

Coordinate descent

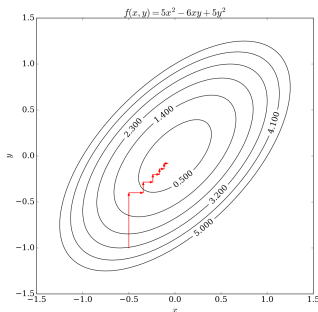
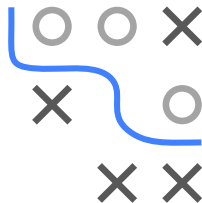


- Axes as descent direction
- CD on linear model and Lasso
- Soft thresholding



COORDINATE DESCENT

- Assumption: objective function not differentiable
- Idea: instead of gradient, use coordinate directions for descent
- First: Select starting point $\mathbf{x}^{[0]} = (x_1^{[0]}, \dots, x_d^{[0]})$
- Step t : Minimize f along x_i for each dimension i for fixed $x_1^{[t]}, \dots, x_{i-1}^{[t]}$ and $x_{i+1}^{[t-1]}, \dots, x_d^{[t-1]}$.



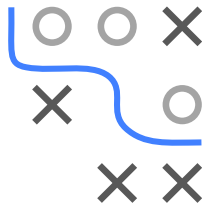
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COORDINATE DESCENT

- Minimum is determined with (exact/inexact) line search
- Order of dimensions can be any permutation of $\{1, 2, \dots, d\}$
- Convergence:
 - f convex differentiable
 - f sum of convex differentiable and *convex separable* function:

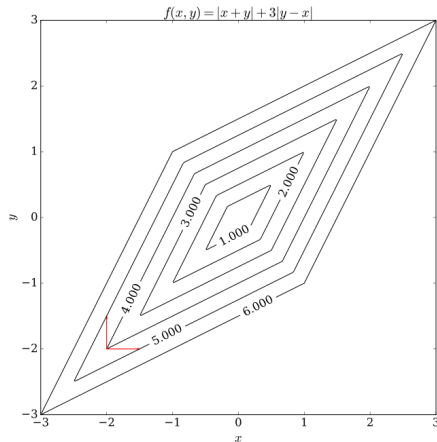
$$f(\mathbf{x}) = g(\mathbf{x}) + \sum_{i=1}^d h_i(x_i),$$

- where g convex differentiable and h_i convex

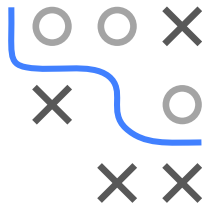


COORDINATE DESCENT

No convergence in general for convex functions, counterexample:



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EXAMPLE: LINEAR REGRESSION

Minimize LM with L2 loss via CD

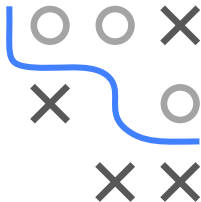
$$\min_{\theta} g(\theta) = \min_{\theta} \frac{1}{2} \sum_{i=1}^n \left(y^{(i)} - \theta^{\top} \mathbf{x}^{(i)} \right)^2 = \min_{\theta} \frac{1}{2} \|\mathbf{y} - \mathbf{X}\theta\|^2$$

where $\mathbf{y} \in \mathbb{R}^n$, $\mathbf{X} \in \mathbb{R}^{n \times d}$ with columns $\mathbf{x}_1, \dots, \mathbf{x}_d \in \mathbb{R}^n$

Assume orthogonal design for intuition, i.e., $\mathbf{X}^{\top} \mathbf{X} = I_d$:

$$\begin{aligned} g(\theta) &= \frac{1}{2} \mathbf{y}^{\top} \mathbf{y} + \frac{1}{2} \theta^{\top} \theta - \mathbf{y}^{\top} \mathbf{X} \theta \\ &\stackrel{(*)}{=} \frac{1}{2} \mathbf{y}^{\top} \mathbf{y} + \frac{1}{2} \theta^{\top} \theta - \mathbf{y}^{\top} \sum_{k=1}^d \mathbf{x}_k \theta_k \end{aligned}$$

$$(*) \quad \mathbf{X} \theta = \mathbf{x}_1 \theta_1 + \mathbf{x}_2 \theta_2 + \dots + \mathbf{x}_d \theta_d = \sum_{k=1}^d \mathbf{x}_k \theta_k$$



EXAMPLE: LINEAR REGRESSION

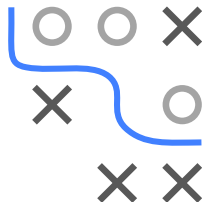
- Exact CD update in direction j :

$$\frac{\partial g(\boldsymbol{\theta})}{\partial \theta_j} = \theta_j - \mathbf{y}^\top \mathbf{x}_j$$

- By solving $\frac{\partial g(\boldsymbol{\theta})}{\partial \theta_j} = 0$ we get

$$\theta_j^* = \mathbf{y}^\top \mathbf{x}_j$$

- Repeat this update for all θ_j



SOFT THRESHOLDING

Minimize LM with L2 loss and L1 regularization via CD

$$\min_{\theta} h(\theta) = \min_{\theta} \frac{1}{2} \|\mathbf{y} - \mathbf{X}\theta\|^2 + \lambda \|\theta\|_1$$

Note that $h(\theta) = \frac{1}{2} \mathbf{y}^\top \mathbf{y} + \frac{1}{2} \theta^\top \theta - \sum_{k=1}^d (\mathbf{y}^\top \mathbf{x}_k \theta_k + \lambda |\theta_k|)$

Again assume $\mathbf{X}^\top \mathbf{X} = I_d$. Since $|\cdot|$ not differentiable, distinguish cases:

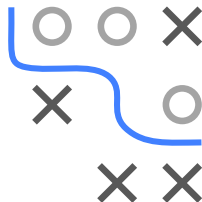
- **Case 1:** $\theta_j > 0$. Then $|\theta_j| = \theta_j$ and

$$0 = \frac{\partial h(\theta)}{\partial \theta_j} = \theta_j - \mathbf{y}^\top \mathbf{x}_j + \lambda \quad \Leftrightarrow \quad \theta_{j,\text{Lasso}}^* = \theta_j^* - \lambda$$

- **Case 2:** $\theta_j < 0$. Then $|\theta_j| = -\theta_j$ and

$$0 = \frac{\partial h(\theta)}{\partial \theta_j} = \theta_j - \mathbf{y}^\top \mathbf{x}_j - \lambda \quad \Leftrightarrow \quad \theta_{j,\text{Lasso}}^* = \theta_j^* + \lambda$$

- **Case 3:** $\theta_j = 0$



SOFT THRESHOLDING

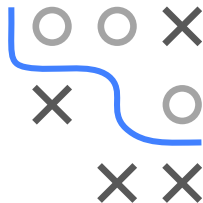
We can write the solution as:

$$\theta_{j,\text{Lasso}}^* = \begin{cases} \theta_j^* - \lambda & \text{if } \theta_j^* > \lambda \\ \theta_j^* + \lambda & \text{if } \theta_j^* < -\lambda \\ 0 & \text{if } \theta_j^* \in [-\lambda, \lambda], \end{cases}$$

This operation is called soft thresholding

Coefs for which solution to unregularized problem is smaller than threshold ($|\theta_j^*| < \lambda$) are shrunk to zero NB: Derivation of soft

thresholding operator not trivial (subgradients)



CD FOR STATISTICS AND ML

Why is it being used?

- Easy to implement
- Scalable: no storage/operations on large objects, just current point
⇒ Good implementation can achieve state-of-the-art performance
- Applicable for non-differentiable (but convex separable) objectives

Examples:

- Lasso regression, Lasso GLM, graphical Lasso
- Support Vector Machines
- Regression with non-convex penalties

