

Consider $Ax = b$ where no soln exists.

Inconsistent

$b \notin \text{colsp}(A)$.

$\|b - A\hat{x}\|^2$ must be minimum.

$$\Rightarrow \underbrace{(b - A\hat{x})^T}_{\checkmark} \underbrace{(b - A\hat{x})}_{\checkmark}$$

$$= (b^T - (A\hat{x})^T)(b - A\hat{x}).$$

$$y = f(x)$$

$$\frac{dy}{dx} = 0$$

$$\frac{d^2y}{dx^2} \text{ at } \frac{dy}{dx} = 0$$

If > 0
 \Rightarrow Min

< Max.

$$\underline{x^T y} = y^T x.$$

$$b^T A \hat{x} = (A\hat{x})^T b$$

$$= \\ x^T A \hat{x} \\ A^T A = L$$

$$\frac{d}{dx} x^T L x \\ = \underbrace{(L + L^T)}_{2L} x$$

$$\begin{aligned} \frac{df}{d\hat{x}} &= \frac{d}{d\hat{x}} \left(b^T b - \underbrace{b^T A \hat{x}}_{\checkmark} - \underbrace{(A\hat{x})^T b}_{\checkmark} + \underbrace{(A\hat{x})^T A \hat{x}}_{\checkmark} \right) \\ &= \frac{d}{d\hat{x}} \left(b^T b - 2b^T A \hat{x} + x^T A^T A x \right). \\ &= 0 - \underbrace{2A^T b}_{\checkmark} + 2(A^T A)x. \\ &\approx 0 = -2A^T b + 2(A^T A)x = 0. \end{aligned}$$

$1 \times n$.

$$= (\underbrace{A^T A}_{n \times n}) \hat{x} = \underbrace{A^T b}_{m \times 1}$$

$$\boxed{\hat{x} = (A^T A)^{-1} \underbrace{A^T b}_{m \times 1}}$$

$A^{m \times n}$

$A^T: n \times m$

$$\hat{x} \rightarrow \underset{x \in \mathbb{R}^n}{\text{Min}} \quad \|Ax - b\|^2.$$

$\hat{x} = (A^T A)^{-1} A^T b$. Minimieren
sq.

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

$$\underbrace{A \hat{x}}_{=} = \underbrace{A (A^T A)^{-1} \underbrace{A^T b}_{m \times 1}}_{=}$$

Projection Matrix

$$\begin{bmatrix} b_1 & b_2 \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$

$$b_1(a_{11}x_1 + a_{12}x_2) + b_2(a_{21}x_1 + a_{22}x_2)$$

$$\frac{\partial}{\partial x_1} = \underbrace{b_{11} a_{11} + b_{21} a_{21}}_{\downarrow}$$

$$\frac{\partial}{\partial x_2} = b_1 a_{12} + b_2 a_{22}$$

$$\nabla = \begin{bmatrix} \downarrow \\ \vdots \end{bmatrix} \cdot ()$$

$$\underbrace{\begin{bmatrix} b_1 a_{11} + b_2 a_{21} \\ b_1 a_{12} + b_2 a_{22} \end{bmatrix}}_{A^T b} = \begin{bmatrix} a_{11} & a_{21} \\ a_{12} & a_{22} \end{bmatrix} \begin{bmatrix} b_1 \\ b_2 \end{bmatrix}$$

Lagrangian Multipliers. \rightarrow Converts a constrained optimization to unconstrained.

$$Ax = \lambda x$$

$$A: RSM.$$

$$A^T = A$$

x : Unit vector

$$A^T A x = A^T (\lambda x) = \lambda (A^T x) = \lambda (Ax) = \lambda^2 x.$$

$$\begin{aligned} x^T (A^T A) x &= x^T \lambda^2 x \\ &= \lambda^2 \underbrace{x^T x}_{\|x\|^2} \\ &= \lambda^2. \end{aligned}$$

$$A = P D P^{-1}$$

for a Corr Matrix 

$$P^{-1} A P$$

Optimization:

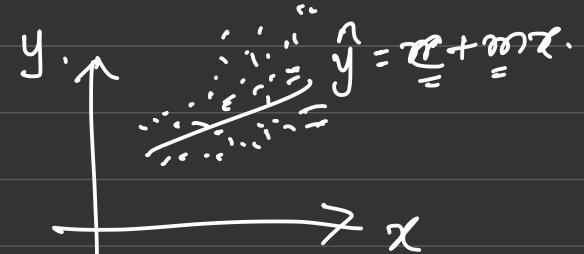
Objective fn $f(\underline{x})$

Cost function.

Minimize or Maximize $f(\underline{x})$

Cost fn: $f(\vec{x}) \rightarrow \min_{\vec{x}} \quad \vec{x} \in \mathbb{R}^n$.

