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Using Support Vector Machine in FoRex Predicting

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***Abstract*—The trend of currency rates can be predicted with supporting from supervised machine learning in the transaction systems such as support vector machine. Not only representing models in use of machine learning techniques in learning, the support vector machine (SVM) model also is implemented with actual FoRex transactions. This might help automatically to make the transaction decisions of Bid/Ask in Foreign Exchange Market by using Expert Advisor (Robotics). The experimental results show the advantages of use SVM compared to the transactions without use SVM ones.**

Keywords— ForReign Exchange Market, Exchange Rates, Machine Learning, Support Vector Machine (SVM), Prediction.

I. INTRODUCTION

Machine learning methods play important role in many areas using computer science such as business decision making, handling or monitoring factory chain, predicting or forecasting stock, and so on. The main task in machine learning is to teach computer systems abilities of learning to classify or cluster from given data set. In business area, machine learning especially to supervised learning methods can help effectively the users to analyze the big data collected from alternative resources to extract the useful knowledge. For example, given currencies exchanging rate of data from online transaction, supervised learning can predict the rise or fall in short or long period. This prediction is based on learning from collected historical data.

Supervised learning is one of machine learning methods for automatically building a predictive function f: x→ y that maps x to a prediction y [1]. This means that the given data set will have a structure of $\{x, y\}$ where x can be seen as the raw data and y will be the target label. The task of supervised learning technique is to predict expected outputs those are based on the historical data.

Almost supervised learning techniques are used for classification and regression tasks. The systems used these techniques are also so-called Intelligent Systems as their development is based on Artificial Intelligence techniques such as Logical/Symbolic, Perceptron-based, and Statistics (Bayesian Networks, Instance-based techniques) [2].

The task is called classification if the target variable (y) is categorical (nominal or discrete) and called regression when y is continuous (real-valued) [1]. For simple, many classification problems are treated as a binary classification task. That means the output variable can be received discrete values.

Support Vector Machines (SVMs) are the supervised machine learning techniques [3]. SVMs revolve around the notion of a "margin"—either side of a hyperplane that separates two data classes. According to [2], maximizing the margin and creating the largest possible distance between the separating hyper-plane and instances on either side of it has been proven to reduce an upper bound on the expected generalization error. Therefore, SVMs can be suitable using for binary problems such as predicting Foreign Exchange (Forex) trend (Up trend or Down trend) based on historical data of Open", "Close", "Low" and "High" in alternative times periods.

This paper has been organized in 4 sections. Section 1 shows the introduction of machine learning technique and Forex problem. The literature review of supervised learning technique applied for classification Forex problem is introduced in section 2. Section 3 shows the experiments of using support vector machine model in predicting the Forex trend and their results. The conclusion is represented in section 4.

II. SUPERVISED SUPPORT VECTOR MACHINES AND FOREIGN EXCHANGE PREDICTION

A. Supervised Support Vector Machine

Support Vector Machines (SVMs) are so-called as linear or un-linear SVMs depending on linear or un-linear hyperplane lines separated the training data set. In linear hyperplane, the formula of linear line as follows:

$$H: w.x + b = 0$$

Where $\mathrm{w} = (\mathrm{w}_1, \mathrm{w}_2, \dots, \mathrm{w}_\mathrm{d}) \in \mathbb{R}^\mathrm{d}$ and $\mathrm{x} = (\mathrm{x}_1, \mathrm{x}_2, \dots, \mathrm{x}_\mathrm{d}) \in \mathbb{R}^\mathrm{d}$ then $\mathrm{w.x} = \sum_{\mathrm{i}=1}^{\mathrm{d}} \mathrm{w}_\mathrm{i}.\mathrm{x}_\mathrm{i}$

Assume that $y_i \in \{+1, -1\}$, $i = \overline{1,n}$. y_i is labelled output class. Then outputs will be separated by:

$$y_i = \begin{cases} 1 \;\; if \;\; w.x_i + b \geq 0 \\ -1 \;\; if \;\; w.x_i + b < 0 \end{cases}$$

The hyperplane H has maximum margins to classes. That means SVMs need to build two others hyperplane as: $H_1: w.x + b = 1$; and $H_2: w.x + b = -1$ where there is no existing x_i in H_1 and H_2, and the margin between in H_1 and H_2 is maximum.

The distance of x in in H_1 and H_2 to H can be calculated as:

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$$\frac{|wx+b\pm 1|}{\|w\|}=\frac{1}{\|w\|}$$

Therefore, the margin can be calculated as: $\frac{2}{\|w\|}$, where $\|w\|=\sqrt{w^2}=\sqrt{w_1^2+w_2^2+\cdots+w_d^2}$

On the other words, the maximum margin will be referred to minimum of $\frac{w^2}{2}$ with the subject to: $y_i(w.x_i+b)\geq 1, i=1,2..n$ (*).

In some cases, the SVM may not be able to find any separating hyperplane at all because the data contains misclassified instances. In this situation, SVM used a soft margin that accepts some misclassifications of the training instances [4]. By using Lagrange multipliers $\alpha=(\alpha_1,\alpha_2,\dots,\alpha_n)\geq 0$, the (*) will be seen as:

$$\mathcal{L}(w,b,\alpha)=\frac{1}{2}w^2-\sum_{i=1}^{n}\alpha_i.y_i(w.x_i+b)+\sum_{i=1}^{n}\alpha_i$$

Or the Lagrange dual problem as

$$\max_{\alpha}\mathcal{L}(w,b,\alpha) \qquad (**)$$

With constrains of:

$$\frac{\partial\mathcal{L}}{\partial w}=w-\sum_{i=1}^{n}\alpha_i.y_i.x_i=0 \qquad (1)$$

$$\frac{\partial\mathcal{L}}{\partial b}=-\sum_{i=1}^{n}\alpha_i.y_i=0 \qquad (2)$$

$$\alpha\geq 0$$

From (1) and (2) we have:

$$w=\sum_{i=1}^{n}\alpha_i.y_i.x_i \quad và \quad \sum_{i=1}^{n}\alpha_i.y_i=0$$

Therefore, $\mathcal{L}(w,b,\alpha)$ will be:

$$\mathcal{L}_D=\mathcal{L}(w,b,\alpha)\equiv\sum_{i=1}^{n}\alpha_i-\frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n}\alpha_i.\alpha_j.y_i.y_jx_i.x_j \quad (***)$$

For each $x\in\mathbb{R}^d$ will be classified by:

$$f(x)=sign(w.x+b)=sign\left(\left(\sum_{i=1}^{n}\alpha_i.y_i.x_i\right).x+b\right)$$

$$=sign\left(\sum_{i=1}^{n}\alpha_i.y_i.(x_i.x)+b\right)$$

Where: $sign(x)=\begin{cases}1\ với\ x\geq 0\\-1\ với\ x<0\end{cases}$

For non- linear hyperplane in non-linear training data set, the solution to the inseparability problem is to map the data onto a higher dimensional space (the transformed feature space), where we can use a linear hyperplane there.

$$\Phi:\mathbb{R}^d\rightarrow\mathbb{R}^{d'}$$
$$x\longmapsto\Phi(x)$$

The Equation of (***) will be:

$$\mathcal{L}_D\equiv\sum_{i=1}^{n}\alpha_i-\frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n}\alpha_i.\alpha_j.y_i.y_j.\Phi(x_i).\Phi(x_j) \qquad (****)$$

Where $\Phi(x_i).\Phi(x_j)=k(x_i,x_j)$ is so-called as "kernel function" [5]. This kernel function is used to map new points into the feature space for classification whenever a hyperplane has been created.

Assume that $E(x,y)$ is prediction error for each pair of (x,y). Therefore,

$$E(x,y)=\sum_{i=1}^{n}\alpha_iy_ix_i.x+b-y$$

According to Platt (1999) in Sequential Minimal Optimization (SMO) algorithm, the selection of α_i,α_j will be performed in two heuristic loops so that $|E_i-E_j|$ will be maximum. The Lagrange multipliers α_i are used in the process to select a α_i so that $0<\alpha_i<C$ and it is not satisfied Karush-Kuhn-Tucker (KKT- 1951) conditions, and α_j $(0<\alpha_j<C)$ so that $|E_i-E_j|$ will be maximum

B. Foreign Exchange Prediction

The Forex prediction problems have usually seen as the binary classification ones because the expected output is one of rise or fall of foreign currencies rate trend. Box and Jenkins' AutoRegressive Integrated Moving Average (ARIMA) technique has been widely used for time series forecasting. However, ARIMA is a general unvaried model and it is developed based on the assumption that the time series being forecasted are linear and stationary [6]. According to [6], exchange rates prediction is one of the most challenging applications of modern time series forecasting. This is because of the inherently noisy or non-stationary rates [7]. In this case, the historical data is the major factor during the prediction process [7], [8], [6] used Radial Basic Function (RBF) and Multilayer Perceptron Network (MLP) for the FoRex classification whereas [9] used gene models. In [6], there has used a data set of 1825 instances including a training of 1600 and testing set of 225 records. It seems that there was a small volume of historical data set in order to train the model. The ANN model included multilayer perceptron network with a structure of 3 input nodes (price, weight, and fluctuation of prices), 2 hidden nodes and 1 output node (change or unchanged). The model weights were calculated by gene algorithm with 8 genes in alternative chromosomes. The disadvantage of this model is simple as well as using of small data set for the experiments so that the quick regression of model might be mistaken. The mining data in Rumani stock using neural network models for price prediction also can be seen in [10]. The MLP (multilayer perceptron) has been used to predict the future price of stock code. The results have been shown the advantages of using supervised learning techniques in the predicting classification problems.

Other research on predicting trend in stock market can be seen in [11], [12], [13], [14]. Their researches have reported using artificial neural networks or decision tree models. However, many of these papers reported that they are able to work in real-time settings and according to [15], there remains a lack of published research using high frequency data.

Many publications have shown that SVMs were extended to solve nonlinear regression estimation problems and have been successfully used to solve forecasting problems in various fields [16], [17] [23], [24], [25]. For example, according to

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[25], Malaysian exchange rate was influenced on commodities' prices (crude oil, palm oil, rubber, and gold). The data set used with SVM produced results nearly the same as the one used random forest (0.021 versus 0.018). But the running time of test SVM was reported better than the one of test Random Forest (0.10 versus 9.750 milliseconds).

However, according to [18], there is few studies for the application of SVM in financial time-series forecasting [19], [20], although SVM has some advantages. Moreover, almost publications have just stopped in the use of machine learning models without running experiments for the FoRex transaction's implementation. Therefore, in this paper, SVM model is chosen to predict the rise or fall of currencies rates in FoRex market. This is because of there are no parameters to tune except the upper bound C [21], and SVM avoids over-fitting problems like other Artificial Neural Networks models [1].

The Forex market can be seen as a special one in the financial markets with its characteristics of high benefits, maintaining the capital in the case of inflation, and its transaction can be performed all time at any location in the world. The investors can buy/sell the pairs of money such as EURUSD (Euro vs US Dollar), USDJPY (US Dollar vs Japanese Yen), GBPUSD (Great Britain Pound vs US Dollar) etc. to get the benefits of different exchange rate between these pairs. In general, the following parameters define the trend of up or down of the rates:

- Target Profit (TP): is positive to indicate the target profit.
- Stop Loss (SL): is positive number to show that the loss is acceptable.
- Time Trend Detection (T): is positive to indicate the forward time starting from current point.

Therefore, given the current rate of (P), the outputs of prediction as:

- The trend of exchange rate is up if the rate is increased of (P+TP) instead of decreasing an amount of (P-SL) in the duration of T.
- The trend of exchange rate is down if the rate is decreased of (P-TP) instead of increasing an amount of P+SL in the duration of T.

The parameters of SL, TP are used with unit of "PIP" (to measure the profit or loss in the market)

III. EXPERIMENTS

A. Data Configuration and Model preparation

Data

The FoRex data is collected by using MetaTrader 4 [22] to download from 01/01/2013 to 30/09/2016. In this paper, the pair of EUR/USD has been selected as it is very popular one in the market. The training data set D included the instances in a period of 01/01/2013 to 31/12/2015, and the test data set D' contained the instances in a period 1/01/2016 to 30/09/2016.

Features

The selection of experimental features is effected to the model results. In this paper, the features are selected basing on the objectives of profits about 10 – 15 Pips for each transaction. The observed exchange rates are the "Open", "Close", "Low" and "High" for the candles in the window time of M1 (1 minute), M5 (5 minutes), M15 (15 minutes), H1 (1 hour) and D1 (1 day). The features are also based on the RSI (Relative Strengh Index), MA (Moving Average), Bollinger (Bollinger Bands), and Custom Indicators. The features are selected in the given data set can be seen in Table 1.

TABLE I. 137 SELECTED FEATURES

Feature#	Data	N0	Note
#1-16	O, H, L, C on Timeframe M1	16	4 values x 4 candlesticks
#17-32	O, H, L, C on Timeframe M5	16	4 values x 4 candlesticks
#33-44	O, H, L, C on Timeframe M15	12	4 values x 3 candlesticks
#45-56	O, H, L, C on Timeframe H1	12	4 values x 3 candlesticks
#57-72	O, H, L, C on Timeframe D1	16	4 values x 4 candlesticks
#73-77	Time data	5	Data Attributes
#78-81	RSI(7) on Timeframe M5, M15	4	1 values x 4 Timeframe
#82-85	RSI(14) on Timeframe M5, M15	4	1 values x 4 Timeframe
#86-101	MA(9), MA(12), MA(100), MA(200)	16	4 values x 4 Timeframe
#102-113	Custom Indicator	12	4 PAX + 8 MKC
#114-119	Bollinger Bands	6	3 Lines x 2 Timeframe
#120-125	Average True Range	6	2 values x 3 Timeframe
#126-137	Highest, Lowest M1, M5	12	4 values x 3 Timeframe

Model configurations

The machine learning technique in the experiments is SVM model. Its model is used with alternative of Gaussian RBF, and Polynomial kernel functions. In detail, the model parameters are:

- RBF: $k(x, y) = e^{-\frac{\|x-y\|^2}{2\sigma}} = e^{-\gamma\|x-y\|^2}$ with $\gamma \in [0; 5]$
- Polynomial: $k(x, y) = (x.y + \theta)^d, \theta \in \mathbb{R}, d \in \mathbb{N}^*$ with $d = 2,3,4$ and $\theta \in [0; 1]$.
- The parameter of C has been used with $C \in [1; 10]$.

According to [19], the upper bound C and the kernel parameter in kernel functions play an important role in the performance of SVMs. Therefore, after many performing experiments, the parameters have been used are follows as if they produce acceptable results.

- RBF: $\gamma \in [1; 2]$.
- Polynomial: $d = 3$ and $\theta = 1$.
- The parameter of $C \in [1; 2]$

TABLE II. EXPERIMENTAL MODEL CONFIGURATIONS

Models	Poly1	Poly2	Poly3	GsR BF1	GsRB F2	GSR BF3
C	1.0	1.0	1.0	2.0	1.0	2.0
Kernel	Poly	Poly	Poly	RBF	RBF	RBF
Parameters	Power	Power	Power	γ=5.	γ=4.0	γ=5.

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	2	3	3	0		0
No of vectors	3000	3000	2000	3000	4500	5000

B. Results

The data is used with the cross validation method. The D data set is divided in to D_{pos} (positive output); and D_{neg} (negative output). They are split to $D_{pos}^1, D_{pos}^2, \dots, D_{pos}^k$ and $D_{neg}^1, D_{neg}^2, \dots, D_{neg}^k$ sub-sets (each sub-sets has $\frac{1}{k}\left|D_{pos/neg}\right|$ samples. D_Test will be each sub-set and k-1 remaining sub-sets will be used for D_Train. In this paper experiment, k is chosen of 5. The results can be seen in Table 3 and Table 4 for 6 above models. The Accuracy Rate, Precision of Positive, Negative, Micro-Averaging and Macro-Averaging results are used to compare the performance between alternative models.

TABLE III. RBF CONFIGURATION MODELS RESULTS

Kernel: Gaussian RBF Features: 137		**GsRBF1**		**GsRBF2**		**GSRBF3**	
		D_Train	D_Test	D_Train	D_Test	D_Train	D_Test
Accurate		82.41%	58.11%	86.08%	58.57%	87.28%	58.36%
Precision	Positive	81.87%	57.61%	85.67%	57.78%	86.83%	57.59%
	Negative	82.96%	58.57%	86.50%	59.38%	87.75%	59.13%
	Micro-Averaging	82.41%	58.11%	86.08%	58.57%	87.28%	58.36%
	Macro-Averaging	82.42%	58.09%	86.09%	58.58%	87.29%	58.36%

TABLE IV. POLY CONFIGURATION MODELS RESULTS

Kernel: Polynomial Features: 137		**Poly1**		**Poly2**		**Poly3**	
		D_Train	D_Test	D_Train	D_Test	D_Train	D_Test
Accurate		76.78%	74.20%	82.46%	74.67%	82.52%	74.60%
Precision	Positive	76.38%	74.69%	82.98%	78.40%	83.07%	78.50%
	Negative	77.19%	73.76%	81.95%	71.95%	81.98%	71.80%
	Micro-Averaging	76.78%	74.20%	82.46%	74.67%	82.52%	74.60%
	Macro-Averaging	76.78%	74.22%	82.47%	75.18%	82.53%	75.15%

C. Discussions

Table 3 and Table 4 show the results of alternative models using alternative kernel functions of Gaussian RBF and Polynomial respectively. The results in Table 3 show that the performance of positive and negative prediction for Test sets has big gap compared to the Training sets (about 53% and 82.5 % respectively). In contrast, there is a little different between performance rates of the training and testing in Table 4.

The accuracy rates taken from two kernel functions of Gaussian RBF and Polynomial are represented in the chart to show the high performance of the use of Polynomial one in general. In Polynomial functions group (Poly1, Poly2, Poly3), there is no different of accuracy rates for the Test sets (about 74.5%) whereas Poly2 and Poly 3 models have better results for the training set (82.5%). These results show that a use of C=1, polynomial power of 3 and alternative support vectors (see in Table 2) does not change the experiment performance.

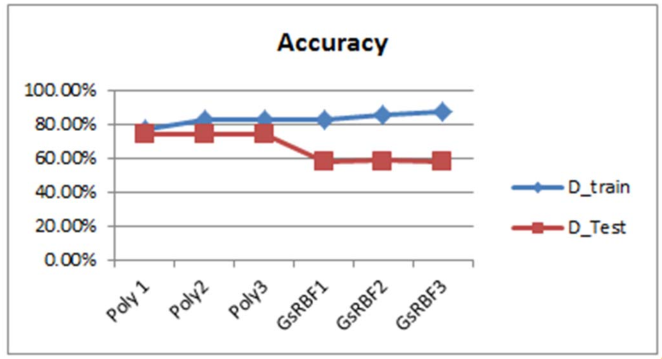


Fig. 1. Accuracy rates of Experimental Model Configurations

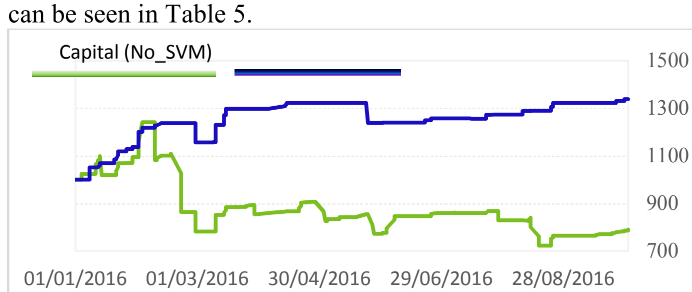
D. Expert Advisor in FoRex Transactions

The Expert Advisor (EA) is a plug-in script implemented in MetaTrader 4 [22]. This script collects the historical data, technical indicators as well as doing the transaction of buy or sell the pair of currencies. In this paper, the advisor does not training the model as if it takes too long of calculation whereas the decision of buying or selling is made in some seconds. This is because of the changing time of currencies rates is happened in seconds or some blocks of second.

For comparison, the expert advisor without of the support of SVM also has been used. The conditions for experiments as follows:

- Use Backtest function
- Broker: ICMarkets
- Currency pair: EUR/USD
- Time: 9 months
- Initial Margin: 1000USD
- Margin Level: 1:500
- Spread: 0.8 – 1.0 pip
- Commission: 7USD

The experiment results can be seen in Figure 2 whereas the detail indicators' results of No_SVM and SVM uses for EA can be seen in Table 5.



Index	**Indicators**	**No_SVM**	**SVM**
1	Net Profits	**-210.46**	**337.94**
2	Gross Profits	718.37	504.7
3	Gross Loss	-928.83	-166.77
4	Profit rate	**0.77**	**3.03**
5	Growth	**-21.0%**	**33.8%**
6	Average Growth	**-2.59%**	**3.29%**

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	(month)				
7	Strict Drawdown		371.72		151.5
8	Fair Drawdown	645.36	**50.67%**	450.67	**34.69%**
9	Volume		189		96
10	Profit Transactions	147	77.8%	85	88.5%
11	Loss Transactions	42	22.2%	11	11.5%
12	Ask Profit Transactions	111	91.0%	71	100.0%
13	Bid Profit Transactions	78	59.0%	25	56.0%

TABLE V. INDICATORS' RESULTS

Table 5 shows the advantage use of SVM in the transaction Robot, in overall. For example, the Volume of use SVM is a half of No_SVM (96 and 189 respectively) whereas the Profit rate is triple (3.03) compared to 0.77. The Fair Drawndown in the use of SVM is a little bit high (34.69%). But it still is a half of the one use without SVM implementation.

IV. CONCLUSIONS

The supervised machine learning technique such as support vector machine can help to solve the Forex problem as it can be represented in binary classification task. The power of use artificial intelligence in learning models helps to deal to a huge, complex and time series data to extract the knowledge for users' purpose. For example, in this paper, an amount of experimental data set is about more than 13500 instances has been performed. By using Gaussian and Polynomial kernel functions, the alternative models with alternative parameters have been performed. The results of using Polynomial Kernel have shown the better results compared to the models used Gaussian in general. The best Poly model is performed in Robotic transactions. Its results shown the advantage use compared to the traditional one (without use of SVM).

The Robotics transaction in this paper is used with demo account, therefore, the further research will focus on continuing to use transactional Robotics in the real foreign exchange market.

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