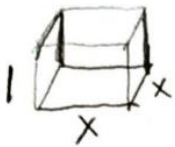


Data Science HW3

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Problem1

1.  X is standard Gaussian distribution

$$f(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2}$$

$$F(x; \mu, \sigma) = \frac{1}{\sqrt{2\pi}\sigma} \int_{-\infty}^x \exp\left(-\frac{(t-\mu)^2}{2\sigma^2}\right) dt \quad \text{for } \mu=0, \sigma=1$$

$$V = X^2$$

$$F_V(v) = P(V < v)$$

$$= P(X^2 < v)$$

$$= P(-\sqrt{v} \leq X \leq \sqrt{v}) =$$

$$= \frac{1}{2} (1 + \text{erf}(\frac{\sqrt{v}}{\sqrt{2}})) - \frac{1}{2} (1 + \text{erf}(-\frac{\sqrt{v}}{\sqrt{2}}))$$

$$= \frac{1}{2} \text{erf}(\frac{\sqrt{v}}{\sqrt{2}}) - \frac{1}{2} \text{erf}(-\frac{\sqrt{v}}{\sqrt{2}}) = \text{erf}(\frac{\sqrt{v}}{\sqrt{2}}) \quad u = \frac{\sqrt{v}}{\sqrt{2}} = (\frac{v}{2})^{\frac{1}{2}}$$

$$\frac{d \text{erf}(x)}{dx} = \frac{1}{\sqrt{\pi}} (e^{-x^2} - (-1)e^{-x^2}) = \frac{2}{\sqrt{\pi}} e^{-x^2}$$

$$1) \text{ PDF} = \frac{dF_V(v)}{dv} = \frac{2}{\sqrt{v}} e^{-\frac{v}{2}} \cdot \frac{1}{2} (\frac{v}{2})^{-\frac{1}{2}} \cdot \frac{1}{2} = \frac{1}{2\sqrt{v}} e^{-\frac{v}{2}} \cdot (\frac{v}{2})^{-\frac{1}{2}} = \frac{1}{\sqrt{2}\sqrt{v}} e^{-\frac{v}{2}} v^{-\frac{1}{2}}$$

2) Gamma Distribution PDF $\text{GAM}(\theta, \alpha)$

$$f(x) = \begin{cases} \frac{1}{\Gamma(\alpha)\theta^\alpha} x^{\alpha-1} e^{-\frac{x}{\theta}} & x > 0 \\ 0 & \text{otherwise} \end{cases}$$

Why dependent? box constrain 100% correlation

$$\alpha - 1 = -\frac{1}{2} \Rightarrow \underline{\alpha = \frac{1}{2}}$$

$$\underline{\theta = 2}$$

Problem2

(1)

X, Y pdf
 $2. f(x) = \begin{cases} e^{-x} & \text{for } x > 0 \\ 0 & \text{elsewhere} \end{cases}$
 $Z = \max(X, Y)$
 $W = \min(X, Y)$
 $\text{cdf } F_x(x) = F_Y(x)$
 $F_x(x) = \int_0^x e^{-u} du$

$(1) F_Z(z) = P(Z \leq z) = P(\max(X, Y) \leq z)$
 $= P(X \leq z) P(Y \leq z) = F_x(z) F_Y(z)$
 $= -e^{-u} \Big|_0^z = -e^{-z} - (-1) = 1 - e^{-z}$

$f_Z(z) = \frac{d}{dz} F_Z(z) = f_x(z) F_Y(z) + F_x(z) f_Y(z)$
 $= e^{-z} \cdot (1 - e^{-z}) + (1 - e^{-z}) e^{-z} = 2e^{-z} (1 - e^{-z})$

(2)

$(2) F_W(w) = P(W \leq w) = P(\min(X, Y) \leq w)$
 $= 1 - P(\min(X, Y) > w)$

$f_w(w) = \frac{dF_w(w)}{dw} = - \frac{dP(\min(X, Y) > w)}{dw} = - \frac{d(P(X > w) P(Y > w))}{dw} = - \frac{d((1 - P(X \leq w))(1 - P(Y \leq w)))}{dw}$
 $= - \frac{d((1 - F_x(w))(1 - F_Y(w)))}{dw} = - \frac{d(1 - F_x(w) - F_Y(w) + F_x(w) F_Y(w))}{dw}$
 $= +f_x(w) + f_Y(w) - f_x(w) F_Y(w) - F_x(w) f_Y(w)$
 $= e^{-w} + e^{-w} - e^{-w} (1 - e^{-w}) - (1 - e^{-w}) e^{-w}$
 $= 2e^{-w} - 2e^{-w} (1 - e^{-w}) = 2e^{-w} (1 - 1 + e^{-w})$
 $= 2e^{-w} (e^{-w})$
 $= 2e^{-2w}$

Problem3

```

1 import numpy as np
2 import pandas as pd
3 import matplotlib.pyplot as plt
4 import cv2
5 import math as mt
6
7 # read image in grayscale
8 img = cv2.imread('A.jpg', 0)
9 img2 = cv2.imread('B.jpg',0)
10 print('img shape',img.shape)
11 print('img2 shape',img2.shape)
12 # obtain svd
13 U, S, V = np.linalg.svd(img2)
14
15 # inspect shapes of the matrices
16 print(U.shape, S.shape, V.shape)
17
18 size = 1936 # 638
19 nSingular = [size, mt.floor(size*0.8), mt.floor(size*0.5), mt.floor(size*0.2), mt.floor(size*0.1), mt.floor(size*0.05)]
20
21 plt.figure(figsize = (32, 16))
22 for i in range(6):
23     low_rank = U[:, :nSingular[i]] @ np.diag(S[:nSingular[i]]) @ V[:nSingular[i], :]
24     if(i == 0):
25         plt.subplot(2, 3, i+1), plt.imshow(low_rank, cmap = 'gray'), plt.axis('off'), plt.title("Original Image with n_Singu
26     else:
27         plt.subplot(2, 3, i+1), plt.imshow(low_rank, cmap = 'gray'), plt.axis('off'), plt.title("Image with n_Singulars =" +

```

