Predicting Diabetes

Import Libraries

In [1]:
```
import pandas as pd                          # pandas is a dataframe library
import matplotlib.pyplot as plt              # matplotlib.pyplot plot data
import numpy as np                           # numpy provides N-dim object sup
port

#  do ploting line instead of in a separate window
%matplotlib inline
```

Load and review data

In [2]:
```
df = pd.read_csv("./data/pima-data.csv")         # Load pima data , adju
st path as necessary
```

In [3]:
```
df.shape        # it returns number or rows and columns , 768 rows and 1
0 columns
```

Out[3]: (768, 10)

In [4]:
```
df.head(5)      # it returns 1st 5 data sets
```

Out[4]:

	num_preg	glucose_conc	diastolic_bp	thickness	insulin	bmi	diab_pred	age	skin
0	6	148	72	35	0	33.6	0.627	50	1.3790
1	1	85	66	29	0	26.6	0.351	31	1.1426
2	8	183	64	0	0	23.3	0.672	32	0.0000
3	1	89	66	23	94	28.1	0.167	21	0.9062
4	0	137	40	35	168	43.1	2.288	33	1.3790

In [5]:
```
df.tail(5)     # it returns last 5 data set
```

Out[5]:

	num_preg	glucose_conc	diastolic_bp	thickness	insulin	bmi	diab_pred	age	sk
763	10	101	76	48	180	32.9	0.171	63	1.89
764	2	122	70	27	0	36.8	0.340	27	1.06
765	5	121	72	23	112	26.2	0.245	30	0.90
766	1	126	60	0	0	30.1	0.349	47	0.00
767	1	93	70	31	0	30.4	0.315	23	1.22

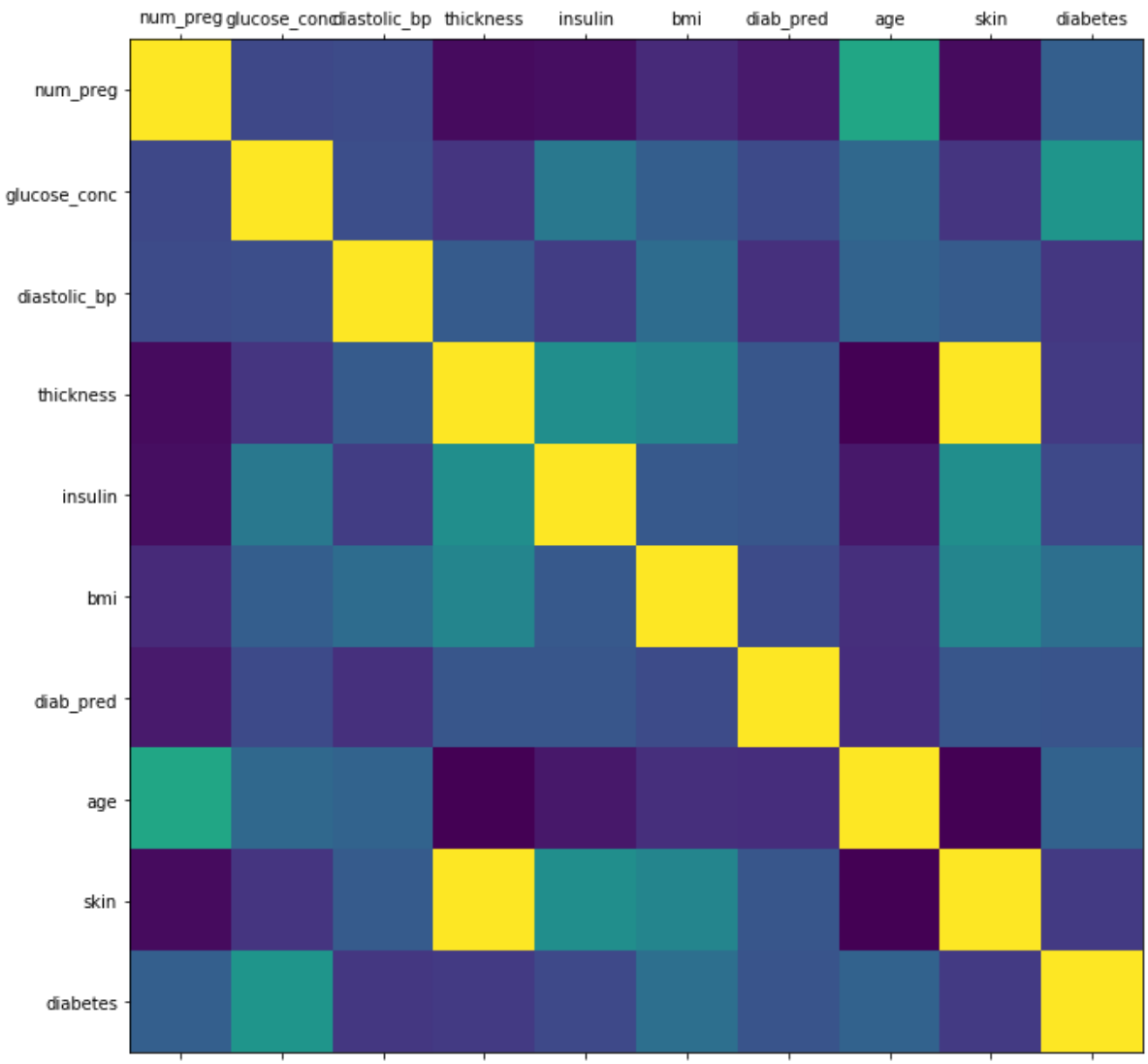
Cleaning the Data : Check for null values in data frame

In [6]:
```
df.isnull().values.any()
```

Out[6]: False

In [7]:
```
def plot_corr(df, size=11):
    """
    function plots a graphical coreleastion matrix for each pair of colu
mn in different dataframe .

    Input :
       df : pandas dataframe
       size : vertical and horizontal size of the plot

    Display :
       matrix of corelation between columns.
         Blue-cyan-yellow  => less to more coreated
         0 ------------------> 1
         Expect a darked light running from top left to bottom right
    """

    corr = df.corr()  # data frame corelation function
    fig , ax = plt.subplots(figsize =(size,size))
    ax.matshow(corr)  # color code the rectanges by corelation value
    plt.xticks (range(len(corr.columns)), corr.columns)    # draw x tick
s mark
    plt.yticks (range(len(corr.columns)), corr.columns)    # draw y tick
s mark
```

In [8]:
```
plot_corr(df)
```



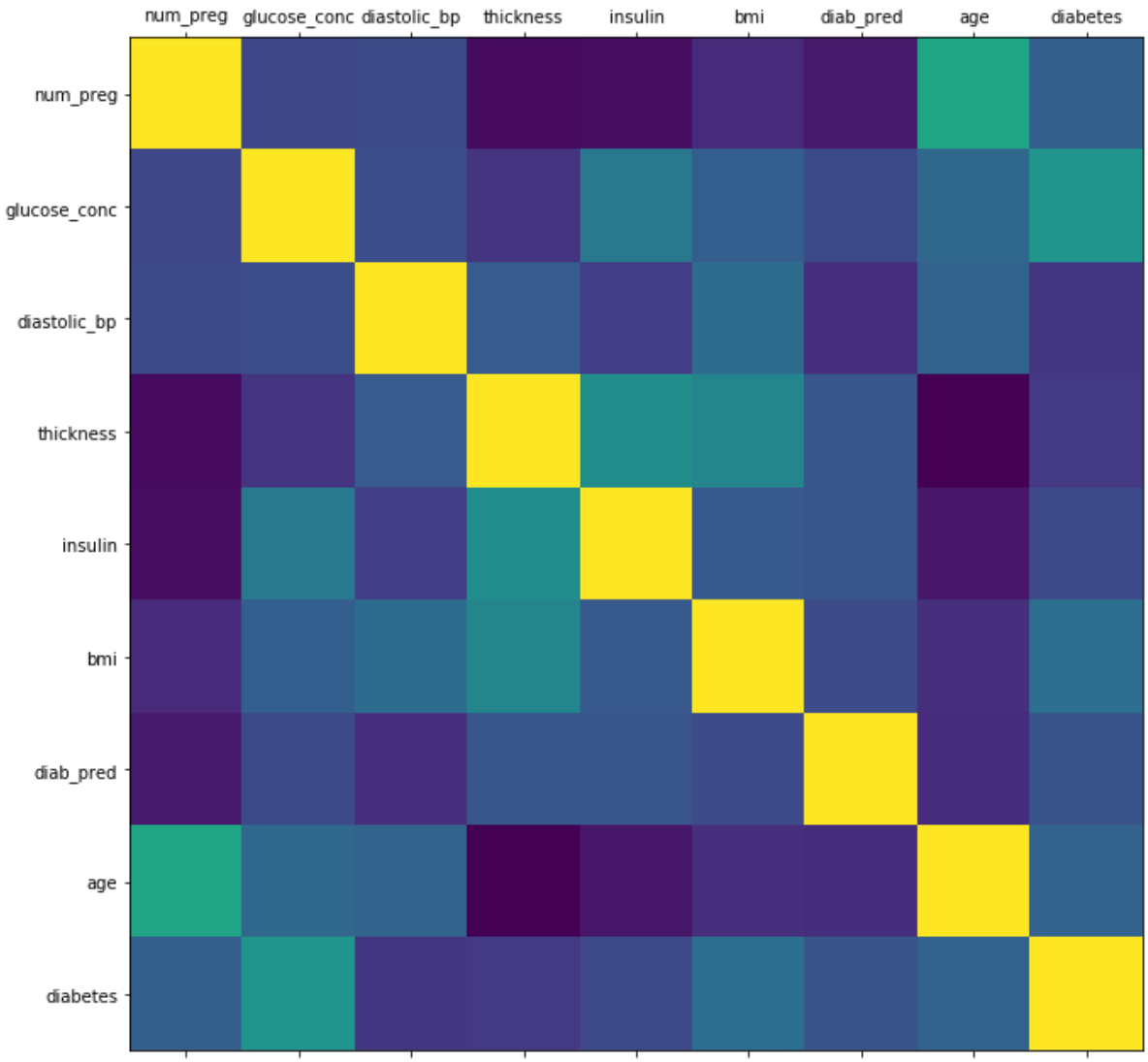
In [9]:
```
df.corr()
```

Out[9]:

	num_preg	glucose_conc	diastolic_bp	thickness	insulin	bmi	dia
num_preg	1.000000	0.129459	0.141282	-0.081672	-0.073535	0.017683	-0.
glucose_conc	0.129459	1.000000	0.152590	0.057328	0.331357	0.221071	0.1
diastolic_bp	0.141282	0.152590	1.000000	0.207371	0.088933	0.281805	0.0
thickness	-0.081672	0.057328	0.207371	1.000000	0.436783	0.392573	0.1
insulin	-0.073535	0.331357	0.088933	0.436783	1.000000	0.197859	0.1
bmi	0.017683	0.221071	0.281805	0.392573	0.197859	1.000000	0.1
diab_pred	-0.033523	0.137337	0.041265	0.183928	0.185071	0.140647	1.0
age	0.544341	0.263514	0.239528	-0.113970	-0.042163	0.036242	0.0
skin	-0.081672	0.057328	0.207371	1.000000	0.436783	0.392573	0.1
diabetes	0.221898	0.466581	0.065068	0.074752	0.130548	0.292695	0.1

In [10]:
```
del df['skin'] # remove the skin row corelated row
```

In [11]:
```
plot_corr(df)
```



In [12]:
```
df.head()
```

Out[12]:

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

Modeling the data : Check data types

Here we have Bool value in diabetes column , Need to change to int True to 1 and False to 0

In [13]:
```
diabetes_map = {True:1 , False:0}
```

In [14]:
```
df['diabetes'] = df['diabetes'].map(diabetes_map)
```

In [15]:
```
df.head(5)
```

Out[15]:

	num_preg	glucose_conc	diastolic_bp	thickness	insulin	bmi	diab_pred	age	diabet
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

Check true false ratio

In [16]:
```
num_true = len(df.loc[df.diabetes == True])
num_false = len(df.loc[df.diabetes == False])
print ("Number of true cases: {0} ({1:2.2f}%)".format(num_true, (num_tru
e / (num_true + num_false))*100))
print ("Number of false cases: {0} ({1:2.2f}%)".format(num_false, (num_f
alse / (num_true + num_false))*100))
```

```
Number of true cases: 268 (34.90%)
Number of false cases: 500 (65.10%)
```

