Master MIAGE: Computer Methods Applied to Business Management

Summary of A Genetic Algorithm (GA) Approach to the Portfolio Design Based on Market Movements and Asset Valuations

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Summary :

Glossary :

- **GA** : Genetic Algorithm
- **CAPM** : Capital Asset Pricing Model
- **MPT** : Modern Portfolio Theory
- **SMT** : Security Market Line
- **E(Ri)** : Expected return of asset i
- **Rf** : Risk-free rate
- **βi** : Beta of asset i $\beta_i = \frac{Cov\,(R_i, R_m)}{Var(R_m)}$
- **E(Rm)**: Expected market return
- **E(Rm)−Rf** : Market risk premium
- **RA , RB** : Returns of assets/strategies A and B
- **d** : Excess return of A over B
- $\sum \mathbf{w_i^2 \sigma_i^2}$: Risk of each asset, adjusted by how much you invest in it (individual variance).
- $\sum\sum \mathbf{w_i w_{\square} \sigma_{i\square}}$: How assets move together (covariance between each pair).

I. Introduction:

Financial markets are inherently uncertain, influenced by a wide range of factors beyond company fundamentals, such as geopolitical events and market sentiment. Traditional approaches like statistical models and classical portfolio theory often struggle to adapt to this complexity. To improve investment decision-making, this study combines portfolio theory, risk-return analysis, and the Capital Asset Pricing Model (CAPM) with genetic algorithms. The goal is to optimize portfolio selection by identifying assets that offer the best trade-off between risk and return, including undervalued stocks with high growth potential. The proposed method was tested over a 10-year period in two distinct financial markets, demonstrating its potential to outperform conventional strategies in dynamic environments.

II. Background:

The expansion of financial markets has increased the number of available assets, making it difficult for individual investors to compete with institutional players. While machine learning has been used to predict market movements, its effectiveness is limited by volatility and external shocks (such as the COVID-19 pandemic) that cannot be predicted from historical data alone. To mitigate this, using asset valuation models and robust portfolio construction techniques helps manage uncertainty and enhance returns. In this study, risk is broadly defined as any unpredictable factor impacting price forecasts, and the strategy builds on prior research to better balance risk and return in investment decisions.

Modern portfolio theory:

Modern Portfolio Theory (MPT), introduced by Markowitz, is based on the idea that rational investors aim to maximize returns while minimizing risk. Since higher returns typically come with higher risk, not all investors will make the same choices—some tolerate more risk for potentially greater rewards, while others prefer safer, lower-return investments.

MPT suggests that instead of investing in a single asset, building a diversified portfolio can offer better results. By combining various assets, the risks of individual investments can offset each other, leading to a more stable overall return. Expected portfolio returns are calculated using the weighted average of each asset's return, while risk is assessed through statistical tools like variance and covariance.

Sharpe ratio:

William F. Sharpe created a new, simplified model that made Markowitz's mean-variance approach more practical. This model, called the diagonal model, assesses a portfolio's total risk with simple regression analysis,

$$\tilde{d} \equiv \tilde{R}_A - \tilde{R}_B$$

$$S \equiv \frac{\bar{d}}{\sigma_d}$$

avoiding time-consuming and costly calculations. Sharpe also introduced the S
harpe ratio to assess the return on invested capital per unit of risk.
The equation defines the differential return between assets and the benchmark. A high Sharpe ratio indicates better risk-adjusted performance, while negative values signify a higher return from a risk-free asset or benchmark.

Fund standardization:

Despite their foundational role in finance, Modern Portfolio Theory (MPT) and the Sharpe Ratio face criticism for computational inefficiency and modeling limitations. Chou et al. highlight that MPT's reliance on pairwise covariance calculations leads to high complexity ($O(n^2)$), making it impractical for large portfolios, while also failing to capture interactions among more than two stocks. The Sharpe Ratio, though useful for measuring risk-adjusted returns, inherits these computational drawbacks. As an alternative, Chou et al. propose Fund Standardization, a simplified method that accounts for all stock interactions and reduces computational complexity to O(1) by using basic arithmetic adjustments for fees and taxes, offering a more scalable solution for portfolio risk assessment.

$$\sigma_p^2 = \sum_{i=1}^{N} \sum_{j=1}^{N} w_i w_j \sigma_{ij}, \ where\ \sigma_{ij} = \sigma_i \sigma_j \rho_{ij}$$

III. Ensemble investment strategy using genetic algorithm :

Successful investing depends on buying low and selling high, but identifying which stocks will perform well is challenging due to the overwhelming number of market variables. Individual investors, in particular, face disadvantages in adapting to market shifts and processing vast financial data. To address this, the strategy focuses on selecting stocks that offer risk-adjusted returns by combining diversification with valuation models. While traditional analytics support this process, they are not sufficient alone. This section explains how genetic algorithms are integrated with financial theories to develop a practical, adaptive investment strategy.

Portfolio design momentum strategy:

Ever since Isaac Newton introduced inertia in his first law of motion, we've seen the continuous motion of objects in various fields. In finance, David Ricardo is credited with developing a theory of continuous motion as an investment tool. He noted that the prices of financial products tend to continue their previous actions. Investors like Jesse Livermore and Wyckoff supported this theory. A. Cowles and H. E. Jones wrote the first academic book on momentum, noting that stocks that have performed well are likely to continue to do well. N. Jegadeesh and S. Titman studied price inertia, yielding positive results in several financial markets. Momentum strategies can be beneficial in the short term and are accessible without in-depth financial analysis.

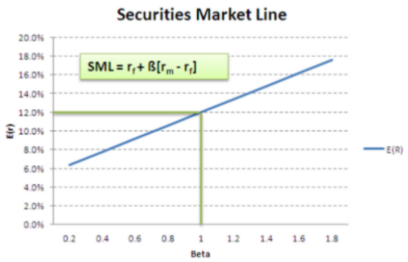
Portfolio design capm strategy:

Momentum investing has theoretical support but faces criticism for inconsistent market performance. A more reliable approach evaluates stock value using the Capital Asset Pricing Model (CAPM). CAPM links an asset's expected return to its systematic risk (Beta), measuring sensitivity to market movements.

$$E(R_i) = R_f + \beta_i(E(R_m) - R_f)$$

- $\beta = 1$: in line
- $\beta > 1$: more volatile
- $0 < \beta < 1$:less volatile
- $\beta < 0$:moves inversely

To enhance precision, Beta is calculated dynamically over rolling 3-year periods, allowing adaptable evaluation over time.



The model factors in the risk-free rate and market risk premium to estimate returns. Total risk includes diversifiable (non-systematic) and unavoidable (systematic) risks. The Security Market Line (SML) acts as a benchmark for fairness: if a stock's return is higher than expected for its risk level, it is undervalued (a good buy); if lower, it is overpriced.

Portfolio optimization genetic algorithm

The goal of the investment strategy is to allocate funds to an optimal portfolio that generates the best risk-adjusted returns. A genetic algorithm facilitates this search through an iterative process detailed below.

1. Encoding and initialization:

The goal is to build a portfolio with maximum risk-adjusted returns using undervalued stocks. Stocks from KOSPI200 and S&P500 are represented as binary chromosomes, where **1** means the stock is included and **0** excluded. An initial population of random chromosomes is generated to represent diverse portfolios, which then evolve through genetic operations over generations.

2. Fitness calculation:

The fitness function evaluates portfolios by combining return, risk, and stock valuation. An initial budget is equally divided among randomly selected stocks, considering prices, fees, and taxes. Two key metrics are computed per stock: fund standardization (investment growth) and CAPM value (based on Beta and market premium). Portfolio fitness is then measured using the Sharpe ratio and Portfolio CAPM, reflecting both profitability and risk-adjusted performance. This guides the algorithm to favor portfolios that are financially sound and profitable.

3. Genetic operations :

Genetic operations mimic natural selection to improve portfolios over time. Starting from random combinations of stocks, the algorithm uses selection, crossover, and mutation to develop better solutions. In each generation, the best-performing portfolios are prioritized, leading to an optimal investment strategy.

- **Selection** favors portfolios with higher fitness, using tournament selection to choose the best candidates for reproduction.
- **Crossover** then mixes segments from two parent portfolios to create new combinations, using a two-point method to preserve strong traits while exploring new options.
- **Mutation** introduces small random changes to maintain diversity and avoid early convergence.
- **Overlap** ensures that the best-performing portfolios are carried over to the next generation, guaranteeing steady or improved fitness over time.

IV. Experimental results :

Past AI models often failed to predict stock prices accurately due to noisy data and unforeseen events. To overcome this, the authors used a genetic algorithm to build a more reliable strategy that reduces risk. They tested its performance through CAPM validation, dynamic market analysis, and overall profitability.

Dynamic market environments

1. Market environments:

The strategy was tested on Korea's KOSPI200 and the U.S. S&P500 markets, chosen for their size, stability, and independence. Data from 2008 and 2018 (representing a financial crisis and a growth period) were used to assess the strategy's adaptability.

2. Parameters and settings:

Realistic trading fees (0.015%) and transaction taxes (0.3%) were applied. The genetic algorithm operated with a 1% mutation rate and 100% crossover rate, preserving the best portfolios each generation. Short-term historical data (1, 3, and 6 months) was used to optimize portfolios, which were then applied for investment in subsequent periods, repeating this process over time.

Ensembled effects validity test:

Two strategies were compared on KOSPI200 data: CAPM combined with momentum (CAPM) and momentum-only (NO-CAPM). The CAPM-based strategy consistently outperformed momentum-only and the stock index, especially in shorter periods (e.g., 1 month), achieving cumulative returns above 400% over 10 years. Momentum-only performed better over longer periods but struggled in downturns. CAPM's advantage lies in identifying undervalued stocks and optimizing portfolios effectively with the genetic algorithm.

Dynamic market validity test:

On the U.S. S&P500, the genetic algorithm required about 300 generations to optimize portfolios. The CAPM strategy again showed strong results, including over 400% short-term (1-month) profit, while momentum-only underperformed during downturns. CAPM consistently outperformed momentum across markets.

Self Analysis:

The CAPM strategy successfully outperformed the KOSPI 200 and S&P 500, generating over 300% gains in 11 years. It remained effective even without strong market trends. Annual evaluations showed consistent profits and reduced losses during downturns like 2008. The strategy's success relied on selecting low-risk, high-potential stocks rather than depending on overall market growth or the number of stocks.

V. Conclusion :

The study shows that using genetic algorithms with CAPM and momentum can build portfolios that balance risk and return well. While not producing extreme gains, the method outperformed simple strategies by identifying undervalued stocks with growth potential. Future work will test this approach with real-time data and refine it using more advanced financial models.