Distant Supervision for Topic Classification of Tweets in Curated Streams

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ABSTRACT
We tackle the challenge of topic classification of tweets in the context of analyzing a large collection of curated streams by news outlets and other organizations to deliver relevant content to users. Our approach is novel in applying distant supervision based on semi-automatically identifying curated streams that are topically focused (for example, on politics, technology, entertainment, or sports). These streams provide a source of labeled data to train topic classifiers that can then be applied to categorize tweets from more topically-diffuse streams. Experiments on both noisy labels and human ground-truth judgments demonstrate that our approach yields good topic classifiers essentially “for free”, and that topic classifiers trained in this manner are able to dynamically adjust for topic drift as news on Twitter evolves.

1 INTRODUCTION
Our work tackles the problem of identifying interesting posts in social media streams that are then delivered to users’ mobile devices in real time as push notifications. In our problem formulation, users are interested in broad topics such as politics, technology, sports, or entertainment, and we focus on tweets due to their widespread availability. Although topic detection on Twitter (i.e., “trends”) is a well-trodden area, we take a novel approach: instead of trying to tame the cacophony of unfiltered tweet streams, we exploit a smaller, but still sizeable, collection of curated streams (accounts) corresponding to different media outlets.

Our approach skirts many thorny issues in traditional approaches to event detection, but requires solving two non-trivial challenges. First, in order to obtain reasonable coverage of topics and locales, we need to consider a volume of tweets that would still be overwhelming for a user, and thus we need to identify tweets that are salient and novel. Second, many streams contain tweets about a multitude of topics, and therefore we need to develop topic classifiers to separate posts into different categories.

This paper is focused on the second problem. We propose a novel distant supervision technique for automatically gathering noisy topic category annotations from topically-focused streams. These can be used to train topic classifiers and applied to topically-diffuse streams to retain only those tweets that a user might be interested in. Experiments on both noisy labels and human ground-truth judgments demonstrate that our approach yields good topic classifiers essentially “for free”. Experimental results show that having more data and more recent data obtained through distant supervision improves classification, and weighting training instances based on recency yields additional gains. Furthermore, our approach is able to dynamically adapt to topic drift as news on Twitter evolves.

2 RELATED WORK
There is already much work on Twitter event detection; see Atefeh and Khreich [2] for a recent survey. However, this paper is primarily focused on topic classification of tweets.

Most work on tweet classification in the past has involved manual judgments. Becker et al. [3] clustered tweets in real time and performed binary classification between real events and non-events. Kinsella et al. [5] used metadata from hyperlinked webpages to classify blog posts into different topics. Lee et al. [6] worked on trending topic detection by classifying tweets into 18 categories. However, obtaining manual annotations is costly and methods that depend on them are likely to perform worse over time due to concept drift, especially in the context of social media [7].

Distant supervision can overcome the challenges of obtaining manual annotations and there has been previous work on using distant supervision in topic classification. Husby and Barbosa [4] used Wikipedia articles labeled with Freebase domains as training data to classify blog posts by topics. Zubiaga et al. [11] used human-edited web page directories to assign topic labels to tweets that contained URLs to those pages. Magdy et al. [8, 9] transferred labels from YouTube videos to tweets that link to those videos. Our work also takes advantage of distant supervision, but in a way that directly leverages human curation “for free”.

3 APPROACH
The starting point of nearly all event detection work on Twitter is an unfiltered stream of tweets—the more tweets, the better. From this cacophony, the system tries to identify events or “trending” topics. Such a needle-in-a-haystack approach is noisy and prone to manipulation (fake news, “astro-turfing”). Our work adopts a completely different approach: we begin with the observation that there already exist many human-curated streams of interesting events, corresponding to the Twitter accounts of various media outlets. The news editors at CNN, for example, tweet breaking news from @cnn and related accounts. Almost every media outlet, large and small, has their own Twitter account. We wonder, why not build event detection techniques on a collection of these curated streams? Especially for “head events” of broad significance to large groups of users, such an approach seems intuitive.

Our approach skirts many thorny issues in event detection, such as the definition of an event, which has been the subject of much debate dating back over a decade [1]. To us, an event is simply what the editors of the underlying curated streams deem interesting. Our problem formulation does indeed simplify the event detection problem, but two unresolved challenges remain:

First, although our techniques operate on curated streams of posts, the combined volume of these streams is still beyond what
any human can consume. In our experiments, we observed around 16,000 tweets per day on average over a period of 21 days from our curated streams. Obviously, it is not possible for a user to consume all these tweets. Furthermore, there are many duplicate tweets corresponding to reports by different outlets. Thus, even over curated streams, we must still identify what the salient and novel tweets are.

Second, curated streams vary in their topical focus. Some accounts have a narrow focus, e.g., only entertainment news, while others have broad coverage, i.e., they contain tweets about multiple topics. Since users are often only interested in particular topics, we need topic classifiers that can identify relevant tweets. This paper focuses on this second problem, taking advantage of distant supervision techniques to automatically acquire up-to-date training labels in real time.

Our problem can be schematically illustrated in Figure 1. For simplicity, we only show three topics. We illustrate streams in terms of the topic combinations that they cover (here, they are streams A, B, and C). Streams can be classified into three types: general, which tweet about a broad spectrum of news, focused, which tweet about a very specific topic, and hybrid, which tweet about a few topics but are not focused (see examples in Table 1). Our intuition is as follows: for event detection, we would benefit from broad coverage tweets for additional signal, but we must develop topic classifiers to discard tweets that a particular user would not be interested in. We can exploit tweets from focused accounts to train topic classifiers using distant supervision, which can then be used to classify tweets from general and hybrid accounts—thus maximizing both coverage as well as relevance.

As a specific example, we might imagine that our user is interested in receiving notifications about politics. We can build classifiers using tweets from accounts with a narrow focus, e.g., “politics” (stream B). We can keep the relevant tweets from hybrid and general accounts (streams A and C) by checking the predicted labels from the politics classifier. Note that our idea for using focused accounts as distantly-supervised labels applies to both topics as well as locales (e.g., US vs. UK), but we only focus on topic classification in this paper.

4 DATA COLLECTION

Facebook published an article in May 2016 providing an overview of their Trending Topics algorithm [10]. The article provided a list of RSS URLs, mapped to countries and topics, that their algorithm uses to identify breaking events. Most of those URLs correspond to popular news media accounts such as CNN and ESPN. Although the Facebook data contain RSS feeds in many languages, in this work we only focus on English feeds. Based on a few simple heuristics and manual verification, we obtained a list of 293 Twitter accounts that correspond to media outlets in the original Facebook dataset. We then manually classified each account as focused, hybrid, or general (based on the previous section).

We monitored tweets from these 293 curated streams from December 13, 2016 00:00 UTC to January 3, 2017 9:11 UTC and received a total of 337,307 tweets. Table 2 shows the number of Twitter accounts mapped to each topic and the number of tweets observed. Note that counts for each topic do not sum up to the total row because a Twitter account can be mapped to more than one topic (e.g., the hybrid accounts). For the purposes of training, the general accounts are not helpful since they do not provide training labels, although we do select tweets from them for our manual evaluation (more details below). In our experiments, we did not consider the category “gaming” due to the low prevalence of tweets during our observation period.

For the experimental condition that we call “noisy labels”, we divided the collected data into an 80/20 training/test split chronologically, using older data for training and newer data for testing. For training, we used tweets from single-topic (i.e., focused) streams as positive examples, and randomly sampled negative examples from other accounts to include up to five times the number of positive examples.
Table 2: Summary of the topics: number of accounts and composition of the test sets.

| Topic      | Accounts | Tweets in Test Set |
|------------|----------|--------------------|
|            |          | Noisy             | Gold             |
| general    | 68       | -                 | -                |
| politics   | 33       | 5641              | 346              |
| business   | 23       | 2401              | 69               |
| health     | 40       | 4031              | 65               |
| sports     | 30       | 9290              | 73               |
| science    | 25       | 947               | 56               |
| technology | 35       | 2616              | 136              |
| entertainment | 50     | 8077              | 332              |
| gaming     | 17       | 931               | -                |
| other      | -        | -                 | 521              |
| total      | 293      | 33934             | 1536             |

To create the ground truth, we performed manual judgments on tweets pooled from 31 December, 2016 to 2 January, 2017. The pool was created by randomly sampling no more than 50 tweets from randomly selected hybrid and general accounts. We ensured that, in total, there were more than 500 tweets each from hybrid and general accounts. Since for many of the tweets we were not able to assign one of the existing topic labels (these we labeled as "other"), we continued pooling and assessing until we had at least 1000 labeled tweets for the topic labels we were interested in. Table 2 shows the distribution of labels in the gold standard test set. Note that in our annotation process we allowed a tweet to be assigned multiple topic labels, hence the individual counts do not sum up to the total. In the experiments using the gold standard test set, the training set consists of tweets till 30 December, 2016.

5 EXPERIMENTAL RESULTS

Based on the data preparation process described above, for each topic, we trained an individual classifier via distant supervision using tweets from single-topic focused accounts. We extracted TF-IDF features from the words in the tweets that were obtained from the NLTK tweet tokenizer. The logistic regression classifier from sci-kit learn was used with default parameters. In addition to the individual classifiers, we also trained a multi-class classifier using the multinomial naive Bayes implementation in sci-kit learn.

In all our experiments, we used the test sets as described in the previous section. Given a list of chronologically-ordered training examples \((t_1, t_2, \ldots, t_N)\), where \(N\) is the total number of available training examples, the training set \(D_{\text{train}}\) represents a continuous sublist \((t_i, t_{i+1}, \ldots, t_{i+m})|i \geq 1, i+m \leq N\). We varied \(D_{\text{train}}\) in two sets of experiments:

In the first set of experiments, we fixed the end of \(D_{\text{train}}\) to the latest available tweet \(t_N\), and varied the amount of training data by moving the start of \(D_{\text{train}}\). More formally, \(D_{\text{train}}\) is a sublist \((t_i, t_{i+1}, \ldots, t_{i+m})|i \geq 1, i+m \leq N\). This lets us examine the effect of providing the classifier more historical training data.

In the second set of experiments, we fixed the size of \(D_{\text{train}}\) to 0.5 · \(N\) for the evaluation by "noisy labels" and to 0.6 · \(N\) for the ground-truth judgments. Then we varied the recency of the training data by moving the start and end of \(D_{\text{train}}\). More formally, \(D_{\text{train}}\) is a sublist \((t_i, t_{i+1}, \ldots, t_{i+R}, N)|i \geq 1, i+R \cdot N \leq N\), where \(R = 0.5\) or \(R = 0.6\). This lets us examine the impact of training on data that is "out of date", thus quantifying the effects of topic drift.

Figure 2 and Figure 3 show the plots of the F1, precision, and recall scores for the different topics on the noisy labels and human-labeled ground truth, respectively. The plots show an upward trend when the split size increases, i.e., more training data is used whose labels were obtained through distant supervision. This result suggests that more data yield better classification accuracy, which is not surprising. The plots on the right-hand side shows that training on recent time splits (keeping the size constant) generally improves topic classification. This suggests that classifier effectiveness suffers from topic drift, which also makes sense since Twitter content reflects successive news cycles.

Overall, evaluation results on both the noisy labels and human-labeled ground truth are consistent and support the same conclusions. Entertainment news shows a decrease in F1 score on the human judgments, but this is likely due to the fact that many tweets from the general accounts—representing a wide variety of topics such as music, travel, food, and film—were labeled as "entertainment" news. The results for "science" news are significantly worse than the other topics due to its low prevalence (so there is little training data to begin with).

In attempt to incorporate advantages of recent data along with more data, we tried weighting training examples based on their recency. Given a list of chronologically-ordered tweets \((t_0, t_1, \ldots, t_n)\), we weight tweet \(t_i\) as \(\exp(p-i)/n\). In other words, we sample weights using an exponential function such that weights for \(t_0\) and \(t_n\) are 1 and \(p\), respectively. When \(p\) is set to 1, the training is equivalent to unweighted training. We observed empirically that classifier effectiveness improves as we increase \(p\) up to 50.0. The rate of improvement decreases as \(p\) increases, and is expected to decrease for higher values of \(p\). However, our experimental results are reported using \(p = 10\).

We trained the logistic regression classifier with and without weighting the training samples, as described above. For evaluation with the noisy labels, we used the same 80/20 training/test split as in the previous experiments. For evaluation using the ground truth labels, we trained on all tweets up until 30 December, 2016 and tested on all available manual judgments. Results in Table 3 show large improvements in F1 scores when our weighting scheme is used in place of uniform weighting.

Table 3: Differences in F1 scores when the samples were weighted \((p = 10)\) during classification.

| Topic      | \(\Delta F1\) - (Noisy) | \(\Delta F1\) - (Truth) |
|------------|-------------------------|-------------------------|
| business   | 0.09                    | 0.13                    |
| entertainment | 0.03                   | 0.07                    |
| science    | 0.10                    | 0.14                    |
| sports     | 0.02                    | 0.05                    |
| health     | 0.06                    | 0.16                    |
| politics   | 0.05                    | 0.10                    |
| tech       | 0.05                    | 0.12                    |
| all        | 0.07                    | 0.04                    |
6 CONCLUSION

In this paper we tackle the problem of topic classification for tweets in the context of pushing useful notifications to users interested in broad topic categories. We use distant supervision to obtain topic labels by identifying Twitter accounts with a narrow focus, the contents of which serves as training data for logistic regression classifiers. Experimental results show that classifier effectiveness improves with more data and also with more recent data. Weighting recent samples yields further improvements, and results suggest that there are noticeable topic drift effects, but that our techniques are able to compensate. Overall, we empirically demonstrate the effectiveness of a novel approach to gathering topic labels for tweets, practically "for free". We are in the process of building a system that leverages these techniques and are planning to conduct field studies involving real users.

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