```
In [1]:
       import pandas as pd
           import seaborn as sns
           import matplotlib.pyplot as plt
           import pylab as pl
           from sklearn.linear model import LogisticRegression
           from sklearn.neighbors import KNeighborsClassifier
           from sklearn.linear model import SGDClassifier
           from sklearn.preprocessing import LabelEncoder
           from sklearn.model_selection import train_test_split
           from sklearn.linear model import LinearRegression, Lasso
           from sklearn.linear_model import Ridge
           from sklearn.model_selection import cross_val_score
           import warnings
           warnings.filterwarnings('ignore')
           import os
```

#### 

# In [3]: ► df.head()

### Out[3]:

	school	sex	age	address	famsize	Pstatus	Medu	Fedu	Mjob	Fjob	•••	famrel	f
0	GP	F	18	U	GT3	А	4	4	at_home	teacher		4	
1	GP	F	17	U	GT3	Т	1	1	at_home	other		5	
2	GP	F	15	U	LE3	Т	1	1	at_home	other		4	
3	GP	F	15	U	GT3	Т	4	2	health	services		3	
4	GP	F	16	U	GT3	Т	3	3	other	other		4	

5 rows × 33 columns

In [4]: ▶ df.describe()

# Out[4]:

	age	Medu	Fedu	traveltime	studytime	failures	famrel	
count	395.000000	395.000000	395.000000	395.000000	395.000000	395.000000	395.000000	3
mean	16.696203	2.749367	2.521519	1.448101	2.035443	0.334177	3.944304	
std	1.276043	1.094735	1.088201	0.697505	0.839240	0.743651	0.896659	
min	15.000000	0.000000	0.000000	1.000000	1.000000	0.000000	1.000000	
25%	16.000000	2.000000	2.000000	1.000000	1.000000	0.000000	4.000000	
50%	17.000000	3.000000	2.000000	1.000000	2.000000	0.000000	4.000000	
75%	18.000000	4.000000	3.000000	2.000000	2.000000	0.000000	5.000000	
max	22.000000	4.000000	4.000000	4.000000	4.000000	3.000000	5.000000	
4								

```
In [5]:

    df.shape

    Out[5]: (395, 33)
In [6]:
            df.dtypes
   Out[6]: school
                           object
                           object
             sex
             age
                            int64
             address
                           object
                           object
             famsize
             Pstatus
                           object
                            int64
            Medu
             Fedu
                            int64
                           object
            Mjob
             Fjob
                           object
                           object
             reason
             guardian
                           object
             traveltime
                            int64
             studytime
                            int64
                            int64
             failures
                           object
             schoolsup
             famsup
                           object
```

