project_part_3_Regression

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1 NOTEBOOK 3: REGRESSION ON DIABETES DATA SET

1.0.1 Team 3

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1.0.2 What this Notebook does?

After Data selection, cleaning, pre-processing and EDA, we will now look at how we can perform continuous variable estimation, i.e. Regression. Based on feedback, we have carried out the below: - Normalization of entire dataset due to varying ranges of different attributes - Correlation analysis, Pairplots and heatmaps with normalized data. - Attribute selection for regression models - Regression models for 5 combinations - Performance Evaluation Metrics - Polynomial Regression with/without regularization - Decision Tree Regression (Max Depth = 2,3,5,7) - Conclusion

1.0.3 1. Import Packages

[1]:
```
# you need   Python 3.5
import sys
assert sys.version_info >= (3, 5)
```

[2]:
```
# Scikit-Learn  0.20 is required
import sklearn
assert sklearn.__version__ >= "0.20"
```

[3]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import time
import warnings
warnings.filterwarnings("ignore")
###############################################
```

1.0.4 2. Read Data and Display

[4]:
```
diabetes = pd.read_csv('./diabetes.csv')
```

[5]:
```
diabetes.head()
```

[5]:
```
   Unnamed: 0  Diabetes    BMI State  HighBP  HighChol  CholCheck  \
0           0       0.0  28.17    AL     1.0       1.0        1.0
1           1       0.0  18.54    AL     0.0       0.0        1.0
2           2       1.0  31.62    AL     1.0       0.0        1.0
3           6       1.0  32.98    AL     0.0       0.0        1.0
4           9       1.0  16.65    AL     0.0       1.0        1.0

   FruitConsume  VegetableConsume  Smoker  …  NoDoctorDueToCost  \
0           1.0               1.0     1.0  …                0.0
1           1.0               1.0     0.0  …                0.0
2           1.0               1.0     0.0  …                0.0
3           1.0               1.0     1.0  …                0.0
4           0.0               0.0     1.0  …                0.0

   PhysicalActivity  GeneralHealth  PhysicalHealth  MentalHealth  \
0               0.0            3.0            15.0           0.0
1               1.0            2.0            10.0           0.0
2               1.0            3.0             0.0          30.0
3               1.0            4.0            30.0           0.0
4               0.0            1.0            20.0           0.0

   DifficultyWalking  Gender   Age  Education  Income
0                1.0     0.0  13.0        3.0     3.0
1                0.0     0.0  11.0        5.0     5.0
2                1.0     0.0  10.0        6.0     7.0
3                1.0     1.0  11.0        6.0     7.0
4                1.0     0.0  11.0        2.0     3.0

[5 rows x 24 columns]
```

[6]:
```
diabetes.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 243317 entries, 0 to 243316
Data columns (total 24 columns):
 #   Column              Non-Null Count   Dtype
---  ------              --------------   -----
 0   Unnamed: 0          243317 non-null  int64
 1   Diabetes            243317 non-null  float64
 2   BMI                 243317 non-null  float64
 3   State               243317 non-null  object
 4   HighBP              243317 non-null  float64
```

```
 5   HighChol           243317 non-null  float64
 6   CholCheck          243317 non-null  float64
 7   FruitConsume       243317 non-null  float64
 8   VegetableConsume   243317 non-null  float64
 9   Smoker             243317 non-null  float64
 10  HeavyDrinker       243317 non-null  float64
 11  Stroke             243317 non-null  float64
 12  HeartDisease       243317 non-null  float64
 13  Healthcare         243317 non-null  float64
 14  NoDoctorDueToCost  243317 non-null  float64
 15  PhysicalActivity   243317 non-null  float64
 16  GeneralHealth      243317 non-null  float64
 17  PhysicalHealth     243317 non-null  float64
 18  MentalHealth       243317 non-null  float64
 19  DifficultyWalking  243317 non-null  float64
 20  Gender             243317 non-null  float64
 21  Age                243317 non-null  float64
 22  Education          243317 non-null  float64
 23  Income             243317 non-null  float64
dtypes: float64(22), int64(1), object(1)
memory usage: 44.6+ MB
```

[7]:
```
#set datatypes of columns to boolean or categorical as appropriate
make_bool_int = ['Diabetes','HighBP','HighChol','CholCheck',\
          ␣
 ↪'FruitConsume','VegetableConsume','Smoker','HeavyDrinker','Stroke','HeartDisease',\
          ␣
 ↪'Healthcare','NoDoctorDueToCost','PhysicalActivity','DifficultyWalking','Gender']
make_categorical_int = ['GeneralHealth','Age','Education','Income']
```

[8]:
```
#drop the extra index column in datafram
diabetes=diabetes.drop(['Unnamed: 0'], axis=1)

#drop the state column in dataframe since it will not be used in the dataframe
diabetes=diabetes.drop(['State'], axis=1)
```

[9]:
```
diabetes.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 243317 entries, 0 to 243316
Data columns (total 22 columns):
 #   Column             Non-Null Count   Dtype
---  ------             --------------   -----
 0   Diabetes           243317 non-null  float64
 1   BMI                243317 non-null  float64
 2   HighBP             243317 non-null  float64
 3   HighChol           243317 non-null  float64
 4   CholCheck          243317 non-null  float64
```

```
 5   FruitConsume       243317 non-null  float64
 6   VegetableConsume   243317 non-null  float64
 7   Smoker             243317 non-null  float64
 8   HeavyDrinker       243317 non-null  float64
 9   Stroke             243317 non-null  float64
 10  HeartDisease       243317 non-null  float64
 11  Healthcare         243317 non-null  float64
 12  NoDoctorDueToCost  243317 non-null  float64
 13  PhysicalActivity   243317 non-null  float64
 14  GeneralHealth      243317 non-null  float64
 15  PhysicalHealth     243317 non-null  float64
 16  MentalHealth       243317 non-null  float64
 17  DifficultyWalking  243317 non-null  float64
 18  Gender             243317 non-null  float64
 19  Age                243317 non-null  float64
 20  Education          243317 non-null  float64
 21  Income             243317 non-null  float64
dtypes: float64(22)
memory usage: 40.8 MB
```

1.0.5 3. Normalize data

[10]:
```
# Using MinMaxScaler to normalize the data

from sklearn.preprocessing import MinMaxScaler
diabetes_norm =diabetes.copy(deep=True)
minmax_scaler = MinMaxScaler(feature_range=(0, 1))

diabetes_norm.iloc[:,:] = minmax_scaler.fit_transform(diabetes_norm)
diabetes_norm.head()
```

[10]:
```
   Diabetes       BMI  HighBP  HighChol  CholCheck  FruitConsume  \
0       0.0  0.186505     1.0       1.0        1.0           1.0
1       0.0  0.075433     0.0       0.0        1.0           1.0
2       1.0  0.226298     1.0       0.0        1.0           1.0
3       1.0  0.241984     0.0       0.0        1.0           1.0
4       1.0  0.053633     0.0       1.0        1.0           0.0

   VegetableConsume  Smoker  HeavyDrinker  Stroke  …  NoDoctorDueToCost  \
0               1.0     1.0           0.0     0.0  …                0.0
1               1.0     0.0           0.0     0.0  …                0.0
2               1.0     0.0           0.0     0.0  …                0.0
3               1.0     1.0           0.0     0.0  …                0.0
4               0.0     1.0           0.0     0.0  …                0.0

   PhysicalActivity  GeneralHealth  PhysicalHealth  MentalHealth  \
0               0.0           0.50        0.500000           0.0
1               1.0           0.25        0.333333           0.0
```

```
2               1.0           0.50        0.000000            1.0
3               1.0           0.75        1.000000            0.0
4               0.0           0.00        0.666667            0.0

   DifficultyWalking  Gender       Age  Education    Income
0                1.0     0.0  1.000000        0.4  0.285714
1                0.0     0.0  0.833333        0.8  0.571429
2                1.0     0.0  0.750000        1.0  0.857143
3                1.0     1.0  0.833333        1.0  0.857143
4                1.0     0.0  0.833333        0.2  0.285714

[5 rows x 22 columns]
```

[11]:
```
diabetes_norm.describe()
```

[11]:
```
            Diabetes            BMI         HighBP       HighChol  \
count  243317.000000  243317.000000  243317.000000  243317.000000
mean        0.145074       0.192309       0.425683       0.388292
std         0.352176       0.073837       0.494447       0.487363
min         0.000000       0.000000       0.000000       0.000000
25%         0.000000       0.142330       0.000000       0.000000
50%         0.000000       0.178316       0.000000       0.000000
75%         0.000000       0.229181       1.000000       1.000000
max         1.000000       1.000000       1.000000       1.000000

           CholCheck   FruitConsume  VegetableConsume         Smoker  \
count  243317.000000  243317.000000     243317.000000  243317.000000
mean        0.962913       0.630293          0.821673       0.426242
std         0.188976       0.482726          0.382789       0.494531
min         0.000000       0.000000          0.000000       0.000000
25%         1.000000       0.000000          1.000000       0.000000
50%         1.000000       1.000000          1.000000       0.000000
75%         1.000000       1.000000          1.000000       1.000000
max         1.000000       1.000000          1.000000       1.000000

        HeavyDrinker         Stroke  …  NoDoctorDueToCost  PhysicalActivity  \
count  243317.000000  243317.000000  …      243317.000000     243317.000000
mean        0.062906       0.043589  …           0.093861          0.752985
std         0.242794       0.204180  …           0.291636          0.431277
min         0.000000       0.000000  …           0.000000          0.000000
25%         0.000000       0.000000  …           0.000000          1.000000
50%         0.000000       0.000000  …           0.000000          1.000000
75%         0.000000       0.000000  …           0.000000          1.000000
max         1.000000       1.000000  …           1.000000          1.000000

       GeneralHealth  PhysicalHealth   MentalHealth  DifficultyWalking  \
count  243317.000000   243317.000000  243317.000000      243317.000000
```

```
mean        0.609973      0.146748      0.122449          0.168061
std         0.265101      0.294392      0.260082          0.373921
min         0.000000      0.000000      0.000000          0.000000
25%         0.500000      0.000000      0.000000          0.000000
50%         0.750000      0.000000      0.000000          0.000000
75%         0.750000      0.100000      0.100000          0.000000
max         1.000000      1.000000      1.000000          1.000000

              Gender            Age      Education          Income
count  243317.000000  243317.000000  243317.000000   243317.000000
mean        0.469573       0.578773       0.814702        0.733314
std         0.499074       0.272755       0.194981        0.294669
min         0.000000       0.000000       0.000000        0.000000
25%         0.000000       0.416667       0.600000        0.571429
50%         0.000000       0.583333       0.800000        0.857143
75%         1.000000       0.750000       1.000000        1.000000
max         1.000000       1.000000       1.000000        1.000000

[8 rows x 22 columns]
```

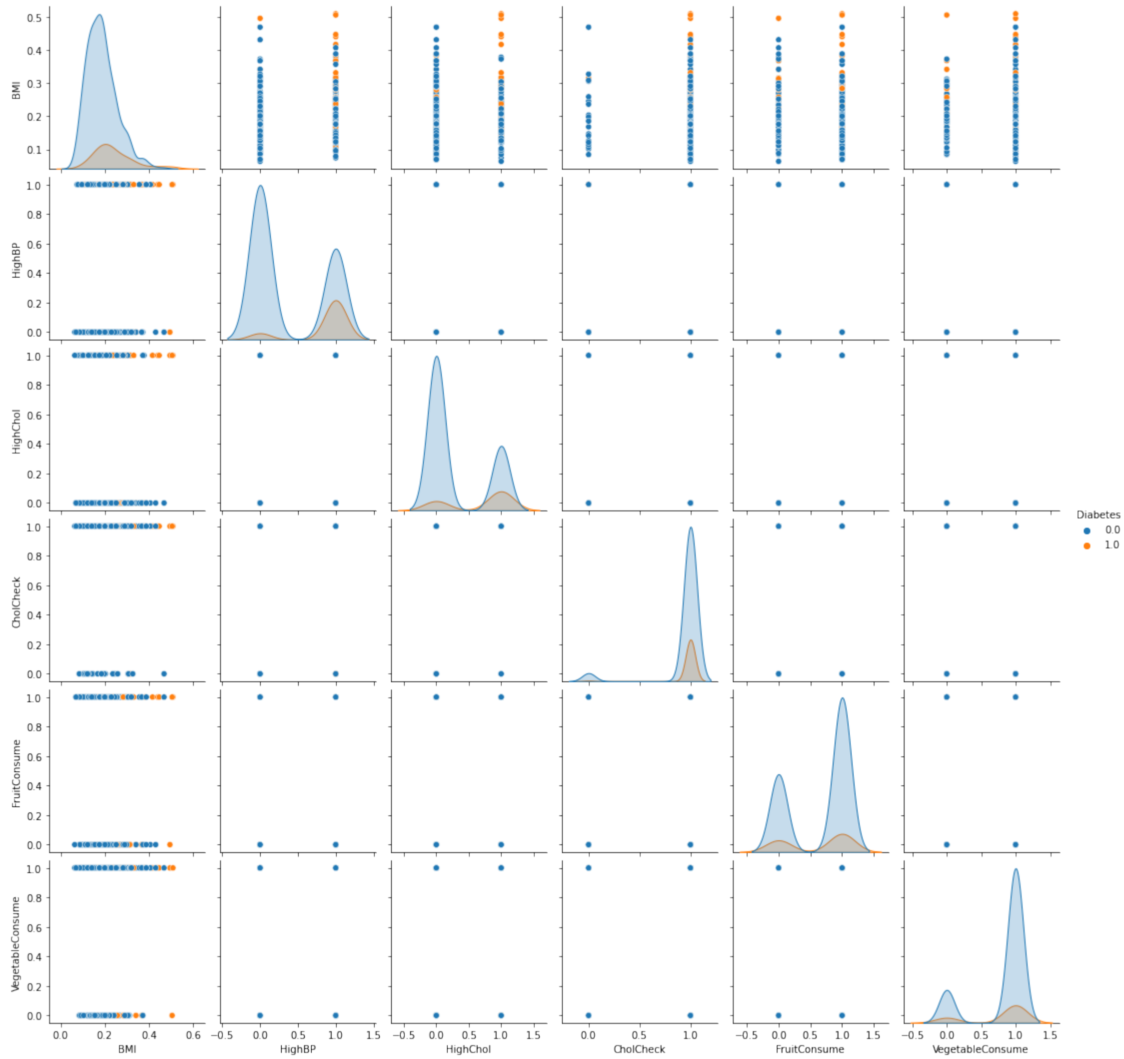
[12]:
```
# write to file
# run only once
#diabetes_norm.to_csv("./diabetes_normalized.csv")
```

1.0.6 4 Exploratory Data Analysis with Normalized Data

4.1 Pairplots

[13]:
```
# trying different color schemes
palette = sns.color_palette("bright")

#sampling a random number of values since plotting all 0.2 million datapoints␣
↪will make the plot unreadable
number_of_samples = 500
diabetes_norm_sample = diabetes_norm.sample(number_of_samples)
df_plot =diabetes_norm_sample.iloc[:,:7]
sns.pairplot(df_plot, hue='Diabetes', plot_kws={'alpha':1})
```

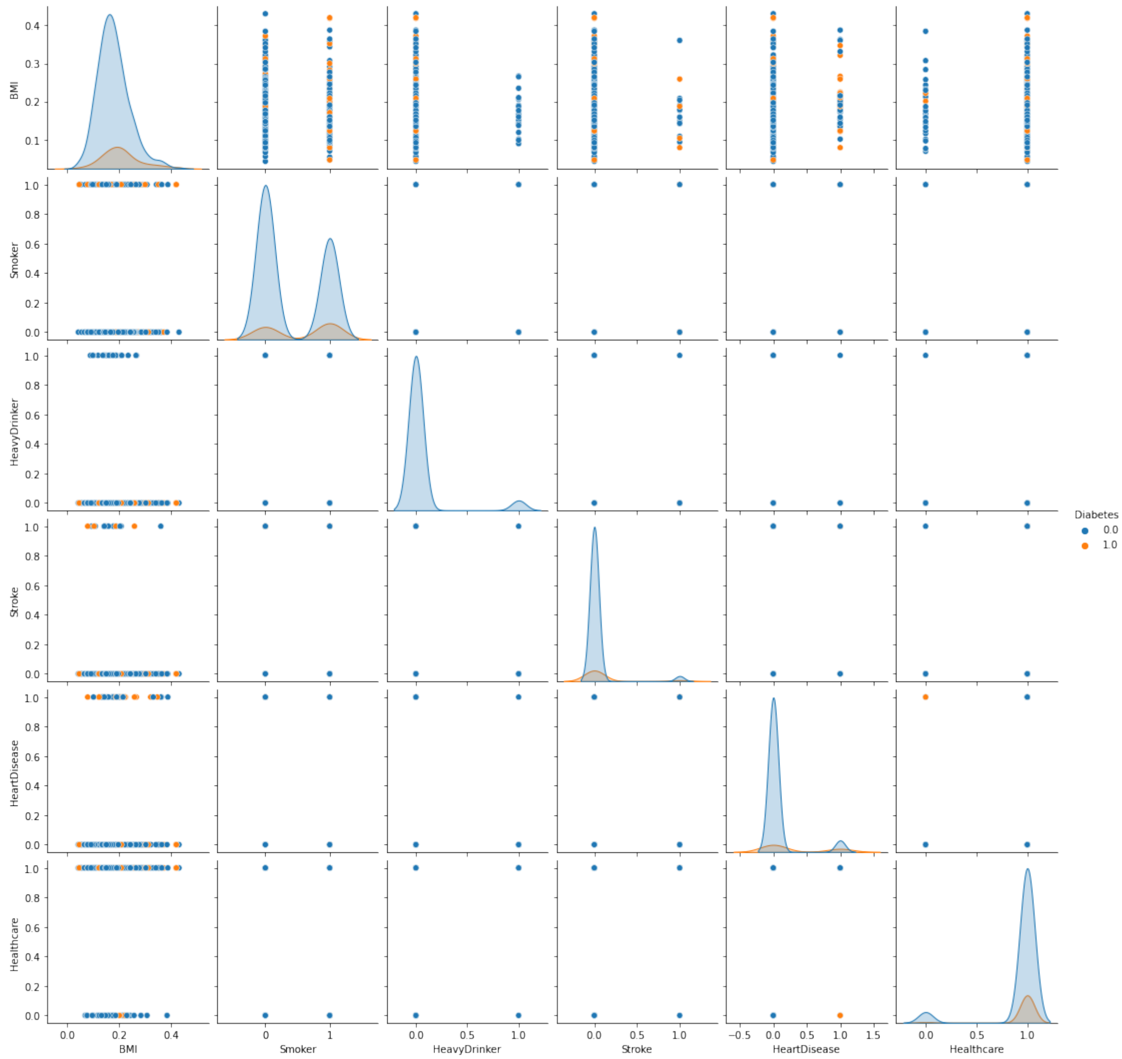
[13]:
```
<seaborn.axisgrid.PairGrid at 0x7f8db0f06c70>
```



Notes: We see a small relation between cholcheck, BMI with respect to diabetes. All Diabetes instances seem to occur only on the second line which is Mid level BMI which Cholcheck as 1. We will use it for classification.

[14]:
```
#sampling a random number of values since plotting all 0.2 million datapoints␣
↪will make the plot unreadable
number_of_samples = 500
diabetes_norm_sample = diabetes_norm.sample(number_of_samples)
df_plot =diabetes_norm_sample.iloc[:,[0,1,7,8,9,10,11]]
sns.pairplot(df_plot, hue='Diabetes', plot_kws={'alpha':1})
```

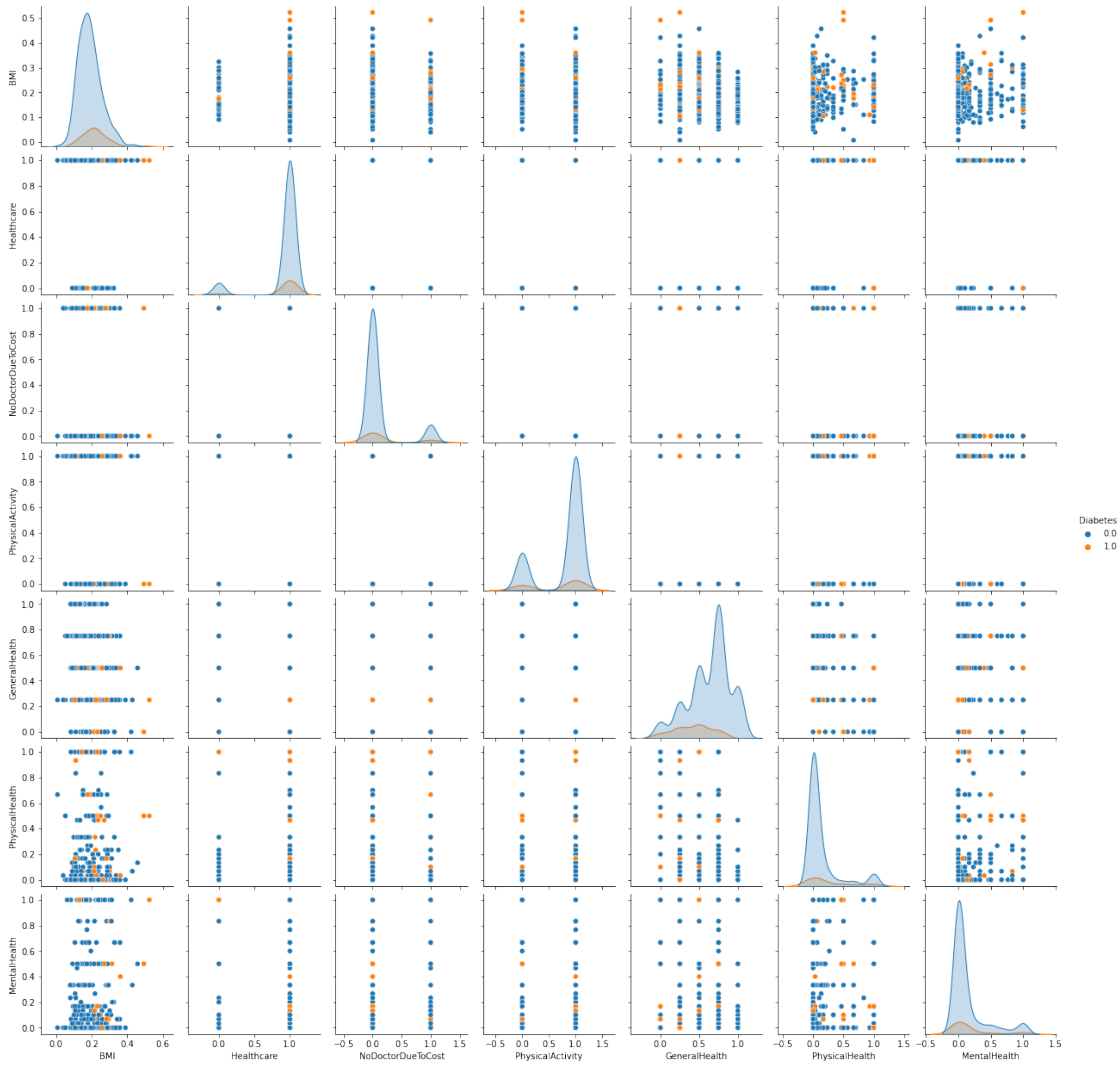
[14]:
```
<seaborn.axisgrid.PairGrid at 0x7f8db24608e0>
```



Notes: For the plots of smoker, heavy drinker, stroke, heartdisease and health care we see that orange dots (occurance of Diabetes) is much higher at the higher BMI levels.

[15]:
```
#sampling a random number of values since plotting all 0.2 million datapoints␣
↪will make the plot unreadable
number_of_samples = 500
diabetes_norm_sample = diabetes_norm.sample(number_of_samples)
df_plot =diabetes_norm_sample.iloc[:,[0,1,11,12,13,14,15,16]]
sns.pairplot(df_plot, hue='Diabetes', plot_kws={'alpha':1})
```

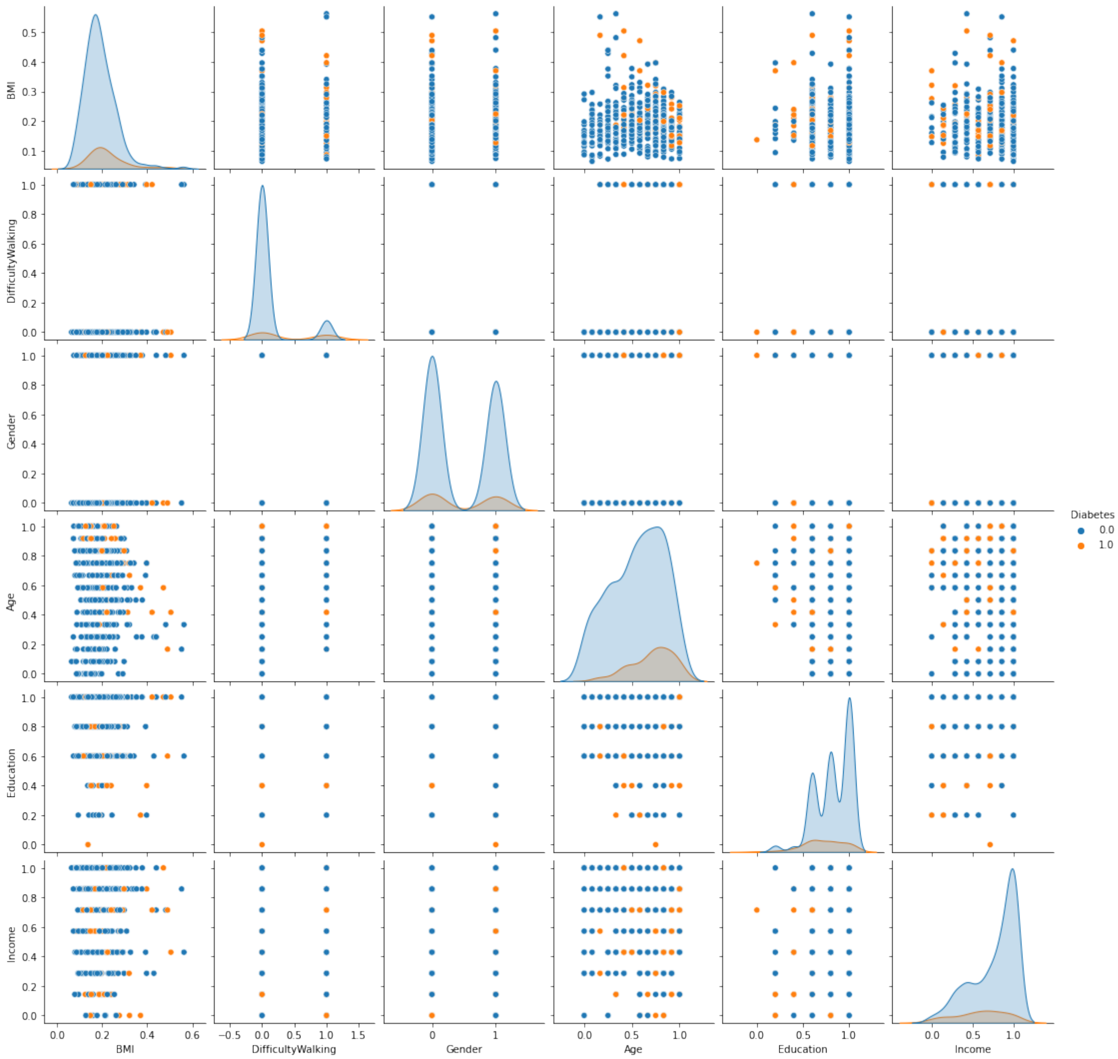
[15]: <seaborn.axisgrid.PairGrid at 0x7f8dc2c83e20>



Notes. There appears to be an none linear realtionship between the following 1. GeneralHealth - BMI (looks like a parabola) 2. PhysicalHealth - BMI (Maybe some curve) 3. MentalHealth - BMI (Maybe some curve)

[16]:
```
#sampling a random number of values since plotting all 0.2 million datapoints␣
↪will make the plot unreadable
number_of_samples = 500
diabetes_norm_sample = diabetes_norm.sample(number_of_samples)
df_plot =diabetes_norm_sample.iloc[:,[0,1,17,18,19,20,21]]
sns.pairplot(df_plot, hue='Diabetes', plot_kws={'alpha':1})
```

[16]: <seaborn.axisgrid.PairGrid at 0x7f8dc2d99490>



Notes : Age - BMI is showing a polynomial (parabola) relation

4.2 Correlation Matrix

[17]:
```
diabetes_norm.corr()
```

[17]:

	Diabetes	BMI	HighBP	HighChol	CholCheck	\
Diabetes	1.000000	0.214406	0.264480	0.206304	0.068309	
BMI	0.214406	1.000000	0.220077	0.102515	0.034871	
HighBP	0.264480	0.220077	1.000000	0.303605	0.100565	
HighChol	0.206304	0.102515	0.303605	1.000000	0.095806	
CholCheck	0.068309	0.034871	0.100565	0.095806	1.000000	
FruitConsume	-0.029148	-0.087788	-0.026848	-0.025939	0.032427	
VegetableConsume	-0.039670	-0.046691	-0.033193	-0.021524	0.018282	
Smoker	0.057439	0.013430	0.098756	0.086088	-0.016649	
HeavyDrinker	-0.061356	-0.040612	-0.005050	-0.013900	-0.031740	

```
Stroke             0.111758  0.017064  0.135123  0.097751   0.027305
HeartDisease       0.177402  0.047898  0.209068  0.184426   0.044321
Healthcare         0.028893 -0.011295  0.060837  0.065566   0.151552
NoDoctorDueToCost  0.018799  0.047957 -0.001732 -0.001932  -0.080688
PhysicalActivity  -0.122594 -0.143925 -0.113580 -0.068055   0.012704
GeneralHealth     -0.284712 -0.250105 -0.280748 -0.194416  -0.033767
PhysicalHealth     0.173316  0.123211  0.159268  0.122674   0.030213
MentalHealth       0.053553  0.083946  0.038884  0.042723  -0.017127
DifficultyWalking  0.216740  0.197330  0.222005  0.145126   0.044470
Gender             0.030739  0.017796  0.056070  0.022587  -0.043166
Age                0.193115 -0.029011  0.349149  0.286603   0.107531
Education         -0.110472 -0.094184 -0.107000 -0.036451   0.030458
Income            -0.149129 -0.080907 -0.136702 -0.057267   0.024746

                   FruitConsume  VegetableConsume    Smoker  HeavyDrinker  \
Diabetes              -0.029148         -0.039670  0.057439     -0.061356
BMI                   -0.087788         -0.046691  0.013430     -0.040612
HighBP                -0.026848         -0.033193  0.098756     -0.005050
HighChol              -0.025939         -0.021524  0.086088     -0.013900
CholCheck              0.032427          0.018282 -0.016649     -0.031740
FruitConsume           1.000000          0.218223 -0.075698     -0.038302
VegetableConsume       0.218223          1.000000 -0.011862      0.014879
Smoker                -0.075698         -0.011862  1.000000      0.102515
HeavyDrinker          -0.038302          0.014879  0.102515      1.000000
Stroke                -0.003581         -0.023225  0.061635     -0.021902
HeartDisease          -0.006263         -0.022327  0.114940     -0.030161
Healthcare             0.037768          0.044930 -0.024031     -0.024515
NoDoctorDueToCost     -0.043225         -0.033074  0.055440      0.016157
PhysicalActivity       0.123372          0.127687 -0.079384      0.014397
GeneralHealth          0.094812          0.107386 -0.172702      0.024280
PhysicalHealth        -0.045607         -0.055045  0.122506     -0.020779
MentalHealth          -0.075855         -0.055464  0.099937      0.035766
DifficultyWalking     -0.037295         -0.065750  0.121155     -0.036412
Gender                -0.058908         -0.053810  0.085604      0.006503
Age                    0.083583          0.022613  0.117582     -0.052640
Education              0.097824          0.133771 -0.167054      0.014218
Income                 0.070095          0.146915 -0.126273      0.046114

                     Stroke  …  NoDoctorDueToCost  PhysicalActivity  \
Diabetes           0.111758  …           0.018799         -0.122594
BMI                0.017064  …           0.047957         -0.143925
HighBP             0.135123  …          -0.001732         -0.113580
HighChol           0.097751  …          -0.001932         -0.068055
CholCheck          0.027305  …          -0.080688          0.012704
FruitConsume      -0.003581  …          -0.043225          0.123372
VegetableConsume  -0.023225  …          -0.033074          0.127687
Smoker             0.061635  …           0.055440         -0.079384
```

HeavyDrinker	-0.021902	…	0.016157	0.014397
Stroke	1.000000	…	0.025504	-0.072490
HeartDisease	0.198837	…	0.022890	-0.087284
Healthcare	0.016116	…	-0.257091	0.048916
NoDoctorDueToCost	0.025504	…	1.000000	-0.062041
PhysicalActivity	-0.072490	…	-0.062041	1.000000
GeneralHealth	-0.173373	…	-0.165447	0.265215
PhysicalHealth	0.146217	…	0.142402	-0.216455
MentalHealth	0.066105	…	0.200595	-0.114531
DifficultyWalking	0.180473	…	0.102695	-0.256284
Gender	0.005716	…	-0.040156	0.039348
Age	0.131658	…	-0.145199	-0.088685
Education	-0.066517	…	-0.100765	0.212526
Income	-0.125590	…	-0.183484	0.221426

	GeneralHealth	PhysicalHealth	MentalHealth \
Diabetes	-0.284712	0.173316	0.053553
BMI	-0.250105	0.123211	0.083946
HighBP	-0.280748	0.159268	0.038884
HighChol	-0.194416	0.122674	0.042723
CholCheck	-0.033767	0.030213	-0.017127
FruitConsume	0.094812	-0.045607	-0.075855
VegetableConsume	0.107386	-0.055045	-0.055464
Smoker	-0.172702	0.122506	0.099937
HeavyDrinker	0.024280	-0.020779	0.035766
Stroke	-0.173373	0.146217	0.066105
HeartDisease	-0.247099	0.185551	0.055431
Healthcare	0.041749	-0.004674	-0.053899
NoDoctorDueToCost	-0.165447	0.142402	0.200595
PhysicalActivity	0.265215	-0.216455	-0.114531
GeneralHealth	1.000000	-0.525281	-0.292687
PhysicalHealth	-0.525281	1.000000	0.333013
MentalHealth	-0.292687	0.333013	1.000000
DifficultyWalking	-0.444813	0.463546	0.204753
Gender	0.005065	-0.039534	-0.083730
Age	-0.134336	0.101041	-0.137868
Education	0.260851	-0.139236	-0.090948
Income	0.349691	-0.260976	-0.198834

	DifficultyWalking	Gender	Age	Education	Income
Diabetes	0.216740	0.030739	0.193115	-0.110472	-0.149129
BMI	0.197330	0.017796	-0.029011	-0.094184	-0.080907
HighBP	0.222005	0.056070	0.349149	-0.107000	-0.136702
HighChol	0.145126	0.022587	0.286603	-0.036451	-0.057267
CholCheck	0.044470	-0.043166	0.107531	0.030458	0.024746
FruitConsume	-0.037295	-0.058908	0.083583	0.097824	0.070095
VegetableConsume	-0.065750	-0.053810	0.022613	0.133771	0.146915

Smoker	0.121155	0.085604	0.117582	-0.167054	-0.126273
HeavyDrinker	-0.036412	0.006503	-0.052640	0.014218	0.046114
Stroke	0.180473	0.005716	0.131658	-0.066517	-0.125590
HeartDisease	0.211135	0.082316	0.218165	-0.083794	-0.129856
Healthcare	0.016965	-0.026192	0.167957	0.153241	0.154977
NoDoctorDueToCost	0.102695	-0.040156	-0.145199	-0.100765	-0.183484
PhysicalActivity	-0.256284	0.039348	-0.088685	0.212526	0.221426
GeneralHealth	-0.444813	0.005065	-0.134336	0.260851	0.349691
PhysicalHealth	0.463546	-0.039534	0.101041	-0.139236	-0.260976
MentalHealth	0.204753	-0.083730	-0.137868	-0.090948	-0.198834
DifficultyWalking	1.000000	-0.071152	0.224090	-0.177320	-0.311283
Gender	-0.071152	1.000000	-0.035372	-0.011613	0.117400
Age	0.224090	-0.035372	1.000000	-0.039169	-0.086128
Education	-0.177320	-0.011613	-0.039169	1.000000	0.436242
Income	-0.311283	0.117400	-0.086128	0.436242	1.000000

[22 rows x 22 columns]

[18]:
```
temp = diabetes_norm.corr()
temp.iloc[:,13:21]
```

[18]:

	PhysicalActivity	GeneralHealth	PhysicalHealth \
Diabetes	-0.122594	-0.284712	0.173316
BMI	-0.143925	-0.250105	0.123211
HighBP	-0.113580	-0.280748	0.159268
HighChol	-0.068055	-0.194416	0.122674
CholCheck	0.012704	-0.033767	0.030213
FruitConsume	0.123372	0.094812	-0.045607
VegetableConsume	0.127687	0.107386	-0.055045
Smoker	-0.079384	-0.172702	0.122506
HeavyDrinker	0.014397	0.024280	-0.020779
Stroke	-0.072490	-0.173373	0.146217
HeartDisease	-0.087284	-0.247099	0.185551
Healthcare	0.048916	0.041749	-0.004674
NoDoctorDueToCost	-0.062041	-0.165447	0.142402
PhysicalActivity	1.000000	0.265215	-0.216455
GeneralHealth	0.265215	1.000000	-0.525281
PhysicalHealth	-0.216455	-0.525281	1.000000
MentalHealth	-0.114531	-0.292687	0.333013
DifficultyWalking	-0.256284	-0.444813	0.463546
Gender	0.039348	0.005065	-0.039534
Age	-0.088685	-0.134336	0.101041
Education	0.212526	0.260851	-0.139236
Income	0.221426	0.349691	-0.260976

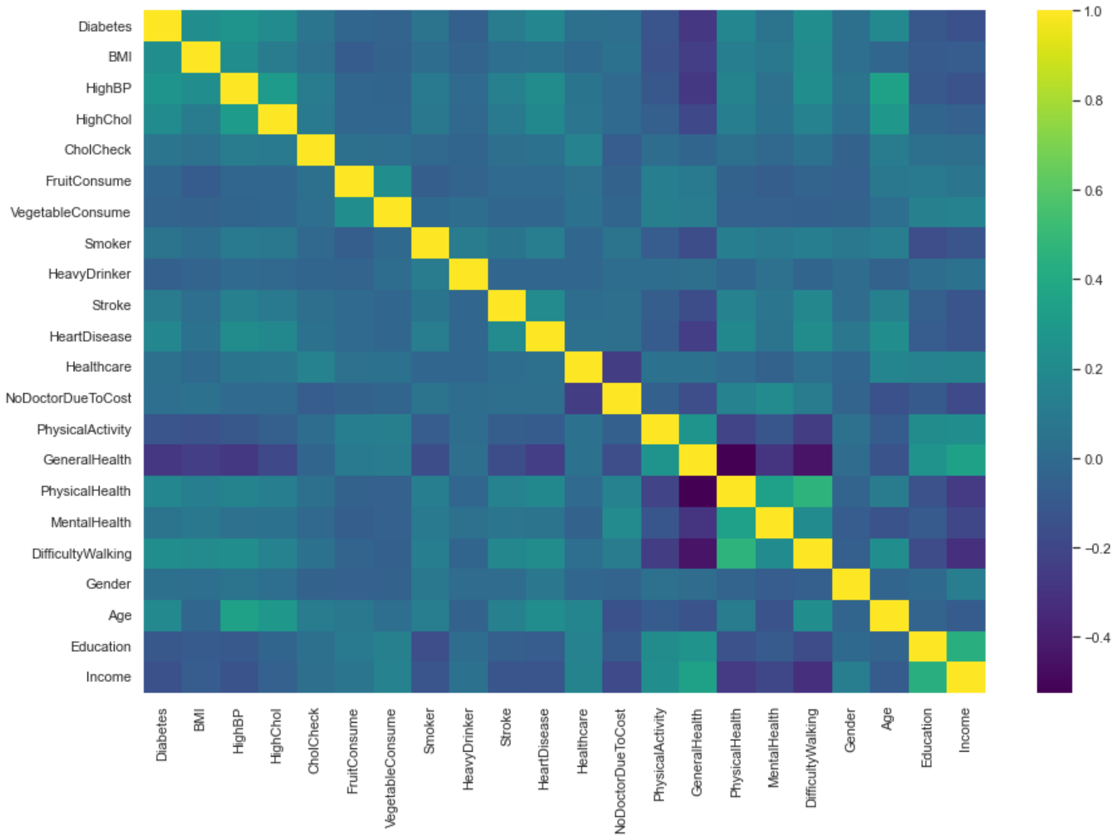
	MentalHealth	DifficultyWalking	Gender	Age \
Diabetes	0.053553	0.216740	0.030739	0.193115

BMI	0.083946	0.197330	0.017796	-0.029011
HighBP	0.038884	0.222005	0.056070	0.349149
HighChol	0.042723	0.145126	0.022587	0.286603
CholCheck	-0.017127	0.044470	-0.043166	0.107531
FruitConsume	-0.075855	-0.037295	-0.058908	0.083583
VegetableConsume	-0.055464	-0.065750	-0.053810	0.022613
Smoker	0.099937	0.121155	0.085604	0.117582
HeavyDrinker	0.035766	-0.036412	0.006503	-0.052640
Stroke	0.066105	0.180473	0.005716	0.131658
HeartDisease	0.055431	0.211135	0.082316	0.218165
Healthcare	-0.053899	0.016965	-0.026192	0.167957
NoDoctorDueToCost	0.200595	0.102695	-0.040156	-0.145199
PhysicalActivity	-0.114531	-0.256284	0.039348	-0.088685
GeneralHealth	-0.292687	-0.444813	0.005065	-0.134336
PhysicalHealth	0.333013	0.463546	-0.039534	0.101041
MentalHealth	1.000000	0.204753	-0.083730	-0.137868
DifficultyWalking	0.204753	1.000000	-0.071152	0.224090
Gender	-0.083730	-0.071152	1.000000	-0.035372
Age	-0.137868	0.224090	-0.035372	1.000000
Education	-0.090948	-0.177320	-0.011613	-0.039169
Income	-0.198834	-0.311283	0.117400	-0.086128

	Education
Diabetes	-0.110472
BMI	-0.094184
HighBP	-0.107000
HighChol	-0.036451
CholCheck	0.030458
FruitConsume	0.097824
VegetableConsume	0.133771
Smoker	-0.167054
HeavyDrinker	0.014218
Stroke	-0.066517
HeartDisease	-0.083794
Healthcare	0.153241
NoDoctorDueToCost	-0.100765
PhysicalActivity	0.212526
GeneralHealth	0.260851
PhysicalHealth	-0.139236
MentalHealth	-0.090948
DifficultyWalking	-0.177320
Gender	-0.011613
Age	-0.039169
Education	1.000000
Income	0.436242

[19]:
```python
sns.set(rc = {'figure.figsize':(15,10)})
sns.heatmap(diabetes_norm.corr(), annot=False, vmax=1, cmap='viridis', square=False)
```

[19]: <AxesSubplot:>



Notes: Looking at the heatmap we see that the highest linear correlation is between 1. Physical Health - General Health 2. Physical Activity - Physical Health 3. Difficulty Walking - General Health 4. Difficulty Walking - Physical Health 5. Education - Income We will try to make linear regression model for some of these relations

1.0.7 5. LINEAR REGRESSION - simple linear regression function with a scatter plot

Based on the scatter plots and correlation calculations we will do simple linear regression for feature with best correlation value. We will non-normalized and normalized values to see the difference. 1. Physical Health - General Health 2. GeneralHealth - BMI 3. Age - BMI 4. DifficultyWalking - GeneralHealth 5. PhyscialHealth - BMI

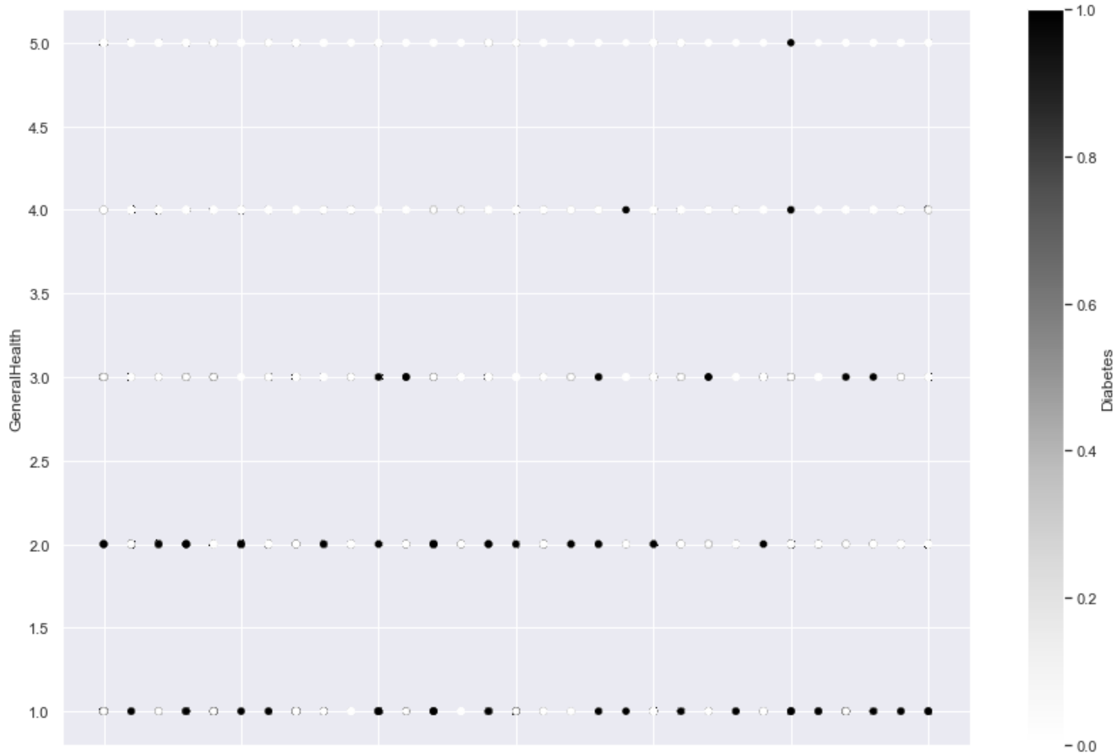
[20]:
```python
diabetes.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 243317 entries, 0 to 243316
Data columns (total 22 columns):
 #   Column             Non-Null Count   Dtype
---  ------             --------------   -----
 0   Diabetes           243317 non-null  float64
 1   BMI                243317 non-null  float64
 2   HighBP             243317 non-null  float64
 3   HighChol           243317 non-null  float64
 4   CholCheck          243317 non-null  float64
 5   FruitConsume       243317 non-null  float64
 6   VegetableConsume   243317 non-null  float64
 7   Smoker             243317 non-null  float64
 8   HeavyDrinker       243317 non-null  float64
 9   Stroke             243317 non-null  float64
 10  HeartDisease       243317 non-null  float64
 11  Healthcare         243317 non-null  float64
 12  NoDoctorDueToCost  243317 non-null  float64
 13  PhysicalActivity   243317 non-null  float64
 14  GeneralHealth      243317 non-null  float64
 15  PhysicalHealth     243317 non-null  float64
 16  MentalHealth       243317 non-null  float64
 17  DifficultyWalking  243317 non-null  float64
 18  Gender             243317 non-null  float64
 19  Age                243317 non-null  float64
 20  Education          243317 non-null  float64
 21  Income             243317 non-null  float64
dtypes: float64(22)
memory usage: 40.8 MB
```

[21]:
```
# split the normalized data into train and test parts
from sklearn.model_selection import train_test_split

train_df, test_df = train_test_split(diabetes,shuffle = True, test_size = 0.20,␣
↪random_state=17)
train_norm_df, test_norm_df = train_test_split(diabetes_norm,shuffle = True,␣
↪test_size = 0.20, random_state=17)
```

LINEAR REGRESSION MODEL 1 : Physical Health - General Health

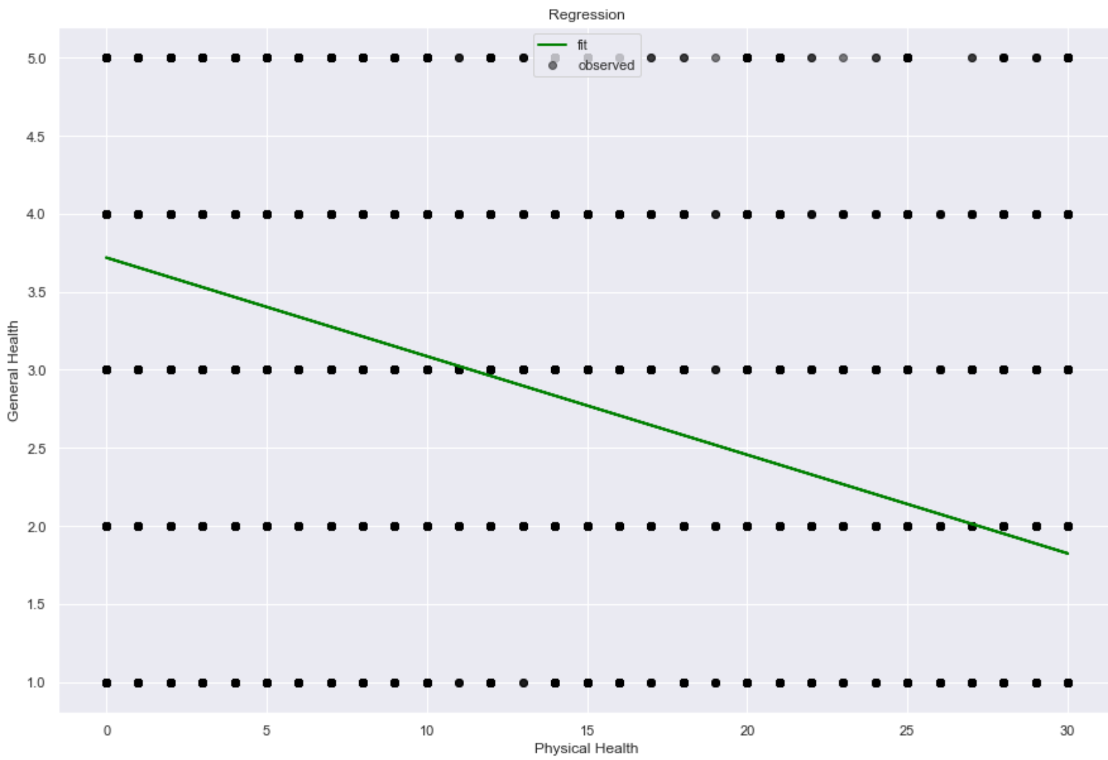
[22]:
```
ax1 = diabetes.plot.scatter(x='PhysicalHealth',
                      y='GeneralHealth',
                      c='Diabetes')
plt.show()
```



[23]:
```
import sklearn
from sklearn import linear_model
from sklearn.linear_model import LinearRegression

# Simple Regression Metrics
from sklearn.metrics import mean_squared_error, r2_score


X= train_df[['PhysicalHealth']]
y= train_df['GeneralHealth']

X_test = test_df[['PhysicalHealth']]
y_test = test_df['GeneralHealth']

X2= np.array(X).reshape(-1,1) # reshape(-1,1) makes the array horizontal, y is␣
↪vertical

# Train the model (we use all data for training -->
model_1 = sklearn.linear_model.LinearRegression()
model_1.fit(X2, y)

# Model score
```

```
r_sq = model_1.score(X2, y)
print("The model Score is ", r_sq)

# Plotting the Regression Line with Scatter plot
plt.scatter(X2, y, color='black', label='observed',alpha=0.5)
plt.plot(X2, model_1.predict(X2), label='fit', color='Green', linewidth=2)
plt.xlabel('Physical Health')
plt.ylabel('General Health')
plt.title('Regression')
plt.legend(loc='best')

plt.show()


# Make predictions using the testing set
diabetes_y_pred = model_1.predict(X_test)

# The coefficients
print('Coefficients =  ', model_1.coef_)
print('Intercept =  ', model_1.intercept_)

# The mean squared error
print('Mean squared error = {:.2f}'.format( mean_squared_error(y_test,␣
↪diabetes_y_pred)))

# The coefficient of determination: 1 is perfect prediction
print('Coefficient of determination = {:.2f}'.format(r2_score(y_test,␣
↪diabetes_y_pred)))
```

```
The model Score is  0.2770993178421167
```

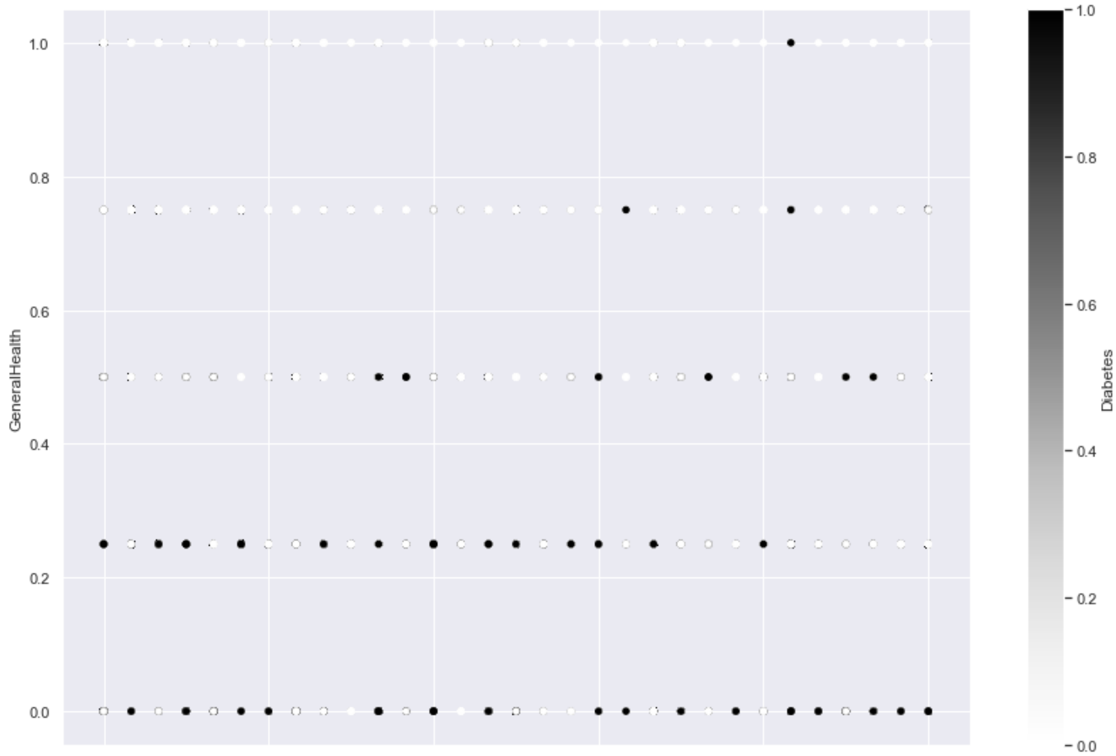



```
Coefficients =   [-0.06319487]
Intercept =   3.719167088813741
Mean squared error = 0.82
Coefficient of determination = 0.27
```

[24]:
```
# Make a prediction
X3= test_df['PhysicalHealth']

X3= np.array(X3).reshape(-1,1)
# what is the price for element 44 of the test house age list.
predicted_charge = model_1.predict([X3[44]])
print('Physical Health = {:.2f}   Predicted GeneralHealth = {:.2f}'.
 ↪format(X3[44][0], predicted_charge[0]))
```

```
Physical Health = 2.00   Predicted GeneralHealth = 3.59
```

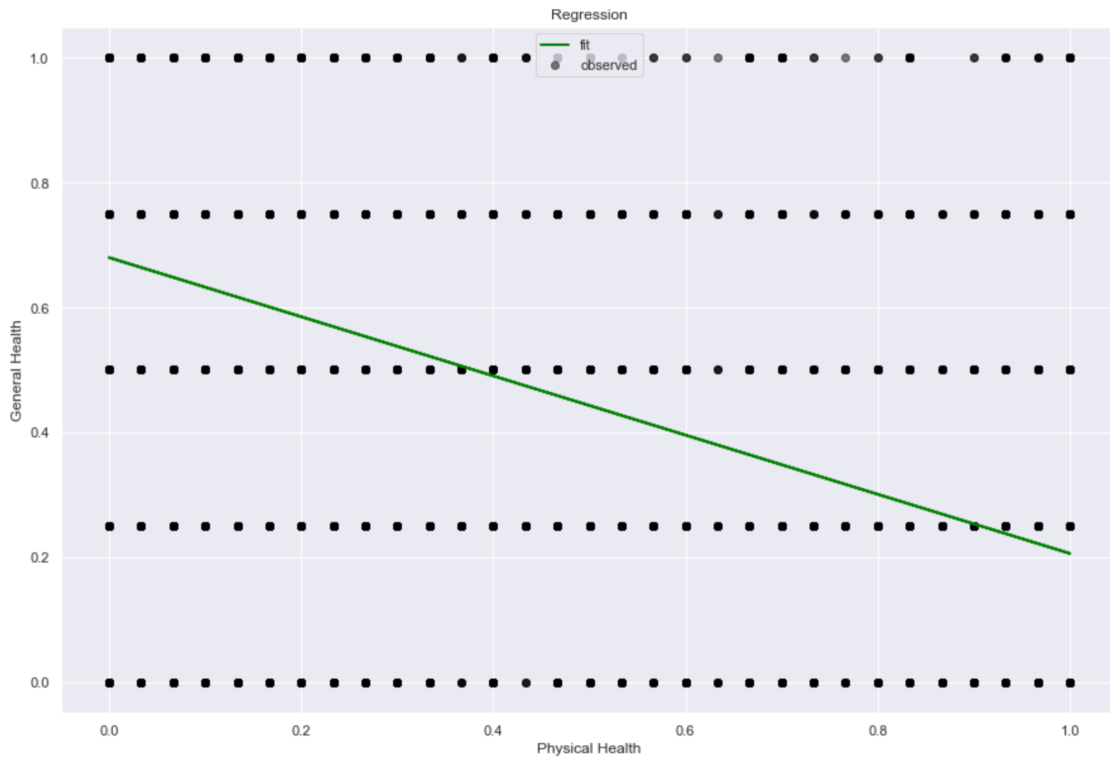
[25]:
```
ax1 = diabetes_norm.plot.scatter(x='PhysicalHealth',
                      y='GeneralHealth',
                      c='Diabetes')
plt.show()
```



[26]:
```
import sklearn
from sklearn import linear_model
from sklearn.linear_model import LinearRegression

# Simple Regression Metrics
from sklearn.metrics import mean_squared_error, r2_score


X= train_norm_df[['PhysicalHealth']]
y= train_norm_df['GeneralHealth']

X_test = test_norm_df[['PhysicalHealth']]
y_test = test_norm_df['GeneralHealth']

X2= np.array(X).reshape(-1,1) # reshape(-1,1) makes the array horizontal, y is␣
↪vertical

# Train the model (we use all data for training -->
model_1 = sklearn.linear_model.LinearRegression()
model_1.fit(X2, y)

# Model score
```

```
r_sq = model_1.score(X2, y)
print("The model Score is ", r_sq)

# Plotting the Regression Line with Scatter plot
plt.scatter(X2, y, color='black', label='observed',alpha=0.5)
plt.plot(X2, model_1.predict(X2), label='fit', color='Green', linewidth=2)
plt.xlabel('Physical Health')
plt.ylabel('General Health')
plt.title('Regression')
plt.legend(loc='best')

plt.show()


# Make predictions using the testing set
diabetes_y_pred = model_1.predict(X_test)

# The coefficients
print('Coefficients =  ', model_1.coef_)
print('Intercept =  ', model_1.intercept_)

# The mean squared error
print('Mean squared error = {:.2f}'.format( mean_squared_error(y_test,␣
 ↪diabetes_y_pred)))

# The coefficient of determination: 1 is perfect prediction
print('Coefficient of determination = {:.2f}'.format(r2_score(y_test,␣
 ↪diabetes_y_pred)))
```

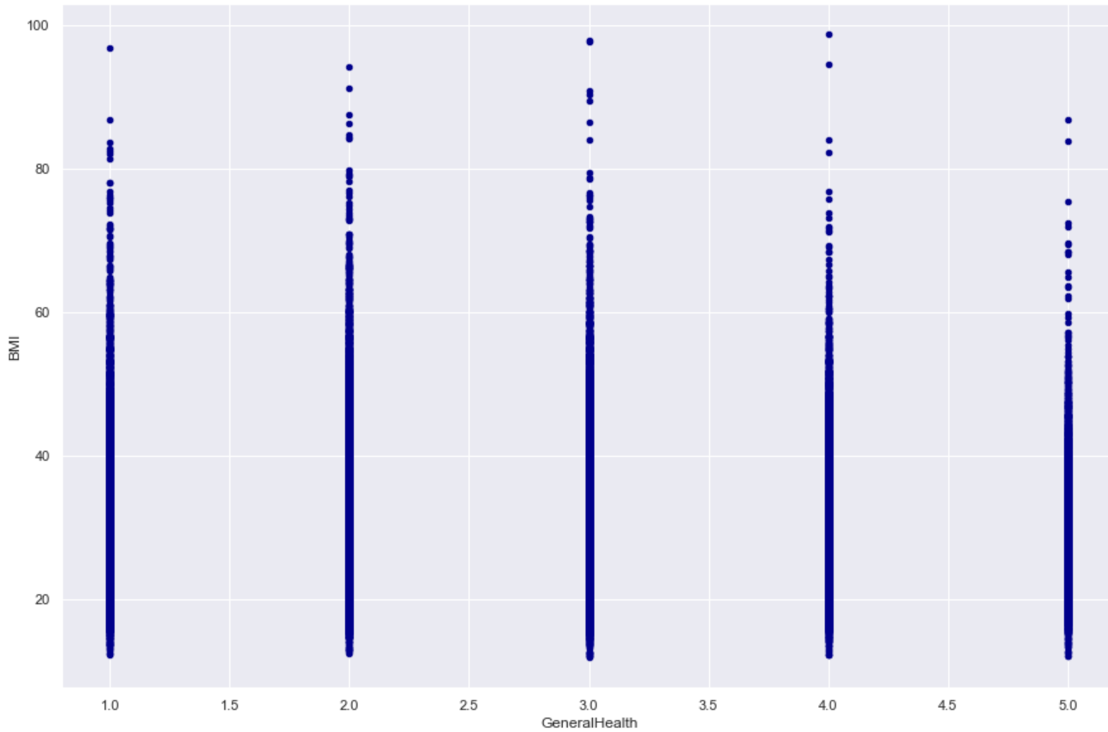
```
The model Score is  0.2770993178421166
```




```
Coefficients =   [-0.4739615]
Intercept =   0.6797917722034564
Mean squared error = 0.05
Coefficient of determination = 0.27
```

1.0.8 LINEAR REGRESSION MODEL 2 : General Health - BMI

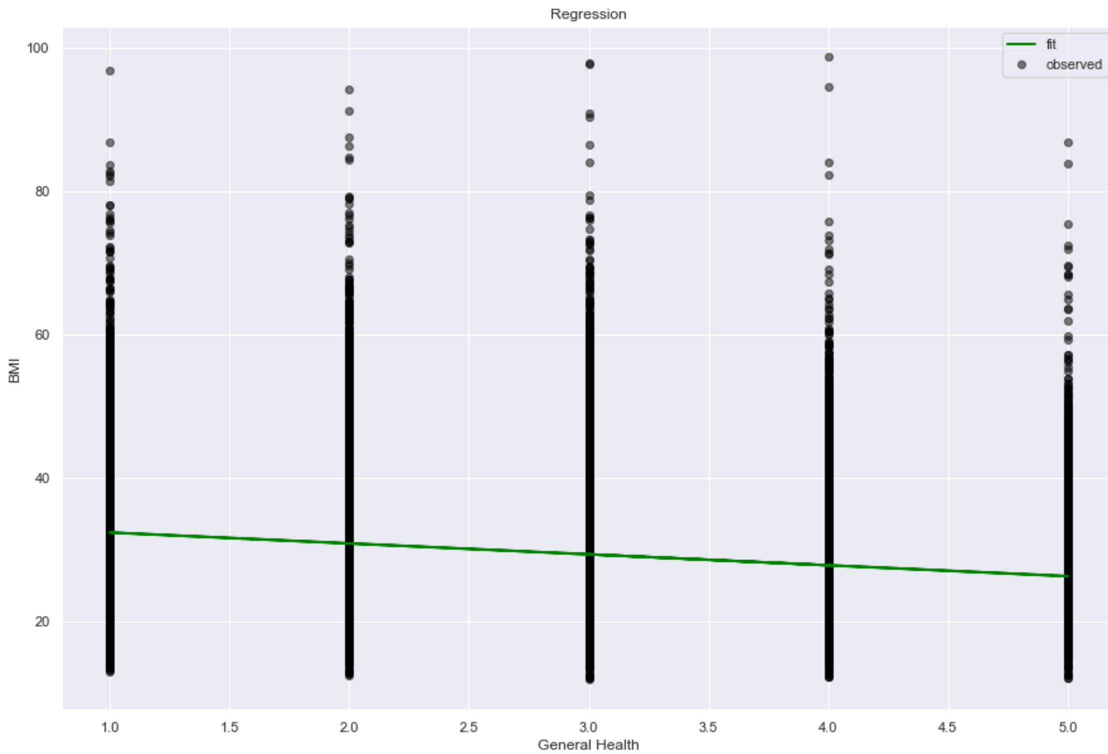
[27]:
```
ax1 = diabetes.plot.scatter(x='GeneralHealth',
                            y='BMI',
                            c='DarkBlue')
plt.show()
```



[28]:
```
import sklearn
from sklearn import linear_model
from sklearn.linear_model import LinearRegression

# Simple Regression Metrics
from sklearn.metrics import mean_squared_error, r2_score


X= train_df[['GeneralHealth']]
y= train_df['BMI']

X_test = test_df[['GeneralHealth']]
y_test = test_df['BMI']

X2= np.array(X).reshape(-1,1) # reshape(-1,1) makes the array horizontal, y is␣
↪vertical

# Train the model (we use all data for training -->
model_1 = sklearn.linear_model.LinearRegression()
model_1.fit(X2, y)

# Model score
r_sq = model_1.score(X2, y)
```

```
print("The model Score is ", r_sq)

# Plotting the Regression Line with Scatter plot
plt.scatter(X2, y, color='black', label='observed',alpha=0.5)
plt.plot(X2, model_1.predict(X2), label='fit', color='Green', linewidth=2)
plt.xlabel('General Health')
plt.ylabel('BMI')
plt.title('Regression')
plt.legend(loc='best')

plt.show()

# Make predictions using the testing set
diabetes_y_pred = model_1.predict(X_test)

# The coefficients
print('Coefficients =  ', model_1.coef_)
print('Intercept =  ', model_1.intercept_)

# The mean squared error
print('Mean squared error = {:.2f}'.format( mean_squared_error(y_test,␣
↪diabetes_y_pred)))

# The coefficient of determination: 1 is perfect prediction
print('Coefficient of determination = {:.2f}'.format(r2_score(y_test,␣
↪diabetes_y_pred)))
```

```
The model Score is  0.06349070218338293
```

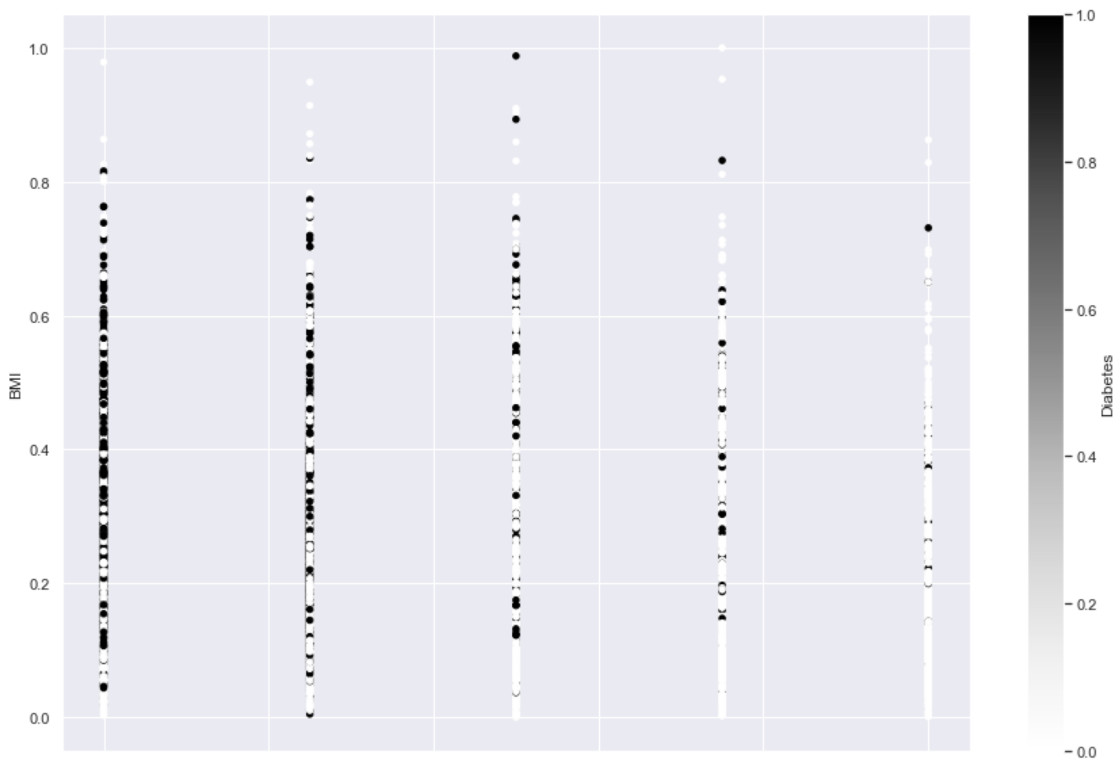



```
Coefficients =   [-1.52366017]
Intercept =   33.9206035093744
Mean squared error = 37.94
Coefficient of determination = 0.06
```

[29]:
```
# Make a prediction
X3= test_df['GeneralHealth']

X3= np.array(X3).reshape(-1,1)
# what is the price for element 44 of the test house age list.
predicted_charge = model_1.predict([X3[44]])
print('General Health = {:.2f}   Predicted BMI = {:.2f}'.format(X3[44][0],␣
↪predicted_charge[0]))
```

```
General Health = 2.00   Predicted BMI = 30.87
```

[30]:
```
ax1 = diabetes_norm.plot.scatter(x='GeneralHealth',
                      y='BMI',
                      c='Diabetes')
plt.show()
```

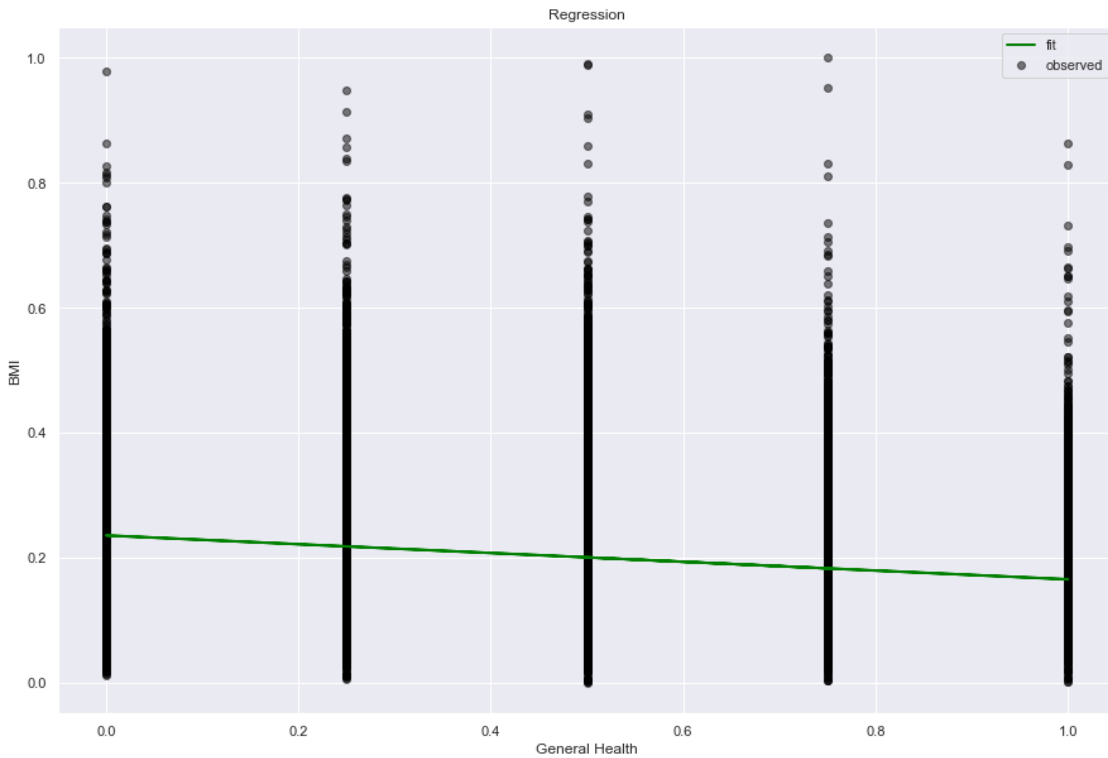


[31]:

```
import sklearn
from sklearn import linear_model
from sklearn.linear_model import LinearRegression

# Simple Regression Metrics
from sklearn.metrics import mean_squared_error, r2_score


X= train_norm_df[['GeneralHealth']]
y= train_norm_df['BMI']

X_test = test_norm_df[['GeneralHealth']]
y_test = test_norm_df['BMI']

X2= np.array(X).reshape(-1,1) # reshape(-1,1) makes the array horizontal, y is␣
↪vertical

# Train the model (we use all data for training -->
model_1 = sklearn.linear_model.LinearRegression()
model_1.fit(X2, y)

# Model score
```

```
r_sq = model_1.score(X2, y)
print("The model Score is ", r_sq)

# Plotting the Regression Line with Scatter plot
plt.scatter(X2, y, color='black', label='observed',alpha=0.5)
plt.plot(X2, model_1.predict(X2), label='fit', color='Green', linewidth=2)
plt.xlabel('General Health')
plt.ylabel('BMI')
plt.title('Regression')
plt.legend(loc='best')

plt.show()


# Make predictions using the testing set
diabetes_y_pred = model_1.predict(X_test)

# The coefficients
print('Coefficients =  ', model_1.coef_)
print('Intercept =  ', model_1.intercept_)

# The mean squared error
print('Mean squared error = {:.2f}'.format( mean_squared_error(y_test,␣
↪diabetes_y_pred)))

# The coefficient of determination: 1 is perfect prediction
print('Coefficient of determination = {:.2f}'.format(r2_score(y_test,␣
↪diabetes_y_pred)))
```

```
The model Score is  0.06349070218338293
```

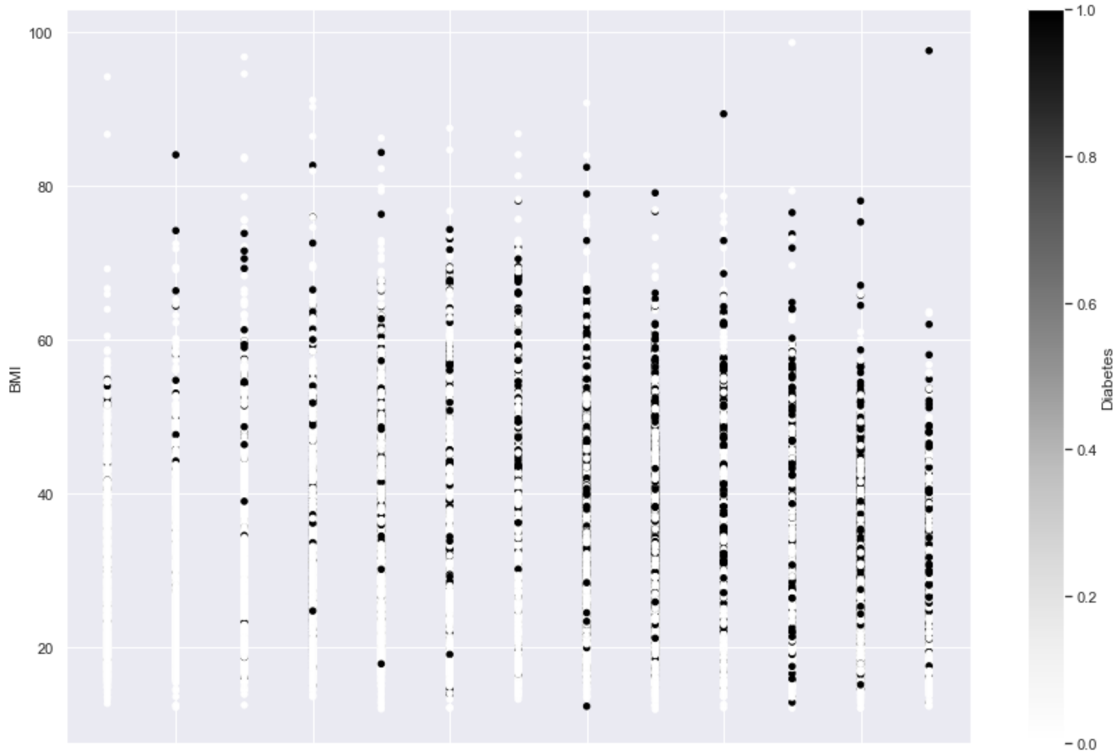



```
Coefficients =    [-0.07029574]
Intercept =    0.2352588619911028
Mean squared error = 0.01
Coefficient of determination = 0.06
```

[32]:
```
# # Make a prediction
# X3= test_df['GeneralHealth']

# X3= np.array(X3).reshape(-1,1)
# # what is the price for element 44 of the test house age list.
# predicted_charge = model_1.predict([X3[44]])
# print('General Health = {:.2f}   Predicted BMI = {:.2f}'.format(X3[44][0],␣
↪predicted_charge[0]))
```

1.0.9 LINEAR REGRESSION MODEL 3 : Age - BMI

[33]:
```
ax1 = diabetes.plot.scatter(x='Age',
                            y='BMI',
                            c='Diabetes')
plt.show()
```

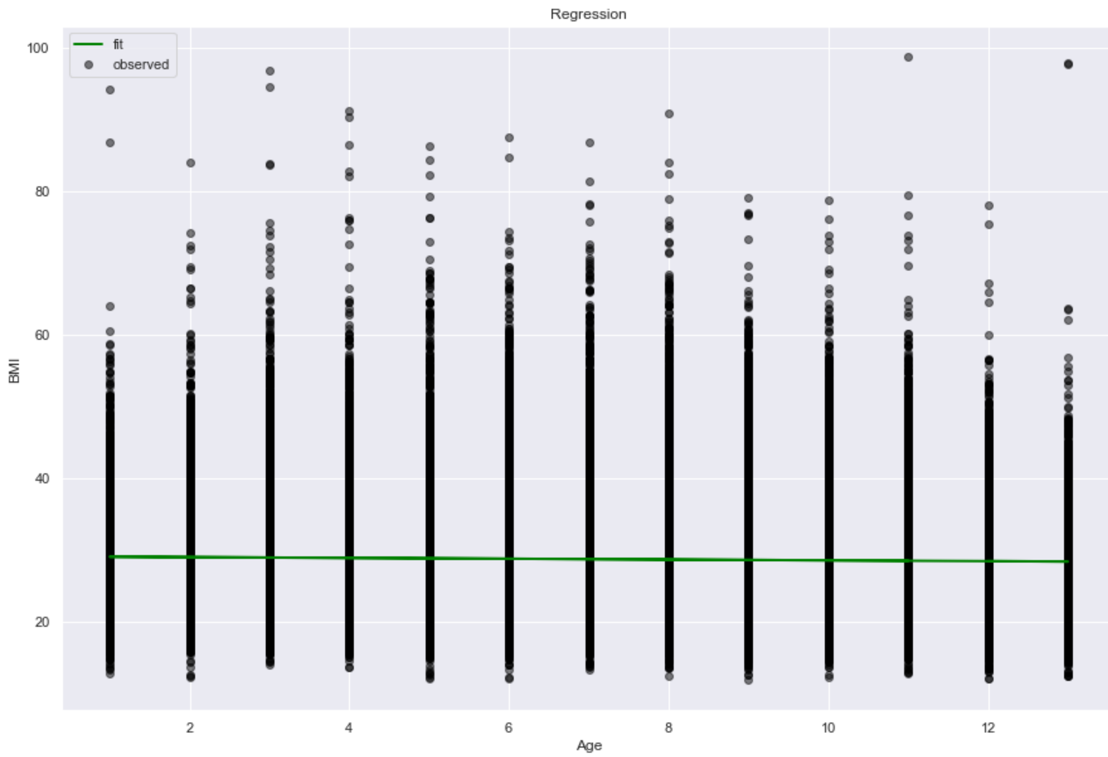


[34]:

```
import sklearn
from sklearn import linear_model
from sklearn.linear_model import LinearRegression

# Simple Regression Metrics
from sklearn.metrics import mean_squared_error, r2_score


X= train_df[['Age']]
y= train_df['BMI']

X_test = test_df[['Age']]
y_test = test_df['BMI']

X2= np.array(X).reshape(-1,1) # reshape(-1,1) makes the array horizontal, y is␣
 ↪vertical

# Train the model (we use all data for training -->
model_1 = sklearn.linear_model.LinearRegression()
model_1.fit(X2, y)

# Model score
```

```
r_sq = model_1.score(X2, y)
print("The model Score is ", r_sq)

# Plotting the Regression Line with Scatter plot
plt.scatter(X2, y, color='black', label='observed',alpha=0.5)
plt.plot(X2, model_1.predict(X2), label='fit', color='Green', linewidth=2)
plt.xlabel('Age')
plt.ylabel('BMI')
plt.title('Regression')
plt.legend(loc='best')

plt.show()


# Make predictions using the testing set
diabetes_y_pred = model_1.predict(X_test)

# The coefficients
print('Coefficients =  ', model_1.coef_)
print('Intercept =  ', model_1.intercept_)

# The mean squared error
print('Mean squared error = {:.2f}'.format( mean_squared_error(y_test,␣
 ↪diabetes_y_pred)))

# The coefficient of determination: 1 is perfect prediction
print('Coefficient of determination = {:.2f}'.format(r2_score(y_test,␣
 ↪diabetes_y_pred)))
```

```
The model Score is  0.0008194515136238367
```



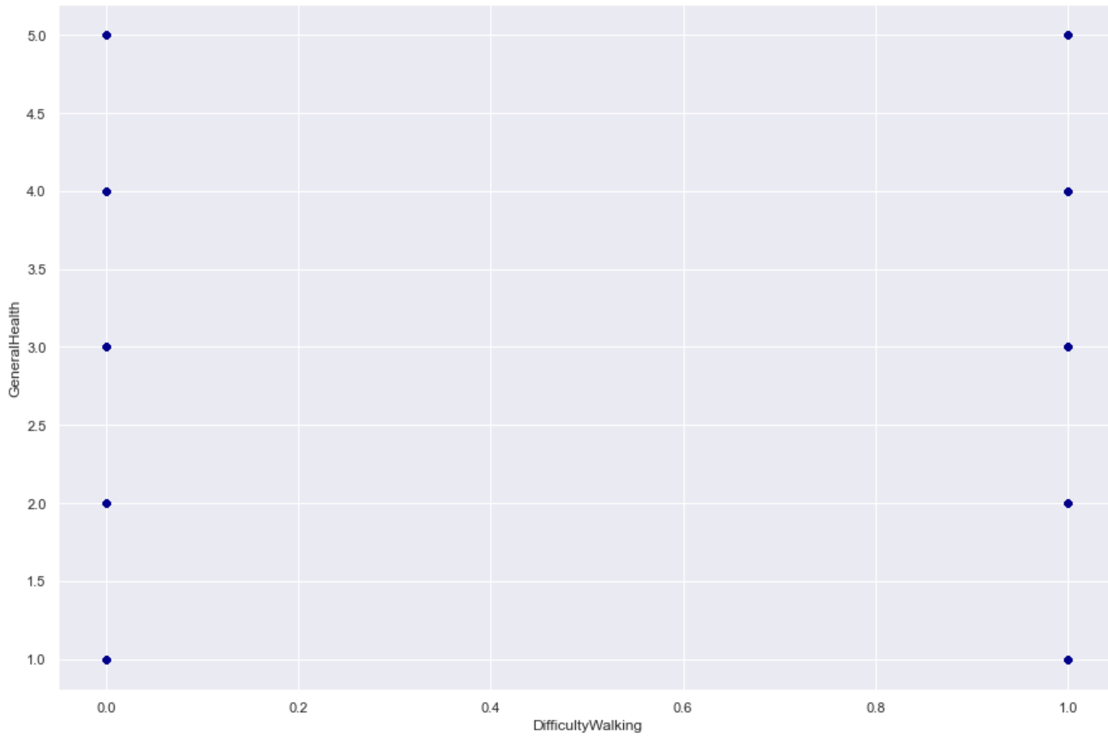

```
Coefficients =   [-0.05612752]
Intercept =   29.124165356215567
Mean squared error = 40.27
Coefficient of determination = 0.00
```

[35]:
```
# Make a prediction
X3= test_df['Age']

X3= np.array(X3).reshape(-1,1)
# what is the price for element 44 of the test house age list.
predicted_charge = model_1.predict([X3[44]])
print('Age Class = {:.2f}   Predicted BMI = {:.2f}'.format(X3[44][0],␣
↪predicted_charge[0]))
```

```
Age Class = 3.00   Predicted BMI = 28.96
```

1.0.10 LINEAR REGRESSION MODEL 4 : Difficulty Walking - General Health

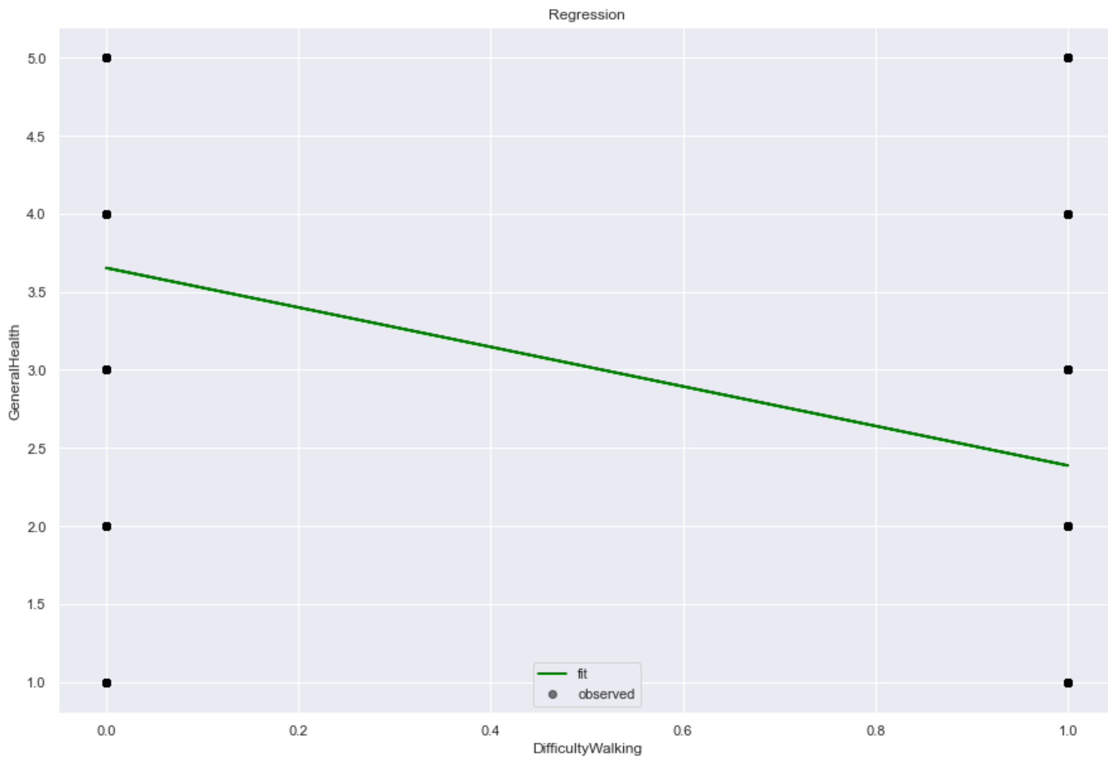
[36]:
```
ax1 = diabetes.plot.scatter(x='DifficultyWalking',
                      y='GeneralHealth',
                      c='Darkblue')
plt.show()
```



[37]:
```
import sklearn
from sklearn import linear_model
from sklearn.linear_model import LinearRegression

# Simple Regression Metrics
from sklearn.metrics import mean_squared_error, r2_score


X= train_df[['DifficultyWalking']]
y= train_df['GeneralHealth']

X_test = test_df[['DifficultyWalking']]
y_test = test_df['GeneralHealth']

X2= np.array(X).reshape(-1,1) # reshape(-1,1) makes the array horizontal, y is␣
↪vertical

# Train the model (we use all data for training -->
model_1 = sklearn.linear_model.LinearRegression()
model_1.fit(X2, y)

# Model score
r_sq = model_1.score(X2, y)
```

```python
print("The model Score is ", r_sq)

# Plotting the Regression Line with Scatter plot
plt.scatter(X2, y, color='black', label='observed',alpha=0.5)
plt.plot(X2, model_1.predict(X2), label='fit', color='Green', linewidth=2)
plt.xlabel('DifficultyWalking')
plt.ylabel('GeneralHealth')
plt.title('Regression')
plt.legend(loc='best')

plt.show()


# Make predictions using the testing set
diabetes_y_pred = model_1.predict(X_test)

# The coefficients
print('Coefficients =  ', model_1.coef_)
print('Intercept =  ', model_1.intercept_)

# The mean squared error
print('Mean squared error = {:.2f}'.format( mean_squared_error(y_test,␣
 ↪diabetes_y_pred)))

# The coefficient of determination: 1 is perfect prediction
print('Coefficient of determination = {:.2f}'.format(r2_score(y_test,␣
 ↪diabetes_y_pred)))
```

```
The model Score is  0.19895907559493897
```



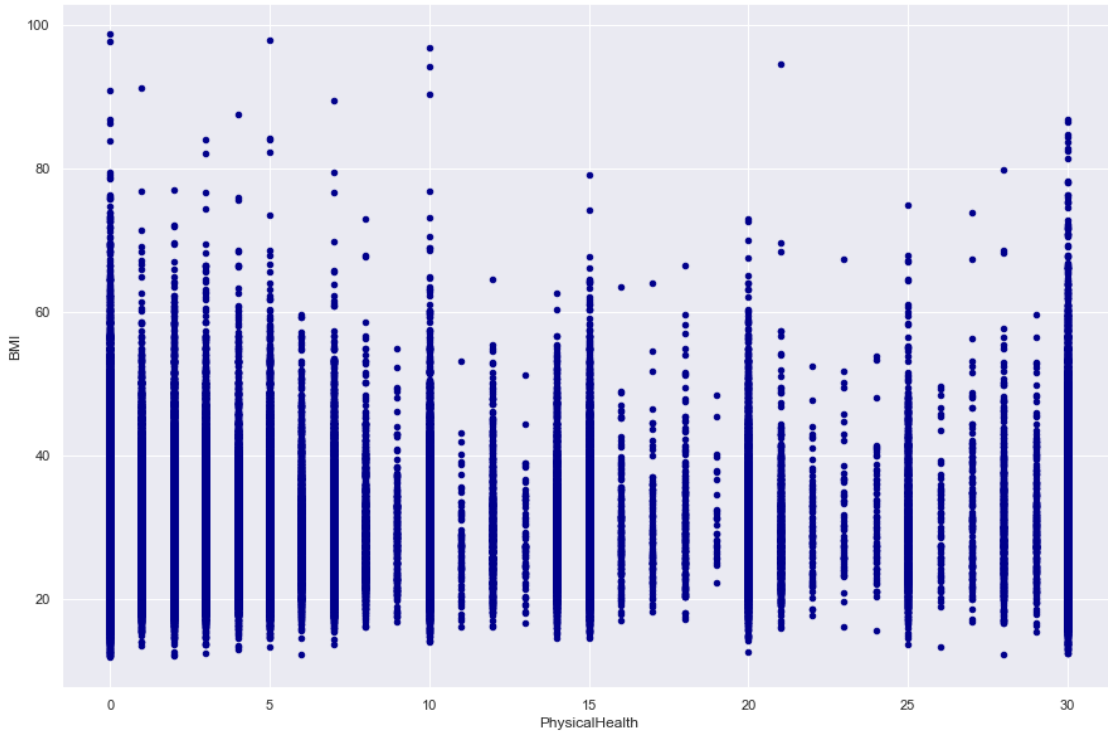

```
Coefficients =    [-1.26609205]
Intercept =    3.6530970064018624
Mean squared error = 0.90
Coefficient of determination = 0.19
```

[38]:
```
# Make a prediction
X3= test_df['DifficultyWalking']

X3= np.array(X3).reshape(-1,1)
# what is the price for element 44 of the test house age list.
predicted_charge = model_1.predict([X3[44]])
print('DifficultyWalking = {:.2f}    Predicted GeneralHealth = {:.2f}'.
 ↪format(X3[44][0], predicted_charge[0]))
```

```
DifficultyWalking = 0.00    Predicted GeneralHealth = 3.65
```

1.0.11 LINEAR REGRESSION MODEL 5 : Physical Health - BMI

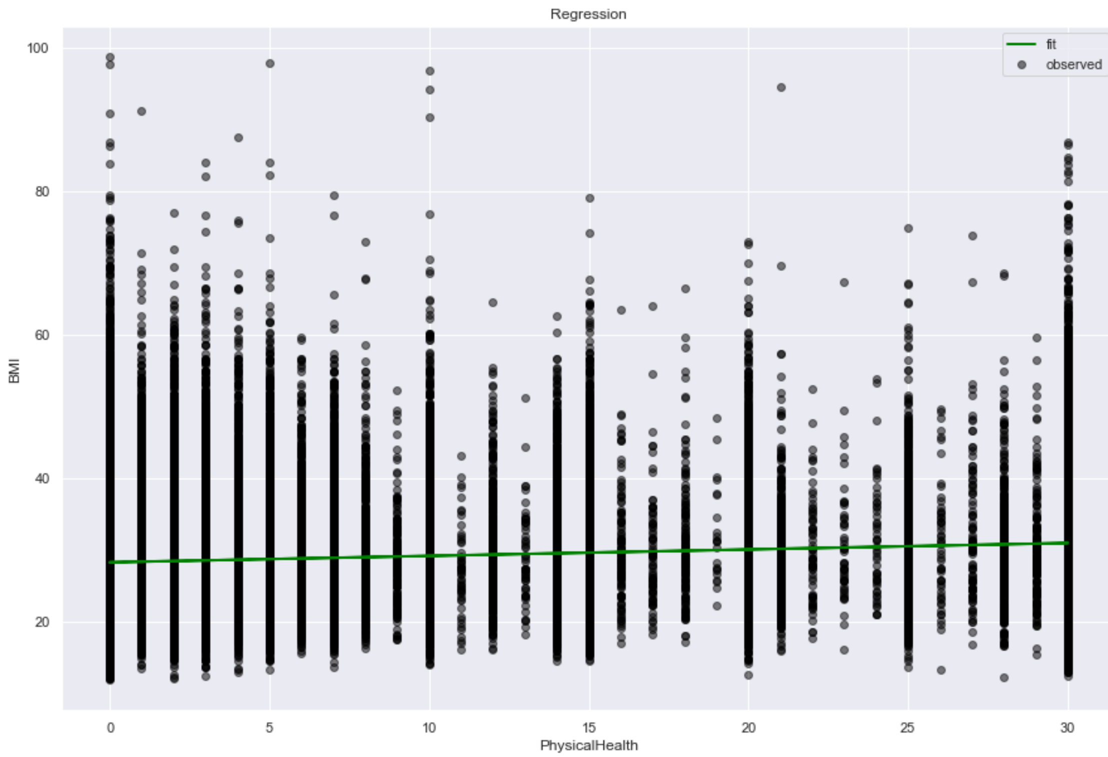
[39]:
```
ax1 = diabetes.plot.scatter(x='PhysicalHealth',
                      y='BMI',
                      c='Darkblue')
plt.show()
```



[40]:
```
import sklearn
from sklearn import linear_model
from sklearn.linear_model import LinearRegression

# Simple Regression Metrics
from sklearn.metrics import mean_squared_error, r2_score


X= train_df[['PhysicalHealth']]
y= train_df['BMI']

X_test = test_df[['PhysicalHealth']]
y_test = test_df['BMI']

X2= np.array(X).reshape(-1,1) # reshape(-1,1) makes the array horizontal, y is␣
 ↪vertical

# Train the model (we use all data for training -->
model_1 = sklearn.linear_model.LinearRegression()
model_1.fit(X2, y)

# Model score
r_sq = model_1.score(X2, y)
```

```
print("The model Score is ", r_sq)

# Plotting the Regression Line with Scatter plot
plt.scatter(X2, y, color='black', label='observed',alpha=0.5)
plt.plot(X2, model_1.predict(X2), label='fit', color='Green', linewidth=2)
plt.xlabel('PhysicalHealth')
plt.ylabel('BMI')
plt.title('Regression')
plt.legend(loc='best')

plt.show()


# Make predictions using the testing set
diabetes_y_pred = model_1.predict(X_test)

# The coefficients
print('Coefficients =  ', model_1.coef_)
print('Intercept =  ', model_1.intercept_)

# The mean squared error
print('Mean squared error = {:.2f}'.format( mean_squared_error(y_test,␣
↪diabetes_y_pred)))

# The coefficient of determination: 1 is perfect prediction
print('Coefficient of determination = {:.2f}'.format(r2_score(y_test,␣
↪diabetes_y_pred)))
```

```
The model Score is  0.015237910488188122
```




```
Coefficients =   [0.08961069]
Intercept =   28.28329131680311
Mean squared error = 39.70
Coefficient of determination = 0.01
```

[41]:
```
# Make a prediction
X3= test_df['PhysicalHealth']

X3= np.array(X3).reshape(-1,1)
# what is the price for element 44 of the test house age list.
predicted_charge = model_1.predict([X3[44]])
print('PhysicalHealth = {:.2f}   Predicted BMI = {:.2f}'.format(X3[44][0],␣
 ↪predicted_charge[0]))
```

```
PhysicalHealth = 2.00   Predicted BMI = 28.46
```

Note : GeneralHealth - BMI (looks like a parabola)

1.0.12 MODEL 6 : POLYNOMIAL REGRESSION WITH REGULARIZATION

- Physical Health vs BMI

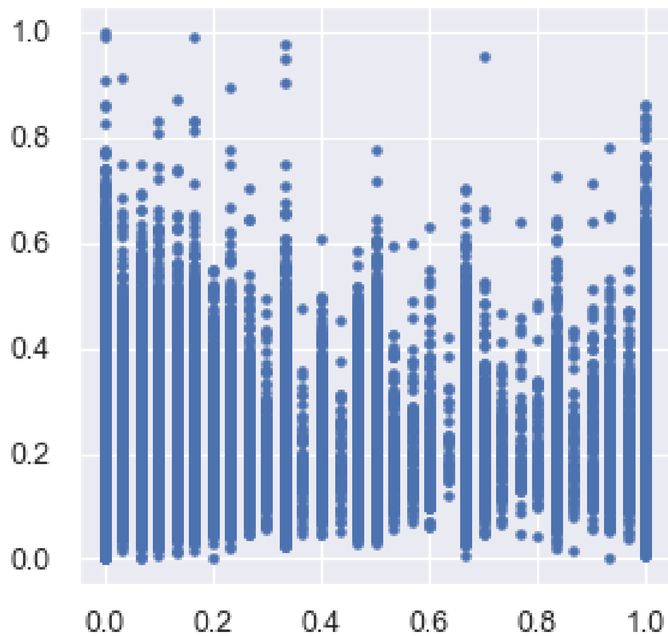
[42]:
```
x= diabetes_norm[['PhysicalHealth']]
y= diabetes_norm['BMI']
data = pd.DataFrame(np.column_stack([x,y]),columns=['x','y'])
```

```
data.head()
```

[42]:

	x	y
0	0.500000	0.186505
1	0.333333	0.075433
2	0.000000	0.226298
3	1.000000	0.241984
4	0.666667	0.053633

[43]:
```
from matplotlib.pyplot import figure
figure(figsize=(4,4), dpi=80)
plt.plot(data['x'],data['y'],'.')
plt.show()
```



[44]:
```
for i in range(2,16):  #power of 1 is already there
    colname = 'x_%d'%i      #new var will be x_power
    data[colname] = data['x']**i
print(data.head())
```

```
          x         y       x_2       x_3       x_4       x_5       x_6  \
0  0.500000  0.186505  0.250000  0.125000  0.062500  0.031250  0.015625
1  0.333333  0.075433  0.111111  0.037037  0.012346  0.004115  0.001372
2  0.000000  0.226298  0.000000  0.000000  0.000000  0.000000  0.000000
3  1.000000  0.241984  1.000000  1.000000  1.000000  1.000000  1.000000
4  0.666667  0.053633  0.444444  0.296296  0.197531  0.131687  0.087791
```

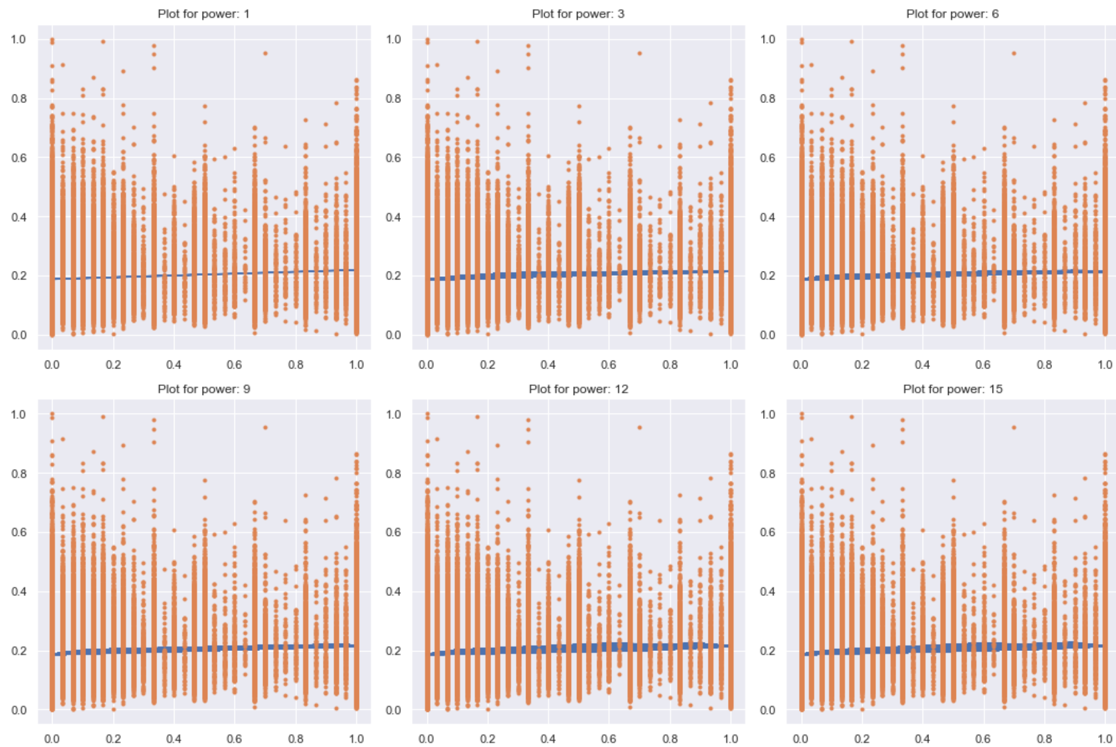
```
        x_7       x_8       x_9      x_10      x_11      x_12          x_13  \
0  0.007812  0.003906  0.001953  0.000977  0.000488  0.000244  1.220703e-04
1  0.000457  0.000152  0.000051  0.000017  0.000006  0.000002  6.272255e-07
2  0.000000  0.000000  0.000000  0.000000  0.000000  0.000000  0.000000e+00
3  1.000000  1.000000  1.000000  1.000000  1.000000  1.000000  1.000000e+00
4  0.058528  0.039018  0.026012  0.017342  0.011561  0.007707  5.138231e-03

           x_14          x_15
0  6.103516e-05  3.051758e-05
1  2.090752e-07  6.969172e-08
2  0.000000e+00  0.000000e+00
3  1.000000e+00  1.000000e+00
4  3.425487e-03  2.283658e-03
```

Without Regularization

[45]:
```python
#Import Linear Regression model from scikit-learn.
from sklearn.linear_model import LinearRegression
def linear_regression(data, power, models_to_plot):
    #initialize predictors:
    predictors=['x']
    if power>=2:
        predictors.extend(['x_%d'%i for i in range(2,power+1)])

    #Fit the model
    linreg = LinearRegression(normalize=True)
    linreg.fit(data[predictors],data['y'])
    y_pred = linreg.predict(data[predictors])

    #Check if a plot is to be made for the entered power
    if power in models_to_plot:

        plt.subplot(models_to_plot[power])
        plt.tight_layout()
        plt.plot(data['x'],y_pred)
        plt.plot(data['x'],data['y'],'.')
        plt.title('Plot for power: %d'%power)

    #Return the result in pre-defined format
    rss = sum((y_pred-data['y'])**2)
    ret = [rss]
    ret.extend([linreg.intercept_])
    ret.extend(linreg.coef_)
    return ret
```

[46]:
```python
#Initialize a dataframe to store the results:
col = ['rss','intercept'] + ['coef_x_%d'%i for i in range(1,16)]
ind = ['model_pow_%d'%i for i in range(1,16)]
```

```
coef_matrix_simple = pd.DataFrame(index=ind, columns=col)

#Define the powers for which a plot is required:
models_to_plot = {1:231,3:232,6:233,9:234,12:235,15:236}

#Iterate through all powers and assimilate results
for i in range(1,16):
    coef_matrix_simple.iloc[i-1,0:i+2] = linear_regression(data, power=i,␣
 ↪models_to_plot=models_to_plot)
```



[47]:
```
#Set the display format to be scientific for ease of analysis
pd.options.display.float_format = '{:,.2g}'.format
coef_matrix_simple
```

[47]:

	rss	intercept	coef_x_1	coef_x_2	coef_x_3	coef_x_4	coef_x_5 \
model_pow_1	1.3e+03	0.19	0.031	NaN	NaN	NaN	NaN
model_pow_2	1.3e+03	0.19	0.083	-0.056	NaN	NaN	NaN
model_pow_3	1.3e+03	0.19	0.13	-0.21	0.11	NaN	NaN
model_pow_4	1.3e+03	0.19	0.18	-0.6	0.86	-0.42	NaN
model_pow_5	1.3e+03	0.19	0.22	-1.1	2.4	-2.5	0.9
model_pow_6	1.3e+03	0.19	0.24	-1.4	4.2	-6.3	4.7
model_pow_7	1.3e+03	0.19	0.2	-0.45	-2.7	16	-32
model_pow_8	1.3e+03	0.19	0.19	-0.17	-5.3	28	-60

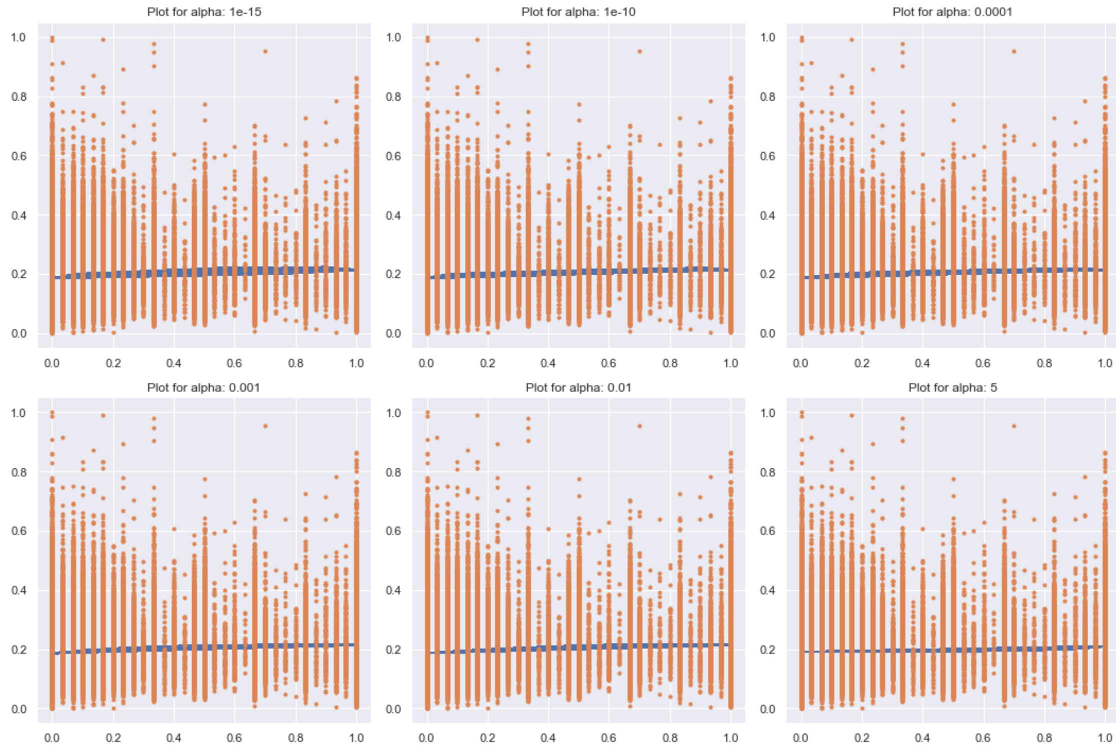
```
model_pow_9  1.3e+03      0.19     0.11       2.4       -35     2e+02 -5.8e+02
model_pow_10 1.3e+03      0.19   -0.082        11 -1.6e+02   1.1e+03 -4.5e+03
model_pow_11 1.3e+03      0.19   -0.063       9.6 -1.4e+02   9.8e+02 -3.8e+03
model_pow_12 1.3e+03      0.19     0.17      -3.4  1.3e+02 -1.9e+03  1.4e+04
model_pow_13 1.3e+03      0.19     0.15      -2.1        95 -1.5e+03  1.1e+04
model_pow_14 1.3e+03      0.19    -0.14        17 -4.1e+02  5.5e+03 -4.7e+04
model_pow_15 1.3e+03      0.19    -0.59        51 -1.4e+03  2.1e+04 -1.9e+05

             coef_x_6 coef_x_7 coef_x_8 coef_x_9 coef_x_10 coef_x_11  \
model_pow_1       NaN      NaN      NaN      NaN       NaN       NaN
model_pow_2       NaN      NaN      NaN      NaN       NaN       NaN
model_pow_3       NaN      NaN      NaN      NaN       NaN       NaN
model_pow_4       NaN      NaN      NaN      NaN       NaN       NaN
model_pow_5       NaN      NaN      NaN      NaN       NaN       NaN
model_pow_6      -1.4      NaN      NaN      NaN       NaN       NaN
model_pow_7        27     -8.7      NaN      NaN       NaN       NaN
model_pow_8        64      -33      6.6      NaN       NaN       NaN
model_pow_9     1e+03   -1e+03  5.4e+02 -1.2e+02       NaN       NaN
model_pow_10  1.1e+04 -1.7e+04  1.5e+04 -7.5e+03   1.6e+03       NaN
model_pow_11  8.7e+03 -1.2e+04  9.1e+03 -2.8e+03  -5.3e+02     4e+02
model_pow_12    -6e+04  1.6e+05 -2.9e+05  3.3e+05  -2.3e+05   9.2e+04
model_pow_13 -4.7e+04  1.2e+05   -2e+05    2e+05  -1.1e+05   1.9e+04
model_pow_14  2.7e+05   -1e+06  2.7e+06 -5.1e+06   6.6e+06  -5.8e+06
model_pow_15  1.2e+06   -5e+06  1.5e+07 -3.2e+07     5e+07  -5.5e+07

             coef_x_12 coef_x_13 coef_x_14 coef_x_15
model_pow_1        NaN       NaN       NaN       NaN
model_pow_2        NaN       NaN       NaN       NaN
model_pow_3        NaN       NaN       NaN       NaN
model_pow_4        NaN       NaN       NaN       NaN
model_pow_5        NaN       NaN       NaN       NaN
model_pow_6        NaN       NaN       NaN       NaN
model_pow_7        NaN       NaN       NaN       NaN
model_pow_8        NaN       NaN       NaN       NaN
model_pow_9        NaN       NaN       NaN       NaN
model_pow_10       NaN       NaN       NaN       NaN
model_pow_11       NaN       NaN       NaN       NaN
model_pow_12  -1.6e+04       NaN       NaN       NaN
model_pow_13   1.1e+04  -4.2e+03       NaN       NaN
model_pow_14   3.3e+06  -1.1e+06   1.6e+05       NaN
model_pow_15   4.2e+07  -2.1e+07   6.4e+06  -8.6e+05
```

With Regularization

[48]:
```python
from sklearn.linear_model import Ridge
def ridge_regression(data, predictors, alpha, models_to_plot={}):
    #Fit the model
    ridgereg = Ridge(alpha=alpha,normalize=True)
```

```
    ridgereg.fit(data[predictors],data['y'])
    y_pred = ridgereg.predict(data[predictors])

    #Check if a plot is to be made for the entered alpha
    if alpha in models_to_plot:
        plt.subplot(models_to_plot[alpha])
        plt.tight_layout()
        plt.plot(data['x'],y_pred)
        plt.plot(data['x'],data['y'],'.')
        plt.title('Plot for alpha: %.3g'%alpha)

    #Return the result in pre-defined format
    rss = sum((y_pred-data['y'])**2)
    ret = [rss]
    ret.extend([ridgereg.intercept_])
    ret.extend(ridgereg.coef_)
    return ret
```

[49]:
```
#Initialize predictors to be set of 15 powers of x
predictors=['x']
predictors.extend(['x_%d'%i for i in range(2,16)])

#Set the different values of alpha to be tested
alpha_ridge = [1e-15, 1e-10, 1e-8, 1e-4, 1e-3,1e-2, 1, 5, 10, 20]

#Initialize the dataframe for storing coefficients.
col = ['rss','intercept'] + ['coef_x_%d'%i for i in range(1,16)]
ind = ['alpha_%.2g'%alpha_ridge[i] for i in range(0,10)]
coef_matrix_ridge = pd.DataFrame(index=ind, columns=col)

models_to_plot = {1e-15:231, 1e-10:232, 1e-4:233, 1e-3:234, 1e-2:235, 5:236}
for i in range(10):
    coef_matrix_ridge.iloc[i,] = ridge_regression(data, predictors,␣
 ↪alpha_ridge[i], models_to_plot)
```



[50]:
```python
#Set the display format to be scientific for ease of analysis
pd.options.display.float_format = '{:,.2g}'.format
coef_matrix_ridge
```

[50]:

	rss	intercept	coef_x_1	coef_x_2	coef_x_3	coef_x_4	coef_x_5
alpha_1e-15	1.3e+03	0.19	0.0023	6.1	-75	3.4e+02	-4e+02
alpha_1e-10	1.3e+03	0.19	0.22	-0.93	1.3	2	-11
alpha_1e-08	1.3e+03	0.19	0.21	-0.89	1.1	0.86	-1.2
alpha_0.0001	1.3e+03	0.19	0.13	-0.24	0.074	0.098	0.043
alpha_0.001	1.3e+03	0.19	0.098	-0.092	-0.02	0.013	0.02
alpha_0.01	1.3e+03	0.19	0.062	-0.015	-0.014	-0.008	-0.0036
alpha_1	1.3e+03	0.19	0.0089	0.0045	0.0027	0.0018	0.0013
alpha_5	1.3e+03	0.19	0.0029	0.002	0.0016	0.0013	0.0012
alpha_10	1.3e+03	0.19	0.0018	0.0014	0.0012	0.0011	0.00099
alpha_20	1.3e+03	0.19	0.0011	0.00089	0.0008	0.00075	0.00071

	coef_x_6	coef_x_7	coef_x_8	coef_x_9	coef_x_10	coef_x_11
alpha_1e-15	-1.7e+03	6.2e+03	-5.8e+03	-3.3e+03	6.2e+03	3.6e+03
alpha_1e-10	18	-0.78	-19	-8	14	21
alpha_1e-08	-1.3	-0.31	0.74	1.3	1.1	0.19
alpha_0.0001	-0.0022	-0.025	-0.031	-0.027	-0.019	-0.0093
alpha_0.001	0.017	0.012	0.0074	0.0033	8.1e-05	-0.0025
alpha_0.01	-0.0011	0.00026	0.00096	0.0013	0.0013	0.0012

```
alpha_1        0.00096  0.00076  0.00062  0.00051   0.00044   0.00038
alpha_5         0.0011   0.0011    0.001    0.001     0.001   0.00099
alpha_10       0.00095  0.00093  0.00091  0.00089   0.00088   0.00087
alpha_20       0.00069  0.00068  0.00067  0.00066   0.00066   0.00065

              coef_x_12 coef_x_13 coef_x_14 coef_x_15
alpha_1e-15    -5.7e+03  -4.4e+03   7.5e+03  -2.5e+03
alpha_1e-10         5.3       -19       -24        21
alpha_1e-08       -0.94      -1.6     -0.94       1.6
alpha_0.0001 -0.00072    0.0062     0.011     0.014
alpha_0.001     -0.0046   -0.0063   -0.0077   -0.0089
alpha_0.01      0.00098   0.00072   0.00044   0.00014
alpha_1         0.00034    0.0003   0.00027   0.00025
alpha_5         0.00097   0.00096   0.00095   0.00095
alpha_10        0.00087   0.00086   0.00086   0.00085
alpha_20        0.00065   0.00065   0.00065   0.00064
```

Note: Even after trying various polynomial degree there is no improvement in the model score. The Regression line is flat and not able to model the data properly. Thus the model model has very high bias and even with very high degree polynomial features no results can be seen. This also implies that the regularization is not not playing any role in improving the model.

1.0.13 MODEL 6: DECISION TREE REGRESSOR

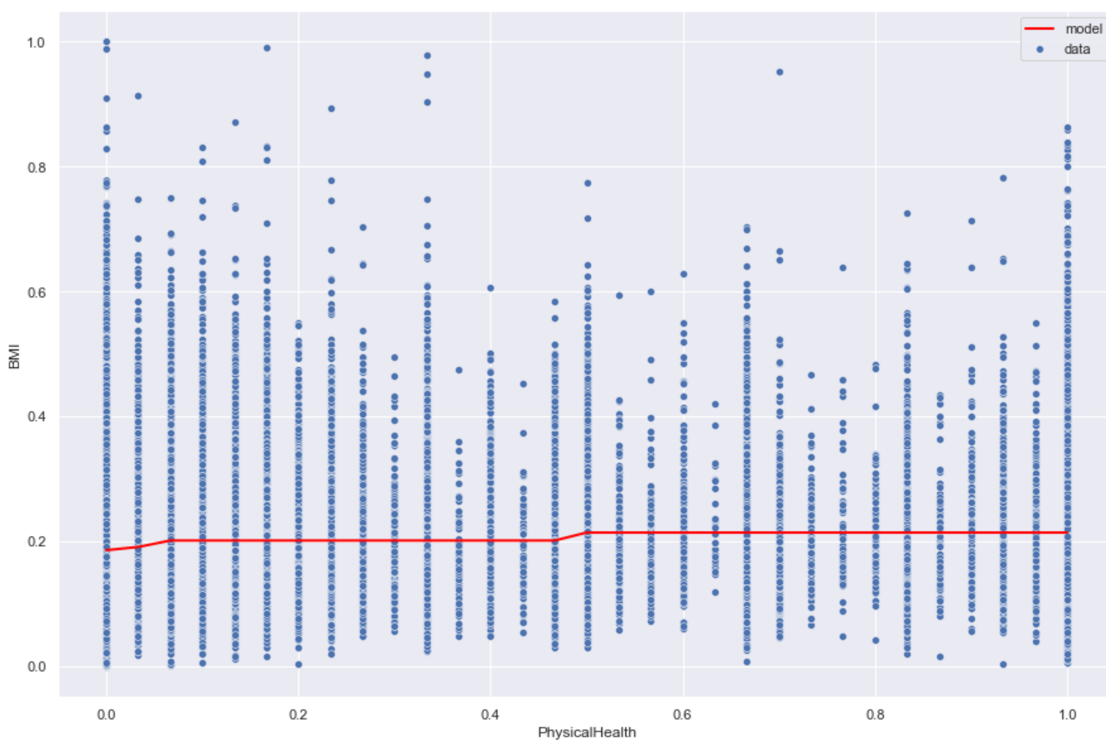
[51]:
```
from sklearn.tree import DecisionTreeRegressor

train_norm_df, test_norm_df = train_test_split(diabetes_norm,shuffle = True,␣
↪test_size = 0.20, random_state=17)

X = train_norm_df[['PhysicalHealth']] #Two-dimensional (pd DataFrame)
y = train_norm_df['BMI'] #One-dimensional (pd Series)

X_test = test_norm_df[['PhysicalHealth']] #Two-dimensional (pd DataFrame)
y_test = test_norm_df['BMI'] #One-dimensional (pd Series)
```

Decision Tree Regressor with Max depth 2

[52]:
```
#Create an object (model)
dtr1 = DecisionTreeRegressor(max_depth=2,
                             random_state=1)

#Fit (train) the model
dtr1.fit(X, y)

sns.scatterplot(x=diabetes_norm['PhysicalHealth'],
                y=diabetes_norm['BMI'],
                label='data')
```

```
plt.plot(diabetes_norm['PhysicalHealth'].sort_values(),
         dtr1.predict(diabetes_norm['PhysicalHealth'].sort_values().to_frame()),
         color='red', label='model',
         linewidth=2)

plt.legend()

plt.savefig('model.png')

# Make predictions using the testing set
y_pred = dtr1.predict(X_test)


print("Model Score = {}".format(dtr1.score(X_test,y_test)))


# The mean squared error
print('Mean squared error = {:.2f}'.format( mean_squared_error(y_test, y_pred)))

# The coefficient of determination: 1 is perfect prediction
print('Coefficient of determination = {:.2f}'.format(r2_score(y_test, y_pred)))
```

```
Model Score = 0.01749066762038165
Mean squared error = 0.01
Coefficient of determination = 0.02
```

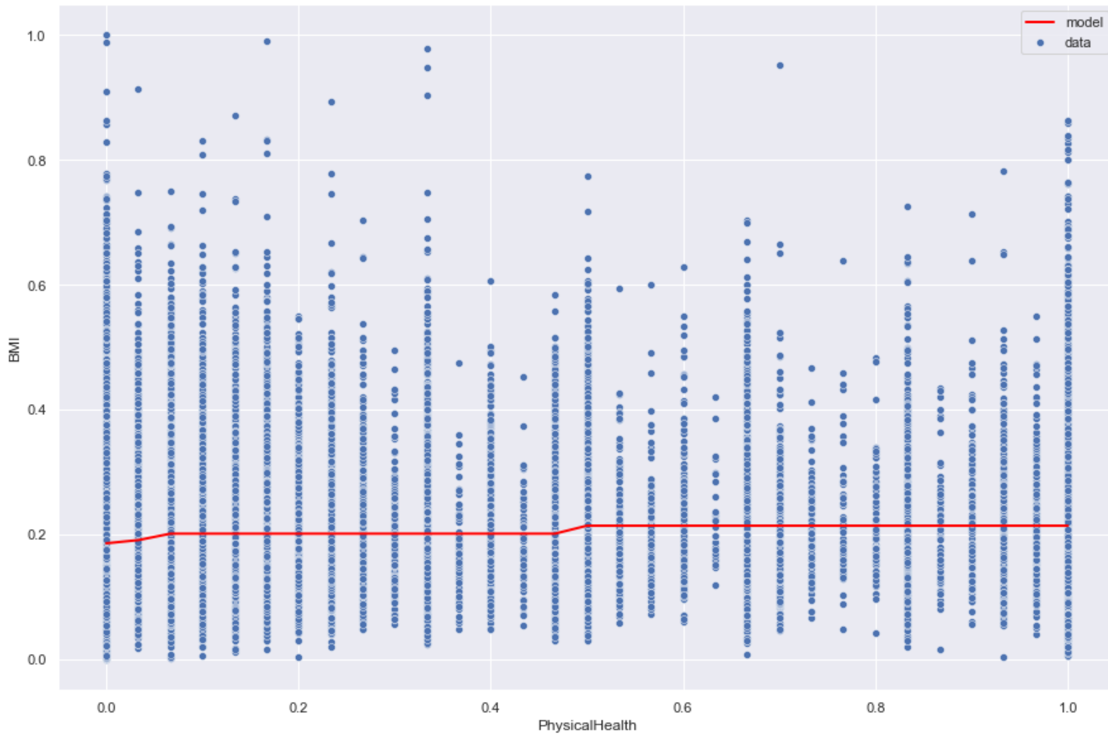


Trying Higher Max Depth

[53]:
```
def vary_max_depth_dtr(max_dp):
    dtr = DecisionTreeRegressor(max_depth=max_dp,random_state=1)
    dtr.fit(X, y)
    sns.scatterplot(x=diabetes_norm['PhysicalHealth'],
                    y=diabetes_norm['BMI'],
                    label='data')
    plt.plot(diabetes_norm['PhysicalHealth'].sort_values(),
         dtr1.predict(diabetes_norm['PhysicalHealth'].sort_values().to_frame()),
         color='red', label='model',
         linewidth=2)
    plt.legend()
    # Make predictions using the testing set
    y_pred = dtr.predict(X_test)
    print("Model Score = {}".format(dtr.score(X_test,y_test)))
    # The mean squared error
    print('Mean squared error = {:.2f}'.format( mean_squared_error(y_test,␣
 ↪y_pred)))

    # The coefficient of determination: 1 is perfect prediction
    print('Coefficient of determination = {:.2f}'.format(r2_score(y_test,␣
 ↪y_pred)))
```

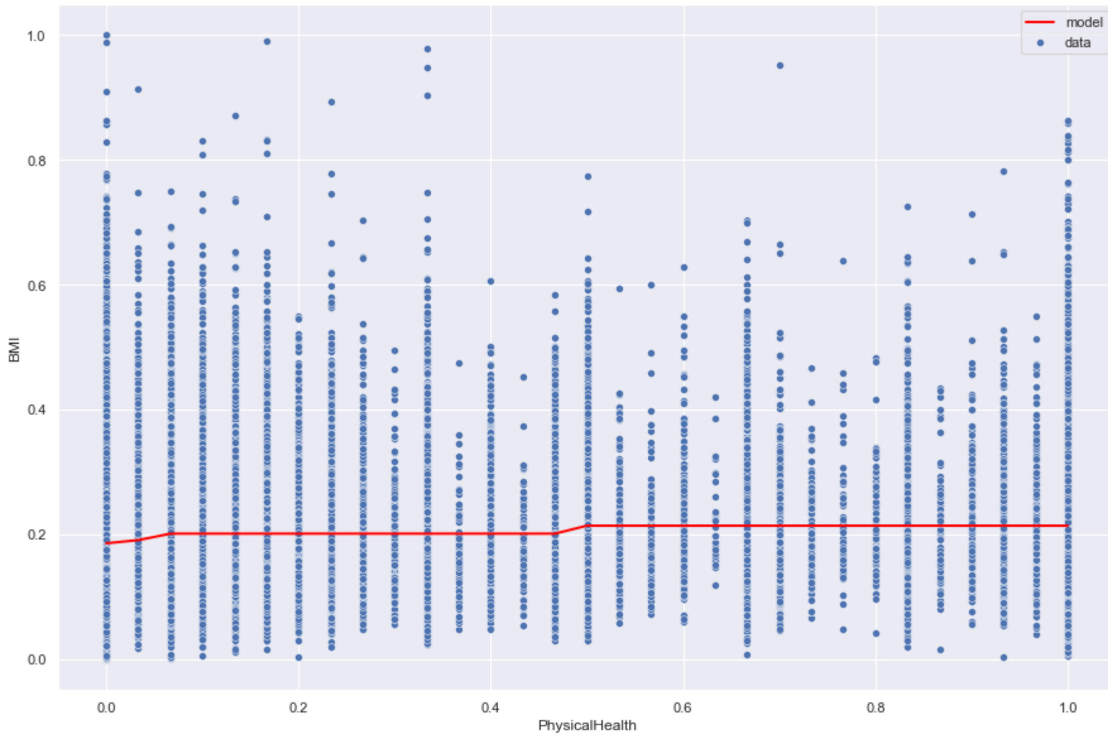
[54]:
```
#max depth set to 3
vary_max_depth_dtr(3)
```

```
Model Score = 0.017697774729233617
Mean squared error = 0.01
Coefficient of determination = 0.02
```



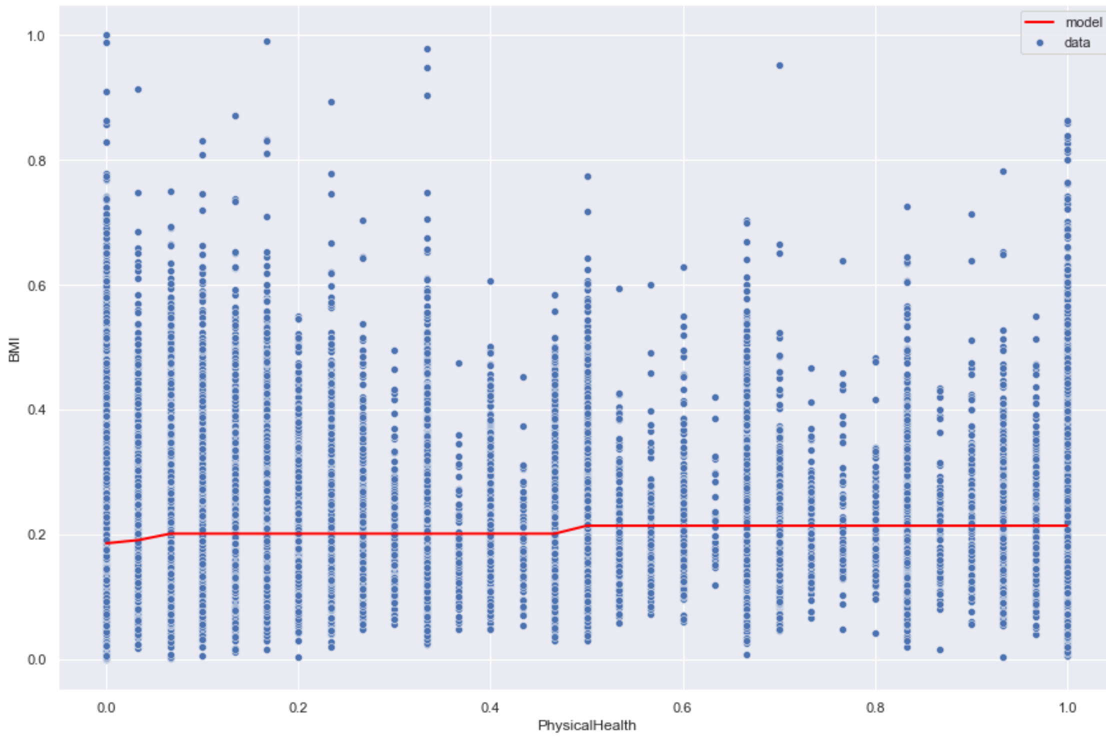
[55]:
```
# max depth set to 5
vary_max_depth_dtr(5)
```

```
Model Score = 0.017786213528891537
Mean squared error = 0.01
Coefficient of determination = 0.02
```



[56]:
```
# max depth set to 7
vary_max_depth_dtr(7)
```

```
Model Score = 0.017569950004698076
Mean squared error = 0.01
Coefficient of determination = 0.02
```



Notes: Using Decision tree regressor and increasing the hyper parameter max depth is not changing the results. The model gets a score of 0.02 across all the decision tree models that we have created.

2 Conclusion

- Normalization of entire dataset due to varying ranges of different attributes. Since the predictor variables had varying ranges, we normalized them with MinMaxScaler. Looking at normalized pairplots, we observed a few correlations which earlier were obscured by noise.
- We did correlation analysis and heatmaps for the normalized data as well.
- We selected most prospective attributes for building regression models with higher correlation
- Below are our observations on linear regression models:-
    1. Physical Health - General Health The model score is around 0.28 for non-normalized data as well as normalized data which was the highest for any combination of attributes. We get same results for normalized and non-normalized data since we are using one feature.
    2. General Health - BMI The observed model score is apx. 0.06. It might have a better chance at non-linear models
    3. Age - BMI The variables dont seem to have a linear correlation again and might perform better with a non-linear model.
    4. Difficulty Walking - General Health The model score is apx. 0.20
    5. Physical Health - BMI The combination is not linearly correlated with model score of 0.015
- We tried to evaluate the linear models performance metrics using Coefficient & Intercept,

Model Score, Mean Squared Error(MSE), Coefficient of determination.

- We tried to perform polynomial regression between Physical Health - BMI. Based on our observations from the polynomial regression with/without regularization we did not see any significant improvement in the models prediction.The Regression line is flat even with high degree polynomial and not able to model the data properly. Thus the model has very high bias and even with very high degree polynomial features no results can be seen.
- We tried to perform decision tree regression between Physical Health - BMI. We tried different max depths = 2,3,5 and 7. Here the max model score achieved is 0.017 which again is not much of an improvement from 0.015 in the linear regression model

Looking at all the models we see that the attributes which has highest correlation (pearson correlation coefficient) that is Physical Health - General (-0.525) also has the best model score in the linear regression model (0.28). Similar trend is observed for other combinations.

Since the results do not have a high degree of correlation, hence the features need to be evaluated differently using hyperplanes, multi-variate regression, or more advanced algorithmns (random forest, Neural networks,etc.).

3 –END–