Unsupervised and Interpretable Domain Adaptation to Rapidly Filter Social Web Data for Emergency Services

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ABSTRACT
During the onset of a natural or man-made disaster event, public often share relevant information for emergency services on social web platforms. However, filtering relevant information from the social web data is challenging due to its sparse availability, and also, practical limitations in training an efficient filtering model that requires large labeled datasets of an ongoing crisis. In this paper, we hypothesize that unsupervised domain adaptation through multi-task learning can be a useful framework to leverage data from past crisis events, as well as exploit additional web resources for training efficient information filtering models during an ongoing crisis. We present a novel method to classify relevant social web posts during an ongoing crisis without seeing any new examples (unsupervised domain adaptation), using the publicly available dataset of TREC incident streams that provides labeled Twitter posts (tweets) with relevant classes (Priority, Factoid, Sentiment) across 10 different crisis events such as Floods, Earthquakes, and Shootings. Additionally, our method addresses a crucial but missing component from current research in web science for crisis data filtering models: interpretability. Specifically, we first identify a standard single-task attention-based neural network architecture and then construct a customized multi-task architecture for the crisis domain: multi-task domain adversarial attention network (MT-DAAN). This model consists of dedicated attention layers for each task and a domain classifier for gradient reversal. Evaluation of domain adaptation for crisis events is performed by choosing a target event as the test set and training on the rest. Our results show that the multi-task model outperformed its single-task counterpart and also, training with additional web-resources (such as amazon reviews and sentiment140 datasets) showed further performance boost for crisis data filtering. For the qualitative evaluation of interpretability, we show that the attention layer can be used as a guide to explain the model predictions and empower emergency services for exploring accountability of the data filtering model, by showcasing the words in a tweet that are deemed important in the classification process. Our research aims to pave the way towards a fully unsupervised and interpretable domain adaptation of low-resource crisis-related web data to aid emergency services in acquiring relevant information for quicker and effective response.

KEYWORDS
Social Media Analytics, Crisis Management, Attention, Domain Adaptation, Interpretability

1 INTRODUCTION
During the sudden onset of a crisis situation, social media platforms such as Twitter provide extremely valuable information to aid crisis response organizations in gaining real-time situational awareness. Effective analysis of important information such as affected individuals, infrastructure damage, medical emergencies, or food and shelter needs can help emergency responders to make time-critical decisions and allocate resources in the most efficient and effective manner [1, 14, 17, 18, 31, 36–38].

Several machine learning systems have been deployed to help towards this humanitarian goal of converting real-time social media streams into actionable knowledge. Classification being the most common task, researchers have designed models [2, 13, 18, 24, 27, 28] that classify tweets into various categories such as priority, affected individuals, type of damage, type of assistance needed, usefulness of the tweet, etc. Social media streams are short, informal, and abbreviated; with potential linguistic errors and sometimes contextually ambiguous. These inherently challenging properties of tweets make their classification task and formulation less trivial when compared to traditional text classification tasks.

In this paper, we address two practically important and underdeveloped aspects of current research in the crisis-domain to classify relevant social web posts (e.g., "@<a> please send medical supplies, paramedics, temporary shelters Asap #NepalQuakeRelief"): a) a fully unsupervised domain adaptation and b) interpretability of predictions. A fully unsupervised domain adaptation uses no data from the ongoing crisis to train the model. Nguyen et al. showed that their convolutional neural network (CNN) model does not require feature engineering and performed better than the state-of-the-art methods; one of their models being completely unsupervised [27]. Similarly, Alam et al. designed a CNN architecture with adversarial training on graph embeddings, but utilizing unlabeled target data [2]. Our goal is to construct an unsupervised model that does not use any unlabeled target data with the capability of being interpretable. We specifically address the problem of data sparsity and limited labels by designing a multi-tasking model and expanding it with additional web resources; which to the authors’ knowledge is not explored in the crisis domain. Another crucial component of our model is interpretability. In prior works, when a top performing model produces an accuracy of 78%, for instance, it is unclear what that score really represent and how trustworthy it is. An interpretable model like ours can present with a convincing evidence of which words the classifier deems important when making a certain prediction. This also brings additional benefits of using them in downstream tasks such as knowledge graph construction.
Contributions: a) We construct a customized multi-task learning architecture (MT-DAAN) to filter social web data for the crisis domain by training four different classification tasks (c.f. examples in Figure 2) across ten different crisis events under domain shift. This multi-task domain adversarial model consists of dedicated attention layers for each task for interpretability and a domain classifier for gradient reversal. b) We present novel insights on how additional web-resources such as online reviews can be exploited to further strengthen the model in times of data sparsity and limited labels. c) We demonstrate that the attention layers provide interpretability for the predictions made by the classifiers; with the goal to aid emergency services in a more meaningful way. d) Additionally, we empirically validate the performance of the underlying single-task attention-based neural network architecture by comparing it to the state-of-the-art methods, for improving generalizability and interpretability for domain adaptation in unsupervised tweet classification tasks in general.

The rest of the paper is organized as follows. Section 2 presents architecturally related works: attention, domain adaptation, and Multi-Task Learning, Section 3 presents the methodology: MT-DAAN. Section 4 presents the experimental evaluation. Finally, the results are discussed in section 5, future directions in section 6, and conclusion in section 7.

2 RELATED WORK AND BACKGROUND

Attention: Attention mechanism [3, 23], originally designed for machine translation problems, has become one of the most successful and widely used methods in deep learning for improving interpretability. This is particularly because of its ability to construct a context vector by weighing on the entire input sequence unlike previous sequence-to-sequence models [35] that used only the last hidden state of the encoder network (typically BiLSTM [34], LSTM [12], or GRU [8]). For example, in a sentence, the context vector is a dot product of the word activations and weights associated with each word; thus leading to an improved contextual memorization, especially for long sentences. Our method incorporates such attention mechanism to enhance interpretability of the data classification model.

Domain Adaptation: Domain Adaptation in text classification tasks has a long line of fruitful research [4, 6, 7, 29, 39] that try to minimize the difference between the domains so that the model trained solely on one domain is generalizable to the unseen test data from a completely different domain. With the introduction of Domain-Adversarial training of Neural Networks (DANN) [9], many state-of-the-art models now utilize unlabeled target data to train classifiers that are indiscriminate toward different domains. The speciality of this architecture is that it consists of an extra branch, which performs domain classification using unlabeled data from different domains. Thus, both task and domain classifiers share some bottom layers but have separate layers towards the top. A negative gradient (gradient reversal) from the domain classifier branch is back-propagated to promote the features at the lower layers of the network incapable of discriminating the domains. Recent works such as Adversarial Memory Network (AMN) [20], utilizes attention, in addition to DANN, to bring interpretability to capture the pivots for sentiment classification. Hierarchical Attention Network (HATN) [19] expands upon AMN by first extracting pivots and then jointly training a pivot and a non-pivot networks.

For filtering social web data for crisis domain, these models do not suffice and need customized expansions due to the following reasons. Collecting and using large unlabeled target data from the new/ongoing crisis event may not be practically viable, thus, we aim for a fully unsupervised modeling. Having access to unlabeled data from multiple crisis events can alleviate the above problem to an extent by using it to train the domain classifier branch. Also, due to the low-resource nature of the dataset, binary classifiers may miss important lower level features that can be potentially improved by a multi-task model that shares the lower layers of the network for all the tasks.

Multi-Task Learning: Multi-Task Learning (MTL) solves multiple tasks at the same time with a goal to improve the overall generalization capability of the model which is crucial for domain adaptation tasks in general. In Deep Learning, MTL is performed by sharing (or constraining) lower level layers and using dedicated upper level layers for various tasks. This has been a successful strategy over the past few years for many research explorations such as relationship networks [22] in computer vision and shice networks [33] in Natural Language Processing (NLP). Similar problems in domain adaptation of semantic classification and information retrieval was addressed by jointly learning to leverage large amounts of cross-task data [21]. In low resource datasets such as the crisis data, the chance of overfitting is very high. For this specific reason, it seems intuitively better for the model to find a shared representation that captures all the different tasks and not just one.

3 METHODOLOGY

3.1 Problem: Unsupervised Domain Adaptation for Crisis Tweet Classification

Table 1: Notations

| Notation | Definition |
|----------|------------|
| $C$ | Set of all crisis events $\{c_1, c_2, \ldots, c_m\}$ |
| $L_{c_k}$ | Set of labeled data from the event $c_k$ |
| $y_{c_k}$ | Set of ground truth labels for $L_{c_k}$ |
| $m$ | Number of tasks (Number of bits in each label) |
| $U_{c_k}$ | Set of unlabeled data from the event $c_k$ |
| $T_k$ | Number of words in a sentence |
| $x^{<k>}$ | $k$-th word of a sentence |
| $\alpha^{<k>}$ | attention from $k$-th word |
| $a^{<k>}$ | BiLSTM activation from $k$-th word |

Using notations in table 1, consider a set $C$ of all crisis events such as Guatemala Earthquake or Typhoon Yolanda. The task of unsupervised crisis domain adaptation is to train a classifier for a specific target crisis $c_t$ using labeled ($L_{C=c_t}$) and unlabeled ($U_{C=c_t}$) data from all other crises. It does not use any data records from the target crisis to train the classifier. In traditional domain adaptation terminology, $X_s = L_{C=c_t}$, represents the labeled data from the source
Figure 1: Multi-Task Crisis Tweet Classification with Domain Adversarial Training. $m$ = Number of Tasks. GRL = Gradient Reversal Layer. ATT = Attention Block.

3.2 Multi-Task Domain Adversarial Attention Network (MT-DAAN)

To align with our goals of interpretability and unsupervised domain adaptation, we adopt the single-task attention network of [16] that performs unsupervised domain adaptation. This standard BiLSTM + Attention model gives us three main advantages:

(1) There is no need to train with unlabeled target data. Many existing domain adaptation methods for text use unlabeled target data to train the domain adversarial component via gradient reversal. We prefer a fully unsupervised baseline so that it can be customized for multi-task learning.

(2) The method uses attention mechanism which in turn weighs each word in a sentence based on its importance. This can be directly utilized for interpretability.

(3) The method also runs much faster (only a few minutes) as compared to the top performing semi-supervised models such as HATN [19] (hours).

This model [16] consists of a BiLSTM layer which produces $T_x$ activations, each corresponding to a word in the sentence. These activations are passed through dense and softmax layers and are combined by dot product to produce the context vector $\sum_{k=1}^{T_x} a^{<k>} a^{<k>}$, where $a^{<k>}$ is the BiLSTM activation from $k$-th word and $a^{<k>}$ is the attention weight of $k$-th word. Sentences with words greater than $T_x$ are stripped and those with words lower than $T_x$ are padded. This model is a combination of the bottom BiLSTM layer plus one of the attention branches shown in Figure 1.

Using this single-task architecture as the building block, we construct MT-DAAN, which is intended to classify problems with multiple tasks or labels. For each task, a dedicated attention layer is allocated from which it predicts binary labels as shown in Figure 1. The BiLSTM layer remains exactly the same as in the single-task model but multiple attention blocks are added for each task along with a domain classifier. In the architecture decision process, we first investigated a multi-label classifier where all layers are shared with the final softmax layer making multi-label predictions. In low resource settings, constructing a multi-label classifier using a shared architecture is challenging for two reasons: a) jointly balancing positive and negative samples across all classes is not trivial and potentially challenging to make it extensible when new classes need.
### Table 2: TREC Dataset Statistics; Showing the number of positive samples for each of the 4 classes

| CRISIS EVENTS                  | Total Tweets | Vocab #words | Avg #words | Priority | Factoid | Sentiment | Irrelevant |
|-------------------------------|--------------|--------------|------------|----------|---------|-----------|------------|
| 2012 Guatemala Earthquake      | 154          | 442          | 18.74      | 104      | 108     | 12        | 15         |
| 2013 Typhoon Yolanda          | 564          | 1746         | 19.47      | 249      | 46      | 119       | 51         |
| 2013 Australia Bushfire        | 677          | 2102         | 20.21      | 152      | 213     | 167       | 36         |
| 2013 Boston Bombings          | 535          | 1755         | 19.30      | 147      | 28      | 234       | 198        |
| 2013 Queensland Floods        | 713          | 2301         | 19.08      | 293      | 54      | 173       | 215        |
| 2014 Chile Earthquake         | 311          | 919          | 16.54      | 48       | 26      | 50        | 10         |
| 2014 Typhoon Hagupit          | 1470         | 2893         | 15.36      | 469      | 375     | 276       | 101        |
| 2015 Nepal Earthquake         | 2048         | 4026         | 13.77      | 1067     | 377     | 741       | 133        |
| 2015 Paris Attacks            | 2066         | 4152         | 18.62      | 306      | 183     | 782       | 429        |
| 2018 Florida School Shooting  | 1118         | 2940         | 21.40      | 329      | 64      | 206       | 70         |

### Table 3: Implementation Details

| Parameter       | Value  |
|-----------------|--------|
| $T_y$           | 5      |
| $T_x$           | 200    |
| Deep Learning Library | Keras |
| Optimizer       | Adam $[lr = 0.005, \beta_1 = 0.9, \beta_2 = 0.999, \text{decay} = 0.01]$ |
| Maximum Epoch   | 40     |
| Dropout         | 0.4    |
| Early Stopping Patience | 3     |
| Batch Size      | 32     |
| Validation Split| 0.15   |

4 DATASETS

4.1 TREC Dataset

TREC-IS\(^2\) (Text Retrieval Conference - Incident Streams) is a program that encourages research in information retrieval from social media posts with the goal to improve the state-of-the-art social media crisis monitoring solutions. We use the dataset from 2018 track proposal. Statistics of this curated dataset of twitter streams downloaded from TREC is shown in Figure 2. The original dataset consisted of 15 crisis events. However, due to very low data, we trimmed the events and tasks such that there are at least 10 positive samples for each task.

The four tasks/classes used in our experiments are shown below:

1. **Priority**: Different priority levels are assigned for each tweet: low, medium, high, critical. We convert this into a binary classification problem where low = 0 and (medium, high, critical) = 1.
2. **Factoid**: ‘Factoid’ is a categorical label that represents if a tweet is stating a fact. Eg: ‘death toll rises in event X...’
3. **Sentiment**: ‘Sentiment’ is a categorical label that represents if a tweet represents a sentiment. Eg: ‘Worried. Thoughts and prayers.’
4. **Irrelevant**: ‘Irrelevant’ is a categorical label that represents if a tweet is irrelevant.

4.2 Amazon Reviews

The standard benchmark dataset\(^3\) of Amazon reviews [5] is widely used for cross-domain sentiment analysis. We chose four domains: Books (B), Kitchen (K), DVD (D), and Electronics (E). The raw data\(^4\), a part of Blitzer’’s original raw dataset, used in this work is from HATN [19]. This dataset consists of 3000 positive and 3000 negative samples for each of the 4 domains.

4.3 Sentiment140

Sentiment140\(^5\) dataset is an automatically constructed dataset (rather than human labeled) with positive and negative labels based on the emotions in the tweets [11]. We randomly sample 2000 each

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\(^1\)http://dcs.gla.ac.uk/~richardm/TREC_IS/
\(^2\)http://dcs.gla.ac.uk/~richardm/TREC_IS/
\(^3\)http://dcs.gla.ac.uk/~mdredze/datasets/sentiment/
\(^4\)https://github.com/hsqmlzno1/HATN/tree/master/raw_data
\(^5\)http://help.sentiment140.com/for-students
of positive and negative tweets for multi-tasking training of TREC dataset.

4.4 Pre-processing
A tweet, as it gets broken down into tokens, undergoes the following pre-processing steps:

1. Contraction such as didn’t is expanded to did not using a basic English contractions dictionary.
2. Simple misspellings are corrected. For example, words with 3 of the same characters appearing consecutively like good is changed to good.
3. Numbers and words with no alpha-numeric characters are converted to special tags.
4. Hashtags (or just the # symbol) can optionally be removed.
5. Stop words are selectively removed keeping words such as ‘but’ and ‘not’ which can impact sentiment phrases such as ‘not good’.

4.5 Choice of Word Embeddings
We use fastText[25] as our word embeddings for tweets because of its sub-word usage and the ability to create vectors for arbitrary and out-of-vocabulary words. Although there exists many alternatives, picking the one that works well for a specific dataset is not trivial. In the next section we compare and contrast the performance of three more options for word vectors: a) GoogleNews [26] vectors as used in the single-task evaluation, b) GloVe Twitter Embeddings [30], and c) CrisisNLP Embeddings [15]. Unlike fastText, we fine-tune these pre-trained vectors using Gensim [32] to create vectors for out-of-vocabulary words. Vectors for words that are already in the vocabulary are locked while tuning for consistency in evaluation.

5 RESULTS & DISCUSSION
For all our experiments, reported scores are based on an average of 5 independent runs of each experiment.

5.1 Validation of Single-Task Architecture
We first validate the performance of the adopted single-task model [16] by comparing it with the following standard neural network architectures and state-of-the-art models used for domain adaption in text. We use the standard benchmark dataset of Amazon reviews. Following the traditional domain adaptation experimental setup, each experiment represented as S → T consists of a source domain (S) on which the model is trained and a target domain (T) on which the model is tested. Implementation details is shown in Table 3.

1. CNN: A standard Convolutional Neural Network is constructed with the following architecture:

Word Embeddings(Tx, 300) → Conv1D(128, 5)
→ MaxPooling1D(5) → Conv1D(128, 5)
→ MaxPooling1D(5) → Conv1D(128, 5)
→ GlobalMaxPooling1D() → Dense(128)
→ Dense(2) → y.

This is combined with dropouts, relu activations, and ending with softmax activation producing labels for binary classification. State-of-the-art deep learning methods [2, 27] in the crisis domain use a similar architecture.

Table 4: Performance comparison (% Accuracy) of the standard single-task model with state-of-the-art models on the standard benchmark dataset of Amazon reviews.

| Model          | CNN | BiLSTM | AMN | HATN | BiLSTM+ATT |
|----------------|-----|--------|-----|------|-----------|
| S → T          |     |        |     |      |           |
| B → K          | 81.20 | 84.45  | 81.88 | 87.03 | 87.22     |
| B → E          | 80.44 | 84.61  | 80.55 | 85.75 | 85.51     |
| B → D          | 82.94 | 83.52  | 85.62 | 87.07 | 86.32     |
| K → B          | 78.78 | 80.67  | 79.05 | 84.88 | 81.85     |
| K → E          | 85.17 | 87.37  | 86.68 | 89.00 | 87.09     |
| K → D          | 76.41 | 78.49  | 79.50 | 84.72 | 81.13     |
| E → B          | 78.08 | 81.18  | 77.52 | 84.03 | 81.50     |
| E → K          | 86.59 | 89.00  | 87.83 | 90.08 | 89.21     |
| E → D          | 78.35 | 78.46  | 85.03 | 84.32 | 81.37     |
| D → B          | 82.26 | 84.83  | 84.53 | 87.78 | 87.02     |
| D → K          | 81.09 | 85.21  | 83.67 | 87.47 | 86.37     |
| D → E          | 79.56 | 83.66  | 80.42 | 86.32 | 85.63     |
| AVG            | 80.91 | 83.45  | 82.52 | 86.54 | 85.02     |

(2) BiLSTM: This is the bottom most layer in Figure 1 with the activation $a^{<T_2>}$ passed through the following: Dense(10) → Dense(2) → y also including dropouts, relu activation, and ending with softmax.

(3) AMN and HATN: AMN [20] and HATN [19] are attention-based methods which use gradient reversal to perform domain adversarial training on the unlabeled data from source and target domains. HATN is an extension to AMN by adding the hierarchical component and jointly training a pivot and a non-pivot networks.

Input to all the models are word vectors5 [26]. This evaluation on Amazon reviews is conducted to show the single-task model’s universal usability for domain adaptation of text classification tasks in general and not just crisis data. This shows how well it can perform when compared with the existing top-performing benchmark models on standardized datasets. Table 4 shows accuracy scores on the Amazon cross-domain sentiment analysis dataset. HATN uses unlabeled target data, gradient reversal, explicit pivot extraction, and joint training making it a computationally expensive method. As shown in the experimental evaluation, we use the same Amazon dataset and GoogleNews word vectors for our experiments. Our baseline model, being unsupervised with no need of unlabeled target data, performed competitively with an overall accuracy of 85.02%.

5.2 MT-DAAN Performance Evaluation
The primary purpose of the MT-DAAN model is to show that sharing the bottom layer of the model (i.e., shared representation) for different tasks along with domain adversarial training can help improve the generalizability of some of the tasks that are otherwise trained alone in the single-task model. The experiments for MT-DAAN are setup in the same unsupervised way as for single-task.

5https://code.google.com/archive/p/word2vec/
Table 5: Crisis Tweet Classification Results: Comparison of Single-Task versus Multi-Task models.

| TARGET                        | Priority | Factoid | Single-Task | Multi-Task |
|-------------------------------|----------|---------|-------------|------------|
|                               | Acc F1   | Acc F1  | Acc F1      | Acc F1     |
| 2012 Guatemala Earthquake     | 59.97±4.0 | 62.39±4.6 | 69.05±2.1 | 69.34±1.5 |
| 2013 Typhoon Yolanda          | 65.53±0.3 | 65.47±0.7 | 67.42±0.8 | 67.30±0.8 |
| 2013 Australia Bushfire       | 62.44±2.5 | 66.69±0.9 | 61.93±2.7 | 64.28±2.8 |
| 2013 Boston Bombings          | 72.08±1.1 | 74.29±2.5 | 73.80±1.2 | 74.74±1.1 |
| 2013 Queensland Floods       | 66.21±0.6 | 65.94±0.7 | 66.74±1.9 | 66.46±2.1 |
| 2014 Chile Earthquake         | 39.23±3.9 | 40.92±4.9 | 41.80±7.1 | 46.33±8.8 |
| 2014 Typhoon Hagupit          | 52.61±1.9 | 50.59±4.4 | 57.50±1.7 | 57.52±2.1 |
| 2015 Nepal Earthquake         | 61.35±0.5 | 59.64±1.8 | 61.65±1.5 | 59.49±2.3 |
| 2015 Paris Attacks            | 71.31±1.8 | 76.26±2.4 | 74.44±2.3 | 77.21±1.6 |
| 2018 Florida School Shooting  | 60.55±0.3 | 61.75±0.6 | 62.51±1.6 | 63.24±1.2 |
| **AVG**                      | 61.13±1.7 | 62.37±2.4 | 63.68±2.3 | 65.49±2.4 |

Table 6: Performance increases when additional web data is added for classifying TREC Priority task.

| TARGET                        | Single-Task | Multi-Task (MTL) | MTL+Amazon | MTL+Sentiment140 |
|-------------------------------|-------------|------------------|------------|------------------|
|                               | Acc F1      | Acc F1           | Acc F1     | Acc F1           |
| 2012 Guatemala Earthquake     | 59.97±4.0   | 62.39±4.6        | 69.05±2.1  | 69.34±1.5        |
| 2013 Typhoon Yolanda          | 65.53±0.3   | 65.47±0.7        | 67.42±0.8  | 67.30±0.8        |
| 2013 Australia Bushfire       | 62.44±2.5   | 66.69±0.9        | 61.93±2.7  | 64.28±2.8        |
| 2013 Boston Bombings          | 72.08±1.1   | 74.29±2.5        | 73.80±1.2  | 74.74±1.1        |
| 2013 Queensland Floods       | 66.21±0.6   | 65.94±0.7        | 66.74±1.9  | 66.46±2.1        |
| 2014 Chile Earthquake         | 39.23±3.9   | 40.92±4.9        | 41.80±7.1  | 46.33±8.8        |
| 2014 Typhoon Hagupit          | 52.61±1.9   | 50.59±4.4        | 57.50±1.7  | 57.52±2.1        |
| 2015 Nepal Earthquake         | 61.35±0.5   | 59.64±1.8        | 61.65±1.5  | 59.49±2.3        |
| 2015 Paris Attacks            | 71.31±1.8   | 76.26±2.4        | 74.44±2.3  | 77.21±1.6        |
| 2018 Florida School Shooting  | 60.55±0.3   | 61.75±0.6        | 62.51±1.6  | 63.24±1.2        |
| **AVG**                      | 61.13±1.7   | 62.37±2.4        | 63.68±2.3  | 65.49±2.4        |

No data from the test crisis is used for training. For example, if we are testing our model for the event ‘Typhoon Yolanda’, no data from this crisis is used for training. Note that the domain classifier component uses unlabeled data only from rest of the crisis; making it a fully unsupervised domain adaptation approach.

Performance scores of the four tasks (Priority, Factoid, Sentiment, and Irrelevant) are shown in Table 5. The results show clear performance improvement for Priority, Factoid, and Irrelevant tasks. However, Sentiment task did not show significant improvement. We speculate that this is because other tasks do not generalize the bottom layer enough to boost the sentiment classification performance. These results show the usefulness of multi-tasking where different tasks help each other when the data is sparse and labels are limited.

5.3 MT-DAAN with Additional Web Datasets

In order to understand if additional web resources can further improve the performance of MT-DAAN, we expand it by adding data from Amazon review dataset and Sentiment140 dataset.

Architecturally, this adds two more attention branches in Figure 1 and two more domains for the domain classifier. We select **Priority** as our primary classification task and design 5 more experiments:

1. Single Task: Train solely on Priority.
2. MTL: Multi-Task Learning where other classes such as Factoid, Sentiment, and Irrelevant are jointly trained.
3. MTL+Amazon: Multi-Task Learning with an additional task to jointly train and classify Amazon reviews.
4. MTL+Sentiment140: Multi-Task Learning with an additional task to jointly train and classify Sentiment140 positive/negative reviews.

Results are shown in Table 6. Both Amazon reviews and Sentiment140 datasets proved to be useful additions to the MTL setup showing that adding additional web resources may in fact help.

5.4 Word Vectors

We conducted experiments to classify TREC Sentiment tweets using four choices of word embeddings: fastText [25], GoogleNews
Table 7: Comparison of four relevant word embedding models on TREC Sentiment task.

| TARGET                  | fastText [25]     | GoogleNews [26]     | Glove [30]          | CrisisNLP [15]        |
|-------------------------|-------------------|---------------------|---------------------|-----------------------|
|                         | Acc ± | F1     | Acc ± | F1     | Acc ± | F1     | Acc ± | F1     | Acc ± | F1     | Acc ± | F1     | Acc ± | F1     | Acc ± | F1     |
| 2012 Guatemala Earthquake | 95.72±0.9 | 96.22±0.8 | 95.27±0.6 | 96.13±0.8 | 97.97±0.6 | 98.04±0.5 | 92.60 | 79.35 | 84.25 | 77.43 | 80.20 | 66.97 | 96.96 | 97.97 |
| 2013 Typhoon Yolanda     | 75.81±1.1 | 77.62±1.6 | 83.30±0.6 | 84.56±1.6 | 86.49±0.3 | 86.27±0.8 | 79.41 | 80.41 | 66.84 | 79.66 | 81.60 | 81.22 | 81.60 | 81.22 |
| 2013 Australia Bushfire   | 75.95±1.5 | 77.58±0.7 | 79.35±0.5 | 79.32±0.6 | 80.24±0.3 | 79.64±0.7 | 75.86 | 75.79 | 67.75 | 75.81 | 68.77 | 81.39 | 77.43 | 77.43 |
| 2013 Boston Bombings     | 81.99±0.6 | 81.11±1.0 | 82.43±0.7 | 82.56±0.9 | 80.55±0.3 | 80.45±0.5 | 81.16 | 81.22 | 81.39 | 81.22 | 81.50 | 81.22 | 81.50 | 81.22 |
| 2013 Queensland Floods   | 81.69±0.5 | 80.39±1.0 | 84.06±0.1 | 83.26±0.6 | 84.01±0.1 | 83.27±0.4 | 81.50 | 79.66 | 81.60 | 79.66 | 81.50 | 79.66 | 81.50 | 79.66 |
| 2014 Chile Earthquake    | 92.69±0.3 | 92.91±0.2 | 92.82±0.3 | 92.57±0.3 | 92.93±0.0 | 92.98±0.5 | 92.60 | 93.01 | 92.60 | 93.01 | 92.60 | 93.01 | 92.60 | 93.01 |
| 2014 Typhoon Hagupit      | 84.98±0.9 | 85.86±0.8 | 87.55±0.5 | 87.90±0.7 | 84.25±0.8 | 84.72±0.6 | 88.76 | 88.83 | 69.88 | 77.63 | 74.21 | 74.21 | 67.50 | 67.82 |
| 2015 Nepal Earthquake     | 67.71±1.7 | 68.42±2.6 | 68.46±1.0 | 67.48±1.0 | 73.63±0.4 | 74.21±0.6 | 67.50 | 67.82 | 69.43 | 74.21 | 74.21 | 74.21 | 67.50 | 67.82 |
| 2015 Paris Attacks        | 76.01±0.4 | 76.63±0.4 | 77.67±0.4 | 77.63±0.6 | 74.49±0.9 | 74.52±0.6 | 77.43 | 77.63 | 69.43 | 74.52 | 74.52 | 74.52 | 77.43 | 77.63 |
| 2018 Florida School Shooting | 68.77±2.3 | 71.77±2.2 | 66.84±1.3 | 69.88±1.3 | 66.97±0.6 | 69.43±0.3 | 65.06±1.0 | 70.43±2.2 |
| AVG                     | 80.93±1.1 | 82.94±0.7 | 81.82±0.6 | 82.09±0.7 | 81.88±0.4 | 82.16±0.9 | 80.73±0.4 | 81.29±0.8 |

[26], Glove [30], and CrisisNLP [15]. Their performance is shown in Table 7. All of them performed similarly with Glove performing slightly better than the rest. Glove vectors are 200-dimensional while the rest are 300-dimensional which also makes the experiment favoring Glove word vectors. This experiment shows that the problem of finding a good word vector model for tweets still remains a challenging task.

5.5 Interpretability: Attention Visualization

The attention weights used to create the context vector by the dot product operation with word activations represent the interpretable layer in our architecture. These weights represent the importance of each word in the classification process. Some examples are shown in Figure 2. Stronger the color intensity stronger the word attention. In the first example, ‘boston police urging’ is the reason why the tweet is classified as +ve priority. Similarly, ‘death toll rises’ in the Factoid example, ‘worried, prayers’ in the Sentiment example, and ‘thoughts with people’ in the Irrelevant example are clear intuitive indicators of +ve predictions. These examples show the importance of having interpretable components as a key criterion in crisis domain adaptation tasks.

6 FUTURE WORK

Empirical evaluation of word vector models showed that for practical purposes with challenging datasets, tweet-trained models such as Glove or CrisisNLP did not significantly outperform other models such as fastText or GoogleNews vectors. This calls for further investigation to improve word embeddings for tweets, specifically in low resource setting. Another direction is to address the non-transferable components. For example, Sentiment is easier to detect than Factoid because there is more linguistic overlap in how sentiments are expressed in different domains. However, Factoid phrases such as ‘Indian army names aid mission’ shown in Figure 2 are more challenging to find transferable representation. This calls for methods such as a combination of named entity recognition and transfer learning in the crisis domain; which is not currently attempted.

7 CONCLUSION

We presented a novel unsupervised domain adaptation with multi-task learning approach to filter crisis-related social web data. We expanded upon a single-task model to construct a multi-task model that consists of dedicated attention layers for each task and a domain classifier for gradient reversal. We showed that a multi-task model that shares the lower layers of the network for different tasks can help improve generalizability. Additionally, we showed that using additional web data can improve the performance of the multi-task model addressing data sparsity and limited label problems. Further more, we showed that using an attention-based architecture can help in interpreting the classifier’s predictions by

Figure 2: Examples of attended words. Recall that no data from the tested crisis is used for training the model. Even then, interpretable keywords such as ‘police urging’, ‘death toll rises’, ‘worried’, and ‘thoughts with people’ are correctly picked up by the attention layer.
highlighting the important words that justify the prediction. We also presented an in-depth empirical analysis of the underlying single-task attention-based neural network architecture from prior work for a fully unsupervised domain adaptation of tweet classification problems with the power to generalize better and interpret the predictions. The application of our generic approach for interpretable and unsupervised domain adaptation with multi-task learning for social web data filtering can benefit social media analytics systems in diverse domains beyond crisis management.

Reproducibility: Source code and instructions for deployment are available at https://github.com/jitinkrishnan/Crisis-Tweet-Multi-Task-DA.

REFERENCES

[1] Adam Acar and Yuya Muraki. 2011. Twitter for crisis communication: lessons learned from Japan’s tsunami disaster. International Journal of Web Based Communities 7, 3 (2011), 392–402.

[2] Firoj Alam, Shaﬁq Joty, and Muhammad Imran. 2018. Domain adaptation with adversarial training and graph embeddings. arXiv preprint arXiv:1805.05151 (2018).

[3] Dimitry Bahdanau, Kyunghyun Cho, and Yoshua Bengio. 2014. Neural machine translation by jointly learning to align and translate. arXiv preprint arXiv:1409.0473 (2014).

[4] Shai Ben-David, John Blitzer, Koby Crammer, and Fernando Pereira. 2007. Analysis of representations for domain adaptation. In Advances in neural information processing systems. 137–144.

[5] John Blitzer, Mark Dredze, and Fernando Pereira. 2007. Biographies, hollywood, boom-boxes and blenders: Domain adaptation for sentiment classiﬁcation. In Proceedings of the 45th annual meeting of the association of computational linguistics. 440–447.

[6] John Blitzer, Ryan McDonald, and Fernando Pereira. 2006. Domain adaptation with structural correspondence learning. In Proceedings of the 2006 conference on empirical methods in natural language processing. 120–128.

[7] Minmin Chen, Zhiyuan Lu, Kilian Weinberger, and Fei Sha. 2012. Marginalized denoising autoencoders for domain adaptation. arXiv preprint arXiv:1206.6803 (2012).

[8] Junyoung Chung, Caglar Gulcehre, Kyunghyun Cho, and Yoshua Bengio. 2015. Gated feedback recurrent neural networks. In International conference on machine learning. 2067–2075.

[9] Yaroslav Ganin and Victor Lempitsky. 2014. Unsupervised domain adaptation by backpropagation. arXiv preprint arXiv:1409.7495 (2014).

[10] Yaroslav Ganin, Evgeniya Ustinova, Hana Ajakan, Pascal Germain, Heiga Zen, François Desse, and Victor Lempitsky. 2016. Domain-adversarial training of neural networks. The Journal of Machine Learning Research 17, 1 (2016), 2096–2030.

[11] Alec Go, Richa Blayani, and Lei Huang. 2009. Twitter sentiment classiﬁcation using distant supervision. CS224N project report, Stanford 1, 12 (2009), 2009.

[12] Sepp Hochreiter and Jürgen Schmidhuber. 1997. Long short-term memory. Neural computation 9, 8 (1997), 1735–1780.

[13] Muhammad Imran, Carlos Castillo, Ji Lucas, Patrick Meier, and Sarah Vieweg. 2014. AIDR: Artificial intelligence for disaster response. In Proceedings of the 23rd International Conference on World Wide Web. 159–162.

[14] Muhammad Imran, Prasenjit Mitra, and Carlos Castillo. 2016. Twitter as a lifeline: Human-annotated twitter corpora for NLP of crisis-related messages. arXiv preprint arXiv:1605.05894 (2016).

[15] Muhammad Imran, Prasenjit Mitra, and Carlos Castillo. 2016. Twitter as a Lifeline: Human-annotated Twitter Corpora for NLP of Crisis-related Messages. In Proceedings of the Tenth International Conference on Language Resources and Evaluation (LREC 2016) (Portoroz, Slovenia, 23-28). European Language Resources Association (ELRA), Paris, France.

[16] Jitin Krishnan, Heman Purohit, and Huzefa Rangwala. 2020. Diversity-Based Generalization for Neural Unsupervised Text Classiﬁcation under Domain Shift. https://arxiv.org/pdf/2002.10937.pdf (2020).

[17] Kathy Lee, Ankit Agrawal, and Alok Choudhary. 2013. Real-time disease surveillance using twitter data: demonstration on ﬂu and cancer. In Proceedings of the 19th ACM SIGKDD international conference on Knowledge discovery and data mining. 1474–1477.

[18] Hongmin Li, Doina Caragea, Cornelia Caragea, and Nic Herndon. 2018. Disaster response aided by tweet classiﬁcation with a domain adaptation approach. Journal of Contingencies and Crisis Management 26, 1 (2018), 16–27.

[19] Zheng Li, Ying Wei, Yu Zhang, and Qiang Yang. 2018. Hierarchical attention transfer network for cross-domain sentiment classiﬁcation. In Thirty-Second AAAI Conference on Artiﬁcial Intelligence.

[20] Zheng Li, Yun Zhang, Ying Wei, Xu Yang, and Qiang Yang. 2017. End-to-End Adversarial Memory Network for Cross-domain Sentiment Classiﬁcation. In IJCAI 2237–2243.

[21] Xiaodong Liu, Jianfeng Gao, Xiaodong He, Li Deng, Kevin Duh, and Ye-Yi Wang. 2015. Representation learning using multi-task deep neural networks for semantic classiﬁcation and information retrieval. (2015).

[22] Mingsheng Long and Jianming Wang. 2015. Learning multiple deep relationships networks. arXiv preprint arXiv:1506.03172 1 (2015), 1.

[23] Minh-Thang Luong, Hieu Pham, and Christopher D Manning. 2015. Effective approaches to attention-based neural machine translation. arXiv preprint arXiv:1508.04025 (2015).

[24] Reza Mazloom, Hongmin Li, Doina Caragea, Cornelia Caragea, and Muhammad Imran. 2019. A Hybrid Domain Adaptation Approach for Identifying Crisis-Related Tweets. International Journal of Information Systems for Crisis Response and Management (IJSCRAM) 11, 2 (2019), 1–19.

[25] Tomas Mikolov, Ilya Sutskever, Kai Chen, Greg S Corrado, and Jeff Dean. 2013. Distributed representations of words and phrases and their compositionality. In Advances in neural information processing systems. 3111–3119.

[26] Dat Tien Nguyen, Kamela Ali Al Mannia, Shaﬁq Joty, Hassan Sajjad, Muhammad Imran, and Prasenjit Mitra. 2016. Rapid classiﬁcation of crisis-related data on social networks using convolutional neural networks. arXiv preprint arXiv:1608.03992 (2016).

[27] Ferda Olli, Patrick Meier, Muhammad Imran, Carlos Castillo, Devis Tuia, Nicolas Rey, Julien Brient, Pauline Mülle, Friedrich Reinhard, Matthew Parkan, et al. 2016. Combining human computing and machine learning to make sense of big (aerial) data for disaster response. Big data 1, 1 (2016), 47–59.

[28] Sinno Jialin Pan, Xiaochuan Ni, Jian-Tao Sun, Qiang Yang, and Zheng Chen. 2010. Cross-domain sentiment classiﬁcation via spectral feature alignment. In Proceedings of the 19th international conference on World wide web. ACM, 751–760.

[29] Jeffrey Pennington, Richard Socher, and Christopher D Manning. 2014. GloVe: Global Vectors for Word Representation. In Empirical Methods in Natural Language Processing (EMNLP). 1532–1543. http://www.aclweb.org/anthology/D14-1162

[30] Nastaran Pourerabeh, Selima Sultana, John Edwards, Amanda Gochanour, and Sonnya Mohanty. 2019. Understanding communication dynamics on Twitter during natural disasters: A case study of Hurricane Sandy. International journal of disaster risk reduction 37 (2019), 101176.

[31] Radim Rehůrek and Petr Sojka. 2010. Software Framework for Topic Modelling with Large Corpora. In Proceedings of the LREC 2010 Workshop on New Challenges for NLP Frameworks: ELRA, Vallatta, Malta, 45–50. http://iu.muni.cz/publication/88493/en.

[32] Sebastian Ruder12, Joachim Bingel, Isabelle Augenstein, and Anders Søgaard. 2017. Shape networks: Learning what to share between loosely related tasks. star.ai (2017), 23.

[33] Mike Schuster and Kuldip K Paliwal. 1999. Bidirectional recurrent neural networks. IEEE Transactions on Signal Processing 45, 11 (1997), 2675–2681.

[34] Ilya Sutskever, Oriol Vinyals, and Quoc V Le. 2014. Sequence to sequence learning with neural networks. In Advances in neural information processing systems. 3104–3112.

[35] Bruno Takahashi, Edson C Tando Jr, and Christine Carmichael. 2015. Communicating on Twitter during a disaster: An analysis of tweets during Typhoon Haiyan in the Philippines. Computers in Human Behavior 50 (2015), 392–398.

[36] István Varga, Motoki Sano, Kentaro Torisawa, Chikara Hashimoto, Kiyoumi Ohtake, Takao Kawau, Jong-Hoon Oh, and Stijn De Saeger. 2013. Aid is out there: combining human computing and machine learning to make sense of big (aerial) data for disaster response. arXiv:1608.03992 (2016).

[37] Pascal Vincent, Hugo Larochelle, Isabelle Lajoie, Yoshua Bengio, and Pierre-Antoine Manzagol. 2010. Stacked denoising autoencoders: Learning useful representations in a deep network with a local denoising criterion. Journal of machine learning research 11, Dec (2010), 3377–3408.