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A Machine Learning Approach to Financial Forecasting: A Case Study

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Abstract: This paper undertakes a machine learning-based forecasting of a subset of financial processes pertaining to the stock market for a particular period in Turkey. There are various machine learning/artificial intelligence algorithms ranging from multilayer perceptron to support vector machines that can be used, with varying degrees of success, for forecasting purposes. The forecasting task to be undertaken in this paper will be carried out in contexts inclusive of a number of crisis-associated complexities generating unusual fluctuations in the financial markets. These fluctuations could pose, for traditional methods, significant difficulties that could be predictably overcome by machine learning/artificial intelligence algorithms which could escape a reasonable range of the possible complications that could be encountered. We will employ a number of algorithms which we will compare and contrast in accordance with a chosen performance metric. Not all algorithms perform equally well but some yield results that could be comfortably and successfully used for further analysis. Successful policy analyses addressing some of the essential intricacies of financial processes are of both theoretical and practical significance. They could produce considerable welfare improvements in emerging economies such as Turkey. Possible ways in which such improvements could be modeled are worthy of future research.

Key Words: Stock market, Machine learning, Forecasting

Introduction

Financial processes may exhibit, in different contexts, a wide array of properties including stability, instability, various degrees of unpredictability and chaos. These properties could create considerable complications for the analysis of financial processes especially at crisis junctures. There are a number of works in the literature dealing with these properties, related issues and associated complications. Among these works are Beker (2014), Fedyk (2017), Ferrara & Guegan (2000) , Klioutchnikov, Musaev, Makshanov & Grigoriev (2023), Sigova, & Beizerov (2017), Rosengren (2014), Scholten (2016), Sinha, Horvath, Beason & Ross (2019), Tropeano (2010), Valenti, Fazio & Spagnolo (2018).

The range of complications associated with the analysis and forecasting of financial processes is fairly wide. Employing some of the state-of-art constructs such as machine learning/artificial intelligence algorithms may well prove to be highly effective in addressing some of those complications, as partly shown in works such as Kumar et. al. (2023), Li (2023), Yu (2008) and Nair & Mohandas (2015). In this paper, we will use a subset of the available algorithms for the purpose of accurately forecasting the changes in stock market averages at a particular juncture in Turkey. We explain the material, methods and results in the second section. The final remarks are presented in the concluding section.

Material, Methods and Results

Consider a stock market where shares of a number of firms are being traded. A diverse list of microeconomic and macroeconomic factors could influence the changes in stock market averages, not to mention the political and other factors that can be multidimensionally interconnected with the economic ones. Abstracting from the detailed modeling of the interconnections of these factors, which is beyond the scope of this short paper, we will, for the sake of simplicity and machine-learning-based-exposition, assume that the changes in stock market averages are influenced by the changes in bond rates, inflation rates, exchange rates and the general course (situation) or prospects of business activity. The particular algorithms we will make use of will enable us to forecast the stock market averages on the basis of algorithm-selected past variables and/or artificially constructed variables associated with the factors/variables within the system.

Forecasting via Machine Learning Algorithms

We can forecast the trajectory of changes in the stock market averages (the closing values) both within the chosen period as well as beyond the relevant period. We will choose a particular period characterized by the military coup-resulting political clashes influencing the financial system. The period in question extends from December 2013 to December 2016. Using the data for the period in question, which could be obtained from the websites of the Central Bank of Turkey, Turkish Statistical Institute and a number of private institutions, we will undertake machine-learning-based forecasting of the key variable chosen for the study.

The algorithms we will make recourse to are Multilayer Perceptron, support vector machines (SVM), M5P, Decision Table, KStar and Random Forest. An open-source program, namely WEKA, will be used to run these algorithms with a set-up where the change in stock market average (dy) is the target variable while the changes inflation rate, the bond rate, the exchange rate and the general course/situation of business as well as the HP-filter extracted cycle for the changes in the stock market averages are the “overlay variables” (General descriptions of the use of these algorithms are available in Witten (2022a,b).) The performance metric we will choose for the forecasting accuracy of the algorithms is “the normalized root mean squared error” (NRMSE), which is defined, for the sake of convenience, as the root mean squared error (RMSE) divided by the range of the changes in the stock market averages over the period in question (s), i.e.,

NRMSE = RMSE/s.

Let N denote the number of observations and s_n and s_n^p represent the actual and predicted values for n=1,…,N. RMSE is the square roof of the sum, from 1 to N, of all $(s_n-s_n^p)^2$ divided by N. The obtained NRMSE values for some of the attribute-selected machine learning algorithms are given in Table 1 below.

Table 1. The NRMSE values for different attribute-selected machine learning algorithms

	Multilayer Perceptron	SVM	M5P	Decision Table	KStar	Random Forset
NRMSE	0.0264	0.0036	0.0465	0.0702	0.0791	0.0970

For the algorithms in question, the NRMSE values pertaining to this particular case range from 0.0036 to 0.0970, which are, on average, fairly low, indicating a high degree of forecasting accuracy.We have used 70 % of the data for training and the rest for testing. For illustration purposes, let us present (in Table 2 and Table 3), for the training and testing period, the predictions which we have obtained via one of these algorithms, namely M5P.

Table 2. Predictions for the target variable with the training data (1-step ahead)

Instance#	Actual	Predicted	Error
13	-4798.31	-4909.387	-111.077
14	-3301.48	-3307.0982	-5.6182
15	3101.01	3347.7172	246.7072
16	-966.04	-789.4578	176.5822
17	-731	-496.4853	234.5147
18	-2340	-2107.2741	232.7259
19	-4700	-4495.5711	204.4289
20	-1005	-647.6348	357.3652
21	5204	5787.8451	583.8451
22	-4176	-3844.1476	331.8524
23	-3506	-3122.0738	383.9262
24	1754	2327.8154	573.8154
25	2333	2952.2177	619.2177

Table 3. Predictions for the target variable with the test data (1-step ahead)

Instance#	Actual	Predicted	Error
26	7454	8256.0979	802.0979
27	2060	2723.2695	663.2695
28	-7525	-7129.4869	395.5131
29	-986	-367.5721	618.4279
30	-1411	-783.4375	627.5625
31	562	1270.8356	708.8356
32	520	1247.8636	727.8636
33	2048	2842.2903	794.2903
34	-4541	-3928.3316	612.6684
35	4144	5040.8616	896.8616

The associated trajectories are given in Figure 1 and Figure 2

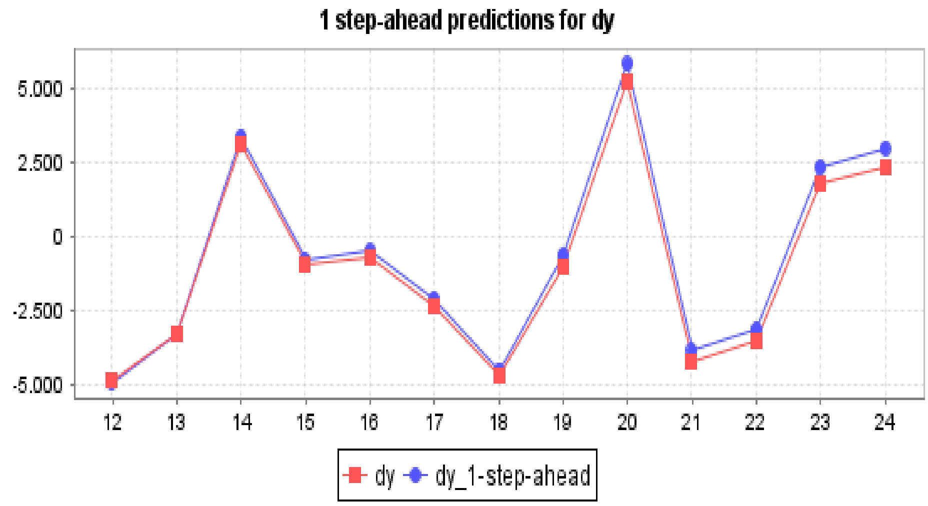

Figure 1. Predictions for the change in the stock market average (dy) with the training data

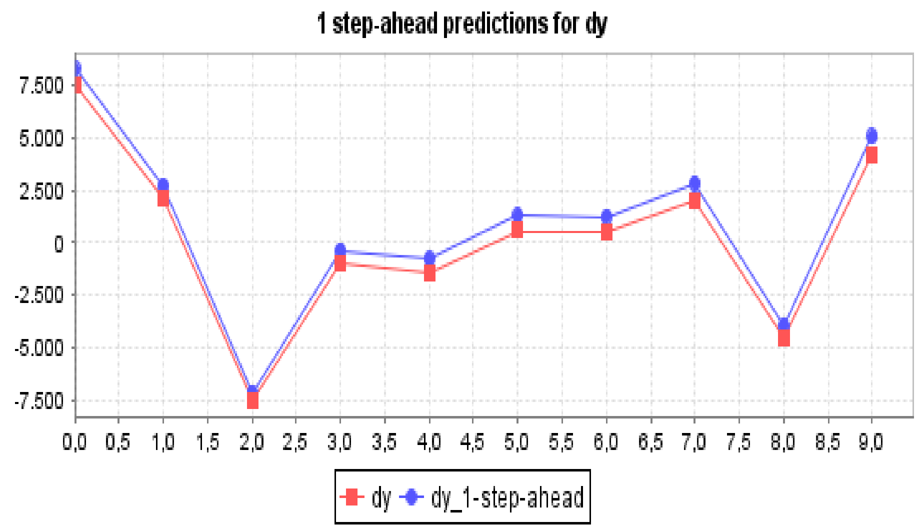

Figure 2. Predictions for the change in the stock market average (dy) with the testing data

Extension

So far, we have used some machine learning algorithms to derive the trajectory of the stock market averages. We can extend this framework so as to incorporate some these algorithms into simulation set-ups with feedback relations that can help better capture the intricacies of the real-life financial processes. Let us consider a system dynamics set-up where the stock market average is the stock variable, the change of which is the flow variable. Suppose that the changes in inflation rate (D-Inflation rate), the bond rate (D-Bond rate), the exchange rate (D-Exchange rate), the general course and prospects of business (D-General business conditions) are auxiliary variables influencing the flow variable. Suppose that there are microeconomic and macroeconomic stochastic factors (shocks/fluctuations) influencing the auxiliary variables in question. We will also assume that general business conditions are affected by the stock market averages. We can use the machine learning algorithms to estimate the weights with which the auxiliary variables influence the change in the stock variable. The system dynamics simulation diagram representing these relationships is given in Figure 4.

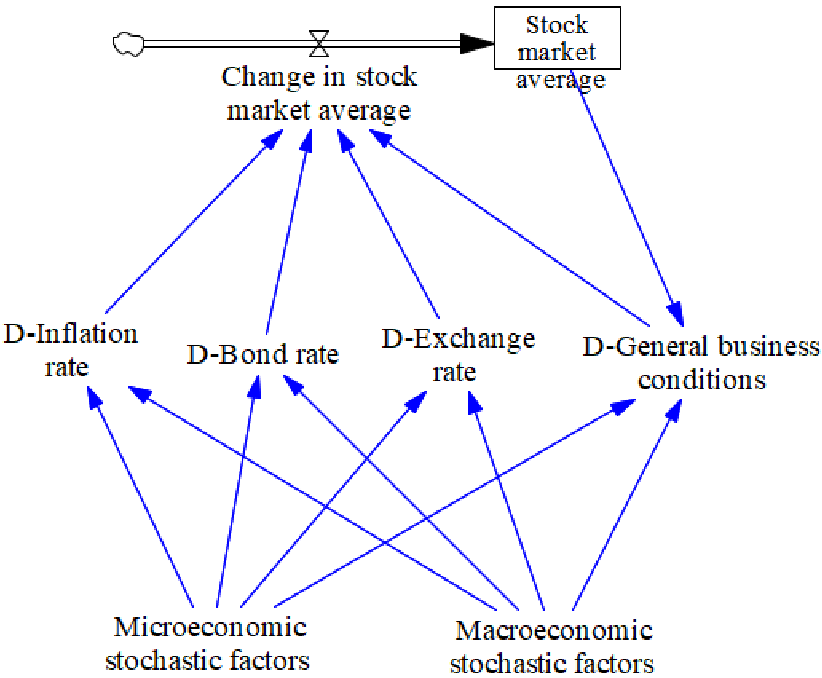

Figure 4. A system dynamics simulation diagram

With properly collected and constructed data set, we can estimate the relationships within the set-up and undertake system dynamics simulations of the trajectory of the stock market average (as well as the changes in the stock market average) incorporating the feedback relations within the system. We can even go further to incorporate additional complexities such as delays, strategic interdependencies and public policy interventions, which will enrich the framework so as to replicate, to a meaningful extent, the convoluted interactions in real-life financial processes.

Concluding Remarks

Machine learning algorithms are shown to be reasonably effective in forecasting the trajectory of the financial processes. The accuracy of the predictions in question may well justify their use for public policy purposes. Machine-learning-integrated hybrid methods could play a significant role in the formulations of optimal financial policies. The topic is worthy of future research.

Scientific Ethics Declaration

The author declares that the scientific ethical and legal responsibility of this article published in EPESS journal belongs to the author.

Acknowledgements or Notes

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