A Trading Decision Support System Based on Neuro-Fuzzy Technique: Evidence from Asian Stock Market

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ABSTRACT

This paper aims to apply the neuro-fuzzy technique to refine the Stochastics technical trading rules to forecast the Asian stock market. Essentially in this hybrid technique, fuzzy logic plays the role to formulate the relationship among the Stochastics indicators and stock price changes by using knowledge base. Neural networking is used to tune the formulated knowledge base based on historical data. The empirical results show that this hybrid technique could capture the relationship among the Stochastics indicators and stock price changes very effectively. The rate of return of this proposed trading system is definitely greater than that of both buy and hold strategy and traditional Stochastics trading system.
Keywords: *neuro-fuzzy, fuzzy logic, neural network, Asian stock market*

INTRODUTION

Owing to the significant influence and implication of the weak form market efficiency hypothesis on investment behavior, this hypothesis testing has been studied by extensively by researchers and practitioners. Some papers claim that the weak form market efficiency hypothesis does exist (Fama, 1965; Fama and Blume, 1966; Jensen, 1967). Investors could not get excess return by doing technical analysis. Others, however, claim that there could be excess return if the technical analysis is applied appropriately (Sweeney, 1988; Brown and Jennings, 1989; Brock, Lakonishok and LeBaron, 1992). In this paper, we would like to see whether the weak form market efficiency exists in the Asian stock market.

Previously, the most commonly used techniques for stock price forecasting are regression methods and ARIMA models (Box and Jenkins, 1970). These methods fail to give an accurate forecast for some series because of their linearity inherent limitations. Although there are ARCH/GARCH models (Engle, 1982; Bollerslev, 1986) to deal with the non-constant variance and non-linear relationship, still some series cannot be explained or predicted satisfactorily. Recent research in the area of artificial intelligence has shown that neural networks possess the properties required for applications, such as nonlinear and smooth interpolation, ability to learn complex non-linear mappings, and self-adaptation for different statistical distributions. In addition, they can improve their performance by learning from past experience. However, a neural network cannot be used to explain the causal relationship between the input and output variables. Besides, it cannot be initialized with prior knowledge. A network usually must learn from scratch. The learning process itself can take very long with no guarantee of success.

On the other hand, the fuzzy expert system approach has been applied to many different forecasting problems (Al-Anbuky, et al 1995, Bolloju, 1996; Kaneko, 1996; Ranaweera et al, 1996; Shaout and Al-Shammari, 1998), whereby the operator's expert knowledge is one of the important parts of the system. Although fuzzy-logic-based forecasting has shown promising results, the construction process is subjective and somewhat heuristic. The choices of membership functions are arbitrary and the rule base needs to be developed heuristically for each scenario. The rules fixed in this way may not always yield the best forecast.

With the advantages and disadvantages of neural network and fuzzy logic, neuro-fuzzy is emerged by combining the learning ability of the neural network and the functionality of the fuzzy expert system. Its application can be found in the work of Dash et al. (1995) and Padmakumari et al. (1999). Such a hybrid model is expected to provide human understandable meanings through the knowledge base and more reliable knowledge base through the learning ability of the neural network.

On the other hand Jacobs and Levy's (1989) research shows that the stock market is not an ordered system that can be explained by simple rules. Neither is it a totally random system for which no prediction is possible. They found the market to be a complex system, in which portions of the system's behavior could be explained and predicted by a set of complex relationships among the variables.

As a result of international financial liberalization and the emergence of Asian countries economies, international institutional traders and individual traders have raised their allocation of capital for Asian markets. Consequently, the trading volume in Asian markets also has increased quite substantially. The Asian markets are more important than before either from the perspective of trading volume or from the impact on global markets. In light of the importance and critical role of Asian stock markets, this study does research on the major four stock indexes, including the Taiwan Stock Exchange (TSEC) Weighted Index, the HANG SENG Index, the Straits Times Index and the KOSPI Composite Index.

With the complex characteristics of the stock market, the availability of Stochastics technical indicators, and the advantages of the neuro-fuzzy technique, this paper tries to combine the Stochastics indicators and this hybrid technique to describe stock market behavior. The purpose of this paper is to investigate the profitability of Stochastics based the neuro-fuzzy system on Asian stock markets. In section 2, past research about the technical analysis is reviewed. Section 3 describes how the Stochastics based neuro-fuzzy system is constructed and how the trading system is implemented. The empirical results are shown in Section 4. Finally section 5 provides some concluding remarks.

LITERATURE REVIEW

In general the approaches to predict stock price could be roughly categorized into two kinds, fundamental analysis and technical analysis. Fundamental analysis assumes that stock price is the function of fundamental variables, such as exports and imports, money supply, interest rates, foreign exchange rates, inflationary rates, unemployment figures, and the basic financial status of companies (Basu, 1977; Fama and French, 1992; Lakonishok, Shleifer and Vishny, 1994, Fernandez-Rodriguez, Gonzalez-Martel, and Sosvilla-Rivero, 2000). Technical analysis assumes that history will repeat itself and that the correlation between price and volume reveals market behavior. Predictions are made by exploiting the implications hidden in past trading activities and by analyzing the patterns and trends shown in the price and volume charts (Epps, 1975; Smirlock and Starks, 1985; Rogalski, 1978; Bohan, 1981; and Brush, 1986).

For technical analysis, some research has explored the statistically significant relationships between stock price and previous prices and/or quantities. Epps (1975) and Smirlock and Starks (1985) suggest that there is a positive correlation between the absolute value of price changes in the market and changes in transaction volume. Rogalski (1978) states that the knowledge of both prices and transaction volume information may be more valuable in predicting future stock movements than prices alone. Gencay (1998) constructed the relationship between the rate of return and signals calculated from the short term moving average and long term average.

On the other hand, since Lane (1957) and Wilder (1978) proposed the Stochastics technical indicators and the relative strength indicator to do the trading respectively, some research has been interested in testing the efficiency of the filter rules. Bohan (1981) and Brush (1986) scientifically examined the usefulness of relative strength indicators and documented a considerable degree of price persistence. Pruitt and White (1988) constructed a trading system based on the moving average, relative strength, and cumulative volume. Bessembinder and Chan (1995) use three simple filter rules, variable length moving average rules, fixed length moving average rules, and trading range break rules, to see whether they can be used to predict stock price movement in Asian markets. Parisi and Vasques (2000) also tested the moving average and trading range break-out rules in the Chilean stock market.

However, based on Jacobs and Levy's (1989) description about the effective forecasting system of stock markets, (it has been found that?) it is possible that the filter rules could be too simple to be effective. Besides, the parameters for the rules are arbitrary. A complex relationship among the technical indicators and stock price may be necessary for an effective trading system. Since (neural networking?) neural network could not utilize the structured knowledge contained in the Stochastics trading system and fuzzy logic is lacking in learning ability, this paper aims to apply the neuro-fuzzy technique to construct an effective trading system by combining the knowledge contained in Stochastics technical indicators and the advantages of the neuro-fuzzy technique.

DATA AND METHODOLOGY

Data

This study wants to predict the volatility of the Asian stock markets. The data series consists of the Taiwan Stock Exchange (TSEC) Weighted Index, the HANG SENG INDEX, the Straits Times Index and the KOSPI Composite Index. To keep from intervention of Asian Financial storm, the data are set as daily close prices based on data from four years from Jan. 1, 2003 to Dec. 31, 2006, and divided into two parts, training data set and testing data set. The training data set begins from Jan. 1, 2003 to Dec. 31, 2004. The testing data set begins from Jan. 1, 2005 to Dec. 31, 2006. The training data is used to train the knowledge base among the technical indicators and stock indexes price changes. Testing data is used to validate the constructed model. In addition to the buy and hold strategy, the Stochastics trading system is also used as the benchmark. Table 1 shows the descriptive statistics of the daily returns for Asia stock indexes. During the period from the beginning of year 2003 to the end of year 2006, where the KOSPI Composite Index performs the best—with a daily return of 0.091; however, the risk is corresponsively higher in that the degree of dispersion—the standard deviation--is also the largest among all of them.

Table 1. Summary statistics for Asia stock indexes daily returns over 01/01/2003-12/31/2006

	TSEC Weighted Index	HANG SENG INDEX	Straits Times Index	KOSPI Composite Index
Mean return (%)	0.062	0.081	0.084	0.091
Max. return (%)	5.568	3.665	3.511	4.998
Min. return (%)	-6.679	-4.097	-3.839	-5.730
S.D. return (%)	1.201	0.943	0.866	1.348

Note: Return is calculated as the percent change: $(P_t - P_{t-1})/P_{t-1}$.

Stochastics Trading System

Stochastics indicators originated as an engineering analytical technique and were adapted by the US analyst George C Lane as a way of indicating overbought/ oversold conditions. The commonly used K D indicators are calculated as follows:

$$RSV_t = (C_t - L_9) \times 100/(H_9 - L_9) \quad (1)$$

$$K_t = 1/3 \times RSV_t + 2/3 \times K_{t-1} \quad (2)$$

$$D_t = 1/3 \times K_t + 2/3 \times D_{t-1} \quad (3)$$

where RSV_t is the raw stochastic value for period t, C_t is the closing price for day t, H_9 and L_9 are the highest price and the lowest price for the latest nine days respectively, K_t and D_t are the values for K and D on day t. If K and D are not available, 50 are used as the initial values for both in general. The trading rules for the Stochastics trading system are as follows:

Rule 1. Overbought conditions are generally taken as occurring when the D is greater than 80; oversold is taken when D is less than 20.

Rule 2. When K breaks through D from up, then sell out. When K breaks through D from down then buy in.

Whenever either rule is satisfied, the trading is conducted accordingly. Essentially Stochastics indicators with the advantages of momentum, relative strength, and moving average, and considering the highest and the lowest prices are expected to be capable of capturing the short-term variance. The above rules are in the spirit of the so called expert system because they are based on the experience of experts.

Neuro-fuzzy System

Basically the idea of a neuro-fuzzy system is to find the parameters of a fuzzy system by means of learning methods obtained from neural networks. Many alternative ways of integrating neural nets and fuzzy logic have been proposed (Buckley and Hayashi 1994, Nauck and kruse 1996, Lin and Lee 1996) which have much in common, but differ in implementation aspects. The most common approach is to use so-called Fuzzy Associative Memories (FAMs). A FAM is a fuzzy logic rule with an associated weight. A mathematical framework exists that maps FAMs to neurons in a neural net. This enables the use of a modified error back propagation algorithm with fuzzy logic. For more details on the math behind this technology, refer to (Kosko 1992). This approach can help to generate and optimize membership functions and a rule base from sample data. Due to its learning capabilities and easy implementation, this approach has been applied in many commercial fuzzy shells (Von Altrock et al 1992, Stoeva 1992, Inform 1993). In our experiments, we implemented the training method to construct the trading system. Please refer to Tong and Bonissone (1984), Zimmermann (1987), and Klir and Yuan (1995) for the details of the implementation of fuzzy logic.

Research model

As Leung, Daouk, and Chen (2000) claimed that trading driven by a certain forecast with a small forecast error may not be as profitable as trading guided by an accurate prediction of the direction of movement (or sign of return). Therefore, predicting the direction of change of a stock market indicator and its return is also significant in the development of effective market trading strategies. In this model, trend, defined as the price change percentage $(P_t - P_{t-1})/P_{t-1}$, is the response variable. Figure 1 shows the proposed structure of the neuro-fuzzy system, including four input variables at the left hand side, one rule block in the middle and one output variable at the right hand side.

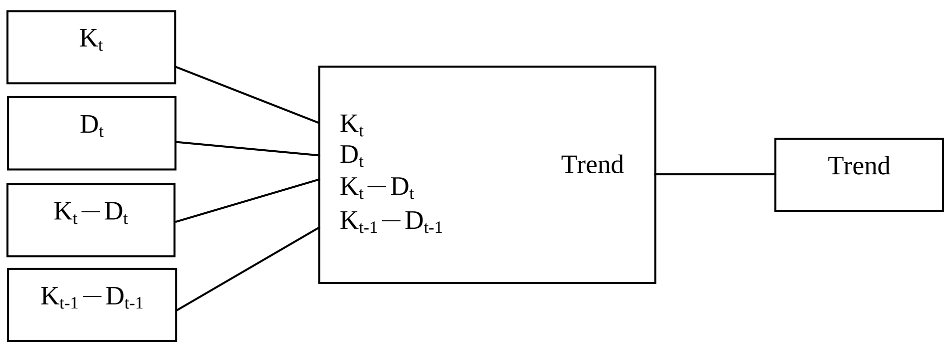
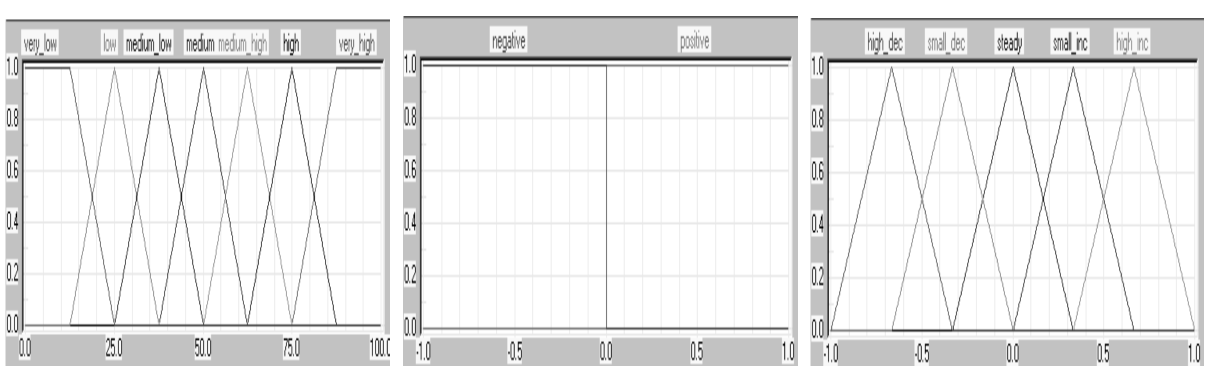


Figure 1. Research model

The connecting lines symbolize the data flow. The fuzzification in the input interfaces translates analog inputs into fuzzy values. The fuzzy inference takes place in rule block that contains the linguistic control rules. The output of the rule block is linguistic variable. The defuzzification in the output interfaces translates them into analog variables. Among the four input variables, K_t and D_t are used to capture the relationship in rule 1, $K_t - D_t$ and $K_{t-1} - D_{t-1}$ is used to capture the relationship in rule 2. Figures 2 is the membership functions for indicators K_t, D_t, $K_t - D_t$, $K_{t-1} - D_{t-1}$ and trend. The membership function for K_t and $K_t - D_t$ is the same as that of D_t and $K_{t-1} - D_{t-1}$.



(a). "K_t" and "D_t" (b). "K_t-D_t" and "K_{t-1}-D_{t-1}" (c). "Trend"

Figure 2. Membership function of input variables and output variable

Training

In general, for evolutionary series, the accuracy of a model in explaining some local condition is not necessarily proportional to its usefulness in discovering and explaining future states. In other words, we assume the history will repeat itself in the future, but with the concern of evolutionary characteristics, we do not intend to optimize the results of the training data set in fitting the model. On the other hand, this method can, more or less, avoid the over-fitting effect. Therefore, the stopping criterion for training the model is to stop when the model has a rate of return greater than that of the buy and hold strategy. The consequent model is used to forecast the ex post data, which is the validity testing of the proposed model.

Trading Rules

Buying signals are recognized when the output, trend, is greater than a predetermined value (buy in threshold value), and selling signals are recognized when trend is less than another predetermined value (sell out threshold value). In this paper, the short sell strategy is not allowed. Stocks are bought when a buying signal comes up, and held until a selling signal comes up. The buying signal is ignored when there are stocks on hold, and the selling signal is ignored when there are no stocks on hold.

EMPIRICAL RESULTS

The detailed simulation results are displayed in Table 2, based on which some of the most popular measures are shown to evaluate the different trading strategies, yearly returns, profit factor, Sharpe ratio, cumulative wealth, maximum drawdown, and average drawdown.

Rate of Return

The geometric average is used to evaluate the rate of return for each trading strategy. The rate of return of neuro-fuzzy is greater than that of the Stochastics trading system and that of the buy and hold strategy for the testing period. But the rate of return of the Stochastics trading system is not definitely greater than that of the buy and hold strategy for the testing period. This result implies that the simple Stochastics trading system is not good enough to describe stock market movement. However, the proposed neuro-fuzzy trading system can effectively capture the relationship between technical indicators and stock price change. This empirical result somehow conforms to the claim of Jacobs and Levy's (1989) research.

Profit Factor

The profit factor is defined as the ratio of the profit on winning trades divided by the loss on losing trades. A value of profit factor less than one implies that the trading system will lose money over the long run. A value is greater than one, implies a profitable trading system. Table 2 also shows the profit factor for the neuro-fuzzy trading system and the Stochastics trading system. It can be seen that only the profit factors of the neuro-fuzzy trading system are definitely greater than 1. In other words, the neuro-fuzzy trading system can be profitable in the long run.

Sharpe ratio

The Sharpe ratio (1966) is simply the mean return of the trading strategy divided by its standard deviation. It measures the risk premium earned per unit of risk exposure. It is calculated as follows: $Sharp\ ratio = roi / \sigma$, where roi is the average daily rate of return, and σ is the standard deviation of the rate of return.

A higher sharpe ratio implies a higher rate of return given a fixed volatility or lower volatility given the fixed rate of return. Table 2 shows the basic statistics of the sharpe ratio for these three trading systems. Except for the HANG SENG INDEX, the sharpe ratio of the neuro-fuzzy trading system is definitely greater than that of the traditional Stochastics trading system and the buy and hold strategy. However, the sharpe ratio of the traditional Stochastics trading system is not definitely greater than that of the buy and hold strategy. This result implies that the neuro-fuzzy trading system can obtain higher rates of return given a fixed volatility or achieve lower volatility given a fixed rate of return when compared with the other two methods.

Maximum Drawdown and Average Drawdown

The drawdown (Magdon-Ismail and Atiya, 2004) is the measure of the decline from a historical peak in some variable (typically the cumulative profit of a financial trading strategy). The drawdown at any given moment is the fractional decrease in equity from the previous equity maximum point. drawdown= 1－(equity/maximum equity), where max equity is the maximum value of the equity ever reached before. The average drawdown is the average value of drawdown over the entire period. Table 2 shows the basic statistics of maximum drawdown and average drawdown for these three trading strategies. It can be found that both the maximum drawdown and average drawdown of the neuro-fuzzy trading system are definitely less than those of both the Stochastics trading system and the buy and hold strategy. The maximum drawdown and average drawdown of Stochastics indicators are also definitely less than those of the buy and hold strategy. In other words, the risk is smaller for the neuro-fuzzy and Stochastics trading system when compared to the buy and hold strategy

Cumulative Wealth

Since smaller mean square error does not promise more profit, cumulative wealth instead of mean square error is reported to evaluate the performance of each trading strategy. Figure 5 shows the cumulative wealth of these three trading strategies. The cumulative wealth of the neuro-fuzzy trading system is definitely greater than that of both the traditional Stochastics trading system and the buy and hold strategy. However, the cumulative wealth of the Stochastics system is less than that of the buy and hold strategy.

CONCLUSION

This paper tries to formulate the technical trading rules in a more complicated way to capture the relationship among the technical indicators and stock price change and to overcome the arbitrary nature of technical trading strategies by using neuro-fuzzy technique. This study presented a rigorous statistical analysis of the performance for three different trading strategies. The empirical results show that the neuro-fuzzy trading system definitely outperforms both the buy and hold strategy and the Stochastics technical trading rules. The empirical results suggest that the weak form efficient market hypothesis does not exist in the Asian stock market if an analyzing appropriate technique is applied.

Table 2. Comparison of Different Trading Strategies for Testing Period Over 01/01/2005-12/31/2006

	Taiwan			Hong Kong			Songapore			Korea		
	TSEC Weighted Index			HANG SENG INDEX			Straits Times Index			KOSPI Composite Index.		
	Neuro fuzzy	Stochastics indicators	Buy and Hold	Neuro fuzzy	Stochastics indicators	Buy and Hold	Neuro fuzzy	Stochastics indicators	Buy and Hold	Neuro fuzzy	Stochastics indicators	Buy and Hold
Yearly return	20.81%	-2.99%	12.85%	22.31%	4.88%	18.42%	25.25%	-0.60%	20.10%	29.03%	6.85%	18.76%
Total no. of trades	177	4	-	150	4	-	244	2	-	214	2	-
No. of profitable trades	144	1	-	141	4	-	186	0	-	159	1	-
No. of unprofitable trades	33	3	-	9	0	-	38	2	-	55	1	-
Avg. return per profitable trades	4.65%	3.93%	-	4.37%	2.41%	-	6.88%	-	-	6.05%	14.17%	-
Avg. return per unprofitable trades	-1.50%	-2.31%	-	-0.22%	-	-	-2.51%	-0.60%	-	-3.11%	-6.91%	-
Profit factor	13.53	0.57	-	311.20	-	-	13.42	-	-	5.62	2.05	-
Avg. return per trades	3.52%	-1.50%	0.05%	4.09%	2.41%	0.07%	5.29%	-0.60%	0.08%	3.71%	3.63%	0.08%
S.D. of return	3.70%	1.41%	0.94%	3.38%	0.55%	0.82%	6.72%	0.57%	0.74%	6.06%	10.54%	1.56%
Sharpe ratio	0.95	-1.06	0.05	1.21	4.35	0.09	0.79	-1.05	0.10	0.61	0.34	0.051
Max drawdown	0.084	0.118	0.160	0.048	0.044	0.105	0.074	0.087	0.142	0.220	0.110	0.230
Avg. drawdown	0.020	0.041	0.051	0.008	0.004	0.023	0.011	0.020	0.027	0.051	0.023	0.075

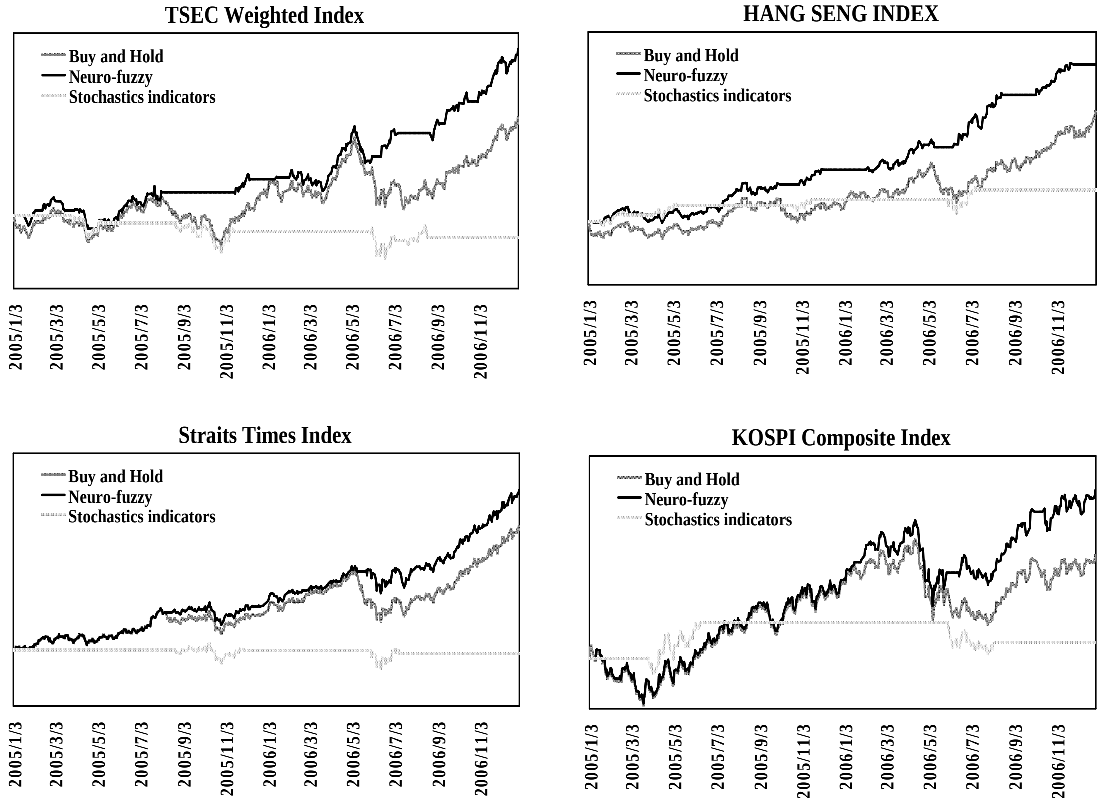


Figure 3. Cumulative Wealth for Three Different Trading Strategies During the Testing Period

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