StudentGradeAnalysis

December 2, 2024

1 Student Grade Analysis & Prediction

Objective: Prediction of the final grade of Portuguese high school students

Data Set Information The data used is from a Portuguese secondary school. The data includes academic and personal characteristics of the students as well as final grades. The task is to predict the final grade from the student information. (Regression) Link to dataset

1.1 Import Libraries

[23]:
```
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import seaborn as sns

sns.set_style('whitegrid')
```

1.2 The Data

Let's start by reading in the student-mat.csv file into a pandas dataframe.

[24]:
```
stud = pd.read_csv('data/StudentGrades.csv')
```

[25]:
```
print('Total number of students:', len(stud))
```

```
Total number of students: 395
```

[26]:
```
stud['G3'].describe()
```

[26]:
```
count    395.000000
mean      10.415190
std        4.581443
min        0.000000
25%        8.000000
50%       11.000000
75%       14.000000
max       20.000000
Name: G3, dtype: float64
```

[27]:
```
stud.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 395 entries, 0 to 394
Data columns (total 31 columns):
 #   Column                       Non-Null Count  Dtype 
---  ------                       --------------  ----- 
 0   school                       395 non-null    object
 1   sex                          395 non-null    object
 2   age                          395 non-null    int64 
 3   address                      395 non-null    object
 4   family_size                  395 non-null    object
 5   parent_cohabitation_status   395 non-null    object
 6   mother_education             395 non-null    int64 
 7   father_education             395 non-null    int64 
 8   mother_job                   395 non-null    object
 9   father_job                   395 non-null    object
 10  reason                       395 non-null    object
 11  guardian                     395 non-null    object
 12  travel_time                  395 non-null    int64 
 13  study_time                   395 non-null    int64 
 14  failures                     395 non-null    int64 
 15  school_support               395 non-null    object
 16  family_support               395 non-null    object
 17  paid                         395 non-null    object
 18  activities                   395 non-null    object
 19  nursery                      395 non-null    object
 20  higher                       395 non-null    object
 21  internet                     395 non-null    object
 22  romantic                     395 non-null    object
 23  family_relation              395 non-null    int64 
 24  freetime                     395 non-null    int64 
 25  goes_out                     395 non-null    int64 
 26  health                       395 non-null    int64 
 27  absences                     395 non-null    int64 
 28  G1                           395 non-null    int64 
 29  G2                           395 non-null    int64 
 30  G3                           395 non-null    int64 
dtypes: int64(14), object(17)
memory usage: 95.8+ KB
```

[28]:
```
stud.columns
```

[28]:
```
Index(['school', 'sex', 'age', 'address', 'family_size',
       'parent_cohabitation_status', 'mother_education', 'father_education',
       'mother_job', 'father_job', 'reason', 'guardian', 'travel_time',
       'study_time', 'failures', 'school_support', 'family_support', 'paid',
       'activities', 'nursery', 'higher', 'internet', 'romantic',
```

```
       'family_relation', 'freetime', 'goes_out', 'health', 'absences', 'G1',
       'G2', 'G3'],
      dtype='object')
```

[29]:
```
stud.describe()
```

[29]:
```
              age  mother_education  father_education  travel_time  \
count  395.000000        395.000000        395.000000   395.000000
mean    16.696203          2.749367          2.521519     1.448101
std      1.276043          1.094735          1.088201     0.697505
min     15.000000          0.000000          0.000000     1.000000
25%     16.000000          2.000000          2.000000     1.000000
50%     17.000000          3.000000          2.000000     1.000000
75%     18.000000          4.000000          3.000000     2.000000
max     22.000000          4.000000          4.000000     4.000000

       study_time    failures  family_relation    freetime    goes_out  \
count  395.000000  395.000000       395.000000  395.000000  395.000000
mean     2.035443    0.334177         3.944304    3.235443    3.108861
std      0.839240    0.743651         0.896659    0.998862    1.113278
min      1.000000    0.000000         1.000000    1.000000    1.000000
25%      1.000000    0.000000         4.000000    3.000000    2.000000
50%      2.000000    0.000000         4.000000    3.000000    3.000000
75%      2.000000    0.000000         5.000000    4.000000    4.000000
max      4.000000    3.000000         5.000000    5.000000    5.000000

           health    absences          G1          G2          G3
count  395.000000  395.000000  395.000000  395.000000  395.000000
mean     3.554430    5.708861   10.908861   10.713924   10.415190
std      1.390303    8.003096    3.319195    3.761505    4.581443
min      1.000000    0.000000    3.000000    0.000000    0.000000
25%      3.000000    0.000000    8.000000    9.000000    8.000000
50%      4.000000    4.000000   11.000000   11.000000   11.000000
75%      5.000000    8.000000   13.000000   13.000000   14.000000
max      5.000000   75.000000   19.000000   19.000000   20.000000
```

[30]:
```
stud.head()
```

[30]:
```
  school sex  age address family_size parent_cohabitation_status  \
0     GP   F   18       U         GT3                           A
1     GP   F   17       U         GT3                           T
2     GP   F   15       U         LE3                           T
3     GP   F   15       U         GT3                           T
4     GP   F   16       U         GT3                           T

   mother_education  father_education mother_job father_job  … internet  \
0                 4                 4    at_home    teacher  …       no
```

```
1                1                1    at_home      other  …      yes
2                1                1    at_home      other  …      yes
3                4                2     health   services  …      yes
4                3                3      other      other  …       no

  romantic  family_relation  freetime  goes_out health absences  G1  G2  G3
0       no                4         3         4      3        6   5   6   6
1       no                5         3         3      3        4   5   5   6
2       no                4         3         2      3       10   7   8  10
3      yes                3         2         2      5        2  15  14  15
4       no                4         3         2      5        4   6  10  10

[5 rows x 31 columns]
```

[31]:
```
stud.tail()
```

[31]:
```
    school sex  age address family_size parent_cohabitation_status  \
390     MS   M   20       U         LE3                          A
391     MS   M   17       U         LE3                          T
392     MS   M   21       R         GT3                          T
393     MS   M   18       R         LE3                          T
394     MS   M   19       U         LE3                          T

     mother_education  father_education mother_job father_job  … internet  \
390                 2                 2   services   services  …       no
391                 3                 1   services   services  …      yes
392                 1                 1      other      other  …       no
393                 3                 2   services      other  …      yes
394                 1                 1      other    at_home  …      yes

    romantic  family_relation  freetime  goes_out health absences  G1  G2  G3
390       no                5         5         4      4       11   9   9   9
391       no                2         4         5      2        3  14  16  16
392       no                5         5         3      3        3  10   8   7
393       no                4         4         1      5        0  11  12  10
394       no                3         2         3      5        5   8   9   9

[5 rows x 31 columns]
```

[32]:
```
stud.isnull().any()
```

[32]:
```
school                      False
sex                         False
age                         False
address                     False
family_size                 False
parent_cohabitation_status  False
```

```
mother_education            False
father_education            False
mother_job                  False
father_job                  False
reason                      False
guardian                    False
travel_time                 False
study_time                  False
failures                    False
school_support              False
family_support              False
paid                        False
activities                  False
nursery                     False
higher                      False
internet                    False
romantic                    False
family_relation             False
freetime                    False
goes_out                    False
health                      False
absences                    False
G1                          False
G2                          False
G3                          False
dtype: bool
```

[33]:
```
import cufflinks as cf

cf.go_offline()
```

[34]:
```
stud.iplot()
```

[35]:
```
stud.iplot(kind='scatter', x='age', y='G3', mode='markers', size=8)
```

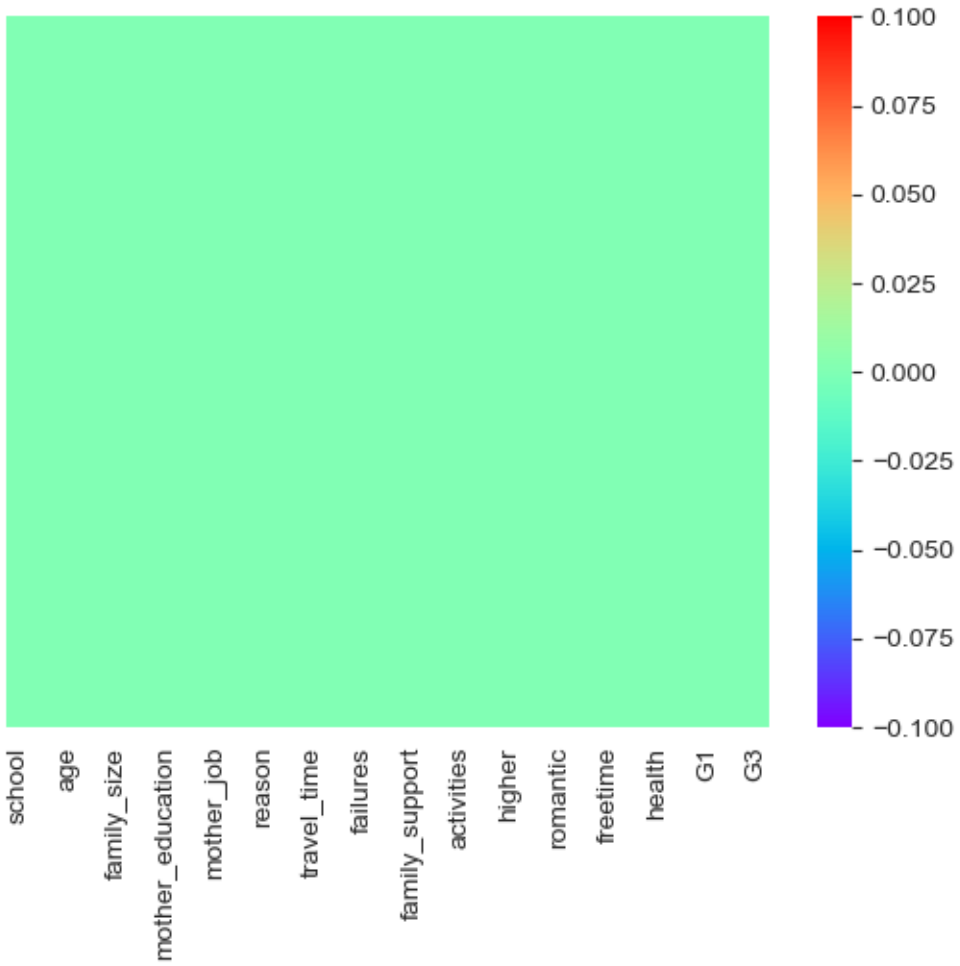
[36]:
```
stud.iplot(kind='box')
```

[37]:
```
stud['G3'].iplot(kind='hist', bins=100, color='blue')
```

2 Data Visualization

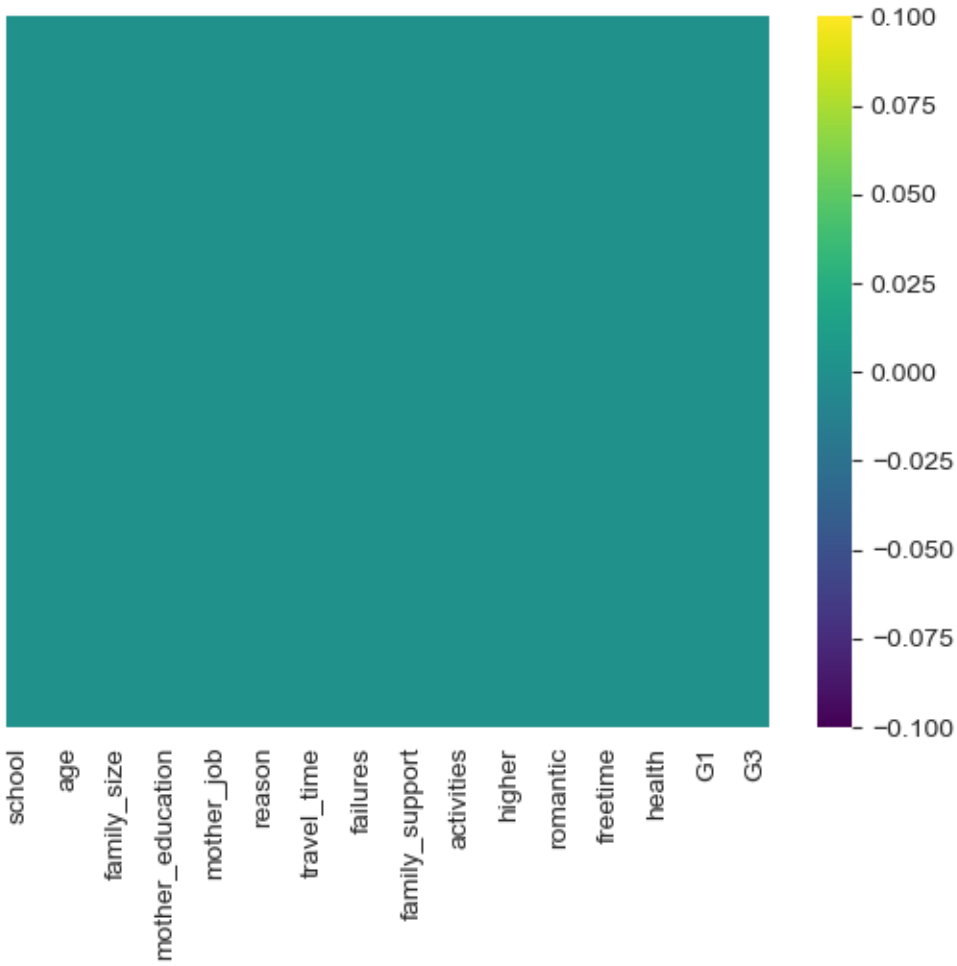
[38]:
```
sns.heatmap(stud.isnull(), cmap="rainbow", yticklabels=False)
```

