Multi-linguality Helps: Event-Argument Extraction for Disaster Domain in Cross-lingual and Multi-lingual Setting

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Abstract
Automatic extraction of disaster-related events and their arguments from natural language text is vital for building a decision support system for crisis management. Event extraction from various news sources is a well-explored area for this objective. However, extracting events alone, without any context provides only partial help for this purpose. Extracting related arguments like Time, Place, Casualties, etc., provides a complete picture of the disaster event. In this paper, we create a disaster domain dataset in Hindi by annotating disaster-related event and arguments. We also obtain equivalent datasets for Bengali and English from a collaboration. We build a multi-lingual deep learning model for argument extraction in all the three languages. We also compare our multi-lingual system with a similar baseline monolingual system trained for each language separately. In order to leverage the information from all the languages while training, and improve the performance of the system, we build a ‘multi-lingual’ argument extraction system. This is done by adding separate language layers for each language to our ‘mono-lingual’ system. To bring the datasets of all the languages to the same vector space, we make use of ‘multi-lingual’ word embeddings. We show that by training our model in this way we are able to utilize the dataset of all the three languages and improve the performance of our system for most arguments in the three languages. We also investigate how the syntactic difference of the languages is handled by our system. Through analysis, we show that ‘multi-lingual’ training is espe-

1 Introduction
The ability to extract real time news of disaster events automatically, can potentially help in better decision-making for planning and coordination of disaster relief efforts. Event extraction from text entails the extraction of particular types of events along with their arguments. Information obtained from extracted event mentions provides a more structured and clear picture when augmented with related arguments like Time, Place, Participant, Casualty etc. In a language rich world where each event is documented in multiple languages, argument extraction in multi-lingual setting stands as a crucial task.

Extraction of events from news is a well-explored area in Natural Language Processing. Competitions such as ACE2005 (Doddington et al., 2004) and TAC-KBP2015 (Mitamura et al., 2015) have investigated the area and provided a large body of literature on event extraction from news articles. Event extraction was done on ACE2005 dataset by Ji and Grishman (2008) by combining global evidence from related documents with local decisions. Hou et al. (2012) introduced a method of event argument extraction based on CRFs model for ACE 2005 Chinese event corpus. Event and its arguments were extracted by Petroni et al. (2018), for the purpose of extracting breaking news. Although extraction of events is quite well examined, there is a scarcity of work in extraction of detailed arguments for disaster domain like casualties, reason, after-effects etc.

In this paper we create and publish a dataset annotated for events in disaster domain, for three different languages, i). Hindi, ii). Bengali and iii). English. This dataset is annotated for the task of argument extraction by expert annotators. We build a ‘mono-lingual’ deep learning system, based on CNN (Convolutional Neural Network) and Bi-LSTM (Bi-Directional Long Short Term Memory) for the task of argument extraction. In order to leverage the information from all the languages while training, and improve the performance of the system, we build a ‘multi-lingual’ argument extraction system. This is done by adding separate language layers for each language to our ‘mono-lingual’ system. To bring the datasets of all the languages to the same vector space, we make use of ‘multi-lingual’ word embeddings. We show that by training our model in this way we are able to utilize the dataset of all the three languages and improve the performance of our system for most arguments in the three languages. We also investigate how the syntactic difference of the languages is handled by our system. Through analysis, we show that ‘multi-lingual’ training is espe-
cially helpful in improving the performance when some argument is under-represented in the ‘monolingual’ training data.

1.1 Problem Definition

Argument extraction entails classifying each word in the sentence into some argument or not argument. Therefore, it has been formulated as a sequence labelling task. Given a sentence of form $w_1, w_2, ..., w_n$, the task is to predict the sequence of event-arguments, of the form $l_1, l_2, ..., l_n$. Six different types of arguments were annotated in the dataset: i). Place, ii). Time, iii). Reason, iv). Casualties, v). Participant and vi). After-effects. To label multi-word event-arguments, IOB-style encoding is used where B, I and O denote the beginning, intermediate and outside token of an event.

- **Input Hindi Sentence**: गुलामल खुंबई के बम विस्फोटों के मद्देनजर इस बात की विशेष तौर पर जांच कर रहा है कि अश्रुधार गुंटका और १९९३ के मुंबई बम-विस्फोटों के फलस्वरूप की प्रतिक्रिया के रूप में तो यह हमले नहीं हुए

- **Translation**: In view of the Mumbai bomb blasts, the Home Ministry is specially investigating the fact that these attacks did not take place as response to the Akshardham Temple and the 1993 Bombay bomb blasts

- **Output**: O O I_Place O O O O O O O O O O O O O O O I_Place I_Place O I_Time O I_Place O O O O O O O O O O O O O O

2 Related Works

A major task in information extraction is detection of event triggers, event classification and event argument extraction. Recent works on event trigger detection and classification discuss efficient feature representation techniques which can help in event extraction. Nguyen and Grishman (2015) proposed a convolutional neural network for event extraction which automatically learns features from text. Chen et al. (2015) introduced dynamic convolutional neural network (DMCNN), which adopt a dynamic multi-pooling layer in accordance with the event triggers and its arguments. In 2016, Nguyen and Grishman (2016) improved their CNN model by introducing the non-consecutive convolution by skipping irrelevant words in a sequence. Feng et al. (2018) designed a combined model of LSTM’s and CNN’s which helped in capturing both sequence level and chunk level information from specific contexts. Nguyen and Grishman (2018) explored graph convolutional network over dependency trees and entity mention-guided pooling. For low resource languages, Liu et al. (2018) came up with Gated Multi-Lingual Attention (GMLATT) and Lin et al. (2018) developed a multi-lingual multi-task architecture alleviating data sparsity problem in related tasks and languages.

Previously, in event argument extraction researchers have experimented with pattern based methods (Patwardhan and Riloff, 2007; Chambers and Jurafsky, 2011) and machine learning based methods (Patwardhan and Riloff, 2009; Lu and Roth, 2012) most of which utilise the various kinds of features obtained from the context of a sentence. Higher level representations such as cross-sentence or cross-event information were also explored by Hong et al. (2011) and Huang and Riloff (2011). Maximum Entropy based classifiers were applied for event and argument labeling by Ahn (2006); Chen and Ji (2009); Zhao et al. (2008). The disadvantage with ME classifier is that it gets stuck in local optima and fails to fully capture the context features. To overcome this Hou et al. (2012) proposes an event argument extraction system based on Conditional Random Fields (CRF) model that can select any features and normalizing these features in overall situation helps in obtaining optimal results. While, these models can get affected by the error propagated from upstream tasks, a joint model can help us utilise the close interaction between one or more similar tasks. Li et al. (2013) presented a joint model for Chinese Corpus which identifies arguments and determines their roles for event extraction using various kinds of discourse-level information. On ACE2005 dataset Sha et al. (2018) proposed a dependency bridge recurrent neural network (dBGRNN) built upon LSTM units for event extraction. They use dependency bridges over Bi-LSTM to join syntactically similar words. A tensor layer is applied to get the various argument-argument interactions. Event triggers and arguments are then jointly extracted utilising a max-margin criterion. Nguyen et al. (2016) presented a GRU model to jointly predict events and its arguments.

We introduce two systems for the task of event argument extraction. First is our monolingual system built using CNN (Convolutional Neural Network) and Bi-LSTM (Bi-Directional Long Short
Term Memory). To exploit the information from related languages, we develop a second system that can use information from all the languages for training. This multi-lingual system is built by using shared vector space of embeddings while training, and by using separate language layers for each language to accommodate for diversity in syntax of the languages.

3 Methodology

In this paper, we propose that joint training of IE system on different language datasets, using ‘multi-lingual’ word embeddings and language layers helps in better extraction of arguments. This is particularly true when the dataset is limited in size. To corroborate our claim, we device two different systems, i) monolingual baseline system, and ii). multi-lingual system. The ‘monolingual baseline’ system only takes input data (sentence wise) from one language and extracts the arguments. For word representation, it uses monolingual word embeddings. The ‘multi-lingual’ argument extraction system uses separate language layers and multi-lingual word embeddings for joint training on all the three languages.

3.0.1 Monolingual Word Embedding

The monolingual word-embeddings that are used in our experiments are also known as fastText\(^1\). It was proposed by Bojanowski et al. (2017), and is based on the skipgram model. However instead of using one-hot vector encoding for each word while training, a vector representation of a word that considers character n-grams occurring in the word is formed. To get this representation, the n-grams from all the words for ‘n’ greater than 2 and smaller than 7 are extracted. After this, a dictionary of all the n-grams appearing in the word; where \(G\) is the size of the n-gram dictionary. With each n-gram in \(G\), a vector representation \(z_g\) is associated. A word representation is obtained by summing up all the n-grams, as described in Equation 1:

\[
V_w = \sum_{g \in G_w} z_g
\]

The continuous skip-gram model used these word vectors \(V_w\), to obtain word-embedding representa-

3.0.2 Multi-lingual Word Embedding

Multi-lingual embeddings are obtained by learning a mapping matrix \(W\), between source embeddings \(X = \{x_1, x_2, x_3, ..., x_n\}\) and target embeddings \(Y = \{y_1, y_2, y_3, ..., y_n\}\) without cross-lingual supervision. Adversarial training was used in this method proposed by Conneau et al. (2017). A discriminator is trained to discriminate between a randomly sampled element from \(WX = \{Wx_1, ..., Wx_n\}\) and \(Y\). At the same time \(W\) is trained to prevent the discriminator from making a correct prediction. Thus making it a two-player game, where the discriminator tries to maximize its capability of identifying the origins of an embedding, and \(W\) aims to prevent the discriminator from doing so by making \(WX\) and \(Y\) as indistinguishable as possible. The \(W\) matrix is trained with near orthogonality constraint, to ensure that while transforming the source vector to the target vector space, the angles and distances between words in the embeddings are not distorted during transformation. To achieve this near orthogonality constraint, weight updation for \(W\) is done using Equation 2.

\[
W \leftarrow (1 + \beta)W - \beta(WW^T)W
\]

Here, \(\beta\) was set to 0.01 for the transformation. For our experiments we trained mapping matrices \(W_{\text{hindi}}\) and \(W_{\text{bengali}}\) that map the Hindi and Bengali word embeddings to the vector space of English embeddings.

3.1 Monolingual Baseline Model

The ‘monolingual baseline’ model (c.f Figure 1) is based on Bi-Directional Long Short Term Memory (Bi-LSTM) (Hochreiter and Schmidhuber, 1997; Schuster and Paliwal, 1997) and Convolutional Neural Networks (CNN) (Kim, 2014). The input to the model is a sentence, represented by a sequence of monolingual word embeddings. Since Bi-LSTM and CNN take sequences of equal lengths, the shorter sequences are padded by zero

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\(^1\)https://github.com/facebookresearch/fastText
vectors. This sequence is passed through Bi-LSTM and CNN having filter size 2 and 3. The Bi-LSTM gives contextual representation of each word, while the CNN extracts the ‘bi-gram’ and ‘tri-gram’ features for the sequence. These features are concatenated and passed through a fully connected layer. This layer gives shared representation for the task of argument extraction. Since the arguments in the dataset are not mutually exclusive (E.g: Place or Participant argument can also be a part of Reason or After-effect argument), we have different layers to predict different arguments independently. We have 6 different fully-connected layers in parallel, each of them specialized for detection of one of the 6 arguments. ‘Softmax’ is used after each of the final layers to classify the representation into I, O or B of an argument.

3.2 Multi-lingual Model

For multi-lingual system, we build a model based on the baseline model, by adding separate language layers ($L_1$, $L_2$ and $L_3$) for each language (c.f Figure 2). A layer $L_i$ and its subsequent layers are only trained when input data is also of language $L_i$. We represent the input sentence as a sequence of multi-lingual word embeddings, and padding with zero vectors is used to make the sequence equal in length. Similar to the ‘monolingual baseline’ model, Bi-LSTM, CNN and a fully connected layer is used. This fully connected layer produces shared language and task representation as output. Three separate language layers for the languages Hindi, Bengali and English are used in parallel. These language layers decode the language specific representation from shared representation. After each language layer we have 6 fully connected layers for each of the 6 arguments. ‘Softmax’ classifier is used to classify the representation into I, O or B of an argument.

4 Dataset and Experiments

In this section, we describe the dataset used and the experiments conducted.

4.1 Dataset

To create the dataset, we crawled news articles in disaster domain from popular news websites in Hindi. These news articles were annotated by three annotators, with good language abilities and having satisfactory knowledge in the relevant area. The guidelines for annotation used were similar to the guidelines given by TAC KBP 2017 Event Sequence Annotation Guidelines.\(^2\) We recorded that the annotators had Kappa agreement score of 0.85

\(^2\)https://cairo.lti.cs.cmu.edu/kbp/2017/event/TAC_KBP_2017_Event_Coreference_and_Sequence_Annotation_Guidelines_v1.1.pdf
| Argument     | Hindi | Bengali | English |
|--------------|-------|---------|---------|
| Time         | 3,953 | 11,042  | 822     |
| Place        | 12,410 | 10,576 | 3,018   |
| Reason       | 1,573  | 1,744   | 544     |
| Casualties   | 12,171 | 15,870  | 4,823   |
| Participant  | 2,264  | 4,311   | 639     |
| After-effects| 13,355 | 9,731   | 274     |

Table 1: Distribution of number of arguments in Hindi, Bengali and English datasets

4.2 Experiments

We conduct two separate experiments to show that dataset from different languages ($L_1$ and $L_2$) can be leveraged to improve the performance of argument extraction system of a different language ($L_3$). First we conduct experiment to obtain baseline results on ‘mono-lingual’ setup. Next, we perform experiment using the combined dataset of all the three languages using ‘multi-lingual’ argument extraction model.

4.2.1 Monolingual Experiment

This experiment is conducted separately on each dataset using the ‘monolingual baseline model’ (c.f. Figure 1) and monolingual fastText embeddings. The results of this experiment is used as a baseline, against which the results of the other experiment is compared. The following set-up is used for the experiment: i). learning rate: $1 \times 10^{-2}$, ii). batch size: 32, iii). optimizer: Adam (Kingma and Ba, 2014), iv). loss function: Binary cross-entropy. The best model based on validation-set accuracy was saved after 100 epochs.

4.2.2 Multi-lingual Experiment

This experiment is conducted on the combined dataset of three languages, using the ‘multi-lingual model’ (c.f Figure 2). Multi-lingual word embeddings (described in Section 3.2) were used for word representation in all the three languages, in this experiment. The same experimental set-up used for the ‘monolingual baseline’ experiment, is also used for this experiment. The training of multilingual system was done batch wise, i.e. each language branch was trained for one batch alternatively. The number of steps per epochs was decided by the number of batches needed to complete one epoch of the largest training set, among the different language datasets.

5 Results and Analysis

In this section, we discuss the results obtained for the two experiments described in Section 4.2. We also provide analysis of the results. F1-Score is used as an evaluation metric, and all the results reported are 5-Fold cross-validated. The results for both, ‘monolingual’ and ‘cross-lingual’ experiments are reported in Table 2. From the results, it can be observed that F1-score for Hindi and English datasets improve for most arguments (5 out of 6 arguments), while the results for Bengali dataset improves for three out of the six arguments.

We also test the statistical significance of each increment in F1-Score for argument extraction. The ‘p-values’ obtained after ‘t-test’ are shown in Table 3. It can be seen that most improvements in F1-score are statistically significant.

It is observed that multi-word Time arguments are better captured by ‘multi-lingual’ model than by the ‘monolingual baseline’ model. An example of this can be seen in the following sentence:

- Hindi Text: एसएसपी संतोष कुमार सिंह ने बताया कि रविवार रात को जालालपुर पर तैनात पुलिसकर्मियों ने बाइक पर सवार दो युवकों को रोकने की कोशिश की

- Transliteration: esesapee santosh kumaar sinh ne bataaya ki ravivaar raat ko jalaalapur par tainaat pulisakarmiyon ne baik par savaar do yuvakon ko rokane kee koshish kee

- Translation: SSP Santosh Kumar Singh said that on Sunday night, policemen stationed at Jalalpur tried to stop two youths riding on bikes.

In the aforementioned sentence the actual phrase denoting time is ‘रविवार रात’ (Sunday night). However the ‘monolingual’ model only detects ‘रविवार’ (Sunday) as the Time argument. However, after multi-lingual training the entire time phrase is correctly detected. This is because the lack of training data for multi-word time arguments in Hindi,
Table 2: Results (F1-Scores) for ‘mono-lingual’ and ‘multi-lingual’ experiments on Hindi, Bengali and English datasets: 5-Fold cross-validated

| Argument | Hindi | Bengali | English |
|----------|-------|---------|---------|
| Time     | 0.60  | 0.86    | 0.56    |
| Place    | 0.58  | 0.61    | 0.57    |
| Reason   | 0.01  | 0.19    | 0.14    |
| Casualties | 0.58  | 0.73    | 0.62    |
| Participant | 0.35  | 0.50    | 0.30    |
| After-effects | 0.25  | 0.28    | 0       |
| Time     | 0.61  | 0.85    | 0.58    |
| Place    | 0.56  | 0.59    | 0.55    |
| Reason   | 0.16  | 0.22    | 0.20    |
| Casualties | 0.59  | 0.71    | 0.63    |
| Participant | 0.41  | 0.53    | 0.32    |
| After-effects | 0.30  | 0.35    | 0.13    |

Table 3: The ‘p-values’ obtained for each improvement in results from the baseline ‘mono-lingual’ to ‘multi-lingual’ experiment (n/a is used for instances where no improvement was observed)

| Argument | Hindi | Bengali | English |
|----------|-------|---------|---------|
| Time     | 0.46  | n/a     | 0.03    |
| Place    | n/a   | n/a     | n/a     |
| Reason   | 0.03  | 0.18    | 0.04    |
| Casualties | 0.39  | n/a     | 0.10    |
| Participant | 0.01  | 0.11    | 0.54    |
| After-effects | 0.04  | 0.09    | 0.01    |

Another interesting observation is that, for *Casualty* argument of *English* dataset, the ‘monolingual’ system often confuses people as casualties, even when they are not. An example of such observation is as follows:

- **Actual:** Over 200000 people in 36 villages located 6 miles (10 km) from the volcano were advised to evacuate immediately.

- **Monolingual Prediction:** Over 200000 people in 36 villages located 6 miles (10 km) from the volcano were advised to evacuate immediately.

- **Multi-lingual Prediction:** Over 200000 people in 36 villages located 6 miles (10 km) from the volcano were advised to evacuate immediately.

In the above example the phrase ‘200000 people’ does not denote casualty, however the ‘monolingual’ model confuses it as casualty. This is due to the lack of training data in *English* to learn the difference between some count of people and actual casualty. However, after ‘multi-lingual’ training the model is able to make this distinction correctly.

The F1-score for *Place* arguments for all the datasets, is better for the ‘monolingual baseline’ model. This is because *Place* argument is present in good numbers for all the datasets, therefore there are enough instances for proper training of deep learning model, even in monolingual setting. Using ‘multi-lingual model’ for such cases is of little help. Furthermore, the syntactic difference between languages confuses the system, thus degrading the performance of the ‘multi-lingual’ system. A good example of this phenomenon is show below:

- **Actual:** Three youths lost their lives when the car they were travelling in collided with a truck near Gaddoli village of Naraingarh in Ambala.

- **Monolingual Prediction:** Three youths lost their lives when the car they were travelling in collided with a truck near Gaddoli village of Naraingarh in Ambala.

- **Multi-lingual Prediction:** Three youths lost their lives when the car they were travelling in collided with a truck near Gaddoli village of Naraingarh in Ambala.

It can be observed that the ‘monolingual baseline’ model predicts the entire phrase describing the *Place* argument correctly. However the prediction by ‘multi-lingual model’ misses the preposition ‘in’, which is present between ‘Naraingarh’ and ‘Ambala’. The same sentence can be written in *Bengali* as follows:

- **Bengali Transliteration:** Ambālāra nārāẏanagaṛēra gāddāli grāmera kāchē ēkaṭi ṭrākēra sāthē ṭrēnēra mukhōmukhi saṅgharṣē tinajana yubaka prāṇa hārāẏa.
The phrase ‘in Ambala’ is represented by a single word ‘Ambālāra’, in Bengali. This difference in syntax between languages, makes the ‘multi-lingual’ system miss the word ‘in’ thus degrading the performance of the system.

The best improvement in F1-score is observed for the arguments Reason and After-effects for the English language. This is because these two arguments have least support in the dataset, and thus multi-lingual training helps by mitigating the scarcity in training examples. The same phenomenon can also be observed for Reason argument which has a low support in Hindi dataset. Thus through our analysis we can conclude that, ‘multi-lingual’ training can help in improving the performance of the system for low support classes. However, it can also cause confusion and deteriorate the performance for high support classes.

6 Conclusion

In this paper we create a dataset for argument extraction for disaster domain, for three languages Hindi, Bengali and English. We then build a deep learning model for extraction of these argument in each language separately. Since the data is limited in size, we build another model that leverages data from all the languages. To make use of different language datasets, we first bring the word embeddings of all the three languages to the same vector space. We also use separate language layers to accommodate divergence in syntax of the languages. Through our experiments we show that training in shared vector space by using ‘multi-lingual’ system helps in improving the performance of low support arguments. We also show that the for high support arguments, the syntactic difference in language can sometimes overcome the benefit of ‘multi-lingual’ training and cost in performance of our proposed ‘multi-lingual’ system.

In future we would like to explore how to handle these syntactic differences so that the performance can be further improved. It would also be interesting to explore the range of languages that can be trained successfully in a multi-lingual setting.

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