Student Alcohol Consumption

Do students who consume alcohol score less in exams?

It contains a lot of interesting social (family background, alcohol consumption), gender and study information about students. You can use it for some EDA or try to predict students final grade.

```
In [4]: %matplotlib inline
import os
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import seaborn as sns # visualize
import matplotlib.pyplot as plt
import matplotlib.pyplot as plt
import scipy.stats as st
from statsmodels.formula.api import ols
if int(os.environ.get("MODERN_PANDAS_EPUB", 0)):
    import prep
```

```
In [6]: #Merging the the files into final
        pd.options.display.max rows = 10
        sns.set(style='ticks', context='talk')
        d1=pd.read csv("/Users/ruchi/data/student-mat.csv")
        d2=pd.read csv("/Users/ruchi/data/student-por.csv")
         final = pd.merge(d1, d2, how='outer',on=["school", "sex", "age", "address",
         "famsize", "Pstatus",
                                      "Medu", "Fedu", "Mjob", "Fjob", "reason", "nurser
        y", "internet",
                                      "guardian", "guardian", "traveltime", "studytim
        e", "failures",
                                      "schoolsup", "famsup", "activities", "higher",
         "romantic",
                                      "famrel", "freetime", "goout", "Dalc", "Walc", "h
        ealth", "absences"])
         final.to csv('final.csv', index=False)
```

In [7]: #Merging both the csv to get students who took both Maths and Portuguese dinner = pd.merge(d1, d2, how='inner',on=["school","sex","age","address" ,"famsize","Pstatus", "Medu", "Fedu", "Mjob", "Fjob", "reason", "nurser y", "internet", "quardian", "quardian", "traveltime", "studytim e", "failures", "schoolsup", "famsup", "activities", "higher", "romantic", "famrel", "freetime", "goout", "Dalc", "Walc", "h ealth", "absences"]) dinner.to_csv('inner.csv', index=False) dinner.shape #Merging both the csv to get students who took either Maths or Portugues douter = pd.merge(d1, d2, how='outer',on=["school","sex","age","address" , "famsize", "Pstatus", "Medu", "Fedu", "Mjob", "Fjob", "reason", "nurser y", "internet", "guardian", "guardian", "traveltime", "studytim e", "failures", "schoolsup", "famsup", "activities", "higher", "romantic", "famrel", "freetime", "goout", "Dalc", "Walc", "h ealth", "absences"]) douter.to csv('outer.csv', index=False) print(douter)

		sex	age a	address f	famsize	Pstatus	Medu	Fedu	Мј	ob	
Fjob 0	\ GP	F	18	U	GT3	А	4	4	at_ho	ome ·	tea
cher 1	GP	F	17	U	GT3	Т	1	1	at ho	me	0
ther									_		
2 ther	GP	F	15	U	LE3	Т	1	1	at_ho	ome	0
3	GP	F	15	U	GT3	Т	4	2	heal	th s	erv
ices 4	GP	F	16	Ū	GT3	Т	3	3	oth	er	0
ther											
• •	•••	• •	•••	• • •	•••	• • •	•••	• • •	•	••	
954 ther	MS	F	19	R	GT3	Т	2	3	servic	es	0
955	MS	F	18	U	LE3	Т	3	1	teach	er s	erv
ices 956	MS	F	18	U	GT3	Т	1	1	oth	or	0
ther	HO	r		O	913	1		1			U
957 ices	MS	М	17	Ŭ	LE3	Т	3	1	servic	es s	erv
958	MS	М	18	R	LE3	Т	3	2	servic	es	0
ther											
2 17	• • •	Walc	health	h absend	ces G1	_x G2_x	G3_x	paid_y	G1_y	G2_y	G
3_y 0		Walc 1		h absend 3		_x G2_x .0 6.0	G3_x 6.0	paid_y NaN	G1_y NaN	G2_y NaN	
0 NaN	•••	1	;	3	6 5	.0 6.0	6.0	NaN	NaN	NaN	
0 NaN 1 NaN		1	:	3	6 5 4 5	.0 6.0	6.0	NaN NaN	NaN NaN	NaN NaN	
0 NaN 1 NaN 2	•••	1	:	3	6 5 4 5	.0 6.0	6.0	NaN	NaN	NaN	
0 NaN 1 NaN 2 NaN 3	•••	1	;	3	6 5 4 5	.0 6.0 .0 5.0 .0 8.0	6.0	NaN NaN	NaN NaN	NaN NaN	
0 NaN 1 NaN 2 NaN	•••	1 1 3	; ;	3 3 3	6 5 4 5 10 7 2 15	.0 6.0 .0 5.0 .0 8.0	6.0 6.0 10.0	Nan Nan Nan	NaN NaN NaN	NaN NaN NaN	
0 NaN 1 NaN 2 NaN 3 NaN 4 NaN		1 1 3	; ;	3 3 3 5	6 5 4 5 10 7 2 15	.0 6.0 .0 5.0 .0 8.0 .0 14.0	6.0 6.0 10.0 15.0	Nan Nan Nan Nan	NaN NaN NaN	Nan Nan Nan Nan	
0 NaN 1 NaN 2 NaN 3 NaN 4		1 1 3	; ;	3 3 3 5	6 5 4 5 10 7 2 15	.0 6.0 .0 5.0 .0 8.0 .0 14.0	6.0 6.0 10.0 15.0	Nan Nan Nan Nan	NaN NaN NaN	Nan Nan Nan Nan	
0 NaN 1 NaN 2 NaN 3 NaN 4 NaN		1 1 3	; ;	3 3 3 5	6 5 4 5 10 7 2 15 4 6	.0 6.0 .0 5.0 .0 8.0 .0 14.0	6.0 6.0 10.0 15.0	Nan Nan Nan Nan	NaN NaN NaN	Nan Nan Nan Nan	
0 NaN 1 NaN 2 NaN 3 NaN 4 NaN		1 3 1 2		3 3 5 	6 5 4 5 10 7 2 15 4 6 4 Na	.0 6.0 .0 5.0 .0 8.0 .0 14.0 .0 10.0	6.0 6.0 10.0 15.0 10.0	NaN NaN NaN NaN NaN	NaN NaN NaN NaN	Nan Nan Nan Nan	
0 NaN 1 NaN 2 NaN 3 NaN 4 NaN 954 0.0 955 6.0		1 3 1 2 2		3 3 5 5 	6 5 4 5 10 7 2 15 4 6 4 Na 4 Na	.0 6.0 .0 5.0 .0 8.0 .0 14.0 .0 10.0 an Nan	6.0 6.0 10.0 15.0 10.0 NaN	NaN NaN NaN NaN no	NaN NaN NaN NaN NaN 10.0	NaN NaN NaN NaN 11.0	1
0 NaN 1 NaN 2 NaN 3 NaN 4 NaN 954 0.0 955 6.0 956 9.0		1 3 1 2		3 3 5 5 1	6 5 4 5 10 7 2 15 4 6 4 Na 4 Na 6 Na	.0 6.0 .0 5.0 .0 8.0 .0 14.0 .0 10.0 an Nan	6.0 6.0 10.0 15.0 10.0 	Nan Nan Nan Nan Nan	NaN NaN NaN NaN 10.0 15.0	NaN NaN NaN NaN 11.0 15.0	1
0 NaN 1 NaN 2 NaN 3 NaN 4 NaN 954 0.0 955 6.0 956 9.0 957		1 3 1 2 2		3 3 5 5 	6 5 4 5 10 7 2 15 4 6 4 Na 4 Na 6 Na	.0 6.0 .0 5.0 .0 8.0 .0 14.0 .0 10.0 an Nan	6.0 6.0 10.0 15.0 10.0 NaN	NaN NaN NaN NaN no	NaN NaN NaN NaN NaN 10.0	NaN NaN NaN NaN 11.0	1
0 NaN 1 NaN 2 NaN 3 NaN 4 NaN 954 0.0 955 6.0 956 9.0		1 3 1 2 2 1		3 3 5 5 1	6 5 4 5 10 7 2 15 4 6 4 Na 4 Na 6 Na 6 Na	.0 6.0 .0 5.0 .0 8.0 .0 14.0 .0 10.0 an Nan an Nan	6.0 6.0 10.0 15.0 10.0 NaN NaN	NaN NaN NaN NaN no no	NaN NaN NaN NaN 10.0 15.0	NaN NaN NaN NaN 11.0 15.0	1 1

[959 rows x 37 columns]

```
In [51]: #Calculating the average of the grades scored by students
d2['AvgGrade']= d2[['G1', 'G2', 'G3']].mean(axis=1)
d1['AvgGrade']= d1[['G1', 'G2', 'G3']].mean(axis=1)
```

Out[52]:

					mean					
					AvgGrade					
				Mjob	at_home	health	other	services	teacher	All
school	sex	famsize	paid	guardian						
GP	F	GT3	no	father	8.11111	6.33333	9.11111	10.3333		9.187
				mother	7.76923	12.1667	9.74074	11.9048	14.5	9.939
				other	11.5556		6.5			9.533
			yes	father	9	16.1667	11.6667	12.8333		12.26
				mother	10.6667	14.5	9.01852	10.4444	10.3333	10.29
•••										
MS	М	LE3	no	mother	10			13.1667		11.58
			yes	father	12.6667					12.66
				mother					13	13.00
				other		_	_	9	_	9.000
All					9.76271	12.2353	10.0591	11.2071	11.2701	10.67

43 rows × 24 columns

Out[53]:

					mean					
					AvgGrade	•				
				Mjob	at_home	health	other	services	teacher	All
school	sex	famsize	paid	guardian						
GP	F	GT3	no	father	13.125	14.8333	12.9091	12.9394		13.19
				mother	12.1884	15.1111	12.3203	12.2222	13.5385	12.59
				other	10	13.3333	11.3333		10	11.26
			yes	mother	10.8889		12	15.6667	11.3333	11.94
				other			11.3333	13		12.16
MS	М	GT3	yes	father			9			9.000
				mother	11		8.66667	10.5		10.33
		LE3	no	father	10.4444	10.5	12.3333		11.6667	11.42
				mother	9.45833		12.5	11.4444	15.6667	11.05
All					10.7358	12.7014	11.4574	11.826	12.7963	11.62

36 rows × 24 columns

In [54]: # The merged table with data of students of both the school
final.describe()

Out[54]:

	age	Medu	Fedu	traveltime	studytime	failures	fam
count	959.000000	959.000000	959.000000	959.000000	959.000000	959.000000	959.0000
mean	16.755996	2.586027	2.364964	1.538060	1.958290	0.279458	3.914494
std	1.242473	1.116704	1.100514	0.739831	0.832741	0.672379	0.950216
min	15.000000	0.000000	0.000000	1.000000	1.000000	0.000000	1.000000
25%	16.000000	2.000000	1.000000	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

```
In [55]: # Categorical Data present in the table
         categorical_features = (final.select_dtypes(include=['object']).columns.
         values)
         categorical features
Out[55]: array(['school', 'sex', 'address', 'famsize', 'Pstatus', 'Mjob', 'Fjo
         b',
                'reason', 'guardian', 'schoolsup', 'famsup', 'paid x', 'activiti
         es',
                'nursery', 'higher', 'internet', 'romantic', 'paid y'], dtype=ob
         ject)
In [56]: # Numerical / Non categorical data present in the table
         numerical features = final.select dtypes(include = ['float64', 'int64'])
         .columns.values
         numerical features
Out[56]: array(['age', 'Medu', 'Fedu', 'traveltime', 'studytime', 'failures',
                'famrel', 'freetime', 'goout', 'Dalc', 'Walc', 'health', 'absenc
         es',
                'G1 x', 'G2 x', 'G3 x', 'G1 y', 'G2 y', 'G3 y'], dtype=object)
```

Correlation between features

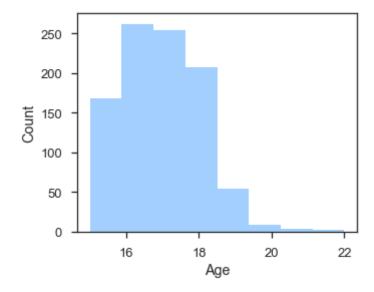
For broad perspective lets look at first correlation of features.

```
In [22]: plt.figure(figsize=(15,15))
              sns.heatmap(d1.corr(),annot = True,fmt = ".2f",cbar = True)
              plt.xticks(rotation=90)
              plt.yticks(rotation = 0)
Out[22]: (array([
                             0.5,
                                        1.5,
                                                  2.5,
                                                             3.5,
                                                                       4.5,
                                                                                  5.5,
                                                                                             6.5,
                                                                                                       7.5,
                                                                                                                  8.5,
                                      10.5,
                                                11.5,
                                                           12.5,
                                                                      13.5,
                                                                                 14.5,
                                                                                           15.5]),
                             9.5,
               <a list of 16 Text yticklabel objects>)
                         1.00 -0.16 -0.16 0.07 -0.00 0.24 0.05 0.02 0.13 0.13 0.12 -0.06 0.18 -0.06 -0.14 -0.16
                  Medu - -0.16 1.00 0.62 -0.17 0.06 -0.24 -0.00 0.03 0.06 0.02 -0.05 -0.05 0.10 0.21 0.22 0.22
                                                                                                                     - 0.8
                  Fedu --0.16 0.62 1.00 -0.16 -0.01 -0.25 -0.00 -0.01 0.04 0.00 -0.01 0.01 0.02 0.19 0.16 0.15
               traveltime - 0.07 -0.17 -0.16 1.00 -0.10 0.09 -0.02 -0.02 0.03 0.14 0.13 0.01 -0.01 -0.09 -0.15 -0.12
               studytime --0.00 0.06 -0.01 -0.10 1.00 -0.17 0.04 -0.14 -0.06 -0.20 -0.25 -0.08 -0.06 0.16 0.14 0.10
                                                                                                                     - 0.4
                 failures - <mark>0.24</mark> -0.24 -0.25 0.09 -0.17 1.00 -0.04 0.09 0.12 0.14 0.14 0.07 0.06 -0.35 -0.36 -0.36
                 famrel - 0.05 -0.00 -0.00 -0.02 0.04 -0.04 1.00 0.15 0.06 -0.08 -0.11 0.09 -0.04 0.02 -0.02 0.05
                freetime - 0.02 0.03 -0.01 -0.02 -0.14 0.09 0.15 1.00 0.29 0.21 0.15 0.08 -0.06 0.01 -0.01 0.01
                                                                                                                     - 0.0
                  goout - 0.13 0.06 0.04 0.03 -0.06 0.12 0.06 0.29 1.00 0.27 0.42 -0.01 0.04 -0.15 -0.16 -0.13
                  Dalc - 0.13 0.02 0.00 0.14 -0.20 0.14 -0.08 0.21 0.27 1.00 0.65 0.08 0.11 -0.09 -0.06 -0.05
                  Walc - 0.12 -0.05 -0.01 0.13 -0.25 0.14 -0.11 0.15 0.42 0.65 1.00 0.09 0.14 -0.13 -0.08 -0.05
                                                                                                                      -0.4
                 health --0.06 -0.05 0.01 0.01 -0.08 0.07 0.09 0.08 -0.01 0.08 0.09 1.00 -0.03 -0.07 -0.10 -0.06
               absences - 0.18 0.10 0.02 -0.01 -0.06 0.06 -0.04 -0.06 0.04 0.11 0.14 -0.03 1.00 -0.03 -0.03 0.03
                    G1 --0.06 0.21 0.19 -0.09 0.16 -0.35 0.02 0.01 -0.15 -0.09 -0.13 -0.07 -0.03 1.00 0.85 0.80
                                                                                                                      -0.8
                    G2 --0.14 0.22 0.16 -0.15 0.14 -0.36 -0.02 -0.01 -0.16 -0.06 -0.08 -0.10 -0.03 0.85 1.00 0.90
                    G3 --0.16 0.22 0.15 -0.12 0.10 -0.36 0.05 0.01 -0.13 -0.05 -0.05 -0.06 0.03 0.80 0.90 1.00
                                                                                             9
```

As it can be seen from correlation map the education of parents, alcohol consumption of students and exam scores are highly correlated with each other.

EDA

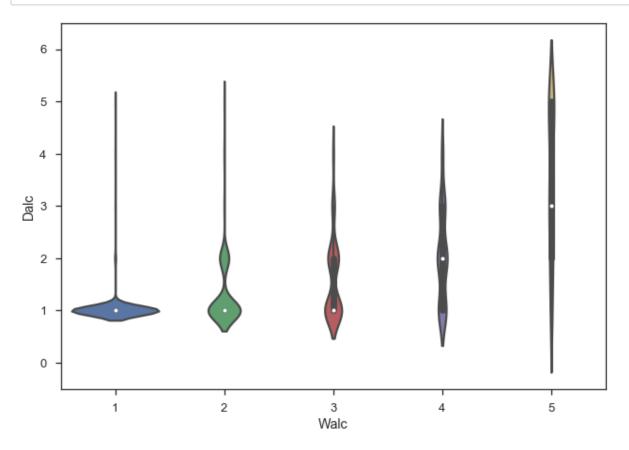
1. At what age students consumes more alcohol?



We conclude that teenagers drink more alcohol compared to adults

2. Students consume more alcohol on weekend or weekday?

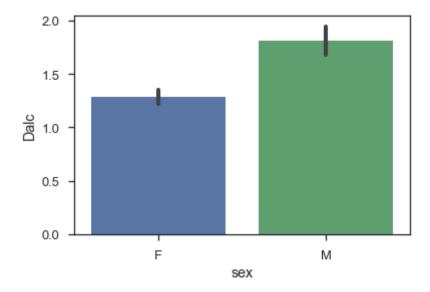
In [16]: sns.violinplot(x="Walc", y="Dalc", data=final);



Students drink more alcohol on Weekend

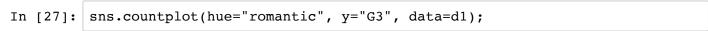
3. Which gender consumes more alcohol on daily basis?

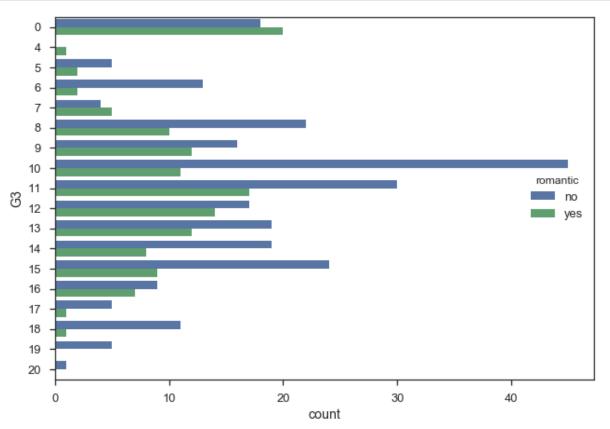
In [20]: sns.barplot(x = "sex", y = "Dalc",data = d2)
Out[20]: <matplotlib.axes._subplots.AxesSubplot at 0x112c2b128>



So, we see that males consume more alcohol as compared to females on daily basis

4. How do students in romantic relationship score?





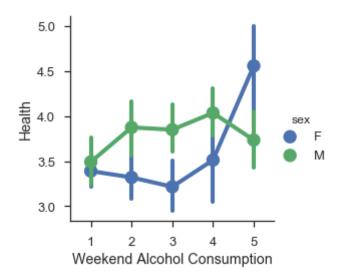
As we see students who are in a romantic relationship score less

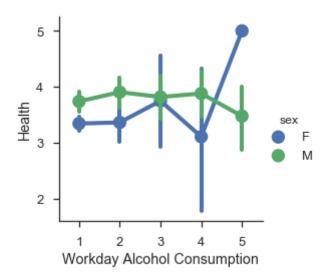
5. The health of which gender is most affected by alcohol consumption?

```
In [34]: plot1 = sns.factorplot(x="Walc", y="health", hue="sex", data=final)
    plot1.set(ylabel="Health", xlabel="Weekend Alcohol Consumption")

plot2 = sns.factorplot(x="Dalc", y="health", hue="sex", data=final)
    plot2.set(ylabel="Health", xlabel="Workday Alcohol Consumption")
```

Out[34]: <seaborn.axisgrid.FacetGrid at 0x185ceed8da0>

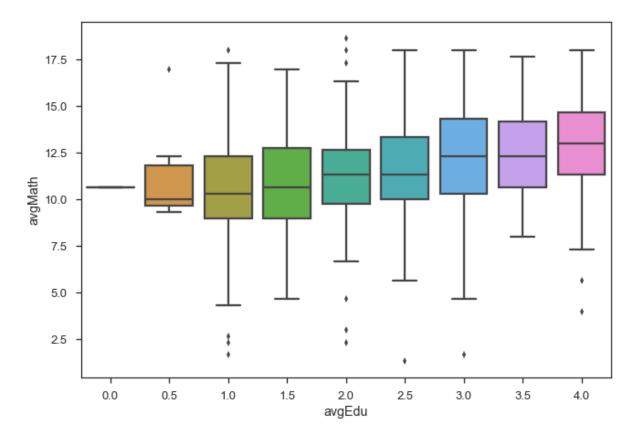




Females heath is more affected by consumption of alcohol

6. Do students whose parents have higher education score good grades?

Out[24]: <matplotlib.axes._subplots.AxesSubplot at 0x11a4379b0>



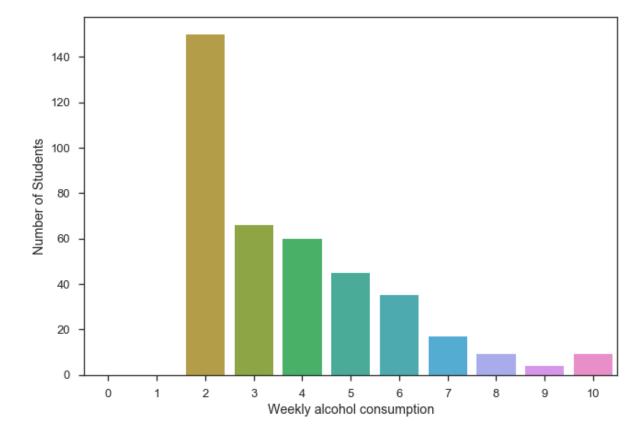
Students whose parents are more qualified tend to get higher grades

7. What is the weekly frequency of students to consume alcohol?

There is no student who does not consume alcohol. However, all students at least 2 times in a week consume alcohol.

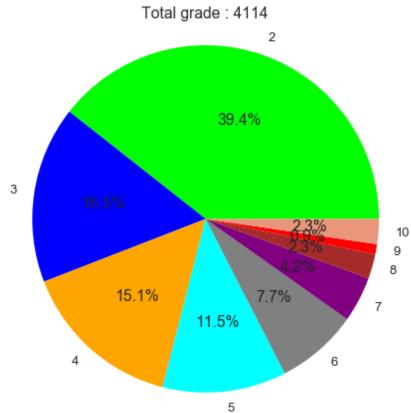
```
In [18]: d1['Dalc'] = d1['Dalc'] + d1['Walc']
list = []
for i in range(11):
    list.append(len(d1[d1.Dalc == i]))
ax = sns.barplot(x = [0,1,2,3,4,5,6,7,8,9,10], y = list)
plt.ylabel('Number of Students')
plt.xlabel('Weekly alcohol consumption')
```

Out[18]: <matplotlib.text.Text at 0x119b1f278>



```
labels = ['2','3','4','5','6','7','8','9','10']
In [20]:
         colors = ['lime','blue','orange','cyan','grey','purple','brown','red','d
         arksalmon']
         explode = [0,0,0,0,0,0,0,0,0]
         sizes = []
         for i in range(2,11):
             sizes.append(sum(d1[d1.Dalc == i].G3))
         total grade = sum(sizes)
         average = total_grade/float(len(d1))
         plt.pie(sizes,explode=explode,colors=colors,labels=labels,autopct = '%1.
         1f%%')
         plt.axis('equal')
         plt.title('Total grade : '+str(total_grade))
         plt.xlabel('Students grade distribution according to weekly alcohol cons
         umption')
```

Out[20]: <matplotlib.text.Text at 0x119b27dd8>



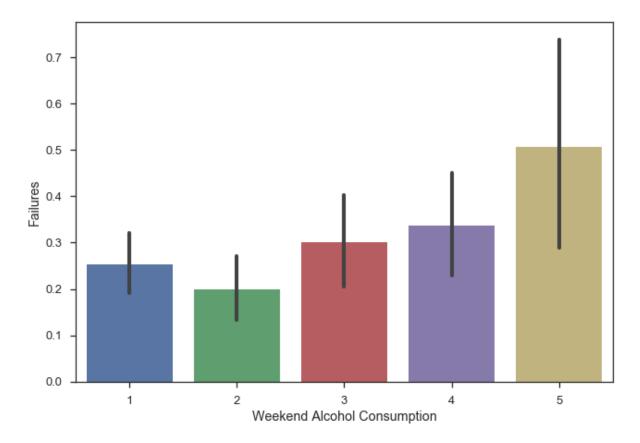
Students grade distribution according to weekly alcohol consumption

We see that students who drink alcohol less score better grades

8. What is failure rate of the students consuming alcohol on weekend?

```
In [39]: plot1 = sns.barplot(x="Walc", y="failures", data=douter)
    plot1.set(ylabel="Failures", xlabel="Weekend Alcohol Consumption")
```

```
Out[39]: [<matplotlib.text.Text at 0x185cf2f6908>, <matplotlib.text.Text at 0x185d0e07fd0>]
```



We see that students who consume more alcohol on weekends tend to have higher failure rate

Machine Learning

```
In [66]: from sklearn.model_selection import train_test_split
    from sklearn import linear_model
    from sklearn.preprocessing import LabelEncoder
    from sklearn.model_selection import cross_val_predict
    import matplotlib.pyplot as plt
```

1. Logistic Regression

```
In [67]: #Machine Learning models - Logistic
X=d2[['traveltime','studytime','G3','Dalc','Walc']] #Predictors
y=d2['sex'] #Response Variable
```

```
In [116]: # 40% Test Data, 60% Training Data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.4, random_state=59)
```

from sklearn.linear_model import LogisticRegression

```
In [91]:
         log=LogisticRegression()
In [92]:
        log.fit(X_train,y_train)
Out[92]: LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=
         True,
                   intercept scaling=1, max iter=100, multi class='ovr', n jobs=
         1,
                   penalty='12', random_state=None, solver='liblinear', tol=0.00
         01,
                   verbose=0, warm_start=False)
In [93]:
         predicts=log.predict(X_test)
         from sklearn.metrics import classification_report,confusion_matrix
In [94]:
In [95]:
         print(classification_report(y_test,predicts))
         print('\n')
         print(confusion_matrix(y_test,predicts))
                       precision
                                    recall f1-score
                                                        support
                                      0.81
                            0.75
                                                0.78
                                                            163
                   F
                            0.63
                                      0.55
                                                0.59
                                                             97
                   М
                                      0.71
         avg / total
                            0.71
                                                0.71
                                                            260
         [[132
                311
```

2. Linear Regression

[44

53]]

```
In [40]: import statsmodels.api as sm
    from sklearn import linear_model
    #Linear Regression
    X=d2[['age','Medu','Fedu','absences','G1','G2']]
    y=d2['G3']
```

/Users/ruchi/anaconda/lib/python3.6/site-packages/statsmodels/compat/pa ndas.py:56: FutureWarning: The pandas.core.datetools module is deprecat ed and will be removed in a future version. Please use the pandas.tseri es module instead.

from pandas.core import datetools

regr = linear_model.LinearRegression() regr.fit(X_train, y_train)# Now we can just create a data frame to store this values of coefficients in a data frame

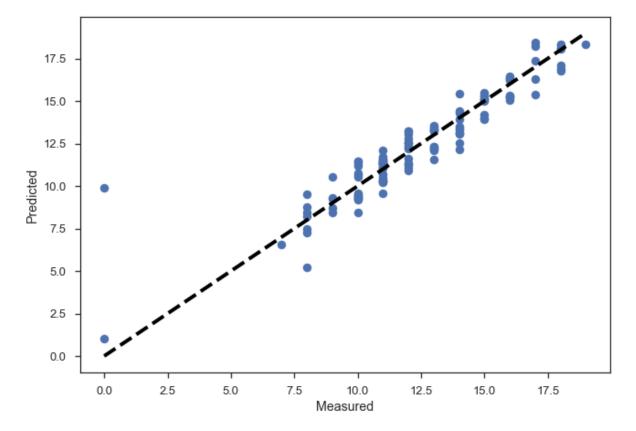
cdf=pd.DataFrame(lm.coef_,X_train.columns,columns= ['Coefficient'])

In [43]: # Now we can just create a data frame to store this values of coefficien
 ts in a data frame
 cdf=pd.DataFrame(regr.coef_,X_train.columns,columns=['Coefficient'])
 cdf

Out[43]:

	Coefficient
age	0.035736
Medu	0.017232
Fedu	0.026441
absences	0.030022
G1	0.173771
G2	0.847473

```
In [100]: #10 samples
    predicted = cross_val_predict(regr, X_test, y_test, cv=10)
    fig, ax = plt.subplots()
    ax.scatter(y_test, predicted)
    ax.plot([y.min(), y.max()], [y.min(), y.max()], 'k--', lw=4)
    ax.set_xlabel('Measured')
    ax.set_ylabel('Predicted')
    plt.show()
```



As we can see that it is a perfect linear fit. So the predictors Age, Medu, Fedu, Absences, G1 and G2 are strongly related to the response variable G3

```
In [45]: model = sm.OLS(y, X)
    results=model.fit()
    results.summary()
```

Out[45]: OLS Regression Results

Dep. Variable:	G3	R-squared:	0.990
Model:	OLS	Adj. R-squared:	0.990
Method:	Least Squares	F-statistic:	1.023e+04
Date:	Mon, 11 Dec 2017	Prob (F-statistic):	0.00
Time:	00:58:21	Log-Likelihood:	-1068.7
No. Observations:	649	AIC:	2149.
Df Residuals:	643	BIC:	2176.
Df Model:	6		
Covariance Type:	nonrobust		

	coef	std err	t	P> t	[0.025	0.975]
age	-0.0152	0.013	-1.196	0.232	-0.040	0.010
Medu	-0.0387	0.058	-0.667	0.505	-0.153	0.075
Fedu	0.0231	0.059	0.391	0.696	-0.093	0.139
absences	0.0202	0.011	1.854	0.064	-0.001	0.042
G1	0.1523	0.036	4.283	0.000	0.082	0.222
G2	0.8985	0.034	26.316	0.000	0.831	0.966

Omnibus:	463.984	Durbin-Watson:	1.855
Prob(Omnibus):	0.000	Jarque-Bera (JB):	10445.450
Skew:	-2.887	Prob(JB):	0.00
Kurtosis:	21.787	Cond. No.	36.3

R-squared which is goodness of fit is 99%, so it is a very good fit

```
In [108]: from sklearn.model_selection import train_test_split
    X=d2[['age','Medu','Fedu','absences','G1','G2']]
    y=d2['G3']
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.20
    , random_state=42)
```

3. Decision Tree Classifier

```
In [106]: from sklearn import tree
    from sklearn import metrics
    clf = tree.DecisionTreeClassifier()
    clf = clf.fit(X_train, y_train)
    clf.score(X_train, y_train)
Out[106]: 0.98714652956298199
```

4. Matrix Accuracy

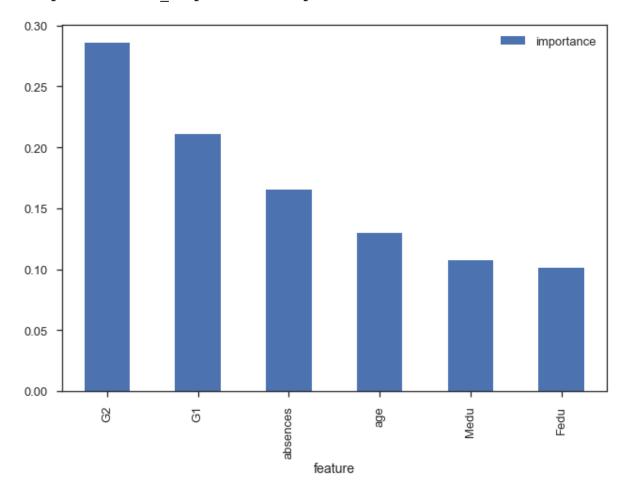
```
In [114]: y_pred = clf.predict(X_test)
    acc_test = metrics.accuracy_score(y_test,y_pred)
    acc_test
Out[114]: 0.76923076923076927
```

5. Random Forest Classifier

Important Features

	importance
feature	
G2	0.286
G1	0.211
absences	0.165
age	0.130
Medu	0.107
Fedu	0.101

Out[111]: <matplotlib.axes._subplots.AxesSubplot at 0x11a722668>



Grades G1 and G2 are most important feature for predicting final grade G3

Conclusion:

- The failure rate of students who consume alcohol frequently is more.
- Students whose parents are more qualified tend to get higher grades

References:

- https://www.kaggle.com/calcifer/alcohol-consumption-and-average-grades/data (https://www.kaggle.com/calcifer/alcohol-consumption-and-average-grades/data)
- https://seaborn.pydata.org/tutorial/categorical.html (https://seaborn.pydata.org/tutorial/categorical.html)

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