Import Necessary Library

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
from scipy import stats
from math import sqrt
%matplotlib inline
```

```
df = pd.read_csv("/kaggle/input/student-performance-data-set/student-
por.csv")
df.head(5)
```

```
  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        4   0  11  11
1      5        3      3     1     1      3        2   9  11  11
2      4        3      2     2     3      3        6  12  13  12
3      3        2      2     1     1      5        0  14  14  14
4      4        3      2     1     2      5        0  11  13  13

[5 rows x 33 columns]
```

```
print("Data Shape: number of Rows = {0}, number of Columns = 
{1}".format(df.shape[0],df.shape[1]))
```

```
Data Shape: number of Rows = 649, number of Columns = 33
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 649 entries, 0 to 648
Data columns (total 33 columns):
 #   Column      Non-Null Count  Dtype 
---  ------      --------------  ----- 
 0   school      649 non-null    object
 1   sex         649 non-null    object
 2   age         649 non-null    int64 
 3   address     649 non-null    object
 4   famsize     649 non-null    object
 5   Pstatus     649 non-null    object
 6   Medu        649 non-null    int64 
 7   Fedu        649 non-null    int64 
 8   Mjob        649 non-null    object
 9   Fjob        649 non-null    object
 10  reason      649 non-null    object
 11  guardian    649 non-null    object
 12  traveltime  649 non-null    int64 
 13  studytime   649 non-null    int64 
 14  failures    649 non-null    int64 
 15  schoolsup   649 non-null    object
 16  famsup      649 non-null    object
 17  paid        649 non-null    object
 18  activities  649 non-null    object
 19  nursery     649 non-null    object
 20  higher      649 non-null    object
 21  internet    649 non-null    object
 22  romantic    649 non-null    object
 23  famrel      649 non-null    int64 
 24  freetime    649 non-null    int64 
 25  goout       649 non-null    int64 
 26  Dalc        649 non-null    int64 
 27  Walc        649 non-null    int64 
 28  health      649 non-null    int64 
 29  absences    649 non-null    int64 
 30  G1          649 non-null    int64 
 31  G2          649 non-null    int64 
 32  G3          649 non-null    int64 
dtypes: int64(16), object(17)
memory usage: 167.4+ KB
```

```
print("Show Statical Descriptopn of numerical columns")
df.describe().T
```

```
Show Statical Descriptopn of numerical columns
```

	count	mean	std	min	25%	50%	75%	max
age	649.0	16.744222	1.218138	15.0	16.0	17.0	18.0	22.0
Medu	649.0	2.514638	1.134552	0.0	2.0	2.0	4.0	4.0
Fedu	649.0	2.306626	1.099931	0.0	1.0	2.0	3.0	4.0
traveltime	649.0	1.568567	0.748660	1.0	1.0	1.0	2.0	4.0
studytime	649.0	1.930663	0.829510	1.0	1.0	2.0	2.0	4.0
failures	649.0	0.221880	0.593235	0.0	0.0	0.0	0.0	3.0
famrel	649.0	3.930663	0.955717	1.0	4.0	4.0	5.0	5.0
freetime	649.0	3.180277	1.051093	1.0	3.0	3.0	4.0	5.0
goout	649.0	3.184900	1.175766	1.0	2.0	3.0	4.0	5.0
Dalc	649.0	1.502311	0.924834	1.0	1.0	1.0	2.0	5.0
Walc	649.0	2.280431	1.284380	1.0	1.0	2.0	3.0	5.0
health	649.0	3.536210	1.446259	1.0	2.0	4.0	5.0	5.0
absences	649.0	3.659476	4.640759	0.0	0.0	2.0	6.0	32.0
G1	649.0	11.399076	2.745265	0.0	10.0	11.0	13.0	19.0
G2	649.0	11.570108	2.913639	0.0	10.0	11.0	13.0	19.0
G3	649.0	11.906009	3.230656	0.0	10.0	12.0	14.0	19.0

Data Cleaning

```
#check for missing values
df.isnull().sum()
```

```
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
```

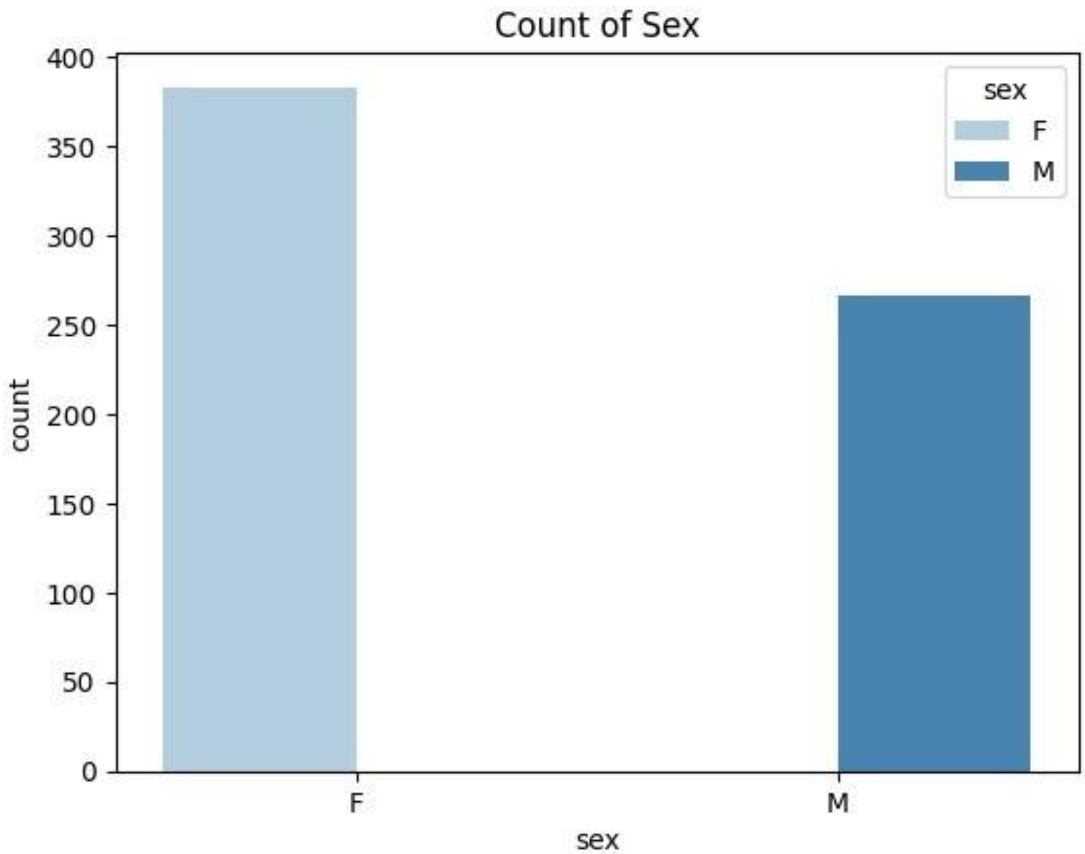
```
famrel        0
freetime      0
goout         0
Dalc          0
Walc          0
health        0
absences      0
G1            0
G2            0
G3            0
dtype: int64
```

No Missing Values in DataSet

```
# check for duplicates
df.duplicated().value_counts()

False    649
Name: count, dtype: int64
```

Visualization

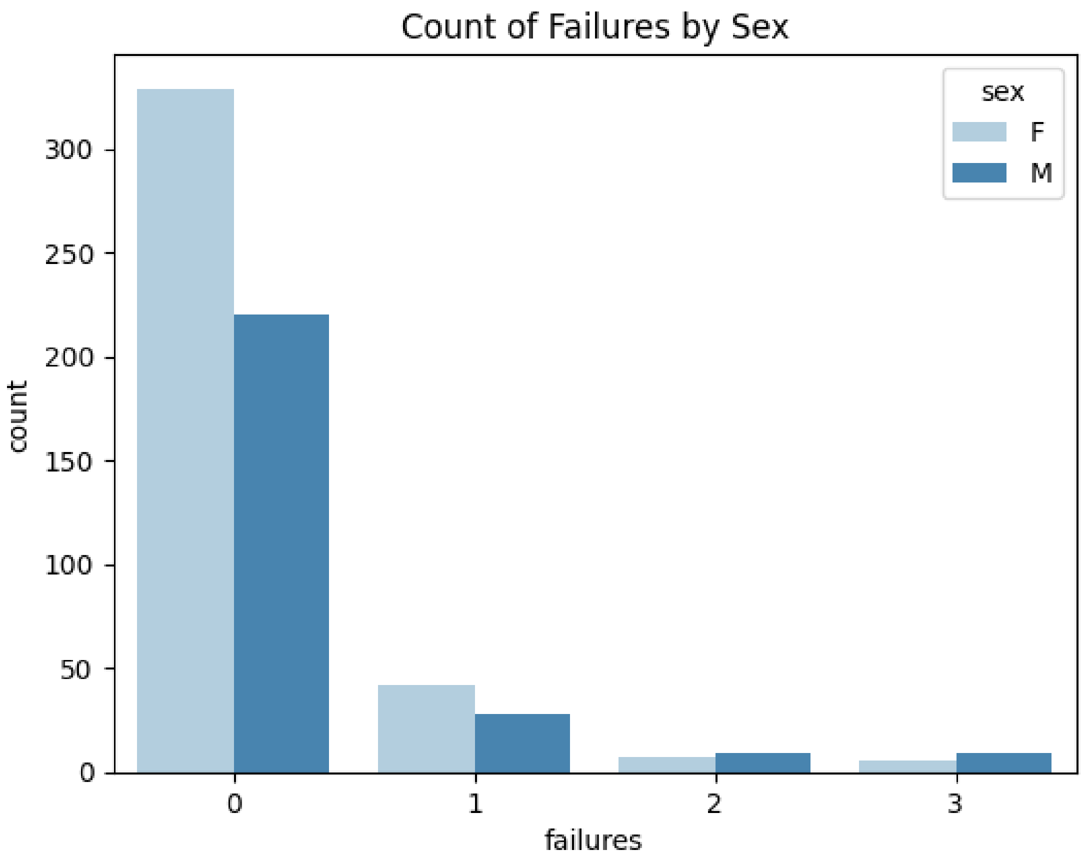
```
# Ignore warnings
warnings.filterwarnings("ignore")

# Count the occurrences of each category in the 'sex' column
target_count = df.sex.value_counts()

# Print the count of females
print('Female:', target_count[0])

# Print the count of males
print('Male:', target_count[1])

# Create a count plot of 'sex' with seaborn
sns.countplot(data=df, x="sex", hue="sex", palette="Blues")

# Set the title of the plot
plt.title('Count of Sex')

Female: 383
Male: 266

Text(0.5, 1.0, 'Count of Sex')
```




```
# Grouping the DataFrame by 'failures' and 'sex', counting the
occurrences, and resetting the index
failure_counts = df.groupby(["failures",
"sex"]).size().reset_index(name="count")

# Printing the DataFrame showing counts of failures by sex
print(failure_counts)

# Creating a count plot of 'failures' with seaborn, differentiated by
'sex'
sns.countplot(data=df, x="failures", hue="sex", palette="Blues")

# Setting the title of the plot
plt.title('Count of Failures by Sex')
```

```
   failures sex  count
0         0   F    329
1         0   M    220
2         1   F     42
3         1   M     28
4         2   F      7
5         2   M      9
```

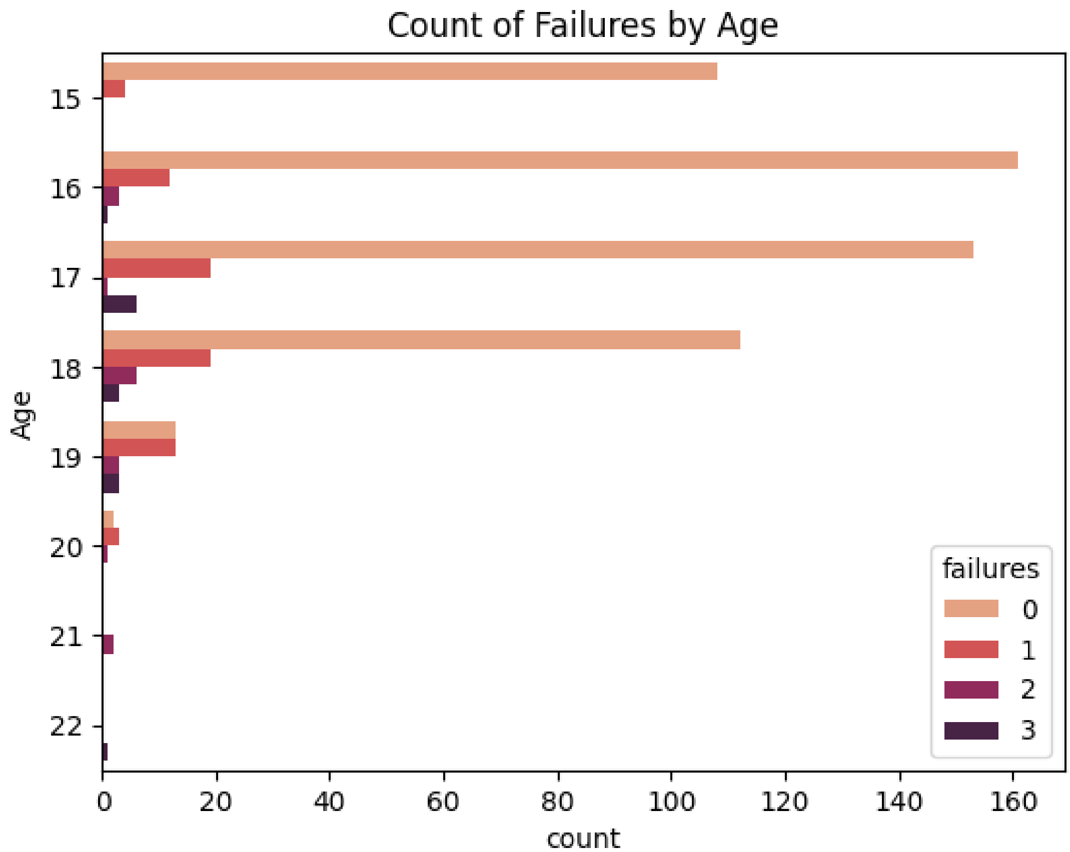
```
6           3   F       5
7           3   M       9

Text(0.5, 1.0, 'Count of Failures by Sex')
```




```
# Grouping the DataFrame by 'failures' and 'age', counting the
occurrences, and resetting the index
failure_counts = df.groupby(["failures",
"age"]).size().reset_index(name="count")

# Printing the DataFrame showing counts of failures by age
print(failure_counts)

# Creating a count plot of 'failures' with seaborn, differentiated by
'age' and plotted horizontally
sns.countplot(data=df, y='age', hue='failures', palette="rocket_r")

# Setting the title of the plot
plt.title('Count of Failures by Age')

# Setting the label for the y-axis
plt.ylabel('Age')
```

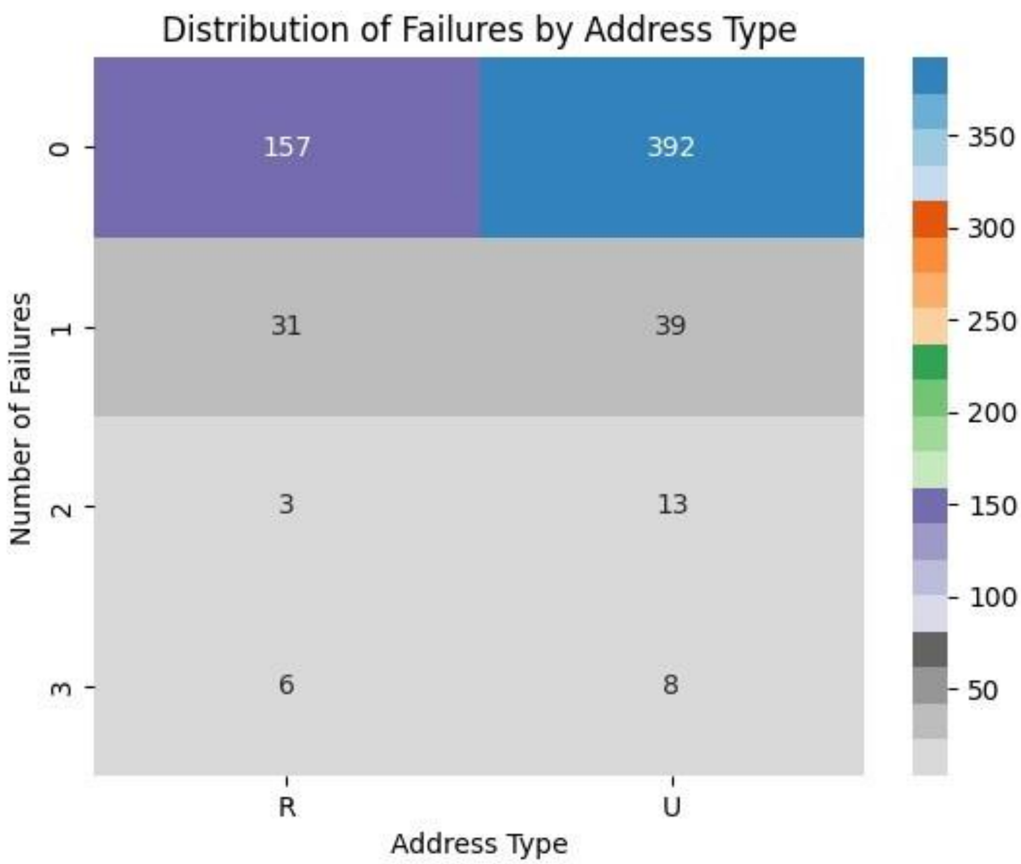
	failures	age	count
0	0	15	108
1	0	16	161
2	0	17	153
3	0	18	112
4	0	19	13
5	0	20	2
6	1	15	4
7	1	16	12
8	1	17	19
9	1	18	19
10	1	19	13
11	1	20	3
12	2	16	3
13	2	17	1
14	2	18	6
15	2	19	3
16	2	20	1
17	2	21	2
18	3	16	1
19	3	17	6
20	3	18	3
21	3	19	3
22	3	22	1

```
Text(0, 0.5, 'Age')
```



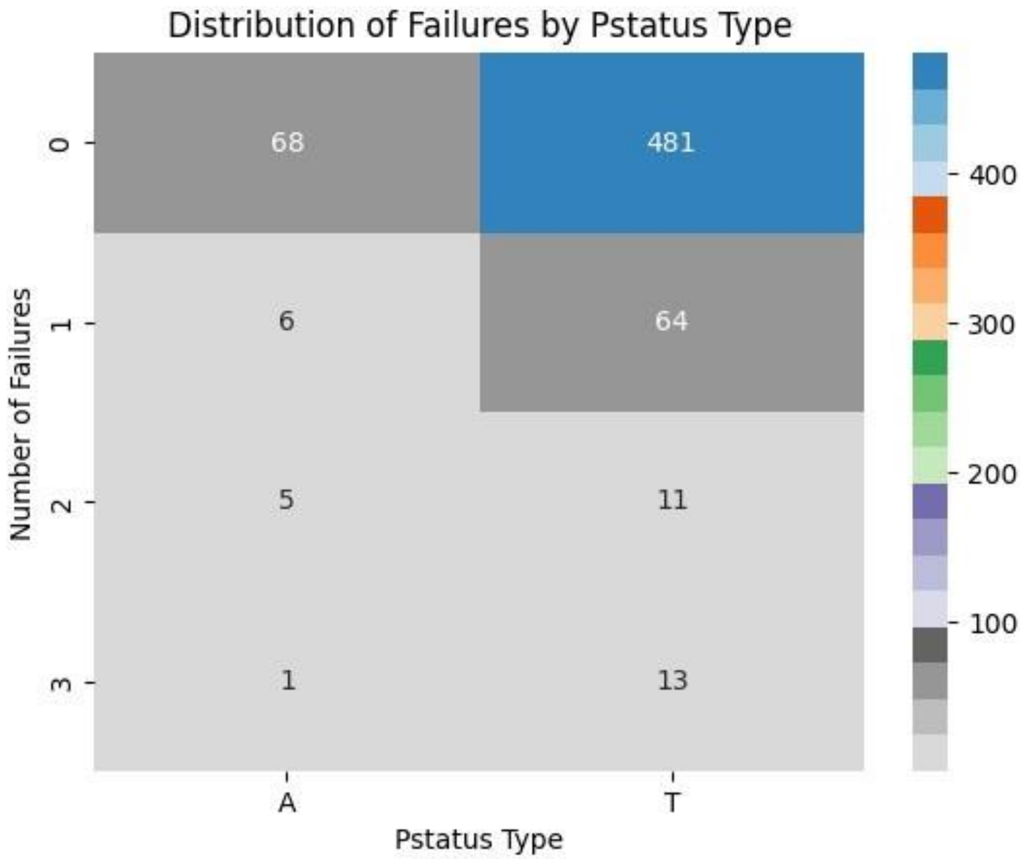

```
# Create a pivot table to count the occurrences of failures for each
address type
pivot_table = df.pivot_table(index='failures', columns='address',
aggfunc='size')

# Plot the heatmap using seaborn, with annotations, a colormap, and
format for annotations
sns.heatmap(pivot_table, annot=True, cmap='tab20c_r', fmt='g')

# Add title to the plot
plt.title('Distribution of Failures by Address Type')

# Add label for the x-axis
plt.xlabel('Address Type')

# Add label for the y-axis
plt.ylabel('Number of Failures')
```

```
Text(50.722222222222214, 0.5, 'Number of Failures')
```



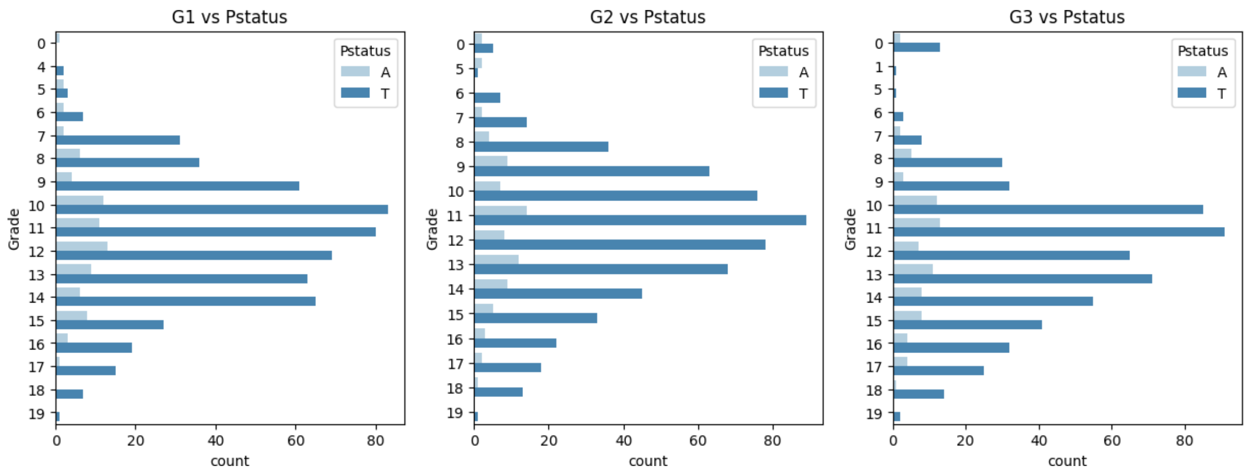

```
# Create a pivot table to count the occurrences of failures for each
Pstatus type
pivot_table = df.pivot_table(index='failures', columns='Pstatus',
aggfunc='size')

# Plot the heatmap using seaborn, with annotations, a colormap, and
format for annotations
sns.heatmap(pivot_table, annot=True, cmap='tab20c_r', fmt='g')

# Add title to the plot
plt.title('Distribution of Failures by Pstatus Type')

# Add label for the x-axis
plt.xlabel('Pstatus Type')

# Add label for the y-axis
plt.ylabel('Number of Failures')
```

```
Text(50.72222222222214, 0.5, 'Number of Failures')
```




```
# Create subplots with 1 row and 3 columns, sharing y-axis
fig, axes = plt.subplots(1, 3, figsize=(15, 5), sharey=False)

# Iterate through grade periods and plot
for i, grade_period in enumerate(['G1', 'G2', 'G3']):
    sns.countplot(ax=axes[i], data=df, y=grade_period, hue="Pstatus",
palette="Blues")  axes[i].set_title(f'{grade_period}
    vs Pstatus')axes[i].set_ylabel("Grade")

# Show the plots
plt.show()

# Define columns for grade periods
columns = ["G1", "G2", "G3"]

# Iterate through grade periods
for i in range(len(columns)):
    # Group the DataFrame by 'Pstatus' and the current grade period,
counting occurrences, and reset the index
    Pstatus_counts = df.groupby(["Pstatus",
columns[i]]).size().reset_index(name="count")
    # Print the results
```

```
    print(columns[i],"\n",Pstatus_counts)
    print("\n")
```




```
G1
     Pstatus  G1   count
0          A   0       1
1          A   5       2
2          A   6       2
3          A   7       2
4          A   8       6
5          A   9       4
6          A  10      12
7          A  11      11
8          A  12      13
9          A  13       9
10         A  14       6
11         A  15       8
12         A  16       3
13         A  17       1
14         T   4       2
15         T   5       3
16         T   6       7
17         T   7      31
18         T   8      36
19         T   9      61
20         T  10      83
21         T  11      80
22         T  12      69
23         T  13      63
24         T  14      65
25         T  15      27
26         T  16      19
27         T  17      15
28         T  18       7
```

29	T	19	1

G2

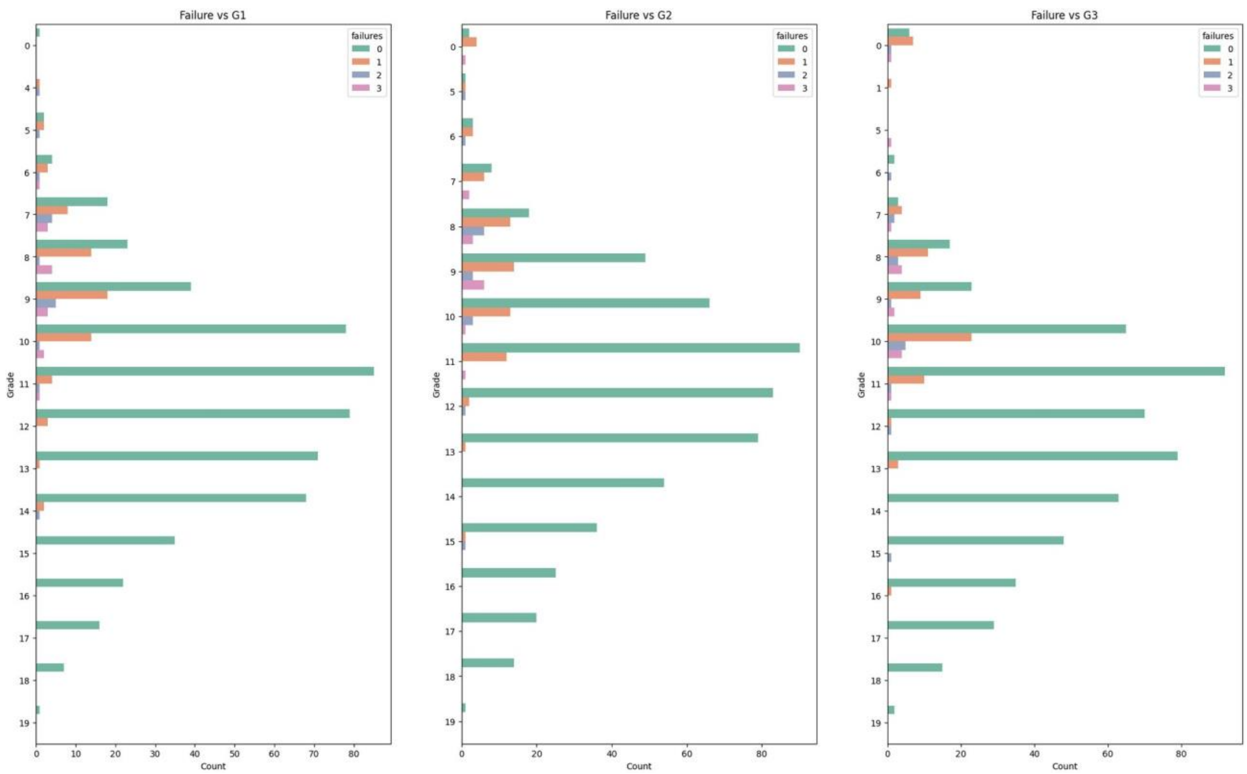
	Pstatus	G2	count
0	A	0	2
1	A	5	2
2	A	7	2
3	A	8	4
4	A	9	9
5	A	10	7
6	A	11	14
7	A	12	8
8	A	13	12
9	A	14	9
10	A	15	5
11	A	16	3
12	A	17	2
13	A	18	1
14	T	0	5
15	T	5	1
16	T	6	7
17	T	7	14
18	T	8	36
19	T	9	63
20	T	10	76
21	T	11	89
22	T	12	78
23	T	13	68
24	T	14	45
25	T	15	33
26	T	16	22
27	T	17	18
28	T	18	13
29	T	19	1

G3

	Pstatus	G3	count
0	A	0	2
1	A	7	2
2	A	8	5
3	A	9	3
4	A	10	12
5	A	11	13
6	A	12	7
7	A	13	11
8	A	14	8
9	A	15	8
10	A	16	4

```
11        A  17      4
12        A  18      1
13        T   0     13
14        T   1      1
15        T   5      1
16        T   6      3
17        T   7      8
18        T   8     30
19        T   9     32
20        T  10     85
21        T  11     91
22        T  12     65
23        T  13     71
24        T  14     55
25        T  15     41
26        T  16     32
27        T  17     25
28        T  18     14
29        T  19      2
```

```
# Create subplots with 1 row and 3 columns, adjusting figure size
fig, axes = plt.subplots(1, 3, figsize=(25, 15))

# Iterate through grade periods and plot
for i, grade in enumerate(['G1', 'G2', 'G3']):
    sns.countplot(data=df, y=grade, hue='failures', ax=axes[i],
palette='Set2', dodge=True)
    axes[i].set_title(f'Failure vs {grade}') # Set title for each
subplot
    axes[i].set_ylabel('Grade')  # Set label for y-axis
    axes[i].set_xlabel('Count')  # Set label for x-axis

# Show the plots
plt.show()

# Define columns for grade periods
columns = ["G1", "G2", "G3"]

# Iterate through grade periods
for i in range(len(columns)):
    # Group the DataFrame by 'failures' and the current grade period,
counting occurrences, and reset the index
    failures_counts = df.groupby(["failures",
columns[i]]).size().reset_index(name="count")
    # Print the results
    print(columns[i],"\n",failures_counts)
    print("\n")
```



G1

	failures	G1	count
0	0	0	1
1	0	5	2
2	0	6	4
3	0	7	18
4	0	8	23
5	0	9	39
6	0	10	78
7	0	11	85
8	0	12	79
9	0	13	71
10	0	14	68
11	0	15	35
12	0	16	22
13	0	17	16
14	0	18	7
15	0	19	1
16	1	4	1
17	1	5	2
18	1	6	3
19	1	7	8
20	1	8	14
21	1	9	18
22	1	10	14
23	1	11	4

24	1	12	3
25	1	13	1
26	1	14	2
27	2	4	1
28	2	5	1
29	2	6	1
30	2	7	4
31	2	8	1
32	2	9	5
33	2	10	1
34	2	11	1
35	2	14	1
36	3	6	1
37	3	7	3
38	3	8	4
39	3	9	3
40	3	10	2
41	3	11	1

G2

	failures	G2	count
0	0	0	2
1	0	5	1
2	0	6	3
3	0	7	8
4	0	8	18
5	0	9	49
6	0	10	66
7	0	11	90
8	0	12	83
9	0	13	79
10	0	14	54
11	0	15	36
12	0	16	25
13	0	17	20
14	0	18	14
15	0	19	1
16	1	0	4
17	1	5	1
18	1	6	3
19	1	7	6
20	1	8	13
21	1	9	14
22	1	10	13
23	1	11	12
24	1	12	2
25	1	13	1
26	1	15	1

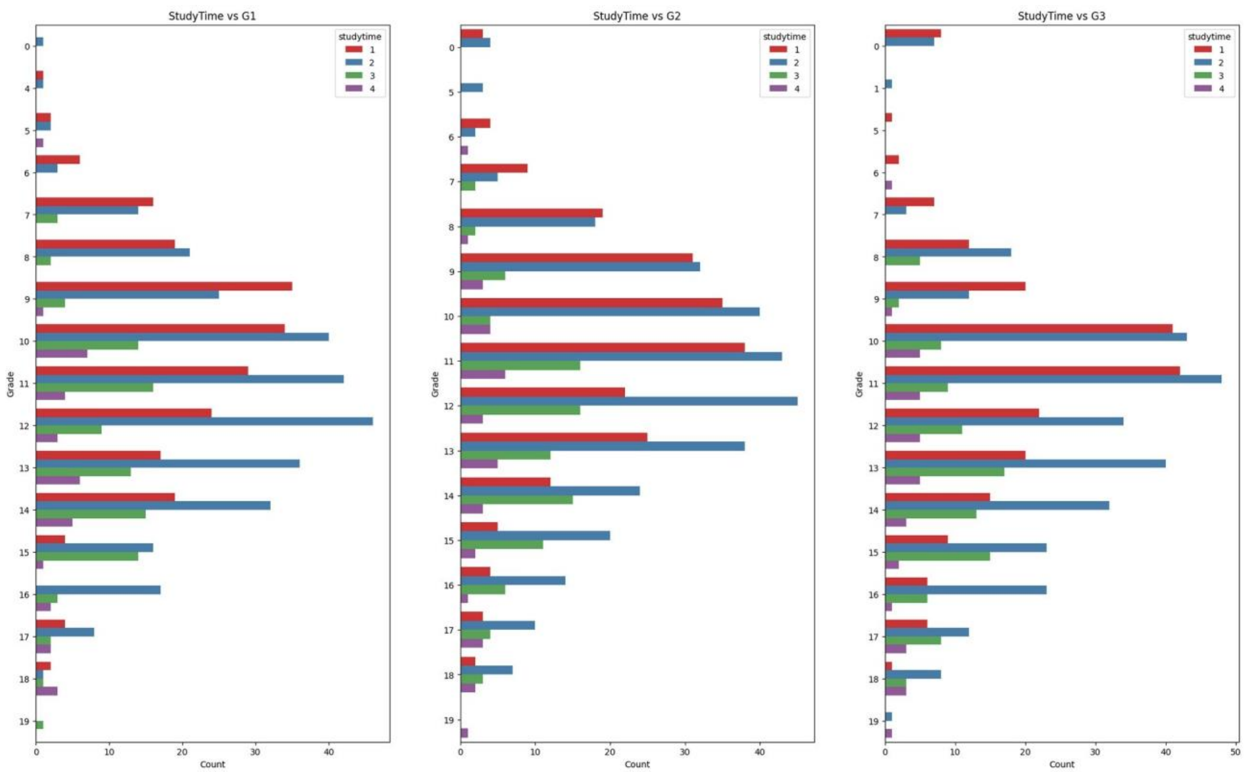
27	2	5	1
28	2	6	1
29	2	8	6
30	2	9	3
31	2	10	3
32	2	12	1
33	2	15	1
34	3	0	1
35	3	7	2
36	3	8	3
37	3	9	6
38	3	10	1
39	3	11	1

G3

	failures	G3	count
0	0	0	6
1	0	6	2
2	0	7	3
3	0	8	17
4	0	9	23
5	0	10	65
6	0	11	92
7	0	12	70
8	0	13	79
9	0	14	63
10	0	15	48
11	0	16	35
12	0	17	29
13	0	18	15
14	0	19	2
15	1	0	7
16	1	1	1
17	1	7	4
18	1	8	11
19	1	9	9
20	1	10	23
21	1	11	10
22	1	12	1
23	1	13	3
24	1	16	1
25	2	0	1
26	2	6	1
27	2	7	2
28	2	8	3
29	2	9	1
30	2	10	5
31	2	11	1

```
32          2  12       1
33          2  15       1
34          3   0       1
35          3   5       1
36          3   7       1
37          3   8       4
38          3   9       2
39          3  10       4
40          3  11       1
```

```python
# Create subplots with 1 row and 3 columns, adjusting figure size
fig, axes = plt.subplots(1, 3, figsize=(25, 15))

# Iterate through grade periods and plot
for i, grade in enumerate(['G1', 'G2', 'G3']):
    sns.countplot(data=df, y=grade, hue='studytime', ax=axes[i], 
palette='Set1', dodge=True)
    axes[i].set_title(f'StudyTime vs {grade}') # Set title for each 
subplot
    axes[i].set_ylabel('Grade')  # Set label for y-axis
    axes[i].set_xlabel('Count')  # Set label for x-axis

# Show the plots
plt.show()

# Define columns for grade periods
columns = ["G1", "G2", "G3"]

# Iterate through grade periods
for i in range(len(columns)):
    # Group the DataFrame by 'studytime' and the current grade period, 
counting occurrences, and reset the index
    studytime_counts = df.groupby(["studytime", 
columns[i]]).size().reset_index(name="count")
    # Print the results
    print(columns[i],"\n",studytime_counts)
    print("\n")
```



G1

	studytime	G1	count
0	1	4	1
1	1	5	2
2	1	6	6
3	1	7	16
4	1	8	19
5	1	9	35
6	1	10	34
7	1	11	29
8	1	12	24
9	1	13	17
10	1	14	19
11	1	15	4
12	1	17	4
13	1	18	2
14	2	0	1
15	2	4	1
16	2	5	2
17	2	6	3
18	2	7	14
19	2	8	21
20	2	9	25
21	2	10	40
22	2	11	42
23	2	12	46

```
24           2  13      36
25           2  14      32
26           2  15      16
27           2  16      17
28           2  17       8
29           2  18       1
30           3   7       3
31           3   8       2
32           3   9       4
33           3  10      14
34           3  11      16
35           3  12       9
36           3  13      13
37           3  14      15
38           3  15      14
39           3  16       3
40           3  17       2
41           3  18       1
42           3  19       1
43           4   5       1
44           4   9       1
45           4  10       7
46           4  11       4
47           4  12       3
48           4  13       6
49           4  14       5
50           4  15       1
51           4  16       2
52           4  17       2
53           4  18       3
```

```
G2
     studytime  G2  count
0            1   0      3
1            1   6      4
2            1   7      9
3            1   8     19
4            1   9     31
5            1  10     35
6            1  11     38
7            1  12     22
8            1  13     25
9            1  14     12
10           1  15      5
11           1  16      4
12           1  17      3
13           1  18      2
14           2   0      4
```

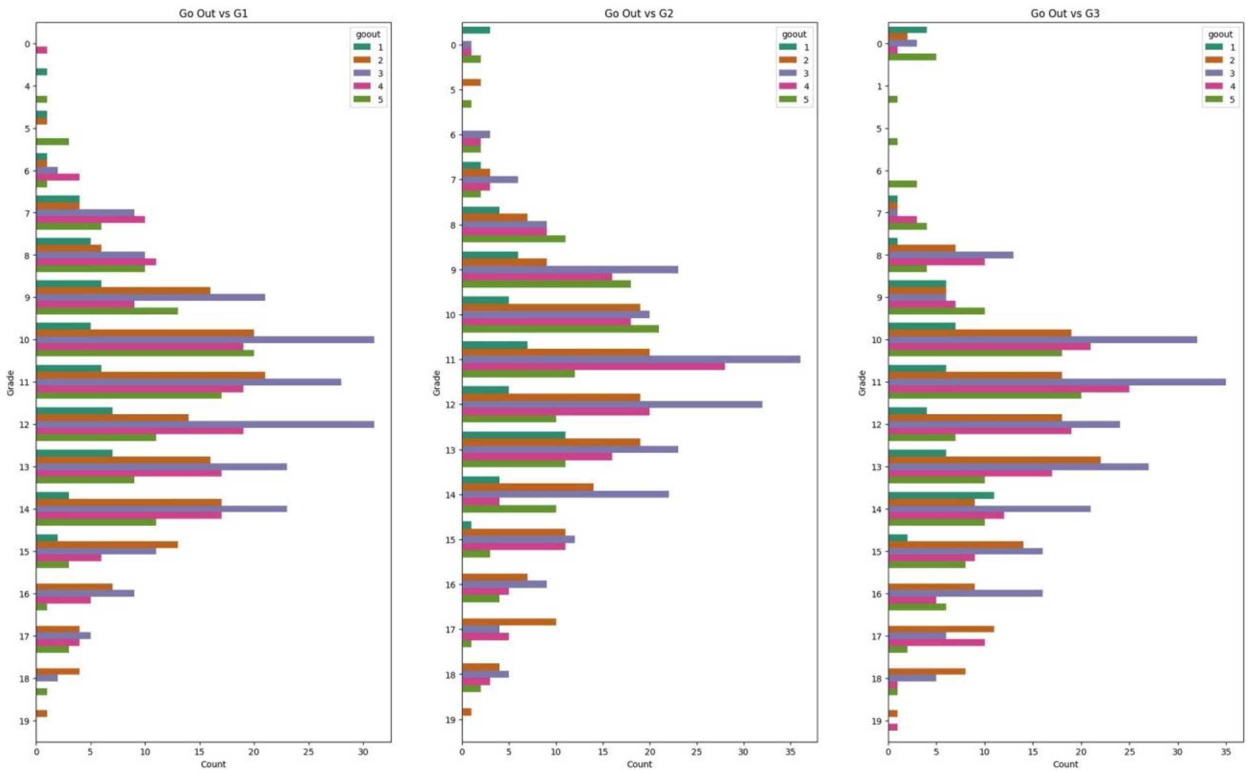
15	2	5	3
16	2	6	2
17	2	7	5
18	2	8	18
19	2	9	32
20	2	10	40
21	2	11	43
22	2	12	45
23	2	13	38
24	2	14	24
25	2	15	20
26	2	16	14
27	2	17	10
28	2	18	7
29	3	7	2
30	3	8	2
31	3	9	6
32	3	10	4
33	3	11	16
34	3	12	16
35	3	13	12
36	3	14	15
37	3	15	11
38	3	16	6
39	3	17	4
40	3	18	3
41	4	6	1
42	4	8	1
43	4	9	3
44	4	10	4
45	4	11	6
46	4	12	3
47	4	13	5
48	4	14	3
49	4	15	2
50	4	16	1
51	4	17	3
52	4	18	2
53	4	19	1

G3

	studytime	G3	count
0	1	0	8
1	1	5	1
2	1	6	2
3	1	7	7
4	1	8	12
5	1	9	20

6	1	10	41
7	1	11	42
8	1	12	22
9	1	13	20
10	1	14	15
11	1	15	9
12	1	16	6
13	1	17	6
14	1	18	1
15	2	0	7
16	2	1	1
17	2	7	3
18	2	8	18
19	2	9	12
20	2	10	43
21	2	11	48
22	2	12	34
23	2	13	40
24	2	14	32
25	2	15	23
26	2	16	23
27	2	17	12
28	2	18	8
29	2	19	1
30	3	8	5
31	3	9	2
32	3	10	8
33	3	11	9
34	3	12	11
35	3	13	17
36	3	14	13
37	3	15	15
38	3	16	6
39	3	17	8
40	3	18	3
41	4	6	1
42	4	9	1
43	4	10	5
44	4	11	5
45	4	12	5
46	4	13	5
47	4	14	3
48	4	15	2
49	4	16	1
50	4	17	3
51	4	18	3
52	4	19	1

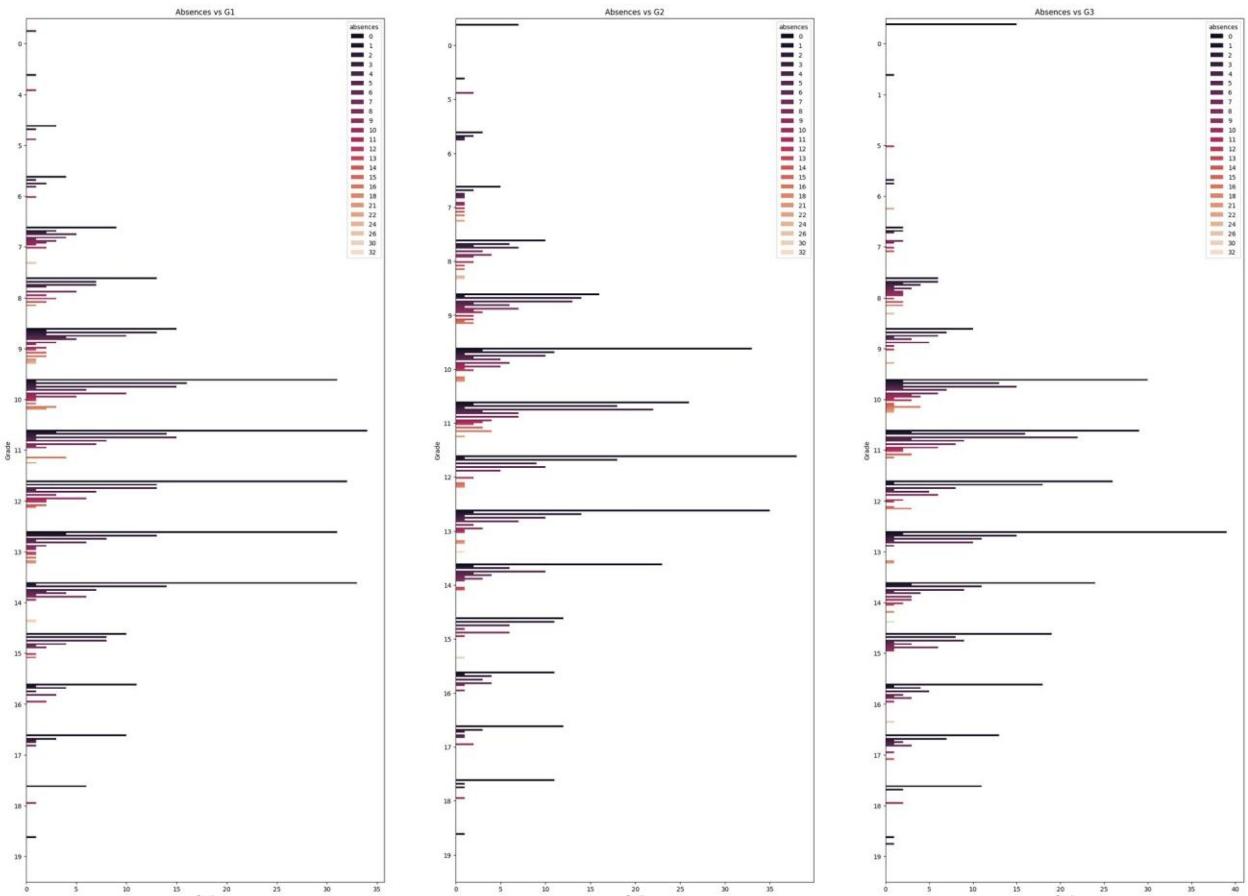
```
# Create subplots with 1 row and 3 columns, adjusting figure size
fig, axes = plt.subplots(1, 3, figsize=(25, 15))

# Iterate through grade periods and plot
for i, grade in enumerate(['G1', 'G2', 'G3']):
    sns.countplot(data=df, y=grade, hue='goout', ax=axes[i],
palette='Dark2', dodge=True)
    axes[i].set_title(f'Go Out vs {grade}') # Set title for each
subplot
    axes[i].set_ylabel('Grade')  # Set label for y-axis
    axes[i].set_xlabel('Count')  # Set label for x-axis

# Show the plots
plt.show()

# Define columns for grade periods
columns = ["G1", "G2", "G3"]

# Iterate through grade periods
for i in range(len(columns)):
    # Group the DataFrame by 'goout' and the current grade period,
counting occurrences, and reset the index
    goout_counts = df.groupby(["goout",
columns[i]]).size().reset_index(name="count")
    # Print the results
    print(columns[i],"\n",goout_counts)
    print("\n")
```




```
G1
    goout  G1  count
0       1   4      1
1       1   5      1
2       1   6      1
3       1   7      4
4       1   8      5
..    ...  ..    ...
63      5  14     11
64      5  15      3
65      5  16      1
66      5  17      3
67      5  18      1

[68 rows x 3 columns]


G2
    goout  G2  count
0       1   0      3
1       1   7      2
2       1   8      4
3       1   9      6
4       1  10      5
..    ...  ..    ...
62      5  14     10
```

```
63        5  15        3
64        5  16        4
65        5  17        1
66        5  18        2

[67 rows x 3 columns]


G3
     goout  G3  count
0        1   0      4
1        1   7      1
2        1   8      1
3        1   9      6
4        1  10      7
..     ...  ..    ...
62       5  14     10
63       5  15      8
64       5  16      6
65       5  17      2
66       5  18      1

[67 rows x 3 columns]



# Create subplots with 1 row and 3 columns, adjusting figure size
fig, axes = plt.subplots(1, 3, figsize=(35, 25))

# Iterate through grade periods and plot
for i, grade in enumerate(['G1', 'G2', 'G3']):
    sns.countplot(data=df, y=grade, hue='absences', ax=axes[i],
palette='rocket', dodge=True)
    axes[i].set_title(f'Absences vs {grade}') # Set title for each
subplot
    axes[i].set_ylabel('Grade')  # Set label for y-axis
    axes[i].set_xlabel('Count')  # Set label for x-axis

# Show the plots
plt.show()

# Define columns for grade periods
columns = ["G1", "G2", "G3"]

# Iterate through grade periods
for i in range(len(columns)):
    # Group the DataFrame by 'absences' and the current grade period,
counting occurrences, and reset the index
    absences_counts = df.groupby(["absences",
columns[i]]).size().reset_index(name="count")
```

```
    # Print the results
    print(columns[i],"\n",absences_counts)
    print("\n")
```

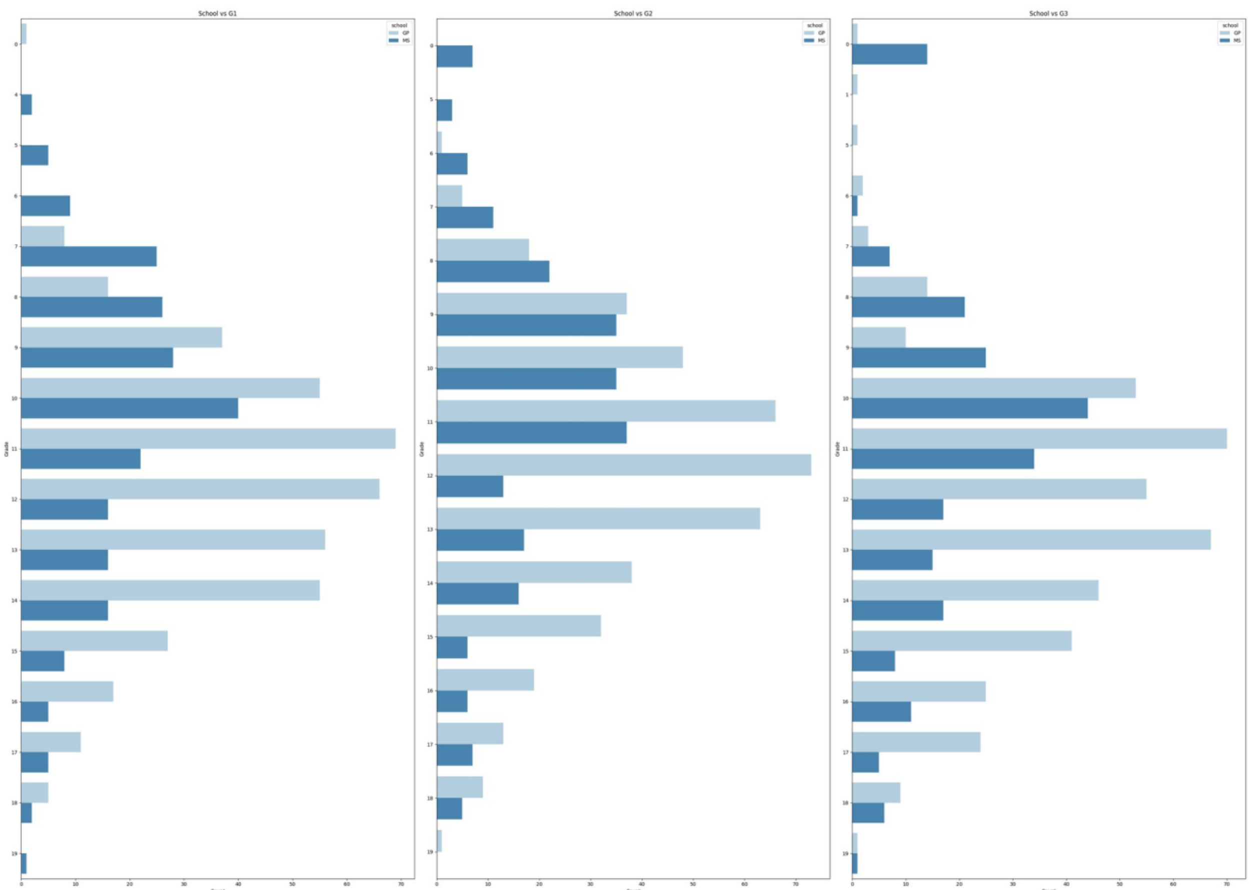



```
G1
      absences  G1  count
0            0   4      1
1            0   5      3
2            0   6      4
3            0   7      9
4            0   8     13
..         ...  ..    ...
127         22  11      1
128         24   9      1
129         26   7      1
130         30  14      1
131         32  14      1

[132 rows x 3 columns]


G2
```

```
     absences  G2  count
0           0   0      7
1           0   5      1
2           0   6      3
3           0   7      5
4           0   8     10
..        ...  ..    ...
128        22  11      1
129        24   8      1
130        26   8      1
131        30  15      1
132        32  13      1

[133 rows x 3 columns]


G3
     absences  G3  count
0           0   0     15
1           0   1      1
2           0   7      2
3           0   8      6
4           0   9     10
..        ...  ..    ...
125        22  10      1
126        24   9      1
127        26   8      1
128        30  16      1
129        32  14      1

[130 rows x 3 columns]
```

```
# Create subplots with 1 row and 3 columns, adjusting figure size
fig, axes = plt.subplots(1, 3, figsize=(35, 25))

# Iterate through grade periods and plot
for i, grade in enumerate(['G1', 'G2', 'G3']):
    sns.countplot(data=df, y=grade, hue='school', ax=axes[i],
palette='Blues', dodge=True)
    axes[i].set_title(f'School vs {grade}') # Set title for each
subplot
    axes[i].set_ylabel('Grade')  # Set label for y-axis
    axes[i].set_xlabel('Count')  # Set label for x-axis

# Adjust layout to prevent overlapping
plt.tight_layout()

# Show the plots
```

```
plt.show()

# Define columns for grade periods
columns = ["G1", "G2", "G3"]

# Iterate through grade periods
for i in range(len(columns)):
    # Group the DataFrame by 'school' and the current grade period, counting occurrences, and reset the index
    school_counts = df.groupby(["school", columns[i]]).size().reset_index(name="count")
    # Print the results
    print(columns[i],"\n",school_counts)
    print("\n")
```




```
G1
   school  G1  count
0      GP   0      1
1      GP   7      8
2      GP   8     16
3      GP   9     37
4      GP  10     55
```

5	GP	11	69
6	GP	12	66
7	GP	13	56
8	GP	14	55
9	GP	15	27
10	GP	16	17
11	GP	17	11
12	GP	18	5
13	MS	4	2
14	MS	5	5
15	MS	6	9
16	MS	7	25
17	MS	8	26
18	MS	9	28
19	MS	10	40
20	MS	11	22
21	MS	12	16
22	MS	13	16
23	MS	14	16
24	MS	15	8
25	MS	16	5
26	MS	17	5
27	MS	18	2
28	MS	19	1

G2

	school	G2	count
0	GP	6	1
1	GP	7	5
2	GP	8	18
3	GP	9	37
4	GP	10	48
5	GP	11	66
6	GP	12	73
7	GP	13	63
8	GP	14	38
9	GP	15	32
10	GP	16	19
11	GP	17	13
12	GP	18	9
13	GP	19	1
14	MS	0	7
15	MS	5	3
16	MS	6	6
17	MS	7	11
18	MS	8	22
19	MS	9	35
20	MS	10	35

21	MS	11	37
22	MS	12	13
23	MS	13	17
24	MS	14	16
25	MS	15	6
26	MS	16	6
27	MS	17	7
28	MS	18	5

G3

	school	G3	count
0	GP	0	1
1	GP	1	1
2	GP	5	1
3	GP	6	2
4	GP	7	3
5	GP	8	14
6	GP	9	10
7	GP	10	53
8	GP	11	70
9	GP	12	55
10	GP	13	67
11	GP	14	46
12	GP	15	41
13	GP	16	25
14	GP	17	24
15	GP	18	9
16	GP	19	1
17	MS	0	14
18	MS	6	1
19	MS	7	7
20	MS	8	21
21	MS	9	25
22	MS	10	44
23	MS	11	34
24	MS	12	17
25	MS	13	15
26	MS	14	17
27	MS	15	8
28	MS	16	11
29	MS	17	5
30	MS	18	6
31	MS	19	1

Data Preprocessing

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 649 entries, 0 to 648
Data columns (total 33 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   school      649 non-null    object
 1   sex         649 non-null    object
 2   age         649 non-null    int64
 3   address     649 non-null    object
 4   famsize     649 non-null    object
 5   Pstatus     649 non-null    object
 6   Medu        649 non-null    int64
 7   Fedu        649 non-null    int64
 8   Mjob        649 non-null    object
 9   Fjob        649 non-null    object
 10  reason      649 non-null    object
 11  guardian    649 non-null    object
 12  traveltime  649 non-null    int64
 13  studytime   649 non-null    int64
 14  failures    649 non-null    int64
 15  schoolsup   649 non-null    object
 16  famsup      649 non-null    object
 17  paid        649 non-null    object
 18  activities  649 non-null    object
 19  nursery     649 non-null    object
 20  higher      649 non-null    object
 21  internet    649 non-null    object
 22  romantic    649 non-null    object
 23  famrel      649 non-null    int64
 24  freetime    649 non-null    int64
 25  goout       649 non-null    int64
 26  Dalc        649 non-null    int64
 27  Walc        649 non-null    int64
 28  health      649 non-null    int64
 29  absences    649 non-null    int64
 30  G1          649 non-null    int64
 31  G2          649 non-null    int64
 32  G3          649 non-null    int64
dtypes: int64(16), object(17)
memory usage: 167.4+ KB
```

```
# Importing necessary library
from sklearn.preprocessing import LabelEncoder

# Creating a LabelEncoder object
label_encoder = LabelEncoder()
```

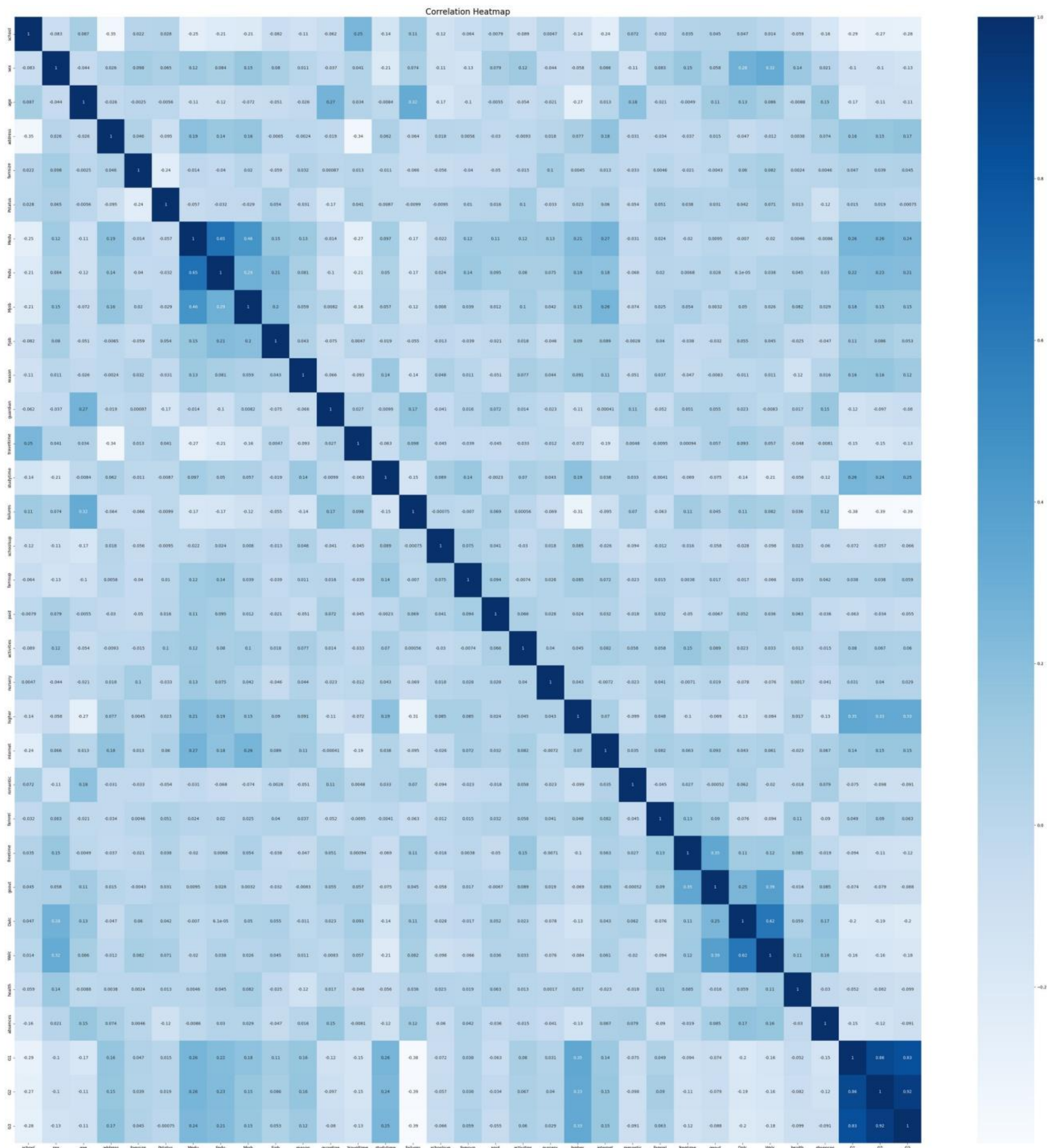
```
# List of columns to be encoded
Columns =
["school","sex","address","famsize","Pstatus","Mjob","Fjob","reason","
guardian","schoolsup","famsup","paid","activities",
                "nursery","higher","internet","romantic"]

# Iterate through each column and perform label encoding
for i in range(len(Columns)):
    # Retrieve the unique values in the column
    Country_keys  =  df[Columns[i]]
    Country_keys = Country_keys.tolist()

    # Perform label encoding
    Country_values = label_encoder.fit_transform(df[Columns[i]])
    Country_values = Country_values.tolist()

    # Update the DataFrame with the encoded values
    df[Columns[i]] = label_encoder.fit_transform(df[Columns[i]])

    # Create a dictionary mapping original values to encoded values
    Country_dict = dict(zip(Country_keys, Country_values))
    # Print the dictionary
    print(Country_dict)
```

```
{'GP': 0, 'MS': 1}
{'F': 0, 'M': 1}
{'U': 1, 'R': 0}
{'GT3': 0, 'LE3': 1}
{'A': 0, 'T': 1}
{'at_home': 0, 'health': 1, 'other': 2, 'services': 3, 'teacher': 4}
{'teacher': 4, 'other': 2, 'services': 3, 'health': 1, 'at_home': 0}
{'course': 0, 'other': 2, 'home': 1, 'reputation': 3}
{'mother': 1, 'father': 0, 'other': 2}
{'yes': 1, 'no': 0}
{'no': 0, 'yes': 1}
{'no': 0, 'yes': 1}
{'no': 0, 'yes': 1}
{'yes': 1, 'no': 0}
{'yes': 1, 'no': 0}
{'no': 0, 'yes': 1}
{'no': 0, 'yes': 1}
```

```
# Calculate the correlation matrix
corr = df.corr()

# Create a figure with a large size
plt.figure(figsize=(50,50))

# Plot the heatmap using seaborn, with annotations and a blue colormap
```

```python
sns.heatmap(corr, annot=True, cmap="Blues")

# Set the title of the plot
plt.title('Correlation Heatmap', fontsize=20)
```

```
Text(0.5, 1.0, 'Correlation Heatmap')
```

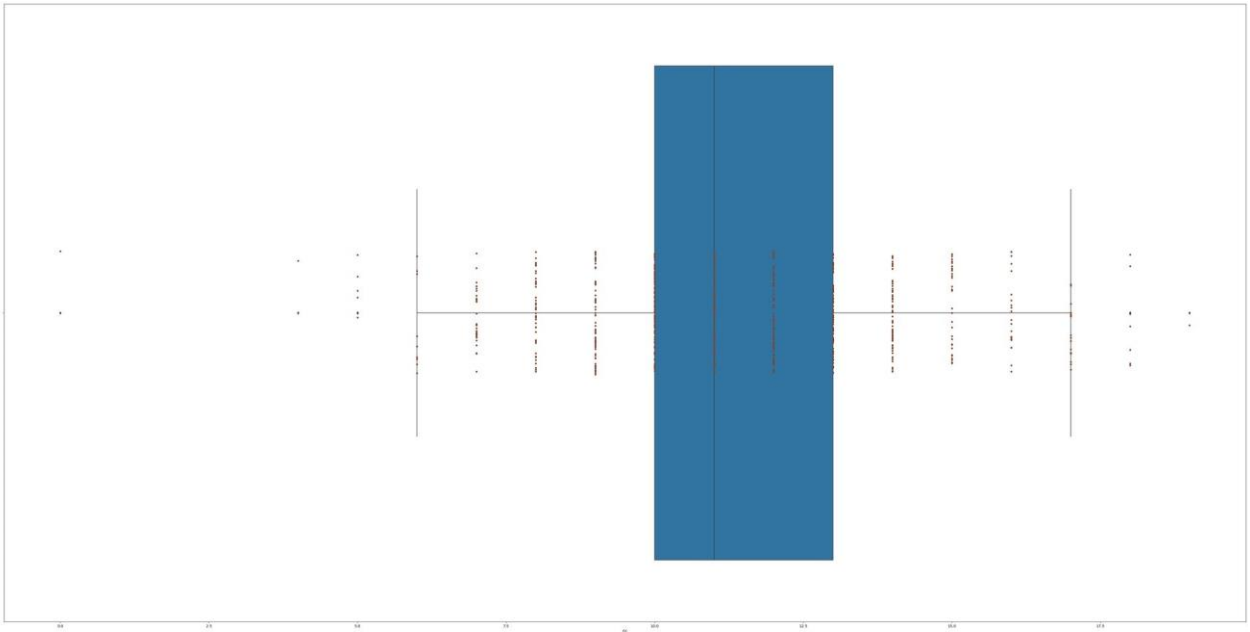



```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 649 entries, 0 to 648
Data columns (total 33 columns):
 #   Column      Non-Null Count  Dtype
                                 ---------
 0   school      649 non-null    int64
 1   sex         649 non-null    int64
 2   age         649 non-null    int64
 3   address     649 non-null    int64
 4   famsize     649 non-null    int64
 5   Pstatus     649 non-null    int64
 6   Medu        649 non-null    int64
 7   Fedu        649 non-null    int64
 8   Mjob        649 non-null    int64
 9   Fjob        649 non-null    int64
 10  reason      649 non-null    int64
 11  guardian    649 non-null    int64
 12  traveltime  649 non-null    int64
 13  studytime   649 non-null    int64
 14  failures    649 non-null    int64
 15  schoolsup   649 non-null    int64
 16  famsup      649 non-null    int64
 17  paid        649 non-null    int64
 18  activities  649 non-null    int64
 19  nursery     649 non-null    int64
 20  higher      649 non-null    int64
 21  internet    649 non-null    int64
 22  romantic    649 non-null    int64
 23  famrel      649 non-null    int64
 24  freetime    649 non-null    int64
 25  goout       649 non-null    int64
 26  Dalc        649 non-null    int64
 27  Walc        649 non-null    int64
 28  health      649 non-null    int64
 29  absences    649 non-null    int64
 30  G1          649 non-null    int64
 31  G2          649 non-null    int64
 32  G3          649 non-null    int64
dtypes: int64(33)
memory usage: 167.4 KB
```

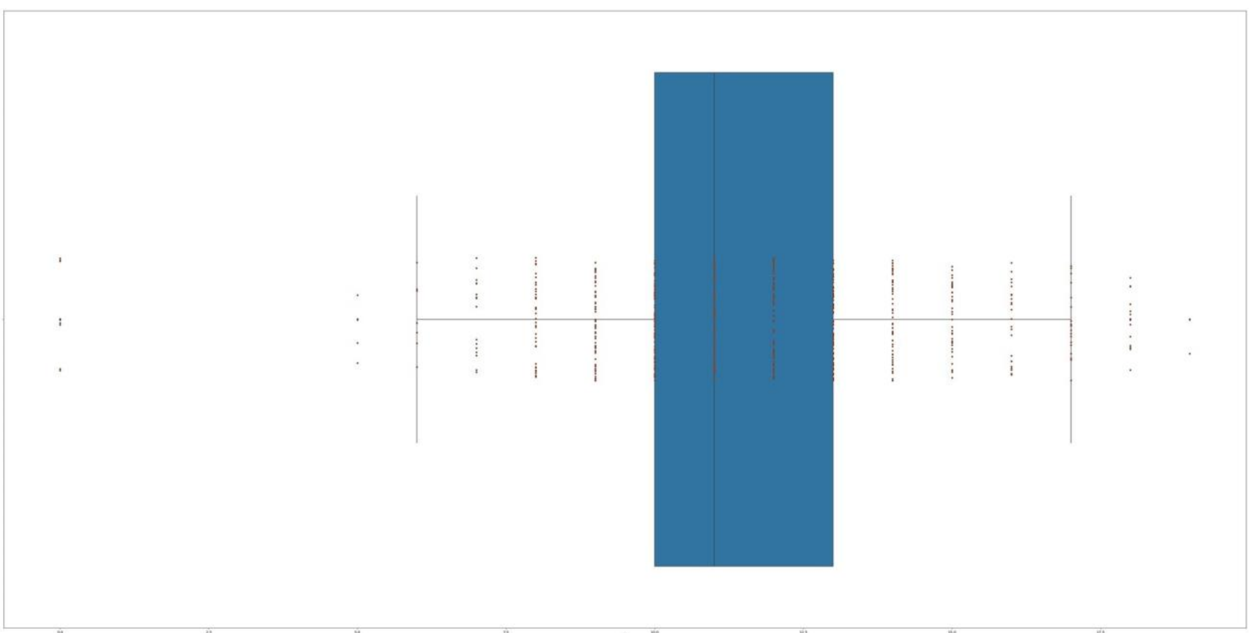
```
# cheaking the outliers in the feature 'G1'
plt.figure(figsize = (60,30))
sns.boxplot(x='G1', data=df)
sns.stripplot(x='G1', data=df, color="#804630")
```

```
<Axes: xlabel='G1'>
```



```
# cheaking the outliers in the feature 'G2'
plt.figure(figsize = (60,30))
sns.boxplot(x='G2', data=df)
sns.stripplot(x='G2', data=df, color="#804630")
```

```
<Axes: xlabel='G2'>
```



```
np.abs(stats.zscore(df))
np.abs(stats.zscore(df)).shape
```

```
df = df[(np.abs(stats. score(df)) < 3).all(axis=1)]
df

     school  sex  age  address  famsize  Pstatus  Medu  Fedu  Mjob
Fjob  ...  \
1         0    0   17        1        0        1     1     1     0
2  ...
2         0    0   15        1        1        1     1     1     0
2  ...
3         0    0   15        1        0        1     4     2     1
3  ...
4         0    0   16        1        0        1     3     3     2
2  ...
5         0    1   16        1        1        1     4     3     3
2  ...
..      ...  ...  ...      ...      ...      ...   ...   ...   ...   .
..  ...
643       1    0   18        0        0        1     4     4     4
0  ...
644       1    0   19        0        0        1     2     3     3
2  ...
645       1    0   18        1        1        1     3     1     4
3  ...
647       1    1   17        1        1        1     3     1     3
3  ...
648       1    1   18        0        1        1     3     2     3
2  ...
```

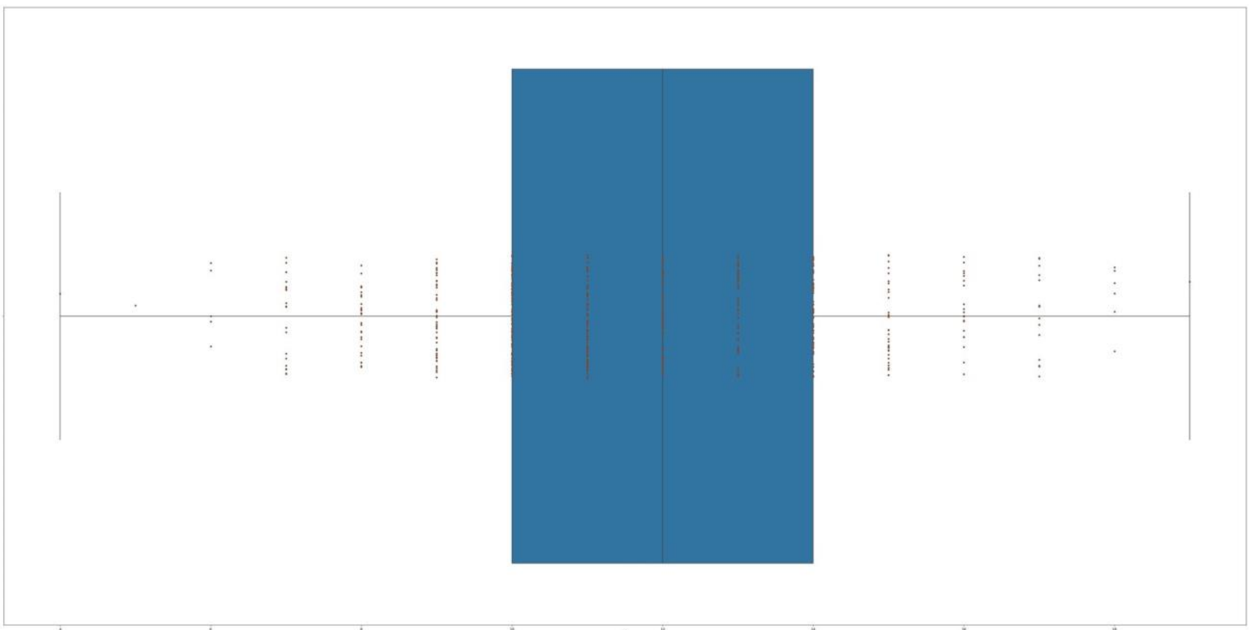
	famrel	freetime	goout	Dalc	Walc	health	absences	G1	G2	G3
1	5	3	3	1	1	3	2	9	11	11
2	4	3	2	2	3	3	6	12	13	12
3	3	2	2	1	1	5	0	14	14	14
4	4	3	2	1	2	5	0	11	13	13
5	5	4	2	1	2	5	6	12	12	13
..	...	...	...	...	...	...	...	..	..	..
643	4	4	3	2	2	5	4	7	9	10
644	5	4	2	1	2	5	4	10	11	10
645	4	3	4	1	1	1	4	15	15	16
647	2	4	5	3	4	2	6	10	10	10
648	4	4	1	3	4	5	4	10	11	11

```
[528 rows x 33 columns]
```

```
#df['G2'] = np.log(df['G2'])
```

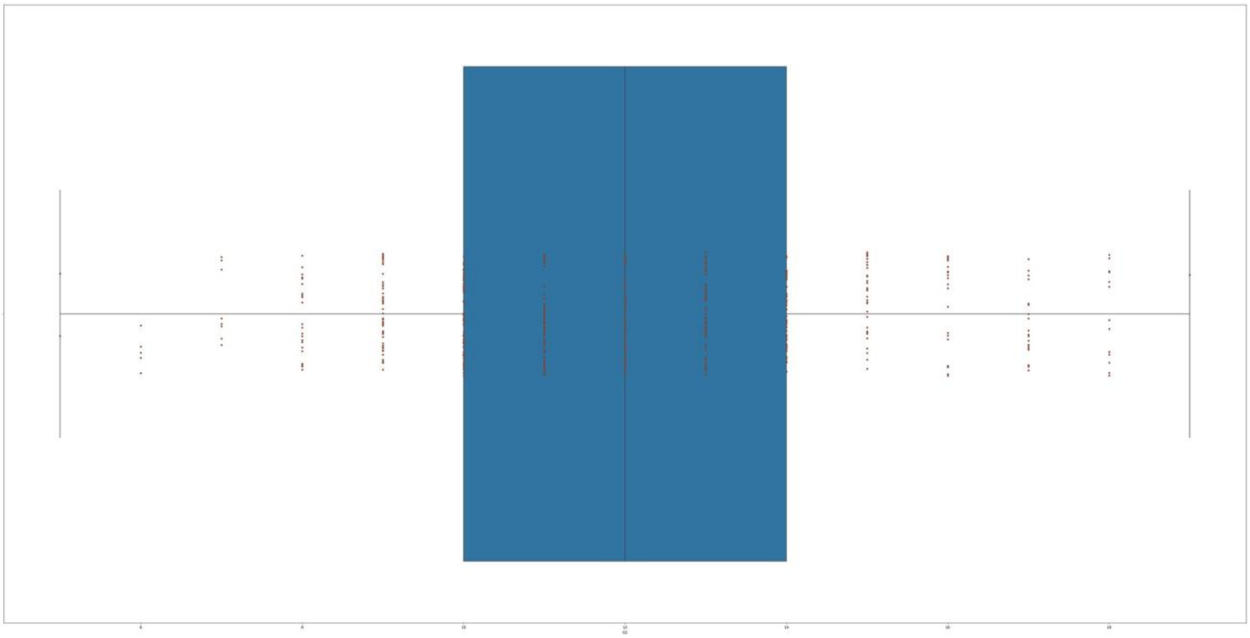
```
# cheaking the outliers in the feature 'G1'
plt.figure(figsize = (60,30))
sns.boxplot(x='G1', data=df)
sns.stripplot(x='G1', data=df, color="#804630")
```

```
<Axes: xlabel='G1'>
```



```
# cheaking the outliers in the feature 'G2'
plt.figure(figsize = (60,30))
sns.boxplot(x='G2', data=df)
sns.stripplot(x='G2', data=df, color="#804630")
```

```
<Axes: xlabel='G2'>
```



Feature selection

```
# We will apply feature selection method that can help us to choose
the effective features in model
# instead of choosing all the effective ones and non-effective ones
that can help us in best modeling

x = df.drop('G3', axis=1)
y = df['G3']

all_features = x.columns
all_features

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'],
      dtype='object')

from sklearn.tree import DecisionTreeClassifier
from sklearn.feature_selection import SelectFromModel

# Taking object from the library to use the model.
# Use gini criterion to define feature importance.
dtc = DecisionTreeClassifier(random_state=0, criterion='entropy')
```

```
selector = SelectFromModel(estimator=dtc)

selector.fit(x, y)

SelectFromModel(estimator=DecisionTreeClassifier(criterion='entropy',
                                                 random_state=0))

selector.get_support(indices=True)

array([27, 29, 30, 31])

selected_features_idx = selector.get_support(indices=True)
selected_features_idx

array([27, 29, 30, 31])

selected_features = all_features[selected_features_idx]
selected_features

Index(['Walc', 'absences', 'G1', 'G2'], dtype='object')

feat = ['Walc', 'absences', 'G1', 'G2']
```

Model and Optimaization

Random Forest Regression model

```
# Random Forest Regression model
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error, r2_score

# Separate features and target variable
features = df[feat]  # Features
target = df['G3']  # Target variable

# Split data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(features, target,
test_size=0.2, random_state=42)

# Initialize the Random Forest Regression with specified parameters
RFR = RandomForestRegressor(random_state=100,
criterion='squared_error', max_depth=30, min_samples_leaf=5, n_jobs=1)

# Train the regression
RFR.fit(X_train, y_train)

# Predict on the testing data
y_pred = RFR.predict(X_test)
```

```
mse = mean_squared_error(y_test, y_pred)

rmse = sqrt(mse)

r2 = r2_score(y_test, y_pred)

print("RFR Mean Squared Error MSE:", mse)
print("RFR Root Mean Squared Error RMSE:", rmse)
print("RFR R^2 Score:", r2)

RFR Mean Squared  Error  MSE:  0.49609031766595857
RFR Root Mean Squared Error RMSE: 0.7043367927816625
RFR R^2 Score: 0.9118082588238923

# using Gridsearch for best performancing Random Forest Regression
model (OPTIMAIZATION)
from sklearn.model_selection import GridSearchCV
number = [5,11,13,41,42,101]
numbers = list(range(1, 31))
param_grid = {'criterion': ["squared_error", "absolute_error"],
              'random_state' : number,
              'n_jobs' : [1, -1],
              'max_depth' :  numbers}
grid = GridSearchCV(RandomForestRegressor(),param_grid,cv = 5)
grid.fit(X_train,y_train)
grid.best_params_

{'criterion': 'squared_error',
 'max_depth': 4,
 'n_jobs': -1,
 'random_state': 13}

grid.best_estimator_

RandomForestRegressor(max_depth=4, n_jobs=-1, random_state=13)

grid_predictions = grid.predict(X_test)

mse = mean_squared_error(y_test, grid_predictions)

rmse = sqrt(mse)

r2 = r2_score(y_test, grid_predictions)

print("Optimaized RFR Mean Squared Error MSE:", mse)
print("Optimaized RFR Root Mean Squared Error RMSE:", rmse)
print("Optimaized RFR R^2 Score:", r2)

Optimaized RFR Mean Squared Error MSE: 0.48853848141867734
Optimaized RFR Root Mean Squared Error RMSE: 0.6989552785541271
Optimaized RFR R^2 Score: 0.9131507756278043
```

```python
# Get the list of available parameters in Random Forest Regression model
parameters = RandomForestRegressor().get_params().keys()

# Print the list of available parameters
print(parameters)
```

```
dict_keys(['bootstrap', 'ccp_alpha', 'criterion', 'max_depth',
'max_features', 'max_leaf_nodes', 'max_samples',
'min_impurity_decrease', 'min_samples_leaf', 'min_samples_split',
'min_weight_fraction_leaf', 'n_estimators', 'n_jobs', 'oob_score',
'random_state', 'verbose', 'warm_start'])
```

Decision Tree Regression model

```python
# Decision Tree Regression model
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeRegressor
from sklearn.metrics import mean_squared_error, r2_score

# Separate features and target variable
features = df[feat]  # Features
target = df['G3']  # Target variable

# Split data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(features, target,
test_size=0.2, random_state=42)

# Initialize the Decision Tree Regression with specified parameters
DTR = DecisionTreeRegressor(random_state=100,
criterion='squared_error', max_depth=30, min_samples_leaf=5)

# Train the regression
DTR.fit(X_train, y_train)

# Predict on the testing data
y_pred = DTR.predict(X_test)

mse = mean_squared_error(y_test, y_pred)

rmse = sqrt(mse)

r2 = r2_score(y_test, y_pred)

print("DTR Mean Squared Error MSE:", mse)
print("DTR Root Mean Squared Error RMSE:", rmse)
print("DTR R^2 Score:", r2)
```

```
DTR Mean Squared Error MSE: 0.5481355283802857
DTR Root Mean Squared Error RMSE: 0.7403617550767231
DTR R^2 Score: 0.9025559965052704
```

```
# using Gridsearch for best performancing Decision Tree Regression
model (OPTIMAIZATION)
from sklearn.model_selection import GridSearchCV
number = [5,11,13,41,42,101]
numbers = list(range(1, 31))
param_grid = {'random_state': number,
              'criterion' : ["squared_error", "absolute_error",
"friedman_mse", "poisson"],
              'max_depth' : numbers,
              'min_samples_leaf' :  numbers}
grid = GridSearchCV(DecisionTreeRegressor(),param_grid,cv = 5)
grid.fit(X_train,y_train)
grid.best_params_
```

```
{'criterion': 'squared_error',
 'max_depth': 5,
 'min_samples_leaf': 12,
 'random_state': 5}
```

```
grid.best_estimator_
```

```
DecisionTreeRegressor(max_depth=5, min_samples_leaf=12,
random_state=5)
```

```
grid_predictions = grid.predict(X_test)

mse = mean_squared_error(y_test, grid_predictions)

rmse = sqrt(mse)

r2 = r2_score(y_test, grid_predictions)

print("Optimaized DTR Mean Squared Error MSE:", mse)
print("Optimaized DTR Root Mean Squared Error RMSE:", rmse)
print("Optimaized DTR R^2 Score:", r2)
```

```
Optimaized DTR Mean Squared Error MSE: 0.5325372877080122
Optimaized DTR Root Mean Squared Error RMSE: 0.7297515246356202
Optimaized DTR R^2 Score: 0.9053289512580339
```

```
# Get the list of available parameters in Decision Tree Regression
model
parameters = DecisionTreeRegressor().get_params().keys()

# Print the list of available parameters
print(parameters)
```

```
dict_keys(['ccp_alpha', 'criterion', 'max_depth', 'max_features',
'max_leaf_nodes', 'min_impurity_decrease', 'min_samples_leaf',
'min_samples_split', 'min_weight_fraction_leaf', 'random_state',
'splitter'])
```

Linear Regression model

```
# Linear Regression model
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score

# Separate features and target variable
features = df[feat]  # Features
target = df['G3']  # Target variable

# Split data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(features, target,
test_size=0.2, random_state=42)

# Initialize the Linear Regression with specified parameters
LR = LinearRegression(fit_intercept= True ,n_jobs = 1)

# Train the regression
LR.fit(X_train, y_train)

# Predict on the testing data
y_pred = LR.predict(X_test)

mse = mean_squared_error(y_test, y_pred)

rmse = sqrt(mse)

r2 = r2_score(y_test, y_pred)

print("LR Mean Squared Error MSE:", mse)
print("LR Root Mean Squared Error RMSE:", rmse)
print("LR R^2 Score:", r2)
```

```
LR Mean Squared Error MSE: 0.4985581258841003
LR Root Mean Squared Error RMSE: 0.7060864861219908
LR R^2 Score: 0.9113695477749233
```

```
# using Gridsearch for best performancing Linear Regression model
(OPTIMAIZATION)
from sklearn.model_selection import GridSearchCV

param_grid = {'fit_intercept': [True, False],
              'n_jobs' : [1, -1]}
```

```
grid = GridSearchCV(LinearRegression(),param_grid,cv = 5)
grid.fit(X_train,y_train)
grid.best_params_
```

```
{'fit_intercept': True, 'n_jobs': 1}
```

```
grid.best_estimator_
```

```
LinearRegression(n_jobs=1)
```

```
grid_predictions = grid.predict(X_test)

mse = mean_squared_error(y_test, grid_predictions)

rmse = sqrt(mse)

r2 = r2_score(y_test, grid_predictions)

print("Optimaized LR Mean Squared Error MSE:", mse)
print("Optimaized LR Root Mean Squared Error RMSE:", rmse)
print("Optimaized LR R^2 Score:", r2)
```

```
Optimaized LR Mean Squared Error MSE: 0.4985581258841003
Optimaized LR Root Mean Squared Error RMSE: 0.7060864861219908
Optimaized LR R^2 Score: 0.9113695477749233
```

```
# Get the list of available parameters in Linear Regression model
parameters = LinearRegression().get_params().keys()

# Print the list of available parameters
print(parameters)
```

```
dict_keys(['copy_X', 'fit_intercept', 'n_jobs', 'positive'])
```

Support Vector Machine Regression model

```
# Support Vector Machine Regression model
from sklearn.model_selection import train_test_split
from sklearn.svm import SVR
from sklearn.metrics import mean_squared_error, r2_score

# Separate features and target variable
features = df[feat]  # Features
target = df['G3']  # Target variable

# Split data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(features, target,
test_size=0.2, random_state=42)

# Initialize the Support Vector Machine Regression  with specified
```

```
parameters
SVMR = SVR(kernel ='poly')

# Train the regression
SVMR.fit(X_train, y_train)

# Predict on the testing data
y_pred = SVMR.predict(X_test)

mse = mean_squared_error(y_test, y_pred)

rmse = sqrt(mse)

r2 = r2_score(y_test, y_pred)


print("SVMR Mean Squared Error MSE:", mse)
print("SVMR Root Mean Squared Error RMSE:", rmse)
print("SVMR R^2 Score:", r2)
```

```
SVMR Mean Squared Error MSE: 0.7646127399188548
SVMR Root Mean Squared Error RMSE: 0.8744213743492635
SVMR R^2 Score: 0.8640720722465627
```

```
# using Gridsearch for best performancing Support Vector Machine
Regression model (OPTIMAIZATION)
from sklearn.model_selection import GridSearchCV
number = [5,11,13,41,42,101]
numbers = list(range(1, 11))
param_grid = {'gamma' : ['scale', 'auto'],
              'kernel' : ['linear', 'rbf', 'sigmoid'],
              'degree' :  numbers}
grid = GridSearchCV(SVR(),param_grid,refit=True, verbose=3, cv = 5)
grid.fit(X_train,y_train)
grid.best_params_
```

```
Fitting 5 folds for each of 60 candidates, totalling 300 fits
[CV 1/5] END degree=1, gamma=scale, kernel=linear;, score=0.924 total
time=   0.0s
[CV 2/5] END degree=1, gamma=scale, kernel=linear;, score=0.927 total
time=   0.0s
[CV 3/5] END degree=1, gamma=scale, kernel=linear;, score=0.904 total
time=   0.0s
[CV 4/5] END degree=1, gamma=scale, kernel=linear;, score=0.878 total
time=   0.0s
[CV 5/5] END degree=1, gamma=scale, kernel=linear;, score=0.855 total
time=   0.0s
[CV 1/5] END .degree=1, gamma=scale, kernel=rbf;, score=0.909 total
time=   0.0s
[CV 2/5] END .degree=1, gamma=scale, kernel=rbf;, score=0.934 total
time=   0.0s
```

```
[CV 3/5] END .degree=1, gamma=scale, kernel=rbf;, score=0.890 total
time=   0.0s
[CV 4/5] END .degree=1, gamma=scale, kernel=rbf;, score=0.853 total
time=   0.0s
[CV 5/5] END .degree=1, gamma=scale, kernel=rbf;, score=0.848 total
time=   0.0s
[CV 1/5] END degree=1, gamma=scale, kernel=sigmoid;, score=-3.880
total time=   0.0s
[CV 2/5] END degree=1, gamma=scale, kernel=sigmoid;, score=-3.774
total time=   0.0s
[CV 3/5] END degree=1, gamma=scale, kernel=sigmoid;, score=-3.345
total time=   0.0s
[CV 4/5] END degree=1, gamma=scale, kernel=sigmoid;, score=-2.696
total time=   0.0s
[CV 5/5] END degree=1, gamma=scale, kernel=sigmoid;, score=-3.858
total time=   0.0s
[CV 1/5] END degree=1, gamma=auto, kernel=linear;, score=0.924 total
time=   0.0s
[CV 2/5] END degree=1, gamma=auto, kernel=linear;, score=0.927 total
time=   0.0s
[CV 3/5] END degree=1, gamma=auto, kernel=linear;, score=0.904 total
time=   0.0s
[CV 4/5] END degree=1, gamma=auto, kernel=linear;, score=0.878 total
time=   0.0s
[CV 5/5] END degree=1, gamma=auto, kernel=linear;, score=0.855 total
time=   0.0s
[CV 1/5] END ..degree=1, gamma=auto, kernel=rbf;, score=0.723 total
time=   0.0s
[CV 2/5] END ..degree=1, gamma=auto, kernel=rbf;, score=0.751 total
time=   0.0s
[CV 3/5] END ..degree=1, gamma=auto, kernel=rbf;, score=0.768 total
time=   0.0s
[CV 4/5] END ..degree=1, gamma=auto, kernel=rbf;, score=0.581 total
time=   0.0s
[CV 5/5] END ..degree=1, gamma=auto, kernel=rbf;, score=0.632 total
time=   0.0s
[CV 1/5] END degree=1, gamma=auto, kernel=sigmoid;, score=-0.004 total
time=   0.0s
[CV 2/5] END degree=1, gamma=auto, kernel=sigmoid;, score=-0.047 total
time=   0.0s
[CV 3/5] END degree=1, gamma=auto, kernel=sigmoid;, score=-0.001 total
time=   0.0s
[CV 4/5] END degree=1, gamma=auto, kernel=sigmoid;, score=-0.140 total
time=   0.0s
[CV 5/5] END degree=1, gamma=auto, kernel=sigmoid;, score=-0.000 total
time=   0.0s
[CV 1/5] END degree=2, gamma=scale, kernel=linear;, score=0.924 total
time=   0.0s
[CV 2/5] END degree=2, gamma=scale, kernel=linear;, score=0.927 total
```

```
time=   0.0s
[CV 3/5] END degree=2, gamma=scale, kernel=linear;, score=0.904 total
time=   0.0s
[CV 4/5] END degree=2, gamma=scale, kernel=linear;, score=0.878 total
time=   0.0s
[CV 5/5] END degree=2, gamma=scale, kernel=linear;, score=0.855 total
time=   0.0s
[CV 1/5] END .degree=2, gamma=scale, kernel=rbf;, score=0.909 total
time=   0.0s
[CV 2/5] END .degree=2, gamma=scale, kernel=rbf;, score=0.934 total
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[CV 3/5] END .degree=2, gamma=scale, kernel=rbf;, score=0.890 total
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[CV 4/5] END .degree=2, gamma=scale, kernel=rbf;, score=0.853 total
time=   0.0s
[CV 5/5] END .degree=2, gamma=scale, kernel=rbf;, score=0.848 total
time=   0.0s
[CV 1/5] END degree=2, gamma=scale, kernel=sigmoid;, score=-3.880
total time=   0.0s
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total time=   0.0s
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total time=   0.0s
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[CV 2/5] END ..degree=2, gamma=auto, kernel=rbf;, score=0.751 total
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[CV 3/5] END ..degree=2, gamma=auto, kernel=rbf;, score=0.768 total
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[CV 5/5] END ..degree=2, gamma=auto, kernel=rbf;, score=0.632 total
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[CV 1/5] END degree=2, gamma=auto, kernel=sigmoid;, score=-0.004 total
time=   0.0s
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[CV 2/5] END degree=2, gamma=auto, kernel=sigmoid;, score=-0.047 total
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[CV 5/5] END degree=2, gamma=auto, kernel=sigmoid;, score=-0.000 total
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[CV 1/5] END ..degree=3, gamma=auto, kernel=rbf;, score=0.723 total
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[CV 2/5] END ..degree=3, gamma=auto, kernel=rbf;, score=0.751 total
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total time=   0.0s
[CV 5/5] END degree=4, gamma=scale, kernel=sigmoid;, score=-3.858
total time=   0.0s
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[CV 1/5] END degree=4, gamma=auto, kernel=linear;, score=0.924 total
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time=   0.0s
[CV 4/5] END degree=4, gamma=auto, kernel=linear;, score=0.878 total
time=   0.0s
[CV 5/5] END degree=4, gamma=auto, kernel=linear;, score=0.855 total
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[CV 1/5] END ..degree=4, gamma=auto, kernel=rbf;, score=0.723 total
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[CV 2/5] END ..degree=4, gamma=auto, kernel=rbf;, score=0.751 total
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[CV 3/5] END ..degree=4, gamma=auto, kernel=rbf;, score=0.768 total
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[CV 4/5] END ..degree=4, gamma=auto, kernel=rbf;, score=0.581 total
time=   0.0s
[CV 5/5] END ..degree=4, gamma=auto, kernel=rbf;, score=0.632 total
time=   0.0s
[CV 1/5] END degree=4, gamma=auto, kernel=sigmoid;, score=-0.004 total
time=   0.0s
[CV 2/5] END degree=4, gamma=auto, kernel=sigmoid;, score=-0.047 total
time=   0.0s
[CV 3/5] END degree=4, gamma=auto, kernel=sigmoid;, score=-0.001 total
time=   0.0s
[CV 4/5] END degree=4, gamma=auto, kernel=sigmoid;, score=-0.140 total
time=   0.0s
[CV 5/5] END degree=4, gamma=auto, kernel=sigmoid;, score=-0.000 total
time=   0.0s
[CV 1/5] END degree=5, gamma=scale, kernel=linear;, score=0.924 total
time=   0.0s
[CV 2/5] END degree=5, gamma=scale, kernel=linear;, score=0.927 total
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[CV 3/5] END degree=5, gamma=scale, kernel=linear;, score=0.904 total
time=   0.0s
[CV 4/5] END degree=5, gamma=scale, kernel=linear;, score=0.878 total
time=   0.0s
[CV 5/5] END degree=5, gamma=scale, kernel=linear;, score=0.855 total
time=   0.0s
[CV 1/5] END .degree=5, gamma=scale, kernel=rbf;, score=0.909 total
time=   0.0s
[CV 2/5] END .degree=5, gamma=scale, kernel=rbf;, score=0.934 total
time=   0.0s
[CV 3/5] END .degree=5, gamma=scale, kernel=rbf;, score=0.890 total
time=   0.0s
[CV 4/5] END .degree=5, gamma=scale, kernel=rbf;, score=0.853 total
time=   0.0s
[CV 5/5] END .degree=5, gamma=scale, kernel=rbf;, score=0.848 total
```

```
time=   0.0s
[CV 1/5] END degree=5, gamma=scale, kernel=sigmoid;, score=-3.880
total time=   0.0s
[CV 2/5] END degree=5, gamma=scale, kernel=sigmoid;, score=-3.774
total time=   0.0s
[CV 3/5] END degree=5, gamma=scale, kernel=sigmoid;, score=-3.345
total time=   0.0s
[CV 4/5] END degree=5, gamma=scale, kernel=sigmoid;, score=-2.696
total time=   0.0s
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total time=   0.0s
[CV 1/5] END degree=5, gamma=auto, kernel=linear;, score=0.924 total
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[CV 3/5] END degree=5, gamma=auto, kernel=linear;, score=0.904 total
time=   0.0s
[CV 4/5] END degree=5, gamma=auto, kernel=linear;, score=0.878 total
time=   0.0s
[CV 5/5] END degree=5, gamma=auto, kernel=linear;, score=0.855 total
time=   0.0s
[CV 1/5] END ..degree=5, gamma=auto, kernel=rbf;, score=0.723 total
time=   0.0s
[CV 2/5] END ..degree=5, gamma=auto, kernel=rbf;, score=0.751 total
time=   0.0s
[CV 3/5] END ..degree=5, gamma=auto, kernel=rbf;, score=0.768 total
time=   0.0s
[CV 4/5] END ..degree=5, gamma=auto, kernel=rbf;, score=0.581 total
time=   0.0s
[CV 5/5] END ..degree=5, gamma=auto, kernel=rbf;, score=0.632 total
time=   0.0s
[CV 1/5] END degree=5, gamma=auto, kernel=sigmoid;, score=-0.004 total
time=   0.0s
[CV 2/5] END degree=5, gamma=auto, kernel=sigmoid;, score=-0.047 total
time=   0.0s
[CV 3/5] END degree=5, gamma=auto, kernel=sigmoid;, score=-0.001 total
time=   0.0s
[CV 4/5] END degree=5, gamma=auto, kernel=sigmoid;, score=-0.140 total
time=   0.0s
[CV 5/5] END degree=5, gamma=auto, kernel=sigmoid;, score=-0.000 total
time=   0.0s
[CV 1/5] END degree=6, gamma=scale, kernel=linear;, score=0.924 total
time=   0.0s
[CV 2/5] END degree=6, gamma=scale, kernel=linear;, score=0.927 total
time=   0.0s
[CV 3/5] END degree=6, gamma=scale, kernel=linear;, score=0.904 total
time=   0.0s
[CV 4/5] END degree=6, gamma=scale, kernel=linear;, score=0.878 total
time=   0.0s
```

```
[CV 5/5] END degree=6, gamma=scale, kernel=linear;, score=0.855 total
time=   0.0s
[CV 1/5] END .degree=6, gamma=scale, kernel=rbf;, score=0.909 total
time=   0.0s
[CV 2/5] END .degree=6, gamma=scale, kernel=rbf;, score=0.934 total
time=   0.0s
[CV 3/5] END .degree=6, gamma=scale, kernel=rbf;, score=0.890 total
time=   0.0s
[CV 4/5] END .degree=6, gamma=scale, kernel=rbf;, score=0.853 total
time=   0.0s
[CV 5/5] END .degree=6, gamma=scale, kernel=rbf;, score=0.848 total
time=   0.0s
[CV 1/5] END degree=6, gamma=scale, kernel=sigmoid;, score=-3.880
total time=   0.0s
[CV 2/5] END degree=6, gamma=scale, kernel=sigmoid;, score=-3.774
total time=   0.0s
[CV 3/5] END degree=6, gamma=scale, kernel=sigmoid;, score=-3.345
total time=   0.0s
[CV 4/5] END degree=6, gamma=scale, kernel=sigmoid;, score=-2.696
total time=   0.0s
[CV 5/5] END degree=6, gamma=scale, kernel=sigmoid;, score=-3.858
total time=   0.0s
[CV 1/5] END degree=6, gamma=auto, kernel=linear;, score=0.924 total
time=   0.0s
[CV 2/5] END degree=6, gamma=auto, kernel=linear;, score=0.927 total
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[CV 3/5] END degree=6, gamma=auto, kernel=linear;, score=0.904 total
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time=   0.0s
[CV 4/5] END degree=6, gamma=auto, kernel=sigmoid;, score=-0.140 total
```

```
time=   0.0s
[CV 5/5] END degree=6, gamma=auto, kernel=sigmoid;, score=-0.000 total
time=   0.0s
[CV 1/5] END degree=7, gamma=scale, kernel=linear;, score=0.924 total
time=   0.0s
[CV 2/5] END degree=7, gamma=scale, kernel=linear;, score=0.927 total
time=   0.0s
[CV 3/5] END degree=7, gamma=scale, kernel=linear;, score=0.904 total
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```

```
[CV 4/5] END ..degree=7, gamma=auto, kernel=rbf;, score=0.581 total
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time=   0.0s
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```

```
time=   0.0s
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time=   0.0s
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```

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total time=   0.0s
[CV 4/5] END degree=9, gamma=scale, kernel=sigmoid;, score=-2.696
total time=   0.0s
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[CV 4/5] END ..degree=9, gamma=auto, kernel=rbf;, score=0.581 total
time=   0.0s
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time=   0.0s
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time=   0.0s
[CV 1/5] END degree=10, gamma=scale, kernel=linear;, score=0.924 total
time=   0.0s
[CV 2/5] END degree=10, gamma=scale, kernel=linear;, score=0.927 total
time=   0.0s
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[CV 5/5] END degree=10, gamma=scale, kernel=linear;, score=0.855 total
time=   0.0s
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time=   0.0s
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```

```
[CV 3/5] END degree=10, gamma=scale, kernel=rbf;, score=0.890 total
time=   0.0s
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total time=   0.0s
[CV 3/5] END degree=10, gamma=auto, kernel=sigmoid;, score=-0.001
total time=   0.0s
[CV 4/5] END degree=10, gamma=auto, kernel=sigmoid;, score=-0.140
total time=   0.0s
[CV 5/5] END degree=10, gamma=auto, kernel=sigmoid;, score=-0.000
total time=   0.0s

{'degree': 1, 'gamma': 'scale', 'kernel': 'linear'}

grid.best_estimator_
```

```
SVR(degree=1, kernel='linear')

grid_predictions = grid.predict(X_test)

mse = mean_squared_error(y_test, grid_predictions)

rmse = sqrt(mse)

r2 = r2_score(y_test, grid_predictions)

print("Optimaized SVMR Mean Squared Error MSE:", mse)
print("Optimaized SVMR Root Mean Squared Error RMSE:", rmse)
print("Optimaized SVMR R^2 Score:", r2)

Optimaized SVMR Mean Squared Error MSE: 0.49498725327903326
Optimaized SVMR Root Mean Squared Error RMSE: 0.7035533052150585
Optimaized SVMR R^2 Score: 0.9120043545053601

# Get the list of available parameters in Support Vector Machine
Regression model
parameters = SVR().get_params().keys()

# Print the list of available parameters
print(parameters)

dict_keys(['C', 'cache_size', 'coef0', 'degree', 'epsilon', 'gamma',
'kernel', 'max_iter', 'shrinking', 'tol', 'verbose'])
```

XGBoost Regression model

```
# XGBoost Regression model
from sklearn.model_selection import train_test_split
from xgboost import XGBRegressor
from sklearn.metrics import mean_squared_error, r2_score

# Separate features and target variable
features = df[feat]   # Features
target = df['G3']  # Target variable

# Split data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(features, target,
test_size=0.2, random_state=42)

# Initialize the XGBoost Regression with specified parameters
XGBR = XGBRegressor(gamma= 0.3, random_state= 42, n_estimators=11,
n_jobs= -1, max_depth=10)

# Train the regression
XGBR.fit(X_train, y_train)
```

```
# Predict on the testing data
y_pred = XGBR.predict(X_test)

mse = mean_squared_error(y_test, y_pred)

rmse = sqrt(mse)

r2 = r2_score(y_test, y_pred)

print("XGBR Mean Squared Error MSE:", mse)
print("XGBR Root Mean Squared Error RMSE:", rmse)
print("XGBR R^2 Score:", r2)

XGBR Mean Squared Error MSE: 0.5637500191466669
XGBR Root Mean Squared Error RMSE: 0.7508328836343456
XGBR R^2 Score: 0.8997801529154492

# using Gridsearch for best performancing XGBoost Regression model
(OPTIMAIZATION)
from sklearn.model_selection import GridSearchCV
number = [5,11,13,41,42,101]
numbers = list(range(1, 11))
param_grid = {'random_state' : number,
              'n_estimators' : numbers,
              'n_jobs' : [1, -1],
              'max_depth': numbers}
grid = GridSearchCV(XGBRegressor(), param_grid, cv = 5)
grid.fit(X_train,y_train)
grid.best_params_

{'max_depth': 2, 'n_estimators': 10, 'n_jobs': 1, 'random_state': 5}

grid.best_estimator_

XGBRegressor(base_score=None, booster=None, callbacks=None,
             colsample_bylevel=None, colsample_bynode=None,
             colsample_bytree=None, device=None,
early_stopping_rounds=None,
             enable_categorical=False, eval_metric=None,
feature_types=None,
             gamma=None, grow_policy=None, importance_type=None,
             interaction_constraints=None, learning_rate=None,
max_bin=None,
             max_cat_threshold=None, max_cat_to_onehot=None,
             max_delta_step=None, max_depth=2, max_leaves=None,
             min_child_weight=None, missing=nan,
monotone_constraints=None,
             multi_strategy=None, n_estimators=10, n_jobs=1,
             num_parallel_tree=None, random_state=5, ...)
```

```
grid_predictions = grid.predict(X_test)

mse = mean_squared_error(y_test, grid_predictions)

rmse = sqrt(mse)

r2 = r2_score(y_test, grid_predictions)

print("Optimaized XGBR Mean Squared Error MSE:", mse)
print("Optimaized XGBR Root Mean Squared Error RMSE:", rmse)
print("Optimaized XGBR R^2 Score:", r2)
```

```
Optimaized XGBR Mean Squared Error MSE: 0.4545592254555986
Optimaized XGBR Root Mean Squared Error RMSE: 0.6742100751661892
Optimaized XGBR R^2 Score: 0.9191913888801483
```

```
# Get the list of available parameters in XGBoost Regression model
parameters = XGBRegressor().get_params().keys()

# Print the list of available parameters
print(parameters)
```

```
dict_keys(['objective', 'base_score', 'booster', 'callbacks',
'colsample_bylevel', 'colsample_bynode', 'colsample_bytree', 'device',
'early_stopping_rounds', 'enable_categorical', 'eval_metric',
'feature_types', 'gamma', 'grow_policy', 'importance_type',
'interaction_constraints', 'learning_rate', 'max_bin',
'max_cat_threshold', 'max_cat_to_onehot', 'max_delta_step',
'max_depth', 'max_leaves', 'min_child_weight', 'missing',
'monotone_constraints', 'multi_strategy', 'n_estimators', 'n_jobs',
'num_parallel_tree', 'random_state', 'reg_alpha', 'reg_lambda',
'sampling_method', 'scale_pos_weight', 'subsample', 'tree_method',
'validate_parameters', 'verbosity'])
```

K Nearest Neighbors Regression model

```
# K Nearest Neighbors Regression model
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsRegressor
from sklearn.metrics import mean_squared_error, r2_score

# Separate features and target variable
features = df[feat]  # Features
target = df['G3']  # Target variable

# Split data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(features, target,
test_size=0.2, random_state=42)
```

```python
# Initialize the K Nearest Neighbors Regression model with specified
parameters
KNNR = KNeighborsRegressor(n_neighbors= 7, n_jobs= 1, metric=
'manhattan')

# Train the regression
KNNR.fit(X_train, y_train)

# Predict on the testing data
y_pred = KNNR.predict(X_test)

mse = mean_squared_error(y_test, y_pred)

rmse = sqrt(mse)

r2 = r2_score(y_test, y_pred)

print("KNNR Mean Squared Error MSE:", mse)
print("KNNR Root Mean Squared Error RMSE:", rmse)
print("KNNR R^2 Score:", r2)
```

```
KNNR Mean Squared Error MSE: 0.5762418174817098
KNNR Root Mean Squared Error RMSE: 0.7591059329775455
KNNR R^2 Score: 0.8975594414716712
```

```python
# using Gridsearch for best performancing K Nearest Neighbors
Regression model (OPTIMAIZATION)
from sklearn.model_selection import GridSearchCV
number = [5,11,13,41,42,101]
numbers = list(range(1, 51))
param_grid = {'n_neighbors': number,
              'n_jobs' :  [1, -1],
              'metric' : ['manhattan','euclidean','minkowski']}
grid = GridSearchCV(KNeighborsRegressor(),param_grid,cv = 5)
grid.fit(X_train,y_train)
grid.best_params_
```

```
{'metric': 'manhattan', 'n_jobs': 1, 'n_neighbors': 13}
```

```python
grid.best_estimator_
```

```
KNeighborsRegressor(metric='manhattan', n_jobs=1, n_neighbors=13)
```

```python
grid_predictions = grid.predict(X_test)

mse = mean_squared_error(y_test, grid_predictions)

rmse = sqrt(mse)

r2 = r2_score(y_test, grid_predictions)

print("Optimaized KNNR Mean Squared Error MSE:", mse)
```

```
print("Optimaized KNNR Root Mean Squared Error RMSE:", rmse)
print("Optimaized KNNR R^2 Score:", r2)
```

```
Optimaized KNNR Mean Squared Error MSE: 0.6091325220497935
Optimaized KNNR Root Mean Squared Error RMSE: 0.7804694241607377
Optimaized KNNR R^2 Score: 0.8917123438745731
```

```
# Get the list of available parameters in K Nearest Neighbors
Regression model
parameters = KNeighborsRegressor().get_params().keys()

# Print the list of available parameters
print(parameters)
```

```
dict_keys(['algorithm', 'leaf_size', 'metric', 'metric_params',
'n_jobs', 'n_neighbors', 'p', 'weights'])
```