naiveBayes

March 22, 2023

1 *NAIVE BAYES CLASSIFIER*

1.1 1. LOAD AND EXPLORATION:

1.1.1 Dataset: Stellar Classification dataset

The data consists of 100,000 observations of space taken by the SDSS (Sloan Digital Sky Survey). Every observation is described by 17 feature columns and 1 class column which identifies it to be either a star, galaxy or quasar.

1) **obj_ID** = Object Identifier, the unique value that identifies the object in the image catalog used by the CAS
2) **alpha** = Right Ascension angle (at J2000 epoch)
3) **delta** = Declination angle (at J2000 epoch)
4) **u** = Ultraviolet filter in the photometric system
5) **g** = Green filter in the photometric system
6) **r** = Red filter in the photometric system
7) **i** = Near Infrared filter in the photometric system
8) **z** = Infrared filter in the photometric system
9) **run_ID** = Run Number used to identify the specific scan
10) **rereun_ID** = Rerun Number to specify how the image was processed
11) **cam_col** = Camera column to identify the scanline within the run
12) **field_ID** = Field number to identify each field
13) **spec_obj_ID** = Unique ID used for optical spectroscopic objects (this means that 2 different observations with he same spec_obj_ID must share the output class)
14) **class** = object class (galaxy, star or quasar object)
15) **redshift** = redshift value based on the increase in wavelength
16) **plate** = plate ID, identifies each plate in SDSS
17) **MJD** = Modified Julian Date, used to indicate when a given piece of SDSS data was taken
18) **fiber_ID** = fiber ID that identifies the fiber that pointed the light at the focal plane in each observation

[43]:
```
#importing libraries

import pandas as pd
import seaborn as sns
import numpy as np
import matplotlib.pyplot as plt
import math
```

```
from sklearn.naive_bayes import GaussianNB
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.metrics import accuracy_score,recall_score, precision_score,
 ↪classification_report,confusion_matrix

import warnings
warnings.filterwarnings('ignore')
%matplotlib inline
```

[44]:
```
#loading the data

df=pd.read_csv('./star_classification.csv')
df.head()
```

[44]:
```
         obj_ID       alpha      delta         u         g         r  \
0  1.237661e+18  135.689107  32.494632  23.87882  22.27530  20.39501
1  1.237665e+18  144.826101  31.274185  24.77759  22.83188  22.58444
2  1.237661e+18  142.188790  35.582444  25.26307  22.66389  20.60976
3  1.237663e+18  338.741038  -0.402828  22.13682  23.77656  21.61162
4  1.237680e+18  345.282593  21.183866  19.43718  17.58028  16.49747

          i         z  run_ID  rerun_ID  cam_col  field_ID   spec_obj_ID  \
0  19.16573  18.79371    3606       301        2        79  6.543777e+18
1  21.16812  21.61427    4518       301        5       119  1.176014e+19
2  19.34857  18.94827    3606       301        2       120  5.152200e+18
3  20.50454  19.25010    4192       301        3       214  1.030107e+19
4  15.97711  15.54461    8102       301        3       137  6.891865e+18

    class  redshift  plate    MJD  fiber_ID
0  GALAXY  0.634794   5812  56354       171
1  GALAXY  0.779136  10445  58158       427
2  GALAXY  0.644195   4576  55592       299
3  GALAXY  0.932346   9149  58039       775
4  GALAXY  0.116123   6121  56187       842
```

[45]:
```
#getting the statiscal information

df.describe()
```

[45]:
```
             obj_ID          alpha          delta              u  \
count  1.000000e+05  100000.000000  100000.000000  100000.000000
mean   1.237665e+18     177.629117      24.135305      21.980468
std    8.438560e+12      96.502241      19.644665      31.769291
min    1.237646e+18       0.005528     -18.785328   -9999.000000
25%    1.237659e+18     127.518222       5.146771      20.352353
```

```
50%    1.237663e+18     180.900700      23.645922      22.179135
75%    1.237668e+18     233.895005      39.901550      23.687440
max    1.237681e+18     359.999810      83.000519      32.781390

                   g              r              i              z  \
count  100000.000000  100000.000000  100000.000000  100000.000000
mean       20.531387      19.645762      19.084854      18.668810
std        31.750292       1.854760       1.757895      31.728152
min     -9999.000000       9.822070       9.469903   -9999.000000
25%        18.965230      18.135828      17.732285      17.460677
50%        21.099835      20.125290      19.405145      19.004595
75%        22.123767      21.044785      20.396495      19.921120
max        31.602240      29.571860      32.141470      29.383740

              run_ID  rerun_ID        cam_col       field_ID   spec_obj_ID  \
count  100000.000000  100000.0  100000.000000  100000.000000  1.000000e+05
mean     4481.366060     301.0       3.511610     186.130520  5.783882e+18
std      1964.764593       0.0       1.586912     149.011073  3.324016e+18
min       109.000000     301.0       1.000000      11.000000  2.995191e+17
25%      3187.000000     301.0       2.000000      82.000000  2.844138e+18
50%      4188.000000     301.0       4.000000     146.000000  5.614883e+18
75%      5326.000000     301.0       5.000000     241.000000  8.332144e+18
max      8162.000000     301.0       6.000000     989.000000  1.412694e+19

            redshift          plate            MJD       fiber_ID
count  100000.000000  100000.000000  100000.000000  100000.000000
mean        0.576661    5137.009660   55588.647500     449.312740
std         0.730707    2952.303351    1808.484233     272.498404
min        -0.009971     266.000000   51608.000000       1.000000
25%         0.054517    2526.000000   54234.000000     221.000000
50%         0.424173    4987.000000   55868.500000     433.000000
75%         0.704154    7400.250000   56777.000000     645.000000
max         7.011245   12547.000000   58932.000000    1000.000000
```

1.2 2. DATA CLEANING

Checking for missing values:

[46]:
```
df.isnull().sum()
```

[46]:
```
obj_ID         0
alpha          0
delta          0
u              0
g              0
r              0
i              0
z              0
```

```
run_ID         0
rerun_ID       0
cam_col        0
field_ID       0
spec_obj_ID    0
class          0
redshift       0
plate          0
MJD            0
fiber_ID       0
dtype: int64
```

1.2.1 *There are no missing values in the dataset*

Checking for duplicate entries:

[47]:
```
df.duplicated().sum()
```

[47]:
```
0
```

[48]:
```
#statisical information of categorical column (i.e object)


df.describe(include=['O'])
```

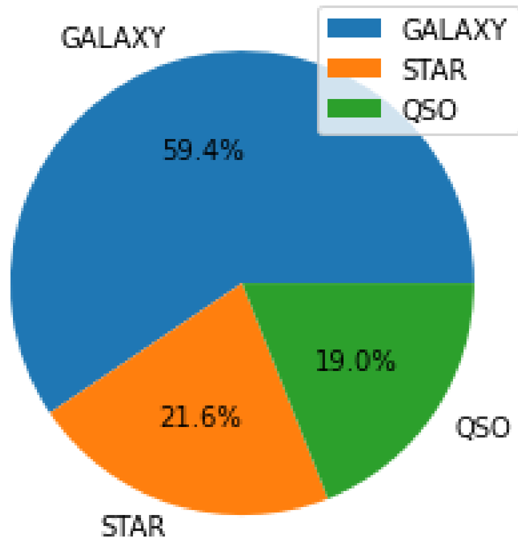
[48]:

	class
count	100000
unique	3
top	GALAXY
freq	59445

[49]:
```
#counting the frequency of each element from the 'class'


df['class'].value_counts()
```

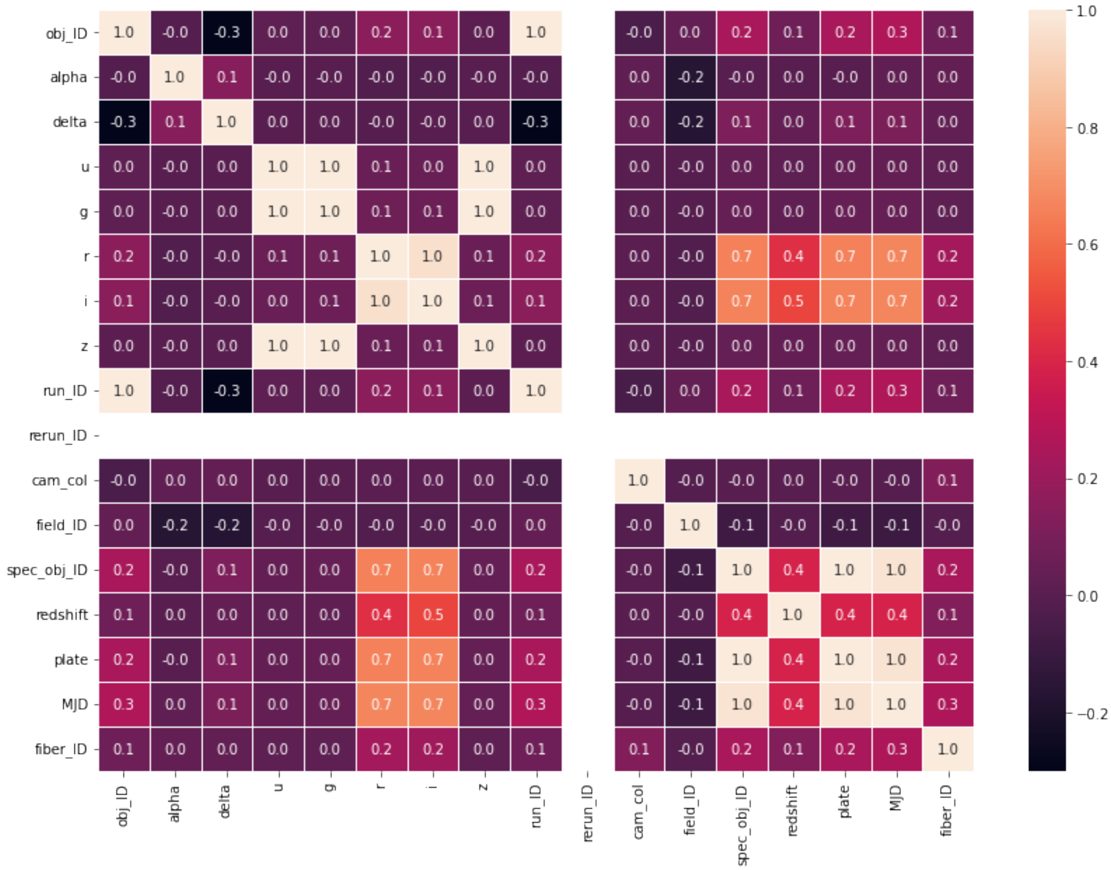
[49]:
```
GALAXY    59445
STAR      21594
QSO       18961
Name: class, dtype: int64
```

[50]:
```
#proportion of different elements of the class


plt.pie(df['class'].value_counts(),autopct="%1.
 ↪1f%%",labels=['GALAXY','STAR','QSO'])
plt.legend();
```



[51]:

```
#correlation between the columns


plt.figure(figsize = (14,10))
sns.heatmap(df.corr(), annot = True, fmt = ".1f", linewidths = .7)
plt.show()
```

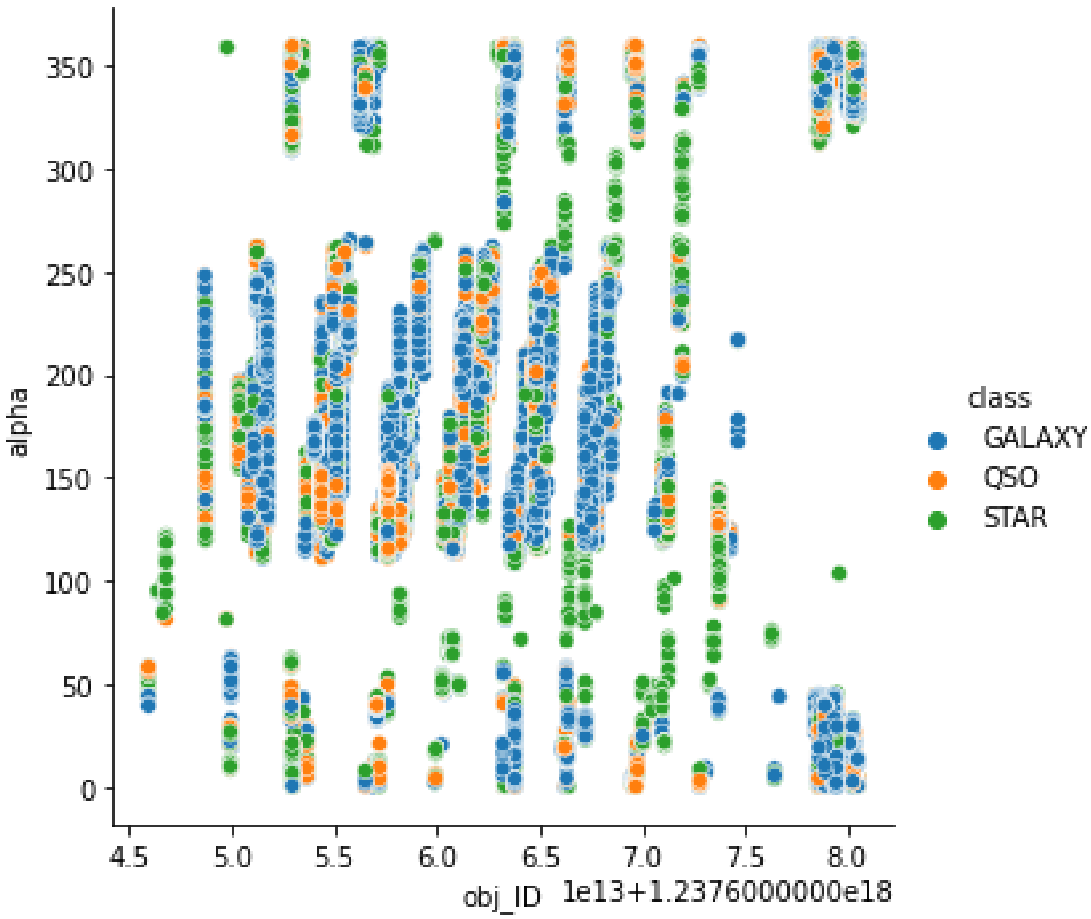


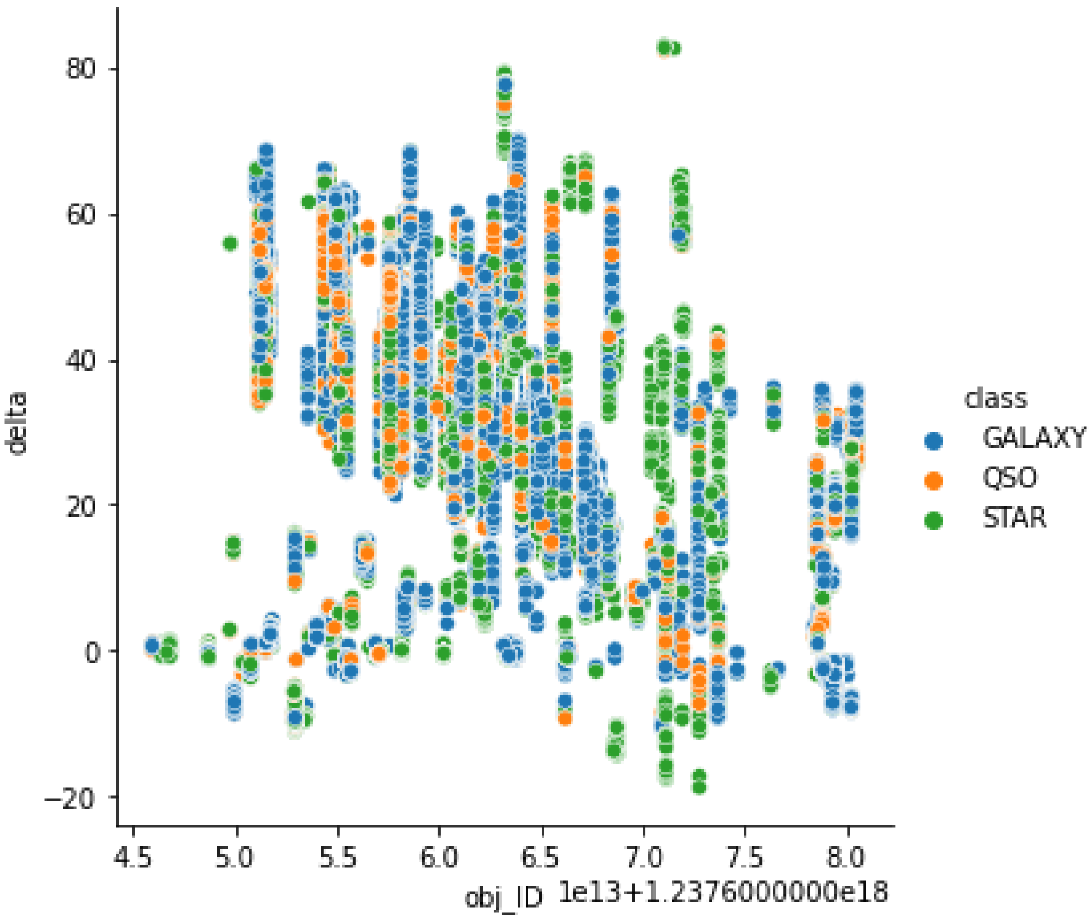
[52]:
```python
print([col for col in df])
```

```
['obj_ID', 'alpha', 'delta', 'u', 'g', 'r', 'i', 'z', 'run_ID', 'rerun_ID',
'cam_col', 'field_ID', 'spec_obj_ID', 'class', 'redshift', 'plate', 'MJD',
'fiber_ID']
```

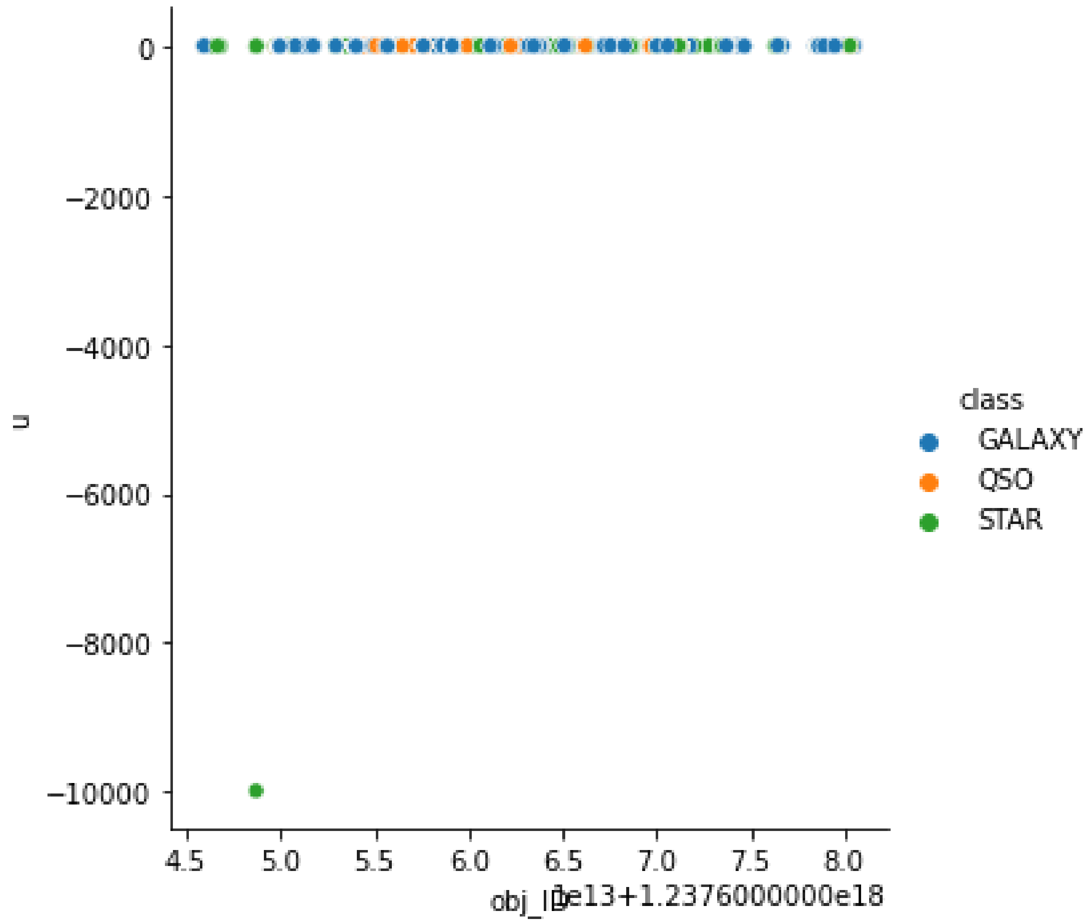
1.2.2 Analyzing the features against the "obj_ID" (primary key) for correlation:

[12]:
```python
#comparing variations of different attributes with 'obj_ID'


plots=[]
for i in ['alpha', 'delta', 'u', 'g', 'r', 'i', 'z', 'run_ID',
        'rerun_ID', 'cam_col', 'field_ID', 'spec_obj_ID', 'redshift',
        'plate', 'MJD', 'fiber_ID']:
    g=sns.relplot(data=df,x ='obj_ID', y=i, hue='class')
    plots.append(g);
```

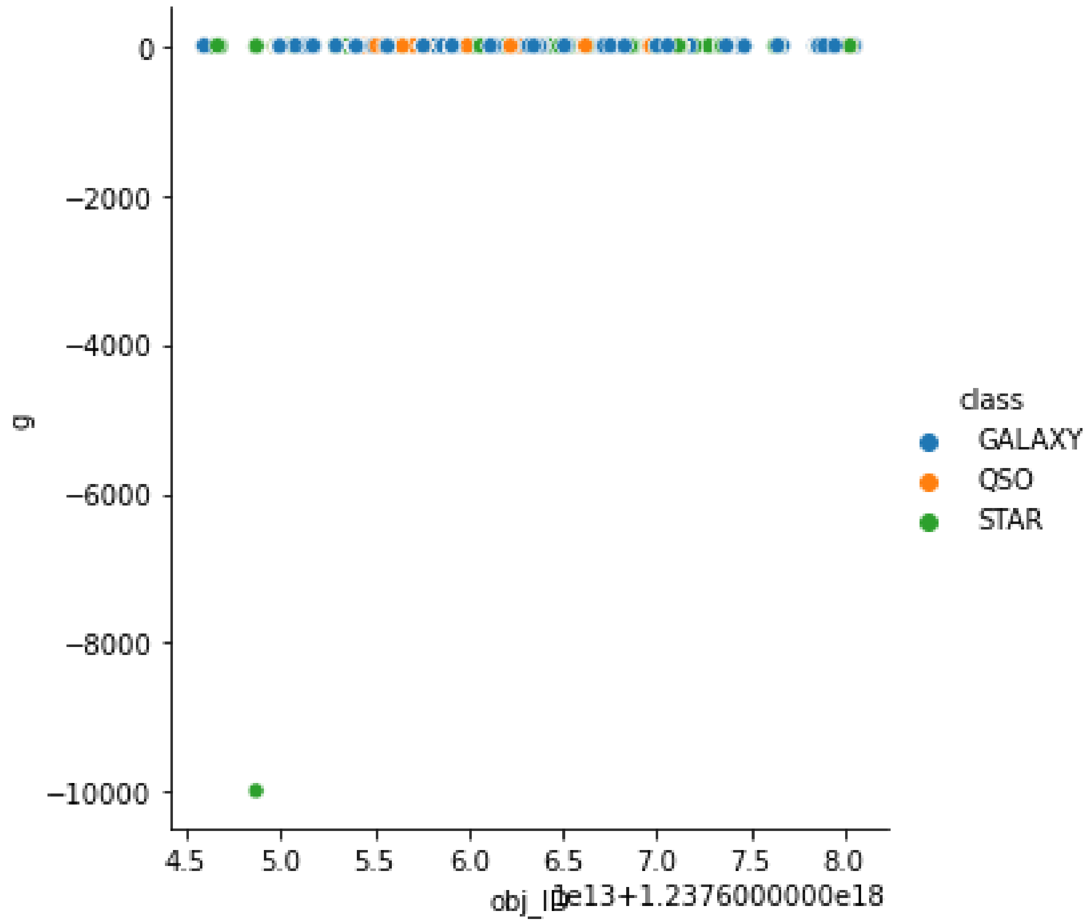

350
300
250
200
150
100
50
0
alpha
4.5
5.0
5.5
6.0
6.5
7.0
7.5
8.0
obj_ID
1e13+1.2376000000e18
class
GALAXY
QSO
STAR

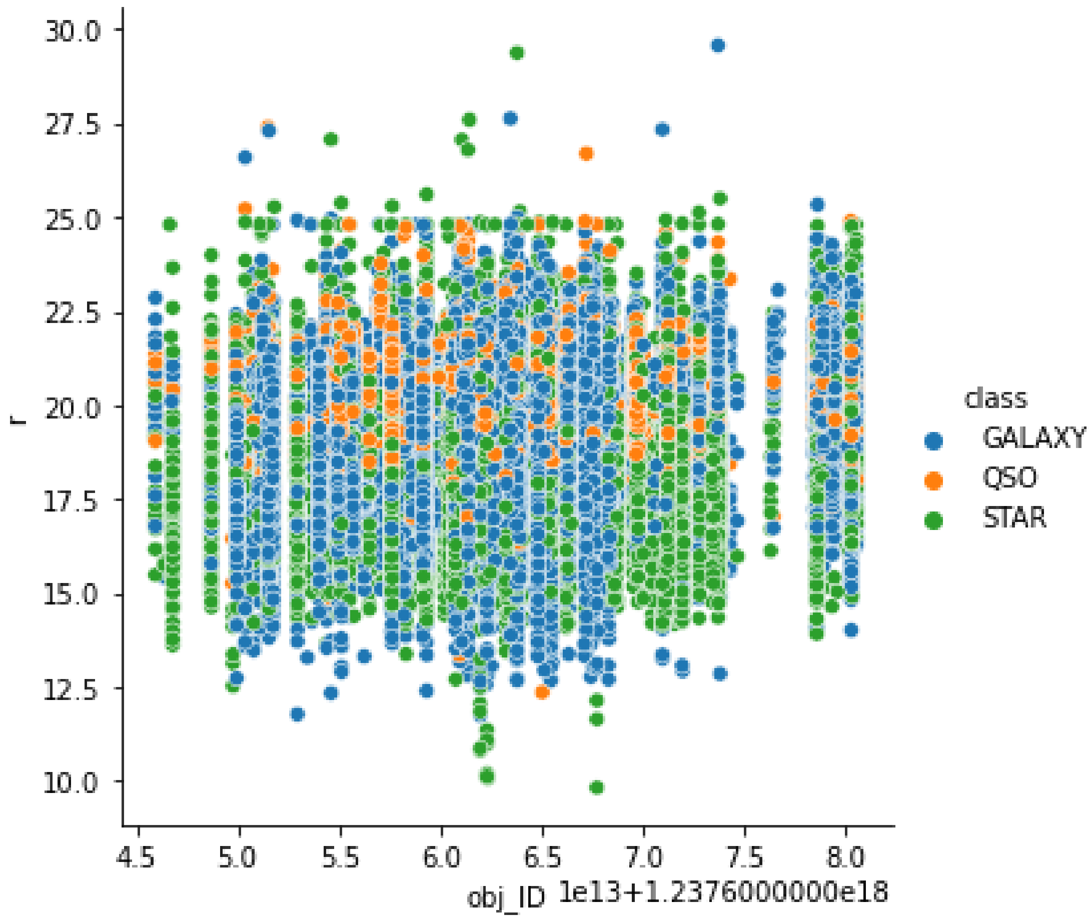


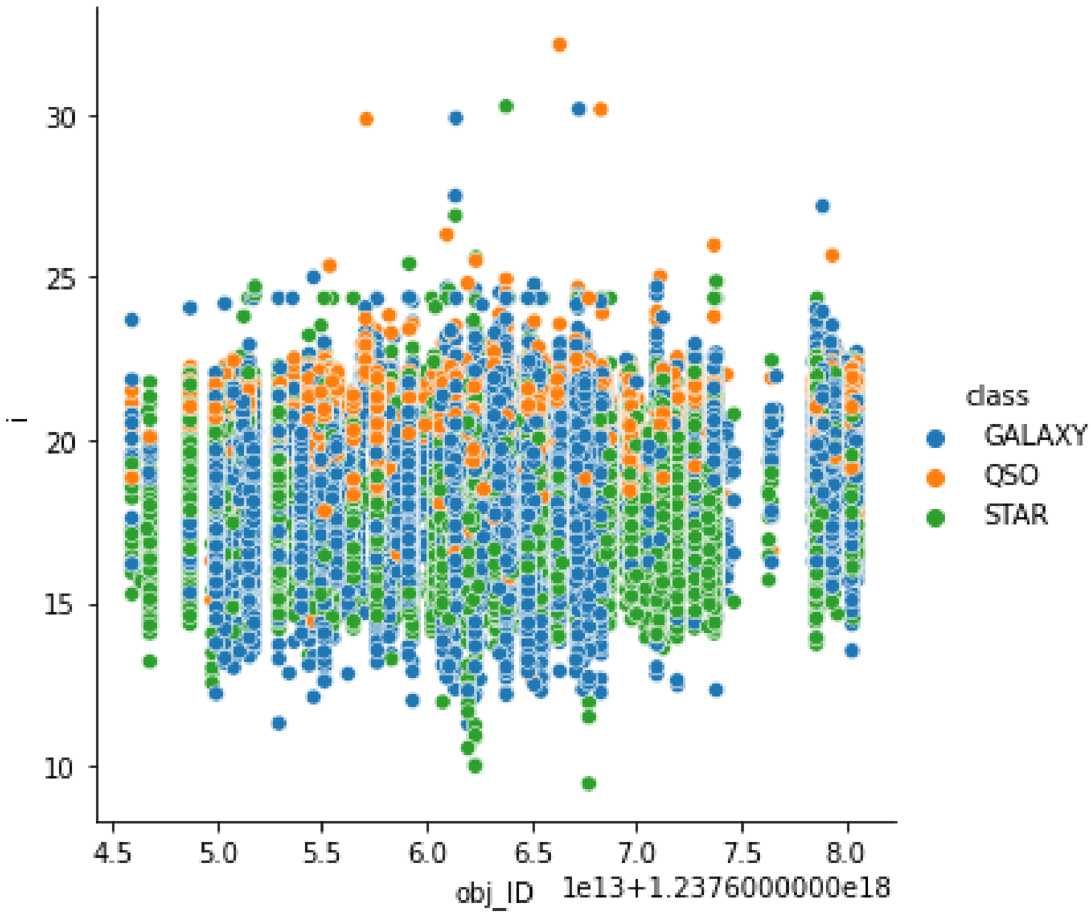
80
60
40
20
0
−20
delta
4.5
5.0
5.5
6.0
6.5
7.0
7.5
8.0
obj_ID
1e13+1.2376000000e18
class
GALAXY
QSO
STAR



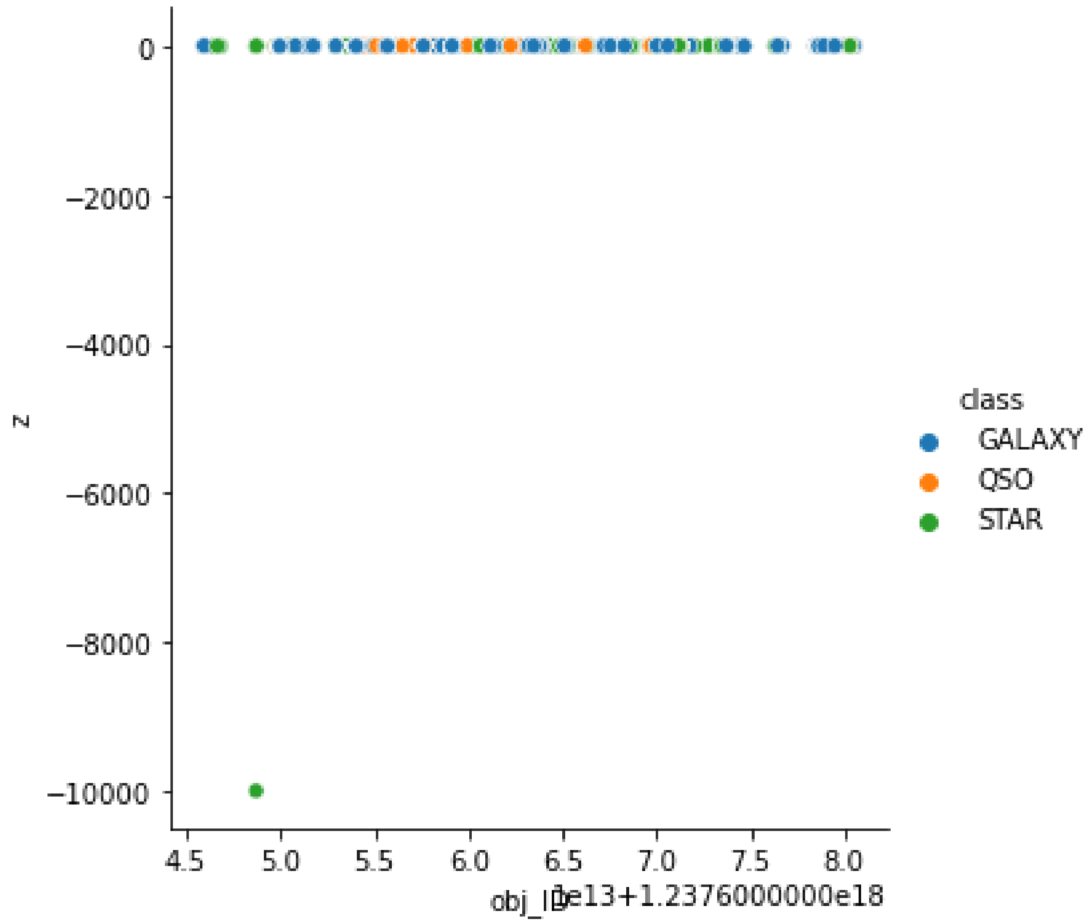
0
−2000
−4000
−6000
−8000
−10000
u
4.5
5.0
5.5
6.0
6.5
7.0
7.5
8.0
obj_ID
1e13+1.2376000000e18
class
GALAXY
QSO
STAR


0
−2000
−4000
−6000
−8000
−10000
g
4.5
5.0
5.5
6.0
6.5
7.0
7.5
8.0
obj_ID
1e13+1.2376000000e18
class
GALAXY
QSO
STAR

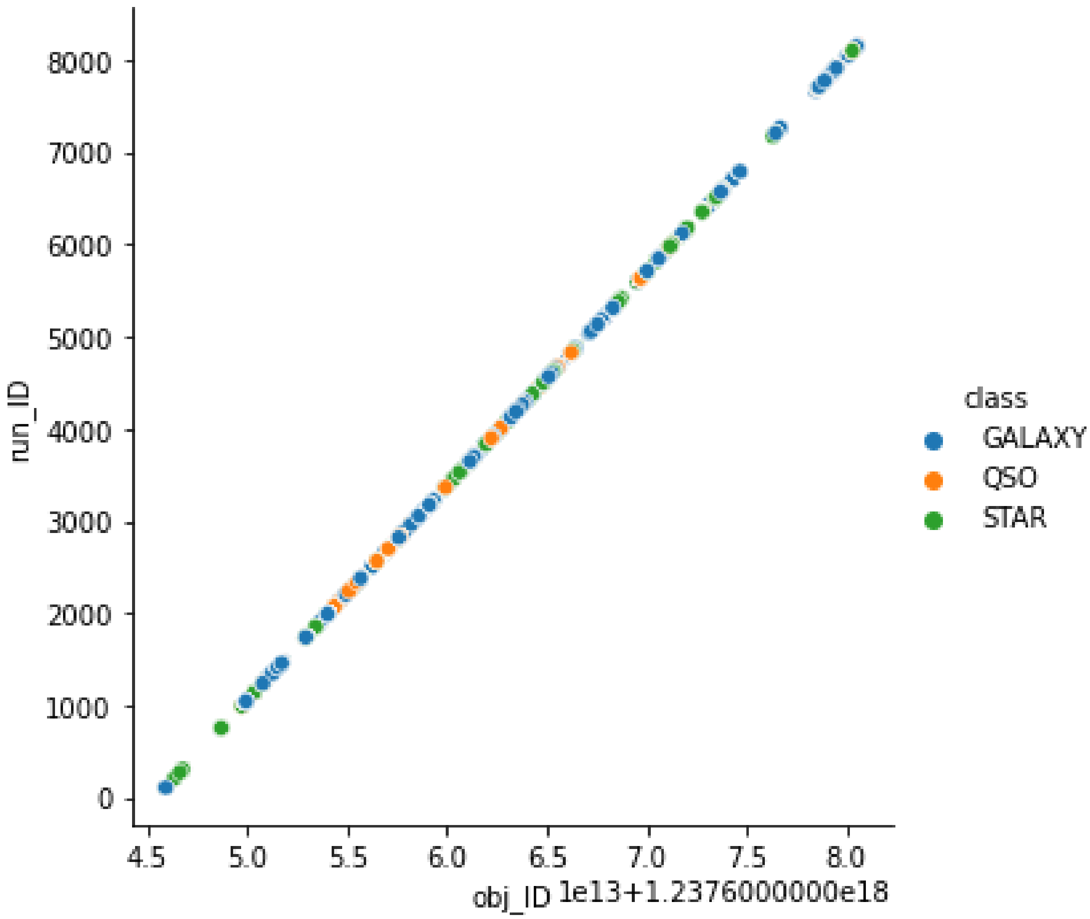

30.0
27.5
25.0
22.5
20.0
17.5
15.0
12.5
10.0
r
4.5
5.0
5.5
6.0
6.5
7.0
7.5
8.0
obj_ID
1e13+1.2376000000e18
class
GALAXY
QSO
STAR



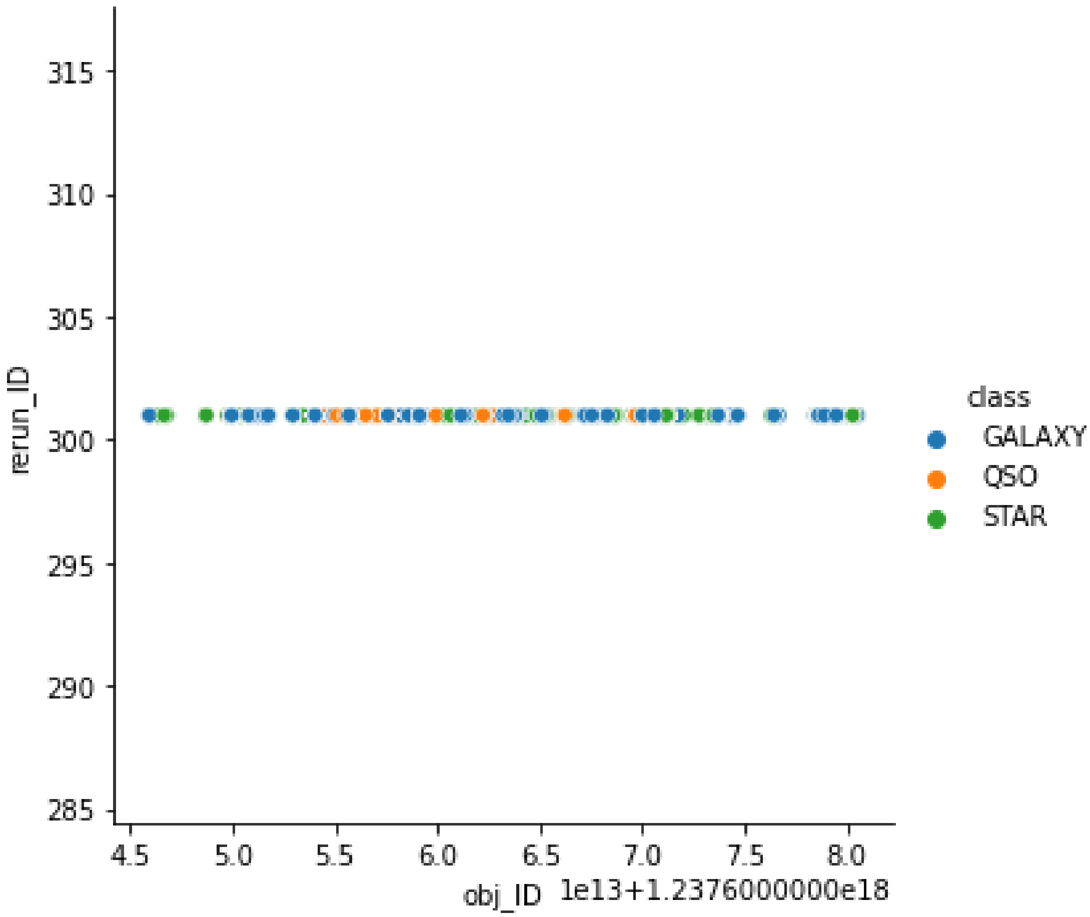
30
25
20
15
10
i
4.5
5.0
5.5
6.0
6.5
7.0
7.5
8.0
obj_ID
1e13+1.2376000000e18
class
GALAXY
QSO
STAR

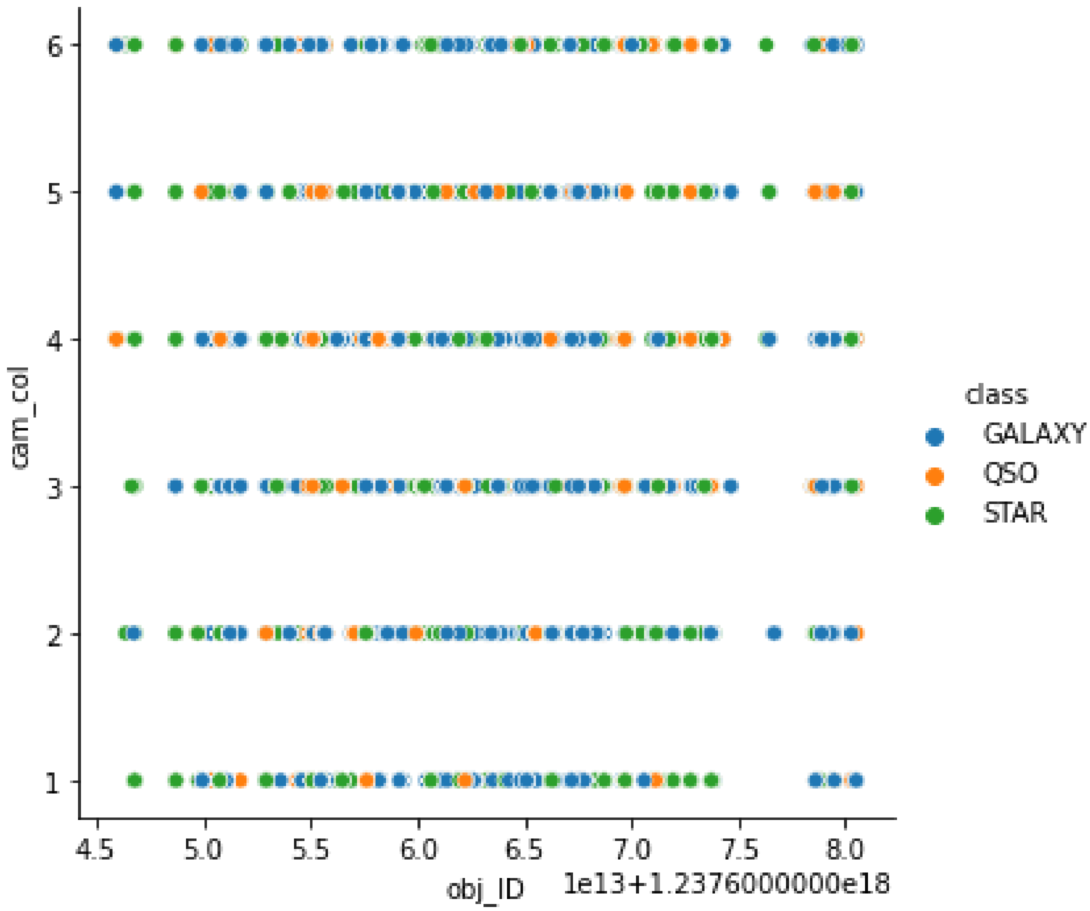


0
−2000
−4000
−6000
−8000
−10000
z
4.5
5.0
5.5
6.0
6.5
7.0
7.5
8.0
obj_ID
1e13+1.2376000000e18
class
GALAXY
QSO
STAR

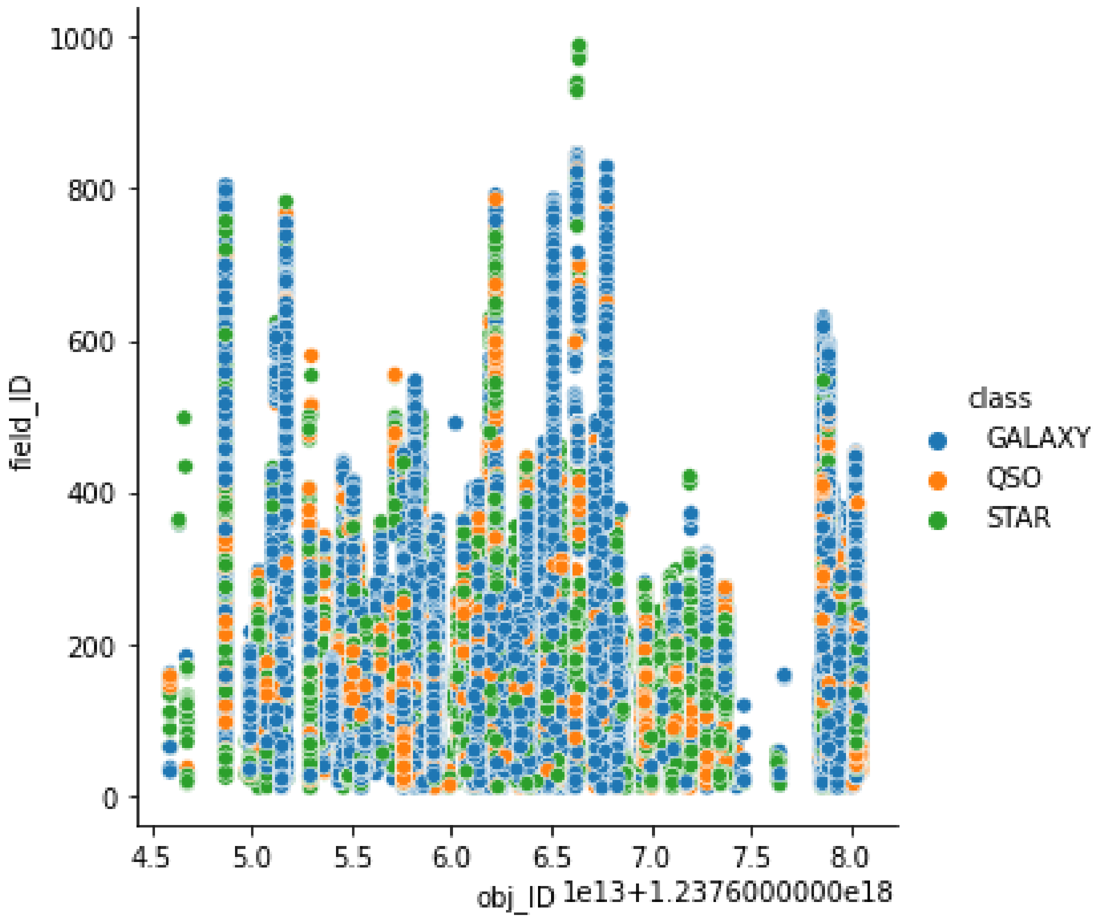


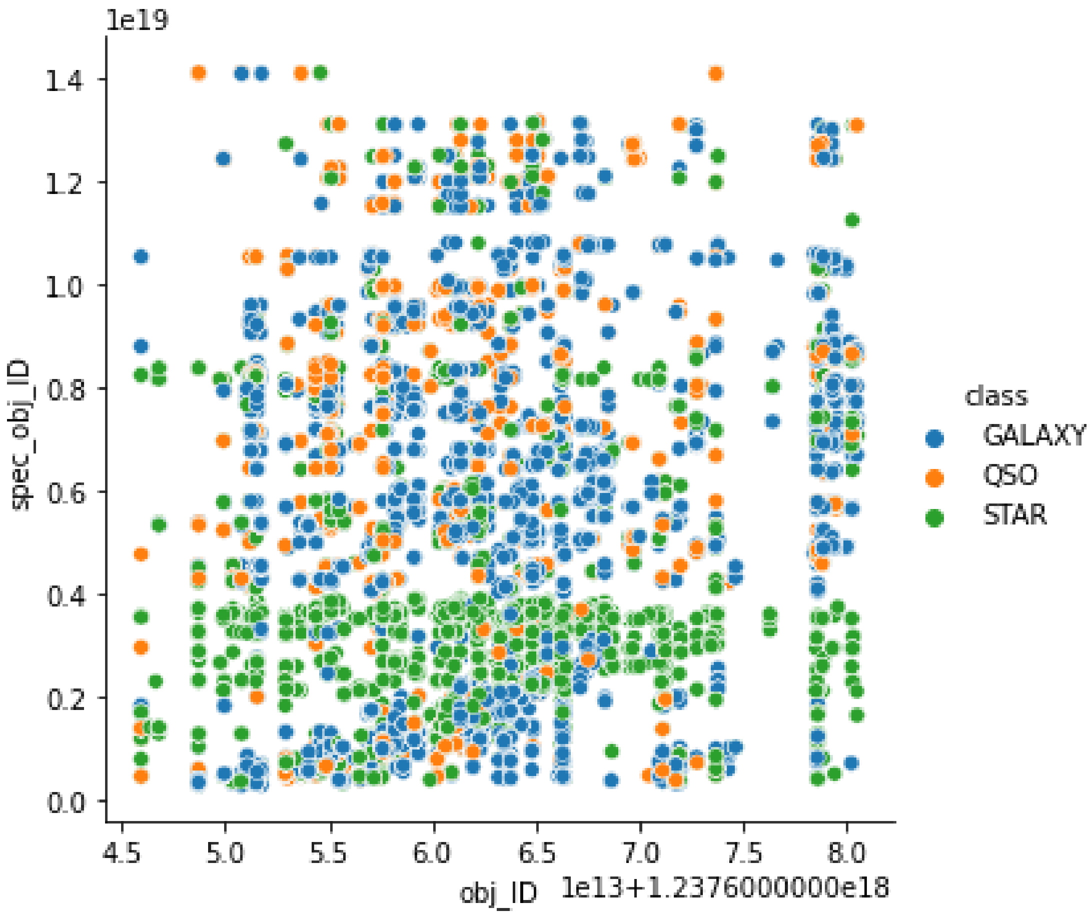
run_ID
obj_ID 1e13+1.2376000000e18
class
GALAXY
QSO
STAR

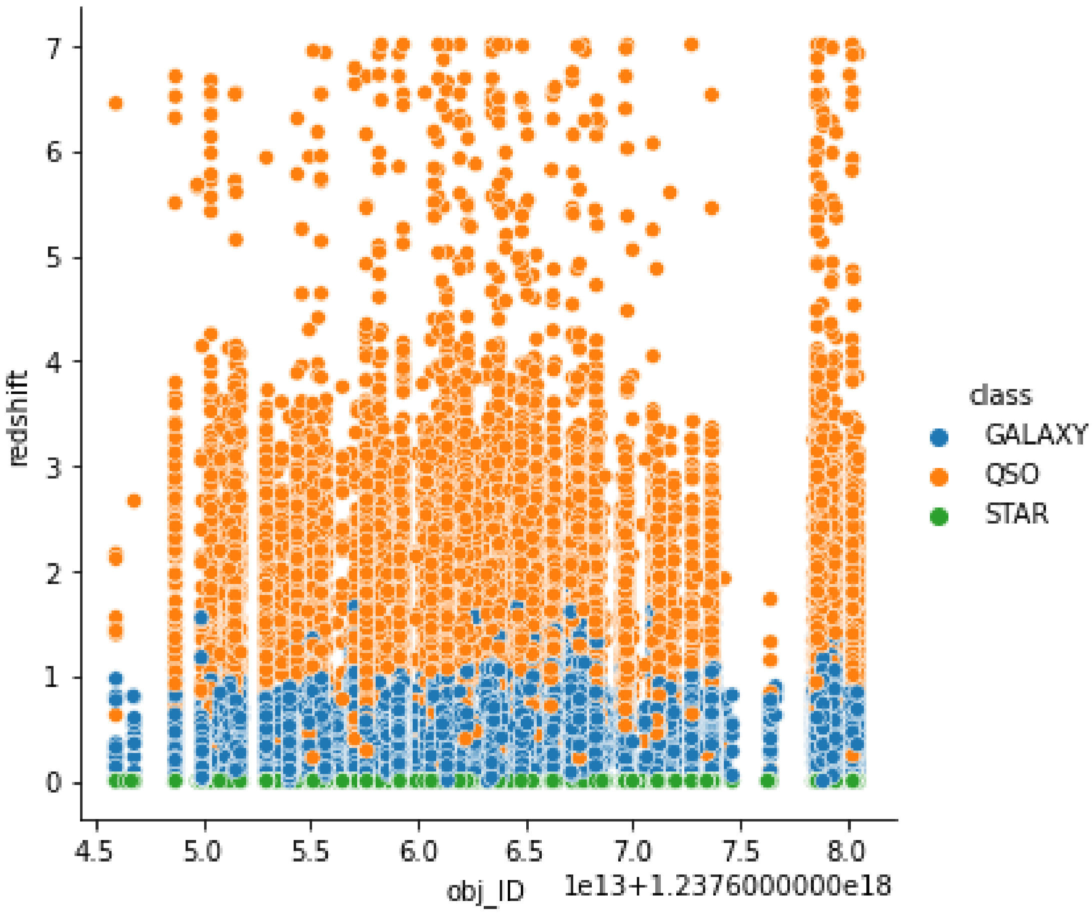

315
310
305
300
295
290
285
rerun_ID
4.5
5.0
5.5
6.0
6.5
7.0
7.5
8.0
obj_ID
1e13+1.2376000000e18
class
GALAXY
QSO
STAR



6
5
4
3
2
1
cam_col
4.5
5.0
5.5
6.0
6.5
7.0
7.5
8.0
obj_ID
1e13+1.2376000000e18
class
GALAXY
QSO
STAR


1000
800
600
400
200
0
field_ID
4.5
5.0
5.5
6.0
6.5
7.0
7.5
8.0
obj_ID 1e13+1.2376000000e18
class
GALAXY
QSO
STAR


1e19
1.4
1.2
1.0
0.8
0.6
0.4
0.2
0.0
spec_obj_ID
4.5
5.0
5.5
6.0
6.5
7.0
7.5
8.0
obj_ID
1e13+1.2376000000e18
class
GALAXY
QSO
STAR


redshift
7
6
5
4
3
2
1
0
4.5
5.0
5.5
6.0
6.5
7.0
7.5
8.0
obj_ID
1e13+1.2376000000e18
class
GALAXY
QSO
STAR

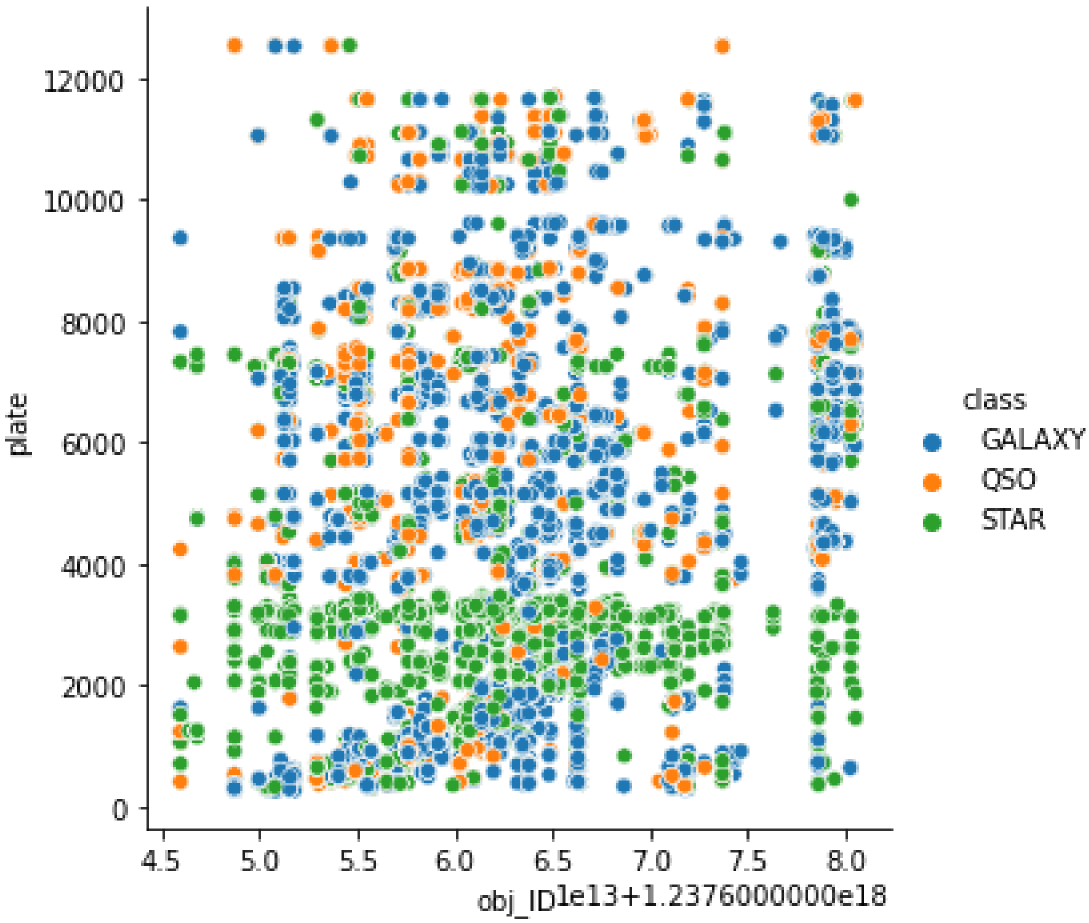
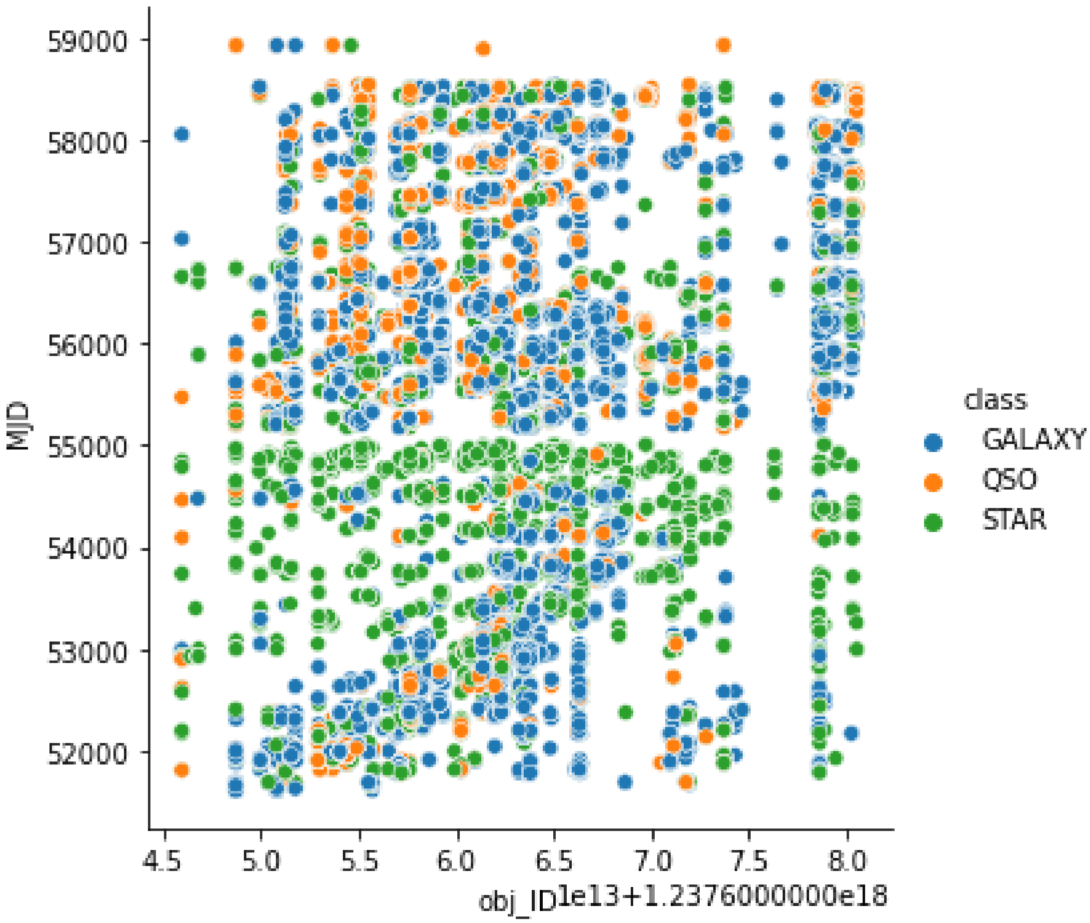
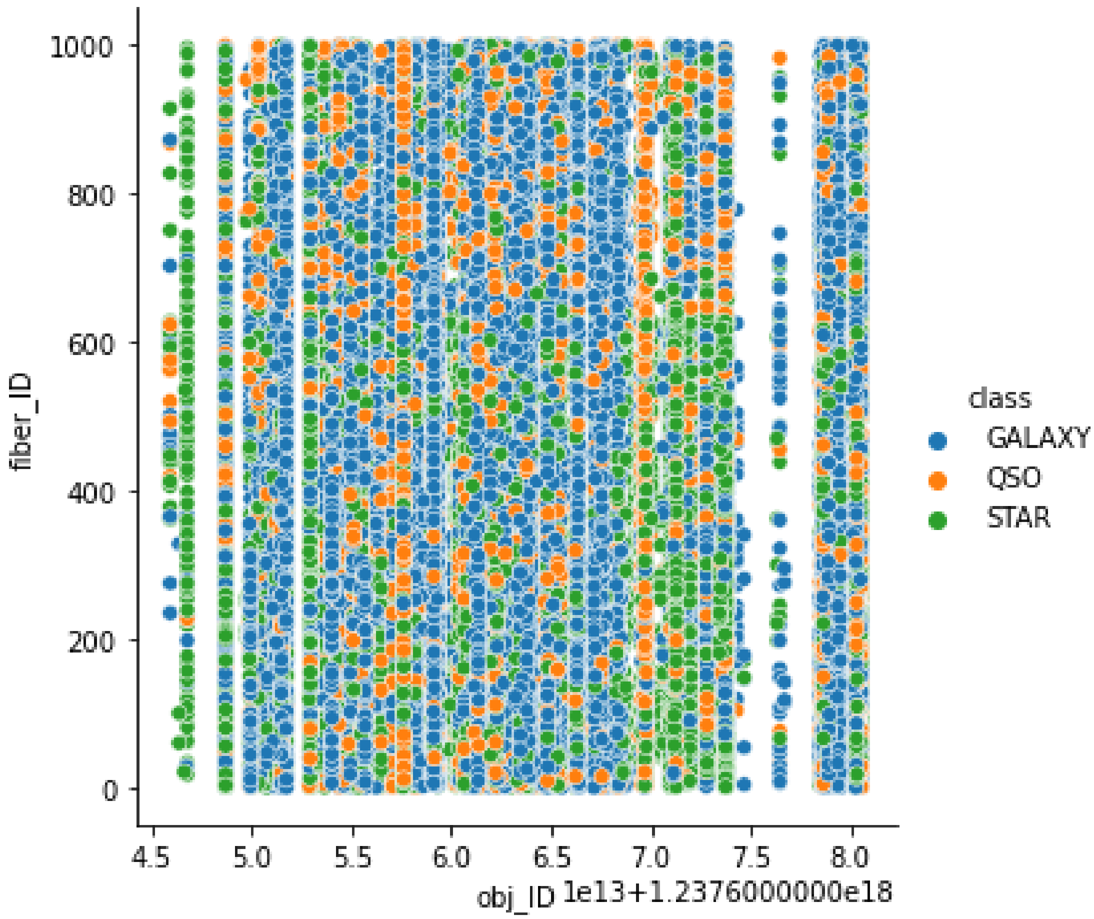


plate
12000
10000
8000
6000
4000
2000
0
4.5
5.0
5.5
6.0
6.5
7.0
7.5
8.0
obj_ID
1e13+1.2376000000e18
class
GALAXY
QSO
STAR



59000
58000
57000
56000
55000
54000
53000
52000
MJD
4.5
5.0
5.5
6.0
6.5
7.0
7.5
8.0
obj_ID
1e13+1.2376000000e18
class
GALAXY
QSO
STAR



The distribution of 'u' , 'g' , 'z' , 'run_ID' , 'rerun_ID' , 'cam_col' are either linear or horizontal straight line to obj_ID. Attributes which are showing y=mx+c relationship with obj_ID are insiginificant and need to removed.

It is clear that 'u' , 'g' , 'z' , 'run_ID' , 'rerun_ID' , 'cam_col' are insiginificant and need to removed.

Here it seems that the redshift plays an important part in the stellar classification since we can clearly distinguish between the various clusters of points.

[53]:
```
#dropping the unnecessary columns


df.drop(['obj_ID','cam_col', 'run_ID', 'rerun_ID'] ,axis=1, inplace=True)
df.shape
```

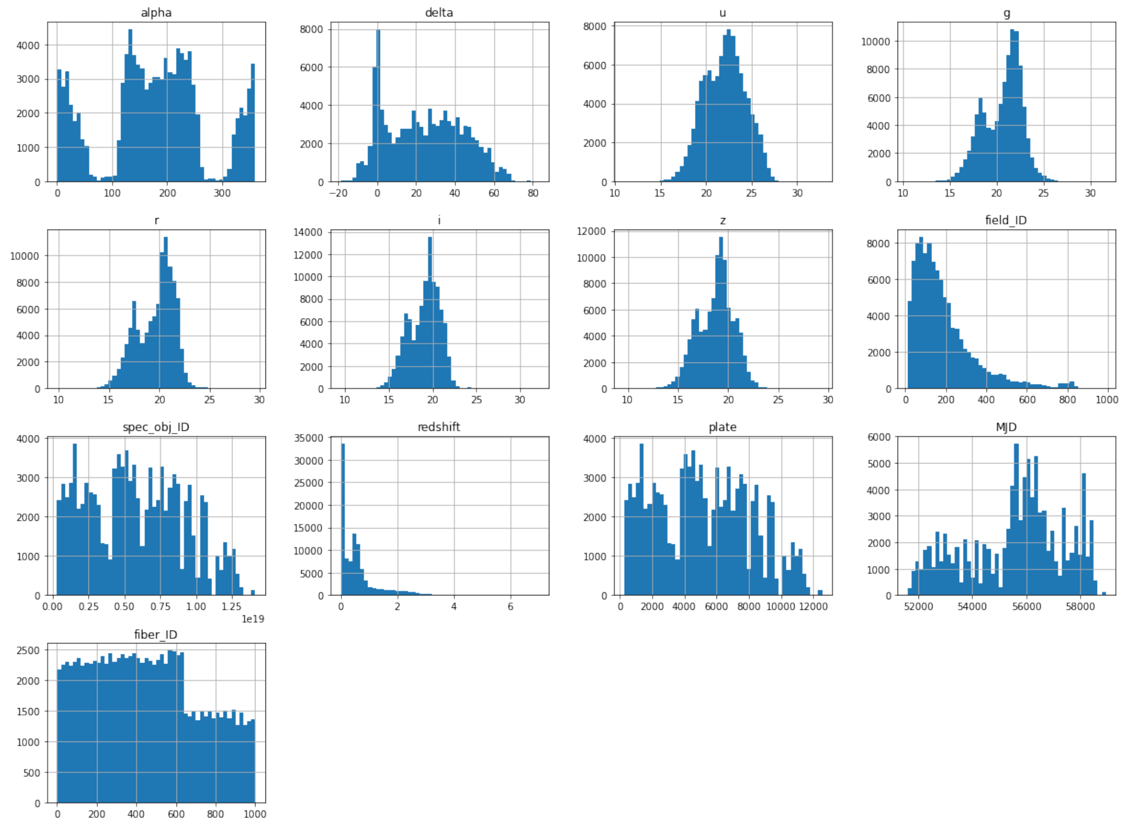
[53]: (100000, 14)

[54]:
```
#Filtering the data
#Removing the outliers

print('Shape before filtering :',df.shape)
df=df[df.z>-2000]
df=df[df.u>-2000]
df=df[df.g>-2000]
print('Shape after filtering :',df.shape)
```

```
Shape before filtering : (100000, 14)
Shape after filtering : (99999, 14)
```

1.2.3 Now Showing the distribution of each feature:

[15]:
```
df.hist(bins=50, figsize=(20,15))
plt.show()
```



1.2.4 Most of the features follow normal distrubution...Hence we can proceed with Gaussian Naive Bayes

[55]:
```
#x,y prepare
y=df['class']
x = df.drop( ['class'],axis=1)
```

[56]:
```
x.shape, y.shape
```

[56]:
```
((99999, 13), (99999,))
```

[57]:
```
y.head()
```

[57]:
```
0    GALAXY
1    GALAXY
2    GALAXY
3    GALAXY
4    GALAXY
Name: class, dtype: object
```

1.2.5 Deal with categorical data

[58]:
```
encoder = LabelEncoder()
```

[59]:
```
y = encoder.fit_transform(y)
```

[60]:
```
y = pd.DataFrame(y)
```

[61]:
```
y.value_counts()
```

[61]:
```
0    59445
2    21593
1    18961
dtype: int64
```

1.2.6 Converting Y to numpy array

[62]:
```
y = y.to_numpy()
y.shape
```

[62]:
```
(99999, 1)
```

[63]:
```
#splitting the processed dataset into train and test dataset

x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.2,␣
↪random_state = 42)
```

[64]:
```
#Normalizing the data for better performance

scaler = StandardScaler()
scaler.fit(x_train)
x_train = scaler.transform(x_train)
x_test = scaler.transform(x_test)
```

2 ALGORITHM FOR GAUSSIAN NAIVE BAYES IMPLEMENTED FROM SCRATCH

[69]:
```
class MyGaussianNaiveBayes:

    #Constructor for class
    def __init__(self):
        self.n_samples = 0
        self.n_features = 0
        self.features_mean = None
        self.features_sdev = None
        self.unique_labels = None
        self.prior_probabilities = None


    #fit function for training the model
    def fit(self, X, y):
        self.n_samples, n_features = X.shape
        self.unique_labels = np.unique(y)

        n_unique_labels = len(self.unique_labels)

        self.features_mean = np.zeros(( n_unique_labels, n_features ), dtype=np.
 ↪float64)
        self.features_sdev = np.zeros(( n_unique_labels, n_features ), dtype=np.
 ↪float64)
        self.prior_probabilities = np.zeros( n_unique_labels, dtype=np.float64)


        for index,label in enumerate(self.unique_labels):
            X_label = X[y == label]
            self.features_mean[index, :] = X_label.mean(axis=0)
            self.features_sdev[index, :] = X_label.var(axis=0)
            self.prior_probabilities[index] = X_label.shape[0] / float(self.
 ↪n_samples)


    #predict function
    def predict(self, X):
```

```
        y_predicted = [ self.predictEach(x) for x in X ]
        return y_predicted

    #helper function for predict method
    def predictEach(self, x):
        posteriors = []

        for index, label in enumerate(self.unique_labels):
            prior = self.prior_probabilities[index]
            class_conditional = np.prod(self.calculate_probabilities(index, x))
            posterior = prior*class_conditional
            posteriors.append(posterior)

        return self.unique_labels[np.argmax(posteriors)]


    #helper method to calculate conditional probabilities
    def calculate_probabilities(self, classIndex, x):
        mean = self.features_mean[classIndex]
        variance = self.features_sdev[classIndex]
        numerator = np.exp( - (x-mean)**2 / (2*variance) )
        denominator = np.sqrt( 2* np.pi * variance)
        return numerator / denominator
```

[70]:
```
y_train
```

[70]: array([0, 0, 0, …, 2, 0, 0])

[71]:
```
#reshaping column vector to 1_D array

y_train = y_train.reshape(-1)
```

[72]:
```
x_train.shape, y_train.shape
```

[72]: ((79999, 13), (79999,))

2.0.1 3. TRAIN THE MODEL

2.0.2 A) GAUSSIAN NAIVE-BAYES IMPLEMENTED FROM SCRATCH

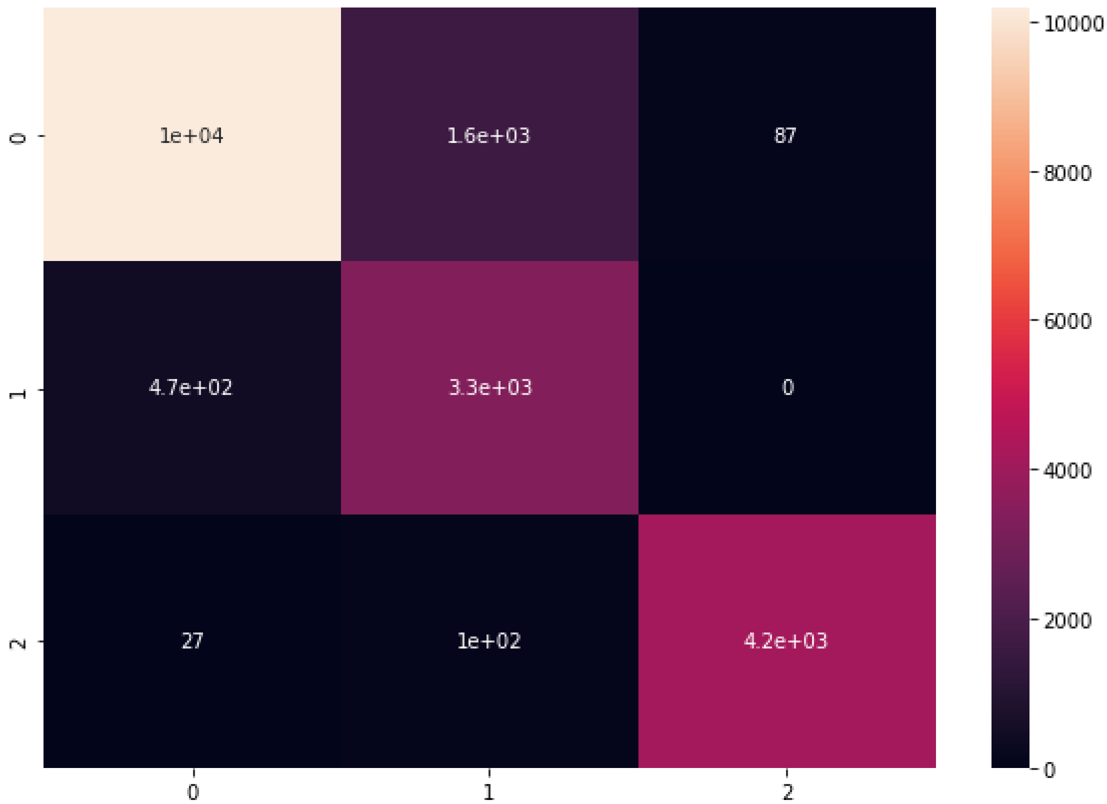
[73]:
```
myModel = MyGaussianNaiveBayes()
```

[74]:
```
#fit the data
myModel.fit(x_train, y_train)
```

2.0.3 Predicting and Performance metrics of the model

[77]:
```python
#predict for test samples
y_predicted_myModel = myModel.predict(x_test)



print("Performace metrics for AGORITHM IMPLEMENTED FROM SCRATCH!!!\n")
print("Accuracy = ", round(accuracy_score(y_test, y_predicted_myModel)*100, 2),␣
 ↪"%")
print("Global Precision = ",precision_score(y_test, y_predicted_myModel,␣
 ↪average='micro'))
print("Global Recall = ",recall_score(y_test, y_predicted_myModel,␣
 ↪average='micro'),"\n")

print(classification_report(y_predicted_myModel,y_test))

cm=confusion_matrix(y_test,y_predicted_myModel)
print("\nconfusion matrix: \n",cm)
plt.figure(figsize = (10,7))
sns.heatmap(cm, annot=True)
print("---------------------------------------")
```

```
Performace metrics for AGORITHM IMPLEMENTED FROM SCRATCH!!!

Accuracy =  88.38 %
Global Precision =  0.88385
Global Recall =  0.88385

              precision    recall  f1-score   support

           0       0.86      0.95      0.90     10674
           1       0.88      0.66      0.75      5081
           2       0.97      0.98      0.97      4245

    accuracy                           0.88     20000
   macro avg       0.90      0.86      0.88     20000
weighted avg       0.89      0.88      0.88     20000


confusion matrix:
 [[10178  1639    87]
 [  469  3341     0]
 [   27   101  4158]]
---------------------------------------
```



2.1 B) GAUSSIAN NAIVE-BAYES from SKLEARN library (Inbuilt modules)

2.2 3. TRAIN THE MODEL

[78]:
```
gaussianModel = GaussianNB()
```

[79]:
```
gaussianModel.fit(x_train, y_train)
```

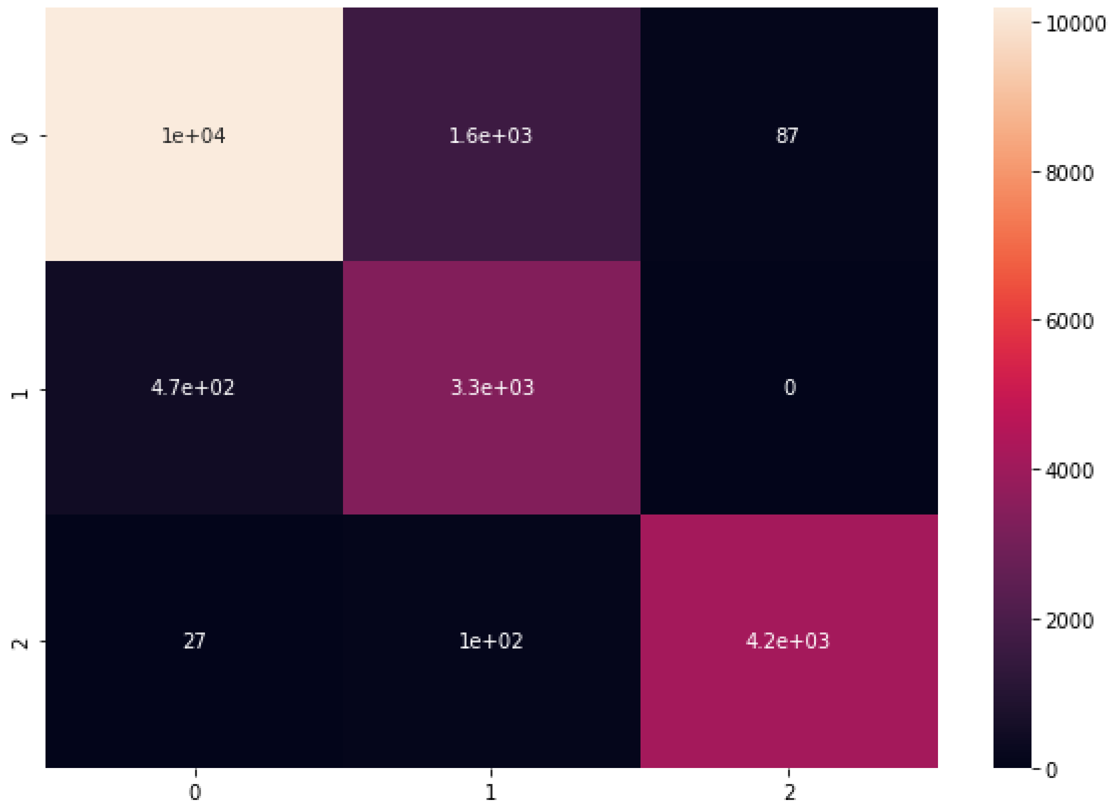
[79]:
```
GaussianNB()
```

2.2.1 Prediction and Performance analysis

[81]:
```
#predict

y_predicted = gaussianModel.predict(x_test)

print("Performance metrics for Naive-bayes from scikit-learn module!\n")
print("Accuracy = ", round(accuracy_score(y_test, y_predicted)*100, 2), "%")
print("Global Precision = ",precision_score(y_test, y_predicted,␣
 ↪average='micro'))
```

```python
print("Global Recall = ",recall_score(y_test, y_predicted,␣
    ↪average='micro'),"\n")

print(classification_report(y_predicted,y_test))

cm=confusion_matrix(y_test,y_predicted)
print("\nconfusion matrix: \n",cm)
plt.figure(figsize = (10,7))
sns.heatmap(cm, annot=True)
print("---------------------------------------")
```

```
Performance metrics for Naive-bayes from scikit-learn module!

Accuracy =  88.38 %
Global Precision =  0.88385
Global Recall =  0.88385

              precision    recall  f1-score   support

           0       0.86      0.95      0.90     10674
           1       0.88      0.66      0.75      5081
           2       0.97      0.98      0.97      4245

    accuracy                           0.88     20000
   macro avg       0.90      0.86      0.88     20000
weighted avg       0.89      0.88      0.88     20000


confusion matrix:
 [[10178  1639    87]
 [  469  3341     0]
 [   27   101  4158]]
---------------------------------------
```



2.3 4. EVALUATE THE PERFORMANCE OF THE ALGORITHMS:

2.4 COMPARISON OF PERFORMANCE OF BOTH IMPLEMENTATION:

2.4.1 NAIVE-BAYES (Gaussian) from scratch:

1. Accuracy = 88.38 %
2. Global Precision = 0.88385
3. Global Recall = 0.88385

2.4.2 NAIVE-BAYES (Gaussian) using SKlearn module:

1. Accuracy = 88.38 %
2. Global Precision = 0.88385
3. Global Recall = 0.88385

[ ]:

[ ]: