In [202]:
```
import sqlite3
import pandas as pd
from sklearn.tree import DecisionTreeRegressor
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error,accuracy_score,recall_score
from math import sqrt
from sklearn.ensemble import BaggingClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.datasets import load_breast_cancer
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.linear_model import LogisticRegression
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from matplotlib import style
import seaborn as sns
%matplotlib inline
from sklearn import svm
from sklearn import datasets
import statsmodels.api as sm
#from sklearn.preprocessing import MinMaxScaler
#from sklearn.preprocessing import StandardScaler
#from sklearn.preprocessing import RobustScaler
#from sklearn.preprocessing import Normalizer
from sklearn.model_selection import cross_val_score
import statsmodels.formula.api as sm
import statsmodels.tools
```

import data

In [203]:
```
df = pd.read_csv("C:/Users/mgirm/Downloads/student-mat.csv",sep=';',encoding=
'utf-8')
```

In [204]:
```
len(df.columns)
```

Out[204]: 33

Setup a Treshold

In [182]:
```
np.percentile(df.G3,[25,50,75,95,99,10])
```

Out[182]: array([8., 11., 14., 17., 19., 5.])

In [183]:
```
pd.Series(np.where(df.G3>14,1,0)).value_counts()
```
Out[183]:
```
0    322
1     73
dtype: int64
```

In [184]:
```
df['Target']=pd.Series(np.where(df.G3>14,1,0))
```

In [185]:
```
df["school"].unique()
```
Out[185]:
```
array(['GP', 'MS'], dtype=object)
```

In [186]:
```
df.loc[df.Target==1,:].shape[0]/df.shape[0]
```
Out[186]:
```
0.1848101265822785
```

In [187]:
```
df.loc[(df.Target==1)& (df.school=='GP'),:].shape[0]/df.shape[0]
```
Out[187]:
```
0.16962025316455695
```

In [188]:
```
df.loc[(df.Target==1)& (df.school=='MS'),:].shape[0]/df.shape[0]
```
Out[188]:
```
0.015189873417721518
```

# of once are 18 % and when school is MS you get only 0.2%

In [189]:
```
x_=df.loc[(df.Target==1)& (df.school=='GP'),:].shape[0]/df.loc[(df.school=='G
P'),:].shape[0]
```

% of GP is high when value is > is 1

In [190]:
```
x_/(df.loc[df.Target==1,:].shape[0]/df.shape[0])
```
Out[190]:
```
1.038780076147113
```

19 are 1

Data Dleaning and Data Exploration

In [205]:
```
df.isnull().any()
```

Out[205]:
```
school        False
sex           False
age           False
address       False
famsize       False
Pstatus       False
Medu          False
Fedu          False
Mjob          False
Fjob          False
reason        False
guardian      False
traveltime    False
studytime     False
failures      False
schoolsup     False
famsup        False
paid          False
activities    False
nursery       False
higher        False
internet      False
romantic      False
famrel        False
freetime      False
goout         False
Dalc          False
Walc          False
health        False
absences      False
G1            False
G2            False
G3            False
dtype: bool
```

In [192]:
```
df.shape
```

Out[192]:
```
(395, 34)
```

In [125]:
```
df.tail(5)
```

Out[125]:

	school	sex	age	address	famsize	Pstatus	Medu	Fedu	Mjob	Fjob	...	famrel	f
390	MS	M	20	U	LE3	A	2	2	services	services	...	5	
391	MS	M	17	U	LE3	T	3	1	services	services	...	2	
392	MS	M	21	R	GT3	T	1	1	other	other	...	5	
393	MS	M	18	R	LE3	T	3	2	services	other	...	4	
394	MS	M	19	U	LE3	T	1	1	other	at_home	...	3	

5 rows × 33 columns

In [126]:
```
df.columns
```

Out[126]:
```
Index(['school', 'sex', 'age', 'address', 'famsize', 'Pstatus', 'Medu', 'Fed
u',
       'Mjob', 'Fjob', 'reason', 'guardian', 'traveltime', 'studytime',
       'failures', 'schoolsup', 'famsup', 'paid', 'activities', 'nursery',
       'higher', 'internet', 'romantic', 'famrel', 'freetime', 'goout', 'Dal
c',
       'Walc', 'health', 'absences', 'G1', 'G2', 'G3'],
      dtype='object')
```

In [127]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 395 entries, 0 to 394
Data columns (total 33 columns):
school        395 non-null object
sex           395 non-null object
age           395 non-null int64
address       395 non-null object
famsize       395 non-null object
Pstatus       395 non-null object
Medu          395 non-null int64
Fedu          395 non-null int64
Mjob          395 non-null object
Fjob          395 non-null object
reason        395 non-null object
guardian      395 non-null object
traveltime    395 non-null int64
studytime     395 non-null int64
failures      395 non-null int64
schoolsup     395 non-null object
famsup        395 non-null object
paid          395 non-null object
activities    395 non-null object
nursery       395 non-null object
higher        395 non-null object
internet      395 non-null object
romantic      395 non-null object
famrel        395 non-null int64
freetime      395 non-null int64
goout         395 non-null int64
Dalc          395 non-null int64
Walc          395 non-null int64
health        395 non-null int64
absences      395 non-null int64
G1            395 non-null int64
G2            395 non-null int64
G3            395 non-null int64
dtypes: int64(16), object(17)
memory usage: 101.9+ KB
```

some students have G3 scores are 0 means student didnt attend exams hence need to drop this data

In [128]:
```
df.describe()
```

Out[128]:

	age	Medu	Fedu	traveltime	studytime	failures	famrel	f
count	395.000000	395.000000	395.000000	395.000000	395.000000	395.000000	395.000000	395
mean	16.696203	2.749367	2.521519	1.448101	2.035443	0.334177	3.944304	3
std	1.276043	1.094735	1.088201	0.697505	0.839240	0.743651	0.896659	0
min	15.000000	0.000000	0.000000	1.000000	1.000000	0.000000	1.000000	1
25%	16.000000	2.000000	2.000000	1.000000	1.000000	0.000000	4.000000	3
50%	17.000000	3.000000	2.000000	1.000000	2.000000	0.000000	4.000000	3
75%	18.000000	4.000000	3.000000	2.000000	2.000000	0.000000	5.000000	4
max	22.000000	4.000000	4.000000	4.000000	4.000000	3.000000	5.000000	5

In [206]:
```
df.drop(df[df.G3==0].index,inplace=True)  #cleanup vlaues where G3 is zero i.e
 Target is 0
```

In [130]:
```
df.describe()
```

Out[130]:

	age	Medu	Fedu	traveltime	studytime	failures	famrel	f
count	357.000000	357.000000	357.000000	357.000000	357.000000	357.000000	357.000000	357
mean	16.655462	2.795518	2.546218	1.431373	2.042017	0.271709	3.955182	3
std	1.268262	1.093999	1.084217	0.686075	0.831895	0.671750	0.885721	1
min	15.000000	0.000000	0.000000	1.000000	1.000000	0.000000	1.000000	1
25%	16.000000	2.000000	2.000000	1.000000	1.000000	0.000000	4.000000	3
50%	17.000000	3.000000	3.000000	1.000000	2.000000	0.000000	4.000000	3
75%	18.000000	4.000000	3.000000	2.000000	2.000000	0.000000	5.000000	4
max	22.000000	4.000000	4.000000	4.000000	4.000000	3.000000	5.000000	5

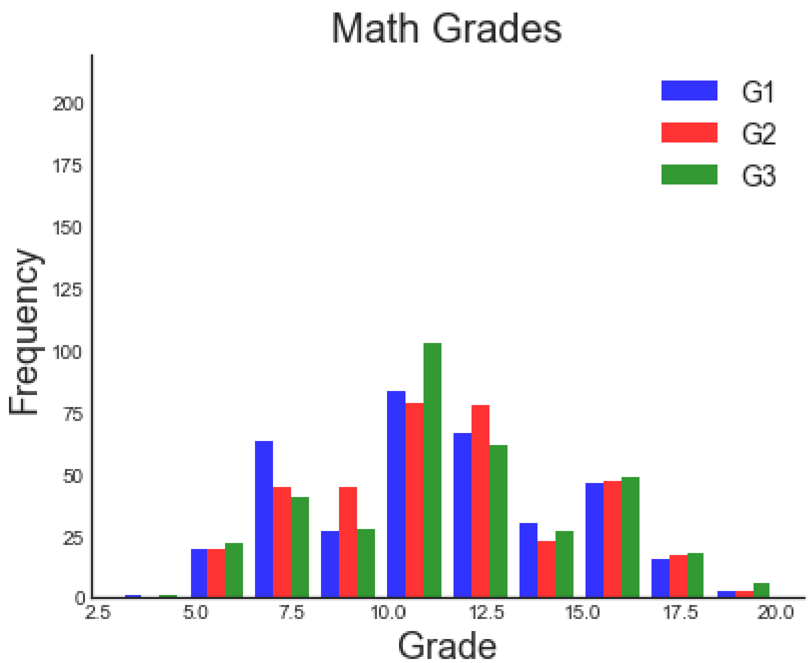
In [207]:
```
df.groupby('sex')['G3'].mean()
```

Out[207]:
```
sex
F    11.205405
M    11.866279
Name: G3, dtype: float64
```

Plotting G1,G2 and G3 to get idea of distribution of Grades

In [208]:
```
fig = plt.figure(figsize=(14,5))
plt.style.use('seaborn-white')
ax1 = plt.subplot(121)
plt.hist([df['G1'], df['G2'], df['G3']], label=['G1', 'G2', 'G3'], color=['blu
e', 'red', 'green' ], alpha=0.8)
plt.legend(fontsize=14)
plt.xlabel('Grade', fontsize=18)
plt.ylabel('Frequency', fontsize=18)
plt.title('Math Grades', fontsize=20)
ax1.spines['top'].set_visible(False)
ax1.spines['right'].set_visible(False)
plt.ylim(0,220)

plt.show()
```



G1,G2 and G3 have similar distributions hence i will use G3 as final Grade to represent students performance

.

In [209]:
```
#Math dataset
#create Aalc
df.loc[:,'Aalc'] = (df['Dalc']*5 + df['Walc']*2)/7
#remove not interested variables
#"paid" has "no" values for all entries, so we will also drop it.
df = df.drop(['G1', 'G2', 'Dalc', 'Walc', 'paid'], axis=1)
```

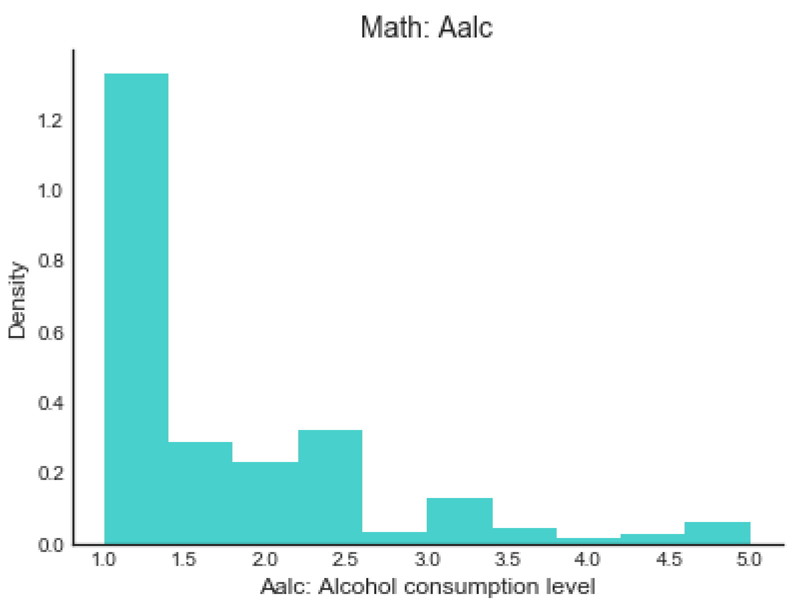
In [210]:
```
df.columns
```

Out[210]:
```
Index(['school', 'sex', 'age', 'address', 'famsize', 'Pstatus', 'Medu', 'Fed
u',
       'Mjob', 'Fjob', 'reason', 'guardian', 'traveltime', 'studytime',
       'failures', 'schoolsup', 'famsup', 'activities', 'nursery', 'higher',
       'internet', 'romantic', 'famrel', 'freetime', 'goout', 'health',
       'absences', 'G3', 'Aalc'],
      dtype='object')
```

In [251]:
```
#visualize Aalc
fig = plt.figure(figsize=(14,10))

ax1 = plt.subplot(221)
plt.hist(df['Aalc'], bins=10, normed=True, color='#48D1CC')
plt.title('Math: Aalc', fontsize=14)
plt.xlabel('Aalc: Alcohol consumption level', fontsize=12)
plt.ylabel('Density', fontsize=12)
ax1.spines['top'].set_visible(False)
ax1.spines['right'].set_visible(False)
```

```
C:\Users\mgirm\Anaconda3\lib\site-packages\matplotlib\axes\_axes.py:6571: Use
rWarning: The 'normed' kwarg is deprecated, and has been replaced by the 'den
sity' kwarg.
  warnings.warn("The 'normed' kwarg is deprecated, and has been "
```



From Desity plot of Aalc most stundents fall in the range of 1-1.5 meaning they consume alcholol at very low.

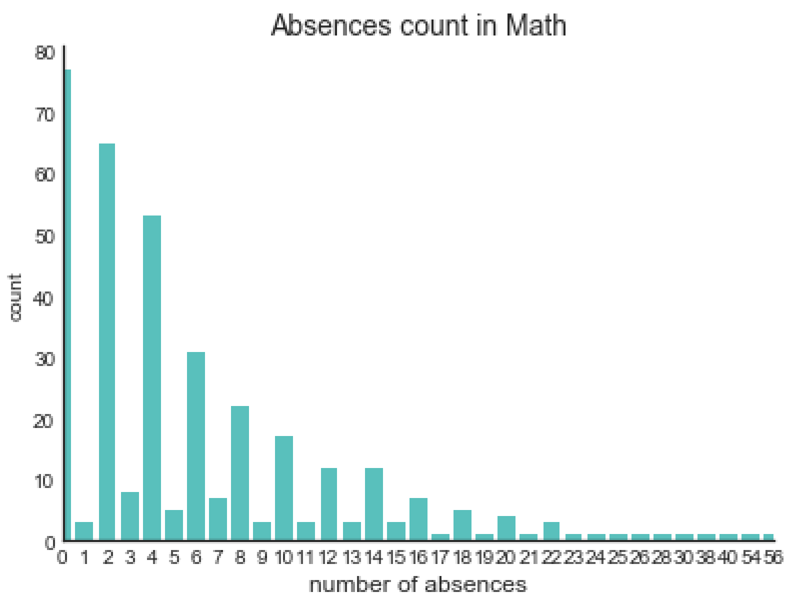
The above graph shows a reverse inverse relation between Aalc and G3

Plotting Absence

In [296]:
```
#Visualize absence
fig = plt.figure(figsize=(14,10))

ax1 = plt.subplot(221)
sns.countplot(df['absences'], color='#48D1CC')
plt.title('Absences count in Math', fontsize=14)
plt.xlabel('number of absences', fontsize=12)
ax1.spines['top'].set_visible(False)
ax1.spines['right'].set_visible(False)
plt.xlim((0,32))
```

Out[296]: (0, 32)



Negative relation between G3 and Absence is shown in above plots

In [214]:
```
df.tail(5)
```

Out[214]:

	school	sex	age	address	famsize	Pstatus	Medu	Fedu	Mjob	Fjob	...	higher	i
390	MS	M	20	U	LE3	A	2	2	services	services	...	yes	
391	MS	M	17	U	LE3	T	3	1	services	services	...	yes	
392	MS	M	21	R	GT3	T	1	1	other	other	...	yes	
393	MS	M	18	R	LE3	T	3	2	services	other	...	yes	
394	MS	M	19	U	LE3	T	1	1	other	at_home	...	yes	

5 rows × 29 columns

Identifying Categorical_Columns

In [245]:
```
Categorical_= df.iloc[:,np.where([type(df[i][0])==str for i in df.columns])[0
]]
[Categorical_Columns for Categorical_Columns in Categorical_.columns]
```

Out[245]:
```
['school',
 'sex',
 'address',
 'famsize',
 'Pstatus',
 'Mjob',
 'Fjob',
 'reason',
 'guardian',
 'schoolsup',
 'famsup',
 'activities',
 'nursery',
 'higher',
 'internet',
 'romantic']
```

In [215]:

```
#Identify target variable y and predictor variables X.
y = df['G3']
X = df[['school', 'sex', 'age', 'address', 'famsize', 'Pstatus', 'Medu', 'Fed
u',
       'Mjob', 'Fjob', 'reason', 'guardian', 'traveltime', 'studytime',
       'failures', 'schoolsup', 'famsup', 'activities', 'nursery',
       'higher', 'internet', 'romantic', 'famrel', 'freetime', 'goout',
       'health', 'absences', 'Aalc']]
#Convert dummy variables values into 0/1.
X.school = X['school'].replace(['GP', 'MS'], [1,0])
X.sex = X['sex'].replace(['F','M'],[1,0])
X.address = X['address'].replace(['U','R'], [1,0])
X.famsize = X['famsize'].replace(['LE3','GT3'], [1,0])
X.Pstatus = X['Pstatus'].replace(['T','A'], [1,0])
X.schoolsup = X['schoolsup'].replace(['yes','no'],[1,0])
X.famsup = X['famsup'].replace(['yes','no'],[1,0])
X.activities = X['activities'].replace(['yes','no'],[1,0])
X.nursery = X['nursery'].replace(['yes','no'],[1,0])
X.higher = X['higher'].replace(['yes','no'],[1,0])
X.internet = X['internet'].replace(['yes','no'],[1,0])
X.romantic = X['romantic'].replace(['yes','no'],[1,0])
#Identify norminal variables
norminal_vars = ['Fjob', 'Mjob', 'reason','guardian']
#Convert norminal variables to dummy variables
X = pd.get_dummies(X, columns = norminal_vars, drop_first=True)
# Split data into training and test data sets.
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.3, ran
dom_state=42)
```

```
C:\Users\mgirm\Anaconda3\lib\site-packages\pandas\core\generic.py:4405: Setti
ngWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/st
able/indexing.html#indexing-view-versus-copy
  self[name] = value
```

In [334]:
```
# Linear Regression without GridSearch

from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn.model_selection import cross_val_score, cross_val_predict
from sklearn.metrics import r2_score

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

lm = LinearRegression()

#Next we do cross validation, which splits apart our training data and fits th
e model on different samples and
# gives scores for each sample to get the best fit model before we test it on
 the testing data.

scores = cross_val_score(lm, X_train, y_train, cv = 5)

#To get predictions (y_hat) and check them all in one using cross validation

predictions = cross_val_predict(lm, X_test, y_test, cv = 5)     #y_test is nee
ded here in predictions to get scores for each fold of cv

accuracy = metrics.r2_score(y_test, predictions)  #this says the accuracy of t
he predictions from the best cv fold
print("accuracy of predictions ",accuracy)

#If this is good, continue to fit the model on the data


lm.fit(X_train, y_train)

y_hat = lm.predict(X_test)      #this gives me my predictions

print("my model performance",lm.score(X_test, y_test))
```

```
accuracy of predictions  -0.02168931768172233
my model performance 0.252392653331171
```

Applying alogriths . Decision Tree

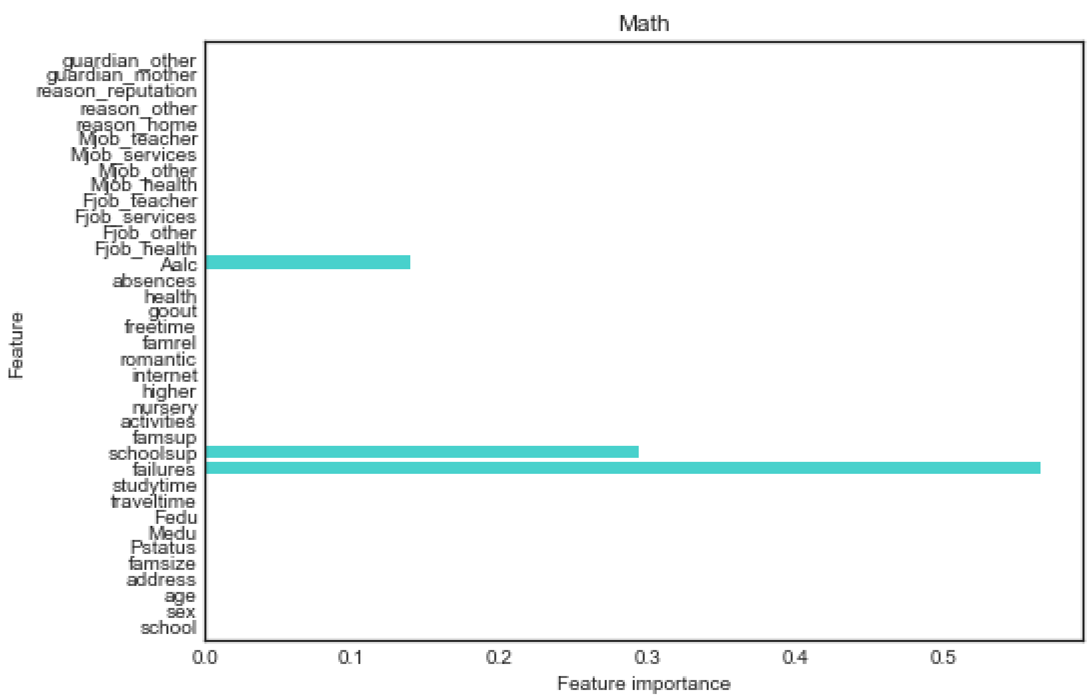
In [293]:
```
from sklearn.tree import DecisionTreeRegressor
from sklearn.model_selection import GridSearchCV
def decisiontree (X_train, y_train, X_test, y_test):
    param_grid = {'max_depth': range(1,100)}
    grid = GridSearchCV(DecisionTreeRegressor(), param_grid, cv=5)
    grid.fit(X_train, y_train)
    print ('Best cross validation score: {:.2f}'.format(grid.best_score_))
    print ('Best parameters:', grid.best_params_)
    print ('Test score:', grid.score(X_test, y_test))
```

In [294]:
```
decisiontree(X_train, y_train, X_test, y_test)
```

```
Best cross validation score: 0.03
Best parameters: {'max_depth': 1}
Test score: 0.047879382104282886
```

In [295]:
```
def plot_feature_importances_m(model):
    n_features = X.shape[1]
    plt.barh(range(n_features), model.feature_importances_, align='center', co
lor='#48D1CC')
    plt.yticks(np.arange(n_features), X.columns)
    plt.xlabel("Feature importance")
    plt.ylabel("Feature")
    plt.ylim(-1, n_features)
    plt.title("Math")

fig = plt.figure(figsize=(14,5))
ax1 = plt.subplot(121)
tree_m = DecisionTreeRegressor(max_depth=2).fit(X_train, y_train)
plot_feature_importances_m (tree_m)
plt.tight_layout()
```



ML Technique CV Score Test Score Parameters 1 Linear Regregsion 0.14 0.25 2 Decision Tree 0.22 0.15 max_depth=2

The heigst test score is 0.25 , that too using Linear Regression technique. However the max score that can be achived is 1 hence the reason for saing that the prediction models have poor performance. Using decision tree we found out that failures is the most important feature forllowed by schoolsup & Aalc respectively.

In [ ]: