Short-Term Price Prediction and the Selection of Indicators

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Although the prediction of the future price is known to be hard due to the strong randomness inherent in the price fluctuation, intra-day price movements are expected to be predicted by reading out the patterns observed in tick-wise price motions. Our first task on this line of thought is to identify the set of effective variables suitable for studying the problem. We have first constructed a price prediction generator that computes the best prediction by reading the data tick by tick. We report in this article the effect of the adaptive choice of the best combination of technical indicators out of ten popular indicators, and also the result of using a set of novel dimensionless dynamical indicators constructed from the local values of derivatives and the second derivatives of the price times series. We have obtained a good performance of nearly 70 percent of correctly predicted direction of motion at 10 ticks ahead of the prediction time by means of adaptive choice of the technical indicators, and even better performance in the second attempt of using the two dimensionless dynamical indicators.

§1. Introduction

The objective of econophysics[1)–3)] is twofold. One is to use the tools that we are familiar with in theoretical physics and apply them upon financial engineering. The other and more important of all is to extend statistical physics in such a way to include dynamical, non-stationery phenomena. In particular, the problem of learning the way to adapt to the environment is the major concern. We attempt to cut into this problem using the tick-wise price data as an environment to adapt. The main thrust of this paper is to present our result of making the short-term price prediction by applying the online learning technique on the real tick data.[4)] To do this, we need identify the effective variables to be used for the formulation of the problem. As a first attempt we borrow some well-known technical charts from the practitioner's toolbox[5),6)] and construct a system that automatically selects the best combination of those charts case by case by reading the pattern of tick-wise price fluctuation.[7),8)]

Technical indicators (charts) have widely been used by investors, mainly for analyzing daily data. However, as pointed out by Stephan Schulmeister[9)] as a result of analyzing 2580 technical models applied on the S&P 500 spot and futures market, the profitability of technical trading system applied on daily data declined since 1960 and has been unprofitable since the early 1990s, while the same models applied on 30 minutes data produce an average gross return of over 7 percent per year between 1983 and 2007. This means the intraday trading still can produce profits when daily trades cannot. The same reference also reports that those models perform worse in

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the period of 2001–2007 compared to the period 1980s and 1990s, indicating that the stock markets have become more efficient in the recent years.

We design the prediction generator in four steps. The first step is to learn the best-fit parameters of those ten indicators. The output of this step is stored in the Parameter File. The second step is to select the best choice of the parameters by learning from the data. The output of this step is stored in the Indicator File. The third step is to figure out the best strategy for every possible pattern learned from the data. The output of this step is stored in the Strategy File. Then the fourth and final steps are to test the learned strategy with a new set of price data and check the performance of the price generator. We have so far obtained a satisfactory performance of getting nearly 70 percent of correct prediction rate in terms of the direction of the price (up/down) at 10 ticks ahead of the prediction time for foreign exchange rates of USD/JPY for 6 years from 1995 to 2000. This is about the same level of performance to the case of eight different stock prices chosen from four different branches of disciplines from New York Stock Exchange markets that we reported elsewhere.[7] Section 2 is devoted to presenting the details of this analysis. In §3, we introduce a new set of two dimensionless indicators constructed by the local values of the first and second derivatives of the price time series and by using them we employ a similar system to the above-mentioned price generator and test its performance in the real tick data.[8] We have obtained even better performance in this attempt compared to the case in §2. Finally, we conclude the paper by §4 stating possible future perspectives.

§2. Technical indicators

2.1. *Pattern recognition by technical indicators*

There are many technical indicators in the literature.[5),6)] They fall into the following three categories:

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(1)  Price trends (rising/falling)
(2)  Trend turnover (rising/falling to falling/rising)
(3)  Market strength (momentum, volume, etc.)
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The first group has many kinds of moving averages (abbreviated as MA), obtained by averaging the price time series over a certain period T. They indicate whether the price is in the phase of increasing trend or decreasing trend. There are many kinds of MAs and we hereafter call them by their characteristics followed by MA, such as **MA. Among them, the SLMA uses information of relative location of the SMA (MA over shorter T), the LMA (MA over longer T), and the original price time series itself. Likewise, the SLEMA uses relative location of two exponential-weighted moving averages (abbreviated as EMA) over different periods, namely, SEMA (EMA over shorter period) and LEMA (EMA over longer period). The second group has various signals that are supposed to indicate the approach of trend turnover. Many investors use combinations of multiple indicators chosen from different categories. However, there is no fundamental guideline as to which indicators to be chosen. The investors use their favorite combinations of those indicators. The period to take MA is also determined ad hoc based on investor's experience and sentiments. Our purpose is to find the way of choosing the most suitable combination of the indicators and the period T to take MA at moment of concern, and establish the automatic prediction generator on the trend of the price movement at ten ticks ahead. We select 10 popular indicators:

(1) MA: moving average
(2) SLMA: relative magnitude of SMA, LMA, the price,
(3) SLEMA: relative magnitude of SEMA, LEMA, price,
(4) MACD: MA convergence vs divergence defined as MACD = SEMA - LEMA
(5) BB: Bolinger Band defined as a belt over MA $\pm k\sigma$,
In this work we take k=3 and split the range into eight states: MA + $3\sigma \leq$ price, MA + $2\sigma \leq$ price $\leq$ MA + 3σ,..., price $\leq$ MA - 3σ.
(6) MO1: One-step momentum defined as the difference between the current price and the previous price
(7) MO2: Two-step momentum defined as the difference between the current price and the price at 2 ticks before
(8) RSI: Relative Strength Index defined as a percentage of average rises in the last T ticks out of average times of moves in the same period
(9) RCI: Rank Correlation Index defined as a percentage of $1 - \frac{6d}{n(n*n-1)}$ where d is a sum of the squares of the difference between the price rank and the time rank.
(10) PL: Psychological Line defined as a percentages of rising events in T ticks period

2.2. *Design of the PG*

Our system consists of the following four steps:

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Step 1: Determine parameters for all the technical indicators.
           (Parameter File created)
Step 2: Select indicators using the Parameter File.
           (Indicator Filecreated)
Step 3: Generate Strategy using the two files stated above.
           (Strategy File created)
Step 4: Predict future price level by using the Strategy File.
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2.3. *Performance of the PG on the foreign exchange data*

We test those prediction strategies on new data. The last half of the data set is served for this purpose. The prediction referred to here is the UP/DOWN motion of the price at 10 ticks ahead compared to the current price. Note that this method is vulnerable for the data in which the situation drastically change for the first half and the second half within the data. The result for the foreign exchange rates is shown in Table I. The first row shows the years, the second row shows the best performance out of ten different choices of the indicators and the third row shows the average

Table I. The best and the average hitting rate of the predictions on the UP/Down direction of the price at 10 ticks ahead for FX data of JPY/USD for five years from 1996 to 2000.

Year	1996	1997	1998	1999	2000
Best	.699	.665	.649	.660	.677
Average	.699	.665	.648	.660	.677

performance of the 10 choices of the indicators. We have obtained nearly 70 percent of the correct prediction. The lower rate from 1997 to 1998 can be attributed to the rapid fall of Yen against Dollar during this period. Note that the best and the average are almost in the same magnitude. However, the time variation within a year is not small. The correct prediction rates fluctuate rather vigorously in each year.

§3. Elements of the dynamical pattern classifier

3.1. *Dynamical price prediction*

The price prediction generator that we discussed in the previous section by using the best combination of popular technical indicators for their best values does not answer to the question of asking the origin of those indicators. Indeed nobody can derive those indicators from the first principle. Moreover, the method in §2 essentially utilizes the differences between the current price and a certain average values of the prices at the neighboring time steps, which does not contain any information of dynamical effect such as the velocity or the acceleration of the prices. We attempt to incorporate those dynamical properties as a new set of indicators and utilize their patterns in order to predict the price range in the near future.[10)]

3.2. *Quadratic least square estimate (QLSE)*

We use the quadratic least square method (QLSE) for each segment of the price time series of length n. Defining the time t being $0 \le t \le n$ within each segment, and the price at the time t to be $p(t)$, we extract the initial price, $p(0)$ and the initial velocity (of the price), $p'(0)$, and the acceleration, $p''(0)$ as the dynamical parameters that represent each segment. For the linear LSE, the initial price and the initial velocity for each segment are defined as A and B, respectively in the following equation:

$$p(t) = A + Bt. \tag{3·1}$$

They are computed by solving the following coupled linear equation,

$$\begin{pmatrix} 1 & \overline{t} \\ \overline{t} & \overline{t^2} \end{pmatrix} \begin{pmatrix} A \\ B \end{pmatrix} = \begin{pmatrix} \overline{p} \\ \overline{tp} \end{pmatrix}. \tag{3·2}$$

For the QLSE, the initial price, velocity and acceleration (of the price) for each segment are defines as α, β, and γ, respectively in the following equation:

$$p(t) = \alpha + \beta t + \frac{1}{2}\gamma t^2. \tag{3·3}$$

Those parameters are obtained by solving the following coupled linear equation,

$$\begin{pmatrix} 1 & \overline{t} & \overline{t^2} \\ \overline{t} & \overline{t^2} & \overline{t^3} \\ \overline{t^2} & \overline{t^3} & \overline{t^4} \end{pmatrix} \begin{pmatrix} \alpha \\ \beta \\ \frac{1}{2}\gamma \end{pmatrix} = \begin{pmatrix} \overline{p} \\ \overline{tp} \\ \overline{t^2 p} \end{pmatrix}. \tag{3·4}$$

Note that A and B that correspond to the initial price and the initial velocity obtained in the linear LSE are slightly different in value to α and β obtained in the QLSE. The third dynamical parameter represents the acceleration for the segment.

3.3. *Dimensionless parameters*

In this section, we define dimensionless dynamical parameters using the velocity and acceleration parameters obtained in the last section, A, B, or α, β, γ. The dimensionless parameters do not depend on the choice of the units of the price and the time thus expected to have a universal value. There is one such parameter made of the variable (in our case, the price), its time derivative (velocity), and the second derivative (acceleration), which is called as F-number. The name comes from the similarity to the F-number[11)] often used in fluid mechanics representing the ratio of inertia of the fluid over the gravity which can be interpreted as follows in our case,

$$F = \frac{\beta^2}{\alpha\gamma}. \tag{3·5}$$

We also define another dimensionless number that consists of time interval, distance, and velocity, which can be interpreted in our case as follows:

$$T = \frac{nB}{A}. \tag{3·6}$$

This parameter is named as T since the major effect comes from the time interval. Unlike F, this parameter T essentially depends on the time scale, since the time interval has to be determined as a pre-determined universal parameter. We assume this to be the length of the segment (n).

3.4. *Dynamical patterns*

We use two dimensionless dynamical parameters, F and T, for the pattern classification. However, tick-wise changes involve extremely short time interval ranging from less than a minute to a few minutes and the price changes are usually very small, 0.01–0.1. For this purpose, we divide the range of velocity β (or B) into 3 regions by two threshold points $\beta_{down} \leq 0$ and $\beta_{up} \geq 0$, and do the same for the range of acceleration γ by two threshold points $\gamma_{down} \leq 0$ and $\gamma_{up} \geq 0$. By doing this, the 2 dimensional spaces of β and γ are divided into 9 regions. Those 9 patterns can handle more delicate classification compared to the standard ways depending solely on price up/down patterns.

3.5. *Intra-day forecast by means of dynamical pattern classifier*

3.5.1. Flow of the dynamical PG

The basic structure of the job flow is as follows, which is similar to the generator that we proposed before in the study of technical indicator combinations.

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(1) Set up the parameters in the prescribed range given by
     a) Pattern length, n in the range of 3-ticks<n<30-ticks
     b) Term of Prediction Experiment, L: data length of one day
     c) Predicted Range, R = 1-10 ticks ahead of the point of computation
(2) Generate a prediction strategy based on the dynamical parameters
(3) Compute the dynamical parameters A, B,,,, F, T from the data
(4) Extract patterns by means of the dynamical parameters
(5) Use the prediction strategy and make a prediction
(6) Repeat (3)-(5) for L times
(7) Compute the hitting rate
(8)Repeat (6)-(7) for all the data applied for prediction experiment.
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In (1)-a), L is 9000 ticks in the year 2000. In (7), the hitting rate is defined as a ratio of correctly predicted direction of move divided by the total number of predictions L, and evaluate the strategies. If there are more than 1000 strategies, select the best 1000 strategies according to the performance in the evaluated hitting rates and perform the same genetic operation as in Ref. 7). Namely, we sort the current strategies according to the order of performance and send the top 10 percent genes and their 9 different mutants to the next generation.

3.5.2. Generation of prediction strategy

The local velocity β and the local acceleration γ obtained by QLSE for each data segment are used as the dynamical parameters for pattern classification. The 9 patterns correspond to the 3 by 3 matrix of β and γ divided by β_{up}, β_{down}, γ_{up}, and γ_{down}, respectively. The prediction strategy is a gene corresponding to the leaves of the tree of order 9, corresponding to the 9 patterns of dynamical variables at each time step. For the case of 9 patterns, there exist 512 possible strategies for the tree of minimum depth, $n = 1$, and 2^{81} possible strategies for the tree of depth 2 corresponding to the memory length $n = 2$. We set the maximum number of strategies to be 1000 for the sake of computational time. We use all the strategies if the total number does not exceed 1000. On the other hand, if the number of strategy exceeds 1000, we follow the same evolutional technique as we used in Ref. 7) to select the 1000 best strategies. The results reported in the following sections are the case of $n = 1$, thus no evolutional algorithm works and all the possible strategies are examined.

3.5.3. Evaluation of hitting rates and evolution of strategies

After repeating the prediction process for L steps, the system terminates the experiment in order to evaluate the strategies by the rate of correct predictions. At this point, the best strategy and its hitting rate, as well as the average hitting rate of 10 best strategies are recorded and new strategies are prepared for the next generation by means of an evolutional algorithm. The hitting rate, or the correctly predicted rate is defined as the ratio of the correctly predicted moves over the total moves. Note that we disregard the unmoved events in taking this ratio.

§4. Results of prediction experiment

In our experiment, we have used one pattern as a conditional part of the conditional probability thus no need of evolutional mechanism. We show the hitting rates of the best strategies of this new generator, compared with the result of old generator in §2 in Fig. 1 applied on the data of foreign exchange rate USD/JPY from 1996 to 2000. The upper two lines are the result of predicting 1 tick ahead of the predicting time and the lower two lines are the result of predicting 10 ticks ahead. Both cases show that the new dynamical version outperforms the old version of our predictor. The hitting rate as a function of the predicted point ranging from 1–10 tick is shown in Fig. 2. We observe in Figs. 1 and 2 that our new result always performs better than the old result of §2.

Another factor is the length of the pattern, n. Using the evolutional method, we obtained the history length to lie in the range of $H = 1$–5.[4),7),8),12),13)] Since the result was obtained at $H = 3$, the number of possible strategies is 3^{27}. In the current analysis of using the dynamical parameters, similar effects have been observed. The result of computing the dynamical parameters over 5 ticks by means of our new method performs worse than the case of using 3 ticks in the same method, they still outperform the results of 'past' method in more than a half of the entire data. However, the new method using more than 10 ticks of history considerably ill-performs and the hitting rate further goes down as we increase the range of history and becomes random after the range reaches 20–30 ticks.

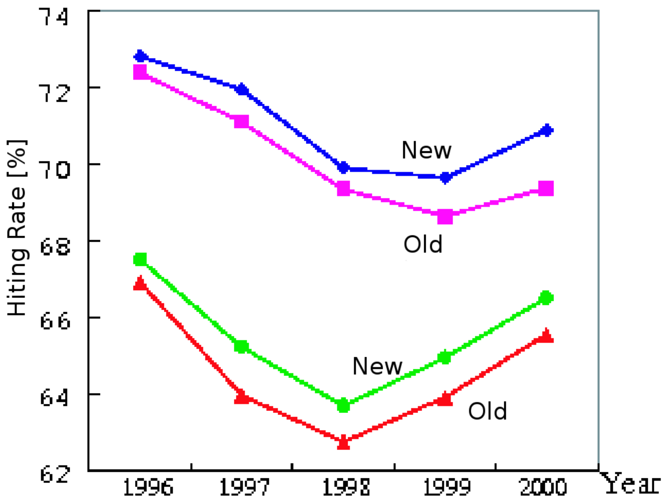

Fig. 1. (Color online) Comparison of the correctly predicted rates of the new/old method. The upper/lower two lines are the results of predicting 1-tick/10-ticks ahead.

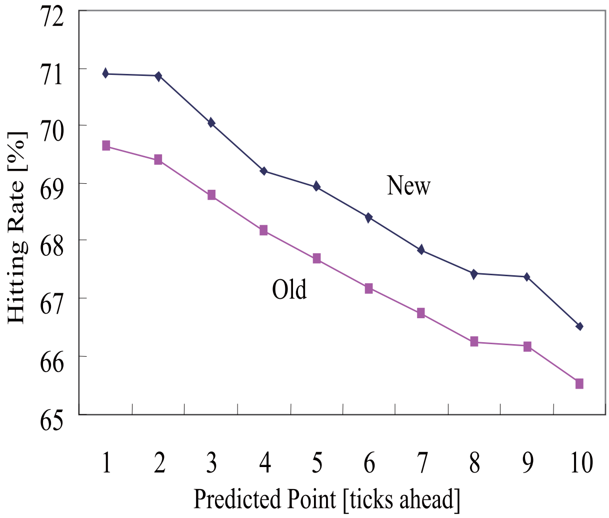

Fig. 2. (Color online) The correctly predicted rates of the new/old method vs the range of the predicted point, 1–10 ticks measured for USD/JPY2000.

§5. Conclusion and future perspectives

In this paper we have presented the idea and the design concept of our price generator and the result of its application on the real tick data. We also have presented the applied a novel version of our prediction generator that reads and uses the patterns of dimensionless dynamical parameters together with the local velocities and accelerations on the tick-wise price changes, reflecting the correlation between tick-wise prices. By doing this, we have successfully improved the rate of correctly predicting the future direction of the price range by 1–2 percent based on the patterns of 3 ticks to 5 ticks in the past. The result of predicting 10 ticks ahead also shows improvement in comparison to the result in §2. However, the use of past patterns of 10 ticks or older considerably lowers the rate of correct prediction on the up/down trends of the price range. The use of past patterns of 20 ticks or older turns out meaningless since the prediction based on those information shows random series of up/down trends. Based on this fact, we conclude that the meaningful size of segments lies between 3 to 6 ticks, and not only the sign of the price changes but the dynamical patterns including velocity and acceleration play important effect on the prediction. Although it is still unclear whether dimensionless parameters are effective on the improvement of the rate of correct prediction of the future price range, the best parametrization have been the 9 patterns of the 3 velocity times the 3 acceleration. This result does not directly mean that the usage of the dynamical indicators gives us significant financial profit, but the result definitely shows the existence of patterns described by those two dynamical parameters F and T in the tick-wise foreign exchange rates. We need further study varieties of data in order to clarify whether tick-wise tradings are indeed profitable, considering many other analysis, for example Dueker and Neel,[14] imply negative conclusion.

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