Linear Regression $\hat{y} = C + mx$.



Original y values $\hat{y} = C + mx$

$$\hat{y} = C + mx$$

$$\theta_0 + \theta_1 x_1 + \theta_2 x_2 + \dots + \theta_n x_n$$

for $\underline{x} \in \mathbb{R}^n$, $\hat{y} = \theta_0 f_1(\vec{x}) + \theta_1 f_2(\vec{x}) + \dots + \theta_n f_n(\vec{x})$.

Feature
Vector

$$f_i(\vec{x}) = f: \mathbb{R}^n \mapsto \mathbb{R}$$

$$\{\underline{x}_1, \dots, \underline{x}_n\}$$

$$\vec{x} \in \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{pmatrix} \rightarrow A^{m \times n} x^{n \times 1} = b^{m \times 1}.$$

$$\begin{bmatrix} 1 \\ 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix}.$$

x_1, \dots, x_n be variables

$$f_1(\vec{x}) = ax_1 + bx_2 \quad x \in \mathbb{R}^2$$

$\|\vec{y} - \hat{\vec{y}}\|^2 \rightarrow \text{Minimize}$

$$\begin{pmatrix} x \\ -1 \\ 1 \\ 2 \end{pmatrix} \begin{pmatrix} y \\ 1 \\ 3 \\ 0 \end{pmatrix}$$

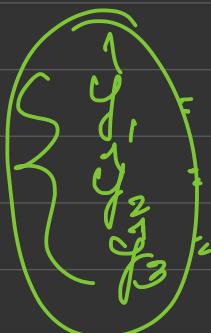
$$(A^T A)^{-1} A^T b.$$

$$y = c + mx$$

$$\begin{cases} y_1 = c + mx_1 \\ y_2 = c + mx_2 \\ y_3 = c + mx_3 \end{cases}$$

$$\begin{bmatrix} b \\ y_1 \\ y_2 \\ y_3 \end{bmatrix} = \begin{bmatrix} 1 & x_1 \\ 1 & x_2 \\ 1 & x_3 \end{bmatrix} \begin{bmatrix} c \\ m \end{bmatrix}$$

$$\boxed{x^* = (A^T A)^{-1} A^T b.}$$



$$\begin{aligned} y_1 &= c + mx_1 \\ y_2 &= c + mx_2 \\ y_3 &= c + mx_3 \end{aligned}$$

$$\hat{y} = \underline{c + mx} \rightarrow \text{Model.}$$

$$\vec{r} = \begin{bmatrix} y_1 - \hat{y}_1 \\ y_2 - \hat{y}_2 \\ y_3 - \hat{y}_3 \end{bmatrix}$$

$\|\vec{r}\|^2$ very small
 \rightarrow Least.

Max Marks. in MAAI. ($\underline{x}_1 + \underline{x}_2 + \dots + \underline{x}_5$)

Subject to given time ≤ 24 hrs.

* $y = f(x)$ $\frac{dy}{dx} = 0$ $\frac{d^2y}{dx^2}$ at that \underline{x} where $\frac{dy}{dx} = 0$.

* Let $z = f(x_1, x_2)$ which is differentiable at (x_0, y_0) .

Critical point: (x_0, y_0) is a critical point of f if

either

a) $\frac{\partial f}{\partial x_1}(x_0, y_0) = \frac{\partial f}{\partial x_2}(x_0, y_0) = 0$

or b) the partial derivatives $\frac{\partial f}{\partial x_1}$ or $\frac{\partial f}{\partial x_2}$ does not exist.

SADDLE Point is a point on a graph where the slopes are all 0, but the point at which the slope is 0 is neither a local max nor a min.

$$Q: f(x, y) = x^3 + 12x^2 + 6y^2 - 24xy + 18x.$$

Critical points of f : $\frac{\partial f}{\partial x} = 0$; $\frac{\partial f}{\partial y} = 0$.

$$\frac{\partial f}{\partial x} = 3x^2 + 24x - 24y + 18 = 0$$

$$3x^2 + 24x - 48x + 18 = 0.$$

$$3x^2 - 24x + 18 = 0$$

$$x^2 - 8x + 6 = 0.$$

$$\frac{\partial f}{\partial y} = 12y - 24x = 0$$

$$y - 2x = 0$$

$$y = 2x.$$

$$x = \frac{8 \pm \sqrt{64 - 24}}{2} = \frac{8 \pm \sqrt{40}}{2} = 4 \pm \sqrt{10}.$$

()

$$H: \begin{bmatrix} \frac{\partial}{\partial x} \left(\frac{\partial}{\partial x} \right) & \frac{\partial}{\partial x} \left(\frac{\partial}{\partial y} \right) \\ \frac{\partial}{\partial y} \left(\frac{\partial}{\partial x} \right) & \frac{\partial}{\partial y} \left(\frac{\partial}{\partial y} \right) \end{bmatrix} = \begin{bmatrix} \checkmark 6x+24 & -24 \\ -24 & 12 \end{bmatrix}$$

Critical points: $(x, 2x)$.

$$= \begin{pmatrix} \checkmark 4 + \sqrt{10}, & 8 + 2\sqrt{10} \\ & (4 - \sqrt{10}, 8 - 2\sqrt{10}) \end{pmatrix}$$

$$H: \begin{bmatrix} 6(4 + \sqrt{10}) & -24 \\ -24 & 12 \end{bmatrix} \quad \begin{bmatrix} 6(4 - \sqrt{10}) & -24 \\ -24 & 12 \end{bmatrix}$$

$$= \begin{bmatrix} 24 + 6(3 \cdot 1) & -24 \\ -24 & 12 \end{bmatrix} \quad \begin{bmatrix} 24 - 6(3 \cdot 1) & -24 \\ -24 & 12 \end{bmatrix}$$

For minima Hessian must be positive definite
 Maxima " " " " negative definite

$$\begin{bmatrix} 42.6 & -24 \\ -24 & 12 \end{bmatrix}$$

↓.

det negative.

Saddle points.

$$\begin{bmatrix} 5.4 & -24 \\ -24 & 12 \end{bmatrix}$$

$$64.8 - 576$$

$\det < 0$

⇒ One of the eigen
val is neg & other is
positive

Indefinite.

eigenval are opposite
signs.

⇒ SADDLE POINT.

$$f(x_1, x_2, x_3) = 2x_1^2 + 2x_2^2 + x_3^2 - x_1 - x_2 - 2x_1x_2.$$

Find the stationary points. Find if the stationary pt is max or min.

$$\frac{\partial}{\partial x_1} = 4x_1 - 2x_2 - 1 \\ = 0$$

$$\frac{\partial}{\partial x_2} = 4x_2 - 2x_1 - 1 \\ = 0$$

$$\frac{\partial}{\partial x_3} = 2x_3 \\ = 0$$

$$\Rightarrow x_3 = 0.$$

$$4x_1 - 2x_2 - 1 = 0 \\ -2x_1 + 4x_2 - 1 = 0$$

$$x_1 = \frac{1}{2} \\ x_2 = \frac{1}{2} \\ x_3 = 0.$$

$$\begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix} = \begin{pmatrix} 1 \\ 1 \\ 0 \end{pmatrix}.$$

$$H : \left[\begin{array}{ccc} \frac{\partial}{\partial x_1} \left(\frac{\partial f}{\partial x_1} \right) & \frac{\partial}{\partial x_1} \left(\frac{\partial f}{\partial x_2} \right) & \frac{\partial}{\partial x_1} \left(\frac{\partial f}{\partial x_3} \right) \\ \frac{\partial}{\partial x_2} \left(\frac{\partial f}{\partial x_1} \right) & \frac{\partial}{\partial x_2} \left(\frac{\partial f}{\partial x_2} \right) & \frac{\partial}{\partial x_2} \left(\frac{\partial f}{\partial x_3} \right) \\ \frac{\partial}{\partial x_3} \left(\frac{\partial f}{\partial x_1} \right) & \frac{\partial}{\partial x_3} \left(\frac{\partial f}{\partial x_2} \right) & \frac{\partial}{\partial x_3} \left(\frac{\partial f}{\partial x_3} \right) \end{array} \right]$$

$$H \cdot \begin{bmatrix} \checkmark & & \\ 4 & -2 & 0 \\ -2 & 4\checkmark & 0 \\ 0 & 0 & 2\checkmark \end{bmatrix} \Rightarrow H - \lambda I = \begin{bmatrix} 4-\lambda & -2 & 0 \\ -2 & 4-\lambda & 0 \\ 0 & 0 & 2-\lambda \end{bmatrix}$$

$$\begin{aligned} \det(H - \lambda I) = 0 &\Rightarrow (4-\lambda)(4-\lambda)(2-\lambda) + 2(-2)(2-\lambda) = 0 \\ &= (2-\lambda)[(4-\lambda)^2 - 4] = 0 \\ 2-\lambda = 0 &\Rightarrow \lambda = 2; \end{aligned}$$

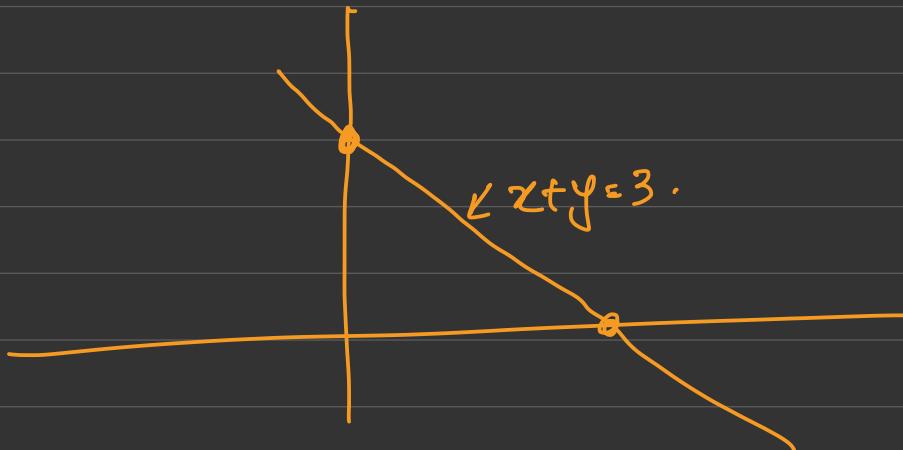
$$\begin{aligned} \lambda^2 - 8\lambda + 16 - 4 &= 0 & \lambda^2 - 8\lambda + 12 &= 0 \\ (\lambda-6)(\lambda-2) &= 0 & \lambda &= \underline{\underline{2, 6, 2}}. \end{aligned}$$

$\therefore H$ is positive definite.

$\therefore f$ has min at $\begin{pmatrix} y_2 \\ y_2 \\ 0 \end{pmatrix}$.

$$\text{Min } 2x^2 + 4y^2 - 3xy.$$

Subject to $x + y = 3$.



Lagrangian Multiplier: Converts a constrained optimization problem to an unconstrained one.

* $f(x, y) = x^2 + 4y^2 - 2x + 8y$ Constraint $x + 2y = 7$

Lagrangian λ .

$$\begin{aligned} &x + 2y - 7 = 0 \\ &\lambda(x + 2y - 7) \end{aligned}$$

Object: $f(x, y) + \lambda g(x, y)$

$$= x^2 + 4y^2 - 2x + 8y + \lambda(x + 2y - 7)$$

$$\frac{\partial}{\partial x} = 2x - 2 + \lambda$$

$$\frac{\partial}{\partial y} = 8y + 8 + 2\lambda$$

$$2x - 2 + \lambda = 0$$

$$0 = 8y + (2\lambda + 8) = 0.$$

$$\Rightarrow 2x + (\lambda - 2) = 0.$$

$$x = \frac{2-\lambda}{2}$$

$$y = -\frac{8+2\lambda}{8}$$

Constraint : $x + 2y = 7$

$$\frac{2-\lambda}{2} + 2 \underbrace{\left(-\frac{8+2\lambda}{8} \right)}_{-4} = 7$$

$$\frac{4 - 2\lambda - 8 - 2\lambda}{4} = 7 \Rightarrow -4 - 4\lambda = 28$$
$$-4\lambda = 32$$
$$\lambda = \underline{-8}$$

$$x = \frac{2+\lambda}{2}$$

$$y = -\frac{8+16}{8}$$

$$(x, y) = (5, 1)$$

Ex: 2

$$x_1^2 + x_2^2 - 4x_1 - 4x_2$$

$$\text{Sub: } x_1 + x_2 = \underline{\underline{2}}$$

Using Lagrange. Find the min value of the fn.

$$\text{obj: } x_1^2 + x_2^2 - 4x_1 - 4x_2 + \lambda(x_1 + x_2 - 2).$$

$$\frac{\partial}{\partial x_1} = 2x_1 - 4 + \lambda \\ = 0$$

$$\frac{\partial}{\partial x_2} = 2x_2 - 4 + \lambda \\ = 0$$

$$x_1 = \frac{4-\lambda}{2} = x_2.$$

$$x_1 + x_2 = 2. \quad \frac{4-\lambda}{2} + \frac{4-\lambda}{2} = 2. \quad (4-\lambda) = 2$$

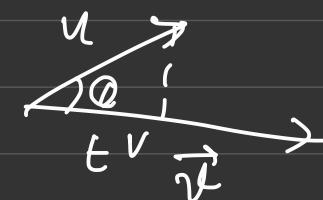
$$x_1 = x_2 = 1 \quad f(1,1) = -6. \quad \lambda = 2.$$

Principal Component Analysis.

→ eigenvectors correspond to dominant eigenvalue
of cov matrix

PCA: Projection of higher dimensional data to
lower dimensional space.

N. data points $\rightarrow \vec{y} \in \mathbb{R}^n$.



Obj. Max $\lambda = w^\top (y - b)$. Subject to $w^\top w = 1$

$$t = \frac{w \cdot v}{v \cdot v}$$

Prove

9:00 → 10:00