Diabetes Project

January 29, 2024

[1]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

import warnings
warnings.filterwarnings('ignore')
```

[2]:

```
diabetes_data = pd.read_csv('health care diabetes.csv')
```

[3]:

```
# Preview data
diabetes_data.head()
```

[3]:

```
   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
```

[4]:

```
# Dataset dimensions - (rows, columns)
diabetes_data.shape
```

[4]:

```
(768, 9)
```

[5]:

```
# Features data-type
diabetes_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 768 entries, 0 to 767
Data columns (total 9 columns):
 #   Column                    Non-Null Count  Dtype  
---  ------                    --------------  -----  
 0   Pregnancies               768 non-null    int64  
 1   Glucose                   768 non-null    int64  
 2   BloodPressure             768 non-null    int64  
 3   SkinThickness             768 non-null    int64  
 4   Insulin                   768 non-null    int64  
 5   BMI                       768 non-null    float64
 6   DiabetesPedigreeFunction  768 non-null    float64
 7   Age                       768 non-null    int64  
 8   Outcome                   768 non-null    int64  
dtypes: float64(2), int64(7)
memory usage: 54.1 KB
```

[6]:
```
# Statistical summary
diabetes_data.describe()
```

[6]:
```
       Pregnancies     Glucose  BloodPressure  SkinThickness     Insulin  \
count   768.000000  768.000000     768.000000     768.000000  768.000000   
mean      3.845052  120.894531      69.105469      20.536458   79.799479   
std       3.369578   31.972618      19.355807      15.952218  115.244002   
min       0.000000    0.000000       0.000000       0.000000    0.000000   
25%       1.000000   99.000000      62.000000       0.000000    0.000000   
50%       3.000000  117.000000      72.000000      23.000000   30.500000   
75%       6.000000  140.250000      80.000000      32.000000  127.250000   
max      17.000000  199.000000     122.000000      99.000000  846.000000   

              BMI  DiabetesPedigreeFunction         Age     Outcome  
count  768.000000                768.000000  768.000000  768.000000  
mean    31.992578                  0.471876   33.240885    0.348958  
std      7.884160                  0.331329   11.760232    0.476951  
min      0.000000                  0.078000   21.000000    0.000000  
25%     27.300000                  0.243750   24.000000    0.000000  
50%     32.000000                  0.372500   29.000000    0.000000  
75%     36.600000                  0.626250   41.000000    1.000000  
max     67.100000                  2.420000   81.000000    1.000000  
```

[8]:
```
# Count of null values
diabetes_data.isnull().sum()
```

[8]:
```
Pregnancies                 0
Glucose                     0
BloodPressure               0
SkinThickness               0
Insulin                     0
BMI                         0
DiabetesPedigreeFunction    0
```

```
Age                         0
Outcome                     0
dtype: int64
```

[9]:

```
diabetes_data.describe().T
```

[9]:

```
                          count        mean         std     min       25%  \
Pregnancies               768.0    3.845052    3.369578   0.000   1.00000
Glucose                   768.0  120.894531   31.972618   0.000  99.00000
BloodPressure             768.0   69.105469   19.355807   0.000  62.00000
SkinThickness             768.0   20.536458   15.952218   0.000   0.00000
Insulin                   768.0   79.799479  115.244002   0.000   0.00000
BMI                       768.0   31.992578    7.884160   0.000  27.30000
DiabetesPedigreeFunction  768.0    0.471876    0.331329   0.078   0.24375
Age                       768.0   33.240885   11.760232  21.000  24.00000
Outcome                   768.0    0.348958    0.476951   0.000   0.00000

                               50%        75%     max
Pregnancies                 3.0000    6.00000   17.00
Glucose                   117.0000  140.25000  199.00
BloodPressure              72.0000   80.00000  122.00
SkinThickness              23.0000   32.00000   99.00
Insulin                    30.5000  127.25000  846.00
BMI                        32.0000   36.60000   67.10
DiabetesPedigreeFunction    0.3725    0.62625    2.42
Age                        29.0000   41.00000   81.00
Outcome                     0.0000    1.00000    1.00
```

[10]:

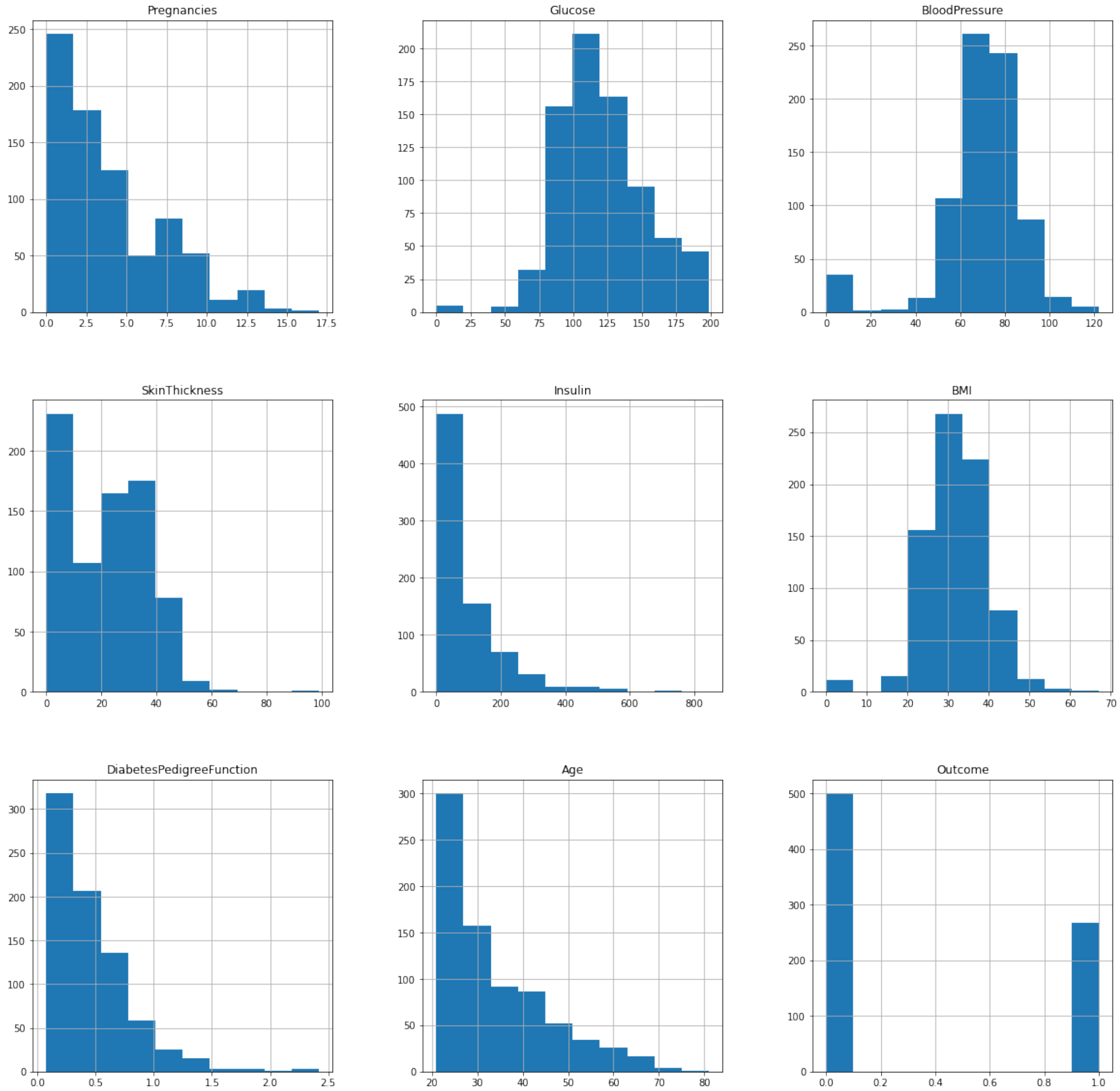
```
diabetes_data_copy = diabetes_data.copy(deep = True)
diabetes_data_copy[['Glucose','BloodPressure','SkinThickness','Insulin','BMI']]␣
 ↪=␣
 ↪diabetes_data_copy[['Glucose','BloodPressure','SkinThickness','Insulin','BMI']].
 ↪replace(0,np.NaN)

## showing the count of Nans
print(diabetes_data_copy.isnull().sum())
```

```
Pregnancies                   0
Glucose                       5
BloodPressure                35
SkinThickness               227
Insulin                     374
BMI                          11
DiabetesPedigreeFunction      0
Age                           0
Outcome                       0
dtype: int64
```

[11]:

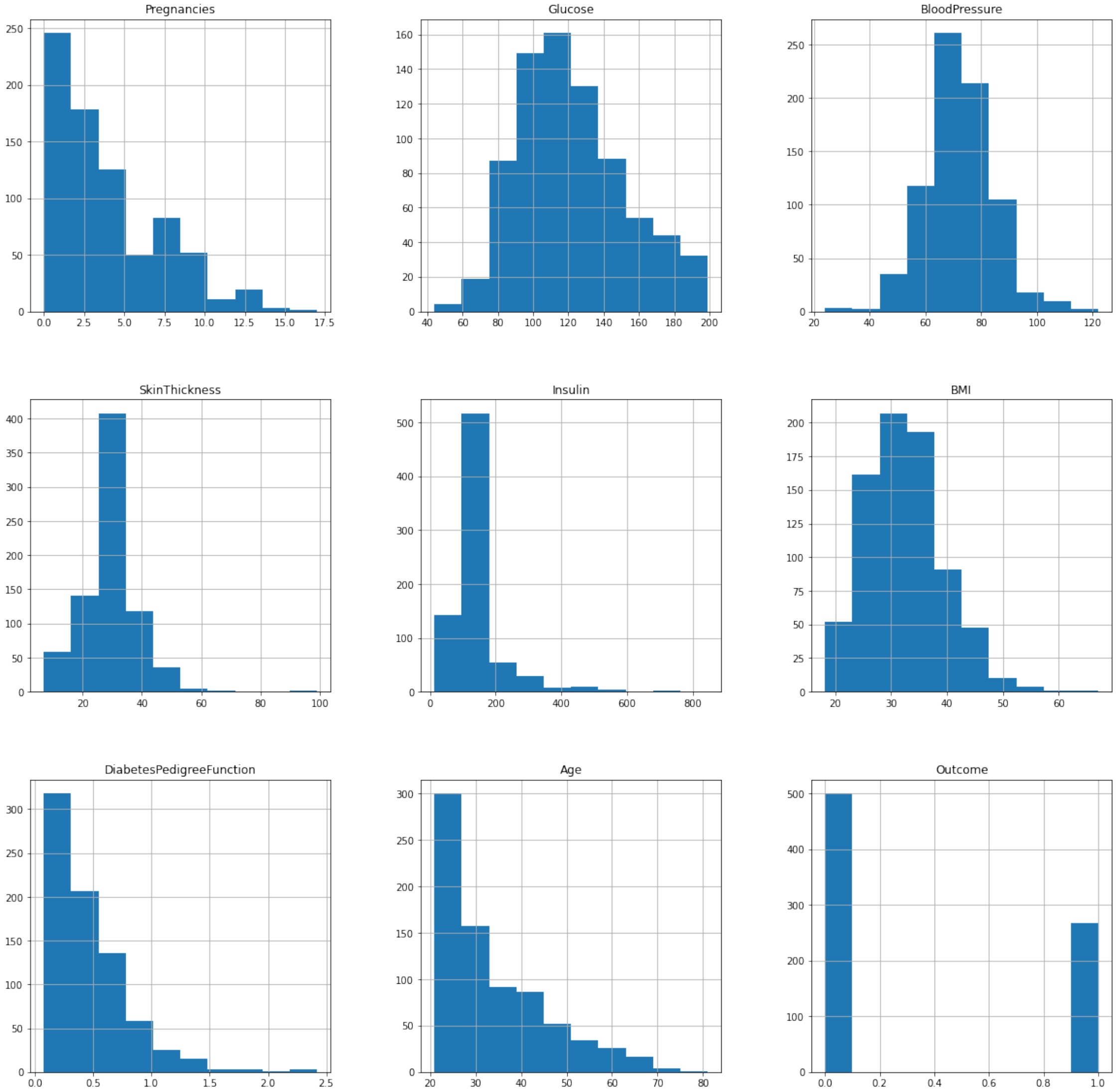
```
p = diabetes_data.hist(figsize = (20,20))
```



[12]:

```
diabetes_data_copy['Glucose'].fillna(diabetes_data_copy['Glucose'].mean(), inplace = True)
diabetes_data_copy['BloodPressure'].fillna(diabetes_data_copy['BloodPressure'].mean(), inplace = True)
diabetes_data_copy['SkinThickness'].fillna(diabetes_data_copy['SkinThickness'].median(), inplace = True)
diabetes_data_copy['Insulin'].fillna(diabetes_data_copy['Insulin'].median(), inplace = True)
diabetes_data_copy['BMI'].fillna(diabetes_data_copy['BMI'].median(), inplace = True)
```

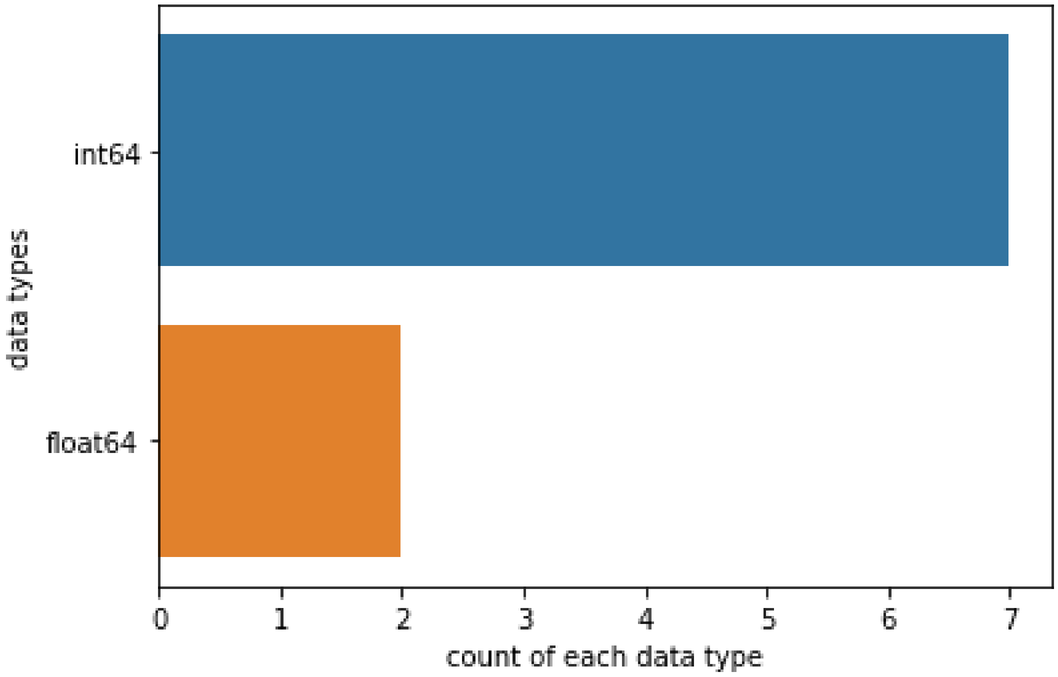
```
[13]: p = diabetes_data_copy.hist(figsize = (20,20))
```



```
[14]: diabetes_data.shape
```

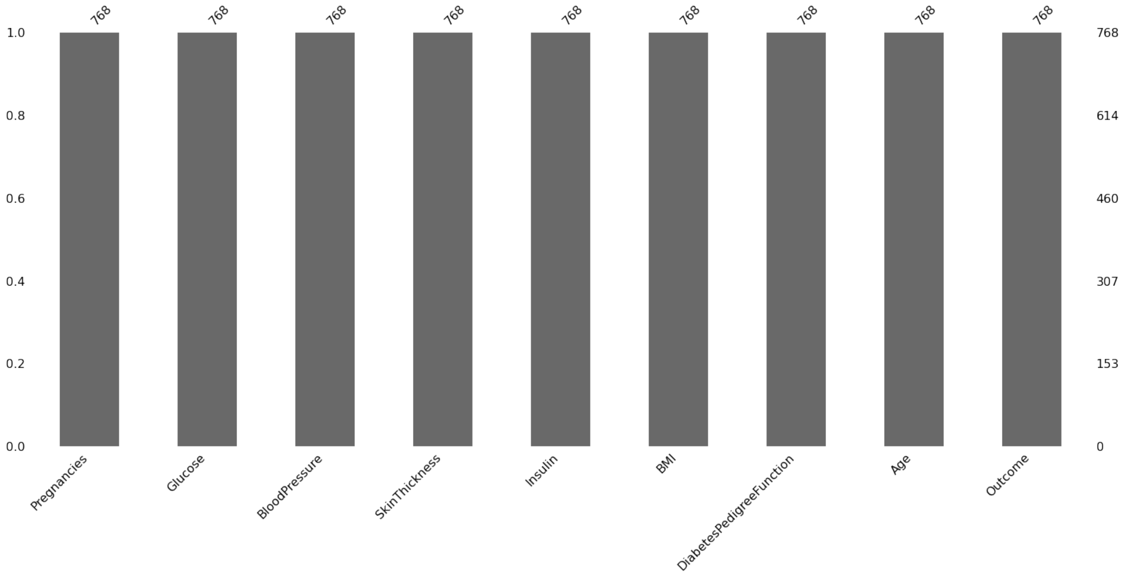
```
[14]: (768, 9)
```

```
[23]: sns.countplot(y=diabetes_data.dtypes ,data=diabetes_data)
      plt.xlabel("count of each data type")
      plt.ylabel("data types")
      plt.show()
```



[24]:

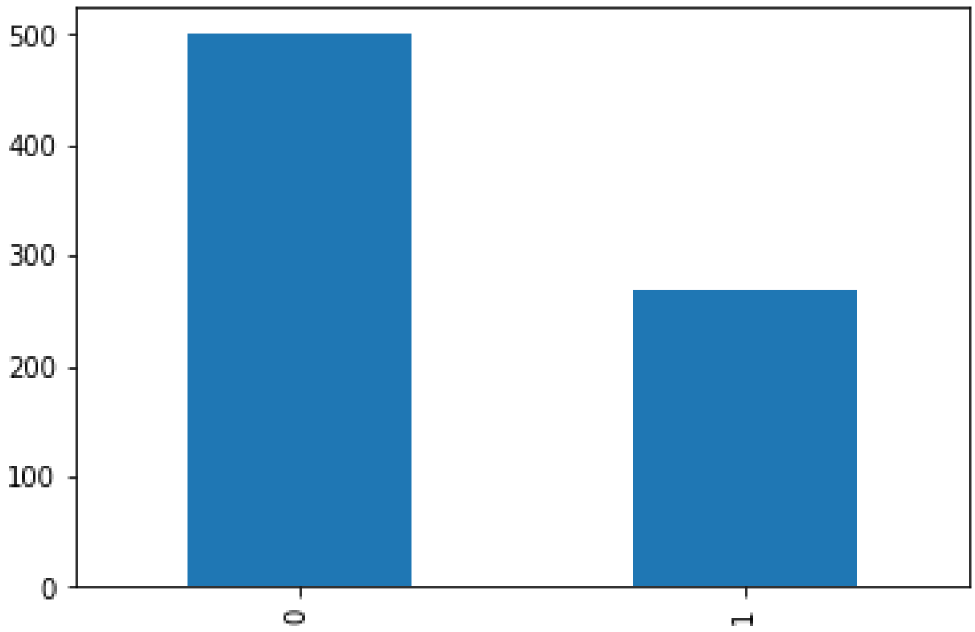
```
## null count analysis
import missingno as msno
p=msno.bar(diabetes_data)
```



[25]:

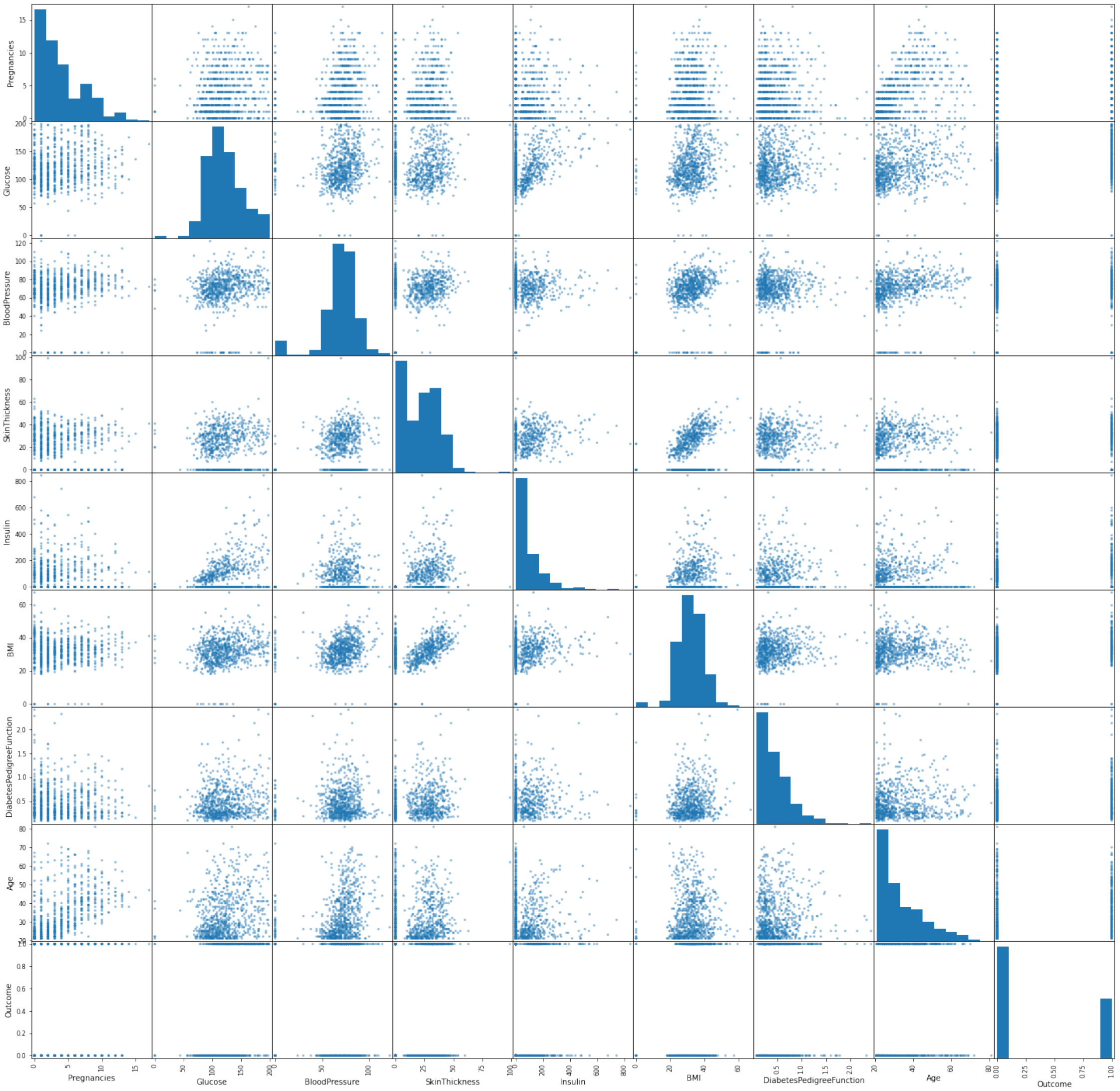
```
## checking the balance of the data by plotting the count of outcomes by their␣
↪value
color_wheel = {1: "#0392cf",
               2: "#7bc043"}
colors = diabetes_data["Outcome"].map(lambda x: color_wheel.get(x + 1))
print(diabetes_data.Outcome.value_counts())
p=diabetes_data.Outcome.value_counts().plot(kind="bar")
```

```
0    500
1    268
Name: Outcome, dtype: int64
```



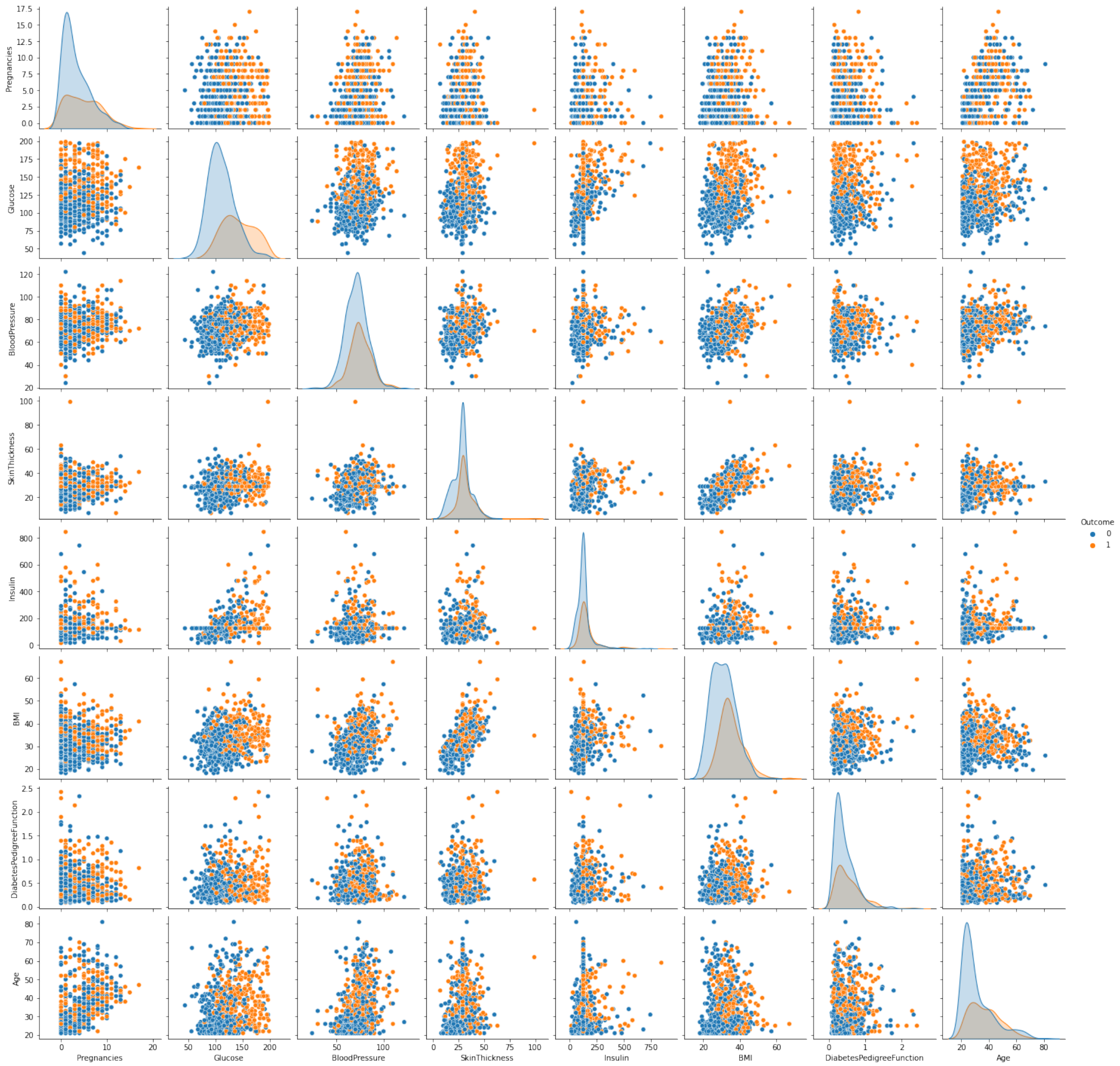
[27]:

```
from pandas.plotting import scatter_matrix
p=scatter_matrix(diabetes_data,figsize=(25, 25))
```



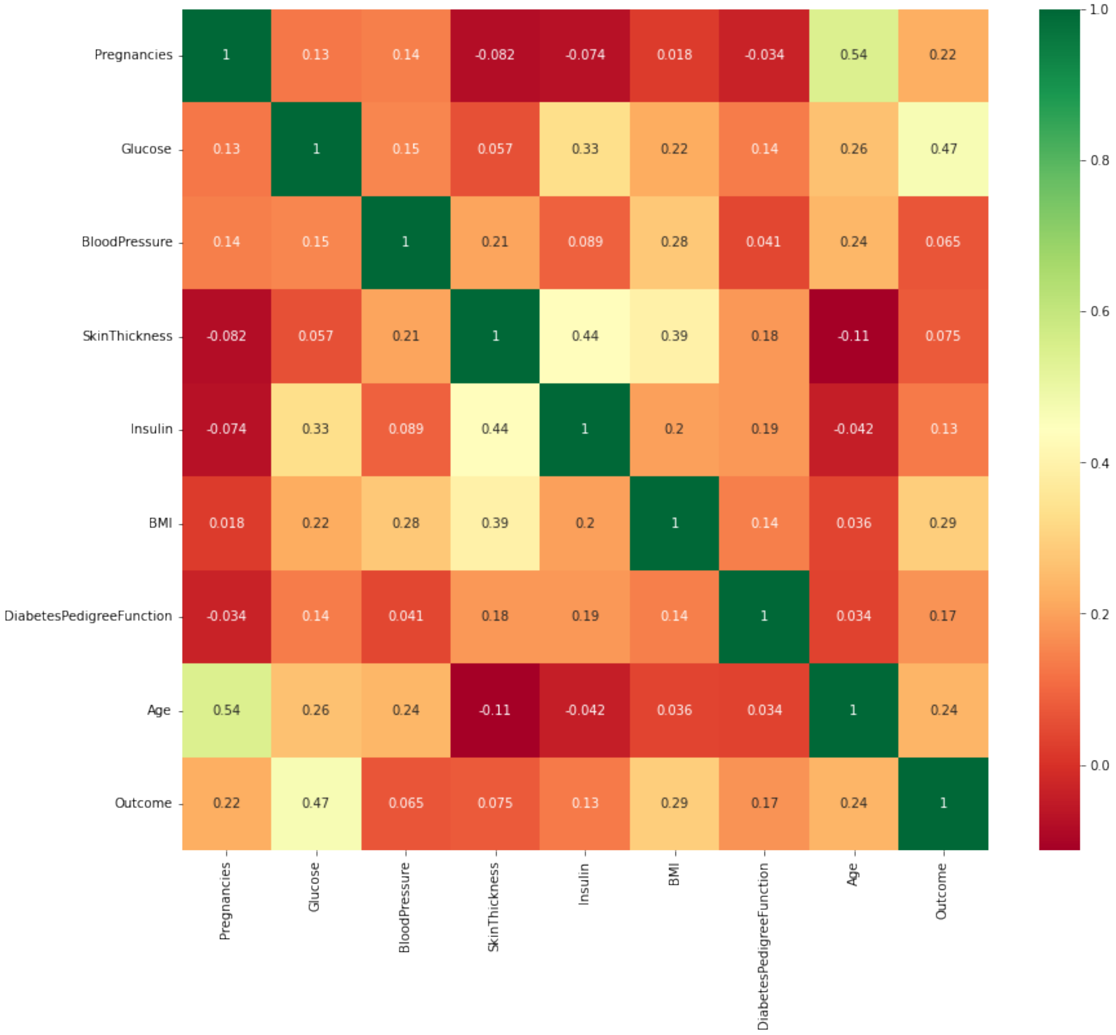
[28]:

```
p=sns.pairplot(diabetes_data_copy, hue = 'Outcome')
```



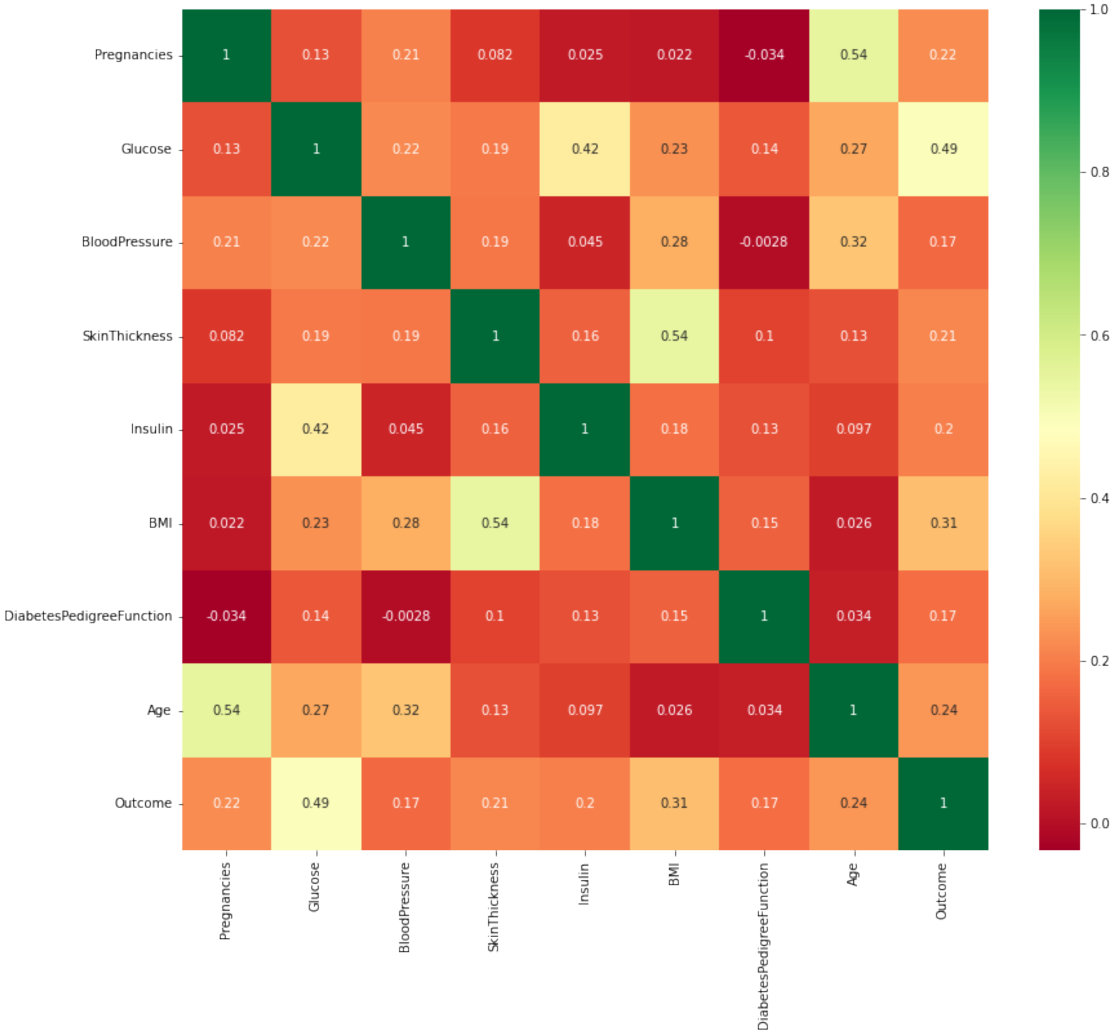
[29]:

```
plt.figure(figsize=(14,12))
p=sns.heatmap(diabetes_data.corr(), annot=True,cmap ='RdYlGn')
```



[31]:

```
plt.figure(figsize=(14,12))
p=sns.heatmap(diabetes_data_copy.corr(), annot=True,cmap ='RdYlGn')
```



[32]:
```
from sklearn.preprocessing import StandardScaler
sc_X = StandardScaler()
X =  pd.DataFrame(sc_X.fit_transform(diabetes_data_copy.drop(["Outcome"],axis =␣
 ↪1),),
        columns=['Pregnancies', 'Glucose', 'BloodPressure', 'SkinThickness',␣
 ↪'Insulin',
       'BMI', 'DiabetesPedigreeFunction', 'Age'])
```

[33]:
```
X.head()
```

[33]:
```
   Pregnancies   Glucose  BloodPressure  SkinThickness   Insulin       BMI  \
0     0.639947  0.865108      -0.033518       0.670643 -0.181541  0.166619
1    -0.844885 -1.206162      -0.529859      -0.012301 -0.181541 -0.852200
2     1.233880  2.015813      -0.695306      -0.012301 -0.181541 -1.332500
3    -0.844885 -1.074652      -0.529859      -0.695245 -0.540642 -0.633881
```

```
4   -1.141852  0.503458     -2.680669      0.670643  0.316566  1.549303

   DiabetesPedigreeFunction       Age
0                  0.468492  1.425995
1                 -0.365061 -0.190672
2                  0.604397 -0.105584
3                 -0.920763 -1.041549
4                  5.484909 -0.020496
```

[34]:
```
y = diabetes_data_copy.Outcome
```

[35]:
```
from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test = train_test_split(X,y,test_size=1/
 ↪3,random_state=42, stratify=y)
```

[36]:
```
from sklearn.neighbors import KNeighborsClassifier


test_scores = []
train_scores = []

for i in range(1,15):

    knn = KNeighborsClassifier(i)
    knn.fit(X_train,y_train)

    train_scores.append(knn.score(X_train,y_train))
    test_scores.append(knn.score(X_test,y_test))
```

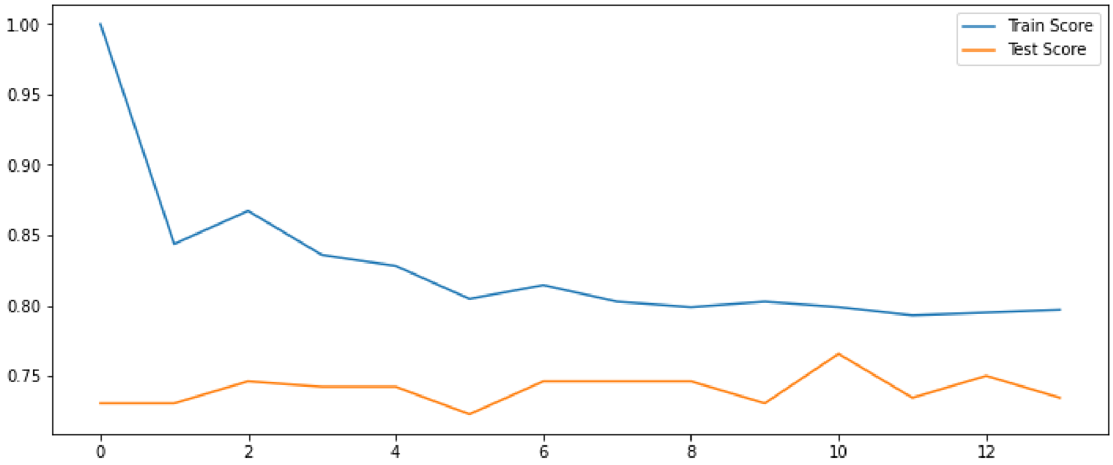
[37]:
```
max_train_score = max(train_scores)
train_scores_ind = [i for i, v in enumerate(train_scores) if v ==␣
 ↪max_train_score]
print('Max train score {} % and k = {}'.
 ↪format(max_train_score*100,list(map(lambda x: x+1, train_scores_ind))))
```

```
Max train score 100.0 % and k = [1]
```

[38]:
```
max_test_score = max(test_scores)
test_scores_ind = [i for i, v in enumerate(test_scores) if v == max_test_score]
print('Max test score {} % and k = {}'.
 ↪format(max_test_score*100,list(map(lambda x: x+1, test_scores_ind))))
```

```
Max test score 76.5625 % and k = [11]
```

[44]:
```
plt.figure(figsize=(12,5))
p = sns.lineplot(train_scores,label='Train Score')
p = sns.lineplot(test_scores,label='Test Score')
```



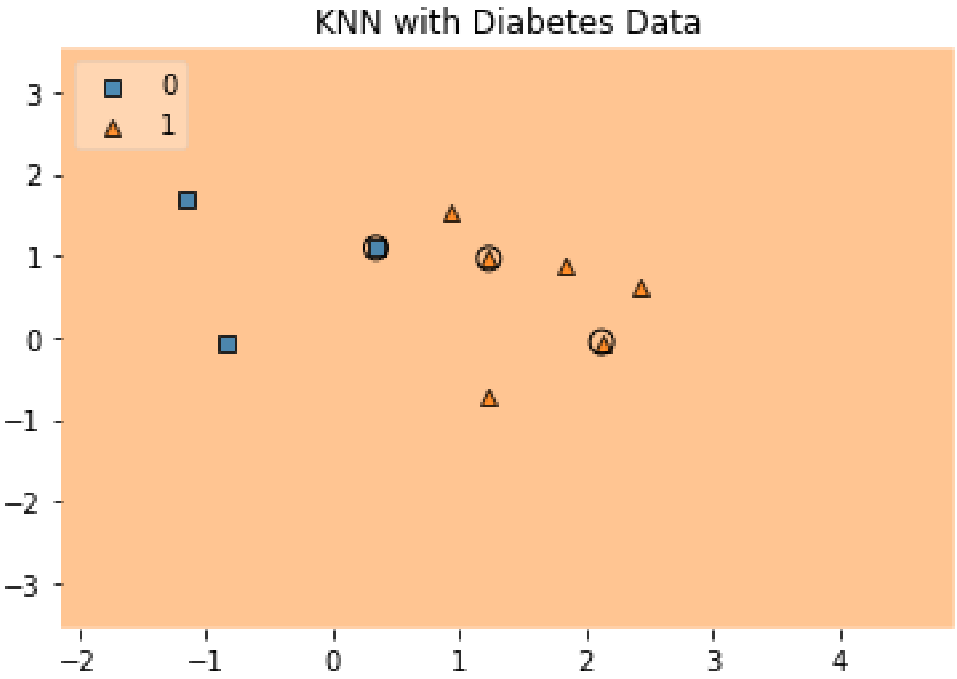
[45]:
```
knn = KNeighborsClassifier(11)

knn.fit(X_train,y_train)
knn.score(X_test,y_test)
```

[45]:
```
0.765625
```

[47]:
```
import matplotlib
matplotlib.use('Agg')
from mlxtend.plotting import plot_decision_regions
import matplotlib.pyplot as plt
value = 20000
width = 20000
plot_decision_regions(X.values, y.values, clf=knn, legend=2,
                      filler_feature_values={2: value, 3: value, 4: value, 5:␣
 ↪value, 6: value, 7: value},
                      filler_feature_ranges={2: width, 3: width, 4: width, 5:␣
 ↪width, 6: width, 7: width},
                      X_highlight=X_test.values)

# Adding axes annotations
#plt.xlabel('sepal length [cm]')
#plt.ylabel('petal length [cm]')
plt.title('KNN with Diabetes Data')
plt.show()
```

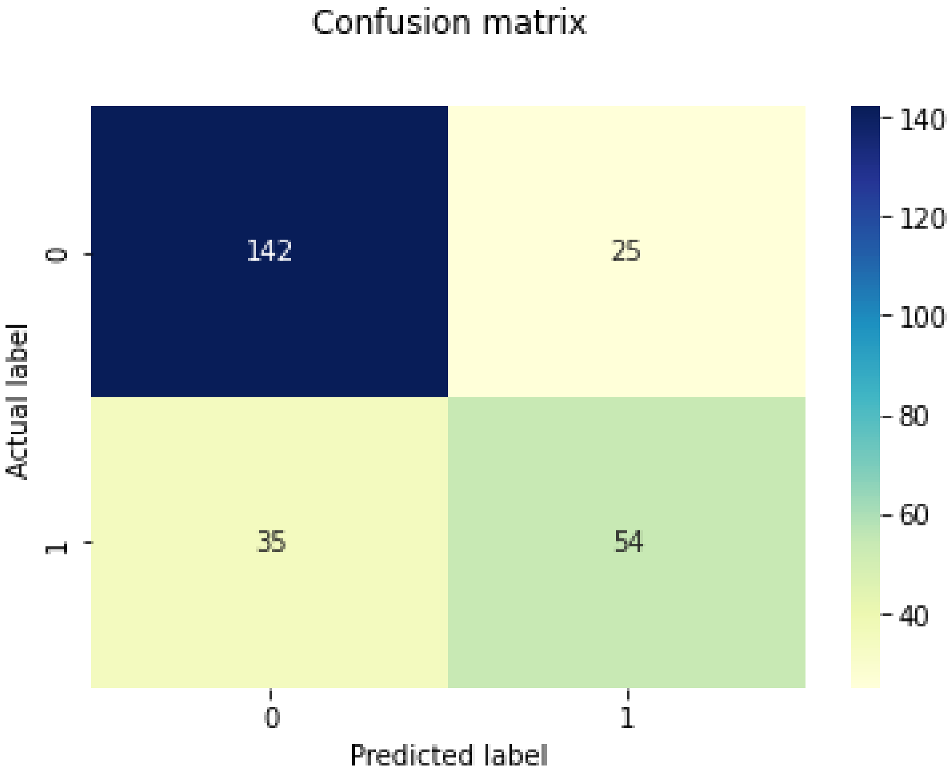


[48]:
```
#import confusion_matrix
from sklearn.metrics import confusion_matrix
#let us get the predictions using the classifier we had fit above
y_pred = knn.predict(X_test)
confusion_matrix(y_test,y_pred)
pd.crosstab(y_test, y_pred, rownames=['True'], colnames=['Predicted'],␣
 ↪margins=True)
```

[48]:
```
Predicted    0   1  All
True
0          142  25  167
1           35  54   89
All        177  79  256
```

[49]:
```
y_pred = knn.predict(X_test)
from sklearn import metrics
cnf_matrix = metrics.confusion_matrix(y_test, y_pred)
p = sns.heatmap(pd.DataFrame(cnf_matrix), annot=True, cmap="YlGnBu" ,fmt='g')
plt.title('Confusion matrix', y=1.1)
plt.ylabel('Actual label')
plt.xlabel('Predicted label')
```

[49]:
```
Text(0.5, 15.0, 'Predicted label')
```



[52]:
```
#import classification_report
from sklearn.metrics import classification_report
print(classification_report(y_test,y_pred))
```

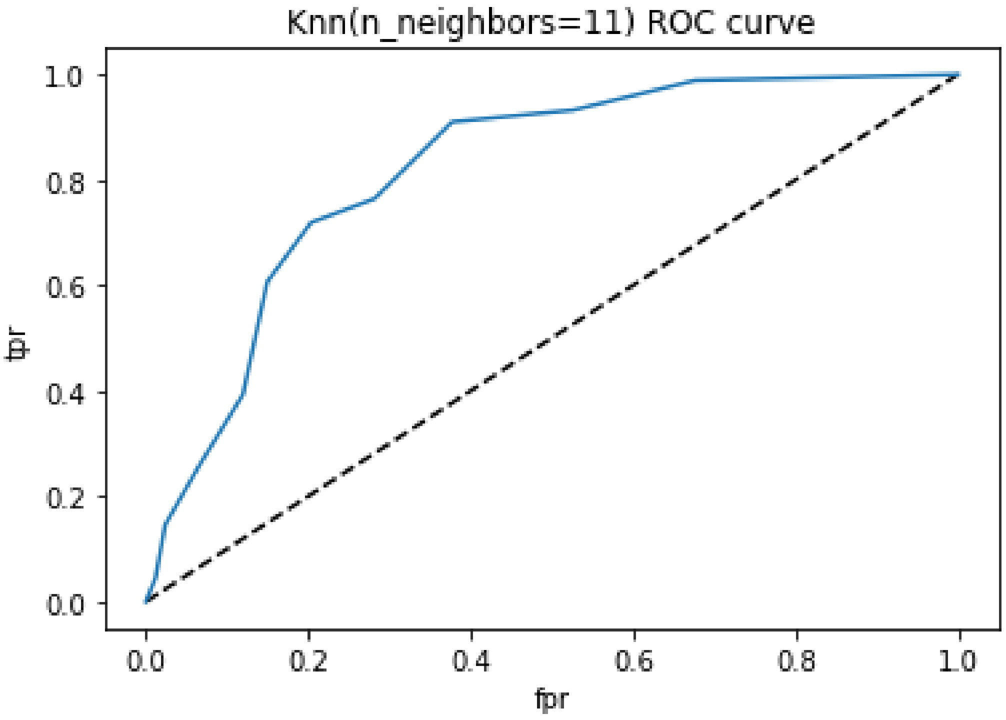
```
              precision    recall  f1-score   support

           0       0.80      0.85      0.83       167
           1       0.68      0.61      0.64        89

    accuracy                           0.77       256
   macro avg       0.74      0.73      0.73       256
weighted avg       0.76      0.77      0.76       256
```

[53]:
```
from sklearn.metrics import roc_curve
y_pred_proba = knn.predict_proba(X_test)[:,1]
fpr, tpr, thresholds = roc_curve(y_test, y_pred_proba)
```

[54]:
```
plt.plot([0,1],[0,1],'k--')
plt.plot(fpr,tpr, label='Knn')
plt.xlabel('fpr')
plt.ylabel('tpr')
plt.title('Knn(n_neighbors=11) ROC curve')
plt.show()
```



[55]:
```
#Area under ROC curve
from sklearn.metrics import roc_auc_score
roc_auc_score(y_test,y_pred_proba)
```

[55]:
```
0.8193500639171096
```

[56]:
```
#import GridSearchCV
from sklearn.model_selection import GridSearchCV
#In case of classifier like knn the parameter to be tuned is n_neighbors
param_grid = {'n_neighbors':np.arange(1,50)}
knn = KNeighborsClassifier()
knn_cv= GridSearchCV(knn,param_grid,cv=5)
knn_cv.fit(X,y)

print("Best Score:" + str(knn_cv.best_score_))
print("Best Parameters: " + str(knn_cv.best_params_))
```

```
Best Score:0.7721840251252015
Best Parameters: {'n_neighbors': 25}
```

[ ]: