

4.10 Use for example min-var model

a) min $\frac{1}{2} w^T \Sigma w$

s.t. $w^T \mu \geq \bar{\mu}$

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

$w \geq 0$

b) $L(w, \alpha_0, \alpha_1, \beta) = \frac{1}{2} w^T \Sigma w + \alpha_0 (\bar{\mu} - w^T \mu) + \alpha_1 (1 - w^T \mathbf{1}) - \beta^T w$

KKT:
- stationarity

$$\frac{\partial L}{\partial w} = 0 \Rightarrow \Sigma w - \alpha_0 \mu - \alpha_1 \mathbf{1} - \beta = 0$$

- primal feasibility

$$\frac{\partial L}{\partial \alpha_0} \leq 0 \Rightarrow \bar{\mu} - w^T \mu \leq 0$$

$$\frac{\partial L}{\partial \alpha_1} = 0 \Rightarrow 1 - w^T \mathbf{1} = 0$$

$$\frac{\partial L}{\partial \beta} \leq 0 \Rightarrow -w \leq 0$$

- dual feasibility

$$\alpha_0 \geq 0$$

$$\beta \geq 0$$

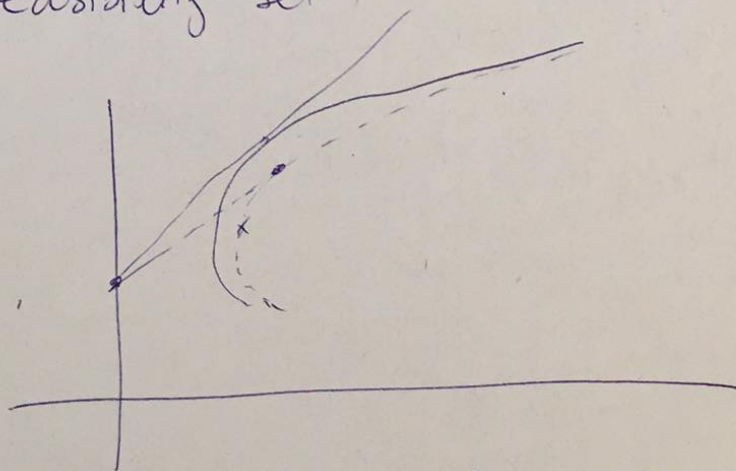
- Complementary-slackness

$$\alpha_0 \cdot (\bar{\mu} - w^T \mu) = 0$$

$$\beta^T w = 0$$

- c)
- 1) use $w^T \mathbf{1} = 1$, plug in for one of the weights and get rid of this inequality constraint, use Lagrange multipliers to calculate the optimal value on a compact set
 - 2) it's convex problem (even quadratic programming problem), hence methods used for this class of problems can be employed.
(feasibility set is a set of linear cuts...)

d) mean-variance frontier
→ would be "smaller", subset of the original feasibility set, and not "smooth"



CAL → only from risk free asset to the new tangency portfolio, and then prolonged by the eff. frontier

4.11 Basically the same as 4.10

a)

$$\min \frac{1}{2} w^T \Sigma w$$

$$\text{s.t. } w^T \mu \geq \bar{\mu}$$

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

$$w \geq 0$$

$$\Rightarrow \text{s.t. } (w_1 \ w_2 \ w_3) \begin{pmatrix} 0.4 \\ 0.08 \\ 0.2 \end{pmatrix} \geq 0.15$$

$$w_1 + w_2 + w_3 = 1$$

$$w_1, w_2, w_3 \geq 0$$

b)

$$L(w_1, w_2, w_3, \alpha_0, \alpha_1, \beta_1, \beta_2, \beta_3) =$$

$$= \frac{1}{2} (w_1 \ w_2 \ w_3) \begin{pmatrix} \Sigma \end{pmatrix} \begin{pmatrix} w_1 \\ w_2 \\ w_3 \end{pmatrix} + \alpha_0 \left(0.15 - (w_1 \ w_2 \ w_3) \begin{pmatrix} 0.14 \\ 0.08 \\ 0.2 \end{pmatrix} \right)$$

$$+ \alpha_1 (1 - w_1 - w_2 - w_3) - \beta_1 w_1 - \beta_2 w_2 - \beta_3 w_3$$

• stationarity

$$\begin{pmatrix} \Sigma \end{pmatrix} \begin{pmatrix} w_1 \\ w_2 \\ w_3 \end{pmatrix} - \alpha_0 \begin{pmatrix} 0.14 \\ 0.08 \\ 0.2 \end{pmatrix} - \alpha_1 \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix} - \begin{pmatrix} \beta_1 \\ \beta_2 \\ \beta_3 \end{pmatrix} = 0$$

• primal feas.

$$0.15 - (w_1 \ w_2 \ w_3) \begin{pmatrix} 0.14 \\ 0.08 \\ 0.2 \end{pmatrix} \leq 0$$

$$1 - w_1 - w_2 - w_3 = 0$$

$$-w_1 \leq 0, \quad -w_2 \leq 0, \quad -w_3 \leq 0$$

• dual feas.

$$\alpha_0 \geq 0, \quad \beta_3 \geq 0, \quad \beta_1 \geq 0, \quad \beta_2 \geq 0$$

• complementary slackness

$$\alpha_0 \cdot (\bar{\mu} - w^T \mu) = 0$$

$$\beta_1 w_1 + \beta_2 w_2 + \beta_3 w_3 = 0$$

c)
solution via
any software
(quadr. programming)

$$w^* = \begin{pmatrix} 0.479 \\ 0.177 \\ 0.344 \end{pmatrix}$$

4.12 Risk = Variance

a) first, we need to calculate μ and Σ

$$\mu = \frac{1}{4}s_1 + \frac{1}{2}s_2 + \frac{1}{4}s_3 = \frac{1}{4} \begin{pmatrix} 24 \\ 28 \\ 4 \end{pmatrix} + \frac{1}{2} \begin{pmatrix} 12 \\ 12 \\ 8 \end{pmatrix} + \frac{1}{4} \begin{pmatrix} 0 \\ 4 \\ 28 \end{pmatrix} = \begin{pmatrix} 12 \\ 14 \\ 12 \end{pmatrix}$$

$$\begin{aligned} \Sigma &= \sum_{i=1}^3 p_i (s_i - \mu)(s_i - \mu)^T \\ &= \frac{1}{4} \begin{pmatrix} 12 \\ 14 \\ -8 \end{pmatrix} (12 \ 14 \ -8) + \frac{1}{2} \begin{pmatrix} 0 \\ -2 \\ -4 \end{pmatrix} (0 \ -2 \ -4) + \frac{1}{4} \begin{pmatrix} -12 \\ -18 \\ 16 \end{pmatrix} (-12 \ -18 \ 16) \\ &= \begin{pmatrix} 72 & 72 & -72 \\ 72 & 76 & -64 \\ -72 & -64 & 88 \end{pmatrix} = 4 \cdot \begin{pmatrix} 18 & 18 & -18 \\ 18 & 19 & -16 \\ -18 & -16 & 22 \end{pmatrix} \end{aligned}$$

model: $\min \frac{1}{2} w^T \Sigma w$ $\bar{\mu} = 14$
 s.t. $w^T \mu \geq \bar{\mu}$ $\mu = (12 \ 14 \ 12)$
 $w^T \mathbf{1} = 1$ $\Sigma = 4 \begin{pmatrix} 18 & 18 & -18 \\ 18 & 19 & -16 \\ -18 & -16 & 22 \end{pmatrix}$

b) optimal solution via formula does not exist, as Σ is singular and hence not invertible.

c) \rightarrow find x such that $x^T \Sigma x = 0$

$$\left(\begin{array}{ccc|ccc} 18 & 18 & -18 & 1 & 0 & 0 \\ 18 & 19 & -16 & 0 & 1 & 0 \\ -18 & -16 & 22 & 0 & 0 & 1 \end{array} \right) \sim \left(\begin{array}{ccc|ccc} 1 & 1 & -1 & 1/18 & 0 & 0 \\ 0 & 1 & 2 & -1 & 1 & 0 \\ 0 & 2 & 4 & 1 & 0 & 1 \end{array} \right) \sim \left(\begin{array}{ccc|ccc} 1 & 1 & -1 & 1/18 & 0 & 0 \\ 0 & 1 & 2 & -1 & 1 & 0 \\ 0 & 0 & 0 & -1 & -2 & 1 \end{array} \right)$$

$$\Rightarrow x = (3 \ -2 \ 1)^T$$

\rightarrow can we invest so we have no risk?

$$w_1 + w_2 + w_3 = 1$$

$$\left. \begin{array}{l} w_3 = t, w_2 = -2t, w_1 = 3t \end{array} \right\} 3t + t - 2t = 1 \rightarrow t = \frac{1}{2}$$

$$\rightarrow w = \begin{pmatrix} 3/2 \\ -1 \\ 1/2 \end{pmatrix} \text{ has zero risk.}$$

\rightarrow optimal return is only 10, we want 14.

→ let us plug in

$$w_3 = 1 - w_1 - w_2$$

then we have

$$\min_{w_1, w_2} \frac{1}{2} (w_1 \ w_2 \ 1-w_1-w_2) \begin{pmatrix} 18 & 18 & -18 \\ +18 & 19 & -16 \\ -18 & -16 & 22 \end{pmatrix} \begin{pmatrix} w_1 \\ w_2 \\ 1-w_1-w_2 \end{pmatrix}$$

$$\text{s.t. } (w_1 \ w_2 \ 1-w_1-w_2) \begin{pmatrix} 12 \\ 14 \\ 12 \end{pmatrix} \geq 14$$

→ that is minimization of a quadratic function with a condition

$$12w_1 + 14w_2 + (1-w_1-w_2) \cdot 12 \geq 14$$

$$\underline{w_2 \geq 1}$$

→ its minimum is 0, and that is at point $(\frac{3}{2}, -1)$, which does not meet the criteria $w_2 \geq 1$.

→ hence the extreme must lie on the boundary of the space

→ note that because it is a quadratic function with positive coefficients for w_1^2 and w_2^2 , we know that the extreme must exist.

⇒ that implies that $w_2 = 1$, hence we can plug this into the derivative and minimize for w_1 .

$$f(w_1) = \frac{1}{2} (w_1 \ 1 - w_1) \begin{pmatrix} 18 & 18 & -18 \\ 18 & 19 & -16 \\ -18 & -16 & 22 \end{pmatrix} \begin{pmatrix} w_1 \\ 1 \\ -w_1 \end{pmatrix}$$

$$= \frac{1}{2} (36w_1 + 18 \quad 34w_1 + 19 \quad -40w_1 - 16) \begin{pmatrix} w_1 \\ 1 \\ -w_1 \end{pmatrix}$$

$$= \frac{1}{2} (36w_1^2 + 18w_1 + 34w_1 + 19 + 40w_1^2 + 16w_1)$$

$$= \frac{1}{2} (76w_1^2 + 52w_1 + 19)$$

$$\frac{df(w_1)}{dw_1} = 2 \cdot 76w_1 + 52$$

$$\frac{df(w_1)}{dw_1} = 0 \Leftrightarrow w_1 = -\frac{52}{2 \cdot 76} = -\frac{17}{38}$$

$$\Rightarrow w^* = \left(-\frac{17}{38}, 1, \frac{17}{38} \right)$$