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RANDOM TEST FOR TRADING SYSTEM

Abstract: Many traders use mechanical systems to trade. Such trading systems usually are tested on historical data. It shows good performance in the past. This paper describes the method for evaluating such trading systems based on the hypothesis that the tested system is trading randomly [1]. Under this null hypothesis we build a random system of the same characteristics as the tested one. The random system presents the same probabilities of taking a long position (betting on the price going up) and taking a short position (betting on the price going down) as tested system. The only distinguishing factor is the performance of the system. Simulations of the random system are run many times to create a performance distribution that is used to verify the null hypothesis. The test system in this paper trades the S&P500 futures from January 2003 until September 2008, taking always either long or short positions (always in the market) and reinvesting the profits.

Keywords: mechanical trades, random signal test

1. Introduction

Mechanical systems are widely used by the traders, and become more and more sophisticated as more powerful computers are available and more complex financial instruments can be traded. Also some systems that perform well in the past, become less efficient now and new systems need to be developed. Over 20 years ago, well known Turtle Trading System was very profitable, but in current market conditions it's not working so well.

The major advantage of using mechanical system over the human trading is eliminating the human emotions. There are many described and well known human behaviours that are destructive during trading [2]. Probably the most destructive is allowing losses to grow. People don't like loosing. They do not want to commit that they make bad decision by keeping losing position in their portfolios. But in the case of profit, they tend to close position very quickly, not allowing for bigger gains. Another advantage of mechanical system is to have fixed money management policy, which secure portfolio from too high risk. Available leverage is very high that could

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make a trader take too big risk. Mechanical systems also reduce the cost of money management and saving investors time, since they do not need to watch market all the time.

Many small investors as well as big hedge funds are using mechanical systems. Probably one of the most sophisticated systems is used by the Renaissance Technologies [3]. The company employs many specialists also with non-financial backgrounds, including mathematicians, physicists, astrophysicists and statisticians. Another famous hedge funds are Global Alpha fund by Goldman Sachs and The Highbridge Statistical Market Neutral Fund by J.P Morgan Chase.

Mechanical systems are developed and tested on historical data. Usually they have some parameters, that can be optimized for higher profit in the past. The result of the same system in the future is unknown. To maximize chances of having similar results is to make sure, that system works in the past:

- for many different market data
- for many time periods
- for the lowest possible system parameters

Additional test for randomness of the system is described in this paper.

2. Random signal test

This methodology described in [1] comparing the system performance with similar random system. Such random system trades the same contracts in the same time period, only difference is that it's deciding on long/short position randomly. If such system is created, it's run many times to produce the distribution of performance. From this distribution critical values are read for desired significance levels. If the system performance is greater then the critical value, we reject the hypothesis of random system trading. Let's c be the critical value, the hypothesis test will be:

- H0: System performance is not significant better then one achieved by the random trading. $Performance(TestedSystem) <= c$
- H1: System performance is significant better then random trading. $Performance(TestedSystem) > c$

As the system performance many different measures can be used. Most common and basic measures are based on total profit. This could be percent profit of the start capital - Return On Investment. In this article annual ROI is used.

$$annualROI = (endcapital/startcapital)^{1/years} - 1 \tag{1}$$

The profit measures could be also adjusted by some of the risk measures. For example Alex Strashny in [1] uses profit divided by three times maximum drawdown. One of the well known risk adjusted measure is Sharp Ratio [6]. Another custom performance measures could also be used in random test, for example: Time to recovery, Percent of Wining Trades. The second one is also tested in this article, it is calculated as the number of profitable trades divided by the total number of trades.

3. Description of tested system

Tested system was run on almost 6 years of historical data. It present a good total return of 1508.37% (fig.1), that gives in average 63.3% annual ROI (return on investment). System always keep either long or short position on S&P500 futures. Decision about changing position is made once per day at the market close. Position is changing very often giving the average holding time 2.3 days. Profit is reinvested. System is using leverage of 2:1. Signal either long or short is calculated based on probability

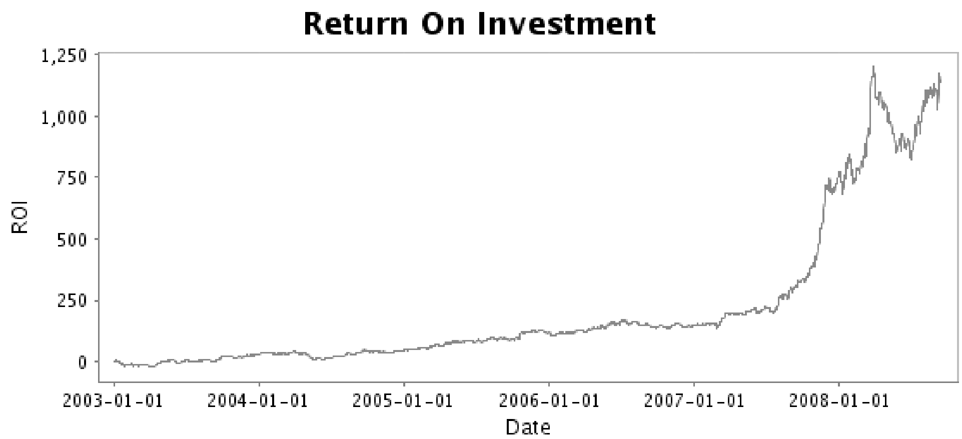

Fig. 1. Return on investment for tested system

distributions of short-term stock price movements. Distributions are calculated from over 5,000 US equity option prices. Then all of this information is used to derive the likely short-term direction of the S&P500. Actual transaction is made on futures contracts on the S&P500.

4. Creating the random system

Random system will be different from tested one only in a point of long/short signal. Tested system is using some rules that traders believe are working on the market giving the edge over other investors, while random system will do decision randomly. Other parameters of the systems stays the same, some of them are:

- transaction costs,
- size of a position,
- transaction time and contracts price, always closing prices
- time period
- used leverage

The random decision should also reflect characteristic of tested system. If system take long position it can keep it for a while as well as short position, that create the time series of positions:

$$LLLSLLSSSSSLLSSSLSLSLLL\ldots\ldots \quad (2)$$

when L stands for long position, and S for short. In this example system keeps long position for the first three days, then change for short for one day, and again for long for two days, and so on.

4.1 Bernoulli process [4]

We assume that every day decision is independent from the current position. Let's call L probability of the system signal saying be long, and according to our assumption $1-L$ is a probability of the system saying be short. The system final path probability could be wrote like this:

$$SystemProbability = L*L*L*(1-L)*L*L*(1-L)\ldots\ldots. \quad (3)$$

Let say that the N is number of days on long position and M is number of days on short position, we can write previous equitation as:

$$SystemProbability = L^N*(1-L)^M \quad (4)$$

Using Maximum Likelihood method we assume that $SystemProbability$ is the highest of possible, and we estimate L as:

$$L = N/(N+M) \quad (5)$$

4.2 Markov process [5]

Let's say that the system is on long position, and it need to decide either to change short or stay long. Let's call $p(LS)$ probability of changing position from long to short, the probability of staying on long position will be $p(LL) = 1 - p(LS)$. Similar we will call $p(SL)$ probability of changing position from short to long, the probability of staying on short will be $p(SS) = 1 - p(SL)$. As an example let's consider that realized path is:

$$LLSLSS \tag{6}$$

Let's assume that probability of the first position is 0.5. Now we can describe probability of realized path 6 as:

$$SystemProbability = 0.5 * p(LL) * p(LS) * p(SL) * p(LS) * p(SS) \tag{7}$$

Let's define:
PL – number of days staying on long position
CL – number of days changing position from long to short
PS – number of days staying on short position
CS – number of days changing position from short to long

Please note that those numbers of days do not include first day. Now we can write the probability of any realized path as:

$$SystemProbability = 0.5 * p(LL)^{PL} * p(LS)^{CL} * p(SS)^{PS} * p(SL)^{CS} \tag{8}$$

Same as the function of 2 variables:

$$0.5 * (1 - p(LS))^{PL} * p(LS)CL * (1 - p(SL))^{PS} * p(SL)^{CS} \tag{9}$$

We are looking for $p(LS)$ and $p(SL)$ that will maximize probability of realized path. Let's notice that this function can be write as $f(p(LS)) * g(p(SL))$, both functions are non negative, so we can search for maximum of

$$(1 - p(LS))^{PL} - p(LS)^{CL} \tag{10}$$

and independently of

$$(1 - p(SL))^{PS} - p(SL)^{CS} \tag{11}$$

Using Maximum Likelihood method we estimate probabilities as:

$$p(LS) = CL/(CL + PL) \tag{12}$$

$$p(SL) = CS/(CS + PS) \tag{13}$$

5. Random System

Markov process was used to create random system since tested system tend to keep chosen position. That was reflected in average holding time of 2.3 days. Simulations was running from January 2nd 2003 until September 26th 2008. There was $PL = 427$ days keeping long position, $CL = 316$ days of changing position from long to short, $PS = 386$ days keeping short position, and $CS = 315$ changing from short to long.

Probabilities for tested system of changing position was calculated using 12 and 13:

- p(LS) = 0.4253
- p(SL) = 0.4487

Software that perform simulations was modified to trade based on calculated probabilities. At each day random number R is generated from unified distribution in range (0,1) and conditions for changing position are checked:

```
if system has long position then
    if R < p(LS) then
        change to short;
    end
end
if system has short position then
    if R < p(SL) then
        change to long;
    end
end
```

Algorithm 1: Random signal execution

1,000 random simulations was run produces distribution for ROI of random system showed in fig.2, since best result wasn't higher then one of the tested system another 10,000 simulations was run fig.3. In this case also the best result wasn't higher then achieved by the tested system. Second tested performance measure is Percent Of Wining Trades (POWD) fig.4.

6. Veryfication hypothesis of random trades

The level of significance is the probability of rejecting the null hypothesis when it is true. In simple case of just one system the critical value of 5% significance is just the 95th percentile of a performance distribution. In case of ROI and 10,000 random

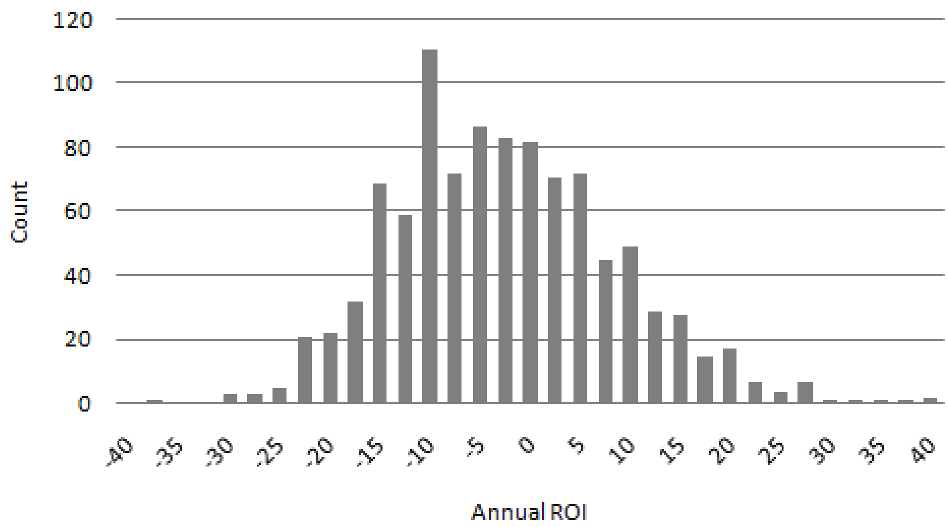

Fig. 2. ROI distribution for 1,000 random system simulations

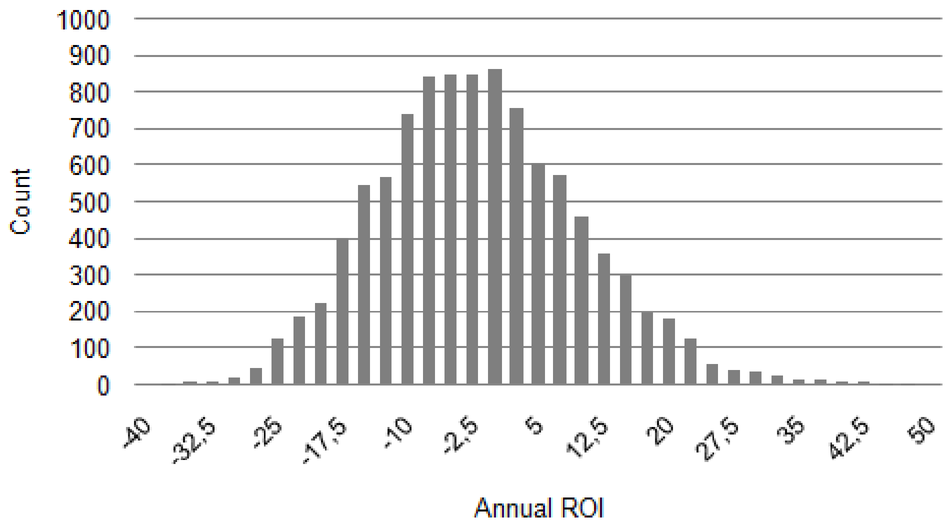

Fig. 3. ROI distribution for 10,000 random system simulations

simulations 95th percentile is 17.48 and 99th percentile is 26.63. For both significance levels we reject the null hypothesis since system annual ROI is 63.3%. Also

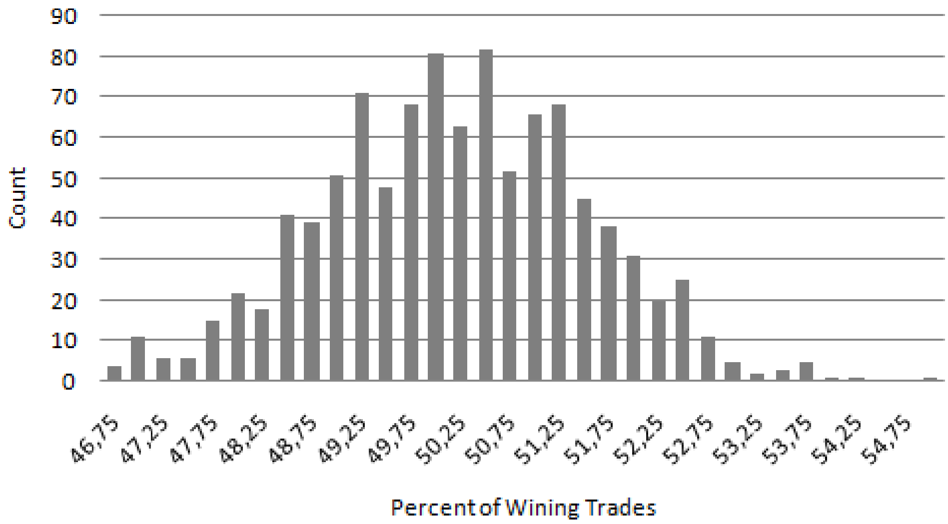

Fig. 4. POWD distribution for 1,000 random system simulations

best results in 10000 simulations was 50.30, so we can reject hypothesis of random trading even with lower significance level. In case of POWD and 1,000 random simulations 95th percentile is 52.27 and 99th percentile is 53.44 and the system Percent Of Winning Trades is 53.24%. In case of this performance measure we can reject null hypothesis only on 5% significance level, but we can not on 1%.

However, tested system got some parameters, and during optimizations best ones was picked up. For example 9 days moving average was used. But during optimizations also other values was tested like 8 and 10 days. If the system is not to much fitted to data, results for similar parameters should also produce good results. Additional tests for 8 and 10 days mean was performed. For each value probabilities p(LS) and p(SL) was calculated and 1,000 simulations was run to read the critical values for 1% and 5% significance levels. As shown in table 6. in all 3 cases hypothesis of random trading is rejected on both significance levels. Results for other values of moving average parameter are shown on fig.5.

7. Conclusion

This paper described the test of random trades for trading system. Long/short signals for random system was created using Markov process, other system properties stays the same. Null hypothesis of random signals was rejected for tested system on both

Table 1. Random test for different values of average moving parameter

moving avg	annual ROI	alfa=0.05	alfa=0.01	p(LS)	p(SL)
8	36.00	15.89	27.38	0.42445	0.42897
9	63.3	17.48	26.63	0.42472	0.44872
10	41.62	16.61	25.69	0.40608	0.44348

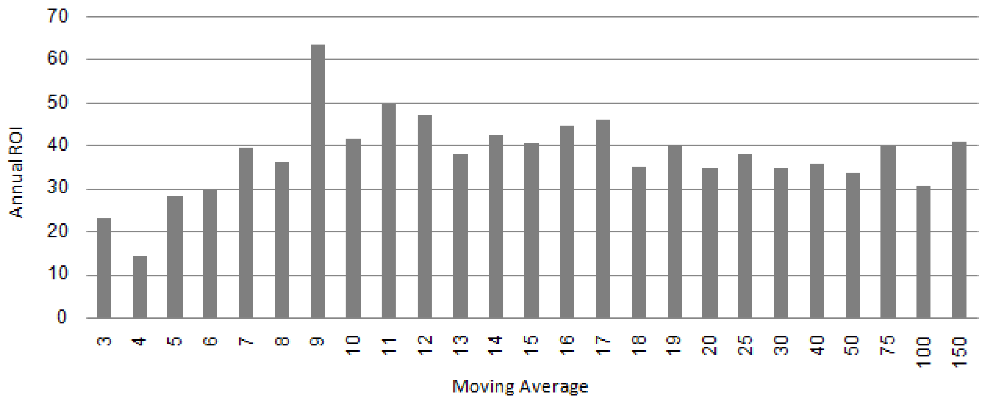

Fig. 5. Tested system results for different values of moving average parameter

1% and 5% significant levels for the ROI, and rejected only on 5% for the POWD performance measure. Is worth to note that any of 10,000 random simulations didn't outperform tested system's ROI . Since tested system goes through some optimizations to chose best parameters, tests for 2 additional moving average parameter was run. In this case also hypothesis of random signals was rejected.

Presented methodology could be the first step of verification trading system that was developed on historical data and show good past performance. It verify hypothesis that similar results could be achieved by the random signals. Even if system pass test for random signals, trader should also consider the ability of the system to work in the future, before using a system in real live. Things that should be considered are time period of the test, different market data and number of parameters used in the system.

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TEST LOSOWOŚCI MECHANICZNYCH SYSTEMÓW TRANSAKCYJNYCH

Streszczenie Wielu inwestorów używa mechanicznych systemów transakcyjnych. Systemy takie testowane są na danych historycznych, gdzie osiągają dobre wyniki. W artykule tym opisano metodę testowania systemów transakcyjnych opartą na hipotezie iż system podejmuje decyzje losowo. Przy założeniu prawdziwości hipotezy konstruowany jest odpowiedni system losowy, który z takimi samymi prawdopodobieństwami generuje sygnały zajęcia pozycji. Opisywany system zajmuje pozycję długą (zakłada wzrost cen) bądź krótką (zakłada spadek cen) na kontraktach futures na indeks S&P500 (system zawsze posiada pozycję, nigdy nie jest poza rynkiem). Obliczenia dla systemu losowego wykonywane są wiele razy i tworzony jest rozkład prawdopodobieństwa wyników systemu. W oparciu o uzyskany rozkład weryfikowana jest hipoteza o losowości testowanego systemu.

Słowa kluczowe: mechaniczne systemy transakcyjne, test losowości

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