Detection of Emotions in Hindi-English Code Mixed Text Data

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Abstract—In recent times, we have seen an increased use of text chat for communication on social networks and smartphones. This particularly involves the use of Hindi-English code-mixed text which contains words which are not recognized in English vocabulary. We have worked on detecting emotions in these mixed data and classify the sentences in human emotions which are angry, fear, happy or sad. We have used state of the art natural language processing models and compared their performance on the dataset comprising sentences in this mixed data. The dataset was collected and annotated from sources and then used to train the models.

Keywords—Emotions, Natural Language Processing, Bilingual Data

I. INTRODUCTION

We have seen an increased use of code-mixed data in social media communication. This has demanded linguistic analysis in this domain as this data is largely unexplored. Especially in south Asian countries like India, this language is the primary source of communication as most people prefer communication over social networks on their smartphones over mailing and faxing. After taking this into account, we analysed this code-mixed data and analysed their linguistic properties and modelling.

We have performed sentiment analysis in this code-mixed data and detected emotions in them (fear, angry, sad and happy). This paper presents the description of the dataset and the predictive modelling performed on that data using the latest state of the art algorithms in natural language processing and linguistic machine learning.

Emotion Prediction is a Natural Language Processing (NLP) task dealing with detection and classification of emotions in various types of languages. Our work aims to detect the emotions in Hindi English bilingual text data using supervised learning as the primary approach and develop and train a dataset of such data.

II. RELATED WORK

While work on sentiment analysis[1] in Hindi-English code mixed Data has been done, but it was primarily comprising of polarity of the sentiment, this work is first in respect to detecting the emotions in this code-mixed Data.

III. DATASET

A. Collecting the Data

The dataset was collected using data scraping tools from twitter and comments section of video streaming platforms.

Each datapoint consists of a sentence in code-mixed language and a corresponding label which is (A- Angry, F-Fear, S-Sad, H-Happy).

B. Annotation

The dataset was annotated by 2 native speakers of both the languages. The interrater reliability was measured as Cohen’s kappa[2] which was found to be 0.94. After the collection of the dataset, we then propose a supervised classification system which uses various machine learning techniques for detecting the emotion associated with the text. Emotion prediction aims to identify different emotions in the text, i.e., Happy, Anger, Fear, Sadness. Initial dataset size was 5986, but after annotating the text our dataset size reduces to 1589. The detailed composition of the dataset is described in table 1 and 2.

| Class (Emotion) | Label |
|-----------------|-------|
| Angry           | 471   |
| Fear            | 304   |
| Sad             | 324   |
| Happy           | 490   |

Table 1. Composition of Dataset

| Sentence          | Label |
|-------------------|-------|
| Kutte chup reh tu | A     |
| Aaaj mei bahut kushh hu | H |
| Bhoot bhoot bachao mujhe | F |
| Mujhe bohot dukh hai RIP | S |

Table 2. Examples of data points.
Fig 1. Illustration of Sub-word LSTM from [1]

IV. NATURAL LANGUAGE PROCESSING

A. Handling code mixed word variations

Transliteration from Hindi to English gives rise to variation in vocabulary in English words having the same Hindi counterpart. For example, word hain in Hindi is written as hai, ha or even h. Another example can be considered with word khoobsurat, when transliterated into English, it is written as kbsrt, kbsurat or khoobsoorat. Notice that the consonants are same in each iteration. This issue is resolved by using clustering of skip-gram vectors. Skip-gram vectors give the representation of a word in the semantic space based on their context. The variations belong to the same word with similar function implying a similar context. Also, the consonants of these variations are same. This property is used in clustering the words. We cluster the words based on a similarity metric that captures both these properties. The similarity metric is formally defined below:

\[ f(v_1, v_2) = \text{sim}(v_1, v_2) \text{ if } v_1, v_2 \text{ have same consonants.} \]

\[ = 0 \text{ otherwise.} \]

Here v1, and v2 are the two words which have the same consonants, sim(x) is the similarity function which is primarily cosine in this case.

This metric gives us the closest variations for the given word. They together form a cluster and the most frequent word replaces all the other words of the cluster. Here, we assume that the word with the highest frequency also has the most probability of being the correct one.

B. Problem Statement

This is primarily a multiclass classification task where the inputs are text streams having bilingual code-mixed data and the output is a label \( y \in \{F, A, S, H\} \) using the categorical cross entropy[3] as the primary loss function:

\[ y * \log(H(x)) + (1 - y) * \log(1 - H(x)) \]

Where \( y \) is the label and \( H(x) \) refers to the output from the baseline model.

C. Baseline Models

The following baseline models were trained and evaluated based on the problem statement:

- Naïve bayes[4] with character n-grams with \( n=8 \). Character n-grams with \( n=8 \) gave the best result when compared to other values of \( n \).
- Naïve bayes[4] with word n-grams of range \( (1,2) \)-Word n-grams yielded the best result when used in a mixed combination of 1 and 2 n-grams than either one of them.
- LSTM[5] trained with word2vec word embeddings-LSTM[5] (Long Short-Term Memory) with a single layer trained using word2vec word embeddings trained simultaneously with the LSTM[5].
- Sub-word LSTM[1] (Character level embeddings convoluted)- Character level embeddings are convoluted after the embedding layer to help the model analyse the sub-word representations of the data.
- SVM[6] on vectorized sequences- A support vector machine trained on vectorized sequences using word vectors obtained from frequency distribution of the words.

D. Metrics and Cross Validation

F1 score and accuracy have been used as the primary evaluation metrics of the above models on the data. The resultant metrics are evaluated from 5-fold cross-validation on the dataset.

E. Experiment and Performance

| F1 Score/ Baseline | Sad  | Angry | Happy | Fear | Accuracy % |
|--------------------|------|-------|-------|------|------------|
| Naïve bayes char n-grams | 0.70 | 0.73  | 0.68  | 0.82 | 72.3       |
| Naïve bayes word n-grams | 0.73 | 0.76  | 0.77  | 0.81 | 75.1       |
| LSTM-Word          | 0.72 | 0.68  | 0.72  | 0.82 | 72.6       |
| Sub-word LSTM      | 0.79 | 0.78  | 0.78  | 0.73 | 76.6       |
| SVM                | 0.68 | 0.66  | 0.70  | 0.82 | 70.1       |

Table 3
All the models have been trained end to end and the resultant metrics are illustrated in Table 3.

V. PERFORMANCE AND LIMITATIONS

After comparing the results from the trained baseline models, it is evident that Sub-Word LSTM[1] outperforms other baseline models, this suggests that character embeddings are more functional in case of bilingual code-mixed data. Other baseline models such as Naïve bayes[4] with word n-grams also give promising results and signal that probabilistic models are more convenient in tasks like detecting emotions in text as emotions are generally conveyed by one or two words in a sentence.

On comparing the performance between LSTM[5] and Sub-word LSTM[1], the latter outperforms the former with significant margin. This is due to the fact that same words transliterate differently in Hindi to English despite the deployment of clustering algorithms to minimize this issue. Character level embeddings are more robust in code mixed data as they tend to overlook this difference in vocabulary.

Size of the dataset can be a bottleneck in performance of models as it is a relatively small dataset compared to standard emotion detection datasets. Also, it was found that Sub-Word[1] or character-level n-grams models are unable to detect emotions in long sentences which shows the limitation of character-level embeddings.

VI. SUMMARY AND FUTURE WORK

We developed a dataset for the task by scraping data through multimedia streaming sites and then annotated according to the emotion they are associated with. We also implement a clustering-based solution to handle the code-mixed word variations during transliteration from Hindi to English.

Hence, we achieve an accuracy of nearly 77% using Sub-word LSTM which can be increased by increasing the size of the dataset. Also, Attention[7] based models can be trained to get a better accuracy, but their computational complexity can pose a challenge in such a simple task. Thus, a larger sample space is the best solution in increasing the performance of the baseline models suggested above along with transformer-based attention[7] models.

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