



COMPUTATIONAL FINANCE & RISK MANAGEMENT

UNIVERSITY *of* WASHINGTON

Department of Applied Mathematics

Markowitz Mean-Variance Optimization

CFRM 425 (016)

R Programming for Quantitative Finance

Lecture References/Package Downloads

- Ang, Ch 7: § § 7.3 – 7.4 (the latter involves short selling)
- Solving Quadratic Programs with R's quadprog package (blog article):
<https://rwalk.xyz/solving-quadratic-programs-with-rs-quadprog-package/>
- Ch 30, www.rmetrics.org/downloads/9783906041025-basicr.pdf
- Topics:
 - The Optimization Problem
 - Using the quadprog package

The Optimization Problem

"Snow Predicted" Oil on canvas.



Portfolio Optimization Example

- The classic Markowitz application is a quadratic optimization problem, to find the optimal weights among several assets that would minimize the risk (variance) subject to a target return (based on the means of historical returns) and correlations between the (risky) assets
- The definition of a *risky asset* here is that the variance of each is greater than zero
- We will see later what happens when a risk-free asset enters into the model
- The optimization problem:
- Where:
 - $\{\omega_i\}$ is the set of fund weights,
 - $\boldsymbol{\mu}$ is the empirical fund mean vector,
 - and $\boldsymbol{\Sigma}$ is the covariance matrix

mean-variance portfolio optimization

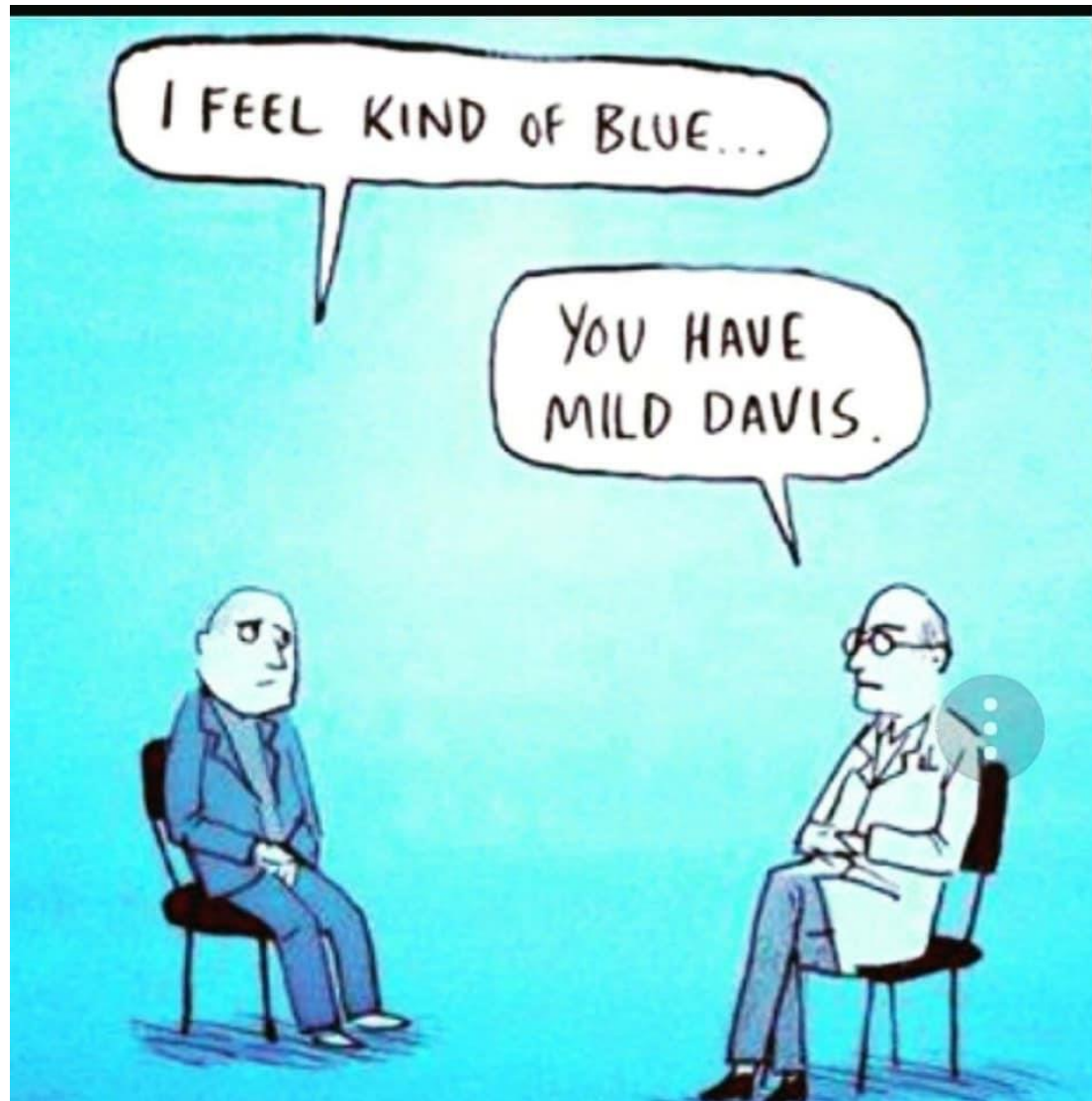
$$\min_{\omega} \quad \omega^T \boldsymbol{\Sigma} \omega$$

$$\text{s.t.} \quad \omega^T \boldsymbol{\mu} = \mu_p$$

$$\omega^T \mathbf{1} = 1$$

$$\omega_{\min} \leq \omega_i \leq \omega_{\max}$$

Using the quadprog package



The quadprog package

- The function to use for the quadratic programming problem is **solve.QP(.)**
- More specifically, it implements the dual method of Goldfarb and Idnani (1982, 1983) for solving quadratic programming problems of the form

$$\min_b -\mathbf{d}^T \mathbf{b} + \frac{1}{2} \mathbf{b}^T \mathbf{D} \mathbf{b}$$

$$\mathbf{S}^T \mathbf{A}^T \mathbf{b} \geq \mathbf{b}_0,$$

$$\mathbf{D} \in \mathbb{R}^{n \times n} \text{ symmetric}$$

$$\mathbf{b}, \mathbf{b}_0 \in \mathbb{R}^n, \mathbf{A} \in \mathbb{R}^{n \times p}$$

- p = number of constraints
- For our case, $\mathbf{d} = \mathbf{0}$, and $\mathbf{D} = 2\mathbf{\Sigma}$
- The factor of 2, however, is not necessary since the first term in the objective function disappears, so just put $\mathbf{D} = \mathbf{\Sigma}$

The quadprog package

- For a first example, let's just enforce the constraints

$$\omega^T \mathbf{1} = 1$$

$$\omega^T \mu = \mu_p$$

- While the weights must sum to 1, they can be positive or negative
- This means short sales are allowed
- The first two rows of \mathbf{A}^T :
 - 1 1 ... 1
 - μ_1 μ_2 ... μ_n

The quadprog package

- In code, given an xts set of asset returns **rtns**, our setup goes as follows:
- Note the use of **coredata(.)** to extract the data matrix from the xts object

```
meansVec <- colMeans(coredata(rtns))
```

```
covMtx <- cov(coredata(rtns))
```

```
# Our D matrix is
```

```
D <- covMtx
```

- The sum of the weights is the same as taking the dot product with a unit vector, so the first row of A is a row of ones

```
A <- matrix(data = 1, nrow = 1, ncol = nrow(D))
```

- The 2nd constraint says the weighted average of means must sum to the target return, so assign the historical means of each asset to get the dot product

```
# Append the expected returns:
```

```
A <- rbind(A, meansVec)
```

- Our constraint vector **b₀** is formed by putting

```
b0 <- c(1, minRtn)
```


The quadprog package

- The `solve.QP(.)` function looks something like the following example:

```
sol <- solve.QP(Dmat=D, dvec = rep(0,nrow(D)), Amat=t(A),  
                bvec=b0, meq=1)
```

- **D** is the matrix 2 x Covariance matrix
- `rep(0, nrow(D))` is a vector of zeros with the same number of elements as the number of rows of the matrix **D** (not used in Markowitz optimization)
- **A** is our matrix of coefficients of the constraints
- **b0** is the vector of real values on the right hand side of the constraints (same as \mathbf{b}_0 in the mathematical description)
- The **meq** parameter means the number of constraints that must attain equality; otherwise, the constraint is $\text{LHS} \geq \text{RHS}$

The quadprog package

- Our matrix **A** in the code is actually $p \times n$, so we need to transpose it to $n \times p$ to satisfy the conditions of the algorithm
- We also require both constraints to be binding (=); setting **meq=2** in the call to **solve.QP(.)** enforces this

- Then:

```
sol <- solve.QP(Dmat=D, dvec = rep(0,nrow(D)), Amat=t(A),  
               bvec=b0, meq=2)
```

- And we get our optimal portfolio weights:

```
sol$solution  
[1] 0.07851751 0.10173572 0.06404380 0.06180230 -0.10318638  
[6] 0.23184826 0.18270103 0.08272886 0.34224685 -0.04243794
```

The quadprog package

- Now, what if we want to prevent short sales
- Append an identity matrix (size = number of assets) to the bottom of our **A** matrix in the code, and the same number of zeroes to the **d0** constraint vector:

```
A_no_short <- rbind(A, diag(nrow(D)))  
b0_no_short <- c(b0, rep(0, nrow(D)))
```

- Run the optimization again:

```
sol_no_short <- solve.QP(Dmat=D, dvec = rep(0,nrow(D)),  
                        Amat=t(A_no_short), bvec=b0_no_short, meq=2)  
  
sol_no_short$solution
```

- Result:

```
[1] 1.277730e-01 5.290414e-17 4.817832e-02 8.949107e-02 -4.164283e-17  
[6] 2.279359e-01 2.162308e-01 1.458849e-02 2.758025e-01 -1.749745e-17
```

- The boxed results can be interpreted as zeroes (no allocations in the portfolio)