Bidirectional Deep Learning Model based on Attention Mechanism in English Cloze Tests

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Abstract. English cloze tests, as a common form of language assessment, aim to evaluate learners' comprehensive understanding of context, vocabulary, and grammar. However, the complex contextual relationships and long-distance dependencies within the questions pose significant challenges for machine learning models. Traditional rule-based or statistical methods struggle to effectively capture the intricate contextual information present in sentences. This study aims to develop a deep learning-based English cloze test answering system to enhance students' ability to tackle such questions. To address the limitations of traditional methods in handling complex contexts and long-distance dependencies, a model that combines bidirectional gated recurrent units (BiGRU) and attention mechanisms is proposed. This model is better equipped to capture the surrounding context of sentences and dynamically adjust attention to accurately predict the missing words. Additionally, integrating the embedding layer with BiGRU and attention mechanisms further improves model performance. Testing results based on the Children's Book Test dataset are highly promising. Our model excels in key metrics such as accuracy, recall, F1 score, and Cohen's Kappa, achieving scores of 77.5%, 77.5%, 0.758, and 0.7649, respectively. Compared to traditional models, our approach demonstrates clear advantages in handling complex contexts and long sentences. This research provides new technical support for developing more intelligent English learning systems.

Keywords: English Cloze Tests; Deep Learning; BiGRU; Attention Mechanisms.

1. Introduction

The importance of English as a global lingua franca is undeniable. As globalization deepens, proficiency in English has become an essential skill across various industries. To assess and enhance learners' language comprehension and application abilities, educational institutions widely employ a variety of question types. Among these, cloze tests have become significant assessment tools due to their comprehensive requirements for vocabulary, grammar, and contextual understanding.

Cloze tests require candidates to fill in appropriate words within a text to complete the meaning of the sentences. This type of question not only evaluates students' knowledge of vocabulary and grammar but also, more importantly, their understanding of context. Given the flexibility and high contextual dependency of cloze tests, they pose significant challenges to candidates, especially when faced with complex sentence structures and long-distance dependencies, often leading to confusion. Therefore, improving students' ability to solve cloze tests has become a crucial task in English teaching.

Traditional cloze test systems are often based on rule matching or statistical methods, which may be effective for simple questions but show evident limitations when dealing with questions that rely heavily on complex contexts. With the continuous advancement of artificial intelligence technologies, particularly in natural language processing (NLP), deep learning models offer new possibilities for addressing cloze test challenges. These models can not only capture the grammatical structures of language but also better understand the intricate relationships between contexts, enabling more accurate judgments in answering cloze questions.

In recent years, recurrent neural networks (RNNs) and their variants, such as long short-term memory networks (LSTMs) and gated recurrent units (GRUs), have achieved significant success in processing sequential data. Compared to traditional methods, these deep learning models better comprehend contextual information, particularly excelling in handling long-distance dependencies [1]. However, even so, there remains room for improvement in the contextual capturing abilities of

LSTMs and GRUs in certain complex situations. Thus, optimizing these models to enhance the accuracy of cloze test solutions has become the primary motivation for our research.

In this context, we propose a cloze test answering model that combines bidirectional GRUs (BiGRUs) and attention mechanisms. The BiGRU processes both forward and backward information simultaneously, allowing for a comprehensive understanding of the overall semantics of a sentence and better capturing complex contextual relationships. Meanwhile, the attention mechanism enables the model to dynamically adjust its focus on the most critical parts of the context when handling long sentences, thereby enhancing the accuracy of the cloze test responses.

2. Related Work

Over the past few decades, solving English cloze test questions has become a significant research focus in the field of natural language processing (NLP). Early methods primarily relied on rule matching and statistical approaches, often depending on handcrafted rules or simple n-gram models. However, these methods exhibit clear limitations when dealing with complex contexts and long-distance dependencies.

With the advancement of deep learning technologies, researchers began applying recurrent neural networks (RNNs) to cloze tasks. RNNs, particularly their variants like long short-term memory networks (LSTMs) and gated recurrent units (GRUs), gained widespread use due to their ability to process sequential data. Mikolov et al. first introduced an RNN-based language model for predicting the next word in a sentence, significantly improving model performance in cloze tasks [2]. However, RNNs still face the vanishing gradient problem when handling long sequences, resulting in poor performance in capturing long-distance dependencies.

