'Beating the news' with EMBERS: Forecasting Civil Unrest using Open Source Indicators

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Abstract

We describe the design, implementation, and evaluation of EMBERS, an automated, 24x7 continuous system for forecasting civil unrest across 10 countries of Latin America using open source indicators such as tweets, news sources, blogs, economic indicators, and other data sources. Unlike retrospective studies, EMBERS has been making forecasts into the future since Nov 2012 which have been (and continue to be) evaluated by an independent T&E team (MITRE). Of note, EMBERS has successfully forecast the uptick and downtick of incidents during the June 2013 protests in Brazil. We outline the system architecture of EMBERS, individual models that leverage specific data sources, and a fusion and suppression engine that supports trading off specific evaluation criteria. EMBERS also provides an audit trail interface that enables the investigation of why specific predictions were made along with the data utilized for forecasting. Through numerous evaluations, we demonstrate the superiority of EMBERS over baserate methods and its capability to forecast significant societal happenings.

1 Introduction

We are constantly reminded of instabilities across the world, e.g., in regions such as Middle East and Latin America. Some of these instabilities arise from extremism or terrorism while others are the result of civil unrest, involving population-level uprisings by disenchanted citizens. Since the Arab Spring revolution began, and especially after Egypt's upheaval, many analysts (e.g., [10]) have pondered: Could we have anticipated these events? Were there precursors and signals that could have alerted us to them? Why did this happen in one country but not another?

Our team is an industry-university partnership charged with developing a system to continually monitor data sources 24x7, mine them to yield emerging trends, and process these trends into forecasts of significant

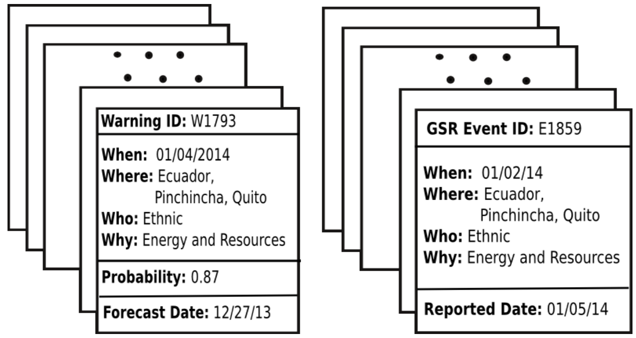

Figure 1: Alerts (left) and events (right) are structured records describing protests.

societal events such as protests. We refer to our system as EMBERS for Early Model Based Event Recognition using Surrogates. Although the scope of EMBERS spans a broad class of events (e.g., protests, disease outbreaks, elections), we focus our attention in this paper on only civil unrest events. Civil unrest is defined as a population-level event wherein people protest against the government or other larger organizations about specific policies, issues, or situations.

The EMBERS project is supported by the IARPA (Intelligence Advanced Research Projects Activity) OSI (Open Source Indicators) program whose objective is to forecast population-level changes using open source data feeds, such as tweets, web searches, news/blogs, economic indicators, Wikipedia, Internet traffic, and other sources. (The term 'open source' here refers to data sources that are openly available without requiring privileged access.) As a performer in the OSI program, EMBERS is a deployed system that has been generating forecasts since Nov 2012 and automatically emailing them in real-time to IARPA upon generation, which have been evaluated by an independent test and evaluation (T&E) team (MITRE). Using human analysts, MITRE organizes a gold standard report (GSR) of protests by surveying newspapers for reportings of civil unrest. Our forecasts have been evaluated against this GSR every month since Nov 2012. Thus, unlike studies of retrospective predictability, EMBERS has been generating (and continues to generate) forecasts into the future.

Our goal in this paper is to present the design, implementation, and evaluation of EMBERS over an extended period of time. Our key contributions are:

1. We outline the system architecture and design of EMBERS, a modular 'big data' processing environment with levels of data transduction from raw feeds to warnings. EMBERS's alerts are meant for analyst consumption, but the system runs continuously 24x7 *without* a human-in-the-loop.
2. Unlike other forecasting/warning generation systems with similar motivations (e.g., [13]), EMBERS warnings are highly structured, capturing (i) when the protest is forecast to happen, (ii) where, with a city-level granularity, (iii) which subgroup of the population will protest, (iv) why will they be protesting, and (v) a probability associated with the forecast. See Fig. 1 (left) for an example of what an alert looks like.
3. EMBERS adopts a multi-model approach wherein each model harnesses different data sources to independently generate predictions and such predictions are then fused to yield final warnings. Using the formalism of probabilistic soft logic (PSL [5]), we demonstrate how we can leverage the selective superiorities of different models and how we can employ collective reasoning to help 'shape' predictions into a final set of warnings.
4. We illustrate the application of EMBERS to 10 countries in Latin America, viz. Argentina, Brazil, Chile, Colombia, Ecuador, El Salvador, Mexico, Paraguay, Uruguay, and Venezuela. We present an exhaustive suite of experiments evaluating EMBERS w.r.t. multiple forecasting criteria and for its capability to forecast significant societal events such as the June 2013 protests in Brazil, also known as the 'Brazilian Spring.'

2 What is Civil Unrest?

Event analysis of the form considered here is an established concept in social science research [2]. Civil unrest is a large concept intended to capture the myriad ways in which people express their protest against things that affect their lives and for which they assume that the government (local, regional or national) has a responsibility (e.g., cost of urban transportation, poor infrastructure, etc.). If the action is directed against private actors, there is normally a connection to government policy or behavior, e.g., a labor strike against a private company can disrupt the rhythm of everyday life for the rest of society, turn violent or lead to a series of disruptive strikes which require government involvement, and thus responsibility in the eyes of citizens. Civil unrest does not include acts by criminals for purely private gain. While authoritarian governments may outlaw civil protest and thus 'criminalize' the participants, social scientists would distinguish illegal political protests from illegal criminal activities. Gang members stopping public buses to extort payoffs from bus owners would not be a civil unrest event, though people protesting afterward against the government's inability to control such gangs would be considered civil unrest.

This expansive definition of civil unrest means that one can find it everywhere, including European protests against austerity or marches against an oil pipeline from Canada across the US to the Gulf of Mexico. Latin America, nevertheless, offers some special characteristics that make it an excellent region for study in our project. The region experiences a plethora of civil unrest events every day (providing a sufficient number of GSR events to train machine learning models), is well covered by international and national news media (facilitating the task of generating ground truth), is the object of detailed empirical research and polling (permitting the description of the social, political and economic context within which civil unrest occurs) and has a significant and growing number of social network users (thus supporting the use of modern data mining algorithms).

3 Related Work

Three broad classes of related work pertinent to EMBERS, are briefly surveyed here. First, there is a rich body of literature in **event coding** [15, 4] wherein structured descriptions of events are extracted from text (e.g., news reports). ICEWS [13] and GDELT [9] are two prominent systems for event coding and significant work has built upon them to develop predictive systems. For instance, ICEWS-coded events have been utilized to forecast the possibility of domestic political crises within countries. Second, there is considerable research on **civil unrest modeling** although much of this work focuses on characterization rather than forecasting. The dynamics by which volunteers are recruited via social networks to the May 2011 Spain protests was studied in [6]. Spatial and temporal distributions of civil unrest over 170 countries were studied in [3]. There are many papers that aim to retrospectively analyze the breadcrumbs of information preceding significant events such as the Arab Spring [10, 8]. Our group has analyzed protests in Latin America paying specific attention to signals that manifest in social media [7]. Finally, there is a growing body of work on **event extraction**. Companies like RecordedFuture and works like [1, 14] aim to recognize planned (future) events from text and Twitter. EMBERS distinguishes from all of the above by supporting highly structured descriptions of protests, emphasizing forecasting rather than characterization or mere detection, and utilizing a broader range of data sources than prior work. Finally, we reiterate that EMBERS is a deployed system that has been successfully issuing alerts for the past 15 months.

4 System Architecture

The EMBERS system is a modular, data-analytics platform for generating warnings of the form described in Fig. 1 (left). It continuously monitors streams of open source data and generates structured alerts in real time, delivered by email to IARPA/MITRE for scoring, with the date of email delivery being the *forecast date*.

The EMBERS architecture, illustrated in Fig. 2, provides a platform for the ingest and warehousing of a variety of raw data sources, and a flexible mechanism for data transfer among ingest, analytics and prediction modules. The four stages—ingest, enrichment, prediction, delivery—are described in detail, respectively, in

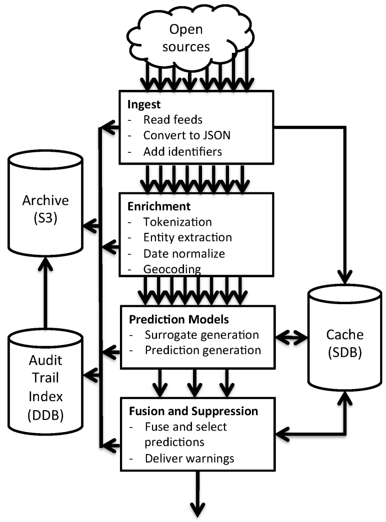

Figure 2: EMBERS system architecture

Table 1: EMBERS system statistics

Archived data	12.4 TB
Archive size	ca. 3 billion messages
Data throughput	200-2000 messages/sec
Daily ingest	15 GB
System memory	50 GB
System core	16 vCPUs
System output	ca. 40 warnings/day

Sections 4.1, 4.2, 5, and 6. EMBERS runs in the commercial AWS cloud. It implements a share-nothing, message-based, streaming architecture using 0MQ as the underlying method of data transport. Processing components are distributed among virtual machines in a configurable, network-secure, auto-deployable, cluster of EC2 instances. With loosely coupled processes and configuration driven communication, EMBERS is able to deliver warnings reliably while facilitating rapid integration and deployment of new components and data sources. The current production cluster consists of 12 EC2 instances with two dedicated to ingest processing, three dedicated to message enrichment, four dedicated to predictive modeling and warnings selection, one each dedicated to archiving and system monitoring. EMBERS became operational in November 2012. It has ingested nearly 13TB of raw data and generated over 12,000 warnings since then. Other notable statistics are listed in Table 1.

4.1 Ingest Processing

The EMBERS ingest module processes data from a variety of different sources: Twitter's public API, Datasift's processed Twitter feed, Healthmap's alerts and reports, RSS news and blog feeds, Talkwalker alerts, NASA satellite meteorological data, Google Flu Trends, Bloomberg financial news, TOR usage data, OpenTable's restaurant cancellation data, the PAHO health survey, and web-pages referenced Tweets. (Some of these, e.g., NASA satellite data and Google Flu Trends are used for other event classes, as described in the introduction.) Each of these has a dedicated configurable ingest processor. Ingested data is packaged into UTF8-encoded JSON messages, assigned unique identifiers and published to a source-specific queue, allowing for simple archiving and subscription. Simple time-series and systems data, such as the store of warnings sent, are stored in a database cache.

One of our central ingest processes makes use of Datasift's Twitter collection engine. Datasift provides the ability to query and stream tweets in real time. These tweets are augmented with various types of metadata including the user profile of the tweeting user or geotagged attributes and the query can target any of these. Targeting tweets that come from a particular geographic area, e.g. Latin America, can be tricky. While some tweets use geotags to specify the location of the tweet, these tweets only comprise about 5% of the total number of tweets and may not be representative of the population overall (i.e. geotagged tweets come from people who have smart phones who also tend to be more affluent). Therefore, it is important to use other information to build a query that targets relevant tweets. In building our query we consider geotag bounding boxes (structured geographical coordinates), Twitter Places (structured data), user profile location (unstructured, unverified strings), and finally mentions of a location contained in the body of the tweet.

4.2 Message Enrichment

Messages with textual content (tweets, newsfeeds, blog postings, etc.) are subjected to shallow linguistic processing prior to analysis. Note that most of our content involves languages from the Latin American region, esp. Spanish, Portuguese, but also French (and of course, English). Applying BASIS technologies' Rosette Language Processing (RLP) tools, the language of the text is identified, the natural language content is tokenized and lemmatized and the named entities identified and classified. Date expressions are normalized and deindexed (using the TIMEN [11] package). Finally, messages are geocoded with a specification of the location (city, state, country), being talked about in the message. An example of this enrichment processing can be seen in Fig. 3.

The EMBERS system makes use of two geocoding systems, one for Tweets and one for news and blog articles. The Twitter geolocater determines not only the city, country and state, but also the approximate latitude and longitude coordinates that a tweet is referring to, or coming from. Geocoding is achieved by first considering the most reliable but least available source, viz. geotags, which give us exact geographic locations that can be reverse geocoded into place names. Second, we consider Twitter places and use place names present in these fields to geocode the place names into geographical coordinates. Finally, we consider the text fields contained in the user profile (location, description) as well as the tweet text itself to find mentions of relevant locations which can then be geocoded into geographical coordinates.

Most news articles and blog posts mention multiple locations, e.g., the location of reporting, the location of the incident, and locations corresponding to the hometown of the newspaper. We developed a probabilistic reasoning engine using probabilistic soft logic (PSL [5]) to infer the most likely city, state, and country which is the main geographic focus the article. The PSL geocoder combines various types of evidence, such as named entities such as locations, persons, and organizations identified by RLP, as well as common names and aliases and populations of known locations. These diverse types of evidence are used in weighted rules that prioritize their influence on the PSL model's location prediction. For example, extracted location tokens are strong indicators of the content location of an article, while organization and person names containing location names are weaker but still informative signals; the rules corresponding to these evidence types are weighted accordingly.

5 Prediction Models

We now outline the five different models considered in our study (see Table 2), paying specific attention to their underlying assumptions, data sources, and scenarios of applicability.

5.1 Planned Protest

Many civil unrest events are planned and organized through calls-for-action by opinion and community leaders who galvanize support for their case. The planned protest model aims at detecting such civil unrest events from traditional media (e.g., news pages, mailing lists, blogs) and from social media (e.g., Twitter, Facebook). The model filters the input streams by matching to a custom multi-lingual lexicon of expressions

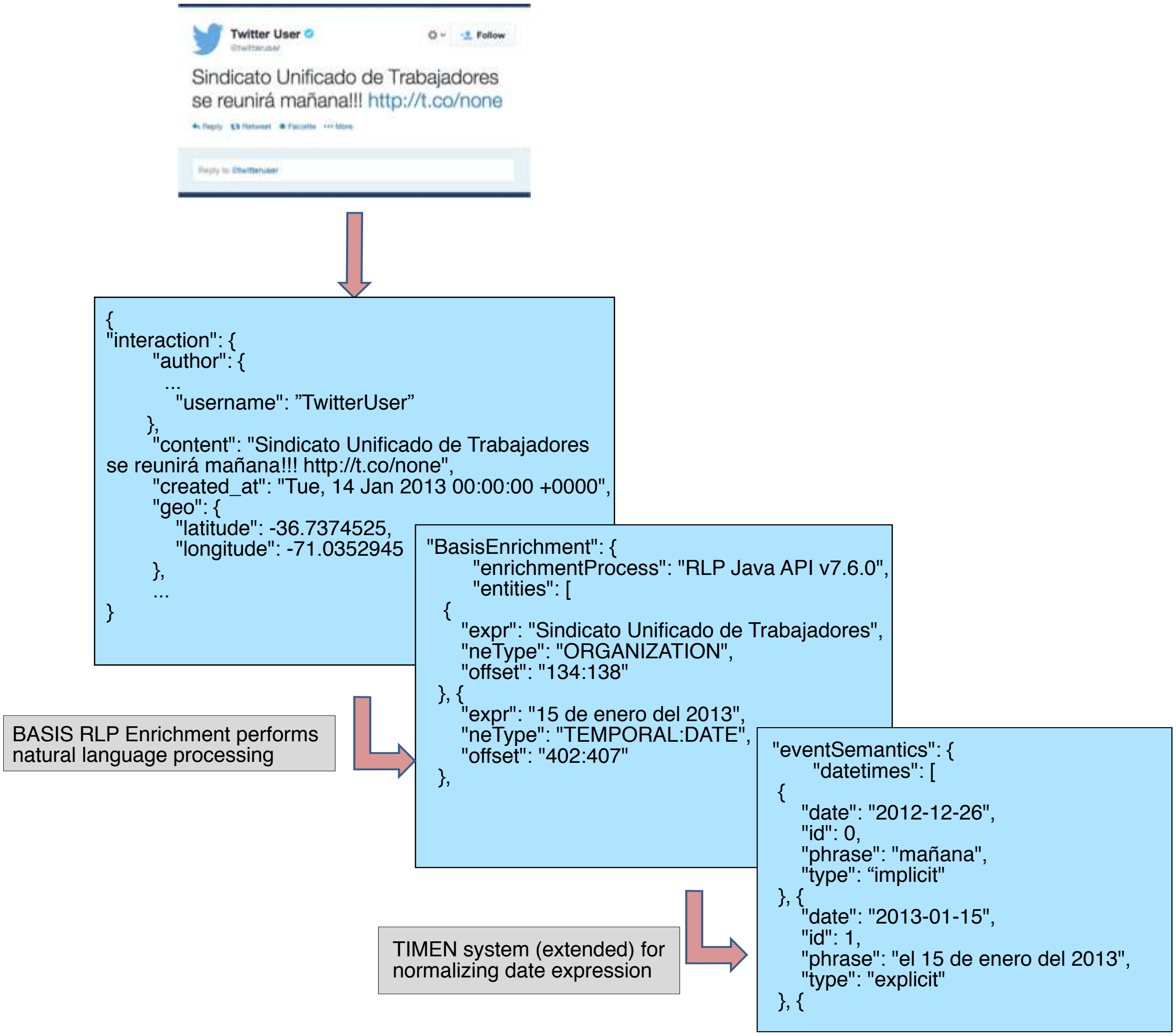

Figure 3: The process of enriching a tweet using Basis RLP enrichment and TIMEN enrichment to generate exact dates. The phrase "Sindicato Unificado de Trabajadores se reunirà manaña" gets enriched to "Sindicato Unificado de Trabajadores se reunirà January 15, 2013."

Table 2: The five different prediction models in EMBERS.

Model	Data sources
Planned protest	RSS (news, blogs), Tweets, Facebook
Volume-based	RSS (news, blogs), Tweets, Exchange rates, TOR, ICEWS, GDELT
DQE	Tweets
Cascades	Tweets
Baseline	GSR

Figure 4: Steps to building a vocabulary using the DQE model. Beginning from a few general phrases about protests, DQE hones in on keywords related to a specific GSR event.

such as *preparación huelga*, *llamó a acudir a dicha movilización* or *plan to strike* which are likely to indicate a planned unrest event. The phrase matching is done in flexible manner making use of the lemmatized, tokenized output of the BASIS enrichment module, to allow for variation and approximations in the matching. Messages that match are then screened for the mention of a future time/date occurring in the same sentence as the phrase. The event type and population are forecast using a multinomial naive Bayes classifier. Location information is determined using the enrichment geocoders. The phrase dictionary is thus a crucial aspect of the planned protest model and was populated in a semi-automatic manner using both expert knowledge and a simple bootstrapping methodology.

The planned protest model reads three kinds of input messages: standard natural language text (RSS news and blog feeds, as well as the content of web pages mentioned in tweets), microblogging text (Twitter), and Facebook Events pages. The RSS feeds and web pages are processed as discussed above. For tweets, in addition to the above processing, we require that the tweet under consideration be retweeted a minimum number of times, to avoid erroneous alerts. (This value is set to 20 in our system.) For Facebook, we use their public API to search for event pages containing the word protest or its synonyms. Most such Facebook event pages already provide significant information such as the planned date of protest, location (sometimes with resolution up to street level), and population/category of people involved.

5.2 Volume-based Model

Next, we developed a traditional machine learning model to map from a large set of volume-based features to protest characteristics. We use a logistic regression model with LASSO (Least Absolute Shrinkage and Selection Operator [16]) to select a sparse feature set, and to predict the probability of occurrence of civil unrest events in different countries. Tweets are one of the primary inputs to this model. Country-level tweets are first filtered using a keyword dictionary which includes 614 civil unrest related words (such as protest, riot), 192 phrases (e.g., right to work), and country-specific actors (public figures, political parties, etc.). For each keyword, its translations in Spanish, Portuguese and English are also used for filtering. In order to reduce the noise in the data, only tweets containing at least 3 keywords are considered. The covariates in the LASSO regression include (i) daily counts of these protest related keywords in filtered tweets, (ii) daily counts of the same keywords in news and blogs, (iii) the exchange rate (country specific currency against dollar), (iv) count of requests to TOR, i.e., the number of online users who have chosen to conceal their location and identity from the online community, (v) count of ICEWS events i.e. events identified by the "Integrated Conflict Early Warning System" [13], (vi) average intensity of the ICEWS events, (vii) the counts of events in publicly available GDELT (Global Data on Events, Location and Tone) dataset [9], which is a record of events in the international system over multiple decades, and (viii) the average tone and the Goldstein scale of these events. A threshold for the probability is determined by maximizing the area under the ROC. This methodology allows for detection as well as prediction of country-specific civil unrest events.

5.3 Dynamic query expansion (DQE)

The dynamic query expansion (DQE) model is based on the idea that the causes for protests can be quite varied and, unlike the Volume model (which uses a fixed set of keywords), we must seek emerging conditions for protests by dynamically growing our vocabularies of interest. This model relies exclusively on tweets. Given a short seed query, DQE first adopts an iterative keyword expansion strategy to dynamically generate a set of extended keywords and tweets pertinent to such keywords. In particular, the seed query consists of a small set of civil unrest related keywords like "protest" and "march.' In the initial iteration, we extract the tweets matching the seed query, and rank the terms in them by their DFIDF weights. Higher ranked terms are used to trigger the second iteration, continuing the process. The iterations are terminated once the set of keywords and their weights become stable (we have observed that DQE converges in approximately 3–5 iterations). See Fig. 4. The resulting tweets are clustered using local modularity and spatial scan statistics, and tweets in the discovered clusters are used by a classification engine to trigger an alert and to determine the event type and population.

5.4 Cascades Model

The cascades model is specifically designed to track activity on social media, especially recruitment of individuals to causes through the use of targeted campaigns, or the popularization of causes through adoption of hashtags. We characterize information diffusion on a (directed) Twitter network using activity cascades. An activity cascade is defined in the following manner: a user posts a tweet; if one of the followers of this user also posts a tweet on the same general topic within a short interval of time after the original poster, we say that the second user was influenced by the first one, and we add this second tweet to the cascade. Then, we consider the followers of the second user, and add them to the cascade if they post a tweet within a short interval of time from then, and so on. The cascade stops growing when none of the followers of the users in the cascade tweet in the general topic soon enough. In our model, we compute cascades over two different networks: the follower graph, which indicates who follows whom in Twitter, and the mention-retweet graph, where the out-neighbors of a user are those who mention or retweet that user. Activity cascades are computed for each day (which potentially could have originated from earlier days and continued growing) and their structural properties (e.g., size, number of participants, duration) are used as input to a machine learning model (generalized linear model; GLM) to forecast the probability of occurrence of a GSR event in the same topic on the following day.

5.5 Baseline model

We also developed a maximum likelihood estimate (MLE) baseline model, making heavy use of the GSR. The idea behind this model is that, even in absence of any explicit signal, the distribution of events that have appeared in the recent past is a good guide to those civil unrest events that will take place in the future. The baseline model makes predictions on the basis of the distribution of "event schema"-frequency in the most recent part of the GSR. An event schema is a combination of a location, an event type, a population and a day of the week. Some high-frequency schemas can appear as many as 10 times in a three-month window, but the vast majority of event schemas appear only once. In a typical three month interval two thirds appear once with the remaining third split evenly between those that appear twice, and those that appear three or more times. Warnings are generated with a minimum threshold of 2 and a three-month training interval, and issued with a lead time of two weeks.

6 Fusion and Suppression

The fusion and suppression engine is responsible for the generation of the final set of warnings to be delivered. It performs several key operations:

- **Duplicate detection and warning updating:** Because our prediction models share data sources and the hypothesis space, duplicate detection is compulsory. An alert is declared as a duplicate (and discarded) if it shares the same $\langle$ location, event type, population, eventDate $\rangle$ tuple as a previously issued alert. If two alerts differ in only the predicted event dates and those dates are at most 2 days apart, then the alerts are considered to be the same event and an update is issued to the already issued alert.

- **Filling missing values:** Certain models are incapable of predicting all details of an alert such as event type, population, or location up to the city level. In such cases, the missing information is filled in based on the likelihood of their appearance in the GSR.

- **Warning rewriting:** At times, a model produces a warning with an improbable $\langle$ location, event type, population $\rangle$ combination. Such a prediction, could either be (1) true, (2) a result of noisy data, or (3) some inherent model error. If the last possibility, one can assume that the model would have identified the broader region correctly. Under such conditions, the fusion model aims to re-write the predicted city to a city that is historically most probable within a given radius, and fills in other aspects accordingly.

- **Balancing the recall-quality tradeoff:** It is desirable to sacrifice some amount of recall if our overall objective is to achieve higher quality of warnings (defined in detail in the next section). We developed two classes of models to explore this tradeoff. First, we developed a random forest regression model to predict likely quality of an alert and alerts that do not pass a desired threshold are suppressed. Second, we trained a PSL engine on matched alerts and events, to learn probabilities of suppressing warnings based on characteristics of the event predicted. We explore the performance of both mechanisms in our results.

7 Audit Trail Interface

In order to facilitate auditing of the warnings and further training of the models, all data that flows through the system is archived to the Amazon S3 cloud and the processing chain recorded in a NoSQL database. Using this infrastructure, the EMBERS system can produce an audit trail for any warning generated, which specifies completely which messages and analytic processes led to the warning. This audit trail can be visualized using the EMBERS web-based dashboard, shown in Fig. 5. The interface enables an analyst to rapidly search through warnings, identify the models (and post-processing) that gave rise to an alert, and the individual data sources that contributed to the alert.

8 Evaluation Methodology

Before we describe our evaluation metrics, it is helpful to review the composition of alerts and GSR events. As introduced in Fig. 1 (left), an alert is a structured record containing four aspects: (i) the where/why/when/who of the protest, (ii) confidence associated with the forecast, and (iii) (implicitly) the date the forecast is being made (*forecast date*). The 'when' is specified in granularities of days. The **where** provides a tiered description specifying the (country, state, city), e.g., (Honduras, Francisco Morazan, Tegucigalpa). The **why** (or event type) captures the main objective or reason for a civil unrest event, and is meant to come from 7 broad classes (e.g., 'Employment & Wages', 'Housing', 'Energy & Resources' etc.) each of which is further categorized into whether the event is forecast to be violent or not. Finally, the **who** (or population) denotes common categories of human populations used in event coding [15] such as Business, Ethnic, Legal (e.g. judges or lawyers), Education (e.g. teachers or students or parents of students), Religious (e.g. clergy), Medical (e.g., doctors or nurses), Media, Labor, Refugees/Displaced, Agricultural (e.g. farmers, or just General Population.

Concomitant with the definitions in the above section, a GSR event contains again the where/why/when/who of a protest that has actually occurred and a *reported date* (the date a newspaper reports the protest as having happened). See Fig. 1 (right). As described earlier, the GSR is organized by an independent third party (MITRE) and the authors of this study do not have any participation in this activity.

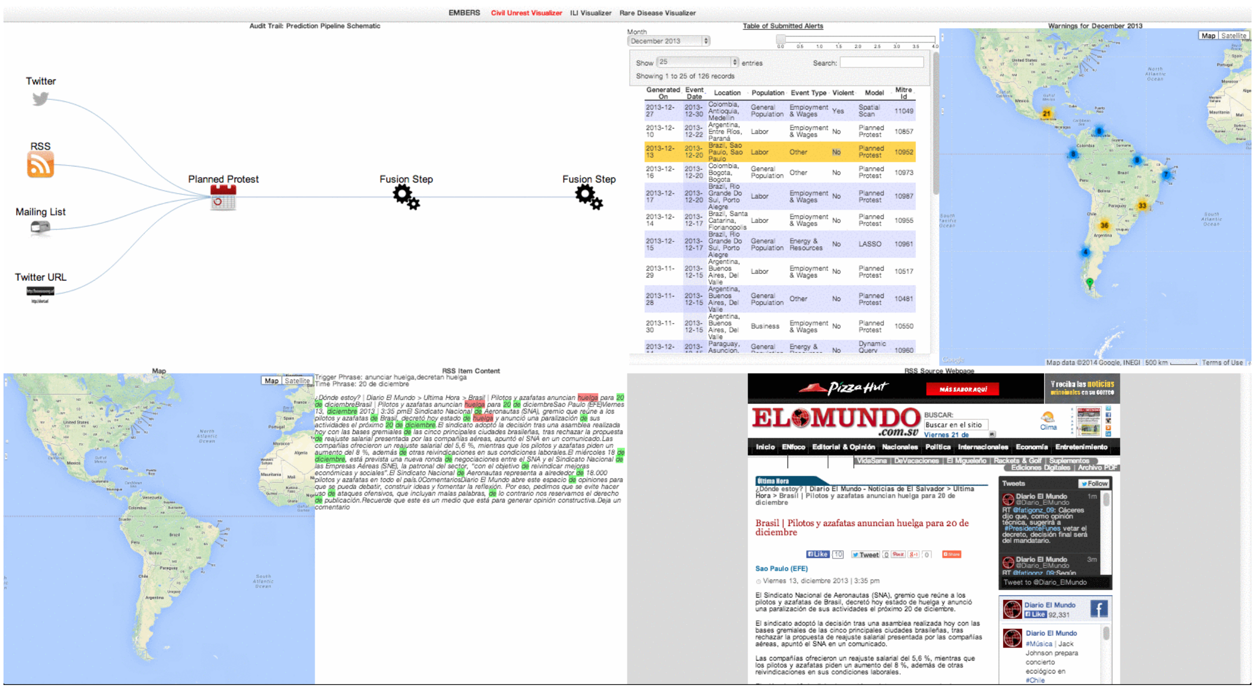

Figure 5: The audit trail visualization interface, displaying the audit trail for an alert from the planned protest model. Explore it at **http://embers.cs.vt.edu/embers/alerts.** (top left) Schema of the planned protest model. (top right) Alert chooser. (bottom panels) Data sources used in this alert, including highlighted sections.

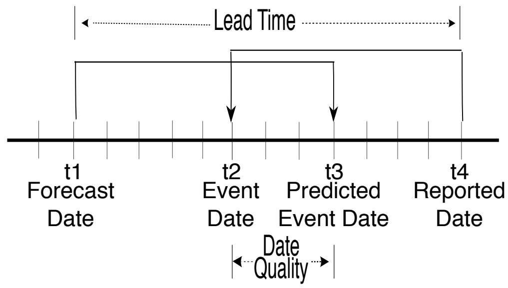

Figure 6: Alert sent at time $t1$ predicting an event at time $t3$ can be matched to a GSR event that happened at time $t2$ and reported at time $t4$ if $t1 < t4$.

8.1 Lead Time vs Accuracy of Forecast Date

Before we explain how alerts are matched to events, it is important to first understand which alerts *can* be matched to specific events. Note that there are four dates in an (alert,event) combination (see Fig. 6):

1. The date the forecast is made (*forecast date*)
2. The date the event is predicted to happen (*predicted event date*)
3. The date the event actually happens (*event date*)
4. The date the event is reported in a GSR source (*reported date*)

For an event to be qualified as having been predicted by a warning, $\textit{forecast date} < \textit{reported date}$ (recall that time is measured in granularities of days). The *lead time* is given as ($\textit{reported date} - \textit{forecast date}$), i.e., the number of days by which we 'beat the news.' In contrast, the difference between *predicted event date* and *event date*, i.e., $|\textit{event date} - \textit{predicted event date}|$. is one of *quality* or accuracy. Ideally we require *lead time* to be as high as possible and $|\textit{event date} - \textit{predicted event date}|$ to be as low as possible.

8.2 Other Quality Aspects

Forecasting the event date accurately is only one aspect of quality. Recall that alerts also forecast the location, event type, and population. We define scores for each of these aspects and quality is defined as a sum over all these scores.

$$\text{Quality score } (QS) = DS + LS + ES + PS$$

where DS, LS, ES, and PS denote the date score, location score, event type score, and population score, respectively. Each of these scores is in turn defined next:

$$DS = 1 - \min(|\textit{event date} - \textit{predicted event date}|, 7)/7$$

If the date of the event listed in the warning is the same as the actual date of the event, then DS is 1. On the other hand, if these dates are farther than 7 days apart, then DS is 0.

Location score (LS) can be defined in many ways. Because location is defined in terms of triples of (country, state, city), one approach is to use a tiered formula. Comparing a GSR event with a warning, we can obtain a score triple of (l_1, l_2, l_3) where l_1 is the country-level score, l_2 is the state-level score, and l_3 is the city-level score. Each of these scores have a value of 0 if they do not match and 1 is they match. Then the match between submitted warning location and the GSR location is given by:

$$LS = \frac{1}{3}l_1 + \frac{1}{3}l_1 l_2 + \frac{1}{3}l_1 l_2 l_3$$

An alternative way to define location score is as:

$$LS = 0.33 + 0.66(1 - \min(\text{dist}, 300)/300)$$

where dist denotes the distance (in km) between the city predicted and the GSR city. All city location names are standardized to the World Gazetteer which provides latitude and longitude values, thus facilitating the computation of distance. The scaling and shifting values of 0.33 and 0.66 ensure that this definition of LS is compatible with the earlier definition. Cities outside a 300km radius from a GSR location will thus be scored 0.33; exact predictions will be scored 1; and cities within a 300km radius will get scores in the range [0.33,1]. We distinguish between these two criteria as the categorical LS versus physical distance-based LS.

Event type score (ES) is scored similar to categorical LS since it naturally maps to a three-level taxonomy: whether a civil unrest is forecast to happen, what objective/reason is behind the unrest, and whether it is violent. Again partial credit applies depending on the level of specification. Population score (PS) is simply a binary (0/1) score denoting whether we forecast the correct population or not. Finally, note that $QS = DS + LS + ES + PS$ is designed to take values in the range $[0, 4]$.

8.3 Inclusion Criteria

Thus far we have demonstrated, given a warning-event pair, how we can score their fitness. Inclusion criteria define which W-E pairs *can* even be considered for scoring. We have already mentioned one inclusion criterion, viz. that lead time must be > 0. The full list of inclusion criteria we will consider are:

1. Lead time > 0
2. Both warning and event are for the same country.
3. The *predicted event date* and *event date* must be within 7 days of each other.

A fourth, optional (and stringent), criterion we will use is:

4. Both predicted location and event location must be within 300km of each other.

It is important to distinguish the inclusion criteria from the scoring criteria. Inclusion criteria define which W-E pairs are allowable. Scoring criteria determine, from these allowable W-E pairs, what their score will be.

8.4 Matching Alerts to Events

Thus far we have assumed that we are matching an alert to a GSR event. In practice, the problem is we are given a set of issued alerts and a set of GSR events and we must determine the quality of the match: which alert would correspond to which event? One strategy is to construct a bipartite graph between the set of alerts and the set of events, where allowable edges are those that satisfy the inclusion criteria, and where weights on these allowable edges denote their quality scores. We then construct a maximum weighted bipartite matching, e.g., see Fig. 7 (middle). Such matchings are conducted on a monthly basis with a lookback period to bring in unmatched warnings from the previous month.

8.5 Non Crossing Matching

A criticism of the matching approach above is that it can lead to criss-cross matches, i.e., the matching process may not respect the temporal order in which warnings were issued or in which events unfold. A non-crossing matching is a more restrictive version of a bipartite matching. Consider two warnings w_1 and w_2 and two events e_1 and e_2. Representing them by their predicted event dates and event dates, and assuming $w_1 < w_2$ and $e_1 < e_2$, then $\{(w_1, e_2), (w_2, e_1)\}$ is a *crossing matching* since the earlier warning is paired to a later event (and vice versa). To respect the temporal order, we also investigate the computation of a maximum non-crossing matching [12] and use it as an additional evaluation criterion (see Fig. 7 (right)).

8.6 Putting it all together: Five criteria

We are now ready to identify all the evaluation criteria used in EMBERS. The overall **quality** is defined as a weighted average across all matched warning-event pairs. Similarly, **lead time** is averaged across all

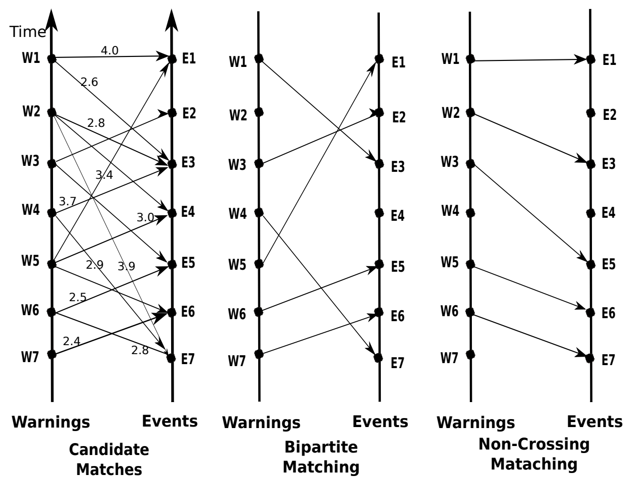

Figure 7: Given a set of candidate warning-event matches (left), we evaluate the performance of EMBERS using either a regular bipartite matching (middle) or by constructing a non-crossing matching (right).

matched warning-event pairs. In addition, we can define **precision** in terms of the number of unmatched warnings as a fraction of the total number of sent warnings. Similarly, **recall** can be defined in terms of the number of unmatched events as a fraction of the total number of events. Finally, a **probability score** is calculated over all warnings, mapped or unmapped. For each warning, it is defined in terms of the Brier score, i.e., $1-(o-p)^2$ where p is the probability assigned to the warning, and o is 1 if the warning is mapped to some event in the GSR, and 0 is the warning is not mapped to an event in the GSR. This score is then averaged over all warnings.

9 Evaluation Results

We present an exhaustive evaluation of EMBERS against multiple aspects as follows:

- **How do each of our models fare for the 10 countries of interest and how well does their integration achieve the five overall metrics?**

Table 3 presents the performance of EMBERS models for a recent month across all the 10 countries of interest here. As is clear here, the models have selective superiorities across the countries studied. While the baseline model captures significant regularities and achieves high quality scores, models like DQE perform better for countries like Brazil, Mexico, and Venezuela, all of which have significant chatter on Twitter. Even when models have comparable performances, their integration is useful because each model will produce only a limited set of warnings and their fusion is necessary to achieve high recall. This is evident in Table 4 that demonstrates that we achieve a quality score of 3.11 with an average lead time of 8.8 days and respectable precision and recall (0.69 and 0.82, respectively). Taking a birds eye view, Fig. 8a and Fig. 8b summarize the distribution of events in the GSR and alerts sent by EMBERS over the past 15 months.

- **How does EMBERS's fusion and suppression engine help 'shape' our quality distribution?**

Fig. 8c describe how our suppression engine can be tuned to steer the quality distribution from a mode around 2.25 to one around 3.2 by learning which warnings to suppress and which ones to issue. This capability directly helps balance the recall-quality tradeoff, as shown in Fig. 8d.

- **How does EMBERS fare against a baserate model with lenient versus stringent inclusion criteria for matching?**

To rigorously evaluate the capabilities of EMBERS, we implemented a baserate model as a yardstick for comparison. The baserate model is similar in spirit to the baseline model described earlier but functions differently. Rather than filtering for frequent combinations of event properties, it generates alerts using the rate of occurrence of events in the past three months. Due to space considerations we are unable to describe these results in detail. Under the lenient (categorical) inclusion criteria constraints, EMBERS exhibits a quality score improvement of approximately +0.4 over baserate methods. Under the strict location-based inclusion criteria, this improvement jumps to a +1.0 over baserate methods.

- **How adept is EMBERS at forecasting 'surprising' events? Did EMBERS forecast significant uprisings such as the June 2013 protests in Brazil?**

Fig. 8e describe the performance of our system in Brazil during the summer of 2013 when Brazil witnessed significant protests that were originally triggered by bus fare increases. As can be seen, EMBERS is able to track the rise in number of protests quite accurately. More recently, Fig. 8f and Fig. 8g describe the performance of EMBERS in Brazil and Venezuela for the Jan-Feb 2014 season. Significant violent protests were witnessed in both countries, due to bus fare increases and student-led demonstrations, respectively. While the GSR for Feb 2014 is not available at the time of this writing, it is clear that the uptick in violence in both countries is captured in EMBERS alerts forecasting violence. Finally, we also conducted a formal maximum entropy evaluation of protest counts, to determine how EMBERS fares on only those protests that are deemed to significantly higher in number relative to the past three months. As Fig. 8h shows, EMBERS demonstrates an improvement of nearly 0.5 over baserate models during months of significant uprisings (e.g., June 2013). During other months (e.g., Nov 2013) there is relatively normal activity and baserate methods perform comparably.

- **How reliable are EMBERS's probability scores?**

Fig. 8i shows that the probability scores emitted by warnings have a monotonic relationship to the likelihood of matches, indicating that EMBERS's use of confidence captures the mapping from model and warning attributes to the possibility of event matches.

- **How does EMBERS's lead time vary with quality scores?**

Fig. 8j illustrates an interesting relationship. As lead time increases from low values, as expected, quality scores decrease. But as lead time crosses a threshold, quality scores actually improve again! This is because data sources like Facebook event pages and other feeds contribute high quality planned protest warnings with high lead time.

- **What is the effect of adopting regular versus non-crossing matching constraints?**

Fig. 8k reveals that, as expected, when adopting non-crossing matching constraints, the number of matches decreases bringing down the overall quality. Nevertheless, a consistent level of improvement over baserate methods is witnessed.

- **How has the performance of EMBERS improved over time?**

Finally, Fig. 8l demonstrates the performance of our deployed EMBERS system over time. From quality scores of just over 2 in the past year, EMBERS has breached the 3.0 barrier in recent months.

10 Discussion

We have presented the architecture of EMBERS, an automated system for generating forecasts about civil unrest from massive, multiple, data sources. Our evaluations over 10 countries illustrate the capabilities of EMBERS 'in the small' (matching specific events to particular warnings) as well as 'in the large' (capturing significant upticks across countries).

Table 3: Comparing the forecasting accuracy of different models in EMBERS. Quality scores in this and other tables are in the range [0,4] where 4 is the most accurate. AR=Argentina; BR=Brazil; CL=Chile; CO=Colombia; EC=Ecuador; SV=El Salvador; MX=Mexico; PY=Paraguay; UY=Uruguay; VE=Venezuela. A $--$ indicates that the model did not produce any warnings for that country in the studied period.

Model	AR	BR	CL	CO	EC	SV	MX	PY	UY	VE	All
Dynamic Query Expansion	3.1	3.31	1.88	3.1	2.43	2.94	3.26	2.88	2.72	2.9	2.97
Volume-based Model	3.0	3.11	-	2.9	-	-	3.15	-	1.72	2.9	2.88
MLE	3.33	3.0	2.87	3.15	2.29	3.11	3.11	3.1	2.57	2.77	3.0
Planned Protest	2.59	2.64	2.4	2.85	1.92	-	3.0	2.89	2.85	2.66	2.76
Cascades Model	3.13	-	-	-	-	-	-	-	-	2.93	3.0

Table 4: EMBERS metrics across multiple countries.

Metric	AR	BR	CL	CO	EC	MX	PY	SV	UY	VE	All
Quality score	3.2	3.39	2.85	2.86	2.59	3.0	3.27	2.85	3.05	3.01	3.11
Recall	1.0	1.0	0.82	0.59	1.0	1.0	0.65	1.0	1.0	0.84	0.82
Precision	0.55	0.45	0.89	0.94	0.77	0.71	1.0	0.69	0.46	0.73	0.69
Lead time (days)	10.44	11.82	6.25	7.85	8.44	8.32	8.61	10.57	8.8	6.03	8.88
Probability measure	0.71	0.66	0.87	0.87	0.75	0.74	0.94	0.74	0.72	0.72	0.76

Future work is targeted at three aspects. First, we are interested in social science theory-based approaches to forecasting, e.g., modeling the rise of grievances into trigger events, capturing the role of opinion leaders, and identifying whether there are both necessary and sufficient conditions for a festering sentiment to transform into a protest. Second, we plan to develop a statistical theory of tradeoffs revolving around the boundaries of precision-recall and quality-lead time. Different analysts are likely to prefer different sweet spots along these boundaries and we seek to situate EMBERS as a tunable forecasting system. Finally, for analyst consumption, we are interested in automated narrative generation, i.e., an English description of an alert providing a contextual summary of the alert (similar to automated weather report generation).

Acknowledgments

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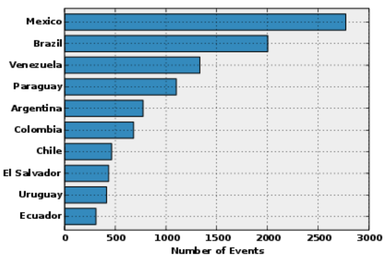
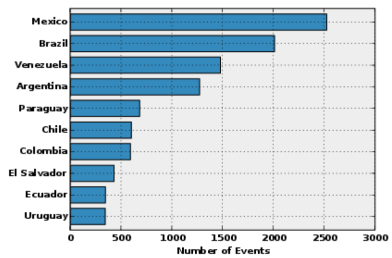
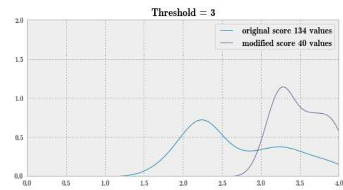


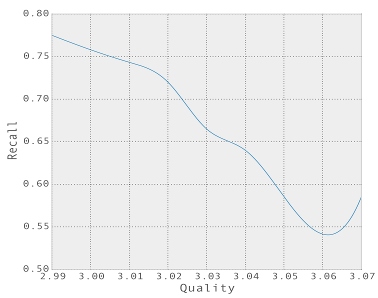
(a) GSR Distribution



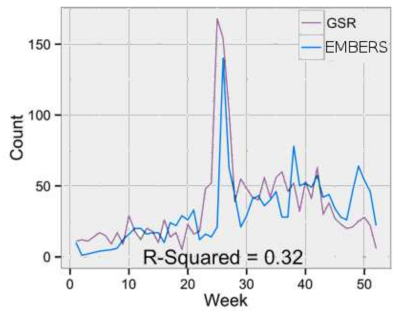
(b) EMBERS Alerts Distribution



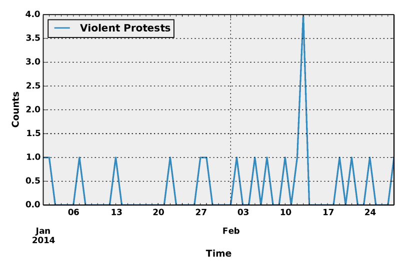
(c) Quality distributions before and after suppression/



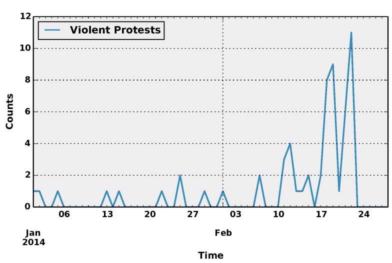
(d) Recall vs Quality Tradeoff



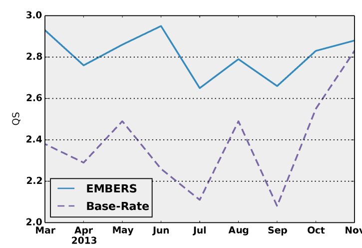
(e) The Brazilian Spring



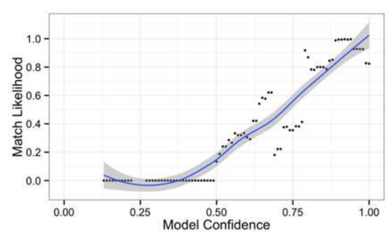
(f) Violent Protests in Brazil



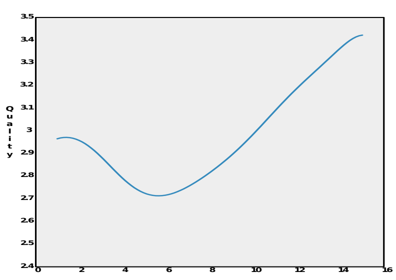
(g) Violent Protests in Venezuela



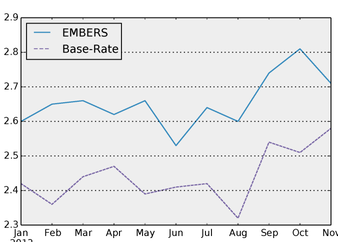
(h) MaxEnt Evaluation



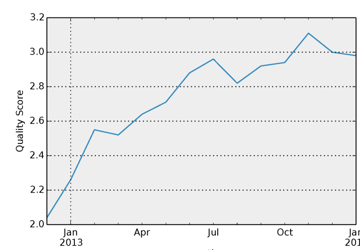
(i) EMBERS Probability Score



(j) Lead time vs Quality Tradeoff



(k) Quality score with non-crossing matches (1 day interval).



(l) Evolution of EMBERS's quality scores over time.

Figure 8: Evaluation of EMBERS

References

[1] H. Becker, D. Iter, M. Naaman, and L. Gravano. Identifying content for planned events across social media sites. In *WSDM 2012*. ACM Press, 2012.

[2] J. M. Box-Steffensmeier and B. S. Jones. *Event History Modeling: A Guide for Social Scientists*. 2004.

[3] D. Braha. Global civil unrest: contagion, self-organization, and prediction. *PLoS One*, 7(10):e48596, Jan. 2012.

[4] P. T. Brandt, J. R. Freeman, and P. A. Schrodt. Real time, time series forecasting of inter-and intra-state political conflict. *Conflict Management and Peace Science*, 28(1):41–64, 2011.

[5] M. Broecheler, L. Mihalkova, and L. Getoor. Probabilistic similarity logic. In *Proc. UAI*, 2010.

[6] S. González-Bailón, J. Borge-Holthoefer, A. Rivero, and Y. Moreno. The dynamics of protest recruitment through an online network. *Sci. Rep.*, 1:197, Jan. 2011.

[7] T. Hua, C.-T. Lu, N. Ramakrishnan, F. Chen, J. Arredondo, D. Mares, and K. Summers. Analyzing Civil Unrest through Social Media. *Computer*, 46(12):80–84, Dec. 2013.

[8] N. Kallus. Predicting Crowd Behavior with Big Public Data. Feb. 2014.

[9] K. Leetaru and P. Schrodt. GDELT: Global data on events, location, and tone, 1979–2012. *ISA Annual Convention*, pages 1979–2012, 2013.

[10] K. H. Leetaru. Culturomics 2.0: Forecasting large-scale human behavior using global news media tone in time and space. *First Monday*, 16:1–22, 2011.

[11] H. Llorens, L. Derczynski, R. J. Gaizauskas, and E. Saquete. TIMEN: An open temporal expression normalisation resource. In *LREC*, pages 3044–3051. European Language Resources Association, 2012.

[12] F. Malucelli, T. Ottmann, and D. Pretolani. Efficient labelling algorithms for the maximum noncrossing matching problem. *Discrete Applied Mathematics*, 47(2):175–179, 1993.

[13] S. P. O'Brien. Crisis Early Warning and Decision Support: Contemporary Approaches and Thoughts on Future Research. *Int. Stud. Rev.*, 12(1):87–104, Mar. 2010.

[14] A. Ritter, O. Etzioni, and S. Clark. Open domain event extraction from twitter. In *ACM SIGKDD 2012*, 2012.

[15] P. A. Schrodt. Automated production of high-volume, near-real-time political event data. In *American Political Science Association meetings*, 2010.

[16] R. Tibshirani. Regression shrinkage and selection via the lasso. *J. R. Stat. Soc. Ser. B*, 58:267–288, 1996.