CELESTIAL OBJECT DETECTOR

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Astronomy is a discipline with an abundance of vast datasets, and machine learning algorithms are sometimes a necessity due to the labor intensity of analyzing all this data and deriving insights and conclusions in a more manual fashion.

Problem Context

The detection of celestial objects observed through telescopes as being either a star, a galaxy or a quasar, is an important classification scheme in astronomy. Stars have been known to humanity since time immemorial, but the idea of the existence of whole galaxies of stars outside our own galaxy (The Milky Way), was first theorized by the philosopher Immanuel Kant in 1755, and conclusively observed in 1925 by the American astronomer Edwin Hubble. Quasars have been a more recent discovery made possible significantly by the emergence of radio astronomy in the 1950s.

Descriptions of these three celestial objects are provided below:

Star:

A star is an astronomical object consisting of a luminous plasma spheroid held together by the force of its own gravity. The nuclear fusion reactions taking place at a star's core are exoergic (there is a net release of energy) and are hence responsible for the light emitted by the star. The closest star to Earth is, of course, the Sun. The next nearest star is Proxima Centauri, which is around 4.25 light years away (a light year refers to the unit of distance travelled by light in one year, around 9.46 trillion kilometers). Several stars are visible to us in the night sky, however they are so far away they appear as mere points of light to us here on Earth.

Galaxy:

Galaxies are gravitationally bound groupings or systems of stars that additionally contain other matter such as stellar remnants, interstellar gas, cosmic dust and even dark matter. Galaxies may contain anywhere between the order of 108 to 1014 stars, which orbit the center of mass of the galaxy.

Quasar:

Quasars, also called Quasi-stellar objects (abbv. QSO) are a kind of highly luminous "Active Galactic Nucleus". Quasars emit an enormous amount of energy, because they have supermassive black holes at their center. (A black hole is an astronomical object whose

gravitational pull is so strong that not even light can escape from it if closer than a certain distance from it) The gravitational pull of the black holes causes gas to spiral and fall into "accretion discs" around the black hole, hence emitting energy in the form of electromagnetic radiation.

Quasars were understood to be different from other stars and galaxies, because their spectral measurements (which indicated their chemical composition) and their luminosity changes were strange and initially defied explanation based on conventional knowledge - they were observed to be far more luminous than galaxies, but also far more compact, indicating tremendous power density. However, also crucially, it was the extreme "redshift" observed in the spectral readings of Quasars that stood out and gave rise to the realization that they were separate entities from other, less luminous stars and galaxies.

Note: In astronomy, redshift refers to an increase in wavelength, and hence decrease in energy/frequency of any observed electromagnetic radiation, such as light. The loss of energy of the radiation due to some factor is the key reason behind the observed redshift of that radiation. Redshift is a specific example of what's called the Doppler Effect in Physics.

While redshift may occur for relativistic or gravitational reasons, the most significant reason for redshift of any sufficiently-far astronomical object is that the universe is expanding - this causes the radiation to travel a greater distance through the expanding space and hence lose energy.

For cosmological reasons, quasars are more common in the early universe, which is the part of the observable universe that is furthest away from us here on earth. It is also known from astrophysics (and attributed to the existence of "dark energy" in the universe) that not only is the universe expanding, but the further an astronomical object is, the faster it appears to be receding away from Earth (similar to points on an expanding balloon), and this causes the redshift of far-away galaxies and quasars to be much higher than that of galaxies closer to Earth.

This high redshift is one of the defining traits of Quasars, as we will see from the insights in this case study.

Problem Statement

The objective of the project is to use the tabular features available to us about every astronomical object, to predict whether the object is a star, a galaxy or a quasar, through the use of supervised machine learning methods.

In this Jupyter notebook, I will use simple non-linear methods such as k-Nearest Neighbors and Decision Trees to perform this classification.

Data Description

The source for this data is the Sloan Digital Sky Survey (SDSS), one of the most comprehensive public sources of astronomical datasets available on the web today. SDSS has been one of the

most successful surveys in astronomy history, having created highly detailed three-dimensional maps of the universe and curated spectroscopic and photometric information on over three million astronomical objects in the night sky. SDSS uses a dedicated 2.5 m wide-angle optical telescope which is located at the Apache Point Observatory in New Mexico, USA.

The following dataset consists of 250,000 celestial object observations taken by SDSS. Each observation is described by 17 feature columns and 1 class column that identifies the real object to be one of a star, a galaxy or a quasar.

objid = Object Identifier, the unique value that identifies the object in the image catalog used by the CAS

u = Ultraviolet filter in the photometric system

ra = Right Ascension angle (at J2000 epoch)

dec = Declination angle (at J2000 epoch)

g = Green filter in the photometric system

r = Red filter in the photometric system

i = Near-Infrared filter in the photometric system

z = Infrared filter in the photometric system

run = Run Number used to identify the specific scan

rerun = Rerun Number to specify how the image was processed

camcol = Camera column to identify the scanline within the run

field = Field number to identify each field

specobjid = Unique ID used for optical spectroscopic objects (this means that 2 different observations with the same spec_obj_ID must share the output class)

class = object class (galaxy, star, or quasar object)

redshift = redshift value based on the increase in wavelength

plate = plate ID, identifies each plate in SDSS

mjd = Modified Julian Date used to indicate when a given piece of SDSS data was taken

fiberid = fiber ID that identifies the fiber that pointed the light at the focal plane in each observation

Imports

In [1]:
```
import numpy as np;
import pandas as pd;
import matplotlib.pyplot as plt;
import seaborn as sns;
import csv,json;
import os;
```

In [2]:
```
import warnings;
warnings.filterwarnings('ignore')
```

In [3]:
```
import random;
random.seed(1);
np.random.seed(1);
```

In [4]:
```
df_astro = pd.read_csv('D:/Skyserver250k.csv')
df_astro.head()
```

Out[4]:

	objid	ra	dec	u	g	r	i	z	ru
0	1237661976015274033	196.362072	7.667016	19.32757	19.20759	19.16249	19.07652	18.86196	384
1	1237661362373066810	206.614664	45.924279	18.95918	17.09173	16.25019	15.83413	15.55686	369
2	1237661360767238272	220.294728	40.894575	17.75587	16.54700	16.67694	16.77780	16.88097	369
3	1237665440983416884	206.315349	27.438152	19.29195	19.12720	19.03992	18.76714	18.73874	464
4	1237665531717812262	228.092653	20.807371	19.19731	18.26143	17.89954	17.76130	17.68726	467

Some Quick EDA

In [5]:
```
df_astro.shape
```

Out[5]:
```
(250000, 18)
```

This dataset has 250,000 rows and 18 columns.

The dataset is quite voluminous, and has a high rows-to-columns ratio.

In [6]:
```
df_astro['class'].value_counts()
```

Out[6]:
```
GALAXY    127117
STAR       96116
QSO        26767
Name: class, dtype: int64
```

In [7]:
```
df_astro.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 250000 entries, 0 to 249999
Data columns (total 18 columns):
 #   Column     Non-Null Count   Dtype  
---  ------     --------------   -----  
 0   objid      250000 non-null  int64  
 1   ra         250000 non-null  float64
 2   dec        250000 non-null  float64
 3   u          250000 non-null  float64
 4   g          250000 non-null  float64
 5   r          250000 non-null  float64
 6   i          250000 non-null  float64
 7   z          250000 non-null  float64
 8   run        250000 non-null  int64  
 9   rerun      250000 non-null  int64  
 10  camcol     250000 non-null  int64  
 11  field      250000 non-null  int64  
 12  specobjid  250000 non-null  uint64 
 13  class      250000 non-null  object 
 14  redshift   250000 non-null  float64
 15  plate      250000 non-null  int64  
 16  mjd        250000 non-null  int64  
 17  fiberid    250000 non-null  int64  
dtypes: float64(8), int64(8), object(1), uint64(1)
memory usage: 34.3+ MB
```

Observations

As we can see above, apart from the class variable (the target variable) which is of the object datatype and is categorical in nature, all the other predictor variables here are numerical in nature, as they have int64 and float64 datatypes.

So this is a classification problem where the original feature set uses entirely numerical features. Numerical datasets like this which are about values of measurements, are quite often found in astronomy, and are ripe for machine learning problem solving, due to the affinity for numerical calculations that computers have.

The above table also confirms what we found earlier, that there are 250,000 rows and 18 columns in the original dataset. Since every column here has the same number (250,000) of non-null values, we can also conclude that there is no missing data in the table (due to the high quality of the data source), and we can proceed without needing to worry about missing value imputation techniques.

In [8]:
```
df_astro = df_astro.sample(n=50000)
df_astro.head()
```

Out[8]:

	objid	ra	dec	u	g	r	i	z
240208	1237674650999914544	174.290983	0.595226	18.70026	18.45845	18.75494	19.05041	19.20823
18744	1237678600235450515	9.388044	16.430042	19.49198	17.55909	16.55254	16.11508	15.74319
207175	1237667542289416372	147.349261	20.509549	19.31644	17.96118	17.20228	16.74182	16.47560
18669	1237663479798235382	339.221808	0.489051	18.97399	17.82409	17.24499	16.77777	16.61536
189086	1237670957325287503	24.841603	-8.761315	18.87783	17.88773	17.52882	17.37216	17.31363

In [9]:
```
# Checking for any missing values just in case
df_astro.isnull().sum()
```

Out[9]:
```
objid        0
ra           0
dec          0
u            0
g            0
r            0
i            0
z            0
run          0
rerun        0
camcol       0
field        0
specobjid    0
class        0
redshift     0
plate        0
mjd          0
fiberid      0
dtype: int64
```

In [10]:
```
# Checking for duplicated data just in case
df_astro.duplicated().sum()
```

Out[10]:
```
0
```

Class Description

In [11]:
```
### Percentage class distribution of the target variable "class"
df_astro['class'].value_counts(1)*100
```

Out[11]:
```
GALAXY    51.074
STAR      38.368
QSO       10.558
Name: class, dtype: float64
```

Observations

More than 50% of the rows in this dataset are Galaxies.

Over 38% of the instances are Stars, and just over 10% of the rows belong to the QSO (Quasar) class.

As mentioned while giving the context for this problem statement, although they are among the most luminous objects in interstellar space, quasars are very rare for astronomers to observe. So it makes sense that they comprise the smallest percentage of the data points present in the class variable.

This can hence be considered a somewhat imbalanced classification problem, but due to the size of the dataset, even the smallest class (QSO - quasar) has over 25,000 examples. Even after train-test splits, that should be enough training data for a machine learning algorithm to understand the patterns leading to that classification.

Defining and Importing Stuff for Models

In [13]:
```
from sklearn import tree;
from sklearn.tree import DecisionTreeClassifier;
from sklearn.ensemble import RandomForestClassifier;

from sklearn.model_selection import train_test_split, GridSearchCV, RandomizedSearchCV
from sklearn.metrics import recall_score, roc_curve, classification_report, confusion_
from sklearn.preprocessing import StandardScaler, LabelEncoder, OneHotEncoder;
from sklearn.compose import ColumnTransformer;
from sklearn.impute import SimpleImputer;
from sklearn.pipeline import Pipeline;
from sklearn import metrics, model_selection;
```

In [14]:
```
le = LabelEncoder()
df_astro["class"] = le.fit_transform(df_astro["class"])
df_astro["class"] = df_astro["class"].astype(int)

df_astro['class']
```

Out[14]:
```
240208    2
18744     0
207175    0
18669     0
189086    2
         ..
12026     0
101461    2
146611    1
152140    0
168265    1
Name: class, Length: 50000, dtype: int32
```

Statistical Summary

Since the predictor variables in this machine learning problem are all numerical, a statistical summary is required so that we can understand some of the statistical properties of the features of our dataset.

In [15]:
```
# Set the format of the values in the table to be simple float numbers with 5 decimal
pd.set_option('display.float_format', lambda x: '%.5f' % x)
```

```
# Let's view the statistical summary of the columns in the dataset
df_astro.describe().T
```

Out[15]:

	count	mean	std	
objid	50000.00000	1237662592402716928.00000	7207093862089.52148	1237645942905438464.(
ra	50000.00000	178.38919	77.87886	0.(
dec	50000.00000	24.46484	20.08817	-19.
u	50000.00000	18.63623	0.82798	11.
g	50000.00000	17.40655	0.98268	9.(
r	50000.00000	16.88019	1.12646	9.(
i	50000.00000	16.62614	1.20586	8.
z	50000.00000	16.46675	1.27357	9.
run	50000.00000	3985.58622	1678.04277	109.(
rerun	50000.00000	301.00000	0.00000	301.(
camcol	50000.00000	3.41080	1.60723	1.(
field	50000.00000	188.63092	142.56631	11.(
specobjid	50000.00000	2932821382617439744.00000	2500435815384516608.00000	299493525735630848.(
class	50000.00000	0.87294	0.93717	0.(
redshift	50000.00000	0.16859	0.43125	-0.(
plate	50000.00000	2604.78306	2220.81942	266.(
mjd	50000.00000	53927.35574	1551.03867	51608.(
fiberid	50000.00000	350.38148	215.46894	1.(

Observations:

The maximum value of redshift is 6.4 and minimum value is 0.16.

The mean of alpha (ra) is 178.3 and standard deviation is 77.87 whereas mean and standard deviation of delta(dec) variable is 24.4 and 20.8.

The statistical summary of r,i and z variables are more or less similar, their range of values are same. The dec and redshift features in the data have negative data points.

In [16]:
```
# Number of unique values in each column
df_astro.nunique()
```

Out[16]:
```
objid        50000
ra           50000
dec          50000
u            44423
g            46340
r            46771
i            47078
z            47286
run            527
rerun            1
camcol           6
field          817
specobjid    50000
class            3
redshift     49713
plate         5726
mjd           2134
fiberid        996
dtype: int64
```

The objid and specobjid columns are clearly unique IDs, that is why they have the same number of values as the total number of rows in the dataset.

Since the objid and specobjid columns are unique IDs, they will not add any predictive power to the machine learning model, and they can be removed.

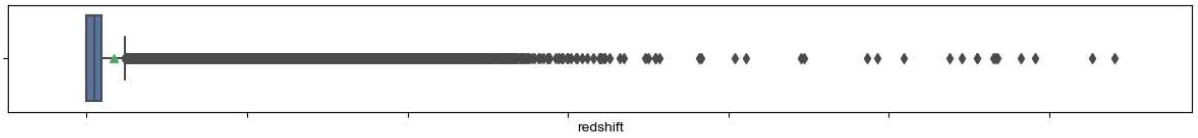
In [17]:
```
df_astro.drop(columns=['objid', 'specobjid'], inplace=True)
```

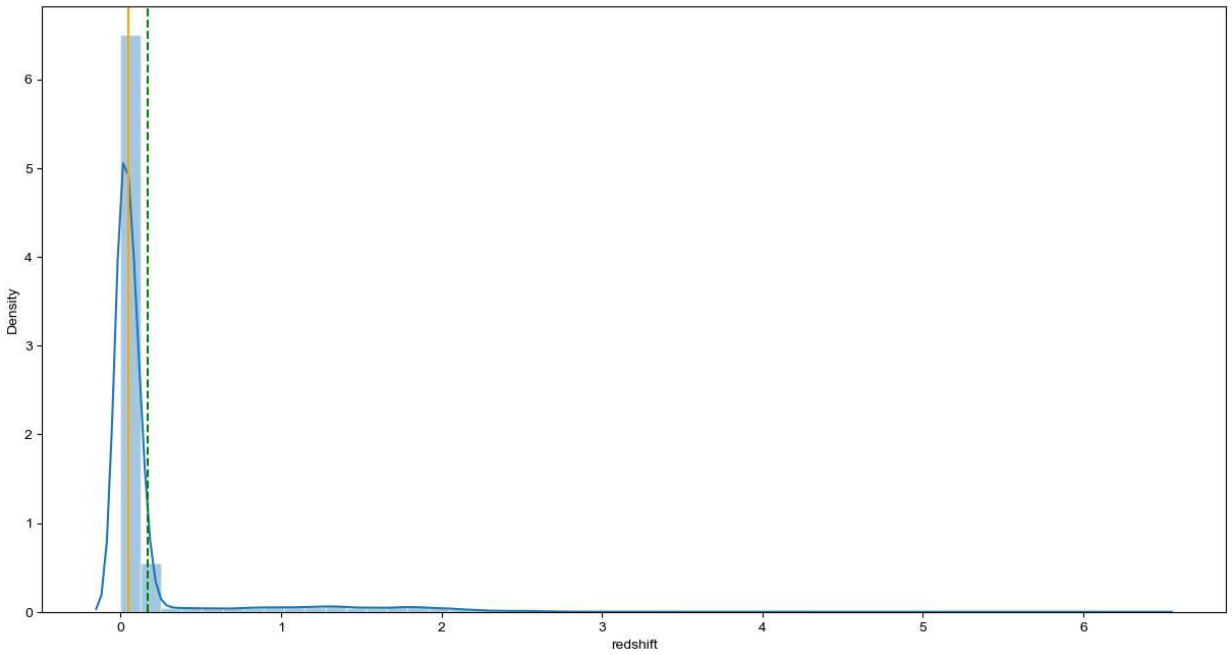
Univariate Analysis

I will use a hist_box() function that provides both a boxplot and a histogram in the same visual, with which we can perform univariate analysis on the columns of this dataset.

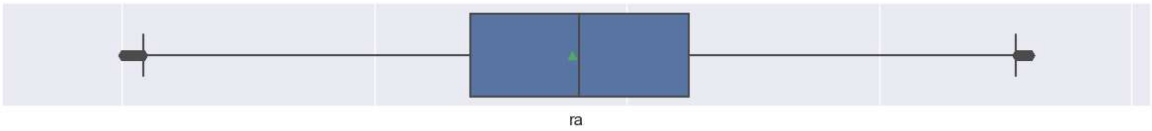
In [18]:
```
def hist_box(col):
  f, (ax_box, ax_hist) = plt.subplots(2, sharex=True, gridspec_kw={'height_ratios': (0
  sns.set(style='darkgrid')
  # Adding a graph in each part
  sns.boxplot(df_astro[col], ax=ax_box, showmeans=True)
  sns.distplot(df_astro[col], ax=ax_hist)
  ax_hist.axvline(df_astro[col].mean(), color='green', linestyle='--') # Green line co
  ax_hist.axvline(df_astro[col].median(), color='orange', linestyle='-') # Orange line
  plt.show()
```

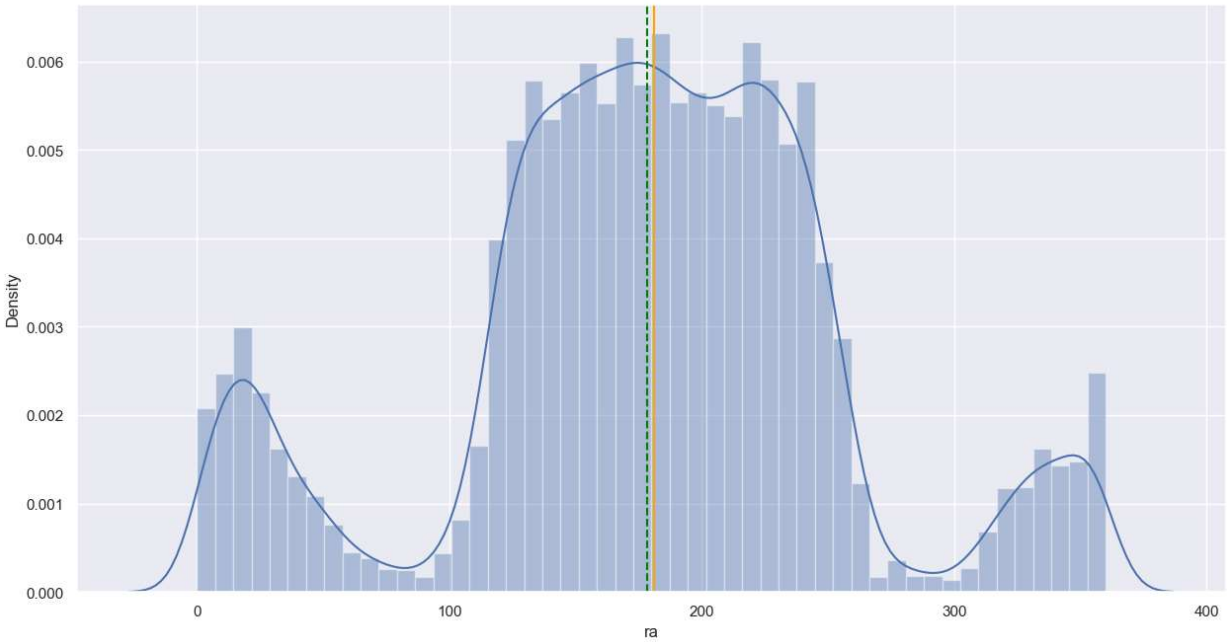
In [19]:
```
hist_box('redshift')
```



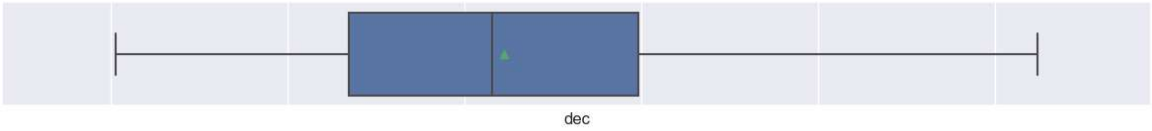


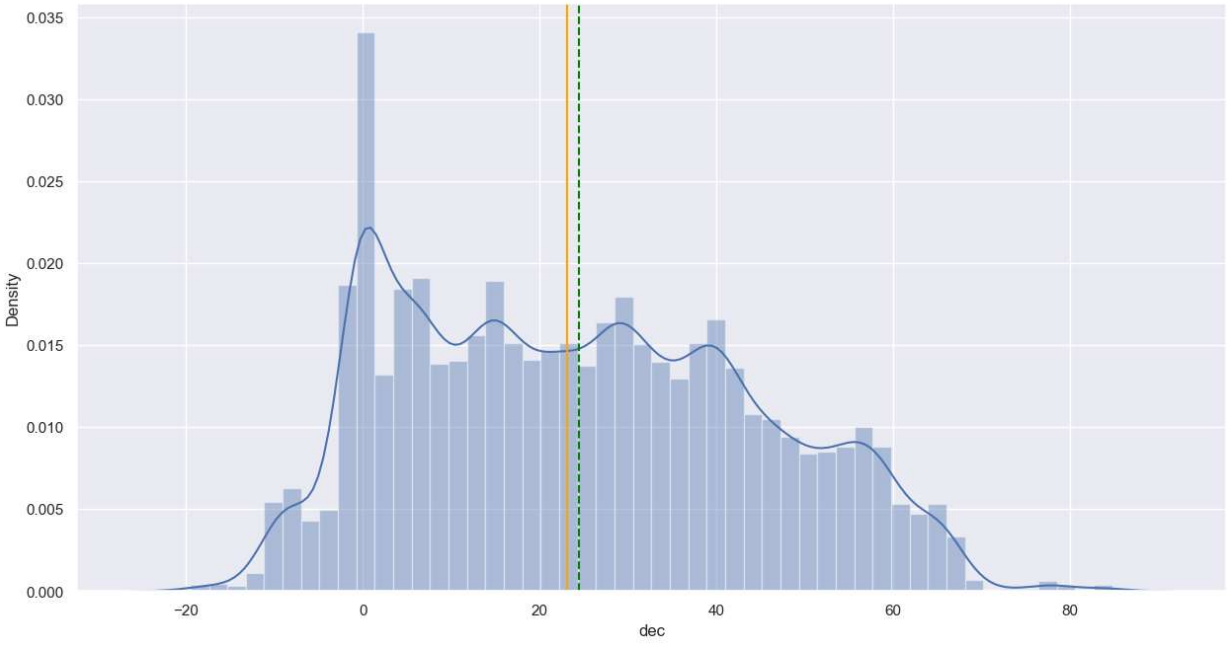
In [20]:
```
hist_box('ra')
```



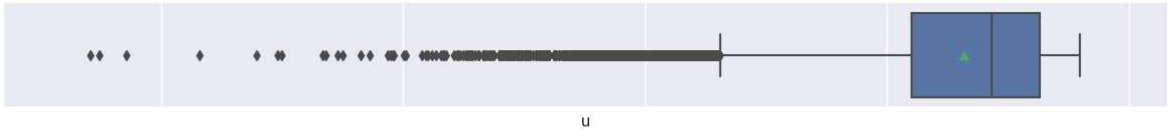


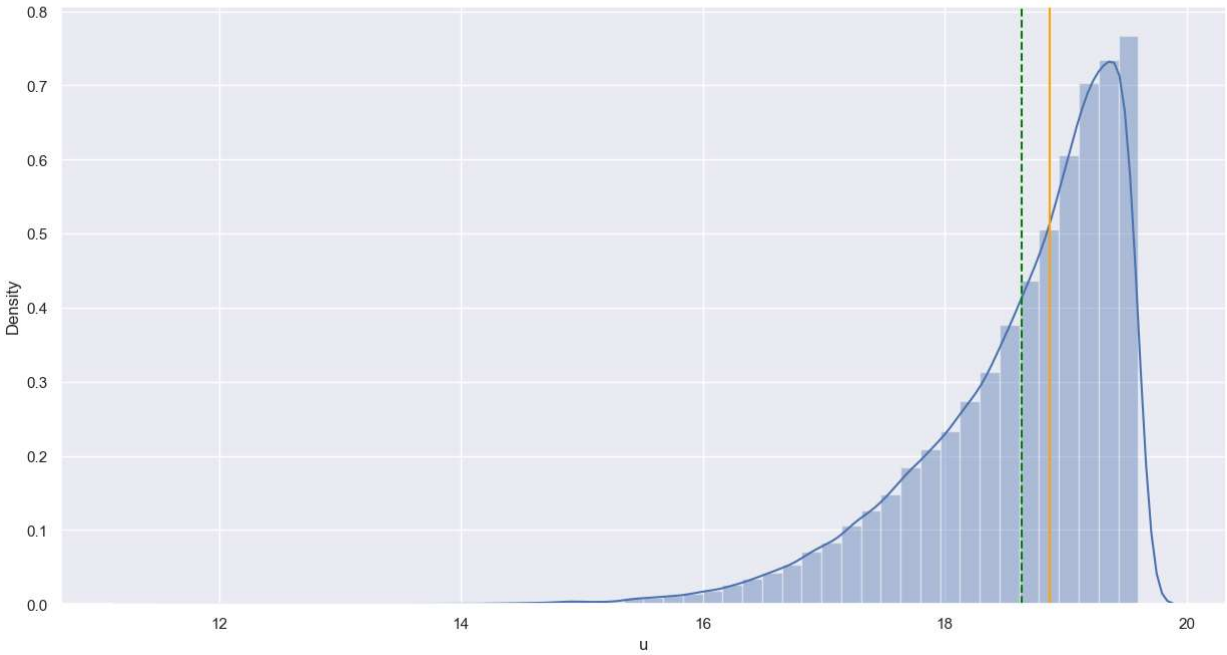
In [21]:
```
hist_box('dec')
```



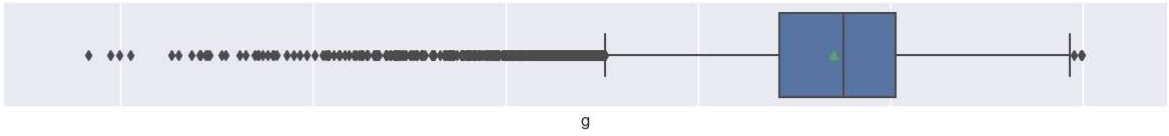


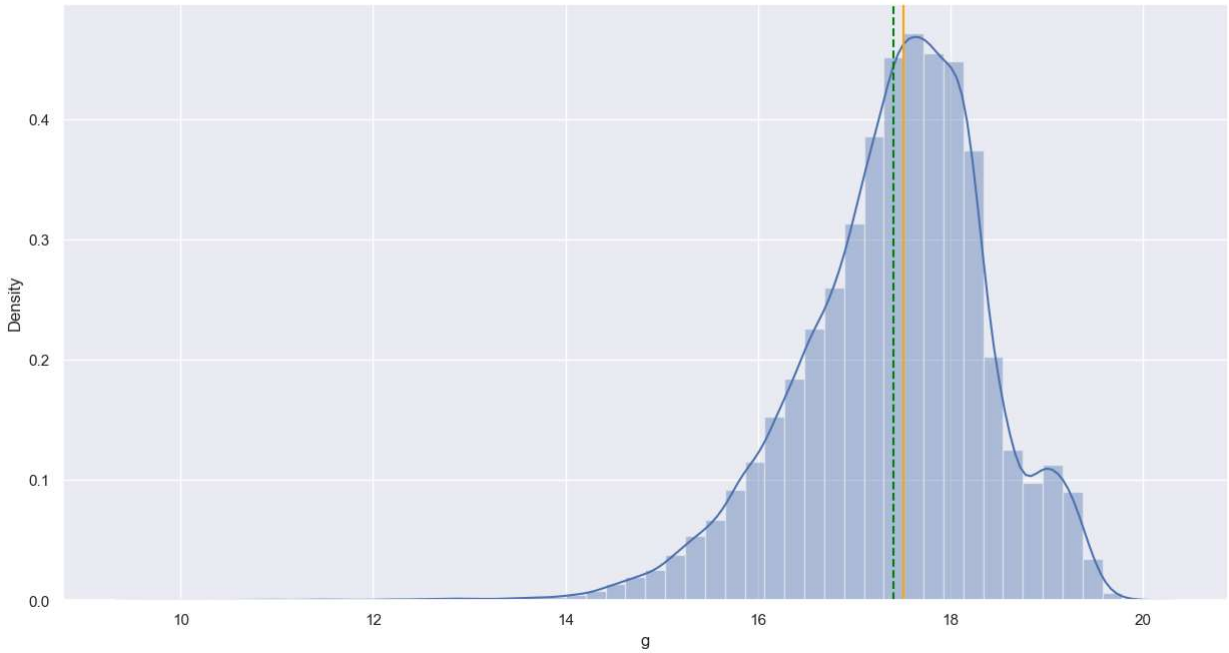
In [22]:
```
hist_box('u')
```



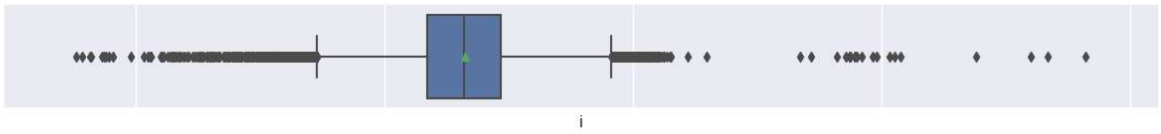


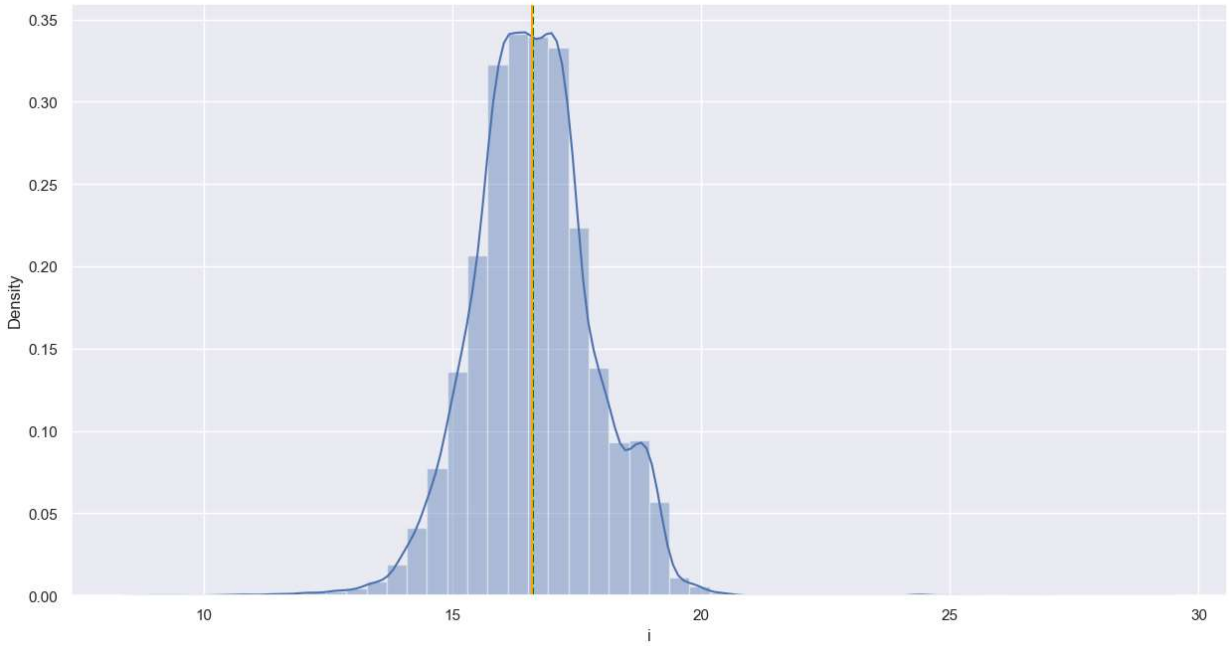
In [23]:
```
hist_box('g')
```



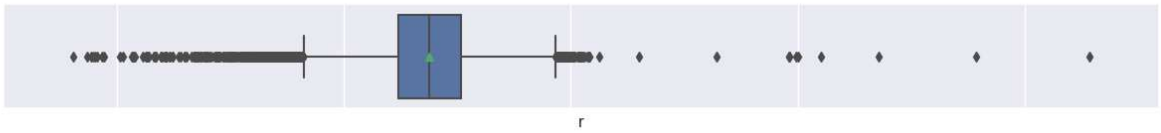


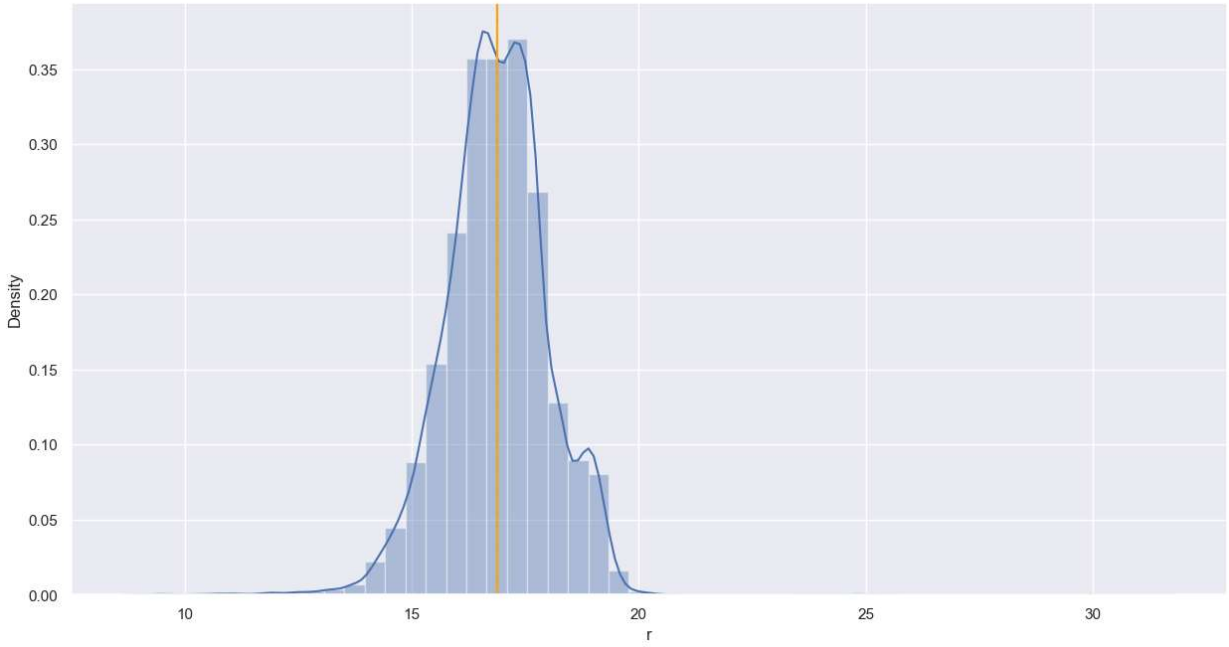
In [24]:
```
hist_box('i')
```



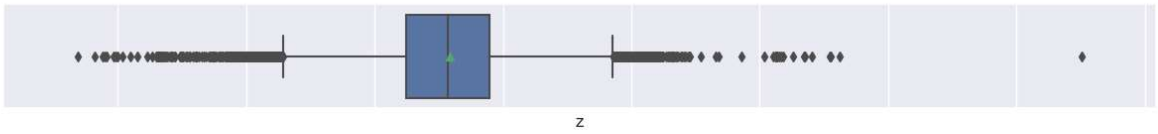


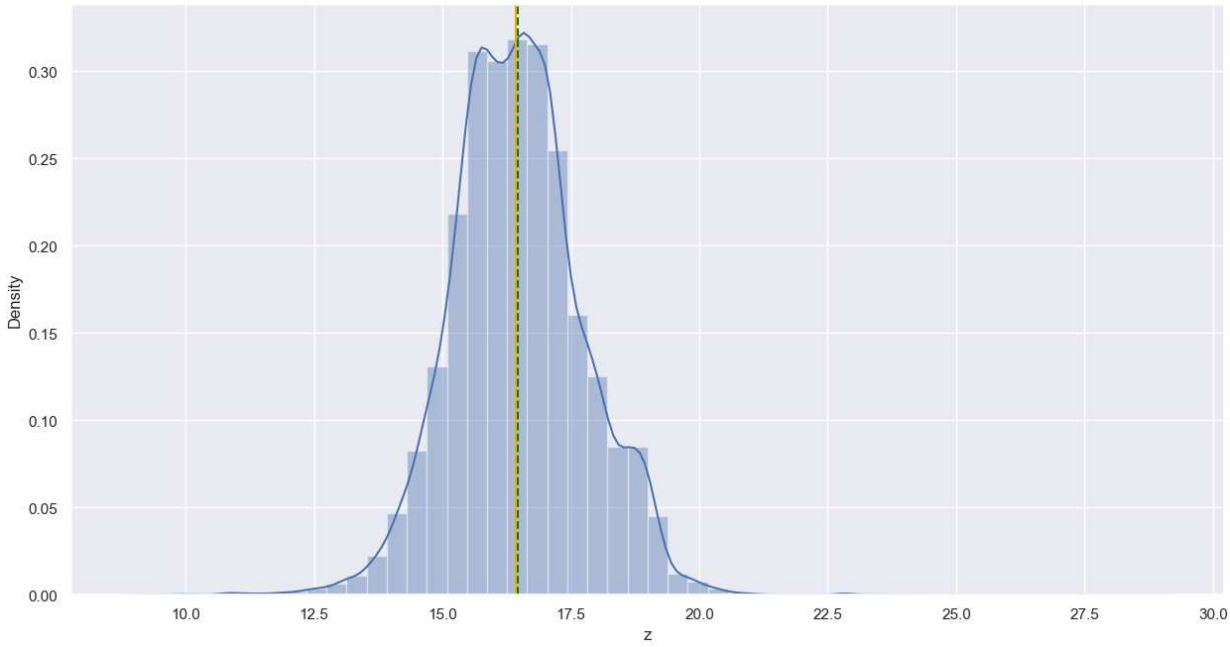
In [25]:
```
hist_box('r')
```



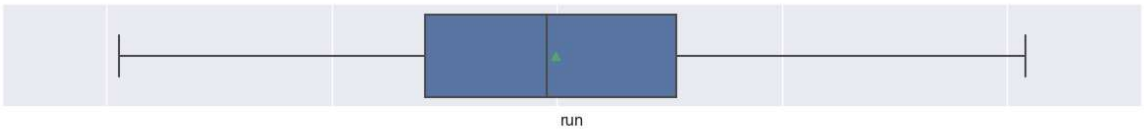


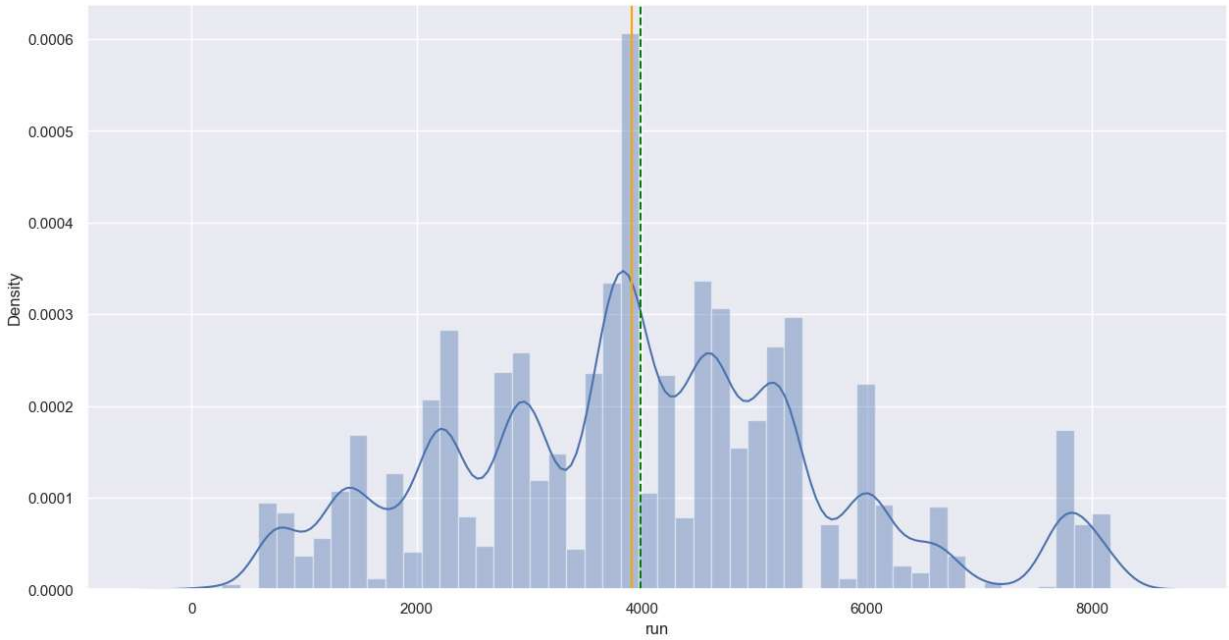
In [26]:
```
hist_box('z')
```



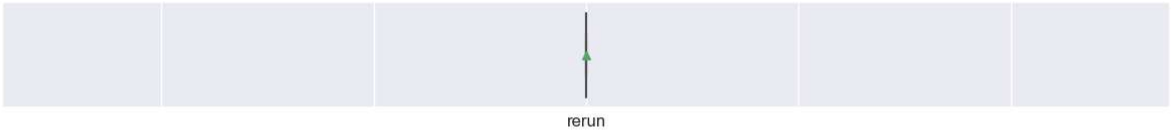


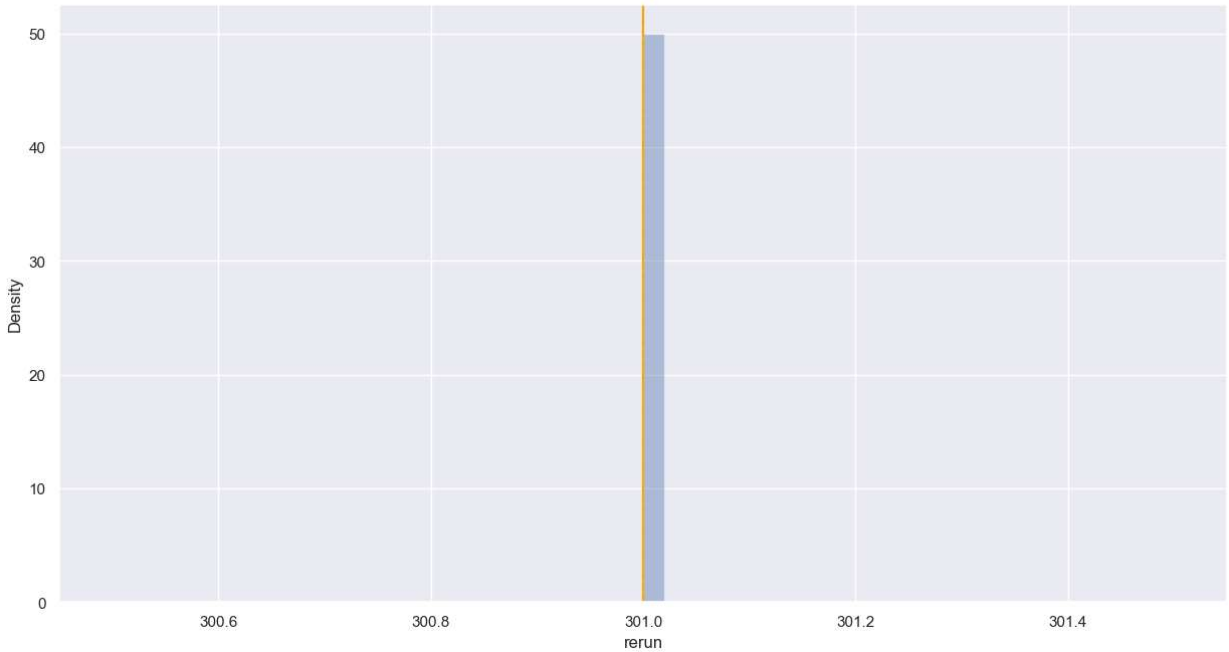
In [27]:
```
hist_box('run')
```



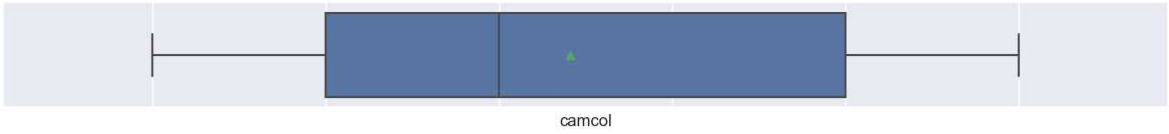


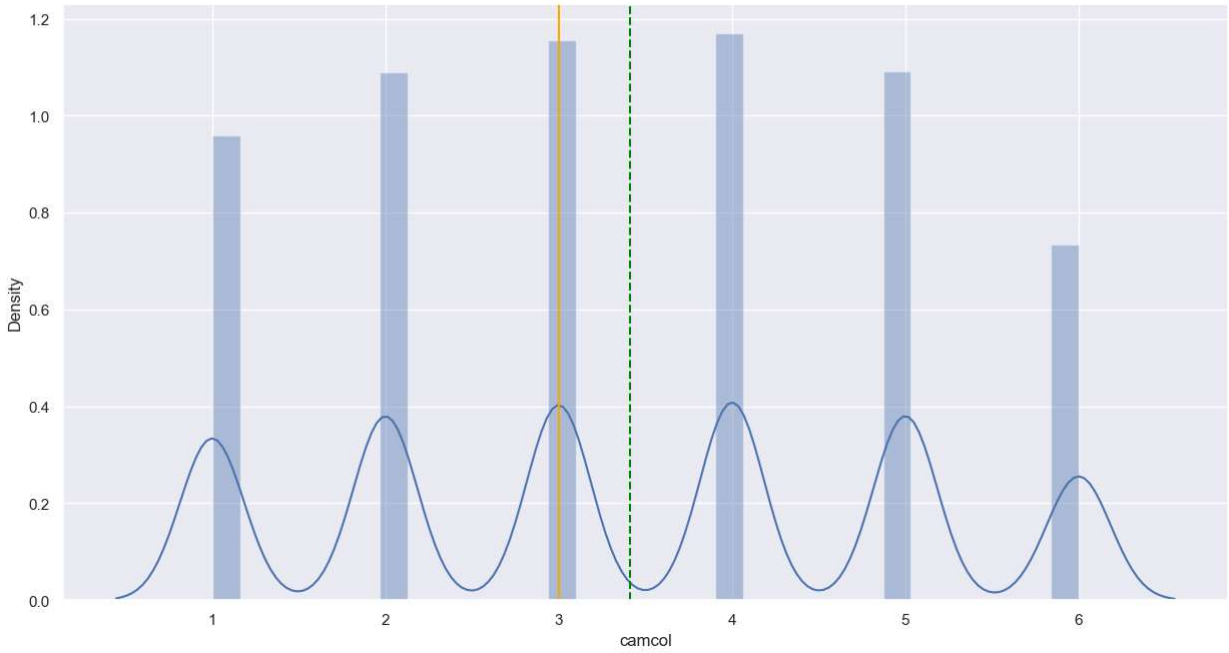
In [28]:
```
hist_box('rerun')
```



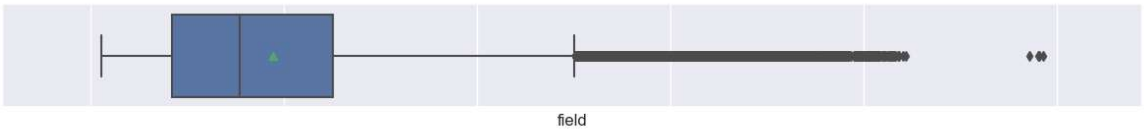


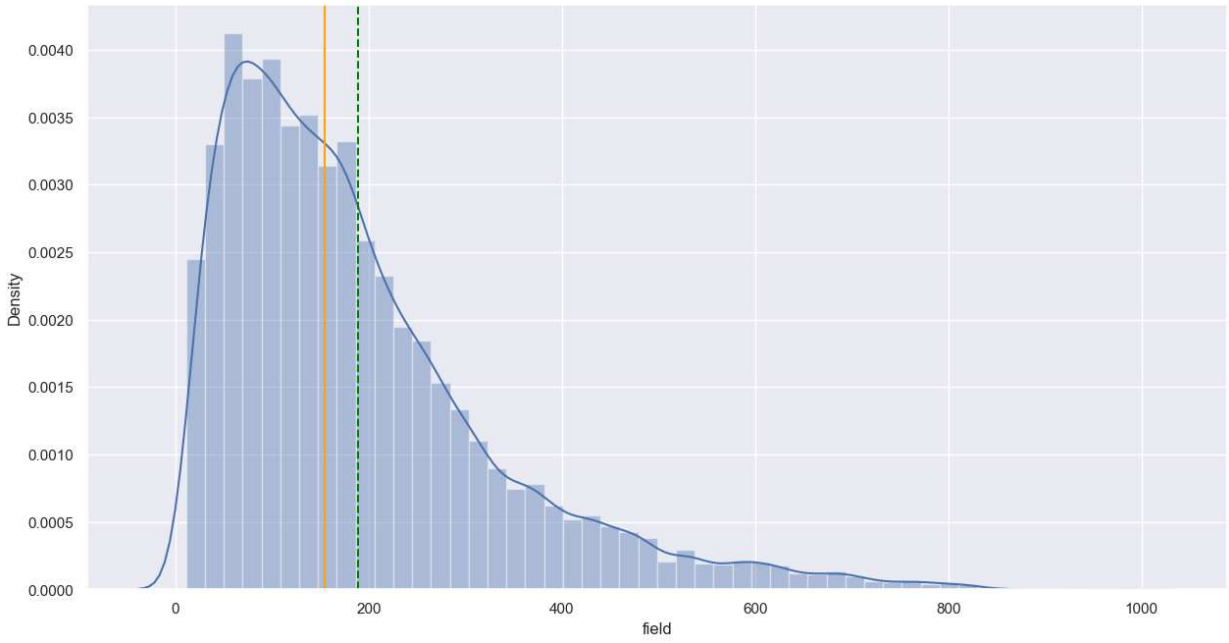
In [29]:
```
hist_box('camcol')
```



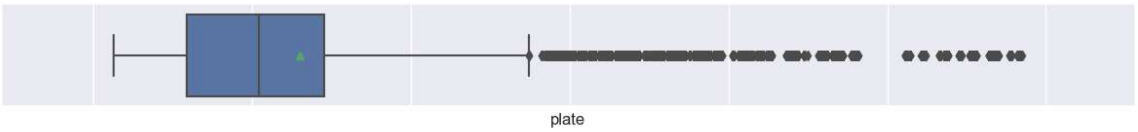


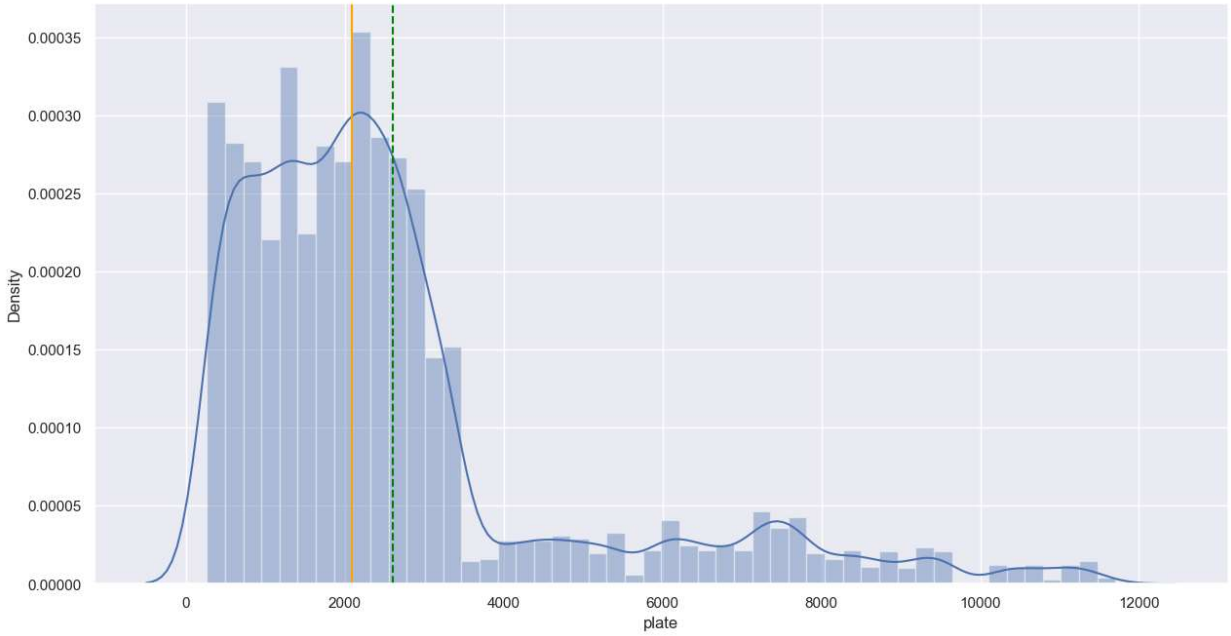
In [30]:
```
hist_box('field')
```



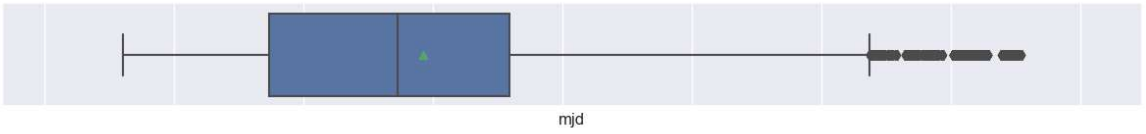


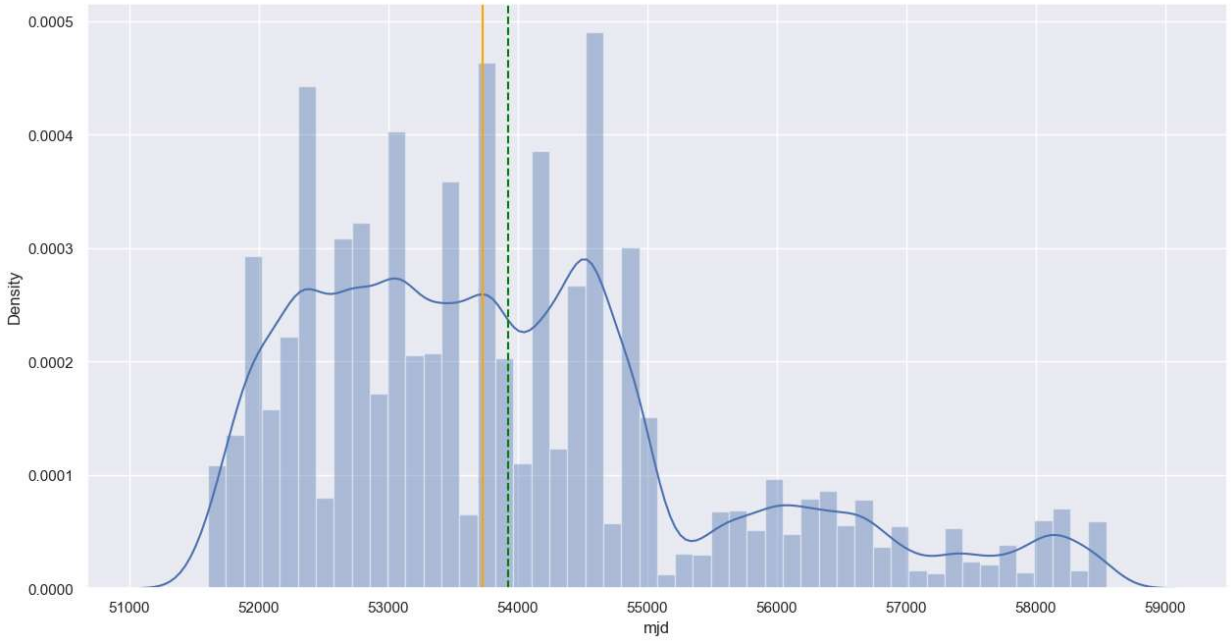
In [31]:
```
hist_box('plate')
```



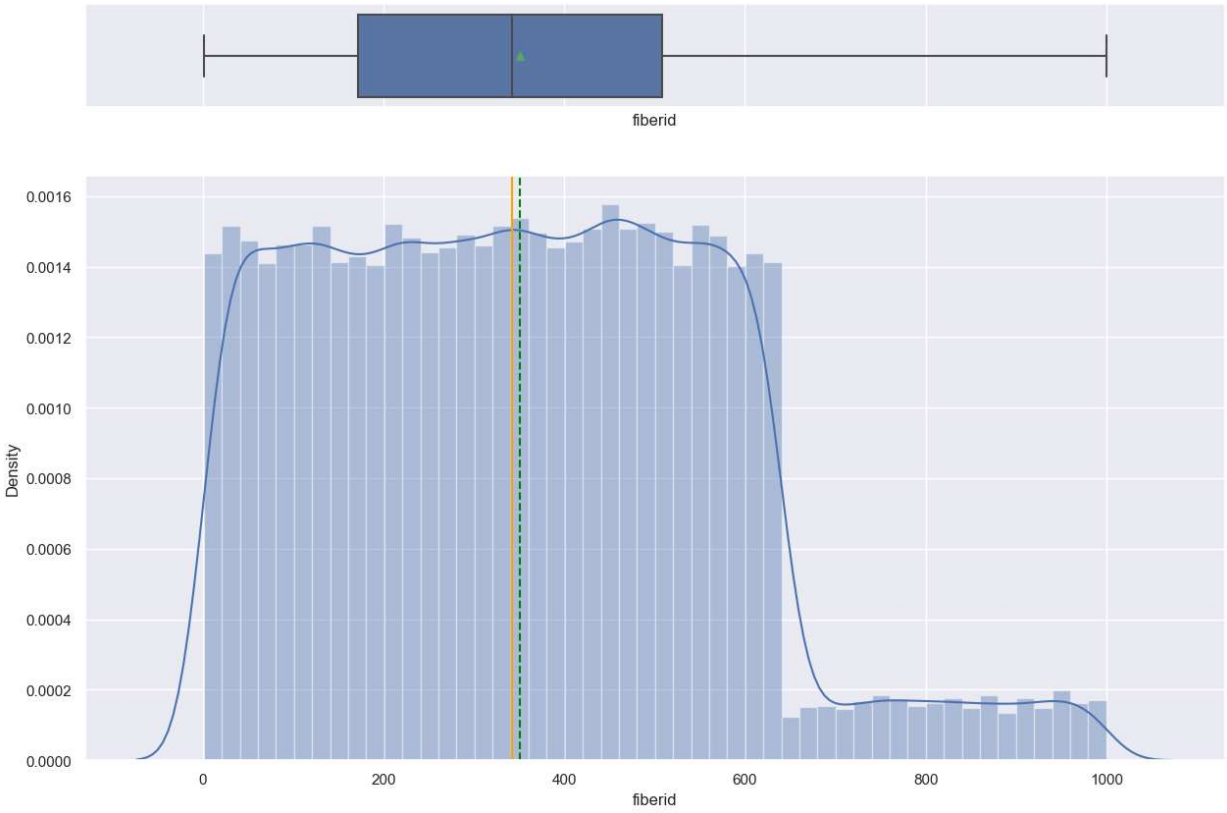


In [32]:
```
hist_box('mjd')
```





In [33]:
```
hist_box('fiberid')
```



Observations:

The distribution plot shows that the plate, field, dec and redhshift variables are right-skewed. It is evident from the boxplots that all these variables have outliers.

The camcol, rerun, run, fiberid and delta are the variables which do not possess outliers in the boxplot.

rerun is the only variable which has one unique value.

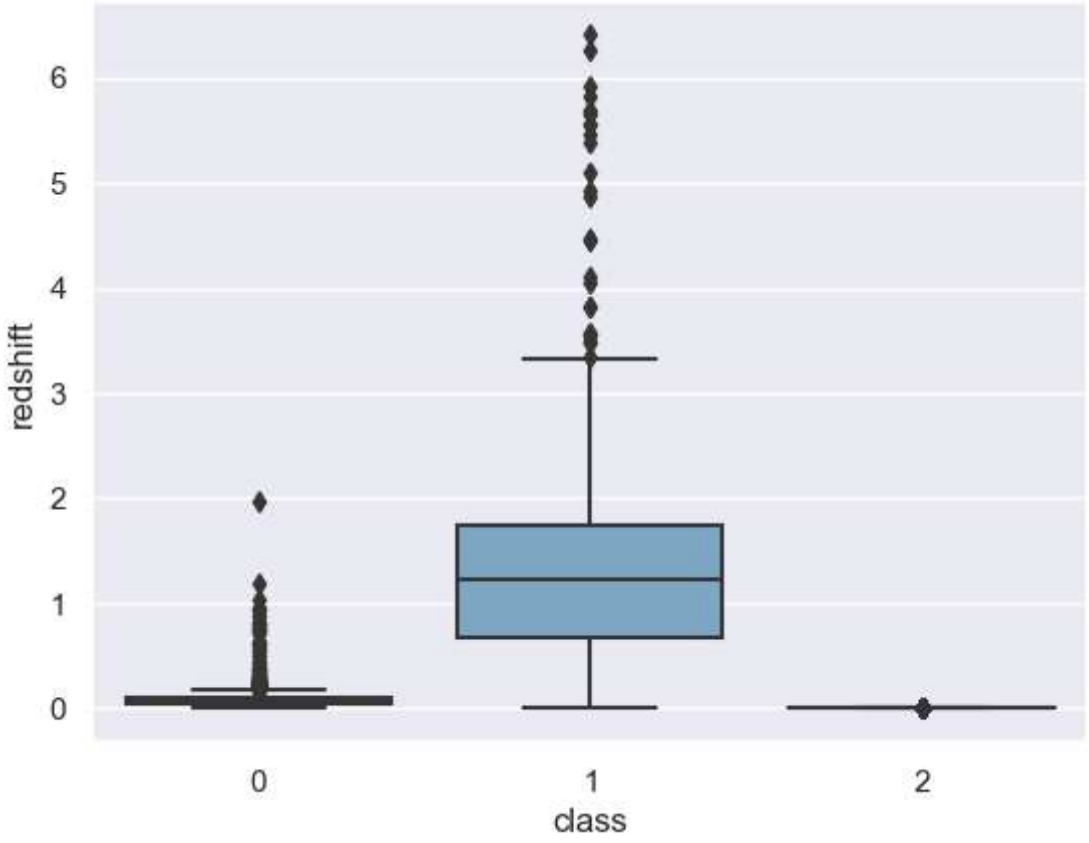
The variables x, i and r have similar distributions.

The variables g and u are slightly left-skewed distributions.

Bivariate Analysis for Categorical and Continuous variables

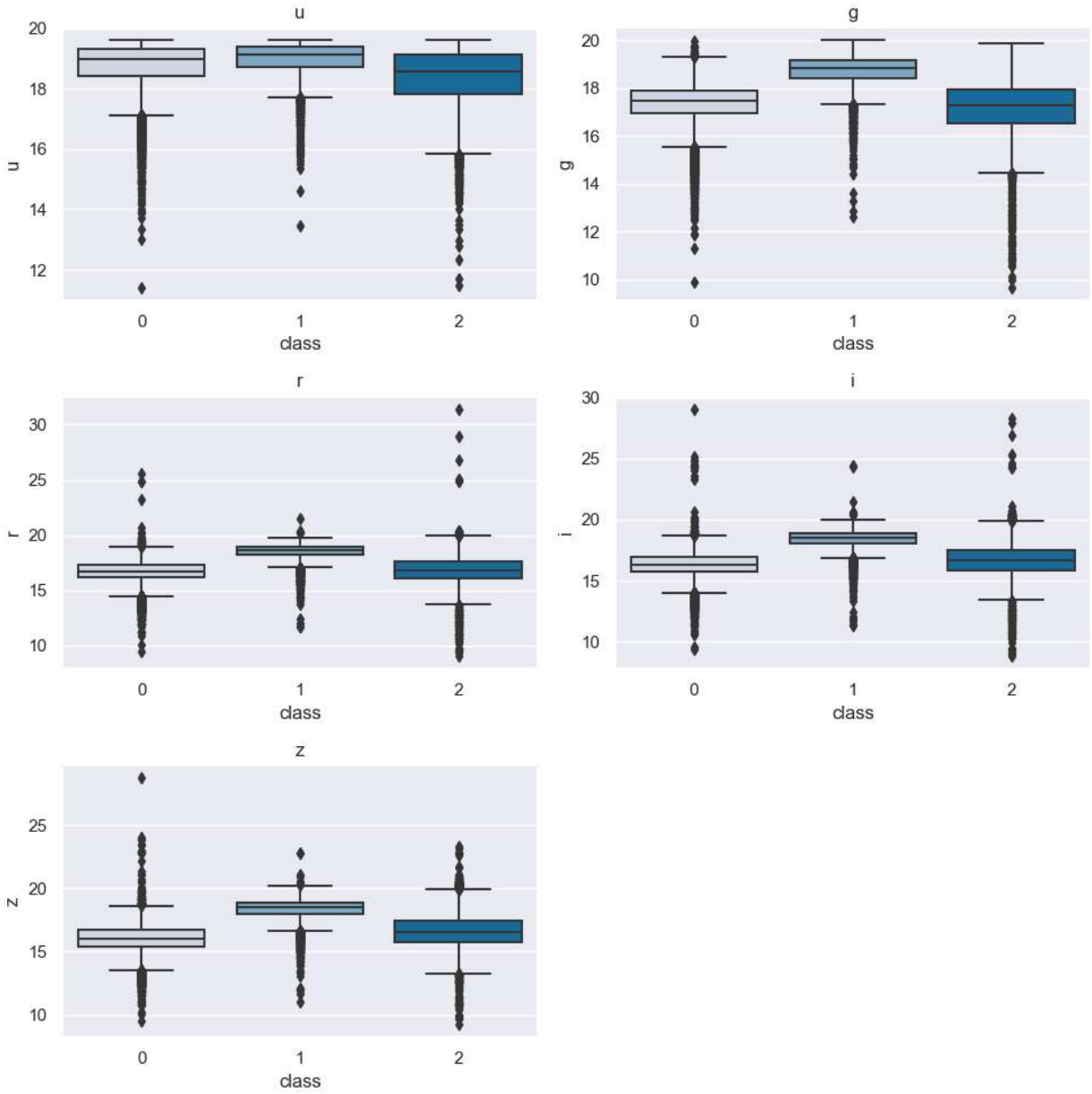
In [34]:
```
#class vs redshift
sns.boxplot(df_astro['class'],df_astro['redshift'],palette="PuBu")
```

Out[34]:
```
<AxesSubplot:xlabel='class', ylabel='redshift'>
```



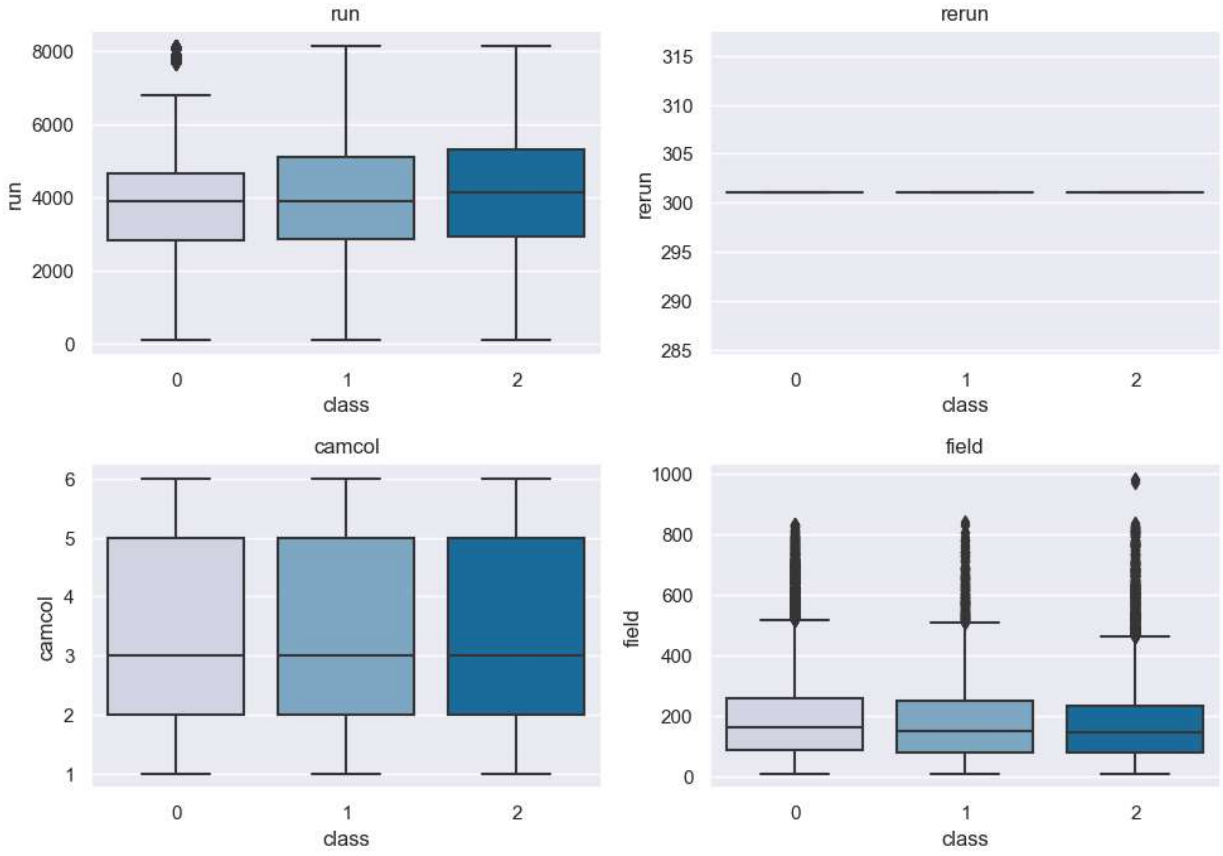
In [35]:
```
# class vs [u,g,r,i,z]
cols = df_astro[['u','g','r','i','z']].columns.tolist()
plt.figure(figsize=(10,10))

for i, variable in enumerate(cols):
                    plt.subplot(3,2,i+1)
                    sns.boxplot(df_astro["class"],df_astro[variable],palette="PuBu")
                    plt.tight_layout()
                    plt.title(variable)
plt.show()
```



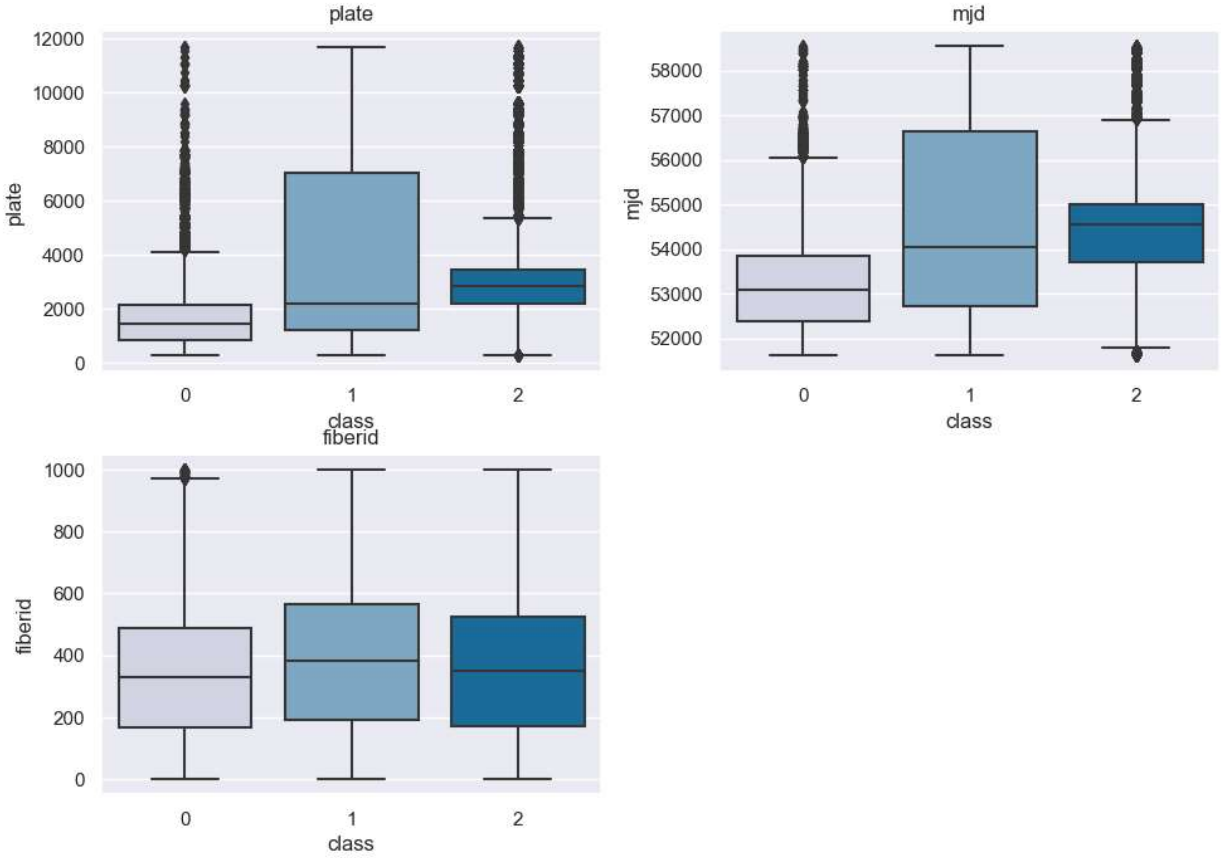
In [37]:
```
cols = df_astro[['run', 'rerun', 'camcol', 'field']].columns.tolist()
plt.figure(figsize=(10,10))

for i, variable in enumerate(cols):
                    plt.subplot(3,2,i+1)
                    sns.boxplot(df_astro["class"],df_astro[variable],palette="PuBu")
                    plt.tight_layout()
                    plt.title(variable)
plt.show()
```



In [38]:
```
cols = df_astro[['plate', 'mjd', 'fiberid']].columns.tolist()
plt.figure(figsize=(10,10))

for i, variable in enumerate(cols):
                    plt.subplot(3,2,i+1)
                    sns.boxplot(df_astro["class"],df_astro[variable],palette="PuBu")
                    plt.tight_layout()
                    plt.title(variable)
plt.show()
```



kdeplot

Recall: The kdeplot is a graph of the density of a numerical variable.

In [39]:
```
def plot(column):
    for i in range(3):
        sns.kdeplot(data=df_astro[df_astro["class"] == i][column], label = le.inverse_
    sns.kdeplot(data=df_astro[column],label = ["All"])
    plt.legend();
```

In [40]:
```
def log_plot(column):
    for i in range(3):
        sns.kdeplot(data=np.log(df_astro[df_astro["class"] == i][column]), label = le.
    sns.kdeplot(data=np.log(df_astro[column]),label = ["All"])
    plt.legend();
```

rerun

Rerun Number to specify how the image was processed

In [41]:
```
df_astro["rerun"].nunique()
```

Out[41]:
```
1
```

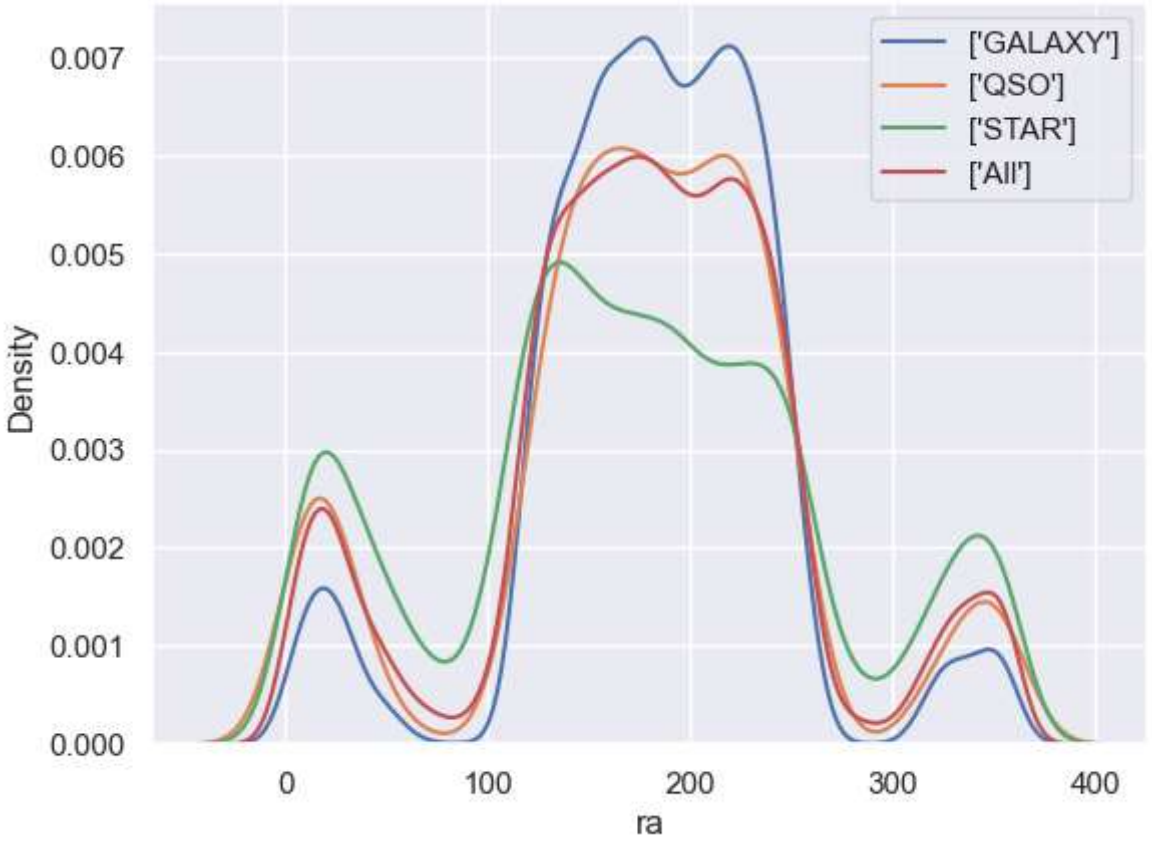
I will drop the column containing this unique value since does not help me train a predictive model.

In [42]:
```
df_astro = df_astro.drop("rerun",axis=1)
```

alpha

Right Ascension angle (at J2000 epoch)

In [43]:
```
plot("ra")
```



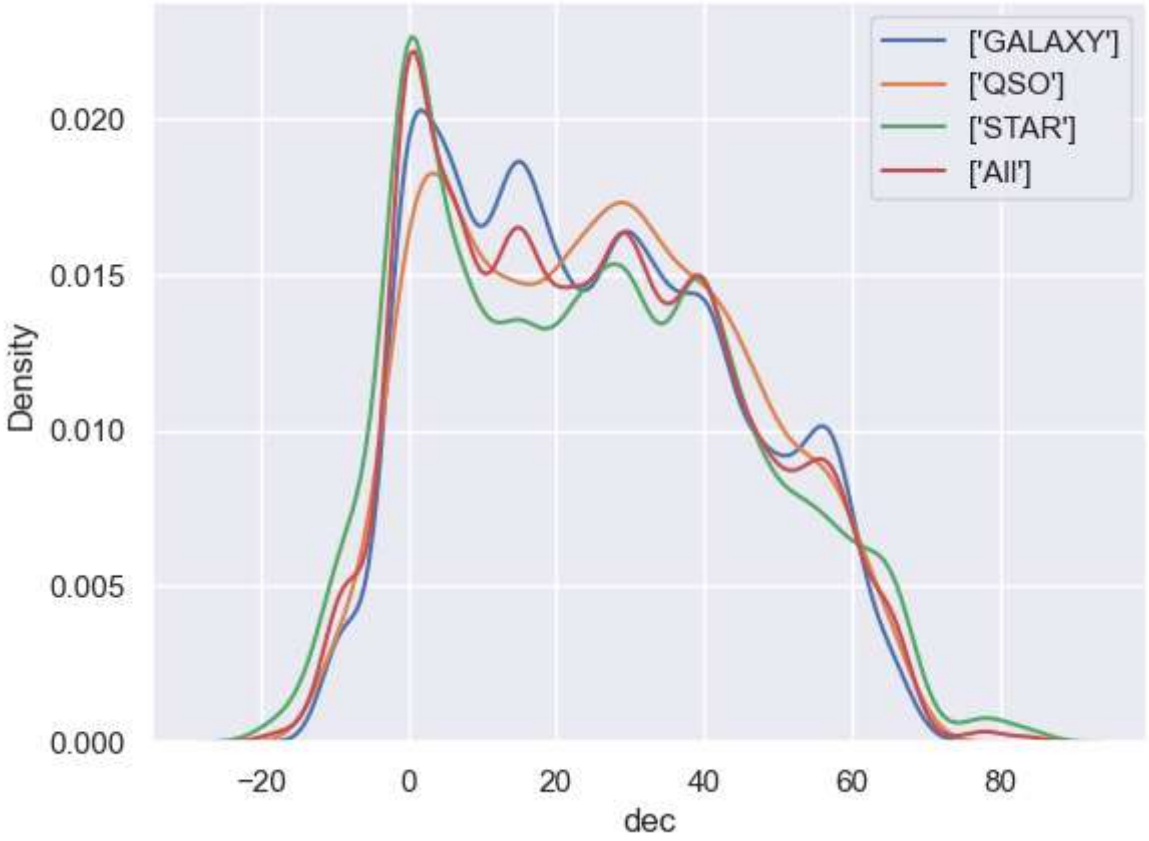
Observations:

There is not much difference in the distribution according to class, but we can see that there are some characteristics that distinguish the STAR class here.

delta

Declination angle (at J2000 epoch)

In [44]:
```
plot("dec")
```



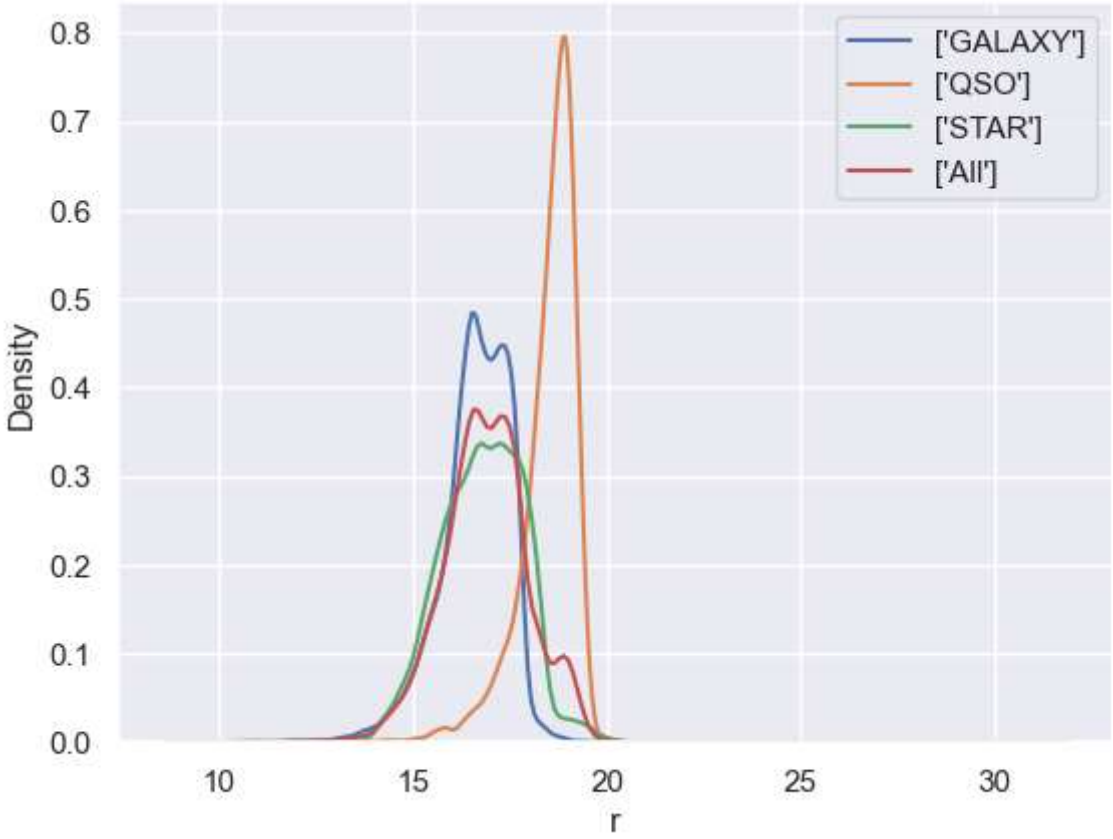
Observations:

Although there is no significant difference in distribution according to class, we can see that there are some characteristics to distinguish QSO class.

r

The red filter in the photometric system

In [45]:
```
plot("r")
```

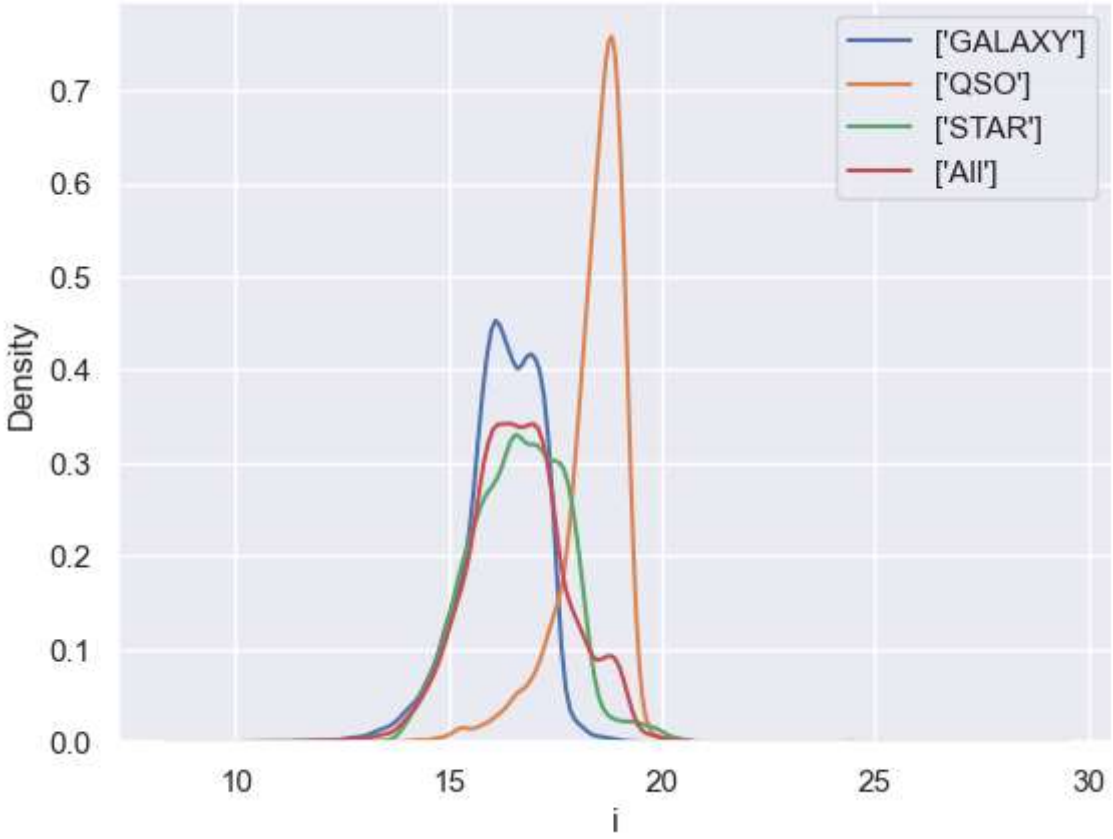


Observation It can be seen that the distribution of the QSO class for this variable is characterized by a different pattern from the other categories.

i

Near Infrared filter in the photometric system

In [46]:
```
plot("i")
```

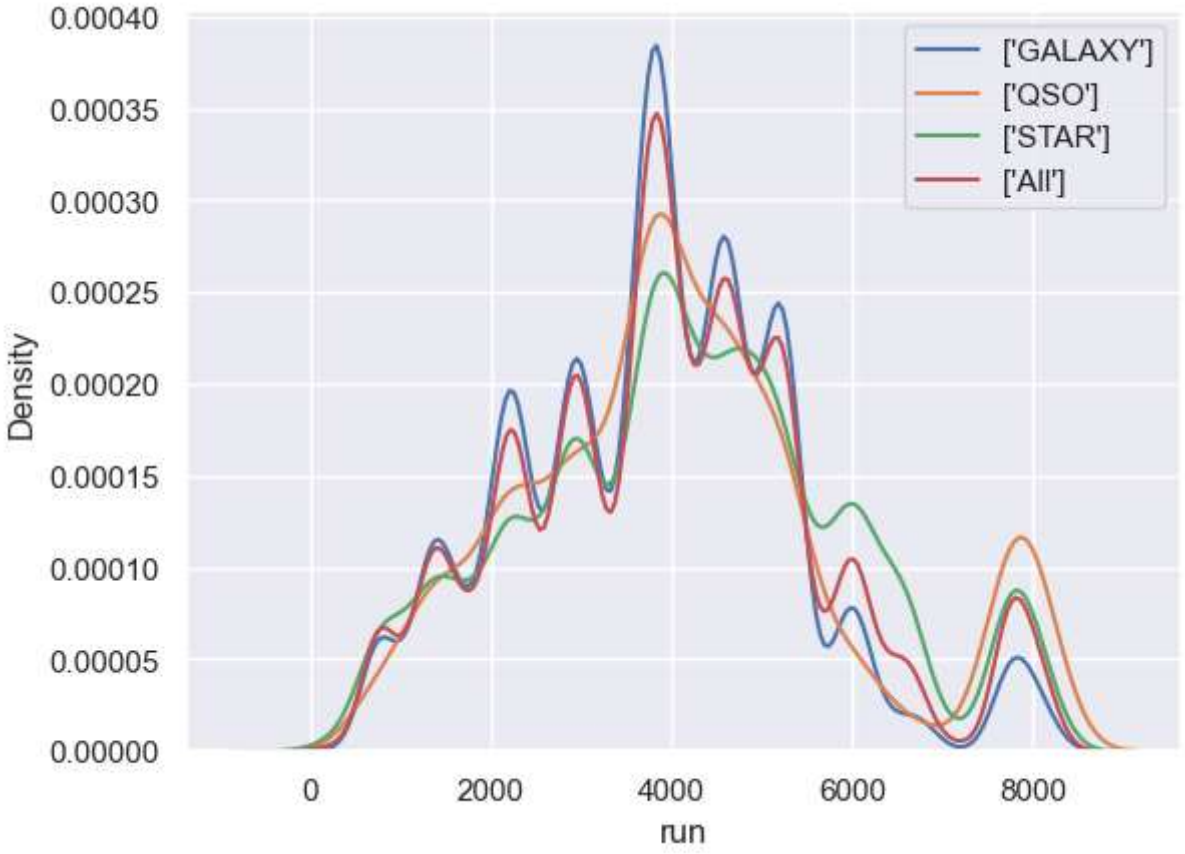


Observation We can see that the distribution of the qso class is characteristic compared to the others.

run

Run Number used to identify the specific scan

In [47]:
```
plot("run")
```



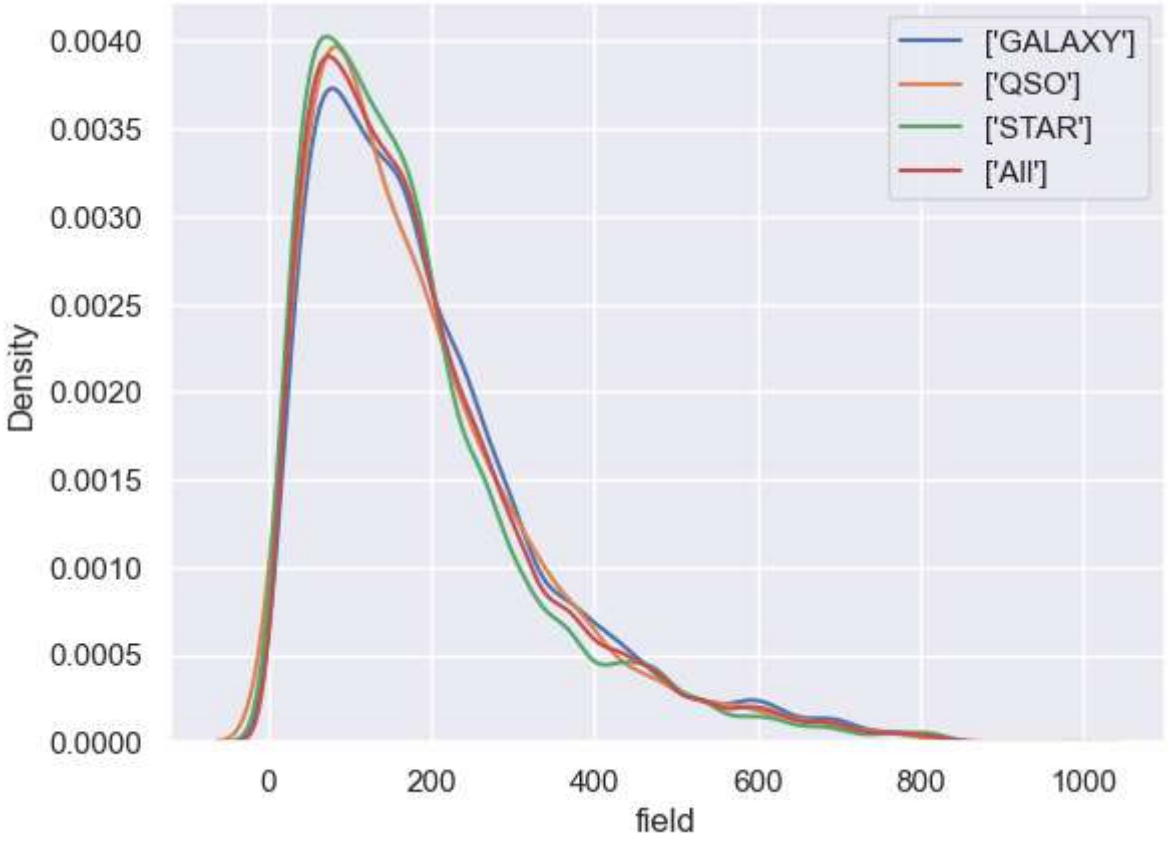
There is no significant difference in distribution by class, so I am going to drop this column.

In [48]:
```
df_astro = df_astro.drop("run",axis=1)
```

field

Field number to identify each field

In [49]:
```
plot("field")
```



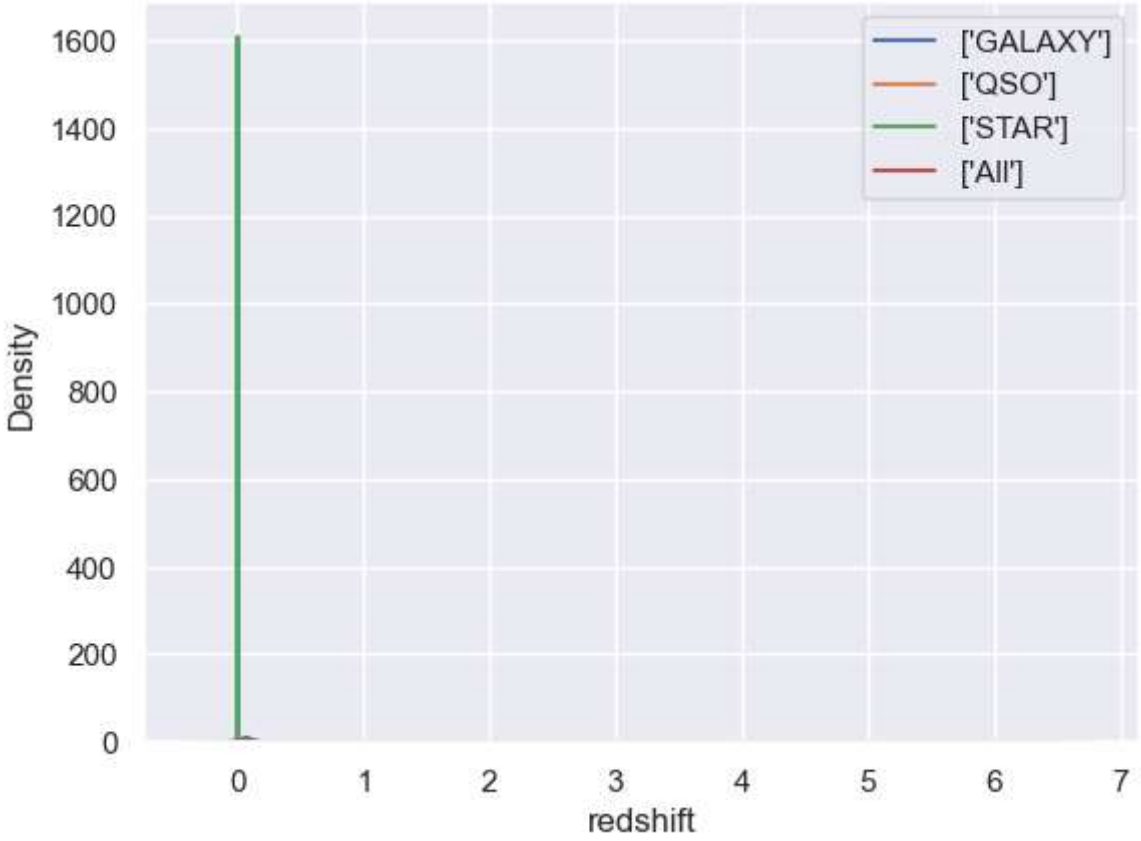
There is no significant difference in distribution by class, and I will alsdo drop this colum.

In [50]:
```
df_astro = df_astro.drop("field",axis=1)
```

redshift

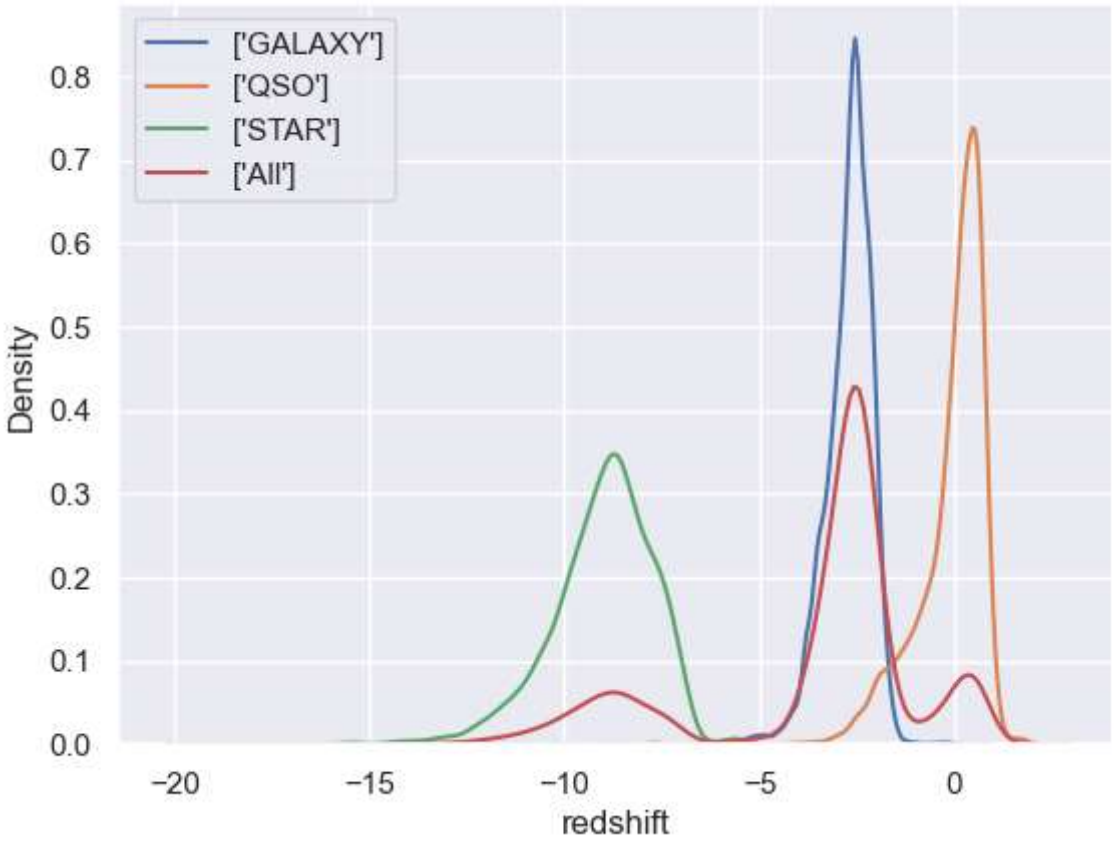
redshift value based on the increase in wavelength

In [51]:
```
plot("redshift")
```



This is hard to see because of the extreme values, so I will log the data and see if it's any better.

In [52]:
```
log_plot("redshift")
```



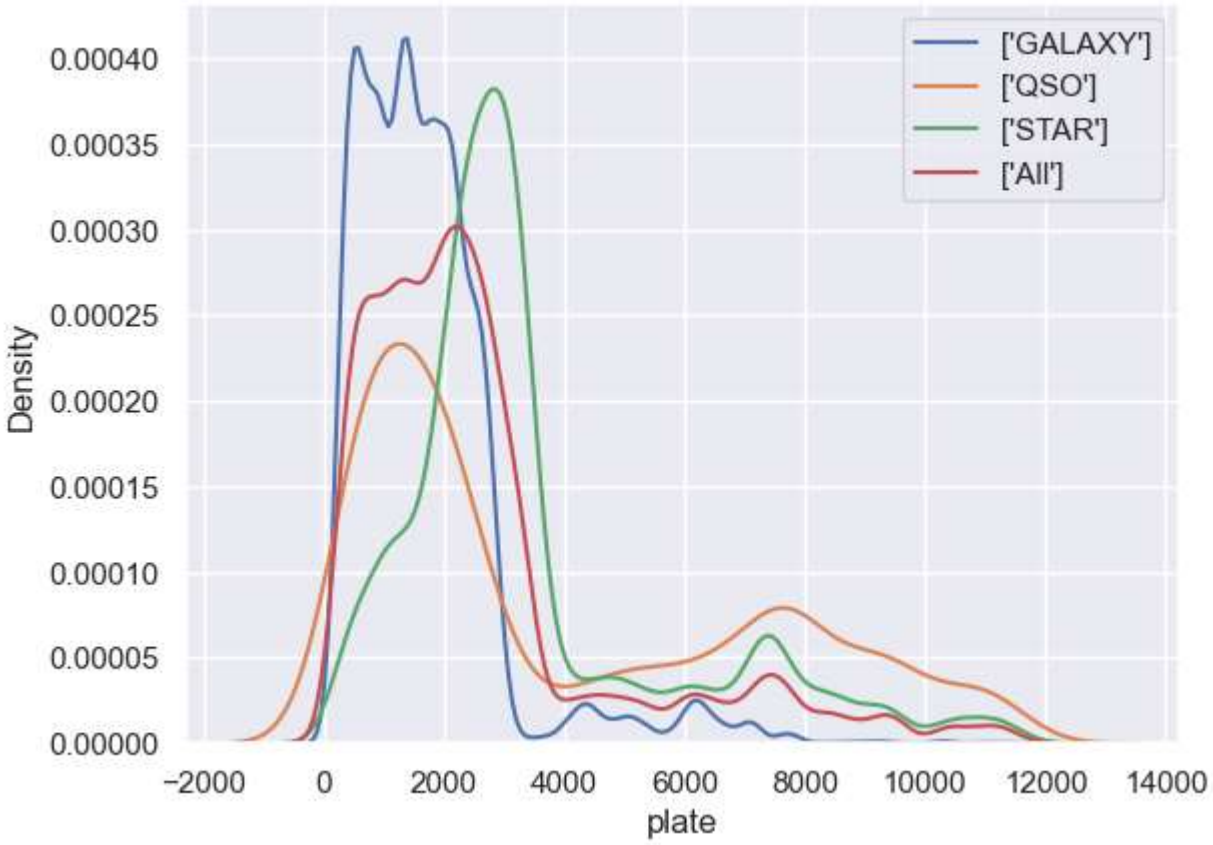
Observation

MUCH MUCH BETTER! I can see that the overall distribution is characterized.

plate

plate ID, identifies each plate in SDSS

In [53]:
```
plot("plate")
```



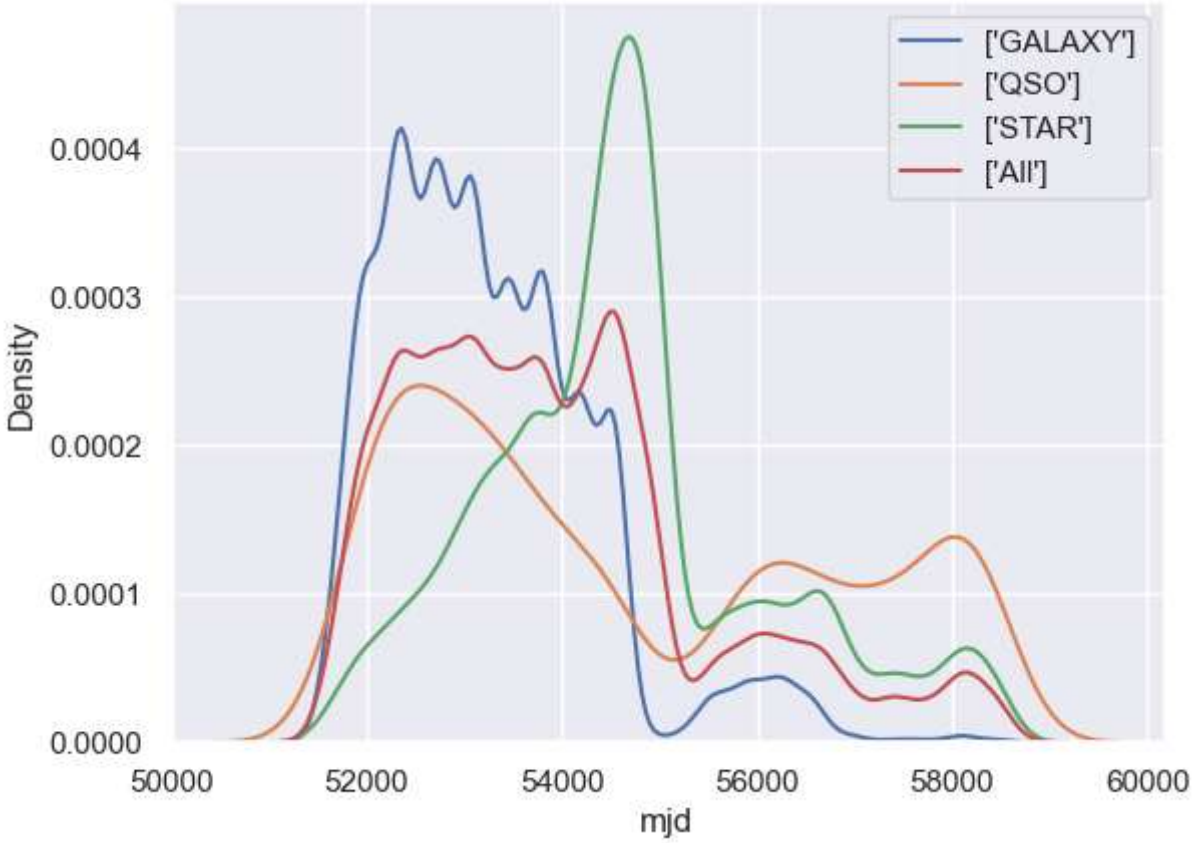
Observation

We can see that the overall distribution has distinct characteristics.

mjd

Modified Julian Date, used to indicate when a given piece of SDSS data was taken

In [54]:
```
plot("mjd")
```



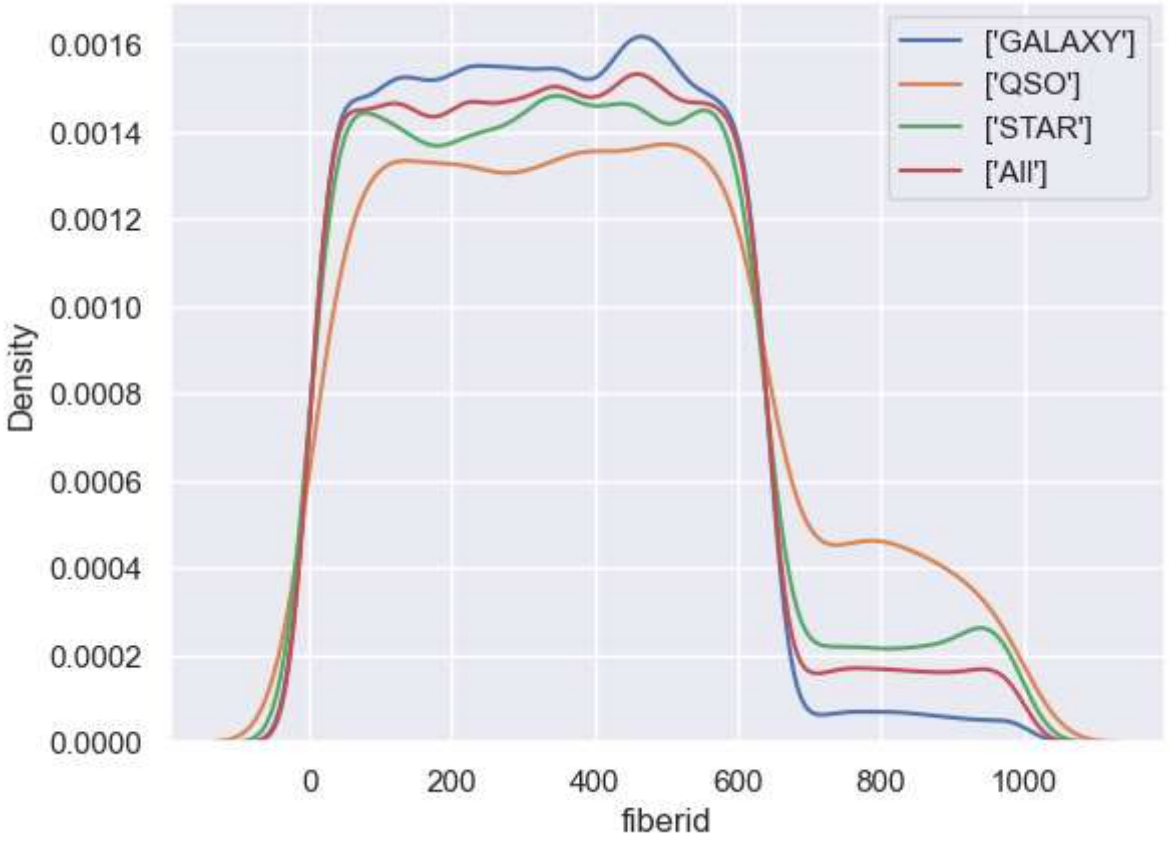
Observation:

Again, we can see that the overall distribution has a distinct characteristic.

fiberid

fiber ID that identifies the fiber that pointed the light at the focal plane in each observation

In [55]:
```
plot("fiberid")
```

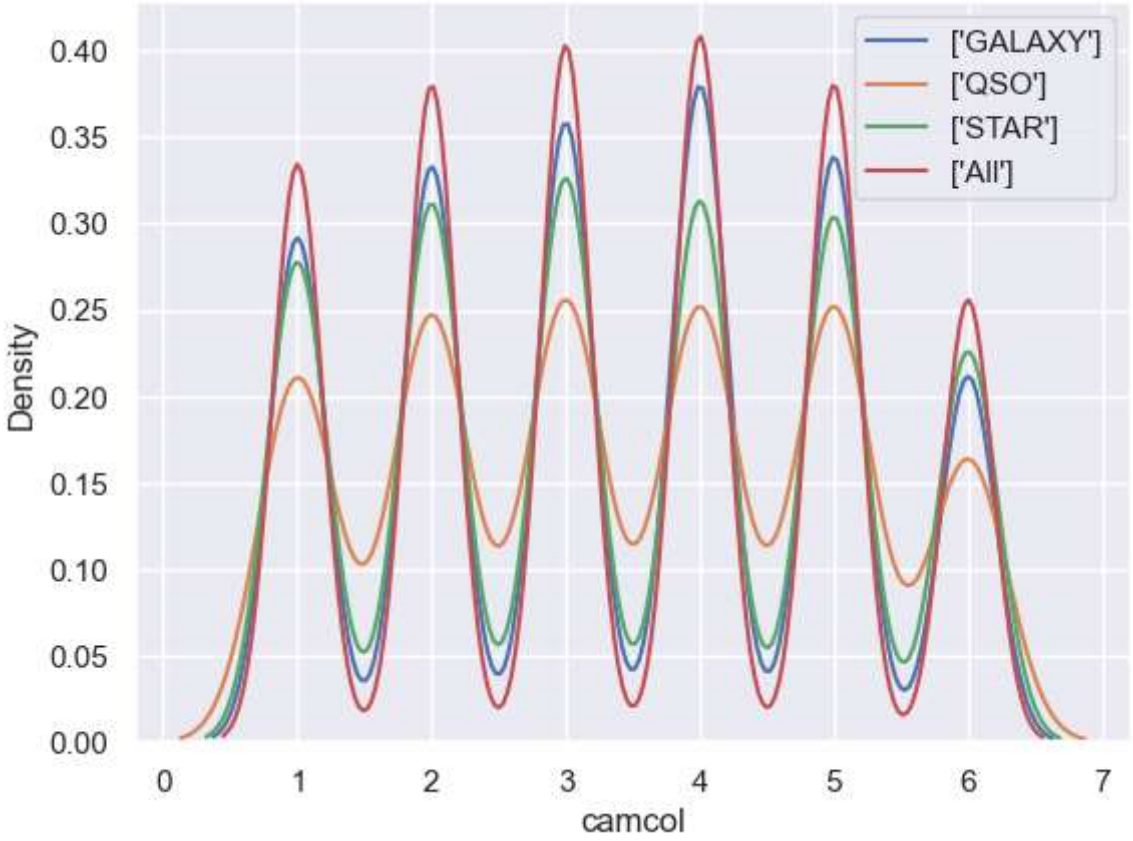


There is no significant difference in distribution by class, but there are minor differences. I will leave this column for now but might delete later.

camcol

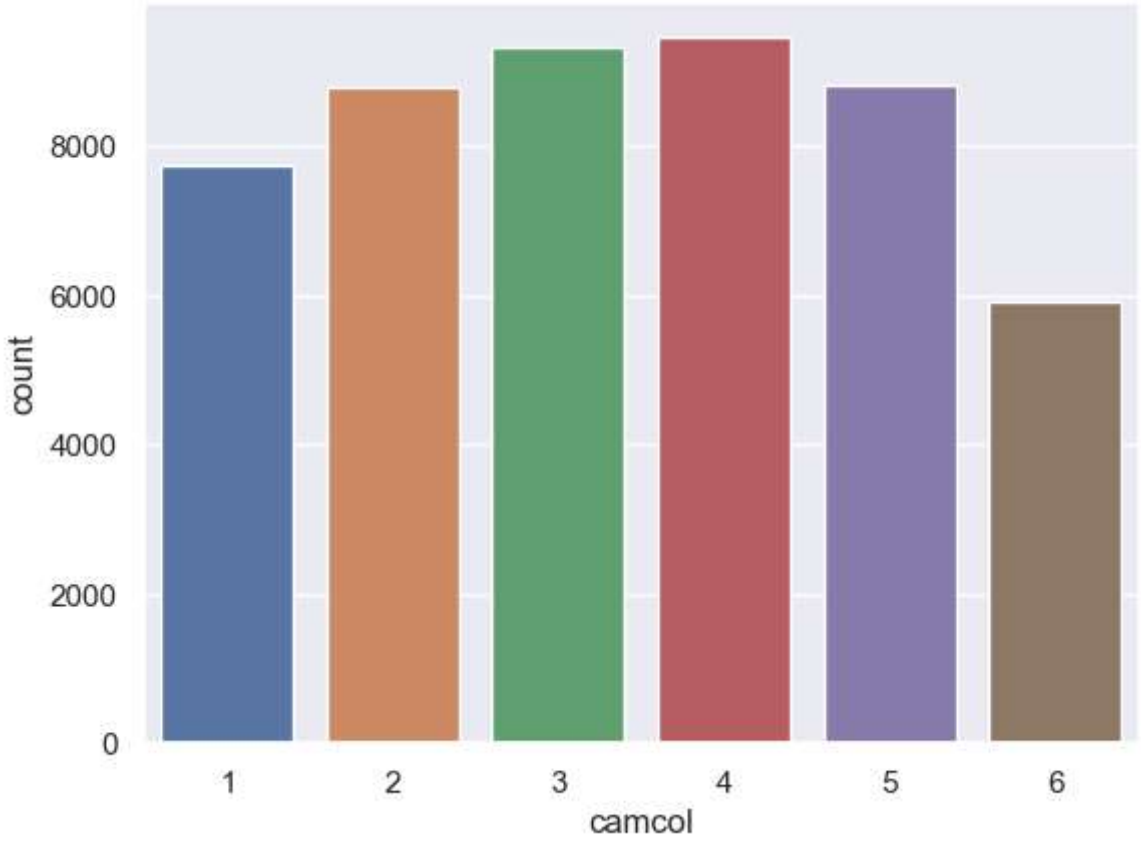
Camera column to identify the scanline within the run

In [56]:
```
plot("camcol")
```



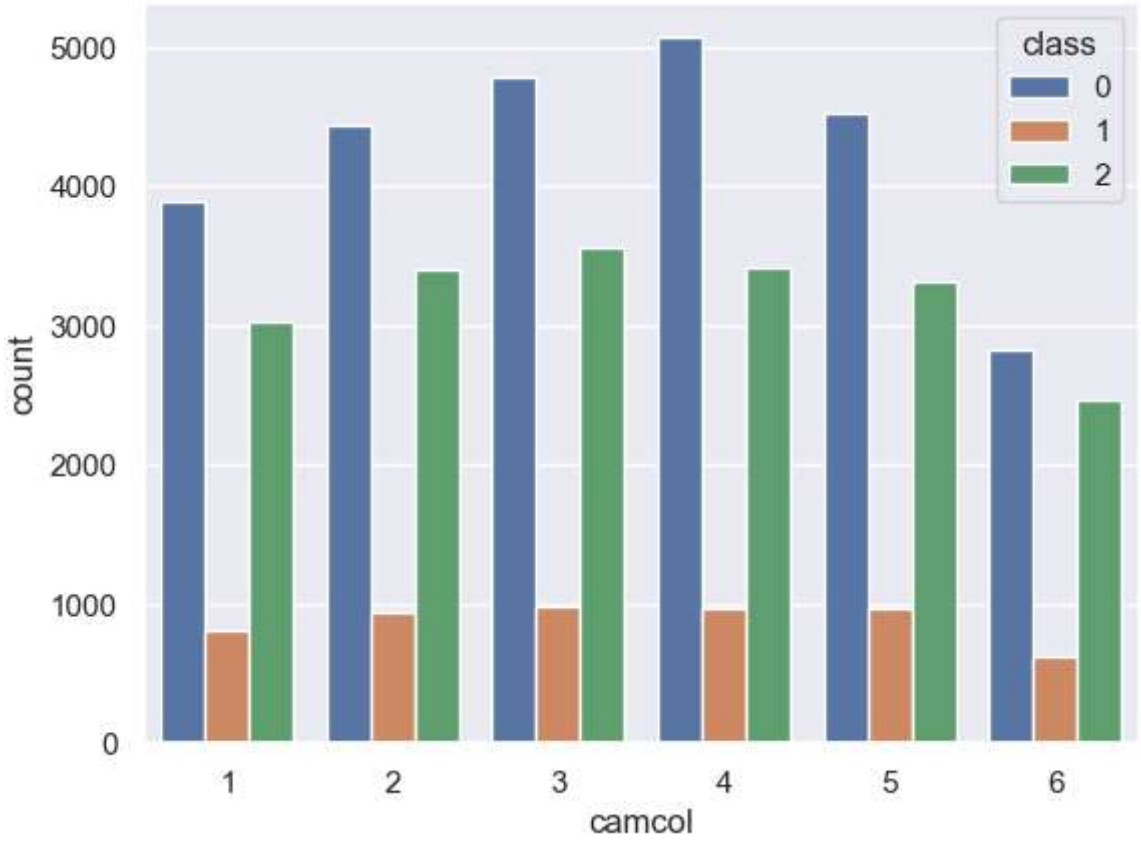
In [57]:
```
sns.countplot(x=df_astro["camcol"])
```

Out[57]:
```
<AxesSubplot:xlabel='camcol', ylabel='count'>
```



In [58]:
```
sns.countplot(x=df_astro["camcol"],hue=df_astro["class"])
```

Out[58]:
```
<AxesSubplot:xlabel='camcol', ylabel='count'>
```



Observations:

So camcol is evenly distributed, and it is difficult to differentiate data according to this, so I will delete this column

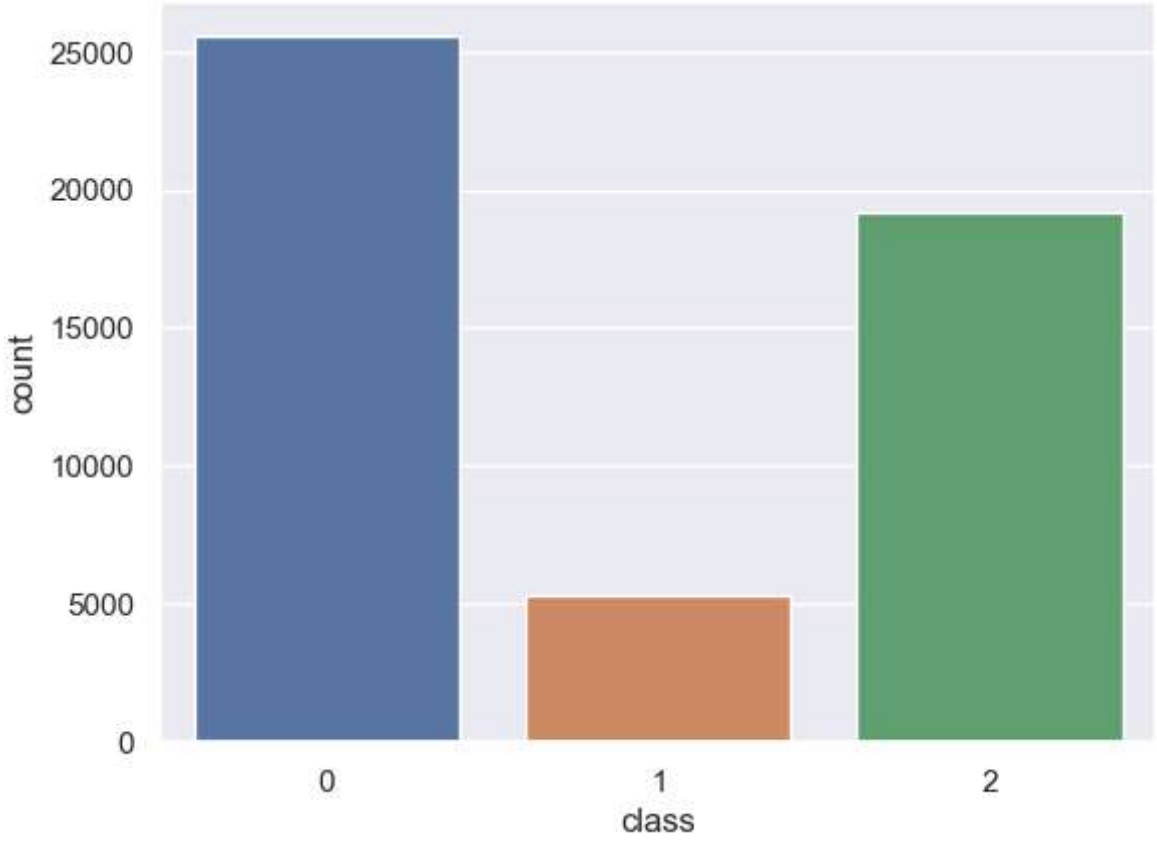
In [59]:
```
df_astro = df_astro.drop("camcol",axis=1)
```

class

object class (galaxy, star or quasar object)

In [60]:
```
sns.countplot(x=df_astro["class"])
```

Out[60]:
```
<AxesSubplot:xlabel='class', ylabel='count'>
```



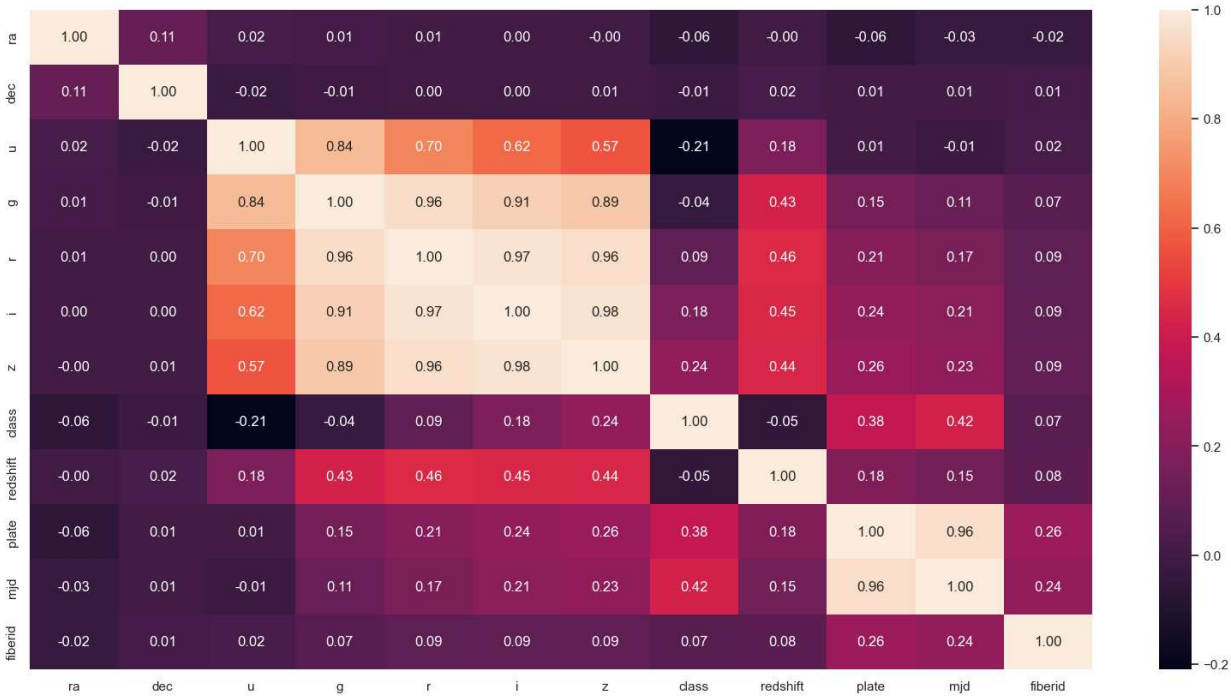
Observation

The distribution of class is unbalanced.

Multivariate Analysis

Pairwise Correlation

In [61]:
```
plt.figure(figsize=(20,10))
sns.heatmap(df_astro.corr(),annot=True,fmt=".2f")
plt.show()
```



Observations:

I observe a high positive correlation among the following variables:

z and g

mjd and plate

z and r

z and i

i and g

i and r

r and g

I observe a high negative correlation among the following variables:

fiberid and ra

mjd and ra

mjd and u

plate and ra

redshift and class

The ra, dec, u, g and redshift are highly negatively correlated with target (class)

The i and g are highly correlated, g and r are highly correlated and r and z are highly correlated.

There is a negative correlation between redshift and class variables. The redshift is clearly going to be a highly influential feature in determining the class of the celestial object.

PREPARING THE DATA FOR ALGORITHM

In [62]:
```
# Separating the dependent and independent columns in the dataset
X = df_astro.drop(['class'], axis=1);
Y = df_astro[['class']];
```

In [63]:
```
df_astro[['class']]
```

Out[63]:

	class
240208	2
18744	0
207175	0
18669	0
189086	2
...	...
12026	0
101461	2
146611	1
152140	0
168265	1

50000 rows × 1 columns

In [64]:
```
# Splitting the dataset into the Training and Testing set
X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.1, random_state=

# Checking the shape of the Train and Test sets
print('X Train Shape:', X_train.shape);
print('X Test Shape:', X_test.shape);
print('Y Train Shape:', y_train.shape);
print('Y Test Shape:', y_test.shape);
```

```
X Train Shape: (45000, 11)
X Test Shape: (5000, 11)
Y Train Shape: (45000, 1)
Y Test Shape: (5000, 1)
```

In [65]:
```
def metrics_score(actual, predicted):
  print(classification_report(actual, predicted));
  cm = confusion_matrix(actual, predicted);
  plt.figure(figsize = (8,5));
  sns.heatmap(cm, annot = True, fmt = '.2f', xticklabels = ['Galaxy', 'Quasar', 'Star'
  plt.ylabel('Actual'); plt.xlabel('Predicted');
  plt.show()
```

K-NEAREST NEIGHBORS MODEL

In [66]:
```
from sklearn.neighbors import KNeighborsClassifier
knn_model= KNeighborsClassifier()
knn_model.fit(X_train,y_train)
knn_train_predictions = knn_model.predict(X_train)
metrics_score(y_train,knn_train_predictions)
```

```
              precision    recall  f1-score   support

           0       0.79      0.96      0.87     22983
           1       0.62      0.27      0.38      4751
           2       0.90      0.78      0.84     17266

    accuracy                           0.82     45000
   macro avg       0.77      0.67      0.69     45000
weighted avg       0.81      0.82      0.80     45000
```

In [67]:
```
y_test_pred_knn = knn_model.predict(X_test);
metrics_score(y_test, y_test_pred_knn)
```

	precision	recall	f1-score	support
0	0.77	0.93	0.84	2554
1	0.39	0.16	0.23	528
2	0.84	0.74	0.79	1918
accuracy			0.78	5000
macro avg	0.67	0.61	0.62	5000
weighted avg	0.76	0.78	0.76	5000

Ok, I'm going to have to scale this data and reduce the dimensionality. For this, I will use standard scaler and PCA.

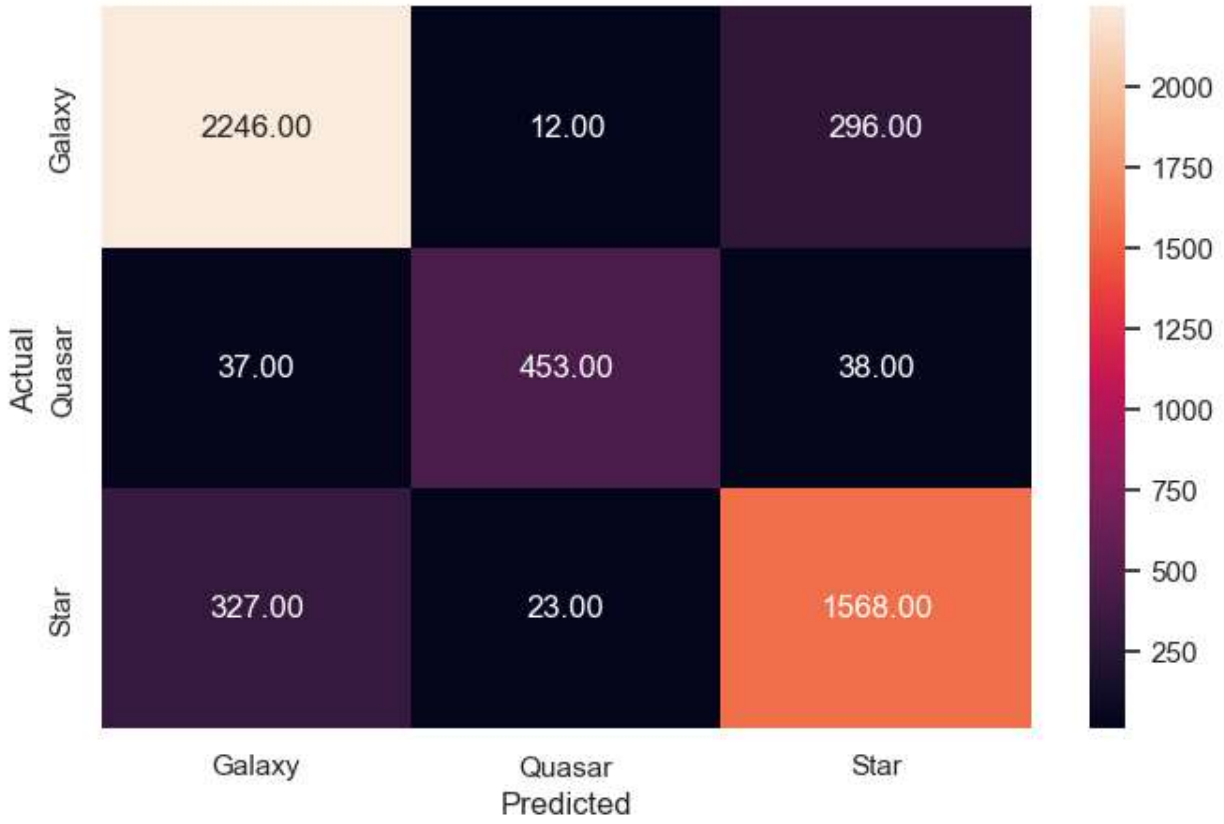
After Scaling and PCA

In [68]:
```
from sklearn.neighbors import KNeighborsClassifier
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
scaler = StandardScaler()
X_train_std = scaler.fit_transform(X_train)
X_test_std = scaler.fit_transform(X_test)
pca = PCA()
X_train_pca = pca.fit_transform(X_train_std)
X_test_pca = pca.fit_transform(X_test_std)
knn_model= KNeighborsClassifier()
knn_model.fit(X_train_pca,y_train)
knn_train_predictions = knn_model.predict(X_train_pca)
metrics_score(y_train,knn_train_predictions)
```

	precision	recall	f1-score	support
0	0.93	0.97	0.95	22983
1	0.99	0.91	0.95	4751
2	0.95	0.92	0.94	17266
accuracy			0.94	45000
macro avg	0.96	0.93	0.94	45000
weighted avg	0.94	0.94	0.94	45000

In [69]:
```
y_test_pred_knn = knn_model.predict(X_test_pca);
metrics_score(y_test, y_test_pred_knn)
```

	precision	recall	f1-score	support
0	0.86	0.88	0.87	2554
1	0.93	0.86	0.89	528
2	0.82	0.82	0.82	1918
accuracy			0.85	5000
macro avg	0.87	0.85	0.86	5000
weighted avg	0.85	0.85	0.85	5000



Observations:

While the performance of the k-Nearest Neighbors algorithm on the test dataset was quite good, it doesn't achieve the 90%+ accuracies and F1-scores we expect from a high-performing Machine Learning model on this dataset, and there is clear scope for improvement there.

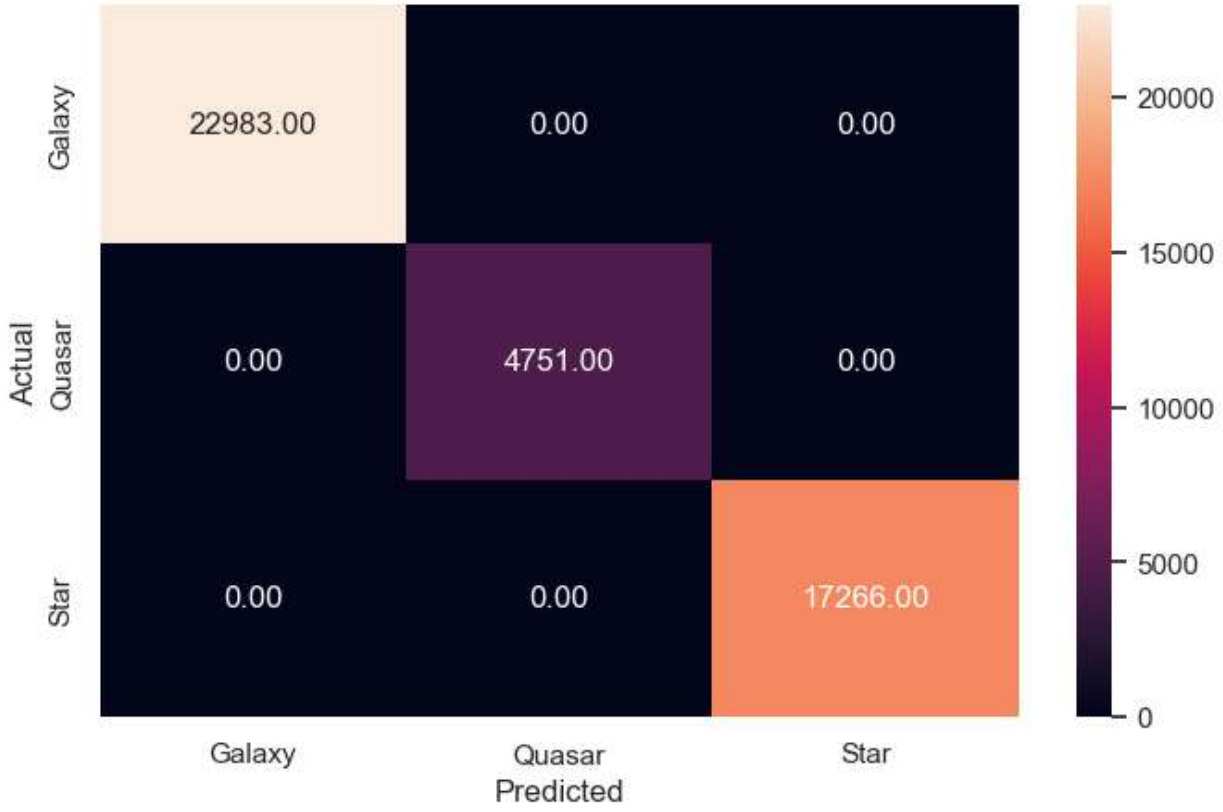
In addition, k-Nearest Neighbors also does not computationally scale well with a large amount of data, and can be infeasible to run on big datasets. For these reasons, we need a more efficient and elegant algorithm that is capable of non-linear classification, and we can turn to Decision Trees for that.

TREE-BASED MODELS

decision Tree Classifier

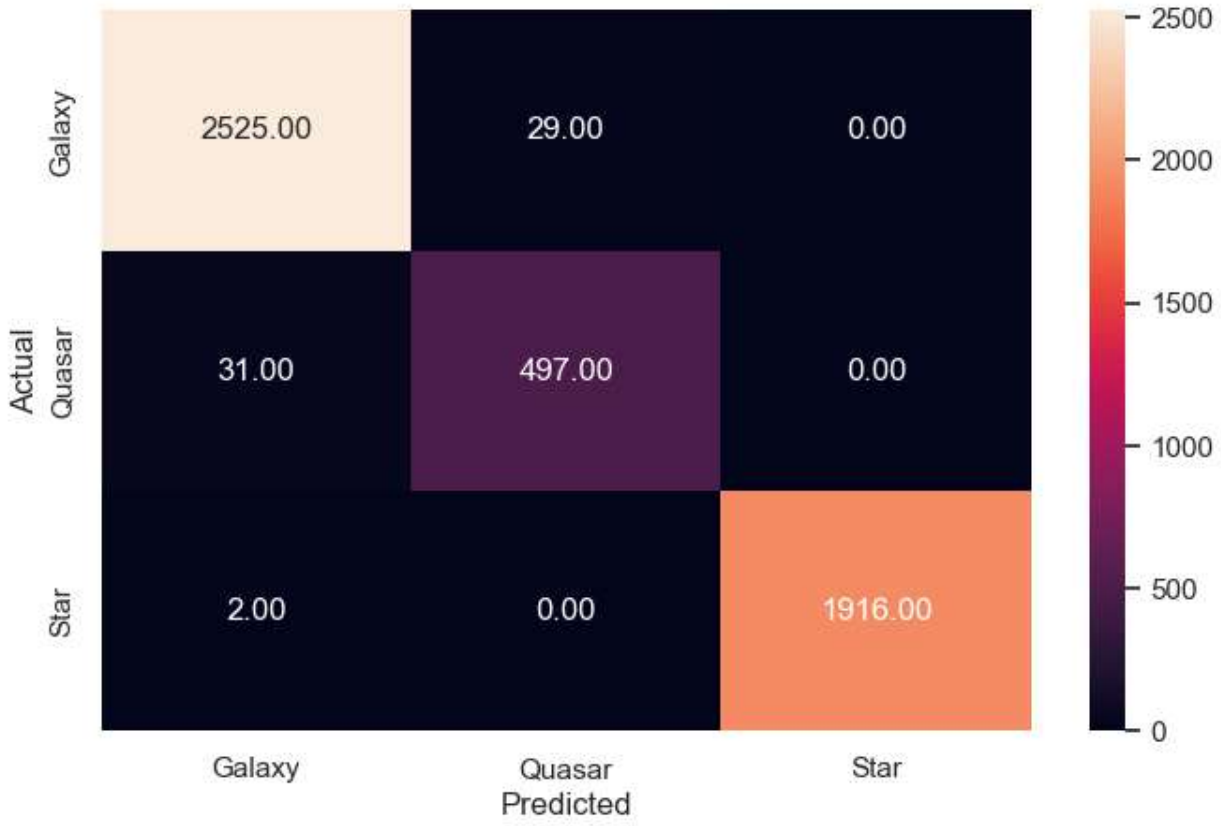
In [70]:
```
dt = DecisionTreeClassifier(random_state=1);
dt.fit(X_train, y_train)
y_train_pred_dt = dt.predict(X_train)
metrics_score(y_train, y_train_pred_dt)
```

	precision	recall	f1-score	support
0	1.00	1.00	1.00	22983
1	1.00	1.00	1.00	4751
2	1.00	1.00	1.00	17266
accuracy			1.00	45000
macro avg	1.00	1.00	1.00	45000
weighted avg	1.00	1.00	1.00	45000



In [71]:
```
y_test_pred_dt = dt.predict(X_test);
metrics_score(y_test, y_test_pred_dt)
```

	precision	recall	f1-score	support
0	0.99	0.99	0.99	2554
1	0.94	0.94	0.94	528
2	1.00	1.00	1.00	1918
accuracy			0.99	5000
macro avg	0.98	0.98	0.98	5000
weighted avg	0.99	0.99	0.99	5000



Evaluating the model with K-Fold Cross Validation

In [72]:
```
from sklearn.model_selection import cross_val_score
scores = cross_val_score(dt, X_test, y_test, cv=5)
print(f"The average score of the model with K-5 Cross validation is {np.average(scores
```

```
The average score of the model with K-5 Cross validation is 0.983
```

Ok that's great.

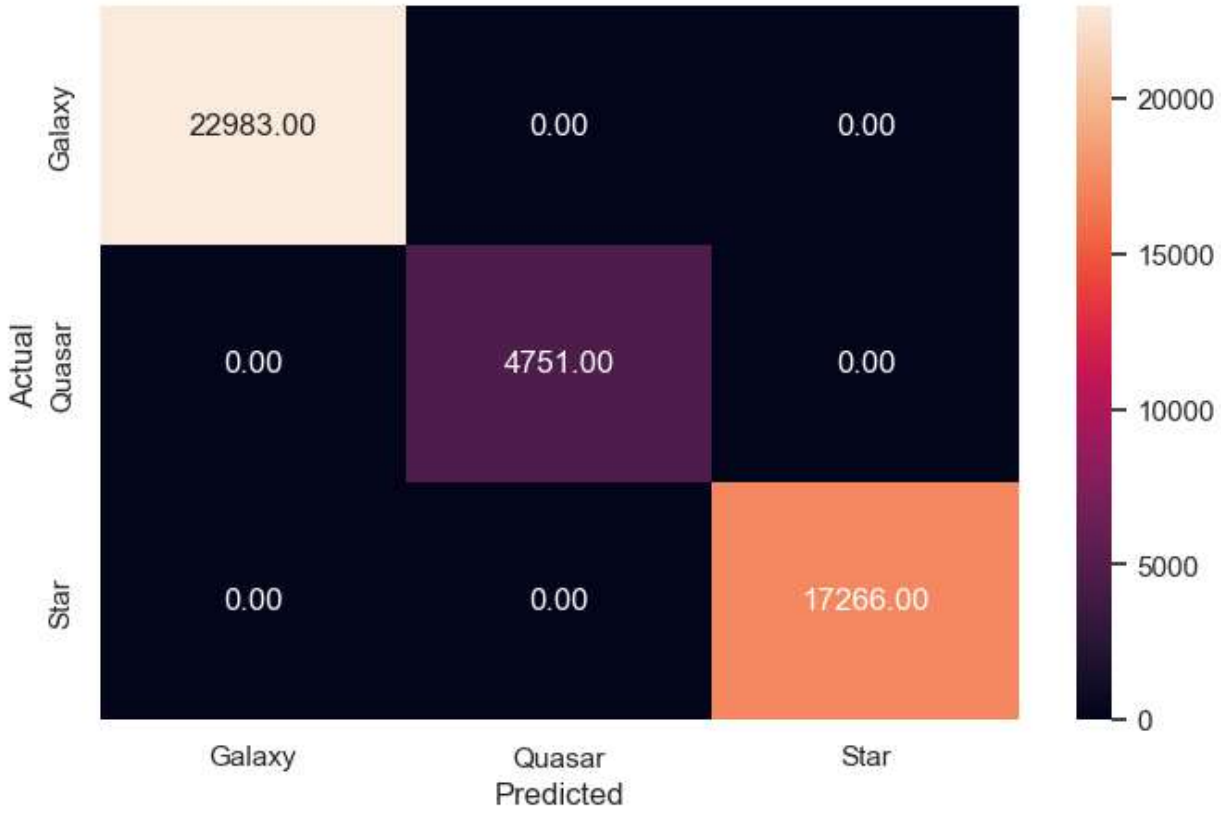
Now I will scale the data.

In [73]:
```
dt = DecisionTreeClassifier(random_state=1);
X_train_std = scaler.fit_transform(X_train)
X_test_std = scaler.fit_transform(X_test)
dt.fit(X_train_std, y_train)
y_train_pred_dt = dt.predict(X_train_std)
metrics_score(y_train, y_train_pred_dt)
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     22983
           1       1.00      1.00      1.00      4751
           2       1.00      1.00      1.00     17266

    accuracy                           1.00     45000
   macro avg       1.00      1.00      1.00     45000
weighted avg       1.00      1.00      1.00     45000
```

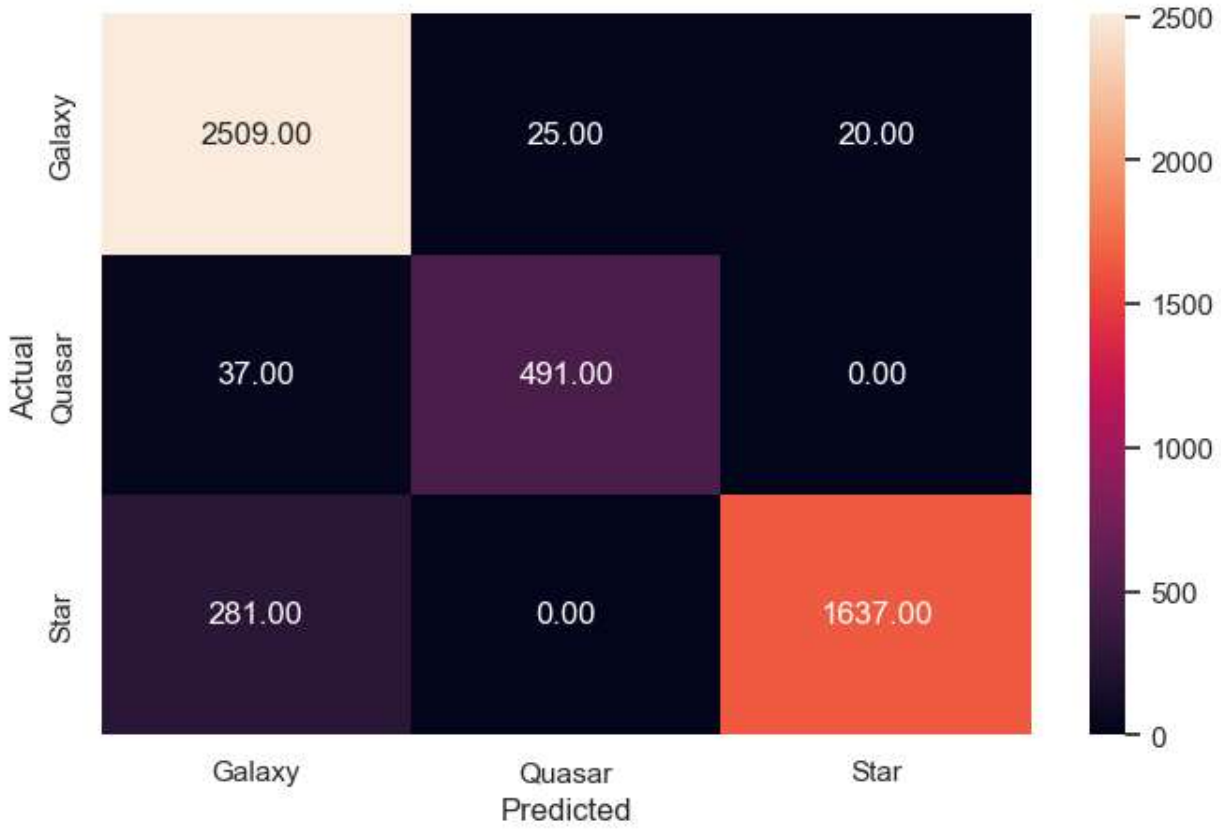


In [74]:
```
y_test_pred_dt = dt.predict(X_test_std);
metrics_score(y_test, y_test_pred_dt)
```

```
              precision    recall  f1-score   support

           0       0.89      0.98      0.93      2554
           1       0.95      0.93      0.94       528
           2       0.99      0.85      0.92      1918

    accuracy                           0.93      5000
   macro avg       0.94      0.92      0.93      5000
weighted avg       0.93      0.93      0.93      5000
```



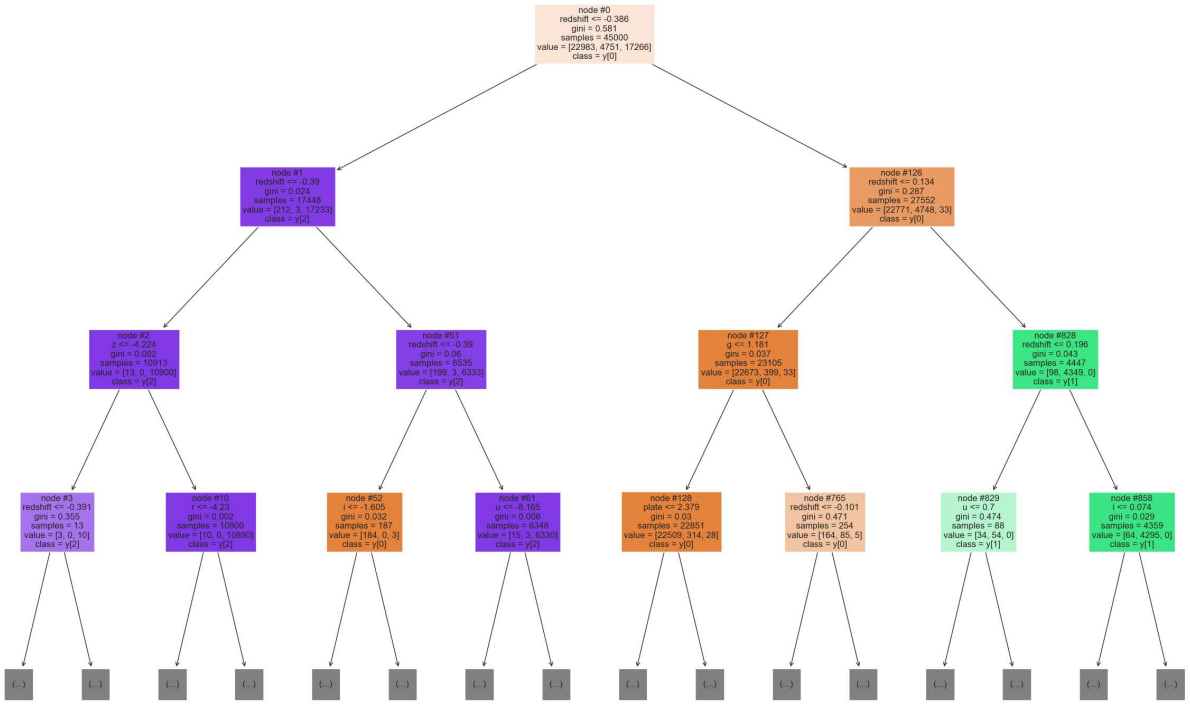
In [75]:
```
from sklearn.model_selection import cross_val_score
scores = cross_val_score(dt, X_test_std, y_test, cv=5)
print(f"The average score of the model with K-5 Cross validation is {np.average(scores
```

```
The average score of the model with K-5 Cross validation is 0.983
```

Observation

As expected, scaling doesn't make much of a difference in the performance of the Decision Tree model, since it is not a distance-based algorithm and rather tries to separate instances with orthogonal splits in a vector space.

In [76]:
```
features = list(X.columns);
plt.figure(figsize=(30,20))
tree.plot_tree(dt, max_depth=3, feature_names=features, filled=True, fontsize=12, node
plt.show()
```



Observation:

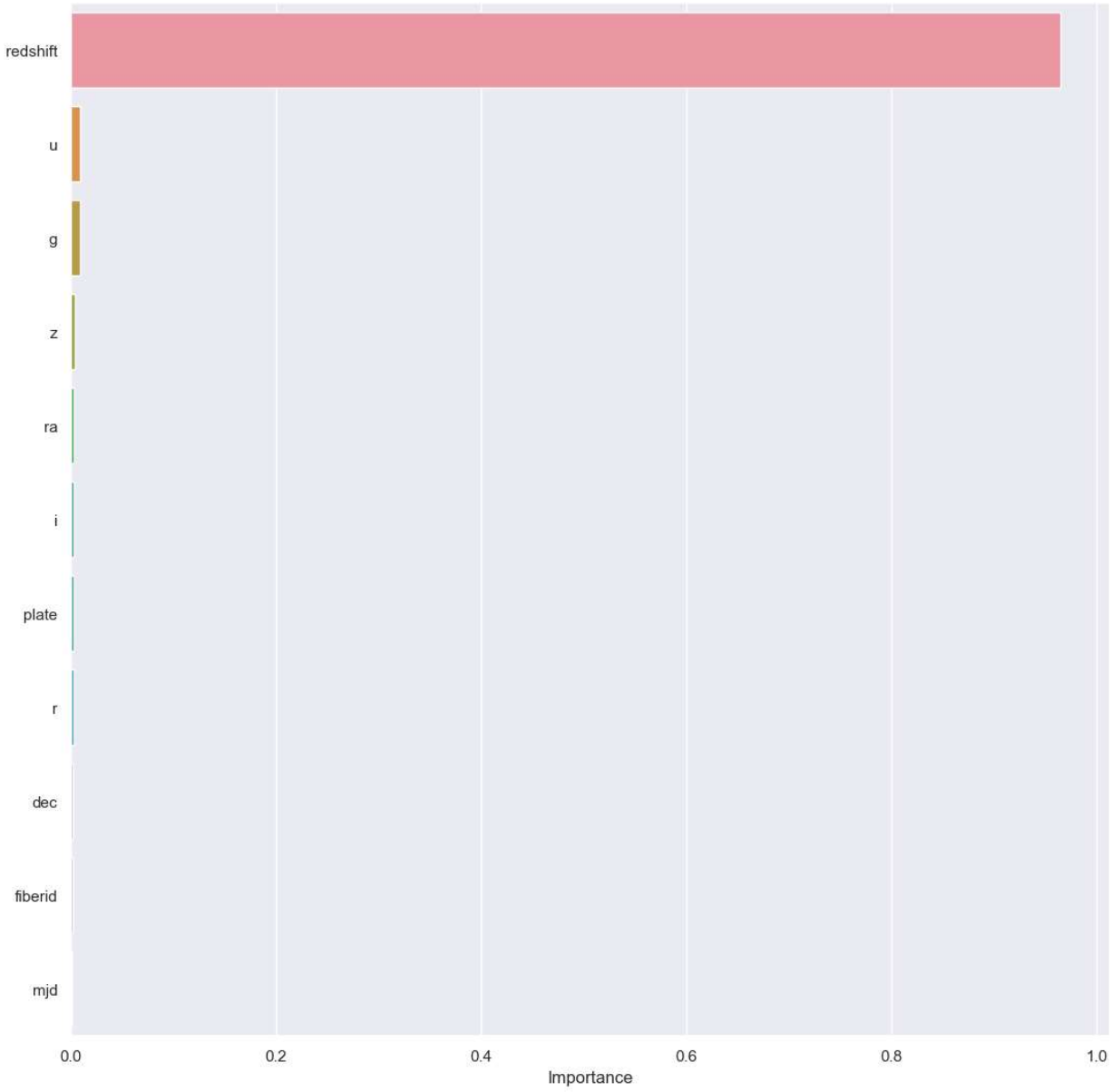
The first split in the decision tree is at the redshift feature, which implies that it is clearly the most important factor in deciding the class of the celestial object.

While this may be common knowledge in astronomy, it is good that machine learning backs it up even if this experiment is being run by a mathematician with no astrophysics degree.

Feature Importance

In [77]:
```
# Plotting the feature importance
importances = dt.feature_importances_
columns = X.columns;
importance_df_astro = pd.DataFrame(importances, index=columns, columns=['Importance'])
plt.figure(figsize=(13,13));
sns.barplot(importance_df_astro.Importance, importance_df_astro.index)
plt.show()

print(importance_df_astro)
```



	Importance
redshift	0.96480
u	0.00905
g	0.00838
z	0.00378
ra	0.00285
i	0.00265
plate	0.00249
r	0.00208
dec	0.00183
fiberid	0.00120
mjd	0.00089

Conclusions and Recommendations

Algorithmic Insights

It is apparent from the efforts above that there are some advantages with Decision Trees when it comes to non-linear modeling and classification, to obtain a mapping from input to output.

Decision Trees are simple to understand and explain, and they mirror the human pattern of if-then-else decision making. They are also more computationally efficient than kNN.

These advantages are what enable them to outperform the k-Nearest Neighbors algorithm, which is also known to be a popular non-linear modeling technique.

Dataset Insights

From a dataset perspective, the fact that the redshift variable is clearly the most important feature in determining the class of a celestial object, makes it tailor-made for a Decision Tree's hierarchical nature of decision-making. As we see in the case study, the Decision Tree prioritizes that feature as the root node of decision splits before moving on to other features.

Another potential reason for the improved performance of the Decision Tree on this dataset may have to do with the nature of the observations. In astronomical observations such as these, the value ranges of the features of naturally occurring objects such as stars, galaxies, and quasars should, for the most part, lie within certain limits outside of a few exceptions. Those exceptions would be difficult to detect purely through the values of the neighbors of that datapoint in vector space, and would rather need to be detected through fine orthogonal decision boundaries. This nuanced point could be the reason why Decision Trees perform relatively better on this dataset.

Although there are more advanced ML techniques that use an ensemble of Decision Trees, such as Random Forests and Boosting methods, they are computationally more expensive, and the 90%+ performance of Decision Trees means they would be my first recommendation to an astronomy team looking to use this Machine Learning model purely as a second opinion to make quick decisions on Celestial Object Detection.

In [ ]: