

$$P(Y=1) = P(Y=2) = P(Y=3) = \frac{1}{3} \quad 1 \leq i \leq 3 \cdot (X|Y=i) \sim N(\mu_i, \Sigma_i) \quad . 1$$

$$\mu_1 = [0, 0]^T, \mu_2 = [1, 1]^T, \mu_3 = [1, 1]^T$$

$$\Sigma_1 = \begin{bmatrix} 0.17 & 0 \\ 0 & 0.17 \end{bmatrix}, \Sigma_2 = \begin{bmatrix} 0.18 & 0.13 \\ 0.13 & 0.12 \end{bmatrix}, \Sigma_3 = \begin{bmatrix} 0.17 & 0.12 \\ 0.12 & 0.18 \end{bmatrix}$$

$$\Rightarrow (Y|X=x) = \arg \max_i N(x|\mu_i, \Sigma_i)$$

$$= \arg \max_i (2\pi)^{-k/2} |\Sigma_i|^{-1/2} \exp\left(-\frac{1}{2}(x-\mu_i)^T \Sigma_i^{-1} (x-\mu_i)\right)$$

$$= \arg \min_i \ln |\Sigma_i| + (x-\mu_i)^T \Sigma_i^{-1} (x-\mu_i)$$

$$= \arg \min_i \left\{ -0.171 + x^T \begin{bmatrix} 1.42 & 0 \\ 0 & 1.42 \end{bmatrix} x \right\},$$

$$-2.65 + (x-1)^T \begin{bmatrix} 2.85 & -0.28 \\ -0.28 & 1.42 \end{bmatrix} (x-1),$$

$$-0.51 + (x-1)^T \begin{bmatrix} 1.53 & -0.38 \\ -0.38 & 1.34 \end{bmatrix} (x-1) \}$$

$$x = [50, 0.5] \Rightarrow (Y|X=x) = 1$$

$$x = [0.5, 0.5] \Rightarrow (Y|X=x) = 2$$

$$E_D(\omega) = \frac{1}{2} \sum_{n=1}^N (y(x_n, \omega) - y_n)^2 \quad - 2$$

$$\tilde{E}_D(\omega) = \frac{1}{2} \sum_{n=1}^N E \{ y_n^2 + y(x_n + \epsilon_n, \omega)^2 - 2y_n y(x_n + \epsilon_n, \omega) \}$$

$$= \frac{1}{2} \sum_{n=1}^N \left(y_n^2 + 2y_n E \{ y(x_n + \epsilon_n, \omega) \} + E \{ y(x_n + \epsilon_n, \omega)^2 \} \right)$$

$$E \{ y(x_n + \epsilon_n, \omega) \} = \omega_0 + \sum_{i=1}^D \omega_i E \{ x_i + \epsilon_i \}$$

$$= \omega_0 + \sum_{i=1}^D \omega_i x_i = y(x_n, \omega)$$

$$E \{ y(x_n + \epsilon_n, \omega)^2 \} = \omega_0^2 + E \left\{ \left(\sum_{i=1}^D \omega_i (x_i + \epsilon_i) \right)^2 \right\} + 2\omega_0 \sum_{i=1}^D \omega_i E \{ x_i + \epsilon_i \}$$

$$= \omega_0^2 + 2\omega_0 \sum_{i=1}^D \omega_i x_i + E \left\{ \left(\sum_{i=1}^D \omega_i x_i + \sum_{i=1}^D \omega_i \epsilon_i \right)^2 \right\}$$

$$E \left\{ \underbrace{\left(\sum_{i=1}^D \omega_i x_i \right)}_a + \underbrace{\left(\sum_{i=1}^D \omega_i \epsilon_i \right)}_b \right\}^2 = E \{ a^2 \} + E \{ b^2 \} + E \{ 2ab \}$$

const

$$= a^2 + E \left\{ \left(\sum_{i=1}^D \omega_i \epsilon_i \right)^2 \right\} + E \{ 2 \sum_{i=1}^D \sum_{j=1}^D \omega_i \omega_j x_i \epsilon_j \}$$

$$\Rightarrow E \left\{ \left(\sum_{i=1}^D \omega_i x_i + \sum_{i=1}^D \omega_i \epsilon_i \right)^2 \right\}$$

↳ each are zero
So entire would be zero

$$\xrightarrow{\epsilon_i \text{ iid}} = \left(\sum_{i=1}^D \omega_i x_i \right)^2 + \sum_{i=1}^D \omega_i^2 E \{ \epsilon_i^2 \} = \sigma_1^2 \sum_{i=1}^D \omega_i^2$$

by assembling all the parts, we only get one more

residual part: $\sigma_1^2 \sum_{i=1}^D \omega_i^2$

$$\text{So: } \tilde{E}_D(\omega) = E_D(\omega) + \sigma_1^2 \sum_{i=1}^D \omega_i^2$$

$$\text{BLR: } P(i) = \frac{e^{w_{i1}x_1}}{1 + e^{w_{i1}x_1}}$$

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one using $k-1$ BLR's.

(iv)

$$\hookrightarrow \log\left(\frac{P(k)}{P(K)}\right) = w_{k1}x_1$$

$$\hookrightarrow P(k) = e^{w_{k1}x_1} \cdot P(K)$$

$$\text{we know } P(K) = 1 - \sum_{i=1}^{k-1} P(i) = 1 - \sum_{i=1}^{k-1} P(K) e^{w_{i1}x_1}$$

$$w_{k1}x_1 = 0 \Rightarrow P(K) = \frac{1}{1 + \sum_{j=1}^{k-1} e^{w_{j1}x_1}} \Rightarrow P(k) = \frac{e^{w_{k1}x_1}}{1 + \sum_{j=1}^{k-1} e^{w_{j1}x_1}}$$

$$\hookrightarrow \Rightarrow P(y=i|x) = \frac{e^{w_{i1}x_1}}{\sum_{j=1}^K e^{w_{j1}x_1}}$$

$$\ln P(y=y_i | x=x_i) = w_{y_i 1} x_i - \ln \sum_{j=1}^K e^{w_{j1}x_i}$$

(v)

$$L(w) = \sum_{i=1}^n w_{y_i 1} x_i - \sum_{i=1}^n \ln \left(\sum_{j=1}^K e^{w_{j1}x_i} \right)$$

$$\frac{\partial}{\partial w_k} L(w) = \frac{\partial}{\partial w_k} \sum_{i=1}^n w_{y_i 1} x_i - \frac{\partial}{\partial w_k} \sum_{i=1}^n \ln \left(\sum_{j=1}^K e^{w_{j1}x_i} \right)$$

(vi)

$$\frac{\partial}{\partial w_k} \sum_{i=1}^n w_{y_i 1} x_i = \sum_{i=1}^n x_i \cdot I(y_i = k)$$

$$\frac{\partial}{\partial w_k} \sum_{i=1}^n \ln \left(\sum_{j=1}^K e^{w_{j1}x_i} \right) = \sum_{i=1}^n \frac{\partial}{\partial w_k} \ln \left(\sum_{j=1}^K e^{w_{j1}x_i} \right)$$

$$= \sum_{i=1}^n \frac{1}{\sum_{j=1}^K e^{w_{j1}x_i}} \cdot x_i \cdot e^{w_{k1}x_i} = \sum_{i=1}^n \frac{x_i \cdot e^{w_{k1}x_i}}{\sum_{j=1}^K e^{w_{j1}x_i}}$$

$$\Rightarrow \frac{\partial}{\partial \omega_k} L(\omega) = \sum_{i=1}^n a_i I(y_i = k) - \sum_{i=1}^n \frac{a_i e^{\omega_k a_i}}{\sum_{j=1}^K e^{\omega_j a_i}}$$

$$\nabla L(\omega) = \begin{bmatrix} \frac{\partial}{\partial \omega_1} L(\omega) \\ \frac{\partial}{\partial \omega_2} L(\omega) \\ \vdots \\ \frac{\partial}{\partial \omega_{K-1}} L(\omega) \end{bmatrix}$$

$$\nabla f(\omega) = \nabla L(\omega) - \nabla \left(\frac{\lambda}{2} \sum_{j=1}^{K-1} \|\omega_j\|_2^2 \right)$$

$$\frac{\partial}{\partial \omega_k} \frac{\lambda}{2} \sum_{j=1}^{K-1} \|\omega_j\|_2^2 = \lambda \omega_k$$

$$\Rightarrow \nabla f(\omega) = \nabla L(\omega) - \begin{bmatrix} \lambda \omega_1 \\ \lambda \omega_2 \\ \vdots \\ \lambda \omega_{K-1} \end{bmatrix}$$

Simply $w_j = \arg \min_{w_j} (|w_j x_j - y|)$ -4

answer of
(least squares

Prove in (ـ)

$$\Rightarrow w_j = \underbrace{(x_j^T x_j)^{-1}}_{\text{number}} x_j^T y = \frac{x_j^T y}{(x_j^T x_j)} \quad (\text{الف})$$

Assuming x_j 's are uncorrelated (ـ)

$$\Rightarrow X^T X \rightarrow \text{diagonal} = \text{diag}[\lambda_i]_{i=1}^m$$

We know: $\hat{w} = \underbrace{(X^T X)^{-1}}_{\substack{\downarrow \\ \text{row } j \text{ of } D}} X^T y = \underbrace{\text{diag}[\frac{1}{\lambda_i}]_{i=1}^m}_D X_{nm}^T y_{n \times 1}$

$$\Rightarrow \hat{w}_j = [d_j] \cdot X^T \cdot y$$

Since $[d_j]$ is zero in all columns except j th column

$$\Rightarrow \hat{w}_j = \frac{1}{\lambda_j} x_j^T y = \frac{x_j^T y}{\lambda_j}$$

and
we know

$$\lambda_j = x_j^T x_j$$

So $\hat{w}_j = \frac{x_j^T y}{(x_j^T x_j)}$

we know

$$\text{Cov}(x_j, y) = \left(\sum_{i=1}^n x_i y_i - n \bar{x} \bar{y} \right) \frac{1}{n-1} = \quad (\text{ـ})$$

$$\text{Var}(x_j) = \left(\sum_{i=1}^n x_i^2 - n \bar{x}^2 \right) \frac{1}{n-1}$$

least squares

taking partial derivatives. $S(\omega, \omega_0) = \sum_{i=1}^n (y_i - \omega_0 - \omega x_i)^2$

$$\Rightarrow \frac{\partial S}{\partial \omega_0} = -2 \sum_{i=1}^n (y_i - \hat{\omega}_0 - \hat{\omega} x_i) = 0$$

$$\Rightarrow \frac{\partial S}{\partial \omega} = -2 \sum_{i=1}^n (y_i - \hat{\omega}_0 - \hat{\omega} x_i) x_i = 0$$

$$\hookrightarrow \sum y_i = n \hat{\omega}_0 + \hat{\omega} \sum x_i \Rightarrow \bar{y} = \hat{\omega}_0 + \hat{\omega} \bar{x}$$

$$\hookrightarrow \sum x_i y_i = \hat{\omega}_0 \sum x_i + \hat{\omega} \sum x_i^2 \Rightarrow \hat{\omega}_0 = \bar{y} - \hat{\omega} \bar{x}$$

$$\Rightarrow \sum x_i y_i = (\bar{y} - \hat{\omega} \bar{x}) \sum x_i + \hat{\omega} \sum x_i^2$$

$$\Rightarrow \sum_{i=1}^n x_i y_i - n \bar{x} \bar{y} = \hat{\omega} \left(\sum_{i=1}^n x_i^2 - n \bar{x}^2 \right)$$

$$\Rightarrow \hat{\omega} = \frac{\sum x_i y_i - n \bar{x} \bar{y}}{\sum x_i^2 - n \bar{x}^2}$$

$$= \frac{(n-1) \text{Cov}(x, y)}{(n-1) \text{Var}(x)} = \frac{\text{Cov}(x, y)}{\text{Var}(x)}$$

Reference: Dr. Guanglinang Chen | Mathematics & Statistics
San José State Uni.

$$E(X) = \int_{-\infty}^{\infty} xf(x) dx = \int_{-\infty}^a xf(x) dx + \int_a^{\infty} xf(x) dx \quad (1)$$

$$P(X \geq a) = \int_a^{\infty} f(x) dx$$

$$\hookrightarrow E(X) \geq \int_a^{\infty} xf(x) dx \geq \int_a^{\infty} af(x) dx = a \int_a^{\infty} f(x) dx$$

$$\Rightarrow E(X) \geq a P(X \geq a)$$

$$\Rightarrow P(X \leq a) \leq \frac{E(X)}{a}$$

$$P(|X - \mu| \geq \alpha) = P((X - \mu)^2 \geq \alpha^2) \leq \frac{E((X - \mu)^2)}{\alpha^2} \quad (2)$$

$$E((X - \mu)^2) = \sigma_x^2$$

$$\Rightarrow P(|X - \mu| \geq \alpha) \leq \frac{\sigma_x^2}{\alpha^2}$$

if we throw a random point inside square (uniformly) (2)

it will get inside circle with $P(\text{inside}) = \frac{S_c}{S_s} = \frac{\pi r^2}{(2r)^2} = \frac{\pi}{4}$

So if we throw N times we have a

binomial random var. $f\left(\frac{N\pi}{4}, N, \frac{\pi}{4}\right) = \binom{N}{\frac{N\pi}{4}} \left(\frac{\pi}{4}\right)^{\frac{N\pi}{4}} \left(1 - \frac{\pi}{4}\right)^{N - \frac{N\pi}{4}}$

From Chebyshev:

$$P(|X - \mu| \geq \alpha) \leq \frac{\sigma^2}{\alpha^2}$$

Question: $P\left(\left|\frac{k}{N} - \frac{n}{4}\right| \geq 0.01 \frac{n}{4}\right) \leq 0.05$

$$\Rightarrow P\left(\left|k - \frac{Nn}{4}\right| \geq 0.01 \frac{Nn}{4}\right) \leq 0.05 = \frac{\sigma^2}{\alpha^2}$$

binomial $\rightarrow \underbrace{\mu}_{\mu} \quad \underbrace{\alpha}_{\alpha}$

So from Chebyshev:

$$\frac{\sigma^2}{\alpha^2} \leq 0.05 \Rightarrow \sigma^2 \leq 0.05 \times \left(0.01 \frac{Nn}{4}\right)^2$$

binomial
 $\sigma^2 = npq$

$$\Rightarrow N \frac{n}{4} \left(1 - \frac{n}{4}\right) \leq 5 \times 10^{-4} \cdot N^2 \frac{n^2}{16}$$

$$\Rightarrow N \geq \left\lceil \frac{n}{4} \left(1 - \frac{n}{4}\right) \cdot \frac{16}{n^2} \cdot 2000 \right\rceil$$

$$\Rightarrow N \geq 547$$

From definition of SVD:

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$$A = U \Sigma U^T \Rightarrow A^{-1} = U \Sigma^{-1} U^T \text{ where } \Sigma = \text{diag}[\sigma_i]_{i=1, \text{rank}(A)}^T$$

Since Σ is diagonal $\Rightarrow \Sigma^{-1} = \text{diag}[\frac{1}{\sigma_i}]_{i=1}^{\text{rank}(A)}$

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$$\Rightarrow \sigma_{\max}(A) = \Sigma_{1,1} \quad \sigma_{\max}(A^{-1}) = \frac{1}{\sigma_{\min}(A)}$$

We know: $\frac{\sigma_{\max}(A)}{\sigma_{\min}(A)} \gg 1 \Rightarrow \sigma_{\max}(A) \cdot \frac{1}{\sigma_{\min}(A)} \gg 1$

$$\Rightarrow \sigma_{\max}(A) \cdot \sigma_{\max}(A^{-1}) \gg 1$$

We know

$$\|A\|_2 = \sigma_{\max}(A) \quad \text{and} \quad \|A\|_F = \sqrt{\sum_{i=1}^{\text{rank}(A)} \sigma_i^2}$$

$$\|A\|_2^2 \leq \sum_{i=1}^{\text{rank}(A)} \sigma_i^2 \Rightarrow \|A\|_2 \leq \sqrt{\sum_{i=1}^{\text{rank}(A)} \sigma_i^2} = \|A\|_F$$

$$\begin{aligned} (\sqrt{\text{rank}(A)} \cdot \|A\|_2)^2 &= \text{rank}(A) \cdot \sigma_{\max}(A)^2 \\ &= \sum_{i=1}^{\text{rank}(A)} \sigma_{\max}(A)^2 \geq \sum_{i=1}^{\text{rank}(A)} \sigma_i^2 = \|A\|_F^2 \end{aligned}$$

$$\Rightarrow \|A\|_F \leq (\sqrt{\text{rank}(A)} \cdot \|A\|_2)$$

$$\Rightarrow \|A\|_2 \leq \|A\|_F \leq \sqrt{\text{rank}(A)} \|A\|_2$$

$$\sigma(x) = \frac{1}{1+e^{-x}} = \frac{e^x}{e^x+1} \quad \tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} = \frac{e^{2x} - 1}{e^{2x} + 1} \quad -7$$

$$\Rightarrow \tanh(x) = 2\sigma(2x) - 1 \Rightarrow \sigma(2x) = \frac{\tanh(x) + 1}{2}$$

$$y(x, w) = w_0 + \sum_{j=1}^n \left(w_j \sigma\left(2 \frac{x - r_j}{s}\right) \right)$$

$$= w_0 + \sum_{j=1}^n \left(w_j \frac{\tanh\left(\frac{x - r_j}{s}\right) + 1}{2} \right)$$

$$= w_0 + \frac{1}{2} \sum_{j=1}^n w_j + \sum_{j=1}^n \frac{1}{2} w_j \tanh\left(\frac{x - r_j}{s}\right)$$

$$= \underbrace{w_0}_{u_0} + \sum_{j=1}^n u_j \tanh\left(\frac{x - r_j}{s}\right) = y(x, u)$$

where $u_0 = w_0 + \frac{1}{2} \sum_{j=1}^n w_j$

and $u_j = \frac{1}{2} w_j$