A System for Efficient Portfolio Management

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Abstract. In this work we perform an automatic data survey to draw up an optimum portfolio, and to automate the one year forecast of a portfolio's payoff and risk, showing the advantages of using formally grounded models in portfolio management and adopting a strategy that ensures, a high rate of return at a minimum risk. The use of neural networks provides an interesting alternative to the statistical classifier. We can take a decision on the purchase or sale of a given asset, using a neural network to classify the process into three decisions: buy, sell or do nothing.

Key words: portfolio payoff risk neural network

1 Introduction

The decision-making process about when, how and what to invest is one of the most evocative issues in the investment world. These decisions challenge the investor's entire range of knowledge, which is always complicated, but particularly nowadays, when the exchange markets are highly volatile. Such is the case of portfolio management, which is still performed as craftwork. Selection is made according to the investor's favourite assets, or following the manager's ratings according to her experience, knowledge or intuition, but seldom based on formal grounds. This means that investors maintain inefficient portfolios that are not adjusted to the expected risk-payoff ratio.

Currently, portfolio analysis can be approached from two points of view. First, we have portfolio selection, which Harry Markowitz introduced in 1952 [9]. The second aspect is portfolio management aimed at finding the optimal structure. Today, financial market problems are often solved using artificial intelligence. Despite the great deal of effort already put into making financial time series predictions [8], support vector machines [5], neural networks [11], prediction rules [3] and genetic algorithms [1], the prediction of a stock market index is still difficult to attain. The main reason for the complexity of this task is the lack of autocorrelation of index value which changes even in a one-day period. The aim of this study is to explore once again the application of neural networks to the portfolio management problem.

According to Markowitz, the selection is grounded in the simple observation of prices that maximize the expected payoff at a given level of risk. Although the information is growing day by day, its in-depth processing is very complicated and not within easy reach of the average investor, who is usually unable to capture and interpret the data. In this work we perform an automatic data survey to draw up an optimum portfolio, to estimate the market risk and, at a given moment, to help the decision process regarding an asset. The main objectives of the system are:

1. To automate the one year forecast of a portfolio's payoff and risk, showing the advantages of using theoretically grounded models in portfolio management and adopting a strategy that ensures a high rate of return at minimum risk.
2. To make the correct decision in the purchase or sale of a given asset, using a neural network to classify the process into three decisions: buy, sell or do nothing.

1.1 Portfolio Theory

Markowitz established the aim of setting up the menu of the possible payoff-risk combinations that are eligible, giving as the decision variable the weight or ratio assigned to each asset (W). Grounded in these ideas, the process of selecting the optimum portfolio can be summarized in the following steps:

1. Specification of a body of assets and investment funds to be considered for the portfolio screening.
2. Asset analysis by means of the estimation of their expected payoffs, variances and covariances.
3. Determination of the investor's efficient frontier and indifference curves.
4. Derivation of the optimum portfolio.
5. Analysis of the Risk Evaluation (VaR) of the optimum portfolio.

These steps are briefly described in Section 2. In Section 3 a description of the system is made. Section 4 deals with the neural network training, Section 5 with the experiments and finally the conclusions of this work are shown in Section 6.

2 Portfolio Selection

Let there be an investor with a budget to be employed in the buying of assets to maximize their expected utility. The Stock Exchange will provide him or her with a lot of investment choices, as many as shares. Nevertheless, the investor must determine the share combination which, while maximizing the proposed objective, uses up the entire available budget. That is, he or she must know what assets to buy and how much to spend on each one of them. To solve this problem we take the following steps:

2.1 Asset Analysis

Following Markowitz, the first step starts with observation and experience and finishes with some specific ideas on the future behaviour of the available assets, particularly concerning the density functions of the future payoffs of the shares.

2.2 Computing the Historical Payoff

Let us see how to compute the historical payoff (R_{it}) of an asset i in a given period of time t. Let $P_{i(t-1)}$ be the price of *asset* i at the end of period *t-1*, that is, at the beginning of period t. Assuming that we buy the share at this moment, it will be the purchase price. Let d_{it} be the cash-flow obtained by the asset in period t. Finally, let P_{it} be considered as the price of the share at the end of period t or, in our case, its selling price. The payoff obtained in period t will be computed as in Eq.1:

$$R_{it} = \frac{P_{it} - P_{i(t-1)} + d_{it}}{P_{i(t-1)}} \tag{1}$$

2.3 Derivation of Efficient Border

Once the individual features of each asset are known, we study features that will comprise the portfolio. For this purpose, we will assume that we have n possible assets, each of them with its mean and variance, as representative of its payoff and risk. A portfolio is a set of assets so it will also have a payoff and variance different from those of its components. Portfolio payoff, $\mathrm{R_c}$ will be a function of the different random variables of payoff of the constituent assets and thus will itself be a random variable. Let us compute the risk. To this end, we will compute the portfolio payoff variance $\mathrm{V(R_c)}$ as a function of the assets payoff variance σ_i^2, as in Eq.2:

$$V_c = [\Sigma_{i=1}^n R_i] = \Sigma_{i=1}^n w_i^2 \sigma_i^2 + \Sigma_{i=1}^n w_i w_j \sigma_{ij} = \Sigma \Sigma_{i=1} w_i w_j \sigma_{ij} \tag{2}$$

That is, the portfolio payoff variance will depend on the covariances of the assets payoffs.

2.4 Computing the Optimum Portfolio

Once the expected values and variance (risk) of payoff are known, we must decide on the optimum portfolio to choose. We will follow the process defined in the mean-variance rule: compute the efficient portfolios and select the portfolio that maximizes the utility of the decision maker. There are several ways to compute the efficient portfolio borders. Markowitz proposes, among others, the following one, maximize $\mathrm{R_c}$, produced in Eq.3:

$$R_c = \Sigma_{i=1}^n w_i R_i. \tag{3}$$

As is apparent, the problem is approached in terms of quadratic programming where a minimum for an investment risk has to be found, with a given payoff level and no possibility of debt.

2.5 Analysis of Risk Evaluation of Optimum Portfolio

The concept of Risk Evaluation (VaR) [10] comes from the need to measure with some level of confidence the percentage of loss that a portfolio will undergo in a predefined time. This is an estimation of the maximum loss that the portfolio can have. In the system implemented, the VaR is calculated for each asset by the Normal Delta Method [12], chosen because it is considered the simplest one to estimate since it requires only the market values, the final portfolio positions and the variance-covariance matrices. To calculate VaR the steps are:

1. Identify the purchase value for each asset.
2. Check that the changes in the associated values for the asset follow a normal distribution.
3. Compute the variance and covariances for each portfolio asset.
4. Compute the portfolio variance.
5. The VaR is calculated by multiplying the portfolio variance by the corresponding factor to the confidence level (1.65 in this case)

Thus, the VaR is a useful tool in that it gives investors a more precise criterion for judgeing the work done by portfolio managers. Furthermore, it allows us to monitor and control the risks through time by verifying that the short term portfolio does not diverge from the long term objectives.

3 System Description

Based on this theoretical background, a system was developed for the automatic, efficient management of investment fund portfolios which takes into account the history over a given period, adapts to dynamic market conditions and upgrades itself via the web every fortnight. It is assumed that the investor owns an amount of money to be spent and he or she can keep the investment for a certain amount of time. With these premises, the system must suggest to the investor what assets to buy and the amount to be invested in each one to obtain a bigger payoff and a lower risk. Besides that it must indicate what is most suitable for the asset according to the daily evolution of prices and payoffs of each asset: keep, sell or buy. In summary, the aforementioned steps are implemented. These are explained herewith:

3.1 Specification of the Asset Set

The system can work with any portfolio on the stock-exchange market, so there are as many possibilities as assets. To perform the prediction computations, for each asset in the portfolio, a data base is defined with the following fields: ISIN code (fund registration), name of the asset, estimated time in portfolio (inversely dependent on risk), date of portfolio participation, value of participation, payoff, equivalent yearly rate (APR), observed volatility, market distribution and number of days to take into account.

3.2 Analysis of Assets Through Estimation of Expected Payoffs, Variances and Covariances

With the previous data the historical payoff is computed for each asset for a period of 321 days, and the following values are obtained: daily payoff (with respect to previous day), daily volatility (standard deviation), average daily payoff, daily profit or loss and VaR for each asset.

3.3 Determination of the Efficient Border

With the results obtained in the historical payoff phase, minimum variance point (MVP) is determined inside the boundary of production possibilities. To do this, the assets are initially given random weights and two restrictions are implicitly imposed:

1. The client has to spend 100 % of the available money.
2. No negative weights are allowed.

The user has the possibility to add his or her own restrictions. For the entire portfolio the MVP is computed with the Solver Excel tool. This gives us the minimum standard deviation of the portfolio (minimum risk). Later on, the portfolio average daily payoff (MRP) is calculated. This is the Sharpe Ratio simplified by considering that the risk free interest rate is 0 % (this is the case with the Goverment Bonds). Finally the MRP/MVP ratio is computed (maximum slope of the straight line) to maximize the payoff/risk ratio or, equivalently, maximum payoff at a minimum risk.

In summary, we try to find the right weights for each one of the portfolio components so that the agent can choose the best distribution. Once the payoff and risk are calculated, we select the efficient portfolio and compute the VaR.

4 Neural Network Classification

In [2] it is pointed out that the market knows everything. In consequence, we must always study it as a source of maximum available information and thus take decisions of buying or selling the stock. It is not necessary to know all this information: we must simply study the evolutions of prices that are formed. The evolutions will indicate to some degree the likely direction that the prices are going to take in the future, since the market remembers the formations of prices that have taken place throughout history and, they will probably occur again with identical consequences on most occasions.

As soon as all the combinations of the list of assets are obtained, in order to guarantee maximum profitability and the minimal risk, it would be desirable to be able to classify the state of the price in a certain period, bearing in mind its behaviour in a previous period and to be able to know if it goes down, up or keeps constant within the fixed period. It might help the investor to take a decision to buy, sell or do nothing.

With this aim, for every asset we train a perceptron neural network with a single hidden layer [6]. For our case the significant input parameters are the value of daily participation, payoff and daily payoff. With them the net is trained to learn the behaviour of the prices in a one-year period, classifying them into three classes according to their daily profitability: Class 0 (do nothing), Class 1 (sell), Class 2 (buy).

In the training phase we use 70 % of the available information and the remaining 30 % is used for the validation. The net has three input neurons, corresponding to the significant input attributes and three output neurons (classes). The number of neurons in the hidden layer is a parameter to play with to achieve a tradeoff between efficiency and speed of training. In our case, with three neurons an acceptable result is reached.

Once the architecture of the net is defined, we train it using the Weka tool [13]. To do this it is necessary to fix some parameters that takes part in the training process. These parameters always depend on the problem to be solved and after performing some simulations the learning rate is fixed at 0.3 the momentum at 0.1 and the number of training cycles is 30. After training, we perform an estimation of the results provided by the network through the test patterns, and we verify that the number of examples correctly classified depends on the fund in question, ranging between 96 % and 100 %, as we show in the results of the experiments, the error in the estimation of the classes being 0.03.

We observed that the network correctly classified the validation pattern. Once the net has been trained with the prices and final earnings, it can be consulted with any other input value in future periods, and they will be classified to help in the decision making on an asset.

5 Experiments

The data sets for performing the forecasting study of profitability and risk in a portfolio of values uses the 14 funds of different managers of the above mentioned values that were taken from the Fibanc Mediulanum Banking Group Platform All Funds [4]. The number of days to bear in mind is determined by the least amount of all the observations of each one of the 14 founds. For the particular study we used the set of assets appearing in Table 1:

Let us suppose that the investor has decided to invest 57000 Euros. The first thing to do is to randomly distribute this amount among 14 investment assets in order to calculate the profitability and the volatility of this distribution in the portfolio. Later the computations previously mentioned in point 3.3 are performed according to the fixed restrictions. The weights which maximize the portfolio of each of the considered assets are found. To obtain the results we click directly on the graph shown in Figure 1 where there appears a series of random points that calculate automatically:

1. The MVP, which is represented in Figure 1 with a continuous line and it represents the minimum risk.

2. The maximum MRP/MVP ratio (discontinuous line), maximum profitability with minimum risk.

With this information we can obtain the ideal portfolio.

Table 1. Set of assets used in the experiments

Name_Assets	Name_Assets
Franklin H.Y. ”A”	Dexia eq l aust ”C”
Dws Invest Bric Plus	Ubam Us Equi Value A
Aberdeen Asia Pac ”A”	Sch Eur Dyn Grwth A
Fortis l Eq Turk ”C”	space Newton Hig Inc
Cre Suis.Cap Jp ”H”	Ing(l)inv Eur h.d ”X”
Challenge Country Mix (S)	Challenge Financial Fund(S)
Challenge Germany Equity	Fidelity Eur S.C. ”E”

5.1 Experimental Results

Taking into account the history of observations in a fixed period for 14 assets and the previous calculations, Table 2 shows the final amount to be allocated to each asset and the time that it must remain in the portfolio to obtain a bigger payoff and lower risk.

Table 2. Final amount and time necessary for efficient portfolio

Name	Amount	Time	Payoff	Risk	%Portfolio
Franklin H.Y. ”A”	17100	10	5.67	0.122	30.00
Dws Invest Bric Plus	4	22.03	1.569	8.00	
Aberdeen Asia Pac ”A”	5 125	5	26.71	0.960	9.00
Fortis l Eq Turk ”C”	0				
Cre Suis.Cap Jp ”H”	4 000	5	8.28	1.532	7.00
Challenge Country Mix	3600	10	8.67	0.707	6.30
Challenge Germany Equity	1821	3	20.72	0.987	3.20
Dexia eq l aust ”c”	0				
Ubam Us Equi Value A	483	1	19.44	0.925	0.80
Newton Hig Inc	4842	5	27.44	0.997	8.50
Ing(l)inv eur h.d ”x”	5 059	5	17.01	0.744	8.87
Challenge Financial Fund	6 800	5	12.54	0.725	11.93
Fidelity ”E”	0				

As can be seen, the amount of Euros is very different from the one initially assigned. In Table 2 it appears beside the amount that it is necessary to invest

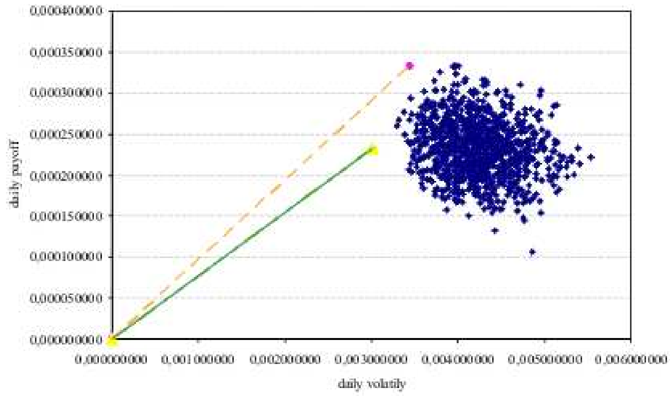

Fig. 1. The graph shows maximum profitability with minimum risk.

in each asset and the time to keep it, the APR profitability in one year that it is possible to obtain and the volatility in 321 days. The assets whose final amount is 0 Euros, are those not recommended to buy. The system also returns the estimated profitability in 321 working days, ensuing from 8 % and from 11 % in one year which means 4836.44 Euros. The VaR analysis is shown in the Table 3.

Table 3. VaR Analysis for portfolio

Profitability estimated in one year	11.00(%)
Daily VaR (in the worst case, the investor will lose)	0.44,(%)
VaR in 321 days	1.72(%)
VaR in one year	3.27(%)
Daily maximum variation assuming 95(%) of the days	251.36

For neural network classification, we performed two fundamental experiments, consistenting of training a neural network for every fund and another one with the information of all the funds in the same period used in the analysis of the portfolio. The worst results on the number of examples classified correctly were obtained by the net that included all the funds for the analyzed period, which could only correctly classify 95.24 % of the cases presented. With one different net for each fund the results range from 96.90 % corresponding to the Fidelity Fund up to 100 % of the majority, as can be seen in Table 4.

Table 4. Examples correctly classified for each asset

Name_Assets	Precision	Name_Assets	Precision
Franklin H.Y. "A"	100.00	Dexia eq l aust "c"	98.25
Dws Invest Bric Plus	100.00	Ubam Us Equi Value A	100.00
Aberdeen Asia Pac "A"	97.90	Sch Eur Dyn Grwth A	100.00
Fortis l Eq Turk "C"	100.00	Newton Hig Inc	100.00
Cre Suis.Cap Jp "H"	98.30	Ing(l)inv Eur h.d "x"	100.00
Challenge Country Mix (S)	98.60	Challenge Financial Fund	100.00
Challenge Germany Equity	97.30	Fidelity Eur S.C. "E"	96.90

The results obtained by means of neural networks were contrasted with those derived from a statistical method. Several approaches were considered based on statistical time series processing and curve adjustments. Results were poor so our conclusion was to use nonparametric approaches, like neural networks, which can learn and adapt to new conditions. The classification errors with Neural Networks were much better in all the cases.

6 Conclusions

A system was created on a formal theorical basis which automates the forecast of the profitability and risk of a portfolio of assets over a one year period, by adopting a strategy that guarantees high profitability and minimal risk for the investor, without restriction in the number and types of assets.

This model offers a methodology for the composition of efficient portfolios, becoming a basic tool for investment decision making. The financial adviser, according to the type of investor (risk adverse, average risk or risk lover), can offer a scale of portfolios with a certain yield, in view of risk level.

The system is able to suggest the asset the investor should buy and the time that it must remain in the portfolio to be profitable. As a consequence, this management is more efficient and achieves better results. Moreover the computer system makes the numerous calculations for the application of the models governing the management mentioned above, as well as the periodic upgrading of the information bases. This system can adapt itself to new trends, since it keeps training with new information, so it can therefore adapt to dynamical market conditions taking into account the good results of previous periods.

The use of neural networks provides an interesting alternative to the statistical classifier. With the results described in previous tables it is clearly shown that with the neural networks classifiers a high level of accuracy can be achieved.

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