

Solving the Least-Squares Problem Using Gradients

Objectives

- Introduce gradients of linear and quadratic functions of \underline{w}
- Use gradients to solve least-squares problem
- Show solution is a minimizer
- Introduce projection matrices

The Least-Squares Problem

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$$\min_{\underline{w}} \| \underline{A} \underline{w} - \underline{d} \|_2^2$$

N features

P model parameters

N labels

Note: $\| \underline{z} \|_2^2 = \underline{z}^T \underline{z}$

$$(\underline{AB})^T = \underline{B}^T \underline{A}^T$$

$$(\underline{A} \underline{w} - \underline{d})^T (\underline{A} \underline{w} - \underline{d})$$

\Rightarrow

$$\min_{\underline{w}} \underbrace{\underline{w}^T \underline{A}^T \underline{A} \underline{w} - \underline{w}^T \underline{A}^T \underline{d} - \underline{d}^T \underline{A} \underline{w} + \underline{d}^T \underline{d}}_{f(\underline{w})}$$

$f(\underline{w})$: quadratic in \underline{w}

Scalar problem: $\min_w \underbrace{a^2 w^2 - 2 \beta w + \gamma^2}_{g(w)}$ set $\frac{d}{dw} g(w) = 0$

$$2a^2 w - 2\beta = 0 \Rightarrow w = a^{-2} \beta \quad a^2 > 0 \Rightarrow \text{concave up, min}$$

Gradients: differentiate $f(\underline{w})$ with respect to vector \underline{w}

$$\frac{\partial}{\partial \underline{w}} f(\underline{w}) = \underline{0}$$

Gradients

$$\nabla_{\underline{w}} f(\underline{w}) = \left[\frac{\partial}{\partial w_1} f(\underline{w}) \quad \frac{\partial}{\partial w_2} f(\underline{w}) \quad \dots \quad \frac{\partial}{\partial w_p} f(\underline{w}) \right]^T \quad 3$$

Suppose $f(\underline{w}) = \underline{w}^T \underline{h} = \underline{h}^T \underline{w} = \sum_{i=1}^p w_i h_i$ $\frac{\partial}{\partial w_j} f(\underline{w}) = h_j$

$$\underline{\nabla_{\underline{w}} f(\underline{w})} = [h_1 \quad h_2 \quad \dots \quad h_p]^T = \underline{h}$$

Suppose $f(\underline{w}) = \underline{w}^T \underline{Q} \underline{w}$ Can show $\nabla_{\underline{w}} f(\underline{w}) = \underline{Q}^T \underline{w} + \underline{Q} \underline{w}$

Symmetric case: $\underline{Q} = \underline{Q}^T \Rightarrow \underline{\nabla_{\underline{w}} f(\underline{w})} = \underline{2Qw}$

If $\underline{Q} = \underline{A}^T \underline{A} \Rightarrow (\underline{A}^T \underline{A})^T = \underline{A}^T \underline{A}$ symmetric

Solution: $\nabla_{\underline{w}} (\underline{w}^T \underline{A}^T \underline{A} \underline{w} - \underline{w}^T \underline{A}^T \underline{d} - \underline{d}^T \underline{A} \underline{w} + \underline{d}^T \underline{d}) = \underline{0}$

$$2 \underline{A}^T \underline{A} \underline{w} - \underline{A}^T \underline{d} - \underline{A}^T \underline{d} = \underline{0} \quad \Rightarrow \quad \underline{w} = (\underline{A}^T \underline{A})^{-1} \underline{A}^T \underline{d}$$

Solution Attributes

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$$\underline{w} = (\underline{A}^T \underline{A})^{-1} \underline{A}^T \underline{d} \quad \underline{A}: N \times P, P \leq N, \text{rank } \underline{A} = P \Rightarrow (\underline{A}^T \underline{A})^{-1} \text{ exists}$$

Minimizer? $f(\underline{w}) = \underline{w}^T \underline{A}^T \underline{A} \underline{w} - \underline{w}^T \underline{A}^T \underline{d} - \underline{d}^T \underline{A} \underline{w} + \underline{d}^T \underline{d}$

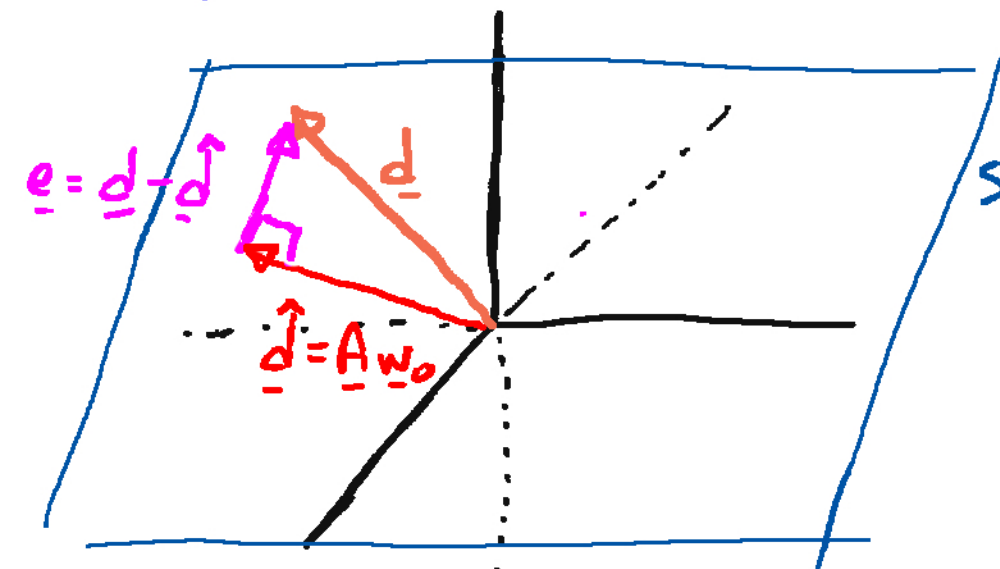
$$\begin{aligned} f(\underline{w}) &= (\underline{w} - (\underline{A}^T \underline{A})^{-1} \underline{A}^T \underline{d})^T \underline{A}^T \underline{A} (\underline{w} - (\underline{A}^T \underline{A})^{-1} \underline{A}^T \underline{d}) + \underline{d}^T \underline{d} - \underline{d}^T \underline{A} (\underline{A}^T \underline{A})^{-1} \underline{A}^T \underline{d} \\ &= \underline{w}^T \underline{A}^T \underline{A} \underline{w} - \cancel{\underline{w}^T \underline{A}^T \underline{A} (\underline{A}^T \underline{A})^{-1} \underline{A}^T \underline{d}} - \cancel{\underline{d}^T \underline{A} (\underline{A}^T \underline{A})^{-1} \underline{A}^T \underline{A} \underline{w}} + \cancel{\underline{d}^T \underline{A} (\underline{A}^T \underline{A})^{-1} \underline{A}^T \underline{A} (\underline{A}^T \underline{A})^{-1} \underline{A}^T \underline{d}} \\ &\quad + \underline{d}^T \underline{d} - \underline{d}^T \underline{A} (\underline{A}^T \underline{A})^{-1} \underline{A}^T \underline{d} \\ &= \underline{w}^T \underline{A}^T \underline{A} \underline{w} - \underline{w}^T \underline{A}^T \underline{d} - \underline{d}^T \underline{A} \underline{w} + \underline{d}^T \underline{A} (\underline{A}^T \underline{A})^{-1} \underline{A}^T \underline{d} + \underline{d}^T \underline{d} - \underline{d}^T \underline{A} (\underline{A}^T \underline{A})^{-1} \underline{A}^T \underline{d} \end{aligned}$$

So $f(\underline{w}) = \underline{z}^T(\underline{w}) \underline{A}^T \underline{A} \underline{z}(\underline{w}) + \underline{d}^T \underline{d} - \underline{d}^T \underline{A} (\underline{A}^T \underline{A})^{-1} \underline{A}^T \underline{d}$

$$\underline{z}(\underline{w}) = \underline{w} - \underline{w}_0; \quad \underline{w}_0 = (\underline{A}^T \underline{A})^{-1} \underline{A}^T \underline{d}$$

$$\left| \underline{A}^T \underline{A} > 0 \Rightarrow \min_{\underline{w}} f(\underline{w}) \text{ when } \underline{w} = \underline{w}_0 \right|$$
$$\min_{\underline{w}} f(\underline{w}) = \underline{d}^T \underline{d} - \underline{d}^T \underline{A} (\underline{A}^T \underline{A})^{-1} \underline{A}^T \underline{d}$$

Projection and the Pythagorean Theorem 5



Right triangle

$$\|d\|_2^2 = \|e\|_2^2 + \|\hat{d}\|_2^2$$

$$\Rightarrow \|e\|_2^2 = \|d\|_2^2 - \|\hat{d}\|_2^2$$

$$= d^T d - d^T P_A d$$

$$= d^T (I - P_A) d$$

$$\hat{d} = A(A^T A)^{-1} A^T d = P_A d$$

$\text{span}\{A\}$

$P_A = A(A^T A)^{-1} A^T$ "projection matrix"

P_A projects d onto $\text{span}\{A\}$

$$P_A^2 = A(A^T A)^{-1} A^T A(A^T A)^{-1} A^T = A(A^T A)^{-1} A^T = P_A$$

$$e = d - \hat{d} = (I - P_A) d = P_{A^\perp} d$$

$P_{A^\perp} = I - P_A$ projects onto space \perp to $\text{span}\{A\}$

$$P_{A^\perp}^2 = (I - P_A)(I - P_A) = I - 2P_A + P_A^2 = I - P_A = P_{A^\perp}$$

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