Hyperiondev

TASK

Exploratory Data Analysis on the Student Performance Data Set

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Introduction

For this EDA we will work with a student performance data set to which a number of questions will be answered, and visualisations will be displayed to explain the data.

All required packages are imported

```
In [1]: import numpy as np
        import pandas as pd
        import matplotlib.pyplot as plt
        import seaborn as sns
        %matplotlib inline

        df = pd.read_csv('student_data.csv')
```

Student performance data set

Using the head() function, the first five rows of the data set is displayed.

```
In [2]: df.head()
```

Out[2]:

	school	sex	age	address	famsize	Pstatus	Medu	Fedu	Mjob	Fjob	...	famrel	freetime	goout	Dalc	Walc	health	absences	G1	G2	G3
0	GP	F	18	U	GT3	A	4	4	at_home	teacher	...	4	3	4	1	1	3	6	5	6	$
1	GP	F	17	U	GT3	T	1	1	at_home	other	...	5	3	3	1	1	3	4	5	5	6
2	GP	F	$	U	LE3	T	1	1	at_home	other	...	4	3	2	2	3	3	10	7	$	10
3	GP	F	15	U	GT3	T	4	2	health	services	...	3	$	2	1	1	5	2	15	14	15
4	GP	F	16	U	GT3	T	3	3	other	other	...	4	3	2	1	2	5	4	$	10	$

5 rows × 33 columns

DATA CLEANING

On inspection, the data contains '$' which needs to be replaced with 'NAN'

```
In [3]: df_new = df.replace('$', np.NAN)
        df_new.head()
```

Out[3]:

	school	sex	age	address	famsize	Pstatus	Medu	Fedu	Mjob	Fjob	...	famrel	freetime	goout	Dalc	Walc	health	absences	G1	G2	G3
0	GP	F	18	U	GT3	A	4	4	at_home	teacher	...	4	3	4	1	1	3	6	5	6	NaN
1	GP	F	17	U	GT3	T	1	1	at_home	other	...	5	3	3	1	1	3	4	5	5	6
2	GP	F	NaN	U	LE3	T	1	1	at_home	other	...	4	3	2	2	3	3	10	7	NaN	10
3	GP	F	15	U	GT3	T	4	2	health	services	...	3	NaN	2	1	1	5	2	15	14	15
4	GP	F	16	U	GT3	T	3	3	other	other	...	4	3	2	1	2	5	4	NaN	10	NaN

5 rows × 33 columns

MISSING DATA

Missing data in list form

We will now check for missing data in the data set by using the .isnull() and .sum() functions.

```
In [4]: df_new.isnull().sum()
```

```
Out[4]: school         0
        sex            0
        age           17
        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      20
        goout          0
        Dalc           0
        Walc           0
        health         0
        absences       0
        G1            18
        G2            18
        G3            17
        dtype: int64
```

Missing data in table form

The missing data can also be displayed in table form as follows:

```
In [5]: df_new.isnull()
```

Out[5]:

	school	sex	age	address	famsize	Pstatus	Medu	Fedu	Mjob	Fjob	...	famrel	freetime	goout	Dalc	Walc	health	absences	G1	G2	G3
0	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False	False	False	False	False	True
1	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False	False	False	False	False	False
2	False	False	True	False	False	False	False	False	False	False	...	False	False	False	False	False	False	False	False	True	False
3	False	False	False	False	False	False	False	False	False	False	...	False	True	False	False	False	False	False	False	False	False
4	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False	False	False	True	False	True
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
390	False	False	False	False	False	False	False	False	False	False	...	False	True	False	False	False	False	False	False	False	False
391	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False	False	False	False	False	False
392	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False	False	False	False	False	True
393	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False	False	False	False	False	False
394	False	False	True	False	False	False	False	False	False	False	...	False	False	False	False	False	False	False	False	False	False

395 rows × 33 columns

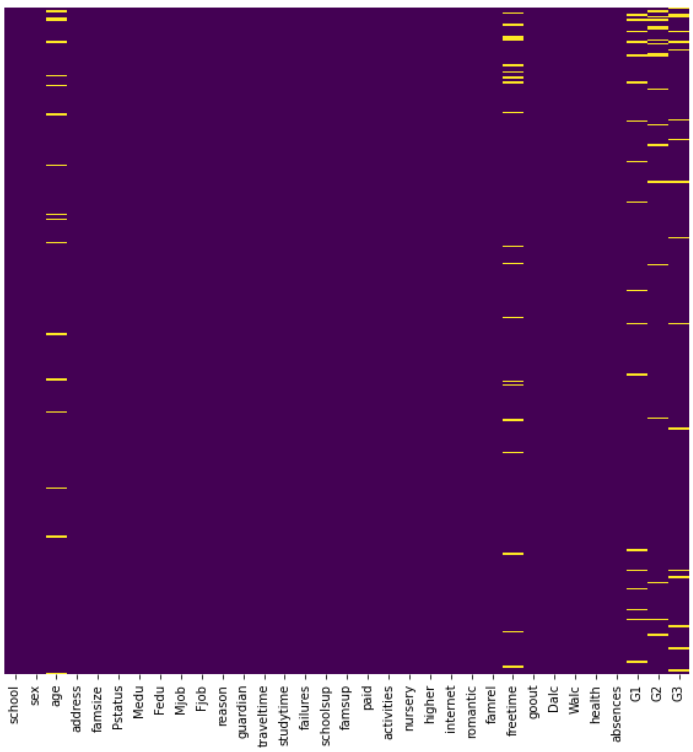
If a value is equal to 'True' in the table above, it means it is missing.

Missing data in graphical form

Using seaborn visualization, we can see the missing data represented as yellow lines

```
In [6]: plt.figure(figsize=(10, 10))
        sns.heatmap(df_new.isnull(),yticklabels=False, cbar=False, cmap= 'viridis')
```

Out[6]: <AxesSubplot:>



Statistics of the data set

The following table shows the statistics of the data set. We can use the mean values to replace the missing data in the data set.

In [7]:
```
df.describe()
```

Out[7]:

	Medu	Fedu	traveltime	studytime	failures	famrel	goout	Dalc	Walc	health	absences
count	395.000000	395.000000	395.000000	395.000000	395.000000	395.000000	395.000000	395.000000	395.000000	395.000000	395.000000
mean	2.749367	2.521519	1.448101	2.035443	0.334177	3.944304	3.108861	1.481013	2.291139	3.554430	5.713924
std	1.094735	1.088201	0.697505	0.839240	0.743651	0.896659	1.113278	0.890741	1.287897	1.390303	8.000107
min	0.000000	0.000000	1.000000	1.000000	0.000000	1.000000	1.000000	1.000000	1.000000	1.000000	0.000000
25%	2.000000	2.000000	1.000000	1.000000	0.000000	4.000000	2.000000	1.000000	1.000000	3.000000	0.000000
50%	3.000000	2.000000	1.000000	2.000000	0.000000	4.000000	3.000000	1.000000	2.000000	4.000000	4.000000
75%	4.000000	3.000000	2.000000	2.000000	0.000000	5.000000	4.000000	2.000000	3.000000	5.000000	8.000000
max	4.000000	4.000000	4.000000	4.000000	3.000000	5.000000	5.000000	5.000000	5.000000	5.000000	75.000000

age

In [8]:
```
df_n = df[df['age'] != '$']

mean = df_n['age'].astype(int).mean()

df['age'] = df['age'].replace('$', mean).astype(int)
```

freetime

In [9]:
```
df_n = df[df['freetime'] != '$']

mean = df_n['freetime'].astype(int).mean()

df['freetime'] = df['freetime'].replace('$', mean).astype(int)
```

G1

In [10]:
```
df_n = df[df['G1'] != '$']

mean = df_n['G1'].astype(int).mean()

df['G1'] = df['G1'].replace('$', mean).astype(int)
```

G2

In [11]:
```
df_n = df[df['G2'] != '$']

mean = df_n['G2'].astype(int).mean()

df['G2'] = df['G2'].replace('$', mean).astype(int)
```

G3

In [12]:
```
df_n = df[df['G3'] != '$']

mean = df_n['G3'].astype(int).mean()

df['G3'] = df['G3'].replace('$', mean).astype(int)
```

Final grade

In [13]:
```
df['G_Final'] = (df['G1'] + df['G2'] + df['G3']) / 3

df.head()
```

Out[13]:

	school	sex	age	address	famsize	Pstatus	Medu	Fedu	Mjob	Fjob	...	freetime	goout	Dalc	Walc	health	absences	G1	G2	G3	G_Final
0	GP	F	18	U	GT3	A	4	4	at_home	teacher	...	3	4	1	1	3	6	5	6	10	7.000000
1	GP	F	17	U	GT3	T	1	1	at_home	other	...	3	3	1	1	3	4	5	5	6	5.333333
2	GP	F	16	U	LE3	T	1	1	at_home	other	...	3	2	2	3	3	10	7	10	10	9.000000
3	GP	F	15	U	GT3	T	4	2	health	services	...	3	2	1	1	5	2	15	14	15	14.666667
4	GP	F	16	U	GT3	T	3	3	other	other	...	3	2	1	2	5	4	10	10	10	10.000000

5 rows × 34 columns

The data set is now complete with all the missing data replaced with the mean values as calculated above.

DATA STORIES AND VISUALIZATIONS

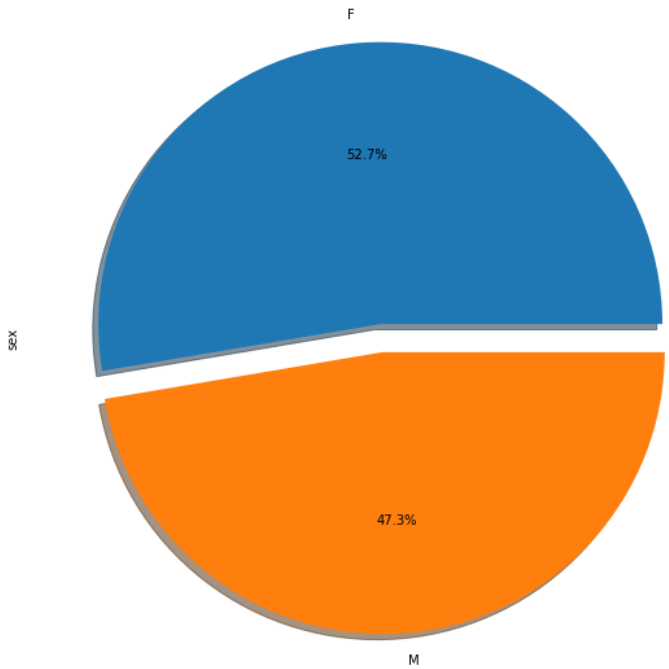
In this section of the EDA we will extract stories and assumptions based on visualizations of the data set

Gender analysis

Below is a pie chart showing the percentage of students divided by gender

In [14]:
```
df.sex.value_counts().plot(kind = 'pie', figsize=(10,10), autopct = '%1.1f%%', shadow=True, explode=[0.05, 0.05])
print(df.sex.value_counts())
```

```
F    208
M    187
Name: sex, dtype: int64
```



Results

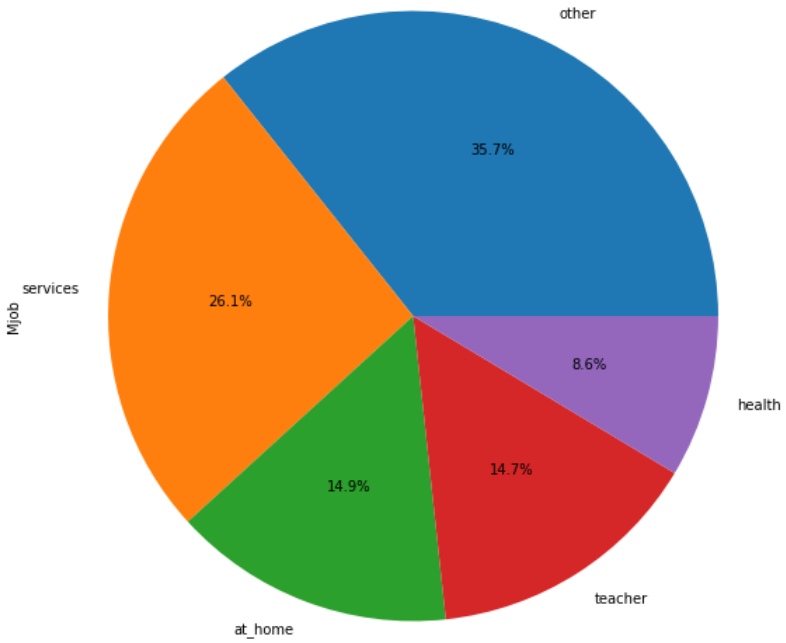
The number of female students is slightly higher than the male students at 52.7%.

