```
%matplotlib inline
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import seaborn as sns
import statsmodels.formula.api as smf
sns.set_theme(style='white', palette='rainbow', font_scale=1.2)
```

```
data = pd.read_csv("data/student-mat.csv")
data.head()
```

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

```
data.shape
```

```
(395, 33)
```

Visualize Resp

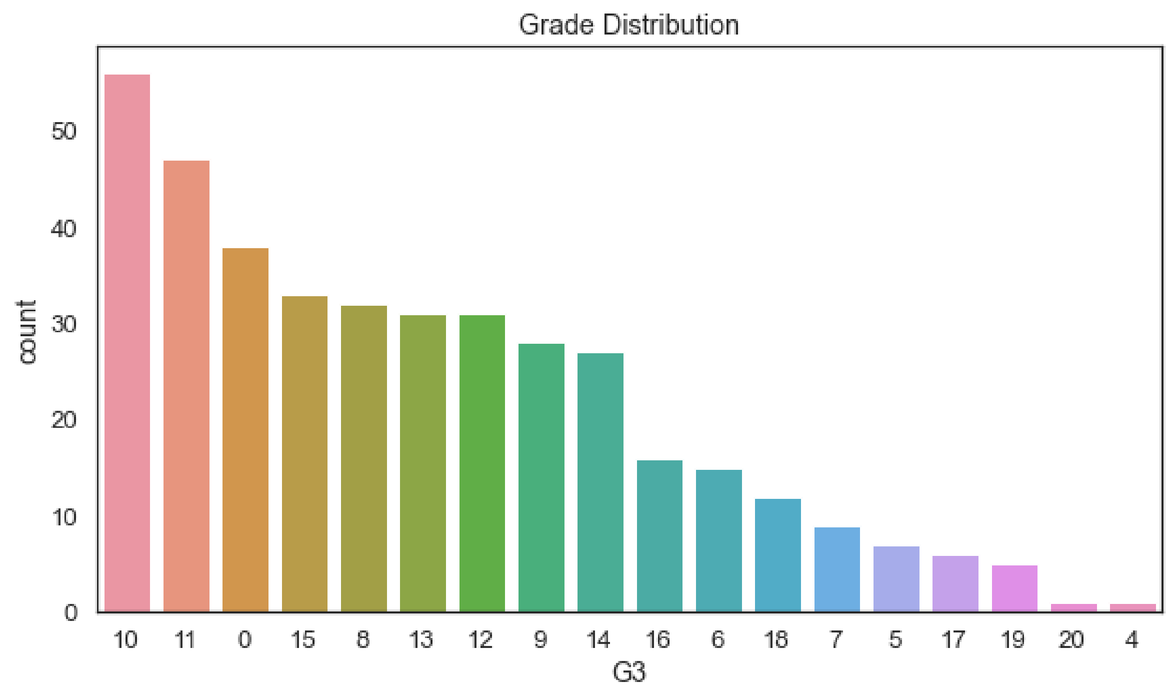
```
fig = plt.figure(figsize=(20, 16))
data.loc[data.G3 < 12, 'G3_binary'] = 0
data.loc[data.G3 >= 12, 'G3_binary'] = 1
data.head()
```

