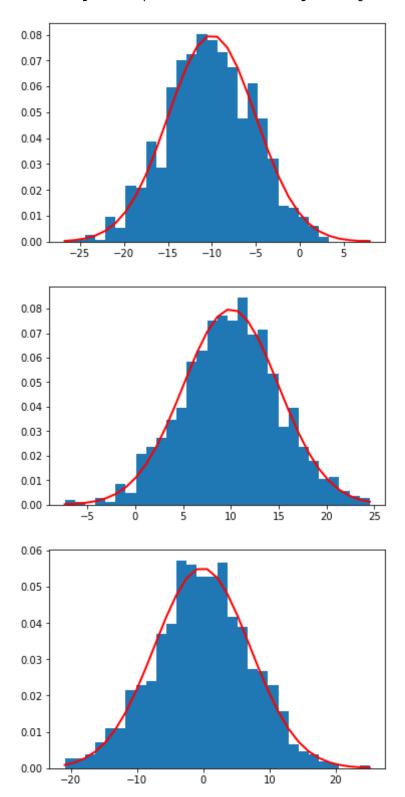
Create 1000 samples from a Gaussian distribution with mean -10 and standard deviation 5. Create another 1000 samples from another independent Gaussian with mean 10 and standard deviation 5.

- (a) Take the sum of 2 these Gaussians by adding the two sets of 1000 points, point by point, and plot the histogram of the resulting 1000 points. What do you observe?
- (b) Estimate the mean and the variance of the sum.

In [17]: import matplotlib.pyplot as plt import numpy as np import matplotlib.mlab as mlab mu, sigma = -10, 5 # mean and standard deviation s = np.random.normal(mu, sigma, 1000) mu2, sigma2 = 10, 5 # mean and standard deviation s2 = np.random.normal(mu2, sigma2, 1000) count, bins, ignored = plt.hist(s, 30, normed=True) plt.plot(bins, 1/(sigma * np.sqrt(2 * np.pi)) * np.exp(- (bins - mu)**2 / (2 * sigma**2)),linewidth=2, color='r') plt.show() count, bins, ignored = plt.hist(s2, 30, normed=True) plt.plot(bins, 1/(sigma2 * np.sqrt(2 * np.pi)) * np.exp(- (bins - mu2)* *2 / (2 * sigma2**2)), linewidth=2, color='r') plt.show() s3 = s + s2mu3 = s3.sum()/s3.sizesigma3 = s3.std() $mu3_var = s3.var()$ count, bins, ignored = plt.hist(s3, 30, normed=True) plt.plot(bins, 1/(sigma3 * np.sqrt(2 * np.pi)) * np.exp(- (bins - mu3)* *2 / (2 * sigma3**2)), linewidth=2, color='r') plt.show() print("The estimated mean is :", mu3) print("The estimated variance is :",mu3_var)

/anaconda3/lib/python3.6/site-packages/matplotlib/axes/_axes.py:6462: U serWarning: The 'normed' kwarg is deprecated, and has been replaced by the 'density' kwarg.

warnings.warn("The 'normed' kwarg is deprecated, and has been "

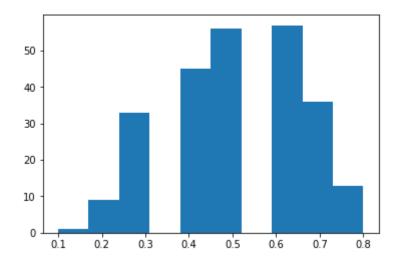


The estimated mean is : -0.18282693942272818The estimated variance is : 52.334462063516604

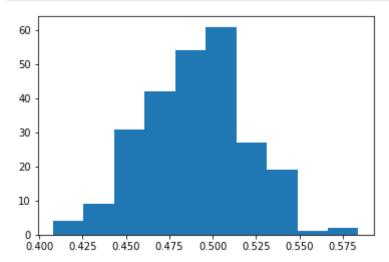
Central Limit Theorem. Let Xi be an iid Bernoulli random variable with value $\{-1,1\}$. Look at the random variable $Zn = 1 \square Xi$. By taking 1000 draws from Zn, plot its histogram. n Check that for small n (say, 5-10) Zn does not look that much like a Gaussian, but when n is bigger (already by the time n = 30 or 50) it looks much more like a Gaussian. Check also for much bigger n: n = 250, to see that at this point, one can really see the bell curve.

```
In [4]: import random
import numpy as np
import matplotlib.pyplot as plt

binomial_samples = np.random.binomial(size = 1000, n = 1, p = 0.5)
samples = [np.mean(random.choices(binomial_samples, k = 10)) for _ in ra
nge(250)]
plt.hist(samples)
plt.show()
```



```
In [5]: binomial_samples = np.random.binomial(size = 1000, n = 1, p = 0.5)
    samples = [np.mean(random.choices(binomial_samples, k = 250)) for _ in r
    ange(250)]
    plt.hist(samples)
    plt.show()
```



Estimate the mean and standard deviation from 1 dimensional data: generate 25,000 samples from a Gaussian distribution with mean 0 and standard deviation 5. Then estimate the mean and standard deviation of this gaussian using elementary numpy commands, i.e., addition, multiplication, division (do not use a command that takes data and returns the mean or standard deviation).

```
In [7]: import numpy as np
mu, sigma = 0, 5 # mean and standard deviation
sample = np.random.normal(mu, sigma, 25000)

estimated_mean = sample.sum()/sample.size
print("The estimated mean is :",estimated_mean)

estimated_variance = sum(pow(x-estimated_mean,2) for x in sample) / sample.size
print("The estimated variance is :",estimated_variance)

estimated_std = np.sqrt(estimated_variance)
print("The estimated standard deviation is :",estimated_std)
```

The estimated mean is: -0.024751599473765592
The estimated variance is: 24.663817819155504
The estimated standard deviation is: 4.966267997113678

Estimate the mean and covariance matrix for multi-dimensional data: generate 10,000 samples of 2 dimensional data from the Gaussian distribution $Xi Yi \sim N - 55$, 20.8.830.

(1) Then, estimate the mean and covariance matrix for this multi-dimensional data using elementary numpy commands, i.e., addition, multiplication, division (do not use a command that takes data and returns the mean or standard deviation).

```
In [99]: import numpy as np
         samples = np.array(([20,.8],[.8,30]))
         print('List')
         number = np.random.multivariate_normal([5,-5],samples,10000)
         print(number)
         estimated mean = sum(number) / len(number)
         print('The estimated Mean is', estimated_mean)
         estimated variance = np.sum((number - estimated mean)**2,axis=0) / 10000
         print("The estimated variance is :",estimated variance)
         estimated_covariance = np.multiply(*(number - estimated_mean).T).sum() /
          9999
         print("The estimated covariance is :",estimated covariance)
         print("Covariance matrix is {}".format([[estimated variance[0], estimate
         d covariance], [estimated covariance, estimated variance[1]]]))
         n = [x - estimated mean for x in number]
         covariance matrix = np.matmul( np.transpose(n), n) / 9999
         print("The estimated covariance using matmul is : ", covariance matrix)
         List
         [[ 3.11009474  0.40876771]
          [ 12.99919485 -12.26232351]
            9.58684442 -11.56425375]
          [ 6.12729268 -1.81861621]
          [ 6.03220957 -8.24918797]
          [ 1.76441483 3.2996818 ]]
         The estimated Mean is [ 4.97993269 -5.01403295]
         The estimated variance is: [20.05730781 29.68609556]
         The estimated covariance is: 0.7934479043078843
         Covariance matrix is [[20.05730781187715, 0.7934479043078843], [0.79344
```

The estimated covariance using matmul is: [[20.05931374 0.7934479]]

79043078843, 29.68609556155429]]

[0.7934479 29.68906447]]

Method 2:

```
In [84]: mean = [-5,5]
    cov = [[20, 0.8], [0.8, 30]];

sample = np.random.multivariate_normal(mean, cov, 10000)
    estimated_mean = np.sum(sample, axis=0) / np.size(sample, axis=0)
    print("The estimated mean is : ", estimated_mean)

numbers = [x - mean for x in sample]
    covariance_matrix = np.matmul( np.transpose(numbers), numbers) / 9999

print("The covariance matrix is :", covariance_matrix)

The estimated mean is : [-4.94798231 5.0118986 ]
    The covariance matrix is : [[20.48170762 0.62789166]
    [ 0.62789166 30.2038061 ]]
```

Each row is a patient and the last column is the condition that the patient has. Do data exploration using Pandas and other visualization tools to understand what you can about the dataset.

(a) How many patients and how many features are there?

```
In [4]: import pandas as pd

    df = pd.read_csv('/Users/aparnaaidith/Desktop/My Python Projects/BIG DAT
    A/PatientData.csv', header=None, na_values=['?'])

In [5]: no_of_patients = df.shape[0]
    print("The total number of patients : ",no_of_patients)
    no_of_features = df.shape[1]
    print("The total number of features : ",no_of_features)

The total number of patients : 452
    The total number of features : 280
```

- (b) What is the meaning of the first 4 features? See if you can understand what they mean.
- 1) Feature Age of the patient
- 2) Feature Gender of the patient 0 : Male 1 : Female
- 3) Feature Height of the patient
- 4) Feature Weight of the patient
- (c) Are there missing values? Replace them with the average of the corresponding feature column

In [6]: df[13]

| Out[6]: | 0 | NaN |
|---------|------------|------------|
| | 1 | NaN |
| | 2 | 23.0 |
| | 3 | NaN |
| | 4 | NaN |
| | 5 | NaN |
| | 6 | NaN |
| | 7 | NaN |
| | 8 | 84.0 |
| | | |
| | 9 | NaN |
| | 10 | NaN |
| | 11 | NaN |
| | 12 | NaN |
| | 13 | NaN |
| | 14 | NaN |
| | 15 | NaN |
| | 16 | NaN |
| | 17 | NaN |
| | 18 | NaN |
| | 19 | NaN |
| | 20 | NaN |
| | 21 | NaN |
| | 22 | NaN |
| | 23 | NaN |
| | 24 | NaN |
| | 25 | NaN |
| | 26 | NaN |
| | 27 | NaN |
| | 28 | NaN |
| | 29 | 160.0 |
| | | |
| | 422 | NaN |
| | 423 | NaN |
| | 424 | 103.0 |
| | 425 | NaN |
| | 426 | -84.0 |
| | 427 | NaN |
| | 428 | NaN |
| | 429 | NaN |
| | 430 | -44.0 |
| | 431 | NaN |
| | 432 | NaN |
| | 433 | NaN |
| | 434 | |
| | 434 | NaN NaN |
| | | NaN |
| | 436 437 | NaN |
| | | NaN |
| | 438 | NaN |
| | 439 | NaN |
| | 440 | -90.0 |
| | 441 | NaN |
| | 442 | NaN |
| | 443 | NaN |
| | 444 | NaN |
| | 445 | NaN |
| | 446 | NaN |
| | 447 | NaN |

```
448 NaN

449 84.0

450 103.0

451 NaN

Name: 13, Length: 452, dtype: float64
```

In [7]: df.fillna(df.mean(),inplace=True)

In [8]: df[13]

| Out[8]: | 0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 | -13.592105 |
|---------|---|--|
| | 27 28 29 | -13.592105 -13.592105 160.000000 |
| | 422 423 424 425 426 427 428 429 430 431 432 433 434 435 436 437 438 439 440 441 442 443 444 | -13.592105 -13.592105 103.000000 -13.592105 -84.000000 -13.592105 -13.592105 -13.592105 -44.000000 -13.592105 |
| | 445 446 447 | -13.592105 -13.592105 -13.592105 |

```
448 -13.592105

449 84.000000

450 103.000000

451 -13.592105

Name: 13, Length: 452, dtype: float64
```

(d) How could you test which features strongly influence the patient condition and which do not?

In [9]: df.corr()[279].sort_values(ascending = False)

| Out[9]: | 279 | 1.000000 |
|---------|-----|-----------|
| ouc[5]. | 90 | 0.368876 |
| | 4 | 0.323879 |
| | 92 | 0.323879 |
| | | |
| | 102 | 0.282523 |
| | 223 | 0.235488 |
| | 233 | 0.218811 |
| | 17 | 0.195198 |
| | 29 | 0.183083 |
| | 94 | 0.174346 |
| | 52 | 0.173243 |
| | 125 | 0.170670 |
| | 191 | 0.165693 |
| | 68 | 0.152534 |
| | 239 | 0.151782 |
| | 77 | 0.143284 |
| | 152 | 0.141506 |
| | 221 | 0.141274 |
| | 56 | 0.141103 |
| | 113 | 0.140502 |
| | 119 | 0.132195 |
| | 181 | 0.132193 |
| | 149 | 0.130360 |
| | | |
| | 228 | 0.128490 |
| | 65 | 0.127210 |
| | 198 | 0.125873 |
| | 249 | 0.124823 |
| | 193 | 0.122928 |
| | 107 | 0.121711 |
| | 88 | 0.120726 |
| | • | |
| | 8 | -0.122003 |
| | 208 | -0.134657 |
| | 161 | -0.135180 |
| | 202 | -0.142731 |
| | 252 | -0.150610 |
| | 172 | -0.158536 |
| | 247 | -0.159612 |
| | 260 | -0.162153 |
| | 270 | -0.164321 |
| | 168 | -0.171763 |
| | 1 | -0.178080 |
| | 242 | -0.189458 |
| | 162 | -0.197555 |
| | 19 | NaN |
| | 67 | NaN |
| | 69 | NaN |
| | 83 | NaN |
| | 131 | NaN |
| | 132 | NaN |
| | 139 | NaN |
| | 141 | NaN |
| | 143 | NaN |
| | 145 | NaN |
| | 151 | |
| | | NaN |
| | 156 | NaN |
| | 157 | NaN |

164 NaN 204 NaN 264 NaN 274 NaN

Name: 279, Length: 280, dtype: float64

Written Questions

Question 1

Consider two random variables X,Y that are not independent. Their probabilities of are given by the following table:

X=1 Y=0 1/4 Y=1 1/3

- (a) What is the probability that X = 1?
- (b) What is the probability that X = 1 conditioned on Y = 1?
- (c) What is the variance of the random variable X?
- (d) What is the variance of the random variable X conditioned that Y = 1?
- (e)WhatisE[$X_3+X_2+3Y_7|Y=1|$]?

SOLUTION

Question 1:-

| | X20 | XZI | |
|-----|------|------|-----|
| Y20 | 1/4 | 1/4 | 1/2 |
| 421 | 1/6 | 1/3 | 1/2 |
| | 5/12 | 7/12 | 1 |

(a) What is the pubability that X 21 ?

(b) What is the purbability that X=1 conditioned on Y=1?

$$\frac{1}{3} \times \frac{2}{3} \times \frac{2}{3}$$

(c) What is the variance of sandom variable x9

1

(d) What is the variance of the random variable X conditioned that 4 = 1?

$$M = 0 \times \frac{1}{6} + 1 \times \frac{1}{3} = 0 + \frac{1}{3} = \frac{1}{3}$$

on conditioned 421:-

$$(0-\frac{1}{3})^2 \times \frac{1}{6} + (1-\frac{1}{3})^2 \times \frac{1}{3}$$

$$\frac{z}{\left(\frac{1}{9} \times \frac{1}{6}\right)} + \left(\frac{4}{9} \times \frac{1}{3}\right)$$

$$\frac{2}{9}\left(\frac{1}{6} + \frac{4}{3}\right) = \frac{1}{9}\left(\frac{1+8}{6}\right)$$

(e) What
$$u \in [x^3+x^2+3y^7|Y=1]$$
?

 $E[c] = c w constant E[c \cdot u[n]] = c \cdot E[v[n]]$.

$$P(x=0|Y=1) = P(x=0 \text{ and } Y=1)$$

$$P(Y=1) = \frac{1}{6} \times \frac{2}{1} = \frac{1}{3}$$

$$P(x=1|Y=1) = P(x=1 \text{ and } Y=1)$$

$$P(y=1) = \frac{1}{3} \times \frac{2}{1} = \frac{2}{3}$$

$$E[x^3+x^2+3y^7|Y=11] = 0^3 \times \frac{1}{3} + 1^3 \times \frac{2}{3} = \frac{2}{3}$$

$$E[x^3|Y=1] = 0^4 \times \frac{1}{3} \times 1^7 \times \frac{2}{3} = \frac{2}{3}$$

$$E[x^7|Y=1] = 0^4 \times \frac{1}{3} \times 1^7 \times \frac{2}{3} = \frac{2}{3}$$

$$E[x^7|Y=1] = 3 \cdot E[y^7|Y=1] = 3 \cdot$$

NOTE: I have a calculation mistake on question (b) of Question 1.So I am submitting that particular question again.

| Question 1:- |
|--|
| (b) What is the probability that X21 |
| conditioned on 4219 |
| P(X21 Y21) 2 P(X21 11 Y21) |
| P(421) |
| $\frac{1}{2} \times \frac{2}{1} = \frac{2}{2}$ |
| 3 1 3 |
| [4,24, 0] , 50 |

Consider the vectors v1 = [1, 1, 1] and v2 = [1, 0, 0]. These two vectors define a 2-dimensional subspace of R3. Project the points P1 = [3,3,3],P2 = [1,2,3],P3 = [0,0,1] on this subspace. Write down the coordinates of the three projected points. (You can use numpy or a calculator to do arithmetic if you want).

SOLUTION

I have used the calculator to perform the matrix multiplic

$$B^{T}X = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 0 & 0 \end{bmatrix} \begin{bmatrix} 3 & 1 & 0 \\ 3 & 2 & 0 \\ 3 & 3 & 1 \end{bmatrix}$$

$$B^{T}B = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 0 & 0 \end{bmatrix} \begin{bmatrix} 1 & 1 \\ 1 & 0 \\ 1 & 0 \end{bmatrix} = \begin{bmatrix} 3 & 1 \\ 1 & 1 \end{bmatrix}$$

$$(B^{T}B)^{-1} = \begin{bmatrix} 1/2 & -1/2 \\ -1/2 & 3/2 \end{bmatrix}$$

$$(B^{T}B)^{-1}B^{T}X = \begin{bmatrix} 1/2 & -1/2 \\ -1/2 & 3/2 \end{bmatrix} \begin{bmatrix} 9 & 6 & 1 \\ 3 & 1 & 0 \end{bmatrix}$$

$$\lambda = \begin{bmatrix} 3 & 5/2 & 1/2 \\ 0 & -3/2 & -1/2 \end{bmatrix}$$

$$T_{u}(x) = B \lambda$$

$$= \begin{bmatrix} 1 & 1 \\ 1 & 0 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} 3 & 5/2 & 1/2 \\ 0 & -3/2 & -1/2 \end{bmatrix} = \begin{bmatrix} 3 & 1 & 0 \\ 3 & 5/2 & 1/2 \\ 3 & 5/2 & 1/2 \end{bmatrix}$$

$$C_{1} = \begin{bmatrix} 3 & 3 & 3 \end{bmatrix}$$

$$C_{2} = \begin{bmatrix} 1 & 5/2 & 5/2 \end{bmatrix}$$

$$C_{3} = \begin{bmatrix} 0 & 1/2 & 1/2 \end{bmatrix}$$

Consider a coin such that probability of heads is 2/3. Suppose you toss the coin 100 times. Estimate the probability of getting 50 or fewer heads. You can do this in a variety of ways. One way is to use the Central Limit Theorem. Be explicit in your calculations and tell us what tools you are using in these.

SOLUTION

P(Heade)
$$2\frac{2}{3}$$
 Toss the coin 100 times.

P(getting so on fewer heads) 29

Let

 $X_1^{\circ} = \begin{cases} 1 & \text{if ith toss is heads} \\ 0 & \text{otherwise} \end{cases}$.

Since X_1° are i.i.d and binomially distinbuted we know,

 $y_1 = EX_1^{\circ}$
 $y_2 = PX_1^{\circ}$
 $y_3 = PX_2^{\circ}$
 $y_4 = PX_1^{\circ}$
 $y_5 = PX_1^$

I used calculator and z score table for the calculation purpose.