Mother's job title (Mjob) analysis

In this section we will look at the different job titles for Mothers. The code below will print a list with the sum of the amount and a pie chart with the percentages.

```
In [15]: df.Mjob.value_counts().plot(kind = 'pie', figsize=(10,10), autopct = '%1.1f%%')
         print(df.Mjob.value_counts())
```

```
other       141
services    103
at_home      59
teacher      58
health       34
Name: Mjob, dtype: int64
```

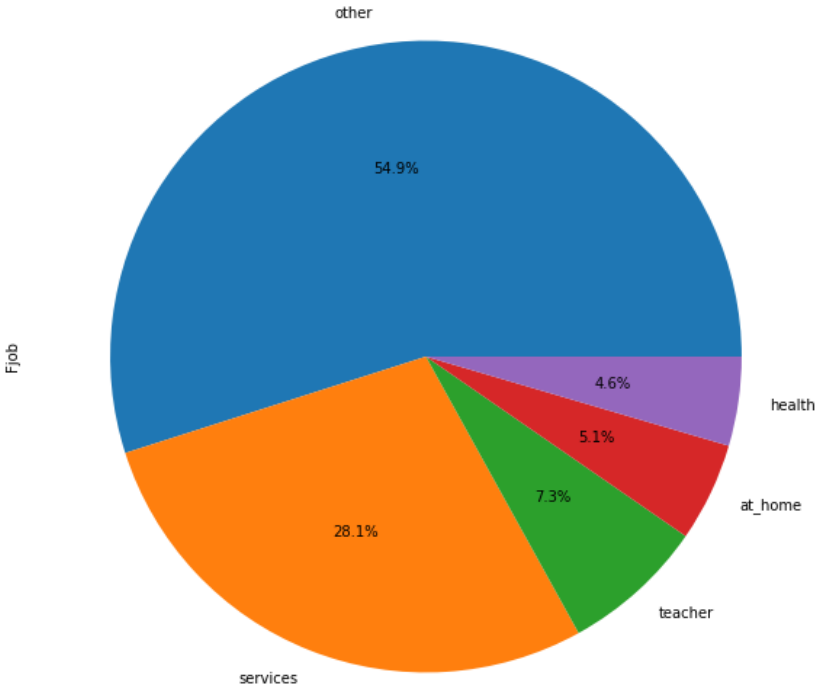


Father's job title (Fjob) analysis

In this section we will look at the different job titles for Fathers. The code below will print a list with the sum of the amount and a pie chart with the percentages.

```
In [16]: df.Fjob.value_counts().plot(kind = 'pie', figsize=(10,10), autopct = '%1.1f%%')
         print(df.Fjob.value_counts())
```

```
other       217
services    111
teacher      29
at_home      20
health       18
Name: Fjob, dtype: int64
```



Results

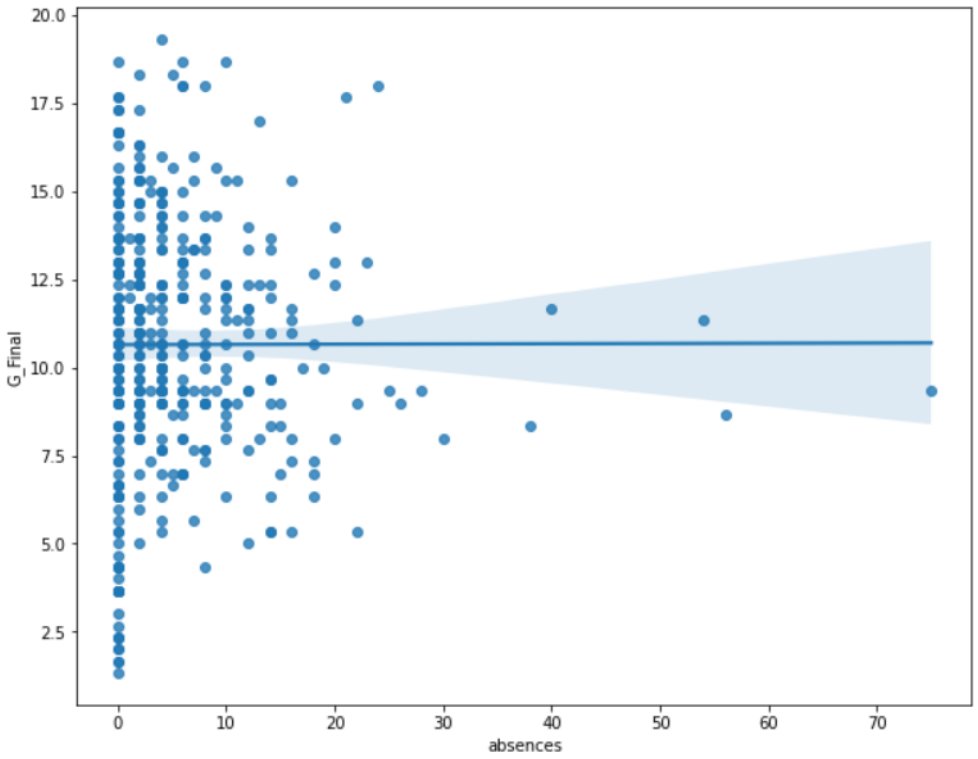
- The results show for both pie charts that 'other' is the majority percentage of the occupations
- 'Health' and 'Teacher' has the lowest percentage as it is specialised occupations

Final grade vs Absences

We will now check if student absences have an effect on their final grades.

```
In [20]: fig = plt.figure(figsize=(10, 8))
         sns.regplot(x='absences', y='G_Final', data=df)
```

```
Out[20]: <AxesSubplot:xlabel='absences', ylabel='G_Final'>
```



Results

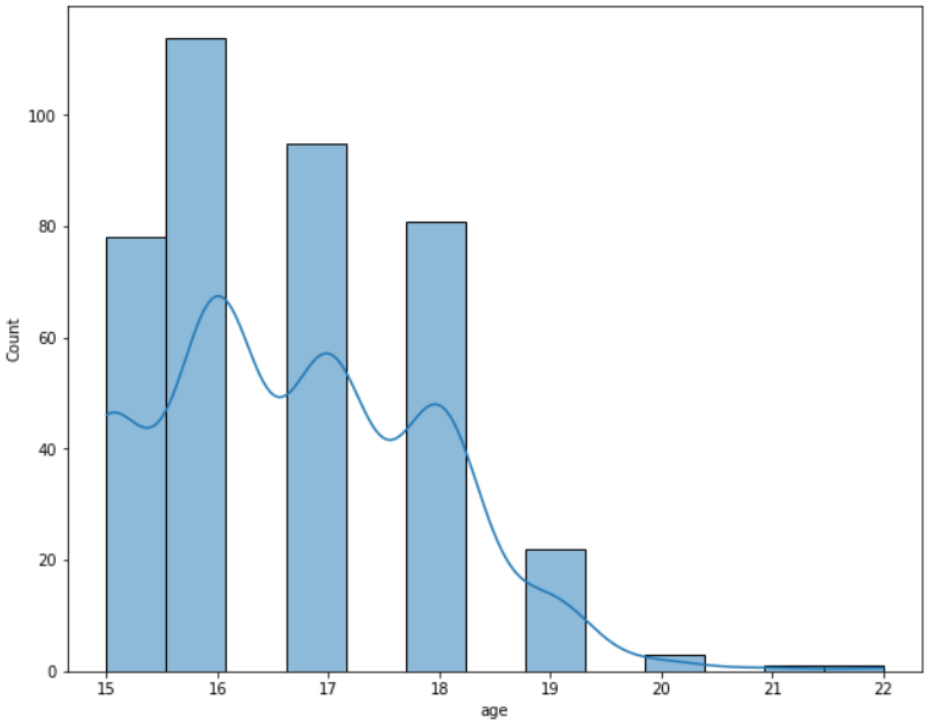
Looking at the scatter distribution, it seems like student absences had no effect on their final grades. This might be because the students caught up on the missed work after school at their own time.

Grade vs Age

In this section we will compare the grades to the ages of the students. Below is a histogram showing that younger students have higher grades.

In [21]:
```
fig = plt.figure(figsize=(10, 8))
sns.histplot(x='age', data=df, kde=True)
```

Out[21]:
```
<AxesSubplot:xlabel='age', ylabel='Count'>
```



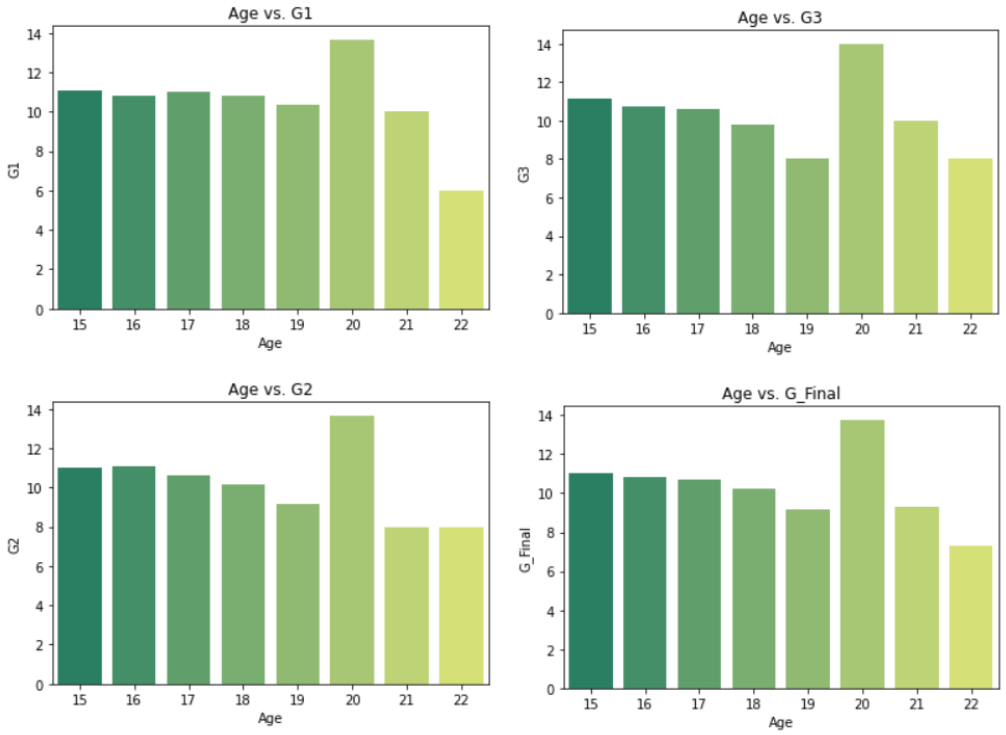
To improve the visualisations, we will treat 'age' as categorical instead of numerical

In [22]:
```
age_cat = df.groupby("age").aggregate({'G_Final': 'mean', 'G1': 'mean', 'G2': 'mean', 'G3': 'mean'})

age_cat.reset_index(inplace=True)

age_cat
```

Out[22]:

	age	G_Final	G1	G2	G3
0	15	11.051282	11.051282	10.987179	11.115385
1	16	10.856725	10.789474	11.043860	10.736842
2	17	10.715789	10.978947	10.600000	10.568421
3	18	10.251029	10.814815	10.135802	9.802469
4	19	9.181818	10.363636	9.136364	8.045455
5	20	13.777778	13.666667	13.666667	14.000000
6	21	9.333333	10.000000	8.000000	10.000000
7	22	7.333333	6.000000	8.000000	8.000000

```
In [25]: all_grades = ['G1', 'G2', 'G3', 'G_Final']

for grade in all_grades:
    sns.barplot(data=age_cat, x='age', y=grade, palette='summer').set(xlabel='Age', ylabel=grade, title=f'Age vs. {grade}')
    plt.show()
```



Results

It is clear from the bar charts that the younger students have better grades, the only exception is that 20 year olds have the highest grades overall.

Parents occupation WordClouds

Below is a WordCloud of the occupations the parents do.

```
In [28]: from wordcloud import WordCloud

text_M = df['Mjob'].values

wordcloud = WordCloud().generate(str(text_M))

plt.imshow(wordcloud)
plt.axis("off")
plt.show()
```

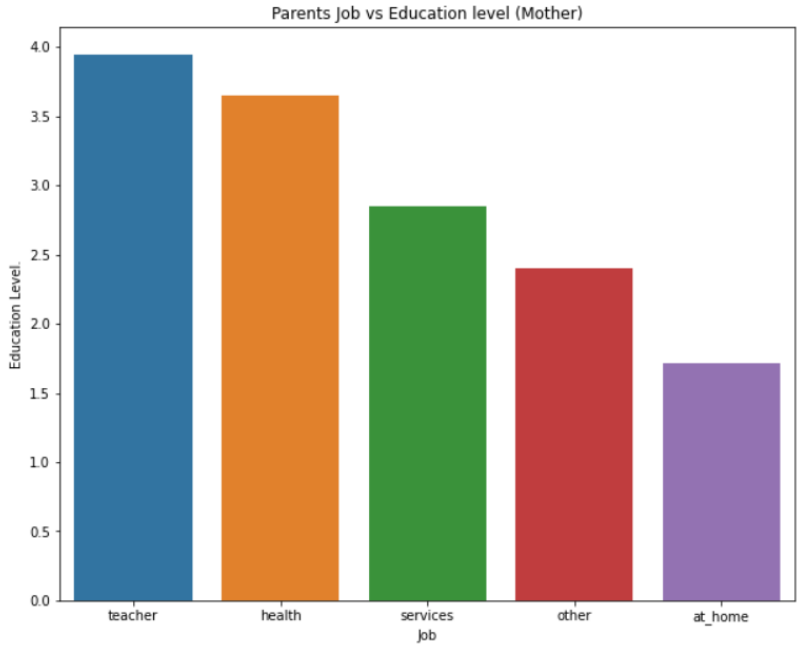
Parents' Job vs Education levels

Here we will compare the Parents' Job to their Education levels

Mothers' data

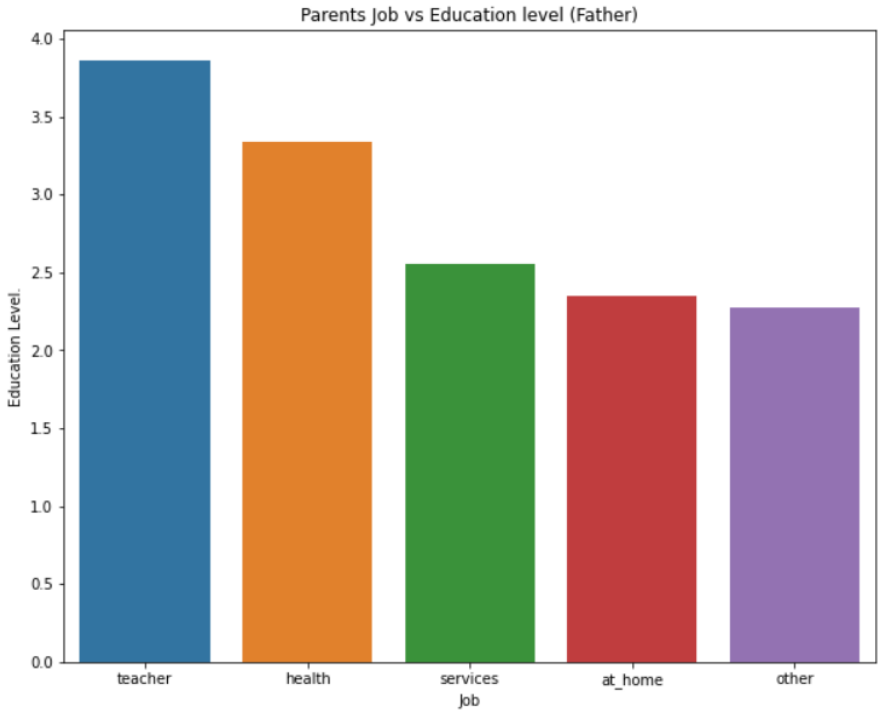
In [35]:
```
fig = plt.figure(figsize=(10, 8))

mjob_edu = df.groupby("Mjob").aggregate({"Medu": "mean"})

mjob_edu.reset_index(inplace=True)

mjob_edu.sort_values(by='Medu', ascending=False, inplace=True)

sns.barplot(x='Mjob', y='Medu', data=mjob_edu).set(xlabel='Job', ylabel='Education Level.',
                                                   title='Parents Job vs Education level (Mother)')
```

Out[35]:
```
[Text(0.5, 0, 'Job'),
 Text(0, 0.5, 'Education Level.'),
 Text(0.5, 1.0, 'Parents Job vs Education level (Mother)')]
```



Fathers' data

In [36]:
```
fig = plt.figure(figsize=(10, 8))

fjob_edu = df.groupby("Fjob").aggregate({"Fedu": "mean"})

fjob_edu.reset_index(inplace=True)

fjob_edu.sort_values(by='Fedu', ascending=False, inplace=True)

sns.barplot(x='Fjob', y='Fedu', data=fjob_edu).set(xlabel='Job', ylabel='Education Level.',
                                                   title='Parents Job vs Education level (Father)')
```



Results

For both Mothers and Fathers 'teacher' and 'Health' has the highest education level. This is because these two professions are specialised.

THIS REPORT WAS WRITTEN BY : CHRISTOPHER KNIGHT