main-algo

March 7, 2022

[ ]:
```
#importing core libraries
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np

#importing essential libraries
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report
from sklearn import metrics
#statistics
from scipy import stats
import statsmodels.api as sm

#importing Machine learning libraries
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.naive_bayes import GaussianNB
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
```

[ ]:
```
#importing and reading dataset

data1=pd.read_csv("student-por.csv",sep=";")
data2=pd.read_csv("student-mat.csv",sep=";")

stu=pd.concat([data1, data2])
stu["total_grades"]=(stu["G1"]+stu["G2"]+stu["G3"])/3

stu=stu.drop(["G1","G2","G3"],axis=1)
max=stu["total_grades"].max()
min=stu["total_grades"].min()
```

[ ]:
```
#defining function for categorizing grades into 3

def marks(total_grades):
    if(total_grades<7):
```

```
        return("low")
    elif(total_grades>=7 and total_grades<14):
        return("average")
    elif(total_grades>=14):
        return("high")
stu["grades"]=stu["total_grades"].apply(marks)
```

[ ]:
```
#data description

stu.dtypes
stu.describe(include="all")
```

[ ]:
```
       school   sex          age address famsize Pstatus         Medu  \
count    1044  1044  1044.000000    1044    1044    1044  1044.000000
unique      2     2          NaN       2       2       2          NaN
top        GP     F          NaN       U     GT3       T          NaN
freq      772   591          NaN     759     738     923          NaN
mean      NaN   NaN    16.726054     NaN     NaN     NaN     2.603448
std       NaN   NaN     1.239975     NaN     NaN     NaN     1.124907
min       NaN   NaN    15.000000     NaN     NaN     NaN     0.000000
25%       NaN   NaN    16.000000     NaN     NaN     NaN     2.000000
50%       NaN   NaN    17.000000     NaN     NaN     NaN     3.000000
75%       NaN   NaN    18.000000     NaN     NaN     NaN     4.000000
max       NaN   NaN    22.000000     NaN     NaN     NaN     4.000000

               Fedu   Mjob   Fjob  … romantic       famrel     freetime  \
count   1044.000000   1044   1044  …     1044  1044.000000  1044.000000
unique          NaN      5      5  …        2          NaN          NaN
top             NaN  other  other  …       no          NaN          NaN
freq            NaN    399    584  …      673          NaN          NaN
mean       2.387931    NaN    NaN  …      NaN     3.935824     3.201149
std        1.099938    NaN    NaN  …      NaN     0.933401     1.031507
min        0.000000    NaN    NaN  …      NaN     1.000000     1.000000
25%        1.000000    NaN    NaN  …      NaN     4.000000     3.000000
50%        2.000000    NaN    NaN  …      NaN     4.000000     3.000000
75%        3.000000    NaN    NaN  …      NaN     5.000000     4.000000
max        4.000000    NaN    NaN  …      NaN     5.000000     5.000000

              goout         Dalc         Walc       health     absences  \
count   1044.000000  1044.000000  1044.000000  1044.000000  1044.000000
unique          NaN          NaN          NaN          NaN          NaN
top             NaN          NaN          NaN          NaN          NaN
freq            NaN          NaN          NaN          NaN          NaN
mean       3.156130     1.494253     2.284483     3.543103     4.434866
std        1.152575     0.911714     1.285105     1.424703     6.210017
min        1.000000     1.000000     1.000000     1.000000     0.000000
25%        2.000000     1.000000     1.000000     3.000000     0.000000
```

```
50%        3.000000     1.000000     2.000000     4.000000      2.000000
75%        4.000000     2.000000     3.000000     5.000000      6.000000
max        5.000000     5.000000     5.000000     5.000000     75.000000

       total_grades   grades
count   1044.000000     1044
unique          NaN        3
top             NaN  average
freq            NaN      744
mean      11.267241      NaN
std        3.218805      NaN
min        1.333333      NaN
25%        9.333333      NaN
50%       11.333333      NaN
75%       13.333333      NaN
max       19.333333      NaN

[11 rows x 32 columns]
```

[ ]:
```
#checking for info & null values

stu.info()
stu.isnull().any()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1044 entries, 0 to 394
Data columns (total 32 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   school        1044 non-null   object
 1   sex           1044 non-null   object
 2   age           1044 non-null   int64
 3   address       1044 non-null   object
 4   famsize       1044 non-null   object
 5   Pstatus       1044 non-null   object
 6   Medu          1044 non-null   int64
 7   Fedu          1044 non-null   int64
 8   Mjob          1044 non-null   object
 9   Fjob          1044 non-null   object
 10  reason        1044 non-null   object
 11  guardian      1044 non-null   object
 12  traveltime    1044 non-null   int64
 13  studytime     1044 non-null   int64
 14  failures      1044 non-null   int64
 15  schoolsup     1044 non-null   object
 16  famsup        1044 non-null   object
 17  paid          1044 non-null   object
```

```
 18  activities    1044 non-null   object
 19  nursery       1044 non-null   object
 20  higher        1044 non-null   object
 21  internet      1044 non-null   object
 22  romantic      1044 non-null   object
 23  famrel        1044 non-null   int64
 24  freetime      1044 non-null   int64
 25  goout         1044 non-null   int64
 26  Dalc          1044 non-null   int64
 27  Walc          1044 non-null   int64
 28  health        1044 non-null   int64
 29  absences      1044 non-null   int64
 30  total_grades  1044 non-null   float64
 31  grades        1044 non-null   object
dtypes: float64(1), int64(13), object(18)
memory usage: 269.2+ KB
```

[ ]:

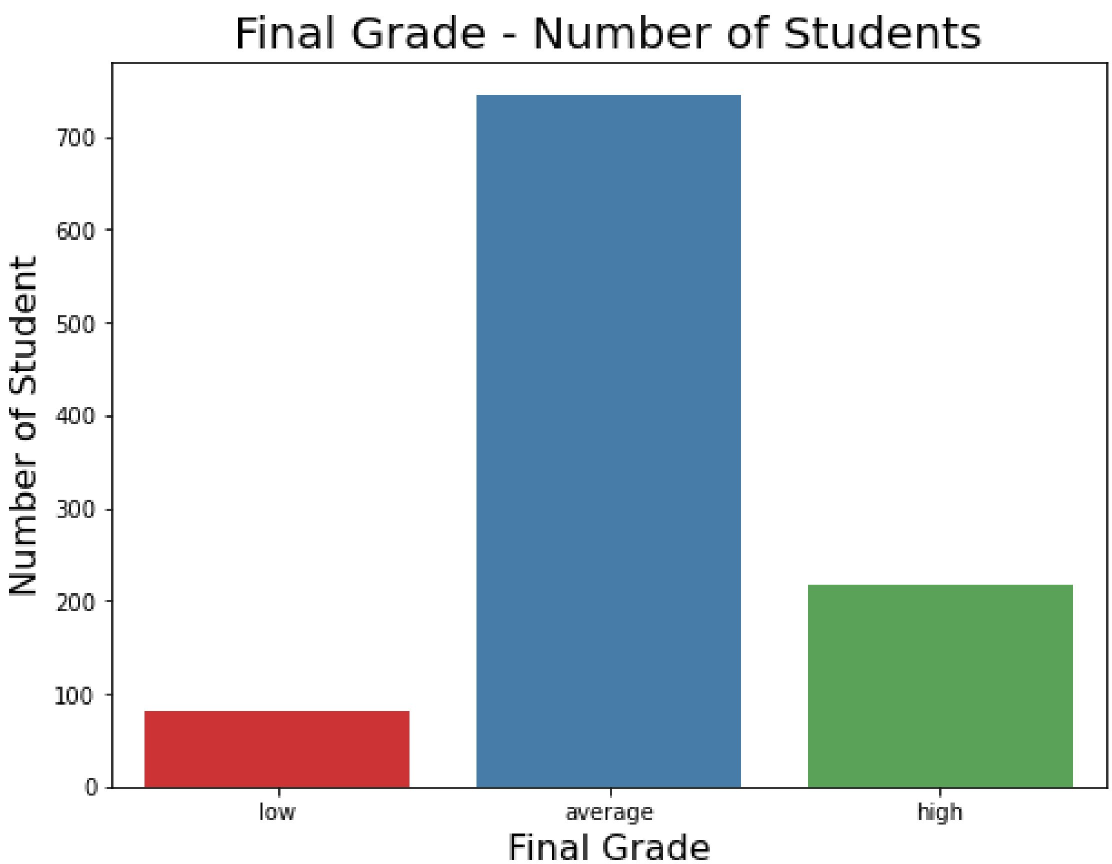
```
school          False
sex             False
age             False
address         False
famsize         False
Pstatus         False
Medu            False
Fedu            False
Mjob            False
Fjob            False
reason          False
guardian        False
traveltime      False
studytime       False
failures        False
schoolsup       False
famsup          False
paid            False
activities      False
nursery         False
higher          False
internet        False
romantic        False
famrel          False
freetime        False
goout           False
Dalc            False
Walc            False
health          False
absences        False
```

```
total_grades    False
grades          False
dtype: bool
```

[ ]:
```
#visualizing the grades per number of students

plt.figure(figsize=(8,6))
sns.countplot(stu["grades"], order=["low","average","high"], palette='Set1')
plt.title('Final Grade - Number of Students',fontsize=20)
plt.xlabel('Final Grade', fontsize=16)
plt.ylabel('Number of Student', fontsize=16)
```

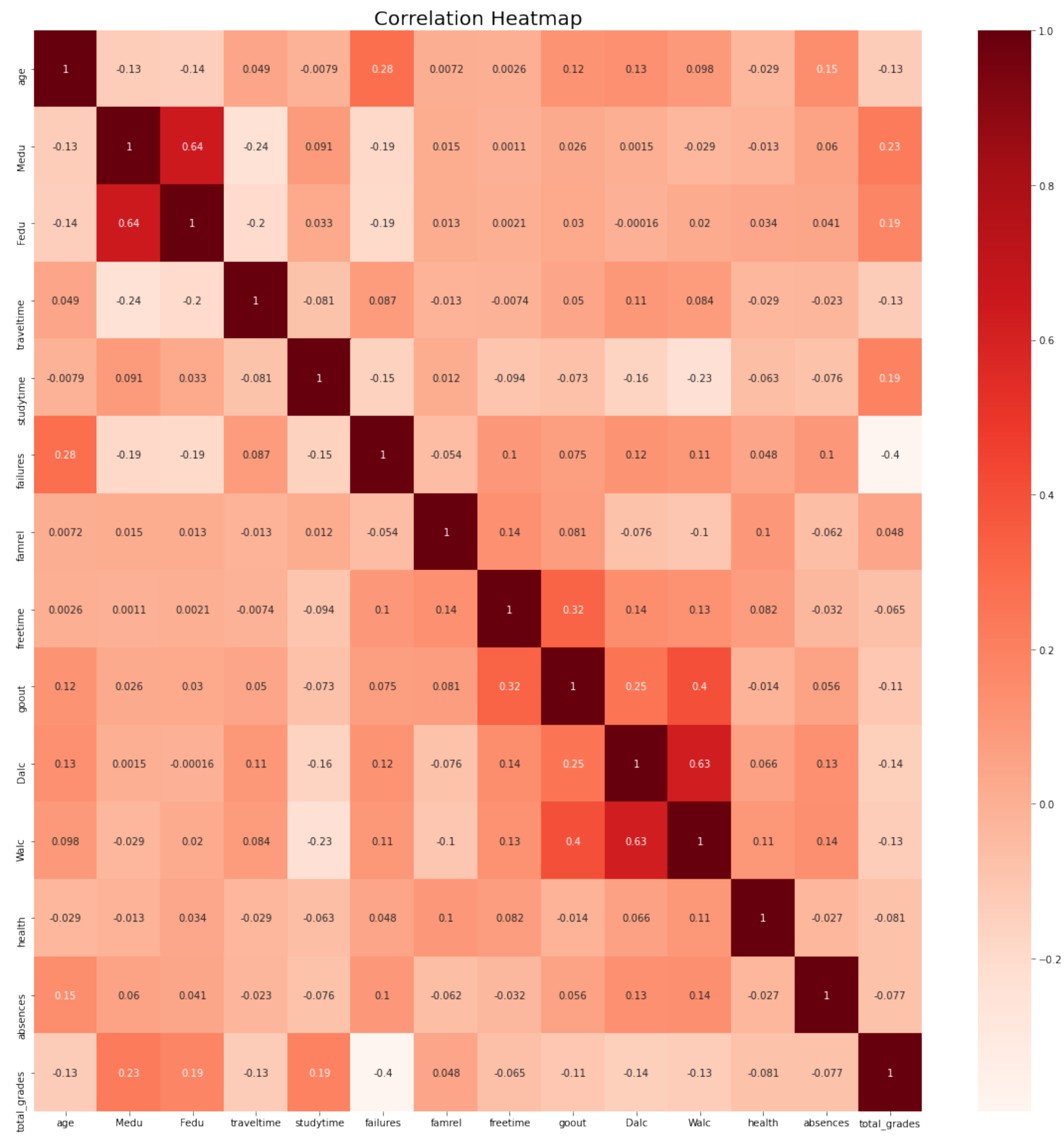
```
/home/el-sunais/anaconda3/lib/python3.8/site-packages/seaborn/_decorators.py:36:
FutureWarning: Pass the following variable as a keyword arg: x. From version
0.12, the only valid positional argument will be `data`, and passing other
arguments without an explicit keyword will result in an error or
misinterpretation.
  warnings.warn(
```

[ ]:
```
Text(0, 0.5, 'Number of Student')
```

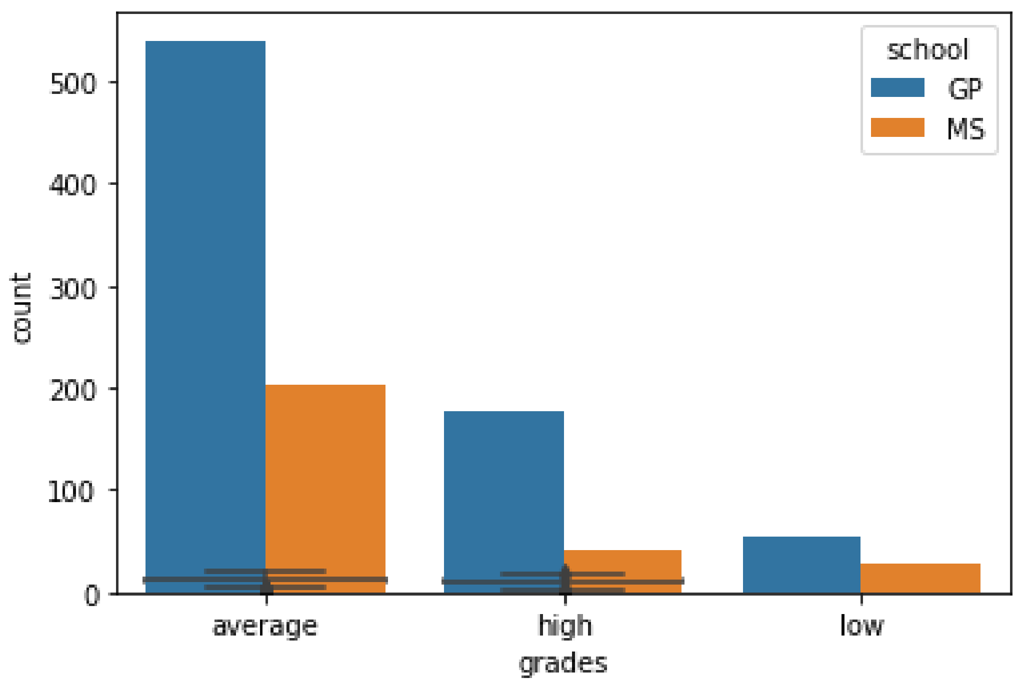


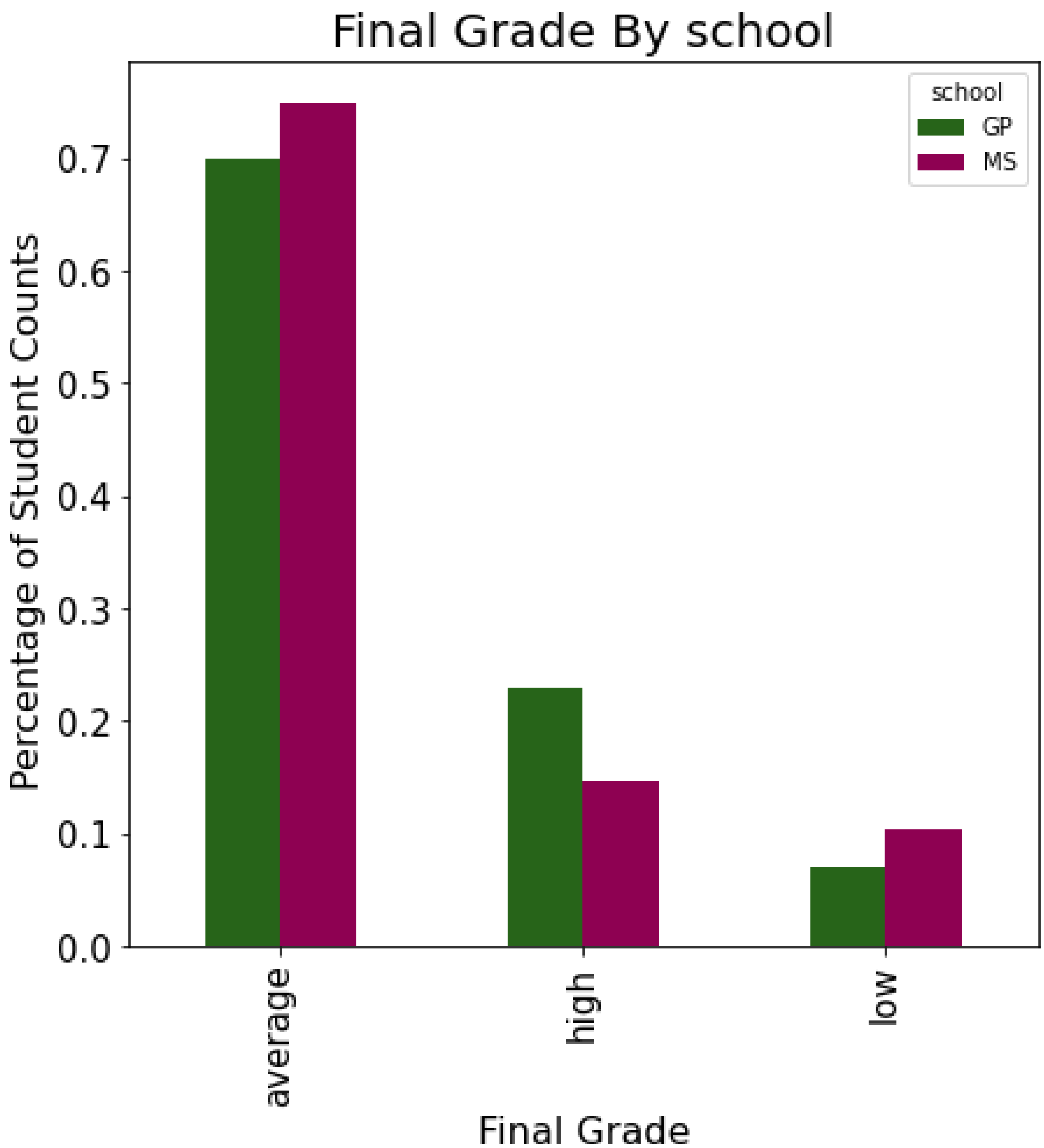
[ ]:
```
#describing by correlation matrix

corr=stu.corr()
plt.figure(figsize=(20,20))
sns.heatmap(corr, annot=True, cmap="Reds")
plt.title('Correlation Heatmap', fontsize=20)
```

[ ]: Text(0.5, 1.0, 'Correlation Heatmap')

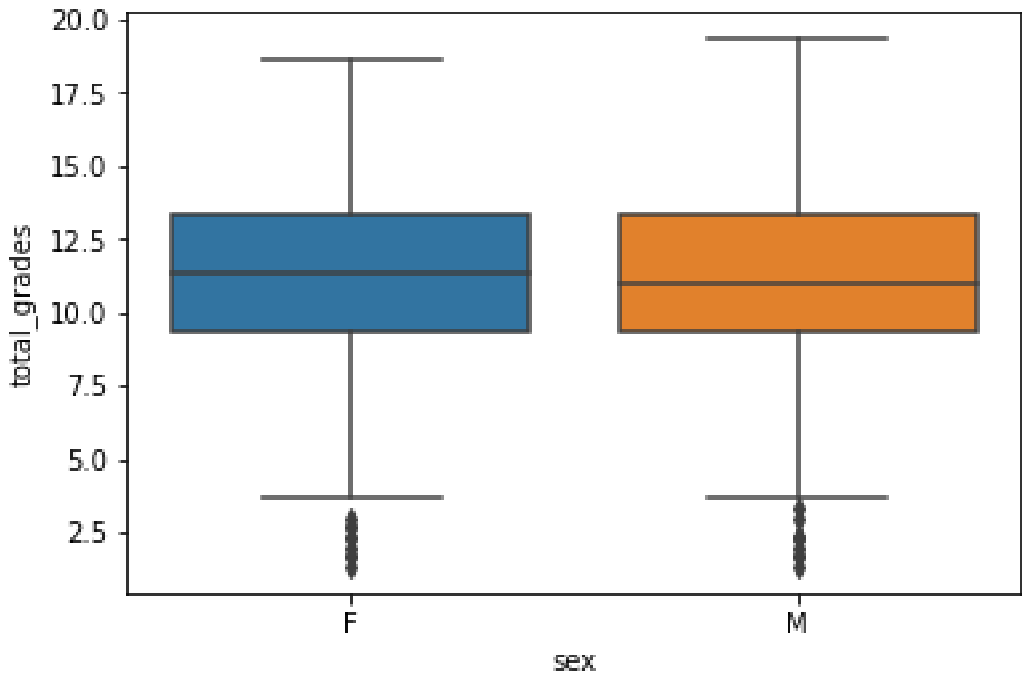


[ ]:
```
#comparing school with grades
sns.boxplot(x="school", y="total_grades", data=stu)

school_counts=stu["school"].value_counts().to_frame()
school_counts.rename(columns={"school":"school_counts"},inplace=True)
school_counts.index.name='school'

school_sns=sns.countplot(hue=stu["school"],x=stu["grades"],data=stu)

#crosstab is expanded form of value counts the the factors inside any variables
perc=(lambda col:col/col.sum())
index=["average","high","low"]
schooltab1=pd.crosstab(columns=stu.school,index=stu.grades)

school_perc=schooltab1.apply(perc).reindex(index)

school_perc.plot.bar(colormap="PiYG_r",fontsize=15,figsize=(7,7))
plt.title('Final Grade By school', fontsize=20)
plt.ylabel('Percentage of Student Counts ', fontsize=16)
plt.xlabel('Final Grade', fontsize=16)
plt.show()

#so by graph we know that school has impact on grades of students
```

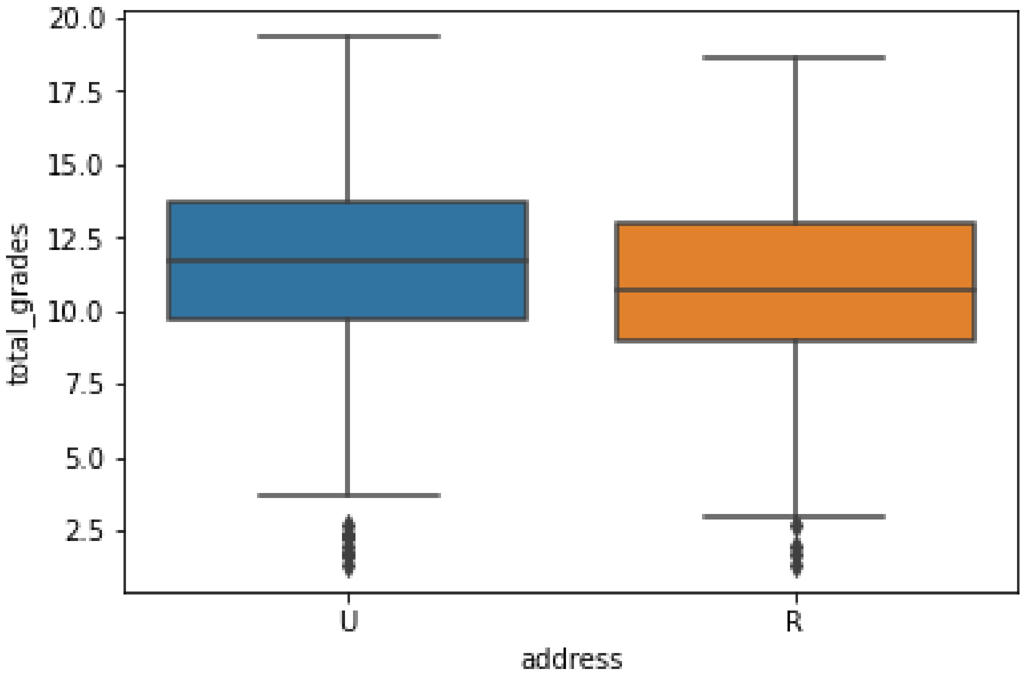


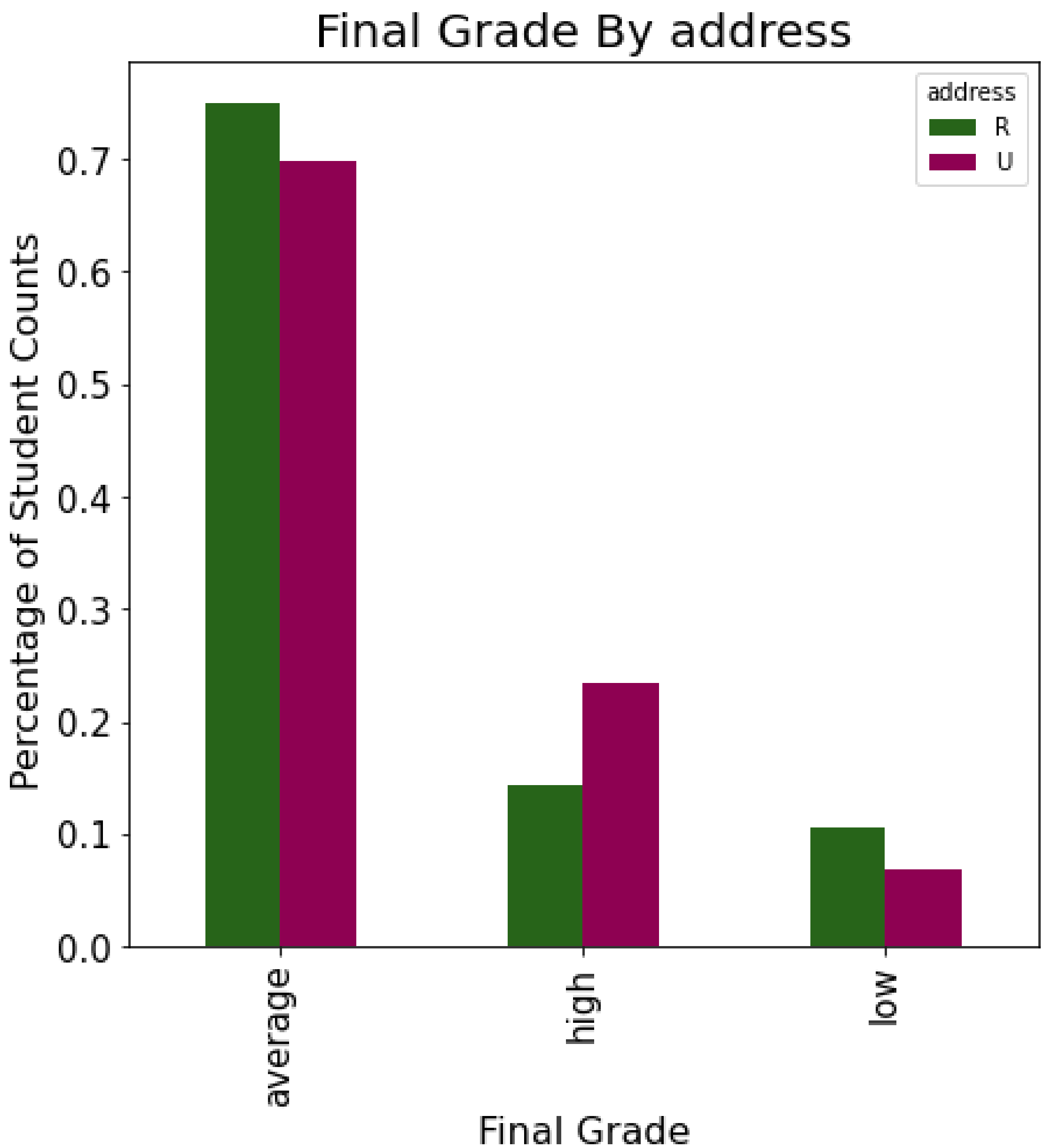


[ ]:
```
#comparing sex with grades
sns.boxplot(x="sex", y="total_grades", data=stu)
school_counts=stu["sex"].value_counts()

#as the graph of sex nearly overlaps so it will not have impact on grades
stu=stu.drop(["sex"],axis=1)
```



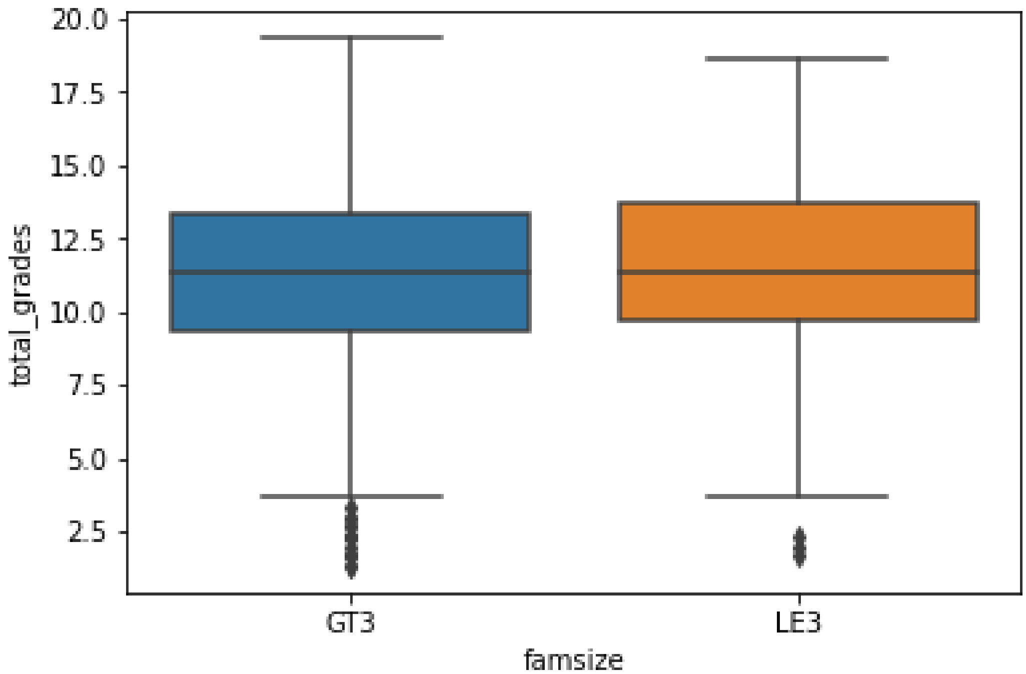
[ ]:
```
#comparing address with grades
sns.boxplot(x="address", y="total_grades", data=stu)
index=["average","high","low"]
addresstab1=pd.crosstab(columns=stu.address,index=stu.grades)

address_perc=addresstab1.apply(perc).reindex(index)

address_perc.plot.bar(colormap="PiYG_r",fontsize=15,figsize=(7,7))
plt.title('Final Grade By address', fontsize=20)
plt.ylabel('Percentage of Student Counts ', fontsize=16)
plt.xlabel('Final Grade', fontsize=16)
plt.show()
#address is factor for the grades
```

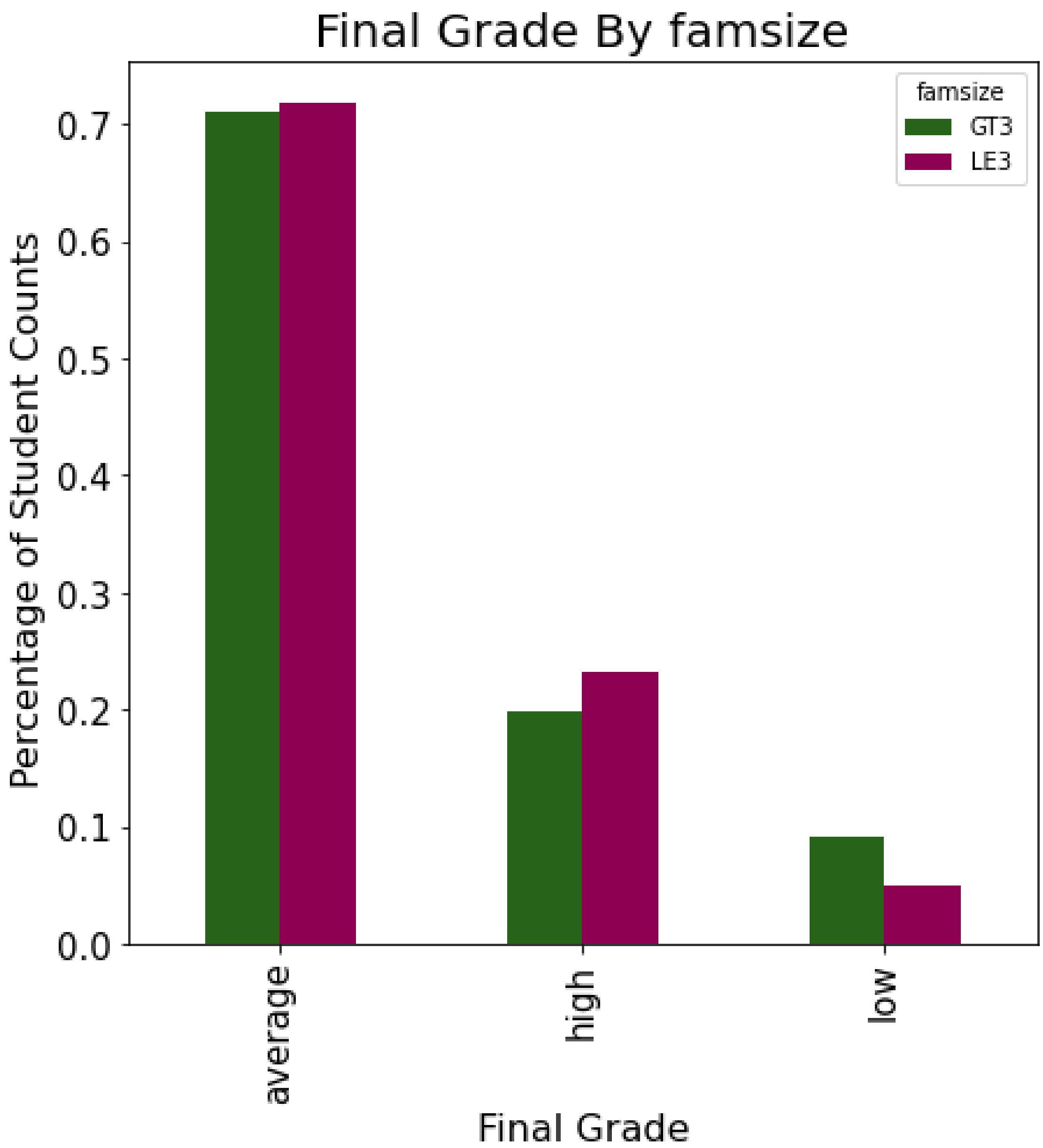

20.0
17.5
15.0
12.5
10.0
7.5
5.0
2.5
total_grades
U
R
address



[ ]:
```
#comparing famsize with grades
sns.boxplot(x="famsize", y="total_grades", data=stu)
famsizetab1=pd.crosstab(columns=stu.famsize,index=stu.grades)

famsize_perc=famsizetab1.apply(perc).reindex(index)

famsize_perc.plot.bar(colormap="PiYG_r",fontsize=15,figsize=(7,7))
plt.title('Final Grade By famsize', fontsize=20)
plt.ylabel('Percentage of Student Counts ', fontsize=16)
```

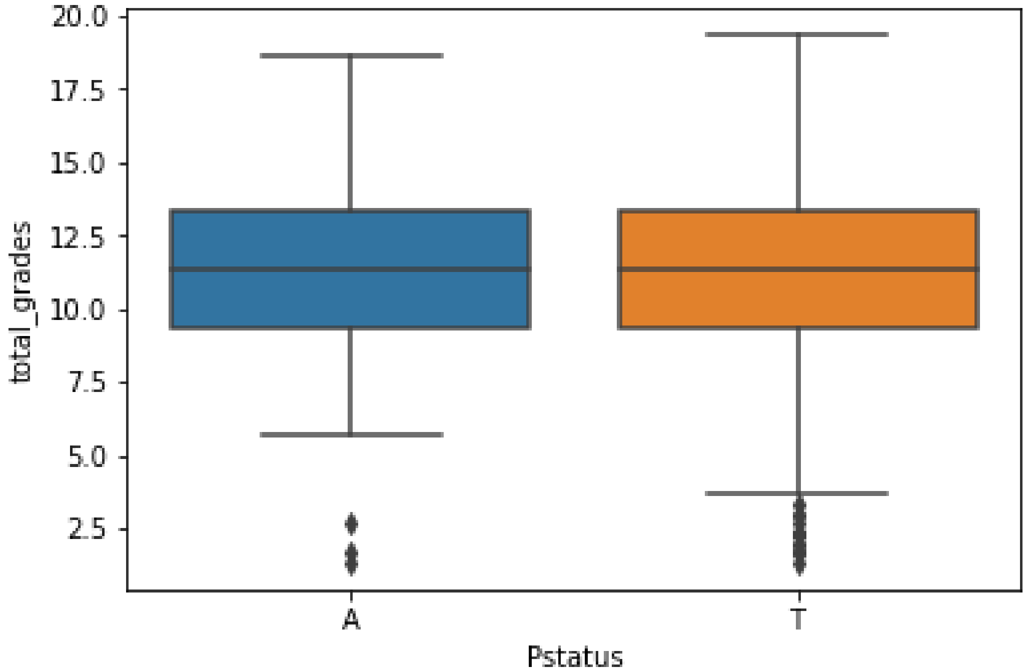
```python
plt.xlabel('Final Grade', fontsize=16)
plt.show()
#famsize has great impact on grades
```

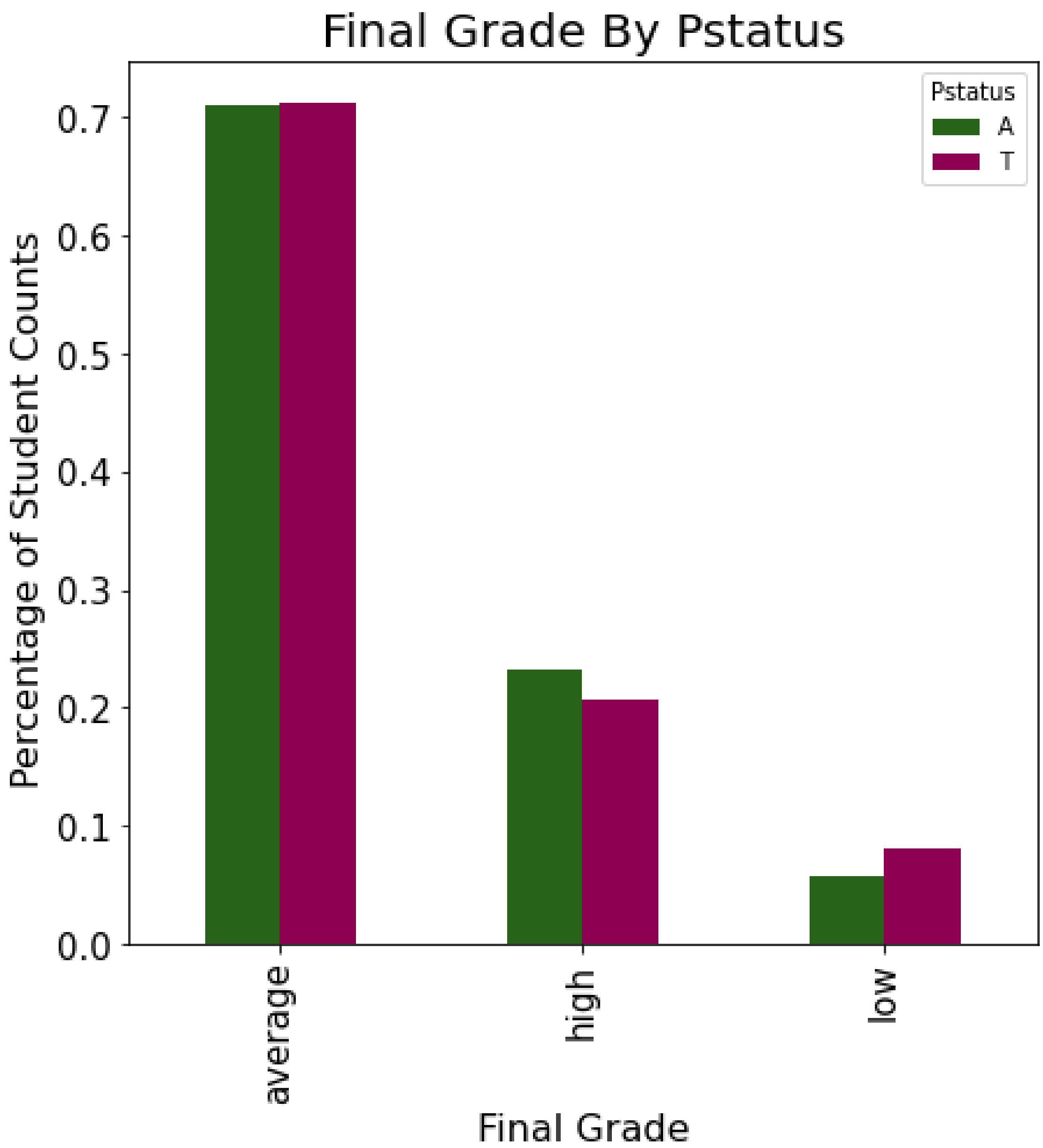




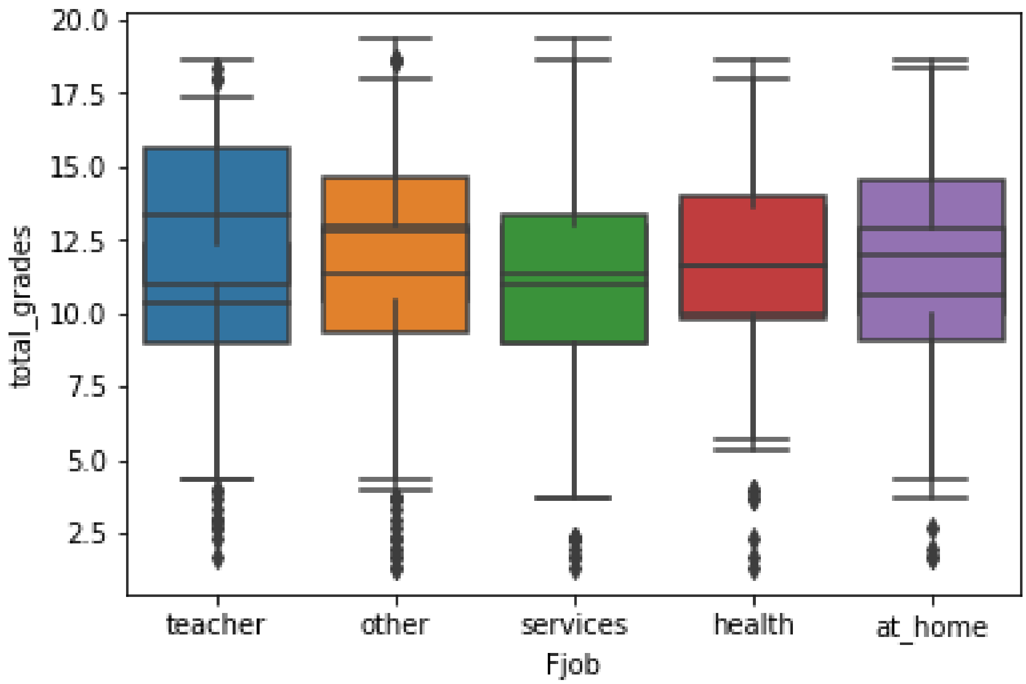
[ ]:
```
#comparing pstatus with grades
sns.boxplot(x="Pstatus", y="total_grades", data=stu)
Pstatustab1=pd.crosstab(columns=stu.Pstatus,index=stu.grades)

Pstatus_perc=Pstatustab1.apply(perc).reindex(index)

Pstatus_perc.plot.bar(colormap="PiYG_r",fontsize=15,figsize=(7,7))
plt.title('Final Grade By Pstatus', fontsize=20)
plt.ylabel('Percentage of Student Counts ', fontsize=16)
```

```
plt.xlabel('Final Grade', fontsize=16)
plt.show()
#it is not a good factor
```



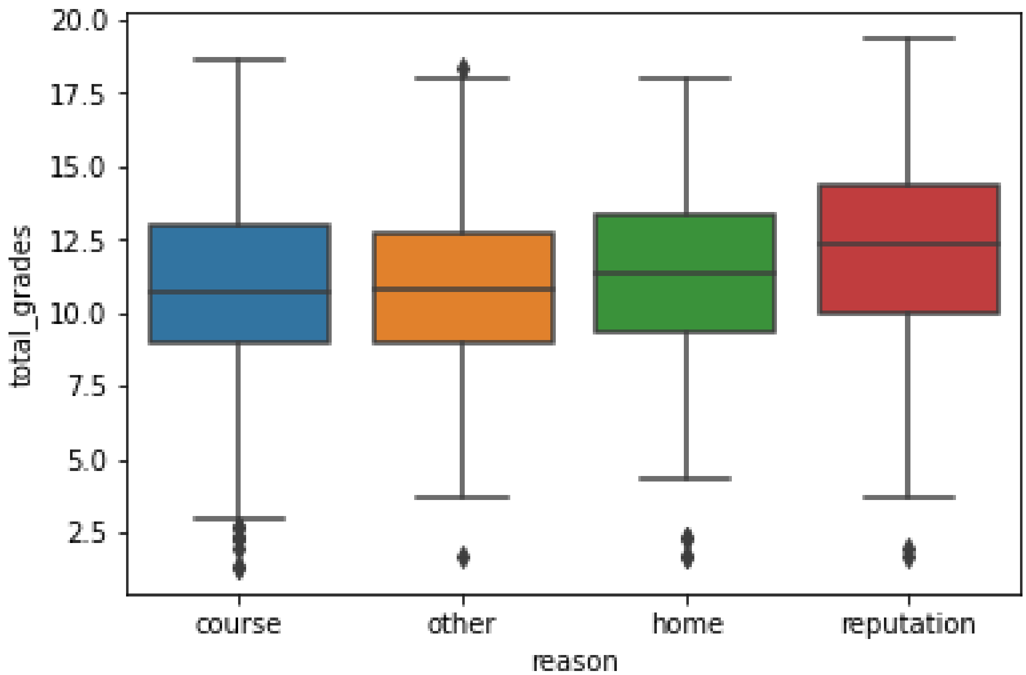


[ ]:
```
#comparing jobs
sns.boxplot(x="Mjob", y="total_grades", data=stu)
sns.boxplot(x="Fjob", y="total_grades", data=stu)
stu1=stu[["Fjob","Mjob","total_grades"]]
job_grp=stu1.groupby(['Mjob','Fjob'],as_index=False).mean()
job_pivot=job_grp.pivot(index='Mjob',columns='Fjob',values='total_grades')

#so father and mother jobs has great impact on grades
```

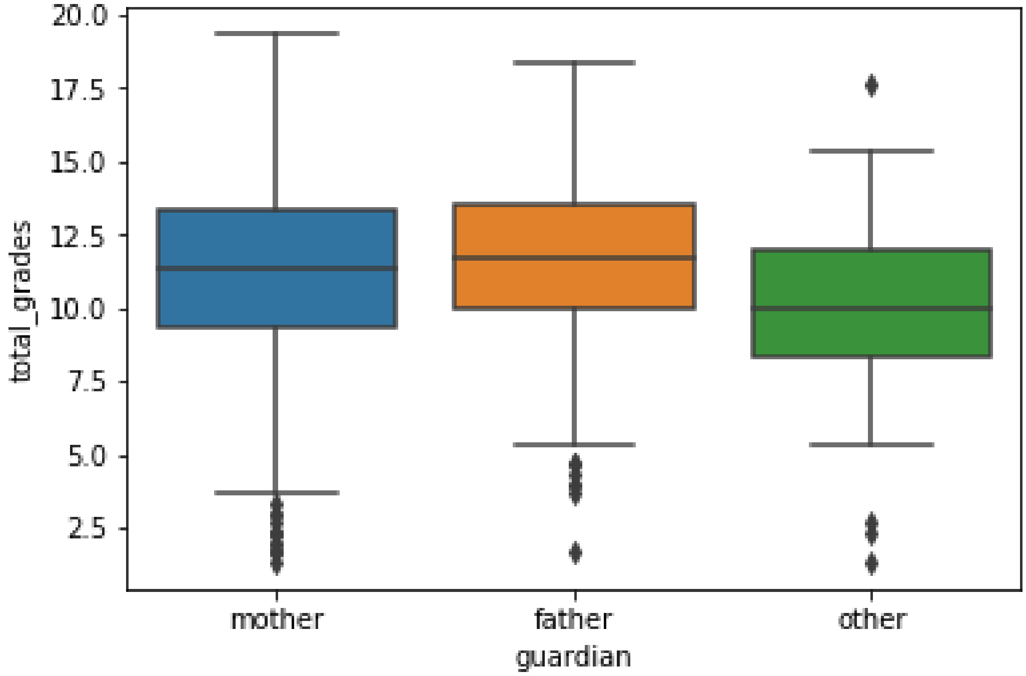


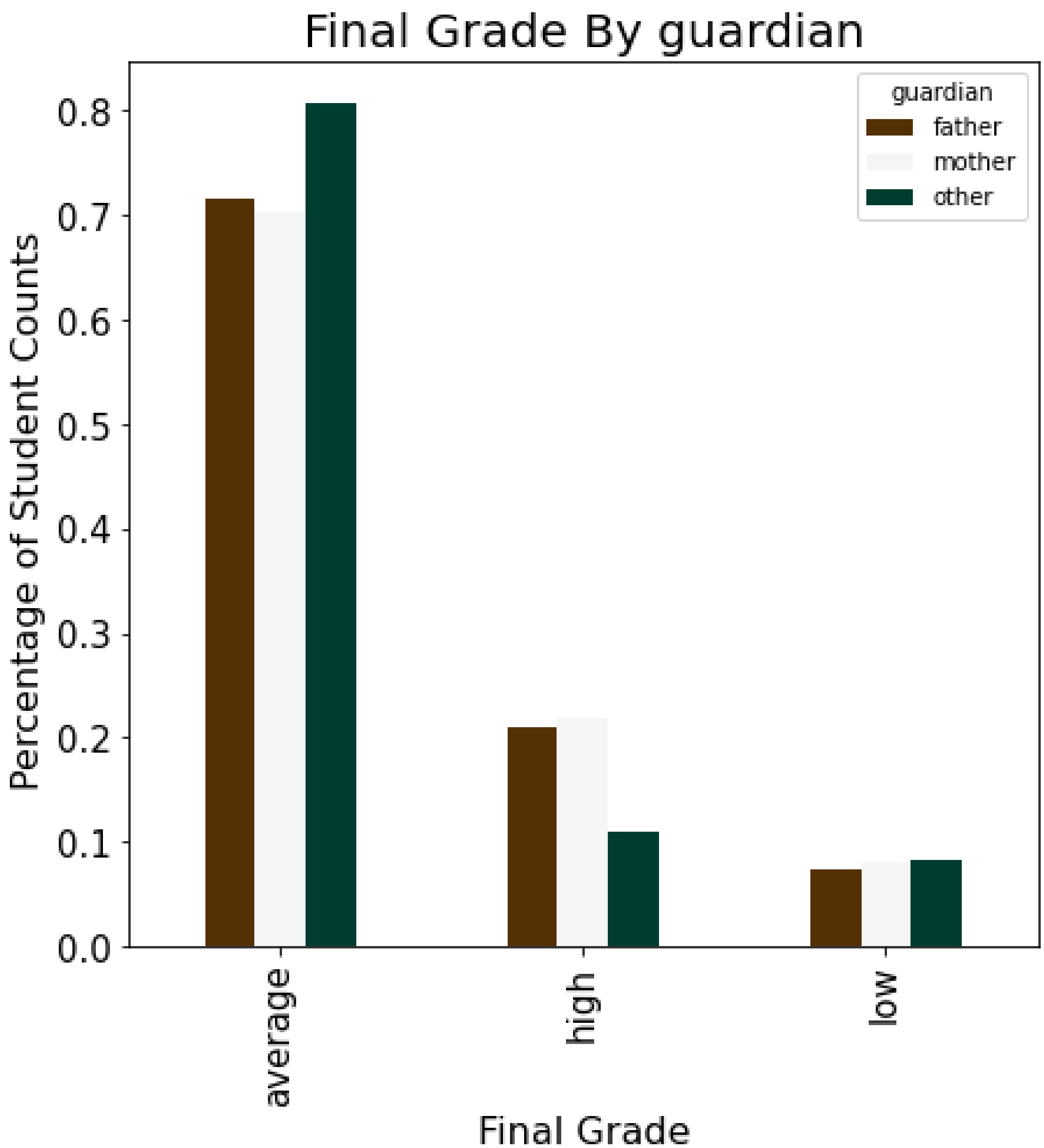
[ ]:
```
#comparing reasons
sns.boxplot(x="reason", y="total_grades", data=stu)

#it has impact on the grades
```

[ ]: <AxesSubplot:xlabel='reason', ylabel='total_grades'>

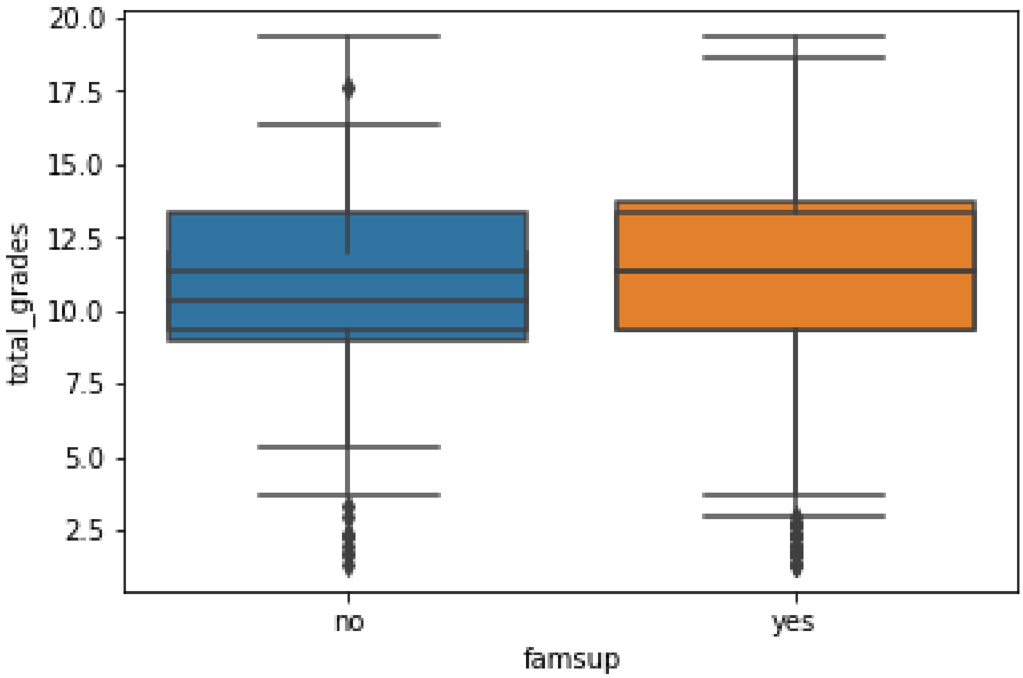


[ ]:
```
#comparing guardians
sns.boxplot(x="guardian", y="total_grades", data=stu)

guardiantab1=pd.crosstab(columns=stu.guardian,index=stu.grades)
guardian_perc=guardiantab1.apply(perc).reindex(index)
guardian_perc.plot.bar(colormap="BrBG",fontsize=15,figsize=(7,7))
plt.title('Final Grade By guardian', fontsize=20)
plt.ylabel('Percentage of Student Counts ', fontsize=16)
plt.xlabel('Final Grade', fontsize=16)
plt.show()

#so guardian has grat impact on grades
```

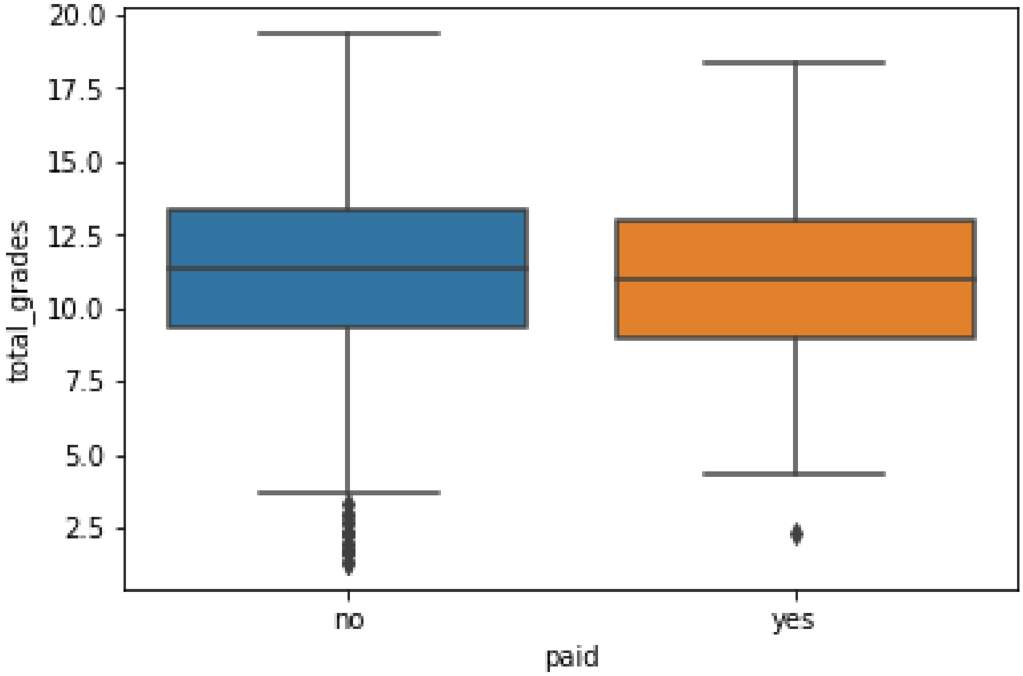

20.0
17.5
15.0
12.5
10.0
7.5
5.0
2.5
total_grades
mother
father
other
guardian

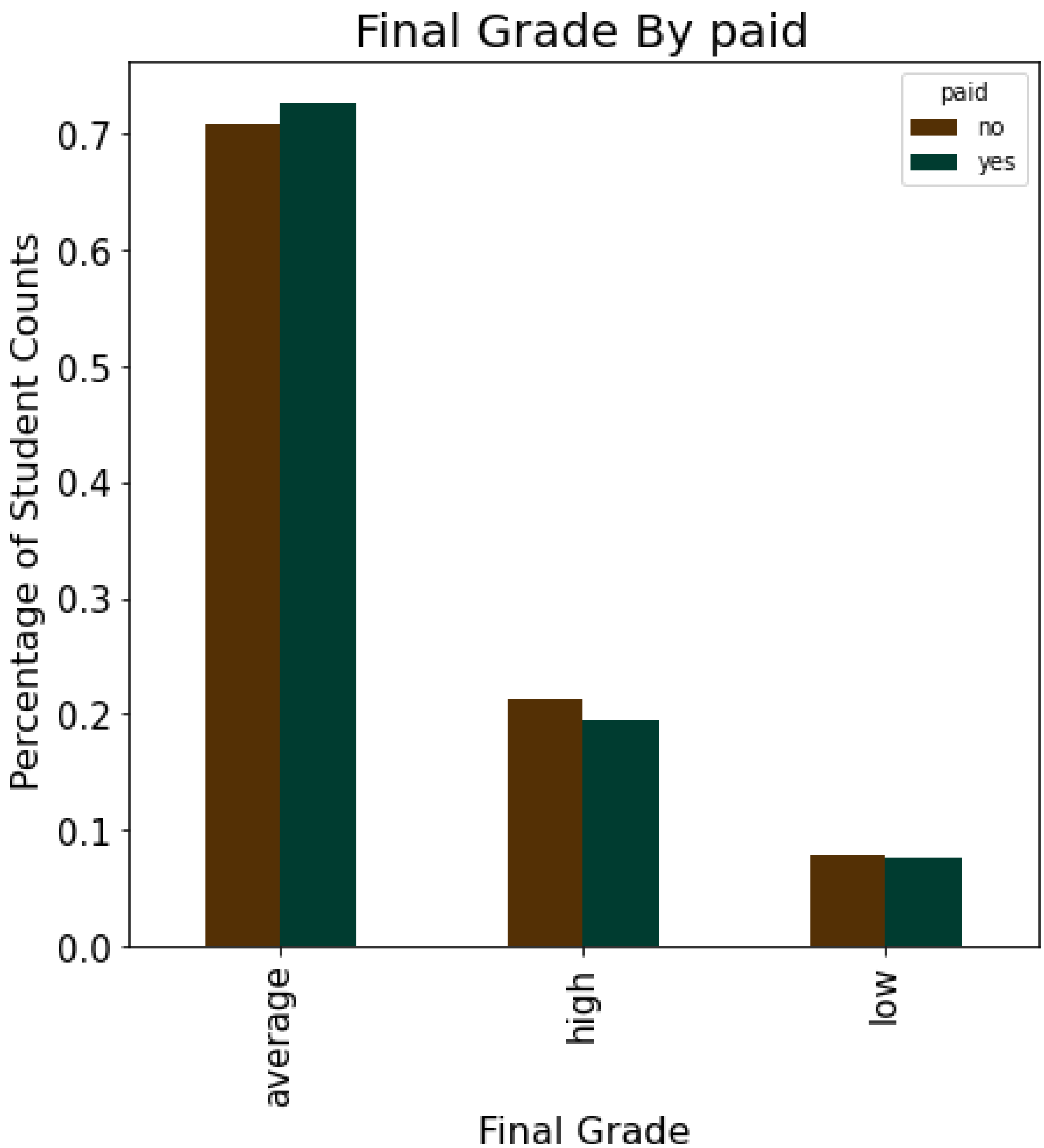


[ ]:
```
#support of family and school
sns.boxplot(x="schoolsup", y="total_grades", data=stu)

#it is the important factor
sns.boxplot(x="famsup", y="total_grades", data=stu)
stu[["famsup","total_grades"]].groupby(["famsup"],as_index=False).mean()

#famsup does not have great impact on grades
stu=stu.drop(["famsup"],axis=1)
```

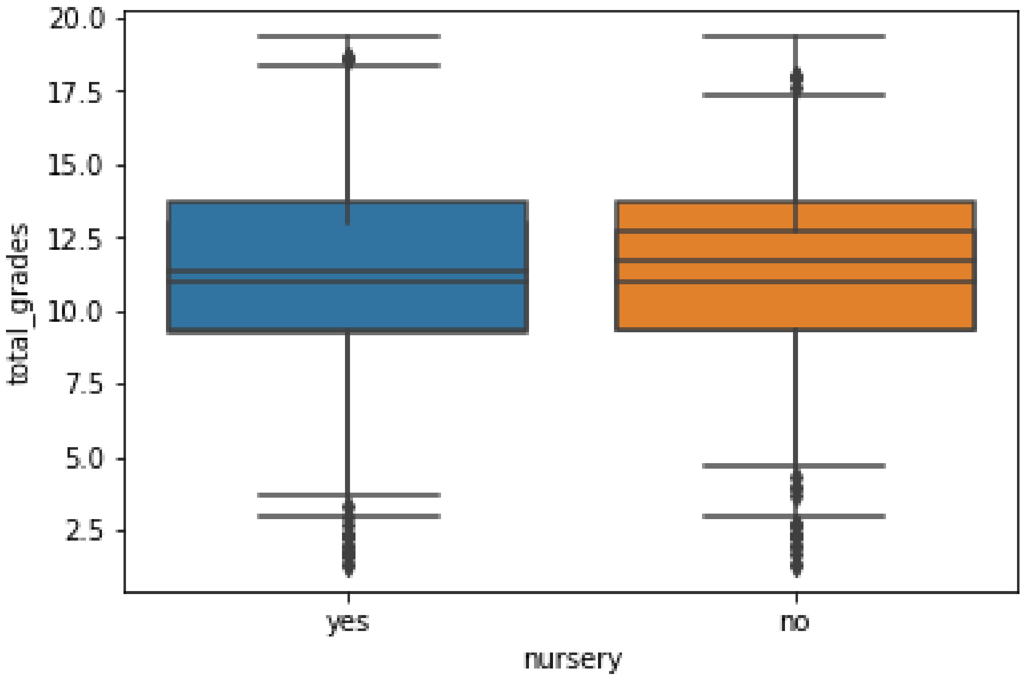


[ ]:
```
#comparing paid attributes
sns.boxplot(x="paid", y="total_grades", data=stu)
paidtab1=pd.crosstab(columns=stu.paid,index=stu.grades)
paid_perc=paidtab1.apply(perc).reindex(index)
paid_perc.plot.bar(colormap="BrBG",fontsize=15,figsize=(7,7))
plt.title('Final Grade By paid', fontsize=20)
plt.ylabel('Percentage of Student Counts ', fontsize=16)
plt.xlabel('Final Grade', fontsize=16)
plt.show()

#paid does not have much influence on grades so
stu=stu.drop(["paid"],axis=1)
```


20.0
17.5
15.0
12.5
10.0
7.5
5.0
2.5
total_grades
no
yes
paid

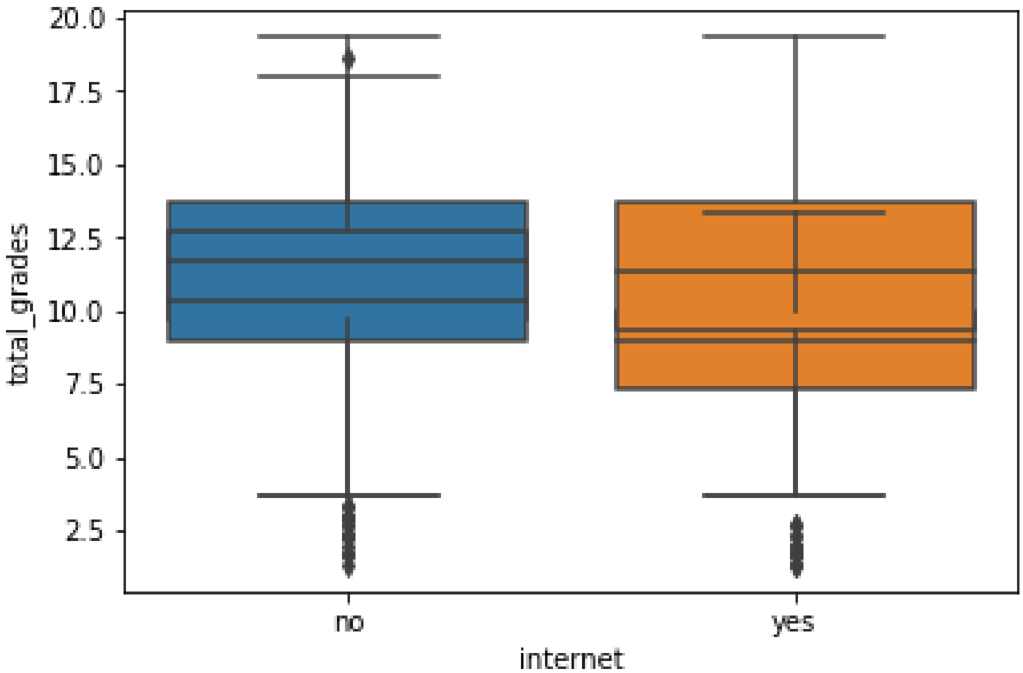


[ ]:
```
sns.boxplot(x="activities", y="total_grades", data=stu)
#is has great impact on student peforamnce

sns.boxplot(x="nursery", y="total_grades", data=stu)
#it does not have great impact on performance

stu=stu.drop(["nursery"],axis=1)
```

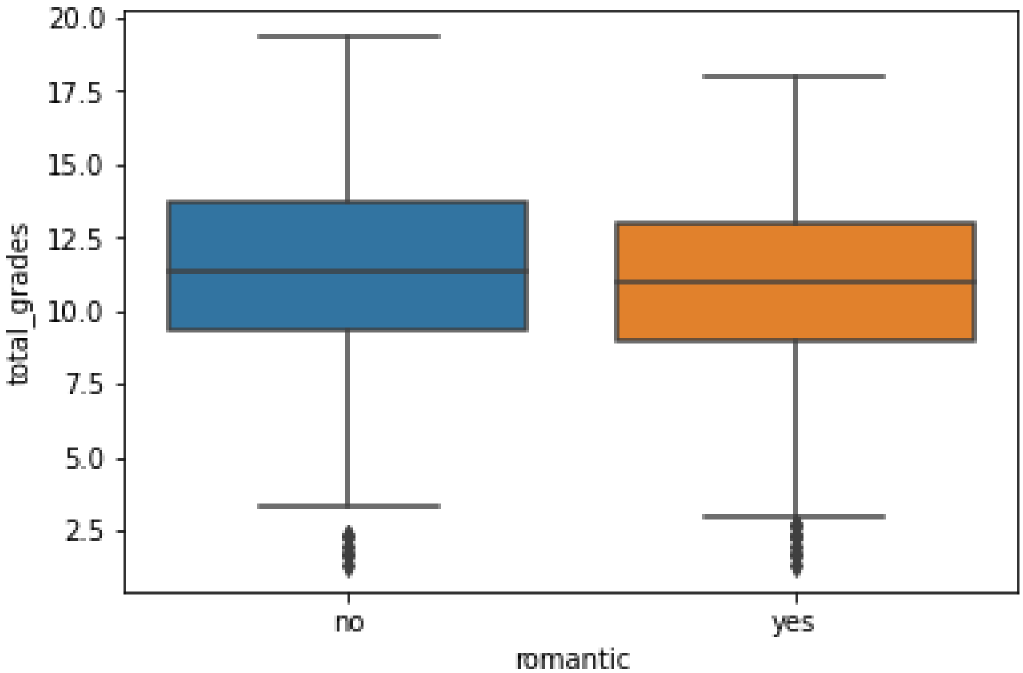


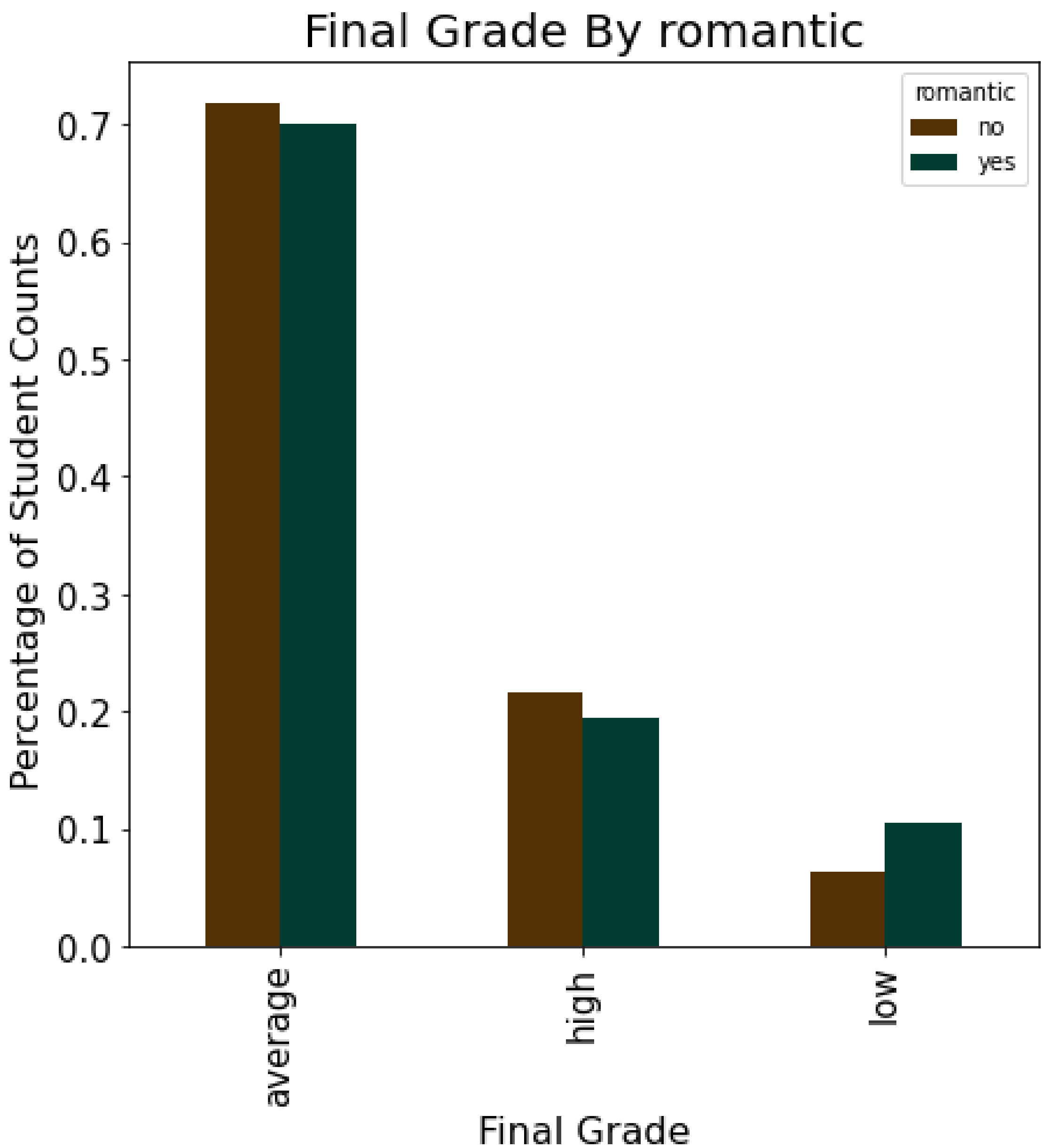
[ ]:
```
#comparing if higher educatiob of students have impact on performance
sns.boxplot(x="higher", y="total_grades", data=stu)

sns.boxplot(x="internet", y="total_grades", data=stu)
#internet also have great impact on performance of individual
```

[ ]: <AxesSubplot:xlabel='internet', ylabel='total_grades'>



[ ]:
```
#high school romance impact on the performance of students
sns.boxplot(x="romantic", y="total_grades", data=stu)
romantictab1=pd.crosstab(columns=stu.romantic,index=stu.grades)
romantic_perc=romantictab1.apply(perc).reindex(index)
romantic_perc.plot.bar(colormap="BrBG",fontsize=15,figsize=(7,7))
plt.title('Final Grade By romantic', fontsize=20)
plt.ylabel('Percentage of Student Counts ', fontsize=16)
plt.xlabel('Final Grade', fontsize=16)
plt.show()

#so high school romance leads to decline in performance of students
#beware of that
```


20.0
17.5
15.0
12.5
10.0
7.5
5.0
2.5
total_grades
no
yes
romantic



[ ]:
```
#labels of remaining features
stu.columns
```

[ ]:
```
Index(['school', 'age', 'address', 'famsize', 'Pstatus', 'Medu', 'Fedu',
       'Mjob', 'Fjob', 'reason', 'guardian', 'traveltime', 'studytime',
       'failures', 'schoolsup', 'activities', 'higher', 'internet', 'romantic',
       'famrel', 'freetime', 'goout', 'Dalc', 'Walc', 'health', 'absences',
       'total_grades', 'grades'],
      dtype='object')
```

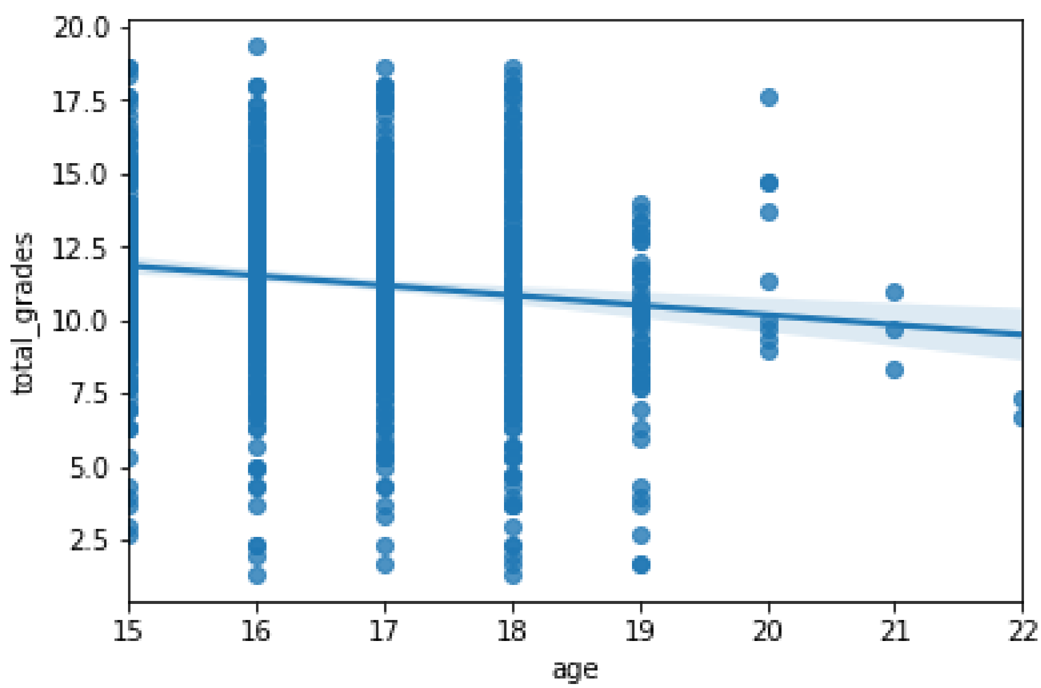
```
[ ]: #creating dummies to replace string with categorical

stu1=pd.
 ↪get_dummies(stu,columns=["school","address","famsize","Pstatus","Mjob","Fjob","reason","gua
 ↪'schoolsup', 'activities', 'higher', 'internet', 'romantic' ])
test_stu1=stu1["grades"]
teststu1=stu1["total_grades"]
train_stu1=stu1.drop(['total_grades','grades'],axis=1)
train_stu=train_stu1.values
train_stu1
```

```
[ ]:      age  Medu  Fedu  traveltime  studytime  failures  famrel  freetime  \
     0     18     4     4           2          2         0       4         3
     1     17     1     1           1          2         0       5         3
     2     15     1     1           1          2         0       4         3
     3     15     4     2           1          3         0       3         2
     4     16     3     3           1          2         0       4         3
     ..   …    …    …          …         …        …      …        …
     390   20     2     2           1          2         2       5         5
     391   17     3     1           2          1         0       2         4
     392   21     1     1           1          1         3       5         5
     393   18     3     2           3          1         0       4         4
     394   19     1     1           1          1         0       3         2

          goout  Dalc  …  schoolsup_no  schoolsup_yes  activities_no  \
     0        4     1  …             0              1              1
     1        3     1  …             1              0              1
     2        2     2  …             0              1              1
     3        2     1  …             1              0              0
     4        2     1  …             1              0              1
     ..     …   …  …           …            …            …
     390      4     4  …             1              0              1
     391      5     3  …             1              0              1
     392      3     3  …             1              0              1
     393      1     3  …             1              0              1
     394      3     3  …             1              0              1

          activities_yes  higher_no  higher_yes  internet_no  internet_yes  \
     0                 0          0           1            1             0
     1                 0          0           1            0             1
     2                 0          0           1            0             1
     3                 1          0           1            0             1
     4                 0          0           1            1             0
     ..              …        …         …          …           …
     390               0          0           1            1             0
     391               0          0           1            0             1
     392               0          0           1            1             0
```

```
393                 0           0             1             0              1
394                 0           0             1             0              1

     romantic_no  romantic_yes
0              1             0
1              1             0
2              1             0
3              0             1
4              1             0
..           …             …
390            1             0
391            1             0
392            1             0
393            1             0
394            1             0

[1044 rows x 48 columns]
```

[ ]:
```python
#comparing age with marks
sns.regplot(x="age",y="total_grades",data=stu)
```

[ ]: <AxesSubplot:xlabel='age', ylabel='total_grades'>



[ ]:
```
#pearson coeffiecient
stu[["age","total_grades"]].corr()

#p-value
pearson_coef , p_value=stats.pearsonr(stu["age"],stu["total_grades"])
print("The Pearson Correlation Coefficient is", pearson_coef, " with a P-value␣
↪of P =", p_value)

#age is not a good factor
```

```
The Pearson Correlation Coefficient is -0.12913452270388814  with a P-value of P
= 2.8516659922093794e-05
```

[ ]:
```
#using backward elimination for finding optimal featrures

#if p-value is greater than 0.6 than we will removethat feature
X=np.append(arr=np.ones((1044,1)).astype(int),values=train_stu,axis=1)
X_opt = X[:, [0, 1, 2, 3, 4,5,6,7,8,9,10,11,12,13]]
regressor_ols=sm.OLS(endog=teststu1,exog=X_opt).fit()
regressor_ols.summary()

X_opt = X[:, [0,2,3,4,5,6,7,8,9,10,11,12,13]]
regressor_ols=sm.OLS(endog=teststu1,exog=X_opt).fit()
regressor_ols.summary()

X_opt = X[:, [0,2,3,4,5,6,7,9,10,11,12,13]]
regressor_ols=sm.OLS(endog=teststu1,exog=X_opt).fit()
regressor_ols.summary()
```

[ ]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:           total_grades   R-squared:                       0.215
Model:                            OLS   Adj. R-squared:                  0.207
Method:                 Least Squares   F-statistic:                     25.74
Date:                Mon, 07 Mar 2022   Prob (F-statistic):           1.53e-47
Time:                        16:50:04   Log-Likelihood:                -2574.8
No. Observations:                1044   AIC:                             5174.
Df Residuals:                    1032   BIC:                             5233.
Df Model:                          11
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         10.9881      0.646     17.005      0.000       9.720      12.256
x1             0.3571      0.105      3.394      0.001       0.151       0.564
```

```
x2              0.1062      0.106      0.998      0.318      -0.103       0.315
x3             -0.1982      0.126     -1.570      0.117      -0.446       0.050
x4              0.4150      0.111      3.743      0.000       0.197       0.632
x5             -1.6060      0.142    -11.344      0.000      -1.884      -1.328
x6              0.1104      0.097      1.133      0.258      -0.081       0.302
x7             -0.1906      0.085     -2.235      0.026      -0.358      -0.023
x8             -0.2267      0.126     -1.798      0.072      -0.474       0.021
x9              0.0377      0.096      0.391      0.696      -0.152       0.227
x10            -0.1392      0.064     -2.190      0.029      -0.264      -0.014
x11            -0.0185      0.015     -1.269      0.205      -0.047       0.010
==============================================================================
Omnibus:                       40.630   Durbin-Watson:                   1.886
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               48.582
Skew:                          -0.426   Prob(JB):                     2.82e-11
Kurtosis:                       3.625   Cond. No.                         73.3
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
"""
```

[ ]:
```python
#now we merge our training data
train_x=np.concatenate((X_opt,X[:,14:49]),axis=1)
stu[["Medu","total_grades"]].corr()
stu[["Fedu","total_grades"]].corr()
```

[ ]:

	Fedu	total_grades
Fedu	1.00000	0.18661
total_grades	0.18661	1.00000

[ ]:
```python
#final feature extraction cleaning
train_stu2=train_stu1.drop(["age","freetime"],axis=1)
np1=[1 for i in range(0,1044)]
train_stu2.insert(loc=0,column= "noimprotance", value=np1)
```

[ ]:
```python
#now after getting the proper features we will split the data
train_stu2.columns
train_stu2.head(30)
```

[ ]:

	noimprotance	Medu	Fedu	traveltime	studytime	failures	famrel	goout	\
0	1	4	4	2	2	0	4	4	
1	1	1	1	1	2	0	5	3	
2	1	1	1	1	2	0	4	2	
3	1	4	2	1	3	0	3	2	
4	1	3	3	1	2	0	4	2	
5	1	4	3	1	2	0	5	2	

```
6             1    2    2          1          2         0       4     4
7             1    4    4          2          2         0       4     4
8             1    3    2          1          2         0       4     2
9             1    3    4          1          2         0       5     1
10            1    4    4          1          2         0       3     3
11            1    2    1          3          3         0       5     2
12            1    4    4          1          1         0       4     3
13            1    4    3          2          2         0       5     3
14            1    2    2          1          3         0       4     2
15            1    4    4          1          1         0       4     4
16            1    4    4          1          3         0       3     3
17            1    3    3          3          2         0       5     2
18            1    3    2          1          1         3       5     5
19            1    4    3          1          1         0       3     3
20            1    4    3          1          2         0       4     1
21            1    4    4          1          1         0       5     2
22            1    4    2          1          2         0       4     1
23            1    2    2          2          2         0       5     4
24            1    2    4          1          3         0       4     2
25            1    2    2          1          1         0       1     2
26            1    2    2          1          1         0       4     2
27            1    4    2          1          1         0       2     4
28            1    3    4          1          2         0       5     3
29            1    4    4          1          2         0       4     5

    Dalc  Walc  …  schoolsup_no  schoolsup_yes  activities_no  \
0      1     1  …             0              1              1
1      1     1  …             1              0              1
2      2     3  …             0              1              1
3      1     1  …             1              0              0
4      1     2  …             1              0              1
5      1     2  …             1              0              0
6      1     1  …             1              0              1
7      1     1  …             0              1              1
8      1     1  …             1              0              1
9      1     1  …             1              0              0
10     1     2  …             1              0              1
11     1     1  …             1              0              0
12     1     3  …             1              0              0
13     1     2  …             1              0              1
14     1     1  …             1              0              1
15     1     2  …             1              0              1
16     1     2  …             1              0              0
17     1     1  …             0              1              0
18     2     4  …             1              0              0
19     1     3  …             1              0              0
20     1     1  …             1              0              1
```

```
21       1       1  …               1               0               1
22       1       3  …               1               0               0
23       2       4  …               1               0               0
24       1       1  …               0               1               0
25       1       3  …               1               0               1
26       1       2  …               1               0               1
27       2       4  …               1               0               1
28       1       1  …               0               1               0
29       5       5  …               1               0               0

    activities_yes  higher_no  higher_yes  internet_no  internet_yes  \
0                0          0           1            1             0
1                0          0           1            0             1
2                0          0           1            0             1
3                1          0           1            0             1
4                0          0           1            1             0
5                1          0           1            0             1
6                0          0           1            0             1
7                0          0           1            1             0
8                0          0           1            0             1
9                1          0           1            0             1
10               0          0           1            0             1
11               1          0           1            0             1
12               1          0           1            0             1
13               0          0           1            0             1
14               0          0           1            0             1
15               0          0           1            0             1
16               1          0           1            0             1
17               1          0           1            1             0
18               1          0           1            0             1
19               1          0           1            0             1
20               0          0           1            0             1
21               0          0           1            0             1
22               1          0           1            0             1
23               1          0           1            0             1
24               1          0           1            0             1
25               0          0           1            0             1
26               0          0           1            0             1
27               0          0           1            0             1
28               1          0           1            0             1
29               1          0           1            0             1

    romantic_no  romantic_yes
0             1             0
1             1             0
2             1             0
3             0             1
```

```
4     1    0
5     1    0
6     1    0
7     1    0
8     1    0
9     1    0
10    1    0
11    1    0
12    1    0
13    1    0
14    0    1
15    1    0
16    1    0
17    1    0
18    1    0
19    1    0
20    1    0
21    1    0
22    1    0
23    1    0
24    1    0
25    1    0
26    1    0
27    1    0
28    1    0
29    0    1

[30 rows x 47 columns]
```

[ ]:
```
#splitting dataset into training and testing data
X_train, X_test, y_train, y_test = train_test_split(train_x,test_stu1,␣
↪test_size = 0.2, random_state = 0)
```

[ ]:
```
#features by importance using RFC
rf_classifier=RandomForestClassifier(n_estimators=80,criterion="entropy",random_state=0)
rf_classifier.fit(X_train,y_train)

sv_classifier = SVC(kernel = 'rbf', random_state = 0)
sv_classifier.fit(X_train, y_train)

lr_classifier=LogisticRegression(random_state=0)
lr_classifier.fit(X_train,y_train)

kn_classifier=KNeighborsClassifier(n_neighbors=5,metric='minkowski',p=2)
kn_classifier.fit(X_train,y_train)

nb_classifier=GaussianNB()
```

```
nb_classifier.fit(X_train, y_train)
```

```
/home/el-sunais/anaconda3/lib/python3.8/site-
packages/sklearn/linear_model/_logistic.py:763: ConvergenceWarning: lbfgs failed
to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  n_iter_i = _check_optimize_result(
```

[ ]: GaussianNB()

[ ]:

```
#Predictions Performance Scores

rf_score = rf_classifier.score(X_test, y_test)
sv_score = sv_classifier.score(X_test, y_test)
lr_score = lr_classifier.score(X_test, y_test)
kn_score = kn_classifier.score(X_test, y_test)
nb_score = nb_classifier.score(X_test, y_test)

print('---------Prediction Scores------')

print('Random Forest Prediction Score is', rf_score*100,'%')
print('Support Vector Prediction Score is', sv_score*100,'%')
print('Logistic Regression Prediction Score is', lr_score*100,'%')
print('K-Nearest Classifier Prediction Score is', kn_score*100,'%')
print('Naive Bayes Prediction Score is', nb_score*100,'%')
```

```
---------Prediction Scores------
Random Forest Prediction Score is 76.55502392344498 %
Support Vector Prediction Score is 73.20574162679426 %
Logistic Regression Prediction Score is 75.5980861244019 %
K-Nearest Classifier Prediction Score is 71.29186602870813 %
Naive Bayes Prediction Score is 33.49282296650718 %
```

[ ]:

```
#predicting the test set re4sults
yrf = rf_classifier.predict(X_test)
ysv = sv_classifier.predict(X_test)
ylr = lr_classifier.predict(X_test)
ykn = kn_classifier.predict(X_test)
ynb = nb_classifier.predict(X_test)

#determining the precision,recall and f1-score
```

```
RF_report=classification_report(y_test,yrf)
SV_report=classification_report(y_test,ysv)
LR_report=classification_report(y_test,ylr)
KN_report=classification_report(y_test,ykn)
NB_report=classification_report(y_test,ynb)
```

```
/home/el-sunais/anaconda3/lib/python3.8/site-
packages/sklearn/metrics/_classification.py:1245: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/home/el-sunais/anaconda3/lib/python3.8/site-
packages/sklearn/metrics/_classification.py:1245: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/home/el-sunais/anaconda3/lib/python3.8/site-
packages/sklearn/metrics/_classification.py:1245: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

[ ]:
```
print('Random Forest Classifier Report:')
print(RF_report)
```

```
Random Forest Classifier Report:
              precision    recall  f1-score   support

     average       0.79      0.93      0.85       153
        high       0.67      0.42      0.52        38
         low       0.40      0.11      0.17        18

    accuracy                           0.77       209
   macro avg       0.62      0.49      0.51       209
weighted avg       0.73      0.77      0.73       209
```

[ ]:
```
print('Support Vector Classifier Report:')
print(SV_report)
```

```
Support Vector Classifier Report:
              precision    recall  f1-score   support

     average       0.73      1.00      0.85       153
        high       0.00      0.00      0.00        38
         low       0.00      0.00      0.00        18

    accuracy                           0.73       209
```

```
   macro avg       0.24      0.33      0.28       209
weighted avg       0.54      0.73      0.62       209
```

[ ]:
```python
print('Logistic Regression Classfier Report:')
print(LR_report)
```

```
Logistic Regression Classfier Report:
              precision    recall  f1-score   support

     average       0.77      0.95      0.85       153
        high       0.69      0.29      0.41        38
         low       0.40      0.11      0.17        18

    accuracy                           0.76       209
   macro avg       0.62      0.45      0.48       209
weighted avg       0.72      0.76      0.71       209
```

[ ]:
```python
print('K-Nearest Classifier Report:')
print(KN_report)
```

```
K-Nearest Classifier Report:
              precision    recall  f1-score   support

     average       0.76      0.90      0.83       153
        high       0.41      0.29      0.34        38
         low       0.00      0.00      0.00        18

    accuracy                           0.71       209
   macro avg       0.39      0.40      0.39       209
weighted avg       0.63      0.71      0.67       209
```

[ ]:
```python
print('Naive Bayes Classifier Report:')
print(NB_report)
```

```
Naive Bayes Classifier Report:
              precision    recall  f1-score   support

     average       0.85      0.18      0.30       153
        high       0.24      0.97      0.39        38
         low       0.22      0.28      0.24        18

    accuracy                           0.33       209
   macro avg       0.44      0.48      0.31       209
weighted avg       0.68      0.33      0.31       209
```