PROFTS: A MultiAgent System for Stock Portfolio Management

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***Abstract*—Portfolio management is a challenging task. When trying to do it autonomously, it becomes more complex. Most of automated trading systems (ATS) focuses on maximizing return, without considering the risk, and just a few of them consider the trade-off between risk-return. In this scenario, MultiAgent Systems are a suitable approach to develop ATSs, given its agent's characteristics. This work proposes a Multiagent System architecture, called PROFTS, to autonomously manage a stock portfolio accordingly to investor's risk profile using both, fundamental and technical analysis. The system will be validated throughout simulations in the Brazilian stock market using AgEx, a financial market simulation for agents. Some prior results regarding the technical agents are promising.**

***Keywords*— automated trading system; portfolio management; multiagent system; machine learning.**

I. Introduction

Portfolio Management is a challenging task, it is necessary to decide which assets to buy, when, its price and quantity. Trying to do it autonomously, with an automated trading system (ATS), increases the problem's complexity. That is why this is a problem with unknown optimal solution.

When talking about equity portfolio management, there are basically two strategies to be adopted, the passive or active management. A passive management tries to replicates the performance of a specific benchmark, such as an index, while an active management tries to earn a return that exceeds the return of a passive benchmark portfolio, net of transaction costs and on a risk-adjusted basis. The amount of value that the active manager has added or subtracted from the portfolio is the generated *alpha* [1].

MultiAgent System (MAS) is a suitable approach to manage an active automated portfolio, because agents are *autonomous*, they operate without human interference and have control about its actions and internal state. They are *social*, they can cooperate or compete to achieve its task. They can be *reactive*, perceiving its environment and act changing it, and can also be *proactive*, acting without a response of its environment, in a goal-directed behavior [2].

The optimal portfolio, is the one that has the highest utility for a given investor. Each investor has its own utility curve, that specify the trade-off between expected return and risk [1], so, it is important to manage a portfolio based on investor's profile.

When analyzing which asset to buy, there are basically two general approaches to adopt, the top-down and the bottom-up, and both can be used with fundamental or technical analysis. In the top-down approach, economy, market and industry affects the return of an individual stock, while in the bottom-up, the manager looks for stocks that are undervalued relative to their market price, and it is expected that these will provide superior returns regardless of the economy and industry outlook [1].

Using the bottom-up approach for equity valuation with fundamental analysis, the manager can apply a valuation model based on discounted cash flow, where the value of the stock is estimated based in the present value of some measure of cash flow, or relative valuation, where the value of a stock is estimated relatively to the price of similar companies. With Technical analysis, the future price movements are forecast based on past stock price changes or other stock market data [1].

In this work, it will be described a Multiagent System to manage an active automated portfolio, considering different investor's profile and using relative valuation and technical analysis.

II. Related Work

This work is based on [3]. The author developed a multiagent system that uses strategies derived from technical analysis and that are capable of satisfying different investor's profiles, that were: (I1) investor with maximal acceptable risk, (I2) with desired target return, (I3) with limited risk-return and (I4) with free risk and return. The results were simulated using AgEx [4], a financial market simulation tool for software agents, developed by the same author.

Another important reference is [5], where the authors developed a multiagent system based on fundamental analysis. There was an agent called "Price Analyst" that used some models of discounted cash flow (Fundamental Analysis), and "Indexes Analysts" that used strategies based on multiples (e.g. Price/Profit).

Fundamental analysis is rarely used on automated trading systems, most of ATS are based on technical analysis. A very recent survey published by Cavalcante [6] listed 56 work categorized by its main goal, application, input variables (if it used fundamental or technical data), the machine learning techniques used and if it was a Trading System. From 56 work, just 5 of them used Fundamental analysis and from these, just 2 were Trading System.

Another relevant article for this work was published by Junior and Galdi [7]. They compared the valuation performance

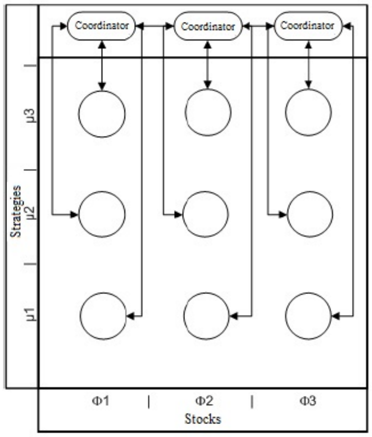

Fig. 1. COAST society to operate with three different strategies and assets. Adapted from [3].

of relative valuation, using cluster analysis (a combination of Ward's method with K-means) and economic sectors when identifying similar companies.

III. Proposed Approach

A. About the Inspiring System

To understand our proposal, it is interesting to firstly introduce the one proposed by Castro [3]. He developed a society called COAST (**CO**mpetitive **A**gent **S**ocie**T**y) composed of advisors and coordinators, and a financial market simulation tool for agents, called AgEx.

The COAST architecture, that is used as reference to this work, is presented at figure 1. In this example we have three different strategies for three different assets. The agents $\mu1$, $\mu2$, and $\mu3$ are based on strategies composed by a single technical indicator, e.g. using RSI (Relative Strength Index) with period of 14 days, the agent recommends to buy if it is higher than 70% and to sell if it is equal or lower than 70%.

The advisors are competitive agents, and they send a recommendation based on their strategy. There are also the coordinators agents, that allocate resources between the advisors and evaluate them. The advisors just communicate with their coordinator, because they are competitive and compete for resources. On the other hand, a coordinator communicate with others coordinators and they negotiate the resources that will be allocated between them.

Accordingly to market situation (state of the environment) and investor's profile, the agents can adopt different goals, such as: (i) risk minimization, (ii) return maximization, or (iii) efficiency maximization (Sharpe Ratio Maximization). It is represented in table I.

B. About our System

We adopted the same investor's profile and goals idea, but with a new architecture called PROFTS (**PRO**fitable **F**undamental and **T**echnical **S**ystem).

TABLE I
Possible goals for different market scenarios and Investor's profile

		Investor Profile			
		Maximum Risk Acceptance (I1)	Minimum Return required (I2)	Limited Risk-Return (I3)	Free Risk-Return (I4)
Market Scenarios	Acceptable Risk and Return	Return Maximization	Efficiency Maximization	Efficiency Maximization	Efficiency Maximization
	High Risk, acceptable Return	Risk Minimization	Risk Min., observing min. return	Risk Minimization	Efficiency Maximization
	Acceptable Risk, Low Return	Return Max., observing max. risk	Return Maximization	Return Maximization	Efficiency Maximization
	High Risk, Low Return	Risk Minimization	Return Maximization	Efficiency Maximization	Efficiency Maximization

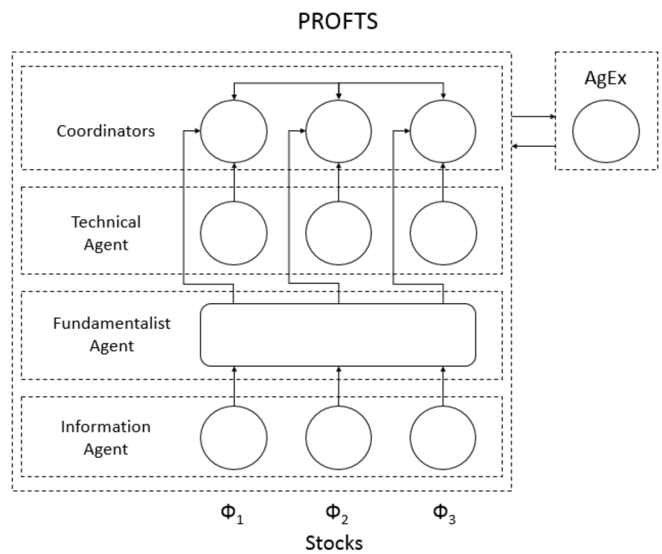

Fig. 2. PROFTS society to operate with three different assets.

The architecture is presented in Figure 2. It is composed of information agents, a fundamentalist agent, technical agents and coordinators.

The information agents are responsible for gathering fundamental data from the internet about each stock, respecting the Robots Exclusion Protocol (/robots.txt). This protocol tells to the agent what it can access or not at a determined domain [8]. They also calculate some fundamental indicators for the regression that will be performed by the fundamentalist agent (e.g. Beta, Payout Ratio, etc), multiples (e.g. Price to Earnings -P/E, etc) and financial health indicators (e.g. Quick Ratio, Net Profit Margin, etc). All these data are passed to the Fundamentalist Agent.

The Fundamentalist Agent performs relative valuation. The idea is simple, if a company is similar to another, their prices should be close. To determine if it is under or over valued, it uses multiples, like the P/E, with a multiple regression, using company's value drivers (risk, growth and potential to generate cash flow). The challenge remains in finding similar companies, as Damodaran [9] pointed out, using companies from the same sector or industry as comparable companies, may be incorrect, since they vary in size, risk profile and others characteristics. To solve this problem in an autonomous way, the fundamentalist agent cluster similar companies using *k-medoids* [10], a.k.a PAM (Partitioning Around Medoids). It is an unsupervised machine learning algorithm that clusters objects based on how similar they are in the same cluster compared to how dissimilar they are in other clusters and it is robust against outliers, since it does not use means. The companies identified as undervalued, are selected to create the portfolio. The portfolio is optimized based on investor's preferences. For example, if investor's profile is of type (I1), with maximal acceptable risk, the weights of each asset in the portfolio is found solving an optimization problem like the one proposed in Equation 1, where the acceptable level of risk σ_p^2 is fixed, and the expected return $E(\mathbf{r})$ is maximized.

$$\begin{aligned} \underset{w}{\text{Minimize}} \quad & -\mathbf{w}'E(\mathbf{r}) \\ \text{subject to} \quad & \sum_{i=1}^{n} w_i = 1 \\ & \sigma_p^2 = \mathbf{w}'\mathbf{V}\mathbf{w} \\ & w_i \geq 0, \ \forall i \end{aligned} \tag{1}$$

If investor's profile is of type (I2), with minimum return required, so the weights for the portfolio are given by Equation 2, that minimizes the risk subject to a $\overline{R}$ level of return. The other constraints ensure that the sum of stocks weights equals 1 and are nonzero.

$$\begin{aligned} \underset{w}{\text{Minimize}} \quad & \mathbf{w}'\mathbf{V}\mathbf{w} \\ \text{subject to} \quad & \sum_{i=1}^{n} w_i = 1 \\ & \mathbf{w}'E(\mathbf{r}) = \overline{R} \\ & w_i \geq 0, \ \forall i \end{aligned} \tag{2}$$

After the optimal portfolio is calculated, based on investor utility, the orders are sent to coordinators, that communicate with the AgEx system. A new portfolio will be optimized after four months, when Ibovespa is also rebalanced.

The technical agents, uses a support vector machine (SVM) to predict stock price's direction. The SVM is fitted using technical indicators. As there are a lot of different technical indicators, and each one of them can be used with different configurations, a feature selection is performed, filtering out relevantes features from 62 possible combinations of technical indicators and its setups. The feature selection method chosen was the Correlation-based Feature Selection (CFS) [11], as a result of a previous study developed by Reis and Sichman [12]. If there is a high probability of price increase, a buy recommendation is sent to the coordinator, that will analyse the current society goal (see Table I), and calculate the new portfolio risk, return, or efficiency, to decide if it will buy or not the stock recommended by the technical agent. Efficiency here, is measured by the Sortino ratio (ST), given by Equation 3. It measures the portfolio's average return ($\overline{\mu}$) in excess to a minimum acceptable return threshold ($\overline{R}$), and consider just the *downside risk* (DR) instead of the *total risk*, to not penalize the "good" risk (the one associated with higher returns).

$$ST = \frac{\overline{\mu} - \overline{R}}{DR} \tag{3}$$

For example, if the portfolio is at an acceptable risk and return level, and investor has a maximal risk that was not reached, then the society goal is to maximize return, so, if the new portfolio, considering the stock recommended from the technical agent, has a higher expected return than the original one, then the stock is bought.

Finally, the coordinators are those that receive and send information for AgEx. They also calculate portfolio statistics, as balance, profit, risk, and other metrics. Coordinators communicate between them, deciding how to allocate resources. At each step more than one recommendation of buy can be received from technical agents, so coordinators will have to decide which, if any, attend to maximize society's utility.

IV. Partial Results

The partial results are for the technical agents. We implemented the framework that will be used to train each technical agent. In this article, we tested different techniques of feature selection to determine the best subset of features. The filter methods used were Information Gain, Symmetrical Uncertainty, ReliefF, CFS, and OneR; Wrappers were SFS-Sequential Forward Search and SBS-Sequencial Backward Search; and a hybrid approach, combining filters and SBS.

In table II it is possible to see which technical indicators were used, and in table III it is possible to see the results obtained. The machine learning technique used was a SVM (Support Vector Machine) with a RBF kernel (Radial Bases Function). The parameters $Cost(C)$ and $gamma(\gamma)$ were obtained through a grid search procedure. The grid space of C was $log_2 C\{-5, -3, ..., 15\}$ and for γ was $log_2 \gamma\{-15, -13, ..., 3\}$. We analyzed the Ibovespa index, and now this model can be expanded to other stocks.

It is possible to see that we achieve good predictive results. More details about the methodology can be obtained at [12]. We chose CFS filter because it had a good accuracy in the test set (69,94%) and it is computationally cheap.

V. Future Work

The fundamentalist agent and information agent are completed. In the next steps we have to implement the coordinators, and make the integration between the other agents and AgEx.

When the system is completed, we will perform a portfolio backtesting to validate our system, and compare its results with those obtained by the Buy and Hold Strategy and the Ibovespa index, that will be used as benchmark.

TABLE II
TECHNICAL INDICATORS AND PARAMETERS FROM TTR PACKAGE (DOCUMENTATION AVAILABLE AT [13]).

Feature	Description	Technical Trading Rules
MACD9	Moving average Convergence/Divergence	*MACD (maType = 'EMA')*
BOLL20	Bollinger Bands	*BBands (n = 20)*
K9	Stochastic	*stock (default)*
WR10	William's Overbought/Oversold Index	*WPR (n = 10)*
RSI6	Relative Strength Index	*RSI (n = 6)*
RSI14	Relative Strength Index	*RSI (default)*
TRIX9	Triple Smoothed Exponential Oscillator	*TRIX (n = 9)*
TRIX20	Triple Smoothed Exponential Oscillator	*TRIX (default)*
CCI14	Commodity Channel Index	*CCI (n = 14)*
CCI20	Commodity Channel Index	*CCI (default)*
SMA5	Simple Moving Average	*SMA (n = 5)*
SMA30	Simple Moving Average	*SMA (n = 30)*
SMA200	Simple Moving Average	*SMA (n = 200)*
EMA5	Exponencial Moving Average	*EMA (n = 5)*
EMA30	Exponencial Moving Average	*EMA (n = 30)*
EMA200	Exponencial Moving Average	*EMA (n = 200)*
ADX14	Welles Wilder's Directional Movement Index	*ADX (maType = 'EMA')*
AROON20	Aroon	*aroon (default)*
ATR14	Average True Range	*ATR (default)*
chaikinvolatility10	Chaikin Volatility	*chaikinVolatility(default)*
CMO14	Chande Momentum Oscillator	*CMO (default)*
DPO10	De-Trended Price Oscillator	*DPO (default)*
ROC	Rate of Change/Momentum	*ROC (default)*
SAR	Parabolic Stop-and-Reverse	*SAR (default)*
ultimateOscillator	The Ultimate Oscillator	*ultimateOscillator (default)*
VHF28	Vertical Horizontal Filter	*VHD (default)*
Volatility10	Volatility	*volatility (default)*
WilliamsAD	Williams Accumulation/Distribution	*williamsAD (default)*
WPR14	William's %R	*WPR (default)*

TABLE III
CLASSIFICATION ACCURACIES FOR EACH MODEL AND DIFFERENT TEST SUBSETS FOR THE IBOVESPA DATASET.

Method	N^o Features	Training/Validation (Accuracy)	Test set (Accuracy)	Cost (C)	gamma (γ)
SVM	33	$70,16 \pm 9,04\%$	69,57%	2^7	2^{-15}
SVM + wrapper_SFS	7	$75,82 \pm 5,57\%$	66,82%	2^{15}	2^{-9}
SVM + wrapper_SBS	24	$72,34 \pm 7,82\%$	69,19%	2^7	2^{-15}
SVM + Information Gain ($t = 0.05$)	13	$72,87 \pm 6,57\%$	68,62%	2^{-1}	2^{-7}
SVM + Symmetrical uncertainty ($t = 0.05$)	15	$72,17 \pm 7,51\%$	69,57%	2^5	2^{-11}
SVM + ReliefF ($t = 0.01$)	22	$66,11 \pm 13,17\%$	66,92%	2^7	2^{-13}
SVM + Cfs	9	$72,50 \pm 7,50\%$	69,94%	2^3	2^{-11}
SVM + OneR ($t = 3.5$)	12	$65,04 \pm 10,86\%$	59,26%	2^{-1}	2^{-1}
SVM + IG_SBS	10	$75,57 \pm 5,94\%$	67,77%	2^5	2^{-7}
SVM + SU_SBS	11	$74,88 \pm 6,87\%$	69,09%	2^{13}	2^{-15}
SVM + ReliefF_SBS	7	$72,01 \pm 7,91\%$	69,75%	2^{15}	2^{-15}
SVM + Cfs_SBS	5	$75,29 \pm 6,07\%$	68,72%	2^9	2^{-7}
SVM + OneR_SBS	5	$69,39 \pm 8,71\%$	70,04%	2^{15}	2^{-15}

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