Karush-Kuhn-Tucker optimality conditions and Lagrangian duality

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Contents of the lessons

- The Abadie constraints qualification (ACQ);
- Karush-Kuhn-Tucker optimality conditions;
- Lagrangian duality.

Consider the constrained optimization problem

$$\begin{cases} \min\ f(x) \\ x \in X := \{x \in \mathbb{R}^n : g_j(x) \leq 0, \quad j = 1, \dots, m, h_k(x) = 0,\ k = 1, \dots, p\} \end{cases} \qquad \text{(P)}$$

where f, g_j and h_k are continuously differentiable for any j, k.

Definition

- The *Tangent cone* at $x^* \in X$, is defined by

$$T_X(x^*) = \left\{ d \in \mathbb{R}^n : \exists\ \{z_k\} \subset X,\ \exists\ \{t_k\} > 0,\ z_k \to x^*,\ t_k \to 0,\ \lim_{k \to \infty} \frac{z_k - x^*}{t_k} = d \right\}$$

- $\mathcal{A}(x^*) = \{j :\ g_j(x^*) = 0\}$ is the set of inequality constraints which are active at $x^* \in X$.
- The set

$$D(x^*) = \left\{ d \in \mathbb{R}^n : \begin{array}{ll} d^{\mathsf{T}} \nabla g_j(x^*) \leq 0 & \forall\ j \in \mathcal{A}(x^*), \\ d^{\mathsf{T}} \nabla h_k(x^*) = 0 & \forall\ k = 1, \dots, p \end{array} \right\}$$

is the *first-order feasible direction cone* at $x^* \in X$.

Definition – Abadie constraint qualification (ACQ)

We say that the Abadie constraint qualification (ACQ) holds at a point $x^* \in X$, if $T_X(x^*) = D(x^*)$.

Theorem 1 (Sufficient conditions for ACQ)

a) (*Affine constraints*)
If g_j and h_k are affine for all $j = 1, \dots, m$ and $k = 1, \dots, p$, then ACQ holds at any $x \in X$.

b) (*Slater condition for convex problems*)
If g_j are convex for all $j = 1, \dots, m$, h_k are affine for all $k = 1, \dots, p$ and there exists $\bar{x} \in X$ s.t. $g(\bar{x}) < 0$ and $h(\bar{x}) = 0$, then ACQ holds at any $x \in X$.

c) (*Linear independence of the gradients of active constraints*)
If $x^* \in X$ and the vectors

$$\begin{cases} \nabla g_j(x^*) & \text{for } j \in \mathcal{A}(x^*), \\ \nabla h_k(x^*) & \text{for } k = 1, \dots, p \end{cases}$$

are linearly independent, then ACQ holds at x^*.

Theorem 2 (Karush-Kuhn-Tucker)

If x^* is a local minimum and ACQ holds at x^*, then there exist $\lambda^* \in \mathbb{R}^m$ and $\mu^* \in \mathbb{R}^p$ s.t. (x^*, λ^*, μ^*) satisfies the KKT system:

$$\begin{cases} \nabla f(x^*) + \displaystyle\sum_{i=1}^{m} \lambda_i^* \nabla g_i(x^*) + \sum_{j=1}^{p} \mu_j^* \nabla h_j(x^*) = 0 \\ \lambda_i^* g_i(x^*) = 0 \qquad \forall\ i = 1, \dots, m \\ \lambda^* \geq 0 \\ g(x^*) \leq 0 \\ h(x^*) = 0 \end{cases}$$

Define the Lagrangian function $L : \mathbb{R}^n \times \mathbb{R}^m \times \mathbb{R}^p \to \mathbb{R}$ by

$$L(x, \lambda, \mu) := f(x) + \sum_{i=1}^{m} \lambda_i\, g_i(x) + \sum_{j=1}^{p} \mu_j\, h_j(x)$$

Then the KKT system can be formulated as:

$$\begin{cases} \nabla_x L(x, \lambda, \mu) \;=\; 0 \\ \lambda_i g_i(x) \;=\; 0, \quad i = 1, .., m \\ \lambda \geq 0,\;\; h(x) = 0, \quad g(x) \leq 0 \end{cases} \tag{1}$$

Note that condition $\lambda_i g_i(x) \;=\; 0$, per $i = 1, .., m$, is equivalent to $\lambda^T g(x) = 0$ or also, $\langle \lambda, g(x) \rangle = 0$.

Example

Find the the minimum points of the function $f(x_1, x_2) = 2x_1 + x_2$ on the set $X = \{(x_1, x_2) \in \mathbb{R}^2 : x_1^2 + x_2^2 \leq 4\}$

Note that X is compact so that from Weierstrass Theorem it follows that f admits global maximum and global minimum on X.
The Lagrangian function is:

$$L(x_1, x_2, \lambda) = 2x_1 + x_2 + \lambda(x_1^2 + x_2^2 - 4)$$

The KKT system is given by:

$$\begin{cases} 2 + 2\lambda x_1 = 0 \\ 1 + 2\lambda x_2 = 0 \\ \lambda(x_1^2 + x_2^2 - 4) = 0 \\ x_1^2 + x_2^2 \leq 4 \\ \lambda \geq 0 \end{cases}$$

Note that for $\lambda = 0$ the system is impossible.

We are led to solve the system:

$$\begin{cases} x_1 = -\frac{1}{\lambda} \\ x_2 = -\frac{1}{2\lambda} \\ x_1^2 + x_2^2 = 4 \\ \lambda \geq 0 \end{cases}$$

Then:

$$\frac{1}{\lambda^2} + \frac{1}{4\lambda^2} = 4$$

from which

$$16\lambda^2 = 5, \quad \lambda = \pm\frac{\sqrt{5}}{4}.$$

- $\lambda = \dfrac{\sqrt{5}}{4} \quad \Rightarrow \quad x_1 = -\dfrac{4}{\sqrt{5}} = -\dfrac{4\sqrt{5}}{5}, \quad x_2 = -\dfrac{2}{\sqrt{5}} = -\dfrac{2\sqrt{5}}{5}$

It follows that $\bar{x} = \left(-\frac{4\sqrt{5}}{5}, -\frac{2\sqrt{5}}{5}\right)$ is a global minimum point.

Remark

Note that in the previous example, ACQ is fulfilled for every $x \in X$. Indeed, there is only the constraint $g(x) = x_1^2 + x_2^2 - 4 \leq 0$, with $\nabla g(x_1, x_2) \neq (0, 0)$, for every $x \in X, s.t.\ x_1^2 + x_2^2 - 4 = 0$.

What about the maximum points of f on X ?

Notice that it is enough to set $\lambda \leq 0$ in the KKT system. In fact, in order to find the maxima of f we have to look for the minima of $-f$. The KKT system for the problem

$$\min(-f(x)) \quad x \in X$$

is:

$$\begin{cases} -2 + 2\lambda x_1 = 0 \\ -1 + 2\lambda x_2 = 0 \\ \lambda(x_1^2 + x_2^2 - 4) = 0 \\ x_1^2 + x_2^2 \leq 4 \\ \lambda \geq 0 \end{cases}$$

which is equivalent to set $\lambda \leq 0$ in the original one.
Choosing in the original system: $\lambda = -\frac{\sqrt{5}}{4}$ we obtain
$x_1 = \frac{4}{\sqrt{5}} = \frac{4\sqrt{5}}{5}, \quad x_2 = \frac{2}{\sqrt{5}} = \frac{2\sqrt{5}}{5}$
so that $\hat{x} = \left(\frac{4\sqrt{5}}{5}, \frac{2\sqrt{5}}{5}\right)$ is a global maximum point for f on the set X.

Remark

ACQ assumption is crucial in the KKT Theorem.

Example

$$\begin{cases} \min x_1 + x_2 \\ (x_1 - 1)^2 + (x_2 - 1)^2 - 1 \leq 0 \\ x_2 \leq 0 \end{cases}$$

$x^* = (1, 0)$ is the global optimum.

$T_X(x^*) = \{0\}$, $D(x^*) = \{d \in \mathbb{R}^2 : \; d_2 = 0\}$, hence ACQ does not hold at x^*.

$\nabla g_1(x^*) = (0, -2)$, $\nabla g_2(x^*) = (0, 1)$, $\nabla f(x^*) = (1, 1)$, hence there is no λ^* s.t. (x^*, λ^*) solves KKT system.

KKT Theorem gives necessary optimality conditions, but not sufficient ones.

Example

$$\begin{cases} \min x_1 + x_2 \\ -x_1^2 - x_2^2 + 2 \leq 0 \end{cases}$$

$x^* = (1,1)$, $\lambda^* = \dfrac{1}{2}$ solves KKT system, but x^* is not a local optimum.

Theorem 3

If the optimization problem is convex and (x^*, λ^*, μ^*) solves KKT system, then x^* is a global optimum.

Recall that (P) is convex if f and g are convex and h is affine.

Exercise 4.1. Prove the previous theorem.

Lagrangian relaxation and dual function

Denote by $v(P)$ denotes the optimal value of (P).

Definition

Given $\lambda \geq 0$ and $\mu \in \mathbb{R}^p$, the problem

$$\begin{cases} \inf \ L(x, \lambda, \mu) \\ x \in \mathbb{R}^n \end{cases}$$

is called Lagrangian relaxation of (P) and
$\varphi(\lambda, \mu) = \inf\limits_{x \in \mathbb{R}^n} L(x, \lambda, \mu)$ is the Lagrangian dual function.

Lagrangian relaxation provides a lower bound to $v(P)$.

Theorem 4

For any $\lambda \geq 0$ and $\mu \in \mathbb{R}^p$, we have $\varphi(\lambda, \mu) \leq v(P)$.

Proof. If $x \in X$, i.e. $g(x) \leq 0, h(x) = 0$, then

$$L(x, \lambda, \mu) = f(x) + \sum_{i=1}^{m} \lambda_i g_i(x) \leq f(x),$$

hence

$$\varphi(\lambda, \mu) = \inf_{x \in \mathbb{R}^n} L(x, \lambda, \mu) \leq \inf_{x \in X} L(x, \lambda, \mu) \leq \inf_{x \in X} f(x) = v(P),$$

assuming that (P) admits a finite optimal value. □

Properties of the dual function

The dual function φ

- is concave because inf of affine functions w.r.t (λ, μ)
- may be equal to $-\infty$ at some point
- may be not differentiable at some point

Lagrangian dual problem

Definition

The problem

$$\begin{cases} \max \ \varphi(\lambda,\mu) \\ \lambda \geq 0 \end{cases} \tag{D}$$

is called Lagrangian dual problem of (P) [and (P) is called primal problem].

- The dual problem (D) consists in finding the best lower bound of $v(P)$.
- (D) is always equivalent to a convex problem, even if (P) is a non-convex problem, indeed, it is a maximization of a concave function on a convex set.

Theorem 4, can be equivalently stated as:

Theorem 4 (weak duality)

For any optimization problem (P), we have $v(D) \leq v(P)$.
The previous inequality is called "weak duality property".

Example - Linear Programming.

Primal problem:

$$\begin{cases} \min \ c^{\mathsf{T}} x \\ Ax \geq b \end{cases} \tag{P}$$

Lagrangian function: $L(x, \lambda) = c^{\mathsf{T}} x + \lambda^{\mathsf{T}}(b - Ax) = \lambda^{\mathsf{T}} b + (c^{\mathsf{T}} - \lambda^{\mathsf{T}} A)x$
Dual function:

$$\varphi(\lambda) = \inf_{x \in \mathbb{R}^n} L(x, \lambda) = \begin{cases} -\infty & \text{if } c^{\mathsf{T}} - \lambda^{\mathsf{T}} A \neq 0 \\ \lambda^{\mathsf{T}} b & \text{if } c^{\mathsf{T}} - \lambda^{\mathsf{T}} A = 0 \end{cases}$$

Dual problem:

$$\begin{cases} \max \ \varphi(\lambda) \\ \lambda \geq 0 \end{cases} \longrightarrow \begin{cases} \max \ \lambda^{\mathsf{T}} b \\ \lambda^{\mathsf{T}} A = c^{\mathsf{T}} \\ \lambda \geq 0 \end{cases} \tag{D}$$

is a linear programming problem.

Exercise 4.2. Find the dual of (D).

Example - Least norm solution of linear equations

Primal problem:

$$\begin{cases} \min \ \dfrac{1}{2}x^\mathsf{T}x \\ Ax = b \end{cases} \tag{P}$$

Lagrangian function: $L(x,\mu) = \frac{1}{2}x^\mathsf{T}x + \mu^\mathsf{T}(b - Ax)$.
Dual function: $\varphi(\mu) = \inf_{x\in\mathbb{R}^n} L(x,\mu)$.
$L(x,\mu)$ is quadratic and strongly convex with respect to x, therefore

$$\varphi(\mu) = \inf_{x\in\mathbb{R}^n} L(x,\mu) = \min_{x\in\mathbb{R}^n} L(x,\mu),$$

thus the global optimum is the stationary point:

$$\nabla_x L = x - A^\mathsf{T}\mu = 0 \Longleftrightarrow x = A^\mathsf{T}\mu,$$

hence $\varphi(\mu) = -\frac{1}{2}\mu^\mathsf{T}AA^\mathsf{T}\mu + b^\mathsf{T}\mu$.
Dual problem:

$$\begin{cases} \max \ -\dfrac{1}{2}\mu^\mathsf{T}AA^\mathsf{T}\mu + b^\mathsf{T}\mu \\ \mu \in \mathbb{R}^p \end{cases} \tag{D}$$

is an unconstrained convex quadratic programming problem.

Exercise 4.3. Find the dual problem of a general convex quadratic programming problem

$$\begin{cases} \min \ \dfrac{1}{2}x^{\mathsf{T}}Qx + c^{\mathsf{T}}x \\ Ax \leq b \end{cases} \tag{P}$$

where Q is a symmetric positive definite matrix.

Definition (Strong duality)

We say that strong duality holds for (P) if $v(D) = v(P)$ and (D) admits an optimal solution.

Strong duality does not hold in general.

Example. Consider the following (non-convex) problem:

$$\begin{cases} \min \; -x^2 \\ x - 1 \leq 0 \\ -x \leq 0 \end{cases} \tag{P}$$

It is easy to check that $v(P) = -1$.
The Lagrangian function is $L(x, \lambda) = -x^2 + \lambda_1(x-1) - \lambda_2 x$, hence

$$\varphi(\lambda) = \inf_{x \in \mathbb{R}} L(x, \lambda) = -\infty \qquad \forall\, (\lambda_1, \lambda_2) \in \mathbb{R}^2,$$

hence $v(D) = -\infty$.

Next theorem provides sufficient conditions which guarantee strong duality for (P).

Theorem 5

Suppose f, g, h are continuously differentiable, the primal problem

$$\begin{cases} \min \ f(x) \\ g(x) \leq 0 \\ h(x) = 0 \end{cases} \tag{P}$$

is convex, there exists a global optimum x^* and ACQ holds at x^*. Then:

- Strong duality holds ($v(D) = v(P)$ and (D) admits an optimal solution);
- (λ^*, μ^*) is optimal for (D) if and only if (λ^*, μ^*) is a KKT multipliers vector associated with x^*.

Proof. $L(x, \lambda, \mu)$ is convex with respect to x since (P) is convex.
Let (λ^*, μ^*) be any KKT vector of multipliers associated with x^*. Then,

$$\nabla_x L(x^*, \lambda^*, \mu^*) = 0 \qquad \lambda^* \geq 0, \qquad (\lambda^*)^{\mathsf{T}} g(x^*) = 0.$$

Thus,

$$\begin{aligned} v(D) \geq \varphi(\lambda^*, \mu^*) = \inf_x L(x, \lambda^*, \mu^*) &\underset{[L \text{ convex}]}{=} L(x^*, \lambda^*, \mu^*) \\ = f(x^*) + (\lambda^*)^{\mathsf{T}} g(x^*) + (\mu^*)^{\mathsf{T}} h(x^*) = f(x^*) = v(P) &\underset{[\text{weak duality}]}{\geq} v(D). \end{aligned}$$

Therefore, $v(P) = v(D)$ and (λ^*, μ^*) is optimal for (D).
Viceversa, if (λ^*, μ^*) is any optimal solution for (D), then

$$\begin{aligned} f(x^*) = v(P) = v(D) = \varphi(\lambda^*, \mu^*) &= \inf_x L(x, \lambda^*, \mu^*) \leq L(x^*, \lambda^*, \mu^*) \\ &= f(x^*) + (\lambda^*)^{\mathsf{T}} g(x^*) + (\mu^*)^{\mathsf{T}} h(x^*) = f(x^*) + (\lambda^*)^{\mathsf{T}} g(x^*) \leq f(x^*), \end{aligned}$$

thus $(\lambda^*)^{\mathsf{T}} g(x^*) = 0$ and $\inf_x L(x, \lambda^*, \mu^*) = L(x^*, \lambda^*, \mu^*)$, hence $\nabla_x L(x^*, \lambda^*, \mu^*) = 0$, i.e., (λ^*, μ^*) is a KKT multipliers vector associated with x^*. □

Strong duality

Strong duality may hold also for some non-convex problems.

Example

Consider the (non-convex) problem

$$\begin{cases} \min \; -x_1^2 - x_2^2 \\ x_1^2 + x_2^2 - 1 \leq 0 \end{cases}$$

We have $v(P) = -1$. The Lagrangian function is

$$L(x, \lambda) = -x_1^2 - x_2^2 + \lambda(x_1^2 + x_2^2 - 1) = (\lambda - 1)x_1^2 + (\lambda - 1)x_2^2 - \lambda.$$

The dual function is

$$\varphi(\lambda) = \inf_{x \in \mathbb{R}} L(x, \lambda) = \begin{cases} -\infty & \text{if } \lambda < 1 \\ -\lambda & \text{if } \lambda \geq 1 \end{cases}$$

The dual problem is

$$\begin{cases} \max \; -\lambda \\ \lambda \geq 1 \end{cases}$$

hence its optimal solution is $\lambda^* = 1$ and $v(D) = -1$.

Strong duality

Theorem 6 (characterization of strong duality)

(x^*, λ^*, μ^*) is a saddle point of L, i.e.

$$L(x^*, \lambda, \mu) \leq L(x^*, \lambda^*, \mu^*) \leq L(x, \lambda^*, \mu^*) \qquad \forall\ x \in \mathbb{R}^n,\ \lambda \in \mathbb{R}^m_+,\ \mu \in \mathbb{R}^p,$$

if and only if x^* is optimum of (P), (λ^*, μ^*) is optimum of (D) and $v(P) = v(D)$.

Proof. If (x^*, λ^*, μ^*) is a saddle point of L, then we can prove that $x^* \in X$, $\langle \lambda^*, g(x^*) \rangle = 0$ which implies $\varphi(\lambda^*, \mu^*) = f(x^*)$.
Viceversa, we have that

$$f(x^*) = \varphi(\lambda^*, \mu^*) = \inf_{x \in \mathbb{R}^n} L(x, \lambda^*, \mu^*) \leq L(x^*, \lambda^*, \mu^*) = f(x^*) + \langle \lambda^*, g(x^*) \rangle,$$

hence $\langle \lambda^*, g(x^*) \rangle = 0$ and $L(x^*, \lambda^*, \mu^*) = f(x^*) = \varphi(\lambda^*, \mu^*) \leq L(x, \lambda^*, \mu^*)$ for all $x \in \mathbb{R}^n$. Moreover

$$L(x^*, \lambda, \mu) = f(x^*) + \langle \lambda, g(x^*) \rangle \leq f(x^*) = L(x^*, \lambda^*, \mu^*) \qquad \forall\ \lambda \in \mathbb{R}^m_+,\ \mu \in \mathbb{R}^p.$$

□