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Project description/introduction text (the background information)

In astronomy, Stellar Classification has become an important factor for astronomers to identify and categorize different kinds of objects in space. The problem is that many scientists have collected an enormous amount of data in space through telescopes and other astronomical devices but most of them are not classified.

We need to classify objects into different categories such as **stars, galaxies, and quasars** to understand more about space and its components. There are many attempts to solve the problem with this type of classification and each of them provides a different approach to the problem.

In this project, I will use the “Stellar Classification Dataset - SDSS17” to build a model to classify those astronomical objects into their spectral characteristics. What I would do differently is that I will try to use many different machine learning techniques to classify the objects and compare those techniques to find a better solution to the problem.

Machine learning algorithm selected for this project

The machine learning algorithms I used in this project are:

- LinearSVC
- SVC with RBF kernel
- Logistic Regression
- K-Nearest Neighbour Classifier(KNN)

- Random Forest Classifier

Dataset source

https://www.kaggle.com/datasets/fedesoriano/stellar-classification-dataset-sdss17

References and sources

https://seaborn.pydata.org/generated/seaborn.countplot.html

https://seaborn.pydata.org/generated/seaborn.heatmap.html

https://seaborn.pydata.org/generated/seaborn.pairplot.html

https://seaborn.pydata.org/generated/seaborn.scatterplot.html

https://scikit-learn.org/stable/modules/generated/sklearn.preprocessing.StandardScaler.html

https://scikit-learn.org/stable/modules/generated/sklearn.svm.SVC.html

https://scikit-learn.org/stable/modules/generated/sklearn.neighbors.KNeighborsClassifier.html

https://scikit-learn.org/stable/modules/generated/sklearn.ensemble.RandomForestClassifier.html

https://scikit-learn.org/stable/modules/generated/sklearn.metrics.ConfusionMatrixDisplay.html

https://scikit-learn.org/stable/modules/generated/sklearn.metrics.classification_report.html

https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.cross_val_score.html

https://www.scikit-yb.org/en/latest/api/classifier/class_prediction_error.html

https://scikit-learn.org/stable/modules/generated/sklearn.linear_model.LogisticRegression.html

Solution

Load libraries and set random number generator seed

In [6]:
```
import numpy as np
```

```
import pandas as pd
from sklearn import datasets
from sklearn.svm import SVC
from sklearn.svm import LinearSVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import cross_val_score
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
from sklearn.cluster import KMeans
from sklearn.model_selection import train_test_split
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler
from mlxtend.plotting import plot_decision_regions
from sklearn.metrics import classification_report
from yellowbrick.classifier import ClassPredictionError
from sklearn.linear_model import LogisticRegression
from yellowbrick.style import set_palette
```

In [7]:

```
np.random.seed(42)
```

Load the dataset

In [8]:

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

In [9]:

```
df.describe()
```

Out[9]:

	obj_ID	alpha	delta	u	g	r	i	z	run_ID
count	1.000000e+05	100000.000000	100000.000000	100000.000000	100000.000000	100000.000000	100000.000000	100000.000000	100000.000000
mean	1.237665e+18	177.629117	24.135305	21.980468	20.531387	19.645762	19.084854	18.668810	4481.366060
std	8.438560e+12	96.502241	19.644665	31.769291	31.750292	1.854760	1.757895	31.728152	1964.764593
min	1.237646e+18	0.005528	-18.785328	-9999.000000	-9999.000000	9.822070	9.469903	-9999.000000	109.000000
25%	1.237659e+18	127.518222	5.146771	20.352353	18.965230	18.135828	17.732285	17.460677	3187.000000
50%	1.237663e+18	180.900700	23.645922	22.179135	21.099835	20.125290	19.405145	19.004595	4188.000000

	obj_ID	alpha	delta	u	g	r	i	z	run_ID
75%	1.237668e+18	233.895005	39.901550	23.687440	22.123767	21.044785	20.396495	19.921120	5326.000000
max	1.237681e+18	359.999810	83.000519	32.781390	31.602240	29.571860	32.141470	29.383740	8162.000000

Only keep useful attributes and remove others.

In [10]:
```
df = df[['alpha', 'delta', 'u', 'g', 'r', 'i', 'z','redshift','class']]
df.head()
```

Out[10]:

	alpha	delta	u	g	r	i	z	redshift	class
0	135.689107	32.494632	23.87882	22.27530	20.39501	19.16573	18.79371	0.634794	GALAXY
1	144.826101	31.274185	24.77759	22.83188	22.58444	21.16812	21.61427	0.779136	GALAXY
2	142.188790	35.582444	25.26307	22.66389	20.60976	19.34857	18.94827	0.644195	GALAXY
3	338.741038	-0.402828	22.13682	23.77656	21.61162	20.50454	19.25010	0.932346	GALAXY
4	345.282593	21.183866	19.43718	17.58028	16.49747	15.97711	15.54461	0.116123	GALAXY

Split X,Y

In [11]:
```
X = df.drop(['class'], axis = 1)
Y = df.loc[:,'class'].values
X, Y
```

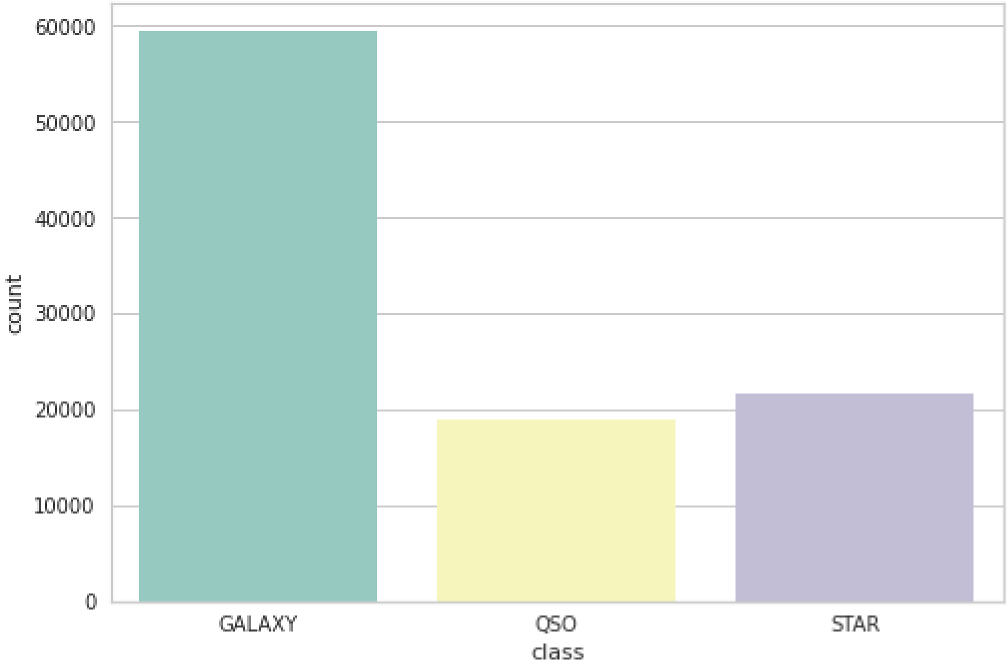
Out[11]:
```
(            alpha      delta         u         g         r         i  \
 0      135.689107  32.494632  23.87882  22.27530  20.39501  19.16573
 1      144.826101  31.274185  24.77759  22.83188  22.58444  21.16812
 2      142.188790  35.582444  25.26307  22.66389  20.60976  19.34857
 3      338.741038  -0.402828  22.13682  23.77656  21.61162  20.50454
 4      345.282593  21.183866  19.43718  17.58028  16.49747  15.97711
 ...           ...        ...       ...       ...       ...       ...
 99995   39.620709  -2.594074  22.16759  22.97586  21.90404  21.30548
 99996   29.493819  19.798874  22.69118  22.38628  20.45003  19.75759
 99997  224.587407  15.700707  21.16916  19.26997  18.20428  17.69034
 99998  212.268621  46.660365  25.35039  21.63757  19.91386  19.07254
 99999  196.896053  49.464643  22.62171  21.79745  20.60115  20.00959
```

```
              z  redshift
0      18.79371  0.634794
1      21.61427  0.779136
2      18.94827  0.644195
3      19.25010  0.932346
4      15.54461  0.116123
...         ...       ...
99995  20.73569  0.000000
99996  19.41526  0.404895
99997  17.35221  0.143366
99998  18.62482  0.455040
99999  19.28075  0.542944

[100000 rows x 8 columns],
array(['GALAXY', 'GALAXY', 'GALAXY', ..., 'GALAXY', 'GALAXY', 'GALAXY'],
      dtype=object))
```

Count the targets. Count how many Galaxy, how many QSO, and how many Stars are there.

In [12]:

```
ax = sns.countplot(x="class", data=df, palette="Set3")
sns.set(rc = {'figure.figsize':(15,9)})
plt.show()
df["class"].value_counts()
```

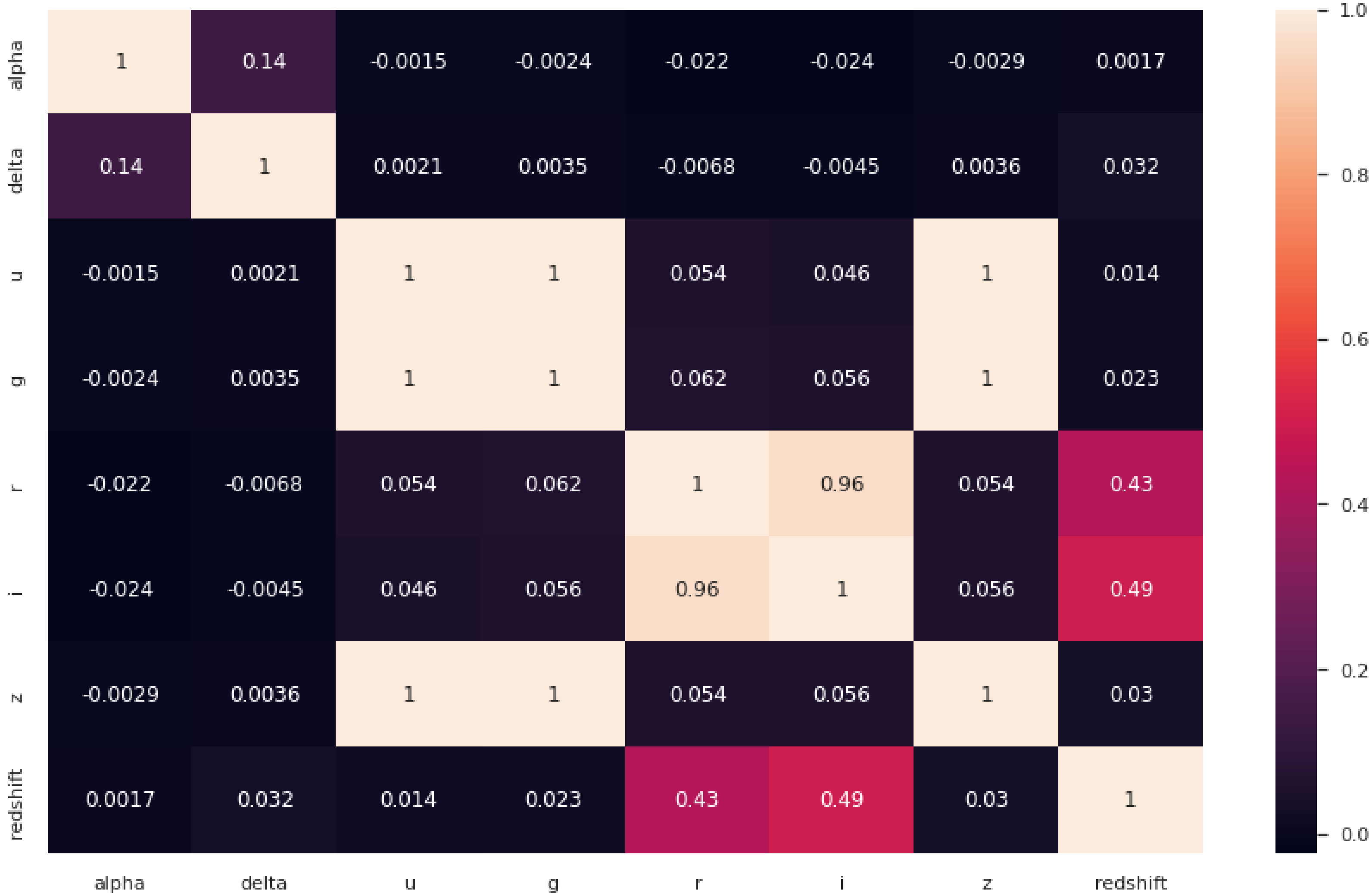


Out[12]:
```
GALAXY    59445
STAR      21594
QSO       18961
Name: class, dtype: int64
```

Heat Map Correlation

In [9]:
```
sns.heatmap(data= df.corr(), annot= True)
```

Out[9]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f3428370750>
```

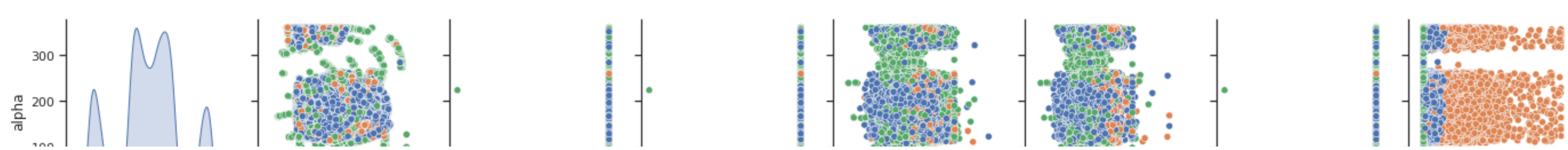


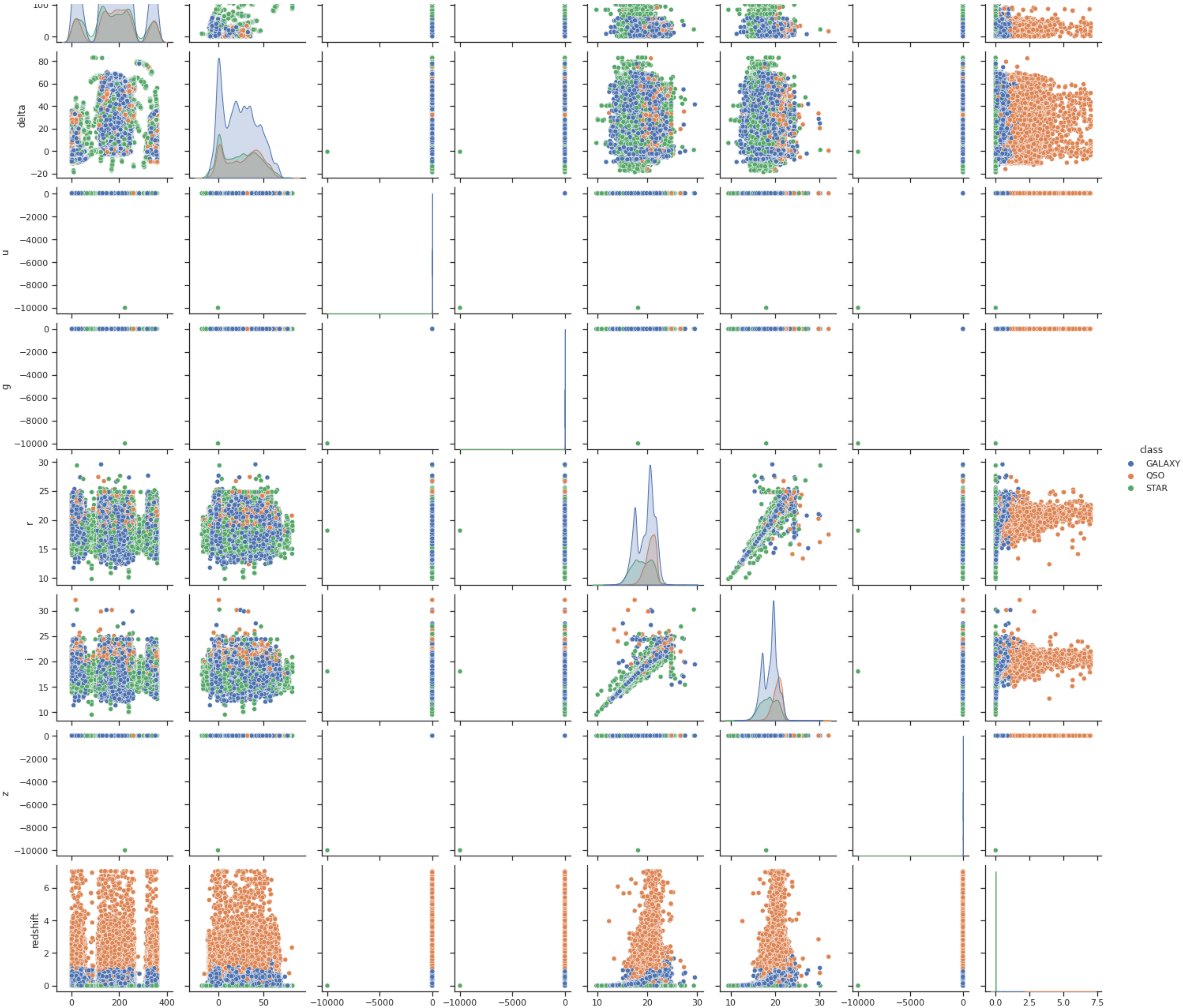
Visualizing data

In [9]:

```
sns.set(style="ticks", color_codes=True)
sns.pairplot(df, hue='class')
```

Out[9]: <seaborn.axisgrid.PairGrid at 0x7f39b340fd50>

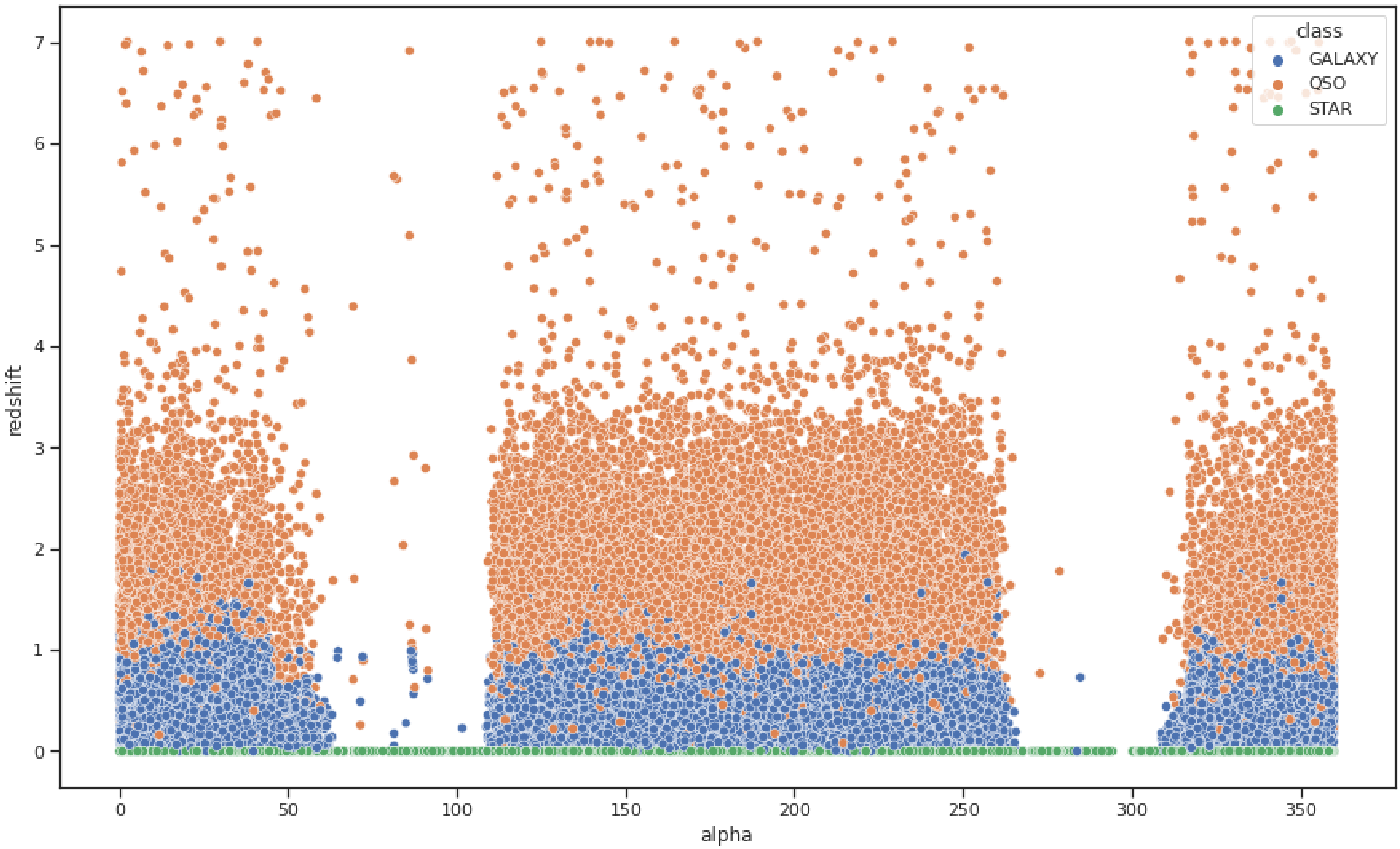



delta
u
g
r
i
z
redshift
class
GALAXY
QSO
STAR

alpha delta u g r i z redshift

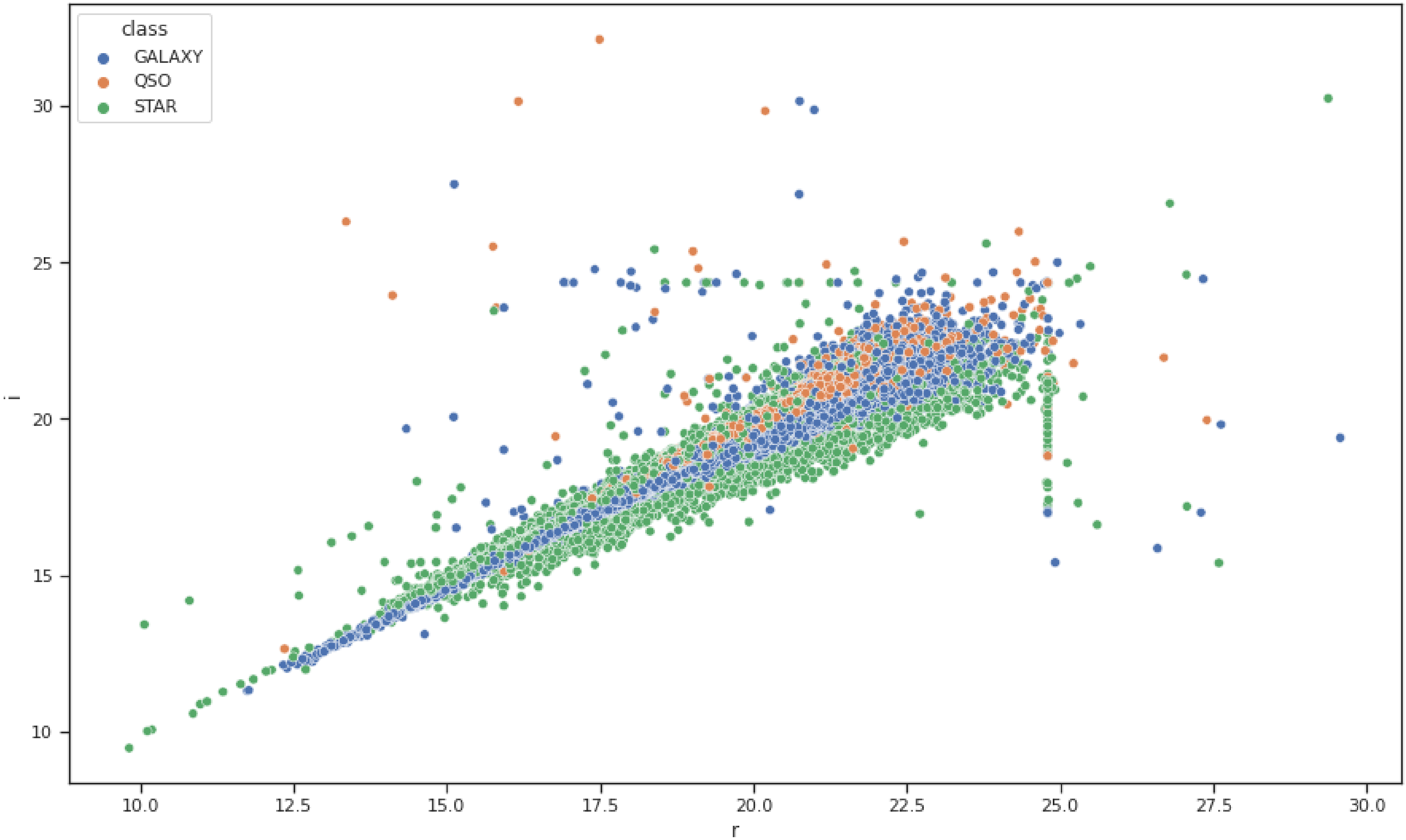
In [10]:
```
sns.scatterplot(x='alpha', y='redshift', hue='class', data=df)
