

# 1. Basic Probability & Statistics

$$(1) F_X(x) = \int_{-\infty}^x f(t) dt = \begin{cases} 0 & x \leq 0 \\ x/4 & x \in (0, 1) \\ 1/4 & x \in [1, 3) \\ (3x-7)/8 & x \in [3, 5] \\ 1 & x \in [5, +\infty) \end{cases}$$

$$(2) F_Y(y) = P\{Y \leq y\} = P\{\frac{1}{X} \leq y\} = P\{X \geq \frac{1}{y}\} = F_X(\frac{1}{y})$$

$$f_Y(y) = f_X(\frac{1}{y}) \cdot (\frac{1}{y})'$$

$$= \begin{cases} \frac{1}{4y^2} & y \in (1, +\infty) \\ \frac{3}{8y^2} & y \in (\frac{1}{5}, \frac{1}{3}) \\ 0 & \text{elsewhere} \end{cases}$$

$$(3) P[Z \geq z] = \int_z^{\infty} f(t) dt = 1 - \int_0^z f(t) dt = 1 - F(z)$$

$$Z = \int_0^{\infty} dt = \int_0^{\infty} I(t) dt \Rightarrow I(t) := \begin{cases} 1 & t \leq Z \\ 0 & \text{elsewhere} \end{cases}$$

$$E[Z] = E\left[\int_0^{\infty} I(t) dt\right] = \int_0^{\infty} E[I(t)] dt = \int_0^{\infty} P(Z > t) dt = \int_0^{\infty} P(Z > z) dz$$

for  $E[X]$ :

$$[X] = \int_0^{\infty} x f(x) dx = \int_0^1 \frac{1}{4} x dx + \int_3^5 \frac{3}{8} x dx$$

$$= \frac{1}{8} x^2 \Big|_0^1 + \frac{3}{16} x^2 \Big|_3^5 = \frac{25}{8}$$

$$[Y] = \int_0^{\infty} y f(y) dy = \int_1^{\infty} \frac{1}{4y} dy + \int_{\frac{1}{5}}^{\frac{1}{3}} \frac{3}{8y} dy$$

$$= +\infty \quad (\text{not exist})$$

## 2. Strong Convexity.

2.1  $\rightarrow$  2.2 :

$$(2.1) \Rightarrow f((1-\alpha)x + \alpha y) \leq (1-\alpha)f(x) + \alpha f(y) - \frac{\lambda}{2} \alpha(1-\alpha) \|x-y\|^2$$

$$\Rightarrow \frac{f(x + \alpha(y-x)) - f(x)}{\alpha} \leq f(y) - f(x) - \frac{\lambda}{2} (1-\alpha) \|x-y\|^2$$

when  $\alpha \rightarrow 0$

$$\Rightarrow \nabla f(x)^T (y-x) \leq f(y) - f(x) - \frac{\lambda}{2} \|x-y\|^2$$

$$\Rightarrow f(y) \geq f(x) + \nabla f(x)^T (y-x) + \frac{\lambda}{2} \|y-x\|^2$$

2.2  $\rightarrow$  2.1 :

$$2.2 \rightarrow f(y) \geq f(x) + \nabla f(x)^T (y-x) + \frac{\lambda}{2} \|y-x\|^2$$

$$\text{set } y = \alpha(x_1) + (1-\alpha)(x_2)$$

$$\Rightarrow \begin{cases} f(x_1) \geq f(y) + \nabla f(y)^T (x_1 - y) + \frac{\lambda}{2} \|x_1 - y\|^2 & (2.2.a) \\ f(x_2) \geq f(y) + \nabla f(y)^T (x_2 - y) + \frac{\lambda}{2} \|x_2 - y\|^2 & (2.2.b) \end{cases}$$

$$(2.2.a) \times \alpha + (2.2.b) \times (1-\alpha)$$

$$\begin{aligned} \Rightarrow \alpha f(x_1) + (1-\alpha) f(x_2) &\geq f(\alpha x_1 + (1-\alpha)x_2) + \frac{\lambda}{2} \alpha \|(1-\alpha)(x_1 - x_2)\|^2 \\ &\quad + \frac{\lambda}{2} (1-\alpha) \|\alpha(x_2 - x_1)\|^2 \end{aligned}$$

$$\text{set } x_1 = x \quad x_2 = y \quad x_1 = y$$

$$\Rightarrow f((1-\alpha)x + \alpha y) \leq (1-\alpha)f(x) + \alpha f(y) - \frac{\lambda}{2} \alpha(1-\alpha) \|x-y\|^2$$

