# MNIST 관련 실습

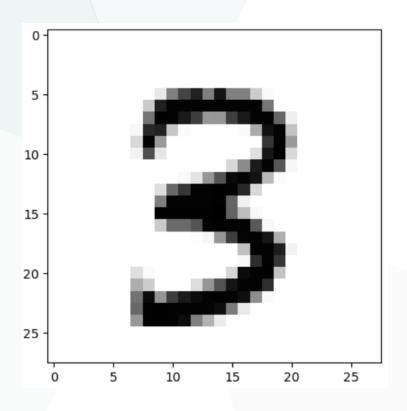
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- ► Xabier / He initalization

### **MNIST**

### MNIST: handwritten digits data set



- -28\*28 image
- 1 channel gray image
- -0~9 digits

training set: 60000 samples

test set : 10000 samples

# MNIST\_introduction 실습

```
In [1]: # Lab 7 Learning rate and Evaluation
        import torch
        import torchvision.datasets as dsets
        import torchvision.transforms as transforms
        import matplotlib.pyplot as plt
        import random
In [2]: device = 'cuda' if torch.cuda.is_available() else 'cpu'
        # for reproducibility
        random.seed(777)
        torch.manual_seed(777)
        if device == 'cuda':
            torch.cuda.manual_seed_all(777)
In [4]: # parameters
        training_epochs = 15
        batch_size = 100
In [5]: # MN/ST dataset
        mnist_train = dsets.MNIST(root='MNIST_data/',
                                  train=True,
                                  transform=transforms.ToTensor(),
                                  download=True)
        mnist_test = dsets.MNIST(root='MNIST_data/',
                                 train=False.
                                 transform=transforms.ToTensor(),
                                 download=True)
```

### torchvision패키지

- -popular datasets
  ex)MNIST,Fashion-MNIST,EMIST...
- -model architecturesex)Alexnet,Resnet
- -common image transformation
- -torchvision.utils
- batch\_size -데이터를 몇개씩 불러올지

# MNIST\_introduction 실습

```
In [6]: # dataset loader
        data_loader = torch.utils.data.DataLoader(dataset=mnist_train,
                                                  batch_size=batch_size,
                                                  shuffle=True.
                                                  drop_last=True)
In [7]: # MN/ST data image of shape 28 * 28 = 784
        linear = torch.nn.Linear(784, 10, bias=True).to(device)
In [8]: # define cost/loss & optimizer
        criterion = torch.nn.CrossEntropyLoss().to(device) # Softmax is internally computed.
        optimizer = torch.optim.SGD(linear.parameters(), lr=0.1)
In [9]: for epoch in range(training_epochs):
            avg cost = 0
            total_batch = len(data_loader)
            for X, Y in data_loader:
                # reshape input image into [batch_size by 784]
                # label is not one-hot encoded
               X = X.view(-1, 28 * 28).to(device)
                Y = Y.to(device)
               optimizer.zero_grad()
                hypothesis = linear(X)
               cost = criterion(hypothesis, Y)
                cost.backward()
               optimizer.step()
                avg_cost += cost / total_batch
            print('Epoch:', '%04d' % (epoch + 1), 'cost =', '{:.9f}'.format(avg_cost))
        print('Learning finished')
```

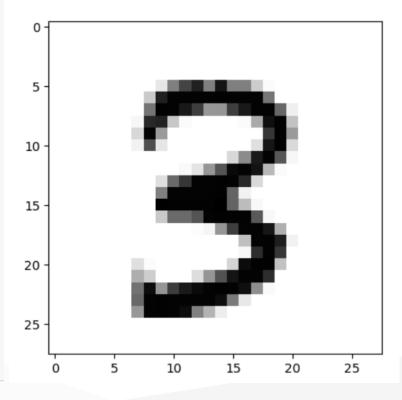
```
Epoch: 0001 \text{ cost} = 0.535150588
Epoch: 0002 \text{ cost} = 0.359577745
Epoch: 0003 \text{ cost} = 0.331264287
Epoch: 0004 \text{ cost} = 0.316404700
Epoch: 0005 \text{ cost} = 0.307106972
Epoch: 0006 \text{ cost} = 0.300456554
Epoch: 0007 \text{ cost} = 0.294933408
Epoch: 0008 \text{ cost} = 0.290956199
Epoch: 0009 \text{ cost} = 0.287074089
Epoch: 0010 \text{ cost} = 0.284515619
Epoch: 0011 \text{ cost} = 0.281914055
Epoch: 0012 \text{ cost} = 0.279526860
Epoch: 0013 \text{ cost} = 0.277636588
Epoch: 0014 \text{ cost} = 0.275874794
Epoch: 0015 \text{ cost} = 0.274422705
Learning finished
```

# MNIST\_introduction 실습

```
In [14]: # Test the model using test sets
        with torch.no_grad():
             X_test = mnist_test.test_data.view(-1, 28 * 28).float().to(device)
             Y_test = mnist_test.test_labels.to(device)
             prediction = linear(X_test)
             correct_prediction = torch.argmax(prediction, 1) == Y_test
             accuracy = correct_prediction.float().mean()
             print('Accuracy:', accuracy.item())
             # Get one and predict
             r = random.randint(0, len(mnist test) - 1)
             X_single_data = mnist_test.test_data[r:r + 1].view(-1, 28 * 28).float().to(device)
             Y_single_data = mnist_test.test_labels[r:r + 1].to(device)
             print('Label: ', Y_single_data.item())
             single_prediction = linear(X_single_data)
             print('Prediction: ', torch.argmax(single_prediction, 1).item())
             plt.imshow(mnist_test.test_data[r:r + 1].view(28, 28), cmap='Greys', interpolation='nearest')
             plt.show()
```

Accuracy: 0.8883000016212463

Label: 3 Prediction: 3



# MNIST\_backprop 실습

```
In [1]: # Lab 10 MN/ST and softmax
        import torch
        import torchvision.datasets as dsets
        import torchvision.transforms as transforms
In [2]: device = 'cuda' if torch.cuda.is_available() else 'cpu'
        # for reproducibility
        torch.manual_seed(777)
        if device == 'cuda':
            torch.cuda.manual_seed_all(777)
In [3]: # parameters
        learning_rate = 0.5
        batch_size = 10
In [4]: # MN/ST dataset
        mnist_train = dsets.MNIST(root='MNIST_data/',
                                  train=True,
                                  transform=transforms.ToTensor(),
                                  download=True)
        mnist_test = dsets.MNIST(root='MNIST_data/',
                                 train=False,
                                 transform=transforms.ToTensor(),
                                 download=True)
In [5]: # dataset loader
        data_loader = torch.utils.data.DataLoader(dataset=mnist_train,
                                                 batch_size=batch_size,
                                                 shuffle=True.
                                                 drop_last=True)
```

# MNIST\_backprop 실습

```
입력 뉴런 : 784
은닉층 뉴런 :30
출력층 뉴런 : 10
```

가중치와 편향 값을 정규 분포에서 샘플링하여 초 기화

평균 0, 표준편차 1인 정규분포를 사용

```
In [8]: def sigmoid(x):
    # sigmoid function
    return 1.0 / (1.0 + torch.exp(-x))
    # return torch.div(torch.tensor(1), torch.add(torch.tensor(1.0), torch.exp(-x)))
In [9]: def sigmoid_prime(x):
    # derivative of the sigmoid function
    return sigmoid(x) * (1 - sigmoid(x))
```

시그모이드 함수 정의 -출력층 활성화 함수로 사용

시그모이드\_도함수 정의 -역전파를 통해 기울기 계산할 때 필요

```
In [10]: X_test = mnist_test.test_data.view(-1, 28 * 28).float().to(device)[:1000]
        Y_test = mnist_test.test_labels.to(device)[:1000]
         while not i == 10000:
            for X, Y in data_loader:
                j += 1
                # forward
                X = X.view(-1, 28 * 28).to(device)
                Y = torch.zeros((batch_size, 10)).scatter_(1, Y.unsqueeze(1), 1).to(device)
                                                                                         # one-hot
                I1 = torch.add(torch.matmul(X, w1), b1)
                a1 = sigmoid(I1)
                12 = torch.add(torch.matmul(a1, w2), b2)
                y_pred = sigmoid(12)
                diff = y_pred - Y
                # Back prop (chain rule)
                d_I2 = diff * sigmoid_prime(I2)
                                                                    체인 룰에 따라 활성화
                d b2 = d 12
                d_w2 = torch.matmul(torch.transpose(a1, 0, 1), d_12)
                                                                    학수의 미분이 곱해짐
                d_a1 = torch.matmul(d_12, torch.transpose(w2, 0, 1))
                d_I1 = d_a1 * sigmoid_prime(I1)
                                                                    체인 룰은 Loss 함수의
                d_b1 = d_11
                                                                    Gradient를 전달하기 위
                d_w1 = torch.matmul(torch.transpose(X, 0, 1), d_I1)
                                                                    해 사용됨
                w1 = w1 - learning_rate * d_w1
                b1 = b1 - learning_rate * torch.mean(d_b1, 0)
                w2 = w2 - learning_rate * d_w2
                b2 = b2 - learning_rate * torch.mean(d_b2, 0)
                if i % 1000 == 0:
                   I1 = torch.add(torch.matmul(X_test, w1), b1)
                    a1 = sigmoid(I1)
                   12 = torch.add(torch.matmul(a1, w2), b2)
                   y_pred = sigmoid(12)
                   acct_mat = torch.argmax(y_pred, 1) == Y_test
                   acct_res = acct_mat.sum()
                   print(acct_res.item())
                if i == 10000:
                    break
```

#### 1000번째 반복마다 테스트의 정확도 출력값

# Weight Initialization

신경망의 학습 과정에서 가중치를 처음 설정하는 방법

Xavier Initialization : 입력 뉴런의 수와 출력 뉴런의 수를 고려해 가중치를 초기화가중치를 정규분포 또는 균등분포에서 샘플링하여 초기화하는 방법

$$W \sim U\left(-\sqrt{rac{6}{n_{
m in}+n_{
m out}}},\sqrt{rac{6}{n_{
m in}+n_{
m out}}}
ight)$$
 균등 분포

$$W \sim N\left(0, rac{2}{n_{
m in} + n_{
m out}}
ight)$$
 정규 분포 ${
m sigmoid}$ 에서 사용

He Initialization : ReLU 및 그 변종(Leaky ReLU 등)을 사용할 때 적합한 초기화 방법

$$W \sim N\left(0, rac{2}{n_{
m in}}
ight)$$
 정규 분포 초기화

$$W \sim U\left(-\sqrt{rac{6}{n_{
m in}}},\sqrt{rac{6}{n_{
m in}}}
ight)$$
 균등 분포 초기화

```
In [1]:
          # Lab 10 MN/ST and softmax
          import torch
          import torchvision.datasets as dsets
          import torchvision.transforms as transforms
          import random
In [2]:
          device = 'cuda' if torch.cuda.is_available() else 'cpu'
          # for reproducibility
          random.seed(777)
          torch.manual_seed(777)
          if device == 'cuda':
              torch.cuda.manual_seed_all(777)
In [3]:
          # parameters
          learning_rate = 0.001
          training_epochs = 15
          batch_size = 100
In [4]:
          # MN/ST dataset
          mnist_train = dsets.MNIST(root='MNIST_data/',
                                   train=True,
                                   transform=transforms.ToTensor(),
                                   download=True)
          mnist_test = dsets.MNIST(root='MNIST_data/',
                                  train=False.
                                  transform=transforms.ToTensor(),
                                  download=True)
```

```
In [5]:
           # dataset loader
           data loader = torch.utils.data.DataLoader(dataset=mnist train.
                                                    batch size=batch size,
                                                    shuffle=True.
                                                    drop last=True)
 In [6]:
           # nn layers
           linear1 = torch.nn.Linear(784, 256, bias=True)
           linear2 = torch.nn.Linear(256, 256, bias=True)
           linear3 = torch.nn.Linear(256, 10, bias=True)
           relu = torch.nn.ReLU()
 In [7]:
           # xavier initialization
           torch.nn.init.xavier uniform (linear1.weight)
           torch.nn.init.xavier_uniform_(linear2.weight)
           torch.nn.init.xavier uniform (linear3.weight)
Out[7]: Parameter containing:
         tensor([[-0.0215, -0.0894, 0.0598, ..., 0.0200, 0.0203, 0.1212],
                  [ 0.0078,  0.1378,  0.0920,  ...,  0.0975,  0.1458,  -0.0302]
                 [ 0.1270, -0.1296, 0.1049, ..., 0.0124, 0.1173, -0.0901],
                 [0.0661, -0.1025, 0.1437, ..., 0.0784, 0.0977, -0.0396],
                 [0.0430, -0.1274, -0.0134, \ldots, -0.0582, 0.1201, 0.1479],
                 [-0.1433, 0.0200, -0.0568, ..., 0.0787, 0.0428, -0.0036]]
               requires_grad=True)
```

입력 뉴런 : 784 히든층 뉴런 : 256 히든층 뉴런 : 256 출력층 뉴런 : 10

torch.nn.init.xavier\_uniform\_() : Xabier 초기화 / 균등 분포를 사용

```
In [8]:
          model = torch.nn.Sequential(linear1, relu, linear2, relu, linear3).to(device)
In [9]:
           # define cost/loss & optimizer
          criterion = torch.nn.CrossEntropyLoss().to(device) # Softmax is internally computed.
          optimizer = torch.optim.Adam(model.parameters(), Ir=learning rate)
In [10]:
          total batch = len(data loader)
          for epoch in range(training_epochs):
              avg_cost = 0
              for X, Y in data_loader:
                  # reshape input image into [batch_size by 784]
                  # label is not one-hot encoded
                  X = X.view(-1, 28 * 28).to(device)
                  Y = Y.to(device)
                  optimizer.zero_grad()
                  hypothesis = model(X)
                  cost = criterion(hypothesis, Y)
                  cost.backward()
                  optimizer.step()
                  avg_cost += cost / total_batch
              print('Epoch:', '%04d' % (epoch + 1), 'cost =', '{:.9f}'.format(avg_cost))
          print('Learning finished')
```

```
Epoch: 0001 \text{ cost} = 0.249897048
Epoch: 0002 \text{ cost} = 0.094330102
Epoch: 0003 \text{ cost} = 0.061055195
Epoch: 0004 \text{ cost} = 0.042816643
Epoch: 0005 \text{ cost} = 0.032796543
Epoch: 0006 \text{ cost} = 0.024419624
Epoch: 0007 \text{ cost} = 0.020511184
Epoch: 0008 \text{ cost} = 0.018132176
Epoch: 0009 \text{ cost} = 0.015536907
Epoch: 0010 \text{ cost} = 0.016846467
Epoch: 0011 \text{ cost} = 0.012203062
Epoch: 0012 \text{ cost} = 0.012871196
Epoch: 0013 \text{ cost} = 0.011348661
Epoch: 0014 \text{ cost} = 0.010990168
Epoch: 0015 \text{ cost} = 0.006201488
Learning finished
```

```
In [11]:
           # Test the model using test sets
           with torch.no_grad():
              X_test = mnist_test.test_data.view(-1, 28 * 28).float().to(device)
              Y_test = mnist_test.test_labels.to(device)
              prediction = model(X_test)
              correct_prediction = torch.argmax(prediction, 1) == Y_test
              accuracy = correct_prediction.float().mean()
              print('Accuracy:', accuracy.item())
              # Get one and predict
               r = random.randint(0, len(mnist_test) - 1)
              X_single_data = mnist_test.test_data[r:r + 1].view(-1, 28 * 28).float().to(device)
               Y_single_data = mnist_test.test_labels[r:r + 1].to(device)
              print('Label: ', Y_single_data.item())
              single_prediction = model(X_single_data)
              print('Prediction: ', torch.argmax(single_prediction, 1).item())
        Accuracy: 0.9804999828338623
```

Label: 8 Prediction: 8