step 1: load data into jupyter

In [1]:
```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np

%matplotlib inline
```

In [2]:
```
df = pd.read_excel('pima-data.xlsx')
df.head()
```

Out[2]:

	num_preg	glucose_conc	diastolic_bp	thickness	insulin	bmi	diab_pred	age	diabetes_orig
0	6	148	72	35	0	33.6	0.627	50	1
1	1	85	66	29	0	26.6	0.351	31	0
2	8	183	64	0	0	23.3	0.672	32	1
3	1	89	66	23	94	28.1	0.167	21	0
4	0	137	40	35	168	43.1	2.288	33	1

In [3]:
```
df.tail()
```

Out[3]:

	num_preg	glucose_conc	diastolic_bp	thickness	insulin	bmi	diab_pred	age	diabetes_orig
763	10	101	76	48	180	32.9	0.171	63	0
764	2	122	70	27	0	36.8	0.340	27	0
765	5	121	72	23	112	26.2	0.245	30	0
766	1	126	60	0	0	30.1	0.349	47	1
767	1	93	70	31	0	30.4	0.315	23	0

In [4]:
```
len(df)
```

Out[4]: 768

step 2: clean data

2.a - let us find if there are any null values

In [5]:
```
df.isnull().values.any()
```

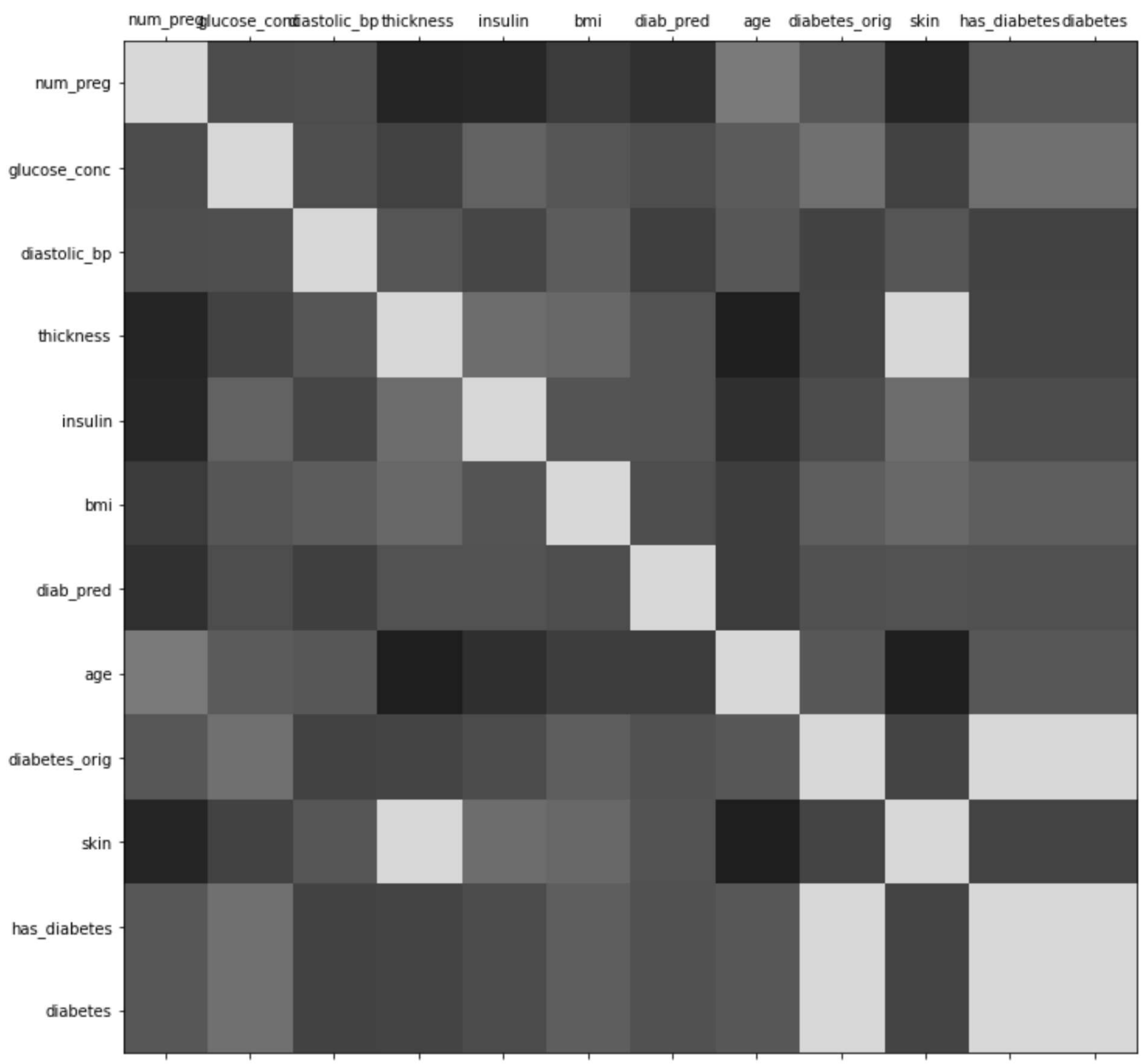
Out[5]:
```
False
```

2.b - let us find duplicate columns or co-related columns

In [6]:
```
# frist check how many columns are there
```

In [7]:
```
def plot_corr(df, size=12):
    corr = df.corr() #pandas data frame correlation function
    fig, ax = plt.subplots(figsize=(size,size))
    ax.matshow(corr) #color code the rectangles by correlation values
    plt.xticks(range(len(corr.columns)), corr.columns)
    plt.yticks(range(len(corr.columns)), corr.columns)
```

In [8]:
```
# lets call above  fuction
plot_corr(df)
```



In [9]:

```
# we are going to remove thickness,diabetes_orig,has_diabetes
```

In [10]:

```
del df['thickness']
del df['has_diabetes']
del df['diabetes_orig']
```

In [11]:

```
df.head()
```

Out[11]:

	num_preg	glucose_conc	diastolic_bp	insulin	bmi	diab_pred	age	skin	diabetes
0	6	148	72	0	33.6	0.627	50	1.3790	True
1	1	85	66	0	26.6	0.351	31	1.1426	False
2	8	183	64	0	23.3	0.672	32	0.0000	True
3	1	89	66	94	28.1	0.167	21	0.9062	False
4	0	137	40	168	43.1	2.288	33	1.3790	True

2.c - lets convert text to numbers

machine learning algorithms will not understand text. so conver to numbers.

In [12]:

```
diabetes_map = {True:1, False:0}
df['diabetes'] = df['diabetes'].map(diabetes_map)

```

In [13]:

```
df.head()
```

Out[13]:

	num_preg	glucose_conc	diastolic_bp	insulin	bmi	diab_pred	age	skin	diabetes
0	6	148	72	0	33.6	0.627	50	1.3790	1
1	1	85	66	0	26.6	0.351	31	1.1426	0
2	8	183	64	0	23.3	0.672	32	0.0000	1
3	1	89	66	94	28.1	0.167	21	0.9062	0
4	0	137	40	168	43.1	2.288	33	1.3790	1

lets check proportion of diabetes vs non - diabetes data

we need to ensure that the proportions should be balanced(50-50) diabetes and non diabetes pr at least close enough to proceed

In [14]:

```
num_true = len(df.loc[df['diabetes'] == True]) #loc returns no of items with
num_false = len(df.loc[df['diabetes'] == False])
print('true = ', (num_true/ (num_true+num_false) )*100 ) #34% is decent figu
print('false = ', (num_false/ (num_true+num_false) )*100 ) #65% is decent fi

```

```
true =  34.895833333333336
false =  65.10416666666666
```

in case of data imbalancing we use SMOTE technique to increse lesser data samples

step 3 - train test split

let us split our data for training and testing the algorithm

In [15]:

```
 from sklearn.model_selection import train_test_split
feature_col_names = ['num_preg','glucose_conc', 'diastolic_bp', 'skin','insu
                     'bmi','diab_pred','age']
predicted_class_names = ['diabetes']
x = df[feature_col_names].values #predictor feature columns (8Xm)
y = df[predicted_class_names].values #predicted class [1=true, 0=false] colu
split_test_size = 0.30
x_train, x_test, y_train, y_test = train_test_split(x,y, test_size=split_tes

```

In [16]:

```
print('# rows in dataframe {0}'.format(len(df)))
print('# rows missing glucose_conc : {0}'.format(len(df.loc[df['glucose_conc
== 0])))
print('# rows missing diastolic_bp : {0}'.format(len(df.loc[df['diastolic_bp
== 0])))
print('# rows missing thickness : {0}'.format(len(df.loc[df['skin']== 0
])))
print('# rows missing insulin : {0}'.format(len(df.loc[df['insulin']== 0])))
print('# rows missing bmi : {0}'.format(len(df.loc[df['bmi']== 0])))
print('# rows missing diab_pred : {0}'.format(len(df.loc[df['diab_pred']== 0
])))
print('# rows missing age : {0}'.format(len(df.loc[df['age']== 0])))

```

```
# rows in dataframe 768
# rows missing glucose_conc : 5
# rows missing diastolic_bp : 35
# rows missing thickness : 227
# rows missing insulin : 374
# rows missing bmi : 11
# rows missing diab_pred : 0
# rows missing age : 0
```

In [17]:
```
# lets  fill 0's with valid data (either mean or mode)
```

In [18]:
```
from sklearn.impute import SimpleImputer
fill_0 = SimpleImputer(missing_values = 0, strategy='mean')
x_train = fill_0.fit_transform(x_train)
x_test = fill_0.fit_transform(x_test)
```

In [19]:
```
x_train[0:10]
```

Out[19]:
```
array([[1.00000000e+00, 9.50000000e+01, 6.00000000e+01, 7.09200000e-01,
        5.80000000e+01, 2.39000000e+01, 2.60000000e-01, 2.20000000e+01],
       [5.00000000e+00, 1.05000000e+02, 7.20000000e+01, 1.14260000e+00,
        3.25000000e+02, 3.69000000e+01, 1.59000000e-01, 2.80000000e+01],
       [4.34056399e+00, 1.35000000e+02, 6.80000000e+01, 1.65480000e+00,
        2.50000000e+02, 4.23000000e+01, 3.65000000e-01, 2.40000000e+01],
       [4.00000000e+00, 1.31000000e+02, 6.80000000e+01, 8.27400000e-01,
        1.66000000e+02, 3.31000000e+01, 1.60000000e-01, 2.80000000e+01],
       [1.00000000e+00, 1.03000000e+02, 3.00000000e+01, 1.49720000e+00,
        8.30000000e+01, 4.33000000e+01, 1.83000000e-01, 3.30000000e+01],
       [2.00000000e+00, 8.20000000e+01, 5.20000000e+01, 8.66800000e-01,
        1.15000000e+02, 2.85000000e+01, 1.69900000e+00, 2.50000000e+01],
       [3.00000000e+00, 1.28000000e+02, 7.80000000e+01, 1.12871227e+00,
        1.55333333e+02, 2.11000000e+01, 2.68000000e-01, 5.50000000e+01],
       [1.00000000e+00, 1.22000000e+02, 6.40000000e+01, 1.26080000e+00,
        1.56000000e+02, 3.51000000e+01, 6.92000000e-01, 3.00000000e+01],
       [4.34056399e+00, 1.38000000e+02, 7.22413127e+01, 1.12871227e+00,
        1.55333333e+02, 3.63000000e+01, 9.33000000e-01, 2.50000000e+01],
       [4.34056399e+00, 1.25000000e+02, 6.80000000e+01, 1.12871227e+00,
        1.55333333e+02, 2.47000000e+01, 2.06000000e-01, 2.10000000e+01]])
```

step 4 - TRAIN THE MODEL

In [20]:
```
from sklearn.naive_bayes import GaussianNB
#create gaussian naive bayes model object and train it with data
nb_model = GaussianNB()
nb_model.fit(x_train, y_train.ravel())
```

Out[20]:
```
GaussianNB()
```

In [21]:
```
# lets test the algorithm's accuracy with training data it self.
```

In [22]:
```
nb_predict_train = nb_model.predict(x_train)
from sklearn import metrics
print('accuracy : {0:.4f}'.format(metrics.accuracy_score(y_train, nb_predict

```

```
accuracy : 0.7542
```

step 5 - TESTING MODEL

In [23]:
```
nb_predict_test = nb_model.predict(x_test)
from sklearn import metrics
print('accuracy : {0:.4f}'.format(metrics.accuracy_score(y_test, nb_predict_

```

```
accuracy : 0.7359
```

step 6 - ANALYZE THE MODEL ACCURACY

WITH THE HELP OF "CONFUSION MATRIX" WE CAN ANALYZE ALGORITHMS PERFORMANCE

In [24]:
```
print('confusion matrix')
print('{0}'.format(metrics.confusion_matrix(y_test, nb_predict_test)))
print('')
print('classification report')
print(metrics.classification_report(y_test, nb_predict_test))
```

```
confusion matrix
[[118  33]
 [ 28  52]]

classification report
              precision    recall  f1-score   support

           0       0.81      0.78      0.79       151
           1       0.61      0.65      0.63        80

    accuracy                           0.74       231
   macro avg       0.71      0.72      0.71       231
weighted avg       0.74      0.74      0.74       231
```

final observation of navive bayes algo ==> accuracy 73%,recall 81%

type 2 error values should be less compared to type 1 error

In [25]:
```
# let us try random forest algorithm
```

In [26]:
```
from sklearn.ensemble import RandomForestClassifier
rf_model = RandomForestClassifier(random_state=42)
rf_model.fit(x_train, y_train.ravel())
rf_predict_test = rf_model.predict(x_test)

#training metrics
print('accuracy : {0:.4f}'.format(metrics.accuracy_score(y_test, rf_predict_

```

```
accuracy : 0.7403
```

In [27]:
```
# lest us see confusion matrix and classification report
```

In [28]:
```
print(metrics.confusion_matrix(y_test, rf_predict_test))
print('')
print('classification report')
print(metrics.classification_report(y_test, rf_predict_test))

```

```
[[119  32]
 [ 28  52]]

classification report
              precision    recall  f1-score   support

           0       0.81      0.79      0.80       151
           1       0.62      0.65      0.63        80

    accuracy                           0.74       231
   macro avg       0.71      0.72      0.72       231
weighted avg       0.74      0.74      0.74       231

```

In [29]:
```
# let us try with logistic regression algorithm
```

In [30]:

```python
from sklearn.linear_model import LogisticRegression
lr_model = LogisticRegression(class_weight='balanced', C=0.2, random_state =
lr_model.fit(x_train, y_train.ravel())
lr_predict_test = lr_model.predict(x_test)

print('accuracy: {0:.4f}'.format(metrics.accuracy_score(y_test, lr_predict_t
print('')
print(metrics.confusion_matrix(y_test, lr_predict_test))
print('')
print('classification report')
print(metrics.classification_report(y_test, lr_predict_test))

```

```
accuracy: 0.7143

[[111  40]
 [ 26  54]]

classification report
              precision    recall  f1-score   support

           0       0.81      0.74      0.77       151
           1       0.57      0.68      0.62        80

    accuracy                           0.71       231
   macro avg       0.69      0.71      0.70       231
weighted avg       0.73      0.71      0.72       231


C:\Users\91918\AppData\Local\Programs\Python\Python39\lib\site-packages\sklearn
\linear_model\_logistic.py:814: ConvergenceWarning: lbfgs failed to converge (s
tatus=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html (https://scikit-
learn.org/stable/modules/preprocessing.html)
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regressi
on (https://scikit-learn.org/stable/modules/linear_model.html#logistic-regressi
on)
  n_iter_i = _check_optimize_result(
```

final conclusion - we are suggesting random forest lgorithm for this project as the accuracy is 75% and recall value is 82% which is higher than other two algorithms

In [ ]:

```python

```