

Statistical Models & Computing Methods

Lecture 2: Optimization



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- ▶ Consider the following least square problem

$$\text{minimize } L(\beta) = \frac{1}{2} \|Y - X\beta\|^2$$

- ▶ Note that this is a quadratic problem, which can be solved by setting the gradient to zero

$$\begin{aligned}\nabla_{\beta} L(\beta) &= -X^T(Y - X\hat{\beta}) = 0 \\ \hat{\beta} &= (X^T X)^{-1} X^T Y\end{aligned}$$

given that the Hessian is positive definite:

$$\nabla^2 L(\beta) = X^T X \succ 0$$

which is true iff X has independent columns.



- ▶ In practice, we would like to solve the least square problems with some constraints on the parameters to control the complexity of the resulting model
- ▶ One common approach is to use Bridge regression models (Frank and Friedman, 1993)

$$\begin{aligned} \text{minimize} \quad & L(\beta) = \frac{1}{2} \|Y - X\beta\|^2 \\ \text{subject to} \quad & \sum_{j=1}^p |\beta_j|^\gamma \leq s \end{aligned}$$

- ▶ Two important special cases are ridge regression (Hoerl and Kennard, 1970) $\gamma = 2$ and Lasso (Tibshirani, 1996) $\gamma = 1$



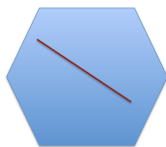
- ▶ In general, optimization problems take the following form:

$$\begin{aligned} & \text{minimize} && f_0(x) \\ & \text{subject to} && f_i(x) \leq 0, \quad i = 1, \dots, m \\ & && h_j(x) = 0, \quad j = 1, \dots, p \end{aligned}$$

- ▶ We are mostly interested in **convex** optimization problems, where the objective function $f_0(x)$, the inequality constraints $f_i(x)$ and the equality constraints $h_j(x)$ are all **convex** functions.

- ▶ A set C is *convex* if the line segment between any two points in C also lies in C , i.e.,

$$\theta x_1 + (1 - \theta)x_2 \in C, \quad \forall x_1, x_2 \in C, 0 \leq \theta \leq 1$$



Convex Set

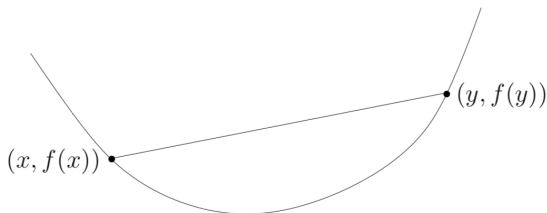


Non-convex Set

- ▶ If C is a convex set in \mathbb{R}^n and $f(x) : \mathbb{R}^n \rightarrow \mathbb{R}^n$ is an affine function, then $f(C)$, i.e., the image of C is also a convex set.

- ▶ A function $f : \mathbb{R}^n \rightarrow \mathbb{R}$ is *convex* if its domain D_f is a convex set, and $\forall x, y \in D_f$ and $0 \leq \theta \leq 1$

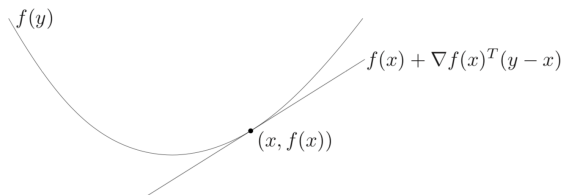
$$f(\theta x + (1 - \theta)y) \leq \theta f(x) + (1 - \theta)f(y)$$



- ▶ For example, many norms are convex functions

$$\|x\|_p = \left(\sum_i |x_i|^p \right)^{1/p}, \quad p \geq 1$$





- First order conditions. Suppose f is differentiable, then f is convex iff D_f is convex and

$$f(y) \geq f(x) + \nabla f(x)^T(y - x), \quad \forall x, y \in D_f$$

Corollary: For convex function f ,

$$f(\mathbb{E}(X)) \leq \mathbb{E}(f(X))$$

- Second order conditions. $\nabla^2 f(x) \succeq 0, \forall x \in D_f$

- ▶ Optimal value $p^* = \inf\{f_0(x) \mid f_i(x) \leq 0, h_j(x) = 0\}$
- ▶ x is feasible if $x \in D = \bigcap_{i=0}^m D_{f_i} \cap \bigcap_{j=1}^p D_{h_j}$ and satisfies the constraints.
- ▶ A feasible x^* is optimal if $f(x^*) = p^*$
- ▶ Optimality criterion. Assuming f_0 is convex and differentiable, x is optimal iff

$$\nabla f_0(x)^T (y - x) \geq 0, \quad \forall \text{ feasible } y$$

Remark: for unconstrained problems, x is optimal iff

$$\nabla f_0(x) = 0$$



Local Optimality

x is locally optimal if for a given $R > 0$, it is optimal for

$$\begin{aligned} & \text{minimize} && f_0(z) \\ & \text{subject to} && f_i(z) \leq 0, \quad i = 1, \dots, m \\ & && h_j(z) = 0, \quad j = 1, \dots, p \\ & && \|z - x\| \leq R \end{aligned}$$

In convex optimization problems, any locally optimal point is also globally optimal.

- ▶ Consider a general optimization problem

$$\begin{aligned} & \text{minimize} && f_0(x) \\ & \text{subject to} && f_i(x) \leq 0, \quad i = 1, \dots, m \\ & && h_j(x) = 0, \quad j = 1, \dots, p \end{aligned}$$

- ▶ To take the constraints into account, we augment the objective function with a weighted sum of the constraints and define the **Lagrangian** $L : \mathbb{R}^n \times \mathbb{R}^m \times \mathbb{R}^p \rightarrow \mathbb{R}$ as

$$L(x, \lambda, \nu) = f_0(x) + \sum_{i=1}^m \lambda_i f_i(x) + \sum_{j=1}^p \nu_j h_j(x)$$

where λ and ν are dual variables or *Lagrangian multipliers*.

- ▶ We define the **Lagrangian dual function** as follows

$$g(\lambda, \nu) = \inf_{x \in D} L(x, \lambda, \nu)$$

- ▶ The dual function is the pointwise infimum of a family of affine functions of (λ, ν) , it is concave, even when the original problem is not convex.
- ▶ If $\lambda \geq 0$, for each feasible point \tilde{x}

$$g(\lambda, \nu) = \inf_{x \in D} L(x, \lambda, \nu) \leq L(\tilde{x}, \lambda, \nu) \leq f_0(\tilde{x})$$

- ▶ Therefore, $g(\lambda, \nu)$ is a lower bound for the optimal value

$$g(\lambda, \nu) \leq p^*, \quad \forall \lambda \geq 0, \nu \in \mathbb{R}^p$$

- ▶ Finding the best lower bound leads to the **Lagrangian dual problem**

$$\text{maximize } g(\lambda, \nu), \quad \text{subject to } \lambda \geq 0$$

- ▶ The above problem is a convex optimization problem.
- ▶ We denote the optimal value as d^* , and call the corresponding solution (λ^*, ν^*) the dual optimal
- ▶ In contrast, the original problem is called the primal problem, whose solution x^* is called primal optimal

- ▶ d^* is the best lower bound for p^* that can be obtained from the Lagrangian dual function.

- ▶ **Weak Duality**

$$d^* \leq p^*$$

- ▶ The difference $p^* - d^*$ is called the *optimal dual gap*

- ▶ **Strong Duality**

$$d^* = p^*$$

- ▶ Strong duality doesn't hold in general, but if the primal is convex, it usually holds under some conditions called *constraint qualifications*
- ▶ A simple and well-known constraint qualification is **Slater's condition**: there exist an x in the relative interior of D such that

$$f_i(x) < 0, \quad i = 1, \dots, m, \quad Ax = b$$

- ▶ Consider primal optimal x^* and dual optimal (λ^*, ν^*)
- ▶ If strong duality holds

$$\begin{aligned} f_0(x^*) &= g(\lambda^*, \nu^*) \\ &= \inf_x \left(f_0(x) + \sum_{i=1}^m \lambda_i^* f_i(x) + \sum_{i=1}^p \nu_j^* h_i(x) \right) \\ &\leq f_0(x^*) + \sum_{i=1}^m \lambda_i^* f_i(x^*) + \sum_{i=1}^p \nu_j^* h_i(x^*) \\ &\leq f_0(x^*). \end{aligned}$$

- ▶ Therefore, these are all equalities

- ▶ Important conclusions:
 - ▶ x^* minimize $L(x, \lambda^*, \nu^*)$
 - ▶ $\lambda_i^* f_i(x^*) = 0, \quad i = 1, \dots, m$
- ▶ The latter is called **complementary slackness**, which indicates

$$\begin{aligned}\lambda_i^* > 0 &\Rightarrow f_i(x^*) = 0 \\ f_i(x^*) < 0 &\Rightarrow \lambda_i^* = 0\end{aligned}$$

- ▶ When the dual problem is easier to solve, we can find (λ^*, ν^*) and then minimize $L(x, \lambda^*, \nu^*)$. If the resulting solution is primal feasible, then it is primal optimal.

- ▶ Consider the entropy maximization problem

$$\begin{aligned} & \text{minimize} && f_0(x) = \sum_{i=1}^n x_i \log x_i \\ & \text{subject to} && -x_i \leq 0, \quad i = 1, \dots, n \\ & && \sum_{i=1}^n x_i = 1 \end{aligned}$$

- ▶ Lagrangian

$$L(x, \lambda, \nu) = \sum_{i=1}^n x_i \log x_i - \sum_{i=1}^n \lambda_i x_i + \nu \left(\sum_{i=1}^n x_i - 1 \right)$$

- ▶ We minimize $L(x, \lambda, \mu)$ by setting $\frac{\partial L}{\partial x}$ to zero

$$\log \hat{x}_i + 1 - \lambda_i + \nu = 0 \Rightarrow \hat{x}_i = \exp(\lambda_i - \nu - 1)$$



- ▶ The dual function is

$$g(\lambda, \nu) = - \sum_{i=1}^n \exp(\lambda_i - \nu - 1) - \nu$$

- ▶ Dual:

$$\text{maximize } g(\lambda, \nu) = - \exp(-\nu - 1) \sum_{i=1}^n \exp(\lambda_i) - \nu, \quad \lambda \geq 0$$

- ▶ We find the dual optimal

$$\lambda_i^* = 0, \quad i = 0, \dots, n, \quad \nu^* = -1 + \log n$$

- ▶ We now minimize $L(x, \lambda^*, \nu^*)$

$$\log x_i^* + 1 - \lambda_i^* + \nu^* = 0 \quad \Rightarrow \quad x_i^* = \frac{1}{n}$$

- ▶ Therefore, the discrete probability distribution that has maximum entropy is the uniform distribution

Exercise

Show that $X \sim \mathcal{N}(\mu, \sigma^2)$ is the maximum entropy distribution such that $EX = \mu$ and $EX^2 = \mu^2 + \sigma^2$. How about fixing the first k moments at $EX^i = m_i$, $i = 1, \dots, k$?



- ▶ Suppose the functions $f_0, f_1, \dots, f_m, h_1, \dots, h_p$ are all differentiable; x^* and (λ^*, ν^*) are primal and dual optimal points with zero duality gap
- ▶ Since x^* minimize $L(x, \lambda^*, \nu^*)$, the gradient vanishes at x^*

$$\nabla f_0(x^*) + \sum_{i=1}^m \lambda_i^* \nabla f_i(x^*) + \sum_{j=1}^p \nu_j^* \nabla h_j(x^*) = 0$$

- ▶ Additionally

$$\begin{aligned} f_i(x^*) &\leq 0, & i = 1, \dots, m \\ h_j(x^*) &= 0, & j = 1, \dots, p \\ \lambda_i^* &\geq 0, & i = 1, \dots, m \\ \lambda_i^* f_i(x^*) &= 0, & i = 1, \dots, m \end{aligned}$$

- ▶ These are called **Karush-Kuhn-Tucker (KKT) conditions**



- ▶ When the primal problem is convex, the KKT conditions are also sufficient for the points to be primal and dual optimal with zero duality gap.
- ▶ Let $\tilde{x}, \tilde{\lambda}, \tilde{\nu}$ be any points that satisfy the KKT conditions, \tilde{x} is primal feasible and minimizes $L(\tilde{x}, \tilde{\lambda}, \tilde{\nu})$

$$\begin{aligned}g(\tilde{\lambda}, \tilde{\nu}) &= L(\tilde{x}, \tilde{\lambda}, \tilde{\nu}) \\&= f_0(\tilde{x}) + \sum_{i=1}^m \tilde{\lambda}_i f_i(\tilde{x}) + \sum_{j=1}^p \tilde{\nu}_j h_j(\tilde{x}) \\&= f_0(\tilde{x})\end{aligned}$$

- ▶ Therefore, for convex optimization problems with differentiable functions that satisfy Slater's condition, the KKT conditions are necessary and sufficient

- ▶ Consider the following problem:

$$\begin{aligned} & \text{minimize} && \frac{1}{2}x^T Px + q^T x + r, \quad P \succeq 0 \\ & \text{subject to} && Ax = b \end{aligned}$$

- ▶ KKT conditions:

$$\begin{aligned} Px^* + q + A^T \nu^* &= 0 \\ Ax^* &= b \end{aligned}$$

- ▶ To find x^*, ν^* , we can solve the above system of linear equations



- ▶ We now focus on numerical solutions for unconstrained optimization problems

$$\text{minimize } f(x)$$

where $f : \mathbb{R}^n \rightarrow \mathbb{R}$ is twice differentiable

- ▶ Descent method. We can set up a sequence

$$x^{(k+1)} = x^{(k)} + t^{(k)} \Delta x^{(k)}, \quad t^{(k)} > 0$$

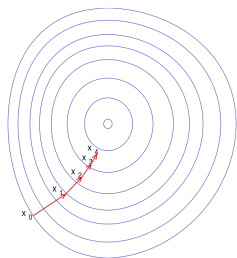
such that $f(x^{(k+1)}) < f(x^{(k)})$, $k = 0, 1, \dots$,

- ▶ $\Delta x^{(k)}$ is called the **search direction**; $t^{(k)}$ is called the **step size** or **learning rate** in machine learning.

A reasonable choice for the search direction is the negative gradient, which leads to gradient descent methods

$$x^{(k+1)} = x^{(k)} - t^{(k)} \nabla f(x^{(k)}), \quad k = 0, 1, \dots$$

- ▶ step size $t^{(k)}$ can be constant or determined by line search
- ▶ every iteration is cheap, does not require second derivatives



- ▶ First-order Taylor expansion

$$f(x + v) \approx f(x) + \nabla f(x)^T v$$

- ▶ v is a descent direction iff $\nabla f(x)^T v < 0$
- ▶ Negative gradient is the steepest descent direction with respect to the Euclidean norm.

$$\frac{-\nabla f(x)}{\|\nabla f(x)\|_2} = \arg \min_v \{ \nabla f(x)^T v \mid \|v\|_2 = 1 \}$$



- ▶ Consider the second-order Taylor expansion of f at x ,

$$\begin{aligned} f(x+v) &\approx f(x) + \nabla f(x)^T v + \frac{1}{2} v^T \nabla^2 f(x) v \\ &\triangleq \tilde{f}(x) \end{aligned}$$

- ▶ We find the optimal direction v by minimizing $\tilde{f}(x)$ with respect to v

$$v = -[\nabla^2 f(x)]^{-1} \nabla f(x)$$

- ▶ If $\nabla^2 f(x) \succeq 0$ (e.g., convex functions)

$$\nabla f(x)^T v = -\nabla f(x)^T [\nabla^2 f(x)]^{-1} \nabla f(x) < 0$$

when $\nabla f(x) \neq 0$

- ▶ The search direction in Newton's method can also be viewed as a steepest descent direction, but with a different metric
- ▶ In general, given a positive definite matrix P , we can define a quadratic norm

$$\|v\|_P = (v^T P v)^{1/2}$$

- ▶ Similarly, we can show that $-P^{-1}\nabla f(x)$ is the steepest descent direction w.r.t. the quadratic norm $\|\cdot\|_P$

$$\text{minimize } \nabla f(x)^T v, \quad \text{subject to } \|v\|_P = 1$$

- ▶ When P is the Hessian $\nabla^2 f(x)$, we get Newton's method

- ▶ Computing the Hessian and its inverse could be expensive, we can approximate it with another positive definite matrix $M \succ 0$ which is easier to use
- ▶ Update $M^{(k)}$ to learn about the curvature of f in the search direction and maintain a **secant condition**

$$\nabla f(x^{(k+1)}) - \nabla f(x^{(k)}) = M^{(k+1)}(x^{(k+1)} - x^{(k)})$$

- ▶ Rank-one update

$$\Delta x^{(k)} = x^{(k+1)} - x^{(k)}$$

$$y^{(k)} = \nabla f(x^{(k+1)}) - \nabla f(x^{(k)})$$

$$v^{(k)} = y^{(k)} - M^{(k)} \Delta x^{(k)}$$

$$M^{(k+1)} = M^{(k)} + \frac{v^{(k)}(v^{(k)})^T}{(v^{(k)})^T \Delta x^{(k)}}$$



- ▶ Easy to compute the inverse of matrices for low rank updates by **Sherman-Morrison-Woodbury formula**

$$(A + UCV)^{-1} = A^{-1} - A^{-1}U(C^{-1} + VA^{-1}U)^{-1}VA^{-1}$$

where $A \in \mathbb{R}^{n \times n}$, $U \in \mathbb{R}^{n \times d}$, $C \in \mathbb{R}^{d \times d}$, $V \in \mathbb{R}^{d \times n}$

- ▶ Another popular rank-two update method: the **BFGS** (Broyden-Fletcher-Goldfarb-Shanno) method

$$M^{(k+1)} = M^{(k)} + \frac{y^{(k)}(y^{(k)})^T}{(y^{(k)})^T \Delta x^{(k)}} - \frac{M^{(k)} \Delta x^{(k)} (M^{(k)} \Delta x^{(k)})^T}{(\Delta x^{(k)})^T M^{(k)} \Delta x^{(k)}}$$

- ▶ In the frequentist framework, we typically perform statistical inference by maximizing the log-likelihood $L(\theta)$, or equivalently minimizing negative log-likelihood, which is also known as the energy function
- ▶ Some notations we introduced before
 - ▶ Score function: $s(\theta) = \nabla_{\theta} L(\theta)$
 - ▶ Observed Fisher information: $J(\theta) = -\nabla_{\theta}^2 L(\theta)$
 - ▶ Fisher information: $\mathcal{I}(\theta) = \mathbb{E}(-\nabla_{\theta}^2 L(\theta))$
- ▶ Newton's method for MLE:

$$\theta^{(k+1)} = \theta^{(k)} + (J(\theta^{(k)}))^{-1} s(\theta^{(k)})$$



- ▶ If we use the Fisher information instead of the observed information, the resulting method is called the *Fisher scoring* algorithm

$$\theta^{(k+1)} = \theta^{(k)} + (\mathcal{I}(\theta^{(k)}))^{-1} s(\theta^{(k)})$$

- ▶ It seems that the Fisher scoring algorithm is less sensitive to the initial guess. On the other hand, the Newton's method tends to converge faster
- ▶ For exponential family models with natural parameters and generalized linear models (GLMs) with canonical links, the two methods are identical

- ▶ A generalized linear model (GLM) assumes a set of independent random variables Y_1, \dots, Y_n that follow exponential family distributions of the same form

$$p(y_i|\theta_i) = \exp(y_i b(\theta_i) + c(\theta_i) + d(y_i))$$

- ▶ The parameters θ_i are typically not of direct interest. Instead, we usually assume that the expectation of Y_i can be related to a vector of parameters β via a transformation (**link function**)

$$E(Y_i) = \mu_i, \quad g(\mu_i) = x_i^T \beta$$

where x_i is the observed covariates for y_i .

- ▶ Using the link function, we can now write the score function in terms of β
- ▶ Let $g(\mu_i) = \eta_i$, we can show that for j th parameter

$$s(\beta_j) = \sum_{i=1}^n \frac{(y_i - \mu_i)x_{ij}}{\text{Var}(Y_i)} \frac{\partial \mu_i}{\partial \eta_i}$$

where $\partial \mu_i / \partial \eta_i$ depends on the link function we choose

- ▶ It is also easy to show that the Fisher information matrix is

$$\begin{aligned} \mathcal{I}(\beta_j, \beta_k) &= \mathbb{E}(s(\beta_j)s(\beta_k)) \\ &= \sum_{i=1}^n \frac{x_{ij}x_{ik}}{\text{Var}(Y_i)} \left(\frac{\partial \mu_i}{\partial \eta_i} \right)^2 \end{aligned}$$



- ▶ Note that the Fisher information matrix can be written as

$$\mathcal{I}(\beta) = X^T W X$$

where W is the $n \times n$ diagonal matrix with elements

$$w_{ii} = \frac{1}{\text{Var}(Y_i)} \left(\frac{\partial \mu_i}{\partial \eta_i} \right)^2$$

- ▶ Rewriting Fisher scoring algorithm for updating β as

$$\mathcal{I}(\beta^{(k)})\beta^{(k+1)} = \mathcal{I}(\beta^{(k)})\beta^{(k)} + s(\beta^{(k)})$$

- ▶ After few simple steps, we have

$$X^T W^{(k)} X \beta^{(k+1)} = X^T W^{(k)} Z^{(k)}$$

where

$$z_i^{(k)} = \eta_i^{(k)} + (y_i - \mu_i^{(k)}) \frac{\partial \eta_i^{(k)}}{\partial \mu_i^{(k)}}$$

- ▶ Therefore, we can find the next estimate as follows

$$\beta^{(k+1)} = (X^T W^{(k)} X)^{-1} X^T W^{(k)} Z^{(k)}$$

- ▶ The above estimate is similar to the weighted least square estimate, except that the weights W and the response variable Z change from one iteration to another
- ▶ We iteratively estimate β until the algorithm converges



- ▶ Recall that the Log-likelihood for logistic regression is

$$L(Y|p) = \sum_{i=1}^n y_i \log \frac{p_i}{1-p_i} + \log(1-p_i)$$

- ▶ The natural parameters are $\theta_i = \log \frac{p_i}{1-p_i}$. We use $g(x) = \log \frac{x}{1-x}$ as the link function, $\theta_i = g(p_i) = x_i^T \beta$
- ▶ We now write the log-likelihood as follows

$$L(\beta) = Y^T X \beta - \sum_{i=1}^n \log(1 + \exp(x_i^T \beta))$$

- ▶ The score function is

$$s(\beta) = X^T (Y - p), \quad p = \frac{1}{1 + \exp(-X\beta)}$$



- ▶ The observed Fisher information matrix is

$$J(\beta) = X^T W X$$

where W is a diagonal matrix with elements

$$w_{ii} = p_i(1 - p_i)$$

- ▶ Note that $J(\beta)$ does not depend on Y , meaning that it is also the Fisher information matrix $\mathcal{I}(\beta) = J(\beta)$
- ▶ Newton's update

$$\beta^{(k+1)} = \beta^{(k)} + \left(X^T W^{(k)} X \right)^{-1} \left(X^T (Y - p^{(k)}) \right)$$



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