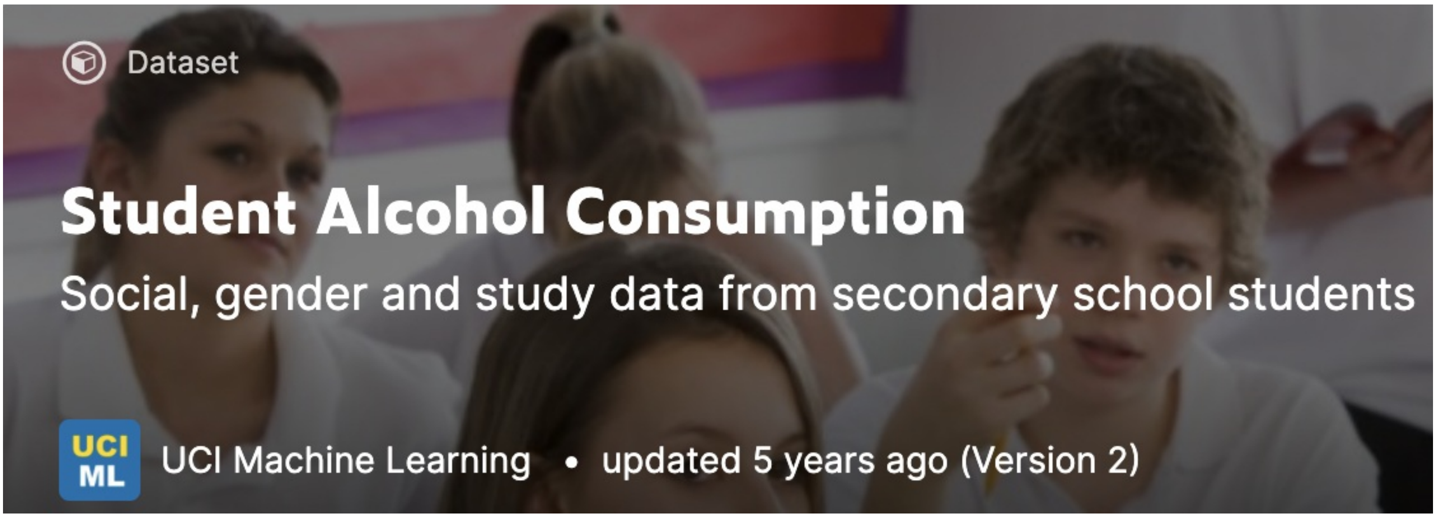
DSBA 2021 - M1: (Mandatory) Assignment

Welcome to the *M1 Assignment notebook*. This project contains data manipulation, exploration, unsupervised and supervised Machine Learning.

Application: the Student Alcohol Consumption dataset

The dataset was published on Kaggle by *UCI Machine Learning* 5 years ago.



Kaggle Description

Context:

The data were obtained in a survey of students math and portuguese language courses in secondary school. It contains a lot of interesting social, gender and study information about students. You can use it for some EDA or try to predict students final grade.

Content:

For all the attributes for both student-mat.csv (Math course) and student-por.csv (Portuguese language course) datasets, look at the datasets page:

https://www.kaggle.com/uciml/student-alcohol-consumption

Additional note:

There are several (382) students that belong to both datasets. These students can be identified by searching for identical attributes that characterize each student.

Import Libraries and Data

In [1]:

```
# Import Libraries

# EDA
import pandas as pd
import numpy as np

# Visualization
import seaborn as sns
import matplotlib.pyplot as plt

# ML
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split

# SML: Classification
from sklearn.linear_model import LogisticRegression
from sklearn import metrics
from sklearn.metrics import log_loss
from sklearn.metrics import classification_report

# SML: Regression
from sklearn.linear_model import LinearRegression
from xgboost import XGBRegressor
from sklearn.ensemble import RandomForestRegressor

# UML: Clustering
from sklearn.decomposition import PCA
from sklearn.cluster import KMeans
import altair as alt
```

In [2]:

```
# Read CSV files

student_mat = pd.read_csv('/content/student-mat.csv')
student_por = pd.read_csv('/content/student-por.csv')
```

In [3]:

```
# Merge the two files

student = pd.concat([student_mat, student_por], ignore_index=True, sort=False)

student.head()
```

Out[3]:

	school	sex	age	address	famsize	Pstatus	Medu	Fedu	Mjob	Fjob	reason	guardian	traveltime	studytime	fail
0	GP	F	18	U	GT3	A	4	4	at_home	teacher	course	mother	2	2	
1	GP	F	17	U	GT3	T	1	1	at_home	other	course	father	1	2	
2	GP	F	15	U	LE3	T	1	1	at_home	other	other	mother	1	2	
3	GP	F	15	U	GT3	T	4	2	health	services	home	mother	1	3	
4	GP	F	16	U	GT3	T	3	3	other	other	home	father	1	2	

In [4]:

```
# Verify data shapes

print(student_mat.shape)
print(student_por.shape)
print(student.shape)

print('Rule of thumb validated: minimum > 500 observations, > 10 features')
```

```
(395, 33)
(649, 33)
(1044, 33)
Rule of thumb validated: minimum > 500 observations, > 10 features
```

In [5]:

```
# Inspect data

student.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1044 entries, 0 to 1043
Data columns (total 33 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   school      1044 non-null   object
 1   sex         1044 non-null   object
 2   age         1044 non-null   int64
 3   address     1044 non-null   object
 4   famsize     1044 non-null   object
 5   Pstatus     1044 non-null   object
 6   Medu        1044 non-null   int64
 7   Fedu        1044 non-null   int64
 8   Mjob        1044 non-null   object
 9   Fjob        1044 non-null   object
 10  reason      1044 non-null   object
 11  guardian    1044 non-null   object
 12  traveltime  1044 non-null   int64
 13  studytime   1044 non-null   int64
 14  failures    1044 non-null   int64
 15  schoolsup   1044 non-null   object
 16  famsup      1044 non-null   object
 17  paid        1044 non-null   object
 18  activities  1044 non-null   object
 19  nursery     1044 non-null   object
 20  higher      1044 non-null   object
 21  internet    1044 non-null   object
 22  romantic    1044 non-null   object
 23  famrel      1044 non-null   int64
 24  freetime    1044 non-null   int64
 25  goout       1044 non-null   int64
 26  Dalc        1044 non-null   int64
 27  Walc        1044 non-null   int64
 28  health      1044 non-null   int64
 29  absences    1044 non-null   int64
 30  G1          1044 non-null   int64
 31  G2          1044 non-null   int64
 32  G3          1044 non-null   int64
dtypes: int64(16), object(17)
memory usage: 269.3+ KB
```

Clean Data: Duplicates and NaN

In [6]:

```
# Spot the duplicates: 382 students

student.duplicated(subset=["school","sex","age","address","famsize","Pstatus","Medu","Fed
u","Mjob","Fjob","reason","nursery","internet"]).sum()
```

Out[6]:

```
382
```

In [7]:

```
# Drop the duplicates

student.drop_duplicates(subset=["school","sex","age","address","famsize","Pstatus","Medu"
,"Fedu","Mjob","Fjob","reason","nursery","internet"], keep='first', inplace=True, ignore
_index=True)
print(student.shape)
```

```
(662, 33)
```

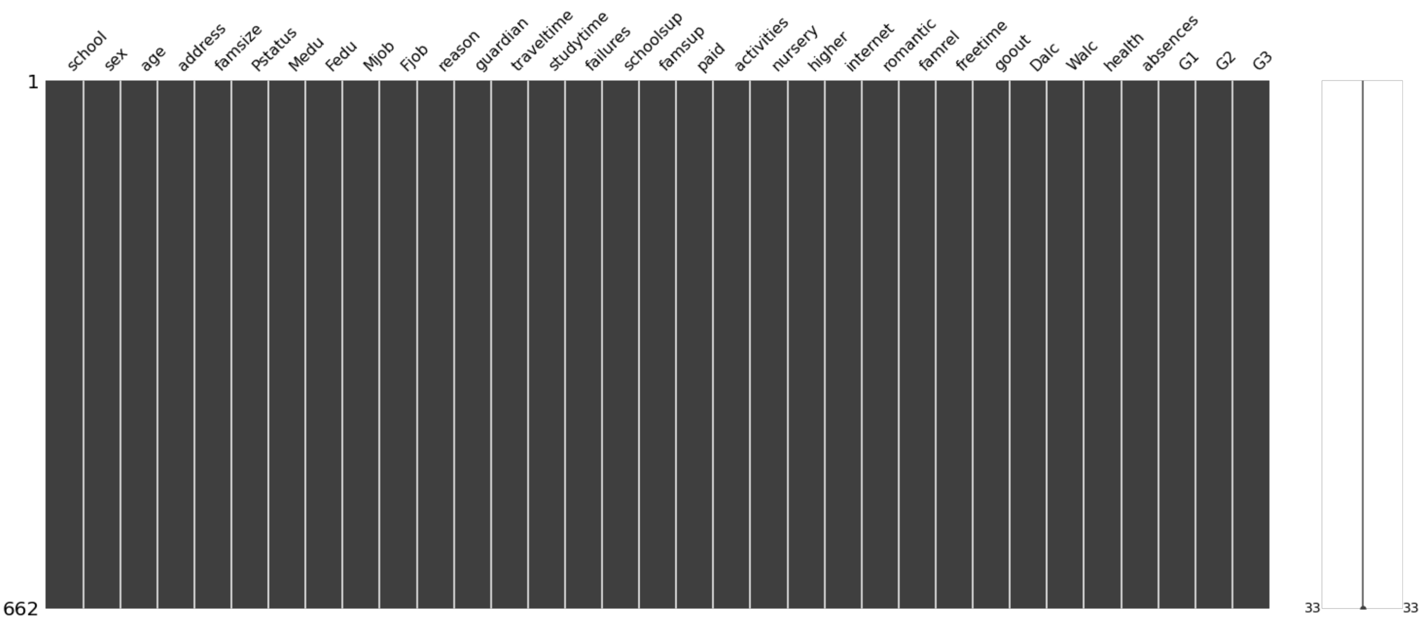
In [8]:

```
# Check for NaN values

print(student.isnull().sum().sum())

import missingno as msno
msno.matrix(student)
```

```
0
```

Out[8]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f4ae9646150>
```



In [9]:

```
# Encoding

student['school'].replace(to_replace=['GP','MS'], value=[0,1],inplace=True)
student['sex'].replace(to_replace=['M','F'], value=[0,1],inplace=True)
student['address'].replace(to_replace=['U','R'], value=[0,1],inplace=True)
student['famsize'].replace(to_replace=['GT3','LE3'], value=[0,1],inplace=True)
student['Pstatus'].replace(to_replace=['A','T'], value=[0,1],inplace=True)
student['schoolsup'].replace(to_replace=['no','yes'], value=[0,1],inplace=True)
student['famsup'].replace(to_replace=['no','yes'], value=[0,1],inplace=True)
student['paid'].replace(to_replace=['no','yes'], value=[0,1],inplace=True)
student['activities'].replace(to_replace=['no','yes'], value=[0,1],inplace=True)
student['nursery'].replace(to_replace=['no','yes'], value=[0,1],inplace=True)
student['higher'].replace(to_replace=['no','yes'], value=[0,1],inplace=True)
student['internet'].replace(to_replace=['no','yes'], value=[0,1],inplace=True)
student['romantic'].replace(to_replace=['no','yes'], value=[0,1],inplace=True)
```

Explore the variables: Analysis and Visualization

In [10]:

```python
# describe all the columns in student

student.describe(include = "all")
```

Out[10]:

	school	sex	age	address	famsize	Pstatus	Medu	Fedu	Mjob	Fjob	reasor
count	662.000000	662.000000	662.000000	662.000000	662.000000	662.000000	662.000000	662.000000	662	662	66
unique	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	5	5	4
top	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	other	other	course
freq	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	259	373	28
mean	0.344411	0.589124	16.812689	0.303625	0.303625	0.874622	2.492447	2.293051	NaN	NaN	NaN
std	0.475535	0.492365	1.269194	0.460170	0.460170	0.331397	1.130958	1.094027	NaN	NaN	NaN
min	0.000000	0.000000	15.000000	0.000000	0.000000	0.000000	0.000000	0.000000	NaN	NaN	NaN
25%	0.000000	0.000000	16.000000	0.000000	0.000000	1.000000	2.000000	1.000000	NaN	NaN	NaN
50%	0.000000	1.000000	17.000000	0.000000	0.000000	1.000000	2.000000	2.000000	NaN	NaN	NaN
75%	1.000000	1.000000	18.000000	1.000000	1.000000	1.000000	4.000000	3.000000	NaN	NaN	NaN
max	1.000000	1.000000	22.000000	1.000000	1.000000	1.000000	4.000000	4.000000	NaN	NaN	NaN

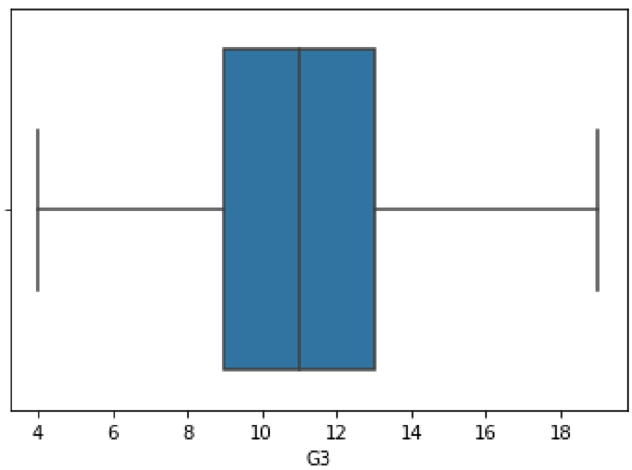
In [11]:

```python
# Plot the student performance (G3)

sns.boxplot(student.G3, showfliers=False)
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass the following variable as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.
  FutureWarning
```

Out[11]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f4adfde9fd0>
```



In [12]:

```python
# Set Performance bins

bins = np.linspace(min(student["G3"]), max(student["G3"]), 4)
grade_levels = ['Low', 'Medium', 'High']

student["G3_binned"] = pd.cut(student["G3"], bins, labels=grade_levels, include_lowest=True )
student[['G3','G3_binned']].head(5)
```

Out[12]:

	G3	G3_binned
0	6	Low
1	6	Low
2	10	Medium
3	15	High
4	10	Medium

In [13]:

```
# Count the values per bin

student["G3_binned"].value_counts(normalize = True)
```

Out[13]:

```
Medium    0.648036
High      0.247734
Low       0.104230
Name: G3_binned, dtype: float64
```

In [14]:

```
# Retrieve the G3 bins proportion group by Dalc

student.groupby(['Dalc'])['G3_binned'].value_counts(normalize=True)
```

Out[14]:

```
Dalc  G3_binned
1     Medium       0.608696
      High         0.289130
      Low          0.102174
2     Medium       0.680328
      High         0.180328
      Low          0.139344
3     Medium       0.822222
      High         0.155556
      Low          0.022222
4     Medium       0.777778
      Low          0.111111
      High         0.111111
5     Medium       0.882353
      Low          0.117647
Name: G3_binned, dtype: float64
```

In [15]:

```
# Retrieve the G3 bins proportion group by Walc

student.groupby(['Walc'])['G3_binned'].value_counts(normalize=True)
```

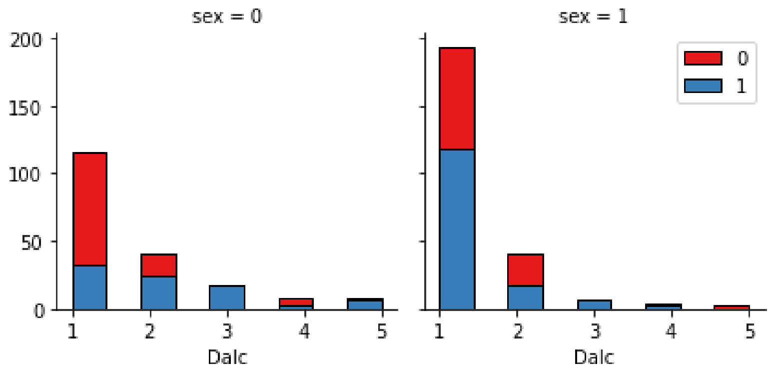
Out[15]:

```
Walc  G3_binned
1     Medium       0.588235
      High         0.298039
      Low          0.113725
2     Medium       0.598639
      High         0.285714
      Low          0.115646
3     Medium       0.685484
      High         0.233871
      Low          0.080645
4     Medium       0.788889
      High         0.122222
      Low          0.088889
5     Medium       0.760870
```

```
        High          0.130435
        Low           0.108696
Name: G3_binned, dtype: float64
```

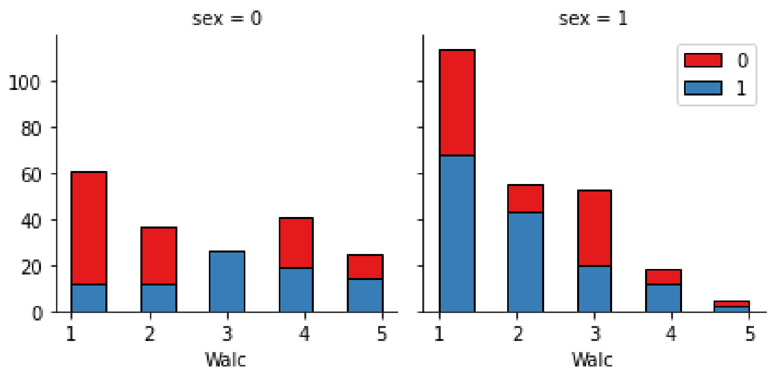
In [16]:

```python
# Relation between workday alcohol consumption (Dalc), sex and school

bins = np.linspace(student.Dalc.min(), student.Dalc.max(), 10)
g = sns.FacetGrid(student, col="sex", hue="school", palette="Set1", col_wrap=2)
g.map(plt.hist, 'Dalc', bins=bins, ec="k")

g.axes[-1].legend()
plt.show()
```



In [17]:

```python
# Relation between weekend alcohol consumption (Walc), sex and school

bins = np.linspace(student.Walc.min(), student.Walc.max(), 10)
g = sns.FacetGrid(student, col="sex", hue="school", palette="Set1", col_wrap=2)
g.map(plt.hist, 'Walc', bins=bins, ec="k")

g.axes[-1].legend()
plt.show()
```



Supervised Machine Learning: Classification

We will use Logistic Regression to categorize unknown items with binary data.

> ***Can we categorize the final grades of students with binary data?***

In [18]:

```python
# Define the variables

X = student[['school','sex','age', 'address', 'famsize', 'Pstatus', 'Medu','Fedu','trave
ltime', 'studytime', 'failures',
             'schoolsup', 'famsup', 'paid', 'activities', 'famrel', 'freetime', 'goout',
'Dalc', 'Walc', 'health',
             'nursery', 'higher', 'internet', 'romantic', 'absences']]
```

```
y = student['G3_binned']
```

In [19]:

```
# Standardized and labelled variables

scaler = StandardScaler()
X = scaler.fit_transform(X)

labelencoder_y = LabelEncoder()
y = labelencoder_y.fit_transform(y)
```

In [20]:

```
# Split the data

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state
= 42)
```

In [21]:

```
# Fit a simple logistic model

model = LogisticRegression(multi_class="ovr") # since we have 3 bins
model.fit(X_train, y_train)
```

Out[21]:

```
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, l1_ratio=None, max_iter=100,
                   multi_class='ovr', n_jobs=None, penalty='l2',
                   random_state=None, solver='lbfgs', tol=0.0001, verbose=0,
                   warm_start=False)
```

In [22]:

```
# Prediction and Accuracy of the model

yhat = model.predict(X_test)
yhat_prob = model.predict_proba(X_test)

print("Model's Accuracy: ", metrics.accuracy_score(y_test, yhat))
print("Model's Log Loss: %.4f" % log_loss(y_test, yhat_prob))
```

```
Model's Accuracy:  0.7218045112781954
Model's Log Loss: 0.7121
```

In [23]:

```
# Model Evaluation

true_bin = labelencoder_y.inverse_transform(y_test)
predicted_bin = labelencoder_y.inverse_transform(model.predict(X_test))

print(classification_report(true_bin,predicted_bin, labels=labelencoder_y.classes_))
```

```
              precision    recall  f1-score   support

        High       0.67      0.43      0.52        28
         Low       0.00      0.00      0.00        15
      Medium       0.74      0.93      0.82        90

    accuracy                           0.72       133
   macro avg       0.47      0.45      0.45       133
weighted avg       0.64      0.72      0.67       133
```

Supervised Machine Learning: Regression

We will use three Linear Regression models to predict a continuous variable.

> ***Can we predict the final performance of students with multiple variables?***

In [24]:

```
# Look at variables correlation

student.corr(method ='kendall')
```

Out[24]:

	school	sex	age	address	famsize	Pstatus	Medu	Fedu	traveltime	studytime	failures	s
school	1.000000	0.069007	0.089322	0.344108	0.033001	0.015226	-0.223410	-0.182388	0.270534	-0.137011	0.041864	·
sex	0.069007	1.000000	0.046439	0.017268	-0.089567	-0.065855	-0.087744	-0.072890	-0.036943	0.234754	-0.036876	
age	0.089322	0.046439	1.000000	0.022146	0.015368	-0.009776	-0.093747	-0.100655	0.039904	0.025285	0.249695	·
address	0.344108	0.017268	0.022146	1.000000	-0.057360	0.081357	-0.173905	-0.126713	0.323650	-0.062232	0.069285	·
famsize	0.033001	-0.089567	0.015368	-0.057360	1.000000	-0.236098	-0.031462	-0.042284	0.020772	-0.014652	-0.044587	·
Pstatus	0.015226	-0.065855	-0.009776	0.081357	-0.236098	1.000000	-0.052096	-0.032918	0.038397	-0.026599	-0.011095	·
Medu	-0.223410	-0.087744	-0.093747	-0.173905	-0.031462	-0.052096	1.000000	0.558045	-0.204450	0.090413	-0.170880	·
Fedu	-0.182388	-0.072890	-0.100655	-0.126713	-0.042284	-0.032918	0.558045	1.000000	-0.178692	0.053566	-0.148357	
traveltime	0.270534	-0.036943	0.039904	0.323650	0.020772	0.038397	-0.204450	-0.178692	1.000000	-0.084756	0.070738	·
studytime	-0.137011	0.234754	0.025285	-0.062232	-0.014652	-0.026599	0.090413	0.053566	-0.084756	1.000000	-0.115261	
failures	0.041864	-0.036876	0.249695	0.069285	-0.044587	-0.011095	-0.170880	-0.148357	0.070738	-0.115261	1.000000	
schoolsup	-0.125180	0.107448	-0.164203	-0.013394	-0.056127	-0.003316	-0.019080	0.021875	-0.057976	0.089234	0.006828	
famsup	-0.069977	0.127772	-0.091987	-0.016460	-0.050049	0.010737	0.122293	0.123098	-0.039152	0.135890	-0.030618	
paid	-0.262107	0.022288	-0.046744	-0.127218	-0.040477	0.072247	0.220433	0.162988	-0.121452	0.176266	-0.129714	
activities	-0.088224	-0.116322	-0.066084	0.007518	-0.012206	0.109510	0.103934	0.070212	-0.025250	0.052065	-0.029721	·
nursery	0.001446	0.043275	-0.039947	-0.011380	0.094038	-0.047030	0.119168	0.082857	-0.014898	0.032975	-0.081625	
higher	-0.128901	0.067748	-0.211323	-0.068399	0.005918	0.016189	0.201208	0.185443	-0.095905	0.196328	-0.281052	
internet	-0.242993	-0.049832	0.004972	-0.185169	-0.007916	0.076946	0.236623	0.164893	-0.168409	0.044452	-0.033010	·
romantic	0.069527	0.126214	0.164228	0.031905	-0.029178	-0.046239	-0.026304	-0.069589	0.015361	0.071249	0.117423	·
famrel	0.014598	-0.065970	-0.012157	0.029084	0.007838	0.016905	0.011930	0.015909	-0.022145	0.022956	-0.067931	·
freetime	0.039248	-0.158836	-0.009957	0.032321	-0.012941	0.031556	-0.015465	0.002610	-0.009426	-0.072131	0.092653	·
goout	0.039372	-0.056140	0.092229	-0.020800	0.000938	0.016128	0.018581	0.044774	0.020198	-0.075291	0.045542	·
Dalc	0.063076	-0.279222	0.063180	0.060479	0.085410	0.052422	-0.013780	-0.015473	0.054963	-0.156461	0.119690	·

	school	sex	age	address	famsize	Pstatus	Medu	Fedu	traveltime	studytime	failures	s
Walc	0.032574	-0.277067	0.062835	0.024019	0.083547	0.054967	-0.030539	0.019199	0.029717	-0.198442	0.061557	-
health	-0.036043	-0.127390	-0.019963	0.010102	0.016203	-0.006947	0.006768	0.031037	-0.050899	-0.061113	0.040769	
absences	-0.208827	-0.047241	0.128547	-0.079561	0.029528	-0.102737	0.061212	0.037540	-0.050590	-0.026183	0.096031	
G1	-0.084856	-0.023286	-0.082489	-0.049529	0.048601	-0.008363	0.156893	0.143492	-0.061016	0.137002	-0.321990	-
G2	-0.075287	-0.023952	-0.108616	-0.063381	0.051858	-0.000837	0.167596	0.141180	-0.082977	0.103403	-0.334102	-
G3	-0.065578	-0.014211	-0.100719	-0.065691	0.054780	-0.011345	0.151645	0.119840	-0.065799	0.095637	-0.335036	-

In [25]:

```
# Set target field

y = student['G3']
```

In [26]:

```
# Set, encoding and standardized variables

X = student[['Medu', 'Fedu', 'higher', 'G1', 'G2']]
X = pd.get_dummies(X)
X = StandardScaler().fit_transform(X)
```

In [27]:

```
# Create train and test sets

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.3)
```

In [28]:

```
# Initiate models

model_ols = LinearRegression()
model_rf = RandomForestRegressor()
model_xgb = XGBRegressor()
```

In [29]:

```
# Fit models with train data

model_ols.fit(X_train, y_train)
model_rf.fit(X_train, y_train)
model_xgb.fit(X_train, y_train)
```

```
[10:24:28] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now dep
recated in favor of reg:squarederror.
```

Out[29]:

```
XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
             colsample_bynode=1, colsample_bytree=1, gamma=0,
             importance_type='gain', learning_rate=0.1, max_delta_step=0,
             max_depth=3, min_child_weight=1, missing=None, n_estimators=100,
             n_jobs=1, nthread=None, objective='reg:linear', random_state=0,
             reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
             silent=None, subsample=1, verbosity=1)
```

In [30]:

```
# Performance score on test data
```

```
print("OLS score: %.4f" % model_ols.score(X_test, y_test))
print("RF score: %.4f" % model_rf.score(X_test, y_test))
print("XGB score: %.4f" % model_xgb.score(X_test, y_test))
```

```
OLS score: 0.8749
RF score: 0.7986
XGB score: 0.8750
```

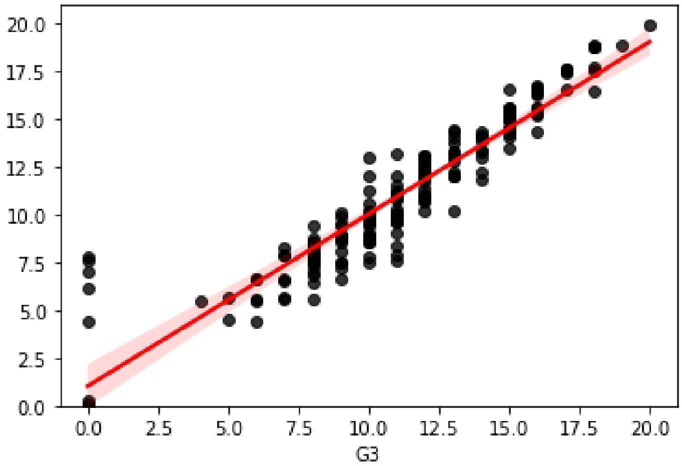
In [31]:

```
# Plot the predictions of one the most efficient model: OLS

y_pred_ols = model_ols.predict(X_test)
sns.regplot(y_test, y_pred_ols, data = student,
            scatter_kws = {"color" : "black"}, line_kws = {"color" : "red"})
plt.ylim(0,)
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass the
following variables as keyword args: x, y. From version 0.12, the only valid positional a
rgument will be `data`, and passing other arguments without an explicit keyword will resu
lt in an error or misinterpretation.
  FutureWarning
```

Out[31]:

```
(0.0, 20.974555085784623)
```



Unsupervised Machine Learning: Clustering

We will use K-Means Clustering to divide data into non-overlapping subsets based on all the data.

> ***Can we segment the data into three specific clusters?***

In [32]:

```
# Set scaled data

X = pd.concat([student.iloc[:,0:8], student.iloc[:,12:33]], axis = 1)
X = StandardScaler().fit_transform(X)
```

In [33]:

```
# Use PCA to transform the data

pca = PCA(n_components=2) # we explicitly ask for 2 components
pca_data = pca.fit_transform(X)
pca_data.shape # 662 rows, 2 columns - just as we wanted
```

Out[33]:

```
(662, 2)
```

In [34]:

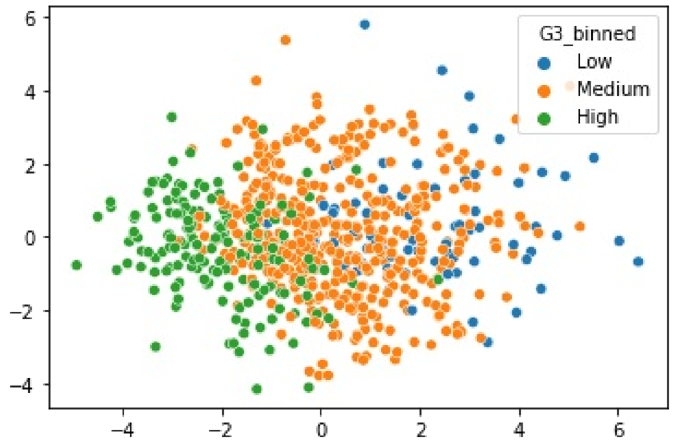
In [34]:

```
sns.scatterplot(pca_data[:,0], pca_data[:,1], hue = student['G3_binned'] )
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass the following variables as keyword args: x, y. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.
  FutureWarning
```

Out[34]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f4adda5ba50>
```



In [35]:

```
# Instantiate KMeans to create 3 clusters

clusterNum = 3
k_means = KMeans(init = "k-means++", n_clusters = clusterNum, n_init = 12)
k_means.fit(X)
labels = k_means.labels_
```

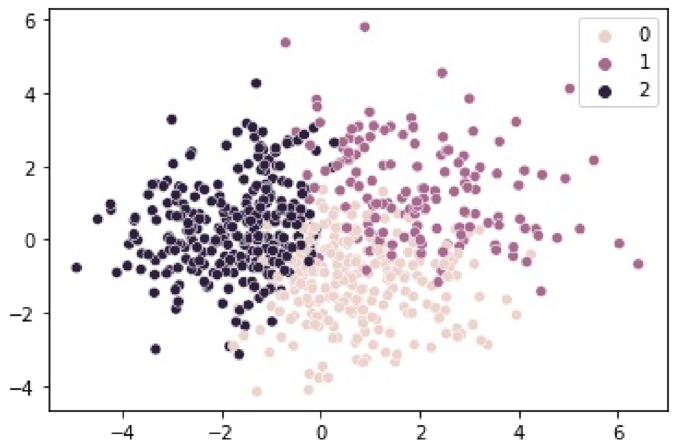
In [36]:

```
# Let's see how well the clusters fit with the performance bins

sns.scatterplot(pca_data[:,0], pca_data[:, 1], hue = k_means.labels_)
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass the following variables as keyword args: x, y. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.
  FutureWarning
```

Out[36]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f4add9d7350>
```



In [37]:

```
# Visualize the clusters with Altair
```

```
vis_data = pd.DataFrame(pca_data)
vis_data['cluster'] = labels
vis_data['G3_binned'] = student['G3_binned']
vis_data.columns = ['x', 'y', 'cluster', 'G3_binned']

alt.Chart(vis_data).mark_circle(size=60).encode(
    x='x',
    y='y',
    color='cluster',
    tooltip=['G3_binned']
).interactive()
```

Out[37]:

In [38]:

```
# Inspect the clusters

print(student.loc[k_means.labels_ == 0, student.columns[25:33]].describe())
print(student.loc[k_means.labels_ == 1, student.columns[25:33]].describe())
print(student.loc[k_means.labels_ == 2, student.columns[25:33]].describe())
```

```
            goout        Dalc        Walc  ...          G1          G2          G3
count  253.000000  253.000000  253.000000  ...  253.000000  253.000000  253.000000
mean     2.814229    1.142292    1.671937  ...    9.411067    9.249012    9.098814
std      1.127345    0.431302    0.899230  ...    2.354706    2.890400    3.870180
min      1.000000    1.000000    1.000000  ...    4.000000    0.000000    0.000000
25%      2.000000    1.000000    1.000000  ...    8.000000    8.000000    8.000000
50%      3.000000    1.000000    1.000000  ...    9.000000   10.000000   10.000000
75%      4.000000    1.000000    2.000000  ...   11.000000   11.000000   11.000000
max      5.000000    4.000000    5.000000  ...   16.000000   17.000000   18.000000

[8 rows x 8 columns]
            goout        Dalc        Walc  ...          G1          G2          G3
count  142.000000  142.000000  142.000000  ...  142.000000  142.000000  142.000000
mean     3.880282    2.500000    3.676056  ...    8.697183    8.429577    8.401408
std      1.075071    1.241996    1.075513  ...    2.224906    3.049004    3.565118
min      1.000000    1.000000    1.000000  ...    3.000000    0.000000    0.000000
25%      3.000000    2.000000    3.000000  ...    7.000000    7.000000    8.000000
50%      4.000000    2.000000    4.000000  ...    9.000000    9.000000    9.000000
75%      5.000000    3.000000    4.000000  ...   10.000000   10.000000   10.000000
max      5.000000    5.000000    5.000000  ...   16.000000   16.000000   16.000000

[8 rows x 8 columns]
            goout        Dalc        Walc  ...          G1          G2          G3
count  267.000000  267.000000  267.000000  ...  267.000000  267.000000  267.000000
mean     3.134831    1.318352    2.119850  ...   13.056180   13.303371   13.501873
std      1.071058    0.671493    1.157137  ...    2.537062    2.560858    2.800879
min      1.000000    1.000000    1.000000  ...    7.000000    8.000000    0.000000
25%      2.000000    1.000000    1.000000  ...   11.000000   12.000000   11.000000
50%      3.000000    1.000000    2.000000  ...   13.000000   13.000000   14.000000
75%      4.000000    1.000000    3.000000  ...   15.000000   15.000000   15.000000
max      5.000000    5.000000    5.000000  ...   19.000000   19.000000   20.000000

[8 rows x 8 columns]
```

Observations and Conclusion

Analysis and Visualization:

- **The majority of grades (> 60%) are part of the medium bin.**
- **We can see that workday alcohol consumption (Dalc) seems to have a significant negative impact on student final grade. However, the effet of weekend alcohol consumption is more nuanced, specially for moderate levels.**
- **Students consume more alcohol during the weekend which is reassuring. The alcohol consumption is clearly higher for men and also slightly more significant for Mousinho da Silveira school.**

Classification:

- We used Logistic Regression to classify final performance with the target field G3_binned. The model presents a modest performance with an average score of 72%.
- Looking at the classification report, we can see that the model performs well on medium bins but not on High and Low bins.
- This performance may be due to the dataset size which doesn't allow the model to fit well with small bins.

Regression:

- We defined with the .corr() method the top 5 variables positively correlated with G3 performance. Then we use these variables to predict this target field.
- From the three models used, OLS was the most performant with an average score of 85% on test data.
- The Regplot showed that the model was more performant on predicting high grades.

Clustering:

- The first cluster with the highest goout and alcohol consumption rates presents the lowest performance grades (< 9).
- The second cluster with the lowest goout and alcohol consumption rates also presents low performance grades (< 10).
- The third cluster which have slightly higher goout and alcohol consumption rates than the second cluster presents the highest performance grades (> 13).