Sanskrit Sandhi Splitting using $seq2(seq)^2$

Neelamadhav Gantayat, Rahul Aralikatte, Naveen Panwar, Anush Sankaran, Senthil Mani

\{neelamadhav,rahul.a.r,naveen.panwar,anussank,sentmani\}@in.ibm.com

IBM Research, India

Abstract

In Sanskrit, small words (morphemes) are combined through a morphophonological process called Sandhi to form compound words. Sandhi splitting is the process of splitting a given compound word into its constituent morphemes. Although rules governing the splitting of words exist, it is highly challenging to identify the location of the splits in a compound word, as the same compound word might be broken down in multiple ways to provide syntactically correct splits. Existing systems explore incorporating these pre-defined splitting rules, but have low accuracy since they don’t address the fundamental problem of identifying the split location.

With this work, we propose a novel Double Decoder RNN (DD-RNN) architecture which i) predicts the location of the split(s) with an accuracy of 95% and ii) predicts the constituent words (i.e. learning the Sandhi splitting rules) with an accuracy of 79.5%. To the best of our knowledge, deep learning techniques have never been applied to the Sandhi splitting problem before. We further demonstrate that our model out-performs the previous state-of-the-art significantly.

1 Introduction

Sanskrit is one of the oldest languages in the world, having its origin in the Indo-Aryan civilization. Aṣṭādhyāyī (meaning, a collection of eight chapters) by Pāṇini, is one of the foundational texts of Sanskrit’s grammar, syntax, and semantics.

As defined in the grammar, morphemes are basic morphological units that form the building blocks of words in Sanskrit. Compound word formations are governed by a set of deterministic rules following a well-defined structure. The process of merging two or more morphemes to form a word in Sanskrit is called Sandhi. On the other hand, the process of breaking a compound word into its constituent morphemes is called Sandhi splitting. This process is akin to other languages such as in English; ‘come’ + ‘ing’ → ‘coming’, where we lose the additional ‘e’ in the word ‘come’ while merging. Other examples include ‘indirect’, ‘impossible’, and ‘illuminate’, where all these words have the same prefix ‘in’ that is modified when merging with root words. In Japanese, Rendaku (‘sequential voicing’) is similar to Sandhi. For example, ‘origami’ consists of ‘ori’ (paper) + ‘kami’ (folding), where ‘kami’ changes to ‘gami’ due to Rendaku.

Learning the process of sandhi splitting for Sanskrit could provide linguistic insights into the formation of words in a wide-variety of Dravidian languages. From an NLP perspective, automated learning of word formations in Sanskrit could provide a framework for learning word organization in other Indian languages as well (Bharati et al., 2006). In literature, past works have explored sandhi splitting (Gillon, 2009) (Kulkarni and Shukl, 2009), as a rule based problem by applying the rules from Aṣṭādhyāyī in a brute force manner. For a given compound word, all applicable rules are applied to every character in the word and a large potential candidate list of word splits is obtained. Then, they use a morpheme dictionary of Sanskrit words or other heuristics to remove infeasible word split combinations. However, none of the approaches address the fundamental problem of identifying the location of the split before applying the rules, which will significantly reduce the number of rules that can be ap-
Figure 1: Different possible splits for the word *paropakāraḥ* and *protsāhah*, provided by a standard Sandhi splitter.

plied, hence resulting in more accurate splits.

Consider the example in Figure 1 illustrating the different possible splits of a compound word *paropakāraḥ*. While the split *para* + *upakāraḥ* is the correct split, other forms of splits such as, *para* + *apa* + *kāraḥ* is syntactically possible while semantically incorrect¹. Another example is *protsāhah*, where *pra* + *utsāhah* is the correct split while the other splits are incorrect. Thus, knowing all the rules of splitting is insufficient and it is essential to identify the location(s) of split(s) in a given compound word.

