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Quant Portfolio Management System

COMP4105 Designing Intelligent Agents

## Introduction

This report documents and summarizes the what, the why and the how behind the project titled “Quant Portfolio Management System”.

The Quant Portfolio Management System comprises of intelligent agents which analyze their environment, do some data processing and modelling, and then take decisions.

The entire system is built using R programming.

Additionally, to aid ease of visualizing the evolution of our intelligent system, an R-Shiny Dashboard is developed. This dashboard runs locally displaying the resulting graphs in a systematic way. For a demo video on YouTube and more information refer to: {[Appendix E](#_Appendix_E_–)}.

GitHub Link for code :

### What is algorithmic trading?

Algorithmic trading uses an automated program/agent following some set of instructions to place a trade. These defined sets of instructions are based on timing, price, quantity, or any mathematical model. Apart from profit opportunities, algorithmic trading makes the markets more liquid and trading more systematic as it is not influenced by human emotions while trading. [[9]](#_[9]_Online_Article) [[10]](#_[10]_Research_paper)

## Background Story

Mr. Harilal, a middle-aged man from India seeks a portfolio management system to take care of his portfolio. He holds a total of 10 stocks of 15 Indian companies operating across different industries. He trades daily on the National Stock Exchange (NSE).

On his request, we put the intelligence of the Quant Portfolio Management system to test, taking control over his portfolio from 25th April 2024. The aim is to use different agents to trade portfolio over a span of 10-trading days from 26th April to 9th May 2024.

## Environment

The National Stock Exchange (NSE) is one of leading stock exchanges in India. It was incorporated in 1993 to bring transparency in the Indian Equity Markets.

Yahoo Finance offers accurate and timely data on basic stock information like price, volume, market cap, earnings, dividends, basic financial ratios, analyst ratings and news.

Web-scrapping data from Yahoo Finance allows us to acquire essential historical closing stock prices for each of the 15 companies. We scrape data from 1st Jan 2023 to 25th April 2024. This data retrieval is made easy by the *quantmod* package in R, which is empowered by Yahoo Finance API in the backend.

### Portfolio

Let’s peep into the stocks held by Mr. Harilal.

A group of logos of companies

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Figure 1: Portfolio of 15 Indian Companies

The portfolio held by Mr. Harilal spans across various industries from IT Services, Banking and Finance, FMCG, Chemicals, Energy, Insurance, Textiles, Pharmacy, Automobile, Telecommunications to Airlines. In the world of finance, it is considered good to hold a portfolio which is diversified i.e. spans across various industries.

## Structural Blueprint

Let’s look how different parts of the Quant PMS operate to make the whole.

### Overall Strcuture

|  |  |  |  |
| --- | --- | --- | --- |
|  | **Forecasting Agent** | **Portfolio Optimization Agent** | **Trading Agent** |
| **Decision Making** | What is tomorrow’s closing price? | How much money should be invested in each stock? | When to buy/sell the stocks? |
| **Modus Operandi** | Analyze historical share price and forecast using different time series strategies. | Based on forecast and historical data, determine % investment using different portfolio optimization strategies. | Analyze how stock prices behave when the market is open. Buy/sell on specified conditions being satisfied. |



Figure 2: Overall Structure

### Family Structure

The agents in Quant PMS can be viewed under a hierarchical family-like structure. Every Forecasting Agent or Forecaster has four Portfolio Optimization (PO) Agents. There are 4 Forecasters in the model, thus, we end up with 16 total agents (combinations). This can be viewed as 4 Family of agents.

Then there is one trading agent common to all four families.

A diagram of trading agent

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Figure 3: Family Structure

## Forecasting Agents

Our aim here is to predict tomorrow's closing price for each stock. For this noble task, the Quant PMS deploys a univariate time series modelling approach. There are four models spanning from naïve, statistical, machine and deep learning:

1. Seasonal Naive
2. SARIMA
3. Support Vector Machine
4. Elman Neural Network

### SNaive Forecaster

This model is a simpleton. It says that tomorrow’s price is today’s closing price. The “S” in SNaive extends the Naïve model to incorporate some underlying seasonality, if present. This model acts as a baseline for forecasting performance. In the figure below, the green arrows indicate this prediction strategy.

A graph with arrows and lines

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Figure 4: Predictions for Infosys

### SARIMA Forecaster

This is a foundational statistical model for modeling stationary time series using past values & errors of the series. The “S” in ARIMA extends it to include an element of seasonality. The book by Rob Hyndman & George A is a good resource for time series forecasting [[1]](Forecasting:#_[1]_Book_).

For training the SARIMA model, the entire dataset till 25th April is used to predict 26th April. Then we roll-forward to predict 27th April, including the actual closing price for 26th now.

### SVM Forecaster

Support Vector Machine (SVM) is a supervised Machine Learning Model able to capture underlying non-linear relationships in a time series based on lagged values. There are a few kernel options under SVM. Here we went ahead with the linear kernel. This research paper outlines the behaviors of different kernels [[2]](#_[2]_Research_paper).

The SVM model is re-trained every day by including the most recent closing price.

### Elman Forecaster

Elman is a Recurrent Neural Network which remembers the hidden state values of the time step ‘t’ to ‘t+1’. This attention mechanism allows the neural network to capture complex underlying non-linear relationships [[3]](Neural#_[3]_Book_).

To train the Elman Neural Network, a grid search [{Appendix A & B}](#_Appendix_A_–) is performed to find the most optimal number of neurons in the two hidden layers. For the first layer, we consider 2 to 25 neurons. For the second layer, we consider 2 to 10 neurons. About 216 networks are trained. The structure with the lowest test RMSE & MAPE is selected. This entire process is repeated for each of the 15 companies, for all 10 days.

### Forecasting Performance

To find the best forecaster we look at the RMSE values during our 10-day trading window.

A table with numbers and text

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Figure 5: Forecasting Accuracy MAPE

The SNaive and SARIMA forecasters have the lowest error followed by SVM & Elman.

But this does not entirely guarantee which of these agents will lead to the most successful trading outcome. The best portfolio performance will depend on the interaction between the PO and Forecaster Agents.

## Portfolio Optimization (PO) Agents

Portfolio optimization involves figuring out how much % investment should be made in each stock. This % investment is called “weights” in the realm of portfolio optimization. There are various optimization strategies using different constraints. Here we have 4 PO Agents operating on different strategies.

### Naïve PO Agent

The Naïve PO Agent is a simpleton. It simply tells us to invest equal amounts in all stocks. As a result of this, we end up “holding” i.e. not selling or buying any of the stocks for all 10 days.

### Min\_Var PO Agent

The Minimum Variance PO Agent is based on the concept of minimizing overall portfolio variance. This method was developed under the Modern Portfolio Theory by Harry Markowitz [[4]](#_[4]_Wikipedia_Markowitz).

The optimization problem requires finding optimal weights which minimize portfolio variance given by:

Subject to constraints that all the weights should sum up to 1.

### Max\_SR PO Agent

The Maximum Sharpe Ratio PO Agent is based on the concept of maximizing this ratio called “Sharpe ratio” developed by William F. Sharpe [[5]](#_[5]_Research_paper). This ratio provides a measure of excess return on portfolio over risk free investment.

Where, Rp is return on portfolio, Rf is risk-free return and is portfolio variance.

The idea here is that if we are investing in stocks (risky assets) and not in government bonds (risk free assets), we should earn a good return for taking this risk. The Max\_SR PO Agent seeks to find weights which maximize this return.

### Risk\_PP PO Agent

The Risk Parity Portfolio Agent allocates money based on the risk or volatility of each stock. The idea is to find optimal weights such that the contribution to portfolio risk is same for every individual stock [[6]](#_[6]_Research_paper).

subject to

In doing so, stocks with higher volatility end up having lower investment and vice versa.

### Optimization Approach

After we under the optimization approaches of each PO Agent, we can come down to the optimization approach.

The Quant PMS follows a Monte-Carlo simulation-based approach. Every day, 50,000 portfolios with random weights are evaluated. Alongside their expected returns, standard deviation and sharpe ratio values are also evaluated.

The optimization requires the forecasted share prices as inputs. These values are used to find optimal weights such that when markets close tomorrow, our expected return is maximized.

The Min\_Var PO Agent picks the portfolio with minimum variance, The Max\_SR Agent picks the portfolio with maximum sharpe ratio value.

The Risk parity portfolio is evaluated in R using the “*riskParityPortfolio*” package which evaluates the weights based on the annual covariance of returns on the stocks.

One notable constraint while optimization is that the total number of stocks is maintained at 150 shares. This is done to avoid scenarios where we end up having say – 12 shares of RELIANCE on a particular share.

### Efficient Frontier

Let’s represent these 50,000 portfolios and agents on a graph. We consider Annualized Risk (i.e. standard deviation) vs. Returns.

A blue and white cloud

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Figure 6: Efficient Frontier

In the plot above, we can spot the Max\_SR, Risk Parity and Min\_Var PO Agents’ chosen portfolios. There are plots showing weight distribution for each individual company for all days [{Appendix C}](#_Appendix_C_–).

## Trading Agent

After forecasting the closing price and figuring out the % investments, we can go ahead and trade when the markets open.

For this project, the trading is not implemented real-time in the real world. We operate in a simulation and evaluate “what would have happened” if the decisions of the agents were implemented.

### Tasks-at-hand

* Compare weights received from the families and see which shares must be bought and sold.
* Analyze the development of each stock’s price when the market is open and execute the buy/sell decision.
* When the market closes, the portfolio value is updated based on the actual closing price.

### When to trade?

To decide when to trade shares, the Trading Agent monitors the share price evolution in real time. If the share price increases by 2% from the opening price, we sell that share and on 2% fall we buy. Otherwise, there is no trade. This is how a stop-loss validation is implemented in the Quant PMS.

In our simulation setting, after the market closes, we look at the day’s highest price and lowest price. If the highest price is greater than equal to the selling price (2% higher than opening) then the share is deemed to be sold & vice versa.

## Evaluation

After 10 days of trading, we can evaluate the performance of our Quant Portfolio Management System. To examine what happened we look at the various metrics.

### Portfolio Value

The system evaluates the value of the portfolio every day after the market closes. In the graphs below, we can see the daily portfolio values.

A group of graphs showing different types of data

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Figure 7: Daily Portfolio Value

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Figure 8: Portfolio Value, 9th May 2024

We can see a lot of variation within each Forecaster family. This indicates that pairing up Forecasters and Optimizers is very crucial. The overall performance of the whole is not determined just by the individual forecaster or optimizer, but by their interactive and joint efforts.

Figure 7 shows the portfolio values at end of 10-days of trading. For each family we can see that the lowest portfolio value yielded by the Naïve PO Agent. Thus, investing equal amounts in each share and no trading is not a good strategy.

The portfolio value on 25th April stands at Rs. 252,000 approx. The highest portfolio value is yielded by the *Elman family with Max\_SR* PO Agent of Rs. 319,560 (26% rise) approx. Family-wise highest portfolio values are highlighted green in figure 7.

However, total portfolio value by itself is not a sufficient metric to evaluate the system. Let’s look at a very common metric, Profit/Loss.

### Unrealized Profit/Loss

Why does the heading read “unrealized” profit/loss?

This is because the profit and losses we report are indeed unrealized, meaning that Mr. Harilal will incur that profit or loss if he decides to sell all his shares at that point.

How is this calculated?

*Profit = Portfolio Value Today – Transaction Amount – Portfolio Value Yesterday.*

* Portfolio value is simply the value of all shares held when the market closes.
* Transaction amount is defined as the net additional funds spent or released due to buying/selling activity during the day.
* Suppose we sell high-worth shares and buy low-worth shares, then on the net, we end up having a cash outflow. Otherwise, Mr. Harilal must invest some extra funds. So, we remove this net transaction to evaluate the profit/loss.

A graph of different colored lines

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Figure 9: Unrealized Profit/Loss

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Figure 10: Unrealized P&L 9th May 2024

The Naïve and SARIMA families coupled with the Max SR PO Agent yield the highest profits of Rs 88,000 approx. on the 10th day of trading. The SVM & Elman families with Min Var PO agent are runner ups.

The unrealized loss-making agents only make minimal losses of about Rs 2500.

(In terms of pounds, we make a loss of 2.5 pounds on an investment of 2500 pounds).

While the SARIMA family yields the highest profit with Max SR OP agent, it also yields the highest loss with Min Var OP Agent. This might indicate that SARIMA forecaster does not sit well with the Min Var OP Agent. We will evaluate the PO Agents below.

### Buy/Sell Tendency

Here we look at the daily net transactions by each family of agents. The idea is to spot if there are agents which are buying more stocks to increase the value of the portfolio. Ideally, there should not be biased behavior towards either just buying or selling.

A screenshot of a graph

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Figure 11: Daily Net Transactions

The Naïve PO Agent, across all families, does not participate in the market. This is consistent with its strategy for investing equal amounts and holding all shares for 10 days.

The Risk Parity PO Agent’s transactions are very few because it operates on annualized covariances which vary less daily.

All agents have a similar buying/selling tendency over 10 days.

### What happened in the Market?

Since we have looked at our portfolio values, profits, and losses. We can create a backdrop to enhance our understanding by looking at how the market performed in these 10 days.

To judge the market performance, there are various indexes out there. The most famous and widely used index is NIFTY 50. This index considers the top 50 companies in the Indian market across various industries.

A graph with blue lines and red lines

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Figure 12: NIFTY50 performance.

The above graph clearly indicates that the market rose in the 1st three days and then over the last 7 days it fell. Based on this backdrop, most of our agents make minimal losses and some yield good profits even when the market is falling.

Let’s evaluate our PO Agents across all four families now. For this we look at Sharpe and Sortino Ratio.

### Sharpe Ratio Analysis

Sharpe ratio measures the excess return per unit of risk [[7]](#_[7]_Research_paper). So, if we have a SR of 0.05, it implies that for every additional unit of risk, our return goes up by 0.05 units.

A screenshot of a graph

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Figure 13: Sharpe Ratio Analysis

For Naïve PO Agent, across all forecasting families, the SR values are consistently negative indicating that this strategy underperforms the risk-free rate. Meaning, we are better off investing in risk free assets than following this strategy.

For Min Var PO Agent, the SR values have a lot of variation indicating that this agent is sensitive to the choice of forecasting agent. Here, the SARIMA forecaster has the best risk-adjusted returns.

For Max SR PO Agent, there is a similar variation. Here, the Elman forecaster performs best, which may be due to its ability to capture underlying non-linear relationships.

For Risk Parity PO Agent, the SR values are high across all forecasting families, indicating that this strategy is effectively balancing the risk across different assets and is less sensitive to forecasting errors or variability. Here, the SVM forecaster performs the best.

If Mr. Harilal is a risk adverse investor (people who don’t like risk) then the Risk Parity PO Agent becomes a suitable strategy.

### Sortino Ratio Analysis

Unlike the Sharpe Ratio, Sortino Ratio specifically focuses on downside volatility rather than total standard deviation, offering a more targeted insight into risk-adjusted performance regarding negative returns [[8]](Managing#_[8]_Book_).

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Figure 14: Sortino Ratio Analysis

For Naïve PO Agent, the ratios are consistently negative across all forecasting families. This is clearly not a good strategy.

For Min Var PO Agent, the ratios vary a lot, like the variation in Sharpe ratios indicating sensitivity to forecasting agents. The SARIMA forecaster performs well, indicating its ability to capture and predict market downswings, allowing Min Var PO Agent to adjust weights minimizing downside exposure effectively.

For Max SR PO Agent, we see a significant performance with the Elman forecaster suggesting that it might be capturing beneficial asymmetrical risk-return characteristics, possibly due to Elman’s better handling of non-linear patterns which are pertinent in calculating downside risk.

For Risk Parity PO Agent, we see exceptionally high Sortino ratios across all models, indicating that it manages downside risk robustly.

This also confirms that if Mr. Harilal is risk-averse, we lean more towards agents with Risk parity portfolio optimization.

If Mr. Harilal is risk-loving (a person who is more profit focused and less caring about risk) then we lean towards agents with higher profits like “*SARIMA + Max SR PO”*.

## Further Work

In this section, I would like to list out a few possibilities which are interesting and demand eager exploration.

* *Choice of different forecasting agents* - there are a lot of time series forecasting models ranging from statistical, machine learning to deep learning.
* *Exploration of other portfolio optimization strategies*
* *Expansion of the 10-day trading window.*
* *Data used –* Expansion of train-test data, incorporation of different financial information about the companies and the market.
* *Modeling Approach -* Exploring a multi-variate time series approach.
* *Adaptive Stop loss validation –* instead of a fixed % for all companies.

## References & Resources

[1] Book [“Forecasting: Principles and Practice”](https://otexts.com/fpp3/) by Rob J Hyndman and George Athanasopoulos.

[2] Research paper titled “[SVM kernels for Time Series Analysis](https://hdl.handle.net/10419/77140)”.

[3] Book “Neural Networks for Time Series Forecasting With R” by N.D Lewis

[4] [Wikipedia](https://en.wikipedia.org/wiki/Markowitz_model) Markowitz Model and Modern Portfolio Theory

[5] Research paper titled “[The Statistics of Sharpe Ratios](https://doi.org/10.2469/faj.v58.n4.2453)”

[6] Research paper titled "[An Introduction to Risk Parity](https://www.caia.org/sites/default/files/3-all_about_parity.pdf)”

[7] Research paper titled "[Evaluating Trading Strategies by Campbell R Harvey & Yan Liu](https://people.duke.edu/~charvey/Research/Published_Papers/P116_Evaluating_trading_strategies.pdf)”.

[8] Book “[Managing Downside Risk in Financial Markets](https://books.google.co.uk/books?hl=en&lr=&id=4X7b-gKHoPkC&oi=fnd&pg=PR7&dq=sortino+ratios+&ots=pQpaqkW_vC&sig=KVYtzgC-HKfNJHQ_eszpPeNwy-g&redir_esc=y#v=onepage&q=sortino%20ratios&f=false)”

[9] Online Article “[Basic of Algorithmic trading: Concepts and Examples](https://www.investopedia.com/articles/active-trading/101014/basics-algorithmic-trading-concepts-and-examples.asp)”

[10] Research paper titled "[Algorithmic Trading and Market Dynamics](https://www.cmegroup.com/education/files/Algo_and_HFT_Trading_0610.pdf)" by Terrence Hendershott and Ryan Riordan.

[11] Online projects acting as a source of inspiration – [Stock Market Prediction and Portfolio Optimization](https://github.com/vicdotcom/Stock-Market-Prediction-Portfolio-Optimization/tree/main). The structure of this GitHub project is very different, yet it acted as source of inspiration.

[12] Source of inspiration 2 : 2023-24 Coursework submission by Mr. Unays Angus who built a quantitative trading agent in python. This project was the initial source of inspiration for me.

## Appendix

In this section I will present some graphs to support the analysis above.

Appendix A – Elman Neural Network Grid Search

A screenshot of a computer

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Figure 15: Grid Search Results

In this snapshot we can see files named “Model Performance Elman” saved across different dates. These excel files contain results of the grid search. Each excel file stores the performance of 216 models for each of the 15 companies.

Appendix B – Forecasted Closing Price Excels

A screenshot of a computer

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Figure 16: Forecast Results

In this snapshot we see the forecast & ROI values stored for different dates.

Appendix C – Portfolio Optimization files

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Figure 17: Portfolio Optimization results.

In this snapshot we see the files stored while the portfolio optimization agents operate. The graph shows the % investment determined for 9th May by Elman + Min Var PO agent as an example. Similar files are created for each forecasting family for all 10 days.

Appendix D – How to run the system?

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Figure 18: R scripts.

There are 4 scripts for each forecasting agent. Here we take the example of Elman forecaster. We mainly run the “run\_elman” R script.

The “Forecaster Elman” R script deals with forecasting the next day’s closing price. The “Portfolio Optimization Elman” R script deals with portfolio optimization agents. The “Trade & Evaluator Elman” acts as the trading agent and helps evaluate performance as well.

The “run\_elman” R script runs the entire Elman family of agents over 10 trading days. To run for any specific day, the “*pred\_dates”* variable must include that specific date.

Similar is the structure for remaining forecaster families.

Appendix E – R Shiny Dashboard

To aid visualization of results and market behavior, an R shiny Dashboard is developed. There are 3 sections – first showing the results of the PO Agents and overall portfolio metrics. The second section shows the results of the train-test train for forecasting agents. The third section shows the historical share price of respective companies along with market performance.

The dashboard is user-interactive in nature, along with every graph made using plotly.

Demo video link : <https://youtu.be/gw_2zPcNdtQ>