Trading on natural disasters: prediction model of stock prices on earthquakes.

Aitore Issadykova
Data Science
Nazarbayev University
Nur-Sultan, Kazakhstan
aitore.issadykova@nu.edu.kz

Assem Kussainova
Data Science
Nazarbayev University
Nur-Sultan, Kazakhstan
assem.kussainova@nu.edu.kz

Selim Temizer
Computer Science
Nazarbayev University
Nur-Sultan, Kazakhstan
selim.temizer@nu.edu.kz

***Abstract*—The natural disasters have a great impact on the world economy and stock market as well. There is a huge difference in the impact on each industry sector which caused by natural disaster. On earthquake period the stock price of the companies which produced and deliver first aid product is increasing. However, there is no any proposed mechanisms ad financial model for prediction and trading on the earthquakes. This study was oriented to build a prediction model for six technology related companies' stocks: Google, Amazon, IBM, Facebook, Apple and Microsoft- during an earthquakes period by using Machine Learning such as LSTM method and Statistical approaches like AR, MA and ARIMA. Moreover, the proposed models were used to generate "Buy-Hold-Sell" model for financial trading on the earthquakes and were compared between each other by their performance.**

***Index Terms*—algorithmic trading, financial forecasting,machine learning, models, stocks, natural disasters, earthquakes.**

I. Introduction

The natural disaster are highly unpredictable events. Hurricanes, tornadoes, earthquakes damage the infrastructure's of countries and cause the huge losses for companies. Stock prices on the period of natural disaster change their behaviour for the small period and cause the earthquake in the financial market. While, it is common that the stock prices for the companies which produced and deliver first aid products are in favor on that periods, the effect on the stock price for other industries are not foreseeable.

The technology related companies form one of the biggest industry in the world economy. During earthquakes period they will face a negative impact on their business and their stocks, since the major earthquakes can damage the Internet connection, electricity, warehouses and companies buildings. However,t here is no particular behaviour analysis and model for forecasting stock prices for tech sector in the period of stock prices.

The main goal of the current study is to build a prediction model for the stock prices of six technology related companies and to evaluate their performances. Furthermore, there will be suggested a "Buy-Hold-Sell" model for financial trading on the earthquake period. The proposed models will be evaluated by their performances with some metrics and the results will be compared with the real maximum achievable outcome.

II. Methods

A. Major Earthquakes

Earthquakes can be categorized in different groups depends on their magnitude. The major earthquakes with magnitude more than 7.0 points always appears after some minor earthquake fluctuations, which can be treated as early warning of the incoming natural disaster. The some connection between earthquakes can be observed on Table 1, by looking into year 2016. Both earthquakes in Ecuador and Japan were in April 16 with small difference in the magnitude.

TABLE I
List of major earthquakes

Year	*Country*	*Magnitude*	*Date*
2019	*Peru*	*8.0*	*May 26*
2018	*Fiji*	*8.2*	*August 19*
2017	*Mexico*	*8.2*	*September 7*
2016	*Ecuador*	*7.8*	*April 16*
2016	*Japan*	*7.0*	*April 16*
2011	*Japan*	*9.0*	*March 11*

The earthquake with epicenter near to Ecuador caused the second wave of earthquake in Japan. Hence, it is a probable to catch the early signs of changing in the financial markets due to first minor earthquake waves in other regions which can lead the major earthquake waves.

B. Stock Market during Earthquake period

The behaviour of each stock price during natural disaster is unique. While some stocks may react one early indications of the oncoming earthquake, others may react only after some period. The stocks of Google and Microsoft companies reacted slower than other companies, when stocks of IBM company reacts on the minor earthquakes before the major earthquake wave. Figure 1 represents the price of Google company stock for 15 days before earthquakes in Japan and Ecuador in April 16, 2016 and shows the dynamics of changes of the price during the month after. Figure 2 and Figure 3 represents same time period for IBM company stocks during earthquake period in Peru in May 26, 2019 and Microsoft company stocks for period of Mexico earthquake in April 16, 2017. The red line indicated the date of the earthquake and clearly separates the post effects of earthquake on company stock respectively.

Fig. 1. Google company's stocks during earthquakes in 2016

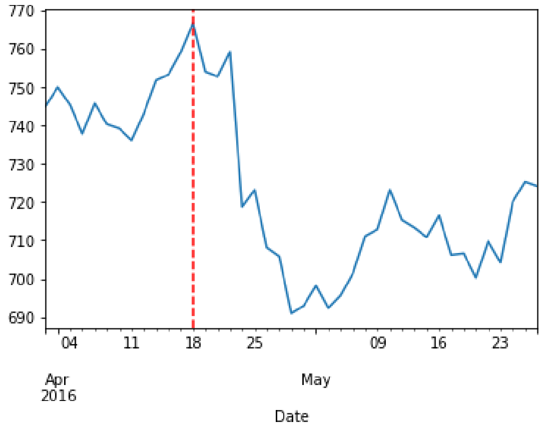


Fig. 2. IBM company's stocks during earthquake in 2019

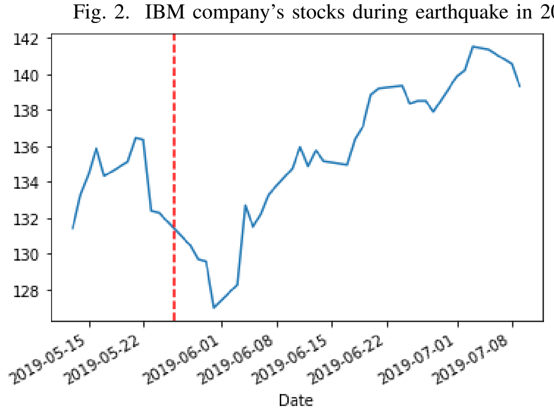
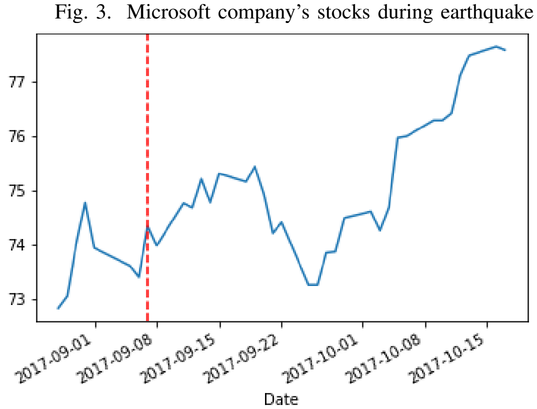


Fig. 3. Microsoft company's stocks during earthquake in 2017



C. Related Works

Donadelli et al. [2] studied the effect of North American Tornado on house prices and stock prices for companies of nearby tornado place. The authors indicated that the tornadoes are beneficial for all industrial companies which operates in the nearby area which are not hit by tornado. Moreover, they conclude that there is a negative effect on the utilities firms' stocks. These firms should recover all necessary resources supply such as gas, water and electricity which led to some additional costs for the companies.

The study conducted by Grindsted [3] proposed high-frequency trading for earthquakes period. The research analyzed the stock prices of Tokyo electric company during three earthquake period. It was concluded that the stock prices raised significantly when the Japanese government's alert system informed about the forthcoming earthquake and tsunami in Japan. Researcher proposed the high frequency trading for couple of days of the natural disaster by looking up the historical hourly prices.

Kawashima and Fumiko [4] also analyzed the stock prices of Japanese electrical companies before and after major earthquake and tsunami in 2011. They indicated the huge loss in the financial market for electrical companies because of Fukushima nuclear accident and covered 2 year period from March 2010 to March 2012 to show the financial situation of electricity sector in Japan.

Other related works are similar to Kawashima and Fumiko works and concentrated only on the earthquake in 2011 in Japan. Moreover, the researchers mostly covered either electricity sector or insurance sector which faced the major negative impact of this event.

III. Forecasting Algorithms and Models

AR, MA, ARIMA and LSTM models were used for creating the forecasting algorithms for stock prices and "Buy-Hold-Sell" models.

A. AutoRegressive (AR) Model

AutoRegressive Model or AR model is a statistical model for forecasting future values given past values of the time series.The process is basically a linear regression of the data in the current series against one or more past values in the same series.

$$y_t = \beta_0 + \beta_1 * y_{t-1} + ...\beta_p * y_{t-p-1} + \epsilon \tag{1}$$

Equation (1) represents the general formula for AR model, where y_t and y_{t-1} are stock values at time t ad t-1 respectively, ϵ is a white noise and β_0 and β_1 are parameters of the equation and p is the number of auto-regressive terms.

B. Moving Average (MA) model

Moving Average Model or MA Model is another statistical model for forecasting future values of time series which depends linearly on the current and various past values of a stochastic,imperfectly predictable term or past error term. The MA model is also can be represented as regression model (2):

$$y_t = c + \epsilon_t + \epsilon_{t-1} * \theta_1 + ... + \epsilon_{t-q} * \theta_q \tag{2}$$

where ϵ are past error terms, c is a constant, θ is coefficient and q is the number of lagged forecast errors in the prediction equation. There are several types of MA model: simple

MA, exponential MA, random walk MA and others. For this research purposes was used random walk AutoRegressive Moving Average Model or ARMA model with coefficients, which requires parameters p be equal to 1 and q be equal to 0.

C. AutoRegressive Integrated Moving Average (ARIMA) model

AutoRegressive Integrated Moving Average (ARIMA) model is a statistical model which is generalization of ARMA model. ARIMA model mostly used for non-stationary time-series and Integrated part of this model replaces the data values with the difference between their values and the previous values and this differentiation process may be applied more than once.

There are two general types of ARIMA models: seasonal and non-seasonal. Since there is no seasonality in the earthquakes events, the proposed model will be non-seasonal. Non-seasonal ARIMA requires three coefficients: p,d,q - where p and q coefficients from AR and MA models and d is the number of nonseasonal differences needed for stationarity (3) - (5).

$$d = 0 : y_t = Y_t; \tag{3}$$

$$d = 1 : y_t = Y_t - Y_{t-1}; \tag{4}$$

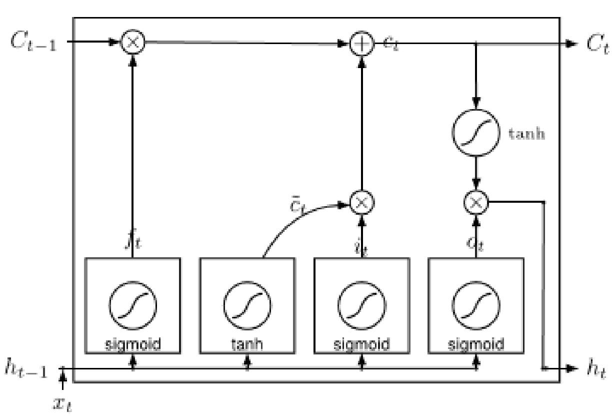
$$d = n : y_t = Y_t - Y_{t-1} - (Y_{t-1} - Y_{t-2}) - ... - (Y_{t-n+1} - Y_{t-n}) \tag{5}$$

The y_t is a new output values for regression in ARIMA model and Y_t are real time-series output values. This study uses random walk ARIMA model with parameters (p,d,q) =(0,1,0).

D. LSTM

Long Short-Term Memory Networks (LSTMs) are special kind of Recurrent neural network (RNN). Long sequences can be difficult to learn from standard RNN because it is trained by back-propagation through time (BPTT) and that causes the problem of vanishing/exploding gradient [5]. To solve this, the RNN cell is replaced by a gated cell, like LSTMs cell. Figure 4 shows the basic architecture of LSTMs cell.

Fig. 4. LSTM cell architecture. [1]



The proposed forecasting LSTM Model are trained with 30 epochs and 4 neurons with batch size equals to 1. Moreover, the "adam" optimizer and "Mean Squared Error (MSE)" loss functions was applied.

E. Buy-Hold-Sell Model

All four forecasting algorithms was used to build a a "Buy-Hold-Sell" Model. Since the earthquake post-effect lasts in average for one month period without several troughs, the "Buy-Hold-Sell" model will signal to buy a stock of company in the day where minimum price will be predicted. Then "Hold" part of algorithm will work while model will not signal that the maximum predicted price appeared in one month period and "Sell" the purchased stock.

F. Experimental Setup

The forecasting price models was constructed by using pair of earthquakes due to the fact that statistical methods took only one time series as an input. Therefore, four train/test pairs created on earthquakes data: Japan in 2011 as a train and Japan 2016 as test, Ecuador in 2016 as a train and Mexico in 2017 as a test, Mexico in 2017 as a train and Fiji in 2018 as a test, and Fiji in 2018 and Peru in 2019 as a train set and test set respectively.

Performance of the created models evaluated by Mean Square Error and Mean Absolute Percentage Error.

$$MSE = (\frac{1}{n}) \sum_{t=1}^{n} (y_t - \hat{y}_t)^2 \tag{6}$$

$$MAPE = \frac{100\%}{n} \sum_{t=1}^{n} |\frac{y_t - \hat{y}_t}{y_t}|. \tag{7}$$

$\hat{y}_t$ is a predicted value of stock price by forecasting model and y_t is an actual value of stock price for testing dataset.

The performance of the "Buy-Hold-Sell" model will be evaluated by Rate of Return (ROR) and Percent Profitability (PP) metrics. For computations of these metrics the minimum price is calculated as by taking the real stock price value in the predicted by model day for minimum price. The maximum price will be founded as a real price value on the day when the maximum value was occurred by prediction of forecasting models. The ROR and PP of four models will be compared with the maximum ROR and PP that were achievable for certain pair of earthquakes.

$$ROR = \frac{max_{t:} - min_t}{min_t} \tag{8}$$

$$PP = \frac{100\% * (max_{t:} - min_t)}{max_{t:}} \tag{9}$$

All models were trained on CPU with 8 GB RAM and Windows system with Python Anaconda packages.

IV. Results

The four models were trained and tested on four earthquake pairs for all companies, except the Japanese earthquake pair for Facebook company, since the company stocks weren't publicly listed in 2011. The average results of models for

TABLE II
AVERAGE MODELS RESULTS ON GOOGLE COMPANY STOCKS'

Metrics	MA model	AR model	ARIMA model	LSTM model
MSE	46.99	107.81	13.90	255.63
MAPE	2.27%	11.58%	1.11%	28.56%
ROR	0.022	0.044	0.052	-0.026
PP	1.846%	4.184%	4.94%	-2.559%

TABLE III
AVERAGE MODELS RESULTS ON AMAZON COMPANY STOCKS'

Metrics	MA model	AR model	ARIMA model	LSTM model
MSE	40.63	119.17	21.87	474.16
MAPE	2.08%	10.34%	1.32%	40.05%
ROR	0.097	0.026	0.088	0.046
PP	8.719%	2.442%	7.949%	4.603%

TABLE IV
AVERAGE MODELS RESULTS ON IBM COMPANY STOCKS'

Metrics	MA model	AR model	ARIMA model	LSTM model
MSE	1.99	3.37	1.41	8.18
MAPE	0.87%	1.94%	0.71%	5.38%
ROR	0.057	0.022	0.052	0.018
PP	5.317%	2.029%	4.835%	1.786%

TABLE V
AVERAGE MODELS RESULTS ON APPLE COMPANY STOCKS'

Metrics	MA model	AR model	ARIMA model	LSTM model
MSE	5.65	19.37	2.53	8.18
MAPE	2.13%	11.03%	1.23%	5.38%
ROR	0.057	0.027	0.087	0.018
PP	5.099%	2.328%	7.872%	1.786%

TABLE VI
AVERAGE MODELS RESULTS ON MICROSOFT COMPANY STOCKS'

Metrics	MA model	AR model	ARIMA model	LSTM model
MSE	2.40	8.42	1.21	26.67
MAPE	1.82%	11.35%	1.00%	32.41%
ROR	0.031	0.041	0.063	0.028
PP	2.562%	3.599%	5.903%	2.807%

TABLE VII
AVERAGE MODELS RESULTS ON FACEBOOK COMPANY STOCKS'

Metrics	MA model	AR model	ARIMA model	LSTM model
MSE	3.38	16.92	2.87	27.55
MAPE	1.47%	9.26%	1.22%	15.05%
ROR	0.066	0.057	0.085	-0.026
PP	5.738%	5.181%	7.441%	-2.594%

each company are presented in Tables II-VII.

For all six companies ARIMA model forecasts stock prices more accurate than other methods. Moreover, for four companies the results of "Buy-Hold-Sell" model based on ARIMA model outperformed other methods results. For other two companies MA model performed slightly better than ARIMA model. According to Table VIII which represents the average results of methods for all companies and all earthquake pairs, the ARIMA method outperforms in general other methods in both predicting and "Buy-Hold-Sell" models. In average the real ROR and PP for all companies were 0.095 and 8.506% respectively. The results given by ARIMA model provides ROR and PP values which are 75.2% and 76.95% from original values. For Apple company stocks it was possible to get the return on stocks with ARIMA model with 98.2% accuracy from real maximum ROR and PP.

TABLE VIII
AVERAGE MODELS RESULTS ON ALL COMPANIES STOCKS'

Metrics	MA model	AR model	ARIMA model	LSTM model
MSE	16.84	45.84	7.30	133.40
MAPE	1.77%	9.25%	1.10%	21.14%
ROR	0.055	0.036	0.071	0.010
PP	4.880%	3.294%	6.490%	0.972%

In overall statistical methods outperformed the machine learning methods due to the fact that LSTM method is mostly used for large datasets and the current train dataset for 30 days is insufficient for accurate model building. Moreover, the SVM models with linear, polynomial and rbf kernels performed worse than LSTM and the results weren't included for this study.

V. DISCUSSION

Among all four proposed models the ARIMA model presented the outstanding results. The main issue for machine learning methods were the capacity of the data, which limited the performance of LSTM and SVM models. The given parameters for MA models and ARIMA models were optimized before analyzing results.

Since earthquakes are commonly occurred in some areas, the ARIMA model can be used for financial trading of stocks for companies in this region. Moreover, for the future works the hourly data before earthquake can be used for high-frequency trading in order to increase the financial benefits on earthquake return for ARIMA Model.

The same models can be applied for prediction different sector for different natural disaster. For prospective researches it is required to collect more data with higher frequency. For example, Kazakhstani companies' stock prices also slightly affected by earthquake;nonetheless, the data for stock prices are given only twice per week for earthquakes period.

VI. CONCLUSION

Natural disaster, especially earthquakes, have a significant impact on the financial market. Companies stock prices may react earlier, at the time and after the earthquake event. There is a different impact on stock market for each sector of business. This paper studied the impact of the major earthquakes on the stock market for technology related companies.

Among proposed models: LSTM, AR, MA, ARIMA - the last one surpassed the results of other models. The ARIMA model was able to perform for 98.2% similar as the real stock return. For forecasting part this method had only 1.1% error in predicting the stock price for one moth period. The results indicate that the model can create profitable trades, however the overall efficiency of the model can be improved.

The future researches can be conducted by evaluating the forecasting and "Buy-Hold-Sell" models for other natural disasters such as hurricane. Moreover, there is a possibility to propose a general model for any type of natural event with slight adjustment in parameters for different regions and industry sectors. As for model part, it can be suggested to build hybrid models such as ARIMA-CNN-LSTM model which may perform better than random walk ARIMA model. The hybrid models may be trained on the multiple time-series data.

To conclude, the proposed models performed profitable trades in the majority of the cases. The limitations of this paper were the availability of only historic daily data and inability of statistical methods to train on multiple time-series data. The recommendations for the future researches were provided by indicating improvement in the model and research for other natural disasters events.

REFERENCES

[1] Alhagry, Salma Aly, Aly El-Khoribi, Reda. (2017). "Emotion Recognition based on EEG using LSTM Recurrent Neural Network." International Journal of Advanced Computer Science and Applications. 8. 10.14569/IJACSA.2017.081046.

[2] Donadelli, M., Jüppner, M., Paradiso, A., Ghisletti, M. (2020). "Tornado activity, house prices, and stock returns." The North American Journal of Economics and Finance, 52, 101162.

[3] Grindsted, Thomas Skou. "Trading on earthquakes–Algorithmic financialization of tectonic events at global stock exchanges." Geoforum 108 (2020): 80-87.

[4] Kawashima, Shingo, and Fumiko Takeda. "The effect of the Fukushima nuclear accident on stock prices of electric power utilities in Japan." Energy Economics 34.6 (2012): 2029-2038.

[5] Sepp Hochreiter and J¨urgen Schmidhuber. "Long short-term memory." Neural computation, 9(8):1735–1780, 1997