Microblog Retrieval for Post-Disaster Relief: Applying and Comparing Neural IR Models

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ABSTRACT

Microblogging sites like Twitter are important sources of real-time information on ongoing events, such as socio-political events, disaster events, and so on. Hence, reliable methodologies for microblog retrieval are needed for various applications. In this work, we experiment with microblog retrieval techniques for a particular application—identifying tweets that inform about resource needs and availabilities, for effective coordination of post-disaster relief operations. Traditionally, pattern matching techniques are adopted to identify such tweets. In this work, we experiment with a number of neural network based retrieval models, including word-level embeddings and character-level embeddings, for automatically identifying these tweets. We perform experiments over tweets posted during two recent disaster events, and show that neural IR models outperform the pattern-matching techniques of prior works. We also propose two novel neural IR models which perform competitively with several state-of-the-art models. Further, recognising that the large training time of neural IR models is an obstacle in deploying such models in practice, we also explore the reusability of neural IR models trained over past events, for retrieval during future events.

CCS CONCEPTS

-Information systems →Information retrieval;

KEYWORDS

Microblog retrieval; Disaster; Neural IR; Word embeddings; Character embeddings

1 INTRODUCTION

Microblogging sites like Twitter and Weibo have emerged as important sources of real-time information on ongoing events, including socio-political events, emergency events, and so on. For instance, during emergency events (such as earthquakes, floods, terror attacks), microblogging sites are very useful for gathering situational information in real-time [5, 17]. During such an event, typically only a small fraction of the microblogs (tweets) posted are relevant to the information need. Hence, it is necessary to design effective methodologies for microblog retrieval, so that the relevant tweets can be automatically extracted from large sets of documents (tweets).

Microblog retrieval is a challenging IR problem, primarily due to the noisy vocabulary and very short length of tweets. The 140-character limit on tweets prompts users to use arbitrary shortenings of words, and non-standard abbreviations [1]. Additionally, different users can express the same information in very different ways. Hence, traditional Information Retrieval / Natural Language Processing techniques often do not perform well on noisy microblogs. This limitation of standard methodologies has motivated the IR community in recent years to adopt neural network-based IR models [11, 19] for microblogs (see Section 2).

In this work, we apply and compare various neural network-based IR models for microblog retrieval for a specific application, as follows. In a disaster situation, one of the primary and practical challenges in coordinating the post-disaster relief operations is to know about what resources are needed and what resources are available in the disaster-affected area. Thus, in this study, we focus on extracting these two specific types of microblogs or tweets.

Need-tweets: Tweets which inform about the need or requirement of some specific resources such as food, water, medical aid, shelter, etc. Note that tweets which do not directly specify the need, but point to scarcity or non-availability of some resources are also included in this category.

Availability-tweets: Tweets which inform about the availability of some specific resources. This class includes both tweets which inform about potential availability, such as resources being transported or despatched to the disaster-struck area, as well as tweets informing about the actual availability in the disaster-struck area, such as food being distributed, etc.

Table 1 shows some examples of need-tweets and availability-tweets posted during the 2015 Nepal earthquake. Apart from the noisy vocabulary of the tweets (e.g., ‘without’ abbreviated to ‘w/o’, ‘including’ abbreviated to ‘incl’), it can be observed that needs and availabilities are expressed in many diverse ways. While some tweets might be easier to retrieve due to presence of intuitive terms like ‘need’, ‘require’, or ‘available’, many of the tweets do not contain such terms. Given the wide diversity in the tweets, use of neural IR models seems promising, since they might be able to capture the semantic relationships among various terms.

Present work: In this work, we apply and compare various neural network-based models for retrieval of need-tweets and availability-tweets, including word-level embeddings (Word2vec [10]), models
that combine both word-level and character-level embeddings [3], models using such combined embeddings with attention [2], and so on. We also propose two novel models which combine word-level and character-level embeddings. We perform a comprehensive evaluation of the methodologies using tweets posted during two recent disaster events – the Nepal earthquake in April 2015, and the earthquake in Italy in August 2016. We observed that word-level embedding models usually perform better in terms of Recall, while models combining word and character embeddings generally achieve better Precision. Further, the proposed models perform better than most of the state-of-the-art models.

Note that, traditionally, pattern matching based schemes have been employed by prior works for identifying specific types of tweets [12, 16]. We also compare the neural IR models with pattern matching techniques of prior works, and show that neural IR models are much more effective in microblog retrieval.

It can be noted that a primary obstacle in deploying neural IR models for retrieval during ongoing events is the large time needed to train such models. To this end, we also explore the reusability of neural IR models trained over past events, for retrieval during future events with minimal re-training.

2 RELATED WORK

Application of neural network models over microblogs: Traditional IR / NLP approaches often do not perform well over microblogs, primarily due to their short size and noisy, informal vocabulary. As a result, neural network based IR models [6, 11, 19] are increasingly being applied over microblogs. For instance, Severyn et al. applied deep convolutional neural networks for sentiment analysis of tweets [13], while Wang et al. composing word embeddings with Long Short-Term Memory for identifying the polarity of tweets [18]. Again, Ganguly et al. used neural IR models for retrieving code-mixed microblogs [4], while Ma et al. used recurrent neural networks for detecting rumors from microblogs [8]. Our prior work [1] proposed a contextual stemming algorithm using word embeddings for retrieving tweets posted during disasters.

Utilising online social media for disaster relief: In recent years, there has been a lot of work on utilizing Online Social Media (OSM) for aiding disaster relief operations [5]. However, to our knowledge, there have been only a few prior works that have specifically focused on the problem of identifying OSM posts that inform about need and availability of resources. Varga et al. [17] developed NLP techniques to identify such tweets. However, a large fraction of the tweets in the dataset is in Japanese, and it is unclear whether the methodology in [17] can be readily applied to tweets in English.

Some prior studies also identified patterns / lexicons which can be used to identify specific types of tweets, including tweets informing about need and availability of resources [12, 16]. However, a large fraction of the patterns identified in this study (referred to as EM-Terms), can be used to identify need and availability of various types of resources.

Thus, the task of identifying need-tweets and availability-tweets has traditionally been approached as a pattern matching task. In the present work, we adopt a different approach – we view the tasks as Information Retrieval (search) tasks and use neural network based retrieval models for the tasks. We demonstrate that neural IR methodologies perform better than the prior pattern matching approaches [12, 16] for this application.

3 DATASETS

This section describes the datasets used for the experiments in this work, and also how the gold standard for evaluating the methodologies was developed.

3.1 Microblogs related to two disaster events

For the present work, we collected tweets related to two major earthquakes that occurred in recent times – (i) the earthquake in Nepal and India in April 2015, and (ii) the earthquake in central Italy in August 2016. For both the disaster events, we used the Twitter Search API³ to collect tweets that were posted during the days immediately following the event. The queries ‘nepal quake’ and ‘italy quake’ respectively, were used to collect the tweets relevant to the two events. In total, about 480K tweets were collected for the Nepal earthquake, and about 200K tweets for the Italy earthquake. For this work, we consider only tweets in English, as identified by the Twitter language identification system.

It has been observed that tweets frequently contain duplicates and near-duplicates as the same information is often retweeted / re-posted by many users [15]. Presence of duplicates can result in over-estimation of the performance of retrieval / extraction

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Table 1: Examples of need-tweets and availability-tweets posted during a recent disaster event (2015 Nepal earthquake).

| Need-tweets                                                                 | Availability-tweets                                                                 |
|----------------------------------------------------------------------------|-------------------------------------------------------------------------------------|
| Mobile phones are not working, no electricity, no water in #Thamel, #Nepal #earthquake #NepalQuakeRelief | # Langar meals available at Sikh Gurdwara at Kupondol near Bagmati Bridge #Nepal #NepalQuakeRelief |
| Over 1400 killed. Many Trapped. Medical Supplies Required.                  | #India to set up Field Hospital in #Nepal by tomorrow morning to provide medical facilities #NepalEarthquake |
| @canvasses @skynesli @YouthForBlood they are in search of blood donors for the people who are injured in earthquake... help | 4 PAF aircraft w/ rescue & relief assistance, incl a 30-bed mobile hospital have left for #Nepal |
| Nepalis, r/w/o water & electricity. Water is essential to be supplied to the affected people in Nepal. | Earthquake emergency numbers VRed cross ambulance service Nepal +00977 422 8094 |
| World Community #Nepal needs humanitarian aid. rescue & medical aid #NepalEarthquake | can anyone we know pick the 2000 second hand tents from Sunauli and distribute it to the people in need in Nepal? #NepalQuake |

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¹https://en.wikipedia.org/wiki/August_2016_Central_Italy_earthquake
²https://en.wikipedia.org/wiki/August_2016_Central_Italy_earthquake
³https://dev.twitter.com/rest/public/search
⁴https://dev.twitter.com/rest/public/search
methodologies, and can also create information overload for human annotators while developing the gold standard [7]. Therefore, we eliminated duplicate and near-duplicate tweets using a simplified version of the methodologies discussed in [15]. Specifically, similarity of a pair of tweets was estimated by the Jaccard similarity of the set (bag) of words contained in the two tweets (after ignoring stopwords, URLs and @user mentions). If two tweets were found to be more similar than a threshold value, only one of the tweets was retained in the corpus.

After removing duplicates and near-duplicates, we obtained a set of 50,068 tweets for the Nepal earthquake dataset, and 70,487 tweets for the Italy earthquake dataset. These sets were used for all experiments reported in this study. For brevity, we will denote the two datasets as nepal-quake and italy-quake respectively.

### 3.2 Developing gold standards for evaluation

Evaluation of the methodologies discussed in this work required a gold standard containing the need-tweets and availability-tweets contained in the datasets. We engaged three human annotators to develop this gold standard, each of whom is proficient in English and is a regular user of Twitter, but none of whom is an author of this paper. Each annotator was given the two datasets of tweets (nepal-quake or italy-quake), and was asked to identify all need-tweets and availability-tweets in both datasets.

Each annotator was first asked to identify need-tweets and availability-tweets independently, i.e., without consulting the other annotators. While many tweets were identified by all three annotators in common, there were some tweets which were identified by two or only one of the annotators. Hence, we conducted a second phase, where all need-tweets and availability-tweets that were identified by at least one annotator (in the first phase) were considered. The gold standard set of need-tweets and availability-tweets were finalized through discussion with all the annotators and mutual agreement.

Finally, through the human annotation process described above, the following number of tweets were identified – 499 need-tweets and 1333 availability-tweets for nepal-quake dataset, and 177 need-tweets and 233 availability-tweets for the italy-quake dataset. Note that, even though the italy-quake dataset is larger than the nepal-quake dataset, the italy-quake dataset has much fewer need-tweets and availability-tweets. Hence, retrieving these tweets is likely to be more difficult in case of the italy-quake dataset.

### 4 BASELINE METHODOLOGIES

In this section, we discuss three baseline methodologies for identifying need-tweets and availability-tweets.

#### 4.1 Pattern matching baselines

As stated earlier, most prior studies have used pattern matching approaches for identifying specific types of tweets posted during disaster events, including need-tweets and availability-tweets. We consider two such studies as baselines, as described below.

(1) Purohit et al. [12] proposed a set of 18 regular expressions to identify tweets that ask for donation of resources, and tweets that inform about availability of resources to be donated. We obtained, on request, from the authors of [12], the 18 regular expressions and use these on our dataset to identify need-tweets and availability-tweets.

(2) Temnikova et al. [16] proposed a large set of patterns (referred to as EMTerms) to identify specific types of tweets during emergencies. We employed three annotators (the same as those who developed our gold standard, as described in the previous section) to select those patterns which are relevant to need and availability of resources. The patterns in EMTerms are grouped into several categories, out of which the annotators identified six categories as relevant to need and availability of resources. These six categories contain 935 patterns in total. Table 2 shows the six categories, along with some example patterns in each category.

| Category Code and Name | # Patterns | Examples of patterns |
|------------------------|------------|----------------------|
| T06: Need of / offered supplies, such as food, water, clothing, medical supplies or blood | 297 | {Number} bags, aid, aids, bottled water, donate any supplies |
| T07: Volunteer or professional services needed or offered | 232 | volunteer heads, relief aid, help victims |
| C02: Needs food, or able to provide food | 40 | {Number} bags of rice, distributes food, donations like canned goods |
| C04: Logistics and transportation | 232 | {Number} trucks, helicopter, rescue boats |
| C05: Need of shelters, including location and conditions of shelters and camps | 92 | {Number} homeless, camps, hotel, shelter, shelter kit |
| C06: Availability and access to water, sanitation, and hygiene | 59 | need clean water, no drinking water, restoring water |

| Table 2: Examples of patterns from EMTerms [16] that are related to need / availability of resources (as identified by annotators) |

#### 4.2 Language model baseline

We consider a language model-based IR methodology as a third baseline. Here the need and availability of resources are considered as broad topics (information needs), and tweets relevant to each topic are retrieved and ranked based on their relevance to the topics. We consider two stages in the retrieval process - first, an initial query is used to retrieve tweets, and subsequently, the query is expanded by adding some terms to the initial query, and another round of retrieval is performed with the expanded query.

**Pre-processing the tweets:** All tweets are pre-processed by case-folding to lower case, removal of a standard set of English stopwords, URLs and user-mentions, and subsequent stemming.

**Retrieval with initial query:** We start with initial queries consisting of a few terms selected based on our intuition and observation of need-tweets and availability-tweets in general. For retrieval of need-tweets, we use an initial query consisting of two terms – ‘need’ and ‘requir’ (which is the stemmed form of ‘require’ or ‘required’). For retrieval of availability-tweets, we use the initial query consisting of three (stemmed) terms – ‘avail’, ‘distribut’ and ‘send’.
We employ the Indri IR system [14] for the retrieval. The preprocessed tweets were indexed using Indri, and then ranked retrieval of tweets was done using the default language model based retrieval model of Indri [14].

**Query expansion:** The motivation of the query expansion phase is to add to the query, some dataset-specific (event-specific) terms, so that more relevant tweets can be retrieved. We apply the well-known Rocchio expansion scheme [9] for determining the candidate expansion terms. After documents are retrieved using a particular (initial) query, the top-ranked document scores are determined for expanding the query. Specifically, for each distinct term in the top-ranked k (a small number) documents are assumed to be relevant, and certain terms are selected from the top retrieved documents to expand the query. Similarly, for each distinct term in the k = 10 top-ranked tweets retrieved by the original query, we compute the \( tf \times idf \) Rocchio scores, where \( tf \) is the frequency of the term among the 10 top-ranked tweets, and \( idf \) is the inverse document frequency of the term over the entire dataset. The top \( p = 3 \) terms in the decreasing order of Rocchio scores are selected for expanding the query.

We will compare the performance of these baselines with that of several neural IR retrieval models described in the next section.

## 5 NEURAL NETWORK METHODOLOGIES

We consider several types of neural network-based models for retrieving need-tweets and availability-tweets, as described below.

### 5.1 Neural network models

We consider one word level embedding model, and four models which combine word level embeddings and character level embeddings (out of which two are novel models proposed in this work).

(1) **Word embeddings (W2V):** We use the popular Word2vec tool [10] as a representative word embedding model. We first train Word2vec on the tweets (of a certain dataset). Then we use word vector models to model the embedding of every token. We consider each tweet as a list of tokens \( \{u_1, u_2, u_3, \ldots, u_n\} \) and therefore for every token we consider a window of size \( k \). For example for token \( u_i \) the window is \( \{u_{i-k}, u_{i-k+1}, \ldots, u_{i+k-1}, u_{i+k}\} \). We look up the embedding of every token \( u_i \) and try to predict from every token its context tokens. Embedding \( u_i = W[u_i] \) where \( W \) is a \( d_{word} \) dimensional vector look up table for every token. We try

\[
\text{out}(\text{token, } \theta) = U(\theta)W[\text{token}]
\]

where the \( \text{out} \) function approximator computes the probability that a said token is in the context window of token under consideration. \( \theta \) are the weights of the function approximator.

\[
L_1(B; \theta) = \frac{1}{B} \sum_{\text{tokens} \in B} \text{out}(\text{token, } \theta) \log p_t^{\text{word}}
\]

where \( p_t^{\text{word}} \) is the inferred probability that a word lies in the context of the token under consideration.

For training Word2vec, we use the skip-gram model, along with Hierarchical softmax. The hyperparameters embedding size \( d_{word} \) was taken to be 256, context size was 5, learning rate was 0.5. We use Stochastic Gradient Descent for training.

(2) **Combining word embeddings with character-level embeddings:** We have used the following three models:

(i) **WC: This model, proposed in [3], aims at inferring character level embedding along with word level embeddings, from word level context of the token under consideration. The model tries to generalize by inferring the token embedding from how the character occurs in its context. The last layer of the model remains the same as W2V [10], while the hidden layer combines word level and character level embedding before feeding into the last layer. The embeddings are trained to predict the context of the token under consideration, and therefore is predicted to encode the semantics of the language:**

\[
E[u_i] = \lambda_2 W[u_i] + (1 - \lambda_2) \frac{1}{N} \sum_{c_j \in u_i} C[c_j]
\]

where \( \lambda_2 \) is a self learned parameter, \( C \) is a \( d_{chr} \) (size of embedding) dimensional vector look up table for every character in the character vocabulary, and \( W \) is a \( d_{word} \) dimensional vector look up table for every token in the vocabulary.

The loss function is

\[
L(B; \theta) = \frac{1}{B} \sum_{\text{tokens} \in B} \text{out}(\text{token, } \theta) \log p_t^{\text{tot}}
\]

where \( \text{out}(\text{token, } \theta) = U(\theta)E[u_i] \) where \( p_t^{\text{tot}} \) is the inferred probability that the said token is in the context of the token under consideration.

The model is run with embedding size \( d_{word} = d_{chr} = 256 \), word level context size as 5, and a learning rate of 0.5 and Adam decay rate \( \beta_1 = 0.001 \). We use Adam Optimizer for training, it being more robust for deeper models.

(ii) **WCAL:** This model was originally proposed by Cao and Rei [2]. The main advantage of this model is that a model which encodes memory, can embed the morphological features of a word/token into its embedding and helps in predicting the context. Relating the morphological features of a word to its context, theoretically improves generalization of the model to out of vocabulary tokens, and also seemingly different tokens with the same morphological features will have similar embedding in the said model.

Therefore, in this model, we obtain character level embeddings and feed them to a biLSTM, and then apply an attention layer over the embedding before we combine them with word level embeddings. The biLSTM model is fed all the character embedding \( C[c_1, c_2, \ldots, c_n] \) to give us \( \{h^c_1, h^c_2, \ldots, h^c_n\} \) and \( \{h^b_1, h^b_2, \ldots, h^b_n\} \). We concatenate to get \( h = [h^c_1, h^b_1] \) for every character. The embedding is

\[
E[u_i] = \lambda_2 W[u_i] + (1 - \lambda_2) \sum_{c_j \in u_i} \alpha_j(u_i)h_j
\]

where

\[
\alpha_j(u_i) = \frac{\exp(v^T \tanh(W(\theta)c_j))}{\sum \exp(v^T \tanh(W(\theta)c))}
\]

The softmax layer ensures \( \sum \alpha_j(u_i) = 1 \), which implies that \( \alpha \) is effectively a probability distribution. \( \lambda_2 \) is a self learned parameter.
The loss function
\[ L(B; \theta) = \frac{1}{B} \sum_{token \in B} out(token, \theta) \log p_{tot}^t \]
where \( out(token, \theta) = U(\theta)E[u_i] \) where \( p_{tot}^t \) is the inferred probability that the said token is in the context of the token under consideration.

