

**Constraints**

Let  $f(x) = -x_1 - x_2$ ,  $x \in \mathbb{R}^2$ .  $\min f(x)$  yields  $x_1$  and  $x_2$  tending toward infinity. With constraints (subject to)

$$x_1^2 + x_2^2 - 1 = 0 \quad (1)$$

The feasible set is the unit circle.

**Taylor series**

A function can be approximated by

$$f(x + \delta) \approx f(x) + \nabla f(x)^T \delta \quad (2)$$

Use Taylor for the above problem

$$\begin{aligned} g(x) &= x_1^2 + x_2^2 - 1 \\ g(x^* + \delta) &\approx g(x^*) + \nabla g(x^*)^T \delta \\ &= \nabla f(x^*)^T \delta \end{aligned}$$

We have that

$$\nabla f(x^*)^T \delta = 0 \quad (3)$$

Set

$$\nabla f(x^*) = \lambda \nabla g(x^*), \quad \lambda \in \mathbb{R} \quad (4)$$

Write a Langrangian

$$\begin{aligned} \mathbf{L}(x, \lambda) &= f(x) + \lambda g(x) \\ \mathbf{L}(x^*, \lambda^*) &= \nabla f(x^*) - \lambda \nabla g(x^*) = 0 \end{aligned}$$

**Multiple equality constraints**

$$g_i(x) = 0, i = 1, \dots, K$$

The Jacobian is given by  $D\bar{g}$ ,  $\bar{g}$  being a vector.

$$D\bar{g}(x) = \begin{bmatrix} (\nabla g_1(x))^T \\ \vdots \\ (\nabla g_K(x))^T \end{bmatrix} \in \mathbb{R}^{K \times N} \quad (5)$$

Assume  $D\bar{g}$  has full row rank

$$\bar{G}(x + \delta) \approx \bar{g} + D\bar{g}(x)\delta = 0$$

This is because of  $g$  being 0 for all  $x$ .

Let  $G = \{\nabla g_8(x), \dots, \nabla g_K(x)\}$ .

Let the orthogonal projection of  $\nabla f(x^*)$  onto  $G$  be

$$\sum_{i=1}^K \lambda_i \nabla g_i(x^*) \quad (6)$$

This gives

$$\nabla f(x^*) = \sum_{i=1}^K \lambda_i \nabla g_i(x^*) + r \quad (7)$$

with  $r$  being the residual orthogonal to the projection. Choose  $s = -r$ . Is this a feasible step?

$$\begin{aligned} s^T \nabla f(x^*) &= s^T \left( \sum_{i=1}^K \lambda_i \nabla g_i(x^*) - s \right) = -s^T s \\ &= -\|s\|_2^2 \end{aligned}$$

Start at an optimal point and take step  $s$

$$f(x^* + s) \approx f(x^*) + \nabla f(x^*)^T s \quad (8)$$

The right term can not be negative, as the optimal point is not a minimum then. The norm is always positive, and  $s$  can therefore not be a feasible step.

### Necessary condition for optimization

$$\nabla f(x^*) - \sum_{i=1}^K \lambda_i \nabla g_i(x^*) = 0 \quad (9)$$

### Example

Write the lagrangian

$$\mathcal{L}(x, \lambda) = -x_1 - x_2 + \lambda(x_1^2 + x_2^2 - 1) \quad (10)$$

Minimize  $\mathcal{L}(x, \lambda)$ . Take the derivative  $\nabla \mathcal{L}(x, \lambda)$ .

$$\begin{aligned} \frac{\partial}{\partial x_1} \mathcal{L}(x, \lambda) &= -1 + 2\lambda x_1 = 0 \\ \frac{\partial}{\partial x_2} \mathcal{L}(x, \lambda) &= -1 + 2\lambda x_2 = 0 \end{aligned}$$

This means that  $\lambda = \frac{1}{2x_2}$ . From this we know, that  $x_1 = x_2$ . We know that  $g(x) = 0$ .

### Inequality constraints

If the constraints are inequalities the following holds

$$\nabla f(x^*) = \sum_{i=1}^K \mu_i \nabla h_i(x^*) \quad (11)$$

where  $h(x) \geq 0$  and  $\mu \geq 0$

$$\begin{aligned} f(x^* + s) &\approx f(x^*) + (\nabla f(x^*))^T s \\ &= f(x^*) + ((Dh(x^*)^T \mu)^T s \\ &= f(x^*) + \mu^T \mathbf{e} \\ &= f(x^*) + \mu_1 \end{aligned}$$

### KKT

$$\begin{aligned} D\mathcal{L}(x, \mu) &= 0 \\ \nabla f(x^*) &= \sum_{i=1}^P \mu_i - \lambda \nabla h_i(x^*) \\ \mu_i &\geq 0, \quad i = 1, \dots, P \\ h_i(x^*) &\geq 0, \quad \forall i \\ \mu_i h_i(x^*) &= 0, \quad \forall i \end{aligned}$$

### Linear Program

Minimize  $f(x)$

s.t.  $g(x) \geq 0$

Constraints and objectives have to be linear.

Minimize  $c^T x + q$  subject to  $Ax = b$ .

### Linearizing a Problem

Minimize  $\|x\|_1$  subject to  $Ax = b$ . This is equal to minimizing  $\sum_{i=1}^K t_i$  with

1.  $x_i \leq t_i$
2.  $-x_i \leq t_i$
3.  $Ax = b$