## Chapter 11 - Risk Parity Portfolio

## **Exercises**

Exercise 11.1 Show why  $\Sigma x = b/x$  can be equivalently solved as Cx = b/x, where C is the correlation matrix defined as  $C = D^{-1/2}\Sigma D^{-1/2}$  with D a diagonal matrix containing  $\operatorname{diag}(\Sigma)$  along the main diagonal. Would it be possible to use instead  $C = M^{-1/2}\Sigma M^{-1/2}$ , where M is not necessaryly a diagonal matrix?

Exercise 11.2 If the covariance matrix is diagonal  $\Sigma = D$ , then the system of nonlinear equations  $\Sigma x = b/x$  has the closed-form solution  $x = \sqrt{b/\text{diag}(D)}$ . Explore whether a closed-form solution can be obtained for the rank-one plus diagonal case  $\Sigma = uu^{\mathsf{T}} + D$ .

Exercise 11.3 The solution to the formulation

$$\begin{array}{ll} \underset{x \geq \mathbf{0}}{\text{maximize}} & \boldsymbol{b}^\mathsf{T} \log(\boldsymbol{x}) \\ \text{subjectto} & \sqrt{\boldsymbol{x}^\mathsf{T} \boldsymbol{\Sigma} \boldsymbol{x}} \leq \sigma_0 \end{array}$$

is

$$\lambda \Sigma x = b/x \times \sqrt{x^{\mathsf{T}} \Sigma x}.$$

Can you solve for  $\lambda$  and rewrite the solution in a more compact way without  $\lambda$ ?

**Exercise 11.4** Newton's method requires computing the direction  $\mathbf{d} = \mathsf{H}^{-1} \nabla f$  or, equivalently, solving the system of linear equations  $\mathsf{H}\mathbf{d} = \nabla f$  for  $\mathbf{d}$ . Explore whether a more efficient solution is possible exploiting the structure of the gradient and Hessian:

$$abla f = oldsymbol{\Sigma} oldsymbol{x} - oldsymbol{b}/oldsymbol{x} \ \mathsf{H} = oldsymbol{\Sigma} + \mathsf{Diag}(oldsymbol{b}/oldsymbol{x}^2).$$

Exercise 11.5 The MM algorithm requires the computation of the largest eigenvalue  $\lambda_{\text{max}}$  of matrix  $\Sigma$ , which can be obtained from the eigenvalue decomposition of the matrix. A more efficient alternative is the power iteration method. Program both methods and compare the computational complexity.

## Exercise 11.6 Consider the vanilla convex formulation

$$\label{eq:loss_equation} \begin{aligned} & \underset{x \geq \mathbf{0}}{\text{minimize}} & & \frac{1}{2} \boldsymbol{x}^\mathsf{T} \boldsymbol{\Sigma} \boldsymbol{x} - \boldsymbol{b}^\mathsf{T} \log(\boldsymbol{x}). \end{aligned}$$

Implement the cyclical coordinate descent method and the parallel SCA method in a high-level programming language (e.g., R, Python, Julia, or Matlab) and compare the converge vs CPU time for these two methods. Then, re-implement these two methods in a low-level programming language (e.g., C, C++, C#, or Rust) and compare the convergence again. Comment on the difference observed.