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LINGUISTIC SCRUTINY OF AUTOMATED TRANSLATION DEFICIENCIES: ENGLISH-TO-UKRAINIAN NMT SYSTEMS IN FOCUS

The contemporary landscape of machine translation has been revolutionized by neural network paradigms (NMT), with systems like Google Translate or DeepL delivering remarkable velocity and superficial fluency. Nonetheless, cross-linguistic transformations involving complex syntax, idiomatic expressions, and culturally rooted concepts still pose significant obstacles. These structural constraints frequently result in distinct grammatical flaws, lexical mismatches, and stylistic anomalies, necessitating a comprehensive linguistic critique to evaluate the actual precision of automated outputs [1, p. 122; 2, p. 45].

To systematically explore these phenomena, a heterogeneous text corpus comprising literary works, journalistic articles, technical documentation, and casual discourse was compiled. This diverse empirical data allowed for a thorough evaluation of how deep-learning translation engines decode English source syntax and reconstruct it within the grammatical framework of the Ukrainian language. High-quality human translations served as the benchmark for identifying deviations from normative usage[3, p. 14; 4, p. 88].

The academic literature indicates that diagnosing flaws in NMT must extend beyond mere technical metrics, requiring a robust translational perspective. Despite sophisticated neural architectures, automated systems consistently exhibit recurrent vulnerabilities, including complete omissions, terminological volatility, and severe syntactic misalignments. Such errors escalate when encountering polysemous units, culture-bound idioms, or structurally ambiguous sentences, reflecting deep typographic contrasts between the source and target languages. Utilizing standardized diagnostic frameworks, such as the Multidimensional Quality Metrics (MQM), enables a rigorous and systematic categorization of these linguistic failures [3, p. 18; 4, p. 91].

Our empirical observation confirms that lexical discrepancies are highly prevalent in domain-specific nomenclature and polysemous words. Morphosyntactic breakdowns typically manifest as flawed case assignments, incorrect grammatical agreement, and unnatural word order. Furthermore, instances of under-translation and information omission remain frequent, demonstrating the system's occasional inability to process the full semantic load of the source text. Finally, the resulting register often feels unnatural, revealing the ongoing struggle of NMT with stylistic adaptation [4, p. 95; 6, p. 3].

Barring these limitations, the role of human specialists remains paramount. Expert proofreaders not only rectify immediate grammatical and lexical errors but also restore delicate semantic nuances, cultural integrity, and stylistic harmony. A cooperative framework, where neural engines generate a preliminary draft and human translators execute thorough post-editing, proves to be exceptionally productive. This synergy ensures context refinement, ambiguity resolution, and natural text flow [4, p. 98; 6, p. 7].

Looking ahead, NMT refinement must prioritize the integration of advanced context-aware modules, semantic disambiguation tools, and stylistic adaptation filters. Concurrently, modern translator training curricula should incorporate post-editing methodologies and strategies for managing complex contrastive phenomena. Merging technological efficiency with human cognitive expertise represents the ultimate path toward achieving linguistically flawless and culturally appropriate translations. In summary, while automated tools expedite the process, human oversight is indispensable for preserving genuine linguistic precision and cultural adequacy [1–7].

REFERENCES

1. Diab N. Out of the BLEU: An error analysis of statistical and neural machine translation. *Journal of Translation Studies*. 2021. № 14(2). P. 120–136.
2. Isabelle P., Cherry C., Foster G. Human evaluation of neural machine translation: The case of deep learning. *ACL Anthology*. 2019. P. 45–60.
3. Klubička M., et al. Quantitative fine-grained human evaluation of machine translation systems. *ArXiv*. 2018. P. 1–18.
4. MDPI. Translation quality and error recognition in professional neural machine translation post-editing. *Informatics*. 2021. № 6(3). P. 41–55.
5. Šorak V. From terminological inconsistencies to major mistranslations: A qualitative analysis of NMT errors in public health communication. *AI Linguistics*. 2024. № 2. P. 45–61.
6. Tang G., Rönchen P., Sennrich R., Nivre J. Revisiting negation in neural machine translation. *ArXiv*. 2021. P. 1–12.
7. Ye Y., Toral A. Fine-grained human evaluation of transformer and recurrent approaches to neural machine translation for English–Chinese. *ArXiv*. 2020. P. 1–15.