

CPSC 536F

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- Ridge Regression Dual Form: given $X, y, \lambda > 0$

$$\min_{\vec{w} \in \mathbb{R}^d} \|X\vec{w} - y\|^2 + \lambda \|\vec{w}\|^2$$

GNCS $(X^T X + \lambda I_d) \vec{w} = X^T y$. Bad if $d > n$

Equiv:

$$\min_{(\vec{w}, \vec{z}) \in \mathbb{R}^d \times \mathbb{R}^n} f(\vec{w}, \vec{z}) = \|\vec{z}\|^2 + \lambda \|\vec{w}\|^2$$

$$\vec{z} = X\vec{w} - y$$

Lagrangian: $g(\vec{w}, \vec{z}) = X\vec{w} - y - \vec{z} = 0$

Etc. min-max vs max-min

Conceptualize (Abstract nonsense):

Thm (The Representer Theorem,

Simple Form):

$\left\{ \begin{array}{l} H \text{ could be } \mathbb{R}^d \\ \text{Hilbert Space } d \text{ large} \end{array} \right.$

Let $\Phi: \mathcal{X} \rightarrow H$ be a set

theoretic map, and consider

data points

$$(x_1, y_1), \dots, (x_n, y_n) \in \mathcal{X} \times \mathbb{R}$$

Let $\lambda > 0$, and consider $g: H \rightarrow \mathbb{R}$

$$g(w) = \lambda \|w\|_H^2$$

$$+ \sum_{i=1}^n \left(\langle \Phi(x_i), w \rangle_H - y_i \right)^2$$

Then minimum at w_0 satisfies

$$(X^*X + \lambda I_H)w_0 = X^*y$$

where $X: H \rightarrow \mathbb{R}^n$ given by

$$X(w) = \begin{bmatrix} \langle \Phi(x_1), w \rangle_H \\ \vdots \\ \langle \Phi(x_n), w \rangle_H \end{bmatrix}.$$

One remarkable fact ...

$$\left[\begin{array}{l} \text{So } \mathbb{R}^d \rightsquigarrow H \text{ inner product space} \\ \left(\begin{array}{l} \dim(H) = \infty, \text{ we} \\ \text{want a Hilbert space} \end{array} \right) \\ X^T \rightsquigarrow X^* \\ X: \mathbb{R}^d \rightarrow \mathbb{R}^n \rightsquigarrow X: H \rightarrow \mathbb{R}^n \end{array} \right]$$

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$$\vec{y} = \begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix} \quad X = \begin{bmatrix} -x_1^T \\ \vdots \\ -x_n^T \end{bmatrix}$$

w best coefficients, $w \in \mathbb{R}^d$, $d \gg n$
=

$$\min f(\vec{x})$$

$$\text{s.t.} \quad \vec{g}(\vec{x}) = \vec{0}$$

at optimum (min/max/saddle)

$$\nabla f(\vec{x}) = 0 \quad \text{if no } g\text{'s}$$

$$\nabla f(\vec{x}) \text{ in span } \nabla \vec{g}, \text{ i.e.}$$

$$\nabla g_1, \nabla g_2, \dots, \nabla g_a$$

$$\nabla f(\vec{x}) + \alpha^T \cdot \nabla \vec{g} = 0 \quad \text{some } \alpha$$

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$$L(x, \alpha) = f(x) + \alpha \cdot g(x)$$

For any $\vec{x}$

$$\max_{\alpha \in \mathbb{R}^a} f(\vec{x}) + \alpha \cdot \vec{g}(\vec{x})$$

$$= +\infty \text{ unless } \vec{g}(\vec{x}) = \vec{0}$$

$$\min_{\vec{x}} \max_{\alpha} L(\vec{x}, \vec{\alpha}) = \min_{\substack{\vec{x} \text{ s.t.} \\ \vec{g}(\vec{x}) = \vec{0}}} f(\vec{x})$$

Now consider

$$\max_{\alpha} \min_{\vec{x}} L(\vec{x}, \vec{\alpha})$$

if these two are equal, then

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$f(w)$ ☹️

$\min_{\vec{w} \in \mathbb{R}^d}$

$$\lambda \|\vec{w}\|^2 + \|\mathbf{X}\vec{w} - \vec{y}\|^2$$

rewrite! Key step (ad hoc)
to get a good dual problem

$\min$

$(\vec{w}, \vec{z}) \in \mathbb{R}^d \times \mathbb{R}^n$

$$\lambda \|\vec{w}\|^2 + \|\vec{z}\|^2$$

$f(w, z)$ 😊

s.t.,

$$\vec{z} = \mathbf{X}\vec{w} - \vec{y}, \text{ i.e.}$$

$$\vec{g}(\vec{w}, \vec{z}) = 0, \text{ where}$$

$$\vec{g}(\vec{w}, \vec{z}) = \mathbf{X}\vec{w} - \vec{y} - \vec{z}$$

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$$\max_{\vec{\alpha}} \left(\min_{(\omega, z)} \underbrace{L((\omega, z); \alpha)} \right)$$

$$\|\vec{z}\|^2 + \lambda \|\vec{\omega}\|^2 + \vec{\alpha} \cdot \vec{g}(\vec{\omega}, \vec{z})$$

fix $\vec{\alpha} \in \mathbb{R}^a$

Which (ω, z) pairs minimize

$$L((\omega, z); \alpha)$$

$$\underbrace{\vec{z} \cdot \vec{z}}_{(1)} + \lambda \underbrace{\vec{\omega} \cdot \vec{\omega}}_{(2)} + \underbrace{\vec{\alpha} \cdot (\lambda \vec{\omega} - \vec{y} - \vec{z})}_{(3)}$$

$\vec{\alpha}$ fixed, $\|\vec{\omega}\|, \|\vec{z}\| \rightarrow \infty$

$$L \rightarrow \infty$$

So ... say min is at $\vec{\omega} = \vec{\omega}_0, \vec{z} = \vec{z}_0$

Vary: fix $\vec{z}_1, \vec{\omega}_1$

Consider

$$\vec{\omega}(\varepsilon) = \vec{\omega}_0 + \varepsilon \vec{\omega}_1$$

$$\vec{z}(\varepsilon) = \vec{z}_0 + \varepsilon \vec{z}_1$$

$$(1) \quad \vec{z}(\varepsilon) \cdot \vec{z}(\varepsilon)$$

$$= (\vec{z}_0 + \varepsilon \vec{z}_1) \cdot (\vec{z}_0 + \varepsilon \vec{z}_1)$$

$$= \vec{z}_0 \cdot \vec{z}_0 + (2 \vec{z}_0 \cdot \vec{z}_1) \varepsilon + O(\varepsilon^2)$$

$$\varepsilon \text{ term is } 2 \vec{z}_0 \cdot \vec{z}_1$$

$$(2) \quad \varepsilon \text{ term is } 2 \vec{\omega}_0 \cdot \vec{\omega}_1 \quad \Big|$$

$$\textcircled{3} \quad \vec{\alpha} \left(X(\vec{w}_0 + \varepsilon \vec{w}_1) - \vec{y} - (\vec{z}_0 + \varepsilon \vec{z}_1) \right)$$

$$\varepsilon \text{ term} \quad \vec{\alpha} \left(X \vec{w}_1 - \vec{z}_1 \right)$$

So at min $\vec{z}_0, \vec{w}_0$; $\forall \vec{z}_1, \vec{w}_1$:

$$\begin{aligned} 2 \vec{z}_0 \cdot \vec{z}_1 + 2 \lambda \vec{w}_0 \cdot \vec{w}_1 + \vec{\alpha} \left(X \vec{w}_1 - \vec{z}_1 \right) &= \vec{0} \\ &= (2 \vec{z}_0 - \vec{\alpha}) \cdot \vec{z}_1 + (2 \lambda \vec{w}_0 + X^T \vec{\alpha}) \cdot \vec{w}_1 = \vec{0} \end{aligned}$$

$$S_0 = \vec{0} \quad \forall \vec{z}_1, \forall \vec{w}_1$$

$$\begin{cases} 2 \vec{z}_0 - \vec{\alpha} = \vec{0} \\ 2 \lambda \vec{w}_0 + X^T \vec{\alpha} = \vec{0} \end{cases}$$

$$\begin{cases} \vec{z}_0 = \vec{\alpha} / 2 & (\text{less important}) \\ \vec{w}_0 = \left(\frac{-1}{2\lambda} \right) X^T \vec{\alpha} \end{cases} \quad \text{😊}$$

$\Rightarrow \vec{\omega}_0$ is proportional to $X^T \vec{\alpha}$

Plug & chug:

We guess $\vec{\omega}^*$ at mvr is

$$X^T \vec{\alpha}_{\text{plug \& chug}}$$

Duality:

$$\vec{\omega}^* \text{ is } \begin{pmatrix} -1 \\ \vec{z}_1 \end{pmatrix} X^T \vec{\alpha}_{\text{dual}}$$

$$= X^T \left(\begin{pmatrix} -1 \\ \vec{z}_1 \end{pmatrix} \vec{\alpha}_{\text{dual}} \right)$$