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THE ANALYSIS AND THE ADAPTIVE CORRECTION OF LEARNING TRAJECTORIES WITH THE HELP OF AGENTS

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This paper proposes a novel architecture of a multi-agent system and its formal specification for analyzing and adaptively correcting students' learning trajectories using software agents in digital learning environments. The proposed approach integrates artificial intelligence tools, temporal logic, and a multi-agent system architecture to ensure personalized adaptation of educational content. The main objective is to create a system capable of automatically collecting data on students' academic activities, analyzing this data using machine learning techniques, and generating and evaluating individual recommendations. These recommendations can include participation in group studies, additional consultations, or enrolling in advanced courses depending on the students' performance dynamics. The proposed system model also includes metrics for evaluating the system's effectiveness, such as improved academic performance, increased engagement, reduced reaction time to difficulties, and student satisfaction. Neural network-based prediction is used to detect trends or deviations in students' learning patterns, which serve as the basis for dynamic adaptation of their learning path. The system uses Python and Keras frameworks to implement the analytical core, while monitoring and feedback mechanisms ensure real-time responsiveness. The proposed system model also includes metrics for evaluating the system's effecttiveness, such as improved academic performance, increased engagement, reduced reaction time to difficulties, and student satisfaction. Experimentally, the system was tested on a simulated student group studying "Parallel and Distributed Computing", with results indicating measurable improvement in performance and motivation. The study demonstrates that the use of intelligent software agents can enhance personalization in education and support students more effecttively. Future work may include deeper analysis of emotional and social factors, ethical considerations of AI-based decision-making, and large-scale deployment in institutional LMS platforms.

Keywords – learning trajectories, e-learning, cloud computing, agent, distributed computing, monitoring, machine learning, multi-agent systems.

Problem Statement

Howard Gardner's theory has caused a great resonance in the field of education, because knowing the strengths and weaknesses of students opens up the possibility for teachers to adapt learning to their individual abilities. Understanding students' strengths can significantly increase their self-confidence, unlock their potential, and improve their quality of life. According to Harvard University's philosophy, learning should not be an end in itself. The main thing is to instill in students an interest in learning, to make learning enjoyable and to help them unlock their potential (Morgan, 2021). The process of acquiring knowledge should be fun and help to reveal talents.

However, in today's environment, when teachers cannot pay enough attention to each student, it becomes almost impossible to optimize the curriculum for individual needs. There are numerous problems that prevent individualization of education at a sufficient level:

- Students have different academic backgrounds, interests, motivations, and learning styles. This makes it difficult to create one-size-fits-all learning paths that would suit everyone.
- For effective analysis, it is necessary to collect large amounts of data about students, including their grades, participation in the learning process, progress in learning, etc. The problem is that this data may be incomplete, inaccurate, or difficult to interpret.
- Sophisticated algorithms and models, such as machine learning or statistical analysis methods, are used to analyze learning trajectories. The problem is that these algorithms may require a large amount of data to train and may not always accurately predict student success or difficulties.
- One of the tasks of adjustment is to adapt learning trajectories to a specific student. The problem is that individualization can be difficult in massive learning environments where resources are limited.
- Personalizing learning paths requires evaluating their effectiveness, which can be difficult to do because learning outcomes cannot always be clearly measured using traditional assessment methods.
- Current learning management systems (LMS) may have limited functionality for collecting, analyzing, and using learning path data, making it difficult to implement personalized adjustments to learning trajectories.

Addressing these issues requires relies on methods from data analysis and approaches in educational psychology and pedagogy, supported by modern learning technologies.

The solution to these problems can be the use of agent-based systems. The main advantage of such systems is the automation of all processes. This is achieved by using data from learning management systems, which reduces the time it takes to process information about each student and improves the quality of this processing compared to the manual method. Agents are able to analyze and identify trends and patterns in data that may seem unrelated at first glance, enabling the system to make more accurate decisions. A personalized approach based on intelligent agent learning uses machine learning to ensure that decisions made by the system are based on the experience it has already gained. With each new generation of data, such solutions will allow for a more personalized approach and meet the needs of different groups of students.

