Abstract

Language usage changes over time, and this can impact the effectiveness of NLP systems. This work investigates methods for adapting to changing discourse during crisis events. We explore social media data during crisis, for which effective, time-sensitive methods are necessary. We experiment with two separate methods to accommodate changing data: temporal pretraining, which uses unlabeled data for the target time periods to train better language models, and a model of embedding shift based on tools for analyzing semantic change. This shift allows us to counteract temporal drift by normalizing incoming data based on observed patterns of language change. Simulating scenarios in which we lack access to incoming labeled data, we demonstrate the effectiveness of these methods for a wide variety of crises, showing we can improve performance by up to 8.0 F1 score for relevance classification across datasets.

1 Introduction

Patterns of language usage change over time, often in predictable and analyzable ways (Hamilton et al., 2016b; Kulkarni et al., 2015; Sommerauer and Fokkens, 2019). As language changes, the applicability of NLP systems can be negatively impacted. In social media, these changes can happen extremely rapidly (Kulkarni et al., 2015; Eisenstein, 2013). Word usage and topics can even change over the span of a single day (Golder and Macy, 2011). Accounting for this change is critical in crisis situations, in which information patterns can vary greatly between the phases of emergency management for crisis (Reynolds and Seeger, 2005; Yang et al., 2013). In order to best apply NLP technology to crisis situations, for example, by classifying relevant tweets to aid first responders, affected populations, and researchers, we need to account for temporal patterns of usage.

Consider the following sequence of tweets progressing through a hurricane event:

1. Out on my block, looks like a big storm is coming in this weekend
2. Evacuation! heading 6 blocks up to stay with my cousin
3. Just learned our block won’t have power or train service for a month

The contextual importance of the word "block" changes as the event progresses. A system trained to only handle the unassuming usage in 1 will be unable to identify the importance of the word in other contexts as the crisis evolves: those of evacuation and recovery. More formally, our problem is that of having a model trained for classification using embedding representations learned from time $B_{0...t-1}$. This model can then classify text from this time period. Language use then changes from $B_t$ onward, making the previously trained model less effective (Figure 1).

We model the problem as a predictable change: we learn how language usage will change, and use this information to adapt incoming data to existing models. Unlike existing approaches, which react to incoming annotated data to update their models, we instead make predictions about potential change,
creating better input representations for models trained on potentially out-of-date data.

We employ two methods: **temporal pretraining** and **embedding shift**. For the first, we use additional pretraining of masked language models using unlabeled data from the target time. We explicitly model temporality by adding date information directly into tweet texts. For the second, we incorporate conceptualizations of semantic change. We predict the natural shift of meaning during a typical crisis lifespan, applying this shift to adapt future unseen data to a model trained on available data. The first requires only unlabeled data from the target time; the second requires no additional data. Both only yield changes in input representations, and are thus model agnostic.

We evaluate these methods by simulating crisis scenarios, providing a model with tagged data only from early in a crisis event and testing our approach on unseen future data. Our research is unique in it’s focus on temporal changes over very short time periods (i.e. days). We show both methods are effective, with embedding shift in particular improving F1 scores by between 1.46 and 8.0 average F1 over the best baseline.

Our contribution can be summed as follows:

1. We demonstrate the effectiveness of additional temporal pretraining using additional unlabeled data for crisis events.
2. We develop embedding shift methods that adapt future data to known models, improving classification with no additional labeled data.
3. We show significant improvements in performance using temporal adaptation without changing model architecture or adding additional labeled data.

These methods are used here for crisis classification, but the methodology is broadly applicable to any classification procedure for which the data is likely to change predictably over time.

2 Background

Our task is to enable consistent classification of language that is changing. From a computational perspective, we view this as a change in the relationship between input data and target data over time, which we refer to as ”temporal drift”.\(^1\)

---

\(^1\)Terminology varies here: the task is alternately referred to as “conceptual drift” (Gama et al., 2014), “temporal drift/adaptation” (Huang and Paul, 2019), or “evolutionary classification” (He et al., 2018).

We follow the definition of He et al. (2018): we are presented with consecutive time steps, each of which contains a sequential set of data. These data points (both features and labels) are drawn from a distribution unique to the current time step. We follow the assumption that the feature space at each step changes smoothly over time: that is, language change is gradual, so that the data from each time step will be related but not equal, requiring adaptation to changes in the data.

2.1 Language Change

Word embeddings have opened the way for extensive computational research into semantic shift using quantitative methods (Hamilton et al., 2016b,a; Kim et al., 2014; Kulkarni et al., 2015; Martinc et al., 2020). These methods typically identify the degree to which certain words have changed by training separate embeddings for separate time periods. These changes are then used to validate known changes or identify new changes in lexical semantics. While there remains some doubt as to the impact of frequency effects, polysemy, and other methodological issues (Dubossarsky et al., 2017), these methods have yielded substantial advancement in computational linguistics and digital humanities (Sommerauer and Fokkens, 2019).

While these methods are widely used to study linguistic change, applications for improving classification based on temporal drift have been relatively limited. Previous work can be broadly categorized into three areas: modifying training data, improving model architecture to account for time, and improving input representations.

2.2 Temporal Drift

There are multiple approaches in the field of NLP for social media that rely on augmenting training data via adaptive learning procedures. Fromreide et al. (2014) use crowdsourcing to “catch up” to conceptual drift on Twitter. They show the danger in using off-the-shelf systems on temporal displaced data, and show that crowdsourcing can provide a feasible alternative to handle language drift.

The named entity recognition model of Derczynski et al. (2015) accommodates drift by negatively weighting older examples, reporting positive results. This mirrors domain adaptation, treating older samples as out-of-domain and lowering their weights (Cherry and Guo, 2015). Another method is using drift detection to determine when a shift has occurred via processes such as change-point de-
tection, and fully or partially retraining the model at this time (Sun et al., 2018). These methods all have benefits, but require adding or modifying their data as incoming data arrives. We instead focus on being predictive: learning from the data we have to predict the signal change.

He et al. (2018) focus on model improvements, using two processes: temporal smoothing and diachronic propagation. Temporal smoothing ensures model parameters across time spans undergo minimal deviation. This then generates a chain of evolving classifiers, each constrained to be similar to the one before it. They also include a diachronic propagation component, connecting layers at previous time steps to the current layer.

With regard to updating embedding representations to handle temporal changes, Bjerva et al. (2020) employ sequential subspace alignment, mapping embeddings across time periods. This is done by extracting principal components for the source time and applying a transformation to map them to target time components. They then modify this procedure to perform alignment on a per-class basis using a small set of supervised examples. This process, semi-supervised subspace alignment (SSSA), provides significant performance gains when they align previous time period data to the present time. For comparison, we utilize their system, however, rather than aligning historical data to match the present, we align future data to match classification trained on the past (Section 5.2).

Huang and Paul (2019, 2018) employ both building better embedding models and adding temporal modeling components. They use diachronic word embedding methods by directly adding temporal bin information to the input to embedding models. They improve modeling by using temporally-aware LSTM models, in which the activations output from previous time LSTMs can be fed into the current time. They show that these methods can improve performance on a variety of temporally sensitive datasets. However, their models focus on making predictions about known data. They know the time period of each data point during training, and use this information to build better classifiers: we instead are focused on adapting models to data from unseen time periods. We build on their temporal bin modification by incorporating time information directly in embedding training (Section 5.1).

2.3 Classification in Crisis

There is a broad array of work classifying tweets during hazard events based on various categories, with specific attention towards limited data scenarios. For classifying multiple disasters with limited data, convolutional neural networks using pre-trained word embeddings have proven effective at overcoming small data scenarios (Nguyen et al., 2017; Aipe et al., 2018). With regard to input representations, crisis-specific embeddings have been shown to be particularly effective (Nguyen et al., 2016). Recently, work has shown the effectiveness of deep contextualized word representations for classifying disaster-based tweets (Madichetty and M, 2020), particularly with regard to classifying over multiple disaster types (Zahera et al., 2019; Ray Chowdhury et al., 2020).

The temporal issues present in crises have also been highlighted. Nguyen et al. (2016) use online learning to train neural networks during active crises, highlighting the importance of adapting to variability as crises evolve. Nguyen et al. (2017) shows that using neural networks combined with data from external events can improve classification in the early hours of new events, when training data is lacking. Alam et al. (2018) use semi-supervised learning to leverage unlabeled samples early in crisis events, when data is sparse. This architecture allows them to find similar tweets based on node similarity, and while it provides strong performance for small labeled datasets, it doesn’t account for temporal change over the course of an event. Recent work from from Kaufhold et al. (2020) experiment with active, incremental, and online learning to classify relevance of tweets during crises. They use feature-based machine learning algorithms to classify German tweets related to two disasters. However, while their methods focus on minimizing data requirements, they employ human annotators for active learning; we instead focus on scenarios where incoming data is unlabeled.

These approaches all require significant training data, and don’t account for predictable change during the event. Our work builds upon recent work in temporal adaptation (Huang and Paul, 2019) by combining unlabeled data for pretraining with independently learned knowledge of temporal drift. This allows us to make better predictions about future data, rather than reacting to annotations as they become available.
3 Data

We will explore these methods for two datasets. These are the Hurricane Sandy dataset (Stowe et al., 2018), and the CrisisLex T26 dataset (Olteanu et al., 2015). These each contain unique characteristics relevant to the problem at hand.

3.1 Hurricane Sandy

The Hurricane Sandy dataset contains approximately 22,000 tweets spanning 17 days centered on landfall of Hurricane Sandy in New York City in 2012, annotated for relevance to the storm and its effects. The advantages of this dataset are its relatively large size and the method of collection. They collected tweets by first identifying users impacted by the event, then retroactively pulling their data from before, during, and after the event. This provides numerous benefits over keyword collection including a relatively broad collection of both relevant and non-relevant tweets and a more complete dataset to evaluate language change, as each tweet doesn’t necessarily contain the same keyword. Additionally, there are numerous resources of unlabeled data collected pretraining to Hurricane Sandy, which we will leverage in Section 5.1.

3.2 CrisisLex

The CrisisLex T26 (T26) dataset includes approximately 1,000 labeled tweets for 26 different crisis events, labeled by informativeness into three different categories: (1) related to the crisis and informative, (2) related to the crisis but not informative, and (3) not related to the crisis. These datasets reflect a wide variety of events covering natural and human-created emergencies. We additionally split these datasets into two categories based on their temporal features, indicated by the authors: progressive and instantaneous. Progressive events are those that are preceded by a warning period. This includes hurricanes, floods, wildfires, and the Singapore Haze event. We anticipate these events to be susceptible to shift, as they have more time for surrounding language to evolve. Instantaneous events are defined as those that “(do not allow pre-disaster mobilization of workers or pre-impact evacuation of those in danger”. These include earthquakes, terrorist attacks, catastrophic accidents, and the Russia meteor event.

The T26 dataset is particularly useful as it contains a wide variety of events. One downside is that each individual dataset is relatively small, with each event containing only approximately 1,000 tweets. They also contain additional unlabeled tweets which can be used for additional language modeling, but these unlabeled sets are also extremely small. This gives us some perspective on how our methods work with extremely limited data, which is likely to be the case during crises.

4 Experimental Setup

For our experimental setup, we split each dataset into temporal “bins”, using bin sizes of one day. We will adopt the following terminology: for each event we consider a set of time bins $B_0...r$, marking the start and end of data for that event. We refer the bin at current time as $B_{t-1}$, with the bin we are making predictions about as $B_t$. Previous bins are indicated via $B_{t-2}, B_{t-3}$, etc. Our task is given a set of annotated training data, we need to perform classification over the next bin $B_{t}$.

For each dataset, we split the data into training and test. For our training set, we use the section of data from bins $B_{0...r}$, where $r$ is defined as the first bin where the number of samples $s \in B_{0...r}$ is greater than 25% of the total samples. We chose 25% to model the “pre-crisis” phase, but this will of course vary based on multiple factors. We theorize that much lower than 25% and there won’t be enough data to learn shifts; much greater and the training phase extends too far into the acute phase of the crisis.

We use the next bin after training $(r+1)$ for development. We then evaluate our models on the remaining data. This is to mimic a crisis scenario where our model is developed in the pre-crisis phase then deployed in the acute- and post-crisis phases. However, note that not all events have a “pre-crisis” phase: the T26 dataset is split into two partitions, one of which (progressive) contains a pre-crisis phase while the other (instantaneous) does not. In these cases, the early data better reflects the acute crisis phase.

---

2To ensure user privacy, we collected all tweets for this research using the Hydrator interface (https://github.com/DocNow/hydrator) to the Twitter API.

3https://github.com/Project-EPIC/chime-annotation

4http://www.crisislex.org/data-collections.html#CrisisLexT26

5Details of the entire array of datasets are shown in Appendix A.

6Values for $r$ across all datasets spanned from 1 to 7.
We continue pretraining a bert-based model using unlabeled data from the target bin. This is then used for fine-tuning the task specific model.

5 Methods

We account for changes in crisis tweets via two methods: learning better embeddings via temporally-focused pretraining, and shifting future embeddings to match models trained on seen data.

5.1 Learning Embeddings

As a first step to improving temporal classification on unseen data, we develop methods for training time-specific embeddings. This follows assumptions of the benefits of additional pretraining to fit the target domain (Gururangan et al., 2020; Han and Eisenstein, 2019). In our case, we consider the target time period as the domain that we are trying to fit. We start with the standard bert-base-cased model, and additionally train using the masked-language-modeling objective over unlabeled data specific to our domain. This is done by fine-tuning masked language models using data from up to the target-time bin $B_t$.

For Hurricane Sandy, we use the unlabeled dataset of Wang et al. (2015), which includes 6.5 million keyword based tweets spanning October 25th to November 6th. In order to minimize variance between time periods, we restrict each bin to a limit of 300,000 unlabeled tweets for training. For the T26 dataset, each event contains a relatively small set of additional unlabeled tweets (see Appendix A). This provides a contrast in experimentation: we have substantial additional pretraining data for Hurricane Sandy, but extremely limited data for the T26 dataset.

As an alternative to standard additional pretraining for each bin, we also implement an adaptation following intuitions from previous work by directly encoding temporality information before training (Huang and Paul, 2019; Daumé III, 2007). Specifically, Huang and Paul (2019) shows that for classification of events over time, concatenating the time bin directly to each word piece while training embeddings allows the model to then learn bin-specific word embeddings. While the bin information doesn’t encode temporality in a linear fashion, but rather discretely, it still yields better embeddings which improve performance. As we are evaluating on data from unseen bins, this method isn’t directly applicable: applying bin information to tokens in unseen bins makes them unknown words to the model trained on previous bins.

We instead use a modification designed specifically for contextual representations: rather than including bin information for each word, we concatenate a time stamp (date, hour, and minute) to the text of each tweet. We include this information only at the tweet level, without modifying individual tokens: this avoids unknown tokens in the input, and contextual embedding methods can utilize this temporal information attached to the input text.

An overview of these temporal pretraining methods is shown in Figure 2. We use unlabeled data up to the target time $t$ for additional temporal pretraining. This data is augmented optionally by a function $d$ to encode explicit date information. For the TARGET model the text is unmodified; for the TIME model it encodes exact time information at the sentence level. This embedding architecture is relatively flexible: depending on model and data situations, different data augmentation functions for $d$ can be employed to improve temporal encoding.

5.2 Embedding shift

Temporal pretraining allows us to leverage relevant unlabeled data. However, we would like to be able to adapt to change with no additional data, under the assumption that language change during crises is predictable. We hypothesize that the same kinds of methodologies used to identify linguistic change over time can be used to adapt embedding-based machine learning to accommodate temporal shift. This is a practical implementation of the work of Hamilton et al. (2016b), in that rather than identifying and studying shifts, we directly apply their methodology to classification. We learn embedding-based transformations, and apply them to future data, adapting it to better fit trained mod-
Our method involves learning and applying an *embedding shift*, or regular change in word embeddings over time. We believe this shift can happen relatively quickly in crisis, and particularly on social media. Once we’ve identified the direction of the shift, we can then apply it in reverse to future data. Our goal is to be able to predict changes in the data, and use them to shift future data to better match the distributions we’ve observed in model training.

### 5.2.1 Learning Embedding Shifts

As we are working with contextual embeddings, we focus on applying the shift the sentential representation via the [CLS] token. To learn the shift, we extract embeddings for each sentence in our unlabeled data at each time bin $B_0...B_r$ using our task-specific fine-tuned model. We then generate the average sentence embedding by taking the mean across all [CLS] tokens from the BERT-based model. This yields a set of bin-specific [CLS] embeddings. From these, we learn a linear regression model with time as the input and the successive vectors as the target. This model is then used to predict the embedding at the target time $t$. The difference between the predicted embedding at the target time $t$ and the learned embedding at time $t-1$ is defined as the shift: the expected change in the embedding for the [CLS] token.

As the [CLS] token is used for sentence level classification, it functions as an overall embedding for the sentence: changes in individuals words are thus likely also reflected in changes in the [CLS] token. While this process is broadly applicable to all tokens, we limit this work to this singular token as we are focused here on sentence level classification, which allows us to use a simple logistic regression prediction head.

### 5.2.2 Applying Embedding Shift

At test time, we can then apply this shift $s$ in reverse to the test embeddings at time $t$, adapting the test embeddings to better match the distribution the current models are trained on. We also introduce an intensity parameter $i$ in order to adjust the degree to which the shift is applied. We can then represent the embedding for word $w$ at time $t$ by shifting it to match the distribution of the training data:

1. $E_{t-shifted}(w) = E_t(w) - s \cdot i$

These embeddings, adapted to match the historical distribution, are then fed to the model trained on data from $B_0...t-1$, as visualized in Figure 3. Note that this assumes a linear change in meaning over time: more complex models could be used to learn the shift $s$, although they carry the risk of overfitting.

As far as we are aware, we are the first to attempt to account for temporal change over these relatively short time spans. For comparison, we follow the work of Bjerva et al. (2020) who align temporal embeddings using semi-supervised subspace alignment (SSSA). This method projects samples from different spaces into lower dimensionality, providing a small number (<10) of labeled samples from test time to facilitate better alignment, and has proven effective for a wide variety of temporal tasks. They provide a number of variants: we choose the normal semi-supervised alignment as it performs best on their dataset with the shortest time periods (weeks), which aligns best with our tasks. We align the vectors at time $B_t$ to those in the training data $B_0...B_r$. Note that instead of shifting training data to match the current time, we instead shift test data backwards to match the training data, as there is substantially less test data.

### 6 Results

As a baseline, we fine-tuned a bert-base-cased model for the relevance-based classification tasks for Hurricane Sandy and T26 datasets. We use the training data from the bins $B_0...r$. This gives us a fine-tuned BERT model based on the early phases of each event. We experiment with each type of temporal language modeling (TARGET and TIME), and additionally add each type of embedding adap-
Semi-supervised subspace alignment improves results for Hurricane Sandy for both baseline and TIME embeddings, but is inconsistent when applied to the TARGET embeddings. It is also ineffective on the T26 dataset: this is likely due to the smaller dataset sizes. This method requires sufficient samples from each class to perform supervised alignment. As many of the T26 datasets contain only a small number of samples spread unevenly over three classes, the maximum dimensionality retained is necessarily small. This isn’t a problem for Hurricane Sandy, as there are plentiful examples of both classes.

6.1 Temporal Embeddings

The temporal embedding methods (TARGET and TIME) improve results consistently for Hurricane Sandy and the instantaneous T26 events, which improve by 2.6 F1 score. The progressive events don’t improve significantly, although we still see small improvements from both TARGET and TIME models. Encoding time information directly improves over the baseline but not significantly over the TARGET model.

6.2 Embedding Shift

Applying embedding shift directly to base embeddings yields the best performance for Hurricane Sandy, improving over the baseline by 8.0 F1 score. For the T26 progressive events, we do see significant improvement (1.5 F1 score, on average) for the progressive events.

It is less effective when applied to the instantaneous T26 events. This is likely due to the nature of our data split. For the instantaneous events, the vast bulk of tweets occurs during the first one or two days, meaning the shift is learned over a very short period of time. This makes the shift less likely to be robust. In progressive events, the distribution of data is more spread out, giving more days of training to learn the shift. This is a fact of crises that matches the human response: when we have more time to prepare, we are better able to react.

While the lower performance on the T26 events may be due to fewer unlabelled samples available for the TARGET and SHIFT methods, we find no significant correlation between unlabelled data size and method performance (see Appendix C). It may be an affect of the collection process: the T26 datasets are keyword based, which mitigates the impact of changing language over time. The Sandy dataset was collected from user streams which can better reflect changes over time.

6.3 Tweet Analysis

We further qualitatively explore the model performance to assess the impact of the lexical shift. We hypothesize that the SHIFT model will improve cases that are ambiguous without temporal information or otherwise temporally difficult. These are likely to be misclassified by the baseline model: our hope is that by adapting embeddings to match the input data, we can better classify these samples. We randomly sample 10 tweets for which

Table 1: Scores averaged over all time bins. For the T26 events, we report mean macro F1 over type (instantaneous vs progressive). For Hurricane Sandy, we report F1 score. Italics indicates significant improvement over the baseline (p < .05), bold indicates the best result for that task.

|                | Sandy | T26 inst. | T26 prog. |
|----------------|-------|-----------|-----------|
| Bert Base      | .7202 | .5172     | .5419     |
| TARGET Embs.   | .7316 | .5432     | .5501     |
| TIME Embs.     | .7398 | .5383     | .5489     |
| Base+SSSA      | .7306 | .4322     | .4366     |
| TARGET+SSSA    | .6601 | .4384     | .4349     |
| TIME+SSSA      | .7884 | .4352     | .4280     |
| Base+SHIFT     | .8013 | .5178     | .5566     |
| TARGET+SHIFT   | .7595 | .5253     | .5061     |
| TIME+SHIFT     | .7457 | .5182     | .5218     |
the SHIFT model corrects the baseline.\textsuperscript{9} We use the Hurricane Sandy dataset, where the SHIFT was most effective, and we have sufficient samples to build a clear picture of the results.\textsuperscript{10}

Table 2: Tweets misclassified by the base model which were correctly classified with the SHIFT model.

| Tweet                                                                 | Context                                                                 |
|----------------------------------------------------------------------|------------------------------------------------------------------------|
| (1) packing. be back in a few                                       | (1) packing. be back in a few                                           |
| (2) if I’m swept out to sea, it was nice knowing you and maybe we   | (2) if I’m swept out to sea, it was nice knowing you and maybe we       |
| can get together in my next life                                    | can get together in my next life                                        |
| (3) sandy is a twat                                                  | (3) sandy is a twat                                                    |
| (4) yeah! my favourite market had flashflight batteries! I’m        | (4) yeah! my favourite market had flashflight batteries! I’m           |
| ready for this!                                                     | ready for this!                                                        |
| (5) good morning, hurricane or not, i’m still getting it            | (5) good morning, hurricane or not, i’m still getting it                |
| (6) why did everyone get this emergency alert but me, lmao          | (6) why did everyone get this emergency alert but me, lmao             |
| (7) this halloween is gonna be bad if it rains on halloween         | (7) this halloween is gonna be bad if it rains on halloween            |
| (8) queensbridge, hallets cove in astoria, industrial parts of    | (8) queensbridge, hallets cove in astoria, industrial parts of         |
| maspeth, lindenwood, both airports                                  | maspeth, lindenwood, both airports                                     |
| (9) we were actually able to book hotel rooms, it’s gonna be a      | (9) we were actually able to book hotel rooms, it’s gonna be a mini    |
| mini vacation                                                       | vacation                                                               |
| (10) bad taste - screams and power outages on the way. “without    | (10) bad taste - screams and power outages on the way. “without screams we have no power!” #monstersinc3d |
| screams we have no power!” #monstersinc3d                           |                                                                       |

The majority of samples are ambiguous without contextual knowledge about the ongoing impacts of the hurricane. Many of the occurring themes: packing (1), being swept out to sea (2), emergency alerts (6) and hotel rooms (9) may not be present in the model during the pre-crisis phase, but as the event unfolds these tweets become more important. The ambiguity between event names and personal names such as (3) is a common problem with keyword searches: shifting embeddings improves classification in these cases. Also the impacts on events like Halloween (7) and locations (8) became more important as the impact of the storm becomes evident over time.

Our training data is only from the pre-crisis phase, and thus many of the model lacks exposure to many of themes that later become important. The usage of evacuation terminology, emergency alerts, and prominent locations aren’t directly connected to the event, and temporal adaptation is necessary to capture these details. Almost all of the above examples are unclear or ambiguous without context. The annotation procedure for this dataset allows us to better capture this kind of data: the embedding shift methodology then allows us to more effectively classify these ambiguities as the event proceeds.

\textsuperscript{9}Tweets anonymized to protect user privacy.
\textsuperscript{10}Note that the samples in Table 2 are all positive samples: the SHIFT model improves exclusively recall, correcting previously misclassified positive samples.

7 Conclusions and Future Work

We’ve shown two methods that can be used to significantly improve performance in classifying temporally sensitive events, even those that unfold in a very short time frame (ie., days). Additional temporally-based pretraining can improve performance, adapting to shifts in time without additional labeled data. We can also adapt our input representations to predictable language changes by learning embedding shifts, using only observed data. Both improve performance for events that progress over time, with additional pretraining gaining up to 2.5 F1 score and embedding shift up to 8.0. While we limit our analysis to crisis events, these methods can be broadly applied to problems that change predictably over time. This is particularly relevant for social media data, as language usage therein tends to change rapidly.

With regard to temporal pretraining, better architecture and objectives could prove essential. Our method of employing masked language modeling with explicit temporal markers is relatively simple: we could also explore including the time period as a learning objective in a multi-task setup, combining language and temporal information in the pretraining architecture. For embedding shift, we only learn and apply the shift for the [CLS] tokens: as there is a wealth of research in lexical change, these methods could also be explored for words that are likely to change, giving more fine-grained control over the shift on a lexical level.

Our models are learned on a crisis-to-crisis basis. We should be able to learn better, more robust representations by applying our methodology to a larger array of crisis events simultaneously, leveraging the power of transfer learning. As we learn from more events, our methods will get more accurate and more robust. As crises are inherently difficult to manage, benefits must come from implementing temporal adaptations beforehand, and have them ready to apply when crises emerge.

We must also be aware of the dangers inherent in making predictions about crises based on past events. Incorrect predictions can lead to potential harm, and new events may be unique, hindering the transferability of models. While we show the benefits of temporal awareness and prediction during crises, we always need to ensure robustness and be aware of potential consequences whenever predictions are made.
8 Ethics Statement

We use data under Twitter’s terms of service, collecting Tweet text and date information under Twitter privacy policies. We don’t release any data, and the tweets presented in examples are paraphrased to avoid user identification. For dataset that include user information (ie. Stowe et al. (2018)), we take care to divorce all user information from each tweet, treating them as a separate, random collection, and thus this work should have minimal impact at the user level.

This work presents tools that can improve adaptability of models over time, and doesn’t directly develop or release tools that have the potential for harm. Nonetheless, any research into socially generated data comes with dual-use concerns, particularly in cases of crisis where populations are vulnerable: identifying relevant tweets can help first responders react to dangerous situations, but can also be used to harm affected populations by individuals, organizations, and governments that are willing to take advantage of vulnerable populations.

There’s also the issue of the model’s ability, and the risk of misclassification. Our methods improve classification of crisis tweets, but as we note in Section 7, there is inherent risk using these models: false classifications can engender dangerous situations, and both users and NLP practitioners need to be aware of the risks.

In many ways, the problems of using Twitter for health monitoring are similar, in that vulnerable populations can be adversely affected. We can thus generally follow the suggestions for ethical research of (Benton et al., 2017). In the end, while we cannot prevent malicious agents from attempting to misuse publicly available data, we can take practical steps: protecting user data and keeping both researchers and the general public informed of possible unethical use.

References

Alan Aipe, Asif Ekbal, Mukuntha Narayanan Sundararaman, and S. Kurohashi. 2018. Linguistic feature assisted deep learning approach towards multi-label classification of crisis related tweets. In Proceedings of the 15th International Conference on Information Systems for Crisis Response and Management (ISCRAM), pages 705–717, Rochester, NY. Rochester Institute of Technology.

Firoj Alam, Shafiq Joty, and Muhammad Imran. 2018. Graph based semi-supervised learning with convolutional neural networks to classify crisis related tweets. In Proceedings of the Twelfth International Conference on Web and Social Media (ICWSM 2018), Stanford, California.

Adrian Benton, Glen Coppersmith, and Mark Dredze. 2017. Ethical research protocols for social media health research. In Proceedings of the First ACL Workshop on Ethics in Natural Language Processing, pages 94–102, Valencia, Spain. Association for Computational Linguistics.

Taylor Berg-Kirkpatrick, David Burkett, and Dan Klein. 2012. ”An Empirical Investigation of Statistical Significance in NLP”. In Proceedings of the 2012 Joint Conference on Empirical Methods in Natural Language Processing and Computational Natural Language Learning, pages 995–1005. Association for Computational Linguistics.

Johannes Bjerva, Wouter Kouw, and Isabelle Augenstein. 2020. Back to the future — sequential alignment of text representations. In Proceedings of the AAAI Conference on Artificial Intelligence, volume 34, pages 7440–7447, United States. AAAI Press.

Colin Cherry and Hongyu Guo. 2015. The unreasonable effectiveness of word representations for Twitter named entity recognition. In Proceedings of the 2015 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 735–745, Denver, Colorado. Association for Computational Linguistics.

Hal Daumé III. 2007. Frustratingly easy domain adaptation. In Proceedings of the 45th Annual Meeting of the Association of Computational Linguistics, pages 256–263, Prague, Czech Republic. Association for Computational Linguistics.

Leon Derczynski, Isabelle Augenstein, and Kalina Bontcheva. 2015. USFD: Twitter NER with drift compensation and linked data. In Proceedings of the Workshop on Noisy User-generated Text, pages 48–53, Beijing, China. Association for Computational Linguistics.

Haim Dubossarsky, Daphna Weinshall, and Eitan Grossman. 2017. Outta control: Laws of semantic change and inherent biases in word representation models. In Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing, pages 1136–1145, Copenhagen, Denmark. Association for Computational Linguistics.

Bradley Efron. 1979. Bootstrap methods: Another look at the jackknife. The Annals of Statistics, 7(1):1–26.

Jacob Eisenstein. 2013. What to do about bad language on the internet. In Proceedings of the 2013 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 359–369, Atlanta, Georgia. Association for Computational Linguistics.
Hege Fromreide, Dirk Hovy, and Anders Søgaard. 2014. Crowdsourcing and annotating NER for Twitter #drift. In Proceedings of the Ninth International Conference on Language Resources and Evaluation (LREC’14), pages 2544–2547, Reykjavik, Iceland. European Language Resources Association (ELRA).

João Gama, Indrundeﬁned Žliobaitundeﬁned, Albert Bifet, Mykola Pechenizkiy, and Abdelhamid Bouchachia. 2014. A survey on concept drift adaptation. ACM Computing Surveys, 46(4).

Scott A. Golder and Michael W. Macy. 2011. Diurnal and seasonal mood vary with work, sleep, and daylength across diverse cultures. Science, 333(6051):1878–1881.

Suchin Gururangan, Ana Marasović, Swabha Swayamdipta, Kyle Lo, Iz Bellagy, Doug Downey, and Noah A. Smith. 2020. Don’t stop pretraining: Adapt language models to domains and tasks. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 8342–8360, Online. Association for Computational Linguistics.

William L. Hamilton, Jure Leskovec, and Dan Jurafsky. 2016a. Cultural shift or linguistic drift? comparing two computational measures of semantic change. In Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing, pages 2116–2121, Austin, Texas. Association for Computational Linguistics.

William L. Hamilton, Jure Leskovec, and Dan Jurafsky. 2016b. Diachronic word embeddings reveal statistical laws of semantic change. In Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 1489–1501, Berlin, Germany. Association for Computational Linguistics.

Xiaochuang Han and Jacob Eisenstein. 2019. Supervised domain adaptation of contextualized embeddings for sequence labeling. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 4238–4248, Hong Kong, China. Association for Computational Linguistics.

Yu He, Jianxin Li, Yangqiu Song, Mutian He, and Hao Peng. 2018. Time-evolving text classiﬁcation with deep neural networks. In Proceedings of the Twenty-Seventh International Joint Conference on Artiﬁcial Intelligence, IJCAI-18, pages 2241–2247, Stockholm, Sweden. International Joint Conferences on Artiﬁcial Intelligence Organization.

Xiaolei Huang and Michael J. Paul. 2018. Examining temporality in document classiﬁcation. In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers), pages 694–699, Melbourne, Australia. Association for Computational Linguistics.

Xiaolei Huang and Michael J. Paul. 2019. Neural temporality adaptation for document classiﬁcation: Diachronic word embeddings and domain adaptation models. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 4113–4123, Florence, Italy. Association for Computational Linguistics.

Marc-André Kaufhold, Markus Bayer, and Christian Reuter. 2020. Rapid relevance classiﬁcation of social media posts in disasters and emergencies: A system and evaluation featuring active, incremental and online learning. Information Processing & Management, 57(1):102132.

Yoon Kim, Yi-I Chiu, Kentaro Hanaki, Darshan Hegde, and Slav Petrov. 2014. Temporal analysis of language through neural language models. In Proceedings of the ACL 2014 Workshop on Language Technologies and Computational Social Science, pages 61–65, Baltimore, Maryland. Association for Computational Linguistics.

Vivek Kulkarni, Rami Al-Rfou, Bryan Perozzi, and Steven Skiena. 2015. Statistically signiﬁcant detection of linguistic change. In Proceedings of the 24th International Conference on World Wide Web, pages 1384–1397, Florence, Italy. Association for Computing Machinery.

Sreenivasulu Madichetty and Sridevi M. 2020. Improved classiﬁcation of crisis-related data on twitter using contextual representations. Procedia Computer Science, 167:962 – 968.

Matej Martinc. Petra Kralj Novak, and Senja Pollak. 2020. Leveraging contextual embeddings for detecting diachronic semantic shift. In Proceedings of the 12th Language Resources and Evaluation Conference, pages 4811–4819, Marseille, France. European Language Resources Association.

Dat Tien Nguyen, Shafiq Joty, Muhammad Imran, Hassan Sajjad, and Prasenjit Mitra. 2016. Applications of online deep learning for crisis response using social media information. In Fourth International Workshop on Social Web for Disaster Management (SWDM’16), New York, New York. Association for Computing Machinery.

Dat Tien Nguyen, Kamela Ali Al Mannai, Shafiq Joty, Hassan Sajjad, Muhammad Imran, and Prasenjit Mitra. 2017. Robust classiﬁcation of crisis-related data on social networks using convolutional neural networks. In Proceedings of the Eleventh International AAAI Conference on Web and Social Media (ICWSM 2017), pages 632–635, Montréal, Québec, Canada.

Alexandra Olteanu, Sarah Vieweg, and Carlos Castillo. 2015. What to expect when the unexpected happens: Social media communications across crises. In Proceedings of the 18th ACM Conference on Computer Supported Cooperative Work and Social Computing, CSCW ’15, page 994–1009, New York, New York. Association for Computing Machinery.
F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay. 2011. Scikit-learn: Machine learning in Python. *Journal of Machine Learning Research*, 12:2825–2830.

Jishnu Ray Chowdhury, Cornelia Caragea, and Doina Caragea. 2020. Cross-lingual disaster-related multi-label tweet classification with manifold mixup. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics: Student Research Workshop*, pages 292–298, Online. Association for Computational Linguistics.

Barbara Reynolds and Mathew W. Seeger. 2005. Crisis and emergency risk communication as an integrative model. *Journal of Health Communication*, 10(1):43–55.

Pia Sommerauer and Antske Fokkens. 2019. Conceptual change and distributional semantic models: an exploratory study on pitfalls and possibilities. In *Proceedings of the 1st International Workshop on Computational Approaches to Historical Language Change*, pages 223–233, Florence, Italy. Association for Computational Linguistics.

Kevin Stowe, Jennings Anderson, Martha Palmer, Leysia Palen, and Ken Anderson. 2018. Improving classification of Twitter behavior during hurricane events. In *Proceedings of the Sixth International Workshop on Natural Language Processing for Social Media*, pages 67–75, Melbourne, Australia. Association for Computational Linguistics.

Nick Sun, Ke Tang, Zexuan Zhu, and Xin Yao. 2018. Concept drift adaptation by exploiting historical knowledge. *IEEE Transactions on Neural Networks and Learning Systems*, 29(10):4822–4832.

Hamada M. Zahera, Ibrahim Elgendy, Richa Jalota, and Mohamed Ahmed Sherif. 2019. Fine-tuned bert model for multi-label tweets classification. In *Proceedings of the 28th Text REtrieval Conference (TREC)*, Gaithersburg, Maryland.
Figure 4: Improvements over the baseline based on the size of unlabelled data for T26 datasets.

A Appendix A

Counts and splits for training and test data for each of the T26 datasets are shown in Table 3. Note that the Typhoon Pablo event from the original dataset had only seven unlabelled tweets that could be successfully recovered: we therefore remove it from all experiments.

B Appendix B

Performance of each method on each of the T26 datasets is shown in Table 4.

C Appendix C

Figure 4 shows the effect of unlabelled data size on performance gains for each method. The Boston Bombings event is removed from the graph as an outlier. With and without this event, we see no significant correlation between unlabelled data size and performance improvements (Pearson correlation -.14 to .17, .410 < p < .487).

D Appendix D

Here we provide model parameters used in training our temporal language models and fine-tuned BERT models. Note that the embedding shift methods is designed to be model agnostic, functioning purely on the embedding representations, and thus should be applicable regardless of the embeddings used.

D.1 Temporal Language Models

For temporal language modeling, we used the transformers package (Wolf et al., 2020). We started with the bert-base-cased model and tokenizer. We trained each model for 3 epochs with a batch size of 64. We used a weight decay and learning rates each set to 1e-4.

D.2 Fine-Tuned BERT Models

We used the transformers platform to fine-tune models on each individual task. For the baseline we used the bert-base-cased model; for others we used the temporal language models described. We fine tuned these for 3 epochs with weight decay of 1e-3 and a learning rate of 1e-4. These models were then used to extract the [CLS] token embeddings. We then used stock logistic regression via scikit-learn to train and evaluate our models (Pedregosa et al., 2011).

D.3 Embedding Shift

We learned embedding shift using logistic regression from scikit-learn. Of note, the models can sometimes be sensitive to the intensity parameter $i$. We used validation to identify the best value: typically either 5 and 10 performed best. We also borrowed extensively from the GitHub repository from Hamilton et al. (2016b) for embedding manipulation.11

11https://github.com/williamleif/histwords
### Progressive

| Event                             | Dates          | Total Days | Train Days | Test Days | # Labeled | # Unlabeled |
|-----------------------------------|----------------|------------|------------|-----------|-----------|-------------|
| Colorado floods                   | 09.08.13-10.01.13 | 19         | 3          | 16        | 1019      | 1231        |
| Sardinia floods                   | 11.16.13-11.28.13 | 13         | 4          | 9         | 1013      | 824         |
| Philippines floods                | 08.07.12-08.15.12 | 13         | 5          | 8         | 1013      | 1341        |
| Alberta floods                    | 06.20.13-07.16.13 | 24         | 2          | 22        | 1024      | 4040        |
| Manila flood                      | 08.17.13-08.27.13 | 11         | 3          | 8         | 1011      | 1068        |
| Queensland floods                 | 01.17.13-02.05.13 | 19         | 10         | 9         | 1219      | 727         |
| Typhoon Yolanda                   | 05.11.13-12.30.13 | 53         | 6          | 47        | 1099      | 253         |
| Australia bushfire                | 10.12.13-11.03.13 | 22         | 6          | 16        | 1221      | 1244        |
| Colorado wildfires                | 06.12.13-07.08.12 | 31         | 13         | 18        | 1231      | 2901        |
| Singapore haze                    | 06.14.13-07.04.13 | 18         | 6          | 12        | 1018      | 1572        |

### Instantaneous

| Event                             | Dates          | Continuous | Total Days | Train Days | Test Days | # Labeled | # Unlabeled |
|-----------------------------------|----------------|------------|------------|------------|-----------|-----------|-------------|
| Italy earthquakes                 | 05.18.12-06.14.12 | 28         | 4          | 24         | 1028      | 5219      |
| Costa Rica earthquake             | 09.05.12-09.21.12 | 18         | 2          | 16         | 1430      | 1641      |
| Bohol earthquake                  | 10.14.13-10.25.13 | 12         | 2          | 10         | 1012      | 1131      |
| Guatemala earthquake              | 11.06.12-11.25.12 | 20         | 2          | 18         | 1070      | 2233      |
| LA airport shootings              | 11.01.13-11.12.13 | 12         | 1          | 11         | 1044      | 1737      |
| Boston bombings                   | 04.15.13-06.11.13 | 46         | 1          | 45         | 1046      | 81172     |
| West Texas explosion              | 04.18.13-05.15.13 | 27         | 1          | 26         | 1027      | 8152      |
| Venezuela refinery                 | 12.08.24-12.09.05 | 13         | 3          | 10         | 1013      | 2007      |
| Brazil nightclub fire             | 01.27.13-02.11.13 | 16         | 1          | 15         | 1016      | 2644      |
| Savar building collapse           | 04.23.13-06.01.13 | 39         | 5          | 34         | 1289      | 2646      |
| Spain train crash                 | 07.24.13-08.07.13 | 14         | 1          | 13         | 1014      | 2288      |
| Lac Megantic train crash          | 07.06.12-07.26.12 | 21         | 2          | 19         | 1021      | 1755      |
| NY train crash                    | 12.01.13-12.08.13 | 9          | 1          | 7          | 1008      | 667       |
| Glasgow helicopter crash          | 11.29.13-12.29.13 | 30         | 2          | 28         | 1130      | 1541      |
| Russia meteor                     | 02.14.13-03.05.13 | 19         | 2          | 17         | 1461      | 4289      |

Table 3: Summary of the T26 datasets. Training data was split such that the training days encompass at least 25% of the data. Thus, some events had only one day of training, while others had many.

| Event                             | Baseline | Baseline + SSSA | Baseline + SHIFT | TARGET | TARGET + SSSA | TARGET + SHIFT | TIME | TIME + SSSA | TIME + SHIFT |
|-----------------------------------|----------|-----------------|-----------------|--------|---------------|---------------|------|-------------|--------------|
| Colorado floods                   | 45.24    | -3.22           | 0.75            | 0.38   | -3.46         | -1.73         | 1.44 | -5.53       | -5.70        |
| Sardinia floods                   | 43.77    | -4.05           | -0.01           | 2.01   | 0.30          | 1.67          | -1.17| -2.22       | -0.20        |
| Philippines floods                | 48.30    | -14.91          | 4.39            | 4.51   | -14.40        | 0.71          | -4.16| -13.00      | 1.25         |
| Alberta floods                    | 52.64    | -11.88          | 0.41            | 3.79   | -13.23        | 2.41          | 4.60 | -9.27       | 4.13         |
| Manila floods                     | 50.11    | -33.40          | 0.53            | 20.43  | -33.17        | -0.65         | -21.85| 25.04       |              |
| Queensland floods                 | 64.96    | -15.02          | -1.02           | -0.98  | -11.53        | -1.28         | 1.72 | -21.52      | 2.36         |
| Typhoon Yolanda                   | 54.90    | -2.07           | 4.10            | 0.66   | -0.95         | 2.40          | -5.11| 2.59        |              |
| Australia bushfire                | 70.29    | -15.98          | 0.11            | -1.50  | -16.73        | -0.40         | -16.73| -0.88       |              |
| Colorado wildfires                | 57.70    | -10.94          | 3.32            | -2.08  | -13.61        | -3.15         | 0.79 | -9.48       | 0.61         |
| Singapore haze                    | 54.04    | -7.85           | -0.57           | 0.93   | -4.96         | -0.01         | 2.30 | -7.24       | -1.27        |

Table 4: Baseline and difference (Macro F1) for each event type in the T26 dataset. Note that six events in the Instantaneous category had only one day of training day, prohibiting the usage of embedding shift.