

ReadMe

- 1.) Read the whole file.
- 2.) Total 3 types of distributions were used to model data distribution within the dataset. 1. Histograms, 2. Uni-axial Gaussian Model, and 3. Uni-axial Gaussian Mixture models.
- 3.) File 'Results' has all parameters values with distribution graphs.
- 4.) Datasets used. 1. Iris Data set, 2. Indian Liver Patient Dataset
- 5.) Note: My major is civil engineering and this is the first time I used python. So files are hard coded specifically, categorical distribution files. Gaussian model and Gaussian mixture model files can be used for other datasets by changing the input variables as explained below.

Categorical Files: File name starts with 'Cat_'.

Step 1: Import Libraries and read excel file. Save column data in variables.

```
1 import numpy as np
2 import pandas as pd
3 import matplotlib.pyplot as plt
4
5 data = pd.read_excel('Indian Liver Patient Dataset.xlsx')
6 data = data.to_numpy()
7 classdata = data[:,10]
```

Step 2: Create variables corresponding to data type. Loop through all data and count the no. of occurrence of that data type.

```
# Create variables corresponding to class type in data
a = 0 # for Male
b = 0 # for Female

for x in classdata:
    if x == 'Male':
        a = a+1
    else:
        b = b+1
```

Step 3: Sum the total no. of data/events occurrences. Find probability by dividing data type to total no. of data/event occurrence.

```
# Total weight to find probability/Normalization
sum = a + b

# Probability of getting Male, Female
pa = a/sum #Male
pb = b/sum #Female
```

Step 4: Print the probability of data type occurrence and plot the data to visualize distributions.

```
# Print the probability of data type
print('Probability of Male =', pa)
print('Probability of Female =', pb)

# Plotting categorical Data to visualize
xaxis = ['Male','Female']
yaxis = [pa,pb]
plt.title('Categorical Distribution of Data')
plt.xlabel('Gender Type')
plt.ylabel('Probability')
plt.bar(xaxis,yaxis)
plt.show()
```

→ **Gaussian Files: File name 'Gaussian.py'**

Step 1: Import Libraries and read excel file. Save column data in variable. To run this file enter excel file name containing data in red rectangle box. Type the no. of column in green box to find Gaussian distribution of that data.

```
1 import numpy as np
2 import pandas as pd
3 import matplotlib.pyplot as plt
4
5 data = pd.read_excel('Indian Liver Patient Dataset.xlsx')
6 data = data.to_numpy()
7 sepal_length = data[:,9]
```

Step 2: Create bins of the data to display the frequency, find out mean and standard deviation of the data and print these parameters.

```
10 # bins and histogram
11 count, bins, ignored = plt.hist(sepal_length,15, density=True)
12 print(count)
13 print(bins)
14
15 #Calculate mean and std
16 mean = np.mean(sepal_length)
17 sd = np.std(sepal_length)
18 print('Mean of this data =',mean)
19 print('Standard Deviation of this data =',sd)
```

Step 3: Create function to find out the Gaussian probability density of the data point and apply function to data.

```
19 # Creating a Function
20 def normal_dist(bins, mean, sd):
21     #prob_density = (np.pi*sd) * np.exp(-0.5*((data_age-mean)/sd)**2)
22     prob_density = 1/(sd*np.sqrt(2*np.pi)) * np.exp(-(bins.astype(float) - mean)**2/(2*sd**2))
23     return prob_density
24
25 #Apply function to data.
26 pdf = normal_dist(bins,mean,sd)
```

Step 4: Plot the results.

```
28 #Plotting the results
29 plt.plot(bins,pdf, color = 'red')
30 plt.xlabel(xlabel)
31 plt.ylabel(['Probability Density'])
32 plt.title(Title)
33 plt.show()
```

→ **Gaussian Mixture Files:** File name 'GaussianMixture.py' (Code gives different parameters each time)

Step 1: Import Libraries and read excel file. Save column data in variable. To run this file enter excel file name containing data in red rectangle box. Type the no. of column in green box to find Gaussian distribution of that data.

```
1 import numpy as np
2 import pandas as pd
3 import math
4 import matplotlib.pyplot as plt
5
6 # Read the data
7 data = pd.read_excel('iris.xlsx')
8 data = data.to_numpy()
9 sepal_length = data[:,2]
```

Step 2: Input no. of classes, and iteration no.

```
11 # Input: no. of classes, no. of iterations
12 k = 2
13 iter = 150
```

Step 3: Divide the data into bins

```
15 # Calculate Mean and Standard Deviation
16 count, bins, ignored = plt.hist(sepal_length, 20, density=True)
17
```

Step 4: Initialize some variables in E-step and M-step

```

18 # Create Pi, mu, and sigma
19 mu = np.random.randint(5, size=(k,1))
20 sigma = np.random.randint(5, size=(k,1))
21 pi = np.random.dirichlet(np.ones(k),size=1).transpose()
22
23 Gamma = np.zeros((len(bins),k))
24 pdf = np.zeros((len(bins),k))
25 xGamma = np.zeros((len(bins),k))
26 xsigma = np.zeros((len(bins),k))
27

```

$\mu = \begin{bmatrix} \quad \end{bmatrix}_{k \times 1}$
 $k = \text{no. of classes}$
 $1 \rightarrow \text{one variable}$

$\sigma = \begin{bmatrix} \quad \end{bmatrix}_{k \times 1}$
 $k = \text{no. of classes}$
 $1 \rightarrow \text{one variable}$

$\pi = \begin{bmatrix} \quad \end{bmatrix}_{k \times 1}$
 $k = \text{no. of classes}$
 $1 \rightarrow \text{one variable}$

2. **E step.** Evaluate the responsibilities using the current parameter values

$$\gamma(z_{nk}) = \frac{\pi_k \mathcal{N}(\mathbf{x}_n | \boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k)}{\sum_{j=1}^K \pi_j \mathcal{N}(\mathbf{x}_n | \boldsymbol{\mu}_j, \boldsymbol{\Sigma}_j)} \quad (9.23)$$

$\text{Gamma} = \begin{bmatrix} \quad \end{bmatrix}_{n \times k}$
 $n \rightarrow \text{no of data points}$
 $k \rightarrow \text{no of classes}$

$\text{PDF} = \begin{bmatrix} \quad \end{bmatrix}_{n \times k}$
 $n \rightarrow \text{no of data points}$
 $k \rightarrow \text{no of classes}$
 \downarrow
 Probability
 Density
 Function

Step 4: Create function to find out the Gaussian probability density of the data point.

```
28 # Creating a Function for calculating gaussian distribution probability
29 v def normal_dist(data, mean, sd):
30     prob_density = 1/(sd*np.sqrt(2*np.pi)) * np.exp(-(data.astype(float) - mean)**2/(2*sd**2))
31     return prob_density
32
```

Step 5: E-Step

```
33 # E STEP CALCULATION
34 v def estep(mu,sigma,pi):
35     # Calculate PDF
36     v for x in range(k):
37         pdf[:,x] = normal_dist(bins,mu[x],sigma[x])
38
39     # Calculate pipdf2
40     pipdf2 = pdf.copy()
41     v for x in range(k):
42         pipdf2[:,x] = pi[x] * pipdf2[:,x]
43     pipdf2 = pipdf2.sum(axis=1)
44
45     # Calculate pipdf
46     pipdf = pdf.copy()
47     v for x in range(k):
48         pipdf[:,x] = pi[x] * pdf[:,x]
49
50     # Calculate Gamma
51     v for x in range(k):
52         Gamma[:,x] = pipdf[:,x] / pipdf2[:]
53
54     return Gamma
```

$$\gamma(z_{nk}) = \frac{\pi_k \mathcal{N}(\mathbf{x}_n | \boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k)}{\sum_{j=1}^K \pi_j \mathcal{N}(\mathbf{x}_n | \boldsymbol{\mu}_j, \boldsymbol{\Sigma}_j)}.$$

Step 5: M-Step

```
56 # M STEP CALCULATION
57 def mstep(responsibility):
58     xGamma = np.zeros((len(bins),k))
59     xsigma = np.zeros((len(bins),k))
60     # Calculate NK
61     NK = Gamma.sum(axis=0)
62
63     # Calculate new mu
64     for x in range(k):
65         xGamma[:,x] = bins * Gamma[:,x]
66     xGamma = xGamma.sum(axis=0)
67     munew = xGamma / NK
68
69     # Calculate Sigma
70     for x in range(k):
71         xsigma[:,x] = Gamma[:,x] * (bins-munew[x])*(bins-munew[x])
72     xsigma = xsigma.sum(axis=0)
73     sigmanew = np.sqrt(xsigma / NK)
74
75     # Calculate pinew
76     pinew = NK / len(bins)
77
78     return munew,sigmanew,pinew
```

3. **M step.** Re-estimate the parameters using the current responsibilities

$$\mu_k^{\text{new}} = \frac{1}{N_k} \sum_{n=1}^N \gamma(z_{nk}) \mathbf{x}_n \quad (9.24)$$

$$\Sigma_k^{\text{new}} = \frac{1}{N_k} \sum_{n=1}^N \gamma(z_{nk}) (\mathbf{x}_n - \mu_k^{\text{new}}) (\mathbf{x}_n - \mu_k^{\text{new}})^T \quad (9.25)$$

$$\pi_k^{\text{new}} = \frac{N_k}{N} \quad (9.26)$$

where

$$N_k = \sum_{n=1}^N \gamma(z_{nk}). \quad (9.27)$$

Step 6: Iterations. (input value)

```
80     for x in range(iter):
81         responsibility = estep(mu,sigma,pi)
82         mu,sigma,pi = mstep(responsibility)
83
```

Step 7: Calculate final PDFs, print parameters, and plot the distribution. PDF need to be multiplied by weightages.

```
84     pdf1 = normal_dist(bins,mu[0],math.sqrt(sigma[0]))
85     pdf2 = normal_dist(bins,mu[1],math.sqrt(sigma[1]))
86
87     print('mu =', mu)
88     print('sigma =', sigma)
89     print('pi =', pi)
90
91
92     #Plotting the results
93     plt.plot(bins,pi[0]*pdf1, color = 'red')
94     plt.plot(bins,pi[1]*pdf2, color = 'red')
95     plt.xlabel('Age')
96     plt.ylabel('Probability Density')
97     plt.show()
```

Files on Github

/Iris Data Set/bezdekiris.data	x
/Iris Data Set/Cat_Iris_types.py	x
/Iris Data Set/class_type.png	x
/Iris Data Set/Gaussian.py	x

These files are for
Iris data set

/Indian Liver Patient Dataset/Alkphos.png	x
/Indian Liver Patient Dataset/Alkphos.py	x

These files are for
Indian Liver Patient
Dataset