The Application of Fuzzy Sets in Finding the Best Stock-Rule Pairs

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Abstract: *Stock markets are playing more and more important role in our daily life and research. But, many problems also emerged with the development of the markets. Such as: how to find the best stocks and trading rules to make more profit, etc. Many other researchers have done some work to solve the problems, but, they concerned on how to find a best rule for all stocks, or a best stock for any rules to make profit. In this paper, we pay our attention on finding the best stock-rule pairs which can make more successful in stock market. Firstly, we create a table for stock and trading rule pairs. Secondly, we test every stock-rule pair and divide the stocks into different rule set for the better evaluation results (higher Sharpe ratio, etc). Every element in a set with a weight is the "Sharpe ratio". Finally, we can give the users suggestions according to the stock-rule set which has a fuzzy weight.*

Keywords: *Stock-rules pair; Fuzzy set; Technical trading rules; Rank.*

1. Backgrounds

To conduct our research, we need to specify the background of this work done by other researchers. The stock market technical trading rules have been presented fifty years ago, such as: Moving average, Filter rules, Break-out Channel, Abnormal return, etc. And, they are playing an increasing role in the stock market research and applications.

R. Edwards and J. Magee [14] defined Technical trading rules as "the science of recording the actual history of trading (price changes, volume of transactions, etc.) in a certain stock or in "the Averages" and then deducing from that pictured history the probable future trend." However, the most researchers concerned to find a universal trading rule that can be used to any stocks, and the universal methods to find the best parameters [8, 15]. Obviously – it is suitable to some of the stocks but not all.

In this paper, our work is to find the best pair of stocks and trading rules ("stock-rule pair" in briefly), and the best parameters associated to the stock-rule pairs. We presented an optimized algorithm

In this paper, all of the computation is optimized by Genetic Algorithm, so the system can be implemented in a reasonable running time.

2. How to create the Fuzzy set for stocks

In the stock markets, there are many stocks and technical trading rules ("rule" in briefly). When we want to make profit through trading (buy and sell stocks), which stock is better? Which rule is better? Why the stock or rule is better? How to choose the better stocks and rules?

To answer this question, we must infer a criterion to evaluate it. In this paper, we use "Sharpe Ratio (SR)" (which is defined by $SR = (R_p - R_f)/\sigma_p$, where R_p is Expected portfolio return, R_f is Risk free rate that can be found from the government report, in this paper, we set it as 5%, and σ_p is portfolio standard deviation [17].) as the criterion. It considers both the profit and the risk, and becomes a popular criterion in more and more researches. It means to get the more profit and take the lower risk.

Definition 1 (**Fuzzy set,** [10]). Given an arbitrary set X , a fuzzy set (on X) is a function from X to the unit interval I =[0,1],

$$\mu : X \to I$$

For convenient, we use the following notation to stand for a fuzzy set,

$$X = \{x_1, x_2, x_3, \ldots x_n\}.$$

Then a fuzzy set μ on X has been denoted by the collection of pairs of the functional relation μ ,

$$\{(x_1, \mu(x_1)), (x_2, \mu(x_2)), (x_3, \mu(x_3)), \ldots (x_n, \mu(x_n))\}.$$

Here, $\mu(x)$ is the membership degree of x . In our system, for each rule R , we build a fuzzy set for it, and the element of the set is the stocks (S), the membership degree is RS .

$$R = \{(s_1, SR(s_1)), (s_2, SR(s_2)), (s_3, SR(s_3)), \ldots (s_n, SR(s_n))\}$$

$SR(s)$ is the best Sharpe ratio of stock s under the rule R . Sometimes, the $SR(s)$ is larger than 1 or less than 0, for this situation, we can use a linear transformation to transfer it into unit interval [0, 1].

So, we can weigh all the stocks with Definition 1.

Algorithm 1. The algorithm to classify a stock associated to a rule:

Step 1: Select a stock S and a rule R , we divided the historical data into two parts: training set and testing set, which is one year data and continued one month data, respectively;

Step 2: On the training set, we compute the best SR with GA, and keep the parameters;

Step 3: On the testing set, we compute the SR with the parameters we got from the training set;

Step 4: SR is the membership degree of the stock S associated to the rule R .

Step 5: Insert S in the set R with the weight SR if it is higher than a threshold. (The threshold can be changed by user or other criterion.)

From the above algorithm, we can see if a stock with the higher weight, it will be with the better performance (more profit and lower risk). And it maybe belong to more set, on the contrary, if a set with lower Sharpe ratio, it may belong to less set. This is acceptable in a stock trading system.

3. Evaluation and Conclusions

Obviously, after we fixed a rule, we can select the stock from the set which will let us make more profit and take less risk. Because the fuzzy set is created by Algorithm 1.

If the stocks/rules are more than one, we can choose the intersection / union (lower/upper boundary) rules/stocks of the stocks/rules associated sets. Here, we can use the set function to do some choice more easily. So, we use fuzzy set to build the relationship of a stock and a rule.

From Table 1 and Figure 1, we know the different stock-rule pairs can get the different results. So there are not the best stocks or rules, just the best stock-rule pairs for making more profit and taking less risk.

Table 1 The comparison of Sharpe Ratio (SR) in testing sets of Filter rule and Moving Average.

Stocks	Filter rule	Moving Average
TEL	0.716	0.875
JHX	0.251	0.855
AGL	0.938	0.468
WSF	0.254	0.708
AXA	0.854	0.228
BIL	0.199	0.540
ORG	0.332	0.692
AMC	0.283	0.765

In Table 1 and Figure 1, the training set is one year, the testing set is one month just next to the training set.

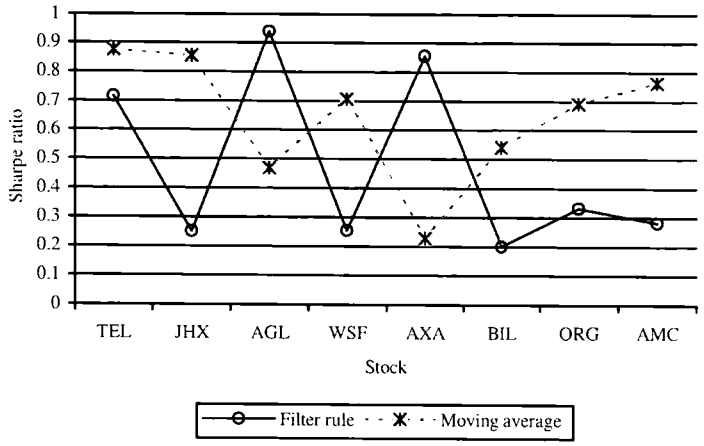

Figure 1 The comparison of Sharpe Ratio of Filter rule and Moving average.

The set of Filter rules is: {AGL (0.938), AXA (0.854), TEL (0.716), ORG (0.332), ~~AMC (0.283), WSF (0.254), JHX (0.251), BIL (0.199)~~};

The set of Moving Average rules is: {TEL (0.875), JHX (0.855), AMC (0.765), WSF (0.708), ~~ORG (0.692), BIL (0.540), AGL (0.468), AXA (0.228)~~}.

The number in the bracket is the associated membership function value (Sharpe ratio) it belongs to the set. The membership function is the half number of the support fuzzy set , so we remove the half members with lower weight from the support set [7]. So, each set only contains four stocks.

The best stock-rule pairs are:

AGL-Filter, AXA-Filter, TEL-Filter, ORG-Filter and TEL-MA (Moving Average), JHX-MA, AMC-MA, WSF-MA.

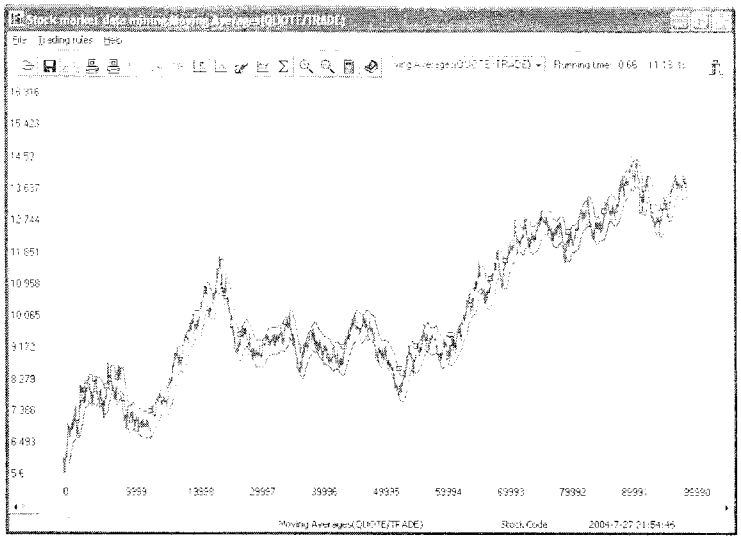

Figure 2 The user-interface of the system.

Recently, most investors and brokers consider not only profit, but also risk. So, in this paper, we use Sharpe ratio as the bench mark to evaluate the stock-rule pairs.

In the future, we will consider how to find the stock-rule pairs efficiently, and get the more evaluation metrics include Profit, Return, Sharpe ratio and Sortino ratio [1-3], etc. And, we also want to optimize the parameters and visualization, some of them are finished.

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[19] http://www-staff.it.uts.edu.au/~linli/

Session: G1 - Data Mining
Chair: Prof. Christoph Schommer
Saturday 18 December / 9:30 - 10:45 **ROOM: DICE 1**

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Rough Sets As a Tool To Predict Risk In Financial Operations

Raquel del Saz.Universidad Politecnica de Madrid, Spain
Covadonga Fernandez, Universidad Politecnica de Madrid, Spain
Ernestina Menasalvas, Universidad Politecnica de Madrid, Spain
Concepcion Perez, Universidad de Oviedo, Spain

Abstract: Our aim is to briefly show the development of a method of estimation of the "financial risk" when a credit is granted to a firm , having

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