CSE 5524 HW Utkarsh Pratap Singh Jadon

Question1

Import necessary libraries ¶

In [1]:
```
import matplotlib.pyplot as plt
import matplotlib.image as mpimg
from skimage.color import rgb2gray
import cv2 as cv
import numpy as np
import math
from PIL import Image
import glob
import os
import skimage
from os import listdir
from os.path import join, isfile
from skimage import morphology
from skimage import measure,color
from skimage import io, data
from numpy.linalg import eig
```

Read and normalise input grayscale images

In [2]:
```
#Following section reads input Grayscale box images
boxImage1Gray = skimage.io.imread(fname="boxIm1.bmp")
boxImage2Gray = skimage.io.imread(fname="boxIm2.bmp")
boxImage3Gray = skimage.io.imread(fname="boxIm3.bmp")
boxImage4Gray = skimage.io.imread(fname="boxIm4.bmp")

#Following section plots all 4 grayscale images(Commented out as not re
# plt.subplot(2,2,1)
# plt.imshow(boxImage1Gray, cmap="gray")
# plt.subplot(2,2,2)
# plt.imshow(boxImage2Gray, cmap="gray")
# plt.subplot(2,2,3)
# plt.imshow(boxImage3Gray, cmap="gray")
# plt.subplot(2,2,4)
# plt.imshow(boxImage4Gray, cmap="gray")

#Normalizing input grayscale images to get range 0-1
boxImage1Normalised = boxImage1Gray / 255
boxImage2Normalised = boxImage2Gray / 255
boxImage3Normalised = boxImage3Gray / 255
boxImage4Normalised = boxImage4Gray / 255
```

Create function to compute 7 similitude moment shape descriptors

In [3]:

```
def similitudeMoments(inputImage):

    a,b = inputImage.shape
    x=0
    y=0
    m10 = 0
    m01 = 0
    m00 = 0
    centroidX = 0
    centroidY = 0
    for x in range(a):
        for y in range(b):
                m10 += (x**1)*(y**0)*inputImage[x,y]
                m01 += (x**0)*(y**1)*inputImage[x,y]
                m00 += (x**0)*(y**0)*inputImage[x,y]

    centroidX = (m10) / (m00)
    centroidY = (m01) / (m00)

    # For similitudeMoment1, p=0, q=2
    # For similitudeMoment2, p=0, q=3
    # For similitudeMoment3, p=1, q=1
    # For similitudeMoment4, p=1, q=2
    # For similitudeMoment5, p=2, q=0
    # For similitudeMoment6, p=2, q=1
    # For similitudeMoment7, p=3, q=0

    N = np.array([[0,2],[0,3],[1,1],[1,2],[2,0],[2,1],[3,0]])
    numerator1 = 0
    denominator1 = 0
    numerator2 = 0
    denominator2 = 0
    numerator3 = 0
    denominator3 = 0
    numerator4 = 0
    denominator4 = 0
    numerator5 = 0
    denominator5 = 0
    numerator6 = 0
    denominator6 = 0
    numerator7 = 0
    denominator7 = 0
    #print(N)
    for x in range(a):
        for y in range(b):
                numerator1 += ((x - centroidX)**N[0,0]) * ((y - centroi
                denominator1 = (m00)**(((N[0,0] + N[0,1]) / 2) + 1)

                numerator2 += ((x - centroidX)**N[1,0]) * ((y - centroi
                denominator2 = (m00)**(((N[1,0] + N[1,1] / 2)) + 1)

                numerator3 += ((x - centroidX)**N[2,0]) * ((y - centroi
                denominator3 = (m00)**(((N[2,0] + N[2,1]) / 2) + 1)

                numerator4 += ((x - centroidX)**N[3,0]) * ((y - centroi
                denominator4 = (m00)**(((N[3,0] + N[3,1]) / 2) + 1)
```

```
57
58                  numerator5 += ((x - centroidX)**N[4,0]) * ((y - centroi
59                  denominator5 = (m00)**(((N[4,0] + N[4,1]) / 2) + 1)
60
61                  numerator6 += ((x - centroidX)**N[5,0]) * ((y - centroi
62                  denominator6 = (m00)**(((N[5,0] + N[5,1]) / 2) + 1)
63
64                  numerator7 += ((x - centroidX)**N[6,0]) * ((y - centroi
65                  denominator7 = (m00)**(((N[6,0] + N[6,1]) / 2) + 1)
66
67
68      similitudeMoment1 = numerator1 / denominator1
69      similitudeMoment2 = numerator2 / denominator2
70      similitudeMoment3 = numerator3 / denominator3
71      similitudeMoment4 = numerator4 / denominator4
72      similitudeMoment5 = numerator5 / denominator5
73      similitudeMoment6 = numerator6 / denominator6
74      similitudeMoment7 = numerator7 / denominator7
75
76      Nvals = [similitudeMoment1,similitudeMoment2,similitudeMoment3,simi
77      return Nvals
78
79
```

Computing 7 similitude moment shape descriptors for all 4 images

In [4]:

```
1 print(similitudeMoments(boxImage1Normalised))         # 7 Similitude mom
2 print(similitudeMoments(boxImage2Normalised))         # 7 Similitude mom
3 print(similitudeMoments(boxImage3Normalised))         # 7 Similitude mom
4 print(similitudeMoments(boxImage4Normalised))         # 7 Similitude mom
```

```
[0.1646090534979424, 0.0, 0.0, 0.0, 0.04215597711532671, 0.0, 0.0]
[0.1646090534979424, 0.0, 0.0, 0.0, 0.04215597711532671, 0.0, 0.0]
[0.1641025641025641, 0.0, 0.0, 0.0, 0.04226884226884227, 0.0, 0.0]
[0.04215597711532671, 0.0, 0.0, 0.0, 0.1646090534979424, 0.0, 0.0]
```

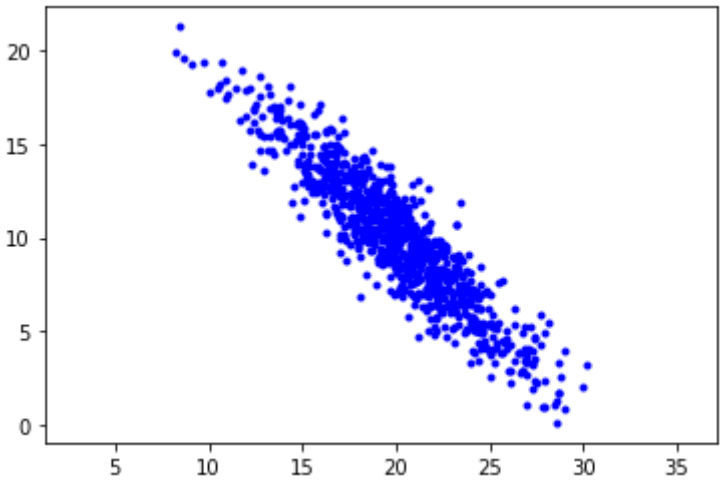
Discussion

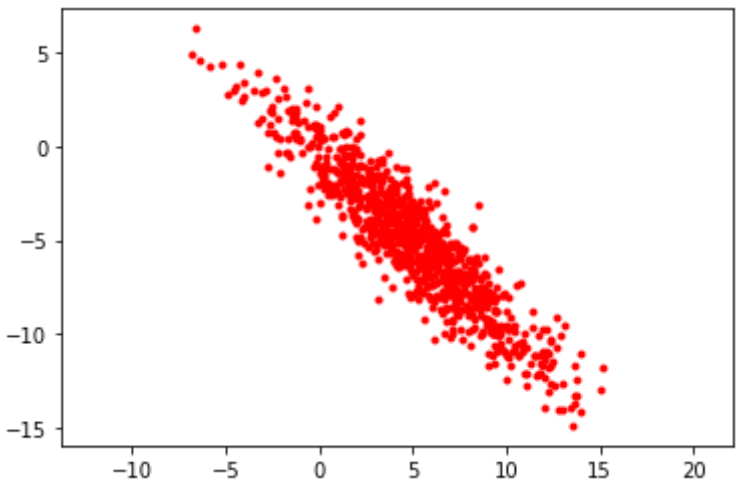
We see that the change in moments across image is minute. Similitude moments are supposed to be same for a particular class of images and are invariant to size, position, and orienation. Although, this holds true assuming the images are continuous. But in reality, images are discrete and have some noise values, which contributes to this minor change amongst moment values for four box images.

Some of the moments are zero because they may not have any contribution towards making the image unique.

Question 2

In [5]:
```
#Load data from 'eigendata.txt' file and store as numpy array in X
X = np.loadtxt("eigdata.txt")

#Plot first column vs first row as plot 1
plt.subplot(1,1,1)
plt.plot(X[:,0],X[:,1],'b.')
plt.axis('equal')
plt.show()

#Plot mean-subtract data as plot 2
m = np.mean(X)
a,b = X.shape
Y = X - np.ones((a,1))*m
plt.subplot(1,1,1)
plt.plot(Y[:,0],Y[:,1],'r.')
plt.axis('equal')
plt.show()
```





Discussion

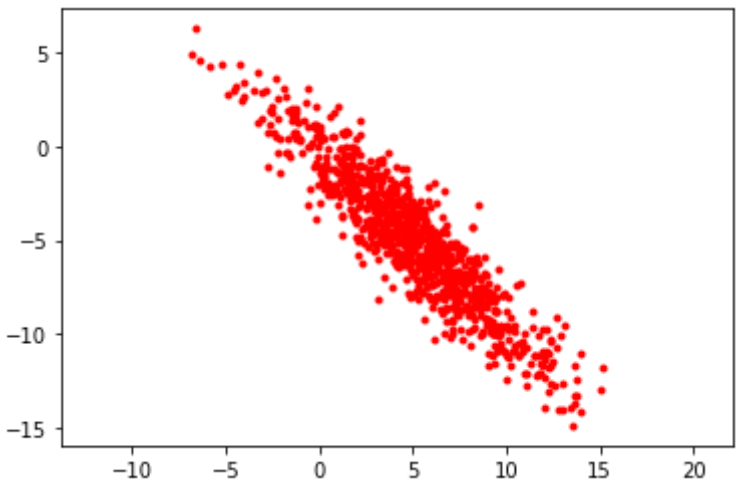
Successfully able to read data from given text file, store the values in X, plot the data present inside X and plot mean shifted data Y using relevant python functions

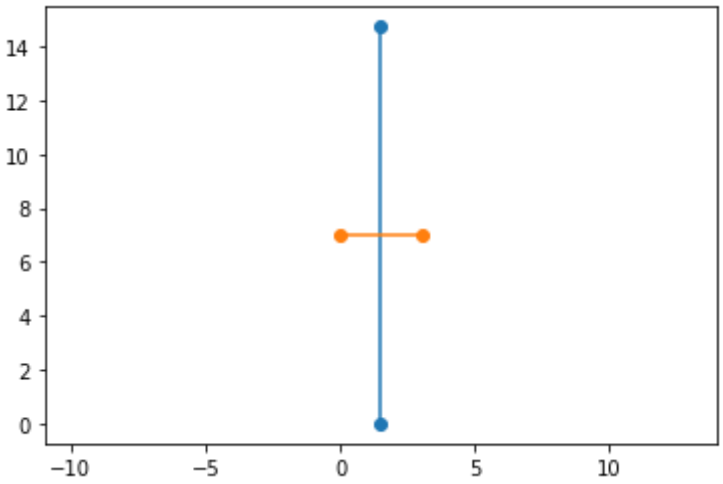
Question 3

In [6]:

```
import matplotlib

K = np.cov(Y.transpose(), bias=True)    #Generate covariance matrix for
K_inv = np.linalg.inv(K)

V,U=eig(K)                  #eig() function returns Eigen Values (V) and

xm = np.mean((Y[:,0]))
ym = np.mean((Y[:,1]))    #Computes x and y coordinates of mean of Y

C = 9

axis1 = math.sqrt(C) * (math.sqrt(V.max()))
axis2 = math.sqrt(C) * (math.sqrt(V.min()))
print("Lenght of axis 1 and axis 2 are: ")
print(axis1,axis2)

plt.subplot(1,1,1)
plt.plot(Y[:,0],Y[:,1],'r.')
plt.axis('equal')
plt.show()


x1, y1 = [(axis2)/2,(axis2)/2], [0,axis1]
x2, y2 = [0,axis2], [(axis1)//2,(axis1)//2]

plt.plot(x1, y1, x2, y2, marker = 'o')
plt.axis('equal')
plt.show()

```

```
Lenght of axis 1 and axis 2 are:
14.731906093236422 3.0197483581527385
```



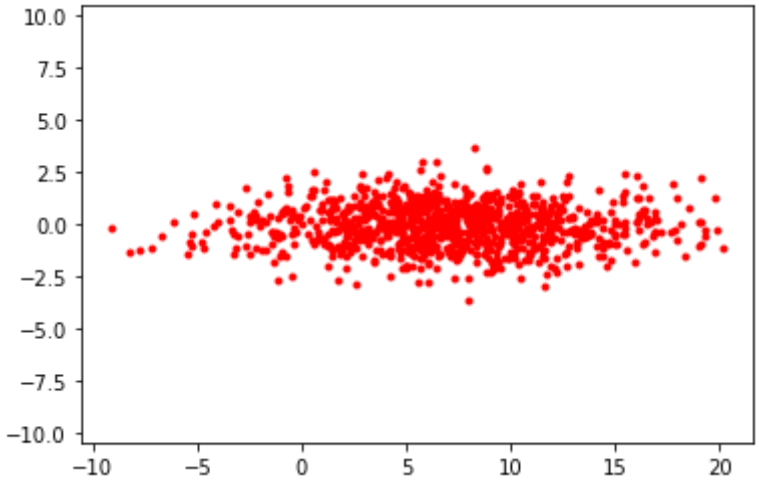


Discussion

I used covariance matrix (K) to generate eigen values (V) and eigen vectors (U) of the given mean shifted data (Y). Since covariance matrix was used, the lamda obtained from V is enough to calculate the length of axis ((C*lamda)^0.5). If I had taken inverse covariance matrix (K^-1), I would have to invert the lamda to get axis lenghth (((C/lamda)^0.5). Since there are #3 standard deviations, we take C=9 to calculate the axis length. After getting the lengths (14.731,3.019), I drew mutually perpendicular lines, as shown above, that acts as 2-D Gaussian ellipse axis.

Question 4

In [7]:
```
rotatedData = np.zeros((1000,2))                                    #Create an emp
i = 0
for dataValue in Y:                                                 #Creating a lo
    rotatedData[i] = np.dot(U.transpose(),dataValue)
    i+=1
plt.plot(rotatedData[:,0], rotatedData[:,1], 'r.')
plt.axis('equal')
plt.show()

```



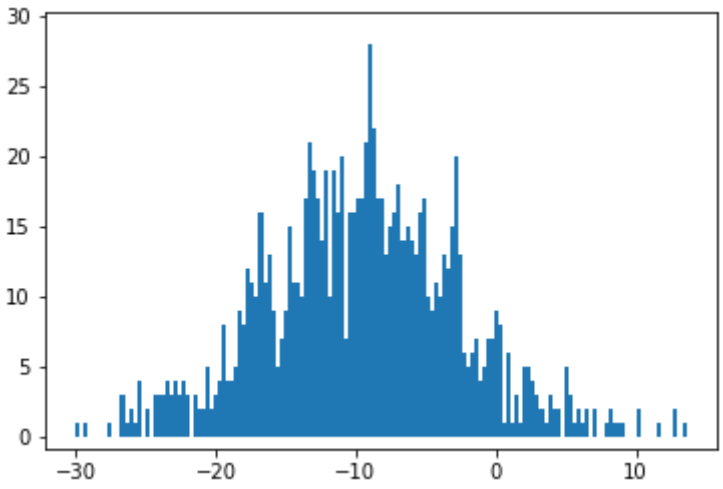
Discussion

The transpose of eigen vector matrix acts as a rotation matrix. I applied dot product between transpose of eigen vector and each data point in Y which gives us uncorrelated/rotated data

Question 5

In [8]:
```
projectedData = np.zeros((1000,1))
i = 0
for dataValue in Y:
    projectedData[i] = np.dot(Y[0],dataValue)
    i += 1
plt.hist(projectedData,bins=150)
plt.axis('equal')
```

Out[8]: (-32.17857863012391, 15.73148498523162, 0.0, 29.4)



Discussion

I projected the values from mean shifted data (Y) onto the eigen vector corresponding the largest eigen value of covariance matrix (K). Plotted histogram looks like a 1-D Gaussian.