Abstract

This paper describes Centre for Development of Advanced Computing’s (CDACM) submission to the shared task: 'Tool Contest on POS tagging for Code-Mixed Indian Social Media (Facebook, Twitter, and Whatsapp) Text’, collocated with ICON-2016. The shared task was to predict Part of Speech (POS) tag at word level for a given text. The code-mixed text is generated mostly on social media by multilingual users. The presence of the multilingual words, transliterations, and spelling variations make such content linguistically complex. In this paper, we propose an approach to POS tag code-mixed social media text using Recurrent Neural Network Language Model (RNN-LM) architecture. We submitted the results for Hindi-English (hi-en), Bengali-English (bn-en), and Telugu-English (te-en) code-mixed data.

1 Introduction

Code-Mixing and Code-Switching are observed in the text or speech produced by a multilingual user. Code-Mixing occurs when a user changes the language within a sentence, i.e. a clause, phrase or word of one language is used within an utterance of another language. Whereas, the co-occurrence of speech extract of two different grammatical systems is known as Code-Switching.

The language analysis of code-mixed text is a non-trivial task. Traditional approaches of POS tagging are not effective, for this text, as it does not adhere to any grammatical structure in general. Many studies have shown that RNN based POS taggers produced comparable results and, is also the state-of-the-art for some languages. However, to the best of our knowledge, no study has been done for RNN based POS tagging of code-mixed data.

In this paper, we have proposed a POS tagger using RNN-LM architecture for code-mixed Indian social media text. Earlier, researchers have adopted RNN-LM architecture for Natural Language Understanding (NLU) (Yao et al., 2013; Yao et al., 2014) and Translation Quality Estimation (Patel and Sasikumar, 2016). RNN-LM models are similar to other vector-space language models (Bengio et al., 2003; Morin and Bengio, 2005; Schwenk, 2007; Mnih and Hinton, 2009) where we represent each word with a high dimensional real-valued vector. We modified RNN-LM architecture to predict the POS tag of a word, given the word and its context. Let’s consider the following example:

Input: behen ki shaaadi and m not there
Output: G_N G_PRP G_N CC G_V G_R G_R

In the above sentence, to predict POS tag (G_N) for the word shaaadi using an RNN-LM model with window size 3, the input will be ki shaaadi and. Whereas, in standard RNN-LM model, ki and will be the input with shaaadi as the output. We will discuss details of various models tried and their implementations in section 3.

In this paper, we show that our approach achieves results close to the state-of-the-art systems such as \[1\]Stanford (Toutanova et al., 2003), and \[2\]HunPos (Halácsy et al., 2007).

\[1\]http://nlp.stanford.edu/software/tagger.shtml (Maximum-Entropy based POS tagger)
\[2\]https://code.google.com/archive/p/hunpos/ (Hidden Markov Model based POS tagger)
2 Related Work

POS tagging has been investigated for decades in the literature of Natural Language Processing (NLP). Different methods like a Support Vector Machine (Márquez and Giménez, 2004), Decision Tree (Schmid and Laws, 2008), Hidden Markov Model (HMM) (Kupiec, 1992) and Conditional Random Field Auto Encoders (Ammar et al., 2014) have been tried for this task. Among these works, Neural Network (NN) based models is mainly related to this paper. In NN family, RNN and HMM techniques for POS tagging of Chinese is found to be better for modeling of long-range dependencies than Simple RNN. Simple RNN also suffers from the problem of vanishing and exploding gradient (Bengio et al., 1994). LSTM and other complex RNN models tackle this problem by introducing a gating mechanism. Many variants of LSTM (Graves, 2013; Yao et al., 2014; Jozefowicz et al., 2015) have been tried in literature for the various tasks. We implemented the following set of equations:

\[ h_t = \text{sigm}(W_{xh}x_t + W_{hh}h_{t-1} + b_h) \]  
\[ y_t = \text{softmax}(W_{hy}h_t + b_y) \]  

3 Experimental Setup

3.1 RNN Models

There are many variants of RNN networks for different applications. For this task, we used elaman (Elman, 1990), Long Short-Term Memory (LSTM) (Hochreiter and Schmidhuber, 1997), Deep LSTM, Gated Recurrent Unit (GRU) (Cho et al., 2014), which are widely used RNN models in the NLP literature.

In the following sub-sections, we gave a brief description of each model with mathematical equations (1, 2, and 3). In the equations, \( x_t \) and \( y_t \) are the input and output vectors respectively. \( h_t \) and \( h_{t-1} \) represent the current and previous hidden states respectively. \( W \) are the weight matrices and \( b \) are the bias vectors. \( \odot \) is the elementwise multiplication of the vectors. We used \( \text{sigm} \), the logistic sigmoid and \( \text{tanh} \), the hyperbolic tangent function to add nonlinearity in the network with \( \text{softmax} \) function at the output layer.

3.1.1 ELMAN

Elman and Jordon (Jordan, 1986) networks are the simplest network in RNN family and are known as Simple RNN. Elman network is defined by the following set of equations:

\[ h_t = \text{sigm}(W_{xh}x_t + W_{hh}h_{t-1} + b_h) \]  
\[ y_t = \text{softmax}(W_{hy}h_t + b_y) \]

3.1.2 LSTM

LSTM is found to be better for modeling of long-range dependencies than Simple RNN. Simple RNN also suffers from the problem of vanishing and exploding gradient (Bengio et al., 1994). LSTM and other complex RNN models tackle this problem by introducing a gating mechanism. Many variants of LSTM (Graves, 2013; Yao et al., 2014; Jozefowicz et al., 2015) have been tried in literature for the various tasks. We implemented the following version:

\[ i_t = \text{sigm}(W_{xi}x_t + W_{hi}h_{t-1} + b_i) \]  
\[ o_t = \text{sigm}(W_{xo}x_t + W_{ho}h_{t-1} + b_o) \]  
\[ f_t = \text{sigm}(W_{xf}x_t + W_{hf}h_{t-1} + b_f) \]  
\[ j_t = \text{tanh}(W_{xj}x_t + W_{hj}h_{t-1} + b_j) \]  
\[ c_t = c_{t-1} \odot f_t + i_t \odot j_t \]  
\[ h_t = \text{tanh}(c_t) \odot o_t \]  
\[ y_t = \text{softmax}(W_{hy}h_t + b_y) \]

where \( i, o, f \) are input, output and forget gates respectively. \( j \) is the new memory content and \( c \) is updated memory.

3.1.3 Deep LSTM

In this paper, we used Deep LSTM with two layers. Deep LSTM is created by stacking multiple LSTM on the top of each other. The output of lower LSTM forms input to the upper LSTM. For example, if \( h_t \) is the output of lower LSTM, then we apply a matrix transform to form the input \( x_t \) for the upper LSTM. The Matrix transformation enables us to have two consecutive LSTM layers of different sizes.
3.1.4 GRU

GRU is quite a similar network to the LSTM, without any memory unit. GRU network also uses a different gating mechanism with reset ($r$) and update ($z$) gates. The following set of equations defines a GRU model:

$$
    r_t = \text{sigmoid}(W_{xr}x_t + W_{hr}h_{t-1} + b_r)
$$

$$
    z_t = \text{sigmoid}(W_{xz}x_t + W_{hz}h_{t-1} + b_z)
$$

$$
    \tilde{h}_t = \tanh(W_{x\tilde{h}}x_t + W_{h\tilde{h}}(r_t \odot h_{t-1}) + b_{\tilde{h}})
$$

$$
    h_t = z_t \odot h_{t-1} + (1 - z_t) \odot \tilde{h}_t
$$

$$
    y_t = \text{softmax}(W_{hy}h_t + b_y)
$$

3.2 Implementation

All the models were implemented using THEANO framework (Bergstra et al., 2010; Bastien et al., 2012). For all the models, the word embedding dimensionality was 100, no of hidden units were 100 and the context word window size was 5 ($w_{t-2}w_{t-1}w_tw_{t+1}w_{t+2}$). We initialized all the square weight matrices as random orthogonal matrices. All the bias vectors were initialized to zero. Other weight matrices were sampled from a Gaussian distribution with mean 0 and variance 0.0001.

We trained all the models using Truncated Back-Propagation-Through-Time (T-BPTT) (Werbos, 1990) with the stochastic gradient descent. Standard values of hyper-parameters were used for RNN model training, as suggested in the literature (Yao et al., 2014; Patel and Sasikumar, 2016). The depth of BPTT was fixed to 7 for all the models. We trained each model for 50 epochs and used Ada-delta (Zeiler, 2012) to adapt the learning rate of each parameter automatically ($\epsilon = 10^{-6}$ and $\rho = 0.95$).

3.3 Data

We used the data shared by the contest organizers (Jamatia and Das, 2016). The code-mixed data of bn-en, hi-en and te-en was shared separately for the Facebook (fb), Twitter (twt) and What-sapp (wa) posts and conversations with Coarse-Grained (CG) and Fine-Grained (FG) POS annotations. We combined the data from fb, twt, and wa for CG and FG annotation of each language pair. The data was divided into training, testing, and development sets. Testing and development sets were randomly sampled from the complete data. Table 1 details sizes of the different sets at the sentence and token level. Tag-set counts for CG and FG are also provided.

We preprocessed the text for Mentions, Hashtags, Smilies, URLs, Numbers and, Punctuations. In the preprocessing, we mapped all the words of a group to a single new token as they have the same POS tag. For example, all the Mentions like @dhoni, @bcci, and @iitb were mapped to @user; all the Hashtags like #dhoni, #bcci, #iitb were mapped to #user.

3.4 Methodology

The RNN-LM models use only the context words’ embedding as the input features. We experimented with three RNN model configurations. In the first setting (Simple_RNN, LSTM, Deep LSTM, GRU), we learn the word representation from scratch with the other model parameters. In the second configuration (GRU_Pre), we trained word representations (pre-training) using word2vec (Mikolov et al., 2013b) tool and fine-tuned with the training of other parameters of the network. Pre-training not only guides the learning towards minima with better generalization in non-convex optimization (Bengio, 2009; Erhan et al., 2010) but also improves the accuracy of the system (Kreutzer et al., 2015; Patel and Sasikumar, 2016). In the third setting (GRU_Pre_Lang), we also added language of the words as an additional feature with the context words. We learn the vector representation of languages similar to that of words, from scratch.

4 Results

We used F1-Score to evaluate the experiments, results are displayed in the Table 2. We trained models as described in the section 3.4. To compare our results, we also trained the Stanford and HunPos taggers on the same data, accuracy is given in Table 2.

From the table, it is evident that pre-training and language as an additional feature is helpful. Also, the accuracy of our best system (GRU_Pre_Lang) is comparable to that of Stanford and HunPos. GRU models are out-performing other models (Simple_RNN, LSTM, Deep LSTM) for this task also as reported by Chung et al. (2014) for a suit of NLP tasks.
Table 1: Data Distribution; CG: Coarse-Grained, FG: Fine-Grained

| code-mix | #sentences | #tokens | #tags |
|----------|------------|---------|-------|
|          | training   | dev     | testing |          | training   | dev     | testing | CG | FG |
| hi-en    | 2430       | 100     | 100    | 37799   | 1888      | 1457    | 18      | 40 |
| bn-en    | 524        | 50      | 50     | 11977   | 1477      | 1231    | 18      | 38 |
| te-en    | 1779       | 100     | 100    | 26470   | 1436      | 1543    | 18      | 50 |

Table 2: F1 scores for different experiments

| model      | hi-en %F1 score | bn-en %F1 score | te-en %F1 score |
|------------|-----------------|-----------------|-----------------|
|            | CG | FG  | CG | FG  | CG | FG  |
| Simple_RNN | 78.16 | 68.73 | 70.16 | 64.49 | 72.27 | |
| LSTM       | 62.75 | 53.94 | 41.91 | 35.05 | 57.59 | 51.45 |
| Deep LSTM  | 70.07 | 59.78 | 54.64 | 46.88 | 65.86 | 59.45 |
| GRU        | 78.29 | 69.32 | 71.90 | 64.96 | 72.40 | 68.72 |

|            | CG | FG  | CG | FG  | CG | FG  |
|------------|----|-----|----|-----|----|-----|
| GRU_Pre    | 80.51 | 71.72 | 74.77 | 68.54 | 74.02 | 70.05 |
| GRU_Pre_Lang | 80.92 | 73.10 | 74.05 | 69.23 | 74.00 | 70.33 |
| HunPos     | 77.50 | 69.04 | 76.55 | 71.02 | 74.30 | 70.73 |
| Stanford   | 79.89 | 73.91 | 79.36 | 73.44 | 77.05 | 73.42 |

5 Submission to the Shared Task

The contest was having two type of submissions, first, constrained: restricted to use only the data shared by the organizers with the participants’ implemented systems; second, unconstrained: participants were allowed to use the publicly available resources (training data, implemented systems etc.).

We submitted for all the language pairs (hi-en, bn-en and, te-en) and domains (fb, twt and, wa). For constrained submission, the output of GRU_Pre_Lang was used. We trained Stanford POS tagger with the same data for unconstrained submission. Jamatia and Das (2016) evaluated all the submitted systems against another gold-test set and reported the results.

6 Analysis

We did a preliminary analysis of our systems and reported few points in this section.

- The POS categories, contributing more in the error are G_X, G_V, G_N and G_J for coarse-grained and V_VM, JJ, N_NN and N_NNP for fine-grained systems. Also, we did the confusion matrix analysis and found that these POS tags are mostly confused with each other only. For instance, G_J POS tag was tagged 28 times wrongly to the other POS tags in which 17 times it was G_N.

- RNN models require a huge amount of corpus to train the model parameters. From the results, we can observe that for hi-en and te-en with only approx 2K training sentences, the results of best RNN model (GRU_Pre_Lang) are comparable to Stanford and HunPos. For bn-en, the corpus was very less (only approx 0.5K sentences) for RNN training which resulted into poor performance compared to Stanford and HunPos. With this and the earlier work on RNN based POS tagging, we can expect that RNN models could achieve state-of-the-art accuracy with given the sufficient amount of training data.

- In general, LSTM and Deep LSTM models perform better than Simple_RNN. But here, Simple_RNN is outperforming both LSTM and Deep LSTM. The reason could be less amount of data for training such a complex model.

- Few orthographically similar words of English and Hindi, having different POS tags are given with examples in Table 3. System confuses in POS tagging of such words. With adding language as an additional feature, we were able to tag these type of words correctly.
Table 3: Similar words in hi-en data

| word | lang | example | POS   |
|------|------|---------|-------|
| are  | hi   | are shyaam kidhar ho? | PSP   |
| are  | en   | they are going. | G_V   |
| to   | hi   | tumane to dekha hi nhi. | G_PRT |
| to   | en   | they go to school. | CC    |
| hi   | hi   | mummy to aisi hi hain. | G_V   |
| hi   | en   | hi, how are you. | G_PRT |

7 Conclusion and Future Work

We developed language independent and generic POS tagger for social media text using RNN networks. We tried Simple_RNN, LSTM, Deep LSTM and, GRU models. We showed that GRU outperforms other models, and also benefits from pre-training and language as an additional feature. Also, the accuracy of our approach is comparable to that of Stanford and HunPos.

In the future, we could try RNN models with more features like POS tags of context words, prefixes and suffixes, length, position, etc. Word characters also have been found to be a very useful feature in RNN based POS taggers.

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