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Quantitative trading system based on machine learning in Chinese financial market

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Abstract. Quantitative Trading based on Machine Learning can increase the stock exchanging competitive and further enhance stability in the Chinese financial market, while the Risk to income ratio in the A share sector haven't been studied well enough so far in the Quantitative Trading. The paper study the risk and opportunity in the Chinese share market over the period 2005–2013 under Hidden Markov Model (HMM) system estimator. And then, the quantitative stock selection strategy based on neural network is studied based on multiple factors of the total market value of the constituent stocks in the SSE 50 Index, the OBV energy wave, the price-earnings ratio, the Bollinger Bands, the KDJ stochastic index, and the RSI indicators. Back testing obtained the conclusion that the Machine Learning strategy is equally valid for Chinese finical market. By analysing the risk of strategic returns, we can also conclude that the Chinese share market is effective in Quantitative Trading.

Keywords: Machine learning, quantitative trading, hidden markov, neural network

1. Introduction

Quantitative investment refers to a kind of transaction method for the purpose of obtaining stable income through issuing trading instructions by quantitative method and computer programming. The distinctive feature that quantitative investment differs from qualitative investment is the model. We can take an instance to illustrate the relationship between models and people in quantitative investment. First let's take a look at doctors' treating of illness. The methods of diagnosis and treatment of traditional Chinese medicine and Western medicine are different. For traditional Chinese medicine, its diagnosis and treatment methods are looking, listening, questioning and feeling the pulse; its results upon final judgment are largely based on experience of traditional Chinese medicine and are largely qualitative. While the Western medicine is different as patients need to take X-rays and get tests first, and conclusions are reached based on medical instruments to apply appropriate treatment to them.

Investors treat the mistakes in the finance market is similar to doctors treat diseases of patients, so what are mistakes of the finance market? The answer is wrong pricing and valuation. The market is effective or weak effective if the market is healthy or slightly sick, and the more serious the illness,

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the more ineffective the market will be. Investors invest their funds into undervalued securities until their prices are forced to a reasonable level.

But there are some differences between specific practices of qualitative investment and quantitative investment. These differences are similar to those between traditional Chinese medicine and Western medicine. Qualitative investment is more like traditional Chinese medicine which relies more on experience and feeling to determine where the disease is. While quantitative investment is more like Western medicine which makes judgment based on models whose function to quantitative investment fund managers is what CT machines to doctors. Before each day's investment operation, fund managers first conduct comprehensive inspections and scans to the entire market by models and then they make investment decisions based on the inspection and scan results.

There have been many studies on the effectiveness of quantitative transactions. Wee Ching Pok, J.L. Ford and Sunil S. Poshakawale mainly conducts research on imperfect financial markets, through threshold autoregressive conditions heteroscedastic model and bivariate generalized autoregressive heteroscedasticity mode l [1]. Finally, it is concluded that the use of hedging strategies has been successful. The results are not much different from the results of more developed financial markets such as Europe and the United States, but the strategy of not perfecting the financial market must continuous parameter adjustment and optimization are required, and the limitation of the execution channel is difficult to perform. Christian A. Salm and Michael Schuppli mainly study the implementation results of the trend trading strategy and positive feedback and negatives in the financial market [2]. The feedback phenomenon uses an asset pricing method based on heterogeneous beliefs. Research results: accounted for a large proportion in the market, it is a positive feedback transaction. Yu Siqin and Yuan Xiang studied the problem of mean recovery between stock index futures and spot, the reason for the mean recovery, and later proposed how to use the BVaR model to effectively control the risk when extreme stocks emerge [3]. Ba Shusong and Zhao Yong empirically tested the risk status of China's trading index. Index funds can follow the trend of the index well and draw the risk structure of the index fund and the risk characteristics of the trading index [4]. With the development of machine learning in finical market, its affectivity need further study.

2. Background

James Simons, Wall Street's legendary figure, is the representative of quantitative investment. This discerning investment giant is the youngest professor at the Department of Mathematics of Harvard University; at the age of 37, he and the Chinese mathematician Shiing Shen Chern published jointly the famous paper Typical Group and Geometric Invariant and created the famous Chern-Simons Theory; at the age of 40, he established its own private investment fund by the fundamental analysis method; at the age of 43, he redeveloped the trading strategy with mathematician Henry Laufer of the Princeton University and turned from fundamental analysis to quantitative analysis since then; and at the age of 45, he founded the Renaissance Technology Corp. formally and finally became a well-known overlord of investment. The seemingly smooth path to become famous proves to the world once again that the technological innovation in the field of contemporary finance is mostly stemmed from resources integration of cross-disciplines rather than invention and creation that are developed from nothing. Specifically, even smart as Simmons, he did not think of invest by quantitative methods at first but focused on the foreign exchange market as like many other investors. But ambitious Simmons was not willing to follow the traditional investment strategies simply. As his experience accumulated, he began to ponder why he did not use the mathematical methods that he was most familiar with to build investment models to predict trend changes in the currency market scientifically and accurately. This adventurous interdisciplinary attempt ultimately changed his life direction [5–7].

By skilfully integrating mathematics theories into investment practices, Simmons transformed himself from a highly talented mathematician to a top "Mr. Model" in the investment community. The Medallion operated by him achieved average annual rate of return of 35% in the 20 years from 1989 to 2009. If the 44% commission was counted in, then annual rate of return of the fund could be as high as 60%, more than 20 percentage points higher than the average annual rate of return of the S&P 500 Index over the same period. Even if compared with stock trading performance of financial magnate Soros and stock deity Buffett, it was more than a dozen percentage points higher. It is most valuable that even in 2008, the year when the subprime crisis broke out on a full scale, the fund's rate of return on investment still kept stable at an amazing level of around 80%. By combining mathematics models with investment strategies, Simmons gradually worked his way up to create a quantitative era where he held the banner. His sudden wealth myth gave the world a most intuitive and shallow understanding of quantitative investment that it can make money and it can make a lot of money.

However, the financial industry is changing rapidly and the God has not blindly favored the all-powerful “Mr. Model". Since 2012, the Renaissance Technology Corp. which was presided over by Simmons has been undergoing disasters and misfortune. RIFF, under the command of it, had achieved profit growth rate of only 1.84% in 2011. By 2012, it had suffered unprecedented loss of 3.17% which was even higher than the average decline in Barclays CTA index of the same year (1.59%). RIFF mainly realized absolute returns through global futures and forward transactions. Although it belonged to smaller fund products of Renaissance Corp., as the company’s star “banknote printing machine”, its rate of return suddenly dropped to the industry average level and would inevitably made everyone surprised. By the end of 2012, RIFF’s asset size had been declined to 788 million dollars, far below the 4 billion dollars in 2011. By the end of October 2015, the Renaissance Corp. had officially announced the closure of RIFF at last, a generation of “literary” star RIFF thus fell [8, 9].

Quantitative investment have undergone more than 30 years of development in the overseas with stable investment performance, enlarging market size and share and more and more investors’ recognition. The spring-up and development of foreign quantitative investment are mainly divided into three phases:

The First Stage (1971–1977): In 1971, Barclays International Investment Management Corporation issued the world’s first passive quantitative fund. In 1977, it also issued the world’s first active quantitative fund with issuing scale of 7 billion dollars, which marked the beginning of quantitative investment in the United States.

The Second Stage (1977–1995): From 1977 to 1995, quantitative investment experienced slow development at abroad, which was affected by many factors. With tremendous advances in information technology and computer technology, quantitative investment has finally ushered in its era of rapid development.

The Third Stage (1995 to Present): From 1995 to now, the quantitative investment technology has gradually matured and meanwhile, it has been accepted by people. Quantitative investment account is for approximately 30% of all investment. Quantitative technologies are adopted in all index investment and approximately 20% to 30% of all the active investment.

In fact, development of the Internet has made it very fast for the spread of new concepts around the world. As a concept, quantitative investment is not very new and domestic investors have already heard of them earlier. However, development of true quantitative funds in China is still in its infancy. With 30 years of China’s reform and opening up and the foundation of the securities market for 20 years, already 9 funds under the label of “quantitative investment” has appeared in China in only a few years. With the addition of Changxin quantitative pioneer that will be issued recently, the number of quantitative funds will reach 10. Performance of the previous 9 quantitative funds varies due to different fund strategies and as a result, quantitative investment is highly controversial. Because of particularities of China’s A-shares, using of quantitative strategies in China’s A-share market is more like blind people’s perception. Performance of the first a few quantitative funds in the market are once highly criticized. Disputes over quantitative funds mainly focus on two points: first, whether there is soil in the A-share market for quantitative fund; second, whether fund’s quantitative strategies can stand long-term test of the market [10, 11].

Compared to mature markets in the overseas, A-share market has a short history of development. Investors’ teams are uneven and investment philosophies are not mature enough. It leaves great potential and space for active investment to discover ineffectiveness of the market and generate Alfa earnings. Diversified investment philosophies also create diversified and decentralized Alfa earning opportunities. There are scarcely competitors within China in terms of techniques and methods of quantitative investment. Traditional Chinese medicine and Western medicine treat diseases that they are good at respectively. If the securities market is treated as a patient, then each investor is the doctor [12, 13]. Qualitative investors explore opportunities for qualitative investment and treat diseases for qualitative investment. There are too many qualitative investors in the securities market but with few opportunities and fierce competition; while there are too little quantitative investors but with many opportunities and few competitions, which create sound development opportunities for quantitative investment. In general, differences between quantitative and qualitative investment are like those between traditional Chinese medicine and Western medicine with their respective strengths and weaknesses. It can be seen that with the introduction of stock index futures in April 2010, the development potential of quantitative investment in the domestic market has gradually emerged. The Peking University HSBC Business School and the Antai College of Economics & Management, Shanghai Jiao Tong University have invested several million in establishing professional quantitative investment finance laboratories and setting up senior seminars for quantitative investment to provide sound academic and practice environment for the market development of domestic quantitative investment.

3. Process of quantitative investment

Quantitative investment is generally applied to scientific analysis, market monitoring and transaction execution.

Scientific analysis: Computer technologies are mainly adopted by scientific analysis to process historical data to come to scientific conclusions ultimately. For example, if investors want to know whether the financial data of earnings per share can be used as an investment reference, they can analyze and process the historical data, and then buy stocks with higher and lower earnings per share respectively and hold them for a period. If profitability of stocks with higher earnings per share is much greater than that of stocks with lower earnings per share, it is proved that data of stocks' earnings per share does actually affect the rise or fall of the stock price in the past period. But the opposite is not always true.

Market monitoring: Computer programs are mainly adopted by market monitoring to monitor the entire market in real time, including individual stock price fluctuations, market information, and emergencies and so on. At present, there are more than 3,000 listed companies in China's stock market. If trend of the entire market are monitored by people, it will consume a lot of manpower and material resources and the final results will not as sound as expectations. While the market monitoring function of quantitative investment can better solve the problem, so that all listed stocks can be monitored in real time through computer programs.

Transaction execution: Computer programs are mainly adopted by transaction execution to complete accurate and timely transaction work. In general, execution of multi-account and multi-strategy transaction requires computer programs. People's inability to operate multiple accounts at the same time will lead to inaccurate trades and sluggish conditions. Besides, computer programs can also achieve algorithmic trading to effectively reduce the transaction cost [14].

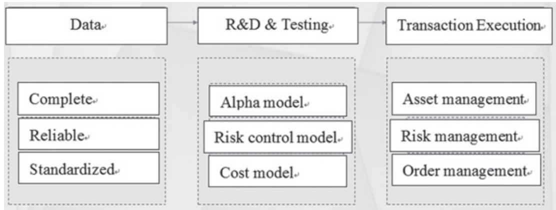


Fig. 1. Process of quantitative investment.

In general, the process of quantitative investment is Data - R&D & Regression Testing - Transaction Execution as shown in Fig. 1.

Data: Quantitative investment requires analysis and research on a large amount of data. These data should be complete, reliable and standardized to make the final analysis and research conclusions correct and reliable.

R&D & Regression Testing: Alpha model, risk control model and cost model need to be taken into consideration in the process of research and development of strategies. Alpha model is the implementation of investment logic of strategies. Function of the risk control model is to control risks, and cost model can achieve maximized benefit.

Transaction execution: Transaction execution needs to consider asset management, order management and risk management. Asset management mainly includes the use and allocation of funds. Order management mainly reprocesses orders and there are unfinished orders in real transactions. Risk control management mainly controls account risks and external risks, such as network interruptions, computer failures, etc.

4. Test platform

In this paper, MindGo quantitative trading platform, an artificial intelligence (AI) investment platform subordinate to Hithink RoyalFlush Information Network Co., Ltd., is adopted. MindeGo is a simulated trading platform closest to the real market environment, which has high-quality financial data, zero-latency back-test engines, clean and complete API documents and supports the currently widely-used scripting language - the Python language [15], and MindeGo also provides the following services:

Data: The MindGo data are based on the full Level-2 data from 2014 up to now, including a complete suspension and rehabilitation data, and updated on the next morning. In addition, MindeGo also provides financial data of listed companies, off-the-counter (OTC) fund data, industry index data, stock index futures data, and so on.

Regression Testing Engine: MindGo provides high-efficiency and fast back-test environment and concise API documents, supports Regression Testing of Shanghai-Shenzhen A share and ETF by day or minute with back-test results displayed in real time, fast responded and comprehensively covered for check and strategic optimization at any time by users. The back-test engine provided by MindeGo runs on Python 3.5 above, so the policy code must be compatible with Python3.5, and the entire back-test environment must support all Python standard libraries and parts of the common third-party libraries, including Python's machine learning module Sklearn VERI0. 18, Talib 0.4. 10 for technical analysis on data in financial markets, Pyhton deep learning library Lasagne 0.1 and so on.

Simulated transaction: MindGo offers real-time simulated trading tools of Shanghai-Shenzhen A share and ETFs, and support minute-level and day-level operations, presenting policy performance in real time, so as to provide a comprehensive, timely, professional and customized one-stop service for quantitative trading enthusiast. The rules for simulated transactions are as follows: Before opening (9:00), run the function of before_trading_start(); In the main trading session, run the function of handle_data(), day-level Regression Testing (9:30:00) run once; minute-level Regression Testing (9:30:00-11:30,13:00:00-15:00:00), run once per minute; After the session (15:30), run the function of after_trading_end().

Order Processing: For the order placed at certain unit time according to your policy, the back-test engine will conduct Regression Testing by day-level Regression:

Trading price: ① Market order: Opening price + slip point. ② Limit Order: Delegated price + slip point.

Maximum trading volume: The default value is 25% of the total turnover of the ordering stock on the current day. If the order quantity is lower than the maximum volume, the order quantity shall prevail; while if the order quantity is greater than the maximum volume, the maximum transaction volume shall prevail.

Trade matching method: ① Market Order: Order upon opening day, one-time trade matching, and the transactions not or not to be completed will be cancelled immediately. If the opening price is upper limit price, buy-in will not clinch a deal; while if the opening price is lower limit price, sell-not will not clinch a deal. ② Limit Order: Order upon opening, match the price per minute each minute, and the uncompleted part is extended to the next minute, till the fully completed closing or the end of closing day.

5. Algorithmic trading

The order execution algorithm is mainly used in entities with enormous capital, such as fund companies, brokers, etc. The algorithmic Trading employed in this paper is called Volume Weighted Average Price (VWAP). As we all know, every transaction has costs, including commissions, taxes, market shocks, sliding points, etc. Even if it buys and sells the same stocks with two strategies, it also possibly leads to different ultimate yield because of the different methods of controlling costs. Especially for large investors, if you can save costs each time you trade, the performance of your portfolio will be better. One obvious corollary is that the more you trade, the more important you save costs each time you trade. However, it is inevitably required to contact with algorithmic trading to save transaction costs, so it is important for a rational quantitative trader to master a set of algorithmic transactions that are effective in saving costs.

One more example, if I have selected a stock and want to buy 2 million shares, but it is a bit difficult to buy the above number of shares merely by the traders' massive operation orders; however, if I buy 2 million shares at one time by pending order, I will expose, which may ultimately lead to an increase of transaction cost. So how to split the order at this point to prevent the impact cost? Only algorithmic trading will do.

According to different active degrees of algorithms in each algorithm trading, the algorithm trading can be divided into the passive algorithm trading, the active algorithm trading and the comprehensive algorithm trading three types. The TWAP (Time Weighted Average Price) and VWAP (Volume Weighted Average Price) belong to the passive algorithm trading, which are the most widely used strategy algorithm in daily arithmetic trading.

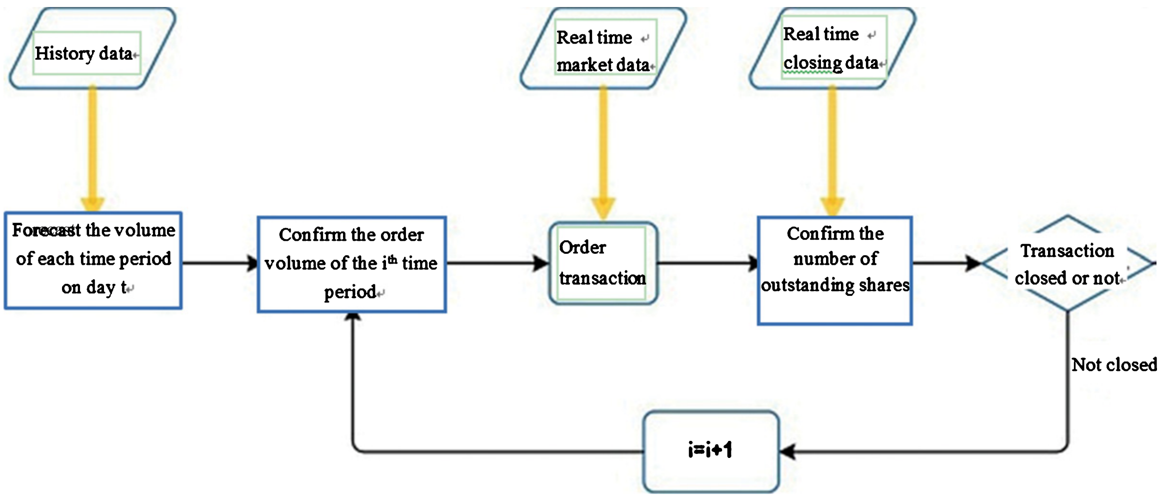


Fig. 2. Process of VWAP algorithm trading.

VWAP is an arithmetic trading strategy that it splits large orders to execute in batch in given period, so as to make the volume average price ultimately bought or sold as close as possible to the whole market's in the period. The specific formula is as follows:

$$VWAP^{(S)} = \frac{x_1 p_1 + x_2 p_2 + \cdots x_N p_N}{x_1 + x_2 + \cdots x_N} = w_1 p_1 + w_2 p_2 + \cdots w_N p_N \qquad (1)$$

Where, $w_i = x_i/(x_1 + x_2 + \ldots + x_N)$ refers to that the price of the ith trade is calculated according to the volume weight. Similarly, we can calculate the current VWAP(m) of certain stock of the whole market.

There are four important factors in the VWAP algorithm trading: history volume, future volume forecast, market dynamic total volume, split time period, and the entire process is as shown in Fig. 2.

The key of the VWAP algorithm is to effectively solve the volume distribution in the future. Suppose we already know the volume distribution of the next trading day, then you only need to split the large order into N small ones according to the volume distribution, and then buy the N small orders in the corresponding trading period. Usually a transaction is conducted in 5 minutes, 48 times a day.

So, how to solve the volume distribution problem in the future? Generally, we estimate the volume distribution of the next trading day according to the average values of each time period obtained from the volume distribution of the past 20 trading days, and determine the volume of unit time based on the total market dynamic volume of the current market and the deviation from the average values of the past 20 days.

We construct the VWAP algorithm trading and conduct a 5-day algorithm transaction test for Ping An Bank. The result is as follows Table 1:

6. Multi-factor share selection based on hidden markov model

As one of the most popular technologies as present, Machine Learning and Data Mining are becoming increasingly familiar. And the Hidden Markov model (HMM), as an important branch in machine learning, is widely used. The Medallion Fund founded by the famous mathematician - Simmons, solely takes the technology quantization method to make investment, and from its establishment to 2008, its average annual net return was 35. 6%. HMM is an important part of the Medallion Fund. This article will introduce HMM firstly, then analyze the characteristics of HMM and stock market and give the strategy of HMM multi-factor selection at last.

HMM is a statistical model that it describes a Markov process containing hidden unknown parameters. HMM contains an observable sequence and a hidden status sequence, for example, I don't know if some region is rich, but I can speculate that the region is rich in terms of what I see, the number of tall buildings in the region, the number of cars, and so on. Whether it is rich is a hidden state, while the number of high-rise cars is an observation variable. HMM is a typical black box model, but there are a lot of the same black box models in financial markets, for

Table 1
5-day algorithm transaction test for Ping An Bank Share

VWAP Algorithm	Result	Conclusion
The 1st test	Trading date: 20180124; VWAP Algorithm Trading; final cost price: 14.841; average market price: 14.814; deviation: 0.0018; total order quantity: 128800; total completed: 1.2883	1. The deviation of the average price is relatively small, which highlights the advantage of VWAP Algorithm 2. Properly increase or decrease the target order volume according to transaction activity of the current market
The 2nd test	Trading date: 20180125; VWAP Algorithm Trading; final cost price: 14.189; average market price: 14.181; deviation: 0.0006; total order quantity: 1139700; total completed: 1.1397	
The 3rd test	Trading date: 20180126; VWAP Algorithm Trading; final cost price: 14.230; average market price: 14.191; deviation: 0.0013; total order quantity: 918600; total completed: 0.9186	
The 4th test	Trading date: 20180129; VWAP Algorithm Trading; final cost price: 13.944; average market price: 13.927; deviation: 0.0013; total order quantity: 969200; total completed: 0.9692	
The 5th test	Trading date: 20180130; VWAP Algorithm Trading; final cost price: 13.944; average market price: 13.927; deviation: 0.0013; total order quantity: 482300; total completed: 0.4823	

example, in financial markets, especially in the stock market, we don't know whether it is a bull market or a bear market, which we can regard as a hidden state. And then we can get a series of observable data, such as volume, yield, volume difference and so on, which we can take as the observable sequence to forecast the market hidden state, and decide whether to buy according to the state of the present market. Thus, it is obvious that we have constructed a hidden Markov model. But it also has a big disadvantage that we can't directly know which state is the buy state or which state is the sell state, so we have to buy or sell in comparison with the earnings of each state.

Micro polypropylene fiber is more effective in reducing pore pressure than macro polypropylene fiber or steel fiber. Steel fiber plays some roles in

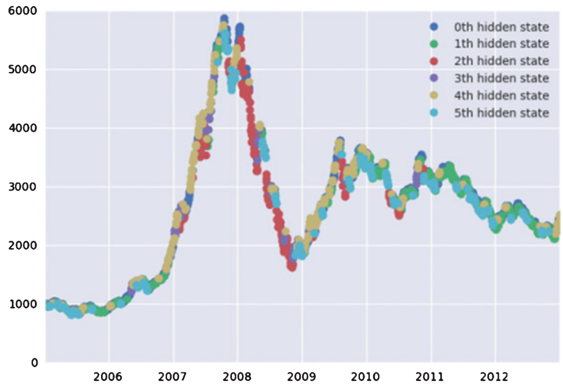


Fig. 3. Model Test of A-Share of China using HMM.

pore pressure reduction in deeper regions, while the macro polypropylene fiber has a better effect in shallow regions than in deep regions during fire exposure. The positive hybrid effect in pore pressure reduction of steel and micro polypropylene fiber is better than that of steel fiber hybrid macro polypropylene fiber reinforced SCC. The pore pressure in SCC exposed to fire is obviously lower than that of other concrete exposed to electric heating. Larger internal destruction in SCC during fire exposure maybe explains this phenomenon.

6.1. Model test

The HMM test on training set data extraction and training samples have been carried out in CSI 300 market from Jan. 1, 2005 to Jan. 1, 2013. And for the matching situation of CSI 300 in each state see the following Fig. 3:

Number of hidden state: 6

Eigenvector: 1-day logarithmic yield, 5-day logarithmic yield, and 5-day volume Logarithmic difference.

From the diagram we can see that the yellow dots are obviously in the ascendant state, while the red dots basically occur in descent state, but we need to make clear the meaning of each state more intuitively, so we calculate the revenue in each state, and the result is as shown in Fig. 4:

It is clear from the diagram that the state 0 and 3 are obvious bull market, the state 2 and 5 are the obvious bear market, and the state 1 is an oscillation state. Therefore, we can easily get a strategy that open position in status 0 and 3, close a position if any in state 2 and 5, and in status 1 and 4 which we regard as oscillation states, do not operate.

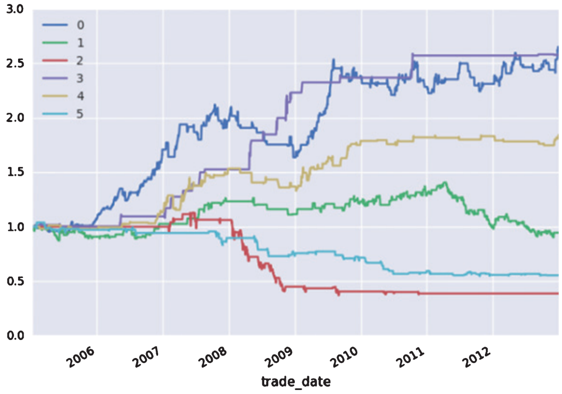


Fig. 4. The revenue in each state of HMM from A-Share.

However, since the HMM is a probability model, that is, the state 0 and 3 are not always the best performance for Regression Testing of each data set, so we choose two states with the best performance as buying state and two states of the worst performance as selling state each time.

In addition, because HMM needs a set of sequences for the input of the eigenvalues, we will cycle the back-test period to form a set of series. Thus, we get a simple strategy.

6.2. Ideology of hidden markov model strategy

Step 1. Select the 1-day logarithmic yield, 5-day logarithmic yield, and 5-day volume Logarithmic difference of the trading dates from Jan. 1, 2012 to Jan. 1, 2015 in CSI 300 as observing sequence attributes.

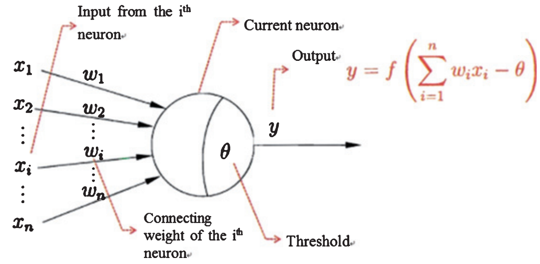
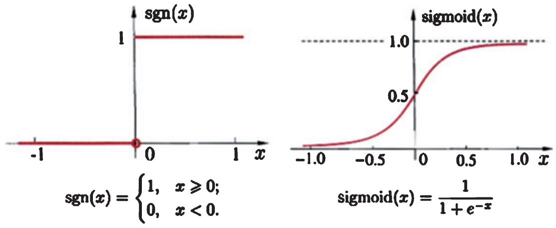


Fig. 6. M-P neuron model of Machine Learning.



(a) Step function (b) Sigmoid function

Fig. 7. Typical neuronal activation function.

Step 2. Given these attribute values are subject to the normal Gaussian distribution (strong assumptions of HMM), we can use these historical data to complete the HMM structure directly, and calculate two states with the best performance as buying state and two states of the worst performance as selling state.

Step 3. Constitute the characteristic data of the current back-test date and feature data of the previous training set into a observable sequence in the back-test course and put it in the HMM for forecast of state sequence.

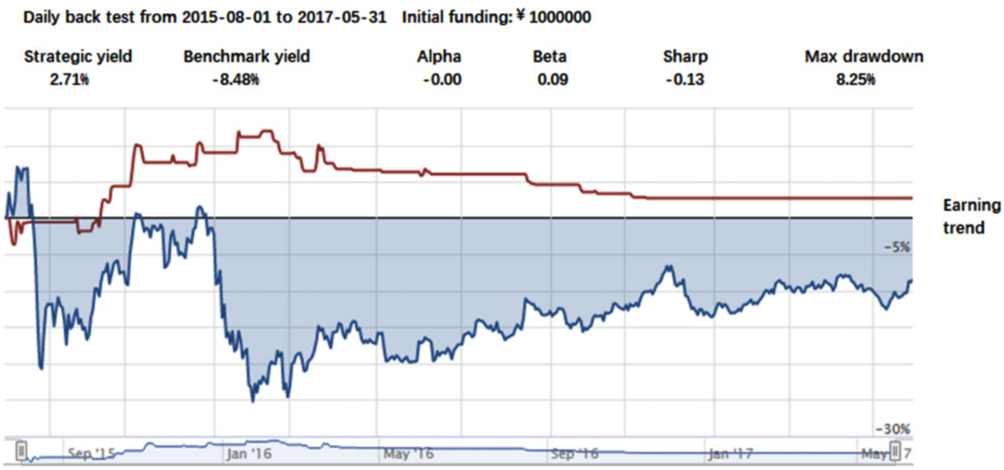


Fig. 5. Regression test result of HMM from A-Share.

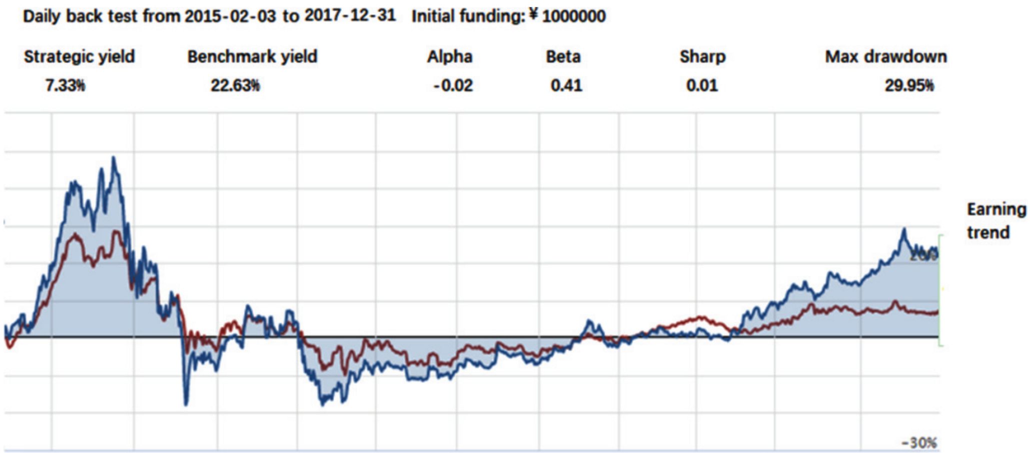


Fig. 8. Regression test result of Neural Network from A-Share.

Step 4. Pick out the status of the previous day of each back-test date. If this status is in the buying status, then buy the CSI 300 while if this status is in the selling status and we have a position, then sell the CSI 300.

Final result:

Regression -test interval: 2015. 08. 01-2017. 05. 31
Regression -test frequency: day-level Regression Testing
Regression -test capital: 10000000
Regression test result: The red curve is the yield curve of the strategy and the blue curve is the yield curve of the corresponding benchmark index

7. Quantitative selection strategy based on neural network

The neural network is a widely parallel and interconnected network consisted of simple units that its organization can simulate the interaction given by the biological nervous system to the real world. The neural network is widely used, and this article applies the neural network algorithm to quantitative selection strategy in the financial field.

7.1. Principle of neural network

Neuron model, as the most basic component of neural network, is mutually connected in biological neural network that when it is "excited", it will pass chemicals to the connected neurons, so as to change the potential of these neurons; If the potential of a neuron exceeds one "Threshold", then it will be activated, that is, it will be "excited" and send chemicals to other neurons. The M-P neuron model is as follows:

In this model, neurons receive input signals passed from n other neurons and the input signals are passed through a weighted connection, and the total input value received by the neuron will be compared to the threshold of the neuron, and then processed through "Activation Function" to produce the output of the neuron.

The (a) step function in the previous figure is an ideal activation function, which maps the input value into the output value "0" or "1". It's obvious that "1" refers to the neuronal excitation, "0" refers to neuronal inhibition; however, the (b) Sigmoid function is actually used as an activation function because of its discontinuous and rough nature. By connecting many such neurons in a certain hierarchical structure, a neural network comes out.

7.2. Quantitative selection strategy based on neural network

Ideology of the strategy: select some common technical indexes as training sample set. In terms of the category, if the increase exceeds 10% in the next 20 working days, marked "1"; otherwise, marked "–1". And then use the neural network algorithm for training that buy it if the forecasted result is 1 and we have no position while sell it if the forecasted result is –1 and we have positions.

Selection of feature factor: This paper employs the neural network algorithm to solve the classification problem of supervised learning. The feature factor selects the total market value, On Balance Volume

(OBV), price-earnings ratio, Boll, KDJ random index and RSI 6 indicators in total of the SSE 50 index component stock on Jan. 05, 2015,

Data standardization: There are a lot of data standardization methods, and in this paper it uses the Gaussian pre-processing method, that is, each feature factor deducts its corresponding mean and then is divided by its standard deviation ((x-x. mean)/ x.std).

Final result:
Regression -test interval: 2015. 02. 03-2017. 12. 31
Regression -test frequency: day-level Regression Testing
Regression -test capital: 10000000
Regression -test result: The red curve is the yield curve of the strategy and the blue curve is the yield curve of the corresponding benchmark index.

Where,

(1). Alpha: refer to non-systemic risks that the investment is facing;

$$\text{Alpha} = \alpha = R_p - \left[R_f + \beta_p\left(R_m - R_f\right)\right]. \tag{2}$$

R_p = Strategic annualized return
R_m = Benchmark annualized return
R_f = Risk -free interest rate (0.04 by default)

(2). Beta: refer to systemic risks that the investment is facing, which reflect the sensitivity of strategy to market change.

$$\text{Beta} = \beta_p = \frac{CovD_p,\ D_m}{VarD_m} \tag{3}$$

D_p = Strategic daily earnings
D_m = Benchmark daily earnings
$CovD_p,\ D_m$ = Covariance between the strategic daily earnings and benchmark daily earnings
$\mathrm{VarD_m}$ = Variance of benchmark daily earnings

(3). Sharpe: refer to the total risk of every unit it bears that how much excess earnings will be generated.

$$Sharpe\ Ratio = \frac{R_p - R_f}{\sigma_p} \tag{4}$$

R_p = Strategic annualized return
R_f = Risk-free interest rate (0.04 by default)
σ_p = Volatility of strategic earnings

(4). Volatility: it is used to measure the risk of assets;

$$\text{Volatility} = \sigma_p = \sqrt{\frac{250}{n}\sum_{i=1}^{n}\left(r_p - \overline{r_p}\right)^2} \tag{5}$$

r_p = Strategic daily earnings
$\overline{r_p} = \frac{1}{n}\sum_{i=1}^{n} r_p$, Strategic daily earning mean
n = Implementing days of the strategy

(5). Information Ratio: is used to measure the excess earnings arising from excess risk per unit;

$$Information\ Ratio = \frac{R_p - R_m}{\sigma_t} \tag{6}$$

R_p = Strategic annualized return
R_m = Benchmark annualized return
σ_t = Annualized standard deviation between the strategic and benchmark daily yield difference

(6). MaxDrawdown = $\mathrm{Max}\left(P_x - P_y\right)/P_x$
Px, Py refer to the total value of stock and cash certain strategic day, y>x

(7). Sortino: it is a method to measure the relative performance of investment portfolio.

$$\text{Sortino} = \frac{R_p - R_f}{\sigma_{pd}} \tag{7}$$

R_p = Strategic annualized return
R_f = Risk-free interest rate (0.04 by default)
σ_{pd} = Strategic descending Volatility

8. Conclusion

This article focuses on both the Hidden Markov model and neural network model trading strategies. For the two types of trading strategies, we provide theoretical proofs, strategy constructions, empirical tests, and results interpretation. Under the quantified financial framework, we first examined the effectiveness of VWAP algorithm trading in the A-share market, and found that the VWAP algorithm average price deviation degree is small. According to the trading activity of the current day market, it can be appropriately expand or weaken the quantity of the order. Then, based on Hidden Markov Model, the trend of Hushen 300 was studied, and the judgment criteria and operation strategy of bull market state, bear market state and shock state were given. The results were tested back and the strategy was better than market performance. Finally, the quantitative stock selection strategy based on neural network is studied whose feature factor including the total market value of the constituent stocks in the SSE 50 Index, the OBV energy wave, the price-earnings ratio, the Bollinger Bands, the KDJ stochastic index, and the RSI indicators. Back testing obtained the conclusion that the quantitative stock selection strategy of neural network is equally valid for A shares of China. By analyzing the risk of strategic returns, we can also conclude that the Chinese market is not weakly effective. In quantitative finance, although the new strategy can produce significant positive returns, it cannot overcome some deficiencies of the A-share T+1 system and the restriction on the number of stock index futures. This paper presents the construction of two types of strategies, empirical tests, and interpretation of results. Methods In the future research, we use this method to study more strategies and to promote the methods.

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