On an abstract level, the Chinese word segmentation problem looks very similar to Sandhi splitting. But in Chinese, when words combine, they do not change morphologically. The *n*th morpheme is just appended to the *(n − 1)*th morpheme. For example: 致以+ 切+ 的+ 候 → 致以切的候. Thus, the Chinese segmentation problem boils down as a special case of sandhi splitting. LSTMs and Gated Recurrent Neural Networks (GRNNs) have been applied to this problem by (Chen et al., 2015b) and (Chen et al., 2015a) respectively. We compare our model with these approaches and show the effectiveness of the proposed model in Section 5.

In this research, we propose an approach for automated generation of split words by first learning the potential split locations in a compound word. We use a deep bi-directional character RNN encoder and two decoders with attention. The accuracy of our approach on the benchmark dataset for split location prediction is 95% and for split words prediction is 79.5% respectively.

To summarize, the major research contributions are enumerated as follows:

1. A novel sandhi split word generation technique is proposed for compound words in Sanskrit using a deep bi-directional recurrent encoder and two decoders with attention (DD-RNN) with Long Short-Term Memory (LSTM) units (Hochreiter and Schmidhuber, 1997).

2. Further, the proposed DD-RNN is compared against other standard deep learning models, models used for word segmentation in Chinese, and the performances are benchmarked.

The rest of the paper is organized as follows. Section 2 details collation of dataset, while Section 3 talks about existing sandhi splitting tools. Section 4 explains our proposed deep learning architecture and section 5 discusses the experimental performance and analysis of the proposed approach. Finally, section 6 concludes the research and provides a direction for future work.

## 2 Data Curation

Most automated algorithms in computational linguistics are data driven and require labelled data both for learning and evaluating models. Thus, the availability of a dataset is fundamental for research to be conducted in this domain. One of the contributions of this research is collating of a benchmark dataset from available repositories as listed below:

1. **SandhiKosh** It is a benchmark sandhi split corpus, developed by (Shubham Bhardwaj, 2018). This comprises of manually-annotated dataset as well as dataset from popular open-source repositories such as UoH². It consists of five different corpora which covers most of the sandhi rules specified in *Aṣṭādhyāyī*.

2. **UoH subset** The corpus created by the University of Hyderabad³ contains a total off 113,913

¹Different syntactic splits given by one of the popular Sandhi splitters: [https://goo.gl/QM5CP5 and https://goo.gl/JHnpJw](https://goo.gl/QM5CP5 and https://goo.gl/JHnpJw)

²Available at: [http://sanskrit.uohyd.ac.in/Corpus/](http://sanskrit.uohyd.ac.in/Corpus/)

³Available at: [http://sanskrit.uohyd.ac.in/Corpus/](http://sanskrit.uohyd.ac.in/Corpus/)
words in the corpus with cases of typing errors, insufficient and incorrect splits. In SandhiKosh, there was stringent filtering of the split words applied, where as we considered flexible filtering. We removed duplicate entries and restricted length of the compound word to an upper threshold of 31 characters. Finally, our filtered error free subset contains 67,183 words and splits.

For all our experiments, we converted the Sanskrit Devanagari unicode script to Sanskrit Library Phonetic Basic encoding scheme (SLP1). SLP1 maps each Sanskrit alphabet to a unique equivalent English character, ensuring that the transliteration between Devanagari to SLP1 be unique. We release combined benchmark dataset of 71,747 compound words along with their ground truth splits in SLP1 format.

3 Existing Tools and Challenges

In this section, we discuss the techniques used by the three most popular publicly available automated tools to perform Sandhi splitting. We also identify issues and challenges faced by these tools.

3.1 JNU sandhi splitter

This tool is specifically designed for a particular class of Sandhi known as vowel based Sandhi. (Sachin, 2007) Using a dictionary of possible morphemes, this tool, at every location recursively checks for binary splits. To be a valid split, both the left and right split segments must be available in the dictionary. If the second segment has more than one sound marked for Sandhi, then only the first segment is matched against the dictionary.

3.2 UoH sandhi splitter

(Kumar et al., 2010) developed this tool at the Department of Sanskrit Studies, University of Hyderabad (UoH). This tool also recursively breaks a word at every possible position and applies appropriate Sandhi rules to generate possible morpheme candidates and passes them through a morphological analyzer. The split words are considered as valid only if all its constituents are recognized by the morphological analyzer. Weights are assigned to the accepted candidates and then ranked based on the descending order of weights.

3.3 INRIA sanskrit reader companion

(Huet, 2003) (Goyal and Huet, 2013) developed this tool at INRIA, France. Initially, the word is analyzed to gather stems and their morphological parameters, such as permitted genders of nominal stems, allowed classes, and attested pre-verbs for roots. In the next stage, another round of stem generation is performed considering the various tenses, moods, absolutes, and participles in 10 varieties. Finally, inflexional morphology paradigms derive the inflected forms according to the morphological parameters, some of which are read from the word itself, while the others are defined in specific tables.

Comparison of these tools with our technique using the benchmark data set is provided in Section 5.

4 Model Description

In this section, we present our approach of using a double decoder model to address the sandhi splitting problem. We first outline the issues with basic deep learning architectures and highlight conceptually how the double decoder model addresses these issues, with implementation details.

4.1 Issues with standard architectures

Consider the different kinds of splitting possibilities illustrated in Figure 1. For all the possibilities, the common primary task is to identify d as the split location. Further, for a given location d in a character sequence abcdeffg, the algorithm should take into account (i) the context of character sequence abc, (ii) the immediate previous character c, (iii) the immediate succeeding character e. For such sequence learning problems, RNNs have become the most popular choice (Pascanu et al., 2013) (Sak et al., 2014).
Specifically in the domain of natural language processing, these algorithms have been highly successful and have produced state-of-art performance in language modeling (Hermans and Schrauwen, 2013) and machine translation (Cho et al., 2014a).

A basic RNN encoder-decoder model (Cho et al., 2014b) with LSTM units (Hochreiter and Schmidhuber, 1997) was trained similar to how a language translation model is trained. The compound word’s characters, which is fed as input to the encoder is translated to a sequence of characters representing the split words (‘+’ symbol acts as a separator between the generated split words). However, the model did not yield adequate performance as it encoded only the context of the characters that appeared before the potential split location(s). Though we tried making the encoder bi-directional, the model resulted in poor performance due to the presence of long character sequences. Adding global attention to the decoder enabled the model to attend to the characters surrounding the potential split location(s) and improved the split prediction performance, making it comparable with some of the best performing tools in the literature.

4.2 Double decoder RNN (DD-RNN) model

The critical part of learning to split compound words is to correctly identify the location(s) of the split(s). Therefore, we added another decoder to our encoder-decoder model as shown in figure 4.1. The bi-directional encoder is now connected to two decoders. (i) the location decoder which learns to predict the split locations and (ii) the character decoder which generates the split words.

A compound word is fed into the encoder character by character. It’s character embeddings \( x_i \) is passed on to the encoders LSTM units. There are two LSTM layers which encode the word, one in forward direction and the other backward. The encoded context vector \( e_i \) is then passed to a global attention layer.

In the first phase of training, only the location decoder is trained and the character decoder is frozen. The character embeddings are learned from scratch in this phase along with the attention weights and other parameters. Here, the model learns to identify the split locations. For example, if the inputs are the embeddings for the compound word protṣaḥaḥ, the location decoder will generate a binary vector \([0, 0, 1, 0, 0, 0, 0, 0, 0]\) which indicates that the split occurs between the third and fourth characters.

In the second phase, the location decoder is frozen and the character decoder is trained. The encoder and attention weights are allowed to be fine-tuned. This decoder learns the underlying rules of Sandhi splitting. Since the attention layer is already pre-trained to identify potential split locations in the previous phase, the character decoder can use this context and learn to split the words more accurately. For example, for the same input word protṣaḥaḥ, the character decoder will generate \([p, r, a+u, t, s, ā, h, a, ḷ] \) as the output. Here the character \( o \) is split into two characters \( a \) and \( u \).

In both the training phases, we use negative log likelihood as the loss function. Let \( X \) be the sequence of the input compound word’s characters and \( Y \) be the binary vector which indicates the location of the split(s) in the first phase and the true target sequence of characters which form the split words in the second phase. If \( Y = y_1, y_2, \ldots, y_n \), then the loss function is defined as:

\[
loss = - \sum_{i=1}^{[Y]} \log P(y_i|y_{i-1}, \ldots, y_1, X)
\]

We compare and evaluate this double decoder (DD-RNN) model with the standard architectures mentioned previously in Section 5. We summarize the reasoning behind the various components in our model as follows:

- We use two decoders which essentially split the learning process between them. The location decoder allows the model to learn the locations of the splits whereas the character decoder generates the split words.
- The encoder is bidirectional (Graves et al., 2013) which considers the input sequence in both forward (first to last) and backward (last to first) directions and merges them to generate the encoding. Thus, the context of a character \( d \) includes both the preceding (abc) and succeeding characters (efg).
- The attention mechanism (Luong et al., 2015) is used with the decoders. In the first phase of training, it learns to attend to certain portions of
the word where the splits are most likely to occur. In the second phase, it helps the character decoder to apply to splitting rules at the correct indexes.

4.3 Implementation details

We used a character embedding size of 128. The bi-directional encoder and the two decoders are 2 layers deep with 512 LSTM units in each layer. A dropout layer with $p = 0.3$ is applied after each LSTM layer. The entire network is implemented in Torch.\(^9\)

Of the 71,747 words in our benchmark dataset, we randomly sampled 80% of the data for training our deep learning algorithms. The remaining 20% was used for testing. We used stochastic gradient descent (Bottou, 2010) with an initial learning rate of 1.0. The learning rate was decayed by a factor of 0.5 if the validation perplexity did not improve after an epoch. We used a batch size of 64 and trained the network for 10 epochs on four Tesla K80 GPUs. This setup remains the same for all the experiments we conduct.

5 Evaluation and Results

We evaluated the performance of our DD-RNN model by:

1. comparing the split prediction accuracy with other publicly available sandhi splitting tools,
2. comparing the split prediction accuracy with other standard RNN architectures such as RNN, B-RNN, and B-RNN-A,
3. comparing the location prediction accuracy with the RNNs used for Chinese word segmentation (as they only predict the split locations and do not learn the rules of splitting)

Further, we show how these metrics vary with input compound word lengths. We also provide some interesting insights about the models.

5.1 Comparison with publicly available tools

The tools discussed in Section 3 take a compound word as input and provide a list of all possible splits as output (UoH and INRIA splitters provide weighted lists). Initially, we compared only the top prediction in each list with the true output. This gave a very low precision for the tools as shown in

\(^9\)http://torch.ch/
Figure 3: Split prediction accuracy comparison of different publicly available tools (Top-1) with DD-RNN (Top-1).

Therefore, we relaxed this constraint and considered an output to be correct if the true split is present in the top ten predictions of the list. This increased the precision of the tools as shown in Figure 4 and Table 1.

Even though DD-RNN generates only one output for every input, it clearly out-performs the other publicly available tools by a fair margin.

5.2 Comparison with standard RNN architectures

To compare the performance of DD-RNN with other standard RNN architectures, we trained the following three models to generate the split predictions on our benchmark dataset:

1. uni-directional encoder and decoder without attention (RNN)
2. bi-directional encoder and decoder without attention (B-RNN)
3. bi-directional encoder and decoder with attention (B-RNN-A)

As seen from the middle parts of Table 1, the DD-RNN performs much better than the other architectures with an accuracy of 79.5%. It is to be noted that B-RNN-A is the same as DD-RNN without the location decoder. But the accuracy of DD-RNN is 14.7% more than that the B-RNN-A and it consistently outperforms B-RNN-A on almost all word lengths (Refer Figure 5). This indicates that the attention mechanism of DD-RNN has learned to better identify the location(s) of the split(s) due to its pretraining with the location decoder.

5.3 Comparison with similar works

We also compared our proposed DD-RNN with models with (Chen et al., 2015b) (LSTM-4) and (Chen et al., 2015a) (GRNN-5). These models were used to get state of the art results for Chinese word segmentation and their source code is made available online.\footnote{https://github.com/FudanNLP} Since these models can only predict the location(s) of the split(s) and cannot generate the

<table>
<thead>
<tr>
<th>Model</th>
<th>Location Prediction</th>
<th>Split Prediction</th>
</tr>
</thead>
<tbody>
<tr>
<td>JNU (Top 10)</td>
<td>-</td>
<td>8.1</td>
</tr>
<tr>
<td>UoH (Top 10)</td>
<td>-</td>
<td>47.2</td>
</tr>
<tr>
<td>INRIA (Top 10)</td>
<td>-</td>
<td>59.9</td>
</tr>
<tr>
<td>RNN</td>
<td>-</td>
<td>56.6</td>
</tr>
<tr>
<td>B-RNN</td>
<td>-</td>
<td>58.6</td>
</tr>
<tr>
<td>B-RNN-A</td>
<td>-</td>
<td>69.3</td>
</tr>
<tr>
<td>DD-RNN</td>
<td>95.0</td>
<td>79.5</td>
</tr>
<tr>
<td>LSTM-4</td>
<td>70.2</td>
<td>-</td>
</tr>
<tr>
<td>GRNN-5</td>
<td>67.7</td>
<td>-</td>
</tr>
</tbody>
</table>

Table 1: Location and split prediction accuracy of all the tools and models under comparison.
split words themselves, we used the location prediction accuracy as the metric. The two models are:

1. uni-directional LSTM with a depth of 4 (LSTM-4)
2. a Gated Recursive Neural Network with a depth of 5 (GRNN-5)

We trained these models on our benchmark dataset and the results are shown in Table 1. DD-RNN’s precision is 35.3% and 40.3% better than LSTM-4 and GRNN-5 respectively. We try to provide some intuition as why that is the case in the following paragraphs.

The LSTM-4 model (Chen et al., 2015b) is similar to our first basic RNN model. It is four layers deep, but does not follow our encoder-decoder paradigm. Since the RNN is not bi-directional and the whole word is not encoded before making the split location predictions, this model suffers from incomplete information. That is, if the model has to predict whether a split occurs at location $i$, it can do so only by looking at the previous characters (indices 0 to $i-1$). It does not have information about latter characters (indices $i+1$ to $n$) in the word which may influence the probability of a split.

The hierarchical GRNN model used in (Chen et al., 2015a) has the ability to capture context from the entire word by recursively building up complex features from the bottom layer to the top. We notice that, this model works very well for smaller words and fails when the word length is long or there are multiple splits. This might again be attributed to the split location identification problem mentioned in the previous sections.

To summarize, we have used our benchmark dataset to compare the DD-RNN model with existing publicly available Sandhi splitting tools, other RNN architectures and models used for Chinese word segmentation task. Among the existing tools, the INRIA splitter gives the highest split prediction accuracy of 59.9%. Among the standard RNN architectures, B-RNN-A performs the best with a split prediction accuracy of 69.3%. LSTM-4 performs the best among the Chinese word segmentation models with a location prediction accuracy of 70.2%. DD-RNN out-performs all the models both in location and split predictions, with accuracies of 95% and 79.5% respectively.

6 Conclusion and Future Work

In this research, we released a dataset containing 71,747 compound Sanskrit words and their ground truth splits. We also proposed a novel double decoder RNN architecture with attention for Sanskrit Sandhi splitting. Learning such a model would provide further insights into the fundamental linguistic word formation rules of the language. A deep bidirectional encoder is used to encode the character sequence of a Sanskrit word. Using this encoded context vector, a location decoder is first used to learn the location(s) of the split(s). Then the character decoder is used to generate the split words. We benchmarked the performance of the proposed approach on our dataset in comparison with other publicly available tools, standard RNN architectures and with prior work which tackle similar problems in other languages.

As future work, we intend to tackle the Samasa problem which is harder than Sandhi as it requires semantic information of the word in addition to the characters’ context. Further we intend to increase the generalizability of the DD-RNN model to work on word segmentation tasks of other languages.

References

posium on Modelling and Shallow Parsing of Indian Languages, IIT-Bombay.


Kumar Sachin. 2007. Sandhi splitter and analyzer for sanskrit (with reference to ac sandhi). M. Phil. degree at SCSS, JNU (submitted, 2007).
