Deep Learning

11 Training DNNs II

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Issues with SGD

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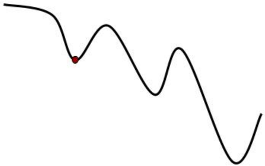
  - May have local minima
  - May have saddle points

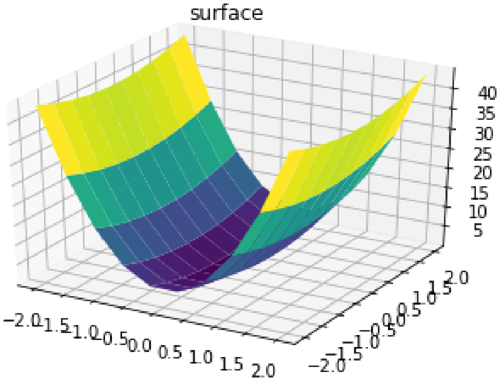


Stuck at a local minimum

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 direction and slowly in the other



Issues with SGD

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

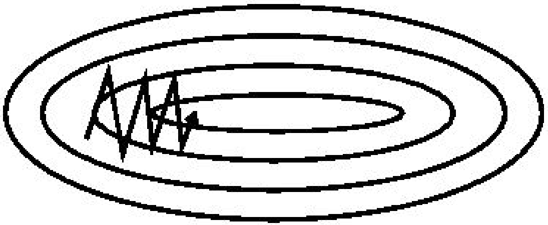


Figure credits: Sebastian Ruder

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

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

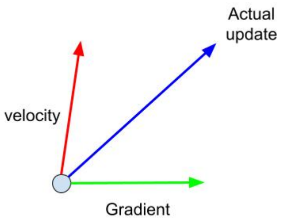
SGD+Momentum

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

$v_0 = 0$
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

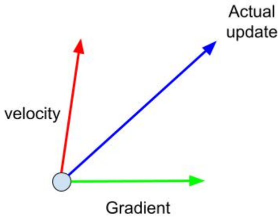


Momentum Update

1. How can momentum help?

I Sutskever et al., ICML 2013

SGD+Momentum



Momentum Update

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

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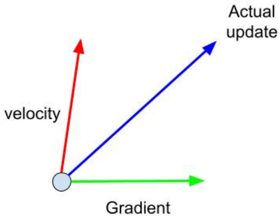

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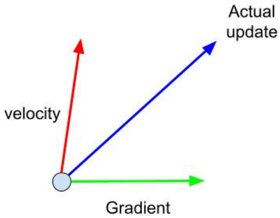


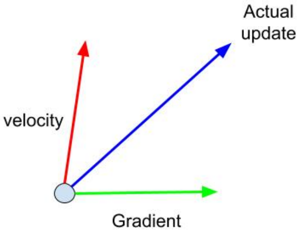
Momentum Update

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)

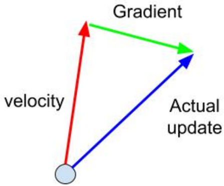
I Sutskever et al., ICML 2013

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$(J, W + \rho \cdot v, x, y)$

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

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

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Ada Grad

1. 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
```
$\rightarrow w- = \eta \cdot dw/($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)

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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):
→ dw = →grad(J,w,x,y)
→grad_sq = ρ· grad_sq + (1 − ρ) · dw
→ w− = η · dw/(sqrt(grad_sq) + ϵ)
```

Adam

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

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   Adam = RMSProp + Momentum
2. $m1 = 0$
   $m2 = 0$
   `for i in range(max_iters):`
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   $\rightarrow\ m1 = \beta_1 \cdot m1 + (1 - \beta_1) \cdot dw$
   $\rightarrow\ m2 = \beta_2 \cdot m2 + (1 - \beta_2) \cdot dw^2$
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2. Bias correction is performed (since the estimates start from 0)

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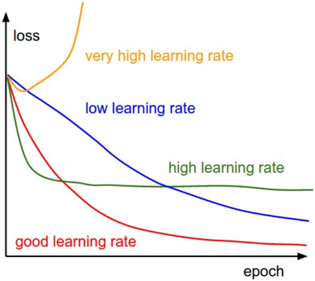
   $\rightarrow w- = \eta \cdot m1/(\texttt{sqrt}(m2) + \epsilon)$
2. Bias correction is performed (since the estimates start from 0)
3. Adam works well in practice (mostly with a fixed set of values for the hyper-params)

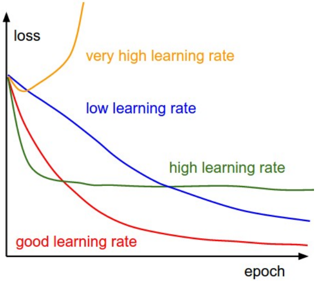
Learning rate (lr)



- 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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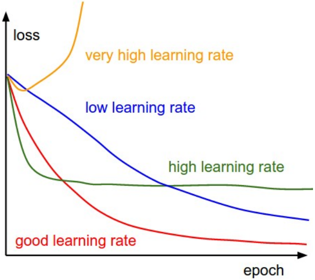
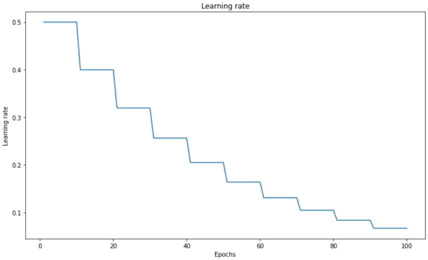
Learning rate (lr)



- 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

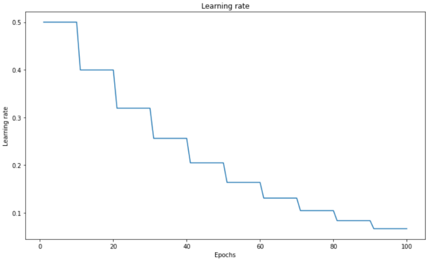
Learning Rate decay: Step



1. Reduce the lr after regular intervals

Figure credits: Katherine Li

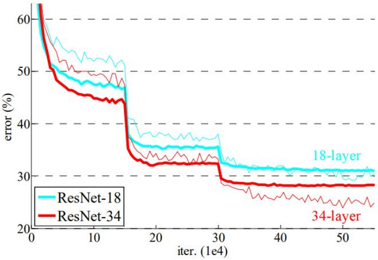
Learning Rate decay: Step



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

Figure credits: Katherine Li

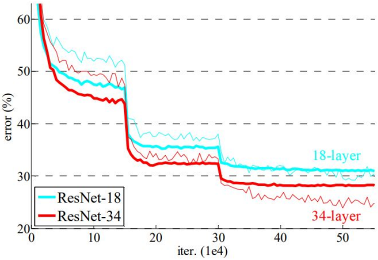
Learning Rate decay: Step



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

Figure credits: Kaiming He et al. 2015, ResNets

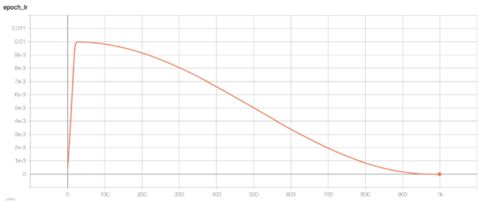
Learning Rate decay: Step



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

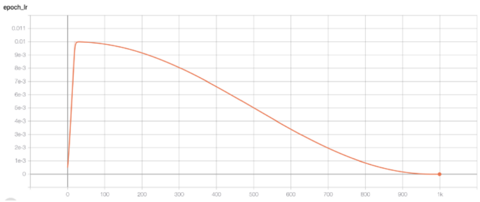
Learning Rate decay: Cosine



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

Figure credits: Sebastian Correa and Medium.com

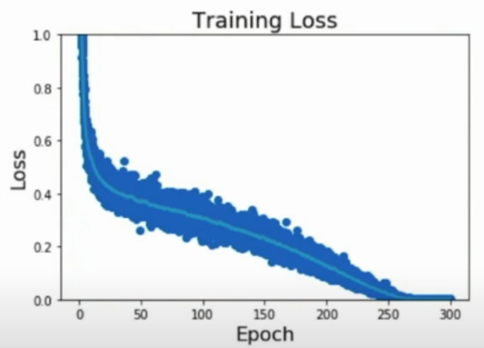
Learning Rate decay: Cosine



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

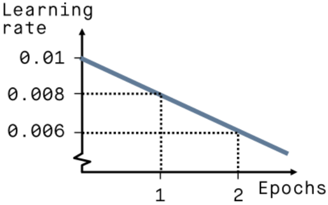
Learning Rate decay: Cosine



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

Figure credits: Dr Justin Johnson, U Michigan

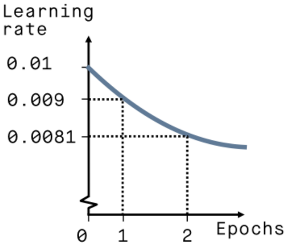
Learning Rate decay: Linear



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

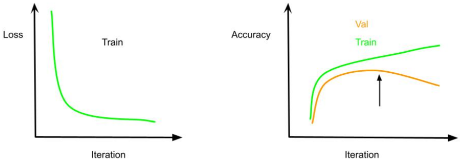
Learning Rate decay: Constant lr

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)

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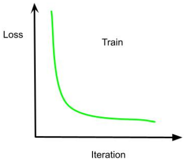

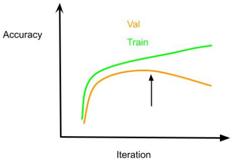

1. Train as long as the validation performance improves (Stop when it deteriorates)
2. Practice: train for a long number of epochs, saving the intermediate snapshots regularly, pick the one with the best val performance!

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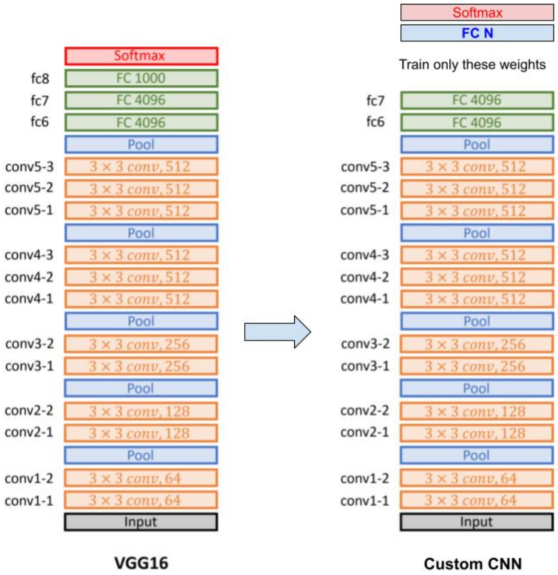
- Sometimes, we may get away with lesser training data!
- Take a DNN trained on a huge training data (task), use it as a feature extractor!!

Transfer learning: Pretrained features



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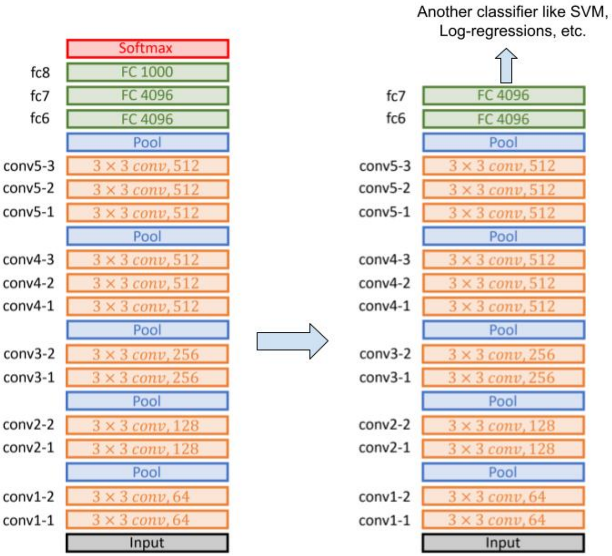
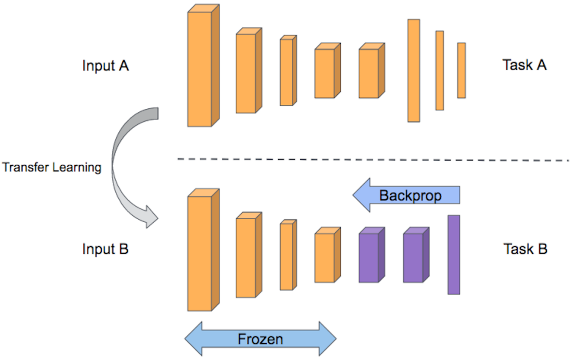


VGG16

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

Convex function

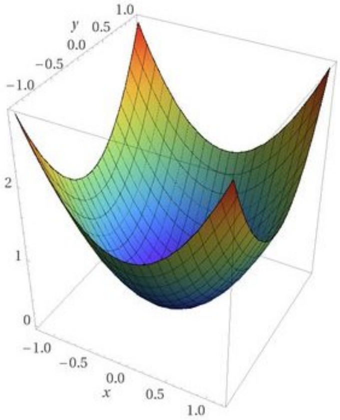


Figure credits: Paperspace blog

Level sets and ravine

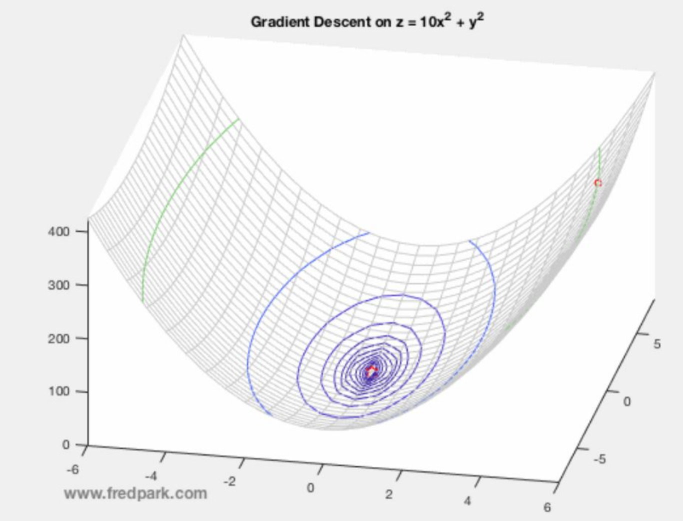


Figure credits: fredpark.com