Verifying RRLyare Stars from GAIA DR3 using Machine Learning

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ABSTRACT

This final project is to comprehend the knowledge of data analysis and machine learning covered in ASTR 3300, Astro-statistics. Main goal for this project is to use machine learning to verify RR Lyrae stars from variable stars data. The target dataset is GAIA Data Release 3. From the list a handful of stars will be carefully selected that we are certain of RRL and used to train the module. After such the module will analyse dataset of variable stars to sort out RRL stars. The project could also be modified to verify other binary stars. Target size is approximately 100 random selected stars. Target data size can be increased once the module is fully complete and functional.

1. Introduction

The Gaia DR3 catalogue is the outcome of the processing of raw data collected with the Gaia instruments during the first 34 months of the mission by the Gaia Data Processing and Analysis Consortium. The Gaia DR3 catalogue contains the same source list, celestial positions, proper motions, parallaxes, and broad band photometry in the G, GBP, and GRP passbands already present in the Early Third Data Release, Gaia EDR3. Gaia DR3 introduces an impressive wealth of new data products.

The GAIA mission is able to identify variable stars in its catalogue because it visits each target multiple times. The classifications of these variables, however, may or may not be accurate. To investigate this, a magnitude limited sample of 237 were taken that are RR Lyrae variables identified by GAIA as being RRd (double mode) type. In previous research, analysis of data from the Transiting Exoplanet Survey Satellite (TESS) was made to confirm this classification and look at their properties. Taking a step back, instead of accessing each star observation data, machine learning package from python will analyse GAIA DR3 directly. This project will work on the same sample of 237 since each star was examined and categorised into four labels of G (Good), L (requires another Look), N (No or bad data), and A (Abnormal).

In ASTR3300 course, various methods of data analysing model using machine learning packages in python was covered. This project will practice such skills with GAIA DR3, as presented.

2. Dataset

The data can be downloaded from VizieR. (see Reference [Webpages] – (data source) This dataset includes RR Lyrae type d stars with G < 16 mag. The dataset includes 237 stars. Columns selected were; Source, SolID, PF, P1O, EpochG, Gmagavg, BPmagavg, RPmagavg, RVavg, ptpG,

ptpRV, R21G, R31G, phi21G, phi31G, FuNFreq1, FuNFreq2, Class, Pratio.

Each column of the data and their explanation is described on Table 1. Description follows the VizieR webpage. Each star in the dataset has been analysed using Tess Observation data. Each star is then labelled and separated to individual files, RRL_G, RRL_nG, and RRL_B. RRL_G are the stars that are going to be used to train as a normal RR Lyrae stars, RRL_nG is dataset excluding RRL_G. RRL_B are the stars with bad dataset. File format is in .csv.

For "Good" RRd stars, observational data plot looks like [plot] in Appendix.

Table 1. Data Columns and Explanation

Column	Explain
Source	Unique source identifier
SolID	Solution Identifier
PF	Period corresponding to the fundamental pulsation mode in the G band time series
P1O	Period corresponding to the first overtone pulsation mode in the G band time series
EpochG	Epoch of the maximum of the light curve in the G band
Gmagavg	Intensity-averaged magnitude in the G band
BPmagavg	Intensity-averaged magnitude in the BP band
RPmagavg	Intensity-averaged magnitude in the RP band
RVavg	Mean radial velocity
ptpG	Peak-to-peak amplitude of the G band light curve
ptpRV	Peak-to-peak amplitude of the radial velocity curve
R21G	Fourier decomposition parameter R21G: A2/A1
R31G	Fourier decomposition parameter R31G: A3/A1
phi21G	Fourier decomposition parameter phi21G: phi2 - 2*phi1
phi31G	Fourier decomposition parameter phi31G: phi3 - 3*phi1
FundFreq1	First frequency of the non-linear Fourier modelling
FundFreq2	Second frequency of the non-linear Fourier modelling in the G band
Class	[Rabcd] Best RR Lyrae classification estimate

3. Method

For the analysis methods, two models were used. Simple Logistic Regression and Random Forest Classification. Simple Logistic Regression was performed in comparison with Random Forest.

Figure 1. shows how the stars are scattered in Gmagavg vs. PF and P1O vs. PF.

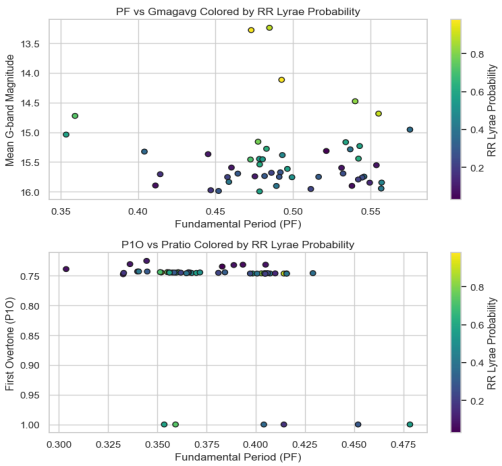


Figure 1. RF plot (PF vs. Gmagavg, P1O vs. PF)

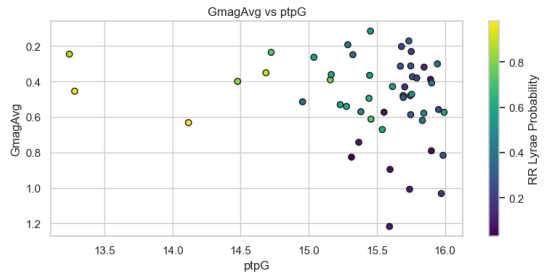
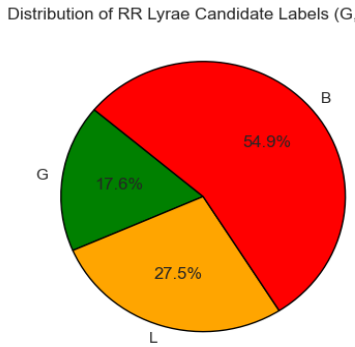


Figure 2. RF plot (Gmagavg vs. ptpG)

Figure 2 was plotted additional to the original plots for comparison with dimensionally reduced dataset.




```
RR_label
G      9
L     14
B     28
```

Figure 3. Pie Chart Distribution

Above is the Pie chart to show how many stars are falling into which category.

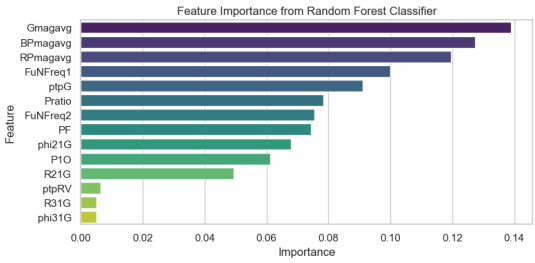


Figure 4. Feature Importance

Feature Importance shows the focus of the Random Forest model on which Column data. Based on this plot, features were selected in Dimensionality Reduction step.

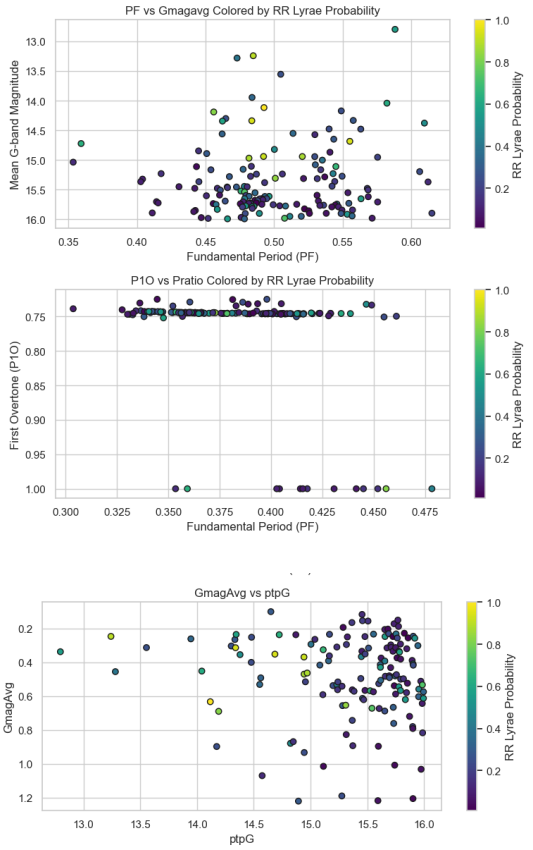
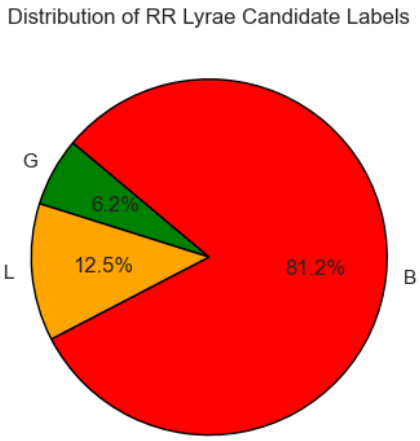


