

3a) PE 2014

Plt

$$p(y; \phi) = ((1-\phi)^{y-1} \phi$$

~~2 Koeff exp(lik)~~

$$= \exp((y-1) \cdot \log(1-\phi) + \log(\phi))$$

$$= \exp(-y \cdot \log(1-\phi) - \log(1-\phi) + \log(\phi))$$

$$= \exp\left(\log(1-\phi) \cdot y + \log\left(\frac{\phi}{1-\phi}\right)\right)$$

$$\Rightarrow T(y) = y \quad n = \log(1-\phi) \Rightarrow e^n = 1-\phi$$

$$a(n) = -\log\left(\frac{\phi}{1-\phi}\right) = -\log\left(\frac{1-e^n}{1+e^n}\right) \quad \phi = 1-e^n$$

$$b(y) = -\log\left(\frac{1-e^n}{e^n}\right) \\ = -\log\left(\frac{1}{e^n} - 1\right)$$

$$= -\log(1-e^n) + n$$

y_i ii.)

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$$h_{\theta}(x) = E[x|x \geq \theta]$$

$$p(y_i | n) = (1 - \phi)^{y_i - 1} \phi \approx \phi$$

$$\phi = 1 - e^{-n}$$

$$\Rightarrow p(y_i | n) = (1 - (1 + e^{-n}))^{y_i - 1} \cdot (1 - e^{-n}) \\ = e^{-n \cdot (y_i - 1)} \cdot (1 - e^{-n}) = e^{-n}$$

$$\Rightarrow \log(p(y_i | n)) = n \cdot (y_i - 1) + \log(1 - e^{-n})$$

$$\Rightarrow \log \prod_{i=1}^m p(y_i | x^{(i)}, \theta) = \sum_{i=1}^m x^{(i)} \cdot \theta (y_i - 1) + \log(1 - e^{-x^{(i)} \theta})$$

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Classifer rule:

$$p(x|y=1) \cdot p(y=1) - p(x|y=0) \cdot p(y=0) \geq 0$$

or with logs:

$$\begin{aligned} & \log\left(\frac{1}{(2\pi)^{\frac{d}{2}} \cdot |\Sigma_0|^{\frac{1}{2}}} \cdot \exp(-\cdot)\right) + \log(\phi) - \log(\cdot) - \log(1-\phi) \\ & = \log\left(\frac{1}{\pi \cdot \sqrt{\Sigma_0}}\right) - \frac{1}{2}(x - \mu_0)^\top \Sigma_0^{-1} (x - \mu_0) + \log(\phi) \\ & \quad - \log\left(\frac{1}{\pi \cdot \sqrt{\Sigma_0}}\right) + \frac{1}{2}(x - \mu_0)^\top \Sigma_1^{-1} (x - \mu_0) - \log(1-\phi) \\ & = \frac{1}{2} \left((x - \mu_0)^\top \Sigma_0^{-1} (x - \mu_0) - (x - \mu_1)^\top \Sigma_1^{-1} (x - \mu_1) \right) \\ & \quad + \underbrace{\log\left(\frac{\phi}{1-\phi}\right)}_{C} + \log\left(\frac{\sqrt{|\Sigma_0|}}{\sqrt{|\Sigma_1|}}\right) \end{aligned}$$

lower part of parents:

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$$\begin{aligned} & X^T \Sigma_0^{-1} X - X^T \Sigma_0^{-1} M_0 - M_0^T \Sigma_0^{-1} X + \underbrace{M_0^T \Sigma_0^{-1} M_0}_C \\ & - X^T \Sigma_1^{-1} X + X^T \Sigma_1^{-1} M_1 + M_1^T \Sigma_1^{-1} X - \underbrace{M_1^T \Sigma_1^{-1} M_1}_C \\ = & X^T \Sigma_0^{-1} X - X^T \Sigma_1^{-1} X - 2(M_0^T \Sigma_0^{-1} X - M_1^T \Sigma_1^{-1} X) \\ = & X^T (\Sigma_0^{-1} - \Sigma_1^{-1}) X + 2 \cdot (M_1^T \Sigma_1^{-1} - M_0^T \Sigma_0^{-1}) \cdot X \\ \Rightarrow & A: \frac{1}{2} (\Sigma_0^{-1} - \Sigma_1^{-1}) \quad \text{(remember the } \frac{1}{2} \text{ from before)} \end{aligned}$$

$$B: \frac{1}{2} \cdot (\Sigma_0^{-1} M_1 - \Sigma_1^{-1} M_0)$$

$$C: \log\left(\frac{d}{1-\phi}\right) + \log\left(\frac{\sqrt{|\Sigma_0|}}{\sqrt{|\Sigma_1|}}\right) + \frac{1}{2}(M_0^T \Sigma_0^{-1} M_0 - M_1^T \Sigma_1^{-1} M_1)$$

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2) Naive Bayes Classification

Show: NB: $\sum w_i c_i + b \geq 0$; $w_i = \text{count of word } i \text{ in document}$

Classify 1 if $p(y=1|x) > p(y=0|x)$

\Rightarrow if $p(y=1|x) - p(y=0|x) > 0$

words

$\Rightarrow p(x|y=1)p(y=1) - p(x|y=0)p(y=0) > 0$

$\Rightarrow \sum_{j=1}^n (\log(p(x_j|y=1)) + \underbrace{[\log(p(y=1)) - \log(p(y=0))]}_{b}) > 0$

$\Rightarrow b = \log\left(\frac{\phi_y}{1-\phi_y}\right)$

$\sum_{j=1}^n (\log(p(x_j|y=1)) - \log(p(x_j|y=0)))$

$= \sum_{j=1}^n (\log(\phi_{x_j|y=1}) - \log(\phi_{x_j|y=0}))$

$\Rightarrow w_i = \log\left(\frac{\phi_{x_i|y=1}}{\phi_{x_i|y=0}}\right)$

c) PE 2014 1/28
Prove:

$$V^T V = I$$

$$V V^T V = V$$

$$(V V^T y)^T = y^T (V V^T)^T = y^T (V V^T)$$

$$\tilde{J}(\hat{\theta}_{\text{new}}) \leq J(\hat{\theta})$$

\Rightarrow Show:

$$2 \cdot (X X^T y)^T (V V^T y) - 2 \cdot y^T (V V^T y) + 4 (w^T)^T (V V^T y) \leq 0$$

know: $\theta = X^T y$

$$\begin{aligned} & \cancel{2 \cdot (V V^T y)^T (X X^T y - y^T + \frac{V V^T y}{2})} \\ & \cancel{(X X^T + w^T)^T y - \frac{y^T}{2}} \end{aligned}$$

$$\cancel{X X^T y - \frac{y^T}{2}}$$

$$\cancel{2 (X X^T y)^T (w^T y) + (V V^T y)^T (w^T y)} \leq \cancel{2 y^T (V V^T y)}$$

$$\cancel{2 \cdot (w^T)^T (X X^T y - y^T) + (V V^T y)^T (V V^T y)}$$

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(b)₂ =

$$\begin{aligned} & \underbrace{(XX^T\vec{y})^T(XX^T\vec{y})}_{+} + \underbrace{(XX^T\vec{y})^Tvv^T\vec{y}}_{-} - \underbrace{(XX^T\vec{y})^T\vec{y}}_{+} \\ & + \underbrace{(vv^T\vec{y})^T(XX^T\vec{y})}_{+} + \underbrace{(vv^T\vec{y})^T(vv^T\vec{y})}_{-} - \cancel{\underbrace{(vv^T\vec{y})^T\vec{y}}_{+}} \\ & - \cancel{\underbrace{\vec{y}^T(XX^T\vec{y})}_{+}} - \underbrace{\vec{y}^T(vv^T\vec{y})}_{+} + \underbrace{\vec{y}^T\vec{y}}_{+} \\ & = 3(\theta) + 2 \cdot (XX^T\vec{y})^Tvv^T\vec{y} - 2\vec{y}^T(vv^T\vec{y}) + (w^T\vec{y})^2 \end{aligned}$$

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$$2 \cdot y^T x x^T v v^T y - 2 \cdot y^T v v^T y + y^T \underline{v v^T} \underline{v v^T} y \leq 0$$

$$2 \cdot y^T x x^T v v^T y - 2 \cdot y^T v v^T y + y^T v v^T y \leq 0$$

$$2 \cdot y^T x \cancel{x^T v v^T y} - y^T v v^T y \leq 0$$

$$\cancel{(x^T y)} \cancel{(v^T y)} - (v^T y)^T (v^T y)$$

$\downarrow = 0$ because of orthonormality

$$\Rightarrow -y^T v v^T y \leq 0$$

$$\Leftrightarrow -(v^T y)^T (v^T y) \leq 0$$

$$- " (v^T y)^2 " \leq 0$$

(a)

$$\theta = (X^T X)^{-1} X^T \tilde{y} \quad (\text{from Notes - Normal Equation})$$

$$\Rightarrow J(\theta) = (X\theta - \tilde{y})(X\theta - \tilde{y})$$

Side calc: $(X\theta - \tilde{y}) = (X(X^T X)^{-1} X^T \tilde{y} - \tilde{y})$
 $\stackrel{=I}{\sim}$ according to orthonormality assumption

$$\begin{aligned} &= (X X^T \tilde{y} - \tilde{y}) \\ \Rightarrow &\boxed{J(\theta) = (X X^T \tilde{y} - \tilde{y})^T (X X^T \tilde{y} - \tilde{y})} \end{aligned}$$

b) 

$$\nabla_{\theta} \tilde{J}(\theta) = \nabla_{\theta} J(\theta) + QW_p.$$

$$\theta_{\text{new}} = \tilde{X}^T \tilde{y}$$

$$\Rightarrow \tilde{J}(\theta_{\text{new}}) = (\tilde{X} \tilde{X}^T \tilde{y} - \tilde{y})^2$$

$$\begin{aligned} \Rightarrow A &= (\tilde{X} \tilde{X}^T \tilde{y} - \tilde{y}) - (X X^T \tilde{y} - \tilde{y}) \\ &= \tilde{X} \tilde{X}^T \tilde{y} - X X^T \tilde{y} \end{aligned}$$

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16)

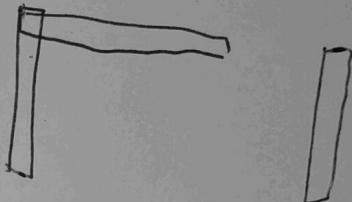
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AB

$$\tilde{X}\theta = \tilde{X}\theta_{\text{new}} -$$

$$\tilde{X}\theta_{\text{new}} = X\theta + \vec{v} \cdot p$$

$$\vec{J}_p = \tilde{X}\theta_{\text{new}} - X\theta$$



$$\tilde{X}\tilde{X}^T = XX^T + VV^T$$

$$\begin{matrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{matrix}$$

$$\Rightarrow \tilde{\sigma}(\theta_{\text{new}}) =$$

$$= \left((XX^T + VV^T)\tilde{y} - \tilde{y} \right)^2$$

$$= (XX^T\tilde{y} + VV^T\tilde{y} - \tilde{y})^2$$

$$(XX^T\tilde{y} - \tilde{y})^T (XX^T\tilde{y} - \tilde{y}) = \frac{(XX^T\tilde{y})^T (XX^T\tilde{y})}{2} - 2(XX^T\tilde{y})^T y + \frac{y^T y}{2}$$