To further enhance model performance, Vaswani et al. proposed the Transformer model, which significantly improves the ability to capture long-distance dependencies through self-attention mechanisms. The Transformer-based BERT model has achieved remarkable results across various NLP tasks, including cloze tests [3]. By pre-training a language model, BERT can better understand the contextual relationships of words, providing strong feature representations for downstream tasks.

In recent years, researchers have attempted to combine attention mechanisms with traditional RNNs to improve model performance. Zhou et al. proposed a model that integrates bidirectional GRUs and attention mechanisms for cloze tasks. Experimental results demonstrated that the attention mechanism effectively aids the model in selecting the most relevant vocabulary within complex contexts, significantly enhancing fill-in accuracy [4].

Understanding context is crucial in cloze tasks. Thus, maximizing the use of contextual information has become a research priority. Devlin et al. introduced bidirectional encoding representations in the BERT model to capture richer contextual information, providing a stronger foundational model for cloze tasks [5]. Additionally, Sun et al. explored fine-tuning pre-trained models to meet specific task requirements, achieving favorable results in cloze tasks as well [6].

Overall, existing research indicates that solutions combining deep learning models with attention mechanisms can significantly enhance accuracy in English cloze test tasks. Our approach further integrates bidirectional GRUs and attention mechanisms, with experimental results showing outstanding performance when handling complex contexts and long sentences.

3. Bidirectional Deep Learning Model Based on Attention Mechanism

This paper presents a neural network model that combines bidirectional GRU (Gated Recurrent Unit) and attention mechanisms to address the challenges of complex context understanding and long-distance dependency modeling in English cloze tasks. The main approach is outlined as follows.

Current cloze tasks require models to fully comprehend the context and accurately predict missing words in complex situations. Traditional methods often struggle with long-distance dependencies; thus, we integrate the latest techniques from the field of natural language processing. First, a

systematic preprocessing of the existing English cloze datasets was conducted, which included text tokenization and the generation of pairs for context, questions, and answers. This step provides structured data input for model training.

For model construction, a bidirectional GRU is employed to process the input context and questions. The bidirectional GRU captures semantic features from both directions, enabling a better understanding of the overall meaning of the text and the dependencies between words. Additionally, an attention mechanism is incorporated into the model. This mechanism dynamically adjusts the model's focus on different parts of the text, allowing it to more accurately concentrate on relevant contextual information when predicting missing words. The specific model workflow structure is as follows:

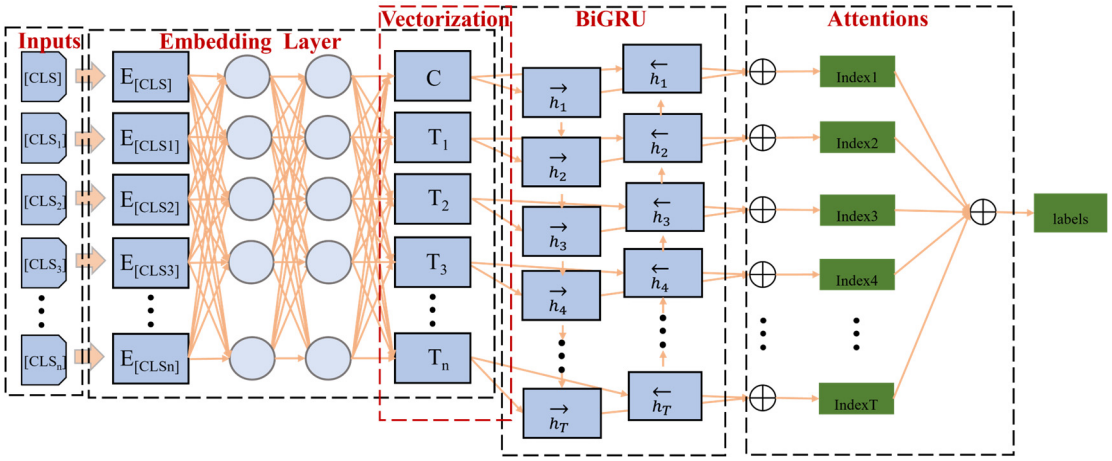

Fig 1. Overall flow of the model

Specifically, the bidirectional GRU first encodes the context and questions in the text, generating corresponding semantic representations. The attention mechanism then assigns different weights to various parts of the context based on the semantic representation of the question, resulting in a weighted semantic representation that is ultimately used to predict the correct answer. This approach allows the model not only to capture semantic features more effectively but also to improve prediction accuracy by dynamically adjusting its focus.

Based on this methodology, a neural network model has been designed and implemented to effectively tackle cloze tasks, with experimental results validating its superiority in understanding complex contexts.

3.1 Vctorization Model

When selecting a model for text processing, considering the complexity and resource requirements is crucial. This study opts for an embedding layer combined with a neural network model rather than a pre-trained BERT model. The embedding layer provides an efficient representation of text data by mapping vocabulary to a lower-dimensional vector space, requiring less computational resources [7]. In contrast, BERT, as a large pre-trained language model, features a complex multi-layer Transformer architecture, demanding substantial computational resources for training and fine-tuning, which may be impractical in resource-constrained environments [8].

While BERT excels at capturing deep contextual information and performs well on complex natural language tasks, the embedding layer proves to be more efficient and economical in scenarios with limited data or computational resources. Furthermore, the training process for the embedding layer is straightforward, with high interpretability and ease of adjustment, whereas BERT's intricate mechanisms complicate debugging and optimization [9]. Therefore, the choice of an embedding layer in conjunction with a neural network model effectively addresses text data while offering satisfactory performance and interpretability.

The embedding layer is critical for enhancing model performance. Within the dataset, the embedding layer converts words into dense vector representations, better capturing semantic

relationships and contextual information among words. The core concept involves mapping discrete vocabulary through an embedding matrix into a lower-dimensional continuous vector space [10]. With V distinct words in the vocabulary, each word is represented as a d-dimensional vector, resulting in an embedding matrix W of dimensions V×d. Given an input word's one-hot vector representation x_i, the embedding vector for that word is represented as:

$$Embedding(x_i) = W \times x_i \quad (1)$$

Here, $\boldsymbol{W}$ represents the embedding matrix, and x_i is the one-hot vector for a specific word. The embedding layer maps this one-hot vector into a lower-dimensional vector space through matrix multiplication. The parameters of matrix $\boldsymbol{W}$ are trained via the model's backpropagation algorithm, gradually learning the semantic relationships between words.

In the implementation process, the dataset is first preprocessed to generate a vocabulary that includes all unique words, assigning each word a unique index. The steps for vectorizing the text data using the embedding layer include reading pre-trained word vector data from an external file and storing it in a dictionary structure, initializing the embedding matrix, assigning pre-trained vectors based on the dictionary, and using random initialization for words not found in the pre-trained data. During model training, the parameters of the embedding matrix W are adjusted through backpropagation. Each word's embedding vector is gradually optimized throughout training, ultimately reflecting the semantic relationships among words. After vectorizing the text input, the resulting sequence of word vectors serves as input for subsequent model layers for analysis and prediction.

The optimized structure of the embedding layer is as follows:

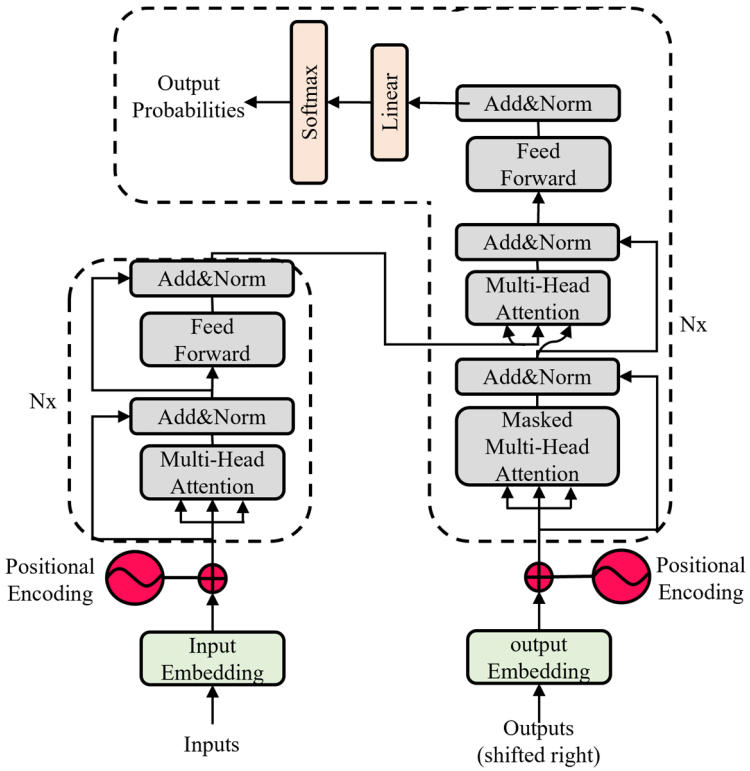

Fig 2. Optimised embedding layer

3.2 Deep Learning Models

In selecting a model for processing sequence data, we initially considered LSTM, unidirectional GRU, and bidirectional GRU (BiGRU). LSTM is widely used in natural language processing due to its ability to capture long-range dependencies [11], but its complex structure leads to high computational costs and a risk of overfitting. In contrast, unidirectional GRU has a simplified structure that improves computational efficiency but only utilizes information from a single direction,

limiting its ability to handle bidirectional dependencies. Ultimately, we chose BiGRU, which combines both forward and backward GRU units, allowing it to capture contextual information from both directions. This makes it particularly suitable for cloze tasks, enhancing overall context understanding [12]. Considering model complexity, computational efficiency, and contextual capture capabilities, BiGRU is best suited to meet the needs of our dataset.

3.2.1 Establishment of the BiGRU Model

BiGRU, an extension of the Gated Recurrent Unit (GRU), processes sequence data by simultaneously capturing both forward and backward information. Traditional GRUs are limited to unidirectional information, which can result in loss of critical context in many natural language processing tasks. By incorporating a reverse pathway, BiGRU enhances its context awareness, enabling it to capture dependencies from both directions.

The BiGRU architecture consists of two GRU units: one that processes the sequence from start to finish (forward GRU) and another that processes it in reverse (backward GRU). The outputs from these units are combined at each time step, yielding a comprehensive representation of the sequence. This dual approach allows BiGRU to gain a more nuanced understanding of the input context.

3.2.2 Model Principles

The BiGRU is an advanced model designed to optimize sequence input processing. Research indicates that BiGRU effectively mitigates the vanishing gradient problem prevalent in long sequences by integrating backward hidden states with gating mechanisms to leverage bidirectional context [13]. In contrast, unidirectional GRUs may overlook overall semantics, leading to misinterpretations in tasks such as sentiment analysis. BiGRU's capability to synthesize information from both directions allows for a more accurate capture of semantic nuances [14, 15]. Consequently, BiGRU stands out as an efficient sequence modeling technique, significantly enhancing performance and accuracy.

At a specific time t, given the input and the previous hidden state, the forward computation of the GRU involves several steps that incorporate activation functions, weight matrices, and bias vectors.

In BiGRU, in addition to the forward hidden state sequence, there is also a backward hidden state sequence. The backward GRU's computations mirror those of the forward GRU, but it processes the sequence from right to left.

In the bidirectional calculation, the forward and backward hidden state sequences are concatenated to form the final output sequence.

The architecture diagram for BiGRU is as follows:

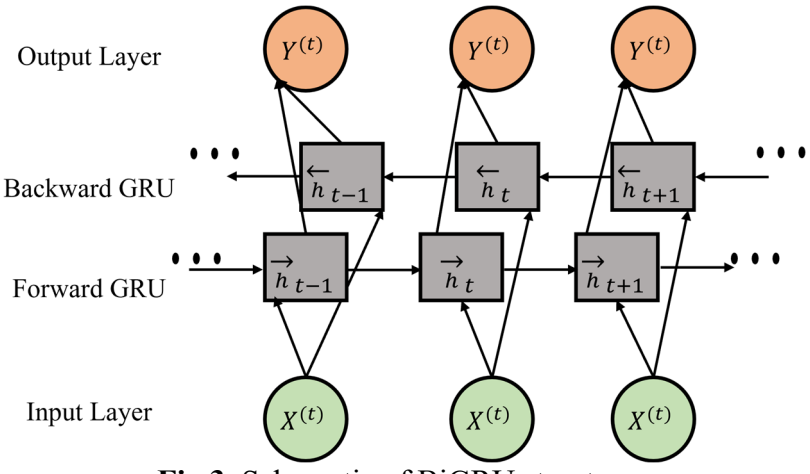

Fig 3. Schematic of BiGRU structure

Applying the BiGRU model to text sequence modeling enhances the ability to capture contextual information and improves semantic representation, leading to better performance and accuracy in sequence tasks.

3.3 Attention Mechanisms

The core idea of the attention mechanism is to dynamically compute a context vector for each output prediction, rather than simply relying on the last hidden state of the input sequence. This context vector is a weighted sum of the hidden states of all words in the input sequence, with the weights determined by attention scores [17]. The following diagram effectively illustrates the attention mechanism, demonstrating how humans allocate limited attention resources when viewing an image. The red areas indicate targets that the visual system focuses on more intensively; notably, people tend to direct more attention toward facial features.

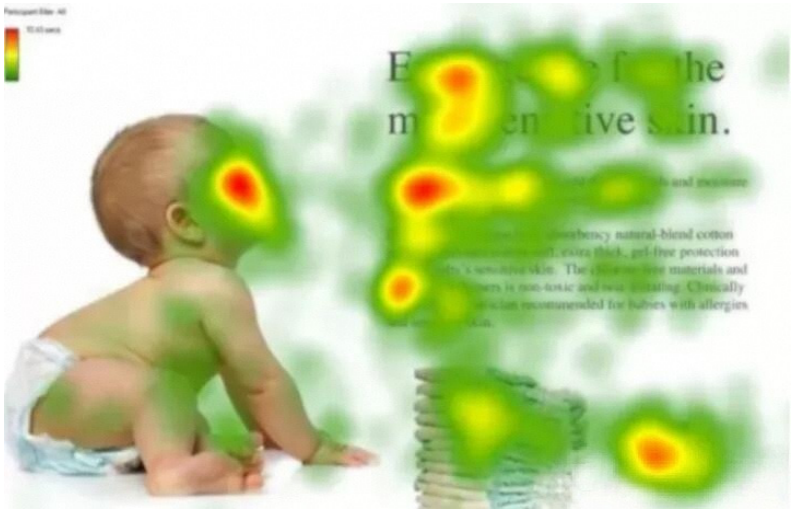

Fig 4. Schematic of Attention Mechanisms

Specifically, the calculation process of the attention mechanism can be divided into several steps:

Score Calculation: Initially, we compute the relevance score between each word in the input sequence and the current time step. This score is typically represented using a simple affine transformation. For a given time step t and the i-th word in the input sequence, the score e_{ti} can be expressed as:

$$e_{ti} = score(h_t, h_i) = h_t^T W_a h_i \tag{2}$$

where h_t is the hidden state vector at the current time step, h_i is the hidden state vector of the i-th word in the input sequence, and W_a is a learnable parameter matrix.

Attention Weights Calculation: Next, we apply the Softmax function to the scores to obtain weights that reflect the importance of each word in the input sequence for the current time step. The weight α_{ti} for the i-th word can be expressed as:

$$\alpha_{ti} = \frac{\exp(e_{ti})}{\sum_{j=1}^{T} \exp(e_{tj})} \tag{3}$$

where T is the length of the input sequence.

Context Vector Calculation: Finally, we use these weights to compute a weighted average of the hidden states of the input sequence, resulting in the context vector c_t, which encapsulates the most relevant information for the current time step. The calculation of the context vector is given by:

$$c_t = \sum_{i=1}^{T} \alpha_{ti} h_i \tag{4}$$

Output Generation: The context vector c_t is combined with the current hidden state h_t to generate the final output. This combination typically involves concatenating the context vector and the hidden state, which is then fed into a fully connected layer:

$$\tilde{h}_t = \tanh(W_c[c_t; h_t]) \tag{5}$$

where W_c is a learnable parameter matrix, and $[c_t; h_t]$denotes the concatenation of the context vector and the hidden state.

By incorporating the attention mechanism, our BiGRU model can more effectively focus on the parts of the context that are most relevant to the answer in the cloze test task, thereby enhancing the model's accuracy and generalization capabilities. This mechanism is particularly effective in handling long texts and complex contexts, as it grants the model the flexibility to attend to different pieces of information, allowing it to better capture the key elements within the text.

4. Introduction to the Dataset

The Children's Book Test (CBT) dataset, developed by the University of Cambridge, is specifically designed to assess the reading comprehension capabilities of natural language processing (NLP) systems. The CBT dataset is derived from children's literature, encompassing a wide range of children's books, and is structured to simulate real reading comprehension tasks, challenging models in understanding and reasoning.

Each sample in the CBT consists of a story paragraph (context), a question based on that paragraph, and the target answer, facilitating the model's ability to use context for reasoning when addressing the question. The dataset includes a substantial number of training, validation, and test samples, sufficient to support deep learning training while mitigating the risk of overfitting.

The questions in the CBT primarily take the form of fill-in-the-blanks or multiple-choice items, assessing the model's semantic understanding and multitasking abilities, thus providing comprehensive evaluation criteria. Given that the dataset originates from children's books, the language is clear and straightforward, with relatively simple textual contexts that allow for accurate understanding and answer generation by the model. The design of the context and questions in CBT aligns closely with cloze tasks, making it suitable for training and evaluating models.

Therefore, the choice of the CBT dataset is based on its strong alignment with the design of cloze tasks, ensuring effective training and evaluation of the model.

5. Data Processing and Model Development

5.1 Data Preprocessing

This study systematically preprocesses the original dataset to ensure data quality and model performance. The data import process includes reading data, tokenization and segmentation, sample organization and shuffling, and data saving.

First, the data file is read line by line to extract context, questions, and answer information, organizing them into structured samples. Tokenization is performed using regular expressions to remove punctuation and whitespace, facilitating subsequent vocabulary generation and data vectorization [18]. All words are standardized to ensure data consistency [19].

The processed samples must be organized and randomly shuffled to create training, validation, and test sets. Sample integration combines the context, questions, and answers into complete samples, while random shuffling prevents order bias in the data, ensuring model generalization capability.

Vocabulary generation and data vectorization are key steps to convert textual data into numerical forms that the model can process. The vocabulary contains all unique words and assigns a unique index to each. This mapping is created by flattening, deduplicating, and sorting the words. The vocabulary size equals the number of unique words plus one, reserving index 0 for out-of-vocabulary words. The vocabulary mapping converts each word to an index as follows:

$$V = |unique\_words| + 1 \tag{6}$$

$$word2idx(w) = i \tag{7}$$

where $|\boldsymbol{unique\_words}|$ represents the number of unique words, and $\boldsymbol{i}$ is the index assigned to each word.

During vectorization, the text is transformed into numerical vectors. The words in the context and questions are flattened and converted into vocabulary indices. Samples that do not meet the maximum length requirement are standardized using padding or truncation. Finally, the vectorized data files are saved for subsequent model training and testing.

5.2 Model and Parameter Configuration

Given the characteristics of our dataset, which includes a substantial number of context and question pairs (with each context potentially containing up to 256 words and each question up to 64 words), the choice of the BiGRU model is critical. The vocabulary size is 52,463, necessitating an embedding layer that provides sufficient representational capacity. To effectively capture semantic information, we opted for an embedding dimension of 384. This choice ensures the richness of semantic information while avoiding the computational overhead associated with excessively high dimensions.

In terms of the GRU layer configuration, we selected a hidden state dimension of 128. This decision is based on the requirements of the maximum lengths of the context and questions, which are 256 and 64 words, respectively. A hidden state dimension of 128 effectively extracts key features from the sequences without overburdening computational resources. While a higher-dimensional hidden state could enhance the model's expressiveness, it may also lead to overfitting in scenarios with relatively limited data. Therefore, we chose 128 dimensions to balance performance and computational efficiency.

To ensure the efficiency and convergence of model training, we utilized the Adam optimizer with a learning rate set at 0.001. The Adam optimizer is well-suited for handling data with sparse gradients and can adaptively adjust the learning rate, accelerating the convergence speed during training. The model is trained for 30 epochs to ensure it adequately learns the feature patterns in the training data while mitigating the risk of overfitting.

Through these carefully tuned configurations, the BiGRU model effectively manages the complex context and question sequences in our dataset, enhancing the model's accuracy and performance, thereby achieving superior results in the cloze task.

6. Analysis of Model Testing Results

In this study, the test set comprises four categories of labeled data:

- **Category A**: Represents option A, with 500 samples.
- **Category B**: Represents option B, with 500 samples.
- **Category C**: Represents option C, with 500 samples.
- **Category D**: Represents option D, with 500 samples.

From the data distribution perspective, the four options are evenly represented in the test set, as we established corresponding options for each blank segment. This ensures that the model can comprehensively assess the classification performance of each category during the testing phase. Each sample's feature data is processed by the model, yielding the corresponding classification results. The following is the confusion matrix of the model's classification results:

Table 1. Confusion matrix

	Actual Class 0	Actual Class 1	Actual Class 2	Actual Class 3
Predicted 0	363	82	39	16
Predicted 1	74	411	13	2
Predicted 2	49	37	373	41
Predicted 3	30	39	28	403

From the confusion matrix, we observe:

- **Category A (Option A)**: Out of 500 samples, the model correctly classified 363, misclassified

82 as Category B, 39 as Category C, and 16 as Category D. The model performs well for Category A but still exhibits some misclassification, mainly with Categories B and C.

- **Category B (Option B)**: For 500 samples, the model correctly identified 411, misclassifying 74 as Category A, 13 as Category C, and 2 as Category D. The model shows good performance in recognizing Category B, but there is some confusion with Categories A and C.
- **Category C (Option C)**: Among 500 samples, the model correctly classified 373, misclassifying 49 as Category A, 37 as Category B, and 41 as Category D. The recognition of Category C shows significant overlap with Categories A and B, potentially due to feature similarities.
- **Category D (Option D)**: For 500 samples, the model correctly identified 403, misclassifying 30 as Category A, 39 as Category B, and 28 as Category C. The model performs well for Category D, with misclassifications primarily occurring with other categories.

Based on the classification report, we further analyze the precision, recall, and F1 scores for each category:

Table 2. Classification Report

Option	Precision	Recall	F1-Score	Support
0	0.703	0.726	0.714	500
1	0.722	0.822	0.769	500
2	0.823	0.746	0.784	500
3	0.873	0.806	0.839	500

The classification report indicates the model's performance across categories: Category 0 has a precision of 0.703, a recall of 0.726, and an F1 score of 0.714, indicating relatively high accuracy and consistency in handling samples for this option. Despite a slightly lower precision, the model demonstrates good capability in correctly identifying samples. For Category 1, the precision is 0.722, recall is 0.822, and F1 score is 0.769, showcasing strong recognition ability. The higher recall suggests the model effectively captures samples from this category, despite a moderate precision.

For Category 2, the precision is 0.823, recall is 0.746, and F1 score is 0.784, reflecting stable performance in distinguishing this category from others. The high precision indicates strong reliability in predicting this category, although recall could be improved. Category 3 has a precision of 0.873, recall of 0.806, and an F1 score of 0.839, showing high recognition performance, indicating the model's good classification ability for samples of this category. The high precision and recall indicate a favorable balance in predictions for this category.

Overall, the model achieved an accuracy of 77.5% and a Cohen's Kappa index of 0.7649, demonstrating good classification ability and category consistency across different classification tasks. While there is room for improvement in certain categories, the model exhibits strong classification performance and practical application value. These results indicate the model's effectiveness in multi-class tasks, laying a foundation for future optimization and application.

7. Conclusion

In this study, we developed a neural network-based attention mechanism model for multi-class physiological signal classification in cloze tasks, achieving an overall accuracy of 77.5%, significantly higher than the mainstream accuracy of 60-70%. By integrating current deep learning techniques with natural language processing methods, the model demonstrates exceptional performance, showcasing substantial innovation and application potential. The main innovations and practical applications of this work are reflected in the following aspects:

Innovations:

1. **Integration of Data Processing and Embedding Layer:** We combined data preprocessing and the application of an embedding layer in our model, thoroughly preprocessing the context and

questions to transform them into vector representations. By employing an embedding layer, we effectively mapped the vocabulary from the vocabulary list into a high-dimensional space, capturing semantic information efficiently.

2. **Innovative Application of Neural Network Structure:** We utilized a hierarchical neural network, leveraging GRU units to capture sequential information from the context and questions while employing an attention mechanism to focus on key features. This architecture not only enhances the flexibility of information extraction but also improves the model's performance in complex language tasks, particularly in semantic understanding and contextual relevance.

Practical Application Value:

1. **Broad Applications in Natural Language Processing:** The proposed attention mechanism model is not only applicable to cloze tasks but also suitable for various other text understanding and natural language processing tasks, such as question-answering systems and dialogue systems. This model is well-suited for integration into various smart devices and applications, providing efficient text processing capabilities with excellent scalability and practicality.
2. **Improved Detection Accuracy and Stability:** Experimental results indicate that our model achieved an accuracy of 77.5% with a Cohen's Kappa coefficient of 0.7649, reflecting superior performance in detecting different categories and stability across various text environments. This efficient detection tool offers technical support for education, psychological research, and personal learning.

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