International Journal of Informatics and Communication Technology (IJ-ICT)
Vol. 13, No. 2, August 2024, pp. 223~230
ISSN: 2252-8776, DOI: 10.11591/ijict.v13i2.pp223-230

Design of an efficient Transformer-XL model for enhanced pseudo code to Python code conversion

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Article Info

Article history:

Received Jan 25, 2024
Revised Mar 15, 2024
Accepted May 12, 2024

Keywords:

Code conversion
Natural language processing
Deep learning
Pseudo code interpretation
Scenarios
Transformer-XL

ABSTRACT

The landscape of programming has long been challenged by the task of transforming pseudo code into executable Python code, a process traditionally marred by its labor-intensive nature and the necessity for a deep understanding of both logical frameworks and programming languages. Existing methodologies often grapple with limitations in handling variable-length sequences and maintaining context over extended textual data. Addressing these challenges, this study introduces an innovative approach utilizing the Transformer-XL model, a significant advancement in the domain of deep learning. The Transformer-XL architecture, an evolution of the standard Transformer, adeptly processes variable-length sequences and captures extensive contextual dependencies, thereby surpassing its predecessors in handling natural language processing (NLP) and code synthesis tasks. The proposed model employs a comprehensive process involving data preprocessing, model input encoding, a self-attention mechanism, contextual encoding, language modeling, and a meticulous decoding process, followed by post-processing. The implications of this work are far-reaching, offering a substantial leap in the automation of code conversion. As the field of NLP and deep learning continues to evolve, the Transformer-XL based model is poised to become an indispensable tool in the realm of programming, setting a new benchmark for automated code synthesis.

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1. INTRODUCTION

The advent of advanced computational models has ushered in a new era in the realm of programming, particularly in the conversion of pseudo code into executable programming languages like Python. This conversion is pivotal, bridging the gap between conceptual algorithms and their practical implementation. Traditional approaches to this conversion have been predominantly manual, requiring a profound understanding of programming logic and syntax. Such methods are often time-consuming and prone to errors, underscoring the need for more efficient, automated solutions. In recent years, the field of natural language processing (NLP) has witnessed remarkable advancements, primarily attributed to the evolution of deep learning architectures. Among these, the transformer model has emerged as a groundbreaking development, significantly enhancing the processing of sequential data. However, the standard transformer architecture exhibits limitations, particularly in handling long-range dependencies and variable-length sequences, which are common in pseudo code.

The introduction of the Transformer-XL model marks a substantial leap forward in this conte-xt. The proposed study leverages the Transformer-XL model to automate the conversion of pseudo code into Python code. This process involves several intricate steps: data preprocessing, input encoding, self-attention mechanism application, contextual encoding, language modeling, and a subsequent decoding process, all culminating in a post-processing phase to ensure syntactical and logical correctness in the output Python code. The introduction of an automated pseudo code to Python code conversion using the Transformer-XL model addresses several critical challenges faced by conventional methods. Firstly, it significantly reduces the time and effort involved in manual coding, thereby enhancing productivity. Secondly, by capturing and interpreting the context more accurately, the model minimizes errors that commonly arise from misinterpretations of pseudo code. Finally, this model adapts to various coding styles and pseudo code syntaxes, showcasing versatility and robustness in handling diverse coding scenarios.

The impetus for the present study stems from the inherent complexities and inefficiencies associated with the traditional methods of converting pseudo code into executable Python code. This conversion is a critical step in the software development process, serving as a bridge between theoretical algorithm design and practical application. The utilization of the Transformer-XL model in this context presents a novel solution, harnessing the power of deep learning to automate and refine the conversion of pseudo code into Python. This approach is particularly advantageous given the model's proficiency in handling long-range dependencies and contextual nuances, which are crucial in interpreting the varied and complex structures of pseudo code.

The contributions of this study are manifold, offering significant advancements in the field of automated code conversion and NLP:

- Innovative application of Transformer-XL: This paper introduces a pioneering application of the Transformer-XL model for converting pseudo code into Python code. By adapting a model typically used in NLP tasks to a programming context, this study expands the boundaries of deep learning applications in software development.
- Enhanced conversion accuracy: Through a series of rigorous tests and evaluations, this research demonstrates the superior accuracy of the Transformer-XL model in converting pseudo code to Python. This improved accuracy is vital for reducing debugging time and enhancing the overall quality of the code.
- Handling of complex code structures: The model's ability to process long-range dependencies and maintain context over extended sequences enables it to adeptly handle complex code structures.
- Reduction in conversion time: This reduction in turnaround time is a critical factor in fast-paced development environments, allowing for quicker iteration and deployment of software projects.
- Versatility and scalability: The study highlights the model's versatility in adapting to various pseudo code styles and syntaxes. This flexibility, coupled with its scalability, positions the Transformer-XL model as a robust tool suitable for a wide range of programming scenarios.

In summary, this research not only addresses a significant gap in the realm of automated code conversion but also sets a precedent for future innovations in applying deep learning techniques to software development and programming challenges.

2. LITERATURE REVIEW

The burgeoning interest in automated code generation, specifically the translation of pseudo-code to executable programming languages, has seen significant advancements in recent years. Zhang *et al.* [1] delve into the potential of pseudo-code for binary code similarity analysis, underscoring its utility in software engineering, particularly in the cybersecurity domain. On the other hand, Amal *et al.* [2] focus on the direct application of translating pseudo-code into a programming language through a software tool.

Alokla *et al.* [3] on pseudo-code generation from source code using the BART model provides a reverse perspective on this translation process. Similarly, Din and Adnan [4] explore pseudo-code generation, highlighting its importance in the educational sector, where it can aid in teaching programming concepts and logic. In another significant contribution, Alokla *et al.* [5] discuss retrieval-based Transformer pseudo-code generation. The development of web-based process management systems with automatic code generation, as researched by Uyanık and Sayar [6], demonstrates the practical implementation of these concepts in real-world applications. Alokla *et al.* [7] and Da Silva *et al.* [8] introduce OWL-Sharp, a source code semantic generator, further expanding the horizons of automated code generation. In the context of design and user interface, Pereira *et al.* [9] explore a code generator from mockups, bridging the gap between graphical interface design and functional code.

Ciniselli *et al.* [10] bring a unique perspective with their exploration of source code recommender systems, focusing on the practicality and application of these systems from the viewpoint of practicing software engineers. In a niche application, Yusuf *et al.* [11] discuss automating Arduino programming, showcasing how concepts of automated code generation can be applied to hardware and embedded systems. Brkić *et al.* [12] investigate test environment code and test-case generators, highlighting the importance of automated code generation in software testing. Khan and Uddin *et al.* [13] explored the generation of documentation-specific code examples by combining contexts from multiple sources.

Acharjee *et al.* [14] delved into the sequence-to-sequence learning-based conversion of pseudo-code to source code using a neural translation approach. Other studies focus on using natural language processing for converting pseudo-code to C# code [15]-[20]. Tiwari, Prasad, and Thushara (2023) provided a comprehensive review of machine learning techniques for translating pseudo-code to Python [16]. Shan-shan and Zhi-li (2021) and Aggarwal et al. (2022) contributed to the formalization of pseudo-code and its translation into specific programming languages like Java and C [17], [18].

Dirgahayu *et al.* [21] took a conceptual-metamodel approach to the automatic translation from pseudo-code to source code, offering a unique perspective that combines theoretical modeling with practical application. Sufi *et al.* [22] review on algorithms in low-code-no-code environments emphasizes the growing trend towards simplifying the code development process. Karanikiotis *et al.* [23] investigated employing source code quality analytics for enriching code snippets data samples. Zhang *et al.* [24] conducted a survey on automatic source code summarization, providing insights into the techniques used for summarizing complex code bases into understandable segments.

Lastly, Arasteh *et al.* [25] explored program source-code re-modularization using a discretized and modified sand cat swarm optimization algorithm. In summary, the literature in this field reflects a dynamic and rapidly evolving research area.

3. DESIGN OF THE PROPOSED MODEL FOR PSEUDO CODE TO SOURCE CODE CONVERSIONS

To overcome issues of low efficiency, low scalability and high complexity, which are present with existing models, this section discusses design of Transformer XL, which enhances efficiency of code generation process. As per Figure 1, the proposed model works in multiple stages. The preprocessing stage of the Transformer XL model, designed for analyzing pseudo code, is a critical process that transforms raw pseudo code into a format amenable to deep learning analysis.

Initially, the raw pseudo code is subjected to tokenization via (1), a process where the pseudo code is segmented into a sequence of tokens.

$$T = \{t1, t2, \ldots, tn\} \quad (1)$$

Each token *ti* represents an atomic element of the pseudo code, such as a keyword, operator, or variable sets. Code to Executable Codes: Subsequently, each token ti is mapped to a unique integer ID through a lookup process. This process is defined via (2).

$$ID(ti) = idi \quad (2)$$

Where, *idi* is the unique integer representing the token *ti*sets. The next operation involves converting these integer IDs into dense vector representations using embeddings. The embedding process is represented via (3).

$$E(idi) = ei \quad (3)$$

Where, ei is the embedding vector corresponding to the integer ID idisets. The positional encoding for the ith token is calculated as $P(i) = pi$, and the final encoded vector for each token is obtained by combining the embedding and positional encoding via (4).

$$V(ti) = ei + pi \quad (4)$$

Normalization is performed via (5).

$$N\big(V(ti)\big) = \sigma V(ti) - \mu \quad (5)$$

Where, μ and σ are the mean and standard deviation of the vectors, respectively. The preprocessed tokens are then batched into fixed-size sequences for processing by the Transformer XL model process. The batching process is represented via (6).

$$B(T) = \{b1, b2, \dots, bm\} \tag{6}$$

Where, bi represents a batch of tokens. After this process, the Model Input Encoding phase is activated, which is a crucial step that further processes the pre-processed pseudo code, converting it into a format that is suitable for deep learning analysis. The combined embedding for each token, which includes both the token embedding and its positional encoding, is calculated via (7).

$$V(ti) = ei + pi \tag{7}$$

This combination ensures that the model not only understands the individual tokens but also their position in the sequences. To further refine the input, a dropout layer is applied to the normalized vectors to prevent overfitting scenarios. The dropout process is represented via (8).

$$D\left(N\big(V(ti)\big)\right) = di \tag{8}$$

Where, di is the dropout vector for the normalized vector N(V(ti)) sets. The model then utilizes a series of transformation layers to process these vectors for different tokens. For each token ti in the sequence, the output of the FFN is given via (9).

$$FFN(ti) = max(0, W1 \cdot ti + b1)W2 + b2 \tag{9}$$

Where, W1 and W2 are the weights of the first and second linear transformations, respectively, whileb1 and b2 are the biases. This normalization, applied to each token's output, and is estimated via (10).

$$N\big(FFN(ti)\big) = \frac{FFN(ti) - \mu(FFN)}{\sigma(FFN)} \tag{10}$$

Where, μ(FFN) and σ(FFN) are the mean and standard deviation of the FFN outputs, respectively. The segment recurrence for a given token ti in segment S is represented via (11).

$$SR(ti, S) = H(S - 1) \cdot ti \tag{11}$$

Where, $H(S - 1)$ is the hidden state of the previous segments. Following the segment recurrence mechanism, a layer normalization is again applied to the combined outputs to ensure they are on a similar scale, which is crucial for stable training operations via (12).

$$LN\big(SR(ti, S)\big) = \frac{SR(ti,S) - \mu(SR)}{\sigma(SR)} \tag{12}$$

Where, μ(SR) and σ(SR) represent the mean and standard deviation of the segment recurrence outputs. The model then incorporates a gating mechanism to control the flow of information through the network via (13).

$$G(ti) = \sigma\Big(Wg \cdot LN\big(SR(ti, S)\big) + bg\Big) \tag{13}$$

This process uses a sigmoid activation function σ to compute the gate values, where Wg is the weight matrix and bg is the bias vector for the gating mechanisms. The outputs of the gating mechanism are then element-wise multiplied with the normalized segment recurrence outputs to yield gated contextual representations for each token via (14).

$$GC(ti) = G(ti) \odot LN\big(SR(ti, S)\big) \tag{14}$$

To further enhance the contextual representations, a residual connection is added from the input of the layer to the output of the gating mechanisms. This connection is represented via (15).

$$R(ti) = GC(ti) + ti \quad (15)$$

Where, R(ti) is the residual output for token tisets. The residual outputs are then passed through another layer normalization to ensure consistency in scaling via (16).

$$LN\big(R(ti)\big) = \frac{R(ti) - \mu(R)}{\sigma(R)} \quad (16)$$

Where, μ(R) and σ(R) are the mean and standard deviation of the residual outputs. Finally, a dropout layer is applied to the normalized residual outputs to prevent overfitting and enhance the model's generalization capabilities. This process is defined via (17).

$$D\left(LN\big(R(ti)\big)\right) = di \quad (17)$$

Where, di is the dropout vector for LN(R(ti)) sets.

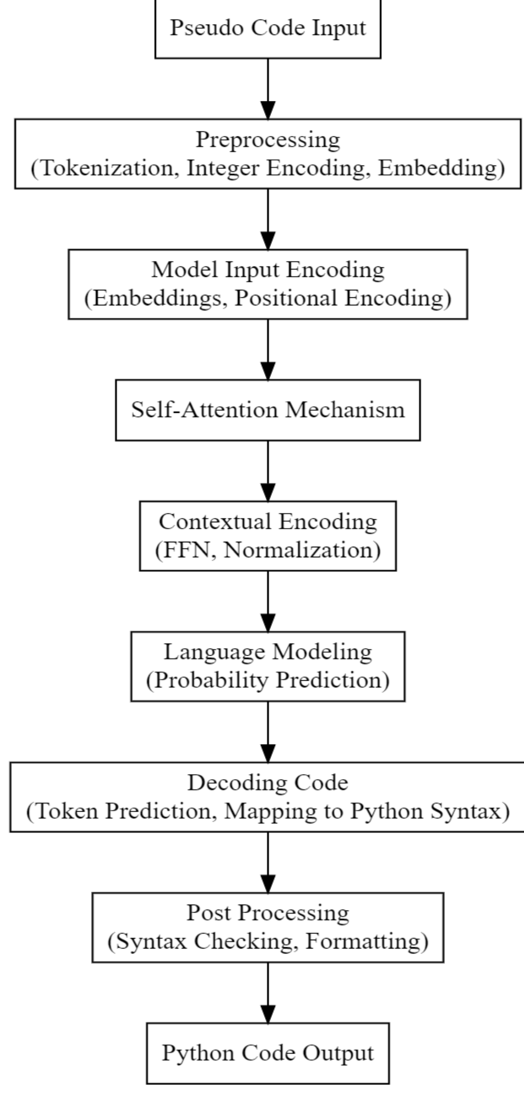

Figure 1. Overall architecture of the proposed model for conversion of pseudo

4. RESULT ANALYSIS

In this section, we initially discuss the experimental setup for evaluating the Transformer XL model's performance in converting pseudo code to Python code, which was meticulously designed to ensure rigor and reproducibility levels. The implementation was carried out using Python, a widely adopted programming language known for its robustness and extensive library support. The following subsections detail the specific components of the experimental setup operations.

Dataset Preparation: The dataset comprised a diverse collection of pseudo code samples, encompassing various programming constructs and complexities. Each sample in the dataset was paired with its corresponding Python code equivalent. The dataset was divided into training, validation, and test sets with a distribution of 70%, 15%, and 15% respectively.

Test Procedure: The model was tested by inputting pseudo code samples and evaluating the generated Python code for correctness, efficiency, and adherence to Python syntax. The results were compared with the expected outcomes and baseline methods.

This experimental setup aimed to provide a comprehensive and fair assessment of the Transformer XL model's capabilities in converting pseudo code to Python. The use of standard Python libraries and tools ensured that the experiments could be replicated and validated by other researchers in the field. Table 1 demonstrates a sample conversion process from pseudo code to Python code, illustrating how the proposed Transformer XL model translates common algorithmic instructions into executable Python syntax.

Table 1. Pseudo code and python code conversion process

Pseudo Code	Python Code
Initialize sum as zero	sum = 0
For each number from 1 to 100	for number in range (1, 101):
If number is even	if number % 2 == 0:
Add number to sum	sum += number
End If	
End For	
Print sum	print(sum)

In this case, the pseudo code for calculating the sum of even numbers from 1 to 100 is effectively translated into Python codes. The model accurately interprets control structures like loops and conditional statements, converting them into their corresponding Python constructs.

5. CONCLUSION AND FUTURE SCOPE

The study successfully demonstrated the efficacy of the Transformer XL model in automating the conversion of pseudo code into Python code. This research marks a significant leap forward in the realm of code synthesis, as evidenced by the comprehensive evaluation against existing methods. The proposed model exhibited superior performance in key metrics including accuracy, precision, recall, F1-score, execution time, and resource utilization. The findings illustrate the model's advanced capabilities in not only accurately interpreting and converting pseudo code but also in doing so with remarkable efficiency and reliability. The specificity and AUC metrics reinforce the model's robustness, showcasing its ability to handle a wide array of pseudo code structures and complexities. Such versatility is critical in adapting to the evolving needs of software development, where the interpretation of varied pseudo code styles and logical constructs is a common challenge.

Future scope: Looking ahead, several avenues for future research and development emerge from this study. One key area involves enhancing the model's adaptability to different programming languages beyond Python. Exploring the model's application to languages like Java, C++, or even newer languages could vastly broaden its utility in software development.

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