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TIME PORTRAIT OF THE STUDENT'S BEHAVIOR AND POSSIBILITIES OF ITS USE

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The article is devoted to the study of the possibilities of a formalized description of the student's behavior during a certain cycle of education. A time portrait, which is a stylized representation of a time series, is offered as a typical description of student behavior. Aspects of the use of neural networks for the analysis and classification of student behavior for application in information systems supporting educational activities are considered.

Keywords*:* classification, student behavior, supporting educational activities, time series, neural network, machine learning.

1. Introduction

The limitation of human capabilities and the need to cover huge volumes of information, knowledge, and experience that have been accumulated for decades lead to the need for the emergence of computer intelligent systems that are capable not only of accumulating but also of analyzing data and processes.

This fully applies to information systems to support educational activities. Ensuring the ability of such systems to automatically store, in addition to traditional data, also time series creates the problem of analysis and classification of large volumes of such information. The development of artificial intelligence systems provides opportunities for solving these tasks and creates prerequisites for the growth of the functional capabilities of educational activity support systems.

2. Literature review and problem statement

It can be said that even now, the activities of each student during their studies at the university are described by numerous information tables, which are stored in the relevant archives. But quite often there is a need for an objective analysis of the activity of a specific student during a certain cycle of educational activity. So, for example, when admitting graduates to the next level of education, when preparing recommendations for exchange studies, etc. Only the numerical values of the obtained grades and the average score are often not enough, especially in the conditions of competitive selection. Therefore, it is necessary to use additional information, for example, motivational letters – but they are essentially subjective self-assessments and therefore not very suitable for a thorough analysis of the capabilities and habits of a certain individual.

The topic of using computer technologies to support the educational process has already been devoted to a large number of studies and publications. Several automated systems of this type have been created and are known in Ukraine, in particular, the Campus of Igor Sikorsky Kyiv Polytechnic Institute [1]. In recent years, this university has also created and implemented the MYKPI system to support the planning of the educational process [2]. These and similar information systems, as a rule, are built on the platforms of database management systems, and the main function implemented in such systems is the storage and accumulation of information on the conduct of classes, a list of tasks, and evaluations for their completion. As it seems, such information systems should be supplemented with elements of data analysis.

There are already quite a lot of publications on data analysis methodologies and approaches to creating intelligent support systems for educational activities. In particular, in [3] it is declared that conventional statistical evaluations are limited in providing good predictions about the quality of university education. The main approaches with both conventional statistical analysis and neural network modeling/prediction of students' performance were analyzed. Conventional statistical assessments are used to identify factors likely to influence student performance [3].

Research is actively being conducted on the implementation of ideas, methods, and tools of artificial intelligence, in particular its use in the field of providing educational services (AIEd). So, in particular, there is the International Society for Artificial Intelligence in Education (IAIED) – this is an interdisciplinary community in the advanced fields of computer science, education, and psychology. It promotes thorough research and development of interactive and adaptive learning environments for students of all ages in all areas.

In [4] proposed a student model with performance-related attributes using a student attribute matrix that quantifies student attributes for further analysis. This article also discusses student performance assessment tools using a neural network for classification, which can evaluate students' performance according to their prior knowledge, as well as the performance of other students who have similar knowledge. Indicators of student progress are proposed for a comprehensive description of student progress from various aspects, taking into account cause-and-effect relationships [4].

In [5] it is asserted that as an advanced field of artificial intelligence in education that depends on advanced computing technologies, the performance prediction model is widely used to identify at-risk students who tend to fail, establish student-centered learning paths, and optimize the design of learning and development [5].

In [6] it is declared that the trend of growth of educational data creates a need to extract useful information from models of learning behavior. It is proposed to use a publicly available set of educational data to study patterns of learning behavior to facilitate innovative management of education.

In [7] attempted to link and compare behavior patterns with known parameters of individual differences, such as self-esteem, gender, and knowledge monitoring skills. It is argued that the data-driven individual differences model performs significantly better than traditional individual differences models in predicting important parameters of the learning process, such as performance and engagement.

The idea of a graphical portrait of behavior was expressed in [8]. It seems that the issue of behavior classification based on a model in the form of such a portrait should be investigated in more detail. Then it is planned to use some known approaches to the analysis of time series [9].

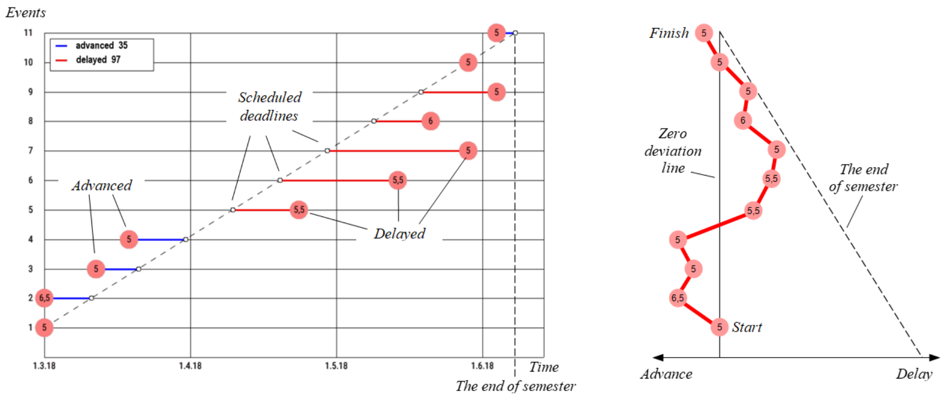
3. The aim and objectives of the study

The aim of this study is to create a formalized description of the behavior of students regarding the performance of tasks during a certain learning cycle to improve the reliability of the characteristics of each student during automated data analysis in information systems.

4. The study materials and methods of research student behavior

4.1. The object and hypothesis of the study

The object of the proposed research is a time portrait of student behavior. This is a stylized representation of a time series (Fig. 1).



The history of tasks performed by the student

The time portrait

Fig. 1. Time portrait – student’s behavior in time

The portrait graph (right) is a counter-clockwise rotated image of the task history graph (left). The vertical axis represents the control events and is the line of zero deviation in time from the planned deadlines for all tasks. A time portrait of a student is offered as a typical description of student behavior

4.2. Classification of student behavior during the semester

If we classify the behavior of students from the point of view of the timely completion of tasks, then several main varieties can be distinguished. This can be visualized by appropriate portraits of behavior. Each such portrait is distinguished by the geometric shape of a polyline that runs along the event nodes. To facilitate the recognition-classification of geometrical forms of portraits, it is possible to propose normalizing the dimensions, for example, scaling each portrait to size 1 vertically (events normalization) and horizontally (time normalization) (Fig 2).

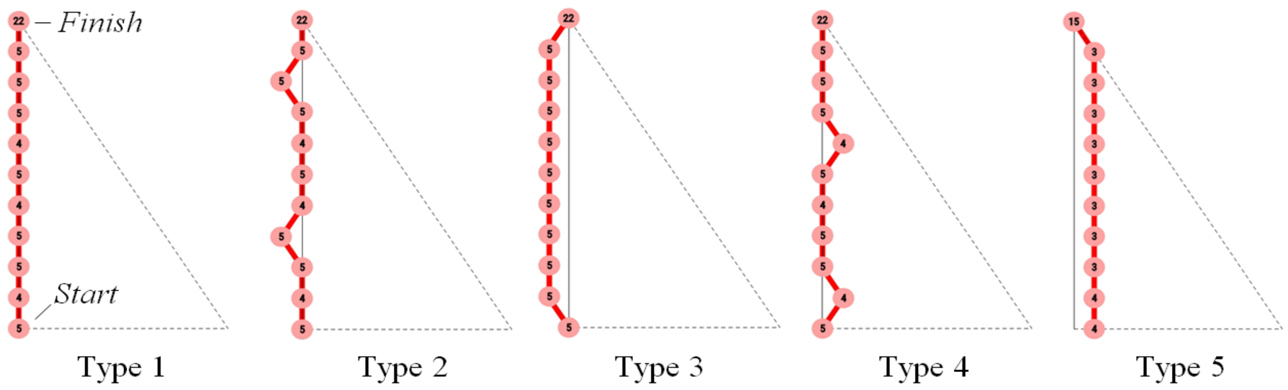


Fig.2. Types of portraits of excellent or good behavior

Type 1. Timely and systematic execution of all tasks. This can be considered an ideal model of behavior.

Type 2. Episodic small advance.

Type 3. Constant small advance. If this happens to many students, then this may be the first sign of the need to significantly change the package of tasks for the next academic year.

Type 4. Episodic slight delay (no more than a week)

Type 5. Constant slight delay (no more than a week). The student may try to complete assignments on time, but may not be able to adjust to the pace and/or difficulty of the assignments.

The next group consists of portraits of problematic behavior (Fig. 3).

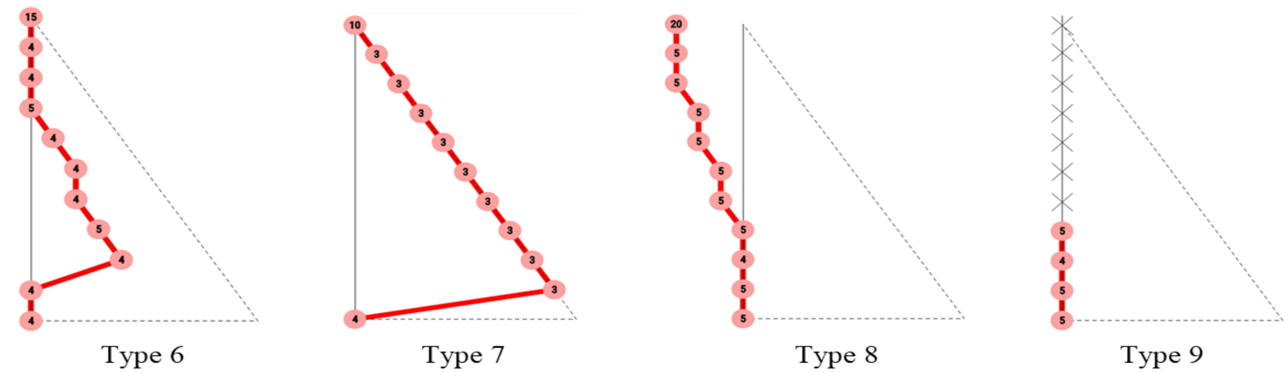


Fig.3. Types of portraits of some problematic behavior

Type 6. An episode of significant delay (for example, illness)

Type 7. No work during the semester – completion of all assignments at the end of the semester at the same time. This type of behavior usually indicates a student's poor attitude toward learning. There may be suspicions of falsification of assignments, and plagiarism.

Type 8. Significant advance, premature surrender. A somewhat exotic type, but it took place in individual cases, for example, in connection with a referral for part-time study (internship) in an educational institution in another country.

Type 9. Termination of studies or temporary suspension (academic leave).

The above types are quite idealized. In reality, there can be an infinite set of portraits of student's behavior. It is necessary to somehow classify the types of behavior, given the fact that the boundaries for each type may be fuzzy. So, in particular, the question may arise – to what type should such behavior portraits be classified? (Fig. 4).

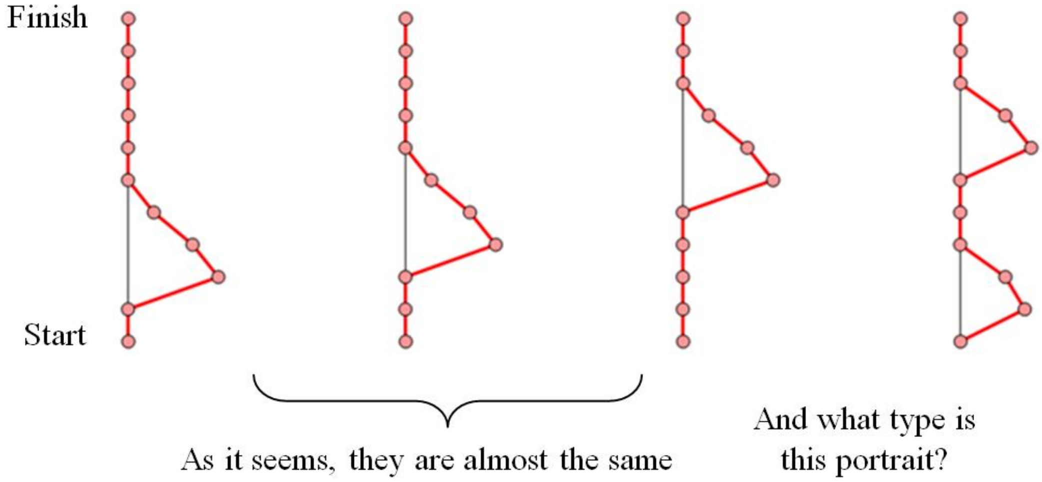


Fig. 4. Similarities and differences in the forms of portraits

To what type are these portraits classified? It seems obvious enough to classify the three portraits on the left as Type 6. The line of the portrait on the right also indicates the presence of significant task lag. If the main feature of Type 6 is not the shape of the line, but the presence of one or more episodes of significant delay, then the portrait on the right can also be classified as Type 6. But here everything may not be so unambiguous.

It is often quite difficult for a human to analyze and classify data when it needs to be processed quickly.

4.3. Using the neural networks for behavior recognition

A neural network may be useful for solving such classification tasks. For the classification of the types of academic performance, a neural network of the multilayer perceptron type was chosen with separate outputs for each type of classification. From the point of view of memory costs and speed, one network with several outputs is better. From the point of view of recognition accuracy, it is more expedient to use separate subnetworks with single outputs for each type of classification. In the latter case, the setup of an ensemble of subnetworks will be described by a large number of weight coefficients, which will indicate potentially greater diversity, while the training process can be performed for each subnetwork separately, which allows you to appropriately limit the training time at the subnetwork level (Fig. 5).

Thus, the main parameters of the classification model are the number of types of student behavior that a neural network should be able to recognize. Another important parameter will be the length of the time series being analyzed, i.e., the number of tasks, or, generally speaking, the events of the occurrence of which need to be analyzed. It is also required to provide that a system configured and trained, for example, to analyze the implementation of 10 tasks, could analyze the implementation of a different number of tasks without significant restructuring.

To facilitate the automatic recognition of various geometric shapes of portraits, it is possible to propose normalizing the dimensions, for example, scaling each portrait to size 1 vertically (events) and horizontally (time). Just as when recognizing objects in photographs, it is advisable to bring them to uniform dimensions (resolution), so it can be useful when recognizing images of time portrait lines. Such scaling can be performed by spatial interpolation.

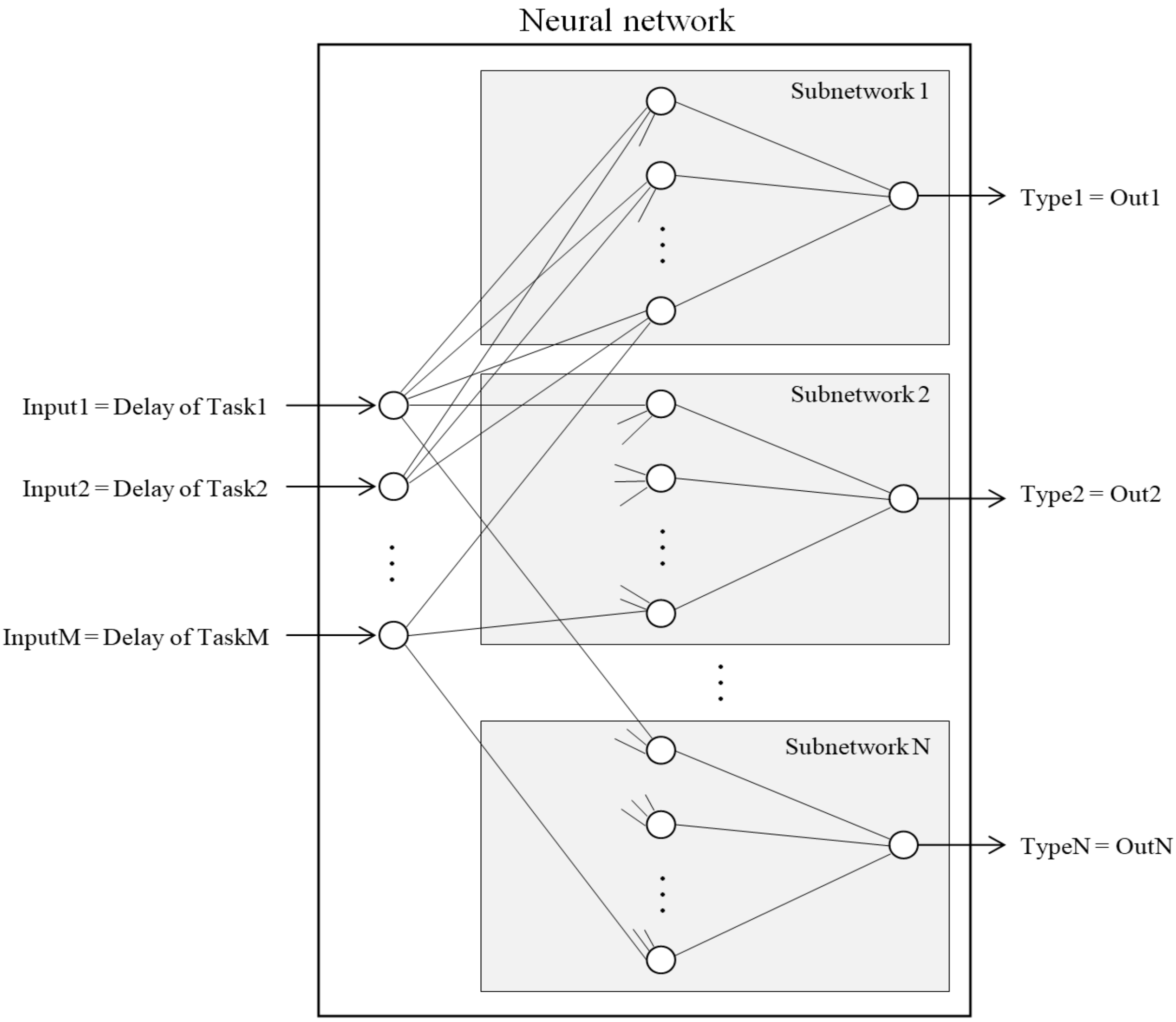


Fig. 5. A model of a classification neural network

The neural network is implemented by the author of the article in the form of a C++ program module for the Windows platform for research purposes, as well as a Java class for embedding in Android applications. The neural network was simulated at the software level. The set of values of weight coefficients obtained as a result of network training is stored in a file. To perform classification tasks, the values of the weighting coefficients are loaded from a file into working arrays in memory.

5. Results of investigations of portraits recognition

To train the neural network, the results of solving the tasks of several groups of students were used. Data sets were formed, each of which is classified as one of the above-mentioned types of student behavior portraits.

The training was performed by the method of *back-propagation errors* [10]. When calculating the increments of the weights of connections Δw, the following training parameters were used: ε – is the learning rate and α – is the coefficient taking into account the change in the weight increment of the given link at the previous iteration. The formula for incrementing the connection weight from neuron *A* to neuron *B* is as follows:

$$\Delta w_{A-B}^{i} = \varepsilon \cdot \delta_B \cdot OUT_A + \alpha \cdot \Delta w_{A-B}^{i-1}, \tag{1}$$

where: OUT_A is the output value of neuron A; δ_B is the fraction of the error calculated for neuron B taking into account the layer in which the neuron is located.

The learning process is designed as a sequence of epochs. In each epoch ($Epoch_i$) the network scans all input data sets (Set_j) selected for training. Thus, $Epoch_i = \{Set_1, Set_2, \ldots, Set_n\}$. During the network training cycle, for each epoch, the total square error of the dataset was calculated separately for each output. For one m-th network output, which indicates the corresponding classified m-th type, the error was calculated by the formula:

$$\Delta epoch_{i,m} = \frac{1}{n}\sum_{j=1}^{n}\left(OUTideal_{j,m} - OUTactual_{j,m}\right)^2, \tag{2}$$

where: *OUTideal* is the desired value, *OUTactual* is the output of the network. If a student has to complete 7 tasks, then the neural network must have 7 inputs. Aspects of network learning in the presence of additional elements that calculate *Min* and *Max* input values were also analyzed (Fig 6).

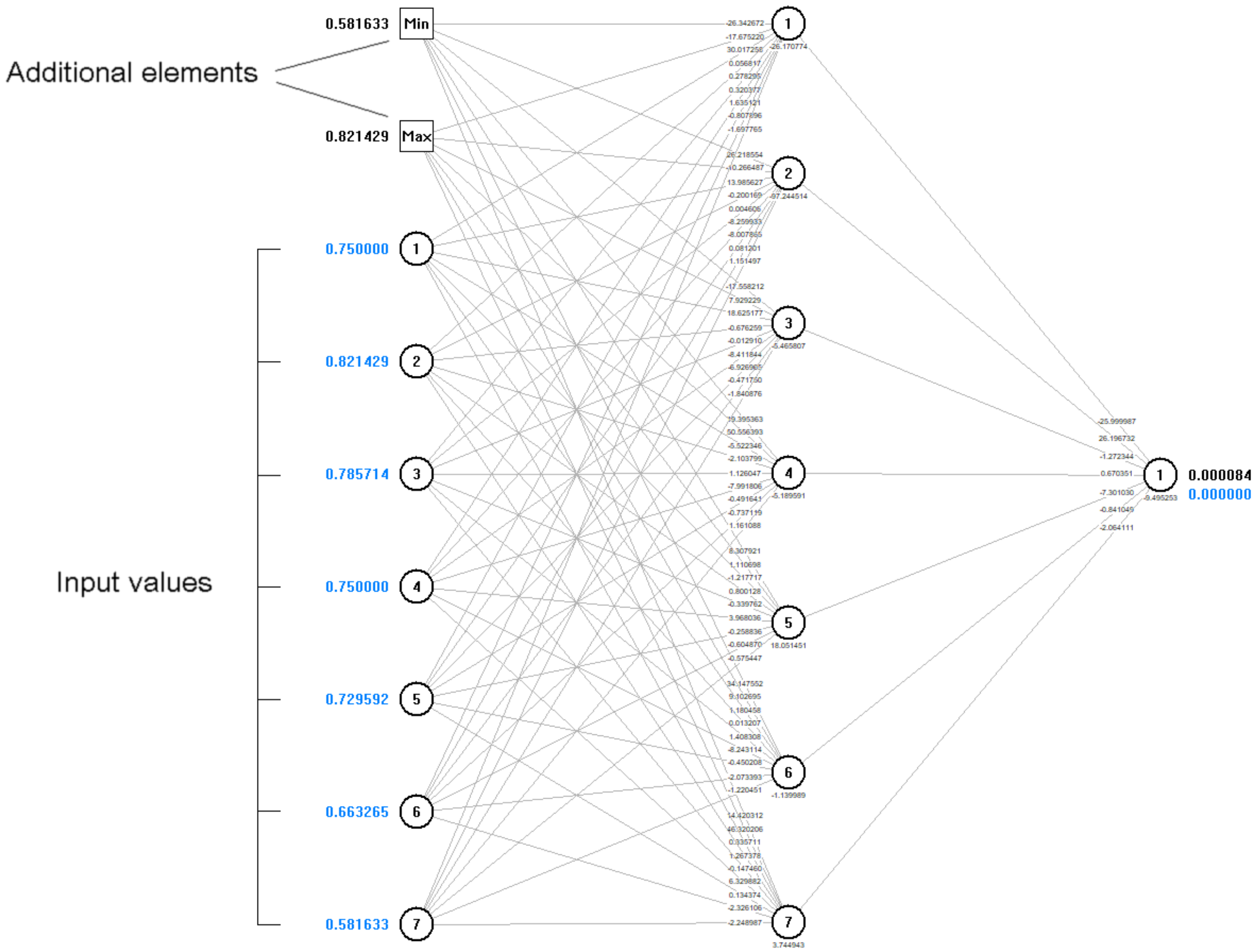


Fig. 6. A current state of neural subnetwork for one type of portrait recognition

Below are some results of neural network training experiments for parameter values $\alpha = 0.3$ and $\varepsilon = 0.05$, 0.1, 0.2 and 0.3 with and without additional *Min*, *Max* elements (Fig. 7).

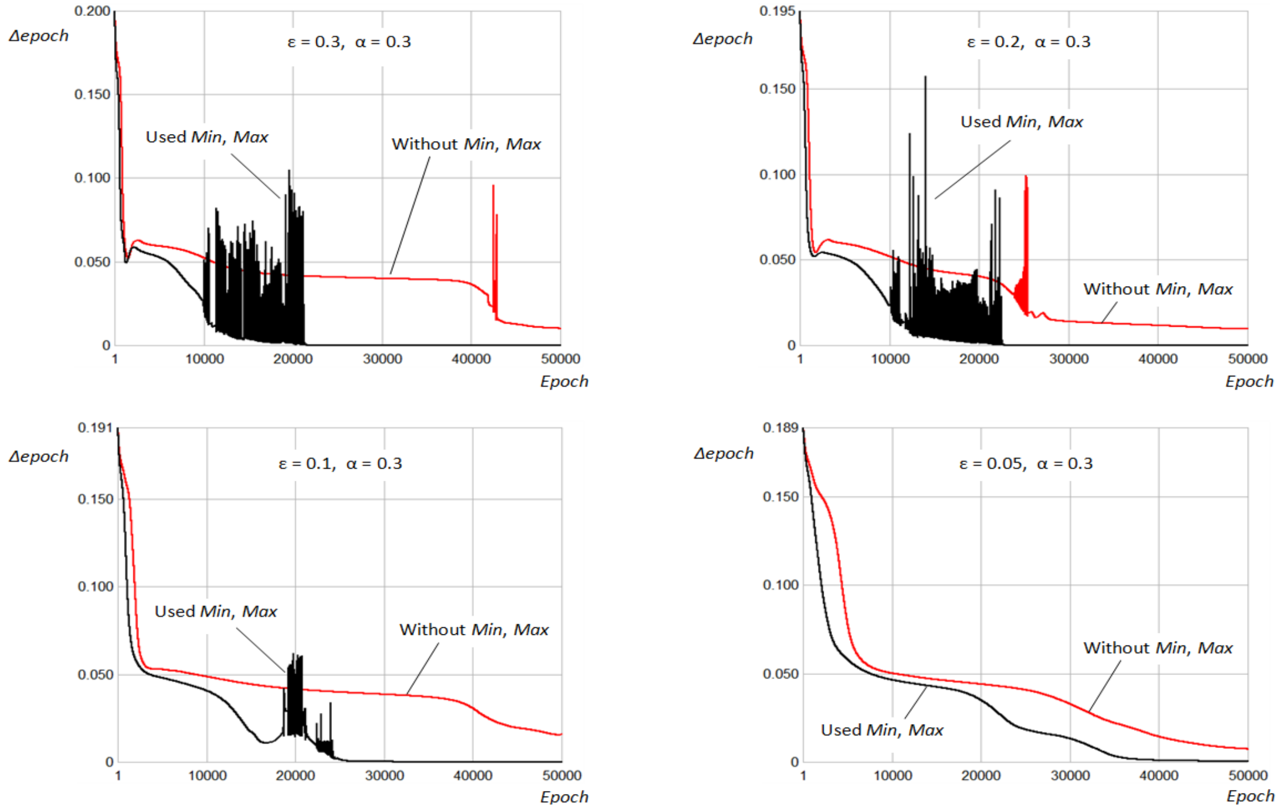


Fig. 7. Network learning curves for classification Type 4

The training process was performed by the network on a dataset containing 67 samples. For each set of values of the parameters ε and α, 50000 epochs of error back-propagation were performed with the same starting values of the wires coefficients. According to the results of the experiments, it can be noted that the presence of additional *Min*, *Max* elements generally has a positive effect on the training result, in particular, an acceptable value of the classification error is achieved for a smaller number of epochs.

6. Analysis of the obtained results of of portraits recognition

It can be claimed that as a result of the conducted experiments, the possibility of automated classification of student behavior during the semester has been proven. Classification accuracy is largely determined by the completeness of training datasets for neural networks. The effect of the numerical values of parameters of the back-propagation errors process on the stability and convergence of the learning process of the neural network when working with time portraits was also revealed.

It should be noted that the use of the convolutional neural network technique can also be considered to solve the problems of identifying typical forms of time series curves [11].

It should not be assumed that a comprehensive description of the student's activities is an end in itself and can only be used for recording and documentation. So, for example, for students whose behavior portrait classification is type 7, it seems quite risky to issue positive characteristics for involvement in research work.

As it seems, the student's behavior is determined not only by his characteristics. There are at least three important factors that determine the behavior of students – the education system, family, and society. It is important to be able to identify trends and use them to improve processes.

The possibilities of describing and analyzing the behavior of individual students can be used as a component of the analysis of the education system at different levels of consideration. For example, when analyzing certain types of student groups. The formalization of the description of student behavior during education opens up opportunities for the use of various data analysis tools to identify the influence of external factors on student behavior and learning outcomes at all levels – from the excellence of courses and educational programs, the characteristics of student interaction with teachers, to the quality of university management, the state of the employment market and to the state of society in general. It is also possible to set the task of researching the impact of student behavior on other elements of some system. This can become a direction of further research on this topic.

7. Conclusions

A method of formalized description of students' behavior during a defined learning cycle is proposed. This description is called a temporary portrait of a student. It is proposed to store a time portrait of each student to ensure further analysis of the behavior of both an individual student and a certain team.

The storage of such portraits in the information system of the educational institution opens the possibility of in-depth data analysis to make decisions regarding the optimization of the management of the educational process.

The possibility of using neural networks of artificial intelligence for the analysis of learning processes by classifying the behavior of students during the semester has been proven.

The results of the research can be used in various computerized systems for supporting educational activities.

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ЧАСОВИЙ ПОРТРЕТ ПОВЕДІНКИ СТУДЕНТА ТА МОЖЛИВОСТІ ЙОГО ВИКОРИСТАННЯ

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Об'єктом дослідження, представленим у цій статті, є процес класифікації поведінки студентів на основі формалізованого опису виконання завдань впродовж певного циклу навчання.

Метою дослідження є створення формалізованого опису поведінки студентів щодо виконання завдань впродовж певного циклу навчання задля покращення достовірності характеристики кожного студента при автоматизованому аналізі даних в інформаційних системах.

Для того, щоб досягти цієї мети, запропоновано часовий портрет студента поведінки студента. Це стилізоване представлення часового ряду у вигляді лінії, форма якої репрезентує запізнення або випередження термінів виконання завдань при вивченні певної дисципліни. Виділено основні типи поведінки студентів. Кожному типу поведінки відповідає форма лінії на часовому портреті.

Для наділення інформаційних систем можливостями аналізу поведінки досліджено питання класифікації портретів нейронними мережами. Запропоновано виконувати класифікацію з використанням багатошарової нейронної мережі. Задля прискорення навчання та зручності подальшої класифікації запропоновано розділити мережу на декілька субмереж, кожна з яких може навчатися окремо. Проаналізовані питання відповідного навчання нейронної мережі на основі датасетів реальних навчальних занять з групами студентів. Доведена здатність нейронної мережі класифікувати портрети поведінки студентів.

Результати виконаного дослідження можуть бути використані для аналізу даних у комп'ютеризованих системах підтримки навчання

Ключові слова: класифікація, поведінка студентів, підтримка навчальної діяльності, часові ряди, нейронні мережі, машинне навчання.