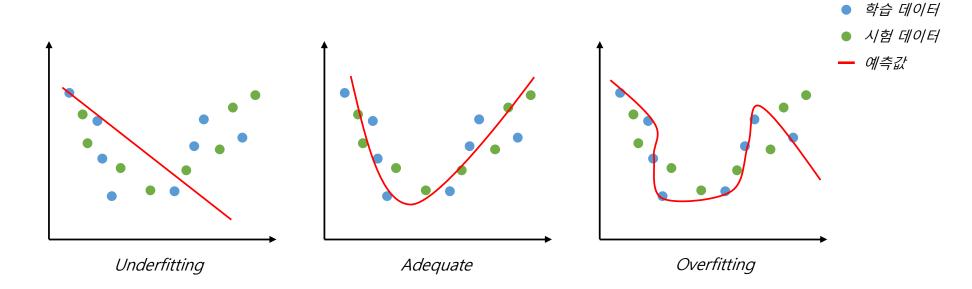
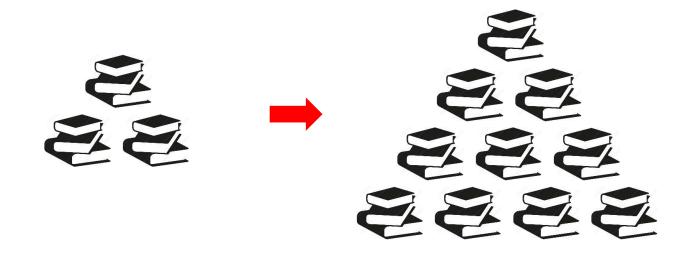


- 오버피팅(Overfitting): 학습데이터를 과하게 학습하여 그 외의 데이터에는 대응하지 못하는 상태
- 오버피팅이 주로 일어나는 경우
 - ▶ 매개변수가 많은 모델
 - ▶ 학습데이터가 적음



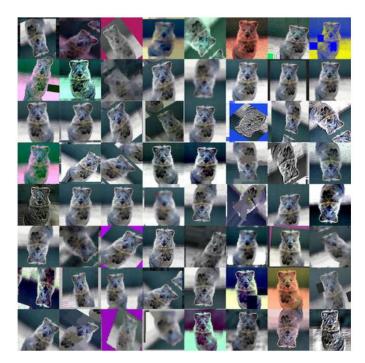


■ 해결방법 1 → 데이터 확보

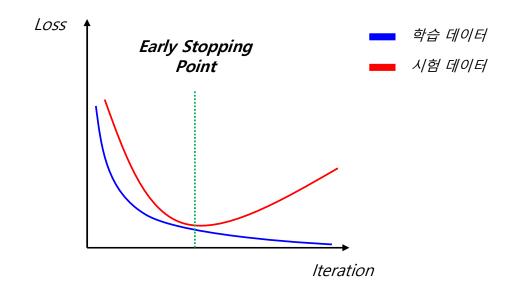




- 해결방법 → 데이터 증식(Data Augmentation)
 - ▶ 입력 이미지(학습 이미지)를 '인위적'으로 확장
 - ▶ 회전(Rotation), 이동(Move), 자르기(Crop), 대칭(Symmetry) 등

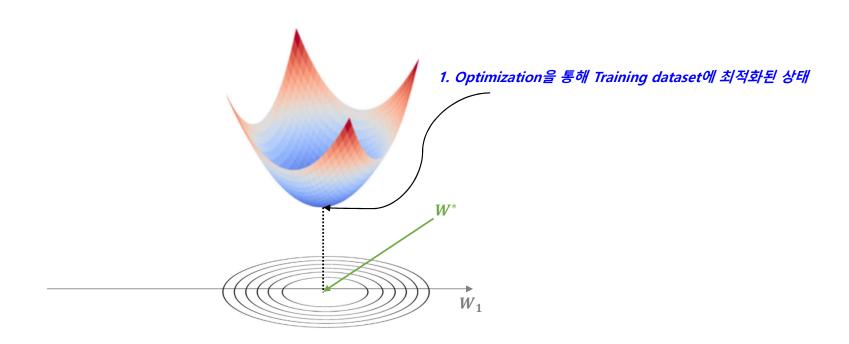


- 해결방법 2 → 조기 종료(Early Stopping)
 - ▶ Epoch, Iteration을 많이 돌린 후, 특정 시점에서 멈추는 것

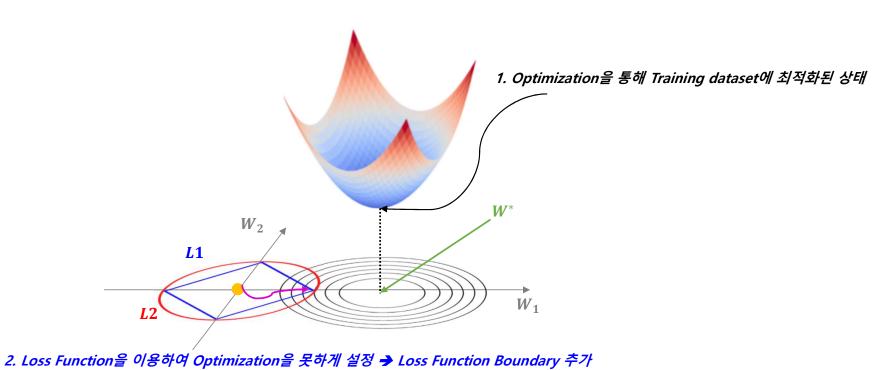




■ 해결방법 3 → L1, L2 정규화(L1, L2 Regularization)

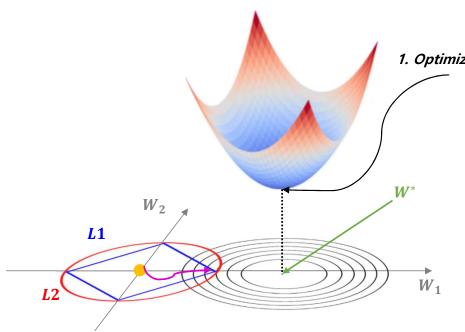


■ 해결방법 → L1, L2 정규화(L1, L2 Regularization)





■ 해결방법 → L1, L2 정규화(L1, L2 Regularization)



1. Optimization을 통해 Training dataset에 최적화된 상태

3. Loss Function뒤에 정규화 Term(Loss Function Boundary)을 추가

$$\tilde{L} = L(y, \hat{y}) + \lambda \Omega(w), \lambda \geq 0$$

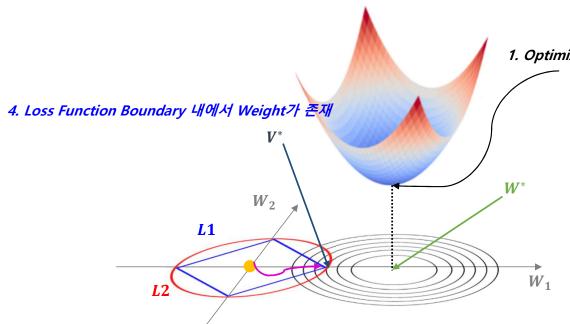
$$L1: \Omega(w) = \sum_{i=1}^{n} |w_i|$$

$$L2: \Omega(w) = \sum_{i=1}^{n} w_i^2$$

2. Loss Function을 이용하여 Optimization을 못하게 설정 → Loss Function Boundary 추가



■ 해결방법 → L1, L2 정규화(L1, L2 Regularization)



2. Loss Function을 이용하여 Optimization을 못하게 설정 → Loss Function Boundary 추가

1. Optimization을 통해 Training dataset에 최적화된 상태

3. Loss Function뒤에 정규화 Term(Loss Function Boundary)을 추가

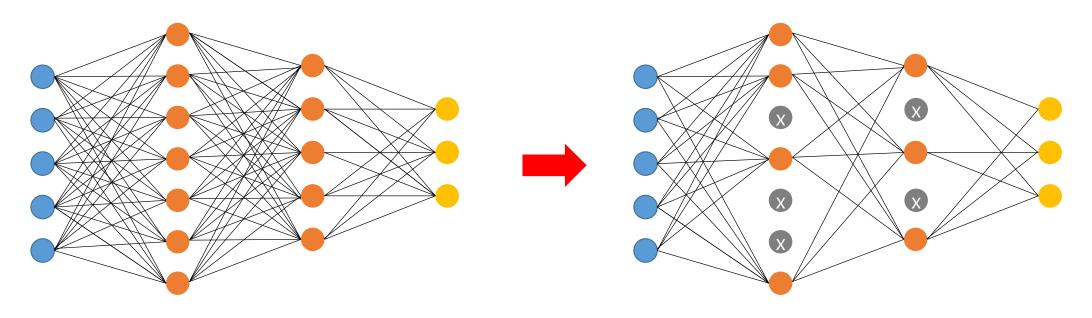
$$\tilde{L} = L(y, \hat{y}) + \lambda \Omega(w), \lambda \geq 0$$

$$L1: \Omega(w) = \sum_{i=1}^{n} |w_i|$$

$$L2: \Omega(w) = \sum_{i=1}^{n} w_i^2$$



- 해결방법 4 → 드롭아웃(Dropout)
 - ➤ <u>Backpropagation시</u> 모든 Weight가 업데이트 되는 것을 방지
 - ▶ 일부 Node를 랜덤하게 제거

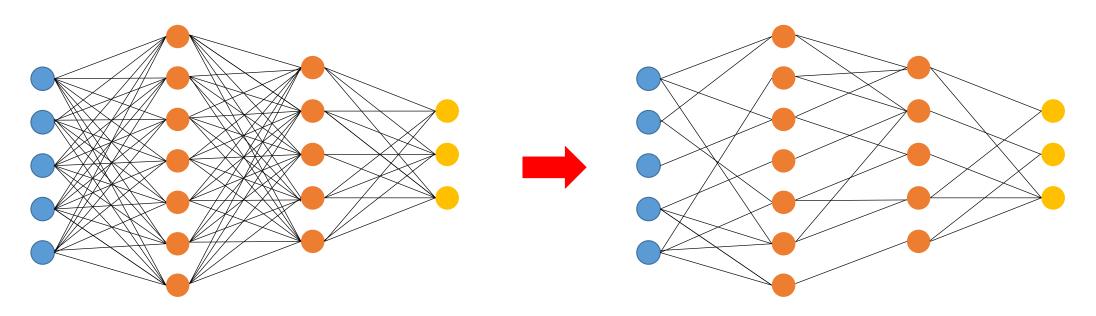


Dropout 적용 전

Dropout 적용 후



- 해결방법 5 → 드롭 커넥트(Drop Connect)
 - ➤ Backpropagation시 모든 Weight가 업데이트 되는 것을 방지
 - ➤ 일부 Weight를 랜덤하게 제거



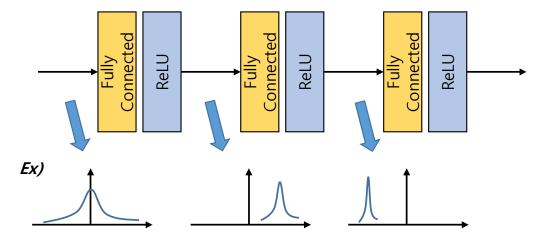
Drop Connect 적용 전

Drop Connect 적용 후

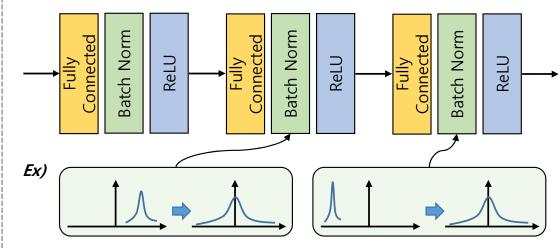


- 해결방법 6 → 배치 정규화(Batch Normalization)
 - ▶ 출력값을 정규화하는 작업

<배치 정규화 적용 전>



학습 과정에서 계층별로 입력의 데이터 분포가 달라지는 현상을 내부 공변량 변화(Internal Covariate Shift)라고 함 <배치 정규화 적용 후>



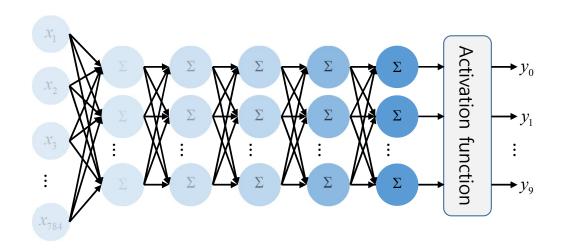
학습 과정에서 배치별로 평균과 분산을 이용해 정규화하는 계층을 배치 정규화 계층이라 함



실습

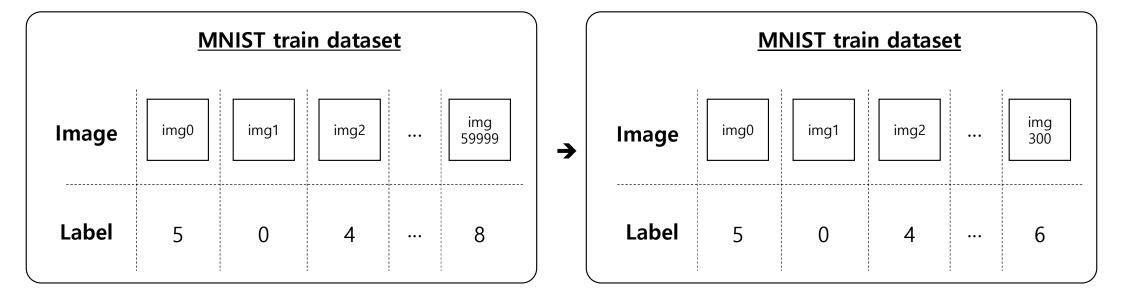


- Overfitting 이 주로 일어나는 경우
 - ▶ 매개변수가 많은 표현력이 높은 모델
 - ▶ 훈련데이터가 적음

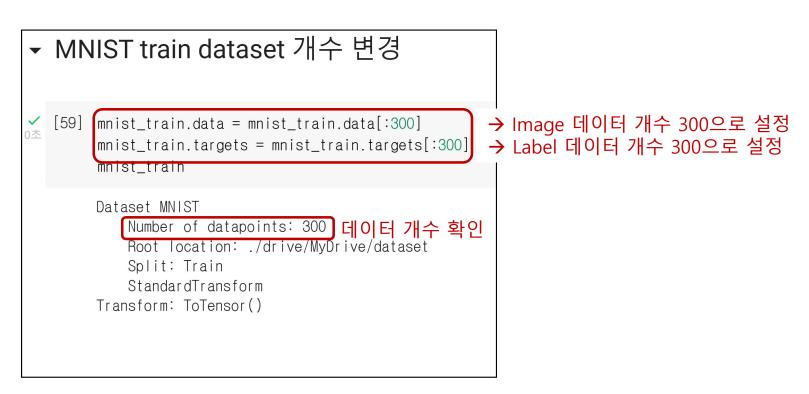




- Overfitting 문제 확인
 - (1) MNIST train dataset 개수 변경 60000 → 300



- Overfitting 문제 확인
 - (1) MNIST train dataset 개수 변경 60000 → 300





- Overfitting 문제 확인
 - (2) MLP 모델 정의

```
▼ Multi-layer Perceptron 모델 정의: 5-layer
  [ ] class MLP(nn.Module):
          def __init__(self):
            super(MLP, self).__init__()
            self.fc1 = nn.Linear(in_features=784, out_features=100)
            self.fc2 = nn.Linear(in_features=100, out_features=100)
            self.fc3 = nn.Linear(in_features=100, out_features=100)
            self.fc4 = nn.Linear(in_features=100, out_features=100)
            self.fc5 = nn.Linear(in_features=100, out_features=10)
            self.relu = nn.ReLU()
          def forward(self, x):
            x = x.view(-1, 28*28)
            y = self.relu(self.fc1(x))
            y = self.relu(self.fc2(y))
            y = self.relu(self.fc3(y))
            y = self.relu(self.fc4(y))
            y = self.fc5(y)
            return y
```



- Overfitting 문제 확인
 - (3) Hyper-parameter 지정



- Overfitting 문제 확인
 - (4) MLP 학습을 위한 반복문 선언

```
▼ Network Training 진행
        1 for epoch in range(training_epochs):
              avg_cost = 0
               total_batch = len(data_loader)
              for img, label in data_loader:
                  pred = network(img)
                  loss = loss_function(pred, label)
                  optimizer.zero_grad()
                  loss.backward()
        10
                  optimizer.step()
        11
        12
                  avg_cost += loss / total_batch
        13
        14
              print('Epoch: %d Loss = %f' %(epoch+1, avg_cost))
        16 print('Learning finished')
```



- Overfitting 문제 확인
 - (4) MLP 학습을 위한 반복문 선언

```
▼ Network Training 진행
       1 for epoch in range(training epochs):
               avg_cost = 0
               total_batch = len(data_loader)
               for img, label in data_loader:
                  pred = network(img)
                   loss = loss function(pred, label)
                   optimizer.zero_grad()
        10
                   loss.backward()
        11
                   optimizer.step()
        12
        13
                   avg cost += loss / total batch
        14
              print('Epoch: %d Loss = %f' %(epoch+1, avg cost))
        16 print('Learning finished')
```



```
Epoch: 85 \text{ Loss} = 0.000251
Epoch: 86 \text{ Loss} = 0.000246
Epoch: 87 \text{ Loss} = 0.000242
Epoch: 88 \text{ Loss} = 0.000238
Epoch: 89 \text{ Loss} = 0.000235
Epoch: 90 \text{ Loss} = 0.000231
Epoch: 91 \text{ Loss} = 0.000227
Epoch: 92 \text{ Loss} = 0.000224
Epoch: 93 \text{ Loss} = 0.000221
Epoch: 94 \text{ Loss} = 0.000217
Epoch: 95 \text{ Loss} = 0.000214
Epoch: 96 \text{ Loss} = 0.000211
Epoch: 97 \text{ Loss} = 0.000208
Epoch: 98 \text{ Loss} = 0.000205
Epoch: 99 \text{ Loss} = 0.000202
Epoch: 100 \text{ Loss} = 0.000200
Learning finished
```



- Overfitting 문제 확인
 - (5) MNIST Train dataset, MNIST Test dataset 분류 성능 확인

```
[24] with torch.no_grad():
    img_test = mnist_train.data.float()
    label_test = mnist_train.targets

    prediction = network(img_test)

    correct_prediction = torch.argmax(prediction, 1) == label_test
    accuracy = correct_prediction.float().mean()

    print('Accuracy: ',accuracy.item())

Accuracy: 1.0 정답률: 100%
```

```
[22] with torch.no_grad():
    img_test = mnist_test.data.float()
    label_test = mnist_test.targets

    prediction = network(img_test)

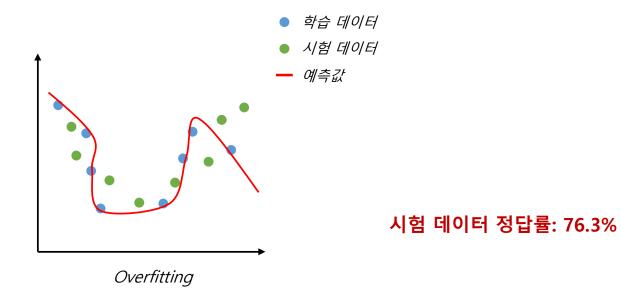
    correct_prediction = torch.argmax(prediction, 1) == label_test
    accuracy = correct_prediction.float().mean()

    print('Accuracy: ',accuracy.item())

Accuracy: 0.763700008392334 정답률: 76.3%
```



- Overfitting 문제 확인
 - (5) MNIST Train dataset, MNIST Test dataset 분류 성능 확인



학습 데이터 정답률: 100%

Overfitting 문제 발생!



- Overfitting 문제 해결(1): Batch Normalization
 - (1) MLP 모델 재정의
 - Batch Normalization 선언 및 적용

```
[25] class MLP(nn.Module):
       def __init__(self):
         super(MLP, self).__init__()
         self.fc1 = nn.Linear(in_features=784, out_features=100)
                                                                                                           Batch Norm
         self.fc2 = nn.Linear(in_features=100, out_features=100)
         self.fc3 = nn.Linear(in_features=100, out_features=100)
         self.fc4 = nn.Linear(in_features=100, out_features=100)
         self.fc5 = nn.Linear(in_features=100, out_features=10)
         self.relu = nn.ReLU()
         self.bn = nn.BatchNorm1d(100) → Batch Normalization 수행 선언 (100 features)
       def forward(self, x):
         x = x.view(-1, 28*28)
         y = self.relu(self.bn(self.fc1(x)))
         y = self.relu(self.bn(self.fc2(y)))
                                                → Batch Normalization 적용
         y = self.relu(self.bn(self.fc3(y)))
         y = self.relu(self.bn(self.fc4(y)))
         y = self.fc5(y)
         return y
```



- Overfitting 문제 해결(1): Batch Normalization
 - (2) Hyper-parameter 지정 및 Training 진행

```
[24]
      1 for epoch in range(training epochs):
            avg_cost = 0
            total_batch = len(data_loader)
            for img, label in data_loader:
                pred = network(img)
                loss = loss_function(pred, label)
                optimizer.zero_grad()
                loss.backward()
     10
                optimizer.step()
     11
     13
                avg_cost += loss / total_batch
     14
            print('Epoch: %d Loss = %f' %(epoch+1, avg_cost))
     16 print('Learning finished')
```



- Overfitting 문제 해결(1): Batch Normalization
 - (3) MNIST Test dataset 분류 성능 확인

```
[29] with torch.no_grad():
    img_test = mnist_test.data.float()
    label_test = mnist_test.targets

    prediction = network(img_test)

    correct_prediction = torch.argmax(prediction, 1) == label_test
    accuracy = correct_prediction.float().mean()

    print('Accuracy: ',accuracy.item())

Accuracy: 0.7935000061988831
```

정답률: 79.3%



- Overfitting 문제 해결(2): Dropout
 - (1) MLP 모델 재정의
 - Dropout 선언 및 적용

```
[31] class MLP(nn.Module):
      def __init__(self):
        super(MLP, self).__init__()
        self.fc1 = nn.Linear(in_features=784, out_features=100)
        self.fc2 = nn.Linear(in_features=100, out_features=100)
        self.fc3 = nn.Linear(in_features=100, out_features=100)
        self.fc4 = nn.Linear(in_features=100, out_features=100)
        self.fc5 = nn.Linear(in_features=100, out_features=10)
        self.relu = nn.ReLU()
                                          → Dropout 선언 (0.2 비율)
        self.dropout = nn.Dropout(0.2)
      def forward(self, x):
        x = x.view(-1, 28*28)
        y = self.relu(self.fc1(x))
         y = self.dropout(y)
         y = self.relu(self.fc2(y))
        y = self.dropout(y)
                                       → Dropout 적용
        y = self.relu(self.fc3(y))
        y = self.dropout(y)
        y = self.relu(self.fc4(y))
        y = self.dropout(y)
        y = self.fc5(y)
        return y
```



- Overfitting 문제 해결(2): Dropout
 - (2) Hyper-parameter 지정 및 Training 진행

```
[24]
      1 for epoch in range(training epochs):
            avg_cost = 0
            total_batch = len(data_loader)
            for img, label in data_loader:
                pred = network(img)
                loss = loss_function(pred, label)
                optimizer.zero_grad()
                loss.backward()
     10
                optimizer.step()
     11
     13
                avg_cost += loss / total_batch
     14
            print('Epoch: %d Loss = %f' %(epoch+1, avg_cost))
     16 print('Learning finished')
```



- Overfitting 문제 해결(2): Dropout
 - (3) MNIST Test dataset 분류 성능 확인

```
[120] with torch.no_grad():
    network.eval() → Network Dropout 비활성
    img_test = mnist_test.data.float()
    label_test = mnist_test.targets

    prediction = network(img_test)

    correct_prediction = torch.argmax(prediction, 1) == label_test
    accuracy = correct_prediction.float().mean()

    print('Accuracy: ',accuracy.item())

Accuracy: 0.7954000234603882
```

정답률: 79.3%



- Overfitting 문제 해결(3): Data Augmentation
 - (1) MNIST Train Data Rotation 변환

```
[121] import torchvision.transforms as transform

trans_rotation_left_15=transform.RandomRotation((-15,-15))
rotation_data_left_15=trans_rotation_left_15(mnist_train.data)

trans_rotation_left_30=transform.RandomRotation((-30,-30))
rotation_data_left_30=trans_rotation_left_30(mnist_train.data)

trans_rotation_right_15=transform.RandomRotation((15,15))
rotation_data_right_15=trans_rotation_right_15(mnist_train.data)

trans_rotation_right_30=transform.RandomRotation((30,30))
rotation_data_right_30=transform.RandomRotation((30,30))
rotation_data_right_30=trans_rotation_right_30(mnist_train.data)

→ 시계 방향 30도 Rotation 수행

→ 시계 방향 30도 Rotation 수행
```



- Overfitting 문제 해결(3): Data Augmentation
 - (2) rotation_data 형태확인
 - (3) rotation 수행된 데이터 MNIST Train Dataset 에 합치기

```
2
149] print(rotation_data_left_15.shape)
print(rotation_data_left_30.shape)
print(rotation_data_right_15.shape)
print(rotation_data_right_30.shape)

torch.Size([300, 28, 28])
```

3 29] mnist_train.data = torch.cat((mnist_train.data, rotation_data_left_15, rotation_data_left_30, rotation_data_right_15, rotation_data_right_30),0) mnist_train.data.shape

torch.Size([1500, 28, 28])



- Overfitting 문제 해결(3): Data Augmentation
 - (4) Train Dataset label 늘리기

```
[159] print(mnist_train.targets[0])
    print(mnist_train.targets[300])
    print(mnist_train.targets[600])
    print(mnist_train.targets[900])
    print(mnist_train.targets[1200])

    tensor(5)
    tensor(5)
    tensor(5)
    tensor(5)
    tensor(5)
    tensor(5)
```

```
[160] print(mnist_train.targets[1])
    print(mnist_train.targets[301])
    print(mnist_train.targets[601])
    print(mnist_train.targets[901])
    print(mnist_train.targets[1201])

    tensor(0)
    tensor(0)
    tensor(0)
    tensor(0)
    tensor(0)
```



- Overfitting 문제 해결(3): Data Augmentation
 - 300 Train Dataset → 1500 Train Dataset

MNIST train dataset													
lmage	img0	img1			img 300	•••	img 600	•••	img 900		img 1200	•••	img 1499
Label	5	0	4	•••	5	•••	5	•••	5		5		6

- Overfitting 문제 해결(3): Data Augmentation
 - 300 Train Dataset → 1500 Train Dataset

MNIST train dataset													
Image	3				5	•••	5	•••	٣.	•••		•••	img 1499
Label	5	0	4	•••	5	•••	5	•••	5	•••	5	•••	6

- Overfitting 문제 해결(3): Data Augmentation
 - (5) MLP 모델 재정의

```
▼ Multi-layer Perceptron 모델 정의: 5-layer
  [ ] class MLP(nn.Module):
          def __init__(self):
            super(MLP, self).__init__()
            self.fc1 = nn.Linear(in_features=784, out_features=100)
            self.fc2 = nn.Linear(in features=100, out features=100)
            self.fc3 = nn.Linear(in_features=100, out_features=100)
            self.fc4 = nn.Linear(in_features=100, out_features=100)
            self.fc5 = nn.Linear(in_features=100, out_features=10)
            self.relu = nn.ReLU()
          def forward(self, x):
            x = x.view(-1, 28*28)
            y = self.relu(self.fc1(x))
            y = self.relu(self.fc2(y))
            y = self.relu(self.fc3(y))
            y = self.relu(self.fc4(y))
            y = self.fc5(y)
            return y
```



- Overfitting 문제 해결(3): Data Augmentation
 - (6) Hyper-parameter 지정 및 Training 진행

```
[24]
      1 for epoch in range(training epochs):
      2
            avg_cost = 0
            total_batch = len(data_loader)
            for img, label in data_loader:
                pred = network(img)
                loss = loss_function(pred, label)
                optimizer.zero_grad()
                loss.backward()
     10
                optimizer.step()
     11
     13
                avg_cost += loss / total_batch
     14
            print('Epoch: %d Loss = %f' %(epoch+1, avg_cost))
     16 print('Learning finished')
```



- Overfitting 문제 해결(3): Data Augmentation
 - (7) MNIST Test dataset 분류 성능 확인

```
[173] with torch.no_grad():
    img_test = mnist_test.data.float()
    label_test = mnist_test.targets

    prediction = network(img_test)

    correct_prediction = torch.argmax(prediction, 1) == label_test
    accuracy = correct_prediction.float().mean()

    print('Accuracy: ',accuracy.item())

Accuracy: 0.8073999881744385
```

정답률: 80.73%



Questions & Answers

Dongsan Jun (dsjun@dau.ac.kr)

Image Signal Processing Laboratory (<u>www.donga-ispl.kr</u>)

Division of Computer AI Engineering

Dong-A University, Busan, Rep. of Korea