Optimization Models

EECS 127 / EECS 227AT

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LECTURE 20

Optimality Conditions

Duality, in mathematics, principle whereby one true statement can be obtained from another by merely interchanging two words.

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Outline

Overview

In this lecture, we describe the so-called "optimality conditions" that characterize optimality for convex programs, and generalize the "zero-gradient" condition that arises in convex unconstrained problems.

Theese conditions have many uses, in particular in

- the theoretical analysis of solutions to convex problems;
- the design of convex optimization algorithms.

We will first look at an "abstract" form of optimality conditions that offer geometric insight and work well for equality constraints only; then develop optimality conditions for the general case.

Primal problem

In this lecture, we consider the following "primal" problem

$$p^* = \min_{x \in \mathbb{R}^n} f_0(x) \text{ subject to: } \quad f_i(x) \leq 0, \quad i = 1, \ldots, m,$$
$$Ax = b,$$

where

- $f_0, \ldots, f_m$ are convex differentiable functions, which we assume to be defined everywhere (hence the domain of the problem is $\mathcal{D} = \mathbb{R}^n$);
- matrix $A \in \mathbb{R}^{q \times n}$ and vector $b \in \mathbb{R}^q$ are given.

We denote by $\mathcal{D}$ the domain of the problem: $\mathcal{D} \doteq \bigcap_{i=0}^m \mathrm{dom}\, f_i$.

We make a few assumptions on the above problem:

- it is strictly feasible (so that Slater's condition holds);
- it is attained: there exist $x^* \in \mathcal{D}$ such that $p^* = f_0(x^*)$.

Abstract form of optimality conditions

The primal problem can be written in abstract form

$$\min_{x \in \mathcal{X}} f_0(x),$$

where $\mathcal{X} \subseteq \mathcal{D}$ denotes the feasible set.

Proposition 1

Consider the optimization problem $\min_{x \in \mathcal{X}} f_0(x)$, *where* f_0 *is convex and differentiable, and* $\mathcal{X}$ *is convex. Then,*

$$x \in \mathcal{X} \text{ is optimal} \quad \Leftrightarrow \quad \nabla f_0(x)^\top (y - x) \geq 0, \quad \forall y \in \mathcal{X}. \tag{1}$$

Note: the above conditions are often hard to work with, due to the presence of the "$\forall\, y \ldots$" statement, which requires checking a condition over the entire feasible set.

Proof

First let us show the implication from right to left in (1). Since f_0 is convex, for every $x, y \in \mathrm{dom}\, f_0$, we have

$$f_0(y) \geq f_0(x) + \nabla f_0(x)^\top (y - x). \tag{2}$$

The implication from right to left in (1) is immediate, since

$$\nabla f_0(x)^\top (y - x) \geq 0 \text{ for every } y \in \mathcal{X}$$

implies, from (2), that $f_0(y) \geq f_0(x)$ for all $y \in \mathcal{X}$, i.e., that x is optimal.

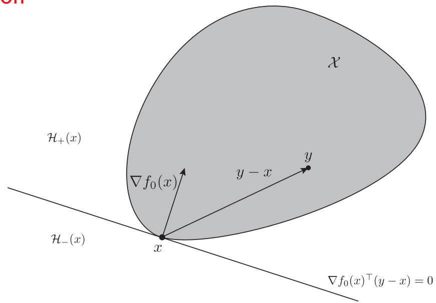
Conversely, assume that x is optimal. We show that then $\nabla f_0(x)^\top (y - x) \geq 0$ for all $y \in \mathcal{X}$. If $\nabla f_0(x) = 0$, then the claim holds trivially. Assume now that $\nabla f_0(x) \neq 0$, and that there exist $y \in \mathcal{X}$ such that $\nabla f_0(x)^\top (y - x) < 0$. Consider the function

$$g \;:\; t \in [0, 1] \rightarrow f_0(x(t)),$$

where $x(t) = ty + (1 - t)x$; note that $x(t) \in \mathcal{X}$ for every $t \in [0, 1]$, since $\mathcal{X}$ is convex. Further, $g'(0) = \nabla f_0(x)^\top (y - x)$. Hence, for sufficiently small $t > 0$, $g(t) < g(0)$, which translates as $f(x(t)) < f(x)$; with $x(t) \in \mathcal{X}$, this contradicts the optimality of x. $\square$

Optimality conditions

Geometric interpretation



If $\nabla f_0(x) \neq 0$, then $\nabla f_0(x)$ is a normal direction defining an hyperplane $\{y : \nabla f_0(x)^\top (y - x) = 0\}$ such that:

- x is on the boundary of the feasible set $\mathcal{X}$, and
- the whole feasible set lies on one side of this hyperplane, that is in the halfspace defined by

$$\mathcal{H}_+(x) = \{y : \nabla f_0(x)^\top (y - x) \geq 0\}.$$

Optimality conditions

Geometric interpretation

Notice that the gradient vector $\nabla f_0(x)$ defines two set of directions:

- for directions v_+ such that $\nabla f_0(x)^\top v_+ > 0$ (i.e., directions that have positive inner product with the gradient), if we make a move away from x in direction v_+, then the objective f_0 *increases*.
- for directions v_- such that $\nabla f_0(x)^\top v_+ < 0$ (i.e., *descent* directions, that have negative inner product with the gradient), if we make a sufficiently small move away from x in direction v_-, then the objective f_0 locally *decreases*.

Condition (1) then says that x is an optimal point if and only if there is no feasible direction along which we may improve (decrease) the objective.

Optimality conditions for unconstrained problems

Proposition 2

In a convex unconstrained problem with differentiable objective, x is optimal if and only if

$$\nabla f_0(x) = 0. \tag{3}$$

Proof: When the problem is unconstrained, i.e., $\mathcal{X} = \mathbb{R}^n$, then the optimality condition (1) requires that

$$\begin{aligned}
\forall\, y \in \mathbb{R}^n \;:\; \nabla f_0(x)^\top (y - x) \geq 0 \quad &\iff \quad \forall\, z \in \mathbb{R}^n \;:\; \nabla f_0(x)^\top z \geq 0 \\
&\iff \quad \forall\, z \in \mathbb{R}^n \;:\; \nabla f_0(x)^\top z = 0 \\
&\iff \quad \nabla f_0(x) = 0.
\end{aligned}$$

Optimality conditions for equality-constrained problems

Consider the problem

$$\min_x \; f_0(x) \;:\; Ax = b, \tag{4}$$

where $A \in \mathbb{R}^{m \times n}$, $b \in \mathbb{R}^m$ are given. We assume that $y \in \mathcal{R}(A)$, so the problem is feasible. Here the feasible set is

$$\mathcal{X} = \{y \;:\; Ay = b\}.$$

Proposition 3

A point x is optimal for problem (4) if and only if

$$Ax = b \text{ and } \exists\, \nu \in \mathbb{R}^m \;:\; \nabla f_0(x) + A^\top \nu = 0.$$

Proof

The point $x \in \mathcal{X}$ is optimal iff

$$\nabla f_0(x)^\top (y - x) \geq 0, \quad \forall y \in \mathcal{X}.$$

Since $Ax = b$, the feasible set can be written as

$$\mathcal{X} = \{x + z \;:\; z \in \mathcal{N}(A)\}.$$

The optimality condition becomes

$$\forall\, z \in \mathcal{N}(A) \;:\; \nabla f_0(x)^\top z \geq 0.$$

Since $z \in \mathcal{N}(A)$ if and only if $-z \in \mathcal{N}(A)$, we see that the condition is equivalent to

$$\forall\, z \in \mathcal{N}(A) \;:\; \nabla f_0(x)^\top z = 0.$$

That is, $\nabla f_0(x) \in \mathcal{N}(A)^\perp$. Recall the fundamental theorem of linear algebra, which states that $\mathcal{N}(A)^\perp = \mathcal{R}(A^\top)$; we obtain that there exist $\nu \in \mathbb{R}^m$ such that $\nabla f_0(x) + A^\top \nu = 0$.

Example

Minimum-norm solutions to linear equations

Consider the Euclidean projection problem seen in lecture 8:

$$\min_x \ \frac{1}{2}x^\top x \ : \ Ax = b.$$

(The solution is the projection of 0 on the affine subspace $\mathcal{X}$.)

We obtain that x is optimal if and only if there exist $\nu \in \mathbb{R}^m$ such that

$$Ax = b, \ \ x + A^\top \nu = 0. \tag{5}$$

Assuming that A is full row rank (hence, $AA^\top \succ 0$), we get the unique solution:

$$\nu^* = -(AA^\top)^{-1}b, \ \ x^* = A^\top \nu^* = A^\top (AA^\top)^{-1} b.$$

General case

Dual problem

Turning to the general problem (1), recall the expression of the problem dual to (1), as seen in lecture 18:

$$d^* = \max_{\lambda \geq 0} g(\lambda), \tag{6}$$

where g is the dual function

$$g(\lambda) = \min_{x} \mathcal{L}(x, \lambda, \nu),$$

with $\mathcal{L}$ the Lagrangian

$$\mathcal{L}(x, \lambda) = f_0(x) + \sum_{i=1}^{m} \lambda_i f_i(x).$$

- Since Slater's condition hold, we have strong duality: $p^* = d^*$.
- We make the further assumption that d^* is attained by some $\lambda^* \geq 0$.

Karush-Kuhn-Tucker (KKT) conditions

For the convex problem (1), we say that a pair $(x, \lambda) \in \mathbb{R}^n \times \mathbb{R}^m$ satisfies the Karush-Kuhn-Tucker (KKT) conditions if

1. Primal feasibility: x is feasible for the primal problem:

$$x \in \mathcal{D}, \quad f_i(x) \leq 0, \quad i = 1, \ldots, m.$$

2. Dual feasibility: $\lambda \geq 0$.
3. Complementary slackness: $\lambda_i f_i(x) = 0$, $i = 1, \ldots, m$.
4. Lagrangian stationarity: $x \in \arg\min \mathcal{L}(\cdot, \lambda)$, which, in the case when the functions f_i, $i = 0, \ldots, m$ are differentiable, writes

$$\nabla_x f_0(x) + \sum_{i=1}^{m} \lambda_i \nabla_x f_i(x) = 0.$$

Proposition 4

Assume that the primal problem (1) is convex, and attained; that its dual is also attained; and that strong duality holds. Then, a primal-dual pair (x, λ) is optimal if and only if it satisfies the KKT conditions.

Proof: sufficiency

Assume that the KKT conditions are satisfied for some pair (x^*, λ^*). The first two conditions imply that x^* is primal feasible, and λ^* is dual feasible. Further, since $\mathcal{L}(x, \lambda^*)$ is convex in x, the fourth condition states that x^* is a global minimizer of $\mathcal{L}(x, \lambda^*)$, hence

$$
\begin{aligned}
g(\lambda^*, \nu^*) &= \min_{x \in \mathcal{D}} \mathcal{L}(x, \lambda^*) = \mathcal{L}(x^*, \lambda^*) \\
&= f_0(x^*) + \sum_{i=1}^{m} \lambda_i^* f_i(x^*) \\
&= f_0(x^*),
\end{aligned}
$$

where the last equality follows from complementary slackness.

The above proves that the primal-dual feasible pair (x^*, λ^*) is optimal: the corresponding duality gap $p^* - d^*$ is zero, since x^* (resp. λ^*) attains the lower bound d^* (resp. upper bound p^*).

Proof: necessity

Assume that (x^*, λ^*) is an optimal primal-dual pair.

- Since $p^* = f_0(x^*)$, $d^* = g(\lambda^*)$, and $p^* = d^*$, we have

$$f_0(x^*) = g(\lambda^*) = \inf_{x \in \mathcal{D}} \mathcal{L}(x, \lambda^*) \leq \mathcal{L}(x, \lambda^*), \quad \forall\, x \in \mathcal{D}.$$

- Since the last inequality holds for all $x \in \mathcal{D}$, it must hold also for x^*, hence

$$f_0(x^*) = \inf_{x \in \mathcal{D}} \mathcal{L}(x, \lambda^*) \leq \mathcal{L}(x^*, \lambda^*) = f_0(x^*) + \sum_{i=1}^{m} \lambda_i^* f_i(x^*) \leq f_0(x^*),$$

  where the last inequality follows from the fact that x^* is optimal, hence feasible, for the primal problem, therefore $f_i(x^*) \leq 0$, and λ^* is optimal, hence feasible, for the dual, therefore $\lambda_i^* \geq 0$, whereby each term $\lambda_i^* f_i(x^*)$ is ≤ 0.

- Observing the last chain of inequalities, since the first and the last terms are equal, we must conclude that all inequalities must actually hold with equality, that is

$$f_0(x^*) = \inf_{x \in \mathcal{D}} \mathcal{L}(x, \lambda^*) = \mathcal{L}(x^*, \lambda^*).$$

Complementary slackness and Lagrangian stationarity

These two conditions are at the heart of the KKT conditions.

The complementary slackness property prescribes that a primal and the corresponding dual inequality cannot be slack simultaneously, that is, if $f_i(x^*) < 0$, then it must be $\lambda_i^* = 0$, and if $\lambda_i^* > 0$, then it must be $f_i(x^*) = 0$.

The second property (i.e., the fact that x^* is a minimizer of $\mathcal{L}(x, \lambda^*)$) can, in some cases, be used to recover a primal-optimal variable from the dual-optimal variables (see later).

Recovering primal solutions from the dual

- First observe that if the primal problem is convex, then $\mathcal{L}(x, \lambda^*)$ is also convex in x. Global minimizers of this function can then be determined by unconstrained minimization techniques. For instance, if $\mathcal{L}(x, \lambda^*)$ is differentiable, a necessary condition for x to be a global minimizer is determined by the zero-gradient condition $\nabla_x \mathcal{L}(x, \lambda^*) = 0$, that is,

$$\nabla_x f_0(x) + \sum_{i=1}^{m} \lambda_i^* \nabla_x f_i(x) = 0.$$

- However, $\mathcal{L}(x, \lambda^*)$ may have multiple global minimizers, and it is *not* guaranteed that *every* global minimizer of $\mathcal{L}$ is a primal-optimal solution—what is guaranteed is that the primal-optimal solution x^* is among the global minimizers of $\mathcal{L}(\cdot, \lambda^*)$.
- A particular case arises when $\mathcal{L}(\cdot, \lambda^*)$ has an *unique* minimizer. In this case the unique minimizer x^* of $\mathcal{L}$ is either primal feasible, and hence it is the primal-optimal solution, or it is not primal feasible, and then we can conclude that the no primal-optimal solution exists.

Example

Power allocation in a communication channel[1]

We seek to best allocate a power level to n communication channels. The problem can be formulated as

$$p^* = \max_x \sum_{i=1}^n \log(\alpha_i + x_i) \;:\; x \geq 0,\; \sum_{i=1}^m x_i = 1.$$

where $\alpha_i > 0$ is a measure of the noise over the channel. Here the objective function is related to the communication rate. We use the Lagrangian (with $\lambda \in \mathbb{R}_+^n$, $\nu \in \mathbb{R}$)

$$\mathcal{L}(x, \lambda, \nu) = \sum_{i=1}^n \log(\alpha_i + x_i) - \lambda^\top x + \nu(\sum_{i=1}^m x_i - 1).$$

[1] From Boyd & Vandenberghe's book, *Convex Optimization*.

KKT conditions

Slater's conditions are satisfied. The KKT conditions are:

- Primal feasibility: $x \geq 0$ and $\mathbf{1}^\top x = 1$;
- Dual feasibility: $\lambda \geq 0$;
- Stationarity: $1/(x_i + \alpha_i) = \nu - \lambda_i$, $i = 1, \dots, n$.
- Complementarity: $\lambda_i x_i = 0$, $i = 1, \dots, n$.

For an optimal pair (x^*, λ^*, ν^*):

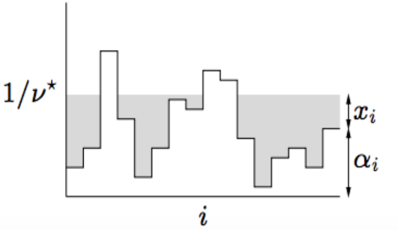
- if $\nu^* \leq 1/\alpha_i$: $\lambda_i = 0$ and $x_i^* = 1/\nu^* - \alpha_i$;
- Otherwise, $\lambda_i^* = \nu^* - 1/\alpha_i$ and $x_i^* = 0$.

Thus, we have $x_i^* = \max(0, 1/\nu^* - \alpha_i)$ for every i. Summing:

$$1 = \sum_{i=1}^{n} x_i^* = \sum_{i=1}^{n} \max(0, 1/\nu^* - \alpha_i).$$

Waterfilling algorithm

We can solve this 1D equation using a simple method called the waterfilling algorithm. Once ν^* is found, we then recover a primal optimal point via $x_i^* = \max(0, 1/\nu^* - \alpha_i)$, $i = 1, \ldots, n$.



The height of patch i is given by α_i. The region is flooded to a level $1/\nu$, using a total quantity of water equal to one. The height of the water (shown shaded) above each patch is the optimal value of x_i.

Example

Maximum entropy distribution

Consider the problem

$$\min_x \; f_0(x) \doteq \sum_{i=1}^{n} x_i \log x_i \;\; : \;\; x \geq 0, \;\; \mathbf{1}^\top x = 1.$$

The feasible set is the set of discrete distributions in $\mathbb{R}^n$; The objective function is called the negative entropy of the distribution x.

- Lagrangian: $\mathcal{L}(x, \lambda, \nu) = f_0(x) - \lambda^\top x + \nu(1 - \mathbf{1}^\top x)$.
- KKT conditions: $x \geq 0$, $\mathbf{1}^\top x = 1$, $\lambda \geq 0$, and

$$\lambda_i x_i = 0, \;\; \log x_i = \lambda_i + \nu - 1, \;\; i = 1, \ldots, n.$$

The stationarity conditions imply that $x^* > 0$, hence $\lambda^* = 0$, and thus x_i does not depend on i. Since $\mathbf{1}^\top x = 1$, we obtain that $x^* = (1/n)\mathbf{1}$, which is the uniform distribution.

This fact illustrates why the (negative) entropy function is used as a measure of "distance" between a distribution, to the uniform one.

Example

Risk parity portfolio

Consider a portfolio optimization problem: to find a portfolio weight vector $x \in \mathbb{R}^n_{++}$, containing positive dollar amounts to invest in various assets, such that the risk parity condition holds:

$$\forall\, i \;:\; x_i(Cx)_i = \frac{1}{n} x^\top Cx,$$

where $C = C^\top \succ 0$ is the (positive-definite) covariance of the assets. The interpretation of a risk-parity portfolio is that, since

$$\sum_{i=1}^{n} x_i(Cx)_i = x^\top Cx,$$

all the partial contributions $x_i(Cx)_i (> 0)$ of each asset i to the total risk in the portfolio, as measured by its variance $x^\top Cx$, are equal ("at parity").

Risk parity portfolio

Consider the optimization problem

$$\min_x \; f_0(x) + x^\top C x, \tag{7}$$

where

$$f_0(x) \doteq \begin{cases} -\sum_{i=1}^{n} \log x_i & \text{if } x > 0, \\ +\infty & \text{otherwise.} \end{cases}$$

Lagrangian:

$$\mathcal{L}(x, \lambda) = -\sum_{i=1}^{n} \log x_i + x^\top C x - \lambda^\top x.$$

KKT conditions: $x > 0$ (since $\mathcal{D} = \mathbb{R}^n_{++}$), $\lambda \geq 0$,

$$\lambda_i x_i = 0, \quad -\frac{1}{x_i} + (Cx)_i = \lambda_i, \quad i = 1, \ldots, n.$$

Since $x > 0$, we have $\lambda = 0$, and we obtain $x_i(Cx)_i = 1$, $i = 1, \ldots, n$; summing, we get $x^\top C x = n$, which implies that the risk parity conditions hold.

This means that by solving the convex problem (7), we obtain a risk parity portfolio.