[38]:
```
<Axes: >
```



[39]:
```
sns.heatmap(stud.isnull(), cmap="viridis", yticklabels=False)
```

[39]: <Axes: >



- There are no null values in the given dataset

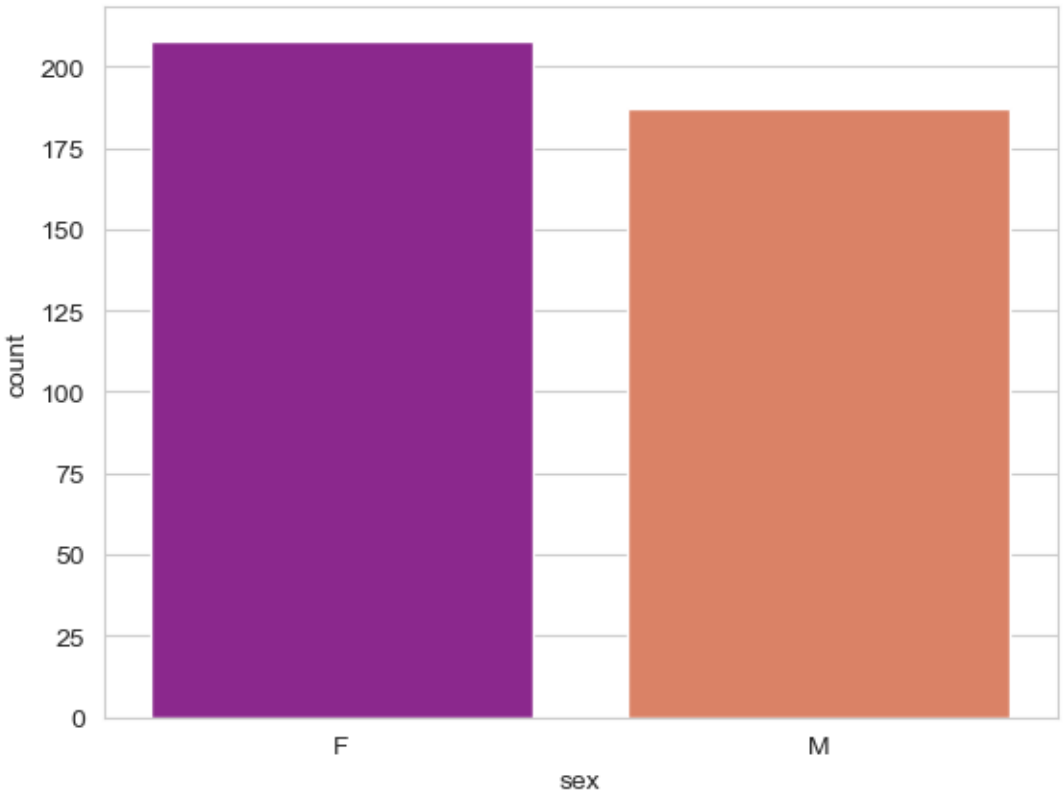
2.1 Student's Sex

[40]:
```
f_stud = len(stud[stud['sex'] == 'F'])
print('Number of female students:', f_stud)
m_stud = len(stud[stud['sex'] == 'M'])
print('Number of male students:', m_stud)
```

```
Number of female students: 208
Number of male students: 187
```

[41]:
```
sns.countplot(x='sex', data=stud, palette='plasma', hue='sex')
```

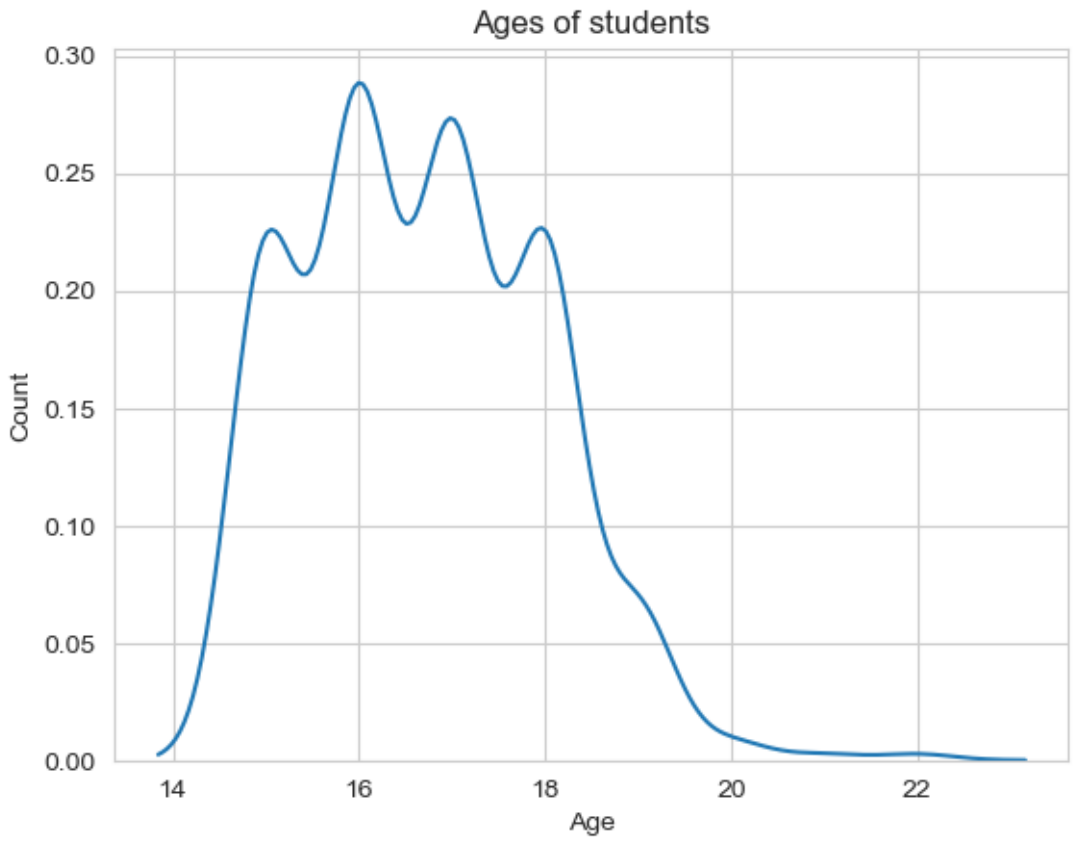
[41]:
```
<Axes: xlabel='sex', ylabel='count'>
```



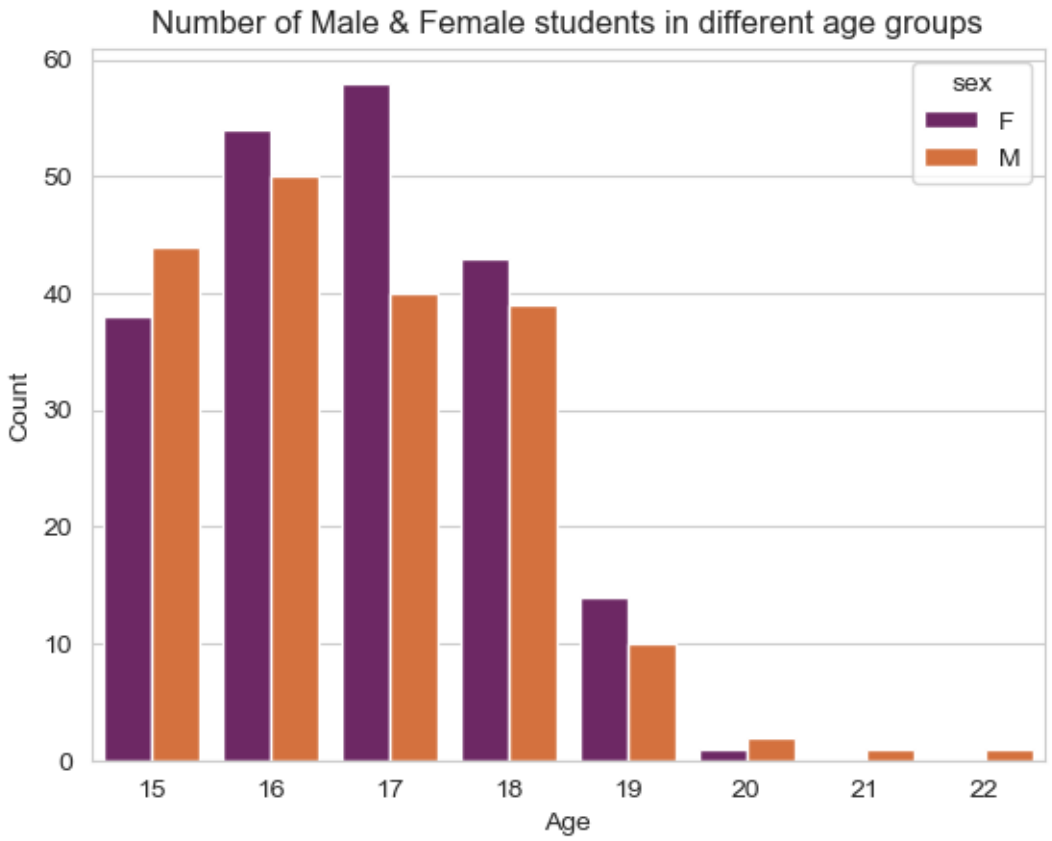
- The gender distribution is pretty even.

2.2 Age of Students

[42]:
```
b = sns.kdeplot(stud['age'])
b.axes.set_title('Ages of students')
b.set_xlabel('Age')
b.set_ylabel('Count')
plt.show()
```



[43]:
```
b = sns.countplot(x='age', hue='sex', data=stud, palette='inferno')
b.axes.set_title('Number of Male & Female students in different age groups')
b.set_xlabel("Age")
b.set_ylabel("Count")
plt.show()
```



- The student age seems to be ranging from 15-19, where gender distribution is pretty even in each age group.
- The age group above 19 may be outliers, year back students or droupouts.

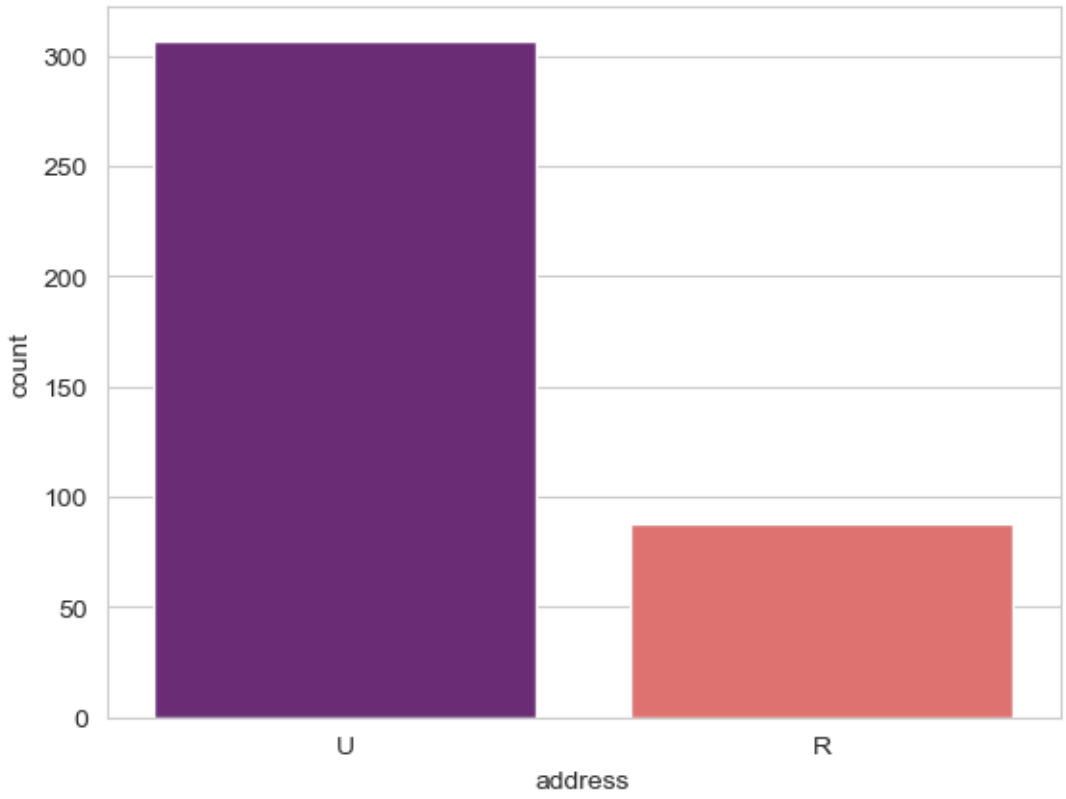
2.3 Students from Urban & Rural Areas

[44]:
```
u_stud = len(stud[stud['address'] == 'U'])
print('Number of Urban students:', u_stud)
r_stud = len(stud[stud['address'] == 'R'])
print('Number of Rural students:', r_stud)
```

```
Number of Urban students: 307
Number of Rural students: 88
```

[45]:
```
sns.countplot(x='address', hue='address', data=stud, palette='magma')
```

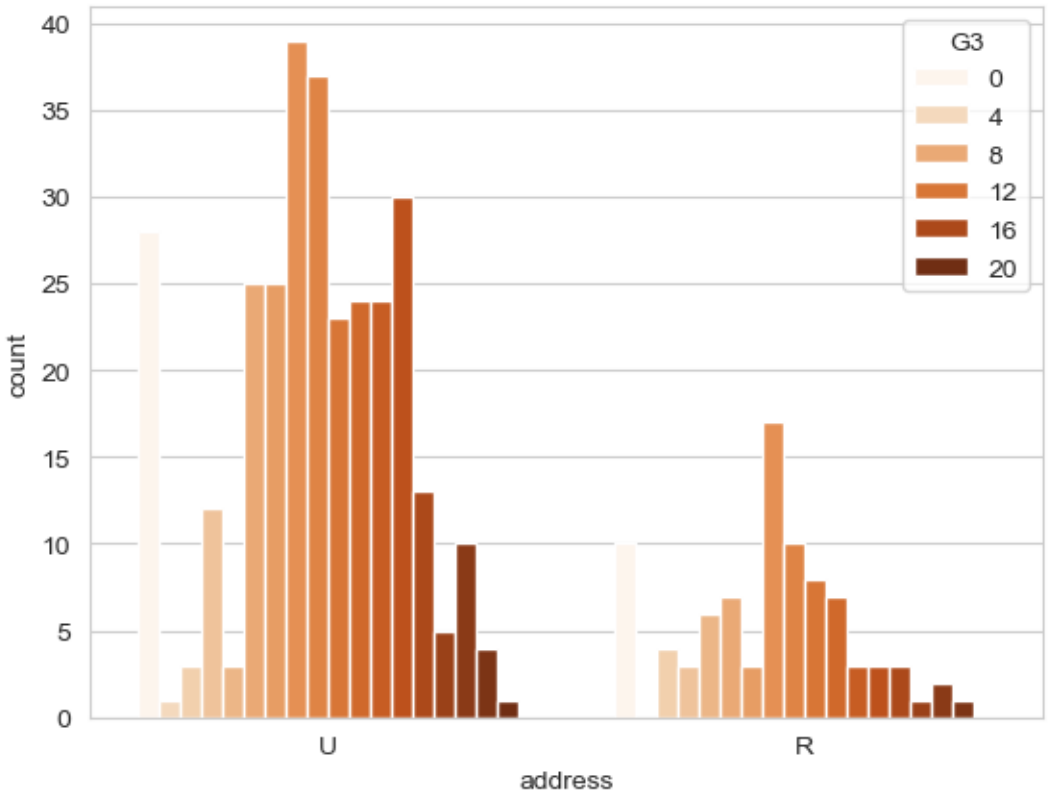
[45]:
```
<Axes: xlabel='address', ylabel='count'>
```



- Approximately 77.72% students come from urban region and 22.28% from rural region.

[46]:
```
sns.countplot(x='address', hue='G3', data=stud, palette='Oranges')
```

[46]:
```
<Axes: xlabel='address', ylabel='count'>
```



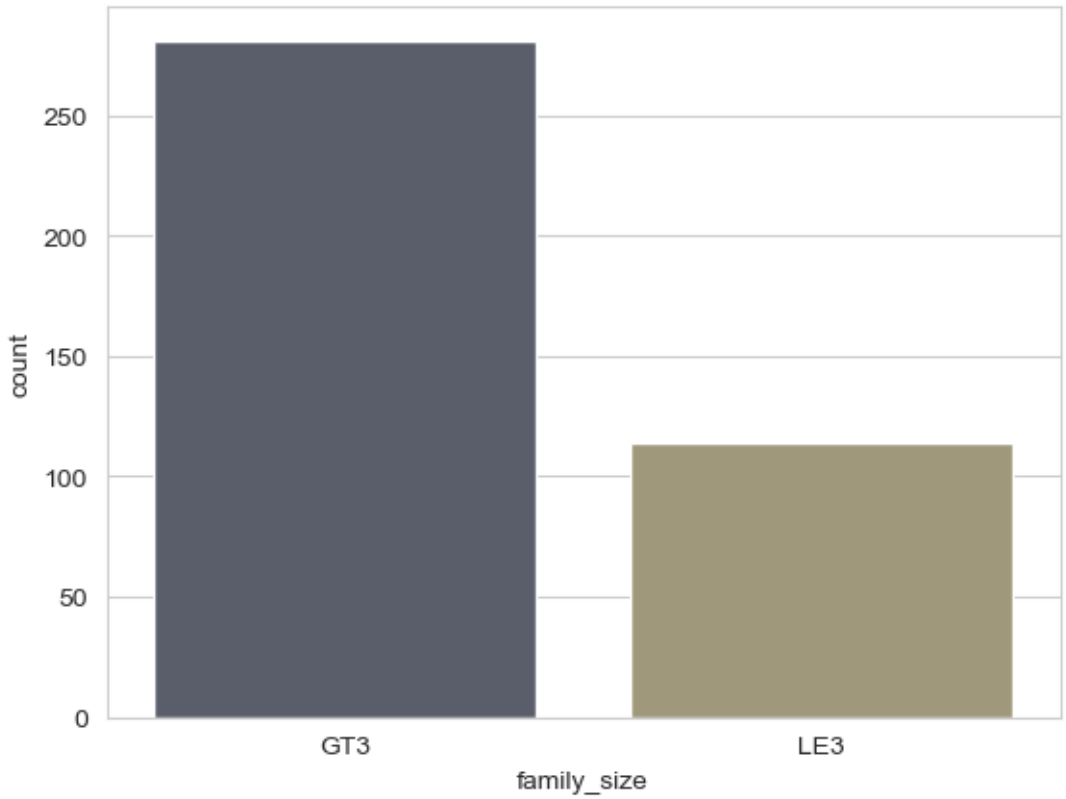
2.4 Students family size

[47]:
```
gt3_stud = len(stud[stud['family_size'] == 'GT3'])
print('Number of students with more than 3 members:', gt3_stud)
le3_stud = len(stud[stud['family_size'] == 'LE3'])
print('Number of students with less than 3 members:', le3_stud)
```

```
Number of students with more than 3 members: 281
Number of students with less than 3 members: 114
```

[48]:
```
sns.countplot(x='family_size', hue='family_size', data=stud, palette='cividis')
```

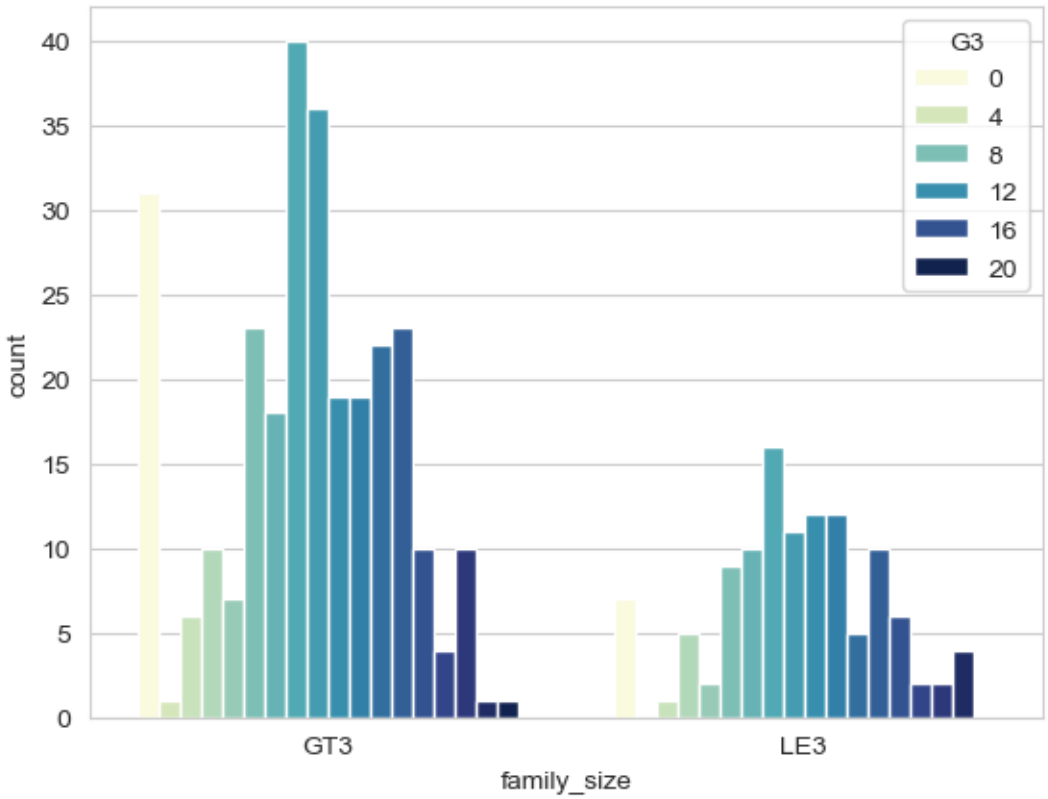
[48]:
```
<Axes: xlabel='family_size', ylabel='count'>
```



- Approximately 71.14% students come from families with more than 3 members and 28.86% students come from families with less than 3 members

[49]:
```
sns.countplot(x='family_size', hue='G3', data=stud, palette='YlGnBu')
```

[49]:
```
<Axes: xlabel='family_size', ylabel='count'>
```



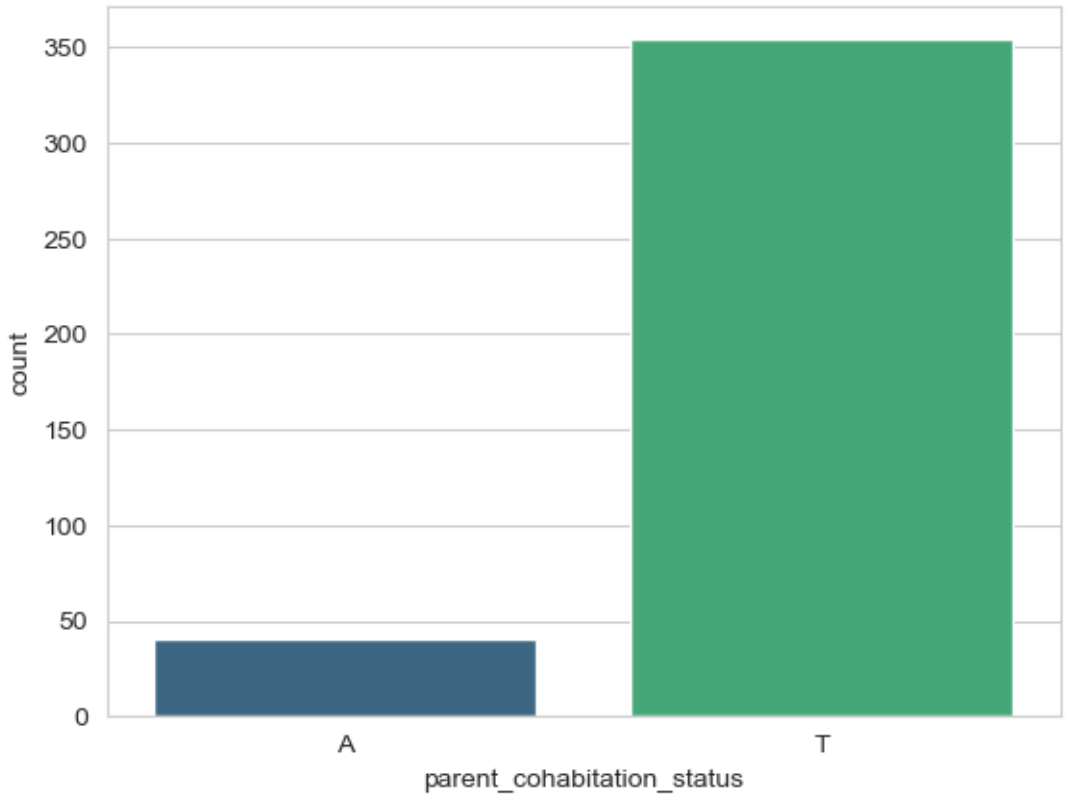
2.5 Students parent cohabitation status

[50]:
```
a_stud = len(stud[stud['parent_cohabitation_status'] == 'A'])
print('Number of students with parents living away:', a_stud)
t_stud = len(stud[stud['parent_cohabitation_status'] == 'T'])
print('Number of students with parents living together:', t_stud)
```

```
Number of students with parents living away: 41
Number of students with parents living together: 354
```

[51]:
```
sns.countplot(x='parent_cohabitation_status', hue='parent_cohabitation_status',␣
↪data=stud, palette='viridis')
```

