

# Pattern Recognition HW 3

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## 1 06 FLD 3

1.  $A^T (A^{-1})^T = (A^{-1}A)^T = E$ , thus  $\text{inv}(X)' = \text{inv}(X')$ ,  $AA'$  and  $A'A$  have same eigenvalues, thus  $(\text{inv}(X)'\text{inv}(X))$  is similar to  $((\text{inv}(X)\text{inv}(X)^T) = \text{inv}(X)\text{inv}(X') = (X'X)^{-1}$ . Thus  $\kappa_2(X) = \frac{\sigma_1}{\sigma_n}$ .
2. By  $Ax = b$ ,  $A\Delta x = \Delta b$  and  $\|b\| = \|Ax\| \leq \|A\|\|x\|$ ,  $\|\Delta x\| = \|A^{-1}\Delta b\| \leq \|A^{-1}\|\|\Delta b\|$ .  $\frac{\|\Delta x\|}{\|x\|} \leq \|A^{-1}\|\|A\| \frac{\|\Delta b\|}{\|b\|}$ . A large condition number will loss its control of error of  $x$ .
3. If  $A$  is orthogonal matrix,  $\|A\| = \|A^{-1}\| = 1$ . Thus  $\kappa(A) = 1$ .

## 2 06 FLD 6

1. .
2. .
3. PCA is unsupervised learning while FLD is supervised, which provides different type of discriminate method. This also results in difference in dims of eigenspace. Eigenface generally has a larger dim.
4. Around 300.

## 3 07 SVM 1

1. .
2. (a) 66.925% (b) Scale should be  $[0,1]$ . (c) 95.675% (d) 87.7%. (e)  $C=1048.0, \gamma=5.04$ .
3. The first data set a1a is inbalanced with 395 positive class and 1210 negative class. It did not significantly improve something.

## 4 08 Probabilistic 2

1.  $\int_{x_m}^{\infty} \frac{c}{x^{a+1}} dx = 1$  thus  $\frac{c}{\alpha} x_m^{-\alpha} = 1 \Rightarrow c = \alpha x_m^{\alpha}$ .
- 2.

$$\begin{aligned} l(x_1, \dots, x_n) &= \prod_{i=1}^n \frac{\alpha x_i^{\alpha}}{x_i^{\alpha+1}} \\ &= (\alpha + 1) \sum \log x_i + \alpha \cdot n \ln \alpha + n\alpha \log x_m \end{aligned}$$

By taking partial derivative,  $\hat{x}_m = \max(x_1, \dots, x_n)$ ,  $\hat{\alpha} = \frac{1}{n \log \prod \frac{x_i}{x_m}}$

3.

$$\begin{aligned}
 P(\theta|x) &\propto p(x|\theta)P(\theta|x_m, k) \\
 &= \begin{cases} \left(\frac{1}{\theta}\right)^n & \theta \geq \max(x_i) \\ 0 & \theta < \max(x_i) \end{cases} \begin{cases} \frac{kx_m^k}{\theta^{k+1}} & \theta \geq x_m \\ 0 & \theta < x_m \end{cases} \\
 &\propto \begin{cases} \frac{1}{\theta^{n+k+1}} & \theta \geq \min(\max(x_i), x_m) \\ 0 & \text{others} \end{cases}
 \end{aligned}$$

Thus  $\alpha' = n + k + 1$  and  $x_m = \min(\max(x_i), x_m)$ .

## 5 09 Metric 6

1. .
2. Around 85%.
3. Around 65%.
4. Every feature is push to 1 thus harder to discriminate.

## 6 10 IT 2

1.  $d(x,y)=d(y,x)$ ,  $d(x,x)\geq 0$  and  $d(x,x) = 0 \Leftrightarrow x = \theta$ ,  $d(x+y)+d(y+z)\geq d(x+z)$ .
2. No.

$$KL(A||A) = 0 \quad (1)$$

$$KL(A||B) = \frac{1}{2} \log \frac{2}{3} \quad (2)$$

$$KL(B||A) = \frac{1}{4} \log \frac{31}{8} \quad (3)$$

$$KL(B||C) = \frac{1}{4} \log \frac{2274}{2058} \quad (4)$$

$$KL(A||C) = \frac{1}{2} \log \frac{32}{7} \quad (5)$$

(1) rejects the second, (2)(3) reject the first, (2)(4)(5) reject the last.

3.

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import numpy as np
def KL(x,y):
    return x[1]*(np.log(x[1])-np.log(y[1]))+x[0]*(np.log(x[0])-np.log(y[0]))
A=np.array([0.5,0.5])
B=np.array([0.25,0.75])
C=np.array([0.125,0.875])
print(KL(A,A),KL(A,B)-KL(B,A),KL(A,B)+KL(B,C)-KL(A,C))

out:0.0 0.013029000284753484 -0.2118244650968008

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## 7 10 IT 6

$$h(X) = - \int_0^\infty \lambda e^{-\lambda x} (\ln \lambda + -\lambda x) dx$$

And

$$\begin{aligned}
 0 &\leq KL(p||q) \\
 &= \int p(x) \ln \frac{p(x)}{q(x)} \\
 &= \int p(x) \ln p(x) - \int p(x) \ln q(x)
 \end{aligned}$$

and

$$\begin{aligned}& \int p(x) \log q(x) \\&= \int p(x) (\log \lambda - \lambda x) dx \\&= \log \lambda - 1\end{aligned}$$

Thus proved.