120040025 Yohandi

p.
$$t^{2}(\lambda) = b(\lambda = \lambda)$$

$$= {\binom{20}{30}} {\binom{20}{30}} + {\binom{20}{30}}$$

$$\frac{g(x|y) = \frac{f_{y}(y)}{f_{y}(y)}}{\frac{f_{y}(y)}{(\frac{30}{y})} \left(\frac{1}{5}\right)^{x} \left(\frac{y}{5}\right)^{30-x-y}}$$

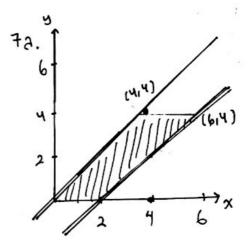
$$= \frac{\binom{30-y}{y}}{\binom{30-y}{y}} \left(\frac{1}{5}\right)^{x} \left(\frac{y}{5}\right)^{30-x-y}$$

5.
$$\int_{2}^{2.5} \int_{c}^{2.3} dy dx = 1$$

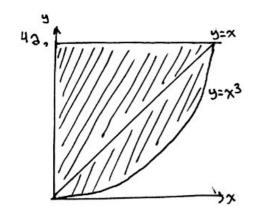
$$f(y|1x-y|40.1): \int_{1}^{2.1} (y+0.1)-2) dy + \int_{2}^{2.3} (y+0.1)-2 dy$$

$$= \frac{11}{30}$$

$$E(Y|X) = E(X) = \int_{-\infty}^{\infty} (2e^{-2(X-0.2)}) dx = \frac{7}{10}$$
 ethnusand



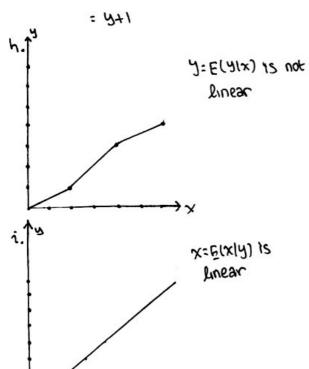
$$b.f_{x}(x)=\frac{1}{8}(min(x,u)-max(x-2,0)$$



d.
$$h(y|x) = \frac{1}{8}((y+2)-y) = \frac{1}{4}$$

d. $h(y|x) = \frac{f(x,y)}{f_x(x)} = \frac{1}{min(x,y) - max(x-2,0)}$

$$f. F(y|x): \begin{cases} s^{\frac{x}{2}} dy = \frac{x}{2}, & x \in (0,2) \\ s^{\frac{x}{2}} dy = x - 1, & x \in [2,4] \\ x - 2 & 6 - x \end{cases}$$



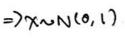
$$\lambda. E(y|x=2):10+\left(\frac{3}{5}\right)\frac{3}{5}(2\sim(-3))=\frac{59}{5}$$

$$U_{y|x}^2=9-\left(\frac{3}{5}\right)^29=\frac{144}{25}$$

$$P(3\times y) < 6(x=2): \phi\left(\frac{16-\frac{59}{5}}{\frac{12}{5}}\right)-\phi\left(\frac{7-\frac{59}{5}}{\frac{12}{5}}\right) \approx 0.9371$$

€ 8.8608

≈ 0.7210



5. 0.25 0.25 0.15 0.10 0.26

·) similarly we can prove that 'Y also follows normal distribution with mean = 0 and standard deviation 2/ (suap x and y)

10.
$$\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x,y) dx dy$$

$$= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} e^{-\frac{x^2 + y^2}{2}} (1 + xy e^{-\frac{x^2 + y^2}{2}}) dx dy$$

$$= \frac{1}{2\pi} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} e^{-\frac{x^2 + y^2}{2}} dx dy + \frac{1}{2\pi} \int_{-\infty}^{\infty} xy e^{-\frac{x^2 + y^2}{2}} dx dy$$

$$= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} e^{-\frac{x^2}{2}} dx$$

$$= \frac{1}{2\pi} \int_{-\infty}^{\infty} e^{-\frac{x^2}{2}} dx$$

$$= \frac{1}{2\pi} \int_{-\infty}^{\infty} e^{-\frac{x^2}{2}} dx$$

$$= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} e^{-\frac{x^2}{2}} dx$$

$$= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} e^{-\frac{x^2}{2}} dx$$

=> this shows that fixiy) is a joint poly

=1

$$\frac{1}{2\pi} e^{-\frac{x^{2}}{2}} \int_{0}^{\infty} e^{-\frac{x^{2}}{2}} + xy \cdot e^{-\frac{x^{2}}{2}} e^{-\frac{x^{2}}{2}} dy$$

$$= \frac{1}{2\pi} e^{-\frac{x^{2}}{2}} \int_{0}^{\infty} e^{-\frac{x^{2}}{2}} + xy \cdot e^{-\frac{x^{2}}{2}} e^{-\frac{x^{2}}{2}} e^{-\frac{x^{2}}{2}} dy$$

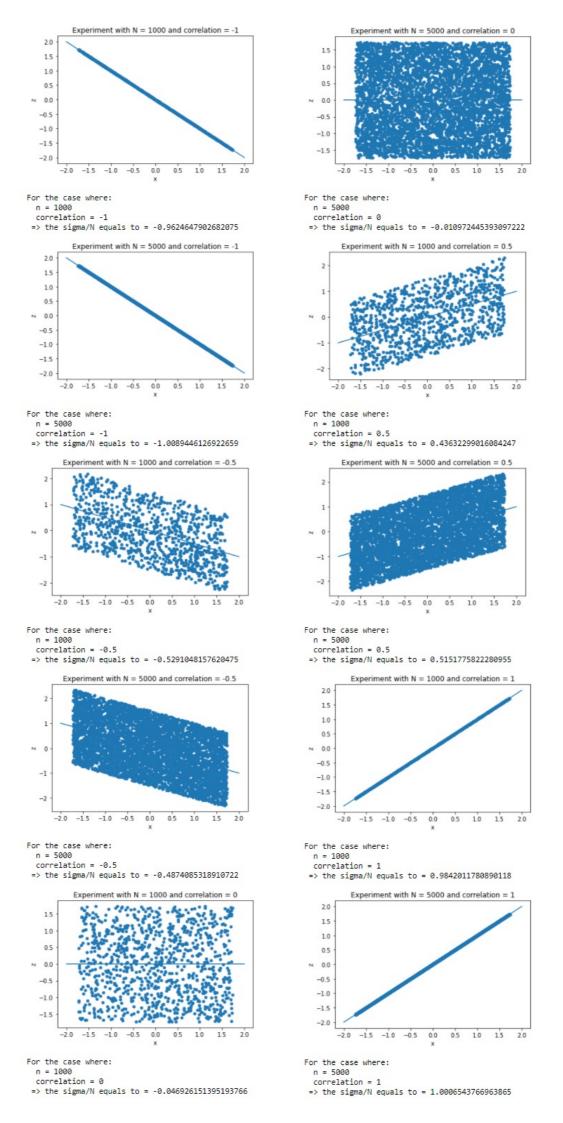
$$= \frac{1}{2\pi} e^{-\frac{x^{2}}{2}} e^{-\frac{x^{2}}{2}}$$

$$= \frac{1}{2\pi} e^{-\frac{x^{2}}{2}}$$

```
Yohandi - assignment 8 (computer-based)
for X~U(-L,+L),
    E(X) = (-1)+1 = 0
    Var(x) = (1-1-1)/2 12
 given that Var(x)=1;
    => 1/2=1
    => L= ±13
 In the same way, we can generate independent
 samples of a zero-mean, uniform random
 varable Y with var(Y)=1.
  suppose we have coefficient p. as the
  correlation of both x and Y distributions,
   for Z=px+ J1-p2 Y,
   ·> E(Z)=E(px+11-p2 Y) ·> Var(Z)= Var(px+11-p2 Y)
                                        = p2 Var(x) + (1-p2) Var(Y) + 2 Cov(x, Y).p 11-p2

E[(x-mx)(Y-mx)]
          = E(px)+ E(JI-p2 Y)
          = p E(x)+ \( \int_{p^2} \) E(Y)
                                                                   since X and Y are
                                                                      indepention t
                                        = p2+(1-p2)
 ·> E(XZ) = E(pX2+J(-p2 XY)
           = E(px2)+E(JT-p2 XY)
           = PE(X2)+ VI-P2 E(XY)
           = P (Var(x)+E(x)2) + 11-p2 E(x) E(Y)
```

= P



```
from knose graphs,
    Two can observe that when p=-1 or p=1, the points are neatly scattered
      along the line z=px
     .) on the other hand the points (xx, ti) = are diffused for P=-0.5 or P=0.5 o
     Although, compared with the case where Ip1=1, the points are widely spread
     along the line z=px
      on the case where p=0, the points are blindly spread evenly
      > in here, the larger N, the stronger the intensity of points plotted
those observations imply:
     >p=0 indicates no linearship between the RVs
     >1pt= 1 inducates a perfect linear relationship between the RVs
from the computed sigma,
     theore tically,
        em 12xizi = P
     cthis can be observed by comparing the value error
```

```
import math
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
def experiment(n, correlation):
    x = np.random.uniform(-math.sqrt(3), math.sqrt(3), n)
   y = np.random.uniform(-math.sqrt(3), math.sqrt(3), n)
   z = [correlation * x[i] + math.sqrt(1 - correlation ** 2) * y[i] for i in range(n)]
   df = pd.DataFrame({'x' : x, 'z' : z}, columns = ['x', 'z'])
   df.plot(x = 'x', y = 'z', kind = 'scatter')
plt.plot(np.linspace(-2, 2, 100), correlation * np.linspace(-2, 2, 100))
   plt.title("Experiment with N = " + str(n) + " and correlation = " + str(correlation))
   plt.show()
   print("For the case where:")
print(" n =", n)
   print(" correlation =", correlation)
   print(" => the sigma/N equals to =", sum([x[i] * z[i] for i in range(n)]) / n)
correlationList = [-1, -0.5, 0, 0.5, 1]
nList = [1000, 5000]
for correlation in correlationList:
   for n in nList:
       experiment(n, correlation)
```

of each N=1000 and N=5000 with P=P)