Basic Student Performance Analysis

November 2, 2024

0.1 Name Lakshman Chaudhary

0.2 Poject Title: Basic Student Performance Analysis

0.2.1 Importing Libraries

[135]:
```python
import pandas as pd

import numpy as np

import matplotlib.pyplot as plt
import seaborn as sns
from matplotlib.axes import Axes

# To ignore the warnings
import warnings
warnings.filterwarnings('ignore')

# for pre-processing
from sklearn.preprocessing import LabelEncoder, OneHotEncoder, StandardScaler

# For Feature Selection
from sklearn.feature_selection import SelectKBest, f_regression

# To split the data
from sklearn.model_selection import train_test_split

# Models
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor
from sklearn.svm import SVR
from sklearn.neural_network import MLPRegressor

# To evaluate the models
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score
```

0.2.2 Importing Data

[1]:
```
# Importing the necessary library
import pandas as pd

# Reading the CSV file
df = pd.read_csv('student-dataset.csv', delimiter=',')  # Change the delimiter␣
↪if necessary

# Creating a copy of the DataFrame
data = df.copy()  # .copy() creates a true copy, while data = df would just␣
↪make data refer to df

# Optionally, you can check the first few rows of the DataFrame
print(data.head())  # Displays the first 5 rows of the copied DataFrame
```

```
  school;sex;age;address;famsize;Pstatus;Medu;Fedu;Mjob;Fjob;reason;guardian;tra
veltime;studytime;failures;schoolsup;famsup;paid;activities;nursery;higher;inter
net;romantic;famrel;freetime;goout;Dalc;Walc;health;absences;G1;G2;G3
0  GP;"F";18;"U";"GT3";"A";4;4;"at_home";"teacher…
1  GP;"F";17;"U";"GT3";"T";1;1;"at_home";"other";…
2  GP;"F";15;"U";"LE3";"T";1;1;"at_home";"other";…
3  GP;"F";15;"U";"GT3";"T";4;2;"health";"services…
4  GP;"F";16;"U";"GT3";"T";3;3;"other";"other";"h…
```

[2]:
```
# Creating a copy of the DataFrame
data = df.copy()  # .copy() creates a true copy, while data = df would just␣
↪make data refer to df
```

[3]:
```
# Optionally, you can check the first few rows of the DataFrame
print(data.head())  # Displays the first 5 rows of the copied DataFrame
```

```
  school;sex;age;address;famsize;Pstatus;Medu;Fedu;Mjob;Fjob;reason;guardian;tra
veltime;studytime;failures;schoolsup;famsup;paid;activities;nursery;higher;inter
net;romantic;famrel;freetime;goout;Dalc;Walc;health;absences;G1;G2;G3
0  GP;"F";18;"U";"GT3";"A";4;4;"at_home";"teacher…
1  GP;"F";17;"U";"GT3";"T";1;1;"at_home";"other";…
2  GP;"F";15;"U";"LE3";"T";1;1;"at_home";"other";…
3  GP;"F";15;"U";"GT3";"T";4;2;"health";"services…
4  GP;"F";16;"U";"GT3";"T";3;3;"other";"other";"h…
```

[5]:
```
# Verify the data
print(data.head())  # Display the first 5 rows of the DataFrame
```

```
  school;sex;age;address;famsize;Pstatus;Medu;Fedu;Mjob;Fjob;reason;guardian;tra
veltime;studytime;failures;schoolsup;famsup;paid;activities;nursery;higher;inter
net;romantic;famrel;freetime;goout;Dalc;Walc;health;absences;G1;G2;G3
0  GP;"F";18;"U";"GT3";"A";4;4;"at_home";"teacher…
1  GP;"F";17;"U";"GT3";"T";1;1;"at_home";"other";…
```

```
2  GP;"F";15;"U";"LE3";"T";1;1;"at_home";"other";…
3  GP;"F";15;"U";"GT3";"T";4;2;"health";"services…
4  GP;"F";16;"U";"GT3";"T";3;3;"other";"other";"h…
```

1 1. Understanding the Data

[137]:
```python
# Checking the top 5 rows
data.head()
```

[137]:
```
  school sex  age address famsize Pstatus  Medu  Fedu     Mjob      Fjob  …  \
0     GP   F   18       U     GT3       A     4     4  at_home   teacher  …
1     GP   F   17       U     GT3       T     1     1  at_home     other  …
2     GP   F   15       U     LE3       T     1     1  at_home     other  …
3     GP   F   15       U     GT3       T     4     2   health  services  …
4     GP   F   16       U     GT3       T     3     3    other     other  …

  famrel freetime  goout  Dalc  Walc health absences  G1  G2  G3
0      4        3      4     1     1      3        6   5   6   6
1      5        3      3     1     1      3        4   5   5   6
2      4        3      2     2     3      3       10   7   8  10
3      3        2      2     1     1      5        2  15  14  15
4      4        3      2     1     2      5        4   6  10  10

[5 rows x 33 columns]
```

[11]:
```python
print(data.columns)
```

```
Index(['school;sex;age;address;famsize;Pstatus;Medu;Fedu;Mjob;Fjob;reason;guardi
an;traveltime;studytime;failures;schoolsup;famsup;paid;activities;nursery;higher
;internet;romantic;famrel;freetime;goout;Dalc;Walc;health;absences;G1;G2;G3'],
dtype='object')
```

[12]:
```python
import pandas as pd

# Read the CSV file with the correct delimiter
data = pd.read_csv('student-dataset.csv', delimiter=';')

# Check the column names to verify they are separated correctly
print(data.columns)
```

```
Index(['school', 'sex', 'age', 'address', 'famsize', 'Pstatus', 'Medu', 'Fedu',
       'Mjob', 'Fjob', 'reason', 'guardian', 'traveltime', 'studytime',
       'failures', 'schoolsup', 'famsup', 'paid', 'activities', 'nursery',
       'higher', 'internet', 'romantic', 'famrel', 'freetime', 'goout', 'Dalc',
       'Walc', 'health', 'absences', 'G1', 'G2', 'G3'],
      dtype='object')
```

[13]:
```
# Check the minimum and maximum age of students
min_age = data['age'].min()  # Get the minimum age
max_age = data['age'].max()  # Get the maximum age

# Display the results
print('Minimum age of student:', min_age)
print('Maximum age of student:', max_age)
```

```
Minimum age of student: 15
Maximum age of student: 22
```

[138]:
```
# Checking the minmum and maximum age so we can understand the spread
print('min age of student:', min(data['age']))
print('max age of student:',max(data['age']))
```

```
min age of student: 15
max age of student: 22
```

[14]:
```
# Checking the shape i.e number of rows & columns
data.shape
```

[14]:
```
(395, 33)
```

[15]:
```
data['absences'].unique()
```

[15]:
```
array([ 6,  4, 10,  2,  0, 16, 14,  7,  8, 25, 12, 54, 18, 26, 20, 56, 24,
       28,  5, 13, 15, 22,  3, 21,  1, 75, 30, 19,  9, 11, 38, 40, 23, 17],
      dtype=int64)
```

