Implementation of SVC ¶

- 1. Accessing the Dataset
- 2. Splitting the Data
- 3. Building the Model
- 4. Checking the Performance
- 5. Hyper-parameter Tuning
- 6. The Final Model

Accessing the Dataset

```
In [1]: import numpy as np
         import pandas as pd
         import matplotlib.pyplot as plt
         import seaborn as sns
In [2]: db = pd.read_csv('diabetes.csv')
In [3]: |db.head()
Out[3]:
            Pregnancies Glucose BloodPressure SkinThickness Insulin BMI DiabetesPedigreeFunction Age Outcome
         0
                     6
                            148
                                          72
                                                        35
                                                                0 33.6
                                                                                        0.627
                                                                                               50
                                                                                                          1
         1
                             85
                                          66
                                                        29
                                                                0 26.6
                                                                                        0.351
                                                                                               31
                                                                                                         0
         2
                     8
                            183
                                          64
                                                        0
                                                                0 23.3
                                                                                        0.672
                                                                                               32
                             89
                                          66
                                                        23
                                                               94 28.1
                                                                                        0.167
                                                                                               21
                     0
                            137
                                          40
                                                        35
                                                              168 43.1
                                                                                        2.288
In [4]: | y = db['Outcome']
Out[4]: 0
                1
         1
                0
         2
                1
         4
                1
         763
                0
         764
                0
         765
         766
         767
         Name: Outcome, Length: 768, dtype: int64
In [5]: y.value_counts()
Out[5]: 0
              500
              268
         Name: Outcome, dtype: int64
In [6]: X = db.drop(['Outcome'], axis = 1) # dropping target variable
In [7]: X.head()
Out[7]:
            Pregnancies Glucose BloodPressure SkinThickness Insulin BMI DiabetesPedigreeFunction Age
                            148
                                                                                                50
         0
                     6
                                          72
                                                        35
                                                                0 33.6
                                                                                        0.627
         1
                     1
                             85
                                          66
                                                       29
                                                               0 26.6
                                                                                        0.351
                                                                                               31
                                                         0
         2
                     8
                            183
                                          64
                                                                0 23.3
                                                                                        0.672
                                                                                               32
         3
                                                       23
                     1
                            89
                                          66
                                                               94 28.1
                                                                                        0.167
                                                                                               21
                     0
                            137
                                          40
                                                        35
                                                              168 43.1
                                                                                        2.288
                                                                                               33
In [8]: X.shape
Out[8]: (768, 8)
```

```
In [9]: X.describe()
Out[9]: Pregnancies Glucose BloodPressure SkinThickness Insulin BMI DiabetesPedigreeFunction Age
```

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	ВМІ	DiabetesPedigreeFunction	Age
count	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000
mean	3.845052	120.894531	69.105469	20.536458	79.799479	31.992578	0.471876	33.240885
std	3.369578	31.972618	19.355807	15.952218	115.244002	7.884160	0.331329	11.760232
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.078000	21.000000
25%	1.000000	99.000000	62.000000	0.000000	0.000000	27.300000	0.243750	24.000000
50%	3.000000	117.000000	72.000000	23.000000	30.500000	32.000000	0.372500	29.000000
75%	6.000000	140.250000	80.000000	32.000000	127.250000	36.600000	0.626250	41.000000
max	17.000000	199.000000	122.000000	99.000000	846.000000	67.100000	2.420000	81.000000

no null values, only numerical values

Splitting the Data

Building the Model

```
In [11]: from sklearn.svm import SVC
        svc_lin = SVC(kernel = 'linear', probability = True) #we don't have a predicted class, we need prob val
        svc_lin = svc_lin.fit(X_train, y_train)
        y_pred = svc_lin.predict(X_test)
        y_pred
Out[11]: array([1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 1, 0, 0, 1, 0, 0,
               0, 0, 0, 1, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0,
               1, 0, 0, 1, 1, 0, 1, 1, 0, 0, 1, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0,
               1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 1, 0, 0, 0, 1, 1, 0, 1,
               0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0,
              1, 0, 0, 0, 0, 1, 1, 1, 0, 0, 0, 0, 1, 0, 0, 1, 1, 0, 0, 0, 1, 0], dtype=int64)
In [12]: y_test
Out[12]: 568
        620
               0
               0
        456
        197
               1
        714
        264
              1
        706
               1
        194
               0
        179
        514
        Name: Outcome, Length: 154, dtype: int64
```

Calculating the Performance

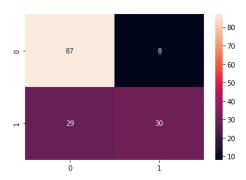
```
In [13]: from sklearn.metrics import confusion_matrix, classification_report, roc_curve, roc_auc_score

cm = confusion_matrix(y_test, y_pred)
    report = classification_report(y_test, y_pred)
    score = roc_auc_score(y_test, y_pred)
    fpr, tpr, _ = roc_curve(y_test, y_pred)#false positive rate & true positive rate

sns.heatmap(cm, annot = True)
    print('The Report,:\n', report)
    print('The ROC-AUC-Score', score)
```

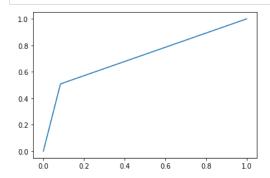
The Report,:					
,-	precision	recall	f1-score	support	
0	0.75	0.92	0.82	95	
1	0.79	0.51	0.62	59	
accuracy			0.76	154	
macro avg	0.77	0.71	0.72	154	
weighted avg	0.77	0.76	0.75	154	

The ROC-AUC-Score 0.7121320249776985



- 87 --> true positive
- 8 --> false positive
- 29 --> false positive
- 30 --> true negative

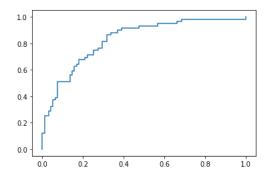
In [14]: plt.plot(fpr, tpr);



```
In [15]: y_pred_prob = svc_lin.predict_proba(X_test) #probability values are different in different machines due to 5-fold cross validation
         y_pred_prob
Out[15]: array([[0.45441093, 0.54558907],
                [0.78710559, 0.21289441],
                [0.51941624, 0.48058376],
                [0.87749624, 0.12250376],
                [0.88402775, 0.11597225],
                [0.93732449, 0.06267551],
                [0.89674568, 0.10325432],
                [0.68440209, 0.31559791],
                [0.91873041, 0.08126959],
                [0.60758483, 0.39241517],
                [0.90784189, 0.09215811],
                [0.73960385, 0.26039615],
                [0.14436853, 0.85563147],
                [0.68257124, 0.31742876],
                [0.87392465, 0.12607535],
                [0.31487872, 0.68512128],
                [0.25121606, 0.74878394],
                [0.94036901, 0.05963099],
                [0.88671946, 0.11328054],
In [16]: y_pred
Out[16]: array([1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 1, 0, 0, 1, 0, 0,
                0, 0, 0, 1, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0,
                0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
                1, 0, 0, 1, 1, 0, 1, 1, 0, 0, 1, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0,
                1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 1, 0, 0, 0, 1, 1, 0, 1,
                0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0,
                1, 0, 0, 0, 0, 1, 1, 1, 0, 0, 0, 0, 1, 0, 0, 1, 1, 0, 0, 0, 1, 0]
               dtype=int64)
In [17]: from sklearn.metrics import confusion_matrix, classification_report, roc_curve, roc_auc_score
         cm = confusion_matrix(y_test, y_pred)
         report = classification_report(y_test, y_pred)
         score = roc_auc_score(y_test, y_pred)
         fpr, tpr, _ = roc_curve(y_test, y_pred_prob[:,1])#false positive rate & true positive rate
         sns.heatmap(cm, annot = True)
         print('The Report,:\n', report)
         print('The ROC-AUC-Score', score)
         The Report,:
                        precision
                                     recall f1-score
                                                        support
                            0.75
                                       0.92
                    0
                                                 0.82
                                                             95
                            0.79
                                      0.51
                                                             59
                                                0.62
             accuracy
                                                0.76
                                                            154
                            0.77
                                      0.71
                                                 0.72
                                                            154
            macro avg
         weighted avg
                            0.77
                                      0.76
                                                0.75
                                                            154
         The ROC-AUC-Score 0.7121320249776985
                                                    - 80
                                                    50
                                                    40
                                                    30
                     ò
                                      í
```

```
In [18]: plt.plot(fpr, tpr)
```

Out[18]: [<matplotlib.lines.Line2D at 0x1a9284bf520>]



doesn't have adjusted values now

Area under the curve:

random model-- 0.5

perfect model-- 1

our model-- 0.71

Hyper-paramter Tuning

changing the value of a parameter for maximum accuracy

kernel

```
In [19]: def SVC_tuning_kernel(kernel):
    model = SVC(kernel = kernel)
    model = model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    cm = confusion_matrix(y_test, y_pred)
    report = classification_report(y_test, y_pred)
    score = roc_auc_score(y_test, y_pred)
    print('The SVC with kernel:\n', kernel)
    print()
    print()
    print('********************************
    print('Confusion Matrix:\n', cm)
    print('The report:\n', report)
    print('The ROC-AUC-Score:', score)
    sns.heatmap(cm, annot = True);
```

```
In [20]: ## Calling the function
         SVC_tuning_kernel('linear')# argument to be passed has to be of type str
         The SVC with kernel:
```

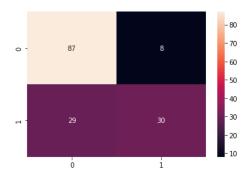
linear

Confusion Matrix: [[87 8]

[29 30]]

The report:	precision	recall	f1-score	support
0 1	0.75 0.79	0.92 0.51	0.82 0.62	95 59
accuracy macro avg weighted avg	0.77 0.77	0.71 0.76	0.76 0.72 0.75	154 154 154

The ROC-AUC-Score: 0.7121320249776985



In [21]: # Calling the function again with another kernel SVC_tuning_kernel('poly')

The SVC with kernel:

poly

Confusion Matrix:

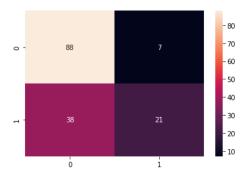
[[88 7]

[38 21]]

The report:

	precision	recall	f1-score	support
0	0.70	0.93	0.80	95
1	0.75	0.36	0.48	59
accuracy			0.71	154
macro avg	0.72	0.64	0.64	154
weighted avg	0.72	0.71	0.68	154

The ROC-AUC-Score: 0.6411239964317573



In [22]: SVC_tuning_kernel('rbf')

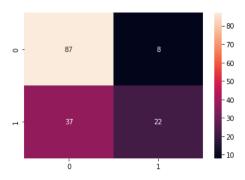
The SVC with kernel: rbf

Confusion Matrix:

[[87 8] [37 22]]

The report:	precision	recall	f1-score	support
0 1	0.70 0.73	0.92 0.37	0.79 0.49	95 59
accuracy macro avg weighted avg	0.72 0.71	0.64 0.71	0.71 0.64 0.68	154 154 154

The ROC-AUC-Score: 0.6443354148082068



In [23]: SVC_tuning_kernel('sigmoid')

The SVC with kernel: sigmoid

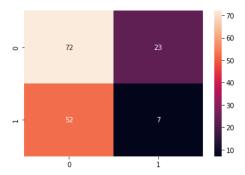
Confusion Matrix:

[[72 23] [52 7]]

The report:

·	precision	recall	f1-score	support
0 1	0.58 0.23	0.76 0.12	0.66 0.16	95 59
accuracy	0.23	0.12	0.51	154
macro avg weighted avg	0.41 0.45	0.44 0.51	0.41 0.47	154 154 154

The ROC-AUC-Score: 0.4382694023193577



The best kernel after tuning is linear

```
In [27]: # Tuning regularisation paramter
         # Regularisation -
         def SVC_tuning_C(C_list): # C_list --> a list of C values
             for c in C_list:
                 model = SVC(kernel = 'linear', C = c)
                 model = model.fit(X_train, y_train)
                 y_pred = model.predict(X_test)
                 score = roc_auc_score(y_test, y_pred)
                 print('C:', c, '===>', 'Score:', score)
In [28]: C_list = [0.1, 1, 1.1, 2, 3, 4, 5, 10, 15, 20, 25, 30]
In [29]: SVC_tuning_C(C_list)
         C: 0.1 ===> Score: 0.703657448706512
         C: 1 ===> Score: 0.7121320249776985
         C: 1.1 ===> Score: 0.7121320249776985
         C: 2 ===> Score: 0.7068688670829617
         C: 3 ===> Score: 0.7068688670829617
         C: 4 ===> Score: 0.7068688670829617
         C: 5 ===> Score: 0.7068688670829617
         C: 10 ===> Score: 0.7016057091882248
         C: 15 ===> Score: 0.7016057091882248
         C: 20 ===> Score: 0.7290811775200713
         C: 25 ===> Score: 0.7068688670829617
         C: 30 ===> Score: 0.7068688670829617
In [30]: C_list2 = [18, 19, 21, 22]
         SVC_tuning_C(C_list2)
         C: 18 ===> Score: 0.715343443354148
         C: 19 ===> Score: 0.7068688670829617
         C: 21 ===> Score: 0.7068688670829617
         C: 22 ===> Score: 0.7068688670829617
         After tuning the best value of C is 20
```

The best model is the one with **kernel = linear** and **C = 20**

The Final Model

```
In [31]: | svc = SVC(kernel = 'linear', C = 20, probability = True)
         svc = svc.fit(X_train, y_train)
         y_pred = svc.predict(X_test)
         y_pred_prob = svc.predict_proba(X_test)
         cm = confusion_matrix(y_test, y_pred)
         score = roc_auc_score(y_test, y_pred)
         report = classification_report(y_test, y_pred)
         dpr, tpr,_ = roc_curve(y_test, y_pred_prob[:,1])
         print('The Confusion Matrix:')
         sns.heatmap(cm, annot = True)
         print('ROC-AUC-Score:', score)
         print('The report:', report)
         The Confusion Matrix:
         ROC-AUC-Score: 0.7290811775200713
         The report:
                                   precision
                                                recall f1-score
                                                                    support
                    0
                            0.76
                                       0.92
                                                 0.83
                                                             95
                             0.80
                                       0.54
                                                 0.65
                                                             59
                                                 0.77
                                                            154
             accuracy
                             0.78
                                       0.73
                                                 0.74
                                                            154
            macro avg
                                                            154
         weighted avg
                             0.78
                                       0.77
                                                 0.76
                     87
                                                    50
                                                     40
                                                    30
                     ò
                                      í
```