The 20th century witnessed the rapid development of AI. Starting with theoretical considerations about the possibility of creating artificial people, AI has turned into a powerful scientific discipline with many practical applications.

It should be noted that the development of AI has not been linear. There have been periods of rapid progress and periods of stagnation. However, the general trend is that AI is becoming more powerful and sophisticated, and has many potential applications to improve our lives.

Despite significant progress, AI still faces a number of challenges:

– Ethical issues – AI can have negative consequences for society, such as job losses, bias and abuse;

– Black box problem – some AI algorithms are unclear, making it difficult to understand their solutions;

– Security issues – AI can be used to create autonomous weapons or other dangerous systems.

4.2. The role of time series forecasting in the development and use of AI models for ICS

AI has a wide range of applications in many industries, such as:

– Medicine – for diagnosis of diseases, development of new drugs and personalization of treatment;

– Production – for optimization of production processes, demand forecasting and supply chain management;

– Transport – for the development of self-driving cars, optimization of routes and management of transport networks;

– Finance – to detect fraud, predict market trends and automate trade.

It should be noted that time series forecasting is an important task in various fields and industries due to its ability to predict future values or patterns based on historical data. Accurate forecasting can provide valuable insights and support decision-making processes, leading to improved planning, resource allocation, and risk management. Here are some key points highlighting the importance of time series forecasting and its applied fields:

1. Business and finance:

– Sales and revenue forecasting: Predicting future sales figures and revenue streams is crucial for budgeting, inventory management, and resource planning.

– Stock market forecasting: Forecasting stock prices, indices, and trends can aid in investment decisions and portfolio management.

– Demand forecasting: Predicting customer demand for products or services helps optimize production, logistics, and supply chain management.

2. Economics and government:

– Economic forecasting: Predicting macroeconomic indicators like GDP, inflation, unemployment rates, and interest rates supports policymaking and economic planning.

– Population forecasting: Estimating future population growth or decline aids in urban planning, resource allocation, and social program development.

3. Energy and utilities:

– Energy demand forecasting: Predicting energy consumption patterns helps utility companies plan generation, distribution, and pricing strategies.

– Renewable energy forecasting: Forecasting wind, solar, and other renewable energy sources supports integration into the grid and optimizes energy storage systems.

4. Transportation and logistics:

– Traffic flow forecasting: Predicting traffic patterns and congestion helps optimize route planning, transportation scheduling, and infrastructure development.

– Demand forecasting for transportation services: Forecasting demand for services like ride-sharing, public transportation, and freight can improve resource allocation and pricing strategies.

5. Healthcare:

– Epidemic and disease forecasting: Predicting the spread and progression of diseases or epidemics aids in preparedness, resource allocation, and targeted interventions.

– Patient demand forecasting: Forecasting patient volumes and admissions supports staff scheduling, bed management, and resource planning in hospitals.

6. Meteorology and environmental sciences:

– Weather forecasting: Predicting weather patterns, temperature, precipitation, and extreme events is crucial for various industries, agriculture, and public safety.

– Climate change forecasting: Forecasting long-term climate trends and patterns supports mitigation strategies, adaptation planning, and policy development.

7. Manufacturing and production:

– Predictive maintenance: Forecasting equipment failures or degradation allows for timely maintenance, reducing downtime and increasing operational efficiency.

– Inventory management: Predicting demand for raw materials and finished goods optimizes inventory levels and reduces costs associated with overstocking or stockouts.

These are just a few examples of the applied fields where time series forecasting plays a vital role. As data collection and analysis capabilities continue to advance, the importance of accurate forecasting will only increase, enabling better planning, decision-making, and resource allocation across various sectors.

For the purposes of analysis and forecasting of time series (both for regression and classification tasks), an extensive arsenal of ML methods is currently used. Therefore, let's look at the main ML approaches to the problem of modelling and forecasting time series.

To identify and evaluate nonlinear dependencies, ML models are widely used. The most widespread are ANNs, models based on support vectors (Support Vector Machines, SVM), Classification and Regression Trees (C&RT), in particular, Random Forest (RF) and Gradient Boosting (Gradient Boosting Machine, GBM) and so on [6-11].

It should be noted that the regression problem (predicting a continuous variable) can be reduced to the classification problem (predicting changes in direction of movement target variable).

Feed Forward ANNs. The main advantages of ANNs are their ability to take into account any nonlinear dependencies in the data without requiring prior knowledge of clear dependencies or logical connections between variables, while ANN models have the ability to generalize the found properties or patterns in the data.

The most popular is feed forward architecture which is named the Multilayer Perceptron, (MLP) (Fig. 4.2).

Numerous empirical studies tested the effectiveness of the application of ANNs to the forecasting time series, in particular, in the financial field. Results of papers [8, 10] showed that MLP-type ANNs have better predictive properties than time series models and other ML algorithms for the time series forecasting task.

SVM. The main idea behind using SVMs for time series forecasting is to treat the forecasting problem as a regression task. SVMs are typically used for classification problems, but they can be adapted for regression tasks, such as time series forecasting, by introducing an alternative cost function known as the epsilon-insensitive loss function.

The SVM model attempts to find the optimal hyperplane that maximizes the margin between the data points and the hyperplane, allowing for some error (determined by the epsilon parameter). The kernel function, which maps the input data into a higher-dimensional space, plays a crucial role in capturing non-linear relationships in the data.

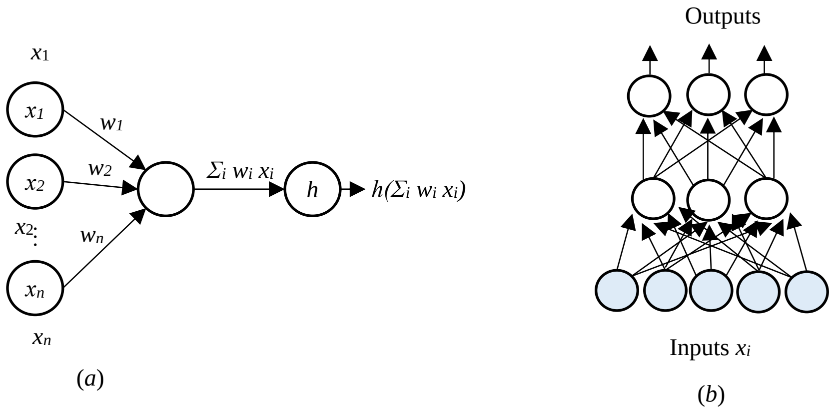

Figure 4.2. The main idea of the architecture of a multi-ball perceptron
(a) Computational graph of single neuron;
(b) Fully connected ANN with one hidden layer
and one output layer

Source: designed by the authors based on [11]

Once the SVM regression model is trained, it can be used to make predictions on new, unseen data. The model takes the input features (including lagged values and engineered features) and predicts the future value(s) of the time series.

One advantage of using SVMs for time series forecasting is their ability to handle non-linear relationships and high-dimensional data. Additionally, SVMs are less prone to overfitting than some other regression techniques, thanks to their regularization mechanisms.

However, SVMs can be computationally expensive, especially for large datasets, and their performance can be sensitive to the choice of kernel function and hyperparameters (such as the regularization parameter and epsilon). Furthermore, SVMs may struggle with certain types of time series patterns, such as long-range dependencies or complex seasonality.

In practice, SVMs are often used in combination with other techniques, such as feature selection or ensemble methods, to improve their forecasting performance for time series data.

By the way, SVM models are widely used for the financial time series forecasting, in particular, to predict the price movement of assets on financial markets [12]. At the same time, they often give better results than other algorithms [13].

C&RTs and ensembles. Another powerful class of machine learning models are C&RT and their ensembles. In the C&RT algorithm, each tree node has two splits. At each step, the given rule divides the training sample into two parts – the part in which the rule is fulfilled (right branch) and the part in which the rule is not fulfilled (left branch) (Fig. 4.3). Splitting occurs up to a certain depth or number of training examples in the leaves on which the prediction is directly performed.

However, in their pure form, models of this type are not very effective due to low accuracy. Ensembles of models built on the basis of C&RT trees are used in practice, in particular, the Random Forest (RF) and Gradient Boosting (Gradient Boosting Machine, GBM) models.

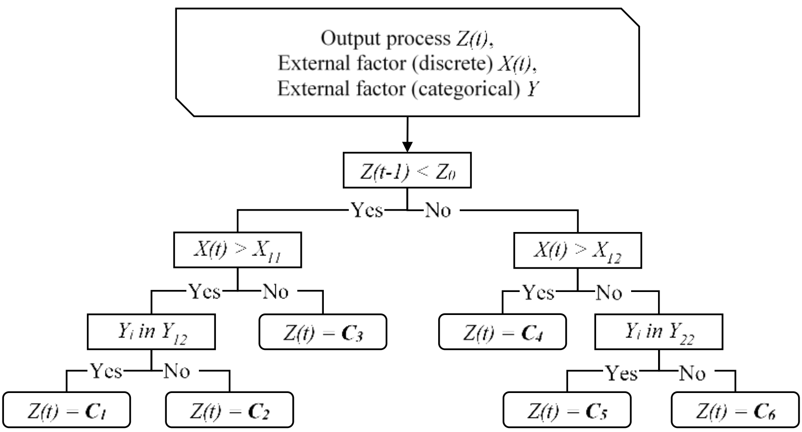

Figure 4.3. Schematic representation of C&RT model

Source: designed by the authors based on [11]

The RF algorithm is based on the construction of an ensemble of classification (regression) trees, each of which is built from subsamples of the original training sample using bagging.

In the RF algorithm, bagging is combined with the method of random subspaces: that is, each tree is built based on different randomly selected subsets of features (features). This process is called subspace sampling.

The main idea behind using GBM for time series forecasting is to leverage the power of ensemble learning and boosting algorithms to capture complex patterns and trends in the data.

GBMs are a type of ensemble learning technique that combines multiple weak learners, typically decision trees, into a strong predictive model. In the context of time series forecasting, GBMs work by iteratively fitting weak learners (decision trees) to the residuals of the previous iteration, with the goal of minimizing the overall prediction error.

The GBM algorithm is initialized with a set of hyperparameters, such as the number of trees, the maximum depth of the trees, the learning rate, and the loss function (e.g., squared error for regression tasks). The algorithm then iteratively fits decision trees to the residuals of the previous iteration, with each new tree focusing on the instances that were poorly predicted by the previous ensemble.

The main advantages of using GBM for time series forecasting include:

– Ability to capture non-linear relationships and complex patterns in the data.

– Robustness to outliers and noise due to the ensemble nature of the algorithm.

– Automatic feature selection and handling of feature interactions through the decision tree structure.

– Regularization techniques, such as shrinkage and subsampling, help prevent overfitting.

However, GBMs can be prone to overfitting if not properly tuned, and they may struggle with long-range dependencies or highly non-stationary time series. Additionally, GBM models can be relatively complex and computationally expensive, especially for large datasets or deep trees.

In practice, GBMs also are often used in combination with other techniques, such as feature engineering, rolling-window validation, and ensemble methods, to improve their forecasting performance for time series data.

4.3. Deep Neural Networks (DNNs)

Recently, more powerful computing platforms and cloud services have appeared thanks to the development of hardware and software tools that enable the implementation of more complex forecasting algorithms – DNNs with dozens and hundreds of layers, the theoretical foundations of which were laid in the work [10].

DNNs have proven to be quite effective for the tasks of image recognition and segmentation, streaming video processing, machine translation and many other applications. During the last ten years, there