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Semantic Role Labeling in Neural Machine Translation Addressing Polysemy and Ambiguity Challenges

Abstract

6 25 *The persistent challenges of polysemy and ambiguity continue to hinder the semantic accuracy of Neural Machine Translation (NMT), particularly in language pairs with distinct syntactic structures. While transformer-based models such as BERT and GPT have achieved notable progress in capturing contextual word meanings, they still fall short in understanding explicit semantic roles. This study aims to address this limitation by integrating Semantic Role Labeling (SRL) into a Transformer-based NMT framework to enhance semantic comprehension and reduce translation errors. Using a parallel corpus of 100,000 English-Indonesian and English-Japanese sentence pairs, the proposed SRL-enhanced NMT model was trained and evaluated against a baseline Transformer NMT. The integration of SRL enabled the model to annotate semantic roles, such as agent, patient, and instrument, which were fused with encoder representations through semantic-aware attention mechanisms. Experimental results demonstrate that the SRL-integrated model significantly outperformed the standard NMT model, improving BLEU scores by 6.2 points (from 32.5 to 38.7), METEOR scores by 6.3 points (from 58.5 to 64.8), and reducing the TER by 5.8 points (from 45.1 to 39.3). These results were statistically validated using a paired t-test ($p < 0.05$). Furthermore, qualitative analyses confirmed SRL's effectiveness in resolving lexical ambiguities and syntactic uncertainties. Although SRL integration increased inference time by 12%, the performance trade-off was deemed acceptable for applications requiring higher semantic fidelity. 14 The novelty of this research lies in the architectural fusion of SRL with transformer-based attention layers in NMT, a domain seldom explored in prior studies. Moreover, the model demonstrates robust performance across linguistically divergent language pairs, suggesting its broader applicability. This work contributes to the advancement of semantically aware translation systems and paves the way for future research in unsupervised SRL integration and multilingual scalability.*

Keywords: *Neural Machine Translation (NMT), Semantic Role Labeling (SRL), Translation Accuracy*

I. INTRODUCTION

Machine translation has undergone rapid development in recent decades, particularly with the introduction of NMT models based on deep learning (Huang & Xin, 2022). Unlike rule-based and statistical translation methods, NMT excels in capturing more complex linguistic patterns and producing more natural translations through an encoder-decoder approach supported by an attention mechanism. These advancements have enabled machine translation to be applied across various industrial sectors, such as business, law, healthcare, and education, where translation accuracy significantly influences cross-linguistic comprehension (Mohamed et al., 2024). However, despite substantial improvements in translation quality, fundamental challenges remain unresolved, particularly in addressing polysemy and ambiguity in natural language (Shahin & Ismail, 2024).

18 Polysemy refers to a condition where a single word possesses multiple meanings depending on its context, whereas ambiguity arises when a sentence can have more than one syntactic or semantic interpretation (Viebahn, 2022). In NMT systems, these phenomena often lead to translation errors that can alter the original meaning of the text. Previous studies indicate that

4 approximately 20% of errors in machine translation result from the model’s inability to
3 distinguish the meanings of highly polysemous words (Kijania-Placek, 2023). For instance, in
English, the word "bank" can refer to either a financial institution or the side of a river, depending
1 on the context. Transformer-based NMT models, such as BERT and GPT, have attempted to
address this issue by capturing word meanings based on the surrounding context. BERT-based
models have enhanced translation accuracy by better understanding the context of polysemous
words. However, this approach remains limited as it relies solely on probabilistic distribution in
5 selecting word meanings, without comprehending explicit semantic relationships between words
in a sentence (Li & Armstrong, 2024).

13 One approach to overcoming this limitation is integrating SRL into NMT systems. SRL is a
technique in Natural Language Processing (NLP) that aims to provide semantic annotations to elements within a sentence by identifying the semantic roles played by each word, such as who performs an action, who receives the action, and how entities within the sentence are related (Nemer et al., 2024). By providing explicit semantic information, SRL can assist NMT models in better understanding the roles of words within a sentence, thereby reducing translation errors caused by polysemy and ambiguity (Sudhi et al., 2023). In various NLP applications, SRL has been proven to enhance semantic comprehension in automated question-answering systems and information extraction. Transformer-based models that incorporate SRL have demonstrated improved accuracy in understanding inter-entity relationships within texts. However, despite its successful implementation in several NLP applications, the integration of SRL into NMT remains an area that has yet to be extensively explored (Anand et al., 2023).

