Intelligent Tactical Asset Allocation Support System

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Introduction

This paper presents an advanced support system for Tactical Asset Allocation. Asset allocation explains over 90% of portfolio performance (Brinson, Hood and Beebower, 1988). Tactical asset allocation adjusts a strategic portfolio on the basis of short-term market outlooks. The system includes a prediction model that forecasts quarterly excess returns on the S&P500, an optimization model that adjusts a user-specified strategic portfolio on the basis of the excess return forecast, and a component to simulate and evaluate tactical asset allocation policies using historic data. Each model is based on a proven concept and implemented with state-of-the-art technology. The support system is easy to use, and simulations on nearly 20 years of market data demonstrate its added value. The quarterly adjustments recommended by the system generate an investment strategy with higher expected return and lower volatility as a buy-and-hold strategy of the strategic portfolio, while managing active risk.

The first section discusses system architecture. The next three sections discuss the subsystems. The final section summarizes the system's functionality and added value.
System Architecture

- **Functionality**
  The system combines a S&P500 forecasting support system, a portfolio optimization support system, and a policy support system. The system is useful for any investor active in more than one asset class.

- **Key characteristics**
  - advanced prediction and optimization model
  - policy support system
  - numerous graphical functions and animations for sensitivity analysis
  - customizing of built-in functions
  - configurable interface, help function
  - higher return and lower volatility in comparison to passive management

A mutual fund can use the system to beat the S&P500. An institutional investor can use the system to outperform passive management of a particular asset mix. At the same time, the system reduces risk exposure.

- **Consultation**
  The system has a very friendly user interface and offers interactive problem solving. The general format of the interface conveniently organizes all functionality, and guides the consultation. The user can configure functionality to create customized applications. Basic functionality can be very easily tailored to generate particular effects.

- **Design**
  The system's architecture basically has three components: a model base containing the models for forecasting, optimization and simulation, a database, and a dialog manager. The dialog manager provides a uniform user interface for all system functionality. The dialog manager functions as a front end by which the user can access all system functionality, and configure and save consultations at will.

  The application interface has the form of a hierarchically structured document, made up by cells. A cell can contain input, output, text, or graphics. The user can open or close cells to control the information on the screen, and insert or delete a cell anywhere. This way the user can configure the interface, and document a particular consultation by saving his work.

- **Implementation**
  The system is implemented using the Mathematica environment (Wolfram, 1991), and is available for various platforms (Microsoft Windows, Macintosh, Sun, Next). The implementation offers full interactivity and powerful graphics. Built-in functions can be conveniently adapted by specifying options to create particular effects.

  The system's graphics engine provides many options to fine tune the rendering of graphics. Among others, the user can specify plot range, color settings, view point, graphics type (3D, contour, density plots), and surface rendering.
The Forecasting Support System

- **Concept**
  The system predicts excess returns on the S&P 500 at the quarterly frequency, using a fundamental approach. Model inputs are inflation rate (cpi), change in industrial production (dip), short-term interest rate (Sir), and dividend yield (ysp). Several finance studies support the fundamental approach, see for example Chen, Roll and Ross (1986), Ferson and Harvey (1991), Pesaran and Timmernann (1994) and Solnik (1993). This approach does not contradict market efficiency, but rather exploits nonstationarity in the return generating process.

- **Model**

  - **Principles**
    The forecasting support system is built around a neural network trained to predict S&P 500 excess returns. The impact of one variable in the fundamental model depends upon the values of other variables. For example, the meaning of a high inflation rate is related to economic activity. This is another way of stating that the fundamental model is nonlinear. In addition, the functional relationship between inputs and the excess return is unknown. Neural networks are universal approximators that can approximate any input-output relation, and a neural network learns a relationship from a set of examples without a specification of the functional relationship in the data. Also, neural nets can handle arbitrary distributions and are robust, noise-tolerant estimators when distribution shapes are non-Gaussian.

  - **Performance**
    Out-of-sample test on nearly 25 years of market data proof the model's predictive power. The correlation of actual excess returns and out-of-sample forecasts is 0.29, and the error rate, the fraction of incorrect sign predictions, is 0.42 (Hemstra, 1994). At the quarterly frequency, a correlation of 0.29 more than justifies active management (Dubois, 1902). The neural network beats the alternative linear model by a significant margin.

- **Functionality**

  - **Key characteristics**
    The forecasting support system offers
    - inspection of the sample set
    - evaluation of the neural network learning
    - performance analysis
    - comparison to ordinary least squares
    - sensitivity analysis to inspect and understand predictions
Interactive Graphics Examples

Neural network learning

Training a neural net is directed at minimizing the sum of the squared errors on a training set of input-output examples collected from historic data, as a function of the weights associated with the network connections. The figure below shows the sum squared error as a function of two weights. The objective is to find the lowest point on the surface. Finding the optimal weights involves an iterative search along the surface starting at an arbitrary point. Because the search is local, it may get stuck in a local minimum. The graphic illustrates the complexity of the search.

Performance Analysis

The filled plot shows actual versus out-of-sample predictions of S&P500 excess returns (actual excess returns in black, predictions in gray or, on a color display, red). The graphic shows quarterly predictions for the period 1970-1993. Note that the model predicts negative excess returns at the three steepest downturns.
A scatter diagram further illustrates predictive power. Ideally, the scatter diagram should show a straight line at a 45 degree angle. Note that the correct bias is present.

## Sensitivity Analysis

The neural network predicts excess returns on the basis of four inputs. Sensitivity analysis reveals the character of the relationship between inputs and the excess return. 2D and 3D graphics show how the network's predictions change when inputs vary. As color plays a crucial role, black and white output can only give an impression of the actual visualization.

The density plot below shows how forecasts change when dip and cpi inputs vary between -1, 1 and 0.15, respectively. The other two inputs were fixed at their sample average. The plot illustrates significant nonlinearity.
The four 3D graphics show which combinations of macroeconomic inputs produce an excess return forecast of 0, for four increasing levels of the dividend yield. The input combinations below the surface produce a positive forecast, the points above a negative forecast.

This graphic shows a plane in the same input space, the coloring of which represents the forecast. The user can specify how to map colors on the range of excess return forecasts. In this particular graphic, light blue indicates a 0 excess return forecast, and corresponds to the surface in the graphics above.

An animation can be set up to shift or rotate the plane through the input space.
The Optimization Support System

Concept
The optimization model provides a seamless integration of strategic asset allocation and tactical asset allocation within the mean-variance framework. The model balances additional expected return generated by moving away from the strategic portfolio with the increment in active risk. Active risk is the risk of underperforming the strategic portfolio, and is measured by tracking error volatility, the volatility of the portfolio's return minus the strategic portfolio's return. The higher the increment in expected return per unit active risk, the more the selected portfolio deviates from the benchmark portfolio. The model generates the highest multiperiod expected return for the sustained level of active risk, under the constraint that the portfolio never exceeds the risk exposure of the strategic portfolio. The model considers only portfolios that in the short run dominate the strategic portfolio. A portfolio that exceeds the strategic portfolio's risk exposure is not allowed, since the objective is to add return, but not at the expense of more risk. From the set of dominant portfolios, only the portfolios that offer the highest expected return for respective levels of active risk are worth considering. These portfolios form a curve running from the strategic portfolio to the short-term efficient portfolios on the tactical path (Hiemstra, 1994). From the portfolios on the tactical path, the model selects the portfolio with the tradeoff between additional expected return and active risk that corresponds to the investor's preference as to taking active risk. Cautious investors demand a higher compensation for active risk than do aggressive investors. We refer to this methodology as tactical path optimization (TPO).

Model

Principles
Finding the portfolios on the tactical path is a hard, nonlinear optimization problem. Genetic programming (see for example Goldberg, 1989) can solve such a problem. Genetic programming is inspired by the evolution of biological systems and applies operators to a population of potential solutions. By repeatedly applying operators which mutate, combine or select potential solutions, the population converges towards a solution, producing an efficient and robust search.

Performance
To evaluate the optimization model, we compared the approach to a policy that simply selects the portfolio with the highest expected return for a particular level of active risk. An important performance criterion is probability of loss: the probability of not generating a particular threshold return over the investment horizon (Fong and Fabozzi, 1992). A Monte Carlo simulation shows that TPO produces lower probability of loss for any level of active risk than the approach that does not integrate strategic and tactical asset allocation.

The figure above shows active risk versus probability of loss. POL refers to the probability of not generating an average 2% quarterly return over a 10 year investment horizon. Active risk is measured by tracking error volatility (TEV). The quarterly return distributions were estimated on the basis of historic data. The top line shows the results obtained by selecting the portfolio with the highest expected return for a particular level of active risk, the bottom line shows the results of applying TPO. Preferences as to taking active risk determine the level of active risk.
Interactive Graphics Examples

Portfolio Analysis

This 3D graphic shows tracking error volatility as a function of portfolio weights, assuming a 70-30 bonds-stocks strategic portfolio. Bonds weights along the x-axis, stocks weights along the y-axis. The closer to the origin, the higher the cash weight.

Of any plot, the user can specify which range to plot, to zoom in on a particular segment. This graphic is a contour plot of the same information. The user can conveniently choose the preferred type of graphics (3D, contour, or density plot). Contours can be selected to represent particular function values.
Asset Allocation Optimization

This 2D graphic shows the tactical path for a particular set of mean-variance inputs. The tactical path is the curve connecting the strategic portfolio and the short-term efficient frontier. User preferences in taking active risk determine which portfolio on the tactical path to select. Note that portfolios on the short-term efficient line dominate portfolios on the tactical path. Portfolios on the tactical path are attractive in spite of being inefficient as they compensate short-term inefficiency by lower active risk. No portfolios exist with higher expected return for the respective levels of active risk.

This graphic illustrates the tradeoff among additional expected return and active risk for a particular strategic portfolio and a set of mean-variance inputs.
The Policy Support System

The policy support system evaluates the active policy recommended by the forecasting and optimization components by simulations on the basis of nearly 20 years of market data. The system offers support in specifying a particular policy and provides many alternative ways to compare policies. The policy support system demonstrates the support system's added value.

- Concept

The policy support system's objective is to compare alternative policies. Many alternative metrics may be used to compare portfolio performance, e.g. the Sharpe index, Treynor index, information ratio, probability of loss, or maximum drawdown. Other important properties are turnover and tracking error. The support system generates all this information, but the analysis focuses on policy efficient frontiers (PEF). A policy efficient frontier (Hiemstra 1994) represents the annualized ex post risk-return properties of a particular tactical investment policy for those strategic portfolios that, given the policy, produced the highest return for the respective risk exposures. A PEF differs from the regular efficient frontier in two important ways: a PEF is ex post, and a point on the PEF represents a (strategic) portfolio plus a policy, instead of just a portfolio. In addition the support system offers various statistical tests to evaluate performance.

- Model

The support system provides a flexible simulation model to simulate buy and hold, rebalance, timing and TPO policies. Parameters of timing and TPO policies are easy to specify. Calculation of the various metrics and tests is straightforward. The policy results are compared using historic quarterly market data starting at 1976. The S&P500, the Shearson Lehman Aggregate Bond Index, and 3-month T-bill rates are used to generate asset class returns.

- Functionality

The system offers:
- simulation of active policies
- inspection of portfolio behavior (weight pattern, turnover, tracking error, etc.)
- statistical tests
- performance analysis (analysis of the return distribution, PEF, various metrics)
- sensitivity analysis

- Interactive Graphics Examples

Interactive Graphics Examples

Many plots illustrate portfolio behavior in terms of asset class weights, turnover, value relative to the benchmark, tracking error, etc. This plot shows the stocks, bonds and cash weights (from top to bottom) over a particular time period fluctuate.
Performance analysis

The figure below shows three policy efficient frontiers. The policies operate on a strategic portfolio consisting of stocks and bonds, exiting the stock market when the excess return prediction is negative. The policies were tested on the period 1978-1993 (net of trading costs), the Shearson-Lehman Aggregate Bond index representing bond returns. The bottom line indicates the results of a buy-and-hold policy, a 100% bonds portfolio located at the low end, a 100% stocks portfolio located at the high end. The line in between shows the results of a tactical policy using a linear model instead of the neural network to predict excess returns. The upper line shows the results using the predictions of the neural network.

![Annual Return Graph](image)

The figure shows that active management has a dramatic payoff. For a particular risk exposure, an OLS-based policy can add easily over 100 basis points annually, and the neural network can generate a similar additional return on top of that.

The next figure shows the relative value over time of an initial investment in 1976 when the three policies operate on a strategic portfolio of 100% stocks. Buy-and-hold is the bottom line, the line above buy-and-hold represents OLS results. The top line shows the results using the neural network. The active policy based on the neural network produces an end value over 40% higher than buy and hold.

![Relative Value Graph](image)
Sensitivity analysis

2D plots can be used to combine the return patterns of various policies. The graphic below shows the return pattern of buy-and-hold and a timing policy. This graphic can be animated to visualize the effect of varying a policy parameter on the return pattern, e.g., the willingness to take active risk.

Summary

The intelligent support system implements proven concepts with state-of-the-art technology. Objective out-of-sample tests and simulations on nearly 20 years of market data point out that the system can add dozens of basis points to portfolio return (net of trading cost), while at the same time reducing risk, and managing active risk. The system combines powerful functionality with ease of use, and offers interactive problem solving.
References

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