International Journal of Science and Research (IJSR)
ISSN: 2319-7064
SJIF (2022): 7.942

Optimizing Neural Network Language Models for Healthcare - A Focus on Speech Recognition and Spelling Correction

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Abstract: ***This study presents a novel approach to enhancing neural network-based language models for healthcare applications, particularly focusing on medical speech recognition and spelling correction. By introducing a tokenization strategy that segments words into prefix, stem, and suffix components, the model achieves reduced computational complexity while improving key performance metrics like perplexity and word error rate. Evaluations conducted on English and Arabic datasets demonstrate substantial advancements in accuracy and efficiency, highlighting the model's suitability for real-time applications in healthcare.***

Keywords: Neural networks, Healthcare applications, speech recognition, spelling correction, computational efficiency

1. Introduction

The use of artificial intelligence (AI) and machine learning in healthcare is rapidly expanding, with significant applications in medical speech recognition, automatic transcription, and automated diagnosis systems. One key area of advancement has been the development of language models that can accurately predict the likelihood of a sequence of words. In healthcare, these language models play a crucial role in ensuring accurate transcription of medical conversations and diagnosing conditions from verbal input.

Traditional language models, such as n-grams, struggle with complex vocabularies and morphologically rich languages like Arabic, which is commonly used in medical settings in the Middle East. Recurrent neural networks (RNNs) have been shown to outperform n-grams in terms of accuracy due to their ability to retain contextual information over longer sequences (Graves, 2012). However, RNN-based models often come with significant computational costs, particularly when trained on large, medical corpora.

This paper introduces a modified RNN model, which splits words into prefix, stem, and suffix components, before feeding them into the network. This segmentation aims to reduce the input space size and computational complexity, particularly in real-time medical applications where speed is critical. The proposed model's performance was evaluated using both English and Arabic datasets for speech recognition and spelling correction, demonstrating a notable improvement over traditional model.

2. Related Work

Language models have evolved significantly over the last few decades, with neural networks emerging as one of the most successful approaches (Bengio et al., 2003). Early models, such as n-grams, provided a statistical approach to estimating the likelihood of word sequences but often failed to capture long-range dependencies in text (Elman, 1990). RNNs, on the other hand, have been widely adopted for their ability to model sequential data by maintaining an internal state that can capture temporal dependencies (Graves, 2012).

In healthcare, speech recognition systems that use RNNs have demonstrated significant improvements over traditional methods. For instance, recent advances in deep learning have enabled more accurate speech-to-text systems, especially when trained on specialized medical corpora (Sundermeyer et al., 2012). However, existing models still face challenges in handling languages with rich morphological structures, such as Arabic, which is commonly used in medical texts. Some models have attempted to incorporate morphological information directly into their architectures but often at the cost of increased computational complexity (Vinyals et al., 2015).

3. Methodology

The proposed model is based on an RNN architecture, with a novel modification: the tokenization of words into three components: prefix, stem, and suffix. This approach is designed to address the computational inefficiencies of traditional models by reducing the input size and focusing on the core elements of each word.

- Data Preprocessing: The model was trained on two datasets: an English medical speech corpus and an Arabic medical spelling correction corpus. In both cases, words were tokenized into prefix, stem, and suffix components before being fed into the neural network.
- Model Architecture: The network consists of an embedding layer, followed by multiple RNN layers. The output layer generates a prediction for the next word in the sequence, or in the case of spelling correction, the corrected word form.
- Training Process: The training process utilized stochastic gradient descent (SGD) with a learning rate of 0.01. The model was trained for 30 epochs, with early stopping based on validation loss.

4. Experiments and Results

The model was evaluated on two distinct tasks: medical speech recognition for English and spelling correction for Arabic.

Medical Speech Recognition (English): For the English dataset, the model demonstrated a 30% improvement in

perplexity over a baseline n-gram model and a 15% improvement over a basic RNN-based model. The word error rate (WER) was reduced by 5% when compared to the traditional n-gram approach.

Arabic Spelling Correction: For the Arabic dataset, the model demonstrated a 3.5% improvement in spelling correction accuracy compared to existing models. This improvement was particularly evident in handling words with complex morphological structures, which are common in medical Arabic.

The reduction in computational complexity was also notable. The model required significantly less memory and training time compared to traditional RNN-based models, making it more suitable for real-time applications in healthcare environments.

5. Model Complexity and Efficiency

One of the most important advantages of the proposed model is its reduced computational complexity. By breaking down words into smaller, more manageable components (prefix, stem, and suffix), the input layer becomes smaller, which leads to reduced memory usage and faster processing times. In real-time healthcare applications such as medical speech recognition, where system responsiveness is crucial, this reduction in complexity ensures that the model can be deployed efficiently without sacrificing accuracy.

Additionally, the model was implemented on GPU hardware, and its efficiency was significantly higher than traditional models, enabling faster training and inference times in large-scale healthcare environments.

6. Conclusion

This paper presents a novel approach to language modeling for healthcare applications, specifically focusing on medical speech recognition and spelling correction. By segmenting words into their component parts (prefix, stem, and suffix), the proposed model reduces computational complexity while improving performance in terms of perplexity, word error rate, and spelling correction accuracy. The results indicate that this approach is effective for both English and Arabic, particularly in medical contexts where real-time performance is critical.

The improvements observed in this study demonstrate that neural network-based models can be made more efficient without sacrificing accuracy, offering significant potential for real-world applications in healthcare, including automated transcription, diagnosis, and other language processing tasks.

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