A POS Tagger for Code Mixed Indian Social Media Text — ICON-2016
NLP Tools Contest Entry from Surukam

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Abstract
Building Part-of-Speech (POS) taggers for code-mixed Indian languages is a particularly challenging problem in computational linguistics due to a dearth of accurately annotated training corpora. ICON, as part of its NLP tools contest has organized this challenge as a shared task for the second consecutive year to improve the state-of-the-art. This paper describes the POS tagger built at Surukam to predict the coarse-grained and fine-grained POS tags for three language pairs — Bengali-English, Telugu-English and Hindi-English, with the text spanning three popular social media platforms — Facebook, WhatsApp and Twitter. We employed Conditional Random Fields as the sequence tagging algorithm and used a library called sklearn-crfsuite — a thin wrapper around CRFsuite for training our model. Among the features we used include — character n-grams, language information and patterns for emoji, number, punctuation and web-address. Our submissions in the constrained environment, i.e., without making any use of monolingual POS taggers or the like, obtained an overall average F1-score of 76.45%, which is comparable to the 2015 winning score of 76.79%.

1 Introduction
The burgeoning popularity of social media in India has produced enormous amounts of user-generated text content. India’s rich linguistic diversity coupled with its affinity towards English — India has the largest number of speakers of English as a Second Language (ESL) in the world — has led to the online conversations being rife with Code Switching (CS) and Code Mixing (CM). Code Switching is the practice of alternating between two or more languages or varieties of a language in the course of a single utterance (Gumperz, 1982). In Code Switching, unlike Code Mixing where one or more linguistic units of a language such as phrases, words and morphemes are embedded into an utterance of another language (Myers-Scotton, 1997), there is a distinct boundary separating the chunks corresponding to each language used in the discourse. So, a combination of language identification and monolingual language taggers could be used for Code Switched utterances. Solorio and Liu (2008) used a Spanish POS tagger and Vyas et al. (2014) used a Hindi POS tagger in conjunction with English monolingual taggers to handle Spanish-English and Hindi-English code-switched discourses respectively.

Part-of-speech (POS) tagging, the process of assigning each word its proper part of speech, is one of the most fundamental parts of any natural language processing pipeline and it is also an integral part of any syntactic analysis. There are highly accurate monolingual POS taggers available for resource-rich languages like English and French, the state-of-the-art being 97.6% (Choi, 2016) and 97.8% (Denis and Sagot, 2009), in large part due to extensively annotated million word corpora such as PennTreeBank (Santorini, 1990) and French TreeBank (Abeillé et al., 2003) respectively. Annotated data for code-mixed data is extremely scarce and the efforts to build a POS tagger for it have mostly advanced through the shared tasks organized at FIRE (Choudhury et al., 2014), EMNLP (Barman et al., 2014; Solorio et al., 2014) and ICON (Soman, 2015; Pimpale and Patel, 2016) in the past 2 years. In this paper, we describe our POS tagger for three widely spoken Indian languages (Hindi, Bengali, and Telugu), mixed with English, which was sub-
Table 1: Code-Mixing-Index: Facebook Corpus

| Language (English+) | CMI all | CMI mixed | Num utt. | Mixed (%) |
|---------------------|---------|-----------|----------|-----------|
| Telugu              | 31.94   | 39.10     | 989      | 81.70     |
| Hindi               | 11.78   | 20.06     | 882      | 58.73     |
| Bengali             | 23.76   | 24.77     | 762      | 95.93     |

Table 2: Code-Mixing Index: Twitter Corpus

| Language (English+) | CMI all | CMI mixed | Num utt. | Mixed (%) |
|---------------------|---------|-----------|----------|-----------|
| Telugu              | 34.94   | 35.37     | 991      | 98.79     |
| Hindi               | 25.66   | 28.13     | 1206     | 91.21     |
| Bengali             | 29.45   | 29.50     | 585      | 99.83     |

Table 3: Code-Mixing Index: WhatsApp Corpus

| Language (English+) | CMI all | CMI mixed | Num utt. | Mixed (%) |
|---------------------|---------|-----------|----------|-----------|
| Telugu              | 11.62   | 32.60     | 617      | 35.66     |
| Hindi               | 18.76   | 23.37     | 728      | 80.22     |
| Bengali             | 3.71    | 24.72     | 3718     | 15.01     |

Table 4: Code-Mixing Index: ICON 2015

| Language (English+) | CMI all | CMI mixed | Num utt. | Mixed (%) |
|---------------------|---------|-----------|----------|-----------|
| Telugu              | 36.55   | 36.88     | 690      | 99.13     |
| Hindi               | 5.88    | 27.60     | 981      | 21.30     |
| Bengali             | 0.31    | 30.05     | 1052     | 1.05      |

We observed that the WhatsApp corpus for Bengali has a very low fraction of code-mixed sentences i.e., there are an extremely low number of words tagged as en in the data-set. On closer inspection of the dataset, there were exactly 13 instances of words that were tagged en and these were actually words such as Kolkata and San Antonio, that should have been annotated as ne instead. Effectively, CMI for WhatsApp-Bengali corpus is 0.
3 Model and Results

POS tagging is considered to be a sequence labelling task, where each token of the sentence needs to be assigned a label. These labels are usually interdependent, because the sentence follows grammar rules inherent to the language.

We have used the CRF implementation of sklearn-crfuite because it is particularly well suited for sequence labelling tasks.

3.1 Features

The feature-set consisted of character-case information, character n-grams of gram size up to 3, which would thereby also encompass all prefixes and suffixes, patterns for email and web-site urls, punctuations, emoticons, numbers, social media specific characters like @,# and also the language tag information.

We chose a CRF window size of two and performed grid-search to choose the best optimization algorithm and L1/L2 regularization parameters. There were a total of 18 models trained using this pipeline, one for each case in the cross-product:

{bn-en, hi-en, te-en} X {WhatsApp, Twitter, Facebook} X {Fine-Grained, Coarse-Grained}

3.2 Results

The F1 measure of our model against the social networks is depicted in Table 5 and the results with respect to the POS granularity is shown in Table 6. These results were calculated on the private test data-set shared by the organizers. With the system described in the paper, we achieved an overall average score of 76.45%, across all 18 models. This is only marginally lesser than 76.79%, which was the score of winning entry of ICON 2015, and we are awaiting the results of ICON 2016.

4 Conclusion & Future Work

In this paper, we presented a CRF based POS tagger for code-mixed social media text in the constrained environment, without making use of any external corpora or monolingual POS taggers. We achieved an overall F1-Score of 76.45%.

Table 5: Model Performance (F1-Score) w.r.t Social Networks

| Language (English +) | WhatsApp | Twitter | Facebook |
|----------------------|----------|---------|----------|
| Telugu               | 74.43    | 79.15   | 74.10    |
| Hindi                | 75.68    | 86.80   | 77.44    |
| Bengali              | 76.71    | 69.64   | 74.1     |

Table 6: Model Performance (F1-Score) w.r.t POS Granularity

| Language (English +) | Fine-Grained | Coarse-Grained |
|----------------------|--------------|----------------|
| Telugu               | 73.50        | 78.30          |
| Hindi                | 83.40        | 76.60          |
| Bengali              | 73.28        | 76.39          |

We would like to evaluate the performance improvement or lack thereof upon training a POS tagger in an unconstrained environment by utilizing monolingual taggers trained on Indic languages. Multilingual tools are still a ways off from matching the state-of-the-art of the tools available for monolingual linguistic analysis. There is promising research in the field of developing tools for resource poor languages by applying Transfer Learning (Zoph et al., 2016), which could also be evaluated in the future. Upon inspecting the dataset, we observed a few inaccuracies in annotation, which could be addressed by leveraging crowd-sourcing platforms that can execute Human Intelligence Tasks.

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