CA4

Imports

In [74]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np

from sklearn.model_selection import train_test_split, GridSearchCV, StratifiedKF
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis as LDA
from sklearn.decomposition import PCA

from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay, f1_score,
```

Reading data

In [26]:
```
df = pd.read_csv("./assets/train.csv", index_col = 0)
```

Data exploration and visualisation

In [27]:
```
df.describe()
```

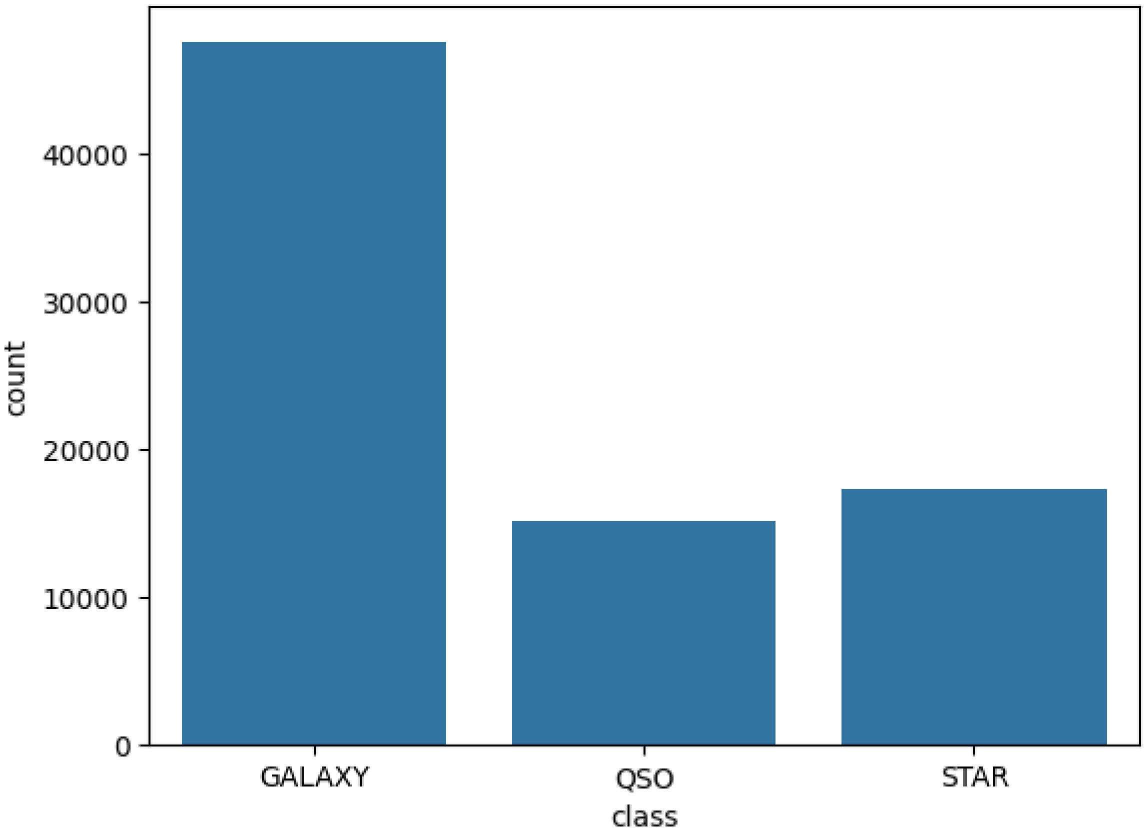
Out[27]:

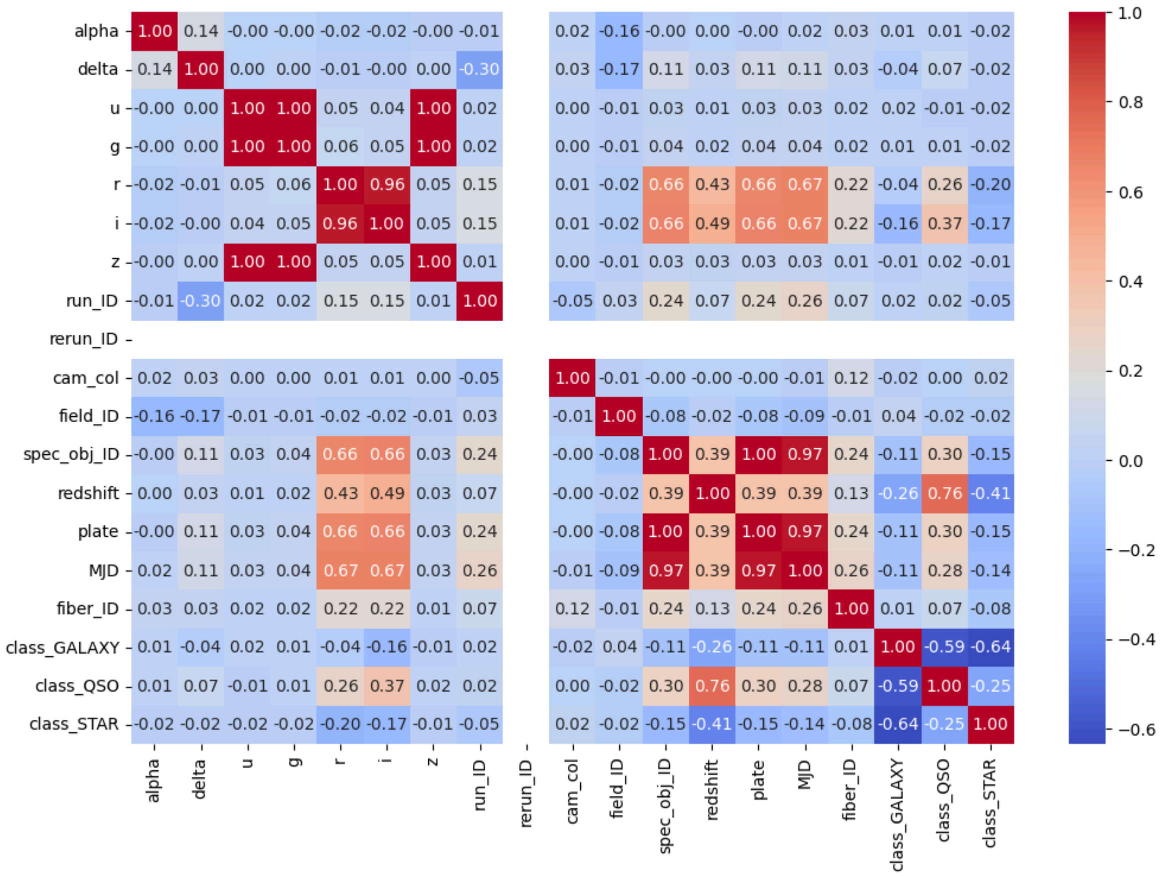
	alpha	delta	u	g	r	
count	80000.000000	80000.000000	79638.000000	80000.000000	80000.000000	80000.000
mean	177.579220	24.132590	21.961115	20.507677	19.647426	19.085
std	96.409584	19.650113	35.581856	35.483302	1.855636	1.757
min	0.005528	-18.785328	-9999.000000	-9999.000000	9.822070	9.469
25%	127.643892	5.170723	20.353990	18.963188	18.135523	17.732
50%	180.761747	23.603480	22.187965	21.101015	20.127550	19.405
75%	233.815698	39.904905	23.698457	22.125007	21.047242	20.401
max	359.999615	83.000519	32.781390	31.602240	29.571860	32.141

In [28]:
```
# Checking data types
print(df.dtypes)
```

```
alpha          float64
delta          float64
u              float64
g              float64
r              float64
i              float64
z              float64
run_ID           int64
rerun_ID         int64
cam_col          int64
field_ID         int64
spec_obj_ID    float64
class           object
redshift       float64
plate            int64
MJD              int64
fiber_ID         int64
dtype: object
```

In [ ]:
```python
sns.countplot(x = df["class"])
plt.show()

# Doing classes to numbers so we can explore more, using onehotencoder since the
df_decoded = pd.get_dummies(df, columns = ["class"], dtype = int)

plt.figure(figsize = (12, 8))
sns.heatmap(df_decoded.corr(), annot = True, cmap = "coolwarm", fmt = ".2f")
plt.show()
```





In [30]:
```
# Checking dimensions
print(df.shape)
```

```
(80000, 17)
```

Conclusion

There is a noticeable imbalance in the dataset,
with a significantly higher number of galaxy observations compared to other types of stellar objects.
This imbalance may introduce bias in the analysis and should be taken into consideration.
In addition, we are working with a huge dataset. We should therefore use Stratified K-Fold as a Cross Validation

Such uneven distribution can also influence the choice of models.
like Logistic Regression, Decision Trees,
and Support Vector Classifiers (SVC) may have difficulty performing well under these conditions.
We will still try out SVC.

The heatmap indicates complex correlations among several features.
There is a perfect positive correlation between the variables:
u and z, g and z, and g and u.
A strong positive correlation is also observed between i and r.
In addition, strong positive relationships are found between MJD and spec_obj_ID, and between MJD and plate.

Spec_obj_ID and plate show a perfect positive correlation as well.
Lastly, there is a strong negative correlation among the different target classes.

Data cleaning

In [31]:
```
print("missing values: \n", df.isnull().sum())
print("\nduplicates: \n", df[df.duplicated()].sum())
```

```
missing values:
 alpha          0
delta          0
u            362
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

duplicates:
 alpha        0.0
delta        0.0
u            0.0
g            0.0
r            0.0
i            0.0
z            0.0
run_ID         0
rerun_ID       0
cam_col        0
field_ID       0
spec_obj_ID  0.0
class          0
redshift     0.0
plate          0
MJD            0
fiber_ID       0
dtype: object
```

In [32]:
```
# Dropping missing values
df = df.dropna()

print(f"Shape: {df.shape}")
```

```
Shape: (79638, 17)
```

In [33]:
```
# We want to see the visualize the complex patterns
sns.pairplot(df)
plt.show()
```

In [41]:
```
# Splitting Data
X = df.drop(columns = ["class"])
y = df["class"]
```

PCA could help us with noice and dimention reduction

Data preprocessing and visualisation

In [ ]:
```
# Creating Pipelines,
RFC = Pipeline([
    ("lda", LDA()),
    ("clf", RandomForestClassifier(random_state = 42))
])


svc = SVC(kernel="rbf")
SVM = Pipeline([
    ("scaler", StandardScaler()),
    ("pca", PCA(n_components = 0.995)),      # To keep the 99.5% variance
    ("svc", svc)
])
```

Modelling

In [52]:
```
# Grid Search with cross-validation, StritifiedKFold because of the large datase
def grid_search(pipeline, param_grid):
    gs = GridSearchCV(estimator = pipeline,
                      param_grid = param_grid,
                      scoring = 'f1_macro',
                      cv = StratifiedKFold(n_splits = 2),
                      n_jobs = -1)

    gs.fit(X, y)
    print("CV: DONE")

    y_pred = gs.predict(X)
    score = f1_score(y, y_pred, average = 'macro')
    print("F1 Macro:", score)

    return gs
```

In [53]:
```
# Random Forest, parts of the code is taken from Chapter_6_part_2a.ipynb from Ca
param_grid = {
    'clf__n_estimators': [100, 200],
    'clf__max_depth': [None, 10, 20],
    'clf__min_samples_split': [2, 5],
}

gs_RFC = grid_search(RFC, param_grid)
```

```
CV: DONE
F1 Macro: 0.916249843887992
```

In [70]:
```
# SVC
param_grid = {
    'svc__C': [1, 10, 100],
    'svc__gamma': ['scale', 0.01, 0.001],
}

gs_SVC = grid_search(SVM, param_grid)
```

```
CV: DONE
F1 Macro: 0.9592984259200682
```

Final evaluation

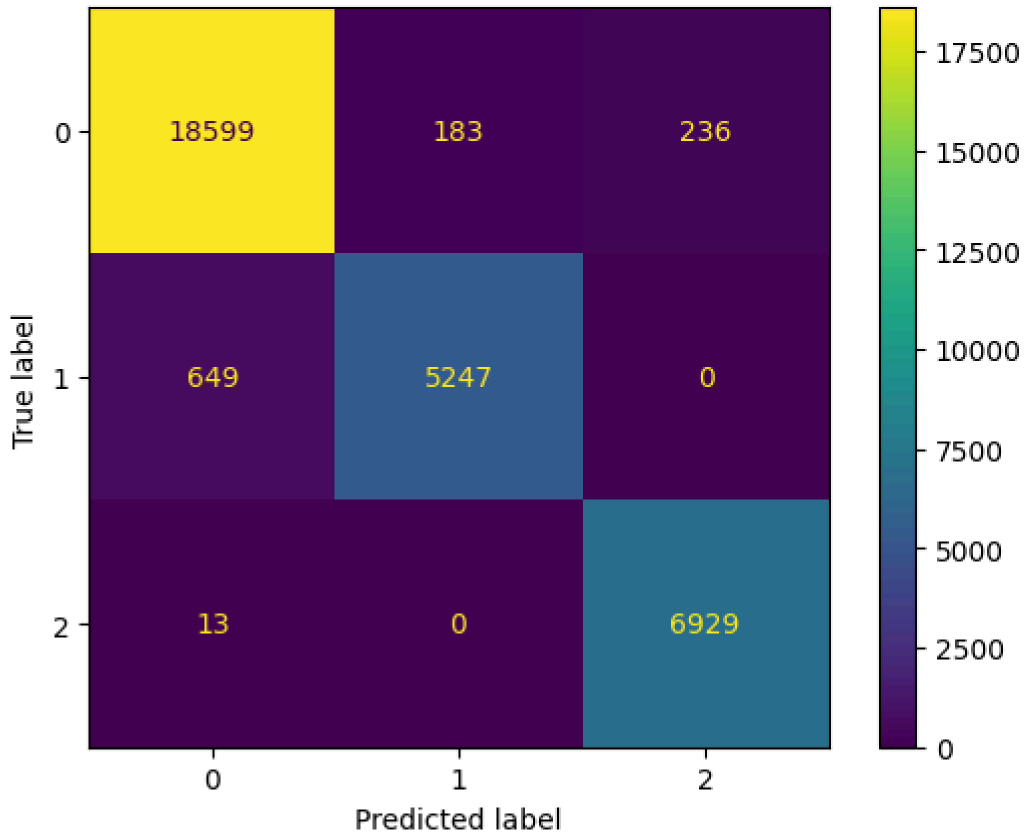
In [71]:
```
# Looking at the best models parameters
model = gs_SVC.best_estimator_
print(gs_SVC.best_params_)

cv_scores = cross_val_score(model, X, y, cv = 5, scoring = 'f1_macro')
print("Mean CV F1-macro:", np.mean(cv_scores))
```

```
{'svc__C': 100, 'svc__gamma': 0.01}
Mean CV F1-macro: 0.9585605242136388
```

In [72]:
```
# Confusion Matrix & F1 Evaluation
X_train60, X_test40, y_train60, y_test40 = train_test_split(X, y, test_size = 0.
y_pred = model.predict(X_test40)
```

```
cm = confusion_matrix(y_test40, y_pred)
disp = ConfusionMatrixDisplay(confusion_matrix = cm)
disp.plot()

print(f"F1-macro: {f1_score(y_test40, y_pred, average = 'macro')} \n")
print(classification_report(y_test40, y_pred))
```

```
F1-macro: 0.9602166213283221

              precision    recall  f1-score   support

      GALAXY       0.97      0.98      0.97     19018
         QSO       0.97      0.89      0.93      5896
        STAR       0.97      1.00      0.98      6942

    accuracy                           0.97     31856
   macro avg       0.97      0.96      0.96     31856
weighted avg       0.97      0.97      0.97     31856
```



Kaggle submission

In [73]:
```
df_test = pd.read_csv("./assets/test.csv", index_col = 0)

submission = model.predict(df_test)
submission = pd.DataFrame(submission, columns = ["class"])
submission.index.name = "ID"

label_map = {"GALAXY": 0, "QSO": 1, "STAR": 2}
submission["class"] = submission["class"].map(label_map)

submission[["class"]].to_csv("submission.csv")
```