Figure 5. Train dataset modification

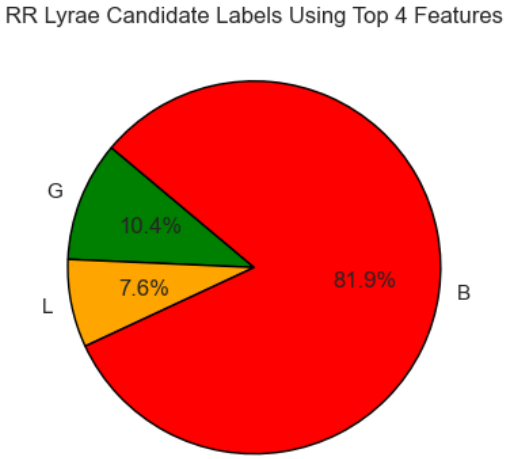
Figure 5 is the plot from changing the train dataset. In this procedure, there were two train datasets, Good and Bad. Plots are slightly different, and “Good” stars tend to be more scattered within the whole dataset.




```
RR_label
G      9
L     18
B    117
```

Figure 6. Pie chart after Train Dataset Mod.

Figure 6 shows the pie chart after the modification of training dataset.




```
RR_label
G     15
L     11
B    118
```

Figure 7. Pie Chart after Dimension Reduction

Figure 7 shows the pie chart after the Dimension Reduction. After reduction, the guess of "Good" stars slightly increased.

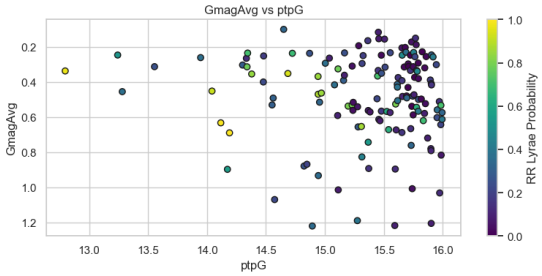
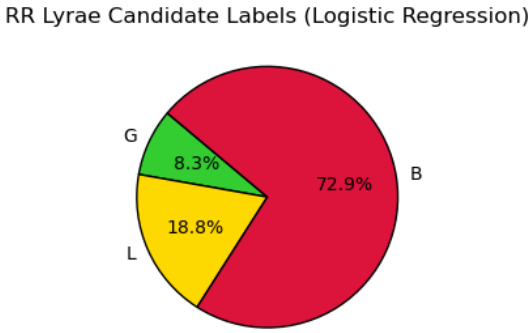


Figure 8. Gmagavg vs. ptpG after Dim. Reduction

Figure 8 shows the scatter plot after the Dimension Reduction. Other two plots were unable to plot since we are not using PF column.




```
RR_label
G     12
L     27
B    105
```

Figure 9. Pie chart of Logistic Regression

Above is the pie chart of Logistic Regression. By looking at just the pie chart, it seemed fined, other than group "L" increased.

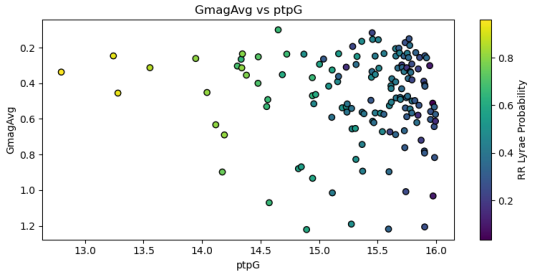


Figure 10. scatter plot of Logistic Regression

However, looking at Gmagavg vs. ptpG scatter plot, it is shown that Logistic Regression is not a good model. Unlike Random Forest, it seems the probability of being RRL is highly dependent on ptpG.

For each model, further verifications are required with actual TESS observation data.

4. Results and Future Steps

In result, Random Forest Classification performed better at learning and verifying variable stars data. As shown in Simple Logistic Regression plots, turned out as plots having possibility based on ptpG, where more expected to scattered.

With result of Random Forest Classification, setting RRL_nG as the target data, turned out doing a decent verification. Compared to prior analysis, number wise it was good.

Future step would include verify each "Good" stars in the RRL_nG dataset.

If those stars were originally in "L" label but classified as "G" according to the model, this can be an indicator to take a closer look or look for smaller details in the dataset. Also this can be used to determine the list of stars for additional observation.

Reference

[Journals / Publications]

Ryu, S., Choi, Y., Lockett, J., Patterson, A. & Carrell, K. (2023) *Double-mode RR Lyrae Variables in GAIA and TESS*.

GAIA Collaboration et al. (2023) "Gaia Data Release 3. Summary of the content and survey properties" A&A, 674, A1

[Web sources]

https://www.cosmos.esa.int/web/gaia/data-release-3

https://vizier.cds.unistra.fr/viz-bin/VizieR-3?-source=I/358/vrrlyr (data source)

[Class Material]

https://github.com/Holang2/ASTR_3300_S2025 (ASTR3300 class material)

Appendix

[Plot]

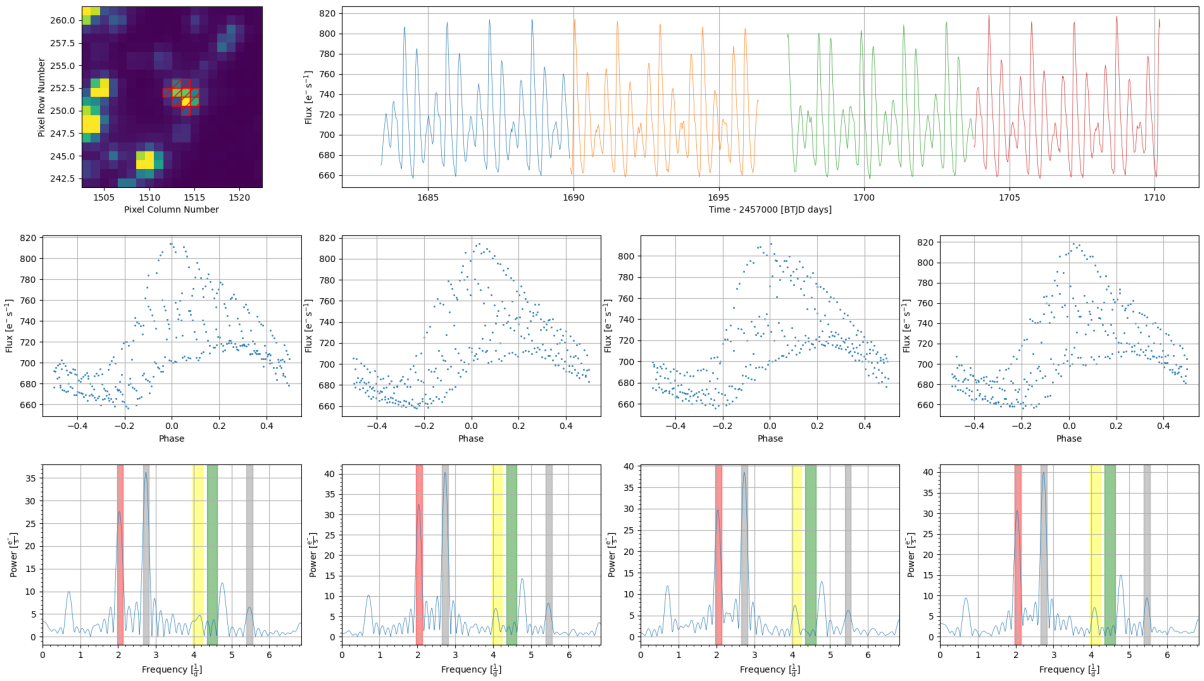


Figure above is how a plot TESS data for each stars looks like. Example of a good RRLd star.

[Code]

Code can also be accessed in a form of Jupyter Notebook.

Code cell 1

```
################################

#####  ASTR 3300 Project  #####

##### SeungJun Ryu (June) #####

################################


# imports

import pandas as pd

import matplotlib.pyplot as plt

from sklearn.ensemble import RandomForestClassifier
```

```
from sklearn.preprocessing import StandardScaler
import numpy as np

# Load data
rrl_g = pd.read_csv("./RRL_G.csv")
rrl_ng = pd.read_csv("./RRL_nG.csv")

# Label confirmed RR Lyrae
rrl_g['label'] = 1

# negative from part of rrl_ng
rrl_ng_negative = rrl_ng.sample(n=len(rrl_g), random_state=42).copy()
rrl_ng_negative['label'] = 0

# Combine for training
training_data = pd.concat([rrl_g, rrl_ng_negative], ignore_index=True)

# Define features
features = [
    'PF', 'P1O', 'Gmagavg', 'BPmagavg', 'RPmagavg',
    'ptpG', 'ptpRV', 'R21G', 'R31G', 'phi21G', 'phi31G',
    'FuNFreq1', 'FuNFreq2', 'Pratio'
]

# Fill missing values
X_train = training_data[features].fillna(training_data[features].mean())
y_train = training_data['label']
```

```
# Scale features

scaler = StandardScaler()

X_train_scaled = scaler.fit_transform(X_train)


# Train classifier

clf = RandomForestClassifier(n_estimators=100, random_state=45)

clf.fit(X_train_scaled, y_train)


# Predict on entire rrl_ng dataset (excluding those used for negative
training)

rrl_ng_eval        =        rrl_ng.drop(index=rrl_ng_negative.index,
errors='ignore').copy()

X_target_scaled                                                    =
scaler.transform(rrl_ng_eval[features].fillna(training_data[features
].mean()))

rrl_ng_eval['predicted_label'] = clf.predict(X_target_scaled)

rrl_ng_eval['RR_probability'] = clf.predict_proba(X_target_scaled)[:,
1]


# Visualisation

import seaborn as sns

sns.set(style="whitegrid")



# Scatter plot of Period (PF) vs G-band magnitude, colored by
probability

plt.figure(figsize=(8, 4))

sc = plt.scatter(rrl_ng_eval['PF'], rrl_ng_eval['Gmagavg'],

                 c=rrl_ng_eval['RR_probability'],    cmap='viridis',
edgecolor='k')

plt.colorbar(sc, label='RR Lyrae Probability')

plt.title("PF vs Gmagavg Colored by RR Lyrae Probability")
```

```
plt.xlabel("Fundamental Period (PF)")
plt.ylabel("Mean G-band Magnitude")
plt.gca().invert_yaxis()
plt.tight_layout()
plt.show()


plt.figure(figsize=(8, 4))
sc = plt.scatter(rrl_ng_eval['P1O'], rrl_ng_eval['Pratio'],
                 c=rrl_ng_eval['RR_probability'],    cmap='viridis',
edgecolor='k')
plt.colorbar(sc, label='RR Lyrae Probability')
plt.title("P1O vs Pratio Colored by RR Lyrae Probability")
plt.xlabel("Fundamental Period (PF)")
plt.ylabel("First Overtone (P1O)")
plt.gca().invert_yaxis()
plt.tight_layout()
plt.show()


plt.figure(figsize=(8, 4))
sc = plt.scatter(rrl_ng_eval['Gmagavg'], rrl_ng_eval['ptpG'],
                 c=rrl_ng_eval['RR_probability'],    cmap='viridis',
edgecolor='k')
plt.colorbar(sc, label='RR Lyrae Probability')
plt.title("GmagAvg vs ptpG")
plt.xlabel("ptpG")
plt.ylabel("GmagAvg")
plt.gca().invert_yaxis()
plt.tight_layout()
plt.show()
```

code cell 2

```
# import
import pandas as pd
import matplotlib.pyplot as plt

# Reload data files
rrl_g = pd.read_csv("./RRL_G.csv")
rrl_ng = pd.read_csv("./RRL_nG.csv")

# Rebuild training and model
from sklearn.ensemble import RandomForestClassifier
from sklearn.preprocessing import StandardScaler

# Label confirmed RR Lyrae
rrl_g['label'] = 1

# Simulate a negative class from part of rrl_ng
rrl_ng_negative = rrl_ng.sample(n=len(rrl_g), random_state=45).copy()
rrl_ng_negative['label'] = 0

# Combine training data
training_data = pd.concat([rrl_g, rrl_ng_negative], ignore_index=True)

# Define features
features = [
    'PF', 'P1O', 'Gmagavg', 'BPmagavg', 'RPmagavg',
    'ptpG', 'ptpRV', 'R21G', 'R31G', 'phi21G', 'phi31G',
```

```
    'FuNFreq1', 'FuNFreq2', 'Pratio'
]

# Fill missing values and scale features
X_train = training_data[features].fillna(training_data[features].mean())
y_train = training_data['label']

scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)

# Train classifier
clf = RandomForestClassifier(n_estimators=100, random_state=45)
clf.fit(X_train_scaled, y_train)

# Predict on remaining rrl_ng entries
rrl_ng_eval = rrl_ng.drop(index=rrl_ng_negative.index, errors='ignore').copy()
X_target_scaled = scaler.transform(rrl_ng_eval[features].fillna(training_data[features].mean()))
rrl_ng_eval['predicted_label'] = clf.predict(X_target_scaled)
rrl_ng_eval['RR_probability'] = clf.predict_proba(X_target_scaled)[:, 1]

# Categorize stars based on RR Lyrae probability
def label_star(prob):
    if prob > 0.75:
        return 'G'  # Good candidate
    elif prob < 0.5:
        return 'B'  # Bad candidate
```

```
    else:
        return 'L'  # Needs a Look

rrl_ng_eval['RR_label'] = rrl_ng_eval['RR_probability'].apply(label_star)

# Count labels
label_counts = rrl_ng_eval['RR_label'].value_counts().reindex(['G', 'L', 'B'], fill_value=0)

# Plot pie chart
plt.figure(figsize=(4,4))
plt.pie(label_counts, labels=label_counts.index, autopct='%1.1f%%', startangle=140,
        colors=['green', 'orange', 'red'], wedgeprops={'edgecolor': 'black'})
plt.title("Distribution of RR Lyrae Candidate Labels (G, L, B)")
plt.tight_layout()
plt.show()

label_counts
```

Code cell 3

```
# Feature importance

importances = clf.feature_importances_

feature_importance_df = pd.DataFrame({'Feature': features, 'Importance': importances})

feature_importance_df.sort_values(by='Importance', ascending=False, inplace=True)


plt.figure(figsize=(8, 4))

sns.barplot(x='Importance', y='Feature', data=feature_importance_df, palette="viridis")

plt.title("Feature Importance from Random Forest Classifier")

plt.tight_layout()

plt.show()
```

code cell 4

```
########## Labeling both good and bad ##########


# imports

import pandas as pd

from sklearn.preprocessing import StandardScaler

from sklearn.ensemble import RandomForestClassifier


# Load files

rrl_g = pd.read_csv("./RRL_G.csv")        # confirmed RR Lyrae

rrl_b = pd.read_csv("./RRL_B.csv")        # confirmed NOT RR Lyrae

rrl_eval = pd.read_csv("./RRL_nG.csv")    # unknown stars


# Label the training data

rrl_g['label'] = 1
```

```
rrl_b['label'] = 0

# Combine for training
training_data = pd.concat([rrl_g, rrl_b], ignore_index=True)

# Define features
features = [
    'PF', 'P1O', 'Gmagavg', 'BPmagavg', 'RPmagavg',
    'ptpG', 'ptpRV', 'R21G', 'R31G', 'phi21G', 'phi31G',
    'FuNFreq1', 'FuNFreq2', 'Pratio'
]

# Fill missing and scale
X_train = training_data[features].fillna(training_data[features].mean())
y_train = training_data['label']

scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)

# Train model
clf = RandomForestClassifier(n_estimators=100, random_state=45)
clf.fit(X_train_scaled, y_train)

# Prepare unknown stars
X_eval = rrl_eval[features].fillna(training_data[features].mean())
X_eval_scaled = scaler.transform(X_eval)

# Predict
```

```
rrl_eval['predicted_label'] = clf.predict(X_eval_scaled)
rrl_eval['RR_probability'] = clf.predict_proba(X_eval_scaled)[:, 1]


def label_star(prob):
    if prob > 0.75:
        return 'G'
    elif prob < 0.5:
        return 'B'
    else:
        return 'L'


rrl_eval['RR_label'] = rrl_eval['RR_probability'].apply(label_star)


import matplotlib.pyplot as plt


label_counts = rrl_eval['RR_label'].value_counts().reindex(['G', 'L',
'B'], fill_value=0)


# Pie chart
plt.figure(figsize=(4, 4))
plt.pie(label_counts, labels=label_counts.index, autopct='%1.1f%%',
startangle=140,
        colors=['green', 'orange', 'red'], wedgeprops={'edgecolor':
'black'})
plt.title("Distribution of RR Lyrae Candidate Labels")
plt.tight_layout()
plt.show()


print(label_counts)
```

```
# more plots
plt.figure(figsize=(8, 4))
sc = plt.scatter(rrl_eval['PF'], rrl_eval['Gmagavg'],
                 c=rrl_eval['RR_probability'],       cmap='viridis',
edgecolor='k')
plt.colorbar(sc, label='RR Lyrae Probability')
plt.title("PF vs Gmagavg Colored by RR Lyrae Probability")
plt.xlabel("Fundamental Period (PF)")
plt.ylabel("Mean G-band Magnitude")
plt.gca().invert_yaxis()
plt.tight_layout()
plt.show()

plt.figure(figsize=(8, 4))
sc = plt.scatter(rrl_eval['P1O'], rrl_eval['Pratio'],
                 c=rrl_eval['RR_probability'],       cmap='viridis',
edgecolor='k')
plt.colorbar(sc, label='RR Lyrae Probability')
plt.title("P1O vs Pratio Colored by RR Lyrae Probability")
plt.xlabel("Fundamental Period (PF)")
plt.ylabel("First Overtone (P1O)")
plt.gca().invert_yaxis()
plt.tight_layout()
plt.show()

plt.figure(figsize=(8, 4))
sc = plt.scatter(rrl_eval['Gmagavg'], rrl_eval['ptpG'],
                 c=rrl_eval['RR_probability'],       cmap='viridis',
edgecolor='k')
```

```
plt.colorbar(sc, label='RR Lyrae Probability')

plt.title("GmagAvg vs ptpG")

plt.xlabel("ptpG")

plt.ylabel("GmagAvg")

plt.gca().invert_yaxis()

plt.tight_layout()

plt.show()
```

code cell 5

```
########## Dimentionality Reduction ##########


# Load data

rrl_g = pd.read_csv("./RRL_G.csv")

rrl_b = pd.read_csv("./RRL_B.csv")

rrl_eval = pd.read_csv("./RRL_nG.csv")


# Assign labels

rrl_g['label'] = 1

rrl_b['label'] = 0

training_data = pd.concat([rrl_g, rrl_b], ignore_index=True)


# 4 features from above (feature importance)

features = ['Gmagavg', 'ptpG', 'BPmagavg', 'RPmagavg']


# Preprocess training data

X_train                                                                =
training_data[features].fillna(training_data[features].mean())

y_train = training_data['label']

scaler = StandardScaler()
```

```
X_train_scaled = scaler.fit_transform(X_train)


# Train classifier
clf = RandomForestClassifier(n_estimators=100, random_state=45)
clf.fit(X_train_scaled, y_train)


# Predict on evaluation data
X_eval = rrl_eval[features].fillna(training_data[features].mean())
X_eval_scaled = scaler.transform(X_eval)
rrl_eval['predicted_label'] = clf.predict(X_eval_scaled)
rrl_eval['RR_probability'] = clf.predict_proba(X_eval_scaled)[:, 1]


# Labeling function
def label_star(prob):
    if prob > 0.75:
        return 'G'
    elif prob < 0.5:
        return 'B'
    else:
        return 'L'


rrl_eval['RR_label'] = rrl_eval['RR_probability'].apply(label_star)



# Pie chart
label_counts = rrl_eval['RR_label'].value_counts().reindex(['G', 'L',
'B'], fill_value=0)
plt.figure(figsize=(4,4))
```

```
plt.pie(label_counts, labels=label_counts.index, autopct='%1.1f%%',
startangle=140,

        colors=['green', 'orange', 'red'], wedgeprops={'edgecolor':
'black'})

plt.title("RR Lyrae Candidate Labels Using Top 4 Features")

plt.tight_layout()

plt.show()


label_counts
```

code cell 6

```
# plots

plt.figure(figsize=(8, 4))

sc = plt.scatter(rrl_eval['Gmagavg'], rrl_eval['ptpG'],

                 c=rrl_eval['RR_probability'],       cmap='viridis',
edgecolor='k')

plt.colorbar(sc, label='RR Lyrae Probability')

plt.title("GmagAvg vs ptpG")

plt.xlabel("ptpG")

plt.ylabel("GmagAvg")

plt.gca().invert_yaxis()

plt.tight_layout()

plt.show()
```

code cell 7

```
##### Other Model - Logistic Regression #####


# import
```

```
import pandas as pd
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
import matplotlib.pyplot as plt

# Load data
rrl_g = pd.read_csv("./RRL_G.csv")        # Confirmed RR Lyrae
rrl_b = pd.read_csv("./RRL_B.csv")        # Confirmed NOT RR Lyrae
rrl_eval = pd.read_csv("./RRL_nG.csv")    # Unknown candidates

# Add labels
rrl_g['label'] = 1
rrl_b['label'] = 0
training_data = pd.concat([rrl_g, rrl_b], ignore_index=True)

# Use only the top 4 features
features = ['Gmagavg', 'ptpG', 'BPmagavg', 'RPmagavg']

# Training data
X_train                                                    =
training_data[features].fillna(training_data[features].mean())
y_train = training_data['label']

scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)

# Train logistic regression model
clf = LogisticRegression(max_iter=1000, random_state=42)
clf.fit(X_train_scaled, y_train)
```

```
# Evaluation data
X_eval = rrl_eval[features].fillna(training_data[features].mean())
X_eval_scaled = scaler.transform(X_eval)

# Predict labels and probabilities
rrl_eval['predicted_label'] = clf.predict(X_eval_scaled)
rrl_eval['RR_probability'] = clf.predict_proba(X_eval_scaled)[:, 1]

# Labeling prob
def label_star(prob):
    if prob > 0.75:
        return 'G'
    elif prob < 0.5:
        return 'B'
    else:
        return 'L'

rrl_eval['RR_label'] = rrl_eval['RR_probability'].apply(label_star)

# Pie chart visualization
label_counts = rrl_eval['RR_label'].value_counts().reindex(['G', 'L',
'B'], fill_value=0)
plt.figure(figsize=(4, 4))
plt.pie(label_counts, labels=label_counts.index, autopct='%1.1f%%',
startangle=140,
        colors=['limegreen', 'gold', 'crimson'],
wedgeprops={'edgecolor': 'black'})
plt.title("RR Lyrae Candidate Labels (Logistic Regression)")
plt.tight_layout()
```

```
plt.show()


print(label_counts)


# plots
plt.figure(figsize=(8, 4))
sc = plt.scatter(rrl_eval['Gmagavg'], rrl_eval['ptpG'],
                 c=rrl_eval['RR_probability'],       cmap='viridis',
edgecolor='k')
plt.colorbar(sc, label='RR Lyrae Probability')
plt.title("GmagAvg vs ptpG")
plt.xlabel("ptpG")
plt.ylabel("GmagAvg")
plt.gca().invert_yaxis()
plt.tight_layout()
plt.show()
```