es21btech11025-assign5

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EP4130: Data Science Analysis

Assignment 5

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All imports

[21]:
```
import numpy as np
import matplotlib.pyplot as plt
import scipy as sp
import pandas as pd
from scipy import stats
```

Question 1

Take the dataset from https://astrostatistics.psu.edu/datasets/asteroid_dens.dat, and apply the Shapiro-Wilk test to the densities and the log of the densities. From the p-values, which of these is closer to a Gaussian? Verify this by plotting the histograms of both density and logarithms of the densities and overlay the best-fit Gaussian Distribution.

[22]:
```
data = np.array([[1, 2.12, 0.04], [2, 2.71, 0.11], [4, 3.44, 0.12],
[10, 2.76, 1.20], [11, 2.72, 0.12], [15, 0.96, 0.30],
[16, 2.00, 0.60], [20, 3.26, 0.60], [22, 2.50, 0.30],
[45, 1.20, 0.40], [87, 1.62, 0.30], [90, 1.30, 0.0],
[121, 1.96, 0.34], [243, 2.60, 0.50], [253, 1.30, 0.20],
[433, 2.67, 0.03], [704, 4.40, 2.10], [762, 1.80, 0.80],
[804, 4.90, 3.90], [1999, 2.39, 0.90], [2000, 1.62, 1.05],
[2000, 1.47, 0.95], [854, 0.89, 0.13], [1089, 2.52, 0.30],
[1313, 1.21, 0.25], [4492, 0.90, 0.10], [617, 0.80, 0.15]])

density_values = data[: , 1]
```

[23]:
```
statistics1, pvalue1 = stats.shapiro(density_values)
mu1, sigma1 = stats.norm.fit(density_values)
```

[24]:
```
print('shapiro-walk test -> density values :','w =', statistics1, 'p_val =',␣
↪pvalue1 )
```

```
shapiro-walk test -> density values : w = 0.9246721863746643 p_val =
0.051220282912254333
```

[25]:
```python
statistics2, pvalue2= stats.shapiro(np.log(density_values))
mu2, sigma2 = stats.norm.fit(np.log(density_values))
```

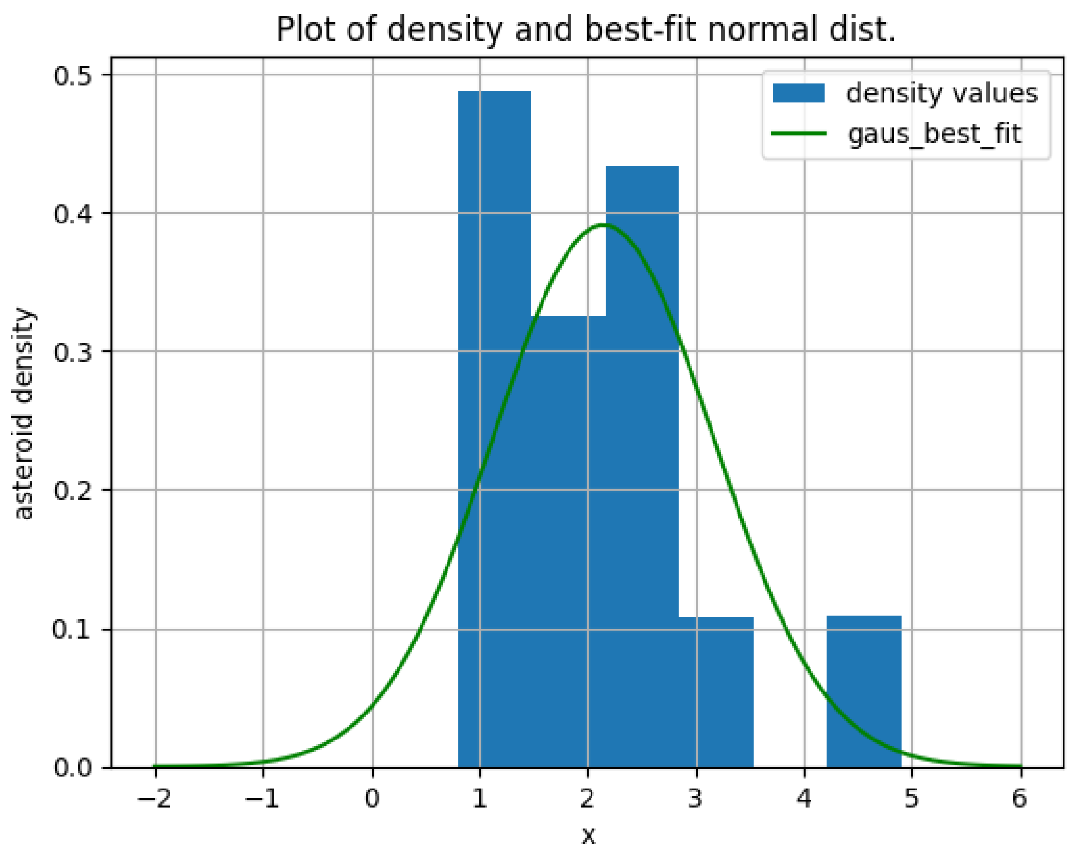
[26]:
```python
print('shapiro-walk test --> natural_log density values :','w =', statistics2,␣
↪'p_val =', pvalue2 )
```

```
shapiro-walk test --> natural_log density values : w = 0.9686306715011597 p_val
= 0.5660613775253296
```

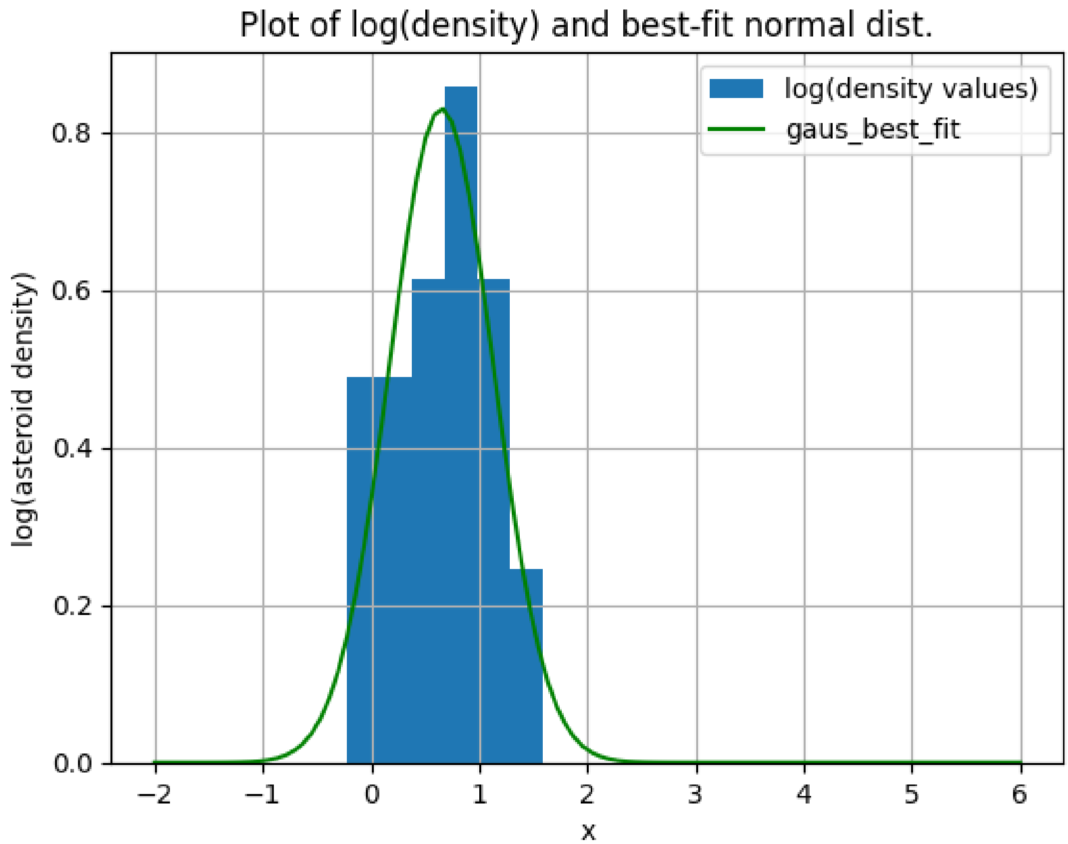
Ploting

[27]:
```python
x = np.linspace(-2 , 6 , 100)
pdf1 = stats.norm.pdf(x, mu1, sigma1)
pdf2 = stats.norm.pdf(x, mu2, sigma2)
```

[28]:
```python
# plot 1
plt.figure()
plt.hist(density_values, density = True, bins='auto', alpha = 1, label='density␣
↪values')
plt.plot(x, pdf1, label='gaus_best_fit', color='g')
plt.title('Plot of density and best-fit normal dist.')
plt.xlabel('x')
plt.ylabel('asteroid density')
plt.legend(loc='best')
plt.grid()
plt.show()
```



[29]:
```python
# plot 2
plt.figure()
plt.hist(np.log(density_values), density = True, bins='auto', alpha=1,␣
 ↪label='log(density values)')
plt.plot(x, pdf2, label='gaus_best_fit', color='g')
plt.title('Plot of log(density) and best-fit normal dist.')
plt.xlabel('x')
plt.ylabel('log(asteroid density)')
plt.legend(loc='best')
plt.grid()
plt.show()
```



Clearly, According to the p-values, the logarithms of the densities are more likely to belong to normal distribution.

Question 2

Download the Hipparcos star catalog from http://iith.ac.in/~shantanud/HIP_star.dat. Detailed explanation of the columns in this dataset can be found in http://astrostatistics.psu.edu/datasets/HIP_star.html under "Dataset". Calculate using two-sample t-test whether the color (B-V) of the Hyades stars differs from the non-Hyades ones. The Hyades stars have Right Ascension between 50∘ and 100∘ , declinations between 0 and 25∘ , proper motion in RA between 90 and 130 mas/year, proper motion in DEC between -60 and -10 mas/year. Any other star which does not satisfy any of the above conditions is considered a non-Hyades star.

[30]:
```
data = pd.read_csv("HIP_star.dat.csv" , sep = " ")
data
```

[30]:
```
          HIP   Vmag         RA         DE    Plx    pmRA    pmDE  e_Plx
0           2   9.27   0.003797 -19.498837  21.90  181.21   -0.93   3.10  \
1          38   8.65   0.111047 -79.061831  23.84  162.30  -62.40   0.78
```

```
2          47  10.78    0.135192 -56.835248  24.45  -44.21 -145.90   1.97
3          54  10.57    0.151656  17.968956  20.97  367.14  -19.49   1.71
4          74   9.93    0.221873  35.752722  24.22  157.73  -40.31   1.36
…         …    …           …          …        …       …       …        …
2714   118207   8.38  359.662248  77.262113  23.37   18.87  -44.04   0.70
2715   118213   8.28  359.690763  31.939823  20.33   76.66 -134.59   0.94
2716   118251   8.16  359.778318  41.170547  22.91   82.20    3.56   0.82
2717   118254   7.72  359.787381  41.201736  22.19   80.21    4.40   0.80
2718   118311  11.85  359.954685 -38.252603  24.63  337.76 -112.81   2.96

        B-V
0     0.999
1     0.778
2     1.150
3     1.030
4     1.068
…       …
2714  0.651
2715  0.734
2716  0.652
2717  0.563
2718  1.391

[2719 rows x 9 columns]
```

[31]:

```python
hyades = data[(data['RA'] >= 50) & (data['RA'] <= 100) & (data['DE'] >= 0) &␣
↪(data['DE'] <= 25) & \
    (data['pmRA'] >= 90) & (data['pmRA'] <= 130) & (data['pmDE'] >= -60) &␣
↪(data['pmDE'] <= -10)]
hyades
```

[31]:

```
       HIP   Vmag         RA         DE    Plx    pmRA   pmDE  e_Plx    B-V
532  18735   5.89  60.202858  18.194069  21.99  129.49 -28.27   0.81  0.319
536  18946  10.12  60.912353  19.455094  23.07  119.02 -34.19   2.12  1.095
540  19148   7.85  61.566899  15.698168  21.41  118.53 -19.59   1.47  0.593
542  19207  10.49  61.754794  15.335078  23.57  122.63 -18.96   2.26  1.180
544  19261   6.02  61.924609  15.162843  21.27  127.06 -22.75   1.03  0.397
..     …      …        …          …       …      …      …      …      …
679  21762   9.47  70.105891  16.513734  23.65   91.94 -30.69   2.53  1.096
688  22044   5.39  71.107373  11.146169  20.73   98.87 -13.47   0.88  0.251
694  22224   9.60  71.705813  17.748406  24.11   96.93 -33.93   1.72  0.967
704  22496   7.10  72.599450  17.202738  22.96  102.78 -29.70   1.17  0.563
709  22607   6.30  72.958017  13.655194  23.91  106.84 -16.00   1.04  0.502

[93 rows x 9 columns]
```

[32]:
```
non_hyades = data[~data.index.isin(hyades.index)]
non_hyades
```

[32]:
```
         HIP   Vmag          RA         DE    Plx    pmRA    pmDE  e_Plx  \
0          2   9.27    0.003797 -19.498837  21.90  181.21   -0.93   3.10
1         38   8.65    0.111047 -79.061831  23.84  162.30  -62.40   0.78
2         47  10.78    0.135192 -56.835248  24.45  -44.21 -145.90   1.97
3         54  10.57    0.151656  17.968956  20.97  367.14  -19.49   1.71
4         74   9.93    0.221873  35.752722  24.22  157.73  -40.31   1.36
…        …     …          …          …      …       …       …
2714  118207   8.38  359.662248  77.262113  23.37   18.87  -44.04   0.70
2715  118213   8.28  359.690763  31.939823  20.33   76.66 -134.59   0.94
2716  118251   8.16  359.778318  41.170547  22.91   82.20    3.56   0.82
2717  118254   7.72  359.787381  41.201736  22.19   80.21    4.40   0.80
2718  118311  11.85  359.954685 -38.252603  24.63  337.76 -112.81   2.96

        B-V
0     0.999
1     0.778
2     1.150
3     1.030
4     1.068
…       …
2714  0.651
2715  0.734
2716  0.652
2717  0.563
2718  1.391

[2626 rows x 9 columns]
```

[33]:
```
hyad_colrs = np.array(hyades['B-V'].tolist())
non_hyades_colors = np.array(non_hyades['B-V'].tolist())
```

[34]:
```
print('The p-value for the null hypothesis that the color of Haydes stars and␣
↪non-Haydes stars have identical means is {}'.\
   format(sp.stats.ttest_ind(hyad_colrs , non_hyades_colors)[1]))
```

```
The p-value for the null hypothesis that the color of Haydes stars and non-
Haydes stars have identical means is 0.00011582222192442334
```

Since the p-value is very small, the colors of the two kinds of stars are not very similar.

Question 3

The T90 distribution for Beppo-Sax T90 data can be found at http://www.iith.ac.in/~shantanud/beppoSax.txt. Apply GMM to log10 of T90 data and find the optimum number of components using AIC and BIC by plotting BIC as a function of number of componts (Hint: Look at the source code for astroML figure 6.6)

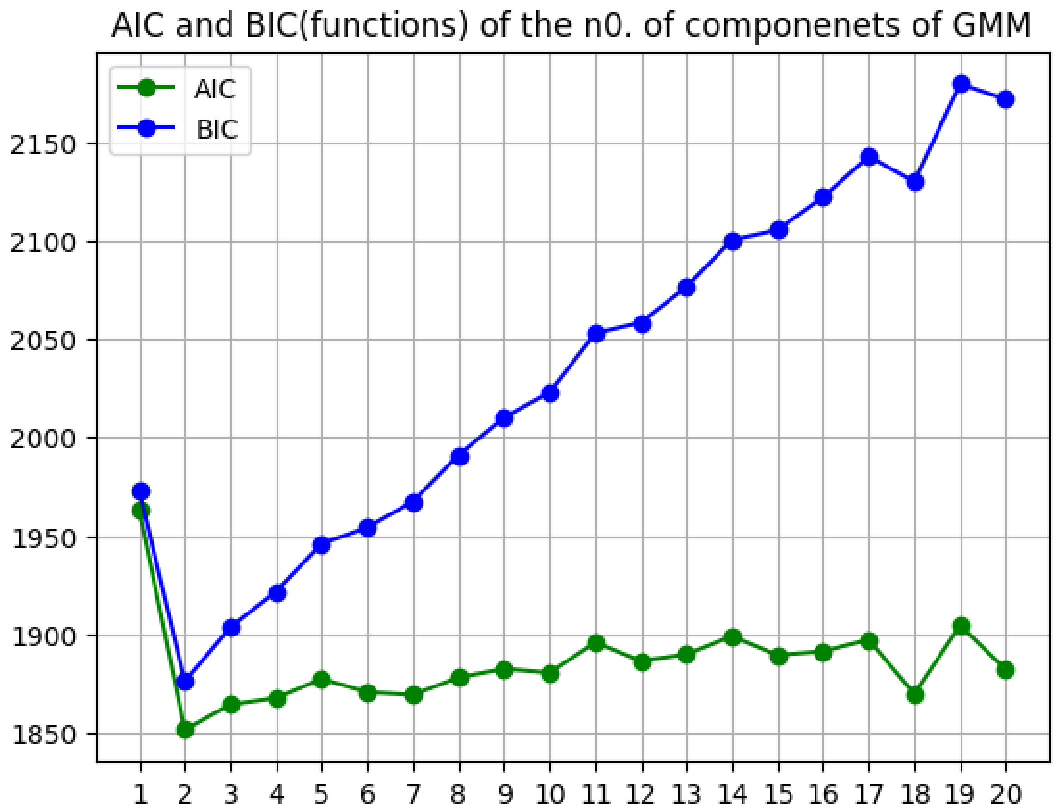
[35]:
```
from sklearn.mixture import GaussianMixture
data = np.genfromtxt("bappoSax.csv")
```

[36]:
```
log_data = np.log10(data)
log_data = log_data.reshape(-1 , 1)
```

[37]:
```
n_components = np.arange(1 , 21)
models = []
AIC = []
BIC = []
for n in n_components:
    models.append(GaussianMixture(n_components = n , max_iter = 1000).
 ↪fit(log_data))
    AIC.append(models[-1].aic(log_data))
    BIC.append(models[-1].bic(log_data))
```

Plotting AIC and BIC

[40]:
```
plt.plot(n_components , AIC , 'go-' ,label = 'AIC')
plt.plot(n_components , BIC , 'bo-' ,label = 'BIC')
plt.grid()
plt.xticks(n_components)
plt.title("AIC and BIC(functions) of the n0. of componenets of GMM")
plt.legend()
plt.show()
```



[39]:
```
print("The optimal number of components is 2.")
```

```
The optimal number of components is 2.
```

#Optimum number of models = 2 ,as the BIC value is lowest when number of models are 2.