FE630 - Homework #2

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Pledge: I pledge my honor that I have abided by the Stevens Honor System.

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Topics

- Algebra & Optimization;
- Geometry of Efficient Frontiers;
- Applications of One-Fund & Two-Fund Theorems.

P1 - Optimization w/Equality Constraints (40 pts)

Consider the optimization problem **Max Expected Return w/Target Risk**:

$$\begin{cases} \max\limits_{\omega_1,\omega_2} & R_p(\omega_1,\omega_2) = \mu_1\omega_1 + \mu_2\omega_2 \\ \text{s.t.} & \sqrt{\sigma_1^2\omega_1^2 + 2\rho_{1,2}\sigma_1\sigma_2\omega_1\omega_2 + \sigma_2^2\omega_2^2} = \sigma_T \\ & \omega_1 + \omega_2 = 1 \end{cases} \tag{1}$$

where we have two securities with **Expected Returns** μ_1 and μ_2 for the column vector $(\mu_1, \mu_2)^\intercal \in \mathbb{R}^{2\times 1}$, **volatilities** $(\sigma_1, \sigma_2) \in \mathbb{R}^+$, and **Pearson correlation coefficient** $\rho_{1,2} \in [-1, 1]$. Additionally, $\sigma_T \in \mathbb{R}^+$ denotes the **target risk/vol**.

1. Solve the *problem (3)* using a **Lagrangian approach**. You will denote the solution (the ***optimal solution***) by $\omega^*(\sigma_T)$ and the ***optimal value*** of the problem by $R_p(\omega_1^*(\sigma_T), \omega_2^*(\sigma_T))$ by $R_p(\sigma_T)$.

2. Assume that $\mu_1 = 5\%$, $\mu_2 = 10\%$, $\sigma_1 = 10\%$, $\sigma_2 = 20\%$, and $\rho_{1,2} = -0.5$ (moderate negative correlation).

- Consider a sequence of successive values of σ_T in the range $[2\%, 30\%]$ by step of 0.5%
- Plot the efficient frontier: namely, the graph from the *mapping* $\sigma_T \mapsto R_p(\sigma_T)$.

The (aforementioned) graph maps the sequence of values of σ_T from the x-axis into the sequence of values $R_p(\sigma_T)$ on the y-axis.

Efficient Frontier Mapping

In [ ]:
```
import numpy as np
import matplotlib.pyplot as plt
from scipy.optimize import minimize
```

In [ ]:
```
from typing import Tuple, List

# Constants
mu1: float = 0.05  # Expected return of the first security
mu2: float = 0.10  # Expected return of the second security
sigma1: float = 0.10  # Volatility of the first security
sigma2: float = 0.20  # Volatility of the second security
rho: float = -0.5  # Correlation coefficient between the securities

# Target risk values
sigma_T_values: np.ndarray = np.arange(0.02, 0.305, 0.005)
```

In [ ]:
```
def portfolio_return(weights: np.ndarray, mu1: float, mu2: float) -> float:
    """
    Calculate the portfolio return based on given weights and expected returns.

    Parameters:
        weights (np.ndarray): Array of weights for the securities.
        mu1 (float): Expected return of the first security.
        mu2 (float): Expected return of the second security.

    Returns:
        float: The calculated portfolio return.
    """
    return weights[0] * mu1 + weights[1] * mu2
```

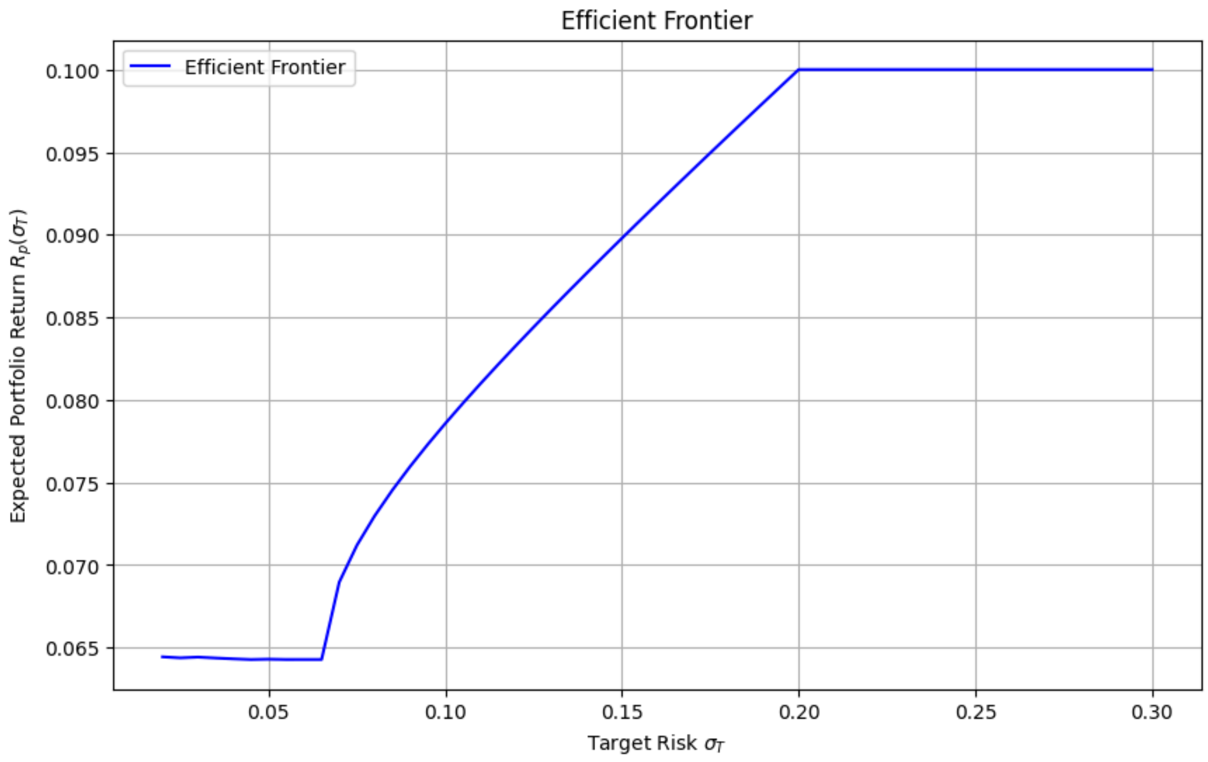
In [ ]:
```
def portfolio_risk(weights: np.ndarray, sigma1: float, sigma2: float, rho: float) -
    """
    Calculate the portfolio risk based on weights, individual volatilities, and cor

    Parameters:
        weights (np.ndarray): Array of weights for the securities.
        sigma1 (float): Volatility of the first security.
        sigma2 (float): Volatility of the second security.
        rho (float): Correlation coefficient between the securities.

    Returns:
        float: The calculated portfolio risk.
    """
    return np.sqrt((sigma1 * weights[0]) ** 2 + (sigma2 * weights[1]) ** 2 +
                   2 * rho * sigma1 * sigma2 * weights[0] * weights[1])
```

In [ ]:
```
def objective(weights: np.ndarray) -> float:
    """
    Objective function for minimization, used to maximize portfolio return.

    Parameters:
        weights (np.ndarray): Array of weights for the securities.

    Returns:
        float: Negative of the portfolio return (for minimization).
    """
    return -portfolio_return(weights, mu1, mu2)
```

In [ ]:
```
def constraint(weights: np.ndarray, sigma_T: float) -> float:
    """
    Constraint for the optimizer to achieve a specific target risk.

    Parameters:
        weights (np.ndarray): Array of weights for the securities.
        sigma_T (float): Target risk level.

    Returns:
        float: Difference between current and target risks.
    """
    return portfolio_risk(weights, sigma1, sigma2, rho) - sigma_T
```

In [ ]:
```
results_rp: List[float] = []

for sigma_T in sigma_T_values:
    cons = ({'type': 'eq', 'fun': lambda x: np.sum(x) - 1},
            {'type': 'eq', 'fun': lambda x: constraint(x, sigma_T)})
    bounds: Tuple[Tuple[float, float], Tuple[float, float]] = ((0, 1), (0, 1))
    initial_weights: List[float] = [0.5, 0.5]
    result = minimize(objective, initial_weights, bounds=bounds, constraints=cons)
    results_rp.append(-result.fun)
```

In [ ]:
```
# Plotting the efficient frontier
plt.figure(figsize=(10, 6))
plt.plot(sigma_T_values, results_rp, 'b-', label='Efficient Frontier')
plt.title('Efficient Frontier')
plt.xlabel('Target Risk $\sigma_T$')
plt.ylabel('Expected Portfolio Return $R_p(\sigma_T)$')
plt.grid(True)
plt.legend()
plt.show()
```



Frontier Analysis

The graph above depicts the relationship between the target risk (σ_T) and the expected portfolio return ($R_p(\sigma_T)$). Below are the key takeaways:

1. ***Monotonic Increase***: As expected, the expected portfolio return increases with an increase in target risk, σ_T. This reflects the classic **risk-return trade-off** in portfolio management.
2. ***Plateau at Higher Risks***: The plateau observed at higher risk levels suggests that increasing risk beyond a certain point does **not proportionally increase returns**. This could be indicative of the constraints imposed by the maximum returns achievable based on the securities' parameters.
3. ***Sharp Rise at Lower Risks***: The initial sharp rise suggests that minimal increases in risk from the lower end are highly compensated by increased returns. This can be attributed to the efficient allocation of weights in response to changes in σ_T under the given constraints.