Predicting the Unpredictable: Stock Markets in the Face of Brexit

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Abstract

The limited success of econometric models in making financial predictions especially during highly volatile periods, such as when reacting to the announcement of Brexit, has created a need to look at more novel techniques. With the recent advent in technology, learning from highly complicated data has become more feasible. In this paper, we implement Deep Neural Networks (DNNs) and Support Vector Machines (SVMs) adaptively in order to test a hypothesis about the behavior of equity markets before and after the Brexit announcement. We use minute by minute data to test if a systematic pattern is observed in the flow of information from high-value to low-value stocks, aiding financial prediction. The performance of the adaptive machine learning algorithms is evaluated by a direction measure, and the results are presented and discussed.

Keywords: Adaptive Deep Learning, Information Flow, Financial Markets

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Maybe you can add a sentence to summarize the results? E.g. This algorithm successfully improve and predict …What is the conclusion of the paper? What problem did it successfully solve? Tell the readers why it's important to read this paper.

1. Introduction

On certain rare market trading days, unanticipated events occur that change the systematic risk in the entire market. One such event was the United Kingdom's (UK) European Union (EU) membership referendum, also known as the Brexit referendum. The general

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expectation before the vote was that the UK would remain in the EU. Thus, the global markets plunged on the unexpected victory of the movement calling for the UK to leave the EU.

The FTSE 250, which serves as an accurate reflection of the British economy since it tracks firms that do most of their business inside Britain, plummeted 7.2% (Quaye et al., 2016). US stocks followed plunging global markets. The New York Stock Exchange (NYSE) opened a few hours after the Brexit announcement and remained open throughout the day while information continued to flow in as the UK and foreign nations reacted. Some major news events that occurred during the course of the trading day included the resignation of UK Prime Minister David Cameron, a sharp devaluation of the pound, and downgrades announced in the credit ratings of British bonds and global corporations in general. The Dow ended the day down 611 points, or over 3.4%, while the Nasdaq composite index dropped 4.12% and into correction territory, or down 10% from its recent high (Quaye et al., 2016). Brexit provides a unique opportunity to analyze market behavior because there was a high period of sustained market volatility driven by continuous media coverage throughout the day. This sustained coverage over the course of the NYSE/Nasdaq trading day included David Cameron's resignation and statements from the presidents of the European Council, ministers, and financial institutions such as the International Monetary Fund (IMF) and European Central Bank (ECB).

Any stats about how NYSE was affected?

The transition here seems to be a bit abrupt, since the previous paragraph focuses on the impact of Brexit on the market, while this paragraph introduces other researchers work. I think you can emphasize the absence of relative research in this area and why your work is important.

Researchers have long been interested in market reaction to information. Most recent studies focus on the general trend of information flow during normal trading days. Kwon and Yang studied the information flow between stock indices and concluded that the S&P 500 Index is generally located at the focal point of the information source for world stock markets (Kwon and S.Yang, 2008). Studies on information flow during critical events are mostly concerned with events such as earnings announcements, dividend announcements, and analyst forecasts (Donelson et al., 2012) (Kross and Schroeder, 1984) (Beaver et al., 2008). Popular methods adopted in previous research relate to causality tests between non-stationary time series. For example, Yao used the Wald Test of one-way causality to study the information flow between different stock indices (Yao et al., 2010). Kwon and S.Yang

(2008) used transfer entropy to analyze the direction of information transfer among different stock sectors.

In this paper, we provide new insight about the information flow in financial markets. This insight provides a novel way to look at how information propagates between high-value stocks and low-value stocks. Several factors such as valuation ratio, nominal interested rates, and aligned technical analysis have been proposed to predict market excess returns (equity market premium) (Lin, 2017) (Campbell et al., 2002) (Campbell and Yogo, 2006). We believe that our insight can also be used to forecast equity market premiums, which is an essential quantity in asset allocation and macroeconomics.

The objective of this paper is twofold. Our primary objective is to study the information
What is the importance of studying information flow? Why study it on high-volatility trading days?
flow using predictive models. The method we adopt to determine the information flow is as follows: for two parties A and B in the market, if including the extra information of A into the input can significantly improve the prediction performance of B, but not vice versa, then we conclude the information flows from A to B. If the converse is true, we can conclude the information flows from B to A. Our study focuses on the information flow between high-value and low-value stocks on Brexit day. The use of high-value and low-value simply refers to the price of the stock itself where a more expensive stock is considered to have relatively higher value. Our working hypothesis is that, on high-volatility trading days such as Brexit, the market information flows from high-value stocks to low-value stocks. An intuitive justification for this hypothesis is that, since high-value stocks are monitored more actively by investment and hedge funds, they react faster to information and, thus, lead the market. This is also supported by that fact that investors overreact to large price movements (Angelovska, 2016), leading them to react negatively and sell high-value stocks first in order to minimize their loses.

The second objective is to compare the prediction accuracy of different machine learning algorithms during an abnormal day. Taking all the relevant data in financial forecasting into consideration is both unreasonable and impractical. Traditional predictive models suffer from over-fitting and poor predictive out-of-sample performance because they fail to explain the non-linear interactions in the data (Sirignano et al., 2016) (Heaton et al., 2017). We implement Deep Neural Networks (DNNs) adaptively in our paper to address these shortcomings. The results obtained by DNNs are compared to another popular machine learning algorithm, an adaptive Support Vector Machines (SVMs).

The rest of the paper is presented as follows. Section 2 reviews the prediction models. Section 3 discusses the adaptive implementation. Section 4 presents the results. Section 5 concludes the paper.

2. Prediction Models

This section reviews the methods used to examine the proposed hypothesis. The goal of the following models is to predict the direction of a stock price a minute ahead given only a subset of the historical stock prices (i.e. training data).

2.1. Deep Neural Networks (DNNs)

Machine learning algorithms have impacted many aspects of life; from recommender systems to social networks. In conventional form, machine learning techniques are not fully able to process raw data. Thus, building a machine learning system has been a challenge for decades as it requires expertise in feature extraction and design to detect patterns in the data. However, in recent years, the development of Artificial Neural Networks (ANNs) has made it possible to extract features automatically in the machine (LeCun et al., 2015).

An ANN (Figure 1) consists of an input layer, hidden layers, and an output layer. Each layer has at lease one neuron, which, in turn, is linked to a neighbor layer's neurons through connectivity weights (Kara et al., 2011).

The units in a layer of a neural network use a function to map the linear transformation of an input x_i from the lower layer to a scalar y_i. which then sends it to the above layer.

$$y_i^l = f_l(x_i^l), \text{ for } l = 2, \cdots, L. \tag{1}$$

$$x_i^l = b_i^l + \sum_j y_j^l w_{ji}^l. \tag{2}$$

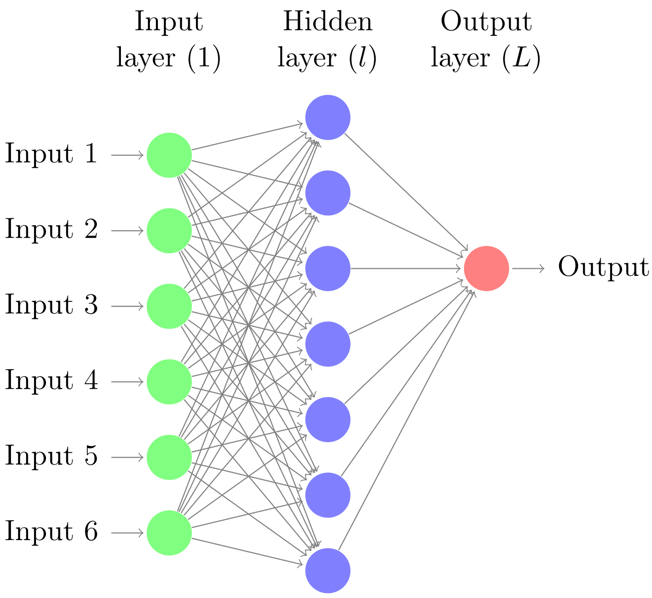


Figure 1: Artificial Neural Network

where j is the index of a unit in the layer below, b_i is the bias of unit i, w_{ji} is a weight of the connection between i and j from the layer below (Hinton et al., 2012), and l denotes the layer number. Throughout the paper, we assume that $f_L(\cdot) = Sigmoid$ [2] and $f_l(\cdot) = tanh$ for all $l < L$.

Deep Neural Networks (DNNs) are ANNs with multiple hidden layers. In this paper, a deep neural network is developed to predict the movement within the financial markets. The inputs are the stock's historical prices and movements. The output is the direction of the stock price with a value of either 0 (down) or 1 (up). The weights in the networks are adjusted using a learning algorithm such that the number of classification mismatches is minimized. The back-propagation method is used to train the DNNs and the gradient descent method is used to update the weights while minimizing the classification mismatch (Wolkowicz et al., 2012).

2.2. Support Vector Machines (SVMs)

Another machine learning technique is the Support Vector Machine (SVM) algorithm, which is also implemented as an alternative method to predict the movement of stocks in the

[2] $Sigmoid(x) = \frac{1}{1+e^{-x}}$.

Maybe include a graph to illustrate SVM? What kind of SVM are you using?

financial markets. SVM aims to map the input vector x through a non-linear function into a high-dimensional feature space. A linear model is then developed to represent a non-linear decision boundary in the original space (Vapnik and Vapnik, 1998). Overall, the algorithm finds the optimal separating hyperplane between two classes (Kim, 2003).

Assume that we have training data $(x_i, y_i), ..., (x_N, y_N)$, where $x_i \in \mathbb{R}^q$ and $y_i \in \{-1, 1\}$. The input x_i is the stock's historical prices and movements and y_i is the desired output which is the direction of the stock price (-1 indicating a decrease in stock price and 1 indicating an increase). Consider a problem of separating the training data sets into two classes with a hyperplane

$$y = f(x) = w^t \phi(x) + b \tag{3}$$

where $\phi : \mathbb{R}^q \rightarrow \mathbb{R}^m$ maps the input space into a high-dimensional feature space. The classification rule is therefore defined as

$$Rule(x) = sign[w^T \phi(x) + b] \tag{4}$$

The data is mapped into a high-dimensional space to make it linearly separable. The distance of a data point x_i from the hyperplane is defined as

From what I learned in EECS445, the denominator of this distance function does not have a square, and the margin is 1/llwll

$$d(w, b, x_i) = \frac{| \, w^T \phi(x_i) + b \, |}{||w||^2} \tag{5}$$

The objective of the SVM algorithm is to maximize the smallest distance between the data points and the hyperplane, which is referred to as the margin. Using the definition of distance in (5), we can prove that the margin is $\frac{2}{||w||}$. The coefficients w and b in (3) are obtained by solving the optimization problem to maximize the margin from either side of the hyperplane. This optimization problem can be reformulated as (Boser et al., 1992) (Cortes and Vapnik, 1995):

$$\begin{aligned} \min_{w \in \mathbb{R}^m, b \in \mathbb{R}} \quad & \tfrac{1}{2}||w||^2 \\ y_i(w^t \phi(x) + b) \quad & \geq \quad 1 \qquad i = 1, \ldots, N. \end{aligned} \tag{6}$$

The constraint in the above optimization problem enforces the separation of data points according to their classes. More information about support vector machine can be found in (Scholkopf and Smola, 2001).

3. Adaptive Implementation

The generalized models presented in Section 2 are implemented adaptively with select parameters to test our hypothesis. The primary hypothesis being tested in this paper is that, on high-volatility trading days, the market information flows from high-value stocks to low-value stocks. An intuitive reasoning for this is that shareholders hold high-value stocks tend to react faster when faced with systematic risk.(The underlying assumption here is that there is a strong correlation between high-value and high market capitalization stocks.) Alternatively, this could be because high-value stocks are more actively followed (and traded) by institutional investors. Such institutional investors are more likely to have more comprehensive and elaborate trading algorithms allowing for much quicker reaction to market volatility. Hence our hypothesis that high-value stocks lead the market during high-volatility trading events creating the opportunity to predict the future movement of low-value stocks.

3.1. Data Collection

In order to accurately capture the effect of Brexit on the market, we collected data for both the day of the announcement of the referendum results (June 24, 2016) as well as the day before. The market sentiment for the day before was largely one where the Brexit referendum was expected to be unsuccessful and that the UK would remain a member of the EU. Thus, the data from the following day isolates the impact of the Brexit vote on the market insofar as possible to allow for more robust analysis. While there may still be other market events that were independent of the Brexit vote and influenced stock movement, our assumption is that the effect of these events was negligible compared to Brexit.

The data for our analysis was collected from a Bloomberg terminal located at the University of Michigan. We used minute by minute prices of 4000 stocks traded on the New

York Stock Exchange (NYSE) from 9:30 am to 4:00 pm of each day in our analysis. This information was imported into Python for data cleaning, training (fitting), and testing. If a stock on the exchange had not traded during a particular minute, the price of the stock was maintained the same as the last trade. Stocks whose price had not changed for at least 25% of the 390 minutes in our daily window were removed from the analysis. Following this filtering process, we were left with 500 stocks for June 23, and 1000 stocks for June 24. These stocks were then sorted in decreasing order according to their prices.

3.2. Model Selection

For the machine learning algorithms, various combinations and permutations of network architecture and number of parameters were tested. Specifically for SVMs, we explored various kernel functions to glean a deeper level of insights. In sum, we used one DNN and three SVMs for our analysis.

3.2.1. DNN Parameters

The optimal DNN parameters (number of Epochs [3], number of hidden layers and number of neurons) are determined through a grid search method. In gird search method, the DNN is trained using different combination of parameters and the combination that performs best is selected. Thus, the parameters used in our analysis are:

Table 1: Summary of finalized DNN Parameters

Epochs	**Hidden Layers**	**Neurons**
250	6	11

3.2.2. SVM Parameters

We tested three different kernel functions for SVMs with the respective functional forms (Tibshirani et al., 2001) given:

[3] An Epoch is a single pass over the training set. In training (fitting) DNN, the back-propagation algorithm takes several passes through the training set to converge to the optimal combination of weights.

Table 2: Summary of SVM kernels

Kernel	Functional Form
Linear	$K(x, x') = x^\top x'$
Polynomial	$K(x, x^\top) = (1 + x^\top x')^d$, for any $d > 0$
Gaussian (Radial Basis Function)	$K(x, x^\top) = exp(-\|\|x - x'\|\|^2)$

For polynomial function SVMs, we tested polynomial kernel degrees of 2 and 3 with both giving similar results. The analysis presented in our paper uses a polynomial kernel with a degree of 3.

3.3. Adaptive Prediction Process

After finalizing the parameters for each model and refining the data, we proceeded to test our hypotheses. This was done by including different data sets as input variables followed by running each predictive model for high-value stocks as well as low-value stocks individually.

In order to predict the direction of one high-value stock, the first set of input variables used was 5 previous minute-wise prices of the stock plus the latest moving direction (increase or decrease) of the stock. The second set consisted of the first set of input variables as well as the latest moving direction of the 15 lowest-value stocks. By adding only this piece of information about low-value stocks in the second set of input variables, we were able to determine its impact on accurately predicting the performance of high-value stocks. Similarly, we tested similar predictions on a low-value stock, where the first input set only consisted of low-value stocks' data and the second set included the latest moving direction of the 15 highest-value stocks.

To aid in testing the second hypothesis relating to the relative performance of each model, we utilized a moving window of 140 minutes. This window size was determined as part of the parameter optimization outlined in Sections 3.2. The data from a given 140 minute window was used to train the model and predict the following minute's data. This methodology was continuously applied for the 390 minute duration of the day. In order to try and observe any time-based variation in the data, the results were broadly divided as shown in Table 2:

Table 3: Breakdown of testing periods

Morning	**Afternoon**	**Evening**
Minutes 141-220	Minutes 221-300	Minutes 301-380

In each of the three periods on June 23 and June 24, the prediction programs were run on the top 15% and bottom 15% of the stocks with respect to the stock price and for each of the four models (one DNN and three SVMs). The metric used to evaluate a model's performance was the percentage of time the model successfully predicted the direction in which the stock was going to move in the next minute. The average training and testing prediction performance are recorded and discussed in further detail in Section 4.

4. Results

The performance of the two types of prediction, low-to-high and high-to-low, is shown in Tables 4 and 5.

Table 4: Accuracy of prediction of high-value stocks with additional input data of low-value stocks

Model	**Date**	**Morning**		**Afternoon**		**Evening**	
		Training	**Testing**	**Training**	**Testing**	**Training**	**Testing**
Deep Learning	June 23	0.97	0.53	1.00	0.52	1.00	0.53
	June 24	0.95	0.50	1.00	0.55	1.00	0.56
SVM (Polynomial)	June 23	1.00	0.52	1.00	0.49	1.00	0.53
	June 24	1.00	0.52	1.00	0.52	1.00	0.51
SVM (Gaussian)	June 23	1.00	0.55	1.00	0.55	1.00	0.52
	June 24	1.00	0.62	1.00	0.58	1.00	0.51
SVM (Linear)	June 23	0.79	0.55	0.75	0.54	0.72	0.51
	June 24	0.84	0.57	0.80	0.55	0.76	0.52

First, we checked whether the performance of the predictive models is better in general on Brexit day. The Testing results on June 23 and June 24 were compared using a paired sample t-test with the following hypotheses:

$$H_0 : \mu_{24} - \mu_{23} = 0$$

Table 5: Accuracy of prediction on low-value stocks with additional input data of high-value stocks

Model	**Date**	**Morning**		**Afternoon**		**Evening**	
		Training	**Testing**	**Training**	**Testing**	**Training**	**Testing**
Deep Learning	June 23	0.98	0.55	1.00	0.56	1.00	0.54
	June 24	0.95	0.57	0.98	0.57	1.00	0.59
SVM (Polynomial)	June 23	1.00	0.53	1.00	0.55	1.00	0.55
	June 24	1.00	0.56	1.00	0.58	1.00	0.55
SVM (Gaussian)	June 23	1.00	0.63	1.00	0.64	1.00	0.64
	June 24	1.00	0.64	1.00	0.65	1.00	0.65
SVM (Linear)	June 23	0.80	0.55	0.76	0.61	0.74	0.59
	June 24	0.85	0.59	0.81	0.61	0.78	0.60

$$H_1 : \mu_{24} - \mu_{23} \neq 0$$

where μ_{23} is the average testing accuracy on June 23. The results of the t-test are given in Table 6. The two-tail t critical value at $\alpha = 0.05$ is 2.069. Therefore, we concluded that the performance of the predictive models was significantly better on Brexit day (June 24) than on the day before. As the same set of models were used for both days, this could be attributed to there being more observable patterns on Brexit day which may have assisted the predictive models. Hence, though the stock market was volatile, there may still have been a general sentiment to sell which was better captured by the predictive models through the course of the day.

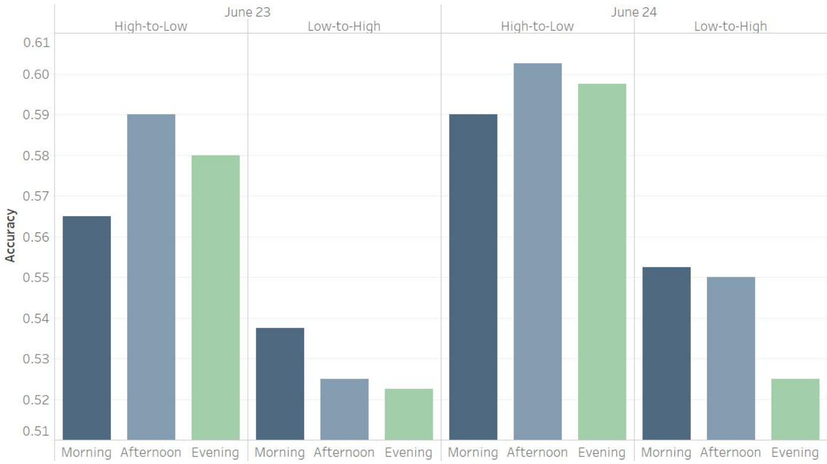
Table 6: t-test comparison of the results on each day

Date	**Observations**	**Mean**	**Std. dev.**	**t**	**two-tail p-value**
June 23	24	0.5532	0.0394	-3.602	0.0015
June 24	24	0.5692	0.0436	-	-

We then explored the promptness of the reaction to information of high-value and low-value stocks. In other words, we wanted to see which type of stocks lead the market, especially throughout Brexit day. Using the six testing periods on June 23 and June 24, we calculated and plotted the average performance of both prediction types as shown in Figure 2.

Figure 2 reveals that including additional information of high-value stocks to predict

Figure 2: Average performance of two types of prediction during six different testing periods



low-value stocks always produces better accuracy than doing it conversely. This pattern is observed in all six testing periods over the two days. This observation was then tested using a paired sample t-test with the following hypotheses:

$$H_0 : \mu_{H-L} - \mu_{L-H} = 0$$

$$H_1 : \mu_{H-L} - \mu_{L-H} \neq 0$$

where μ_{H-L} is the average testing accuracy for predicting high-value stocks. The t-test results shown in Table 7 further confirm the better performance of high-to-low value stock prediction.

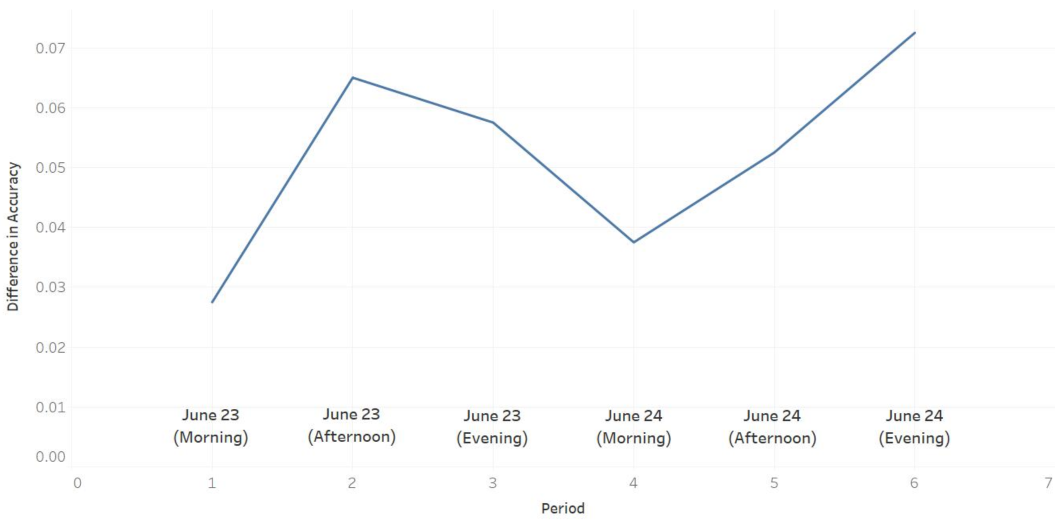
Table 7: t-test comparison of the two prediction types

Prediction Type	**Observations**	**Mean**	**Std. dev.**	**t**	**two-tail p-value**
Low to High	24	0.5359	0.0286	-6.9562	0.0000
High to Low	24	0.5865	0.0379	-	-

The observation that high-to-low value stock prediction has better performance could have several reasons. Firstly, predicting low-value stocks could be inherently easier than predicting high-value ones due to them being more closely held. This would mean that any underlying pattern is more easily observed by a predictive model than for high-value stocks which are more widely held and, thus, have more variables to be factored into prediction. Alternatively, predicting low-value stocks may not necessarily be easier than predicting high-value stocks. Additional information relating to high-value stocks may just be more valuable to predicting market movements as they lead the stock market. Hence, knowing low-value stock information may not be helpful when predicting high-value stocks but knowing high-value stock information may be very helpful when predicting low-value stocks as observed in our analysis. Determining which of these explanations is correct is beyond the scope of this paper, and is left for future study.

Figure 3 shows the difference in the performance of the two types of methods during each time period, which is calculated by subtracting the low-to-high value stock prediction accuracy from the high-to-low value stock prediction accuracy.

Figure 3: Performance difference of the two types of methods



As the positive values on the plot illustrate the leading effect of high-value stocks, we wanted to see whether this effect is reinforced during the Brexit day. We first calculated the differences in the performance of the two types of predictions for each predictive models, and then conducted a paired sample t-test to compare the differences on each day. The hypotheses for this test were as follows:

$$H_0 : \mu_{24,H-L} - \mu_{23,H-L} = 0$$

$$H_1 : \mu_{24,H-L} - \mu_{23,H-L} \neq 0$$

where $\mu_{24,H-L}$ is the average testing accuracy for predicting high-value stocks on June 24. The results of the t-test are shown in Table 8.

Table 8: t-test comparison of the differences of the two types of predictions

Date	Observations	Mean	Std. dev.	t	two-tail p-value
June 23	12	0.0480	0.0379	-0.6185	0.5488
June 24	12	0.0532	0.0328	-	-

As the two-tail t critical value at $\alpha = 0.05$ is 2.201, we could not conclude the performance difference is more significant on Brexit day than on the day before. This means that there is no evidence that the leading effect of high-value stocks is strengthened on the Brexit day. We further tested the strength of the two prediction types on Brexit day (June 24) alone using a paired sample t-test with the following hypotheses:

$$H_0 : \mu_{24,H-L} - \mu_{24,L-H} = 0$$

$$H_1 : \mu_{24,H-L} - \mu_{24,L-H} \neq 0$$

The results of the t-test are shown in Table 9.

Table 9: t-test comparison of the differences of the two types of predictions on Brexit Day

Prediction Type	Observations	Mean	Std. dev.	t	two-tail p-value
Low to High	12	0.5425	0.0357	-5.439	0.0002
High to Low	12	0.5967	0.0345	-	-

The two-tail t critical value at $\alpha = 0.05$ is 2.201. Therefore, we concluded that the performance of the high-to-low prediction type was significantly better on Brexit day (June 24). This simply reinforces the superiority of the prediction type on the single day of Brexit compared to the previous conclusion drawn for both days in tandem. This is particularly illuminating as we note that the abnormality of Brexit day did not impact the comparative performances of the prediction types. This could indicate the robustness of the high-to-low prediction type irrespective of the market volatility.

Finally, we wanted to find the best predictive model for each day. Figures 4 and 5 show a box-plot of the performance on June 23 and June 24 respectively. Each model is represented by a box, and the box represents the region between the upper and lower quartiles of the prediction accuracy. The box plots shows that the Radial Basis Function (RBF) SVM produces the best accuracy on both June 23 and June 24. However, on Brexit day (June 24), its advantages over the other models are less significant. While the RBF SVM model understandably outperforms the other two, less sophisticated SVMs, the comparison with the DNN is particularly interesting. This could be due to the RBF SVM better incorporating the underlying nuances of the stock market compared to the DNN. Still, we remain cognizant of the fact that this was a bespoke application of these models which could provide very different results based on different model configurations.

Figure 4: Box-plot of the performance of different models on June 23

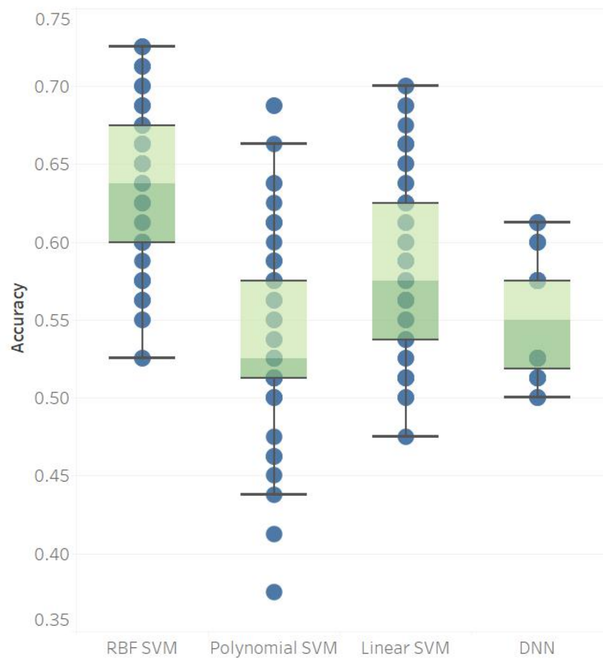
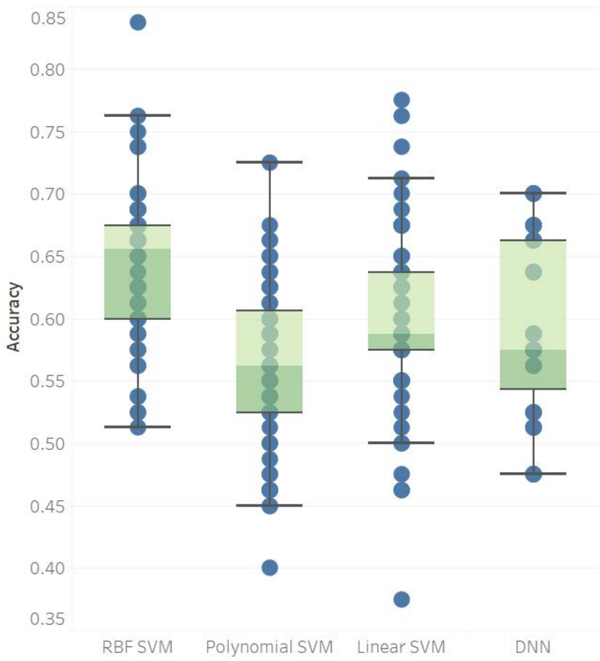


Figure 5: Box-plot of the performance of different models on June 24



5. Conclusion

In this paper, we inspected the difference in the reaction speed to market information between high-value and low-value stocks. We tested two machine learning algorithms, namely DNNs and SVMs, to investigate our hypothesis that high-value stocks react faster, and thus, can serve as a "premonition" of the movement of the wider market. We observed that predicting low-value stocks with the additional information of high-value stocks has better performance than vice versa. Therefore, our initial hypothesis is validated leaving us with the conclusion that high-value stocks in our analysis lead the market. Further, we observed that the leading effect of high-value stocks in our analysis was not significantly better on either day. In terms of machine learning algorithms, we found that the adaptive Radial Basis Function Support Vector Machines (RBF SVMs) performed the best on both days.

With the above considerations in mind, our analysis highlights the opportunity to develop a trading strategy for high-volatility days using the adaptive RBF SVM machine learning algorithm that incorporates information from high-value stocks to predict low-value stocks. Having said that, we recognize that machine learning algorithms generally require large volumes of data to have reliable accuracy. Hence, our dataset of trading information for one day may be perceived as being insufficiently large. However, this paper focuses on intra-day trading instead of day-to-day trading. Thus, the dataset used is limited by the duration of the trading day. This also makes generalization of our observations to other high-volatility days or to day-to-day trading more challenging and would likely require a more focused and detailed exploration. Regarding the differing observations seen in our research and other contemporary insights, there is certainly an opportunity to delve deeper into the direction of information and shock flows to understand the underlying drivers for these different observations.

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