Journal of Business, Economics & Finance ISSN: 2146-7943

Journal of Business, Economics & Finance
Year: 2012 Volume: 1 Issue: 3

AN INTERACTIVE TOOL FOR MUTUAL FUNDS PORTFOLIO COMPOSITION USING ARGUMENTATION

Konstantina Pendaraki[1] and Nikolaos I. Spanoudakis[2]

[1]University of Western, Department of Business Administration in Food and Agricultural Enterprises, Greece.
[2]Technical University of Crete,Department of Sciences, Greece.

KEYWORDS

Mutual funds, portfolio management, decision support systems, knowledge-based systems.

ABSTRACT

This paper presents the PORTRAIT (PORTfolioconstRuction based on ArgumentatIon Technology) tool for constructing Mutual Funds investment portfolios. This work, from the field of finance, uses argumentation-based decision making that provides a high level of adaptability in the decisions of the portfolio manager, or investor, when his environment is changing and the characteristics of the funds are multidimensional. Argumentation allows for combining different contexts and preferences in a way that can be optimized, thus, resulting in higher returns on the investment. It allows for defining a set of different investment policy scenarios and supports the investor/portfolio manager in composing efficient portfolios that meet his profile. Moreover, the tool employs a hybrid evolutionary method for forecasting the status of financial market. This seamless merging of the investors profile, preferences and the market context is a capability which is rarely addressed by portfolio construction methods in the literature. The PORTRAIT tool is intended for use by decision makers such as investors, fund managers, brokers and bankers.

1. INTRODUCTION

Portfolio management is concerned with constructing a portfolio of securities (e.g., stock, bonds, mutual funds, etc.) that maximizes the investor's utility. Taking into account the considerable amount of the available investment alternatives, the portfolio management problem is often addressed through a two-stage procedure. At a first stage an evaluation of the available securities is performed. This involves the selection of the most proper securities on the basis of the decision makers' investment policy. At a second stage, on the basis of the selected set of securities, the portfolio composition is performed.

The PORTRAIT (PORTfolioconstRuction based on ArgumentatIon Technology) tool that this paper aims to present, uses, for the first time, argumentation-based decision making (Kakas and Moraitis, 2003) for selecting the proper securities, in our case, mutual funds (MF). More precisely, for the first stage of our analysis, the proposed methodological framework that is implemented by our tool gives the opportunity to an investor/portfolio manager to define different investment scenarios according to his preferences, attitude (aggressive or moderate) and the financial environment (e.g. bull or bear market), including the possibility to forecast the status of financial market for the next investment period, in order to select the best mutual funds which will compose the portfolio. For the second stage (portfolio composition), we use four different strategies, based on the MFs' performance in the past, to define the magnitude of its participation in the final portfolio.

The endeavour of the argumentation-based decision making is to select MFs through rules that are based on evaluation criteria of fund performance and risk. The performance of the MFs on these criteria is inserted to a knowledge base as facts along with facts describing the market condition.Then, in a first level, the basic inference rules that refer directly to the financial domain are edited and an MF is selected or not based on the above mentioned facts (e.g. “select an MF with a high return”). Following, in the second level, experts express their theories (or arguments) for selecting funds, either for simple contexts, or for expressing the needs and directives of different investor roles, by defining priorities between the first level rules. Finally, in the third level, the decision maker combines the theories defined at the previous level by expressing his combination policy, again using priority rules.

In the present study we aim to show that argumentation is well-suited for addressing the needs of this type of application, thus its results can be adapted to be applied to other such managerial problems (where decision is dependent on user preferences, profile and context of application), and also to show that the composed portfolios can help an individual investor or fund manager to outperform a broad domestic market index by applying profitable investment strategies.This is important for decision makers, such as investors, fund managers, brokers and bankers, especially in private banking. Argumentation allows for seamless merging of the investors profile and preferences with the context of the financial environment, which, to our knowledge, is rarely addressed by existing methods on portfolio construction in the literature.

The rest of the paper is organized as follows. Section two reviews and discusses the related literature. Section three describes the data set that we used for validating our approach and the different methods that we employed. We also describe how the different methods were instantiated and our knowledge engineering approach. In section four we present the PORTRAIT tool, its architecture and usage. Section five presents the PORTRAIT tool validation and obtained results. Finally, section six concludes the paper hinting on our future research directions.

2. LITERATURE REVIEW

In international literature, a series of programming approaches upon the performance of mutual funds have been proposed, but only few of them (see, e.g. Gladish et al., 2007) deal with both the portfolio evaluation and the stock selection problem.

The traditional portfolio theories (Markowitz, 1959; Sharpe, 1964) accommodate the portfolio composition problem on the basis of the existing trade-offs between the maximization of the expected return of the portfolio and the minimization of its risk (mean-variance model). On the same mean-variance basis or in other similar probabilistic measures of return and risk, several other approaches have been developed, including the Capital Asset Pricing Model-CAPM (Mossin, 1969), the Arbitrage Pricing Theory-APT (Ross, 1976), single and multi-index models, average correlation models, mixed models, utility models and models using different criteria such as the geometric mean return, stochastic dominance, safety first and skewness (see Elton and Gruber, 1995). Many of these models used in the past were based on a unidimensional nature of risk approach, and they did not capture the complexity presented in the data. This study, aims to resolve this troublesome situation using, for the first time, a technology from the artificial intelligence domain, namely argumentation-based decision making, which provides a high level of adaptability in the decisions of the portfolio manager or investor, when his environment is changing and the characteristics of the funds are multidimensional.