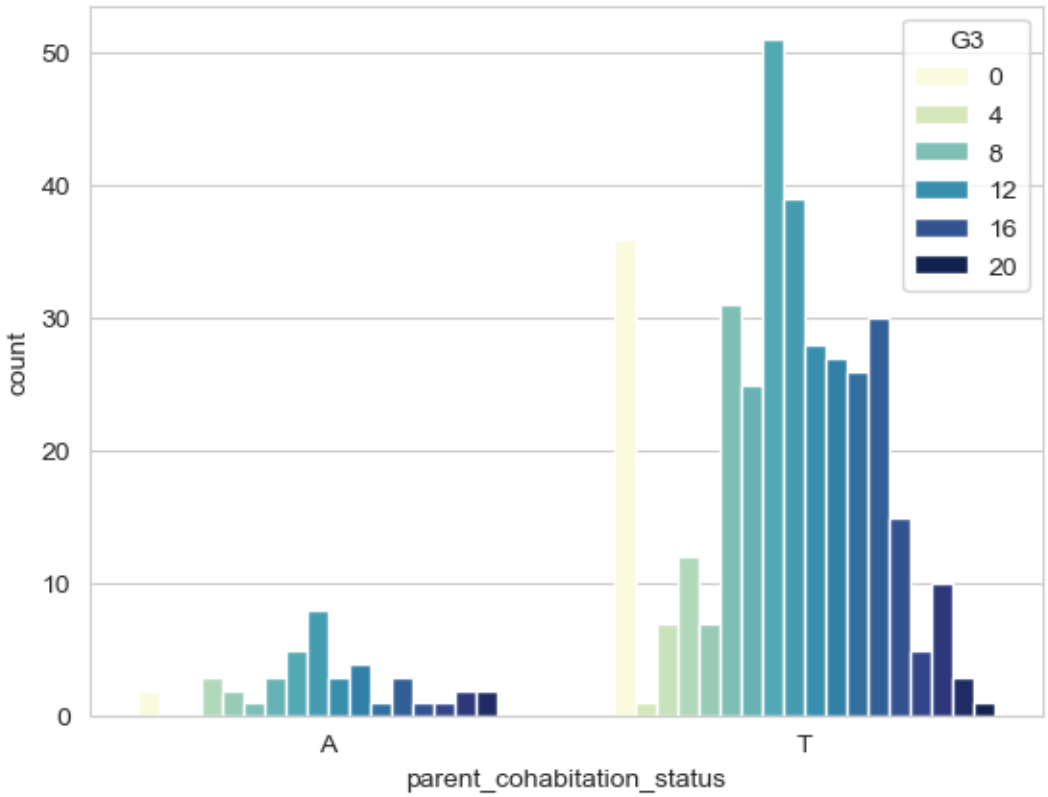
[51]:
```
<Axes: xlabel='parent_cohabitation_status', ylabel='count'>
```



- Approximately 10.38% students come from families with parents living away and 89.62% students come from families with parents living together

[52]:
```
sns.countplot(x='parent_cohabitation_status', hue='G3', data=stud,␣
↪palette='YlGnBu')
```

[52]:
```
<Axes: xlabel='parent_cohabitation_status', ylabel='count'>
```



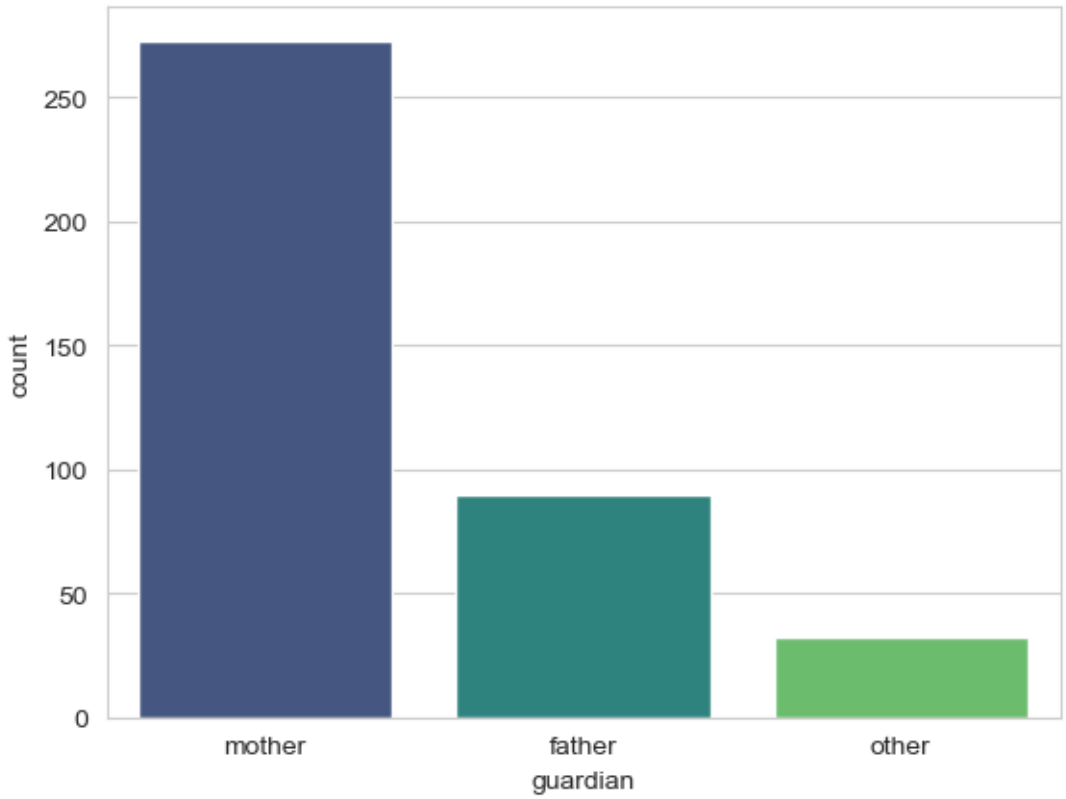
2.6 Students guardian

[53]:
```
f_stud = len(stud[stud['guardian'] == 'father'])
print('Number of students with father as guardian:', f_stud)
m_stud = len(stud[stud['guardian'] == 'mother'])
print('Number of students with mother as guardian:', m_stud)
o_stud = len(stud[stud['guardian'] == 'other'])
print('Number of students with other guardian:', o_stud)
```

```
Number of students with father as guardian: 90
Number of students with mother as guardian: 273
Number of students with other guardian: 32
```

[54]:
```
sns.countplot(x='guardian', hue='guardian', data=stud, palette='viridis')
```

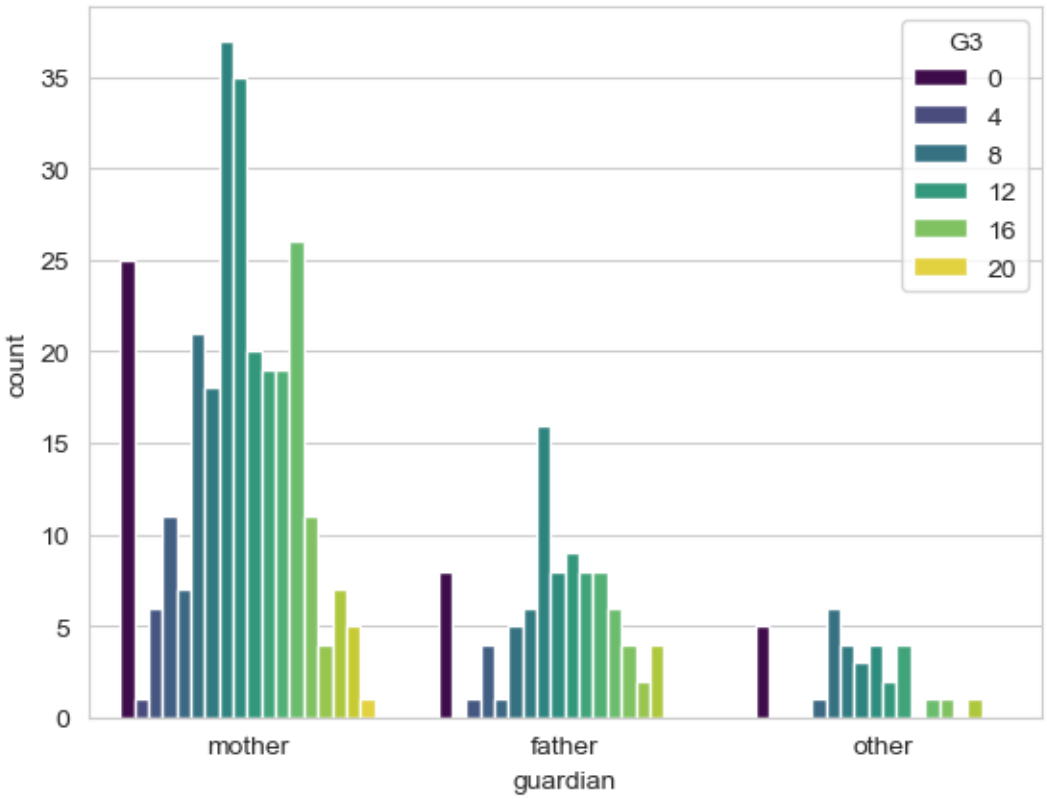
[54]:
```
<Axes: xlabel='guardian', ylabel='count'>
```



- Approximately 69.11% students have mother as guardian, 22.78% students have father as guardian and 8.10% have other guardian

[55]:
```
sns.countplot(x='guardian', hue='G3', data=stud, palette='viridis')
```

[55]:
```
<Axes: xlabel='guardian', ylabel='count'>
```

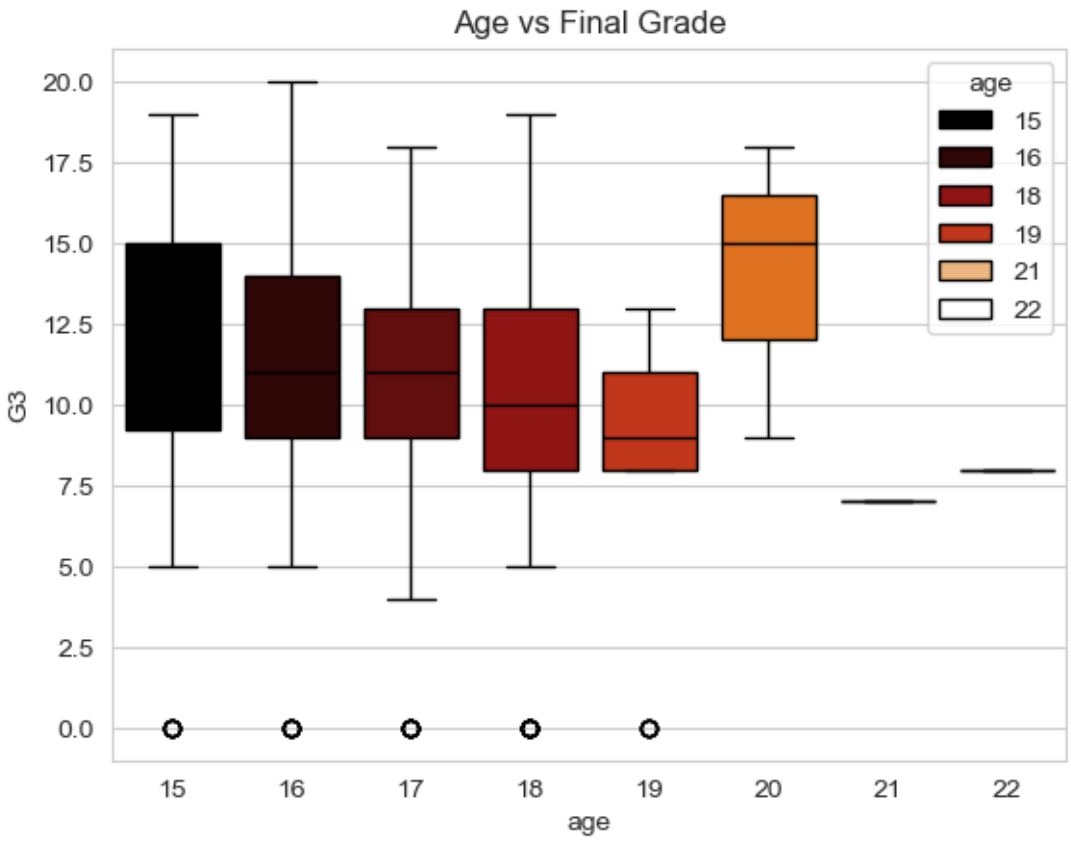


3 EDA - Exploratory Data Analysis

3.1 1. Does age affect final grade?

[56]:
```
b = sns.boxplot(x='age', y='G3', hue='age', data=stud, palette='gist_heat')
b.axes.set_title('Age vs Final Grade')
```

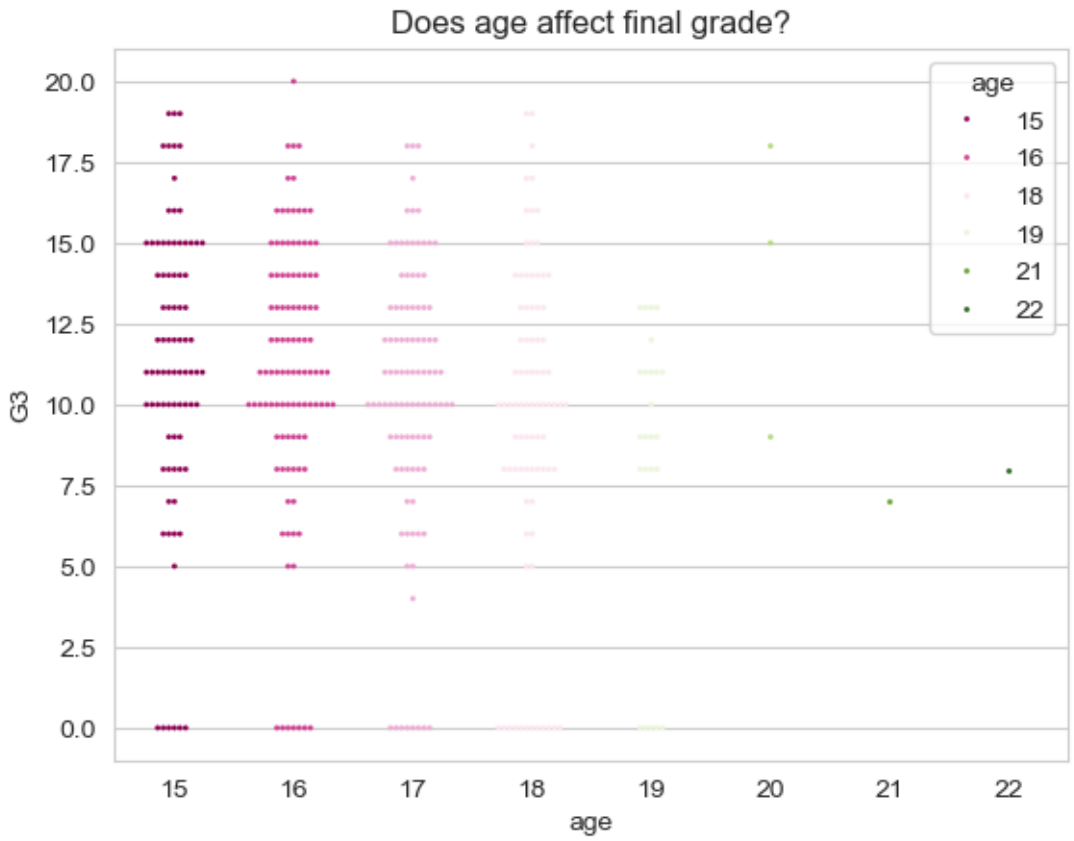
[56]: Text(0.5, 1.0, 'Age vs Final Grade')



- Plotting the distribution rather than statistics would help us better understand the data.
- The above plot shows that the median grades of the three age groups(15,16,17) are similar. Note the skewness of age group 19. (maybe due to sample size). Age group 20 seems to score highest grades among all.

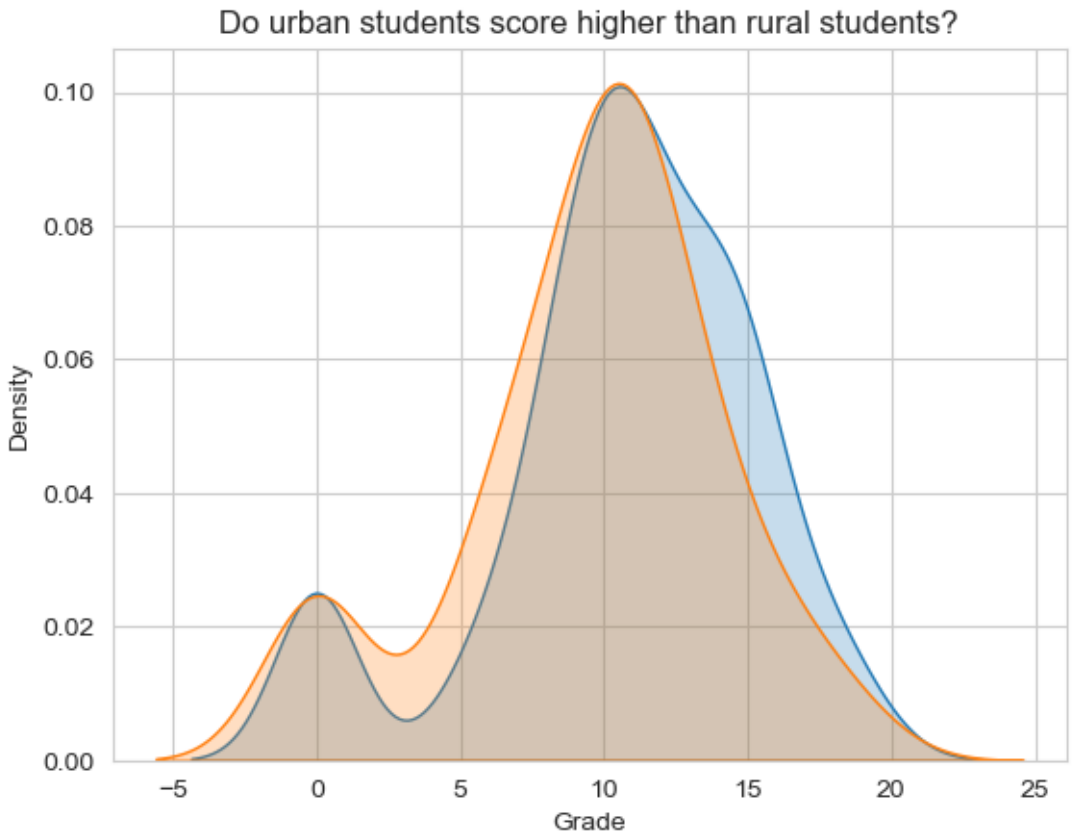
[57]:
```
b = sns.swarmplot(x='age', y='G3', hue='age', data=stud, palette='PiYG', size=2)
b.axes.set_title('Does age affect final grade?')
```

[57]:
```
Text(0.5, 1.0, 'Does age affect final grade?')
```



3.2 2. Do urban students perform better than rural students?

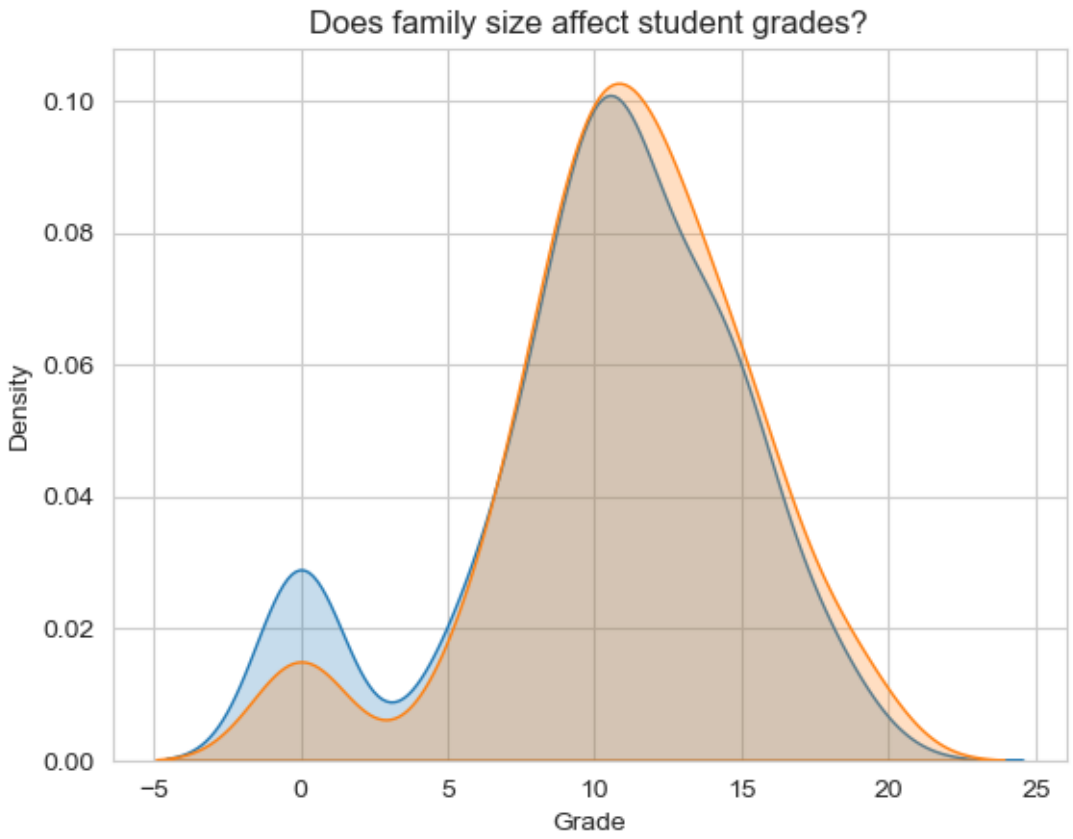
[58]:
```
sns.kdeplot(stud.loc[stud['address'] == 'U', 'G3'], label='Urban', fill=True)
sns.kdeplot(stud.loc[stud['address'] == 'R', 'G3'], label='Rural', fill=True)
plt.title('Do urban students score higher than rural students?')
plt.xlabel('Grade')
plt.ylabel('Density')
plt.show()
```



- The above graph clearly shows there is not much difference between the grades based on location.

3.3 3. Does family size affect student grades?

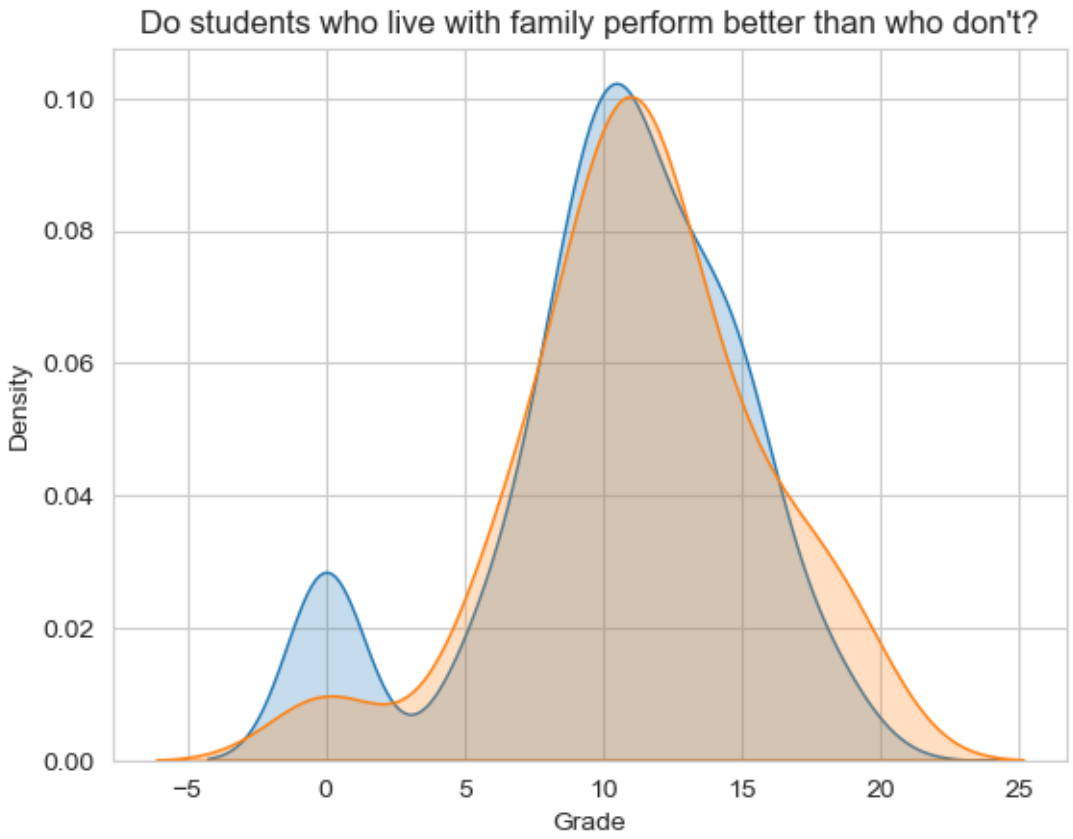
[59]:
```
sns.kdeplot(stud.loc[stud['family_size'] == 'GT3', 'G3'], label='Greater than␣
↪3', fill=True)
sns.kdeplot(stud.loc[stud['family_size'] == 'LE3', 'G3'], label='Less than 3',␣
↪fill=True)
plt.title('Does family size affect student grades?')
plt.xlabel('Grade')
plt.ylabel('Density')
plt.show()
```



- The above graph clearly shows there is not much difference between the grades based on family size.

3.4 4. Do students who live with family perform better than who don't?

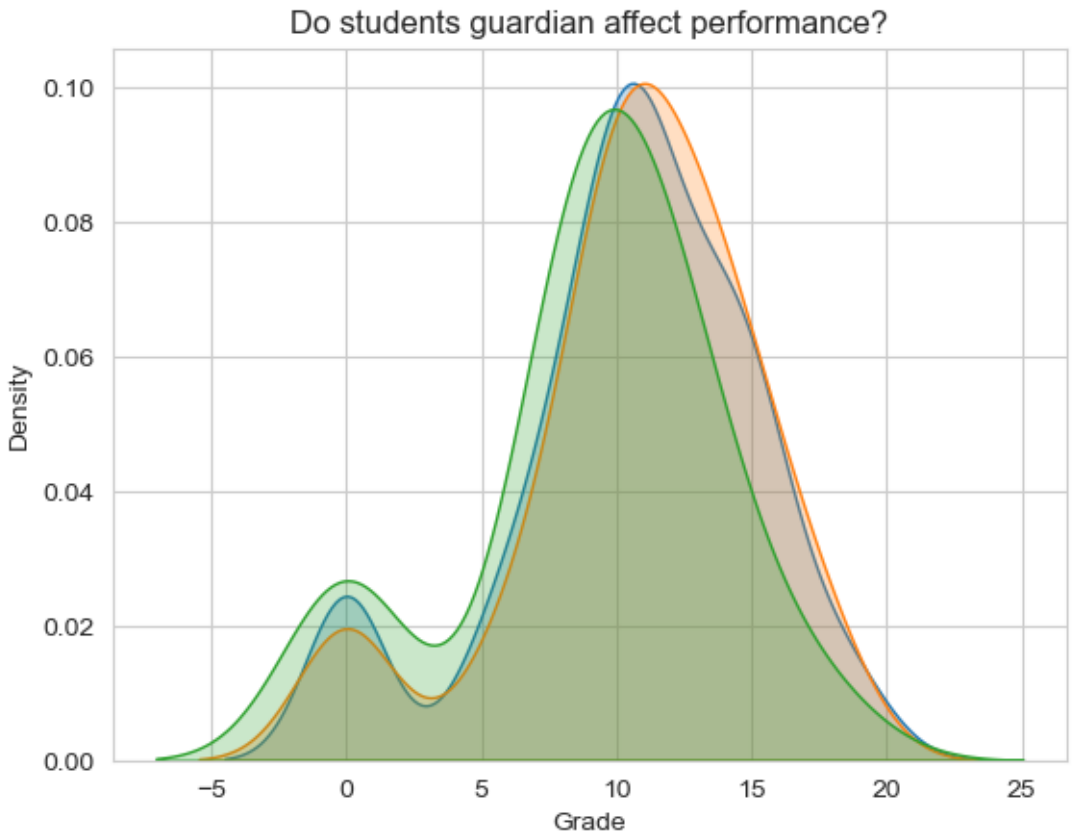
[60]:
```
sns.kdeplot(stud.loc[stud['parent_cohabitation_status'] == 'T', 'G3'],␣
 ↪label='Together', fill=True)
sns.kdeplot(stud.loc[stud['parent_cohabitation_status'] == 'A', 'G3'],␣
 ↪label='Apart', fill=True)
plt.title('Do students who live with family perform better than who don\'t?')
plt.xlabel('Grade')
plt.ylabel('Density')
plt.show()
```



- The above graph clearly shows there is not much difference between the grades based on family cohabitation.

3.5 5. Do students guardian affect performance?

[61]:
```
sns.kdeplot(stud.loc[stud['guardian'] == 'mother', 'G3'], label='Mother',␣
 ↪fill=True)
sns.kdeplot(stud.loc[stud['guardian'] == 'father', 'G3'], label='Father',␣
 ↪fill=True)
sns.kdeplot(stud.loc[stud['guardian'] == 'other', 'G3'], label='Other',␣
 ↪fill=True)
plt.title('Do students guardian affect performance?')
plt.xlabel('Grade')
plt.ylabel('Density')
plt.show()
```



- The above graph clearly shows there is not much difference between the grades based on guardian.

[62]:
```
stud.corr(numeric_only=True)['G3'].sort_values()
```

[62]:
```
failures           -0.360415
age                -0.161579
goes_out           -0.132791
travel_time        -0.117142
health             -0.061335
freetime            0.011307
absences            0.034247
family_relation     0.051363
study_time          0.097820
father_education    0.152457
mother_education    0.217147
G1                  0.801468
G2                  0.904868
G3                  1.000000
Name: G3, dtype: float64
```

3.6 Encoding categorical variables using LabelEncoder()

[63]:
```
from sklearn.preprocessing import LabelEncoder

le = LabelEncoder()
stud.iloc[:, 0] = le.fit_transform(stud.iloc[:, 0])
stud.iloc[:, 1] = le.fit_transform(stud.iloc[:, 1])
stud.iloc[:, 3] = le.fit_transform(stud.iloc[:, 3])
stud.iloc[:, 4] = le.fit_transform(stud.iloc[:, 4])
stud.iloc[:, 5] = le.fit_transform(stud.iloc[:, 5])
stud.iloc[:, 8] = le.fit_transform(stud.iloc[:, 8])
stud.iloc[:, 9] = le.fit_transform(stud.iloc[:, 9])
stud.iloc[:, 10] = le.fit_transform(stud.iloc[:, 10])
stud.iloc[:, 11] = le.fit_transform(stud.iloc[:, 11])
stud.iloc[:, 15] = le.fit_transform(stud.iloc[:, 15])
stud.iloc[:, 16] = le.fit_transform(stud.iloc[:, 16])
stud.iloc[:, 17] = le.fit_transform(stud.iloc[:, 17])
stud.iloc[:, 18] = le.fit_transform(stud.iloc[:, 18])
stud.iloc[:, 19] = le.fit_transform(stud.iloc[:, 19])
stud.iloc[:, 20] = le.fit_transform(stud.iloc[:, 20])
stud.iloc[:, 21] = le.fit_transform(stud.iloc[:, 21])
stud.iloc[:, 22] = le.fit_transform(stud.iloc[:, 22])
```

[64]:
```
stud.head()
```

[64]:

	school	sex	age	address	family_size	parent_cohabitation_status	\
0	0	0	18	1	0	0	
1	0	0	17	1	0	1	
2	0	0	15	1	1	1	
3	0	0	15	1	0	1	
4	0	0	16	1	0	1	

	mother_education	father_education	mother_job	father_job	…	internet	\
0	4	4	0	4	…	0	
1	1	1	0	2	…	1	
2	1	1	0	2	…	1	
3	4	2	1	3	…	1	
4	3	3	2	2	…	0	

	romantic	family_relation	freetime	goes_out	health	absences	G1	G2	G3
0	0	4	3	4	3	6	5	6	6
1	0	5	3	3	3	4	5	5	6
2	0	4	3	2	3	10	7	8	10
3	1	3	2	2	5	2	15	14	15
4	0	4	3	2	5	4	6	10	10

[5 rows x 31 columns]

[65]:
```
stud.tail()
```

[65]:
```
     school sex  age address family_size parent_cohabitation_status  \
390      1   1   20       1           1                           0
391      1   1   17       1           1                           1
392      1   1   21       0           0                           1
393      1   1   18       0           1                           1
394      1   1   19       1           1                           1

     mother_education  father_education mother_job father_job  … internet  \
390                 2                 2          3          3  …        0
391                 3                 1          3          3  …        1
392                 1                 1          2          2  …        0
393                 3                 2          3          2  …        1
394                 1                 1          2          0  …        1

    romantic  family_relation  freetime  goes_out health absences  G1  G2  G3
390        0                5         5         4      4       11   9   9   9
391        0                2         4         5      2        3  14  16  16
392        0                5         5         3      3        3  10   8   7
393        0                4         4         1      5        0  11  12  10
394        0                3         2         3      5        5   8   9   9

[5 rows x 31 columns]
```

[66]:
```
stud.corr()['G3'].sort_values()
```

[66]:
```
failures                    -0.360415
age                         -0.161579
goes_out                    -0.132791
romantic                    -0.129970
travel_time                 -0.117142
school_support              -0.082788
guardian                    -0.070109
health                      -0.061335
parent_cohabitation_status  -0.058009
school                      -0.045017
family_support              -0.039157
freetime                     0.011307
activities                   0.016100
absences                     0.034247
father_job                   0.042286
family_relation              0.051363
nursery                      0.051568
family_size                  0.081407
study_time                   0.097820
internet                     0.098483
```

```
paid                        0.101996
mother_job                  0.102082
sex                         0.103456
address                     0.105756
reason                      0.121994
father_education            0.152457
higher                      0.182465
mother_education            0.217147
G1                          0.801468
G2                          0.904868
G3                          1.000000
Name: G3, dtype: float64
```

[67]:
```
stud = stud.drop(['school', 'G1', 'G2'], axis='columns')
```

- Although G1 and G2 which are period grades of a student and are highly correlated to the final grade G3, we drop them. It is more difficult to predict G3 without G2 and G1, but such prediction is much more useful because we want to find other factors affect the grade.

[68]:
```
most_correlated = stud.corr().abs()['G3'].sort_values(ascending=False)

most_correlated = most_correlated[:9]
most_correlated
```

[68]:
```
G3                  1.000000
failures            0.360415
mother_education    0.217147
higher              0.182465
age                 0.161579
father_education    0.152457
goes_out            0.132791
romantic            0.129970
reason              0.121994
Name: G3, dtype: float64
```

[69]:
```
stud = stud.loc[:, most_correlated.index]
stud.head()
```

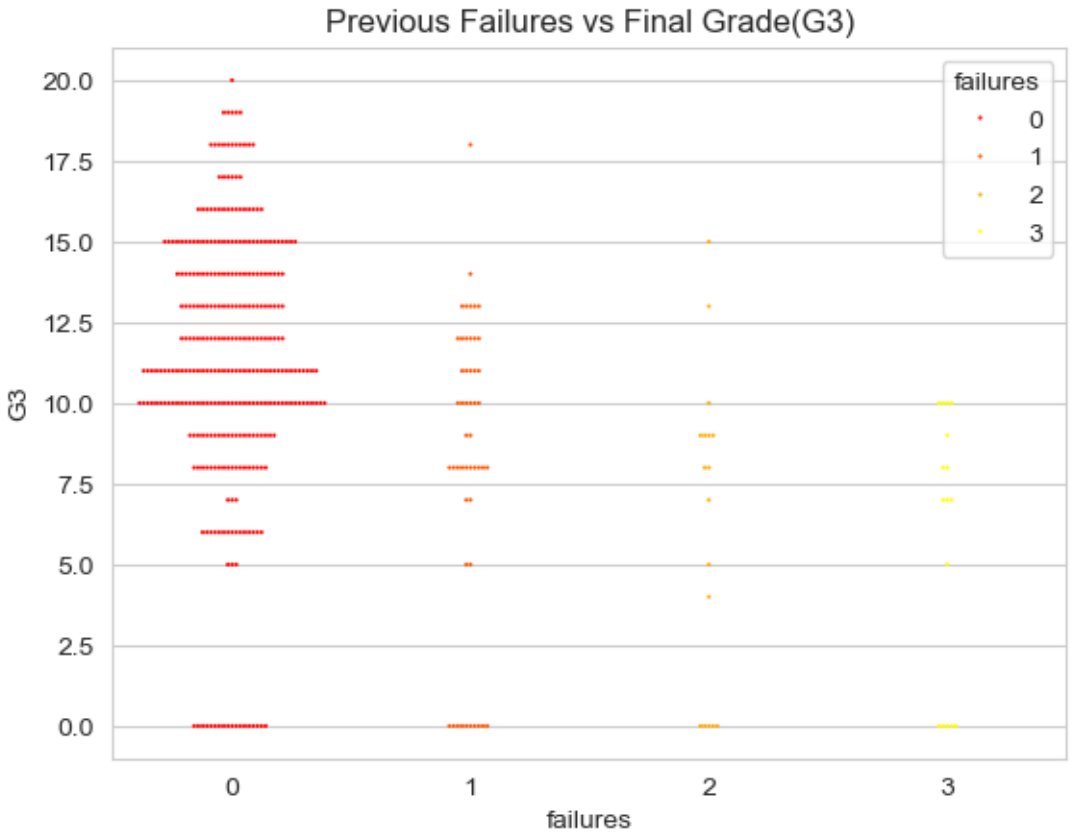
[69]:
```
   G3  failures  mother_education higher  age  father_education  goes_out  \
0   6         0                 4      1   18                 4         4
1   6         0                 1      1   17                 1         3
2  10         3                 1      1   15                 1         2
3  15         0                 4      1   15                 2         2
4  10         0                 3      1   16                 3         2

  romantic reason
0        0      0
1        0      0
```

2	0	2
3	1	1
4	0	1

3.6.1 Failure Attribute

[70]:
```
b = sns.swarmplot(x=stud['failures'], y=stud['G3'], hue=stud['failures'],␣
↪palette='autumn', size=1.5)
b.axes.set_title('Previous Failures vs Final Grade(G3)')
```

[70]:
```
Text(0.5, 1.0, 'Previous Failures vs Final Grade(G3)')
```

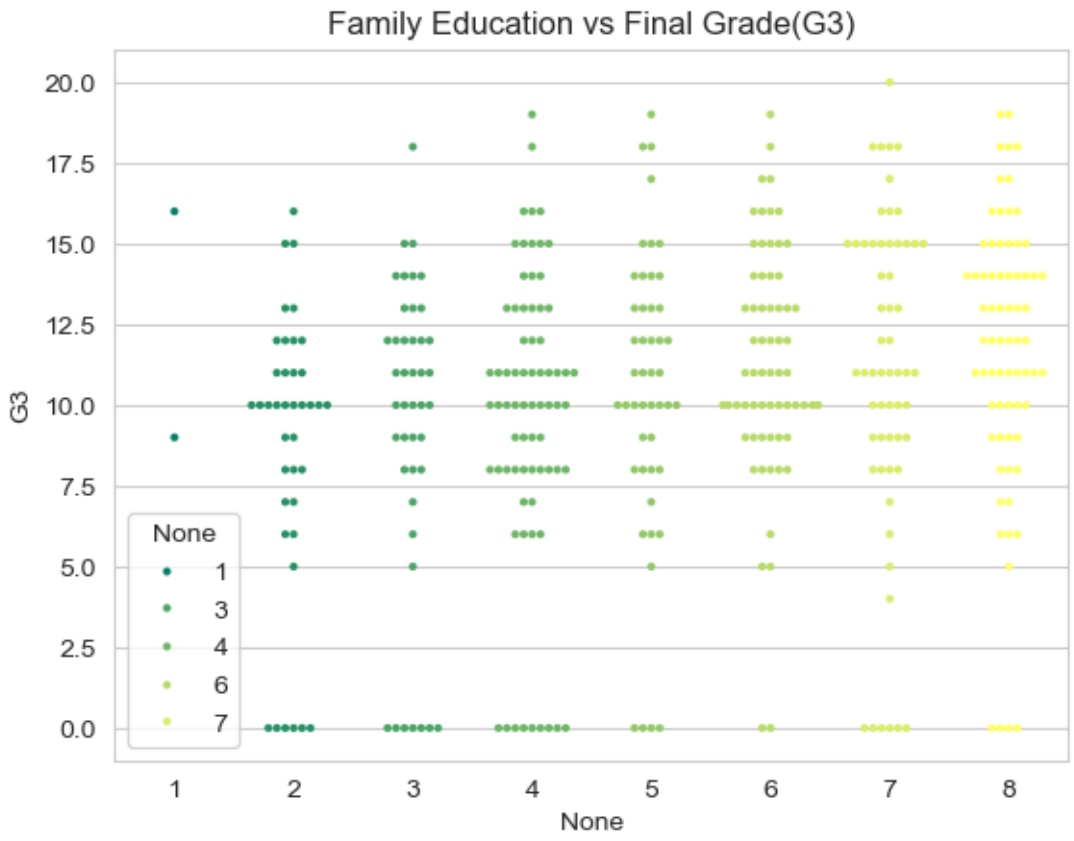


Observation : Student with less previous failures usually score higher

3.6.2 Family Education Attribute (Father's education + Mother's education)

[71]:
```
family_education = stud['father_education'] + stud['mother_education']
b = sns.swarmplot(x=family_education, y=stud['G3'], hue=family_education,␣
↪palette='summer', size=3)
b.axes.set_title('Family Education vs Final Grade(G3)')
```

[71]: Text(0.5, 1.0, 'Family Education vs Final Grade(G3)')

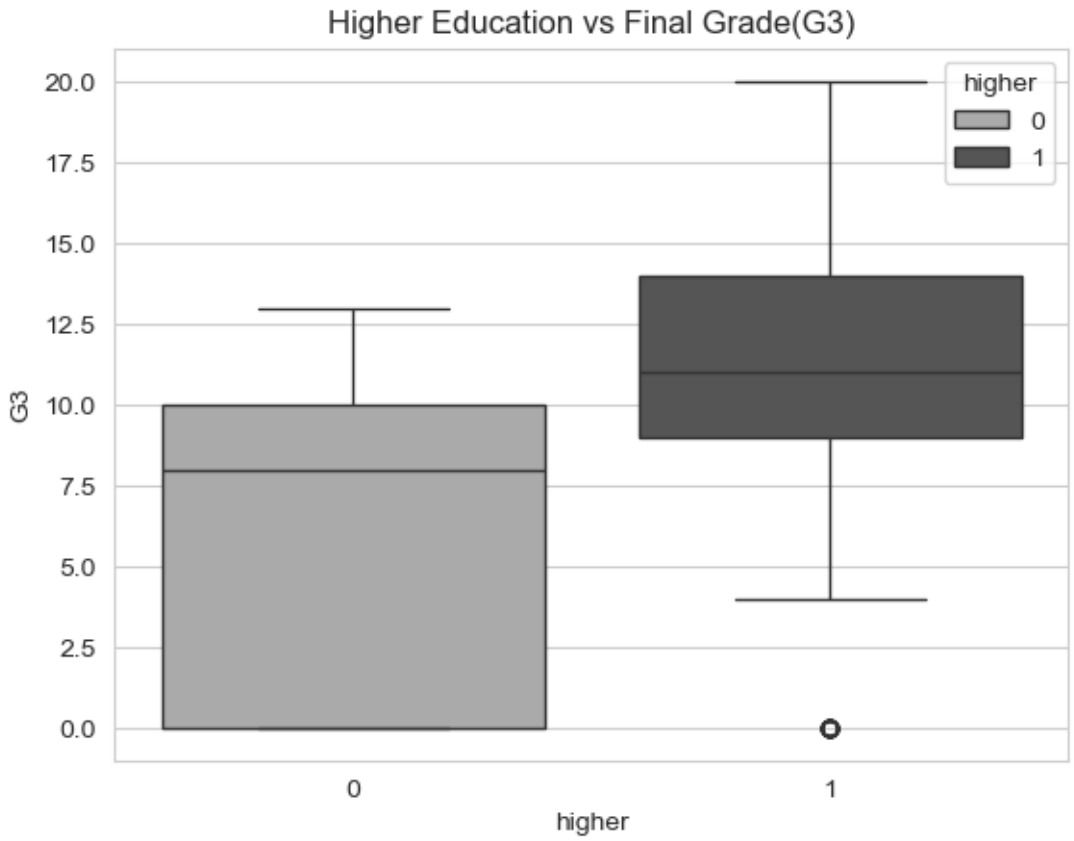


Observation : Educated families result in higher grades

3.6.3 Wish to go for Higher Education Attribute

[72]:
```
b = sns.boxplot(x=stud['higher'], y=stud['G3'], hue=stud['higher'],␣
↪palette='binary')
b.axes.set_title('Higher Education vs Final Grade(G3)')
```

[72]: Text(0.5, 1.0, 'Higher Education vs Final Grade(G3)')

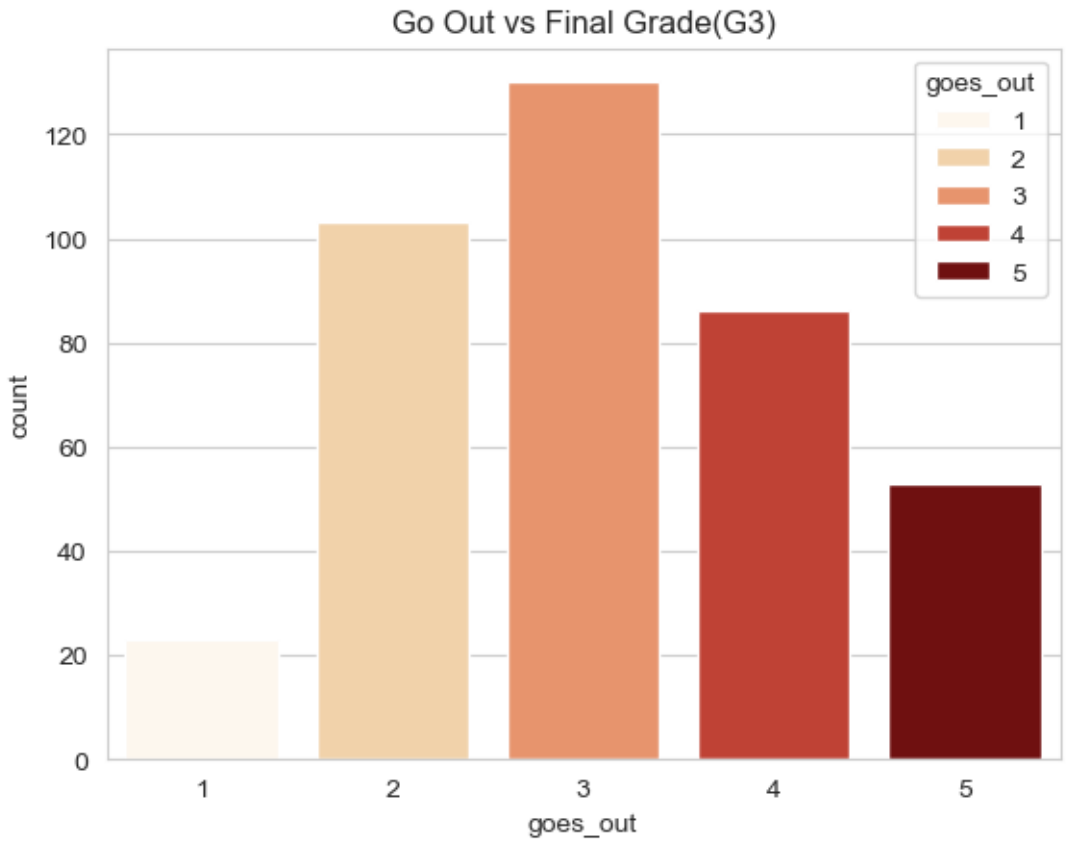


Observation : Students who wish to go for higher studies score more

3.7 Going Out with Friends Attribute

[73]:
```
b = sns.countplot(x=stud['goes_out'], hue=stud['goes_out'], palette='OrRd')
b.axes.set_title('Go Out vs Final Grade(G3)')
```

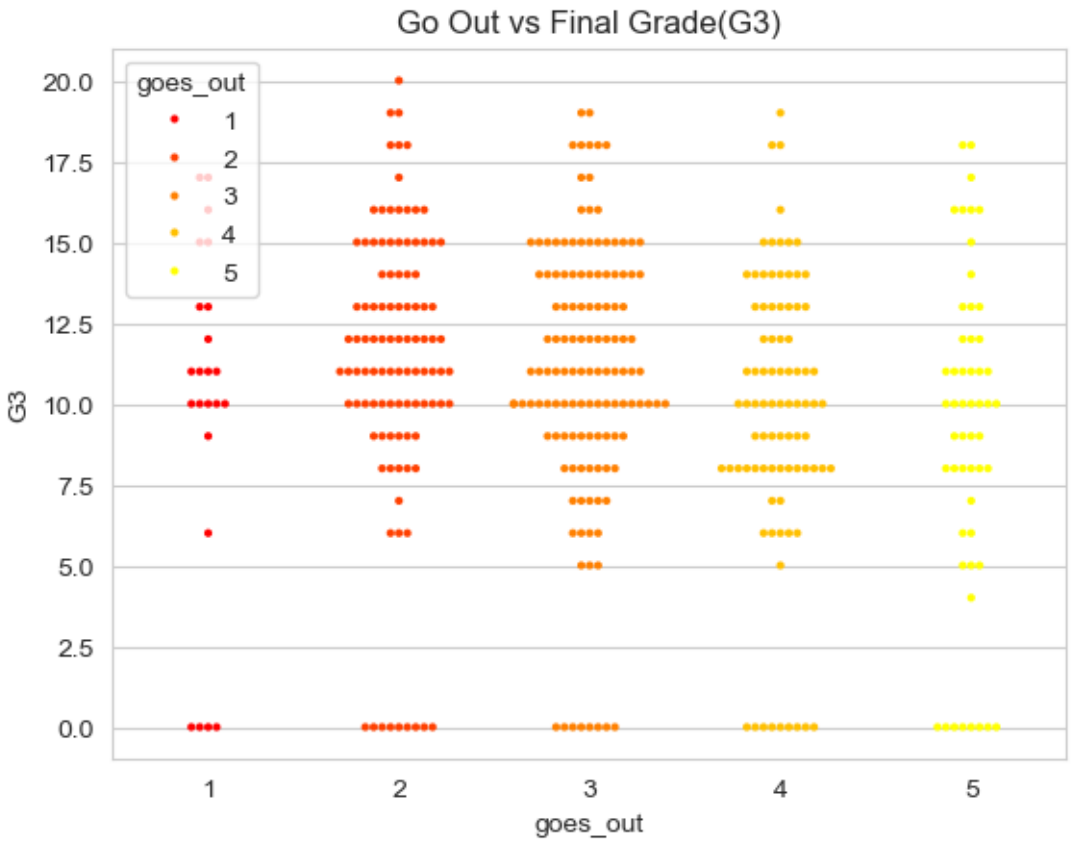
[73]:
```
Text(0.5, 1.0, 'Go Out vs Final Grade(G3)')
```



Observation : The students have an average score when it comes to going out with friends.

[74]:
```
b = sns.swarmplot(x=stud['goes_out'], y=stud['G3'], hue=stud['goes_out'],␣
↪palette='autumn', size=3)
b.axes.set_title('Go Out vs Final Grade(G3)')
```

[74]:
```
Text(0.5, 1.0, 'Go Out vs Final Grade(G3)')
```

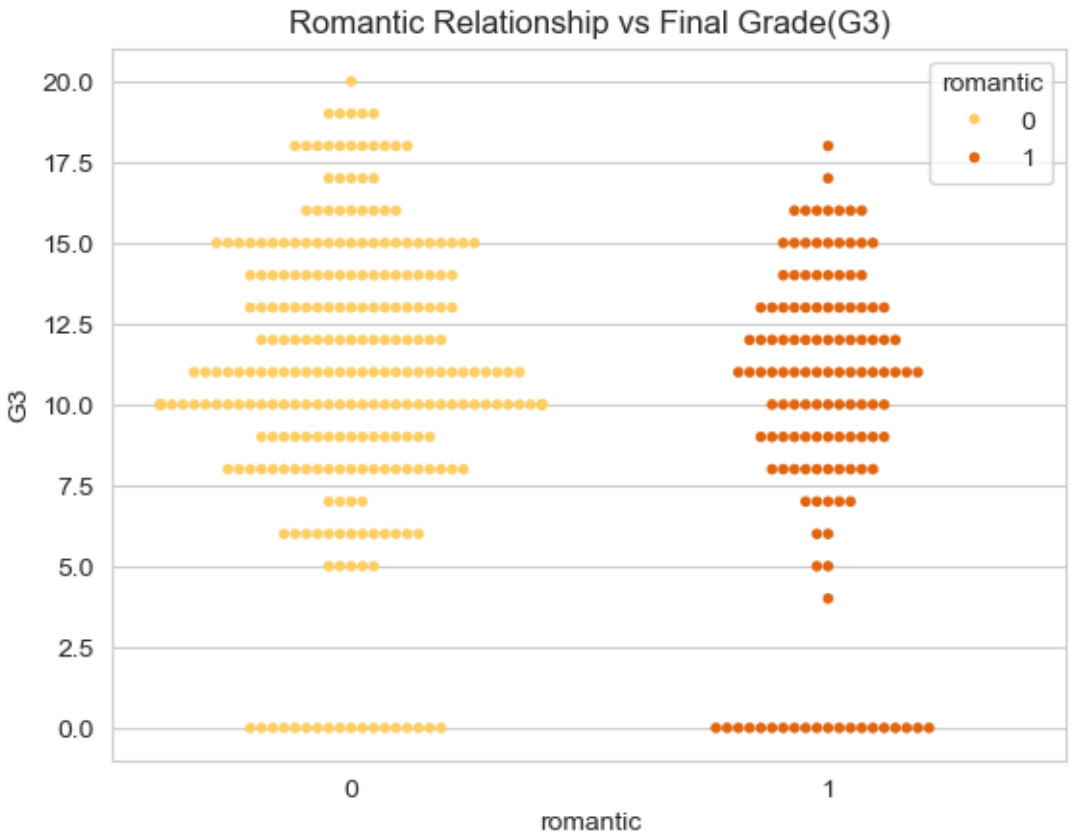


Observation : Students who go out a lot score less

3.7.1 Romantic relationship Attribute

[75]:
```
b = sns.swarmplot(x=stud['romantic'], y=stud['G3'], hue=stud['romantic'],␣
↪palette='YlOrBr', size=4)
b.axes.set_title('Romantic Relationship vs Final Grade(G3)')
```

[75]:
```
Text(0.5, 1.0, 'Romantic Relationship vs Final Grade(G3)')
```



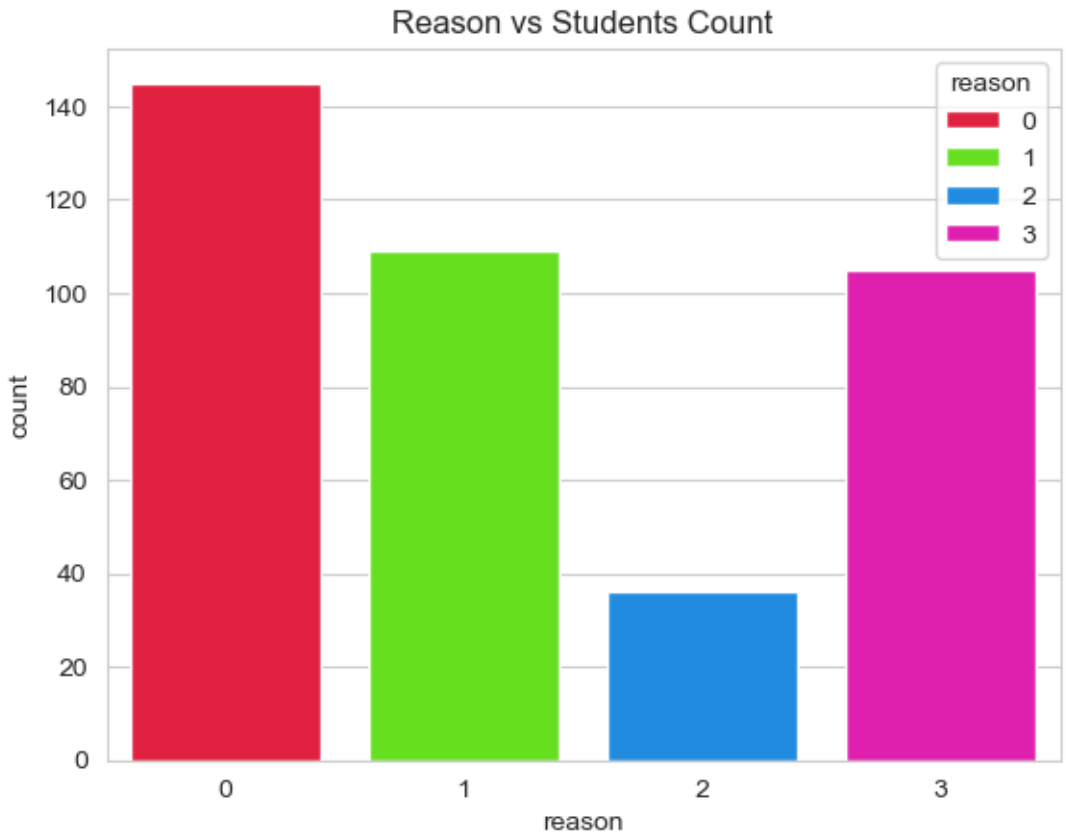
- Here romantic attribute with value 0 means no relationship and value with 1 means in relationship

Observation : Students with no romantic relationship score higher

3.7.2 Reason Attribute

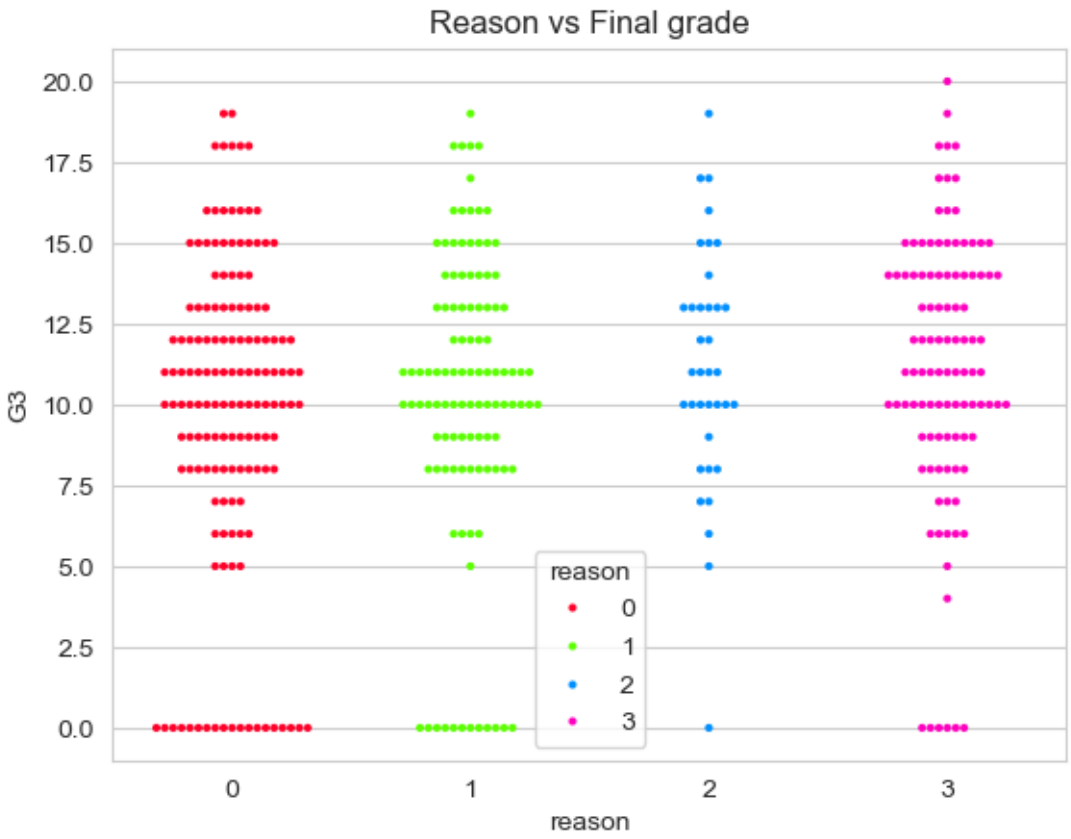
[76]:
```
b = sns.countplot(x='reason', hue='reason', data=stud, palette='gist_rainbow')
b.axes.set_title('Reason vs Students Count')
```

[76]:
```
Text(0.5, 1.0, 'Reason vs Students Count')
```



[77]:
```
b = sns.swarmplot(x='reason', y='G3', hue='reason', data=stud,␣
↪palette='gist_rainbow', size=3)
b.axes.set_title('Reason vs Final grade')
```

[77]: Text(0.5, 1.0, 'Reason vs Final grade')



Observation : The students have an equally distributed average score when it comes to reason attribute.

4 Machine Learning Algorithms

[78]:
```
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import ElasticNet
from sklearn.ensemble import RandomForestRegressor
from sklearn.ensemble import ExtraTreesRegressor
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.svm import SVR

from sklearn.model_selection import train_test_split
```

[79]:
```
X_train, X_test, Y_train, Y_test = train_test_split(stud, stud['G3'],␣
↪test_size=0.25, random_state=42)
```

[80]:
```
X_train.head()
```

[80]:
```
      G3  failures  mother_education higher  age  father_education  goes_out  \
16    14         0                 4      1   16                 4         3
66    12         0                 4      1   15                 4         3
211   13         0                 4      1   17                 4         5
7      6         0                 4      1   17                 4         4
19    10         0                 4      1   16                 3         3

     romantic reason
16          0      3
66          1      3
211         1      1
7           0      1
19          0      1
```

4.1 MAE - Mean Absolute Error & RMSE - Root Mean Square Error

[81]:
```
def evaluate_predictions(predictions, true):
    mae = np.mean(abs(predictions - true))
    rmse = np.sqrt(np.mean((predictions - true) ** 2))

    return mae, rmse
```

[82]:
```
median_prediction = X_train['G3'].median()
median_predictions = [median_prediction for _ in range(len(X_test))]

true = X_test['G3']
```

[83]:
```
mb_mae, mb_rmse = evaluate_predictions(median_predictions, true)
print('Median Baseline  MAE: {:.4f}'.format(mb_mae))
print('Median Baseline RMSE: {:.4f}'.format(mb_rmse))
```

```
Median Baseline  MAE: 3.7879
Median Baseline RMSE: 4.8252
```

[84]:
```
def evaluate(x_train, x_test, y_train, y_test):
    x_train = x_train.drop('G3', axis='columns')
    x_test = x_test.drop('G3', axis='columns')

    models = {
        "Linear Regression": LinearRegression(),
        "ElasticNet Regression": ElasticNet(alpha=1.0, l1_ratio=0.5),
        "Random Forest": RandomForestRegressor(n_estimators=100),
        "Extra Trees": ExtraTreesRegressor(n_estimators=100),
        "SVM": SVR(kernel='rbf', degree=3, C=1.0, gamma='auto'),
        "Gradient Boosted": GradientBoostingRegressor(n_estimators=50)
    }
    results = pd.DataFrame(columns=['mae', 'rmse'], index=models.keys())
```

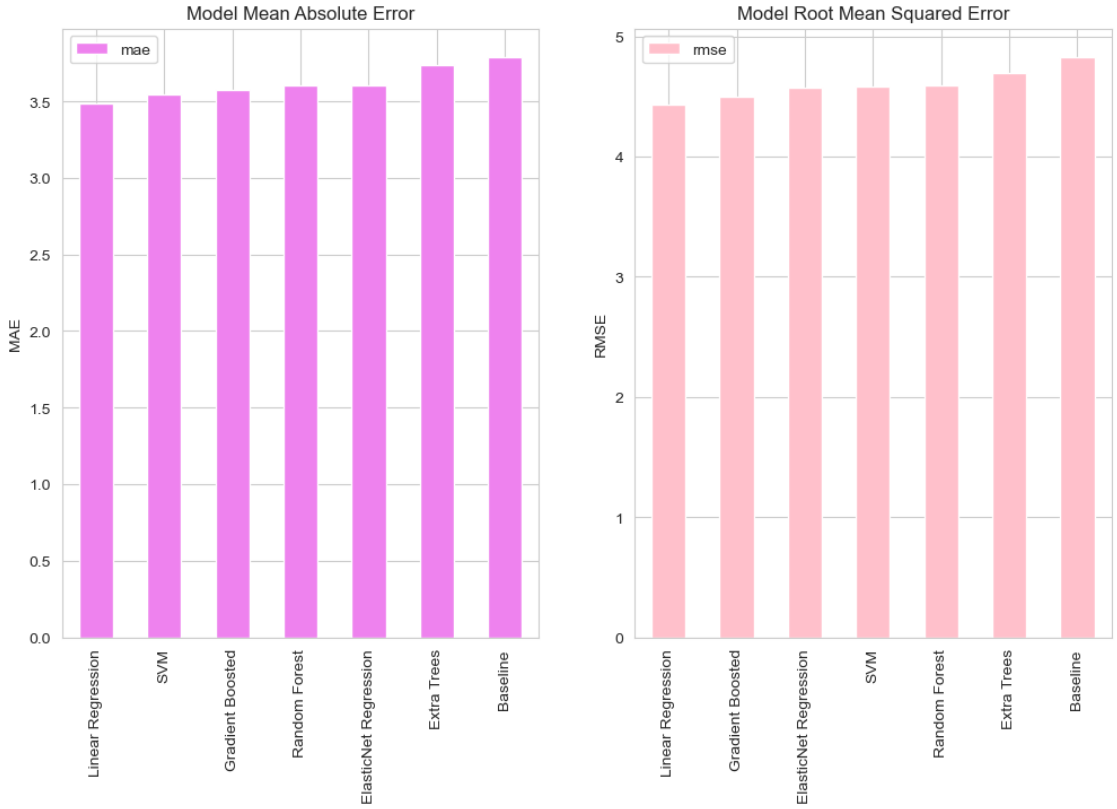
```
    for model_name, model in models.items():
        model.fit(x_train, y_train)
        predictions = model.predict(x_test)

        mae = np.mean(abs(predictions - y_test))
        rmse = np.sqrt(np.mean((predictions - y_test) ** 2))

        results.loc[model_name, :] = [mae, rmse]

    baseline = np.median(y_train)
    baseline_mae = np.mean(abs(baseline - y_test))
    baseline_rmse = np.sqrt(np.mean((baseline - y_test) ** 2))

    results.loc['Baseline', :] = [baseline_mae, baseline_rmse]

    return results, models
```

[85]:
```
results, models = evaluate(X_train, X_test, Y_train, Y_test)
results
```

[85]:

	mae	rmse
Linear Regression	3.485115	4.432597
ElasticNet Regression	3.608051	4.573274
Random Forest	3.601608	4.591128
Extra Trees	3.737744	4.693737
SVM	3.549266	4.581466
Gradient Boosted	3.572309	4.500573
Baseline	3.787879	4.825228

[86]:
```
plt.figure(figsize=(12, 7))

ax = plt.subplot(1, 2, 1)
results.sort_values('mae', ascending=True).plot.bar(y='mae', color='violet',␣
 ↪ax=ax)
plt.title('Model Mean Absolute Error')
plt.ylabel('MAE')

ax = plt.subplot(1, 2, 2)
results.sort_values('rmse', ascending=True).plot.bar(y='rmse', color='pink',␣
 ↪ax=ax)
plt.title('Model Root Mean Squared Error')
plt.ylabel('RMSE')

plt.show()
```



Conclusion: As we see both Model Mean Absolute Error & Model Root Mean Squared Error that the linear regression is performing the best in both cases