the Violin plots of Fig. 4, the general pattern is that the greater the number of tweets, users, or hashtag count a feature has, the more informative the feature is in general. This pattern also exists to some extent on the attributes of the *From* feature, although the pattern is less visible in general and not clear (or very weak) for the follower or friend count. In general, the informativeness of a user appears to have little correlation with their follower or friend count.

Fig. 5 provides a further analysis by showing density plots of favorite count, follower count, friends count, and hashtag count attributes of the *From* feature. Here we see an interesting phenomenon that was not clear in the Violin plots: there is a very clear bimodality of the density. On further investigation it turns out that the top mode feature occurs in at least one topical tweet whereas the bottom mode occurs in no topical tweets. While the bottom mode features may serve as good indicators of non-topicality, the top mode are inherently more indicative of topicality, which justifies feature selection by mutual information.

6 Related Work

Aside from highly related work on supervised topic classifiers for Twitter (Lin, Snow, and Morgan 2011; Yang et al. 2014; Magdy and Elsayed 2014) that motivated this study as discussed in the introduction as well as unsupervised topic discovery, e.g., (Vicient and Moreno 2015), that departs drastically from the supervised learning approach evaluated here, the concept of *topical tweet detectors* is prevalent in the literature. In this section we survey four highly related areas of active research: (1) trending topic detection, (2) tweet recommendation, (3) friend sensors, (4) and specific event detection such as earthquake or influenza sensors. Despite the partial overlap and superficial similarities between this paper and related work, we argue no prior work has performed a longitudinal analysis of supervised Twitter topical classifiers as done in this paper.

Trending Topic Detection represents one of the most popular types of topical tweet detector and can be subdivided into many categories. The first general category of methods define trends as topically coherent content and focus on clustering across lexical, linguistic, temporal and/or spatial dimensions (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). The second general category of methods define trends as temporally coherent patterns of terms or keywords and focus largely on detecting bursts of terms or phrases (Mathioudakis and Koudas 2010; Cui et al. 2012; Zhao et al. 2011; Nichols, Mahmud, and Drews 2012; Aiello et al. 2013). The third category of methods extends the previous categories by additionally exploiting network structure properties (Budak, Agrawal, and El Abbadi 2011). Despite this important and very active area of work that can be considered a type of topical tweet detector, trending topic detection is intrinsically unsupervised and not intended to detect targeted topics. In contrast, the work in this paper is based on supervised learning of a specific topical tweet detector trained on the topical set of hashtags provided by the user.

Tweet Recommendation represents an alternate use of tweet classification and falls into two broad categories: personalized or content-oriented recommendation and retweet recommendation. For the first category, the objective of personalized recommendation is to observe a user's interests and behavior from their user profile, sharing or retweet preferences, and social relations to generate tweets the user may like (Yan, Lapata, and Li 2012; Chen et al. 2012). The objective of content-oriented recommendation is to use source content (e.g., a news article) to identify and recommend relevant tweets (e.g., to allow someone to track discussion of a news article) (Krestel et al. 2015). For the second category, there has been a variety of work on retweet prediction that leverages retweet history in combination with tweet-based, author-based, and social network features to predict whether a user will retweet a given tweet (Can, Oktay, and Manmatha 2013; Xu and Yang 2012; Petrovic, Osborne, and Lavrenko 2011). Despite the fact that all of these methods recommend tweets, they — and recommendation methods in general — are not focused on a specific topic but rather on predicting tweets that correlate with the preferences of a specific user or that are directly related to specific content. Rather the focus with learning topical classifiers is to learn to predict for a broad theme (independent of a user's profile) in a way that generalizes beyond existing labeled topical content to novel future topical content.

Specific Event Detection builds topical tweet detectors as we do in this work but focuses on highly specific events such as disasters or epidemics. For the use case of earthquake detection, an SVM can be trained to detect earthquake events and coupled with a Kalman filter for localization (Sakaki, Okazaki, and Matsuo 2013). In another example use case to detect health epidemics such as influenza, researchers build purpose-specific classifiers targeted to this specific epidemic (Culotta 2010; Aramaki, Maskawa, and Morita 2011), e.g, by exploiting knowledge of users' proximity and friendship along with the contageous nature of influenza (Sadilek, Kautz, and Silenzio 2012). While these targeted event detectors have the potential of providing high precision event detection, they are highly specific to the target event and do not easily generalize to learn arbitrary topic-based classifiers for Twitter as analyzed in this work.

Friend Sensors are a fourth and final class of social sensors intended for early event detection (Kryvasheyeu et al. 2014; García-Herranz et al. 2012) by leveraging the concept of the "friendship paradox"(Feld 1991), to build user-centric social sensors. We note that our topical classifiers represent a *superset* of friend sensors since our work includes author features that the predictor may learn to use if this proves effective for prediction. However, as shown in our feature analysis, user-based features are among the least informative feature types for our topical classifier suggesting that general topical classifiers can benefit from a wide variety of features well beyond those of author features alone.

7 Conclusions and Future Work

This work provides a long-term study of topic classifiers on Twitter that further justifies classification-based topical filtering approaches while providing detailed insight into the feature properties most critical for topic classifier performance. Our results suggest that these learned topical classifiers generalize well to unseen future topical content over a long time horizon (i.e., one year) and provide a novel paradigm for the extraction of high-value content from social media. Furthermore, an extensive analysis of features and feature attributes across different topics has revealed key insights including the following two: (i) largely independent of topic, generic terms are the most informative features followed by topic-specific locations, and (ii) the number of unique hashtags and tweets by a user correlates more with their informativeness than their follower or friend count.

Among many interesting directions, future work might evaluate a range of topical classifier extensions: (1) optimizing rankings not only for topicality but also to minimize the lag-time of novel content identification, (2) optimizing queries for boolean retrieval oriented APIs such as Twitter, (3) identification of long-term temporally stable predictive features, and (4) utilizing more social network structure as graph-based features. Altogether, we believe these insights will facilitate the continued development of effective topical classifiers for Twitter that learn to identify broad themes of topical information with minimal user interaction and enhance the overall social media user experience.

References

[Aiello et al. 2013] Aiello, L. M.; Petkos, G.; Martín, C. J.; Corney, D.; Papadopoulos, S.; Skraba, R.; Göker, A.; Kompatsiaris, I.; and Jaimes, A. 2013. Sensing trending topics in twitter. *IEEE Transactions on Multimedia* 15(6):1268–1282.

[Aramaki, Maskawa, and Morita 2011] Aramaki, E.; Maskawa, S.; and Morita, M. 2011. Twitter catches the flu: Detecting influenza epidemics using Twitter. In *Proceedings of the Conference on Empirical Methods in Natural Language Processing*, EMNLP '11.

[Becker, Naaman, and Gravano 2011] Becker, H.; Naaman, M.; and Gravano, L. 2011. Beyond trending topics: Real-world event identification on twitter. In *Proceedings of the Fifth International Conference on Weblogs and Social Media, Barcelona, Catalonia, Spain, July 17-21, 2011*.

[Budak, Agrawal, and El Abbadi 2011] Budak, C.; Agrawal, D.; and El Abbadi, A. 2011. Structural trend analysis for online social networks. *PVLDB* 4(10):646–656.

[Can, Oktay, and Manmatha 2013] Can, E. F.; Oktay, H.; and Manmatha, R. 2013. Predicting retweet count using visual cues. In *22nd ACM International Conference on Information and Knowledge Management, CIKM'13, San Francisco, CA, USA, October 27 - November 1, 2013*, 1481–1484.

[Chen et al. 2012] Chen, K.; Chen, T.; Zheng, G.; Jin, O.; Yao, E.; and Yu, Y. 2012. Collaborative personalized tweet recommendation. In *Proceedings of the 35th International ACM SIGIR Conference on Research and Development in Information Retrieval*, SIGIR '12, 661–670. ACM.

[Cui et al. 2012] Cui, A.; Zhang, M.; Liu, Y.; Ma, S.; and Zhang, K. 2012. Discover breaking events with popular hashtags in Twitter. In *21st ACM International Conference on Information and Knowledge Management, CIKM'12, Maui, HI, USA, 2012*, 1794–1798.

[Culotta 2010] Culotta, A. 2010. Towards detecting influenza epidemics by analyzing Twitter messages. In *Proceedings of the First Workshop on Social Media Analytics*, SOMA '10.

[Fan et al. 2008] Fan, R.; Chang, K.; Hsieh, C.; Wang, X.; and Lin, C. 2008. LIBLINEAR: A library for large linear classification. *Journal of Machine Learning Research* 9:1871–1874.

[Feld 1991] Feld, S. L. 1991. Why your friends have more friends than you do. *American Journal of Sociology* 1464–1477.

[García-Herranz et al. 2012] García-Herranz, M.; Egido, E. M.; Cebrián, M.; Christakis, N. A.; and Fowler, J. H. 2012. Using friends as sensors to detect global-scale contagious outbreaks. *PloS one* abs/1211.6512.

[Ishikawa et al. 2012] Ishikawa, S.; Arakawa, Y.; Tagashira, S.; and Fukuda, A. 2012. Hot topic detection in local areas using Twitter and wikipedia. In *ARCS Workshops (ARCS), 2012*, 1–5.

[Krestel et al. 2015] Krestel, R.; Werkmeister, T.; Wiradarma, T. P.; and Kasneci, G. 2015. Tweet-recommender: Finding relevant tweets for news articles. In *Proceedings of the 24th International Conference on World Wide Web*, WWW '15 Companion, 53–54. Republic and Canton of Geneva, Switzerland: International World Wide Web Conferences Steering Committee.

[Kryvasheyeu et al. 2014] Kryvasheyeu, Y.; Chen, H.; Moro, E.; Hentenryck, P. V.; and Cebrián, M. 2014. Performance of social network sensors during hurricane sandy. *PLoS one* abs/1402.2482.

[Lee and Lin 2014] Lee, C.-P., and Lin, C.-J. 2014. Large-scale linear RankSVM. *Neural Computing* 26(4):781–817.

