Using GPT-4 has made the educational website not just a repository of information, but a full-fledged learning assistant. AI has enhanced engagement, provided flexibility and personalisation - something that is lacking in traditional platforms. This approach can become the basis for new formats of online learning in Kazakhstan and beyond [5].

In conclusion, we would like to note that the introduction of artificial intelligence in personalised adaptive learning is a promising direction for the development of the educational system. Kazakhstan demonstrates activity in this direction by introducing innovative platforms and conducting research in the field of AI. International experience confirms the effectiveness of using AI to individualise learning and improve student performance. Further development and integration of AI in education requires a systematic approach, including training of specialists, developing infrastructure and providing access to modern technologies.

References

[1] Rysbekov, K.J., Zhumataeva, J.A. (2023). Realisation of personalised adaptive learning in the education system on the basis of artificial intelligence technology. Bulletin of NCPC "Өrleu No. 1(45), 72-79

[2] Nazarbayev Intellectual Schools. (2023). Beyim.ai - a new educational platform based on AI. URL: https://www.nis.edu.kz

[3] KAZ-LLM. (2024). Kazakh language model for the development of AI in education. URL: https://issai.nu.edu.kz/ru/kazllm-rus

[4] OpenAI. (2023). ChatGPT API Documentation. Retrieved from: https://platform.openai.com/docs

[5] Ministry of Science and Higher Education of the Republic of Kazakhstan. (2023). Digitalisation of education and introduction of AI into educational processes. URL: https://edu.gov.kz

MODEL THEORY AND MACHINE LEARNING:POINTS OF INTERSECTION

Issayeva A.[1], **Popova N.**[2], **Pankin Y.**[3]

[1,2]Karaganda Buketov University, Karaganda, Kazakhstan
[3]Karaganda University of Kazpotrebsoyuz
[1]E-mail: isaevaaiga@gmail.com

Annotation

This paper explores the key points of intersection between model theory—a branch of mathematical logic concerned with the interpretation of formal languages—and machine learning techniques. It examines the potential of using tools from model theory to formalize data models and learning algorithms, thereby enabling a deeper understanding of the expressive power and limitations of data-driven models. Particular attention is paid to generalization, formal verification, correctness of inference, as well as the formalization of environments and interaction rules in reinforcement learning tasks. The contribution of model theory to the development of hybrid and explainable artificial intelligence models is also discussed. The findings demonstrate that integrating model-theoretic approaches into machine learning opens new opportunities for building more robust, interpretable, and formally grounded intelligent systems.

Keywords: artificial intelligence, model theory, knowledge formalization, machine learning, explainable AI, hybrid systems.

Machine learning (ML) is a broad class of artificial intelligence techniques aimed at automatically discovering patterns in data and constructing models capable of generalization without explicitly programmed rules. Model theory, a subfield of mathematical logic, investigates the interpretations of formal languages and properties of logical structures, providing a powerful apparatus for describing and analyzing formal systems and semantic dependencies.

The synthesis of these disciplines creates a robust foundation for interpreting, explaining, and formally analyzing the behavior of learned models, which is especially crucial in high-stakes applications such as medicine, law, and autonomous systems.

A learning model in ML is a mapping $f : X\text{ß}Y$, where X is the feature space and Y is the set of target labels or actions. Model theory allows such mappings to be represented in formal languages, describing classes of functions as models of logical theories. For instance, classes of models approximable by neural networks can be represented as elementary classes in first-order logic (or its extensions, such as $L_(1,)$.)

This approach enables the investigation of expressive power, i.e., the set of functions that models can approximate, while preserving logical properties such as consistency, completeness, and correctness.

Generalization—the ability to perform well on previously unseen data—is a central goal in ML. A related concept in logic is the preservation of formula truth across models. Model-theoretic tools allow us to formalize the stability of a model with respect to data variation, for instance via theory stability (in the sense of Shelah), VC-dimension, or -categoricity, which ensures the uniqueness of countable models.

This also enables the identification of hypotheses about data that are logically well-founded and robust to noise and missing values.

An essential task in ML is verifying the correctness of a model: does it meet the required accuracy, avoid overfitting, and satisfy constraints? Model theory provides tools for formal verification of such properties:

- specifying a model as a structure satisfying a formula ;
- checking model compliance with invariants $_1, \ldots ,_n$;
- analyzing counterexamples via model checking.

These methods are especially important in applications where reliability is paramount, such as medical diagnostics, autonomous control, and financial forecasting.

In reinforcement learning (RL), an agent interacts with a dynamic environment and learns based on rewards and penalties. The environment can be formalized as a model over a signature that includes:

- a set of states S;
- a set of actions A;
- a transition function $T : S \times A \to Dist(S)$;
- a reward function $R : S \times A \to R$.

Model theory enables the formalization of such environments as structures MMM, defining the rules of dynamics. The learning process can then be analyzed as logical inference over a sequence of observations. This is crucial for the formal analysis of strategy correctness, environmental robustness, and principled selection of meta-strategies.

Modern AI approaches increasingly utilize hybrid models that combine heuristic, symbolic, and probabilistic components. Model theory serves as a foundation for:

- formalizing explainable decisions (explainable AI, XAI);
- constructing models with explicit semantics;
- logical inference over learned representations (e.g., Hoare logic applied to neural architectures);
- building trustworthy user interfaces where model behavior is formally interpretable.

Such systems, grounded in semantically meaningful representations, offer not only accuracy but also interpretability and verifiability, which is critical in socially significant domains.

Integrating model theory into machine learning enables the development of logically sound approaches to modeling and analysis. This deepens our understanding of generalization, reliability, logical expressiveness, and interpretability in artificial intelligence systems.

Thus, the synthesis of these disciplines opens promising avenues—from formalizing learning environments to constructing trusted hybrid systems that merge logical reasoning with the heuristic strength of statistical models.

References

[1] Кейслер Г., Чэн Ч.Ч. Теория моделей. М.: Мир, 1977. 615 с

[2] Yeshkeyev A.R., Issayeva A.K., Popova N.V.PAC-learning and J-o-minimality. Традиционная международная апрельская математическая конференция в честь Дня работников науки Республики Казахстан . – Алматы, 2025. –С. 289.

[3] Mitchell T. Machine Learning. — McGraw-Hill Science/Engineering/Math, 1997. ISBN 0-07-042807-7.

USING ARTIFICIAL INTELLIGENCE IN COMPUTER SCIENCE LESSONS

Kauymbek I.[1], **Seitimbetova A.**[2], **Tolegenkyzy D.**[3]

[1,2,3]Karaganda Buketov University, Karaganda, Kazakhstan
[1]E-mail: Indira_k79@mail.ru
[2]E-mail: Sab.buketov.2022@gmail.com
[3]E-mail: Dilnaz @gmail.com

Modern society is experiencing a stage of rapid technological progress. Artificial intelligence is becoming a part of everyday life, and education cannot stay away from these processes. Computer science as a subject has been teaching students the basics of digital literacy for several decades, and now it faces a new challenge — integrating AI into the educational process. This article discusses the possibilities and prospects of using AI in computer science lessons [1].

AI offers a wide range of opportunities to transform the learning process. Thanks to machine learning algorithms, it is possible to analyze students' academic performance, identify knowledge gaps, and form individual learning trajectories. For example, based on data analysis, AI can recommend certain tasks or topics to repeat.