

Learning Hyperparameters

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The effect of depth on training

Now that we can implement a network, let's understand some core learning behaviors and tradeoffs

The architecture, initialization, and learning hyperparameters all can change the performance of a network dramatically

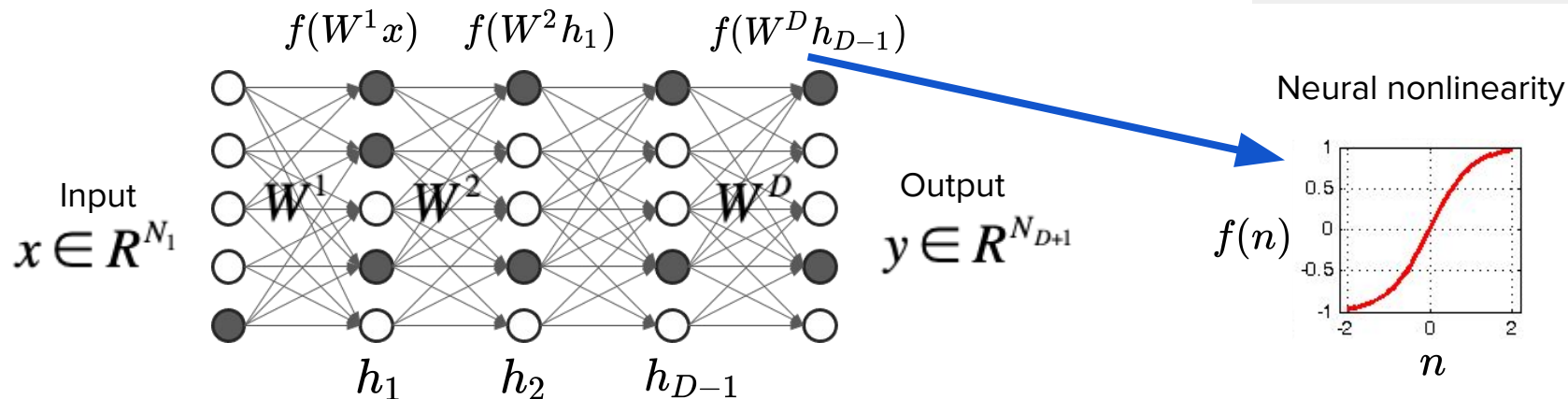
To be proficient at training deep networks, we have to build our intuition

Opening the black box

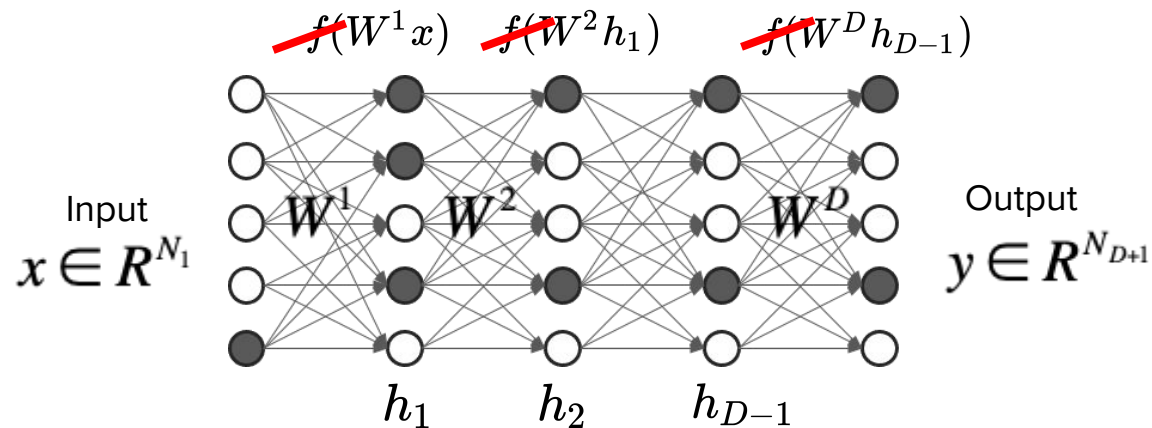


Deep Network

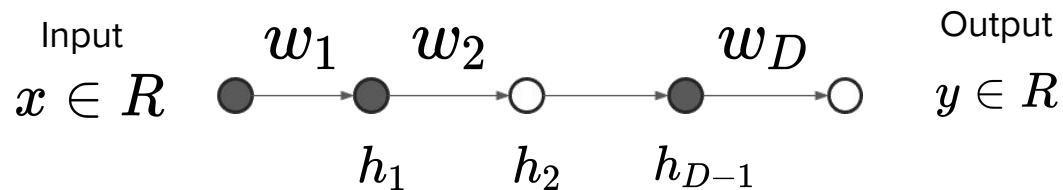
Little hope to understand full modern systems in detail



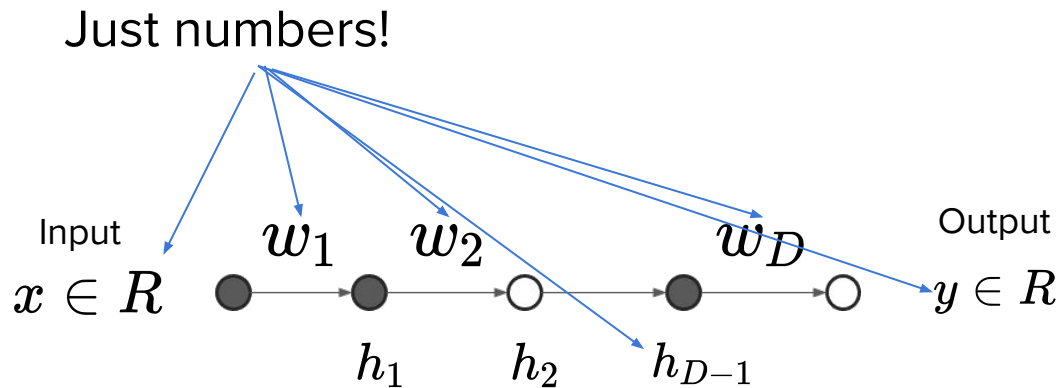
Deep *Linear* Network



Deep *Narrow* Linear Network



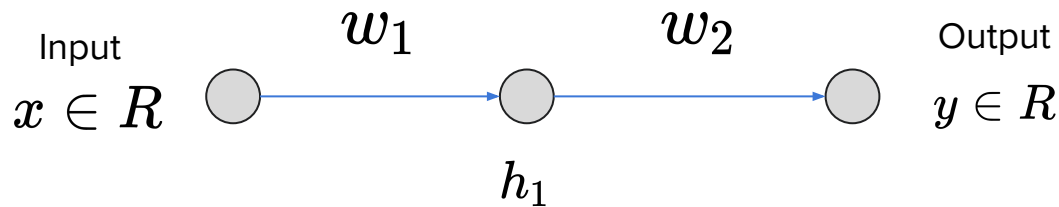
Deep *Narrow* Linear Network



$$y = w_D w_{D-1} \cdots w_1 x$$



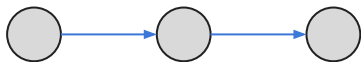
1 Layer Narrow Linear Network



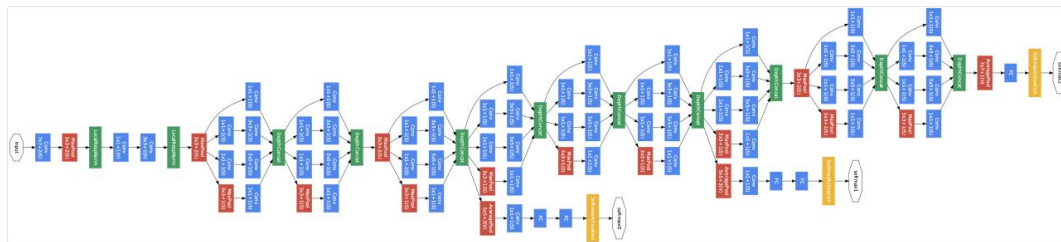
$$y = xw_1w_2$$

Simple models

Today



The rest of your career

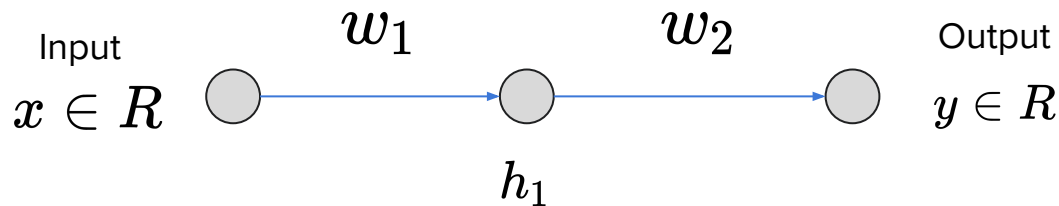


Szegedy et al., CVPR 2015

1 Layer Narrow Linear Network

Dataset: $\mathcal{D} = \{(x_1, y_1), (x_2, y_2), \dots, (x_P, y_P)\}$

Mean squared error loss: $L(w_1, w_2) = \frac{1}{P} \sum_{p=1}^P (y_p - \hat{y}_p)^2$



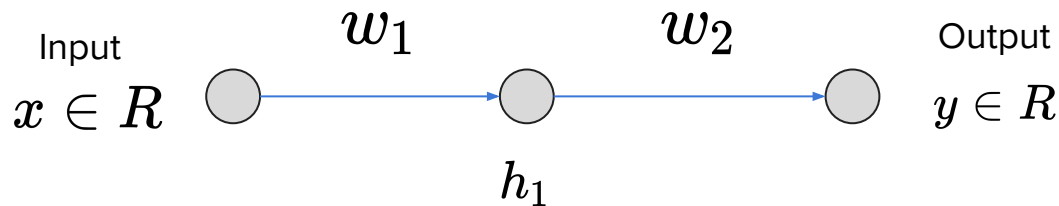
$$y = xw_1w_2$$

Loss from one example $= \frac{1}{P} (y_p - x_p w_1 w_2)^2$

1 Layer Narrow Linear Network

Dataset: $\mathcal{D} = \{(x_1, y_1), (x_2, y_2), \dots, (x_P, y_P)\}$

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$$y = xw_1w_2$$

Implement gradient descent

Training landscape

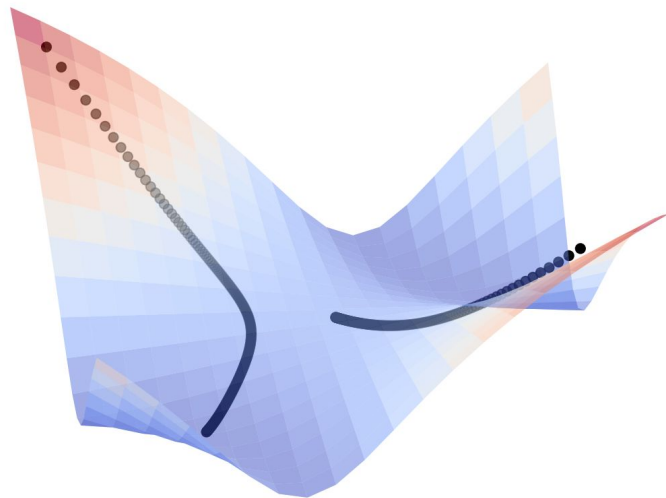
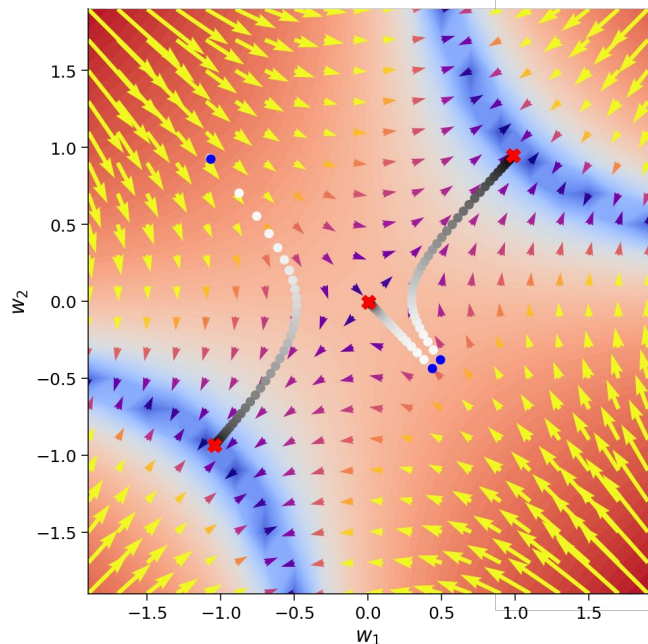
We train networks by minimizing the loss function

What do these loss landscapes actually look like?

Usually loss landscapes are impossible to plot because they are in high dimensions, but here we can examine it directly

Explore this loss landscape and the resulting GD trajectories

Anatomy of a landscape



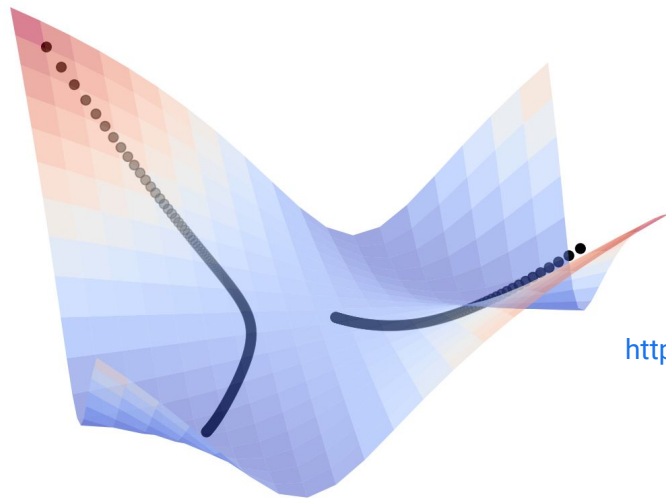
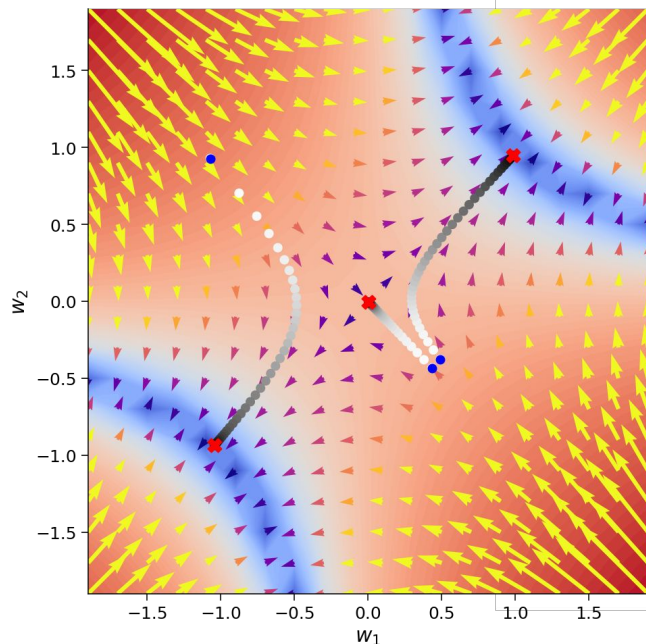
Critical points: where the gradient is zero and dynamics stop

Minimum: surrounding points are not lower

Maximum: surrounding points are not higher

Saddle point: some descent directions, some ascent directions

Anatomy of a landscape



<https://losslandscape.com/explorer>

Critical points: where the gradient is zero and dynamics stop

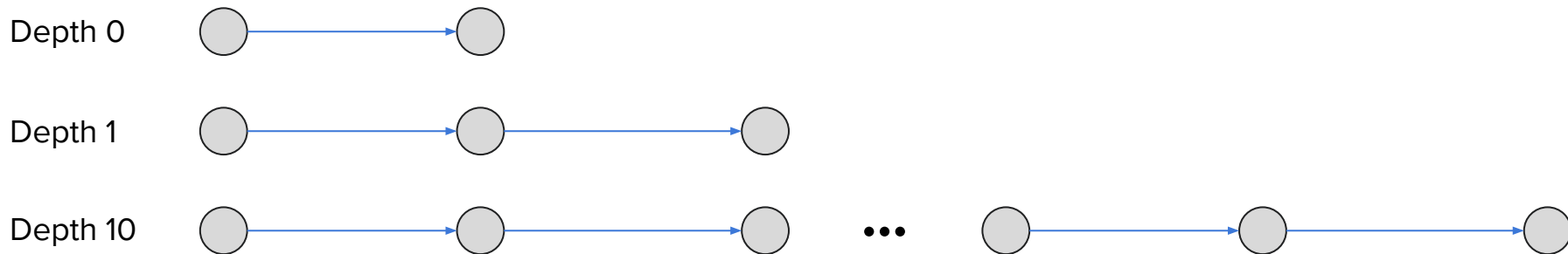
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The effect of depth on training

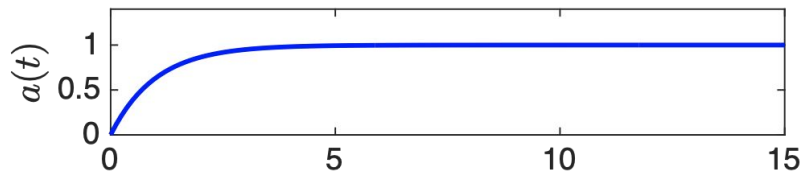
How does network depth impact training speed, everything else being equal?



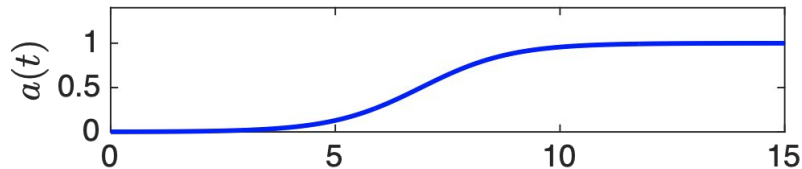
Explore how depth changes learning trajectories

The effect of depth on training

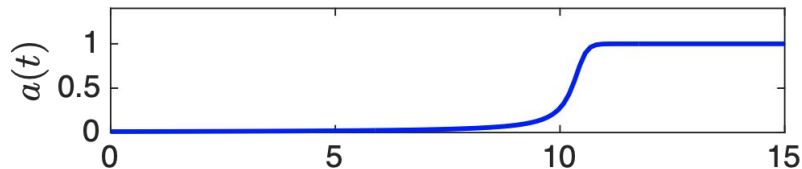
Shallow ($D=0$):



Deep ($D=1$):



V. Deep ($D \rightarrow \infty$):



Epochs

$$a(t) = w_{D+1} w_D \cdots w_2 w_1$$

Choosing a learning rate

How to pick η ? $\mathbf{w}^{(t+1)} = \mathbf{w}^{(t)} - \eta \nabla L(\mathbf{w}^{(t)})$

The gradient points in the steepest descent direction for *infinitesimal* step sizes

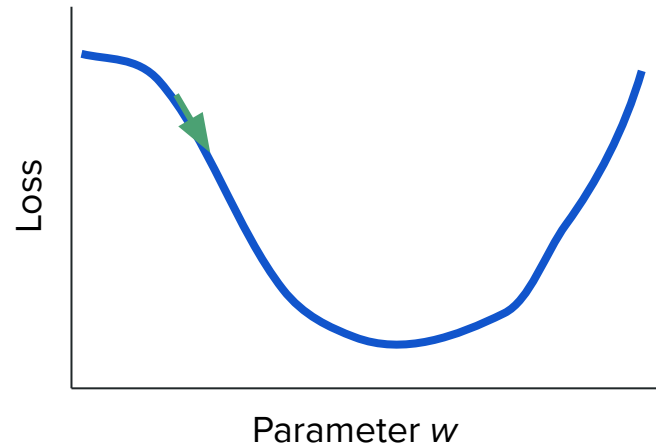
But infinitesimal step sizes don't take you very far!

Play with learning rate. Learn to diagnose issues from error curves.

Choosing a learning rate

How to pick η ? $\mathbf{w}^{(t+1)} = \mathbf{w}^{(t)} - \eta \nabla L(\mathbf{w}^{(t)})$

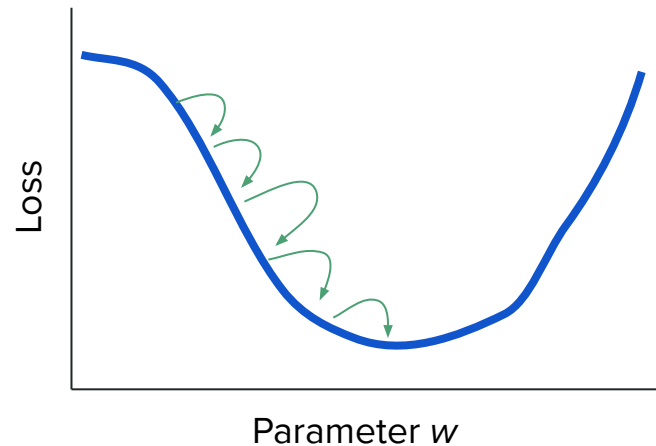
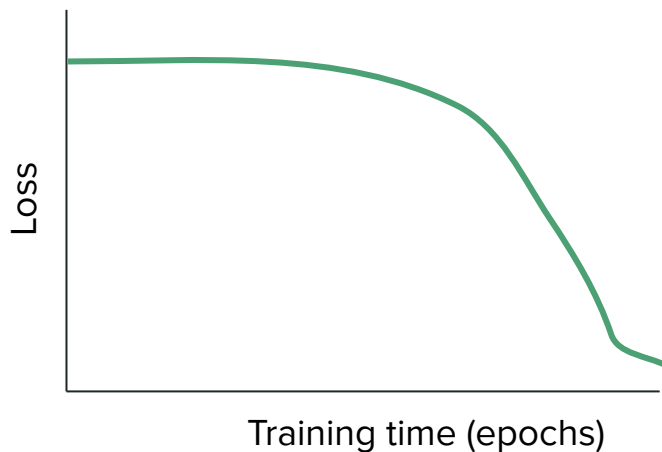
Too small:
flat line



Choosing a learning rate

How to pick η ? $\mathbf{w}^{(t+1)} = \mathbf{w}^{(t)} - \eta \nabla L(\mathbf{w}^{(t)})$

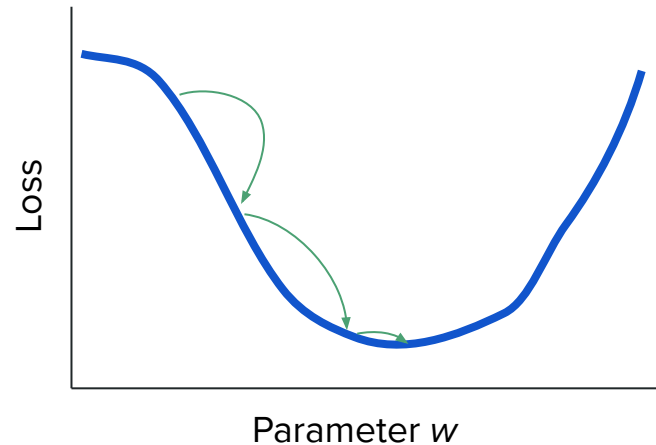
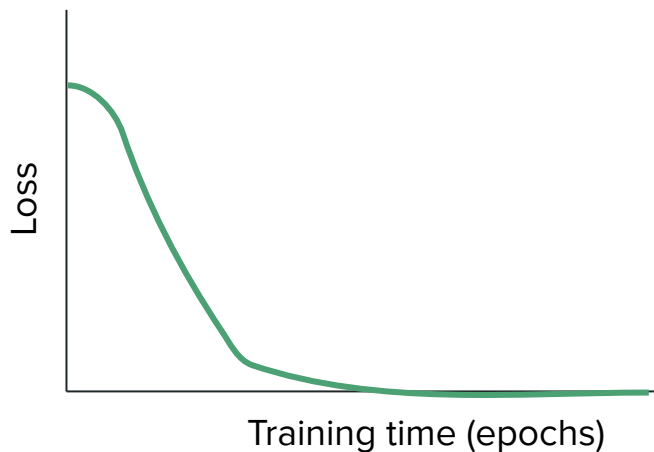
Slightly
too small:
works but
slow



Choosing a learning rate

How to pick η ? $\mathbf{w}^{(t+1)} = \mathbf{w}^{(t)} - \eta \nabla L(\mathbf{w}^{(t)})$

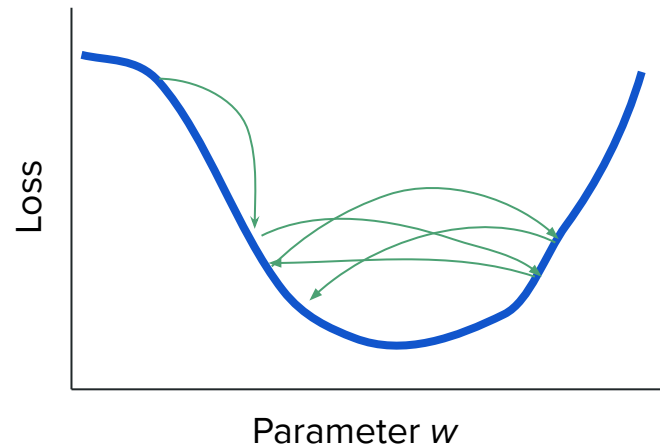
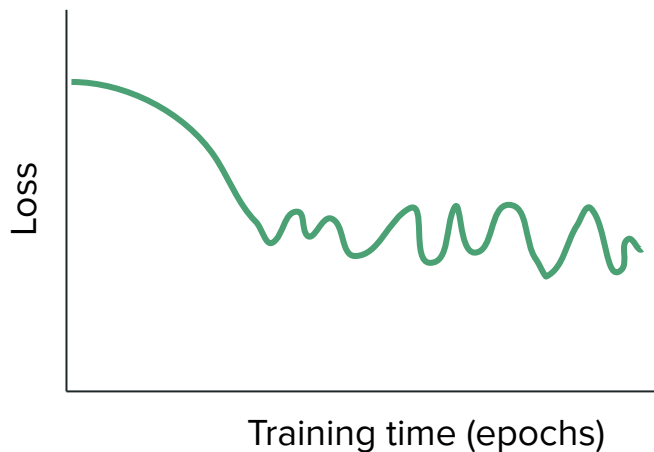
Just right:
converges
quickly
and
cleanly



Choosing a learning rate

How to pick η ? $\mathbf{w}^{(t+1)} = \mathbf{w}^{(t)} - \eta \nabla L(\mathbf{w}^{(t)})$

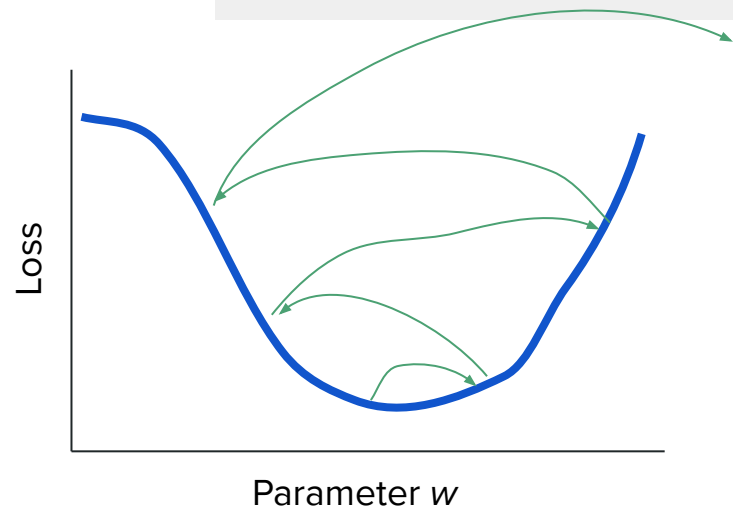
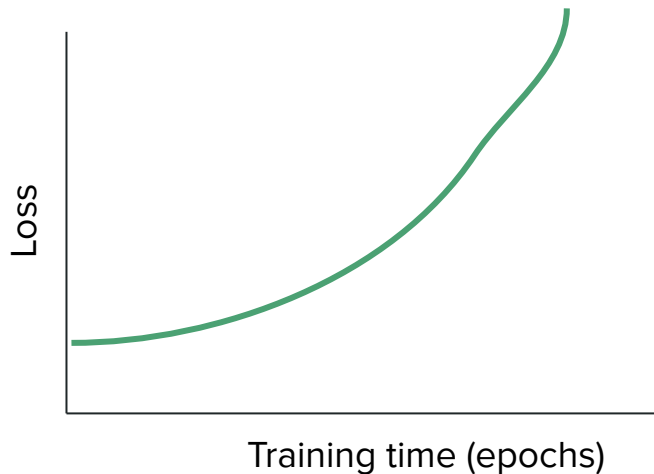
Slightly
too big:
chaotic



Choosing a learning rate

How to pick η ? $\mathbf{w}^{(t+1)} = \mathbf{w}^{(t)} - \eta \nabla L(\mathbf{w}^{(t)})$

Way too big:
Divergence



Choosing a learning rate

How to pick η ? $\mathbf{w}^{(t+1)} = \mathbf{w}^{(t)} - \eta \nabla L(\mathbf{w}^{(t)})$

Lesson for practice: Aim for the maximum stable learning rate

Depth and learning rate

Unfortunately, hyperparameters interact

The right learning rate for one depth may not be the right learning rate for another

Do deeper networks need larger or smaller learning rates? Are deep networks still slower to train if you optimize the learning rate for each?

Play with both depth and learning rate.



Depth and learning rate

Unfortunately, hyperparameters interact

The right learning rate for one depth may not be the right learning rate for another

In general, deeper networks need smaller learning rates

Lesson for practice: Carefully optimise all hyperparameters for every architecture you try (this may require many computers :)

Initialisation matters

Unlike in shallow networks, learning in deep networks is exquisitely sensitive to initialisation

Basic reason: products of numbers vanish or explode $y = (\prod_{i=1}^D w_i)x$



$$y = (0.9)^{100}x = 0.0000265x$$

Initialisation matters

Unlike in shallow networks, learning in deep networks is exquisitely sensitive to initialisation

Basic reason: products of numbers vanish or explode $y = (\prod_{i=1}^D w_i)x$



$$y = (1.1)^{100}x = 13780.6x$$

Initialisation matters

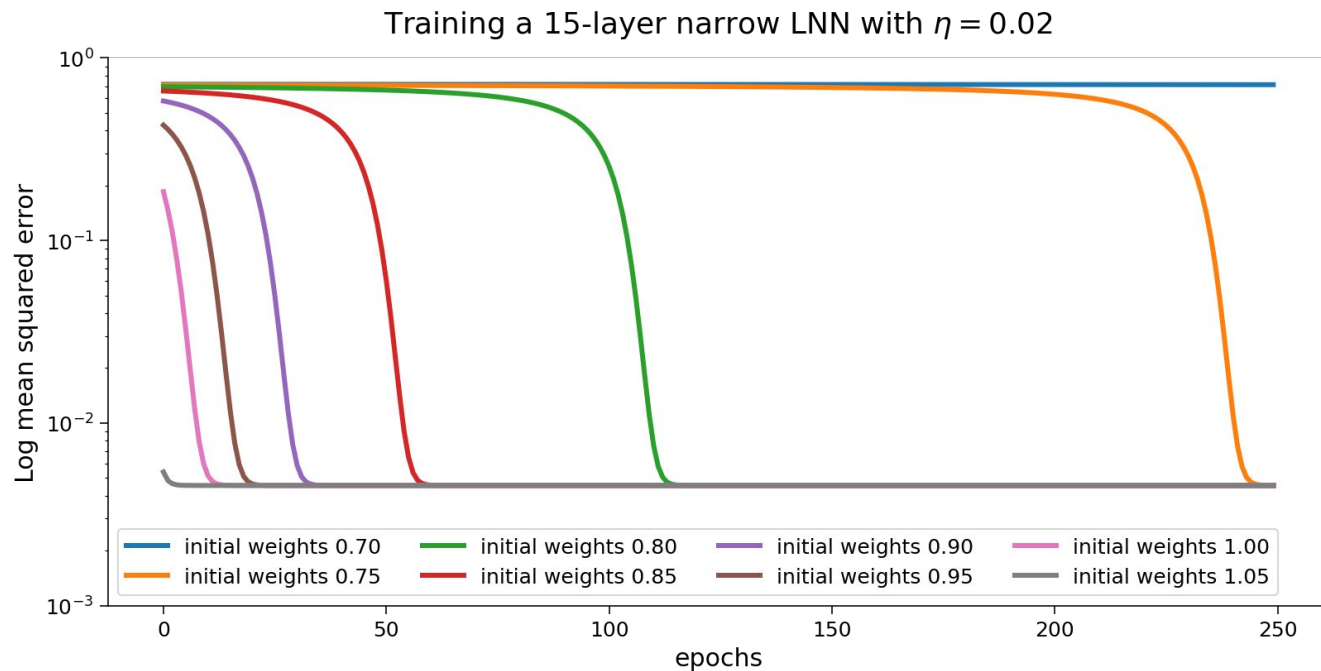
Unlike in shallow networks, learning in deep networks is exquisitely sensitive to initialisation

Basic reason: products of numbers vanish or explode $y = (\prod_{i=1}^D w_i)x$



Explore how initialisation impacts learning in a deep network.

Initialisation matters



Initialisation matters

Initialisations in deep networks need to be carefully chosen so that activity and gradients have similar magnitude across the network

Initialisations that preserve variance across depth are known as “dynamic isometry” initialisations

For deep narrow linear network, this corresponds to weights near 1

$$y = 1^{100}x = x$$

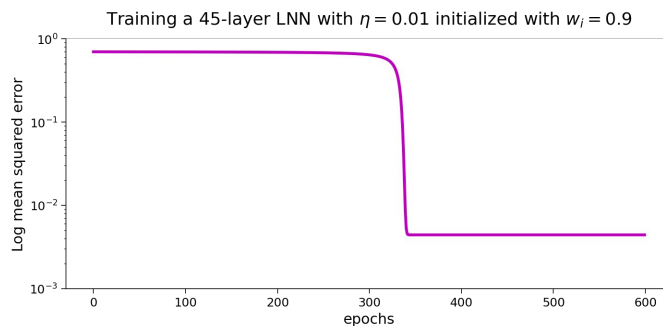
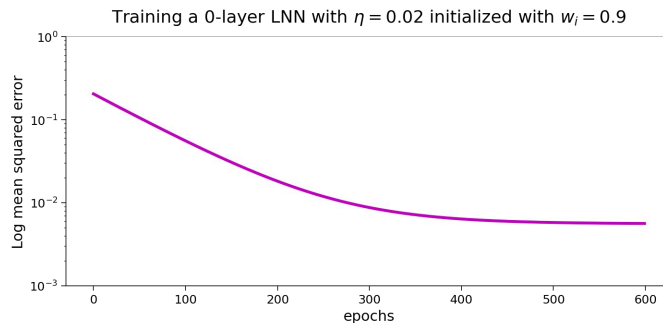
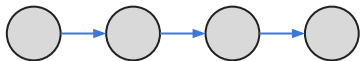


Wrap up: the effect of depth

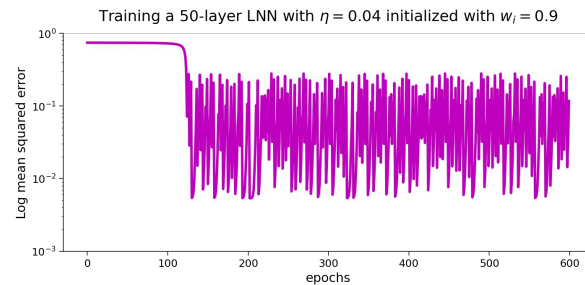
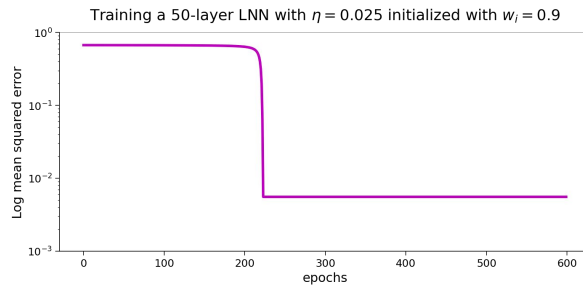
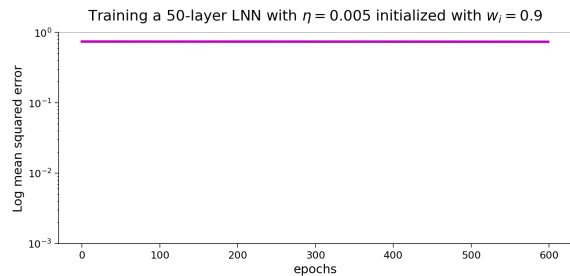
Shallow



Deep



Wrap up: learning rate



Wrap up: initialization

Training a 15-layer narrow LNN with $\eta = 0.02$

