Q 1

In [45]:
```
# Importing necessary libraries


from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score
from sklearn.metrics import precision_score
from sklearn.metrics import recall_score
from sklearn.metrics import PrecisionRecallDisplay

from scipy.stats import zscore,norm
import pandas as pd
import matplotlib.pyplot as plt


from scipy.stats import zscore,norm
import numpy as np

import numpy as np
import matplotlib.pyplot as plt
from sklearn.neighbors import LocalOutlierFactor
```

1. Anomaly Detection (30 points)

Part A (5 Points):

By dividing a data set into quartiles, IQR is used to measure variability. The data is sorted ascending and divided into four equal parts. Q1, Q2, Q3, also known as the first, second, and third quartiles, are the values that separate the four equal parts.

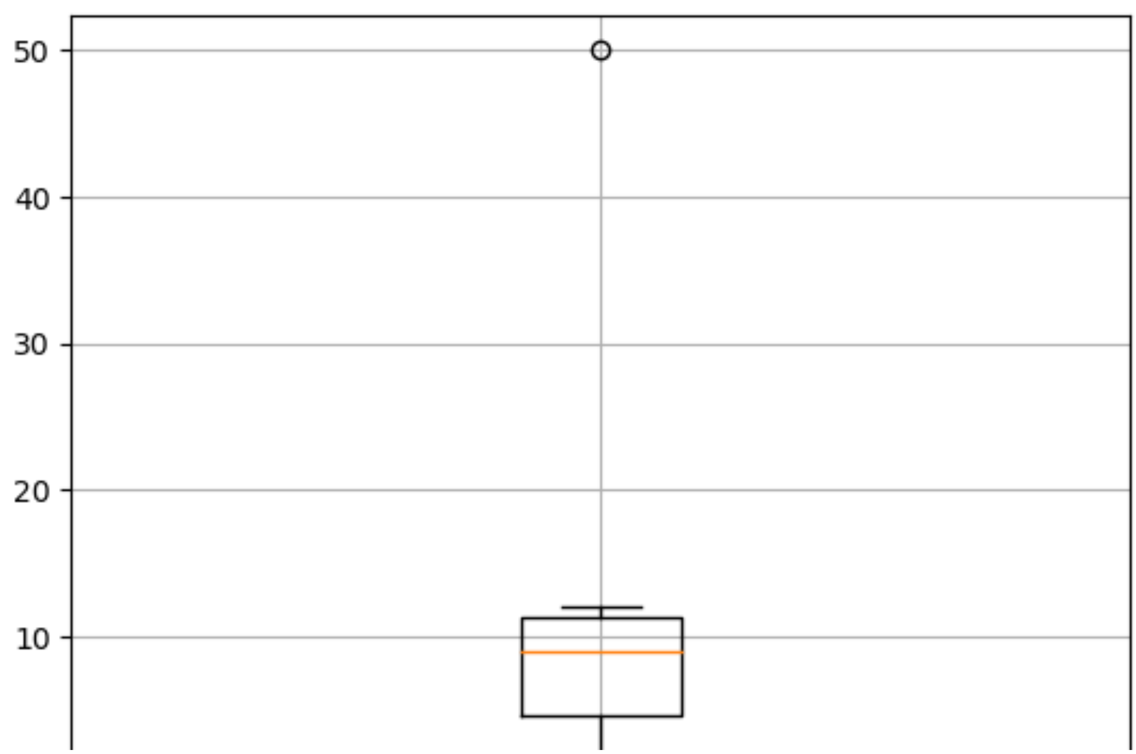
Use the following data points to calculate outliers in the data data = [11, 3, 8, 10, 12, 5, 1, 50]

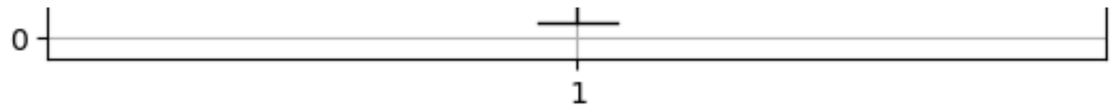
Using a box plot, show the outliers in the box plot.

In [46]:

```python
datapoints=np.array([11,3,8,10,12,5,1,50])
sorted=np.sort(datapoints)

q3,q1 = np.percentile(datapoints, [75, 25])

iqr=q3-q1
print("Q1 = ",q1, ", Q3=",q3,", IQR",iqr) #4.5

# Finding the outliers: points outside the range (Q1 − 1.5 ∗ IQR) ,  (

lb = q1-(1.5*iqr)
ub= q3+(1.5*iqr)


outlier = datapoints[(datapoints < lb) | (datapoints > ub)]

print("Lower Bound is (", lb,") \nUpper Bound is (", ub,")")

print("Outlier is : ", outlier )

plt.boxplot(datapoints)
plt.grid(True)
plt.show()
```

```
Q1 =  4.5 , Q3= 11.25 , IQR 6.75
Lower Bound is ( -5.625 )
Upper Bound is ( 21.375 )
Outlier is :  [50]
```



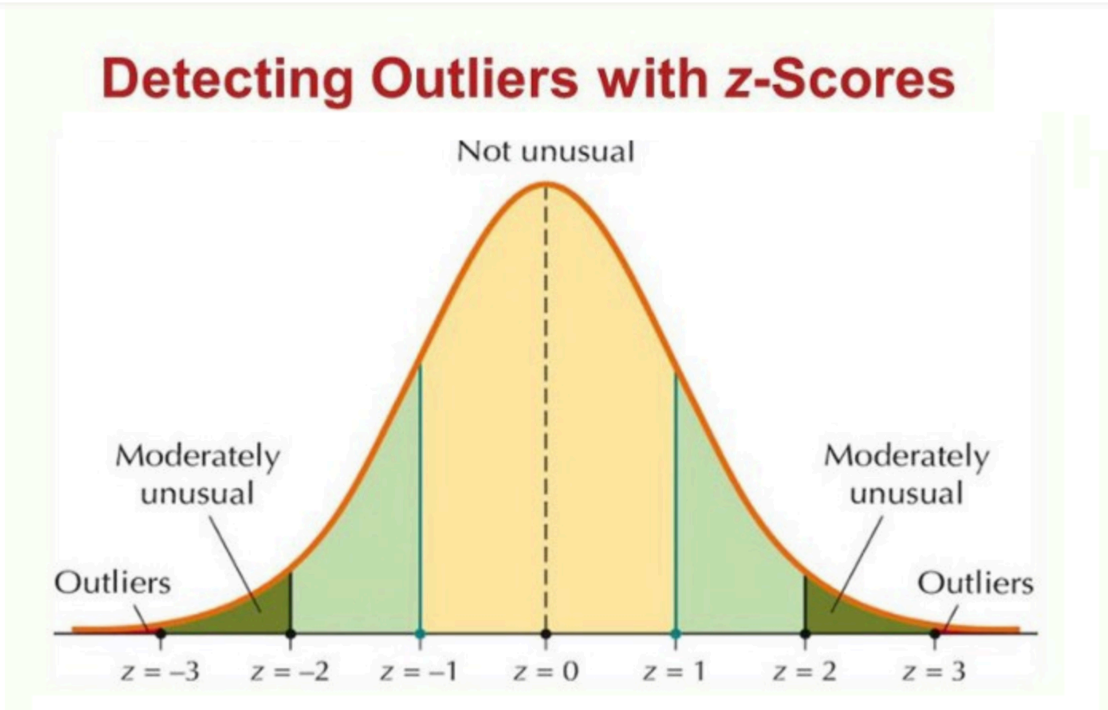


In [ ]:

Part B (5 points):

Using the formula to calculate the Z-score detect outliers in the following data points. data = [6, 3, 9, 6, 9, 20, 3, 10, 3, 50, 6, 5, 9, 9, 3, 6, 3] Using a box plot, show the outliers in the box plot.

Zscore is used to understand how close or far a dpoint is from its mean

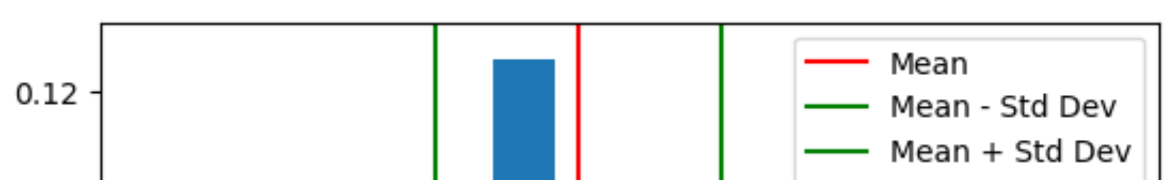


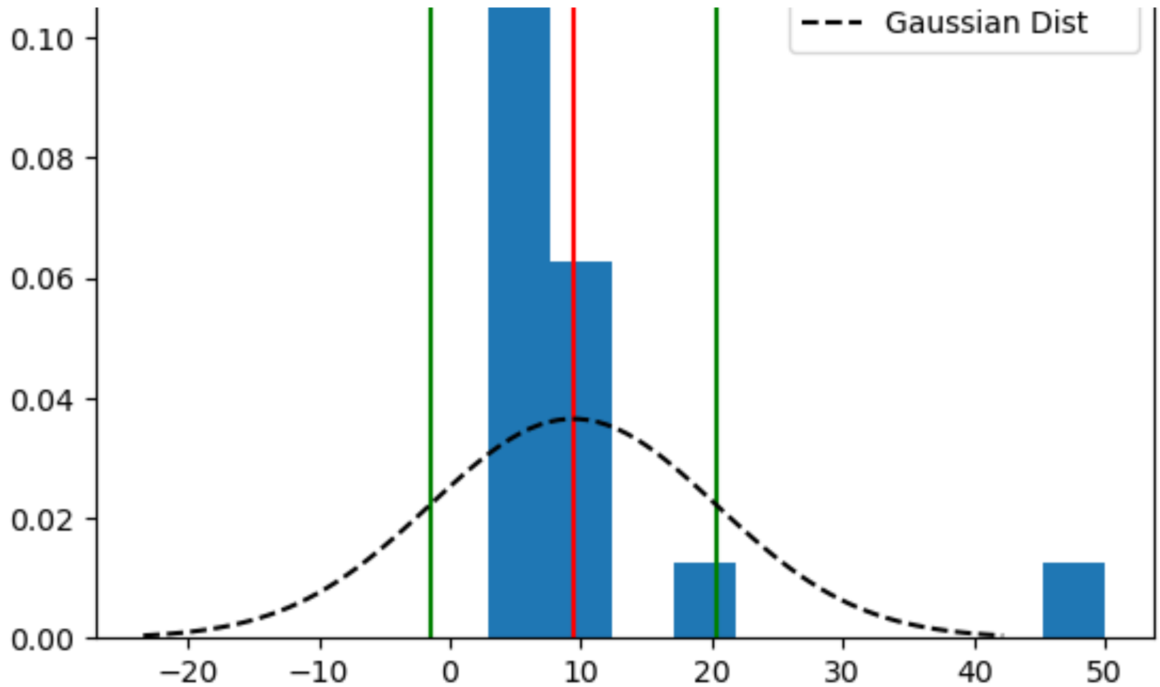
Source: Analytics Vidhya

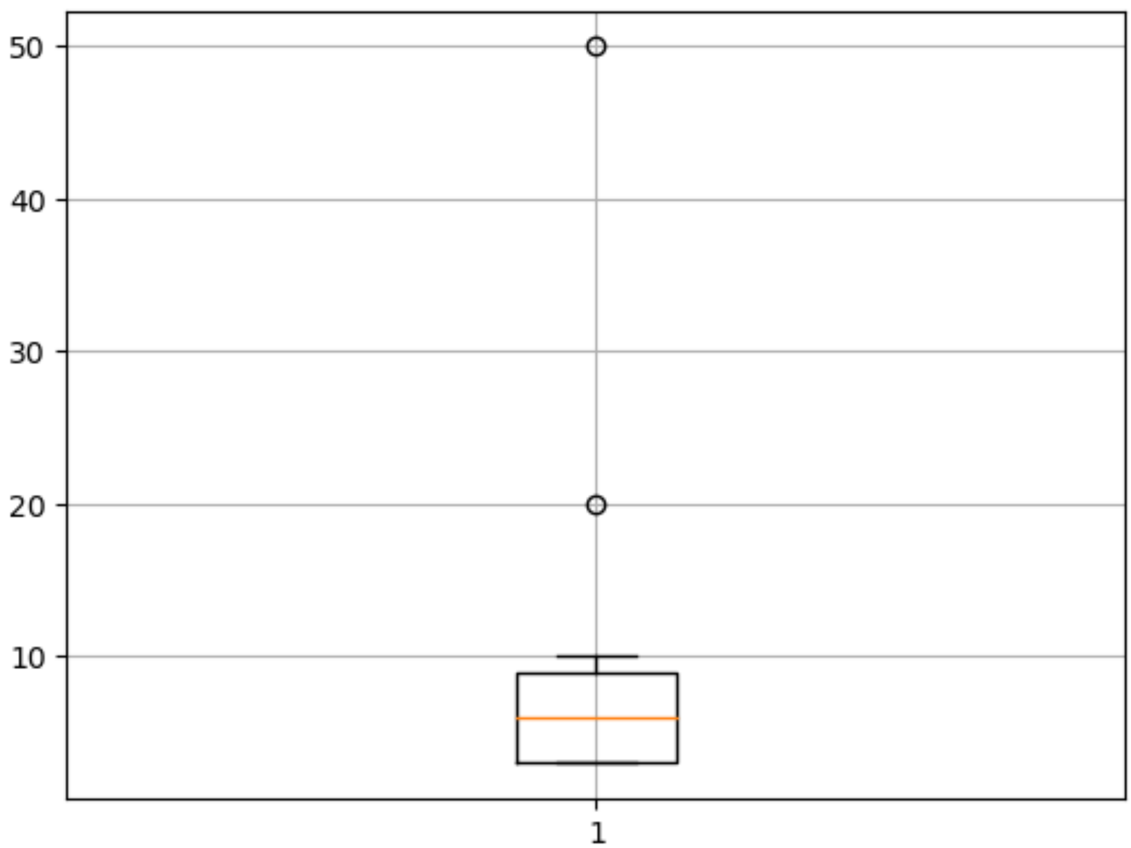
In [85]:

```python
dp = np.array([6, 3, 9, 6, 9, 20, 3, 10, 3, 50, 6, 5, 9, 9, 3, 6, 3])

mean = np.mean(dp)
std= np.std(dp)
zs= zscore(dp)

print("Mean : ", np.round(mean,2))
print("Std Dev : ", np.round(std, 2))
print("\nZ Score : \n ", np.round(zs,2))

#Setting a threshold


plt.hist(dp,density=5)

x = np.linspace( (mean - 3 * std), (mean + 3 * std) , 90)
y = norm.pdf(x, mean, std)

plt.axvline(mean, color='red', label='Mean')
plt.axvline(mean - std, color='green' ,label='Mean - Std Dev')
plt.axvline(mean + std, color='green', label='Mean + Std Dev')

plt.plot(x, y, '--', color='black', label='Gaussian Dist')
plt.legend()
plt.show()


plt.boxplot(dp)
plt.grid(True)
plt.show()

print("Outliers are 20 and 50 ")
```

```
Mean :  9.41
Std Dev :  10.93

Z Score : 
  [-0.31 -0.59 -0.04 -0.31 -0.04  0.97 -0.59  0.05 -0.59  3.71 -0.31 -0.4
 -0.04 -0.04 -0.59 -0.31 -0.59]
```








```
Outliers are 20 and 50
```

In [ ]:

Part C (20 points):

Use the dataset attached for identifying the outliers using Z-score.

Steps to follow in this question

- Step1(5 points): Show outliers using histograms and scatterplots. Then
- Step2(7 points): Identify the outliers using Z-score for SalePrice column by using atleast 4 different thresholds.
- Step3(4 points): Print the number of outliers removed.
- Step4(4 points): Use LocalOutlierFactor as discussed in the class to plot the outliers from SalePrice and LotArea columns.

STEP 1 - Show outliers using histograms and scatterplots

In [98]:
```
data = pd.read_csv("/Users/mumukshapant/Downloads/ML/Assignments/Assig

data
```

Out[98]:

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandCont
0	1	60	RL	65.0	8450	Pave	NaN	Reg	
1	2	20	RL	80.0	9600	Pave	NaN	Reg	
2	3	60	RL	68.0	11250	Pave	NaN	IR1	
3	4	70	RL	60.0	9550	Pave	NaN	IR1	
4	5	60	RL	84.0	14260	Pave	NaN	IR1	
...	...	...	...	...	...	...	...	...	
1455	1456	60	RL	62.0	7917	Pave	NaN	Reg	
1456	1457	20	RL	85.0	13175	Pave	NaN	Reg	
1457	1458	70	RL	66.0	9042	Pave	NaN	Reg	
1458	1459	20	RL	68.0	9717	Pave	NaN	Reg	
1459	1460	20	RL	75.0	9937	Pave	NaN	Reg	

1460 rows × 81 columns

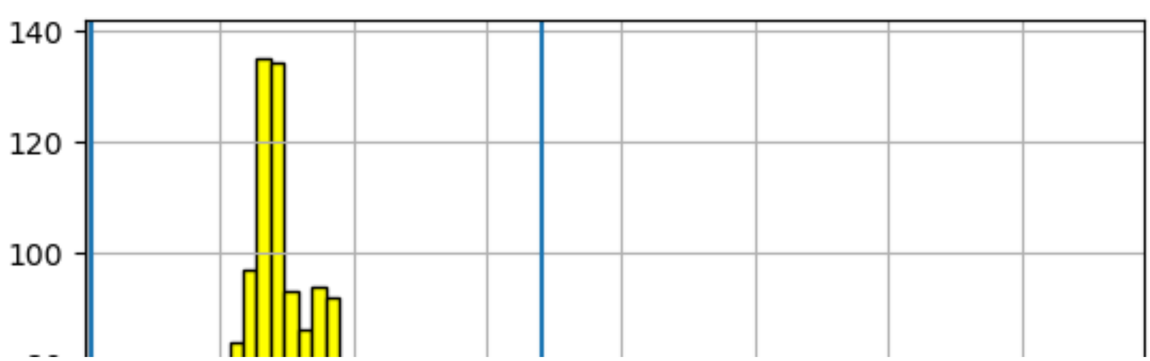
In [ ]:

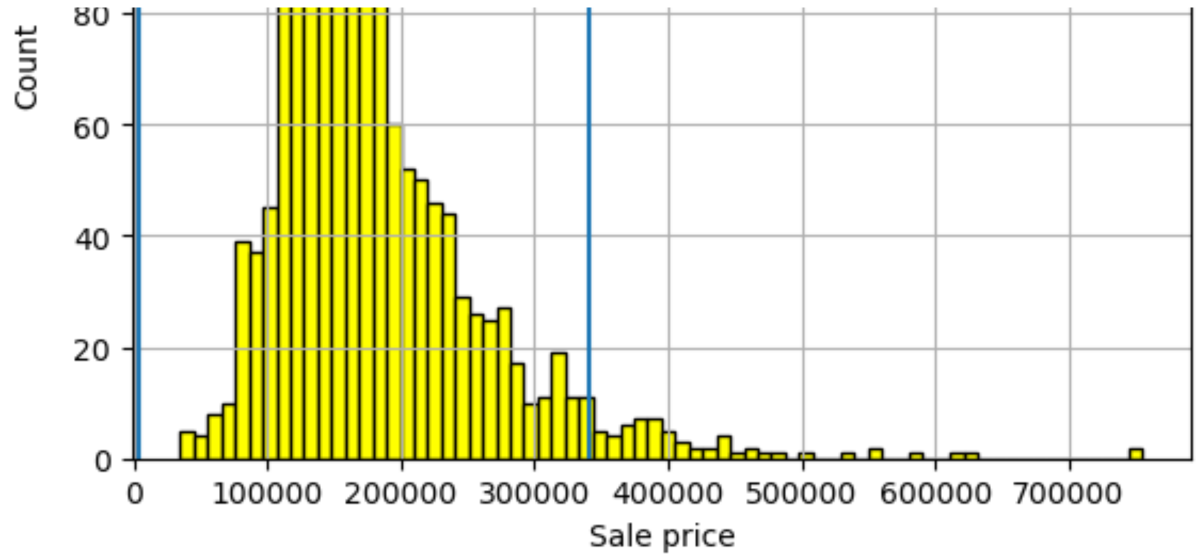
In [ ]:

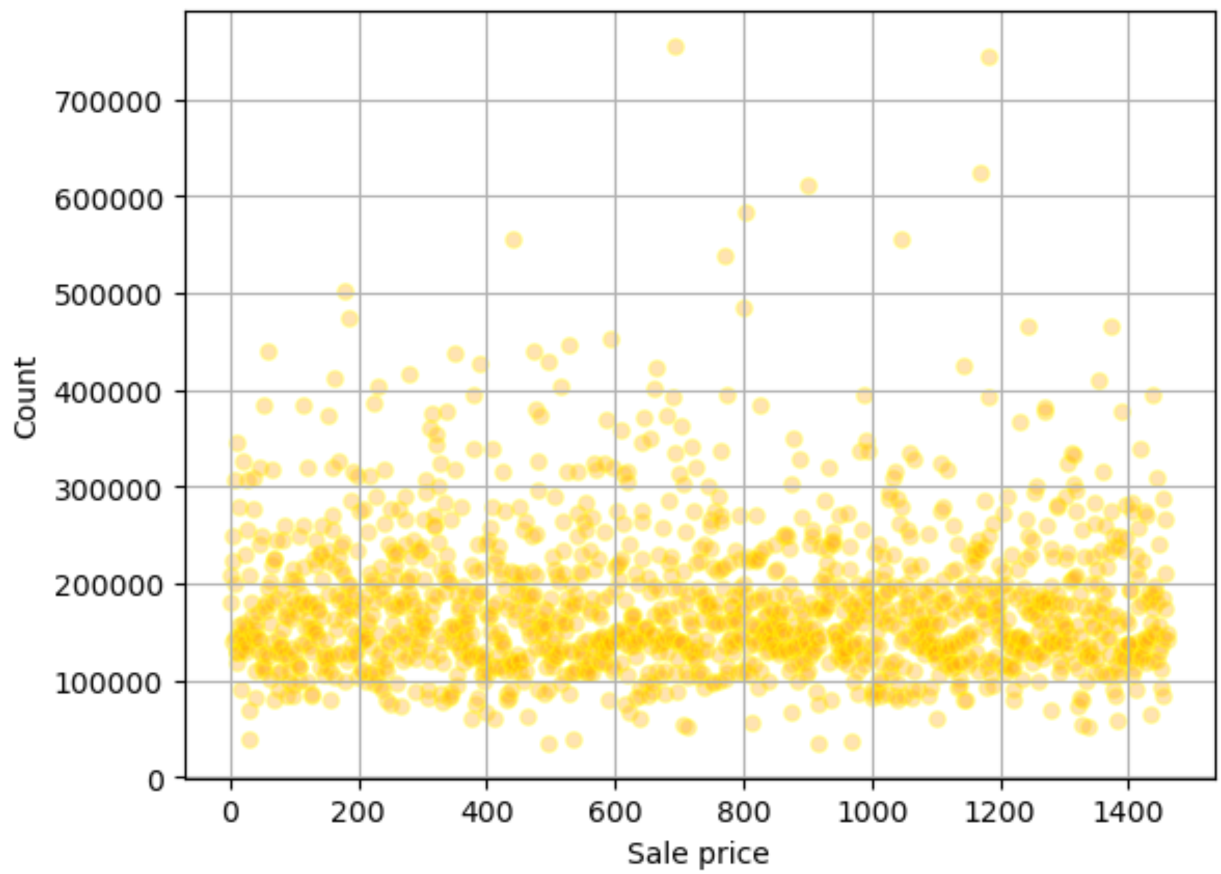
In [108]:

```
y= data["SalePrice"]

#calculating IQR And using it for outlier detection
q3, q1 = np.percentile(y, [75, 25])

iqr = q3 - q1
print("Q1 =", q1, ", Q3 =", q3, ", IQR =", iqr)

# Finding the outliers: points outside the range (Q1 - 1.5 * IQR), (Q3
lb = q1 - (1.5 * iqr)
ub = q3 + (1.5 * iqr)

#Histogram
plt.hist(y, edgecolor='black', bins=70, color='yellow')
plt.xlabel("Sale price")
plt.ylabel("Count")

#highlighting the points below and above threshold
plt.axvline(x=lb)
plt.axvline(x=ub)
plt.grid(True)
plt.show()

# Scatter plot
plt.scatter(data['Id'], y, s=30, alpha=0.3, edgecolors='yellow', color
plt.xlabel("Sale price")
plt.ylabel("Count")
plt.grid(True)
plt.show()
```

```
Q1 = 129975.0 , Q3 = 214000.0 , IQR = 84025.0
```







STEP 2 , 3 -

Identify the outliers using Z-score for SalePrice column by using atleast 4 different thresholds.

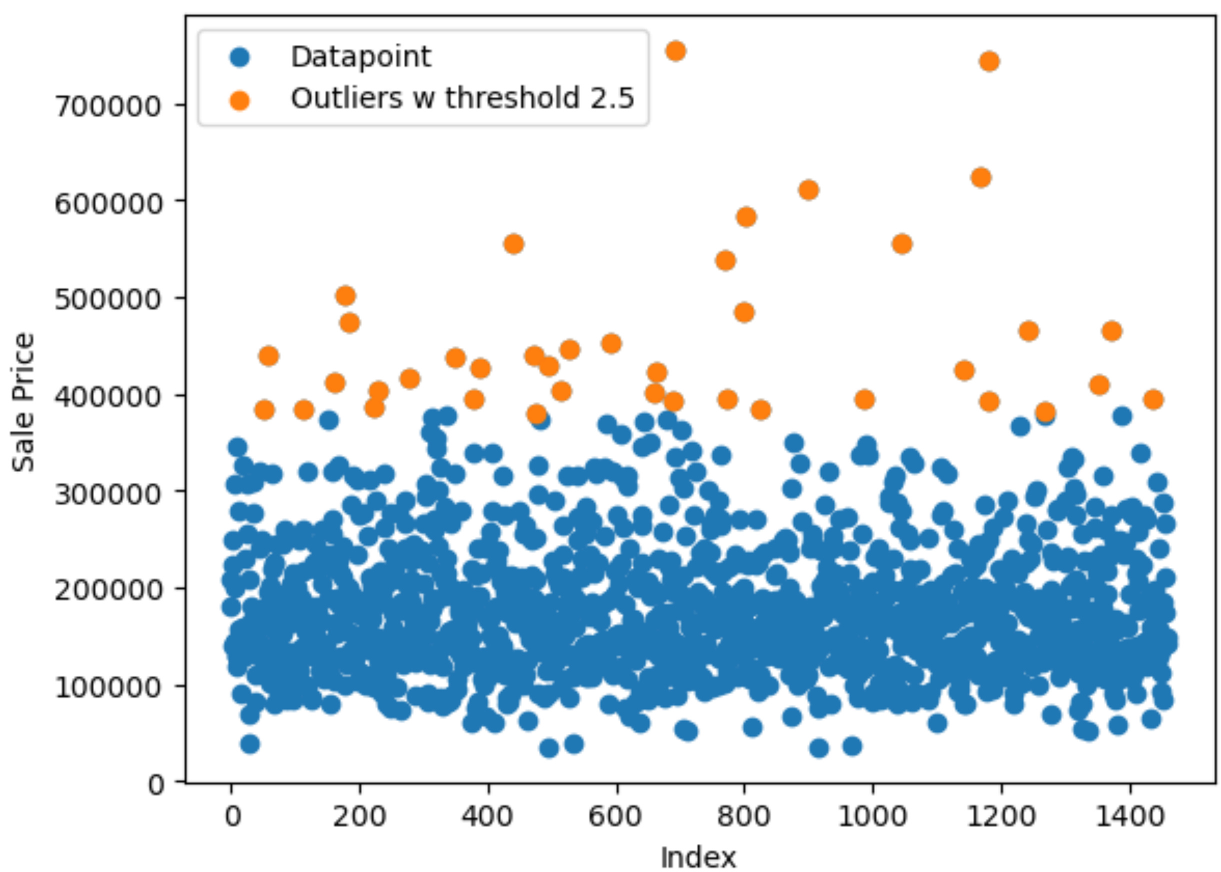
Print the number of outliers removed.

In [50]:

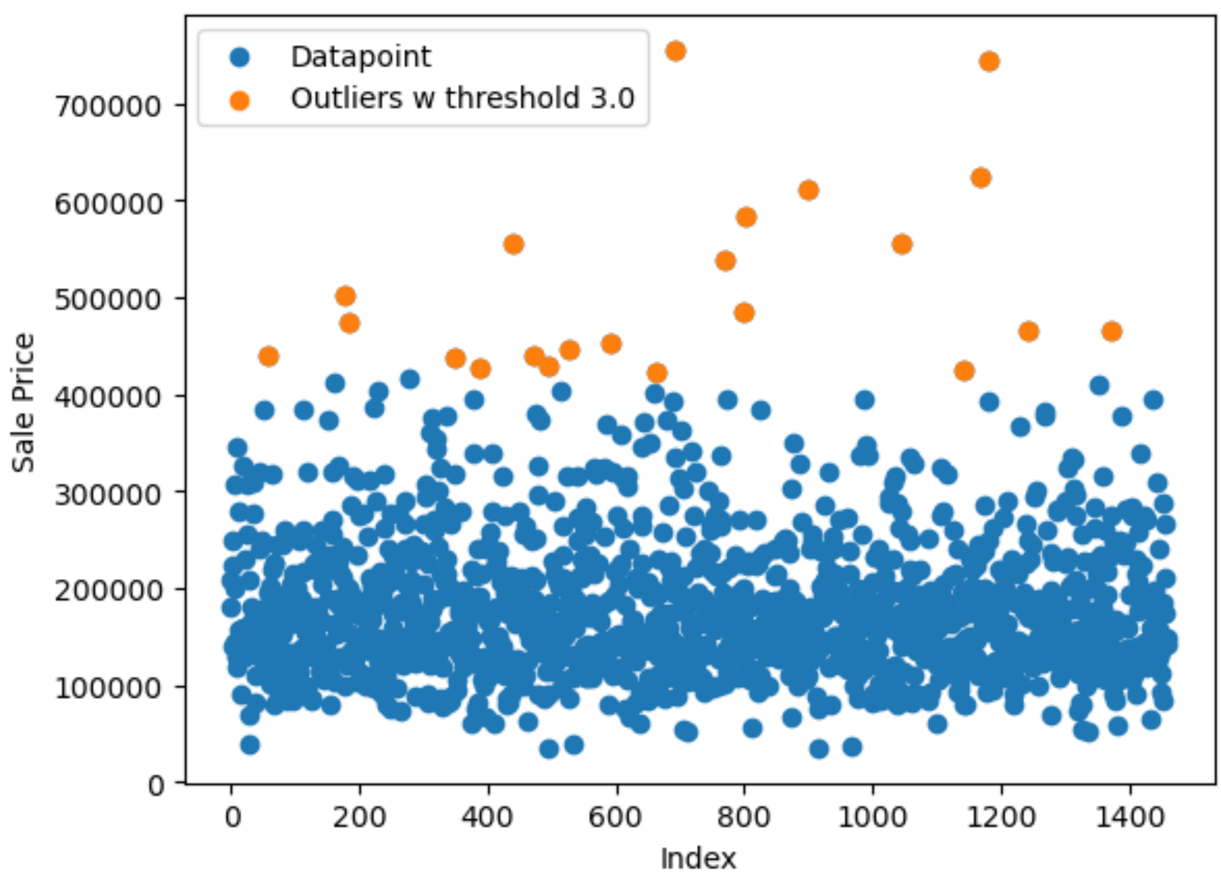
```python
# Mean and std dev for Sale Price
y= data['SalePrice']
mean_y = y.mean()
std_y = y.std()

#Zscore
zscore_y = zscore(y)

tholds= [2.5, 3.0, 3.5, 4.0]
colors = ['red']

for t in tholds:

    outliers = y[np.abs(zscore_y) > t]

    print("Threshold",t,"\nOutliers ", outliers)
    # Create a new figure

    # Data points
    plt.scatter(data.index, y, label='Datapoint')

    #outliers
    plt.scatter(outliers.index, outliers, label=f'Outliers w threshol

    plt.ylabel("Sale Price")
    plt.xlabel("Index")
    plt.legend()
    plt.show()
    print("\n\n\n\n")
```

```
Threshold 2.5
Outliers  53      385000
58      438780
112     383970
161     412500
178     501837
185     475000
224     386250
231     403000
278     415298
349     437154
378     394432
389     426000
440     555000
473     440000
```

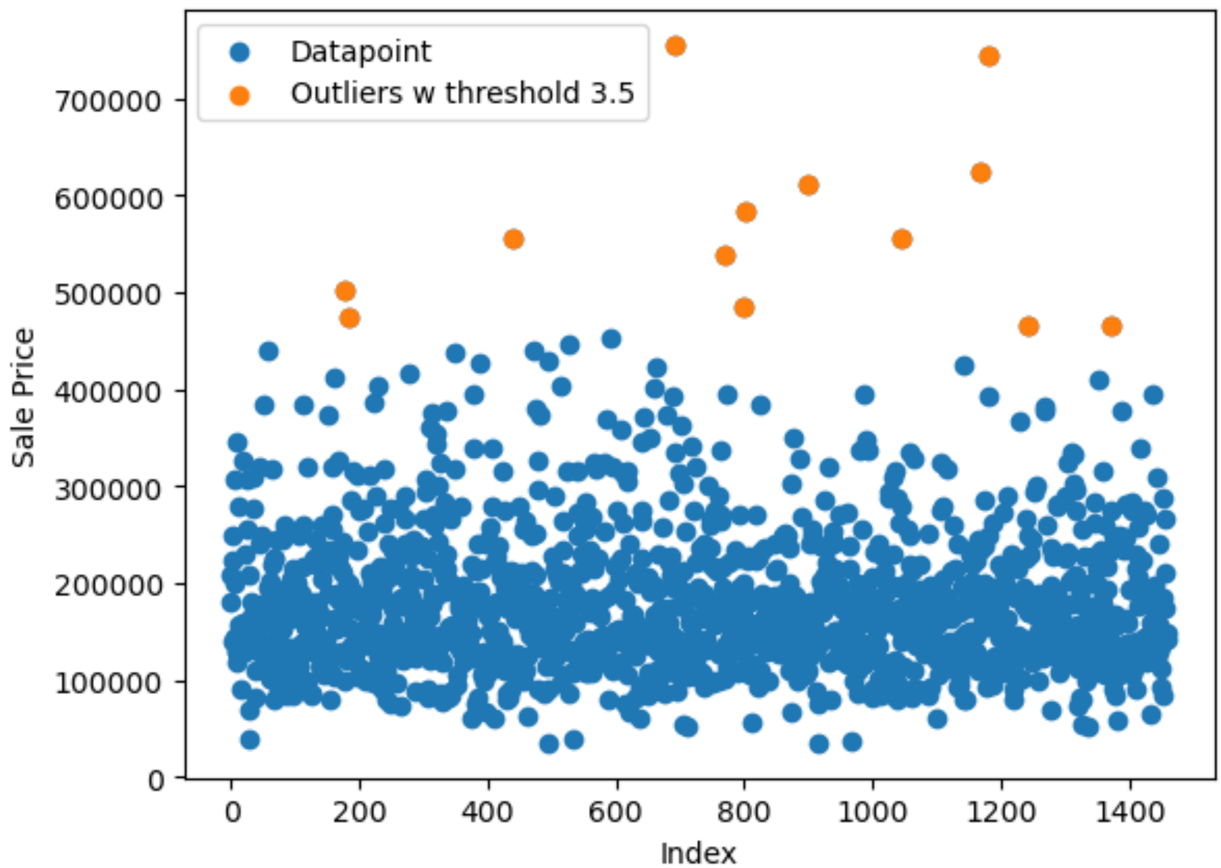
```
477     380000
496     430000
515     402861
527     446261
591     451950
661     402000
664     423000
688     392000
691     755000
769     538000
774     395000
798     485000
803     582933
825     385000
898     611657
987     395192
1046    556581
1142    424870
1169    625000
1181    392500
1182    745000
1243    465000
1268    381000
1353    410000
1373    466500
1437    394617
Name: SalePrice, dtype: int64
```



```
Threshold 3.0
Outliers  58      438780
178     501837
185     475000
349     437154
389     426000
440     555000
473     440000
496     430000
527     446261
591     451950
664     423000
691     755000
769     538000
798     485000
803     582933
898     611657
1046    556581
1142    424870
1169    625000
1182    745000
1243    465000
1373    466500
Name: SalePrice, dtype: int64
```

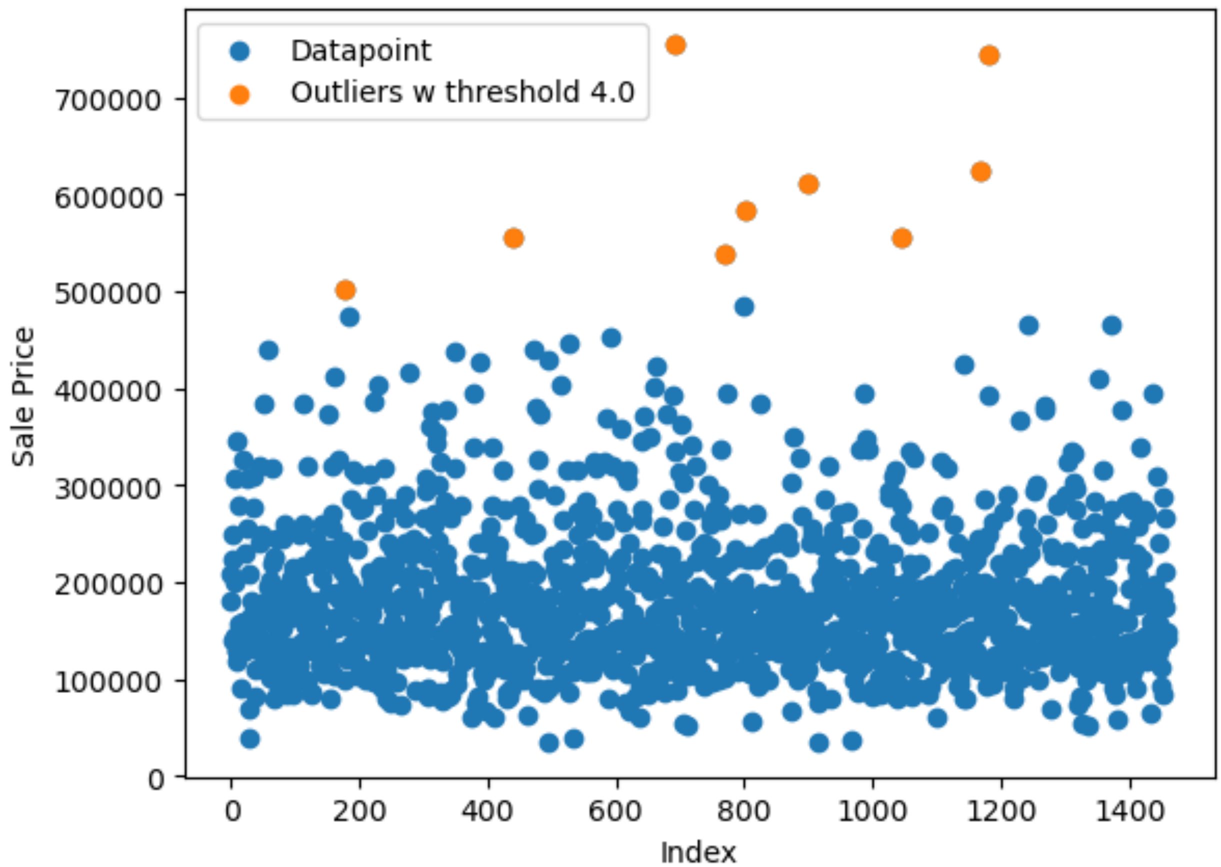


```
Threshold 3.5
Outliers  178     501837
185     475000
440     555000
691     755000
769     538000
798     485000
803     582933
898     611657
1046    556581
1169    625000
1182    745000
1243    465000
1373    466500
Name: SalePrice, dtype: int64
```




```
Threshold 4.0
Outliers  178     501837
440     555000
```

```
440     555000
691     755000
769     538000
803     582933
898     611657
1046    556581
1169    625000
1182    745000
Name: SalePrice, dtype: int64
```



In [ ]:

```

```

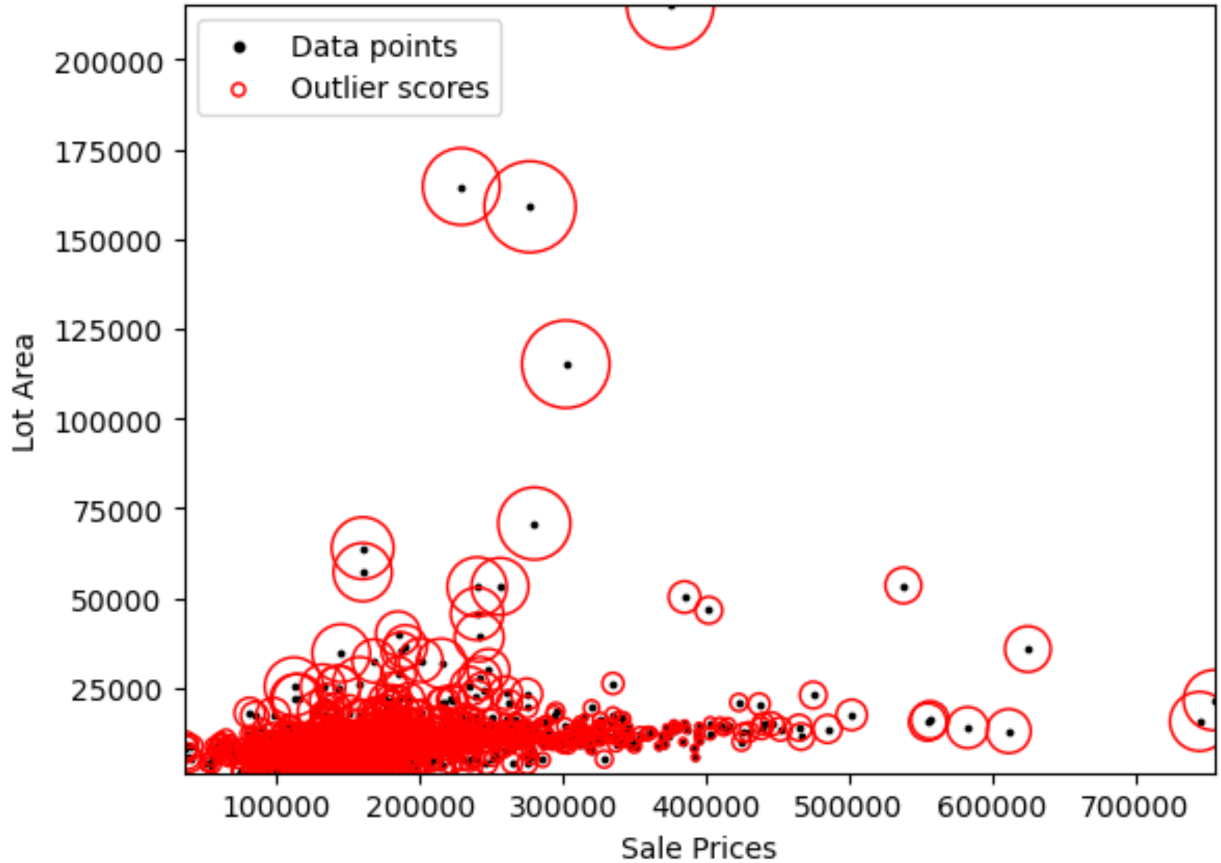
Step 4 - Use LocalOutlierFactor as discussed in the class to plot the outliers from SalePrice and LotArea columns.

In [88]:

```
CODE
dLot = data[["SalePrice","LotArea"]].values
```

```
LocalOutlierFactor(n_neighbors=20, contamination=0.1)


fit_predict to compute the predicted labels of the training samples
 = lor.fit_predict(saleAndLot)
r_score = lor.negative_outlier_factor_

 of outliers.
of_outlier= (y_pred== -1).sum()

er plot
atter(saleAndLot[:,0], saleAndLot[:,1], color="k", s=3.0, label="Data

e the radius of the circles with outlier scores
 = (outlier_score.max() - outlier_score) / (outlier_score.max() - outl

circles
atter(saleAndLot[:,0], saleAndLot[:,1],
      s=1000*radius,
      edgecolors="r",
      facecolors="none",
      label="Outlier scores",
     )


mising the plot
is("tight")

abel("Lot Area")
abel("Sale Prices")

im((data["SalePrice"].min(), data["SalePrice"].max()))
im((data["LotArea"].min(), data["LotArea"].max()))

 = plt.legend(loc="upper left")
.legendHandles[0]._sizes = [10]
.legendHandles[1]._sizes = [20]

"\nNo. of Outliers are : ", count_of_outlier)

ow()
```

```
No. of Outliers are :  146
```



Q 2 - PCA

In [11]:
```
# Importing necessary Libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn import preprocessing
from sklearn.preprocessing import StandardScaler

dataset=pd.read_csv("/Users/mumukshapant/Downloads/ML/Assignments/Assi
dataset.shape
```

Out[11]: (756, 755)

In [12]:
```
# To getinformation about dataset :
info=dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 756 entries, 0 to 755
Columns: 755 entries, id to class
dtypes: float64(749), int64(6)
memory usage: 4.4 MB
```

2.1) Seperate and standardize the disease classification dataset.

In [13]:
```
X = dataset.drop("class", axis=1) # 1 means to drop columns
y = dataset["class"]
```

Standardise the data

In [14]:
```
X_std = preprocessing.scale(X)

#Convert it into dataFrame to see it in Tabular Form
df = pd.DataFrame(X_std, columns=X.columns)
print(df.head())
```

```
         id    gender       PPE       DFA      RPDE  numPulses  \
0 -1.725191  0.968742  0.627644  0.256144  0.605835  -0.846892
1 -1.725191  0.968742  0.121620 -0.080433  0.368415  -0.907404
2 -1.725191  0.968742  0.617950 -0.349839  0.733609  -0.927575
3 -1.711445 -1.032266 -1.980560  1.382279  0.753631  -1.472186
4 -1.711445 -1.032266 -2.472989  1.398068  0.300123  -0.887233

   numPeriodsPulses  meanPeriodPulses  stdDevPeriodPulses  locPctJitt
er  ...  \
0         -0.842373          0.933328           -0.407251     -0.0549
93  ...
1         -0.902773          1.040014           -0.426092     -0.1425
70  ...
2         -0.922907          1.084576           -0.443557     -0.2149
16  ...
3         -1.466513          2.464215           -0.275316      0.7103
53  ...
4         -0.882640          0.987044            3.143597      1.1520
45  ...

   tqwt_kurtosisValue_dec_27  tqwt_kurtosisValue_dec_28  \
0                  -0.445877                  -0.584822
1                  -0.445730                  -0.584895
```

```
2                -0.446030               -0.584767
3                -0.321598               -0.532242
4                -0.300835               -0.475545

   tqwt_kurtosisValue_dec_29  tqwt_kurtosisValue_dec_30  \
0                  -0.619412                  -0.576762
1                  -0.589778                   0.193084
2                  -0.629033                  -0.356261
3                  -0.591137                  -0.522406
4                  -0.521356                  -0.490090

   tqwt_kurtosisValue_dec_31  tqwt_kurtosisValue_dec_32  \
0                  -0.482286                  -0.399331
1                   0.016183                  -0.067120
2                  -0.156055                  -0.067593
3                   0.008400                  -0.449894
4                  -0.404833                  -0.249678

   tqwt_kurtosisValue_dec_33  tqwt_kurtosisValue_dec_34  \
0                  -0.484533                  -0.775137
1                  -0.175566                  -0.526647
2                  -0.463462                  -0.756063
3                  -0.470865                  -0.633475
4                  -0.042021                  -0.419354

   tqwt_kurtosisValue_dec_35  tqwt_kurtosisValue_dec_36
0                  -0.814727                  -0.366595
1                  -0.582972                   0.400396
2                  -0.804390                  -0.780935
3                  -0.588387                  -0.801583
4                  -0.672216                  -0.741477

[5 rows x 754 columns]

/Users/mumukshapant/anaconda3/envs/pytorchenv/lib/python3.9/site-pack
ages/sklearn/preprocessing/_data.py:247: UserWarning: Numerical issue
s were encountered when centering the data and might not be solved. D
ataset may contain too large values. You may need to prescale your fe
atures.
  warnings.warn(
```

In [ ]:

2.2) Do Eigen decomposition using any LA library of your choice. Display scree plot. (10 points)

Eigen Decomposition

In [16]:
```
# Calculating the covariance matrix
cov=df.cov()

#Calculating eigen values
eigen_vals, eigen_vecs = np.linalg.eigh(cov)
```

...

In [17]:
```
# print the Eigenvalues
print("Eigenvalues: \n", eigen_vals)
```

```
 6.91099254e-20 8.90418970e-20 9.47827857e-20 1.02578701e-19
 1.26784647e-19 1.49851309e-19 1.60768492e-19 2.10392652e-19
 8.38234165e-15 1.40818189e-14 1.29434226e-13 1.66298199e-13
 4.78924545e-13 1.04082078e-12 1.19402347e-12 2.44968536e-12
 3.20934483e-12 5.40290178e-12 7.02978091e-12 1.11474666e-11
 1.15603719e-11 1.55623515e-11 1.74190240e-11 1.84880452e-11
 3.04633034e-11 4.16773206e-11 5.45006969e-11 6.77158577e-11
 9.29819670e-11 1.59971259e-10 2.07596053e-10 2.64893692e-10
 3.74468240e-10 4.34770285e-10 4.83926499e-10 5.16724558e-10
 6.79370932e-10 7.90552682e-10 1.17603580e-09 1.38595516e-09
 1.58276466e-09 1.93951874e-09 2.85872929e-09 3.29674530e-09
 4.59898598e-09 7.33392866e-09 7.81783889e-09 1.09033326e-08
 1.64331798e-08 2.00987644e-08 2.24957799e-08 2.60422079e-08
 3.31319381e-08 5.05457671e-08 5.57860993e-08 6.31965364e-08
 9.10301134e-08 1.19959698e-07 1.33145463e-07 1.71667431e-07
 2.06411489e-07 2.25804289e-07 2.96231254e-07 3.17184620e-07
 3.60579165e-07 4.00748115e-07 4.23713646e-07 5.51068554e-07
 5.73838742e-07 6.31948399e-07 7.48612555e-07 7.91529456e-07
 9.10789400e-07 9.99026416e-07 1.12053755e-06 1.40608615e-06
```

scree plot is a line plot of the eigenvalues of factors . Used for determining no of factors to retain

In [28]:
```python
# Sorting in DESC order.
eval_sorted = np.flip(eigen_vals)
evec_sorted = np.flip(eigen_vecs, axis=1)
print(eval_sorted)
```

```
  7.33392866e-09  4.59898598e-09  3.29674530e-09  2.85872929e-09
  1.93951874e-09  1.58276466e-09  1.38595516e-09  1.17603580e-09
  7.90552682e-10  6.79370932e-10  5.16724558e-10  4.83926499e-10
  4.34770285e-10  3.74468240e-10  2.64893692e-10  2.07596053e-10
  1.59971259e-10  9.29819670e-11  6.77158577e-11  5.45006969e-11
  4.16773206e-11  3.04633034e-11  1.84880452e-11  1.74190240e-11
  1.55623515e-11  1.15603719e-11  1.11474666e-11  7.02978091e-12
  5.40290178e-12  3.20934483e-12  2.44968536e-12  1.19402347e-12
  1.04082078e-12  4.78924545e-13  1.66298199e-13  1.29434226e-13
  1.40818189e-14  8.38234165e-15  2.10392652e-19  1.60768492e-19
  1.49851309e-19  1.26784647e-19  1.02578701e-19  9.47827857e-20
  8.90418970e-20  6.91099254e-20  5.37805383e-20  3.88415213e-20
  3.46398474e-20  2.78423314e-20  1.76820243e-20  1.22952494e-20
  6.60989885e-21  2.88411295e-21 -6.71369227e-21 -1.99187807e-20
 -2.35991629e-20 -3.18727046e-20 -4.12168792e-20 -4.35013424e-20
 -4.81176251e-20 -6.04141537e-20 -7.26039189e-20 -7.48211471e-20
 -8.19463246e-20 -9.89039181e-20 -1.12485528e-19 -1.16555034e-19
 -1.24006129e-19 -1.29038597e-19 -1.54971347e-19 -1.92552746e-19
 -2.74971850e-19 -1.48205413e-16]
```

Explained Variance Ratio

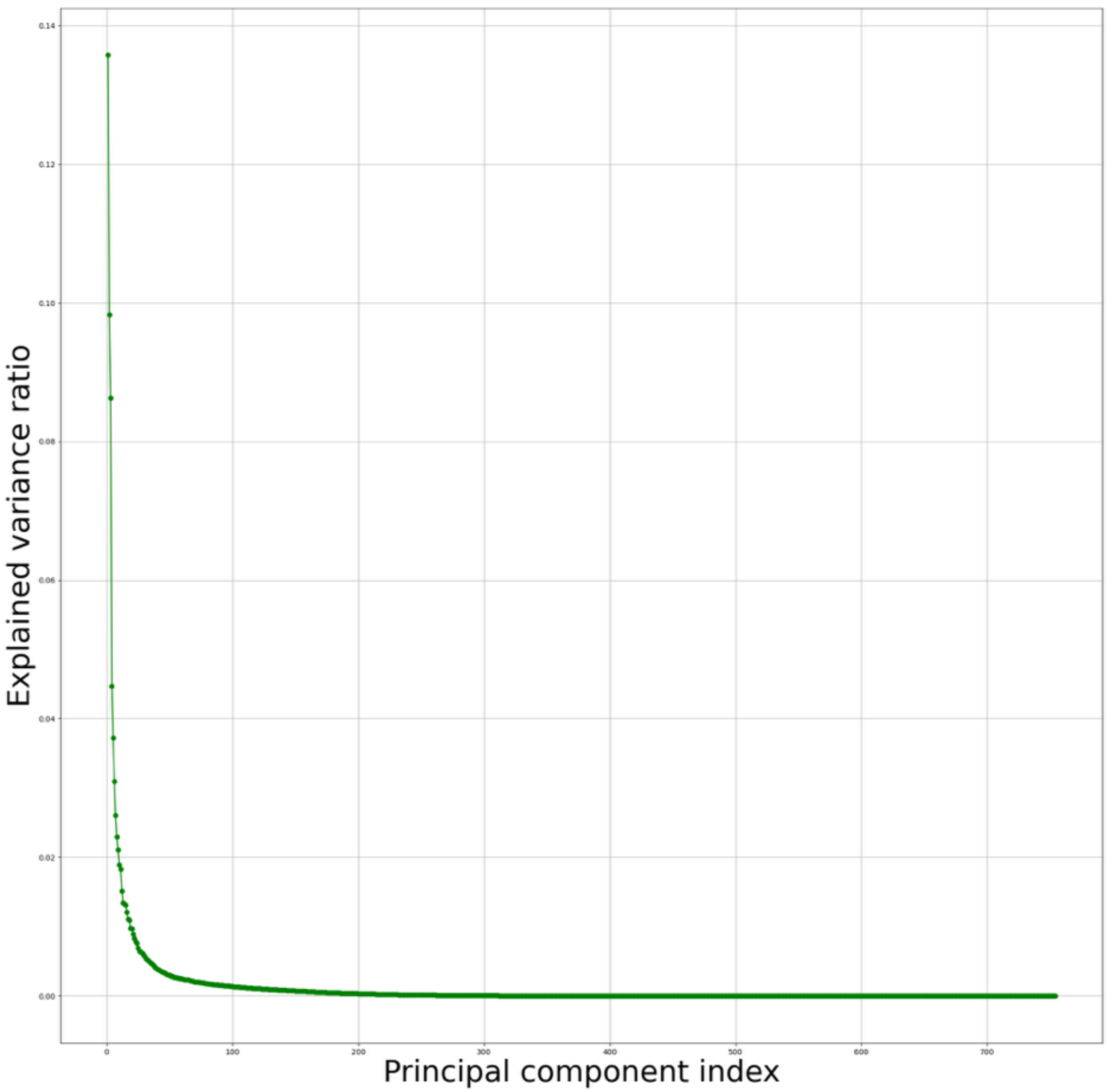
Divide each eigenvalue by the sum of all eigenvalues to get the explained variance ratio for each principal component

In [29]:
```python
# Explained Variance Ratio forevery eigenvalue
exp_var_ratio = eval_sorted / np.sum(eval_sorted)
```

In [30]:
```python
# Cumulative of EVR ( This will give us the number of Principal Compor
# The length of "cum_var_exp" is 754 meaning 754 PCs are there.
cum_var_exp = np.cumsum(exp_var_ratio)
len(cum_var_exp)
```

Out[30]: 754

In [53]:
```
#Now Lets Plot this in Scree Graph

# make a bar plot of the variance associated with each component

plt.figure(figsize=(25,25))
plt.plot(range(1,755), exp_var_ratio, label='Individual Explained Vari
plt.grid(True)


plt.ylabel('Explained variance ratio',fontsize=40)
plt.xlabel('Principal component index', fontsize=40)
plt.show()
```



2.3) Primary Componenet Selection

Primary Component Selection. (Select the first 6 components) (5 points)

In [32]:
```
# Primary Component Selection - Select First 6 components
selected_pc= evec_sorted[:,:6]
```

In [67]:
```
selected_pc
```

Out[67]:
```
array([[ 0.0073493 , -0.00113214,  0.00645179,  0.01483515, -0.022943
54,
         0.02161094],
       [-0.04502733, -0.04704606, -0.00621151, -0.02455892,  0.010382
42,
         0.00845405],
       [ 0.01737329, -0.01053272, -0.05773324, -0.01277535, -0.005155
63,
         0.02344555],
       ...,
       [-0.01325227,  0.00853193, -0.02178402, -0.01337081,  0.035945
81,
        -0.02532667],
       [-0.01943189,  0.01712986, -0.02276268, -0.01811131,  0.023486
2 ,
        -0.02214931],
       [-0.02903146,  0.03566218, -0.02912439, -0.0245805 ,  0.014237
84,
        -0.02128807]])
```

2.4) Projected In a New Feature Space

take the dot product of the centered data with the matrix formed by the selected eigenvectors. Each row in the resulting matrix represents the transformed data point in the new feature space. The transformed data in the new feature space is often referred to as the "scores" of the principal components.

In [33]:
```
projected = np.dot(X_std, selected_pc)
projected
```

Out[33]:
```
array([[-10.03502652,  -1.48001792,  -6.86079382,   0.74234696,
          3.50698233,  -0.12879346],
       [-10.65564499,  -1.60059183,  -6.81985852,  -1.38472895,
          3.1615515 ,   1.56188126],
       [-13.52369673,   1.23889751,  -6.82535545,  -1.43849935,
          2.27903112,   2.45921587],
       ...,
       [  8.29457088,  -2.3699335 ,  -0.91200327,   2.17403474,
          0.98473691,   1.04919861],
       [  4.01690645,  -5.35231374,  -0.82366311,   3.99787378,
         -0.25536571,   0.91921577],
       [  3.99782396,  -6.09710837,  -1.98566314,   1.9253788 ,
         -2.19041036,  -2.47473713]])
```

In [ ]:

2.5) Principal Component Analysis

In [34]:
```
# Cumulative of EVR ( This will give us the number of Principal Compon
# The length of "cum_var_exp" is 754 meaning 754 PCs are there.
cum_var_exp = np.cumsum(exp_var_ratio)
len(cum_var_exp) , exp_var_ratio
```

Out[34]:
```
(754,
 array([ 1.35716192e-01,  9.82999394e-02,  8.62218386e-02,  4.4660202
3e-02,
         3.72649780e-02,  3.09793804e-02,  2.60872410e-02,  2.2990511
9e-02,
         2.11165249e-02,  1.89576113e-02,  1.82846515e-02,  1.5167874
1e-02,
         1.34523962e-02,  1.32601329e-02,  1.31622549e-02,  1.2103372
2e-02,
         1.11294553e-02,  1.09146226e-02,  9.77097492e-03,  9.6811587
2e-03,
         8.97427620e-03,  8.29035811e-03,  7.87232824e-03,  7.5847859
2e-03,
         6.91079603e-03,  6.48723155e-03,  6.41414761e-03,  6.2591764
5e-03,
         5.98824403e-03,  5.75738420e-03,  5.38295046e-03,  5.2760154
6e-03,
         5.09703113e-03,  4.91555549e-03,  4.72530032e-03,  4.6894283
7e-03,
```

In [ ]:

```

```

2.6) Compare the presision and recall for the data using logistic regression before and after PCA.

In [35]:

```
### Split Data
from sklearn.model_selection import train_test_split

X_train ,X_test, y_train, y_test = train_test_split(X,y, test_size=0.3
```

Logistic Regression

In [36]:
```
# instance of a model
logR = LogisticRegression()
logR.fit(X_train, y_train)
y_predicted= logR.predict(X_test)

accuracy = accuracy_score(y_test, y_predicted)
precision = precision_score(y_test, y_predicted)
recall= recall_score(y_test, y_predicted)

print("Logistic Regression Performance Metrics without PCA")
print("Accuracy is", accuracy)
print("Precision is", precision)
print("RecalL is ", recall)
```

```
Logistic Regression Performance Metrics without PCA
Accuracy is 0.73568281938326
Precision is 0.7644230769230769
RecalL is  0.9352941176470588

/Users/mumukshapant/anaconda3/envs/pytorchenv/lib/python3.9/site-pack
ages/sklearn/linear_model/_logistic.py:460: ConvergenceWarning: lbfgs
failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as sho
wn in:
    https://scikit-learn.org/stable/modules/preprocessing.html
(https://scikit-learn.org/stable/modules/preprocessing.html)
Please also refer to the documentation for alternative solver options
:
    https://scikit-learn.org/stable/modules/linear_model.html#logisti
c-regression (https://scikit-learn.org/stable/modules/linear_model.ht
ml#logistic-regression)
  n_iter_i = _check_optimize_result(
```

PCA

In [37]:
```
#Split data into Training and Testing
X_train_pca, X_test_pca, _, _ = train_test_split(projected,y , test_siz
```

In [38]:
```
logR_pca= LogisticRegression()
logR_pca.fit(X_train_pca, y_train)
y_predicted_pca= logR_pca.predict(X_test_pca)

accuracy_pca= accuracy_score(y_test, y_predicted_pca)
precision_pca = precision_score(y_test, y_predicted_pca)
recall_pca= recall_score(y_test, y_predicted_pca)

print("After PCA :\n ")
print("Accuracy is ", accuracy_pca)
print("Precision is ", precision_pca)
print("Recall is ", recall_pca)
```

```
After PCA :

Accuracy is  0.8105726872246696
Precision is  0.8324607329842932
Recall is  0.9352941176470588
```

Q3 . EM Algorithm (35 points)

Etimate the probability distribution in a 1-dimensional dataset There are two Normal distributions $N(\mu 1,\sigma 1\text{^}2)$ and $N(\mu 2,\sigma 2\text{^}2)$. There are 5 paramaters to estimate: $\theta=(w,\mu 1,\sigma 1\text{^}2,\mu 2,\sigma 2\text{^}2)$ where w is the probability that the data comes from the first normal probability distribution and (1-w) comes from the second normal probability distribution. The probability density function (PDF) of the mixture model is: $f(x|\theta)=w\ f1(x\mid\mu 1,\sigma 1\text{^}2)+(1-w)\ f2(x\mid\mu 2,\sigma 2\text{^}2)$ Your goal is to best fit a given probability density by finding $\theta=(w,\mu 1,\sigma 1\text{^}2,\mu 2,\sigma 2\text{^}2)$ through EM iterations.

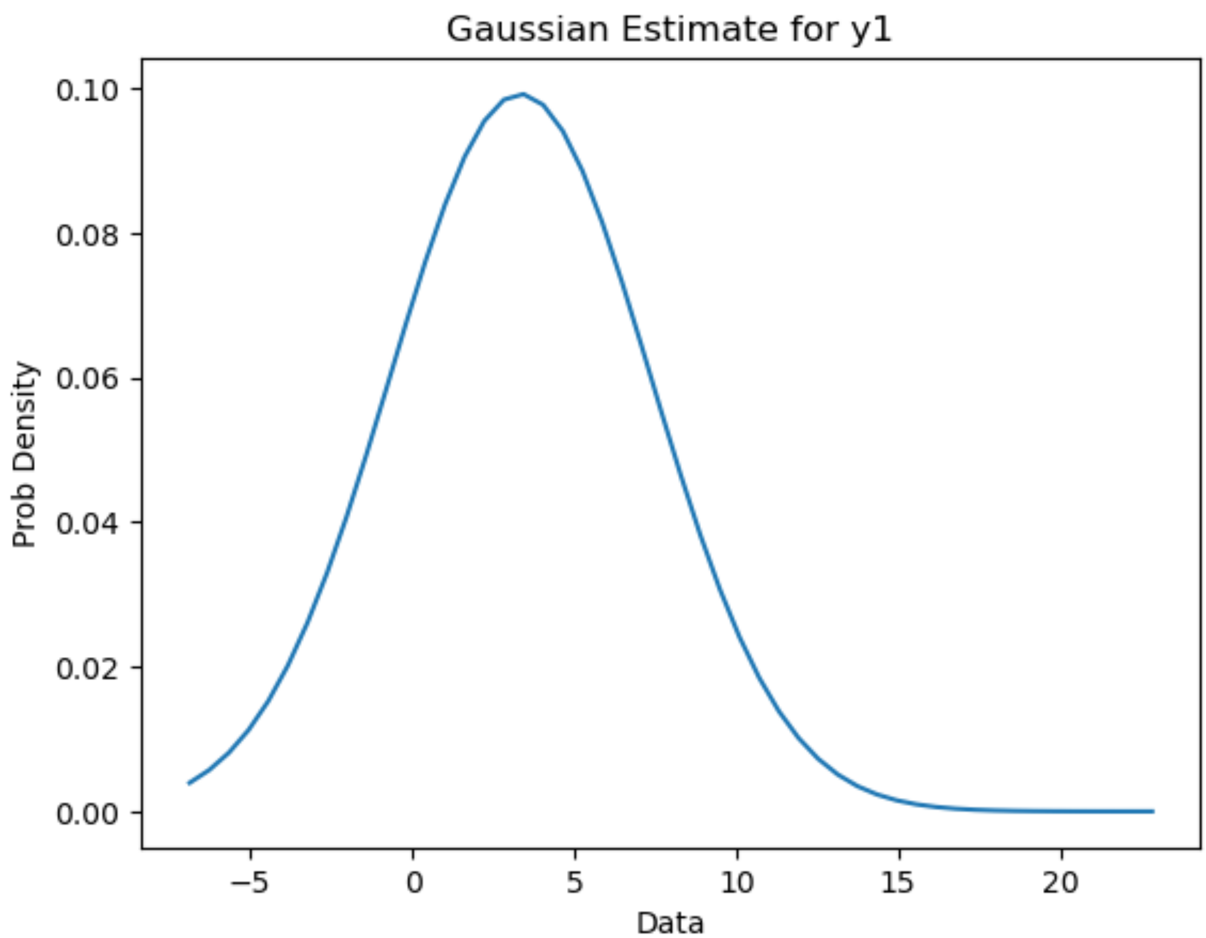
Using the following way to produce data:

In [93]:
```

```

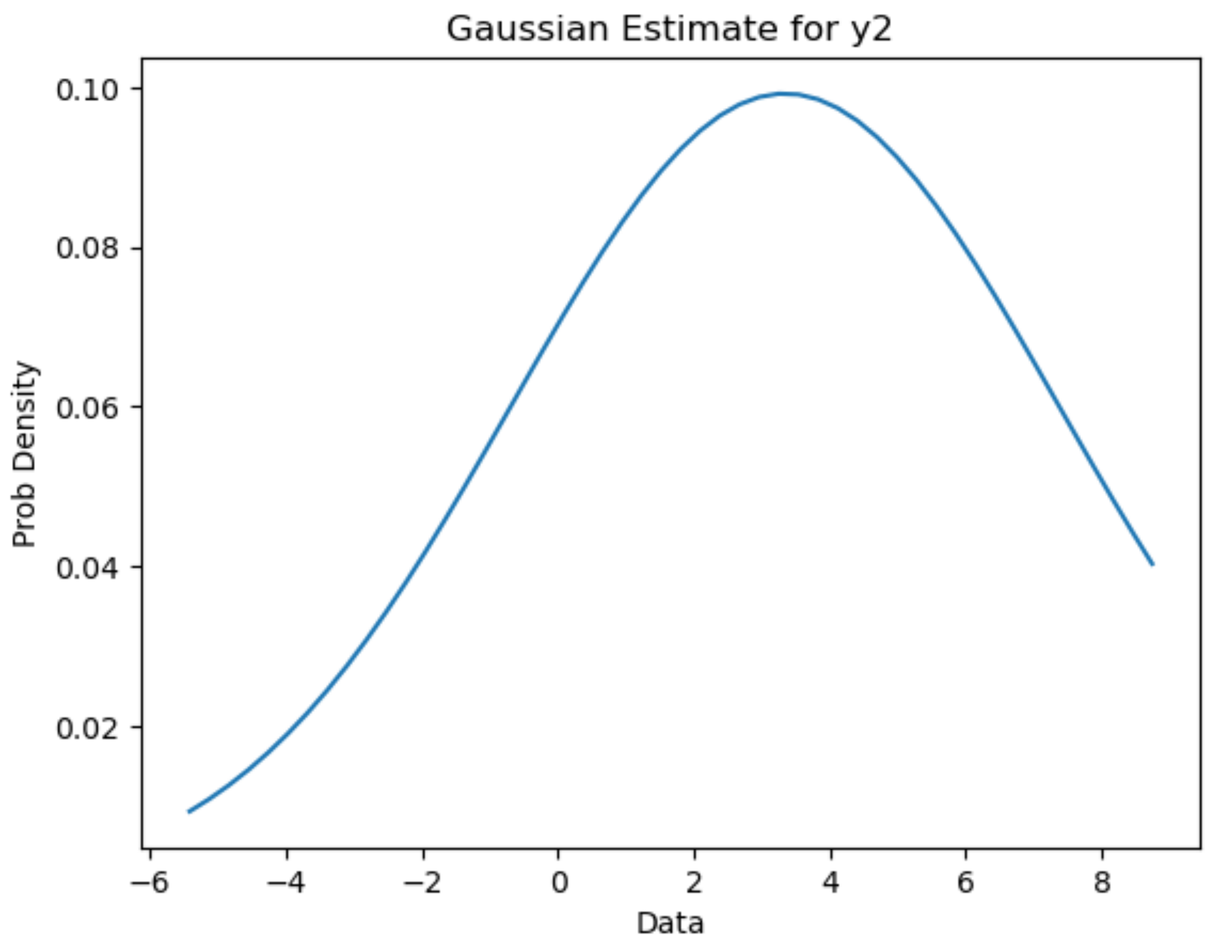
In [60]:
```python
# Generating data
random_seed = 36784765
np.random.seed(random_seed)

Mean1 = 9.0
Standard_dev1 = 5.0
Mean2 = 2.0
Standard_dev2 = 2.0

# generate data
y1 = np.random.normal(Mean1, Standard_dev1, 500)
y2 = np.random.normal(Mean2, Standard_dev2, 2000)
data = np.append(y1, y2)



class Gaussian:
    "Model univariate Gaussian"
    def __init__(self, mu, sigma):
        # Mean and standard deviation
        self.mu = mu
        self.sigma = sigma

    def pdf(self, datum):
        "Probability of a data point given the current parameters"
        u = (datum - self.mu) / abs(self.sigma)
        y = (1 / (np.sqrt(2 * np.pi) * abs(self.sigma))) * np.exp(-u *
        return y



# Fitting Gaussian to the data
mu_est = data.mean()
std_est = data.std()
g_est = Gaussian(mu_est, std_est)
```

In [ ]:
```python

```

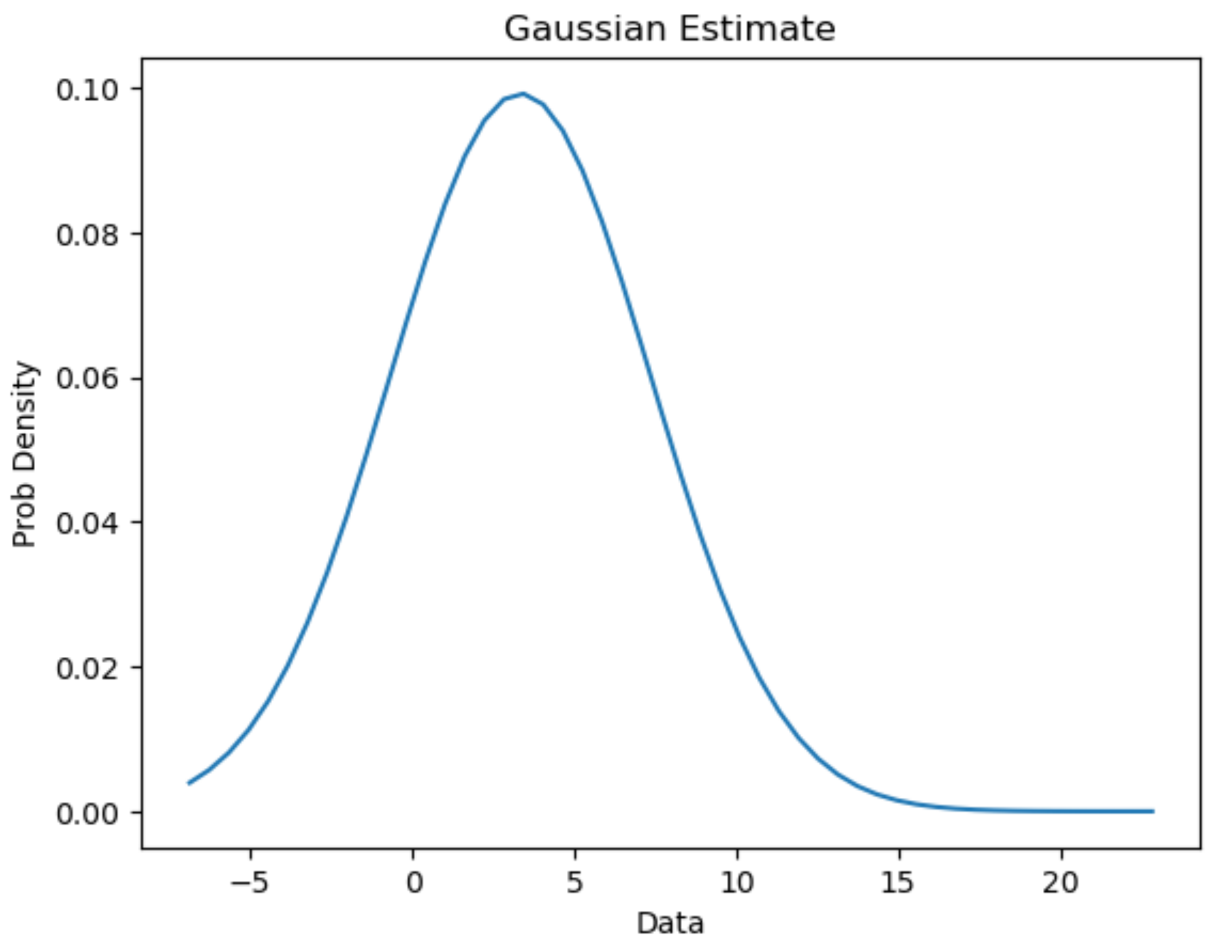
In [61]:
```
# y1
x_vals = np.linspace(min(y1), max(y1))

plt.plot(x_vals, g_est.pdf(x_vals))

plt.xlabel('Data')
plt.ylabel('Prob Density')
plt.title('Gaussian Estimate for y1')

plt.show()
```



In [62]:
```
# y2
x_vals = np.linspace(min(y2), max(y2))

plt.plot(x_vals, g_est.pdf(x_vals))

plt.xlabel('Data')
plt.ylabel('Prob Density')
plt.title('Gaussian Estimate for y2')

plt.show()
```



In [63]:
```
# combined y1 and y2

x_vals = np.linspace(min(data), max(data))

plt.plot(x_vals, g_est.pdf(x_vals))

plt.xlabel('Data')
plt.ylabel('Prob Density')
plt.title('Gaussian Estimate')

plt.show()
```



In [ ]:

In [76]:
```
# (2 PART )
class GaussianMixture_self:

    def __init__(self, data, mu_min=None, mu_max=None, sigma_min=1, si
        # Data points
        self.data = data
```

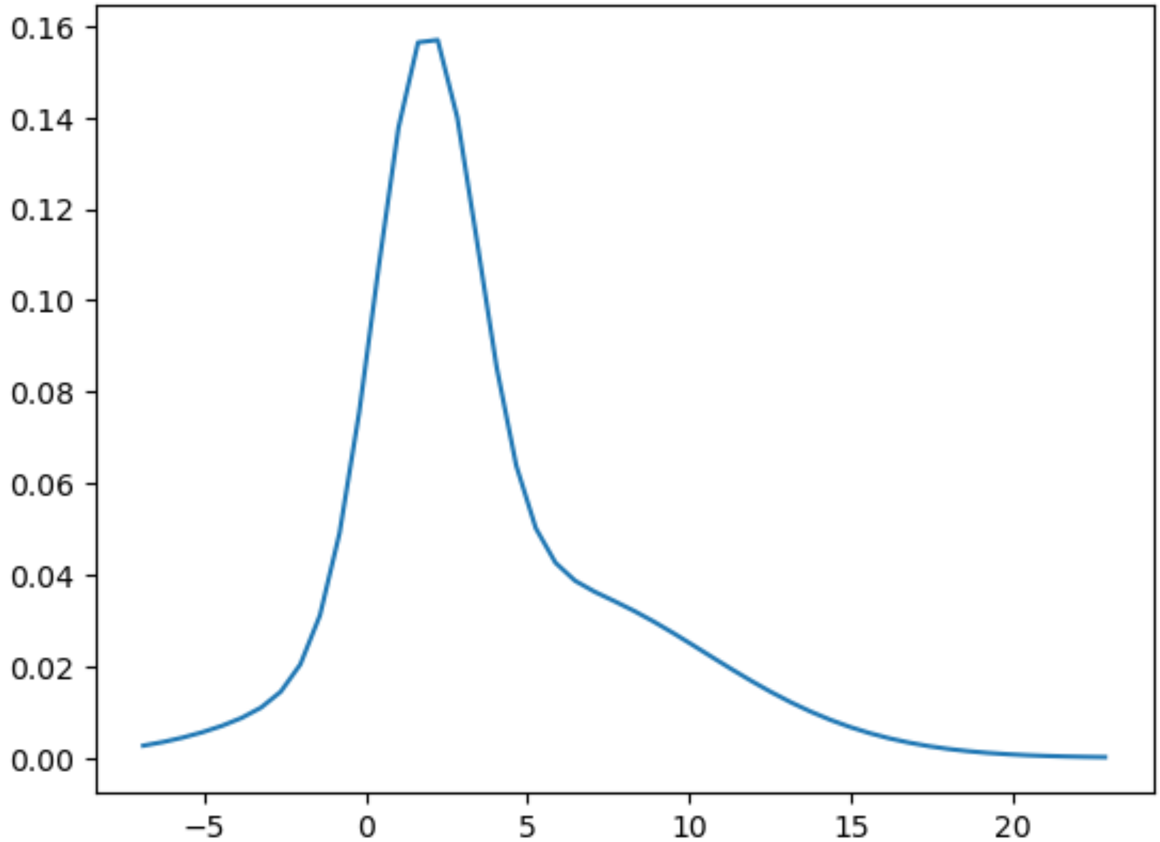
```
        # Initialize two Gaussian components with specified min/max va
        self.g1 = Gaussian(mu_min if mu_min is not None else min(data)
        self.g2 = Gaussian(mu_max if mu_max is not None else max(data)

        self.mix = mix

    def Estep(self):
        "Perform an E(stimation)-step"
        # Calculate the probability of each data point belonging to Ga
        pdf1 = self.g1.pdf(self.data)
        pdf2 = self.g2.pdf(self.data)

        # Responsibilities of both Gaussian for each dpoint
        res1 = pdf1 * self.mix
        res2 = pdf2 * (1 - self.mix)

        # Normalise the responsibilities
        self.wt = res1 / (res1 + res2)

    def Mstep(self):
        "Perform an M(aximization)-step"

        # Updating mu & sigma basis wts.
        self.g1.mu = np.sum(self.wt * self.data) / np.sum(self.wt)
        self.g2.mu = np.sum((1 - self.wt) * self.data) / np.sum(1 - se

        self.g1.sigma = np.sqrt(np.sum(self.wt * (self.data - self.g1.
        self.g2.sigma = np.sqrt(np.sum((1 - self.wt) * (self.data - se


    def iterate(self, N=1, verbose=False):
        "Perform N iterations, then compute log-likelihood"
        for i in range(N):
            # E-step
            self.Estep()

            # M-step
            self.Mstep()

    def pdf(self, x):
        # Probability density function of the mixture model
        return self.mix * self.g1.pdf(x) + (1 - self.mix) * self.g2.pd

class Gaussian:
    "Univariate Gaussian distribution"

    def __init__(self, mu, sigma):
        self.mu = mu
        self.sigma = sigma

    def pdf(self, x):
        # Probability density function of the Gaussian distribution
        u = (x - self.mu) / abs(self.sigma)
```

```python
        y = (1 / (np.sqrt(2 * np.pi) * abs(self.sigma))) * np.exp(-u *
        return y
```

In [81]:

```python
# Instantiate class with data
gmm = GaussianMixture_self(data)

# EM iterations
gmm.iterate(N=100)
```

In [83]:
```
# Plot graph
x = np.linspace(min(data), max(data))

plt.plot(x, gmm.pdf(x))

plt.show()
```



In [ ]:

In [ ]: