hw4

June 6, 2022

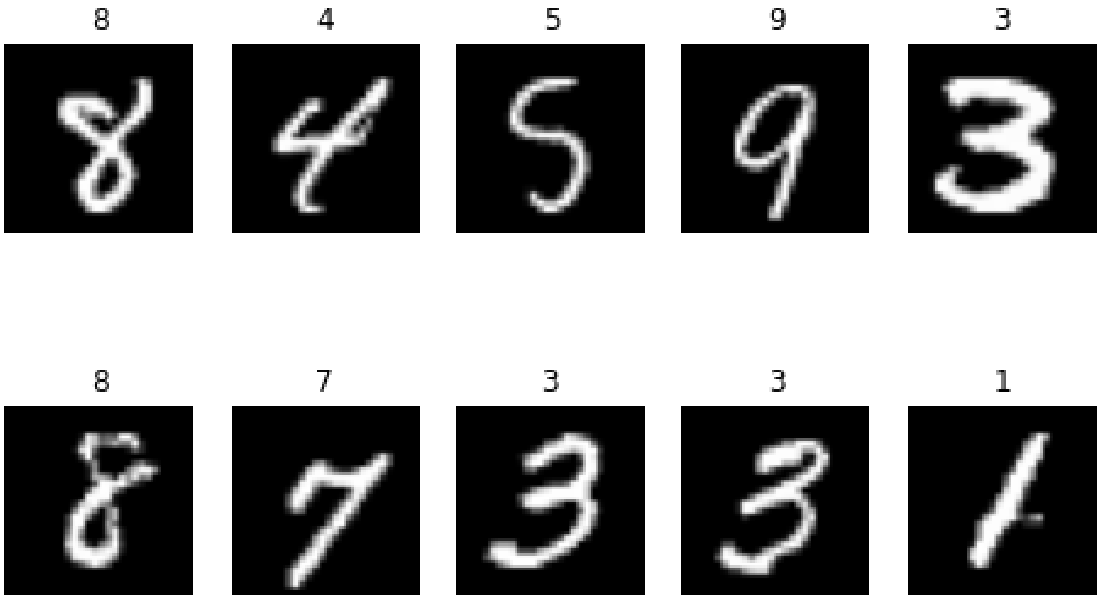
1 Homework 4 : Model Selection

The goal of this homework is find a suitable model that can distinguish handwritten digits.

[ ]:
```
import random
import torchvision
import numpy as np
from matplotlib import pyplot as plt
from sklearn.model_selection import KFold
from sklearn.metrics import accuracy_score
import sklearn

def prepareData(n=1000):
    """
    Downloads the dataset. Displays some examples.
    Returns the labeled dataset.

    Parameters
    ----------
    n : number of data sample (max 70 000)

    Returns
    -------
    X : Data Matrix
        (n, 28, 28).
    y : labels
        n

    """
    mnist_train = torchvision.datasets.MNIST("./data", download=True,)
    mnist_test = torchvision.datasets.MNIST("./data", download=True, train =␣
↪False)



    X = []
    y = []
    for x,label in mnist_train:
```

```python
        X.append(np.array(x))
        y.append(label)

    X_test = []
    y_test = []
    for x,label in mnist_test:
        X_test.append(np.array(x))
        y_test.append(label)

    X = np.array(X)
    y = np.array(y)
    X_test= np.array(X_test)
    y_test = np.array(y_test)


    sample = random.sample(range(len(X)), n)
    X = np.concatenate((X,X_test))[sample]
    y = np.concatenate((y,y_test))[sample]


    return X,y

def showSamples(X,y):
    fig=plt.figure(figsize=(8, 5))
    columns = 5
    rows = 2
    imgs = [X[i,:,:] for i in range(10)]
    for i in range(1, columns*rows +1):
        fig.add_subplot(rows, columns, i)
        plt.imshow(X[i-1,:,:] , cmap ="gray")
        plt.axis('off')
        plt.title(str(y[i-1]))
    plt.show()
```

[ ]:
```python
X,y = prepareData(1000)
showSamples(X,y)
print("Shape of data matrix X:", X.shape)
print("Shape of labels y:", y.shape)
```




```
Shape of data matrix X: (1000, 28, 28)
Shape of labels y: (1000,)
```

2 Extract features and Train Model

TODO: - Use any feature extraction method. Compute edges, histogram of oriented gradients, contours etc. to get a more concise representation of the images. - Train different models to learn a classification. - You can use any classification model. However, it is easier to use the models from sklearn: https://scikit-learn.org/stable/auto_examples/classification/plot_classifier_comparison.html

[ ]:
```
from skimage import filters

def featureExtraction(x):
    """
    Detects edges on a singular image.

    Parameters
    ----------
    x : ndarray
        a numpy array of shape 28x28

    Returns
    -------
    ndarray
        The resulting feature should be one-dimensional (use x.flatten())
    """
```

```
    #TODO: Define a feauture extraction method.
    # This method is called individually on each data point.
    # You can also look into methods that do feature extraction on the complete␣
 ↪dataset.
    return x.flatten()

def edges(x):
    """
    Detects edges on a singular image.

    Parameters
    ----------
    x : ndarray
        a numpy array of shape 28x28

    Returns
    -------
    ndarray
        The resulting feature should be one-dimensional (use x.flatten())
    """
    #TODO: Define a feauture extraction method.
    # This method is called individually on each data point.
    # You can also look into methods that do feature extraction on the complete␣
 ↪dataset.
    return filters.sobel(x).flatten()

from skimage.feature import hog
def hog_feature(x):
    """
    Computes histogram of oriented gradients on a singular image.

    Parameters
    ----------
    x : ndarray
        a numpy array of shape 28x28

    Returns
    -------
    ndarray
        The resulting feature should be one-dimensional (use x.flatten())
    """
    #TODO: Define a feauture extraction method.
    # This method is called individually on each data point.
    # You can also look into methods that do feature extraction on the complete␣
 ↪dataset.
    _, hog_image = hog(x, orientations=8, pixels_per_cell=(4, 4),
                       cells_per_block=(3, 3), visualize=True)
```

```
    return hog_image.flatten()

def preprocessDataset(X, featureExtraction):
    """
    Applies a feature extraction on a dataset

    Parameters
    ----------
    X : ndarray
        Data matrix of size nx28x28
    Returns
    -------
    X_prep : ndarray
        Data matrix of size nxd where d is some dimension of the feature
    """

    # TODO: (Optional) You can change this if necessary
    X_prep = []
    for i in range(len(X)):
        x = X[i,:,:]
        x = featureExtraction(x)
        X_prep.append(x)
    X_prep = np.array(X_prep)
    return X_prep


def train_bayes(X,y):
    # TODO: Select a classifier from sklearn and train it on the data
    from sklearn.naive_bayes import GaussianNB
    model = GaussianNB()
    model.fit(X,y)
    return model

def train_neural(X,y):
    # TODO: Select a classifier from sklearn and train it on the data
    from sklearn.neural_network import MLPClassifier
    model = MLPClassifier()
    model.fit(X,y)
    return model
```

3 K-fold Cross Validation

TODO: - Implement K-Fold Cross Validation - Split data into k partitions - Train model on k-1 partitions - Evaluate model on remaining partition using **Accuracy** as a metric - repeat k-times and compute **average Accuracy** over all splits

The following code computes cross-validation on a single data split. Adjust the code to evaluate on multiple splits.

```
[ ]: # Number of data samples (reduce number during initial test runs if procedure␣
     ↪takes too long)
     n = 50000
     X,y = prepareData(n)

     # Feature extraction
     D_null = preprocessDataset(X, featureExtraction)
     D_edge = preprocessDataset(X, edges)
     D_hog = preprocessDataset(X, hog_feature)

     def k_fold_cross_validation(D: np.ndarray, y: np.ndarray, n_splits: int=5,␣
      ↪classifier: str="neural") -> tuple:
         accu_training = 0.0
         accu_test = 0.0
         split_size = len(D)//n_splits
         for i in range(1, n_splits+1):
             X_train = np.concatenate((D[:(n_splits - i)*split_size], D[(n_splits +␣
      ↪1 - i)*split_size:]), axis=0)
             X_test = D[(n_splits - i)*split_size:(n_splits + 1 - i)*split_size]
             y_train = np.concatenate((y[:(n_splits - i)*split_size], y[(n_splits +␣
      ↪1 - i)*split_size:]), axis=0)
             y_test = y[(n_splits - i)*split_size:(n_splits + 1 - i)*split_size]

             # Train model
             if classifier == "bayes":
                 model = train_bayes(X_train,y_train)
             elif classifier == "neural":
                 model = train_neural(X_train, y_train)

             # Evaluate model on unseen data
             y_pred = model.predict(X_test)
             y_pred_train = model.predict(X_train)

             # scores
             accu_training += accuracy_score(y_train,y_pred_train)
             accu_test += accuracy_score(y_test,y_pred)
         return accu_training/n_splits, accu_test/n_splits

     #train with neural classifier
     acc_train_null_neural, acc_test_null_neural =␣
      ↪k_fold_cross_validation(D_null,y,5)
     acc_train_edge_neural, acc_test_edge_neural =␣
      ↪k_fold_cross_validation(D_edge,y,5)
     acc_train_hog_neural, acc_test_hog_neural = k_fold_cross_validation(D_hog,y,5)
```

```
print("Accuracy training (k-fold cross validated)(neural classifier): null: ",␣
 ↪acc_train_null_neural , " edge: ", acc_train_edge_neural, " hog: ",␣
 ↪acc_train_hog_neural)
print("Accuracy test (k-fold cross validated)(neural classifier): null: ",␣
 ↪acc_test_null_neural , " edge: ", acc_test_edge_neural, " hog: ",␣
 ↪acc_test_hog_neural)
#train with bayesian classifier
acc_train_null_bayes, acc_test_null_bayes = k_fold_cross_validation(D_null,y,5,␣
 ↪classifier="bayes")
acc_train_edge_bayes, acc_test_edge_bayes =␣
 ↪k_fold_cross_validation(D_edge,y,5,classifier="bayes")
acc_train_hog_bayes, acc_test_hog_bayes =␣
 ↪k_fold_cross_validation(D_hog,y,5,classifier="bayes")
print("Accuracy training (k-fold cross validated)(bayesian classifier): null:␣
 ↪", acc_train_null_bayes , " edge: ", acc_train_edge_bayes, " hog: ",␣
 ↪acc_train_hog_bayes)
print("Accuracy test (k-fold cross validated)(bayesian classifier): null: ",␣
 ↪acc_test_null_bayes , " edge: ", acc_test_edge_bayes, " hog: ",␣
 ↪acc_test_hog_bayes)
```

```
Accuracy training (k-fold cross validated)(neural classifier): null:  0.99365
edge:  1.0  hog:  0.9941650000000001
Accuracy test (k-fold cross validated)(neural classifier): null:  0.96036  edge:
0.95716  hog:  0.9676199999999999
Accuracy training (k-fold cross validated)(bayesian classifier): null:
0.5633800000000001  edge:  0.50939  hog:  0.68062
Accuracy test (k-fold cross validated)(bayesian classifier): null:  0.56004
edge:  0.50776  hog:  0.6788200000000002
```

4 Document your model selection

TODO: - Repeat the previous steps, adjust your feature extraction and classification methods until you get satisfying accuracy results. - Document your experiments. - **Tip:** Adjust the previous code, such that you can run multiple experiments, e.g. run different combinations of feature extractors and classifiers.

We used both the bayesian classifier that came with the notebook as well as an MPLClassifier, the MLPCLassifier vastly outperforms the bayesian classifier for every type of feature extraction method that we used.