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AUTOMATIC MACHINE LEARNING METHODS USAGE TO PREDICT NATURAL PHENOMENA

Automated machine learning, also named as automated ML or AutoML is the process of automating the complex, time-consuming and repetitive tasks of developing machine learning models. Machine learning methods enable computers to operate autonomously without explicit programming.

***The purpose** of the work is to investigate the use of automatic machine learning methods for forecasting progenitor phenomena. Machine learning applications are fed with new data, and they can independently learn, grow, develop, and adapt. Machine learning is based on finding complex and non-obvious dependencies in existing data about past emergency and risky situations. Machine learning uses data from other earthquakes, natural disasters or other various processes.*

***The scientific novelty** is to use machine learning to predict the occurrence of a natural phenomenon. As a result, the algorithm finds patterns that may signal an approaching disaster. With the help of it data scientists can subsequently build machine learning models with high scalability, efficiency, and performance while maintaining model quality.*

***The methodology** is based on machine learning algorithms formed on the basis of a training data set to create a model. As new input data is introduced to the trained machine learning algorithm, it uses the developed model to make a prediction.The usage of automated machine learning could help effectively forecast local disasters and subsequently improve forecasting performance. Machine learning algorithms typically consume and process data to learn the related patterns about individuals, business processes, transactions, events, and so on. The function of a machine learning system can be descriptive, meaning that the system uses the data to explain what happened; predictive, meaning the system uses the data to predict what will happen; or prescriptive, meaning the system will use the data to make suggestions about what action to take. In the following, we discuss various types of real-world data as well as some categories of machine learning algorithms.*

***Conclusion:** as a result of this article, the new software product and the performed analysis can be used for further integration, analysis and research.*

***Key words:** Automated machine learning, AutoML, natural phenomena.*

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ВИКОРИСТАННЯ МЕТОДІВ АВТОМАТИЧНОГО МАШИННОГО НАВЧАННЯ ДЛЯ ПРОГНОЗУВАННЯ ПРИРОДНИХ ЯВИЩ.

У статті описані методи автоматичного навчання для прогнозування природних явищ. Автоматизоване машинне навчання, яке також називають автоматизованим ML або AutoML, – це процес автоматизації складних, трудомістких і повторюваних завдань розробки моделей машинного навчання. Методи машинного навчання дозволяють комп'ютерам працювати автономно без явного програмування.

***Мета роботи** полягає в дослідженні використання методів автоматичного машиного навчання для прогнозування прородних явищ. Програми машинного навчання отримують нові дані, і вони можуть самостійно навчатися, рости, розвиватися та адаптуватися. Машинне навчання засноване на пошуку складних і неочевидних залежностей в існуючих даних про минулі надзвичайні та ризиковані ситуації. Машинне навчання використовує дані інших землетрусів, стихійних лих або інших різних процесів.*

***Наукова новизна** полягає у тому щоб за допомогою машиного навчання спрогнозувати появу стихійного явища. У результаті алгоритм знаходить закономірності, які можуть сигналізувати про наближення катастрофи. За допомогою цього науковці можуть згодом створювати моделі машинного навчання з високою масштабованістю, ефективністю та продуктивністю, зберігаючи при цьому якість моделі.*

***Методолгія** базується на алгоритми машинного навчання формуються на основі навчального набору даних для створення моделі. Коли нові вхідні дані вводяться в навчений алгоритм машинного навчання, він використовує розроблену модель для прогнозування. Використання автоматизованого машинного навчання може допомогти ефективно прогнозувати локальні катастрофи та згодом покращити ефективність прогнозування. Алгоритми машинного навчання зазвичай споживають і обробляють дані, щоб вивчати пов'язані шаблони про людей, бізнес-процеси, транзакції, події тощо. Функція системи машинного навчання може бути описовою, тобто система використовує дані, щоб пояснити, що сталося; прогнозний, тобто система використовує дані, щоб передбачити, що станеться; або наказовий, що означає, що система використовуватиме дані, щоб вносити пропозиції щодо того, які дії вжити. Далі ми обговорюємо різні типи даних реального світу, а також деякі категорії алгоритмів машинного навчання.*

***Висновок:** як результат цієї статті новий програмний продукт та виконаний аналіз може бути використанним для подальшого інтегрування, аналізу та дослідження.*

***Ключові слова:** Автоматизоване машинне навчання, алгоритми машинного навчання, AutoML, природне явище.*

Introduction. A natural disaster is a destructive natural event or process of significant scale, as a result of which a threat may arise or has arisen to the life and health of people, destruction or destruction of components of the natural environment. Natural disasters can occur independently of each other or together: one of them can lead to another, for example, earthquakes cause landslides, fires, avalanches, mudflows, tsunamis, floods, gas pipeline ruptures, damage to communications, power lines, water supply and sewerage, accidents at chemical enterprises with emissions (spills) of hazardous chemicals, as well as at nuclear power plants with leaks (emissions) of radioactive substances into the atmosphere, etc. In turn, disasters such as tornadoes and flash floods are short-term destructive events affecting a relatively small area. Other disasters, such as droughts, develop slowly but can affect almost an entire continent and entire countries within months or even years. In temperate latitudes, severe thunderstorms can be accompanied by large destructive hailstones, tornadoes, strong winds and rain leading to flash floods. Winter thunderstorms with strong winds, heavy snowfall or freezing rain can also contribute to avalanches on some mountain slopes and high runoff or flooding during the following snowmelt season. Natural disasters often arise as a result of not always reasonable human activity (for example, peat and forest fires), industrial explosions in mountainous areas, during the construction and operation of dams, quarries, which often leads to landslides, snow avalanches, and glacier collapses. Regardless of the source of occurrence, natural disasters are characterized by significant scale, destruction and varying duration – from several seconds and minutes (earthquakes, avalanches) to several hours (mudflows), days (landslides) and months (floods). Disaster management aims to significantly reduce the number of casualties, as well as reduce social and environmental damage. But some of them cannot be predicted when they will appear and what areas they will cover.

Disaster monitoring and forecasting. The main goal of monitoring dangerous disasters and processes in nature is to improve the accuracy and reliability of the forecast of natural phenomena based on a combination of technological, intellectual and information capabilities of various organizations monitoring certain types of hazards. Monitoring data serves as the basis for further forecasting of dangerous disasters. Also, the more accurate and faster forecasting data is obtained, the more timely and better people will have time to prepare for the danger that awaits them.

Forecasting is based on many factors and different elements. One of them is information about the forecast object, revealing its behavior in the past and present, as well as the patterns of its behavior. But there are also disasters that can appear unexpectedly and behave unpredictably, which makes it difficult to further predict the occurrence of this disaster, as well as its further behavior after its occurrence.

Disaster predictions methods.

Natural disaster forecasting consists of scientifically based forecasting of their development, occurrence, nature and scale. The method of forecasting natural disasters should be understood as a method for solving the problem of forecasting a specific natural disaster with a certain lead time and using certain initial observational materials. Obviously, as the lead time of the forecast decreases, its accuracy should increase.

Depending on the waiting time for a natural disaster, forecasts are divided into short-term (less than 12-15 days) and long-term (with greater lead time).

Method – a complex technique, an ordered set of simple techniques aimed at developing a forecast as a whole, a way to achieve the goal, based on knowledge of the most general laws.

Forecasting methods (methods) – a certain set of techniques (methods) for performing forecasting operations, obtaining and processing information about the future based on homogeneous forecasting methods. Forecasting methodology is a field of knowledge about methods, methods, forecasting systems. Forecasting methodologies were divided into the following categories: foresight, goal setting, planning, programming, design, process development prospects in order to identify problems to be solved.

A forecast development methodology is a selected specific combination of forecasting techniques and methods. A forecasting system ("forecasting system") is an ordered set of techniques and technical means designed to predict complex phenomena or processes.

Forecasting technique – a specific form of theoretical or practical approach to the development of a forecast; one or more mathematical or logical operations aimed at obtaining a specific result in the process of developing a forecast. At the heart of all methods, methods and techniques of forecasting is a heuristic or mathematical approach. The essence of the heuristic approach is to use the opinions of experts. It finds applications for predicting processes that cannot be formalized.

The mathematical approach consists in using the available data on some characteristics of the predicted object, processing them by mathematical methods, obtaining a dependence that connects these characteristics with time, and calculating the dependence of the object's characteristics at a given point in time according to the data.

This approach involves the use of modeling or extrapolation. Forecasting in most cases is the basis for the prevention of natural and man-made emergencies.

In the mode of daily activities, the possibility of natural disasters is predicted – the occurrence of an emergency, its place, time and intensity, the possible scale and other characteristics of the upcoming event.

In the event of a natural disaster, the course of the development of the situation, the effectiveness of certain planned measures to eliminate the emergency, the required composition of forces and means are predicted. The most important of all these forecasts is the forecast of the likelihood of a natural disaster. Its results can be most effectively used to prevent accidents and reduce possible losses and damage in advance.

Overview of machine learning methods.

Machine learning is a branch of artificial intelligence (AI) that studies methods and algorithms that allow computer systems to automatically learn from data and make predictions or decisions without explicit programming. Unlike traditional programming, where the developer explicitly defines the instructions used by the system, in machine learning the model is trained based on the data provided, and the results of the training become the basis for making further decisions (Кримінісі, Шоттон, 2011, с. 5).

There are several main approaches to machine learning:

1. Supervised learning – process of training a model based on labeled data, where each example has a corresponding label–the desired output of the model. (Гертс, Ернст, Вехенкель, 2006, с. 20). The goal of the model is to find patterns in the data in order to predict labels for new, unknown examples. This approach includes the following methods:

a. Support Vector Machine (SVM). SVM is a powerful algorithm for classification and regression problems. It constructs a hyperplane that separates examples of different classes with the largest gap.

b. Decision trees and random forest. Decision trees are a tree-like structure of decisions, where each node contains a condition on one of the data features. A random forest is an ensemble of decision trees. They are widely used for classification and regression.

c. Neural networks. A model created based on the functioning of the human brain. Neural networks consist of artificial neurons and connections between them. They have been successfully applied in various fields, including computer vision, natural language processing and speech recognition.

2. Unsupervised learning – is a branch of machine learning in which models analyze data and find hidden structures in it without pre-labeled data. This approach can automatically extract information from large amounts of data, making it especially useful when working with unstructured data such as images or audio recordings (Рендл, 2012, с. 2). The use of unsupervised learning allows you to solve problems such as:

a. clustering. It is the process of grouping objects based on their similarities. Clustering methods divide data into groups so that the objects within each group are similar to each other. Clustering is used for social network analysis, outlier detection, and data mining tasks;

b. dimension reduction. For problems where the feature space is too large or noisy, unsupervised learning can help reduce the dimensionality of the data while preserving the most important information. Dimensionality reduction using a method such as principal component analysis allows data to be projected onto a new lower dimensional space with minimal loss of information;

c. associative analysis. The goal of association analysis is to discover hidden relationships or rules between objects in a data set. Associative analysis algorithms find frequently occurring combinations of products or attributes and allow you to build recommendation systems, analyze purchasing behavior, or conduct marketing research.

3. Weak supervision is one of the machine learning approaches that combines the advantages of both supervised and unsupervised learning. In this method, the model is trained on data where only some part has labeling (Хакелінг, 2017, с. 2). This can be especially useful in cases where it is difficult to obtain labeled data. There are several approaches to learning with weak supervision:

a. clustering based methods. In this approach, unlabeled data is first clustered and then each cluster is assigned a class label based on the available labeled data;

b. graph-based methods. In this approach, data is represented as a graph, where nodes represent examples of data and edges represent connections between them. Markup propagation techniques are then used to extend the class labels based on the existing ones.

4. Reinforcement learning is teaching a software agent how to behave in an environment by telling it how well it's doing (Педрегоса, 2011, с. 6). The environment can be real or virtual. The agent interacts with the environment and learns to accept a sequence of actions in the environment, after which it receives feedback in the form of a reward or penalty. One of the main components of reinforcement learning is the state estimation function, which predicts the expected reward. The agent's goal is to adjust its action strategy in such a way as to maximize the accumulated reward throughout its interaction with the environment. The agent uses this function to select optimal actions and evaluate its current state. One of the most popular algorithms in reinforcement learning is the Q-learning method. In this method, an agent is trained to evaluate and select actions based on the value of a Q-function, which represents the expected total reward for performing an action in a certain state (Сейєд-Мохсен, Альгусейн, Паскал, 2016, с. 2574). The Q-learning algorithm is based on the principle of iteratively updating the value of the Q-function based on the accumulated reward and subsequent selection of optimal actions.

Statement of the problem. In this work, a solution using a forecasting intelligence system as well as machine learning methods for the system is proposed and will be considered. The main advantages of forecasting systems based on artificial intelligence compared to other methods are:

- ability to self-learn
- significant potential for analyzing large volumes of statistical data to search for correlations and patterns between events.
- the ability to model non-linear processes without explicitly specifying correlations between actual and expected data
- increased forecasting accuracy compared to other "classical" forecasting methods
- high performance due to distributed and parallel calculations

The most tangible advantage of artificial intelligence based on neural networks over mathematical forecasting methods is not only the ability to learn from data, but also to adapt taking into account newly acquired data and accumulated experience, which is an integral part of cognitive computing, which increases the effectiveness of forecasting on large volumes of data.

To solve the forecasting problem a model containing the following data set can be created:

- event date
- place/region of event
- event type
- power/destructiveness of the event

- caused material damage
- human casualties
- related events.

Prediction comes down to the task of reconstructing a function in the context of supervised learning. Additionally, it is proposed to use gradient boosting – at the initial iterations, weak algorithms will be used with gradual complication and improvement of those data sets where the previous iterations showed a result that does not meet acceptable reliability criteria (Карліні, 2017, с. 52).

The model for predicting emergency events can be presented as follows:

$$M = \{PS, TS, AS, LFS, RI\} ,$$

where *PS* – input parameters set, *TS* – training set, *AS* – set of basic algorithms used for gradient boosting, *LFS* – set of loss functions, *RI* – result information.

Solving a forecasting problem using machine learning consists of the following processes:

- initialization and normalization of input data
- forecasting over a given time interval
- visualization of forecasting results
- making decisions.

The proposed architecture of the forecasting system, which solves the problems described above, is presented in Figure 1. On low level we propose to chose perceptron architecture (see Figure 2).

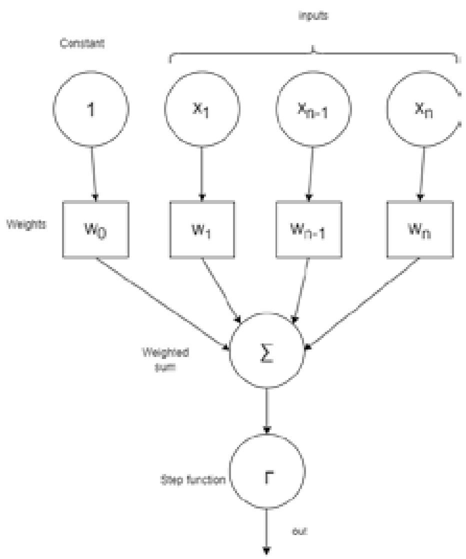

Fig. 1. Perceptron architecture diagram

Perceptron architecture – is a linear classifier (binary). And it is used in supervised learning. We would use – a multilayer perceptron. Which would help us to see will there be a natural phenomenon. But we also need to teach our neural network. To teach it we would use standard algorithm for reverse error propagation. propagation the way to move from the Input layer to the Output layer in the neural network. This algorithm is universal and it solving many problems also it has low computational complexity.

On Figure 2 present key modules:

- Database – represents data models and storage with all necessary data to training or testing forecasting system;
- Testing set – is a set of subsets of real data about occurred natural disaster for different periods of time. This set allow us to check how accurate our system can predict already known disasters which not present in testing set;
- Training set – is a set with data on which system analyzing ant learning how to predict disasters;
- Knowledge database – specific kind of database which contains well-formed data for analysis and making predictions. This database contains metadata – result of dimensionality reduction of high=dimensional human readable data models;
- Forecasting module – software which exactly do analysis of Knowledge database, using artificial intelligence and neural networks for make forecasting;
- Forecasting result visualization module – module for displaying statistics and other common data as a result of Forecasting module work;
- Decision making module – module for analysis result of Forecasting module work, do filtering and exactly make decision about natural disaster occurrence.

Gradient boosting method.

The forecasting problem is solved using various methods, including machine learning. The usage of neural networks or decision trees allows one to model processes using a set of pairs of input and output parameters. Therefore, solving the forecasting problem comes down to using high-quality input and output parameters. The more parameters that can be used as input, the better the gradient boosting model will be trained.

Gradient boosting can solve one problem: the problem of classification and finding the objective function. The second option is suitable for solving our problem. We need to restore the previously specified function of dependence of input and output data (Арінта, 2019, с. 252). There is a set of features x and result variables y, which are taken from many input parameters PS. These sets form a pair of sets on which the algorithm will be trained (TS), restoration of functional dependence $y = f(x)$:

$$TS = \{(x_i, y_i)\},$$

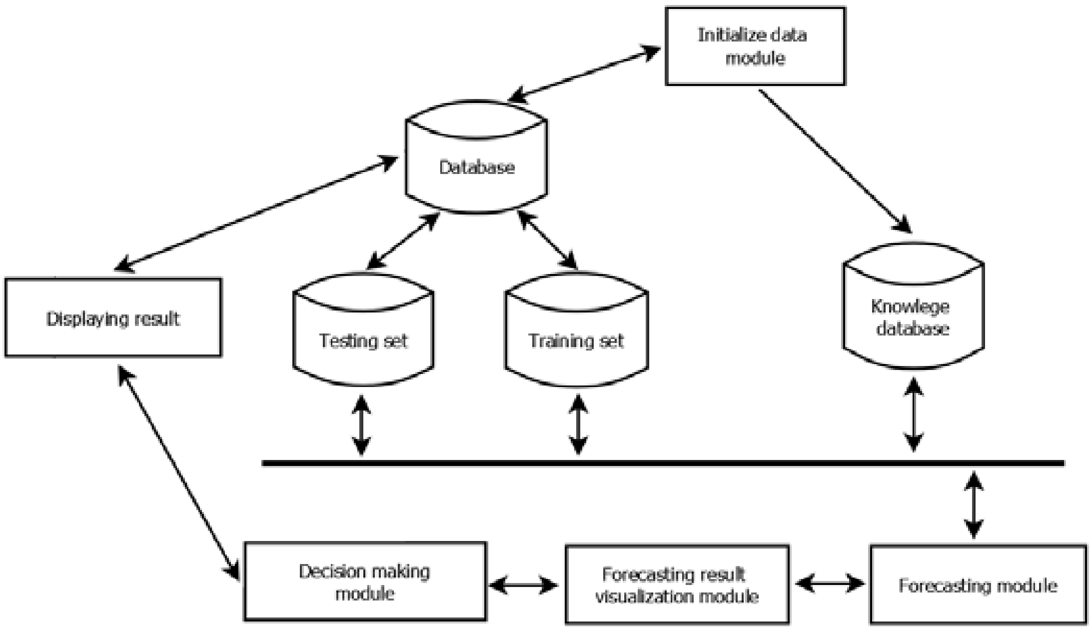

Fig. 2. Forecasting and decision-making flowchart

where x_i – set of features, y_i – result variables from PS.

Recovery occurs when approaching $f(x)$, but to determine the most acceptable approximation it is necessary to introduce a loss function $L(y,f)$. The problem comes down to minimizing the loss function:

$$y = \hat{f}(x) \;;$$

$$\hat{f}(x) = arg\,min L(y,f(x)).$$

Since forecasting occurs on a finite set of data, the loss minimization function can be reduced to the following form

$$\hat{f}(x) = \arg min_{f(x)} = E_{x,y}\left[L(y,f(x))\right].$$

The choice of function $f(x)$ to solve the problem must be limited to a family of functions $f(x,\theta)$ with parameters. Using this approach, you can significantly simplify the solution, reducing it to the solvable minimization of parameters:

$$\hat{f}(x) = f(x,\hat{\theta});$$

$$\hat{\theta} = arg\,min_0\, E_{x,y}\left[L(y,f(x,\theta))\right].$$

To obtain the most optimal parameters $\hat{\theta}$ they must be approximated iteratively. The approximation and loss function of the model taking into account the M iteration have the following form:

$$\hat{\theta} = \sum_{i=1}^{M} \widehat{\theta_i} \;;$$

$$L_0(\hat{\theta}) = \sum_{i=1}^{N} L(y_i, f(x_i,\hat{\theta})).$$

Gradient descent can be used as a suitable algorithm to solve this problem. Its essence is to add iterative estimates $\widehat{\theta_i}$ to the gradient $\nabla L_\theta(\hat{\theta})$.

Taking these parameters into account, the gradient enhancement algorithm has the following form:

1. Initialize approximation of initial parameter $\hat{\theta} = \widehat{\theta_0}$.
2. For each iteration $t = 1,...,M$ repeat:

a. calculate the gradient of the loss function $\nabla L_\theta(\hat{\theta})$ on the current approximation $\hat{\theta}$

$$\nabla L_\theta(\hat{\theta}) = \left[\frac{\partial L(y,f(x,\theta))}{\partial\theta}\right]_{\theta=\hat{\theta}} \;;$$

b. set current iterative approximation $\widehat{\theta_i}$ based on calculated gradient

$$\widehat{\theta_i} \leftarrow -\nabla L_0(\hat{\theta}) \;;$$

c. update parameter approximation $\hat{\theta}$:

$$\hat{\theta} \leftarrow \hat{\theta} + \widehat{\theta_i} \sum_{t=0}^{t} \theta_i \,.$$

3. Save final approximation $\hat{\theta}$:

$$\hat{\theta} = \sum_{i=0}^{M} \widehat{\theta_i} \,.$$

Gradient boost options.

To determine the components needed to solve the forecasting problem, it is necessary to begin optimization in function space (Акшья, Пріядарсіні, 2019, с. 2). The approximation $\hat{f}(x)$ should be sought in the form of the functions themselves. To solve the forecasting problem, you can limit the search to a group of functions $\hat{f}(x) = h(x,\theta)$.

For the algorithm to work the following information needed:

1. data set $TS = \{(x_i, y_i)\}_{i=1,\ldots,n}$;
2. number of iterations M;
3. selection of loss functions $L(y,f)$ with recorded gradient;
4. selection of a family of functions of basic algorithms $AS = h(x,\theta)$ with the procedure for their training;
5. additional hyperparameters $h(x,\theta)$, tree depth for decision trees as example.

The TS data of the training set is a set of parameters of an emergency event, as well as a parameter that determines the occurrence of this emergency event. The following algorithms can be used as function sets of basic forecasting algorithms:

- decision tree;
- linear regression;
- logistic regression.

Result. The solution which present in the work using neural network and algorithm which help us to predict disaster and natural phenomena. Our system would help our user to know:

- when and where natural phenomena expecting
- how powerful it would be
- where he can find shelter
- user could have warning notification if near would be natural phenomena.

Thus, the system of detecting natural phenomena gives the chance to save lives when near starts natural disaster.

Conclusions. Natural disasters are one of the major causes of human lives loss and damage to infrastructure and property. Advances in machine learning and deep learning have been increasingly used to manage with the complexity of disasters. This paper represents methods of automated machine learning for natural phenomena prediction system. Also in this work, a model was developed that takes into account all necessary components for effective and accurate forecasting. Boosting based on gradient descent was chosen as a forecasting method. In that case, gradient boosting is considered in the context of solving a regression problem – searching for a functional relationship between sets of input and output data. The accuracy and quality of the forecasting depend on the detail of the description of emergency situations that have already occurred, but the computational complexity of the solution also increases.

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