

# Poster: A Novel Approach for POS Tagging of Pashto Language

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**Abstract**— Pashto is a language that belongs to the Indo-European family, mostly spoken in South Asian countries, especially in Pakistan and Afghanistan. To build software that enables us to translate Pashto sentences into various languages and building Natural Language Understand (NLU) applications to make interactive Pashto software requires a well-defined corpus and Parts of Speech (POS) tagging approach. Therefore, a well-defined corpus is developed by scraping data from different websites. We have prepared dataset according to the guidelines written for Persian and Arabic languages, as these languages are somehow similar to these languages. Training of POS tagging using BiLSTM with GloVe embedding shows the effectiveness of our proposed approach and achieved 97% accuracy.

**Keywords**—Pashto, POS tagging, LSTM, Bidirectional LSTM, Corpus.

## I. INTRODUCTION

Pashto is an eastern Iranian language mainly spoken in the northwest region of Pakistan and Afghanistan. It is estimated that there are over 45-60 million Pashto speakers worldwide. Due to this vast amount of Pashto speakers worldwide, it is necessary to build Natural Language Processing (NLP) based software for native speakers. Therefore, a well-defined corpus is developed, where some words are manually written, and some of them are scraped from different Pashto dictionary websites such as thepashto.com, yorku.ca, etc. Parts of Speech tagging (POS tagging) is a process in which we have to assign parts of speech to each word in a sentence not based on its meaning but also on context as well, because of the different meanings of the same word in different sentences.

Tagging words in sentences manually is a very time-consuming process. But due to advancement in NLP, this process is computed automatically by POS tagging algorithms [1]. Automatic POS tagging is not just an approach to assign tags in given sentences, but it could also aid in removing ambiguous words within a sentence. For example, given two English sentences have different parts of speech for one word. Aslam's conduct is always ethical. Hina conducts herself in a professional manner. In the first sentence the word 'conduct' is used as a noun, whereas in the second sentence, the word 'conduct' is used as a verb. Also, the noun is further subdivided into common or proper, singular or plural. Before developing a POS tagger, a well-defined tagset and dictionary is necessary.

A limited number of researchers have conducted research related to POS tagging of Pashto. A first-ever rule-based approach for POS tagging in Pashto language has been done by Rabbi et al. in [2]. They also built a tagset for POS tagging in Pashto language [3]. After getting motivated from this, we developed a tag set of over 18000 Pashto words and for POS tagging, and Bidirectional LSTM is used in this study. The rest of the paper is divided as follows: In section 2 we discussed the related work done in Pashto language, then in section 3 our proposed scheme is explained. Results and experiments are discussed in section 4 and Conclusion and future work are discussed in section 5.

## II. RELATED WORK

### A. Related Work in the Pashto Language

A finite number of research work has been published by researchers related to natural language processing in Pashto language, Rabi et al. developed a first ever tagset for Pashto language. They follow the EAGLES guidelines, which were written for the languages of European Union. They used a tagset of 215 tags [3]. A first ever rule based tagset also built in [2]. They used 54 tags and developed a simple algorithm for POS tagging. Their POS tagger shows better results when number of words in lexicon and rules increases. They achieve 88% accuracy with 120 rules and 100,000 tagged words.

Persian is also called the sister language of Pashto and has very much lexical similarity with Pashto. Khan et al. used Bijankhan Corpus (A freely available Pashto corpus which was manually tagged by Tehran University in Iran) to tag Pashto. They also used Hidden Markov Model trigram tagger (HMM TnT) for tagging the dataset. They achieved 70.84% accuracy.

A Pashto Corpus is developed using Xaira tool, a tool used for building corpus. They collected data from books, novels, news and research

publications. Their corpus contains 1.225 million words. Based on their corpus they built a morphological system of Pashto language [4]. They also built a general purpose corpus for written Pashto [5]. This corpus contains 10,000 words provided by Pashto Academy, University of Peshawar (UoP). A user friendly interface is also built for searching words in corpus.

In previous studies, various machine learning and traditional approaches have been used for POS tagging which uses hand-crafted based features and shows good results. Whereas, our study uses deep learning based approach for POS tagging.

### B. Related Work in other Languages

Most of the work done in NLP is in languages like Arabic, English, Chinese and German etc. Several POS taggers have been developed for these languages. For instance, Arabic has many neural network based POS taggers [6], [7], [8], for English [9] and for Chinese language [10].

However, from recent years neural networks achieved better results over various traditional machine learning techniques. Most of the methods used for POS tagging in Pashto language are traditional, and vast research area in Pashto language is still pending. Therefore, in this research study we built a well-defined POS tagging of Pashto using Bidirectional LSTM technique.

## III. PROPOSED SCHEME

### A. Proposed Tagset

There exist several tag sets for different languages. For English there are many tagsets available i.e ENGLISH PENN TREEBANK, Oxford POS tagset, SUSANNE Corpus and HISTORICAL PENN TREEBANK etc [11][12]. For Arabic Khoja et al. developed a tagset [13] and Andrew Hardie developed a tagset for Urdu [14]. But every language has specific grammar and set of rules, therefore a separate dictionary of words with tags are necessary for this study. We built a dataset as there are no publicly available POS tagging datasets and there is a need for large-scale POS tagging dataset

### B. Building Lexicon

To build lexicon, Pashto words are scraped from various Pashto dictionary websites and some of them are manually written. For scraping Beautiful Soup (BS) library is used in python and data is pre-processed with pandas and numpy libraries. The proposed lexicon is based on 18000 properly annotated unique words and also can be used for other purposes.

#### Algorithm 1 Algorithm for POS tagging

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0: Read Input text from the file
0: Tokenize the text into tokens
0: Read each token in text.
0: for each token in lexicon do
1: if found then
2: append the tag with a token
3: else if multiple tags exist then
4: tag with given rules
5: end if
5: end for
5: Write the appended tag with a token to file.
5: If not ask for user to tag, otherwise leave blank
5: Add the tag with new word to the lexicon.
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Figure 1 shows the visual representation of proposed algorithm used to perform this study and Algorithm of the said approach is shown in Algorithm 1. The ratio of occurrence of manual tagging is 5-10 % which are manually tagged by us. For manual tagging in case of multiple tags exists we 1) search from Pashto dictionary for given tag and 2) uses rules given in [2]

### C. Bi-LSTM RNN for POS Tagging

From recent years, Recurrent Neural Networks (RNN) has been shown very effective for tagging of sequential data such as speech recognition and non-segmental handwritten characters. The idea of RNN was to connect information with previous information that is why it is very useful for sequential data. But the problem RNN is that it cannot handle huge data due to vanishing and exploiting gradient problems.

Long Short Term Memory (LSTM) is a type of RNN that came to overcome the problem of RNN and have long term dependencies. Due to this property LSTM is commonly used in NLP related problems. Bi-Directional

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graph TD
    A[Input: Untagged text files] --> B[Tokenize the text into words]
    B --> C[Find Word on Lexicon]
    C --> D[Tag Not found on Lexicon]
    C --> E[Tag found on Lexicon]
    D --> F[Manually Given tag by User]
    F --> G[Tagged Sentence]
    E --> G
    B --> G
  
```

The flowchart illustrates the manual tagging process. It begins with 'Input: Untagged text files', which leads to 'Tokenize the text into words'. This step shows a sample sentence 'گرافیک نشه په پورتی قوانیر گران' and its tokens: 'گرافیک', 'نشه', 'په', 'پورتی', 'قوانیر', 'گران'. The process then branches: one path goes to 'Find Word on Lexicon', which leads to 'Tag Not found on Lexicon' and then to 'Manually Given tag by User'. The other path from 'Find Word on Lexicon' leads to 'Tag found on Lexicon'. Both paths lead to the final 'Tagged Sentence' box, which shows the sentence with tags: 'گران/ Noun', 'قوانیر/ Noun', 'پورتی/ Noun', 'په/ Adverb', 'نشه/ Adverb', 'گرافیک/ Noun'.

Given a sentence set  $s = \{S_1, S_2, S_3, \dots, S_n\}$  with tags  $t = \{t_1, t_2, t_3, \dots, t_n\}$ . Bi-LSTM RNN is used to predict the tag probability distribution of each word. Where  $S_i$  is the one hot representation of word in a sentence and  $f(S_i)$  returns a three-dimensional representation vector for a word. The input vector  $I_i$  is represented as:

Where  $S_1$  and  $S_2$  are Weight matrices connected to two layers. For word representation of tagged corpus, Global Vectors for word representation (GloVe), an unsupervised algorithm is used [15]. Each of the word used in their original form doesn't give semantic meaning. However, defining a word in vector form gives more information. These vectors contain both semantic and syntactic information. GloVe vectors are generated by creating co-occurrence matrix of all words in corpus by Singular Value Decomposition (SVD) to which create k dimension representation of each word. The detailed description of GloVe vector is given in [15].

- Embedding Layer: This layer converts the input word into unique number to the GloVe vector
- Bi-LSTM Layer: This layer learns the sequence of data so that it creates feature pattern that would be given to fully connected layer for prediction.
- Fully Connected Layer: This layer takes input from Bi-LSTM layer and gives to lower dimension form. The output layer is further given to Softmax function for prediction that gives probability values. The output layer dimension is the number of tags.

## IV. EXPERIMENTS AND RESULTS

For building corpus, we took 19 articles from BBC Pashto (A well-known British Broadcasting Service Pashto news site) [17] which consists of 18000 words. For training, size of input layer is 64, hidden layer is 50 and output layer is 14 as we have 14 tags in our corpus. Table 1 shows the impact of accuracy on the number of words in lexicon. By using 5000 words in lexicon and 5 epochs gives 56% accuracy. On 10000 words, the accuracy increase to 77% and using 18000 words it achieves 97% accuracy which shows increasing the numbers of words in lexicon improves the performance in terms of accuracy. The learning curve of training and validation using 18000 words lexicon of accuracy score is shown in Figure 3(a) and loss curves of training and validation set is shown in Figure 3(b).

Words in lexicon	Number of Epochs	Accuracy
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The figure consists of two line plots side-by-side, both sharing the same x-axis: 'num of Epochs' ranging from 0.0 to 4.0.

**Left Plot: train\_acc vs val\_acc**

- Y-axis:** accuracy, ranging from 0.982 to 0.998.
- Legend:** 'train' (blue line) and 'val' (orange line).
- Data:**

num of Epochs	train_acc	val_acc
0.0	0.9845	0.9945
1.0	0.9955	0.9955
2.0	0.9965	0.9965
3.0	0.9970	0.9970
4.0	0.9975	0.9975

**Right Plot: train\_loss vs val\_loss**

- Y-axis:** loss, ranging from 0.01 to 0.07.
- Legend:** 'train' (blue line) and 'val' (orange line).
- Data:**

num of Epochs	train_loss	val_loss
0.0	0.070	0.020
1.0	0.018	0.015
2.0	0.012	0.011
3.0	0.010	0.009
4.0	0.008	0.007

## CONCLUSION

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