MACHINE LEARNNING PREDICTION OF SCHOOL GRADES IN SIERRA LEONE

HELLO MENTORS

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- INTRODUTION :
- In this session I am going to explain to you how to use machine learning technology to predict grades in schools.

- However, this data set is also available in kaggle website were I took it and implemented it as a prediction of schools grades in Sierra Leone for both junior and senior secondary school pupils.
- CONTEXT:
- It is important for all teachers in Sierra Leone to use machine learning technology to predict the grades of student . Infact, that will help the country to mach to international standards
- CONTENT:
- I was hoping to have real dataset from Sierra Leone since its impossible to have it, I decided to took it from kaggle website in order to built a module so that in the future I can do the same thing for a real dataset in Sierra Leone to predict student grades.
- The dataset contains prediction of student grades from schools within Sierra Leone.


A+

We want to know Student's Final Grade through ML !

Library

+ Code + Markdown

[1]:

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import matplotlib
%matplotlib inline
import pandas_profiling as pp
```

Data Loading

[2]:

```
data = pd.read_csv("../input/student-grade-prediction/student-mat.csv")
```

[3]:

```
data.head()
```

[3]:

	school	sex	age	address	famsize	Pstatus	Medu	Fedu	Mjob	Fjob	...	famrel	freetime	goou
0	GP	F	18	U	GT3	A	4	4	at_home	teacher	...	4	3	
1	GP	F	17	U	GT3	T	1	1	at_home	other	...	5	3	
2	GP	F	15	U	LE3	T	1	1	at_home	other	...	4	3	
3	GP	F	15	U	GT3	T	4	2	health	services	...	3	2	
4	GP	F	16	U	GT3	T	3	3	other	other	...	4	3	

5 rows × 33 columns

Variable

Attribute Information:

1. school - student's school (binary: 'GP' - Gabriel Pereira or 'MS' - Mousinho da Silveira)
2. sex - student's sex (binary: 'F' - female or 'M' - male)
3. age - student's age (numeric: from 15 to 22)
4. address - student's home address type (binary: 'U' - urban or 'R' - rural)
5. famsize - family size (binary: 'LE3' - less or equal to 3 or 'GT3' - greater than 3)
6. Pstatus - parent's cohabitation status (binary: 'T' - living together or 'A' - apart)
7. Medu - mother's education (numeric: 0 - none, 1 - primary education (4th grade), 2 â€" 5th to 9th grade, 3 â€" secondary education or 4 â€" higher education)
8. Fedu - father's education (numeric: 0 - none, 1 - primary education (4th grade), 2 â€" 5th to 9th grade, 3 â€" secondary education or 4 â€" higher education)
9. Mjob - mother's job (nominal: 'teacher', 'health' care related, civil 'services' (e.g. administrative or police), 'at_home' or 'other')
10. Fjob - father's job (nominal: 'teacher', 'health' care related, civil 'services' (e.g. administrative or police), 'at_home' or 'other')
11. reason - reason to choose this school (nominal: close to 'home', school 'reputation', 'course'

12. guardian - student's guardian (nominal: 'mother', 'father' or 'other')
13. traveltime - home to school travel time (numeric: 1 - <15 min., 2 - 15 to 30 min., 3 - 30 min. to 1 hour, or 4 - >1 hour)
14. studytime - weekly study time (numeric: 1 - <2 hours, 2 - 2 to 5 hours, 3 - 5 to 10 hours, or 4 - >10 hours)
15. failures - number of past class failures (numeric: n if 1<=n<3, else 4)
16. schoolsup - extra educational support (binary: yes or no)
17. famsup - family educational support (binary: yes or no)
18. paid - extra paid classes within the course subject (Math or Portuguese) (binary: yes or no)
19. activities - extra-curricular activities (binary: yes or no)
20. nursery - attended nursery school (binary: yes or no)
21. higher - wants to take higher education (binary: yes or no)
22. internet - Internet access at home (binary: yes or no)
23. romantic - with a romantic relationship (binary: yes or no)
24. famrel - quality of family relationships (numeric: from 1 - very bad to 5 - excellent)
25. freetime - free time after school (numeric: from 1 - very low to 5 - very high)
26. goout - going out with friends (numeric: from 1 - very low to 5 - very high)
27. Dalc - workday alcohol consumption (numeric: from 1 - very low to 5 - very high)
28. Walc - weekend alcohol consumption (numeric: from 1 - very low to 5 - very high)
29. health - current health status (numeric: from 1 - very bad to 5 - very good)
30. absences - number of school absences (numeric: from 0 to 93)

30. absences - number of school absences (numeric: from 0 to 93)
31. G1 - score
32. G2 - score
33. G3 - socre

[4]:

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 395 entries, 0 to 394
Data columns (total 33 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   famsize     395 non-null    object
 5   Pstatus     395 non-null    object
 6   Medu        395 non-null    int64
 7   Fedu        395 non-null    int64
```

HELLOW EVERYONE

```
 8   Mjob        395 non-null    object
 9   Fjob        395 non-null    object
 10  reason      395 non-null    object
 11  guardian    395 non-null    object
 12  traveltime  395 non-null    int64
 13  studytime   395 non-null    int64
 14  failures    395 non-null    int64
 15  schoolsup   395 non-null    object
 16  famsup      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  famrel      395 non-null    int64
 24  freetime    395 non-null    int64
 25  goout       395 non-null    int64
 26  Dalc        395 non-null    int64
 27  Walc        395 non-null    int64
 28  health      395 non-null    int64
 29  absences    395 non-null    int64
 30  G1          395 non-null    int64
 31  G2          395 non-null    int64
 32  G3          395 non-null    int64
dtypes: int64(16), object(17)
memory usage: 102.0+ KB
```

```
[5]: import pandas_profiling as pp
     pp.ProfileReport(data)
```

```
Summarize dataset: 100%          46/46 [00:15<00:00, 1.39it/s, Completed]
Generate report structure: 100%  1/1 [00:12<00:00, 12.66s/it]
Render HTML: 100%                1/1 [00:01<00:00, 1.71s/it]
```

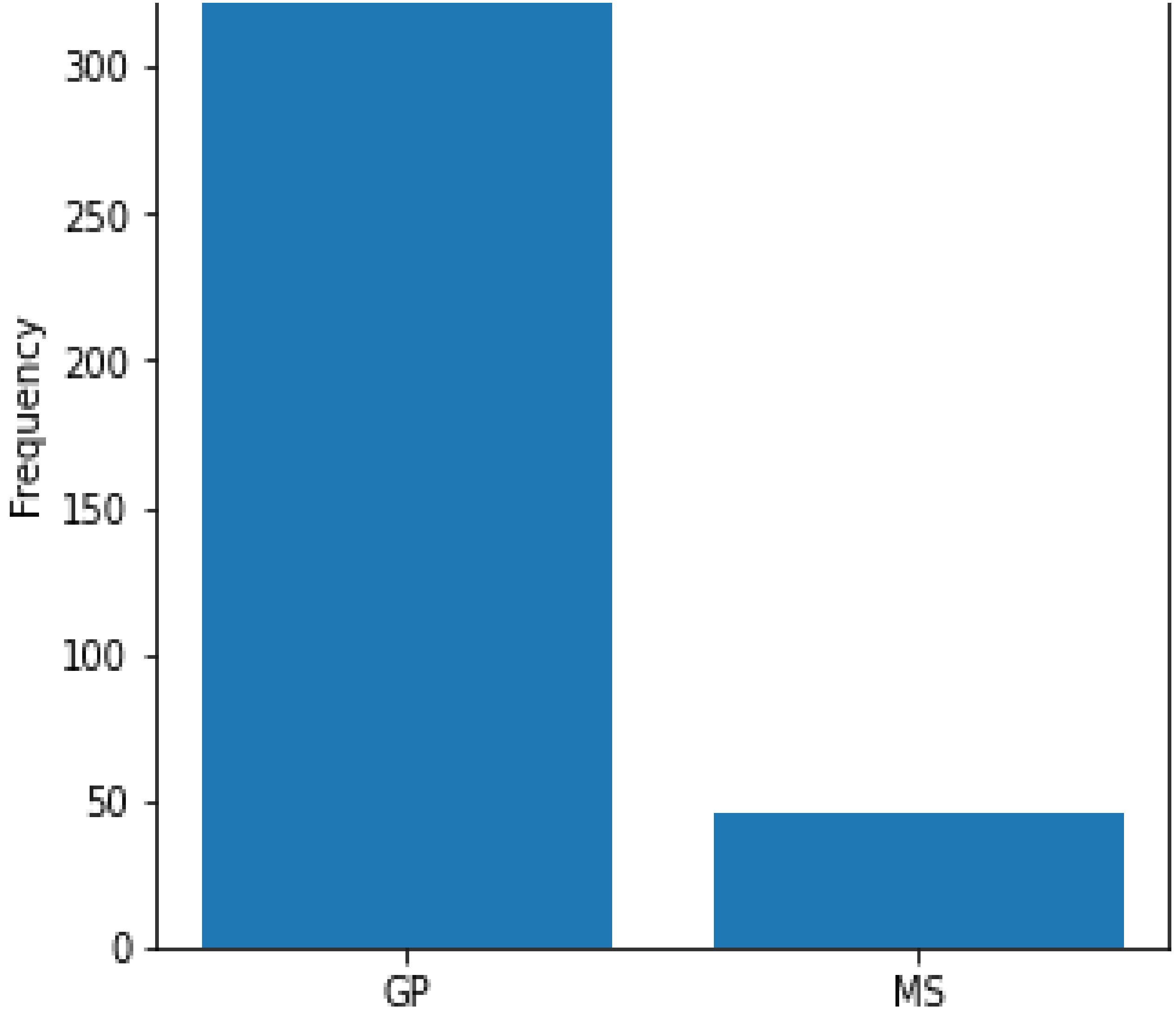
Pandas Profiling Report

Visualization

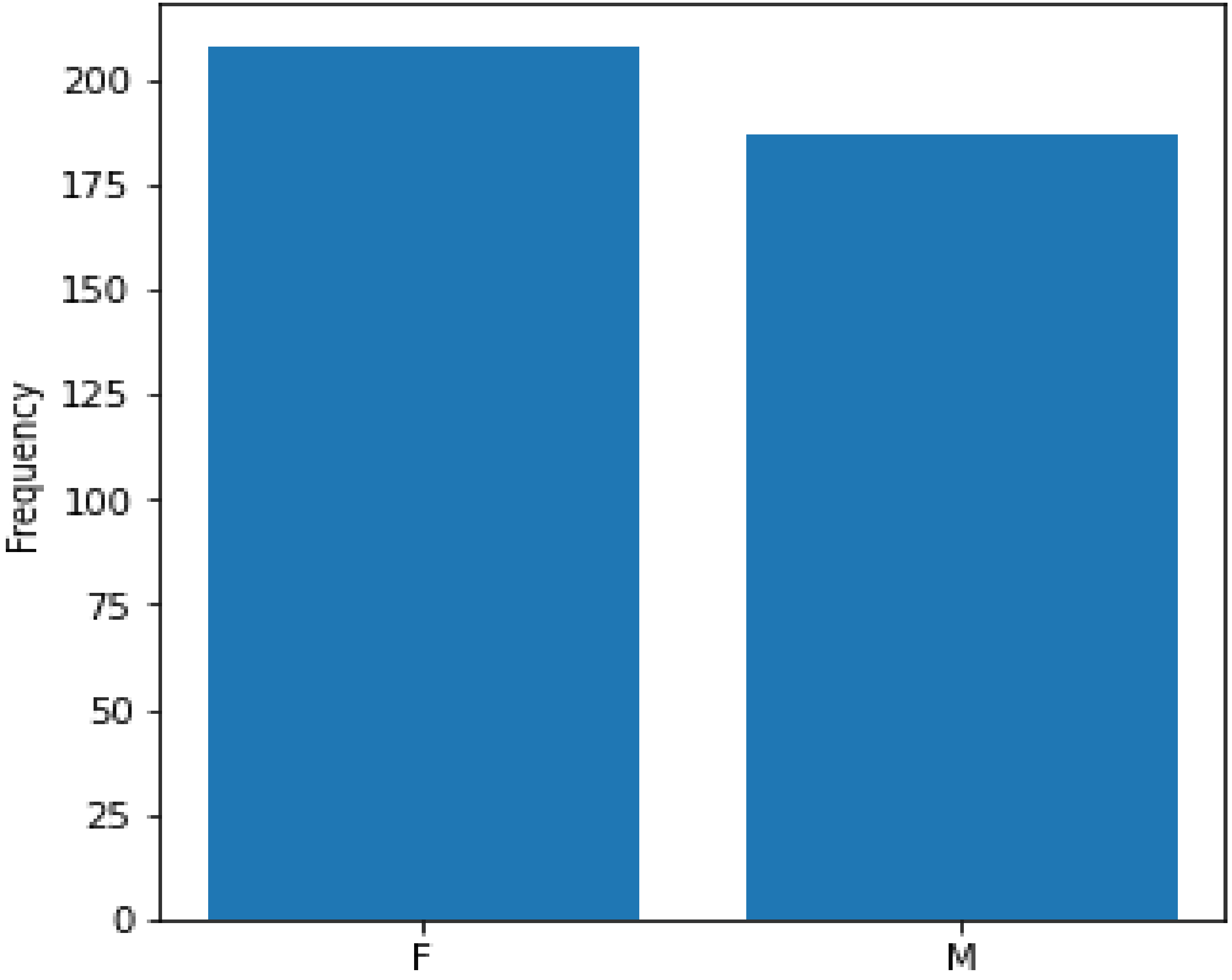
[6]:

```
def bar_plot(variable):
    var = data[variable]
    var_c = var.value_counts()

    plt.figure(figsize= (5,5))
    plt.bar(var_c.index, var_c)
    plt.ylabel('Frequency')
    plt.show()
    print("{}\n{}".format(variable, var_c))
```

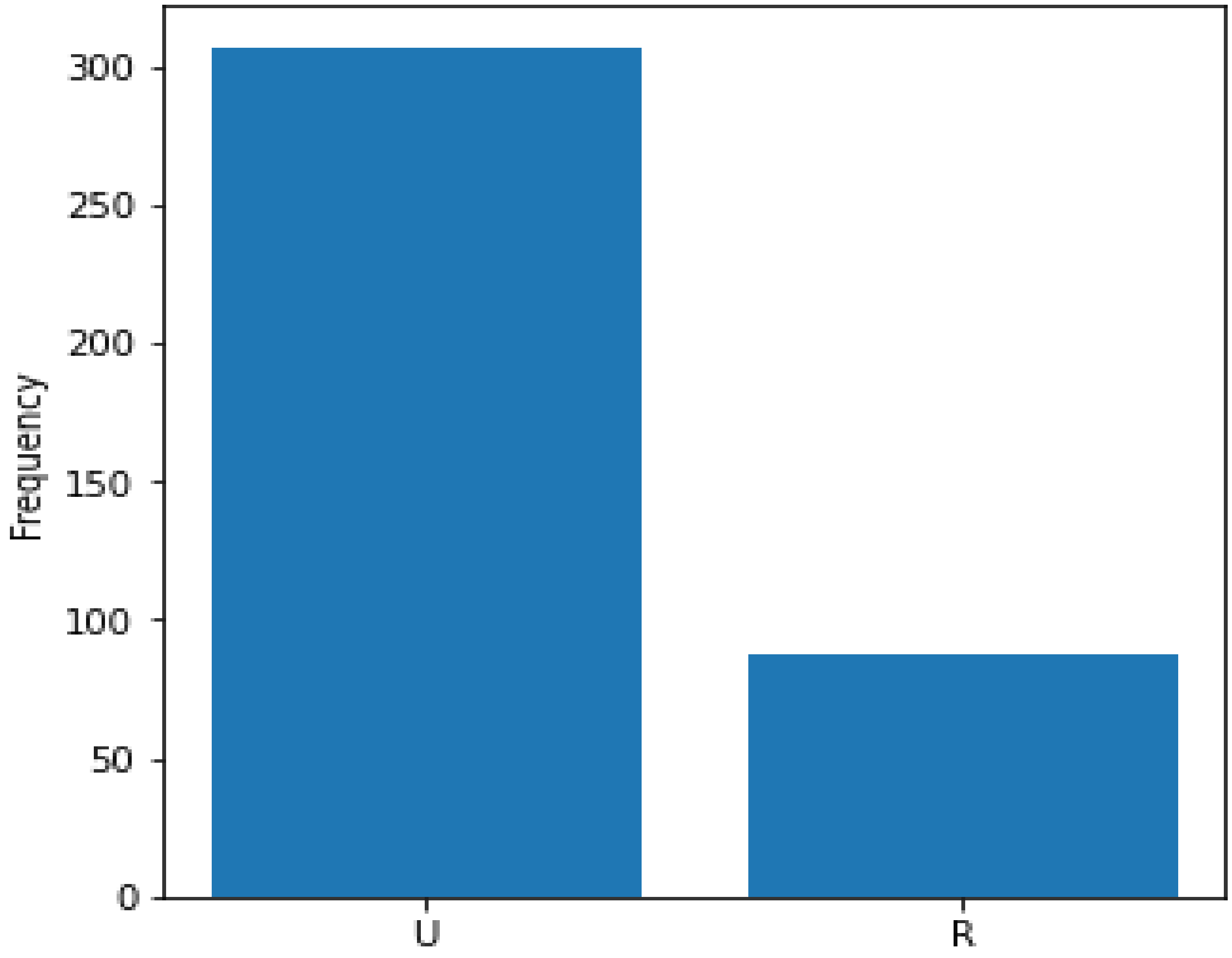
```
categorical = data.dtypes=='object'
categorical_list = list(categorical[categorical].index)
categorical_list


for i in categorical_list:
    bar_plot(i)
```



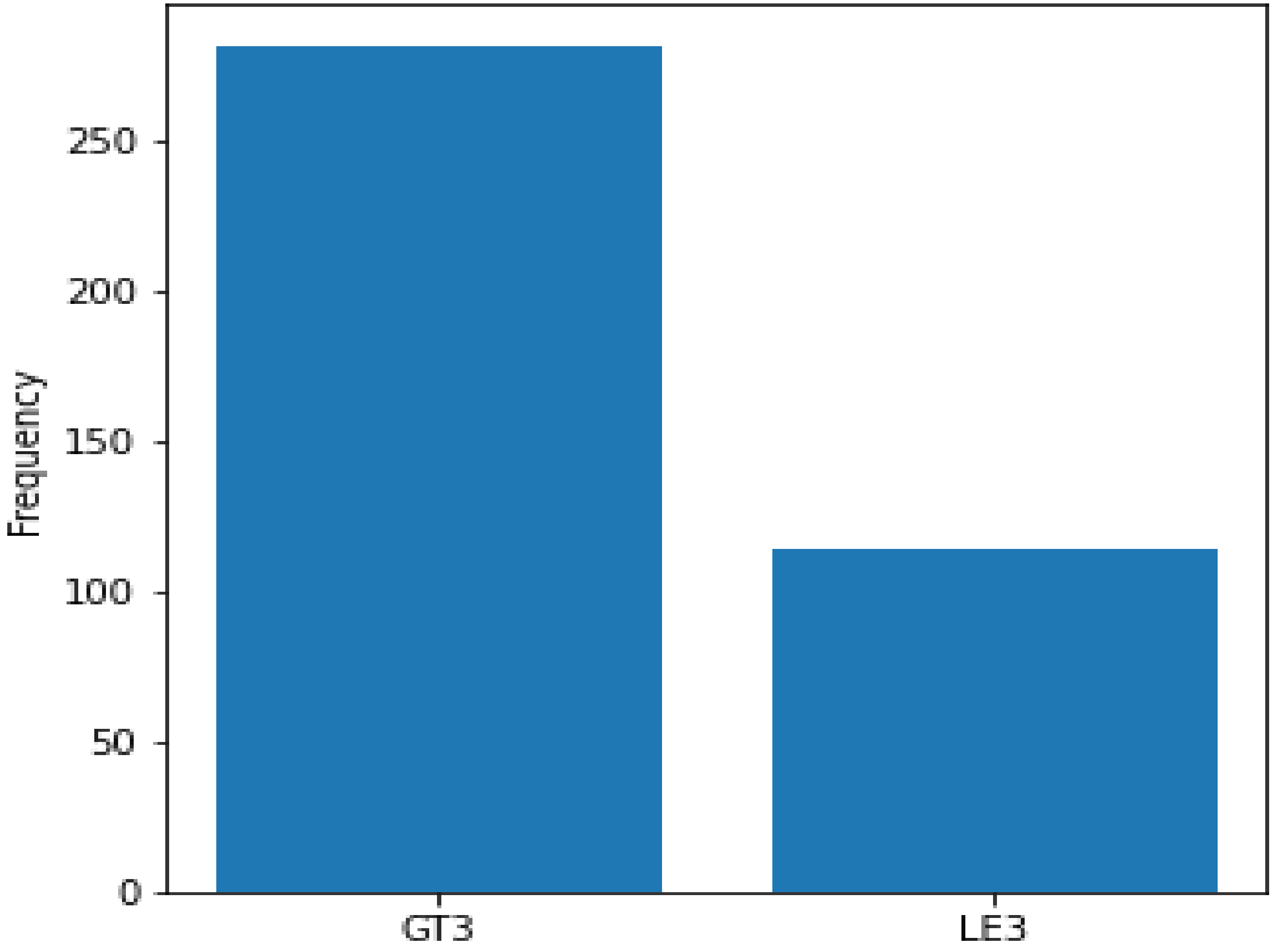

```
school
GP    349
MS     46
Name: school, dtype: int64
```



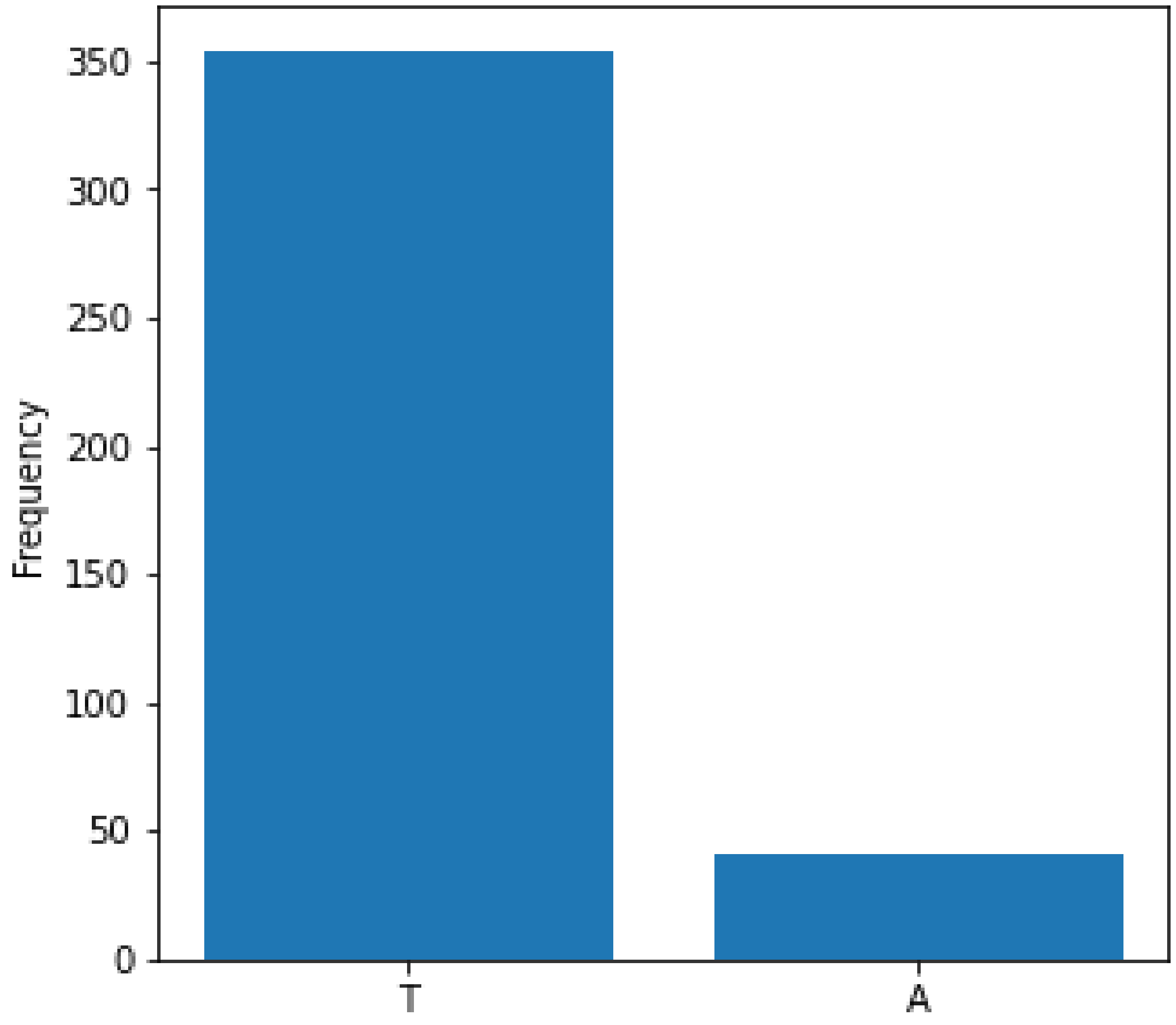

```
sex
F    208
M    187
Name: sex, dtype: int64
```



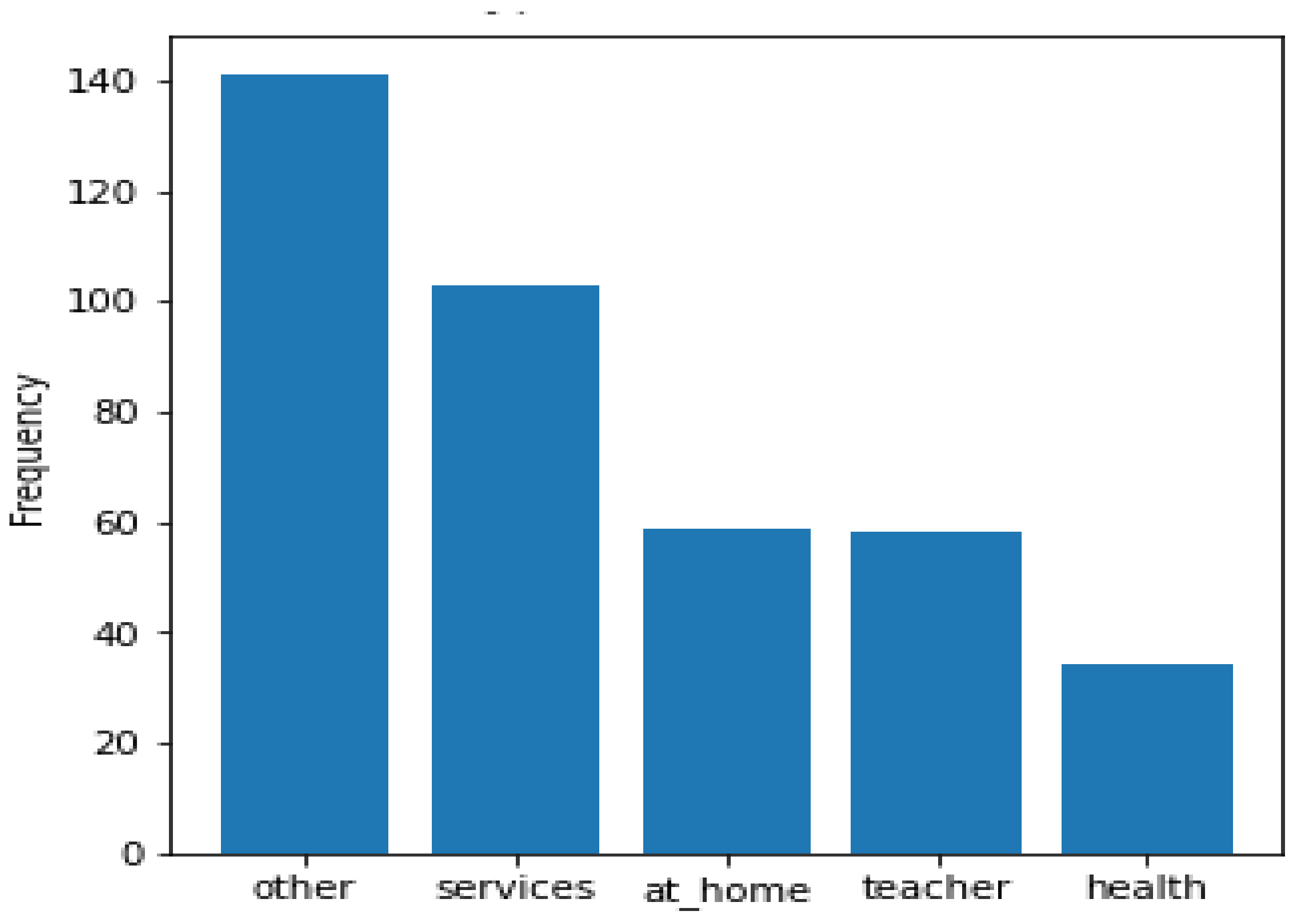

```
address
U    307
R     88
Name: address, dtype: int64
```



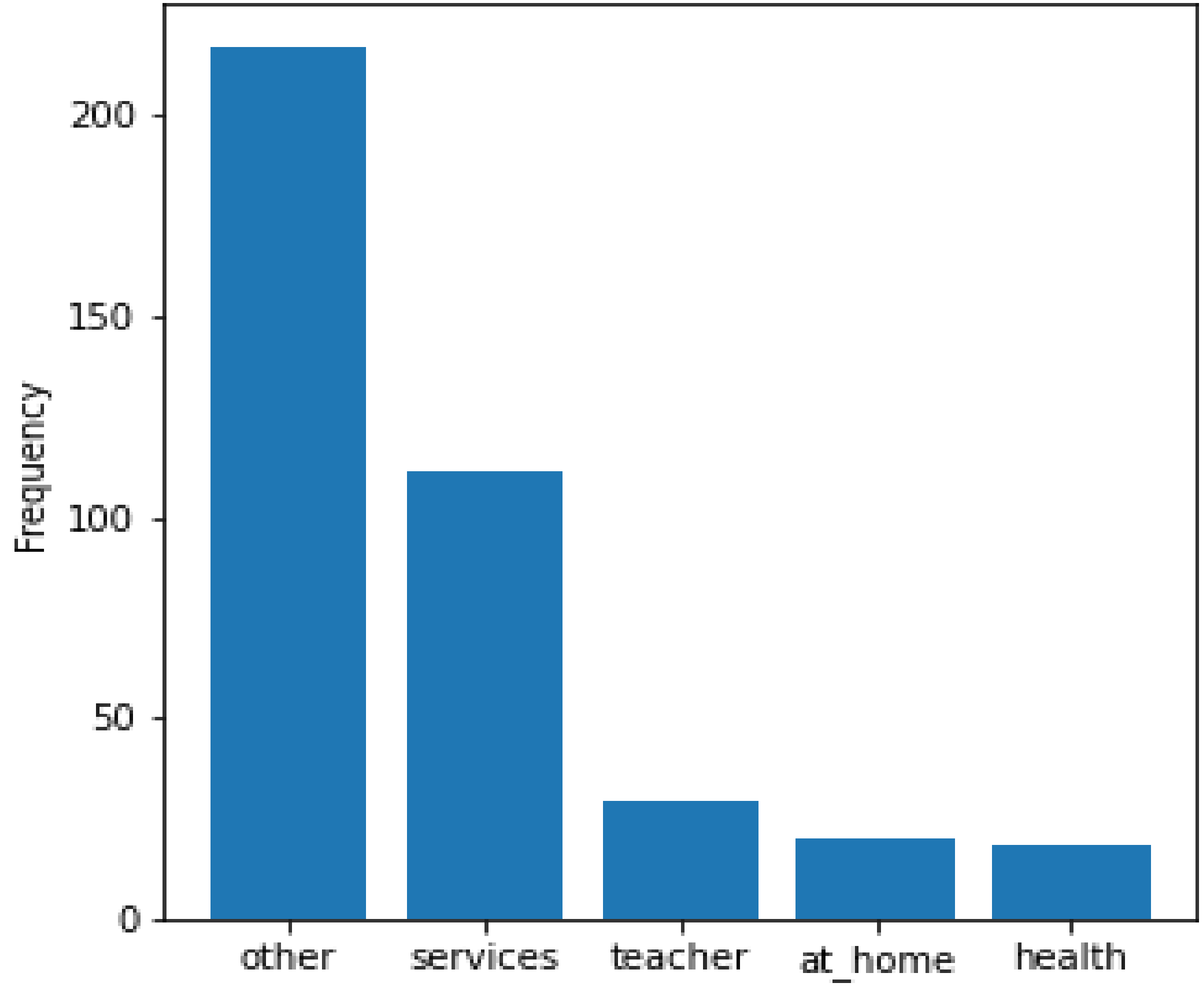

```
famsize
GT3    281
LE3    114
Name: famsize, dtype: int64
```



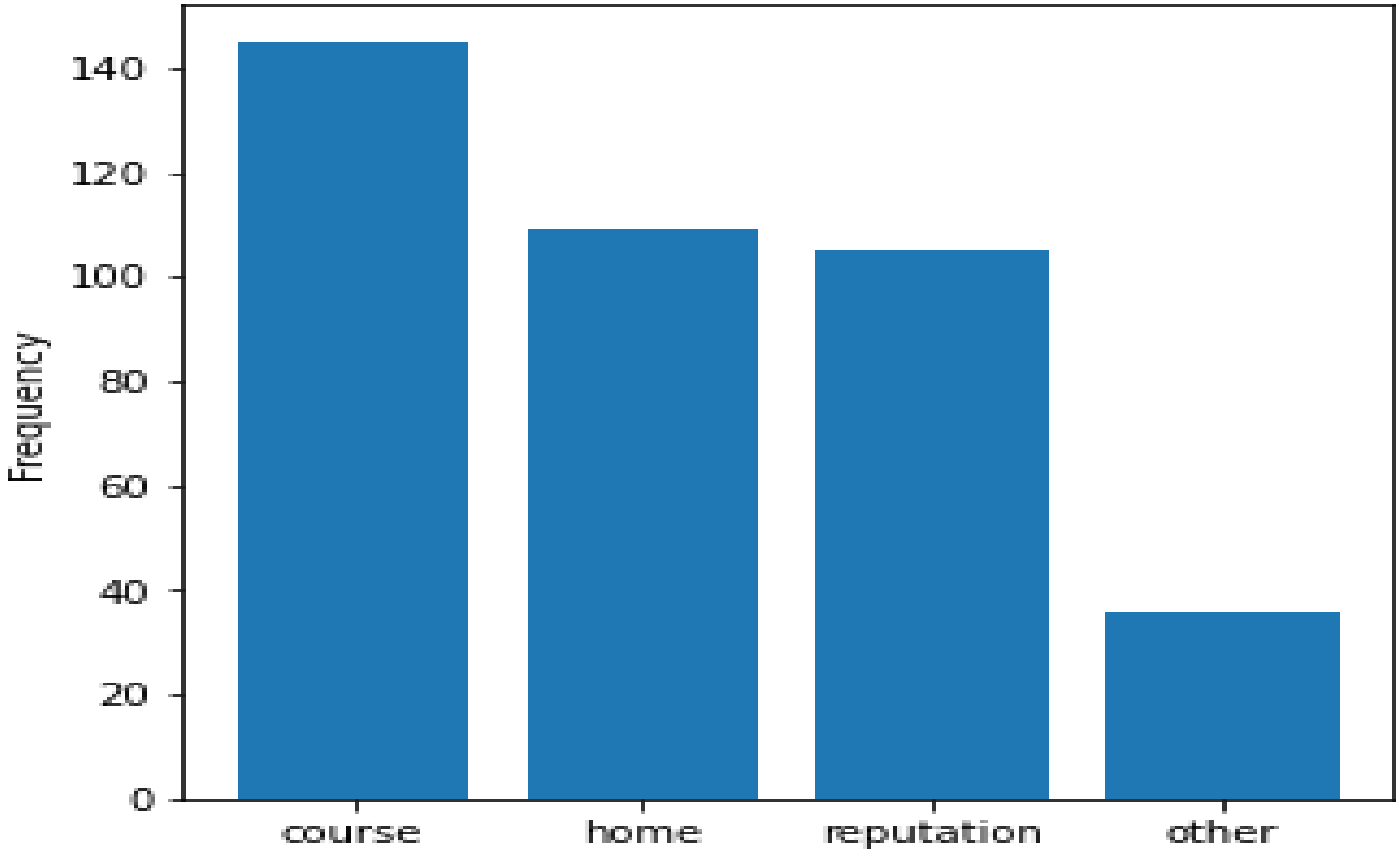

```
Pstatus
T    354
A     41
Name: Pstatus, dtype: int64
```



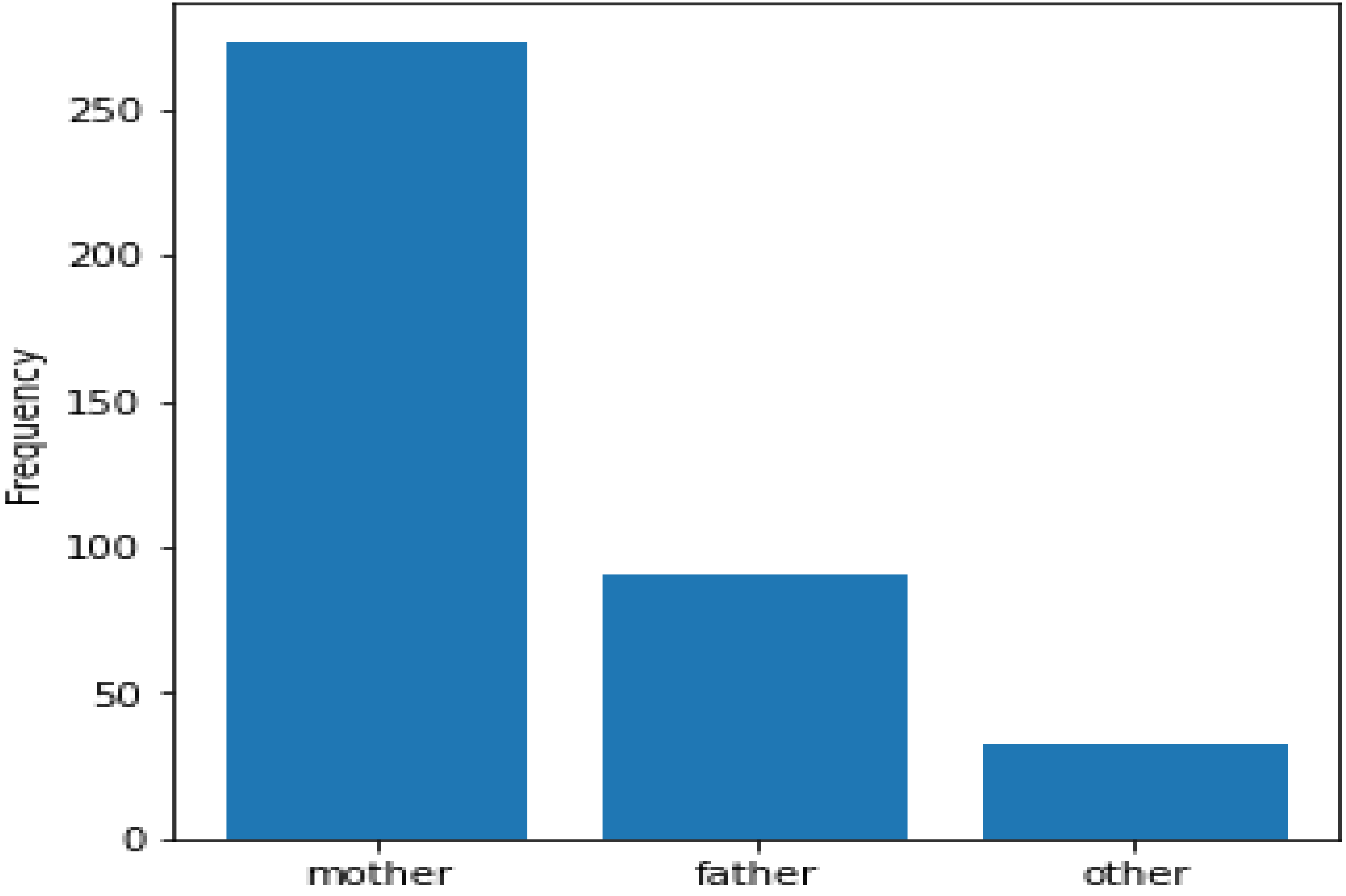

```
Mjob
other       141
services    103
at_home      59
teacher      58
health       34
Name: Mjob, dtype: int64
```



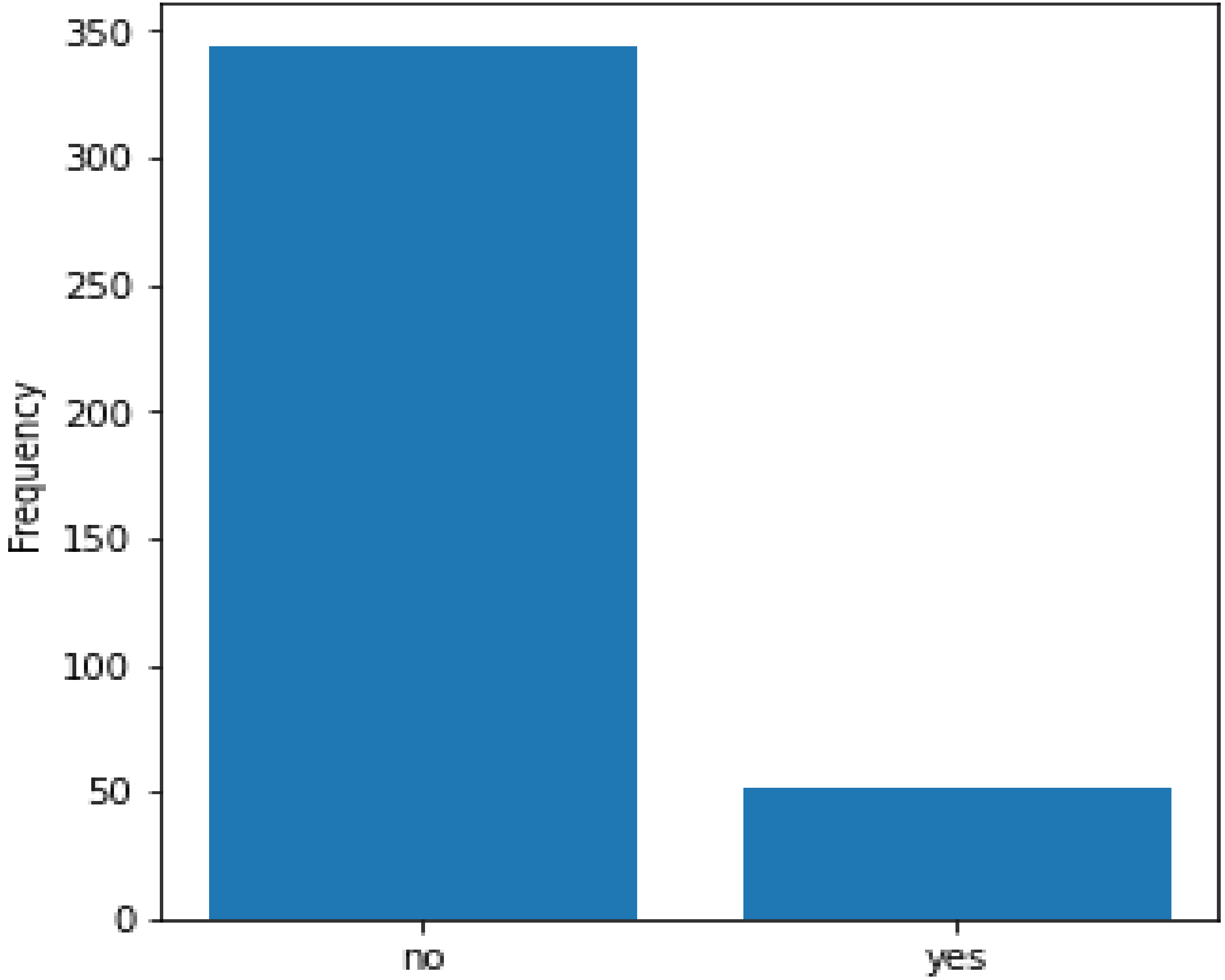

```
Fjob
other       217
services    111
teacher      29
at_home      20
health       18
Name: Fjob, dtype: int64
```




```
reason
course        145
home          109
reputation    105
other          36
Name: reason, dtype: int64
```




```
guardian
mother    273
father     90
other      32
Name: guardian, dtype: int64
```

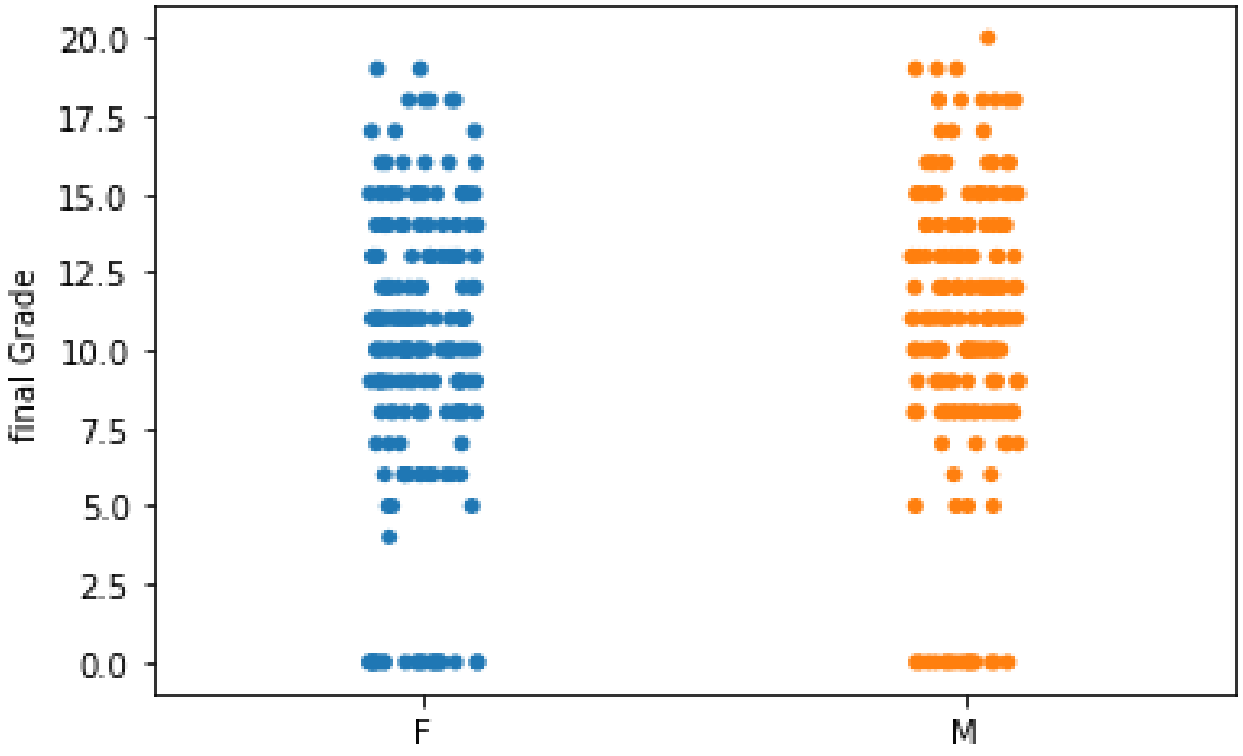



```
schoolsup
no      344
yes      51
Name: schoolsup, dtype: int64
```

Sex

[8]:

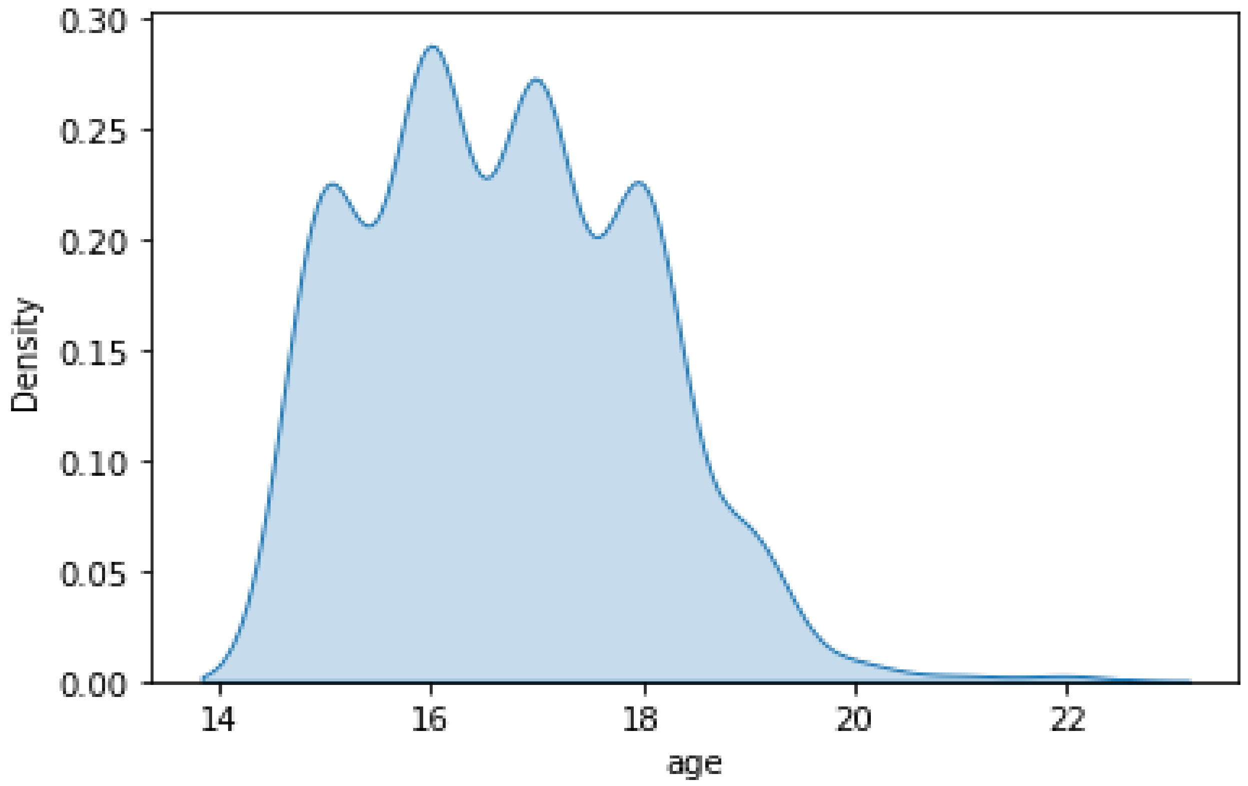
```
sns.stripplot(x=data['sex'], y=data['G3'])
plt.ylabel('final Grade')
plt.show()
```



Age

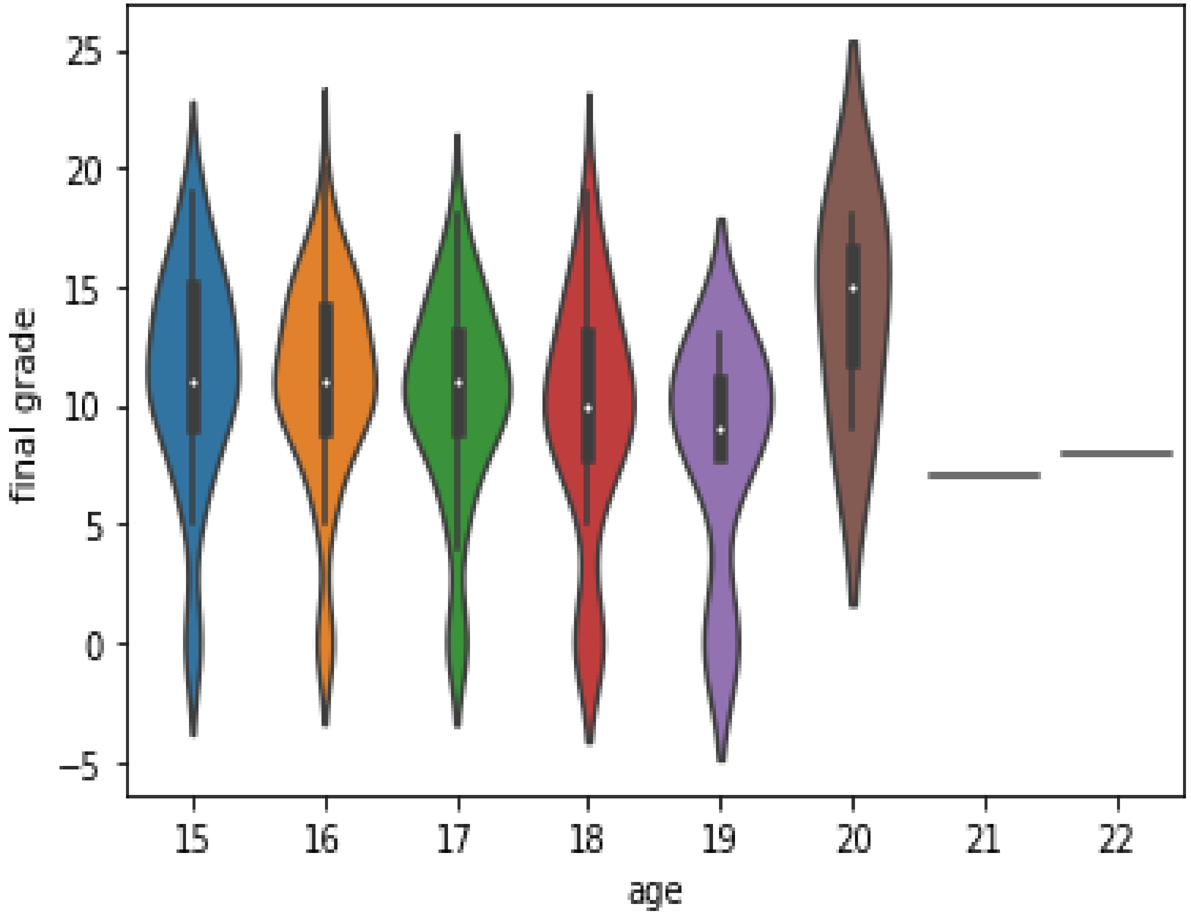
[9]:

```
#1 age's dist
sns.kdeplot(data['age'], shade=True)
plt.show()
```



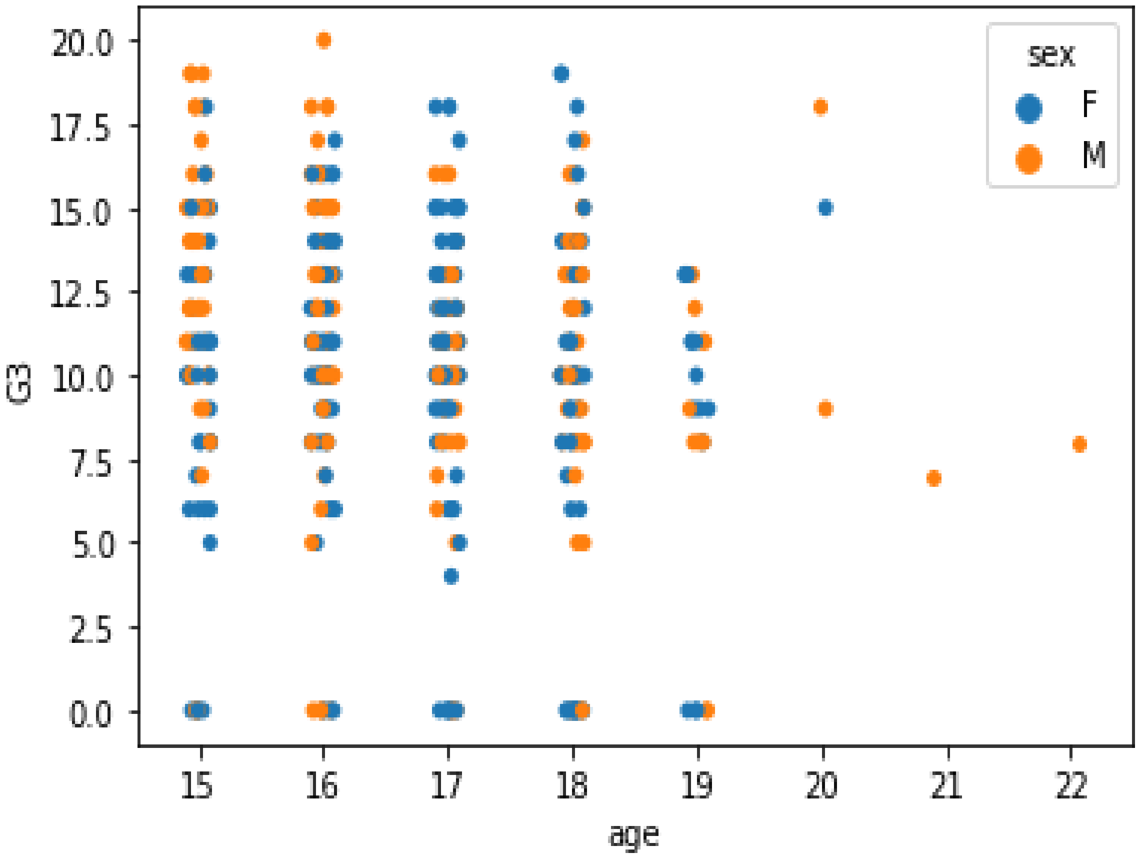
[10]:

```
sns.violinplot(data=data, x='age',y='G3')
plt.ylabel("final grade")
plt.show()
```



[11]:

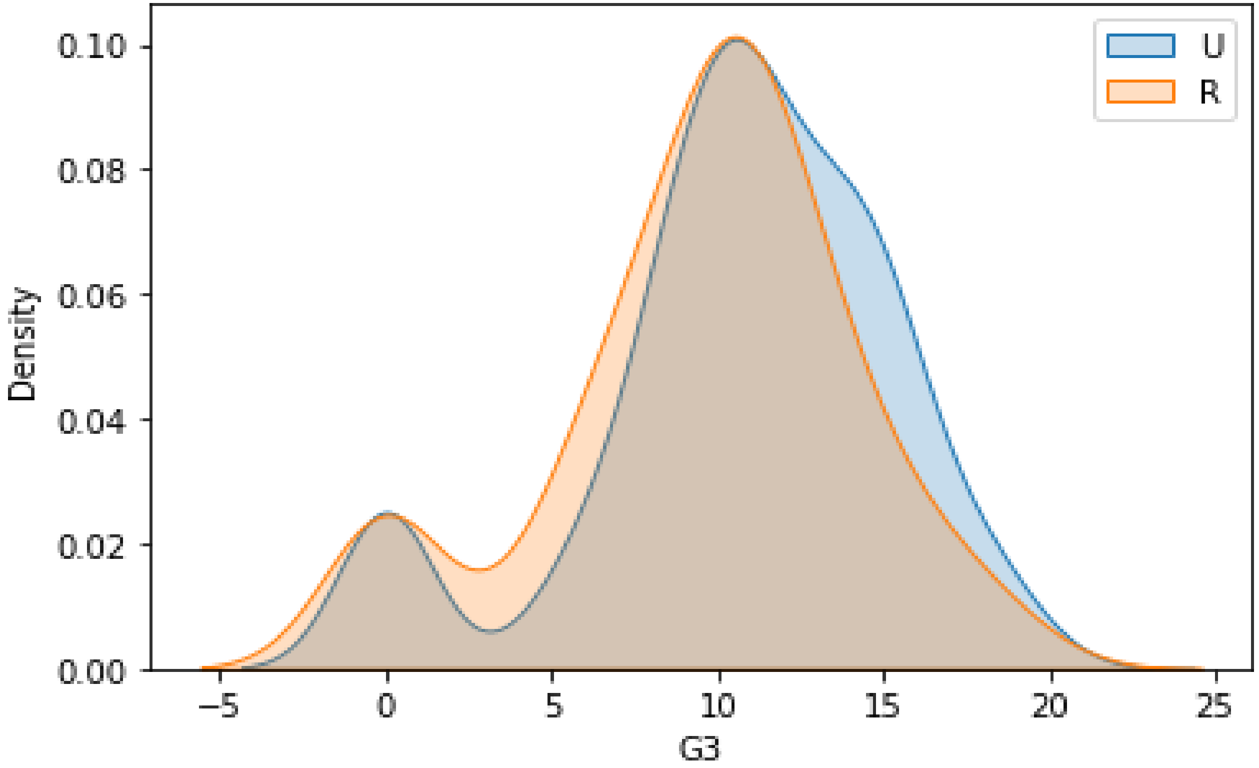
```
sns.stripplot(data=data, x='age',y='G3', hue='sex')
plt.show()
```



address

[12]:

```
sns.kdeplot(data.loc[data['address']== 'U', 'G3'], shade=True)
sns.kdeplot(data.loc[data['address']== 'R','G3'],shade= True)
plt.legend(data['address'].unique())
plt.show()
```



We can find out urban students make high scores.

I think it is inefficient to find significant with all variables,

So then, I will use variables with high correlation to G3

[13]:

```
numeric = data.dtypes=='int64'
numeric_list= numeric[numeric].index
```

[14]:

```
for i in numeric_list:
    print(i ,':', np.round(data['G3'].corr(data[i]), 2))
```

```
age : -0.16
Medu : 0.22
Fedu : 0.15
traveltime : -0.12
studytime : 0.1
failures : -0.36
famrel : 0.05
freetime : 0.01
goout : -0.13
Dalc : -0.05
Walc : -0.05
health : -0.06
absences : 0.03
G1 : 0.8
G2 : 0.9
G3 : 1.0
```

[26]:

```python
#e.g.,
pred = best_grid.predict(test_input)
pd.DataFrame(pred, test_target)
```

[26]:

	0
G3	
12	11.75
10	9.25
12	10.50
9	10.00
12	12.75
...	...
0	2.00
7	6.50

[27]:

```python
from sklearn.metrics import mean_absolute_error, mean_squared_error
print(mean_absolute_error(test_target, pred)) #평균오차
print(mean_squared_error(test_target, pred))
```

```
1.4113924050632911
4.780063291139241
```

Dtr

[28]:

```python
from sklearn.tree import DecisionTreeRegressor
dtr= DecisionTreeRegressor()
dtr.fit(train_input, train_target)
print(dtr.score(test_input, test_target))
```

```
0.6328056142218084
```

CONCLUSION

I couldn’t use dataset of Sierra Leone, but in the further, since I have built a model, I am planning to use a real dataset from Cards Fraud in Sierra Leone.