[Lin, Snow, and Morgan 2011] Lin, J.; Snow, R.; and Morgan, W. 2011. Smoothing techniques for adaptive online language models: topic tracking in tweet streams. In *Proceedings of the 17th ACM SIGKDD international conference on Knowledge discovery and data mining*, 422–429. ACM.

[Magdy and Elsayed 2014] Magdy, W., and Elsayed, T. 2014. Adaptive method for following dynamic topics on twitter. In *ICWSM*.

[Manning, Raghavan, and Schütze 2008] Manning, C. D.; Raghavan, P.; and Schütze, H. 2008. *Introduction to Information Retrieval*. New York, NY, USA: Cambridge University Press.

[Mathioudakis and Koudas 2010] Mathioudakis, M., and Koudas, N. 2010. Twittermonitor: trend detection over the Twitter stream. In *Proceedings of the ACM SIGMOD International Conference on Management of Data, SIGMOD 2010, Indianapolis, Indiana, USA*, 1155–1158.

[McCallum and Nigam 1998] McCallum, A., and Nigam, K. 1998. A comparison of event models for naive bayes text classification. In *In AAAI-98 Workshop On Learning For Text Categorization*, 41–48. AAAI Press.

[Nichols, Mahmud, and Drews 2012] Nichols, J.; Mahmud, J.; and Drews, C. 2012. Summarizing sporting events using Twitter. In *17th International Conference on Intelligent User Interfaces, IUI '12, Lisbon, Portugal, February 14-17, 2012*, 189–198.

[O'Connor, Krieger, and Ahn 2010] O'Connor, B.; Krieger, M.; and Ahn, D. 2010. Tweetmotif: Exploratory search and topic summarization for Twitter. In *Proceedings of the Fourth International Conference on Weblogs and Social Media, ICWSM 2010, Washington, DC, USA, May 23-26, 2010*.

[Petrović, Osborne, and Lavrenko 2010] Petrović, S.; Osborne, M.; and Lavrenko, V. 2010. Streaming first story detection with application to twitter. In *Human Language Technologies: The 2010 Annual Conference of the North American Chapter of the Association for Computational Linguistics*, HLT '10, 181–189. Stroudsburg, PA, USA: Association for Computational Linguistics.

[Petrovic, Osborne, and Lavrenko 2011] Petrovic, S.; Osborne, M.; and Lavrenko, V. 2011. Rt to win! predicting message propagation in Twitter. In *ICWSM*.

[Phuvipadawat and Murata 2010] Phuvipadawat, S., and Murata, T. 2010. Breaking news detection and tracking in Twitter. In *Proceedings of the 2010 IEEE/WIC/ACM International Conference on Web Intelligence and International Conference on Intelligent Agent Technology - Workshops, Toronto, Canada, August 31 - September 3, 2010*, 120–123.

[Sadilek, Kautz, and Silenzio 2012] Sadilek, A.; Kautz, H. A.; and Silenzio, V. 2012. Modeling spread of disease from social interactions. In *Proceedings of the Sixth International Conference on Weblogs and Social Media, Dublin, Ireland, June 4-7, 2012*.

[Sakaki, Okazaki, and Matsuo 2013] Sakaki, T.; Okazaki, M.; and Matsuo, Y. 2013. Tweet analysis for real-time event detection and earthquake reporting system development. *Knowledge and Data Engineering, IEEE Transactions on* 25(4):919–931.

[Vicient and Moreno 2015] Vicient, C., and Moreno, A. 2015. Unsupervised topic discovery in micro-blogging networks. *Expert Syst. Appl.* 42(17):6472–6485.

[Weng and Lee 2011] Weng, J., and Lee, B. 2011. Event detection in Twitter. In *Proceedings of the Fifth International Conference on Weblogs and Social Media, Barcelona, Catalonia, Spain, July 17-21, 2011*.

[Xu and Yang 2012] Xu, Z., and Yang, Q. 2012. Analyzing user retweet behavior on Twitter. In *International Conference on Advances in Social Networks Analysis and Mining, ASONAM 2012, Istanbul, Turkey, 26-29 August 2012*, 46–50.

[Yan, Lapata, and Li 2012] Yan, R.; Lapata, M.; and Li, X. 2012. Tweet recommendation with graph co-ranking. In *Proceedings of the 50th Annual Meeting of the Association for Computational Linguistics: Long Papers - Volume 1*, ACL '12, 516–525. Stroudsburg, PA, USA: Association for Computational Linguistics.

[Yang et al. 2014] Yang, S.-H.; Kolcz, A.; Schlaikjer, A.; and Gupta, P. 2014. Large-scale high-precision topic modeling on twitter. In *Proceedings of the 20th ACM SIGKDD international conference on Knowledge discovery and data mining*, 1907–1916. ACM.

[Zhao et al. 2011] Zhao, S.; Zhong, L.; Wickramasuriya, J.; and Vasudevan, V. 2011. Human as real-time sensors of social and physical events: A case study of Twitter and sports games. *Technical Report TR0620-2011, Rice University and Motorola Mobility* abs/1106.4300.