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AUTOMATED TRANSLATION TOOLS: EFFICIENCY AND PROSPECTS

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Annotation. This article provides an overview of modern automated translation tools and offers a comparative analysis of classical, neural, and hybrid systems, evaluating their efficiency and prospects. The study examines the advantages and disadvantages of each approach and offers recommendations for optimizing current translation systems and developing new models capable of enhancing translation accuracy and speed.

Keywords: automated translation, machine translation, neural networks, efficiency, hybrid models, prospects.

Introduction. Historically, translation systems have evolved from traditional, rule-based and statistical algorithms to modern neural network models, as well as to their hybrid variations that combine the advantages of both approaches [1, 2]. The purpose of this article is to conduct a comparative analysis of existing translation methods with an emphasis on their effectiveness, to identify the strengths and weaknesses of each approach, and to formulate recommendations for further improvement of translation systems.

Main part. Modern translation systems rely on character processing algorithms that allow text parsing, syntactic and semantic analysis, which is the basis for the formation of a correct translation. One of the key parameters for assessing the quality of translation is the BLEU metric, which allows you to quantify the compliance of the translation with the standard. BLEU is calculated as follows formula 1:

$$BLEY = exp\left(\sum_{n} w_n \cdot log\ p_n\right), \tag{1}$$

where p_n – is the accuracy of n-grams;

w_n – is a weight factor that depends on the order of n-grams.

To illustrate the comparative analysis, the conditional data presented in Table 1 are presented, which are obtained on the basis of generalization of information from open sources (a review of articles on CyberLeninka, Science Forum and materials describing the principles of translation systems [3, 4, 5, 6]). It should be noted that the data in the table are conditional and may vary depending on specific testing conditions, algorithm versions and system settings.

Table 1 – Comparative analysis of translation systems

№	System Name	Approach	BLEU	Processing time (sec)	Features
1	Google Translate	Neural	0.32	0.8	Deep Learning, High Quality for Major Languages
2	Microsoft Translator	Neuronal/Hybrid	0.29	1.0	Integration with cloud services
3	DeepL	Neural	0.35	0.9	Emphasis on European languages
4	Yandex Translation	Classical	0.27	0.7	Fast processing, limited adaptability

Analysis of the data suggests that neural systems (e.g., Google Translate and DeepL) demonstrate high translation accuracy due to their ability to take into account complex context, but at the same time require significant computational resources. Classical systems tend to provide shorter processing times due to the simplicity of the algorithms, but their adaptability and accuracy raise questions when working with complex texts. Hybrid models that combine neural translation algorithms with traditional methods are able to compensate for the weaknesses of both approaches, which makes them especially promising for the further development of automated translators.

Comparative analysis suggests several key improvements for existing translation systems. Firstly, **integrating neural and classical algorithms** into hybrid models can boost accuracy by applying strict rules to specialized terminology while leveraging neural networks for broader semantic understanding. Secondly, **optimizing computational load** through neural network compression and adaptive learning is crucial for reducing resource costs, particularly for systems with limited technical capacity. Finally, **training on specialized corpora**, such as technical, legal, or medical texts, will significantly enhance translation quality within those specific domains.

The general scheme of optimization of the computer-aided translation system is presented in Figure 1, which shows the stages of text pre-processing, translation with subsequent post-processing and evaluation of the quality of the results.

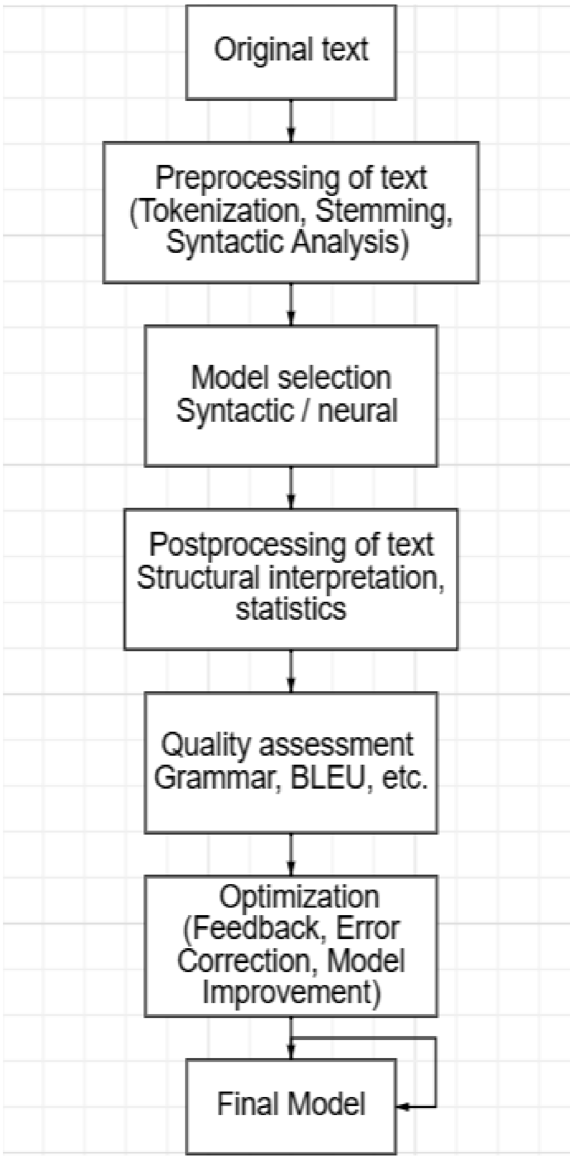

Figure 1 – Algorithm for optimizing a computer-aided translation system

The machine translation process begins with the **source text**, which is then fed into the system. **Text preprocessing** follows, involving tokenization, normalization, and parsing to prepare the data for translation. Next, the **translation module** implements the core translation algorithm using methods like neural networks, hybrid approaches, or classical techniques. **The text post-processing stage** refines the translated text through adjustments to grammar, style, and formatting.

To evaluate the translation's success, **quality assessment** is performed using various metrics. Finally, the **optimization module** analyzes the results and any errors, using this feedback to enhance the translation model, which then re-enters the optimization cycle for continuous improvement. This algorithm illustrates the cyclical process of optimizing the translation system, which allows you to regularly adjust and improve the quality of the automated translator's work. Such approaches and recommendations contribute to the development of a new generation of systems that meet the modern requirements of interlingual communication and have a high degree of accuracy at a moderate computational cost.

Conclusion. The analysis shows neural translation excels in adaptability and accuracy, while classical methods struggle with context and text specifics. Hybrid models, merging the strengths of both, hold the most promise for future development, suggesting their adaptation and optimization to enhance translation system effectiveness. Implementing recommendations for integration and resource optimization is key to creating next-generation translation systems that meet the increasing demands of the global information landscape.

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