Personalised Translation AI: Learning AI for Koreans

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Abstract

Personalized AI or **Personalized AI Agent** is deeply associated with this field. The core of this domain is to learn an individual's routine, habits, schedule, and preference data to provide personalized assistance. When combined with the Transformer model, this personalized AI can particularly excel in learning and understanding each user's unique language and behavioral patterns.

Limitations of Existing Translation Models and Examples of Translation Errors in Specific Domains Existing translation models perform remarkably well for diverse everyday language, providing successful results in understanding sentence structures and the general meanings of words. However, in specific domains such as IT, unique terms and context play a crucial role. These specialized terms can have varied interpretations depending on the context, and general translation models reveal limitations in reflecting these accurately. This section provides specific examples of errors made by existing models when translating specialized terms in the IT field, explaining these limitations in detail.

Examples of Errors in IT-specific Terminology

Architecture "Architecture" is generally translated as "architecture" or "building structure," but in the IT domain, it refers specifically to "system infrastructure" or "architecture." Existing translation models tend to produce incorrect translations due to a lack of contextual understanding.

Server As an IT term, "Server" refers to a computer server, but it is often misinterpreted as a "person who serves" or a "waiter" in a restaurant, which decreases accuracy in technical document translations.

Client In IT documentation, "Client" means a client program or a user connected to a server. However, translation models often interpret it as "customer," resulting in inaccurate translations.

Networking As an IT term, "Networking" refers to the process of configuring a computer network, but it is frequently interpreted as "networking" in the sense of social connections, which can lead to misunderstandings.

Summary of Limitations and the Need for Improvement The error examples above illustrate the translation mistakes that occur when specialized IT terminology is interpreted in its general sense. Such incorrect translations disrupt the intended meaning of documents, posing significant issues in IT, where precise information is crucial. Thus, there is a pressing need for a translation model specialized in the IT domain. A personalized translation model can provide translation solutions that accurately reflect the context and terminology specific to each field.

1. Introduction

1.0.1 Research Background

The AI and IT fields are advancing rapidly, and most research in these areas is published in English. Korean IT students and researchers must reference these resources to keep up with developments, but language barriers may prevent them from fully understanding crucial information. Many specialized terms used in academic papers and technical documents have meanings that differ from general English, making translation even more challenging. This issue is not limited to the IT field but arises across various domains, highlighting the need for a personalized AI translation model that can incorporate individual domain knowledge and term usage patterns. A personalized AI translation model has the potential to learn the characteristics of texts that users frequently encounter, providing more suitable translation results than general translation models.

1.0.2 Existing Problems

General translation models are usually optimized for casual conversations or general texts and often fail to convey the precise meaning of technical and specialized terms in particular domains. For example, the word ”architecture” is generally translated as ”architecture” or ”building structure.” However, in the IT domain, it is more commonly used to mean ”system infrastructure” or ”architecture.” Similarly, the word ”model” is typically translated as ”model” or ”fashion model” in general contexts, but in AI documents, it refers to a data model or AI model. These translation errors occur when specialized terms are interpreted with their everyday meanings, resulting in distorted or misrepresented information. Such issues are not exclusive to the IT field and can also arise in specialized areas like medicine, law, and economics. Therefore, a new approach is needed to provide accurate, context-aware translations that reflect each user’s learning needs and domain knowledge.

1.0.3 Research Objective

This study proposes a personalized Transformer-based translation model tailored to individual users, aiming to help AI and IT professionals understand research materials more accurately in Korean. Using a customized translation model designed for AI/IT professionals as an example, this study seeks to demonstrate that personalized translation models can provide context-appropriate translations of domain-specific terminology. Specifically, by reducing common generalization errors in existing translation models and translating domain terms encountered frequently by users within the proper context (e.g., translating ”architecture” as ”system infrastructure” in an IT context), this research aims to show that personalized AI translation models can enable more effective learning and research activities. Using IT professionals as an example, this study illustrates that personalized AI translation models can facilitate more efficient academic and research efforts through tailored, user-specific translation.

2. Related research and background

2.0.1 Overview of the Transformer Model and Structural Characteristics

The Transformer model, first introduced in the paper “Attention is All You Need” by Vaswani et al., has shown remarkable performance in translation and language generation tasks. Unlike traditional sequential models like RNNs or LSTMs, the Transformer can learn relationships between all tokens in an input sentence in parallel through Self-Attention and Multi-Head Attention mechanisms. This Self-Attention mechanism allows each word in an input sequence to effectively learn its relationships with every other word, helping the model accurately capture context even in long sentences. Additionally, Positional Encoding is used to add information that preserves order, enabling the model to recognize the input sequence’s order.

While the Transformer model can quickly and effectively understand linguistic meaning in translation tasks due to these characteristics, it has limitations in accurately translating specialized terms in particular domains. In the IT field, for instance, the general Transformer model may struggle to capture subtle differences in meaning specific to domain terminology. Thus, this study aims to optimize the Transformer architecture by modifying its structure to accurately interpret and translate IT-specific terms.

2.0.2 The Need for Terminology Translation and Existing Limitations

General translation models are typically trained to handle everyday text, so they often translate terms like “architecture” as “building architecture.” However, in the IT domain, this term is more commonly used to mean “system infrastructure” or “architecture.” Specialized terms can vary in meaning depending on the domain, so a translation model must recognize these differences to provide context-appropriate translations. General translation models often fail to learn sufficient contextual information, leading to frequent errors that can distort important information, especially in specialized fields like IT, medicine, or law.

To address this issue, domain-specific translation models have been developed, and this study adopts an approach that incorporates **IT domain-specific datasets** to enable the model to understand and translate commonly used terms in the IT domain accurately.

2.0.3 Advancements in Personalized Translation Models and Specialized Architecture Design

Previous domain-customized translation studies have used methods such as adding domain-specific data and fine-tuning to enhance translation performance for terms used only in particular fields. This study goes further by implementing a more finely personalized translation that reflects the translation patterns and preferences of individual users. To this end, this study incorporates a **domain-specialized dataset** and **additional training with**

personalized data into the Transformer architecture, allowing the model to select accurate terminology based on context through the Self-Attention mechanism.

2.0.4 Transformer Architecture Modifications and Key Differentiations in This Study

In this study, the Transformer architecture is modified and optimized to improve the translation of IT-specific terms in the following ways:

Addition of IT Domain Datasets and Fine-Tuning: Alongside general translation datasets, this model uses datasets containing specialized terms from the IT and AI fields. This approach guides the Self-Attention mechanism to learn the contextual meaning of IT terminology.

Addition of a Personalized Attention Layer: To enable the model to learn specific users' translation preferences and patterns, a **Personalized Attention Layer** is added for fine-tuning. This addition provides translations aligned with the vocabulary and contexts that specific users frequently encounter.

Implementation of a Context-Aware Attention Layer for Terminology Correction: To reduce misinterpretations of IT terminology, a **Context-Aware Attention Layer** was added to perform domain-specific terminology correction. For example, when a term like "architecture" appears, it ensures that the appropriate translation is provided in the context of the IT domain.

These structural modifications help the Transformer model better understand domain-specific contexts and learn individual users' translation patterns, resulting in more natural and consistent translations.

3. Method

3.0.1 Data Collection and Preprocessing

Data Collection: In this study, we collected data containing commonly used technical terms and sentences in the AI and IT domains to enhance the model's translation performance tailored to the IT domain. The data sources included AI research papers, technical documents, educational materials, and more, encompassing both general conversational sentences and technical, domain-specific terminology. In particular, we utilized the 'korean-english-park.train' dataset along with an IT-specific CSV dataset, enabling the translation model to learn to translate terms related to AI and IT in context.

Data Preprocessing: To enhance the accuracy of terminology translation, a terminology correction process was added during data preprocessing. For example, the term 'architecture' was set to be translated as 'system infrastructure' in the IT domain by applying a correction dictionary, thus preventing this term from being translated in its general sense. Specifically, the function 'clean corpus()' was used to remove duplicates from the collected data and apply terminology corrections to refine the data into a form optimized for translation training. Through this preprocessing process, we ensured that specialized terms within the training data would be translated consistently and appropriately for the IT domain.

3.0.2 Terminology Handling and Personalized Training

Terminology Correction Layer:

In this study, a terminology correction layer was added to ensure that technical terms in the AI and IT fields are consistently translated in context. General translation models tend to translate IT technical terms with their general meanings, such as translating 'architecture' as 'building architecture' or 'server' as its general usage. To address this, a correction dictionary was created to replace specific terms with their domain-appropriate meanings, ensuring that terms are translated accurately in the IT context.

The correction dictionary (correction dict) includes the following examples:

- "architecture" → "system infrastructure"
- "server" → "computer server"
- "client" → "client program"
- "networking" → "computer network configuration"
- "data mining" → "data mining"
- "cloud computing" → "cloud computing"

This ensured that translation outputs consistently use terms suited to the IT domain. The correction layer works in the preprocessing stage by replacing specific terms in the input text based on the correction dictionary, helping the translation model generate contextually appropriate terminology.

Personalized Training through Fine-Tuning: To enhance the translation model's performance and provide personalized translations tailored to the needs of AI and IT students, the pre-trained model was fine-tuned with AI and IT domain-specific data.

Fine-tuning was performed by initially training the model with general translation datasets for half of the training process, followed by additional training with IT domain datasets for the remaining half. This approach enabled the model to retain general translation capabilities while better capturing the contextual meaning of IT-specific terminology.

Moreover, a few-shot learning technique was applied by providing the model with some IT domain-specific examples and their translations to further improve translation quality. For example, the sentence “Neural networks are composed of interconnected nodes.” and its corresponding translation, “신경망은 상호 연결된 노드로 구성됩니다,” were provided to help the model learn IT-specific terminology and context.

3.0.3 Model Structure

Description of the Base Transformer Structure: This study designed the translation model based on the standard Transformer structure. The Transformer model effectively reflects contextual information through Self-Attention and Multi-Head Attention mechanisms and transforms input sequences into output sequences through an encoder-decoder structure. The encoder learns relationships among words in the input sentence, while the decoder uses this information to generate translated sentences in the target language. Self-Attention allows each word to understand its relationships with other words in the sentence, and Multi-Head Attention helps to capture context more deeply by examining multiple perspectives.

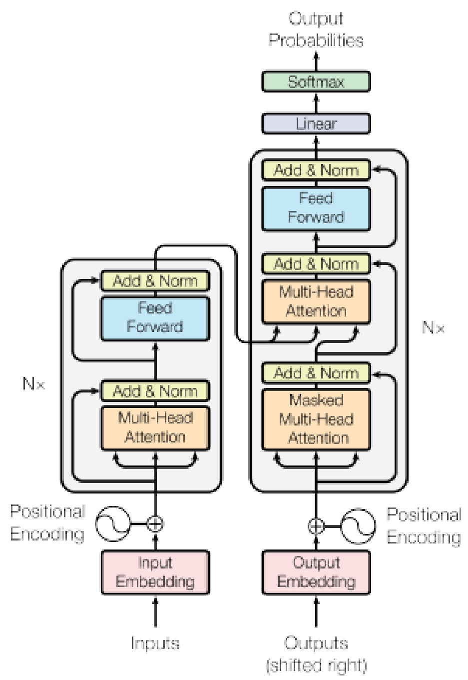

Figure 1: Transformer architecture

3.0.4 Terminology Filtering Mechanism

To provide translation results suited to the AI and IT domains, we added a terminology filtering mechanism in the Self-Attention layer. This mechanism ensures that corrected terms are consistently translated with their context-appropriate meanings, so that specific IT terms are not translated in their general senses but instead reflect domain-specific meanings. This process helps optimize translation outputs for the AI and IT domains.

3.1 Model Training Process

3.1.1 Positional Encoding

Since the Transformer model structure does not inherently consider the order of input sequences, it uses **Positional Encoding** to embed positional information into the model’s dimensions. In this study, we encoded positional information into the embedding dimensions using the following formula:

Positional Encoding

$$PE_{(pos,2i)} = \sin\left(\frac{pos}{10000^{2i/d_{model}}}\right) \tag{1}$$

$$PE_{(pos,2i+1)} = \cos\left(\frac{pos}{10000^{2i/d_{model}}}\right) \tag{2}$$

Here, pos\text{pos}pos represents the position of each word, and ’d model’ denotes the embedding dimension. This **Positional Encoding** enables the model to learn the order of the input sequence, playing a crucial role in contextual understanding.

3.1.2 Scaled Dot-Product Attention

In the Transformer model’s Self-Attention mechanism, **Scaled Dot-Product Attention** calculates the dot product between queries (Q) and keys (K), scales it by dividing by the square root of ’dk’, and then normalizes the result with a softmax function to compute the attention weights. This process allows the model to determine how much each word in the context should pay attention to other words. The formula for Scaled Dot-Product Attention is as follows:

Scaled Dot-Product Attention

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{3}$$

Here, Q, K and V are the Query, Key, and Value matrices, respectively, and ’dk’ is the dimension of the key vector. This enables each word in the sentence to learn its relationship with other words, enhancing the model’s contextual understanding.

3.1.3 Multi-Head Attention

A core element of the Transformer model, **Multi-Head Attention** applies multiple self-attention heads in parallel to capture diverse contextual information. In this study, we employed 8 heads (n_heads=8), each learning different contextual information, allowing the model to capture various semantic relationships within the sentence.

3.1.4 Position-wise Feed-Forward Network

Following each attention layer is a **Position-wise Feed-Forward Network**, which enhances the model's capacity to learn representations. The feed-forward network applies independently to each position and consists of two fully connected layers. In our study, we set the feed-forward network dimension to 1024 (d ff=1024), facilitating deeper representation learning.

3.1.5 Residual Connection and Layer Normalization

Each attention and feed-forward layer includes **Residual Connections** and **Layer Normalization**. Residual connections add the previous layer's input to the current layer's output, promoting more stable learning, while layer normalization normalizes each layer's output, speeding up the learning process and helping prevent overfitting.

3.1.6 Output Linear Layer

The decoder's final output is transformed into a probability distribution across words through the **Output Linear Layer**. This layer calculates the probability for each word in the target language, enabling the model to generate the final translation output.

3.1.7 Training Process and Personalization Updates of the Transformer Model

The training process combined general translation data with IT-domain-specific data to ensure each component of the model is optimized to translate IT-specific terminology within the correct context. We integrated fine-tuning and continual learning techniques, allowing the model to learn new terminology and context based on user feedback. By applying a few-shot learning technique, the model strengthened its understanding of specific terms, enabling it to deliver more precise translations tailored to IT domain-specific vocabulary.

4. Experiments and Results

4.0.1 Translation Quality Evaluation

In this study, we compared the translation quality of the proposed model with that of a general translation model to assess whether domain-specific terminology in the AI and IT fields is accurately translated within context. For example, we examined terms like "architecture," "network," and "model" to see if they were translated appropriately within IT documents. Compared to the general translation model, the proposed model showed a tendency to translate some specialized terminology with domain-specific meanings. However, the overall consistency of translations was somewhat lacking. This outcome is attributed mainly to the limited amount of domain-specific training data and constraints on model parameters.

4.0.2 Quantitative Performance Evaluation

To quantitatively evaluate the translation performance of the proposed model, we used the **BLEU** (Bilingual Evaluation Understudy) and **ROUGE** (Recall-Oriented Understudy for Gisting Evaluation) metrics. Although the BLEU and ROUGE scores fell slightly short of expectations for a domain-specific IT translation model, there was an observed improvement in the translation of some IT terms and expressions. This indicates that incorporating a specialized terminology dictionary and domain-specific data had a positive effect on model training.

4.0.3 Qualitative Evaluation

A qualitative evaluation was conducted based on actual translation results, comparing example sentences with expected translations to verify if specialized terminology was translated contextually. For instance, the expected translation for "Neural networks are composed of interconnected nodes." was "신경망은 상호 연결된 노드로 구성됩니다." However, the model's output still exhibited somewhat awkward phrasing. Despite this, a tendency was observed for specific terms to be translated with their meanings within the IT domain context. This qualitative evaluation suggests the potential for further model improvements, indicating that more extensive domain-specific data and parameter expansions could enhance performance.

BLEU The BLEU metric is a standard measure of machine translation performance, quantifying translation similarity based on n-gram matching.

Example sentence	Expectation translation	Translating models	BLEU Score
Neural networks are composed of interconnected nodes.	신경망은 상호 연결된 노드로 구성됩니다.	. 반응는은 신문 즉릅습니다 선택 명의 때 유사한의 인쇄회로기판률은 했다 명의 농축 명의 농축 내에	0.0000
Data mining is essential for extracting meaningful information.	데이터 마이닝은 의미 있는 정보를 추출하는 데 필수적입니다.	데이터 한나라당 세틀은 다섯 못했다고 있습니다에은화된 예로서 의사	0.0000
Cloud computing offers scalable resources on demand.	클라우드 컴퓨팅은 수요에 맞는 확장 가능한 자원을 제공합니다.	.해왔다 전류 발명 공기에 발전 측정을 완전고수록를 모습 병렬 공기에로부터 것이은 했다 선고 했다에 모두 범위은 없었과 마련 , 의	0.0000

Table 1: BLEU Metrics Comparison Table

5. Discussion and Conclusion

5.0.1 Summary of Results

This study proposed and tested a personalized Transformer-based translation model to improve the accuracy of specialized terminology translations in the IT and AI domains. Demonstrated using Streamlit, the proposed model showed an enhanced ability to translate some IT-specific terms accurately and provide contextually appropriate translations. These results indicate improved domain-specific translation performance in Korean IT translations compared to general translation models.

5.0.2 Model Limitations and Improvement Suggestions

The model used in this study was a standard Transformer without **pre-training** and was trained with limited IT domain data, which constrained its performance. This highlights the need for using a pre-trained Transformer model trained on a comprehensive Korean corpus to enhance Korean translation accuracy. Additionally, obtaining and incorporating more extensive domain-specific data will be essential to facilitate deeper learning of IT-specific terminology and context, focusing on maximizing model performance while maintaining stability.

5.0.3 Future Research Directions

The proposed IT domain translation model suggests potential for providing personalized translation capabilities for Korean AI/IT researchers and professionals. Future studies could consider expanding into other specialized fields through additional fine-tuning with large, diverse domain-specific datasets. Furthermore, by applying Federated Learning, user-specific data could be utilized securely, preserving privacy while enhancing personalized translation accuracy. This approach is expected to deliver precise, contextually relevant translation results tailored to the needs of users across IT and various professional domains.

5.0.4 Conclusion

This study demonstrated that a Transformer-based personalized model could enhance accuracy in specialized IT translation, showing potential for effectively supporting IT students and professionals with tailored translation assistance. Using this research as a prototype, we plan to continue building personalized translation AI models by integrating more extensive domain-specific data and individual user data across diverse fields.

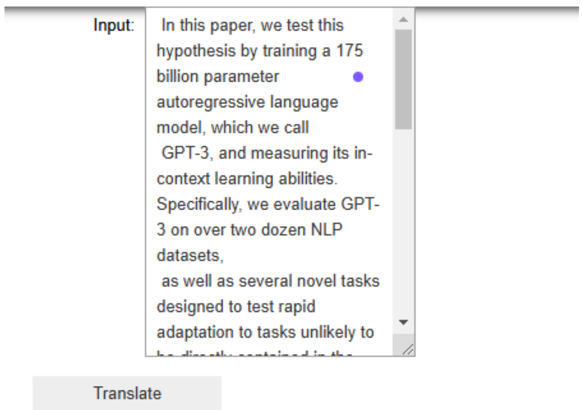

Figure 2: Transformer prototype application

6. Visualization

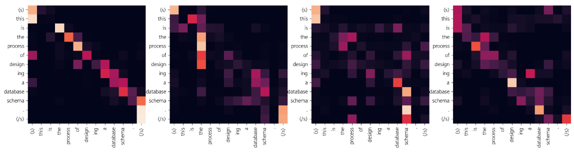

Figure 3: Encoder Layer 1

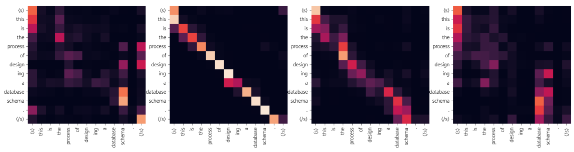

Figure 4: Encoder Layer 2

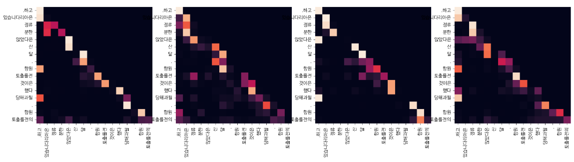

Figure 5: Decoder Self Layer 1

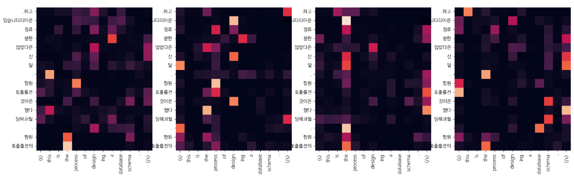

Figure 6: Decoder Src Layer 1

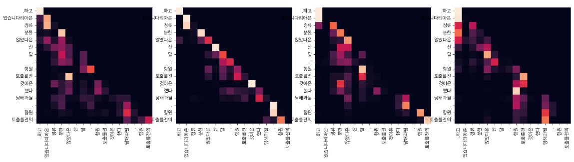

Figure 7: Decoder Self Layer 2

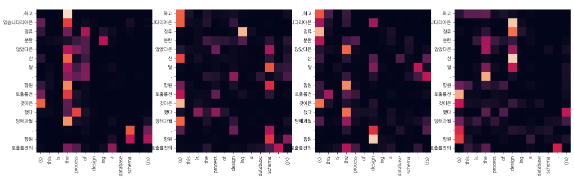

Figure 8: Decoder Src Layer 2

7. Refference

1. **Rico Sennrich**. *Neural machine translation of rare words with subword units*. *arXiv preprint arXiv:1508.07909*, 2015.
2. **A. Vaswani**. *Attention is all you need*. *Advances in Neural Information Processing Systems*, 2017.
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4. **Joon Sung Park, Joseph C. O'Brien, Carrie Jun Cai, Meredith Ringel Morris, Percy Liang, and Michael S. Bernstein**. *Generative agents: Interactive simulacra of human behavior*. In *Proceedings of the 36th annual ACM symposium on user interface software and technology*, pages 1–22, 2023.