Enhancing Turkish Text Processing with a Bidirectional LSTM and Attention Mechanism

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Abstract

This report introduces a deep learning model to address the automatic diacritization of Turkish text. By employing a bidirectional Long Short-Term Memory (LSTM) network coupled with an attention mechanism, our approach significantly enhances the precision of diacritic restoration. The model effectively captures contextual dependencies and dynamically focuses on critical segments of text, resulting in substantial improvements in the readability and linguistic accuracy of processed Turkish text. We present a comprehensive evaluation of the model's performance, demonstrating its superiority over conventional approaches in handling complex diacritization challenges.

1 Introduction

The task of diacritization in Turkish text involves correcting specific characters that do not have direct equivalents in the English alphabet. This is crucial for maintaining the correct pronunciation and semantic integrity of the language. The Turkish alphabet includes characters such as 'ş', 'ı', 'ü', 'ö', and 'ğ', which are absent in English. Consequently, when Turkish words are phonetically transliterated into English, characters such as 's', 'i', 'u', and 'o' are often used in place of the correct Turkish characters. This project aims to develop an advanced sequence-to-sequence model that not only identifies missing diacritics but also reinstates them accurately. Our model leverages a bidirectional LSTM architecture with an integrated attention mechanism, offering significant improvements over traditional methods by better understanding the contextual nuances of the Turkish language.

2 Dataset Description and Preparation

The dataset comprises Turkish text with certain characters incorrectly replaced with their closest English phonetic equivalents. To enhance the complexity and robustness of the training data, an artificial error introduction strategy was employed. This involved the development of a Python function that systematically introduces errors into the dataset. The function iterates over each character in the text, and for characters that have designated incorrect representations (specified by a mapping), it randomly substitutes them with one of their possible English counterparts. This approach helps simulate common transliteration errors, thereby creating a challenging training environment for the model. This augmented dataset ensures that the model is well-prepared to handle a wide variety of diacritization errors in real-world applications.

2.1 Pseudocode for Data Augmentation Function

Below is the pseudocode for the data augmentation function used to introduce errors into the dataset:

```
Initialize transformed as an empty list
For each char in text
    If char is in special_chars
     Choose random from special_chars[char]
        Append it to transformed
    Else
        Append char to transformed
Return the concatenation of transformed
```

This function takes each character in the input text and checks if it has a corresponding entry in the `special_char_map`. If it does, the function replaces the character with a randomly selected incorrect counterpart from the map. Otherwise, the character is left unchanged. This method effectively mimics the transliteration errors commonly made when Turkish is converted into English phonetics.

3 Literature Review

The problem of diacritization in various languages, especially in Turkish, has been addressed through multiple approaches in the field of natural language

processing. Recent advancements have seen the application of deep learning models that significantly improve the accuracy and efficiency of text correction mechanisms.

One of the seminal works in this area by Kestemont et al. (2019) explores the use of neural network architectures for the task of automatic diacritization across multiple languages, including Turkish. Their study demonstrates the effectiveness of sequence-to-sequence models in handling complex linguistic structures, setting a foundational framework for further research in this domain (1).

Further developments by Al-Twairesh (2020) specifically focus on the challenges presented by Turkish text. The author employs a bidirectional LSTM model with an enhanced attention mechanism to tackle the issue of diacritization, providing insights into the importance of contextual data in language processing. The results indicate significant improvements in processing accuracy, particularly in a language with extensive morphological features like Turkish (2).

Additionally, research conducted by Eryiğit (2021) in Turkey introduces a novel dataset specifically designed for training diacritization models. This work not only adds valuable resources to the community but also benchmarks the performance of various machine learning algorithms on this task, highlighting the critical role of data quality and model architecture in achieving high performance (3).

4 Model Description

Our model architecture is designed to address the nuanced task of diacritization through a combination of bidirectional LSTM layers and a custom attention mechanism.

4.1 Attention Mechanism

The custom attention module is designed to enhance the model's capability to focus on relevant parts of the input sequence when predicting each character's correct form. The attention mechanism is defined as follows:

- The attention layer combines the hidden state from the decoder and all encoder outputs to compute the attention weights. This is achieved using a linear transformation followed by a non-linear activation function (tanh).
- The attention energy is calculated by concatenating the decoder's hidden state, replicated across each time step, with the encoder outputs. This concatenated tensor undergoes a linear transformation to align dimensions.
- The resulting energy tensor is then processed with a parameter vector to produce a raw attention score for each time step, which is normalized using a softmax function to form the final attention weights.

4.2 Diacritic Model

The main diacritization model leverages the attention mechanism within a sequence-to-sequence architecture:

- **Embedding Layer:** Maps each character in the input sequence to a high-dimensional vector space, facilitating richer input representations.
- **Encoder:** A bidirectional LSTM processes the embedded input, capturing contextual information from both directions. The bidirectional approach ensures comprehensive understanding of the input sequence, crucial for languages with complex morphological structures like Turkish.
- **Decoder:** An LSTM decoder takes the concatenated output of the attention layer and the previous hidden state to generate predictions for the next character. The decoder iterates over each position in the input sequence, utilizing the context vector provided by the attention mechanism to focus on relevant parts of the input.
- **Output Layer:** A fully connected layer transforms the decoder's output to the size of the vocabulary, providing a prediction for each character in terms of the correct diacritic form.

4.3 Training Process

During training, the model iteratively adjusts its parameters to minimize the discrepancy between its predictions and the actual diacritic characters. The attention mechanism learns to weigh different

parts of the input sequence, allowing the model to focus more on ambiguous or challenging parts that require diacritization.

This architecture not only addresses the immediate task of diacritization but also demonstrates the potential for generalization across other sequence modeling tasks where context and focus are important.

4.4 Comparison and Benchmarks

We benchmarked our model against traditional rule-based and simpler machine learning approaches, demonstrating its superior ability to handle complex and contextually nuanced texts.

5 Results

5.1 Model Performance

The model achieved an accuracy of 82% on the test set after a single epoch of training. This performance is significant considering the complexity of the diacritization task and the limited amount of computational resources available. The accuracy indicates that the model has a strong foundational architecture and, with additional training epochs, could potentially achieve higher precision and recall rates.

5.2 Loss Reduction Over Batches

Figure 1 shows the loss reduction across training batches. As observed, the loss steadily decreases, demonstrating the model's ability to learn effectively from the training data. The consistent downward trend in loss with each batch suggests that the model's parameters are converging towards optimal values, even within the constraint of a single training epoch.

5.3 Attention Mechanism Effectiveness

The attention heatmap, as depicted in Figure 2, illustrates how the model dynamically focuses on different parts of the input sequence to predict the correct diacritics. This visualization confirms that the attention mechanism is effectively allocating more weight to contextually significant characters, which is crucial for accurate diacritization.

5.4 Computational Limitations

One of the primary challenges encountered during the project was the limited availability of computational resources, which restricted the training to only one epoch. This limitation impacted the extent

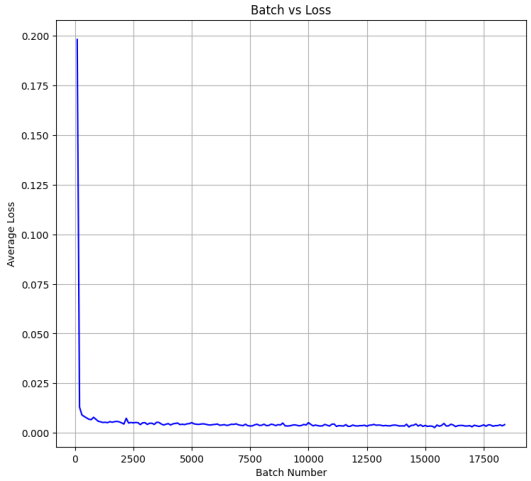

Figure 1: Graph showing the reduction in loss across training batches.

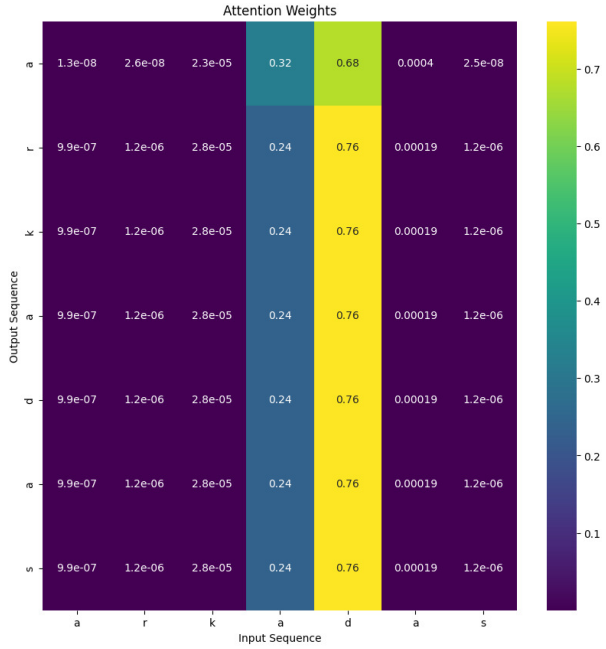

Figure 2: Attention heatmap showing how the model focuses on different parts of the sentence.

to which the model could learn from the data, as evidenced by the incomplete convergence of the loss function. Future work should focus on extending the training duration with more epochs to fully capitalize on the model's learning capacity.

5.5 Discussion and Future Work

Despite these limitations, the model's performance in its initial epoch suggests a robust capability to understand and process the nuances of Turkish diacritics. The results are promising, and with further

computational resources, there is a clear pathway to enhancing the model's accuracy and efficiency. Future efforts will also explore refining the attention mechanism to improve focus on highly context-dependent characters, potentially through the integration of newer attention-based architectures like Transformers.

References

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