### 3. Doubly Stochastic Matrix

use second-order condition for convexity.  $f(x) = -x \log x$ .

$$(1) \quad (x \log x)' = -\left(x \cdot \frac{1}{x} \cdot \frac{1}{\ln 10} + \log x\right) = -\left(\frac{1}{\ln 10} + \log_{10} x\right)$$

$$(x \log x)'' = -\frac{1}{x \ln 10} \geq 0 \quad (\text{for all } x \in [0, 1])$$

$\Rightarrow x \log x$  is a convex function, then use Jensen's Inequality.

$$f\left(\sum_{i=1}^d \theta_i x_i\right) \leq \sum_{i=1}^d \theta_i f(x_i)$$

$$\text{here, } \theta_i = 1 \quad f(x) = x \log x$$

$$\begin{aligned} \Rightarrow -\sum_{i=1}^d \sum_{j=1}^d x_{ij} \log(x_{ij}) &\leq -\log\left(\sum_{i=1}^d \sum_{j=1}^d x_{ij}\right) \cdot \left(\sum_{i=1}^d \sum_{j=1}^d x_{ij}\right) \\ &= -d \cdot \log(d) \end{aligned}$$

(2) Using Perron-Frobenius eigenvalue inequality.

$$\min_i \sum_j a_{ij} \leq \rho(X) \leq \max_i \sum_j a_{ij}$$

$$\text{while } \min_i \sum_j a_{ij} = \max_i \sum_j a_{ij} = 1$$

$$\Rightarrow \rho(X) = 1$$

Also

$$X \cdot \underbrace{(1, 1, \dots, 1)^T}_{d \times 1} = \left( \sum_j a_{1j}, \dots, \sum_j a_{dj} \right) = 1 \cdot \underbrace{(1, 1, \dots, 1)^T}_{d \times 1}$$

$\Rightarrow 1$  is  $X$ 's eigenvalue

(actually  $\rho(X)$  is defined as the largest eigenvalue...)

#### 4. Hypothesis Testing.

$$\chi^2 = \frac{k-1}{k} \frac{12N}{k-1} \sum_{i=1}^k (r_i - \frac{k+1}{2})^2$$

$N \sim \text{dataset}$

$k \sim \text{algorithm}$

$$= \frac{12N}{k(k+1)} \left( \sum_{i=1}^k r_i^2 - \frac{k(k+1)^2}{4} \right)$$

$$= \frac{12 \times 5}{5 \times 6} \cdot (3.8^2 + 4^2 + 3.2^2 + 1.2^2 + 2.8^2 - \frac{5 \times 6^2}{4})$$

$$= 9.92$$

$$\chi_F = \frac{(N-1) \chi^2}{N(k-1) - \chi^2} = 3.9365 > \chi_F(5, 5, \alpha=0.05) = 3.007$$

$\rightarrow$  这些算法性能不同.

Algorithm	A	B	C	D	E
Average Performance	3.8	4	3.2	1.2	2.8

for Nemenyi Test:

$$CD = q_{\alpha} \sqrt{\frac{k(k+1)}{6N}}$$

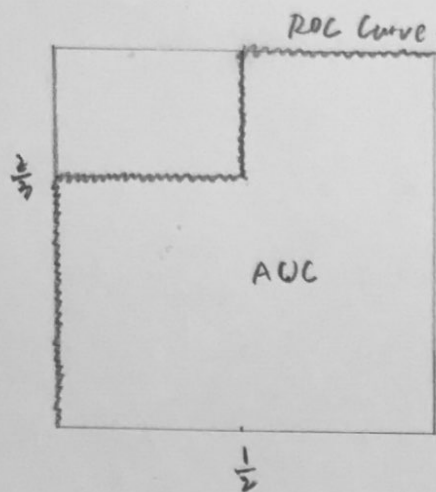
$$= 2.728 \times \sqrt{\frac{5 \times 6}{6 \times 5}} = 2.728$$

$1.2 + 2.728 = 3.928 \Rightarrow \text{Algorithm B \& D are different on performance.}$



# 5. ROC and AUC.

(1).



$$m^+ = 2 \quad m^- = 2$$

样本	$x_1$	$x_4$	$x_5$	$x_2$	$x_3$
分数	0.9	0.7	0.4	0.2	0.1
标记	+	+	-	+	-

$$AUC = \frac{1}{2} \left( \frac{2}{3} + 1 \right) = \frac{5}{6} \approx 0.83$$

$$Crank = \frac{1}{6} (1) = \frac{1}{6}$$

(2) 文字叙述即可.