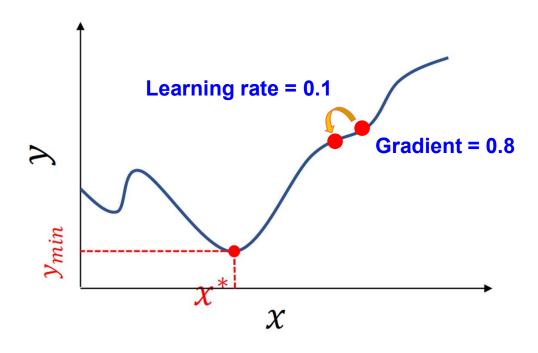


Review: Gradient decent algorithm



- ❖ X (W, b): Trainable parameters
- ❖ Y: Loss function

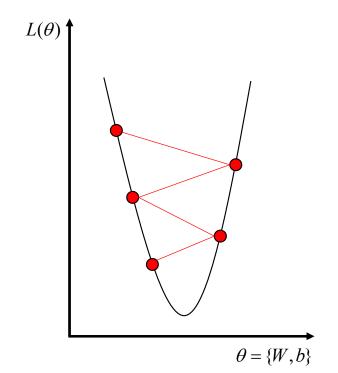
Gradient decent algorithm

- ① 현재 지점에서 미분을 이용해 gradient 계산
- ② Gradient에 learning rate를 곱하고 반대 방향으로 weight update

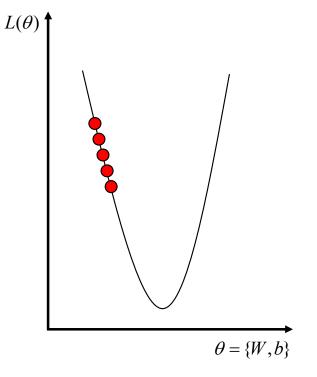
$$W_{new} = W_{prev} - \alpha \frac{\partial L}{\partial W}$$
Learning rate
Gradient



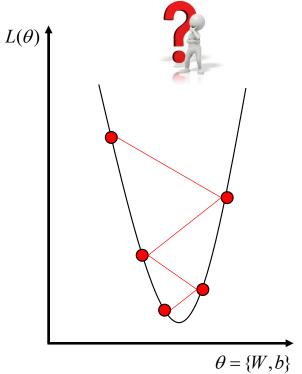
- Learning rate control (decay)
 - 빠른 시간내에 정확도 높은 학습 파라미터를 구하기 위해 learning rate를 조절하는 방법



Learning rate가 큰 경우



Learning rate가 작은 경우





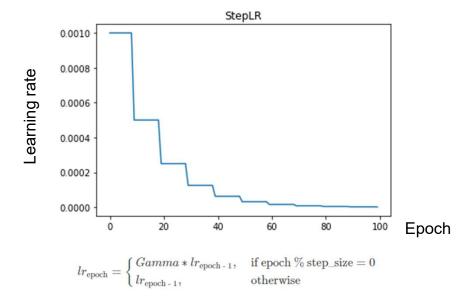
■ 이전 실습까지 고정된 learning rate를 사용해 학습 수행 (LR: 0.1)

```
batch_size = 10
learning_rate = 0.1
training_epochs = 100
loss_function = nn.CrossEntropyLoss()
network = FMLP()
optimizer = torch.optim.SGD(network.parameters(), | Ir = learning_rate)
data_loader = DataLoader(dataset = mnist_train,
                         batch_size = batch_size,
                         shuffle = True,
                         drop_last = True)
```

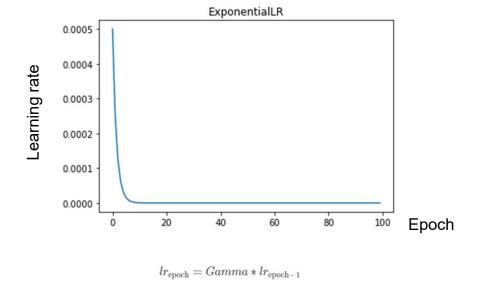
5주차 overfitting 실습 자료 중 일부 (Hyper-parameter 지정)



- Pytorch에서 제공하는 learning rate control 기능
 - StepLR: 지정된 step (epoch) 단위마다 learning rate 조절
 - ExponentialLR: 매 step (epoch) 단위마다 learning rate 조절
 - etc...



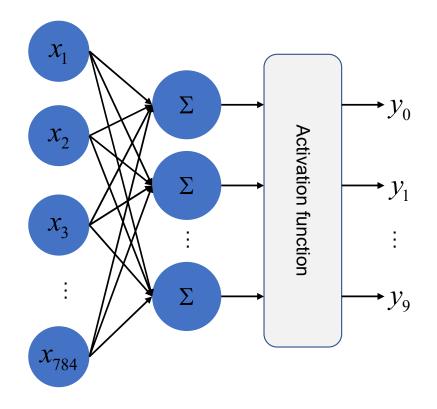
StepLR (step_size: 10, gamma: 0.5)



ExponentialLR (step_size: 10, gamma: 0.5)



■ 금일은 Single Layer Perceptron (SLP)을 이용해 실습 진행

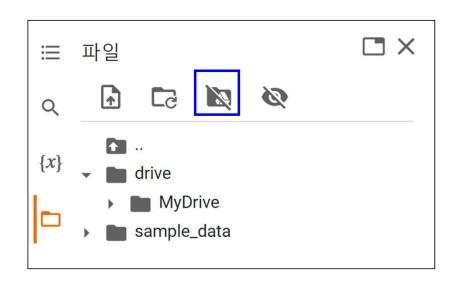


```
class SLP(nn.Module):
    def __init__(self):
        super(SLP, self).__init__()
        self.fc1 = nn.Linear(in_features=784, out_features=100)

def forward(self, x):
        x = x.view(-1, 28*28)
        y = self.fc1(x)
        return y
```



- [실습 1] Learning rate control을 수행하지 않는 SLP 학습
 - 1) 6주차 LMS에 업로드 된 기본 소스코드 다운로드
 - 2) 구글 드라이브 마운트 (파라미터 및 데이터셋 경로 확인 필요)
 - 3) 전체 셀 실행







- [실습 1] Learning rate control을 수행하지 않는 SLP 학습
 - 1) 6주차 LMS에 업로드 된 기본 소스코드 다운로드
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 - 3) 전체 셀 실행
 - 4) 결과 확인

```
Epoch: 1. LR: 0.100000.
                         Loss: 0.537231
Epoch: 2. LR: 0.100000.
                        Loss: 0.359334
Epoch: 3, LR: 0.100000.
                        Loss: 0.331079
Epoch: 4, LR: 0.100000,
                        Loss: 0.316594
Epoch: 5, LR: 0.100000,
                        Loss: 0.307029
Epoch: 6, LR: 0.100000,
                        Loss: 0.300397
Epoch: 7, LR: 0.100000.
                         Loss: 0.294995
Epoch: 8, LR: 0.100000,
                         Loss: 0.290815
Epoch: 9. LR: 0.100000.
                         Loss: 0.287408
                          Loss: 0.284473
Epoch: 10 LR: 0.100000.
Epoch: 11 LR: 0.100000.
                          Loss: 0.281891
Epoch: 12 LR: 0.100000,
                          Loss: 0.279587
Epoch: 13
          LR: 0.100000.
                          Loss: 0.277830
Epoch: 14. LR: 0.100000,
                          Loss: 0.275999
Epoch: 15 LR: 0.100000,
                          Loss: 0.274663
Learning finished
```



- [실습 2] StepLR 기법을 이용한 SLP 학습
 - [5] Hyper-parameter 및 [6] Training loop 일부 수정

[5] Hyper-parameter 지정

- 이미 학습을 수행한 상태로 다시 학습을 수행할 때 이 셀을 재실행해야함
- Step [4] 모델 구조 선언에 사용한 class 명과 일치한지 반드시 확인

```
[6] Training loop

[20] 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()
    optimizer.step()
    avg_cost += loss / total_batch

print('Epoch: %d, LR: %f, Loss: %f' %(epoch+1, optimizer.param_groups[0]['Ir'], avg_cost))
scheduler.step()
```

StepLR → 매 5epoch 마다 learning rate에 0.5 곱하기



print('Learning finished')

- [실습 2] StepLR 기법을 이용한 SLP 학습
 - 결과 확인

```
Epoch: 1, LR: 0.100000,
                        Loss: 0.535101
Epoch: 2, LR: 0.100000,
                        Loss: 0.359083
Epoch: 3, LR: 0.100000,
                        Loss: 0.330872
Epoch: 4, LR: 0.100000.
                        Loss: 0.316319
Epoch: 5. LR: 0.100000.
                        Loss: 0.306708
Epoch: 6, LR: 0.050000.
                        Loss: 0.299735
Epoch: 7. LR: 0.050000.
                        Loss: 0.296768
Epoch: 8, LR: 0.050000,
                        Loss: 0.294234
Epoch: 9, LR: 0.050000,
                        Loss: 0.291917
Epoch: 10, LR: 0.050000, Loss: 0.289835
Epoch: 11, LR: 0.025000,
                         Loss: 0.287472
Epoch: 12, LR: 0.025000.
                          Loss: 0.286501
Epoch: 13. LR: 0.025000.
                          Loss: 0.285718
Epoch: 14. LR: 0.025000.
                          Loss: 0.284972
Epoch: 15, LR: 0.025000,
                          Loss: 0.284091
Learning finished
```

❖ 고정된 learning rate 사용 시

Accuracy: 0.8845999836921692



1.3% 성능 향상

❖ Learning rate control 사용 시



- [실습 3] ExponentialLR 기법을 이용한 SLP 학습
 - [5] Hyper-parameter 일부 수정

```
[6] Training loop

[20] 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()
    optimizer.step()
    avg_cost += loss / total_batch

print('Epoch: %d, LR: %f, Loss: %f' %(epoch+1, optimizer.param_groups[0]['Ir'], avg_cost))
scheduler.step()

print('Learning finished')
```



- [실습 3] ExponentialLR 기법을 이용한 SLP 학습
 - 결과확인

```
Epoch: 1, LR: 0.100000,
                        Loss: 0.536337
Epoch: 2, LR: 0.080000, Loss: 0.361799
Epoch: 3, LR: 0.064000, Loss: 0.337062
Epoch: 4, LR: 0.051200, Loss: 0.325141
Epoch: 5. LR: 0.040960. Loss: 0.317976
Epoch: 6. LR: 0.032768. Loss: 0.313117
Epoch: 7, LR: 0.026214, Loss: 0.309792
Epoch: 8, LR: 0.020972,
                        Loss: 0.307415
Epoch: 9, LR: 0.016777,
                        Loss: 0.305586
Epoch: 10 LR: 0.013422.
                        Loss: 0.304185
Epoch: 11 LR: 0.010737.
                         Loss: 0.303148
Epoch: 12 LR: 0.008590,
                         Loss: 0.302284
Epoch: 13 LR: 0.006872.
                         Loss: 0.301671
Epoch: 14 LR: 0.005498.
                         Loss: 0.301167
Epoch: 15 LR: 0.004398,
                         Loss: 0.300759
Learning finished
```

❖ 고정된 learning rate 사용 (Ir: 0.1)

Accuracy: 0.8845999836921692

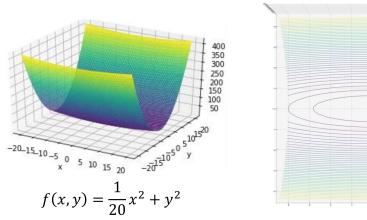
StepLR (step_size: 5, gamma: 0.5)

Accuracy: 0.897599995136261

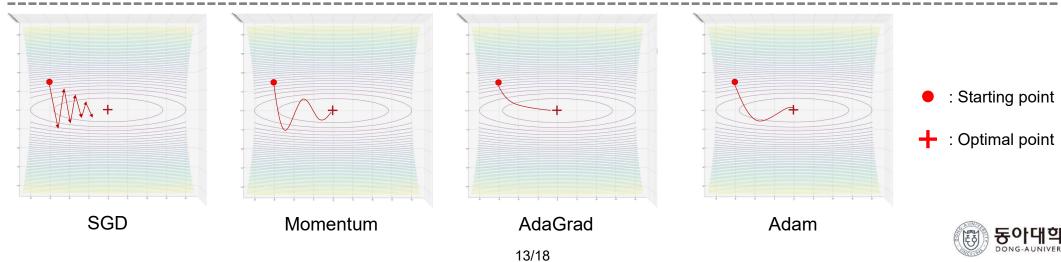
* ExponentialLR (gamma: 0.8)



■ 대표적인 optimizer 기법 비교



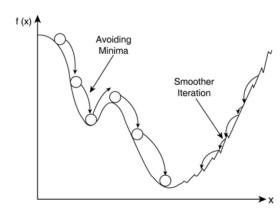
- ❖ f(x,y): loss function으로 가정
- ❖ x, y: trainable parameter로 가정



- [실습 1] Momentum 기법을 이용한 SLP 학습
 - [5] Hyper-parameter 및 [6] Training loop 부분 변경

[5] Hyper-parameter 지정

- 이미 학습을 수행한 상태로 다시 학습을 수행할 때 이 셀을 재실행해야함
- Step [4] 모델 구조 선언에 사용한 class 명과 일치한지 반드시 확인



$$\begin{split} W_{t+1} &= W_t + v_t \\ v_t &= \alpha v_{t-1} - \eta \frac{\partial L}{\partial W_t} \\ &\uparrow \\ \text{momentum 계수} \end{split}$$



- [실습 1] Momentum 기법을 이용한 SLP 학습
 - [5] Hyper-parameter 및 [6] Training loop 부분 변경

```
▼ [6] Training loop
                                                                               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()
               optimizer.step()
               avg_cost += loss / total_batch
           print('Epoch: %d, LR: %f, Loss: %f' %(epoch+1, optimizer.param_groups[0]['Ir'], avg_cost))
           # scheduler.step()
       print('Learning finished')
```



- [실습 1] Momentum 기법을 이용한 SLP 학습
 - 결과 확인

```
Epoch: 1, LR: 0.100000, Loss: 0.382954
Epoch: 2, LR: 0.100000, Loss: 0.300450
Epoch: 3, LR: 0.100000, Loss: 0.290717
Epoch: 4. LR: 0.100000. Loss: 0.285352
Epoch: 5, LR: 0.100000, Loss: 0.279600
Epoch: 6. LR: 0.100000.
                        Loss: 0.277274
Epoch: 7, LR: 0.100000, Loss: 0.273616
Epoch: 8, LR: 0.100000, Loss: 0.271986
Epoch: 9. LR: 0.100000. Loss: 0.271436
Epoch: 10, LR: 0.100000, Loss: 0.270345
Epoch: 11, LR: 0.100000, Loss: 0.268834
Epoch: 12, LR: 0.100000, Loss: 0.266973
Epoch: 13, LR: 0.100000, Loss: 0.264558
Epoch: 14, LR: 0.100000, Loss: 0.264766
Epoch: 15, LR: 0.100000, Loss: 0.264690
Learning finished
```

❖ SGD

Accuracy: 0.8845999836921692

❖ SGD + Momentum



- [실습 2] Adam 기법을 이용한 SLP 학습
 - [5] Hyper-parameter 변경

[5] Hyper-parameter 지정

- 이미 학습을 수행한 상태로 다시 학습을 수행할 때 이 셀을 재실행해야함
- Step [4] 모델 구조 선언에 사용한 class 명과 일치한지 반드시 확인



- [실습 2] Adam 기법을 이용한 SLP 학습
 - 결과확인

```
Epoch: 1, LR: 0.100000, Loss: 0.895777
Epoch: 2, LR: 0.100000, Loss: 0.939572
Epoch: 3, LR: 0.100000, Loss: 0.984272
Epoch: 4, LR: 0.100000, Loss: 1.049648
Epoch: 5, LR: 0.100000, Loss: 1.028599
Epoch: 6, LR: 0.100000, Loss: 1.010980
Epoch: 7, LR: 0.100000, Loss: 1.042650
Epoch: 8, LR: 0.100000, Loss: 1.008793
Epoch: 9. LR: 0.100000. Loss: 1.028753
Epoch: 10, LR: 0.100000, Loss: 1.043825
Epoch: 11, LR: 0.100000, Loss: 0.993260
Epoch: 12, LR: 0.100000, Loss: 1.024413
Epoch: 13, LR: 0.100000, Loss: 1.077637
Epoch: 14, LR: 0.100000, Loss: 1.024739
Epoch: 15, LR: 0.100000, Loss: 1.040391
Learning finished
```

❖ SGD

Accuracy: 0.8845999836921692

❖ SGD + Momentum

Accuracy: 0.8580999970436096

❖ Adam



Questions & Answers

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