Diversified Portfolio Optimization for Indian Equities

Using Sharpe Ratio Maximisation

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Research Objective

Problem Statement

Investors face the challenge of constructing optimal portfolios that balance risk and return while ensuring diversification across sectors. This project addresses this by developing a **data-driven portfolio optimization model** using **25 stocks from 5 key sectors** (Tech, Banking, Consumer, Healthcare, Infrastructure). Leveraging some concepts of Modern Portfolio Theory, the model maximizes the **Sharpe ratio** (risk-adjusted return) by optimizing stock weights under certain constraints.

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Data Description

About the Dataset

The dataset comprises 25 stocks from 5 key sectors (Technology, Banking & Finance, Consumer, Healthcare, Infrastructure) listed on the NSE (National Stock Exchange of India), with historical price data fetched using the Yahoo Finance API (yfinance).

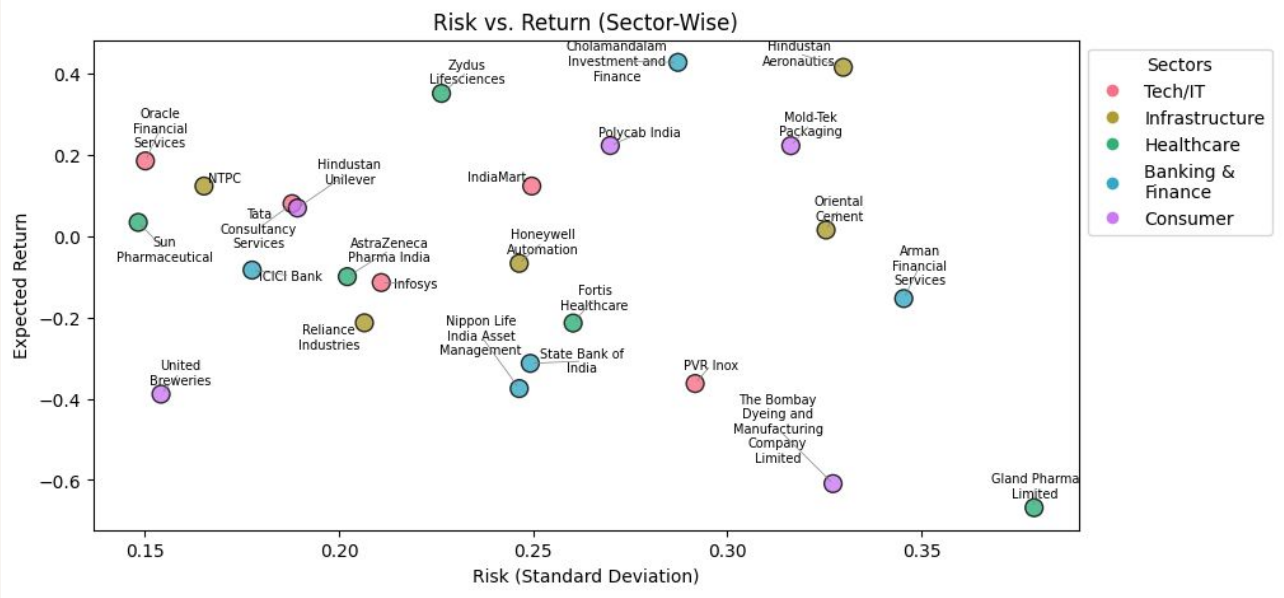
Stock Selection Approach:

To ensure a balanced and realistic portfolio, the stocks were chosen by:

1. Analyzing 2-3 prominent sectoral funds to understand their allocation across market capitalizations (large-cap, mid-cap, small-cap, other).
2. Mirroring a similar distribution in the portfolio to avoid skewness towards any single company size.
3. Ensuring sector diversification while maintaining a scalable structure that resembles real-world investment strategies.

This method helps create a well-diversified, risk-aware portfolio that aligns with professional fund management practices.

Risk vs. Return Analysis



This graph illustrates the risk-return distribution of stocks, grouped by sector. Color coding highlights how stocks within the same industry cluster or differ, revealing patterns and potential outliers.

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Methodology

Feasible Set Construction

User Input

- Investment Budget
- Risk Appetite

To promote diversification, we generate all possible combinations by selecting **one stock from each of the five sectors**, resulting in:

$$\text{Total Combinations} = 5^5 = 3125$$

We assign **equal weights** to each stock and compute portfolio risk:

$$\sigma_p = \sqrt{w^T \cdot \Sigma \cdot w}$$

Where:

- $w = [0.2, 0.2, 0.2, 0.2, 0.2]$
- Σ = Covariance matrix of returns

Only combinations satisfying:

$$\sigma_p \leq \text{Risk Appetite} + 5\%$$

are retained. These form the **feasible set** for further optimization.

Sharpe Ratio

The goal is to construct an **optimal portfolio** that **maximizes the Sharpe Ratio**, defined as:

$$\text{Sharpe Ratio} = \frac{\text{Expected Return - Risk Free Rate}}{\text{Portfolio Risk}}$$

where:

- Expected Return is the weighted sum of individual stock returns
- Risk-Free Rate is the theoretical return from a zero-risk investment, often approximated using government bond yields as a benchmark.
- Portfolio Risk refers to the potential for losses in a portfolio due to fluctuations in the value of its assets

Objective Function

$$\max_{w} \left(\frac{(w^{T} \cdot r) - \text{Risk Free Rate}}{\sqrt{(w^{T} \cdot \Sigma \cdot w)}} \right)$$

Where,

- $w = [w_1, w_2, \ldots, w_n]^{\top}$ is the vector of stock weights, representing the proportion of the investment allocated to each stock.
- $r = [r_1, r_2, \ldots, r_n]^{\top}$ is the vector of annualized returns for each stock in the portfolio.
- Σ is the covariance matrix of the stock returns, capturing the relationships between their fluctuations.
- According to latest data the Risk-Free Rate in India is about 6.7%

Constraints:

1. Budget Constraint: $\sum_{i=1}^{n} w_i = 1$

   This constraint ensures that the entire investment budget is allocated across the selected stocks, with no funds left uninvested.

2. No Short-Selling: $w_i \geq 0.01 \ \forall \ i \in \{1, 2, \ldots, n\}$

   This constraint prevents short-selling. We set the lower bound to 0.01 (1%) to avoid any stock receiving a zero allocation.

Optimizing Using SLSQP

Our objective involves a **nonlinear objective function**, making linear programming unsuitable.
Thus we employ **Sequential Least Squares Programming (SLSQP)**, a robust algorithm. for constrained nonlinear optimization with smooth objective functions.

General problem structure:

$$\min_{x \in \mathbb{R}n} f(x)$$

$$\begin{aligned} \text{subject to: } & c_i(x) = 0, \ \forall \ i = 1, \ldots, m \\ & d_j(x) \geq 0, \ \forall \ j = 1, \ldots, p \\ & l_k \leq x_k \leq u_k, \ \forall \ k = 1, \ldots, n \end{aligned}$$

Where:

- $f(x)$ represents the **negative of the Sharpe Ratio**, as SLSQP is a minimization algorithm.
- $c_i(x)$ ensures **the weights sum to 1** (budget constraint)
- $d_j(x)$ ensures the **non-negativity** of the portfolio weights (no short selling)
- $l_k \leq x_k \leq u_k$ ensures the **portfolio weights are bounded** between 0.01 and 1.

Working Mechanism of SLSQP

SLSQP solves constrained nonlinear problems by iteratively approximating them as Quadratic Programs (QPs), since quadratic objectives and linear constraints are faster to solve. Each iteration involves solving a QP subproblem to update the solution.

Step 1: Quadratic Approximation of Objective
The nonlinear function is locally approximated using second-order Taylor expansion:

$$f(x + \Delta x) \approx f(x) + \nabla f(x)^T \Delta x + \tfrac{1}{2} \Delta x^T B \Delta x$$

Where,

- B: Hessian approximation, captures curvature
- $\nabla f(x)$: gradient (steepest ascent direction)
- Δx: step direction for updating weights

Step 2: Linearization of Constraints
Nonlinear constraints are approximated using first-order Taylor expansion:

$$c_i(x + \Delta x) \approx c_i(x) + \nabla c_i(x)^T \Delta x$$

$$d_j(x + \Delta x) \approx d_j(x) + \nabla d_j(x)^T \Delta x$$

Working Mechanism of SLSQP

Step 3: Solve QP Subproblem

The QP formed by steps 1 and 2 is solved to get an updated step. Portfolio weights are updated:

$$x_{new} = x_{current} + \Delta x$$

Implementation of SLSQP

We implemented it in Python via the scipy library which computed the gradients internally using forward difference:

$$f'(x) \approx \frac{f(x + h) - f(x)}{h}$$

And we got the final optimal weight vector w* that maximizes the Sharpe Ratio, giving the optimal investment allocation.

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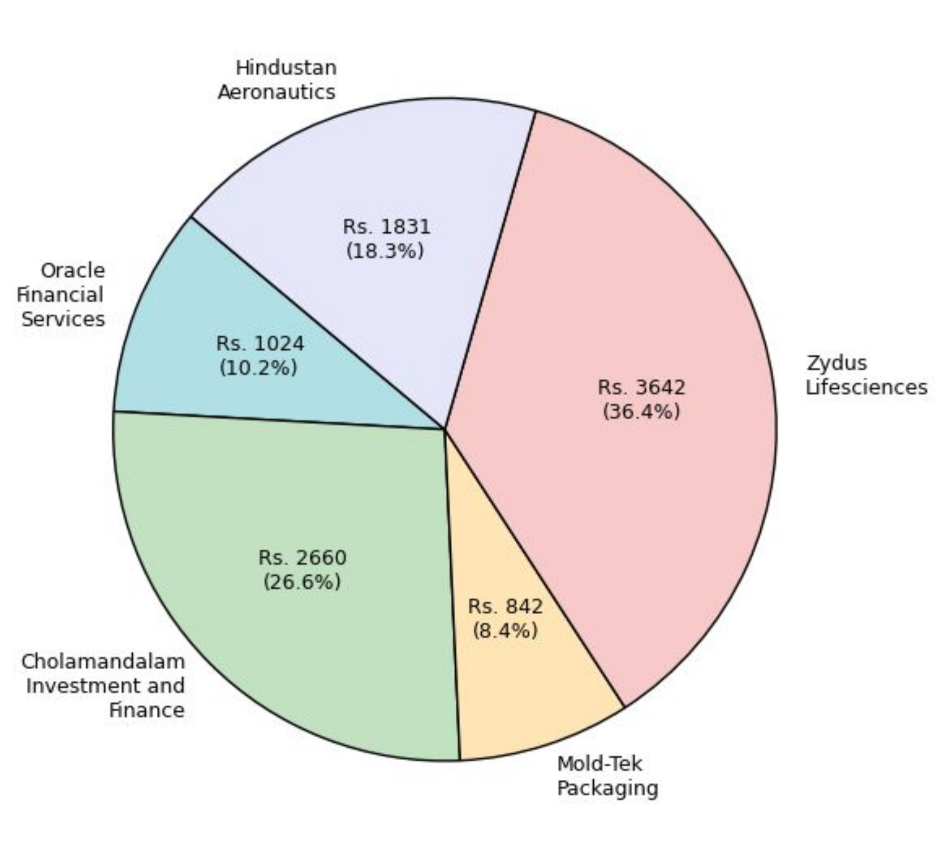
Results

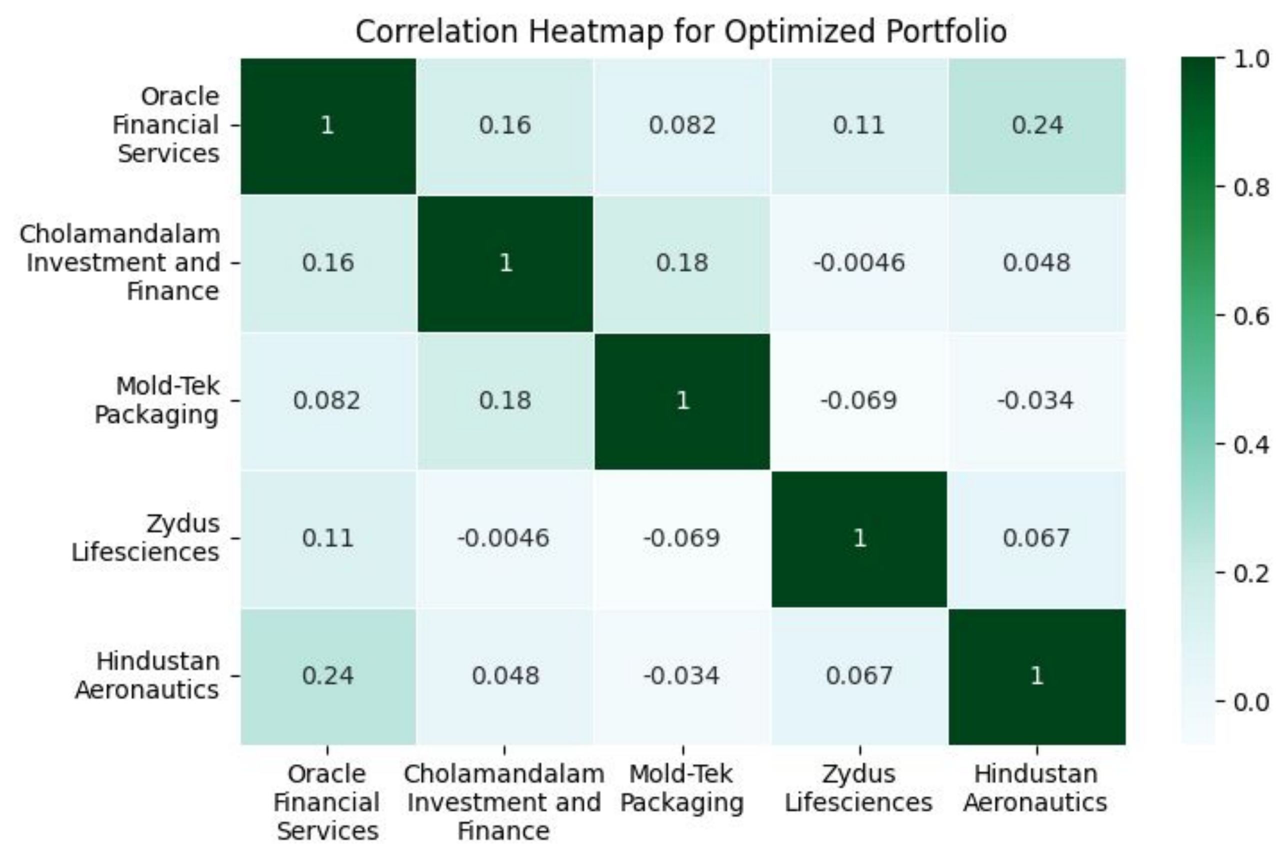
Optimized Portfolio Allocation



User Inputs :

- Investment Budget : INR 10,000
- Risk Appetite : 15%

Diversification



Portfolio Performance

Metric	Optimized Portfolio (Expected)	Optimized Portfolio (Actual)	Equal-Weighted Portfolio
Expected Return	35.43%	35.64%	24.62%
Portfolio Risk (Volatility)	14.06%	20.20%	14.26%
Sharpe Ratio	2.04	1.43	1.26
Sortino Ratio	3.90	2.43	1.99
Max Drawdown	-14.51%	-58.55%	-46.66%

Our optimized portfolio performed strongly during training, and while risk increased in the evaluation period, it remained within our threshold making it acceptable. Despite some decline in risk-adjusted metrics like the Sharpe and Sortino ratios, the portfolio still outperformed the equal-weighted strategy across all key metrics, offering better returns and improved overall efficiency.

Interface

Portfolio Optimizer

Investment Amount (₹)

10000

Risk Tolerance (%) (5-25: Low, 25-45: Medium, >45: High)

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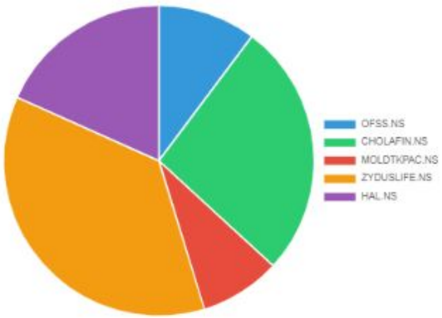
Optimize Portfolio

Optimized Portfolio

Allocation

Stock	Company	Amount (₹)	Weight
OFSS.NS	Oracle Financial Services	₹1,024	10.24%
CHOLAFIN.NS	Cholamandalam Investment and Finance	₹2,660	26.60%
MOLDTKPAC.NS	Mold-Tek Packaging	₹842	8.42%
ZYDUSLIFE.NS	Zydus Lifesciences	₹3,642	36.42%
HAL.NS	Hindustan Aeronautics	₹1,831	18.31%

Portfolio Composition



Portfolio Performance Metrics

Expected Return
35.43%

Portfolio Risk
14.06%

Sharpe Ratio
2.0436
Risk-adjusted return relative to risk-free rate

Sortino Ratio
3.9038
Return adjusted for downside risk only

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Limitation, Future Work & Conclusion

Limitation & Future Work

1. Requiring exactly one stock per sector is a rigid constraint. Future versions can move beyond the rigid “one stock per sector” rule by allowing dynamic sector allocation based on market signals and user preferences.
2. We are currently considering only 25 companies, hence the possible optimal portfolios are very limited. Expanding the stock pool to include a wider range of companies and developing a comprehensive automated methodology to pick companies to be included in the database would further enhance portfolio diversity and real-world applicability.
3. Reliance on historical data assumes that past performance patterns will continue, which may not always be true in dynamic or volatile market. The model does not account for sudden or unforeseen market events which can significantly affect stock performance. Incorporating mechanisms to account for sudden market shifts would improve model robustness.
4. The filtering step based on a strict risk threshold may eliminate all possible combinations in certain scenarios; a more flexible or adaptive filtering mechanism would better accommodate varying user risk levels.

Conclusion

In conclusion, this project delivers a practical and easy-to-use tool for retail investors navigating the complexities of the Indian equity market. While the framework is relatively basic, it serves as a strong starting point for more advanced, customizable investment solutions. Despite its simplicity, the model demonstrates decent performance across both training and test periods, offering competitive risk-adjusted returns. By combining sectoral diversification, user-defined risk filtering, and Sharpe ratio optimization, the system provides a structured yet accessible approach to portfolio construction. In an age of overwhelming financial information, this project shows how even a straightforward, data-driven model can empower better decision-making for individual investors.

Thank You

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