Developing Multi-Time Frame Trading Rules with a Trend Following Strategy, using GA

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ABSTRACT

This paper describes a novel way to develop trading rules with a trend following philosophy, combining several time-frames which average the Rate of Return of the several components and decrease the Maximum Drawdown. This represents strategy diversification and is an effective way to reduce risk. The resulting trading systems have the interesting characteristic of producing an output that is not binary in terms of market position, giving a varying degree of confidence in the future direction of the market. Tests performed with a sliding window on American stock index S&P500, produced annualized Rates of Return in excess of 10% in some configurations.

Categories and Subject Descriptors

I.2.M [Artificial Intelligence]: Miscellaneous

General Terms

Algorithms, Economics, Experimentation.

Keywords

Computational Finance; Financial Market; Genetic Algorithm; Technical Analysis; Technical Indicators; Trading Rules Optimization; Trend following.

1. **INTRODUCTION**

Financial markets have received increasing attention from academics in the past decades and particular interest has been devoted to the creation of automated trading rules that adapt to changing conditions. Markets are complex dynamic systems with a high number of active agents (investors, traders and hedgers), influenced by each other and by external information (news, economic data, events). This produces a behavior with high randomness and noise which is very difficult to predict. Nonetheless, the majority of markets form price patterns that tend to repeat themselves, produced by underlying economic fundamentals, trader behavior/psychology and system dynamics. The most basic and common patterns that exist in markets are trends (auto-correlation of price) and reversal to a mean (theoretic consensus of a fair price).

In the Hedge Fund Industry, trend following is the main trading philosophy used by the professionals [1] consisting in 1) identifying a consistent change in price, upwards or downwards,

GECCO'15 Companion, July 11-15, 2015, Madrid, Spain. ACM 978-1-4503-3488-4/15/07

http://dx.doi.org/10.1145/2739482.2764885

2) opening positions to profit from the trend and 3) maintain those positions open until the trend disappears or reverses.

This work proposes a methodology to develop trading rules with a trend following philosophy, using genetic algorithms, sliding window optimization and a novel way to combine different timeframes.

2. **STATE OF THE ART**

Trend following as a trading philosophy has been studied in many works such as [2] and its capability of generating consistent profits established in many types of markets. Several optimization methods have been used to generate trading rules that adapt to the asset characteristics and to current market conditions. One of the most used is Genetic Algorithms with a sliding window like in [3] and [4]. A big challenge in this area is being able to optimize solutions that profit from structural and repeating market patterns, and not momentary patterns that don't repeat themselves.

3. **PROPOSED SOLUTION**

Historical data was used for training purposes in order to define a set of trading rules capable of reacting to market trends. Technical indicators like MACD (Moving Average Convergence Divergence), RVI (Relative Volatility Index) and SAR (Stop and Reverse) were used to compose the set of trading rules. In order to increase the robustness of the resulting solution, several timeframes are considered simultaneously: Long-Term (LT), Medium-Term (MT) and Short-Term (ST). Each time-frame contributes with a percentage of the final market position and the several time-frame outputs can be concordant or discordant. If all timeframes agree on the direction, the system will be 100% long or short (using 100% of the available capital), otherwise it will use only a fraction of the capital. This allows the system to have varying degrees of confidence depending on the market conditions. Each time-frame has a set of trading rules for the long side and another for the short side. Each set of rules is defined by a chromosome which has a tree structure. Each node in the tree is a gene being either a terminal or an operator and having a Boolean or Float output. The result of the chromosome is given by the root gene.

In this work the trees are limited to one level using only Boolean genes. The genes used are trading rules based on technical indicators like MACD, with parameters adjusted by genetic evolution

A complete solution is defined as a "genome" and its structure can be seen in figure 1. Each time-frame component produces a vector with its prediction of the best position the system should assume in each trading day (1 for long, 0 for neutral and -1 for short).

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These components are then combined with different weights to form the final market position of the system for each day. Genomes compete between themselves and are evaluated with a fitness function that combines the annualized Rate of Return (aRoR) and the maximum drawdown in percentage of the capital (%MDD), see equation (1).

$$fitness\ score = aRoR + \ 6\ \frac{aRoR}{5-\%MDD} \tag{1}$$

Greater weight is given to the aRoR in order to maximize profits but, solutions that achieve those profits with too much drawdown tend to be surpassed by more balanced solutions.



Figure 1: Structure of a genome

To differentiate the rules produced by the 3 time-frame components, the allowed range of operator parameters is different for each time-frame. ST Indicators tend to react more quickly than MT indicators and LT indicators are the slowest to react. Another measure adopted was to enforce allowed ranges for the annualized average number of trades that the rules of each time-frame produce. The ST produces the most trades, and the LT produces the fewest trades in average.

4. **RESULTS**

Tests were performed on the American stock index S&P500 with a large optimized sliding window of 6 years and an out of sample window of 6 months. The optimization window used data from Jan. 2000 to Jun. 2014 and the out of sample window used data from Jan. 2006 to Dec. 2014. A commission of 0.1% per order was used (0.2% open & close).

The 3 time-frames were combined with weights of 0.42 for the long-term, 0.42 for the medium-term and 0.16 for the short-term. The long and medium term components have greater importance reflecting experimental results in which they achieve the highest returns although with significant drawdowns. Since the drawdown patterns of these two time-frames are different, when they are combined with similar weights, profits are averaged and drawdown reduced. The short-term rules constantly reverse positions penalizing profits. Even so, they can sometimes prevent greater drawdowns since they react faster to price change. The combination of these three sets of rules (especially long and medium term) work as strategy diversification lowering the risk.

Figure 2 shows the results of a simulation in S&P500 with 3 timeframes. From bottom to top, the image shows S&P500 percentage variation and percentage profits, final market position (F), longterm output, medium-term output and short-term output.

The trading rules obtained with this method perform well in markets with strong trends, long and short, reacting well to fast

and strong price changes like in stock market crashes. They tend to produce negative results when the market moves sideways with no defined trend.



Figure 2: Simulation on S&P500 with 3 time-frames

Table 1 summarizes tests performed on S&P500 with different setups. Results are the average of 5 simulations. The simulation in figure 2 corresponds to the third entry from top (LT+MT+ST).

Fable 1: Results	s with	various	setups
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Test setup	Annualized RoR	MaxDD
Only long-term	12.79 %	-35.32 %
Only medium-term	9.18 %	-36.99 %
LT+MT+ST (42%; 42%; 16%)	9.11 %	-26.66 %
LT + MT (50% ; 50%)	11.16 %	-24.69 %

5. CONCLUSIONS

This work presents a novel way to develop trading rules with a trend following philosophy, combining several time-frames which average the Rate of Return of the several components and decrease the Maximum Drawdown. This represents strategy diversification and is an effective way to reduce risk.

The resulting trading systems have the interesting characteristic of producing an output that is not binary in terms of market position, giving a varying degree of confidence in the future direction of the market.

6. ACKNOWLEDGMENTS

This work was supported in part by *Fundação para a Ciência e a Tecnologia* project (UID/EEA/50008/2013).

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