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ENHANCING UZBEK-ENGLISH NEURAL MACHINE TRANSLATION WITH DOMAIN-SPECIFIC BERT PRETRAINING

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Annotation: This article investigates the enhancement of Uzbek-English neural machine translation (NMT) by leveraging domain-specific BERT pretraining. Due to the low-resource nature and morphological complexity of Uzbek, standard NMT models often struggle with domain-specific terminology and contextual nuances. By pretraining BERT models on monolingual corpora tailored to general, medical, and legal domains, and integrating them into a transformer-based NMT framework, the study achieves significant improvements in translation quality. Results demonstrate that domain-specific pretraining notably outperforms general pretraining and baseline models, highlighting its effectiveness for specialized translations in low-resource language pairs.

Keywords: Uzbek-English translation, neural machine translation, BERT pretraining, domain-specific language models, low-resource languages, transformer architecture, machine translation evaluation, domain adaptation, morphological complexity, natural language processing.

Introduction. Neural Machine Translation (NMT) has revolutionized the field of automated language translation by utilizing deep learning techniques, particularly transformer architectures, to produce high-quality translations. While NMT models have demonstrated remarkable success for high-resource language pairs such as English-French or English-Chinese, their performance on low-resource languages remains limited. Uzbek, a Turkic language spoken by over 30 million people primarily in Central Asia, is considered a low-resource language due to the scarcity of large-scale parallel corpora and annotated datasets. This poses significant challenges for developing robust Uzbek-English machine translation systems.

Several linguistic characteristics of Uzbek add to these challenges. As an agglutinative language, Uzbek uses a rich system of suffixes and inflections, resulting in a large vocabulary and complex morphological structures. Moreover, the syntactic order of Uzbek (typically subject-object-verb) differs from English (subject-verb-object), requiring NMT models to effectively learn cross-lingual syntactic transformations. In addition to these linguistic difficulties, domain-specific translation remains a critical problem. Many existing Uzbek-English translation models are trained on general-domain corpora such as news or Wikipedia, limiting their ability to accurately translate specialized texts in areas like medicine, law, or technology. Domain-specific terminology, idiomatic expressions, and context-sensitive meanings are often inadequately captured, leading to translations that are either incorrect or lack fluency.

To overcome these challenges, recent advances in natural language processing have leveraged pretrained language models such as BERT (Bidirectional Encoder Representations from Transformers). BERT's masked language modeling allows it to learn deep contextual representations of language from large monolingual corpora, improving downstream tasks including machine translation. While pretrained multilingual BERT models have been applied to

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low-resource languages, fine-tuning BERT on domain-specific monolingual data can further enhance its ability to capture specialized vocabulary and contextual nuances.

This article explores the integration of domain-specific BERT pretraining into Uzbek-English NMT systems. By training BERT models on Uzbek corpora drawn from medical, legal, and general domains, and incorporating these models as encoders within a transformer-based NMT framework, we aim to improve translation quality, especially in specialized fields. Our study demonstrates that domain-specific BERT pretraining significantly boosts translation accuracy and fluency compared to baseline NMT systems and those enhanced with general-domain BERT models. In the following sections, we review relevant literature, describe our data collection and preprocessing methods, detail our pretraining and NMT architecture, and present comprehensive evaluation results. The findings underscore the importance of domain adaptation and contextual pretraining for advancing Uzbek-English machine translation and provide insights applicable to other low-resource language pairs.

Literature review. The field of neural machine translation has witnessed significant advancements since the introduction of sequence-to-sequence models with attention mechanisms by Bahdanau et al. (2015). The subsequent development of the Transformer architecture by Vaswani et al. (2017) marked a milestone by eliminating recurrent structures and relying entirely on self-attention, greatly improving translation quality and training efficiency. These architectures form the backbone of modern NMT systems, including those targeting low-resource languages like Uzbek. Low-resource languages, including many Turkic languages such as Uzbek, face persistent challenges due to limited availability of parallel corpora necessary for supervised NMT training (Koehn & Knowles, 2017). The scarcity of annotated data leads to issues such as overfitting and poor generalization, especially for specialized domains where terminological accuracy is critical (Zoph et al., 2016). Uzbek's agglutinative morphology further exacerbates data sparsity problems by increasing the effective vocabulary size (Salloum & Habash, 2014). Efforts to address these challenges have included data augmentation techniques such as back-translation (Sennrich et al., 2016), transfer learning from high-resource languages (Nguyen & Chiang, 2017), and multilingual modeling (Johnson et al., 2017).

The advent of pretrained language models such as BERT (Devlin et al., 2019) has transformed numerous natural language processing (NLP) tasks. BERT's deep bidirectional transformer encoder is pretrained on large-scale unlabeled corpora using masked language modeling, capturing rich contextual representations that can be fine-tuned for downstream tasks. The effectiveness of BERT has spurred research into integrating pretrained language models with NMT. Yang et al. (2019) explored initializing NMT encoders with pretrained BERT weights, reporting improvements in translation quality. Liu et al. (2020) further proposed BERT-fused NMT models that combine BERT contextual embeddings with the NMT encoder to enhance semantic representation. These methods have shown particular promise in low-resource scenarios where large parallel corpora are unavailable.

While general-domain pretrained models provide broad linguistic knowledge, domain-specific models have been shown to significantly improve performance on specialized tasks. Lee et al. (2019) introduced BioBERT, a BERT model pretrained on large biomedical corpora, which outperformed general BERT in medical NLP benchmarks. Similarly, Gururangan et al. (2020) demonstrated that domain-adaptive pretraining (continued pretraining on in-domain corpora) yields substantial gains in downstream tasks across various domains. In machine translation,

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domain adaptation techniques often involve fine-tuning NMT models on in-domain parallel corpora (Chu et al., 2017), or incorporating domain-specific terminology databases (Zhao et al., 2020). However, for languages with limited in-domain parallel data like Uzbek, domain-specific pretraining of language models on large monolingual corpora is a practical alternative.

Research specifically addressing Uzbek-English NMT remains limited. Early work by Tursun et al. (2017) focused on rule-based and statistical approaches, constrained by data scarcity. More recent efforts have applied transformer-based models using available datasets, showing incremental improvements (Sultanov & Mukhamedov, 2021). Multilingual transfer learning from related Turkic languages (e.g., Turkish, Kazakh) has been explored to leverage shared linguistic features (Ziyadin et al., 2020). Few studies have yet integrated pretrained language models for Uzbek, and even fewer have addressed domain-specific challenges. This gap underscores the importance of the current study, which leverages domain-specific BERT pretraining to enrich Uzbek contextual representations and improve NMT outcomes.

Research methodology. This study investigates the impact of domain-specific BERT pretraining on Uzbek-English neural machine translation (NMT). Our methodology encompasses several key stages: data collection and preprocessing, domain-specific BERT pretraining, NMT model architecture design, training and fine-tuning, and evaluation.

To build and evaluate Uzbek-English NMT systems, we curated parallel corpora across three domains:

- General Domain: Comprised of news articles, Wikipedia entries, and publicly available general Uzbek-English datasets.
- Medical Domain: Extracted from health guidelines, medical research papers, and clinical reports, primarily sourced from publicly accessible multilingual medical databases.
- Legal Domain: Compiled from translated legal documents, contracts, and legislative texts available through government publications and international legal repositories.

The parallel corpora were tokenized using domain-appropriate tokenizers. For Uzbek, special attention was given to morphological segmentation to handle agglutinative suffixes and reduce vocabulary sparsity. Sentence pairs with significant length imbalance or low alignment confidence were filtered out to ensure data quality.

For domain-specific BERT pretraining, large monolingual Uzbek corpora were gathered from:

- General Uzbek news websites and digital libraries.
- Medical texts from domain-specific Uzbek resources and international health portals.
- Legal Uzbek texts from national legal databases and law-focused websites.

Monolingual English corpora were also collected for alignment verification and complementary pretraining, though the primary focus remained on Uzbek BERT pretraining.

Text normalization included lowercasing, punctuation standardization, and removal of noisy content such as advertisements and HTML tags.

We pretrained separate BERT models for each domain using the masked language modeling (MLM) objective (Devlin et al., 2019). This involved masking random tokens in the input and training the model to predict them, enabling it to learn deep contextualized representations.

- Model Architecture: The BERT-base architecture was selected, comprising 12 transformer encoder layers, 768 hidden units, and 12 attention heads.

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- Training Setup: Models were trained from scratch on the respective domain monolingual corpora using the Hugging Face Transformers library. Training continued until convergence based on validation perplexity.
- Domain Adaptation: By focusing pretraining on domain-relevant text, each BERT model captured specialized terminology and stylistic patterns critical for domain-aware translation.

Research discussion. The experimental results of this study highlight the significant benefits of incorporating domain-specific BERT pretraining into Uzbek-English neural machine translation (NMT) systems. Across all evaluated domains—general, medical, and legal—the models initialized with domain-adaptive pretrained BERT encoders consistently outperformed both the baseline transformer models and those using general-domain BERT pretraining. The most striking improvements were observed in the specialized domains of medicine and law, where domain-specific terminology and phraseology play critical roles in conveying accurate meaning. The domain-specific BERT models demonstrated a superior ability to capture nuanced vocabulary and context-dependent meanings compared to general BERT and baseline models. This supports previous findings in NLP that domain adaptation through continued pretraining enables language models to internalize domain-specific semantics and stylistic features (Gururangan et al., 2020; Lee et al., 2019). For example, medical terms that were often mistranslated or omitted in baseline models were translated more accurately and consistently when using domain-specific BERT pretraining. Similarly, legal language, known for its formal and complex structure, was rendered with greater syntactic fidelity and terminological precision, which is essential for downstream applications such as contract translation and legal compliance.
Uzbek's agglutinative morphology and syntactic divergence from English pose significant challenges for NMT systems. The domain-specific BERT pretraining helped mitigate these challenges by providing rich contextual embeddings that incorporate morphological and syntactic nuances, reducing the effective vocabulary sparsity and enabling the model to better handle inflected forms and syntactic reorderings. Moreover, the scarcity of large-scale parallel corpora for Uzbek-English translation, particularly in specialized domains, makes supervised NMT training alone insufficient. Our approach leverages large monolingual corpora for pretraining, thus capitalizing on abundant unlabeled text data to enhance the encoder's linguistic representation before fine-tuning on smaller parallel datasets. This is a practical and scalable strategy for other low-resource languages facing similar constraints.
While domain-specific BERT pretraining clearly improves translation quality, the gains in the general domain were relatively modest. This suggests that domain adaptation yields the greatest benefits when domain characteristics diverge significantly from general language use. The general-domain pretrained BERT model already captures broad linguistic patterns, limiting the margin for further improvement without domain specialization. However, some limitations remain. The quality and size of domain-specific monolingual corpora directly affect pretraining effectiveness. In domains with scarce or noisy data, BERT's ability to learn meaningful representations is constrained. Additionally, fine-tuning large pretrained models requires substantial computational resources, which may limit accessibility for researchers and practitioners in resource-constrained environments.
Our findings open several avenues for future research. Multilingual and cross-lingual pretrained models could be explored to transfer knowledge from related Turkic languages with richer

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resources, potentially further enhancing Uzbek translation performance. Incorporating morphological analyzers or explicit linguistic features within the pretraining or NMT pipeline may improve handling of agglutinative structures. Furthermore, experimenting with other pretrained architectures such as mT5 or domain-specific encoder-decoder models could provide additional insights into optimizing translation for low-resource, morphologically rich languages. Finally, expanding domain adaptation efforts to include more specialized fields—such as technical or financial texts—would increase the practical utility of Uzbek-English NMT systems.

Conclusion. This study explored the enhancement of Uzbek-English neural machine translation through the integration of domain-specific BERT pretraining. Given the challenges posed by Uzbek's low-resource status, morphological complexity, and domain-specific translation needs, conventional NMT models often fall short in delivering accurate and fluent translations, especially in specialized fields such as medicine and law. By pretraining BERT models on large monolingual corpora tailored to general, medical, and legal domains, and incorporating these models as encoders within a transformer-based NMT framework, our approach demonstrated clear improvements over baseline systems and general-domain pretrained models. Domain-specific BERT pretraining enriched the contextual representations, enabling better handling of specialized terminology, complex morphological structures, and syntactic differences between Uzbek and English.

The results highlight the value of domain adaptation in low-resource language translation and confirm that leveraging domain-relevant monolingual data can significantly improve NMT performance without requiring large-scale parallel corpora. These findings contribute to bridging the gap in machine translation quality for Uzbek and other similarly under-resourced languages. Future work can extend this approach by incorporating multilingual pretraining, exploring alternative pretrained architectures, and expanding domain coverage to further improve translation accuracy and applicability. Overall, domain-specific BERT pretraining presents a promising direction for advancing neural machine translation in challenging linguistic and resource contexts.

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