In [1]:
```
from IPython.core.interactiveshell import InteractiveShell
InteractiveShell.ast_node_interactivity = "all"
```

In [2]:
```
%matplotlib inline
import numpy as np
import pandas as pd
import sklearn

import warnings
warnings.filterwarnings('ignore')
```

In [3]:
```
## Read data from csv file 'student-por.csv'
port_data = pd.read_csv('student-por.csv', sep=';')
```

In [4]:
```
port_data.head()
```

Out[4]:

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

5 rows × 33 columns

In [5]:
```
# checking the shape of the dataset
port_data.shape
```

Out[5]:
```
(649, 33)
```

In [6]:

```
# Making dummy variables in portugese data and saving

portdata_dummy = pd.get_dummies(port_data,columns=['school','sex','address','famsize','Pstatus','Mjob','Fjob','reason','guardian','schoolsup','famsup','paid','activities','nursery','higher','internet','romantic'], drop_first=True)


portdata_dummy.head()
```

Out[6]:

	age	Medu	Fedu	traveltime	studytime	failures	famrel	freetime	goout	Dalc	...	guardian_
0	18	4	4	2	2	0	4	3	4	1	...	
1	17	1	1	1	2	0	5	3	3	1	...	
2	15	1	1	1	2	0	4	3	2	2	...	
3	15	4	2	1	3	0	3	2	2	1	...	
4	16	3	3	1	2	0	4	3	2	1	...	

5 rows × 42 columns

In [7]:
```
# Starting Regression

# PX - selecting only the predictor variables and not the response variable G3
including G1 and G2

PX = portdata_dummy[['age',
 'Medu',
 'Fedu',
 'traveltime',
 'studytime',
 'failures',
 'famrel',
 'freetime',
 'goout',
 'Dalc',
 'Walc',
 'health',
 'absences',
 'school_MS',
 'sex_M',
 'address_U',
 'famsize_LE3',
 'Pstatus_T',
 'Mjob_health',
 'Mjob_other',
 'Mjob_services',
 'Mjob_teacher',
 'Fjob_health',
 'Fjob_other',
 'Fjob_services',
 'Fjob_teacher',
 'reason_home',
 'reason_other',
 'reason_reputation',
 'guardian_mother',
 'guardian_other',
 'schoolsup_yes',
 'famsup_yes',
 'paid_yes',
 'activities_yes',
 'nursery_yes',
 'higher_yes',
 'internet_yes',
 'romantic_yes']]


PX.head()

print(PX.shape)
```

Out[7]:

	age	Medu	Fedu	traveltime	studytime	failures	famrel	freetime	goout	Dalc	...	guardian_
0	18	4	4	2	2	0	4	3	4	1	...	
1	17	1	1	1	2	0	5	3	3	1	...	
2	15	1	1	1	2	0	4	3	2	2	...	
3	15	4	2	1	3	0	3	2	2	1	...	
4	16	3	3	1	2	0	4	3	2	1	...	

5 rows × 39 columns

```
(649, 39)
```

In [8]:
```
# listing the columns of portuguese_dummy dataset

list(portdata_dummy.columns)
```

Out[8]:
```
['age',
 'Medu',
 'Fedu',
 'traveltime',
 'studytime',
 'failures',
 'famrel',
 'freetime',
 'goout',
 'Dalc',
 'Walc',
 'health',
 'absences',
 'G1',
 'G2',
 'G3',
 'school_MS',
 'sex_M',
 'address_U',
 'famsize_LE3',
 'Pstatus_T',
 'Mjob_health',
 'Mjob_other',
 'Mjob_services',
 'Mjob_teacher',
 'Fjob_health',
 'Fjob_other',
 'Fjob_services',
 'Fjob_teacher',
 'reason_home',
 'reason_other',
 'reason_reputation',
 'guardian_mother',
 'guardian_other',
 'schoolsup_yes',
 'famsup_yes',
 'paid_yes',
 'activities_yes',
 'nursery_yes',
 'higher_yes',
 'internet_yes',
 'romantic_yes']
```

In [9]:
```
# Y dependent variable of portdata_dummy

PY = portdata_dummy['G3']

PY.head()
```

Out[9]:
```
0    11
1    11
2    12
3    14
4    13
Name: G3, dtype: int64
```

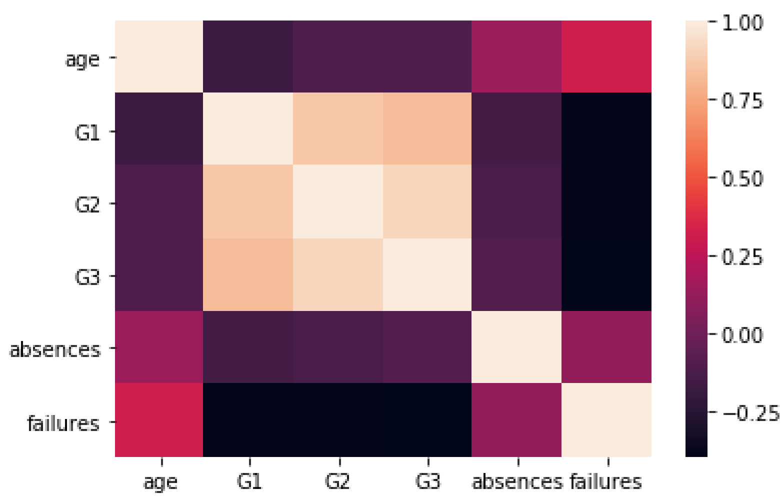
In [10]:
```
# checking correlation between numeric variables
PXGrade = portdata_dummy[['age','G1','G2','G3','absences','failures']]
correlation1 = PXGrade.corr()
correlation1

# heatmap of numeric variables
import seaborn
seaborn.heatmap(correlation1)
```

Out[10]:

	age	G1	G2	G3	absences	failures
age	1.000000	-0.174322	-0.107119	-0.106505	0.149998	0.319968
G1	-0.174322	1.000000	0.864982	0.826387	-0.147149	-0.384210
G2	-0.107119	0.864982	1.000000	0.918548	-0.124745	-0.385782
G3	-0.106505	0.826387	0.918548	1.000000	-0.091379	-0.393316
absences	0.149998	-0.147149	-0.124745	-0.091379	1.000000	0.122779
failures	0.319968	-0.384210	-0.385782	-0.393316	0.122779	1.000000

Out[10]: `<matplotlib.axes._subplots.AxesSubplot at 0x1bbaa26b630>`



In [11]:
```
PXGrade.head()
```

Out[11]:

	age	G1	G2	G3	absences	failures
0	18	0	11	11	4	0
1	17	9	11	11	2	0
2	15	12	13	12	6	0
3	15	14	14	14	0	0
4	16	11	13	13	0	0

In [12]:
```
#Excluding G1 and G2 as they are higly correlated with G3

# PORTUGUESE REGRESSION MODEL

import statsmodels.api as sm

PX = sm.add_constant(PX)

mod1 = sm.OLS(PY,PX)

fii1 = mod1.fit()
fii1
```

Out[12]:
```
<statsmodels.regression.linear_model.RegressionResultsWrapper at 0x1bbab594ac
8>
```

In [13]:
```
som1 = fii1.summary()
```

In [14]:
```
som1
```

Out[14]:

