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L. Gryzun

Simon Kuznets Kharkiv National University of Economics, Kharkiv

PRACTICAL ISSUES OF THE ESTIMATION AND CHOICE OF MACHINE LEARNING MODELS FOR THE FORECASTS BUILDING IN DIFFERENT SUBJECT DOMAINS

The paper is devoted to the practical issues of machine learning models estimation for predicting processes in different subject domains. In the progress of work, there were undertaken the number of core steps. An analysis of theoretical and practical scientific sources on the use of traditional and modern models for forecasting in various domains is conducted to identify possible consequences of the use of different models risks. The features of building predictive models in selected domains (medicine, meteorology, finance, and sales) are determined. The criteria and their metrics for the models' estimation are determined. To perform a comparative analysis and estimation of machine learning models for forecasting processes in selected subject areas, a web application was developed. A number of predictive models are constructed with the help of the developed web application. The results of forecasting using traditional and modern models in the selected subject domains are analyzed and evaluated according to criteria of accuracy, speed and complexity. Based on the comparative analysis of machine learning predictive models, the practical recommendations have been formulated for the correct choice of a model for specific domain forecasting tasks. The prospects of the research are outlined in the lines of automatizing the selection of better model.

Keywords: *comparative analysis of predictive models; estimation of machine learning models; forecasting for different subject domains; machine learning; practical recommendations; web application.*

Introduction

Statement of the problem. Machine learning (ML) as one of the leading branches of artificial intelligence provides powerful tools for effective analysis of a significant amount of data and establishment of patterns based on such analysis. On the other hand, the demand for efficient forecasting of processes in various fields of activity is constantly growing, which actualizes the justification of a balanced choice and implementation of predictive machine learning models based on their comparative analysis.

The conducted study of scientific and practical sources indicates a significant interest of the experts in the problems of comparative analysis of ML models by various metrics. However, most works provide results of evaluation of models for building forecasts in one specific field or for solving a specific prediction problem [1; 3; 4] and others.

At the same time, it is necessary to underline the need for the models estimation in the context of the specifics of building forecasts for different subject areas. This is due to the fact that each sphere has its own specific features and requirements for forecasting. For example, in the financial sector it is essential to predict market trends, while in medicine it is paramount to anticipate the progress of diseases and predict the number of incidents.

On the other hand, ML offers a large number of models today, each of which has its own advantages and disadvantages. The models estimation based on their comprehensive comparative analysis will help identify the most effective algorithms and models for specific types of data and tasks, which helps to increase the forecasts accuracy that determines the effectiveness of decision-making in the domains of economics, medical service, education, meteorology, astronomy, etc. [1; 2; 4; 5]. It is also essential that ML is used in various industries, such as finance, medicine, technology, logistics, marketing, education, etc. Therefore, comparative analysis of models and their estimation will allow adapting best practices from one area to resolve the tasks in another one, promoting the interdisciplinary approaches.

Thus, ML models estimation based on their comparative analysis in terms of the peculiarities of forecasting in different subject areas is important for increasing the efficiency and accuracy of forecasts.

Analysis of recent research and publications. As it was mentioned above, an analysis of theoretical and practical scientific sources on the use of traditional and modern models for forecasting in various domains is a way to identify possible consequences of the use of different models, which actualizes the learning of recent studies on the theme of the current research. In this context, based on the sources learning [10–12; 23; 24] and others, it was made a sort of generalization of the features of selected models (Holt-Winters, SARIMA, LSTM, Random Forest, XGBoost, Prophet, Gaussian process, polynomial regression) presented below.

Thus, according to studies, the Holt-Winters model is effective in simple forecasting scenarios where fast forecast updates are critical. Due to its simplicity and low computational requirements, it is well suited for tasks where it is necessary to respond quickly to changes in trends [12].

SARIMA model allows modeling both nonseasonal and seasonal components of time series, which makes it an excellent choice for economic and financial data, which often include both cyclical and seasonal fluctuations [13; 14].

LSTM networks are a powerful tool in deep learning for time series forecasting, especially when it is essential to regard long-term dependencies in the data. This makes them ideal for complex tasks where patterns in the data are distributed over large time intervals [18].

The Random Forest model is used to process time series that have a high degree of nonlinearity and relationships between features. It is suitable for a variety of industries due to its ability to perform classification and regression, making it a universal choice [21; 22].

The Gaussian process works effectively with small data sets and high uncertainty in the data. It is especially useful for problems where it is necessary to estimate the uncertainty of predictions [20].

Polynomial regression is considered to be a leader in forecasting and trend analysis. It is well suited for tasks where the data is relatively simple and does not contain complex nonlinear interactions [22].

The XGBoost model is characterized by high performance and efficiency in large and complex datasets, providing high forecast accuracy. Its application is especially relevant in the financial sector and retail [23].

The Prophet model, developed by Facebook to solve forecasting problems in business, can be applied to daily data with strong seasonal effects and a large number of missing values [24; 25].

The researchers also point out [9; 24; 25] that models such as Exponential Smoothing and ARIMA are excellent for traditional forecasting tasks where trends and seasonality are important. Neural networks (such as LSTM) can detect complex relationships in data with long feedback loops, making them extremely useful for highly dynamic and complex systems. Ensemble methods (e.g. Random Forest and XGBoost) apply a combination of forecasts from multiple models to improve the forecasts stability, which is ideal for tasks where a lot of input variables has to be considered. Gaussian processes are suitable for scenarios where smoothness and continuity of data are important, and they are commonly implemented in domains where these properties are key. Prophet models are often used in retail and event planning due to their ability to effectively handle seasonal fluctuations and the impact of special events.

Therefore, the conducted analysis of recent research testifies that the said models meet a broad range of time series forecasting demands in various industries, from simple to complex datasets, and provide flexibility in choosing approaches depending on the specifics of the task. Besides, each of these models has its own unique features and advantages in certain domains and situations, which emphasizes the significance of justified model selection depending on the specific requirements and data characteristics to achieve the best forecasting results. These models may be applied individually or in combination to achieve the best results in specific forecasting scenarios.

In addition, based on the learning of research [4–8; 15–17; 18], four main subject areas were identified in which there is an increased demand for the building of effective predictive models: medicine and healthcare, meteorology, finance and sales. Below we are describing the selected domains from the standpoint of the need and challenges of building accurate forecasts, as well as the features of forecasting tasks. The features of building forecasts in the selected domains can vary significantly depending on the specifics of the data, the dynamics of processes and the final goals of applying the predictive models of machine learning.

Medicine and healthcare are the most paramount areas of our lives in the context of predicting the spreading of epidemics that pose a global threat to humanity. The facilities to accurately forecast morbidity is key to planning responses to threats to human health, optimizing the resources of medical institutions, and public information policies. The challenges in forecasting are taking into account a wide range of essential factors (like social habits, population mobility, changes in health policies, and the variability of virus strains).

The specificity of predictive tasks in the field of medicine is that forecasting disease cases can include seasonality and random spikes. It is often important to consider seasonal fluctuations and sudden spikes in morbidity that can cause pandemics. Another feature is the power of external factors, i.e. vaccination, government measures, changes in population behavior can dramatically change trends. There is also high dynamism in this field, as data can change rapidly over time, which requires flexible and rapidly adaptive forecasting models [7; 8].

Meteorology is also a branch where accurate forecasting is urgent. Weather forecasting is important for many sectors, including agriculture, aviation, energy and others. Efficient weather forecasts can significantly reduce economic losses and increase safety. The challenges and features of weather forecasting are regarding a large number of variables which are interdependent and difficult to model (temperature, wind, humidity, precipitation, and others), as well as climate change, which introduces additional difficulties [6; 19]. In addition, weather forecasting has to deal with high unpredictability, as changes in weather conditions can be abrupt and unexpected.

One more domain that requires effective forecasting is economics and finance, especially in the context of predicting stock price trends or cryptocurrencies. Financial markets depend on forecasts to make investment decisions. Accurately predicting market movements can significantly increase profits and reduce risks.

The challenges in forecasting here are high volatility, unpredictability of markets, and the impact of unexpected global events that can radically change market trends. The specificity of forecasting is that prices can change dramatically due to political events, global and local economic changes affecting markets, and psychological influences. Investment decisions are often based on human emotions and psychology, which makes accurate forecasting difficult.

Business is an integral part of economic life, and sales are an important part of it. Accurate sales forecasting allows companies to optimally manage inventory, reducing storage costs and reducing losses from undersales or overproduction, plan production and develop marketing strategies. This is especially important in industries with fast cycles, such as retail and e-commerce. Effective forecasting also supports strategic planning of business operations based on expected demand, providing a better understanding of market trends.

Challenges in forecasting sales and demand include taking into account seasonality, fashion trends, economic conditions and competitive actions. Specifics of sales forecasting [18] include the impact of economic cycles. Economic slowdowns and booms, as well as pronounced seasonal trends, can significantly affect demand. Another feature of forecasting in this industry is the consideration of promotions, as special offers and marketing campaigns can increase sales in the short term, making it difficult to build an accurate forecast.

Thus, understanding the above features is key to developing effective forecasting approaches in each of these areas, that allow to select or adapt forecasting models to anticipate future trends accurately.

In addition, based on the analysis of relevant sources the following generalization was done. Each of the identified subject areas requires a unique approach to modeling and data analysis, and the selected forecasting methods have certain advantages that may be applied to resolve specific tasks in each area. For example, deep learning enables to reveal complex patterns in morbidity data, while classical statistical models can effectively predict seasonal fluctuations in sales or weather.

The choice of these four subject areas for comparative analysis of predictive models is caused by several key reasons that reflect their urgency in the contemporary world, as well as their relevance for demonstrating the potential of using the considered forecasting models. They do not just represent a wide range of applications for estimating predictive models but are also crucial for the progress of key sectors of the global economy and society.

The aim of the work is to build and compare predictive machine learning models in selected subject domains to evaluate them and select the most effective solutions for the specific tasks of each branch.

To achieve the said goal, there were undertaken the number of steps that make main contribution of the paper. A review of theoretical and practically-driven scientific sources on the use of traditional and modern models for forecasting in various domains is conducted to identify possible consequences of different models implementation, including potential risks. The features of building predictive models in selected domains are determined. A web application is developed that allows building a number of forecasting models. The results of forecasting using traditional and modern models in different subject domains are learnt and evaluated according to certain criteria.

Main part

1. Preparation stage

The presented above learning of the essence of ML models, the identified features of forecasting in selected subject areas, and the purpose of the work made us define criteria for evaluating models, which will allow us to establish the compatibility and feasibility of using different predictive models in the chosen subject domains.

According to the learnt studies, time series models may be analyzed based on various aspects that help determine their suitability and effectiveness for specific tasks. Among the numerous criteria for the estimation of forecasting models the following ones were selected based on [26; 27]. Accuracy is considered one of the most significant criteria, since it determines how well the model predicts real values and determines how relevantly the constructed forecasts match the actual data. For any subject area, it is essential that forecasts are as close as possible to real values, since the effectiveness of actions based on these forecasts depends on this [26; 27]. Accuracy is often quantified using statistical measures: mean absolute error (MAE), root mean square error (RMSE), mean absolute percentage error (MAPE), etc.

MAPE assesses the average absolute percentage error for predicted and actual values and is expressed as a percentage. As was mentioned above, linear regression is a statistical method which enables to estimate connection between two numerical variables according to the ration:

$$\mathrm{MAPE} = \frac{1}{n} \cdot \sum_{i=1}^{n} \left| \frac{A_i - F_i}{A_i} \right| \cdot 100 , \qquad (1)$$

where A_i – actual value;

F_i – predicted value;

n – number of observations.

Lower MAPE values indicate better forecasting accuracy. However, MAPE can be biased by values close to zero.

RMSE measures the square root of the mean of the squares of the differences between the forecasted and real values detecting how well the model's predictions match the actual values:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(A_i - F_i\right)^2} . \qquad (2)$$

It is essential to mind that RMSE tends to increase significantly when outliers are present, as it squared the errors before averaging.

When comparing ML models, it is needed to assess the prediction performance of multiple methods at once, as this allows for a more complete picture [26; 27]. One method may be more dependent on outliers, whereas another one may be more sensitive to small values. If one method has limitations (for example, MAPE may be ineffective at zero values), combining it with other metrics can help reduce the impact of these limitations. Different metrics can emphasize different aspects of accuracy. For instance, RMSE can be helpful for revealing large errors, while MAPE gives an idea of relative accuracy. Combining methods can also tailor better the estimate to the specific conditions or features of the data we are working with.

A criterion of model complexity affects how difficult it is to understand, configure, and maintain. The simplicity of a model often makes it more understandable and accessible to a wide range of specialists. Simple models, such as polynomial regression, are easier to understand and use, while complex models, such as LSTM, require more in-depth knowledge and experience.

The speed of a model's calculations is also an important criterion, especially when working with large amounts of data or in real time. High execution speed allows you to get results faster and reduces the cost of computing resources. For instance, in the case you need to update forecasts frequently or work with large data sets, the speed of the model's execution is critical.

According to sources [24–26], a criterion such as scalability determines how well a model can work with increasing amounts of data. This is important to ensure that the model works stably as the amount of data increases. In cases where data is constantly growing, such as when analyzing social media or large financial markets, the model should be able to manage increasing amounts of information without losing efficiency.

Regarding these criteria, model evaluation becomes a multifaceted process that allows not only to select the most effective model, but also to optimize its application in a specific domain. This, in turn, can lead to more informed decisions and improved results in each selected field of activity.

Thus, given the above analysis of ML models, the specific features of forecasting in selected subject domains, and also taking into account the above criteria, the feasibility of using the specified predictive models to solve problems in specific subject domains was established (Tab. 1).

Table 1

The feasibility of applying predictive ML models to the tasks solving in specific subject areas

Model/ Domain	Finan-cial	Medi-cine	Mete-orology	Sales
Holt-Winters method	+	–	+	+
SARIMA	+	–	+	+
LSTM	+	+	+	+
Random Forest	+	+	–	+
Gaussian process	–	+	+	–
Polynomial regression	–	+	–	–
XGBoost	+	+	+	+
Prophet	+	–	–	–

Source: obtained by the author.

It should also be underlined that the selection of the most influential criteria for evaluating a predictive model depends on the specific goal. For example, for a medical diagnosis model, accuracy may be the strongest factor, while for a traffic prediction model, speed may be more important. Evaluating predictive models against these criteria helps researchers and developers compare different models and choose the best one for a particular task, identify and correct errors in the models, generally improve their performance and increase confidence in the models, and promote their wider adoption.

2. Results

To perform a comparative analysis of ML models for forecasting processes in selected subject areas, a web application was developed. Python was chosen as the main programming language for implementing the forecasting models themselves and for developing the server side, i.e. implementing the MVC model. The client side was created using the html/css/javascript technology stack, the ChartJS library for building graphs and Ajax for dynamic data display.

Data sources were selected (mostly APIs and open-access datasets). For forecasting processes in the financial sector, Finance was used – a popular Python library that provides an API for obtaining historical market data from Yahoo Finance. It is widely used in financial applications, like stock or cryptocurrency analysis, as it provides an easy and convenient way to obtain financial data without complex settings or paid services.

The open-access repository Repository by the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University was chosen as the data resource for building models in healthcare field. It provides comprehensive information, including daily data on cases, deaths, and recoveries taken from different sources (e.g. government reports and medical institutions).

To build weather forecasts, data from Meteostat was used, which is an open API that provides access to historical and current meteorological data for their analysis. It enables to receive information from various world weather stations, including data on temperature, precipitation, wind, and other weather parameters. Meteostat uses data from state meteorological services, aviation weather stations, and other open sources, which allows you to obtain highly accurate information. The data itself can include daily average/maximum/minimum temperature, precipitation, solar radiation, hourly data on temperature, humidity, direction, and speed.

The resource from which the dataset for sales was selected is Data World. Data World is a data sharing, storage, and analysis platform that allows users to access a variety of data sets, including commercial, academic, and open-source resources. Users can upload, share, and analyze data, as well as participate in collaborative projects.

Besides the resources with available datasets, several tools and libraries were implemented to create each of the ML models, as some models require a comprehensive approach, from building the model itself to finding the optimal parameters to reach the highest accuracy minimizing also the time for calculations.

The developed application has one page which contains two drop-down lists for selecting a subject area (weather, stocks, sales, medicine) and a list of built models (LSTM, Holt-Winters, XGBoost, etc.). Besides, the application page has a field for displaying graphs and the obtained metric values (RMSE, MAPE and execution time).

After user's selecting a specific subject domain and model, the application sends a request for the relevant data to the backend, and after processing, receives this data in JSON format and displays the training, test, and predicted datasets on a graph using Chart.js, which allows you to compare real and anticipated values for different models and areas. Metrics for assessing the accuracy and speed of the model are also returned in the JSON response, so they are also updated dynamically when a specific model and domain are selected, which allows the user to evaluate the effectiveness of each model in real time. Selected results of building a forecast by the developed web application are shown in Fig. 1–4 below.

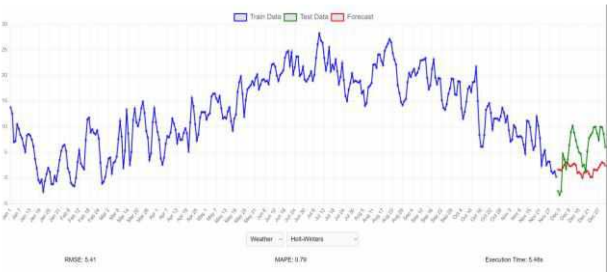

Fig. 1. Prediction for average temperature
in the meteorology area built by Holt-Winters method
Source: built by the author's developed application.

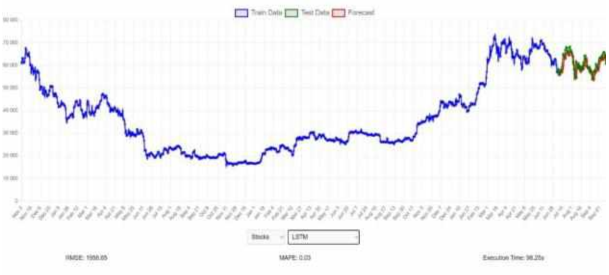

Fig. 2. Prediction for bitcoin in the financial domain
built by LSTM method
Source: built by the author's developed application.

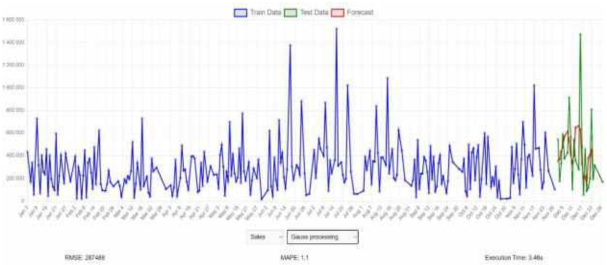

Fig. 3. Prediction of goods sales
built by Gaussian processing
Source: built by the author's developed application.

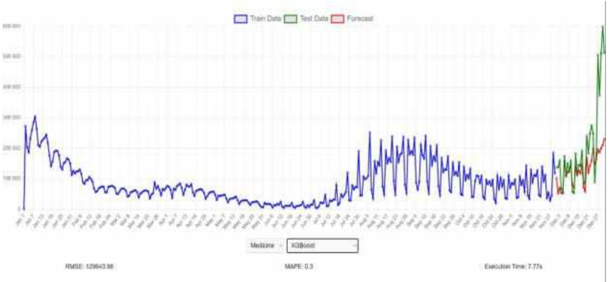

Fig. 4. Prediction of the amount of COVID-19 patients
in the medicine domain built by XGBoost model
Source: built by the author's developed application.

Let us present the results of a comparative analysis of all eight models in four subject domains according to the criteria of accuracy (RMSE and MAPE metrics) and speed (Tab. 2–5), obtained using the developed app.

Table 2

Results of building predictive models for average temperature for meteorology

Model	Accuracy		Speed (s)
	RMSE	MAPE (%)	
Holt-Winters method	5.41	79	5.38
SARIMA	5.06	68	22.36
Polynomial regression	5.06	96	0.28
Gaussian process	1.9	26	6.35
Prophet	5.29	87	0.4
LSTM	2.27	44	38.37
Random Forest	2.34	44	0.25
XGBoost	2.18	41	6

Source: obtained using the author's developed app.

Table 3

Results of building predictive models for bitcoin in a financial domain

Model	Accuracy		Speed (s)
	RMSE	MAPE (%)	
Holt-Winters method	5.41	79	5.38
SARIMA	5.06	68	22.36
Polynomial regression	5.06	96	0.28
Gaussian process	1.9	26	6.35
Prophet	5.29	87	0.4
LSTM	2.27	44	38.37
Random Forest	2.34	44	0.25
XGBoost	2.18	41	6

Source: obtained using the author's developed app.

Table 4

Results of building predictive models in a sales domain

Model	Accuracy		Speed (s)
	RMSE	MAPE (%)	
Holt-Winters method	315313	98	0.45
SARIMA	301848	84	16.12
Polynomial regression	326409	89	0.28
Gaussian process	287488	110	3.46
Prophet	375686	90	33.18
LSTM	318664	84	5.74
Random Forest	55820	9	0.22
XGBoost	52743	11	7.55

Source: obtained using the author's developed app.

Table 5

Results of building models for predicting the incidence of COVID-19 in the medical domain

Model	Accuracy		Speed (s)
	RMSE	MAPE (%)	
Holt-Winters method	156834	32	3.43
SARIMA	127756	31	5.19
Polynomial regression	141350	52	0.27
Gaussian process	87375	32	4.67
Prophet	166199	35	10.6
LSTM	111139	45	36.68
Random Forest	137759	36	0.23
XGBoost	129643	30	7.77

Source: obtained using the author's developed app.

Summing up the comparing and estimation of the obtained predictive models as for the criteria of accuracy and speed in different subject domains, we could conclude the following.

The Holt-Winters model works well over time when there is clearly defined seasonality or trends. It is most effective in the financial domain for predicting bitcoin, where there are cyclical patterns. However, in the sales domain with more chaotic data that do not have a clear seasonal structure, the outcomes are much worse. On the whole, the model does not demonstrate high results in any of the areas (they are either average or generally low). Perhaps this model would be a good solution when trying to predict on even smaller datasets. ML models are not effective when working with very small datasets, so the Holt-Winters model and SARIMA can be useful.

SARIMA, like the previous model, is unable to manage large data amount, demonstrating good results only for the medicine sphere. In other subject domains, it poorly understood data patterns and could not efficiently adapt and build an accurate forecast. This model also adapts poorly for the data with noise, which is obtained in the results for the sales and financial domains.

Polynomial regression demonstrates high speed in all domains, but this model demonstrates generally low accuracy. It does not cope with nonlinear and complex dependencies, which is typical for most forecasting tasks. Polynomial regression can be useful in simple domains with clear trends, where there is not a significant amount of variable data.

Gaussian process builds an accurate forecast but is a complex model. It shows the best results in most domains (except sales with chaotic data). At the same time, the model has average speed values on small data sets, which can be a universal choice for small datasets.

The Prophet model performs poorly in most domains. It does not detect trends well and produces poor quality forecasts.

LSTM performs well in accuracy in most domains (except sales) and works well with nonlinear and complex dependencies. However, the model is quite slow and quite difficult to tune. At the very least, it can be sped up a bit by a few seconds or even tens of seconds (which can be significant) without losing model accuracy, but it may take longer to tune.

The Random Forest model demonstrates the highest speed in all domains, while maintaining fairly high accuracy everywhere, except for the medical domain (it can be assumed that the increase in uncertainty and dynamism in the data of this domain worsens its results). This model easily adapts to scalability, understands complex patterns, and can also provide effective forecasting in chaotic data conditions (for example, in the sales domain).

The XGBoost model is a powerful tool in all domains. This model demonstrates high accuracy, scalability, and average speed values. In the sales domain, this model showed the best results because it is able to process complex data sets. One of its main disadvantages is the complexity of its setup.

Therefore, regarding the universality of use, such models are Random Forest and XGBoost, which showed stable results in all domains. Random Forest works well in a wide range of tasks, showing a good balance between accuracy and speed. The XGBoost model has a high ability to adapt to different types of data, providing accurate results in all domains. The constructed models and forecast results were also analyzed by the level of complexity of their construction in the context of prediction based on historical data. Below we highlighted several main indicators that should be considered when assessing the models complexity:

– the amount of data preprocessing that detects whether the model requires scaling, normalization, filling in missing values, or specific data transformation;

– the number of hyperparameters answers the question of how many parameters need to be adjusted or how many combinations of possible settings;

– the interpretability of the model indicates the complexity of understanding the results and the reasons for the model's decision;

– tuning and optimization are one of the most important indicators providing information about whether it is easy to adjust the model to new data and if the model requires a lot of time to find optimal parameters;

– the toolset required to implement the model is also an important parameter: the tools, libraries, and programming skills needed to build the model and how easily a beginner can master them.

The model complexity was defined by the levels regarding the above indicators.

Level 1 – Basic. The model is easy to implement and does not require specific data processing, is easy to interpret.

Level 2 – Intermediate. The model requires some simple parameter settings and optimization, is easy to interpret, does not require additional data transformations or large number of tools for construction.

Level 3 – Medium. The model may require additional setup of the dataset, may have many parameters to set. The results are also easy to interpret, and the model does not take many tools to build it or much efforts for its optimization.

Level 4 – High. The model uses many tools, requires a lot of time to optimize hyperparameters, requires good skills in working with certain libraries and interpreting the results of prediction.

The complexity assessment of each model is given in Tab. 6.

Table 6

Estimation of the complexity of building ML models for processes predictions

Model	Level of complexity	Justification
Polynomial regression	Basic	The model does not need complex data processing or setup, the set of hyperparameters is very small, so the setup is simple; does not take complicated optimization or a lot of efforts for data preparation, so it is ideal for basic level.
Holt-Winters method	Inter-mediate	The model requires some basic data processing and setup but remains simple to interpret and to implement. Requires minor adjustment of smoothing for trend and seasonality.
SARIMA Prophet	Medium	The models require more attention to data processing. SARIMA requires the identification and transformation of seasonal components, optimization of parameters (integration order and autocorrelation). Prophet also requires tuning for seasonality, trends, and the impact of certain events. Both models allow for flexible forecasting, but for their correct operation, require significant training and some skills in working with libraries.
LSTM, XGBoost, Random Forest, Gaussian process, Polynomial regression	High	LSTM requires extensive data preparation (scaling, time-series transformation) and a complex architecture for training. XGBoost requires fine-tuning of a large number of hyperparameters (number of trees, depth of trees, and training coefficients). Gaussian processes also involve a complex mathematical framework and require careful tuning of kernel functions. These models require a deep understanding of machine learning techniques and a significant amount of time to optimize and fit parameters. For this reason, they are difficult to interpret and optimize.

Source: obtained by the author.

Thus, it can be concluded that the choice of a prediction model rests on several crucial factors (the scale of the data, the needed accuracy, the computation time, and the model tuning). These factors vary depending on the specifics of the domain, so the models must be selected coming from the exact task and goals that are intended to reach.

First of all, the scale of the data has an crucial role in the choice of model. For large datasets, such as financial markets, models that can efficiently process large amounts of information are suitable. For example, XGBoost and LSTM scale well and can work with large data sets. At the same time, in the areas of healthcare or economic analysis with smaller amount of data, traditional models can be applied, which take more computational resources, but can be more effective for accurate predictions on smaller samples.

The accuracy of the prediction is another important factor. In critical industries such as medicine or finance, where any error can have serious consequences, complex models are used that can model subtle dependencies in the data. For example, models like LSTM, XGBoost, or Gaussian processes can provide high accuracy.

Computational time is also a determining factor, especially for real-time tasks such as trading or traffic management. In such cases, it is important that the model can learn and predict quickly, so models that provide speed, such as Random Forest, are used. However, in long-term forecasts, such as production or sales planning, training time is not as critical, and therefore more computationally expensive models such as XGBoost, LSTM, or Gaussian processes can be used.

Besides, different models take different time consumption to tune and optimize. More complex ones like XGBoost or LSTM have many hyperparameters that need to be optimized, making them more time-consuming to implement. Thus, when speed is a priority, models with minimal tuning requirements, such as Holt-Winters, may provide a better choice.

Therefore, the choice of a model should always be driven by the balance between accuracy, speed, data processing requirements and tuning complexity. In each specific case, the specifics of the subject area and the forecasting goals should be regarded to choose the optimal model.

3. Practical recommendations

Based on the conducted estimations of ML predictive models, the following practical recommendations have been formulated for the correct choice of a model for specific industry forecasting tasks.

1. Before choosing a model, it is essential to analyze thoroughly the historical data on which the prediction will be built. This includes an analysis of the data features (size, quality, number of missing values, data distribution, etc.) that may affect the model selection.

2. It is advisable to assess the specific needs of the industry and the specific task, which will help to choose the most relevant model. This may include requirements for accuracy, model response speed, the facility to interpret results, and robustness data to noise.

3. It is advisable to test several different models on a subset of the data to find out which one copes better with the given conditions. The cross-validation use and other evaluation methods can help to objectively compare models.

4. The model used should contribute to improving the quality and decision-making efficiency in the relevant field. Therefore, it is advisable to analyze how the model's results affect decision-making processes and what risks may arise from incorrect predictions. An assessment of the model's ability to scale with increasing data volumes and its technical support in the long term is also recommended.

In the context of the prospects of the research, it would be beneficial to automatize the selection of better ML model.

Conclusions

The paper is devoted to the practical issues of ML models estimation for predicting processes in different subject domains.

In the progress of work, there were undertaken the number of core steps.

An analysis of theoretical and practical scientific sources on the use of traditional and modern models for forecasting in various domains is conducted to identify possible consequences of the use of different models risks. The features of building predictive models in selected domains (medicine, meteorology, finance, and sales) are determined.

The criteria and their metrics for the models' estimation are determined.

To perform a comparative analysis and estimation of ML models for forecasting processes in selected subject areas, a web application was developed. A number of predictive models are constructed with the help of the developed web application. The results of forecasting using traditional and modern models in the selected subject domains are analyzed and evaluated according to criteria of accuracy, speed and complexity.

Based on the comparative analysis of ML predictive models, the practical recommendations have been formulated for the correct choice of a model for specific domain forecasting tasks.

The prospects of the research are outlined in the lines of automatizing the selection of better machine learning model.

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Відомості про автора:

Гризун Людмила Едуардівна
доктор педагогічних наук професор
професор
Харківського національного економічного
університету ім. С. Кузнеця,
Харків, Україна
https://orcid.org/0000-0002-5274-5624

Information about the author:

Liudmyla Gryzun
Doctor of Pedagogical Science Professor
Professor
of Simon Kuznets Kharkiv
National University of Economics,
Kharkiv, Ukraine
https://orcid.org/0000-0002-5274-5624

ПРАКТИЧНІ ПИТАННЯ ОЦІНЮВАННЯ І ВИБОРУ МОДЕЛЕЙ МАШИННОГО НАВЧАННЯ ДЛЯ ПОБУДОВИ ПРОГНОЗІВ У РІЗНИХ ПРЕДМЕТНИХ ГАЛУЗЯХ

Л.Е. Гризун

Стаття присвячена практичним питанням оцінки моделей машинного навчання для прогнозування процесів у різних предметних областях. Оцінювання моделей машинного навчання на основі їх порівняльного аналізу з точки зору особливостей прогнозування в різних предметних галузях є актуальним для підвищення ефективності та точності прогнозів. Метою роботи є побудова та порівняння прогнозних моделей машинного навчання у вибраних предметних областях для їх оцінки та вибору найефективніших рішень для конкретних завдань кожної галузі. У процесі роботи було здійснено низку основних кроків. Проведено аналіз теоретичних та практичних наукових джерел щодо використання традиційних та сучасних моделей для прогнозування в різних областях з метою виявлення можливих наслідків використання різних моделей, пов'язаних з ризиками. Визначено особливості побудови прогнозних моделей у вибраних областях (медицина, фінанси, продажі та метеорологія). Визначено критерії та їх метрики для оцінки моделей. Для проведення порівняльного аналізу та оцінки моделей машинного навчання для прогнозування процесів у вибраних предметних областях було розроблено веб-додаток. За допомогою розробленого веб-додатку побудовано ряд прогнозних моделей. Результати прогнозування з використанням традиційних та сучасних моделей у вибраних предметних областях проаналізовано та оцінено за критеріями точності, швидкості та складності. Для оцінки складності виділено індикатори та рівні, відповідно до яких згруповано моделі за рівнями з відповідним обґрунтуванням. На основі порівняльного аналізу прогнозних моделей машинного навчання сформульовано практичні рекомендації щодо ефективного вибору моделі для конкретних задач прогнозування в обраних предметних галузях, що може бути використаним фахівцями при побудові прогнозів. Окреслено перспективи дослідження в напрямках автоматизації вибору кращої моделі.

Ключові слова: *веб-застосування; машинне навчання; оцінювання моделей машинного навчання; порівняльний аналіз прогнозних моделей; практичні рекомендації; прогнозування для різних предметних областей.*