IP Assignment 3: Machine Learning for Portfolio Construction

Riya Shyam Huddar
Roll Number: MDS202431

1 Introduction

This assignment explores the use of machine learning as a tool to enhance return estimation and assess whether it leads to improved portfolio outcomes in practice.

Lagged returns and rolling statistical features are used to predict average future returns, which are then incorporated into a mean-variance optimization pipeline. The resulting ML-based portfolio is compared against a traditional Markowitz portfolio and simple baseline strategies to evaluate whether machine learning adds meaningful value beyond standard portfolio construction methods.

1.1 Dataset

The dataset consists of daily closing prices for multiple stocks, stored as individual CSV files and merged into a single panel dataset. After basic cleaning and date alignment, closing prices are arranged into a date-symbol matrix. Due to differing listing dates across stocks, two universes are considered: a full universe with complete data availability and an extended-history universe that removes a small number of stocks with extensive missing values. Daily returns are computed as percentage changes in closing prices and used for all subsequent analysis.

2 ML-Based Return or Risk Estimation

Next-period stock returns are modeled using a supervised regression framework. The target variable is the one-day-ahead return, while input features consist of 1-day, 2-day, and 5-day lagged returns, a 5-day rolling mean return, and a 10-day rolling volatility, all computed using information available up to time t.

A linear regression model is trained using a time-based split, with data prior to January 1, 2019 used for training and data from January 1, 2019 onward used for testing. Two data universes are considered: a full universe with complete data availability and an extended-history universe that excludes stocks with extensive missing values.

On the test set, the model achieves a mean squared error of 7.07×10^{-4} for the full universe and 7.77×10^{-4} for the extended-history universe. While these values are small in absolute magnitude, daily asset returns exhibit low variance, and a naive baseline predicting zero returns would achieve comparable error. This indicates that the linear model provides limited incremental predictive power, and its primary role is to generate structured expected return inputs for portfolio construction.

3 Portfolio Construction Using ML Outputs

ML-predicted expected returns are annualized and combined with an annualized sample covariance matrix estimated using in-sample (training-period) returns only. The covariance matrix is treated as fixed during the out-of-sample evaluation period. Portfolio weights are obtained by solving a variance- constrained Markowitz optimization problem with full investment and no short- selling constraints. Portfolios are constructed at the first test-date rebalance (January 1, 2019) and evaluated out-of-sample.

Performance is compared against a classic Markowitz portfolio based on historical mean returns and an equal-weight baseline. Results are reported across multiple risk targets to assess sensitivity to the risk constraint.

3.1 Out-of-Sample Performance

Table 1: Out-of-Sample Performance: Full Universe

Risk Target	Portfolio	Return (%)	Volatility (%)	Sharpe
0.12	ML Markowitz	10.16	19.36	0.53
0.12	Classic Markowitz	13.49	20.02	0.67
0.12	Equal Weight	15.06	24.33	0.62
0.15	ML Markowitz	3.16	23.08	0.14
0.15	Classic Markowitz	11.41	26.35	0.43
0.15	Equal Weight	15.06	24.33	0.62
0.20	ML Markowitz	-6.13	28.70	-0.21
0.20	Classic Markowitz	5.75	37.73	0.15
0.20	Equal Weight	15.06	24.33	0.62

Table 2: Out-of-Sample Performance: Extended Universe

Risk Target	Portfolio	Return (%)	Volatility (%)	Sharpe
0.17	ML Markowitz	14.18	21.91	0.65
0.17	Classic Markowitz	16.24	21.94	0.74
0.17	Equal Weight	14.39	25.22	0.57
0.20	ML Markowitz	8.90	26.48	0.34
0.20	Classic Markowitz	14.99	26.20	0.57
0.20	Equal Weight	14.39	25.22	0.57
0.25	ML Markowitz	2.58	32.62	0.08
0.25	Classic Markowitz	15.92	31.74	0.50
0.25	Equal Weight	14.39	25.22	0.57

3.2 Portfolio Concentration

Table 3: Portfolio Concentration and Top Holdings (Full Universe)

Risk Target	Portfolio	N_{eff}	Top Holdings (Weights)
0.12	ML Markowitz	13.71	COALINDIA (0.12), NESTLEIND (0.11), HEROMOTOCO (0.10), HINDUNILVR (0.09)
0.12	Classic Markowitz	13.44	NESTLEIND (0.13), HINDUNILVR (0.12), POWERGRID (0.11), DRREDDY (0.07)
0.15	ML Markowitz	6.03	COALINDIA (0.27), HEROMOTOCO (0.24), BAJAJ-AUTO (0.11), TCS (0.09)
0.15	Classic Markowitz	7.53	HINDUNILVR (0.21), EICHERMOT (0.17), BAJAJFINSV (0.13), SHREECEM (0.13)
0.20	ML Markowitz	2.34	HEROMOTOCO (0.47), COALINDIA (0.45), BAJAJ-AUTO (0.06)
0.20	Classic Markowitz	4.07	EICHERMOT (0.38), BAJAJFINSV (0.26), BRITANNIA (0.14), BAJFINANCE (0.09)

Table 4: Portfolio Concentration and Top Holdings (Extended Universe)

Risk Target	Portfolio	N_{eff}	Top Holdings (Weights)
0.17	ML Markowitz	8.48	HEROMOTOCO (0.24), BRITANNIA (0.12), DRREDDY (0.12), HINDUNILVR (0.11)
0.17	Classic Markowitz	11.02	HINDUNILVR (0.13), BRITANNIA (0.13), SHREECEM (0.12), HEROMOTOCO (0.11)
0.20	ML Markowitz	3.77	HEROMOTOCO (0.47), DRREDDY (0.11), BRITANNIA (0.11), BPCL (0.09)
0.20	Classic Markowitz	7.45	SHREECEM (0.24), EICHERMOT (0.14), BRITANNIA (0.11), HINDUNILVR (0.11)
0.25	ML Markowitz	1.79	HEROMOTOCO (0.73), BPCL (0.10), EICHERMOT (0.09), BRITANNIA (0.04)
0.25	Classic Markowitz	4.23	SHREECEM (0.37), EICHERMOT (0.22), BAJFINANCE (0.18), TITAN (0.11)

As the risk constraint is relaxed, both optimization-based portfolios become increasingly concentrated. This effect is substantially stronger for the ML-based portfolios, where small differences in predicted expected returns are amplified by the optimizer, leading to extreme concentration and deteriorating out-of-sample performance at higher risk targets.

4 Pattern Discovery in the Same Dataset

Time-series patterns are analyzed independently of machine learning using aggregate market returns, computed as the cross-sectional mean of individual asset returns. Autocorrelation analysis shows a small positive correlation at lag 1 , which decays rapidly. This indicates very weak short-term linear dependence in daily returns.

Consistent with this result, rolling averages of market returns over 20-day and 100-day windows remain close to zero throughout most of the sample period, despite substantial day-to-day volatility. Deviations in short-horizon averages are short-lived and reverse quickly, suggesting limited and unstable mean predictability.

In contrast, rolling volatility displays strong persistence and clustering. Using a 30-day rolling annualized volatility measure, several high-volatility episodes are clearly visible. Periods in which volatility exceeds the 75th percentile correspond to major stress events, most notably during the 2008–2009 financial crisis and the 2020 COVID-19 shock. These episodes coincide with large drawdowns, characterized by rapid losses followed by prolonged recovery phases.

5 Critical Reflection: Where ML Helps vs Hurts

Machine learning was helpful as a structured way to test whether daily stock returns are predictable using historical price-based features. It also helped illustrate how sensitive mean-variance portfolio optimization is to small changes in expected return estimates.

However, at the daily frequency, return predictability was weak and ML-based expected returns were noisy out of sample. When used directly in Markowitz optimization, this noise was amplified, leading to highly concentrated portfolios and reduced diversification, especially at higher risk targets.

Overall, ML-based portfolios did not outperform equal-weight or classic Markowitz benchmarks and were less robust during periods of market stress. The main value of ML in this setting was diagnostic and interpretive rather than performance-enhancing, suggesting that ML may be better suited for modeling risk or regimes rather than short-horizon returns.