Learning Topical Social Sensors

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Abstract

Social media sources such as Twitter represent a massively distributed social sensor over a kaleidoscope of topics ranging from social and political events to entertainment and sports news. However, due to the overwhelming volume of content, it can be difficult to identify novel and significant content within a broad theme in a timely fashion. To this end, this paper proposes a scalable and practical method to automatically construct social sensors for generic topics. Specifically, given minimal supervised training content from a user, we learn to identify topical tweets from millions of features capturing content, user and social interactions on Twitter. On a corpus of over 800 million English Tweets collected from the Twitter streaming API during 2013 and 2014 and learning for 10 diverse themes ranging from social issues to celebrity deaths to the "Iran nuclear deal", we empirically show that our learned social sensor automatically generalizes to unseen future content with high ranking and precision scores. Furthermore, we provide an extensive analysis of features and feature types across different topics that reveals, for example, that (1) largely independent of topic, simple terms are the most informative feature followed by location features and that (2) 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 novel, effective, and efficient way to learn topical social sensors requiring minimal user curation effort and offering strong generalization performance for identifying future topical content.

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 spam and otherwise low-value content for most users' information needs where filtering out irrelevant content is extremely time-consuming. Hence, while it is widely acknowledged that social media sources can be used as topical content sensors (indeed, an entire European Union project was focused on related "Social Sensor" research[1].), automatically learning high-precision sensors (i.e., ranking and retrieval methods) for arbitrary topics that generalize to future unseen content remains an open question in the literature and comprises the key problem we seek to address in this paper.

In this work, we contribute a novel supervised method for training social sensors with minimal user curation by using a small seed set of hashtags as topical proxies for automatic supervised data labeling. Then we proceed to train supervised classification and ranking methods to learn topical content from a large feature space of source users and their locations, terms, hashtags, and mentions. On a corpus of over 800 million English Tweets collected from the Twitter streaming API during 2013 and 2014 and covering 10 diverse topics ranging from social issues to celebrity deaths to the "Iran nuclear deal", 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 mean average precision (MAP) and Precision@n for a range of n. 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 fills a major gap in event detection and tracking from social media on identifying emerging topics from long-running themes with minimal user supervision. Our results suggest that these sensors generalize well to unseen future topical content and provide a novel paradigm for the extraction of high-value content from social media.

2 Related Work

The concept of social media as a sensor is prevalent in the literature and in this section we survey four related areas of active research: (1) trending topic detection, (2) tweet recommendation, (3) friend sensors, and (4) and specific event detection such as earthquake or influenza sensors. Despite the partial overlap and superficial similarities between this paper and related social sensor work, we argue that no prior work has learned targeted social sensors for arbitrary topics using supervised learning methods as done in this paper.

Trending Topic Detection represents one of the most popular types of social sensor and can be subdivided into many

[1] http://www.socialsensor.eu/

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 social sensor, 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 social sensor derived from the topical set of hashtags provided by the user.

Tweet Recommendation represents an alternate use of social sensors 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 that the fact 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 social sensors 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 social sensors as we do in this work but focuses on highly specific events such as a 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 event-based or topic-based social sensors as provided 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 social sensors 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 social sensors suggesting that general social sensors benefit from a wide variety of features well beyond those of author features alone.

3 Learning Topical Social Sensors

Our objective in learning social sensors is to train an automatic system for ranking documents by their topical relevance. Formally, given an arbitrary document d and a set of topics $T = \{t_1, \ldots, t_K\}$, we wish to train a scoring function $f : d \rightarrow \mathbb{R}$ over a set of training documents $D = \{d_1, \ldots, d_N\}$ where each $d_i \in D$ has a boolean feature vector $(d_i^1, \ldots, d_i^M) \in \{0,1\}^M$ and boolean label $d_i^t \in \{0,1\}$ indicating whether the document d_i is topical (1) or not (0). We define the set of positively occurring features for a document d_i as $D_i^+ = \{d_i^j | d_i^j = 1\}_{j=1\ldots M}$ and note that D_i^+ may include features for the content of d_i (e.g., terms, hashtags) as well as its meta-data (e.g., author, location).

There are two catches that make our training setting somewhat non-standard and which underlie subtle but critical contributions in this work: (1) Manually labeling documents is time-consuming so we need a way to manually label a large number of tweets with minimal user curation effort; *We achieve this by using hashtags as topical proxies.* (2) We need to train our social sensor on known topical content, but tune it on novel topical validation content that ensures the tuning achieves optimal generalization; *We achieve this by excising training content from our validation data so that our scoring function hyperparameter tuning ensures generalization.* We next explain these key innovations in detail.

A critical bottleneck for learning targeted topical social sensors 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 and 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. Hence as a simple enabling insight that serves as a catalyst for effective topical social sensor learning, 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 will provide the formal procedure for labeling data with H^t and training.

With the data labeling bottleneck resolved, we proceed to train supervised classification and ranking methods to learn topical content from a large feature space (e.g., for Twitter, this feature space includes terms, hashtags, mentions, authors and their locations). The training process includes the following two steps:

1. **Temporally split train and validation using H^t:** As usual 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 identification of previously unseen hashtags as a proxy for topical generalization, we do not simply split our data temporally into train and test sets as usually done. Instead, we split H^t into two disjoint sets H^t_{train} and H^t_{val} according to a time stamp t_{split} and the first usage time stamp $h_{\text{time}*}$ of hashtags $h \in H^t$. 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 document d_i as follows:

$$D^t_{\text{train}} = \{d_i | d_i \in D \wedge d_{i,\text{time}*} < t_{\text{split}}\},$$
$$D^t_{\text{val}} = \{d_i | d_i \in D \wedge d_{i,\text{time}*} \geq t_{\text{split}}\}.$$

   Then for $s \in \{\text{train}, \text{val}\}$, we use the respective hashtag sets H^t_{train} and H^t_{val} for labeling each $d^t_i \in D^t_s$:

$$d^t_i = \begin{cases} 1 : \exists_{h \in H^t_s}\ h \in D^+_i \\ 0 : \text{otherwise} \end{cases}.$$

   The critical insight here is that we not only divide the train and validation temporally, but we 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).

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 on D^t_{train} and select hyperparameters to optimize Mean Average Precision (MAP) on D^t_{val}. Once the optimal f is found for D_{val}, we return it as our final learned topical scoring function for topic t.

Having defined our topical social sensor learning paradigm, it now remains to empirically evaluate this methodology in a social media setting, which we describe next.

#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	Max entity
From	10,196	8.67	2	running_status
Hashtag	1,653,159	13.91	1	#retweet
Mention	6,291	1.26	1	null
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

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

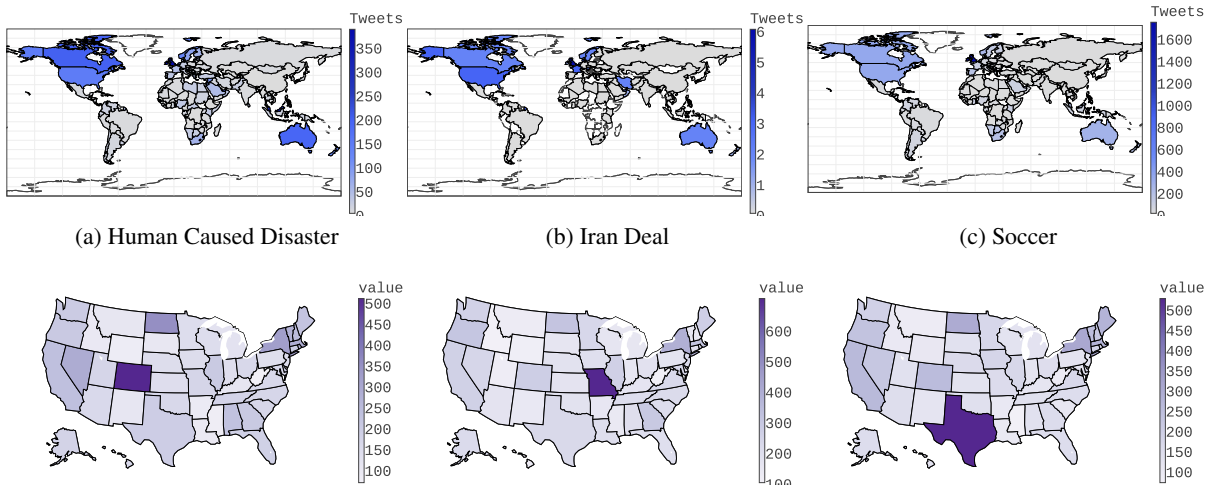
4 Data Description

Now we provide details of the Twitter testbed for topical social sensor learning that we evaluate in this paper. We crawled Twitter data using Twitter Streaming API for two years spanning 2013 and 2014 years. The total number of tweets collected is $829,026,458$. 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 unique hashtags.

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 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.



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

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

Figure 1: Distribution of tweets across International locations (top row) and U.S. locations (bottom row)

5 Empirical Evaluation

With the 5 set of features defined as *From*, *Mention*, *Location*, *Term*, *Hashtag*, we proceed to define the methodology for retrieving ranked list of tweets for a given topic. The list of topics were defined to be a set of 10 various topics covering very specific and very broad topics:

Tennis, *Space*, *Soccer*, *IranDeal*, *HumanDisaster* (HumanCausedDisaster), *CelebrityDeath*, *SocialIssues*, *NaturalDisaster*, *Epidemics*, and *LGBT*.

As defined in Sec 3 Our goal is to retrieve a ranked list of tweets $D \in \Re^N$ by employing machine learning methods on defined features $F \in \Re^M$. We provided unique number of values for each feature in Fig. 1. These values sum up to a total number of $538,365,507$ features and as noted earlier, we are working on $829,026,458$ tweet corpus. This shows the need for techniques to annotate the data and select a subset of features for learning. The tweet labeling process was explained in the Sec 3.

Each *Hashtag* has a birthday which is defined as the first time it has been used in our dataset. After choosing topical hashtag sets H^t, we label each tweet using the Eq. **??**.

In order to conduct our experiments on train, validation and test datasets, tweets are temporally divided over 2 years. Since our tweet labeling is through topical hashtags, this division is done in a way to preserve enough number of hashtags for train, validation, and test timespan. To this purpose, hashtags are divided based on their birthday with 50 percent of hashtags being born at train timespan, 10 percent born at validation timespan, and the last 40 percent born at test timespan. Table. 3 provides samples of hashtags, number of train hashtags, test hashtags, and topical tweets for each topic. As illustrated, some topics such as *HumanDisaster* and *Soccer* are more general 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.

Regarding feature selection, it is clear that it is not possible to learn a model with total number of $538,365,507$ features. In which case, we would have to provide a much larger training samples, and, in addition, our feature vectors would be extremely sparse considering 140 characters limitation of Twitter. Therefore, we performed a primary feature selection based on frequency of each feature. The feature selection process included:

- Cleaning *Term* feature to remove stop-words
- Choosing a cut-off threshold on the frequency of features

This results in a little over 1 million features, considered as defined $F \in \Re^M$ feature vector. The detailed values of cut-off thresholds and number of remaining unique values for each feature is shown in Table. 2. Since *Term* and *Location* features had much lower number of unique values in the corpus, we chose a lower threshold for these features.

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

Table 2: Cut-off threshold and selected number of unique values of features for selection of *SF* learning feature set

Classification Algorithms

Now that we defined the primary steps for preparing the features and dataset, we can use them to build an approach for topical tweet selection. Our method is based on classification/ranking approaches defined in the literature. The learned weights are further used to rank tweets for each topic. Here, we use the following classification approaches:

1. Logistic Regression

	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	#policebrutality	#ebola	#loveislove
	#novakdjokovic	#astronauts	#lovesoccer	#iranfreedom	#childrenofsyria	#ripmandela	#michaelbrown	#michaelbrown	#virus	#gaypride
	#wimbledon	#satellite	#fifa	#irantalk	#iraqwar	#ripjoanrivers	#justice4all	#justice4all	#vaccine	#uniteblue
	#womenstennis	#spacecraft	#realmadrid	#rouhani	#bombthreat	#mandela	#freetheweed	#freetheweed	#chickenpox	#homo
	#tennisnews	#telescope	#beckham	#nuclearpower	#isis	#paulwalker	#newnjgunlaw	#newnjgunlaw	#theplague	#gaymarriage

Table 3: Test/Train Hashtag samples and statistics

2. Naive Bayes
3. Rocchio (centroid)
4. RankSVM

To this purpose, based on the problem setting defined in Sec 3, we have D as our tweet corpus, and the goal is to assign a measure of similarity for the tweet d_i to the given topic $t \in \{T\}$ noted as $Sim(d_i, t)$.

W_i is the sum of weights of features in the x_i

$$W_i = \sum_k w_k \times f_k \tag{1}$$

where w_k is the weight of feature f_k and $f_k \in \{true, false\}$ represents whether each of the features in $SF_m, m = \{1, .., 1166582\}$ is present in tweet X or not. The weights w_k are learned by applying one of the classification algorithms.

In order to learn the models, we take the following steps for each topic:

1. Preprocess: The set of tweets for learning is selected by including all the positive tweets for the given topic, in addition to sub-sampled set of negative tweets
2. Hyper-parameter tuning: The number of features K^* and model's hyper-parameter c^* (if applicable) are tuned on validation set by following steps:
   (a) Feature Selection: A set of top $K \in \{10E1, 10E2, 10E3, 10E4, 1166582\}$ features are selected based on the Mutual Information values of features for the given topic. K is selected during hyper-parameter tuning phase.
   (b) Train, validation, and train set of tweets are further modified based on the division process explained in Sec 5 and using only selected set of top K features.
   (c) The best number of features K^*, and c^* are selected on the validation set, based on MAP scores computed from learned weights
3. Learning: The final values of weight vector W is learned on full set of train and test tweets

The Liblinear (Fan et al. 2008) package is used for implementing *LR* and *RankSVM*. The reason for deciding to tune the models on top N features based on Mutual Information, comes from our primary feature analysis on the dataset which showed the ability of Mutual Information measure to pick more correlated features for each topic. This is discussed in more details in Sec 6. The model hyper-parameters are tuned for *LR* and *NB*. The *Rocchio* method is parameter free and the LibLinear (Fan et al. 2008) implementation of *RankSVM* does not provide manual tuning of the model's hyper-parameter.

Analysis

After experimenting each mentioned model on our dataset, we provide the following metrics:

- MAP: Mean average precision for a set of topics is the mean of the average precision scores for each topic.
- P@K: Precision at K for $K \in \{10, 100, 1000\}$, the number of relevant results on the first K search results page

The model's hyper-parameters are tuned based on MAP scores, having MAP as our most important metrics. Table 4 provides these metrics for each topic. Logistic Regression method is the method that performs best on average. Generally, Naive Bayes performed comparable/better to Logistic Regression having second best average value of MAP. We also provide the top 5 tweets returned by Logistic Regression for each topic as anecdotal results in Table 5. In this table, the signs in the beginning of the tweet represent the following:

- ✗represents the tweets that are method has incorrectly ranked as highly topical
- ✓represents the tweets correctly ranked as highly topical
- ★represents the tweets that don't have any topical hashtags and therefore are not labeled as correctly ranked topical. However, looking at the tweets, we can see that they are in fact related to the topic

The fact that there are cases of tweets not being correctly labeled as topical, provides evidence that our method of labeling tweets has limitations and our MAP and P@K values are actually suffering from this problem. However, this shows the power of Logistic Regression method in generalizing from a small set of hashtags.

6 Feature Analysis

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

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

		Tennis	Space	Soccer	IranDeal	HumanDisaster	CelebrityDeath	SocialIssues	NaturalDisaster	Epidemics	LGBT	Mean
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 4: Different learning methods results on topics with hyper-parameter tuning based on MAP

Tennis	**Space**
✓rt @espntennis: shock city. darcis drops rafa in straight sets. first time nadal loses in first rd of a. major in career. #espnwimbledon #w	✗rt @jaredleto: rt @30secondstomars: icymi: mars performing a cover of @rihanna's #stay on australia's @triplemmelb - video _ http://t.co/uq
✓@ESPNTennis: Shock city. Darcis drops Rafa in straight sets. First time Nadal loses in first rd of a. Major in career.	✗voting mars @30secondstomars @jaredleto @shannonleto @tomofromearth xobest group http://t.co/dlsozvjinf
✓@ESPNTennis: Djokovic ousts the last American man standing @Wimbledon, beating Reynolds 7-6 6-3 6-1 #ESPNWimbledon	✗rt @jaredleto_com: show everyone how much you are proud of @30secondstomars !#mtvhottest 30 seconds to mars http://t.co/byxnri4t67
✓Nadal's a legend. After 3 years; Definitely He's gonna be the best of all the time. Unbelievable performance. @RafaelNadal #USOpenFinal	✗rt @30secondstomars: missed the big news? mars touring with @linkinpark + special guests @afi this summer!_ http://t.co/3e5rm9pwrd
✓@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 weekly, nov 30 _ htt
Soccer	**IranDeal**
✗rt @tomm_dogg: #thingstodobeforeearthends spend all my money.	✓rt @iran_policy: @vidalquadras:@isjcommittee has investigated 10 major subjects of irans controversial #nuclear program #irantalksvienna
★@mancityonlineco nice performance	✓rt @iran_policy: @vidalquadras:@isjcommittee has investigated 10 major subjects of irans controversial #nuclear program #irantalksvienna
★rt @indykaila: podolski: "let's see what happens in the winter. the fact is that i'm not happy with it, that's clear." @arsenal	✗rt @negarmortazavi: thank you @hassanrouhani for retweeting. let's hope for a day when no iranian fears returning to their homeland. http:/
★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/sdzuakqdiv #iran #humanrights
✗@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. #iranhrviolations http://t.co/1g6dhx1znu
HumanDisaster	**CelebrityDeath**
✓rt @baselsyrian: there've been peaceful people in #homs not terrorists! #assad,enemy of #humanity destroyed it. #eyeonhoms #withsyria http:	★rt @sawubona_chris: today is my birthday & also the day my hero @nelsonmandela has died. lets never forget what he taught us. forgiveness i
✓what a helpless father, he can do nothing under #assad's siege!#speakup4syrianchildren http://t.co/vgle3byebw#syria #syriawarcrimes #un	★rt @nelsonmandela: death is something inevitable.when a man has done what he considers to be his duty to his people&his country,he can res
★exclusive: us formally requested #un investigation; russia pressured #assad to no avail;chain of evidence proof hard http://t.co/560t2rvdfw	★rt @nelsonmandela: 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
★#save_aleppo from #assadwarcrimes#save_aleppo from #civilians -targeted shelling of #assad regime#syria #aleppo http://t.co/k3dfxh0pxl	✗#jacques #kallis: a phenomenal cricketing giant of all time - #cricket #history #southafrica http://t.co/ms5pmwoag9
✓rt @canine_rights: why does the #un allow this to continue? rt@tintin1957 help raise awareness of the suffering in #syriawarcrimes http://t	✗@sudesh1304 south africa has the most beautiful babies....so diverse,so unique...so god!! lol #durban #southafrica
SocialIssues	**NaturalDisaster**
★the us doesn't actually borrow is the thing. i believe in a creationist theory of the us dollar @usanationdebt @nationaldebt	✗us execution in #oklahoma : not cruel and unusual? maybe just barbaric, inhumane and reminiscent of the dark ages!
★rt @2anow: according to @njsenatepres women's rights do not include this poor nj mother's right to defend herself http://t.co/xzbslnqkh6 #	✗#haiti #politics - the haiti-dominican crisis - i agree with how martelly is handling the situation: i totally... http://t.co/ro4pswszs
★rt @2anow: confiscation ? how many carry permits are in the senate and assembly? give us ours or turn them in. @senatorloretta @lougreenw	★rt @soilhaiti: a new reforestation effort in #haiti. local compost, anyone? http://t.co/xpad0rqbjk @richardbranson @clintonfdn @virginunite
★rt @2anow: vote with your wallet against #guncontrolforest city enterprises does not support the #2a http://t.co/tpkok3berm#nj2as #tcot	✗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 allowed to take our guns	✓tony burgener of @swisssolidarity says you can't compare the disaster response in #haiti with the response to #haiyan in #philippines @iheid
Epidemics	**LGBT**
✓rt @who: fourteen of the susp. & conf. ebola cases in #conakry, #guinea, are health care workers, of which 11 died #askebola	★rt @jackmcoldcuts: @lunaticrex @fingersmalloy @toddkincannon @theanonliberal anthony kennedy just wrote opinion granting...
✗@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 to stem http://t.co/rjzqhydb3d	✗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 the survey in at https://t.co/aj59x	✗rt @t3h_arch3r: @toddkincannon thanks for your tl having the female realbrother. between them is 600 lbs. 104 iq points. and a lot of hate.
✗augmentation vertigineuse de 57,4% en 1 an des actes islamophobes en france, dit le collectif contre l'islamophobie http://t.co/2qjhocegi5	✗@toddkincannon who us dick trickle.

Table 5: Top Tweets for each topic based on MAP tuned results

A general 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 $f_k \in \{from, hashtag, mention, term, location\}$ provides w.r.t $t_i \in \{NaturalDisaster, Epidemics, ...\}$, mutual information is defined as:

$$I(t_i, f_k) = \sum_{t_i \in \{true, false\}} \sum_{f_k \in \{true, false\}} p(f_k, t_i) \log \left(\frac{p(f_k, t_i)}{p(f_k)p(t_i)} \right) \quad (2)$$

Where higher values for this metric indicate more informative features for the specified topic.

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

- The *Term* and *Location* features are the most prevalent features.
- A few topics such as *IranDeal* and *tennis* are less sensitive to the selection of a specific set of features.
- The Location feature provides more information regarding *HumanDisaster*, *LBGT*, and *Soccer* topics.
- Sorting features based on their average mean values across different topics results in the following order for informativeness measure of features: *Term*, *Location*, *Hashtag*, *Mention*, *From*.

In general, this presents evidence on the need for learning the weights of features for each topic as there is no specific selection of features that would separate various topics from each other.

Also, in order to show the power of Mutual Information criteria, in Table 6 we present the top 5 features for each topic. It can be observed that the different locations, hashtags, or terms shown as the top features based on Mutual Information are actually in relation with the specific topic.

In order to answer the second question on whether any attributes correlate with importance for each feature, we pro-

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: Top 5 features for each topic based on Mutual Information

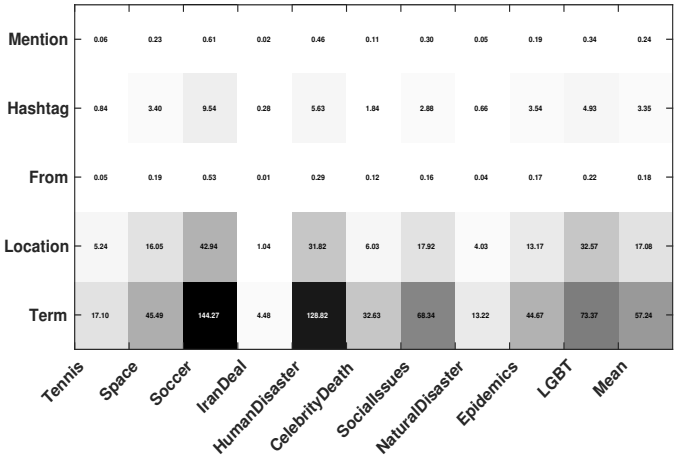


Figure 2: Mean MI values for different features vs. Topics with the last column as average of mean values across all topics

vide two group of analysis. The first group, provides Mutual Information values for each feature across the feature's attribute values shown by violin plots in Fig. 3. The attributes for each feature are:

- From: favorite count (the number of tweets the user has favorited), followers count (the number of users who follow the user), friends count (the number of users followed by the user), hashtag count (number of hashtags used by the user), tweet count (the number of tweets from the user)
- Hashtag: tweet count, user count (the number of users using the hashtag)
- Location: user count
- Mention: tweet count
- Term: tweet count

As we can see in the violin plots, the general pattern is that the greater the number of tweets, users, or hashtag count a feature has, the greater the chance of becoming topical will be. This pattern exists on other attributes of *From* feature, although the pattern is less visible in comparison with the tweets, users, or hashtag count attributes. In addition, we further analyzed the density plots of favorite count, follower count, friends count, hashtag count attributes of *From* feature as demonstrated in Fig. 4. Fig. 4 represents a bimodality in the distribution of Mutual Information values across attributes dimension. Further analysis of data showed that the top mode belongs to users who have at least one topical tweet while the bottom mode are users with no topical tweets.

7 Conclusions and Future Work

This work fills a major gap in event detection and tracking from social media on identifying emerging topics from long-running themes with minimal user supervision. Our results suggest that these sensors generalize well to unseen future topical content and provide a novel paradigm for the extraction of high-value content from social media. Future work should explore the following enhanced topical social sensor learning tasks: (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, and (3) utilizing more social network structure to exploit a more expressive graph-based features.

