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

In [2]:
```
df_mat = pd.read_csv('student-mat.csv',sep = ';')
```

In [3]:
```
df_mat.head()
```

Out[3]:

	school	sex	age	address	famsize	Pstatus	Medu	Fedu	Mjob	Fjob	...	famrel	freetime	goout	Dalc	Walc	health	absences	G1	G2
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
2	GP	F	15	U	LE3	T	1	1	at_home	other	...	4	3	2	2	3	3	10	7	8
3	GP	F	15	U	GT3	T	4	2	health	services	...	3	2	2	1	1	5	2	15	14
4	GP	F	16	U	GT3	T	3	3	other	other	...	4	3	2	1	2	5	4	6	10

5 rows × 33 columns

In [4]:
```
df_mat.drop('school',axis = 1, inplace = True)
```

In [5]:
```
df_mat.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 395 entries, 0 to 394
Data columns (total 32 columns):
 #   Column      Non-Null Count  Dtype 
---  ------      --------------  ----- 
 0   sex         395 non-null    object
 1   age         395 non-null    int64 
 2   address     395 non-null    object
 3   famsize     395 non-null    object
 4   Pstatus     395 non-null    object
 5   Medu        395 non-null    int64 
 6   Fedu        395 non-null    int64 
 7   Mjob        395 non-null    object
 8   Fjob        395 non-null    object
 9   reason      395 non-null    object
 10  guardian    395 non-null    object
 11  traveltime  395 non-null    int64 
 12  studytime   395 non-null    int64 
 13  failures    395 non-null    int64 
 14  schoolsup   395 non-null    object
 15  famsup      395 non-null    object
 16  paid        395 non-null    object
 17  activities  395 non-null    object
 18  nursery     395 non-null    object
 19  higher      395 non-null    object
 20  internet    395 non-null    object
 21  romantic    395 non-null    object
 22  famrel      395 non-null    int64 
 23  freetime    395 non-null    int64 
 24  goout       395 non-null    int64 
 25  Dalc        395 non-null    int64 
 26  Walc        395 non-null    int64 
 27  health      395 non-null    int64 
 28  absences    395 non-null    int64 
 29  G1          395 non-null    int64 
 30  G2          395 non-null    int64 
 31  G3          395 non-null    int64 
dtypes: int64(16), object(16)
memory usage: 98.9+ KB
```

In [6]:
```
df_mat.shape
```

Out[6]: (395, 32)

In [7]:
```
df_mat.head()
```

Out[7]:

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

5 rows × 32 columns

In [8]:
```
# our dataset has some Non categorical Values let's change it:
#  categorize age into 3 classes:
def age(age):
    new_age=[]
    for i in age:
        if(i < 17):
            i=0
        elif (i < 19):
            i=1
        else:
            i=2
        new_age.append(i)
    return new_age

df_mat['age']=age(df_mat['age'])
df_mat.head()
```

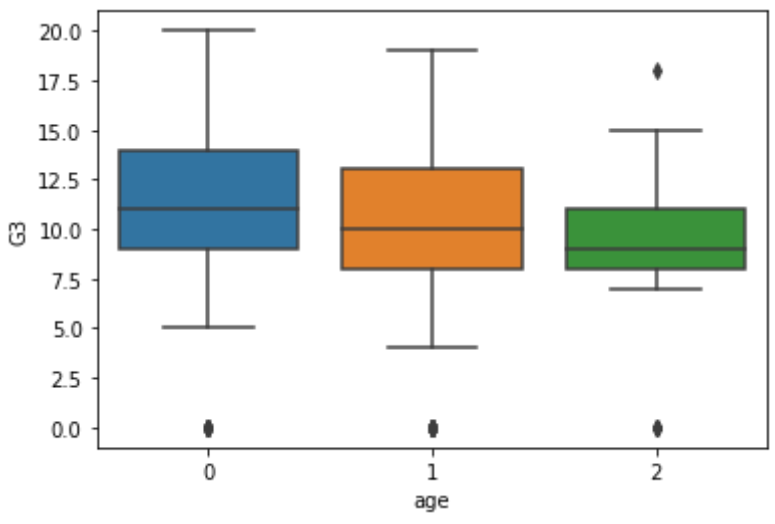
Out[8]:

	sex	age	address	famsize	Pstatus	Medu	Fedu	Mjob	Fjob	reason	...	famrel	freetime	goout	Dalc	Walc	health	absences	G1	G
0	F	1	U	GT3	A	4	4	at_home	teacher	course	...	4	3	4	1	1	3	6	5	
1	F	1	U	GT3	T	1	1	at_home	other	course	...	5	3	3	1	1	3	4	5	
2	F	0	U	LE3	T	1	1	at_home	other	other	...	4	3	2	2	3	3	10	7	
3	F	0	U	GT3	T	4	2	health	services	home	...	3	2	2	1	1	5	2	15	1
4	F	0	U	GT3	T	3	3	other	other	home	...	4	3	2	1	2	5	4	6	1

5 rows × 32 columns

In [9]:
```
sns.boxplot(x='age',y='G3',data=df_mat)
```

Out[9]:
```
<AxesSubplot:xlabel='age', ylabel='G3'>
```



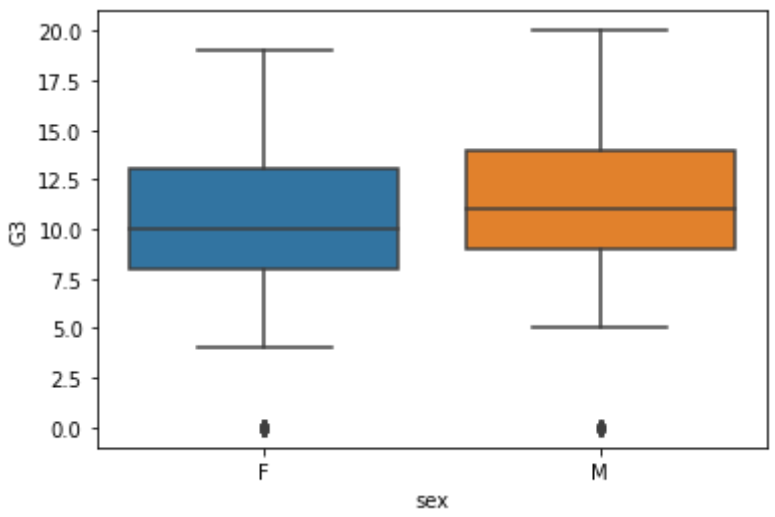
Students of Age Less than 17 has higher median of scoring whereas students of age> 19 has lowest mean.

In [10]:
```
# comparing Performance of male and female students
df_mat['sex'].value_counts
```

Out[10]:
```
<bound method IndexOpsMixin.value_counts of 0      F
1      F
2      F
3      F
4      F
      ..
390    M
391    M
392    M
393    M
394    M
Name: sex, Length: 395, dtype: object>
```

In [11]:
```
sns.boxplot(x ='sex', y ='G3', data = df_mat)
```

Out[11]:
```
<AxesSubplot:xlabel='sex', ylabel='G3'>
```



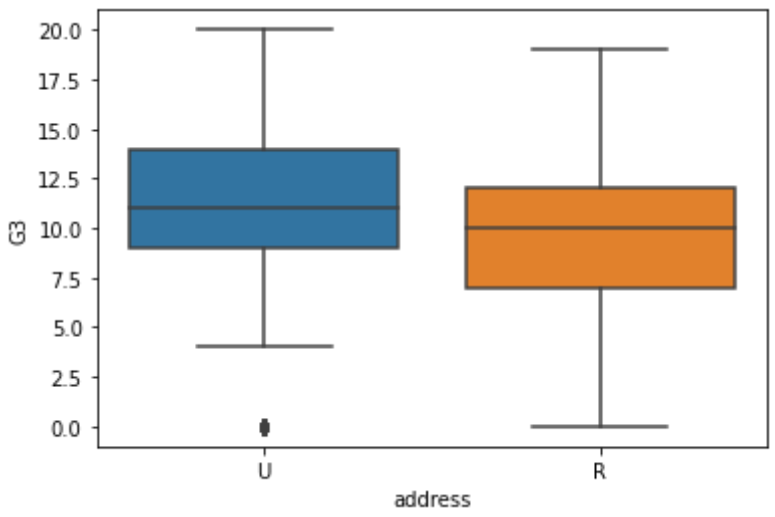
Male students have better performance in school than the female students. Since the median score of boys is more than girls and the maximum marks also

In [12]:
```
df_mat['address'].value_counts()
```

Out[12]:
```
U    307
R     88
Name: address, dtype: int64
```

In [13]:
```
sns.boxplot('address','G3',data=df_mat)
```

Out[13]:
```
<AxesSubplot:xlabel='address', ylabel='G3'>
```



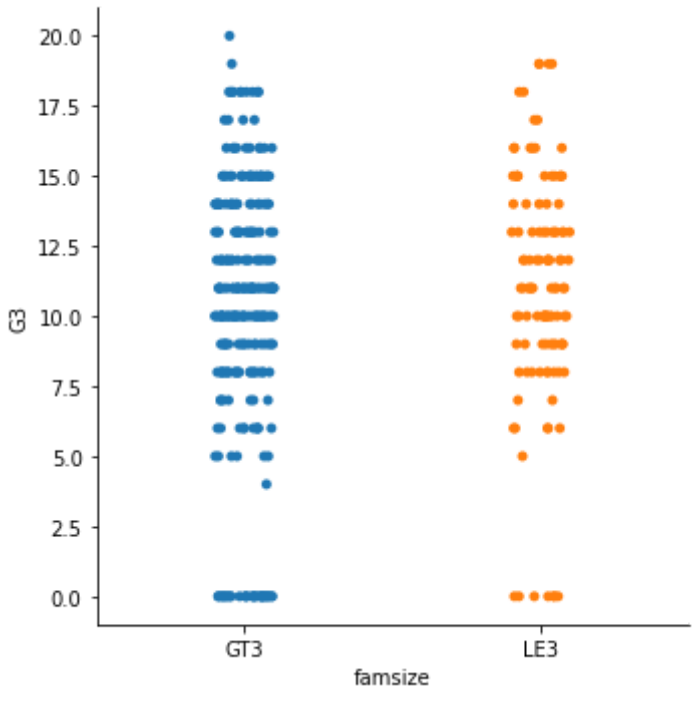
Students living in Urban Areas has better performance than students coming from Rural Areas.

In [14]:
```
df_mat['famsize'].value_counts()
```

Out[14]:
```
GT3    281
LE3    114
Name: famsize, dtype: int64
```

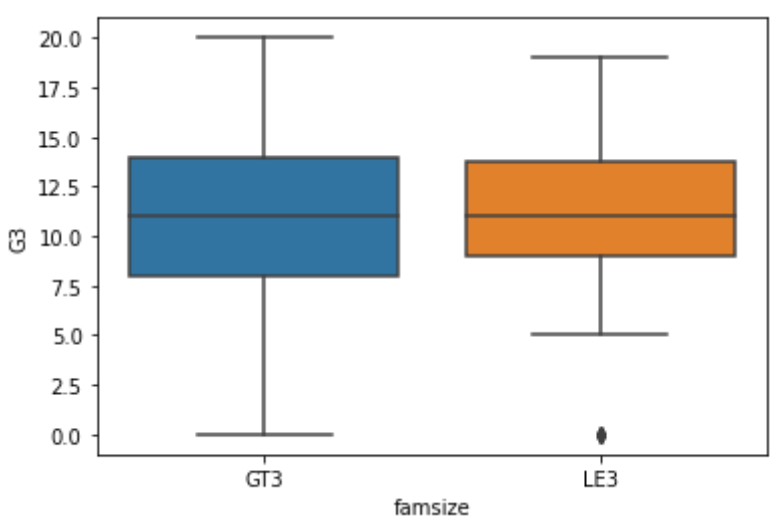
In [15]:
```
sns.catplot(x="famsize", y="G3", data=df_mat)
```

Out[15]:
```
<seaborn.axisgrid.FacetGrid at 0x223bdc8fb08>
```



In [16]:
```
sns.boxplot(x = 'famsize', y = 'G3', data = df_mat)
```

Out[16]:
```
<AxesSubplot:xlabel='famsize', ylabel='G3'>
```



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In [17]:
```
df_mat.drop('famsize', axis = 1)
```

Out[17]:

	sex	age	address	Pstatus	Medu	Fedu	Mjob	Fjob	reason	guardian	...	famrel	freetime	goout	Dalc	Walc	health	absences	G1
0	F	1	U	A	4	4	at_home	teacher	course	mother	...	4	3	4	1	1	3	6	5
1	F	1	U	T	1	1	at_home	other	course	father	...	5	3	3	1	1	3	4	5
2	F	0	U	T	1	1	at_home	other	other	mother	...	4	3	2	2	3	3	10	7
3	F	0	U	T	4	2	health	services	home	mother	...	3	2	2	1	1	5	2	15
4	F	0	U	T	3	3	other	other	home	father	...	4	3	2	1	2	5	4	6
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
390	M	2	U	A	2	2	services	services	course	other	...	5	5	4	4	5	4	11	9
391	M	1	U	T	3	1	services	services	course	mother	...	2	4	5	3	4	2	3	14
392	M	2	R	T	1	1	other	other	course	other	...	5	5	3	3	3	3	3	10
393	M	1	R	T	3	2	services	other	course	mother	...	4	4	1	3	4	5	0	11
394	M	2	U	T	1	1	other	at_home	course	father	...	3	2	3	3	3	5	5	8

395 rows × 31 columns

In [18]:
```
df_mat['Pstatus'].value_counts()
```

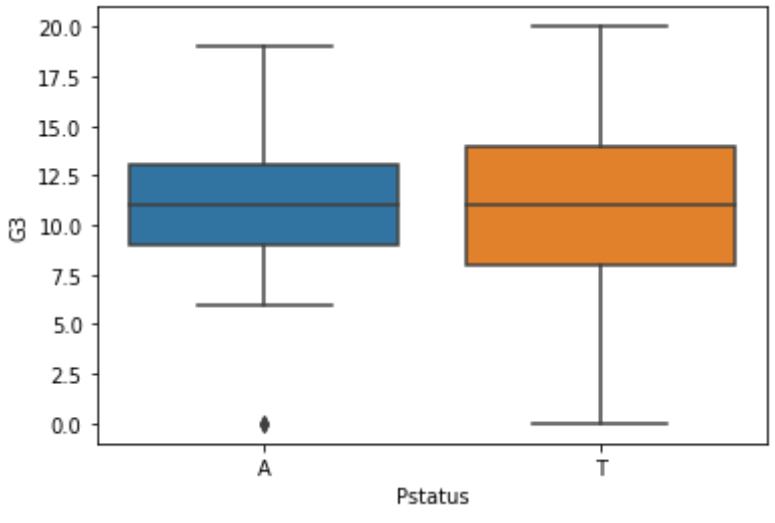
Out[18]:
```
T    354
A     41
Name: Pstatus, dtype: int64
```

In [ ]:
```

```

In [19]:
```
sns.boxplot("Pstatus","G3", data = df_mat)
```

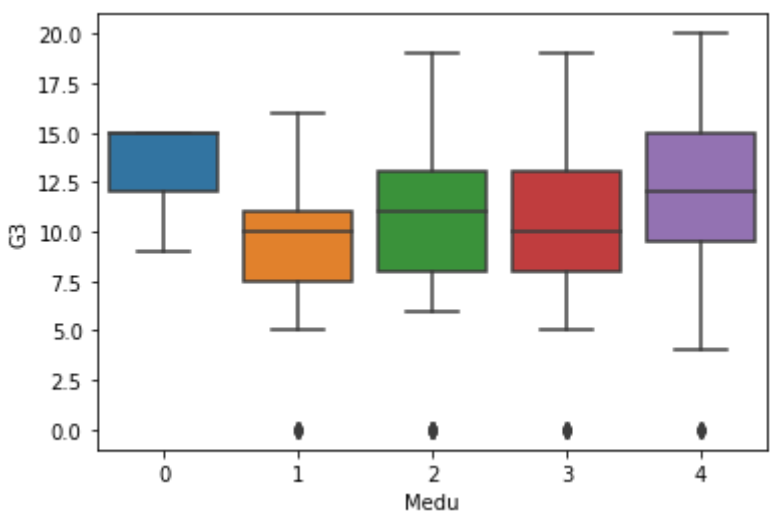
Out[19]:
```
<AxesSubplot:xlabel='Pstatus', ylabel='G3'>
```



Students whose parents lived togethar tend to perfor better

In [20]:
```
sns.boxplot(x='Medu',y='G3',data=df_mat)
```

Out[20]:
```
<AxesSubplot:xlabel='Medu', ylabel='G3'>
```



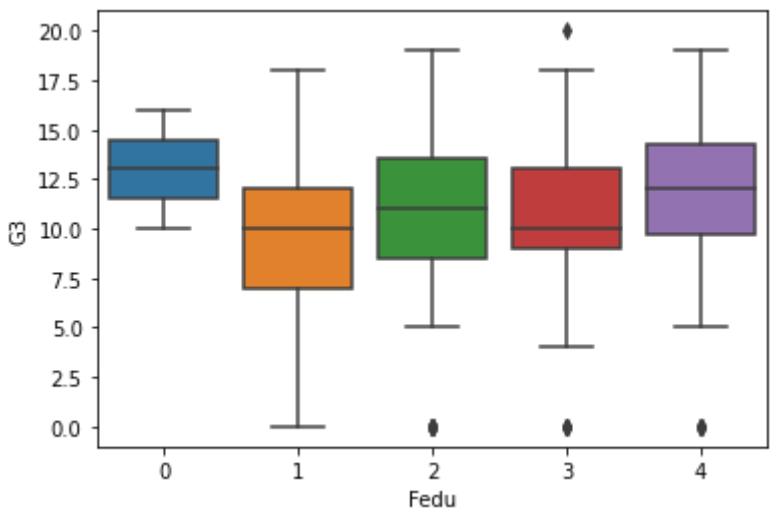
Students whose mother has been more educated tend to perform better

