EE5253Report___4434_4875_GP73

December 12, 2024

1 Student GPA Predictor

2 Group 73

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3 Introduction

The "Student GPA Predictor" project uses machine learning to predict students' GPAs based on factors like gender, study time, absences, and activities. It analyzes data from over 2,300 students to find patterns and help understand what affects academic performance.

4 Literature Survey

The "Student GPA Predictor" project uses Random Forest and Linear Regression models to predict GPAs based on factors like study time, absences, and extracurricular activities. Random Forest excels in handling complex, non-linear relationships, offering higher accuracy, while Linear Regression provides a simpler, interpretable model to understand the influence of individual factors. Both methods are widely used in educational prediction tasks, with Random Forest often outperforming in accuracy.

5 Importing Libraries

[9]:
```
#import library
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
```

6 Dataset Description

This dataset contains comprehensive information on 2,392 high school students, detailing their demographics, study habits, parental involvement, extracurricular activities, and academic performance. The target variable, GradeClass, classifies students' grades into distinct categories, providing a robust dataset for educational research, predictive modeling, and statistical analysis

[12]:
```
data_url = "https://drive.google.com/uc?
 ↪export=download&id=1qXcTk1ytpMgskP1aTDB1p0Bh1kpW0jW5"
df = pd.read_csv(data_url)
df.head()
```

[12]:

	StudentID	Gender	StudyTimeWeekly	Absences	Tutoring	Extracurricular	\
0	1001	1	19.833723	7	1	0	
1	1002	0	15.408756	0	0	0	
2	1003	0	4.210570	26	0	0	
3	1004	1	10.028829	14	0	1	
4	1005	1	4.672495	17	1	0	

	Sports	GPA	GradeClass
0	0	2.929196	2
1	0	3.042915	1
2	0	0.112602	4
3	0	2.054218	3
4	0	1.288061	4

[13]:
```
df.shape
```

[13]:
```
(2392, 9)
```

[15]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2392 entries, 0 to 2391
Data columns (total 9 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   StudentID        2392 non-null   int64
 1   Gender           2392 non-null   int64
 2   StudyTimeWeekly  2392 non-null   float64
 3   Absences         2392 non-null   int64
 4   Tutoring         2392 non-null   int64
 5   Extracurricular  2392 non-null   int64
 6   Sports           2392 non-null   int64
 7   GPA              2392 non-null   float64
 8   GradeClass       2392 non-null   int64
dtypes: float64(2), int64(7)
memory usage: 168.3 KB
```

[16]:
```
df.describe()
```

[16]:

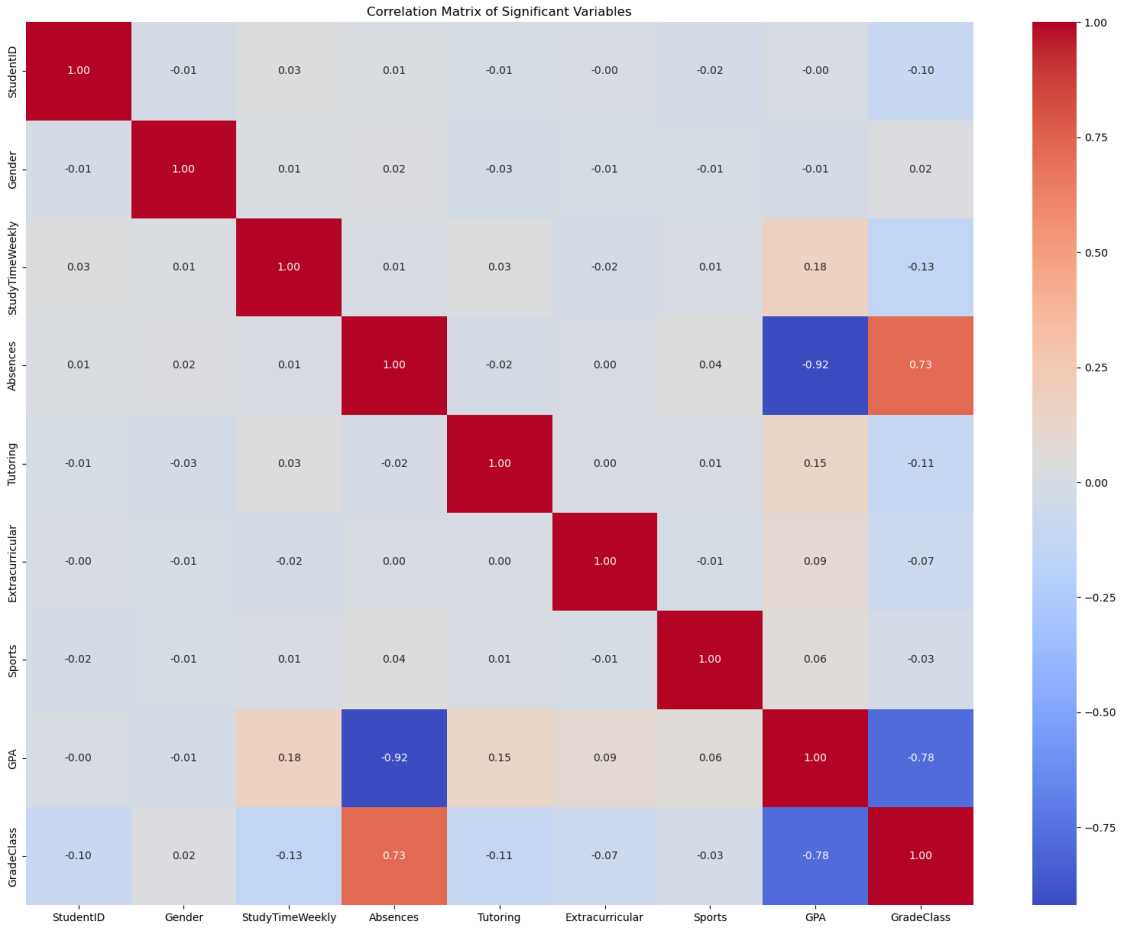
	StudentID	Gender	StudyTimeWeekly	Absences	Tutoring	\
count	2392.000000	2392.000000	2392.000000	2392.000000	2392.000000	
mean	2196.500000	0.510870	9.771992	14.541388	0.301421	
std	690.655244	0.499986	5.652774	8.467417	0.458971	

```
min    1001.000000     0.000000         0.001057     0.000000     0.000000
25%    1598.750000     0.000000         5.043079     7.000000     0.000000
50%    2196.500000     1.000000         9.705363    15.000000     0.000000
75%    2794.250000     1.000000        14.408410    22.000000     1.000000
max    3392.000000     1.000000        19.978094    29.000000     1.000000
```

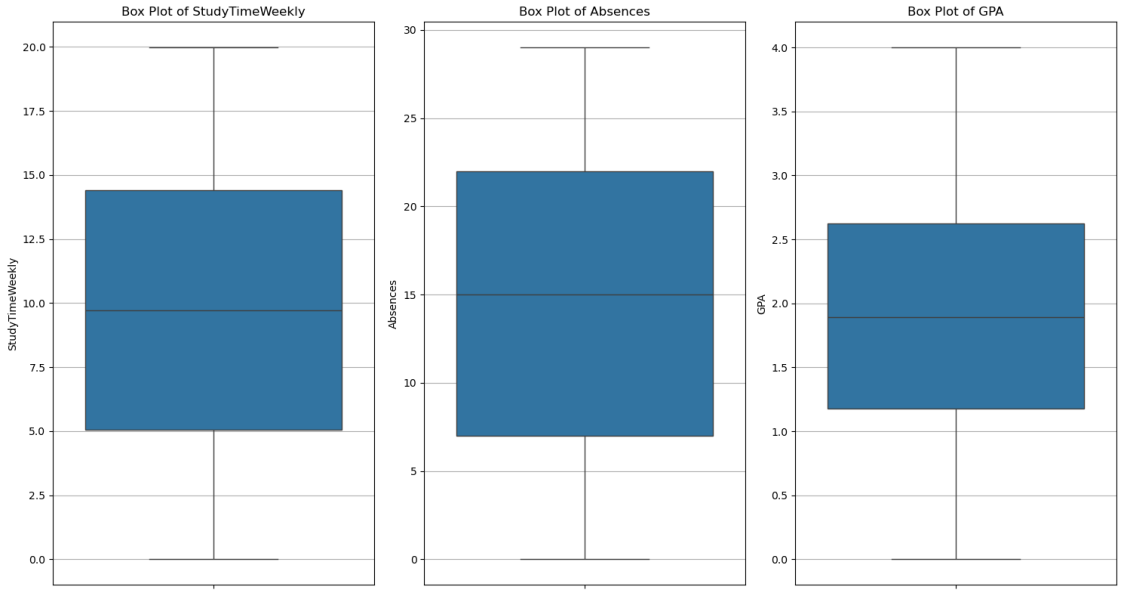
```
       Extracurricular       Sports          GPA   GradeClass
count      2392.000000  2392.000000  2392.000000  2392.000000
mean          0.383361     0.303512     1.906186     2.983696
std           0.486307     0.459870     0.915156     1.233908
min           0.000000     0.000000     0.000000     0.000000
25%           0.000000     0.000000     1.174803     2.000000
50%           0.000000     0.000000     1.893393     4.000000
75%           1.000000     1.000000     2.622216     4.000000
max           1.000000     1.000000     4.000000     4.000000
```

7 Exploratory Data Analysis

[18]:
```
eda_columns = [
    'StudentID',
    'Gender',
    'StudyTimeWeekly',
    'Absences',
    'Tutoring',
    'Extracurricular',
    'Sports',
    'GPA',
    'GradeClass'
]

# Extract relevant data
eda_data = df[eda_columns]

# Generate summary statistics
summary_stats = eda_data.describe()

# Compute correlation matrix
correlation_matrix = eda_data.corr()

# Plot the correlation matrix
plt.figure(figsize=(20, 15))
sns.heatmap(correlation_matrix, annot=True, fmt='.2f', cmap='coolwarm')
plt.title('Correlation Matrix of Significant Variables')
plt.show()
```



[19]:
```
eda_columns = [
    'StudyTimeWeekly',
    'Absences',
    'GPA'
]

plt.figure(figsize=(15, 8))
for i, column in enumerate(eda_columns, 1):
    plt.subplot(1, len(eda_columns), i)
    sns.boxplot(y=df[column], flierprops={"marker": "o", "markerfacecolor":␣
 ↪"red", "markersize": 8})
    plt.title(f'Box Plot of {column}')
    plt.ylabel(column)
    plt.grid(axis='y')

plt.tight_layout()
plt.show()
```



8 Data Preprocessing

[21]:
```
#checking null values
df.isna().sum()
```

[21]:
```
StudentID          0
Gender             0
StudyTimeWeekly    0
Absences           0
Tutoring           0
Extracurricular    0
Sports             0
GPA                0
GradeClass         0
dtype: int64
```

[22]:
```
#unique values
df.nunique()
```

[22]:
```
StudentID          2392
Gender                2
StudyTimeWeekly    2392
Absences             30
Tutoring              2
Extracurricular       2
Sports                2
GPA                2371
```