```

Out[10]: <matplotlib.axes._subplots.AxesSubplot at 0x7f39acc56850>

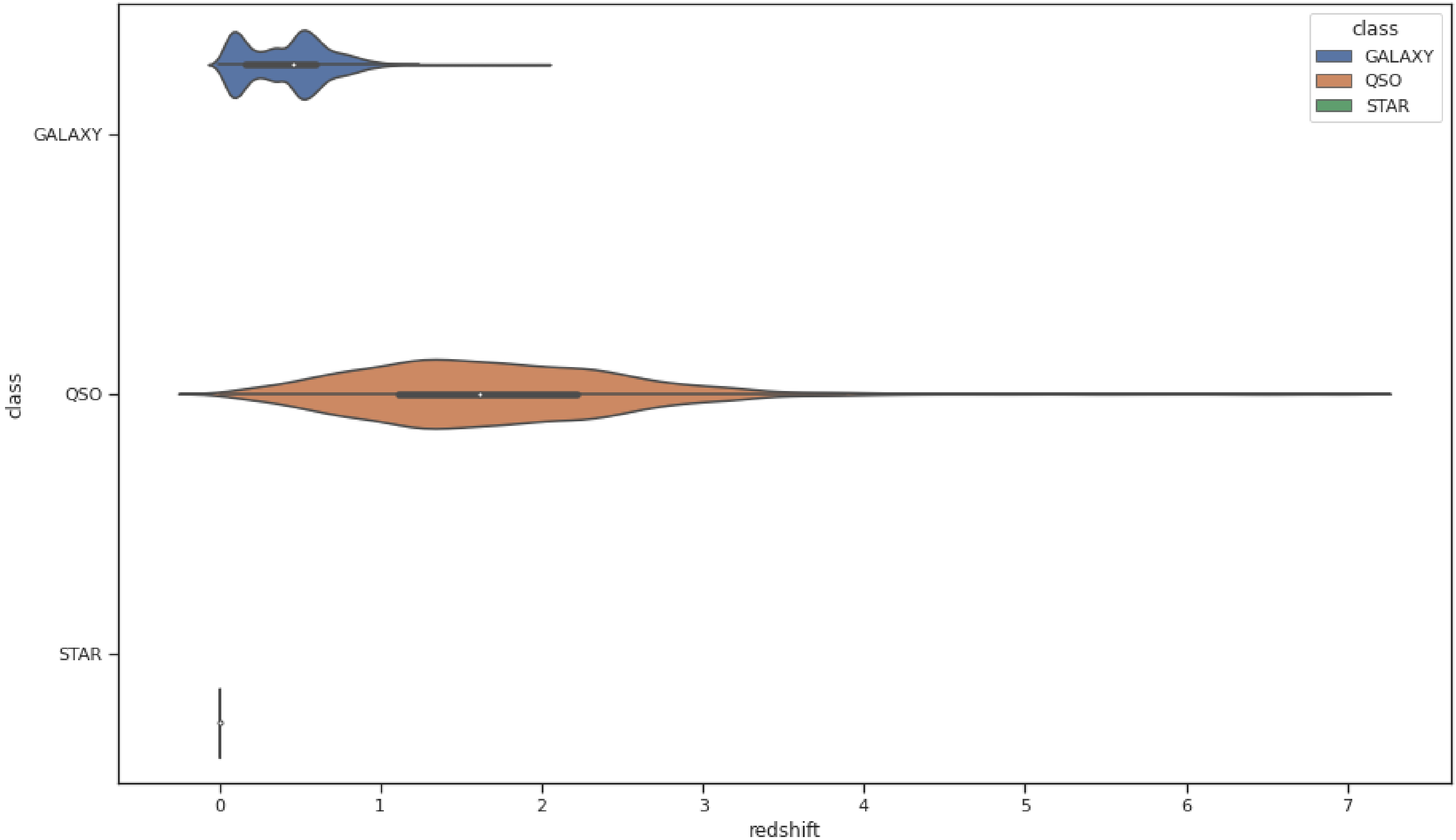


In [11]:
```
sns.scatterplot(x='r', y='i', hue='class', data=df)
```

Out[11]: <matplotlib.axes._subplots.AxesSubplot at 0x7f39ac9eeb10>



In [17]:
```
ax = sns.violinplot(x=df["redshift"], y=df["class"], hue="class", data=df)
```



Data preprocessing

In [13]:

```
scaler = StandardScaler()
scaler.fit(X)
X_rescaled = scaler.transform(X)
```

Split into random train, validation, and test subsets

In [14]:

```
X_train, X_test, Y_train, Y_test = train_test_split(X_rescaled, Y, test_size=0.2, random_state=0)
X_train.shape, Y_train.shape, X_test.shape, Y_test.shape
```

Out[14]:
```
((80000, 8), (80000,), (20000, 8), (20000,))
```

Define the models with different algorithms

In [19]:
```
models = {
    "Linear SVC" : LinearSVC(dual=False,max_iter=100000),
    "RBF SVC" : SVC(C=10, kernel='rbf',random_state = 0),
    "Logistic Regression" : LogisticRegression(solver='lbfgs', max_iter=100000,random_state=0),
    "K-Nearest Neighbour" :  KNeighborsClassifier(n_neighbors=3),
    "Random Forest" : RandomForestClassifier(random_state=0)
}
```

Training the models

In [20]:
```
for model in models.values():
    print(model)
    model.fit(X_train,Y_train)
```

```
LinearSVC(dual=False, max_iter=100000)
SVC(C=10, random_state=0)
LogisticRegression(max_iter=100000, random_state=0)
KNeighborsClassifier(n_neighbors=3)
RandomForestClassifier(random_state=0)
```

Cross validation check

In [21]:
```
for model_name, model in models.items():
    score = cross_val_score(model, X, Y, scoring='accuracy', cv=2)
    print('Acuracy of ', model_name, " is ", score.mean())
```

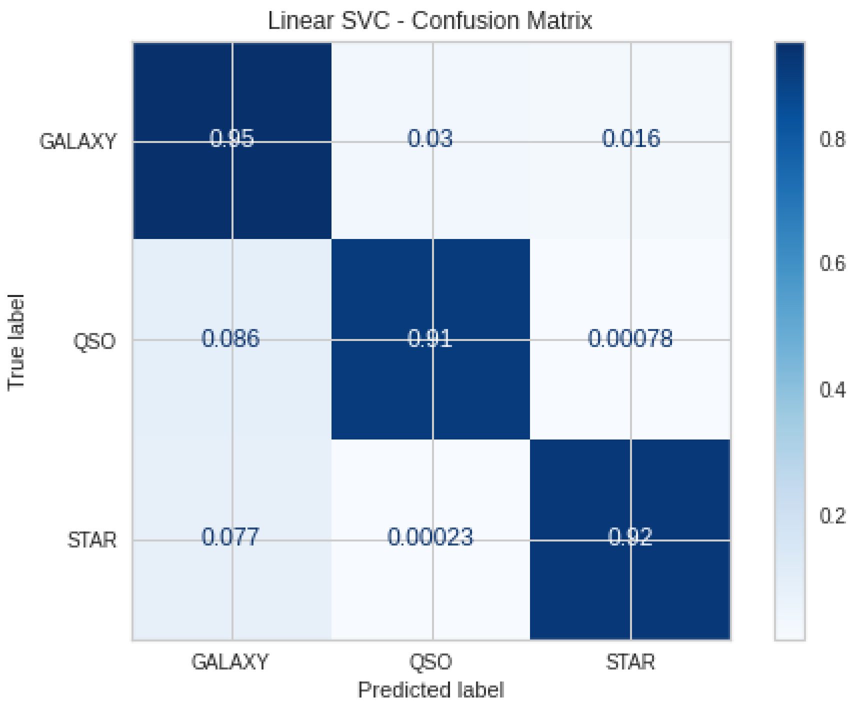
```
Acuracy of  Linear SVC  is  0.93173
Acuracy of  RBF SVC  is  0.8380799999999999
Acuracy of  Logistic Regression  is  0.95352
Acuracy of  K-Nearest Neighbour  is  0.7567699999999999
Acuracy of  Random Forest  is  0.9774499999999999
```

Confusion matrix to measure how well the models perform

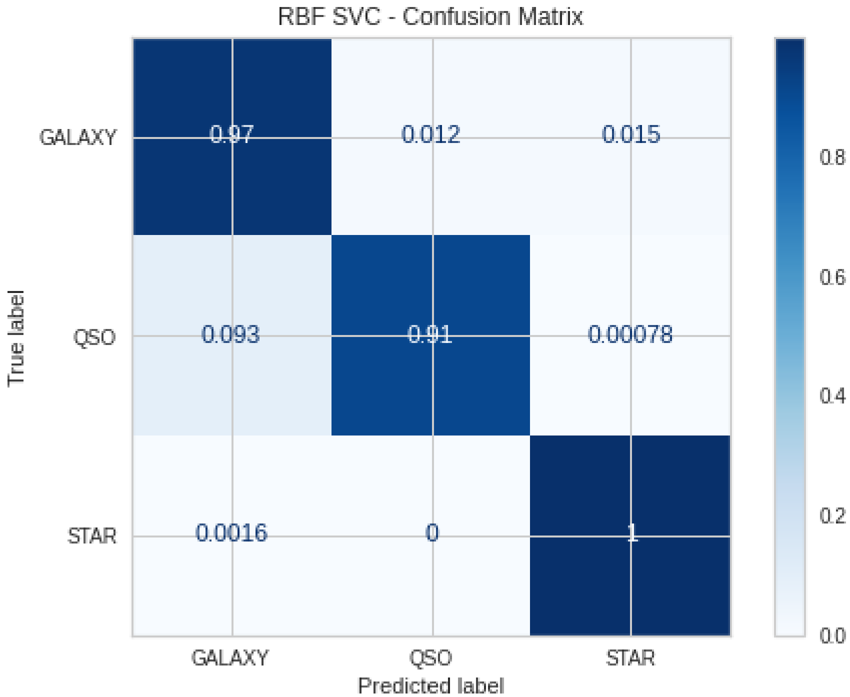
In [29]:
```
for model_name, model in models.items():
    print("")
    title = str(model_name)+" - Confusion Matrix"
```

```
    predictions = model.predict(X_test)
    plt.figure(figsize=(3,3))
    cm = confusion_matrix(Y_test, predictions, labels=model.classes_)
    disp = ConfusionMatrixDisplay.from_estimator(model,
          X_test,
          Y_test,
          display_labels=model.classes_,
          cmap=plt.cm.Blues,
          normalize='true')
    disp.ax_.set_title(title)
    plt.show()
```

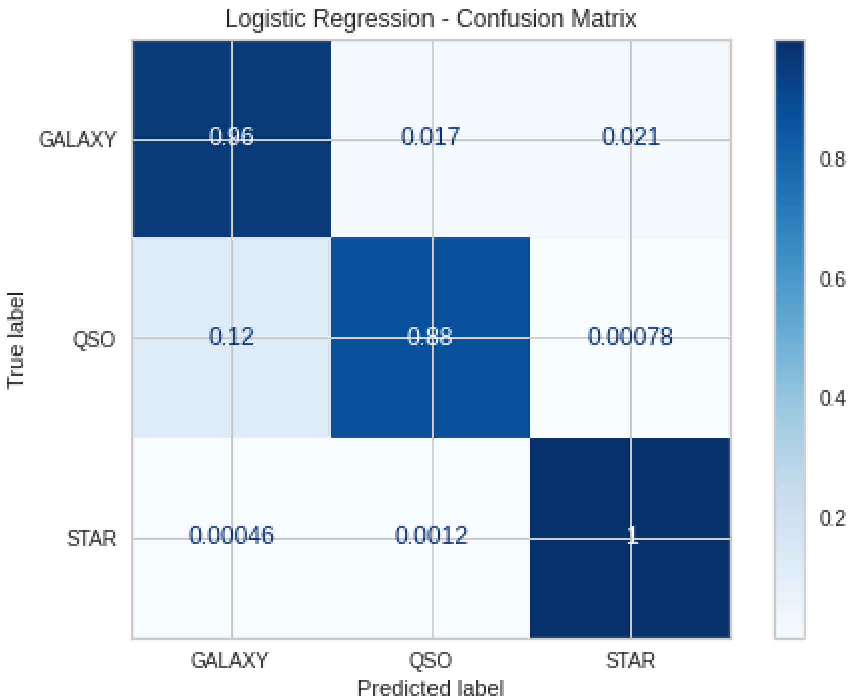
```
<Figure size 216x216 with 0 Axes>
```



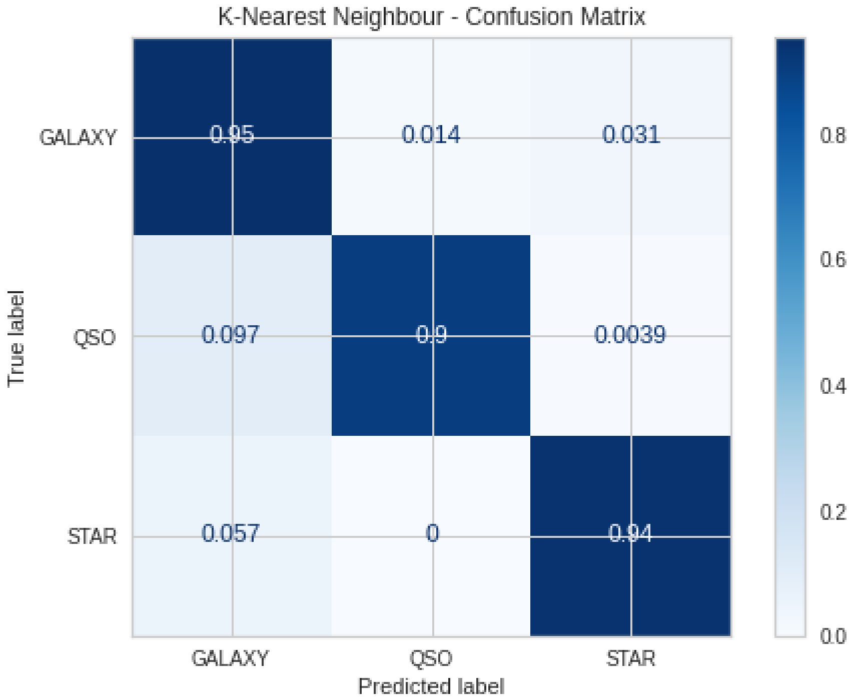

```
<Figure size 216x216 with 0 Axes>
```



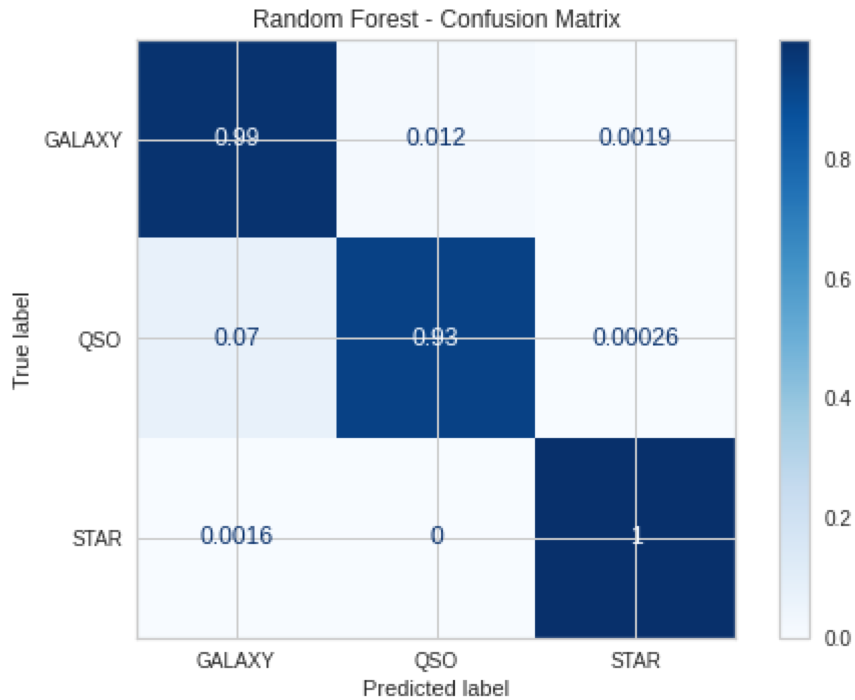

```
<Figure size 216x216 with 0 Axes>
```




```
<Figure size 216x216 with 0 Axes>
```




```
<Figure size 216x216 with 0 Axes>
```



Generate a classification report

In [30]:
```python
for model_name, model in models.items():
    Y_predicted = model.predict(X_test)
    print(f"------------ Classification Report - {model_name} ------------")
    print(classification_report(Y_test,Y_predicted))
```

```
------------ Classification Report - Linear SVC ------------
              precision    recall  f1-score   support

      GALAXY       0.94      0.95      0.95     11851
         QSO       0.91      0.91      0.91      3835
        STAR       0.95      0.92      0.94      4314

    accuracy                           0.94     20000
   macro avg       0.94      0.93      0.93     20000
weighted avg       0.94      0.94      0.94     20000

------------ Classification Report - RBF SVC ------------
              precision    recall  f1-score   support
```

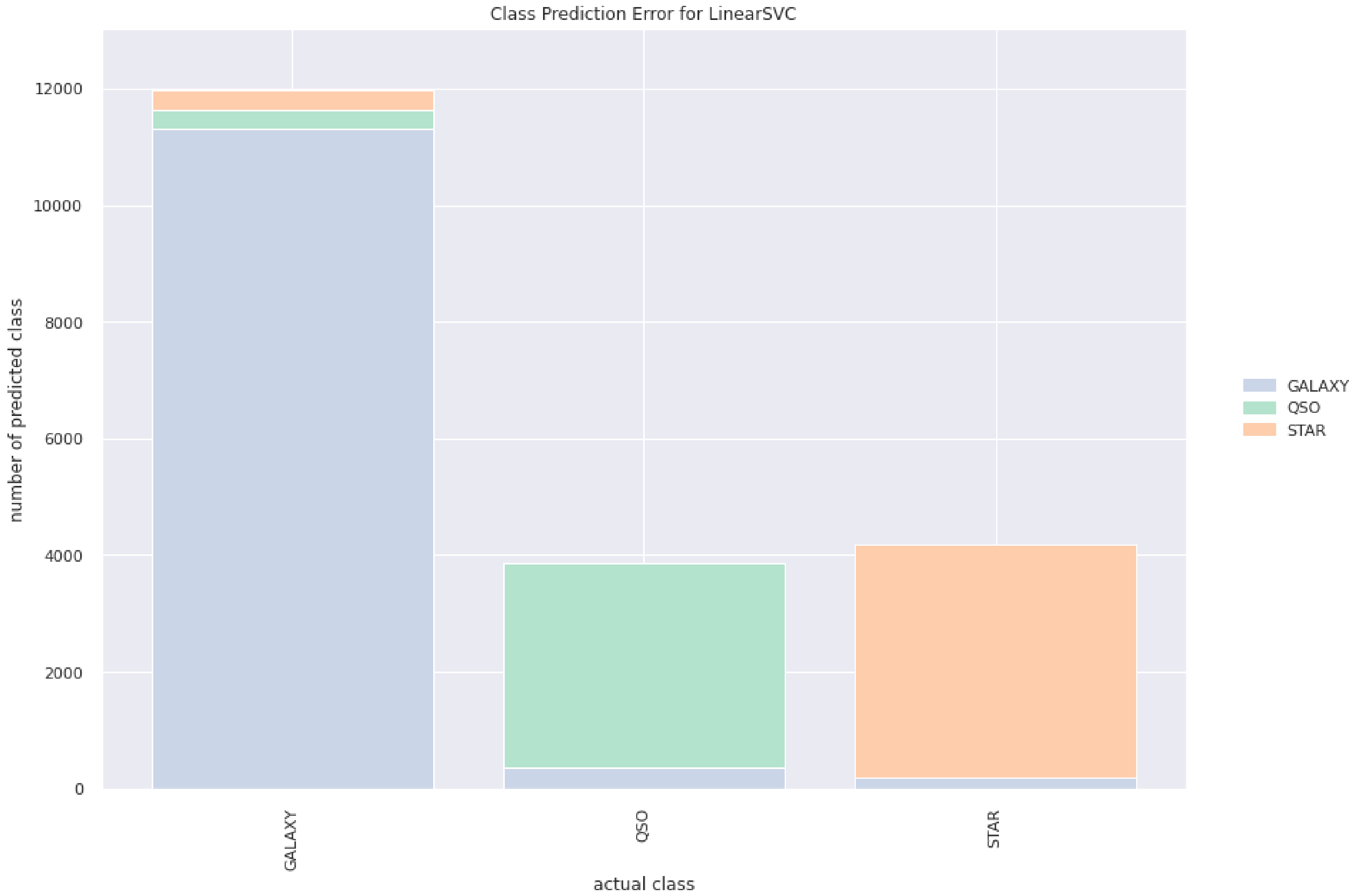
```
      GALAXY       0.97      0.97      0.97     11851
         QSO       0.96      0.91      0.93      3835
        STAR       0.96      1.00      0.98      4314

    accuracy                           0.97     20000
   macro avg       0.96      0.96      0.96     20000
weighted avg       0.97      0.97      0.97     20000

------------ Classification Report - Logistic Regression ------------
              precision    recall  f1-score   support

      GALAXY       0.96      0.96      0.96     11851
         QSO       0.94      0.88      0.91      3835
        STAR       0.95      1.00      0.97      4314

    accuracy                           0.95     20000
   macro avg       0.95      0.95      0.95     20000
weighted avg       0.95      0.95      0.95     20000

------------ Classification Report - K-Nearest Neighbour ------------
              precision    recall  f1-score   support

      GALAXY       0.95      0.95      0.95     11851
         QSO       0.95      0.90      0.93      3835
        STAR       0.91      0.94      0.93      4314

    accuracy                           0.94     20000
   macro avg       0.94      0.93      0.94     20000
weighted avg       0.94      0.94      0.94     20000

------------ Classification Report - Random Forest ------------
              precision    recall  f1-score   support

      GALAXY       0.98      0.99      0.98     11851
         QSO       0.96      0.93      0.95      3835
        STAR       0.99      1.00      1.00      4314

    accuracy                           0.98     20000
   macro avg       0.98      0.97      0.97     20000
weighted avg       0.98      0.98      0.98     20000
```

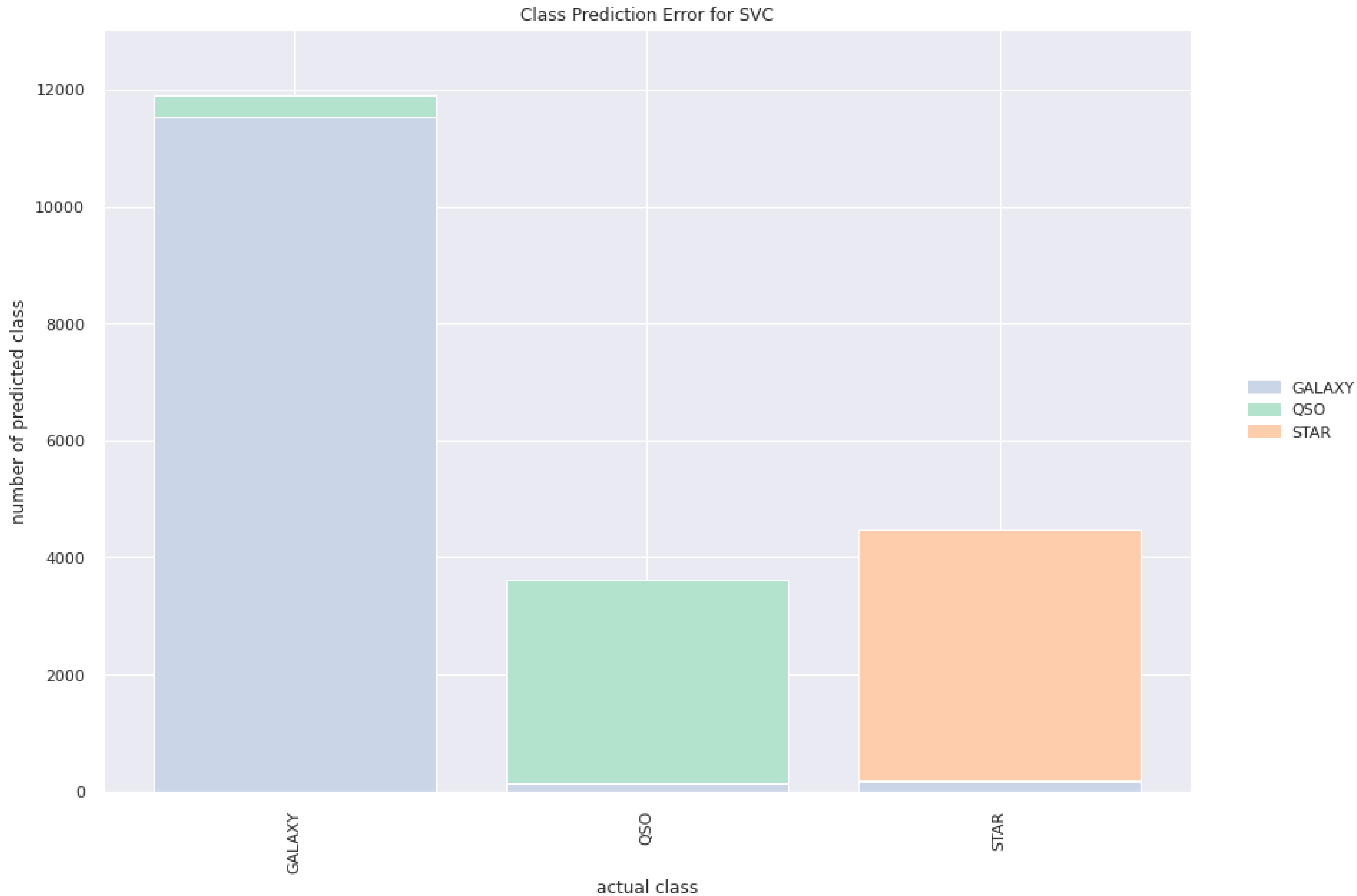
Class Prediction Error

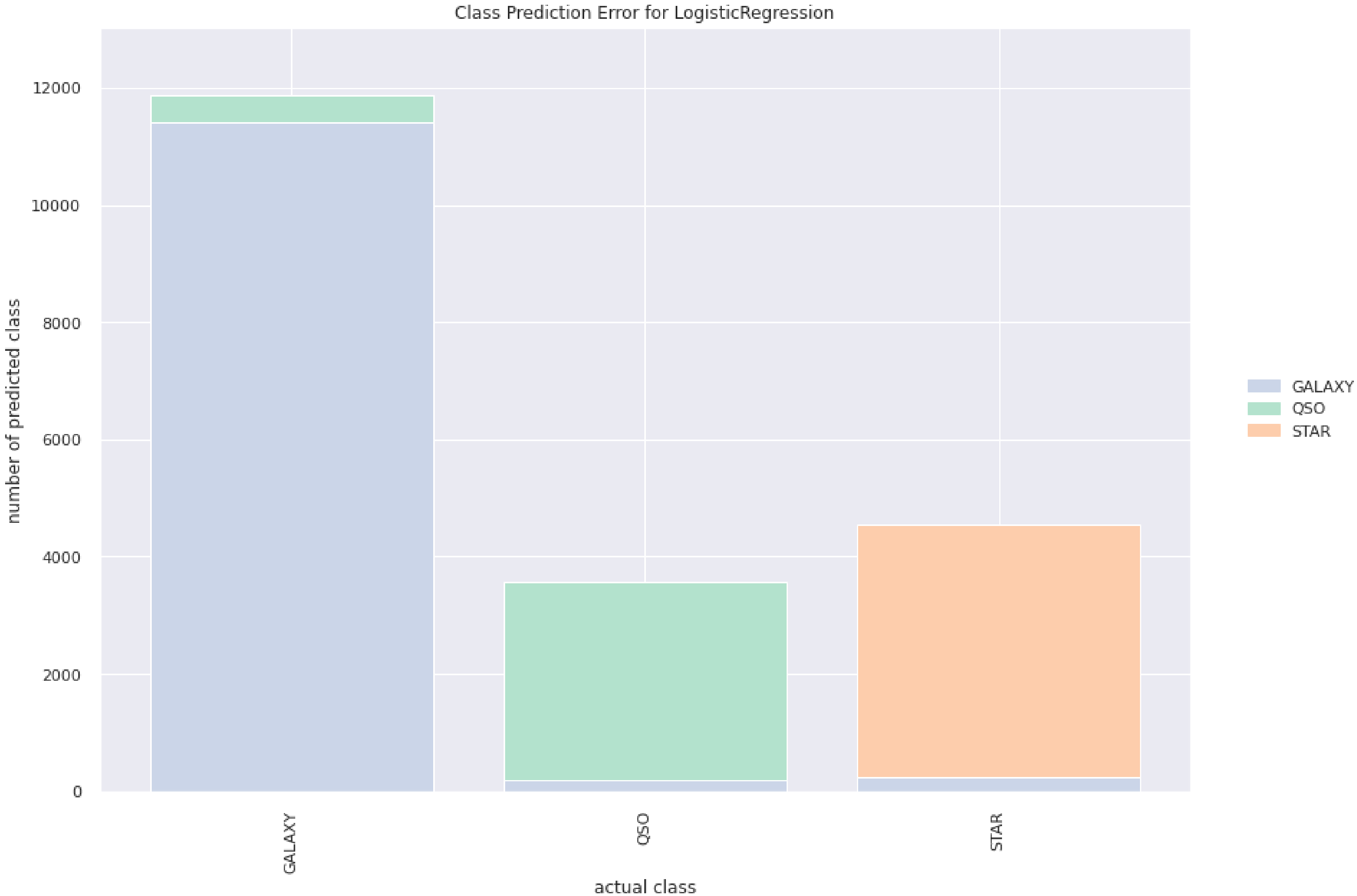
In [22]:

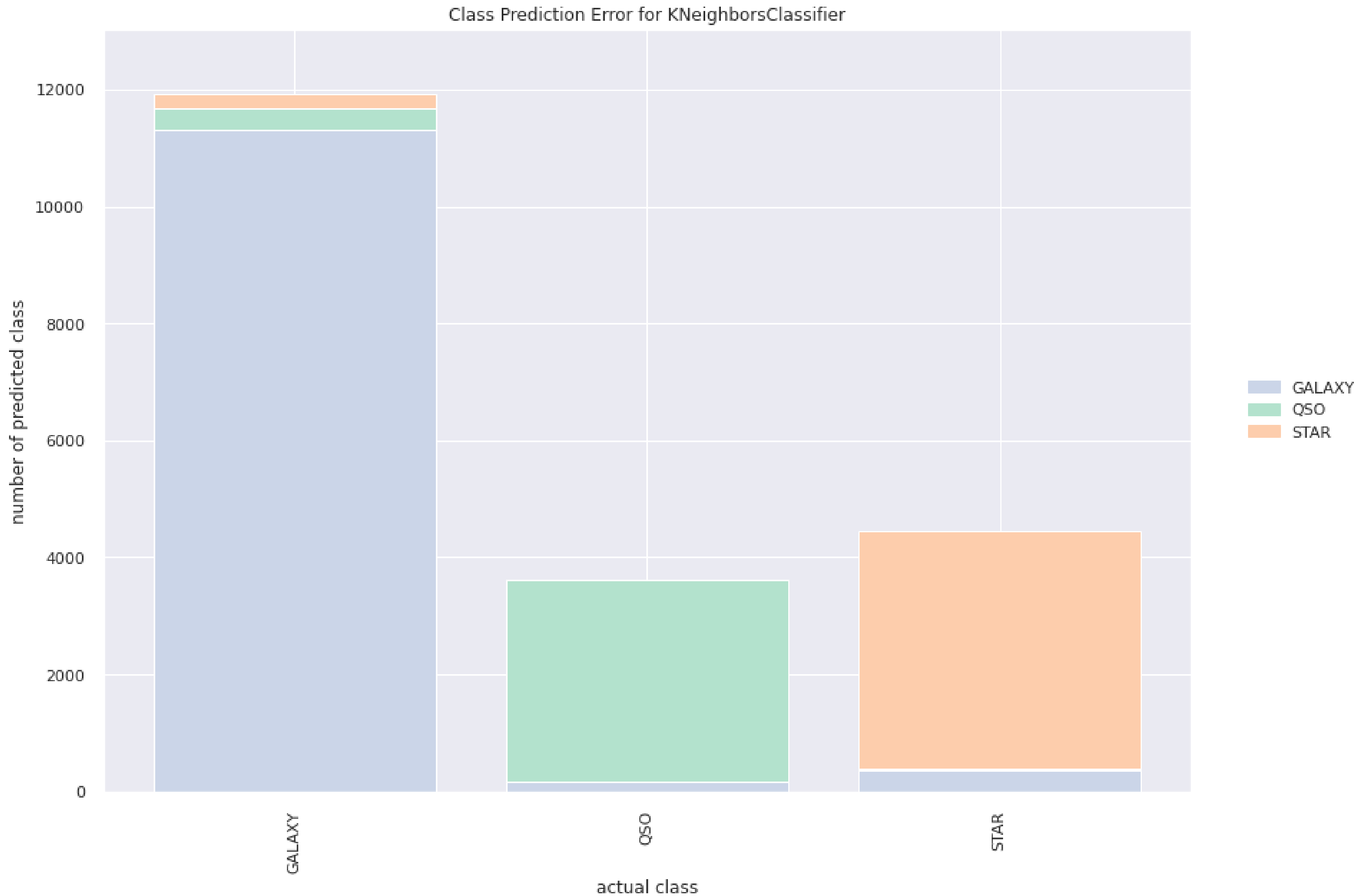
```
for model_name, model in models.items():
```

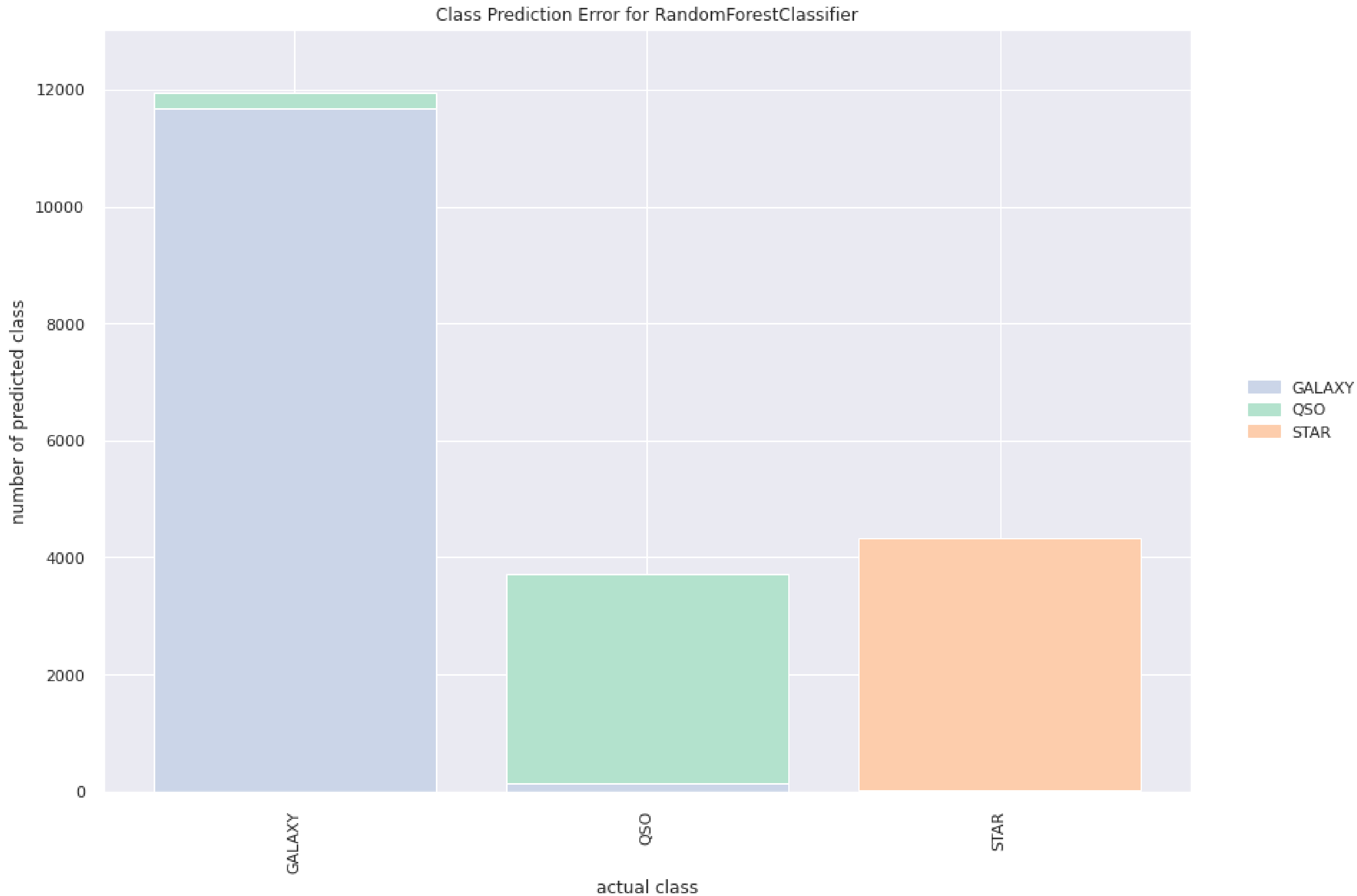
```
    visualizer = ClassPredictionError(model, classes=model.classes_)
    set_palette('pastel')
    visualizer.fit(X_train, Y_train)
    visualizer.score(X_test, Y_test)
    visualizer.show()
```




Class Prediction Error for SVC
number of predicted class
12000
10000
8000
6000
4000
2000
0
GALAXY
QSO
STAR
actual class
GALAXY
QSO
STAR


Class Prediction Error for LogisticRegression
number of predicted class
0
2000
4000
6000
8000
10000
12000
GALAXY
QSO
STAR
actual class
GALAXY
QSO
STAR


Class Prediction Error for KNeighborsClassifier
12000
10000
8000
6000
4000
2000
0
number of predicted class
GALAXY
QSO
STAR
actual class
GALAXY
QSO
STAR


Class Prediction Error for RandomForestClassifier
number of predicted class
12000
10000
8000
6000
4000
2000
0
GALAXY
QSO
STAR
actual class
GALAXY
QSO
STAR