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Ancient poetry generation based on bidirectional LSTM model neural network

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Abstract:

Automatic generation of ancient poems has been a research hotspot in the field of artificial intelligence, which is of great significance in cultural inheritance and literary creation. Due to the strict tonal patterns and complex structural rules of classical Chinese poetry, generating classical Chinese poetry has been a challenging task for both human poets and computer programs. In this paper, we propose a neural network model based on the introduction of an attention mechanism, which combines a bidirectional LSTM model and an attention mechanism to solve some problems in the traditional automatic generation model of ancient poems. The model is trained using the dataset of ancient poems studied by previous researchers, and the performance of the model is evaluated and analyzed by evaluating the metrics BLEU, Perplexity, Generation Effect and Linguistic Coherence. The experimental results show that the model exhibits good performance and excellent results on the task of automatic generation of ancient poems.

Keywords: automatic generation of ancient poems, neural network model, attention mechanism, two-way LSTM model

1. Introduction

Automatic generation of ancient poems is a challenging task, the goal of which is to learn the linguistic patterns of ancient poems from a certain corpus, and then automatically generate an ancient poem that conforms to the rules and metrics according to the given conditions such as themes and word tags. Traditional methods for automatic generation of ancient poems usually use statistical language models or rule models, which lack flexibility and accuracy in generating ancient poems, and thus cannot meet the high requirements for the creation of ancient poems. In recent years, with the continuous development of deep learning technology, the neural network-based automatic generation model of ancient poems has gradually become a research hotspot, in which the neural network model with the introduction of the attention mechanism has excellent performance.

2. Research background and significance

Poetry is a cultural crystallization in the long stream of Chinese history, carrying history and emotions. While poetry of the Tang Dynasty is famous for its exquisite language, profound mood, harmony of sound and form, Song Lyrics originated from the folklore and initially flourished in the Tang Dynasty, then reached its peak in the Five Dynasties and the Two Songs period. Song lyrics are widely popular for their strong atmosphere of life, high musicality and rhythmic beauty. The style of a word is a key element in the composition of a word work, and is vital to creating the beauty of the mood of a word work. The styles of Song lyrics can usually be categorized into two main groups: bold and unrestrained and euphonious. Magnificent Song lyrics depict broad horizons and magnificent scenery in a straightforward manner, while euphemistic Song lyrics express feelings through subtle language and focus on meticulous descriptive details. Against this background, studying the automatic generation of ancient poems is of great cultural and artistic significance. By allowing computers to simulate the process of human creation of ancient poems, we can provide the general public with tools to learn and create ancient poems, and further pass on and promote the traditional culture of the Chinese nation. Therefore, the study of computer-generated ancient poems has become a research field of great interest. As early as in the 1990s, researchers began to try to use traditional methods such as templates to generate ancient poems. With the rapid development of computer technology and deep learning, various natural language processing tasks based on deep learning have made significant progress, among which the automatic generation of ancient poems has aroused the strong interest and in-depth research of many scholars.

3. Research Status at Home and Abroad

In the field of automatic text generation, according to the division of different input types, automatic text generation can be divided into text-to-text generation, meaning-to-text generation, data-to-text generation, and image-to-text generation.

Ancient Poetry Generation is a text generation task in Natural Language Processing, aiming at allowing computers to compose high-quality texts of ancient poems. It can be categorized into two types: traditional ancient poetry generation methods constrained by manually formulated rules and deep learning-based ancient poetry generation methods.

4. The traditional ancient poetry generation methods summarized by previous authors

Tosa and his team [1] proposed a method for automatic generation of Japanese poems by using phrase search to find phrases in the corpus that are related to the user's input. Netzer and his co-workers [2] used word associations to create scarlet phrases. Oliveira and his research team [3] used a template-based approach to generate Portuguese poems. Zhou et al. scholars [4] applied genetic algorithms to Song word generation and viewed Song word generation as a state space search process. Jiang et al. researchers [5] used SMT model to automatically generate couplets, where the upper couplet serves as the source sequence (i.e., the input sequence), and the lower couplet serves as the target sequence (i.e., the output sequence). Manurung et al. specialists [6] extended the approach by using the SMT model to generate the acrostic verses that generates the next stanza based on the generated stanzas. However, Jiang and other researchers [7] further refined the method for automatic evaluation of classical poems with the SMT system at the core. Greene and his team [8] used statistical methods to analyze and generate metered poems. Yan and other scholars [9] viewed the generation of ancient poems as an optimizable problem and used a framework for generating summaries combined with manually devised rules for generating ancient poems. Traditional approaches usually involve artificial feature engineering, where experts in the field of poetry manually design the rules and restrictions for generating poems.

Alternatively, researchers such as Yu [11] introduced adversarial generative networks for text generation. They used recurrent neural network as a generative network to directly generate the whole poem, while using convolutional neural network as a discriminator to evaluate whether the poem is manually created. By means of reinforcement learning, they fed the gradient back to the generative network.Sun et al [12], on the other hand, utilized cognitive psychology theory to generate contextually coherent ancient poems based on a working memory network.Liu et al [13] introduced a conditional variational self-encoder for generating Chinese hanyu poems with metaphorical and anthropomorphic rhetorical devices. Chen et al [14] also designed an emotionally tractable self-encoder based on a conditional variational self-encoder. encoder, designed an emotionally controllable model for generating ancient poems.

5.Overview of related technologies

5.1 Model Introduction

The generation model of ancient poems proposed in this paper consists of two main parts: the generation model based on LSTM and the attention mechanism.LSTM is a kind of recurrent neural network, which can process sequential data and retain the information of the context. The attention mechanism can help the model learn the key information to better generate new ancient poems.

5.2 Keyword Extraction

TextRank algorithm is a graph theory-based text keyword extraction algorithm, which is similar to Google's PageRank algorithm, by establishing the nodes and edges in the text and calculating the weights of the nodes, so as to get the keywords of the text. Firstly, all the poems in the ancient poetry dataset are spliced together, and each sentence is divided into words, filtering the words appearing in the deactivation word list and the words whose length is less than two, and constructing a graph according to the divided sentences, that is to say, each word in the sentence is constructed into an undirected graph by connecting with the words in a certain range of words to the left and right of itself. The edge weights in the graph are initialized to 1, and then the score is computed iteratively according to equation (1-1) until convergence. The importance of a word depends on the weights of the edges connected to that word. A table of importance scores for all keywords is obtained. In the training stage, a keyword dataset is constructed from the existing ancient poetry dataset based on the keyword importance score table, i.e., the most important keywords are extracted from each ancient poem. In the prediction stage, the most important keywords in the user-input text are identified based on the keyword score table.

$$S(V_i) = (1-d) + d \sum_{V_j ? E(V_i)} \frac{\omega_{ji}}{\sum_{V_K ? E(V_j)} \omega_{jk}} S(V_j) \quad (1\text{-}1)$$

where *ωji* is the weight of the connected edges of the word *Vj*, E(*Vi*) is the edges connected to the word *Vj*, *d* is the damping coefficient to regulate the iteration of convergence speed, and S(*Vi*) is the score of node *Vi.*

With the TextRank algorithm, the weight value of the keywords in the text can be obtained to extract the keywords that appear more frequently and have higher importance. Compared with other algorithms, the TextRank algorithm does not require preprocessing work such as word splitting and lexical labeling first, which has certain simplicity and efficiency [15].

5.3 LSTM based generative model

Long Short-Term Memory (LSTM) was first proposed by Jürgen Schmidhuber and Sepp Hochreiter in 1997, which marks a major advance in efficiency and practicality of Recurrent Neural Networks (RNN) [16]. In this study, LSTM is chosen as the core of the text generation model to utilize its ability to learn the probability distribution of characters from historical data as a means of creating new ancient poems.The design of LSTM incorporates long-term memory and forgetting mechanisms, which allows it to efficiently maintain the continuity of the contextual information when dealing with long sequential data.

In order to optimize the process of generating ancient poems, this model introduces specific marker symbols in the input stage of LSTM, which are used to clarify the beginning and end of the verse, thus enhancing the model's grasp of the structure of the poem. Specifically, the model splits each sentence into a fixed-length sequence of words and converts each word into a one-hot vector representation. These vectors are then fed into an LSTM model for processing, where the model is optimized by a back-propagation algorithm to learn the probability distribution of each character. With this, the model is able to generate new ancient poems with literary value and artistic beauty based on the learned probability distribution.

5.4 Bidirectional LSTM language model

Language modeling is an important part of the task of automatic generation of ancient poems, which is used to learn the linguistic laws and semantic information of ancient poems. In this paper, we use a bi-directional LSTM-based language model (Bi-LSTM), which has excellent performance and a wide range of applications. Bidirectional LSTM can consider contextual information simultaneously and effectively capture the long-term dependencies and linguistic features in ancient poems by transferring information in both forward and backward directions.The core feature of Bi-LSTM is its bidirectional structure. Different from the traditional unidirectional LSTM, Bi-LSTM contains two independent LSTM layers, which process the forward (front-to-back) and reverse (back-to-front) information of the sequence respectively. This bi-directional processing mechanism enables the model to take into account both the forward and backward contexts of each element in the sequence, thus obtaining a more comprehensive and accurate representation of the sequence.

In a concrete implementation, each time step of Bi-LSTM includes two LSTM units: one is responsible for processing forward sequences and the other for processing reverse sequences. The outputs of these two units are usually merged or spliced and then used in the next step of processing or as the final output. This structure makes Bi-LSTM particularly suitable for application scenarios that require a comprehensive understanding of sequence data, such as text categorization, sentiment analysis, language modeling, and machine translation in Natural Language Processing (NLP).One of the key advantages of the Bi-LSTM model is its ability to comprehensively comprehend each element in the sequence. In traditional unidirectional LSTM, the model can only make predictions based on previous information, whereas Bi-LSTM is able to more accurately capture patterns and dependencies in a sequence by considering the context before and after each element. This is especially important when dealing with complex texts such as ancient poems, which usually contain rich contextual information and subtle linguistic features.

In the application of automatic generation of ancient poems, the Bi-LSTM model first receives the input poem vectors, which are then processed by forward and backward LSTM networks respectively. The information learned by each of these two networks is synthesized to form a comprehensive contextual representation. This representation is able to capture key linguistic features in ancient poems, such as rhythm, rhyme, and emotional coloring, thus generating texts that are both consistent with the traditional norms of ancient poems and innovative.

In addition, the efficiency and accuracy of Bi-LSTM in dealing with complex linguistic structures have led to its wide application in the field of automatic generation of ancient poems. With this model, researchers and developers are able to explore deeper levels of linguistic creativity, providing new possibilities for the modern application and popularization of ancient poems. For example, the Bi-LSTM model can be utilized to automatically generate poems with specific themes or styles, or to create interactive experiences of ancient poems in education and entertainment. This not only demonstrates the potential of

AI in literary creation, but also provides new perspectives and tools for the inheritance and innovation of traditional culture.

