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Article

Design of an English translation system using convolutional neural networks based on biological mechanisms

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Abstract: The application of neural network methods, especially convolutional neural networks (CNNs), has led to significant advances in machine translation technology. CNNs, inspired by the hierarchical organization and functional principles of biological systems, akin to how biomechanical structures adapt and respond, are able to effectively solve problems such as remote dependency and contextual nuances in language tasks, thus improving translation quality. In this study, multilayer CNN is introduced into neural machine translation (NMT), which significantly improves the BLEU score on the Chinese-English translation dataset. The optimal structure is a 6-layer CNN with 3 × 1 convolutional kernel, which performs well in context understanding. In terms of theoretical background, theories related to biological neural networks provide important insights. For example, biological neurons process information in a hierarchical structure to achieve decomposition and comprehension of complex tasks through feature extraction at different levels. CNNs mimic this biomechanically-inspired mechanism in language processing, employing convolutional layers to distill local traits and amalgamate them into comprehensive global knowledge. By exploring the successful mechanism of CNNs in language processing, this paper further reveals the transformative potential of neural hierarchical structures in computational linguistics, and opens up new paths for realizing more natural and accurate translation.

Keywords: biomechanical structures; neural machine translation; convolutional neural networks; biologically inspired computing; machine translation; linguistic contextualization

1. Introduction

Biology, as an important branch of natural science, studies the essence and laws of life, as well as the structure and function of living organisms, covering a wide range of fields from the micro molecular level to the macro ecological system level. From the tiniest DNA molecules that encode the genetic instructions for all life forms to the vast ecosystems teeming with diverse species, biology offers a comprehensive view of the living world. At the molecular level, researchers are delving into the intricacies of gene editing technologies like CRISPR—Cas9, which has the potential to revolutionize medicine and agriculture. On the macro scale, ecologists are studying how climate change impacts entire ecosystems, from the melting of polar ice caps affecting polar bear habitats to the loss of coral reefs due to ocean acidification. This discipline has been continuously deepened in the past few decades due to technological revolutions, especially in the fields of neuroscience and bioinformatics where significant progress has been made [1,2]. In neuroscience, advanced imaging techniques such as functional magnetic resonance imaging (fMRI) have allowed scientists to peer into the human brain, mapping neural activity during various cognitive processes. This has led to a better understanding of neurological disorders like Alzheimer's and Parkinson's. In bioinformatics, the development of powerful algorithms and high—performance computing has enabled the analysis of massive amounts of biological data, such as the entire human genome. This has opened doors to personalized medicine, where treatments can be tailored to an individual's genetic makeup. The study of neural networks, a crucial area of interdisciplinary study between computing science and biology, has greatly influenced the advancement of artificial intelligence. Neural networks bridge the gap between the biological understanding of how the brain processes information and the computational world. Neuroscientists have discovered the complex network of neurons in the brain, with each neuron communicating with thousands of others through synapses. Computer scientists have taken this knowledge and created artificial neural networks. These networks consist of interconnected nodes, or "neurons", that can learn from data, much like the human brain learns from experiences. By successfully simulating the information processing powers of biological nervous systems, neural network models based on bionics have established a theoretical basis for contemporary technologies like machine translation, image recognition, and pattern analysis [3,4]. For machine translation, neural network models can analyze the grammar, semantics, and context of a source language text, just as a human translator would. In image recognition, they can identify patterns in pixels, similar to how the human visual cortex processes visual information. And in pattern analysis, these models can detect and classify various types of patterns, whether it's in financial data, seismic waves, or biological signals, all thanks to their ability to mimic the information—processing capabilities of biological neural networks.

