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Data Analysis and Visualization

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Final Report - Stars Classification

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Contents

1 Objective

The primary objective of our analysis is to explore the relationship between the classification of star types and various stellar properties, including surface temperature, luminosity, radius and absolute magnitude.

The findings from this analysis will contribute to a better understanding of the life cycles of stars and the evolution of galaxies as well as provide insights into the Hertzsprung-Russell Diagram. Additionally, the classification models developed through this analysis can be employed to classify stars based on their observed properties, help make more informed conclusions about the nature and characteristics of stars in the universe.

By achieving this objective, the analysis contributes to the broader field of astrophysics and expands our knowledge of stellar phenomena.

2 Overview

2.1 Spectral Star Types and Absolute Magnitude

The spectral type of a star is primarily a measure of its surface temperature [3]. The classification system, known as the Harvard classification scheme, uses seven spectral types (OBAFGKM) with O stars being the hottest and M stars being the coolest. [3] [8]

Absolute magnitude, on the other hand, is a measure of the intrinsic brightness of a star. It is the brightness that we would observe if the star were placed at a standard distance of 10 parsecs away from us. [6]

There is a relationship between a star's spectral type and its absolute magnitude. This relationship is complex and depends on the star's stage of evolution and its mass. For example, in a cluster of stars, more massive objects tend to be more centrally concentrated. However, the apparent magnitude has no direct correlation to spectral type. [14]

2.2 Spectral Star Types and Luminosity

Luminosity is the total amount of energy emitted by a star per unit time. It's directly related to a star's size (radius) and its surface temperature [4]. Therefore, since the spectral type of a star is a measure of its surface temperature, there is a correlation between spectral type and luminosity. [8] [12]

The hotter a star (i.e., stars of spectral type O), the more energy it emits per unit surface area, and thus, the more luminous it is. Conversely, cooler stars (i.e., stars of spectral type M) emit less energy per unit surface area and are less luminous. [8]

2.3 Spectral Star Types and Radius

The radius of a star can be derived from the star's luminosity and surface temperature using the Stefan-Boltzmann equation [11]. Since the spectral type of a star gives us information about its surface temperature, we can infer a relationship between spectral type and radius.

However, this relationship is not straightforward. For instance, a star that has exhausted its core hydrogen supply will have its core collapse, but its outer envelope expands, increasing the star's radius. Therefore, the relationship between spectral type and radius also depends on the star's stage of evolution.

In conclusion, while there are correlations between spectral star types and absolute magnitude, luminosity, and radius, these relationships are complex and depend on several factors, including the star's mass and stage of evolution. The study of these relationships helps astronomers understand the life cycles of stars and the evolution of galaxies.

2.4 Spectral Star Types and Surface Temperature

O stars have the highest surface temperature, while M stars have the lowest.

As we move from O to M stars, the surface temperature decreases. O stars are extremely hot, with temperatures reaching tens of thousands of degrees Kelvin, while M stars are relatively cool, with temperatures around a few thousand degrees Kelvin. [13]

The spectral type serves as a measure of the star's surface temperature because it is determined by the absorption lines present in the star's spectrum. These lines are caused by specific elements and molecules in the star's atmosphere, and their presence and characteristics provide insights into the star's temperature.

3 About the dataset

Our report presents an analysis and classification of star types based on the open dataset we got from Kaggle [2] and look like this when opened:

data.csv Open with

	A	B	C	D	E	F	G
1	Temperature (K)	Luminosity(L/Lo)	Radius(R/Ro)	Absolute magnitude(	Star type	Star color	Spectral Class
2	3068	0.0024	0.17	16.12	0	Red	M
3	3042	0.0005	0.1542	16.6	0	Red	M
4	2600	0.0003	0.102	18.7	0	Red	M
5	2800	0.0002	0.16	16.65	0	Red	M
6	1939	0.000138	0.103	20.06	0	Red	M
7	2840	0.00065	0.11	16.98	0	Red	M
8	2637	0.00073	0.127	17.22	0	Red	M
9	2600	0.0004	0.096	17.4	0	Red	M
10	2650	0.00069	0.11	17.45	0	Red	M
11	2700	0.00018	0.13	16.05	0	Red	M
12	3600	0.0029	0.51	10.69	1	Red	M
13	3129	0.0122	0.3761	11.79	1	Red	M
14	3134	0.0004	0.196	13.21	1	Red	M
15	3628	0.0055	0.393	10.48	1	Red	M
16	2650	0.0006	0.14	11.782	1	Red	M
17	3340	0.0038	0.24	13.07	1	Red	M
18	2799	0.0018	0.16	14.79	1	Red	M
19	3692	0.00367	0.47	10.8	1	Red	M
20	3192	0.00362	0.1967	13.53	1	Red	M
21	3441	0.039	0.351	11.18	1	Red	M
22	25000	0.056	0.0084	10.58	2	Blue White	B
23	7740	0.00049	0.01234	14.02	2	White	A
24	7220	0.00017	0.011	14.23	2	White	F
25	8500	0.0005	0.01	14.5	2	White	A
26	16500	0.013	0.014	11.89	2	Blue White	B

There are many more lines in the file itself. It consists of 240 stars that have been categorized into six classes: Brown Dwarf, Red Dwarf, White Dwarf, Main Sequence, Supergiant, and Hypergiant, which are represented by numbers from 0 to 5, respectively.

The dataset also includes several features that provide insights into the nature of stars, including surface temperature (K), relative luminosity (L/Lo), relative radius (R/Ro), absolute magnitude (Mv), star color, and spectral class (O, B, A, F, G, K, M). The luminosity and radius values are expressed relative to the average luminosity (Lo = 3.828 x 10^{26} Watts) and average radius (Ro = 6.9551 x 10^{8} meters) of the Sun, respectively.

The missing values in the dataset were manually calculated using the following: The luminosity of each star was determined using Stefan-Boltzmann's law of black body radiation. Wienn's displacement law was applied to estimate surface temperature based on the wavelength, and the absolute magnitude and radius of stars were determined using the parallax method.

4 Methods

4.1 Starter Pack

We analyzed using the following libraries in Python.

```
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import confusion_matrix,
    ConfusionMatrixDisplay
import seaborn as sns
import matplotlib.pyplot as plt
```

First of all we need to read the data.

```
data = pd.read_csv('data.csv')
data.head()
```

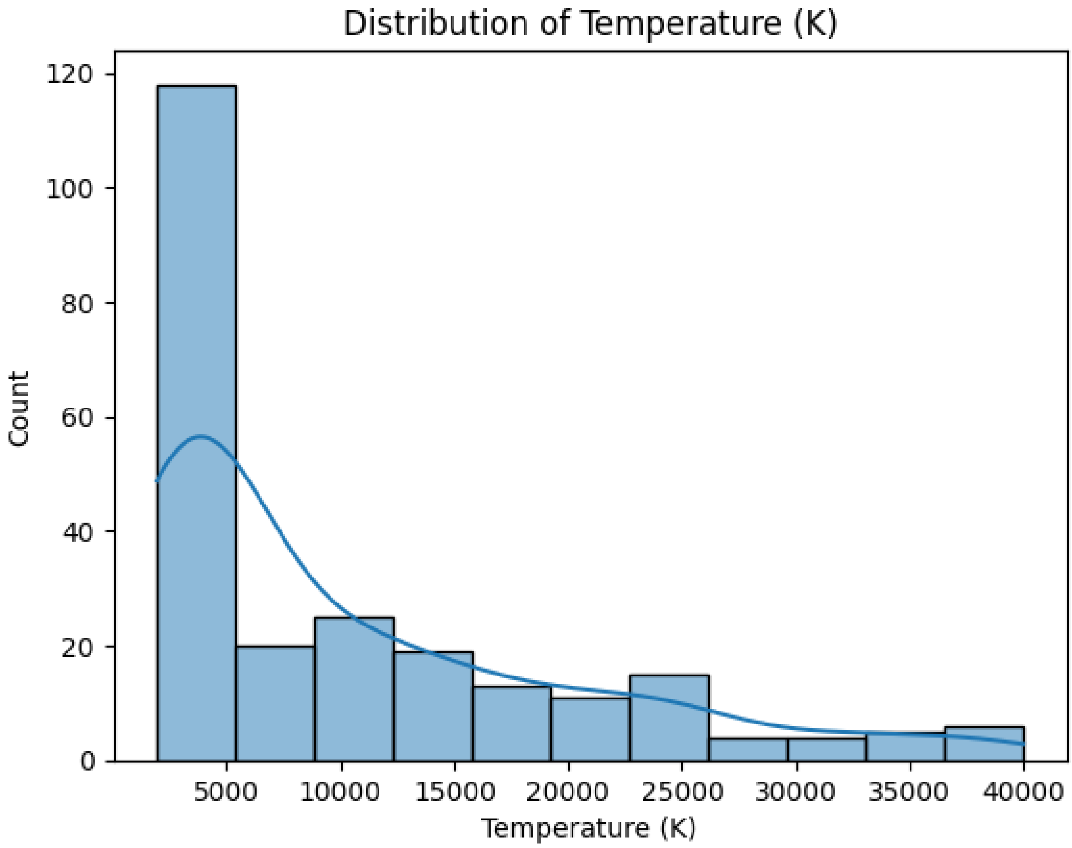
	Temperature (K)	Luminosity(L/Lo)	Radius(R/Ro)	Absolute magnitude(Mv)	Star type	Star color	Spectral Class
0	3068	0.002400	0.1700	16.12	0	Red	M
1	3042	0.000500	0.1542	16.60	0	Red	M
2	2600	0.000300	0.1020	18.70	0	Red	M
3	2800	0.000200	0.1600	16.65	0	Red	M
4	1939	0.000138	0.1030	20.06	0	Red	M

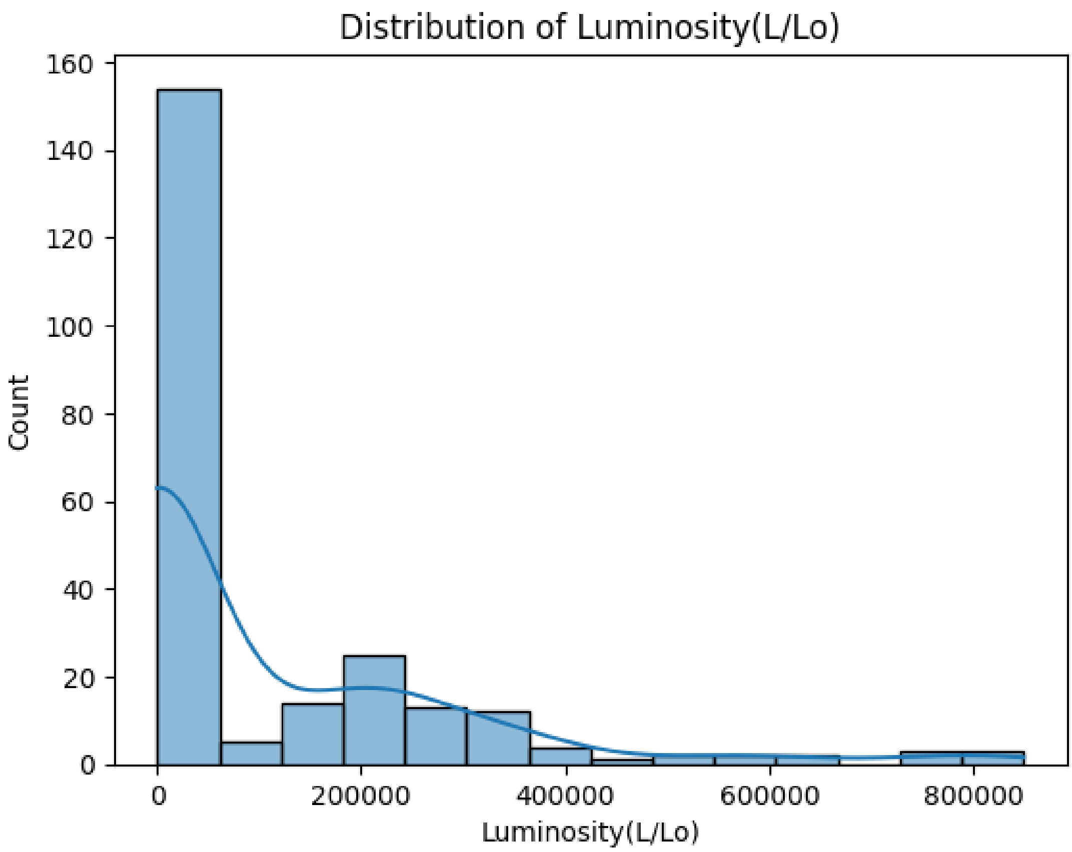
4.2 Data Visualization

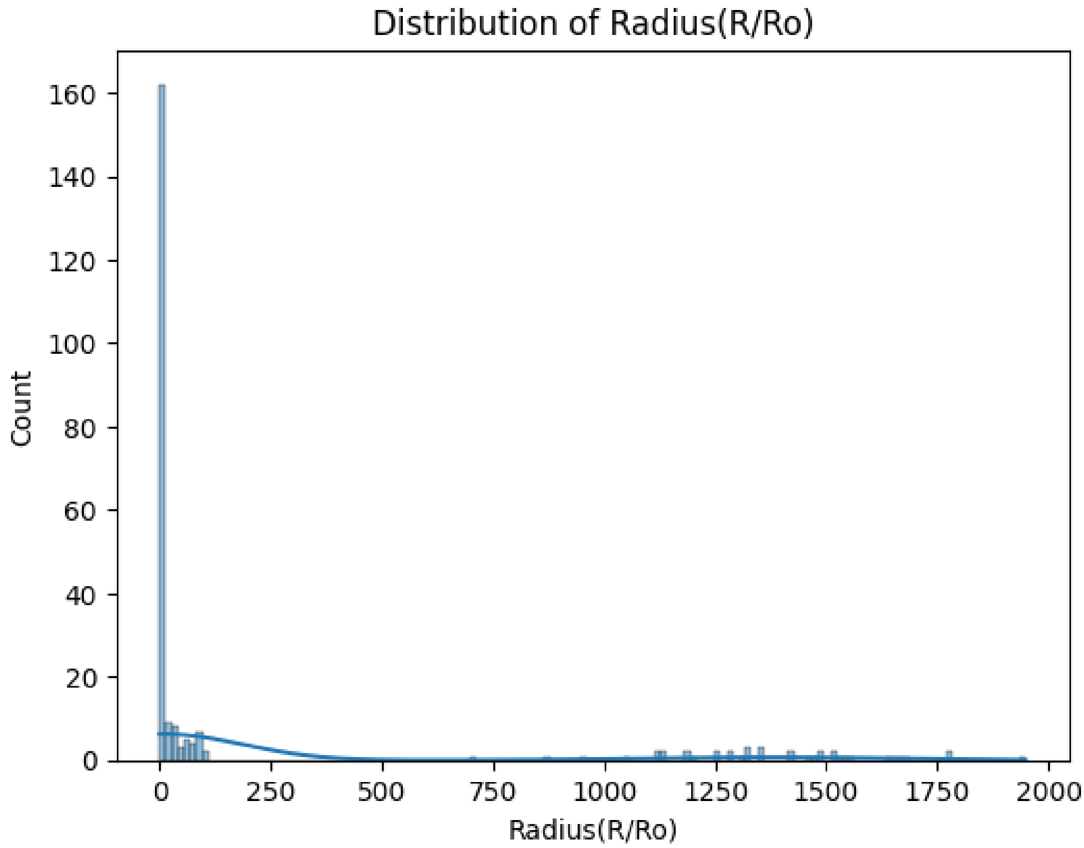
The following code visualizes the distributions of each features and sets the x-label to the current feature name and the y-label to Count.

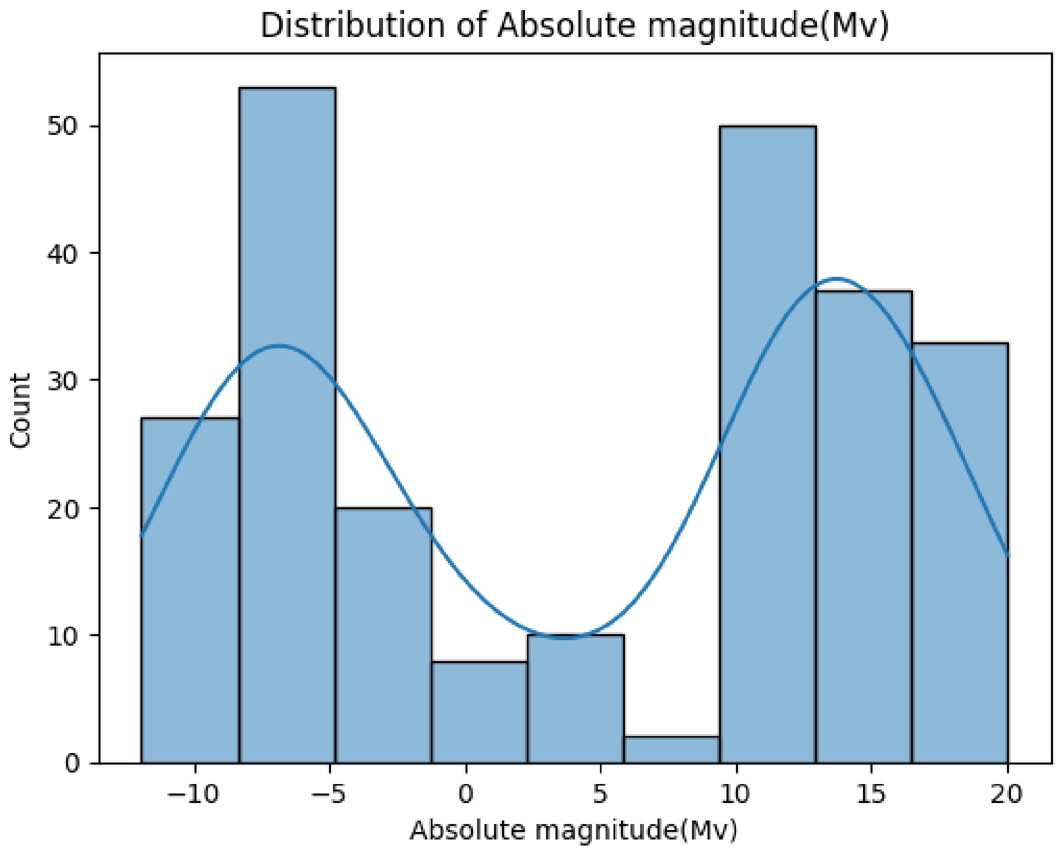
```
feature_cols = data.columns

for feature in feature_cols:
    sns.histplot(data=data, x=feature, kde=True)
    plt.xlabel(feature)
    plt.ylabel('Count')
    plt.title(f'Distribution of {feature}')
    plt.show()
```

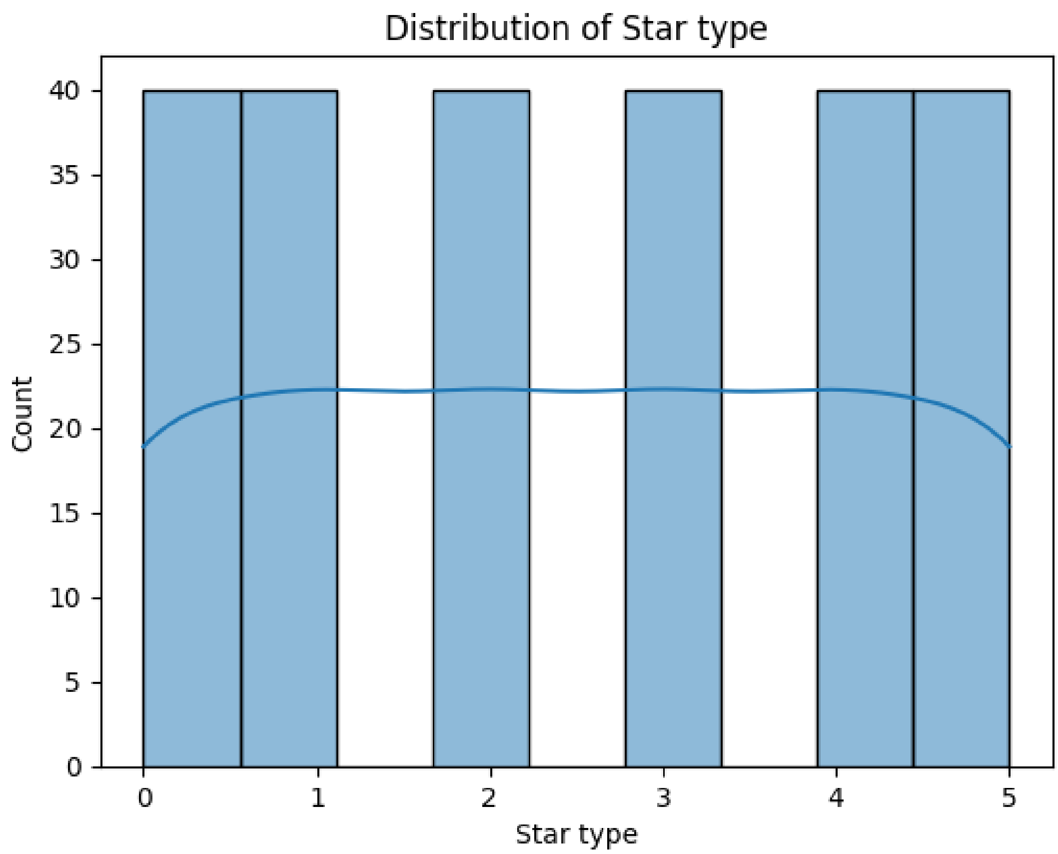
Following are some plots of some features with the most significant fluctuations or variations.


Distribution of Temperature (K)
Count
0
20
40
60
80
100
120
5000
10000
15000
20000
25000
30000
35000
40000
Temperature (K)


Distribution of Luminosity(L/Lo)
Count
0
20
40
60
80
100
120
140
160
0
200000
400000
600000
800000
Luminosity(L/Lo)


Distribution of Radius(R/Ro)
160
140
120
100
80
60
40
20
0
Count
0
250
500
750
1000
1250
1500
1750
2000
Radius(R/Ro)

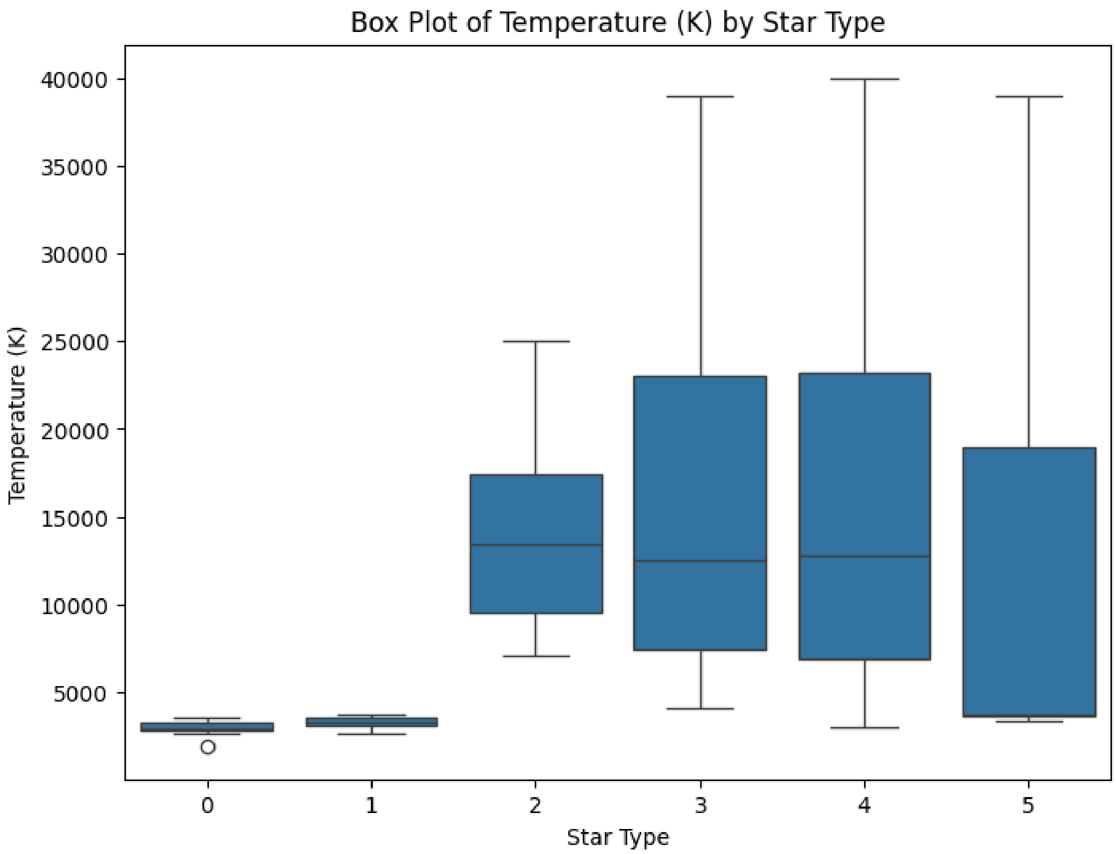

Distribution of Absolute magnitude(Mv)
50
40
30
20
10
0
Count
−10
−5
0
5
10
15
20
Absolute magnitude(Mv)

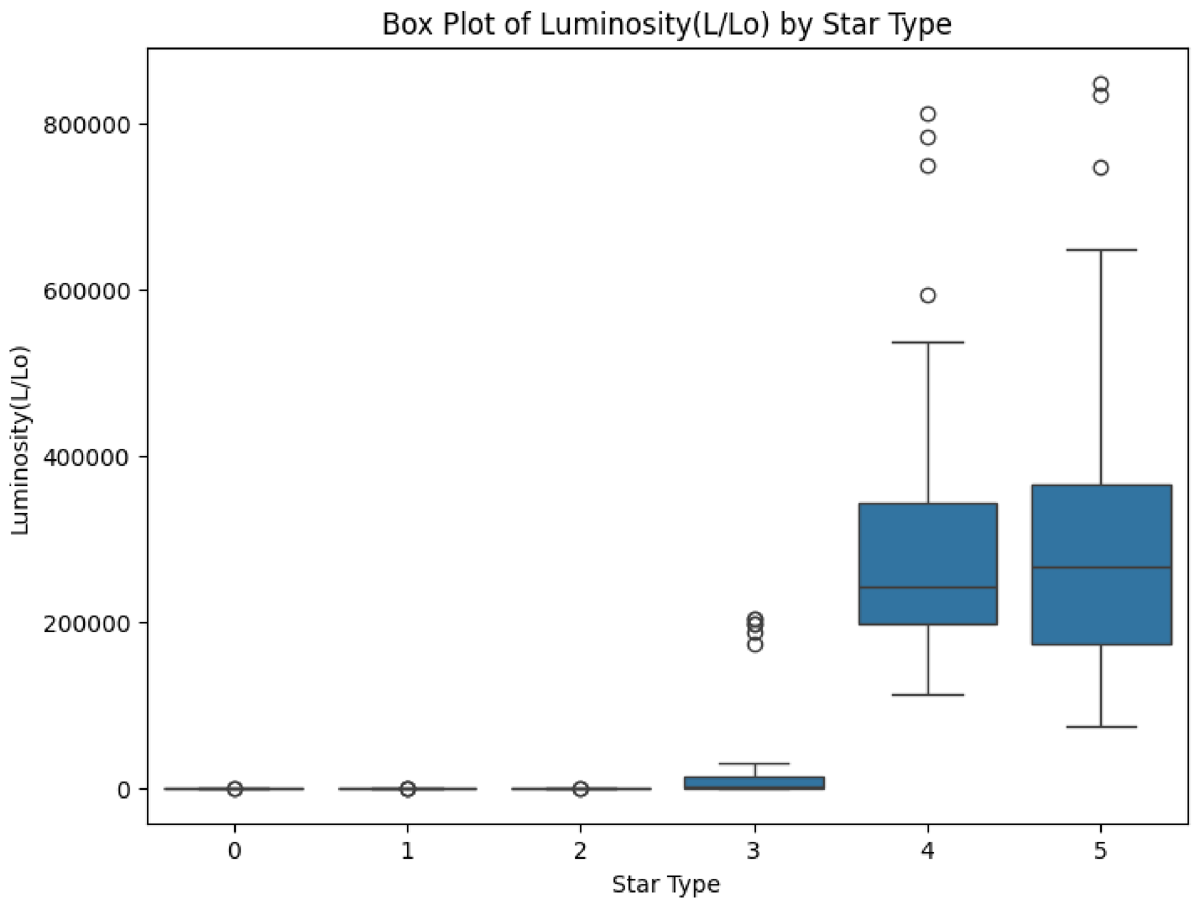


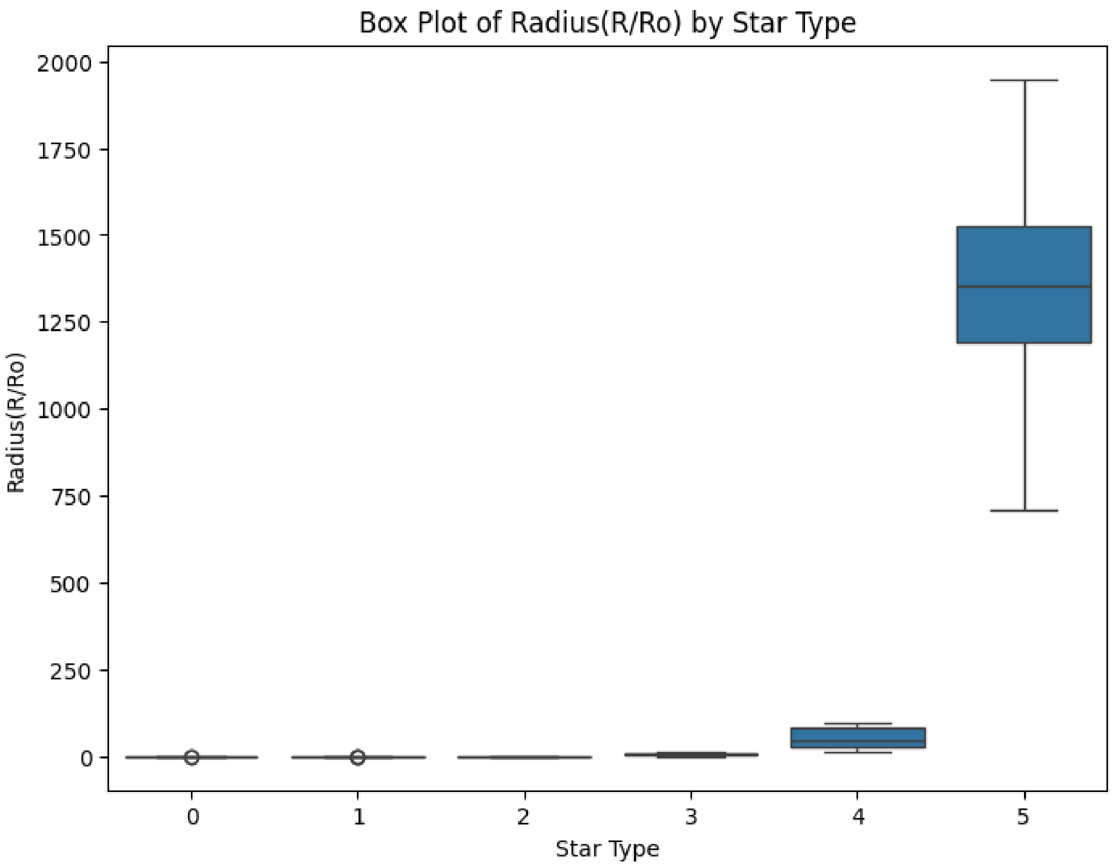
We also generate box plots for abundant and richness.

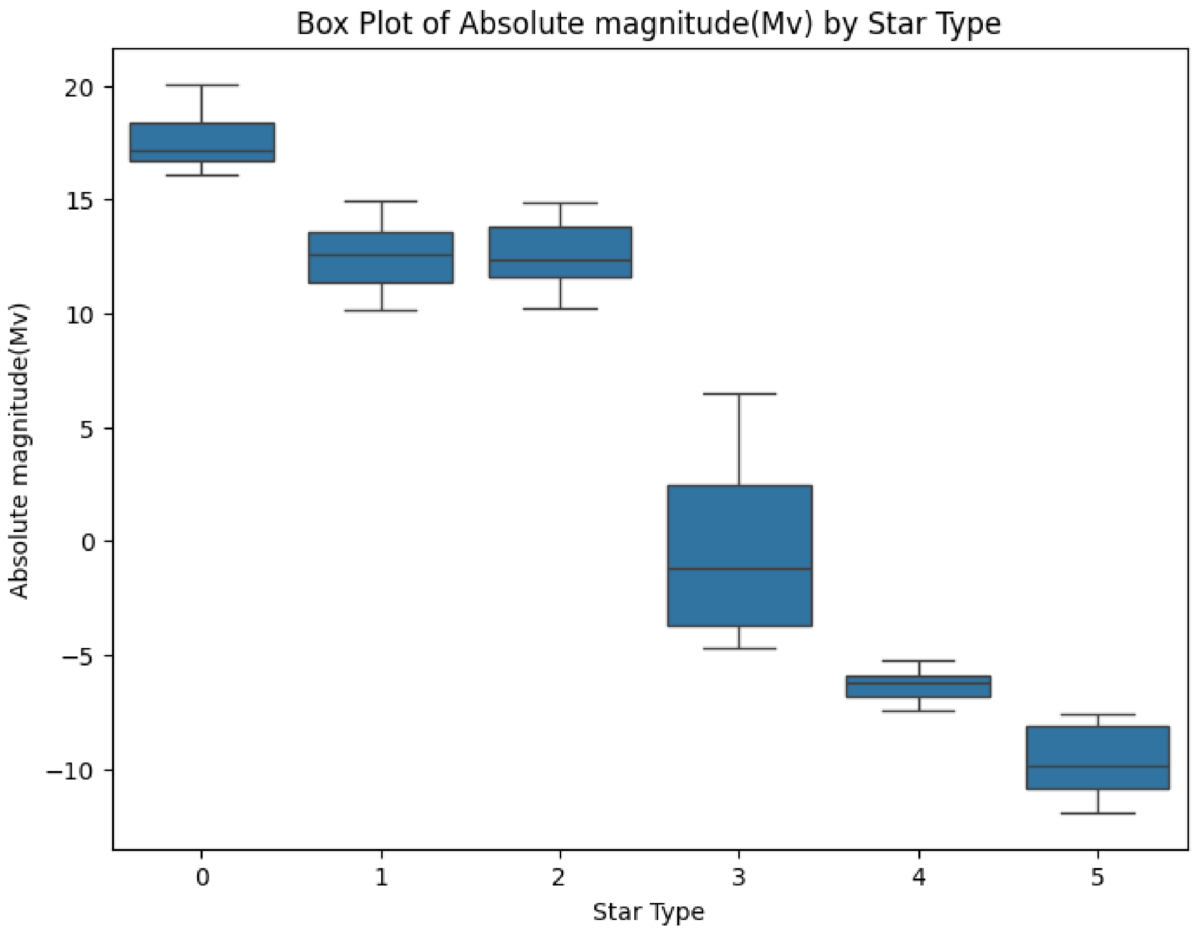
```python
for feature in feature_cols:
    plt.figure(figsize=(8, 6))
    sns.boxplot(x='Star type', y=feature, data=data)
    plt.xlabel('Star Type')
    plt.ylabel(feature)
    plt.title(f'Box Plot of {feature} by Star Type')
    plt.show()
```

The central box of the plot shows the interquartile range. The whiskers extend from the box visualize the range of the data, excluding outliers. Outliers are shown as individual points outside the whiskers.


Box Plot of Temperature (K) by Star Type
Temperature (K)
40000
35000
30000
25000
20000
15000
10000
5000
0
1
2
3
4
5
Star Type


Box Plot of Luminosity(L/Lo) by Star Type
Luminosity(L/Lo)
800000
600000
400000
200000
0
0
1
2
3
4
5
Star Type


Box Plot of Radius(R/Ro) by Star Type
Radius(R/Ro)
2000
1750
1500
1250
1000
750
500
250
0
0
1
2
3
4
5
Star Type


Box Plot of Absolute magnitude(Mv) by Star Type
Absolute magnitude(Mv)
20
15
10
5
0
−5
−10
0
1
2
3
4
5
Star Type

4.3 Preprocessing

We check for missing values by counting the non-null values. The code is to calls the info() method on a pandas DataFrame object.

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 240 entries, 0 to 239
Data columns (total 7 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   Temperature (K)         240 non-null    int64
 1   Luminosity(L/Lo)        240 non-null    float64
 2   Radius(R/Ro)            240 non-null    float64
 3   Absolute magnitude(Mv)  240 non-null    float64
 4   Star type               240 non-null    int64
 5   Star color              240 non-null    object
 6   Spectral Class          240 non-null    object
dtypes: float64(3), int64(2), object(2)
memory usage: 13.2+ KB
```

The outcome table includes information about the range of the data, features, data types (integer, float, object) and memory usage. As being seen, all the data are non-null, which mean there is no missing values.

We use get_dummies() function from the pandas library to create dummy variables for preprocessing and visualization. By converting categorical variables into binary columns, it allowed the models to work with categorical data.

```
data = pd.get_dummies(data, drop_first=True)
data.head()
```

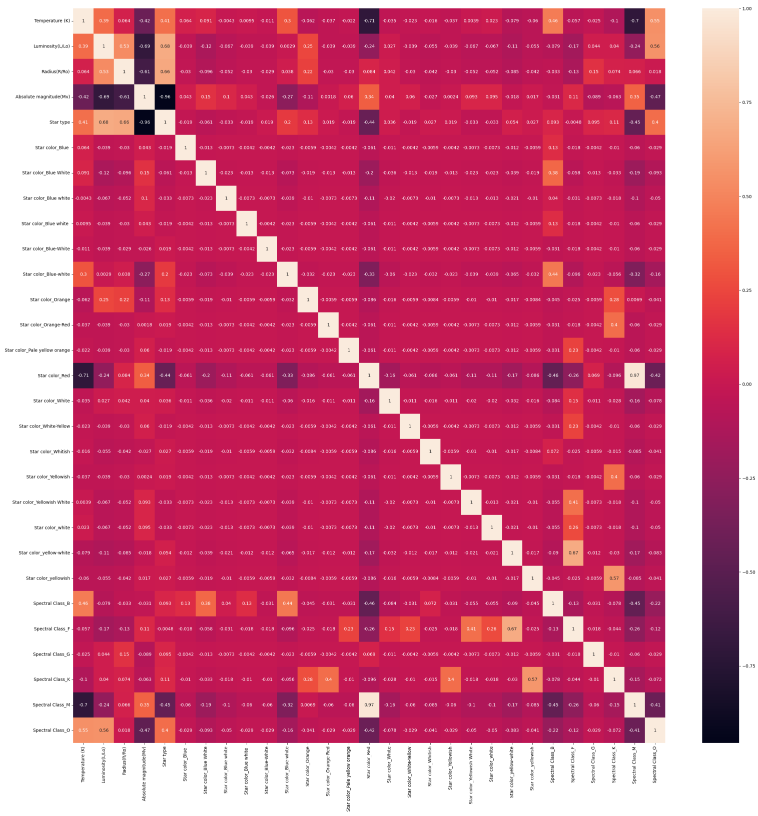
	Temperature (K)	Luminosity(L/Lo)	Radius(R/Ro)	Absolute magnitude(Mv)	Star type	Star color_Blue	Star color_Blue White	Star color_Blue white	Star color_Blue white	Star color_Blue-White	...	color_Yello
0	3068	0.002400	0.1700	16.12	0	False	False	False	False	False	...	
1	3042	0.000500	0.1542	16.60	0	False	False	False	False	False	...	
2	2600	0.000300	0.1020	18.70	0	False	False	False	False	False	...	
3	2800	0.000200	0.1600	16.65	0	False	False	False	False	False	...	
4	1939	0.000138	0.1030	20.06	0	False	False	False	False	False	...	

5 rows × 29 columns

The outcome table is a modified DataFrame where the categorical columns have been replaced with binary columns. It only shows 5 rows and 29 columns, but the complete DataFrame have many more rows. From some columns 'Star color_Blue', 'Star Color_Blue White' and onwards, the values indicate whether the corresponding feature is present (True) or not (False) as they are objects.

We generate a heatmap visualization of the correlation matrix. We set the size of the plot with dimensions of 30 inches by 30 inches.

```
plt.figure(figsize=(30, 30))
sns.heatmap(data.corr(), annot=True)
plt.show()
```



Next, we use the MinMaxScaler from scikit-learn to perform scale the features to 0 - 1 range to ensures that all numerical features have a consistent scale.

```
scaler = MinMaxScaler()
data_rescale = pd.DataFrame(scaler.fit_transform(data.drop('Star
    type', axis=1)), columns=data.drop('Star type', axis=1).
    columns)
data_rescale.head()
```

	Temperature (K)	Luminosity(L/Lo)	Radius(R/Ro)	Absolute magnitude(Mv)	Star color_Blue	Star color_Blue White	Star color_Blue white	Star color_Blue white	Star color_Blue-White	Star color_Blue-white	...	colo
0	0.029663	2.731275e-09	0.000083	0.876798	0.0	0.0	0.0	0.0	0.0	0.0	...	
1	0.028980	4.944550e-10	0.000075	0.891807	0.0	0.0	0.0	0.0	0.0	0.0	...	
2	0.017367	2.590003e-10	0.000048	0.957473	0.0	0.0	0.0	0.0	0.0	0.0	...	
3	0.022622	1.412729e-10	0.000078	0.893371	0.0	0.0	0.0	0.0	0.0	0.0	...	
4	0.000000	6.828189e-11	0.000049	1.000000	0.0	0.0	0.0	0.0	0.0	0.0	...	

5 rows × 28 columns

The rescaled dataset is assigned to the training and testing sets, which are X_train, y_train and X_test, y_test, respectively. The test size parameter is set to 0.8, indicating that the testing set will comprise 80% of the data, while the training set will consist of the remaining 20%. The random state parameter is set to 42, which ensures reproducibility of the split. By specifying the same random state, the same split will be generated each time the code is executed. The training set will be used to train the model, while the testing set will be used to evaluate its performance.

```
X = data_rescale
y = data['Star type']
X_train, X_test, y_train, y_test = train_test_split(X, y,
    test_size=0.8, random_state=42)
```

4.4 Model Training and Evaluation

We trains a decision tree classifier using the training data then then evaluates the accuracy on the testing data.

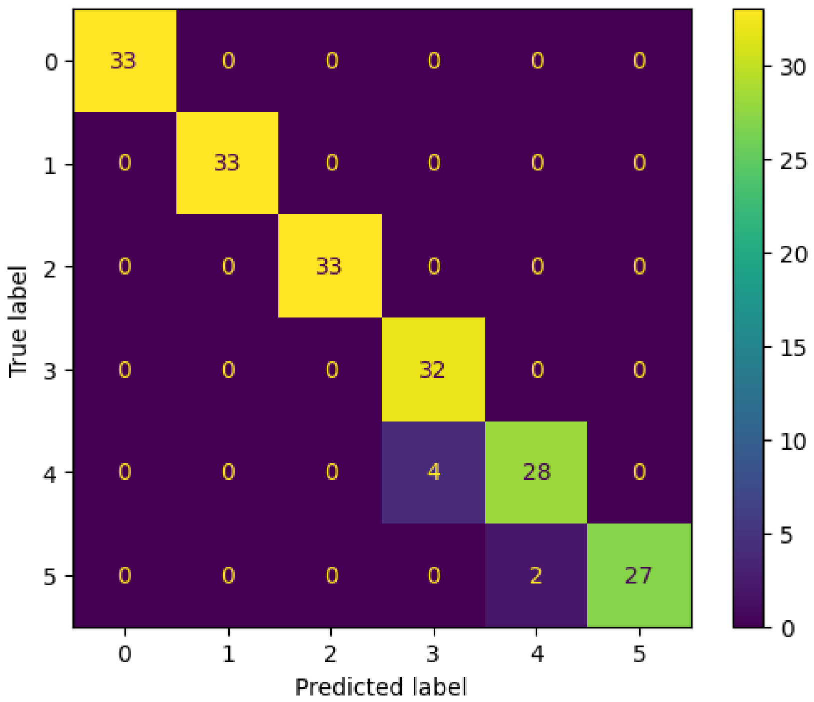
```
dtree = DecisionTreeClassifier()
dtree.fit(X_train, y_train)
dtree.score(X_test, y_test)
```

```
0.96875
```

The result indicates that the decision tree classifier correctly predicted the target variable for approximately 96.875% of the samples in the testing set.

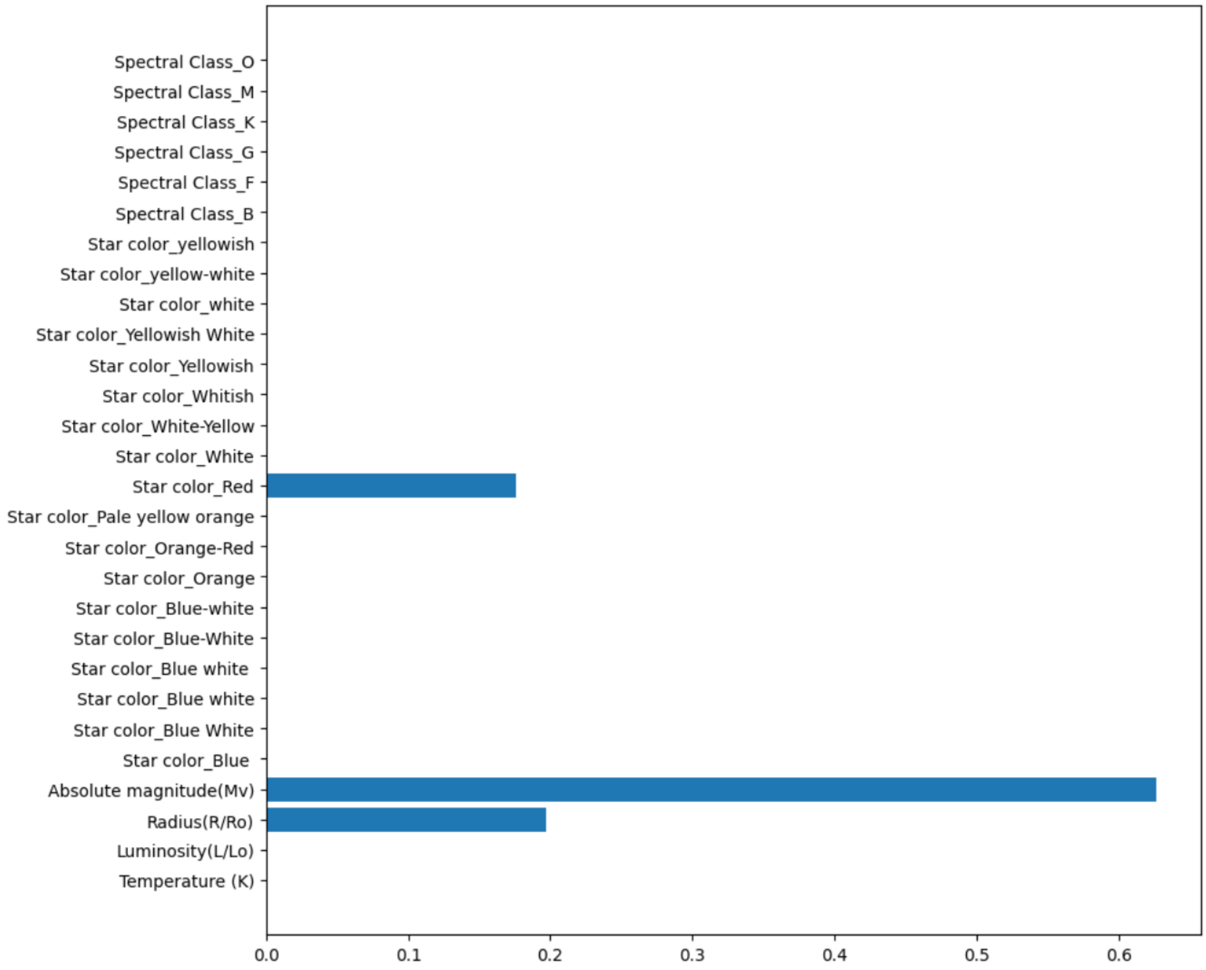
We generate a confusion matrix based on the true labels and the predicted labels obtained from the decision tree classifier.

```
cfs_mat = confusion_matrix(y_test, dtree.predict(X_test))
disp = ConfusionMatrixDisplay(cfs_mat, display_labels=dtree.
    classes_)
disp.plot()
```



The following code is to create a horizontal bar plot to visualize the feature importances of the decision tree classifier. By that, we can gain insights into which features have more impact on the decision tree classifier.

```
plt.figure(figsize=(10, 10))
plt.barh(X.columns, dtree.feature_importances_)
plt.show()
```



As being seen, Absolute Magnitude and Radius are the features with highest importance.

4.5 Further Analysis and Model Comparison

We call out X.keys() to represent the names of the features present in the dataset.

```
X.keys()
```

```
Index(['Temperature (K)', 'Luminosity(L/Lo)', 'Radius(R/Ro)',
       'Absolute magnitude(Mv)', 'Star color_Blue ', 'Star color_Blue White',
       'Star color_Blue white', 'Star color_Blue white ',
       'Star color_Blue-White', 'Star color_Blue-white', 'Star color_Orange',
       'Star color_Orange-Red', 'Star color_Pale yellow orange',
       'Star color_Red', 'Star color_White', 'Star color_White-Yellow',
       'Star color_Whitish', 'Star color_Yellowish',
       'Star color_Yellowish White', 'Star color_white',
       'Star color_yellow-white', 'Star color_yellowish', 'Spectral Class_B',
       'Spectral Class_F', 'Spectral Class_G', 'Spectral Class_K',
       'Spectral Class_M', 'Spectral Class_O'],
      dtype='object')
```

We drop the two features with highest importance to improve computational efficiency and reduce the risk of overfitting by focusing on a subset of the most informative features.

```
X = data_rescale.drop(['Absolute magnitude(Mv)','Radius(R/Ro)'],
    axis=1)
```

Then we retrain the decision tree classifier with the same test size parameter and random state parameter.

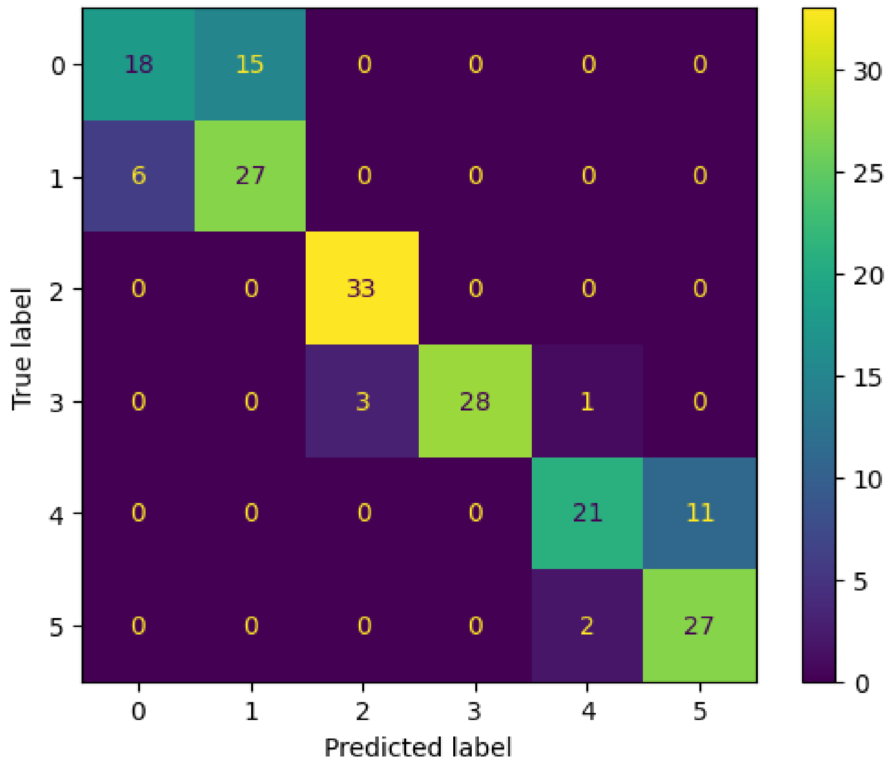
```
X_train, X_test, y_train, y_test = train_test_split(X, y,
    test_size=0.8, random_state=42)
dtree = DecisionTreeClassifier()
dtree.fit(X_train, y_train)
dtree.score(X_test, y_test)
```

```
0.8020833333333334
```

The outcome score is lower as we have removed the two most important features.

The following code is just for another confusion matrix.

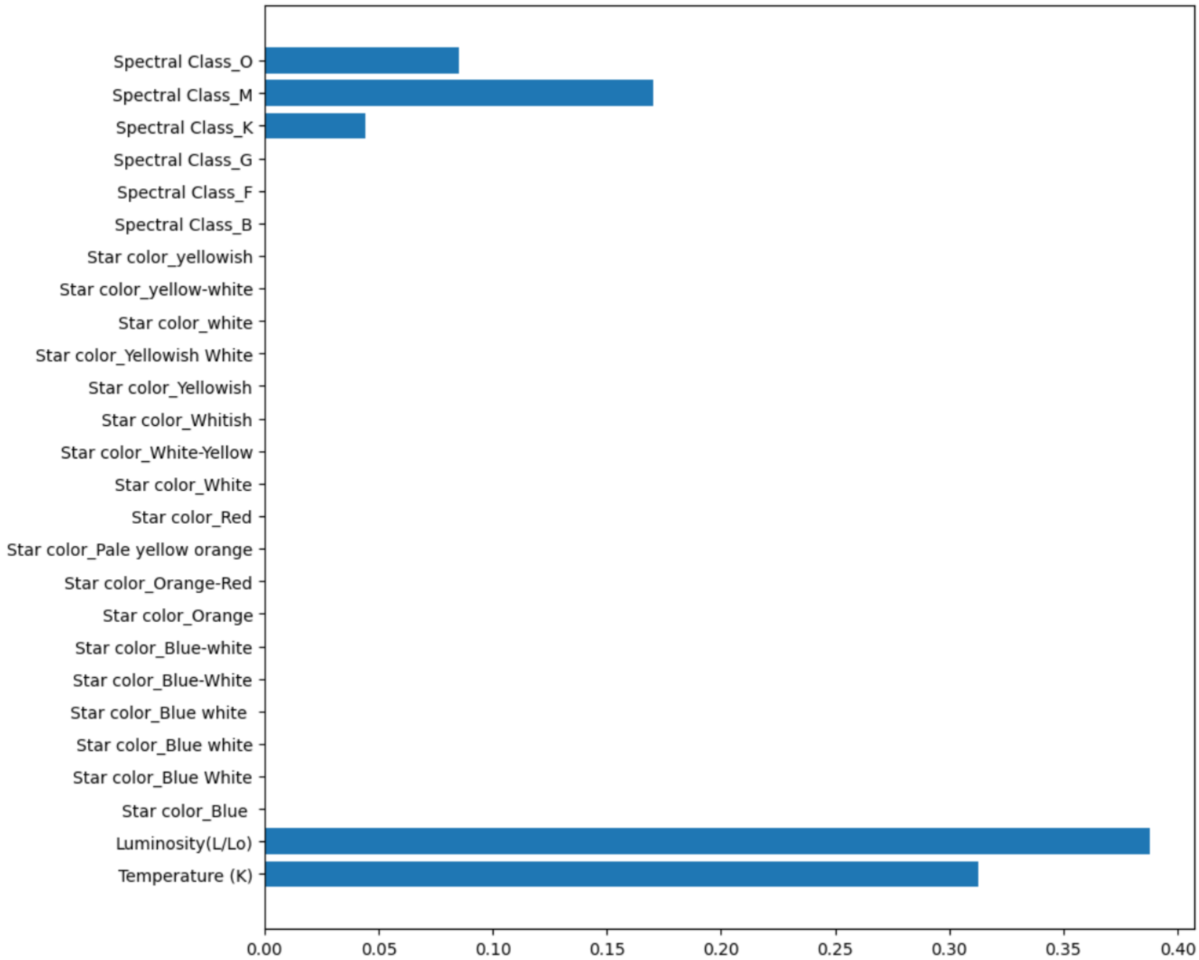
```
cfs_mat = confusion_matrix(y_test, dtree.predict(X_test))
disp = ConfusionMatrixDisplay(cfs_mat, display_labels=dtree.
    classes_)
disp.plot()
```



As being seen, it is less accurated than before.

We recheck the feature importances.

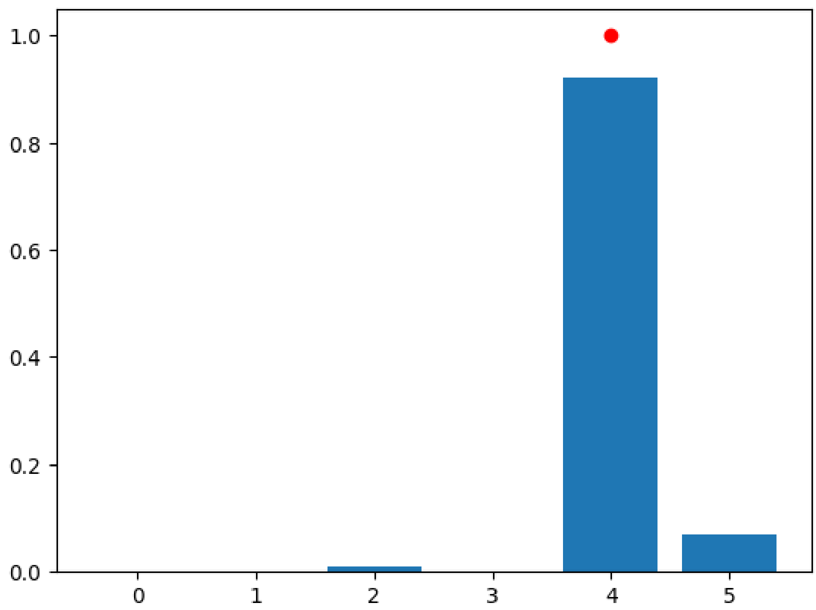
```
plt.figure(figsize=(10, 10))
plt.barh(X.columns, dtree.feature_importances_)
plt.show()
```



This time, Luminosity and Temperature are the two features with the highest importances.

Then we create a RandomForestClassifier class and assigned to the variable rf. The n_estimators is to specify the number of decision trees in the random forest, and random_state ensures reproducibility of the results. The following code is to calculate the accuracy of the random forest classifier on the testing data and returns the accuracy score of the predictions made by the model.

```
from sklearn.ensemble import RandomForestClassifier
rf = RandomForestClassifier(n_estimators=200, random_state=42)
rf.fit(X_train, y_train)
print(rf.score(X_test, y_test))
x_prob = rf.predict_proba(X_test.iloc[42].values.reshape(1, -1))
plt.bar( rf.classes_,x_prob[0])
plt.scatter(y_test.iloc[42], 1, color='red', alpha=1)
```



The x-axis represents the classes, and the y-axis represents the probabilities. The red dot in the represents the true label from the testing data. As being seen, class 4, which is Supergiant, has the highest score.

4.6 Cross-Validation

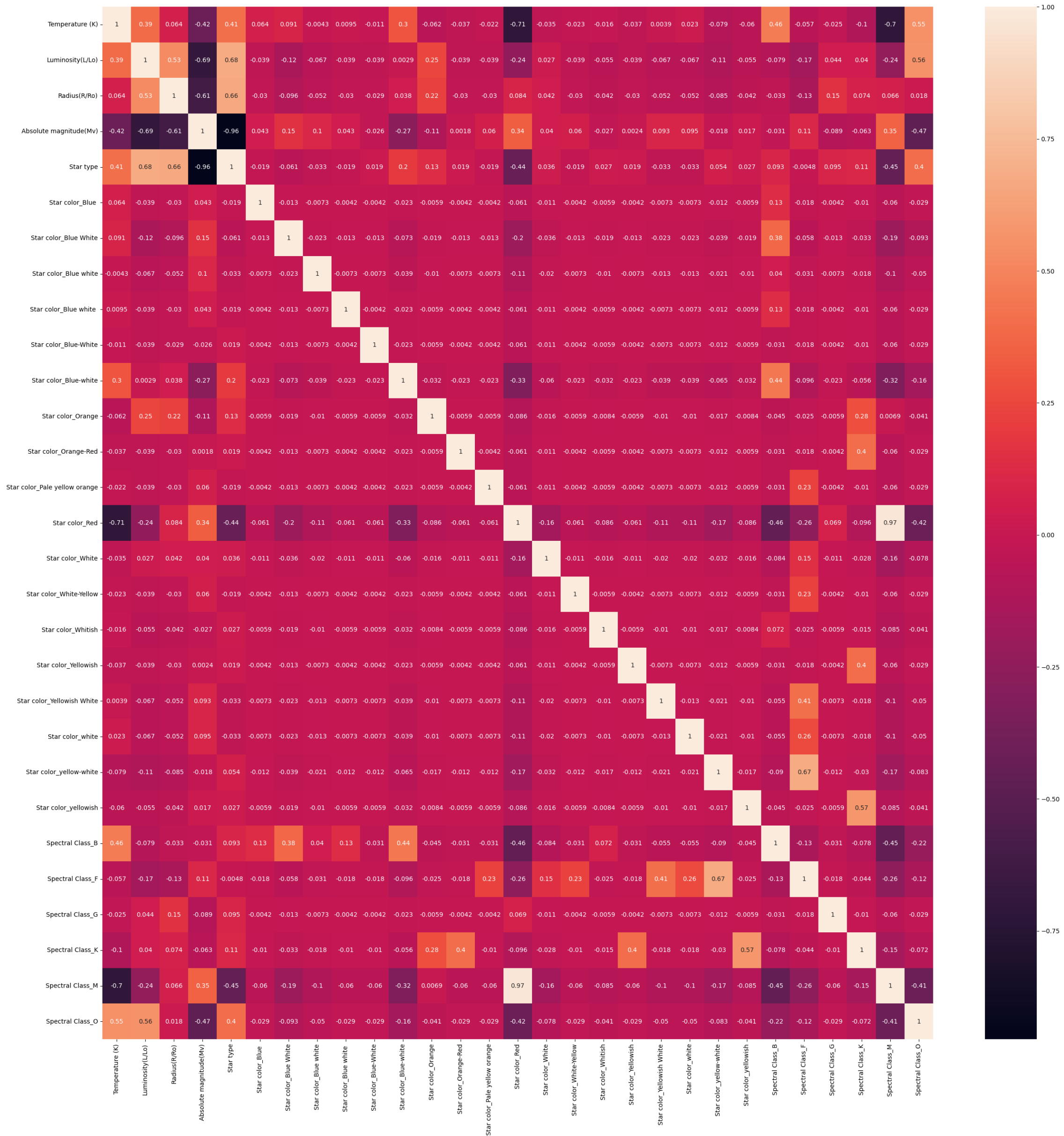
We import the cross_val_score() function from the scikit-learn library and the np.mean() function from the NumPy library to evaluate the performance of the decision tree classifier and calculate the mean score, respectively.

```
from sklearn.model_selection import cross_val_score

scores = cross_val_score(dtree, X, y, cv=5)
mean_score = np.mean(scores)

print("Cross-Validation Scores:")
for fold, score in enumerate(scores, start=1):
    print(f"- Fold {fold}: {score}")
print(f"Mean Score: {mean_score}")
```

```
Cross-Validation Scores:
- Fold 1: 0.6666666666666666
- Fold 2: 0.7083333333333334
- Fold 3: 0.8125
- Fold 4: 0.875
- Fold 5: 0.7708333333333334
Mean Score: 0.7666666666666667
```

The output scores scores range from 0.666 to 0.875. The mean score of 0.767 suggests that the model performs reasonably well on average. Based on these numbers, we can say that the model shows a quite good performance.

5 Discussions



The Hertzsprung-Russell Diagram, a fundamental tool in the field of astrophysics, plots stars according to their absolute magnitudes and spectral classifications. Our analysis has provided a clearer understanding of the usefulness of this diagram, showing how it effectively illustrates the relationships between different properties of stars. This has allowed us to better understand the stages of stellar evolution, from the main sequence phase where stars spend the majority of their lives, to the giant and supergiant phases, and finally to the white dwarf phase.

Moreover, the classification models developed through this analysis is an effective tools for classifying stars based on their observed properties. These models can help make more informed conclusions about the nature and characteristics of stars in the universe. For instance, we can now more accurately predict a star's future evolution based on its current classification and properties.

In conclusion, the exploration of the relationship between the classification of star types and various stellar properties has yielded valuable insights. The findings from this analysis have not only contributed to a better understanding of the life cycles of stars and the evolution of butaxies but also have practical applications in the field of astrophysics. Future research can build upon these findings, further expanding our knowledge of the universe.

And now we will discuss how those correlations help us to classify star types based on H-R diagram.

5.1 Spectral Class and Temperature

The spectral class of a star is a fundamental property that is closely related to its surface temperature. In the Hertzsprung-Russell (H-R) diagram, the spectral class (or equivalently, the surface temperature) of a star is plotted along the horizontal axis, with the hottest stars (O type) on the left and the coolest stars (M type) on the right. [10]

The H-R diagram reveals a clear pattern in the distribution of stars. Most stars, including our Sun, lie along a diagonal band known as the Main Sequence. These stars are in a stable phase of their life cycle, burning hydrogen into helium in their cores. The position of a star along the Main Sequence is determined by its mass: more massive stars are hotter, brighter, and hence occupy the upper left of the Main Sequence.

Above the Main Sequence, we find the Giants and Supergiants. These are stars that have exhausted the hydrogen in their cores and have begun burning heavier elements. They are cooler but much brighter than Main Sequence stars of the same spectral class, due to their larger size.

Below the Main Sequence, we find the White Dwarfs. These are the remnants of stars that have shed their outer layers and left behind a hot, dense core. Despite their high surface temperatures, White Dwarfs are faint due to their small size. [1]

The H-R diagram thus provides a snapshot of stellar evolution. By studying the distribution of stars of different spectral classes on the H-R diagram, we can gain insights into the life cycles of stars and the physical processes that govern their evolution. [9]

Furthermore, the H-R diagram is not only a tool for understanding the properties of individual stars but also a powerful tool for investigating the properties of galaxies. The distribution of stars in a galaxy on the H-R diagram can reveal the galaxy's age and star formation history. [1]

In conclusion, the spectral class of a star, as represented on the H-R diagram, is a key to understanding the star's physical properties and evolutionary state. It is an essential tool in the field of astrophysics, providing insights into the life cycles of stars, the structure and evolution of galaxies, and the physical processes occurring in the universe. [10]

5.2 Absolute Magnitude and Luminosity

In astronomy, absolute magnitude is a measure of the intrinsic brightness of a celestial object. It is the apparent magnitude that an object would have if it were located at a standard distance of exactly 10 parsecs (32.6 light-years) away from the observer. This allows for a fair comparison of the brightness of celestial objects as if they were all placed at the same distance from the observer.

The luminosity of a star, on the other hand, is the total amount of energy emitted by the star per unit time. It includes all forms of electromagnetic radiation, not just visible light. Luminosity is an absolute measure of radiant power; it is dependent on the size of the star and its surface temperature.

The relationship between absolute magnitude and luminosity is logarithmic. The more luminous an object, the smaller the numerical value of its absolute magnitude. A difference of 5 magnitudes between the absolute magnitudes of two objects corresponds to a ratio of 100 in their luminosities. For example, a star of absolute magnitude $M_V = 3.0$ would be 100 times as luminous as a star of absolute magnitude $M_V = 8.0$.

In the Hertzsprung-Russell (H-R) diagram, these two properties (absolute magnitude and spectral class) are used to classify stars and understand their life cycles. The vertical axis represents the absolute magnitude (or luminosity), and the horizontal axis represents the spectral class (or surface temperature). [7]

In conclusion, absolute magnitude and luminosity are two fundamental properties of stars that provide insights into their physical characteristics and stages of evolution. They are key to our understanding of the universe and form the basis of the H-R diagram, a vital tool in the field of astrophysics.

5.3 Stellar Evolution

Stellar evolution is the process by which a star undergoes a sequence of radical changes during its lifetime. Depending on the mass of the star, its lifetime can range from a few million years for the most massive to trillions of years for the least massive.

All stars begin their lives from collapsing clouds of gas and dust, often called nebulae or molecular clouds. Over the course of millions of years, these protostars settle down into a state of equilibrium, becoming what is known as a main-sequence star. The energy of a star in this stage is generated by the fusion of hydrogen atoms at the core.

So the star becomes simultaneously more luminous and cooler. On the H–R diagram, the star therefore leaves the main-sequence band and moves upward (brighter) and to the right (cooler surface temperature). Over time, massive stars become red supergiants, and lower-mass stars like the Sun become red giants. (We first discussed such giant stars in The Stars: A Celestial Census; here we see how such “swollen” stars originate.) You might also say that these stars have “split personalities”: their cores are contracting while their outer layers are expanding.

Eventually, all the hydrogen in a star's core, where it is hot enough for fusion reactions, is used up. The core then contains only helium, "contaminated" by whatever small percentage of heavier elements the star had to begin with. The helium in the core can be thought of as the accumulated "ash" from the nuclear "burning" of hydrogen during the main-sequence stage.

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The end phase of a Sun-like star in which all the material contained in the star, minus the amount blown off in the red giant phase, is packed into a volume one millionth the size of the original star forming white dwarf. [5]

The end product of stellar evolution depends on the initial mass of the star. It can be a white dwarf, a neutron star, or a black hole[1]. Although the universe is not old enough for any of the smallest red dwarfs to have reached the end of their existence, stellar models suggest they will slowly become brighter and hotter before running out of hydrogen fuel and becoming low-mass white dwarfs.

Stellar evolution is not studied by observing the life of a single star, as most stellar changes occur too slowly to be detected, even over many centuries. Instead, astrophysicists come to understand how stars evolve by observing numerous stars at various points in their lifetime, and by simulating stellar structure using computer models.

In conclusion, stellar evolution is a fascinating and complex process that depends on the initial conditions of the star and the physical laws that govern the universe. Understanding this process is crucial for understanding the life cycle of stars and the evolution of galaxies.

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