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Features of Hybrid Machine Learning in Modern Computational Linguistics: Navigating Systemic Risks, Turbulence and Uncertainty Through the Lens of SHIVA and WARMI Paradigms

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Abstract. *The article explores the features and specifics of hybrid machine learning in modern computational linguistics in conditions of dynamic uncertainty, turbulence and systemic risks. The main directions of hybridization of neural, symbolic, statistical and linguistic methods are considered, as well as the possibilities of integrating large language models, knowledge graphs and adaptive learning mechanisms. The prospects of hybrid architectures for increasing the accuracy, stability, adaptability and comprehensibility of intelligent linguistic systems in conditions of SHIVA and WARMI paradigms of the external environment are substantiated.*

Keywords: *Digital Philology; Machine Linguistics; Hybrid machine learning; Computational linguistics; Artificial intelligence; Natural language processing; Large language models; Neurosymbolic technologies; Knowledge graphs; Adaptive learning; Uncertainty; Turbulence; Systemic risks; SHIVA; WARMI.*

INTRODUCTION. Modern philology is developing in conditions of qualitatively more complicated external environment [1], which is characterized by acceleration of changes, growth of uncertainty [2], turbulence of information flows, increase in volume and heterogeneity of language data [3], as well as strengthening of

systemic risks of digital environment. These processes are especially clearly manifested in computational linguistics, where research and applied tasks directly depend on dynamics of language corpora, digital communications, algorithmic platforms, social networks and artificial intelligence models [4], which are changing rapidly. In such conditions, traditional orientation on relatively stable data sets and fixed algorithmic procedures becomes insufficient [5]. Computational linguistics needs intelligent technologies capable not only to obtain regularities from large arrays of text, but also to adapt to changing context, take into account linguistic knowledge, control uncertainty and ensure stability of results [6].

One of the most promising areas of such development is hybrid machine learning, based on the integration of several algorithmic, mathematical, statistical and linguistic approaches [7]. Unlike the use of a separate machine learning model [8], the hybrid architecture allows combining the advantages of different methods [9]: neural networks and symbolic models, deep and traditional machine learning, transformative models and expert knowledge, machine learning and knowledge from ontologies or knowledge graphs, supervised and reinforced learning, centralized and distributed. Modern research on Hybrid NLP directly indicates the prospects of combining machine and symbolic methods [10], since the former effectively reveal statistical patterns, while the latter provide knowledge representation and logical interpretation. Hybridization acquires particular importance in the context of modern large language models (Large Language Models, LLM), which have significantly expanded the capabilities of automatic processing, understanding and generation of natural language [11]. However, the high performance of LLM does not eliminate the problems of actual reliability, comprehensibility, data change resistance, computational resource intensity, reproducibility and control of results. Modern research on LLM in NLP shows that the further development of this field is associated not only with an increase in model parameters, but also with the search for new architectures, methods of adaptation, combination of models and mechanisms of their intelligent management.

In this article, the SHIVA and WARMI paradigms are considered as conceptual models for describing the current external environment of modern philology, which is characterized by a high degree of uncertainty, turbulence, volatility, interdependence of processes, acceleration of changes and systemic risks. Their application allows us to consider computational linguistics not only as an area of text processing automation, but also as a complex intellectual system operating in a constantly changing environment. At the same time, these paradigms are used precisely as a research conceptualization of external conditions, and not as generally accepted independent standards of machine learning.

Therefore, taking into account the above, the current relevance of the study is determined by the need for a theoretical understanding of the place of hybrid machine

learning in modern computational linguistics and the identification of its specific capabilities in conditions of dynamic uncertainty. The purpose of the article is to systematize the features and specifics of the application of hybrid machine learning in computational linguistics, taking into account the complex conditions of the SHIVA and WARMI environments. To achieve this goal, it is necessary to reveal the essence of hybrid machine learning, determine the main directions of its integration with modern linguistic technologies, identify the advantages and limitations of hybrid models and substantiate the prospects for their use to increase the adaptability, stability, understandability and intelligence of modern philological information systems.

THE MAIN PART.

1. Hybrid Machine Learning as the Architectural Basis of Modern Computational Linguistics. Hybrid Machine Learning is the integration of various algorithmic, statistical, neural, symbolic, and linguistic methods into a single intelligent system. Unlike a separate algorithm, a hybrid architecture distributes functions between complementary components, which allows simultaneously increasing the accuracy, adaptability, robustness, and interpretability of language data processing. For computational linguistics, this approach is especially relevant due to the multi-level nature of natural language, which combines statistical, structural, semantic, and pragmatic patterns. Neural models effectively reveal hidden patterns and generalize large data sets, while symbolic methods allow the use of formalized rules, ontologies, and expert knowledge. Their combination provides a transition from the “data → algorithm → result” model to a more complex “data → learning → knowledge → interpretation → verification → adaptation” system.

2. Main directions of hybridization in computational linguistics. One of the key directions is neurosymbolic hybridization, which combines neural models with rules, ontologies, thesauri and knowledge graphs. It allows combining the generalization ability of neural networks with a formalized representation of linguistic knowledge. Also important is the combination of different machine learning models - transformers, deep neural networks, ensemble methods, classifiers and generative models. Different components can perform specialized functions: obtaining features, forming semantic representations, classifying and checking results. Promising is the combination of machine learning with reinforcement learning, especially for dialog systems and adaptive intelligent agents, as well as the integration of ML with knowledge graphs and structured databases for semantic search, knowledge extraction and processing of specialized texts. A separate direction is related to distributed and federated learning, which allows working with heterogeneous and sensitive language data without their complete centralized unification. In this case, additional problems of data heterogeneity, security and communication costs arise.

3. Specificity of hybrid machine learning in the conditions of SHIVA and WARMI environments. Modern computational linguistics operates in a dynamic information environment, where language norms, terminology, digital communication, thematic structures and distribution of language data are constantly changing. Therefore, static models gradually lose their relevance. In the conditions of SHIVA and WARMI environments, there is a need to transition to adaptive hybrid learning, capable of detecting data changes, connecting new knowledge, adjusting models and changing the rules used. Hybridization here becomes not only a means of increasing accuracy, but also a mechanism for ensuring the stability of the intelligent system. Of particular importance is the resistance to uncertainty caused by polysemy, homonymy, incomplete context, metaphoricity, irony and pragmatic ambiguity. Therefore, the system must be able to assess the degree of confidence, form alternative hypotheses and refer to additional sources of knowledge. No less important is the resistance to data turbulence, including the sudden emergence of new terms, topics and communicative models. To counteract data drift, dynamic updating of corpora, adaptive retraining, obtaining new knowledge and ensemble forecasting are necessary. Finally, hybrid systems must take into account systemic risks. The error of a large-scale language model can propagate through interconnected information processes, so mechanisms for verification, confidence assessment, anomaly detection, monitoring of model drift and human-machine control are needed.

4. Hybrid architectures and large language models. The development of large language models (LLM) has significantly expanded the capabilities of computational linguistics, but at the same time has exacerbated the problems of actual reliability, comprehensibility, relevance of knowledge and control of the generated results. Therefore, the architecture of LLM + external knowledge + specialized models + verification mechanisms becomes promising. In such a system, the LLM can form a language hypothesis, the knowledge graph - provide a structured context, a specialized classifier - check a separate parameter, and the symbolic module - control compliance with formal rules. Architectures that use external extraction of relevant information and knowledge-variable approaches are especially promising. They allow to reduce the system's dependence on the exclusively parametric memory of the language model and increase its adaptability to a rapidly changing information environment.

5. Advantages and limitations of the hybrid approach. The main advantage of hybrid machine learning lies in the complementarity of methods. For computational linguistics, this means the ability to simultaneously increase the accuracy of language processing, take into account formalized knowledge, improve interpretability, adapt to the subject area, and increase the resistance to data changes. However, hybridization increases the architectural and computational complexity of the system. Problems arise in the coordination of different representations, error transmission between

components, model compatibility, and the cost of training and maintenance. Therefore, the hybrid approach should be considered as a universal replacement for individual machine learning methods. Its effectiveness is determined by the correspondence of a specific linguistic task and the rational distribution of functions between system components.

6. A promising model of hybrid machine learning for computational linguistics. The promising architecture of a hybrid linguistic system can be described as a sequence: dynamic language data → preprocessing → neural representation → specialized ML modules → external knowledge and graphs → symbolic rules → integration and decision-making → verification → adaptive feedback. The key element of such an architecture should be a closed adaptive loop: "learning → interpretation → verification → correction → retraining". Unlike linear processing, such a system is able to return to previous stages when errors are detected, data changes or confidence decreases. It is this adaptability that makes hybrid technologies particularly promising for computational linguistics in the SHIVA and WARMI environments. They allow combining the intellectual capabilities of modern neural models with formalized knowledge, control mechanisms, adaptation and human expertise, forming more intelligent, stable, understandable and reliable philological information systems.

CONCLUSIONS. The analysis conducted allows us to conclude that hybrid machine learning is becoming one of the promising areas of development of modern computational linguistics, as it meets the objective complexity of modern language data and the requirements of a dynamic digital environment. Its fundamental advantage lies in the ability to integrate various algorithmic and linguistic paradigms, compensating for the limitations of individual methods.

The specificity of hybrid machine learning in computational linguistics is determined primarily by the need to simultaneously take into account the statistical regularities of language, structured knowledge, semantic and pragmatic context, data dynamics and the degree of uncertainty of the results obtained. The most promising areas are neurosymbol systems, a combination of transformer and specialized models, the integration of machine learning with reinforcement learning, knowledge graphs, external databases, search engines and distributed learning technologies.

In the conditions of the analyzed SHIVA and WARMI paradigms of the external environment, hybridization acquires additional significance. It allows moving from mostly static text processing models to adaptive intelligent systems that are able to take into account data dynamics, detect changes in the information environment, use relevant external knowledge, control uncertainty, and organize multi-level verification of results.

The combination of large language models with external knowledge, specialized ML modules, and verification mechanisms becomes especially important. This approach allows us to consider LLM not as an isolated universal tool, but as one of the components of a more complex intelligent linguistic architecture. Modern literature on Hybrid NLP confirms the prospects of such integration of machine and symbolic approaches.

At the same time, hybrid machine learning is associated with an increase in architectural and computational complexity, the need to coordinate heterogeneous models, control error transmission, and ensure interpretability. Therefore, the prospects of hybridization should be associated not with the maximum number of technologies that are combined, but with the rational design of their functional complementarity.

In the future, the development of hybrid machine learning in computational linguistics will shift towards adaptive, context-aware, neurosymbolic, and multi-agent architectures that combine LLM, knowledge graphs, specialized models, reinforcement learning, mechanisms for obtaining relevant information, and human-machine verification. It is such systems that are able to provide the combination of intelligence, adaptability, stability, understandability, and reliability necessary for modern philology in the conditions of uncertainty, turbulence, and systemic risks of the digital environment.

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