Analysis of recent research and publications

Papers by Tapalova and Zhiyenbayeva (2022), Akhuseyinoglu et al. (2021), Walkington and Bernacki (2020), and Schmid et al. (2022) showed the results of analyzing the impact of teaching methods on students' academic performance. These conclusions became the basis for the creation of an agent-based system that can automatically detect trends in students' learning trajectories and correct them. The use of this data helped to improve the agent-based approach, in particular, to add functions for monitoring and analyzing students' behavioral patterns, which increased the accuracy of recommendations.

The study by Axak, Kushnaryov, and Tatarnykov (2023) demonstrated the need for an interactive platform for distance learning, which laid the foundation for the development of an intelligent agent-based system that allows not only to organize interaction between students and teachers, but also to automatically respond to changes in students' academic performance. This approach has been adapted in our methodology, where agents adjust learning trajectories based on students' current performance.

The work of Tseng (2020), with an emphasis on the use of agents for coordination and collaboration, inspired the creation of a multilayer system in which each agent has a specific function. This model allows for collective management of learning processes with the ability to quickly respond to individual student needs through constant monitoring and correction.

Studies by Fuady et al. (2021), Falcão et al. (2019), Ardini et al. (2022), Lismardayani and Oktavia (2021), Darko-Adjei and Ankrah (2020), and Al-Shaikhli (2023) have pointed out the shortcomings of existing LMSs, which were taken into account when developing our system. For example, the lack of flexibility of existing systems encouraged us to develop agents for individualized adjustment of learning trajectories, which eliminates these limitations. Our approach also solves communication problems between students and teachers through regular feedback that is integrated into the system.

Education systems include many components, such as learning management, progress tracking systems, electronic textbooks, and others. The main challenge is to integrate computer diagnostic methods to ensure their effective interaction.

Formulation of article objectives

The purpose of this study is to propose a novel architecture and a formal specification for analyzing and adaptively correcting students' learning trajectories using software agents, which will ensure individualization of the learning process, improve academic performance, and adapt educational content to the individual needs and characteristics of each student. The research is aimed at creating an effective system for monitoring and correcting learning trajectories that would automatically respond to changes in student performance, providing timely support and personalized corrective recommendations.

Main Results

Terminological framework of the study

The methodology of this study consists in designing a multi-agent system that implements the following methods:

− a data collection method using software agents;
− a method for predicting academic performance based on neural networks (using the Keras library);
− a method for formalizing processes by means of temporal logic (LTL);
− a method for adaptive correction of the learning plan.

We use:

− he system architecture of the multi-agent system (Fig. 1);
− a mathematical model of the monitoring and correction process formalized with temporal-logic operators (formulas (1) – (6));
− a predictive model based on a neural network (architecture, activation functions, optimizer, etc.).

Our work is grounded in the following approaches: an agent-based approach, a systems approach, and a personalized learning approach.

A formal specification (in the context of this study) is a description of the multi-agent system's behavior using the operators of temporal logic. It defines the obligations and interactions of agents through a set of logical formulas (1) – (6), ensuring unambiguous interpretation and verification of the system's properties, such as liveness (guaranteed reaction) and safety (continuous monitoring).

Research Result

The main outcome of this research is a model of a multi-agent system for the analysis and adaptive correction of learning trajectories. This model comprises several key components:

A system architecture (Fig. 1) that defines the interaction of specialized agents: data collection, analysis, modeling, correction, monitoring, and feedback.

A formal specification of agent behavior using temporal logic operators (formulas (1) − (6)), which ensures unambiguous interpretation and verification of system properties.

A decision-making mechanism based on neural network predictions, enabling the dynamic selection of optimal corrective strategies.

The proposed model is implemented using Python and the Keras framework, and it is designed for integration into modern learning management systems (LMS).

The method of the analysis and the adaptive correction of students' educational trajectories using agents

Let the system consist of a set of students $S = \{s_1, s_2, \ldots, s_n\}$ and the set of agents $A= \{a_1, a_2, \ldots, a_m\}$, where each agent performs a specific function related to the analysis, modeling, correction and monitoring of learning trajectories.

Fig. 1 shows the architectural model that involves the creation of a multi-layered system where different agents perform specific tasks aimed at adjusting students' learning trajectories.

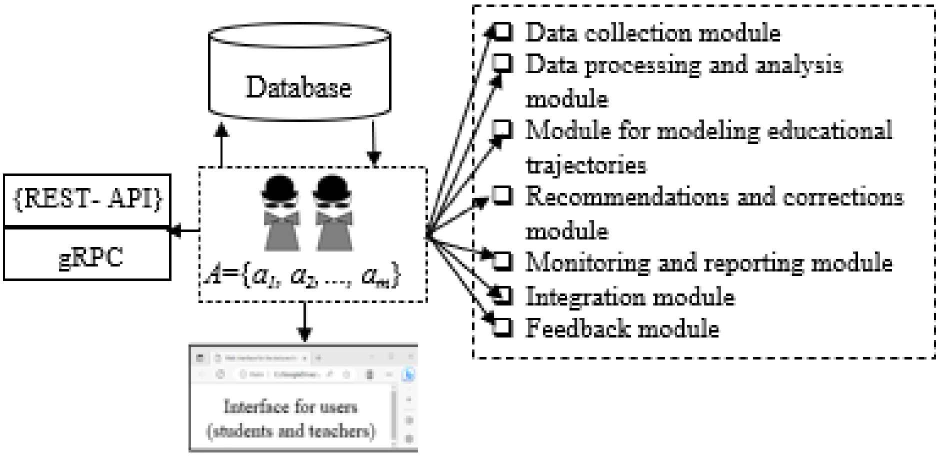

Fig.1. The system architecture for analyzing and adaptively correcting students' learning trajectories using software agents

To build a methodology for analyzing and adaptively correcting students' learning trajectories with the help of intelligent agents using temporal logic, we will use the following approach:

Data collection and processing. Input data vector hi there is a history of grades in various subjects $E_i=(e_1, e_2, e_3, \ldots)$; time spent studying the material $T_i= (\tau_1, \tau_2, \tau_3, \ldots)$; participation in scientific research $R_i= (r_1, r_2, r_3, \ldots)$; $P_i= (p_1, p_2, p_3, \ldots)$.

In this paper, we use temporal logic operators to formalize the system's operation. The main operators include: □ (or **G** «Globally») – means that some property must be fulfilled in all future states of the system; **F** («Future») – indicates that an event is to occur in the future.

For each student s_i data collection agent a_1 must at any given time t (i.e. constantly) be able to collect all the necessary data:

$$\forall s_i \in S \,\square\, \exists t\, \mathbf{G}\, a_1(t,s_i,E_i,T_i,R_i,P_i). \tag{1}$$

Creating agents for data collection and analysis. The data collection agent collects information about student progress from various sources.

The analysis agent applies a neural network in Python using Keras. The neural network analyzes the historical data of each student, identifies patterns and trends in learning - potential problems (lower performance, need for counseling, etc.) or successes (high performance, readiness for more complex tasks). Analysis agent a_2 for each student s_i from the set of students S at each time stage t conducts analysis, which results in “predict” - a prediction operation performed by a neural network:

$$\forall s_i \in S \,\square\, \exists t\, (a_2(t,s_i) \rightarrow \mathbf{F}\ \text{predict}(h_i,(E_i,T_i,R_i,P_i))). \tag{2}$$

Modeling learning trajectories. Based on neural network predictions, the trajectory modeling agent a_3 generates individualized recommendations.

The trajectory modeling agent a_3 should generate a learning trajectory for each student s_i after completing the analysis:

$$\forall s_i \in S \,\square\, (\mathbf{G}\, a_2(t,s_i) \rightarrow \mathbf{F}\, a_3(t',s_i)). \tag{3}$$

Adaptive correction of trajectories. The recommendation agent suggests individualized learning strategies, additional materials, or a change of trajectory based on continuous monitoring. The recommendation agent analyzes the neural network's predictions and suggests an individualized learning strategy from a set of possible actions (e.g., offering additional materials, recommending consultations, or adjusting the learning pace). The correction agent then automatically applies the most suitable corrective strategy based on the identified type of deviation and the predicted effectiveness of the intervention. Correction agent a_4 shall at any time t be able to select and execute the most suitable corrective strategy for the student's learning trajectory s_i, based on the type and severity of the detected deviation.:

$$\forall s_i \in S \; \Box \; (\mathbf{G} \; \text{deviation} \; (t,s_i) \rightarrow \mathbf{F} \; a_4(t',s_i)). \tag{4}$$

Monitoring and control. The monitoring agent continuously monitors students' progress, records changes in their learning trajectories and the effectiveness of corrective actions. The a_5 monitoring agent must continuously monitor the progress of each student s_i and provide reports:

$$\forall s_i \in S \; \Box \; \mathbf{G} \; a_5(t,s_i). \tag{5}$$

Feedback is provided through regular reports to teachers and students on progress and recommendations. Feedback agent a6 should receive and take into account feedback from students and teachers at any given time t:

$$\forall s_i \in S \; \Box \; \mathbf{G} \; a_6(t,s_i). \tag{6}$$

Performance evaluation. The following indicators are used to evaluate the results of adaptive correction of learning paths:

- Changes in students' academic performance, i.e. comparing the average grades of students before and after the implementation of individual trajectories. The metric is the percentage increase in average grades with the goal of increasing average grades by 10-15 %.
- Student engagement in the learning process is a measure of student activity in learning (the number of assignments completed on time, attendance, and active behavior in class). The metric is the number of completed assignments and tests before and after adaptive correction to increase engagement by 20 %.
- System response time is a measurement of the speed with which agents adjust learning paths after detecting problems with students. The metric is the average time between detecting a problem and correcting the trajectory, with the goal of reducing the response time to 24 hours.
- Student satisfaction - assessment of student satisfaction through surveys before and after the application of individualized recommendations. The metric is the level of satisfaction on a scale from 1 to 10 with the goal of increasing the level of satisfaction by 15 %.

Integration into the educational process. The integration agent integrates the results into the LMS or other learning system for ongoing use, taking into account the specifics of the course and the requirements of the instructors.

This specification provides a formal way to describe the behavior of a system of software agents that analyze and adaptively correct students' learning trajectories using temporal logic.

Experiments

To validate the proposed approach, the formal specification of the agent system's behavior, defined by the temporal logic formulas (1) – (6), was implemented in a simulated learning scenario. Let's consider an example where the specification is used to monitor and adjust a student's learning trajectory. A modeled situation in which students s_i are enrolled in the course "Parallel and distributed computing". During the first few weeks, students showed average results, but after the middle of the course, their performance began to decline. The program agent system should detect this trend and adjust the learning trajectory of such students.

Data collection agent a1 constantly collects information for each student in the form of a vector h_i= [e_1, e_2, e_3, τ_1, τ_2, τ_3, r_1, r_2, r_3, p_1, p_2, p_3]. The property of specification (1) ensures that the data is collected continuously.

Data normalization is performed using MinMaxScaler from the library scikit-learn. The simulation involves 100 students with 12 characteristics for each. The architecture of the neural network consists of three hidden layers for tasks with a relatively small amount of data. The ReLU (Rectified Linear Unit) activation function is used for the hidden layers. The activation function is used on the output layer sigmoid, which converts values in the range [0, 1] − the target result is success or a learning problem. To predict a successful trajectory or problems in learning, the loss function is used binary crossentropy. The main metrics are accuracy, which shows the percentage of correct predictions. The Adam optimizer was used because it adaptively adjusts the learning rate. The initial value learning rate is 0.001. For the tested model, 50 epochs were sufficient. Batch size Batch Size consists of 16 samples. To avoid overfitting the model, regularization techniques are used Dropout (disabling random neurons during training). Based on the predictions, the network generates individualized recommendations. For example, if a student has a decline in one subject, additional training or counseling may be recommended. If a student shows good results, more challenging assignments or participation in projects may be offered. Analysis agent a_2 reveals that student performance s_i is reduced according to specification (2). Based on the analysis, the system selects and applies a tailored corrective strategy. For instance, if a student shows a decline in a specific topic, the agent may choose to recommend additional training materials on that topic. Alternatively, if the decline is sharp, it might prioritize scheduling a consultation with a tutor. The system dynamically selects the most appropriate action from its available interventions based on the severity and nature of the predicted problem. Specification (3) ensures that this happens after analysis. If the student continues to deviate from the optimal trajectory, the correction agent a_4 Makes additional changes, for example, recommends other learning methods or contacting a tutor in accordance with the specification (4). Monitoring agent a_5 continues to monitor the student's progress after making adjustments. Specification (5) provides continuous control over the learning process. Feedback agent a6 collects feedback from the student about the new trajectory, and based on this, makes further adjustments or provides additional support according to the specification (6).

Correction agent a_4 found that the student s1 has problems with parallel numerical methods and recommended additional materials. These recommendations will be saved in the database, also available through the user interface and can be displayed in the console (Fig. 2).

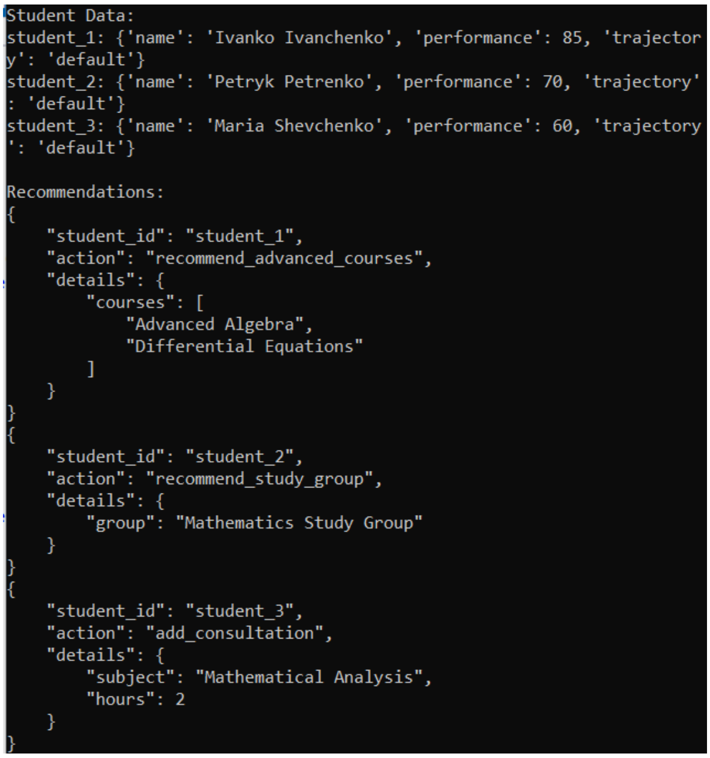

Fig. 2. Individualized recommendations

Student s_1 has an initial score of 50 in Parallel Computing. After applying the recommendations, the score is updated to 60. The system checks whether there is an improvement and displays a corresponding message (Fig. 3). As a result, the student improved his score by 20 % in the final test.

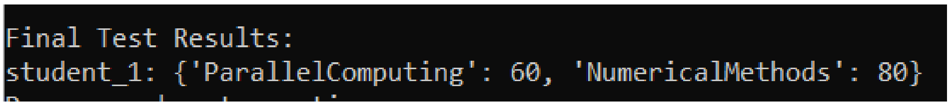

Fig. 3. The impact of recommendations on students' performance

Monitoring agent a_5 checks whether the student is having difficulty learning the material at the standard pace. It analyzes student data, and if the student's performance is below 75 %, the agent detects that the student is not coping with the standard pace of learning and makes adjustments (Fig. 4).

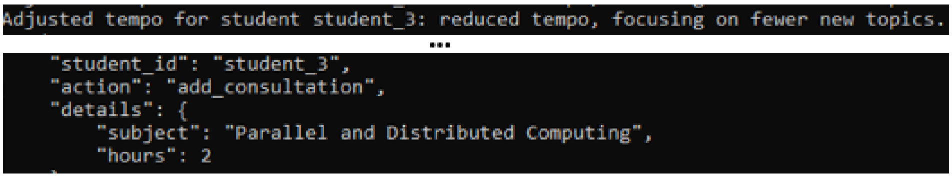

Fig. 4. The results of pace correction are displayed for each student

If the student's current pace is standard and his or her performance is below 75 %, the agent changes the pace to “reduced”. In addition to changing the pace, the agent also reduces the number of new topics that the student has to learn. If the student was learning 5 new topics for a certain period, this figure is reduced by 2 (but at least to 1 topic). The agent changes the number of new topics to a maximum between 1 and the current topics minus 2 (to avoid a situation where the student does not study new topics at all). For students with a productivity below 60 %, additional hours of consultation are added (5 hours). For students with a productivity of 60 % to 70 %, 2 hours of consultations are added. Students with a performance of 70 % to 80% are recommended to join a parallel computing study group. Students with performance above 80 % are recommended to take advanced courses in parallel algorithms and distributed systems.

