

Introduction to constrained optimization

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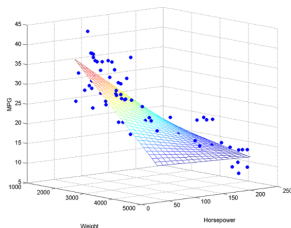
Plan

- 1 Introduction
- 2 Formulation
- 3 Concept of Lagrangian and duality, condition of optimality
 - Concept of Lagrangian
 - Concept of duality
- 4 QP Problem

Constrained optimization problems

- Where do these problems come from?
- How to formulate them?

Example 1: sparse Regression



- Output to be predicted: $y \in \mathbb{R}$
- Input variables: $x \in \mathbb{R}^d$
- Linear model: $f(x) = x^\top \theta$
- $\theta \in \mathbb{R}^d$: parameters of the model

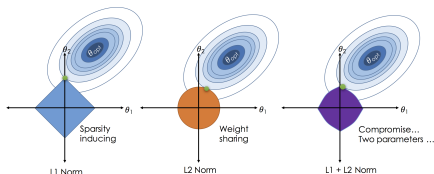
Determination of a sparse θ

- Minimization of square error
- Only a few parameters are non-zero

$$\min_{\theta \in \mathbb{R}^d} \frac{1}{2} \sum_{i=1}^N (y_i - x_i^\top \theta)^2$$

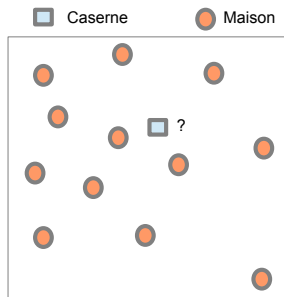
s.t. $\|\theta\|_p \leq k$

with $\|\theta\|_p^p = \sum_{j=1}^d |\theta_j|^p$



http://www.ds100.org/sp17/assets/notebooks/linear_regression/Regularization.html

Example 2: where to settle the firehouse?



- House M_i : defined by its coordinates $z_i = [x_i \ y_i]^T$
- Let θ be the coordinates of the firehouse
- Minimize the distance from the firehouse to the farthest house

Problem formulation

$$\min_{\theta} \max_{i=1, \dots, n} \|\theta - z_i\|^2$$

Equivalent problem

$$\begin{aligned} & \min_{t \in \mathbb{R}, \theta \in \mathbb{R}^2} t \\ & \text{s.t. } \|\theta - z_i\|^2 \leq t \quad \forall i = 1, \dots, n \end{aligned}$$

Constrained optimization problem

Notations and assumptions

- $\theta \in \mathbb{R}^d$: vector of unknown real parameters
- $J : \mathbb{R}^d \rightarrow \mathbb{R}$, the function to be minimized on its domain $\text{dom} J$
- f_i and g_j are differentiable functions of \mathbb{R}^d on \mathbb{R}

Primal problem \mathcal{P}

$$\begin{array}{ll}
 \min_{\theta \in \mathbb{R}^d} & J(\theta) \\
 \text{s.t.} & f_i(\theta) = 0 \quad \forall i = 1, \dots, n \\
 & g_j(\theta) \leq 0 \quad \forall j = 1, \dots, m
 \end{array}$$

objective function
 n Equality Constraints
 m Inequality Constraints

Feasibility

Let $p^* = \min_{\theta} \{J(\theta) \text{ such that } f_i(\theta) = 0 \forall i \text{ and } g_j(\theta) \leq 0 \forall j\}$

- If $p^* = \infty$ then the problem does not admit a feasible solution

Characterization of the solutions

Feasibility domain

The feasible domain is defined by the set of constraints

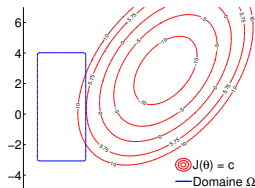
$$\Omega(\theta) = \left\{ \theta \in \mathbb{R}^d ; f_i(\theta) = 0 \ \forall i \text{ and } g_j(\theta) \leq 0 \ \forall j \right\}$$

Feasible points

- *θ_0 is feasible if $\theta_0 \in \text{dom}J$ and $\theta_0 \in \Omega(\theta)$ ie θ_0 fulfills all the constraints and $J(\theta_0)$ has a finite value*
- *θ^* is a global solution of the problem if θ^* is a feasible solution such that $J(\theta^*) \leq J(\theta)$ for every θ*
- *$\hat{\theta}$ is a local optimal solution if $\hat{\theta}$ is feasible and $J(\hat{\theta}) \leq J(\theta)$ for every $\|\theta - \hat{\theta}\| \leq \epsilon$*

Example 1

$$\begin{aligned}
 \min_{\boldsymbol{\theta}} \quad & 0.9\theta_1^2 - 0.74\theta_1\theta_2 \\
 & + 0.75\theta_2^2 - 5.4\theta_1 - 1.2\theta_2 \\
 \text{s.t.} \quad & -4 \leq \theta_1 \leq -1 \\
 & -3 < \theta_2 < 4
 \end{aligned}$$



- Parameters: $\boldsymbol{\theta} = \begin{pmatrix} \theta_1 \\ \theta_2 \end{pmatrix}$
- Objective function:

$$J(\boldsymbol{\theta}) = 0.9\theta_1^2 - 0.74\theta_1\theta_2 + 0.75\theta_2^2 - 5.4\theta_1 - 1.2\theta_2$$

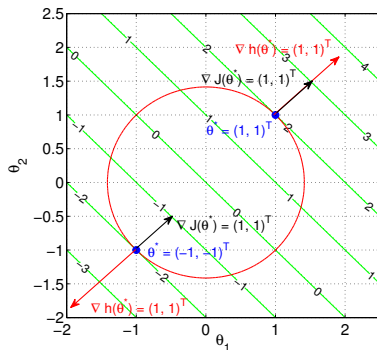
- Feasibility domain (four inequality constraints):

$$\Omega(\boldsymbol{\theta}) = \{\boldsymbol{\theta} \in \mathbb{R}^2; -4 \leq \theta_1 \leq -1 \text{ and } -3 \leq \theta_2 \leq 4\}$$

Example 2

Example

$$\begin{aligned} \min_{\theta \in \mathbb{R}^2} \quad & \theta_1 + \theta_2 \\ \text{s.t.} \quad & \theta_1^2 + \theta_2^2 - 2 = 0 \end{aligned}$$



- An equality constraint
- Domain of feasibility: a circle with center at 0 and diameter equals to 2
- The optimal solution is obtained for $\theta^* = (-1 \ -1)^T$ and we have $J(\theta^*) = -2$

Optimality

- How to assess a solution of the primal problem?
- Do we have optimality conditions similar to those of unconstrained optimization?

Notion of Lagrangian

Primal problem \mathcal{P}

$$\begin{aligned} \min_{\theta \in \mathbb{R}^d} \quad & J(\theta) \\ \text{s.t.} \quad & f_i(\theta) = 0 \quad \forall i = 1, \dots, n \quad n \text{ equality constraints} \\ & g_j(\theta) \leq 0 \quad \forall j = 1, \dots, m \quad m \text{ inequality constraints} \end{aligned}$$

θ is called primal variable

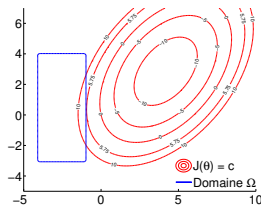
Principle of Lagrangian

- Each constraint is associated to a scalar parameter called **Lagrange multiplier**
- Equality constraint $f_i(\theta) = 0$: we associate $\lambda_i \in \mathbb{R}$
- Inequality constraint $g_j(\theta) \leq 0$: we associate $\mu_j \geq 0^a$
- Lagrangian allows to transform the problem with constraints into a problem without constraints with additional variables: λ_i and μ_j .

^aBeware of the type of inequality i.e. $g_j(\theta) \leq 0$

Example

$$\begin{aligned}
 \min_{\theta \in \mathbb{R}^2} \quad & 0.9\theta_1^2 - 0.74\theta_1\theta_2 \\
 & + 0.75\theta_1^2 - 5.4\theta_1 - 1.2\theta_2 \\
 \text{s.t.} \quad & -4 \leq \theta_1 \leq -1 \\
 & -3 \leq \theta_2 \leq 4
 \end{aligned}$$



Constraints (inequality)

- ① $-4 \leq \theta_1 \Leftrightarrow -\theta_1 - 4 \leq 0$
- ② $\theta_1 \leq -1 \Leftrightarrow \theta_1 + 1 \leq 0$
- ③ $-3 \leq \theta_2 \Leftrightarrow -\theta_2 - 3 \leq 0$
- ④ $\theta_2 \leq 4 \Leftrightarrow -\theta_2 - 4 \leq 0$

Related Lagrange Parameters

- ① $\mu_1 \geq 0$
- ② $\mu_2 \geq 0$
- ③ $\mu_3 \geq 0$
- ④ $\mu_4 \geq 0$

Lagrangian formulation

$$\begin{array}{ll} \min_{\boldsymbol{\theta} \in \mathbb{R}^d} & J(\boldsymbol{\theta}) \\ & f_i(\boldsymbol{\theta}) = 0 \quad \forall i = 1, \dots, n \\ \text{s.c.} & g_j(\boldsymbol{\theta}) \leq 0 \quad \forall j = 1, \dots, m \end{array}$$

Associated Lagrange parameters

None

λ_i any real number $\forall i = 1, \dots, n$

$\mu_j \geq 0 \quad \forall j = 1, \dots, m$

Lagrangien

The Lagrangian is defined by :

$$\mathcal{L}(\boldsymbol{\theta}, \boldsymbol{\lambda}, \boldsymbol{\mu}) = J(\boldsymbol{\theta}) + \sum_{i=1}^n \lambda_i f_i(\boldsymbol{\theta}) + \sum_{j=1}^m \mu_j g_j(\boldsymbol{\theta}) \quad \text{avec} \quad \mu_j \geq 0, \forall j = 1, \dots, m$$

- Lagrange parameters $\lambda_i, i = 1, \dots, n$ and $\mu_j, j = 1, \dots, m$ are called **dual variables**
- **Dual variables are unknown parameters** to be determined

Examples

Example 1

$$\begin{aligned} \min_{\theta \in \mathbb{R}^2} \quad & 0.9\theta_1^2 - 0.74\theta_1\theta_2 + 0.75\theta_1^2 - 5.4\theta_1 - 1.2\theta_2 \\ \text{s.t.} \quad & -4 \leq \theta_1 \leq -1 \quad \text{and} \quad -3 \leq \theta_2 \leq 4 \end{aligned}$$

Lagrangian

$$\begin{aligned} \mathcal{L}(\mu, \theta) = & 0.9\theta_1^2 - 0.74\theta_1\theta_2 + 0.75\theta_1^2 - 5.4\theta_1 - 1.2\theta_2 \\ & + \mu_1(-\theta_1 - 4) + \mu_2(\theta_1 + 1) + \mu_3(-\theta_2 - 3) + \mu_4(-\theta_2 - 4) \end{aligned}$$

with $\mu_1 \geq 0, \mu_2 \geq 0, \mu_3 \geq 0, \mu_4 \geq 0$ (because of inequality constraints)

Example 2

$$\begin{aligned} \min_{\theta \in \mathbb{R}^3} \quad & \frac{1}{2} (\theta_1^2 + \theta_2^2 + \theta_3^2) \\ \text{s.t.} \quad & \theta_1 + \theta_2 + 2\theta_3 = 1 \quad \text{equality constraint} \\ & \theta_1 + 4\theta_2 + 2\theta_3 = 3 \quad \text{equality constraint} \end{aligned}$$

Lagrangian

$$\mathcal{L}(\lambda, \theta) = \frac{1}{2} (\theta_1^2 + \theta_2^2 + \theta_3^2) + \lambda_1(\theta_1 + \theta_2 + 2\theta_3 - 1) + \lambda_2(\theta_1 + 4\theta_2 + 2\theta_3 - 3)$$

with $\lambda_1, \lambda_2 \in \mathbb{R}$ (equality constraints)

Necessary optimality conditions

Assume that J, f_i, g_j are differentiable functions. Let θ^* be a feasible solution to the problem \mathcal{P} . Then there exists dual variables $\lambda_i^*, i = 1, \dots, n, \mu_j^*, j = 1, \dots, m$ such that the following conditions are satisfied.

Karush-Kuhn-Tucker (KKT) Conditions

Stationarity

$$\begin{aligned}\nabla \mathcal{L}(\lambda, \mu, \theta) &= 0 \quad \text{ie} \\ \nabla J(\theta) + \sum_{i=1}^n \lambda_i \nabla f_i(\theta) + \sum_{j=1}^m \mu_j \nabla g_j(\theta) &= 0\end{aligned}$$

Primal feasibility

$$\begin{aligned}f_i(\theta) &= 0 & \forall i = 1, \dots, n \\ g_j(\theta) &\leq 0 & \forall j = 1, \dots, m\end{aligned}$$

Dual feasibility

$$\mu_j \geq 0 \quad \forall j = 1, \dots, m$$

Complementary slackness

$$\mu_j g_j(\theta) = 0 \quad \forall j = 1, \dots, m$$

Example

$$\begin{array}{ll}\min_{\theta \in \mathbb{R}^2} & \frac{1}{2}(\theta_1^2 + \theta_2^2) \\ \text{s.t.} & \theta_1 - 2\theta_2 + 2 \leq 0\end{array}$$

- Lagrangian : $\mathcal{L}(\lambda, \theta) = \frac{1}{2}(\theta_1^2 + \theta_2^2) + \mu(\theta_1 - 2\theta_2 + 2)$, $\mu \geq 0$

- KKT Conditions

- Stationarity: $\nabla_{\theta} \mathcal{L}(\mu, \theta) = 0 \quad \Rightarrow \quad \begin{cases} \theta_1 = -\mu \\ \theta_2 = -2\mu \end{cases}$

- Primal feasibility : $\theta_1 - 2\theta_2 + 2 \leq 0$

- Dual feasibility : $\mu \geq 0$

- Complementary slackness : $\mu(\theta_1 - 2\theta_2 + 2) = 0$

- Remarks on the complementary slackness

- If $\theta_1 - 2\theta_2 + 2 < 0$ (inactive constraint) $\Rightarrow \mu = 0$ (no penalty required as the constraint is satisfied)
- If $\mu > 0 \Rightarrow \theta_1 - 2\theta_2 + 2 = 0$ (active constraint)

Duality

Dual function

Let $\mathcal{L}(\boldsymbol{\theta}, \boldsymbol{\lambda}, \boldsymbol{\mu})$ be the lagrangian of the primal problem \mathcal{P} with $\mu_j \geq 0$. The corresponding **dual function** is defined as

$$\mathcal{D}(\boldsymbol{\lambda}, \boldsymbol{\mu}) = \min_{\boldsymbol{\theta}} \mathcal{L}(\boldsymbol{\theta}, \boldsymbol{\lambda}, \boldsymbol{\mu})$$

Theorem [Weak duality]

Let $p^* = \min_{\boldsymbol{\theta}} \{J(\boldsymbol{\theta}) \text{ such that } f_i(\boldsymbol{\theta}) = 0 \forall i \text{ and } g_j(\boldsymbol{\theta}) \leq 0 \forall j\}$ be the optimum value (supposed finite) of the problem \mathcal{P} . Then, for any value of $\mu_j \geq 0, \forall j$ and $\lambda_i, \forall i$, we have

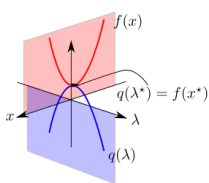
$$\mathcal{D}(\boldsymbol{\lambda}, \boldsymbol{\mu}) \leq p^*$$

Dual problem

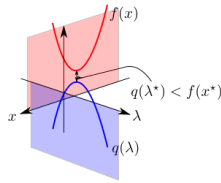
- The weak duality indicates that the dual function $\mathcal{D}(\lambda, \mu) = \min_{\theta} \mathcal{L}(\theta, \lambda, \mu)$ is a lower bound of p^*
- Bridge the gap: maximize the dual w.r.t. dual variables λ and μ to make this lower bound close to p^*

Dual problem

$$\begin{array}{ll} \max_{\lambda, \mu} & \mathcal{D}(\lambda, \mu) \\ \text{s.t.} & \lambda_j \geq 0 \quad \forall j = 1, \dots, m \end{array}$$



strong duality



weak duality

<http://www.onmyphd.com/?p=duality.theory>

Interest of the dual problem

Remarks

- Transform the primal problem into an equivalent dual problem possibly much simpler to solve
- Solving the dual problem can lead to the solution of the primal problem
- Solving the dual problem gives the optimal values of the Lagrange multipliers

Example : inequality constraints

$$\begin{aligned} \min_{\theta \in \mathbb{R}^2} \quad & \frac{1}{2}(\theta_1^2 + \theta_2^2) \\ \text{s.t.} \quad & \theta_1 - 2\theta_2 + 2 \leq 0 \end{aligned}$$

- Lagrangian : $\mathcal{L}(\theta, \mu) = \frac{1}{2}(\theta_1^2 + \theta_2^2) + \mu(\theta_1 - 2\theta_2 + 2)$, $\mu \geq 0$

- Stationarity of the KKT Condition :

$$\nabla_{\theta} \mathcal{L}(\mu, \theta) = 0 \quad \Rightarrow \quad \begin{cases} \theta_1 = -\mu \\ \theta_2 = 2\mu \end{cases} \quad (1)$$

- Dual function $\mathcal{D}(\mu) = \min_{\theta} L(\theta, \mu)$: by substituting (1) in \mathcal{L} we obtain

$$\mathcal{D}(\mu) = -\frac{5}{2}\mu^2 + 2\mu$$

- Dual problem : $\max_{\mu} \mathcal{D}(\mu)$ s.c. $\mu \geq 0$

- Dual solution

$$\nabla \mathcal{D}(\mu) = 0 \Rightarrow \mu = \frac{2}{5} \quad (\text{that satisfies } \mu \geq 0) \quad (2)$$

- Primal solution : (2) and (1) lead to $\theta = \left(-\frac{2}{5} \quad \frac{4}{5}\right)^{\top}$

Convex constrained optimization

$$\begin{array}{ll} \min_{\boldsymbol{\theta} \in \mathbb{R}^d} & J(\boldsymbol{\theta}) \\ \text{s.t.} & f_i(\boldsymbol{\theta}) = 0 \quad \forall i = 1, \dots, n \\ & g_j(\boldsymbol{\theta}) \leq 0 \quad \forall j = 1, \dots, m \end{array}$$

Convexity condition

J is a convex function

f_i are linear $\forall i = 1, n$

g_j are convex functions $\forall j = 1, m$

Problems of interest

- Linear Programming (LP)
- Quadratic Programming (QP)
- Off-the-shelves toolboxes exist for those problems (Gurobi, Mosek, CVX ...)



QP convex problem

Standard form

$$\begin{array}{ll}
 \min_{\boldsymbol{\theta} \in \mathbb{R}^d} & \frac{1}{2} \boldsymbol{\theta}^\top \mathbf{G} \boldsymbol{\theta} + \mathbf{q}^\top \boldsymbol{\theta} + r \\
 \text{s.t.} & \mathbf{a}_i^\top \boldsymbol{\theta} = b_i \quad \forall i = 1, \dots, n \quad \text{affine equality constraint} \\
 & \mathbf{c}_j^\top \boldsymbol{\theta} \geq d_j \quad \forall j = 1, \dots, m \quad \text{linear inequality constraints}
 \end{array}$$

with $\mathbf{q}, \mathbf{a}_i, \mathbf{c}_j \in \mathbb{R}^d$, d_i and d_j real scalar values and $\mathbf{G} \in \mathbb{R}^{d \times d}$ a **positive definite matrix**

Examples

SVM Problem

$$\begin{array}{ll}
 \min_{\boldsymbol{\theta} \in \mathbb{R}^2} & \frac{1}{2} (\theta_1^2 + \theta_2^2) \\
 \text{s.t.} & \theta_1 - 2\theta_2 + 2 \leq 0
 \end{array}$$

$$\begin{array}{ll}
 \min_{\boldsymbol{\theta}, b \in \mathbb{R}} & \frac{1}{2} \|\boldsymbol{\theta}\|^2 \\
 \text{s.t.} & y_i (\boldsymbol{\theta}^\top \mathbf{x}_i + b) \geq 1 \quad \forall i = 1, N
 \end{array}$$

Summary

- Optimization under constraints: involved problem in the general case
- Lagrangian: allows to reduce to an unconstrained problem via Lagrange multipliers
- Lagrange multipliers
 - to a constraint corresponds a multiplier \Rightarrow
 - act as a penalty if the corresponding constraints are violated
- Optimally: Stationary condition + feasibility conditions + Complementary conditions
- Duality: provides lower bound on the primal problem. Dual problem sometimes easier to solve than primal.

A reference book

