[IEDA4500] Robo-Advisor App with Sentiment Analysis

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Table of Contents

1. Background and Introduction

1.1 Background

This study explores the design and performance of robo-advisory systems through the development of an interactive robo-advisor application. The first part focuses on implementing a Markowitz-based Mean-Variance Optimization (MVO) strategy and examining how various parameters, user assessments, and feature selections influence investment outcomes. In the second part, the study investigates the use of sentiment as a predictive feature for short- to medium-term price movement. The goal is to understand how predictive signals can be incorporated into the robo-advisory framework to enhance portfolio decision-making.

1.2 Motivation for Robo-Advisory Solutions

Cost Efficiency

Traditional financial advisory services often come with high fees, making them accessible primarily to high-net-worth individuals. Robo-advisory platforms provide a more affordable, on-demand alternative that democratizes access to investment guidance.

Reduction of Behavioral Biases

As discussed in the course lectures, individual investors commonly exhibit behavioral biases such as:

(i) the disposition effect—selling winners too early,

(ii) trend chasing—buying based on recent upward movements, and

(iii) the rank effect—overweighting top-ranked assets.

Robo-advisors apply systematic, rules-based strategies that help reduce the impact of these biases.

Improved Portfolio Diversification

Empirical findings suggest that robo-advising improves portfolio diversification. Investors holding fewer than ten stocks before adopting robo-advisory tools typically increase their holdings and experience significantly reduced volatility. Meanwhile, those already holding ten or more stocks may reduce their positions slightly, also achieving a modest decrease in volatility.

2. Robo-Advisor Design and Implementation

2.1 Markowitz Mean-Variance Optimization (MVO)

Markowitz Mean-Variance Optimization (MVO) forms the core investment logic of the robo-advisor. This approach seeks to maximize an investor's utility by balancing expected returns against risk, represented as variance. The utility function used is concave and non-decreasing, aligning with traditional economic assumptions of diminishing marginal utility. A lookback period of 100 days is adopted to support a time-consistent optimal investment strategy.

Maximizing Utility Function

Maximize	$\omega \cdot \mu - \frac{\gamma^2}{2}\sigma^2$	
Subject To	$\omega_i \geq \theta_s$	**Short Threshold**
	$\omega_i \leq \theta_l$	**Long Threshold**
	$\sum_i \omega_i \geq \kappa$	**Long-Short Threshold**
	$\sum_i \lvert\omega_i\rvert \leq \lambda$	**Leverage**
	$\sqrt{\sigma^2} \leq \rho$	**Risk Level**
	$\frac{\lvert w_T - w_t \rvert}{2} \leq \phi$	**Turnover**

Conventional Investment Wisdom

This utility framework aligns well with widely accepted investment principles:

Conventional Investment Wisdom	Parameters
Longer investment horizons generally justify higher allocation to risky assets	Leverage
Avoid short-selling indices with long-term expected returns above the risk-free rate	Short Threshold, Long-Short Threshold

2.2 Backtesting Framework

To evaluate the effectiveness of parameter settings, a simulation spanning April 2022 to April 2024 was conducted. The simulation explores a wide range of parameter configurations with the following definitions and candidate values:

Variable	Parameter	Possible Values
τ	Rebalance Period	3, 5, 10, 21, 30
γ	Gamma (risk preference)	0.5, 1, 1.5, 2.0, 2.5
θ_{short}	Short Threshold	-0.2, -0.15, -0.1, -0.0, 0

θ_{long}	Long Threshold	0.05, 0.1, 0.15, 0.2, 0.25
κ	Long-Short Ratio	1, 0.9, 0.8, 0.7, 0.6
λ	Leverage	0.8, 0.9, 1, 1.1, 1.2
ρ	Risk Level	0.01, 0.03, 0.05, 0.1, 0.15
ϕ	Turnover	0.05, 0.1, 0.15, 0.2, 0.25

Out of 390,625 total combinations, 5,000 were sampled for efficiency.

Figure 1. Best Performance in the 5,000 Sampled Portfolios

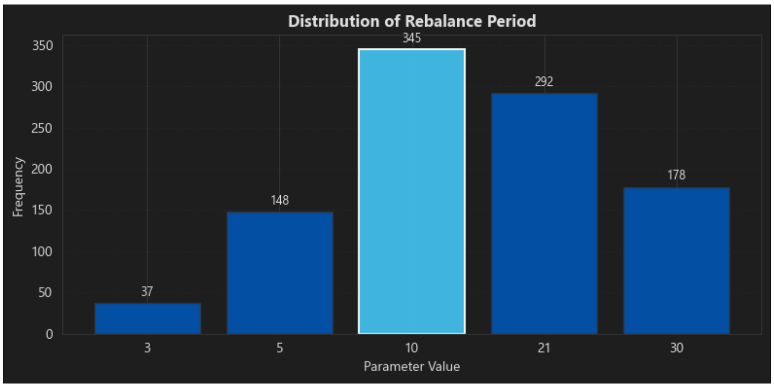
Figure 2. Top 100 Performers in Terms of Sharpe Ratio

Results show that robo-advised portfolios generally outperform traditional benchmarks such as the S&P 500 and Equal-Weighted Portfolio, especially over long-term investment horizons.

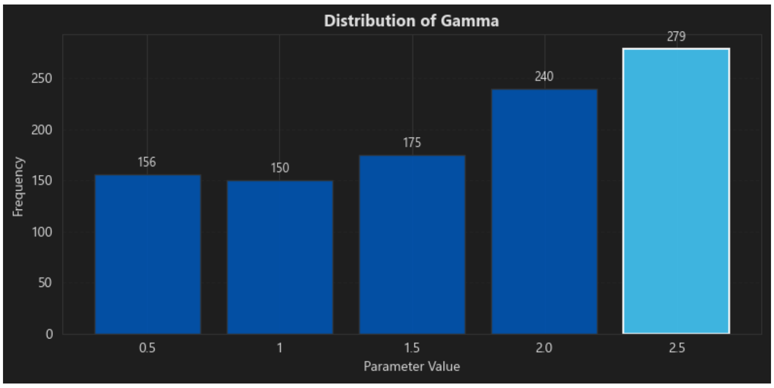
2.3 Parameter Tuning

To understand which parameter values consistently lead to strong performance, distributions were visualized from the top 1,000 simulated portfolios.

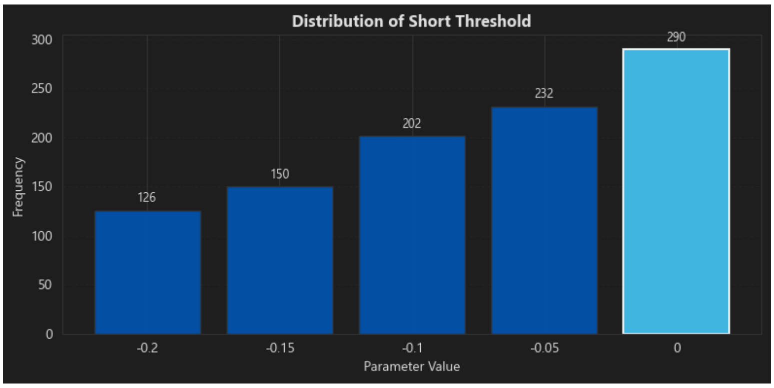
Figure 3. Distribution of Parameters from Top 1,000 Performers



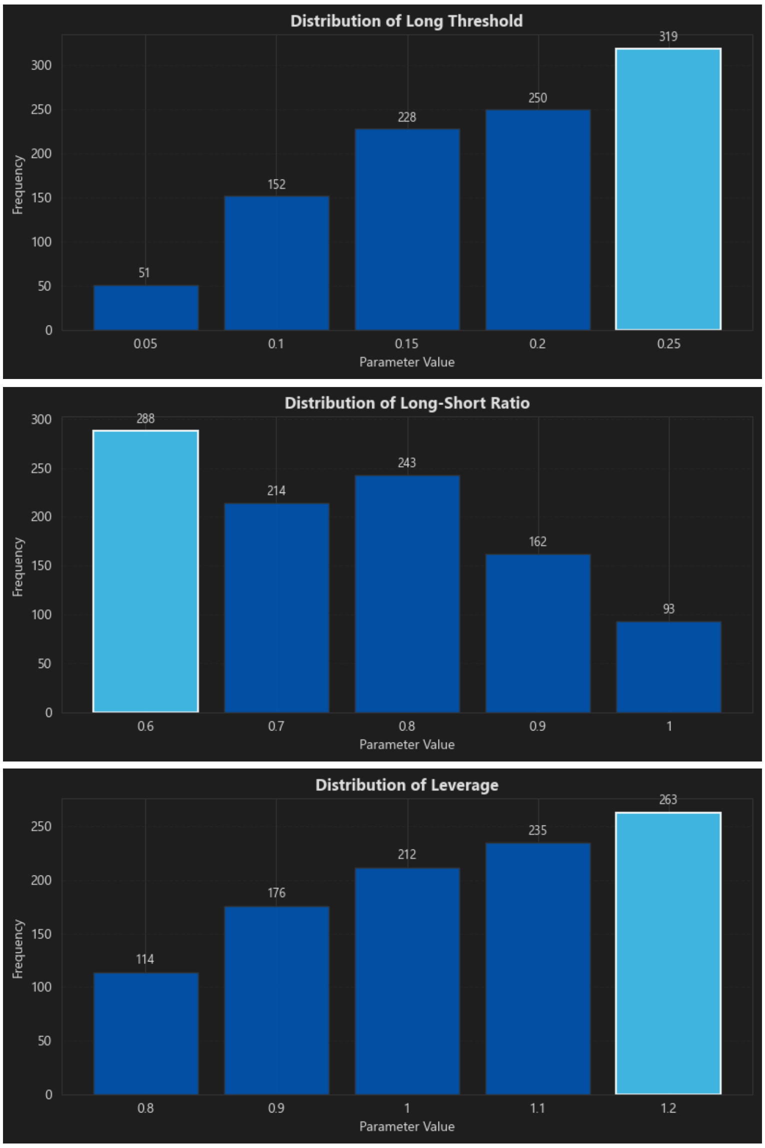
Mid-to-long rebalance periods are generally favorable



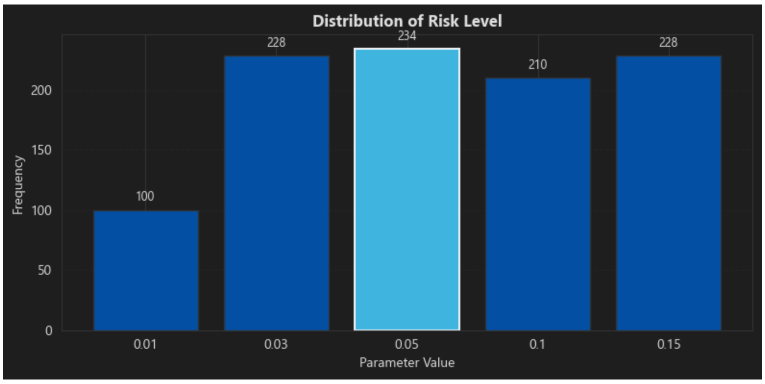
Investors who are more return-seeking benefit from higher γ (risk appetite)



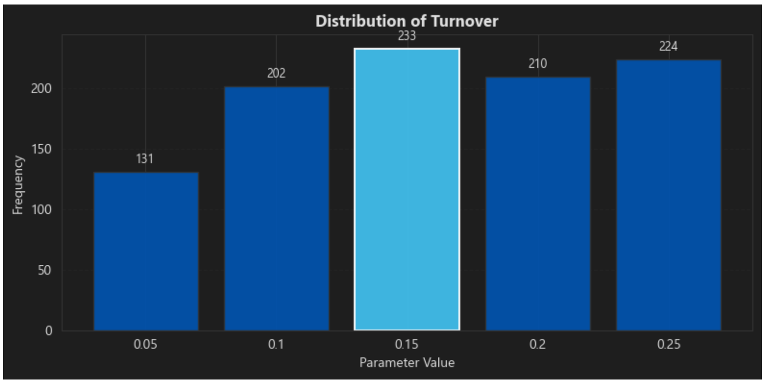
Excessive shorting reduces portfolio robustness



Higher leverage and long weights can contribute positively if properly constrained



Risk level (ρ) and gamma (γ) interact; balancing both is key



Allowing higher turnover enhances flexibility in portfolio response

These patterns align with conventional investment intuition. However, simply selecting the most frequent parameter values does not guarantee optimal performance due to interdependencies among parameters.

2.4 User Behavior Simulation and Assessment

To bridge the gap between technical parameters and user understanding, a questionnaire was designed to derive suitable portfolio settings from user-friendly inputs. The assessment covers:

- Personal Investment Goals
- Risk Tolerance
- Financial Situation
- Investment Preferences

Each option maps to parameter values using a structured framework:

Parameter Index Table

Parameter/Index	0	1	2	3	4
Rebalance Period	3	5	10	21	30
Gamma	0.5	1	1.5	2.0	2.5
Short Threshold	-0.2	-0.15	-0.1	-0.05	0
Long Threshold	0.05	0.1	0.15	0.2	0.25
Long-Short Ratio	1	0.9	0.8	0.7	0.6
Leverage	0.8	0.9	1	1.1	1.2
Risk Level	0.01	0.03	0.05	0.1	0.15
Turnover	0.05	0.1	0.15	0.2	0.25

Portfolio Assessment & Decision Tables

Mappings for each question (e.g., investment goal, time horizon, income level) are provided through decision tables. Parameter adjustments are incremented or decremented based on index logic, allowing dynamic customization.

Personal Investment Goals

1. Investment Goal

Options/Parameters	Short Threshold	Long Threshold	Leverage	Gamma	Risk Level
Growth	4 (0)	3 (0.2)	3 (1.1)	2 (1.5)	3 (0.1)
Income	4 (0)	1 (0.1)	1 (0.9)	3 (2)	1 (0.03)
Capital Preservation	4 (0)	0 (0.05)	0 (0.8)	4 (2.5)	0 (0.01)
Balanced Growth & Income	4 (0)	2 (0.15)	2 (1)	3 (1.5)	2 (0.05)

2. Investment Time Horizon

Options/Parameters	Rebalance Period	Long-Short Ratio	Turnover
A few months to 1 year	0 (3)	2 (0.8)	3 (0.2)
2 to 3 years	1 (5)	2 (0.8)	3 (0.2)
4 to 5 years	2 (10)	2 (0.8)	2 (0.15)
Over 5 years	3 (21)	0 (1)	1 (0.1)

Risk Tolerance

3. Risk Tolerance Level

Options/Parameters	Gamma	Risk Level
Very Low	[i] -> [i+1]	[i] -> [i-1]
Low		
Moderate		
High		
Very High	[i] -> [i-1]	[i] -> [i+1]

4. Market Reaction

Options/Parameters	Gamma	Risk Level	Turnover
Sell everything	[i] -> [i+1]	[i] -> [i-1]	[i] ->[i+1]
Sell some			
Hold			
Buy more	[i] -> [i-1]	[i] -> [i+1]	[i] ->[i+1]

Financial Situation

5. Annual Income

Options/Parameters	Short Threshold	Leverage
Under $50,000		[i] -> [i-1]
50 to 100k		
100 to 200k	[i] -> [i-1]	
Over $200,000	[i] -> [i-1]	[i] -> [i+1]

6. Liquid Assets Available for Investment

Options/Parameters	Long Threshold	Leverage	Turnover
Under $50,000		max([i] -> [i-1], 1)	

$50,000 - $100,000			
$100,000 - $200,000	min([i] -> [i+1], 3)	[i] -> [i+1]	max([i] -> [i-1], 2)
Over $200,000	[i] -> [i+2]	[i] -> [i+1]	max([i] -> [i-2], 1)

Investment Preferences

7. Target Annual Return

Options/Parameters	Gamma	Risk Level
4%	[i] -> [i+2]	[i] -> [i-2]
6%		
10%	max([i] -> [i-1], 1)	min([i] -> [i+1], 3)
12%	[i] -> [i-2]	[i] -> [i+2]

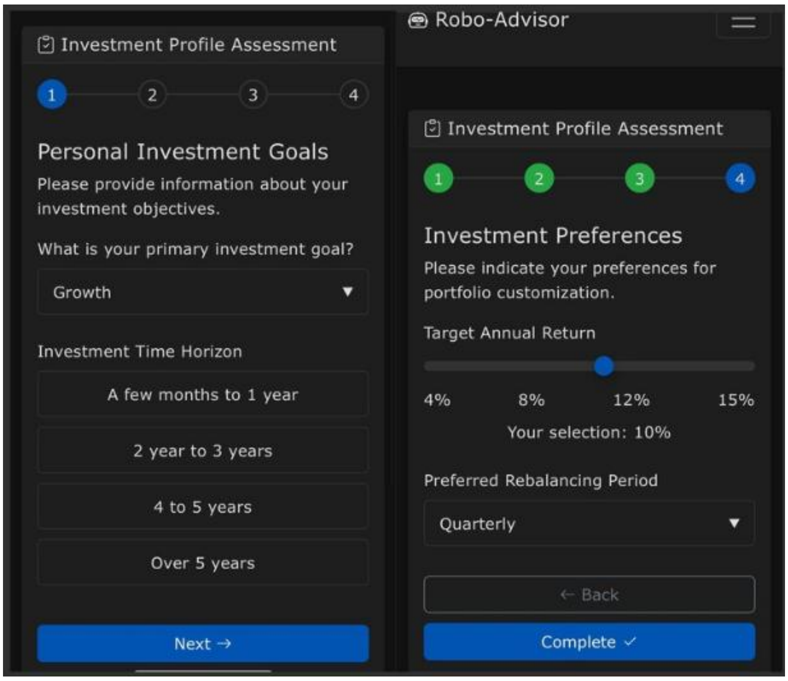
8. Preferred Rebalancing Period

Options/Parameters	Rebalance Period	Turnover
Monthly	[i] -> [i-1]	[i] -> [i+1]
Quarterly		
Bi-annually	[i] -> [i+1]	
Annually	[i] -> [i+2]	

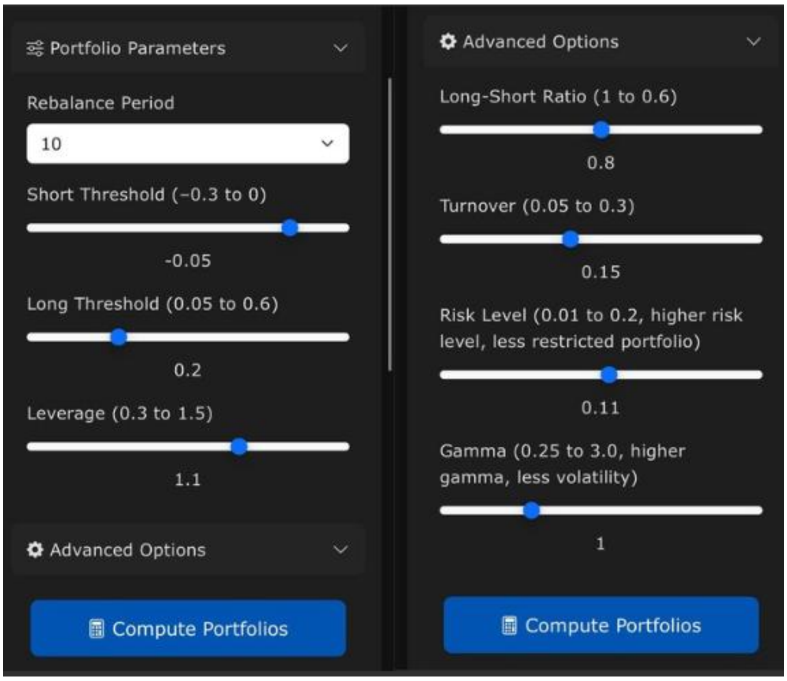
Users may further refine parameters under "Portfolio Parameters" and "Advanced Options" sections after the initial assessment.

2.4 Application Demonstration

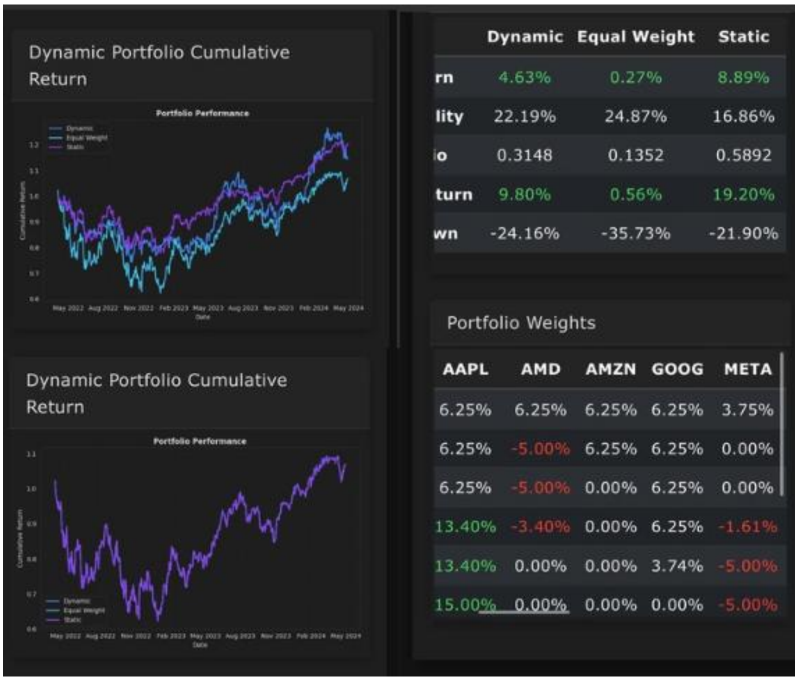
Figure 4. App Prototype Demonstration



New users complete the questionnaire to initialize technical parameters.



Users can fine-tune settings based on their investment insights.



Portfolio performance is visualized over rebalance periods.

User engagement during the class trial was positive, highlighting the app's feasibility. However, further research is needed to quantify how assessment design, parameter translation, and performance outcomes interact.

3. Integrating Sentiment for Price Prediction

3.1 Objective and Methodology

On top of the robo-advisor application, sentiment-based features are introduced to support active investment strategies. Traditional investment strategies typically favor longer rebalancing periods (e.g., 20 days), but many retail investors prefer shorter-term trading. Sentiment analysis, especially from social media, can complement short-to-medium-term trading decisions.

In this section, we explore the potential to improve portfolio performance by using sentiment to predict short-term price movements. The investment strategy is then adjusted accordingly based on these predictions.

To establish a performance baseline, we reuse the previously implemented Mean-Variance Optimization (MVO) strategy with fixed technical parameters. In parallel, we collect stock-related tweets from a Kaggle dataset and extract sentiment scores using the *SentimentIntensityAnalyzer* from NLTK. Daily predictions are made within each rebalancing period, and a majority vote determines the final signal (up/down) for that period.

3.2 Feature Engineering and Model Evaluation

Two feature sets are constructed to evaluate predictive performance:

- **Feature Set 1** includes basic stock attributes such as open, close, and volume, along with sentiment scores, log returns, and 7-day and 14-day moving averages.
- **Feature Set 2** extends Set 1 by including technical indicators: Moving Average Convergence Divergence (MACD), 14-day standard deviation, upper/lower Bollinger bands, and log momentum.

We evaluate several classification models, including Logistic Regression (LR), Random Forest (RF), AdaBoost (AB), and their PCA-augmented versions.

	LR	RF	AB	LR_PCA	RF_PCA	AB_PCA	LR	RF	AB	LR_PCA	RF_PCA	AB_PCA
AAPL	0.391304	0.565217	0.521739	0.391304	0.608696	0.608696	0.391304	0.608696	0.608696	0.391304	0.391304	0.608696
AMD	0.565217	0.217391	0.217391	0.782609	0.217391	0.782609	0.565217	0.217391	0.347826	0.782609	0.782609	0.782609
AMZN	0.391304	0.565217	0.608696	0.521739	0.521739	0.521739	0.391304	0.608696	0.695652	0.521739	0.521739	0.521739
GOOG	0.608696	0.347826	0.304348	0.652174	0.652174	0.347826	0.608696	0.347826	0.347826	0.652174	0.565217	0.565217
META	0.565217	0.434783	0.347826	0.565217	0.565217	0.565217	0.565217	0.434783	0.434783	0.565217	0.565217	0.565217
MSFT	0.478261	0.391304	0.347826	0.391304	0.391304	0.391304	0.478261	0.478261	0.521739	0.391304	0.391304	0.391304
NIO	0.434783	0.521739	0.739130	0.521739	0.521739	0.521739	0.434783	0.652174	0.608696	0.521739	0.521739	0.521739
PG	0.391304	0.478261	0.434783	0.391304	0.608696	0.608696	0.391304	0.434783	0.478261	0.391304	0.608696	0.608696
TSLA	0.608696	0.478261	0.521739	0.478261	0.478261	0.478261	0.608696	0.478261	0.608696	0.478261	0.521739	0.478261
TSM	0.565217	0.608696	0.434783	0.304348	0.304348	0.695652	0.565217	0.478261	0.391304	0.304348	0.304348	0.304348
Model Mean	0.500000	0.460870	0.447826	0.500000	0.486957	0.552174	0.500000	0.473913	0.504348	0.500000	0.517391	0.534783

Model Performance for Feature Sets 1 and 2 (left and right)

Although the overall model accuracy is moderate, performance improves significantly for stocks with higher tweet volume and sentiment variation, suggesting a strong dependence on data richness.

3.3 Benchmarking and Baseline Models

Baseline MVO and Parameters

Maximize $\omega \cdot \mu - 0.1\sigma^2$

Subject to $\omega_i \geq -0.2$

$$\omega_i \leq 0.2$$

$$\sum_i \omega_i = 1$$

$$\sum_i |\omega_i| \leq 1.4$$

$$\sqrt{\sigma^2} \leq 0.1$$

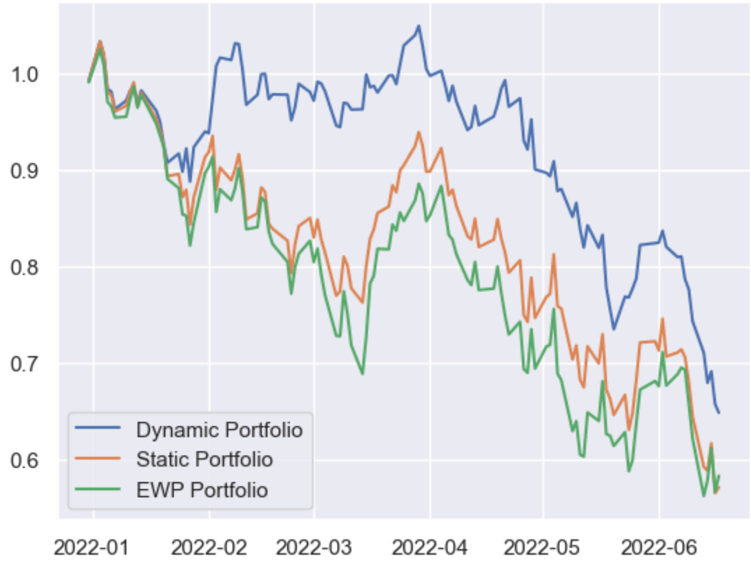
$$\frac{|w_T - w_t|}{2} \leq 0.15$$

Baseline Performance

To assess the added value of sentiment-based adjustments, we define three baseline portfolio strategies:

- **Dynamic Rebalancing Portfolio (MVO)**
- **Static Portfolio (fixed allocation)**
- **Equal-Weighted Portfolio (EWP)**

Figure 5. Baseline Performance for Different Strategies



	Dynamic Portfolio	Static Portfolio	EWP Portfolio
Annual Return	-0.5637	-0.6033	-0.6112
Annual Volatility	0.3263	0.4061	0.4296
Sharpe Ratio	-2.3753	-2.0702	-1.9814
Cumulative Return	0.6463	0.6163	0.6116
Max Drawdown	-0.3474	-0.3823	-0.3958

The dynamic MVO strategy shows the strongest performance in a bear market, serving as a robust baseline for further comparison.

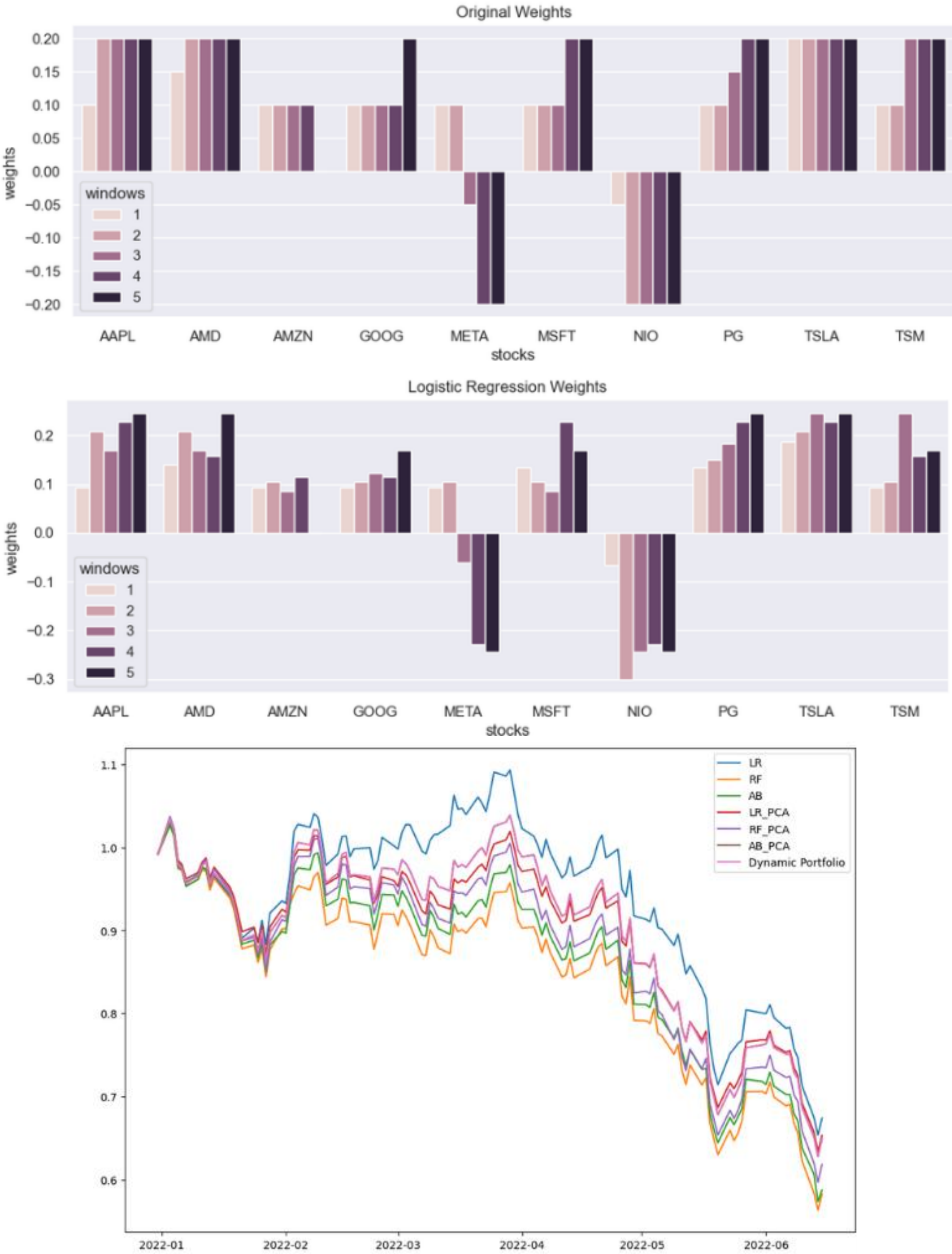
3.4 Sentiment-Adjusted Portfolio Allocation

We apply the trained sentiment-based models to predict daily price movement within each rebalancing window. If the prediction aligns with the stock's existing allocation (e.g., both indicate a positive trend), we amplify the weight using a multiplier *match_weight*. Otherwise, the weight is reduced.

