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Machine learning for liquidity prediction on Vietnamese stock market

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Abstract

As a critical consideration in investment decisions, stock liquidity has significance for all stakeholders in the market. It also has implications for the stock market's growth. Liquidity enables investors and issuers to meet their requirements regarding investment, financing or hedging, reducing investment costs and the cost of capital. The aim of this paper is to develop the machine learning models for liquidity prediction. The subject of research is the Vietnamese stock market, focusing on the recent years - from 2011 to 2019. Vietnamese stock market differs from developed markets and emerging markets. It is characterized by a limited number of transactions, which are also relatively small. The Multilayer Perceptron, Long-Short Term Memory and Linear Regression models have been developed. On the basis of the experimental results, it can be concluded that the LSTM model allows for prediction characterized by lowest value of MSE. The results of research can be used for developing the methods for decision support on stock markets.

Keywords: stock market; liquidity; machine learning; prediction

1. Introduction

Numerous previous empirical studies have argued that the term 'liquidity' is an essential feature of the financial market and the macroeconomy. The importance of liquidity has been proved in vast theoretical and practical research projects such as e.g. [1], [2]. Researchers have a growing interest in the role of liquidity in international markets.

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Liquidity illustrates considerable differences among securities and over time [3] thus, every stock market explores the puzzle of market liquidity.

As a critical consideration in investment decisions, stock liquidity has significance for all stakeholders in the market. Because the unpredictability of market liquidity is a substantial source of risk for investors [4], it also has implications for the stock market's growth. Liquidity enables investors and issuers to meet their requirements regarding investment, financing or hedging, reducing investment costs and the cost of capital. While developed markets maintain high liquidity across products, many emerging markets suffer significantly low levels, effectively placing a constraint on economic and market development.

The aim of this paper is to develop the machine learning models for liquidity prediction. The subject of research is the Vietnamese stock market, focusing on the recent years - from 2011 to 2019. Vietnamese stock market differs from developed markets and emerging markets. It is characterized by a limited number of transactions, which are also relatively small. Listed companies trade infrequently, and the trading volume is low. Vietnam has lower development level comparing to the existing "mainstream" emerging markets but is developing fast last years. Therefore, analysis of liquidity of Vietnamese stock market is justified and important. This research was conducted for two stock exchanges in Vietnam: Ho Chi Minh Stock Exchange (HOSE) and Hanoi Stock Exchange (HNX). Liquidity prediction can be used for financial decision support, because the relationships between liquidity and share prices appear [5].

Machine learning provides an automated technique of data analysis. Specifically, machine learning is defined as a set of methods that enable to identify patterns in data, and then uncover patterns to predict the further data, or to support decision making under uncertainty [6], [7], [8]. This paper adopts the best way to predict the liquidity on a frontier equity market is to use the machine learning. In machine learning technique, we generalize learning algorithms to learn from data and perform a prediction.

The paper includes four sections. The related works are documented in the second section. The third section provides the description of materials and the research methodology. In the next section, we compare the different approaches developed in this study. We discuss the main conclusions and the future work in the last section of the paper.

2. Related works

Buehler H., Gonon L., Teichmann J., et al. discussed application of reinforcement learning to the problem of hedging a portfolio of derivatives in the time of market frictions and issues with trading costs and liquidity [9]. This is the extended version of their recent work where they also discussed the same problem and how standard Reinforcement Learning can be applied to non-linear reward structures. In that case convex risk measures [10]. Sebastião H., Godinho P., Westgaard S. analysed the profitability of trading strategies of the Nordic Electricity Base Week Features. They used information retrieved from the daily spot and futures prices. In article they used several Machine Learning methods to create forecasts of the signal of the risk premium. They used combinations of ML methods like Regression Trees, Random Forests and Support Vector Machine, using financial information set. After the prediction an additional step must be taken to control the trading cost and liquidity constraints to prove if the method offers abnormal returns [11]. Kong A., Zhu H., Azencott R. used liquidity measures and technical indicators to predict intraday stock jumps. They used level-2-high-frequency data and divide trading day into a series of 5-minute intervals to forecast whether a stock jump will occur in the next 5 minutes. They characterized ten types of liquidity measures and eighteen types of technical indicators. The model is tested universally on the data of 1271 stocks in Chinese stock exchange. They used four Machine Learning algorithms to develop the optimal jump prediction model: Support Vector Machine, Artificial Neural Networks, Random Forest, K-nearest neighbours [12]. Fang B. and Feng Y. proposed a model to mine the information of the order book for high-frequency traders using Volume-synchronized probability of Informed Trading (VPIN), Generalized Autoregressive Conditional Heteroscedasticity (GARCH) and Support Vector Machine (SVM). VPIN would prejudge market liquidity and predict changing volatility. Authors backtested the effectiveness with CSI300 futures return [13].

Bhattacharya S., Sengupta P., Bhattacharya M., et al. provided evidences of importance of liquidity measures like: trading volume, trading probability, spread, market efficiency coefficient, and turnover rate in the Indian stock market using tools like Artificial Neural Network (ANN) and Random Forest (RF). Findings reveal that liquidity measures explain the movements of stock markets [14]. Bali T. G., Peng L., Shen Y., Tang Y. found that stock market under reacts to stock level liquidity shocks. Liquidity shocks are not only positively associated with returns, but they also predict future return continuations for up to six months [15].

Amihud Y. presented new tests on the effects of stock illiquidity on stock return [16]. Fischer T. created a survey about Reinforcement Learning in financial markets. The author stated that, important constraints, such as transaction costs, market liquidity, and the investor's degree of risk-aversion, could be conveniently considered. He also stated that over last two decades, most attention still being devoted to supervised learning methods but RL research community also made advances in the finance domain. Author noted that constraints like: lack of liquidity and transaction costs, in the majority of cases are not considered at all [17]. Zhai J., Cao Y., Yao Y., et al. used different Machine Learning methods that could analyze and detect disruptive activities based on direct studies of trading behaviors. Models were evaluated using huge volumes of real tick data from NASDAQ [18]. Conegundes L., Pereira A. investigated the potential of using Deep Reinforcement Learning (DRL) in today's trade stocks, taking into account the constraints such as: liquidity, latency, slippage and transaction costs at Brazil Stock Exchange [19]. Alvim L., Dos Santos C., Milidiú R. investigated daily volume forecasting using intraday information by the use of two Machine Learning predictors: Support Vector Regression (SVR) and Partial Least Squares (PLS). They tested the method using top nine high liquidity Bovespa traded stocks [20].

E. Boehmer, Kingsley Y. L. Fong, J. Wu used large amount of data from 39 exchanges to assess the effect of algorithmic trading (AT) on liquidity in the equity market, short-term volatility, and the informational efficiency of stock prices. They found that greater AT intensity improves liquidity and informational efficiency but increases volatility [21]. Hiroshi M., Wee M., Yu J. were also checking the effects of algorithmic trading on stock market liquidity and commonality in liquidity under different market conditions on the Tokyo Stock Exchange [22]. Pavinee H. investigated the impact of algorithmic trading (AT) on liquidity in Thailand. The main question is if algorithmic trading improve liquidity in Emerging Markets [23]. Mestel R., Murg., and Theissen E. checked the relation between algorithmic trading and liquidity on the Austrian equity market. Samples from almost 4,5 years identified the market share of algorithmic trading at the stock-day level [24].

Deep learning is a sub-division of machine learning, majorly concerning with algorithms. It has received the deserved attention in the financial sector. The technique is diversified in application such as market price prediction, bankruptcy prediction and credit evaluation. Due to sophisticated algorithms, deep learning enables providing accuracy and efficiency in time-series data prediction in financial sectors.

Odom and Sharda were one of the first authors used deep learning in prediction models [25]. Naidu and Govinda applied data processing for Polish companies during the period from 2000 to 2012 to predict the bankruptcy situation [26]. The predictive model was trained by learning algorithm based on artificial neural networks and the random forest. Alexandropoulos et al. generated a predictive model to forecast bankruptcy of 150 companies in Greece. They compared the efficiency between the algorithms, i.e., Logistic Regression, Deep Dense Multilayer Perceptron, the simple Multi-layer Perceptron, and the Naıve Bayes. They argued that Deep Dense Multilayer Perceptron had better performance than remaining algorithms [27]. Moghaddam et al. achieved predictive analytics for NASDAQ Index through the scaled conjugate gradient (SCG). They constructed their predictive model by using the Levenberg-Marquardt approach [28]. Four different models were applied in Moghaddam et al. (2015) such as: Long-Short Term Memory, Convolutional Neural Networks, Gated Recurring Unit and Extreme Learning Machines. Balaji et al. employed deep learning techniques for market prediction in the SP BSE-BANKEX index from July 2005 to November 2017 [29].

Summarizing, the existing research is related to using liquidity measures for prediction the quotations on financial markets or to the analysis of influence of different trading algorithms on liquidity. There is a lack of research related to liquidity prediction, and it is the main contribution of this research. In our previous research, we developed the deep learning model for liquidity prediction of selected companies on HOSE stock exchange [30]. This research is related to aggregated liquidity measures for HOSE and HNX stock markets.

3. Materials and methods

3.1. Data description and preparation

The paper covers the sample period from January 2011 to December 2019, which contains 2,242 trading days. The eligible stocks in the sample consist of 378 companies in two stock exchanges, which included 179 stocks on the

HOSE and 199 stocks on the HNX. Stock market liquidity is represented by seven liquidity measure following [31], [32], [33], [34]:
(i) quoted spread (SPRD) is the difference in the best bid and best ask prices;
(ii) relative spead (RESPRD) is proportion of quoted spread over the mid-price;
(iii) effective spread (EFSPRD) two times the absolute difference between the trade price and the bid-ask midpoint;
(iv) trading volume (VOL) is the number of traded shares on each stock;
(v) trading value (VAL) is the amount of traded value during a specified period on each stock;
(vi) turnover ratio (TO) is a ratio of the traded volume over the number of shares outstanding;
(vii) Amihud (AMIHUD) measure is a ratio of the absolute stock returns over trading value;

The study calculates seven liquidity measures (SPRD, RESPRD, EFSPRD, VOL, VAL, TO, AMIHUD) over the trading day. VOL, VAL and TO are liquid measures, the higher measures are, the better liquidity is. SPRD, RESPR, EFSPRD and AMIHUD have negative relation with the stock liquidity. Table 1 and 2 present the Spearman coefficient of correlations between liquidity measures on the HOSE and the HNX.

Table 1. Correlation among liquidity measures on the HOSE

Liquidity measure	SPRD	RESPRD	EFSPRD	VOL	VAL	TO	AMIHUD
SPRD	1.000						
RESPRD	0.0553	1.000					
	(0.0088)*						
EFSPRD	0.9585	0.0214	1.000				
	(0.000)*	0.3109					
VOL	0.3589	-0.4360	0.3544	1.000			
	(0.000)*	(0.000)*	(0.000)*				
VAL	0.5745	-0.4442	0.5755	0.8626	1.000		
	(0.000)*	(0.000)*	(0.000)*	(0.000)*			
TO	-0.0204	-0.4087	-0.0264	0.7924	0.5447	1.000	
	(0.335)	(0.000)*	(0.000)*	(0.000)*	(0.000)*		
AMIHUD	0.1551	0.4200	0.1709	-0.3194	-0.1825	-0.4203	1.000
	(0.000)*	(0.000)*	(0.000)*	(0.000)*	(0.000)*	(0.000)*	

* denotes statistical significance at the 5 level
Source: own elaboration

Table 2. Correlation among liquidity measures on the HNX

Liquidity measure	SPRD	RESPRD	EFSPRD	VOL	VAL	TO	AMIHUD
SPRD	1.000						
RESPRD	0.6502	1.000					
	(0.000)*						
EFSPRD	0.9463	0.5435	1.000				
	(0.000)*	(0.000)*					
VOL	0.0711	-0.0968	0.0897	1.000			
	(0.000)*	(0.000)*	(0.000)*				
VAL	0.4080	0.0756	0.4064	0.8223	1.000		

	(0.000)*	(0.000)*	(0.000)*				
				(0.000)*			
TO	-0.2835	-0.4322	-0.2371	0.5451	0.3184	1.000	
	(0.3353)	(0.000)*	(0.000)*	(0.000)*	(0.000)*		
AMIHUD	0.1982	0.5408	0.1373	-0.2853	-0.2129	-0.3661	1.000
	(0.000)*	(0.000)*	(0.000)*	(0.000)*	(0.000)*	(0.000)*	

* denotes statistical significance at the 5 level
Source: own elaboration

In both cases, the high correlation appears between SPRD and EFSPR measures and between VOL and VAL measures. Therefore, EFSPR and VAL measures has been removed during building prediction models.

3.2. Methods

The research is based on three machine learning methods often used for financial time series prediction: two neural networks models - Multi Layer Perceptron (MLP), Long Short-Term Memory (LSTM) and linear regression model, MLP is a supplement of feed forward neural network. MLP consists of three layers [35]:
- input layer - receives the input signal to be processed
- hidden layer - computational engine of the MLP
- output layer - performs task for example prediction or classification

MLP can approximate any continuous function and solve not linearly separable problems. MLP is used as pattern classification, recognition, prediction and approximation.

Long Short-Term Memory (LSTM) is s an artificial recurrent neural network architecture used in deep learning. LSTM networks compensate the problem of vanishing gradients and short-term memory of traditional recurrent neural network. The architecture of LSTM are cell state (memory unit of the network) and its regulators. The cell state carries information that can be stored in, written to, or read from a previous cell state via gates. LSTM is used in deep learning tasks such as stock market prediction or handwriting and speech recognition [36].

Linear regression is a machine learning algorithm based on supervised learning. It is mostly used for finding out the relationship between variables and forecasting. Linear regression predicts a dependent variable value y based on a given independent variable x. Thus, linear regression finds out a linear relationship between x - input and y - output the regression line is the best fit line for a model [37].

4. Results

The experiments aim to predict the AMIHUD measure on the basis of historical values of AMIHUD and SPRD, RESPRD, VOL and TO measures. The one-day prediction is performed. We developed two neural networks model based on Multi-Layer Perceptron and Long Short-Term Memory. In addition, model based on regression has been developed. The developed models are based on related works and our experience. The optimal structure of networks was determined based on experimental results.

Several dozen experiments have been performed with different parameters and hyper-parameters (e.g. type of layers, number of layers, number of neurons, activation function, batch size, and number of epochs). We use *Keras* framework based on *Tensorflow* engine for neural networks models and *sci-kit learn* library (link: https://scikit-learn.org/stable/modules/generated/sklearn.linear_model.LinearRegression.html) for regression model. The Mean Square Error (MSE) has been used for model's assessment. Table 3 presents the results of MLP for HOSE data (for all neural networks models the following parameters has been used: (remaining parameters: batch size:32, activation function: linear).

Table 3. Results of MLP for HOSE.

Neurons in hidden layers	Epochs	Min. MSE
32	7	0.0367
64	12	0.0332
128, 64, 32,8	12	0.0303
128, 64, 32, 16, 8	12	**0.0268**
128, 64, 32, 16, 8	20	0.0271

The best results (0.0268) have been achieved by model consist of five hidden layers.

Table 4 presents the results of LSTM for HOSE data.

Table 4. Results of LSTM for HOSE.

Neurons in hidden layers	Epochs	Min. MSE
16	3	0.0320
32	5	0.0315
64, 32, 8	5	0.0299
64, 32, 16, 8	5	**0.0252**
64, 32, 16, 8	10	0.0261

The best results (0.0252) have been achieved by model consist of four hidden layers.

Table 5 presents the results of MLP for HNX data.

Table 5. Results of MLP for HNX.

Neurons in hidden layers	Epochs	Min. MSE
32	7	0.0293
64	18	0.0218
128, 64, 32,8	18	0.0186
128, 64, 32, 16, 8	18	**0.0177**
128, 64, 32, 16, 8	25	0.0178

The best results (0.0177) have been achieved also by model consist of five hidden layers.

Table 6 presents the results of LSTM for HNX data.

Table 6. Results of LSTM for HNH.

Neurons in hidden layers	Epochs	Min. MSE
16	3	0.0280
32	9	0.0207
64, 32, 8	9	0.0174
64, 32, 16, 8	9	**0.0169**
64, 32, 16, 8	15	0.0172

The best results (0.0169) have been achieved also by model consist of four hidden layers.

In addition, linear regression model has been developed. The MAE values:
- HOSE data: 0.0257
- HNX data: 0.0215

Generally, the lowest value of MSE has been achieved using LSTM model. However, taking into consideration the HOSE data, the MSE achieved by LSTM is similar to MSE achieved by linear regression and value of MSE achieved by MLP is lower than linear regression. It indicates the existence of mainly linear relationships between the variables. In case of HNX data both MLP and LSTM models have a lower value of MSE than a linear regression model. Therefore, non-linear relationships between variables can appear.

Conclusions

The machine learning models allows for prediction the liquidity on Vietnamese stock market. On the basis of the experimental results, it can be concluded that the LSTM model allows for prediction characterized by lowest value of MSE. The results of research can be used for developing the methods for decision support on stock markets. On the basis of the liquidity prediction, the portfolio of financial instruments can be built. The main disadvantage of proposed approach is the performing prediction only for one day. Therefore, future research works should be related to developing the model performing prediction for week or month. In addition, models for other stock markets should be developed.

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