In biology, the function and interactions of neurons provide a paradigm for understanding complex systems. Neurons, the fundamental units of the brain and nervous system, communicate through intricate networks, forming circuits that enable the processing and transmission of information. This biological framework serves as a model for computational approaches, leading to the development of artificial neural networks that mimic these processes. Inspired by this, convolutional neural networks (CNN), as a type of brain computing model, achieves efficient processing of spatial data and sequence information by simulating the perception mechanism of the visual cortex. Just as the biological nervous system can capture complex environmental information and respond quickly, CNN can capture multi-level feature relationships, demonstrating significant advantages in processing multidimensional data. The architecture of CNNs is particularly effective for tasks involving visual data, as it incorporates layers that automatically detect and learn features at various levels of abstraction. For instance, initial layers may identify simple edges and textures, while deeper layers can recognize complex shapes and objects. This hierarchical feature learning is akin to the way the human brain processes visual stimuli, allowing CNNs to excel in image classification and object detection tasks. Moreover, the pooling layers in CNNs help reduce dimensionality, making the models more computationally efficient and resistant to variations in input data, such as translations and distortions. This model not only provides powerful tools for the field of image processing, but has also been proven to have strong adaptability in natural language processing tasks such as machine translation [5,6].

The principles underlying CNNs can be extended to sequence data, where they are employed to analyze text and speech. For example, in natural language processing, CNNs can capture local patterns in text, allowing for the effective extraction of features that contribute to understanding context and meaning. This capability has led to improvements in various applications, including sentiment analysis, language modeling, and automated summarization.

Machine translation, as a key tool for language communication in modern society, is constantly benefiting from the development of neural network technology. In the fast—paced digital age, the demand for quick and accurate language translation across various fields such as business, education, and international relations has skyrocketed. Neural network technology has emerged as a game—changer in this regard. It provides machine translation with the computational power and intelligent algorithms necessary to process vast amounts of language data in a short time. Drawing on the architecture of biological neural networks, machine translation technology can better capture the contextual relationships of language, understand the deep meaning of semantics, and simulate cognitive patterns in human translation processes. Biological neural networks are highly complex and efficient systems. Neurons in the brain communicate with each other through synapses, transmitting and processing information in a way that enables humans to understand context—rich language. By mimicking this structure, machine translation models can break down language into smaller components, analyze their relationships, and piece together a more comprehensive understanding of the text's meaning. Research has shown that translation models based on convolutional neural networks can effectively handle long-distance dependency problems, thereby optimizing the semantic accuracy and fluency of translation. Long-distance dependencies occur when elements in a sentence that are far apart grammatically and syntactically are semantically related. For example, in a sentence like "The book that I read last week, which was recommended by my professor, was truly fascinating". The relationship between "book" and "fascinating" needs to be correctly understood. Convolutional neural networks use convolutional layers with filters to scan the text, extracting relevant features at different levels. This allows them to capture these long-distance relationships accurately. Similar to gene expression regulation or neural signal propagation in biological research, this translation model establishes deep mapping relationships between languages through a hierarchical feature extraction mechanism [7,8]. Gene expression regulation controls which genes are turned on or off in a cell, dictating its function. Neural signal propagation enables the rapid transfer of information in the nervous system. In a translation model, hierarchical feature extraction works in a similar way. Lower-level features are first identified, such as individual words and their basic syntactic roles. Then, as the model progresses through higher levels, it combines these features to form a more profound understanding of the text, ultimately establishing a deep mapping between the source and target languages.

Take the translation from Chinese to English as an example, and translate the statement "A hundred flowers bloom in the park, beautiful and beautiful". Machine translation is performed. A few years ago, a software based on statistical machine translation translated "The park all flowers bloom together, brilliant purples and reds". The translation result is basically a direct translation according to the words, and there are grammatical errors [9]. The translation result is basically a direct translation of the words, and there are grammatical errors, which is not very good from the human point of view. This illustrates a significant limitation of traditional statistical machine translation approaches, which often struggle with nuances and the contextual flow of language. Since 2014, with neural machine translation coming into the public eye, machine translation has reached a new level. The phrase translated by the software based on neural machine translation is "The flowers in the park are blooming and colorful". The translation result not only eliminates grammatical errors, but also has better translation quality. This improvement is largely due to the ability of NMT systems to consider entire sentences rather than translating word by word. By employing a more holistic approach, these systems can capture the intended meaning and tone, resulting in translations that sound more natural and fluent. The advancements in machine translation are not merely technical; they have profound implications for global communication. As societies become increasingly interconnected, the need for effective language translation tools grows. NMT systems enable smoother interactions across language barriers, facilitating international business, diplomacy, and cultural exchange. For instance, companies can expand their markets by reaching non-native speakers more effectively, while individuals can access a wealth of information and experiences that were previously limited by language differences. Moreover, the continuous improvement of machine translation technologies contributes to the development of the economy and society by enhancing access to education and resources. In educational contexts, students can utilize translation tools to aid their learning in foreign languages, making educational content more accessible. In healthcare, accurate translation can bridge communication gaps between patients and providers, ensuring better understanding and care. As machine translation technology evolves, it also raises important questions about the future of human translators. While NMT has made significant strides, it is essential to recognize that human translators bring cultural context, emotional nuance, and creativity to their work—qualities that machines may struggle to replicate fully. Therefore, the future may lie in a collaborative approach, where human expertise complements machine efficiency. This synergy can lead to even higher-quality translations, combining the strengths of both human and machine capabilities. It can be seen that the level of machine translation is improving, and the faster and more accurate machine translation method can better serve the public and contribute to the development of economy and society. As neural network technology continues to advance, we can expect further enhancements in translation accuracy and fluency. The ongoing research and development in this field will likely yield even more sophisticated models that can navigate the complexities of human language. Ultimately, the evolution of machine translation represents a remarkable intersection of technology and linguistics, paving the way for a more connected and communicative world.

2. Our method

2.1. Neural machine translation model

The benchmark neural machine translation uses the translation model, which directly models the conditional probability $P(Y|X)$ of the target statement $Y = y_1, y_2, \ldots, y_{|Y|}$ under the condition of given source statement $X = x_1, x_2, \ldots, x_{|X|}$. The benchmark neural machine translation model is shown in **Figure 1** (taking the target word at time j as an example).

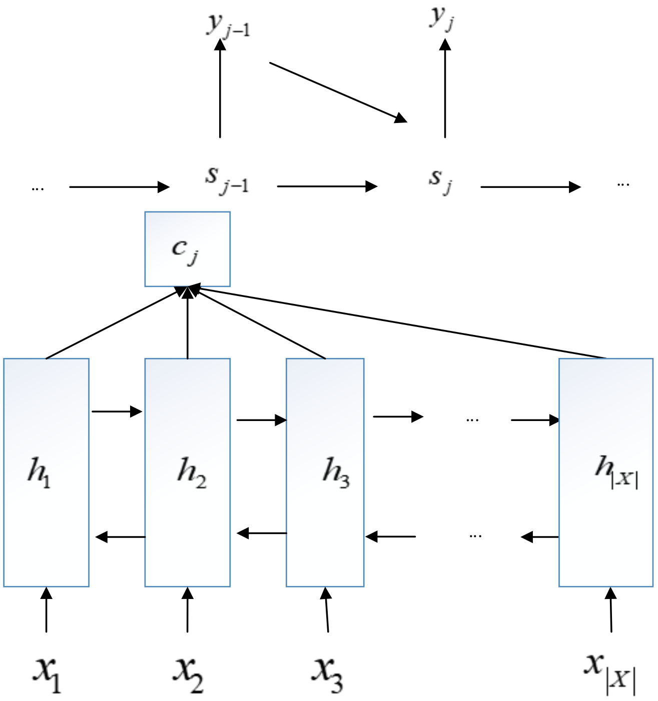

Figure 1. Benchmark NMT model.

Both encoder and decoder use recurrent neural networks to encode and decode the utterances, and the encoder encodes the source-side utterances as source-side hidden layer vectors $H = h_1, h_2, \ldots, h_{|X|}$, usually using LSTM or GRU.

$$h_i = f(x_i, h_{i-1}) \tag{1}$$

where x_i is the source-side word at moment f, h_{i-1} is the source-side hidden layer vector at moment $i-1$, and f is the LSTM or GRU method, which is modified in this paper to CNN to obtain attention distribution with phraseology, improve the model's ability to understand the source-side utterance, optimize the context vector, and improve the performance of machine translation.

2.2. English translation model based on CNN

CNN is made up of neurons that have the ability to learn weights. Each neuron takes in data, computes it using a nonlinear function or dot product, and then sends the finished product to the next neuron. CNN is mostly utilized in checkers games, medication discovery, video analysis, and image recognition.

Using 1D convolution as an example, the convolution kernel needs to be a 1D array if the input is a 1D array. Both the one-dimensional discrete convolution formula and the one-dimensional continuous convolution formula are displayed. The convolution layer previously mentioned has $x(k)$ as its input, $h(k)$ as its convolution kernel, and $y(k)$ as its output.

$$y(k) = \int_{-\infty}^{+\infty} h\,(p)x(k-p)dp = h(k) * x(k) \tag{2}$$

$$y(k) = \sum_{p=0}^{P-1} h\,(p)x(k-p) = h(k) * x(k) \tag{3}$$

In the formula, $h(k)$, $x(k)$ can be regarded as a function of variables to perform the convolution operation, p is the integral variable, k denotes the number of shifted bits, and * denotes the convolution operation. Take one-dimensional discrete convolution as an example, p is the upper limit of convolution. Suppose there is a sequence H and X. If $H = h_0, h_1, h_2$, $X = x_0, x_1, x_2, x_3, x_4, x_5$, here the subscripts 0, l, 2…, in the sequence correspond to (k) and $(k-p)$ in Eq. In the initial state, H is first rotated by 180. to obtain $H = h_2, h_1, h_0$, then the sequence H began to move to x, starting from the 0 th moment, assuming that each moment move step is 1, when k = 0, h_0, x_0, overlap, h_1, h_2 and X sequence without overlap part, then set the fill to 2, the default fill value is 0, then $y_0 = h_0 \times x_0$, that is, 4 $y_0 = h_0 \times x_0 + h_1 \times 0 + h_2 \times 0$, when k = 1, $y_1 = h_0 \times x_1 + h_1 \times x_0 + h_2 \times 0$, and so on. When k = 7, the H sequence is about to leave the x sequence, the entire convolution process that is the end, it can be seen that the count from 0, enough to have 8 values, that is, $0 \le k < (6 + 3)$, for each k, p values in the range $0 \le p \le k$, so in this case there are $0 \le p < 8$, so the upper limit of convolution p = 8, the following list of all the y sequence formula.

$$y_0 = h_0 \times x_0 \tag{4}$$

$$y_1 = h_0 \times x_1 + h_1 \times x_0 \tag{5}$$

$$y_2 = h_0 \times x_2 + h_1 \times x_1 + h_2 \times x_0 \tag{6}$$

$$y_3 = h_0 \times x_3 + h_1 \times x_2 + h_2 \times x_1 \tag{7}$$

$$y_4 = h_0 \times x_4 + h_1 \times x_3 + h_2 \times x_2 \tag{8}$$

If L denotes the length of the input sequence, padding denotes the padding value, kernel denotes the shape of the convolution kernel, stride denotes the step size, and L_y denotes the length of the output sequence, the one-dimensional convolution output sequence length is calculated as follows.

$$L_y = \frac{L_x + 2 \times padding - kernel}{stride} + 1 \tag{9}$$

3. Experiments and analysis

A parallel corpus makes up the dataset in the field of machine translation, and the size and caliber of the dataset significantly affect how well machine translation works. The test and development sets are taken from the National Institute of

Standards and Technology 2002 data, and the experiment uses a high-quality public Chinese-English LDC dataset (Linguistic Data Consortium) with a training set of 1.25 million sentences [10,11].

The corpus is initially preprocessed before the experiments begin:

1) The corpus for Chinese data is word-sorting processed, mainly, using Stanford word-sorting to slice Chinese utterances into words, as listed in **Table 1**;
2) The corpus for English data is symbolic processed, using Moses system word splitting foot tokenizer to insert space characters between words and punctuation marks in English data, as listed in **Table 2**;
3) Converting upper case to lower case in English data;
4) Selecting the first 30,000 high-frequency words in the processed training corpus for retention, and replacing the rest of words with <unk>.

Table 1. Sample Chinese word separation.

Chinese utterance	**A large-scale campus cultural exhibition will also be held during the conference.**
After the participle	During the conference, a sizable campus cultural exhibition will also take place.

Table 2. Sample English symbol processing.

English statement	**The official said that children, women and the elderly are those worst hit by food shortages.**
After symbol processing	According to the official, the elderly, women, and children are the groups most affected by food shortages.

3.1. Machine translation evaluation indexes

To evaluate the model's translation performance, this paper uses the size-independent BLEU metric, employing the multi-bleu. perl script. BLEU is a widely used international standard for machine translation evaluation, which assesses translation quality by comparing n-gram phrase similarities between the translated text and reference translation, known as the *N-gram* matching rule [12–14].

For example, given the translated text "I have my own room" and the reference "I have my OWN bedroom", the unigram match rate is 4/5, and the bigram match rate is 3/4, and so forth. To address this, BLEU incorporates a correction mechanism, as shown in Equation (10).

$$p_n = \frac{\sum_{C\in\{Candidates\}} \sum_{n-gram\in C} Count_{clip}(n-gram)}{\sum_{C'\in\{Candidates\}} \sum_{n-gram'\in C} Count\ (n-gram')} \tag{10}$$

where, $Count(n-gram)$ is the number of occurrences of $n-gram$ in the machine translated translation, $Count_{clip}(n-gram)$ is the minimum value taken between $Count(n-gram)$ and the number of occurrences of $n-gram$ in the reference translation, C is the translated translation, C' is the reference translation, and in the calculation, $n-gram$ is generally set to $4-gram$at the highest.

This matching rule has a defect, that is, for long sentence translation, if the translated text only translates part of the utterance and is more accurate, then the calculated matching degree will still be high, so that the translation effect is poor from the manual point of view, in order to avoid the drawback brought by this situation, BLEU into the length penalty factor l (Brevitv Penalty, BP for short), if c denotes the length of the translated utterance and r denotes the length of the corresponding reference translated utterance, then the BP calculation formula is shown in Equation (11).

$$\mathrm{BP} = \begin{cases} 1 & \text{if} \quad c \geq r \\ e^{(1-r/c)} & \text{if} \quad c < r \end{cases} \tag{11}$$

When BP: 1 means no penalty, and the penalty factor comes into play only when the length of the translation is smaller than the reference translation. The range of BLEU value is obtained as [0, 100], and the higher value indicates the better machine translation. The final BLEU value is calculated by the formula shown in Equation (12).

$$\mathrm{BLEU} = \mathrm{BP} \cdot \exp\left(\sum_{n=1}^{N} w_n \log(p_n)\right) \tag{12}$$

where, $W_n = \frac{1}{N}$, N is the number of elements, if the highest is taken to $4 - gram$, then N = 4, and in the evaluation method of this paper, N = 4 is used in all.

3.2. Experimental results

As shown in **Table 3**, the convolution kernel is set to a 2 × 1 shape, with the number of convolution layers set to 3, 6, 10, and 12. The results in the last column show that the optimal performance occurs with 6 layers, improving the BLEU score by 0.958 compared to the baseline. With 3 layers, the BLEU score increases by 0.912; with 10 layers, by 0.936; and with 12 layers, only by 0.706. These results indicate that a 2 × 1 convolution kernel achieves the best translation performance with 6 or 10 layers in a multilayer CNN.

Table 3. Convolution kernel shape is 2 × 1 value of BLEU.

Model	**NIST02**	**NIST03**	**NIST04**	**NIST05**	**NIST08**	**AVG.**	**Δ**
Benchmark model	37.79	35.01	38.77	35.21	26.55	34.782	-
+ 3 floors	38.99	35.62	39.68	36.03	27.25	35.519	+ 0.922
+ 6 floors	38.41	36.39	39.32	36.57	27.22	35.546	+ 0.965
+ 10 floors	38.77	35.89	39.17	37.02	27.22	35.521	+ 0.946
+ 12 floors	38.55	35.93	39.21	36.09	26.81	35.321	+ 0.711

Based on this, the number of convolutional layers is fixed and the shape of the convolutional kernel is set to 3 × 1 for comparison experiments, and the experimental results are listed in **Table 4**. The experimental results are listed in **Table 4**. Among them, when the number of layers is set to 6, the BLEU value can be improved by 0.98, and when the number of layers is set to 12, the BLEU value can be improved by 0.832, both of which exceed the BLEU value corresponding to the same number of layers in **Table 3**, but when the number of layers is 10, the BLEU value can only be improved by 0.84.

Table 4. Convolution kernel shape is 3 × 1 value of BLEU.

Model	NIST02	NIST03	NIST04	NIST05	NIST08	AVG.	Δ
Benchmark model	37.79	35.01	38.65	35.19	26.35	34.557	-
+ 6 floors	38.51	35.88	39.71	36.55	27.63	35.558	+ 0.99
+ 10 floors	38.79	35.79	39.32	36.29	27.19	35.476	+ 0.85
+ 12 floors	38.72	36.23	39.29	36.12	26.81	35.397	+ 0.831

4. Discussion

The integration of neural network methods, particularly convolutional neural networks (CNNs), has revolutionized the landscape of machine translation technology [15]. CNNs, inspired by the hierarchical organization and functional principles observed in biological systems, have demonstrated remarkable efficacy in addressing challenges inherent in language processing. This approach mirrors the adaptability and responsiveness of biomechanical structures, which can adjust to various stimuli and contexts. As a result, CNNs have become a powerful tool for overcoming issues such as remote dependencies and contextual nuances that often hinder the quality of translations. The architecture of CNNs, particularly the optimal structure comprising six layers with 3 × 1 convolutional kernel, has proven effective in enhancing context understanding. This layered approach allows for the extraction of features at multiple levels, facilitating a deeper comprehension of the linguistic elements involved. By processing information hierarchically, CNNs can decompose complex language tasks into manageable components, similar to how biological neurons operate [16]. Biological neurons engage in a sophisticated process of feature extraction, where information is distilled through various stages to achieve a comprehensive understanding of intricate tasks. This biological analogy underscores the significance of hierarchical processing in both natural and artificial systems. Moreover, the theoretical frameworks surrounding biological neural networks provide valuable insights into the functioning of CNNs in language tasks. The ability of biological systems to process and integrate information from diverse sources is mirrored in the convolutional layers of CNNs, which distill local features and integrate them into a cohesive understanding of global context. This mechanism not only enhances the translation quality but also reflects the underlying principles of how humans comprehend language. The success of CNNs in language processing thus highlights the transformative potential of neural hierarchical structures in computational linguistics.

As we delve deeper into the mechanisms of CNNs, it becomes evident that their application extends beyond mere translation tasks. The principles governing their operation can inform advancements in various domains of natural language processing, including sentiment analysis, text summarization, and question-answering systems. The ability of CNNs to capture intricate patterns within language data opens new avenues for developing more natural and accurate language models. Furthermore, the exploration of CNNs in the context of machine translation raises important questions about the future of human-computer interaction. As these models become increasingly adept at understanding and generating human language, the potential for seamless communication between humans and machines grows.

This evolution may lead to more intuitive interfaces and applications that can adapt to user preferences and contexts, ultimately enhancing the user experience. In conclusion, the application of CNNs in machine translation exemplifies the intersection of biological inspiration and computational innovation. By leveraging the hierarchical processing capabilities inherent in both biological and artificial neural networks, researchers can unlock new possibilities in language technology. The transformative impact of these neural structures not only advances machine translation but also paves the way for a deeper understanding of language itself, fostering a future where communication barriers may be significantly diminished.

5. Conclusion

In this paper, we have conducted experiments on the benchmark machine translation model using multilayer CNN to improve the quality of machine translation, and to further enhance it by the method of model fusion. However, the research method in this paper still has many aspects that deserve further research and optimization, mainly considering that in the process of building a multilayer CNN, the new context vector is obtained by directly multiplying the new attention weight distribution with the hidden layer vector at the source end, and in future work, we can consider adding the location information of the source end, such as the hidden layer vector of the source end location, in order to strengthen the newly obtained context vector to provide better help for target-side prediction.

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