Stellar Classification

Imports

In [1]:

```
import numpy as np
import pandas as pd
from matplotlib import rcParams
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.stats import zscore
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier, export_graphviz
import graphviz
from sklearn.svm import SVC
from sklearn.model_selection import train_test_split, GridSearchCV, cross_val_score
from sklearn.preprocessing import StandardScaler, OneHotEncoder, minmax_scale
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay, classification_re
```

Read the data and take a first look

In [2]:

```
df = pd.read_csv('https://raw.githubusercontent.com/Deelane/CST383---Final/main/star_cl
```

In [3]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100000 entries, 0 to 99999
Data columns (total 18 columns):
 #   Column       Non-Null Count   Dtype  
---  ------       --------------   -----  
 0   obj_ID       100000 non-null  float64
 1   alpha        100000 non-null  float64
 2   delta        100000 non-null  float64
 3   u            100000 non-null  float64
 4   g            100000 non-null  float64
 5   r            100000 non-null  float64
 6   i            100000 non-null  float64
 7   z            100000 non-null  float64
 8   run_ID       100000 non-null  int64  
 9   rerun_ID     100000 non-null  int64  
 10  cam_col      100000 non-null  int64  
 11  field_ID     100000 non-null  int64  
 12  spec_obj_ID  100000 non-null  float64
 13  class        100000 non-null  object 
 14  redshift     100000 non-null  float64
 15  plate        100000 non-null  int64  
 16  MJD          100000 non-null  int64  
 17  fiber_ID     100000 non-null  int64  
dtypes: float64(10), int64(7), object(1)
memory usage: 13.7+ MB
```

The dataset has no null entries, but we will still need to check for outliers

In [4]:
```
df.describe()
```

Out[4]:

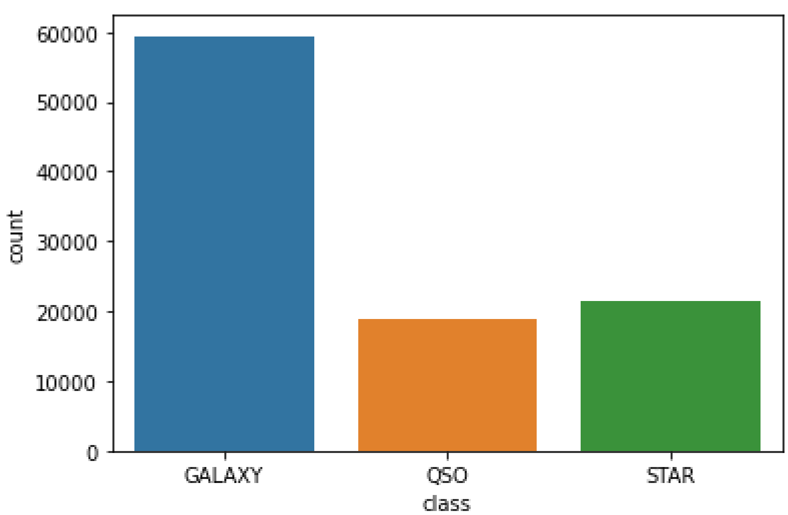
	obj_ID	alpha	delta	u	g	r	
count	1.000000e+05	100000.000000	100000.000000	100000.000000	100000.000000	100000.000000	10000
mean	1.237665e+18	177.629117	24.135305	21.980468	20.531387	19.645762	1
std	8.438560e+12	96.502241	19.644665	31.769291	31.750292	1.854760	
min	1.237646e+18	0.005528	-18.785328	-9999.000000	-9999.000000	9.822070	
25%	1.237659e+18	127.518222	5.146771	20.352353	18.965230	18.135828	1
50%	1.237663e+18	180.900700	23.645922	22.179135	21.099835	20.125290	1
75%	1.237668e+18	233.895005	39.901550	23.687440	22.123767	21.044785	2
max	1.237681e+18	359.999810	83.000519	32.781390	31.602240	29.571860	3

Note the -9999 values as min for columns u, g, and z. Is this missing/bad data?

In [5]:
```
print(df['class'].value_counts())
sns.countplot('class', data=df);
bad_index = df[df['g'] == -9999].index[0]
df.drop([bad_index], inplace=True) #drop the bad data
df.reset_index(drop=True, inplace=True)
```

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

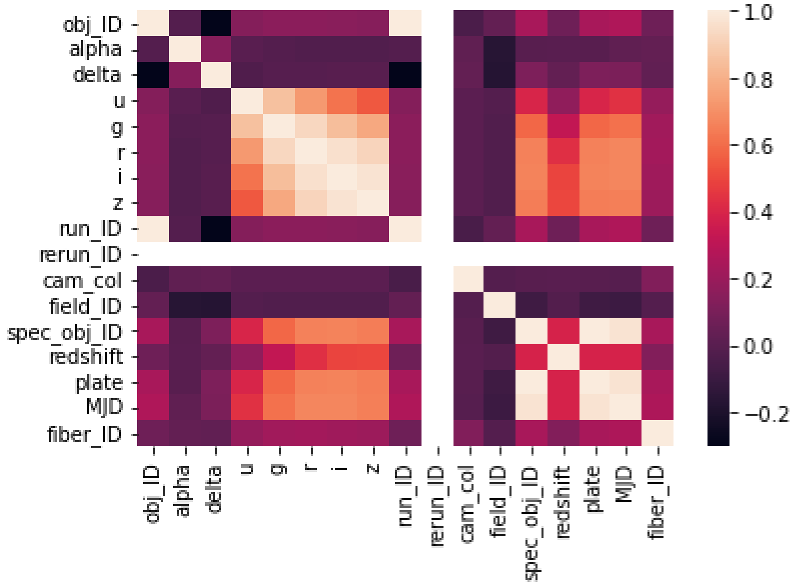
```
C:\Users\Jordan\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pa
ss the following variable as a keyword arg: x. From version 0.12, the only valid positio
nal argument will be `data`, and passing other arguments without an explicit keyword wil
l result in an error or misinterpretation.
  warnings.warn(
```



As you can see, this is an unbalanced dataset. There are significantly more 'GALAXY' entries than

'QSO' and 'STAR'

In [6]:
```
corr = df.corr()
sns.heatmap(corr, xticklabels=corr.columns, yticklabels=corr.columns);
```



Data Visualization / Preprocessing:

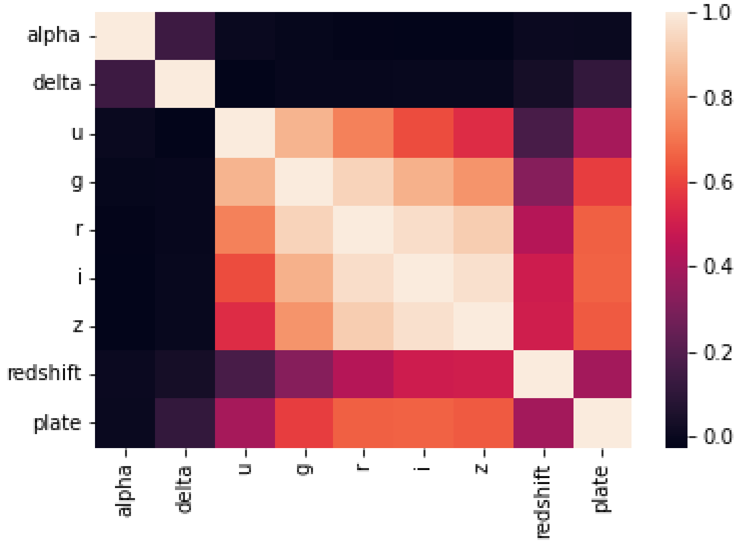
Dropping ID columns

In [7]:
```
df.drop(columns=['obj_ID', 'run_ID', 'rerun_ID', 'field_ID','fiber_ID', 'spec_obj_ID',
```

Remaining columns

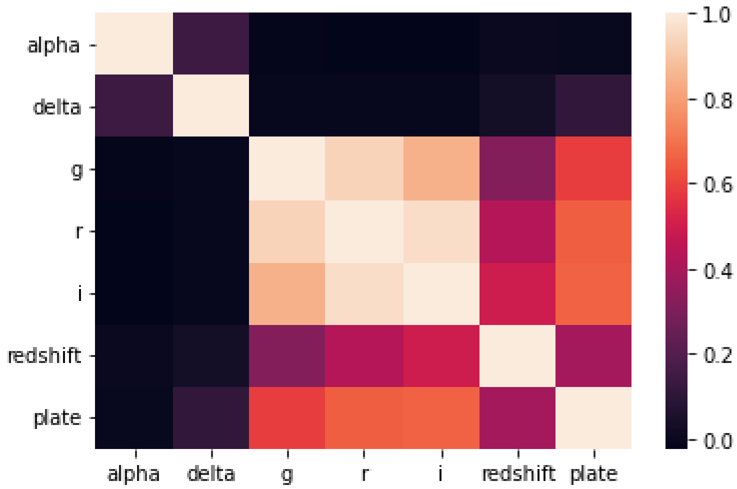
Columns ['u', 'g', 'z'] and ['r', 'i'] correlate to the other columns in almost excactly same way. 'r' and 'i' are different enough with regards to redshift (our biggest predictor) so we will keep them.

In [8]:
```
sns.heatmap(df.corr());
```



Final columns

In [9]:
```
df.drop(columns=['u', 'z'], inplace=True)
sns.heatmap(df.corr());
```



Pairplot

'redshift', 'g', and 'redshift' vs 'g' show to be very good at classifying, with each class clearly having its own value range for each.

In [10]:
```
sns.pairplot(df, hue='class')
```

Out[10]:
```
<seaborn.axisgrid.PairGrid at 0x211eb05a6a0>
```

One Hot Encoding

In [11]:

```
enc = OneHotEncoder()
enc_df = pd.DataFrame(enc.fit_transform(df[['class']]).toarray())
enc_df.columns = ['GALAXY', 'QSO', 'STAR']
df = pd.concat([df, enc_df], axis=1)
```

Forward Selection - Manual Testing

Selecting Predictors

In [12]:

```
targets = ['GALAXY', 'QSO', 'STAR']

# run 1
# predictors = ['alpha', 'delta', 'g', 'r', 'i', 'redshift', 'plate']

# run 2
# redshift provides highest accuracy:
# predictors = ['alpha', 'delta', 'g', 'r', 'i', 'plate']
```

```
# run 3
# g + redshift provides highest accuracy:
# predictors = ['alpha', 'delta', 'r', 'i', 'plate']

# run 4
# r + g + redshift provides highest accuracy:
# predictors = ['alpha', 'delta', 'i', 'plate']

# run 5
# i + r + g + redshift provides highest accuracy:
predictors = ['alpha', 'delta', 'plate']
```

Getting Accuracy

In [13]:

```
for p in predictors:
  # run 1 - for all predictors:
  # X = df[[p]].values

  # run 2
  # redshift provides highest accuracy: 94.31, add to predictors
  # X = df[[p, 'redshift']].values

  # run 3
  # g + redshift provides highest accuracy: 95.4, add to predictors
  # X = df[[p, 'redshift', 'g']].values

  # run 4
  # r + g + redshift provides highest accuracy: 95.08, add to predictors
  # X = df[[p, 'redshift', 'g', 'r']].values

  # run 5
  # i + r + g + redshift provides highest accuracy: 93.86
  X = df[[p, 'redshift', 'g', 'r', 'i']].values

  y = df[targets].values

  X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.30, random_stat
  scaler = StandardScaler()
  X_train = scaler.fit_transform(X_train)
  X_test = scaler.transform(X_test)

  # implement kNN classification with default value of k
  knn = KNeighborsClassifier(weights='distance', metric='manhattan')
  knn.fit(X_train, y_train)

  # get predictions
  predictions = knn.predict(X_test)

  predictions_enc = pd.DataFrame(predictions).idxmax(axis=1)
  y_test_enc = pd.DataFrame(y_test).idxmax(axis=1)

  print (p, (predictions_enc == y_test_enc).mean())
```

```
alpha 0.9565
delta 0.9546
plate 0.9620666666666666
```

Set Predictors and Targets

In [14]:

```
# Set predictors and targets
predictors = ['alpha', 'delta', 'g', 'r', 'i', 'redshift', 'plate']
targets = ['GALAXY', 'QSO', 'STAR']

X = df[predictors].values
y = df[targets].values
```

Train, Test, Split

In [15]:

```
#Train, Test, Split (Random Seed 42)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=4
```

Choosing a model

KNN Exploration

In [16]:

```
#WARNING, COSTLY COMPUTATIONS

#use gridsearch on cross validation to find the best n and p for knn
n_sqrt = round(np.sqrt(X_train.shape[0]))
grid = [{'n_neighbors': [3, 5, 7, 9, n_sqrt], 'p':[1,2]}]
knnCV = GridSearchCV(KNeighborsClassifier(), grid, cv=5, scoring='accuracy')
knnCV.fit(X_train, y_train)
print(knnCV.best_params_)

#Best hyperparameters evaluate to {'n_neighbors': 3, 'p': 1}, so 3 neighbors and the di
#This will likely change as it is possible that we are overfitting
```

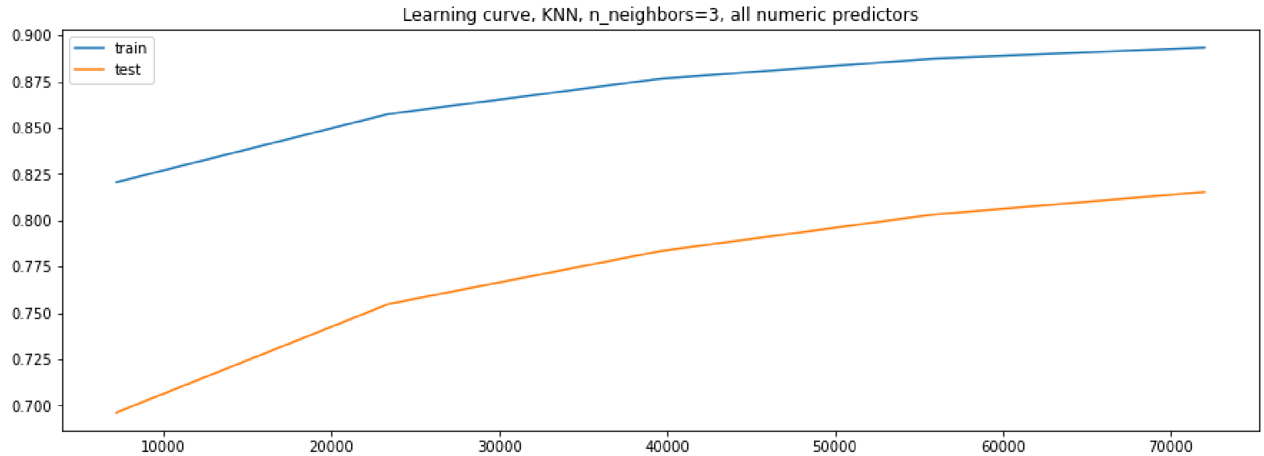
```
{'n_neighbors': 3, 'p': 1}
```

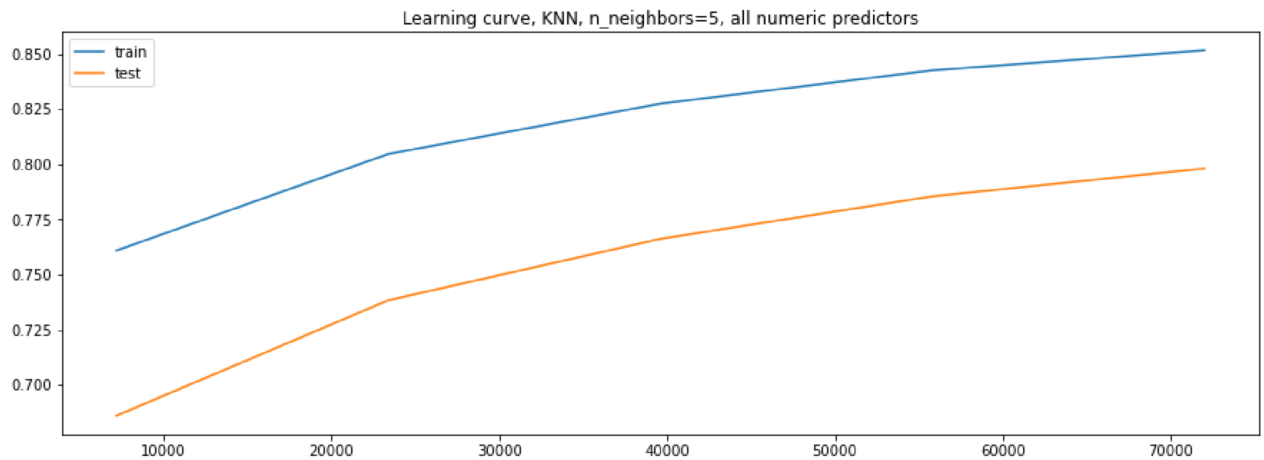
Learning Curves

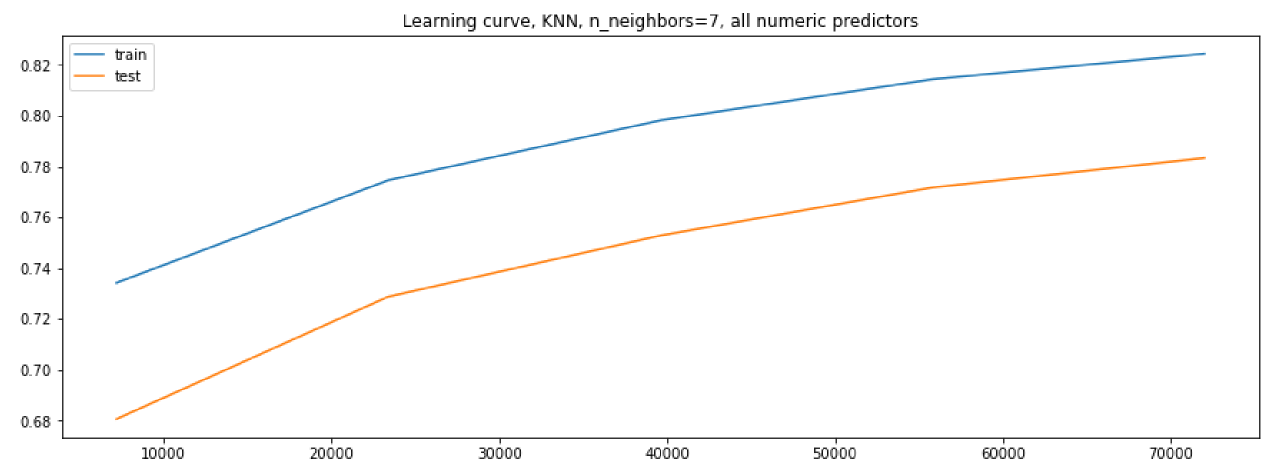
In [17]:

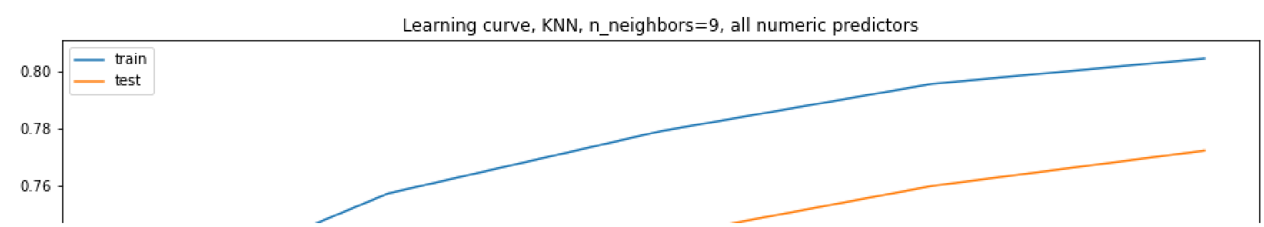
```
from sklearn.model_selection import learning_curve

#cell height
# from IPython.display import Javascript
# display(Javascript('''google.colab.output.setIframeHeight(0, true, {maxHeight: 5000})

#WARNING, EXTREMELY COSTLY COMPUTATIONS
#14mins on local, likely much more on colab

n_neighbors_list = [3, 5, 7, 9, round(np.sqrt(X_train.shape[0]))]
fig, axs = plt.subplots(len(n_neighbors_list), figsize=(15,30))
learning_curve_df = pd.DataFrame({ 'n_neighbors':[], 'train_scores_mean':[], 'test_scor

for i in range(len(n_neighbors_list)):
    knn = KNeighborsClassifier(n_neighbors = n_neighbors_list[i], p = 1) #Manhattan dis
    train_sizes, train_scores, test_scores = learning_curve(knn, X_train, y_train, cv=1
    train_scores_mean = np.mean(train_scores, axis=1)
```

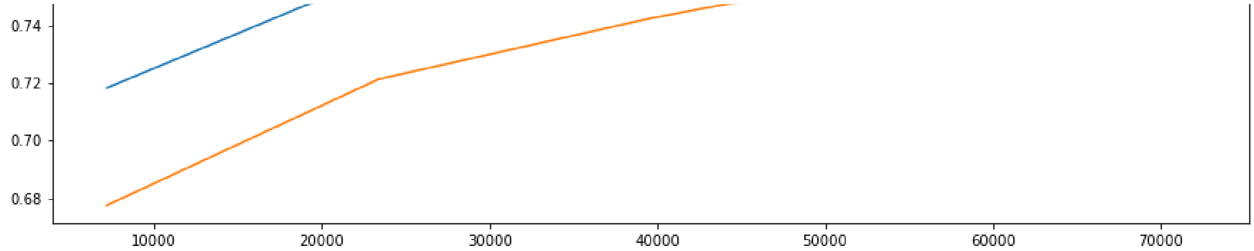
```
    test_scores_mean = np.mean(test_scores, axis=1)
    df_temp = pd.DataFrame([[n_neighbors_list[i], train_scores_mean, test_scores_mean]]
    learning_curve_df = pd.concat([learning_curve_df, df_temp], ignore_index=True)
    axs[i].plot(train_sizes, train_scores_mean, label='train')
    axs[i].plot(train_sizes, test_scores_mean, label='test')
    axs[i].legend()
    title = "Learning curve, KNN, n_neighbors=" + str(n_neighbors_list[i]) + ", all num
    axs[i].set_title(title)
```

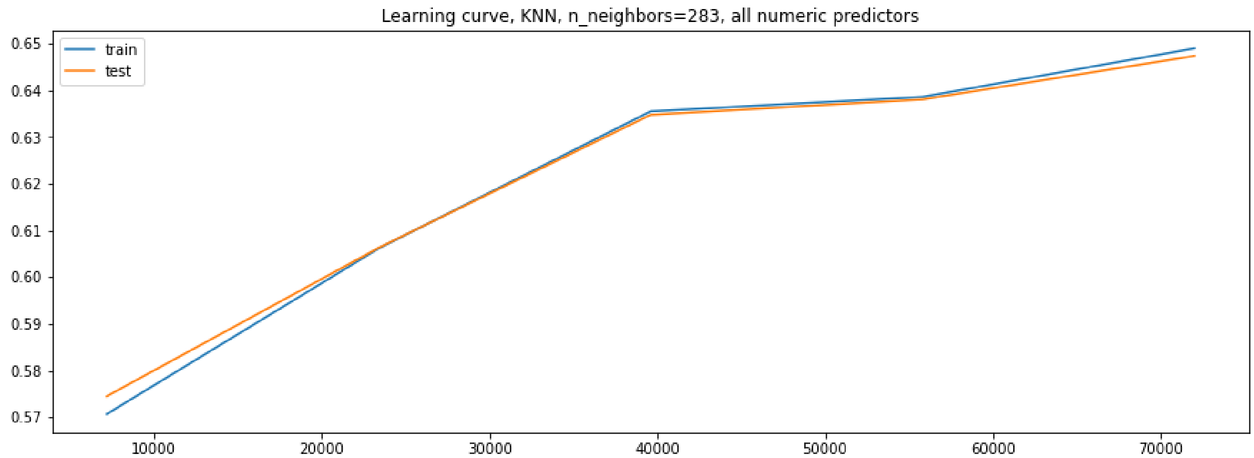












Logistic Regression Exploration

Label Encoding

In [18]:

```
df['class_cat'] = df['class'].astype('category').cat.codes
```

Grid Search for each solver

In [19]:

```
predictors = ['alpha', 'delta', 'g', 'r', 'i', 'redshift', 'plate']

X = df[predictors].values
y = df['class'].values

#Train, Test, Split (Random Seed 42)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=4

# The other solvers are giving us Convergence warnings. This is another reason we stuck
grid = [{'solver':['liblinear', 'sag', 'saga']}]
clf_cv = GridSearchCV(LogisticRegression(), grid, cv=5, scoring='accuracy')
clf_cv.fit(X_train, y_train)
print(clf_cv.best_params_)
```

```
C:\Users\Jordan\anaconda3\lib\site-packages\sklearn\linear_model\_sag.py:328: Convergenc
eWarning: The max_iter was reached which means the coef_ did not converge
  warnings.warn("The max_iter was reached which means "
C:\Users\Jordan\anaconda3\lib\site-packages\sklearn\linear_model\_sag.py:328: Convergenc
eWarning: The max_iter was reached which means the coef_ did not converge
  warnings.warn("The max_iter was reached which means "
C:\Users\Jordan\anaconda3\lib\site-packages\sklearn\linear_model\_sag.py:328: Convergenc
eWarning: The max_iter was reached which means the coef_ did not converge
  warnings.warn("The max_iter was reached which means "
C:\Users\Jordan\anaconda3\lib\site-packages\sklearn\linear_model\_sag.py:328: Convergenc
```

```
eWarning: The max_iter was reached which means the coef_ did not converge
  warnings.warn("The max_iter was reached which means "
C:\Users\Jordan\anaconda3\lib\site-packages\sklearn\linear_model\_sag.py:328: Convergenc
eWarning: The max_iter was reached which means the coef_ did not converge
  warnings.warn("The max_iter was reached which means "
C:\Users\Jordan\anaconda3\lib\site-packages\sklearn\linear_model\_sag.py:328: Convergenc
eWarning: The max_iter was reached which means the coef_ did not converge
  warnings.warn("The max_iter was reached which means "
C:\Users\Jordan\anaconda3\lib\site-packages\sklearn\linear_model\_sag.py:328: Convergenc
eWarning: The max_iter was reached which means the coef_ did not converge
  warnings.warn("The max_iter was reached which means "
C:\Users\Jordan\anaconda3\lib\site-packages\sklearn\linear_model\_sag.py:328: Convergenc
eWarning: The max_iter was reached which means the coef_ did not converge
  warnings.warn("The max_iter was reached which means "
C:\Users\Jordan\anaconda3\lib\site-packages\sklearn\linear_model\_sag.py:328: Convergenc
eWarning: The max_iter was reached which means the coef_ did not converge
  warnings.warn("The max_iter was reached which means "
C:\Users\Jordan\anaconda3\lib\site-packages\sklearn\linear_model\_sag.py:328: Convergenc
eWarning: The max_iter was reached which means the coef_ did not converge
  warnings.warn("The max_iter was reached which means "
{'solver': 'liblinear'}
```

Drop labels

In [20]:

```python
df.drop(columns=['class_cat'], inplace=True)
```

Decision Tree Classifier Exploration

Testing different hyperparameters

In [21]:

```python
# we will test max_depth values ranging from 2 to 10
params = {'max_depth':np.arange(2,11)}

# grid search using 5-fold cross validation
clf_cv = GridSearchCV(DecisionTreeClassifier(), params, cv=5)
clf_cv.fit(X_train, y_train)

# print results
print('Best estimator:', clf_cv.best_estimator_)
print('Best accuracy:', clf_cv.best_score_)
```

```
Best estimator: DecisionTreeClassifier(max_depth=9)
Best accuracy: 0.9742871757609851
```

Testing Models using best parameters from exploration

Set Predictors and Targets

In [22]:

```python
# Set predictors and targets
predictors = ['alpha', 'delta', 'g', 'r', 'i', 'redshift', 'plate']
targets = ['GALAXY', 'QSO', 'STAR']
```

```
X = df[predictors].values
y = df[targets].values
```

Split and Scale Data

In [23]:

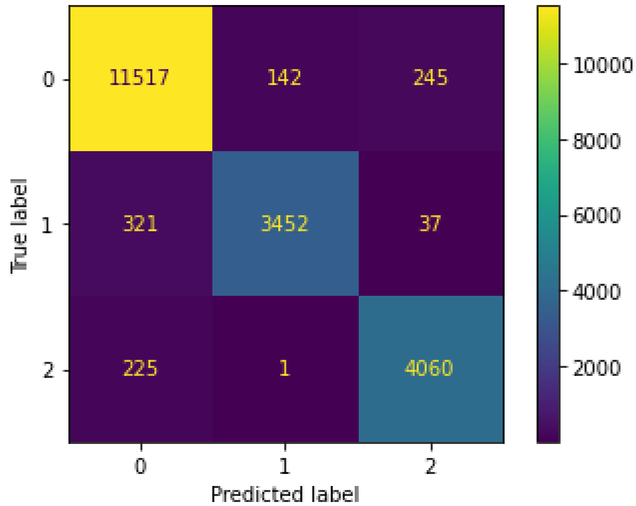
```
#Train, Test, Split (Random Seed 42)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=4

# Scale X_train and X_test
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

kNN Classification

In [24]:

```
knn = KNeighborsClassifier(weights='distance', metric='manhattan')
knn.fit(X_train, y_train)

# get predictions
predictions = knn.predict(X_test)

# inverse the one hot encoding
predictions_enc = pd.DataFrame(predictions).idxmax(axis=1)
y_test_enc = pd.DataFrame(y_test).idxmax(axis=1)
# print accuracy
print('Accuracy: ', (predictions_enc == y_test_enc).mean())

# print classification report
print(classification_report(y_test_enc, predictions_enc))

# print confusion matrix
cm = confusion_matrix(y_test_enc, predictions_enc)
print(cm)

# display confusion matrix as heatmap
display = ConfusionMatrixDisplay(cm).plot()
```

```
Accuracy:  0.95145
              precision    recall  f1-score   support

           0       0.95      0.97      0.96     11904
           1       0.96      0.91      0.93      3810
           2       0.94      0.95      0.94      4286

    accuracy                           0.95     20000
   macro avg       0.95      0.94      0.94     20000
weighted avg       0.95      0.95      0.95     20000

[[11517   142   245]
 [  321  3452    37]
 [  225     1  4060]]
```



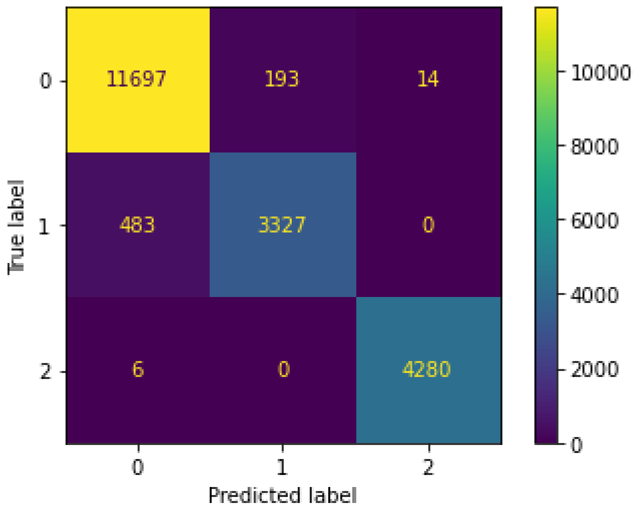
Decision Tree Classification

In [25]:

```
clf = DecisionTreeClassifier(max_depth=5)
clf.fit(X_train, y_train)

print('Feature Importances: ', clf.feature_importances_)

# get predictions
predictions = clf.predict(X_test)

# inverse one hot encoding
predictions_enc = pd.DataFrame(predictions).idxmax(axis=1)
y_test_enc = pd.DataFrame(y_test).idxmax(axis=1)

# print accuracy
print('Accuracy: ', (predictions_enc == y_test_enc).mean())

# print classification report
print(classification_report(y_test_enc, predictions_enc))

# print confusion matrix
cm = confusion_matrix(y_test_enc, predictions_enc)
print(cm)

# display confusion matrix as heatmap
display = ConfusionMatrixDisplay(cm).plot()
```

```
Feature Importances:  [0.00000000e+00 0.00000000e+00 4.87853578e-02 0.00000000e+00
 8.97544233e-04 9.46872377e-01 3.44472091e-03]
Accuracy:  0.9652
              precision    recall  f1-score   support

           0       0.96      0.98      0.97     11904
           1       0.95      0.87      0.91      3810
           2       1.00      1.00      1.00      4286

    accuracy                           0.97     20000
   macro avg       0.97      0.95      0.96     20000
weighted avg       0.96      0.97      0.96     20000

[[11697   193    14]
```

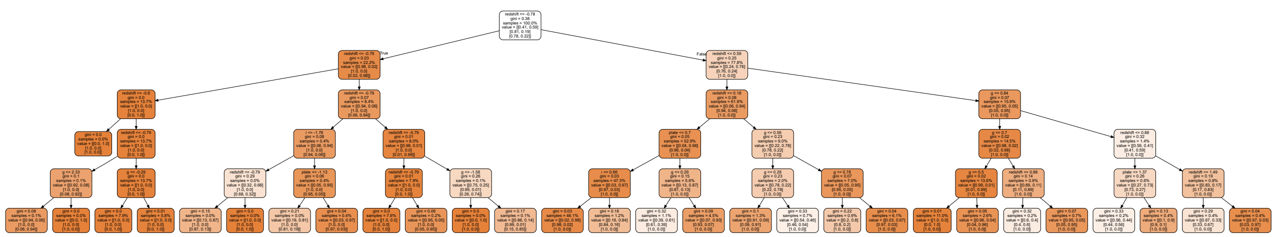
```
[  483  3327     0]
[    6     0  4280]]
```



In [26]:

```python
target_names = ['GALAXY', 'QSO', 'STAR']
dot_data = export_graphviz(clf, precision=2, feature_names=predictors, proportion=True,
                           class_names=target_names, filled=True, rounded=True)
graph = graphviz.Source(dot_data)
graph
```

Out[26]:



SVC

SVC does not require one-hot encoding, so we will instead use the 'class' column as our target.

In [27]:

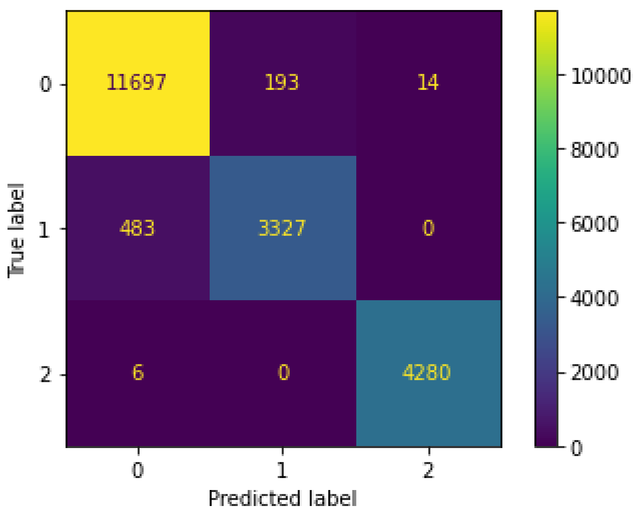
```python
# Set target
target = ['class']

# Set y
y = df[target].values.ravel()

# Train, Test, Split (Random Seed 42)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=4

# Scale X_train and X_test
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

In [28]:

```python
svc = SVC()
svc.fit(X_train, y_train)

predictions = svc.predict(X_test)
```

```
# print accuracy
print('Accuracy: ', (predictions == y_test).mean())

# print classification report
print(classification_report(y_test, predictions))

# get  confusion matrix
cm = confusion_matrix(y_test_enc, predictions_enc)
print(cm)

# display confusion matrix as heatmap
display = ConfusionMatrixDisplay(cm).plot()
```

```
Accuracy:  0.9625
              precision    recall  f1-score   support

      GALAXY       0.97      0.97      0.97     11904
         QSO       0.97      0.91      0.94      3810
        STAR       0.95      0.99      0.97      4286

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

[[11697   193    14]
 [  483  3327     0]
 [    6     0  4280]]
```



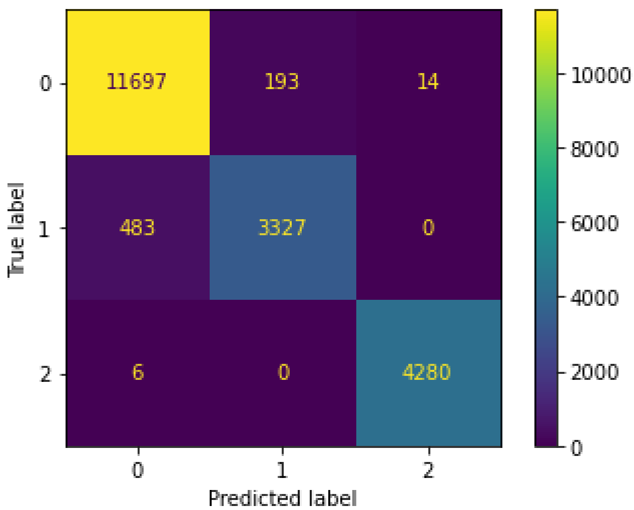
Logistic Regression

In [29]:

```
clf = LogisticRegression(solver='liblinear')
clf.fit(X_train, y_train)

predictions = clf.predict(X_test)

# print accuracy
print('Accuracy: ', (predictions == y_test).mean())

# print classification report
print(classification_report(y_test, predictions))

# get  confusion matrix
```

```
cm = confusion_matrix(y_test_enc, predictions_enc)
print(cm)

# display confusion matrix as heatmap
display = ConfusionMatrixDisplay(cm).plot()
```

```
Accuracy:  0.93425
              precision    recall  f1-score   support

      GALAXY       0.94      0.95      0.95     11904
         QSO       0.91      0.90      0.91      3810
        STAR       0.93      0.92      0.93      4286

    accuracy                           0.93     20000
   macro avg       0.93      0.92      0.93     20000
weighted avg       0.93      0.93      0.93     20000

[[11697   193    14]
 [  483  3327     0]
 [    6     0  4280]]
```



Chosen Model

Show decision tree code, graph of hits vs misses and where the majority occurred

Accuracy

In [30]:

```
#Label encoding
df['class_cat'] = df['class'].astype('category').cat.codes
predictors = ['alpha', 'delta', 'g', 'r', 'i', 'redshift', 'plate']
X = df[predictors]
y = df['class_cat']
#TTS
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=4

#default
clf = DecisionTreeClassifier()
clf.fit(X_train, y_train)
train_predict = clf.predict(X_train)
train_error = (train_predict != y_train).mean()
```

```
test_predict = clf.predict(X_test)
test_error = (test_predict != y_test).mean()
train_accuracy = 1 - train_error
test_accuracy = 1 - test_error

print("Training accuracy:", str("{:.2f}".format(100*train_accuracy)) + "%")
print("Test accuracy:", str("{:.2f}".format(100*test_accuracy)) + "%")
```

```
Training accuracy: 100.00%
Test accuracy: 96.32%
```

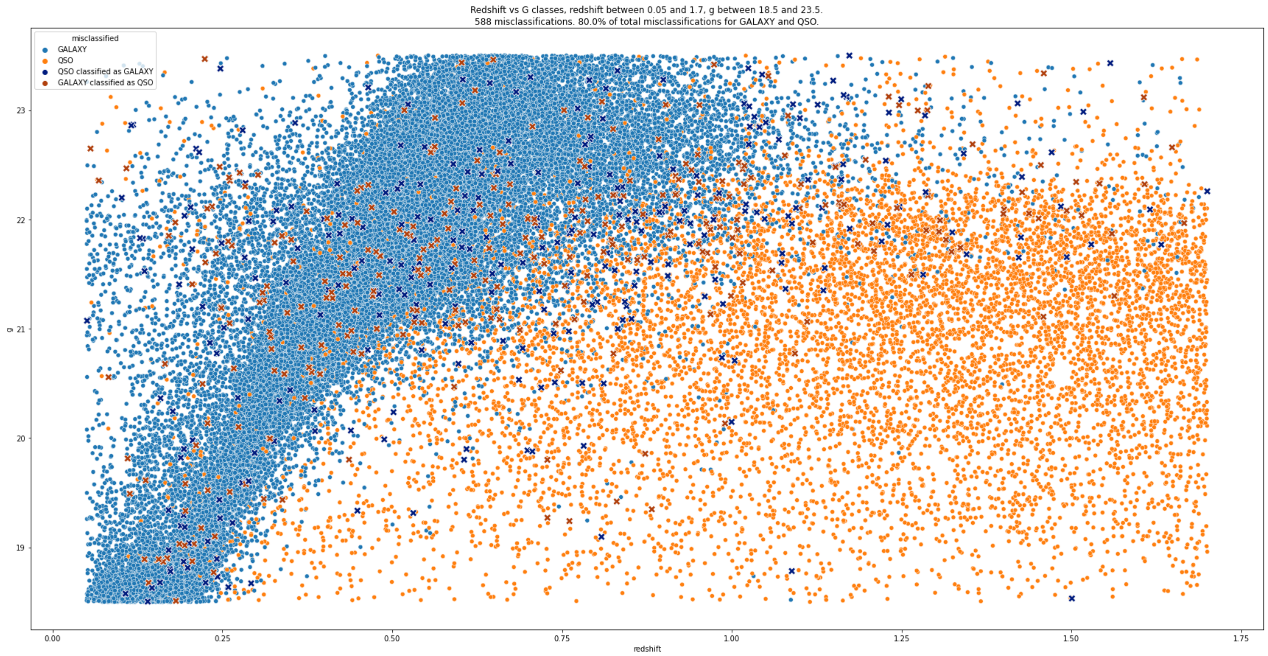
Misclassifications

Per the previous section's confusion matrix, it can be seen that the majority of misclassifications are GALAXY/QSO misclassifications. Furthermore, these misclassifications tend to happen in a specific redshift and g range. Let's take a look at them

In [31]:

```
#Data
fig, ax = plt.subplots(figsize = (30,15))
redshift_range_upper = 1.7
redshift_range_lower = 0.05
g_range_upper = 23.5
g_range_lower = 18.5
# df_small = df[(df['redshift'] < redshift_range_upper) & (df['redshift'] > redshift_ra
df_small = df[(df['redshift'] < redshift_range_upper) & (df['redshift'] > redshift_rang
object_counts = df_small['class'].value_counts()
object_percentages = 100*(df_small['class'].value_counts() / df['class'].value_counts()
sns.scatterplot(x='redshift', y='g', hue='class', data=df_small, ax=ax)
handles, labels  =  ax.get_legend_handles_labels()
labels = [ 'GALAXY: ' + str(object_counts['GALAXY']) + ' (' + str(round(object_percenta
          'QSO: ' + str(object_counts['QSO']) + ' (' + str(round(object_percentages['QS
ax.legend(handles, labels, loc='lower left')

#Misclassifications
misclassified_train = X_train[train_predict != y_train]
misclassified_test = X_test[test_predict != y_test]
shared_indices = []
for index in misclassified_test.index.values:
    if (index in df_small.index):
        shared_indices.append(index)
misclassified_in_df_small = df_small.loc[shared_indices]
misclassified_in_df_small['misclassified'] = misclassified_in_df_small['class'].apply(l
sns.scatterplot(x='redshift', y='g', hue='misclassified', data=misclassified_in_df_smal

ax.set_title('Redshift vs G classes, redshift between ' + str(redshift_range_lower) + '
# ax.set_title('Redshift vs G classes, redshift between ' + str(redshift_range_lower) +
print("\nTotal misclassified:", misclassified_test.shape[0])
print("Total misclassified in redshift range:[", str(redshift_range_lower), str(redshif
#Drop labels
df.drop(columns=['class_cat'], inplace=True)
```

```
Total misclassified: 736
Total misclassified in redshift range:[ 0.05 1.7 ]: 588
 GALAXY classified as QSO    301
QSO classified as GALAXY    287
Name: misclassified, dtype: int64
```



Bonus: Our model in action

Import SDSS data set from previous year (2016)

We have to be wary of overlap between our set and the set from the former year. Let's clean up the columns and get rid of the duplicates

In [32]:

```
#2016 SDSS data
df_sdss_2016 = pd.read_csv(r"C:\Users\Jordan\Downloads\archive\sdss.csv")

#Clean up data and match columns to main data
df_sdss_2016.rename(columns={'object_id': 'obj_ID', 'right_ascension': 'alpha', 'declin
                           'g_magnitude': 'g','r_magnitude': 'r','i_magnitude': 'i','z_magn
                           'obs_run_number': 'run_ID', 'rerun_number': 'rerun_ID', 'camera_
                           'field_number': 'field_ID', 'spectro_object_id': 'spec_obj_ID',
                           'observation_date': 'MJD', 'fiber_id': 'fiber_ID'}, inplace=True

#drop duplicates in 2016 set
df_sdss_2016.drop_duplicates(subset=['obj_ID'], inplace=True)

#reread the original dataframe to get obj_ID back
df_og = pd.read_csv("https://raw.githubusercontent.com/Deelane/CST383---Final/main/star

#find overlapping rows in main set and 2016 set
obj_id_set = set(df_sdss_2016['obj_ID'])
ids_to_drop = []
for obj_id in df_og['obj_ID']:
    if obj_id in obj_id_set:
        ids_to_drop.append(obj_id)

#remove overlapping rows between main set and 2016 set
df_sdss_2016 = df_sdss_2016[df_sdss_2016['obj_ID'].isin(ids_to_drop) == False]

#drop non-used columns
df_sdss_2016.drop(columns=['obj_ID', 'run_ID', 'rerun_ID', 'field_ID','fiber_ID', 'spec
```

```
#drop bad data
bad_indices = df_sdss_2016[(df_sdss_2016['i'] == -9999)].index
df_sdss_2016.drop(bad_indices, inplace=True) #drop the bad data
df_sdss_2016.reset_index(drop=True, inplace=True)
```

Testing our model against these 732,646 new objects

In [33]:

```
#Label encoding
df_sdss_2016['class_cat'] = df_sdss_2016['class'].astype('category').cat.codes
predictors = ['alpha', 'delta', 'g', 'r', 'i', 'redshift', 'plate']
X = df_sdss_2016[predictors].values
y = df_sdss_2016['class_cat'].values

#Using our already trained model to predict all 732,646 new objects
test_predict = clf.predict(X)
test_error = (test_predict != y).mean()
test_accuracy = 1 - test_error
print("Number of objects predicted:", len(test_predict))
print("Accuracy:", str("{:.2f}".format(100*test_accuracy)) + "%")
```

```
Number of objects predicted: 732646
Accuracy: 98.29%
```