Splitting the data

70% for training , 30% for testing

In [17]:
```
from sklearn.cross_validation import train_test_split

feature_col_names = ['num_preg', 'glucose_conc' , 'diastolic_bp', 'thick
ness', 'insulin', 'bmi', 'diab_pred', 'age']
predicted_class_names = ['diabetes']

X = df[feature_col_names].values # predictor feature coloumns ( 8 X m )
y = df[predicted_class_names].values # predicted class ( 1= true , 0=fal
se ) column ( 1 X m )
split_test_size = 0.30

X_train , X_test , y_train , y_test = train_test_split(X, y, test_size =
 split_test_size, random_state = 42)
          # test size = 0.30 is 30% , 42 is the answer to everything , a
ny number can be used for random state
```

```
/Library/Frameworks/Python.framework/Versions/3.6/lib/python3.6/site-pa
ckages/sklearn/cross_validation.py:41: DeprecationWarning: This module
 was deprecated in version 0.18 in favor of the model_selection module
 into which all the refactored classes and functions are moved. Also no
te that the interface of the new CV iterators are different from that o
f this module. This module will be removed in 0.20.
  "This module will be removed in 0.20.", DeprecationWarning)
```

In [18]:
```
print("{0:0.2f}% in training set".format((len(X_train)/len(df.index))*10
0))
print("{0:0.2f}% in test set".format((len(X_test)/len(df.index))*100))
```

```
69.92% in training set
30.08% in test set
```

verifying predicted value was split correctly

In [19]:
```
print ("Origional True: {0}
({1:0.2f}%)".format(len(df.loc[df['diabetes'] == 1]),(len(df.loc[df['dia
betes'] == 1]) / len(df.index))*100.0))
print ("Origional False: {0} ({1:0.2f}%)".format(len(df.loc[df['diabete
s'] == 0]),(len(df.loc[df['diabetes'] == 0]) / len(df.index))*100.0))
print(" ")
print ("Training True: {0} ({1:0.2f}%)".format(len(y_train[y_train[:] ==
 1]),(len(y_train[y_train[:] == 1]) / len(y_train))*100.0))
print ("Training False: {0} ({1:0.2f}%)".format(len(y_train[y_train[:] =
= 0]),(len(y_train[y_train[:] == 0]) / len(y_train))*100.0))
print(" ")
print ("Testing True: {0} ({1:0.2f}%)".format(len(y_test[y_test[:] ==
1]),(len(y_test[y_test[:] == 1]) / len(y_test))*100.0))
print ("Testing False: {0} ({1:0.2f}%)".format(len(y_test[y_test[:] ==
0]),(len(y_test[y_test[:] == 0]) / len(y_test))*100.0))
```

```
Origional True: 268 (34.90%)
Origional False: 500 (65.10%)

Training True: 188 (35.01%)
Training False: 349 (64.99%)

Testing True: 80 (34.63%)
Testing False: 151 (65.37%)
```

Post Split data preparation

hidden missing values , we already check the null values , but still their might be some 0 values .. like in thinkness. Are the 0 values possible ? we need to find out these unexpected 0 values.

In [20]:
```
print("# rows in dataframe {0}".format(len(df)))
print("# rows missing glucose_conc: {0}".format(len(df.loc[df['glucose_c
onc'] == 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['thickness']
== 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 [21]:
```
from sklearn.preprocessing import Imputer
#impute with mean all 0 readings

fill_0 = Imputer(missing_values = 0 , strategy ="mean", axis=0)

X_train = fill_0.fit_transform(X_train)
X_test = fill_0.fit_transform(X_test)
```

Naive Bayes algorithim

In [22]:
```
from sklearn.naive_bayes import GaussianNB

# Create Gaussian naive bayes model object and train it with the data
nb_model = GaussianNB()
nb_model.fit(X_train, y_train.ravel())
```

Out[22]:
```
GaussianNB(priors=None)
```

Performance on Training Data

In [23]:
```
# predict values using the Training data
nb_predict_train = nb_model.predict(X_train)

# import the performance metrices library
from sklearn import metrics

# Accuracy
print("Accuracy : {0:.4f}".format(metrics.accuracy_score(y_train, nb_pre
dict_train)))
print()
```

```
Accuracy : 0.7542
```

In [24]:
```
# predict values using the Texting data
nb_predict_text = nb_model.predict(X_test)

# import the performance metrices library
from sklearn import metrics

# Accuracy
print("Accuracy : {0:.4f}".format(metrics.accuracy_score(y_test, nb_pred
ict_text)))
print()
```

```
Accuracy : 0.7359
```

In [25]:
```
print("Confusion Matrix")

# the use of labels to set 1=True to upper left and 0=False to lower rig
ht

print("{0}".format(metrics.confusion_matrix(y_test, nb_predict_text, lab
els = [1,0])))
print(" ")

print(" Classification Report ")
print(metrics.classification_report(y_test, nb_predict_text, labels =
[1,0]))


# * left column : Predictive true
#   right column : predictive false

#   top row : actual true
#   bottom row : actual false

#   TP FP
#   FN TN

#   Perfect classifier :
#    TP = 80
#    FP = 0
#    FN = 0
#    TN = 151

#    In Classification matrix ::
#    recall = TP / [TP+FN] >= 70%
#    precision = TP / [TP+FP] >= 70%
```

```
Confusion Matrix
[[ 52  28]
 [ 33 118]]

 Classification Report
             precision    recall  f1-score   support

          1       0.61      0.65      0.63        80
          0       0.81      0.78      0.79       151

avg / total       0.74      0.74      0.74       231
```

Random Forest algorithim

In [26]:
```
from sklearn.ensemble import RandomForestClassifier
rf_model = RandomForestClassifier(random_state = 42) # create random for
est object
rf_model.fit(X_train, y_train.ravel())
```

Out[26]:
```
RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gi
ni',
            max_depth=None, max_features='auto', max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, n_estimators=10, n_jobs=1,
            oob_score=False, random_state=42, verbose=0, warm_start=Fal
se)
```

Predicting Training data

In [27]:
```
rf_predict_train = rf_model.predict(X_train)
# training metrics
print("Accuracy : {0:.4f}".format(metrics.accuracy_score(y_train, rf_pre
dict_train)))
print()
```

```
Accuracy : 0.9870
```

Predicting Test data

In [28]:
```
rf_predict_test = rf_model.predict(X_test)
# training metrics
print("Accuracy : {0:.4f}".format(metrics.accuracy_score(y_test, rf_pred
ict_test)))
print()
```

```
Accuracy : 0.7100
```

In [29]:
```
print("Confusion Matrix")

# the use of labels to set 1=True to upper left and 0=False to lower rig
ht

print("{0}".format(metrics.confusion_matrix(y_test, rf_predict_test, lab
els = [1,0])))
print(" ")

print(" Classification Report ")
print(metrics.classification_report(y_test, rf_predict_test, labels =
[1,0]))
```

```
Confusion Matrix
[[ 43  37]
 [ 30 121]]

 Classification Report
             precision    recall  f1-score   support

          1       0.59      0.54      0.56        80
          0       0.77      0.80      0.78       151

avg / total       0.70      0.71      0.71       231
```

Random Forest performs well with Training data , but seems to be low performance with Text data

Logistic Regression

In [30]:
```
from sklearn.linear_model import LogisticRegression
lr_model = LogisticRegression(C=0.7, random_state=42) # create random fo
rest object
lr_model.fit(X_train, y_train.ravel())
```

Out[30]:
```
LogisticRegression(C=0.7, class_weight=None, dual=False, fit_intercept=
True,
          intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=
1,
          penalty='l2', random_state=42, solver='liblinear', tol=0.000
1,
          verbose=0, warm_start=False)
```

In [31]:
```
lr_predict_test = lr_model.predict(X_test)
# training metrics
print("Accuracy : {0:.4f}".format(metrics.accuracy_score(y_test, lr_pred
ict_test)))
print()
```

```
Accuracy : 0.7446
```

In [32]:
```
print("Confusion Matrix")

# the use of labels to set 1=True to upper left and 0=False to lower rig
ht

print("{0}".format(metrics.confusion_matrix(y_test, lr_predict_test, lab
els = [1,0])))
print(" ")

print(" Classification Report ")
print(metrics.classification_report(y_test, lr_predict_test, labels =
[1,0]))
```

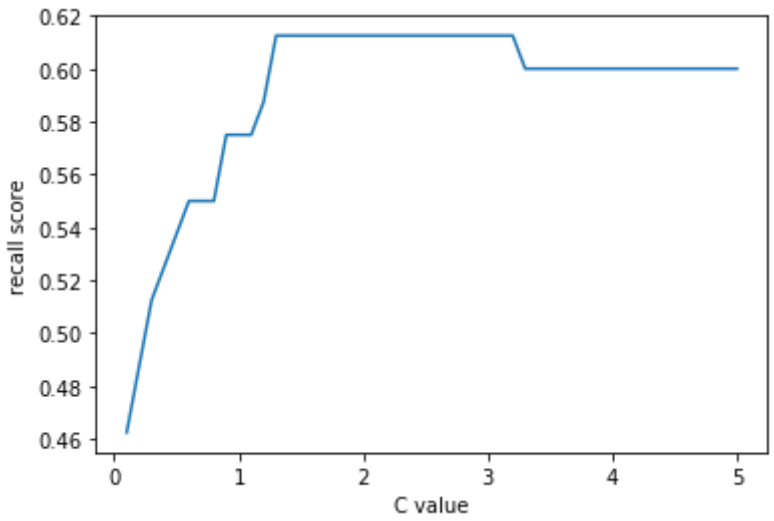
```
Confusion Matrix
[[ 44  36]
 [ 23 128]]

 Classification Report
             precision    recall  f1-score   support

          1       0.66      0.55      0.60        80
          0       0.78      0.85      0.81       151

avg / total       0.74      0.74      0.74       231
```

Setting Regularziation Parameter

In [33]:
```
C_start = 0.1
C_end = 5
C_inc = 0.1


C_values, recall_scores = [] , []
C_val = C_start
best_recall_score = 0

while (C_val < C_end):
    C_values.append(C_val)
    lr_model_loop = LogisticRegression(C=C_val , random_state=42)
    lr_model_loop.fit(X_train , y_train.ravel())
    lr_predict_loop_test = lr_model_loop.predict(X_test)
    recall_score = metrics.recall_score(y_test, lr_predict_loop_test)
    recall_scores.append(recall_score)
    if (recall_score > best_recall_score):
        best_recall_score = recall_score
        best_lr_predict_test = lr_predict_loop_test

    C_val = C_val + C_inc

best_score_C_val = C_values[recall_scores.index(best_recall_score)]
print("1st max value of {0:.3f} occured at c={1:.3f}".format(best_recall
_score,best_score_C_val))

%matplotlib inline
plt.plot(C_values , recall_scores, "-")
plt.xlabel("C value")
plt.ylabel("recall score")
```

```
1st max value of 0.613 occured at c=1.300
```

Out[33]:
```
<matplotlib.text.Text at 0x10bd327b8>
```



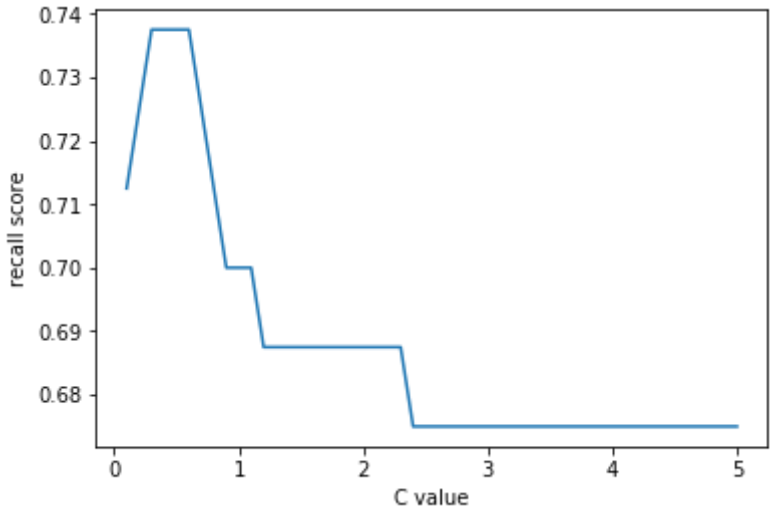
We have inbalace data , having more non diabetics results than diabetics . This is casuing an issue so mac value is not exceeding mote than 0.70

Logisitic Regression with class_weight = 'balanced'

In [34]:
```
C_start = 0.1
C_end = 5
C_inc = 0.1


C_values, recall_scores = [] , []
C_val = C_start
best_recall_score = 0

while (C_val < C_end):
    C_values.append(C_val)
    lr_model_loop = LogisticRegression(C=C_val ,
class_weight='balanced', random_state=42)
    lr_model_loop.fit(X_train , y_train.ravel())
    lr_predict_loop_test = lr_model_loop.predict(X_test)
    recall_score = metrics.recall_score(y_test, lr_predict_loop_test)
    recall_scores.append(recall_score)
    if (recall_score > best_recall_score):
        best_recall_score = recall_score
        best_lr_predict_test = lr_predict_loop_test

    C_val = C_val + C_inc

best_score_C_val = C_values[recall_scores.index(best_recall_score)]
print("1st max value of {0:.3f} occured at c={1:.3f}".format(best_recall
_score,best_score_C_val))

%matplotlib inline
plt.plot(C_values , recall_scores, "-")
plt.xlabel("C value")
plt.ylabel("recall score")
```

```
1st max value of 0.738 occured at c=0.300
```

Out[34]:
```
<matplotlib.text.Text at 0x10bd94748>
```



In [35]:
```
from sklearn.linear_model import LogisticRegression
lr_model = LogisticRegression(class_weight='balanced' , C=best_score_C_v
al, random_state=42)
lr_model.fit(X_train, y_train.ravel())
```

Out[35]:
```
LogisticRegression(C=0.30000000000000004, class_weight='balanced', dual
=False,
          fit_intercept=True, intercept_scaling=1, max_iter=100,
          multi_class='ovr', n_jobs=1, penalty='l2', random_state=42,
          solver='liblinear', tol=0.0001, verbose=0, warm_start=False)
```

In [36]:
```
lr_predict_test = lr_model.predict(X_test)
# training metrics
print("Accuracy : {0:.4f}".format(metrics.accuracy_score(y_test, lr_pred
ict_test)))
print()
```

```
Accuracy : 0.7143
```

In [37]:
```
print("Confusion Matrix")

# the use of labels to set 1=True to upper left and 0=False to lower rig
ht

print("{0}".format(metrics.confusion_matrix(y_test, lr_predict_test, lab
els = [1,0])))
print(" ")

print(" Classification Report ")
print(metrics.classification_report(y_test, lr_predict_test, labels =
[1,0]))
```

```
Confusion Matrix
[[ 59  21]
 [ 45 106]]

 Classification Report
             precision    recall  f1-score   support

          1       0.57      0.74      0.64        80
          0       0.83      0.70      0.76       151

avg / total       0.74      0.71      0.72       231
```

LogisticRegression CrossValidation

In [38]:
```
from sklearn.linear_model import LogisticRegressionCV
lr_cv_model = LogisticRegressionCV(n_jobs=-1, random_state=42, Cs=3,
cv=10, refit=True, class_weight='balanced')
lr_cv_model.fit(X_train, y_train.ravel())
```

Out[38]:
```
LogisticRegressionCV(Cs=3, class_weight='balanced', cv=10, dual=False,
           fit_intercept=True, intercept_scaling=1.0, max_iter=100,
           multi_class='ovr', n_jobs=-1, penalty='l2', random_state=42,
           refit=True, scoring=None, solver='lbfgs', tol=0.0001, verbos
e=0)
```

Predict on Test data

In [39]:
```
lr_cv_predict_test = lr_cv_model.predict(X_test)
# training metrics
print("Accuracy : {0:.4f}".format(metrics.accuracy_score(y_test, lr_cv_p
redict_test)))
print()
```

```
Accuracy : 0.7013
```

In [40]:
```
print("Confusion Matrix")

# the use of labels to set 1=True to upper left and 0=False to lower rig
ht

print("{0}".format(metrics.confusion_matrix(y_test, lr_cv_predict_test,
labels = [1,0])))
print(" ")

print(" Classification Report ")
print(metrics.classification_report(y_test, lr_cv_predict_test, labels =
 [1,0]))
```

```
Confusion Matrix
[[ 53  27]
 [ 42 109]]

 Classification Report
             precision    recall  f1-score   support

          1       0.56      0.66      0.61        80
          0       0.80      0.72      0.76       151

avg / total       0.72      0.70      0.71       231
```