

EECS 127

Admin (1) : April 30, during class time

Admin (2) : Project will have extra credit that can be used to offset midterm + final

Material

- ① 1D version of LASSO
 - ② Coordinate descent algorithm
 - ③ Demos
 - ④ Quadratic Programs
-

LASSO Problem.

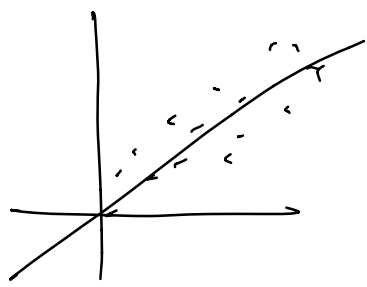
$$\min_{\vec{x}} \|A\vec{x} - \vec{b}\|_2^2 + \underbrace{\lambda \cdot \|\vec{x}\|_1}_{\text{regularizer}}$$

Simplest 1D regression case -

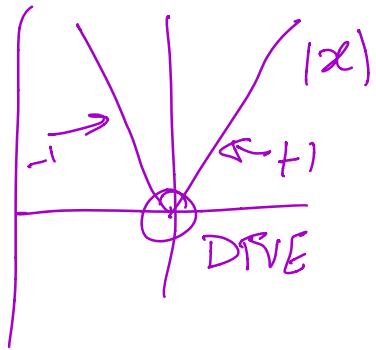
$\min_x \frac{1}{2} \sum_{i=1}^n (a_i x - b_i)^2 + \lambda |x|$

(a_i, b_i) → find x that best fits.

Labels: λ is a scalar, $(a_i x - b_i)^2$ is a scalar, $f(x)$ is the function.



CONVEX



$\frac{d}{dx} |x| = 1$ if $x > 0$
 $= -1$ if $x < 0$
 DNE $x = 0$

$\frac{d}{dx} f(x)$

$f(x) = \begin{cases} \frac{1}{2} \sum_{i=1}^n (a_i x - b_i)^2 + \lambda x & \text{if } x > 0 \\ \frac{1}{2} \sum_{i=1}^n (a_i x - b_i)^2 - \lambda x & \text{if } x < 0 \\ \frac{1}{2} \sum_{i=1}^n (a_i x - b_i)^2 & \text{if } x = 0 \end{cases}$

usual calculus, but we made cases

$\frac{d}{dx} f(x) = \begin{cases} \sum_{i=1}^n (a_i x - b_i) a_i + \lambda & \text{if } x > 0 \\ \sum_{i=1}^n (a_i x - b_i) a_i - \lambda & \text{if } x < 0 \end{cases}$

$$\frac{1}{2} \sum_{i=1}^n a_i (a_i x - b_i) u - \lambda \quad 0$$

DNE

$$x=0$$

we are trying to find x

Case 1: Consider $x > 0$.

x is not known yet!

$$\left(\sum_{i=1}^n a_i^2 \right) \cdot x - \sum_{i=1}^n a_i b_i + \lambda = 0$$

to find a critical point.

$$x = \frac{\sum_{i=1}^n a_i b_i - \lambda}{\sum_{i=1}^n a_i^2}$$

denom. always > 0

This calculation was done under the assumption that $x > 0$. We

better verify this assumption
we need.

$$\Rightarrow \sum a_i b_i - \lambda > 0 \Rightarrow \boxed{\sum a_i b_i > \lambda}$$

if $\sum a_i b_i > \lambda$ then

$$x = \frac{\sum a_i b_i - \lambda}{\sum a_i^2}$$

② Consider $x < 0$ | ASSUMPTION

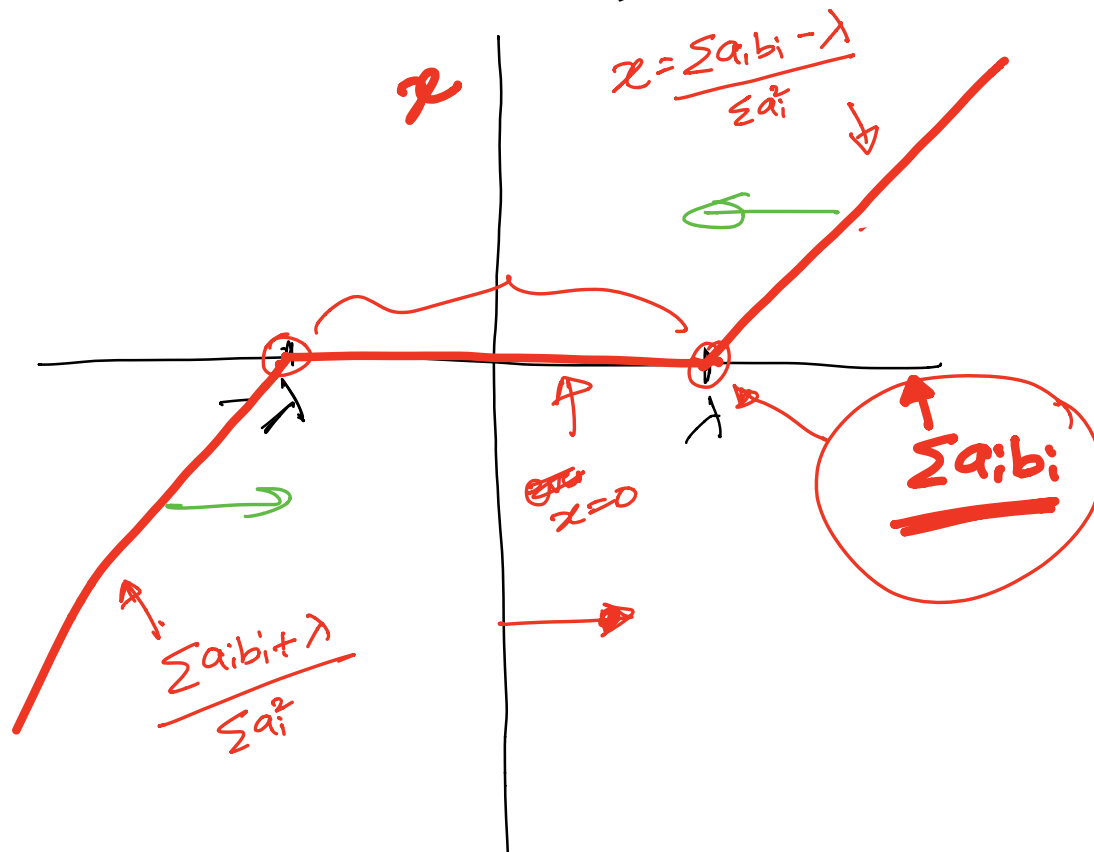
Set $\frac{d}{dx} () = 0$

$$\Rightarrow x = \frac{\sum_{i=1}^n a_i b_i + \lambda}{\sum_{i=1}^n a_i^2}$$

Valid only when $\sum_{i=1}^n a_i b_i + \lambda < 0$

$$\boxed{\sum a_i b_i < -\lambda.}$$

At all other times, $x = 0$.



"Soft thresholding.

Recall: Standard LS solution:

$$x = \frac{\sum a_i b_i}{\sum a_i^2}$$

$$(A^T A)^{-1} A^T b$$

Coordinate descent

$\min f(x)$ - function.

$x(0) = [x_1(0), x_2(0), \dots, x_n(0)]$. "guess for the minimum"

$$x_1(k) = \underset{x_1}{\operatorname{argmin}} f([x_1, \overset{\circ}{x_2(k-1)}, \overset{\circ}{x_3(k-1)}, \dots, \overset{\circ}{x_n(k-1)}])$$

fixed
↑
var

$$x_2(k) = \underset{x_2}{\operatorname{argmin}} f([x_1(k), \overset{\uparrow}{x_2}, \overset{\uparrow}{x_3(k-1)}, \dots, \overset{\uparrow}{x_n(k-1)}])$$

↑
var
k

$$x_n(k) = \underset{x_n}{\operatorname{argmin}} f([x_1(k), x_2(k), \dots, x_{n-1}(k), x_n])$$

↑
var
k-1

$\|Ax - b\|_2^2 + \lambda \|x\|$ 2D version

$$\left\| \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} - \begin{bmatrix} b_1 \\ b_2 \end{bmatrix} \right\|_2^2 + \lambda (|x_1| + |x_2|)$$

$$\begin{aligned}
 &\downarrow \\
 &= \left(\underbrace{a_{11}x_1 + a_{12}x_2 - b_1}_{\text{constant}} \right)^2 + \lambda |x_1| + \lambda |x_2| \\
 &\quad + \left(\underbrace{a_{21}x_1 + a_{22}x_2 - b_2}_{\text{const.}} \right)^2
 \end{aligned}$$

\downarrow const.
 \downarrow const.
 $\rightarrow g(x_1, x_2)$

Start at $(x_1(0), x_2(0))$

Freeze $x_2(0)$

$$\begin{aligned}
 &\min_{x_1} g(x_1, x_2(0)) \\
 &\uparrow
 \end{aligned}$$

LASSO is one example of what is called a Quadratic Program.

$$\begin{aligned}
 &\min \quad \frac{1}{2} \vec{x}^T H \vec{x} + \vec{c}^T \vec{x} + d \\
 &\text{s.t.} \quad A \vec{x} \leq b \\
 &\quad \quad C \vec{x} = \ell
 \end{aligned}$$

- QP: f
- ① $H = H^T$
 - ② objective function is CONVEX.
 - ③ Constraints are linear.

⊖ Non-convex quadratic : hyperbola.

Unconstrained quadratic.

$$f(\vec{x}) = \frac{1}{2} \vec{x}^T H \vec{x} + \vec{c}^T \vec{x} + d.$$

$H \geq 0$
PSD.
Symmetric

Set $\nabla f = 0$

Equality constrained quadratic.

$$\min \frac{1}{2} \vec{x}^T H \vec{x} + \vec{c}^T \vec{x} + d.$$

s.t. $A\vec{x} = b.$

→ Can be transformed into an

unconstrained quadratic optimization

Constraints:

Feasible: $\{ \vec{x} \mid \vec{x} = \vec{x}_0 + N\vec{z} \}$

$A\vec{x} = \vec{b}$

\vec{x}_0 any solution to $A\vec{x} = \vec{b}$

N nullspace of A .

$$\min_{\vec{z}} \frac{1}{2} (\vec{x}_0 + N\vec{z})^T H (\vec{x}_0 + N\vec{z}) + \vec{c}^T (\vec{x}_0 + N\vec{z}) + d$$

Quadratic in \vec{z}