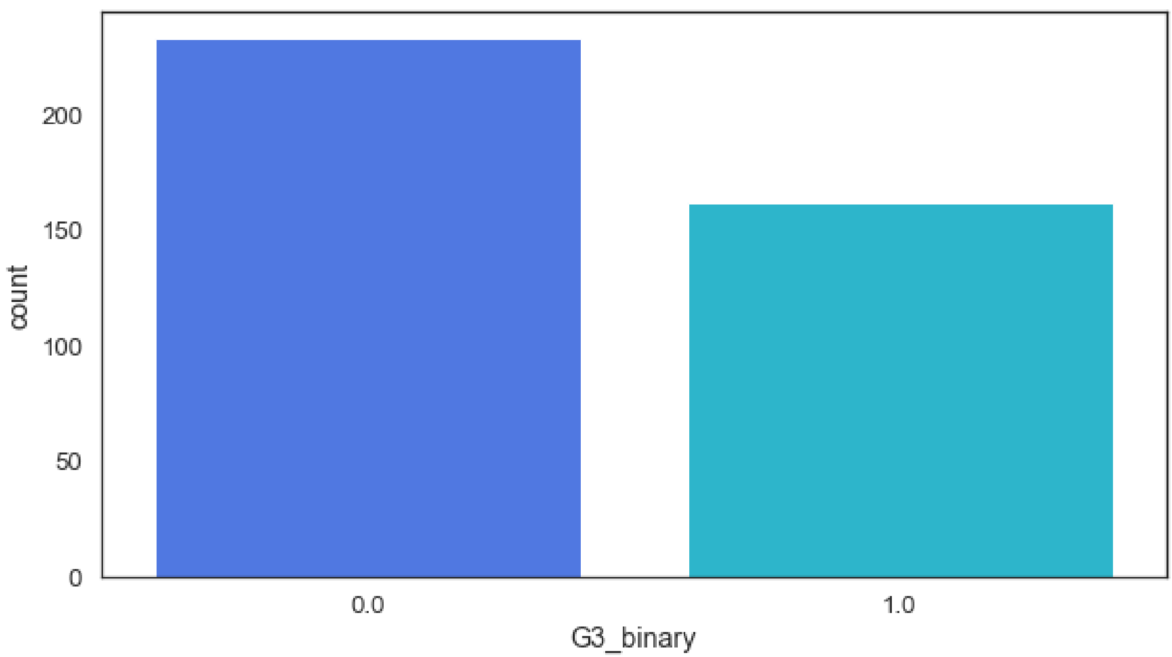
	school	sex	age	address	famsize	Pstatus	Medu	Fedu	Mjob	Fjob	...	freetime	goout
0	GP	F	18	U	GT3	A	4	4	at_home	teacher	...	3	4
1	GP	F	17	U	GT3	T	1	1	at_home	other	...	3	3
2	GP	F	15	U	LE3	T	1	1	at_home	other	...	3	2
3	GP	F	15	U	GT3	T	4	2	health	services	...	2	2
4	GP	F	16	U	GT3	T	3	3	other	other	...	3	2

```
<Figure size 1440x1152 with 0 Axes>
```

```
fig = plt.figure(figsize=(10, 12))
fig.add_subplot(2, 1, 1)
sns.countplot(x='G3', data=data, order=data['G3'].value_counts().index).set_title("Grade D
fig.add_subplot(2, 1, 2)
sns.countplot(x=data.G3_binary, order=data.G3_binary.value_counts().index)
```

```
<AxesSubplot: xlabel='G3_binary', ylabel='count'>
```






```
# plt.figure(figsize=(25, 16))
# sns.heatmap(data.corr(numeric_only=True), annot=True, cmap='Blues')
```

Study-related

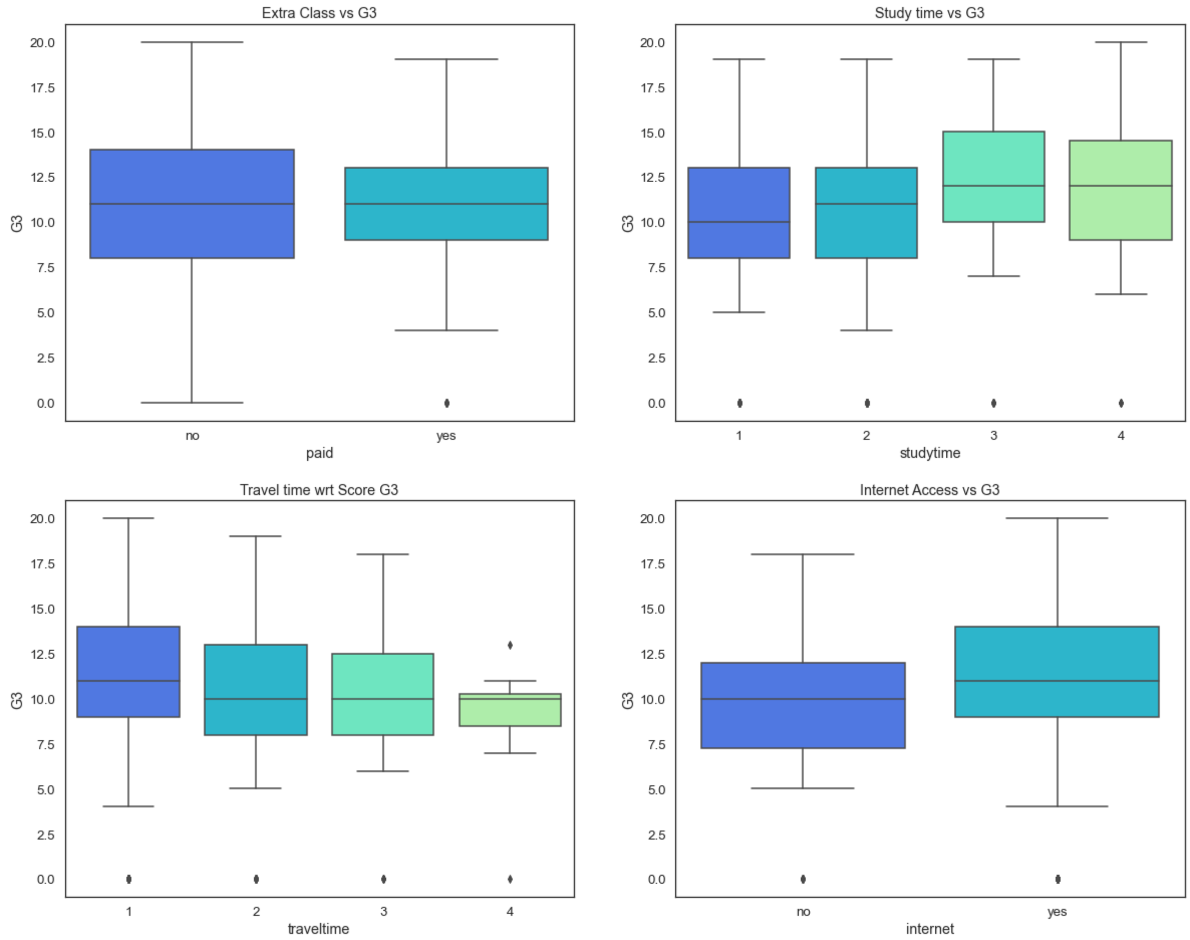
```
fig = plt.figure(figsize=(20, 16))
fig.add_subplot(2, 2, 1)
sns.boxplot(x='paid', y='G3', data=data).set_title('Extra Class vs G3')

fig.add_subplot(2, 2, 2)
sns.boxplot(x='studytime', y='G3', data=data).set_title('Study time vs G3')

fig.add_subplot(2, 2, 3)
sns.boxplot(x='traveltime', y='G3', data=data).set_title('Travel time wrt Score G3')

fig.add_subplot(2, 2, 4)
sns.boxplot(x='internet', y='G3', data=data).set_title('Internet Access vs G3')
```

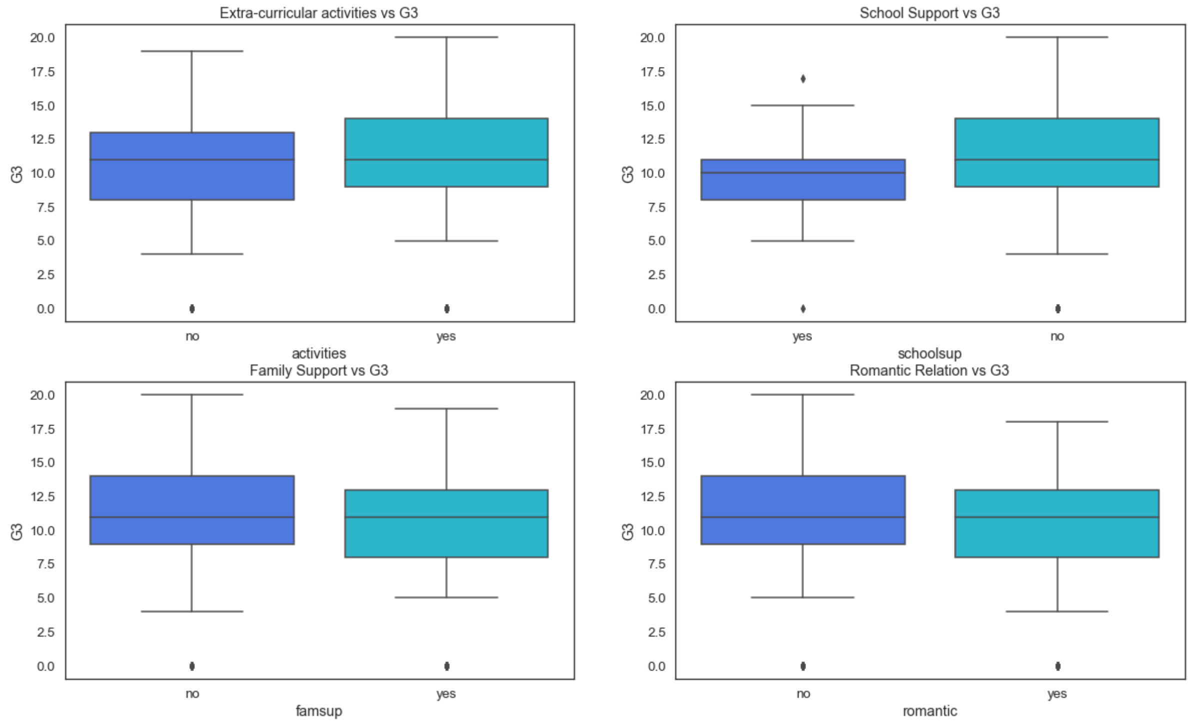
```
Text(0.5, 1.0, 'Internet Access vs G3')
```



Social Factors

```
fig = plt.figure(figsize=(20, 12))
fig.add_subplot(2, 2, 1)
sns.boxplot(x='activities', y='G3', data=data).set_title('Extra-curricular activities vs G
fig.add_subplot(2, 2, 2)
sns.boxplot(x='schoolsup', y='G3', data=data).set_title('School Support vs G3')
fig.add_subplot(2, 2, 3)
sns.boxplot(x='famsup', y='G3', data=data).set_title('Family Support vs G3')
fig.add_subplot(2, 2, 4)
sns.boxplot(x='romantic', y='G3', data=data).set_title('Romantic Relation vs G3')
```

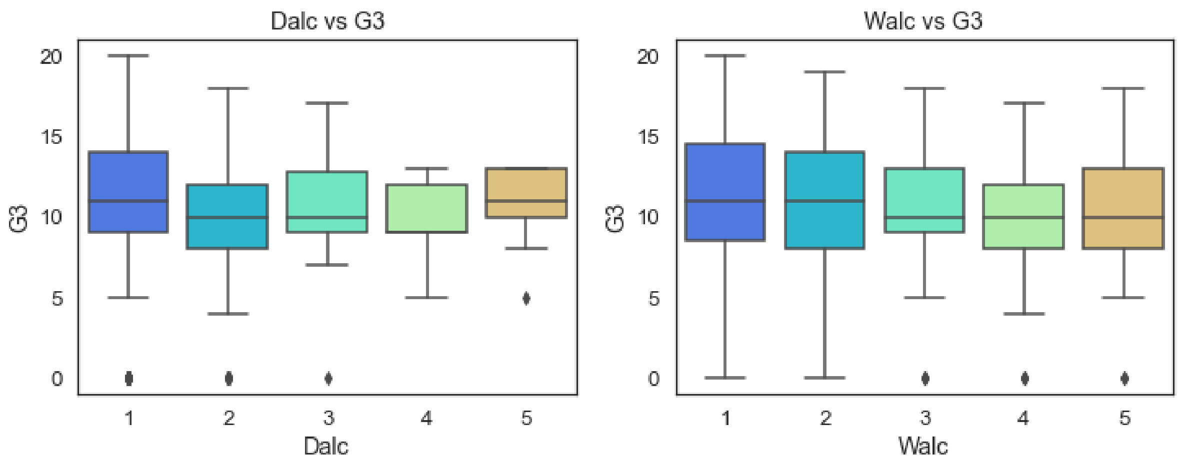
```
Text(0.5, 1.0, 'Romantic Relation vs G3')
```



Behavioral

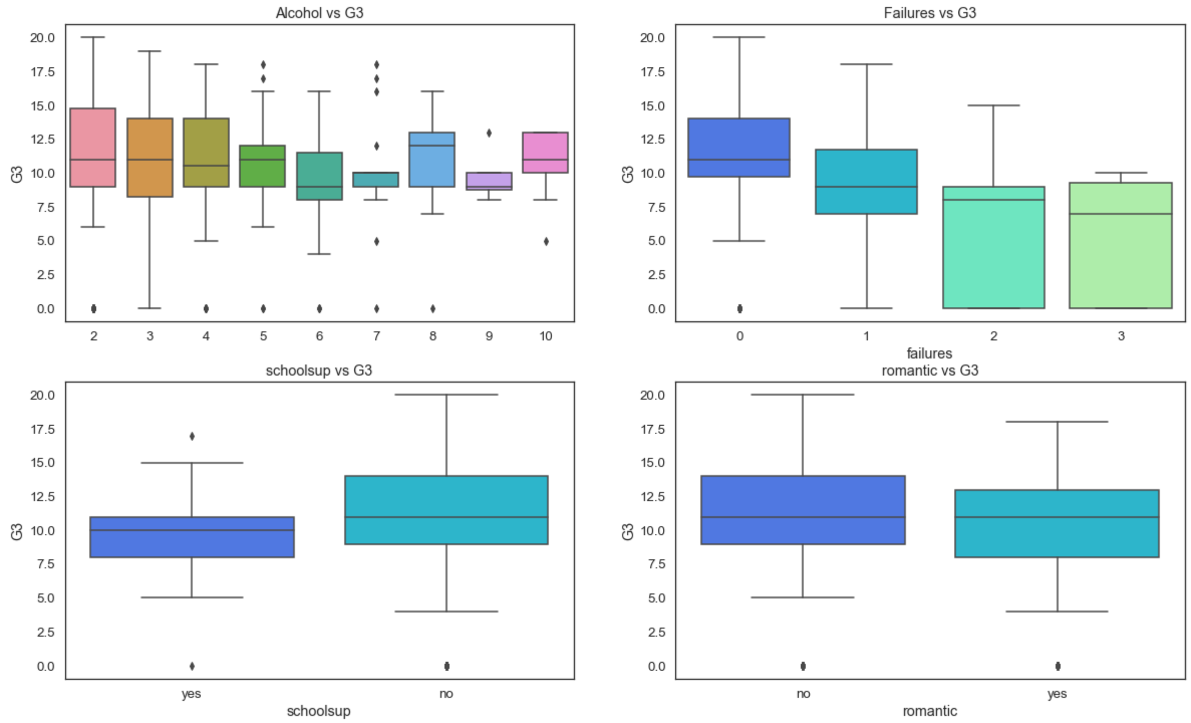
```
fig = plt.figure(figsize=(12, 4))
fig.add_subplot(1, 2, 1)
sns.boxplot(x='Dalc', y='G3', data=data).set_title('Dalc vs G3')
fig.add_subplot(1, 2, 2)
sns.boxplot(x='Walc', y='G3', data=data).set_title('Walc vs G3')
```

```
Text(0.5, 1.0, 'Walc vs G3')
```



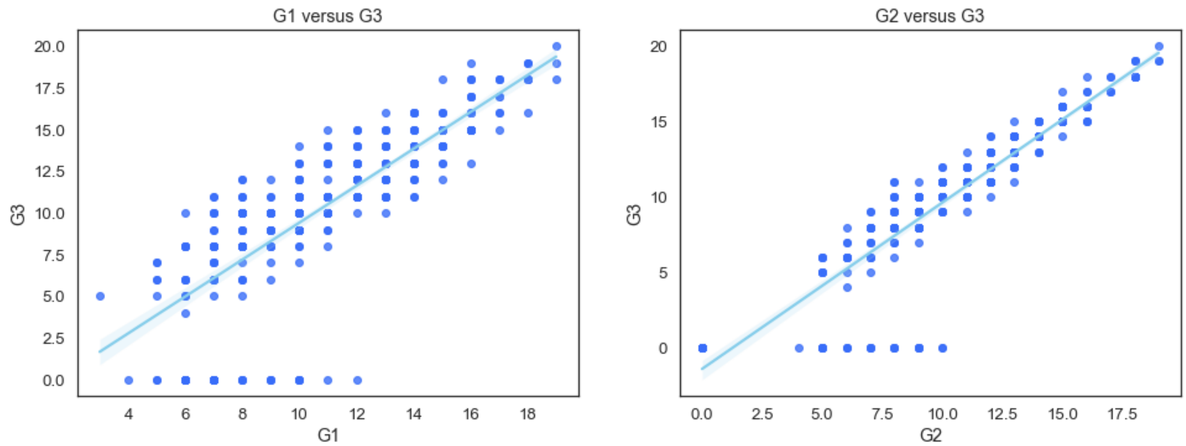

```
fig = plt.figure(figsize=(20, 12))
fig.add_subplot(2, 2, 1)
alc = data['Dalc'] + data['Walc']
sns.boxplot(x=alc, y='G3',  data=data).set_title('Alcohol vs G3')
fig.add_subplot(2, 2, 2)
sns.boxplot(x='failures', y='G3',  data=data).set_title('Failures vs G3')
fig.add_subplot(2, 2, 3)
sns.boxplot(x='schoolsup', y='G3',  data=data).set_title('schoolsup vs G3')
fig.add_subplot(2, 2, 4)
sns.boxplot(x='romantic', y='G3',  data=data).set_title('romantic vs G3')
```

```
Text(0.5, 1.0, 'romantic vs G3')
```




```
fig = plt.figure(figsize=(16, 12))
fig.add_subplot(2, 2, 1)
sns.regplot(x='G1', y='G3', data=data, line_kws={'color': 'skyblue'}).set_title('G1 versus
fig.add_subplot(2, 2, 2)
sns.regplot(x='G2', y='G3', data=data, line_kws={'color': 'skyblue'}).set_title('G2 versus
```

```
Text(0.5, 1.0, 'G2 versus G3')
```



Pre-Processsing

```
# read data
data = pd.read_csv("data/student-mat.csv")

# binary_mapping
data['school'] = data['school'].map({'GP':0, 'MS':1})
data['sex'] = data['sex'].map({'F':0, 'M':1})
data['famsize'] = data['famsize'].map({'GT3':0, 'LE3':1})
data['address'] = data['address'].map({'R':0, 'U':1})
data['Pstatus'] = data['Pstatus'].map({'A':0, 'T':1})

binary_mapping = {'yes':1, 'no':0}
data['schoolsup'] = data['schoolsup'].map(binary_mapping)
data['famsup'] = data['famsup'].map(binary_mapping)
data['paid'] = data['paid'].map(binary_mapping)
data['activities'] = data['activities'].map(binary_mapping)
data['nursery'] = data['nursery'].map(binary_mapping)
data['higher'] = data['higher'].map(binary_mapping)
data['internet'] = data['internet'].map(binary_mapping)
data['romantic'] = data['romantic'].map(binary_mapping)

# level-encoding
job_encoding = {'other':0, 'at_home': 1, 'services':2, 'health': 3, 'teacher': 4}
data['Mjob'] = data['Mjob'].map(job_encoding)
data['Fjob'] = data['Fjob'].map(job_encoding)
data['reason'] = data['reason'].map({'other': 0, 'home': 1, 'reputation': 2, 'course': 3})
```

```python
data['guardian'] = data['guardian'].map({'other': 0, 'mother': 1, 'father': 2})

# combine Dalc and Walc into alc
data.loc[:,'alc']= data['Dalc'] + data['Walc']
# drop Dalc and Walc
data = data.drop(columns=['Dalc', 'Walc'])
# drop G1 and G2
data = data.drop(columns=['G1', 'G2'])

data.head(3)
# data.dtypes
```

	school	sex	age	address	famsize	Pstatus	Medu	Fedu	Mjob	Fjob	...	higher	internet	rom
0	0	0	18	1	0	0	4	4	1	4	...	1	0	0
1	0	0	17	1	0	1	1	1	1	0	...	1	1	0
2	0	0	15	1	1	1	1	1	1	0	...	1	1	0

```python
# data.isna().sum()
```

```python
X = data
y = data.G3
```

```python
from sklearn.feature_selection import SelectKBest, chi2
k_best = SelectKBest(score_func=chi2, k=10)
k_best.fit(X, y)
df_score = pd.Series(data=k_best.scores_, index=X.columns)
df_score.sort_values(ascending=False)[1:6]
```

```
absences     648.166848
failures     140.934898
alc           41.036997
Fjob          32.603524
schoolsup     28.319018
dtype: float64
```

```python
features_selected = df_score.nlargest(3).index
features_selected
```

```
Index(['G3', 'absences', 'failures'], dtype='object')
```

```
# train = split
from sklearn.model_selection import train_test_split, KFold, cross_val_score
k_fold = KFold(n_splits=10, random_state=1, shuffle=True)
train, test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=1)
train.head()
```

	school	sex	age	address	famsize	Pstatus	Medu	Fedu	Mjob	Fjob	...	higher	internet	r
23	0	1	16	1	1	1	2	2	0	0	...	1	1	0
296	0	0	19	1	0	1	4	4	3	0	...	1	1	0
13	0	1	15	1	0	1	4	3	4	0	...	1	1	0
249	0	1	16	1	0	1	0	2	0	0	...	1	1	0
61	0	0	16	1	0	1	1	1	2	2	...	1	1	1

```
# from sklearn.linear_model import LinearRegression
# from sklearn.linear_model import Lasso
# from sklearn.linear_model import Ridge
# classifiers = {
#     'Linear Regression' : LinearRegression(),
#     'Lasso': Lasso(),
#     'Ridge': Ridge(),
# }

# for key, clf in classifiers.items():
#     print(key, clf)
#     score = cross_val_score(clf, X_train, y_train, cv=k_fold, scoring='neg_mean_squared_
#     rmse = np.sqrt(-score)
#     rmse_score = np.mean(rmse)
#     print('RMSE score with CV of {0} is {1}'.format(key, rmse_score))
```

```
# lm_fit = LinearRegression().fit(X_train, y_train)
# lm_fit.coef_
```

```
# pred_score = lasso_fit.predict(X[selected])
# df_res = pd.DataFrame([pred_score,y], index=["pred","true"]).T
# df_res.loc[pred_score < 12] = 0
# df_res.loc[pred_score >= 12] = 1
# y[y < 12] = 0
```

```
# y[y >= 12] = 1
# # df_res
# np.mean(df_res.pred == df_res.true)
```

Linear Regression Model

```
train = pd.DataFrame(train)
# train.head()
```

G3 ~ absences * failures + schoolsup + romantic

```
df_score.sort_values(ascending=False)[1:8]
```

```
absences     648.166848
failures     140.934898
alc           41.036997
Fjob          32.603524
schoolsup     28.319018
Mjob          28.144005
romantic      20.089526
dtype: float64
```

```
import statsmodels.formula.api as smf
# function to test prediction accuracy
def acc(lm, _Xtest, _ytest):
    pred_test = lm.predict(_Xtest)
    data = pd.concat([pred_test, _ytest], axis = 1)
    test_res = pd.DataFrame(data, columns=["predicted", "actual"], dtype="float64")
    test_res[pred_test < 12],test_res[pred_test >= 12] = 0,1
    test_res[pred_test < 6],test_res[pred_test >= 12] = 0,1
    y_test[y_test < 12],y_test[y_test >= 12] = 0,1
    return np.mean(test_res.predicted == test_res.actual)

# function to format and print result
def display_res(lm_formula):
    lm = smf.ols(formula = lm_formula, data=train).fit()
    r2 = lm.rsquared
```

```
    acc_test = acc(lm, test, y_test)
    acc_full = acc(lm, X, y)
    print(f"{lm_formula}\nR-Squared = {r2:.4f}\nAccuracy on test set: {acc_test}\tfull dat
```

```
lm0 = 'G3 ~ absences'
display_res(lm0)
```

```
G3 ~ absences
R-Squared = 0.0016
Accuracy on test set: 1.0   full dataset: 1.0
```

```
lm1 = 'G3 ~ absences + failures'
display_res(lm1)
```

```
G3 ~ absences + failures
R-Squared = 0.1237
Accuracy on test set: 1.0   full dataset: 1.0
```

```
lm2 = 'G3 ~ absences + failures  + alc'
display_res(lm2)
```

```
G3 ~ absences + failures  + alc
R-Squared = 0.1238
Accuracy on test set: 1.0   full dataset: 1.0
```

```
lm3 = 'G3 ~ absences + failures + alc + Fjob'
display_res(lm3)
```

```
G3 ~ absences + failures + alc + Fjob
R-Squared = 0.1300
Accuracy on test set: 1.0   full dataset: 1.0
```

```
lm4 = 'G3 ~ absences + failures + schoolsup + romantic'
display_res(lm4)
```

```
G3 ~ absences + failures + schoolsup + romantic
R-Squared = 0.1517
Accuracy on test set: 1.0   full dataset: 1.0
```