lab1_compiled

January 28, 2018

```
In [1]: import numpy as np
        import matplotlib.pyplot as plt
        import pandas as pd
```

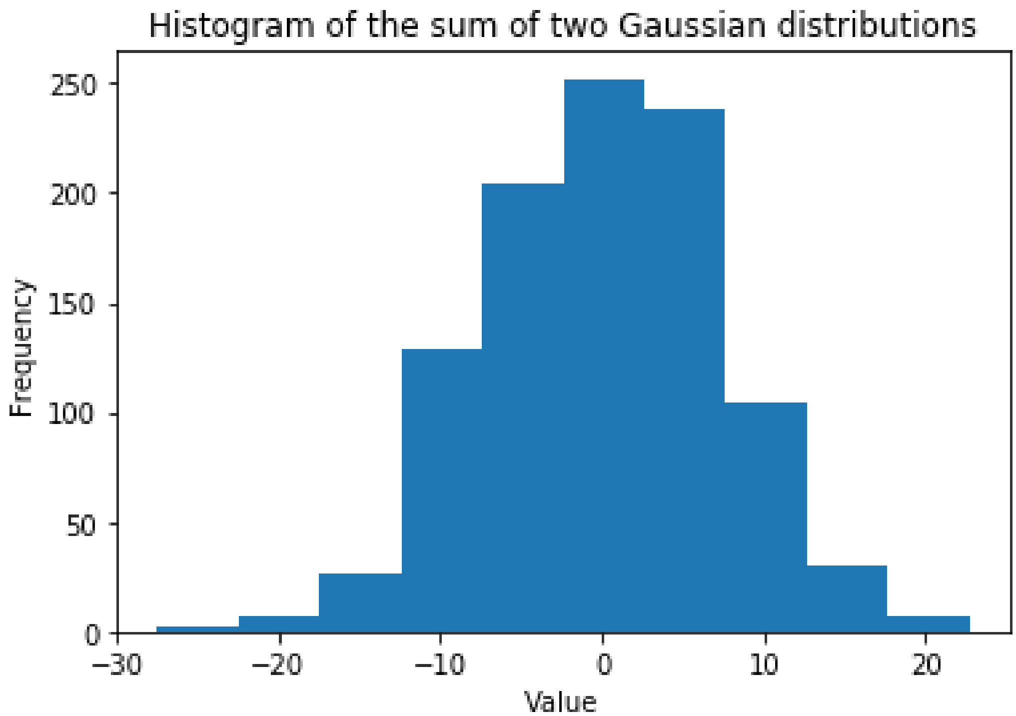
1 Problem 1

Generate two gaussian distributions with mean of 10 and -10, stddev = 5 and size =1000 Add both of the distributions and plot a histogram Estimate mean and variance

```
In [23]: %matplotlib inline

         # Generating two gaussian distributions using numpy function
         distribution_1 = np.random.normal(loc = -10 , scale = 5 , size = 1000)
         distribution_2 = np.random.normal(loc = 10, scale = 5, size =1000)

         # Calculating sum of the entries from both the distributions
         sum_dist = distribution_1 + distribution_2

         #calculating mean using numpy function mean
         mean = np.mean(sum_dist)

         #calculating variance using numpy function var
         var = np.var(sum_dist)
         print("The estimated mean of the sum of the two generated gaussian distribution is {}".
         print("The estivated variance of the sum of the two generated gaussian distribution is

         #plotting histogram using matplotlib of the distribution generated by adding two gaussi

         plt.hist(sum_dist)

         #setting x and y labels
         plt.xlabel("Value")
         plt.ylabel("Frequency")

         #setting the title of the plot
         plt.title("Histogram of the sum of two Gaussian distributions")
```

```
#displaying the plot
plt.show()
```

```
The estimated mean of the sum of the two generated gaussian distribution is 0.013391783296487575
The estivated variance of the sum of the two generated gaussian distribution is 51.9620360252322
```



2 Problem 2

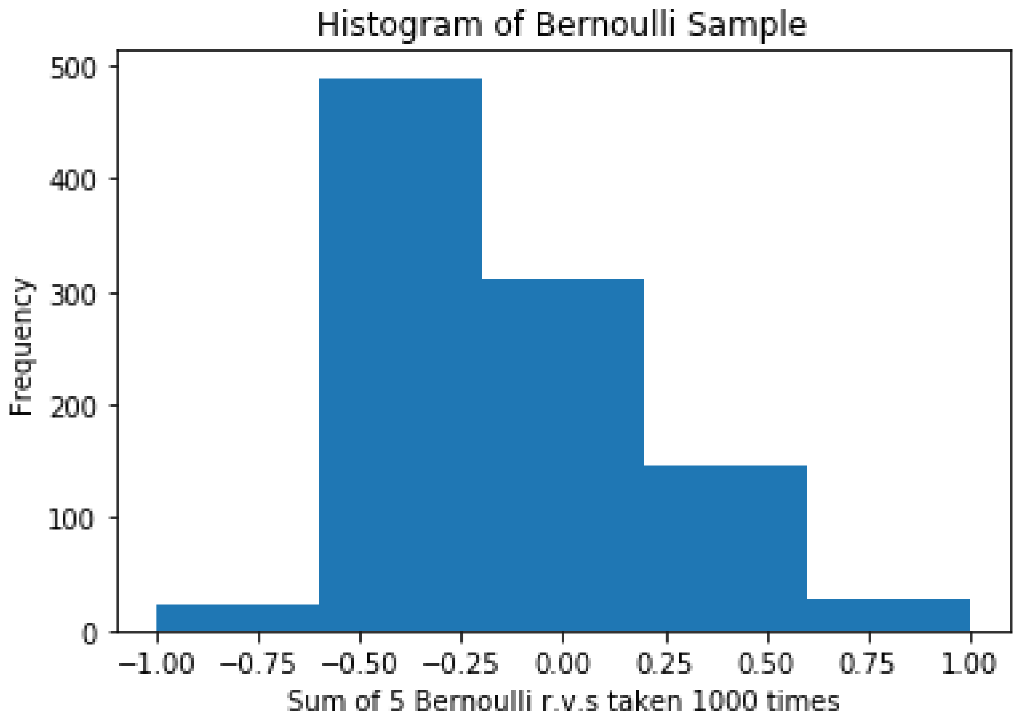
Let Xi be an iid Bernoulli random variable with value f-1,1g. Look at the random variable Zn = 1/n sum Xi. By taking 1000 draws from Zn, plot its histogram. Check that for small n (say, 5-10) Zn does not look that much like a Gaussian, but when n is bigger (already by the time n = 30 or 50) it looks 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.

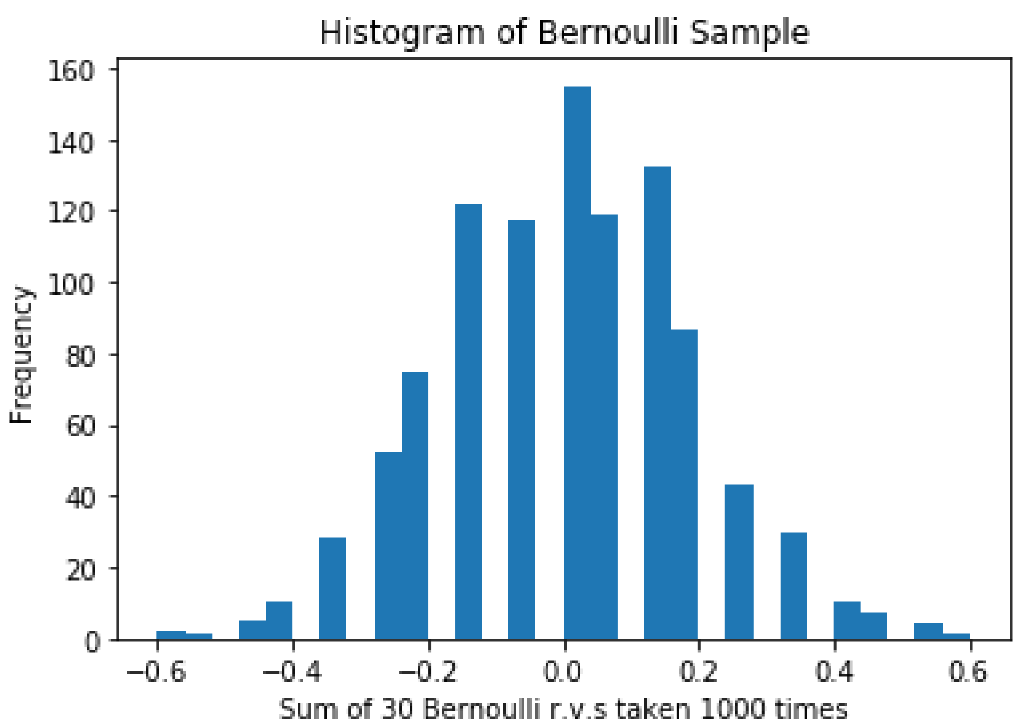
```
In [3]: # Function to generate samples
        def getSample(n, p = 0.5):
            draws = np.ones((n))
            for i in range(n):
                draw = np.random.uniform()
                if draw < p:
                    draws[i] = -1
```

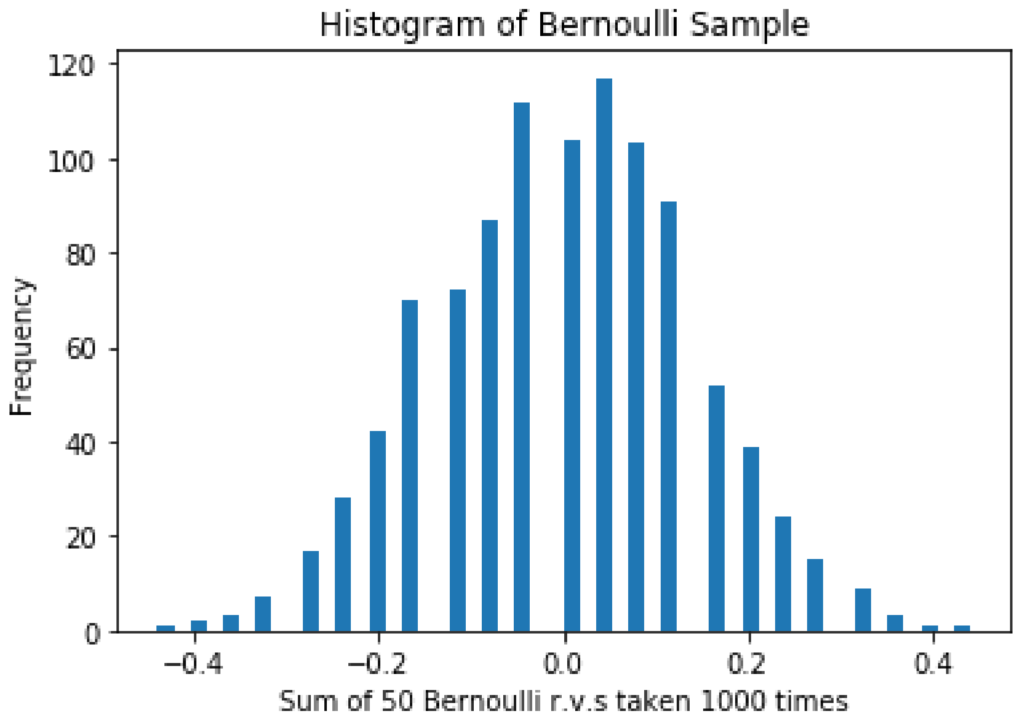
```
    return np.sum(draws)/n

# Function to generate historgram
# takes n as input for number of samples
def getHistogram(n, num_draws=1000):
    Zn = np.zeros((num_draws))

    for i in range(num_draws):
        Zn[i] = getSample(n)

    plt.title('Histogram of Bernoulli Sample')
    plt.xlabel('Sum of {} Bernoulli r.v.s taken {} times'.format(n, num_draws))
    plt.ylabel('Frequency')
    plt.hist(Zn, bins = n)
    plt.show()

'''
class Bernoulli:
    def __init__(self, p):
        draw = np.random.uniform()
        if draw > p:
            self.value = 1
        else:
            self.value = -1
'''
```

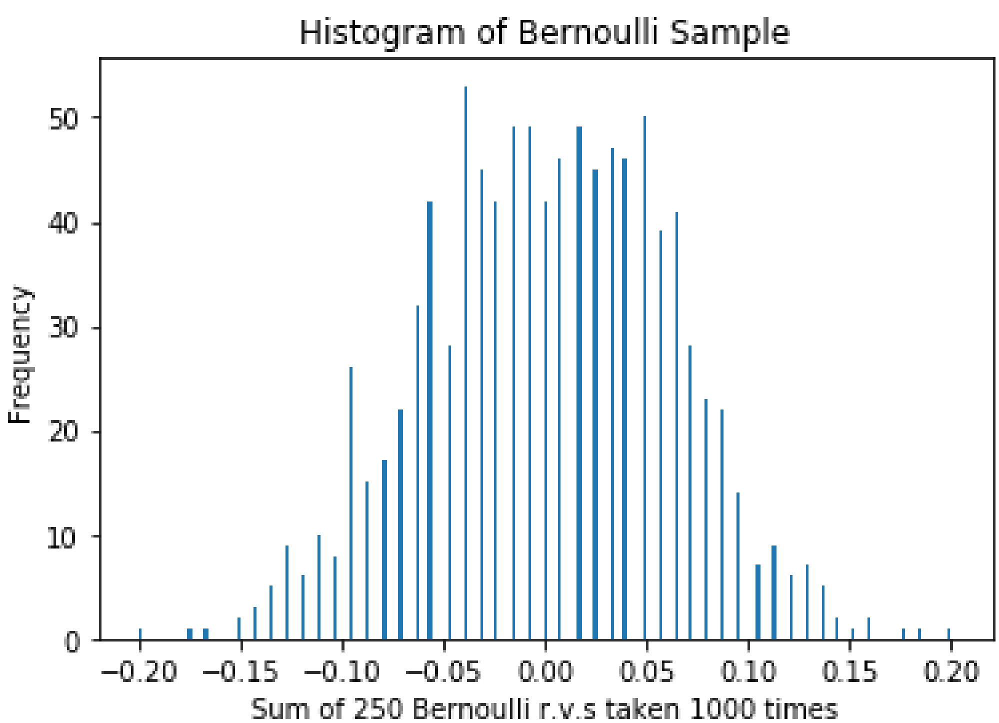
Out[3]: '\nclass Bernoulli:\n   def __init__(self, p):\n   draw = np.random.uniform()\n

In [4]:
```
# Calling getHistogram function for different values of n to notice how the curve
# changes into bell curve for large n
getHistogram(5)
getHistogram(30)
getHistogram(50)
getHistogram(250)
```


Histogram of Bernoulli Sample
Frequency
500
400
300
200
100
0
−1.00
−0.75
−0.50
−0.25
0.00
0.25
0.50
0.75
1.00
Sum of 5 Bernoulli r.v.s taken 1000 times


Histogram of Bernoulli Sample
Frequency
160
140
120
100
80
60
40
20
0
−0.6
−0.4
−0.2
0.0
0.2
0.4
0.6
Sum of 30 Bernoulli r.v.s taken 1000 times


Histogram of Bernoulli Sample
Frequency
0
20
40
60
80
100
120
−0.4
−0.2
0.0
0.2
0.4
Sum of 50 Bernoulli r.v.s taken 1000 times


Histogram of Bernoulli Sample
Frequency
0
10
20
30
40
50
−0.20
−0.15
−0.10
−0.05
0.00
0.05
0.10
0.15
0.20
Sum of 250 Bernoulli r.v.s taken 1000 times

3 Problem 3

Generate 25000 sample points from Gaussian distribution with mean =0, std dev = 5 Calculate mean and std dev without using library functions

```
In [5]: # Generating the desired normal distribution with mean = 0, std dev = 5 and 25000 entrie
        distribution = np.random.normal(loc =0,scale=5,size = 25000)

        # Calculating the mean of generated distribution by adding all the entries and dividing
        # distribution
        calc_mean = np.sum(distribution)/(distribution.size)
        print("Mean of sample points from Gaussian is {} ".format(calc_mean))

        # Calculating the quantity (X-E[x])^2 to find variance
        distribution_subtracted_mean_square = (distribution - calc_mean)*(distribution-calc_mean

        # Calculating variance by using the definition of variance as expected value of (X-E[x])
        variance_of_distribution = np.sum(distribution_subtracted_mean_square)/distribution_subt

        # Using the fact that standard deviation is square root of variance to calculate standar
        std_dev = np.sqrt(variance_of_distribution)

        print("Standard deviation of the samples points is {}".format(std_dev))
```

```
Mean of sample points from Gaussian is 0.05107647452877015
Standard deviation of the samples points is 5.033393089259453
```

4 Problem 4

Estimate the mean and covariance matrix for multi-dimensional data: generate 10,000 samples of 2 dimensional data from the Gaussian distribution given.

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 [6]: mean = [-5,5]
        covariance = [[20,0.8],[0.8,30]]

        #Generating a bivariate gaussian distribution with given mean and covariance matrix
        x1,x2 =np.random.multivariate_normal(mean,covariance,10000).T

        #Mean of x1 and x2 are simply sum of the values divided by the size of the distribution
        mean_of_x1 = (np.sum(x1)/x1.size)
        mean_of_x2 = (np.sum(x2)/x2.size)

        #Mean of bivariate gaussian distribution is simply the sum of individual means of x1 and
        mean_of_bivariate_gaussian = mean_of_x1 + mean_of_x2
```

```
print("Calculated mean of generated bivariate distribution is {}".format(mean_of_bivaria

#Calculating the variance of x1 to be used in covariance matrix
distribution_subtracted_mean_square_of_x1 = (x1 - mean_of_x1)*(x1-mean_of_x1)
variance_of_distribution_x1 = np.sum(distribution_subtracted_mean_square_of_x1)/distribu

#Calculating the variance of x2 to be used in covariance matrix
distribution_subtracted_mean_square_of_x2 = (x2 - mean_of_x2)*(x2-mean_of_x2)
variance_of_distribution_x2 = np.sum(distribution_subtracted_mean_square_of_x2)/distribu

#Calculating the covariance of x1 and x2 as expected value of (x1-E[x1])*(x2-E[x2])
distribution_of_x1_and_x2_with_subtracted_mean = (x1-mean_of_x1)*(x2-mean_of_x2)
covariance_of_x1_and_x2 = np.sum(distribution_of_x1_and_x2_with_subtracted_mean)/distrib

#Generating covariance matrix as list of lists
covariance_matrix = []

covariance_matrix_row1 =[variance_of_distribution_x1,covariance_of_x1_and_x2]
covariance_matrix.append(covariance_matrix_row1)

covariance_matrix_row2 = [covariance_of_x1_and_x2,variance_of_distribution_x2]
covariance_matrix.append(covariance_matrix_row2)

#converting covariance matrix into data frame for better visual display
data_frame = pd.DataFrame(covariance_matrix)

#changing index from numbering to distribtution names

data_frame.rename(index={0:'x1',1:'x2'}, columns={0:'x1',1:'x2'}, inplace=True)
print("Covariance matrix of the generated bivariate gaussian distribution is displayed b
print(data_frame)
```

```
Calculated mean of generated bivariate distribution is -0.047783869093271925
Covariance matrix of the generated bivariate gaussian distribution is displayed below
           x1         x2
x1  19.683774   0.621428
x2   0.621428  30.195189
```

5 Problem 5

Download from Canvas/Files the dataset PatientData.csv. 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.

For example: 1. How many patients and how many features are there? 2. What is the meaning of the first 4 features? See if you can understand what they mean. 3. Are there missing values? Replace them with the average of the corresponding feature column. 4. How could you test which features strongly influence the patient condition and which do not?

List what you think are the three most important features.

```
In [7]: import pandas as pd
        import matplotlib.pyplot as plt

        file_path = 'PatientData.csv'
        patient_data = pd.read_csv(file_path)
        patient_data.columns
        patient_data.values
```

