Thai **J**ournal of **M**athematics : (2019) 153–165
Special Issue: Structural Change Modeling
and Optimization in Econometrics 2018

http://thaijmath.in.cmu.ac.th
ISSN 1686-0209

Prediction the Direction of SET50 Index Using Support Vector Machines

Chongkolnee Rungruang[†,1], **Wilawan Srichaikul**[‡],
Somsak Chanaim[§,$] **and Songsak Sriboonchitta**[‡,£]

[†]Faculty of Commerce and Management, Prince of Songkla University
Trang Campus, Trang 92000, Thailand
e-mail : chongkolnee.r@psu.ac.th (C. Rungruang)

[‡]Center of Excellence in Econometrics, Faculty of Economics
Chiang Mai University, Chiang Mai 50200, Thailand
e-mail : srichaikul.w@gmail.com (W. Srichaikul)

[§]International College of Digital Innovation, Chiang Mai University
Chiang Mai 50200, Thailand

[$]Faculty of Economics and Business Administration, Thaksin University
Songkla 90000, Thailand
e-mail : somsak_ch@cmu.ac.th (S. Chanaim)

[£]Faculty of Economics, Chiang Mai University, Chiang Mai 50200, Thailand
e-mail : songsakcon@gmail.com (S. Sriboonchitta)

Abstract : Support vector machine (SVM) is a very specific type of learning algorithms characterized by the capacity control of the decision function, the use of the kernel functions and the sparsity of the solution. In this paper, we investigate the predictability of stock index movement direction with SVM by forecasting the daily movement direction of SET 50 index over the period 5 April, 2000 to 22 August, 2018. The experiment results show that SVM with autoregressive lag $p = 10$ and training data equal 37 have accuracy(ACC) 92.56%.

Keywords : prediction; SET50 index; support vector machines.
2010 Mathematics Subject Classification : 35K05; 91G20.

[1]Corresponding author.

1 Introduction

The direction of the stock market index refers to the movement of the price index or the trend of fluctuation in the stock market index in the future. Predicting the direction is a practical issue that heavily influences a financial trader's decision to buy or sell an instrument. Accurate forecast of the trends of the stock index can help investors to acquire opportunities for gaining profit in the stock exchange. Hence, precise forecasting of the trends of the stock price index can be extremely advantageous for investors Gholamiang-onabadi et al. [1].

Previous studies have applied support vector machines (SVM) in forecasting the direction of the stock market index movement. For instance, Kim [2] used SVM to predict the direction of daily stock price change in the Korea composite stock price index (KOSPI). Huang et al. [3] forecasted stock market movement using support vector machines (SVM), and concluded that the model was good at predicting the direction. Kara et al. [4] study of predicting direction of stock price index movement use artificial neural networks and support vector machines on the Istanbul Stock Exchange. Madge and Bhatt [5] study uses daily closing prices for 34 technology stocks to calculate price volatility and momentum for individual stocks and for the overall sector. These are used as parameters to the SVM model. Inthachot et al. [6] study two machine learning methods, Artificial Neural Network (ANN) and Support Vector Machine (SVM), for predict the trend of Thailand's emerging stock market, SET50 index. In addition, Karathanasopoulos et al. [7] study stock market prediction using evolutionary support vector machines, an application to the ASE20 index.

Therefore, the main objective of this study is prediction accuracy the direction of SET50 index in Stock Exchange of Thailand movement by using the Support Vector Machines (SVM) model. The SVM was developed by Vapnik et al. [8]. Its popularity has been increasing due to many attractive features, and its promising empirical performance in a variety of applications such as pattern recognition, regression estimation, time series prediction. Moreover, SVM is shown to be very resistant to the over-fitting problem, eventually achieving a high generalization performance. Another key property of SVM is that training SVM is equivalent to solving a linearly constrained quadratic programming problem so that the solution of SVM is always unique and globally optimal, unlike neural networks training which requires nonlinear optimization with the danger of getting stuck at local minima.

The structure of the rest of this paper is as follows. The next section provides the model used in this study. Section 3 presents data, Section 4 presents the empirical results. Finally, the conclusion is provided in Section 5.

2 Methodology

2.1 Support Vector Machine

For classification and regression problem, support vector machine (SVM) is the one popular machine learning tool. Vapnik V. introduced the tool in 1995 [8]. SVM relies on kernel functions s0 that the method is a nonparametric technique.
Given the training data $\{(x_1, y_1, \cdots, (x_n, y_n)\}$ where $x_1 = (x_{11}, x_{12}, \cdots, x_{1m}), \cdots,$ $x_n = (x_{n1}, x_{n2}, \cdots, x_{nm})$, $y \in \mathscr{R}$. For the linear function f can write in form:

$$y = f(x) =< \omega, x > +b \tag{2.1}$$

where $\omega \in \mathscr{R}^m$, $v \in \mathscr{R}$ and $< \cdot, \cdot >$ is the inner product. In this case we need to find the the small value of ω. That mean this problem is the minimize the norm of ω. So that we can transform to the convex optimization problem in equation form:

$$\begin{aligned} &\text{minimize} && \frac{1}{2} \parallel \omega \parallel^2 \\ &\text{subject to} && \begin{cases} y_i - < \omega, x_i > -b & \leq \varepsilon \\ < \omega, x_i > +b - y_i & \leq \varepsilon \end{cases} \end{aligned} \tag{2.2}$$

2.2 Confusion Matrix

For classification problem, a confusion matrix is the table to measure the performance of the model. By the check the true of false between predicting from the model and the true value. We can write the confusion matrix in this form:

Table 1: The table of confusion matrix

		true value	
		yes	no
predicted	yes	true positive(TP)	true negative(TN)
	no	false negative(FN)	false negative(FN)

In this paper we need to forecast the direction of stock market movement from the stock market index return by compare the sign of prediction value(positive or negetive) and the sign of the true value.

True positive(TP) is the total number of prediction value is yes and the true value is yes too.

$$\text{TP} = \sum_{i=1}^{N} \frac{\hat{r}_i \geq 0 \text{ and } r_i \geq 0}{N}$$

True negative is the total number of prediction value is yes but the true value is no.

$$\text{TN} = \sum_{i=1}^{N} \frac{\hat{r}_i \geq 0 \text{ and } r_i < 0}{N}$$

False negative is the total number of prediction value is no but the true value is yes.

$$\text{FN} = \sum_{i=1}^{N} \frac{\hat{r}_i < 0 \text{ and } r_i \geq 0}{N}$$

False positive is the total number of prediction value is no and the true value is no too.

$$\text{FP} = \sum_{i=1}^{N} \frac{\hat{r}_i < 0 \text{ and } r_i < 0}{N}$$

We can measure the performance of the model using the accuracy(ACC)

$$\text{ACC} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{2.3}$$

3 Data Description

In this study, the daily price of SET 50 in Stock Exchange of Thailand covering the period of 5 April, 2000 to 22 August 2018 (4496 observations) are used. the data collected from Bloomberg. The data description is provided in Table 1. In this study, we use Minimum Bayes factor (MBF) as the tool for checking the significant result. This MBF can be considered as an alternative of p-value (Held and Ott, [9]). If $1 < MBF < 1/3$, $1/3 < MBF < 1/10$, $1/10 < MBF < 1/30$, $1/30 < MBF < 1/100$, $1/100 < MBF < 1/300$ and $MBF < 1/300$, there are a chance that the MBF favor the weak evidence, moderate evidence, substantial evidence, strong evidence, very strong evidence and decisive evidence for respectively. All data series are stationary as shown by the MBF valued. We conduct the Jarque - Bera normality test and it is evident that stock returns reject the null hypothesis of a normal distribution. The Augmented DickeyFuller test (ADF) unit root test is conducted and it shows that there is decisive evidence for stationary data.

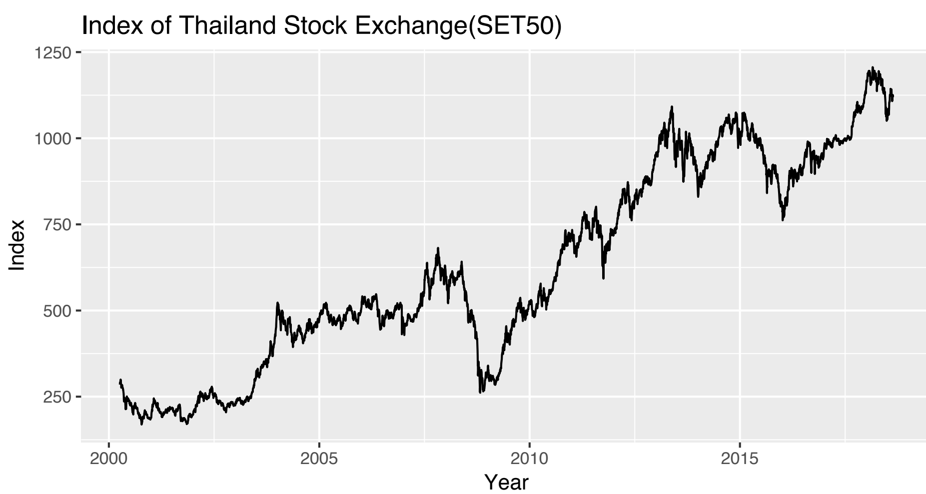

Figure 1: Thailand Stock Exchange(SET50) index.

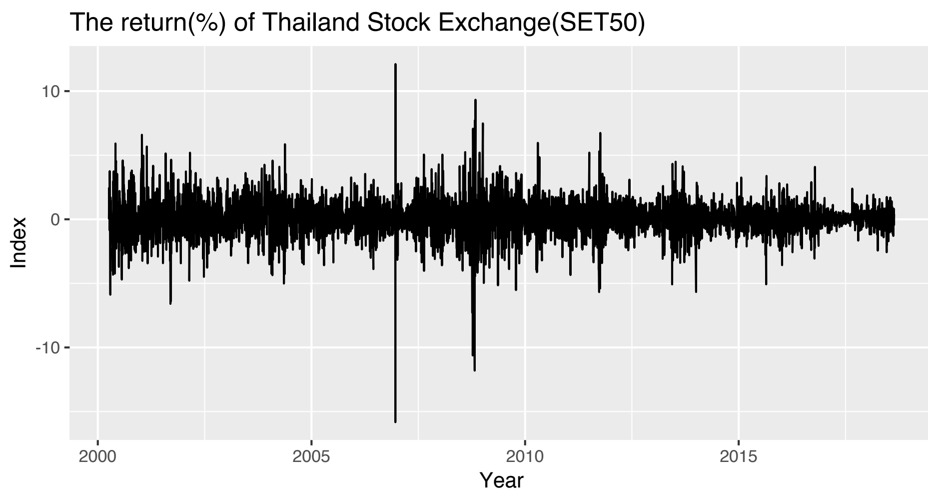

Figure 2: Thailand Stock Exchange(SET50) return.

Table 2: Data description

	SET 50
Mean	0.041
Median	0.032
Maximum	12.1101
Minimum	-15.8281
Std. Dev.	1.4491
Skewness	-0.2868
Kurtosis	11.2584
Jarque-Bera	12838.12
	(0.0000)
Observations	4496
Unit Root test	-44.3184
	(0.0000)

Note: ( ) MBF is Minimum Bayes factor, computed by $e^{p \log p}$, where p is p-value (see, Held and Ott [9]).

4 Empirical Results

In the paper, we use SVM in this form:

$$r_t = f(r_{t-1}, \cdots, r_{t-p}) \tag{4.1}$$

where $p = 1, 2, \cdots, 10$ In this paper, We want to predict the direction of the stock market return $\hat{r}_t$ have the same sign with r_t or not. We find the number of p, $p = 1, 2, \cdots, 10$ and how many number of training $T = 30, 31, \cdots, 100$ which number of p and T give the best accuracy(ACC) using rolling windows technique. Example for $p = 1$ and $T = 30$, we define

$$r_t = f(r_{t-1}), t = 1, 2, \cdots, 30.$$

And compared the sign of $\hat{r}_{30}$ with r_{30}. if correct count 1 for TP or TN or FN or FP.
Next training set is $t = 2, \cdots, 31$. and do the same procedure until the last training set $t = 4967, \cdots, 4996$. After the write the total value into confusion matrix. We do the same for this procedure until $p = 10$ and number of training set $T = 100$. We use package "e1071" in program R for compute SVM, for more detail see Karatzoglou et al.[10] and Mayer D. et al.[11].

Table 3: The accuracy (ACC) of SVM $p = 1, 2, \cdots, 10$ and $T = 30, 31, \cdots, 60$.

	SVM(1)	SVM(2)	SVM(3)	SVM(4)	SVM(5)	SVM(6)	SVM(7)	SVM(8)	SVM(9)	SVM(10)
30	**67.34%**	73.61%	**79.31%**	**83.90%**	**86.52%**	88.49%	90.08%	91.09%	92.03%	92.46%
31	67.00%	73.69%	79.29%	83.90%	86.05%	**88.83%**	90.06%	90.95%	91.78%	92.45%
32	67.01%	**73.89%**	78.88%	83.31%	86.32%	88.35%	**90.19%**	90.84%	91.71%	92.39%
33	66.60%	73.12%	78.90%	82.91%	86.13%	88.26%	89.76%	**91.22%**	91.73%	92.27%
34	66.52%	72.98%	78.98%	82.95%	85.93%	88.12%	89.63%	90.93%	**92.05%**	92.31%
35	66.00%	72.77%	78.46%	82.83%	86.04%	87.67%	89.49%	90.74%	92.00%	92.38%
36	65.81%	72.02%	78.46%	82.60%	85.86%	87.47%	89.28%	90.52%	91.97%	92.38%
37	65.63%	71.79%	77.98%	82.58%	85.65%	87.71%	89.17%	90.49%	91.30%	**92.56%**
38	65.53%	71.70%	77.48%	82.26%	85.06%	87.40%	88.88%	90.29%	91.19%	92.29%
39	65.32%	72.12%	77.25%	81.92%	84.90%	86.99%	88.99%	90.06%	91.09%	92.19%
40	65.38%	71.95%	77.14%	81.60%	84.56%	87.01%	88.42%	89.79%	90.73%	92.19%
41	64.54%	71.61%	76.41%	81.69%	84.49%	86.96%	88.35%	89.86%	90.75%	91.99%
42	63.95%	71.36%	76.77%	81.26%	84.31%	86.71%	88.06%	90.01%	90.77%	91.78%
43	63.74%	70.75%	76.07%	80.96%	84.13%	86.62%	88.15%	89.22%	90.64%	91.72%
44	64.11%	70.58%	76.22%	80.57%	83.54%	86.35%	87.85%	89.31%	90.61%	91.56%
45	64.06%	70.91%	75.76%	80.44%	83.76%	86.03%	87.89%	89.22%	90.54%	91.24%
46	63.85%	70.77%	75.83%	80.34%	83.44%	86.00%	87.60%	88.86%	90.16%	91.13%
47	63.71%	70.25%	75.73%	80.20%	82.70%	85.69%	87.46%	88.85%	90.09%	90.92%
48	63.99%	70.22%	75.43%	80.15%	82.69%	85.48%	87.30%	88.74%	89.66%	90.96%
49	63.89%	70.55%	75.34%	79.97%	82.69%	85.36%	87.10%	88.53%	89.64%	90.69%
50	63.64%	70.32%	75.33%	79.54%	82.37%	85.27%	87.14%	88.24%	89.72%	90.53%
51	63.56%	70.04%	74.81%	79.24%	82.55%	84.71%	86.86%	87.81%	89.36%	90.40%
52	63.53%	69.79%	74.92%	79.15%	82.09%	84.39%	86.73%	87.94%	89.45%	89.99%
53	63.68%	69.62%	74.41%	79.30%	81.98%	84.54%	86.72%	87.80%	89.36%	90.10%
54	63.49%	69.46%	74.25%	79.07%	82.08%	84.24%	86.63%	87.71%	89.13%	89.80%
55	63.51%	69.54%	74.25%	78.77%	81.95%	84.62%	86.38%	87.91%	88.90%	89.44%
56	63.52%	69.24%	73.95%	78.45%	81.67%	84.73%	86.60%	87.77%	88.94%	89.69%
57	62.77%	68.90%	73.94%	78.06%	82.05%	84.32%	86.64%	87.91%	88.90%	89.37%
58	62.78%	68.42%	73.98%	78.15%	81.48%	84.37%	86.57%	87.70%	88.83%	89.23%
59	63.25%	68.61%	74.31%	78.14%	80.76%	84.18%	86.46%	87.65%	88.67%	88.96%
60	63.26%	68.51%	73.95%	78.09%	80.84%	83.91%	86.12%	87.33%	88.44%	89.09%

Table 4: The accuracy (ACC) of SVM $p = 1, 2, \cdots, 10$ and $T = 61, 62, \cdots, 100$.

	SVM(1)	SVM(2)	SVM(3)	SVM(4)	SVM(5)	SVM(6)	SVM(7)	SVM(8)	SVM(9)	SVM(10)
61	62.89%	68.53%	73.78%	77.77%	80.73%	83.79%	85.73%	87.13%	88.21%	89.20%
62	62.91%	68.28%	73.98%	77.88%	80.68%	83.63%	85.66%	86.92%	88.16%	88.95%
63	63.01%	67.95%	73.43%	78.01%	80.29%	83.74%	85.27%	86.56%	88.00%	88.77%
64	63.21%	67.67%	73.81%	77.89%	80.24%	83.67%	85.43%	86.56%	88.07%	88.74%
65	63.13%	68.19%	73.56%	77.66%	80.46%	83.62%	85.06%	86.55%	87.73%	88.85%
66	63.37%	68.16%	73.17%	77.43%	80.57%	83.95%	84.68%	86.39%	87.66%	88.90%
67	62.80%	68.24%	72.96%	77.45%	80.61%	83.59%	84.92%	86.34%	87.77%	88.58%
68	62.72%	67.92%	72.73%	77.06%	80.58%	83.18%	84.94%	86.41%	87.47%	88.62%
69	63.05%	68.18%	72.83%	76.87%	80.31%	82.79%	84.67%	86.09%	87.17%	88.37%
70	62.95%	67.38%	72.51%	77.07%	80.42%	82.74%	84.41%	86.06%	87.08%	88.34%
71	62.58%	67.37%	72.39%	76.82%	80.30%	82.90%	84.61%	85.99%	87.05%	88.30%
72	62.73%	67.05%	72.41%	76.52%	80.09%	82.89%	84.79%	85.85%	86.94%	88.18%
73	62.70%	67.54%	72.63%	76.47%	79.84%	82.91%	84.65%	85.76%	86.84%	88.02%
74	62.36%	67.74%	72.67%	75.94%	80.10%	82.77%	84.51%	85.73%	86.34%	87.84%
75	62.44%	67.23%	72.32%	76.10%	79.60%	82.65%	84.44%	85.91%	86.50%	87.72%
76	62.27%	67.54%	72.52%	76.23%	79.48%	82.38%	84.30%	85.70%	86.56%	87.76%
77	62.04%	67.22%	72.17%	75.86%	79.71%	82.58%	84.34%	85.50%	86.65%	87.94%
78	62.14%	67.46%	72.37%	75.83%	79.72%	82.08%	84.30%	85.25%	86.47%	87.80%
79	61.88%	67.13%	71.98%	75.98%	79.38%	81.89%	83.79%	85.13%	86.65%	87.89%
80	62.30%	67.04%	71.84%	75.53%	78.94%	81.55%	83.43%	85.06%	86.62%	87.59%
81	62.41%	67.12%	72.01%	75.43%	79.14%	81.41%	83.17%	84.74%	86.44%	87.30%
82	62.20%	67.16%	71.66%	75.58%	79.14%	81.18%	83.65%	84.51%	86.43%	87.23%
83	62.17%	66.83%	71.68%	75.42%	78.95%	81.17%	83.64%	84.57%	86.07%	87.11%
84	61.70%	66.44%	71.86%	75.55%	78.77%	81.37%	83.28%	84.43%	85.97%	87.04%
85	61.88%	66.23%	71.58%	75.77%	78.60%	81.07%	83.16%	84.38%	86.02%	87.01%
86	61.73%	66.18%	71.50%	75.27%	78.85%	80.96%	83.20%	84.24%	85.76%	86.81%
87	61.66%	66.46%	71.36%	75.19%	78.66%	80.75%	82.70%	84.38%	85.90%	86.71%
88	61.78%	66.66%	71.22%	75.23%	78.34%	80.86%	82.85%	84.26%	85.87%	86.71%
89	61.46%	66.33%	71.05%	75.16%	78.04%	80.78%	82.40%	84.14%	85.59%	86.66%
90	61.63%	66.73%	71.09%	75.20%	78.26%	80.85%	82.37%	84.23%	85.80%	86.73%
91	61.55%	66.98%	71.36%	75.35%	78.14%	80.87%	82.30%	83.73%	85.38%	86.79%
92	61.84%	66.36%	70.96%	75.07%	78.12%	80.48%	82.54%	83.86%	85.20%	86.65%
93	61.78%	66.71%	71.28%	75.16%	78.09%	80.68%	82.54%	84.11%	85.24%	86.44%
94	61.30%	66.43%	71.45%	75.38%	78.31%	80.94%	82.74%	83.92%	85.12%	86.10%
95	61.36%	65.79%	70.81%	75.19%	78.08%	80.62%	82.64%	83.96%	85.21%	86.46%
96	61.78%	65.85%	70.85%	75.07%	78.12%	80.19%	82.34%	83.66%	85.09%	86.39%
97	61.43%	65.59%	71.16%	74.52%	77.98%	80.57%	82.09%	83.75%	84.95%	86.50%
98	61.26%	65.99%	71.15%	74.52%	77.45%	80.38%	82.11%	83.59%	84.84%	86.41%
99	61.07%	65.69%	70.94%	74.65%	77.06%	80.06%	82.38%	83.88%	84.99%	86.52%
100	61.18%	65.82%	70.89%	74.57%	77.35%	79.78%	82.08%	84.03%	84.99%	86.51%

Table 5: The confusion matrix of $p = 1$ and $T = 30$

		true value	
		yes	no
predicted	yes	35.80%	15.49%
	no	17.19%	31.54%

For the case of $p = 1$, the number of data for training set $T = 30$ with the number of rolling window equal 4,467 has the best accuracy rate equal 67.33%.

Table 6: The confusion matrix of $p = 2$ and $T = 32$

		true value	
		yes	no
predicted	yes	39.24%	12.05%
	no	14.06%	34.65%

For the case of $p = 2$, the number of data for training set $T = 32$ with the number of rolling window equal 4,465 has the best accuracy rate equal 73.89%.

Table 7: The confusion matrix of $p = 3$ and $T = 30$

		true value	
		yes	no
predicted	yes	42.00%	9.27%
	no	11.42%	37.32%

For the case of $p = 3$, the number of data for training set $T = 30$ with the number of rolling window equal 4,467 has the best accuracy rate equal 79.31%.

Table 8: The confusion matrix of $p = 4$ and $T = 30$

		true value	
		yes	no
predicted	yes	44.21%	7.05%
	no	9.04%	39.69%

For the case of $p = 4$, the number of data for training set $T = 30$ with the number of rolling window equal 4,467 has the best accuracy rate equal 83.9%.

Table 9: The confusion matrix of $p = 5$ and $T = 30$

		true value	
		yes	no
predicted	yes	45.29%	5.98%
	no	7.50%	41.24%

For the case of $p = 5$, the number of data for training set $T = 30$ with the number of rolling window equal 4,467 has the best accuracy rate equal 86.52%.

Table 10: The confusion matrix of $p = 6$ and $T = 31$

		true value	
		yes	no
predicted	yes	46.37%	4.90%
	no	6.27%	42.45%

For the case of $p = 6$, the number of data for training set $T = 30$ with the number of rolling window equal 4,467 has the best accuracy rate equal 79.31%.

Table 11: The confusion matrix of $p = 7$ and $T = 32$

		true value	
		yes	no
predicted	yes	46.99%	4.30%
	no	5.51%	43.20%

For the case of $p = 7$, the number of data for training set $T = 32$ with the number of rolling window equal 4,465 has the best accuracy rate equal 90.19%.

Table 12: The confusion matrix of $p = 8$ and $T = 33$

		true value	
		yes	no
predicted	yes	47.45%	3.83%
	no	4.95%	43.77%

For the case of $p = 8$, the number of data for training set $T = 33$ with the number of rolling window equal 4,464 has the best accuracy rate equal 91.22%.

Table 13: The confusion matrix of $p = 9$ and $T = 34$

		true value	
		yes	no
predicted	yes	47.81%	3.47%
	no	4.48%	44.23%

For the case of $p = 9$, the number of data for training set $T = 34$ with the number of rolling window equal 4,463 has the best accuracy rate equal 92.04%.

Table 14: The confusion matrix of $p = 10$ and $T = 37$

		true value	
		yes	no
predicted	yes	47.89%	3.39%
	no	4.06%	44.66%

For the case of $p = 10$, the number of data for training set $T = 37$ with the number of rolling window equal 4,460 has the best accuracy rate equal 92.56%.

By the experiment show that SVM with $p = 10$ and number of training data set $T = 37$ can give the best accuracy(ACC) equal 92.56%

5 Conclusion

Predicting the direction of movements of the stock market index is important for the development of effective market trading strategies. Machine learning methods are popular as a technical analysis tool for making stock index trend prediction because their parameters are highly adjustable. This study used SVM model to predict of Thailand Stock market (SET50) direction trend in a nineteen-year covering the period of 2000-2018. In this paper we need to forecast the direction of stock market movement from the stock market index return by compare the sign of prediction value (positive or negative) and the sign of the true value. According to our estimated results, we find that SVM model can give the best accuracy (ACC) equal 92.56%. That mean from the accuracy rate show that SVM can predict the direction of stock index movement very high.

This paper use only the time series of stock index, so that for the next future research we can use more information (another stock index, interest rate etc.) to predict the stock index direction and use another machine learning technique.

Acknowledgements : We are grateful for financial support from Centre of Excellence in Econometrics, Faculty of Economics, Chiang Mai University. We thanks referee for valuable comment to improve this paper.

References

[1] Gholamiangonabadi, D., Taheri, S. D. M., Mohammadi, A., & Menhaj, M. B. (2014, June). Investigating the performance of technical indicators in electrical industry

[2] Kim, K. J. (2003). Financial time series forecasting using support vector machines. Neurocomputing, 55(1-2), 307-319.

[3] Huang, W., Nakamori, Y., & Wang, S. Y. (2005). Forecasting stock market movement direction with support vector machine. Computers & Operations Research, 32(10), 2513-2522.

[4] Kara, Y., Boyacioglu, M. A., & Baykan, . K. (2011). Predicting direction of stock price index movement using artificial neural networks and support vector machines: The sample of the Istanbul Stock Exchange. Expert systems with Applications, 38(5), 5311-5319.

[5] Madge, S., & Bhatt, S. (2015). Predicting Stock Price Direction using Support Vector Machines. Independent Work Report Spring.

[6] Inthachot, M., Boonjing, V., & Intakosum, S. (2015, June). Predicting SET50 index trend using artificial neural network and support vector machine. In International Conference on Industrial, Engineering and Other Applications of Applied Intelligent Systems (pp. 404-414). Springer, Cham.

[7] Karathanasopoulos, A., Theofilatos, K. A., Sermpinis, G., Dunis, C., Mitra, S., & Stasinakis, C. (2016). Stock market prediction using evolutionary support vector

machines: an application to the ASE20 index. The European Journal of Finance, 22(12), 1145-1163.

[8] Vapnik, V. The Nature of Statistical Learning Theory. Springer, New York, 1995. in Tehran's Stock Exchange using hybrid methods of SRA, PCA and Neural Networks. In Thermal Power Plants (CTPP), 2014 5th Conference on (pp. 75-82). IEEE.

[9] Held, L., & Ott, M. On p-values and Bayes factors. Annual Review of Statistics and Its Application, 5, 393-419 (2018).

[10] Karatzoglou, A., Meyer, D., & Hornik, K. (2005). Support vector machines in R.

[11] Meyer, D., Dimitriadou, E., Hornik, K., Weingessel, A., & Leisch, F. (2018). e1071: misc functions of the department of statistics, probability theory group (formerly: E1071), TU Wien. R package version 1.7-0.

[12] Leung, M. T., Daouk, H., & Chen, A. S. (2000). Forecasting stock indices: a comparison of classification and level estimation models. International Journal of Forecasting, 16(2), 173-190.

[13] Fletcher, T. (2009). Support vector machines explained. Tutorial paper.

(Received 25 November 2018)
(Accepted 2 February 2019)