```
GradeClass            5
dtype: int64
```

[23]:
```
#duplicate values
df.duplicated().sum()
```

[23]:
```
0
```

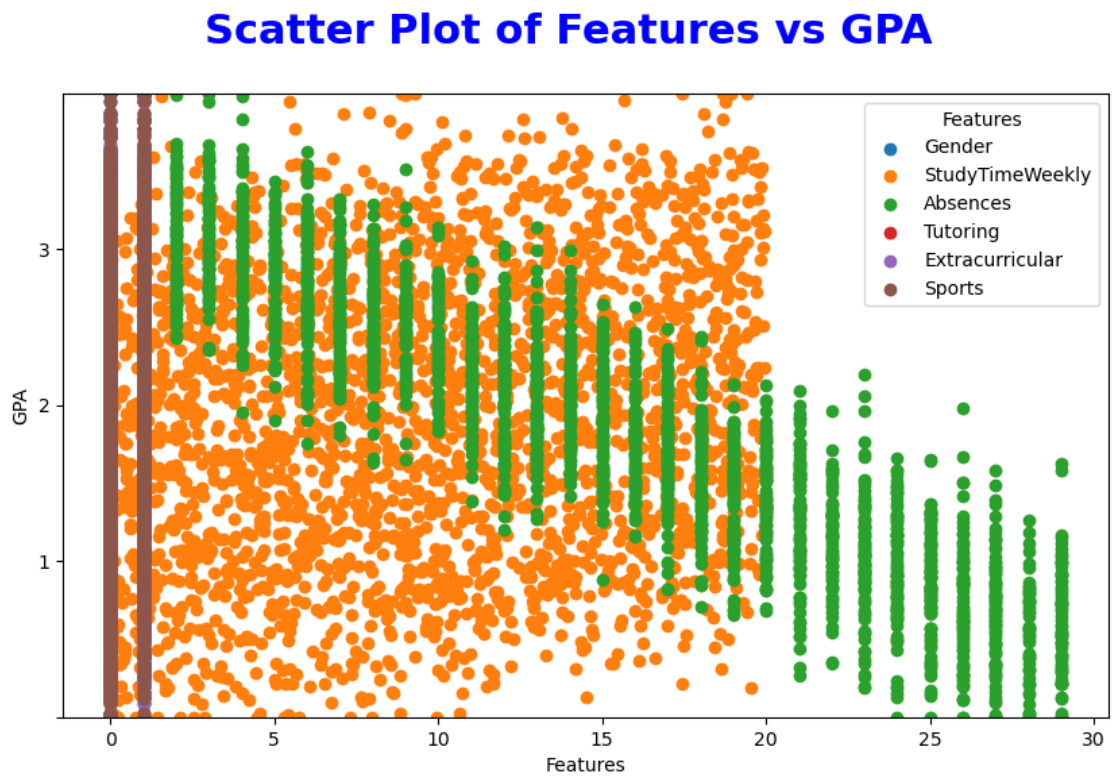
[24]:
```
df.dtypes
#types of data
```

[24]:
```
StudentID            int64
Gender               int64
StudyTimeWeekly    float64
Absences             int64
Tutoring             int64
Extracurricular      int64
Sports               int64
GPA                float64
GradeClass           int64
dtype: object
```

9 Model Implementation

[26]:
```
# Plot each feature separately against GPA
features = ["Gender", "StudyTimeWeekly", "Absences", "Tutoring",␣
 ↪"Extracurricular", "Sports"]
fig, ax = plt.subplots(figsize=(10, 6))

# Loop over each feature and plot
for feature in features:
    ax.scatter(x=df[feature], y=df["GPA"], label=feature)

# Set labels, limits, and ticks
ax.set(xlabel="Features", ylabel="GPA",
       ylim=(0, 4),
       yticks=range(0, 4))

# Customize the plot
ax.legend(title="Features")

ax.yaxis.get_major_ticks()[0].label1.set_visible(False)

fig.suptitle(t="Scatter Plot of Features vs GPA",
             color="blue",
             fontsize=22,
             fontweight="bold")
```

```
# Display the plot
plt.show()
```



Data Splitting and Model Fitting

[28]:
```
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
```

[29]:
```
X = df.drop(["GPA", "GradeClass",'StudentID'], axis=1)
y = df["GPA"]
```

[30]:
```
X.shape
```

[30]: (2392, 6)

[31]:
```
y.shape
```

[31]: (2392,)

[32]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=0)
```

10 Random Forest Regressor

[34]:
```
rf = RandomForestRegressor(n_estimators=100)
rf.fit(X_train,y_train)
rf_train_score = rf.score(X_train,y_train)
print(f"Model Accuracy on training Datasets : {rf_train_score*100:.4f}%")
```

```
Model Accuracy on training Datasets : 98.5165%
```

[39]:
```
rf_test_score = rf.score(X_test,y_test)
print(f"Model Accuracy on Test Datasets : {rf_test_score*100:.4f}%")
```

```
Model Accuracy on Test Datasets : 89.3923%
```

11 Linear Regression

[55]:
```
# Initialize the model
lr = LinearRegression()

# Train the model
lr.fit(X_train, y_train)

# Calculate training accuracy (R² score)
lr_train_score = lr.score(X_train, y_train)

print(f"Model Accuracy on training Datasets: {lr_train_score*100:.4f}%")
```

```
Model Accuracy on training Datasets: 91.4762%
```

[57]:
```
# Calculate test accuracy (R² score)
lr_test_score = lr.score(X_test, y_test)

# Print the model accuracy on the test dataset
print(f"Model Accuracy on Test Datasets: {lr_test_score*100:.4f}%")
```

```
Model Accuracy on Test Datasets: 91.4944%
```

Comparing Actual vs Predicted of Two Models on Test Data

[60]:
```
# Make predictions using the trained models
lr_y_preds = lr.predict(X_test)
rf_y_preds = rf.predict(X_test)

# Create DataFrame with all relevant columns including predictions
vs_df = pd.DataFrame({
```

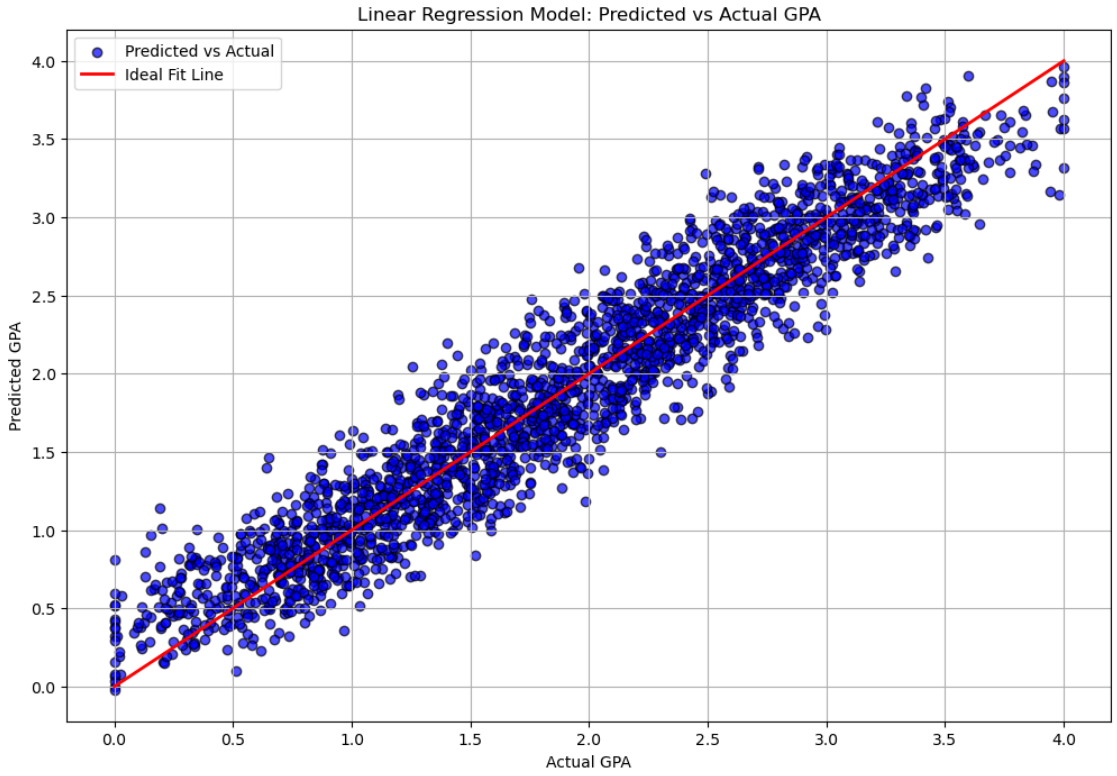
```
    'Gender': X_test['Gender'].values,
    'StudyTimeWeekly': X_test['StudyTimeWeekly'].values,
    'Absences': X_test['Absences'].values,
    'Tutoring': X_test['Tutoring'].values,
    'Extracurricular': X_test['Extracurricular'].values,
    'Sports': X_test['Sports'].values,
    'Actual': y_test.values,
    'LR_Predicted': lr_y_preds,
    'RF_Predicted': rf_y_preds
})

# Display the DataFrame
print(vs_df.head())
```

```
   Gender  StudyTimeWeekly  Absences  Tutoring  Extracurricular  Sports  \
0       0         7.670690         5         0                0       0
1       0        16.070836        12         1                0       1
2       1         4.257002        29         1                1       1
3       1         4.190384        17         0                0       0
4       0        13.274687         3         1                1       0

     Actual  LR_Predicted  RF_Predicted
0  2.224197      2.579502      2.590883
1  2.745859      2.566375      2.230723
2  0.912416      0.715547      0.791591
3  1.482596      1.295136      1.221866
4  2.913888      3.378234      3.472452
```

Plotting Regression line on Scatter Plot

[63]:
```
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import StandardScaler


# Normalize the features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Create and fit the linear regression model
linear_model = LinearRegression()
linear_model.fit(X_scaled, y)

# Predict GPA using the linear model
y_preds = linear_model.predict(X_scaled)

# Plotting
plt.figure(figsize=(12, 8))
```

```
plt.scatter(y, y_preds, color='blue', edgecolors='k', alpha=0.7,␣
 ↪label="Predicted vs Actual")
plt.plot([min(y), max(y)], [min(y), max(y)], color='red', lw=2, label="Ideal␣
 ↪Fit Line")

plt.title("Linear Regression Model: Predicted vs Actual GPA")
plt.xlabel("Actual GPA")
plt.ylabel("Predicted GPA")
plt.grid(True)
plt.legend()
plt.show()
```



Random Forest Regressor line on Scatter Plot

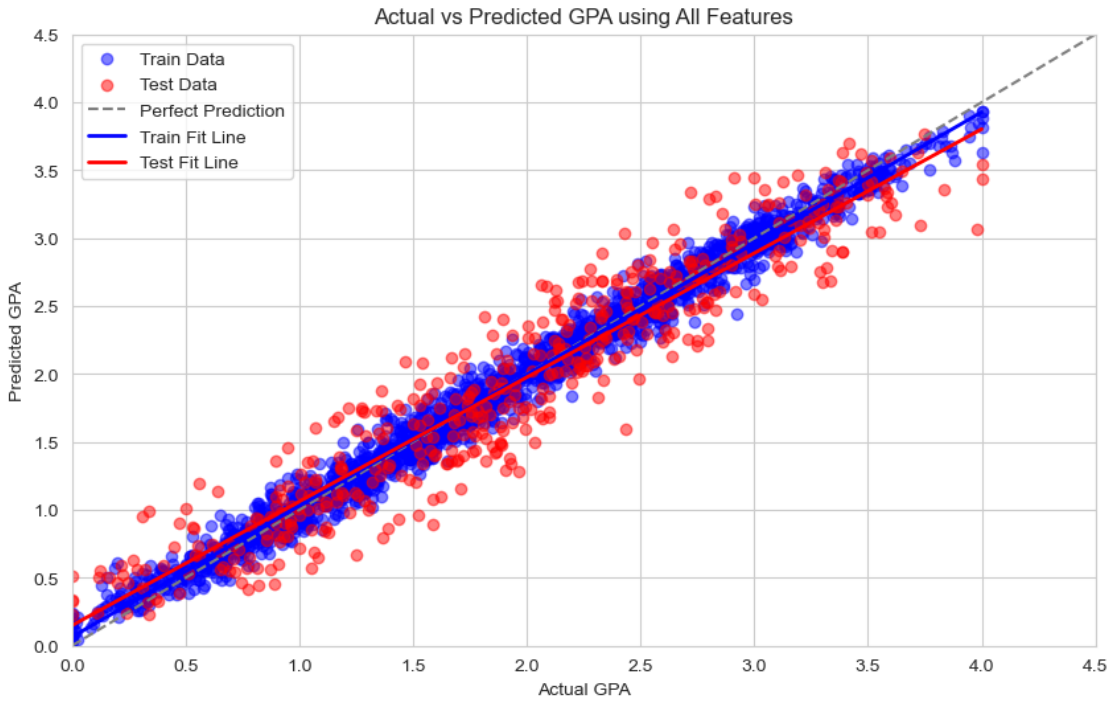
[66]:
```
print(f"X_train shape: {X_train.shape}, y_train shape: {y_train.shape}")
```

```
X_train shape: (1913, 6), y_train shape: (1913,)
```

[73]:
```
y_train_preds = rf.predict(X_train)
y_test_preds = rf.predict(X_test)


print(f"X_train shape: {X_train.shape}, y_train shape: {y_train.shape}")
```

```
sns.set_style("whitegrid")
fig, ax = plt.subplots(figsize=(10, 6))


ax.scatter(y_train, y_train_preds, c="blue", label="Train Data", alpha=0.5)
ax.scatter(y_test, y_test_preds, c="red", label="Test Data", alpha=0.5)


ax.plot([0, 4.5], [0, 4.5], color="gray", linestyle="--", label="Perfect␣
 ↪Prediction")


train_slope, train_intercept = np.polyfit(y_train, y_train_preds, 1)
test_slope, test_intercept = np.polyfit(y_test, y_test_preds, 1)


ax.plot(np.sort(y_train), train_slope * np.sort(y_train) + train_intercept,␣
 ↪color="blue", linewidth=2, label="Train Fit Line")
ax.plot(np.sort(y_test), test_slope * np.sort(y_test) + test_intercept,␣
 ↪color="red", linewidth=2, label="Test Fit Line")


ax.set(
    xlabel="Actual GPA",
    ylabel="Predicted GPA",
    title="Actual vs Predicted GPA using All Features",
    xlim=(0, 4.5),
    ylim=(0, 4.5)
)


ax.legend()


plt.show()
```

```
X_train shape: (1913, 6), y_train shape: (1913,)
```



Prediction on Unseen Data

[75]:
```
def gpa_to_letter_grade(gpa):
    if gpa >= 4.0:
        return "A+"
    elif gpa >= 3.7:
        return "A-"
    elif gpa >= 3.3:
        return "B+"
    elif gpa >= 3.0:
        return "B"
    elif gpa >= 2.7:
        return "B-"
    elif gpa >= 2.3:
        return "C+"
    elif gpa >= 2.0:
        return "C"
    elif gpa >= 1.7:
        return "C-"
    elif gpa >= 1.3:
        return "D+"
    elif gpa >= 1.0:
        return "D"
    elif gpa >= 0.7:
```

```
        return "D-"
    else:
        return "F"


gender = int(input("Enter Gender (0 for male, 1 for female): "))
study_time = float(input("Enter daily study time in hours: "))
absences = int(input("Enter number of absences: "))
tutoring = int(input("Received tutoring? (1 for yes, 0 for no): "))
extracurricular = int(input("Participate in extracurricular activities? (1 for␣
 ↪yes, 0 for no): "))
sports = int(input("Participate in sports? (1 for yes, 0 for no): "))

study_time_week = study_time * 7


study_data = pd.DataFrame({
    "Gender": [gender],
    "StudyTimeWeekly": [study_time_week],
    "Absences": [absences],
    "Tutoring": [tutoring],
    "Extracurricular": [extracurricular],
    "Sports": [sports]
})


lr_score_preds = lr.predict(study_data)


predicted_gpa = min(lr_score_preds[0], 4)


letter_grade = gpa_to_letter_grade(predicted_gpa)


print(f"\nLinear Regression Model Predicted GPA : {predicted_gpa:.4f}")
print(f"Grade Class : {letter_grade}")
```

```
Enter Gender (0 for male, 1 for female):  0
Enter daily study time in hours:  2
Enter number of absences:  3
Received tutoring? (1 for yes, 0 for no):  1
Participate in extracurricular activities? (1 for yes, 0 for no):  1
Participate in sports? (1 for yes, 0 for no):  1


Linear Regression Model Predicted GPA : 3.5860
Grade Class : B+
```

[77]:
```
def gpa_to_letter_grade(gpa):
    if gpa >= 4.0:
        return "A+"
    elif gpa >= 3.7:
        return "A-"
    elif gpa >= 3.3:
        return "B+"
    elif gpa >= 3.0:
        return "B"
    elif gpa >= 2.7:
        return "B-"
    elif gpa >= 2.3:
        return "C+"
    elif gpa >= 2.0:
        return "C"
    elif gpa >= 1.7:
        return "C-"
    elif gpa >= 1.3:
        return "D+"
    elif gpa >= 1.0:
        return "D"
    elif gpa >= 0.7:
        return "D-"
    else:
        return "F"


def get_user_input():
    gender = int(input("Enter Gender (0 for male, 1 for female): "))
    study_time = float(input("Enter Study Time Weekly (in hours): "))
    absences = int(input("Enter Number of Absences: "))
    tutoring = int(input("Enter whether Tutoring is received (1 for yes, 0 for␣
 ↪no): "))
    extracurricular = int(input("Enter whether Extracurricular activities are␣
 ↪participated (1 for yes, 0 for no): "))
    sports = int(input("Enter whether Sports are participated (1 for yes, 0 for␣
 ↪no): "))


    studydata = pd.DataFrame({
        "Gender": [gender],
        "StudyTimeWeekly": [study_time],
        "Absences": [absences],
        "Tutoring": [tutoring],
        "Extracurricular": [extracurricular],
        "Sports": [sports]
    })
```

```
    return studydata


studydata = get_user_input()


rf_score_preds = rf.predict(studydata)


predicted_gpa = min(rf_score_preds[0], 4)


letter_grade = gpa_to_letter_grade(predicted_gpa)


print(f"\nRandom Forest Model Predicted GPA : {predicted_gpa:.4f}")
print(f"Grade Class: {letter_grade}")
```

```
Enter Gender (0 for male, 1 for female):  0
Enter Study Time Weekly (in hours):  2
Enter Number of Absences:  3
Enter whether Tutoring is received (1 for yes, 0 for no):  1
Enter whether Extracurricular activities are participated (1 for yes, 0 for no):
1
Enter whether Sports are participated (1 for yes, 0 for no):  1


Random Forest Model Predicted GPA : 3.2930
Grade Class: B
```

12 Model Evaluation and Discussion

[82]:
```
from sklearn.metrics import mean_absolute_error
from sklearn.metrics import mean_squared_error
from sklearn.metrics import r2_score
```

Mean Absolute Error

[85]:
```
rf_y_preds = rf.predict(X_test)
lr_y_preds = lr.predict(X_test)
print(f"RF_Mean Absolute Error : {mean_absolute_error(y_test, rf_y_preds)}\n")
print(f"LR_Mean Absolute Error : {mean_absolute_error(y_test, lr_y_preds)}\n")
```

```
RF_Mean Absolute Error : 0.23707432358298544

LR_Mean Absolute Error : 0.21156860856772797
```

Mean Squared Error

[92]:
```
rf_y_preds = rf.predict(X_test)
lr_y_preds = lr.predict(X_test)


print(f"RF_Mean Squared Error : {mean_squared_error(y_test, rf_y_preds)}\n")
print(f"LR_Mean Squared Error : {mean_squared_error(y_test, lr_y_preds)}\n")
```

```
RF_Mean Squared Error : 0.08542664120740157

LR_Mean Squared Error : 0.06943617316354136
```

R-squared value

[89]:
```
rf_y_preds = rf.predict(X_test)
lr_y_preds = lr.predict(X_test)


print(f"RF R-squared Value: {r2_score(y_test, rf_y_preds):.4f}\n")
print(f"LR R-squared Value: {r2_score(y_test, lr_y_preds):.4f}\n")
```

```
RF R-squared Value: 0.8946

LR R-squared Value: 0.9149
```

Discussion

The evaluation metrics reveal that both models perform well, but Linear Regression (LR) slightly outperforms Random Forest (RF) across all metrics. The Mean Absolute Error (MAE) shows that LR predicts GPA with a smaller average error (0.2116) compared to RF (0.2371), indicating more accurate predictions. Similarly, the Mean Squared Error (MSE) for LR (0.0694) is lower than RF's (0.0854), suggesting fewer large prediction errors. Moreover, the R-squared (R^2) values indicate that LR explains 91.49% of the variance in GPA, whereas RF explains 89.46%. Overall, LR demonstrates better performance, making it more suitable for this dataset.

13 Conclusion

In conclusion, while the Random Forest model excels in capturing complex patterns with higher training accuracy, its lower test accuracy suggests overfitting. On the other hand, the Linear Regression model demonstrates better generalization with balanced performance across both training and test datasets, making it a more reliable choice for this prediction task.

14 References

https://www.kaggle.com/datasets/rabieelkharoua/students-performance-dataset