## Homework 04 – One-Versus-All Support Vector Classification

#### **Importing Data**

• After importing NumPy, Pandas, Matplotlib, CVXOPT libraries, distance function from the SciPy library, and accuracy\_score metric from Scikit-Learn, I've imported the images and labels datasets using Pandas' read csv() function.

## **Train-Test Split**

• Then, I have divided data into X\_train, y\_train, X\_test, and y\_test sets. I also created an N train and N test variables to use later.

```
X_train = images[:1000]
y_train = np.array(labels[:1000][0])
X_test = images[1000:]
y_test = np.array(labels[1000:][0])

N_train = len(y_train)
N_test = len(y_test)
```

## **Distance and Kernel Functions (Gaussian Kernel)**

• Then, I have defined the gaussian\_kernel function, using the code provided in LAB 08 with the following formulas:

# Distance and Kernel Functions (Gaussian Kernel)

$$d(\mathbf{x}_{i}, \mathbf{x}_{j}) = ||\mathbf{x}_{i} - \mathbf{x}_{j}||_{2} = \sqrt{(\mathbf{x}_{i} - \mathbf{x}_{j})^{T}(\mathbf{x}_{i} - \mathbf{x}_{j})} = \sqrt{\sum_{d=1}^{D} (x_{id} - x_{jd})^{2}}$$
$$k(\mathbf{x}_{i}, \mathbf{x}_{j}) = \exp\left(-\frac{||\mathbf{x}_{i} - \mathbf{x}_{j}||_{2}^{2}}{2s^{2}}\right)$$

```
def gaussian_kernel(X1, X2, s):
    D = dt.cdist(X1, X2)
    K = np.exp(-D**2 / (2 * s**2))
    return(K)
```

### **Learning Algorithm**

• Then, I have defined one\_vs\_all\_classification and predict functions; the former is the learning algorithm that separates multiple classes using support vector machines, and the latter makes the prediction by looking at the maximum of each class's predictions.

```
def one vs all classification(C, class num):
    y_train_ = y_train.copy()
y_train_[y_train_ != class_num] = -1
y_train_[y_train_ == class_num] = 1
     s = 10
    K_train = gaussian_kernel(X_train, X_train, s)
    yyK = np.matmul(y_train_[:,None], y_train_[None,:]) * K_train
    epsilon = 1e-3
    print(f"C = {C}, class = {class_num}")
    P = cvx.matrix(yyK)
    q = cvx.matrix(-np.ones((N_train, 1)))
6 = cvx.matrix(np.vstack((-np.eye(N_train), np.eye(N_train))))
h = cvx.matrix(np.vstack((np.zeros((N_train, 1)), C * np.ones((N_train, 1)))))
    A = cvx.matrix(1.0 * y_train_[None,:])
    b = cvx.matrix(0.0)
    result = cvx.solvers.qp(P, q, G, h, A, b)
alpha = np.reshape(result["x"], N_train)
alpha[alpha < C * epsilon] = 0
alpha[alpha > C * (1 - epsilon)] = C
    support_indices, = np.where(alpha != 0)
    active_indices, = np.where(np.logical_and(alpha != 0, alpha < C))
w0 = np.mean(y_train_[active_indices] * (1 - np.matmul(yyK[np.ix_(active_indices, support_indices)], alpha[support_indices])
    f_predicted = np.matmul(K_train, y_train_[:,None] * alpha[:,None]) + w0
    return f predicted
def predict(C):
     f_predicted_1 = one_vs_all_classification(C=C, class_num=1)
     f_predicted_2 = one_vs_all_classification(C=C, class_num=2)
     f_predicted_3 = one_vs_all_classification(C=C, class_num=3)
     f_predicted_4 = one_vs_all_classification(C=C, class_num=4)
f_predicted_5 = one_vs_all_classification(C=C, class_num=5)
     y_predicted = []
     for i in range(1000):
           predictions = [f_predicted_1[i], f_predicted_2[i], f_predicted_3[i], f_predicted_4[i], f_predicted_5[i]]
           max_value = max(predictions)
           max_index = predictions.index(max_value)
           y_predicted.append(max_index + 1)
     return y predicted
```

• Using these two functions, I first made predictions with C parameter set to 10. Here is the resulting confusion matrix:

y_train	1	2	3	4	5
y_predicted					
1	207	1	0	9	0
2	2	199	1	1	0
3	0	1	204	6	0
4	0	1	4	185	1
5	0	0	0	0	178

• By setting C parameters to values 0.1, 1, 10, 100, and 1000, I have re-run the learning algorithm and saved the prediction accuracies.

• Then, I did the same steps for the test set, saved its prediction accuracies with different C parameters.

#### Visualization

• Lastly, I have visualized the relationship between the regularization parameter (C) and accuracy scores.

