Deep Learning

11 Training DNNs II

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Issues with SGD

भारतीय प्रौद्योगिकी संस्थान हैदराबाद
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- DNNs are trained via SGD: $w_{t+1} = w_t - \eta \cdot \nabla_w J(w)$

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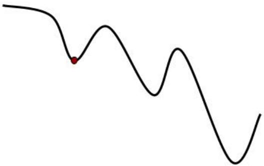
  - May have local minima
  - May have saddle points

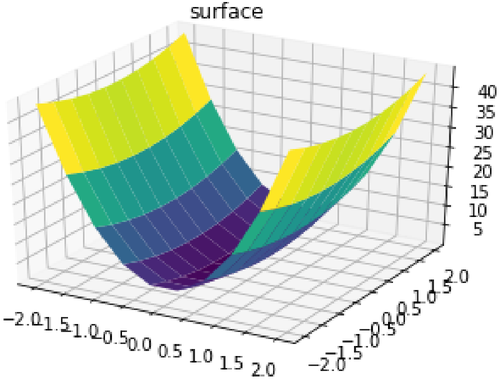


Stuck at a local minimum

Stuck at a saddle point

Issues with SGD

- DNNs are trained via SGD: $w_{t+1} = w_t - \eta \cdot \nabla_w J(w)$
- Loss is a high dimensional function
  - May vary swiftly in one direction and slowly in the other



Issues with SGD

- SGD leads to jitter along the deep dimension and slow progress along the shallow one

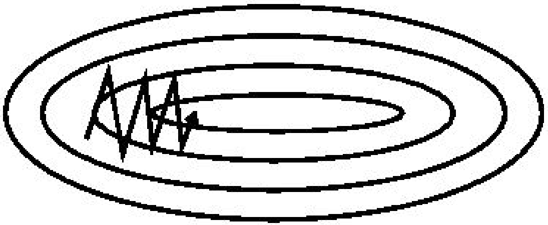


Figure credits: Sebastian Ruder

SGD+Momentum

SGD

$$w_{t+1} = w_t - \eta \cdot \nabla_w J(w)$$

SGD+Momentum

$$\begin{aligned} v_0 &= 0 \\ v_{t+1} &= \rho \cdot v_t + \nabla_w J(w) \\ w_{t+1} &= w_t - \eta \cdot v_{t+1} \end{aligned}$$

I Sutskever et al., ICML 2013

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- Aggregates velocity: exponential moving average over gradients
- ρ is the friction (typically set to 0.9 or 0.99)

I Sutskever et al., ICML 2013

SGD+Momentum

SGD

$$w_{t+1} = w_t - \eta \cdot \nabla_w J(w)$$

for i in range(num_iters):
$\rightarrow$dw = grad(J, W, x, y)
$\rightarrow w- = \eta \cdot dw$

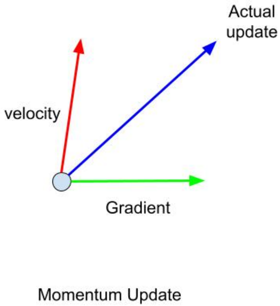
SGD+Momentum

$$v_0 = 0$$
$$v_{t+1} = \rho \cdot v_t + \nabla_w J(w)$$
$$w_{t+1} = w_t - \eta \cdot v_{t+1}$$

$v_0 = 0$
for i in range(num_iters):
$\rightarrow$dw = grad(J, W, x, y)
$\rightarrow v = \rho \cdot v + dw$
$\rightarrow w- = \eta \cdot v$

I Sutskever et al., ICML 2013

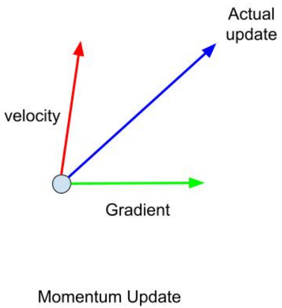
SGD+Momentum



1. How can momentum help?

I Sutskever et al., ICML 2013

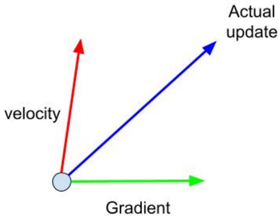
SGD+Momentum



1. How can momentum help?
   - Optimization proceeds even at the local minimum or saddle point (because of the accumulated velocity)

I Sutskever et al., ICML 2013

SGD+Momentum



Momentum Update

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   - Jitter is reduced in ravine like loss surfaces

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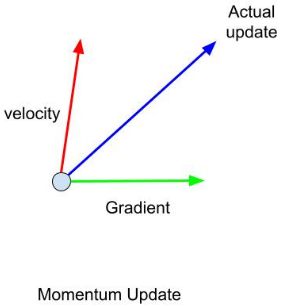
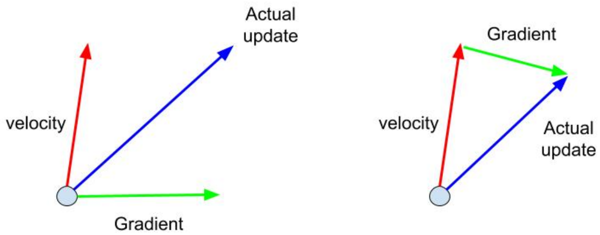


1. How can momentum help?
   - Optimization proceeds even at the local minimum or saddle point (because of the accumulated velocity)
   - Jitter is reduced in ravine like loss surfaces
   - Updates are more smoothed out (less noisy because of the exponential averaging)

I Sutskever et al., ICML 2013

Nesterov Momentum

1. Look ahead with the velocity, then take a step in the gradient's direction



Momentum Update

Nesterov Momentum

I Sutskever et al., ICML 2013

Nesterov Momentum

$v_0 = 0$

`for i in range(num_iters):`

$\rightarrow$`dw = grad(`$J, W + \rho \cdot v, x, y$`)`

$\rightarrow v = \rho \cdot v + dw$

$\rightarrow w- = \eta \cdot v$

NAG allows to change velocity in a faster and more responsive way (particularly for large values of ρ)

I Sutskever et al., ICML 2013

Ada Grad

1. Goal: Adaptive (or, per-parameter) learning rates are introduced

Duchi et al. 2011, JMLR

Ada Grad

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2. Parameter-wise scaling of the learning rate by the aggregated gradient

Duchi et al. 2011, JMLR

Ada Grad

```
 grad_sq = 0
for i in range(max_iters):
→ dw = grad(J,w,x,y)
→grad_sq += dw ⊙ dw
→ w− = η · dw/(sqrt(grad_sq) + ϵ)
```

Duchi et al. 2011, JMLR

Ada Grad

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for i in range(max_iters):
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$\rightarrow w- = \eta \cdot dw/(\texttt{sqrt(grad\_sq)} + \epsilon)$

- Optimization progress along the steep directions is attenuated

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- Optimization progress along the steep directions is attenuated
- Along the flat directions is accelerated

Duchi et al. 2011, JMLR

RMS Prop

1. If Ada Grad is run for too long
   - the gradients accumulate to a big value
   - $\rightarrow$ update becomes too small (or, learning rate is reduced continuously)

RMS Prop

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   - the gradients accumulate to a big value
   - $\rightarrow$ update becomes too small (or, learning rate is reduced continuously)
2. RMS prop (a leaky version of Ada Grad) addresses this using a friction coefficient (ρ)

RMS Prop

grad_sq = 0
for i in range(max_iters):
$\rightarrow$ dw = grad(J,w,x,y)
$\rightarrow$grad_sq = $\rho\cdot$ grad_sq + $(1-\rho)\cdot$ dw $\odot$ dw
$\rightarrow w- = \eta \cdot dw/(\texttt{sqrt(grad\_sq)} + \epsilon)$

Adam

1. Inculcates both the good things: momentum and the adaptive learning rates
   Adam = RMSProp + Momentum

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2. $m1 = 0$
   $m2 = 0$
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   $\rightarrow$ `dw = grad(J,w,x,y)`
   $\rightarrow \; m1 = \beta_1 \cdot m1 + (1 - \beta_1) \cdot dw$
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   $\rightarrow \; w- = \eta \cdot m1 / (\texttt{sqrt}(m2) + \epsilon)$

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2. Bias correction is performed (since the estimates start from 0)

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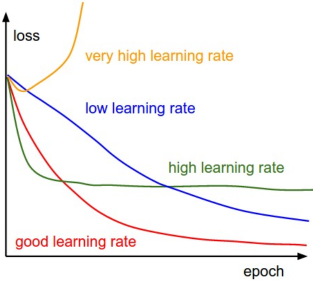
   $\rightarrow w- = \eta \cdot m1/(\texttt{sqrt}(m2) + \epsilon)$
2. Bias correction is performed (since the estimates start from 0)
3. Adam works well in practice (mostly with a fixed set of values for the hyper-params)

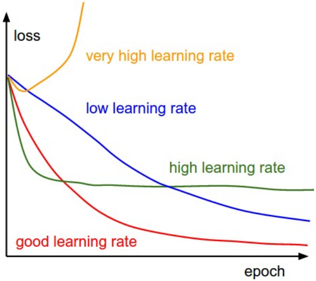
Learning rate (lr)



- What lr to use?

Figure credits: CS231n-Standford

Learning rate (lr)



- What lr to use?
- Different lr at different stages of the training!

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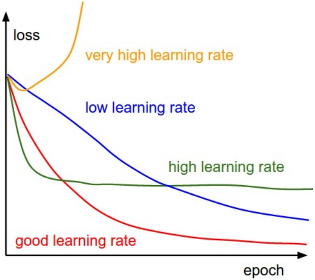
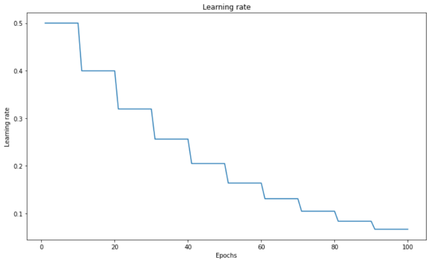
Learning rate (lr)



- What lr to use?
- Different lr at different stages of the training!
- Start with high lr and reduce it with time

Figure credits: CS231n-Standford

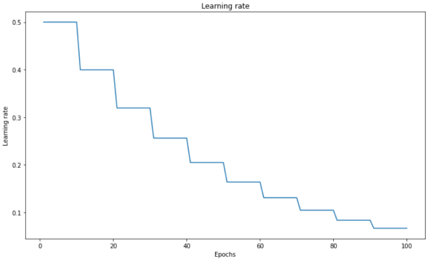
Learning Rate decay: Step



1. Reduce the lr after regular intervals

Figure credits: Katherine Li

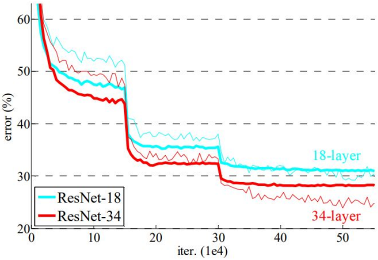
Learning Rate decay: Step



1. Reduce the lr after regular intervals
2. E.g. after every 30 epochs, $\eta* = 0.1 \cdot \eta$

Figure credits: Katherine Li

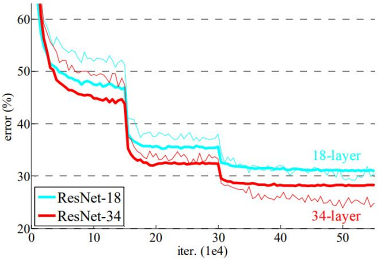
Learning Rate decay: Step



1. Characteristic loss curve: different phases for ''stage'

Figure credits: Kaiming He et al. 2015, ResNets

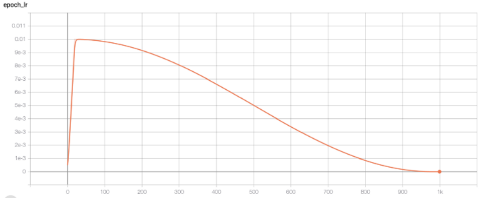
Learning Rate decay: Step



1. Characteristic loss curve: different phases for ''stage'
2. Issues: annoying hyper-params (when to reduce, by how much, etc.)

Figure credits: Kaiming He et al. 2015, ResNets

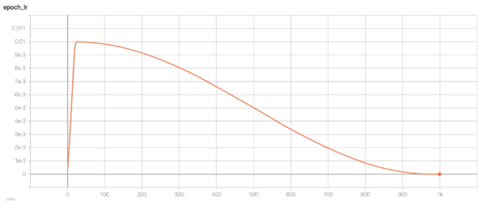
Learning Rate decay: Cosine



1. Reduces the lr continuously $\eta_t = \frac{1}{2}\eta_0(1+cos(t\pi/T))$

Figure credits: Sebastian Correa and Medium.com

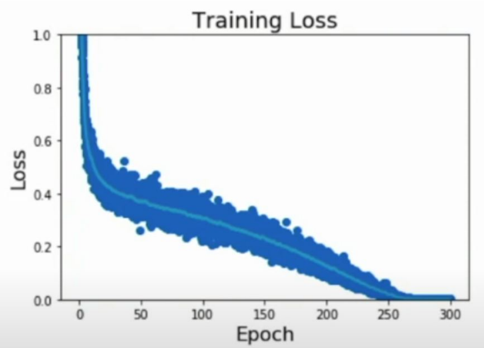
Learning Rate decay: Cosine



1. Reduces the lr continuously
   $\eta_t = \frac{1}{2}\eta_0(1+cos(t\pi/T))$
2. Less number of hyper-parameters

Figure credits: Sebastian Correa and Medium.com

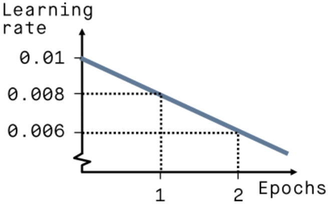
Learning Rate decay: Cosine



1. Training longer tends to work, but initial lr is still a tricky one

Figure credits: Dr Justin Johnson, U Michigan

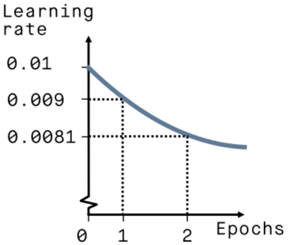
Learning Rate decay: Linear



1. $\eta_t = \eta_0(1 - t/T)$

Figure credits: peltarion.com

Learning Rate decay: Exponential



1. $\eta_t = \eta_0 \cdot (1 - \alpha/100)^t$

Figure credits: peltarion.com

Learning Rate decay: Constant lr

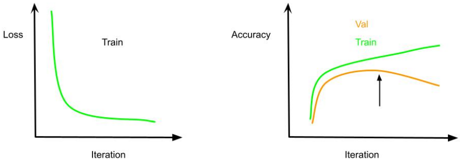
1. No change in the learning rate
   $\eta_t = \eta_0$

Learning Rate decay: Constant lr

1. No change in the learning rate

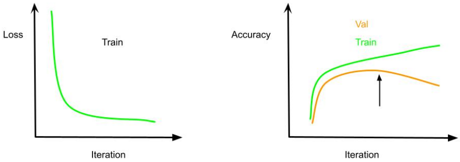
   $\eta_t = \eta_0$
2. Works for prototyping of ideas (other schedules may be better for squeezing in those 1-2% of gains in the performance)

Early stopping



1. Train as long as the validation performance improves (Stop when it deteriorates)

Early stopping



1. Train as long as the validation performance improves (Stop when it deteriorates)
2. Practice: train for a long number of epochs, saving the intermediate snapshots regularly, pick the one with the best val performance!

Good training practices

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- Monitor the learning curves (tell us if poor initialization or over/under/right-fitting)

Good training practices

- Observe the initial loss value (if it is as expected or presence of bugs!)
- One may try to overfit to a very small subset to ensure the basic things are in place
- Monitor the learning curves (tell us if poor initialization or over/under/right-fitting)
- Use frameworks' (or fora) help for observing the learning dynamics (e.g. Tensorboard)

Model Ensembles

- Train multiple models independently and take average inference during testing

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- Generally results in slight performance improvements

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- E.g. trained with a periodic lr scheduling

Model Ensembles

- Moving average of parameters for testing (Polyak Averaging)

```
for i in range(max_iters):
```

$\rightarrow$ `dw = grad(J,w,x,y)`

$\rightarrow w+ = -\eta \cdot dw$

$\rightarrow w_{\texttt{test}} = 0.95 \cdot w_{\texttt{test}} + 0.05 \cdot w$

Transfer learning: Pretrained features

- Sometimes, we may get away with lesser training data!

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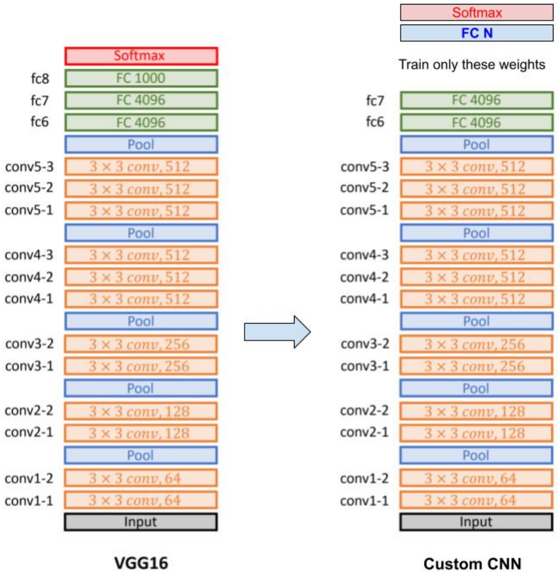
- Sometimes, we may get away with lesser training data!
- Take a DNN trained on a huge training data (task), use it as a feature extractor!!

Transfer learning: Pretrained features



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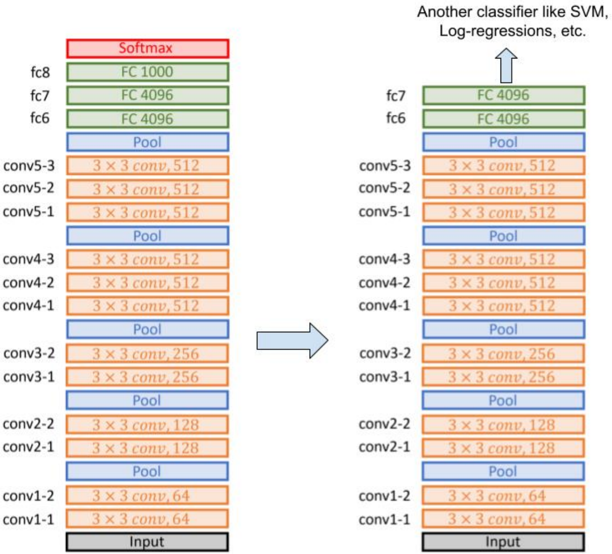
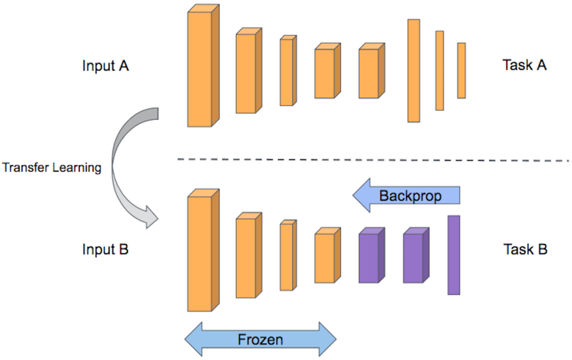


VGG16

Transfer learning: Pretrained features and Finetuning



Some tips: may have to use smaller learning rate for the transferred layers, start with feature extraction then do finetuning, lower layers might be frozen, etc.

Figure credits: Giang Tran and Medium.com