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ANALYSIS OF MACHINE LEARNING METHODS FOR SOLVING ANTENNA TECHNOLOGY PROBLEMS

The scheme of modern machine learning methods classification is considered and presented. The content of each methods in the classification is briefly disclosed. A structural diagram of an adaptive antenna system with an artificial intelligence unit is presented, and the principle of this scheme operation is explained. The role and function of the artificial intelligence unit within the adaptive antenna system are elucidated. The existing classes of machine learning methods are analyzed to determine their potential applicability to adaptive antenna systems for the purpose of intelligent control of the radiation pattern. It was determined that the primary machine learning method that could potentially be utilized by adaptive antenna system with artificial intelligence unit to achieve intelligent control of its directional characteristics is reinforcement learning. It is demonstrated that the reinforcement learning method can be integrated with other machine learning techniques, such as neural network methods, to enhance the precision of directing the directivity characteristics of adaptive antenna system with artificial intelligence unit.
Keywords: adaptive antenna system with artificial intelligence unit, antenna pattern, artificial intelligence, machine learning, wireless communication system.

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АНАЛІЗ МЕТОДІВ МАШИННОГО НАВЧАННЯ ДЛЯ ВИРІШЕННЯ ЗАДАЧ АНТЕННОЇ ТЕХНІКИ

Розглянуто та наведено схему класифікації сучасних методів машинного навчання, коротко розкрито зміст кожного з приведених методів в класифікації. Наведено структурну схему адаптивної антенної системи з модулем штучного інтелекту та пояснено принцип роботи вказаної схеми. Визначено місце та функціонал модуля штучного інтелекту в схемі адаптивної антенної системи. Проведено аналіз наявних класів методів машинного навчання на предмет можливості їх використання в адаптивних антенних системах з метою інтелектуального керування діаграмою спрямованості. Виявлено, що основним методом машинного навчання, який потенційно може використовуватися адаптивною антенною системою з модулем штучного інтелекту для реалізації інтелектуального керування власними характеристиками направленості, є навчання з підкріпленням. Показано, що метод навчання з підкріпленням може бути скомбіновано з іншими методами машинного навчання, наприклад, з методами нейронних мереж для збільшення точності керування характеристиками направленості адаптивної антенної системи з модулем штучного інтелекту.
Ключові слова: адаптивна антенна система з модулем штучного інтелекту, діаграма спрямованості антени, штучний інтелект, машинне навчання, система безпроводового зв'язку.

INTRODUCTION

The development of the modern telecommunications industry, in particular, wireless communication technologies, requires a constant process of improving antenna technology, namely the introduction of the smart antenna concept [1 – 3]. The name of the smart antenna concept itself indicates that in modern antenna technology, in particular, in antenna arrays, methods and systems of artificial intelligence/machine learning will be widely used. It is worth noting that today already there are scientific works describing the use of artificial intelligence methods to develop the structure of antenna elements [4], as well as those describing the possibility of using machine learning methods to optimize the parameters of antennas and adaptive antenna systems [5 – 7].

It is worth noting that the pace of development of machine learning and artificial intelligence, data processing and analysis is quite high today. The study of the principles of use, combination and selection of specific models and methods of machine learning in various fields of science and technology is the basis of modern research of many scientists. The problem in applying machine learning and artificial intelligence in a particular industry is a large number of different methods, each of which has its own characteristics, scope, advantages and disadvantages. When applying artificial intelligence/machine learning methods in adaptive antenna systems, especially for real-time radiation pattern control [5, 6], the authors faced the task of choosing one or another artificial intelligence/machine learning method. In [5, 6], the machine learning method "Intelligent Agent" was considered to be a specific knowledge system on the basis of which it is possible to intelligently control the radiation pattern of an adaptive antenna system. However, the literature lacks an analysis of machine learning methods with respect to their suitability for use in adaptive antenna systems for the purpose of intelligent radiation pattern control.

The objective of this study is to analyze the existing classes of artificial intelligence and machine learning methods to determine their suitability for use in adaptive antenna systems for intelligent directional control.

ADAPTIVE ANTENNA SYSTEM WITH ARTIFICIAL INTELLIGENCE UNIT

In [5], a structural diagram of an Adaptive Antenna System with an Artificial Intelligence Unit (AAS with AIU) was proposed and subsequently substantiated (Fig. 1).

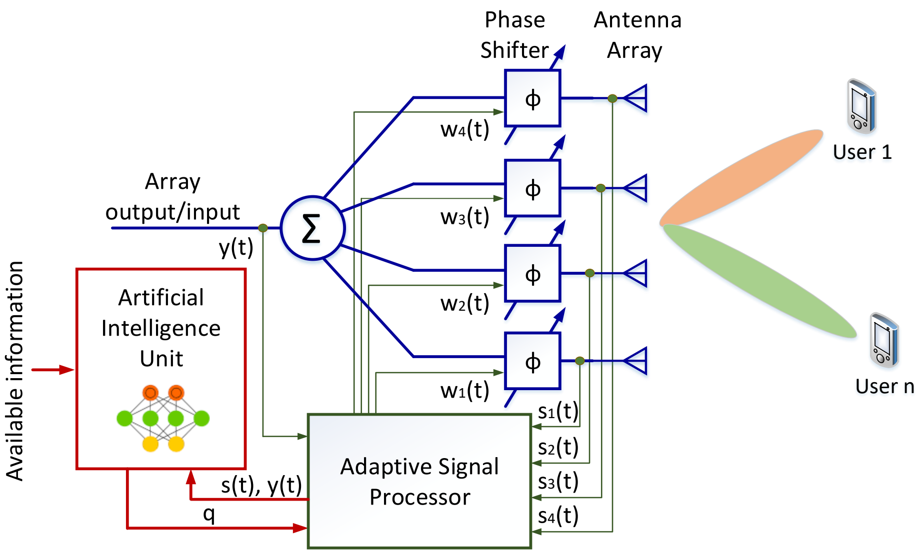

Fig. 1. Block diagram of an adaptive antenna system with AIU [5]

The structural diagram in Fig. 1 shows a diagram consisting of an Antenna Array containing four antenna elements, each antenna element is connected to a Phase Shifter which provides a change in the phase characteristics of the signal emitted by a particular antenna element of the array. The change in phase characteristics occurs in accordance with the control signals – a vector of complex weights [5].

$$w(t)' = q[w_1(t), w_2(t), w_3(t), w_4(t)]^T \, , \tag{1.1}$$

(where T means transposition [5]) which generated by the Adaptive Signal Processor. The Adaptive Signal Processor is a structural unit that controls the antenna array pattern through the use of control signals (1.1). The Adaptive Signal Processor generates control signals (1.1) based on information collected from various sources:

- the complex signal vector (voltage matrix) is formed on the antenna elements of the antenna array [3, 5]

$$s(t) = [s_1(t), s_2(t), s_3(t), s_4(t)]^T \, , \tag{1.2}$$

- feedback signal [3, 5].

$$y(t) = s^T(t) w(t) \, , \tag{1.3}$$

- coefficient q generated by AIU based on the work of a certain machine learning algorithm.

It is important to note that AIU receives data from the core of the communication system, "Available Information," as well as data from the Adaptive Signal Processor, specifically $s(t)$ (1.2) and $y(t)$ (1.3). These data are then processed by one of the machine learning algorithms [5]. The operation of a specific machine learning algorithm results in the formation of a "knowledge system" within AIU regarding the environment in which the adaptive antenna system operates. The Adaptive Signal Processor, in turn, utilizes the "knowledge system" formed in the AIU (receiving the coefficients q) to regulate the antenna array pattern with greater precision [5].

It is shown that the block diagram of the adaptive antenna system with AIU proposed in [5] can use machine learning algorithms to facilitate intelligent control of the characteristics of the adaptive antenna system, particularly the radiation pattern. At this stage of the research, it is necessary to identify which of the machine learning methods described in the current literature can be implemented in an adaptive antenna system with AIU. To achieve this, it is necessary to consider the basic principles and operating conditions of a stationary adaptive antenna system (AAS).

Consequently, AAS operates in a specific, stable, heterogeneous environment, as evidenced by the following sources [1, 2]. Such a heterogeneous environment can be exemplified by an urban area. In this case, the AAS implements a radio signal coverage area with a specific radius, which serves to delineate the environment in which the AAS operates. Consequently, we consider an urban environment constrained by the radius of the AAS, with a uniform grid of streets and a fixed type and height of buildings. In such an environment, the AAS interacts with subscriber terminals that traverse the street grid. Given the consistency of the street grid within the coverage area, it is possible to identify certain spatio-temporal patterns of movement of subscriber terminals. These patterns need to be understood and learned by the AAS through the application of a specific machine learning algorithm [1, 5]. The spatial and temporal movement patterns of subscriber terminals are understood as the peculiarities of the movement of potential subscribers along the grid of streets in the 6G cell coverage area during the day.

Thus, summarizing the above, we can conclude that an AAS with AIU is a certain system that interacts through the beams of the directional pattern with mobile subscriber terminals in a stable environment of a wireless communication cell, and as a result of this interaction, based on a certain machine learning algorithm, can intelligently control its own directional characteristics [1, 5].

In the next stage of the work, taking into account the above, we will analyze which of the machine learning methods described in the current literature can potentially be used by AAS with AIU to realize intelligent control of its own directional characteristics.

Classification of advanced machine learning methods

Machine learning (ML) is a general term that describes the use of automated learning methods to find optimal algorithms for certain processes. From a technical point of view, machine learning is a type of artificial intelligence [8, 9]. Deep learning [8, 9] uses artificial neural networks, but other types of machine learning methods are widely used in practice to train many deep learning algorithms.

The machine learning process is realized based on three key entities [8, 9]: algorithms, data, and features inherent in a particular system where the machine learning process is implemented. The relationship of these entities is often depicted graphically (Fig. 2)

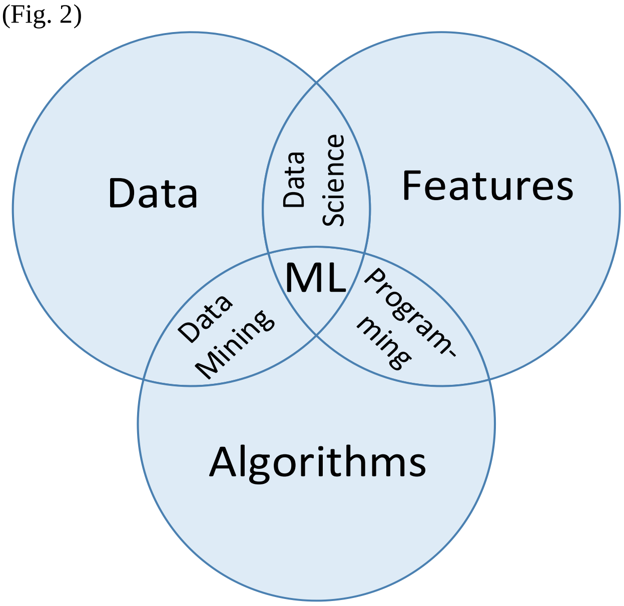

Fig. 2. The essence of machine learning

Analysis of the literature [8, 9] allows us to classify machine learning methods and identify the main eight types: Supervised Learning, Unsupervised Learning, Semi-Supervised Learning, Reinforcement Learning, Multi-task Learning, Ensemble Learning, Neural Network, Instance Based Learning. Each of these types is based on certain learning methods and algorithms. We present an extended classification flowchart [8, 9] in Fig. 3

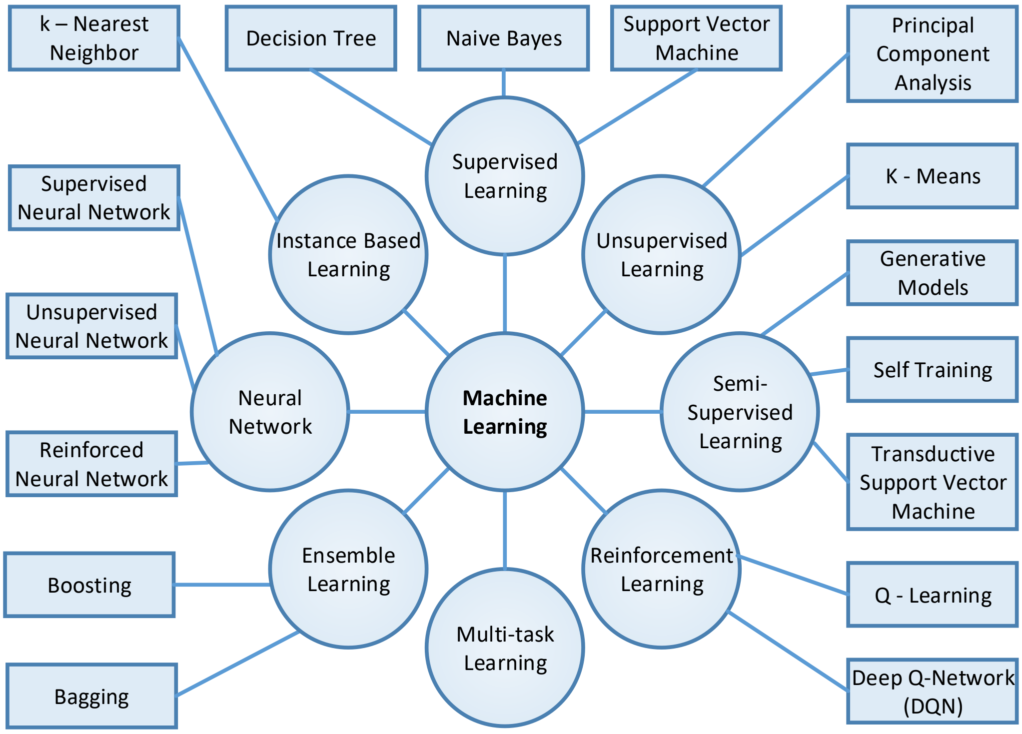

Fig. 3 Flowchart of machine learning types classification

Let us briefly characterize each type of classification (Fig. 2) and analyze the possibility of using the considered AAS with AIU

Supervised Learning is a machine learning that aims to obtain a result by comparing input data with training data [8, 9]. The most common algorithms used in Supervised Learning are Decision Tree, Naive Bayes, and Support Vector Machine.

A Decision Tree is an algorithm of actions where the input data passes through a series of questions, the answer to which is "yes" or "no". The last elements of such a tree represent decisions that can be made by the machine based on the analysis of the input data [8, 9] (Fig. 4).

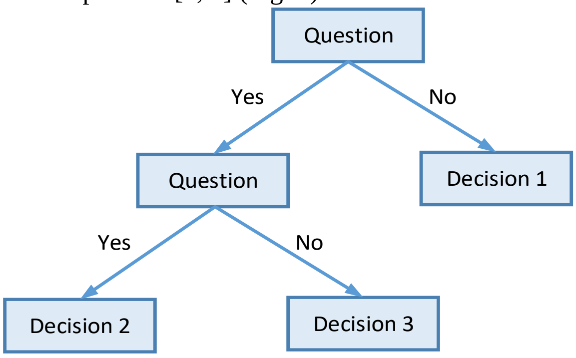

Fig. 4 Decision Tree

Naive Bayes is an action algorithm based on Bayes' theorem with the assumption of predictors independence (4) [8, 9].

$$P(A|B) = \frac{P(B|A) \cdot P(A)}{P(B)}, \tag{2.1}$$

where $P(A|B)$ is a probability A under the condition that event B occurred;

$P(B|A)$ is a probability B under the condition that event A occurred;

$P(A)$ is a probability A;

$P(B)$ is a probability B.

Thus, Naive Bayes describes the probability of an event based on the circumstances that could be associated with that event. Naive Bayes is mainly targeted at the text classification industry. It is mainly used for clustering, and the purpose of the classification depends on the conditional probability of the event.

Support Vector Machine (SVM) is an action algorithm that is one of the most common modern machine learning techniques. In machine learning, SVMs are supervised learning models that analyze data used for classification and regression analysis. Essentially, it is the definition of boundaries between different classes of objects [8, 9]. Fields are drawn in such a way that the distance between them (Gap) and different classes of objects is maximized, which minimizes the classification error (Fig. 5).

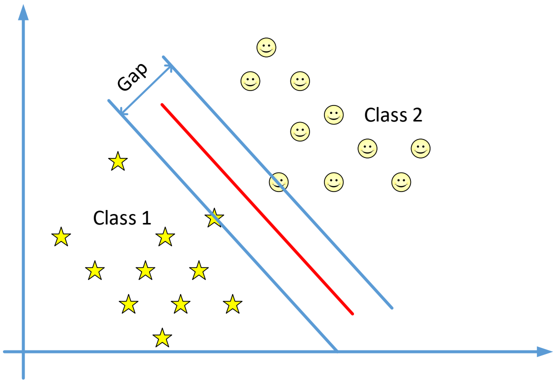

Fig. 5 Support Vector Machine

Thus, ML Supervised Learning methods are mainly used for data classification and rely on training data for implementation. Potentially, ML Supervised Learning methods can be used in AAS with AIU if the AAS with AIU has a training data base.

Unsupervised Learning is learning without a teacher, unlike the above-described learning, there are no correct answers and no teacher. Algorithms rely on their own decisions to detect and classify data. Unsupervised Learning algorithms study only some features of the data and, based on these features, form features that will be used in the future to recognize a particular class. The most common algorithms used in Unsupervised Learning are Principal Component Analysis and K-Means.

Principal Component Analysis is a statistical procedure that uses an orthogonal transformation to transform a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components. In doing so, the dimensionality of the data is reduced to make calculations faster and easier. It is used to explain the variance and covariance structure of a set of variables using linear combinations. It is often used as a method of dimensionality reduction [8, 9].

K-Means is one of the simplest unsupervised learning algorithms that solves the clustering problem. The procedure follows a simple way to classify a given data set using a certain number of clusters. The basic idea is to define k centers, one for each cluster. These centers should be placed in such way as to exclude interaction between cluster members (Fig. 6). So, the best choice is to place them as far away from each other as possible.

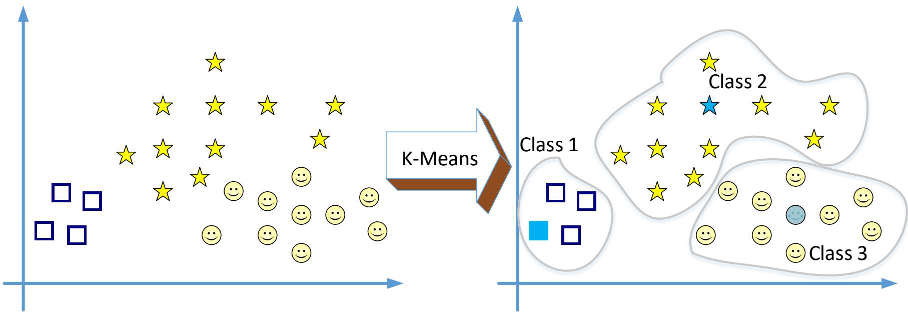

Fig. 6. K-Means

In Fig. 5, the central elements of the cluster differ in color, and the elements of the corresponding class are grouped around the central elements according to certain characteristics of these elements.

Unsupervised Learning algorithms can potentially be applied to AAS with AIU when solving the problem of physical placement of AAS with AIUs in the territory of a settlement and, accordingly, the formation of the optimal radio signal coverage area in a selected settlement. At the same time, Unsupervised Learning algorithms are less suitable for controlling the directional characteristics of AAS with AIU.

Semi-Supervised Learning is a combination of supervised and unsupervised learning. The model has a relatively small dataset with existing labels and a much larger dataset without labels. The goal is to learn relationships from a small amount of labeled information and test these relationships on an unlabeled data set to learn from them [10].

In other words, Semi-Supervised Learning is a type of machine learning that uses both labeled and unlabeled data to train a model. Unlike supervised learning which uses only labeled data, and unsupervised learning which uses only unlabeled data, Semi-Supervised Learning combines the strengths of both approaches.

The most common algorithms used in Semi-Supervised Learning are Generative Models, Self Training, and Graph-Based Methods.

Generative Models learn the underlying distribution of data by training on both labeled and unlabeled data which allows you to generate new labeled data and add it to the training set.

Self Training involves training the model on a small amount of labeled data, using it to predict the labels of unlabeled data, and adding the most reliable predictions to the labeled data set. The model is then retrained on an expanded set of labeled data, and the process is repeated iteratively until the desired level of accuracy is achieved.

Graph-Based Methods create a graph where data points are nodes and edges represent connections between data points, using labeled data to propagate labels to unlabeled data through the graph.

Potentially, Semi-Supervised Learning algorithms can be used by AIU AUVs in combination with other ML algorithms to solve data analysis tasks and plan the processes of controlling the directional characteristics of AAS with AIU.

Reinforcement Learning is a field of machine learning that deals with how software agents should act in an environment to maximize some notion of cumulative reward. Reinforcement learning is one of the three main machine learning paradigms along with supervised and unsupervised learning.

The algorithms used in Reinforcement Learning include Q-Learning and Deep Q-Network (DQN).

The process of reinforcement learning based on the Q-learning technique is implemented according to the following principle [5] – a certain entity "intelligent agent" must study the environment in which it operates and find the best possible actions to achieve the learning goal. After achieving the goal, the agent receives a certain reward in the form of accumulated points [5]. The ultimate goal of the agent is to maximize the reward and learn the optimal behavior for a given Markov decision-making process, i.e., to develop a behavioral model of optimal actions in a given environment. The basis of Q-learning is the so-called quality function (Q-function), which can be defined using the following expression [5]

$$Q(s,a) = (1-\alpha)Q(s,a) + \alpha\left[R(s,a) + \lambda \frac{\max}{a' \in A} Q(s',a')\right]. \tag{2.2}$$

In equation (2.2),
s is the current state of an agent from a set of states $S(s_1, s_2, \ldots s_n)$,
a is the current action of an agent in state S from a set of actions $A(a_1, a_2, \ldots a_n)$,
α is a learning rate that can be set between 0 and 1,
s' is a next state from a set of states $S(s_1, s_2, \ldots s_n)$,
a' is a possible action of an agent from $A(a_1, a_2, \ldots a_n)$ in the state s',
λ is a discount factor that can also be set between 0 and 1 (recommended 0,8 [5]),
$R(s,a)$ is reward for transition between states,
$\frac{\max}{a' \in A} Q(s',a')$ is a next action with maximum reward.

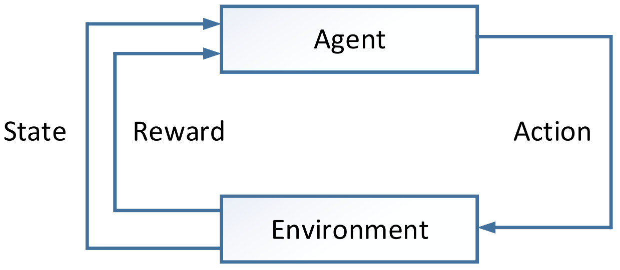

Fig. 7 Diagram of Q-learning

The process of learning an intelligent agent operating in an environment can be illustrated by the diagram in Fig. 7 [5].

More advanced Reinforcement Learning algorithm is the Deep Q-Network (DQN). The DQN algorithm uses a deep neural network to estimate Q-values for each state-action pair in a given environment, and the network, in turn, approximates the optimal Q-function. The combination of Q-learning with a deep neural network is called deep Q-learning, and the neural network that approximates the Q-function is called a deep Q-network. Graphically, the operation of the DQN algorithm is shown in Fig. 8 [11].

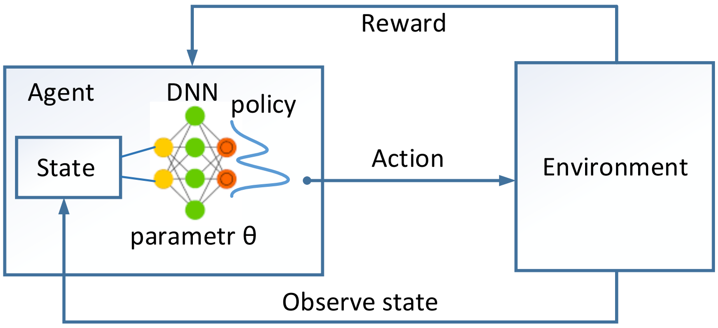

Fig. 8. Diagram of Deep Q-learning

With the help of Reinforcement Learning algorithms, it is potentially possible to realize the intelligent control of the directional characteristics of AAS with AIU with maximum efficiency. A directional pattern petal of an AAS with AIU can be considered as an agent acting in the environment of a wireless communication cell. In the wireless communication cell, the AAS with AIU interacts with the mobile subscriber terminal through the directional pattern petal and, based on the Reinforcement Learning algorithm, can learn and intelligently control its own directional characteristics [5].

Multi-task Learning is a subfield of machine learning that aims to solve several different tasks simultaneously by exploiting the similarities between different tasks. This can improve learning efficiency and also act as a regularizer. Formally, if there are n tasks (conventional deep learning approaches aim to solve only 1 task using 1 specific model), where these n tasks or a subset of them are related but not exactly identical, multitask learning (MTL) will help improve the training of a specific model by using the knowledge contained in all n tasks.

In other words, Multi-task Learning resembles the human learning mechanism because people often acquire skills that can be transferred to other, similar processes, for example, learning to ride a bicycle can easily lead to learning to ride a motorcycle, which is based on similar concepts of human body balance while driving.

The algorithms of the Multi-task Learning method can potentially be considered for use in AAS with AIU as auxiliary algorithms in combination, for example, with Reinforcement Learning algorithms.

Ensemble Learning is widely used in forecasting systems for certain processes, events, and phenomena. Ensemble Learning is a machine learning method that improves the performance of machine learning models by combining predictions from multiple models. By leveraging the strengths of different algorithms, ensemble methods aim to reduce both bias and variance, resulting in more reliable predictions. It also increases the model's resilience to errors and uncertainties, especially in critical areas such as healthcare or finance [12].

Ensemble Learning differs from deep learning in that deep learning focuses on complex recognition tasks, such as patterns, using hierarchical feature learning. Ensemble methods, such as Boosting and Bagging, address different aspects of model training in order to improve the accuracy and reliability of predictions.

Bagging is a technique that improves forecasting accuracy by combining predictions from multiple models. It involves creating random subsets of data, training separate models on each subset, and combining their predictions.

Boosting is a technique that transforms a set of weak learners into strong ones by focusing on the errors of previous iterations. The process involves gradually increasing the weight of misclassified data points, so subsequent models focus more on difficult cases. The final model is created by combining these weak learners and prioritizing those that perform better.

The Ensemble Learning method in AAC with AIU can be useful for predicting the movement of subscribers within a wireless cell. Based on the generated predictions of subscriber movement, the AAS with AIU will be able to provide intelligent directional control. It can be assumed that the effects of intelligent directional control of AAS with AIU can be improved by combining the Ensemble Learning method, for example, with Reinforcement Learning methods.

Neural Network is a series of algorithms that attempt to recognize the underlying relationships in a data set using a process that mimics the human brain [9]. Artificial neural networks consist of artificial neurons (Fig. 9) [13].

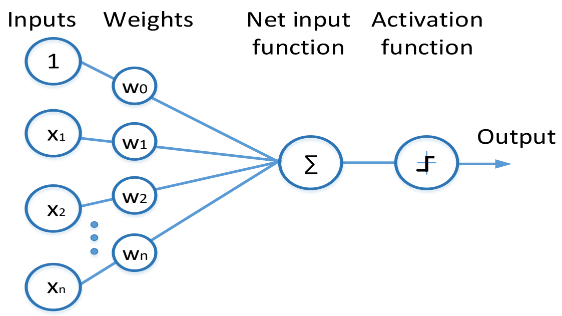

Fig. 9. Artificial Neuron

An artificial neuron contains x_n inputs that correspond to dendrites in a natural neuron. Each input is characterized by a weighting factor w_n and is connected to a neuronal cell. The artificial neuron cell implements the input function S, which, for example, can be written as (2.3) [13].

$$S = \sum_{i=1}^{n} x_i w_i \ . \tag{2.3}$$

The output of an artificial neuron corresponds to an axon in a natural neuron. The output of the artificial neuron is realized through the activation function, which, for example, can be written in the form (2.4) [11].

$$\begin{aligned} &f(x) = 0 \ when \ x < 0, \\ &1 \ \ when \ x \geq 0. \end{aligned} \tag{2.4}$$

Artificial neurons are connected to each other and thus form a neural network. It is customary to distinguish layers in a network neuron, so the first layer is called the input layer, the last layer is called the output layer, and those layers that are located between the input and output layers are called hidden (Fig. 2.9) [13].

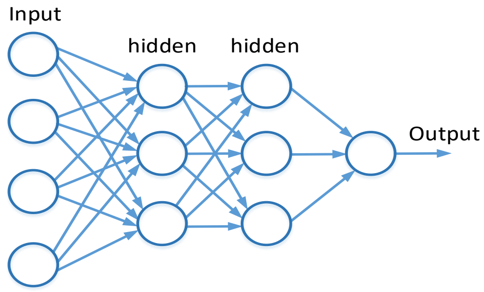

Fig. 10. Neural Network

A layer of a neural network can contain from a few to thousands of neurons, depending on the complexity of the network. The input layer receives data from the outside world that the neural network needs to analyze or learn. This data then passes through one or more hidden layers that transform the input data into data that is valuable to the output layer. Finally, the output layer provides the output in the form of the artificial neural network's response to the provided input data.

In general, neural networks are divided into the following categories: Supervised Neural Network, Unsupervised Neural Network, Reinforced Neural Network [9, 13].

Supervised Neural Network is a neural network that is able to learn based on a ready-made, correct result. During training, the predicted (correct) output data is compared with the output data of the neural network and the error is determined. Based on the determined error, the parameters of the neural network are changed and thus its training takes place.

Unsupervised Neural Network is a neural network that does not have information about the required structure and content of the source data during its operation. In most cases, the task that such a network solves is to classify data according to certain similarity features. Such a neural network checks the correlation between different input data and groups them according to similar features.

Reinforced Neural Network are used in Reinforcement Learning machine learning algorithms. In particular, the basic principle of the Reinforcement Learning algorithm with a neural network was discussed in this paper, and Fig. 2.7 shows the Diagram of Deep Q-learning and, accordingly, the explanation to the diagram.

Thus, the use of neural networks in combination with Reinforcement Learning methods can potentially provide effective intelligent control of the directional characteristics of AAS with AIU. Since the neural network allows for better estimation of the Q-values (5) of state-action pairs in a given environment, and therefore more efficient control of the directional characteristics of AAS with AIU.

Instance Based Learning is based on comparing new input data with the data that has already been analyzed. That is, a machine that works on the basis of the Instance Based Learning algorithm stores all data instances and then uses these instances to predict new data, this approach is called the k-Nearest Neighbor method [8, 9].

The use of the Instance Based Learning method in AAS with AIU is potentially possible in combination with other machine learning methods.

Thus, the analysis of the first and second sections of this paper and works [1, 5] shows that potentially, to varying degrees, all the analyzed machine learning methods can be used to implement various intellectual functions of automated assisted decision making systems with AIU. A detailed study of the use of a particular machine learning method in AAS with AIU requires setting a specific task and detailed research within the framework of the task.

To implement intelligent control of the directional characteristics of AAS with AIU, machine learning methods should be distinguished that can interact with the environment being studied and receive certain results (feedback) from this interaction. Such methods include Reinforcement Learning algorithms. Using Reinforcement Learning algorithms, the beam of the directional pattern of the AAS with AIU can be considered as an intelligent agent that acts in the environment of a wireless communication cell and implements a radio connection between the AAS with AIU and the subscriber terminal.

The analysis of the Reinforcement Learning machine learning method showed that the Deep Q-Network algorithm uses a deep neural network to estimate Q-values for each state-action pair in a given environment. Thus, we can say that Reinforcement Learning algorithms can be combined with Neural Network machine learning algorithms to improve the accuracy and speed of machine learning.

CONCLUSION

Thus, this paper considers and presents a classification scheme for modern machine learning methods, briefly describes the content of each of the methods in the classification. A block diagram of an adaptive antenna system with an Artificial Intelligence Unit is presented and the principle of operation of this scheme is explained. The place and functionality of the Artificial Intelligence Unit in the AAS scheme are determined. The existing classes of machine learning methods are analyzed for the possibility of their use in adaptive antenna systems for the purpose of intelligent control of the radiation pattern. It was found that the main machine learning method that can potentially be used by AAS with AIU to realize intelligent control of its own directional characteristics is Reinforcement Learning. It is shown that the Reinforcement Learning method can be combined with other machine learning methods, such as Neural Network methods, to increase the accuracy of controlling the directivity characteristics of AAS with AIU.

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