In [21]:
```
df_mat['Fedu'].value_counts()
```

Out[21]:
```
2    115
3    100
4     96
1     82
0      2
Name: Fedu, dtype: int64
```

In [22]:
```
sns.boxplot(x='Fedu',y='G3',data=df_mat)
```

Out[22]:
```
<AxesSubplot:xlabel='Fedu', ylabel='G3'>
```

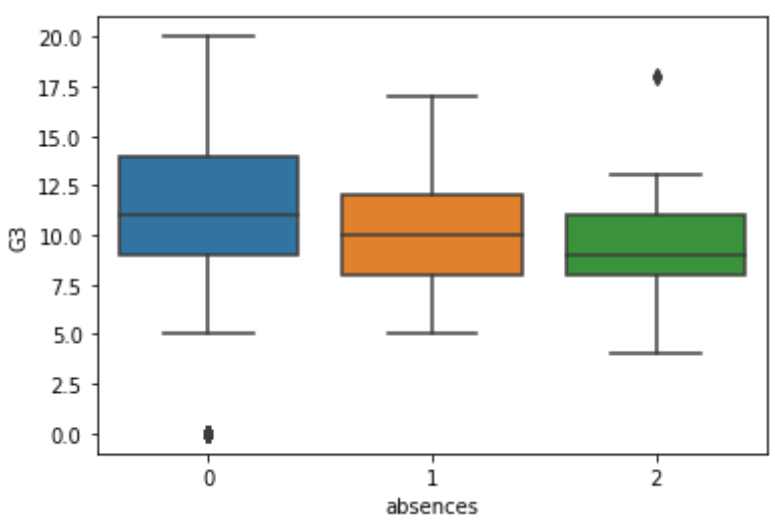


Students whose fathers have completed higher education have slightly better chance of performing well in exams.

In [23]:
```
def absences(n):
    new=[]
    for i in n:
        if (i <= 10):
            i=0
        elif(i <= 20):
            i=1
        else:
            i=2
        new.append(i)
    return new
df_mat['absences']=absences(df_mat['absences'])
```

In [24]:
```
sns.boxplot("absences","G3", data = df_mat)
```

Out[24]: <AxesSubplot:xlabel='absences', ylabel='G3'>



Students who has lower absents tends to perform better

In [25]:
```
df_mat.head()
```

Out[25]:

	sex	age	address	famsize	Pstatus	Medu	Fedu	Mjob	Fjob	reason	...	famrel	freetime	goout	Dalc	Walc	health	absences	G1	G
0	F	1	U	GT3	A	4	4	at_home	teacher	course	...	4	3	4	1	1	3	0	5	
1	F	1	U	GT3	T	1	1	at_home	other	course	...	5	3	3	1	1	3	0	5	
2	F	0	U	LE3	T	1	1	at_home	other	other	...	4	3	2	2	3	3	0	7	
3	F	0	U	GT3	T	4	2	health	services	home	...	3	2	2	1	1	5	0	15	1
4	F	0	U	GT3	T	3	3	other	other	home	...	4	3	2	1	2	5	0	6	1

5 rows × 32 columns

In [26]:
```
# converting string values into categorical values:
df_mat['sex'] = df_mat['sex'].map({'M': 0, 'F': 1})
df_mat['address'] = df_mat['address'].map({'U': 0, 'R': 1})
df_mat['internet'] = df_mat['internet'].map({'yes': 0, 'no': 1})
df_mat['famsize'] = df_mat['famsize'].map({'LE3':0, 'GT3': 1})
df_mat['Pstatus'] = df_mat['Pstatus'].map({'A':0, 'T':'1'})
df_mat['Mjob'] = df_mat['Mjob'].map({'at_home':0, 'health':1, 'teacher':2,'services':3,'other':4})
df_mat['Fjob'] = df_mat['Fjob'].map({'at_home':0, 'health':1, 'teacher':2,'services':3,'other':4})
df_mat['reason'] = df_mat['reason'].map({'reputation':0, 'course':1,'home':2,'other':3})
df_mat['guardian'] = df_mat['guardian'].map({'father':0, 'mother':1,'other':2})

d= {'yes':0, 'no':1}
df_mat['schoolsup'] = df_mat['schoolsup'].map(d)
df_mat['famsup'] = df_mat['famsup'].map(d)
df_mat['paid'] = df_mat['paid'].map(d)
df_mat['activities'] = df_mat['activities'].map(d)
df_mat['nursery'] = df_mat['nursery'].map(d)
df_mat['higher'] = df_mat['higher'].map(d)
df_mat['romantic'] = df_mat['romantic'].map(d)
df_mat.head()
```

Out[26]:

	sex	age	address	famsize	Pstatus	Medu	Fedu	Mjob	Fjob	reason	...	famrel	freetime	goout	Dalc	Walc	health	absences	G1	G2	G3
0	1	1	0	1	0	4	4	0	2	1	...	4	3	4	1	1	3	0	5	6	6
1	1	1	0	1	1	1	1	0	4	1	...	5	3	3	1	1	3	0	5	5	6
2	1	0	0	0	1	1	1	0	4	3	...	4	3	2	2	3	3	0	7	8	10
3	1	0	0	1	1	4	2	1	3	2	...	3	2	2	1	1	5	0	15	14	15
4	1	0	0	1	1	3	3	4	4	2	...	4	3	2	1	2	5	0	6	10	10

5 rows × 32 columns

In [27]:
```
df = df_mat.copy(deep = True)
```

In [28]:
```
def change(df):
    new_G3 = []
    for i in df:
        if(i > 9):
            i = 1
        else:
            i = 0
        new_G3.append(i)
    return new_G3
df_mat['G3'] = change(df_mat['G3'])
```

In [29]:
```
pd.isnull(df_mat).sum()
df_mat.head()
```

Out[29]:

	sex	age	address	famsize	Pstatus	Medu	Fedu	Mjob	Fjob	reason	...	famrel	freetime	goout	Dalc	Walc	health	absences	G1	G2	G3
0	1	1	0	1	0	4	4	0	2	1	...	4	3	4	1	1	3	0	5	6	0
1	1	1	0	1	1	1	1	0	4	1	...	5	3	3	1	1	3	0	5	5	0
2	1	0	0	0	1	1	1	0	4	3	...	4	3	2	2	3	3	0	7	8	1
3	1	0	0	1	1	4	2	1	3	2	...	3	2	2	1	1	5	0	15	14	1
4	1	0	0	1	1	3	3	4	4	2	...	4	3	2	1	2	5	0	6	10	1

5 rows × 32 columns

In [30]:
```
# features selection using chi square:
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import chi2

x = df_mat.iloc[:,0:31]
y = df_mat.iloc[:,-1]
```

In [31]:
```
# select k best features:
best = SelectKBest(score_func = chi2, k = 10)
fit = best.fit(x,y);
```

In [32]:
```
dfscores = pd.DataFrame(fit.scores_)
dfcolumns  = pd.DataFrame(x.columns)
```

In [33]:
```
featurescores = pd.concat([dfcolumns,dfscores], axis  = 1)
featurescores.columns = ['specs','scores']
featurescores
```

Out[33]:

	specs	scores
0	sex	0.932542
1	age	7.363357
2	address	0.839169
3	famsize	0.199588
4	Pstatus	0.079557
5	Medu	2.286991
6	Fedu	2.160517
7	Mjob	0.236990
8	Fjob	0.064922
9	reason	0.000002
10	guardian	1.367847
11	traveltime	0.261497
12	studytime	0.758985
13	failures	74.370431
14	schoolsup	0.508575
15	famsup	0.848672
16	paid	1.554227
17	activities	0.030976
18	nursery	0.024225
19	higher	9.326887
20	internet	1.256146
21	romantic	1.260923
22	famrel	0.175027
23	freetime	0.040784
24	goout	5.283173
25	Dalc	0.694062
26	Walc	0.255976
27	health	0.923946
28	absences	7.192532
29	G1	175.953380
30	G2	273.800569

In [34]:
```
# selecting top 10 best features:  --> which can determine how much impact it have on Result--> The more the value more t
print(featurescores.nlargest(10,'scores'))
```

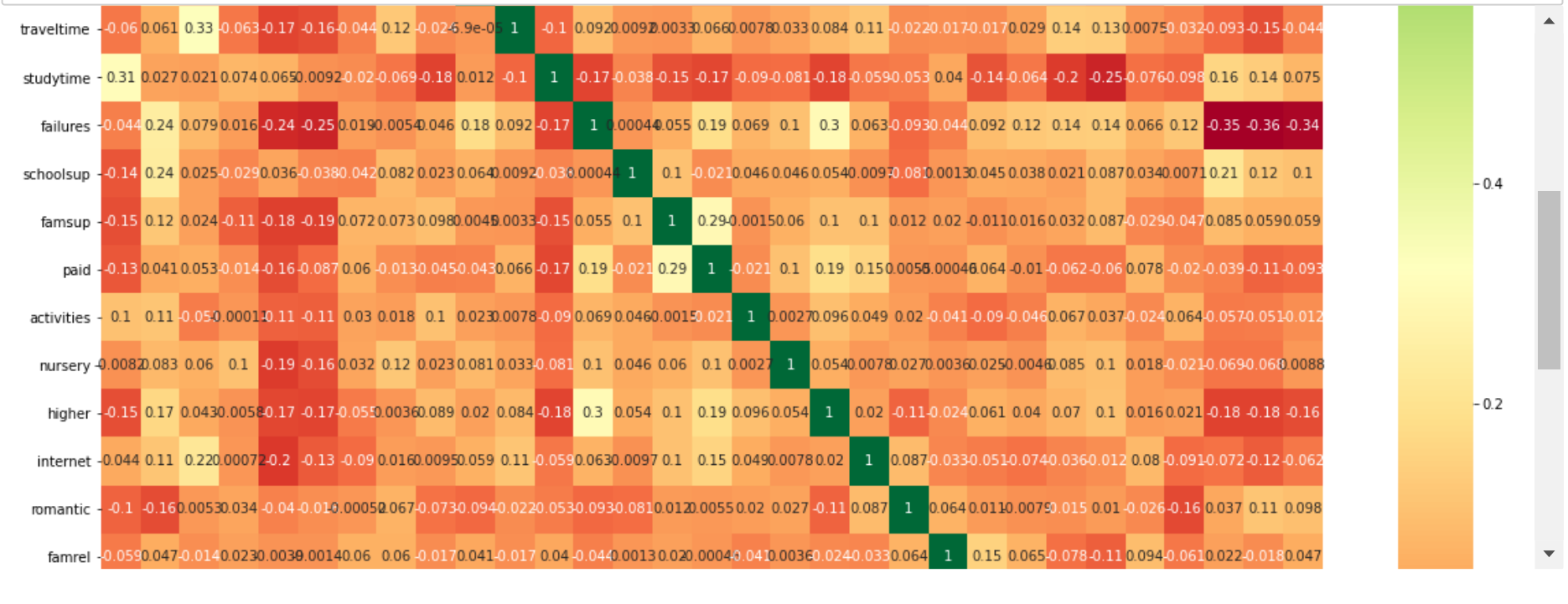
```
       specs      scores
30        G2  273.800569
29        G1  175.953380
13  failures   74.370431
19    higher    9.326887
1        age    7.363357
28  absences    7.192532
24     goout    5.283173
5       Medu    2.286991
6       Fedu    2.160517
16      paid    1.554227
```

In [35]:
```
import seaborn as sns
```

In [36]:
```
# feature selection using Correlation matrix:

cormat = df_mat.corr()
top_corr_features = cormat.index
plt.figure(figsize = (20,20))

#plot heat map
g = sns.heatmap(df_mat[top_corr_features].corr(),annot = True,cmap = 'RdYlGn')
```



as we didn't find any Attributes which are totally not correlated with our Target so we decided not to drop any of the atttributes:

In [37]:
```
# applied KNN ALgorithm
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import train_test_split
import pickle

X = df_mat.iloc[:, 0:31]
y = df_mat['G3']

X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.30, random_state = 42)

knn = KNeighborsClassifier(n_neighbors = 5)

knn.fit(X_train, y_train)

# Predict on dataset which model has not seen before
knn.score(X_test,y_test)
```

Out[37]: 0.907563025210084

In [38]:
```
# applying Logistic regression
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression



X_train, X_test, y_train, y_test = train_test_split(X,y,test_size = 0.30, random_state = 42)
model = LogisticRegression(max_iter=1000)

model1 = model.fit(X_train,y_train)
pickle.dump(model1,open('model_1.pkl','wb'))
prediction1 = model1.predict(X_test)
```

In [39]:
```
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, prediction1)
cm
```

Out[39]:
```
array([[43,  3],
       [ 4, 69]], dtype=int64)
```

In [40]:
```
from sklearn import metrics
metrics.accuracy_score(prediction1,y_test)
```

Out[40]: 0.9411764705882353

Now what if G1 and G2 are not present in the Data. then How is our model is going to predict:

In [41]:
```
# when we don't have G1
X_G2 = df_mat.iloc[:,0:31]
X_G2 = X_G2.drop('G1',axis = 1)

y_G2 =df_mat['G3']

X_train_G2, X_test_G2, y_train_G2, y_test_G2 = train_test_split(X_G2,y_G2, test_size = 0.3, random_state = 42)
model_G2 = LogisticRegression(max_iter = 1000)

model_G2 = model.fit(X_train_G2,y_train_G2)
pickle.dump(model_G2,open('model_G2.pkl','wb'))
prediction2 = model_G2.predict(X_test_G2)
```

In [42]:
```
from sklearn import metrics
metrics.accuracy_score(prediction2,y_test_G2)*100
```

Out[42]: 92.43697478991596

In [43]:
```
# when we don't have G2 values:
X_G1 = df_mat.iloc[:,0:31]
X_G1 = X_G1.drop('G2',axis = 1)
y_G1 =df_mat['G3']

X_train_G1, X_test_G1, y_train_G1, y_test_G1 = train_test_split(X_G1,y_G1, test_size = 0.3, random_state = 42)
model_G1 = LogisticRegression(max_iter = 1000)
model_G1 = model.fit(X_train_G1,y_train_G1)
pickle.dump(model_G1,open('model_G1.pkl','wb'))
prediction3 = model_G1.predict(X_test_G1)
```

In [44]:
```
metrics.accuracy_score(prediction3,y_test_G1)*100
```

Out[44]: 85.71428571428571

In [45]:
```
# when we don't  have both G1 and G2 Values:
X_G1_G2 = df_mat.iloc[:,0:31]
X_G1_G2 = X_G2.drop('G2',axis = 1)


y_G1_G2 =df_mat['G3']

X_train_G1_G2, X_test_G1_G2, y_train_G1_G2, y_test_G1_G2 = train_test_split(X_G1_G2,y_G1_G2, test_size = 0.3, random_sta
model_G1_G2 = LogisticRegression(max_iter = 1000)
model_G1_G2 = model.fit(X_train_G1_G2,y_train_G1_G2)
pickle.dump(model_G1_G2,open('model_G1_G2.pkl','wb'))
prediction4 = model_G1_G2.predict(X_test_G1_G2)
```

In [46]:
```
metrics.accuracy_score(prediction4,y_test_G1_G2)*100
```

Out[46]: 68.0672268907563

As we can see, When We have Both G1 and G2 values Then our Model Accuracy is highest i.e, 94.11

But When We have Only G2 Value then our model accuracy is : 92.43

When we have only G1 Value then our Model accuracy is : 85.71

When we don't have any of these values our Model Accurcay Drops significantly ie, 68.06

In [47]:
```
# Now We will try to create categories of our Data apart from pass and Fail:
print(df)
```

```
     sex  age  address  famsize Pstatus  Medu  Fedu  Mjob  Fjob  reason  ...  \
0      1    1        0        1       0     4     4     0     2       1  ...
1      1    1        0        1       1     1     1     0     4       1  ...
2      1    0        0        0       1     1     1     0     4       3  ...
3      1    0        0        1       1     4     2     1     3       2  ...
4      1    0        0        1       1     3     3     4     4       2  ...
..   ...  ...      ...      ...     ...   ...   ...   ...   ...     ...  ...
390    0    2        0        0       0     2     2     3     3       1  ...
391    0    1        0        0       1     3     1     3     3       1  ...
392    0    2        1        1       1     1     1     4     4       1  ...
393    0    1        1        0       1     3     2     3     4       1  ...
394    0    2        0        0       1     1     1     4     0       1  ...

     famrel  freetime  goout  Dalc  Walc  health  absences  G1  G2  G3
0         4         3      4     1     1       3         0   5   6   6
1         5         3      3     1     1       3         0   5   5   6
2         4         3      2     2     3       3         0   7   8  10
3         3         2      2     1     1       5         0  15  14  15
4         4         3      2     1     2       5         0   6  10  10
..      ...       ...    ...   ...   ...     ...       ...  ..  ..  ..
390       5         5      4     4     5       4         1   9   9   9
391       2         4      5     3     4       2         0  14  16  16
392       5         5      3     3     3       3         0  10   8   7
393       4         4      1     3     4       5         0  11  12  10
394       3         2      3     3     3       5         0   8   9   9

[395 rows x 32 columns]
```

In [48]:
```
def change(df1):
    new_G3 = []
    for i in df1:
        if(i > 16):
            i = 1 # excellent
        elif(i >=14 and i<=15):
            i = 2 # good
        elif(i>=12 and i<=13):
            i = 3 # average
        elif(i >=10 and i<=11):
            i = 4 #
        else:
            i = 5
        new_G3.append(i)
    return new_G3
df['G3'] = change(df['G3'])
print(df)
```

```
     sex  age  address  famsize Pstatus  Medu  Fedu  Mjob  Fjob  reason  ...  \
0      1    1        0        1       0     4     4     0     2       1  ...
1      1    1        0        1       1     1     1     0     4       1  ...
2      1    0        0        0       1     1     1     0     4       3  ...
3      1    0        0        1       1     4     2     1     3       2  ...
4      1    0        0        1       1     3     3     4     4       2  ...
..   ...  ...      ...      ...     ...   ...   ...   ...   ...     ...  ...
390    0    2        0        0       0     2     2     3     3       1  ...
391    0    1        0        0       1     3     1     3     3       1  ...
392    0    2        1        1       1     1     1     4     4       1  ...
393    0    1        1        0       1     3     2     3     4       1  ...
394    0    2        0        0       1     1     1     4     0       1  ...

     famrel  freetime  goout  Dalc  Walc  health  absences  G1  G2  G3
0         4         3      4     1     1       3         0   5   6   5
1         5         3      3     1     1       3         0   5   5   5
2         4         3      2     2     3       3         0   7   8   4
3         3         2      2     1     1       5         0  15  14   2
4         4         3      2     1     2       5         0   6  10   4
..      ...       ...    ...   ...   ...     ...       ...  ..  ..  ..
390       5         5      4     4     5       4         1   9   9   5
391       2         4      5     3     4       2         0  14  16   5
392       5         5      3     3     3       3         0  10   8   5
393       4         4      1     3     4       5         0  11  12   4
394       3         2      3     3     3       5         0   8   9   5

[395 rows x 32 columns]
```

In [49]:
```
# So Now applying KNN algorithm on this first:
X = df.iloc[:, 0:31]
y = df['G3']
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.30, random_state = 42)
knn = KNeighborsClassifier(n_neighbors = 5)
knn.fit(X_train, y_train)

pickle.dump(knn,open('KNNmodel.pkl','wb'))

#Predict on dataset which model has not seen before
knn.score(X_test,y_test)*100
```

Out[49]: 74.78991596638656

In [50]:
```
# Now applying decision Tree
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.30, random_state = 42)
```

In [51]:
```
from sklearn.tree import DecisionTreeClassifier
from sklearn.tree import DecisionTreeRegressor
```

In [52]:
```
dt_model  = DecisionTreeClassifier(random_state = 10)
```

In [53]:
```
dt_model.fit(X_train,y_train)
pickle.dump(dt_model,open('dt_model.pkl','wb'))
```

In [54]:
```
# checking score on Training data
dt_model.score(X_train,y_train)
```

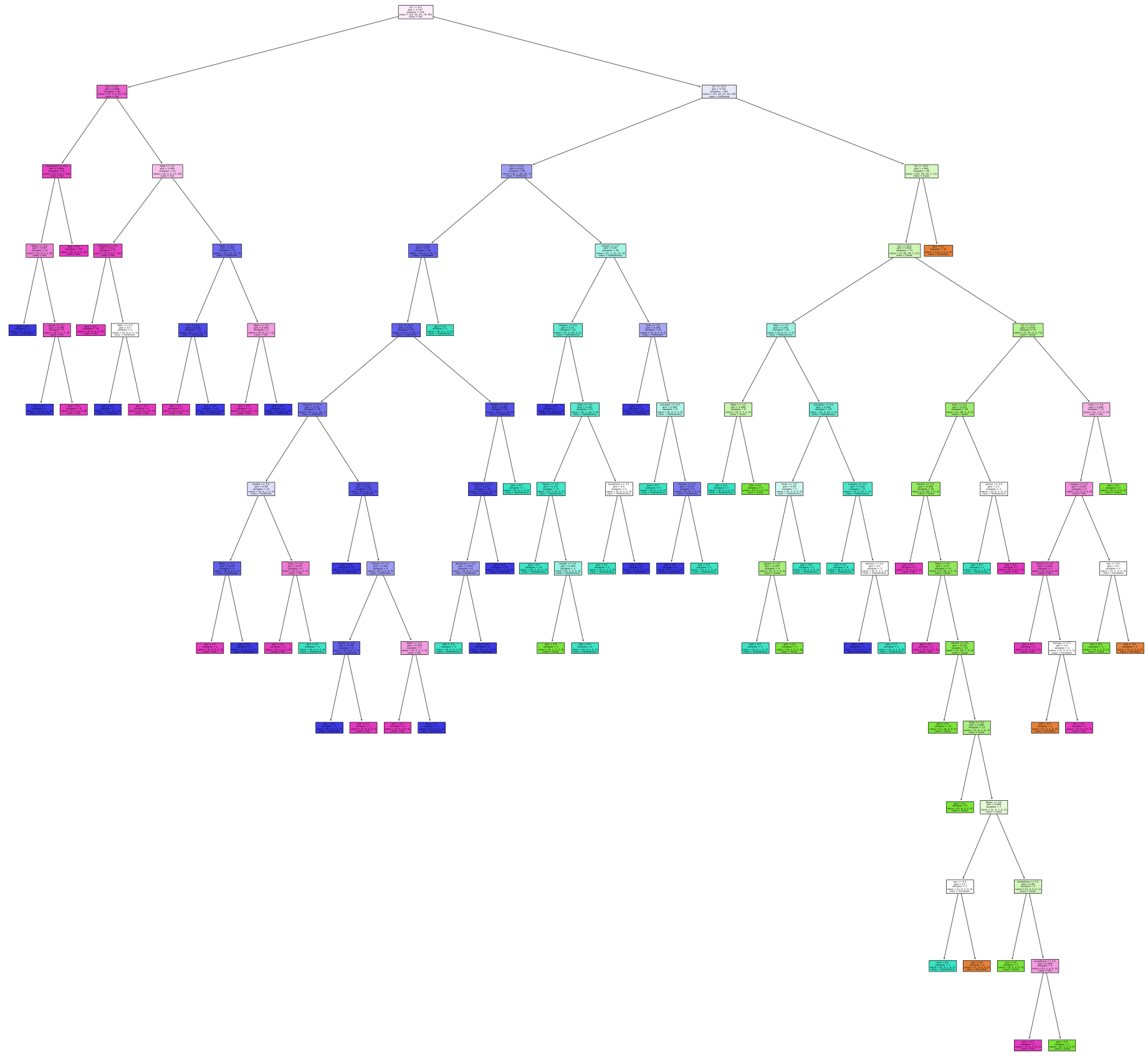
Out[54]: 1.0

In [55]:
```
# finding accuracy of decision tree
from sklearn.metrics import accuracy_score
res_pred = dt_model.predict(X_test)
score = accuracy_score(y_test, res_pred)
score


# another method of finding is:
score = dt_model.score(X_test, y_test)*100
score
```

Out[55]: 72.26890756302521

In [56]:
```
from sklearn import tree
plt.figure(figsize=(50,50))
dec_tree = tree.plot_tree(decision_tree=dt_model, feature_names = X.columns,
                          class_names =["Excellent", "Good", "Satisfactory","Sufficient","Fail"] , filled = True)
plt.show()
```



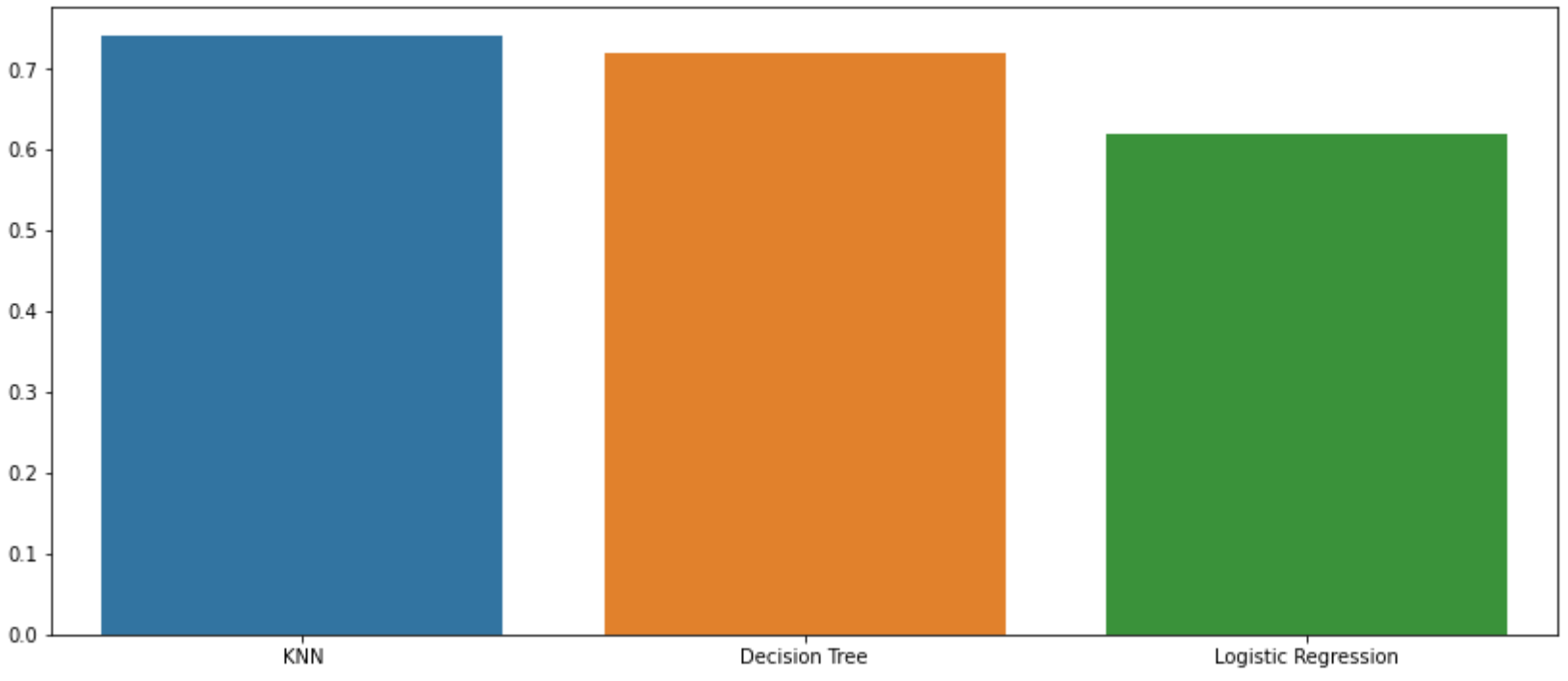
In [57]:
```
# Applying Logistic Regression Here:
model = LogisticRegression(max_iter = 3000)
model_lr = model.fit(X_train,y_train)
prediction1 = model_lr.predict(X_test)
```

In [58]:
```
metrics.accuracy_score(prediction1,y_test)*100
```

Out[58]: 62.18487394957983

In [59]:
```
plt.figure(figsize=(14,6))
data={'KNN' : 0.74,'Decision Tree' : 0.72, 'Logistic Regression' : 0.62}
ML_model = pd.DataFrame(data,index =[1,2,3])
sns.barplot(data=ML_model)
```

Out[59]: <AxesSubplot:>



In [ ]: