machine-learning-star-type-classification

February 5, 2022

[1]:
```
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)

import os
```

1 Part 1: Method-ML Algorithams

[2]:
```
#ML Librarires
from sklearn.model_selection import train_test_split, cross_val_score,␣
↪GridSearchCV
from sklearn.metrics import accuracy_score, precision_score, recall_score,␣
↪roc_auc_score, f1_score, confusion_matrix, precision_recall_curve, roc_curve
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
import lightgbm as lgb

from imblearn.under_sampling import RandomUnderSampler
from imblearn.over_sampling import RandomOverSampler
from imblearn.over_sampling import SMOTE

import seaborn as sns
import missingno as msno
import plotly.express as px
import  matplotlib.pyplot as plt


plt.style.use('seaborn')
%matplotlib inline
```

```
<IPython.core.display.HTML object>
```

2 Data Read

[3]:
```python
df = pd.read_csv('../input/star-type-classification/Stars.csv')
df.head()
```

[3]:
```
   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
```

[4]:
```python
df.shape
```

[4]:
```
(240, 7)
```

[5]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 240 entries, 0 to 239
Data columns (total 7 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   Temperature     240 non-null    int64
 1   L               240 non-null    float64
 2   R               240 non-null    float64
 3   A_M             240 non-null    float64
 4   Color           240 non-null    object
 5   Spectral_Class  240 non-null    object
 6   Type            240 non-null    int64
dtypes: float64(3), int64(2), object(2)
memory usage: 13.2+ KB
```

[6]:
```python
df.describe()
```

[6]:
```
        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
```

[7]:
```python
df=df.sample(frac=1).reset_index(drop=True)
```

df = df.sample(frac=1).reset_index(drop=True)

Here, specifying drop=True prevents .reset_index from creating a column containing the old index entries.

3 Exploratory Data Analysis & Data Pre-Processing

[8]:
```
pd.DataFrame(df.isnull().sum(), columns=["Null Count"])
```

[8]:

	Null Count
Temperature	0
L	0
R	0
A_M	0
Color	0
Spectral_Class	0
Type	0

[9]:
```
#Or
#missing values cheacking
df.apply(lambda x: sum(x.isnull()),axis=0)
```

[9]:
```
Temperature       0
L                 0
R                 0
A_M               0
Color             0
Spectral_Class    0
Type              0
dtype: int64
```

[10]:
```
from sklearn import preprocessing
```

[11]:
```
#Label Encoding

le = preprocessing.LabelEncoder()

# columns to select for encoding
selected_col = ['Color','Spectral_Class']

le.fit(df[selected_col].values.flatten())

df[selected_col] = df[selected_col].apply(le.fit_transform)
```

[12]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 240 entries, 0 to 239
Data columns (total 7 columns):
```

```
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   Temperature     240 non-null    int64
 1   L               240 non-null    float64
 2   R               240 non-null    float64
 3   A_M             240 non-null    float64
 4   Color           240 non-null    int64
 5   Spectral_Class  240 non-null    int64
 6   Type            240 non-null    int64
dtypes: float64(3), int64(4)
memory usage: 13.2 KB
```

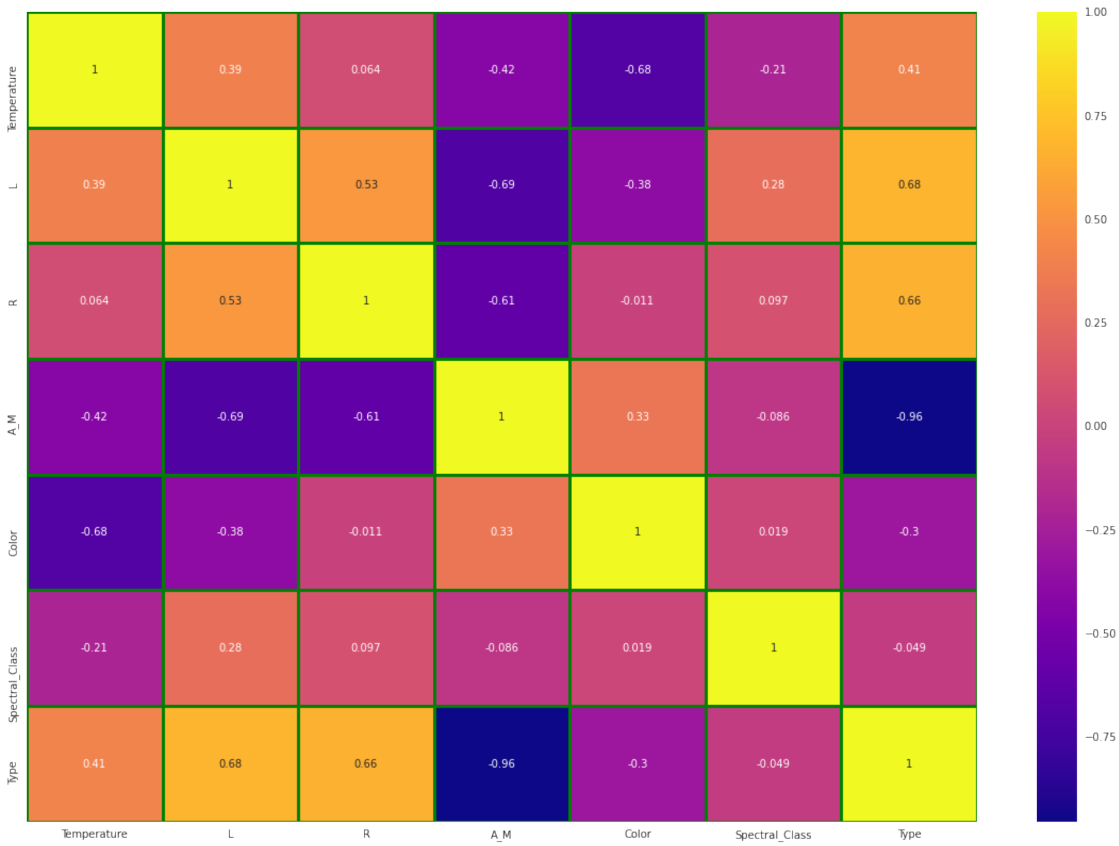
[13]:
```
df.head()
```

[13]:

	Temperature	L	R	A_M	Color	Spectral_Class	Type
0	3752	209000.000000	955.00000	-11.24	8	5	5
1	3180	0.001000	0.35000	11.76	8	5	1
2	2968	0.000461	0.11900	17.45	8	5	0
3	12984	0.000880	0.00996	11.23	1	1	2
4	6757	1.430000	1.12000	2.41	15	2	3

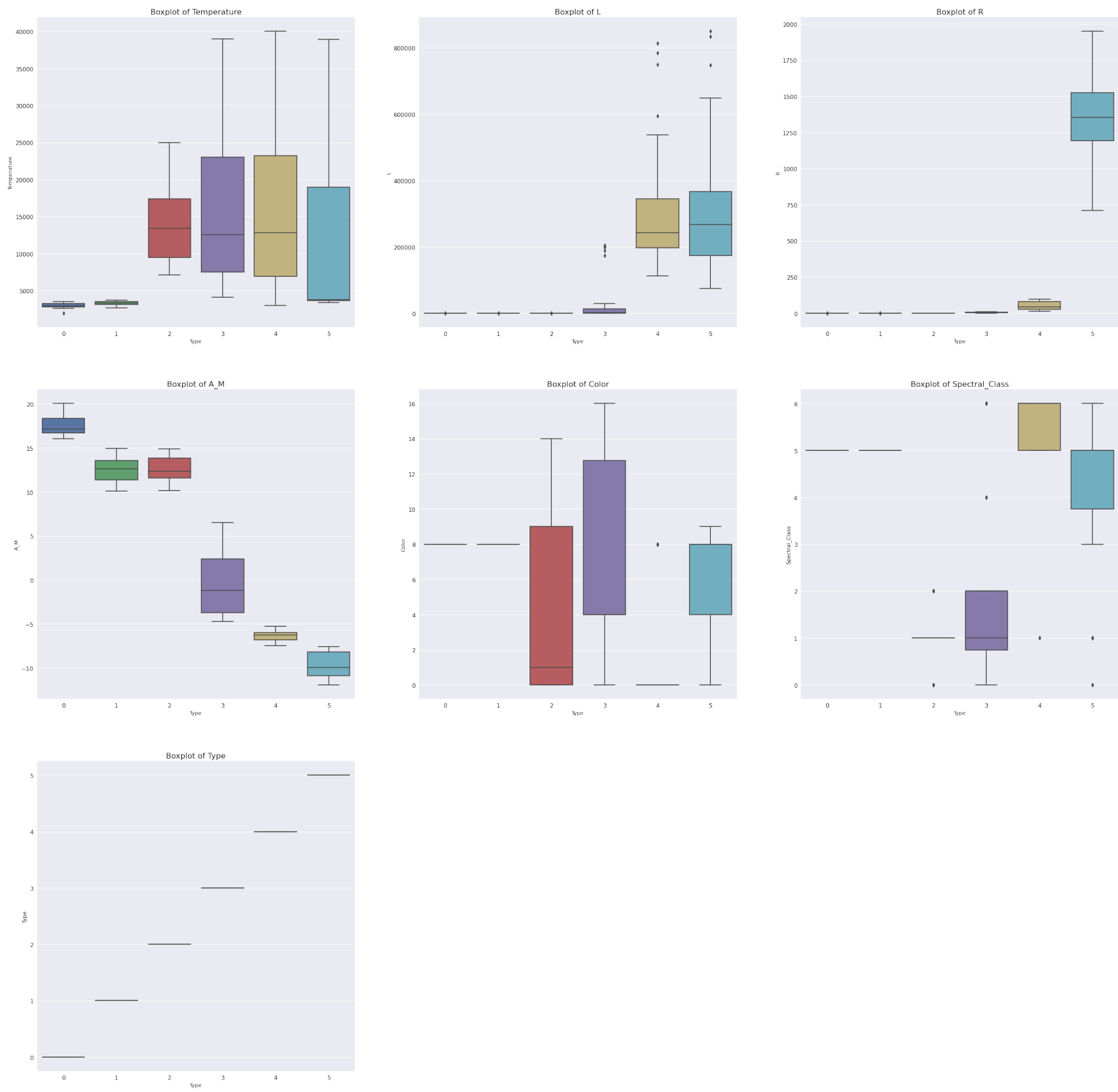
[14]:
```
#Plotting data
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
import plotly.express as px

plt.figure(figsize=(20,14))
sns.heatmap(df.corr(),annot=True,linecolor='green',linewidths=3,cmap = 'plasma')
#Data Cor-Relation
```

[14]: <AxesSubplot:>



[15]:

```
#Box Plotting All features distribution corresponding Target column
i=1
plt.figure(figsize=(40,40))
for c in df.columns[:]:
    plt.subplot(3,3,i)
    plt.title(f"Boxplot of {c}",fontsize=16)
    plt.yticks(fontsize=12)
    plt.xticks(fontsize=12)
    sns.boxplot(y=df[c],x=df['Type'])
    i+=1
plt.show()
```



#Skewness of Data

[16]:
```
# the data columns
cols = ['Temperature', 'L', 'R', 'A_M', 'Color', 'Spectral_Class']
target = ["Type"]
```

[17]:
```
import scipy.stats as stats
pd.set_option('display.max_columns', None)
plt.style.use('ggplot')
```

[18]:
```
fig,ax = plt.subplots(3,2, figsize=(16, 12))
ax = ax.flatten()
i = 0
for col in cols:
```

```
    skew = df[col].skew()
    sns.distplot(df[col], ax = ax[i], fit= stats.norm, kde=False, label='Skew =␣
 ↪%.3f' %(skew))
    ax[i].legend(loc='best')
    i += 1
plt.show()
```

```
/opt/conda/lib/python3.7/site-packages/seaborn/distributions.py:2557:
FutureWarning: `distplot` is a deprecated function and will be removed in a
future version. Please adapt your code to use either `displot` (a figure-level
function with similar flexibility) or `histplot` (an axes-level function for
histograms).
  warnings.warn(msg, FutureWarning)
/opt/conda/lib/python3.7/site-packages/seaborn/distributions.py:2557:
FutureWarning: `distplot` is a deprecated function and will be removed in a
future version. Please adapt your code to use either `displot` (a figure-level
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function with similar flexibility) or `histplot` (an axes-level function for
histograms).
  warnings.warn(msg, FutureWarning)
/opt/conda/lib/python3.7/site-packages/seaborn/distributions.py:2557:
FutureWarning: `distplot` is a deprecated function and will be removed in a
future version. Please adapt your code to use either `displot` (a figure-level
function with similar flexibility) or `histplot` (an axes-level function for
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function with similar flexibility) or `histplot` (an axes-level function for
histograms).
  warnings.warn(msg, FutureWarning)
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FutureWarning: `distplot` is a deprecated function and will be removed in a
future version. Please adapt your code to use either `displot` (a figure-level
function with similar flexibility) or `histplot` (an axes-level function for
histograms).
  warnings.warn(msg, FutureWarning)
```
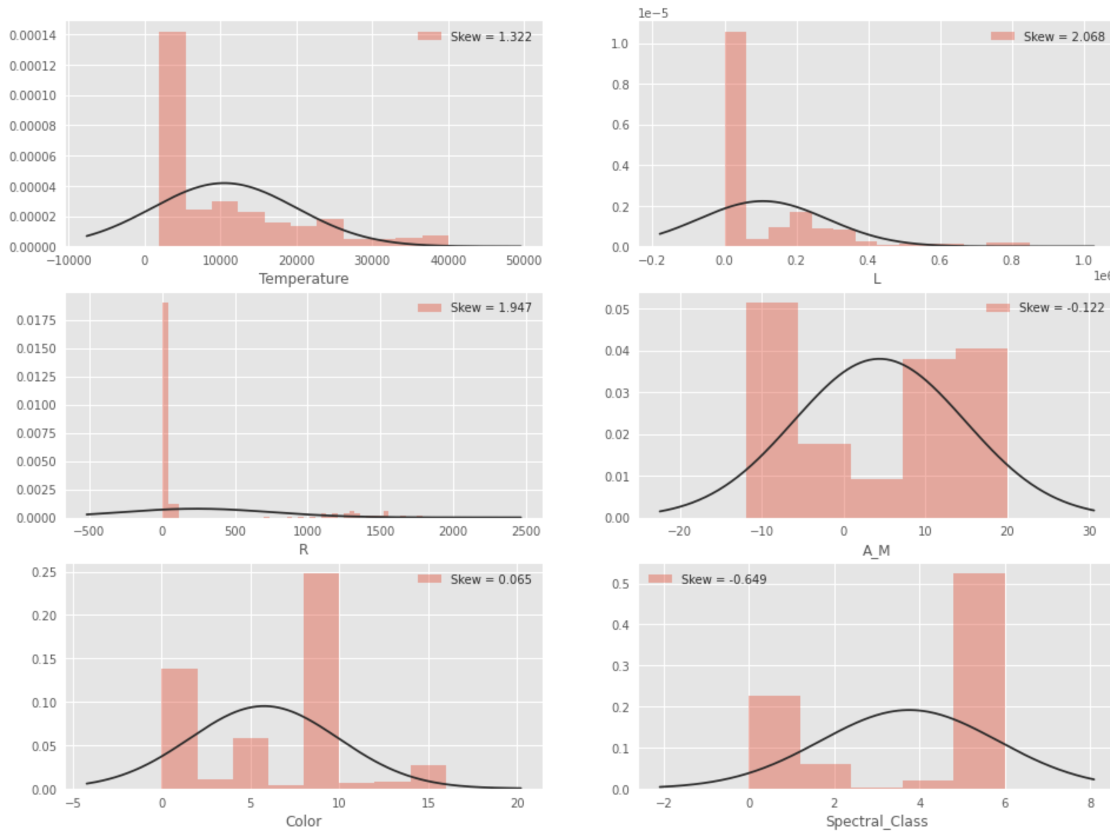



None of the features are normally distributed and some have outliers

Note: Outlier treatment maybe done to check impact on classification

Deatils: https://www.analyticsvidhya.com/blog/2020/07/what-is-skewness-statistics/

[19]:
```
#checking the target variable countplot

print("class :", df["Type"].unique())
print()

print("Value Count :\n",df["Type"].value_counts())
```

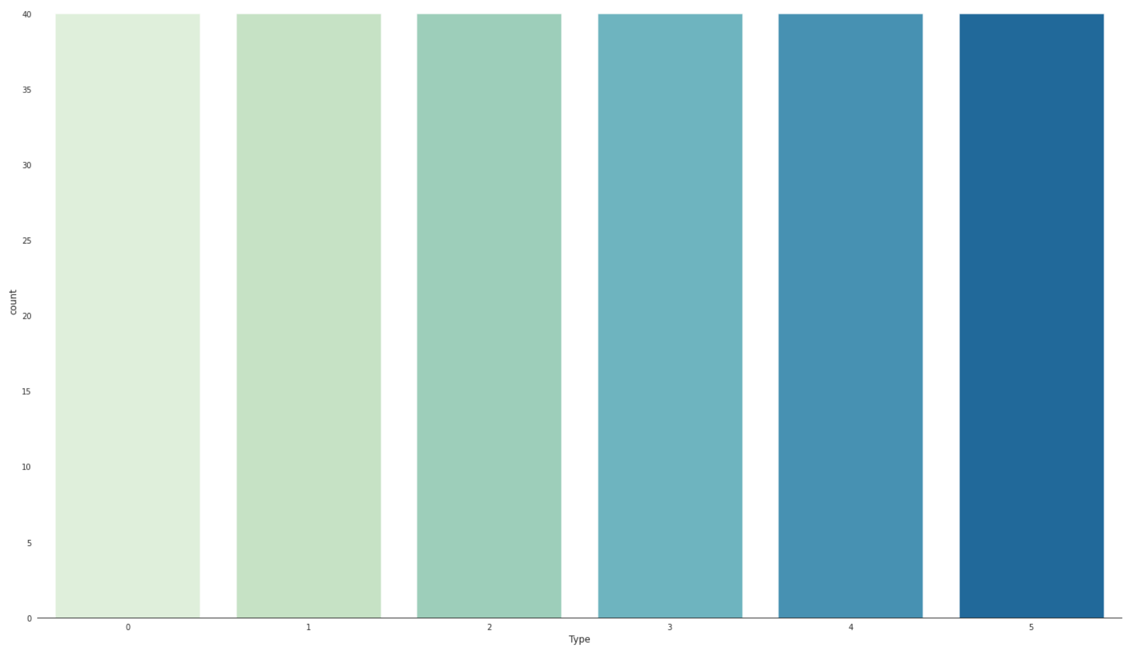
```
class : [5 1 0 2 3 4]

Value Count :
 0    40
1    40
2    40
3    40
4    40
5    40
```

Name: Type, dtype: int64

[20]:
```
len(df["Type"].value_counts())
```

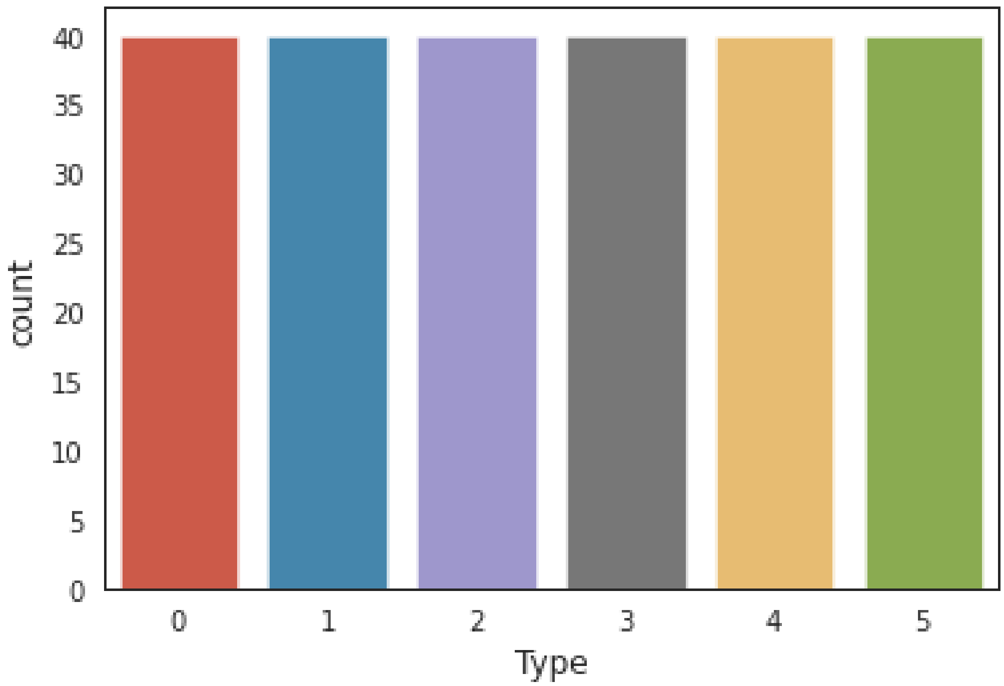
[20]: 6

[21]:
```
#checking the target variable countplot

plt.figure(figsize=(25,15))
sns.set_style('white')
sns.countplot(x='Type', data = df, palette='GnBu')
sns.despine(left=True)
```



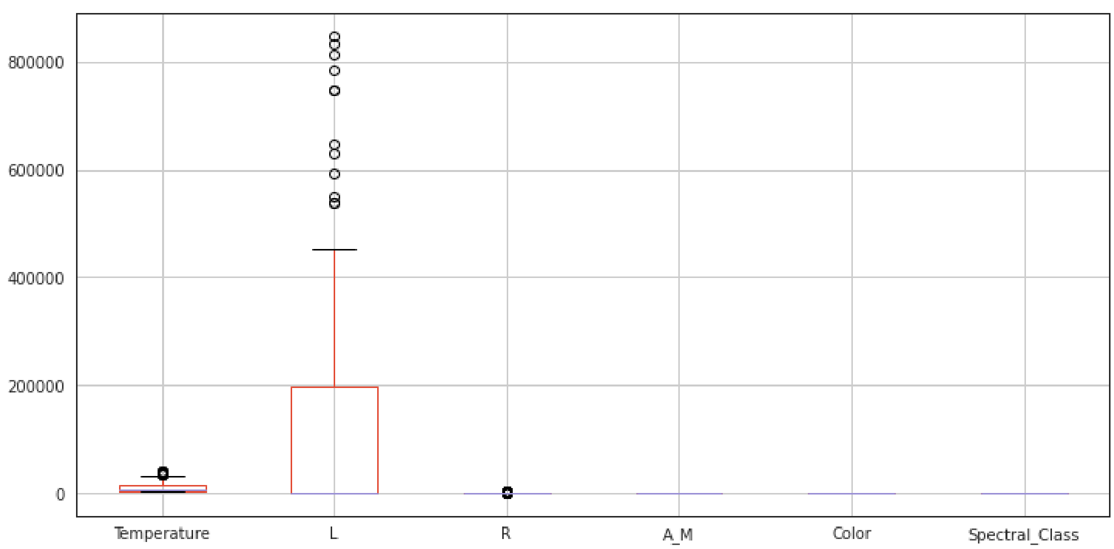
[22]:
```
sns.countplot(df["Type"])
plt.show()
```

```
/opt/conda/lib/python3.7/site-packages/seaborn/_decorators.py:43: FutureWarning:
Pass the following variable as a keyword arg: x. From version 0.12, the only
valid positional argument will be `data`, and passing other arguments without an
explicit keyword will result in an error or misinterpretation.
  FutureWarning
```



Univariate Box Plot

[23]:
```
df.iloc[:,:-1].boxplot(figsize=(12,6))
plt.show()
```



Observations:¶ - L is the main component of Df making more than 70% of composition - Combined temp and L make up around 90% - A_M, Color, R, spectral are the least important components

Above box plot confirms the outliers

I prefer to use models without outlier treatment, in many cases it can improve the model performance. But it also leads to change of information which might alter real/practical situations

Bivariate Box plots

[24]:
```
fig,ax = plt.subplots(3,2, figsize=(16, 12))
ax = ax.flatten()
i = 0
for col in cols:
    sns.boxplot("Type", col, ax = ax[i], data=df)
    ax[i].legend([col], loc='best')
    i += 1
plt.tight_layout()
plt.show()
```

```
/opt/conda/lib/python3.7/site-packages/seaborn/_decorators.py:43: FutureWarning:
Pass the following variables as keyword args: x, y. From version 0.12, the only
valid positional argument will be `data`, and passing other arguments without an
explicit keyword will result in an error or misinterpretation.
  FutureWarning
/opt/conda/lib/python3.7/site-packages/seaborn/_decorators.py:43: FutureWarning:
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valid positional argument will be `data`, and passing other arguments without an
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  FutureWarning
/opt/conda/lib/python3.7/site-packages/seaborn/_decorators.py:43: FutureWarning:
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valid positional argument will be `data`, and passing other arguments without an
explicit keyword will result in an error or misinterpretation.
  FutureWarning
/opt/conda/lib/python3.7/site-packages/seaborn/_decorators.py:43: FutureWarning:
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explicit keyword will result in an error or misinterpretation.
  FutureWarning
/opt/conda/lib/python3.7/site-packages/seaborn/_decorators.py:43: FutureWarning:
Pass the following variables as keyword args: x, y. From version 0.12, the only
valid positional argument will be `data`, and passing other arguments without an
explicit keyword will result in an error or misinterpretation.
  FutureWarning
/opt/conda/lib/python3.7/site-packages/seaborn/_decorators.py:43: FutureWarning:
Pass the following variables as keyword args: x, y. From version 0.12, the only
valid positional argument will be `data`, and passing other arguments without an
explicit keyword will result in an error or misinterpretation.
  FutureWarning
```
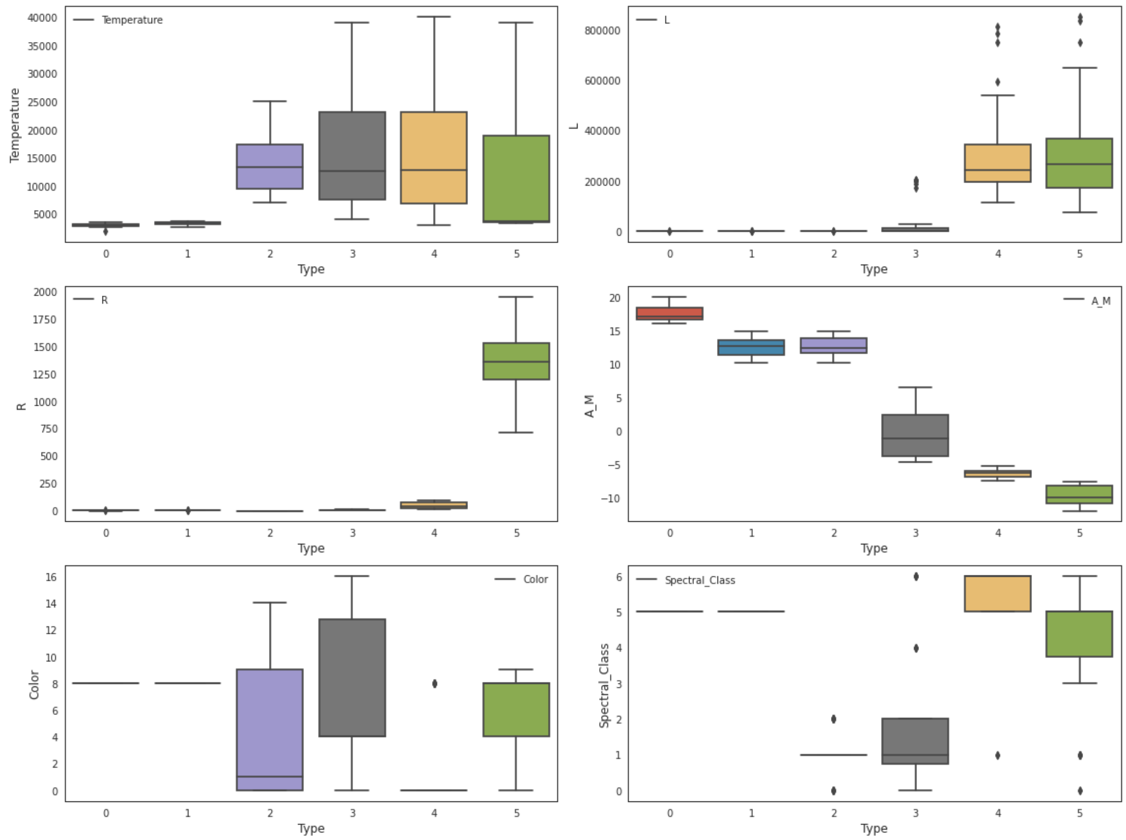
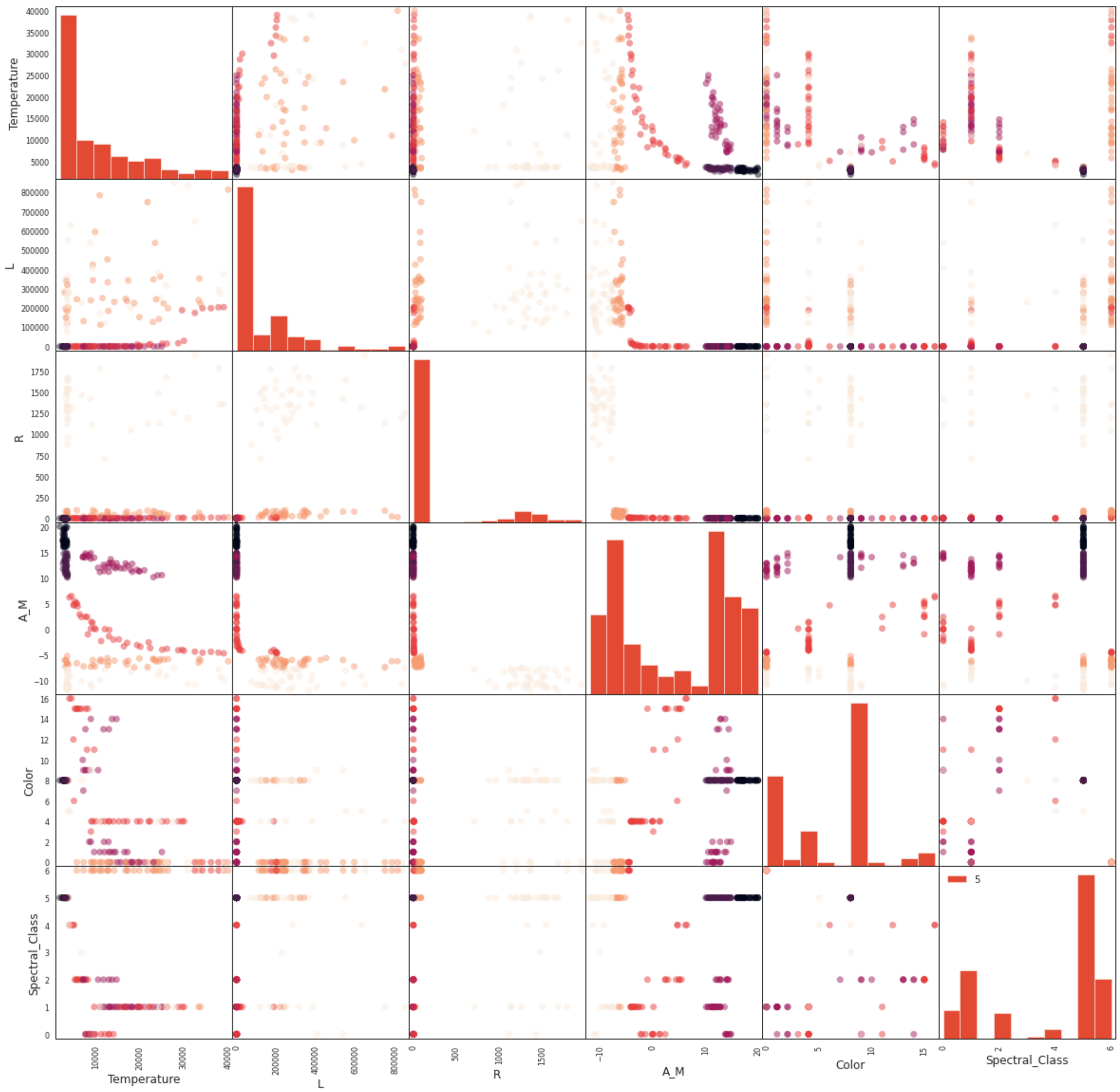



[25]:

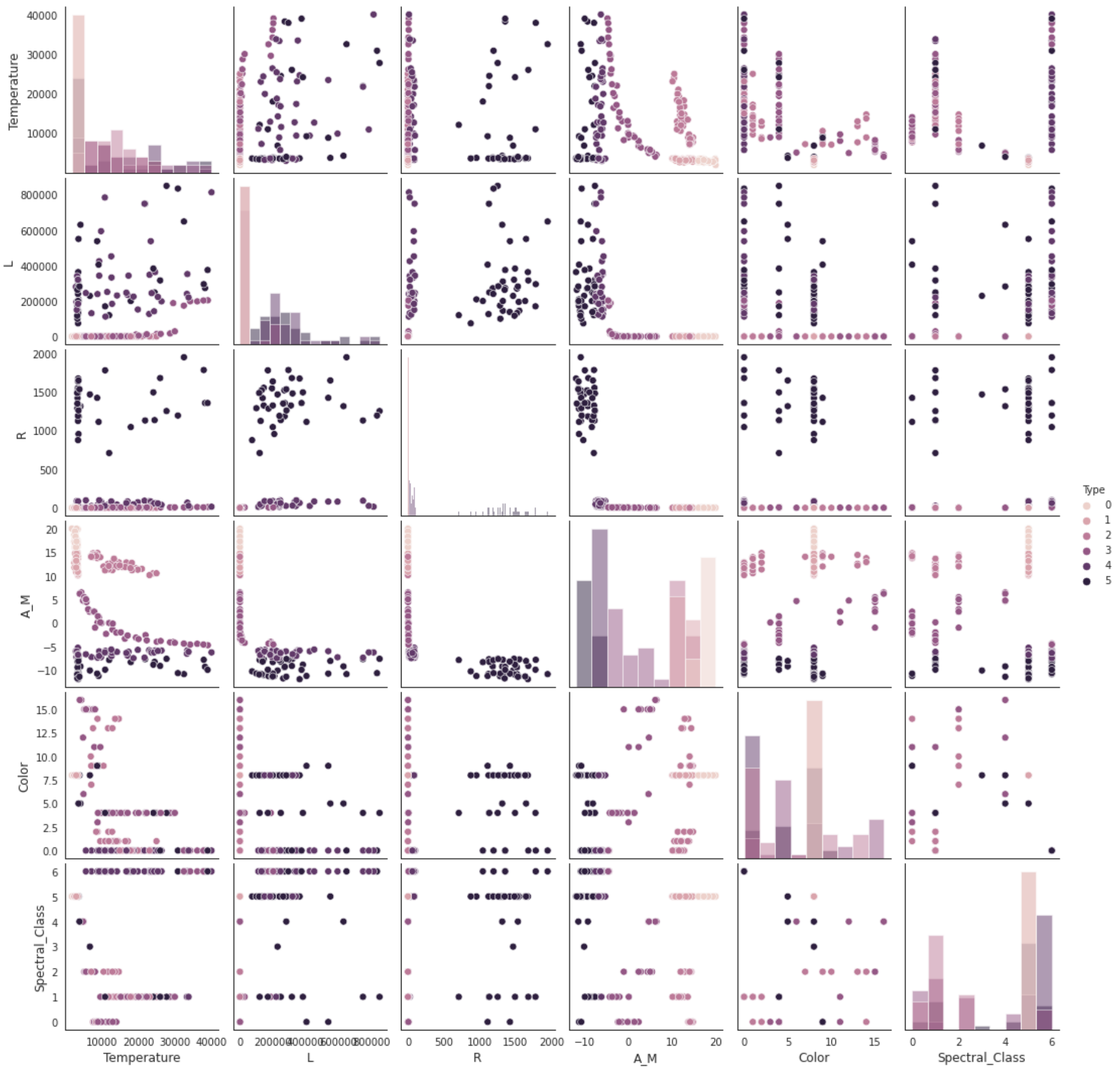
```
#Scatter Matrix
pd.plotting.scatter_matrix(df.iloc[:,:-1], c=df.iloc[:,-1], figsize=(20, 20),␣
↪marker='o')
plt.legend(df["Type"].unique())
plt.show()
```

```
/opt/conda/lib/python3.7/site-packages/pandas/plotting/_matplotlib/tools.py:400:
MatplotlibDeprecationWarning:
The is_first_col function was deprecated in Matplotlib 3.4 and will be removed
two minor releases later. Use ax.get_subplotspec().is_first_col() instead.
  if ax.is_first_col():
```

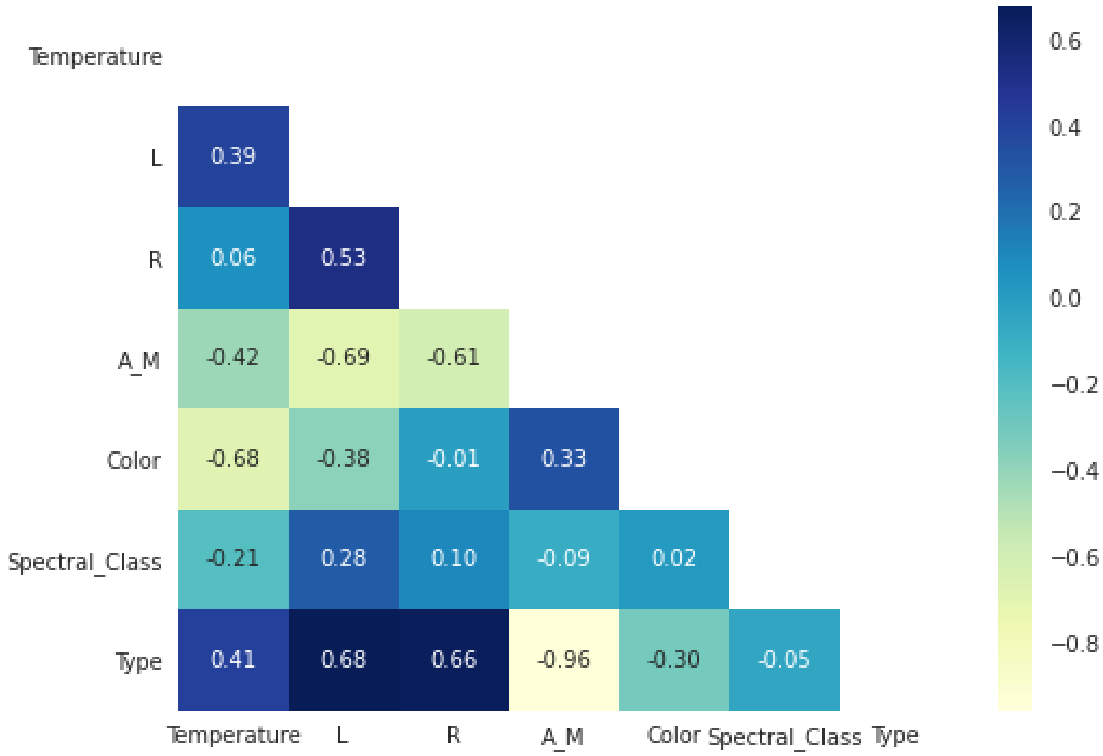


[26]:

```
#Pairplot
sns.pairplot(df, hue='Type', diag_kind='hist')
plt.show()
```



[27]:
```
#Correlation Plot
plt.figure(figsize=(8,6))
corr = df.corr()
mask = np.zeros_like(corr)
mask[np.triu_indices_from(mask)] = True
sns.heatmap(corr, annot=True, fmt= '.2f', cmap='YlGnBu', mask=mask)
plt.show()
```



[28]:
```
#A_M,Color and Spectral have no correlation with Type,
#which means for some type it maybe high for some low causing cancelling effect
```

[29]:
```
df.groupby("Type")["Color"].mean()
```

[29]:
```
Type
0    8.000
1    8.000
2    4.025
3    6.875
4    1.800
5    5.900
Name: Color, dtype: float64
```

[30]:
```
df.groupby("Type")["R"].mean()
```

[30]:
```
Type
0       0.110015
1       0.348145
2       0.010728
3       4.430300
4      51.150000
5    1366.897500
```

```
Name: R, dtype: float64
```

Statistical Importance Check for Variable

```
[31]: import statsmodels.api as sm
      import statsmodels.stats as sms

      for col in cols:
          data = sm.formula.ols(col+"~ Type", data=df).fit()
          pval = sms.anova.anova_lm(data)["PR(>F)"][0]
          print(f"Pval for {col}: {pval}")
```

```
Pval for Temperature: 3.323401956092008e-11
Pval for L: 1.641155523850019e-33
Pval for R: 1.6272694239286276e-31
Pval for A_M: 6.33087509199859e-128
Pval for Color: 1.4684325869921742e-06
Pval for Spectral_Class: 0.44868186785826514
```

Data Preprocessing & Evaluation Functions

```
[32]: seed = 42

      from sklearn.preprocessing import StandardScaler, RobustScaler
      from sklearn.model_selection import RandomizedSearchCV, cross_val_score,␣
       ↪StratifiedKFold
      from sklearn.metrics import classification_report, roc_auc_score, roc_curve
      from sklearn.tree import DecisionTreeClassifier
      from sklearn.ensemble import AdaBoostClassifier, GradientBoostingClassifier,␣
       ↪RandomForestClassifier,\
                                   BaggingClassifier,VotingClassifier
      from sklearn.neighbors import KNeighborsClassifier
      from sklearn.naive_bayes import GaussianNB
      from xgboost import XGBClassifier
      from lightgbm import LGBMClassifier
      from sklearn.linear_model import LogisticRegression
      from sklearn.pipeline import make_pipeline, Pipeline
```

```
[33]: # split the data into train and test
      def split_data(X, Y, seed=42, train_size=0.8):
          xtrain, xtest, ytrain, ytest = train_test_split(X, Y,␣
       ↪train_size=train_size, random_state = seed, stratify=Y)
          xtrain, xtest = preprocess(xtrain, xtest)
          return (xtrain, xtest, ytrain, ytest)

      # preprocess the data for training
      def preprocess(x1, x2=None):
          sc = StandardScaler()
```

```
    x1 = pd.DataFrame(sc.fit_transform(x1), columns=x1.columns)
    if x2 is not None:
        x2 = pd.DataFrame(sc.transform(x2), columns=x2.columns)
        return (x1,x2)
    return x1

# for model evaluation and training
def eval_model(model, X, Y, seed=1):
    xtrain, xtest, ytrain, ytest = split_data(X, Y)
    model.fit(xtrain, ytrain)

    trainpred = model.predict(xtrain)
    trainpred_prob = model.predict_proba(xtrain)
    testpred = model.predict(xtest)
    testpred_prob = model.predict_proba(xtest)

    print("Train ROC AUC : %.4f"%roc_auc_score(ytrain, trainpred_prob,␣
 ↪multi_class='ovr'))
    print("\nTrain classification report\n",classification_report(ytrain,␣
 ↪trainpred))

    ### make a bar chart for displaying the wrong classification of one class␣
 ↪coming in which other class

    print("\nTest ROC AUC : %.4f"%roc_auc_score(ytest, testpred_prob,␣
 ↪multi_class='ovr'))
    print("\nTest classification report\n",classification_report(ytest,␣
 ↪testpred))

def plot_importance(columns, importance):
    plt.bar(columns, importance)
    plt.show()
```

[34]:
```
#Feature Extraction, Importance & Splitting

Y= df['Type']

X = df.drop(['Type'],axis = 1)
```

[35]:
```
X_sc = preprocess(X)
```

Creating array of models

[36]:
```
model_logr = LogisticRegression(random_state=seed,n_jobs=-1)
model_nb = GaussianNB()
model_dt = DecisionTreeClassifier(random_state=seed)
model_dt_bag = BaggingClassifier(model_dt, random_state=seed, n_jobs=-1)
```

```
model_ada = AdaBoostClassifier(random_state=seed)
model_gbc = GradientBoostingClassifier(random_state=seed)
model_rf = RandomForestClassifier(random_state=seed, n_jobs=-1)
model_xgb = XGBClassifier(random_state=seed)
model_lgbm = LGBMClassifier(random_state=seed, n_jobs=-1)
model_knn = KNeighborsClassifier(n_jobs=-1)
```

[37]:
```
models = []
models.append(('LR',model_logr))
models.append(('NB',model_nb))
models.append(('DT',model_dt))
models.append(('Bag',model_dt_bag))
models.append(('Ada',model_ada))
models.append(('GBC',model_gbc))
models.append(('RF',model_rf))
models.append(('XGB',model_xgb))
models.append(('LGBM',model_lgbm))
models.append(('KNN',model_knn))
```

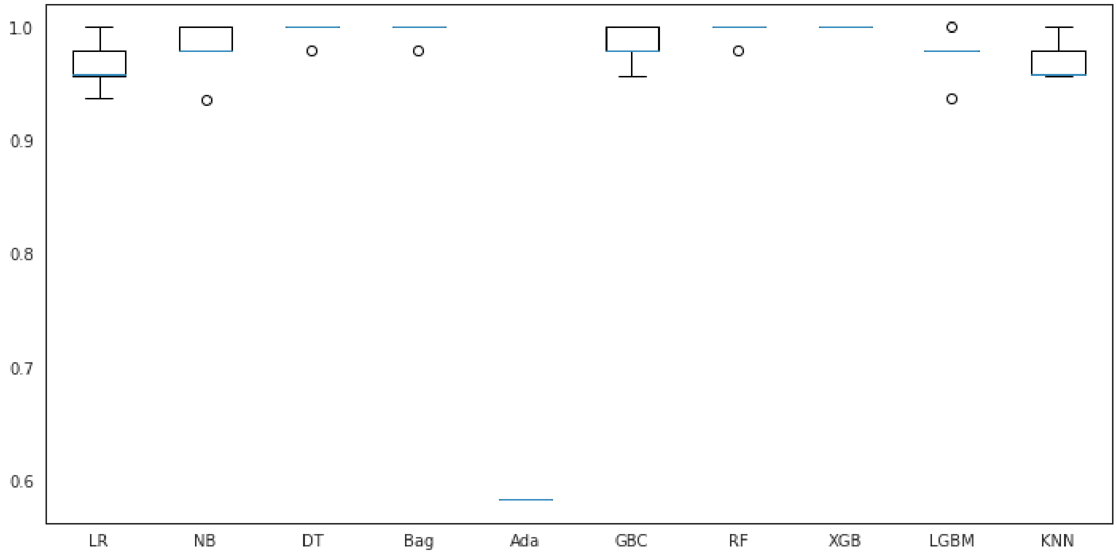
Running the algorithms

[38]:
```
cv = StratifiedKFold(n_splits=5, shuffle=True, random_state=seed)

results = []
names = []

for name, model in models:
    scores = cross_val_score(model, X_sc, Y, scoring='f1_weighted', cv=cv,␣
 ↪n_jobs=-1)
    accuracy = scores.mean()
    std = scores.std()
    print(f"{name} : Mean ROC {accuracy} STD:({std})")
    results.append(scores)
    names.append(name)
```

```
LR : Mean ROC 0.9664091192032369 STD:(0.0214225403052214)
NB : Mean ROC 0.9787675070028012 STD:(0.023492300999750942)
DT : Mean ROC 0.9958169934640523 STD:(0.008366013071895394)
Bag : Mean ROC 0.9958169934640523 STD:(0.008366013071895394)
Ada : Mean ROC 0.5833333333333334 STD:(0.0)
GBC : Mean ROC 0.983168378462496 STD:(0.015811533343763857)
RF : Mean ROC 0.9958169934640523 STD:(0.008366013071895394)
XGB : Mean ROC 1.0 STD:(0.0)
LGBM : Mean ROC 0.9749019607843138 STD:(0.020492463207597888)
KNN : Mean ROC 0.9706356987239341 STD:(0.01679566161186135)
```

Comparison of Models

[39]:
```
fig, ax = plt.subplots(figsize=(12,6))
ax.boxplot(results)
ax.set_xticklabels(names)
plt.show()
```



Only Significant Variables

[40]:
```
X = df.drop(['A_M', 'Color', 'Spectral_Class'], axis=1)
X_sc = preprocess(X)
Y = df['Type']
```

[41]:
```
results = []
names = []

for name, model in models:
    scores = cross_val_score(model, X_sc, Y, scoring='f1_weighted', cv=cv,␣
 ↪n_jobs=-1)
    accuracy = scores.mean()
    std = scores.std()
    print(f"{name} : Mean ROC {accuracy} STD:({std})")
    results.append(scores)
    names.append(name)
```

```
LR : Mean ROC 0.9791176470588236 STD:(0.013176217706879299)
NB : Mean ROC 1.0 STD:(0.0)
DT : Mean ROC 0.9958169934640523 STD:(0.008366013071895394)
Bag : Mean ROC 0.9958169934640523 STD:(0.008366013071895394)
Ada : Mean ROC 0.5833333333333334 STD:(0.0)
GBC : Mean ROC 1.0 STD:(0.0)
```

```
RF : Mean ROC 0.9958169934640523 STD:(0.008366013071895394)
XGB : Mean ROC 0.9958169934640523 STD:(0.008366013071895394)
LGBM : Mean ROC 1.0 STD:(0.0)
KNN : Mean ROC 0.9873513849984438 STD:(0.016906593104650706)
```

[42]:
```python
fig, ax = plt.subplots(figsize=(12,6))
ax.boxplot(results)
ax.set_xticklabels(names)
plt.show()
```