Lecture 9 - Optimization over a Convex Set

Throughout this lecture we will consider the constrained optimization problem (P) given by

$$(\mathrm{P}) \qquad \begin{array}{ll} \min & f(\mathbf{x}) \\ \text{s.t.} & \mathbf{x} \in C. \end{array}$$

- C - closed convex subset of $\mathbb{R}^n$.
- f - continuously differentiable[1] over C. Not necessarily convex.

Definition of Stationarity. Let f be a continuously differentiable function over a closed and convex set C. Then $\mathbf{x}^*$ is called a stationary point of (P) if

$$\nabla f(\mathbf{x}^*)^T(\mathbf{x} - \mathbf{x}^*) \geq 0 \text{ for any } \mathbf{x} \in C$$

[1] We use the convention that a function is differentiable over a given set D if it is differentiable over an open set containing D

Stationarity as a Necessary Optimality Condition

Theorem. Let f be a continuously differentiable function over a nonempty closed convex set C, and let $\mathbf{x}^*$ be a local minimum of (P). Then $\mathbf{x}^*$ is a stationary point of (P).

Proof.

- Let $\mathbf{x}^*$ be a local minimum of (P), and assume in contradiction that $\mathbf{x}^*$ is not a stationary point of (P) $\Rightarrow$ there exists $\mathbf{x} \in C$ such that $\nabla f(\mathbf{x}^*)^T(\mathbf{x} - \mathbf{x}^*) < 0$.
- Thus, $f'(\mathbf{x}^*; \mathbf{d}) < 0$ where $\mathbf{d} = \mathbf{x} - \mathbf{x}^*$.
- Therefore $\exists \varepsilon \in (0, 1)$ s.t. $f(\mathbf{x}^* + t\mathbf{d}) < f(\mathbf{x}^*) \forall t \in (0, \varepsilon)$.
- Since $\mathbf{x}^* + t\mathbf{d} = (1 - t)\mathbf{x}^* + t\mathbf{x} \in C \forall t \in (0, \varepsilon)$, we conclude that $\mathbf{x}^*$ is *not* a local optimum point of (P). Contradiction.

Examples

- $C = \mathbb{R}^n$.
  - $\mathbf{x}^*$ is a stationary point of (P) iff
$$(*)\ \ \nabla f(\mathbf{x}^*)^T(\mathbf{x}-\mathbf{x}^*) \geq 0 \quad \forall \mathbf{x} \in \mathbb{R}^n$$
  - We will show that the above condition is equivalent to $\nabla f(\mathbf{x}^*) = \mathbf{0}$. Indeed, if $\nabla f(\mathbf{x}^*) = \mathbf{0}$, then obviously (*) is satisfied.
  - Suppose that (*) holds.
  - Plugging $\mathbf{x} = \mathbf{x}^* - \nabla f(\mathbf{x}^*)$ in the above implies $-\|\nabla f(\mathbf{x}^*)\|^2 \geq 0$.
  - Thus, $\nabla f(\mathbf{x}^*) = \mathbf{0}$.
- $C = \mathbb{R}^n_+$.
  - $\mathbf{x}^* \in \mathbb{R}^n_+$ is a stationary point iff $\nabla f(\mathbf{x}^*)^T(\mathbf{x}-\mathbf{x}^*) \geq 0$ for all $\mathbf{x} \geq \mathbf{0}$.
  - $\Leftrightarrow \nabla f(\mathbf{x}^*)^T\mathbf{x} - \nabla f(\mathbf{x}^*)^T\mathbf{x}^* \geq 0$ for all $\mathbf{x} \geq \mathbf{0}$.
  - $\Leftrightarrow \nabla f(\mathbf{x}^*) \geq \mathbf{0}$ and $\nabla f(\mathbf{x}^*)^T\mathbf{x}^* \leq 0$.
  - $\Leftrightarrow \nabla f(\mathbf{x}^*) \geq \mathbf{0}$ and $x_i^* \frac{\partial f}{\partial x_i}(\mathbf{x}^*) = 0, \quad i = 1, 2, \ldots, n$.
  - $\Leftrightarrow$
$$\frac{\partial f}{\partial x_i}(\mathbf{x}^*) \begin{cases} = 0 & x_i^* > 0, \\ \geq 0 & x_i^* = 0. \end{cases}$$

Explicit Stationarity Condition

feasible set	explicit stationarity condition
$\mathbb{R}^n$	$\nabla f(\mathbf{x}^*) = \mathbf{0}$
$\mathbb{R}^n_+$	$\frac{\partial f}{\partial x_i}(\mathbf{x}^*) \begin{cases} = 0 & x_i^* > 0 \\ \geq 0 & x_i^* = 0 \end{cases}$
$\{\mathbf{x} \in \mathbb{R}^n : \mathbf{e}^T\mathbf{x} = 1\}$	$\frac{\partial f}{\partial x_1}(\mathbf{x}^*) = \ldots = \frac{\partial f}{\partial x_n}(\mathbf{x}^*)$
$B[\mathbf{0}, 1]$	$\nabla f(\mathbf{x}^*) = \mathbf{0}$ or $\|\mathbf{x}^*\| = 1$ and $\exists \lambda \leq 0 : \nabla f(\mathbf{x}^*) = \lambda \mathbf{x}^*$

Stationarity in Convex Optimization

For convex problems, stationarity is a necessary and sufficient condition

Theorem. Let f be a continuously differentiable convex function over a nonempty closed and convex set $C \subseteq \mathbb{R}^n$. Then $\mathbf{x}^*$ is a stationary point of

$$\text{(P)} \quad \begin{array}{ll} \min & f(\mathbf{x}) \\ \text{s.t.} & \mathbf{x} \in C. \end{array}$$

iff $\mathbf{x}^*$ is an optimal solution of (P).

Proof.

- If $\mathbf{x}^*$ is an optimal solution of (P), then we already showed that it is a stationary point of (P).
- Assume that $\mathbf{x}^*$ is a stationary point of (P).
- Let $\mathbf{x} \in C$. Then

$$f(\mathbf{x}) \geq f(\mathbf{x}^*) + \nabla f(\mathbf{x}^*)^T(\mathbf{x} - \mathbf{x}^*) \geq f(\mathbf{x}^*),$$

- establshing the optimality of $\mathbf{x}^*$.

The Second Projection Theorem

Theorem. Let C be a nonempty closed convex set and let $\mathbf{x} \in \mathbb{R}^n$. Then $\mathbf{z} = P_C(\mathbf{x})$ if and only if

$$(\mathbf{x} - \mathbf{z})^T(\mathbf{y} - \mathbf{z}) \le 0 \text{ for any } \mathbf{y} \in C. \tag{1}$$

Proof.

- $\mathbf{z} = P_C(\mathbf{x})$ iff it is the optimal solution of the problem

$$\begin{array}{ll} \min & g(\mathbf{y}) \equiv \|\mathbf{y} - \mathbf{x}\|^2 \\ \text{s.t.} & \mathbf{y} \in C. \end{array}$$

- By the previous theorem, $\mathbf{z} = P_C(\mathbf{x})$ if and only if

$$\nabla g(\mathbf{z})^T(\mathbf{y} - \mathbf{z}) \ge 0 \text{ for all } \mathbf{y} \in C,$$

  which is the same as (1).

Properties of the Orthogonal Projection: (Firm) Nonexpansivness

Theorem. Let C be a nonempty closed and convex set. Then

1. For any $\mathbf{v}, \mathbf{w} \in \mathbb{R}^n$:
$$(P_C(\mathbf{v}) - P_C(\mathbf{w}))^T(\mathbf{v} - \mathbf{w}) \geq \|P_C(\mathbf{v}) - P_C(\mathbf{w})\|^2. \tag{2}$$

2. **(non-expansiveness)** For any $\mathbf{v}, \mathbf{w} \in \mathbb{R}^n$:
$$\|P_C(\mathbf{v}) - P_C(\mathbf{w})\| \leq \|\mathbf{v} - \mathbf{w}\|. \tag{3}$$

Proof.

- For any $\mathbf{x} \in \mathbb{R}^n$ and $\mathbf{y} \in C$:
$$(\mathbf{x} - P_C(\mathbf{x}))^T(\mathbf{y} - P_C(\mathbf{x})) \leq 0 \quad \forall \mathbf{x} \in \mathbb{R}^n, \mathbf{y} \in C \tag{4}$$
Substituting $\mathbf{x} = \mathbf{v}, \mathbf{y} = P_C(\mathbf{w})$, we have
$$(\mathbf{v} - P_C(\mathbf{v}))^T(P_C(\mathbf{w}) - P_C(\mathbf{v})) \leq 0. \tag{5}$$

Proof Contd.

- Now, by substituting $\mathbf{x} = \mathbf{w}, \mathbf{y} = P_C(\mathbf{v})$, we obtain

$$(\mathbf{w} - P_C(\mathbf{w}))^T (P_C(\mathbf{v}) - P_C(\mathbf{w})) \leq 0. \tag{6}$$

  Adding the two inequalities (5) and (6),

$$(P_C(\mathbf{w}) - P_C(\mathbf{v}))^T (\mathbf{v} - \mathbf{w} + P_C(\mathbf{w}) - P_C(\mathbf{v})) \leq 0,$$

  and hence,

$$(P_C(\mathbf{v}) - P_C(\mathbf{w}))^T (\mathbf{v} - \mathbf{w}) \geq \|P_C(\mathbf{v}) - P_C(\mathbf{w})\|^2.$$

- To prove (3), note that if $P_C(\mathbf{v}) = P_C(\mathbf{w})$, the inequality is trivial. Assume then that $P_C(\mathbf{w}) \neq P_C(\mathbf{w})$. By the Cauchy-Schwarz inequality we have

$$(P_C(\mathbf{v}) - P_C(\mathbf{w}))^T (\mathbf{v} - \mathbf{w}) \leq \|P_C(\mathbf{v}) - P_C(\mathbf{w})\| \cdot \|\mathbf{v} - \mathbf{w}\|,$$

  which combined with (2) yields the inequality

$$\|P_C(\mathbf{v}) - P_C(\mathbf{w})\| \cdot \|\mathbf{v} - \mathbf{w}\| \geq \|P_C(\mathbf{w}) - P_C(\mathbf{w})\|^2.$$

  Dividing by $\|P_C(\mathbf{v}) - P_C(\mathbf{w})\|$, implies (3).

Representation of Stationarity via the Orthogonal Projection Operator

Theorem. Let f be a continuously differentiable function over the nonempty closed convex set C, and let $s > 0$. Then $\mathbf{x}^*$ is a stationary point of

$$\text{(P)} \quad \begin{array}{ll} \min & f(\mathbf{x}) \\ \text{s.t.} & \mathbf{x} \in C. \end{array}$$

if and only if

$$\mathbf{x}^* = P_C(\mathbf{x}^* - s\nabla f(\mathbf{x}^*)).$$

Proof.

- By the second projection theorem, $\mathbf{x}^* = P_C(\mathbf{x}^* - s\nabla f(\mathbf{x}^*))$ iff

$$(\mathbf{x}^* - s\nabla f(\mathbf{x}^*) - \mathbf{x}^*)^T(\mathbf{x} - \mathbf{x}^*) \le 0 \text{ for any } \mathbf{x} \in C.$$

- Equivalent to

$$\nabla f(\mathbf{x}^*)^T(\mathbf{x} - \mathbf{x}^*) \ge 0 \text{ for any } \mathbf{x} \in C,$$

namely to stationarity.

The Gradient Mapping

- It is convenient to define the gradient mapping as

$$G_L(\mathbf{x}) = L\left[\mathbf{x} - P_C\left(\mathbf{x} - \frac{1}{L}\nabla f(\mathbf{x})\right)\right],$$

  where $L > 0$.
- In the unconstrained case $G_L(\mathbf{x}) = \nabla f(\mathbf{x})$.
- $G_L(\mathbf{x}) = \mathbf{0}$ if and only if $\mathbf{x}$ is a stationary point of (P). This means that we can consider $\|G_L(\mathbf{x})\|^2$ to be optimality measure.

The Gradient Projection Method

The Gradient Projection Method

Input: $\varepsilon > 0$ - tolerance parameter.

Initialization: pick $\mathbf{x}_0 \in C$ arbitrarily.
General step: for any $k = 0, 1, 2, \ldots$ execute the following steps:

(a) pick a stepsize t_k by a line search procedure.

(b) set $\mathbf{x}_{k+1} = P_C(\mathbf{x}_k - t_k \nabla f(\mathbf{x}_k))$.

(c) if $\|\mathbf{x}_k - \mathbf{x}_{k+1}\| \leq \varepsilon$, then STOP and $\mathbf{x}_{k+1}$ is the output.

- There are several strategies for choosing the stepsizes t_k.
- When $f \in C_L^{1,1}$, we can choose t_k to be constant and equal to $\frac{1}{L}$.

The Gradient Projection Method with Constant Stepsize

The Gradient Projection Method with Constant Stepsize
Input: $\varepsilon > 0$ - tolerance parameter. $L > 0$ - an upper bound on the Lipschitz constant of ∇f.

Initialization: pick $\mathbf{x}_0 \in C$ arbitrarily. $\bar{t} > 0$ - constant stepsize.
General step: for any $k = 0, 1, 2, \ldots$ execute the following steps:

(a) set $\mathbf{x}_{k+1} = P_C(\mathbf{x}_k - \bar{t}\nabla f(\mathbf{x}_k))$.

(b) if $\|\mathbf{x}_k - \mathbf{x}_{k+1}\| \le \varepsilon$, then STOP and $\mathbf{x}_{k+1}$ is the output.

GPM with Backtracking

Gradient Projection Method with Backtracking
Initialization. Take $\mathbf{x}_0 \in C$ and $s > 0, \alpha \in (0,1), \beta \in (0,1)$.
General Step $(k \geq 1)$

- Pick $t_k = s$. Then, while

$$f(\mathbf{x}_k) - f(P_C(\mathbf{x}_k - t_k \nabla f(\mathbf{x}_k))) < \alpha t_k \| G_{\frac{1}{t_k}}(\mathbf{x}_k)\|^2$$

  set $t_k := \beta t_k$.
- Set $\mathbf{x}_{k+1} = P_C(\mathbf{x}_k - t_k \nabla f(\mathbf{x}_k))$

Stopping Criteria $\|\mathbf{x}_k - \mathbf{x}_{k+1}\| \leq \varepsilon$.

Convergence of the Gradient Projection Method

Theorem Let $\{\mathbf{x}_k\}$ be the sequence generated by the gradient projection method for solving problem (P) with either a constant stepsize $\bar{t} \in \left(0, \frac{2}{L}\right)$, where L is a Lipschitz constant of ∇f or a backtracking stepsize strategy. Assume that f is bounded below. Then

1. The sequence $\{f(\mathbf{x}_k)\}$ is nonincreasing.
2. $G_d(\mathbf{x}_k) \to 0$ as $k \to \infty$, where

$$d = \begin{cases} 1/\bar{t} & \text{constant stepsize,} \\ 1/s & \text{backtracking.} \end{cases}$$

See the proof of Theorem 9.14 in the book

- It is easy to see that this result implies that any limit point of the sequence is a stationary point of the problem.
- When f is convex, it is possible to show that the sequence converges to a global optimal solution.

Sparsity Constrained Problems

The sparsity constrained problem is given by

$$(\mathrm{S}): \quad \begin{array}{ll} \min & f(\mathbf{x}) \\ \text{s.t.} & \|\mathbf{x}\|_0 \le s, \end{array}$$

- $f : \mathbb{R}^n \to \mathbb{R}$ is a lower-bounded continuously differentiable function.
- $s > 0$ is an integer smaller than n.
- $\|\mathbf{x}\|_0$ is the ℓ_0 norm of $\mathbf{x}$, which counts the number of nonzero components in $\mathbf{x}$.
- We do not assume that f is a convex function. The constraint set is of course not convex.

Notation.

- $I_1(\mathbf{x}) \equiv \{i : x_i \neq 0\}$ - the support set.
- $I_0(\mathbf{x}) \equiv \{i : x_i = 0\}$ - the off-support set.
- $C_s = \{\mathbf{x} : \|\mathbf{x}\|_0 \le s\}$.
- For a vector $\mathbf{x} \in \mathbb{R}^n$ and $i \in \{1, 2, \ldots, n\}$, the ith largest absolute value component in $\mathbf{x}$ is denoted by $M_i(\mathbf{x})$.