Information about the data:

```
-> The dataset was taken from PIMA Indian Diabetes Database

-> This dataset is also available in the Kaggle

-> The dataset consists of the following features:

    Pregnancies : Number of times pregnant

    Glucose     : Plasma glucose concentration over 2 hours in  an
oral glucose torelance test

    Blood Pressure : Diastolic blood pressure

    Skin Thickness : Triceps skin fold thickness

    Insulin        : 2 hours serum insulin

    BMI            : Body Mass Index

    Diabetes Pedigree Function : Likelihood of diabates based on fam
ily history

    Age             : Age of the patient

    Outcome(Class label) : Class variable

                                 : 0 IF NON-DIABETIC

                                 : 1 IF DIABETIC
```

OBJECTIVE:

```
USING MACHINE LEARNING ANALYSIS AND MODEL TO PREDICT WHETHER A PERSO
N HAS DIABETES OR NOT
```

Importing the required libraries:

```
Numpy : To convert data into suitable format to feed the classificat
ion model

Pandas : To read data from CSV file and to store the data in form of
Dataframe for further computations

Seaborn and Matplotlib for visualizations
```

```
Sklearn : To import the model and joblib to save the model
```

In [4]:

```python
import numpy as np
import pandas as pd
import seaborn as s
import matplotlib.pyplot as mp
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.externals import joblib
```

-> The shape of data is 768 data points with 9 features each

-> The number of features/columns for each data point are 9

In [9]:

```python
data = pd.read_csv("diabetes.csv")
print(data.shape)
print(data.columns)
print(data.ndim)
```

```
(768, 9)
Index(['Pregnancies', 'Glucose', 'BloodPressure', 'SkinThickness', 'Insulin
',
       'BMI', 'DiabetesPedigreeFunction', 'Age', 'Outcome'],
      dtype='object')
2
```

Sample Data

In [12]:

```python
print(data.head(5))
```

```
   Pregnancies  Glucose  BloodPressure  SkinThickness  Insulin   BMI  \
0            6      148             72             35        0  33.6
1            1       85             66             29        0  26.6
2            8      183             64              0        0  23.3
3            1       89             66             23       94  28.1
4            0      137             40             35      168  43.1

   DiabetesPedigreeFunction  Age  Outcome
0                     0.627   50        1
1                     0.351   31        0
2                     0.672   32        1
3                     0.167   21        0
4                     2.288   33        1
```

Data Pre-Processing and Cleaning:

```
-> Mean imputation for the null values

-> Removing outliers

-> Checking the Correlation between the features
```

In [14]:

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 768 entries, 0 to 767
Data columns (total 9 columns):
Pregnancies                 768 non-null int64
Glucose                     768 non-null int64
BloodPressure               768 non-null int64
SkinThickness               768 non-null int64
Insulin                     768 non-null int64
BMI                         768 non-null float64
DiabetesPedigreeFunction    768 non-null float64
Age                         768 non-null int64
Outcome                     768 non-null int64
dtypes: float64(2), int64(7)
memory usage: 54.1 KB
```

In [16]:

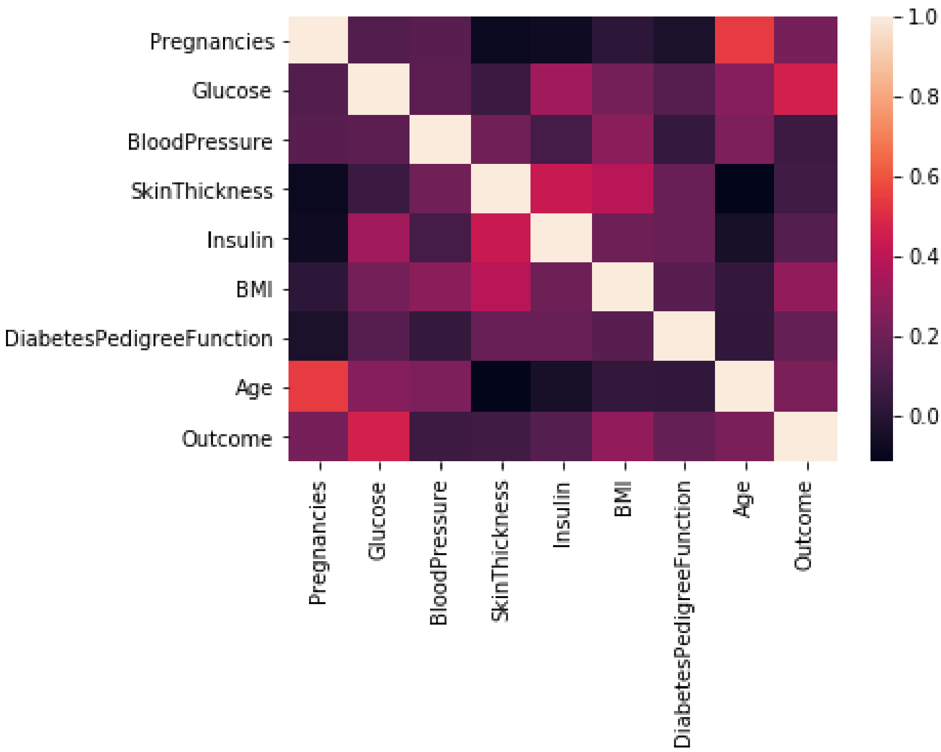
```
corr = data.corr()
print(corr)
s.heatmap(corr, xticklabels=corr.columns, yticklabels= corr.columns)
```

```
                          Pregnancies   Glucose  BloodPressure
SkinThickness  \
Pregnancies                  1.000000  0.129459       0.141282      -0.0816
2
Glucose                      0.129459  1.000000       0.152590
0.057328
BloodPressure                0.141282  0.152590       1.000000       0.2073
1
SkinThickness               -0.081672  0.057328       0.207371       1.0000
0
Insulin                     -0.073535  0.331357       0.088933
0.436783
BMI                          0.017683  0.221071       0.281805
0.392573
DiabetesPedigreeFunction    -0.033523  0.137337       0.041265       0.1839
8
Age                          0.544341  0.263514       0.239528      -
0.113970
Outcome                      0.221898  0.466581       0.065068
0.074752

                           Insulin       BMI  DiabetesPedigreeFunction  \
Pregnancies              -0.073535  0.017683                 -0.033523
Glucose                   0.331357  0.221071                  0.137337
BloodPressure             0.088933  0.281805                  0.041265
SkinThickness             0.436783  0.392573                  0.183928
Insulin                   1.000000  0.197859                  0.185071
BMI                       0.197859  1.000000                  0.140647
DiabetesPedigreeFunction  0.185071  0.140647                  1.000000
Age                      -0.042163  0.036242                  0.033561
Outcome                   0.130548  0.292695                  0.173844

                               Age   Outcome
Pregnancies               0.544341  0.221898
```

```
Glucose                     0.263514  0.466581
BloodPressure               0.239528  0.065068
SkinThickness              -0.113970  0.074752
Insulin                    -0.042163  0.130548
BMI                         0.036242  0.292695
DiabetesPedigreeFunction    0.033561  0.173844
Age                         1.000000  0.238356
Outcome                     0.238356  1.000000
```

Out[16]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x2717159f048>
```



Observation :

```
-> The brighter colors indicates more correlation between the featur
es

-> From the table and heatmap, Glucose levels, BMI, Age, Pregnancies
have more correlation with the outcome
```

-> Splitting the dataset to Train, Test, cross check

-> Seperating the class labels from the data

-> Normalizing the data

In [123]:

```
traindata = data[150:]
testdata = data[18:150]
checkdata = data[0:18]
print(traindata.shape)
print(testdata.shape)
print(checkdata.shape)
```

```
print(checkdata.shape)
```

```
(618, 9)
(132, 9)
(18, 9)
```

In [124]:

```
train_label = np.asarray(traindata['Outcome'])
train_data = traindata.drop('Outcome', 1)
test_label = np.asarray(testdata['Outcome'])
test_data = testdata.drop('Outcome',1)
print(train_data.shape)
print(train_label.shape)
print(test_data.shape)
print(test_label.shape)
```

```
(618, 8)
(618,)
(132, 8)
(132,)
```

In [125]:

```
mean = np.mean(train_data, axis=0)
std = np.std(train_data, axis=0)

train_data = (train_data - mean)/std

test_data = (test_data - mean)/std
print(mean)
```

```
Pregnancies                   3.784790
Glucose                     121.736246
BloodPressure                69.199029
SkinThickness                20.771845
Insulin                      81.527508
BMI                          32.161327
DiabetesPedigreeFunction      0.475333
Age                          33.174757
dtype: float64
```

TRAINING AND EVALUATING MACHINE LEARNING MODEL

In [126]:

```
model = LogisticRegression()
print(model)
model.fit(train_data, train_label)
```

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

Out[126]:

```
LogisticRegression(C=1.0, class_weight=None, dual=False,
fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=1,
          penalty='l2', random_state=None, solver='liblinear', tol=0.0001,
```

```
          verbose=0, warm_start=False)
```

In [127]:

```
accuracy = model.score(test_data, test_label)
accuracy = accuracy*100
print(accuracy)
```

```
80.3030303030303
```

MODEL INTERPRETATION:

To check how different features have greater impact on the model

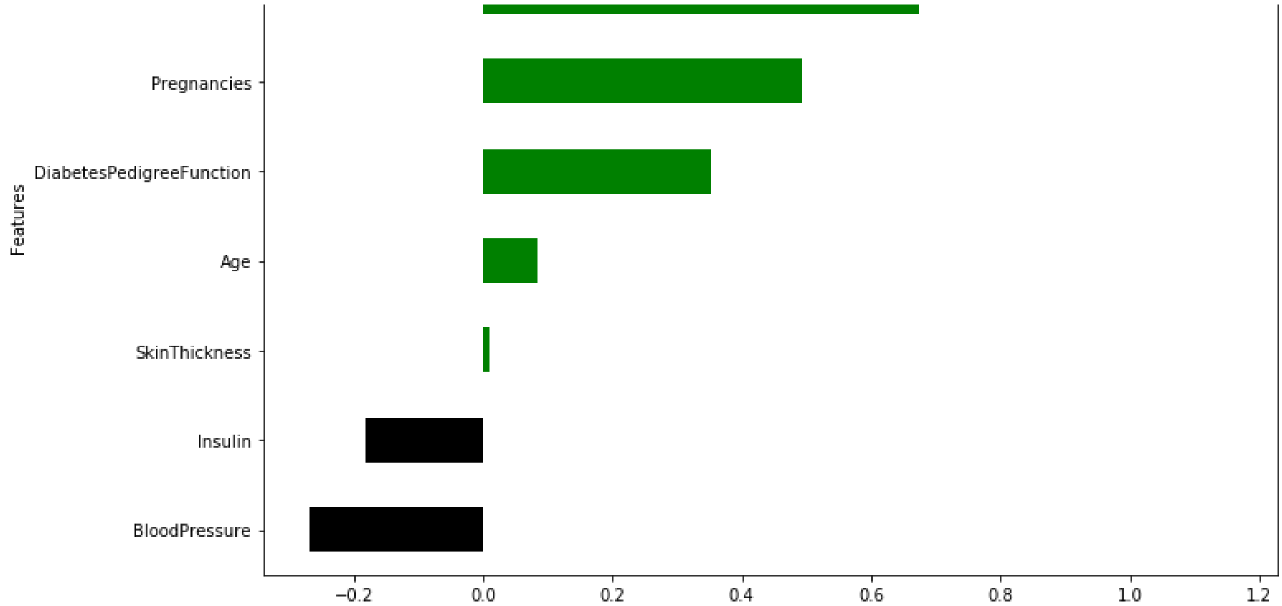
In [128]:

```
coef = list(model.coef_[0])
print(coef)
label = train_data.columns
print(labels)
features = pd.DataFrame()
print(len(coef))
print(len(label))
features['Features'] = label
features['Weights'] = coef
print(features)
features.sort_values(by=['Weights'], ascending= True, inplace=True)
features['positive'] = features['Weights'] > 0
features.set_index("Features", inplace=True)
features.Weights.plot(kind='barh', figsize=(11,8))
features.Weights.plot(kind = 'barh', figsize=(11,8), color =
features.positive.map({True:'green', False:'black'}))
```

```
[0.49342213322606715, 1.1564127300424993, -0.2691681507254062,
0.010539700806471045, -0.18173978760864634, 0.6729906109892765, 0.352934462
6930496, 0.0832145914265438]
Index(['Pregnancies', 'Glucose', 'BloodPressure', 'SkinThickness', 'Insulin
',
       'BMI', 'DiabetesPedigreeFunction', 'Age'],
      dtype='object')
8
8
                   Features   Weights
0               Pregnancies  0.493422
1                   Glucose  1.156413
2             BloodPressure -0.269168
3             SkinThickness  0.010540
4                   Insulin -0.181740
5                       BMI  0.672991
6  DiabetesPedigreeFunction  0.352934
7                       Age  0.083215
```

Out[128]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x27101a7fdd8>
```



Observation:

```
-> From the above plot:

    -> Glucose level, BMI, Pregnancies, DiabetesPedigreeFunction hav
e more impact on the model

    -> Insulin and Blood pressure have negative influence of preicti
on on the model
```

SAVING THE MODEL:

In [129]:

```
joblib.dump([model, mean, std], "diabetes_model")
```

Out[129]:

```
['diabetes_model']
```

Obseravtion:

```
To check our model is saved properly or not, we have test the accura
cy of the model on the test data which we have done

it previously and if there is no change in the accuracy then we save
d our model perfectly
```

In [130]:

```
loaded_model, means, stds = joblib.load('diabetes_model')
score = loaded_model.score(test_data, test_label)
acc = score*100
print("The accuracy before saving the model is : 80.30303030303")
print("The accuracy after saving the model is :", acc)
```

```
The accuracy before saving the model is : 80.30303030303
```

```
The accuracy after saving the model is : 80.3030303030303
```

MODEL PREDIICTION:

    We have used the test data for accuracy check and also we have the U
    nseen data. We have the unseed data in the checkdata

In [141]:

```
checkdata.head(5)
```

Out[141]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunct
0	6	148	72	35	0	33.6	0.627
1	1	85	66	29	0	26.6	0.351
2	8	183	64	0	0	23.3	0.672
3	1	89	66	23	94	28.1	0.167
4	0	137	40	35	168	43.1	2.288

In [173]:

```
sample_data = checkdata[17:]
sample_data_features = np.asarray(sample_data.drop('Outcome',1))
sample_data_features = (sample_data_features-means)/stds
print(sample_data_features)
prediction = loaded_model.predict(sample_data_features)
print(prediction)
```

```
[[  7.    107.     74.      0.      0.     29.6     0.254   31.    ]]
[1]
```

Observation:

    The model has predicted the outcome as 1, which means that the perso
    n has diabetes.

CONCLUSION:

    This is the end to end data science example. Cleaning of data, pre-p
    rocessing, Imputation of missing values,

    Handling categorical values, dividing the data, selecting and traini
    ng the model, accuracy check on the model,

    saving the model, loading the model and checking accuracy with unsee
    n data on model. This models accuracy can

    be improved with the help of domain knowledge.