Portfolio Optimization and Efficient Frontier Analysis
Using Indian Stock Market Data

June 12, 2025

1. Objective-

In the second question, we have to forecast the volatility of the NIFTY 50 stocks using historical data from 1st Jan 2022 to 1st September 2024. After incorporating the investor's view on risk, we will select 3 stocks that align with the investor’s risk profile and assign weights proportional to the inverse of their volatility. Finally, we shall backtest the strategy on a suitable strategy and obtain the backtesting metrics.

2. Volatility Forecasting-

We have used three methods to forecast volatility and then selected the best performing method (based on RMSE):

a. Rolling Mean Forecast -

```
data['vol_forecast_rm'] = data['rolling_vol'].rolling(window=5).mean()
```

b. Exponentially Weighted Moving Average (EWMA)-

EWMA gives more weight to recent observations and less weight to older data. A smoothing parameter (lambda) controls how much weight is given to recent data. Lower lambda values give more weight to recent observations.

```
lambda_= 0.94
data['vol_squared'] = data['returns']**2
data['ewma_vol'] = data['vol_squared'].ewm(alpha=1 - lambda_).mean() **0.5
```

c. AR(1) Model on Volatility-

This method treats volatility as a time series and fits an autoregressive model of order 1 (AR(1)) to it

$\boldsymbol{\sigma}(t) = \boldsymbol{\alpha} + \boldsymbol{\beta} \cdot \sigma(t-1) + \boldsymbol{\epsilon}(t)$

- $\sigma(t)$ represents the forecasted volatility at time t
- α is a constant that captures the long-term average or base level of volatility.
- β is the autoregressive coefficient that measures how strongly the previous period’s volatility ($\sigma(t-1)$) influences the current period’s volatility.
- $\epsilon(t)$ is the random shock or error term for the current time period.

3.Normalizing Forecasted Volatility-

normalized_vol = (vol_forecast - vol_forecast.min()) / (vol_forecast.max() -vol_forecast.min())

Matching Stocks with Investor's Risk Aversion-
We calculated the distance between each stock's normalized forecasted volatility and the investor's risk averseness score

distance = abs(normalized_vol - risk_aversion_score)
We then selected 3 stocks based on the minimum distance
Following stocks were selected-

	forecasted_vol	normalized_vol	distance
HDFCLIFE.NS	0.017667	0.490273	0.009727
TECHM.NS	0.018144	0.513945	0.013945
ADANIPORTS.NS	0.018263	0.519834	0.019834

4.Portfolio Construction-

According to the proportionality to inverse of forecasted volatility of each stock, we have assigned weights to the three stocks and we have considered an initial investment of Rs.10,00,000.

	forecasted_vol	normalized_vol	distance	weight	investment
HDFCLIFE.NS	0.017667	0.490273	0.009727	0.340010	340009.68
TECHM.NS	0.018144	0.513945	0.013945	0.331071	331070.72
ADANIPORTS.NS	0.018263	0.519834	0.019834	0.328920	328919.60

5.Strategy to Generate Trading Signals-

We have used ATR as the strategy to generate signals
In ATR(Average True Range), we have to bands, upper and lower band
If closing price crosses upper band-> buy signal
If closing price goes below lower band-> sell signal
Upper Band= EMA+k*ATR
Lower Band= EMA-k*ATR
Where, k is the multiplier

ATR is calculated using the average of True Range
True Range=max(High-Low, abs(High- prev_close), abs(Low- prev_close))

Fig:- ATR applied on ADANI stock, with buy and sell signals also marked

6.Backtesting -

The following strategy was backtested on the data from 1st Jan 2022 to 1st Jan 2025
We have used stop loss and dynamic exit of 10 % each as the risk management methods.
The backtesting function generates two dataframes- a trade_wise_df and daily_returns_df.
The three stocks have separate trade_wise_ df and there is a combined daily_returns_df for the portfolio.

adani_trade_wise

	Entry Index	Exit Index	Entry Date	Exit Date	Type of Trade	No of stock traded	Return for trade in %	Trade Duration
0	2	14	2022-01-05	2022-01-21	long	443	-4.106498	12
1	58	85	2022-03-29	2022-05-10	long	421	0.938373	27
2	128	181	2022-07-08	2022-09-26	long	452	21.472862	53
3	208	242	2022-11-04	2022-12-23	long	452	-7.973125	34
4	291	307	2023-03-03	2023-03-28	long	525	-13.327977	16
5	334	437	2023-05-11	2023-10-09	long	440	12.212361	103
6	458	542	2023-11-08	2024-03-13	long	424	47.740328	84
7	552	578	2024-03-28	2024-05-09	long	382	-7.251180	26
8	585	595	2024-05-21	2024-06-04	long	343	-9.855650	10
9	607	655	2024-06-21	2024-08-30	long	287	-0.242341	48

```
total_daily
```

	Portfolio Value	Profit from initial Capital	Daily Returns in %	Adani Stocks	HDFC Stocks	Tech Mahindra Stocks
0	1.000000e+06	0.000000	NaN	0	0	0
1	1.000000e+06	0.000000	0.000000	0	0	0
2	1.000000e+06	0.000000	0.000000	443	0	0
3	9.934292e+05	-1.997677	-0.657075	443	0	0
4	9.918192e+05	-2.487170	-0.162069	443	0	0
...	...	...	...	...	...	...
651	1.129949e+06	39.583056	0.901158	287	196	234
652	1.124706e+06	38.000471	-0.463997	287	196	234
653	1.122762e+06	37.409608	-0.172799	287	196	234
654	1.129479e+06	39.439551	0.598193	287	196	234
655	1.128318e+06	39.094836	-0.102767	0	0	0

656 rows × 6 columns

Benchmark Metrics-

```
Benchmark Return: 24.402571818840002 %
Gross Profit: 39.09483602219997 %
Max Holding Time: 103
Average Holding Time: 39.35925925925926
Total Trades: 30
Winning Trades: 13
Losing Trades: 17
Max Drawdown: -18.053750334159737 %
Sharpe Ratio: 0.36303468725542126
```

Portfolio Value Over Time-


Portfolio Value
1.2M
1.1M
1M
0.9M
Jul 2022
Jan 2023
Jul 2023
Jan 2024
Jul 2024