In [42]: import numpy as np import pandas as pd # built on top of numpy import matplotlib as mpl import matplotlib.pyplot as plt import seaborn as sns # built on top of matplotlib from pandas.api.types import Categorical Dtype # enables specifying categorical agetype from sklearn.preprocessing import Imputer, MinMaxScaler from sklearn.svm import SVC from sklearn.metrics import confusion\_matrix, accuracy\_score, classification\_report, x from sklearn.model\_selection import train\_test\_split, GridSearchCV, cross\_val\_score

In [43]:

In [44]:

Out[44]:

	preg	plas	pres	skin	insu	mass	pedi	age	cla
count	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	768.0000
mean	3.845052	120.894531	69.105469	20.536458	79.799479	31.992578	0.471876	33.240885	0.3489
std	3.369578	31.972618	19.355807	15.952218	115.244002	7.884160	0.331329	11.760232	0.4769
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.078000	21.000000	0.0000
25%	1.000000	99.000000	62.000000	0.000000	0.000000	27.300000	0.243750	24.000000	0.0000
50%	3.000000	117.000000	72.000000	23.000000	30.500000	32.000000	0.372500	29.000000	0.0000
75%	6.000000	140.250000	80.000000	32.000000	127.250000	36.600000	0.626250	41.000000	1.0000
max	17.000000	199.000000	122.000000	99.000000	846.000000	67.100000	2.420000	81.000000	1.0000

08-01-2018, 00:02 1 of 10

```
In [45]: diabetes2 = diabetes.copy(deep=True)
          # use replace as pure function:
          diabetes2['plas'] = diabetes['plas'].replace(0,np.NaN)
          diabetes2['pres'] = diabetes['pres'].replace(0,np.NaN)
          diabetes2['skin'] = diabetes['skin'].replace(0,np.NaN)
          diabetes2['insu'] = diabetes['insu'].replace(0,np.NaN)
          diabetes2['mass'] = diabetes['mass'].replace(0,np.NaN)
          # use replace as mutator by setting arg inplace=True
          #diabetes2['pedi'].replace(0,np.NaN, inplace=True)
          #diabetes.describe()
          #diabetes2.describe()
          #len(diabetes2)
          #nullGest = df2.gestation.isnull()# nullGest is array of boolean
          #countNullGest = len(nullGest[nullGest==True]) #take slice to count how many True
          #print countNullGest
          #print df2.isnull()
          #df2.isnull().sum(axis=0) # sum along columns
          #diabetes2=diabetes2.dropna()
          diabetes2.isnull().sum(axis=0)
          #len(diabetes2)
          #class1 =diabetes2['class']==0
                      0
Out[45]: preg
                      5
          plas
                     35
          pres
                    227
          skin
                    374
          insu
          mass
                     11
          pedi
          age
                      0
                      0
          class
          dtype: int64
In [46]: print diabetes2.apply(np.nanmedian, axis = 0) #calculate medians to compare with means
          preq
                      3.0000
                    117.0000
          plas
                    72.0000
          pres
                    29.0000
          skin
          insu
                   125.0000
          mass
                    32.3000
          pedi
                      0.3725
                     29.0000
          age
          class
                      0.0000
          dtype: float64
Out[46]:
                                                    skin
                                                                                  pedi
                                                                                                      cla
                      preg
                                plas
                                          pres
                                                              insu
                                                                       mass
                                                                                             age
           count 768.000000 763.000000 733.000000 541.000000
                                                         394.000000 757.000000 768.000000 768.000000 768.0000
           mean
                   3.845052 121.686763
                                      72.405184
                                                29.153420 155.548223
                                                                    32.457464
                                                                               0.471876
                                                                                        33.240885
                                                                                                   0.3489
                   3.369578
                            30.535641
                                      12.382158
                                                10.476982 118.775855
                                                                                                   0.4769
             std
                                                                     6.924988
                                                                               0.331329
                                                                                        11.760232
                   0.000000
                            44.000000
                                      24.000000
                                                 7.000000
                                                          14.000000
                                                                    18.200000
                                                                               0.078000
                                                                                        21.000000
                                                                                                   0.0000
            min
            25%
                   1.000000
                            99.000000
                                      64.000000
                                                22.000000
                                                          76.250000
                                                                    27.500000
                                                                                        24.000000
                                                                                                   0.0000
                                                                               0.243750
            50%
                   3.000000 117.000000
                                                29.000000 125.000000
                                                                    32.300000
                                                                                        29.000000
                                                                                                   0.0000
                                      72.000000
                                                                               0.372500
            75%
                   6.000000 141.000000
                                      80.000000
                                                36.000000 190.000000
                                                                    36.600000
                                                                               0.626250
                                                                                        41.000000
                                                                                                   1.0000
                  17.000000 199.000000 122.000000
                                                99.000000 846.000000
                                                                    67.100000
                                                                               2.420000
                                                                                        81.000000
                                                                                                   1.0000
            max
```

```
In [47]: X = diabetes2.drop(labels=['class','insu','skin'], axis=1)
         y = diabetes2.loc[:,'class'] # alt: use iloc for index based data selection
         #print y
         print y.unique()
         X col names = X.columns.values
         [1 0]
In [48]: imp x = Imputer(missing values='NaN', strategy='mean', axis=0)
         X train = imp x.fit transform(X train) # # fit AND transform training set
         X test = imp x.transform(X test) # transform test set on scale fitted to training set
         614
In [49]: (_, idx, counts) = np.unique(y_train, return_index=True, return_counts=True)
         [0 1] [2 0] [400 214]
In [50]:
         def svc_call(C_val,gamma_val,kernel_val,class_weight_val,degree_val,cache_size_val,prc
             return SVC(C=C val,gamma=gamma val,kernel=kernel val,class weight=class weight val
         def predict accuracy(y test, y pred):
             pTot = accuracy score(y test, y pred)
             return pTot
         def plot_auc(svc, X_train, y_train, y_test):
             probas = svc.fit(X_train_minmax, y_train).predict_proba(X_test_minmax)
             fpr, tpr, thresholds = roc curve(y test, probas [:, 1]) # use the probs of (class
             roc auc = auc(fpr, tpr)
             #print "thresholds", thresholds
             #print "probas ", probas
             print "AUC using predict_proba", roc_auc
             plt.figure()
             #plt.plot(fpr, tpr, label='ROC curve (area = %0.2f)' % roc auc, lw=4) # plot ROC
             plt.plot(fpr, tpr, label='ROC curve (area = %0.2f)' % roc_auc, lw=3, color ="#0000
             plt.plot([0, 1], [0, 1], 'k--') # also plot black dashed line (k=black) from (0,0)
             # Set x and y ranges, labels, title and legend
             plt.xlim([-0.005, 1.0]) #x range basically from 0 to 1: start range a bit to left
             plt.ylim([0.0, 1.005]) #0 range basically from 0 to 1: extend range a bit above
             plt.xlabel('False Positive Rate')
             plt.ylabel('True Positive Rate')
             plt.title('Receiver operating characteristic example')
             plt.legend(loc="lower right")
             plt.show()
```

```
In [51]: C_val=100
         gamma val='auto'
         kernel_val = 'rbf'
         class_weight_val='balanced'
         cache_size_val=1000
         probability val=True
         degree val=3
         svc = svc call(C val,gamma val,kernel val,class weight val,degree val,cache size val,r
         print svc
         print
         clf = svc.fit(X train, y train) # trains the classifier on the training set
         y pred = svc.predict(X test) # tests the classifier on the test set
         pTot = predict accuracy(y test, y pred)
         print "Prediction accuracy: ",pTot
         SVC(C=100, cache_size=1000, class_weight='balanced', coef0=0.0,
           decision_function_shape='ovr', degree=3, gamma='auto', kernel='rbf',
           max_iter=-1, probability=True, random_state=None, shrinking=True,
           tol=0.001, verbose=False)
         Prediction accuracy: 0.642857142857
In [52]: cm = confusion_matrix(y_test, y_pred)
Out[52]: array([[99, 1],
                [54, 0]], dtype=int64)
In [53]: report = classification_report(y_test, y_pred)
                                recall f1-score
                      precision
                                                    support
                                    0.99
                                                          100
                           0.65
                                               0.78
                                    0.00
                           0.00
                                               0.00
                                                          54
         avg / total
                           0.42
                                   0.64
                                               0.51
                                                         154
```

```
In [54]: print X_test #compare before/after scaling
         min max scaler = MinMaxScaler()
         X_train_minmax = min_max_scaler.fit_transform(X_train) # fit AND transform training set
         X_test_minmax = min_max_scaler.transform(X_test) # test set transform only, no fit
         [[ 4.00000000e+00 9.90000000e+01
                                              7.20000000e+01
                                                              2.56000000e+01
            2.94000000e-01 2.80000000e+01]
                                              7.40000000e+01
                                                              2.62000000e+01
          [ 1.00000000e+00 1.43000000e+02
            2.56000000e-01 2.10000000e+01]
          [ 1.00000000e+00 8.90000000e+01
                                              7.60000000e+01
                                                              3.12000000e+01
            1.92000000e-01 2.30000000e+01]
            7.00000000e+00 1.19000000e+02
                                              7.23118644e+01
                                                              2.52000000e+01
            2.09000000e-01 3.70000000e+01]
          [ 5.00000000e+00 1.26000000e+02
                                              7.80000000e+01
                                                              2.96000000e+01
            4.39000000e-01 4.00000000e+01]
          [ 6.00000000e+00 1.14000000e+02
                                              8.80000000e+01
                                                              2.78000000e+01
            2.47000000e-01 6.60000000e+01]
          [ 1.00000000e+00 9.20000000e+01
                                              6.20000000e+01
                                                              1.95000000e+01
            4.82000000e-01 2.50000000e+01]
           1.00000000e+00 1.09000000e+02
                                              3.80000000e+01
                                                              2.31000000e+01
            4.07000000e-01 2.60000000e+01]
                                              6.80000000e+01 4.24000000e+01
            1.00000000e+00 1.7200000e+02
            7.02000000e-01 2.80000000e+01]
            0.00000000e+00 1.0200000e+02
                                              5.20000000e+01 2.51000000e+01
            7 00000000 00
                            0 10000000-1011
In [55]: | svc = svc_call(C_val,gamma_val,kernel_val,class_weight_val,degree_val,cache_size_val,r
         print svc
         print
         clf = svc.fit(X_train_minmax, y_train) # trains the classifier on the training set
         y pred minmax = svc.predict(X test minmax) # tests the classifier on the test set
         pTot = predict_accuracy(y_test,y_pred_minmax)
         SVC(C=100, cache size=1000, class weight='balanced', coef0=0.0,
          decision_function_shape='ovr', degree=3, gamma='auto', kernel='rbf',
          max_iter=-1, probability=True, random_state=None, shrinking=True,
          tol=0.001, verbose=False)
         Prediction accuracy: 0.75974025974
In [56]: cm = confusion_matrix(y_test, y_pred_minmax)
         print cm
         report = classification_report(y_test, y_pred_minmax)
         [[76 24]
          [13 41]]
                     precision recall f1-score
                                                    support
                                    0.76
                                              0.80
                                                        100
                  0
                          0.85
                  1
                          0.63
                                    0.76
                                              0.69
                                                         54
                          0.78
                                   0.76
                                              0.76
                                                        154
         avg / total
```

```
In [57]: %matplotlib inline
          AUC using predict proba 0.831481481481
                    Receiver operating characteristic example
            1.0
            0.8
          True Positive Rate
            0.6
            0.4
            0.2
                                         ROC curve (area = 0.83)
            0.0
                       0.2
                                0.4
                                        0.6
                                                 0.8
              0.0
                               False Positive Rate
In [58]: C range = 10.0 ** np.arange(-2, 4)
          #gamma_range = 10.0 ** np.arange(-3, 3)
          gamma_range = [.01, .1, 1, 'auto', 10, 100]
          print gamma range
          param grid = dict(gamma=gamma range, C=C range)
          [0.01, 0.1, 1, 'auto', 10, 100]
Out[58]: {'C': array([ 1.00000000e-02,
                                             1.00000000e-01,
                                                               1.00000000e+00,
                    1.00000000e+01, 1.00000000e+02, 1.00000000e+03]),
           'gamma': [0.01, 0.1, 1, 'auto', 10, 100]}
In [59]: # Default is 3-fold cross validation
          grid = GridSearchCV(SVC(kernel='rbf',cache size=1000, probability=True), param grid=pa
          #grid = GridSearchCV(SVC(kernel='rbf', class weight='balanced', cache size=1000, proba
          grid.fit(X_train_minmax, y_train) # run the grid search on the training data only
          best C = grid.best estimator .C
          best gamma = grid.best estimator .gamma
          #print best C
          #print best gamma
          print "The best C and gamma for rbf is: %.5s, %.5s " % (best C, best gamma)
          grid.best_estimator_
```

The best C and gamma for rbf is: 1.0, auto

Out[59]: SVC(C=1.0, cache\_size=1000, class\_weight=None, coef0=0.0, decision\_function\_shape='ovr', degree=3, gamma='auto', kernel='rbf', max\_iter=-1, probability=True, random\_state=None, shrinking=True, tol=0.001, verbose=False)

08-01-2018, 00:02 6 of 10

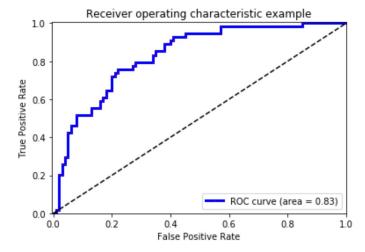
```
In [60]: best_predict_minmax = grid.best_estimator_.predict(X_test_minmax)
         pTot = accuracy_score(y_test, best_predict_minmax)
         print "Prediction accuracy: ",pTot
         cm = confusion_matrix(y_test, best_predict_minmax)
         print cm
         report = classification report(y test, best predict minmax)
        Prediction accuracy: 0.75974025974
         [[92 8]
          [29 25]]
                     precision recall f1-score
                                                   support
                       100
                  0
                                             0.83
                                   0.46
                                             0.57
                                                        54
        avg / total
                        0.76 0.76
                                           0.74
                                                       154
In [61]: C test = 10
         gamma test = 'auto'
         class_weight_val=None
         #test svc = SVC(C=10, gamma='auto',kernel='rbf', cache size=1000, probability=True)
         test_svc = svc_call(C_test,gamma_test,kernel_val,class_weight_val,degree_val,cache_siz
         print test svc
         print
         test_svc.fit(X_train_minmax, y_train)#
         y_pred_test = test_svc.predict(X_test_minmax)
         print "Prediction accuracy: ",predict_accuracy(y_test,y_pred_test)
         SVC(C=10, cache size=1000, class weight=None, coef0=0.0,
          decision function shape='ovr', degree=3, gamma='auto', kernel='rbf',
          max iter=-1, probability=True, random state=None, shrinking=True,
          tol=0.001, verbose=False)
         Prediction accuracy: 0.772727272727
```

The above test SVC gives the best accuracy which takes Soft-margin value(C) as 10, Gamma as 'auto' and the kernel used is 'Radial basis function'

```
In [62]: cm = confusion_matrix(y_test, y_pred_test)
       print cm
       report = classification_report(y_test, y_pred_test)
       [[92 8]
        [27 27]]
                 precision recall f1-score support
               0
                    0.77
                             0.92
                                    0.84
                                              100
               1
                      0.77
                             0.50
                                      0.61
                                               54
       avg / total 0.77 0.76
                                           154
```

```
In [63]:
```

AUC using predict proba 0.832962962963



```
In [64]: kernel_val='poly'
    degree_val=1

svc = svc_call(C_val,gamma_val,kernel_val,class_weight_val,degree_val,cache_size_val,r
#svc = SVC(kernel='rbf', cache_size=1000, probability=True)
print svc
print

svc.fit(X_train_minmax, y_train) # trains the classifier on the training set
y_pred_minmax = svc.predict(X_test_minmax) # tests the classifier on the test set

SVC(C=100, cache_size=1000, class_weight=None, coef0=0.0,
    decision_function_shape='ovr', degree=1, gamma='auto', kernel='poly',
    max_iter=-1, probability=True, random_state=None, shrinking=True,
```

Prediction accuracy: 0.75974025974

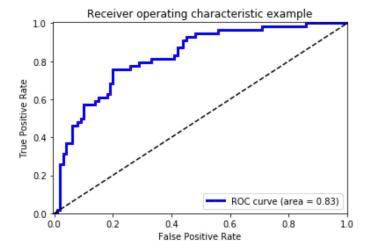
tol=0.001, verbose=False)

```
In [65]: cm = confusion_matrix(y_test, y_pred_minmax)
    print cm
    report = classification_report(y_test, y_pred_minmax)
```

[[91 9] [28 26]] precision recall f1-score support 0 0.76 0.91 0.83 100 1 0.74 0.48 0.58 54 avg / total 0.76 0.76 0.74 154

```
In [66]:
```

AUC using predict proba 0.828518518519



```
In [67]: # Default is 3-fold cross validation
    grid = GridSearchCV(SVC(kernel='poly', degree =1, cache_size=1000, probability=True), pa
    #grid = GridSearchCV(SVC(kernel='rbf', class_weight='balanced', cache_size=1000, proba
    grid.fit(X_train_minmax, y_train) # run the grid search on the training data only
    best_C = grid.best_estimator_.C
    best_gamma = grid.best_estimator_.gamma
    #print best_C
#print best_Gamma
print "The best C and gamma for poly is: %.5s, %.5s " % (best_C, best_gamma)
    grid.best_estimator_
```

The best C and gamma for poly is: 0.01, 100  $\,$ 

```
In [68]: best_predict_minmax = grid.best_estimator_.predict(X_test_minmax)
    pTot = accuracy_score(y_test, best_predict_minmax)
    print "Prediction accuracy: ",pTot
    cm = confusion_matrix(y_test, best_predict_minmax)
    print cm
    report = classification_report(y_test, best_predict_minmax)
```

Prediction accuracy: 0.753246753247 [[91 9]

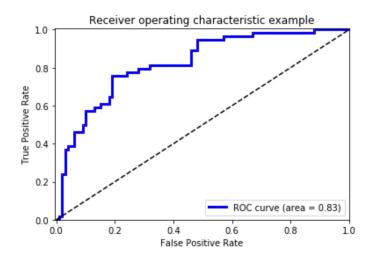
[29 25]]

support	f1-score	recall	precision	F
100	0.83	0.91	0.76	0
54	0.57	0.46	0.74	1
154	0.74	0.75	0.75	avg / total

```
In [69]: C_test = 10
         gamma test = 'auto'
         class_weight_val=None
         #test_svc = SVC(C=10, gamma='auto',kernel='rbf', cache_size=1000, probability=True)
         test_svc = svc_call(C_test,gamma_test,kernel_val,class_weight_val,degree_val,cache_siz
         print test svc
         print
         test svc.fit(X train minmax, y train) # trains the classifier on the training set
         y pred minmax test = test svc.predict(X test minmax) # tests the classifier on the
         print "Prediction accuracy: ",predict_accuracy(y_test,y_pred_minmax_test)
         SVC(C=10, cache size=1000, class weight=None, coef0=0.0,
           decision function shape='ovr', degree=1, gamma='auto', kernel='poly',
           max iter=-1, probability=True, random state=None, shrinking=True,
           tol=0.001, verbose=False)
         Prediction accuracy: 0.753246753247
In [70]: cm = confusion_matrix(y_test, y_pred_minmax_test)
         print cm
         report = classification_report(y_test, y_pred_minmax_test)
         [[91 9]
          [29 25]]
                      precision
                                   recall f1-score
                                                       support
                           0.76
                                     0.91
                                               0.83
                                                          100
                           0.74
                                     0.46
                                               0.57
                                                           54
                           0.75
                                     0.75
                                               0.74
                                                          154
         avg / total
```

## In [71]:

AUC using predict proba 0.827037037037



In [ ]: