EDA

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1 NOTEBOOK 2: EXPLORATORY DATA ANALYSIS ON DIABETES DATA SET

1.0.1 Team 3

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1.0.2 What this Notebook does?

- It fetches the csv file cleaned by Data_selection_cleaning Python File.
- We are going to convert into suitable datatypes and also drop unnecessary columns.
- We will get general idea of the data spread, shape and dispersion.
- To get more insights into the dataset, we will plot the following:-
- Boxplots.
- Histograms.
- Scatter and Pair Plots.
- Pearson Correlation factors.
- Bar graph.
- Heatmap.

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

[7]:
```
#drop the extra index column in datafram
diabetes=diabetes.drop(['Unnamed: 0'], axis=1)

# we are converting categorical values to in and not type category since they␣
↪are oridinal categorical.
diabetes[make_categorical]=diabetes[make_categorical].
↪astype('int64',errors='raise')

#set all boolean features
diabetes[make_bool]=diabetes[make_bool].astype('bool',errors='raise')
```

[8]:
```
diabetes.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 243317 entries, 0 to 243316
Data columns (total 23 columns):
 #   Column              Non-Null Count   Dtype
---  ------              --------------   -----
 0   Diabetes            243317 non-null  bool
 1   BMI                 243317 non-null  float64
 2   State               243317 non-null  object
 3   HighBP              243317 non-null  bool
 4   HighChol            243317 non-null  bool
 5   CholCheck           243317 non-null  bool
 6   FruitConsume        243317 non-null  bool
 7   VegetableConsume    243317 non-null  bool
 8   Smoker              243317 non-null  bool
 9   HeavyDrinker        243317 non-null  bool
 10  Stroke              243317 non-null  bool
 11  HeartDisease        243317 non-null  bool
 12  Healthcare          243317 non-null  bool
 13  NoDoctorDueToCost   243317 non-null  bool
 14  PhysicalActivity    243317 non-null  bool
 15  GeneralHealth       243317 non-null  int64
 16  PhysicalHealth      243317 non-null  float64
 17  MentalHealth        243317 non-null  float64
 18  DifficultyWalking   243317 non-null  bool
 19  Gender              243317 non-null  bool
 20  Age                 243317 non-null  int64
 21  Education           243317 non-null  int64
 22  Income              243317 non-null  int64
dtypes: bool(15), float64(3), int64(4), object(1)
memory usage: 18.3+ MB
```

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

[9]:
```
   Diabetes    BMI State  HighBP  HighChol  CholCheck  FruitConsume  \
0     False  28.17    AL    True      True       True          True
1     False  18.54    AL   False     False       True          True
2      True  31.62    AL    True     False       True          True
3      True  32.98    AL   False     False       True          True
4      True  16.65    AL   False      True       True         False

   VegetableConsume  Smoker  HeavyDrinker  …  NoDoctorDueToCost  \
0              True    True         False  …              False
1              True   False         False  …              False
2              True   False         False  …              False
3              True    True         False  …              False
4             False    True         False  …              False

   PhysicalActivity  GeneralHealth  PhysicalHealth  MentalHealth  \
0             False              3            15.0           0.0
1              True              2            10.0           0.0
2              True              3             0.0          30.0
3              True              4            30.0           0.0
4             False              1            20.0           0.0

   DifficultyWalking  Gender  Age  Education  Income
0               True   False   13          3       3
1              False   False   11          5       5
2               True   False   10          6       7
3               True    True   11          6       7
4               True   False   11          2       3

[5 rows x 23 columns]
```

[10]:
```python
# null values check
print('null values in diabetes after pre-cleaning :\n',diabetes.isnull().
 ↪sum(),'\n')
```

```
null values in diabetes after pre-cleaning :
 Diabetes             0
BMI                  0
State                0
HighBP               0
HighChol             0
CholCheck            0
FruitConsume         0
VegetableConsume     0
Smoker               0
HeavyDrinker         0
Stroke               0
HeartDisease         0
Healthcare           0
```

```
NoDoctorDueToCost     0
PhysicalActivity      0
GeneralHealth         0
PhysicalHealth        0
MentalHealth          0
DifficultyWalking     0
Gender                0
Age                   0
Education             0
Income                0
dtype: int64
```

There are no null values since we have handled these already in previous notebook during data selection and cleaning

1.0.5 3. (a) Descriptive Analysis: The mean, median, and standard deviation

[11]:
```python
# gather all columns of each type - Boolean, category, float, object
cols_boolean = diabetes.select_dtypes(include='bool').columns
print(cols_boolean)
cols_category = diabetes.select_dtypes(include='int64').columns
print(cols_category)
cols_float = diabetes.select_dtypes(include='float64').columns
print(cols_float)
cols_object = diabetes.select_dtypes(include='object').columns
print(cols_object)
```

```
Index(['Diabetes', 'HighBP', 'HighChol', 'CholCheck', 'FruitConsume',
       'VegetableConsume', 'Smoker', 'HeavyDrinker', 'Stroke', 'HeartDisease',
       'Healthcare', 'NoDoctorDueToCost', 'PhysicalActivity',
       'DifficultyWalking', 'Gender'],
      dtype='object')
Index(['GeneralHealth', 'Age', 'Education', 'Income'], dtype='object')
Index(['BMI', 'PhysicalHealth', 'MentalHealth'], dtype='object')
Index(['State'], dtype='object')
```

[12]:
```python
diabetes.describe(include='float64')
```

[12]:

	BMI	PhysicalHealth	MentalHealth
count	243317.000000	243317.000000	243317.000000
mean	28.673176	4.402426	3.673463
std	6.401627	8.831775	7.802452
min	12.000000	0.000000	0.000000
25%	24.340000	0.000000	0.000000
50%	27.460000	0.000000	0.000000
75%	31.870000	3.000000	3.000000
max	98.700000	30.000000	30.000000

- Mean of BMI - 28.673176
- Mean of PhysicalHealth - 4.402426
-

1.1 Mean of MentalHealth - 3.673463

- Median of BMI - 27.460000
- Median of PhysicalHealth - 0
-

1.2 Median of MentalHealth - 0

- Standard Deviation of BMI - 6.401627
- Standard Deviation of PhysicalHealth - 8.831775
- Standard Deviation of MentalHealth - 7.802452

Note: BMI of 98.7 seems very high we will look at boxplot and histogram to see if any outliers need to be removed

[13]:
```
diabetes.describe(include=['int64'])
```

[13]:

	GeneralHealth	Age	Education	Income
count	243317.000000	243317.000000	243317.000000	243317.000000
mean	3.439891	7.945277	5.073509	6.133201
std	1.060404	3.273054	0.974905	2.062683
min	1.000000	1.000000	1.000000	1.000000
25%	3.000000	6.000000	4.000000	5.000000
50%	4.000000	8.000000	5.000000	7.000000
75%	4.000000	10.000000	6.000000	8.000000
max	5.000000	13.000000	6.000000	8.000000

- Mean of GeneralHealth - 3.439891
- Mean of Age - 7.945277
- Mean of Education - 5.073509
-

1.3 Mean of Income - 6.133201

- Median of GeneralHealth - 4
- Median of Age - 8
- Median of Education - 5
-

1.4 Median of Income - 7

- Standard Deviation of GeneralHealth - 1.060404
- Standard Deviation of Age - 3.273054
- Standard Deviation of Education - 0.974905
- Standard Deviation of Income - 2.062683

[14]:
```
diabetes.describe(include=['object'])
```

[14]:
```
         State
count   243317
unique      52
top         MD
freq     10665
```

[15]:
```
diabetes.describe(include=['bool'])
```

[15]:
```
       Diabetes  HighBP HighChol CholCheck FruitConsume VegetableConsume  \
count    243317  243317   243317    243317       243317           243317
unique        2       2        2         2            2                2
top       False   False    False      True         True             True
freq     208018  139741   148839    234293       153361           199927

        Smoker HeavyDrinker  Stroke HeartDisease Healthcare NoDoctorDueToCost  \
count   243317       243317  243317       243317     243317            243317
unique       2            2       2            2          2                 2
top      False        False   False        False       True             False
freq    139605       228011  232711       220821     228085            220479

       PhysicalActivity DifficultyWalking  Gender
count            243317            243317  243317
unique                2                 2       2
top                True             False   False
freq             183214            202425  129062
```

[16]:
```
#Verifying value counts of categorical columns
for col in cols_category:
    print('Value counts in',col,'col in listings :\n',diabetes[col].
 ↪value_counts(),'\n')
```

```
Value counts in GeneralHealth col in listings :
 4    84200
3    75723
5    39314
2    32365
1    11715
Name: GeneralHealth, dtype: int64
```

```
Value counts in Age col in listings :
 10    29388
9     29375
11    25957
8     25881
7     21022
13    17454
6     17305
12    17221
5     15318
4     14407
3     12120
2      9406
1      8463
Name: Age, dtype: int64

Value counts in Education col in listings :
 6    104646
5     68338
4     57912
3      8565
2      3706
1       150
Name: Education, dtype: int64

Value counts in Income col in listings :
 8    92737
7    40474
6    33153
5    23208
4    19561
3    14739
2    10234
1     9211
Name: Income, dtype: int64
```

[17]:
```python
# Data Balance. Looking at what percentage of the data represents people with␣
↪diabetes
diabetes['Diabetes'].value_counts()
```

[17]:
```
False    208018
True      35299
Name: Diabetes, dtype: int64
```

[18]:
```python
diabetes['Diabetes'].value_counts()/diabetes.shape[0]
```

[18]:
```
False     0.854926
True      0.145074
Name: Diabetes, dtype: float64
```

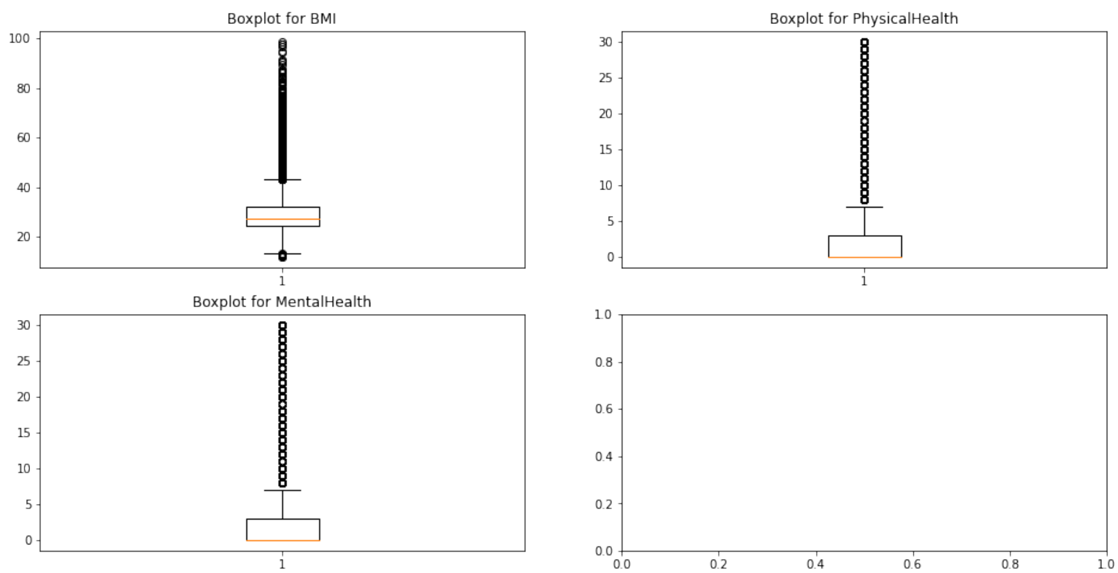
Note: We can see that 14% of the dataset represents those with diabetes. This is the minority class. Going ahead we will have to either oversample the minority class or undersample the majority class for machine learning.

Incidence of Diabetes in our dataset is slighly higher than national average data. According to CDC data 1 in 10 Americans(10%) have diabetes vis-a-vis our dataset where it is 14%. This could be because the samples were only collected from those who are abve the age of 18.

1.4.1 4. (b) Draw boxplots of attributes.

4.1 Boxplots for all Numeric Features

[19]:
```
row = 2
cols = 2
diabetes_float = diabetes[cols_float]
fig, ax = plt.subplots(row, cols, figsize=(16, 8))
for i in range(row):
    for j in range(cols):
        if(i*cols +j < len(diabetes_float.columns)):
            ax[i][j].boxplot(diabetes_float[diabetes_float.columns[i*cols +j]])

            ax[i][j].set_title("Boxplot for " + diabetes_float.columns[i*cols␣
↪+j])
```

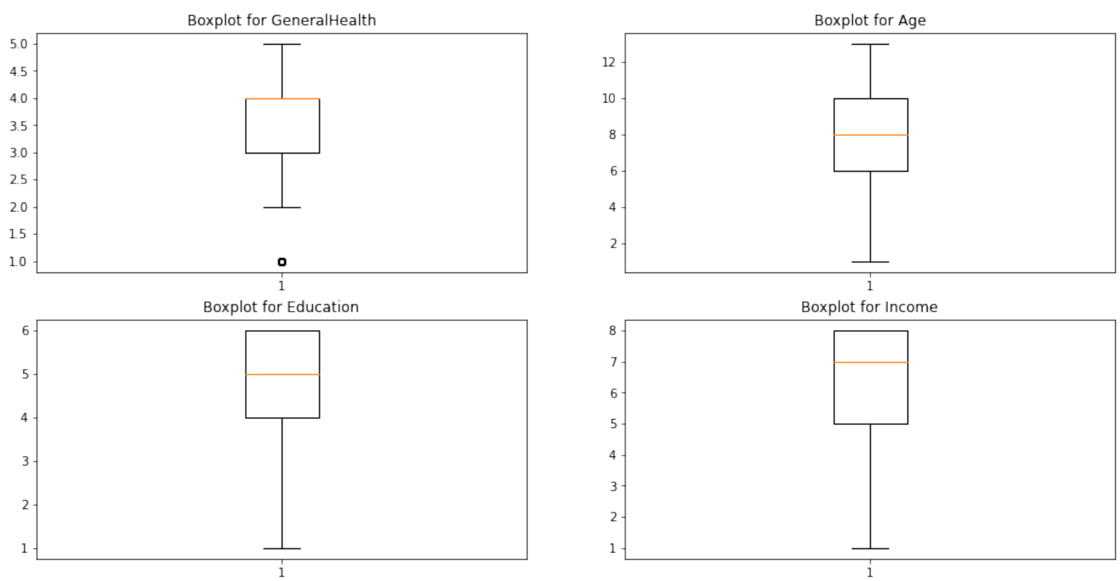


Boxplots' inference Note: Although we noticed that 98 BMI seemed very large. Looking at the boxplot we can see that there is a continous set of ouliers. These data points dont look like anomalies and therefore we are not removing any outlier from BMI.

- BMI - the Q1,Q2(median),Q3 are in expected range i.e. 22 to 25, minimum value = around 10, max value = approx 42 (except outliers)
- Physical Health and Mental Health - They have a similar boxplot with values varying between 0 and 8, Q1,Q2,Q3 as 0,0,4(apx) and outliers from 8 to 30

4.2 Boxplot for all Ordinal Categorical Features

[20]:
```
row = 2
cols = 2
diabetes_category = diabetes[cols_category]
fig, ax = plt.subplots(row, cols, figsize=(16, 8))
for i in range(row):
    for j in range(cols):
        if(i*cols +j < len(diabetes_category.columns)):
            ax[i][j].boxplot(diabetes_category[diabetes_category.columns[i*cols␣
 ↪+j]])
            ax[i][j].set_title("Boxplot for " + diabetes_category.
 ↪columns[i*cols +j])
```

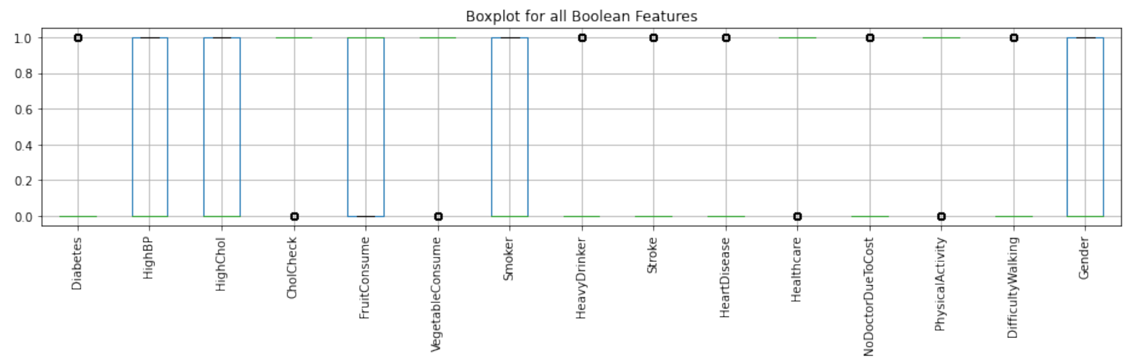


Note: looking at the boxplot we see that the medians for - General Health: category level = 4 which corresponds to Very good (5 is excellent 1 is poor) - Age: category level = 8 which corresponds to those between 55 and 59 years - Education: category level = 5 which corresponds to "College 1 year to 3 years (Some college or technical school)" - Income: category level = 7 which corresponds to income between 50,000 and 75,000 USD

4.3 Boxplot for all Boolean Features

[21]:
```
diabetes[cols_boolean].boxplot(figsize=(16,3), rot=90)
plt.title("Boxplot for all Boolean Features")
```

[21]: Text(0.5, 1.0, 'Boxplot for all Boolean Features')



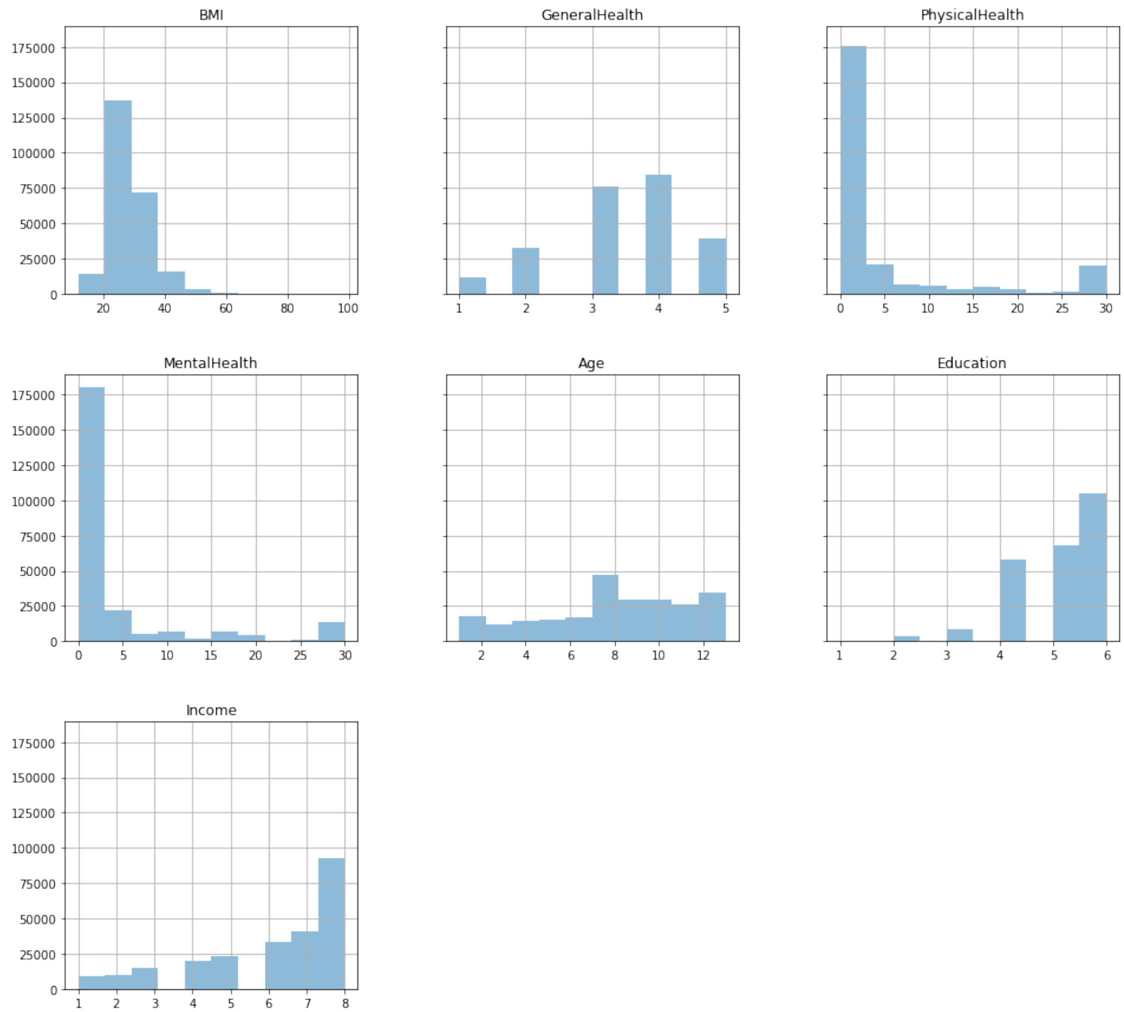
Note: As these are boolean features the boxplot is not very informative. We can tell that features with spread box are more evenly balanced between 0 and 1 value. A bar plot would be more useful.

1.4.2 5. Histograms and Barplots

5.1 Histograms for Numeric and Ordinal Categorical Features

[22]:
```
diabetes.hist(figsize=(16,15),alpha = 0.5,bins = 10, sharey=True)
plt.title("Histograms for Numerical and Ordinal Categorical Features")
```

[22]: Text(0.5, 1.0, 'Histograms for Numerical and Ordinal Categorical Features')



Histograms' inference As depicted by boxplot, histograms have the following characteristics:- - BMI has more values between bins 10 to 50 . It is unimodal and is a near-bell curve. - General Health has more values between bins 10 to 50. It is peaking at level 3 & 4 which is good to very good health. - Physical and Mental health show unimodal curves with right skewed distribution. - Age has a uniform distribution peaking between 7-8 i.e., between 50-60 years. - Education is a left skewed unimodal curve peaking at 6 (College 4 years or more). - Income is also left skewed peaking at 8 (greater than 75000 USD)

5.2 Barplots for Boolean Features and Target

[23]:
```
diabetes_bool = diabetes[cols_boolean]
boolean_percent = diabetes['Diabetes'].value_counts().to_frame()/diabetes.
 ↪shape[0]

for col in diabetes_bool.columns:
    if(col!='Diabetes'):
```

```
        mini = diabetes[col].value_counts().to_frame()/diabetes.shape[0]
        boolean_percent = pd.concat([boolean_percent, mini], axis=1,␣
 ↪ignore_index=True)

boolean_percent.columns = [cols_boolean]
boolean_percent
```

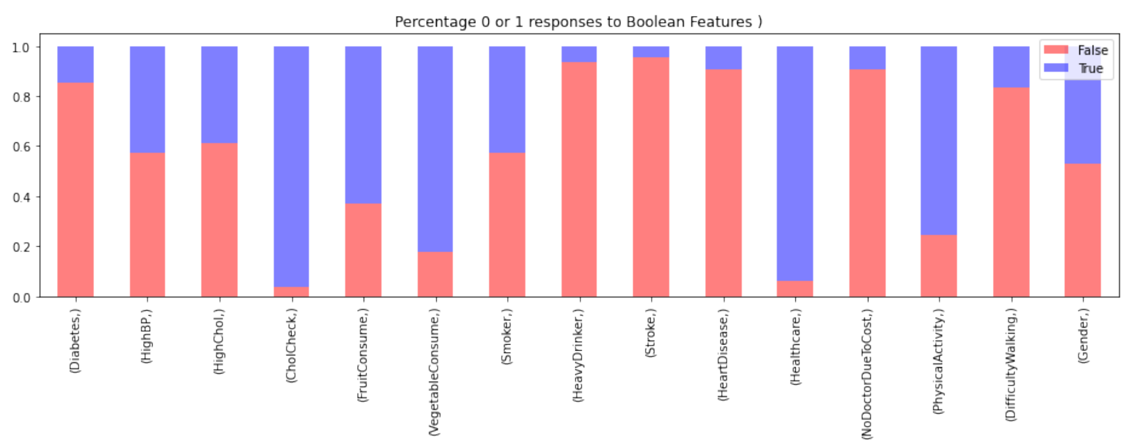
[23]:

```
        Diabetes    HighBP  HighChol  CholCheck FruitConsume VegetableConsume  \
False   0.854926  0.574317  0.611708  0.037087      0.369707          0.178327
True    0.145074  0.425683  0.388292  0.962913      0.630293          0.821673

          Smoker HeavyDrinker    Stroke HeartDisease Healthcare  \
False   0.573758      0.937094  0.956411      0.907544    0.062601
True    0.426242      0.062906  0.043589      0.092456    0.937399

      NoDoctorDueToCost PhysicalActivity DifficultyWalking    Gender
False          0.906139         0.247015          0.831939  0.530427
True           0.093861         0.752985          0.168061  0.469573
```

[24]:

```
boolean_percent = boolean_percent.transpose()
boolean_percent.plot(kind='bar',color=['red', 'blue'],stacked = True, alpha =0.
 ↪5,figsize=(16,4), rot=90)
plt.title("Percentage 0 or 1 responses to Boolean Features )")
```

[24]: Text(0.5, 1.0, 'Percentage 0 or 1 responses to Boolean Features)')

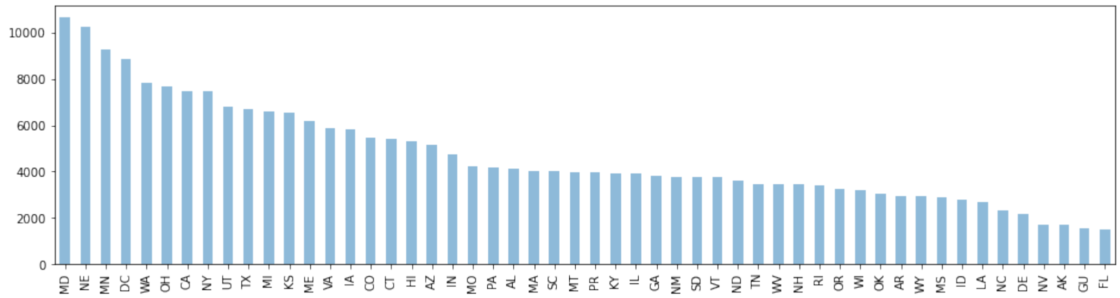


- This shows the data balance between various boolean variables.
- On a generalization perspective, dataset is balanced by the gender ratio.
- As highlighted earlier, diabeletes (target for classification) is imbalanced.

5.3 Data Distribution across Different States

[25]:
```
diabetes['State'].value_counts().plot(kind='bar', alpha =0.5,figsize=(16,4), rot=90)
```

[25]: `<AxesSubplot:>`

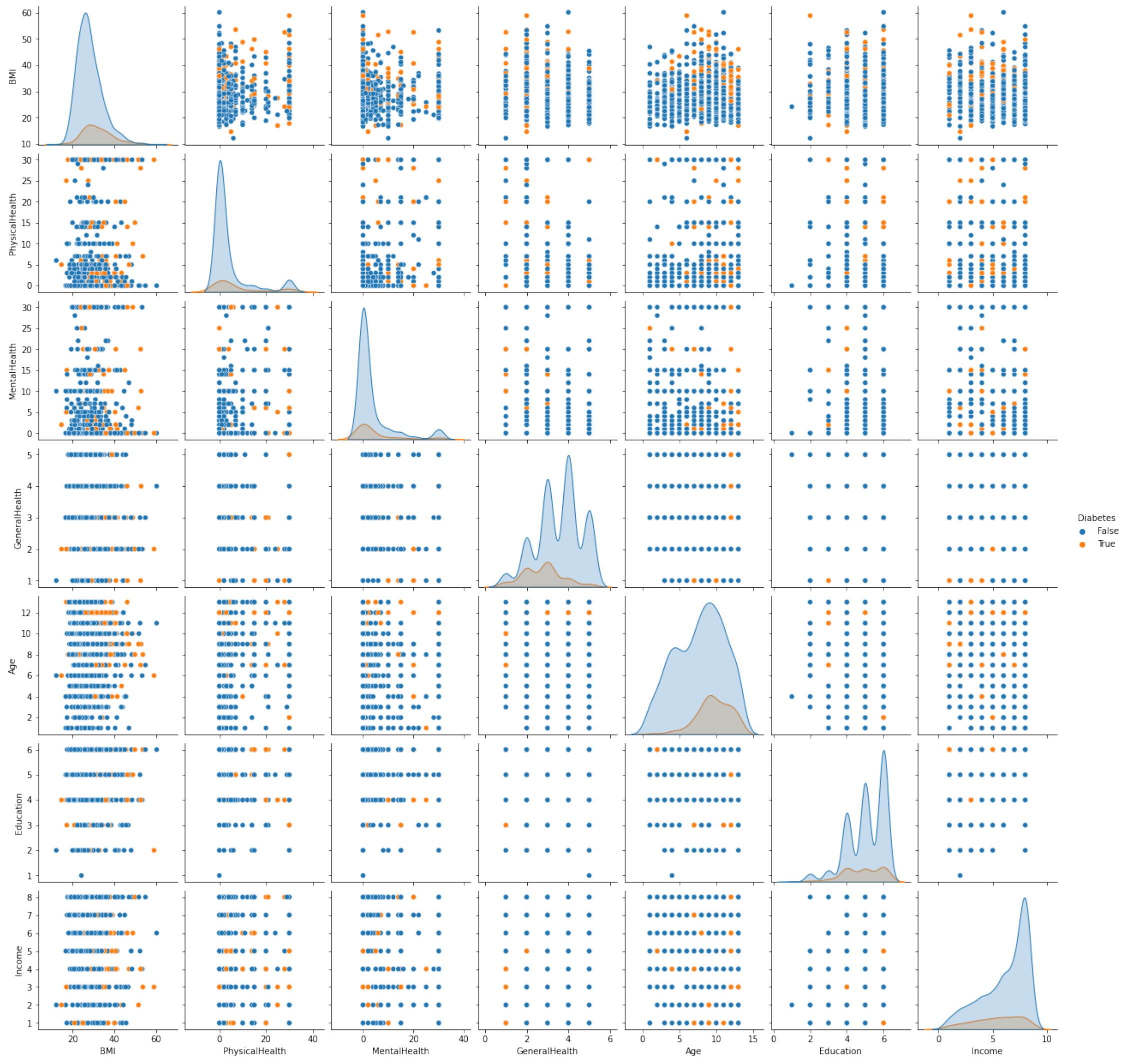


1.4.3 6. (c) Draw Pairplots

- For example, you can use import seaborn as sns;and then use sns.pairplot()

[26]:
```
# trying different color schemes
palette = sns.color_palette("bright")

# creating list of all floats and categorical value + the target
sns_list = cols_float.tolist() + cols_category.tolist() + ['Diabetes']

#sampling a random number of values since plotting all 0.2 million datapoints will make the plot unreadable
number_of_samples = 1000
diabetes_sample = diabetes.sample(number_of_samples)
df_plot =diabetes_sample[sns_list]
sns.pairplot(df_plot, hue='Diabetes', plot_kws={'alpha':1})
```

[26]: `<seaborn.axisgrid.PairGrid at 0x290e2af73d0>`



Pairplots' inference

- Since we have 23 data columns, we are selecting only a subset of columns as pairplots that ordinal or of float type.
- Additionally to reduce computation time we are randomly sampling only 1000 rows for the total (0.2 million+) data frame. This makes the plots clearer to see as well
- From the scatter plots, there isn't an appropriate correlation visible with the naked eye
- Hence, we will make a heatmap and also find correlation among all the columns

1.4.4 7. (d) If the scatter plot shows a correlation among variables, then calculate the correlation. We can use the following command for this purpose.

[27]:
```
diabetes.corr()
```

[27]:

	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	

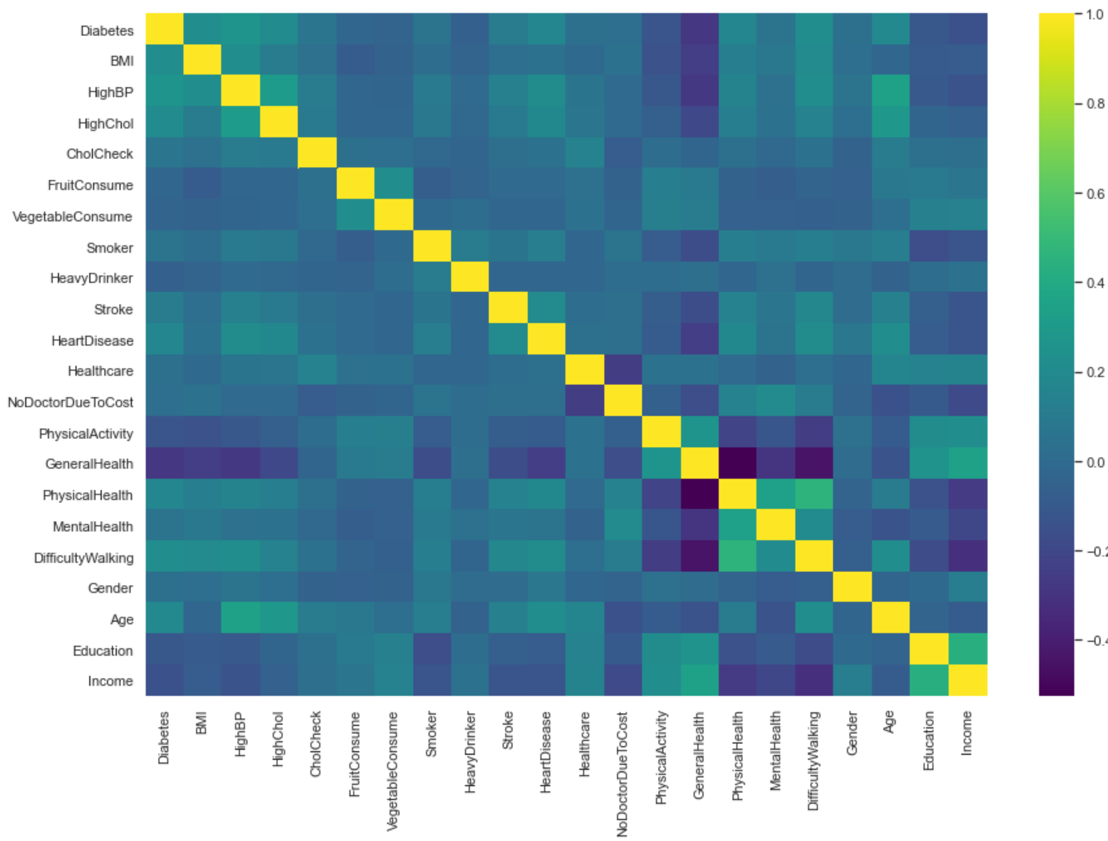
	GeneralHealth	PhysicalHealth	MentalHealth	\
Diabetes	-0.284712	0.173316	0.053553	
BMI	-0.250105	0.123211	0.083946	
HighBP	-0.280748	0.159268	0.038884	
HighChol	-0.194416	0.122674	0.042723	
CholCheck	-0.033767	0.030213	-0.017127	
FruitConsume	0.094812	-0.045607	-0.075855	
VegetableConsume	0.107386	-0.055045	-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]
```

Plotting a sns heatmap for better clarity

[28]:
```
sns.set(rc = {'figure.figsize':(15,10)})
sns.heatmap(diabetes.corr(), annot=False, vmax=1, cmap='viridis', square=False)
```

[28]: <AxesSubplot:>



Correlations' and heatmap's inference

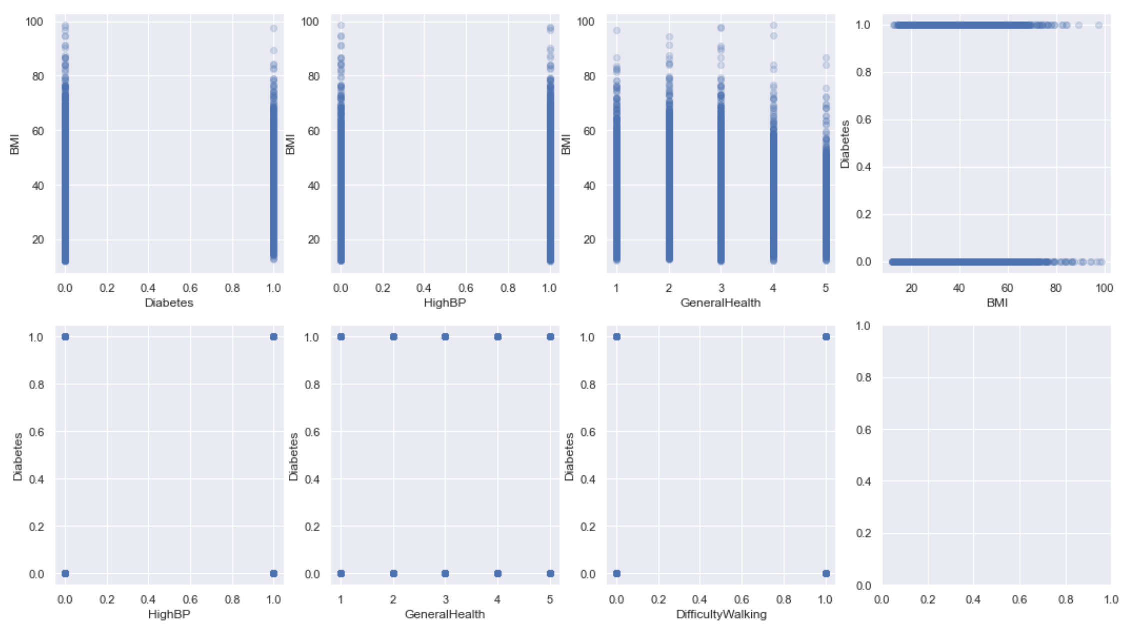
- BMI has a certain degree of correlation with Diabetes, High BP, Physical,Mental Health & Difficulty walking.
- Diabetes has a certain degree of correlation with BMI, High BP, High Chol, Smoker, Stroke, Heart Disease, Physical Health & Difficulty walking.
- Surprisingly, Physical Health, Mental health and Difficulty Walking are correlated.
- General Health and Vegetable & Fruit Consumption is moderately correlated.
- No parameter has very high degree of correlation(yellow).

Plotting the high correlation scatter plots

[29]:
```
fig, ((ax1,ax2,ax3,ax4),(ax5,ax6,ax7,ax8)) = plt.subplots(2,4, figsize=[18,10])
ax1.scatter (x=diabetes['Diabetes'] ,y=diabetes['BMI'], alpha=0.2)
ax1.set_xlabel('Diabetes')
ax1.set_ylabel('BMI')
ax2.scatter (x=diabetes['HighBP'] ,y=diabetes['BMI'],alpha=0.2)
ax2.set_xlabel('HighBP')
ax2.set_ylabel('BMI')
ax3.scatter (x=diabetes['GeneralHealth'] ,y=diabetes['BMI'],alpha=0.2)
ax3.set_xlabel('GeneralHealth')
```

```
ax3.set_ylabel('BMI')
ax4.scatter (x=diabetes['BMI'] ,y=diabetes['Diabetes'],alpha=0.2)
ax4.set_xlabel('BMI')
ax4.set_ylabel('Diabetes')
ax5.scatter (x=diabetes['HighBP'] ,y=diabetes['Diabetes'],alpha=0.2)
ax5.set_xlabel('HighBP')
ax5.set_ylabel('Diabetes')
ax6.scatter (x=diabetes['GeneralHealth'] ,y=diabetes['Diabetes'],alpha=0.2)
ax6.set_xlabel('GeneralHealth')
ax6.set_ylabel('Diabetes')
ax7.scatter (x=diabetes['DifficultyWalking'] ,y=diabetes['Diabetes'],alpha=0.2)
ax7.set_xlabel('DifficultyWalking')
ax7.set_ylabel('Diabetes')
```

[29]: Text(0, 0.5, 'Diabetes')



2 Conclusion

- We converted certain features to boolean which had only True/False values, few as cateogircal (having more than 2 categories). We also dropped the first column which was a duplicate for already existing index.
- We displayed general data shape,spread and dispersion with head, tail, shape and info.
- We displayed the descriptive statistics for bool, categorical, integer features.
- To get more insights into the dataset, we have plotted the following:-
- Boxplots for different quartiles and outliers.
- Histograms for data modality and frequencies.

- Scatter and Pair Plots to get relationship between each set of 2 variables.
- Pearson Correlation factors to get get r-value between each set of 2 variables.
- Bar graph to show data distribution among variables features.
- Heatmap displaying the correlation visually.
- Highly correlated features do not show any linear correlation on the scatter plots so we might see some degree of correlation in Decision Trees and Random Forests. Also, a reason for this is the prominence of categorical & boolean variables over continuous(numerical) variables.

Note : Please refer to individual sections for detailed summaries and inferences