# Lesson 19. Optimization with Equality Constraints, cont.

#### 1 Overview

- Last time: the Lagrange multiplier method for optimization problems with one equality constraint
- Today: multiple equality constraints

### 2 The Lagrange multiplier method – k equality constraints

minimize/maximize 
$$f(x_1,...,x_n)$$
  
subject to  $g_1(x_1,...,x_n) = c_1$   
 $\vdots$   
 $g_k(x_1,...,x_n) = c_k$ 

• The **Lagrangian function** L is

$$L(\lambda_1,\ldots,\lambda_k,x_1,\ldots,x_n)=f(x_1,\ldots,x_n)-\lambda_1\big[g_1(x_1,\ldots,x_n)-c_1\big]-\cdots-\lambda_k\big[g_k(x_1,\ldots,x_n)-c_k\big]$$

• The gradient of *L* is

$$\nabla L(\lambda_1, \dots, \lambda_k, x_1, \dots, x_n) = \begin{bmatrix} -g_1(x_1, \dots, x_n) + c_1 \\ \vdots \\ -g_k(x_1, \dots, x_n) + c_k \\ \frac{\partial f}{\partial x_1}(x_1, \dots, x_n) - \lambda_1 \frac{\partial g_1}{\partial x_1}(x_1, \dots, x_n) - \dots - \lambda_k \frac{\partial g_k}{\partial x_1}(x_1, \dots, x_n) \\ \vdots \\ \frac{\partial f}{\partial x_n}(x_1, \dots, x_n) - \lambda_1 \frac{\partial g_1}{\partial x_n}(x_1, \dots, x_n) - \dots - \lambda_k \frac{\partial g_k}{\partial x_n}(x_1, \dots, x_n) \end{bmatrix}$$

• The Hessian of *L* is

$$H_{L}(\lambda_{1},...,\lambda_{k},x_{1},...,x_{n}) = \begin{bmatrix} 0 & ... & 0 & -\frac{\partial g_{1}}{\partial x_{1}}(x_{1},...,x_{n}) & ... & -\frac{\partial g_{1}}{\partial x_{n}}(x_{1},...,x_{n}) \\ \vdots & \ddots & \vdots & & \vdots & \ddots & \vdots \\ 0 & ... & 0 & -\frac{\partial g_{k}}{\partial x_{1}}(x_{1},...,x_{n}) & ... & -\frac{\partial g_{k}}{\partial x_{n}}(x_{1},...,x_{n}) \\ -\frac{\partial g_{1}}{\partial x_{1}}(x_{1},...,x_{n}) & ... & -\frac{\partial g_{k}}{\partial x_{1}}(x_{1},...,x_{n}) & h_{11} & ... & h_{1n} \\ \vdots & \ddots & \vdots & & \vdots & \ddots & \vdots \\ -\frac{\partial g_{1}}{\partial x_{n}}(x_{1},...,x_{n}) & ... & -\frac{\partial g_{k}}{\partial x_{n}}(x_{1},...,x_{n}) & h_{n1} & ... & h_{nn} \end{bmatrix}$$

where

$$h_{ij} = \frac{\partial^2 f}{\partial x_i \partial x_i}(x_1, \dots, x_n) - \lambda_1 \frac{\partial^2 g_1}{\partial x_i \partial x_i}(x_1, \dots, x_n) - \dots - \lambda_k \frac{\partial^2 g_k}{\partial x_i \partial x_i}(x_1, \dots, x_n)$$

### Finding constrained local optima:

- Step 0. Form the Lagrangian function *L* and find its gradient and Hessian
- **Step 1.** Find the **constrained critical points**  $(\lambda_1, \ldots, \lambda_k, x_1, \ldots, x_n)$  by solving the system of equations:

$$\nabla L(\lambda_1,\ldots,\lambda_k,x_1,\ldots,x_n)=0$$

- Step 2. Classify each constrained critical point as a local minimum, local maximum, or saddle point by applying the second derivative test for constrained extrema:
  - Suppose  $(\lambda_1^*, \dots, \lambda_k^*, x_1^*, \dots, x_n^*)$  is a constrained critical point found in Step 1
  - Compute the principal minors  $d_i = |H_L(\lambda_1^*, \dots, \lambda_k^*, x_1^*, \dots, x_n^*)|$  for  $i = 2k + 1, \dots, n + k$
  - ∘ If  $d_{n+k} \neq 0$ :
    - (1)  $(-1)^k d_{2k+1} > 0$ ,  $(-1)^k d_{2k+2} > 0$ , ...,  $(-1)^k d_{n+k} > 0$

then f has a constrained local minimum at  $(x_1^*, \ldots, x_n^*)$ 

(2)  $(-1)^k d_{2k+1} < 0$ ,  $(-1)^k d_{2k+2} > 0$ ,  $(-1)^k d_{2k+3} < 0$ , ... then f has a constrained local

then f has a constrained local maximum at  $(x_1^*, \ldots, x_n^*)$ 

(3) otherwise,

f has a constrained saddle point at  $(x_1^*, \ldots, x_n^*)$ 

• If  $d_{n+1} = 0$ , then the test gives no information

**Example 1.** Use the Lagrange multiplier method to find the local optima of

minimize/maximize  $x_3$ subject to  $x_1 + x_2 + x_3 = 12$  $x_1^2 + x_2^2 - x_3 = 0$ 

• In this problem, n = and k =

**Step 0.** Form the Lagrangian function *L* and find its gradient and Hessian.

Step 1.	Find the constrained critical points	S.	

## 3 Exercises

**Problem 1.** Use the Lagrange multiplier method to find the local optima of

minimize/maximize 
$$x_1^2 + x_2^2 + x_3^2$$
  
subject to  $3x_1 + x_2 + x_3 = 5$   
 $x_1 + x_2 + x_3 = 1$