

Additional Information for Chapter 3: Portfolio Choice and Mean-Variance Optimization

Advanced Microeconomics I

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Utility Maximization Problem

- K assets
- $r \in \mathbb{R}^K$ asset returns (continuous or discrete distribution)
- expected value of r :

$$E[r] = \mu$$

- variance of r :

$$\text{Var}[r] := E[rr^T] - E[r]E[r^T] = \Sigma$$

Consumer's maximization problem:

$$\begin{aligned} \max_a E[u(\sum_k a_k r_k)] \\ \text{s.t. } \sum_k a_k = b \end{aligned}$$

Quadratic Utility

Take quadratic utility function $u(x) = \beta x - x^2$, then

$$E[u(a \cdot r)] = \beta a \cdot \mu - a \cdot \mu \mu^T a - a \cdot \Sigma a$$

- only μ and Σ matter
- solution to utility maximization problem will have minimal variance $a \cdot \Sigma a$ for a given mean $a \cdot \mu$ (assuming $a \cdot 1 = 1$)

Mean-Variance Optimization

Unconstrained Optimization (a_k can be negative)

$$\begin{aligned} \min_a \quad & \frac{1}{2} \mathbf{a} \cdot \Sigma \mathbf{a} \\ \text{s.t.} \quad & \mathbf{a} \cdot \mathbf{1} = 1 \\ & \mathbf{a} \cdot \boldsymbol{\mu} = \mu_p \end{aligned}$$

Lagrangian

$$L = \frac{1}{2} \mathbf{a} \cdot \Sigma \mathbf{a} - \gamma (\mathbf{a} \cdot \mathbf{1} - 1) - \lambda (\mathbf{a} \cdot \boldsymbol{\mu} - \mu_p),$$

→ Solve

$$\partial_{\mathbf{a}} L = 0, \partial_{\gamma} L = 0, \partial_{\lambda} L = 0 \rightarrow \mathbf{a}^*$$

Mean-Variance Optimization

Constrained Optimization (a_k cannot be negative)

$$\begin{aligned} \min_a \quad & \frac{1}{2} a \cdot \Sigma a \\ \text{s.t.} \quad & a \cdot \mathbf{1} = 1 \\ & a \cdot \mu = \mu_p \\ & a \geq 0 \end{aligned}$$

Assume we know the set of assets with non-zero weights

$$S = \{k : a_k > 0\}$$

Lagrangian

$$L = \frac{1}{2} a_S \cdot \Sigma_S a_S - \gamma (a_S \cdot \mathbf{1}_S - 1) - \lambda (a_S \cdot \mu_S - \mu_p),$$

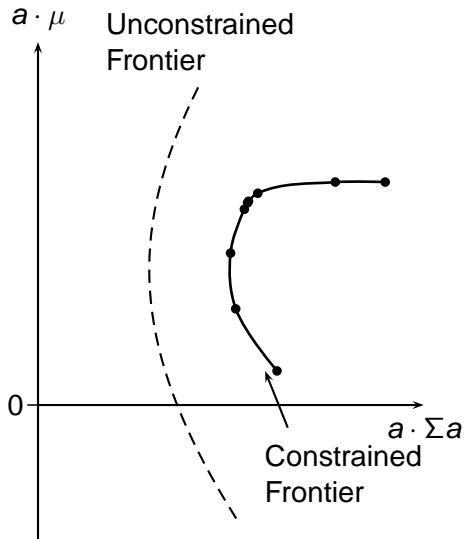
where $a_S > 0$

Using the constraint $a \cdot 1 = a_S \cdot 1_S = 1$ we have (for a given λ):

$$a_S^* = \lambda \Sigma_S^{-1} \left(\mu_S - \frac{1_S \cdot \Sigma_S^{-1} \mu_S}{1_S \cdot \Sigma_S^{-1} 1_S} 1_S \right) + \frac{\Sigma_S^{-1} 1_S}{1_S \cdot \Sigma_S^{-1} 1_S} \quad (1)$$

- trying all 2^K possibilities to choose S would take too much time
- Niedermyer & Niedermyer (forthcoming) propose a fast computational method for solving this problem extending Markowitz's Critical Line Algorithm (CLA)

Constrained Efficient Frontier



Speed Comparison

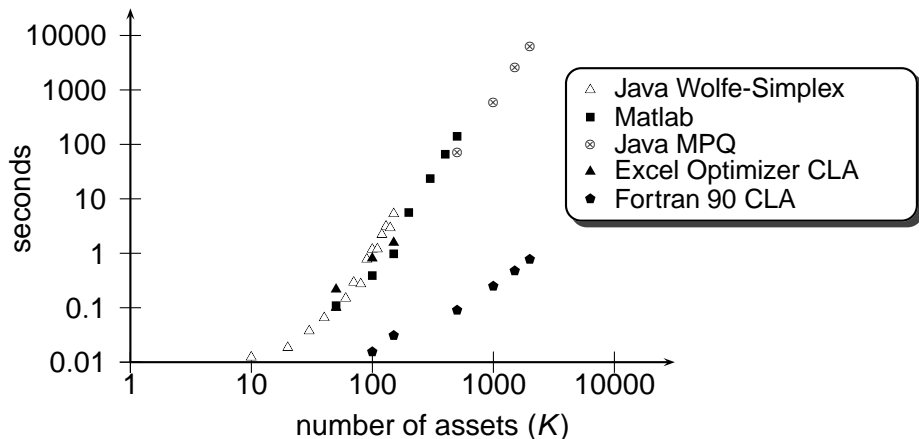


Figure: Testing different algorithms: CPU times for different number of assets and randomly generated positive definite covariance matrix.