Star_Classification

March 11, 2022

1 *Star Classification*

In this project we will determine the type of star based on few parameters given in the dataset by NASA. First, let's go thorugh the dataset and try to understand general terms.

This dataset has been taken from kaggle. The dataset has 7 columns as follows:

1. **Temperature(K)** - Temperature of star in Kelvin
2. **Relative Luminosity** - RL is the value of the amount of light radiated over time relative to the luminosity of the sun.
3. **Relative Radius** - Radius of the star relative to the radius of the sun.
4. **Absolute Magnitude** - An object's absolute magnitude is defined to be equal to the apparent magnitude that the object would have if it were viewed from a distance of exactly 10 parsecs (32.6 light-years). Read more here.
5. **Color** - Color of the star
6. **Spectral_Class** - stellar classification based on the emission spectrum or color spectrum of a star, more here.
7. **Type** - type of star classified based on the hotness level of a star, more here.

From 0 to 5

- Red Dwarf - 0
- Brown Dwarf - 1
- White Dwarf - 2
- Main Sequence - 3
- Super Giants - 4
- Hyper Giants - 5

[640]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
plt.style.use('seaborn-deep')
%matplotlib inline
```

[641]:
```
#reading dataset

df_stars = pd.read_csv("/content/Stars.csv")
df_stars.head()
```

[641]:

	Temperature	L	R	A_M	Color	Spectral_Class	Type
0	3068	0.002400	0.1700	16.12	Red	M	0
1	3042	0.000500	0.1542	16.60	Red	M	0
2	2600	0.000300	0.1020	18.70	Red	M	0
3	2800	0.000200	0.1600	16.65	Red	M	0
4	1939	0.000138	0.1030	20.06	Red	M	0

[642]:
```
df_stars.shape
```

[642]: (240, 7)

[643]:
```
df_stars.describe()
```

[643]:

	Temperature	L	R	A_M	Type
count	240.000000	240.000000	240.000000	240.000000	240.000000
mean	10497.462500	107188.361635	237.157781	4.382396	2.500000
std	9552.425037	179432.244940	517.155763	10.532512	1.711394
min	1939.000000	0.000080	0.008400	-11.920000	0.000000
25%	3344.250000	0.000865	0.102750	-6.232500	1.000000
50%	5776.000000	0.070500	0.762500	8.313000	2.500000
75%	15055.500000	198050.000000	42.750000	13.697500	4.000000
max	40000.000000	849420.000000	1948.500000	20.060000	5.000000

Before we start modeling the data, let's first check for missing values, data types and use data manipulation if required.

2 Exloratory Data Analysis

2.1 Categorical Co-relation

[644]:
```
df_stars.dtypes
```

[644]:
```
Temperature         int64
L                 float64
R                 float64
A_M               float64
Color              object
Spectral_Class     object
Type                int64
dtype: object
```

The datatypes are correctly assigned for each column. Here Temperature is in Kelvin and we will leave its datatype as int64 instead of changing it to float. Color and Spectral_Class will be object datatype since they are string values.

[645]:
```
#checking for the null values
df_stars.isnull().sum(axis=0)
```

[645]:
```
Temperature       0
L                 0
R                 0
A_M               0
Color             0
Spectral_Class    0
Type              0
dtype: int64
```

There are no missing values in our dataset and it looks clean to carry out exploratory analysis.

[646]:
```
#co-relating color and Type of the star
df_stars['Color'] = df_stars['Color'].str.lower()  #converting all color types␣
 ↪to lowercase
df_stars[['Type','Color']].value_counts().sort_values()
```

[646]:
```
Type  Color
3     orange-red             1
2     white-yellow           1
      pale yellow orange     1
3     whitish                2
5     white                  2
      orange                 2
3     yellowish              3
2     yellowish white        3
3     blue                   5
5     blue-white             6
      blue                   7
2     white                  8
3     yellow-white           8
4     red                    9
2     blue                  13
      blue white            14
3     blue-white            21
5     red                   23
4     blue                  31
1     red                   40
0     red                   40
dtype: int64
```

Formatting the color types and merging the color with the similar name.

```
[647]: df_stars['Color'].replace('white-yellow', 'yellow-white', inplace=True)
df_stars['Color'].replace('yellowish white', 'yellow-white', inplace=True)
df_stars['Color'].replace('blue white', 'blue-white', inplace=True)
df_sorted = df_stars[['Type','Color']].value_counts().sort_values()
df_sorted
```

```
[647]: Type  Color
2     pale yellow orange     1
3     orange-red             1
5     white                  2
3     whitish                2
5     orange                 2
3     yellowish              3
2     yellow-white           4
3     blue                   5
5     blue-white             6
      blue                   7
3     yellow-white           8
2     white                  8
4     red                    9
2     blue                  13
      blue-white            14
3     blue-white            21
5     red                   23
4     blue                  31
1     red                   40
0     red                   40
dtype: int64
```

A sorted table to see the counts of Types for each spectral class is given below.

```
[648]: df_stars[['Spectral_Class','Type']].value_counts().sort_values()
```

```
[648]: Spectral_Class  Type
G               5        1
B               4        2
K               5        2
A               5        2
K               3        4
O               3        5
                5        6
B               5        7
A               2        7
F               3        8
                2        9
M               4        9
A               3       10
```

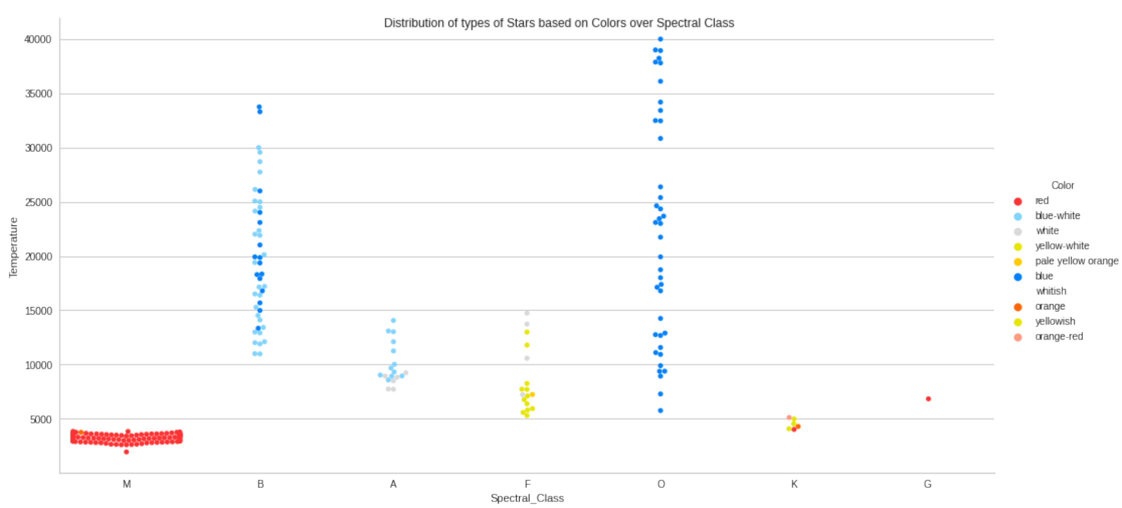
```
B                 3        13
M                 5        22
B                 2        24
O                 4        29
M                 1        40
                  0        40
dtype: int64
```

It seems most of the Types fall in M and O class based on the total counts for each type and conversly most of the Class M and Class O has Type 1, Type 0 and Type 4 stars.

Let's visualize further relationships between other features.

[649]:
```
palette=["#ff3333", "#80d4ff",␣
↪"#d9d9d9","#e6e600","#ffcc00","#0080ff","w","#ff6600","#e6e600","#ff9980"]
sns.catplot(x= 'Spectral_Class',y = 'Temperature', hue='Color',kind='swarm',␣
↪data=df_stars, height=7, aspect=2,ci=None, palette=palette)
plt.suptitle("Distribution of types of Stars based on Colors over Spectral␣
↪Class")
plt.show()
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/categorical.py:1296: UserWarning:
42.3% of the points cannot be placed; you may want to decrease the size of the
markers or use stripplot.
  warnings.warn(msg, UserWarning)
```



Most of the red color stars belong to Spectral Class M and similarly most of the blue stars belong to B and O spectral class. However we can see that there are very few stars that belong to K and G class. These might prove to be impurities during the machine learning process. Let's try to count total number of stars for each color.

[650]:
```
df_colors = df_stars['Color'].value_counts()
df_colors = df_colors.reset_index()
df_colors.columns = ['Color','Counts']
df_colors['percent-accounting'] = round(df_colors['Counts']/df_colors['Counts'].
↪sum(),4)
df_colors
```

[650]:

	Color	Counts	percent-accounting
0	red	112	0.4667
1	blue	56	0.2333
2	blue-white	41	0.1708
3	yellow-white	12	0.0500
4	white	10	0.0417
5	yellowish	3	0.0125
6	whitish	2	0.0083
7	orange	2	0.0083
8	pale yellow orange	1	0.0042
9	orange-red	1	0.0042

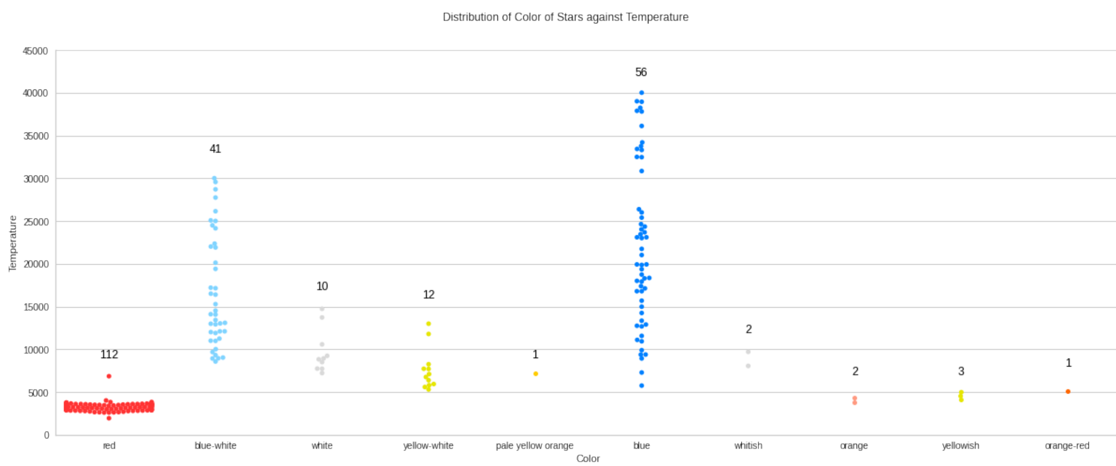
Stars with red color accounts for 46.67 % among all the colors and next is blue color stars with 23.33% weightage. We can see that Whitish, Orange, pale yellow orange and orange-red account for very less amount fo stars.

We will visualize this to better understand the relationship between the colors and type of a star.

[651]:
```
palette=["#ff3333", "#80d4ff",␣
↪"#d9d9d9","#e6e600","#ffcc00","#0080ff","#d9d9d9","#ff9980","#e6e600","#ff6600"]
ax= sns.catplot(x= 'Color',y = 'Temperature', hue='Color',kind='swarm',␣
↪data=df_stars, height=7, aspect=2.4,ci=None, palette=palette)
ax.fig.subplots_adjust(top=0.9)
ax.fig.suptitle("Distribution of Color of Stars against Temperature")

#assigning right color to each color group
plt.text(-0, 9000, str(df_stars['Color'].value_counts()[0]),␣
↪horizontalalignment='center', size='large', color='black')
plt.text(1, 33000, str(df_stars['Color'].value_counts()[2]),␣
↪horizontalalignment='center', size='large', color='black')
plt.text(2, 17000, str(df_stars['Color'].value_counts()[4]),␣
↪horizontalalignment='center', size='large', color='black')
plt.text(3, 16000, str(df_stars['Color'].value_counts()[3]),␣
↪horizontalalignment='center', size='large', color='black')
plt.text(4, 9000, str(df_stars['Color'].value_counts()[8]),␣
↪horizontalalignment='center', size='large', color='black')
plt.text(5, 42000, str(df_stars['Color'].value_counts()[1]),␣
↪horizontalalignment='center', size='large', color='black')
plt.text(6, 12000, str(df_stars['Color'].value_counts()[6]),␣
↪horizontalalignment='center', size='large', color='black')
```

```
plt.text(7, 7000, str(df_stars['Color'].value_counts()[7]),␣
 ↪horizontalalignment='center', size='large', color='black')
plt.text(8, 7000, str(df_stars['Color'].value_counts()[5]),␣
 ↪horizontalalignment='center', size='large', color='black')
plt.text(9, 8000, str(df_stars['Color'].value_counts()[9]),␣
 ↪horizontalalignment='center', size='large', color='black')
plt.ylim(0, 45000)
plt.show()
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/categorical.py:1296: UserWarning:
50.0% of the points cannot be placed; you may want to decrease the size of the
markers or use stripplot.
  warnings.warn(msg, UserWarning)
```



There are very few Types of stars that co relate to Orange, Yellowish and Orange-red colors. They are the outliers which can alter the prediction during the machine learning. There are two actions that can be performed here to eradicate outliers. 1. To remove the outliers 2. To change their classification to the closest type resemblance

For the stars that are *Whitish* in color we can merge them with *White* color as they both have similar temperature range. We can do this by renaming the *whitish* color to *white*, thus merging them.

It is the best practice to remove the remaining outliers since they will alter the prediction of Type of a star.

[652]:
```
print("Type of stars of White color")
print(df_stars[df_stars['Color']=='white'].Type)
print("Type of stars of Whitish color")
print(df_stars[df_stars['Color']=='whitish'].Type)
```

```
Type of stars of White color
21     2
```

```
22     2
23     2
81     2
82     2
88     2
147    2
148    2
237    5
238    5
Name: Type, dtype: int64
Type of stars of Whitish color
33    3
35    3
Name: Type, dtype: int64
```

It appears that the Types don't match hence outliers with Whitish color can be removed.

[653]:

```
print("Type of stars for red color")
print(df_stars[df_stars['Color']=='red'].Type)
print("Type of stars for Orange color")
print(df_stars[df_stars['Color']=='orange'].Type)
print("Type of stars for Orange-red color")
print(df_stars[df_stars['Color']=='orange-red'].Type)
```

```
Type of stars for red color
0      0
1      0
2      0
3      0
4      0
      ..
195    1
196    1
197    1
198    1
199    1
Name: Type, Length: 112, dtype: int64
Type of stars for Orange color
53     5
172    5
Name: Type, dtype: int64
Type of stars for Orange-red color
96    3
Name: Type, dtype: int64
```

Here as well, there is no match in Types of two differencet colors schemes hence outliers having orange and orange-red colors needs to be removed.

[654]:
```
print("Type of stars for yellow-white color")
print(df_stars[df_stars['Color']=='yellow-white'].Type)
print("Type of stars for yellowish color")
print(df_stars[df_stars['Color']=='yellowish'].Type)
```

```
Type of stars for yellow-white color
25     2
27     2
28     2
34     3
36     3
37     3
38     3
39     3
80     2
90     3
97     3
219    3
Name: Type, dtype: int64
Type of stars for yellowish color
91    3
92    3
93    3
Name: Type, dtype: int64
```

For yellowish color stars, we can observe that thier types are similar to the stars having Yellow-white color scheme. Hence we will change the color of Yellowish to yellow-white thus merging them.

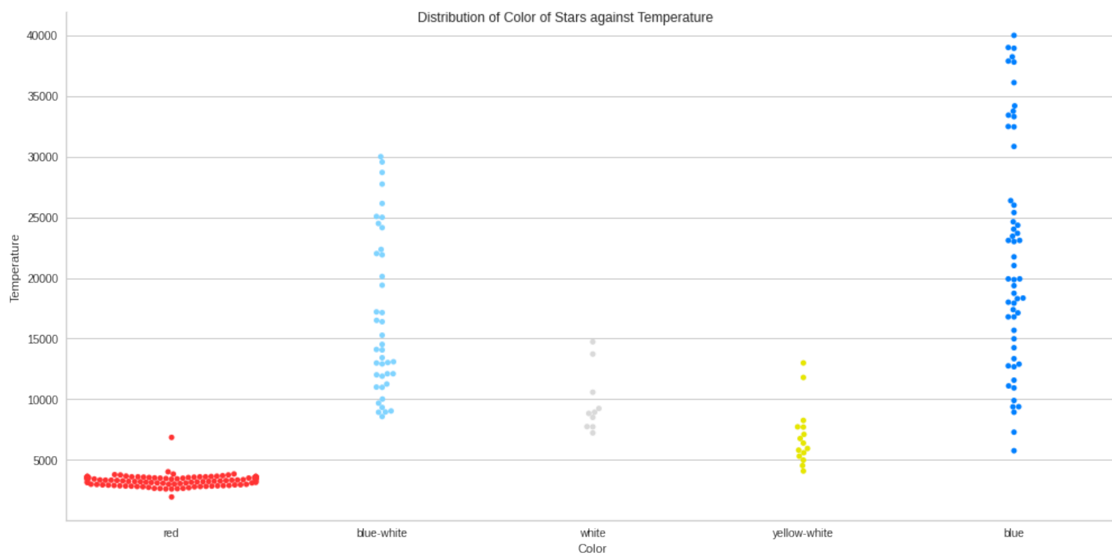
[655]:
```
#dropping the rows with following colors
df_stars.drop(df_stars[df_stars.Color == 'whitish'].index,axis=0, inplace=True)
df_stars.drop(df_stars[df_stars.Color == 'orange'].index, axis=0,inplace=True)
df_stars.drop(df_stars[df_stars.Color == 'orange-red'].
 ↪index,axis=0,inplace=True)
df_stars.drop(df_stars[df_stars.Color == 'pale yellow orange'].
 ↪index,axis=0,inplace=True)

#changing the color of yellowish to yellow-white since they belong to same Type
df_stars.replace('yellowish', 'yellow-white', inplace=True)
```

[656]:
```
#Again having a look at the categorical plot of Temperature, Type and Color

palette=["#ff3333", "#80d4ff", "#d9d9d9","#e6e600","#0080ff","#ff6600"]
ax = sns.catplot(x= 'Color',y = 'Temperature', hue='Color',kind='swarm',␣
 ↪data=df_stars, height=7, aspect=2,ci=None, palette=palette)

ax.fig.suptitle("Distribution of Color of Stars against Temperature")
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/categorical.py:1296: UserWarning:
```

```
24.1% of the points cannot be placed; you may want to decrease the size of the
markers or use stripplot.
  warnings.warn(msg, UserWarning)
```

[656]: Text(0.5, 0.98, 'Distribution of Color of Stars against Temperature')



All the data now looks nicely distriuted among the catergories of colors. It can said that Blue color stars have temperature ranging from 5000 K to 40000 K where as red color stars have temperatures below 5000 K. It is a noticebale difference from the such visualization.

[657]:
```
df_total = df_stars[['Color','Type']]
df_total= pd.DataFrame(df_total[['Type','Color']].value_counts())
df_total = df_total.reset_index()
df_total.columns = ['Type','Color','Counts']
df_total
```

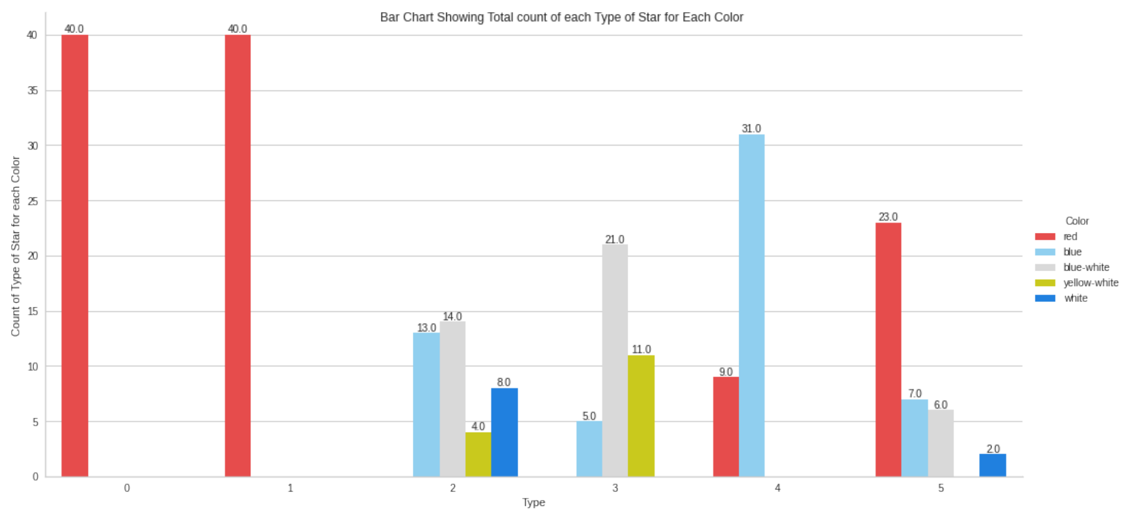
[657]:

	Type	Color	Counts
0	0	red	40
1	1	red	40
2	4	blue	31
3	5	red	23
4	3	blue-white	21
5	2	blue-white	14
6	2	blue	13
7	3	yellow-white	11
8	4	red	9
9	2	white	8
10	5	blue	7
11	5	blue-white	6

```
12     3         blue      5
13     2  yellow-white     4
14     5         white     2
```

Plotting above information in form of a bar plot.

[658]:
```
palette=["#ff3333", "#80d4ff", "#d9d9d9","#e6e600","#0080ff"]
splot = sns.catplot(x= 'Type',y = 'Counts', hue='Color',kind='bar', height=7,␣
 ↪aspect=2, data=df_total,ci=None, palette=palette)

# extract the matplotlib axes_subplot objects from the FacetGrid
ax = splot.facet_axis(0, 0)

# iterate through the axes containers
for c in ax.containers:
    labels = [f'{v.get_height()}' for v in c]
    ax.bar_label(c, labels=labels, label_type='edge')


plt.ylabel("Count of Type of Star for each Color")
plt.suptitle("Bar Chart Showing Total count of each Type of Star for Each␣
 ↪Color")
plt.show()
```



2.2 Numerical Co-relation

[659]:
```
df_stars.corr()
```

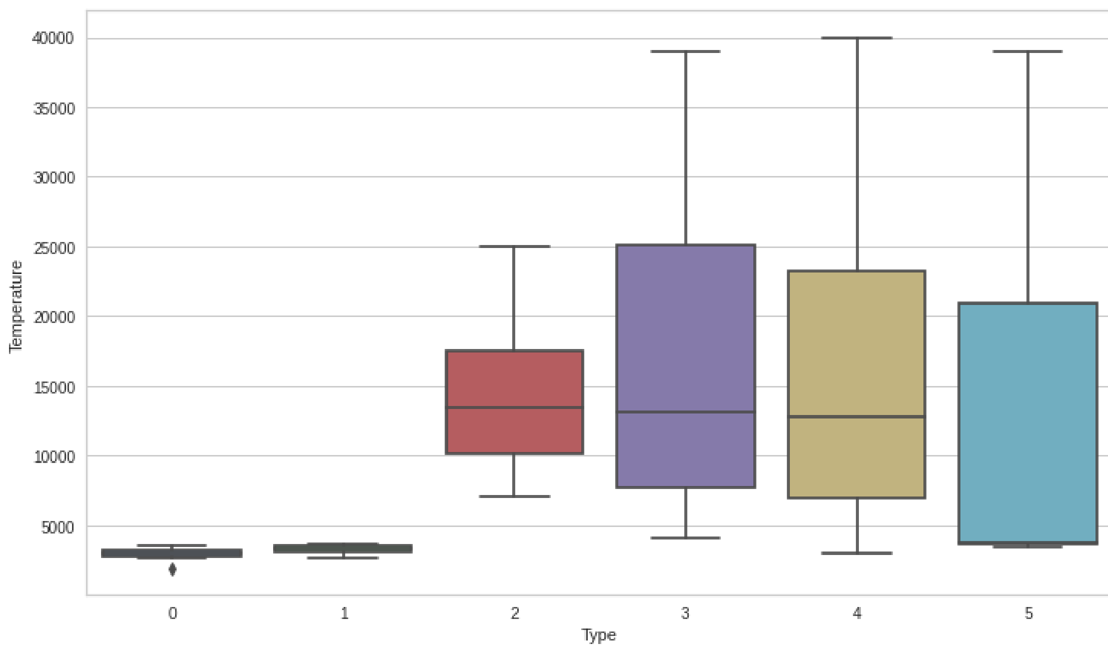
[659]:
```
             Temperature         L         R       A_M      Type
Temperature     1.000000  0.421282  0.078035 -0.431351  0.425730
```

```
L              0.421282  1.000000  0.498144 -0.693158  0.674650
R              0.078035  0.498144  1.000000 -0.604505  0.656357
A_M           -0.431351 -0.693158 -0.604505  1.000000 -0.955797
Type           0.425730  0.674650  0.656357 -0.955797  1.000000
```

A correlation matrix above shows that Type of star is closely related to L (luminosity) and then R (radius of star) than any other numerical parameter. A value closer to 1 has the highest corelation or dependency.

[660]:
```
#visulaize by plotting box plot

fid,ax = plt.subplots(figsize=(12,7))
sns.boxplot(y=df_stars['Temperature'], x=df_stars['Type'], data=df_stars, ax=ax)
```

[660]:
```
<AxesSubplot:xlabel='Type', ylabel='Temperature'>
```



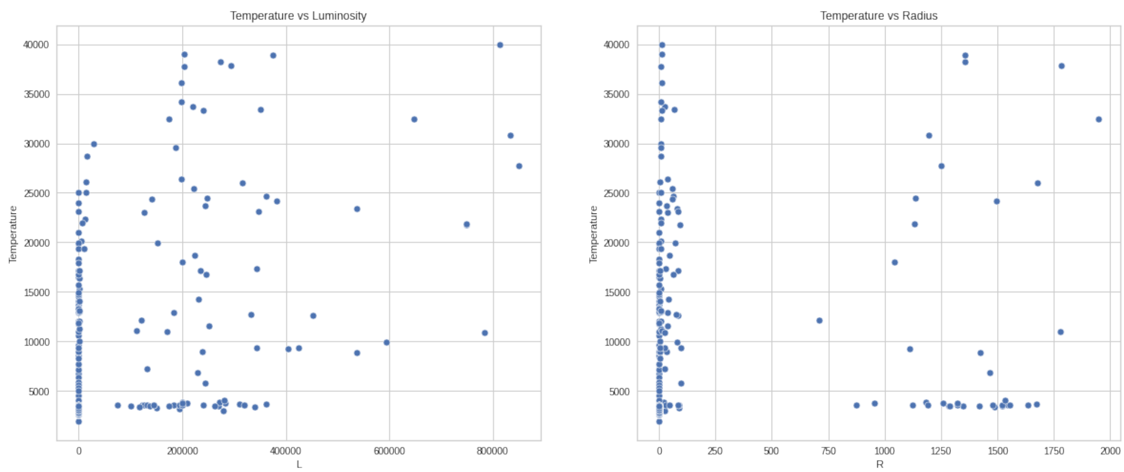
It seems that temperatures lower than approximately 4500 K accounts for Type 0 and Type 1 star. Let's deep dive more into Type 0 and Type 1 stars to find more co-relations.

[661]:
```
#filtering type 0 and type 1 star and grouping them by color
df_01 = df_stars[(df_stars['Type'] ==0) | (df_stars['Type']==1)]
df_01.groupby(['Color']).mean().value_counts()
```

[661]:
```
Temperature  L        R        A_M        Type
3140.8875    0.00305  0.22908  15.051737  0.5     1
dtype: int64
```

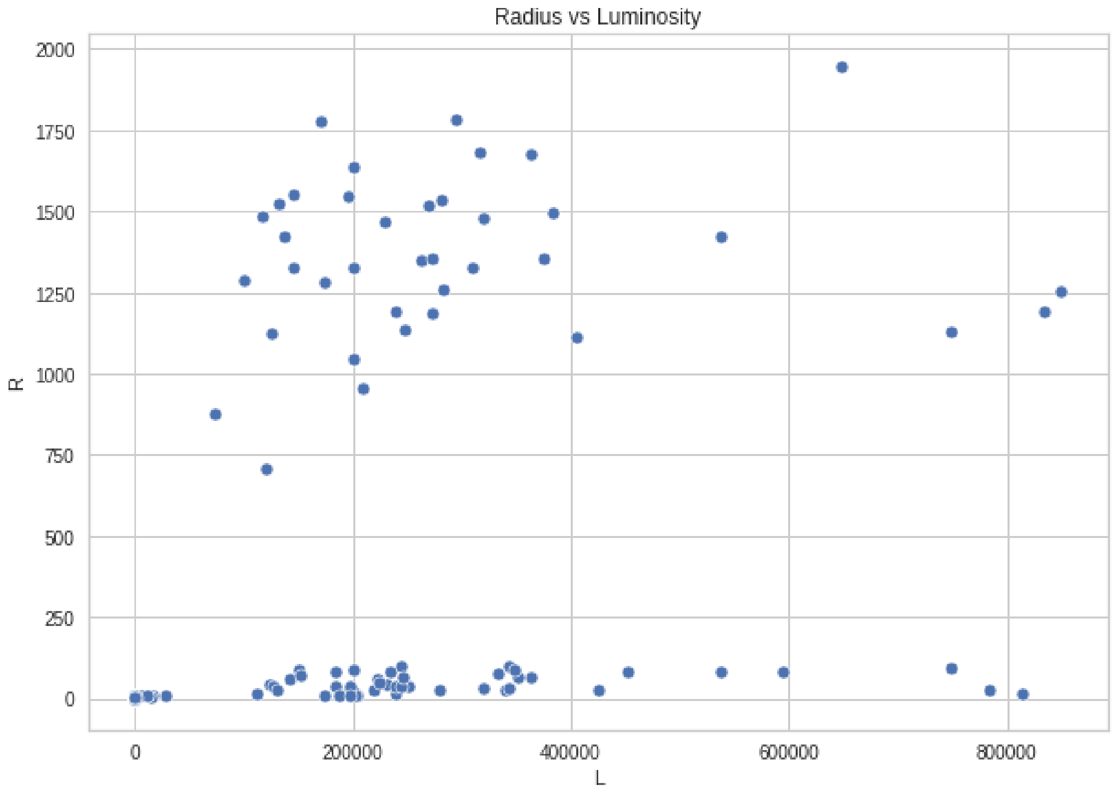
There is only one color of type 0 and type 1 star and it is inferred that temperatures relating to these two types are lower than 4500 K. Now, let's get some insight into temperature and its relation to Luminosity and Radius of a star.

[662]:
```
#plotting a scatter plot between temperature and luminosity
fig, axes = plt.subplots(1,2, figsize=(20,8))
fig.subplots_adjust(hspace=0.5, wspace=0.2)
sns.scatterplot(x=df_stars['L'], y=df_stars['Temperature'], data=df_stars,␣
↪ax=axes[0])
axes[0].set_title("Temperature vs Luminosity")
sns.scatterplot(x=df_stars['R'], y=df_stars['Temperature'], data=df_stars,␣
↪ax=axes[1])
axes[1].set_title("Temperature vs Radius")
plt.show()
```



Neither Luminosity nor Radius have consistent relation with Temperature of the star. They are independent feature of each other but they are directly related to Type of a star. However, the question is what about the relationshio between Luminosity and Radius.

[663]:
```
#relation between luminosity and radius
fig, axes = plt.subplots(figsize=(10,7))
sns.scatterplot(x=df_stars['L'], y=df_stars['R'], data=df_stars, ax=axes)
axes.set_title("Radius vs Luminosity")
plt.show()
```



Even R vs L does not show much consistent dependency on each other, but it is slightly better than afore mentioned other two relations.

[663]:

```

```

2.3 One hot Encoding

Since we wil be including spectral class and Colors into our machine learning model we need to convert it into numerical data beore proceeding. One of the common method used for this purpose is called One Hot Encoding.

[664]:

```
df_stars = pd.get_dummies(df_stars)
df_stars.head()
```

[664]:

```
   Temperature         L       R    A_M  Type  Color_blue  Color_blue-white  \
0         3068  0.002400  0.1700  16.12     0           0                 0
1         3042  0.000500  0.1542  16.60     0           0                 0
2         2600  0.000300  0.1020  18.70     0           0                 0
3         2800  0.000200  0.1600  16.65     0           0                 0
4         1939  0.000138  0.1030  20.06     0           0                 0

   Color_red  Color_white  Color_yellow-white  Spectral_Class_A  \
```

```
0          1         0                   0                  0
1          1         0                   0                  0
2          1         0                   0                  0
3          1         0                   0                  0
4          1         0                   0                  0

   Spectral_Class_B  Spectral_Class_F  Spectral_Class_G  Spectral_Class_K  \
0                 0                 0                 0                 0
1                 0                 0                 0                 0
2                 0                 0                 0                 0
3                 0                 0                 0                 0
4                 0                 0                 0                 0

   Spectral_Class_M  Spectral_Class_O
0                 1                 0
1                 1                 0
2                 1                 0
3                 1                 0
4                 1                 0
```

3 Modeling

Since this is a problem with multi class labels and our features based on analysis don't show any linear relationship, we will use Random Forest alogrithm for better classification. In comparision we will also use AdaBoost Classifier to make some comparisions.

[665]:
```
#imports
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score
from sklearn.model_selection import train_test_split
from sklearn.tree import export_graphviz
from sklearn.ensemble import AdaBoostClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import precision_score
```

Type column is removed from our dataframe to separate it from our predictor features.

[666]:
```
features = df_stars.drop('Type', axis=1)
features.head()
```

[666]:
```
   Temperature         L       R    A_M  Color_blue  Color_blue-white  \
0         3068  0.002400  0.1700  16.12           0                 0
1         3042  0.000500  0.1542  16.60           0                 0
2         2600  0.000300  0.1020  18.70           0                 0
3         2800  0.000200  0.1600  16.65           0                 0
4         1939  0.000138  0.1030  20.06           0                 0
```

```
   Color_red  Color_white  Color_yellow-white  Spectral_Class_A  \
0          1            0                   0                 0
1          1            0                   0                 0
2          1            0                   0                 0
3          1            0                   0                 0
4          1            0                   0                 0

   Spectral_Class_B  Spectral_Class_F  Spectral_Class_G  Spectral_Class_K  \
0                 0                 0                 0                 0
1                 0                 0                 0                 0
2                 0                 0                 0                 0
3                 0                 0                 0                 0
4                 0                 0                 0                 0

   Spectral_Class_M  Spectral_Class_O
0                 1                 0
1                 1                 0
2                 1                 0
3                 1                 0
4                 1                 0
```

3.0.1 Random Forest Model

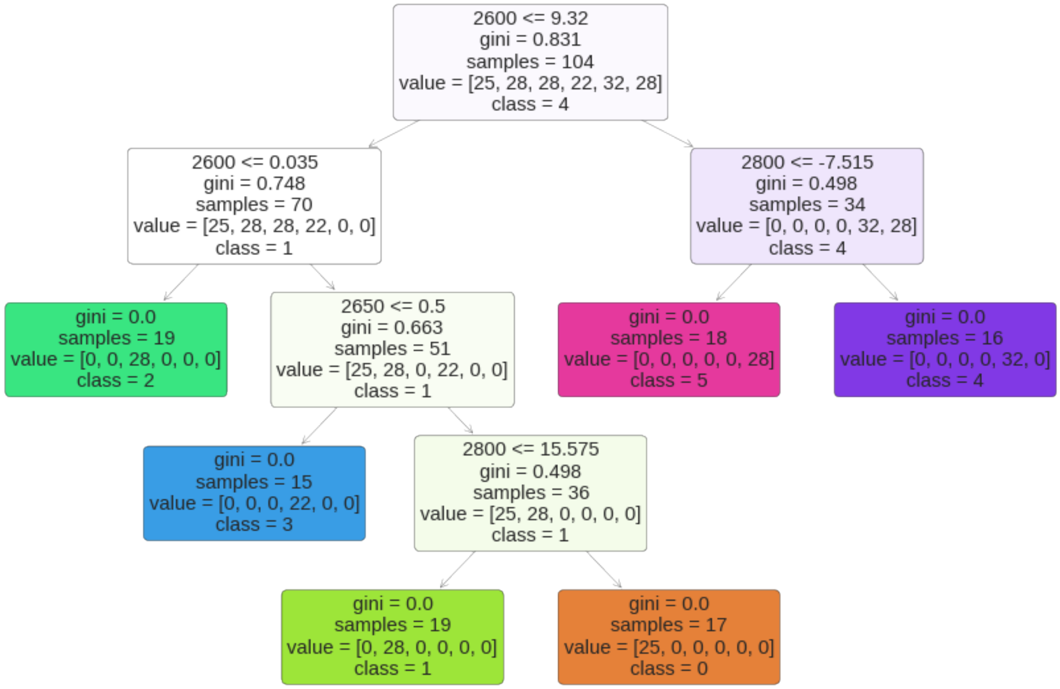
[667]:
```
X = features
y = df_stars.Type

#splitting the data
X_train,X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,␣
↪random_state=42)

#creating object of model
clf = RandomForestClassifier(n_estimators=100, max_depth=5, min_samples_leaf=8,␣
↪min_samples_split=5,bootstrap=True, random_state=23)

clf.fit(X_train, y_train)

#predicting
y_pred = clf.predict(X_test)

#accuracy measure
acc = accuracy_score(y_test, y_pred)

#precision measure
precision = precision_score(y_test, y_pred, average='weighted')

print("accuracy score of Random Forest Classifier is {}".format(acc))
print("Precision score of Random Forest Classifier is {}".format(precision))
```

```
print("Validation score of Random Forest Classifier is {}".format(clf.
 ↪score(X_test,y_test)))
```

```
accuracy score of Random Forest Classifier is 0.9859154929577465
Precision score of Random Forest Classifier is 0.9867957746478874
Validation score of Random Forest Classifier is 0.9859154929577465
```

[668]:
```
#plotting a tree to visualize the decision tree modeling
from sklearn import tree
from sklearn.tree import plot_tree
fig = plt.figure(figsize=(15, 10))
plot_tree(clf.estimators_[0],
          feature_names=df_stars.Temperature,
          class_names=['0','1','2','3','4','5'],
          filled=True, impurity=True,
          rounded=True)
```

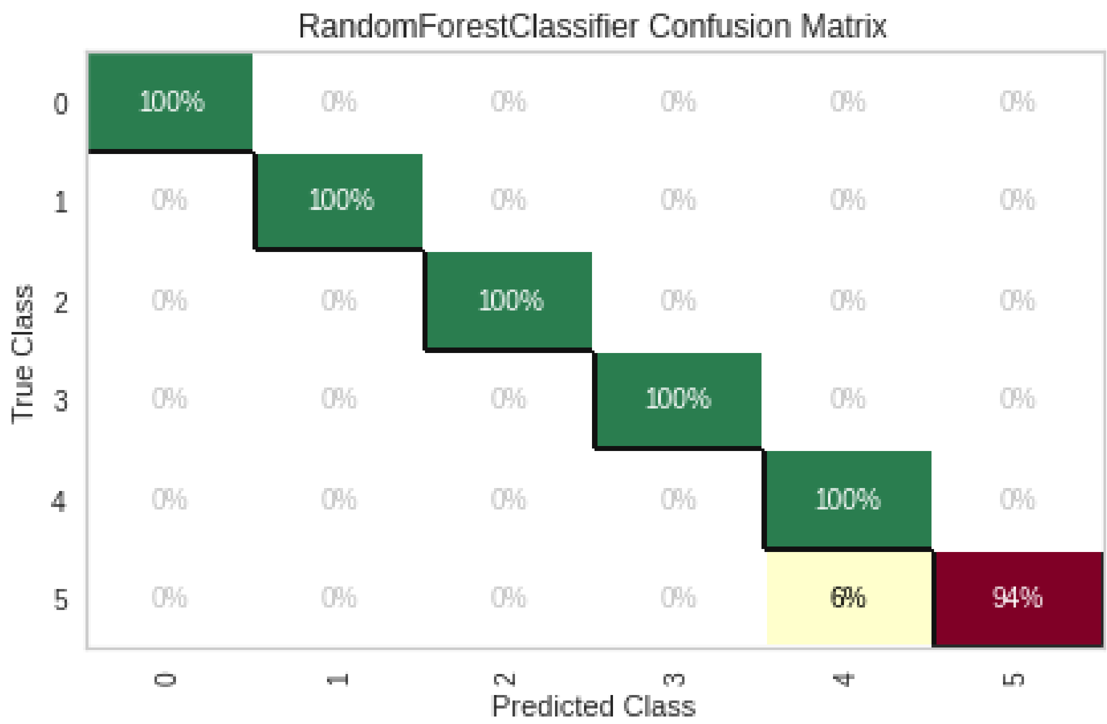
[668]:
```
[Text(0.5, 0.9, '2600 <= 9.32\ngini = 0.831\nsamples = 104\nvalue = [25, 28, 28,
22, 32, 28]\nclass = 4'),
 Text(0.25, 0.7, '2600 <= 0.035\ngini = 0.748\nsamples = 70\nvalue = [25, 28,
28, 22, 0, 0]\nclass = 1'),
 Text(0.125, 0.5, 'gini = 0.0\nsamples = 19\nvalue = [0, 0, 28, 0, 0, 0]\nclass
= 2'),
 Text(0.375, 0.5, '2650 <= 0.5\ngini = 0.663\nsamples = 51\nvalue = [25, 28, 0,
22, 0, 0]\nclass = 1'),
 Text(0.25, 0.3, 'gini = 0.0\nsamples = 15\nvalue = [0, 0, 0, 22, 0, 0]\nclass =
3'),
 Text(0.5, 0.3, '2800 <= 15.575\ngini = 0.498\nsamples = 36\nvalue = [25, 28, 0,
0, 0, 0]\nclass = 1'),
 Text(0.375, 0.1, 'gini = 0.0\nsamples = 19\nvalue = [0, 28, 0, 0, 0, 0]\nclass
= 1'),
 Text(0.625, 0.1, 'gini = 0.0\nsamples = 17\nvalue = [25, 0, 0, 0, 0, 0]\nclass
= 0'),
 Text(0.75, 0.7, '2800 <= -7.515\ngini = 0.498\nsamples = 34\nvalue = [0, 0, 0,
0, 32, 28]\nclass = 4'),
 Text(0.625, 0.5, 'gini = 0.0\nsamples = 18\nvalue = [0, 0, 0, 0, 0, 28]\nclass
= 5'),
 Text(0.875, 0.5, 'gini = 0.0\nsamples = 16\nvalue = [0, 0, 0, 0, 32, 0]\nclass
= 4')]
```



[669]:

```
from sklearn.metrics import confusion_matrix
from yellowbrick.classifier import ConfusionMatrix
visualizer = ConfusionMatrix(clf,␣
↪classes=['0','1','2','3','4','5'],percent=True)
visualizer.fit(X_train, y_train)  # Fit the visualizer and the model
visualizer.score(X_test, y_test)  # Evaluate the model on the test data
visualizer.show()
```

```
/usr/local/lib/python3.7/dist-packages/sklearn/base.py:451: UserWarning: X does
not have valid feature names, but RandomForestClassifier was fitted with feature
names
  "X does not have valid feature names, but"
```

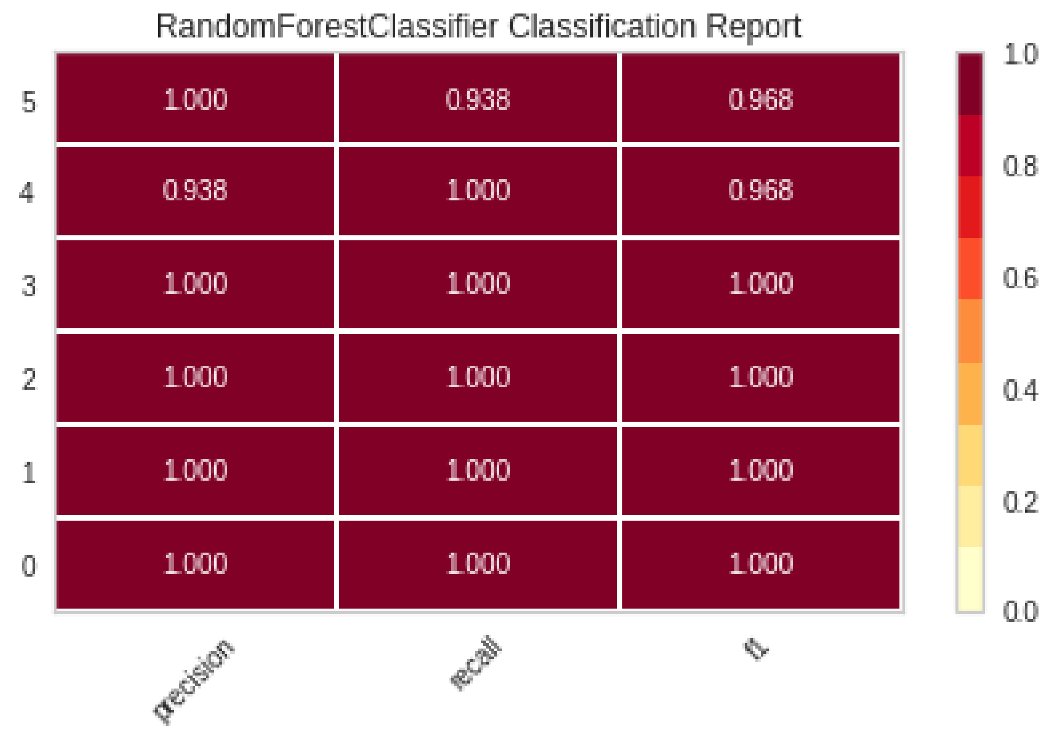


[669]: <AxesSubplot:title={'center':'RandomForestClassifier Confusion Matrix'}, xlabel='Predicted Class', ylabel='True Class'>

Above confusion metrix shows each type of class correctly classified except Type 5 where few labels are wrongly classified as Type 4.

[670]:
```
from yellowbrick.classifier import ClassificationReport
visualizer = ClassificationReport(clf,␣
 ↪classes=['0','1','2','3','4','5'],percent=True)
visualizer.fit(X_train, y_train)  # Fit the visualizer and the model
visualizer.score(X_test, y_test)  # Evaluate the model on the test data
visualizer.poof()
```

```
/usr/local/lib/python3.7/dist-packages/sklearn/base.py:451: UserWarning: X does
not have valid feature names, but RandomForestClassifier was fitted with feature
names
  "X does not have valid feature names, but"
```



[670]: <AxesSubplot:title={'center':'RandomForestClassifier Classification Report'}>

A classification report demonstrates precision, recall and F1 score for all the class labels available for random forest classifier.

3.0.2 AdaBoost Model

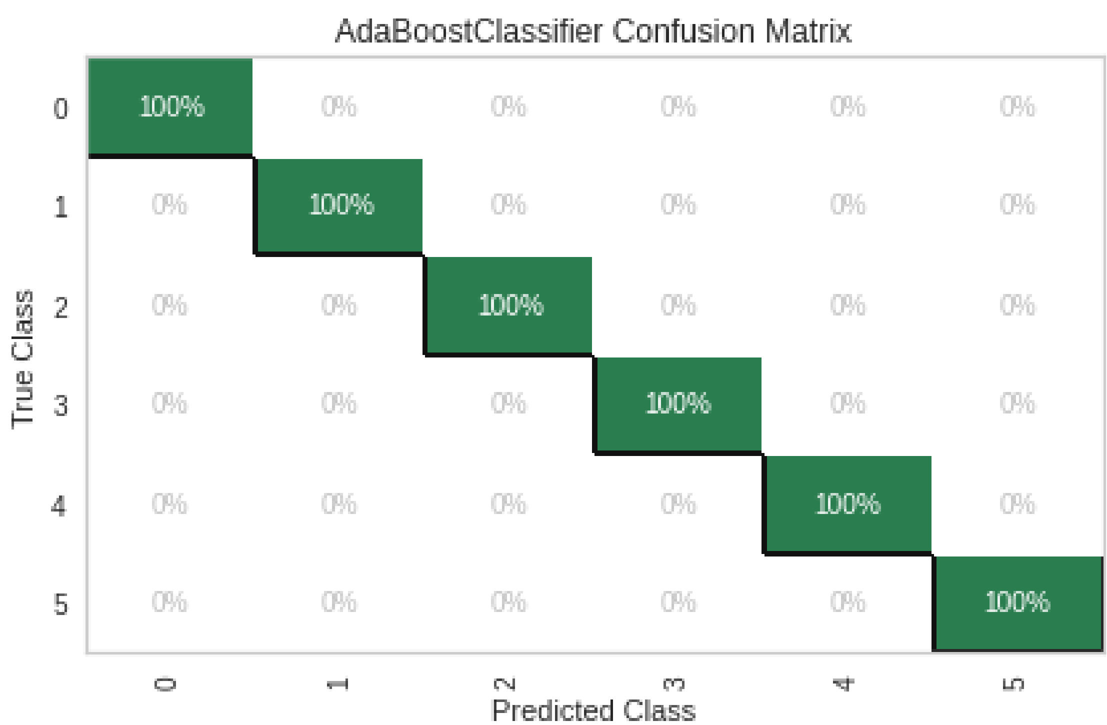
[671]:
```
clf_ada = AdaBoostClassifier( DecisionTreeClassifier(max_depth=5),␣
↪n_estimators=100, learning_rate = 5, random_state=23)

#fitting the model
clf_ada.fit(X_train, y_train)

#predicting
y_pred_ada = clf_ada.predict(X_test)

#accuracy measure
acc = accuracy_score(y_test, y_pred)

#precision measure
precision = precision_score(y_test, y_pred_ada, average='weighted')

print("accuracy score of AdaBoost Classifier is {}".format(acc))
print("Precision score of AdaBoost Classifier is {}".format(precision))
```

```
print("Validation score of AdaBoost Classifier is {}".format(clf.
↪score(X_test,y_test)))
```

```
accuracy score of AdaBoost Classifier is 0.9859154929577465
Precision score of AdaBoost Classifier is 1.0
Validation score of AdaBoost Classifier is 0.9859154929577465
```

[672]:
```
visualizer = ConfusionMatrix(clf_ada,␣
↪classes=['0','1','2','3','4','5'],percent=True)
visualizer.fit(X_train, y_train)  # Fit the visualizer and the model
visualizer.score(X_test, y_test)  # Evaluate the model on the test data
visualizer.poof()
```

```
/usr/local/lib/python3.7/dist-packages/sklearn/base.py:451: UserWarning: X does
not have valid feature names, but AdaBoostClassifier was fitted with feature
names
  "X does not have valid feature names, but"
```

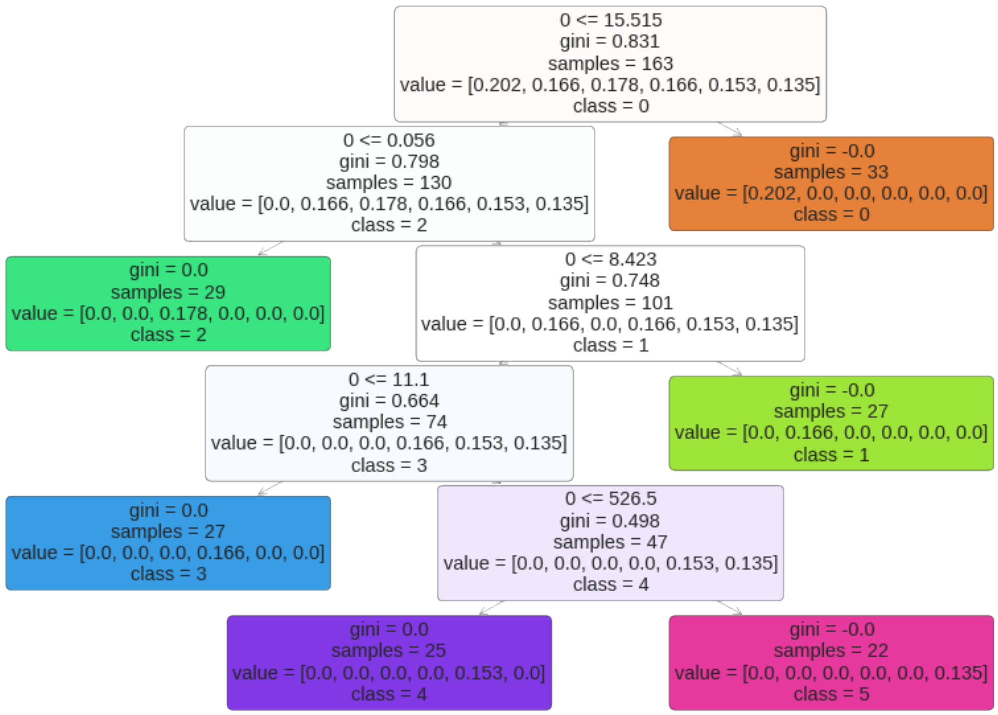


[672]:
```
<AxesSubplot:title={'center':'AdaBoostClassifier Confusion Matrix'},
xlabel='Predicted Class', ylabel='True Class'>
```

AdaBoost Classifier Confusion matrix has 100% classification rate for each type of label.

[673]:
```
fig = plt.figure(figsize=(15, 10))
plot_tree(clf_ada.estimators_[0],
          feature_names=df_stars.Color_blue,
          class_names=['0','1','2','3','4','5'],
          filled=True, impurity=True,
          rounded=True)
```

[673]:
```
[Text(0.6, 0.9166666666666666, '0 <= 15.515\ngini = 0.831\nsamples = 163\nvalue
= [0.202, 0.166, 0.178, 0.166, 0.153, 0.135]\nclass = 0'),
 Text(0.4, 0.75, '0 <= 0.056\ngini = 0.798\nsamples = 130\nvalue = [0.0, 0.166,
0.178, 0.166, 0.153, 0.135]\nclass = 2'),
 Text(0.2, 0.5833333333333334, 'gini = 0.0\nsamples = 29\nvalue = [0.0, 0.0,
0.178, 0.0, 0.0, 0.0]\nclass = 2'),
 Text(0.6, 0.5833333333333334, '0 <= 8.423\ngini = 0.748\nsamples = 101\nvalue =
[0.0, 0.166, 0.0, 0.166, 0.153, 0.135]\nclass = 1'),
 Text(0.4, 0.4166666666666667, '0 <= 11.1\ngini = 0.664\nsamples = 74\nvalue =
[0.0, 0.0, 0.0, 0.166, 0.153, 0.135]\nclass = 3'),
 Text(0.2, 0.25, 'gini = 0.0\nsamples = 27\nvalue = [0.0, 0.0, 0.0, 0.166, 0.0,
0.0]\nclass = 3'),
 Text(0.6, 0.25, '0 <= 526.5\ngini = 0.498\nsamples = 47\nvalue = [0.0, 0.0,
0.0, 0.0, 0.153, 0.135]\nclass = 4'),
 Text(0.4, 0.08333333333333333, 'gini = 0.0\nsamples = 25\nvalue = [0.0, 0.0,
0.0, 0.0, 0.153, 0.0]\nclass = 4'),
 Text(0.8, 0.08333333333333333, 'gini = -0.0\nsamples = 22\nvalue = [0.0, 0.0,
0.0, 0.0, 0.0, 0.135]\nclass = 5'),
 Text(0.8, 0.4166666666666667, 'gini = -0.0\nsamples = 27\nvalue = [0.0, 0.166,
0.0, 0.0, 0.0, 0.0]\nclass = 1'),
 Text(0.8, 0.75, 'gini = -0.0\nsamples = 33\nvalue = [0.202, 0.0, 0.0, 0.0, 0.0,
0.0]\nclass = 0')]
```



3.1 Conclusion

1. Model correctly identifies the Type of a star with an accuracy of 0.98% for Random forest model and 1% accuracy for AdaBoost model.
2. Stars having temperatues below 5000 K and color as red are mostly of Type 1 or 0.
3. There are very few stars with Orange and Orange-red spectrum.
4. There is inconsistent corelation between Temperature vs Luminosity and Radius.

[673]: