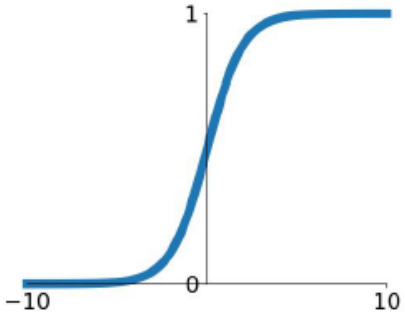
Training Neural Networks

Activation Functions

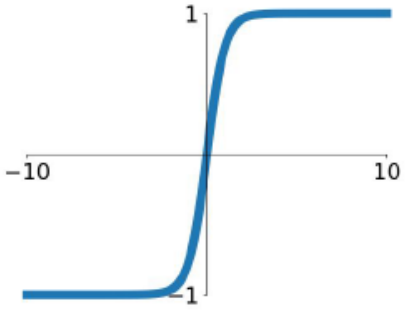
Sigmoid

$$\sigma(x) = \frac{1}{1+e^{-x}}$$



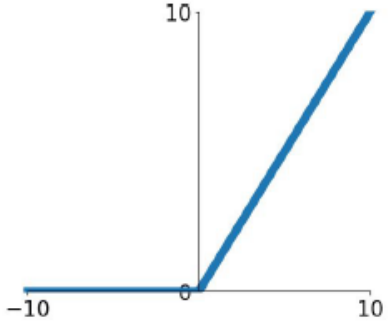
tanh

$$\tanh(x)$$



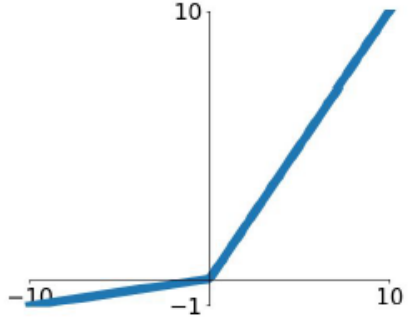
ReLU

$$\max(0, x)$$



Leaky ReLU

$$\max(0.1x, x)$$

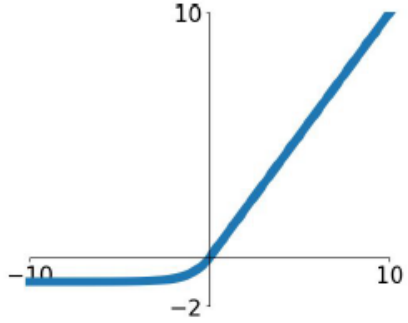


Maxout

$$\max(w_1^T x + b_1, w_2^T x + b_2)$$

ELU

$$\begin{cases} x & x \geq 0 \\ \alpha(e^x - 1) & x < 0 \end{cases}$$



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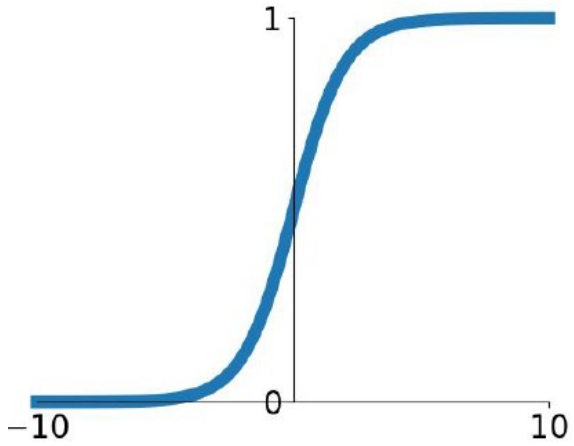
Sigmoid



$$f(x) = \frac{1}{1 + e^{-x}}$$

- Squashes numbers to range [0, 1]
- Historically popular since they have nice interpretation as a saturating "firing rate" of a neuron
- 3 Problems
  - Saturated neurons "kill" the gradients
  - Sigmoid outputs are not zero-centered
  - Exp() is a bit compute expensive

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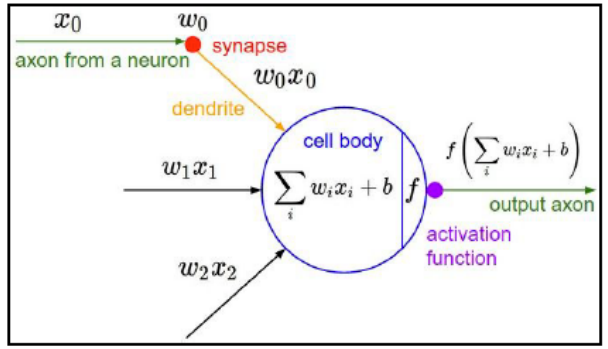
What happens when the input to a neuron is always positive

Consider what happens when the input to a neuron is always positive...

$$f\left(\sum_i w_i x_i + b\right)$$



What can we say about the gradients on **w**?

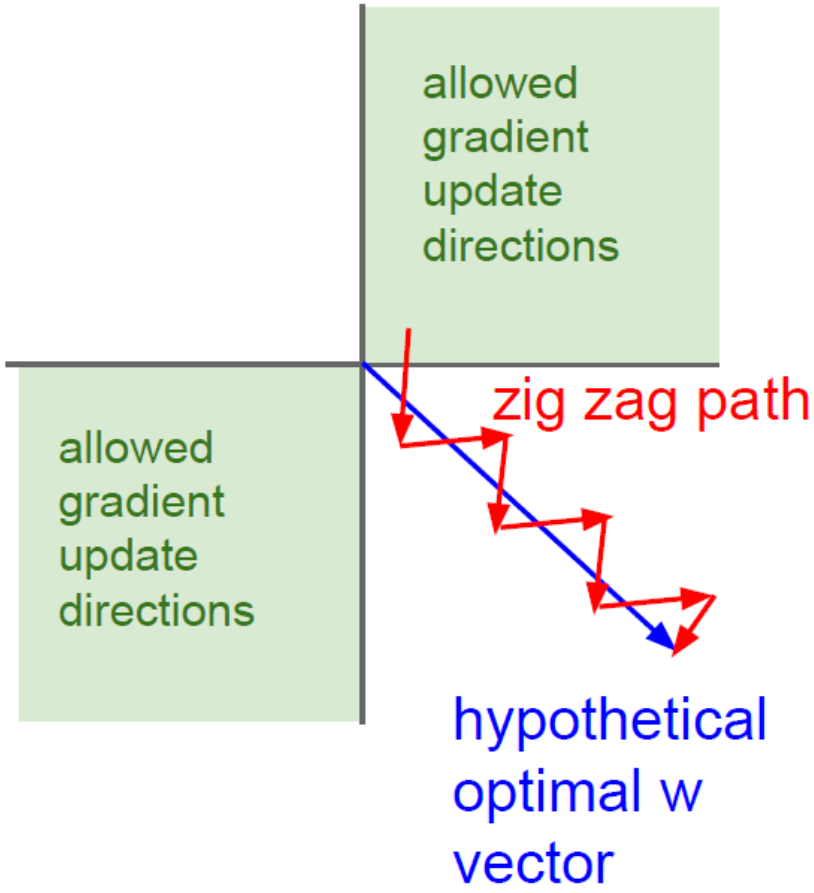
We know that local gradient of sigmoid is always positive
We are assuming x is always positive

So!! Sign of gradient **for all w_i** is the same as the sign of upstream scalar gradient!

$$\frac{\partial L}{\partial w} = \sigma\left(\sum_i w_i x_i + b\right)\left(1 - \sigma\left(\sum_i w_i x_i + b\right)\right) x \times upstream\_gradient$$

What happens when the input to a neuron is always positive

$$f\left(\sum_i w_i x_i + b\right)$$



- What can we say about the gradients on **w**?

→Always all positive or all negative

→This is also why you want zero-mean data

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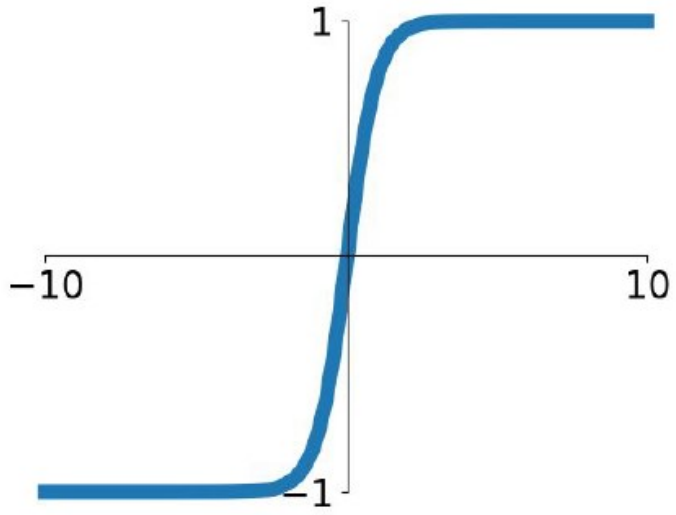
Tanh



$$f(x) = \tanh x = \frac{e^x - e^{-x}}{e^x + e^{-x}}$$

- Squashes numbers to range [-1, 1]
- Zero centered
- Still kills gradient when saturated

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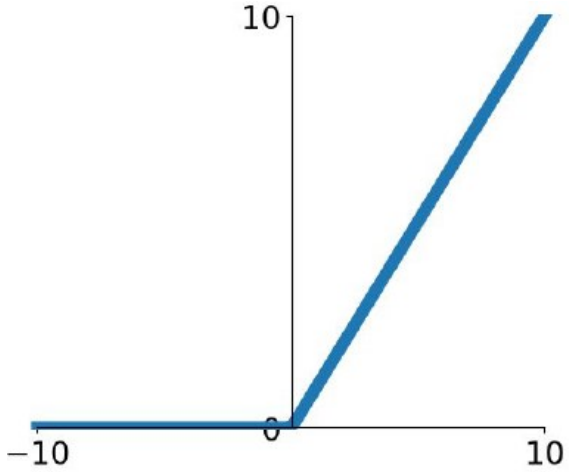
ReLU(Rectified Linear Unit)



Computes **f(x) = max(0,x)**

- Does not saturate
- Very computationally efficient
- Converges much faster than sigmoid/tanh in practice(e.g. 6x)
- Actually more biologically plausible than sigmoid
- Problems
  - Not zero-centered output
  - An annoyance – dead ReLU

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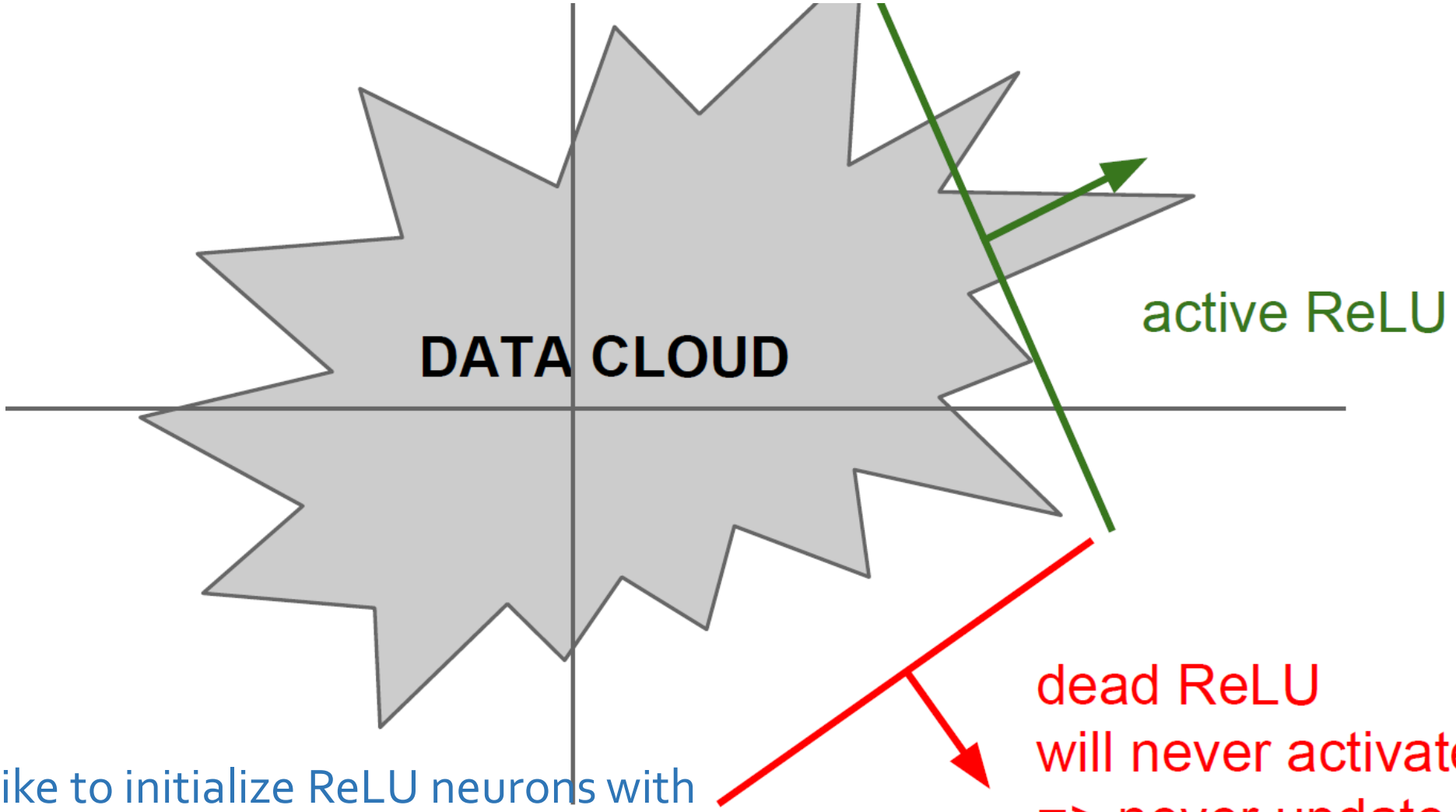
Dead ReLU



People like to initialize ReLU neurons with slightly positive biases (e.g. 0.01)

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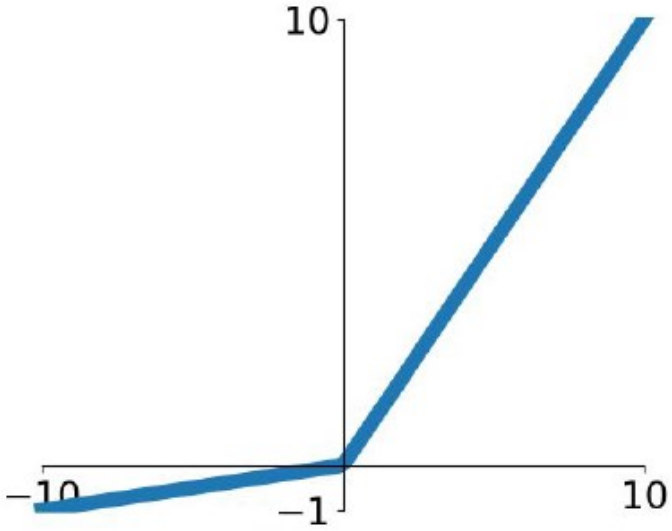
Leaky ReLU, PReLU(Parametric-)



$$f(x) = \max(0.01x, x)$$

$$f(x) = \max(\alpha x, x)$$

- Does not saturate
- Computationally efficient
- Converge much faster than sigmoid/tanh
- Will not 'die'

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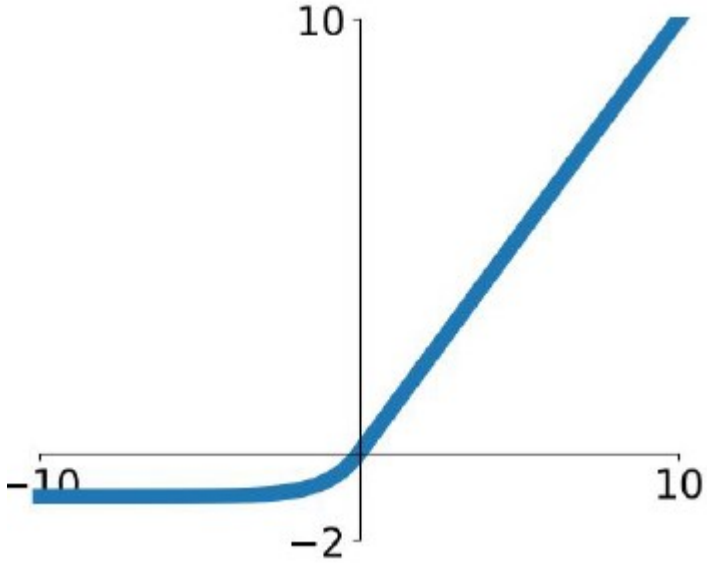
ELU(Exponential Linear Units)



$$f(x) = \begin{cases} x & \text{if } x > 0 \\ \alpha\left(\exp(x) - 1\right) & \text{if } x \leq 0 \end{cases}$$

- All benefits of ReLU
- Closer to zero mean output
- Computation requires exp()

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Maxout

- Generalizes ReLU and Leaky ReLU
- Linear Regime! Does not saturate! Does not die!

$$\max(w_1^T x + b_1, w_2^T x + b_2)$$

- Problem
  - Doubles the number of paramters/neuron

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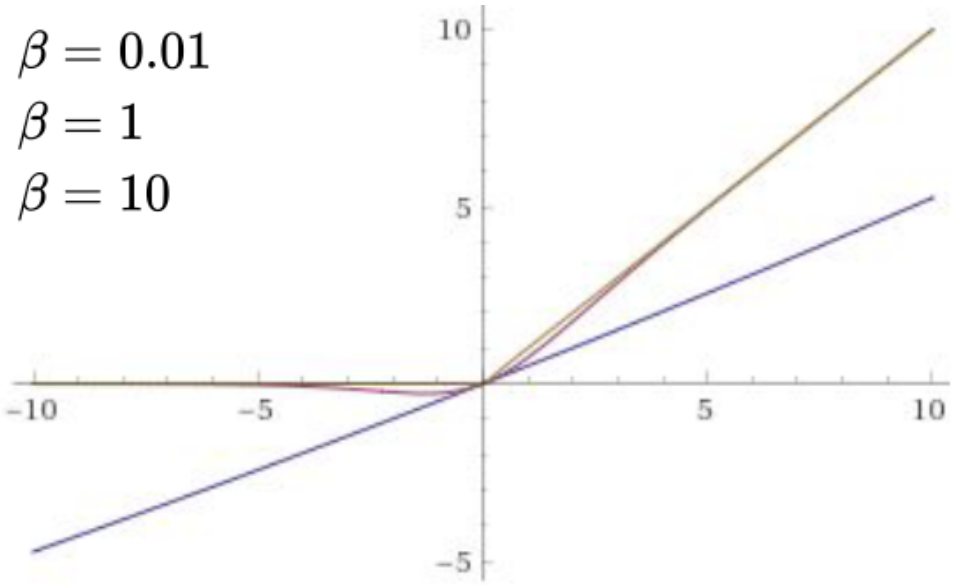
Swish



$$f(x) = x\sigma(\beta x)$$

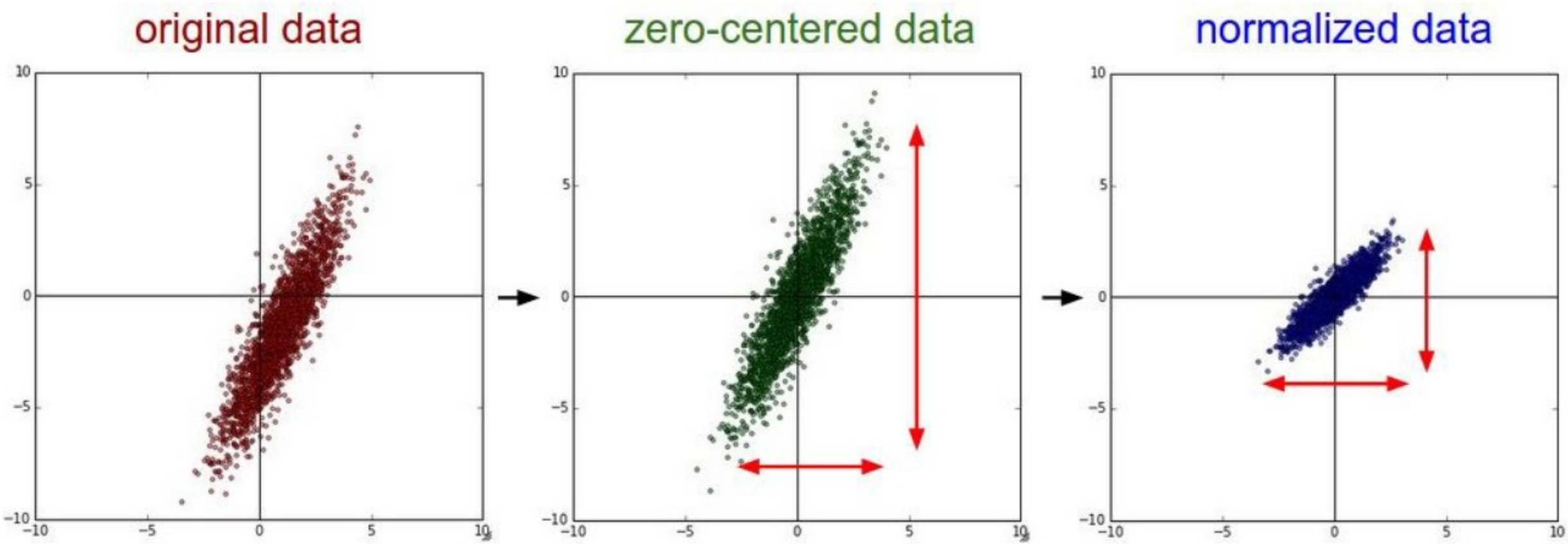
- They trained a neural network to generate and test out different non-linearities.
- Swish outperformed all other options for CIFAR-10 accuracy

Other Activation Functions

- Softmax
- Softplus : $\ln(1 + e^x)$
- SELU: scaled ELU

…

Data Preprocessing



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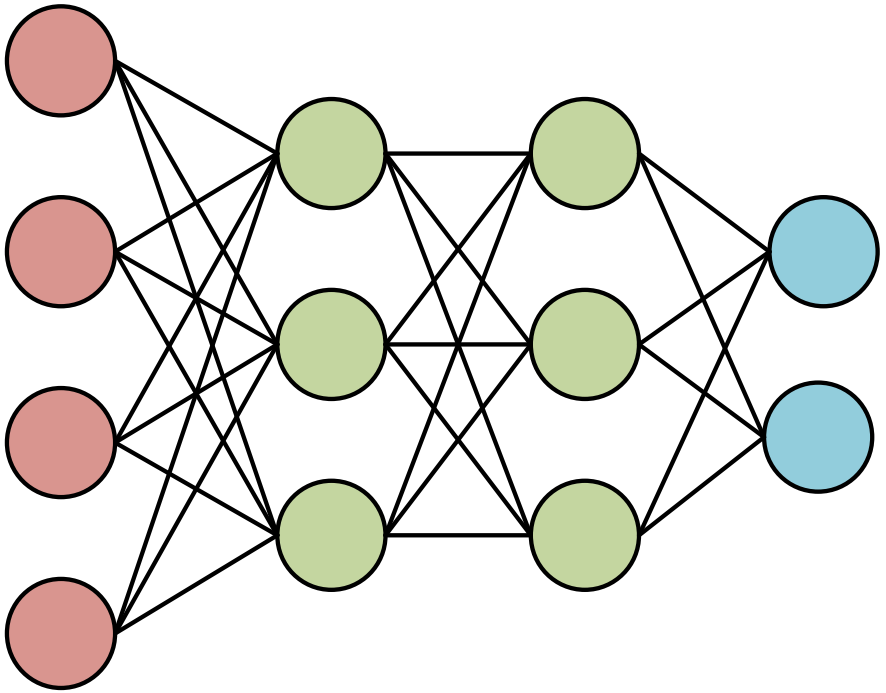
In Practice for Images

- E.g. consider CIFAR-10 example with [32, 32, 3] images
- Subtract the mean image (e.g. AlexNet)
  - Mean image = [32, 32, 3] array
- Subtract per-channel mean (e.g. VGGNet)
  - Mean along each channel = 3 numbers
- Not common to normalize variance

Weight Initialization

- What happens when W=constant init is used?



Weight Initialization

- First idea : Small random numbers
  - Gaussian with zero mean and 1e-2 standard deviation

```
W = 0.01* np.random.randn(D,H)
```

- Let's look at some activation statistics
  - 10-layer network with 500 neurons on each layer
  - Using tanh activation function

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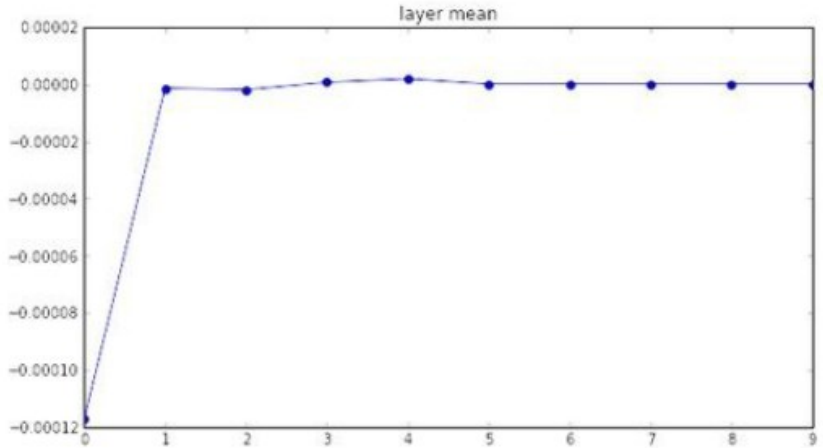
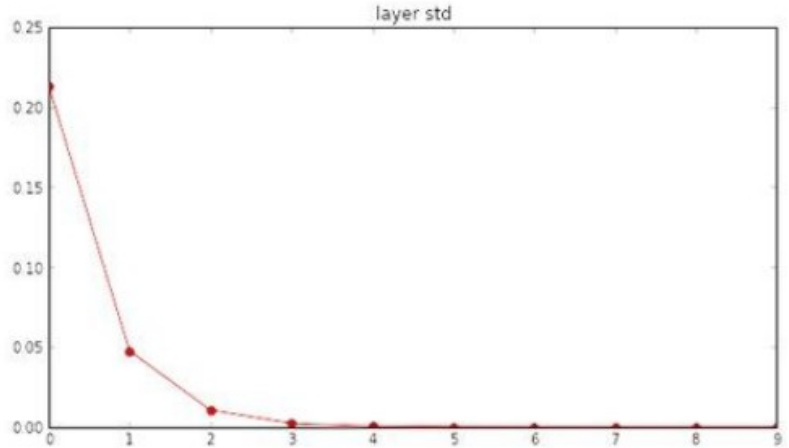
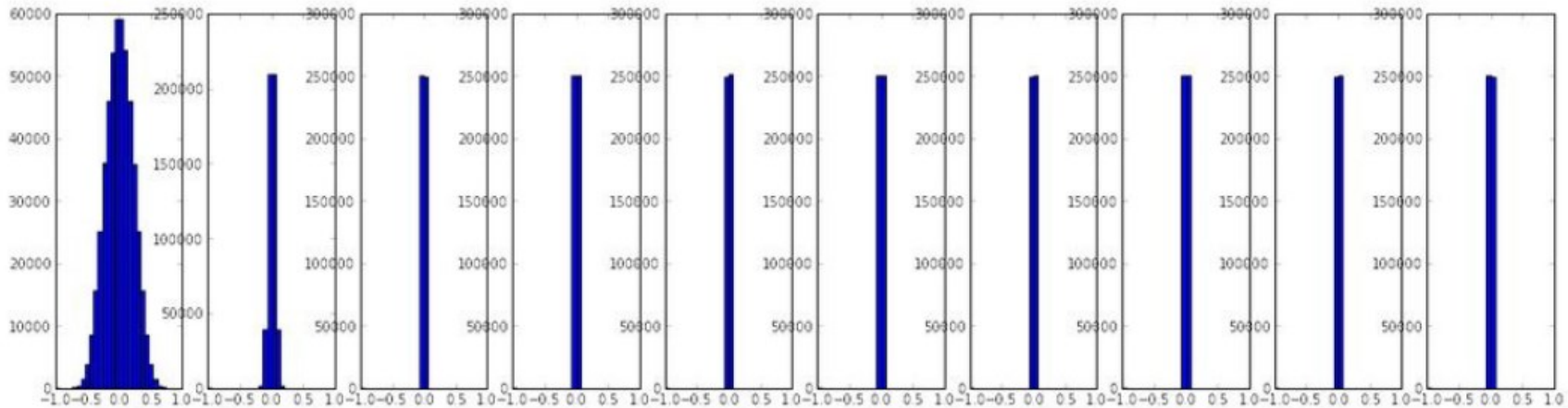
```
input layer had mean 0.000927 and std 0.998388
hidden layer 1 had mean -0.000117 and std 0.213081
hidden layer 2 had mean -0.000001 and std 0.047551
hidden layer 3 had mean -0.000002 and std 0.010630
hidden layer 4 had mean 0.000001 and std 0.002378
hidden layer 5 had mean 0.000002 and std 0.000532
hidden layer 6 had mean -0.000000 and std 0.000119
hidden layer 7 had mean 0.000000 and std 0.000026
hidden layer 8 had mean -0.000000 and std 0.000006
hidden layer 9 had mean 0.000000 and std 0.000001
hidden layer 10 had mean -0.000000 and std 0.000000
```







All activations become zero!

Q: think about the backward pass. What do the gradients look like?

Hint: think about backward pass for a W*X gate.

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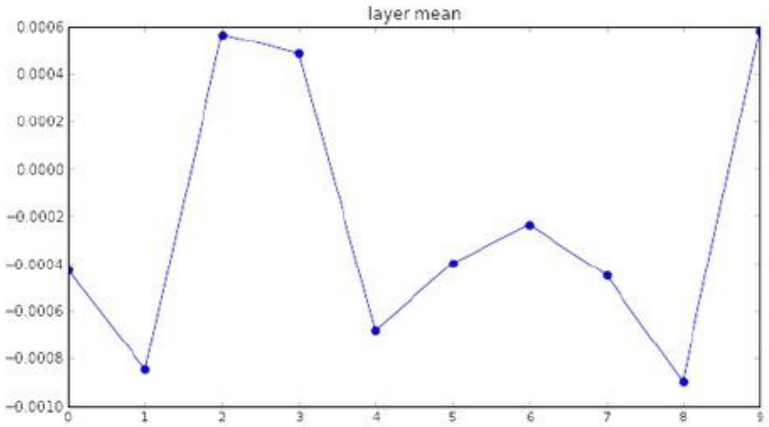
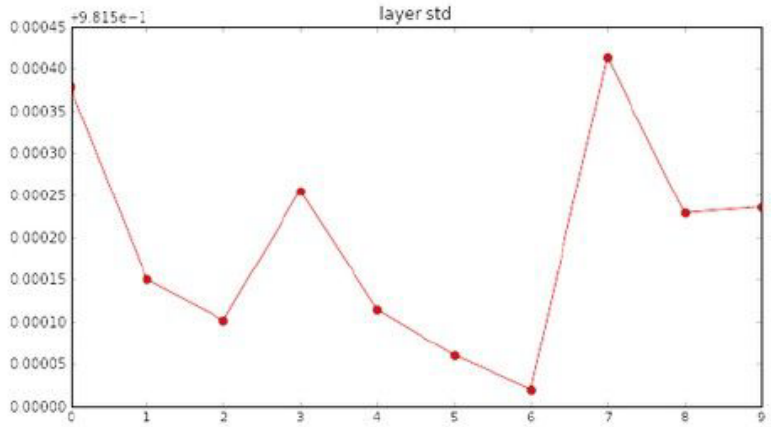
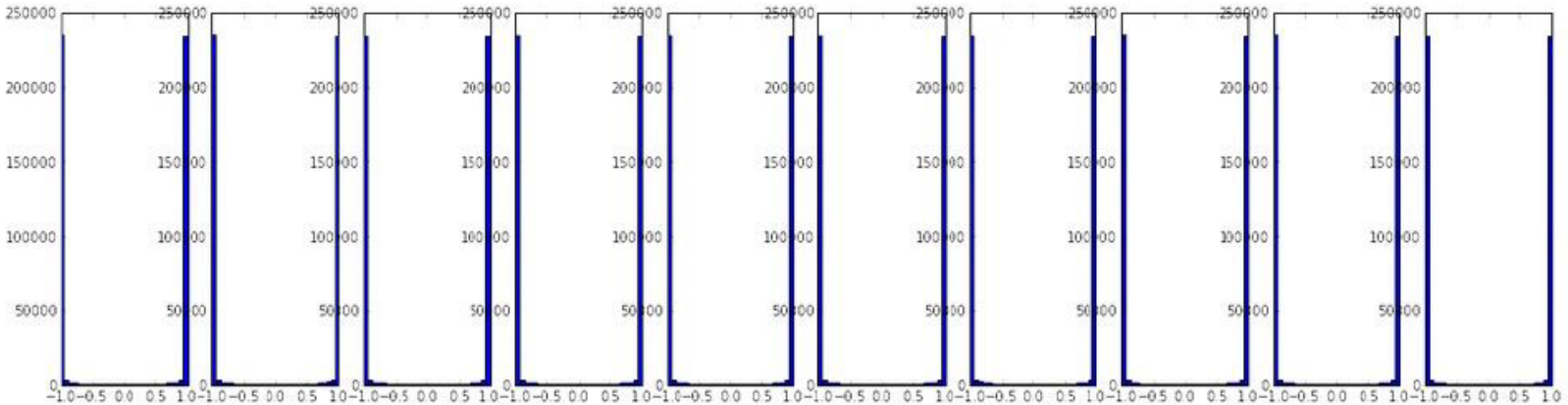
```
W = np.random.randn(fan_in, fan_out) * 1.0 # layer initialization
```

```
input layer had mean 0.001800 and std 1.001311
hidden layer 1 had mean -0.000430 and std 0.981879
hidden layer 2 had mean -0.000849 and std 0.981649
hidden layer 3 had mean 0.000566 and std 0.981601
hidden layer 4 had mean 0.000483 and std 0.981755
hidden layer 5 had mean -0.000682 and std 0.981614
hidden layer 6 had mean -0.000401 and std 0.981560
hidden layer 7 had mean -0.000237 and std 0.981520
hidden layer 8 had mean -0.000448 and std 0.981913
hidden layer 9 had mean -0.000899 and std 0.981728
hidden layer 10 had mean 0.000584 and std 0.981736
```

*1.0 instead of *0.01







Almost all neurons completely saturated, either -1 and 1. Gradients will be all zero.

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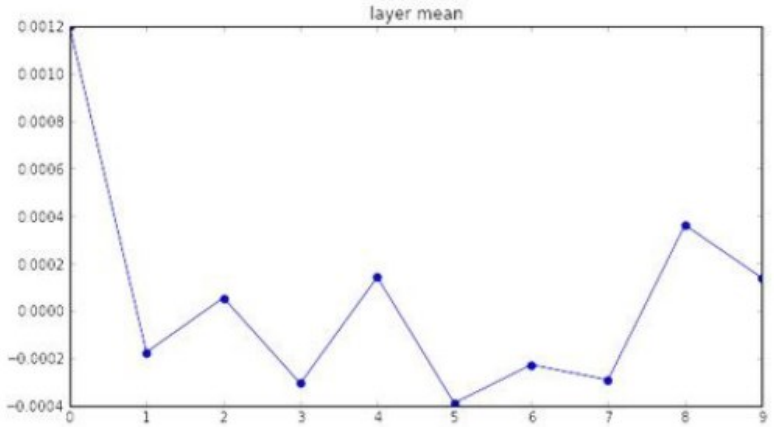
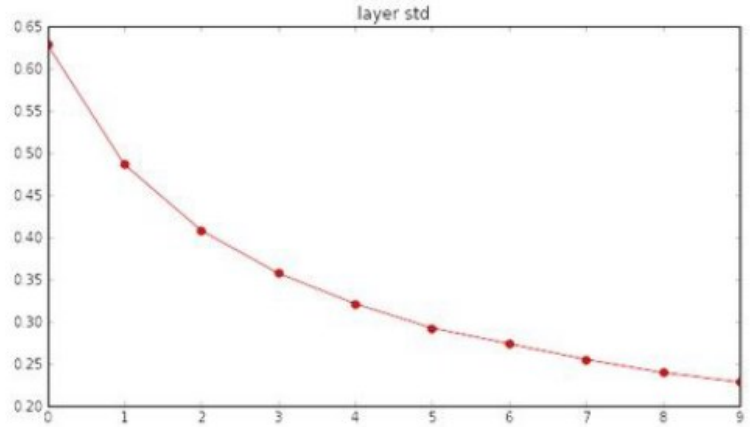
```
input layer had mean 0.001800 and std 1.001311
hidden layer 1 had mean 0.001198 and std 0.627953
hidden layer 2 had mean -0.000175 and std 0.486051
hidden layer 3 had mean 0.000055 and std 0.407723
hidden layer 4 had mean -0.000306 and std 0.357108
hidden layer 5 had mean 0.000142 and std 0.320917
hidden layer 6 had mean -0.000389 and std 0.292116
hidden layer 7 had mean -0.000228 and std 0.273387
hidden layer 8 had mean -0.000291 and std 0.254935
hidden layer 9 had mean 0.000361 and std 0.239266
hidden layer 10 had mean 0.000139 and std 0.228008
```

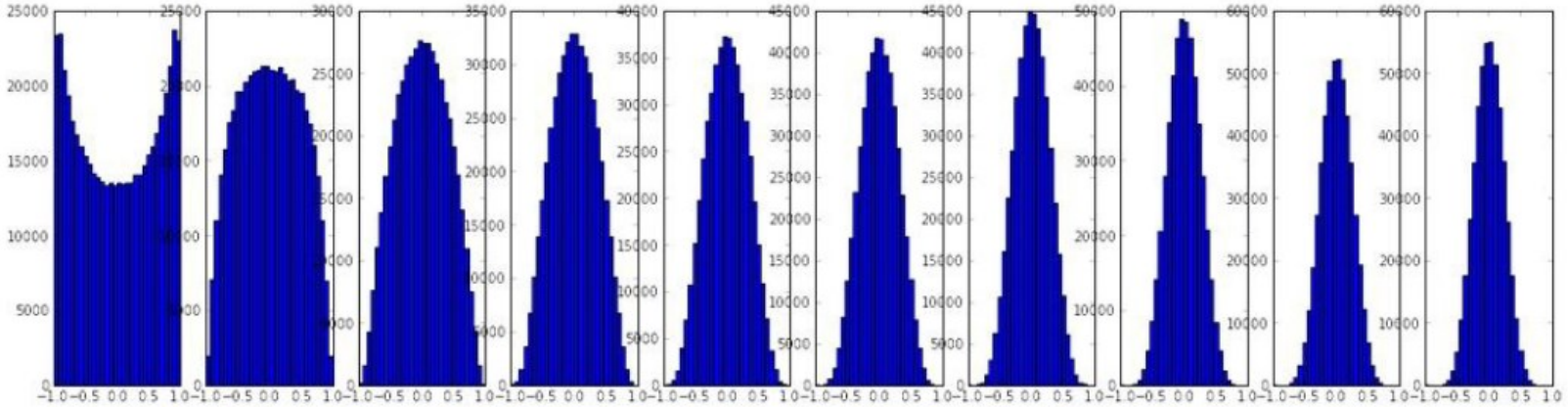
```
W = np.random.randn(fan_in, fan_out) / np.sqrt(fan_in) # layer initialization
```

Input neuron 수가 다른데 같은 initialization 값을 사용하는 것은 문제가 있음
→ input 이 많으면 더 작은 weight 값으로 시작해야함

"Xavier initialization"
[Glorot et al., 2010]







Reasonable initialization.
(Mathematical derivation assumes linear activations)

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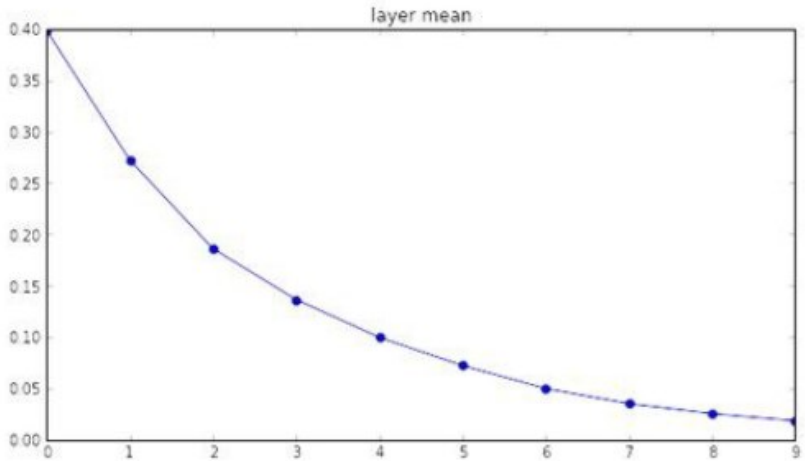
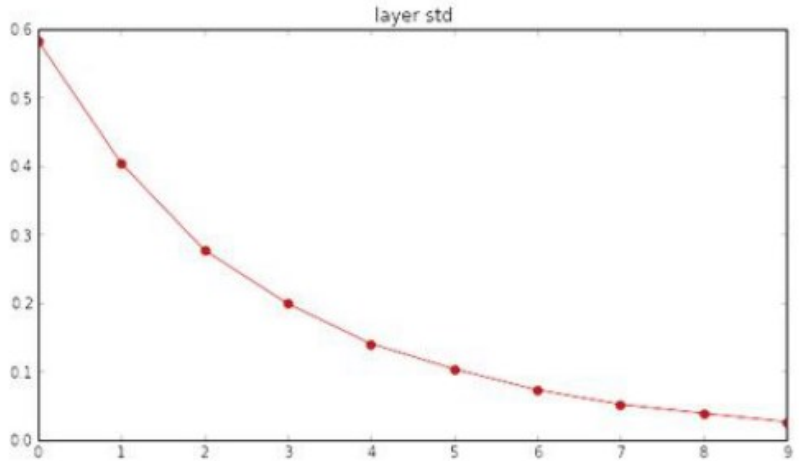
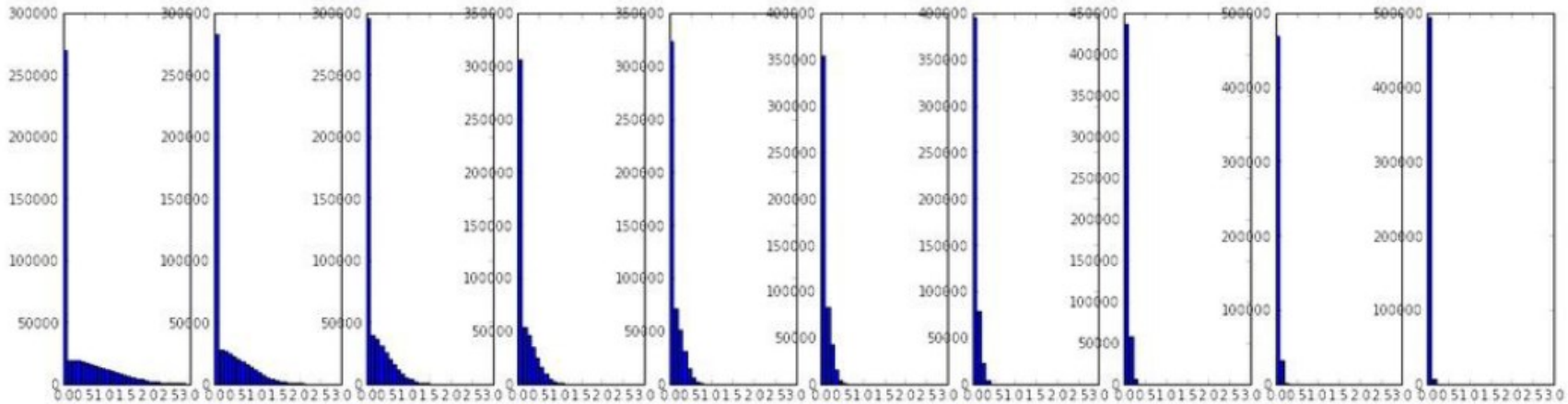
```
input layer had mean 0.000501 and std 0.999444
hidden layer 1 had mean 0.398623 and std 0.582273
hidden layer 2 had mean 0.272352 and std 0.403795
hidden layer 3 had mean 0.186076 and std 0.276912
hidden layer 4 had mean 0.136442 and std 0.198685
hidden layer 5 had mean 0.099568 and std 0.140299
hidden layer 6 had mean 0.072234 and std 0.103280
hidden layer 7 had mean 0.049775 and std 0.072748
hidden layer 8 had mean 0.035138 and std 0.051572
hidden layer 9 had mean 0.025404 and std 0.038583
hidden layer 10 had mean 0.018408 and std 0.026076
```

```
W = np.random.randn(fan_in, fan_out) / np.sqrt(fan_in) # layer initialization
```

but when using the ReLU nonlinearity it breaks.







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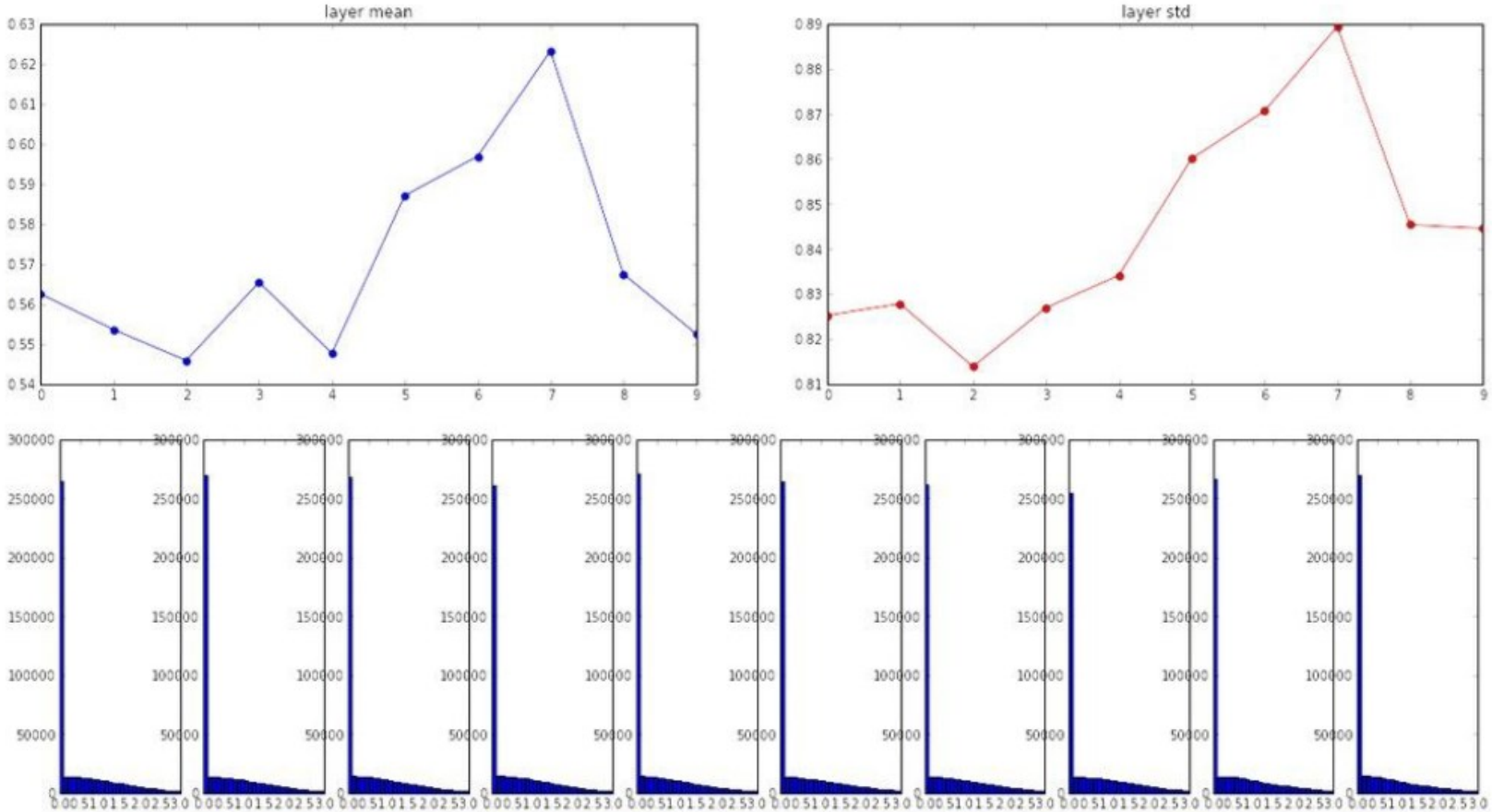
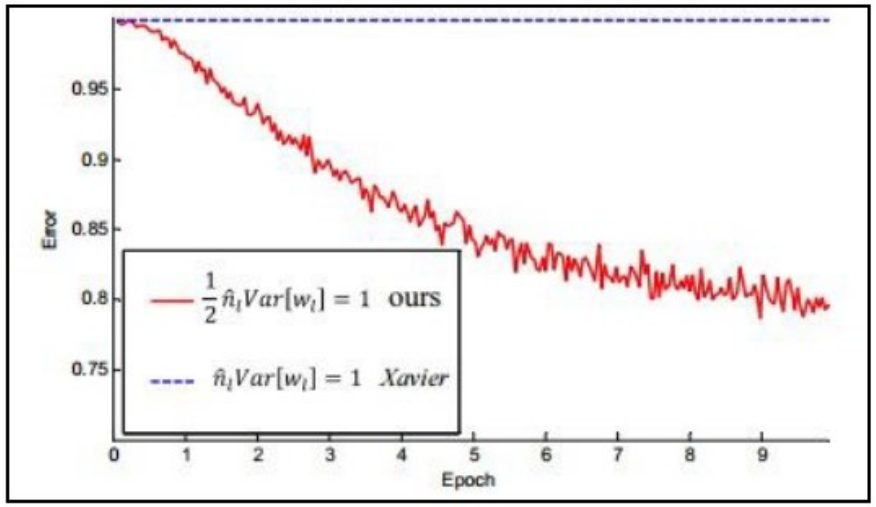
```
input layer had mean 0.000501 and std 0.999444
hidden layer 1 had mean 0.562488 and std 0.825232
hidden layer 2 had mean 0.553614 and std 0.827835
hidden layer 3 had mean 0.545867 and std 0.813855
hidden layer 4 had mean 0.565396 and std 0.826902
hidden layer 5 had mean 0.547678 and std 0.834092
hidden layer 6 had mean 0.587103 and std 0.860035
hidden layer 7 had mean 0.596867 and std 0.870610
hidden layer 8 had mean 0.623214 and std 0.889348
hidden layer 9 had mean 0.567498 and std 0.845357
hidden layer 10 had mean 0.552531 and std 0.844523
```

```
W = np.random.randn(fan_in, fan_out) / np.sqrt(2/fan_in) # layer initialization
```

He et al., 2015 (note additional 2/)





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Weight Initialization

- Xavier Initialization
  - Activation function은 linear라고 가정하고, in/out의 variance를 같게 해보자

forward: $\mathrm{Var}(W_i) = \frac{1}{n} = \frac{1}{n_{\text{in}}}$

backward: $\mathrm{Var}(W_i) = \frac{1}{n_{\text{out}}}$

Xavier Initialization: $\mathrm{Var}(W_i) = \frac{2}{n_{\text{in}} + n_{\text{out}}}$

Weight Initialization

- He Initialization
  - Activation function을 ReLU나 PReLU로 하고, variance를 같게 해보자

ReLU

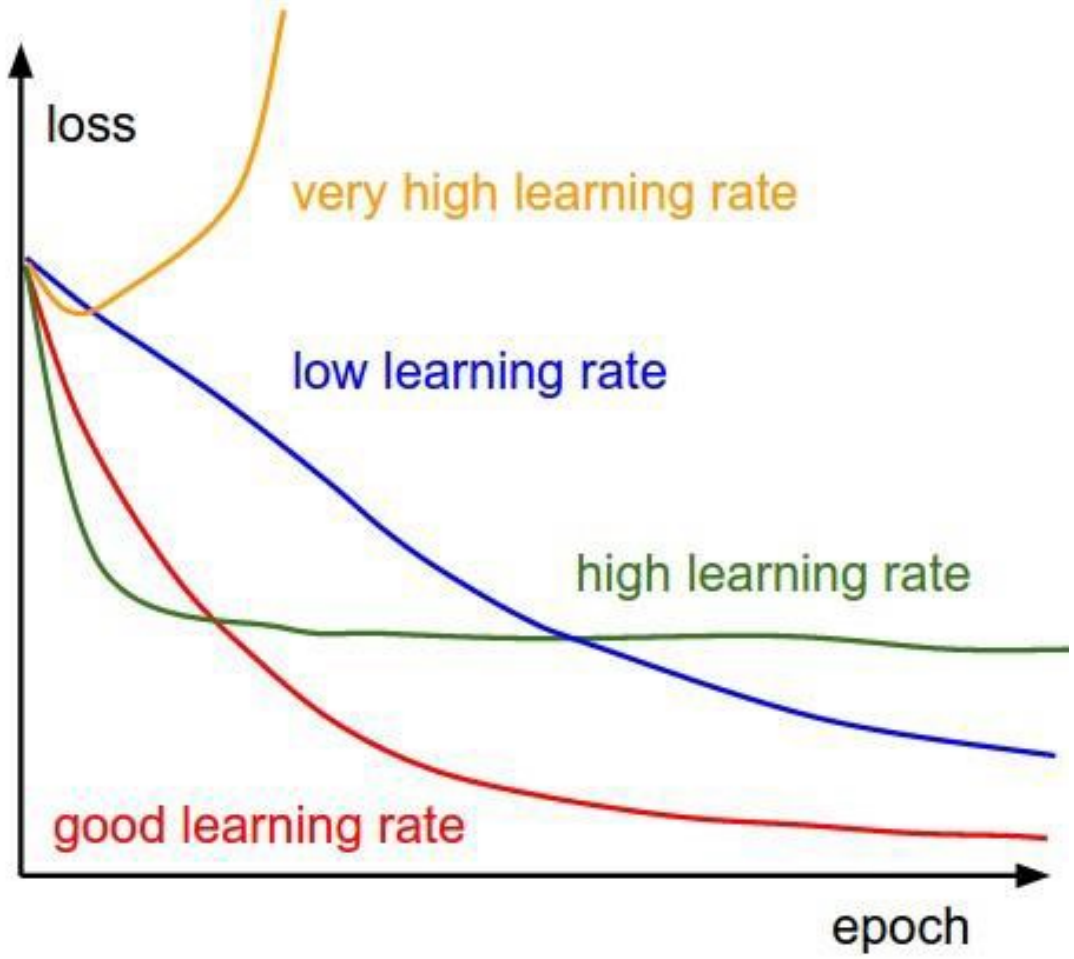
$$\begin{cases} Var[w_l] = \frac{2}{n_l} \implies \text{standard deviation (std)} = \sqrt{\frac{2}{n_l}} \\ W_l \sim \mathcal{N}\left(0, \sqrt{\frac{2}{n_l}}\right) \text{ and } \mathbf{b} = 0 \end{cases}$$

PReLU

$$\frac{1}{2}(1 + a^2) n_l Var[w_l] = 1$$

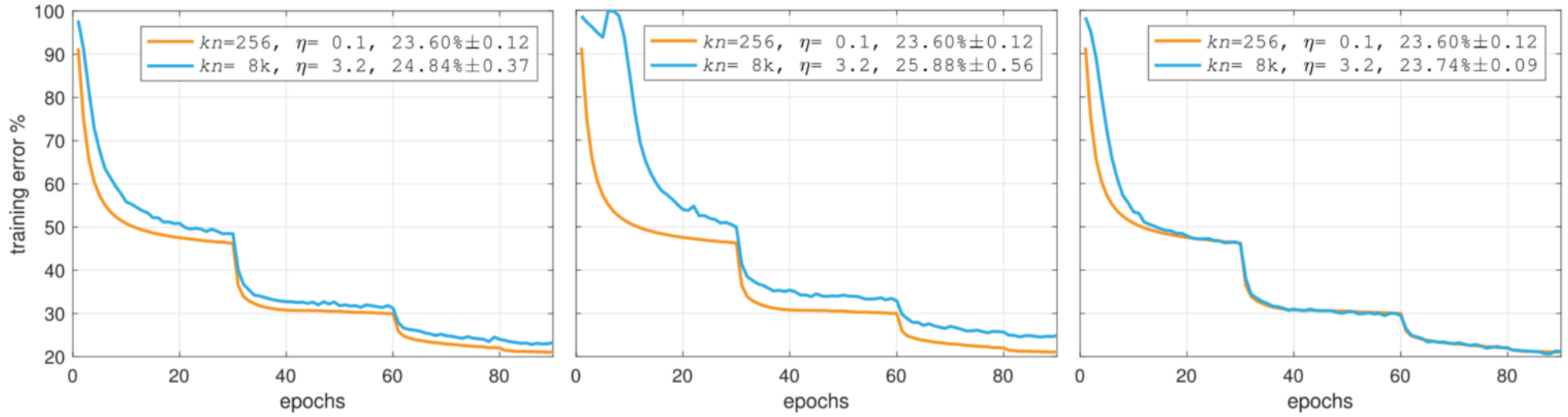
Learning Rate

- learning rate에 따라서 최종 결과가 달라짐



Learning Rate Decay

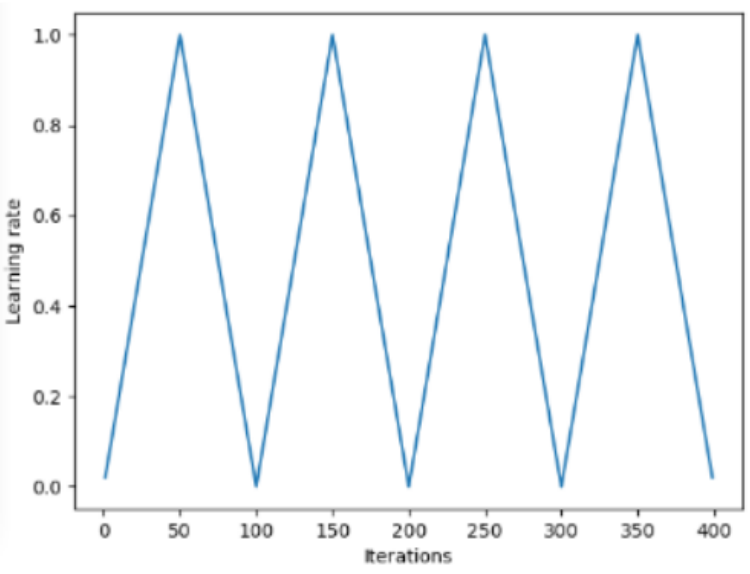
- Learning rate이 너무 크면 수렴을 못할 가능성이 있고, 너무 작으면 local minima 혹은 saddle point에서 못빠져나옴
- Learning Rate Decay
  - 처음에는 크게 움직이다가 일정 조건이 되면 learning rate을 낮춰서 점점 작게 움직이는 방법

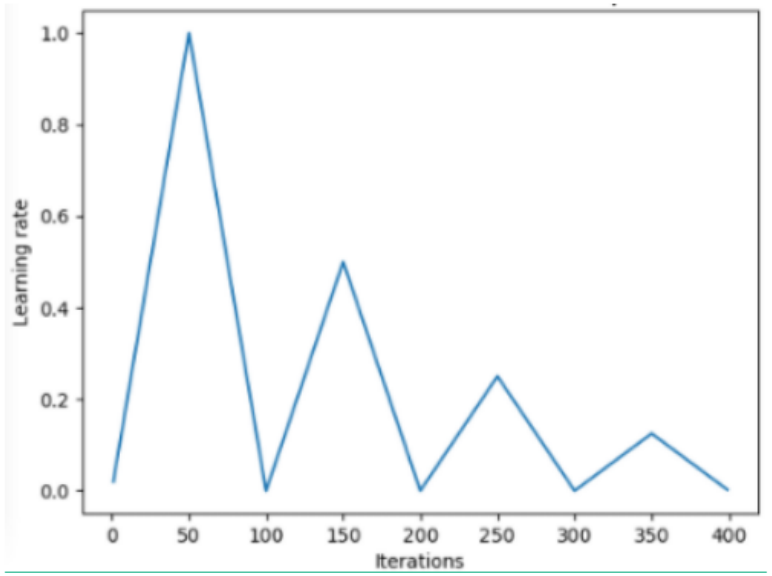


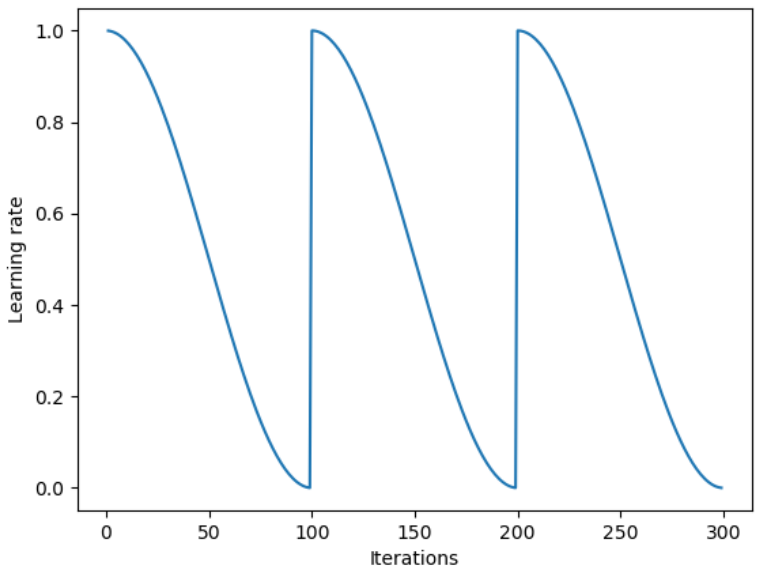
(a) no warmup (b) constant warmup (c) gradual warmup

Cyclic Learning Rate

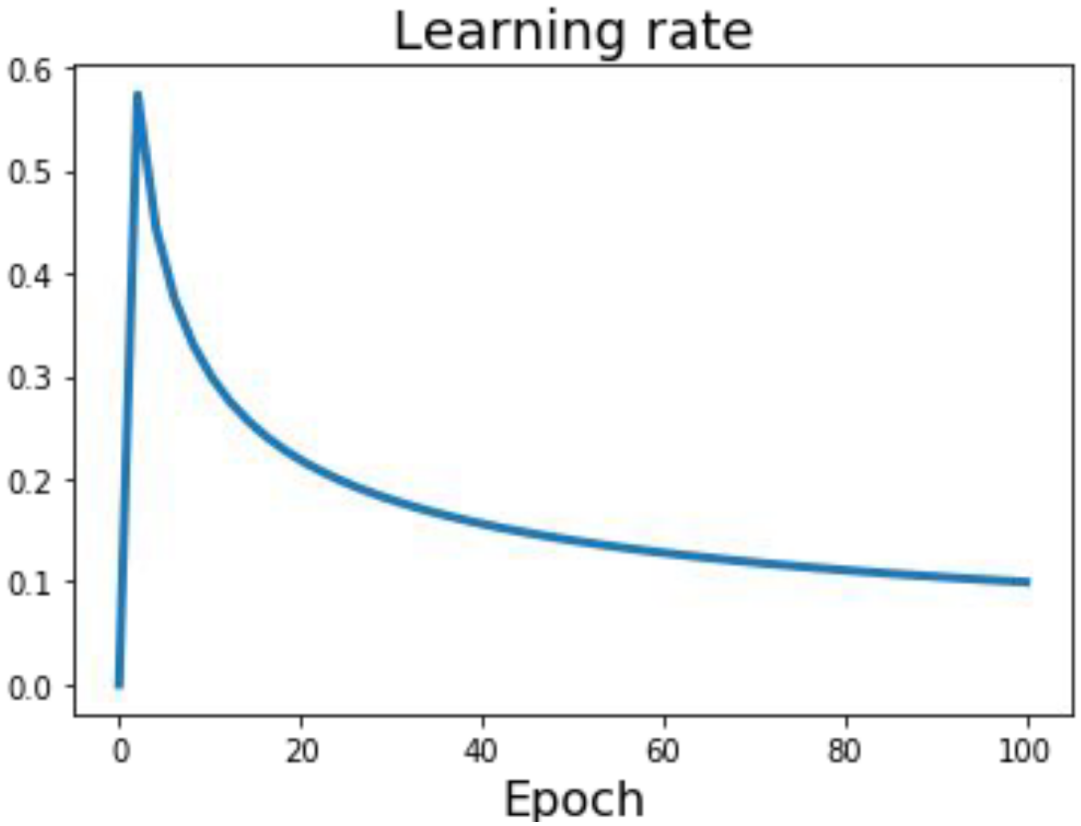
- Learning rate decay로 saddle point를 빠져나갈 수 있을까?
- Saddle point에서는 learning rate을 키워서 빠져나가는 것이 효과적일 수 있음 → Learning rate을 주기적으로 변경해보자







Linear Warmup



High initial learning rates can make loss explode; linearly increasing learning rate from 0 over the first ~5000 iterations can prevent this

Empirical rule of thumb: If you increase the batch size by N, also scale the initial learning rate by N

Underfitting vs Overfitting

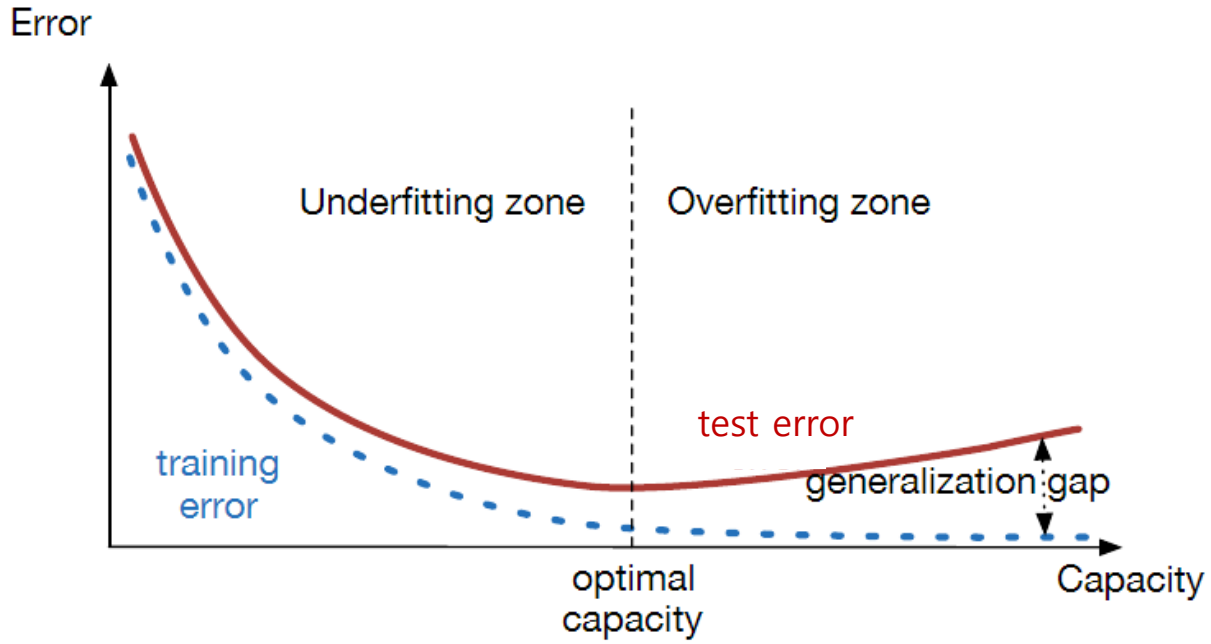
test error = training error + generalization gap

Model capacity가 너무 작으면,
- 아무리 학습을 해도 성능이 안나옴

→underfitting

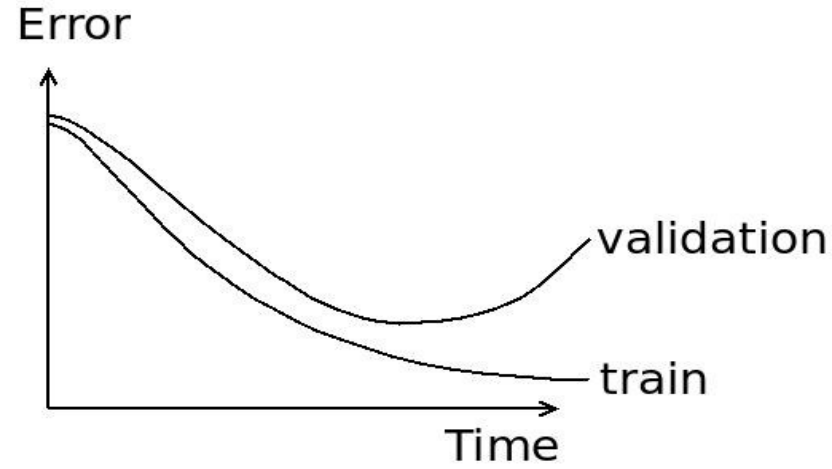
Model capacity가 너무 크면,
- Generalization gap이 커짐

→overfitting

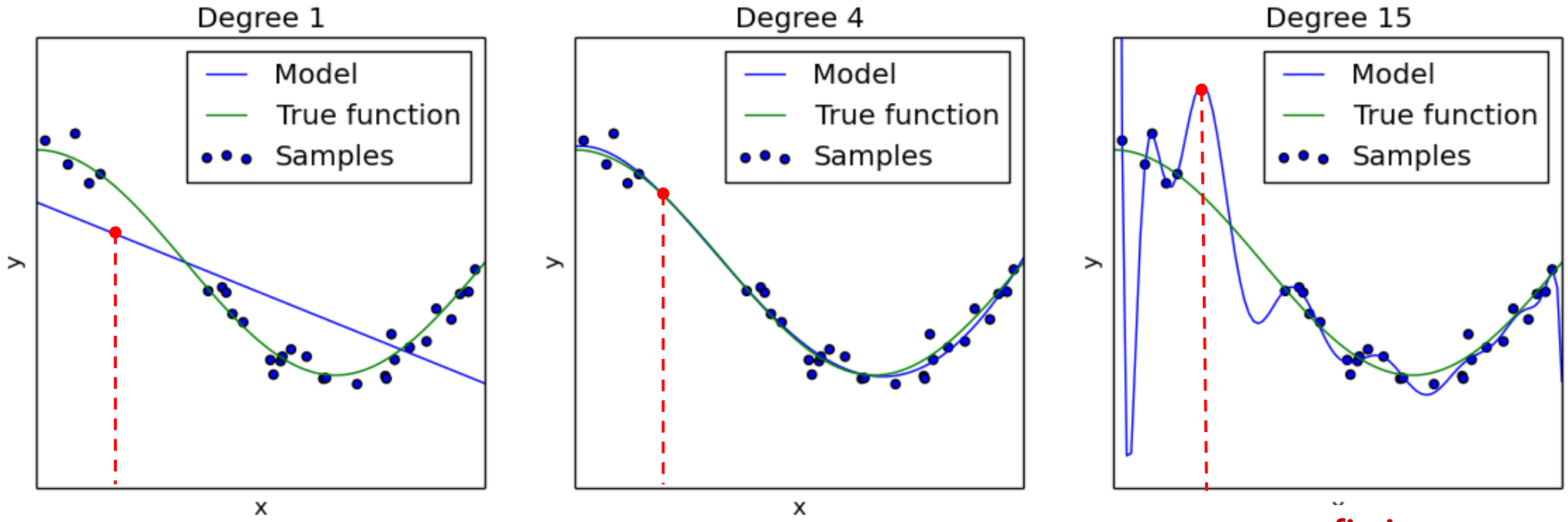


Deep Learning에 사용하는 model은 capacity가 대부분 크기 때문에 overfitting에 취약함

Underfitting vs Overfitting



Overfitting : Training data에 너무 최적화(fitting)를 함으로 인해서 일반화 (generalization) 성능이 떨어지는 현상

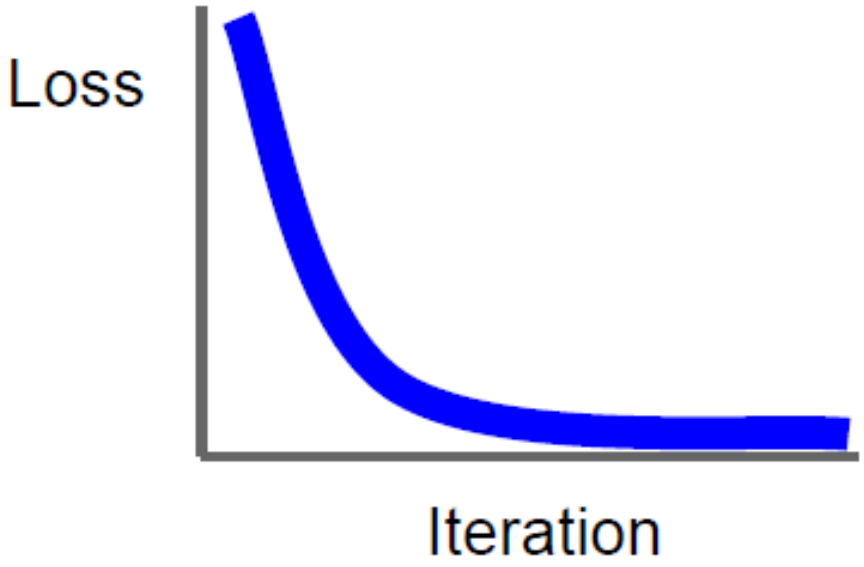


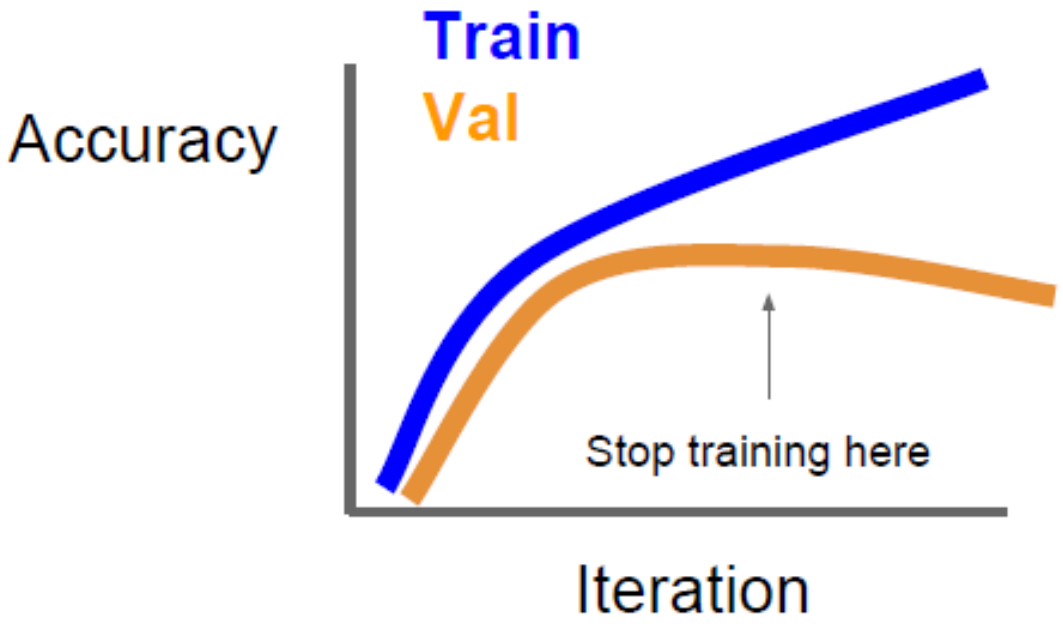
underfitting

overfitting

https://scikit-learn.org/0.15/auto_examples/plot_underfitting_overfitting.html

Early Stopping





Stop training the model when accuracy on the validation set decreases
Or train for a long time, but always keep track of the model snapshot that worked best on val

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Regularization Method

λ = regularization strength (hyperparameter)

$$L(W) = \underbrace{\frac{1}{N}\sum_{i=1}^{N} L_i(f(x_i, W), y_i)}_{\text{Data loss}} + \underbrace{\lambda R(W)}_{\text{Regularization}}$$

Data loss: Model predictions should match training data

Regularization: Prevent the model from doing *too* well on training data

Simple examples

L2 regularization: $R(W) = \sum_k \sum_l W_{k,l}^2$

L1 regularization: $R(W) = \sum_k \sum_l |W_{k,l}|$

Elastic net (L1 + L2): $R(W) = \sum_k \sum_l \beta W_{k,l}^2 + |W_{k,l}|$

More complex:

Dropout

Batch normalization

Stochastic depth, fractional pooling, etc

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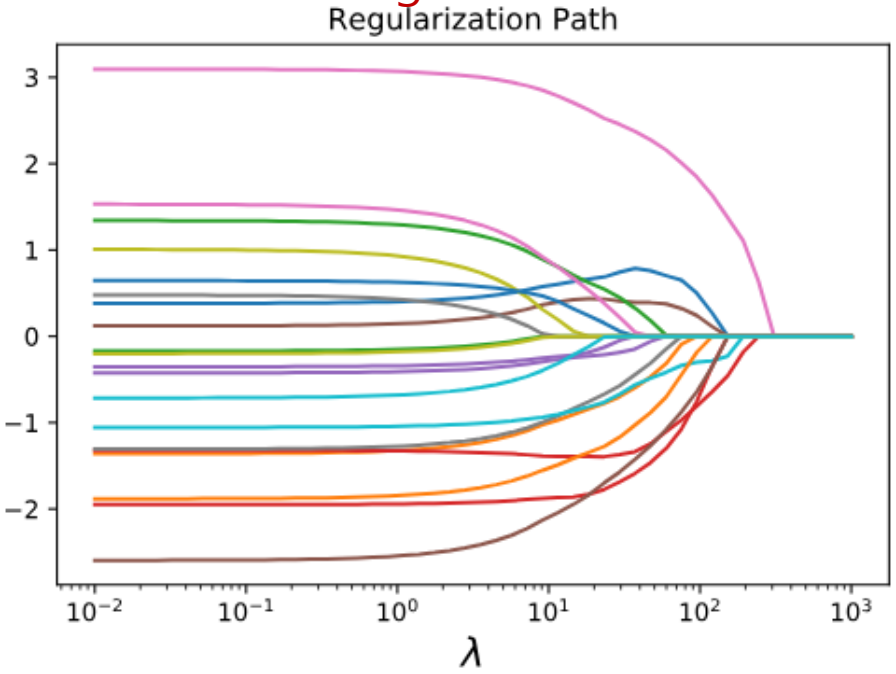
Add Term to Loss

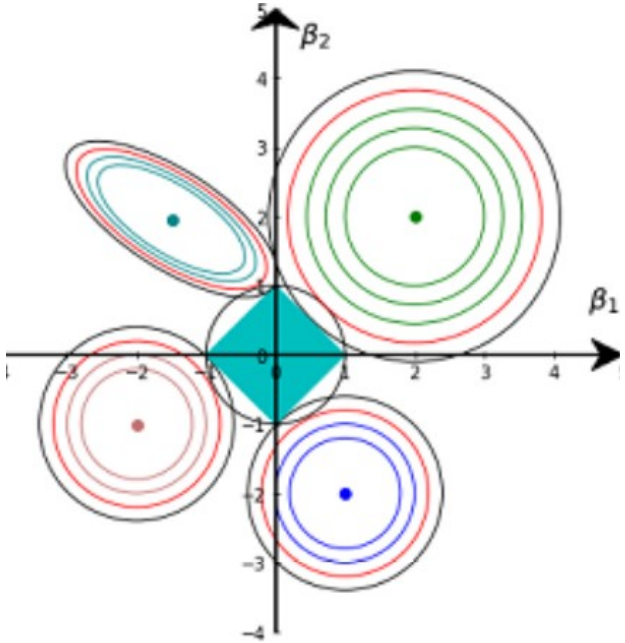
L2 regularization $R(W) = \sum_k \sum_l W_{k,l}^2$ (Weight decay)

L1 regularization $R(W) = \sum_k \sum_l |W_{k,l}|$

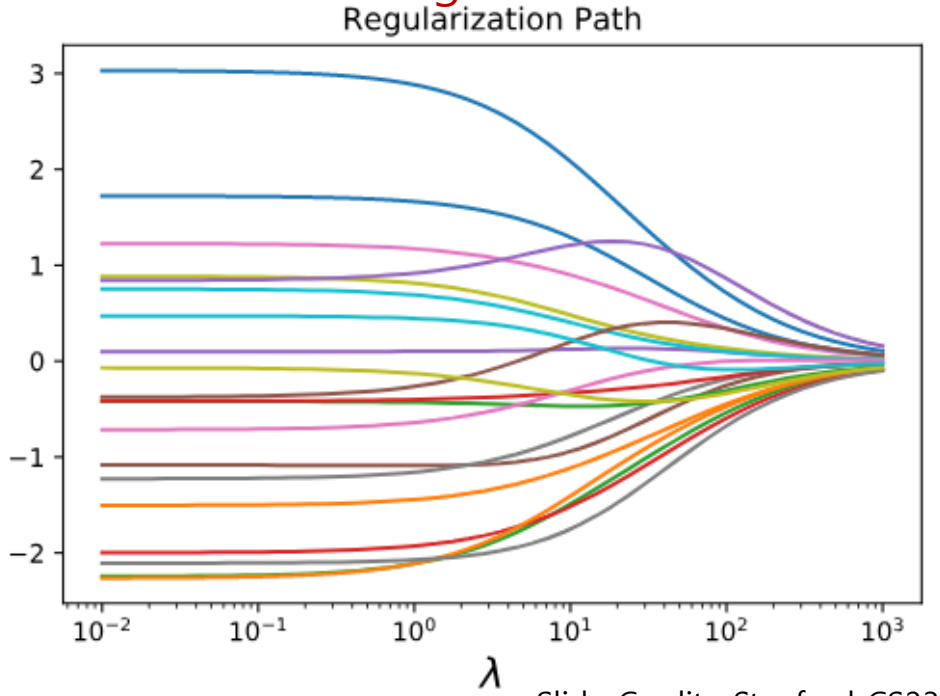
Elastic net (L1 + L2) $R(W) = \sum_k \sum_l \beta W_{k,l}^2 + |W_{k,l}|$

L1 Regularization





L2 Regularization



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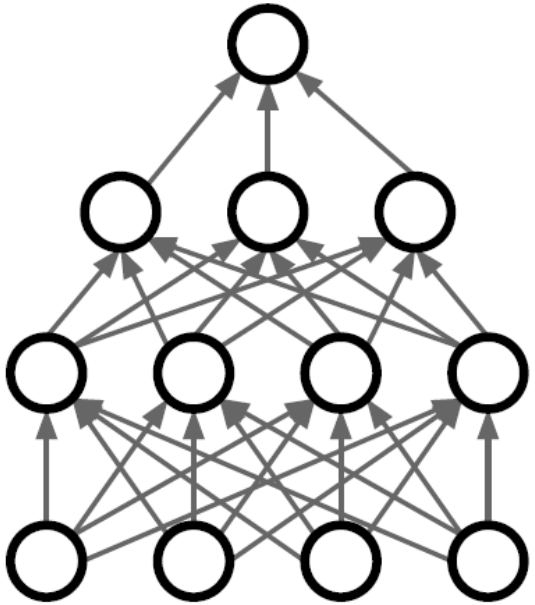
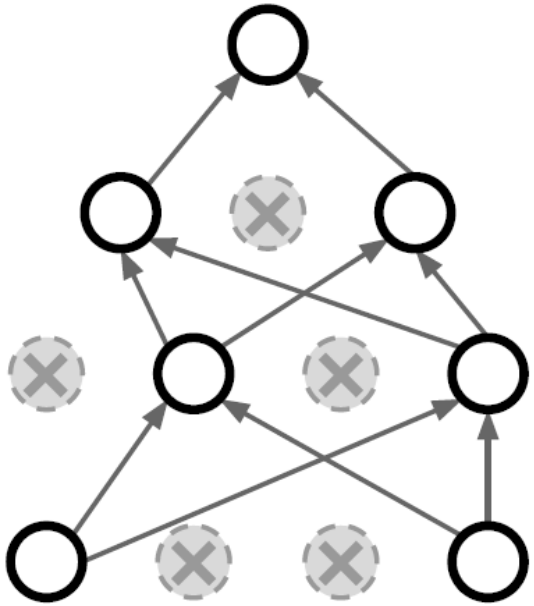
Dropout

- In each forward pass, randomly set some neurons to zero
- Probability of dropping is a hyper-parameter; 0.5 is common





Dropout is training a large **ensemble** of models (that share parameters).

Each binary mask is one model

An FC layer with 4096 units has $2^{4096} \sim 10^{1233}$ possible masks!
Only $\sim 10^{82}$ atoms in the universe...

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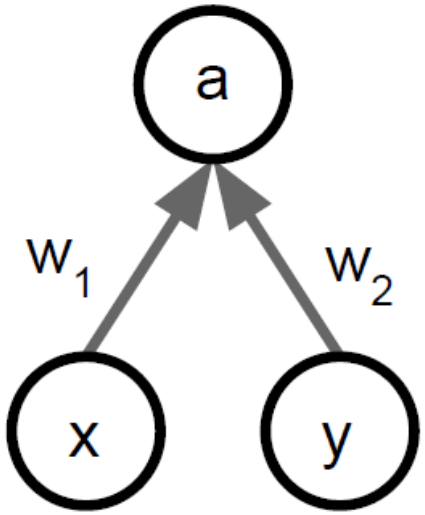
Dropout: Test Time

- Dropout makes the output random!
- Want to average out the randomness at test time



Consider a single neuron.

At test time we have: $E[a] = w_1 x + w_2 y$

During training we have:

$$\begin{aligned} E[a] =& \frac{1}{4}(w_1 x + w_2 y) + \frac{1}{4}(w_1 x + 0y) \\ &+ \frac{1}{4}(0x + 0y) + \frac{1}{4}(0x + w_2 y) \\ =& \frac{1}{2}(w_1 x + w_2 y) \end{aligned}$$

At test time, **multiply** by dropout probability

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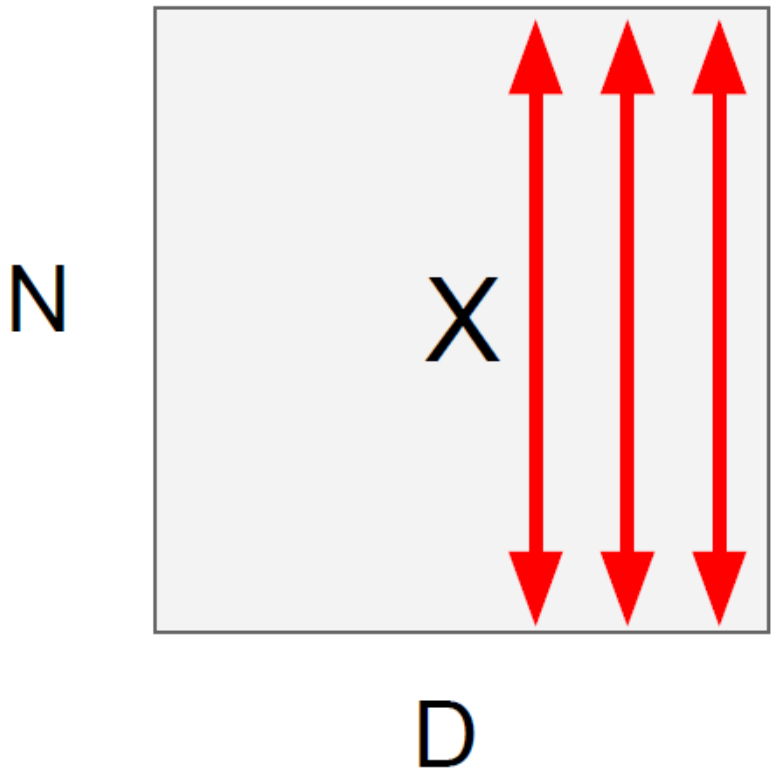
Batch Normalization

"you want zero-mean unit-variance activations? just make them so."



1. compute the empirical mean and variance independently for each dimension.

2. Normalize

$$\widehat{x}^{(k)} = \frac{x^{(k)} - \mathrm{E}[x^{(k)}]}{\sqrt{\mathrm{Var}[x^{(k)}]}}$$

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Batch Normalization

Input: Values of x over a mini-batch: $\mathcal{B} = \{x_{1...m}\}$;
Parameters to be learned: γ, β
Output: $\{y_i = \mathrm{BN}_{\gamma,\beta}(x_i)\}$

$$\mu_{\mathcal{B}} \leftarrow \frac{1}{m}\sum_{i=1}^{m} x_i \qquad \text{// mini-batch mean}$$

$$\sigma^2_{\mathcal{B}} \leftarrow \frac{1}{m}\sum_{i=1}^{m}(x_i - \mu_{\mathcal{B}})^2 \qquad \text{// mini-batch variance}$$

$$\widehat{x}_i \leftarrow \frac{x_i - \mu_{\mathcal{B}}}{\sqrt{\sigma^2_{\mathcal{B}} + \epsilon}} \qquad \text{// normalize}$$

$$y_i \leftarrow \gamma\widehat{x}_i + \beta \equiv \mathrm{BN}_{\gamma,\beta}(x_i) \qquad \text{// scale and shift}$$

After normalization, allow the network to squash the range if it wants to

Note, the network can learn:

$$\gamma^{(k)} = \sqrt{\mathrm{Var}[x^{(k)}]}$$

$$\beta^{(k)} = \mathrm{E}[x^{(k)}]$$

to recover the identity mapping.

- Improves gradient flow through the network
- Allows higher learning rates
- Reduces the strong dependence on initialization
- Acts as a form of regularization during training
- Zero overhead at test-time
- Behaves differently during training and testing: this is a very common source of bugs

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Batch Normalization for ConvNets

Batch Normalization for
fully-connected networks

$x: N \times D$

Normalize

$\mu, \sigma: 1 \times D$

$\gamma, \beta: 1 \times D$

$y = \gamma(x-\mu)/\sigma+\beta$

Batch Normalization for
convolutional networks
(Spatial Batchnorm, BatchNorm2D)

$x: N \times C \times H \times W$

Normalize

$\mu, \sigma: 1 \times C \times 1 \times 1$

$\gamma, \beta: 1 \times C \times 1 \times 1$

$y = \gamma(x-\mu)/\sigma+\beta$

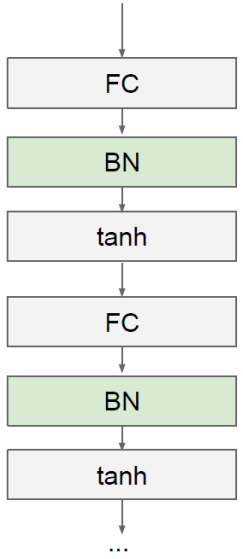
Batch Normalization: Test Time

$\mu_j =$ (Running) average of values seen during training — Per-channel mean, shape is D

$\sigma_j^2 =$ (Running) average of values seen during training — Per-channel var, shape is D

$$\hat{x}_{i,j} = \frac{x_{i,j} - \mu_j}{\sqrt{\sigma_j^2 + \varepsilon}}$$ — Normalized x, Shape is N x D

$$y_{i,j} = \gamma_j \hat{x}_{i,j} + \beta_j$$ — Output, Shape is N x D



- The mean/std are not computed based on the batch. Instead, a single fixed empirical mean of activations during training is used.
- It can be estimated during training with running averages

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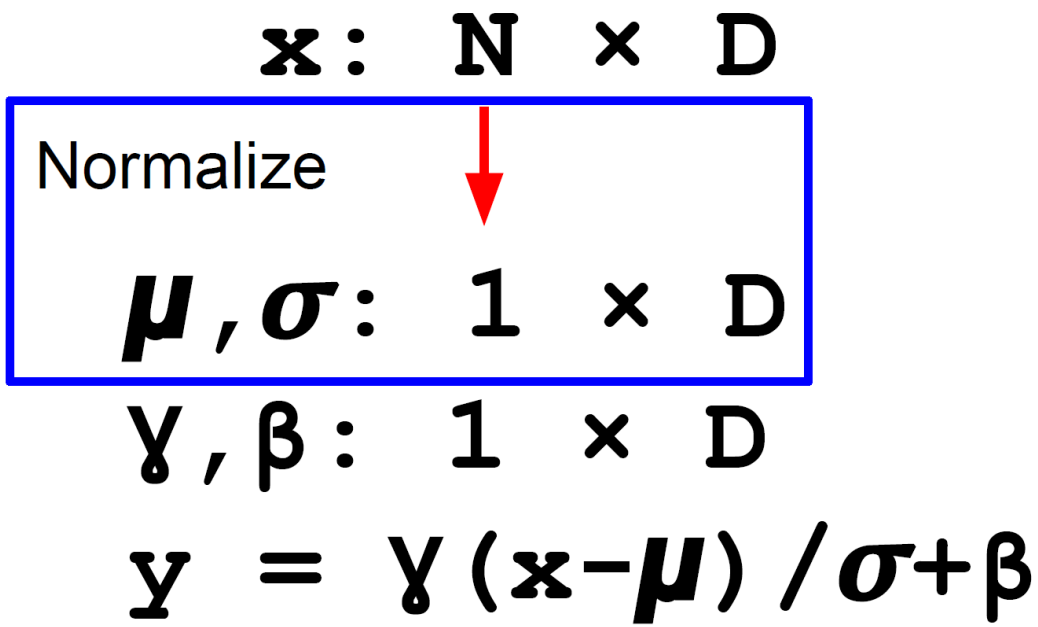
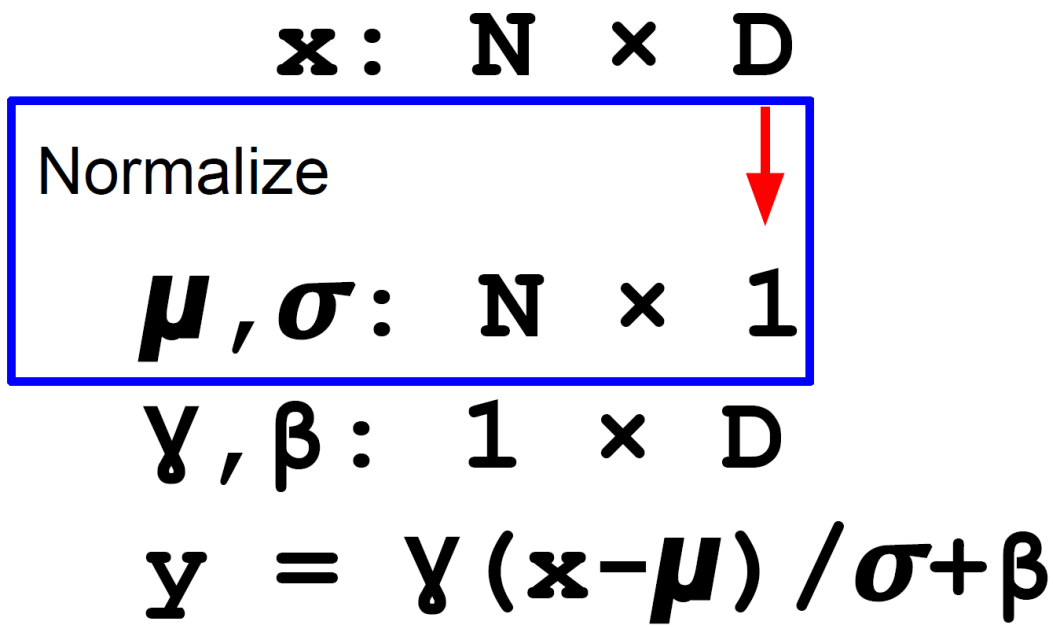
Layer Normalization

Batch Normalization for fully-connected networks

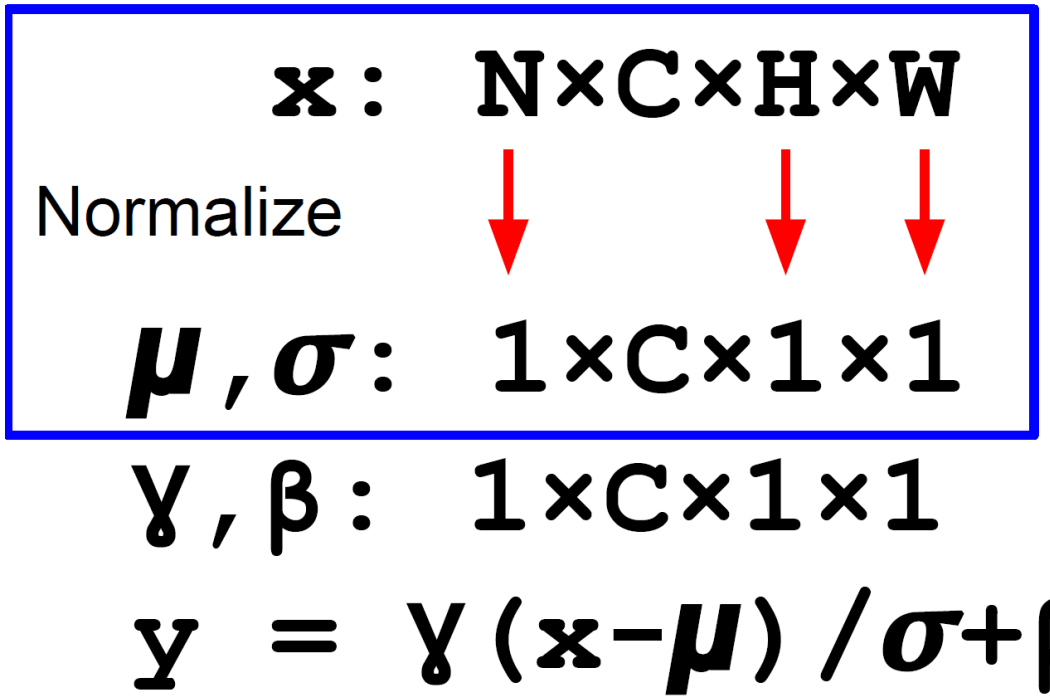


Layer Normalization for fully-connected networks
Same behavior at train and test!
Can be used in recurrent networks

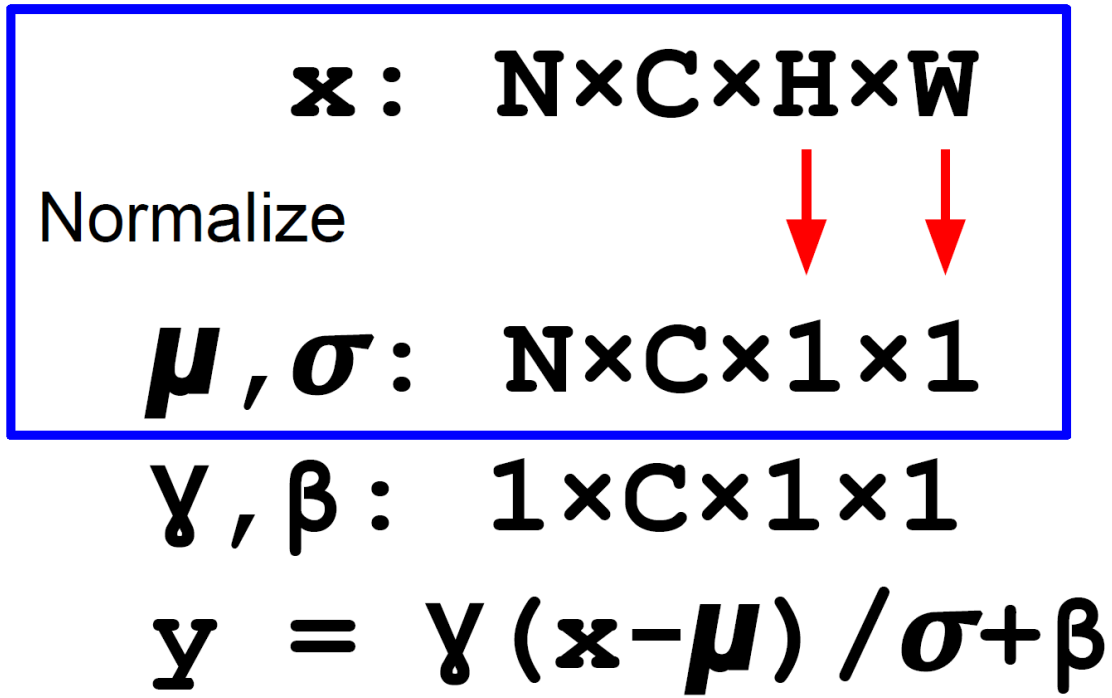


Instance Normalization

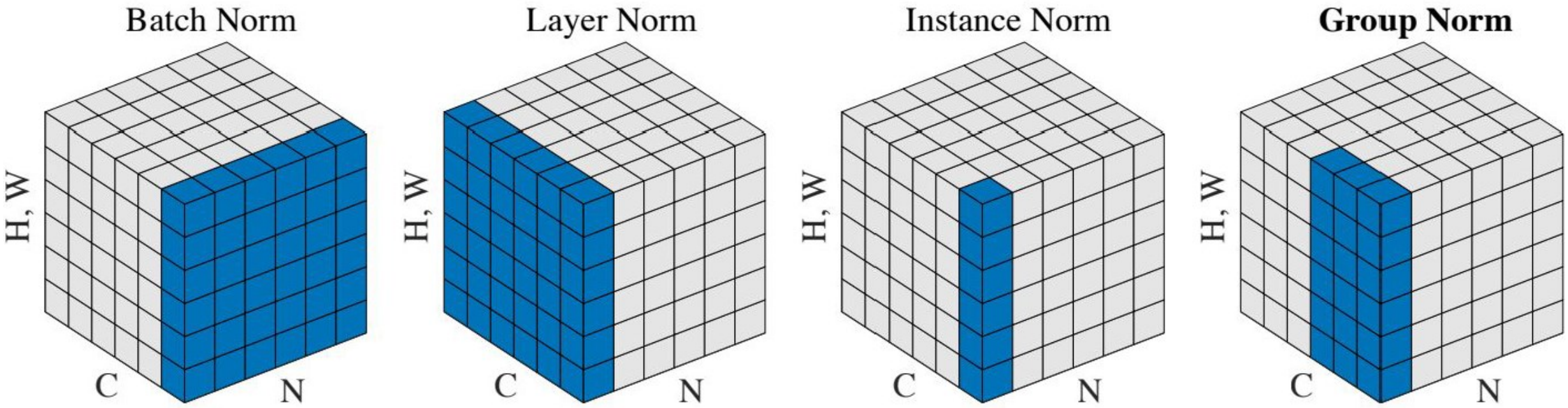
Batch Normalization for convolutional networks



Instance Normalization for convolutional networks
Same behavior at train / test!



Comparison of Normalizations



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Regularization: A Common Pattern

- Training : Add some kind of randomness

Output (label) Input (image)

$$y = f_W(x, z)$$

Random mask

- Testing : Average out randomness

$$y = f(x) = E_z\left[f(x,z)\right] = \int p(z) f(x,z) dz$$

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Regularization: A Common Pattern

- Dropout
  - Training : Randomly set some neurons to zero
  - Testing : Average out the randomness by multiplying dropout probability

- Batch Normalization
  - Training : Normalize using stats from random mini-batches
  - Testing : Use fixed stats to normalize

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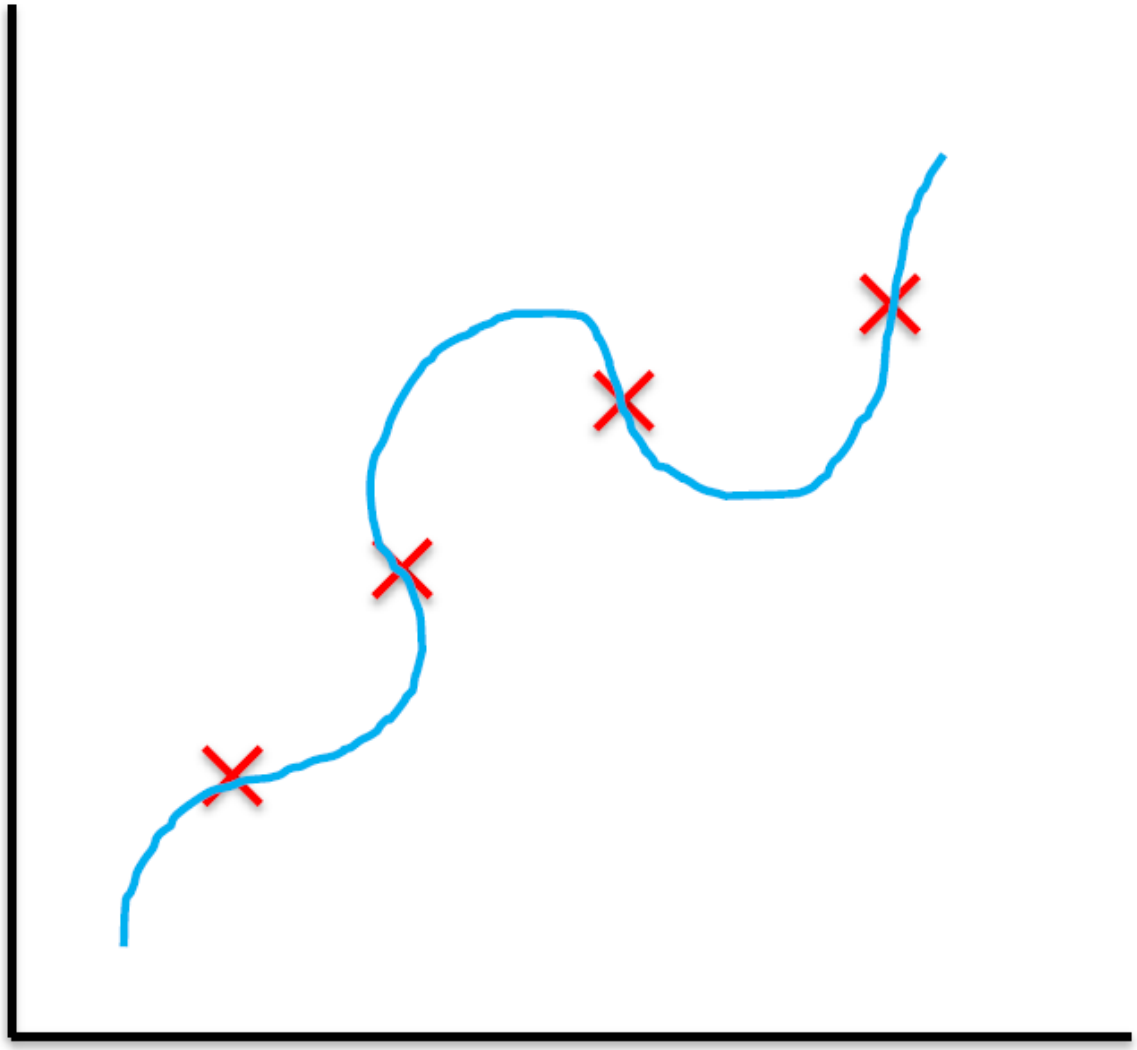
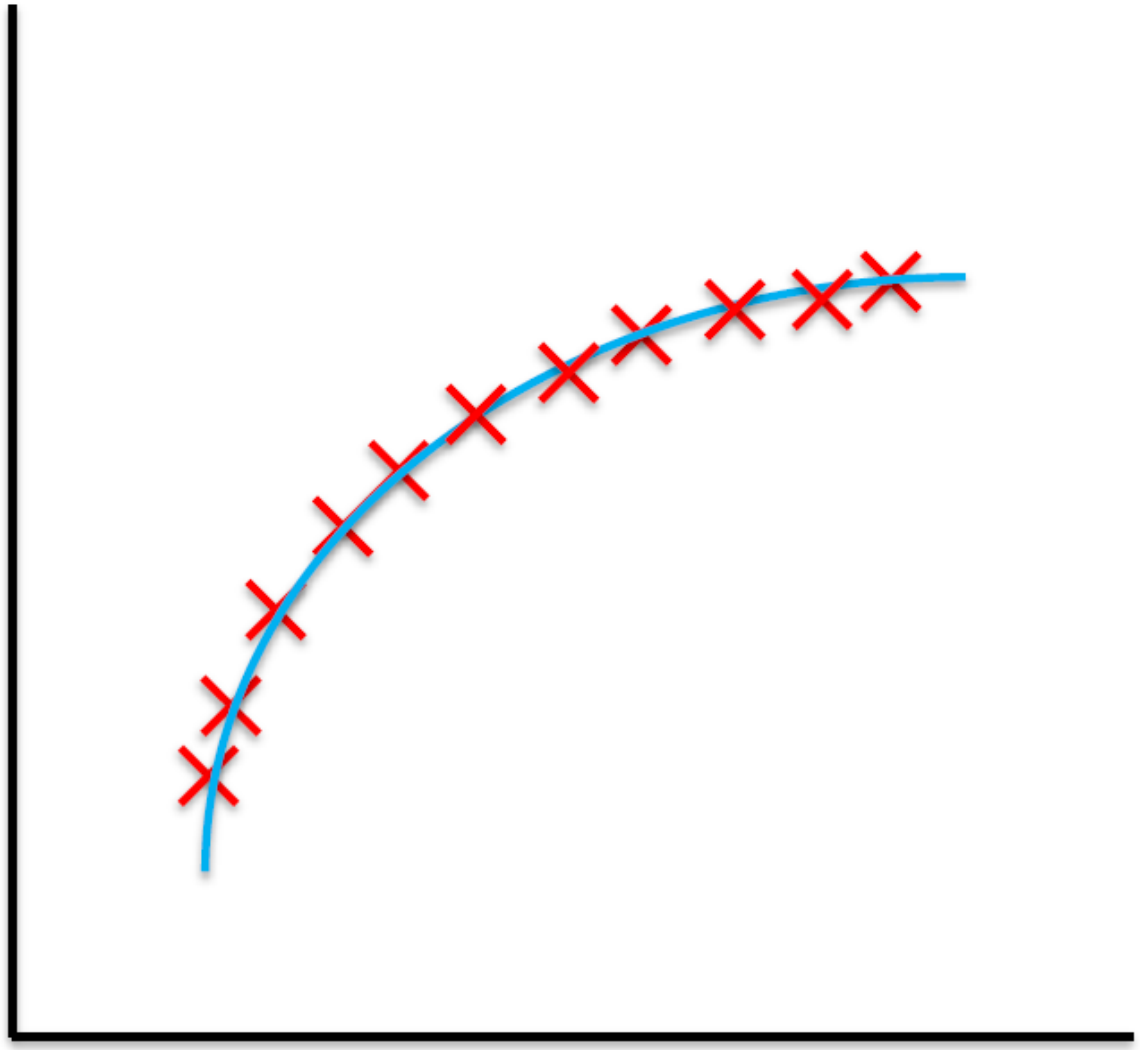
Data Augmentation





Data Augmentation

Crop:

Flip:

Scale:

Rotate:

Translation:

Noise:

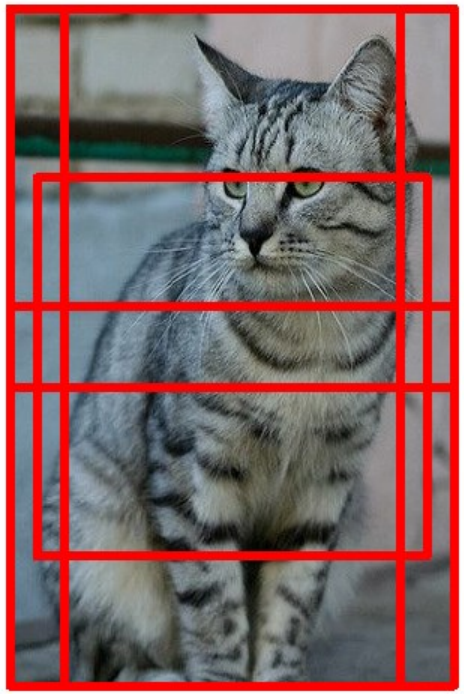
Slide Credit : https://deeplearning.mit.edu

Data Augmentation - Example

- Training : sample random crops / scales

ResNet:

1. Pick random L in range [256, 480]
2. Resize training image, short side = L
3. Sample random 224x224 patch



- Testing : average a fixed set of crops

ResNet:

1. Resize image at 5 scales: {224, 256, 384, 480, 640}
2. For each size, use 10 224x224 crop: 4 corners + center, + flips

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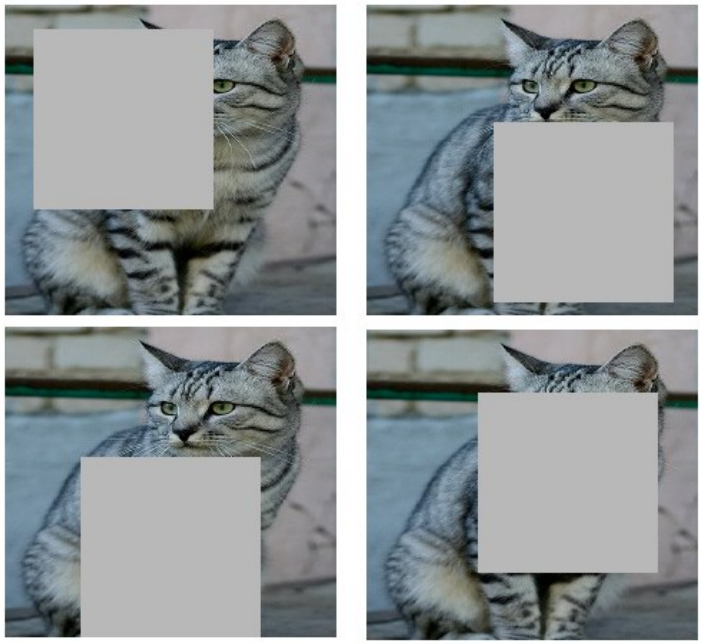
CutOut & MixUp



Works very well for small datasets like CIFAR, less common for large datasets like ImageNet

Randomly blend the pixels of pairs of training images, e.g. 40% cat, 60% dog

CNN

Target label:
cat: 0.4
dog: 0.6

CutMix

	ResNet-50	Mixup [48]	Cutout [3]	CutMix
Image				
Label	Dog 1.0	Dog 0.5 Cat 0.5	Dog 1.0	Dog 0.6 Cat 0.4
ImageNet Cls (%)	76.3 (+0.0)	77.4 (+1.1)	77.1 (+0.8)	**78.6** **(+2.3)**
ImageNet Loc (%)	46.3 (+0.0)	45.8 (-0.5)	46.7 (+0.4)	**47.3** **(+1.0)**
Pascal VOC Det (mAP)	75.6 (+0.0)	73.9 (-1.7)	75.1 (-0.5)	**76.7** **(+1.1)**

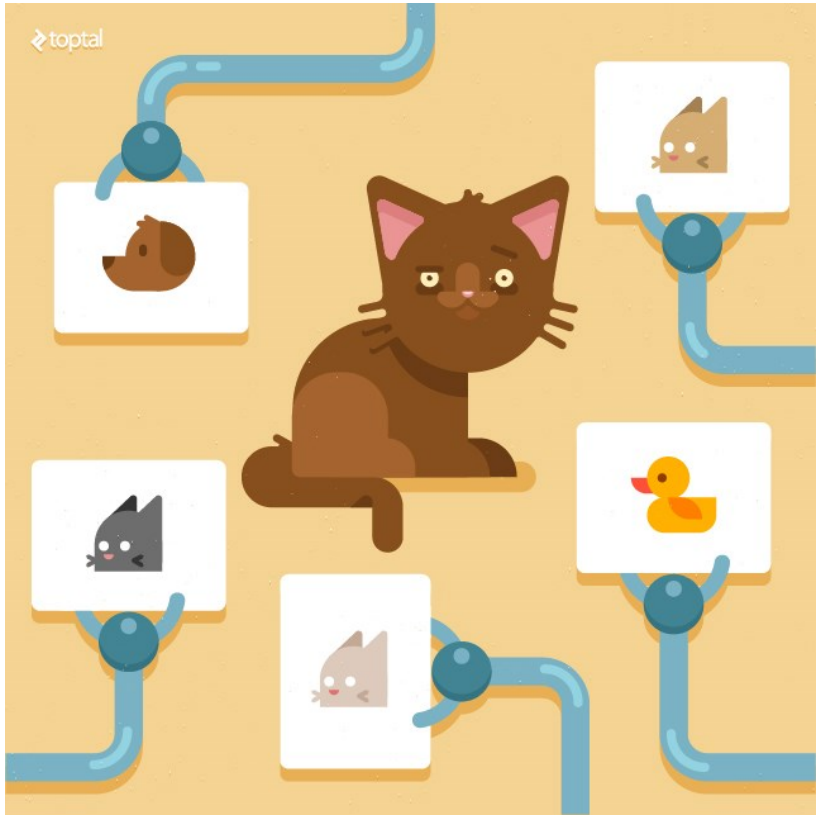
$$\tilde{x} = \mathbf{M} \odot x_A + (\mathbf{1} - \mathbf{M}) \odot x_B$$
$$\tilde{y} = \lambda y_A + (1 - \lambda) y_B,$$

$$r_x \sim \text{Unif}\ (0, W)\,, \quad r_w = W\sqrt{1-\lambda},$$
$$r_y \sim \text{Unif}\ (0, H)\,, \quad r_h = H\sqrt{1-\lambda}$$

Model Ensembles

1. Train multiple independent models
2. At test time average their results
   - Take average of predicted probability distributions, then choose argmax

- Enjoy 2% extra performance!



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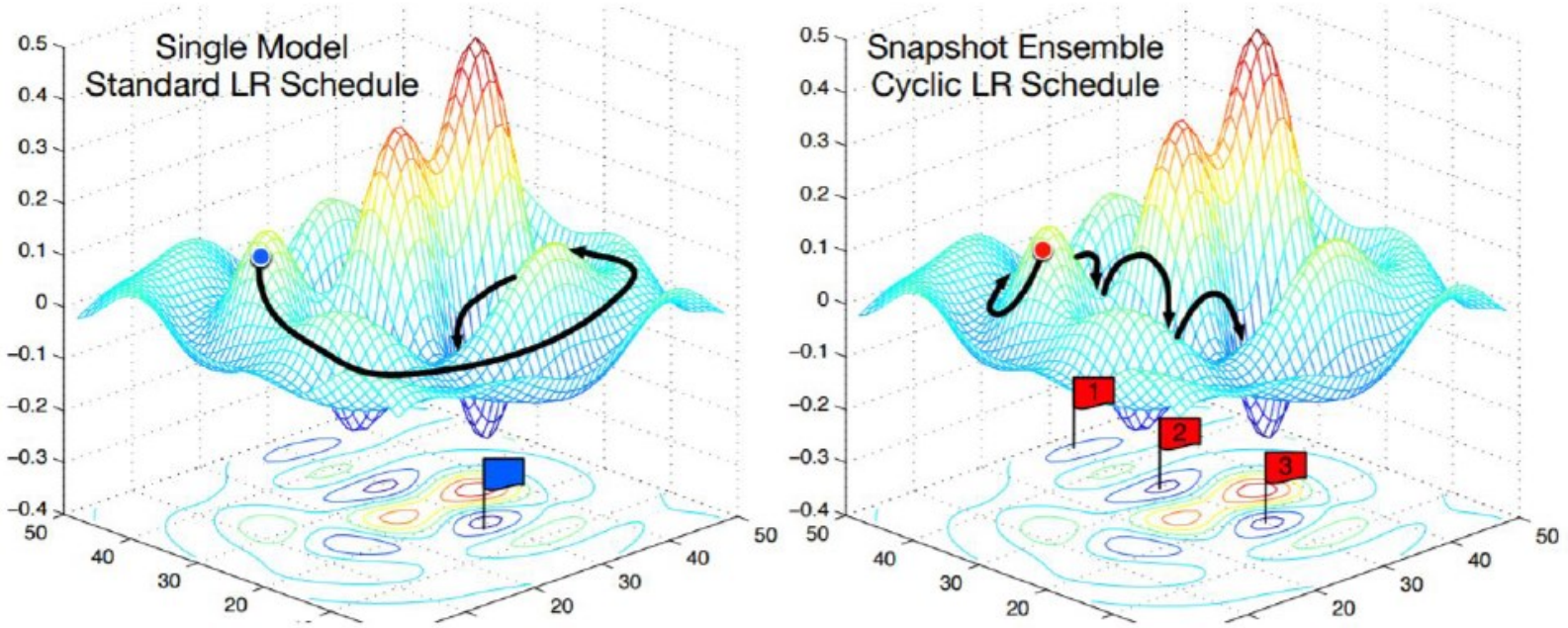
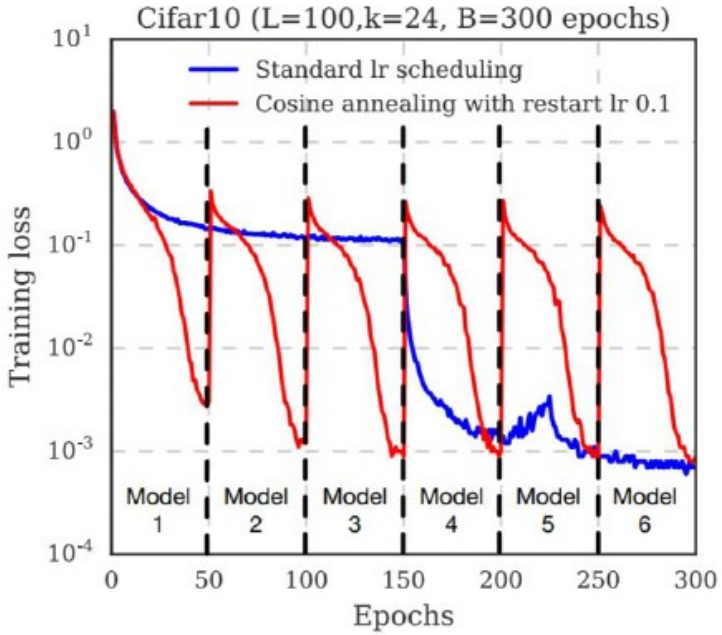
Model Ensembles: Tips and Tricks

- Instead of training independent models, use multiple snapshots of a single model during training!





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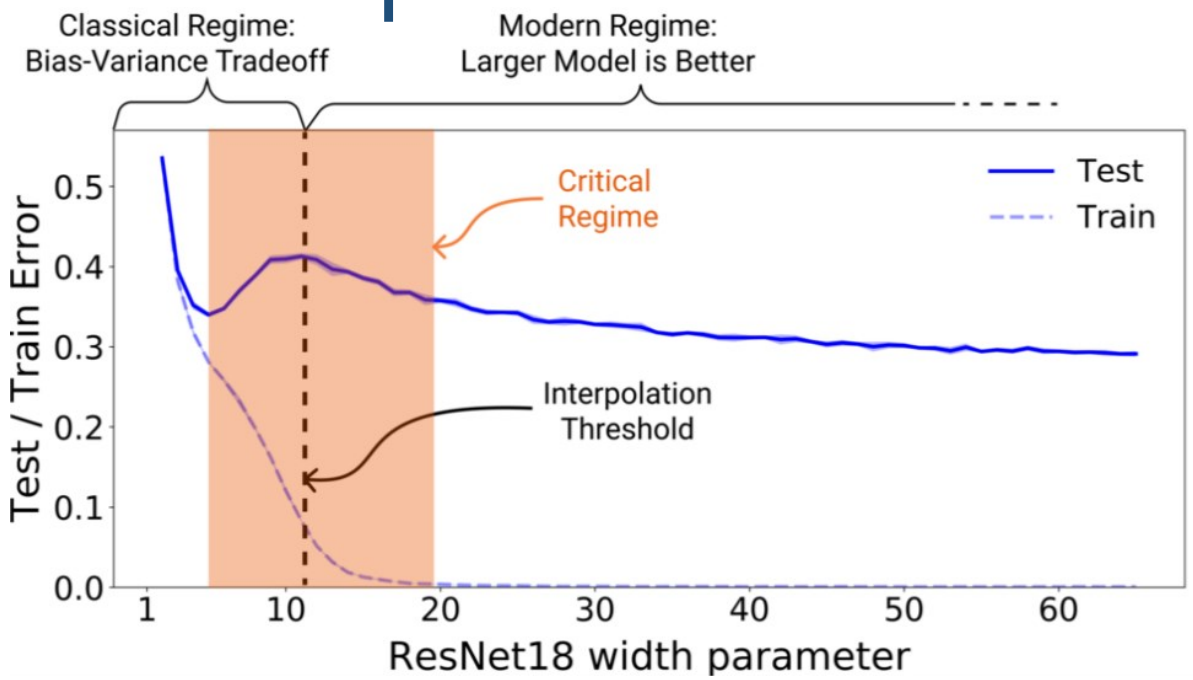
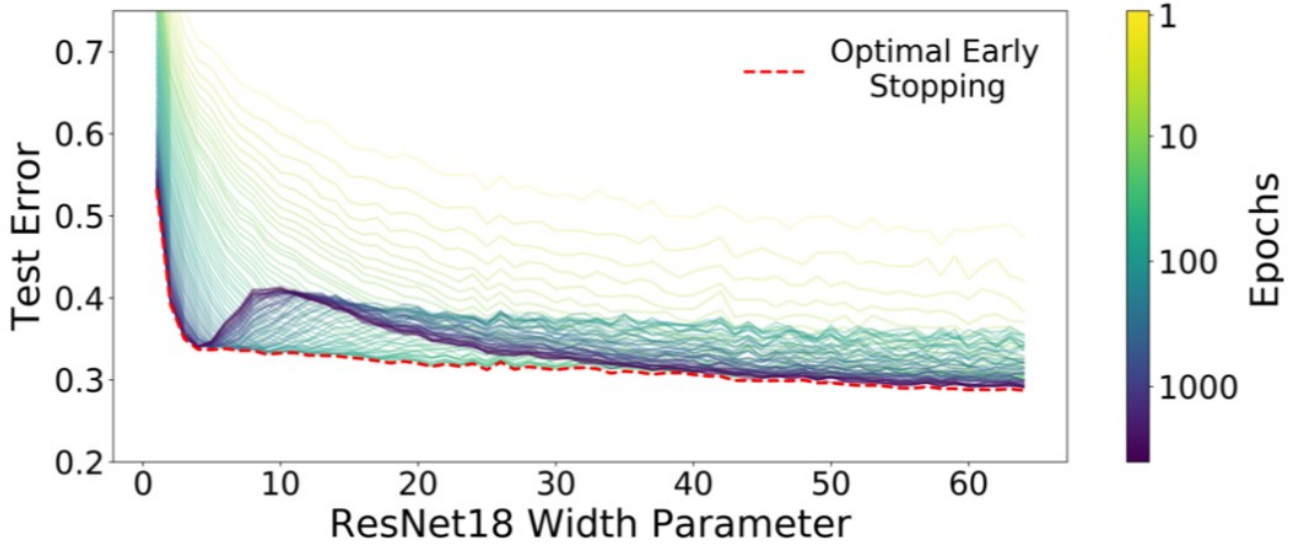
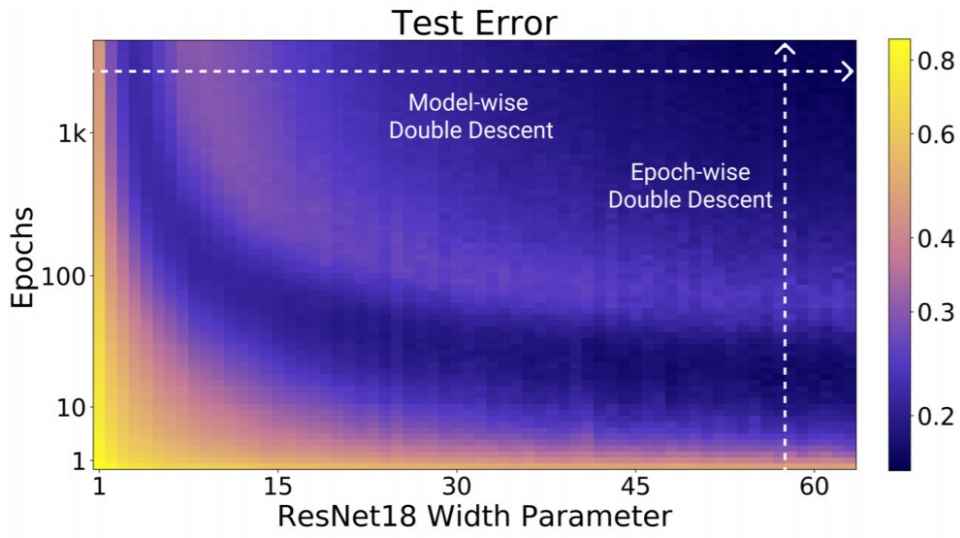
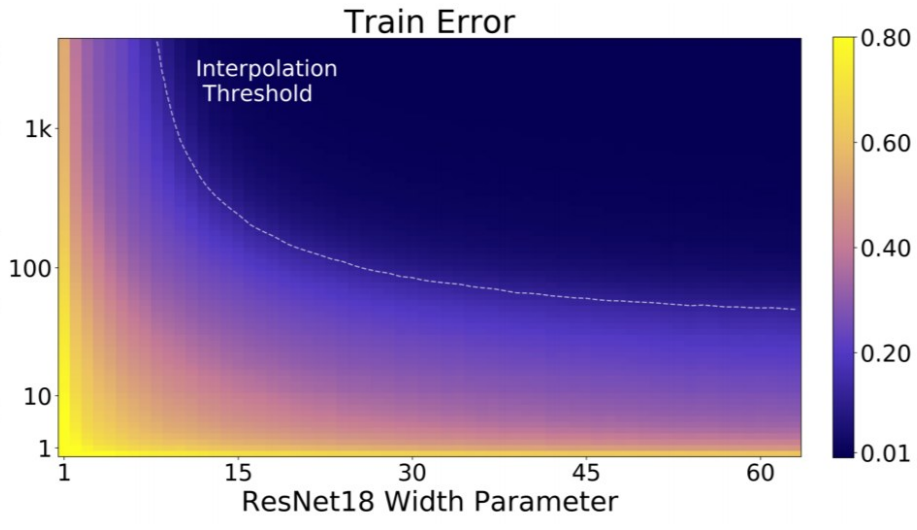
Deep Double Descent

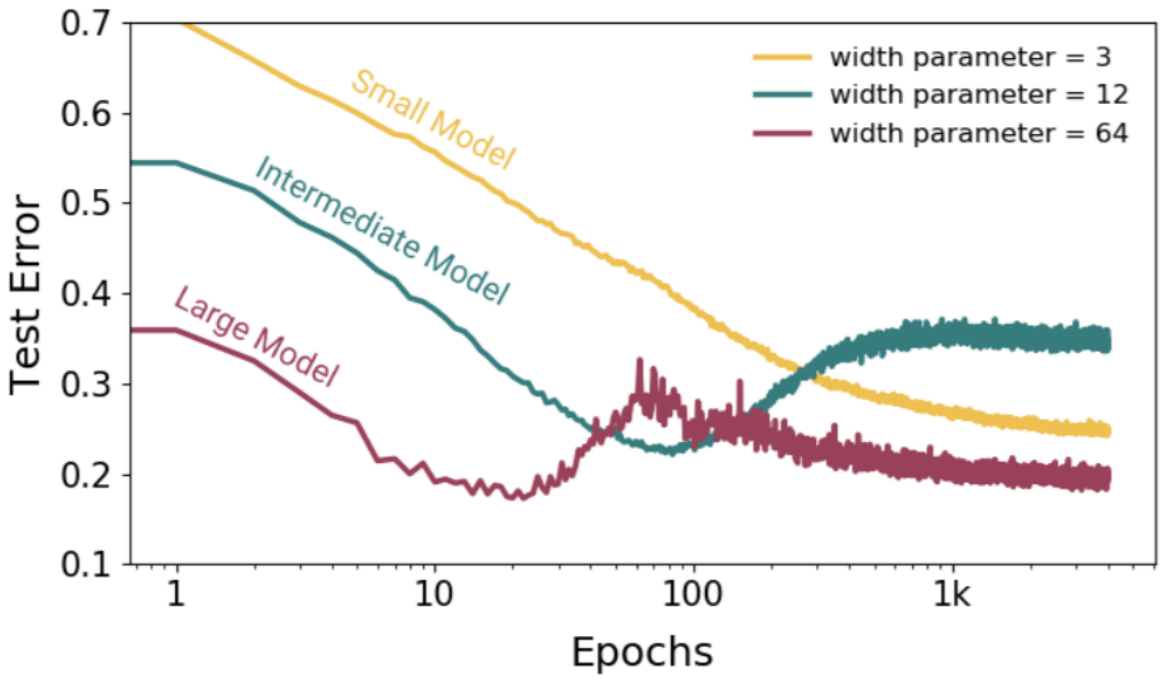


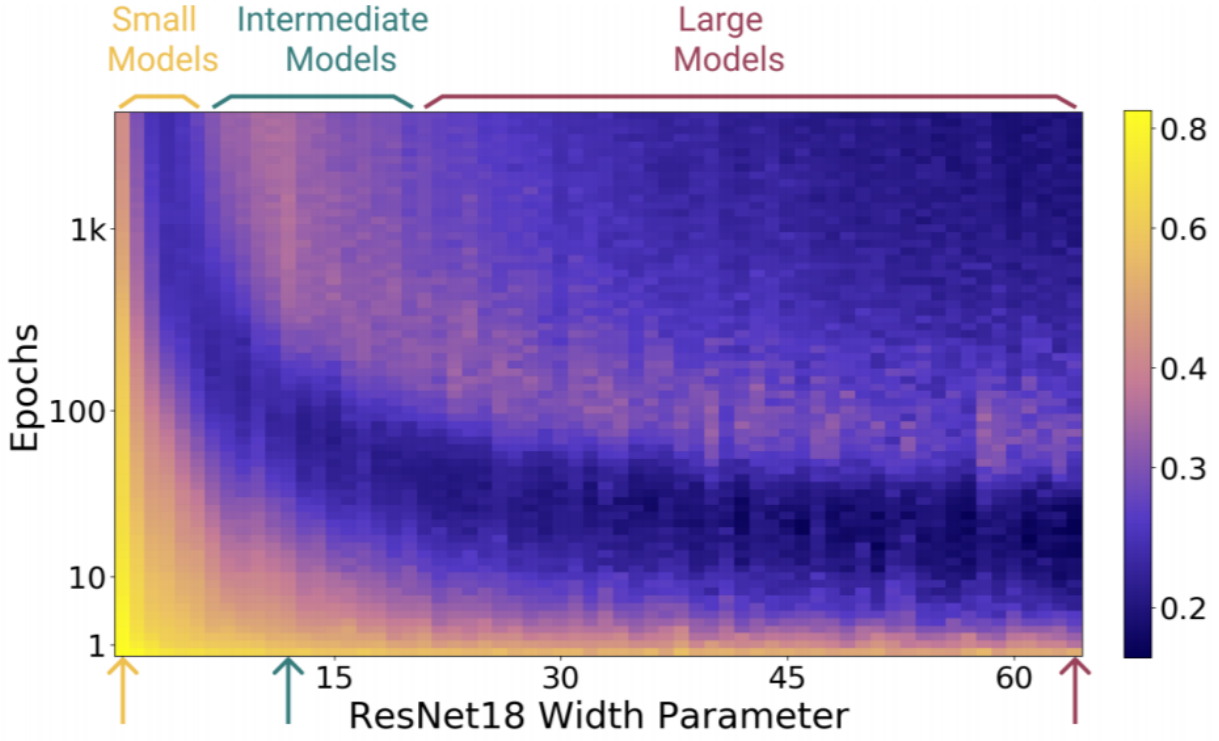




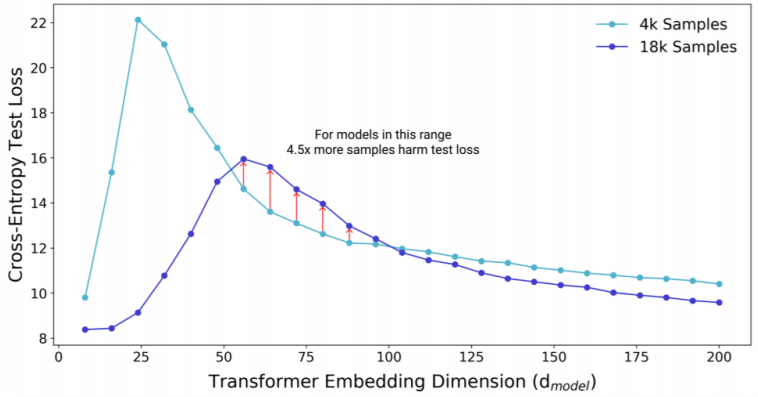


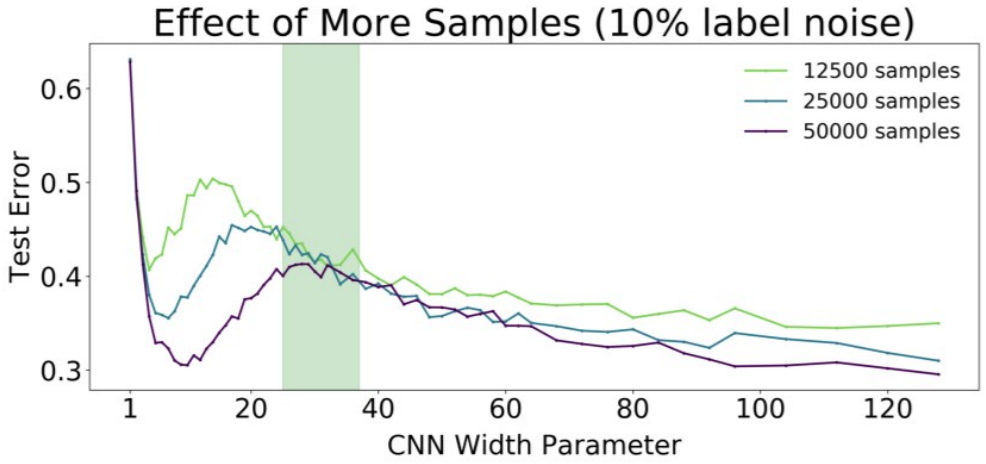
Deep Double Descent

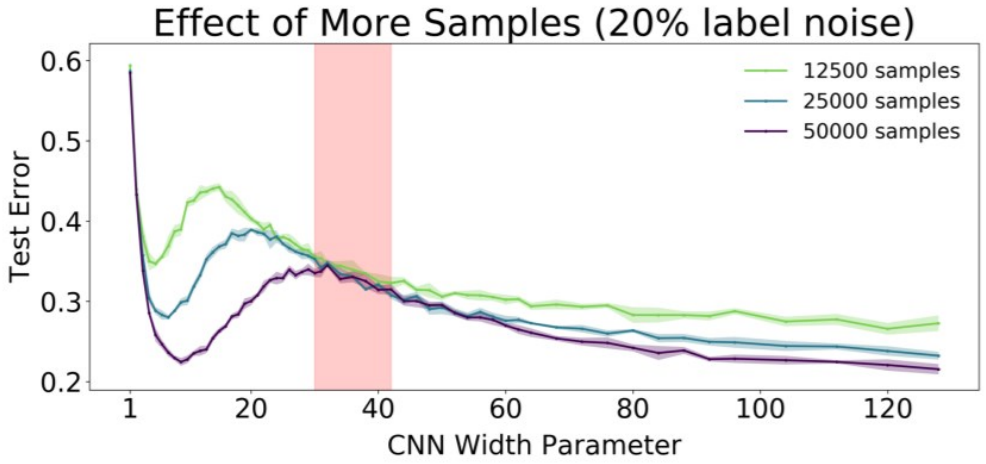


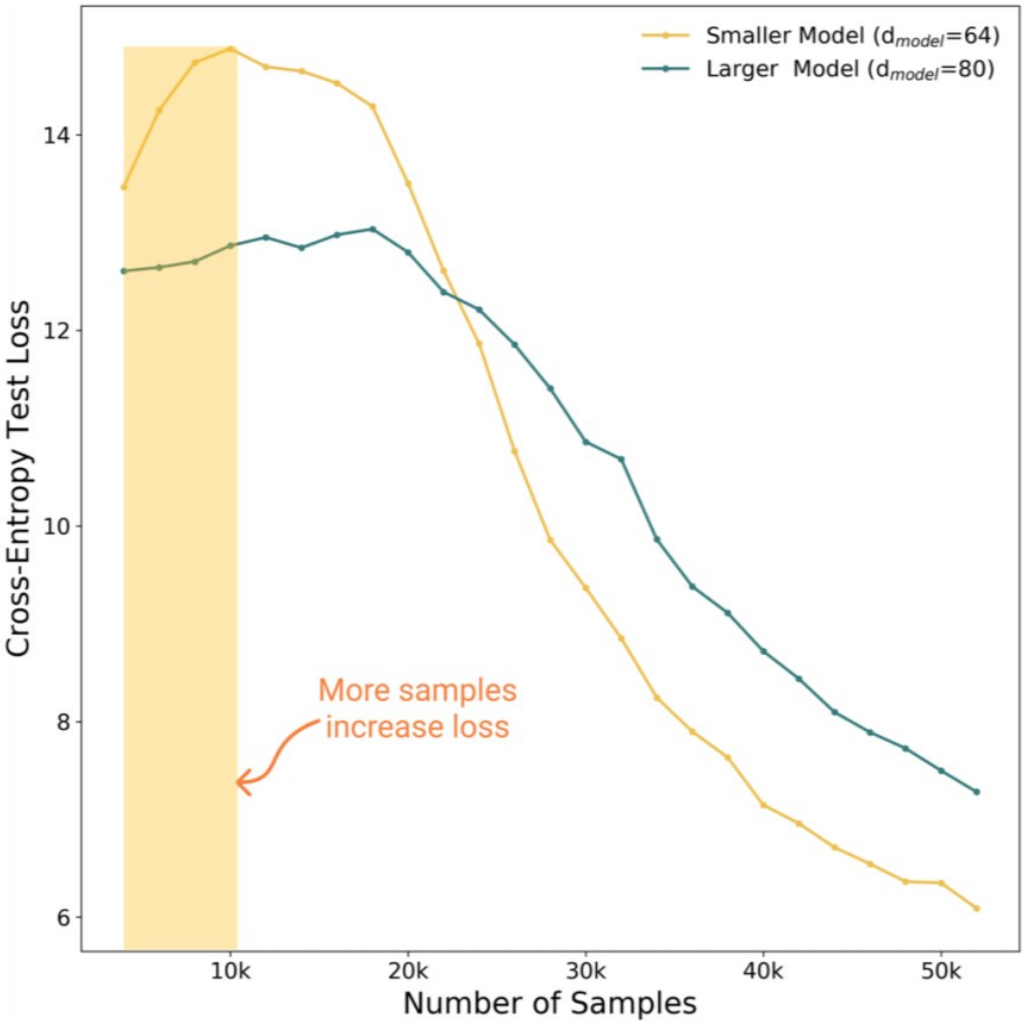


Deep Double Descent



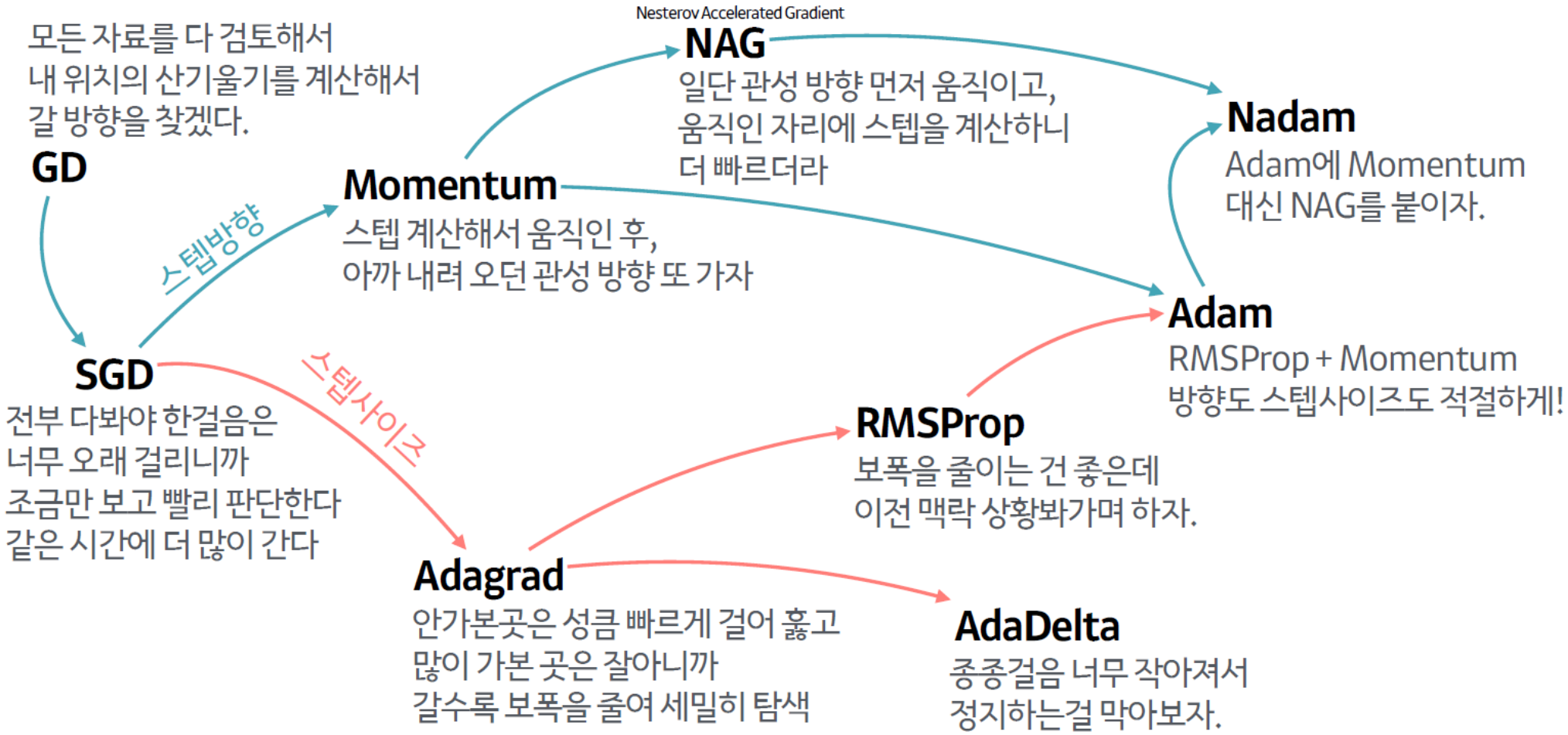






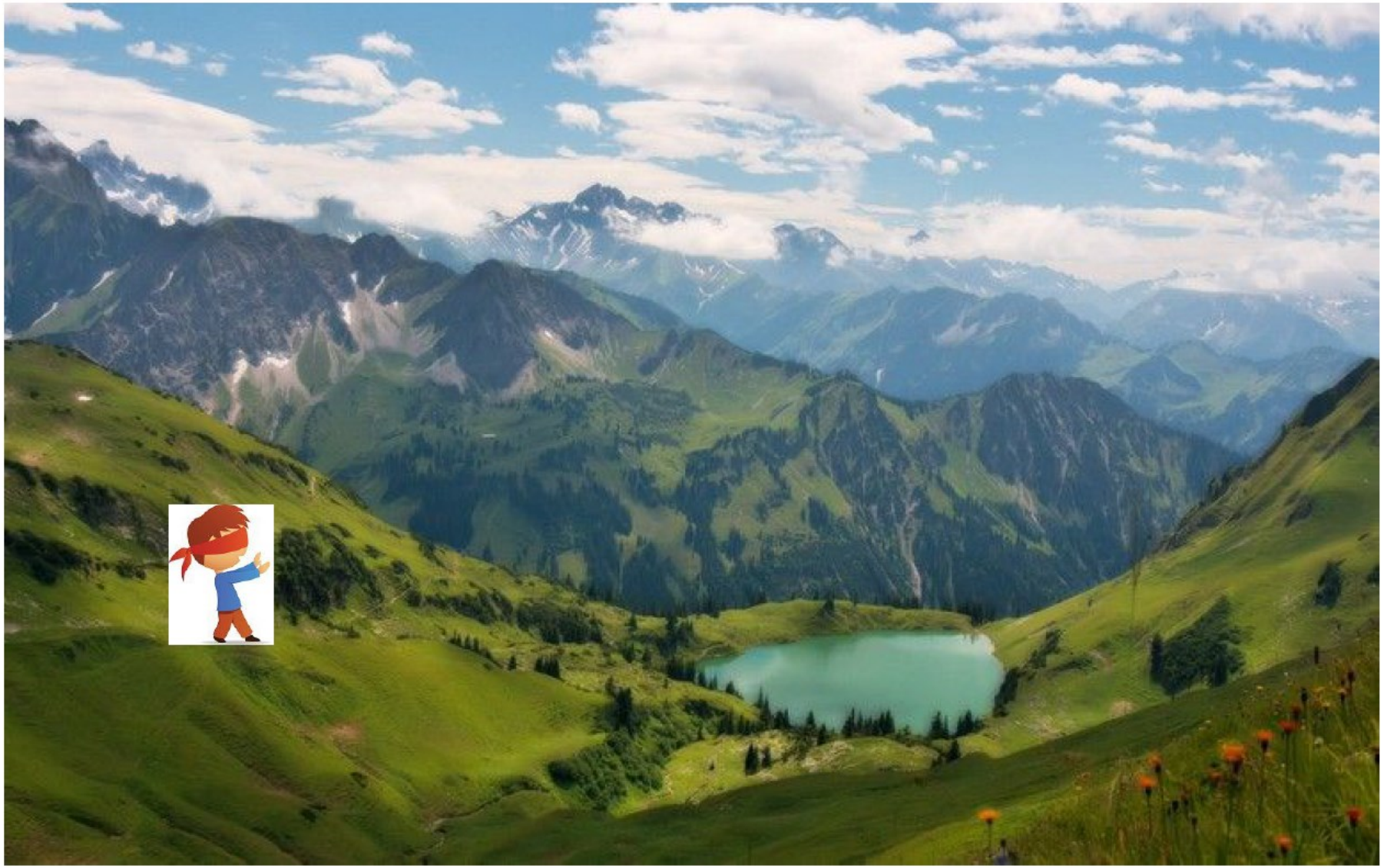
Now we will study

- Optimization Methods



Slide Credit : 하용호@Kakao

Gradient Descent



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Recap : Gradient Descent

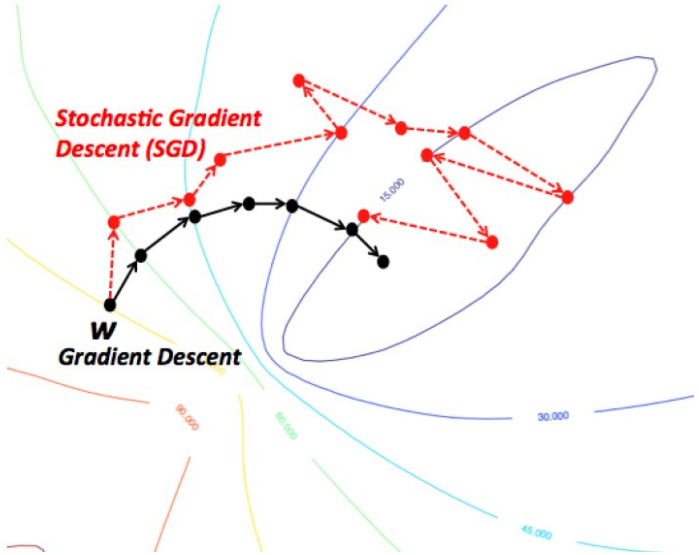
- Batch gradient descent

Previous parameter

Gradient

$$\theta_t = \theta_{t-1} - \eta \cdot \nabla_\theta J(\theta)$$

Learning Rate



- Stochastic gradient descent

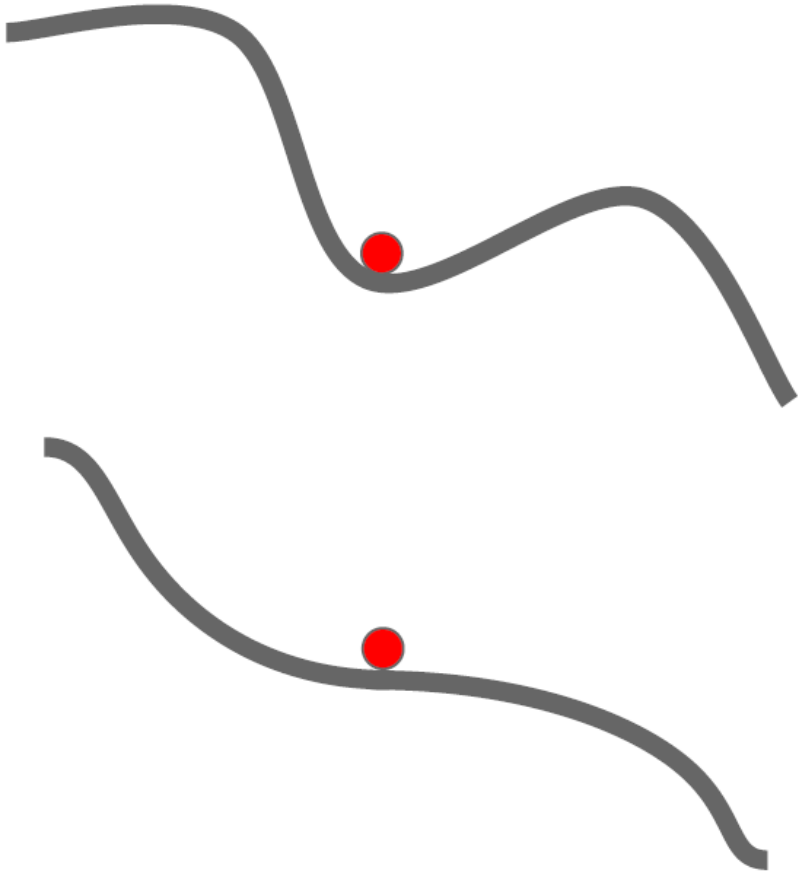
$$\theta_t = \theta_{t-1} - \eta \cdot \nabla_\theta J(\theta; x^{(i)}; y^{(i)})$$

- Mini-batch gradient descent

$$\theta_t = \theta_{t-1} - \eta \cdot \nabla_\theta J(\theta; x^{(i:i+n)}; y^{(i:i+n)})$$

Problems of Gradient Descent

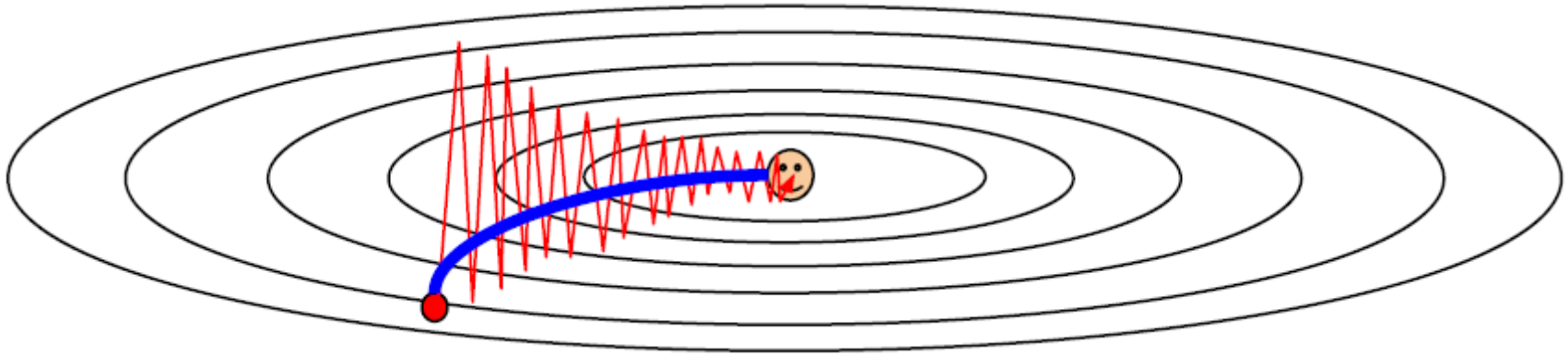
- (It can) stuck at local minima or saddle point(zero gradient)



Picture Credit : Stanford CS231n

Problems of Gradient Descent

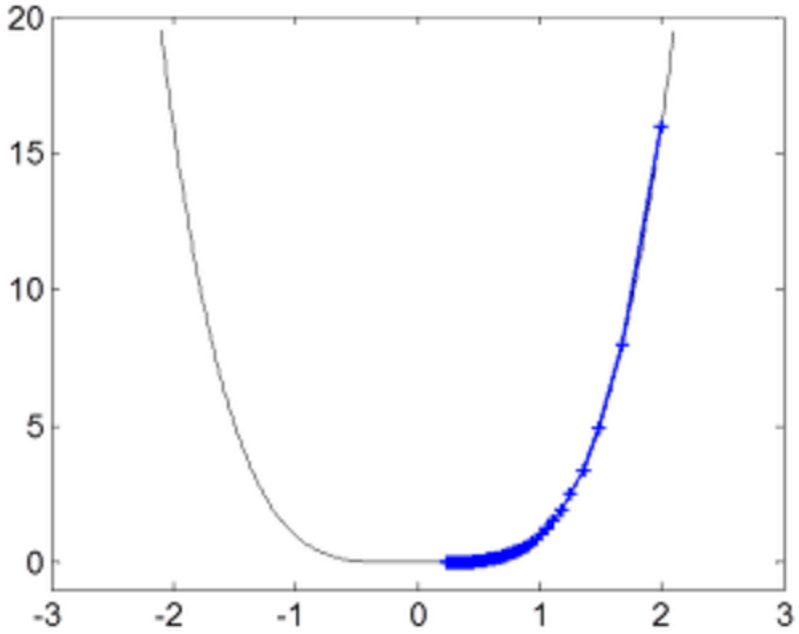
- Poor Conditioning



Picture Credit : Stanford CS231n

Problems of Gradient Descent

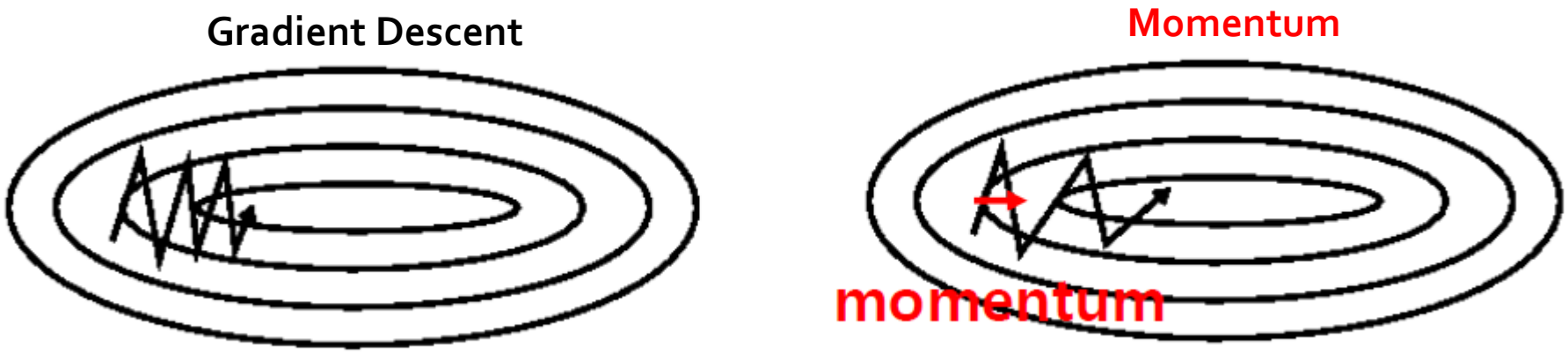
- Slow….
  - The closer to the optimal point, the smaller the gradient becomes.



Momentum

- Let's move with inertia in the direction that we moved earlier.

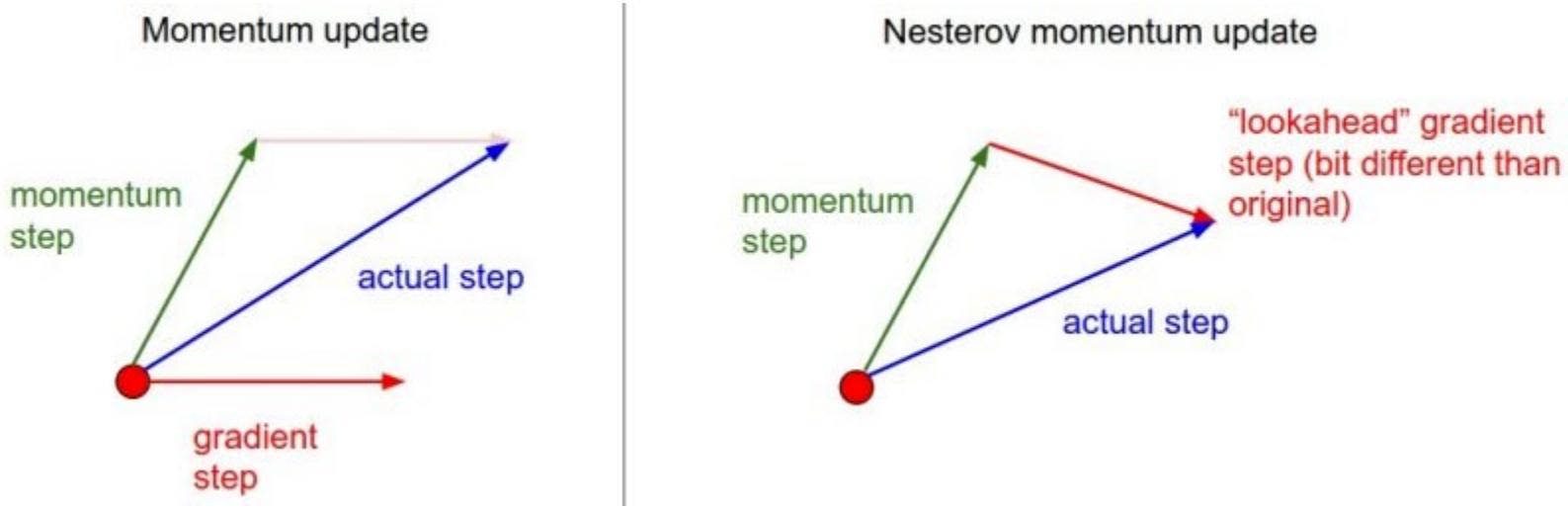
$$v_t = \gamma v_{t-1} + \eta \nabla_\theta J(\theta)$$
$$\theta_t = \theta_{t-1} - v_t$$



NAG(Nesterov Accelerated Gradient)

- Move in the direction we were previously moving, and then calculate the gradient from where we moved.

$$v_t = \gamma v_{t-1} + \eta \nabla_\theta J(\theta - \gamma v_{t-1})$$
$$\theta_t = \theta_{t-1} - v_t$$



Adagrad(Adaptive Gradient)

- It adapts the learning rate to the parameters, performing larger updates for infrequent and smaller updates for frequent parameters.

Element-wise Product

$$G_t = G_{t-1} + (\nabla_\theta J(\theta_t))^2$$

$$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt{G_t + \epsilon}} \cdot \nabla_\theta J(\theta_t)$$

- As the learning continues, the G value continues to increase, so the step size becomes too small to learn

RMSprop

- Use exponentially decaying average of squared gradients

$$G_t = \gamma G_{t-1} + (1-\gamma)(\nabla_\theta J(\theta_t))^2$$

$$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt{G_t + \epsilon}} \cdot \nabla_\theta J(\theta_t)$$

Adam(Adaptive Moment Estimation)

- Adaptive Moment Estimation (Adam) stores both exponentially decaying average of past gradients and squared gradients
- Combination of Momentum and RMSprop
- Compensate the initial momentum biased towards zero

$$m_t = \beta_1 m_{t-1} + (1-\beta_1) g_t$$

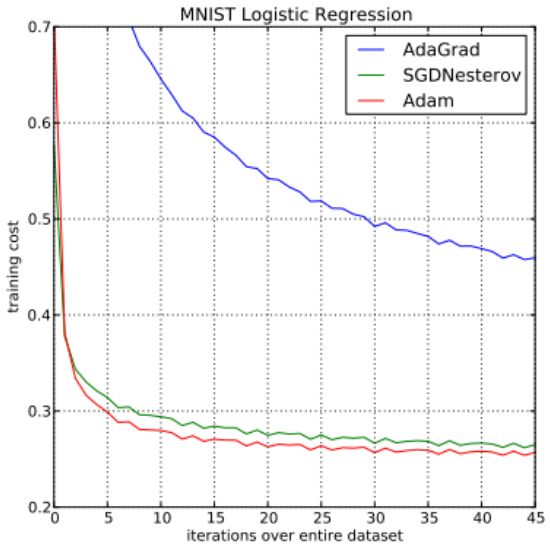
$$v_t = \beta_2 v_{t-1} + (1-\beta_2) g_t^2$$

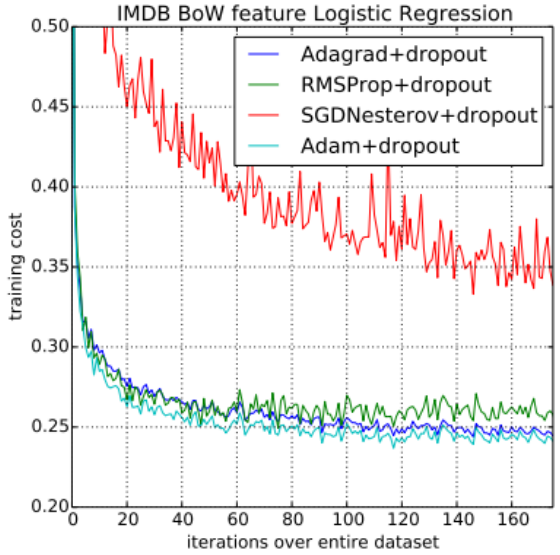
$$\widehat{m_t} = {}^{m_t}/_{1-\beta_1^t} \quad \widehat{v_t} = {}^{v_t}/_{1-\beta_2^t}$$

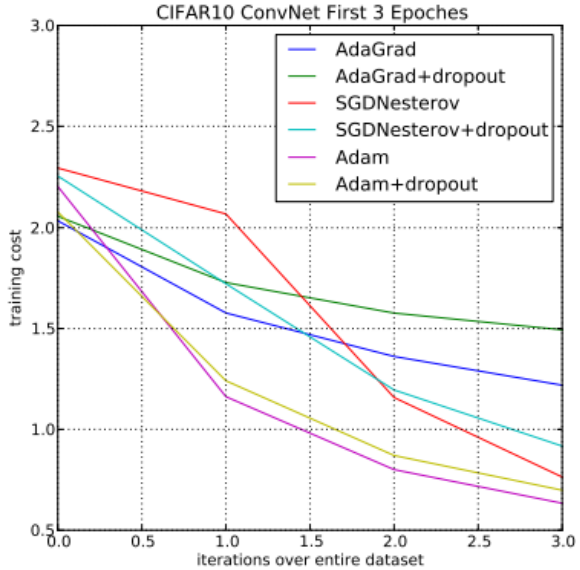
$$\theta_t = \theta_{t-1} - \frac{\eta}{\sqrt{\widehat{v_t}} + \epsilon} \widehat{m_t}$$

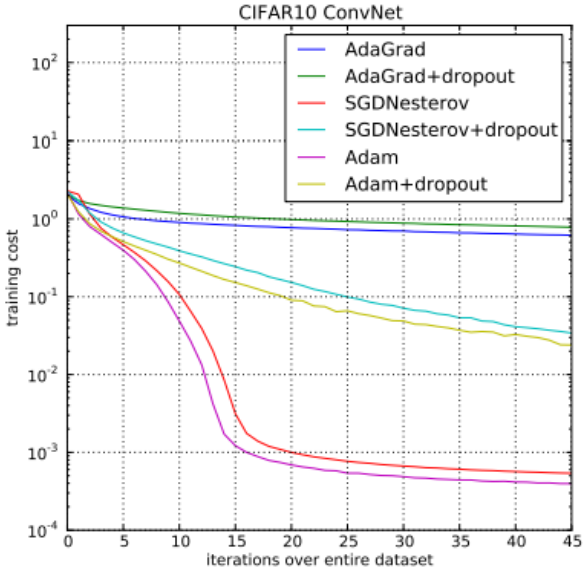
Adam

- Adam is a very popular method

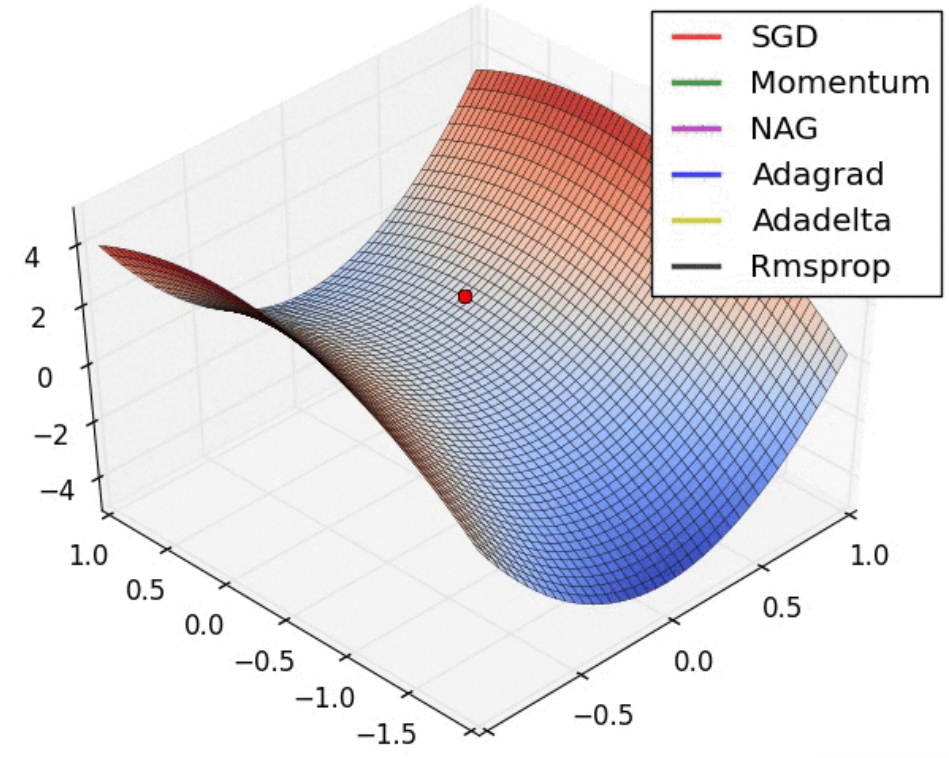


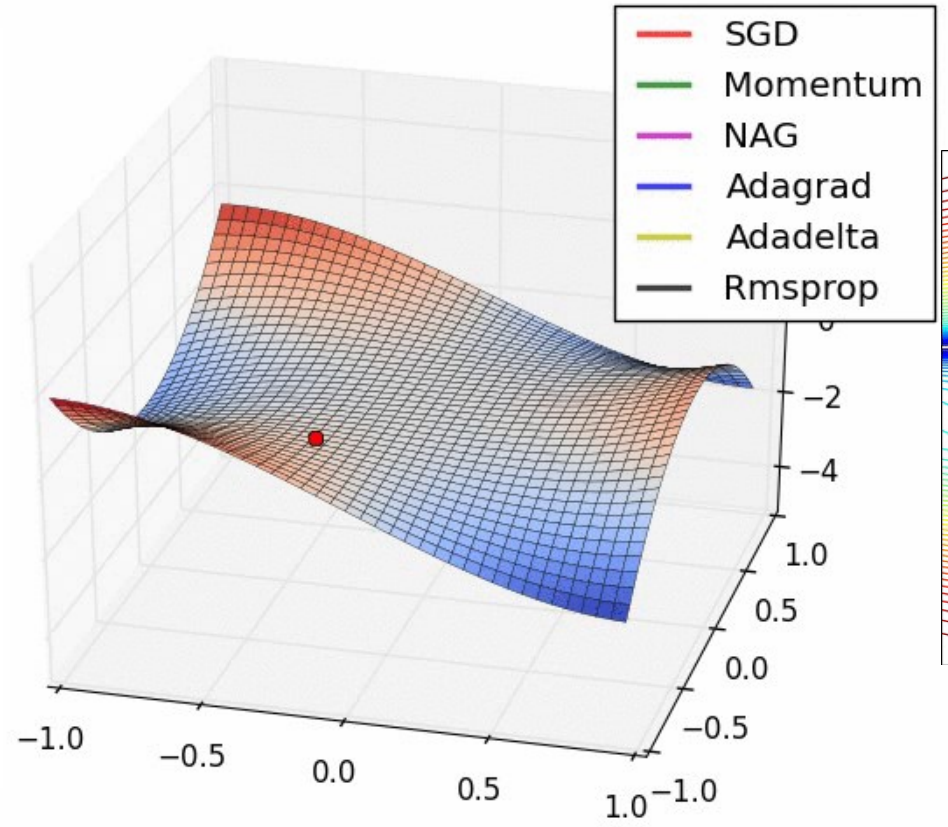


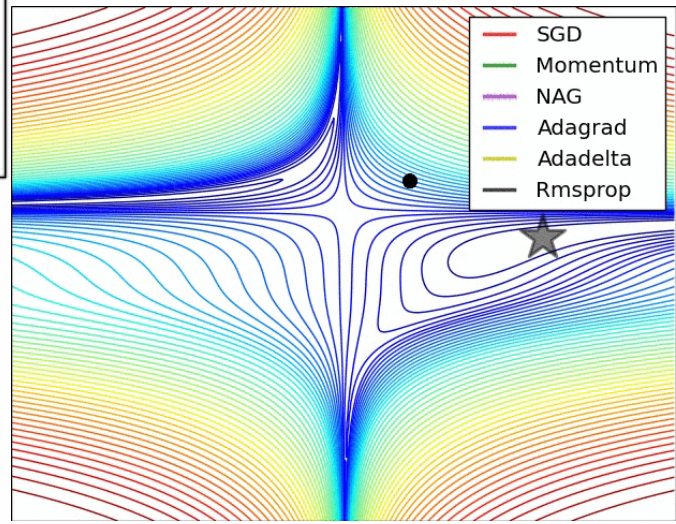




Optimization Methods

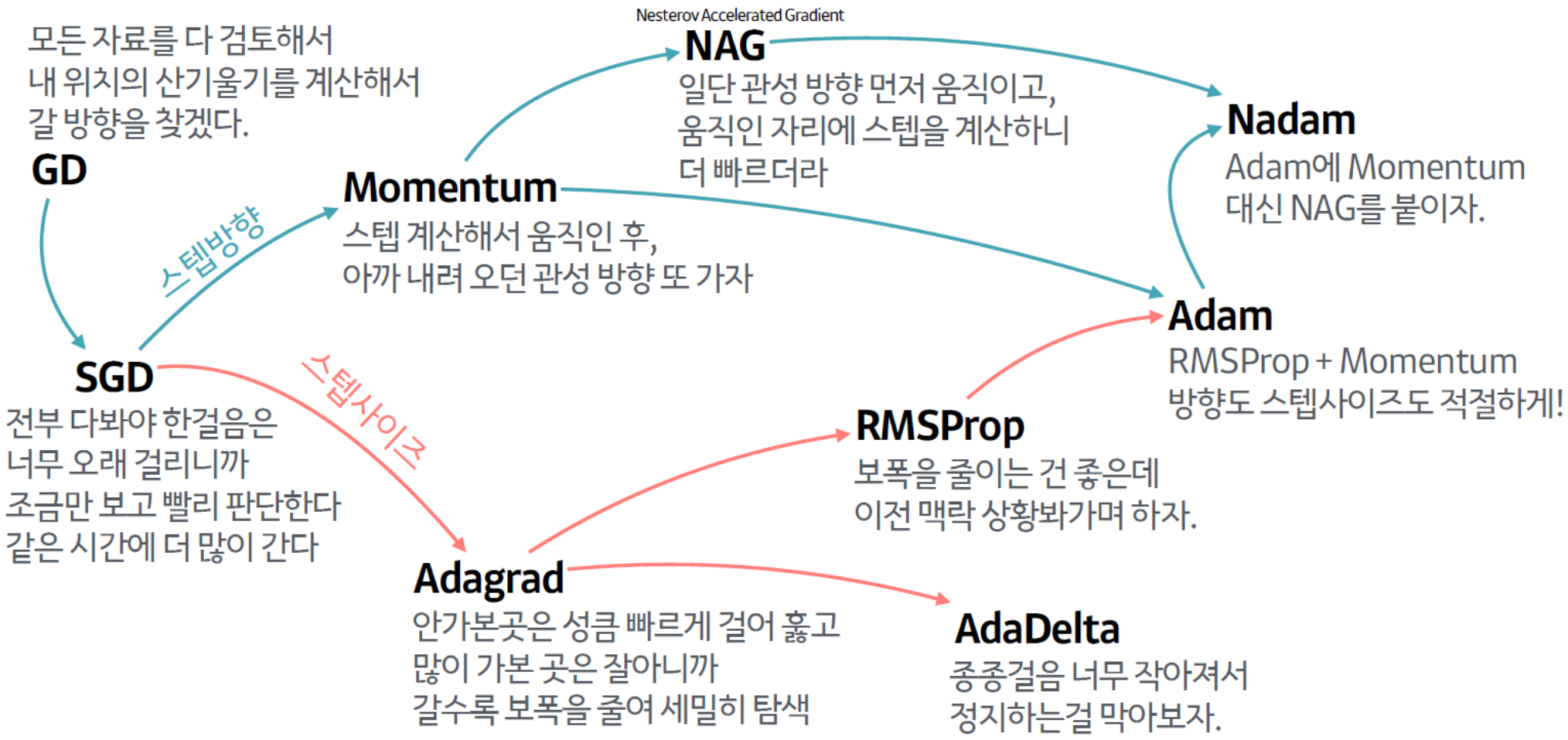






We Studied

- Optimization Methods



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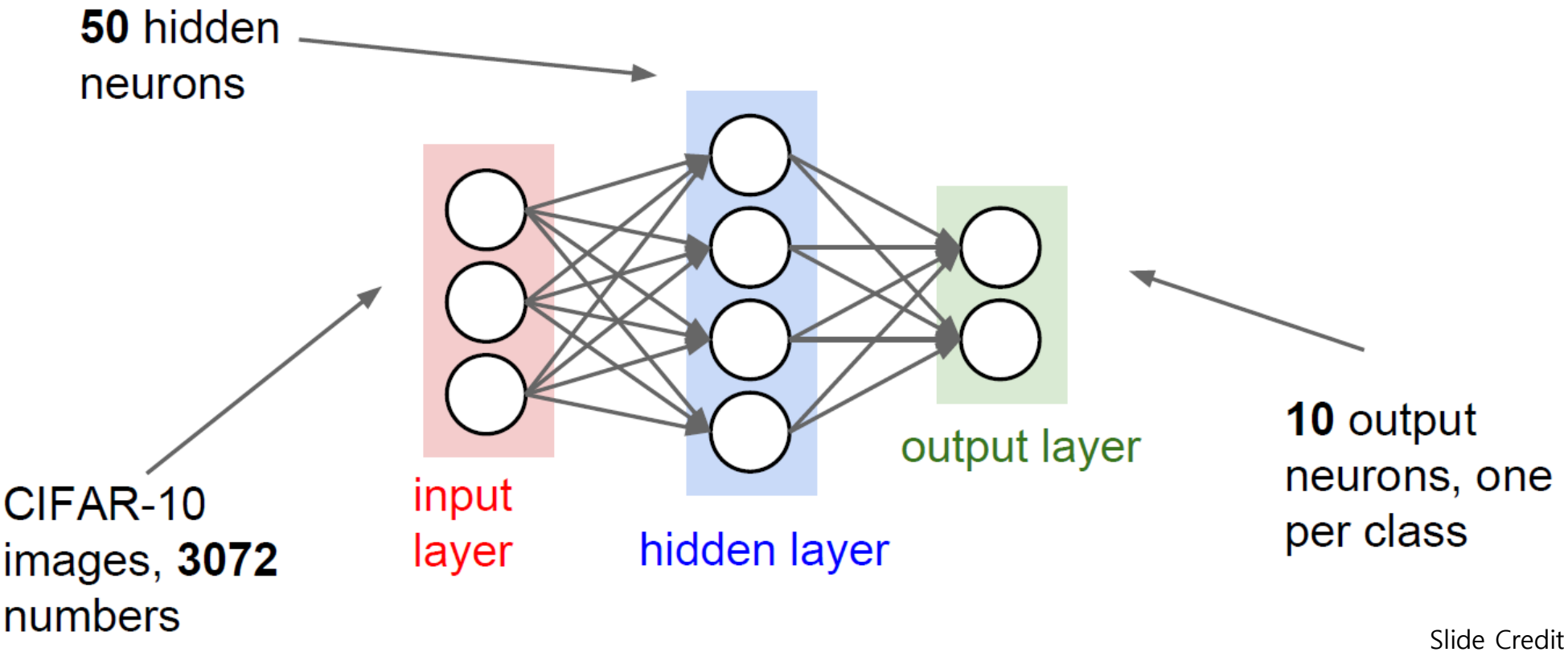
Babysitting the Learning Process

1. Preprocess the data
2. Choose the architecture
   - How many layers? How many hidden neurons? …



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Babysitting the Learning Process

3. Double check that the loss is reasonable
   - Initial loss must be about –log(1/n) w/o regularization loss
   - w/ regularization loss, loss must increase

4. Let's try to train now → make sure that you can overfit very small portion of the training data
   - Take the small examples(e.g. 20) from training set
   - Turn off regularization
   - Use simple vanilla SGD

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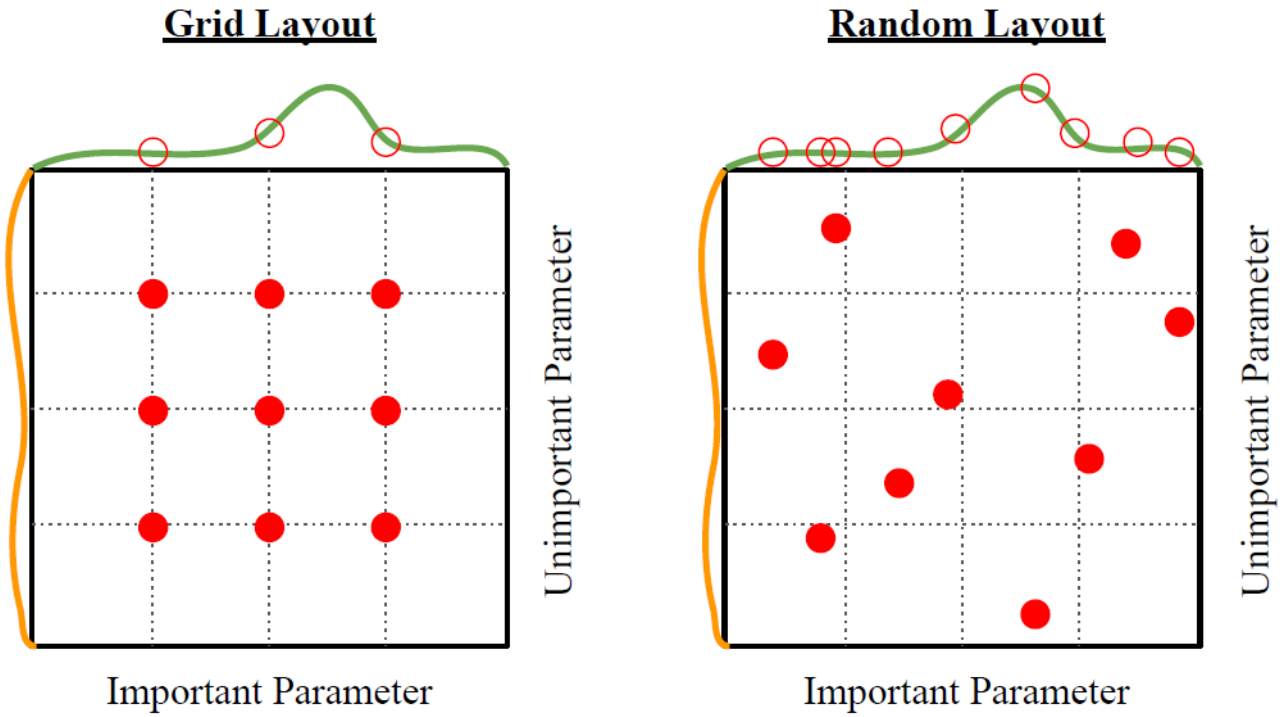
Babysitting the Learning Process

5. Search a good hyper-parameter(cross-validation strategy)

- First stage : only a few epochs to get rough idea of what params work
- Second stage : longer running time, finer search
- Random Search vs Grid Search → Use Random Search!



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Hyper-parameter Tuning

Your input : Hyper parameters

- Architecture (#layers, #kernels, stride, kernel size)
- Learning rate, optimizer (momentum)
- Regularizations (weight decay rate, dropout probability)
- Batchnorm / no batchnorm

Your output: Some diagnostic statistics:

- Loss curves
- Gradient norms
- Accuracy / Visual output (generative models)
- Performance on training vs validation set
- Other abnormal behaviors

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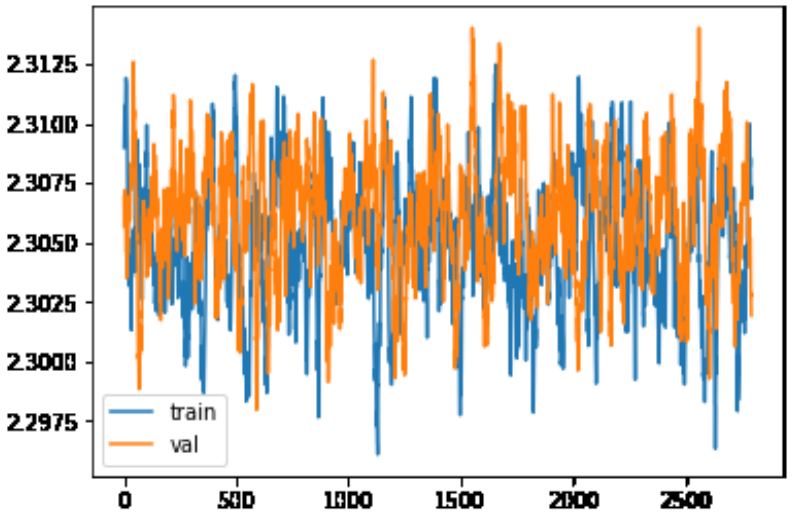
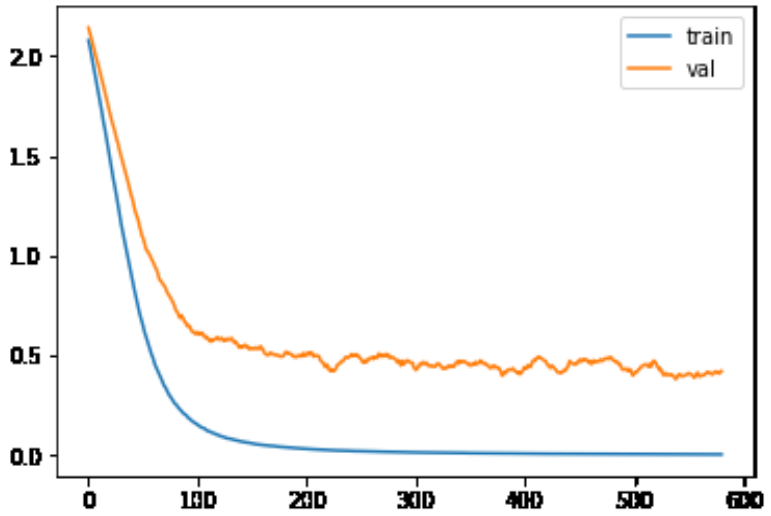
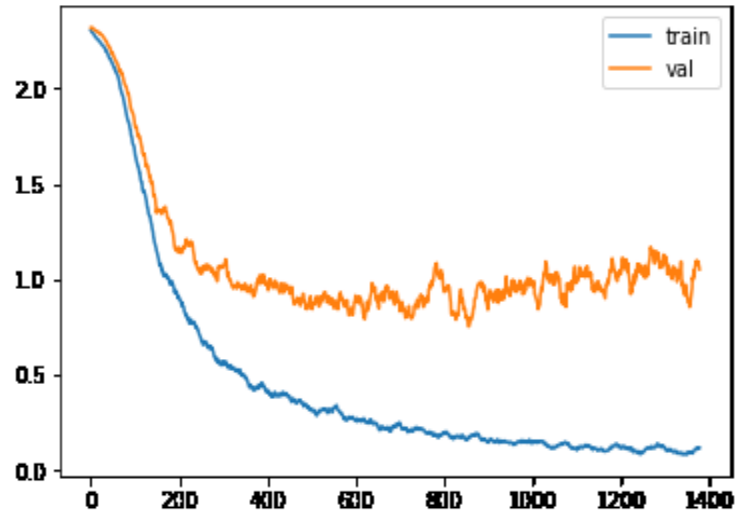
Loss Curves : What are the Problems?



Not learning: gradients not applied to weights



Overfit: model too large/dataset too small



More extreme case of overfitting

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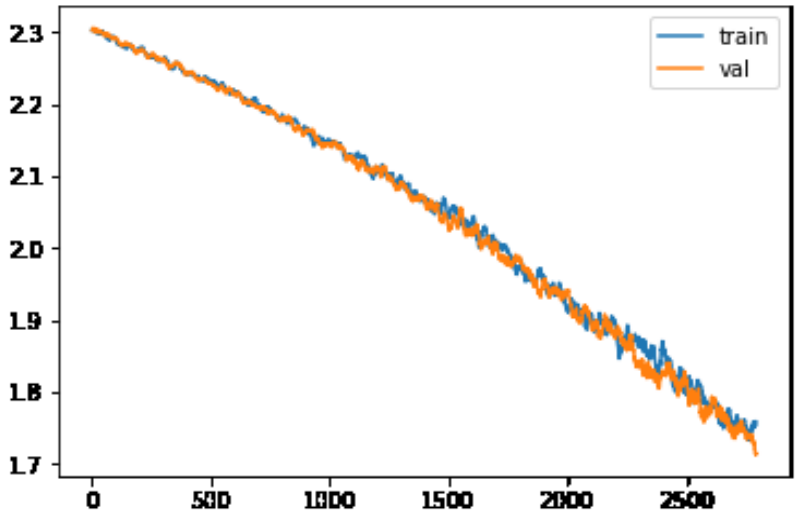
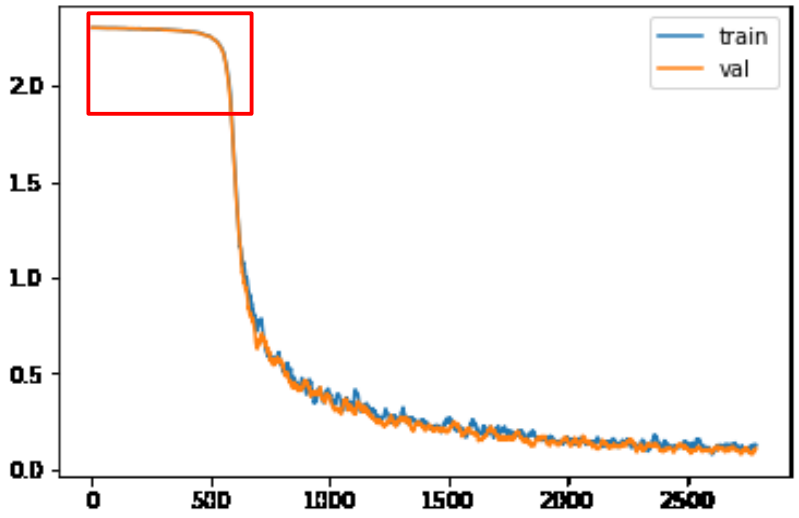
Loss Curves : What are the Problems?

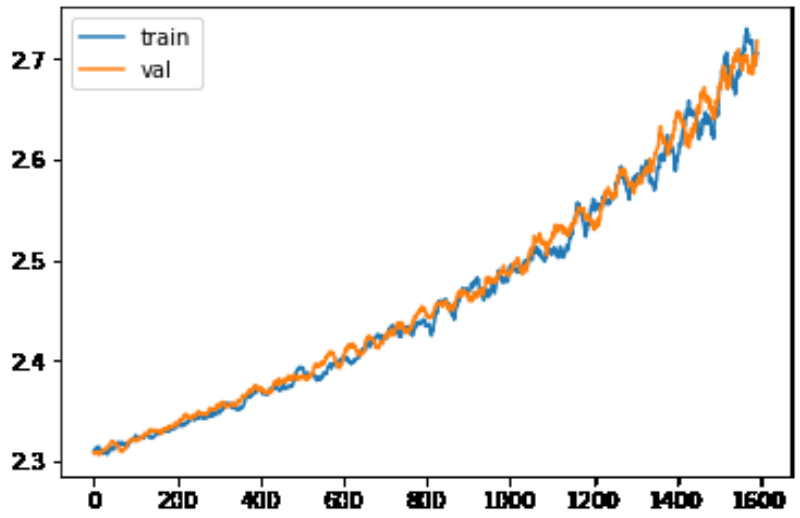


Not converged yet: need longer training

slow start



Slow start: initialization weights too small



Applied the negative of gradients

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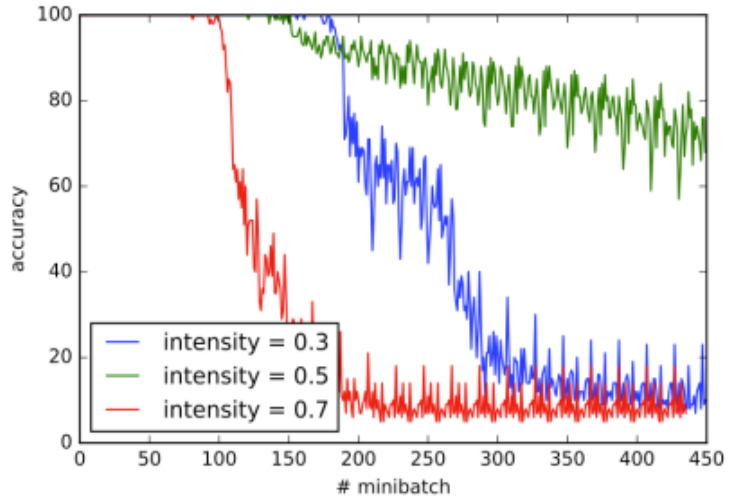
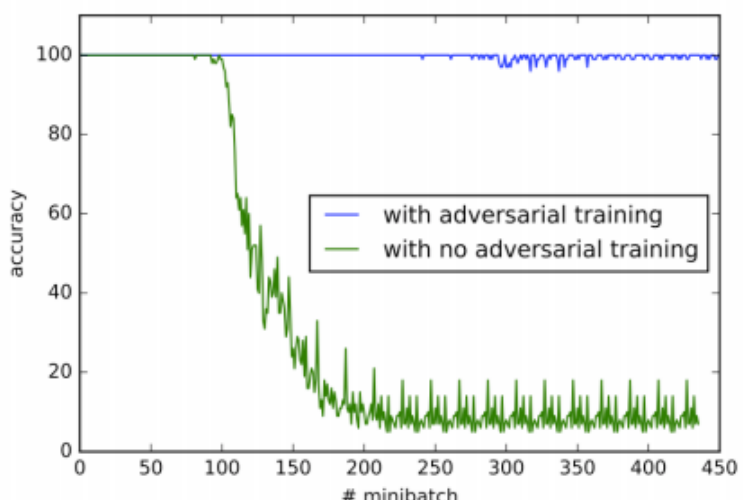
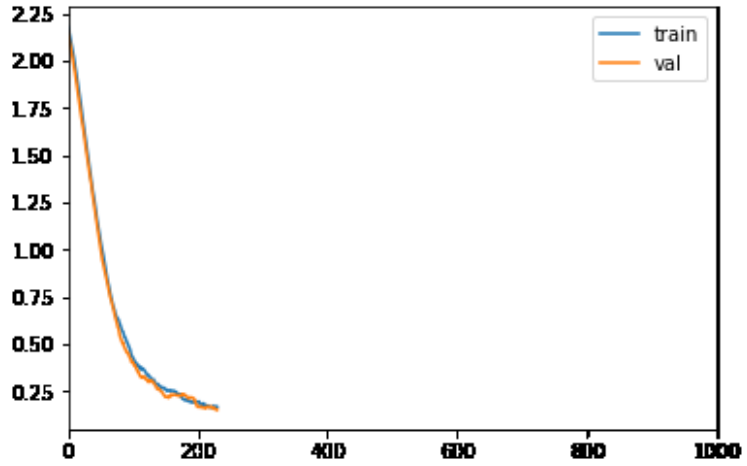
Loss Curves : What are the Problems?

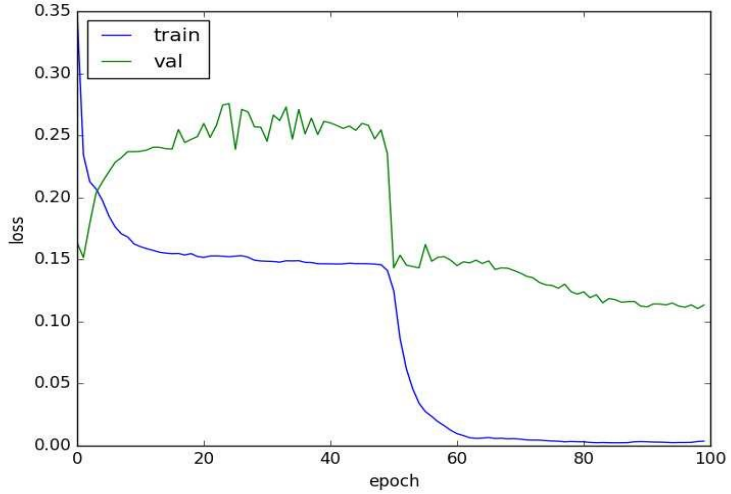




Problem: Not shuffling data, periodical patterns in loss curve



Get nans in the loss after a number of iterations: caused by numerical instability in models



Problem: val set too small, statistics not meaningful

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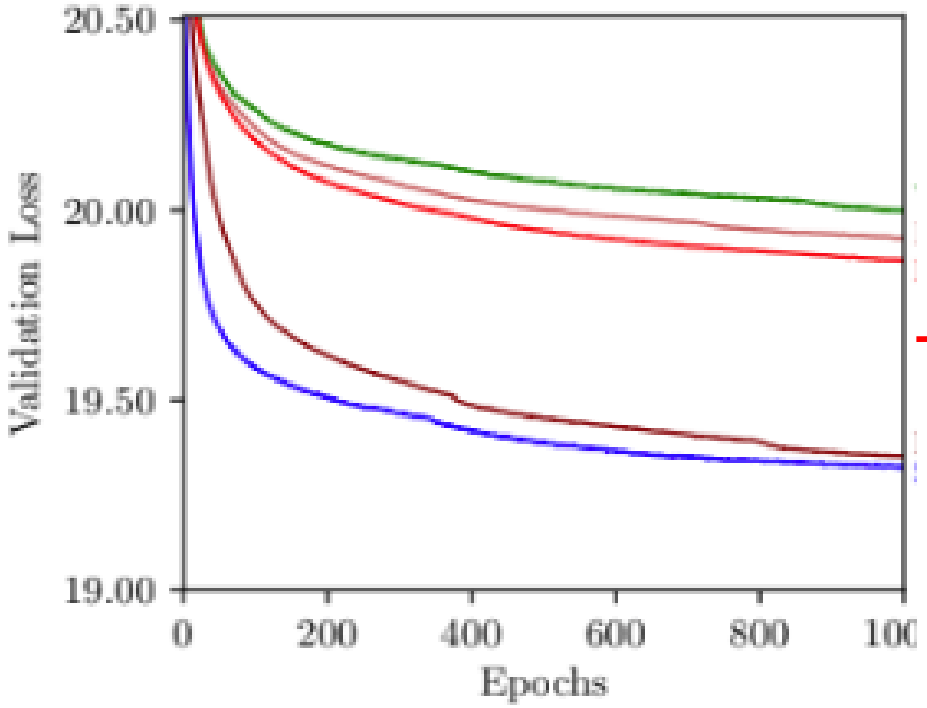
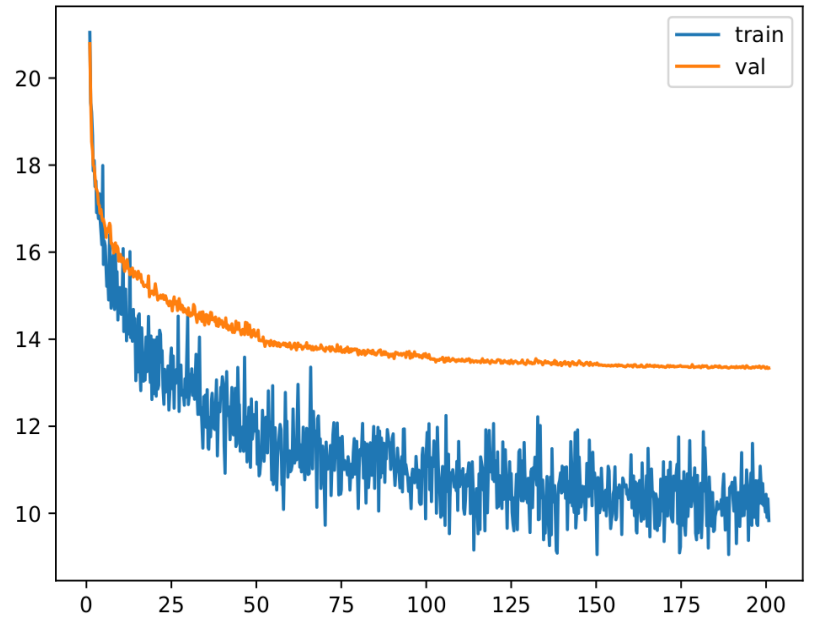
Loss Curves : What are the Problems?





Problem: applied nonlinear activation before softmax

Make sure to optimize correct loss

$$\sigma(z)_j = \frac{e^{z_j}}{\sum_{k=1}^{k} e^{z_k}} \; for \; j = 1, \ldots, k$$

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