

Optimality Conditions for Linearly Constrained Problems

Lecture 10-3 - CMSE 382

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Topics:

- Orthogonal projection onto an affine space
- Orthogonal projection onto hyperplanes

Announcements:

- Quiz today!

Section 1

Orthogonal projection using KKT conditions

Recall: Orthogonal projection

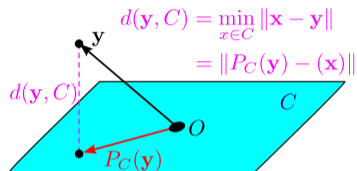
Definition (Recall: Orthogonal projection operator)

Given a nonempty closed convex set C , the orthogonal projection operator $P_C : \mathbb{R}^n \rightarrow C$ is defined by

$$P_C(\mathbf{y}) = \arg \min_{\mathbf{x} \in C} \|\mathbf{x} - \mathbf{y}\|^2.$$

- Returns the vector \mathbf{x} in C that is closest to input vector \mathbf{y} .
- Is a convex optimization problem:

$$\begin{aligned} \min \quad & \|\mathbf{x} - \mathbf{y}\|^2 \\ \text{s.t.} \quad & \mathbf{x} \in C. \end{aligned}$$



Orthogonal Projection onto an Affine Space with KKT conditions

Let C be an affine space

$$\{\mathbf{x} \in \mathbb{R}^n : A\mathbf{x} = \mathbf{b}\},$$

where $A \in \mathbb{R}^{m \times n}$ and $\mathbf{b} \in \mathbb{R}^m$.

Assume that the rows of A are linearly independent.

Given $\mathbf{y} \in \mathbb{R}^n$, find $P_C(\mathbf{y})$ which is the solution to the optimization problem

$$\begin{array}{ll} \min_{\mathbf{x}} & \|\mathbf{x} - \mathbf{y}\|^2 \\ \text{s.t.} & A\mathbf{x} = \mathbf{b}. \end{array}$$

- The Lagrangian simplifies to

$$L(\mathbf{x}, \boldsymbol{\mu}) = \|\mathbf{x} - \mathbf{y}\|^2 + \boldsymbol{\mu}^\top (A\mathbf{x} - \mathbf{b}),$$

for $\boldsymbol{\mu} \in \mathbb{R}^m$

- The KKT stationarity conditions are:

$$\nabla_{\mathbf{x}} L(\mathbf{x}, \boldsymbol{\mu}) = 2\mathbf{x} - 2\mathbf{y} + A^\top \boldsymbol{\mu} = \mathbf{0}$$

- Solving with $A\mathbf{x} = \mathbf{b}$ gives

$$P_C(\mathbf{y}) = \mathbf{y} - A^\top (AA^\top)^{-1} (A\mathbf{y} - \mathbf{b})$$

Orthogonal Projection onto a hyperplane with KKT conditions

Given a hyperplane

$$H = \{\mathbf{x} \in \mathbb{R}^n : \mathbf{a}^\top \mathbf{x} = b\}.$$

Given $\mathbf{y} \in \mathbb{R}^n$, find $P_H(\mathbf{y})$ which is the solution to the optimization problem

$$\begin{array}{ll} \min_{\mathbf{x}} & \|\mathbf{x} - \mathbf{y}\|^2 \\ \text{s.t.} & \mathbf{x} \in H \end{array}$$

- Special case of orthogonal projection onto an affine space with $A = \mathbf{a}^\top$ and $\mathbf{b} = b$.
- Replacing in the previous solution gives

$$\begin{aligned} P_H(\mathbf{y}) &= \mathbf{y} - \mathbf{a}(\mathbf{a}^\top \mathbf{a})^{-1}(\mathbf{a}^\top \mathbf{y} - b) \\ &= \mathbf{y} - \frac{\mathbf{a}^\top \mathbf{y} - b}{\|\mathbf{a}\|^2} \mathbf{a} \end{aligned}$$

Groups - Round 5

Group 1

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Purvi

Group 2

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Tianjian

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Andrew

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Monirul Amin

Group 6

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Atticus, Yousif

Group 7

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Group 8

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Group 9

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Group 10

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Group 11

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