The model is run with embedding size \( d_{word} = 256 \) and \( d_{char} = 128 \) and a learning rate of 0.5 and Adam decay rate \( \beta_1 = 0.001 \). We use Adam Optimizer training.

(iii) WCA (proposed): This is a novel scheme that we propose in this work. In this model, we try to encode the morphological features in the final embedding. To obtain these, we combine word level embeddings with character level embeddings after applying an attention layer over them. We try to give more importance to some sections of the token, and we learn what characters to give more importance in what configurations, by learning the parameters of the attention layer. This model is smaller than RNN or LSTM models for morphological features, and hence requires lesser time and data to train. We also expect it to work better over noisy data such as microblogs.

The model uses an attention layer that computes the values of attention for each character using the character embedding of every character in the token. The embedding is
\[ E[u_i] = \lambda_2 W[u_i] + (1 - \lambda_2) \sum_{c_j \in u_i} \alpha_i(u_i) C[c_j] \]
where
\[ \alpha_i(u_i) = \frac{\exp(v^T \tanh(W(\theta)c_j))}{\sum \exp(v^T \tanh(W(\theta)c_j))} \]
The softmax layer \( \Sigma \alpha_i(u_i) = 1 \), which implies that \( \alpha \) is effectively a probability distribution. \( \lambda_2 \) is a self learned parameter.

The loss function is
\[ L(B; \theta) = \frac{1}{B} \sum_{token \in B} out(token, \theta) \log p_{tot}^t \]
where \( out(token, \theta) = U(\theta)E[u_i] \), while \( p_{tot}^t \) is the inferred probability that the said token is in the context of the token under consideration.

The model is run with token or character embedding size as \( d_{word} = 256 \) and \( d_{char} = 256 \) and a learning rate of 0.5 and 0.005 for word embedding and character embedding respectively. Adam decay rate \( \beta_1 \) is set as 0.001. We use Adam Optimizer training.

(iv) WCInd (proposed): This is another novel method that aims at inferring the semantics of a character inside a token, and hence tries to generalize the morphology of the tokens at a character level.

We adopt the approach of predicting the tokens in the context of the said character, which would help us bring inferring intra-character features (e.g., the high frequency of q,u) in vicinity of each other as a feature.

We first obtain character level embeddings in the same way we obtained embeddings for words – by training for context. For every token, we obtain the embedding by combining the embedding for tokens obtained as in the WC model (described above) with the embedding obtained by finding the mean of the character embeddings of the said token:
\[ E[u_i] = \lambda W[u_i] + (1 - \lambda) \frac{1}{N} \sum_{c_j \in u_i} C[c_j] \]
where \( C \) is a \( d_{char} \) dimensional vector look up table for every character in the character vocabulary, \( W \) is a \( d_{word} \) dimensional vector look up table for every token in the vocabulary, and \( \lambda \) is a hyperparameter.

The loss function is
\[ L_2(B; \theta) = \frac{1}{B} \sum_{c \in B} out(c, \theta) \log p_c^t \]
where \( out(c, \theta) = U(\theta)C[w] \) while \( p_c^t \) is the inferred probability that the said character is in the context of the character under consideration.

The embeddings for words are trained independently using Stochastic Gradient Descent. The embedding size is 256 and the learning rate is 1, while the character embeddings of the same dimension, are trained using Stochastic Gradient Descent with learning rate as 0.05. The hyperparameter \( \lambda \) is set to 0.7.

5.2 Using the neural models for retrieval

Training the models: The models were trained using the hyperparameters as stated above. We trained the models for around 12 epochs, on a single GPU. We found that the models generally give best results after training for around 8 epochs, except the biLSTM model (WCAL) which requires more training.

Pre-processing the tweets: Similar to what was described in Section 4.2, all tweets are pre-processed by case-folding to lower case, removal of a standard set of English stopwords, URLs and user-mentions, and stemming.

Retrieval with initial query: We use the same initial queries as described in Section 4.2 – the terms ‘need’ and ‘require’ for retrieving need-tweets, and the terms ‘avail’, ‘distribute’ and ‘send’ for retrieving availability-tweets.

For a particular query, we construct a query-vector by performing vector addition of the term-vectors of all terms in the query, and then dividing the vector sum by the number of words in the query. Similarly, for each tweet (pre-processed), we construct a tweet-vector by adding the term-vectors of all terms contained in the tweet and then dividing the vector sum by the number of terms in the tweet. For retrieving tweets relevant to a query, we calculate the cosine similarity between the corresponding query-vector and each tweet-vector. We then rank the tweets in decreasing order of the cosine similarity.

In mathematical terms, we find the list of tweets \( T \) from the original list of tweets \( T^* \) as
\[ T^* = \arg\max_{t \in T} \cos(E[t], E[q]) \]
where \( E[u] \) is the embedding of the set of tokens \( u \).

Query expansion: We use an expansion technique that utilises the term embeddings learned by the neural network models. For a particular neural model, we first retrieve tweets using the initial query, and consider the top \( k = 10 \) retrieved tweets. To expand the initial query, we compute the cosine similarity of the query-vector (of the initial query) with the term-vector of every distinct term
We now evaluate the methodologies described in the previous section in the top \( k \) tweets. We select those \( p = 3 \) terms for which the term-vector has the highest cosine similarity with the query-vector.

Table 3 states the query expansion terms identified by the different neural models over the Nepal-quake dataset. It can be observed that different neural models identify widely different expansion terms for the same query. Similar observations were made for the Italy-quake dataset, which we omit for lack of space.

6 EVALUATION OF METHODOLOGIES

We now evaluate the methodologies described in the previous sections, by comparing the tweets retrieved by a methodology with the gold standard identified by human annotators (as described in Section 3).

Evaluation measures: In a disaster situation, it is important both to identify need-tweets and availability-tweets precisely (high precision), as well as to identify as many of the need-tweets and availability-tweets as possible (high recall). Hence, we use the following evaluation measures – (i) Precision@100, (ii) Recall@1000, (iii) F-score, and (iv) MAP (overall).

Note that the pattern matching methodologies (described in Section 4.1) identify unordered sets of tweets, while the retrieval methodologies output ranked lists of tweets. We intend to compare all the methodologies in a common evaluation setting. Hence, for the pattern matching methodologies, we consider all the matched tweets if the number of matched tweets is less than 1,000; otherwise, we randomly select a subset of 1,000 tweets out of the matched tweets, and measure Precision, Recall, and F-score.

Retrieval results: Table 4 shows the performance of various methodologies on the Nepal-quake dataset, while Table 5 shows the results on the Italy-quake dataset. It is evident that, across all methodologies, the performances are significantly better over the Nepal-quake dataset than over the Italy-quake dataset, which again indicates that need-tweets and availability-tweets are much more difficult to retrieve for the Italy-quake dataset. The EMTerms [16] patterns (one of the baselines) match a very large number of tweets – more than 12,000 for Nepal-quake and more than 6,000 for Italy-quake. Considering all the matched tweets, the overall recall achieved is the highest among all methods (e.g., 0.737 for need-tweets and 0.613 for availability-tweets in the Nepal-quake dataset). However, the matched tweets also include many non-relevant tweets, leading to very low precision values, and hence low F-scores. In contrast, the retrieval methodologies achieve both reasonable precision as well as reasonable recall, leading to significantly better F-score values than the pattern matching methods.

In the neural IR models, the word embedding models (W2V) usually achieve better Recall scores, while the models combining word and character level embeddings achieve better Precision scores (except...
One potential solution to this problem is to use pre-trained models, i.e., we pre-train the models on one or more dataset(s) (e.g., tweets posted during past events) and then use the model for retrieval on a new dataset (tweets posted during a future event) with minimal re-training. In this section, we explore the possibility of reusing the neural IR models discussed earlier in the paper. Here we only experiment with the models which combined word and character embeddings. Also, for the experiments in this section, we only consider retrieval with the initial queries (without any query expansion).

In one set of experiments, we consider models pre-trained on the italy-quake dataset, and re-train the models over the nepal-quake dataset for (i) just one epoch, and (ii) five epochs. Table 6 shows the retrieval performance of such models over the nepal-quake dataset. Similarly, we took the models pre-trained over the nepal-quake dataset, and trained them over the italy-quake dataset for one / five epochs; Table 7 shows the performance of such models over the italy-quake dataset.

As expected, we observe a trade-off between the training time (number of epochs trained) and the retrieval performance. For instance, the best MAP-score achieved for the nepal-quake need-tweets was 0.201 (from Table 4, without considering query expansion), obtained via full training over the nepal-quake dataset (which needed close to 4.5 hours). On the other hand, the models pre-trained over italy-quake achieved MAP of 0.120 after just a single epoch re-training on the nepal-quake data (Table 6), which needed less than 30 minutes of re-training.

The performance of pre-trained models is even better over the italy-quake dataset where retrieval is more challenging (as indicated in the previous section). For instance, the models pre-trained on nepal-quake dataset achieves a MAP score of 0.044 for the italy-quake availability-tweets after only a single epoch of re-training, which is higher than the MAP score achieved by any of the models when trained fully on the italy-quake dataset (Table 5, without considering query expansion). In fact, most of the models give better performance for the italy-quake dataset when pre-trained over the nepal-quake dataset, than when trained only over the italy-quake dataset.

These experiments point out the potential for reusing models pre-trained over past events for retrieval during future events, with minimal retraining. Especially, if the new datasets have very sparse relevant information (as is the case for the italy-quake dataset), then pre-training on prior datasets can be helpful in improving retrieval performance, along with minimising re-training time. In future, we look to explore the reusability of models pre-trained over several events together, for retrieval during future events.

7 REUSABILITY OF EMBEDDINGS FOR RETRIEVAL DURING FUTURE EVENTS

A major problem in deploying neural IR models in practice, for tasks like microblog retrieval during an ongoing event, is the high training time for such models. For instance, most of the neural IR models described in the previous section required 4.5 – 5 hours of training (over 8 epochs) over the nepal-quake and italy-quake datasets, while the biLSTM model took even longer (and more epochs) to train. During an ongoing event such as a disaster, when information needs to be retrieved quickly, it is often not practicable to allow such high training times.

| Methodology          | Prec | Recall | F-score | MAP  |
|----------------------|------|--------|---------|------|
| Need-tweets          |      |        |         |      |
| (Baseline) Patterns from [12] | 0.003 | 0.091 | 0.006 | –   |
| (Baseline) EMTerms [16] | 0.013 | 0.073 | 0.022 | –   |
| Random-1000 and Overall | 0.013 | 0.458 | 0.026 | –   |
| (Baseline) Language model | 0.158 | 0.063 | 0.007 | –   |
| W2V [10] with expansion | 0.05 | 0.18 | 0.078 | 0.024 |
| WC [3] with expansion | 0.06 | 0.124 | 0.081 | 0.012 |
| WCAL [2] with expansion | 0.06 | 0.141 | 0.084 | 0.015 |
| WCA (proposed) with expansion | 0.02 | 0.079 | 0.032 | 0.009 |
| WCInd (proposed) with expansion | 0.09 | 0.266 | 0.134 | 0.032 |
| WCInd (proposed) with expansion | **0.10** | 0.271 | **0.146** | 0.035 |

| Availability-tweets |      |        |         |      |
|---------------------|------|--------|---------|------|
| (Baseline) Patterns from [12] | 0.002 | 0.039 | 0.004 | –   |
| (Baseline) EMTerms [16] | 0.022 | 0.100 | 0.038 | –   |
| Random-1000 and Overall | 0.023 | 0.575 | 0.43 | –   |
| (Baseline) Language model | 0.05 | 0.090 | 0.064 | 0.008 |
| (Baseline) Language model, Rocchio expansion | 0.04 | 0.103 | 0.058 | 0.005 |
| W2V [10] with expansion | 0.05 | 0.171 | 0.077 | 0.030 |
| WC [3] with expansion | 0.01 | 0.069 | 0.017 | 0.009 |
| WCAL [2] with expansion | 0.02 | 0.064 | 0.031 | 0.010 |
| WCA (proposed) with expansion | 0.04 | 0.056 | 0.046 | 0.006 |
| WCInd (proposed) with expansion | 0.01 | 0.030 | 0.015 | 0.008 |
| WCInd (proposed) with expansion | 0.03 | 0.039 | 0.033 | 0.005 |
| WCInd (proposed) with expansion | 0.03 | 0.05 | 0.033 | 0.007 |

Table 5: Comparing methodologies for the Italy-quake dataset

in the case of availability-tweets in the italy-quake dataset). Especially, the two proposed neural IR models perform better than most of the state-of-the-art models in terms of MAP and F-score.

Comparing the performance of retrieval with initial queries and that with expanded queries, we observe that for almost all cases, query expansion helps to improve the performance. Hence, the embedding-based query expansion technique is effective in improving microblog retrieval.

8 CONCLUSION

We compared different methodologies for retrieving two specific types of tweets / microblogs that are practically important for post-disaster relief operations, viz., need-tweets and availability-tweets. Using datasets of microblogs posted during two recent disaster events, we compared among pattern matching techniques, language
model based techniques, and several neural IR models for the same task. We also proposed two neural IR models that combine word-level and character-level embeddings, and performs competitively with several state-of-the-art models for the said microblog retrieval problem. We also explored the possibility of reusing neural IR models pre-trained over past events, with the objective of minimizing training time over new datasets.

In future, we plan to experiment with neural IR models for microblog retrieval from other standard datasets (e.g., the TREC microblog datasets). Also, we plan to further explore the possibility of reusing pre-trained neural IR models for practical tasks such as retrieval during disasters, which might facilitate deployment of such models over fast changing data streams.

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**REFERENCES**

[1] M. Basu, A. Roy, K. Ghosh, S. Bandyopadhyay, and S. Ghosh. 2017. A Novel Word Embedding Based Stemming Approach for Microblog Retrieval during Disasters. In Proc. European Conference on Information Retrieval (ECIR) 589–597.

[2] Kris Cao and Marek Rei. 2016. A Joint Model for Word Embedding and Word Morphology. CoRR abs/1606.02601 (2016). http://arxiv.org/abs/1606.02601

[3] Xinxiang Chen, Lei Xu, Zhiyuan Liu, Maosong Sun, and Huabo Luan. 2015. Joint Learning of Character and Word Embeddings. In Proceedings of the 24th International Conference on Artificial Intelligence (ICAI’15). AAAI Press. 1236–1242. http://dl.acm.org/citation.cfm?id=283415.283421

[4] Debasis Ganguly, Ayan Bandyopadhyay, Mandar Mitra, and Gareth F.P. Jones. 2016. Retrievalability of Code Mixed Microblogs. In ACM SIGIR. 973–976.

[5] M. Irman, C. Castillo, F. Diaz, and S. Vieweg. 2015. Processing Social Media Messages in Mass Emergency: A Survey. Comput. Surveys 47, 4 (June 2015), 67:1–67:38.

[6] Hang Li and Zhengdong Lu. 2016. Deep Learning for Information Retrieval. In Proc. ACM SIGIR Conference on Research and Development in Information Retrieval. 1203–1206.

[7] Jimmy Lin, Miles Efron, Yuhu Wang, Garrick Sherman, and Ellen Voorhees. 2015. Overview of the TREC-2015 Microblog Track. Available at: https://cs.uwaterloo.ca/~jimlin/publications/Lin_et_al_TREC2015.pdf.

[8] Jie Wang, W. Gao, and Senjin Mitra, Sejong Woon, Bernard J. Jansen, Kam-Fai Wong, and Meeyoung Cha. 2016. Detecting Rumors from Microblogs with Recurrent Neural Networks. In Proceedings of the Twenty-Fifth International Joint Conference on Artificial Intelligence (IJCAI’16). 3818–3824.

[9] CD. Manning, P. Raghavan, and H. Schütze. 2008. Introduction to Information Retrieval. Cambridge University Press, New York, NY, USA.

[10] T. Mikolov and Nick Craswell. 2017. Neural Models for Information Retrieval. CoRR abs/1705.01509 (2017). http://arxiv.org/abs/1705.01509

[11] H. Purohit, C. Castillo, F. Diaz, A. Sethi, and P. Meier. 2014. Emergency-relief coordination on social media: Automatically matching resource requests and offers. First Monday 19, 1 (Jan 2014).

[12] Aliaksei Severyn and Alessandro Moschitti. 2015. Twitter Sentiment Analysis with Deep Convolutional Neural Networks. In Proc. ACM SIGIR. 959–962.

[13] T. Strohman, D. Metzler, H. Turtle, and W. B. Croft. 2004. Indri: A language model-based search engine for complex queries. In Proc. IJCAI. Available at: http://www.lemurproject.org/indri/.

[14] K. Tao, F. Abel, C. Hauff, G.J. Houben, and M. Gadiroglu. 2013. Groundhog Day: Near-duplicate Detection on Twitter. In Proc. World Wide Web (WWW).

[15] I. Temnikova, C. Castillo, and S. Vieweg. 2015. EMTerms v1.0: A Terminological Resource for Crisis Tweets. In Proc. International Conference on Information Systems for Crisis Response and Management (ISCRAM).

[16] I. Varga et al. 2013. Aid is Out There: Looking for Help from Tweets during a Large Scale Disaster. In Proc. ACL.

[17] Xin Wang, Yuanzhou Liu, Chengjie Sun, Baoxun Wang, and Xiaolong Wang. 2015. Predicting Polarities of Tweets by Composing Word Embeddings with Long Short-Term Memory. In Proceedings of Annual Meeting of the Association for Computational Linguistics and International Joint Conference on Natural Language Processing. 1343–1353.

[18] Ye Zhang, Md Mustafizur Rahman, Alex Braylan, Byron Wallace, Heng-Lu Chang, Henna Kim, Quinten McNamara, Aaron Angert, Edward Banner, Vivek Khetan, Tyler McDonnell, An Thanh Nguyen, Dan Xu, Byron C. Wallace, and Matthew Lease. 2016. Neural Information Retrieval: A Literature Review. CoRR abs/1611.06792 (2016). http://arxiv.org/abs/1611.06792

**Table 6:** Using models pre-trained on italy-quake dataset, for retrieval on nepal-quake (after 1 and 5 epochs of re-training).

| Methodology      | Prec | Recall | F-score | Map | Prec | Recall | F-score |
|------------------|------|--------|---------|-----|------|--------|---------|
| WCInd (proposed) | 0.22 | 0.209  | 0.065   | 0.30| 0.295| 0.297  | 0.113   |
| WC [5]           | 0.34 | 0.326  | 0.120   | 0.37| 0.319| 0.342  | 0.127   |
| WCA (proposed)   | 0.35 | 0.297  | 0.105   | 0.35| 0.283| 0.331  | 0.119   |

**Table 7:** Using models pre-trained on nepal-quake dataset, for retrieval on italy-quake (after 1 and 5 epochs of re-training).

| Methodology      | Prec | Recall | F-score | Map | Prec | Recall | F-score |
|------------------|------|--------|---------|-----|------|--------|---------|
| WCInd (proposed) | 0.08 | 0.129  | 0.099   | 0.15| 0.09 | 0.124  | 0.019   |
| WC [5]           | 0.04 | 0.059  | 0.010   | 0.09| 0.186| 0.121  | 0.025   |
| WCA (proposed)   | 0.06 | 0.215  | 0.093   | 0.20| 0.06 | 0.221  | 0.094  | 0.022 |