Adjusting MVO with Sentiment Signals

Given the sensitivity of MVO to changes in weight, we adopt a conservative adjustment factor of *match_weight = 1.2*.

Figure 6. Weight Changes and Performance of Sentiment-Adjusted MVO (Logistic Regression)



	LR	RF	AB	LR_PCA	RF_PCA	AB_PCA
Annual Return	-0.5377	-0.6204	-0.6164	-0.5564	-0.5925	-0.5626
Annual Volatility	0.3342	0.3236	0.3244	0.3217	0.3462	0.339
Sharpe Ratio	-2.139	-2.8268	-2.7867	-2.3629	-2.4156	-2.2658
Cumulative Return	0.6738	0.5826	0.5875	0.6532	0.6183	0.6494
Max Drawdown	-0.3643	-0.3855	-0.3794	-0.3458	-0.3731	-0.351

Results show slight improvement over the original MVO, validating the benefit of sentiment-informed rebalancing.

Adjusting Equal-Weighted Portfolio (EWP)

For the less-volatile EWP strategy, we use a more aggressive *match_weight = 1.5* to maximize the impact of sentiment signals.

Figure 7. Weight Changes and Performance of Sentiment-Adjusted EWP (Logistic Regression)

	LR	RF	AB	LR_PCA	RF_PCA	AB_PCA
Annual Return	-0.6077	-0.6353	-0.6199	-0.5917	-0.626	-0.6151
Annual Volatility	0.41	0.427	0.4131	0.4216	0.4597	0.4582
Sharpe Ratio	-2.0733	-2.145	-2.1312	-1.9113	-1.9067	-1.8515
Cumulative Return	0.6121	0.582	0.5982	0.6323	0.6	0.6128
Max Drawdown	-0.3908	-0.4093	-0.3888	-0.3871	-0.4166	-0.4066

Similarly, adjusted EWP strategies demonstrate modest performance improvements over their static counterparts.

3.5 Summary of Findings

In summary, incorporating sentiment features into price prediction models showed mixed results. While traditional models like MVO and EWP remain robust, sentiment-adjusted strategies provided slight performance improvements, especially when tweet volume was high. These findings suggest that sentiment has the potential to enhance short-term trading signals, but its effectiveness depends heavily on data availability and model selection. The next section outlines key conclusions and potential directions for improving both the robo-advisor framework and sentiment modeling.

4. Conclusion & Potential Improvements

4.1 Conclusion

This project explored two major components: the development of a robo-advisor system and the integration of sentiment analysis for price movement prediction.

For the robo-advisor, a utility maximization framework was implemented, incorporating technical constraints and investment parameters to align with conventional investment wisdom and behavioral insights discussed in lectures. The system was demonstrated through a web-based app, and various parameter combinations were assessed for portfolio performance.

For sentiment-based prediction, three simple models—(i) Logistic Regression, (ii) Random Forest, and (iii) AdaBoosting—were applied to assess whether sentiment signals from social media can enhance short-term trading decisions. Although these models did not consistently outperform traditional strategies, certain cases showed improved results, highlighting the potential of sentiment features in specific contexts and justifying further exploration.

4.2 Potential Improvements

Robo Advisor

Sensitivity Analysis
The current study uses grid search to evaluate different parameter settings. However, this method does not reveal the individual impact of each parameter. Sensitivity analysis could help identify key drivers of performance and support more targeted parameter tuning.

Assessment Evaluation
Some parameter combinations resulted in underperforming strategies. Beyond basic logic-based assessment, more adaptive tuning techniques or heuristic filters could help identify and exclude weaker configurations dynamically.

Sentiment Analysis

Model Accuracy

The basic models applied do not account for temporal dependencies, which may limit their predictive power. Incorporating sequential models such as LSTM or transformer-based architectures could capture time-based patterns more effectively.

Data Integration

The current sentiment dataset does not cover all stocks in the robo-advisor system. Expanding sentiment sources—such as integrating financial news or building web scrapers for broader coverage—would enhance the feature set and improve model applicability.