goout int64
Dalc int64
Walc int64
health int64
absences int64
G1 int64

object object

object object

object

object

int64

int64

int64

int64

dtype: object

paid

higher

famrel

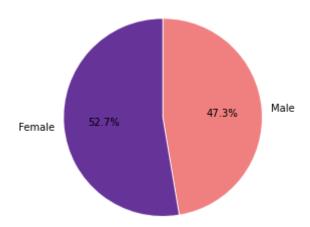
G2

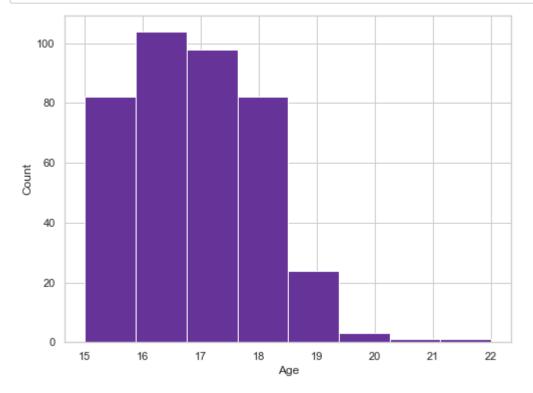
G3

internet
romantic

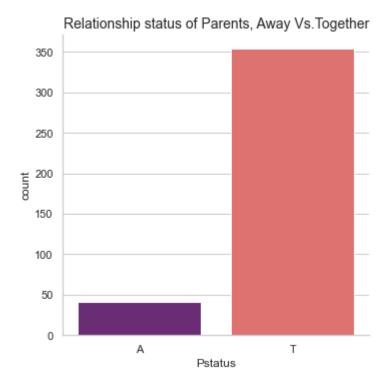
freetime

activities nursery

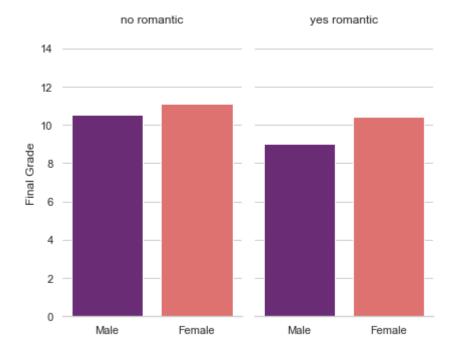




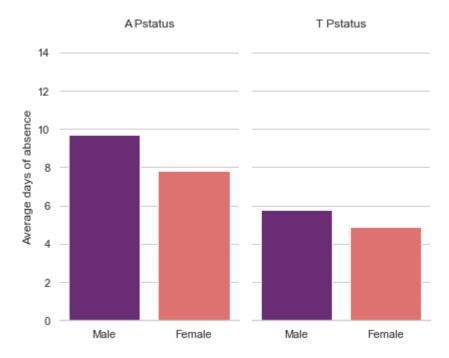
Out[9]: Text(0.5, 1.0, 'Relationship status of Parents, Away Vs.Together')



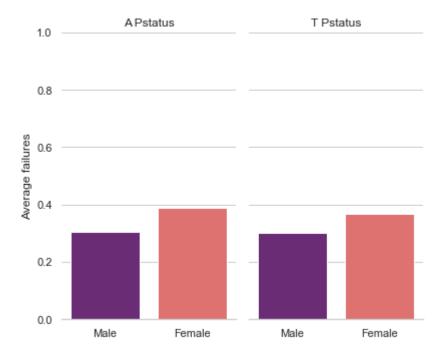
Out[10]: <seaborn.axisgrid.FacetGrid at 0x1796f9c2400>



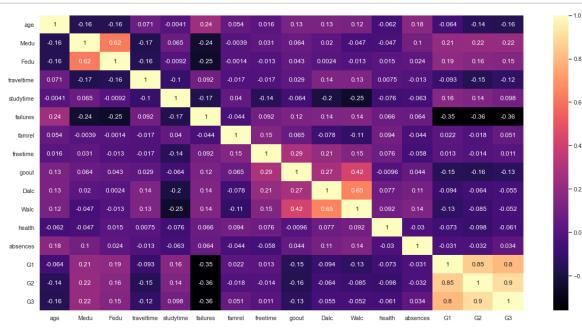
Out[11]: <seaborn.axisgrid.FacetGrid at 0x1796f9c2f10>



Out[12]: <seaborn.axisgrid.FacetGrid at 0x1796fb13dc0>

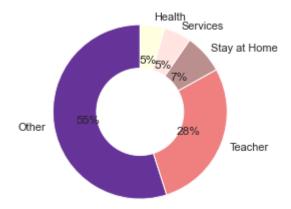


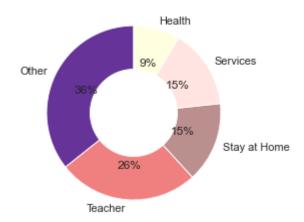
```
In [13]:
             def show correlations(df, show chart = True):
                 fig = plt.figure(figsize = (20,10))
                 corr = df.corr()
                 if show chart == True:
                     sns.heatmap(corr,
                                  xticklabels=corr.columns.values,
                                  yticklabels=corr.columns.values,
                                  annot=True, cmap= "magma")
                 return corr
             correlation_df = show_correlations(df,show_chart=True)
```



0.2

```
In [14]:
                                                                                             plt.pie(df['Fjob'].value_counts().tolist(),
                                                                                                                                                         labels=['Other', 'Teacher', 'Stay at Home', 'Services', 'Health'],
                                                                                                                                                        colors=['rebeccapurple', 'lightcoral', 'rosybrown', 'mistyrose', 'lightcoral', 'rosybrown', 'mistyrose', 'lightcoral', 'rosybrown', 'mistyrose', 'lightcoral', 'rosybrown', 'mistyrose', 'lightcoral', 'mistyrose', 'lightcoral', 'rosybrown', 'rosy
                                                                                                                                                               autopct='%1.0f%%', startangle=90)
                                                                                              my_circle=plt.Circle( (0,0), 0.5, color='white')
                                                                                               p=plt.gcf()
                                                                                              p.gca().add_artist(my_circle)
                                                                                               plt.show()
```

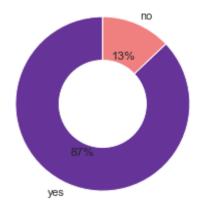


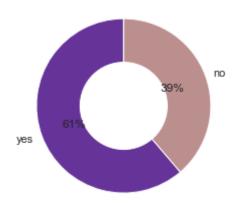


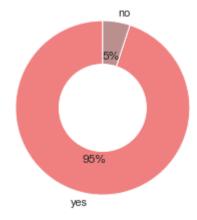
# In [16]: ▶ pip install squarify

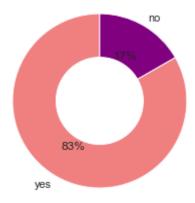
Requirement already satisfied: squarify in c:\users\mumitul\anaconda3\lib\s ite-packages (0.4.3)

Note: you may need to restart the kernel to use updated packages.





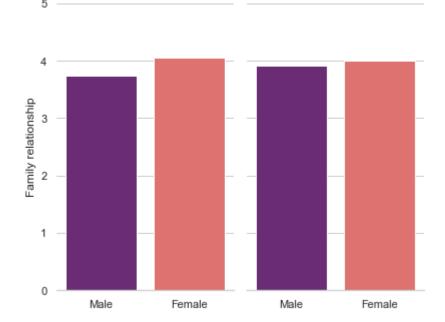




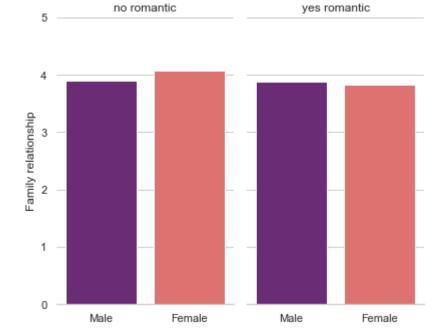
T Pstatus

Out[21]: <seaborn.axisgrid.FacetGrid at 0x17971627190>

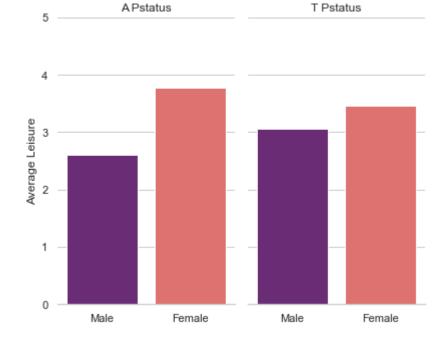
A Pstatus



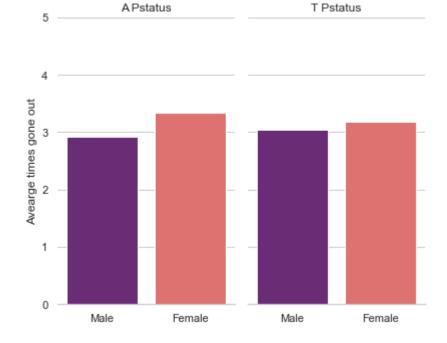
Out[22]: <seaborn.axisgrid.FacetGrid at 0x179716c89d0>



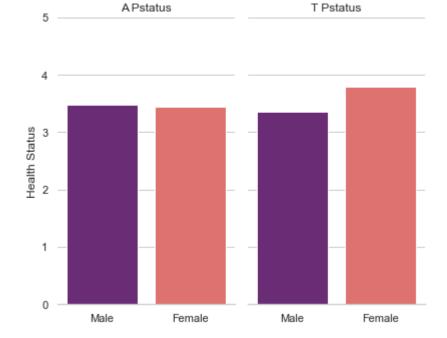
Out[23]: <seaborn.axisgrid.FacetGrid at 0x1797175f250>



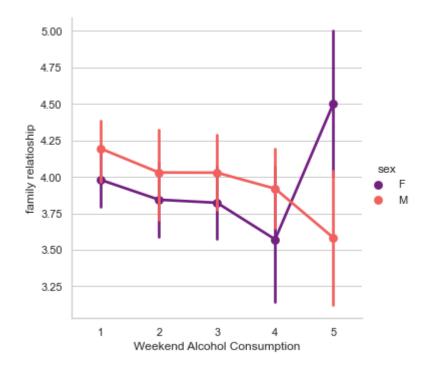
Out[24]: <seaborn.axisgrid.FacetGrid at 0x179717f1fd0>

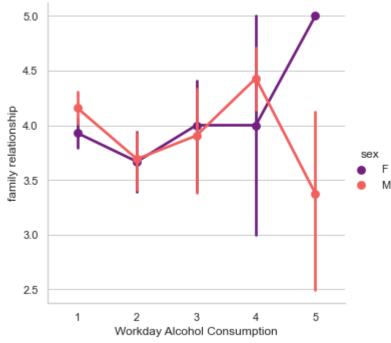


Out[25]: <seaborn.axisgrid.FacetGrid at 0x17971888550>

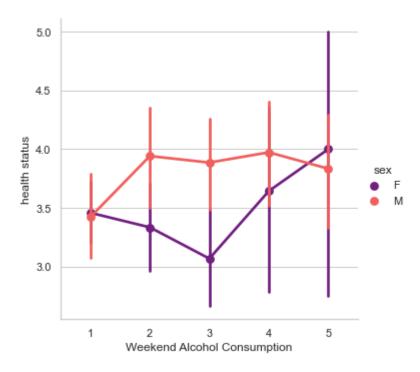


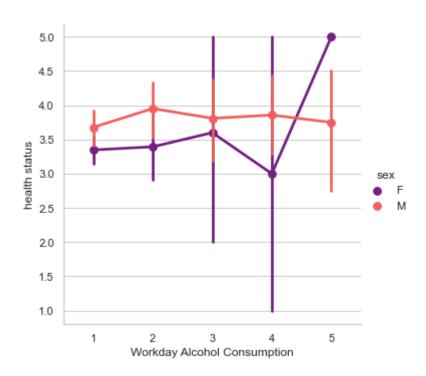
Out[26]: <seaborn.axisgrid.FacetGrid at 0x179718ecfa0>



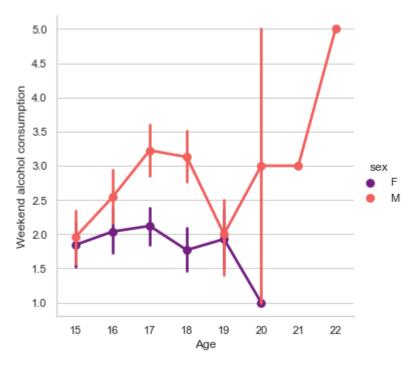


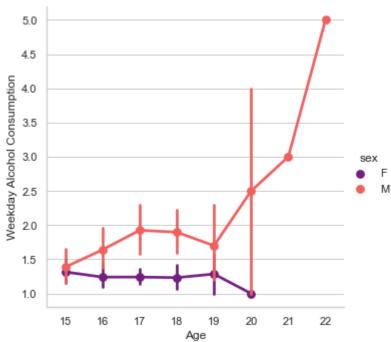
Out[27]: <seaborn.axisgrid.FacetGrid at 0x17971670be0>



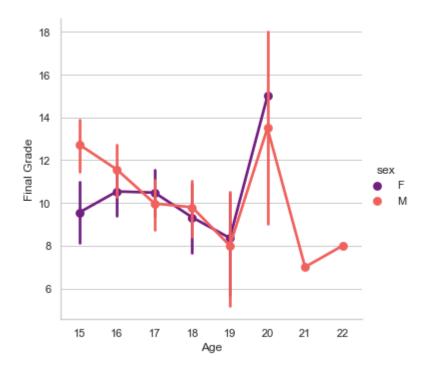


Out[28]: <seaborn.axisgrid.FacetGrid at 0x179717c7580>



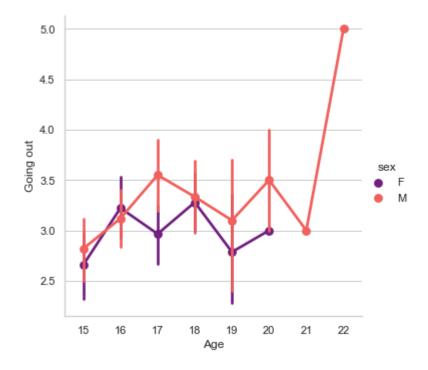


Out[29]: <seaborn.axisgrid.FacetGrid at 0x17971592910>

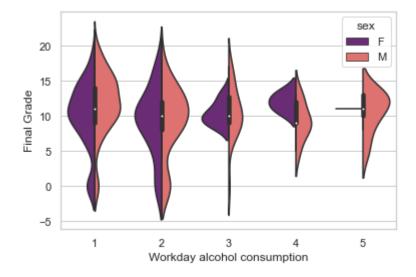


In [30]: plot1 = sns.factorplot(x="age", y="goout", data=df, hue='sex', palette='magma
plot1.set(ylabel="Going out", xlabel="Age")

Out[30]: <seaborn.axisgrid.FacetGrid at 0x1796fc02760>

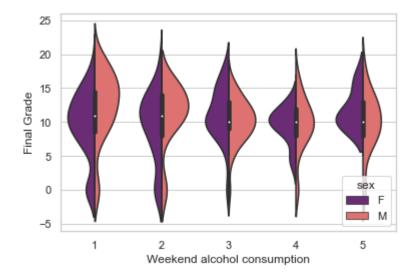


Out[31]: [Text(0, 0.5, 'Final Grade'), Text(0.5, 0, 'Workday alcohol consumption')]

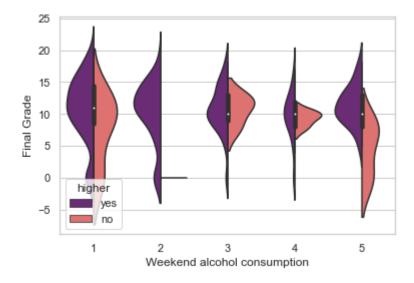


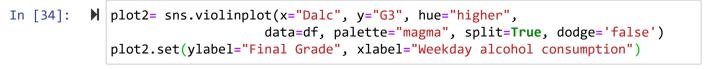


Out[32]: [Text(0, 0.5, 'Final Grade'), Text(0.5, 0, 'Weekend alcohol consumption')]

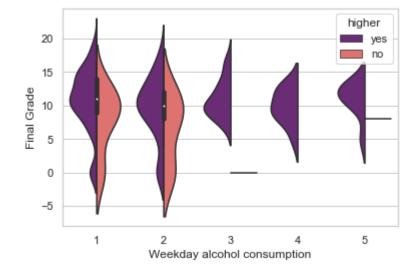


Out[33]: [Text(0, 0.5, 'Final Grade'), Text(0.5, 0, 'Weekend alcohol consumption')]





Out[34]: [Text(0, 0.5, 'Final Grade'), Text(0.5, 0, 'Weekday alcohol consumption')]



```
In [35]:
         len(dfobject.columns)
   Out[35]: 17
In [36]:
         df[columnname] = LabelEncoder().fit_transform(df[columnname])
         In [37]:
                labelencode(dfobject.columns[i])
            df.info()
In [38]:
            <class 'pandas.core.frame.DataFrame'>
            RangeIndex: 395 entries, 0 to 394
            Data columns (total 33 columns):
                            Non-Null Count Dtype
             #
                 Column
                            -----
                 ----
             0
                 school
                            395 non-null
                                           object
             1
                            395 non-null
                 sex
                                           int32
             2
                            395 non-null
                                           int64
                 age
             3
                 address
                            395 non-null
                                           int32
             4
                 famsize
                            395 non-null
                                           int32
             5
                 Pstatus
                            395 non-null
                                           int32
             6
                 Medu
                            395 non-null
                                           int64
             7
                 Fedu
                            395 non-null
                                           int64
             8
                 Mjob
                            395 non-null
                                           int32
             9
                 Fjob
                            395 non-null
                                           int32
             10
                 reason
                            395 non-null
                                           int32
             11
                guardian
                            395 non-null
                                           int32
             12
                traveltime 395 non-null
                                           int64
             13
                studytime
                            395 non-null
                                           int64
             14
                failures
                            395 non-null
                                           int64
             15
                 schoolsup
                            395 non-null
                                           int32
             16
                 famsup
                            395 non-null
                                           int32
             17
                 paid
                            395 non-null
                                           int32
             18
                activities 395 non-null
                                           int32
             19
                nursery
                            395 non-null
                                           int32
             20
                higher
                            395 non-null
                                           int32
             21
                 internet
                            395 non-null
                                           int32
             22
                romantic
                            395 non-null
                                           int32
             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
                            395 non-null
                 absences
                                           int64
             30
                G1
                            395 non-null
                                           int64
             31
                G2
                            395 non-null
                                           int64
```

memory usage: 77.3+ KB

395 non-null

dtypes: int32(16), int64(16), object(1)

int64

32

G3

```
In [39]:
          ▶ #Dropping school name for modelling
             df1 = df.drop(['school'], axis = 1)

    ★ from sklearn.tree import DecisionTreeClassifier

In [40]:
             from sklearn.ensemble import RandomForestClassifier
             from sklearn.naive_bayes import GaussianNB
             from sklearn.neighbors import KNeighborsClassifier
             from sklearn.svm import SVC
             from sklearn.neural network import MLPClassifier
             from sklearn.ensemble import AdaBoostClassifier
             from sklearn.ensemble import GradientBoostingClassifier
             from sklearn.ensemble import ExtraTreesClassifier
             from sklearn.linear_model import LogisticRegression
             from sklearn.model selection import train test split
             from sklearn.metrics import accuracy score
             from sklearn.preprocessing import LabelEncoder
             from xgboost import XGBClassifier
In [41]: X = df1.drop('G3', 1)
             y = df1['G3']
In [42]:
         X_train, X_test, y_train, y_test = train_test_split(X,y,test_size = 0.30, ran
             classifiers = [['DecisionTree :',DecisionTreeClassifier()],
                             ['RandomForest :',RandomForestClassifier()],
['Naive Bayes :', GaussianNB()],
                             ['KNeighbours:', KNeighborsClassifier()],
                             ['SVM :', SVC()],
                             ['LogisticRegression:', LogisticRegression(max iter=500)],
                             ['Neural Network :', MLPClassifier()],
                             ['ExtraTreesClassifier:', ExtraTreesClassifier()],
                             ['AdaBoostClassifier:', AdaBoostClassifier()],
                             ['GradientBoostingClassifier: ', GradientBoostingClassifier()]
             predictions_df = pd.DataFrame()
             predictions df['actual labels'] = y test
             for name, classifier in classifiers:
                 classifier = classifier
                 classifier.fit(X_train, y_train)
                 predictions = classifier.predict(X test)
                 predictions_df[name.strip(" :")] = predictions
                 print(name, accuracy_score(y_test, predictions))
             DecisionTree: 0.2857142857142857
             RandomForest: 0.4957983193277311
             Naive Bayes : 0.2689075630252101
             KNeighbours: 0.3025210084033613
             SVM: 0.226890756302521
             LogisticRegression : 0.3277310924369748
             Neural Network: 0.3445378151260504
             ExtraTreesClassifier: 0.40336134453781514
             AdaBoostClassifier: 0.2773109243697479
```

GradientBoostingClassifier: 0.4789915966386555

```
▶ new = df[['G3','failures','Dalc', 'Walc', 'absences', 'famrel', 'health', 'gc
In [43]:
In [44]:
            ▶ new.describe()
    Out[44]:
                               G3
                                                                                                    health
                                       failures
                                                     Dalc
                                                                 Walc
                                                                         absences
                                                                                       famrel
                count
                       395.000000
                                   395.000000
                                               395.000000
                                                           395.000000
                                                                       395.000000
                                                                                   395.000000
                                                                                               395.000000 3
                 mean
                         10.415190
                                     0.334177
                                                  1.481013
                                                             2.291139
                                                                         5.708861
                                                                                     3.944304
                                                                                                 3.554430
                                     0.743651
                   std
                          4.581443
                                                 0.890741
                                                             1.287897
                                                                         8.003096
                                                                                     0.896659
                                                                                                 1.390303
                                     0.000000
                                                             1.000000
                                                                         0.000000
                                                                                     1.000000
                                                                                                 1.000000
                  min
                          0.000000
                                                  1.000000
                  25%
                          8.000000
                                     0.000000
                                                  1.000000
                                                             1.000000
                                                                         0.000000
                                                                                     4.000000
                                                                                                 3.000000
                  50%
                         11.000000
                                     0.000000
                                                  1.000000
                                                             2.000000
                                                                         4.000000
                                                                                     4.000000
                                                                                                 4.000000
                         14.000000
                                     0.000000
                                                             3.000000
                                                                                                 5.000000
                  75%
                                                  2.000000
                                                                         8.000000
                                                                                     5.000000
                        20.000000
                                      3.000000
                                                  5.000000
                                                                                                 5.000000
                                                             5.000000
                                                                        75.000000
                                                                                     5.000000
                  max
In [45]:
               U = \text{new.drop}('G3', 1)
               V = new['G3']
```

```
In [51]:
          U train, U test, V train, V test = train test split(U,V,test size = 0.30, ran
             classifiers = [['DecisionTree :',DecisionTreeClassifier()],
                            ['RandomForest :',RandomForestClassifier()],
['Naive Bayes :', GaussianNB()],
                            ['KNeighbours:', KNeighborsClassifier()],
                             ['SVM :', SVC()],
                             ['LogisticRegression:', LogisticRegression(max iter=500)],
                            ['Neural Network :', MLPClassifier()],
                            ['ExtraTreesClassifier:', ExtraTreesClassifier()],
                            ['AdaBoostClassifier:', AdaBoostClassifier()],
                             ['GradientBoostingClassifier: ', GradientBoostingClassifier()]
             predictions df = pd.DataFrame()
             predictions df['actual labels'] = V test
             for name,classifier in classifiers:
                 classifier = classifier
                 classifier.fit(U_train, V_train)
                 predictions = classifier.predict(U test)
                 predictions_df[name.strip(" :")] = predictions
                 print(name, accuracy_score(V_test, predictions))
             DecisionTree : 0.2184873949579832
             RandomForest: 0.2857142857142857
             Naive Bayes : 0.25210084033613445
             KNeighbours: 0.2184873949579832
             SVM: 0.33613445378151263
             LogisticRegression : 0.3445378151260504
             Neural Network : 0.31092436974789917
             ExtraTreesClassifier: 0.2184873949579832
             AdaBoostClassifier: 0.2605042016806723
             GradientBoostingClassifier: 0.25210084033613445
          new = df[['G3','failures','G1', 'G2']]
In [53]:
          C = new.drop('G3', 1)
In [54]:
```

D = new['G3']

```
C train, C test, D train, D test = train test split(C,D,test size = 0.30, ran
In [55]:
             classifiers = [['DecisionTree :',DecisionTreeClassifier()],
                             ['RandomForest :',RandomForestClassifier()],
['Naive Bayes :', GaussianNB()],
                             ['KNeighbours:', KNeighborsClassifier()],
                             ['SVM :', SVC()],
                             ['LogisticRegression:', LogisticRegression(max iter=500)],
                             ['Neural Network :', MLPClassifier()],
                             ['ExtraTreesClassifier:', ExtraTreesClassifier()],
                             ['AdaBoostClassifier:', AdaBoostClassifier()],
                             ['GradientBoostingClassifier: ', GradientBoostingClassifier()]
             predictions df = pd.DataFrame()
             predictions df['actual labels'] = D test
             for name,classifier in classifiers:
                 classifier = classifier
                 classifier.fit(C_train, D_train)
                  predictions = classifier.predict(C test)
                  predictions_df[name.strip(" :")] = predictions
                  print(name, accuracy_score(D_test, predictions))
```

DecisionTree : 0.453781512605042 RandomForest : 0.4957983193277311 Naive Bayes : 0.3865546218487395 KNeighbours : 0.42016806722689076

SVM: 0.5042016806722689

LogisticRegression: 0.5126050420168067
Neural Network: 0.3025210084033613
ExtraTreesClassifier: 0.4369747899159664
AdaBoostClassifier: 0.2773109243697479

GradientBoostingClassifier: 0.46218487394957986

```
In [49]: # In these model I tried to see if weekend and weekly alcohol consumption is # in a maths class.Logistic regression seems to be the best model among the b # Based on my analysis, alcohol consumption doesn't actually influence the fi # Naturally, past failures and grades in first and second exams are better pr # More observations will most likely boost up the accuracy.
```