In [2]:
```
from IPython.core.interactiveshell import InteractiveShell
InteractiveShell.ast_node_interactivity = "all"
```

In [3]:
```
%matplotlib inline
import numpy as np
import pandas as pd
import sklearn

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

In [4]:
```
## Read data from csv file 'student-mat.csv'
math_data = pd.read_csv('student-mat.csv', sep=';')

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

In [5]:
```
math_data.head()
port_data.head()
```

Out[5]:

	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

Out[5]:

	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 [6]:
```
math_data.shape
port_data.shape
```

Out[6]: (395, 33)

Out[6]: (649, 33)

In [7]:
```
# Making dummy variables in math data and saving as mathdata_dummy

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


mathdata_dummy.head()
```

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	3	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 [11]:
```
# Starting Regression


# Creating MX AND MX1
# MX - selecting only the predictor variables and not the response variable G3
including G1 and G2

# MX1 - Selecting all the predictor variables including G1 and G2

MX = mathdata_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']]


MX.head()

print(MX.shape)
```

Out[11]:

	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	3	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

```
(395, 39)
```

In [12]:
```
#Listing the column names of math data

list(mathdata_dummy.columns)
```

Out[12]:
```
['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 [13]:
```
# Y dependent variable of mathdata_dummy

MY = mathdata_dummy['G3']

MY.head()
```

Out[13]:
```
0     6
1     6
2    10
3    15
4    10
Name: G3, dtype: int64
```

In [29]:
```
MXGrade = mathdata_dummy[['age','G1','G2','G3','failures','absences']]
```

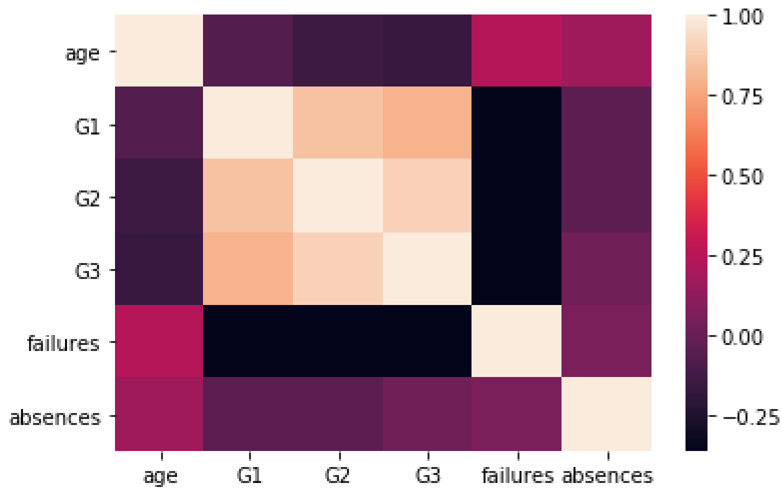
In [30]:
```
correlation1 = MXGrade.corr()
```

In [31]:
```
#checking correlation between age g1 g2 g3

correlation1
import seaborn
seaborn.heatmap(correlation1)
```

Out[31]:

	age	G1	G2	G3	failures	absences
age	1.000000	-0.064081	-0.143474	-0.161579	0.243665	0.175230
G1	-0.064081	1.000000	0.852118	0.801468	-0.354718	-0.031003
G2	-0.143474	0.852118	1.000000	0.904868	-0.355896	-0.031777
G3	-0.161579	0.801468	0.904868	1.000000	-0.360415	0.034247
failures	0.243665	-0.354718	-0.355896	-0.360415	1.000000	0.063726
absences	0.175230	-0.031003	-0.031777	0.034247	0.063726	1.000000

Out[31]: <matplotlib.axes._subplots.AxesSubplot at 0x269fdaffa90>



In [14]:
```
#Regression Model Excluding G1 and G2
import statsmodels.api as sb

MX = sb.add_constant(MX)

mod1 = sb.OLS(MY,MX)

fii1 = mod1.fit()
```

In [15]:
```
fii1
```

Out[15]:
```
<statsmodels.regression.linear_model.RegressionResultsWrapper at 0x269f8f62f9
8>
```

In [16]:
```
som1 = fii1.summary()
```

In [17]:
```
som1
```

Out[17]:

OLS Regression Results

Dep. Variable:	G3	**R-squared:**	0.276
Model:	OLS	**Adj. R-squared:**	0.196
Method:	Least Squares	**F-statistic:**	3.463
Date:	Wed, 27 Nov 2019	**Prob (F-statistic):**	3.32e-10
Time:	16:50:35	**Log-Likelihood:**	-1097.5
No. Observations:	395	**AIC:**	2275.
Df Residuals:	355	**BIC:**	2434.
Df Model:	39		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	14.0777	4.481	3.142	0.002	5.265	22.890
age	-0.3752	0.217	-1.727	0.085	-0.802	0.052
Medu	0.4569	0.323	1.414	0.158	-0.179	1.092
Fedu	-0.1046	0.278	-0.377	0.707	-0.651	0.441
traveltime	-0.2403	0.339	-0.709	0.479	-0.907	0.426
studytime	0.5495	0.288	1.910	0.057	-0.016	1.115
failures	-1.7240	0.333	-5.179	0.000	-2.379	-1.069
famrel	0.2316	0.246	0.942	0.347	-0.252	0.715
freetime	0.3024	0.237	1.274	0.203	-0.164	0.769
goout	-0.5937	0.225	-2.644	0.009	-1.035	-0.152
Dalc	-0.2722	0.331	-0.823	0.411	-0.923	0.378
Walc	0.2634	0.248	1.062	0.289	-0.224	0.751
health	-0.1768	0.161	-1.098	0.273	-0.493	0.140
absences	0.0563	0.029	1.943	0.053	-0.001	0.113
school_MS	0.7256	0.792	0.917	0.360	-0.831	2.282
sex_M	1.2624	0.500	2.525	0.012	0.279	2.246
address_U	0.5513	0.584	0.944	0.346	-0.597	1.700
famsize_LE3	0.7028	0.488	1.439	0.151	-0.257	1.663
Pstatus_T	-0.3201	0.724	-0.442	0.659	-1.744	1.104
Mjob_health	0.9981	1.118	0.893	0.373	-1.201	3.197
Mjob_other	-0.3590	0.713	-0.503	0.615	-1.762	1.044
Mjob_services	0.6583	0.798	0.825	0.410	-0.911	2.227
Mjob_teacher	-1.2415	1.038	-1.196	0.233	-3.283	0.800
Fjob_health	0.3477	1.438	0.242	0.809	-2.480	3.176
Fjob_other	-0.6197	1.023	-0.606	0.545	-2.632	1.392

Fjob_services	-0.4658	1.057	-0.441	0.660	-2.544	1.613
Fjob_teacher	1.3262	1.297	1.023	0.307	-1.224	3.876
reason_home	0.0785	0.554	0.142	0.887	-1.011	1.168
reason_other	0.7771	0.818	0.950	0.343	-0.831	2.385
reason_reputation	0.6130	0.577	1.063	0.288	-0.521	1.747
guardian_mother	0.0698	0.546	0.128	0.898	-1.003	1.143
guardian_other	0.7501	0.999	0.751	0.453	-1.216	2.716
schoolsup_yes	-1.3506	0.667	-2.025	0.044	-2.662	-0.039
famsup_yes	-0.8618	0.479	-1.800	0.073	-1.803	0.080
paid_yes	0.3397	0.478	0.711	0.477	-0.600	1.279
activities_yes	-0.3295	0.445	-0.741	0.459	-1.205	0.546
nursery_yes	-0.1773	0.549	-0.323	0.747	-1.258	0.903
higher_yes	1.3705	1.078	1.272	0.204	-0.749	3.490
internet_yes	0.4981	0.620	0.804	0.422	-0.720	1.717
romantic_yes	-1.0945	0.469	-2.332	0.020	-2.017	-0.172

Omnibus:	30.431	**Durbin-Watson:**	2.054
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	35.239
Skew:	-0.696	**Prob(JB):**	2.23e-08
Kurtosis:	3.450	**Cond. No.**	443.

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

In [22]:
```
# Starting Regression Model with Interaction effects
# Created MX4 which contains all the variables

MX4 = mathdata_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']]

MX4.head()
```

Out[22]:

	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	3	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 [23]:
```
# REGRESSION MODEL WITH INTERACTION EFFECTS

import statsmodels.formula.api as smf
model_interaction = smf.ols(formula='G3 ~ failures + goout + sex_M + schoolsup_yes + romantic_yes + failures:goout + failures:sex_M + failures:schoolsup_yes + failures:romantic_yes + goout:sex_M + goout:schoolsup_yes + goout:romantic_yes + sex_M:schoolsup_yes + sex_M:romantic_yes +schoolsup_yes:romantic_yes', data=MX4).fit()
summary = model_interaction.summary()
summary
```

Out[23]:

OLS Regression Results

Dep. Variable:	G3	**R-squared:**	0.197
Model:	OLS	**Adj. R-squared:**	0.166
Method:	Least Squares	**F-statistic:**	6.210
Date:	Wed, 27 Nov 2019	**Prob (F-statistic):**	9.59e-12
Time:	16:54:45	**Log-Likelihood:**	-1117.8
No. Observations:	395	**AIC:**	2268.
Df Residuals:	379	**BIC:**	2331.
Df Model:	15		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	12.8078	1.137	11.268	0.000	10.573	15.043
failures	-2.9940	0.923	-3.243	0.001	-4.810	-1.178
goout	-0.5200	0.342	-1.521	0.129	-1.192	0.152
sex_M	1.1825	1.338	0.884	0.377	-1.448	3.813
schoolsup_yes	-0.4928	1.896	-0.260	0.795	-4.220	3.234
romantic_yes	-2.3911	1.402	-1.706	0.089	-5.147	0.365
failures:goout	0.3877	0.248	1.561	0.119	-0.101	0.876
failures:sex_M	-1.2273	0.620	-1.980	0.048	-2.446	-0.009
failures:schoolsup_yes	2.0577	0.928	2.217	0.027	0.233	3.883
failures:romantic_yes	-0.2817	0.606	-0.465	0.642	-1.472	0.909
goout:sex_M	-0.0426	0.395	-0.108	0.914	-0.820	0.735
goout:schoolsup_yes	-0.4057	0.552	-0.735	0.463	-1.490	0.679
goout:romantic_yes	0.3432	0.417	0.823	0.411	-0.476	1.163
sex_M:schoolsup_yes	-1.1113	1.378	-0.806	0.421	-3.822	1.599
sex_M:romantic_yes	0.9246	0.926	0.998	0.319	-0.897	2.746
schoolsup_yes:romantic_yes	1.0825	1.494	0.724	0.469	-1.856	4.021

Omnibus:	31.291	**Durbin-Watson:**	2.040
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	36.669
Skew:	-0.692	**Prob(JB):**	1.09e-08
Kurtosis:	3.558	**Cond. No.**	47.0

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

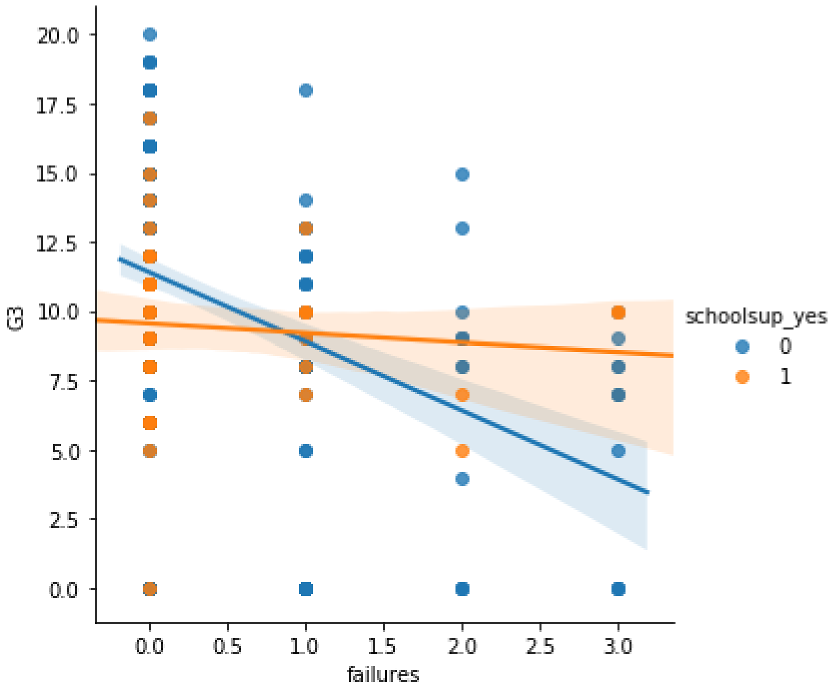
In [28]:
```
# Intersecting lines represent Interaction effect

# Presence of Interaction effect of failures*schoolsup_yes on G3
import seaborn
seaborn.lmplot(y='G3', x='failures', hue='schoolsup_yes', data=MX4)

# Presence of Interaction effect of failures*sex_M on G3
seaborn.lmplot(y='G3', x='failures', hue='sex_M', data=MX4)

# No Presence of Interaction effect between failures*romantic_yes on G3
seaborn.lmplot(y='G3', x='failures', hue='romantic_yes', data=MX4)

# No Presence of Interaction effect between sex_M*schoolsup_yes on G3
seaborn.lmplot(y='G3', x='sex_M', hue='schoolsup_yes', data=MX4)
```

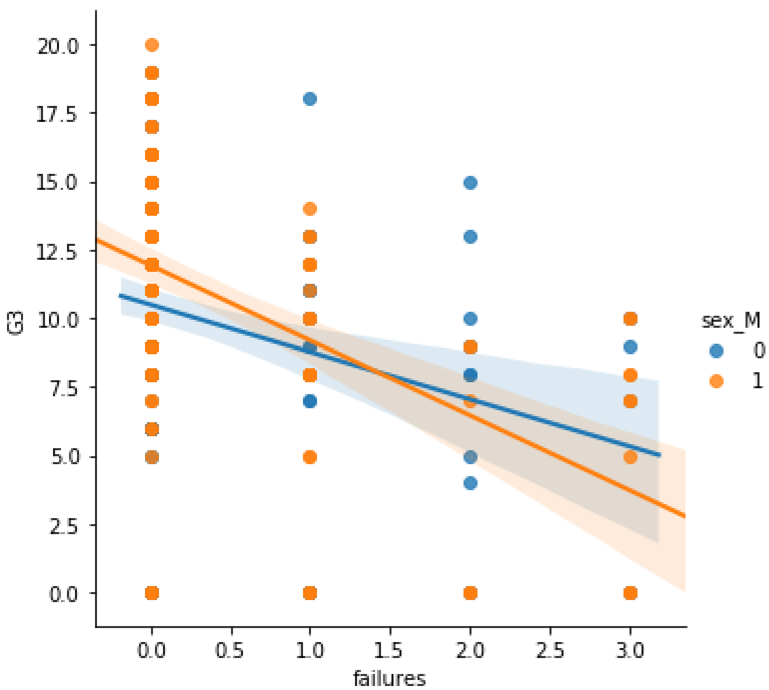
```
Out[28]: <seaborn.axisgrid.FacetGrid at 0x269fdb8b7f0>
```

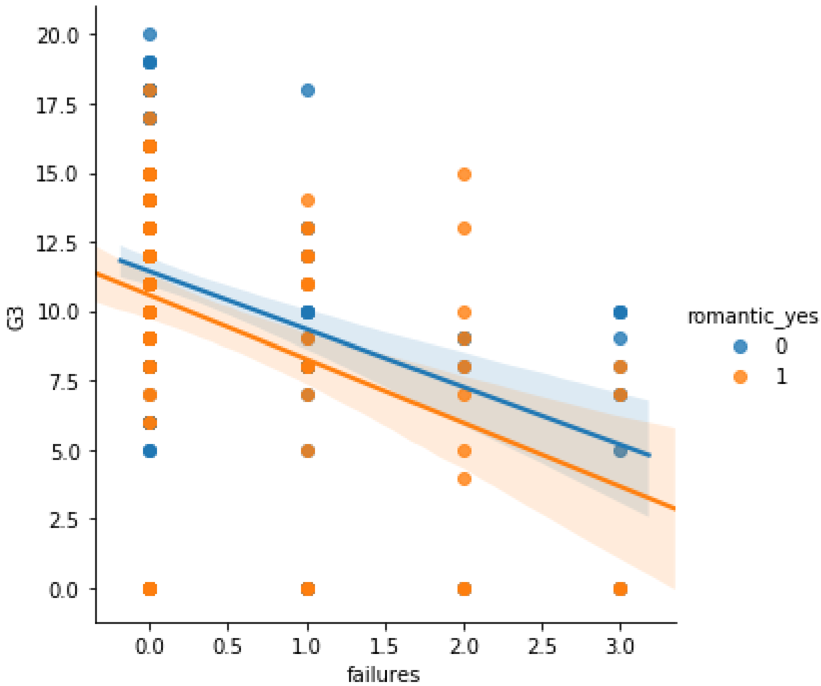
```
Out[28]: <seaborn.axisgrid.FacetGrid at 0x269fdba7588>
```

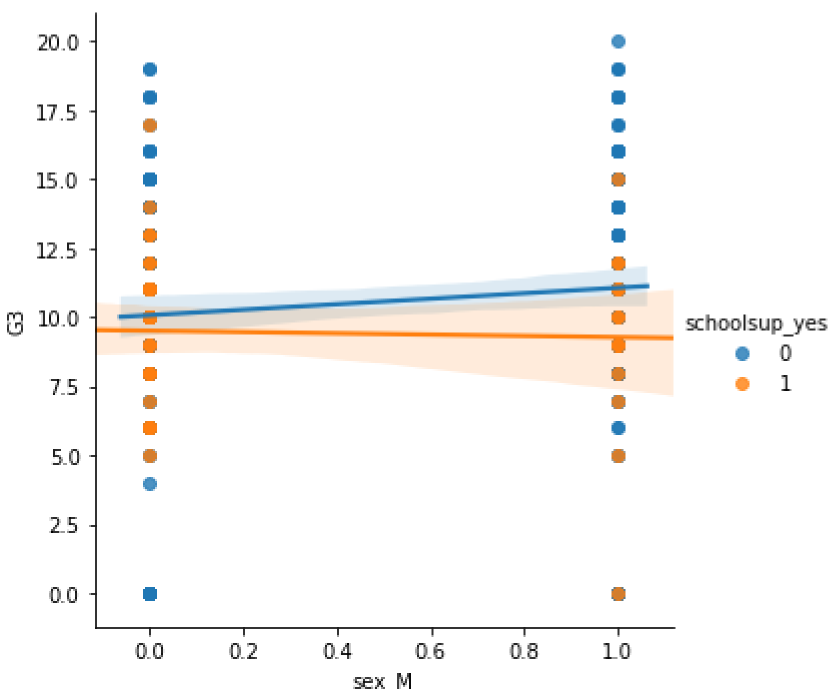
```
Out[28]: <seaborn.axisgrid.FacetGrid at 0x269fdb456d8>
```

```
Out[28]: <seaborn.axisgrid.FacetGrid at 0x269fdc404e0>
```






G3
failures
romantic_yes
0
1
0.0
0.5
1.0
1.5
2.0
2.5
3.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0


G3
sex_M
schoolsup_yes
0
1
0.0
0.2
0.4
0.6
0.8
1.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0

```
In [ ]:
```