HW4_212699581_211709597

June 19, 2022

[1]:
```
import matplotlib.pyplot as plt
from sklearn.svm import SVC
```

Question 3:
a.

[2]:
```
import numpy as np
from sklearn.datasets import fetch_openml
def fetch_mnist():
    # Download MNIST dataset
    X, y = fetch_openml('Fashion-MNIST', version=1, return_X_y=True)
    X = X.to_numpy()
    y = y.to_numpy()

    # Randomly sample 7000 images
    np.random.seed(2)
    indices = np.random.choice(len(X), 7000, replace=False)
    X, y = X[indices], y[indices]
    return X, y
X, y = fetch_mnist()
print(X.shape, y.shape)
```

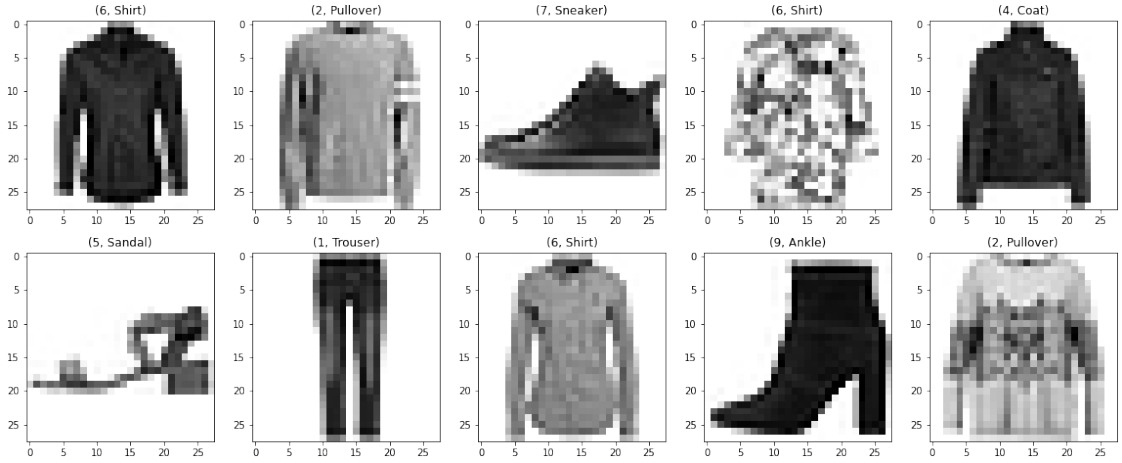
```
(7000, 784) (7000,)
```

b.

[3]:
```
idx2class={'0': 'T-shirt/top', '1': 'Trouser', '2': 'Pullover',
           '3': 'Dress', '4': 'Coat', '5': 'Sandal',
           '6': 'Shirt', '7': 'Sneaker', '8': 'Bag', '9': 'Ankle'}
```

[4]:
```
N = 10
H = 2
W = 5

fig, ax = plt.subplots(H, W)
fig.set_size_inches(20, 8)


point_i = 0
```

```
for i in range(H):
    for j in range(W):
        ax[i, j].imshow(X[point_i, :].reshape((28, 28)), cmap="binary")
        ax[i, j].set_title(f"({y[point_i]}, {idx2class[y[point_i]]})")
        point_i += 1
```



c.

[5]:
```
def cross_validation_error(X, y, model, folds):
    X_k = np.array_split(X, folds)
    y_k = np.array_split(y, folds)

#     print(y_k)

    train_error = list()
    val_error = list()

    for fold_1 in range(folds):
#         print(fold_1)
        X_val_k = X_k[fold_1]
        y_val_k = y_k[fold_1]

        X_train_k = np.array([element for fold_2 in range(folds) if fold_2 !=␣
 ↪fold_1 for element in X_k[fold_2]])
        y_train_k = np.array([element for fold_2 in range(folds) if fold_2 !=␣
 ↪fold_1 for element in y_k[fold_2]])

        model.fit(X_train_k, y_train_k)
```

```
        train_error.append(model.score(X_train_k, y_train_k))
        val_error.append(model.score(X_val_k, y_val_k))

    return (1-(np.array(train_error).mean()), 1-(np.array(val_error).mean()))

# folds = 4
# model = SVC(kernel="linear")
# train_error, val_error = cross_validation_error(X_train, y_train, model,␣
 ↪folds)
```

[6]:
```
def SVM_results(X_train, y_train, X_test, y_test):
    D = [2, 4, 6, 8]
    G = [0.001, 0.01, 0.1, 1.0, 10]
    folds = 4
    error_dict = dict()

    model = SVC(kernel="linear")
    train_error, val_error = cross_validation_error(X_train, y_train, model,␣
 ↪folds)

    model.fit(X_train, y_train)
    test_error = (model.predict(X_test) != y_test).mean()

    error_dict[f"linear_{folds}"] = (train_error, val_error, test_error)

    for d in D:
        model = SVC(kernel="poly", degree=d)
        train_error, val_error = cross_validation_error(X_train, y_train,␣
 ↪model, folds)

        model.fit(X_train, y_train)
        test_error = (model.predict(X_test) != y_test).mean()

        error_dict[f"poly_{d}_{folds}"] = (train_error, val_error, test_error)

    for g in G:
        model = SVC(kernel="rbf", gamma=g)
        train_error, val_error = cross_validation_error(X_train, y_train,␣
 ↪model, folds)

        model.fit(X_train, y_train)
        test_error = (model.predict(X_test) != y_test).mean()

        error_dict[f"rbf_{g}_{folds}"] = (train_error, val_error, test_error)

    return error_dict
```

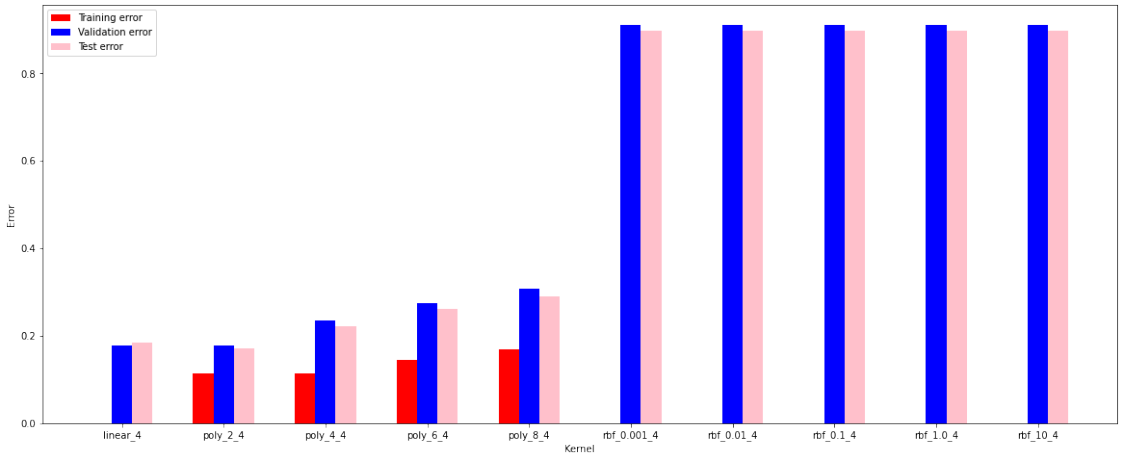
[7]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25,␣
 ↪random_state=42)
```

[8]:
```
errors = SVM_results(X_train, y_train, X_test, y_test)
```

[9]:
```
errors
```

[9]:
```
{'linear_4': (0.0, 0.17809432063046837, 0.18457142857142858),
 'poly_2_4': (0.11492092702316437, 0.1775252865342819, 0.17085714285714285),
 'poly_4_4': (0.11371423111053436, 0.23523965318670703, 0.22285714285714286),
 'poly_6_4': (0.14469827796943557, 0.2754299175227092, 0.2611428571428571),
 'poly_8_4': (0.16869858473084143, 0.30838194044545175, 0.2897142857142857),
 'rbf_0.001_4': (0.0, 0.9114276152638716, 0.8977142857142857),
 'rbf_0.01_4': (0.0, 0.9114276152638716, 0.8982857142857142),
 'rbf_0.1_4': (0.0, 0.9114276152638716, 0.8982857142857142),
 'rbf_1.0_4': (0.0, 0.9114276152638716, 0.8982857142857142),
 'rbf_10_4': (0.0, 0.9114276152638716, 0.8982857142857142)}
```

[10]:
```
fig, ax = plt.subplots()
fig.set_size_inches(20, 8)

width = 0.6

x = np.arange(10)



E = list(zip(*errors.values()))
ax.bar(x - width/3, E[0], width/3, color="red", label="Training error")
ax.bar(x, E[1], width/3, color="blue", label="Validation error")
ax.bar(x + width/3, E[2], width/3, color="pink", label="Test error")



ax.set_xticks(x)
ax.set_xticklabels(errors.keys())
ax.set_xlabel("Kernel")
ax.set_ylabel("Error")

plt.legend()
plt.show()
```



We see that rbf model has the lowest training error but high validation error which might be caused of overfitting
And we see that the poly model have relativly low training and validation errors which is the best of the CV method
The linear and the poly_2 have somewhat the same error on both validation and error sets with slight differences
so the best model w.r.t the test set is poly_2 then the linear