# O PyTorch

## 动量与学习率衰减

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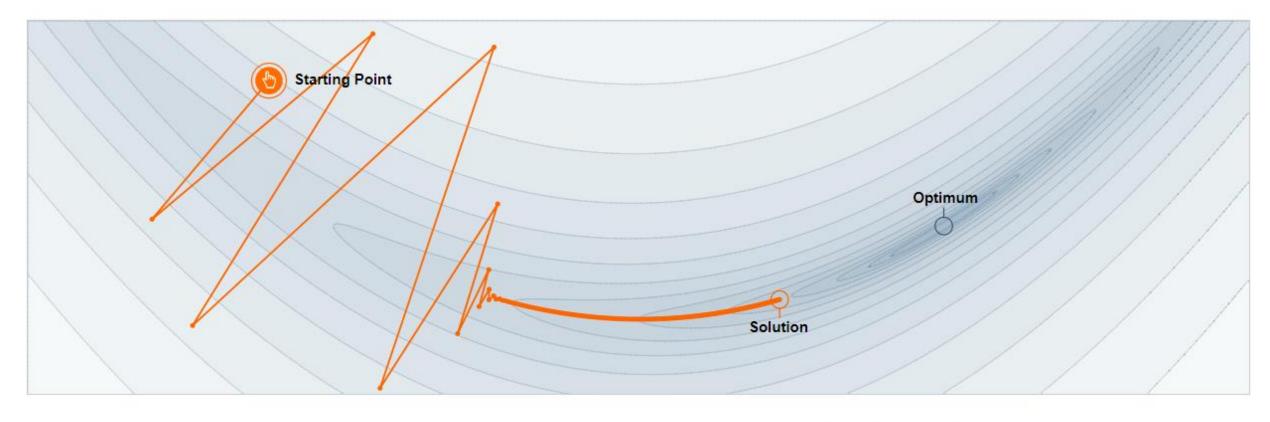
# **Tricks** momentum learning rate decay

#### **Momentum**

$$w^{k+1} = w^k - \alpha \nabla f(w^k).$$

$$z^{k+1} = \beta z^k + \nabla f(w^k)$$
  
 $w^{k+1} = w^k - \alpha z^{k+1}$ 

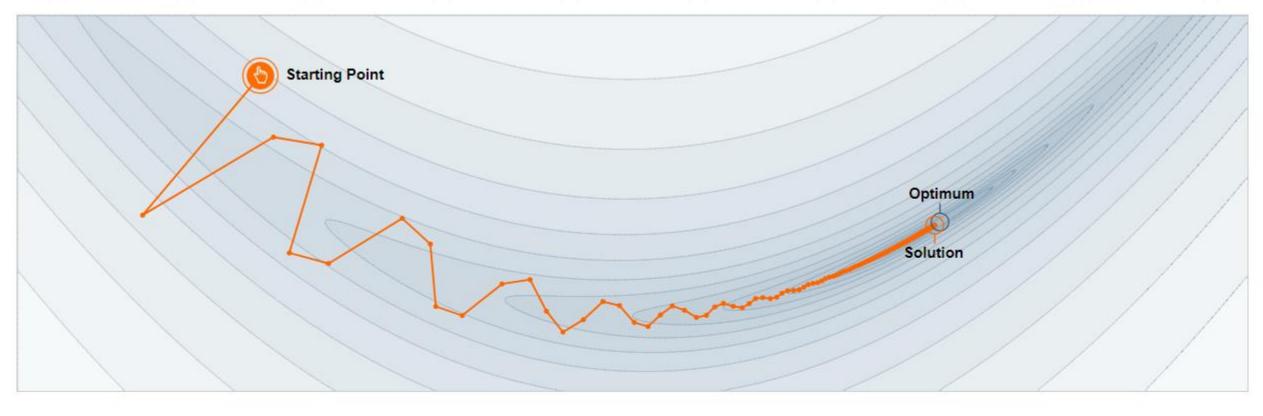
#### No momentum





We often think of Momentum as a means of dampening oscillations and speeding up the iterations, leading to faster convergence. But it has other interesting behavior. It allows a larger range of step-sizes to be used, and creates its own oscillations. What is going on?

#### With appr. momentum



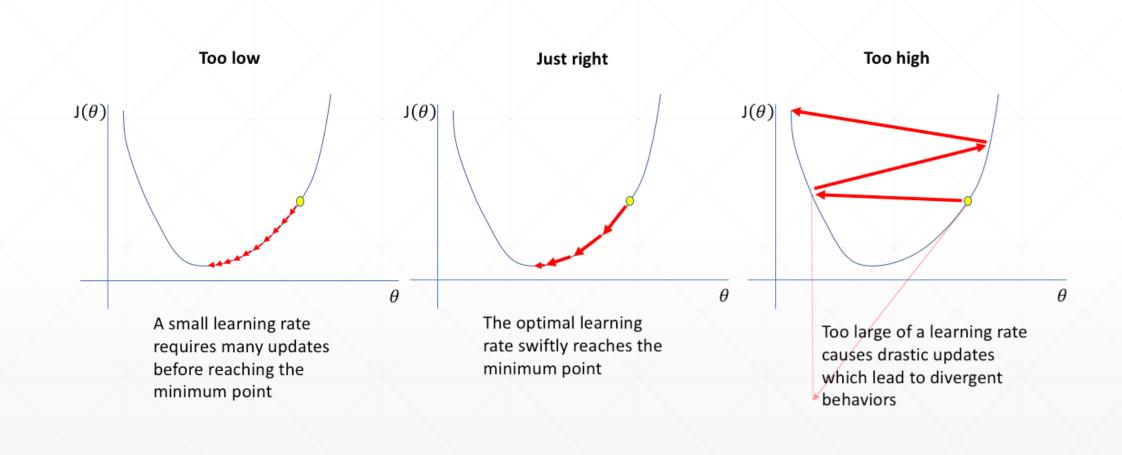


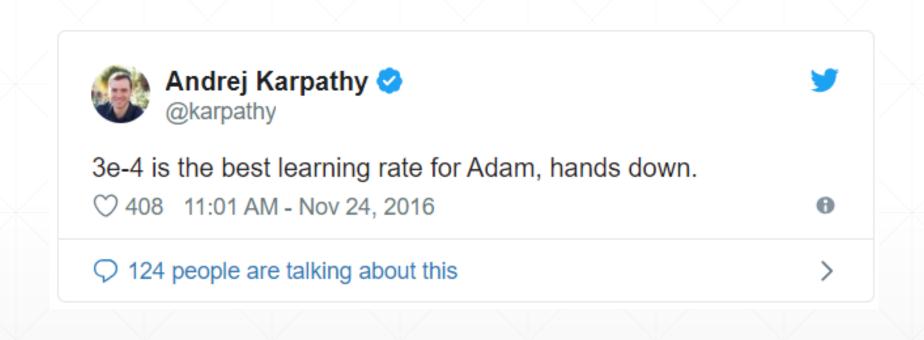
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#### momentum

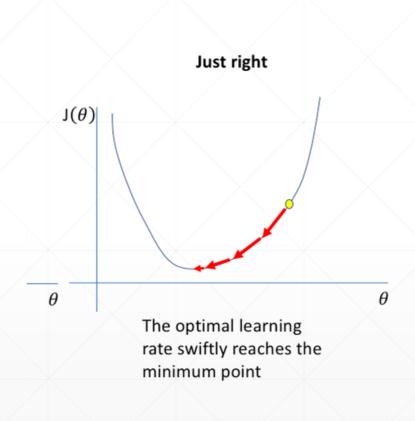
```
optimizer = torch.optim.SGD(model.parameters(), args.lr,
                                    momentum=args.momentum,
                                    weight_decay=args.weight_decay)
scheduler = ReduceLROnPlateau(optimizer, 'min')
for epoch in xrange(args.start_epoch, args.epochs):
       train(train_loader, model, criterion, optimizer, epoch)
       result_avg, loss_val = validate(val_loader, model, criterion, epoch)
       scheduler.step(loss_val)
```

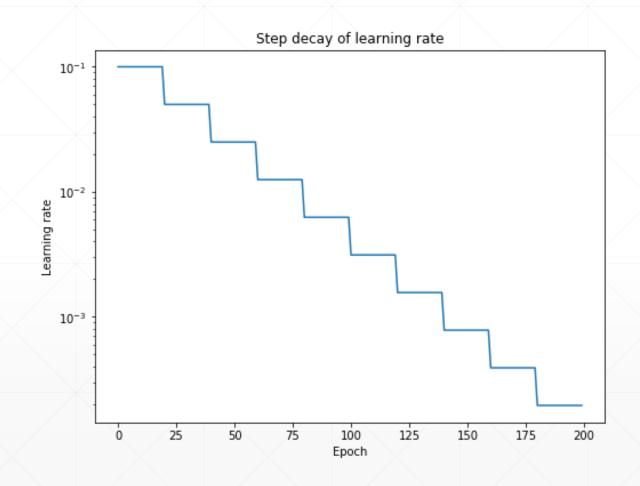
#### Learning rate tunning

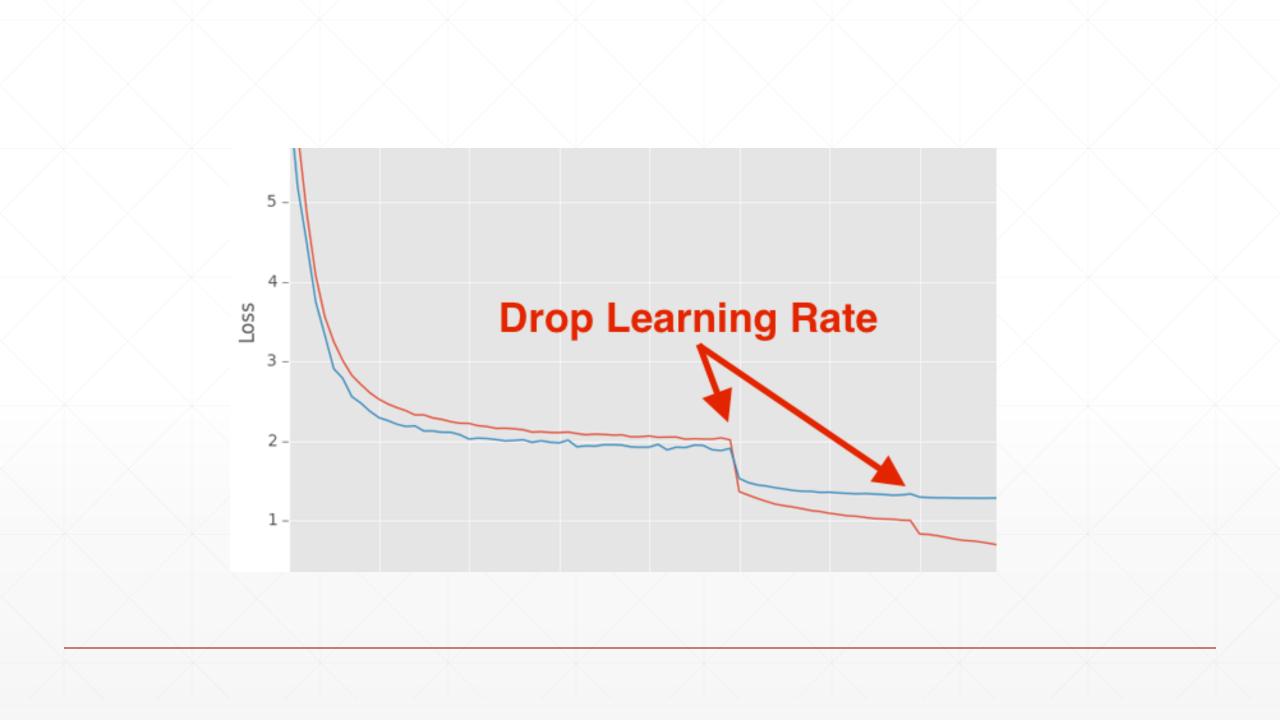




#### Learning rate decay







#### Scheme 1.

CLASS torch.optim.lr\_scheduler.ReduceLROnPlateau(optimizer, mode='min', factor=0.1, patience=10, verbose=False, threshold=0.0001, threshold\_mode='rel', cooldown=0, min\_lr=0, eps=1e-08)

[SOURCE]

```
optimizer = torch.optim.SGD(model.parameters(), args.lr,
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                                    weight_decay=args.weight_decay)
scheduler = ReduceLROnPlateau(optimizer, 'min')
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       scheduler.step(loss_val)
```

#### Scheme 2.

```
# Assuming optimizer uses lr = 0.05 for all groups
# lr = 0.05 if epoch < 30
# lr = 0.005 if 30 <= epoch < 60
# lr = 0.0005 if 60 \le epoch < 90
scheduler = StepLR(optimizer, step_size=30, gamma=0.1)
for epoch in range(100):
   scheduler.step()
   train(...)
   validate(...)
```

### 下一课时

其他Tricks

### Thank You.