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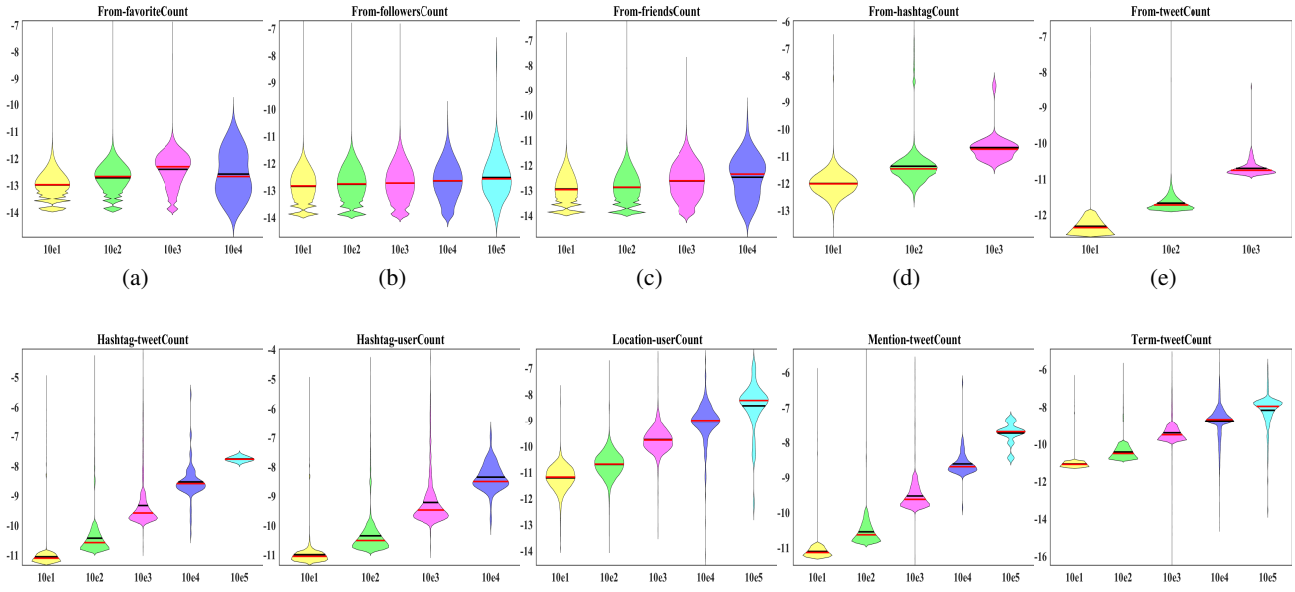

Figure 3: ViolinPlots for the frequency values of feature attributes vs. MI. Plots (a-e) respectively show attributes {favoriteCount, followerCount, friendCount, hashtagCount, tweetCount} for *From* feature. Plots (f-j) respectively show attributes tweetCount and userCount for *Hashtag*, userCount for *Location* feature, tweetCount for *Mention* and *Term* features.

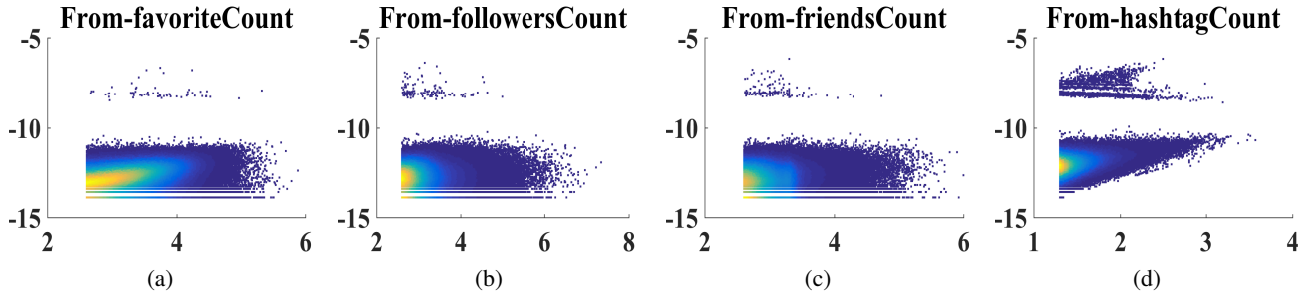

Figure 4: DensityPlots for the frequency values of feature attributes vs. MI. Plots (a-d) respectively show attributes {favoriteCount, followerCount, friendCount, hashtagCount} for *From* feature

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