Overall, the use of argumentation: (a) allows for decision making using conflicting knowledge, (b) allows to definenonstatic priorities between arguments, and (c) the modularity of its representation allows for the easy incorporation of views of different experts (Amgoud and Kaci, 2005). Traditional approaches such as statistical methods need to make strict statistical hypothesis (Sharpe, 1966), multi-criteria analysis methods need significantly more effort from experts (e.g. Electre-tri,Gladish et al., 2007), and neural networks require increased computational effort and are characterized by inability to provide explanations for the results (Subramanian et al., 1993).

Regarding the funds participation strategy in the final portfolio, there is a series of empirical studies in support to the efficient markets hypothesis that past performance is no guide to future performance, even though a series of empirical studies reveal that the relative performance of equity mutual funds persists from period to period. Hendricks et al. (1993) and Gruber (1996) found evidence of performance persistence. On the other hand, Jensen (1969) and Kahn and Rudd (1995) found only slight or no evidence of performance persistence. This evidence is in accordance to our results, which showed that the success of an asset does not depend on its past performance.

Generally speaking, an investor does not invest in individual securities, instead, investors want to combine many assets into well-diversified portfolios in order to reduce the risk of their overall investment and increase their gains (see e.g. Delong et al., 1990; Shy and Stenbacka, 2003). According to our results, the more diversified a portfolio is the higher average return on investment it has. In light of this evidence, diversification represents crucial investment strategies for mutual fund managers.

3. METHODOLOGY AND DATA

3.1. Data Set and Criteria Description

The sample data used in this study is provided from the Association of Greek Institutional Investors and consists of daily data of domestic equity mutual funds (MFs) over the period January 2000 to December 2005. Daily returns for all domestic equity MFs are examined for this six-year period. Further information is derived from the Athens Stock Exchange and the Bank of Greece, regarding the return of the market portfolio and the return of the three-month Treasury bill respectively.

Based on this information, we compute five fundamental variables that measure the performance and risk of the MFs. These variables are frequently used in portfolio management (Brown and Goetzmann, 1995; Elton et al., 1993; Gallo and Swanson, 1996; Ippolito, 1989; Redman et al., 2000) and are the following:

1. the return of the funds,
2. the standard deviation of the returns,
3. the beta coefficient,
4. the Sharpe index, and,
5. theTreynor index.

Appendix A provides a brief description of these criteria. The examined funds are classified in three homogeneous groups for each one of the aforementioned variables. The three groups are defined according to the value of the examined variables for each MF. For example, we have funds with high, medium and low performance (return), funds with high, medium and low beta coefficient, etc. Thus, we have 90 groups (6 years × 3 groups × 5 variables) in total.

This classification is formally defined for the return of the funds criterion as follows. Let the set R^y be the *partially ordered set by* $\leq$ of the return on investment values of a set of funds F for a given year y. Thus, there is a function $f: F \rightarrow R^y$ that defines a one to one relation from the set of funds F to the set of values R^y. If $s \in \mathrm{N}$ is the size of R^y, then the **set of high R funds** $H^y \subset R^y$ can be defined as the last m elements of R^y, where m is defined as:

$$m = \begin{cases} [(3/10)s], (3/10)s - [(3/10)s] = 0 \\ [(3/10)s] + 1, otherwise \end{cases}.$$

Thus, H^y contains the higher 30% (rounded up) of the values in R^y, which represents the return of investment values of the 30% most profitable funds in F. *T*he **set of low R funds** $L^y \subset R^y$ is similarly defined as the first m elements of R^y. Finally, the **set of medium R funds** $M^y \subset R^y$ is defined as $M^y = (R^y \cap L^{yC}) \cap H^{yC}$, i.e. those funds that belong to R^y but not to H^y or L^y.

The classification for the other four criteria is achieved in a similar manner. The resulting thresholds, which determine the MFs grouping for all criteria are presented in Table 1. The Upper (U) threshold separates the funds in the high group with those in the medium group and the Lower (L) threshold separates the funds in the medium group with those in the low group.

Table 1: Thresholds which Determine MFs Groups

Year	*Threshold*	*Return*	*σ*	*β*	*Sharpe*	*Treynor*
2000	U	-4.23	32.80	0.96	-2.55	-0.35
	D	-36.60	27.30	0.82	-2.91	-0.41
2001	U	-20.78	27.87	0.93	-1.41	-0.16
	D	-26.09	24.82	0.84	-1.66	-0.20
2002	U	-26.25	14.97	0.82	-3.08	-0.23
	D	-31.90	13.00	0.73	-3.57	-0.26
2003	U	25.35	16.77	0.84	0.93	0.07
	D	15.73	14.90	0.73	0.41	0.04
2004	U	16.26	13.04	0.84	0.57	0.03
	D	2.46	12.29	0.75	-0.50	-0.03
2005	U	29.29	11.73	0.86	1.51	0.08
	D	25.00	10.79	0.75	1.25	0.07

3.2. The Argumentation Based Decision Making Framework

Argumentation can be abstractly defined as the principled interaction of different, potentially conflicting arguments, for the sake of arriving at a consistent conclusion. The nature of the "conclusion" can be anything, ranging from a proposition to believe, to a goal to try to achieve, to a value to try to promote.

In our work we adopt the argumentation framework proposed by Kakas and Moraitis(2003), where the deliberation of a decision making process is captured through an argumentative evaluation of arguments and counter-arguments. A theory expressing the knowledge under which decisions are taken compares alternatives and arrives at a conclusion that reflects a certain policy.

Briefly, an **argument** for a literal L in a theory ($\mathcal{T}$, $\mathcal{P}$) is any subset, T, of this theory that derives L, $T \vdash L$, under the background logic. A part of the theory $\mathcal{T}_0 \subset \mathcal{T}$, is the **background theory** that is considered as a non defeasible part (the indisputable facts).

An argument attacks (or is a counter argument to) another when they derive a contrary conclusion. These are conflicting arguments. A conflicting argument (from $\mathcal{T}$) is admissible if it counter-attacks all the arguments that attack it. It counter-attacks an argument if it takes along priority arguments (from $\mathcal{P}$) and makes itself at least as strong as the counter-argument.

In defining the decision maker's theory we specify three levels. The first level ($\mathcal{T}$) defines the (background theory) rules that refer directly to the subject domain, called the *Object-level Decision Rules*. In the second level we have the rules that define priorities over the first level rules for each *role* that the agent can assume or *context* that he can be in (including a *default context*). Finally, the third level rules define priorities over the rules of the previous level (which context is more important) but also over the rules of this level in order to define *specific contexts*, where priorities change again.

3.2.1. Experts Knowledge

For capturing the experts knowledge we consulted the literature but also the empirical results of applying the found knowledge in the Greek market. We identified two types of investors, *aggressive* and *moderate*. Further information is represented through variables that describe the general conditions of the market and the investor policy (selection of portfolios with high performance per unit of risk). The general conditions of the market are characterized through the development of funds which have high performance levels, i.e. high Return on Investment (RoI).

Regarding the market context, in a bull market, funds which give larger return in an increasing market are selected. Such are funds with high systematic (the beta coefficient) or total risk (standard deviation). On the other hand, in a bear market, funds which give lower risk and their returns are changing more smoothly than market changes (funds with low systematic and total risk) are selected.

The aim of an aggressive investor is to earn more, independently of the amount of risk that he is willing to take. Thus, an aggressive investor is placing his capital upon funds with high return levels and high systematic risk. Accordingly, a moderate investor wishes to have in his possession funds with high return levels and low or medium systematic risk.

Investors are interested not only in fund's return but also in risks that are willing to take in order to achieve these returns. In particular, the knowledge of the degree of risk incorporated in the portfolio of a mutual fund, gives to investors the opportunity to know how much higher is the return of a fund in relation to the expected one, based to its risk. Hence, some types of investors select portfolios with high performance per unit of risk. Such portfolios are characterized by high performance levels, high reward-to-variability ratio (Sharpe ratio) and high reward-to-volatility ratio (Treynor ratio). These portfolios are the ones with the best managed funds.

Thus, the main properties of our empirical problem is firstly to make decisions under complex preference policies that take into account different factors (market conditions, investor attitudes and preferences) and secondly synthesize together these different aspects that can be conflicting.

3.2.2. The Decision Maker's Argumentation Theory

In our work we needed on one hand to transform the criteria for all MFs and experts knowledge to background theory (facts) and rules of the first and second level of the argumentation framework and on the other hand to define the strategies (or specific contexts) that we would define in the third level rules.
The goal of the knowledge base is to select some MFs to participate to an investment portfolio. Therefore, our object-level rules have as their head the predicate *selectFund/1* and its negation. We write rules supporting it or its negation and use argumentation for resolving conflicts. We introduce the *hasInvestPolicy/2*, *preference/1* and *market/1* predicates for defining the different contexts and roles. For example, Kostas, an aggressive investor is expressed with the predicate *hasInvestPolicy(kostas, aggressive).*

We provide a brief summary of the strategies that we defined in order to validate the use of the argumentation framework. In the specific context of:

- *Bull market* context and *aggressive investor* role, the final portfolio is the union of the individual context and role selections
- *Bear market* context and *aggressive investor* role, the final portfolio is their union except that the aggressive investor now would accept to select high and medium risk MFs (instead of only high)
- *Bull market* context and *moderate investor* role, the moderate investor limits the selections of the bull market context to those of medium or low risk (higher priority to the moderate role)
- *Bear market* context and *moderate investor* role, the final portfolio is their union except that the moderate investor no longer selects a medium risk fund (only low is acceptable)
- *Bull market* context and *high performance per unit of risk* context, the final portfolio is the union of the individual context and role selections
- *Bear market* context and *high performance per unit of risk* context, the final portfolio is their union except that the bear market context no longer selects MFs with low or medium reward-to-variability ratio (Sharpe ratio) or with low or medium reward-to-volatility ratio (Treynor ratio)
- *Aggressive investor* role and *high performance per unit of risk* context, the final portfolio is their union except that the aggressive investor no longer selects MFs with low reward-to-variability ratio or with low reward-to-volatility ratio
- *Moderate investor* role and *high performance per unit of risk* context, the final portfolio is their union except that the moderate investor no longer selects MFs with low reward-to-variability ratio or with low reward-to-volatility ratio
- Every role and context has higher priority when combined with the general context

The knowledge base facts are the performance and risk variables values for each MF, the thresholds for each group of values for each year and the above mentioned predicates characterizing the investor and the market. The following rules are an example of the object-level rules (level 1 rules of the framework - $\mathcal{T}$):

$r_1(Fund)$: *selectFund(Fund) ← highR(Fund)*
$r_2(Fund)$: *¬selectFund(Fund) ← highB(Fund)*

The *highR* predicate denotes the classification of the MF as a high return fund and the *highB* predicate denotes the classification of the MF as a high risk fund. Thus, the r_1 rule states that a high performance fund should be selected, while the r_2 rule states that a high risk fund should not be selected. Such rules are created for the three groups of our performance and risk criteria.

Then, in the second level we assign priorities over the object level rules. The $\mathcal{P}_R$ are the *default context rules* or level 2 rules. These rules are added by experts and express their preferences in the form of priorities between the object level rules that should take place within defined contexts and roles. For example, the level 1 rules with signatures r_1 and r_2 are conflicting. In the default context the first one has priority, while a moderate investor role reverses this priority:

R_1: *h_p(r_1 (Fund), r_2 (Fund)) ← true*
R_2: *h_p(r_2 (Fund), r_1 (Fund)) ← hasInvestPolicy(Investor, moderate)*

Rule R_1 defines the priorities set for the default context (an investor selects a fund that has high RoI even if it has high risk). Rule R_2 defines the default context for the moderate investor (who is cautious and does not select a high RoI fund if it has high risk).

Finally, in $\mathcal{P}_C$ (level 3 rules) the decision maker defines his strategy and policy for integrating the different roles and contexts rules. The decision maker's strategy sets preference rules between the rules of the previous level but also between rules at this level. Relating to the level 2 priorities, the moderate investor priority of not buying a high risk MF even if it has a high return is set at higher priority than that of the general context. Then, the specific context of a moderate investor that wants high performance per unit of risk defines that in the case of both a high Treynor and high Sharpe ratio the moderate preference is inverted (in order to have a union of the individual contexts selections). See the relevant priority rules:

C_1: *h_p(R_2 (Fund), R_1 (Fund)) ← true*
C_2: *h_p(R_1 (Fund), R_2 (Fund)) ← preference(high_performance_per_unit_of_risk), hasInvestPolicy(Investor, moderate), highSharpeRatio(Fund), highTreynorRatio(Fund)*
C_3: *h_p(C_2 (Fund), C_1 (Fund)) ← true*

Thus, a moderate investor would buy a high risk fund only if it has high ratios in the Sharpe and Treynor criteria. In the latter case, the argument r_1 takes along the priority arguments R_1, C_2 and C_3 and becomes stronger (is the only admissible one) than the conflicting r_2 argument that can only take along the R_2 and C_1 priority arguments. Thus, the *selectFund(Fund)* predicate is true and the fund is inserted in the portfolio.

3.3. Forecasting the Status of the Financial Market

The algorithm that we used for forecasting combines Genetic Algorithms (GA), MultiModel Partitioning (MMP) and the Extended Kalman Filters (EKF) technologies (see Beligiannis et al., 2004). This algorithm captured our attention because it had been used in the past successfully for predicting accurately the evolution of stock values in the Greek market (this application on economic data can be found in the work of Beligiannis et al., 2004).

Table 2: Results Obtained After Applying the Presented Forecasting Algorithm in Order to Forecast the Sign of the Return of the Athens Stock Exchange Index for Each Semester.

Semester	*RASE change (%)*	*Forecasted value*
1st sem 2001	-19.112	-2.409
2nd sem 2001	-5.267	-2.989
1st sem 2002	-14.822	-0.826
2nd sem 2002	-21.206	-2.334
1st sem 2003	6.468	-3.412
2nd sem 2003	21.190	1.025
1st sem 2004	1.535	3.391
2nd sem 2004	19.219	6.656
1st sem 2005	8.357	3.067
2nd sem 2005	19.204	1.343
1st sem 2006	0.831	3.118

This algorithm forecasted the behavior of the financial market in relation to its current status. The market was characterized as *bull market* if it was forecasted to rise in the next semester, or as *bear market* if it was forecasted to fall. We used the percentage of the Return of the Athens Stock Exchange (RASE) index variation for each semester (in relation to the previous semester) starting from year 1985 to the years of our sample data (2000 to 2005), plus one (2006) for evaluating the performance of the portfolios constructed for year 2005. Our algorithm indicates a bull market if this percentage is forecasted to be positive or a bear market if it is forecasted to be negative. For achieving better results, we predicted the ASE index variation every semester, however, in the end we just used the values for the 1st semester of each year (the proposed investment period). In Spanoudakis et al. (2009) we present the instantiation of this algorithm in detail along with its integration with the argumentation framework. Table 2 shows the predicted values. The sign of the forecasted values is positive or negative, while the row with the grey background indicates the failed forecast. Note that while the algorithm generally performed very well with a success rate of 90.9 % (10 out of 11 right predictions) for the studied period, the yearly investment plan that we followed got five out of six right predictions (success rate of 83.3%).

3.4. Portfolio Funds Participation Strategies

Having selected the funds that will compose the investment portfolio, through the reasoning phase, we had the challenge of choosing the participation percentage of each one of them to the final portfolio. Therefore, we defined a weight vector $w = (w_1, w_2, ..w_N)$, where each w_i defines the proportion of the available capital invested in the selected funds. We defined four different portfolio construction strategies for computing this vector.

In the first portfolio construction strategy (or equal participation strategy) the portion of the portfolio that is allocated to the i^{th} selected fund ($i=1,...,N$, where N is the number of total funds selected by the reasoning phase) is equal, i.e.:

$$w_i = 1/N \,.$$

In the second strategy (or performance-based participation strategy), w_i is dependent on the performance of the i^{th} fund in the current year:

$$w_i = \frac{r_i^{y_0}}{\sum_{j=1}^{N} r_j^{y_0}} \,,$$

wherey_0 is the current year and r_i^y is the return on investment (RoI) value of the i^{th} selected fund for year y.

In the third strategy (or history-based participation strategy), w_i is dependent on the years where the i^{th} fund had high performance:

$$w_i = \frac{\sum_{y=y_h}^{y_0} h_i^y}{\sum_{j=1}^{N} \sum_{y=y_h}^{y_0} h_j^y} \,,$$

wherey_k is the year from which we have historical data and h_i^y is defined as:

$$h_i^y = \begin{cases} 1, r_i^y \in H^y \\ 0, otherwise \end{cases} \,.$$

In the fourth and final portfolio construction strategy (or history combined with performance-based participation strategy), w_i is defined as follows (a mix of the two previous strategies):

$$w_i = \frac{\sum_{y=y_h}^{y_0} h_i^y r_i^y}{\sum_{j=1}^{N} \sum_{y=y_h}^{y_0} h_j^y r_j^y}$$

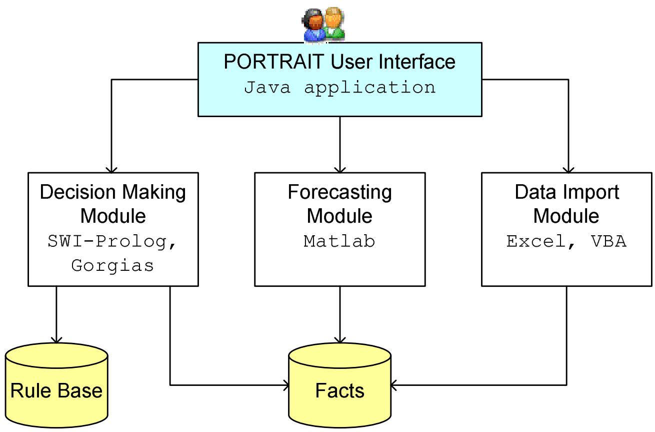
4. THE PORTRAIT TOOL

4.1. Architecture

The PORTRAIT tool is a Java program creating a human-machine interface and managing its modules, namely (see Figure 1):

- the *decision making module*, which is a prolog rule base (executed in the SWI-prolog[1] environment) using the Gorgias[2] argumentation framework,
- the *forecasting module*, which is a Matlab[3] implementation of the forecasting hybrid system,
- the*data import module*, which uses Visual Basic for Applications code in Microsoft Excel to transform the tabular data that are obtained by web sources to the logic format needed by Prolog.

Figure 1: The Portrait Tool Architecture.



[1]SWI-Prolog offers a comprehensive Free Software Prolog environment, http://www.swi-prolog.org
[2]Gorgias is an open source general argumentation framework that combines the ideas of preference reasoning and abduction, http://www.cs.ucy.ac.cy/~nkd/gorgias/
[3]MATLAB® is a high-level language and interactive environment for performing computationally intensive tasks, http://www.mathworks.com/products/matlab

The application connects to the SWI-Prolog module using the provided Java interface (JPL) that allows for inserting facts to an existing rule-base and running it for reaching goals. The goals can be captured and returned to the Java program. The forecasting module writes the results of the algorithm to the Prolog facts base along with the data import module. Thus, after the execution of the forecasting module the predicate market/1 is determined as bull or bear and inserted in the Facts.

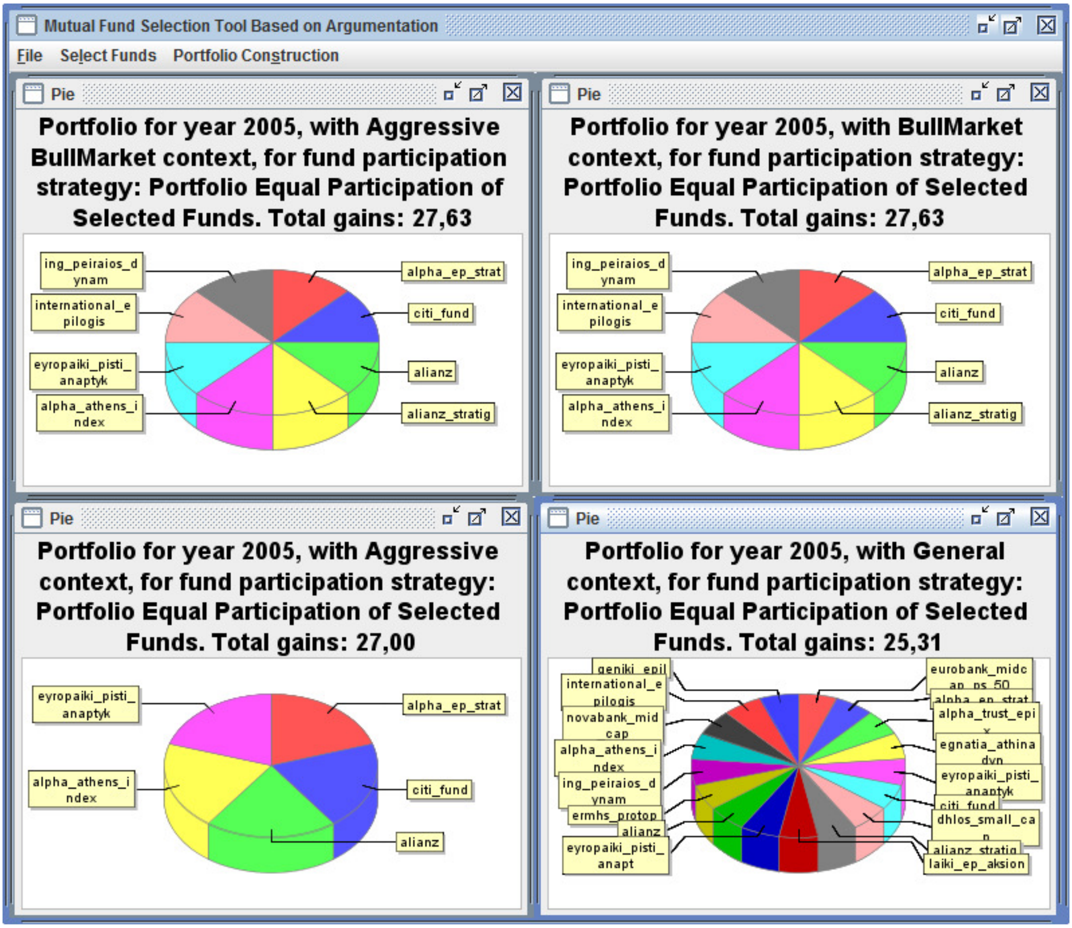
4.2. Tool Usage

The PORTRAIT user can take the following actions:

1. Select the investment period (i.e. the year of the investment)
2. The investor can select his profile that can be:
    a. Either aggressive or moderate in attitude
    b. Possibly seeking a high performance per unit of risk
    c. He might want to not use the forecasting algorithm results at all or dictate his own forecast according to his private information for the financial market (to characterize the market in the following year as bull or bear)
3. The investor chooses the portfolio construction strategy
4. The tool runs the selected scenario outputting the final portfolio

In Figure 2, a screenshot from the tool usage is presented. The user has just run four different investment scenarios for year 2005.

Figure 1: A screenshot for portfolio generation for the general context (bottom right), for the aggressive investor role (bottom left), the growing market context (top right) and the specific context of an aggressive investor in a growing market context for the equal participation strategy (all funds participate equally in the constructed portfolios) for 2005.



5. PORTRAIT VALIDATION AND RESULTS

We run our application on a "Pendium 4" computer with three GHz processor speed and one GByte of RAM. The sample data set provided 2,323 facts. On the first level, we had 140 object rules, while on the second and third level, 43 simple context and 60 specific context rules respectively. The tool performed very well as it produced results for simple contexts within 4 seconds, while for specific contexts within 17 seconds.

For evaluating our results we defined scenarios for all years for which we had available data (2000-2005) and for all combinations of contexts. That resulted to two investor roles (aggressive and moderate) combined with the market status (growing, declining or forecasted), plus these two investor roles combined with the high performance option, plus the market status combined with the high performance option, all together eleven different scenarios run for six years each, plus the simple contexts, roles and preference. Each one of the examined scenarios refers to different investment choices and leads to the selection of different number and combinations of MFs.

The evaluation of the proposed methodological framework and the obtained portfolios (in year *t*) is performed through their comparison to the return of the Athens Stock Exchange General Index (ASE-GI) and the average performance of the examined MFs (in year *t+1*). In Table 3, the reader can inspect the average return on investment (RoI), i.e. the performance of the constructed portfolios, for the six years for all different contexts and for all four different portfolio construction strategies, while in the last two rows of the table the average returns of the ASE-GI and of the examined MFs are presented. This table shows the added value of our approach. While there are roles and/or contexts that are more successful than others they are all better than the average performance of the considered MFs and most of them (14 out of 18) beat the general market index. This validates our approach as it shows that while we allow the investor to insert information relevant to his profile we can also offer high returns, always better than the average performance of the mutual funds of the Greek market. Moreover, we gain information on the Greek market.

Firstly, an investor that uses the bull market rules gains a better average return than by using our forecasting algorithm. Among the six examined years three were positive for the market index (growing or bull market) and three were negative (declining or bear market). An aggressive investor is also quite successful regardless of whether the market rises or not.

Three of the six cases where the constructed portfolios did not beat the market index are scenarios where the moderate context is involved either in simple context or specific context (3^{d}, 12^{th} and 14^{th} scenario). This is maybe due to the fact that in these contexts we have an investor who wishes to earn more without taking any amount of risk in the examined period where the market is characterized by significant variability. The simple general context also performs less than the Athens GI and shows that the successful MFs of one year are not generally successful the next year, however, they provide better performance than the average of all MFs. The remaining two cases where the portfolio returns were less than the market index involve scenarios with the high performance role (i.e. the 17^{th} and the 18^{th}). As we have already mentioned, the high performance context characterizes mutual funds with high reward-to-variability ratio and high reward-to-volatility ratio, i.e. the ones with the best managed securities. In this case the performance of a mutual fund manager is the one that is taken into account. Again, the variability of the market in the examined period makes it very difficult to implement successful investment strategies.

Additionally, there are findings that cannot be depicted in such a concentrative table as Table 3. The most important one is related with the use of argumentation and is that in some specific contexts the results are more satisfying than the results obtained by simple contexts while in others there is little or no difference. This means that using effective strategies in the third preference rules layer the decision maker can optimize the combined contexts. Specifically, in Table 4the reader can see the return of investment for each year for the aggressive role, the high performance context and the specific context of their combination when the portfolio has been constructed with the third strategy. Note that the average RoI of the combination is higher than that of the individual contexts. Moreover, note that for the year 2005 (first column) the RoI of the combination of the scenarios is higher than both scenarios. This shows that by successfully selecting the priority rules at the third level we add knowledge to the knowledge base thus we are able to provide better results. The pies in Figure 2 agree to this finding as when the growing market context and the aggressive investor role for year 2005 are merged, the best RoI choice is selected by the priority rules, thus the specific context has the return of the growing market context (i.e. 27.63%).

In Table 5, we present the return on investment for different diversities of funds participation in the constructed portfolios. Each one of the examined contexts refers to different investment choices and leads to the selection of different number and combinations of MFs. From a total of 59 constructed portfolios, the MFs which composed them ranged between three and 19. Looking at the results of this table, it is obvious that the more diversified a portfolio is, the higher average return on investment it has.

We applied the four strategies detailed in §3.4 to all portfolio construction scenarios for the years 2001 to 2005. Each of these strategies can be combined with each investment context. The investor can choose the strategy that best fits his needs. Our results show that the success of the portfolio is mainly dependent on the selected context. The best average performance, 7.03%, is gained by the first portfolio construction strategy, i.e. the equal participation of all funds in the final portfolio, while according to the second, third and fourth investment strategies, the average gains for all constructed portfolios and all contexts are 6.83%, 6.62% and 6.42% respectively. Thus, our research shows that the success of an asset does not in general depend on its past performance. Figure 3 illustrates these results.

Table 3: Average Return on Investment for Six Years

Scenario ID	*Context type*	*Context*	*RoI*
1	Simple context	General	6.43
2	Role	Aggressive	7.22
3	Role	Moderate	5.85
4	Preference	High performance	6.85
5	Simple context	Growing market	7.18
6	Simple context	Declining market	7.03
7	Simple context	Forecasted Market	6.84
8	Specific context	Aggressive role in a Growing Market	7.18
9	Specific context	Aggressive role in a Declining Market context	6.87
10	Specific context	Aggressive role in a forecasted Market context	7.07
11	Specific context	Aggressive role and High Performance seeking role	7.11
12	Specific context	Moderate role in a Growing Market	5.85
13	Specific context	Moderate role in a Declining Market	6.80
14	Specific context	Moderate role in a forecasted Market context	5.44
15	Specific context	Moderate role and High Performance seeking role	6.85
16	Specific context	Growing Market context with a High Performance seeking role	6.85
17	Specific context	Declining Market context with a High Performance seeking role	6.42
18	Specific context	Forecasted Market context with a High Performance seeking role	6.42
ASE-GI	-	-	6.75
Avg MFs	-	-	4.80

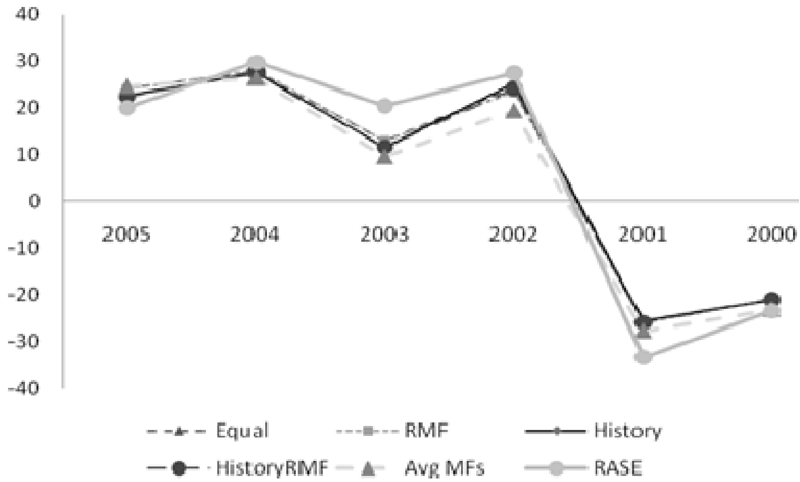
Table 4: The Roifor all Years for the third Strategy for the Specific Scenarios

	Year	*2005*	*2004*	*2003*	*2002*	*2001*	*2000*	*Avg*
Context	Aggressive	19.53	27.56	9.93	29.63	-25.33	-21.31	6.67
	High Perf.	20.73	28.33	14.12	23.79	-27.47	-21.19	6.39
	Aggressive - High Perf.	21.77	27.21	9.54	29.63	-25.33	-21.31	6.92

Table 5: Average Return on Investment for Different Funds Participation Number in the Constructed Portfolios. The Last Column Shows the Percentage of the Constructed Portfolios that Belongs to Each Category.

Number of Funds participating in portfolio	*Average RoI*	*%No*
3-8	5.22	32.20
9-15	7.06	49.15
16-19	10.34	18.64

Figure 2: Average Performance of the Portfolio Construction Strategies Compared with RASE and Average Performance of all MFS for Each Year.



6. CONCLUSIONS AND FUTURE PERSPECTIVES

This paper presented a methodology for the MF portfolio generation problem. The main result of our work is the ability of a decision maker (fund manager) to construct multi-portfolios of MFs under different, possibly conflicting contexts that can achieve higher returns than the ones achieved using simple knowledge. The proposed framework can embody in a direct way the various decision policies and knowledge (Kakas and Moraitis, 2003) and is used for the first time for this type of application.

The empirical results of our study showed that argumentation is well suited for this type of applications and showed our hypothesis "that the proposed methodological framework for the resolution of the presented financial problem" to be true. Thus, with our approach we answered to two questions: (1) which MFs are the most suitable to invest in, and (2) what portion of the available capital should be invested in each of these funds. The proposed methodology gives the opportunity to a decision maker (fund manager) to construct multi-portfolios of MFs in period *t*, that have the ability to achieve higher returns than the ones achieved from the ASE-GI in the next period, *t+1*.

The PORTRAIT tool has been validated using the data set described in this paper and is available for demonstration at the Applied Mathematics and Computers Laboratory (AMCL) of the Technical University of Crete, Greece. It is intended for use by banks, investment institutions and consultants, and the public sector.

Our future work is related to the optimization of the strategies so that all combinations add value to the decision maker. Moreover, it would be of interest to integrate this methodology with trading approaches, so that one could monitor his portfolio in real time and perform changes to the portfolio composition instantly as new information becomes available. Thus, it would be of a great interest to make our tool web-based incorporating: (a) on-line questionnaire for determining the investor role properties, (b) on-line feed from capital market, and (c) capability to determine when to update the portfolio (buy or sell) – possibly with a new knowledge base.

References

L.Amgoud and S.Kaci, An argumentation framework for merging conflicting knowledge bases: The prioritized case, Lecture Notes in Computer Science (LNCS), 3571,(2005), Springer-Verlag, 527–538.

G.N.Beligiannis, L.V .Skarlas and S.D.Likothanassis, A Generic Applied Evolutionary Hybrid Technique for Adaptive System Modeling and Information Mining, IEEE Signal Processing Magazine, special issue in Signal Processing for Mining Information,21(3),(2004), 28-38.

S.J. Brown andW.N. Goetzmann, Performance persistence,Journal of Finance,50 (1995), 679-698.

J.B. DeLong, A. Shleifer, L.H. Summers and R.J.Waldmann, Noise Trader Risk in Financial Markets,Journal of Political Economy, 98(4), (1990), 703-738.

E.J. Elton and M.J. Gruber, Modern Portfolio Theory and Investment Analysis, Fifth edition, John Wiley & Sons, New York,(1995).

E.J. Elton, M.J. Gruber, S. Das and M.Hlavka, Efficiency with costly information: A reinterpretation of evidence from managed portfolios,The Review of Financial Studies,6(1), (1993), 1-22.

J.G. Gallo and P.E. Swanson, Comparative measures of performance for U.S.-based international equity mutual funds,Journal of Banking and Finance,20,(1996), 1635-1650.

B.P. Gladish, D.F. Jones, M. Tamiz and A.B. Terol, An interactive three-stage model for mutual funds portfolio selection,OMEGA35, (2007), 75-88.

M.J. Gruber, Another puzzle: The growth in actively managed mutual funds,Journal of Finance,51, (1996), 783-810.

D. Hendricks, J. Patel and R.Zeckhauser, Hot hands in mutual funds: Short-Run Persistence of relative performance, 1974-1988,Journal of Finance,48(1), (1993), 93-130.

R.A. Ippolito, Efficiency with costly information: A study of mutual fund performance, 1965-1984,Quarterly Journal of Economics, 104,(1989), 1-23.

C.M.Jensen, Risk, the pricing of capital assets, and evaluations of investment portfolio,Journal of Business, 42,(1969), 67-247.

R.N. Kahn and A. Rudd, Does historical performance predict future performance. Financial Analysts Journal, (November-December), (1995), 43-53.

A. Kakas and P. Moraïtis Argumentation based decision making for autonomous agents, Proceedings of the second International Joint Conference on Autonomous Agents and Multi-Agent Systems (AAMAS'03), Australia, July 14-18, (2003), 883-890.

H. Markowitz, Portfolio Selection: Efficient Diversification of Investments, John Wiley, New York (1959).

J. Mossin, Optimal Multiperiod Portfolio Policies,Journal of Business,41, (1969), 215-229.

A. Redman, N. Gullett and H. Manakyan, The performance of global and international mutual funds, Journal of Financial and Strategic Decisions, 13(1), (2000), 75-85.

S. Ross,The Arbitrage Theory of Capital Asset Pricing,Journal of Economic Theory,6 (December), (1976), 341-360.

W.F. Sharpe, Capital asset prices: A theory of market equilibrium under conditions of risk,Journal of Finance,19, (1964), 425-442.

W.F. Sharpe, Mutual fund performance,Journal of Business,39, (1966), 119-138.

O. Shy, R. Stenbacka, Market structure and diversification of mutual funds,Journal of Financial Markets,6, (2003), 607-624.

N. Spanoudakis, K. Pendaraki andG. Beligiannis, Portfolio Construction Using Argumentation and Hybrid Evolutionary Forecasting Algorithms,International Journal of Hybrid Intelligent Systems,6(4), (2009), 231-243.

V. Subramanian, M.S. Hung and M.Y. Hu, An experimental evaluation of neural networks for classification,Computers and Operations Research, 20(7),(1993), 769-782.

J.L. Treynor, How to rate management of investment funds,Harvard Business Review,43, (1965), 63-75.

Appendix A

The *Return of the funds is the actual value of return of an investment.* The *fund's return* in period *t* is defined as follows: $R_{pt} = (NAV_t + DIST - NAV_{t-1}) / NAV_{t-1}$, where R_{pt} is the return of mutual fund in period *t*, NAV_t is the closing net asset value of the fund on the last trading day of the period *t*, NAV_{t-1} is the closing net asset value of the fund on the last trading day of the period *t-1*, and $DIST_t$ is the income and capital distributions (dividend of the fund) taken during period *t*.

The *standard deviation* σ is used to measure the variability of its daily returns, thus representing the total risk of the fund.The standard deviation of a MF is defined as follows: $\sigma = \sqrt{(1/T)\sum(R_{pt} - \overline{R}_{pt})^2}$, where σ is the standard deviation of MF in period *t*, $\overline{R}_{pt}$ is the average return in period *t*, and T is the number of observation (days) in the period for which the standard deviation is being calculated.

The *beta coefficient* (β) is a measure of fund's risk in relation to the capital market. The beta coefficient is defined as follows: β = cov (R_{pt}, R_{Mt}) / var (R_{Mt}), where cov (R_{pt}, R_{Mt}) is the covariance of daily return of MF with market portfolio (Athens Stock Exchange), and var (R_{Mt}) is the variance of daily return of market portfolio.

The *Sharpe index*(Sharpe, 1996) is used to measure the expected return of a fund per unit of risk, defined by the standard deviation. This measure is defined as the ratio (R_{pt}- R_{ft}) / σ, where R_{ft} is the return of the risk free portfolio expressed through the three-month treasury bill.

The *Treynor index*(Treynor, 1965) is obtained by simply substituting volatility for variability in the Sharpe index. This measure is defined as the ratio (R_{pt}- R_{ft}) / β. The evaluation of MFs with these two indices shows that a MF with higher performance per unit of risk is the best-managed fund, while a MF with lower performance per unit of risk is the worst managed fund.