CA4 - Stellar object classification

Import libraries

```
# import libraries for plotting and data manipulation
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np

# import classfier
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier

# import model selection and preprocessing tools
from sklearn.decomposition import PCA
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.pipeline import make_pipeline
from sklearn.model_selection import StratifiedKFold, GridSearchCV,
train_test_split
from sklearn.metrics import confusion_matrix, classification_report,
f1_score
```

Reading the data

```
# load training and test data
training_data = pd.read_csv('data/train.csv')
test_data = pd.read_csv('data/test.csv')
```

Data exploration

Look at the shape of the data

```
# check the shape of the data
training_data.shape, test_data.shape

((80000, 18), (20000, 17))
```

We can see by the shape of the data, that the training and test data is split 80/20

Overview of the data

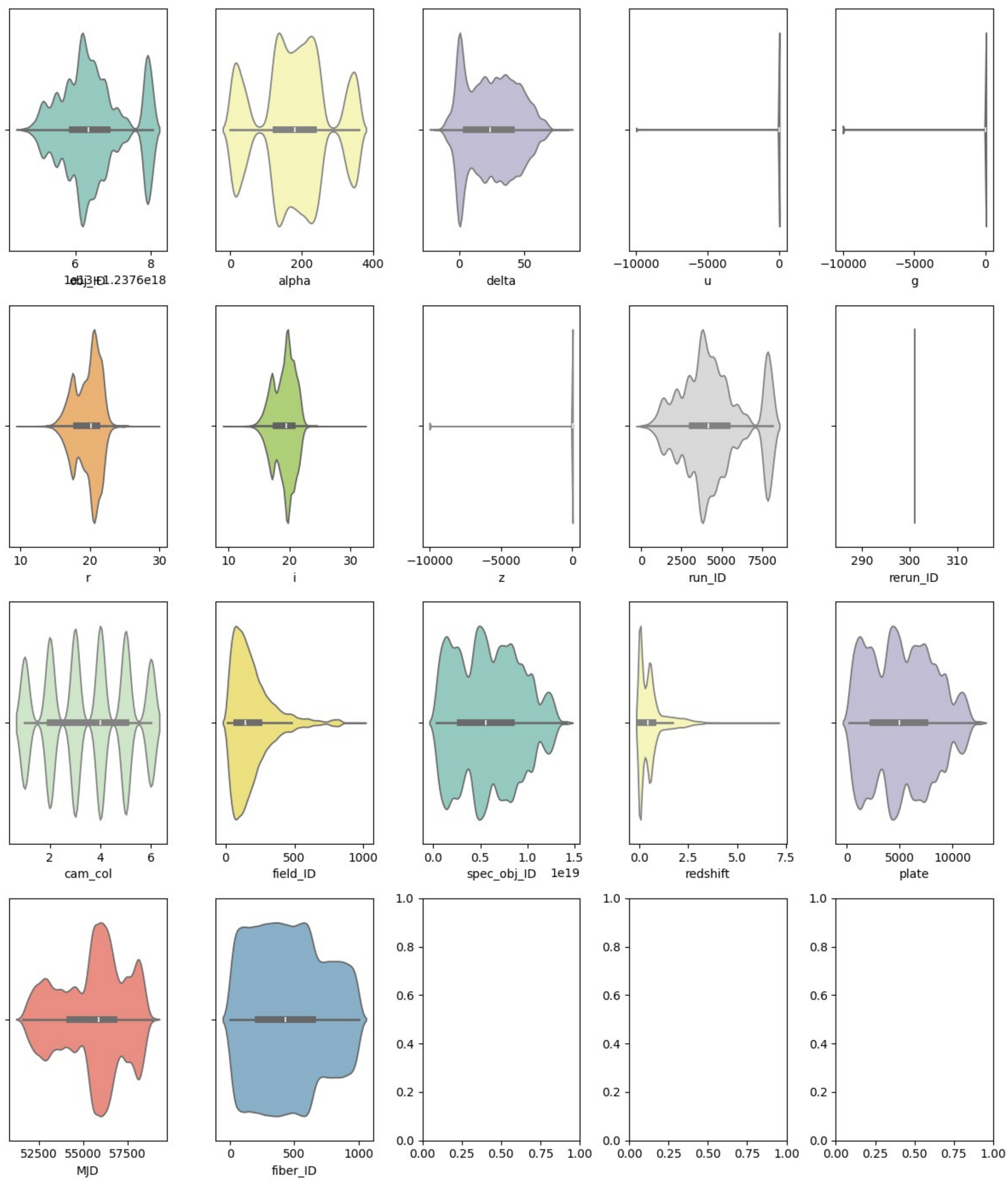
```
training_data.head()

         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
```

The data has 17 columns, where the class column is the class of the stellar object, our target variable y.

Visualize feature distributions using violinplots

```
# visualize feature distributions
fig, axes = plt.subplots(4,5, figsize = (12,14))
axes = axes.flatten()

columns = training_data.columns.to_list()
columns = [col for i, col in enumerate(columns) if i != 13]

colors = sns.color_palette('Set3', n_colors=len(columns))

for i, col in enumerate(columns):
    sns.violinplot(x=col, data=training_data, ax=axes[i],
color=colors[i])

plt.tight_layout()
plt.show()
```



Perform descriptive statistics

```
training_data.describe()

              obj_ID         alpha         delta             u
g  \
count  8.000000e+04  80000.000000  80000.000000  79638.000000
```

```
80000.000000
mean   1.237665e+18    177.579220     24.132590     21.961115
20.507677
std    8.424878e+12     96.409584     19.650113     35.581856
35.483302
min    1.237646e+18      0.005528    -18.785328  -9999.000000  -
9999.000000
25%    1.237659e+18    127.643892      5.170723     20.353990
18.963188
50%    1.237663e+18    180.761747     23.603480     22.187965
21.101015
75%    1.237668e+18    233.815698     39.904905     23.698457
22.125007
max    1.237681e+18    359.999615     83.000519     32.781390
31.602240

                  r             i             z        run_ID
rerun_ID  \
count  80000.000000  80000.000000  80000.000000  80000.000000
80000.0
mean      19.647426     19.085051     18.644640   4477.876713
301.0
std        1.855636      1.757630     35.462189   1961.579187
0.0
min        9.822070      9.469903  -9999.000000    109.000000
301.0
25%       18.135523     17.732600     17.457503   3185.000000
301.0
50%       20.127550     19.405635     19.004420   4188.000000
301.0
75%       21.047242     20.401857     19.923013   5326.000000
301.0
max       29.571860     32.141470     29.383740   8162.000000
301.0

            cam_col      field_ID   spec_obj_ID      redshift
plate  \
count  80000.000000  80000.000000  8.000000e+04  80000.000000
80000.000000
mean       3.511388    185.663050  5.783094e+18      0.577219
5136.309963
std        1.589033    148.433559  3.327780e+18      0.731597
2955.646539
min        1.000000     11.000000  2.995801e+17     -0.009971
266.000000
25%        2.000000     82.000000  2.841535e+18      0.055160
2523.750000
50%        4.000000    146.000000  5.606066e+18      0.425051
4979.000000
```

```
75%        5.000000    240.000000  8.331746e+18      0.704777
7400.000000
max        6.000000    989.000000  1.412694e+19      7.011245
12547.000000

                MJD       fiber_ID
count  80000.000000  80000.000000
mean   55587.191400    448.887437
std     1809.144282    272.328619
min    51608.000000      1.000000
25%    54233.000000    221.000000
50%    55868.000000    432.000000
75%    56777.000000    644.000000
max    58932.000000   1000.000000
```

Data cleaning

Look for missing values

```python
# identify rows with missing values
NaN = training_data.isna().sum()
print(NaN)

print(f'Missing values in the training data: {NaN[3]}')
```

```
obj_ID           0
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
Missing values in the training data: 362

C:\Users\anekl\AppData\Local\Temp\ipykernel_8884\2165697918.py:5:
FutureWarning: Series.__getitem__ treating keys as positions is
deprecated. In a future version, integer keys will always be treated
as labels (consistent with DataFrame behavior). To access a value by
```

```
position, use `ser.iloc[pos]`
  print(f'Missing values in the training data: {NaN[3]}')
```

Remove missing values from the training data

```
# remove rows with missing values
training_data_clean = training_data.dropna()

# check if there are any missing values left
training_data_clean.isna().sum()

print(f'Missing values left in the training data:
{training_data_clean.isna().sum().sum()}')

Missing values left in the training data: 0
```

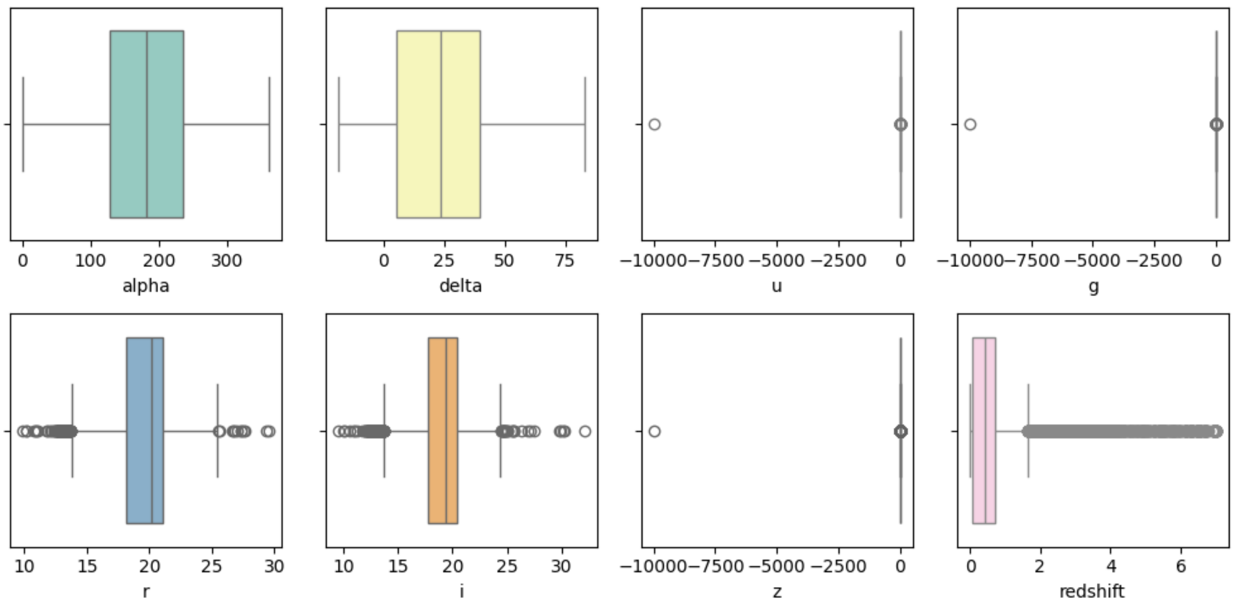
Remove excessive features from the data set

```
training_data_clean = training_data_clean.drop(columns=['obj_ID',
'run_ID', 'rerun_ID', 'cam_col', 'field_ID', 'spec_obj_ID', 'MJD',
'fiber_ID', 'plate', 'fiber_ID'])
training_data_clean.head()

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

    class  redshift
0  GALAXY  0.634794
1  GALAXY  0.779136
2  GALAXY  0.644195
3  GALAXY  0.932346
4  GALAXY  0.116123

# remove excessive features from the test data
test_data_clean = test_data.drop(columns=['obj_ID', 'run_ID',
'rerun_ID', 'cam_col', 'field_ID', 'spec_obj_ID', 'MJD', 'fiber_ID',
'plate', 'fiber_ID'])
test_data_clean.head()

        alpha      delta          u         g         r         i
z  \
```

```
0   16.956890   3.646130  23.33542  21.95143  20.48149  19.60300
19.13094
1  240.063240   6.134131  17.86033  16.79228  16.43001  16.30923
16.25873
2   30.887222   1.188710  18.18911  16.89469  16.42161  16.24627
16.18549
3  247.594401  10.887780  24.99961  21.71203  21.47148  21.30532
21.29109
4   18.896451  -5.261330  23.76648  21.79737  20.69543  20.23403
19.97464

   redshift
0  0.506237
1  0.000345
2  0.000004
3 -0.000291
4 -0.000136
```

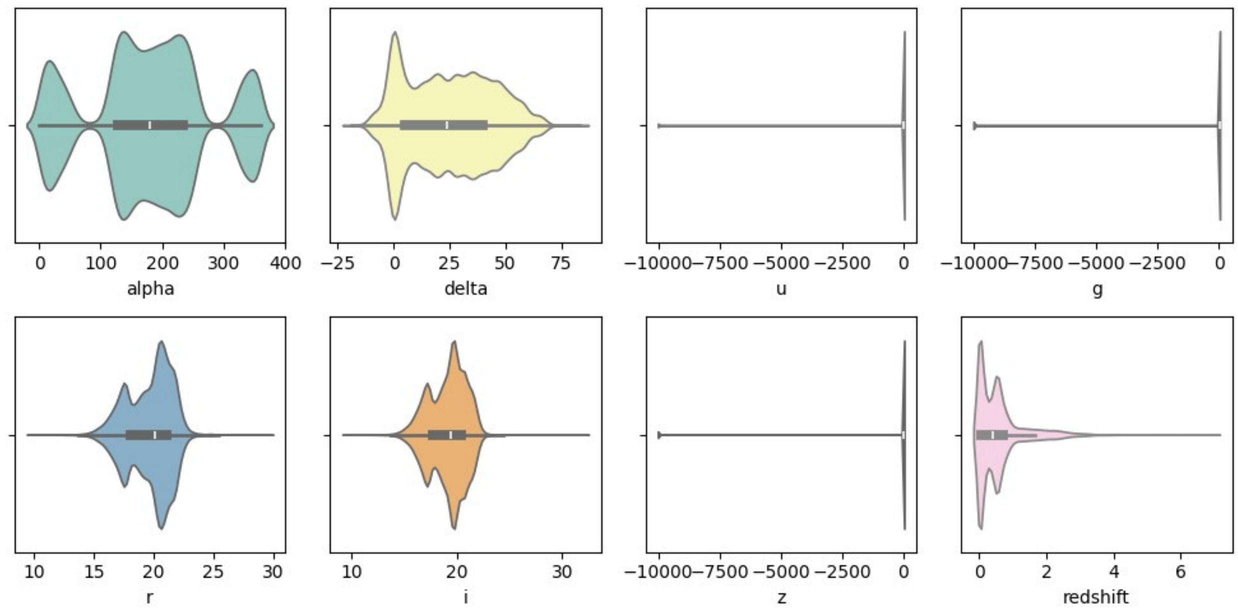
Visualize feature distributions after removing excessive features

```
# visualize feature distributions
fig, axes = plt.subplots(2,4, figsize = (10,5))
axes = axes.flatten()

columns = training_data_clean.columns.to_list()
columns = [col for i, col in enumerate(columns) if i != 7]

colors = sns.color_palette('Set3', n_colors=len(columns))

for i, col in enumerate(columns):
    sns.boxplot(x=col, data=training_data_clean, ax=axes[i],
color=colors[i])

plt.tight_layout()
plt.show()
```



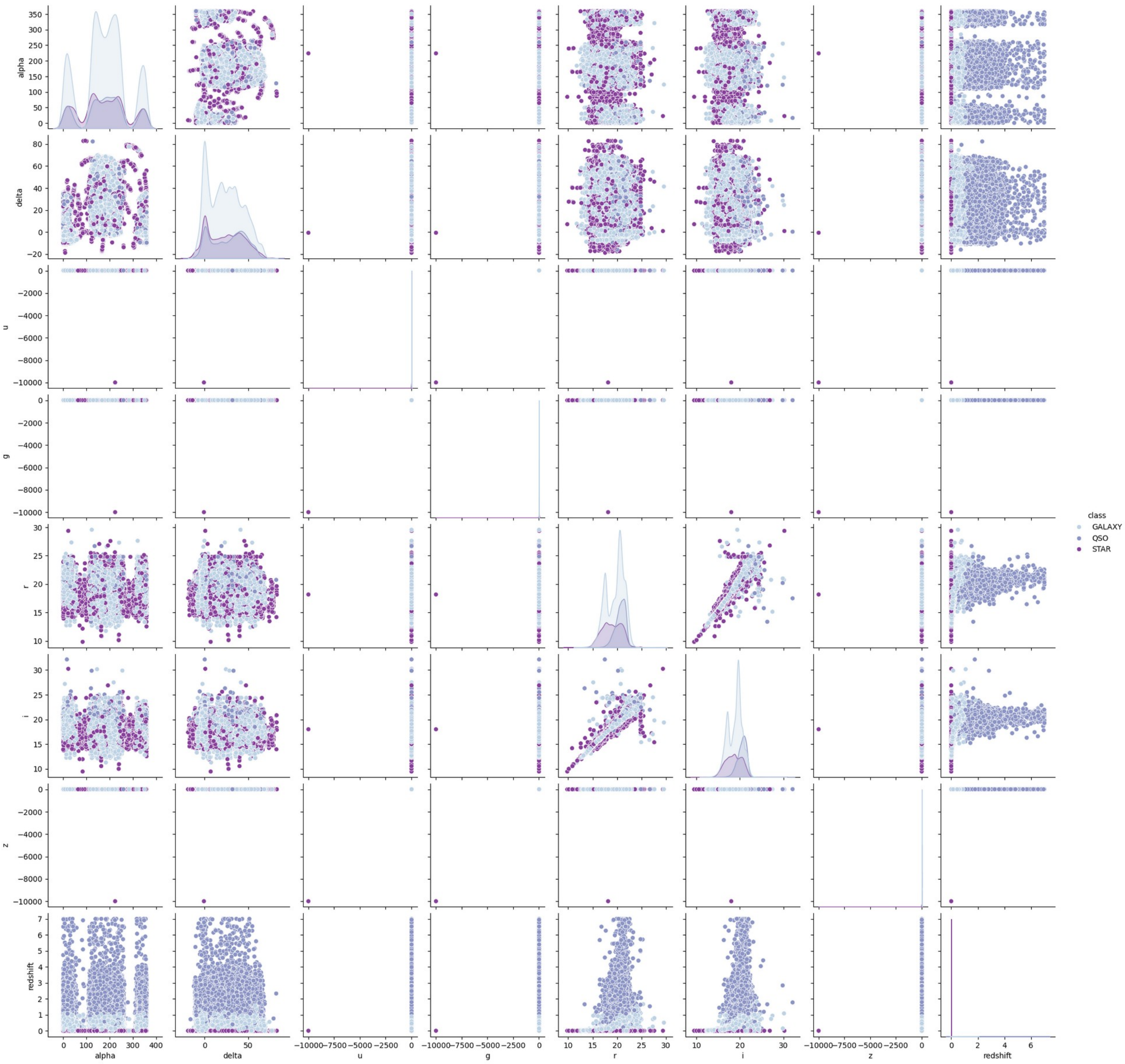
Visualization using violinplots

```
# visualize feature distributions
fig, axes = plt.subplots(2,4, figsize = (10,5))
axes = axes.flatten()

columns = training_data_clean.columns.to_list()
columns = [col for i, col in enumerate(columns) if i != 7]

colors = sns.color_palette('Set3', n_colors=len(columns))

for i, col in enumerate(columns):
    sns.violinplot(x=col, data=training_data_clean, ax=axes[i],
color=colors[i])

plt.tight_layout()
plt.show()
```



Visualize the feature relationships using pairplots from seaborn

```
# make a pairplot of the training data
sns.pairplot(training_data_clean, hue = 'class', palette= 'BuPu')
plt.show()
```



We can see that the features are highly different in their distributions, and therefore should be scaled/standardized.

Data preprocessing and visualization

Split the training data into X_train and y_train

```
X_train = training_data_clean.drop(columns=['class'])
y_train = training_data_clean['class']
X_train.shape, y_train.shape
```

```
((79638, 8), (79638,))
```

Transform the categorical class variable using LabelEncoder

```
le = LabelEncoder()
# encode the target variable
y_train = le.fit_transform(y_train)
le.classes_
```

```
array(['GALAXY', 'QSO', 'STAR'], dtype=object)
```

```
le.transform(['GALAXY', 'QSO', 'STAR'])
```

```
array([0, 1, 2])
```

Look at the target variable distribution

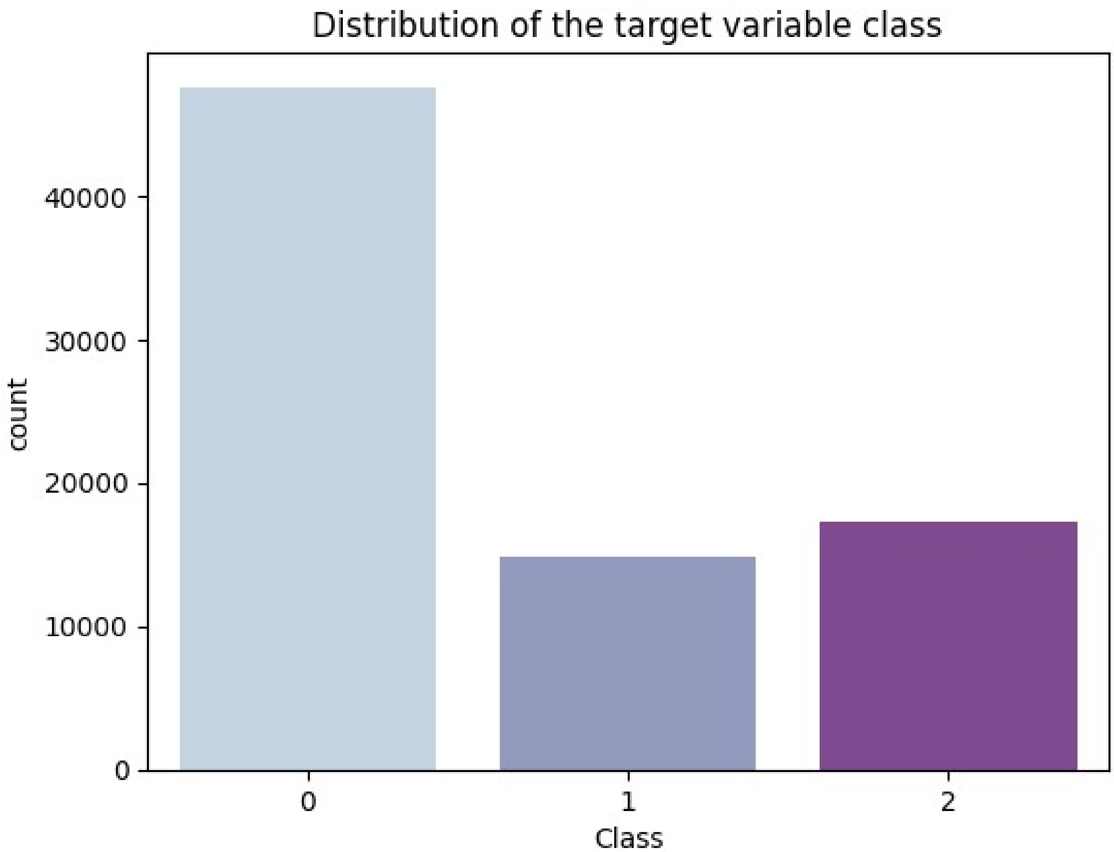
```
(f'The distribution of the target variable is:
{np.bincount(y_train)}')
```

```
'The distribution of the target variable is: [47585 14802 17251]'
```

```
sns.countplot(x=y_train, palette='BuPu')
plt.title('Distribution of the target variable class')
plt.xlabel('Class')
```

```
C:\Users\anekl\AppData\Local\Temp\ipykernel_8884\2183804107.py:1:
FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `x` variable to `hue` and set
`legend=False` for the same effect.

  sns.countplot(x=y_train, palette='BuPu')
```

```
Text(0.5, 0, 'Class')
```

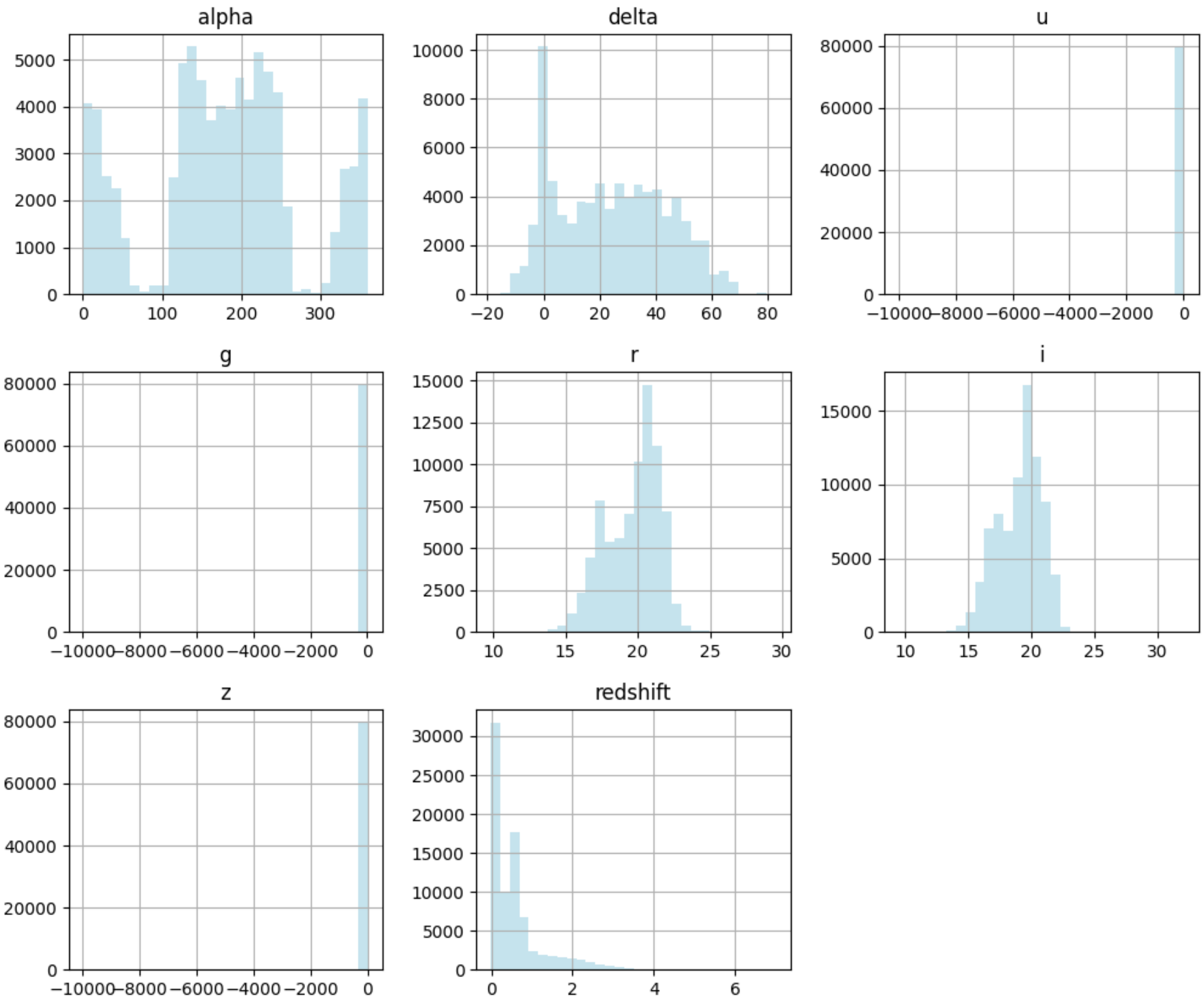


We can see from the plot above that the target variable is quite unbalanced, with more than half of the samples in the first class, galaxy.

Visualize the features before removing outliers

```
X_train.hist(figsize=(12, 10), bins=30, color='lightblue', alpha=0.7)
```

```
array([[<Axes: title={'center': 'alpha'}>,
        <Axes: title={'center': 'delta'}>, <Axes: title={'center':
'u'}>],
       [<Axes: title={'center': 'g'}>, <Axes: title={'center': 'r'}>,
        <Axes: title={'center': 'i'}>],
       [<Axes: title={'center': 'z'}>,
        <Axes: title={'center': 'redshift'}>, <Axes: >]],
dtype=object)
```



Identify and remove outliers using Z-score

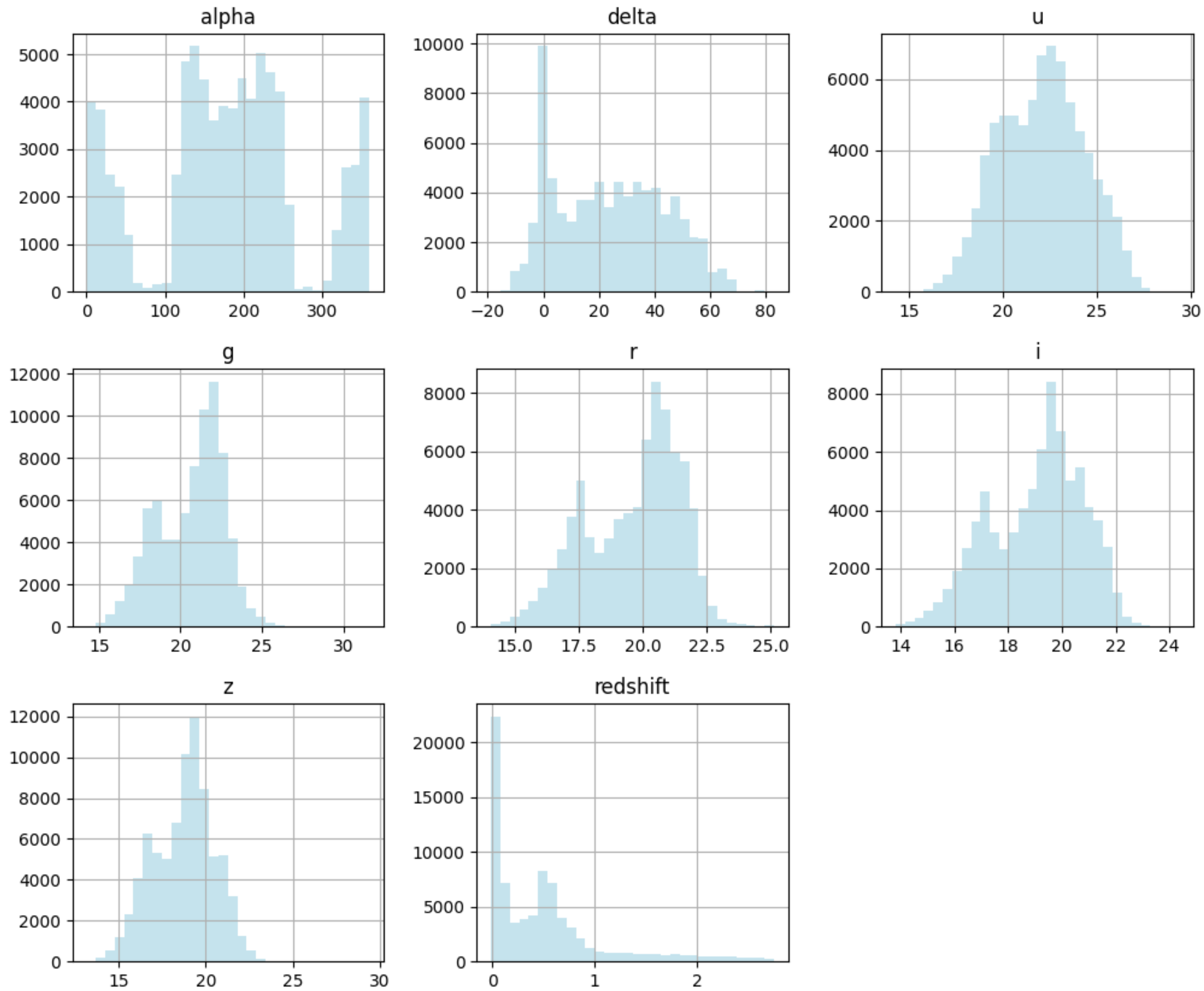
```
# Detect outliers using z-scores

# Compute Z-scores
z_scores = (X_train - X_train.mean()) / X_train.std()

# Identify Outliers (absolute Z-score > 3)
outliers = (np.abs(z_scores) > 3)

# Count total outliers
num_outliers = outliers.sum().sum()  # Summing over all columns

print(f"Total number of outliers: {num_outliers}")

Total number of outliers: 1831

if isinstance(y_train, np.ndarray):
    y_train = pd.Series(y_train, index=X_train.index)
```

```
# Filter rows where all features have Z-score < 3
X_train_clean = X_train[(np.abs(z_scores) < 3).all(axis=1)]

# Remove corresponding rows from y_train
y_train_clean = y_train.loc[X_train_clean.index]

# Print the shapes of the original and cleaned datasets
print("Original X_train shape:", X_train.shape)
print("Original y_train shape:", y_train.shape)
print("Cleaned X_train shape:", X_train_clean.shape)
print("Cleaned y_train shape:", y_train_clean.shape)
```

```
Original X_train shape: (79638, 8)
Original y_train shape: (79638,)
Cleaned X_train shape: (77943, 8)
Cleaned y_train shape: (77943,)
```

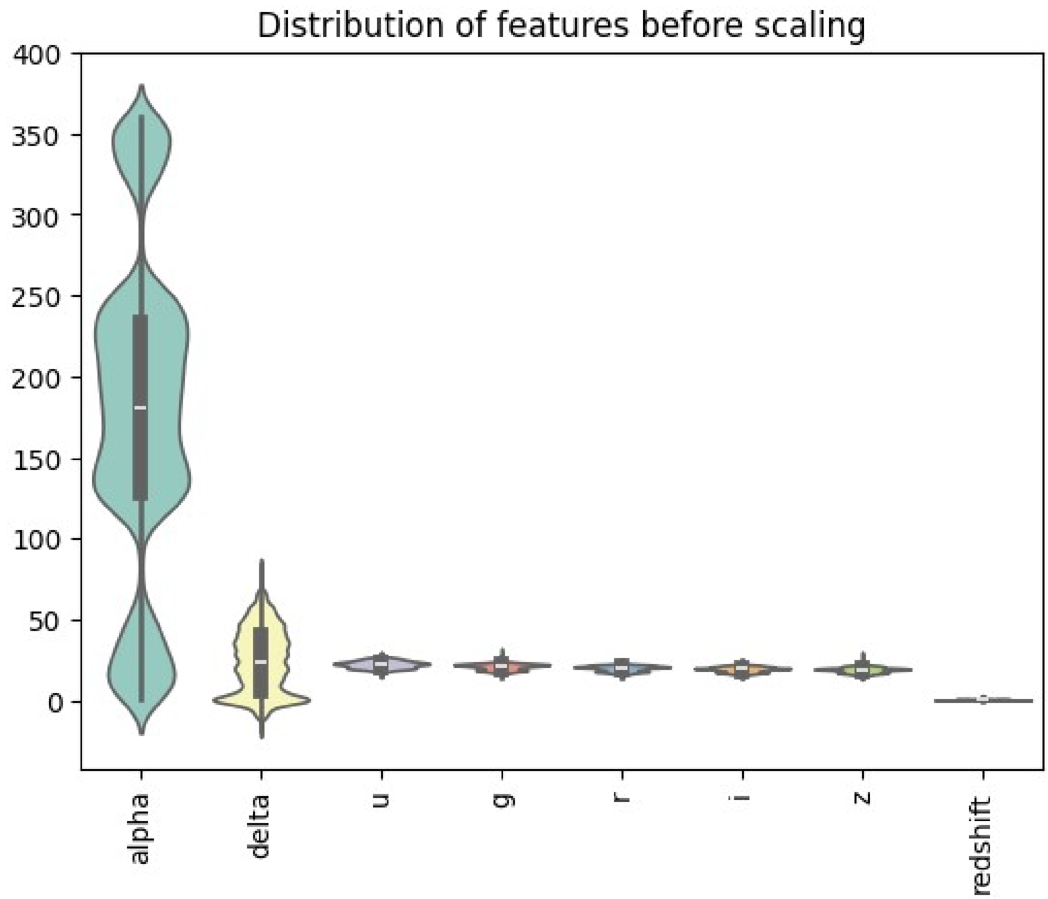
Visualize the features after removing outliers

```
histogram = X_train_clean.hist(figsize=(12, 10), bins=30,
color='lightblue', alpha=0.7)
```



Visualize the data before scaling

```
sns.violinplot(X_train_clean, palette = sns.color_palette('Set3',
n_colors= X_train_clean.shape[1]))
plt.xticks(rotation = 90)
plt.title('Distribution of features before scaling')
plt.show()
```



Modelling

Define pipelines

SVM

```
# Define the SVC pipeline:
pipe_svc = make_pipeline(StandardScaler(), SVC(random_state=1))
pipe_svc.get_params()
```

```
{'memory': None,
 'steps': [('standardscaler', StandardScaler()), ('svc',
SVC(random_state=1))],
 'verbose': False,
 'standardscaler': StandardScaler(),
 'svc': SVC(random_state=1),
 'standardscaler__copy': True,
 'standardscaler__with_mean': True,
 'standardscaler__with_std': True,
 'svc__C': 1.0,
 'svc__break_ties': False,
 'svc__cache_size': 200,
 'svc__class_weight': None,
```

```
 'svc__coef0': 0.0,
 'svc__decision_function_shape': 'ovr',
 'svc__degree': 3,
 'svc__gamma': 'scale',
 'svc__kernel': 'rbf',
 'svc__max_iter': -1,
 'svc__probability': False,
 'svc__random_state': 1,
 'svc__shrinking': True,
 'svc__tol': 0.001,
 'svc__verbose': False}
```

Logistic regression

```
# Define the logistic regression pipeline:
pipe_logistic = make_pipeline(StandardScaler(), PCA(n_components=7),
LogisticRegression(random_state=1))
pipe_logistic.get_params()
```

```
{'memory': None,
 'steps': [('standardscaler', StandardScaler()),
  ('pca', PCA(n_components=7)),
  ('logisticregression', LogisticRegression(random_state=1))],
 'verbose': False,
 'standardscaler': StandardScaler(),
 'pca': PCA(n_components=7),
 'logisticregression': LogisticRegression(random_state=1),
 'standardscaler__copy': True,
 'standardscaler__with_mean': True,
 'standardscaler__with_std': True,
 'pca__copy': True,
 'pca__iterated_power': 'auto',
 'pca__n_components': 7,
 'pca__n_oversamples': 10,
 'pca__power_iteration_normalizer': 'auto',
 'pca__random_state': None,
 'pca__svd_solver': 'auto',
 'pca__tol': 0.0,
 'pca__whiten': False,
 'logisticregression__C': 1.0,
 'logisticregression__class_weight': None,
 'logisticregression__dual': False,
 'logisticregression__fit_intercept': True,
 'logisticregression__intercept_scaling': 1,
 'logisticregression__l1_ratio': None,
 'logisticregression__max_iter': 100,
 'logisticregression__multi_class': 'auto',
 'logisticregression__n_jobs': None,
 'logisticregression__penalty': 'l2',
 'logisticregression__random_state': 1,
```

```
 'logisticregression__solver': 'lbfgs',
 'logisticregression__tol': 0.0001,
 'logisticregression__verbose': 0,
 'logisticregression__warm_start': False}
```

Random Forest

```
# Define the random forest pipeline:
pipe_rf = make_pipeline(RandomForestClassifier(random_state=1))
pipe_rf.get_params()
```

```
{'memory': None,
 'steps': [('randomforestclassifier',
RandomForestClassifier(random_state=1))],
 'verbose': False,
 'randomforestclassifier': RandomForestClassifier(random_state=1),
 'randomforestclassifier__bootstrap': True,
 'randomforestclassifier__ccp_alpha': 0.0,
 'randomforestclassifier__class_weight': None,
 'randomforestclassifier__criterion': 'gini',
 'randomforestclassifier__max_depth': None,
 'randomforestclassifier__max_features': 'sqrt',
 'randomforestclassifier__max_leaf_nodes': None,
 'randomforestclassifier__max_samples': None,
 'randomforestclassifier__min_impurity_decrease': 0.0,
 'randomforestclassifier__min_samples_leaf': 1,
 'randomforestclassifier__min_samples_split': 2,
 'randomforestclassifier__min_weight_fraction_leaf': 0.0,
 'randomforestclassifier__monotonic_cst': None,
 'randomforestclassifier__n_estimators': 100,
 'randomforestclassifier__n_jobs': None,
 'randomforestclassifier__oob_score': False,
 'randomforestclassifier__random_state': 1,
 'randomforestclassifier__verbose': 0,
 'randomforestclassifier__warm_start': False}
```

K-nearest-neighbour (KNN)

```
# Define the KNN pipeline:
pipe_knn = make_pipeline(StandardScaler(), KNeighborsClassifier())
pipe_knn.get_params()
```

```
{'memory': None,
 'steps': [('standardscaler', StandardScaler()),
  ('kneighborsclassifier', KNeighborsClassifier())],
 'verbose': False,
 'standardscaler': StandardScaler(),
 'kneighborsclassifier': KNeighborsClassifier(),
 'standardscaler__copy': True,
 'standardscaler__with_mean': True,
 'standardscaler__with_std': True,
```

```
 'kneighborsclassifier__algorithm': 'auto',
 'kneighborsclassifier__leaf_size': 30,
 'kneighborsclassifier__metric': 'minkowski',
 'kneighborsclassifier__metric_params': None,
 'kneighborsclassifier__n_jobs': None,
 'kneighborsclassifier__n_neighbors': 5,
 'kneighborsclassifier__p': 2,
 'kneighborsclassifier__weights': 'uniform'}
```

Evaluate different models and hyperparameters using GridSearchCV with cross-validation

SVM

```
cv_strategy = StratifiedKFold(n_splits=5, shuffle=True,
random_state=42)

gs_svm = GridSearchCV(estimator=pipe_svc,
                  param_grid={'svc__C': [0.1, 1, 10, 100],
'svc__kernel': ['rbf']},
                  scoring='f1_macro',
                  cv=cv_strategy,
                  n_jobs=-1)

gs_svm = gs_svm.fit(X_train_clean, y_train_clean)
print(gs_svm.best_score_)
print(gs_svm.best_params_)

best_model_svm = gs_svm.best_estimator_

0.9666694954815223
{'svc__C': 100, 'svc__kernel': 'rbf'}
```

Logistic regression

```
cv_strategy = StratifiedKFold(n_splits=5, shuffle=True,
random_state=42)

gs_logistic = GridSearchCV(estimator=pipe_logistic,
                  param_grid={'logisticregression__penalty': ['l2'],
                              'logisticregression__C': [1,10,100]},
                  scoring='f1_macro',
                  cv=cv_strategy,
                  n_jobs=-1)

gs_logistic = gs_logistic.fit(X_train_clean, y_train_clean)
print(gs_logistic.best_score_)
print(gs_logistic.best_params_)

best_model_logistic = gs_logistic.best_estimator_
```

```
0.9529143717852919
{'logisticregression__C': 100, 'logisticregression__penalty': 'l2'}
```

Random forest

```
gs_rf = GridSearchCV(estimator=pipe_rf,
                  param_grid={'randomforestclassifier__n_estimators':
[80, 100, 120],
                              'randomforestclassifier__max_features':
['sqrt', 'log2'],
                              'randomforestclassifier__max_depth':
[5,10,15],
                              'randomforestclassifier__criterion':
['entropy']},
                  scoring='f1_macro',
                  cv=5,
                  n_jobs=-1)

gs_rf = gs_rf.fit(X_train_clean, y_train_clean)
print(gs_rf.best_score_)
print(gs_rf.best_params_)

best_model_rf = gs_rf.best_estimator_

0.9730246117133078
{'randomforestclassifier__criterion': 'entropy',
'randomforestclassifier__max_depth': 15,
'randomforestclassifier__max_features': 'log2',
'randomforestclassifier__n_estimators': 80}
```

KNN

```
cv_strategy = StratifiedKFold(n_splits=5, shuffle=True,
random_state=42)

gs_knn = GridSearchCV(estimator=pipe_knn,
                  param_grid={'kneighborsclassifier__n_neighbors': [3,
5, 7],
                              'kneighborsclassifier__weights':
['distance'],
                              'kneighborsclassifier__metric':
['euclidean', 'manhattan']},
                  scoring='f1_macro',
                  cv=cv_strategy,
                  n_jobs=-1)

gs_knn = gs_knn.fit(X_train_clean, y_train_clean)
print(gs_knn.best_score_)
print(gs_knn.best_params_)

best_model_knn = gs_knn.best_estimator_
```

```
0.9404996981321396
{'kneighborsclassifier__metric': 'manhattan',
'kneighborsclassifier__n_neighbors': 5,
'kneighborsclassifier__weights': 'distance'}
```

Build classifier based on all training samples using the "optimal parameters"

The code below is based on the best model of the Random Forest Classifier, since this had the highest score during GridSearch.

All fitting, predicting and evaluation is done using this classifier.

```
# fit the best model to the training data (random forest)
best_model_rf.fit(X_train_clean, y_train_clean)
```

```
Pipeline(steps=[('randomforestclassifier',
                 RandomForestClassifier(criterion='entropy',
max_depth=15,
                                        max_features='log2',
n_estimators=80,
                                        random_state=1))])
```

Evaluate model performance

Confusion matrix

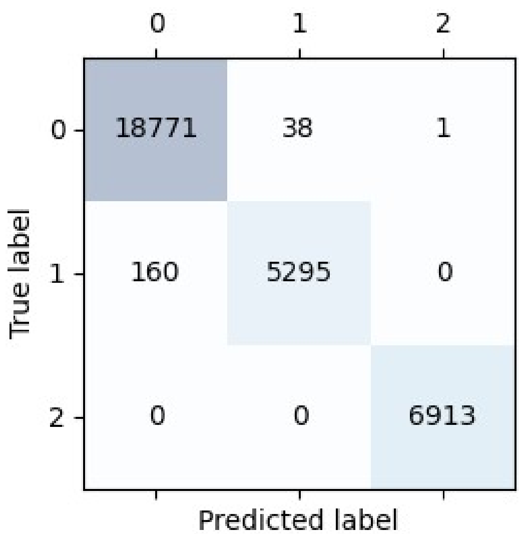
```
# confusion matrix for the random forest model using train/test split
on training data
X_train_data, X_test_data, y_train_labels, y_testlabels =
train_test_split(X_train_clean, y_train_clean, test_size=0.4,
random_state=42)
y_pred = best_model_rf.predict(X_test_data)

confusion = confusion_matrix(y_testlabels, y_pred)
confusion
```

```
array([[18771,    38,     1],
       [  160,  5295,     0],
       [    0,     0,  6913]])
```

Plot the confusion matrix using matplotlib

```
# Code borrowed from lecture 'Chapter_6_part_2b'

fig, ax = plt.subplots(figsize=(3, 3))
ax.matshow(confusion, cmap=plt.cm.Blues, alpha=0.3)
for i in range(confusion.shape[0]):
    for j in range(confusion.shape[1]):
        ax.text(x=j, y=i, s=confusion[i, j], va='center', ha='center')

plt.xlabel('Predicted label')
```

```
plt.ylabel('True label')

plt.tight_layout()
plt.show()
```



Model performance using classification report in Scikit learn

```
classification_rep = pd.DataFrame(classification_report(y_testlabels, y_pred, output_dict=True)).T
classification_rep
```

	precision	recall	f1-score	support
0	0.991548	0.997927	0.994727	18810.000000
1	0.992875	0.970669	0.981646	5455.000000
2	0.999855	1.000000	0.999928	6913.000000
accuracy	0.993617	0.993617	0.993617	0.993617
macro avg	0.994759	0.989532	0.992100	31178.000000
weighted avg	0.993622	0.993617	0.993592	31178.000000

We can see that the output from the classification report gave the same F1 scores as we manually calculated above.

Kaggle submission

```
y_test = best_model_rf.predict(test_data_clean)
y_test = pd.DataFrame(y_test, columns=["class"])
y_test.index.name = "ID"
y_test[['class']].to_csv("data/sample_submission.csv")
```