This approach can be easily scaled or modified to take into account additional factors and provide more complex recommendations.

Conclusions

The main result of this research is the development of a multi-agent system model for the analysis and adaptive correction of students' learning trajectories. The proposed model includes several key components:

A system architecture that defines the interaction of specialized agents: data collection, analysis, modeling, correction, monitoring, and feedback. This multi-layered architecture ensures distributed task execution and system flexibility.

A formal specification of agent behavior using temporal logic operators (LTL), which ensures unambiguous interpretation and verification of system properties, such as liveness (guaranteed reaction) and safety (continuous monitoring). This formal foundation makes the system's behavior rigorous and predictable.

A decision-making mechanism based on neural network predictions, enabling the dynamic selection of optimal corrective strategies based on identified trends and deviations.

The model was implemented using Python and Keras frameworks and is designed for integration into modern Learning Management Systems (LMS). Experimental testing on a simulated group of students studying the "Parallel and Distributed Computing" course demonstrated its functionality. The results showed a measurable improvement in academic outcomes (a 20 % increase in performance in some cases) and student motivation through the timely provision of personalized recommendations, such as additional materials, consultations, or adjustments to the learning pace.

The study proves that the use of intelligent software agents can significantly enhance the level of personalization in education and provide more effective support to students by adapting learning content to their individual needs, learning pace, and specific difficulties in real-time.

Directions for future research include:

A deeper analysis of behavioral, emotional, and social learning factors to improve prediction quality.

The development of mechanisms for enhancing the allocation of learning resources.

Investigating the ethical and legal aspects of using artificial intelligence for decision-making in education.

Scaling the system and its large-scale implementation in institutional LMS platforms.

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**АНАЛІЗ ТА АДАПТИВНА КОРЕКЦІЯ ТРАЄКТОРІЙ НАВЧАННЯ
ЗА ДОПОМОГОЮ АГЕНТІВ**

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У цій статті пропонується нова архітектура багатоагентної системи та її формальна специфікація для аналізу та адаптивної корекції навчальних траєкторій студентів за допомогою програмних агентів у цифрових навчальних середовищах. Запропонований підхід інтегрує інструменти штучного інтелекту, часову логіку та багатоагентну системну архітектуру для забезпечення персоналізованої адаптації освітнього контенту. Головною метою є створення системи, здатної автоматично збирати дані про навчальну діяльність студентів, аналізувати ці дані за допомогою методів машинного навчання, а також генерувати та оцінювати індивідуальні рекомендації. Ці рекомендації можуть включати участь у групових заняттях, додаткові консультації або запис на поглиблені курси залежно від динаміки успішності студентів. Запропонована модель системи також включає показники для оцінки ефективності системи, такі як покращення академічної успішності, підвищення залученості, скорочення часу реакції на труднощі та задоволеність студентів. Прогнозування на основі нейронних мереж використовується для виявлення тенденцій або відхилень у моделях навчання студентів, що слугує основою для динамічної адаптації їхнього навчального шляху. Система використовує фреймворки Python та Keras для реалізації аналітичного ядра, а механізми моніторингу та зворотного зв'язку забезпечують оперативне реагування в режимі реального часу. Запропонована системна модель також включає показники для оцінки ефективності системи, такі як покращення академічної успішності, підвищення залученості, скорочення часу реакції на труднощі та задоволеність студентів. Експериментально систему було протестовано на змодельованій групі студентів, які вивчають «Паралельні та розподілені обчислення», і результати вказують на вимірюване покращення продуктивності та мотивації. Дослідження демонструє, що використання інтелектуальних програмних агентів може покращити персоналізацію в освіті та ефективніше підтримувати студентів. Подальша робота може включати глибший аналіз емоційних та соціальних факторів, етичних міркувань щодо прийняття рішень на основі штучного інтелекту та широкомасштабне впровадження на інституційних платформах LMS.

Ключові слова – траєкторії навчання, електронне навчання, хмарні обчислення, агент, розподілені обчислення, моніторинг, машинне навчання, багатоагентні системи.