[16]:
```
# Checking the average scores
print('mean of G1:', data['G1'].mean())
print('mean of G2:', data['G2'].mean())

### NOTE: G3 is the final year grade (issued at the 3rd period),
###       while G1 and G2 correspond to the 1st and 2nd period grades.
###       G3 is strongly correlated with G1 and G2
print('mean of G3:', data['G3'].mean())
```

```
mean of G1: 10.90886075949367
mean of G2: 10.713924050632912
mean of G3: 10.415189873417722
```

[17]:
```
table = data.groupby('traveltime')['G3'].mean()
table
```

[17]:
```
traveltime
1    10.782101
2     9.906542
3     9.260870
```

```
4     8.750000
Name: G3, dtype: float64
```

[142]:
```
table = data.groupby('traveltime')['G3'].mean()
table
```

[142]:
```
traveltime
1    10.782101
2     9.906542
3     9.260870
4     8.750000
Name: G3, dtype: float64
```

2 2. Data Preparation

2.1 2.1 Data Cleaning

[18]:
```
data.isnull().sum()
```

[18]:
```
school        0
sex           0
age           0
address       0
famsize       0
Pstatus       0
Medu          0
Fedu          0
Mjob          0
Fjob          0
reason        0
guardian      0
traveltime    0
studytime     0
failures      0
schoolsup     0
famsup        0
paid          0
activities    0
nursery       0
higher        0
internet      0
romantic      0
famrel        0
freetime      0
goout         0
Dalc          0
Walc          0
```

```
health        0
absences      0
G1            0
G2            0
G3            0
dtype: int64
```

[144]:
```
# Checking for duplicate data
data.duplicated().sum()
```

[144]:
```
0
```

[145]:
```
# CHecking the number of unique values in each column
data.nunique()
```

[145]:
```
school         2
sex            2
age            8
address        2
famsize        2
Pstatus        2
Medu           5
Fedu           5
Mjob           5
Fjob           5
reason         4
guardian       3
traveltime     4
studytime      4
failures       4
schoolsup      2
famsup         2
paid           2
activities     2
nursery        2
higher         2
internet       2
romantic       2
famrel         5
freetime       5
goout          5
Dalc           5
Walc           5
health         5
absences      34
G1            17
G2            17
```

```
G3            18
dtype: int64
```

[19]:
```
# Information about the data types and the no. of entries in the columns
data['school'].info()
```

```
<class 'pandas.core.series.Series'>
RangeIndex: 395 entries, 0 to 394
Series name: school
Non-Null Count  Dtype
--------------  -----
395 non-null    object
dtypes: object(1)
memory usage: 3.2+ KB
```

3 2.2 Categorizing Features

3.0.1 Categorical features

[20]:
```
# Getting Categorical Features
categorical_features = data.select_dtypes(include=['object']).columns

# Getting Nominal Features
categorical_features_nominal = ['Mjob', 'Fjob', 'reason', 'guardian']

# Ordinal Features - Removing the nominal features from the categorical features
categorical_features_ordinal = [feature for feature in categorical_features if␣
↪feature not in categorical_features_nominal]

# Display the results
print("Nominal Features:", categorical_features_nominal)
print("Ordinal Features:", categorical_features_ordinal)
```

```
Nominal Features: ['Mjob', 'Fjob', 'reason', 'guardian']
Ordinal Features: ['school', 'sex', 'address', 'famsize', 'Pstatus',
'schoolsup', 'famsup', 'paid', 'activities', 'nursery', 'higher', 'internet',
'romantic']
```

3.0.2 Numerical features

[148]:
```
# Getting Numerical Features
numerical_features = list(data.select_dtypes(exclude=['object']).columns)
```

[21]:
```
# Getting Numerical Features
numerical_features = list(data.select_dtypes(exclude=['object']).columns)

# Display the numerical features
print("Numerical Features:", numerical_features)
```

```
Numerical Features: ['age', 'Medu', 'Fedu', 'traveltime', 'studytime',
'failures', 'famrel', 'freetime', 'goout', 'Dalc', 'Walc', 'health', 'absences',
'G1', 'G2', 'G3']
```

4 3. Feature Engineering

4.1 3.1 Final Grades

COnverting marks into percentage and assigning grades - * 16-20 : Excellent * 14-15 : Good * 12-13 : Satisfactory * 10-11 : Poor * 0-9 : Fail

[203]:
```
data.loc[data['G3'] >= 16, 'final_grade'] = 'Excellent' # above 18
data.loc[data['G3'].between(13,16), 'final_grade'] = 'Good' # 15-17
data.loc[data['G3'].between(11,14), 'final_grade'] = 'Satisfactory' # 11-14
data.loc[data['G3'].between(9,12), 'final_grade'] = 'Poor' # 6-10
data.loc[data['G3'] <= 9, 'final_grade'] = 'Fail' # below 6
```

[22]:
```
# Define final grades based on 'G3' score ranges without overlaps
data.loc[data['G3'] >= 18, 'final_grade'] = 'Excellent'   # 18 and above
data.loc[data['G3'].between(15, 17), 'final_grade'] = 'Good'  # 15-17
data.loc[data['G3'].between(11, 14), 'final_grade'] = 'Satisfactory'  # 11-14
data.loc[data['G3'].between(6, 10), 'final_grade'] = 'Poor'  # 6-10
data.loc[data['G3'] < 6, 'final_grade'] = 'Fail'  # below 6

# Display the updated data to check final grades
print(data[['G3', 'final_grade']].head())
```

```
   G3 final_grade
0   6        Poor
1   6        Poor
2  10        Poor
3  15        Good
4  10        Poor
```

5 Plotting function

[150]:
```
def multiplot(x: list, y: str, data: pd.DataFrame, plot_type: str, palette=␣
↪None, grid=False, dpi=100) -> Axes:

  # Checking the DataTypes of the arguments
  if not isinstance(x, list):
    raise TypeError('Input must be a list. Ensure it\'s a list of feature␣
↪column names.')

  if not isinstance(y, str):
    raise TypeError('Input must be a string')
```

```python
if not isinstance(data, pd.DataFrame):
  raise TypeError('Input must be a DataFrame')

if not isinstance(plot_type, str):
  raise TypeError('Input must be a string')

if palette is None:
  palette = sns.color_palette('muted')

if not isinstance(grid, bool):
  raise TypeError('Input must be a boolean')

if not isinstance(dpi, int):
  raise TypeError('Input must be an integer')


# Settings
sns.set_style('white')
if grid is True:
  sns.set_style('whitegrid')


if dpi is None:
  dpi = 100

# creating the plot function from input
plot_func = getattr(sns, plot_type, None)

if plot_func is None or not callable(plot_func):
  raise ValueError(f'Invalid plot type: {plot_type}. Ensure it\'s a valid␣
↪Seaborn plot type.')

# Getting the number of features
length = int(len(x))

# Calculating the size of the plot
rows = int(np.ceil(length/3)) # Such that we have 3 plot in each row

# Dynamically adjusting the figure size
figsize = (3 * 4.7, rows * 4.7)

#creating the plot
f, axs = plt.subplots(rows, 3, figsize=figsize, dpi=dpi)

# Flatten axs for easier indexing if there is only one row or column
axs = axs.flatten()
```

```python
    # iterating through subplots
    for count, ax in enumerate(axs):
      if count < length:
        # Getting the feature to plot
        feature = x[count]

        # Plotting
        plot_func(x=data[feature], y=data[y], palette=palette, ax=ax)
        ax.set_title(f'{y} by {feature}')

      else:
        # Deleting unused subplots
        ax.axis('off')

    # Adding title and finishing touches
    plt.suptitle('Bivariate Data Analysis', fontsize=16)
    plt.tight_layout(rect=[0, 0, 1, 0.96])
    plt.show()

    return f
```

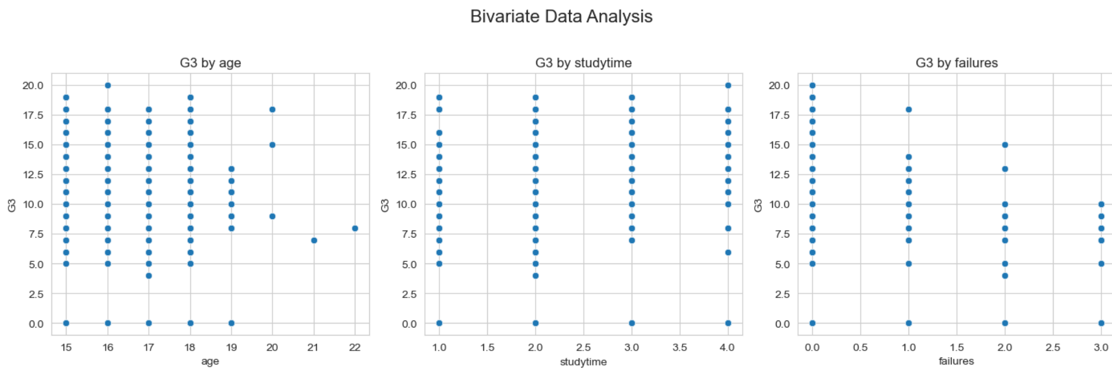
[24]:
```python
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from pandas import DataFrame
from matplotlib.axes import Axes

def multiplot(x: list, y: str, data: DataFrame, plot_type: str, palette=None,␣
 ↪grid=False, dpi=100) -> Axes:
    # Checking argument types
    if not isinstance(x, list):
        raise TypeError("x must be a list of feature column names.")
    if not isinstance(y, str):
        raise TypeError("y must be a string.")
    if not isinstance(data, DataFrame):
        raise TypeError("data must be a pandas DataFrame.")
    if not isinstance(plot_type, str):
        raise TypeError("plot_type must be a string.")
    if not isinstance(grid, bool):
        raise TypeError("grid must be a boolean.")
    if not isinstance(dpi, int):
        raise TypeError("dpi must be an integer.")

    # Settings
    sns.set_style('whitegrid' if grid else 'white')
    palette = palette or sns.color_palette("muted")
```

```
    # creating the plot function from input
    plot_func = getattr(sns, plot_type, None)
    if plot_func is None or not callable(plot_func):
        raise ValueError(f"Invalid plot type: {plot_type}. Ensure it's a valid␣
↪Seaborn plot type.")

    # Calculate layout
    length = len(x)
    rows = int(np.ceil(length / 3))
    figsize = (3 * 4.7, rows * 4.7)

    # Create subplots
    fig, axs = plt.subplots(rows, 3, figsize=figsize, dpi=dpi)
    axs = axs.flatten()

    # Plotting each feature
    for count, ax in enumerate(axs):
        if count < length:
            feature = x[count]
            plot_func(x=data[feature], y=data[y], palette=palette, ax=ax)
            ax.set_title(f"{y} by {feature}")
        else:
            ax.axis("off")

    # Add title and layout adjustments
    plt.suptitle("Bivariate Data Analysis", fontsize=16)
    plt.tight_layout(rect=[0, 0, 1, 0.96])
    plt.show()

    return fig
```

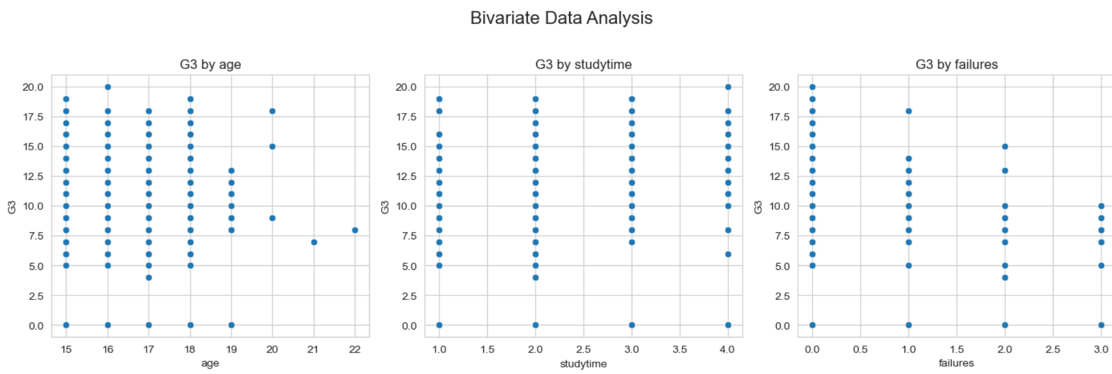
[25]:
```
# Example usage
x_columns = ['age', 'studytime', 'failures']  # replace with actual column␣
↪names from your data
y_column = 'G3'  # replace with your target column

# Call the function
multiplot(x=x_columns, y=y_column, data=data, plot_type="scatterplot",␣
↪grid=True)
```

```
C:\Users\laksh\AppData\Local\Temp\ipykernel_7372\3051787561.py:44: UserWarning:
Ignoring `palette` because no `hue` variable has been assigned.
  plot_func(x=data[feature], y=data[y], palette=palette, ax=ax)
C:\Users\laksh\AppData\Local\Temp\ipykernel_7372\3051787561.py:44: UserWarning:
Ignoring `palette` because no `hue` variable has been assigned.
  plot_func(x=data[feature], y=data[y], palette=palette, ax=ax)
C:\Users\laksh\AppData\Local\Temp\ipykernel_7372\3051787561.py:44: UserWarning:
Ignoring `palette` because no `hue` variable has been assigned.
```

```
plot_func(x=data[feature], y=data[y], palette=palette, ax=ax)
```



[25]:



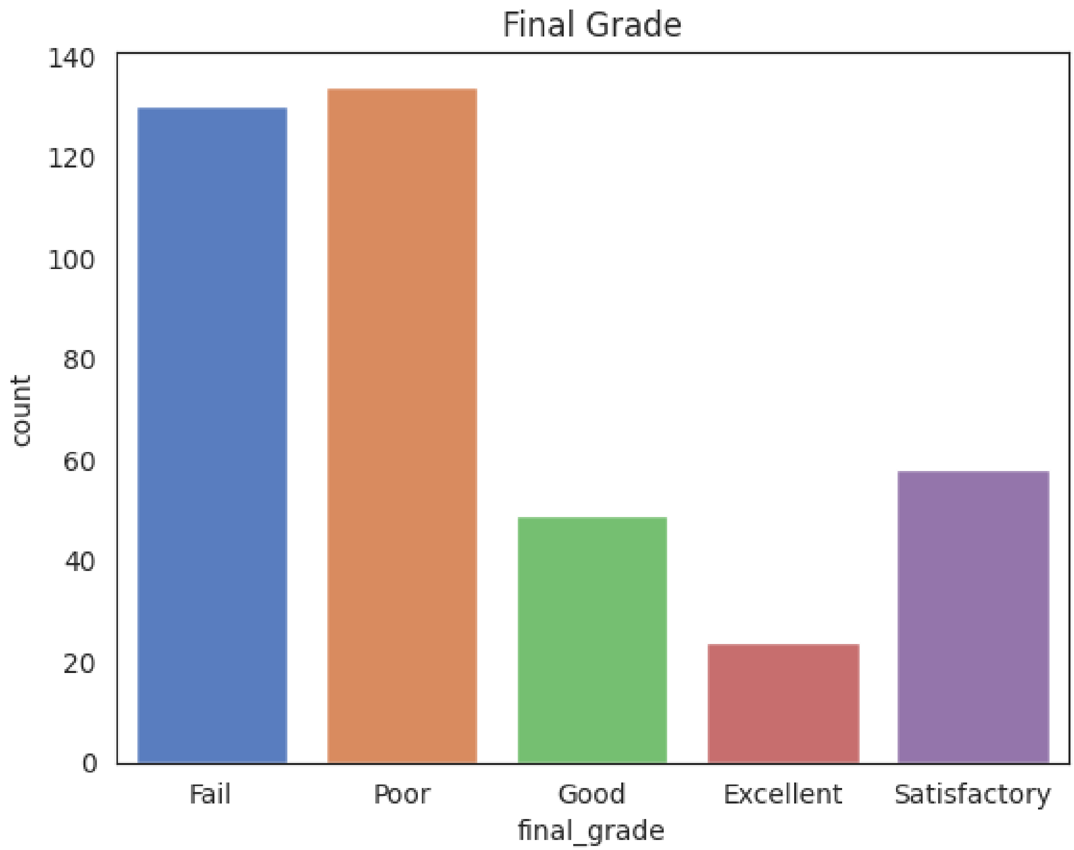
6 4. EDA - Exploratory Data Analysis

[151]:
```
# Setting a color palette for Visuals
color_palette = sns.color_palette('muted')
```

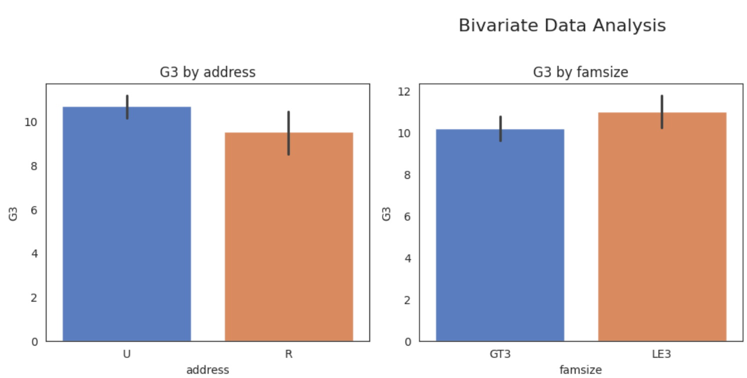
6.1 Documented graphs

6.1.1 For Inisghts, find the link to the complete documentation in the README file.

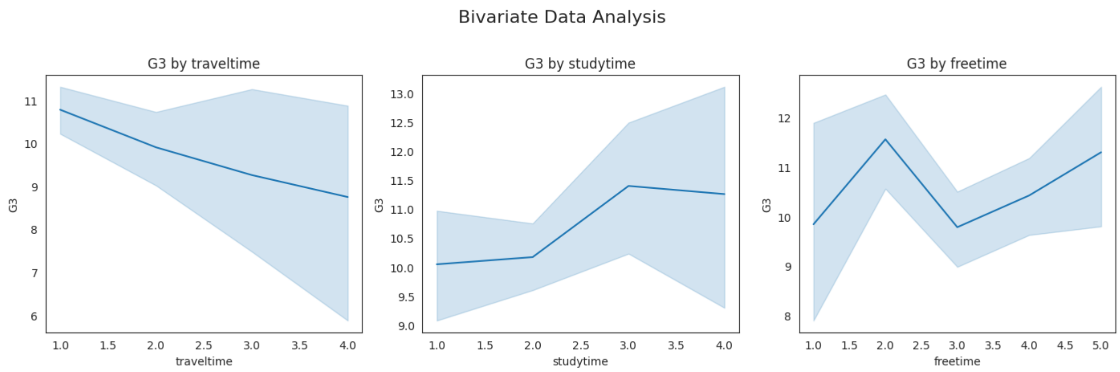
[204]:
```
sns.countplot(x=data['final_grade'], palette=color_palette)
plt.title('Final Grade')
plt.savefig('final_grade.png')
```



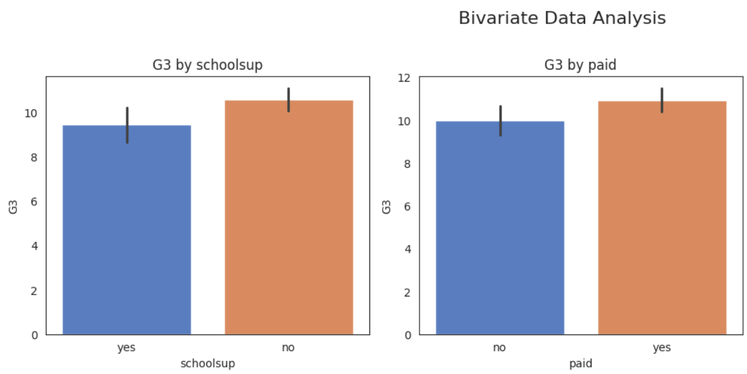
[205]:
```
X, Y = ['address', 'famsize'], 'G3'

plot = multiplot(x=X, y=Y ,data=data, plot_type='barplot',␣
  ↪palette=color_palette)
plot.savefig('plot1')
```



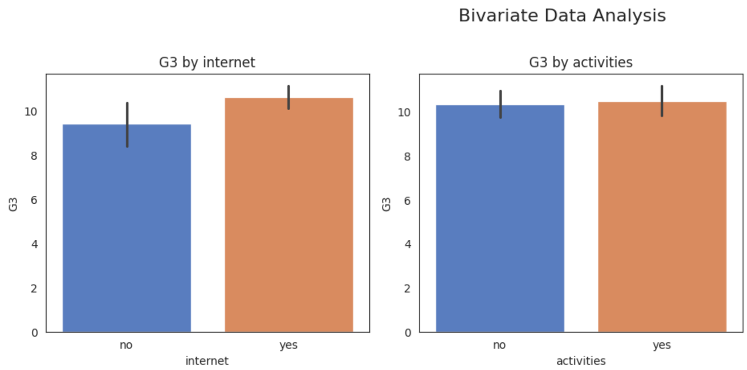
[154]:
```
X, Y = ['traveltime', 'studytime', 'freetime'], 'G3'

plot = multiplot(x=X, y=Y ,data=data, plot_type='lineplot',␣
↪palette=color_palette)
plot.savefig('plot2')
```



[206]:
```
X, Y = ['schoolsup', 'paid'], 'G3'

plot = multiplot(x=X, y=Y ,data=data, plot_type='barplot',␣
↪palette=color_palette)
plot.savefig('plot3')
```



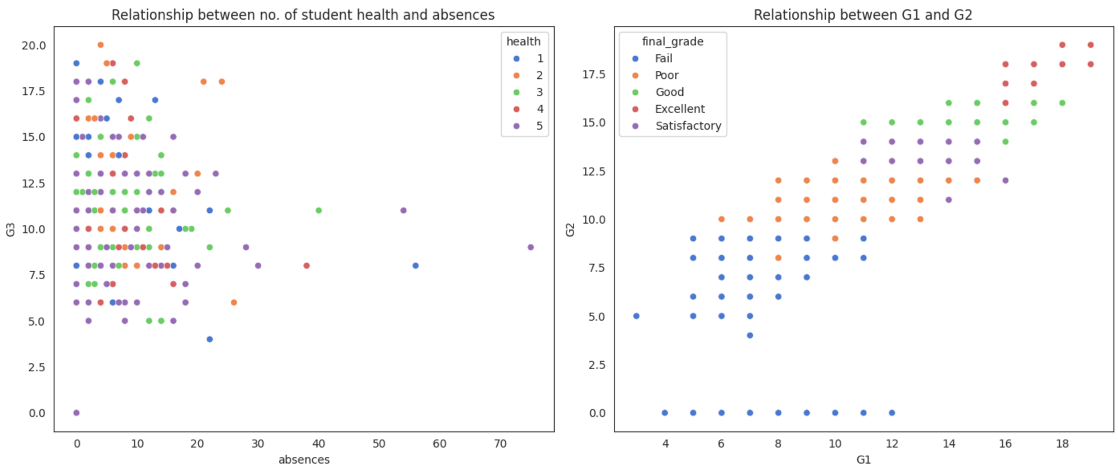
[156]:
```
X, Y = ['internet', 'activities'], 'G3'

plot = multiplot(x=X, y=Y ,data=data, plot_type='barplot',␣
↪palette=color_palette)
plot.savefig('plot4')
```



[157]:
```
data.iloc[:,18]
```

[157]:
```
0       no
1       no
2       no
3      yes
4       no
      ...
390     no
391     no
392     no
393     no
394     no
Name: activities, Length: 395, dtype: object
```

[158]:
```
f, axs = plt.subplots(1,2, figsize=(14.1,6))



ax = axs[0]
sns.scatterplot(x=data['absences'], y=data['G3'], hue=data['health'],␣
 ↪palette=color_palette, ax=ax)
ax.set_title('Relationship between no. of student health and absences')

ax = axs[1]
sns.scatterplot(x=data['G1'], y=data['G2'], hue=data['final_grade'],␣
 ↪palette=color_palette, ax=ax)
ax.set_title('Relationship between G1 and G2')

plt.tight_layout()
plt.savefig('plot5.png')
```

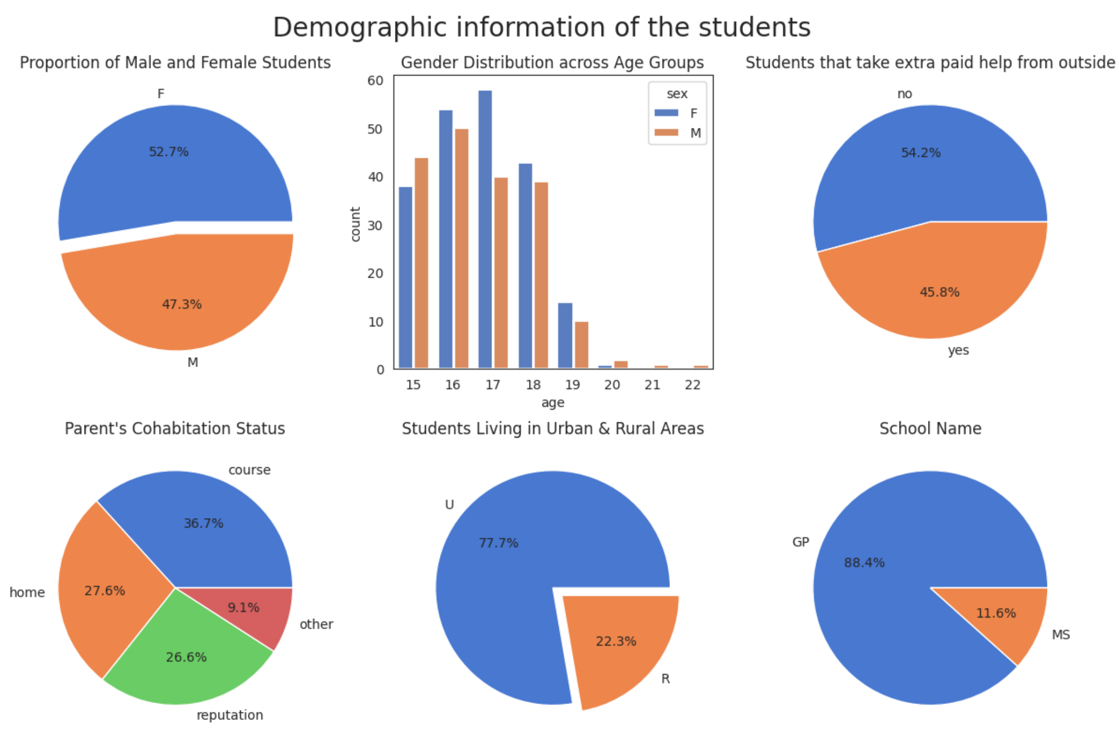


6.2 4.1 Univariate Data Analyis

[159]:

```
# Creating basic plots about the Demographic information of students

f, axs = plt.subplots(2,3, figsize=(12,8))

ax = axs[0,0]
ax.pie(x=data['sex'].value_counts(), labels = data['sex'].value_counts().index,
       colors = color_palette, autopct='%1.1f%%', explode=(0,0.1))
ax.set_title('Proportion of Male and Female Students')

ax = axs[0,1]
sns.countplot(x=data['age'], hue=data['sex'],
              palette = color_palette, linewidth=2, ax=ax)
ax.set_title('Gender Distribution across Age Groups')

ax = axs[0,2]
ax.pie(x=data['paid'].value_counts(),
       labels = data['paid'].value_counts().index,
       colors = color_palette,
       autopct='%1.1f%%')
ax.set_title('Students that take extra paid help from outside')

ax = axs[1,0]
ax.pie(x=data['reason'].value_counts(),
       labels = data['reason'].value_counts().index,
       colors = color_palette,
       autopct='%1.1f%%')
ax.set_title('Parent\'s Cohabitation Status')

ax = axs[1,1]
```

```
ax.pie(x=data['address'].value_counts(),
       labels=data['address'].value_counts().index,
       colors = color_palette, autopct= '%1.1f%%',
       explode = (0,0.1))
ax.set_title('Students Living in Urban & Rural Areas')

ax = axs[1,2]
ax.pie(x=data['school'].value_counts(),
       labels=data['school'].value_counts().index,
       colors = color_palette, autopct= '%1.1f%%')
ax.set_title('School Name')


plt.suptitle('Demographic information of the students', fontsize=20)


#plt.delaxes(ax=axs[1,2])
plt.tight_layout()
plt.show()
```



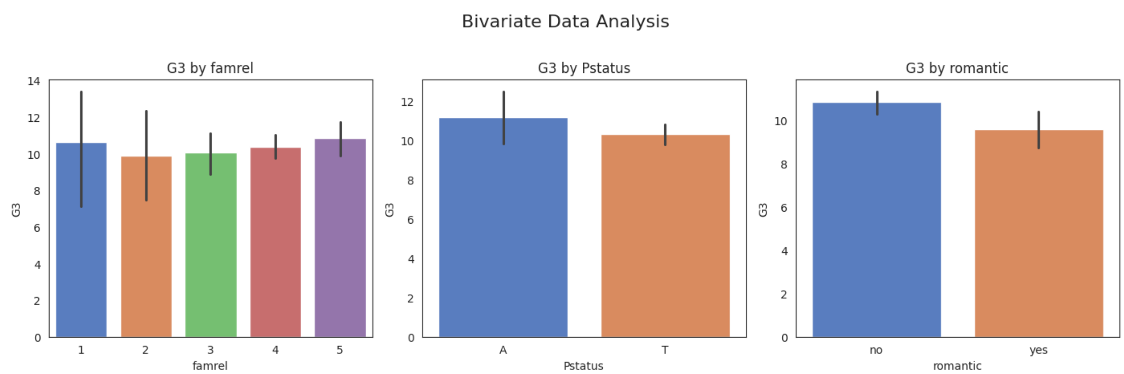
6.2.1 Insights:

- No. of female students and male students is almost equal, no. of female students is slightly higher.

- Most no. of students are between the ages 15-18
- Most of the students are from Gabriel Pereira School.
- Almost 50% of the students take extra paid classes outside of school.
- The reason majority of the students joined is due to the course.
- Distance from home and school reputation.
- 78% of the students come from Urban areas and 22% from Rural areas.

6.3 4.2 Bivariate Data Analysis

[160]:
```
# Creating more graphs that are related to the student's academics

graphs_list = ['famrel', 'Pstatus', 'romantic']

fig = multiplot( x=graphs_list, y='G3', data=data, plot_type='barplot',␣
    ↪palette=color_palette)
fig.savefig('Extra graphs')
```



Insights:

- Family of 3 or less show better family relationship.
- Students with Internet availability show higher marks
- Students taking extra paid classes show higher marks.
- Students who study for 5-10 hours a week show higher average marks.
- Optimal free time after school is 2.
  - 1 - very low; 5 - very high
- Consumption of alcohol during the week increases the more they go out with friends.
- Most students scored poorly.

7 5. Data Pre-Processing

7.1 5.1 Pre-processing

[161]:
```
# Creating a backup
data_backup = data.copy()
```

Label encoder - For Ordinal Data (There is order of significance)
One Hot Encoder - For Nominal Data (No order of significance)

[162]:
```
# Scaling Categorical Ordinal Features

label = LabelEncoder()

# Going through and converting one column at a time
for col in categorical_features_ordinal:
  data[col] = label.fit_transform(data[col])
```

[163]:
```
# Scaling Categorical Nominal Features
one_hot = OneHotEncoder(sparse=False, drop='first')

# Convert the columns
one_hot_encoded = one_hot.fit_transform(data[categorical_features_nominal])

# convert the above into a DataFrame
encoded_df = pd.DataFrame(one_hot_encoded, columns=one_hot.
 ↪get_feature_names_out(categorical_features_nominal))

# Now add the new df in place of the old ones in the Data
data = pd.concat([data.drop(columns=categorical_features_nominal), encoded_df],␣
 ↪axis=1)
```

[164]:
```
# Scaling Numerical Features

scaler = StandardScaler()
data[numerical_features] = scaler.fit_transform(data[numerical_features])
```

[165]:
```
data.head()
```

[165]:
```
   school  sex       age  address  famsize  Pstatus      Medu      Fedu  \
0       0    0  1.023046        1        0        0  1.143856  1.360371
1       0    0  0.238380        1        0        1 -1.600009 -1.399970
2       0    0 -1.330954        1        1        1 -1.600009 -1.399970
3       0    0 -1.330954        1        0        1  1.143856 -0.479857
4       0    0 -0.546287        1        0        1  0.229234  0.440257

   traveltime  studytime  …  Mjob_teacher  Fjob_health  Fjob_other  \
0    0.792251  -0.042286  …           0.0          0.0         0.0
```

```
1   -0.643249  -0.042286  …            0.0            0.0           1.0
2   -0.643249  -0.042286  …            0.0            0.0           1.0
3   -0.643249   1.150779  …            0.0            0.0           0.0
4   -0.643249  -0.042286  …            0.0            0.0           1.0

   Fjob_services  Fjob_teacher  reason_home  reason_other  reason_reputation  \
0            0.0           1.0          0.0           0.0                0.0
1            0.0           0.0          0.0           0.0                0.0
2            0.0           0.0          0.0           1.0                0.0
3            1.0           0.0          1.0           0.0                0.0
4            0.0           0.0          1.0           0.0                0.0

   guardian_mother  guardian_other
0              1.0             0.0
1              0.0             0.0
2              1.0             0.0
3              1.0             0.0
4              0.0             0.0

[5 rows x 43 columns]
```

7.2 5.2 Feature Selection

[166]:
```
# dropping features
data=data.drop(['sex', 'G1', 'G2'], axis=1)
```

[167]:
```
# Independent Variables - Feature table that will be used to predict Y
X = data.drop(columns='G3')
X = data.drop(columns='final_grade')
```

[168]:
```
# Dependent Variable
Y = data['G3']
```

[169]:
```
# Selecting the best Features using SelectKbest and f_regression
feature_selector = SelectKBest(score_func=f_regression, k='all')
X_new = feature_selector.fit_transform(X,Y)
```

[170]:
```
# Saving the new features to variable X
X = X_new
```

7.3 5.3 Train Test Split

[171]:
```
# Splitting the dataset
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.2,
                                                    random_state=44)
```

8 6. Modelling

8.1 6.1 Initialising the models

[172]:
```
# Initialising the models
models = {
    'Linear Regression': LinearRegression(),
    'Random Forest Regressor': RandomForestRegressor(),
    'Support Vector Machine': SVR(),
    'Neural Network': MLPRegressor()
}
```

8.2 6.2 Training

[173]:
```
# Training the models
for name, model in models.items():
  model.fit(X_train, Y_train)
```

9 7 Model Evaluation

9.1 7.1 Calculating metrics

[174]:
```
# Evaluating the models
results = {}
overfit = {}

for name, model in models.items():
  Y_pred = model.predict(X_test)

  mae = mean_absolute_error(Y_test, Y_pred)
  mse = mean_squared_error(Y_test, Y_pred)
  rmse = mean_squared_error(Y_test, Y_pred, squared=False)
  r2 = r2_score(Y_test, Y_pred)

  # Storing results
  results[name] = {'MAE': mae, 'MSE': mse, 'RMSE': rmse, 'r2': r2}



  ### Calculating Overfitting ####

  # Predicting on training data and testing data (Seen and Unseen data)
  training_preds = model.predict(X_train)
  testing_preds = model.predict(X_test)

  # Calculating the MSE
  train_MSE = mean_squared_error(Y_train, training_preds)
```

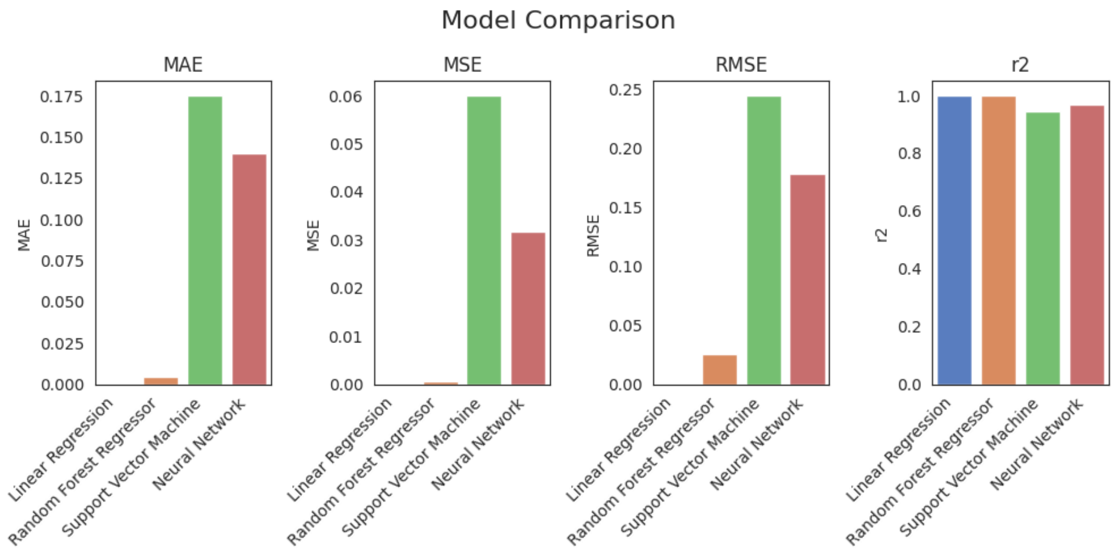
```
    test_MSE = mean_squared_error(Y_test, testing_preds)

    # overfitting values
    overfit[name] = {'Training MSE': train_MSE, 'Testing MSE':test_MSE}

#number of metrics
n = len(results[list(models.keys())[0]])

# Printing the results
results_df = pd.DataFrame.from_dict(results).T # .T to transpose it
overfit_df = pd.DataFrame.from_dict(overfit).T

# calucating difference to check overfitting
overfit_df['Difference'] = abs(overfit_df['Training MSE'] - overfit_df['Testing␣
↪MSE'])

print(results_df)
print(f'\n{overfit_df}')
```

```
                                MAE           MSE          RMSE        r2
Linear Regression        8.637605e-16  1.189023e-30  1.090423e-15  1.000000
Random Forest Regressor  4.204987e-03  6.495839e-04  2.548694e-02  0.999390
Support Vector Machine   1.751369e-01  6.000627e-02  2.449618e-01  0.943675
Neural Network           1.399901e-01  3.180245e-02  1.783324e-01  0.970148

                         Training MSE  Testing MSE    Difference
Linear Regression        1.248376e-30  1.189023e-30  5.935338e-32
Random Forest Regressor  7.864355e-05  6.495839e-04  5.709404e-04
Support Vector Machine   8.173978e-03  6.000627e-02  5.183230e-02
Neural Network           5.842573e-03  3.180245e-02  2.595987e-02
```

9.2 7.2 Comparing models

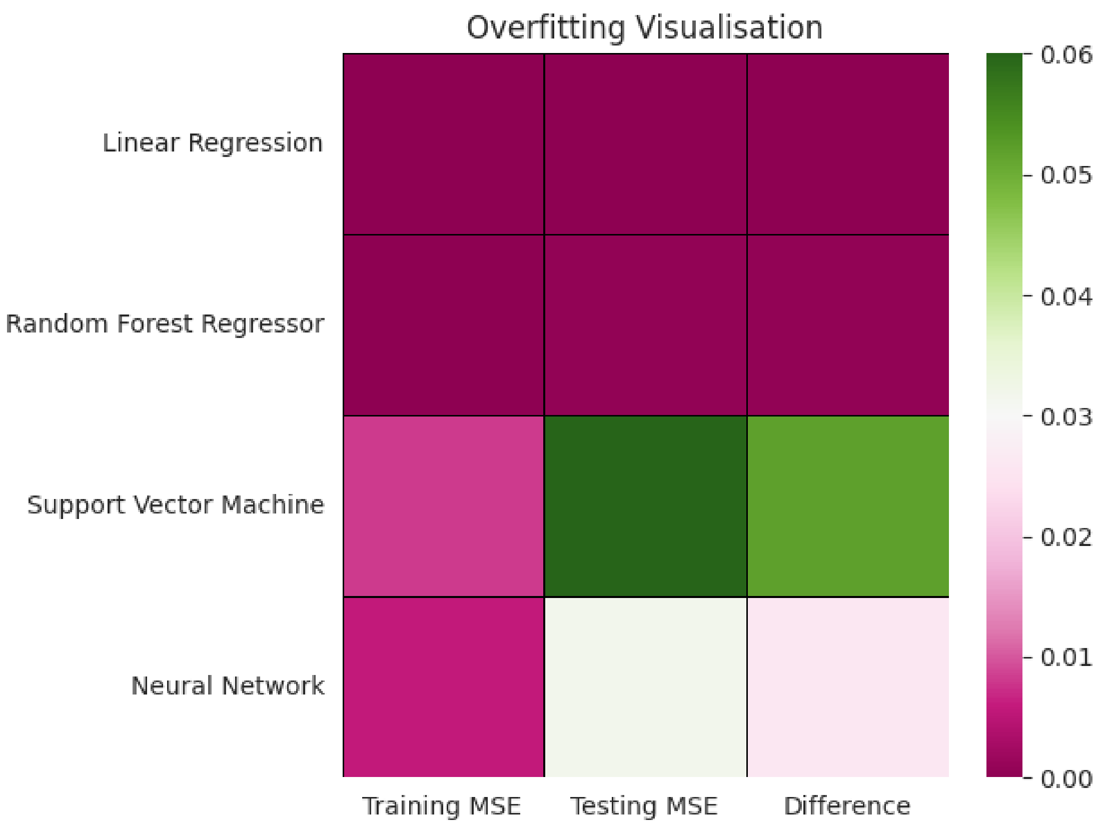
[175]:
```
# creating a figure to compare the model metrics
f, axs = plt.subplots(1,n,figsize=(10,5))

for i in range(0,n):
    ax=axs[i]
    metric = results_df.columns[i]
    sns.barplot(x=results_df.index, y = results_df[metric],␣
↪palette=color_palette, ax=ax)
    ax.set_title(metric)
    ax.set_xticklabels(labels=results_df.index, rotation=45, ha='right')
    ax.set_xlabel('')
    ax.set_ylabel(metric)

plt.suptitle('Model Comparison', fontsize=16)
```

```
plt.tight_layout()
plt.savefig('Model_performance')
plt.show()
```



9.3 7.3 Overfitting Visualisation

[176]:
```
# Creating a heatmap for overfitting values
sns.heatmap(data=overfit_df, cmap="PiYG", linewidth=0.5, linecolor='black')
plt.title('Overfitting Visualisation')
plt.tight_layout()
plt.savefig('overfitting.png')
```



We conclude that Linear Regression is the best fit.

For detailed explanation, see the documentation linked in README file

10 8. Most significant features

[192]:
```
# Intialising our best model
best_model = LinearRegression()
best_model.fit(X,Y)

# getting the coefficients in the model
coefficients = best_model.coef_

# Generating feature_names
feature_names = [(f'feature{i}') for i in range(X.shape[1])]

#Converting to a DataFrame and sorting in descending order
coeff_df = pd.DataFrame({'feature': feature_names, 'coefficient': coefficients})

# Creating a column for absolute values
coeff_df['abs_coeff'] = coeff_df['coefficient'].abs()
```

```python
# Sorting the coefficients in descending order of the absolute coefficients.
coeff_df = coeff_df.sort_values(by='abs_coeff', ascending=False)

print(coeff_df)
```

```
      feature   coefficient     abs_coeff
25  feature25  1.000000e+00  1.000000e+00
5    feature5  9.126349e-16  9.126349e-16
20  feature20 -5.110544e-16  5.110544e-16
10  feature10 -4.543786e-16  4.543786e-16
21  feature21  4.132353e-16  4.132353e-16
9    feature9  3.449417e-16  3.449417e-16
1    feature1  3.191891e-16  3.191891e-16
6    feature6 -3.179384e-16  3.179384e-16
19  feature19  3.106376e-16  3.106376e-16
16  feature16 -2.864035e-16  2.864035e-16
36  feature36 -2.402592e-16  2.402592e-16
2    feature2 -2.389227e-16  2.389227e-16
4    feature4  2.199694e-16  2.199694e-16
37  feature37  2.099015e-16  2.099015e-16
12  feature12  2.083377e-16  2.083377e-16
17  feature17 -2.072266e-16  2.072266e-16
35  feature35  2.059984e-16  2.059984e-16
22  feature22  1.899181e-16  1.899181e-16
34  feature34 -1.691355e-16  1.691355e-16
0    feature0 -1.593287e-16  1.593287e-16
26  feature26 -1.575706e-16  1.575706e-16
38  feature38  1.509209e-16  1.509209e-16
13  feature13  1.473058e-16  1.473058e-16
23  feature23  1.275978e-16  1.275978e-16
33  feature33 -1.275022e-16  1.275022e-16
14  feature14 -1.244925e-16  1.244925e-16
11  feature11  1.014088e-16  1.014088e-16
29  feature29 -9.159466e-17  9.159466e-17
31  feature31 -8.243011e-17  8.243011e-17
28  feature28 -7.834424e-17  7.834424e-17
15  feature15 -7.658321e-17  7.658321e-17
3    feature3 -5.242016e-17  5.242016e-17
8    feature8  5.142891e-17  5.142891e-17
18  feature18  4.569775e-17  4.569775e-17
30  feature30  3.222587e-17  3.222587e-17
27  feature27 -2.377619e-17  2.377619e-17
32  feature32 -1.307502e-17  1.307502e-17
24  feature24 -5.108470e-18  5.108470e-18
7    feature7  2.099499e-18  2.099499e-18
```

Getting the top 4 most significant features

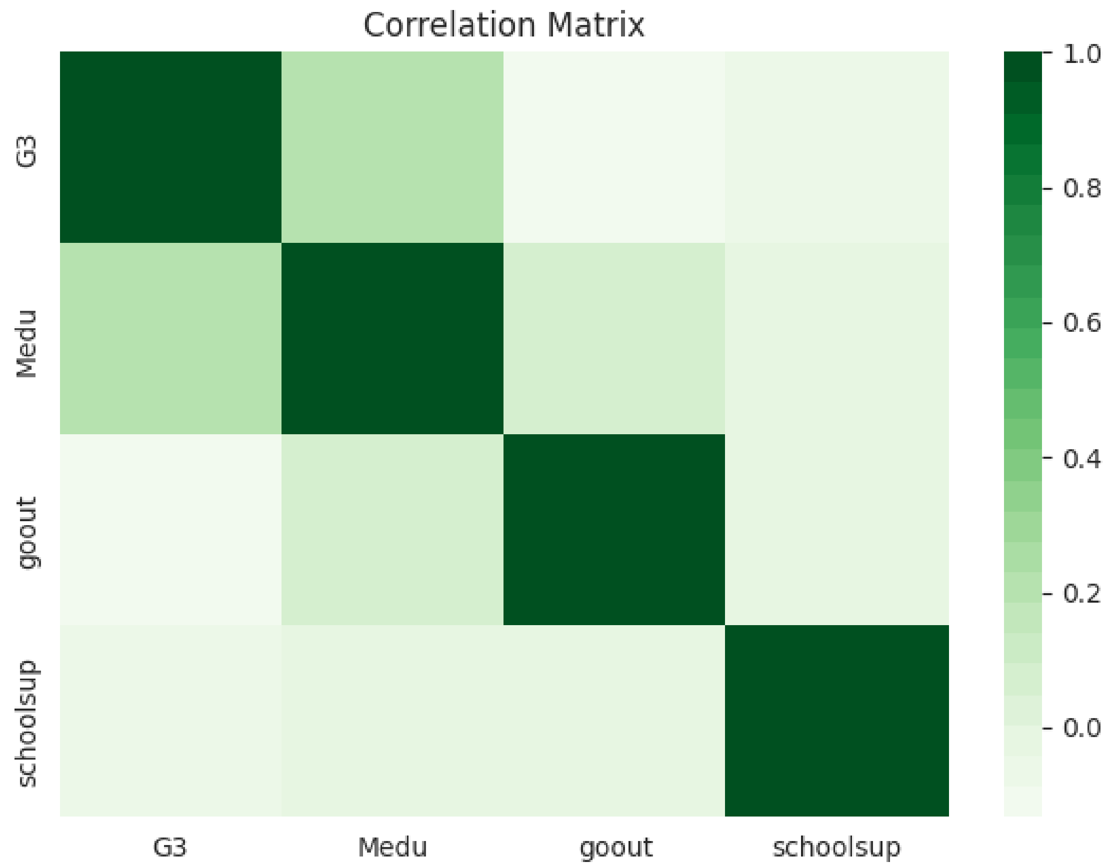
[195]:
```
# Storing the top 4 feature numbers
sig_feature_numbers = coeff_df.head(4).index

# list to store the actual feature names
sig_feature_names = []

# Getting the actual names from feature numbers
sig_feature_names = [data.iloc[:,j].name for j in sig_feature_numbers]

print(sig_feature_names)
```

```
['G3', 'Medu', 'goout', 'schoolsup']
```

We Ignore ‘G3’ as its the target variable

11 9. Interpretation

[196]:
```
# Creating a table with significant features
signif_table = data[sig_feature_names]

# Heatmap of correlation matrix
corr_matrix = signif_table.corr()
sns.heatmap(corr_matrix, cmap=sns.color_palette("Greens",25))
plt.title('Correlation Matrix')
plt.tight_layout()
plt.savefig('correlation_matrix.png')
plt.show()
```


Correlation Matrix
G3
Medu
goout
schoolsup
G3
Medu
goout
schoolsup
1.0
0.8
0.6
0.4
0.2
0.0

[179]: