

Math for Computer Science

Logistic Regression, Neural Network & Image Classification

Quan Minh Phan & Ngoc Hoang Luong

University of Information Technology

Vietnam National University Ho Chi Minh City

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What is an Image Classification problem?

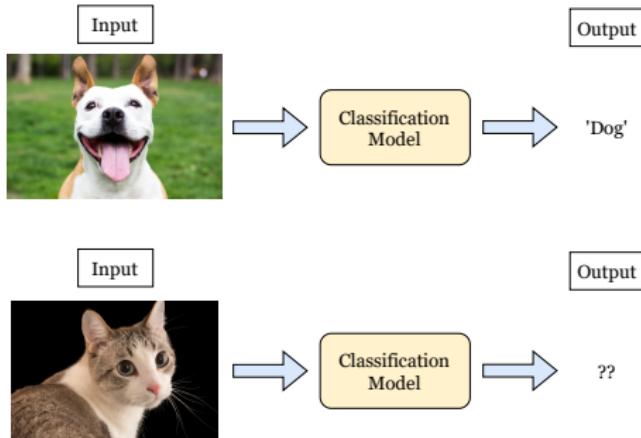


Figure: Example of a 'Dog and Cat' classification problem.

- **Input:** An image contains the object that need to be classified.
- **Output:** The class which the object belongs to.

Handwritten Digits Classification

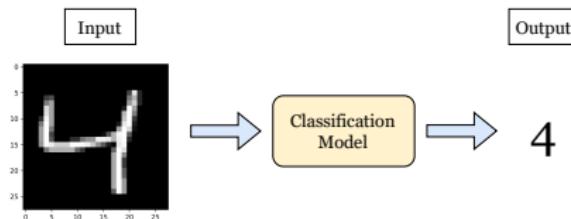


Figure: Example of an image in the MNIST dataset.

MNIST dataset¹

- Grayscale images
- Size (each image): 28×28
- 10 classes (0, 1, 2, ..., 9)
- 60,000 samples in the training set.
- 10,000 samples in the testing set.

¹Deng, L. (2012). The mnist database of handwritten digit images for machine learning research. IEEE Signal Processing Magazine, 29(6), 141–142.

Load MNIST dataset

New package: **PyTorch**²

Import necessary packages

```
>> import torch  
    from torch.utils.data import DataLoader  
    import torchvision.datasets as datasets  
    import torchvision.transforms as transforms
```

Load MNIST dataset

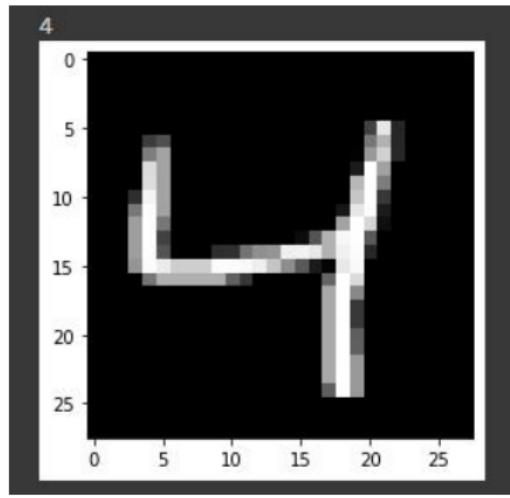
```
>> train_dataset = datasets.MNIST(root='path_to_contain_dataset',  
        train=True, transform=transforms.ToTensor(), download=True)  
test_dataset = datasets.MNIST(root='path_to_contain_dataset',  
        train=False, transform=transforms.ToTensor(), download=True)
```

When experimenting with PyTorch, almost data is represented in Tensor type.

²<https://pytorch.org/docs/stable/index.html>

Show an example image

```
>> import matplotlib.pyplot as plt  
>> plt.imshow(train_dataset[2][0].squeeze(), cmap='gray')  
train_dataset[2][-1]
```



Create train/test data

Setup for getting reproducible results

```
>> import random  
     import numpy as np  
>> seed = 2411  
>> random.seed(seed)  
     np.random.seed(seed)  
     torch.manual_seed(seed)  
     torch.backends.cudnn.deterministic = True  
     torch.backends.cudnn.benchmark = False
```

```
>> train_loader = DataLoader(train_dataset, batch_size=64,  
                           shuffle=True)  
test_loader = DataLoader(test_dataset)
```

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Workflow

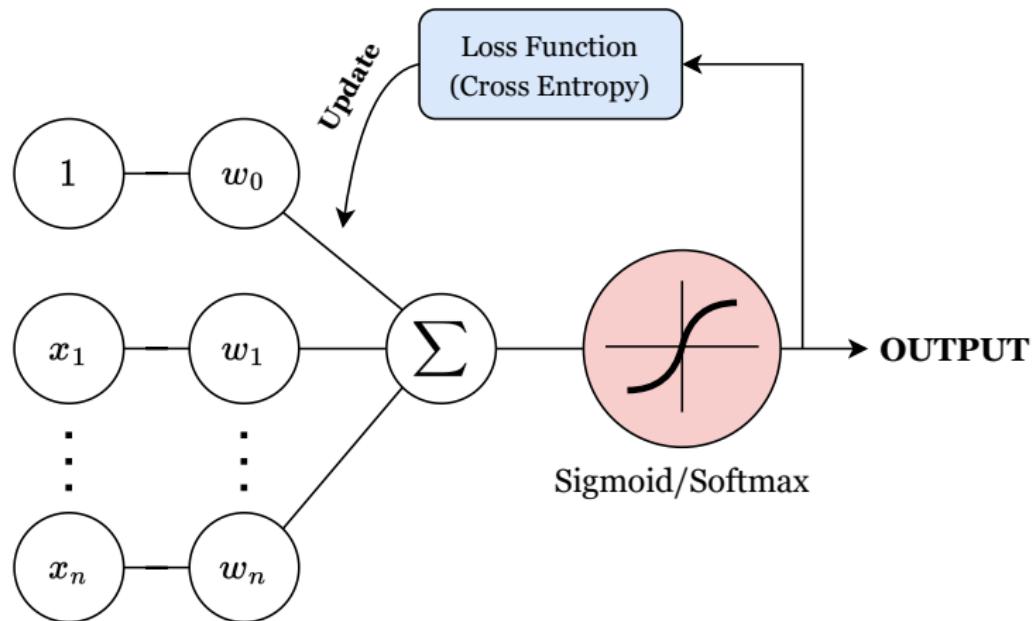


Figure: Workflow of Logistic Regression

Build Logistic Regression model

```
>> import torch.nn as nn  
    import torch.nn.functional as F
```

```
class LogisticRegression(nn.Module):  
    # input_dim → the number of independent variables (attributes)  
    # output_dim → the number of (unique) classes for classification (e.g.,  
    dog-cat: 2; car-bicycle-plane: 3)  
    def __init__(self, input_dim, output_dim):  
        super().__init__()  
        self.linear = nn.Linear(input_dim, output_dim)  
  
    def forward(self, x):  
        logits = self.linear(x)  
        probs = F.softmax(logits, dim=1)  
        return logits, probs
```

Setup for Training

```
>> import torch.optim as optim > load the training algorithm (e.g., SGD, ADAM)  
>> device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')  
      device
```

Design 'Train Model' Function

- Loss Function: **Cross Entropy Loss** (Binary Cross Entropy Loss for binary classification)

Cross Entropy Loss

- In case of Binary Classification ($N = 2$), cross-entropy is given by:

$$l = -(y * \log(p) + (1 - y) * \log(1 - p))$$

where p is the predicted probability (sigmoid), and y is the truth label (0 or 1).

- When $N > 2$, cross-entropy is given by:

$$l = - \sum_{c=1}^N y_c * \log(p_c)$$

where p_c is the predicted probability (softmax) for the c^{th} class, and y_c is the truth label.

Sigmoid and Softmax Activation Functions

- **Sigmoid Function** (2 classes)

$$\text{sigmoid}(z)_{i=1} = \frac{1}{1 + e^{-z}} \quad (1)$$

- **Softmax Function** (C classes)

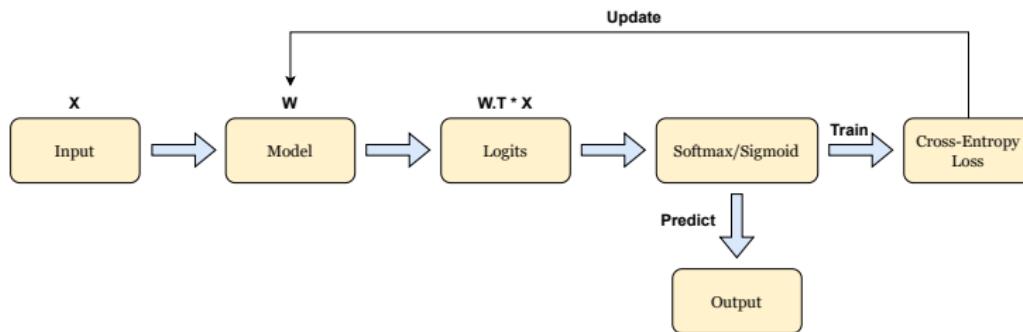
$$\text{softmax}(z)_i = \frac{e^{z(i)}}{\sum_{j=1}^C e^{z(j)}} \quad (2)$$

for $i = 1, 2, \dots, C$

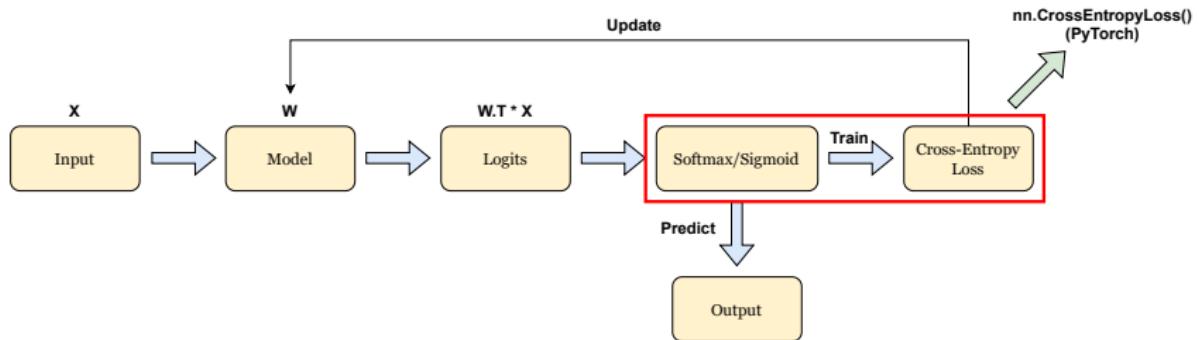
Design 'Train Model' Function (cont.)

- Loss Function: **Cross Entropy Loss** (Binary Cross Entropy Loss for binary classification)
- Optimizer: **Stochastic Gradient Descent**

nn.CrossEntropyLoss() (PyTorch)



`nn.CrossEntropyLoss()` (PyTorch)



Train Logistic Regression model on MNIST dataset

Train model

```
>> clf_LR = LogisticRegression(input_dim= 28 * 28,  
    output_dim=10).to(device)  
loss_each_epoch_LR = train_model(data_loader=train_loader,  
    model=clf_LR, init_lr=0.001, maxEpoch=20)
```

Visualize the trend of loss value

```
>> plt.plot(range(1, len(loss_each_epoch_LR) + 1), loss_each_epoch_LR)  
plt.xlabel('Epoch')  
plt.ylabel('Loss')  
plt.title('LogisticRegression-MNIST')  
plt.show()
```

Visualize the trend of loss value

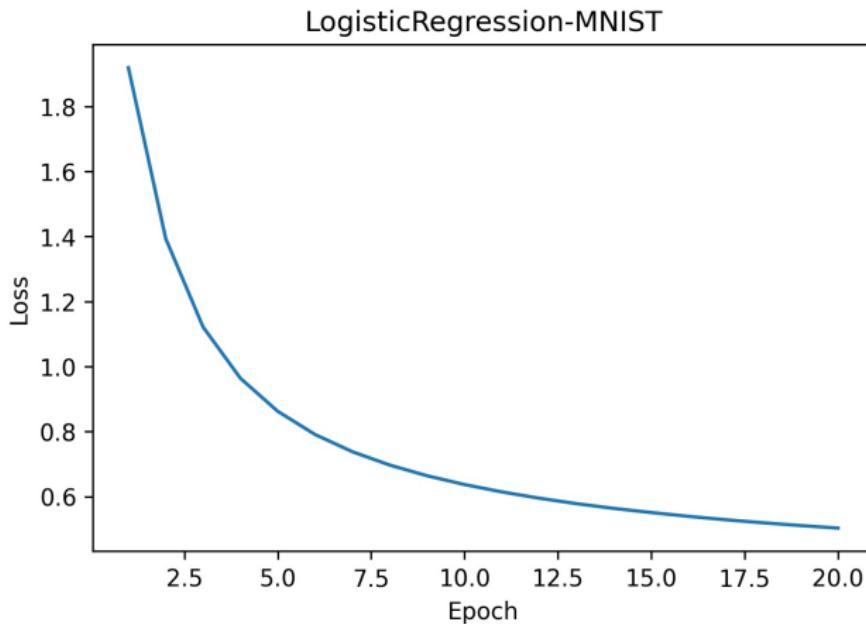


Figure: The loss values of Logistic Regression model over epochs.

Model Evaluation

```
def model_evaluation(data_loader, model):
    nCorrects = 0
    nSamples = 0
    model.eval()    ▷ switch our model to the evaluation mode
    with torch.no_grad():  ▷ ensure that no backprop here.
        for X, y in data_loader:
            X = X.to(device)
            y = y.to(device)
            X = X.reshape(X.shape[0], -1)

            _, probs = model(X)  ▷ get the class probabilities of X
            _, y_pred = probs.max(1)  ▷ X belongs to the class that has the highest
probability
            nCorrects += (y_pred == y).sum()
            nSamples += y_pred.size(0)
            print(f'We got {nCorrects}/{nSamples} correct. Accuracy ='
{((nCorrects/nSamples) * 100:.2f} %')
```

Model Evaluation (cont.)

Train Accuracy

```
>> print('Logistic Regression (Train Accuracy)')  
    model_evaluation(data_loader=train_loader, model=clf_LR)
```

Test Accuracy

```
>> print('Logistic Regression (Test Accuracy)')  
    model_evaluation(data_loader=test_loader, model=clf_LR)
```

Visualize the some predictions

```
>> ROW_IMG, N_ROWS = 10, 5
fig = plt.figure()
for index in range(1, ROW_IMG * N_ROWS + 1):
    plt.subplot(N_ROWS, ROW_IMG, index)
    plt.axis('off')
    plt.imshow(test_dataset.data[index], cmap='gray_r')

with torch.no_grad():
    clf_LR.eval()
    X = test_dataset[index][0].reshape(test_dataset[index][0].shape[0], -1)
    _, probs = clf_LR(X)

    title = f'{torch.argmax(probs)} ({torch.max(probs * 100)..0f}%)'
    plt.title(title, fontsize=7)

fig.suptitle('Logistic Regression - predictions')
plt.savefig('LogisticRegression_pred.jpg', bbox_inches='tight',
            pad_inches=0.1, dpi=300)
```

Logistic Regression - predictions

2 (59%) 1 (88%) 0 (97%) 4 (71%) 1 (94%) 4 (66%) 9 (62%) 6 (36%) 9 (67%) 0 (91%)

2 1 0 4 1 4 9 5 9 0

6 (36%) 9 (76%) 0 (95%) 1 (95%) 5 (51%) 9 (62%) 7 (97%) 3 (39%) 4 (84%) 9 (57%)

6 9 0 1 5 9 7 3 4 9

6 (87%) 6 (54%) 5 (70%) 4 (66%) 0 (99%) 7 (79%) 4 (87%) 0 (96%) 1 (69%) 3 (91%)

6 6 5 4 0 7 4 0 1 3

1 (60%) 3 (80%) 0 (38%) 7 (84%) 2 (95%) 7 (91%) 1 (91%) 3 (34%) 1 (94%) 1 (75%)

1 3 4 7 2 7 1 2 1 1

7 (77%) 4 (81%) 2 (56%) 3 (65%) 5 (47%) 3 (35%) 2 (69%) 4 (86%) 4 (86%) 6 (93%)

7 4 2 3 5 1 2 4 4 6

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Multi Layer Perceptron

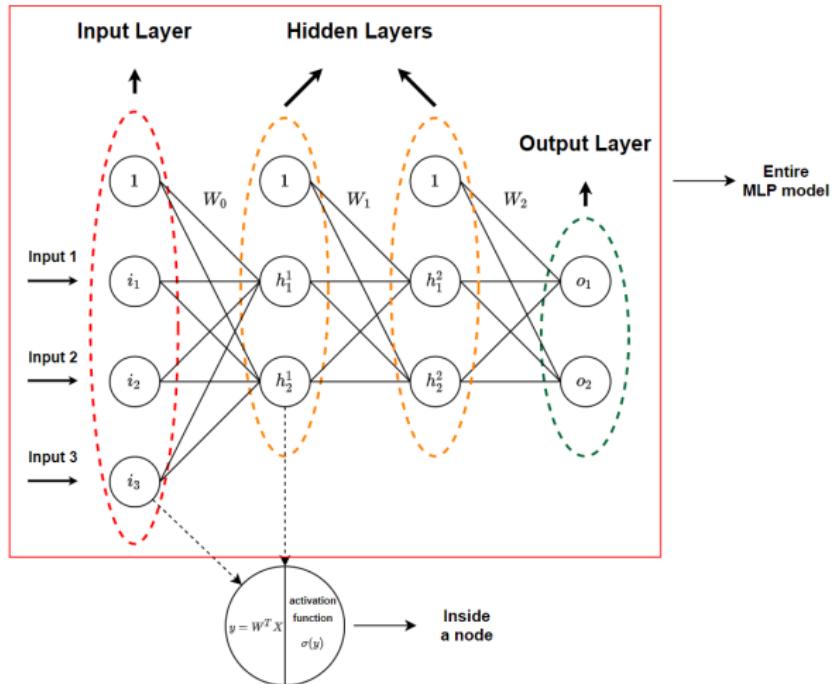


Figure: Example of a Multi Layer Perceptron model.

Build a Multi Layer Perceptron model by using Pytorch

Problem dataset: **MNIST** (10 classes)

Requirements:

- Build an MLP model has 3 layers: 1 'input' layer, 1 'hidden' layer, and 1 'output' layer.
- 'input' layer has 782 nodes (`input_size`), 'hidden' layer has 100 nodes, and 'output' layer has 25 nodes.
- The activation function of nodes in 'input' and 'hidden' layers is 'ReLU'.
- The activation of nodes in 'output' layer is 'Softmax'.

Build a Multi Layer Perceptron model with PyTorch

```
class MLP(nn.Module):
    def __init__(self, input_dim, output_dim):
        super().__init__()
        self.classifier = nn.Sequential(
            nn.Linear(input_dim, 100),    ▷ 'input' layer
            nn.ReLU(),      ▷ activation function of the 'input' layer
            nn.Linear(100, 25),   ▷ 'hidden' layer
            nn.ReLU(),      ▷ activation function of the 'hidden' layer
            nn.Linear(25, output_dim) ▷ 'output' layer
        )
        def forward(self, x):
            logits = self.classifier(x)
            probs = F.softmax(logits, dim=1) ▷ activation function of 'output' layer
            return logits, probs
```

Train MLP model on MNIST dataset

Train model

```
>> clf_MLP = MLP(input_dim= 28 * 28, output_dim=10).to(device)
    loss_each_epoch_MLP = train_model(data_loader=train_loader,
    model=clf_MLP, init_lr=0.001, maxEpoch=20)
```

Visualize the trend of loss value

```
>> plt.plot(range(1, len(loss_each_epoch_MLP) + 1),
    loss_each_epoch_MLP)
    plt.xlabel('Epoch')
    plt.ylabel('Loss')
    plt.title('MLP-MNIST')
    plt.show()
```

Visualize the trend of loss value

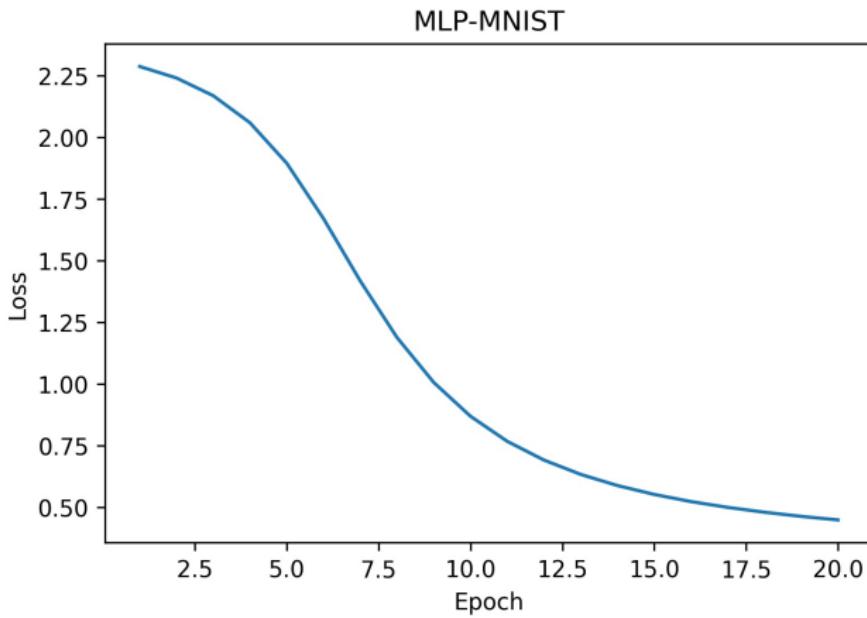


Figure: The loss values of Multi Layer Perceptron model over epochs.

Model Evaluation

Train Accuracy

```
>> print('Multi Layer Perceptron (Train Accuracy)')  
model_evaluation(data_loader=train_loader, model=clf_MLP)
```

Test Accuracy

```
>> print('Multi Layer Perceptron (Test Accuracy)')  
model_evaluation(data_loader=test_loader, model=clf_MLP)
```

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Cake Dataset

- 300 images. Each class has 50 images.
- 6 classes: 'banhmi', 'cookie', 'croissant', 'donut', 'pizza', 'pretzel'
- Size (each image): 500 x 500

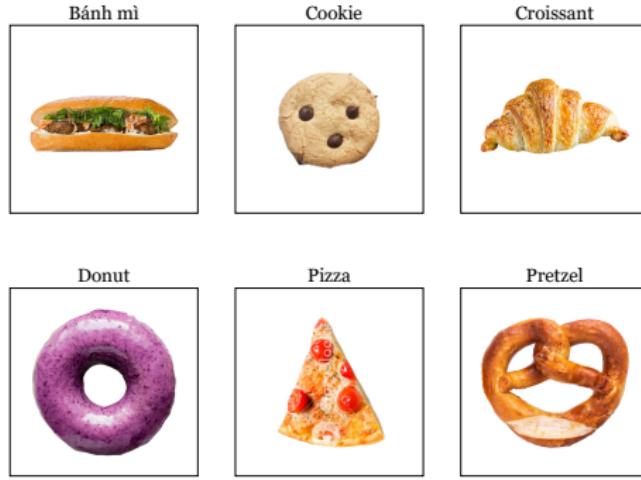


Figure: Example of some images in Cake dataset.

Create train/test data

```
>> import os  
import cv2 ▷ package for image processing (e.g., read, load, save)
```

Load images

```
>> root_dir = 'the storage path of cake dataset'  
>> list_folders = os.listdir(root_dir)  
list_folders  
>> X_cake, y_cake = [ ], [ ]  
>> for folder in list_folders:  
    list_image_paths = os.listdir(root_dir + '/' + folder)  
    for image_path in list_image_paths:  
        img_matrix = cv2.imread(root_dir + '/' + folder + '/' + image_path,  
        0)  
        X_cake.append([img_matrix])  
        y_cake.append(folder)
```

Create train/test data (cont.)

Preprocess Data

```
>> X_cake = np.array(X_cake)/255  
>> from sklearn.preprocessing import LabelEncoder  
    le = LabelEncoder()  
>> y_cake = le.fit_transform(y_cake)
```

Split data into train/test sets

```
>> from sklearn.model_selection import train_test_split  
    X_train, X_test, y_train, y_test = train_test_split(X_cake, y_cake,  
        test_size=0.3, random_state=seed)
```

Create train/test data (cont.)

Convert Numpy to Tensor

```
>> X_train, X_test = np.array(X_train), np.array(X_test)
    y_train, y_test = np.array(y_train), np.array(y_test)

>> X_train = torch.from_numpy(X_train).float()
    X_test = torch.from_numpy(X_test).float()
    y_train = torch.from_numpy(y_train)
    y_test = torch.from_numpy(y_test)
```

Create data loaders

```
>> from torch.utils.data import TensorDataset

>> train_dataset_cake = TensorDataset(X_train, y_train)
    train_loader_cake = DataLoader(train_dataset_cake, batch_size=16,
        shuffle=True)

>> test_dataset_cake = TensorDataset(X_test, y_test)
    test_loader_cake = DataLoader(test_dataset_cake)
```

Train models on Cake Dataset

- $\text{input_dim} = 500 * 500 = 250000$
- $\text{output_dim} = 6$
- $\text{init_lr} = 0.001$
- $\text{maxEpoch} = 200$

Train model

```
>> clf_LR_1 = LogisticRegression(input_dim= 500 * 500,  
                                output_dim=6).to(device)  
loss_each_epoch_LR_1 = train_model(train_loader_cake, clf_LR_1,  
                                    0.001, 200)  
  
>> clf_MLP_1 = MLP(input_dim= 500 * 500, output_dim=6).to(device)  
loss_each_epoch_MLP_1 = train_model(train_loader_cake, clf_MLP_1,  
                                    0.001, 200)
```

Model Evaluation

Logistic Regression - Train Accuracy

```
>> print('Logistic Regression (Train Accuracy)')  
model_evaluation(data_loader=train_loader_cake, model=clf_LR_1)
```

Logistic Regression - Test Accuracy

```
>> print('Logistic Regression (Test Accuracy)')  
model_evaluation(data_loader=test_loader_cake, model=clf_LR_1)
```

Multi Layer Perceptron - Train Accuracy

```
>> print('Multi Layer Perceptron (Train Accuracy)')  
model_evaluation(data_loader=train_loader_cake, model=clf_MLP_1)
```

Multi Layer Perceptron - Test Accuracy

```
>> print('Multi Layer Perceptron (Test Accuracy)')  
model_evaluation(data_loader=test_loader_cake, model=clf_MLP_1)
```

Visualize the some predictions

```
>> ROW_IMG, N_ROWS = 5, 5
fig = plt.figure()
for index in range(1, ROW_IMG * N_ROWS + 1):
    plt.subplot(N_ROWS, ROW_IMG, index)
    plt.axis('off')
    plt.imshow(test_dataset_cake[index][0].squeeze(), cmap='gray_r')
    with torch.no_grad():
        clf_LR_1.eval()
        X =
        test_dataset_cake[index][0].reshape(test_dataset_cake[index][0].shape[0], -1)
        _, probs = clf_LR_1(X)
        title = f'{le.inverse_transform([torch.argmax(probs)])[-1]}'
        ({torch.max(probs * 100):.0f}%)'
        plt.title(title, fontsize=7)
fig.suptitle('Logistic Regression - predictions')
```

Logistic Regression - predictions

croissant (100%)



pretzel (100%)



pizza (100%)



cookie (100%)



cookie (100%)



pretzel (100%)



croissant (100%)



pizza (100%)



pretzel (100%)



cookie (100%)



donut (100%)



cookie (100%)



pizza (100%)



pretzel (100%)



cookie (100%)



croissant (100%)



cookie (100%)



croissant (100%)



pretzel (100%)



donut (100%)



croissant (100%)



cookie (100%)



croissant (100%)



banhmi (100%)



pizza (100%)

