ELL409: Assignment 2

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Part 1

1. Binary Classification using convex optimization (CVXOPT)

SVM dual problem and convex optimization package

$$egin{aligned} \min rac{1}{2} x^T P x + q^T x \ s. \, t. & G x \leq h \ A x = b \end{aligned}$$

The general steps to solve the SVM problem are the following:

- Create ${f P}$ where $H_{i,j} = y^{(i)} y^{(j)} < x^{(i)} x^{(j)} >$
- Calculate $\mathbf{w} = \sum_{i}^{m} y^{(i)} lpha_{i} x^{(i)}$
- Determine the set of support vectors S by finding the indices such that $lpha_i>0$
- Calculate the intercept term using $b = y^{(s)} \sum_{m \in S} lpha_m y^{(m)} < x^{(m)} x^{(s)} >$
- For each new point x' classify according to $y' = \widetilde{sign}(w^Tx' + b)$

Relevant code for fitting using convex optimisation -

```
def cvx_fit(C,X,y) :
    m,n = X.shape
    y = y.reshape(-1,1) * 1.
    X_dash = y * X
    H = np.dot(X_dash , X_dash.T) * 1.

P = matrix(H)
    q = matrix(-np.ones((m, 1)))
    G = matrix(np.vstack((np.eye(m)*-1,np.eye(m))))
    h = matrix(np.hstack((np.zeros(m), np.ones(m) * C)))
    A = matrix(y.reshape(1, -1))
    b = matrix(np.zeros(1))

solvers.options['show_progress'] = False
    sol = solvers.qp(P, q, G, h, A, b)
    alphas = np.array(sol['x'])

return alphas
```

The code which takes the CVX output and uses it to construct the actual classifier to be run on test data:

```
w = np.sum(alphas * y[:, None] * x, axis = 0)
cond = (alphas > 1e-4).reshape(-1)
b = y[cond] - np.dot(x[cond], w)
```

Linear Classifier

```
Class A = 0
Class B = 1
C = 1
CVX OPT results:
w = \begin{bmatrix} 0.50903405 & 0.2151743 & -0.07727033 & 0.06086342 & 0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 & -0.0815154 
0.06419666
   -0.07647347 0.0908558 -0.04182757 0.143932 0.28851191 0.16998405
      0.01984412 -0.02207359 -0.26463624
                                                                                                                                                                                                                                                     0.12112439
                                                                                                                                                                                                                                                                                                                                        0.11990436 -
0.18536296
   -0.10984664 -0.03110624 -0.00899966
                                                                                                                                                                                                                                                         0.10722886 -0.01574708 -
0.11689553
  -0.123775681
b = 0.1450705
train accuracy = 1
test accuracy = 1
```

LIBSVM results:

 $w = \begin{bmatrix} 0.50891035 & 0.21537839 & -0.07721695 & 0.06081666 & 0.08153991 & -0.06415033 \end{bmatrix}$

0.01967119 -0.02200081 -0.26477857 0.12103369 0.11999122 - 0.18536999

-0.10968765 -0.03099504 -0.00902105 0.10743674 -0.01565741 - 0.11685295

-0.12383827]]

b = [0.14523601]

Polynomial Classifier

C = 10

Gamma = 1

CVXOPT result:

Alphas = [0.0223547 0.00532456 0.10067115 0.11565338 0.05470203 0.03265724

 $0.03697998\ 0.03342269\ 0.02443309\ 0.00291996\ 0.03779205\ 0.03806548$ $0.00581801\ 0.03597707\ 0.11595474]$

 $w = [0.50903405 \ 0.2151743 \ -0.07727033 \ 0.06086342 \ 0.0815154 \ -0.06419666$

 $-0.07647347 \ 0.0908558 \ -0.04182757 \ 0.143932 \ 0.28851191 \ 0.16998405$

0.01984412 -0.02207359 -0.26463624 0.12112439 0.11990436 - 0.18536296

-0.12377568]

b = 0.14507054446950562

2. Binary Classification

Train data set – 500

Test data set - 100

5 fold cross-validation

10 features

Linear Kernel

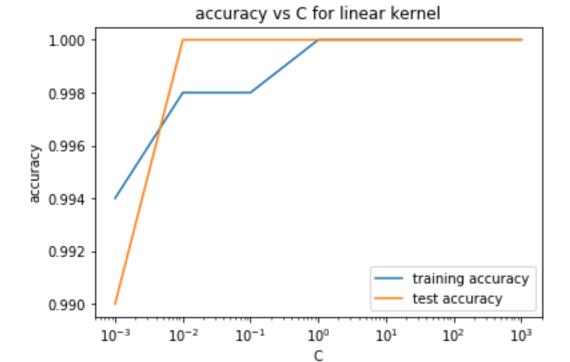
Class A = 0 & Class B = 1

Best Hyperparameter:

'SVM__C': 1

Train Acccuracy = 1.0

Train Accouracy = 1.0



Polynomial Kernel

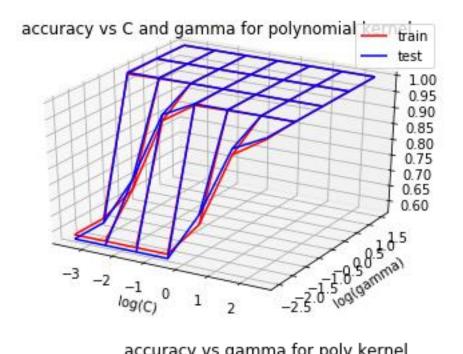
Class A = 0 & Class B = 1

Best Hyperparameter:

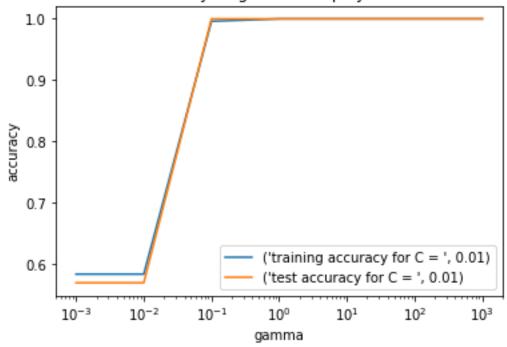
'SVM__C': 0.01

'SVM__gamma': 10

Train Accuracy = 1.0



accuracy vs gamma for poly kernel



Rbf kernel:

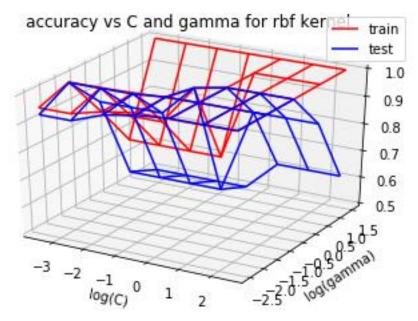
Class A = 0 & Class B = 1

Best Hyperparameter:

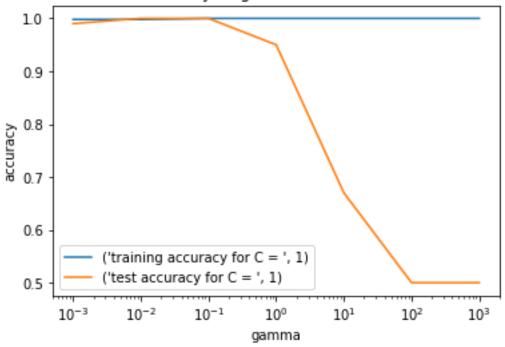
'SVM__C': 1,

'SVM__gamma': 0.01

Train Accuracy = 1.0



accuracy vs gamma for rbf kernel



25 features

Linear Kernel

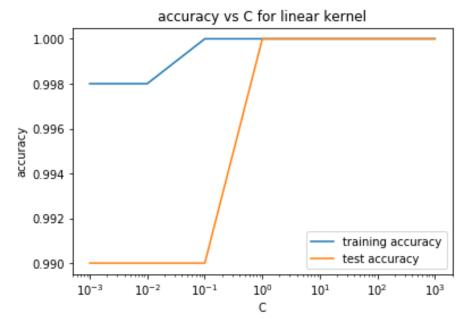
Class A = 0 & Class B = 1

Best Hyperparameter:

'SVM__C': 1

Train Acccuracy = 1.0

Train Acccuracy = 1.0



Polynomial Kernel

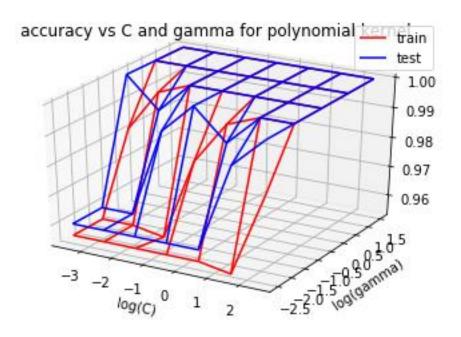
Class A = 0 & Class B = 1

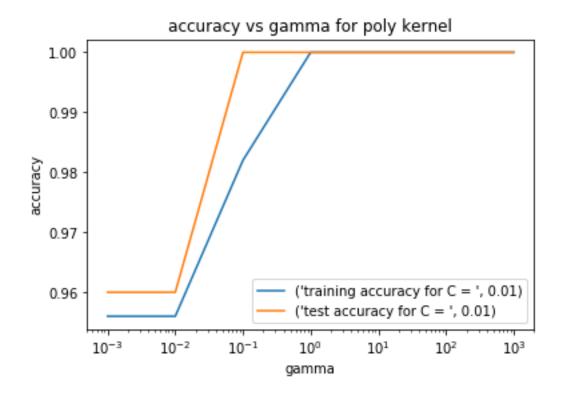
Best Hyperparameter:

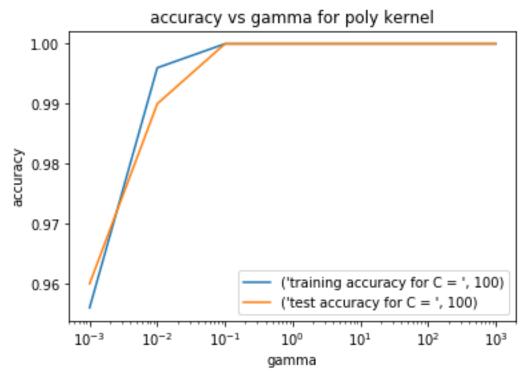
'SVM__C': 0.01

'SVM__gamma': 0.1

Train Accuracy = 1.0







Rbf kernel:

Class A = 0 & Class B = 1

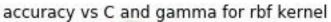
Best Hyperparameter:

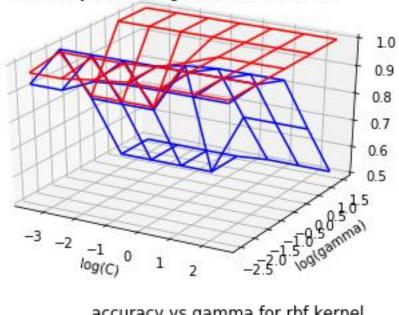
'SVM__C': 10,

'SVM__gamma': 0.01

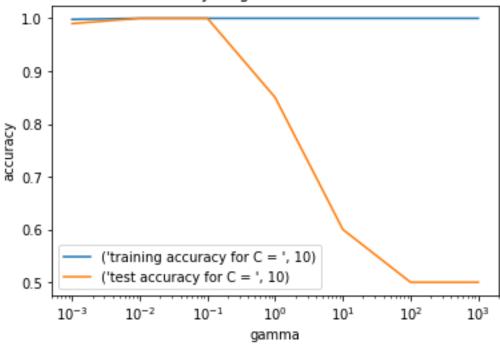
Train Accuracy = 1.0

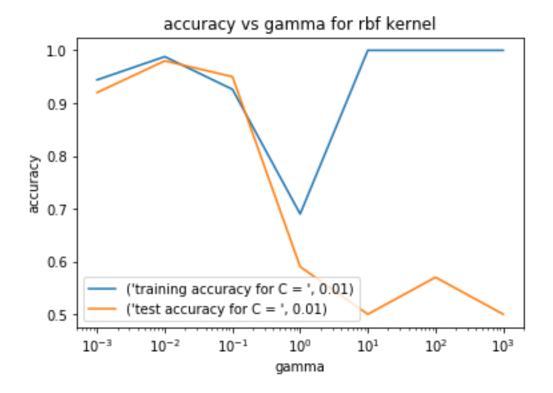
Test accuracy = 1.0





accuracy vs gamma for rbf kernel





Summary of Binary Classification

Train data set -500

Test data set - 100

5 fold cross- validation

25 features

Class A	Class B	Kernel	Best C	Best	Train	Test
				Gamma	Accuracy	Accuracy
0	1	Linear	1.0		1.0	1.0
0	1	Poly	0.1	0.1	1.0	1.0
0	1	rbf	10	0.01	1.0	1.0
8	9	Linear	100		0.99	0.96
8	9	Poly	0.1	0.1	1.0	0.98
8	9	Rbf	10	0.01	1.0	0.97
3	6	Linear	1.0		1.0	1.0
3	6	Poly	0.01	0.1	1.0	0.99
3	6	rbf	1	0.1	1.0	1.0

• For binary classification of given data, both linear and non-linear kernel are equally good.

Reason:

No. of feature = 25

No. of class = 2

Since, feature > class. So, linear kernel will also work fine.

- Different class need different hyper parameter setting.
- Linear
 - o C increment leads to over fitting
- Polynomial
 - o C increment leads to over fitting
 - o gamma increment leads to overfitting
- rbf
 - o C increment leads to over fitting
 - o gamma increment leads to overfitting

3. Multiclass classification

25 Features

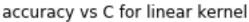
Linear Kernel

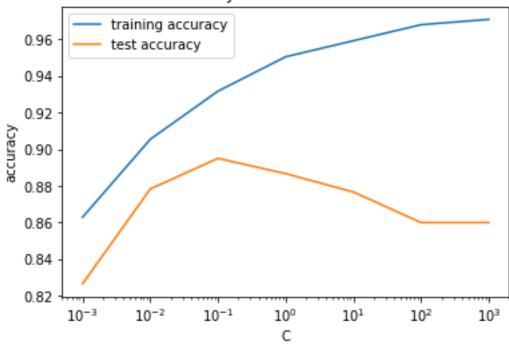
Best Hyperparameter:

'SVM__C': 0.1,

Train Accuracy = 0.925

Test accuracy = 0.89





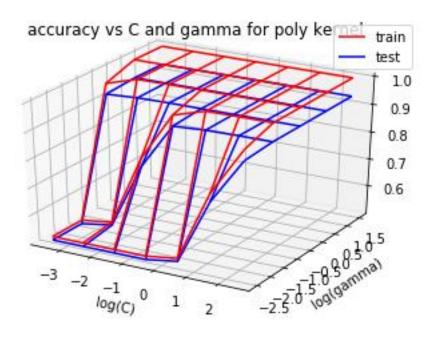
Polynomial Kernel

Best Hyperparameter:

'SVM__C': 0.01,

'SVM__gamma': 10

Train Accuracy = 1.0



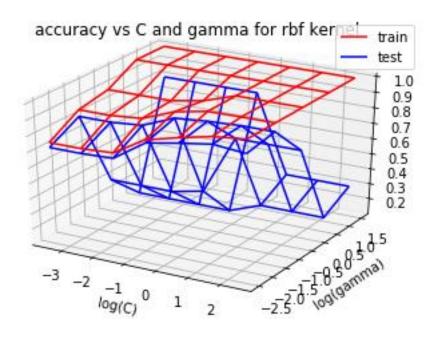
RBF Kernel

Best Hyperparameter:

'SVM__C': 10,

'SVM__gamma': 0.1

Train Accuracy = 1.0



10 Features

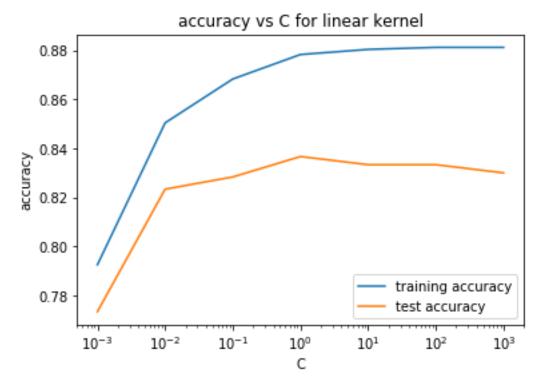
Linear Kernel

Best Hyperparameter:

'SVM__C': 1,

Train Accuracy = 0.87625

Test accuracy = 0.825



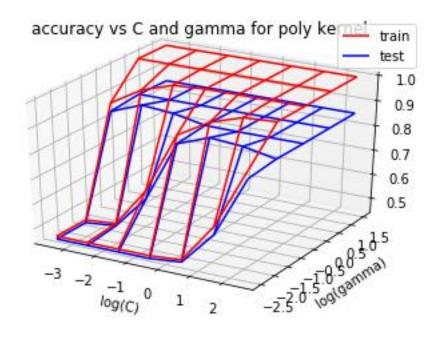
Polynomial Kernel

Best Hyperparameter:

'SVM__C': 1,

'SVM__gamma': 0.1

Train Accuracy = 0.9475



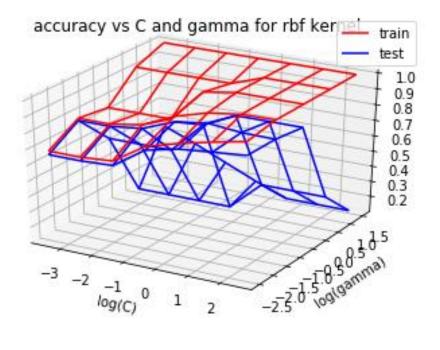
RBF Kernel

Best Hyperparameter:

'SVM__C': 10,

'SVM__gamma': 0.1

Train Accuracy = 0.9925



- Tuned values for muti-classification are different from binary classification. As, in binary classification, hyper parameters value are dependent on the class to be classified.
- Classification using 10 features has less accuracy than one with 25 features. As no. of feature provide more dimension, so data of different classes can be classified better.

Part 2

Approach:

- Scaled down data by 1000 to make data from -10 to 10.
- Fine tuning for hyper parameters through greed search.
- Test accuracy = 0.9588