```
Out[7]: array([[56, 1, 165, ..., 20.4, 38.8, 6],
               [54, 0, 172, ..., 12.3, 49.0, 10],
               [55, 0, 175, ..., 34.6, 61.6, 1],
               ...,
               [36, 0, 166, ..., -44.2, -33.2, 2],
               [32, 1, 155, ..., 25.0, 46.6, 1],
               [78, 1, 160, ..., 21.3, 32.8, 1]], dtype=object)
```

5.1 Part 1

Calling `patient_data.shape` shows the patients and features. There is one less feature than the dimension along the second axis, as the final vector is used for the labels.

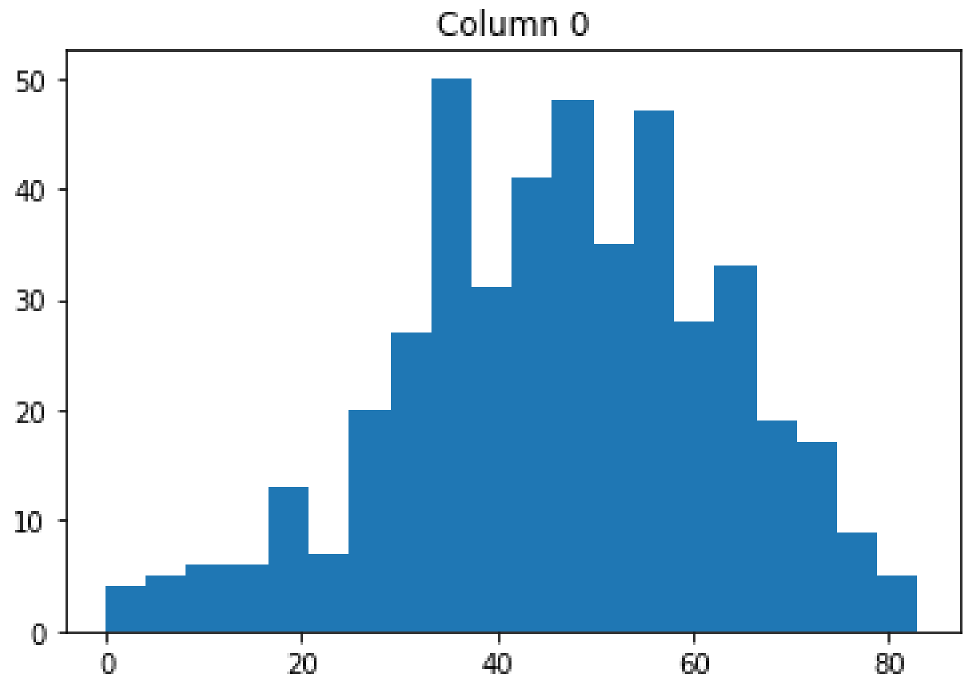
```
In [8]: patient_data.shape
        # 451 patients
        # 279 features
```

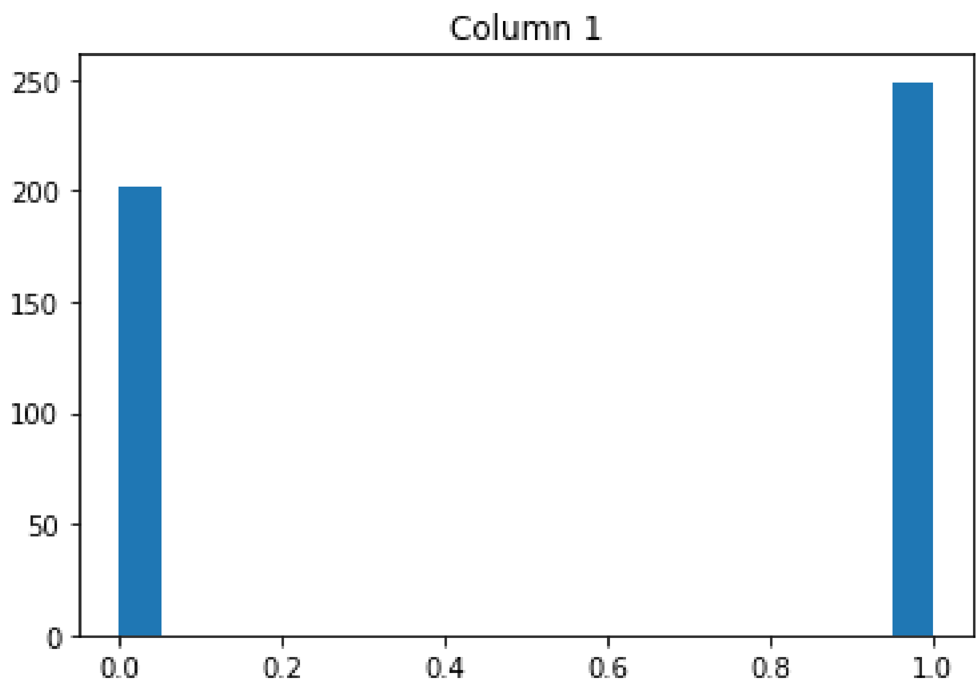
```
Out[8]: (451, 280)
```

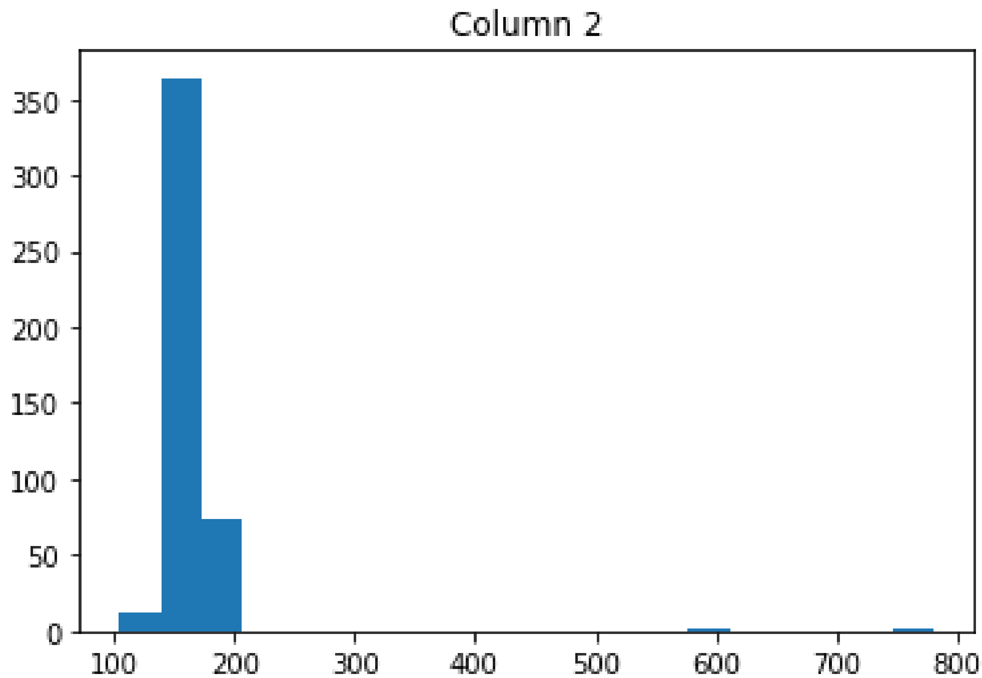
5.2 Part 2

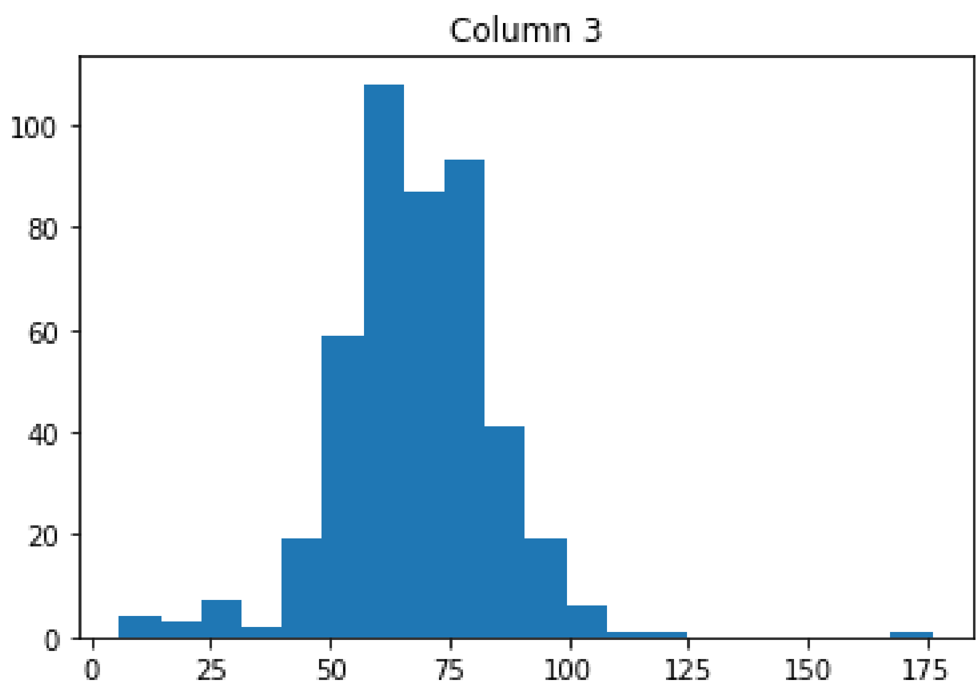
Here we pull the first four columns of our data set, and plot them.

```
In [9]: first_four = []
        i = 0
        for i in range(4):
            first_four.append(patient_data.iloc[:,i])

        for i in range(4):
            plt.hist(first_four[i], bins = 20)
            plt.title('Column {}'.format(i))
            plt.show()
```


Column 0
50
40
30
20
10
0
0
20
40
60
80

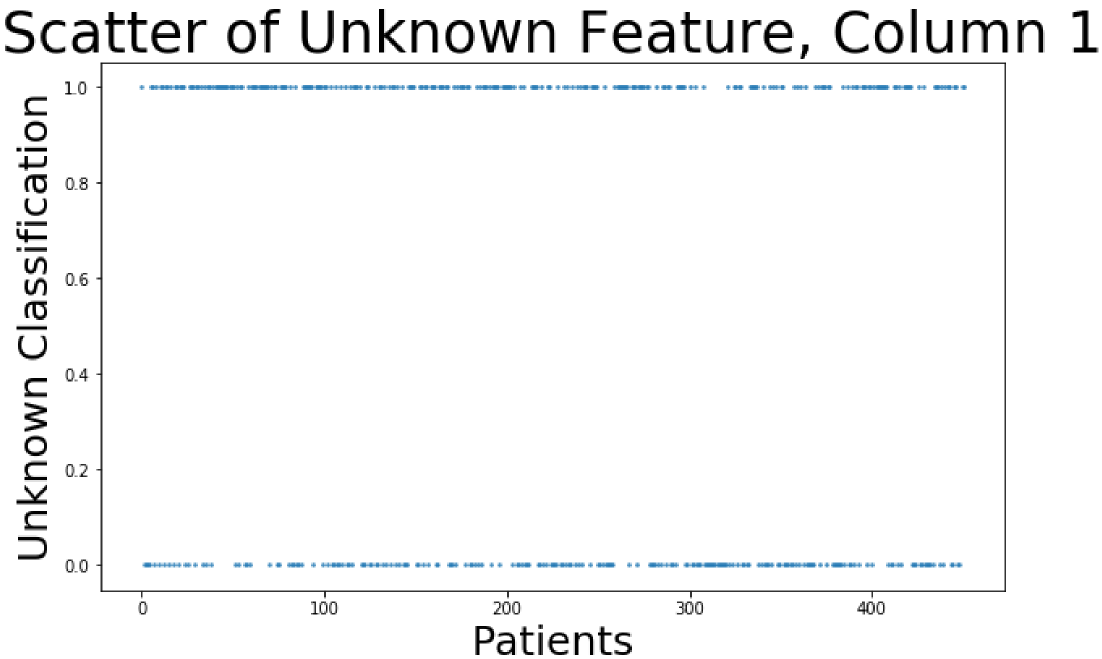

Column 1
250
200
150
100
50
0
0.0
0.2
0.4
0.6
0.8
1.0



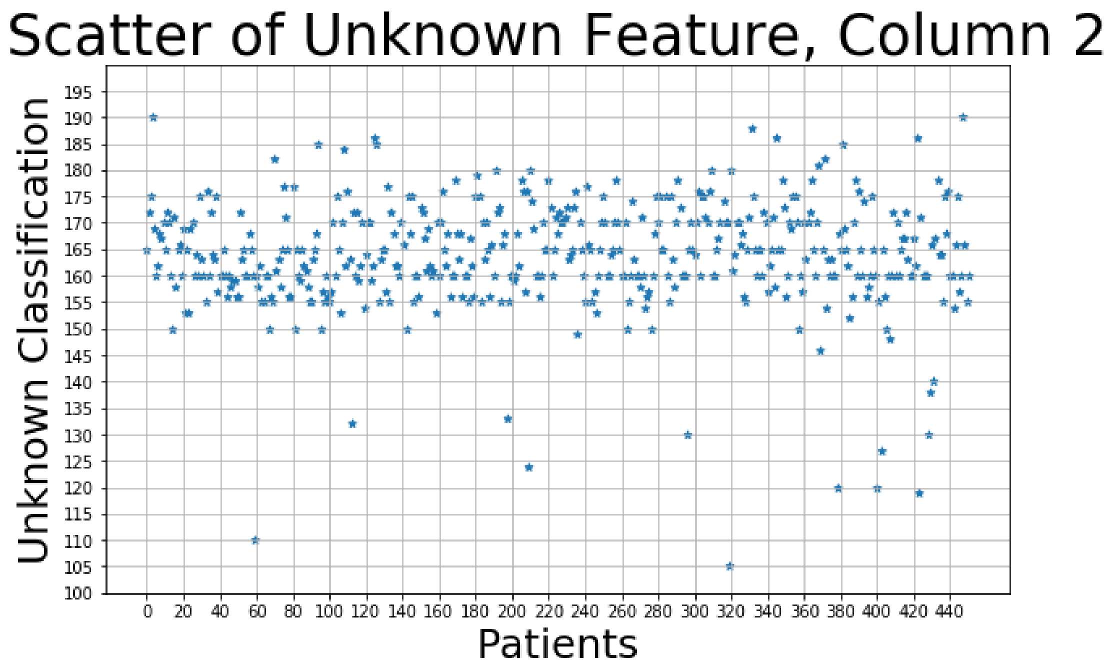


We plot scatters here to get a better idea of the data representation

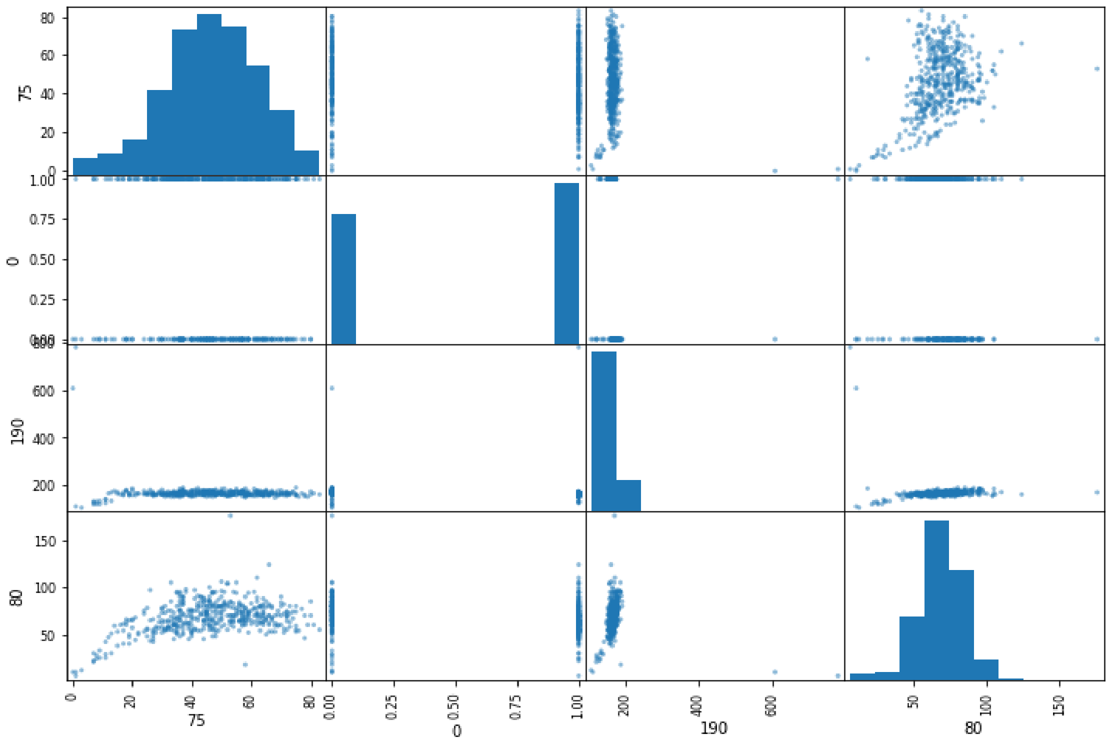
In [11]:
```
import numpy as np
x = np.arange(len(first_four[1]))
plt.figure(figsize=(10,6))
plt.scatter(x, first_four[1], s=3, alpha=0.7)
plt.xlabel('Patients', fontsize = '25')
plt.ylabel('Unknown Classification', fontsize = '25')
plt.title('Scatter of Unknown Feature, Column 1', fontsize='35')
plt.show()
```



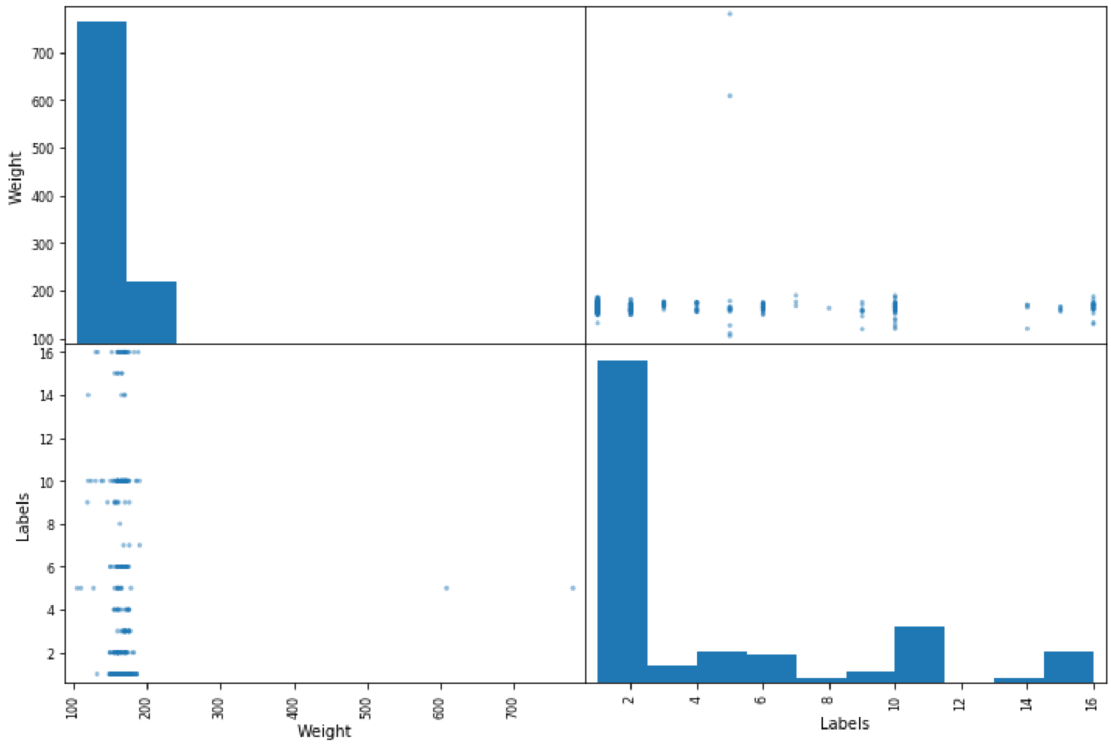
In [14]:
```
import numpy as np
x = np.arange(len(first_four[2]))
fig = plt.figure(figsize=(10,6))
ax = fig.gca()
ax.grid(linestyle='-', linewidth=0.7)
plt.scatter(x, first_four[2], s=25, alpha=1, marker='*')
plt.xlabel('Patients', fontsize = '25')
plt.ylim([100,200])
plt.yticks(np.arange(100, 200, 5.0))
plt.xticks(np.arange(0, 451, 20.0))
plt.ylabel('Unknown Classification', fontsize = '25')
plt.title('Scatter of Unknown Feature, Column 2', fontsize='35')
plt.show()
```




```
In [15]: from pandas.plotting import scatter_matrix
         columns = 4
         scatter_matrix(patient_data.iloc[:,:4], figsize=(12,8))
         plt.show

Out[15]: <function matplotlib.pyplot.show>
```




```
In [16]: df = pd.concat([patient_data['190'], patient_data['8']], axis=1, keys=['Weight', 'Label
         scatter_matrix(df, figsize=(12,8))

Out[16]: array([[<matplotlib.axes._subplots.AxesSubplot object at 0x7fc42d1d8940>,
                 <matplotlib.axes._subplots.AxesSubplot object at 0x7fc42d252e48>],
                [<matplotlib.axes._subplots.AxesSubplot object at 0x7fc42d0199b0>,
                 <matplotlib.axes._subplots.AxesSubplot object at 0x7fc42d02ae48>]],
               dtype=object)
```



5.3 Part 2 Conclusion

In the end, we conclude the columns are as follows: 0. Age

Since the data in column zero goes from to just past 80, we felt that age was a good guess for the data in this column. There were no outliers (nobody that is 200 years old), no negative values, and what looks like something close to a normal distribution of data.

1. Gender
   This guess is mostly based on the binary nature of the data, and the fact that it is pretty evenly distributed between 0 and 1. We could not think of another important evenly distributed binary data point.
2. Height in centimeters
   This column took a little bit longer to figure out, we had to plot it in a few different ways, before finally realizing what it might be. The clue was realizing, what do most people have that is between 160 and 180? Our first thought was weight in lbs., but we realized this wasn't quite right. Thinking that data may be metric, and that may be why we don't recognize it, a quick check of 160 cm -> feet and 180 cm -> feet confirmed our suspicions.
3. Income
   The only good reasoning on this is just looking at data for average salaries. Most people make between 40-80 thousand per year, with the average in Austin specifically being around $55,000.

5.4 Part 3

We calculate the mean of each column, and pass it to the pandas command to fill NaN values.

```
In [20]: patient_data.fillna(patient_data.mean())
         #assert(patient_data.isnull().values.any() == False), "Try again"
         if patient_data.isnull().values.any() == False:
             print("Success!")
         else:
             print("Failure!")
```

```
Success!
```

5.5 Part 4

There are various ways to map the data to the classification given. Investigating the columns with higher correlation to the outcomes could help pinpoint features that have more influence. For example, there are built in methods that can produce a matrix showing correlations between the columns. Checking which columns have greater (absolute value) correlations with the label column would help show the features that more strongly influence the labels.

A classifier such as naive bayes would likely work. Essentially you are looking for a mapping from relevant features to labels.

5.6 Extra

Various calls that we used to try to look at the data at different points

```
In [21]: patient_data.describe()
```

```
Out[21]:               75           0         190          80          91         193  \
         count  451.000000  451.000000  451.000000  451.000000  451.000000  451.000000
         mean    46.407982    0.552106  166.135255   68.144124   88.915743  155.068736
         std     16.429846    0.497830   37.194646   16.599841   15.381143   44.856534
         min      0.000000    0.000000  105.000000    6.000000   55.000000    0.000000
         25%     36.000000    0.000000  160.000000   59.000000   80.000000  142.000000
         50%     47.000000    1.000000  164.000000   68.000000   86.000000  157.000000
         75%     58.000000    1.000000  170.000000   78.500000   94.000000  174.500000
         max     83.000000    1.000000  780.000000  176.000000  188.000000  524.000000

                      371         174         121         -16     ...          0.0.38  \
         count  451.000000  451.000000  451.000000  451.000000    ...      451.000000
         mean   367.199557  169.940133   89.935698   33.787140    ...       -0.279601
         std     33.422017   35.672130   25.813912   45.421423    ...        0.549328
         min    232.000000  108.000000    0.000000 -172.000000    ...       -4.100000
         25%    350.000000  148.000000   79.000000    4.000000    ...       -0.450000
         50%    367.000000  162.000000   91.000000   40.000000    ...        0.000000
         75%    384.000000  179.000000  102.000000   66.000000    ...        0.000000
         max    509.000000  381.000000  205.000000  169.000000    ...        0.000000
```

```
                9.0         -0.9       0.0.39  0.0.40        0.9.3        2.9.1  \
count  451.000000  451.000000  451.000000   451.0  451.000000  451.000000
mean     9.048115   -1.458537    0.003991     0.0    0.513969    1.218625
std      3.476718    2.004481    0.050173     0.0    0.347441    1.425438
min      0.000000  -28.600000    0.000000     0.0   -0.800000   -6.000000
25%      6.600000   -2.100000    0.000000     0.0    0.400000    0.500000
50%      8.800000   -1.100000    0.000000     0.0    0.500000    1.300000
75%     11.200000    0.000000    0.000000     0.0    0.700000    2.100000
max     23.600000    0.000000    0.800000     0.0    2.400000    6.000000

             23.3         49.4           8
count  451.000000  451.000000  451.000000
mean    19.317295   29.429047    3.871397
std     13.517617   18.490566    4.407706
min    -44.200000  -38.600000    1.000000
25%     11.400000   17.500000    1.000000
50%     18.100000   27.900000    1.000000
75%     25.850000   41.050000    6.000000
max     88.800000  115.900000   16.000000

[8 rows x 275 columns]
```

In [22]:
```python
patient_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 451 entries, 0 to 450
Columns: 280 entries, 75 to 8
dtypes: float64(120), int64(155), object(5)
memory usage: 986.6+ KB
```

In [17]:
```python
patient_data.head()
```

Out[17]:
```
   75  0  190  80   91  193  371  174  121  -16 ... 0.0.38   9.0 -0.9 0.0.39  \
0  56  1  165  64   81  174  401  149   39   25 ...     0.0   8.5  0.0    0.0
1  54  0  172  95  138  163  386  185  102   96 ...     0.0   9.5 -2.4    0.0
2  55  0  175  94  100  202  380  179  143   28 ...     0.0  12.2 -2.2    0.0
3  75  0  190  80   88  181  360  177  103  -16 ...     0.0  13.1 -3.6    0.0
4  13  0  169  51  100  167  321  174   91  107 ...    -0.6  12.2 -2.8    0.0

  0.0.40  0.9.3  2.9.1  23.3  49.4   8
0    0.0    0.2    2.1  20.4  38.8   6
1    0.0    0.3    3.4  12.3  49.0  10
2    0.0    0.4    2.6  34.6  61.6   1
3    0.0   -0.1    3.9  25.4  62.8   7
4    0.0    0.9    2.2  13.5  31.1  14

[5 rows x 280 columns]
```