OLS Regression Results

Dep. Variable:	G3	**R-squared:**	0.360
Model:	OLS	**Adj. R-squared:**	0.319
Method:	Least Squares	**F-statistic:**	8.797
Date:	Wed, 27 Nov 2019	**Prob (F-statistic):**	3.27e-38
Time:	18:54:39	**Log-Likelihood:**	-1536.5
No. Observations:	649	**AIC:**	3153.
Df Residuals:	609	**BIC:**	3332.
Df Model:	39		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	8.6815	1.985	4.373	0.000	4.783	12.580
age	0.1562	0.102	1.528	0.127	-0.045	0.357
Medu	0.0353	0.151	0.233	0.816	-0.262	0.332
Fedu	0.1669	0.138	1.211	0.226	-0.104	0.437
traveltime	0.0625	0.159	0.393	0.695	-0.250	0.375
studytime	0.4067	0.140	2.906	0.004	0.132	0.682
failures	-1.4122	0.205	-6.906	0.000	-1.814	-1.011
famrel	0.1616	0.116	1.391	0.165	-0.066	0.390
freetime	-0.1378	0.112	-1.226	0.221	-0.358	0.083
goout	-0.0661	0.107	-0.615	0.539	-0.277	0.145
Dalc	-0.2048	0.153	-1.338	0.181	-0.505	0.096
Walc	-0.0815	0.118	-0.688	0.492	-0.314	0.151
health	-0.1874	0.077	-2.428	0.015	-0.339	-0.036
absences	-0.0381	0.025	-1.531	0.126	-0.087	0.011
school_MS	-1.2003	0.267	-4.490	0.000	-1.725	-0.675
sex_M	-0.6331	0.250	-2.532	0.012	-1.124	-0.142
address_U	0.3227	0.262	1.233	0.218	-0.191	0.837
famsize_LE3	0.3025	0.245	1.235	0.217	-0.179	0.784
Pstatus_T	0.1769	0.347	0.510	0.610	-0.504	0.858
Mjob_health	0.9015	0.538	1.677	0.094	-0.154	1.957
Mjob_other	0.0504	0.303	0.166	0.868	-0.544	0.645
Mjob_services	0.4205	0.373	1.127	0.260	-0.312	1.153
Mjob_teacher	0.5118	0.502	1.020	0.308	-0.474	1.498
Fjob_health	-0.6122	0.752	-0.814	0.416	-2.090	0.865
Fjob_other	-0.1844	0.456	-0.404	0.686	-1.080	0.712

Fjob_services	-0.6434	0.479	-1.343	0.180	-1.585	0.298
Fjob_teacher	0.5797	0.672	0.862	0.389	-0.741	1.900
reason_home	0.0505	0.285	0.177	0.859	-0.509	0.610
reason_other	-0.4349	0.368	-1.183	0.237	-1.157	0.287
reason_reputation	0.2177	0.298	0.730	0.465	-0.368	0.803
guardian_mother	-0.3385	0.265	-1.276	0.202	-0.859	0.182
guardian_other	0.1050	0.532	0.197	0.844	-0.939	1.149
schoolsup_yes	-1.3112	0.364	-3.602	0.000	-2.026	-0.596
famsup_yes	-0.0204	0.228	-0.089	0.929	-0.469	0.428
paid_yes	-0.3716	0.461	-0.805	0.421	-1.278	0.535
activities_yes	0.2192	0.223	0.981	0.327	-0.220	0.658
nursery_yes	-0.2161	0.271	-0.796	0.426	-0.749	0.317
higher_yes	1.7330	0.383	4.528	0.000	0.981	2.485
internet_yes	0.2529	0.276	0.915	0.360	-0.290	0.796
romantic_yes	-0.4316	0.229	-1.883	0.060	-0.882	0.019

Omnibus:	127.139	**Durbin-Watson:**	1.926
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	422.670
Skew:	-0.908	**Prob(JB):**	1.65e-92
Kurtosis:	6.512	**Cond. No.**	372.

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

In [15]:
```
# Creating PX2 with all the variables including G3

PX2 = portdata_dummy[['age',
 'Medu',
 'Fedu',
 'traveltime',
'studytime',
 'failures',
 'famrel',
'freetime',
 'goout',
 'Dalc',
 'Walc',
 'health',
 'absences',
 'G1',
 'G2',
 'G3',
 'school_MS',
 'sex_M',
 'address_U',
 'famsize_LE3',
 'Pstatus_T',
 'Mjob_health',
 'Mjob_other',
 'Mjob_services',
 'Mjob_teacher',
 'Fjob_health',
 'Fjob_other',
 'Fjob_services',
 'Fjob_teacher',
 'reason_home',
 'reason_other',
 'reason_reputation',
 'guardian_mother',
 'guardian_other',
'schoolsup_yes',
 'famsup_yes',
 'paid_yes',
 'activities_yes',
 'nursery_yes',
 'higher_yes',
 'internet_yes',
 'romantic_yes']]

PX2.head()
```

Out[15]:

	age	Medu	Fedu	traveltime	studytime	failures	famrel	freetime	goout	Dalc	...	guardian_
0	18	4	4	2	2	0	4	3	4	1	...	
1	17	1	1	1	2	0	5	3	3	1	...	
2	15	1	1	1	2	0	4	3	2	2	...	
3	15	4	2	1	3	0	3	2	2	1	...	
4	16	3	3	1	2	0	4	3	2	1	...	

5 rows × 42 columns

In [16]:
```
# Portuguese Regression Model with Interaction effects
# Including Interaction Terms

import statsmodels.formula.api as smf
model_interaction = smf.ols(formula='G3 ~ studytime + failures + health + scho
ol_MS + sex_M + schoolsup_yes + higher_yes + studytime:failures + studytime:he
alth + studytime:school_MS + studytime:sex_M + studytime:schoolsup_yes + study
time:higher_yes + failures:health + failures:school_MS + failures:sex_M + fail
ures:schoolsup_yes + failures:higher_yes + health:school_MS + health:sex_M + h
ealth:schoolsup_yes + health:higher_yes + school_MS:sex_M +  school_MS:schools
up_yes + school_MS:higher_yes + sex_M:schoolsup_yes + sex_M:higher_yes', data=
PX2).fit()
summary = model_interaction.summary()
summary
```

Out[16]:

OLS Regression Results

Dep. Variable:	G3	**R-squared:**	0.331
Model:	OLS	**Adj. R-squared:**	0.302
Method:	Least Squares	**F-statistic:**	11.37
Date:	Wed, 27 Nov 2019	**Prob (F-statistic):**	7.88e-39
Time:	18:55:22	**Log-Likelihood:**	-1551.1
No. Observations:	649	**AIC:**	3158.
Df Residuals:	621	**BIC:**	3284.
Df Model:	27		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	9.6265	1.724	5.583	0.000	6.241	13.012
studytime	0.3822	0.608	0.628	0.530	-0.812	1.576
failures	-1.9320	0.912	-2.119	0.034	-3.722	-0.142
health	0.0085	0.340	0.025	0.980	-0.660	0.677
school_MS	-0.8621	1.080	-0.798	0.425	-2.983	1.259
sex_M	-0.1956	1.084	-0.180	0.857	-2.325	1.934
schoolsup_yes	-1.5326	1.497	-1.024	0.306	-4.472	1.406
higher_yes	3.6606	1.575	2.324	0.020	0.567	6.754
studytime:failures	-0.1000	0.328	-0.304	0.761	-0.745	0.545
studytime:health	-0.0002	0.097	-0.002	0.999	-0.191	0.190
studytime:school_MS	0.3593	0.310	1.159	0.247	-0.250	0.968
studytime:sex_M	-0.2732	0.280	-0.975	0.330	-0.823	0.277
studytime:schoolsup_yes	-0.6878	0.461	-1.493	0.136	-1.593	0.217
studytime:higher_yes	0.2073	0.508	0.408	0.683	-0.790	1.205
failures:health	0.2233	0.150	1.488	0.137	-0.071	0.518
failures:school_MS	-0.3565	0.412	-0.865	0.388	-1.166	0.453
failures:sex_M	0.4143	0.433	0.956	0.339	-0.437	1.265
failures:schoolsup_yes	1.5609	0.628	2.485	0.013	0.327	2.794
failures:higher_yes	-0.6825	0.437	-1.561	0.119	-1.541	0.176
health:school_MS	-0.0339	0.163	-0.208	0.835	-0.354	0.286
health:sex_M	0.0219	0.159	0.138	0.891	-0.291	0.334
health:schoolsup_yes	0.3179	0.266	1.195	0.233	-0.205	0.840
health:higher_yes	-0.2745	0.287	-0.956	0.339	-0.838	0.289
school_MS:sex_M	-0.1973	0.498	-0.396	0.692	-1.175	0.781
school_MS:schoolsup_yes	0.9170	0.951	0.964	0.335	-0.951	2.785

school_MS:higher_yes	-1.2122	0.778	-1.558	0.120	-2.740	0.316
sex_M:schoolsup_yes	-0.2618	0.836	-0.313	0.754	-1.903	1.379
sex_M:higher_yes	-0.0048	0.791	-0.006	0.995	-1.558	1.549

Omnibus:	116.763	**Durbin-Watson:**	1.895
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	351.956
Skew:	-0.865	**Prob(JB):**	3.75e-77
Kurtosis:	6.166	**Cond. No.**	235.

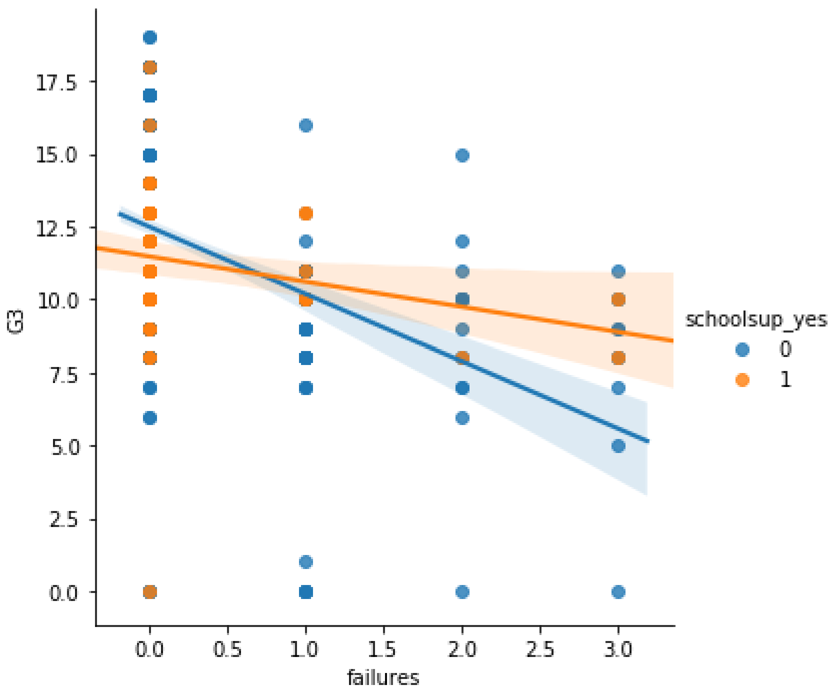
Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

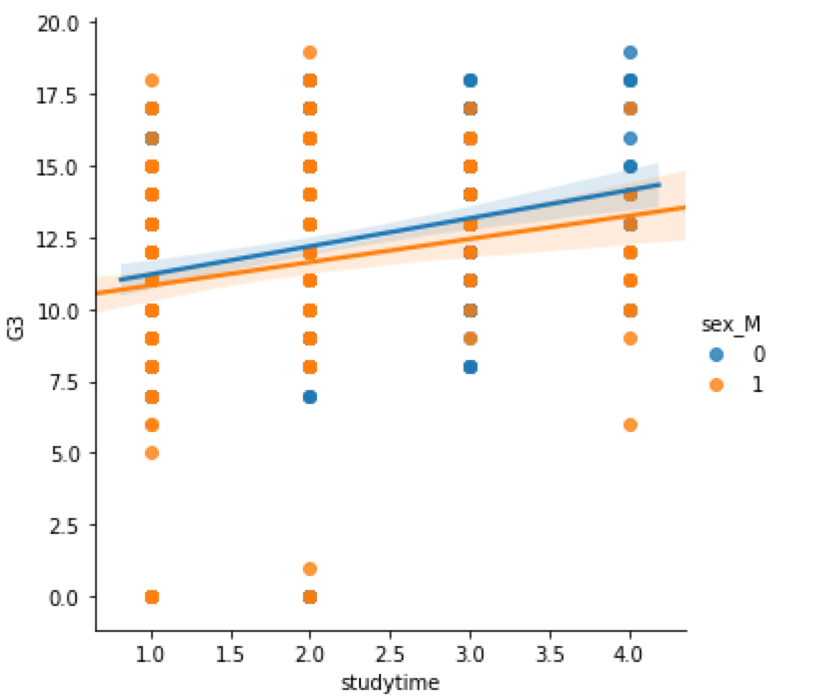
In [21]:
```
# Interaction is present between failures*schoolsup_yes on G3
import seaborn
seaborn.lmplot(y='G3', x='failures', hue='schoolsup_yes', data=PX2)


# No interaction is present between studytime*sex_M on G3
seaborn.lmplot(y='G3', x='studytime', hue='sex_M', data=PX2)
```

Out[21]: <seaborn.axisgrid.FacetGrid at 0x184d938dcf8>

Out[21]: <seaborn.axisgrid.FacetGrid at 0x184d94177f0>





In [ ]:

In [ ]: