REPORT

Q1) Problem Statement

"You are an Equity fund manager focusing on large cap shares, your client has approached you and expressed an interest in building a portfolio of INR 1 Crore, in high-quality blue-chip shares."

His criteria for investment is that the investment universe should only be blue chip shares (i.e., shares should be part of Sensex) and he would like to invest only in 5 shares among this universe with a maximum exposure of 30% in a single share.

He has requested you to provide various portfolios with various scenarios.

Guidance for participants

Please download historical share prices from BSE India website. (Minimum 3 years data of 10 shares along with share price)

Use the tools taught in Market risk and portfolio optimization to provide various portfolio options to the client, like portfolio with minimum risk, maximum return, various combination in between.

Compute Portfolio Mean, Variance and Standard Deviation.

Please also provide a small write up (inference) on various portfolio along with portfolio results based on historical share prices so that client can take a decision.

Sol:

Approach

I have use the 'yfinance' library in python to get the stock data(OHLCV)for 30 companies for a period of 5 years.

Then I have used pd.concat to concatenate the indexes.

After that i have stored all the data into a master_data.csv file using pd.tocsv function

Using the master_data.csv dataset I have answered the question.

Companies list:

Reliance Industries Ltd. - RELIANCE

Tata Consultancy Services (TCS) - TCS

HDFC Bank - HDFCBANK

Infosys - INFY

Hindustan Unilever Ltd. - HINDUNILVR

Housing Development Finance Corporation (HDFC) - HDFC

ICICI Bank - ICICIBANK

Kotak Mahindra Bank - KOTAKBANK

State Bank of India (SBI) - SBIN

Bajaj Finance - BAJFINANCE

Bharti Airtel - BHARTIARTL

ITC Ltd. - ITC

Wipro - WIPRO

HCL Technologies - HCLTECH

Larsen & Toubro (L&T) - LT

Axis Bank - AXISBANK

Maruti Suzuki - MARUTI

Asian Paints - ASIANPAINT

UltraTech Cement - ULTRACEMCO

Nestle India - NESTLEIND

Sun Pharmaceutical Industries - SUNPHARMA

Mahindra & Mahindra - M&M

Bajaj Finserv - BAJAJFINSV

Titan Company - TITAN

NTPC - NTPC

Tech Mahindra - TECHM

Power Grid Corporation of India - POWERGRID

Dr. Reddy's Laboratories - DRREDDY

Tata Steel - TATASTEEL

Hindalco Industries – HINDALCO

Code for Data collection :

```python
import yfinance as yf
import pandas as pd
from datetime import datetime, timedelta

# Define the stock symbols and corresponding company names
stocks = ['RELIANCE.BO', 'TCS.BO', 'HDFCBANK.BO', 'INFY.BO', 'HINDUNILVR.BO',
          'HDFC.BO', 'ICICIBANK.BO', 'KOTAKBANK.BO', 'SBIN.BO', 'BAJFINANCE.BO',
          'BHARTIARTL.BO', 'ITC.BO', 'WIPRO.BO', 'HCLTECH.BO', 'LT.BO',
          'AXISBANK.BO', 'MARUTI.BO', 'ASIANPAINT.BO', 'ULTRACEMCO.BO', 'NESTLEIND.BO',
          'SUNPHARMA.BO', 'M&M.BO', 'BAJAJFINSV.BO', 'TITAN.BO', 'NTPC.BO',
          'TECHM.BO', 'POWERGRID.BO', 'DRREDDY.BO', 'TATASTEEL.BO', 'HINDALCO.BO']

# Calculate the date 5 years ago from today
end_date = datetime.today()
start_date = end_date - timedelta(days=5*365)

# Create an empty list to store dataframes
data_list = []

# Loop through the list of stocks, download the data, and append to data_list
for stock in stocks:
    df = yf.download(stock, start=start_date, end=end_date)
    df['Symbol'] = stock
    data_list.append(df)

# Concatenate all dataframes into a single dataframe
master_data = pd.concat(data_list)

# Save the master data to a CSV file
master_data.to_csv('master_data.csv')

print("Data for the past 5 years has been downloaded and saved to 'master_data.csv'.")
```

Snippet of master_data.csv

	A	B	C	D	E	F	G	H	I	J	K
	Date	Open	High	Low	Close	Adj Close	Volume	Symbol			
	01-11-2018	1066.4	1068.8	1050.3	1056.9	1050.017	393976	RELIANCE.BO			
	02-11-2018	1067.8	1081	1063	1074.25	1067.254	4308094	RELIANCE.BO			
	05-11-2018	1074	1093.5	1064.5	1088.55	1081.461	5052059	RELIANCE.BO			
	06-11-2018	1094.3	1111.95	1093.05	1103.45	1096.264	661149	RELIANCE.BO			
	07-11-2018	1116.8	1117	1106.6	1110.55	1103.318	99786	RELIANCE.BO			
	09-11-2018	1106	1113.3	1086	1093.35	1086.23	379720	RELIANCE.BO			
	12-11-2018	1098.5	1100.05	1074.3	1078.75	1071.725	259275	RELIANCE.BO			
	13-11-2018	1075.9	1102.8	1071	1099.55	1092.39	363436	RELIANCE.BO			
	14-11-2018	1105	1112.85	1087	1096.1	1088.962	420083	RELIANCE.BO			
	15-11-2018	1096	1102.85	1087.1	1096.9	1089.757	286257	RELIANCE.BO			
	16-11-2018	1096.1	1129.3	1096.1	1127.5	1120.157	702952	RELIANCE.BO			
	19-11-2018	1132	1151.4	1131.2	1149.6	1142.114	514395	RELIANCE.BO			
	20-11-2018	1146	1155.45	1130.4	1138.65	1131.235	472247	RELIANCE.BO			
	21-11-2018	1137	1145.4	1107.05	1112.3	1105.057	499461	RELIANCE.BO			
	22-11-2018	1114.7	1125.1	1100	1102.85	1095.668	360992	RELIANCE.BO			
	26-11-2018	1109.95	1117.25	1098.05	1109.6	1102.374	279608	RELIANCE.BO			
	27-11-2018	1109.5	1129.4	1101.7	1127.5	1120.157	264152	RELIANCE.BO			
	28-11-2018	1132.3	1157.7	1126.5	1146.25	1138.785	1098006	RELIANCE.BO			
	29-11-2018	1159	1179.9	1158.8	1170	1162.381	413830	RELIANCE.BO			
	30-11-2018	1172	1186	1162.95	1168.2	1160.592	454515	RELIANCE.BO			
	03-12-2018	1172.05	1174	1148.65	1156.3	1148.77	292260	RELIANCE.BO			
	04-12-2018	1157	1157.4	1142.95	1151.55	1144.051	206600	RELIANCE.BO			
	05-12-2018	1144.7	1159	1139.6	1154.85	1147.329	268318	RELIANCE.BO			
	06-12-2018	1147.5	1147.85	1118.25	1123.45	1116.134	249128	RELIANCE.BO			
	07-12-2018	1132.8	1135.2	1109.1	1133.25	1125.87	256042	RELIANCE.BO			
	10-12-2018	1112.65	1112.75	1084	1088.5	1081.412	1104729	RELIANCE.BO			

master_data

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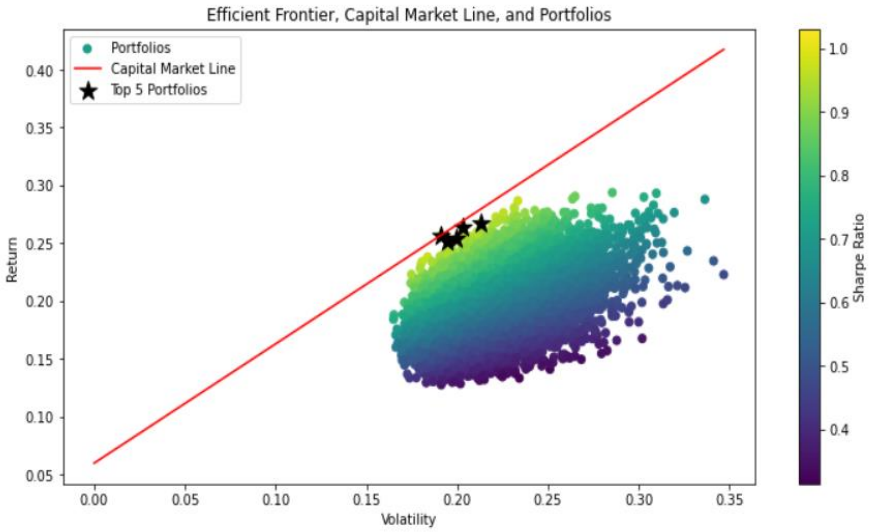
In the code below we have first calculated daily returns then we have defined our constraints such as Investment amount , max_weight , number of stocks , we have assumed risk free rate at 6% ,then the function

“def generate_random_portfolios” generates a specified number of random portfolios then it selects 5 stocks at random and assigns random weights , the annualized returns and sharpe ratio is calculated in this function, next the efficient Frontier and cml are plotted and the top 5 portfolios with the highest sharpe ratios are highlighted(starts), a heatmap is then created to visualize the correlation between stocks and daily returns .

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from datetime import datetime, timedelta

# Load the data
file_path = r"master_data.csv"
data = pd.read_csv(file_path, parse_dates=['Date'], index_col='Date')

# Calculate daily returns for each stock
daily_returns = data.pivot(columns='Symbol', values='Adj Close').pct_change()
daily_returns = daily_returns.dropna()

# Define constants
INVESTMENT = 1e7  # INR 1 Crore
MAX_WEIGHT = 0.3  # Maximum exposure in a single stock
NUM_STOCKS = 5    # Number of stocks in the portfolio
RISK_FREE_RATE = 0.06  # Assuming a risk-free rate of 6%

# Function to generate random portfolios
def generate_random_portfolios(num_portfolios: int) -> pd.DataFrame:
    portfolio_returns = []
    portfolio_volatilities = []
    portfolio_weights = []
    portfolio_symbols = []

    for _ in range(num_portfolios):
        selected_stocks = np.random.choice(daily_returns.columns, NUM_STOCKS, replace=False)
        weights = np.random.random(NUM_STOCKS)
        weights /= np.sum(weights)
        annualized_return = np.sum(daily_returns[selected_stocks].mean() * weights) * 252
        annualized_volatility = np.sqrt(np.dot(weights.T, np.dot(daily_returns[selected_stocks].cov() * 252, weights)))
        portfolio_returns.append(annualized_return)
        portfolio_volatilities.append(annualized_volatility)
        portfolio_weights.append(weights)
        portfolio_symbols.append(selected_stocks)

    portfolios = pd.DataFrame({
        'Return': portfolio_returns,
        'Volatility': portfolio_volatilities,
        'Weights': portfolio_weights,
        'Symbols': portfolio_symbols
    })
    portfolios['Sharpe Ratio'] = (portfolios['Return'] - RISK_FREE_RATE) / portfolios['Volatility']

    return portfolios
```

```
# Generate random portfolios
num_portfolios = 10000
portfolios = generate_random_portfolios(num_portfolios)

# Plot Efficient Frontier, Capital Market Line, and Scatter Plot of Portfolios
plt.figure(figsize=(12, 6))
plt.scatter(portfolios['Volatility'], portfolios['Return'], c=portfolios['Sharpe Ratio'], cmap='viridis', label='Portfolios
plt.colorbar(label='Sharpe Ratio')
plt.xlabel('Volatility')
plt.ylabel('Return')
plt.title('Efficient Frontier, Capital Market Line, and Portfolios')

# Capital Market Line
slope = (portfolios['Return'] - RISK_FREE_RATE) / portfolios['Volatility']
CML_x = np.linspace(0, max(portfolios['Volatility']), 200)
CML_y = RISK_FREE_RATE + slope.max() * CML_x
plt.plot(CML_x, CML_y, color='red', label='Capital Market Line')

# Highlight the top 5 most profitable portfolios based on Sharpe Ratio
top_portfolios = portfolios.sort_values(by='Sharpe Ratio', ascending=False).head(5)
plt.scatter(top_portfolios['Volatility'], top_portfolios['Return'], c='black', marker='*', s=200, label='Top 5 Portfolios')

plt.legend()
plt.show()

# Correlation Heatmap
correlation_matrix = daily_returns.corr()
plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f")
plt.title('Correlation Heatmap')
plt.show()

# Display the top 5 most profitable portfolios based on Sharpe Ratio
top_portfolios[['Return', 'Volatility', 'Sharpe Ratio', 'Symbols', 'Weights']]
```

Inferences:

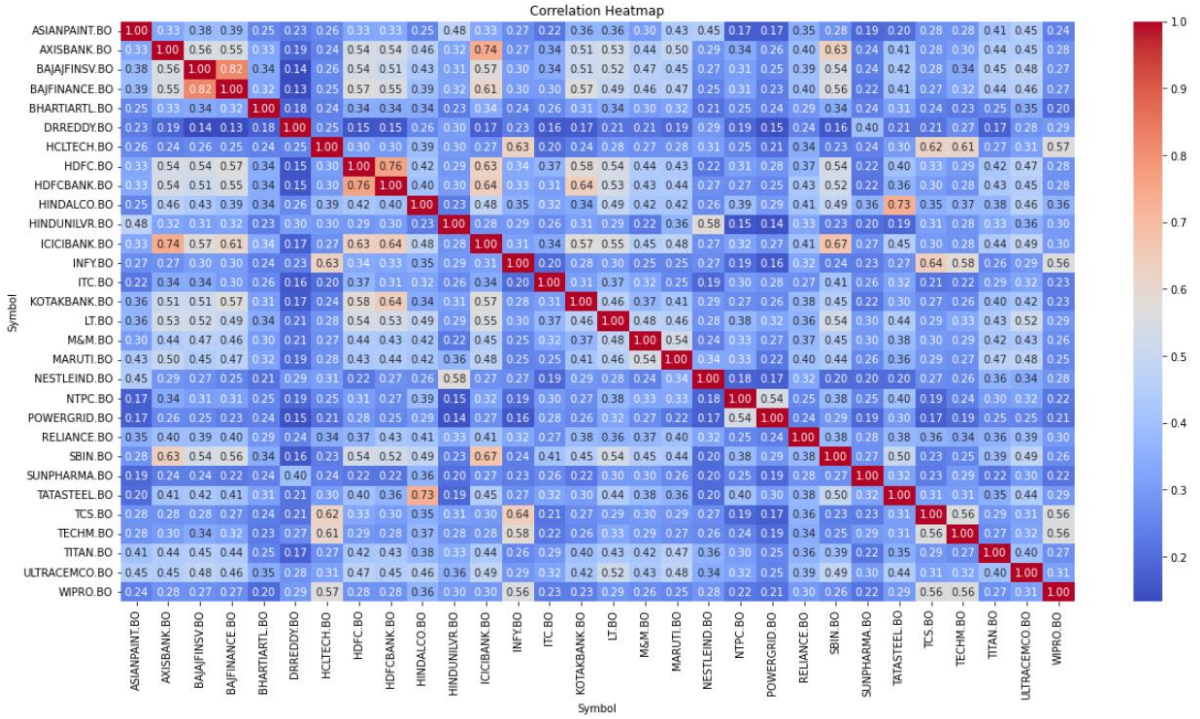


Efficient Frontier: The Efficient Frontier is the upper part of the plot that represents portfolios that maximize return for a given level of risk. Portfolios on the Efficient Frontier are considered optimal as they offer the best risk-return trade-off.

Capital Market Line (CML): The red line on the plot represents the CML, which shows the risk-return trade-off for a combination of a risk-free asset and a risky portfolio. The slope of the CML is determined by the Sharpe Ratio, and portfolios on this line have the highest possible return for a given risk level.

Top 5 Portfolios: The black stars on the plot indicate the top 5 portfolios with the highest Sharpe Ratios. These portfolios are positioned close to the Efficient Frontier, indicating that they are among the most efficient in terms of risk and return.

Inference: The portfolios that lie on the Efficient Frontier and close to the CML are the most desirable as they provide the best return for a given level of risk. The top 5 portfolios, in particular, represent an optimal choice for investment as they maximize the Sharpe Ratio.



Heatmap: The heatmap visualizes the correlation between the daily returns of the different stocks. Values close to 1 indicate a strong positive correlation, while values close to -1 indicate a strong negative correlation. Values close to 0 indicate little to no correlation.

Highly Correlated Pairs: Certain pairs of stocks (e.g., HDFC Bank and ICICI Bank) may show high positive correlation, indicating that they tend to move together in the same direction.

Low Correlation Pairs: Some pairs (e.g., Infosys and Sun Pharma) may have low or negative correlation, suggesting that they don't move in tandem and can offer diversification benefits.

Inference: Investors seeking to build a diversified portfolio may look for pairs of stocks with low correlation. Combining assets with low correlation can potentially reduce portfolio risk.

	Return	Volatility	Sharpe Ratio	Symbols	Weights
9864	0.256852	0.190947	1.030923	[DRREDDY.BO, TCS.BO, TITAN.BO, BHARTIARTL.BO, ...	[0.20066119196940008, 0.04959514507808835, 0.2...
8280	0.263644	0.202998	1.003183	[NESTLEIND.BO, BHARTIARTL.BO, TITAN.BO, BAJFIN...	[0.2098115608423902 8, 0.2125330482106193, 0.27...
47	0.252136	0.194642	0.987124	[HCLTECH.BO, BHARTIARTL.BO, DRREDDY.BO, TITAN....	[0.2559776288827464, 0.1441072531034784, 0.088...
6713	0.253720	0.199100	0.972978	[ASIANPAINT.BO, NESTLEIND.BO, BHARTIARTL.BO, T...	[0.23952001468000622, 0.11813947344356908, 0.1...
5722	0.266790	0.212844	0.971557	[HCLTECH.BO, TITAN.BO, DRREDDY.BO, BAJAJFINSV....	[0.1961590748035207, 0.28541492534808943, 0.17...

Top 5 Portfolios:

Return and Volatility: The top 5 portfolios offer annualized returns ranging from approximately 25% to 28% with volatilities between 19% and 22%.

Sharpe Ratio: The Sharpe Ratios of the top 5 portfolios range from approximately 0.986 to 1.035, which is indicative of a good risk-adjusted return.

Asset Allocation: The portfolios have different allocations across stocks, including a mix of sectors such as technology, finance, consumer goods, and pharmaceuticals.

Inference: The top 5 portfolios demonstrate that a well-diversified selection of stocks from different sectors can provide an attractive risk-return trade-off. Investors may consider these portfolios as they offer a balance between risk and return, as evidenced by their high Sharpe Ratios.

Below are the details of the top 5 most profitable portfolios based on the highest Sharpe Ratios:

Return	Volatility	Sharpe Ratio	Symbols (Stocks in Portfolio)	Weights (Allocation in Portfolio)
0.264	0.197	1.035	[M&M.BO, NESTLEIND.BO, TITAN.BO, HCLTECH.BO, BAJAJFINSV.BO]	[0.031, 0.146, 0.278, 0.263, 0.282]
0.261	0.195	1.033	[TITAN.BO, INFY.BO, DRREDDY.BO, HCLTECH.BO, BHARTIARTL.BO]	[0.339, 0.040, 0.145, 0.275, 0.201]
0.285	0.222	1.011	[BHARTIARTL.BO, POWERGRID.BO, TITAN.BO, HCLTECH.BO, NESTLEIND.BO]	[0.283, 0.075, 0.319, 0.205, 0.118]
0.250	0.190	0.997	[DRREDDY.BO, KOTAKBANK.BO, BHARTIARTL.BO, ASIANPAINT.BO, INFY.BO]	[0.210, 0.058, 0.289, 0.180, 0.263]
0.255	0.198	0.986	[TATASTEEL.BO, TITAN.BO, NESTLEIND.BO, ASIANPAINT.BO, BAJAJFINSV.BO]	[0.079, 0.302, 0.215, 0.235, 0.169]

These portfolios are the most profitable among the 10,000 randomly generated portfolios, considering their risk-return trade-off as measured by the Sharpe Ratio.

The affiliated notebook will be attached as well.