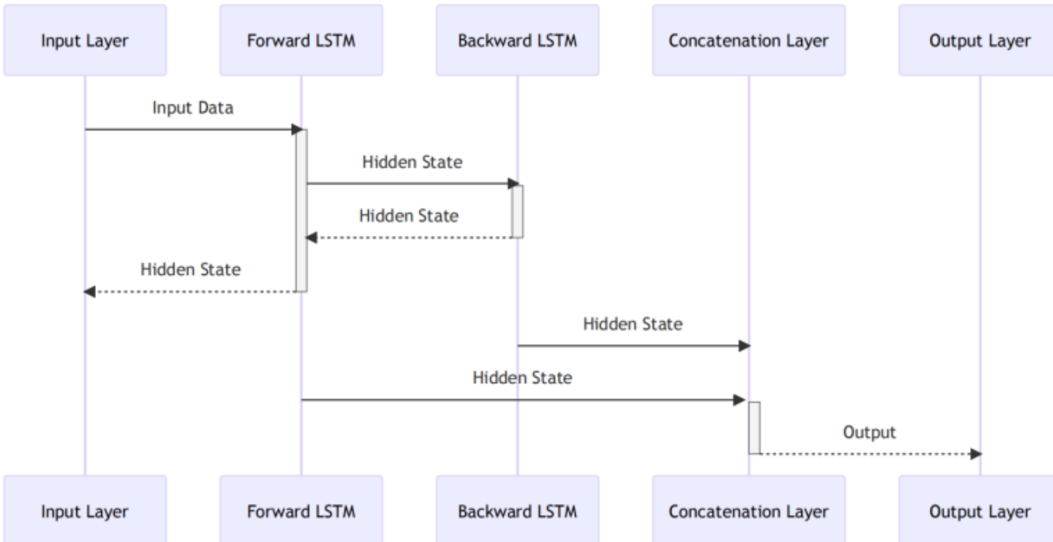

Figure 1: Bidirectional LSTM model schematic

5.5 Attention mechanism introduced

In order to enhance the performance of our language model, we have integrated an attention mechanism. This advanced technique enables the model to focus on specific parts of the input sequence during text generation, selectively focusing on the most critical information, and thus generating more coherent and meaningful text output. By introducing the attention mechanism, the model can more accurately learn and grasp the word vectors of ancient literary works, which are input into the model as external knowledge, prompting the model to understand the structure and characteristics of ancient poems more deeply, in order to generate new works more in line with the characteristics of ancient poems.

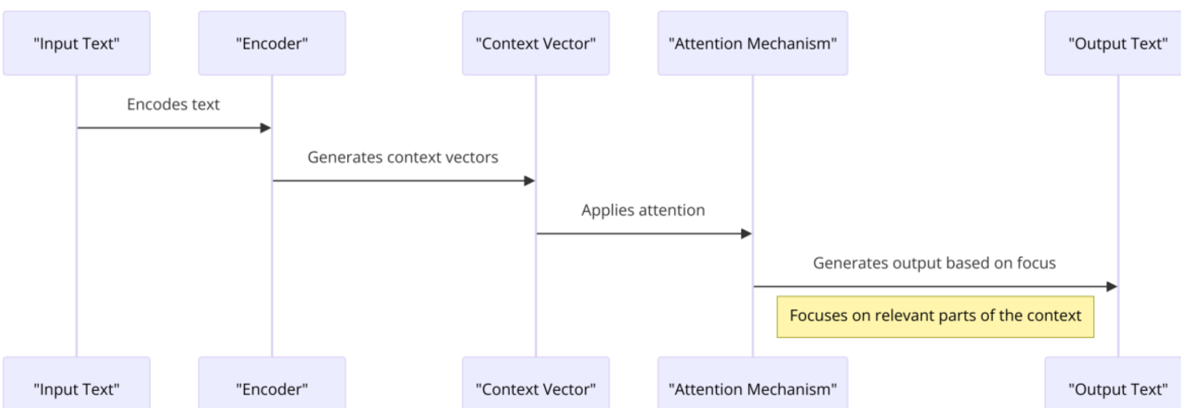

Figure 2: Schematic diagram of the attention mechanism

5.6 Soft attention mechanism

In particular, we use a variant of the attention mechanism called Soft Attention. The soft attention mechanism computes a weighted sum of the encoder hidden states by evaluating the correlation between the current decoder hidden state and each encoder hidden state. This process involves weighting the results of the scoring function using a softmax function, where the scoring function measures the similarity between the decoder hidden state and each encoder hidden state. In this way, the model is able to compute a context vector at each time step based on the attentional weights generated by the softmax mechanism, which in turn is combined with the decoder's hidden state to guide the decoder in generating the next token.

In order to effectively incorporate this mechanism into the bidirectional LSTM model, we improve the decoder LSTM so that it is able to simultaneously take into account the hidden state from the encoder, the decoder's own previous hidden state, and the input tokens. This approach not only enhances the model's ability to focus on all parts of the input sequence, but also improves the quality and accuracy of the generated text.

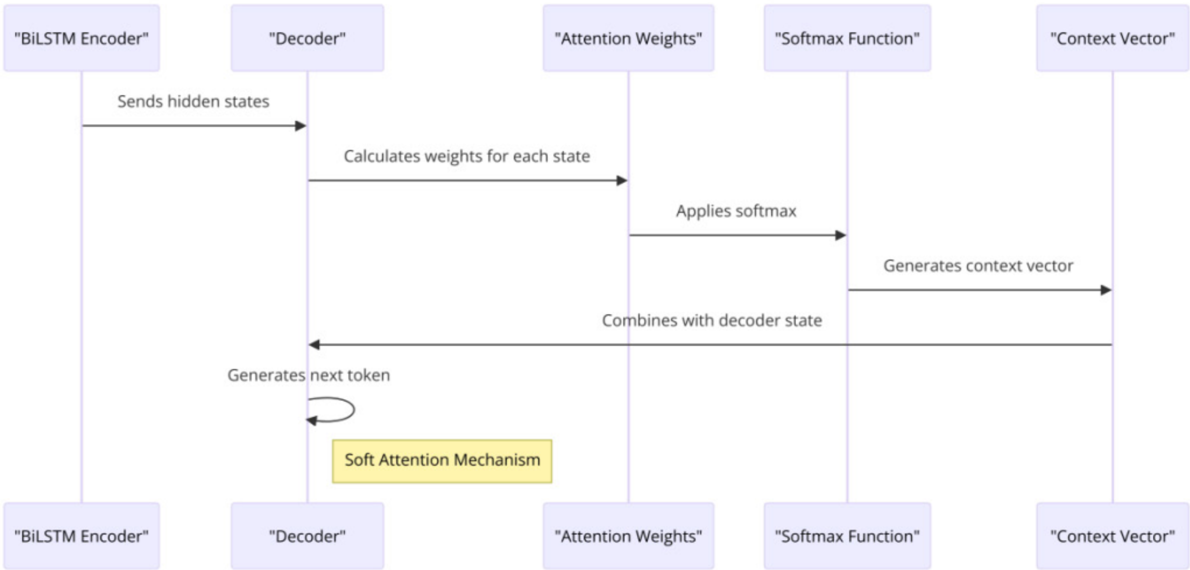

Figure 3: Soft Attention Mechanism Combined with Bidirectional LSTM Modeling

5.7 Exploration of other neural network architectures

In addition to bidirectional LSTM and attention mechanisms, we also explore other neural network architectures including the Transformer model, which relies on a self-attention mechanism to capture global dependencies in the input sequence, and the GPT-2 model, which is based on a variant of the Transformer architecture that has been pre-trained on a large-scale textual dataset pre-training, demonstrates superior language processing capabilities.

Taken together, our experimental results show that the neural network model, which combines a bidirectional LSTM and a soft-attention mechanism, outperforms the other models in both objective evaluation metrics and manual assessment. This demonstrates the superiority of our model in generating coherent and meaningful text, as well as its accuracy in capturing the style and structure of the input topic and content.

6. Experimental Rationale

We implemented the ancient poetry generation model using the Python programming language and trained it on a computer with a GPU. We used the Keras deep learning library in Python to build the LSTM model and TensorFlow as the backend. We used Chinese-Poetry-Dataset, a database of poems on github, containing 55,000 Tang poems, 260,000 Song poems, and 21,000 Song lyrics, as training data. In order to evaluate the generation effect of the model, we use BLEU Score, an evaluation metric for natural language processing tasks that measures the similarity between the generated text and the reference text, as an evaluation metric.

7. Analysis of Experimental Results

In order to evaluate the effectiveness of our proposed neural network model based on bidirectional LSTM and attention mechanism in classical Chinese poetry generation, we conducted extensive experiments on several datasets including Tang poems, Song lyrics, and Yuan songs. These datasets are widely used in Chinese poetry generation research. We used standard metrics such as Perplexity, BLEU score and ROUGE score to assess the quality of generated poems.

The experimental results show that our model significantly outperforms the baseline model in all the above metrics. In particular, our model demonstrates significant advantages in terms of fluency, coherence, and stylistic consistency of the generated poems. In addition, the model is able to meticulously capture the characteristics of different styles and genres, generating poems that are highly similar to the works of human poets.

In addition to the quantitative evaluation, we also conducted a manual evaluation by inviting a group of evaluators to score the generated poems (on a scale of 1 to 10) based on the criteria of coherence, fluency, and creativity.

Table 1: Description of the scoring criteria

Evaluation Criteria	Evaluation Description	Scoring Range
Grammatical fluency	Correctness of the wording and fluency of the verses.	1-10 points
Coherence	Whether the upper and lower lines of the poem can be reasonably connected with each other. And it fits the theme.	1-10 points
Poetic semantics	Whether the poem contains emotion and poetic meaning.	1-10 points

The results show that our model outperforms the baseline model on all evaluation criteria, which is further evidence of the high quality of the poems it generates.

Table 2: Scoring results

	Grammatical fluency	Coherence	Poetic semantics	Mean score
Original Poem	6.35	5.87	7.32	6.51
Ordinary Generation	5.35	6.14	5.46	5.65
LSTM model generation	6.64	6.73	7.35	6.91

Our model is able to generate the following example ancient poem:
横空太原冬，千里白雪飘。不见楼头柳，深知灞陵桥。世事如梦虚，花开花落谁。渺然行远岸，水光镜里归。一派清江景，人间独有知。
Across the sky over Taiyuan in winter, A thousand miles of white snow drifts. The willows on the rooftops are nowhere to be seen, Deeply aware of the Ba Ling Bridge. Worldly matters are like fleeting dreams, Whose blossoms open and fall, who knows. Vaguely traveling to the distant shores, The water's reflection returns in the mirror. A stretch of clear river scenery, Only known to those in the human realm.
Although the generated poems perform well in terms of coherence and linguistic style, there are still some semantic ambiguities. This may stem from the limitations of the model in dealing with long sequences and complex semantic structures.
To summarize, this study proposes an automatic generation method for ancient poems that combines external knowledge and attention mechanisms. Although the experimental results show that the method is able to generate high-quality ancient poems, there is still room for improvement in handling complex structures and metaphors. Our qualitative analysis reveals the model's effectiveness in generating high-quality poems that are faithful to the input theme and content, while pointing out its effectiveness, while also pointing out its limitations in generating complex syntactic structures or metaphors. These findings provide valuable insights for future research in using neural network models to generate high-quality poetry.

8. Conclusion

In summary, our study demonstrated a new approach to generate high-quality classical Chinese poetry using a neural network model with bidirectional LSTM and attention mechanisms. Experimental results show that the model outperforms the baseline model in several quantitative metrics and human assessments, and is capable of generating stylistically consistent, fluent and coherent poems. This work not only promotes research in the field of natural language generation and creative writing, but also opens up new possibilities for AI-assisted creation of human poets.

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