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RELATIVE PROFIT— A NEW METRIC TO EVALUATE THE PERFORMANCE OF STOCK PRICE FORECASTING MODELS

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RELATIVE PROFIT—A NEW METRIC TO EVALUATE THE PERFORMANCE OF STOCK PRICE FORECASTING MODELS

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Abstract

Stock price forecasting models with lower Mean Squared Error (MSE) are more “welcome” than those who have higher MSE. However, this “welcome” may disappear when lower MSE leads to an unexpected loss whereas higher MSE leads to a positive profit in a practical investment. The reason is that MSE aims to evaluate models in the view of “accuracy”, which has nothing to do with profit. We therefore propose the concept of “forecasting efficiency” that aims to evaluate models in the view of investment or profit. A comprehensive but concise metric: Relative Profit (RP) is designed to better evaluate which model really pleases investors. Finally, a comparison is made between RP and other popular metrics to demonstrate that RP is a good supplement to forecasting model evaluation.

Keywords: Stock price, Forecasting performance, Evaluation criterion, Relative profit
INTRODUCTION

Stock price forecasting is an interesting research topic that has spawned a large quantity of literature in decision support field. Over the last decade, researchers have proposed various forecasting models (Donate et al. 2013, Kazem et al. 2013, Park and Shin 2013, Wang et al. 2012) to challenge the unpredictability of efficient market (Fama 1970, 1991). In the eyes of both practical investors and academic researchers, evaluating the performance of different models is a vital procedure, only by which new methods adopted in models can be verified worthy or not. Though there may be several different metrics for performance evaluation, it seems to be widely accepted that a reasonable one should be a business of money.

As far as we know, there is no universal metric that meets this requirement. Mean Squared Error (MSE) is prevalent in existing works; it is, however, none of money business. In fact, MSE is defined as:

\[ MSE = \frac{1}{N} \sum_{i=1}^{n} (\hat{p}_i - p_i)^2, \]  

where \( \hat{p}_i \) is the predicted price, \( p_i \) is the actual price and \( N \) is the total prediction times in a specific period.

MSE focuses on the distance or difference between predicted values and actual values. Lower MSE represents a better performance and high MSE indicates poor performance. Ironically, practical investors regard MSEs as trivial because future stock price trend up or down is the key to return on investment instead. Knowing future price trend is more important, some researchers (Yu et al. 2009) take Directional Accuracy (DA) as an alternative solution, which can be defined as:

\[ DA = \frac{1}{T} \sum_{t=1}^{T} d_t \times 100\%, \]

In summary, MSE focus on the prediction distance accuracy while DA aims to measure future price trend accuracy. Both of them are not directly related to what practical investors really care [return on investment. As we know, the profit from buying or selling stocks depends on two aspects: the future price direction and the distance between future price and current price, at which you buy in or sell out. In fact, larger distance is not welcome if future price trend prediction is wrong. Even though DA is a key factor to profit, higher DA does not definitely lead to higher profit after a series stock transactions.

MSEs and DA pay great attention on “forecasting accuracy” rather than “forecasting efficiency”. By emphasizing “efficiency”, we argue that financial time series forecasting should be evaluated under the view of investment. In other words, if an investor adopts the model as decision support systems in stock market, how much money can be made steadily is the target a proper metric should evaluate. A forecasting model with higher efficiency means that, if it is adopted in the stock market, an investor can gain more profit with less fluctuation. Apparently, investors care more about efficiency rather than accuracy. Consequently, a metric of performance evaluation does make more sense if forecasting efficiency is well exposed.

Even though forecasting efficiency is crucial to investors, surprisingly, little literature pays attention on how to construct such a metric. Almost all of existing studies (Schumaker and Chen 2009...) adopt

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1 People usually adopt forecasting models to assist their decision making in investment, hence it is reasonable that a metric should expose whether a model is better than another in the view of profit.
MSEs and DA as performance metrics, which actually deters forecasting models from being applied in the stock market since investors are not sure about the true profitability via these metrics. To solve this problem, some researchers use an investment simulation to investigate how much money a model can earn during a series of transactions. In fact, a forecasting model can provide trading signals. For example, $p_t$ is the price at the time $t$ and $p_{t+1}$ is the price at the time $t+1$. If the model predicts the future stock price $p_{t+1}$ would be higher than $p_t$, a buy signal, an investor would buy the stock immediately at time $t$ with $p_t$ and sell it at time $t+1$. If the prediction comes true, this leads to a positive profit: $\|p_{t+1} - p_t\|$ and of course negative: $-\|p_{t+1} - p_t\|$ if the prediction is wrong. Specifically, an investment simulation is launched with an initial sum of money and then the final profit after $N$ continuous transactions is calculated based on trading signals of a model. Usually some classical strategies will be counted as benchmarks, for example moving average strategy and momentum strategy, etc. If a new model gains higher final profit than the benchmarks, it is believed to be a success.

Although an investment simulation is convincing to demonstrate a model’s profitability, it does not meet what investors really require. With Markowitz's portfolio theory, variance of return is regard as a representative of risk (Markowitz 1952). Given the same expected return, higher variance of the return is less preferred by risk-averse investors while lower variance of the return will please them. Rather than focusing on forecasting itself, we pay attention on investor satisfaction. Consequently, we introduce the concept “forecasting efficiency”, which can be expressed as a ratio of expected profit$^2$ and variance of the profit in an investment. The higher of the ratio is, the higher of the forecasting efficiency. In existing studies, an investment simulation adopted is usually one-off deal that pays great attention on the final profit rather than the process—how the final profit is gained? Hence, an investment simulation is not enough to verify the exact forecasting efficiency due to lack of evaluation on the simulation process.

Furthermore, another problem of investment simulation is “asset price dependence” (APD). In a simulation, final profit calculation relies on the price of stock or other asset prices, which is called “asset price dependence”. APD actually suffers “money exhaustion” problem during a continuous $N$ transaction simulation. This means the money invested on the $n^{th}$ transaction depends on the accumulated profit gained from $1^{st}$ to $n^{th}$ transactions. Since no one knows what will happen in future, it is possible that a huge loss may abort the simulation halfway. To avoid this exhaustion, initial money should be sufficient enough in case of simulation abortion. However, prices can vary sharply among different assets or stocks; there is not widely accepted sum of money a simulation should have at the beginning of the experiment. If an investment simulation is interrupted by a huge loss, simulations with different amount of initial money should be re-launched on all strategies till the new model’s experiment result is good enough.

In order to evaluate new forecasting models concisely and meaningfully—exposing a model’s forecasting efficiency, we propose a simple metric: Relative Profit (RP)—the ratio of expected return and variance of the return, which is just a model's forecasting efficiency. RP and DA shares the same data in calculation. In other words, if DA can be calculated, RP can also be calculated easily. Additionally, this indicates that RP never suffers money exhaustion problem. Moreover, RP is a metric that expresses forecasting efficiency while MSEs and DA are not related to money business i.e. the magnitude of investment and profit.

To do this, we first introduce an environment with only two traders. One is Ordinary Trader (OT) who makes its buying or selling decisions based on the predictions of a model; another is perfect trader (PT) who knows everything in future. We assume that OT earns money if it follows a correct prediction on price trend and loses money otherwise; On the contrary, PT never loses money in any transaction. Further assumption is that PT only makes counterpart trading with OT, which means that if OT trades

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$^2$ In this paper, we do not differentiate the word “return” and “profit”. 
a stock at time $t$, PT also trade the same stock at the same time $t$. The only different is that OT may win or lose but PT always wins in each transaction.

Under the above assumptions, let $M_o$ be the profit earned by an OT within two continuous transactions and $M_p$ be the profit gained by a PT within the same two transactions. Clearly, the relationship between $M_o$ and $M_p$ can be expressed as the following:

$$-M_p \leq M_o \leq +M_p$$  \hspace{1cm} (3)

where $M_o$ reaches the lower bound $-M_p$ if OT got two wrong predictions on price trend while $M_o$ reaches the upper bound $+M_p$ if OT got two correct predictions on price trend. In other cases, $M_o$ lies between the two bounds.

An OT’s Relative Profit within two continuous transactions is defined

$$\widehat{RP} = M_o/M_p, \widehat{RP} \in [-1, +1].$$  \hspace{1cm} (4)

In fact, $\widehat{RP}$ represents OT’s profitability within two continuous transactions. In N continuous transactions, there are (N-1) $\widehat{RP}$’s in total. The expected value of $\widehat{RP}$ shows how the model’s relative profitability within N continuous transactions. The variance of $\widehat{RP}$ indicates, given this expected $\widehat{RP}$ within N continuous transactions, how the model’s stability is — obtaining the profit sharply or smoothly? Similar to sharp ratio, RP is defined as the ratio of expected $\widehat{RP}$ and it’s variance. In this sense, RP is a concise metric that shows not only a model’s profitability but it’s stability in earning the final profit. Hence, models with positive and higher RP are considered as more suitable candidates in financial decision fields. On the contrary, a model with negative and lower RP is believed as a risk of loss.

The rest of our paper is organized as follows. Section 2 further illustrates the concept of RP over the whole investment process extended on two continuous transactions. Utilizing moving average as a benchmark model, in section 3, we will make a thorough comparison among different metrics. At last section 4 concludes.

2 DEFINITION OF RELATIVE PROFIT

2.1 Basic concepts in the stock market

*Long sale or open a long position*: it means that investors bought a stock anticipating that the future price would rise. If the prediction comes true, selling the stock at future price leads to a positive profit whereas a negative profit if the prediction is wrong future price goes down.

*Short sale or open a short position*: it means that investors have sold a stock that does not belong to them at the time of the sale and have to buy the stocks back at some time in future. Short sale means that investors anticipate future price would decrease and if it comes true, buying back the stocks at future lower price leads to a positive profit whereas a negative profit if the stocks are bought back at future higher prices.

*Ordinary trader and perfect trader*: An ordinary trader (OT) follows trading signals provided by a forecasting model. If a model predicts future price would rise, OT will buy now and sell it at future price—long a stock. OT may win or lose money in one transaction, which depends on a model's
prediction accuracy on future price trend. Meanwhile we introduce a factious trader---perfect trader\(^3\) (PT) in our environment. “Perfect” means it knows the future price at any time and must gain positive profit at every transaction. PT’s profit shows the upper bound and lower bound of profit that OT can make.

\*OT’s profit within two continuous transactions\*: In two given continuous transactions, OT trades two times. Let \(M_o\) be the total profit within two transactions, which can be calculated as:

\[
M_o = (-1)^c ||p_t - p_{t-1}|| + (-1)^c ||p_{t+1} - p_t|| = (-1)^c \Delta p_t + (-1)^c \Delta p_{t+1}\]  \( (5)\)

where \(p_{t-1}, p_t, p_{t+1}\) are the prices at time \(t-1, t, t+1\); \(c\) equals 0 when OT got a correct prediction on price trend and equals 1 when OT got a wrong prediction on price trend.

\*PT’s profit within the same transactions\*: In the same continuous transactions, PT also trades two times. Let \(M_p\) be the total profit, which can be calculated as:

\[
M_p = ||p_t - p_{t-1}|| + ||p_{t+1} - p_t|| = \Delta p_t + \Delta p_{t+1}\]  \( (6)\)

where \(p_{t-1}, p_t, p_{t+1}\) are the prices at time \(t-1, t, t+1\); As PT knows everything in the future, \(M_p\) is the upper bound of profit that OT or PT can make.

Apparently, \(M_o\) has four possible values that depend on four states of prediction results: ① both predictions are correct; ② the first is correct and the second is wrong; ③ the first is wrong and the second is correct; ④ both predictions are wrong. However, \(M_p\) does have only one value as there is no uncertainty in prediction errors. The relationship of \(M_o\) and \(M_p\) can be expressed as:

\[-M_p \leq M_o \leq +M_p\]  \( (7)\)

where \(M_o\) reaches the bound \(M_p\) if OT gets two wrong predictions on price trend while \(M_o\) equals \(+M_p\) if OT gets two correct predictions on price trend. Otherwise, \(M_o\) lies between \(M_p\) and \(+M_p\). As illustrated in Table 1, OT has the same profit with PT only in the first state: both predictions are correct.

<table>
<thead>
<tr>
<th>States</th>
<th>①</th>
<th>②</th>
<th>③</th>
<th>④</th>
</tr>
</thead>
<tbody>
<tr>
<td>DA</td>
<td>100%</td>
<td>50%</td>
<td>50%</td>
<td>0%</td>
</tr>
<tr>
<td>Mo</td>
<td>(\Delta p + \Delta p_{t+1})</td>
<td>(\Delta p - \Delta p_{t+1})</td>
<td>(- \Delta p + \Delta p_{t+1})</td>
<td>(- (\Delta p + \Delta p_{t+1}))</td>
</tr>
<tr>
<td>(\bar{R}P)</td>
<td>+1</td>
<td>((\Delta p - \Delta p_{t+1})/(\Delta p + \Delta p_{t+1}))</td>
<td>((- \Delta p + \Delta p_{t+1})/(\Delta p + \Delta p_{t+1}))</td>
<td>- 1</td>
</tr>
</tbody>
</table>

\*Table 1: OT’s profit within two continuous transactions\*

\(^3\) We introduce the perfect trader in order to set an upper or lower bound of the profit a real investor or ordinary trader can make.
2.2 Relative profit within two continuous transactions

**Definition 1.** In two continuous transactions\(^7\), the ratio of OT’s profit to PT’s profit is called OT’s relative profit: \(\overline{RP}\).

\[
\overline{RP} = \frac{M_o}{M_p}, \overline{RP} \in [-1, +1].\tag{8}
\]

\(\overline{RP}\), whose value depends on both DA and \(\Delta p\), represents the profitability of OT within two continuous transactions. If OT’s DA is 100% (i.e. state 1 in Table 1), OT performs as well as PT and \(\overline{RP} = 1\); if OT’s DA is 0%, \(\overline{RP} = -1\); in other cases, \(\overline{RP}\) lies in \((-1, 1)\).

2.3 A numeric example of \(\overline{RP}\)

Let \(\{p_t\}, t=1,…,T\) be a stock price time series with three realizations: \(p_{t-1}=8.0\); \(p_t=10.0\); \(p_{t+1}=9.0\). An OT trades according to forecasting models A and B (See Table 2 and Table 3) whereas PT makes counterpart transactions (See Table 4). For OT, if predicted price is higher than current price—a long sale signal, OT buys one share of the stock at \(p_{t-1}\) and sell it at \(p_t\); If predicted price is lower than current price—a short sale signal, OT sells one share of the stock at \(p_{t-1}\) and buys it back at \(p_t\). OT’s profit is positive if \((p_t - p_{t-1}) (\hat{p}_t - p_{t-1}) > 0\); Otherwise profit is negative.

<table>
<thead>
<tr>
<th>Transaction:</th>
<th>Current price</th>
<th>Predicted price</th>
<th>Actual price</th>
<th>Trade direction</th>
<th>Profit</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 (p_{t-1}=8.0)</td>
<td>(\hat{p}_t=12.0)</td>
<td>(p_t=10.0)</td>
<td>long</td>
<td>+2.0*</td>
<td></td>
</tr>
<tr>
<td>2 (p_t=10.0)</td>
<td>(\hat{p}_{t+1}=11.0)</td>
<td>(p_{t+1}=9.0)</td>
<td>long</td>
<td>-1.0</td>
<td></td>
</tr>
</tbody>
</table>

*Table 2: OT’s profit based on Model A: Mo\(^A\) #When there is a trading signal, OT follows it. If prediction on price trend is right(wrong), profit is positive(negative) and its value depends on \(\Delta p\) (same situation in Table 3 and Table 4)*

<table>
<thead>
<tr>
<th>Transaction:</th>
<th>Current price</th>
<th>Predicted price</th>
<th>Actual price</th>
<th>Trade direction</th>
<th>Profit</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 (p_{t-1}=8.0)</td>
<td>(\hat{p}_t=7.0)</td>
<td>(p_t=10.0)</td>
<td>short</td>
<td>-2.0</td>
<td></td>
</tr>
<tr>
<td>2 (p_t=10.0)</td>
<td>(\hat{p}_{t+1}=8.0)</td>
<td>(p_{t+1}=9.0)</td>
<td>short</td>
<td>+1.0</td>
<td></td>
</tr>
</tbody>
</table>

*Table 3: OT’s profit based on Model B: Mo\(^B\)*

---

\(^4\) Here we do not consider the monetary unit
Table 4: PT’s profit: Mp

As illustrated in Table 5, MSE and DA represent forecasting accuracy of two models. However, they fail to demonstrate which model has better profitability. MSE and DA are not the proper ones that expose model's forecasting efficiency. In other words, MSE or DA prevents investors from knowing the potential ability of achieving profit in practical transactions. Fortunately, $\bar{R}P$ fills this gap. Model A's $\bar{R}P$ is positive whereas model B's is negative. This means that, if they are adopted as decision support mechanisms, model A’s profitability is higher than model B within two transactions even if DA is the same. Actually, the value of $\bar{R}P$ depends on two aspects. The first is price trend or price direction that determines whether the profit is positive or negative; the second is the difference between current price and future actual price—$\Delta p$. If the prediction on price trend is right, larger difference leads to higher profit whereas if the prediction is wrong, large difference means a huge loss.

Besides concise in calculation, $\bar{R}P$ tells more than MSEs or DA does. A positive (negative) $\bar{R}P$ means that, if following this model's trading signals, OT will earn a positive (negative) profit. As demonstrated in Table 5, model A’s $\bar{R}P$ = +1/3 indicates that model A gains a positive profit within the two transactions. The value of $\bar{R}P$ shows that, if the total potential profit is 3, model A gets one portion, i.e. 1/3 of the whole potential profit—PT’s profit. Negative $\bar{R}P$ indicates a loss that a model would suffer. Model B’s $\bar{R}P$ = -1/3 shows that a loss occurs when model B is used as a decision support system. A relative one third of the total potential profit loses within two transactions.

Table 5: Comparison of MSE, DA and $\bar{R}P$

<table>
<thead>
<tr>
<th>Model</th>
<th>Profit</th>
<th>DA</th>
<th>MSE</th>
<th>$\bar{R}P$</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>+1.0</td>
<td>50%</td>
<td>4.0</td>
<td>+1/3</td>
</tr>
<tr>
<td>B</td>
<td>-1.0</td>
<td>50%</td>
<td>5.0</td>
<td>-1/3</td>
</tr>
<tr>
<td>PT</td>
<td>+3.0</td>
<td>100%</td>
<td>0.0</td>
<td>1</td>
</tr>
</tbody>
</table>

2.4 Relative profit: a formal definition

Although $\bar{R}P$ did a good job in representing model's relative profitability, calculation within two transactions is not enough to expose model's forecasting efficiency. Since investors usually trade more than two times in an actual investment, a series of transactions and the fluctuation in profit should be considered. Consequently, measuring the profitability over the whole of all transactions is definitely important.

Assume a forecasting model provides N (N>2) trading signals, in each transaction (See Table 2), there would be three key prices: current price, predicted price and actual (future) price. It is expected that N (N > 2) should be larger for more credible performance evaluation. Since there is no agreement about what the exact N (N > 2) should be, it is usually believed that the larger the number N is, the better. Obviously, $R^P$ just represents a local profitability—two continuous transactions. More transactions should be counted when a model's forecasting efficiency is evaluated over N (N>2) transactions.

Definition 2. A model's relative profit over N (N > 2) continuous transactions is defined as:
$$RP = \frac{\mathbb{E}[\widetilde{RP}]}{\sqrt{\text{Var}(\widetilde{RP})}},$$  \hspace{1cm} (9)$$

where $$\mathbb{E}[\widetilde{RP}] = \frac{1}{N-1} \sum_{t=1}^{N-1} \widetilde{RP}_t$$, \hspace{1cm} $$\text{Var}(\widetilde{RP}) = \frac{1}{N-1} \sum_{t=1}^{N-1} (\mathbb{E}[\widetilde{RP}] - \widetilde{RP}_t)^2$$

RP is a forecasting efficiency metric that expresses the expected relative profit over one unit fluctuation. Higher (lower) $$\mathbb{E}[\widetilde{RP}]$$ means there is a higher (lower) possibility to earn profit whereas higher (lower) Var($$\widetilde{RP}$$) means there is a sharp (smooth) fluctuation among (N) transactions. Higher RP can be achieved by holding a fixed $$\mathbb{E}[\widetilde{RP}]$$ while lowering Var($$\widetilde{RP}$$), which means that investors suffer less profit fluctuations; Higher RP can also be achieved by holding a fixed Var($$\widetilde{RP}$$) while enhancing $$\mathbb{E}[\widetilde{RP}]$$, which means that investors gain more profit with the same fluctuation. In this sense, RP is a comprehensive and concise metric that can help both practical investors and academic community to estimate forecasting models conveniently.

### 3 EVALUATE MOVING AVERAGE'S PERFORMANCE

In this section, a benchmark strategy—Moving Average is evaluated by different ways: DA, a simulation and RP. The experiment is conducted on HS300 stock index in Chinese stock market.

#### 3.1 Data description

We downloaded the daily HS300 index in the last three years from CSMAR database. HS300 stock index consists of 300 listed corporations from two Chinese Stock Exchanges. It covers more than 60% of total market capitalization and thus is a favourable representative of Chinese stock market (See Table 6).

<table>
<thead>
<tr>
<th>Index</th>
<th>Range</th>
<th>Observations</th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>Min value</th>
<th>Max Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>HS300</td>
<td>2011—2013</td>
<td>725</td>
<td>2600.13</td>
<td>308.07</td>
<td>2108.85</td>
<td>3372.03</td>
</tr>
</tbody>
</table>

*Table 6: Summary statistics of HS300 index*

#### 3.2 Moving Average strategy

Moving Average (MA) has long been a technical analysis tool for financial time series forecasting. Moreover, it is also used as one of the most common benchmarks. A simple form of Moving Average is shown as following. Let \{p_t\}, t=1…T be a financial time series, for each t (t \geq n), we have:

$$MA(n) = \frac{p_{t-n+1} + \cdots + p_t}{n},$$  \hspace{1cm} (10)$$

According to different number of past observations and weight, MA can be classified into different categories. Equation 10 defines the basic unweighted Moving Average based on past n observations. As well as \{p_t\}, t=1…T, MA (n) is also a times series that has (T-n) observations. The two time series do have some intersections because MA(n)'s calculation is based on \{p_t\}, t=1…T. These crossover points exactly are be considered as trading signals, which is the fundamental idea of Moving Average.
Let MA(n1) and MA(n2) be two time series with n1< n2, MA(n1) is called short term moving average curve and MA(n2) is long term moving average curve. A basic strategy based intersections can be described as:

“When a long term MA curve penetrates a short term MA curve on the upside, it is a buy or long signal; when a long term MA curve penetrates a short term MA curve on the downside, it is a sell or short signal; The last position should be closed before opening a new long or short position”

3.3 Evaluation of MA’s performance by DA, an investment simulation and RP

In this evaluation, we use MA(5),MA(10) and MA(20) to form the three MA strategies and their performances are evaluated by DA,RP and an investment simulation. In the investment simulation method, we assume the price of index equals the value of index itself and ignore money exhaustion problem (See the item “Profit” in Table 7).

As shown in Table 7, investment simulation shows MA510 gains -370.01 and MA1020 gains -423.51 even though they have the same DA. A correct prediction on price trend may be accompanied with less △price. That’s why the profit is small or negative even if DA is high. It is also possible that lower DA followed by higher profit and higher DA followed by lower or even negative profit. In this situation, investors may fail to evaluate the true profitability of forecasting models via DA.

Profit from a simulation is a direct method to express how much money a model can make once it is adopted. However, it omits the process of profit gained—sharply or smoothly, which is a key part of forecasting efficiency. RP compensates this concisely by, at first, split series transactions into couples—two continuous transactions. The variance of return from couples would be later calculated and considered as a fluctuation of the investment process.

<table>
<thead>
<tr>
<th>Model</th>
<th>Signals</th>
<th>DA</th>
<th>E[RP]</th>
<th>Var (RP)</th>
<th>RP</th>
<th>Profit</th>
</tr>
</thead>
<tbody>
<tr>
<td>MA510*</td>
<td>70</td>
<td>0.60</td>
<td>0.19</td>
<td>0.78</td>
<td>0.23</td>
<td>-370.01</td>
</tr>
<tr>
<td>MA520</td>
<td>42</td>
<td>0.62</td>
<td>0.24</td>
<td>0.80</td>
<td>0.31</td>
<td>-307.41</td>
</tr>
<tr>
<td>MA1020</td>
<td>30</td>
<td>0.60</td>
<td>0.14</td>
<td>0.77</td>
<td>0.18</td>
<td>-423.51</td>
</tr>
</tbody>
</table>

Table 7: Moving strategies forecasting models. *The model MA510 is comprise of two moving average lines: MA(5) and MA(10). Crossover points of MA510 fromed by the two lines provide trading signals. The same situation with MA520 and MA1020.

It is also interesting to notice that all RPs are positive but the final profit is negative in Table 7. Even if everyone hates loss, MA510, MA520 and MA1020 do deserve a celebration because, in the same period, HS300 index shrink more than 25% in total. These three models lose no more than 15%. The tricky is the concept “relative”. Not only academic researchers but practical investors do hope a positive profit, but it depends on what the investment environment is. It is common that stock market may be in different periods—bullish or bearish. RP actually describe how much a model can gain “relatively” rather than an absolute positive or negative value of profit.

Apparently, E[RP] has the monotonic relationship with final profit in a simulation. In other word, final profit increases (decreases) when E[RP] increases(decreases). Since E[RP] is the expected value of relative profit over N transactions, it is possible that a positive RP is accompanied by a negative profit in the whole transactions. Var(RP) conveys the information about how a model’s final profit is gained. It may magnify or minify the E[RP]’s impact on the value of RP. Risk-averse investors hate huge fluctuation during their trading, consequently, a larger (lower) Var(RP) will reduce (increase) RP. This indicates that investors prefer to models that can gain profit smoothly rather than sharply.
4 CONCLUSION AND FUTURE WORK

When it comes to financial time series forecasting, both practical investors and academic researchers definitely care about profit and how it is gained—sharply or smoothly. Unfortunately, existing metrics like MSE or DA prevent people from knowing this. Rather than an attempt to measure “forecasting accuracy”, RP focuses on “forecasting efficiency”. According to risk-averse assumption, investors care not only final profit but also whether its process is smooth or sharp. This is where RP comes from. RP is a comprehensive but concise metric that can expose model’s forecasting efficiency properly. With RP, forecasting models could be estimated in the stock market conveniently.

Nevertheless, RP is not all-in-one way that guides investors in practical stock market. It is possible that a model's RP may vary hugely when N is long enough and the transactions cover a long time period—bearish or bullish. In future work, we will consider how N is related to RP's value. Furthermore, RP follows a manner of “testing-with-users”, which has great implications in realistic estimation. Actually, existing metrics aim to “forecasting” itself rather than “how users or investors feel”. RP is an attempt to evaluate forecasting models' performance according to users or investors’ satisfactions.

References