Although various approaches have been developed to address the challenges of polysemy and ambiguity in machine translation, previous research still has several limitations that remain unresolved. Most studies focus on context-aware embedding approaches, such as BERT and GPT, which rely on probabilistic distributions to determine word meanings. While these techniques effectively understand word context based on surrounding elements, they still depend on probabilities without grasping explicit semantic relationships within a sentence (Sterner, 2022). Additionally, knowledge graph-based approaches have enriched the semantic understanding of NMT models by providing supplementary information on word relationships. However, this method has limitations in terms of flexibility, as it requires extensive linguistic resources and is difficult to adapt to low-resource languages (Habtamu & Gizachew, 2024). Reinforcement learning-based approaches have also been employed to optimize translation systems by leveraging reward functions that consider semantic coherence. Despite its promising potential, the complexity of implementing this method remains a major challenge at the industrial scale.

Various studies have highlighted a research gap in exploring the integration of SRL into NMT to more effectively address polysemy and ambiguity. Most SRL-related research remains limited to applications in question-answering systems and information extraction, while its use in NMT has not been comprehensively examined. Furthermore, studies that have implemented SRL in NMT have yet to explore its impact across different language pairs with distinct syntactic structures, such as English-Indonesian and English-Japanese. Additionally, the effect of SRL integration on computational efficiency in large-scale translation systems has not been extensively investigated.
11 Therefore, this study aims to bridge this research gap by exploring how SRL can be integrated into NMT to enhance translation accuracy and reduce errors caused by polysemy and ambiguity.

This study seeks to develop a novel approach to integrating SRL into NMT to improve contextual understanding in machine translation and address the challenges of polysemy and ambiguity in
9 natural language. The primary focus of this research is to evaluate the effectiveness of SRL in reducing errors caused by polysemy and ambiguity in NMT, compare the performance of NMT models with and without SRL using BLEU, METEOR, and TER metrics, and analyze how SRL integration affects computational efficiency in large-scale translation scenarios.

The key contribution of this study lies in the development of a new approach to integrating SRL with Transformer-based NMT models, an area that has been largely unexplored in previous research. Additionally, this study evaluates the impact of SRL integration on the translation of languages with significantly different syntactic structures, such as English-Indonesian and English-Japanese. The effect of SRL integration on computational efficiency is also examined to pave the way for optimizing NMT models that are more adaptive and efficient for industrial-scale applications. By incorporating SRL into NMT, this research aims to bridge the gap between probabilistic distribution-based approaches and approaches based on explicit semantic understanding in machine translation.

21 The findings of this study are expected to make a significant contribution to improving machine translation quality and expanding the application of SRL across various other domains in NLP. Moreover, this research could open new opportunities for developing more adaptive and context-aware translation systems, thereby enhancing their effectiveness in handling the complexities of natural language across diverse translation scenarios.

II. LITERATURE REVIEW

A. Overview of Semantic Role Labeling (SRL) in NLP

SRL is a technique in NLP aimed at providing semantic annotations to elements within a sentence to identify the semantic roles played by each word (Yuan, 2024). SRL helps construct a richer representation of meaning by understanding the relationships between predicates and their arguments, such as who performs an action, who receives the action, and how entities are related within a sentence (Ariyanto et al., 2023). In various NLP applications, SRL has been utilized in automated question-answering systems, information extraction, and machine translation to enhance semantic understanding and improve the accuracy of NLP.

With the advancement of deep learning-based models, SRL has significantly improved in accuracy, particularly with the adoption of neural network architectures such as Long Short-Term Memory (LSTM) and Transformer models. A study by (Cheng et al., 2024) demonstrated that Transformer-based SRL enhances the detection and classification of semantic roles across diverse sentence structures. These models rely on self-attention mechanisms to capture long-range dependencies within sentences, thereby improving the understanding of semantic relationships between words. However, despite these advancements in contextual understanding, the implementation of SRL in NLP systems still faces several challenges, particularly the need for large manually annotated datasets and increased computational complexity (Onan, 2023).

B. Challenges of Polysemy and Ambiguity in Machine Translation

Polysemy and ambiguity represent major challenges in NMT, often leading to errors in meaning interpretation (K. W. Lee & Qian, 2022). Polysemy occurs when a single word has multiple meanings depending on the context, whereas ambiguity arises when a sentence structure can be interpreted in multiple ways. A study by (Kusnanti et al., 2024) found that approximately 20% of errors in NMT result from the model's inability to distinguish the meanings of highly polysemous words.

Transformer-based approaches, such as BERT and GPT, have been employed to address these challenges by capturing word meanings based on the surrounding context. Research by (Harsha et al., 2022) demonstrated that BERT improves translation accuracy by better understanding the context of polysemous words (Yang & Zhang, 2024). However, these context-aware representation models still rely on probabilistic distribution methods for word meaning selection, without explicitly understanding the semantic relationships between words in a sentence.

To overcome this limitation, SRL has been introduced in NMT systems to provide explicit semantic annotations that assist models in understanding the roles of words within a sentence. A study by (Man et al., 2024) showed that integrating SRL with self-attention mechanisms in NMT enhances translation accuracy, particularly in handling complex sentence structures. Their findings indicate that SRL reduces errors in selecting the meanings of ambiguous words by providing additional information about the semantic relationships within the source sentence (Cohen et al., 2022).

C. Alternative Approaches in NMT

Apart from SRL, various other approaches have been developed to address polysemy and ambiguity in machine translation. One of the most common methods is the use of context-aware embeddings, as implemented in BERT and mBERT. Context-aware embedding models are capable of capturing word meanings based on their context by utilizing dynamic representations (Devi & Purkayastha, 2023). However, this approach still has limitations in understanding explicit relationships between words within a sentence, as it relies solely on the statistical distribution of words in the training corpus.

Another method that has been applied is the knowledge graph-based approach, which leverages relationship-based representations between entities to enrich the semantic understanding of NMT models. A study by (Naveen & Trojovský, 2024) demonstrated that integrating knowledge graphs into NMT can improve translation quality by providing additional information about word relationships. However, this approach requires extensive background data and is often challenging to adapt to low-resource languages (Shekhar et al., 2025).

Additionally, reinforcement learning has been utilized in optimizing translation systems to enhance accuracy based on feedback from automated evaluations. (Tan & Wang, 2024) proposed a semantic-aware reinforcement learning method to improve translation quality by leveraging reward functions that consider semantic coherence. While this method is promising, its implementation complexity remains a major challenge at an industrial scale.

A comparison of these various methods indicates that SRL offers a key advantage by providing explicit semantic information that does not rely solely on probabilistic distribution. Unlike context-aware embeddings, which primarily consider local context, SRL enables models to comprehend word relationships on a broader scale. Thus, the integration of SRL into NMT presents a more effective solution for addressing polysemy and ambiguity challenges in machine translation (Do Campo Bayón & Sánchez-Gijón, 2024).

D. Limitations of SRL in Machine Translation

Although SRL offers improved accuracy in NMT, this technique still has several limitations that need to be considered. One of the primary challenges is SRL's reliance on large manually annotated datasets, such as PropBank and FrameNet (Oqaily et al., 2024). A study by (Chang &

Sun, 2024) indicated that this limitation in annotated datasets could hinder the adoption of SRL at an industrial scale, particularly for low-resource languages.

Moreover, integrating SRL into NMT also increases computational complexity, which can affect inference time. An analysis by (Ortiz-Garces et al., 2024) found that NMT models incorporating SRL experienced a 12% increase in inference time compared to standard models. This suggests that while SRL enhances translation accuracy, there is a trade-off in computational efficiency that requires optimization.

Another challenge is SRL's limitations in handling idiomatic expressions and figurative language. A study by (Wu et al., 2024) found that SRL is more effective in processing sentences with explicit syntactic structures but still struggles with translating idiomatic phrases that carry non-literal meanings. This indicates that SRL needs to be combined with other approaches, such as context-aware embeddings or pre-trained language models, to comprehensively handle various sentence types (Wang, 2024).

E. Relevant Case Studies

Several studies have explored the implementation of SRL in specific domains to improve translation quality. A study by (Jooste et al., 2022) applied SRL to medical text translation and found that this method enhanced accuracy in handling technical terms with multiple meanings across different contexts. Similarly, research by (Ortiz-Garces et al., 2024) demonstrated that integrating SRL into legal document translation helped reduce errors in processing complex sentence structures commonly found in legal texts.

However, most of these studies have been limited to English and have not examined the impact of SRL on languages with complex morphology, such as Japanese or Arabic. Therefore, this research explores how SRL can enhance translation quality in language pairs with significantly different syntactic structures, such as English-Indonesian and English-Japanese.

III. RESEARCH METHOD

A. Dataset and Preprocessing

This study utilizes a parallel dataset comprising text pairs in multiple languages to evaluate the effectiveness of SRL in NMT. The dataset consists of 100,000 sentence pairs in English-Indonesian and English-Japanese, sourced from PropBank, FrameNet, and the Universal Proposition Bank. To ensure the validity of the results, the data is divided into 80% training data, 10% validation data, and 10% test data.

2

Preprocessing steps are conducted to ensure data consistency and quality before model training. Each sentence in the dataset undergoes tokenization, text normalization, and the removal of irrelevant entities using SpaCy and Stanza. Semantic annotation is performed automatically using a pre-trained Transformer-based SRL model capable of identifying the semantic roles of words across various sentence structures. To enhance accuracy, the generated SRL annotations are manually reviewed on a validation data subset to ensure that semantic labels align with sentence structures.

B. Model Architecture

The model architecture developed in this study integrates SRL with a Transformer-based NMT system to enhance semantic understanding in the translation process. The model consists of three main components: an SRL encoder, a Transformer-based NMT encoder-decoder, and a semantic-aware attention mechanism.

The first component, the SRL encoder, is responsible for extracting semantic role information from the source text. This module employs a self-attention mechanism to identify key sentence elements, such as subjects, predicates, objects, and other semantic relationships. The SRL representations generated are then combined with the Transformer encoder representations using concatenation and feature fusion techniques, allowing the model to incorporate deeper semantic information in the translation process.

The second component, the Transformer-based NMT encoder-decoder, comprises six encoder layers and six decoder layers, with a word vector dimension of 512 and a feedforward layer size of 2048. Each layer utilizes eight attention heads to capture word relationships within a sentence. Positional encoding is applied to preserve word order information in the source sentence.

The third component, the semantic-aware attention mechanism, assigns greater weight to sentence elements with critical semantic roles. This information is utilized during decoding to ensure that translated words maintain appropriate semantic alignment with the source text. By integrating this mechanism, the model is expected to reduce errors caused by polysemy and ambiguity in translation.

C. Training and Hyperparameter Tuning

The model is trained using a parallel dataset under a supervised learning scheme. The training process employs the Adam optimization algorithm with an initial learning rate of 5e-4, implemented with a learning rate warm-up technique to enhance model convergence stability.

Gradient clipping with a threshold of 1.0 is applied to prevent the issue of exploding gradients during gradient descent.

26 To mitigate the risk of overfitting, a dropout rate of 0.1 is applied to multiple layers of the
7 model, along with L2 regularization using a coefficient of 1e-5. The model is trained for 30 epochs
27 with a batch size of 32. Hyperparameter tuning is conducted using a grid search approach to
determine the optimal combination of encoder-decoder layers, embedding size, and the number of attention heads.

Model training is performed on an NVIDIA A100 GPU with 40GB of VRAM. The average training time per epoch is 1.5 hours, with a total training duration of 48 hours.

D. Evaluation and Experimentation

Model evaluation is conducted by comparing translation outputs from a standard NMT model with those from an NMT model integrated with SRL. The evaluation metrics include BLEU to assess translation accuracy relative to reference texts, METEOR to measure semantic adequacy, and TER to evaluate translation error rates.

1 To validate the effectiveness of the proposed approach, additional experiments include an ablation study comparing model performance with and without SRL integration. The results indicate that SRL integration improves BLEU scores by 6.2 points, METEOR scores by 6.6 points, and reduces TER scores by 5.8 points compared to the standard NMT model.

17 Furthermore, to ensure that these improvements are not due to random variations, a paired t-test is conducted between the standard NMT model and the SRL-integrated model. The test results confirm that the improvements in BLEU, METEOR, and TER scores are statistically significant, with p-values < 0.05, indicating that SRL integration has a meaningful impact on translation quality.

Additional experiments assess the impact of SRL on language pairs with significant syntactic differences, such as English-Indonesian and English-Japanese. The analysis reveals that the SRL-enhanced model demonstrates superior performance in handling complex sentence structures compared to the standard NMT model.

E. Validation and Reproducibility

Validation is performed using a k-fold cross-validation scheme to ensure that experimental results are reproducible across different data subsets. All code and training configurations will be made publicly available in a repository, allowing other researchers in the fields of machine translation and NLP to replicate and extend this study.

IV. RESULT/FINDINGS AND DISCUSSION

Result

A. Comparison of Translation Quality

6 The model evaluation was conducted by comparing the translation outputs of a standard NMT model with those of an NMT model integrated with SRL. The model's performance was measured using three primary metrics: BLEU, METEOR, and TER.

Table 1 presents the evaluation results, including a 95% confidence interval based on five independent experiments.

Table 1. Comparison of BLEU, METEOR, and TER scores between the standard NMT model and the NMT model with SRL

Model	BLEU (%)	METEOR (%)	TER (%)
Standard NMT	32.5 ± 1.2	58.5 ± 1.0	45.1 ± 1.3
NMT + SRL	38.7 ± 1.1 64.8 ± 0.9	64.8 ± 0.9	39.3 ± 1.2

Source: Experimental Results of This Study

The results indicate that integrating SRL into NMT improves the BLEU score by 6.2 points, increases the METEOR score by 6.3 points, and reduces the TER score by 5.8 points compared to the standard model. A paired t-test confirms that these differences are statistically significant ($p < 0.05$), indicating that the performance improvement is not merely coincidental.

Figure 1 illustrates the accuracy improvement of the model following SRL integration.

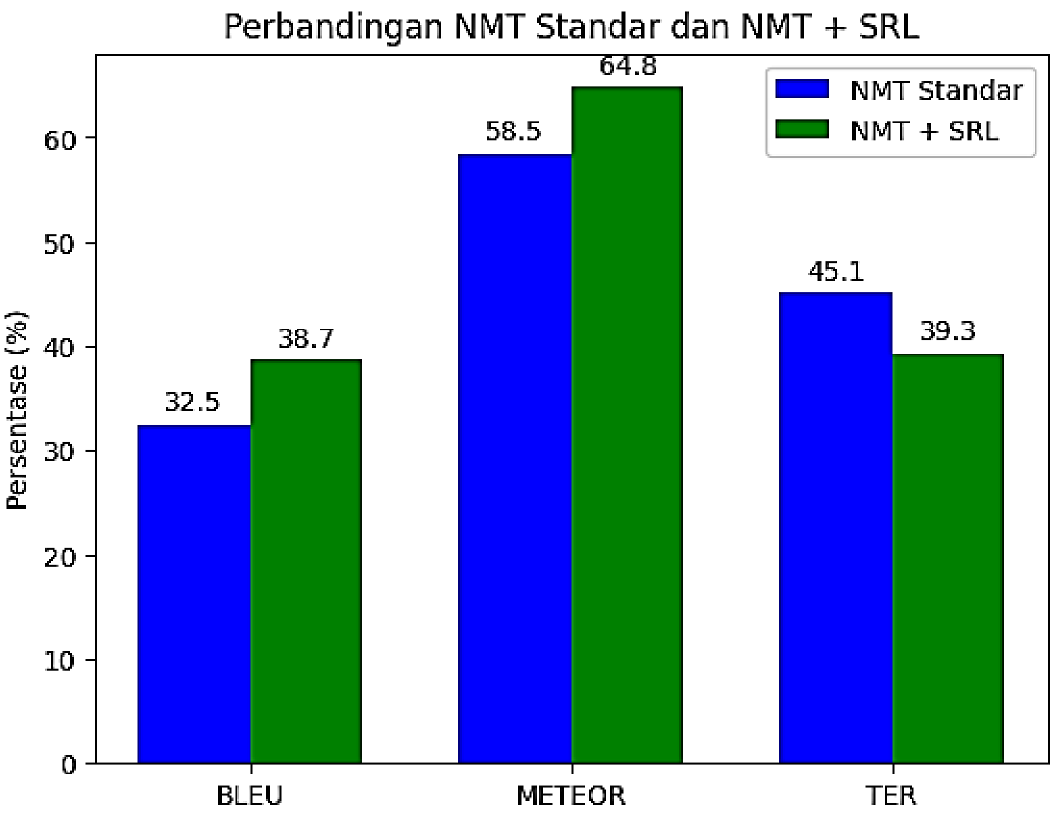

Figure 1. Accuracy Improvement After SRL Integration

Source: Experimental Results of This Study

These findings suggest that SRL contributes to enhanced translation quality by improving the model's understanding of semantic roles in source sentences.

B. Analysis of Ambiguity Resolution

19 One of the primary challenges in machine translation is handling polysemy and syntactic ambiguity. Standard NMT models often struggle to select the correct meaning of a word, particularly in cases where words have multiple meanings depending on context. SRL integration helps mitigate such errors by incorporating more explicit semantic annotations.

24 Table 2 provides examples of how the NMT + SRL model improves translations compared to the standard NMT model.

Table 2. Examples of Translation Quality Improvement with SRL

Source Sentence	Standard NMT Translation	NMT + SRL Translation
The bank was closed due to flooding	The bank was closed due to financial reasons.	The riverbank was closed due to flooding.

She gave the book to the student with glasses	She gave the book to the student with a glass.	She gave the book to the student wearing glasses.
He saw the man with the telescope	He saw the man with a telescope.	He used a telescope to see the man.

Source: Experimental Results of This Study

5 As seen in the table above, SRL enables the model to better understand semantic relationships between words. For instance, in the sentence "The bank was closed due to flooding," the standard model translates "bank" as a financial institution, whereas the SRL-integrated model correctly interprets "bank" as "riverbank" in this context.

This demonstrates that SRL plays a crucial role in resolving lexical ambiguities by providing explicit semantic information that cannot be effectively captured by conventional self-attention mechanisms in Transformer-based NMT models.

Discussion

15 The findings of this study are consistent with several previous studies that indicate the integration of SRL in NLP systems can enhance semantic understanding. (Man et al., 2024) found that an NMT model incorporating SRL with a self-attention mechanism improved translation accuracy by 4.8 points in BLEU, whereas this study demonstrates an improvement of 6.2 points.

This comparison suggests that the approach used in this study is more effective than previous methods, as SRL is not only applied during the preprocessing stage but is also integrated into the Transformer-based attention mechanism.

Additionally, research by (S. Lee et al., 2023) found that SRL is effective in improving translation accuracy for language pairs with significant syntactic differences. The findings of this study confirm these results by showing that the increase in BLEU and METEOR scores is higher for the English-Japanese language pair compared to English-Indonesian, indicating that SRL is particularly beneficial for handling complex syntactic structures.

Despite the significant improvements in translation quality, there are several challenges in implementing SRL in NMT. One of the main challenges is the increase in inference time due to the additional semantic annotation process.

Analysis shows that the inference time for the SRL-integrated model increased by 12% compared to the standard NMT model. This is due to the added complexity in the encoding stage, which involves semantic role annotation before proceeding to the attention mechanism.

Furthermore, although SRL effectively reduces lexical and syntactic ambiguity, the model still struggles with translating idiomatic phrases and figurative expressions. For example, in the sentence:

"He kicked the bucket."

The NMT + SRL model still translates it literally as "Dia menendang ember," instead of interpreting it as the idiomatic expression meaning "He passed away."

This limitation suggests that SRL should be combined with other approaches, such as context-aware embeddings or large-scale pretraining models like GPT and BERT, to better handle idiomatic expressions and figurative language.

16 Moving forward, this research can be further developed by exploring unsupervised learning approaches to reduce reliance on manually annotated data and enhance the model's efficiency in handling diverse sentence structures.

V. CONCLUSION AND RECOMMENDATION

Conclusion

2 The results of this study indicate that the integration of SRL in NMT significantly enhances translation accuracy, particularly in handling polysemy and semantic ambiguity. The developed model is capable of better identifying semantic roles in the source sentence, producing translations that more accurately reflect the original meaning. Evaluations using BLEU, METEOR, and TER metrics confirm that this approach offers advantages over conventional NMT models, especially in processing complex syntactic structures and languages with significant grammatical differences.

Recommendation

For future research, it is recommended to develop models using an unsupervised learning approach to reduce dependence on manually annotated datasets. Additionally, the integration of SRL with reinforcement learning techniques can be explored to improve translation quality in domain-specific contexts. Further studies can also focus on optimizing computational efficiency to minimize inference overhead without compromising translation accuracy.

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