Machine Learning for Image Analysis

Lecture 4: Convolutional Neural Networks: Training

Dagmar Kainmueller, 07.05.2024

Course Outline

- Introduction to Image Analysis
- Basics: Neural Networks
- **Convolutional Neural Networks**
- Transformers
- Model Interpretability
- Self-supervised Learning
- Generative Models (GANs, Diffusion)

Convolutional Neural Networks (CNNs)

- A bit of CNN history
- CNN Layers
    - Convolutions, Pooling, Fully Connected Layers, Normalization
- Training CNNs
    - Advanced Optimization
    - Weight initialization
    - Regularization: Dropout
    - Extended training data: Augmentation, Transfer Learning
    - Sanity-checking the learning process; Hyperparameter tuning strategies
- Famous CNN architectures
- CNNs for image segmentation

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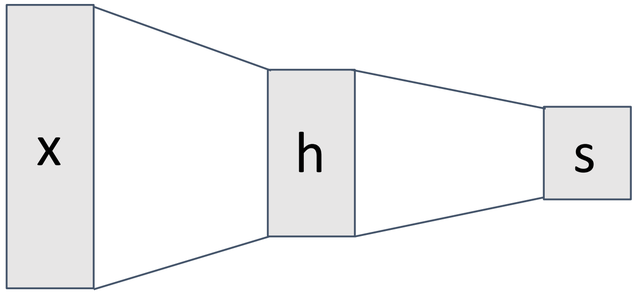
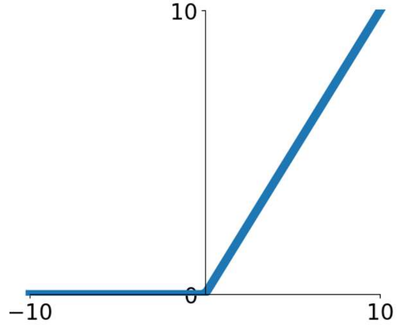
Recap: Convolutional Networks

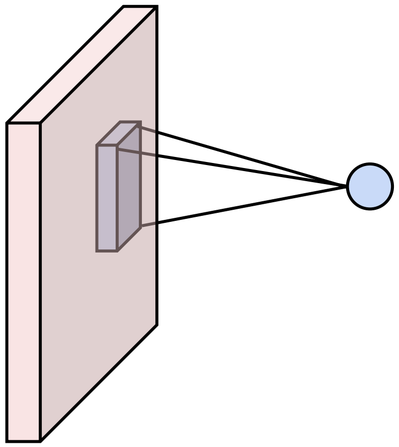
Fully-Connected Layers



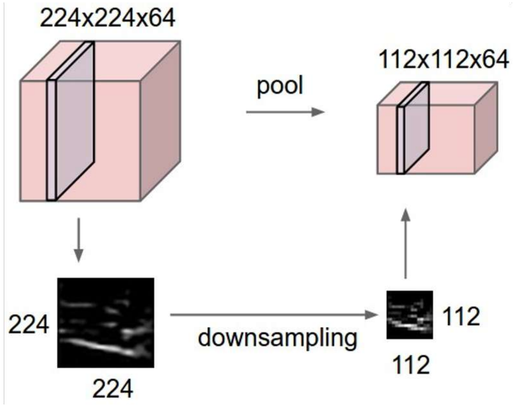
Activation Function



Convolution Layers



Pooling Layers



Normalization

$$\hat{x}_{i,j} = \frac{x_{i,j} - \mu_j}{\sqrt{\sigma_j^2 + \varepsilon}}$$

Credit: Justin Johnson, U Michigan, Deep Learning for Computer Vision 2019

Convolution Layer: Summary

➡ Accepts an input of dimension $width_{input} \times height_{input} \times depth_{input}$

➡ Four hyper-parameters:

- Number of filters K
- Filter spatial extent F
- Stride S
- Padding P

➡ Produces of output of dimension $width_{output} \times height_{output} \times depth_{output}$ where

- $width_{output} = (width_{input} - F + 2P)/S + 1$
- $height_{output} = (height_{input} - F + 2P)/S + 1$
- $depth_{output} = K$

Convolution Layer: Summary

➡ $F \times F \times depth_{input}$ weights and 1 bias per filter

➡ Total of $(F \times F \times depth_{input}) \times K$ weights and K biases

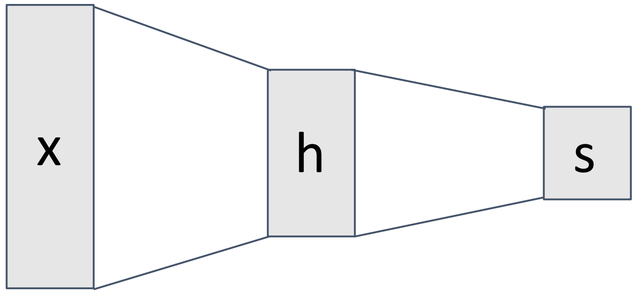
➡ In the output, the nth slice (of size $width_{output} \times height_{output}$) results from convolution of the input with nth filter with stride S and then offset by the nth bias.

➡ Note: usually K = (powers of 2, e.g: 32,64,128,256) “just to be nice”

- F = 3, S = 1, P = 1
- F = 5, S = 1, P = 2
- F = 5, S = 2, P = whatever fits
- F = 1, S = 1, P = 0

Components of Convolutional Networks

Fully-Connected Layers



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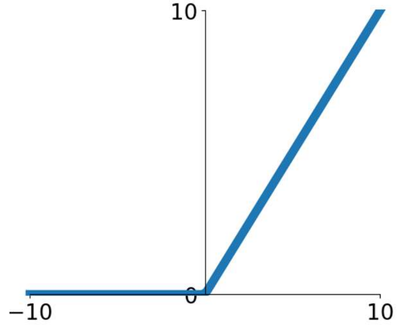

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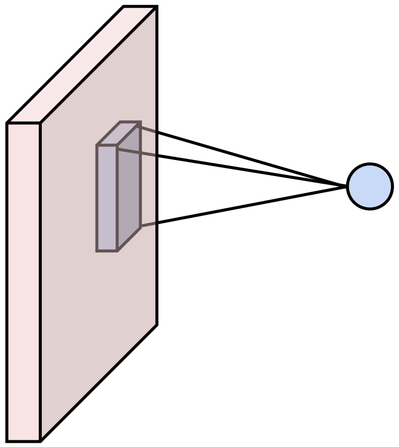
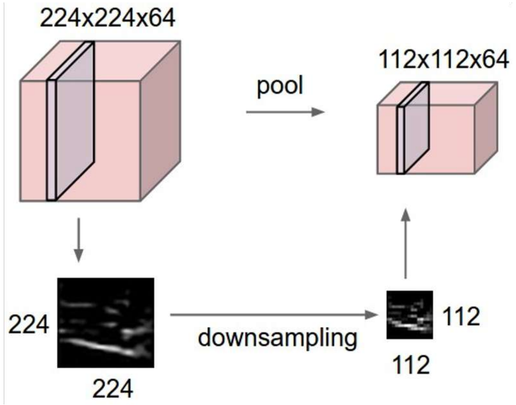


Pooling Layers



Normalization

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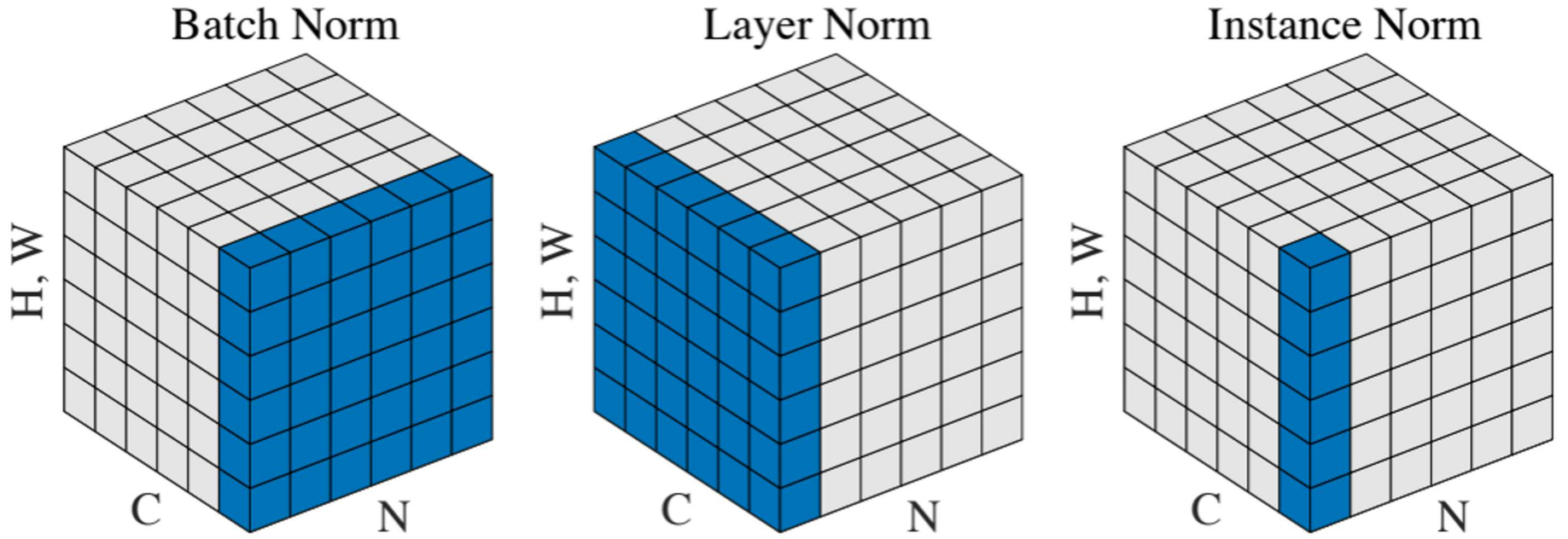
Comparison of Normalization Layers



Wu and He, “Group Normalization”, ECCV 2018

Instance Normalization

Batch Normalization for convolutional networks

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

Normalize

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

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

$$y = \frac{(x - \mu)}{\sigma}\gamma + \beta$$

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Normalize

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

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$$y = \frac{(x - \mu)}{\sigma}\gamma + \beta$$

Convolutional Neural Networks: Summary

- CNNs stack conv-, pooling-, fully connected layers, and normalization
- What is the right way to combine these components?
- Classical classification architectures look like:

  [(conv,ReLU)*N, Pool]*M, (FC,ReLU)*K, Softmax

  Typical M ∈ {5, …, 50}, N ∈ {2, 3}, and K ∈ {0, 1, 2}

- Batch-, Layer- or InstanceNorm after conv or FC for faster convergence

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Advanced Optimization

Stochastic Gradient Descent

Momentum

Adam

Which of the following about SGD are true? Check all that apply

- When the training set size m is very large, SGD can be much faster than gradient descent
- The cost function $J_{train}(\theta) = \frac{1}{2m}\sum_{i=q}^{m}(h_\theta(x^{(i)} - y^{(i)})^2$ should go down with every iteration of batch gradient descent (assuming appropriate α) but not necessarily with SGD
- SGD is applicable only to linear regression but not to other models (like logistic regression or neural networks)
- Before beginning the main loop of SGD, it is a good idea to “shuffle” your training data into a random order.

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Mini-batch Gradient Descent

Batch gradient descent: Use all *m* examples in each iteration
Stochastic gradient descent: Use 1 example in each iteration
Mini-batch gradient descent: Use b examples in each iteration

b = mini-batch size e.g., b= 10

$$\theta_j := \theta_j - \alpha \frac{1}{b} \sum_{i=k \cdot b}^{(k+1) \cdot b - 1} (h_\theta(x^{(i)}) - y^{(i)}) x_j^{(i)}$$

vectorized computation, parallelize

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- Suppose you use mini-batch gradient descent on a training set of size m, and you use a mini-batch size of B. The algorithm becomes the same as batch gradient descent if:

  - B = 1
  - B = m/2
  - B = m
  - NOTA

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Stochastic gradient descent convergence

How to set the learning rate?

Batch gradient descent:

Plot loss as a function of the number of gradient steps

Stochastic gradient descent:

Compute loss contribution of current sample in each gradient step

Every 100 iterations, plot losses averaged over the last 100 samples

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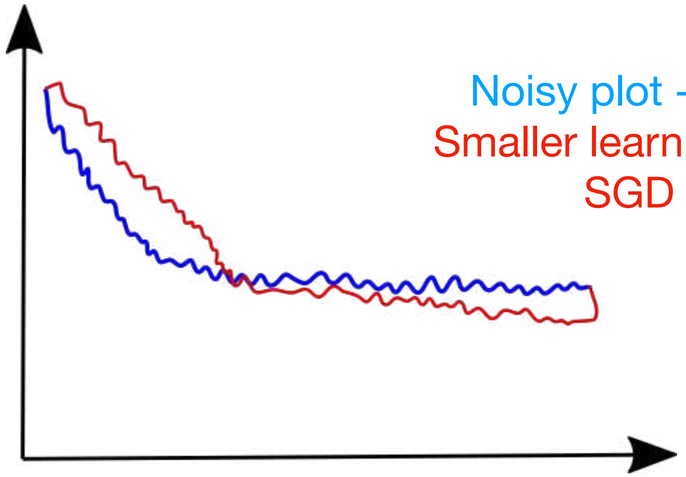
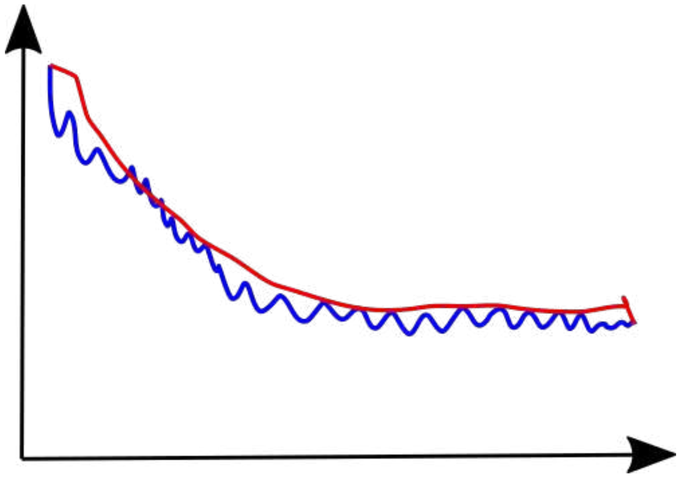
Checking for convergence

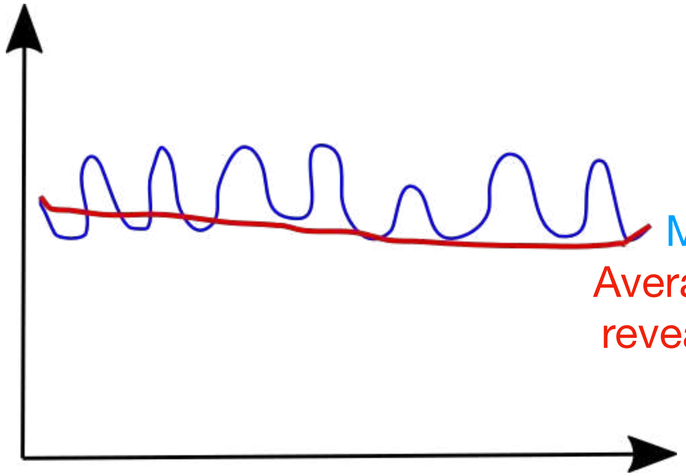
Plot loss averaged over last (e.g.) 1000 samples



Noisy plot - cost is going down
Smaller learning rate -learns slowly
SGD oscillates less

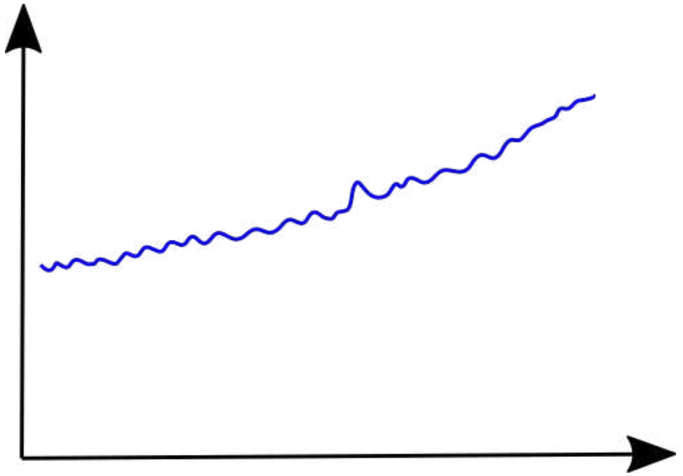
Smoother curve by averaging over more samples





Model is not learning?
Averaging over more samples reveals that cost going down

Diverging model
Decrease learning rate



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Which of the following about SGD are true? Check all that apply

- Picking a learning rate α that is very small has no disadvantage and can only speed up learning
- If we reduce the learning rate α (and run SGD), its possible that we may find a set of better parameters than with larger α
- If we want SGD to converge to a (local) minimum rather than wander or "oscillate" around it, we should slowly increase α over time.
- If we plot $cost(\theta, (x^{(i)}, y^{(i)}))$ (averaged over the last 1000 examples) and SGD does not seem to be reducing the cost, one possible problem may be that the learning rate α is poorly tuned

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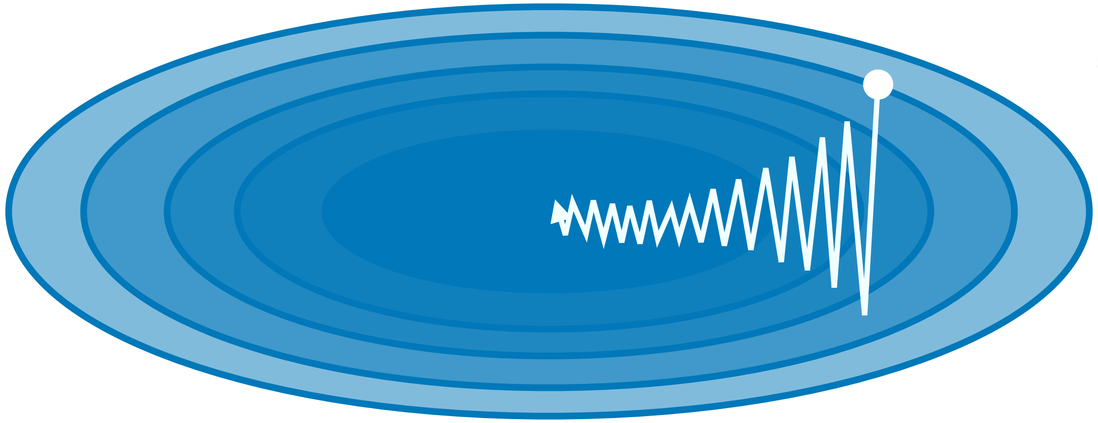
Problems of SGD

#1 Jitter

Large gradient in one direction, small gradient in other

⟶ *Slow progress, jitter*

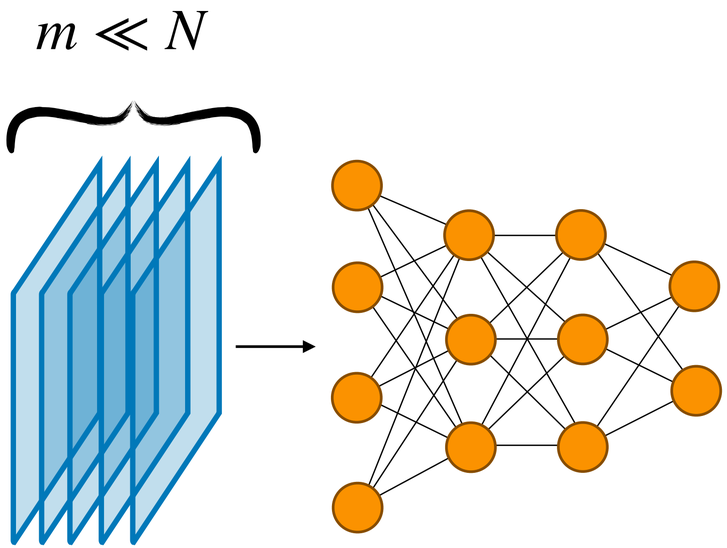


Loss function

High ratio between smallest and largest value in Hessian matrix - loss function has high condition number

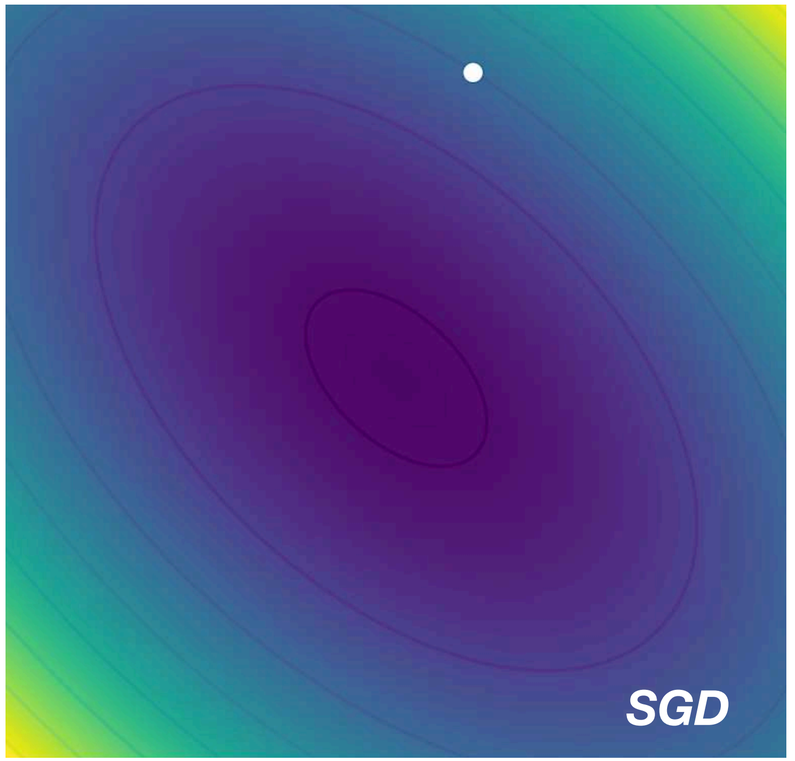
Problems of SGD

#2 noisy gradients



Gradients come from mini-batches

(average gradient of mini-batch)



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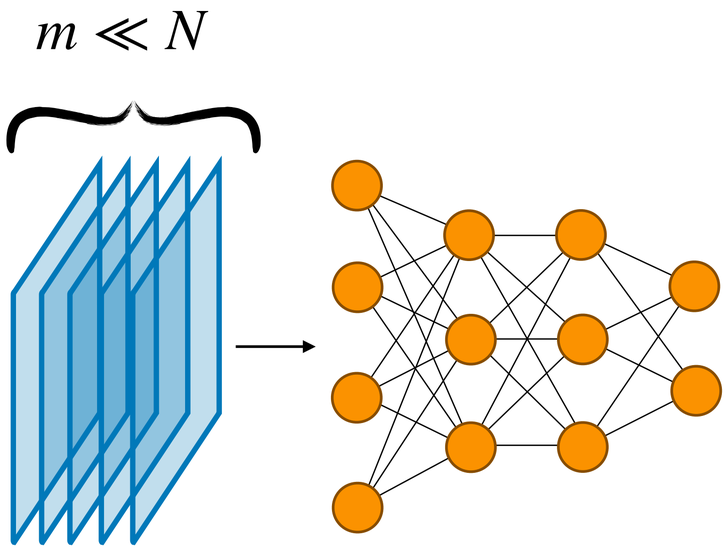

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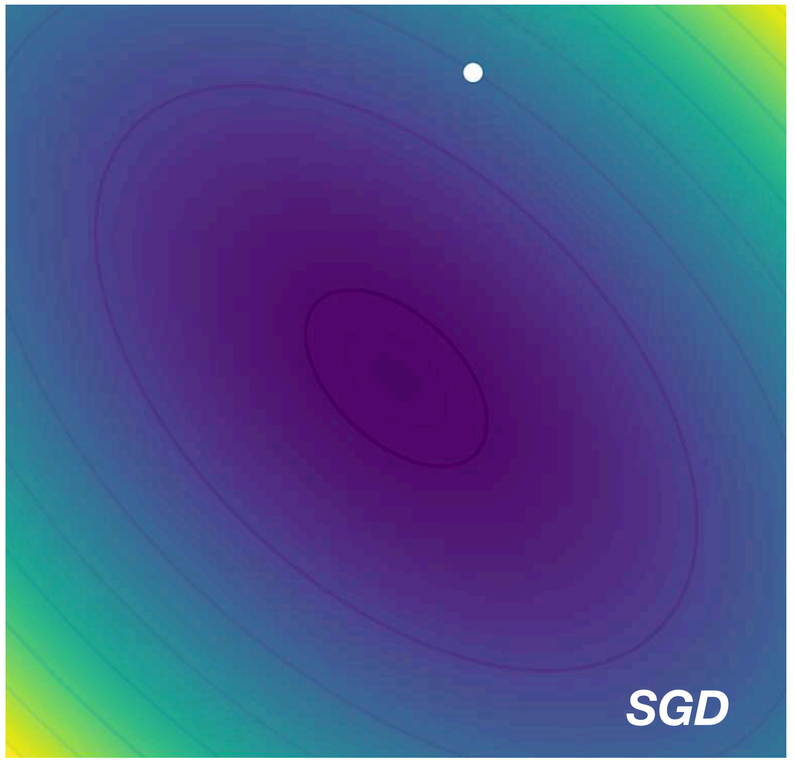
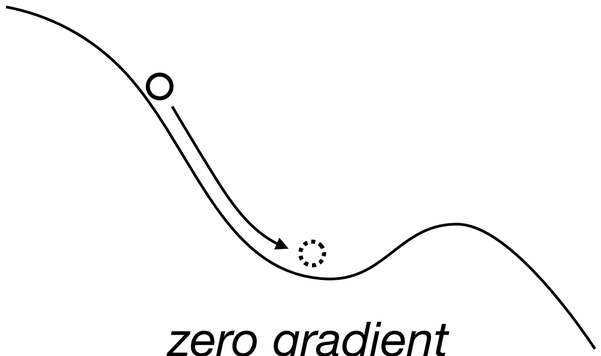


Problems of SGD

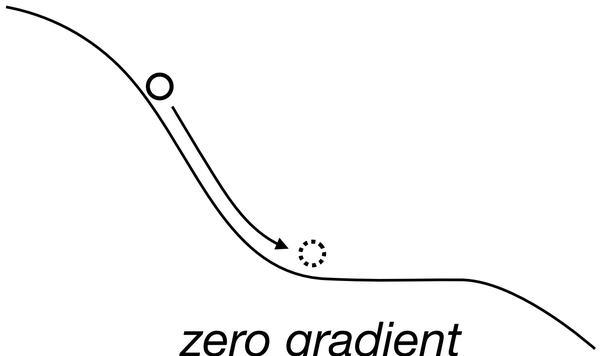
#3 local minima and saddle points

local minimum



zero gradient

saddle point



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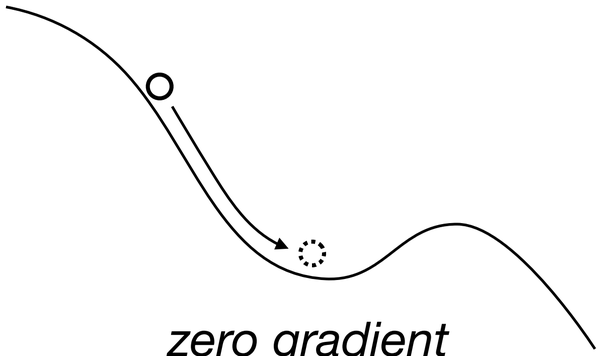
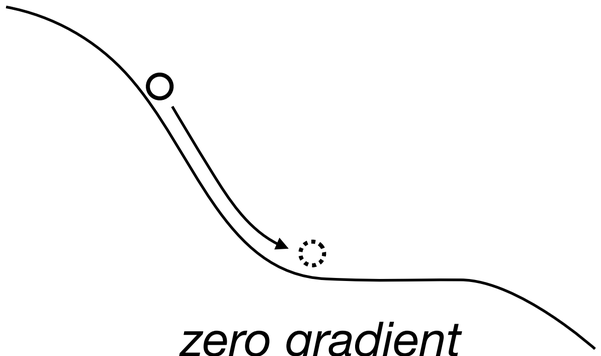


zero gradient

saddle point → *More common in high dimensions*

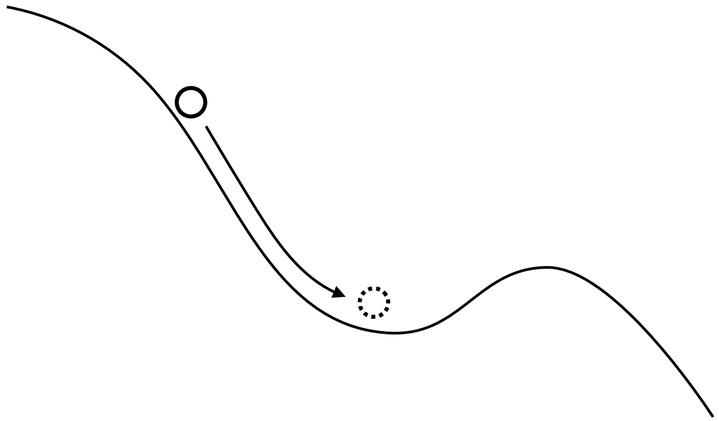


zero gradient

Introducing a momentum

potential picture

SGD: Weightless particle



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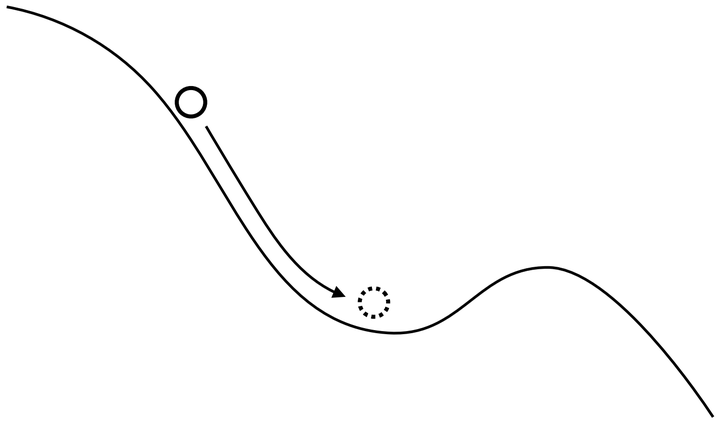
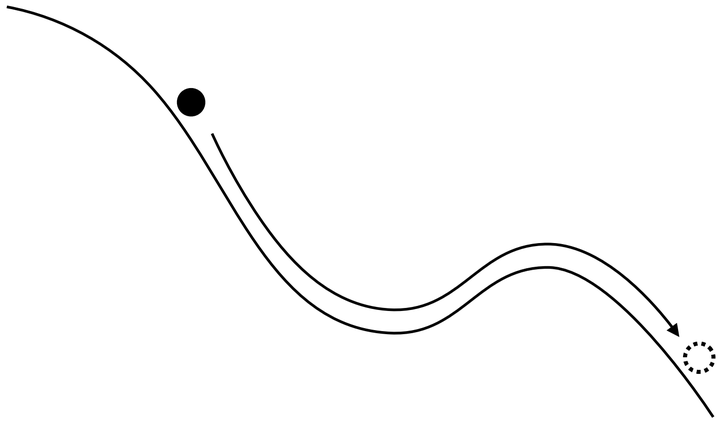


Introduce mass (momentum)



Introducing a momentum

Algorithm

SGD

$$\theta_{t+1} = \theta_t - \alpha \frac{\partial \varepsilon(\theta)}{\partial \theta}$$

```
for trainingSteps:

  weights += -learning_rate*gradient
```

SGD + Momentum

$$v_{t+1} = \rho v_t + (1-\rho)\frac{\partial \varepsilon(\theta)}{\partial \theta}$$

$$\theta_{t+1} = \theta_t - \alpha v_{t+1}$$

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vel = 0

for trainingSteps:

  vel      = rho*vel + (1-rho)*gradient
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Friction ρ *typically set to 0.9 or 0.99*

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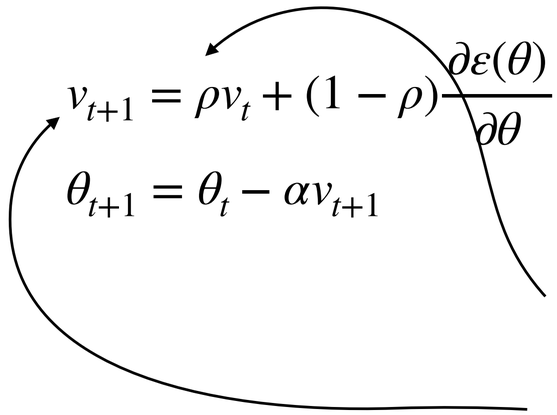


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(negative) ***Velocity*** v *is an accumulation of gradients (exponential decaying influence)*

Introducing a momentum

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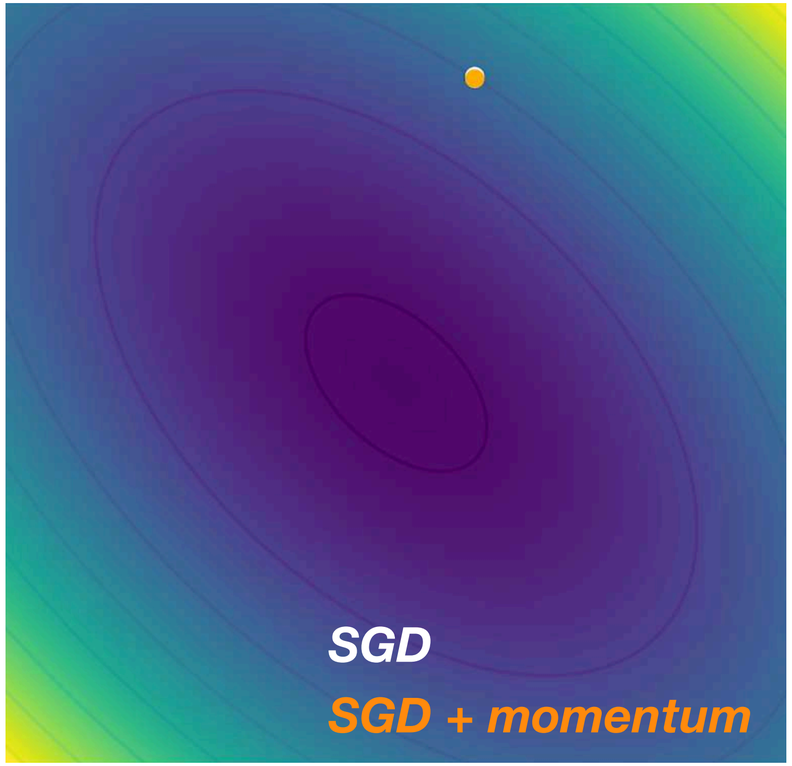
SGD + Momentum

$$v_{t+1} = \rho v_t + (1 - \rho) \frac{\partial \varepsilon(\theta)}{\partial \theta}$$

$$\theta_{t+1} = \theta_t - \alpha v_{t+1}$$

Tackles previous problems (#1 jitter, #2 noisy gradients, #3 local minima / saddle points)



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SGD + Momentum

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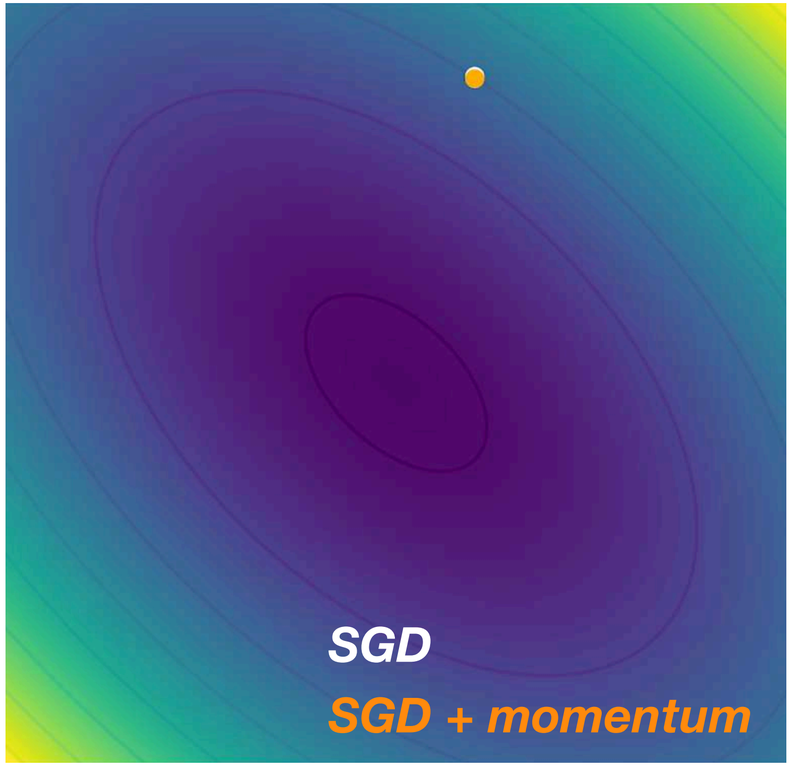
$$\theta_{t+1} = \theta_t - \alpha v_{t+1}$$

Tackles previous problems (#1 jitter, #2 noisy gradients, #3 local minima / saddle points)

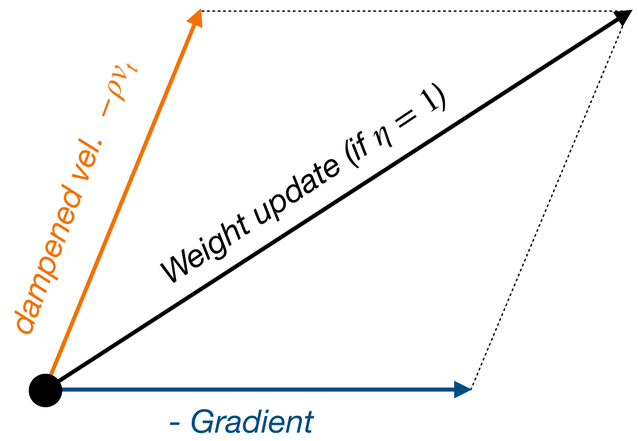


Nesterow Momentum

Momentum:

$$v_{t+1} = \rho v_t + (1-\rho)\nabla\varepsilon(\theta)$$

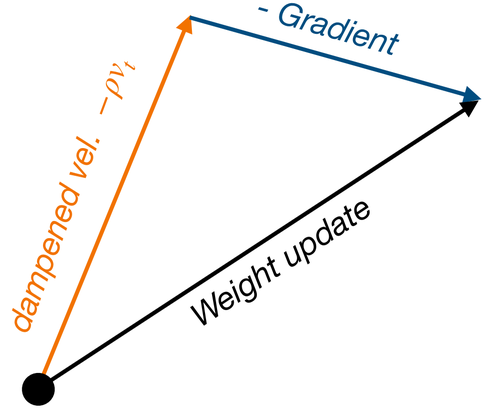
$$\theta_{t+1} = \theta_t - \eta v_{t+1}$$



Nesterov Momentum:

$$v_{t+1} = \rho v_t + (1-\rho)\nabla\varepsilon(\theta_t - \eta\rho v_t)$$

$$\theta_{t+1} = \theta_t - \eta v_{t+1}$$



AdaGrad

SGD

```
for _ in range(training_steps):

  grad = compute_gradients(weights)
  weights += -learning_rate * grad
```

AdaGrad

```
grad_squared = 0

for _ in range(training_steps):

  grad = compute_gradients(weights)
  grad_squared += grad * grad
  weights += -learning_rate * grad / (np.sqrt(grad_squared) + 1e-7)
```

AdaGrad

SGD

```
for _ in range(training_steps):

  grad = compute_gradients(weights)
  weights += -learning_rate * grad
```

AdaGrad

```
grad_squared = 0

for _ in range(training_steps):

  grad = compute_gradients(weights)
  grad_squared += grad * grad
  weights += -learning_rate * grad / (np.sqrt(grad_squared) + 1e-7)
```

Scaling gradients in each dimension by accumulation of squared gradients

RMSprop

AdaGrad

```
grad_squared = 0

for _ in range(training_steps):

  grad = compute_gradients(weights)
  grad_squared += grad * grad
  weights += -learning_rate * grad / (np.sqrt(grad_squared) + 1e-7)
```

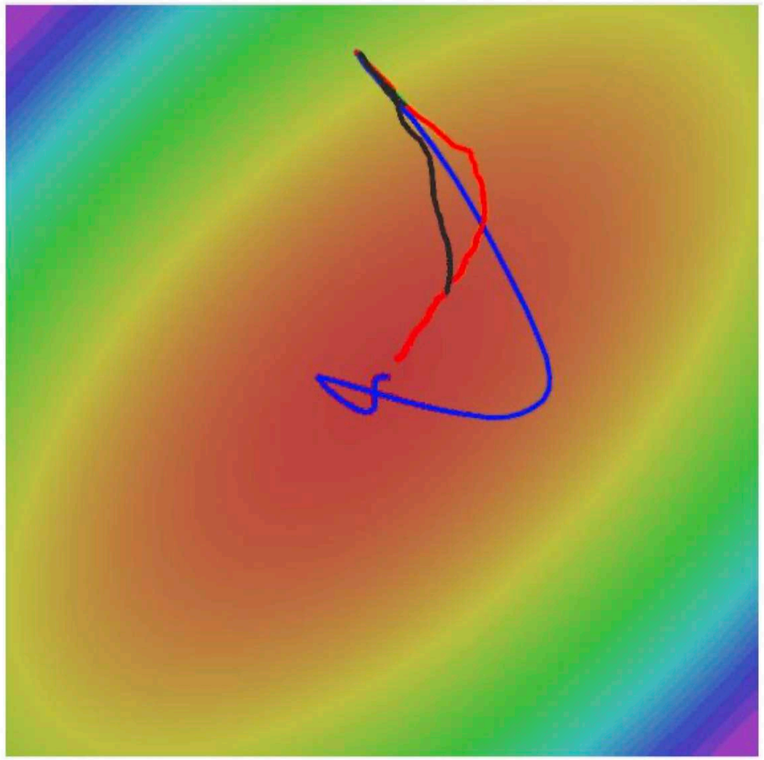
RMSProp

```
grad_squared = 0

for _ in range(training_steps):

  grad = compute_gradients(weights)
  grad_squared += decay_rate * grad_squared + (1 - decay_rate) * grad * grad
  weights += -learning_rate * grad / (np.sqrt(grad_squared) + 1e-7)
```

RMSprop



Adam

Derivation

```
first_moment = 0
second_moment = 0

for _ in range(training_steps):

  grad = compute_gradients(weights)

  first_moment  = beta1 * first_moment  + (1 - beta1) * grad
  second_moment = beta2 * second_moment + (1 - beta2) * grad * grad

  weights -= learning_rate * first_moment / (np.sqrt(second_moment) + 1e-7)
```

Adam

Derivation

```
first_moment = 0
second_moment = 0

for _ in range(training_steps):

  grad = compute_gradients(weights)

  first_moment  = beta1 * first_moment  + (1 - beta1) * grad
  second_moment = beta2 * second_moment + (1 - beta2) * grad * grad

  weights -= learning_rate * first_moment / (np.sqrt(second_moment) + 1e-7)
```

Momentum

Adam

Derivation

```
first_moment = 0
second_moment = 0

for _ in range(training_steps):

  grad = compute_gradients(weights)

  first_moment  = beta1 * first_moment  + (1 - beta1) * grad
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  weights -= learning_rate * first_moment / (np.sqrt(second_moment) + 1e-7)
```

Momentum

AdaGrad / RMSProp

Adam

Derivation

```
first_moment = 0
second_moment = 0

for _ in range(training_steps):

  grad = compute_gradients(weights)

  first_moment  = beta1 * first_moment  + (1 - beta1) * grad
  second_moment = beta2 * second_moment + (1 - beta2) * grad * grad

  weights -= learning_rate * first_moment / (np.sqrt(second_moment) + 1e-7)
```

Momentum

AdaGrad / RMSProp

Q: What happens at first timestep?

Adam

Algorithm

```
first_moment = 0
second_moment = 0

for t in range(1, training_steps + 1):

  grad = compute_gradients(weights)

  first_moment  = beta1 * first_moment  + (1 - beta1) * grad
  second_moment = beta2 * second_moment + (1 - beta2) * grad * grad

  first_unbias  = first_moment  / (1 - beta1 ** t)
  second_unbias = second_moment / (1 - beta2 ** t)

  weights -= learning_rate * first_unbias / (np.sqrt(second_unbias)  +1e-7)
```

Momentum

AdaGrad / RMSProp

Adam

Algorithm

```
first_moment = 0
second_moment = 0

for t in range(1, training_steps + 1):

  grad = compute_gradients(weights)

  first_moment  = beta1 * first_moment  + (1 - beta1) * grad
  second_moment = beta2 * second_moment + (1 - beta2) * grad * grad

  first_unbias  = first_moment  / (1 - beta1 ** t)
  second_unbias = second_moment / (1 - beta2 ** t)

  weights -= learning_rate * first_unbias / (np.sqrt(second_unbias)  +1e-7)
```

Momentum

Bias correction *accounting for first / second moment estimates starting at zero*

AdaGrad / RMSProp

Adam

Algorithm

```
first_moment = 0
second_moment = 0

for t in range(1, training_steps + 1):

  grad = compute_gradients(weights)

  first_moment  = beta1 * first_moment  + (1 - beta1) * grad
  second_moment = beta2 * second_moment + (1 - beta2) * grad * grad

  first_unbias  = first_moment  / (1 - beta1 ** t)
  second_unbias = second_moment / (1 - beta2 ** t)

  weights -= learning_rate * first_unbias / (np.sqrt(second_unbias)  +1e-7)
```

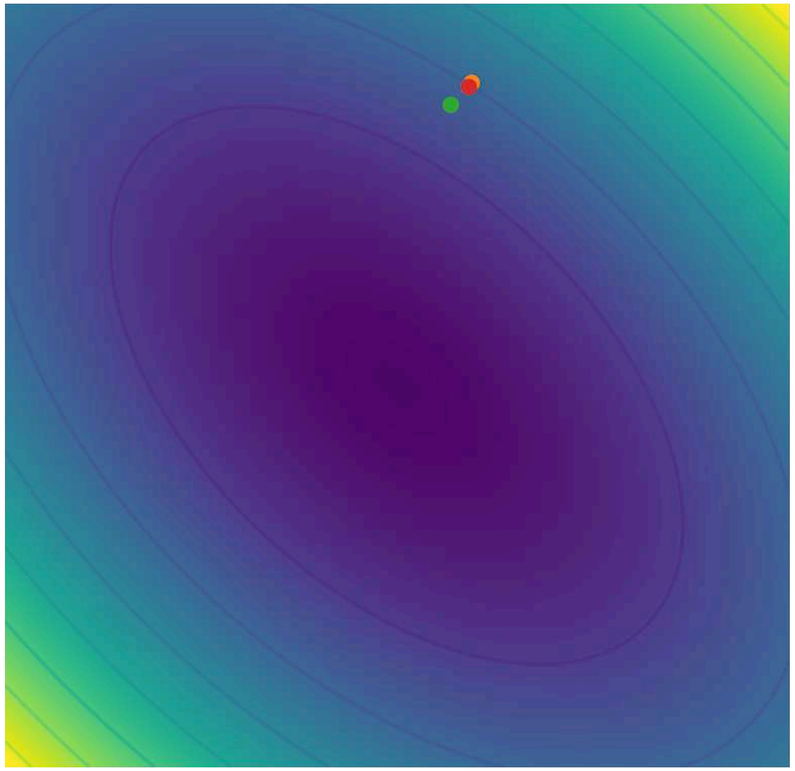
Momentum

Bias correction *accounting for first / second moment estimates starting at zero*

AdaGrad / RMSProp

Practical tip: *Adam with beta1 = 0.9 / 0.999 and learning_rate = 1e-3 / 5e-4 is good first choice for many models.*

Adam



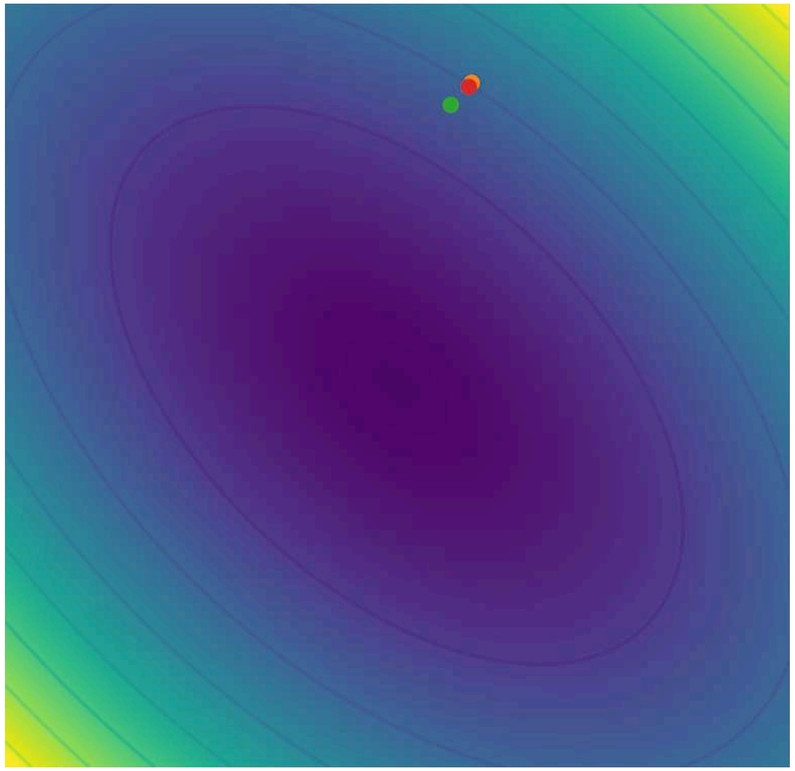
SGD

SGD + momentum

RMSProp

Adam

Adam



SGD

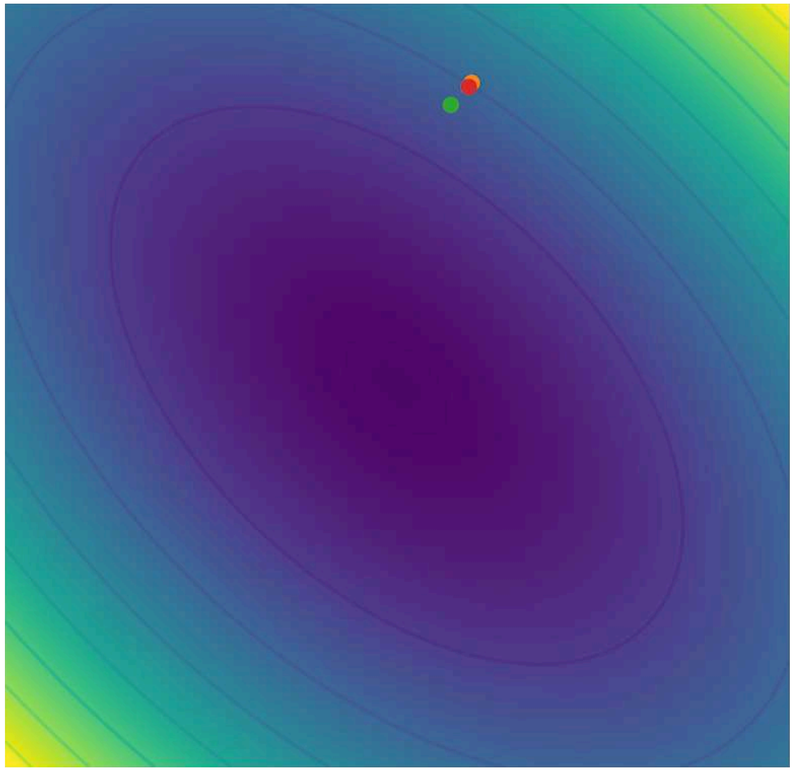
SGD + momentum

RMSProp

Adam

Adam

AdamW: https://arxiv.org/pdf/1711.05101



SGD

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Convolutional Neural Networks (CNNs)

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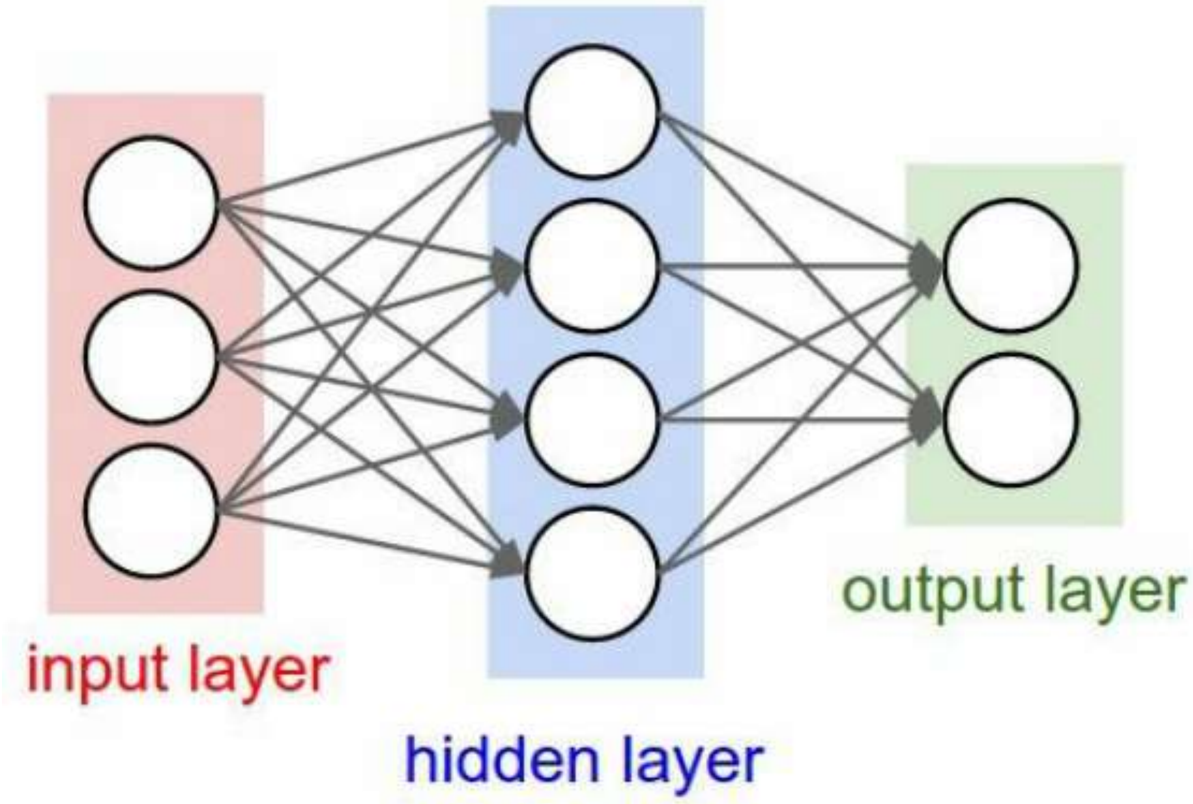
Weight Initialization

Q: What happens when $\theta \equiv$ const initialization is used? E.g., $\theta \equiv 0$?



Credits to Fei-Fei Li, Justin Johnson & Serena Yeung (Stanford CNNs for Visual Recognition, 2017, cs231)

First idea: **Small random numbers**

(gaussian with zero mean and 0.01 standard deviation)

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

Works ~okay for small networks, but problems with deeper networks.

Weight Initialization: Activation Statistics

```
dims = [4096] * 7
hs = []
x = np.random.randn(16, dims[0])
for Din, Dout in zip(dims[:-1], dims[1:]):
    W = 0.01 * np.random.randn(Din, Dout)
    x = np.tanh(x.dot(W))
    hs.append(x)
```

Forward pass for a 6-layer net with hidden size 4096

Weight Initialization: Activation Statistics

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dims = [4096] * 7
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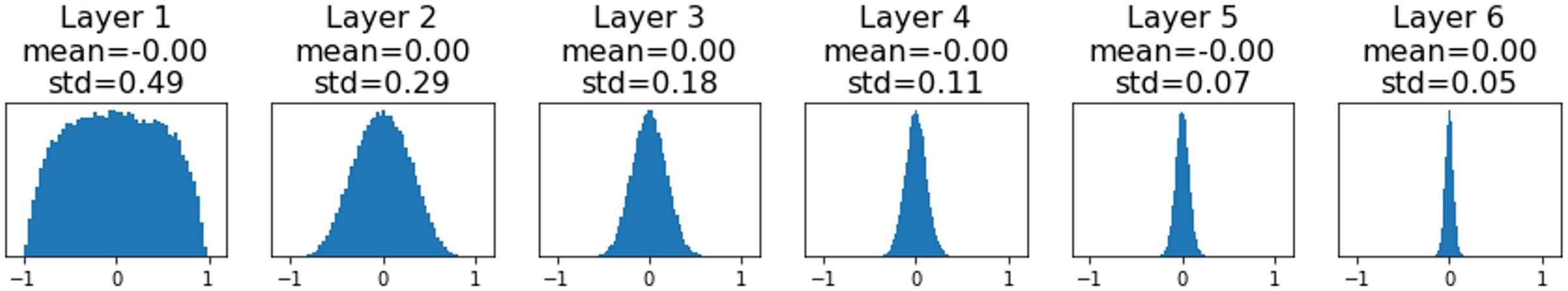
Forward pass for a 6-layer net with hidden size 4096

All activations tend to zero for deeper network layers

Q: What do the gradients dL/dW look like?



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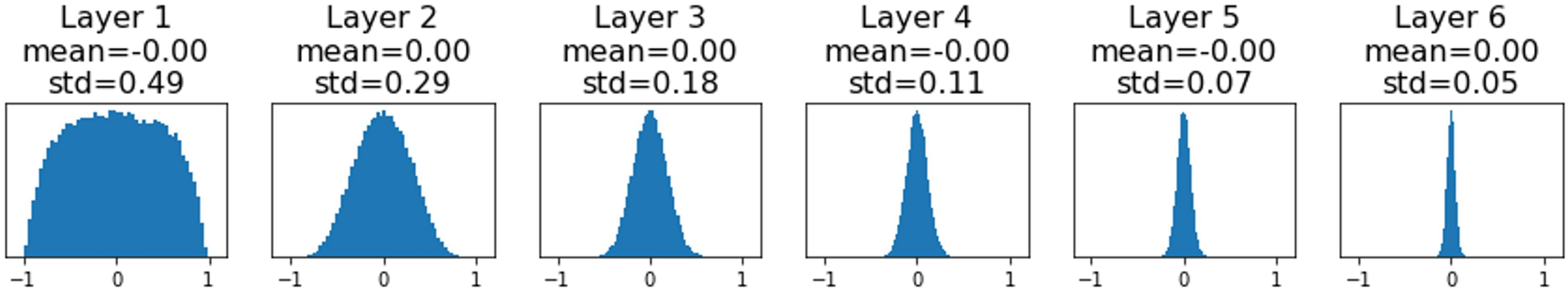
Forward pass for a 6-layer net with hidden size 4096

All activations tend to zero for deeper network layers

Q: What do the gradients dL/dW look like?

A: All zero, no learning =(



Weight Initialization: Activation Statistics

```
dims = [4096] * 7
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x = np.random.randn(16, dims[0])
for Din, Dout in zip(dims[:-1], dims[1:]):
    W = 0.05 * np.random.randn(Din, Dout)
    x = np.tanh(x.dot(W))
    hs.append(x)
```

Increase std of initial weights from 0.01 to 0.05

Weight Initialization: Activation Statistics

```
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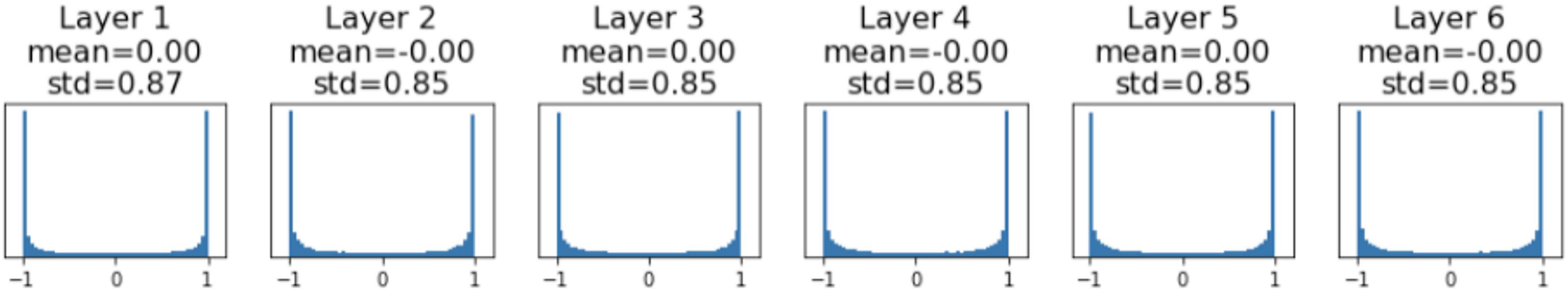
Increase std of initial weights from 0.01 to 0.05

All activations saturate

Q: What do the gradients look like?



Weight Initialization: Activation Statistics

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Increase std of initial weights from 0.01 to 0.05

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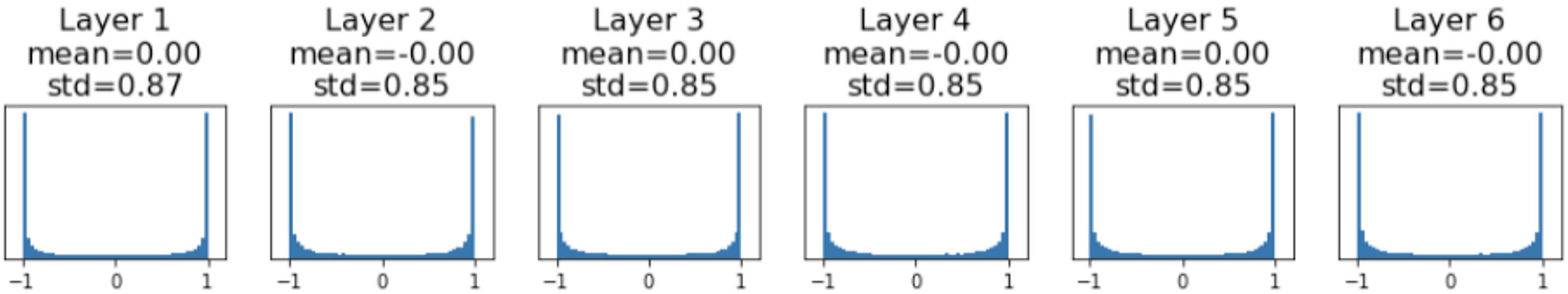

Weight Initialization: Xavier Initialization

```
dims = [4096] * 7
hs = []
x = np.random.randn(16, dims[0])
for Din, Dout in zip(dims[:-1], dims[1:]):
    W = np.random.randn(Din, Dout) / np.sqrt(Din)
    x = np.tanh(x.dot(W))
    hs.append(x)
```

"Xavier" initialization:
std = 1/sqrt(Din)

Glorot and Bengio, "Understanding the difficulty of training deep feedforward neural networks", AISTAT 2010

Weight Initialization: Xavier Initialization

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"Xavier" initialization:
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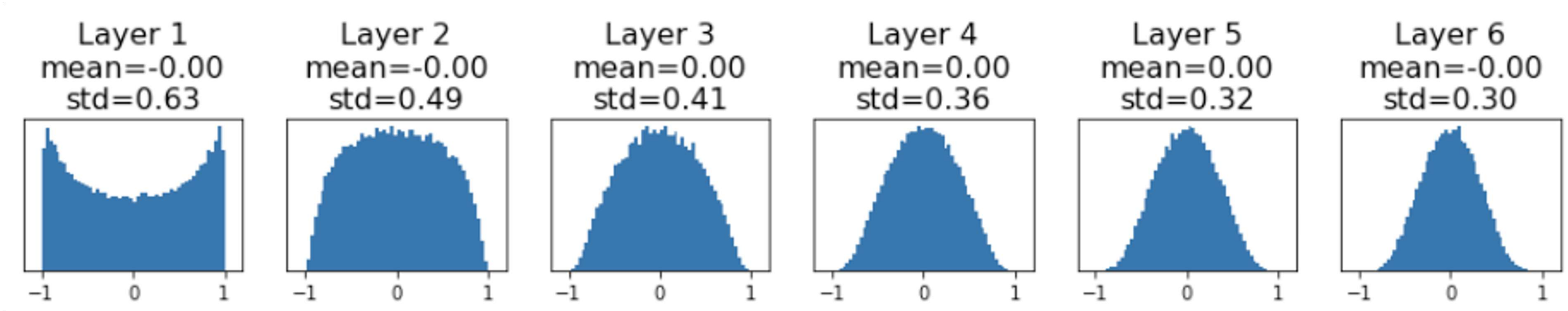
"Just right": Activations are nicely scaled for all layers!



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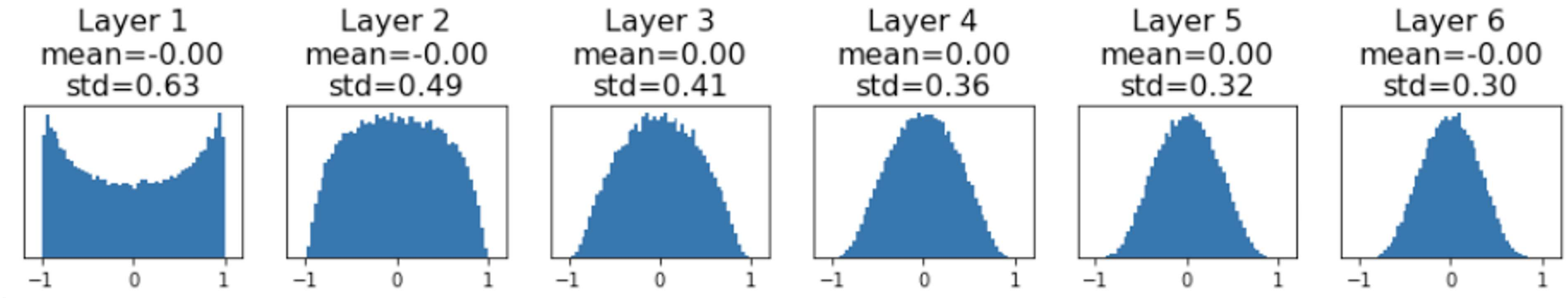
For conv layers, Din is kernel_size^2 * input_channels



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Weight Initialization: Xavier Initialization

"Xavier" initialization:
std = 1/sqrt(Din)

Derivation: Variance of output = Variance of input

y = Wx

$$y_i = \sum_{j=1}^{Din} x_j w_j$$

Weight Initialization: Xavier Initialization

"Xavier" initialization:
std = 1/sqrt(Din)

Derivation: Variance of output = Variance of input

$y = Wx$

$$y_i = \sum_{j=1}^{Din} x_j w_j$$

$Var(y_i) = Din * Var(x_i w_i)$

[Assume x, w are iid]

Weight Initialization: Xavier Initialization

"Xavier" initialization:
std = 1/sqrt(Din)

Derivation: Variance of output = Variance of input

$y = Wx$

$$y_i = \sum_{j=1}^{Din} x_j w_j$$

$Var(y_i) = Din * Var(x_i w_i)$

[Assume x, w are iid]

$= Din * Var(x_i) * Var(w_i)$

[Assume x, w zero-centered,
assume x^2, w^2 uncorrelated]

Weight Initialization: Xavier Initialization

"Xavier" initialization:
std = 1/sqrt(Din)

Derivation: Variance of output = Variance of input

$y = Wx$

$$y_i = \sum_{j=1}^{Din} x_j w_j$$

$Var(y_i) = Din * Var(x_i w_i)$

[Assume x, w are iid]

$= Din * Var(x_i) * Var(w_i)$

[Assume x, w zero-centered,
assume x^2, w^2 uncorrelated]

If $Var(w_i) = 1/Din$ then $Var(y_i) = Var(x_i)$

Weight Initialization: Xavier Initialization

```
dims = [4096] * 7
hs = []
x = np.random.randn(16, dims[0])
for Din, Dout in zip(dims[:-1], dims[1:]):
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    x = np.tanh(x.dot(W))
    hs.append(x)
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"Xavier" initialization:
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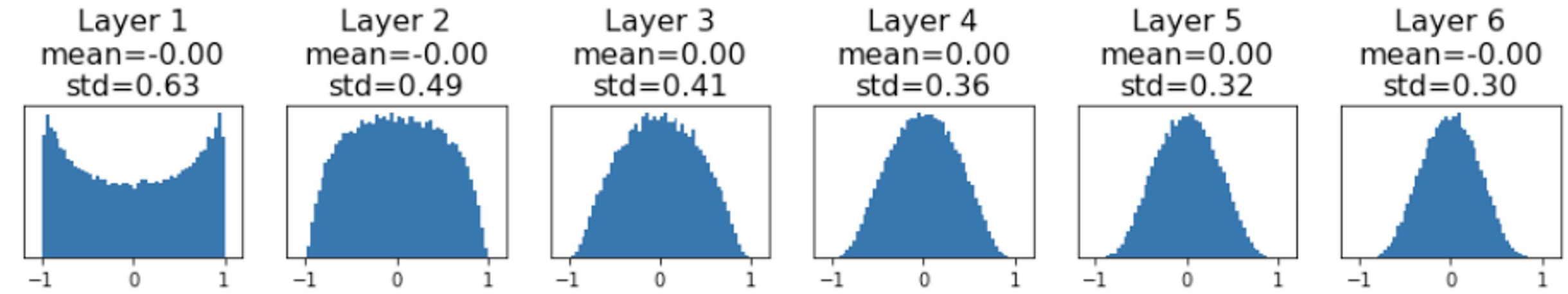


Glorot and Bengio, "Understanding the difficulty of training deep feedforward neural networks", AISTAT 2010

Weight Initialization: What about ReLU?

```
dims = [4096] * 7
hs = []
x = np.random.randn(16, dims[0])
for Din, Dout in zip(dims[:-1], dims[1:]):
    W = np.random.randn(Din, Dout) / np.sqrt(Din)
    x = np.maximum(0, x.dot(W))
    hs.append(x)
```

Change from tanh to ReLU

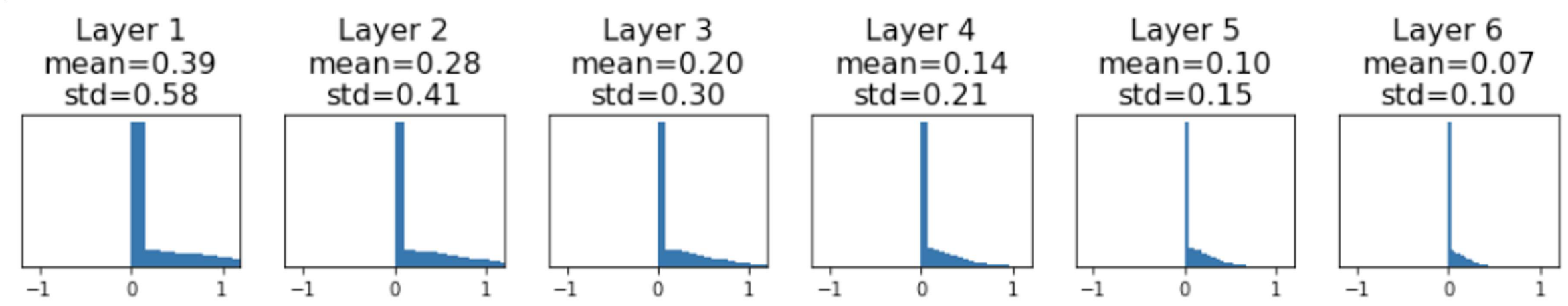
Weight Initialization: What about ReLU?

```
dims = [4096] * 7
hs = []
x = np.random.randn(16, dims[0])
for Din, Dout in zip(dims[:-1], dims[1:]):
    W = np.random.randn(Din, Dout) / np.sqrt(Din)
    x = np.maximum(0, x.dot(W))
    hs.append(x)
```

Change from tanh to ReLU

Xavier assumes zero centered activation function

Activations collapse to zero again, no learning =(

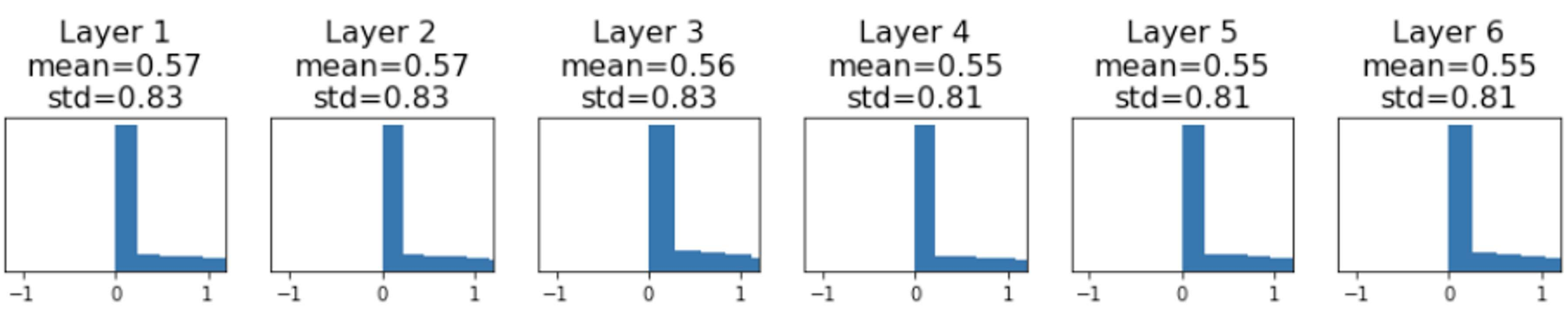


Weight Initialization: Kaiming / MSRA Initialization

```
dims = [4096] * 7
hs = []
x = np.random.randn(16, dims[0])
for Din, Dout in zip(dims[:-1], dims[1:]):
    W = np.random.randn(Din, Dout) / np.sqrt(Din)
    x = np.maximum(0, x.dot(W))
    hs.append(x)
```

ReLU correction: std = sqrt(2 / Din)

”Just right” – activations nicely scaled for all layers



He et al, “Delving Deep into Rectifiers: Surpassing Human-Level Performance on ImageNet Classification”, ICCV 2015

Convolutional Neural Networks (CNNs)

- A bit of CNN history
- CNN Layers
    - Convolutions, Pooling, Fully Connected Layers, Normalization
- Training CNNs
    - Advanced Optimization
    - Weight initialization
    - Regularization: Dropout
    - Extended training data: Augmentation, Transfer Learning
    - Sanity-checking the learning process; Hyperparameter tuning strategies
- Famous CNN architectures
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Advanced Regularization

Dropout, Ensembles

Recap: Additional Term in Loss

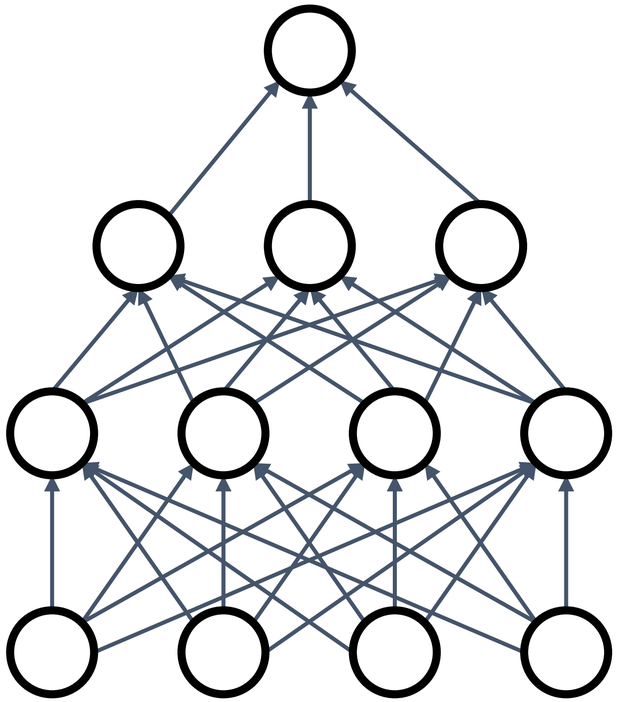
$$L = \frac{1}{N}\sum_{i=0}^{N} cost(h(x_i), y_i, \theta) + \underbrace{\lambda R(\theta)}$$

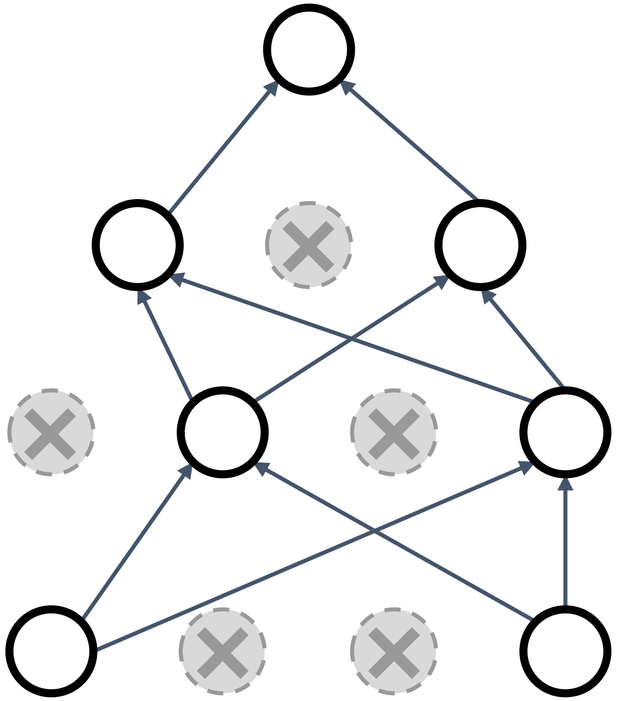
L2 regularization: $R(\theta) = \sum_{i,j} \theta_{i,j}^2$ (weight decay)

L1 regularization: $R(\theta) = \sum_{i,j} |\theta_{i,j}|$

Regularization: Dropout

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



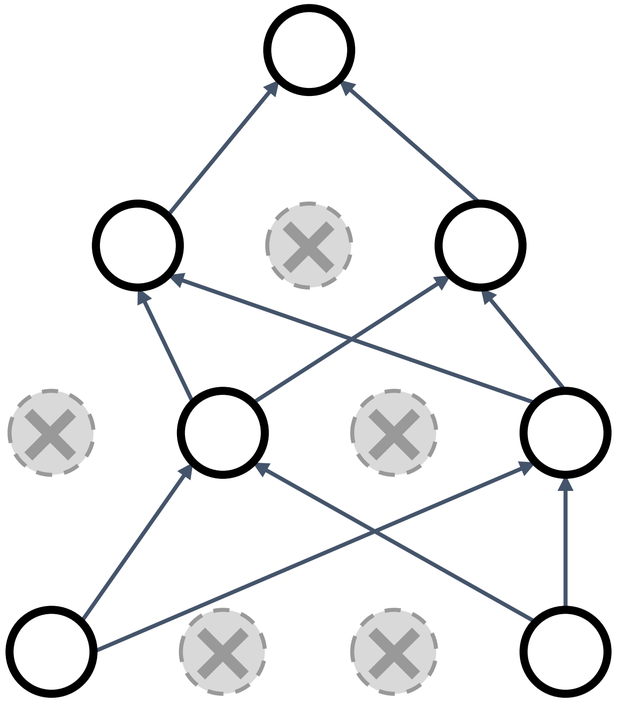


Srivastava et al, “Dropout: A simple way to prevent neural networks from overfitting”, JMLR 2014

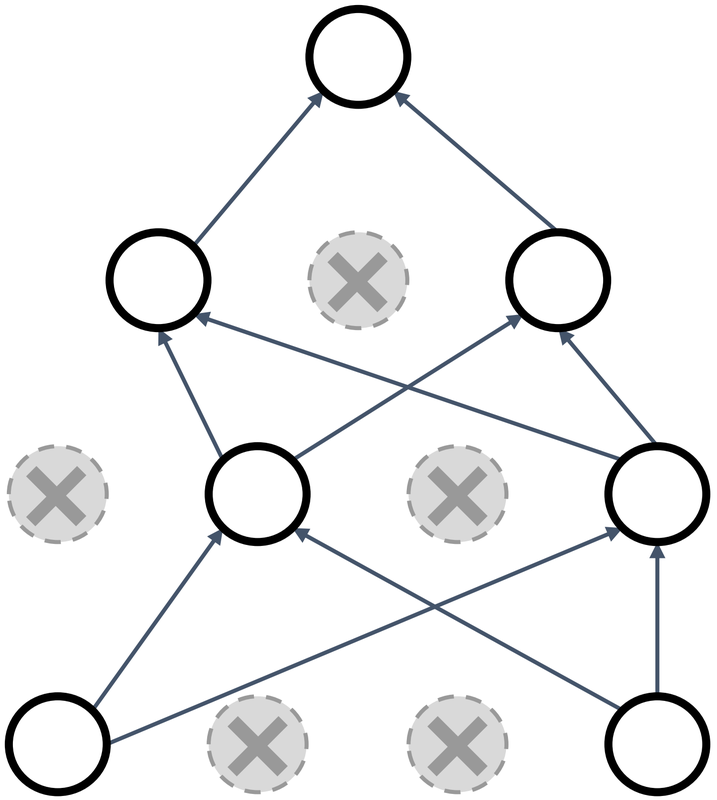
Regularization: Dropout

```python
p = 0.5 # probability of keeping a unit active. higher = less dropout

def train_step(X):
  """ X contains the data """

  # forward pass for example 3-layer neural network
  H1 = np.maximum(0, np.dot(W1, X) + b1)
  U1 = np.random.rand(*H1.shape) < p # first dropout mask
  H1 *= U1 # drop!
  H2 = np.maximum(0, np.dot(W2, H1) + b2)
  U2 = np.random.rand(*H2.shape) < p # second dropout mask
  H2 *= U2 # drop!
  out = np.dot(W3, H2) + b3

  # backward pass: compute gradients... (not shown)
  # perform parameter update... (not shown)
```

Example forward pass with a 3-layer network using dropout

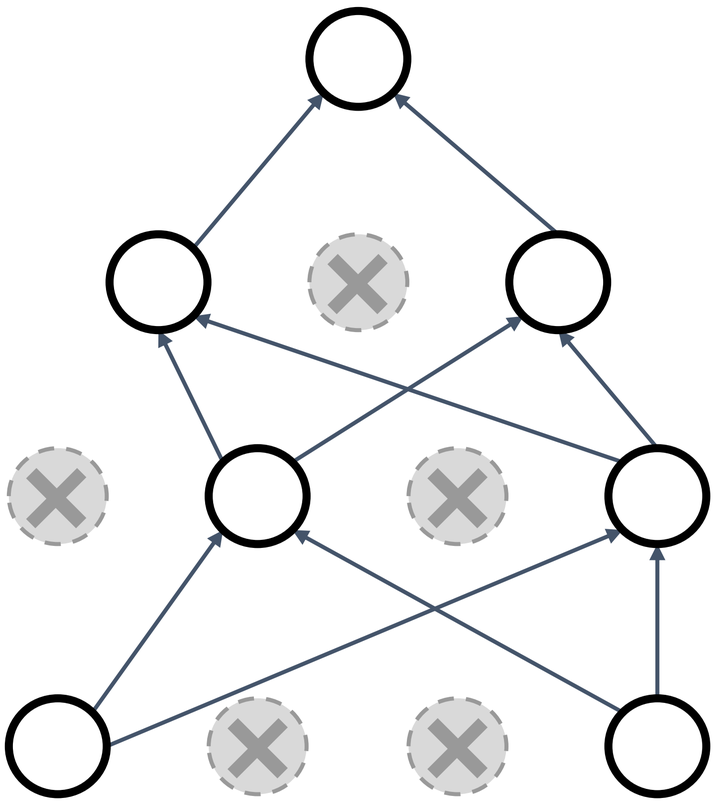


Regularization: Dropout



Forces the network to have a redundant representation; Prevents **co-adaptation** of features

Regularization: Dropout



Another interpretation:

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...

Dropout: Test Time

Dropout makes our output random!

Output (label) Input (image)

$$\boldsymbol{y} = f_W(\boldsymbol{x}, \boldsymbol{z})$$

Random mask

Want to "average out" the randomness at test-time

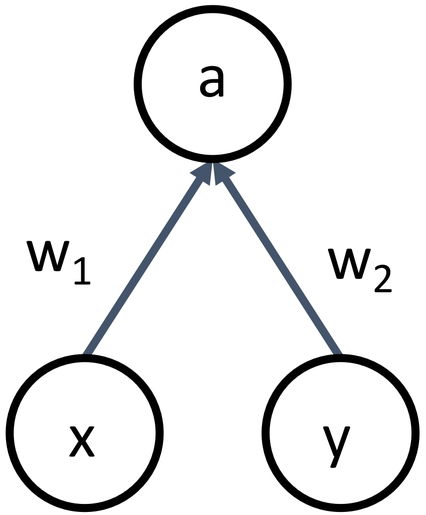
$$y = f(x) = E_z[f(x, z)] = \int p(z) f(x, z) dz$$

But this integral seems hard …

Dropout: Test Time

Want to approximate the integral

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



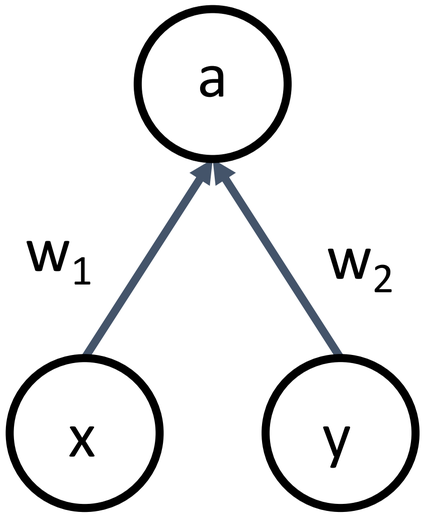
Consider a single neuron:

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

Dropout: Test Time

Want to approximate the integral

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



Consider a single neuron:

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

During training we have:

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

At test time, drop nothing and **multiply** by dropout probability

Dropout: Test Time

```
def predict(X):
  # ensembled forward pass
  H1 = np.maximum(0, np.dot(W1, X) + b1) * p # NOTE: scale the activations
  H2 = np.maximum(0, np.dot(W2, H1) + b2) * p # NOTE: scale the activations
  out = np.dot(W3, H2) + b3
```

At test time all neurons are active always

=> We must scale the activations so that for each neuron:

output at test time = expected output at training time

Dropout Summary

```
""" Vanilla Dropout: Not recommended implementation (see notes below) """

p = 0.5 # probability of keeping a unit active. higher = less dropout

def train_step(X):
  """ X contains the data """

  # forward pass for example 3-layer neural network
  H1 = np.maximum(0, np.dot(W1, X) + b1)
  U1 = np.random.rand(*H1.shape) < p # first dropout mask
  H1 *= U1 # drop!
  H2 = np.maximum(0, np.dot(W2, H1) + b2)
  U2 = np.random.rand(*H2.shape) < p # second dropout mask
  H2 *= U2 # drop!
  out = np.dot(W3, H2) + b3

  # backward pass: compute gradients... (not shown)
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def predict(X):
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  H1 = np.maximum(0, np.dot(W1, X) + b1) * p # NOTE: scale the activations
  H2 = np.maximum(0, np.dot(W2, H1) + b2) * p # NOTE: scale the activations
  out = np.dot(W3, H2) + b3
```

drop in forward pass

scale at test time

More common: “Inverted dropout”

```python
p = 0.5 # probability of keeping a unit active. higher = less dropout

def train_step(X):
  # forward pass for example 3-layer neural network
  H1 = np.maximum(0, np.dot(W1, X) + b1)
  U1 = (np.random.rand(*H1.shape) < p) / p # first dropout mask. Notice /p!
  H1 *= U1 # drop!
  H2 = np.maximum(0, np.dot(W2, H1) + b2)
  U2 = (np.random.rand(*H2.shape) < p) / p # second dropout mask. Notice /p!
  H2 *= U2 # drop!
  out = np.dot(W3, H2) + b3

  # backward pass: compute gradients... (not shown)
  # perform parameter update... (not shown)

def predict(X):
  # ensembled forward pass
  H1 = np.maximum(0, np.dot(W1, X) + b1) # no scaling necessary
  H2 = np.maximum(0, np.dot(W2, H1) + b2)
  out = np.dot(W3, H2) + b3
```

Drop and scale during training

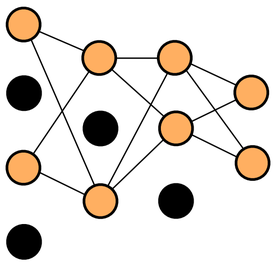
test time is unchanged!

Regularization: A common pattern

Training: add randomness to network

Testing: average over distribution

Dropout



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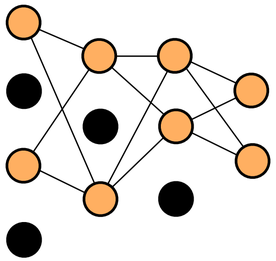
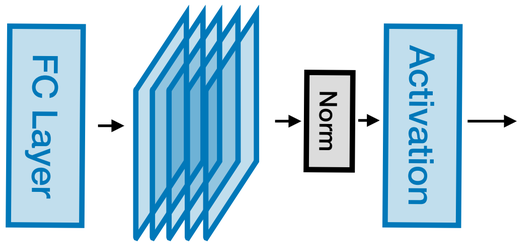
Dropout



Batch Normalization



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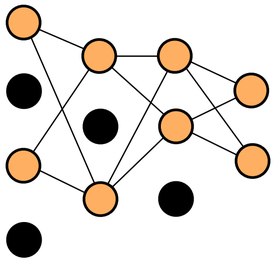
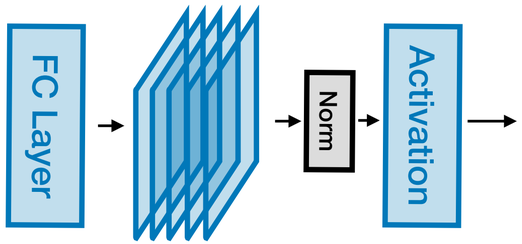
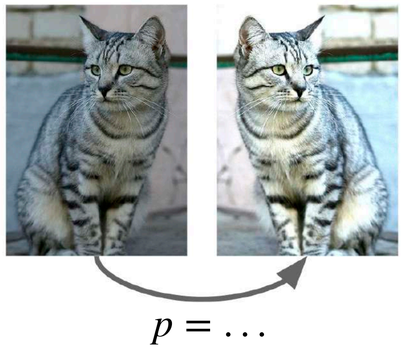


Batch Normalization



Data augmentation



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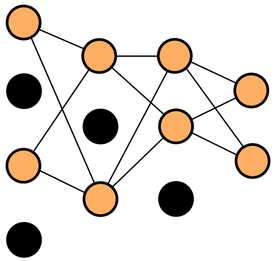
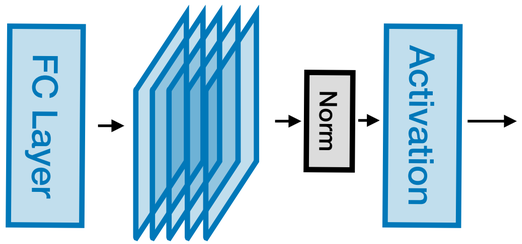
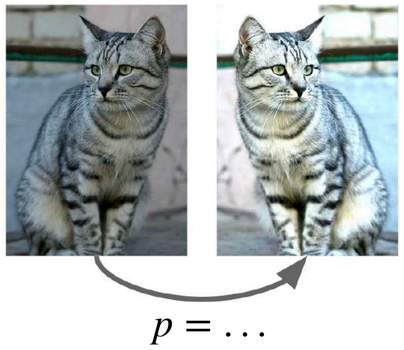
Dropout



Batch Normalization



Data augmentation



And many more:

DropConnect,
Stochastic Depth,
Fractional Max pooling…

Convolutional Neural Networks (CNNs)

- A bit of CNN history
- CNN Layers
    - Convolutions, Pooling, Fully Connected Layers, Normalization
- Training CNNs
    - Advanced Optimization
    - Weight initialization
    - Regularization: Dropout
    - Extended training data: Augmentation, Transfer Learning
    - Sanity-checking the learning process; Hyperparameter tuning strategies
- Famous CNN architectures
- CNNs for image segmentation

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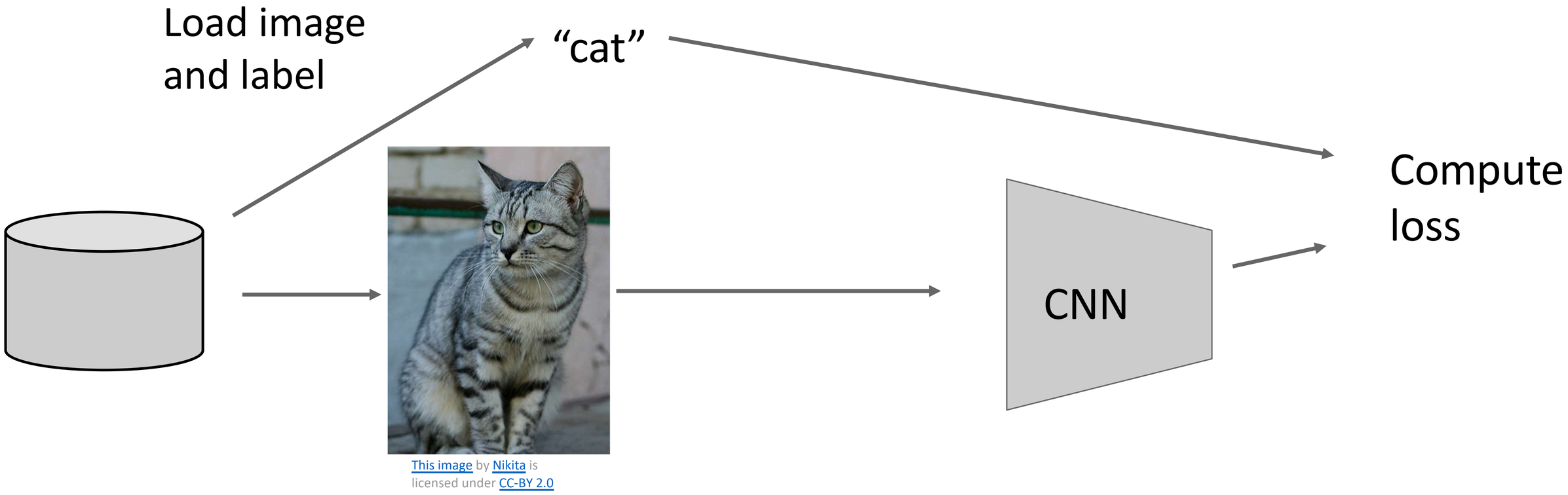
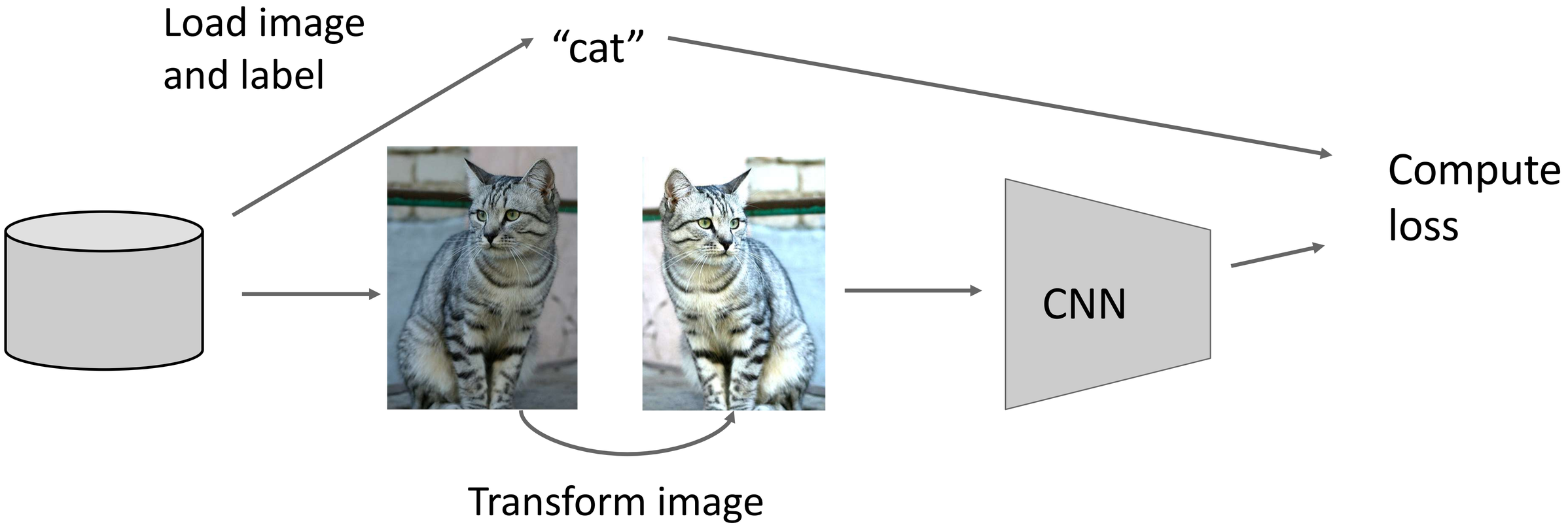
Data Augmentation

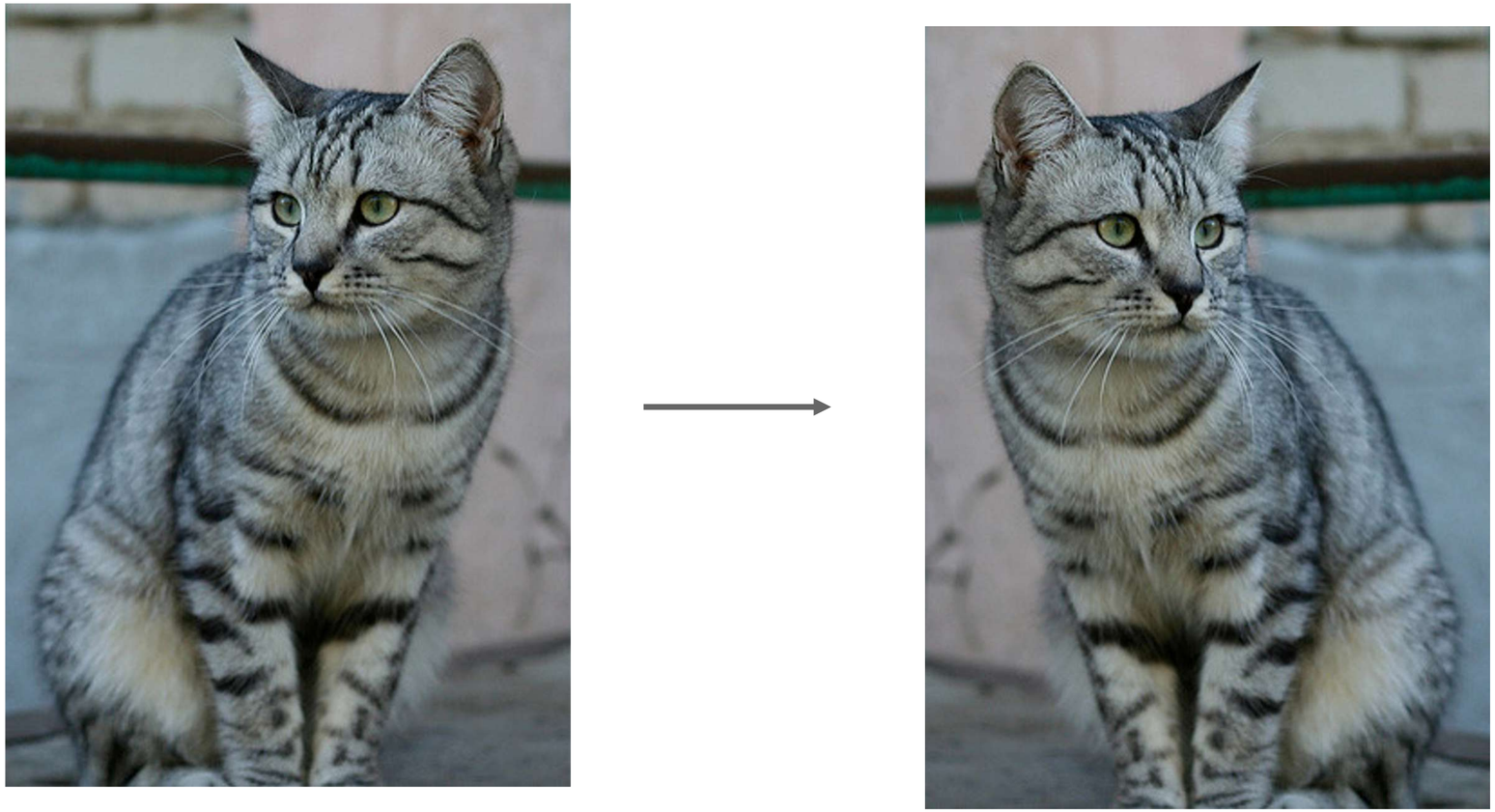
Data Augmentation



Data Augmentation



Data Augmentation: Horizontal Flips



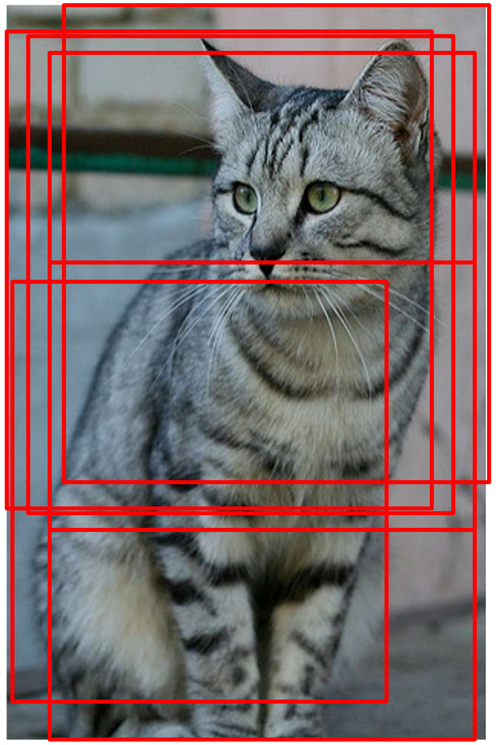
Data Augmentation: Horizontal Flips

Vertical flips?

Data Augmentation: Horizontal Flips

Vertical flips?
Rotations?

Data Augmentation: Random Crops and Scales



Data Augmentation: Color Jitter

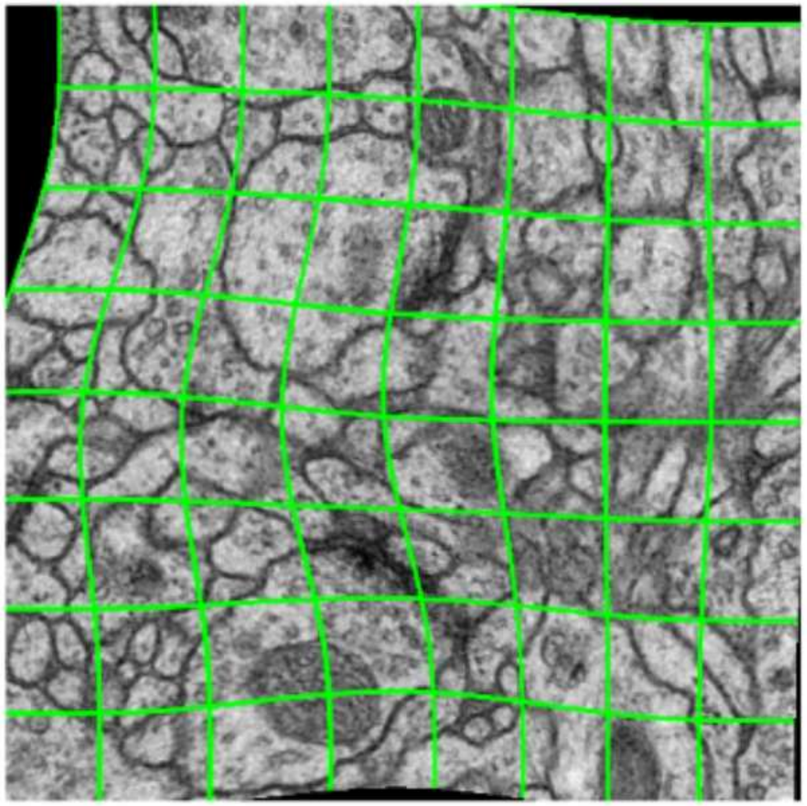
Simple: Randomize contrast and brightness

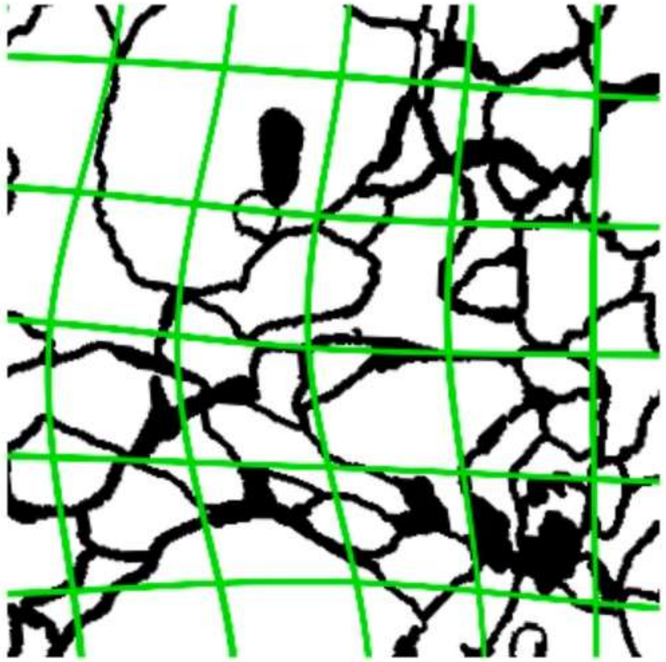
More Complex:

1. Apply PCA to all [R, G, B] pixels in training set
2. Sample a "color offset" along principal component directions
3. Add offset to all pixels of a training image

(Used in AlexNet, ResNet, etc)

Data Augmentation: Elastic Deformation





1. Specify:
   - Grid size
   - Distribution of offsets
2. Sample offsets for grid points
3. Interpolate in-between

Image from Ronneberger et al., MICCAI 2015

Data Augmentation: Test-time Augmentation

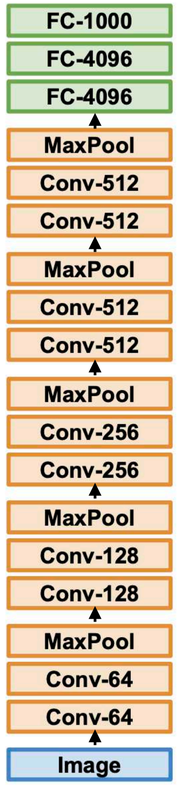
1. Create a set of random augmented versions of your test image, e.g. n=8
2. Average the predictions

=> A different kind of ensemble / randomness
=> often yields improved predictions
=> at the expense of increased computational cost

Transfer Learning

Transfer Learning with CNNs

#1 Train on Imagenet



Transfer Learning with CNNs

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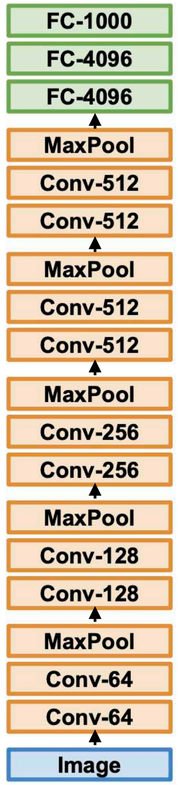
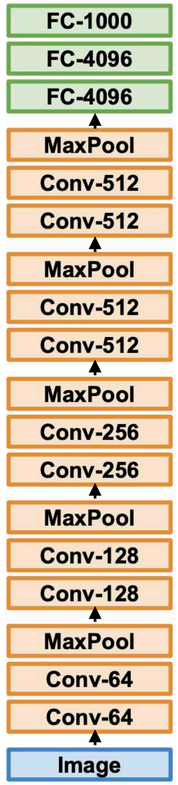


#2 Small Dataset (C classes)



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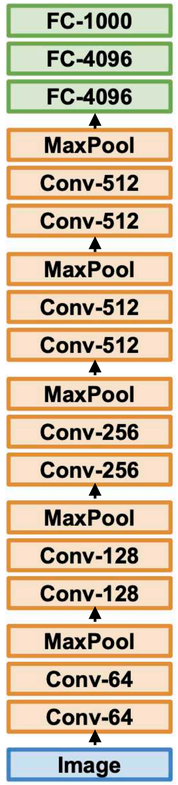

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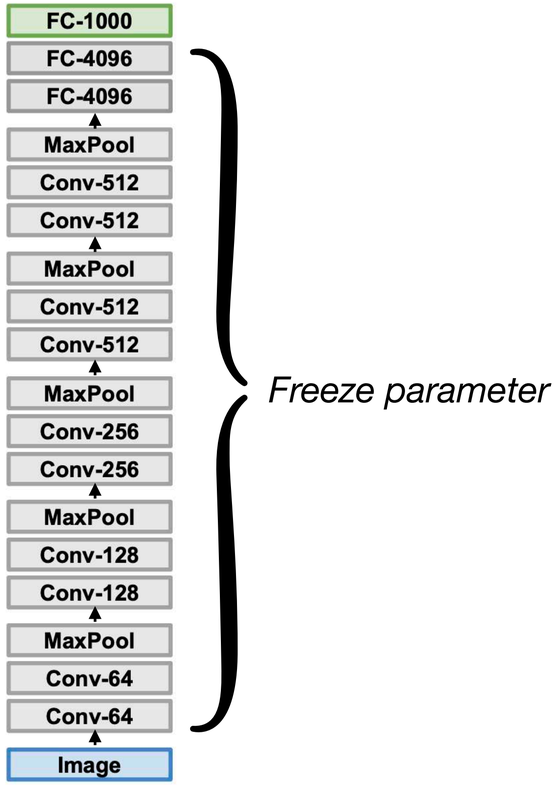

Transfer Learning with CNNs

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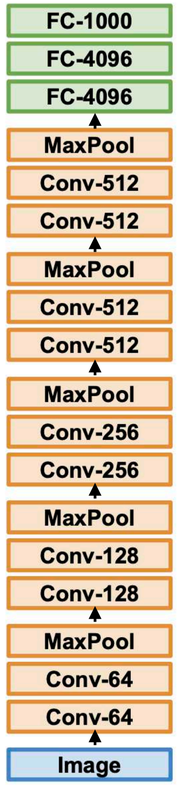

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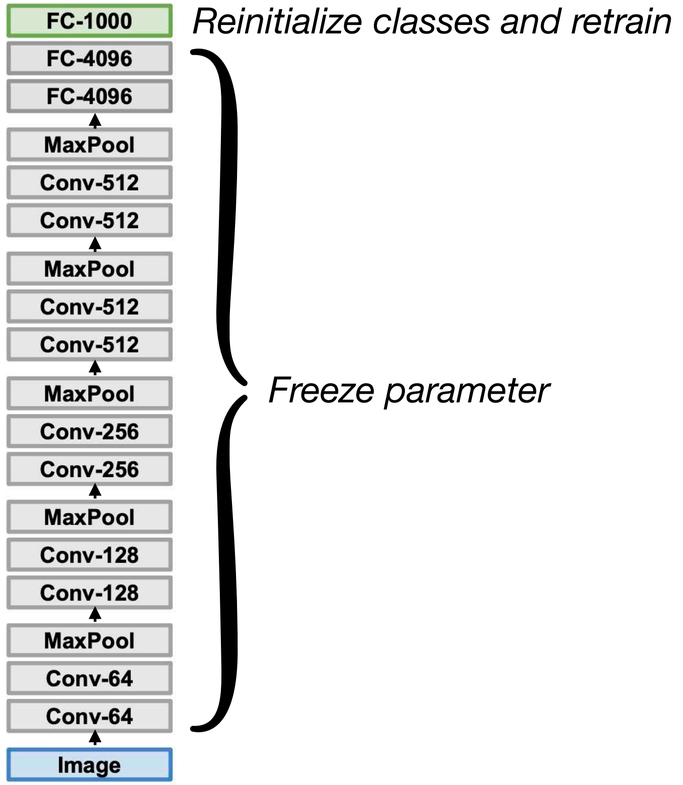

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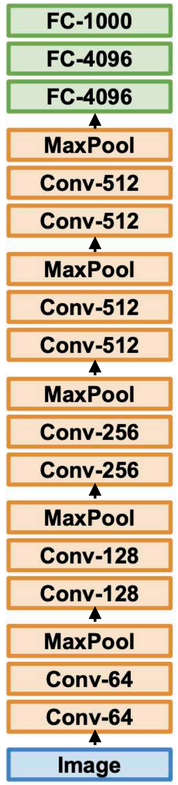

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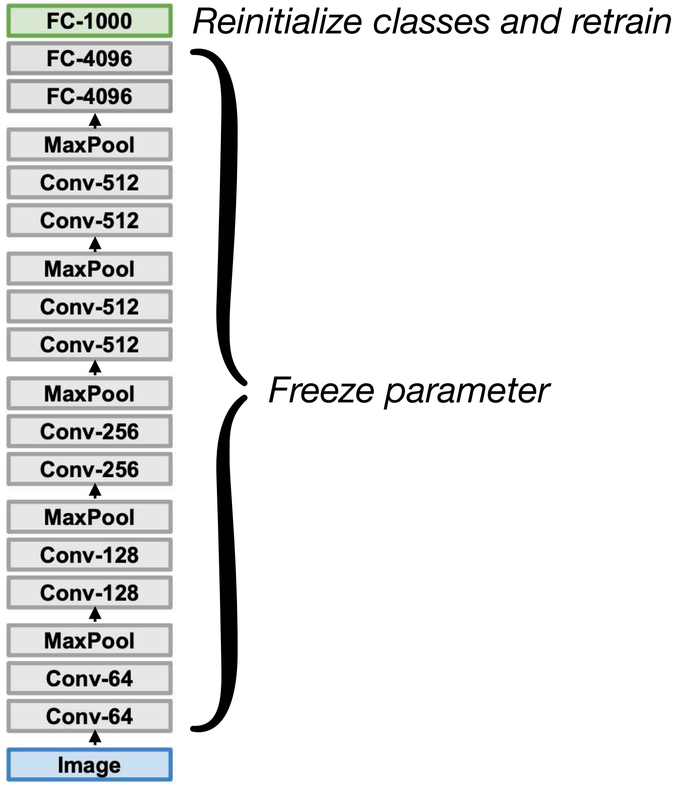
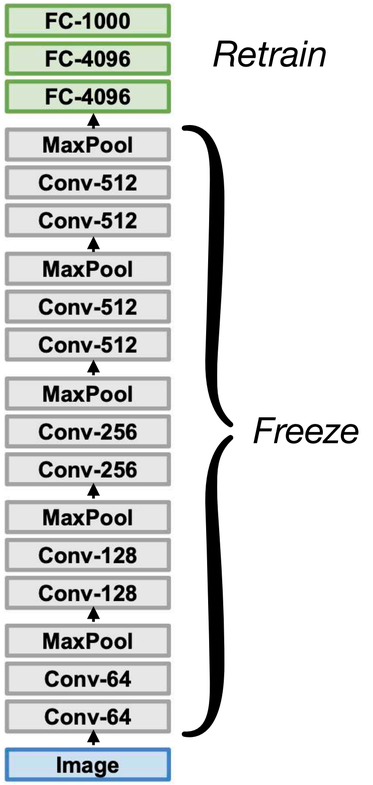


#3 Bigger Dataset



Credits to FeiFei Li & Justin Johnson & Serena Yeung (Stanford CNNs for Visual Recognition, 2017, cs231)

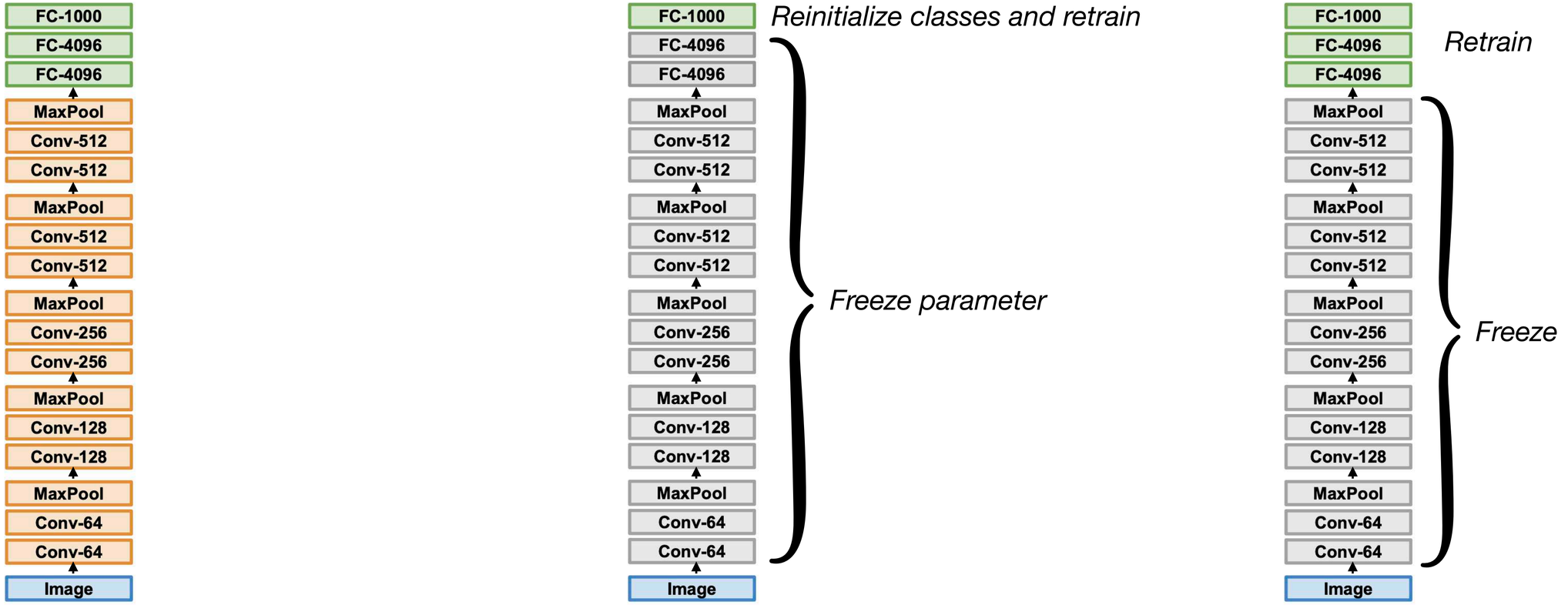
Transfer Learning with CNNs

Try smaller learning rate, e.g. 0.1 of original learning rate

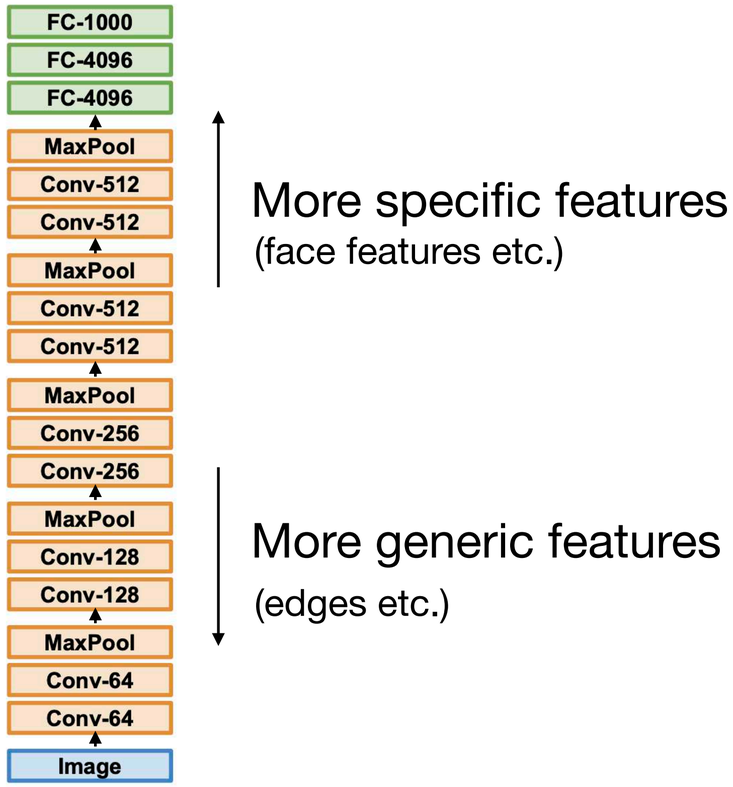
#1 Train on Imagenet

#2 Small Dataset (C classes)

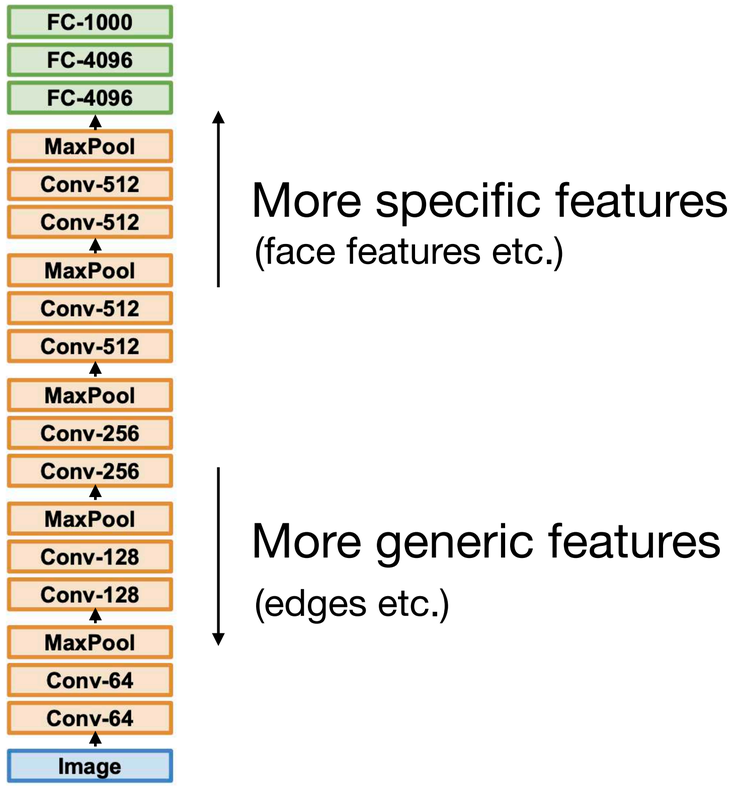
#3 Bigger Dataset



Transfer Learning with CNNs



Transfer Learning with CNNs

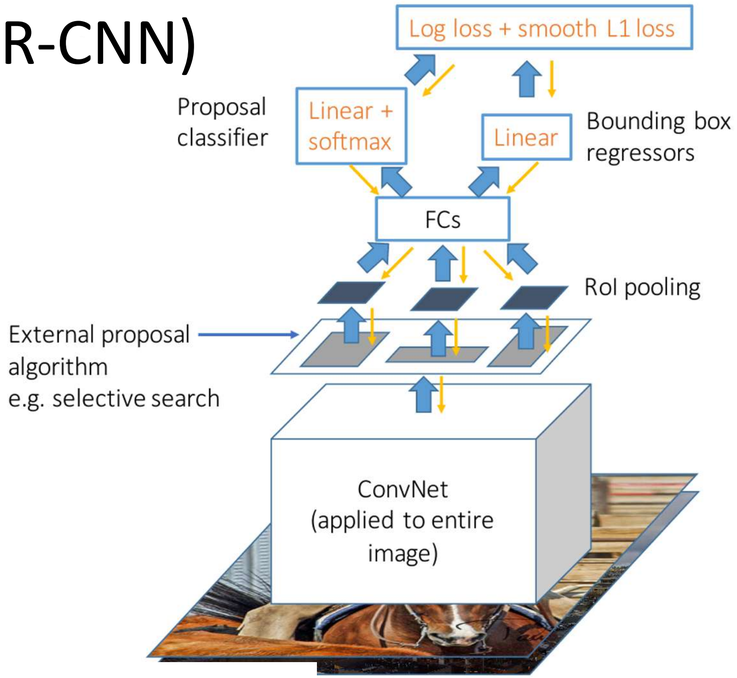


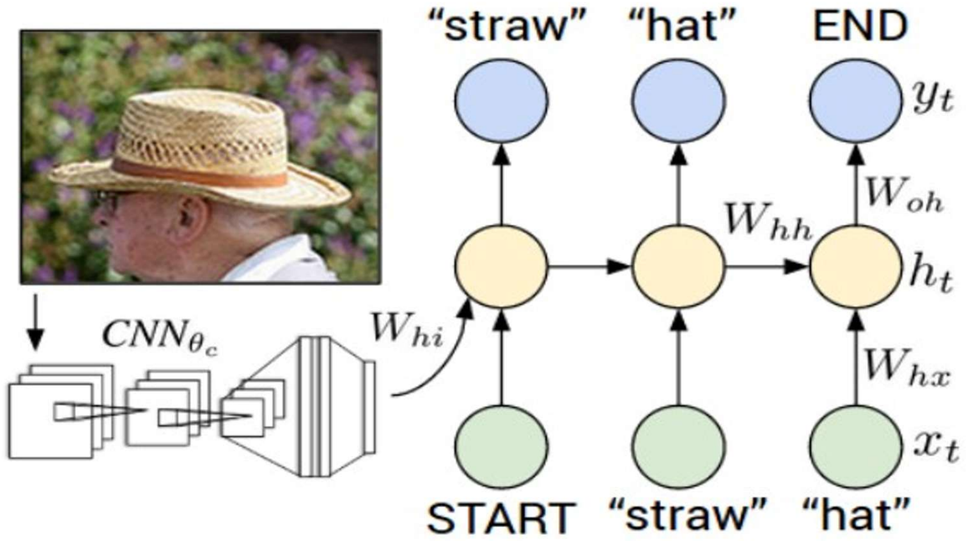
	very similar dataset	**very different dataset**
very little data	Use Linear Classifier on top layer	You're in trouble… Try linear classifier from different stages
quite a lot of data	Finetune a few layers	Finetune a larger number of layers

Credits to FeiFei Li & Justin Johnson & Serena Yeung (Stanford CNNs for Visual Recognition, 2017, cs231)

Transfer learning is pervasive!
It's the norm, not the exception

Object
Detection
(Fast R-CNN)





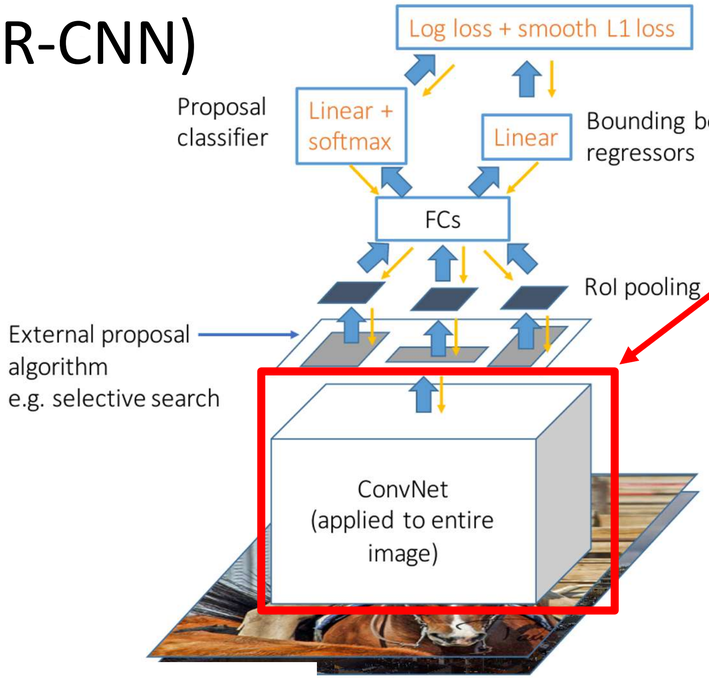
Girshick, "Fast R-CNN", ICCV 2015
Figure copyright Ross Girshick, 2015. Reproduced with permission.

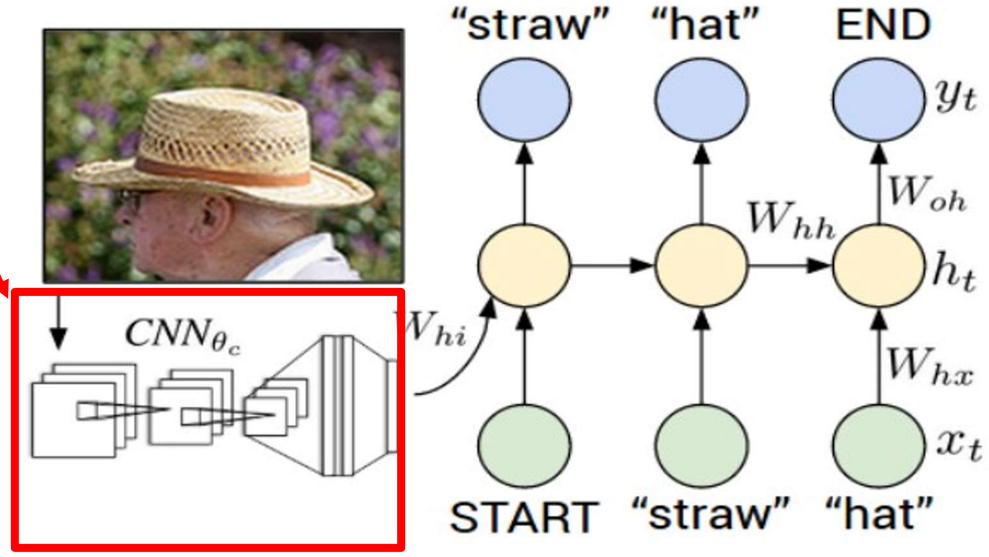
Karpathy and Fei-Fei, "Deep Visual-Semantic Alignments for Generating Image Descriptions", CVPR 2015

Transfer learning is pervasive!
It's the norm, not the exception

Object Detection (Fast R-CNN)

CNN pretrained on ImageNet



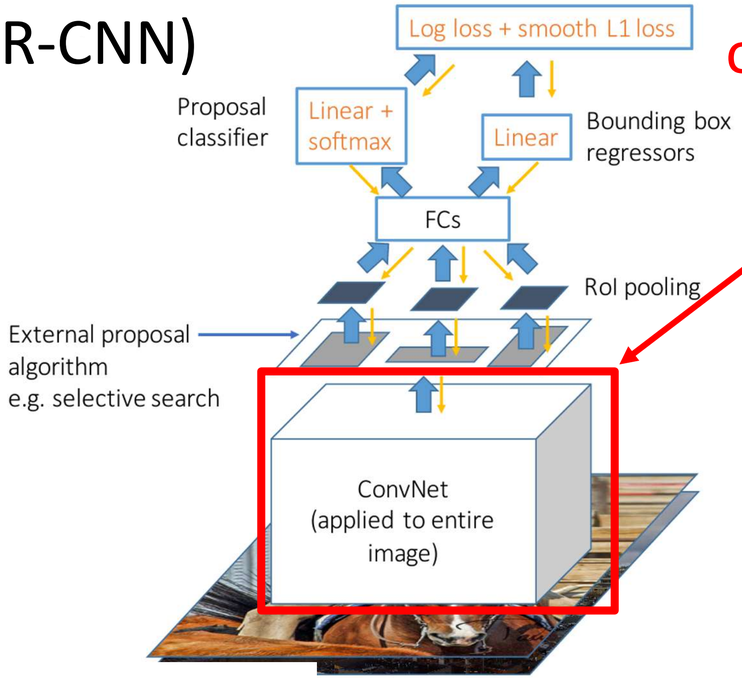


Girshick, "Fast R-CNN", ICCV 2015
Figure copyright Ross Girshick, 2015. Reproduced with permission.

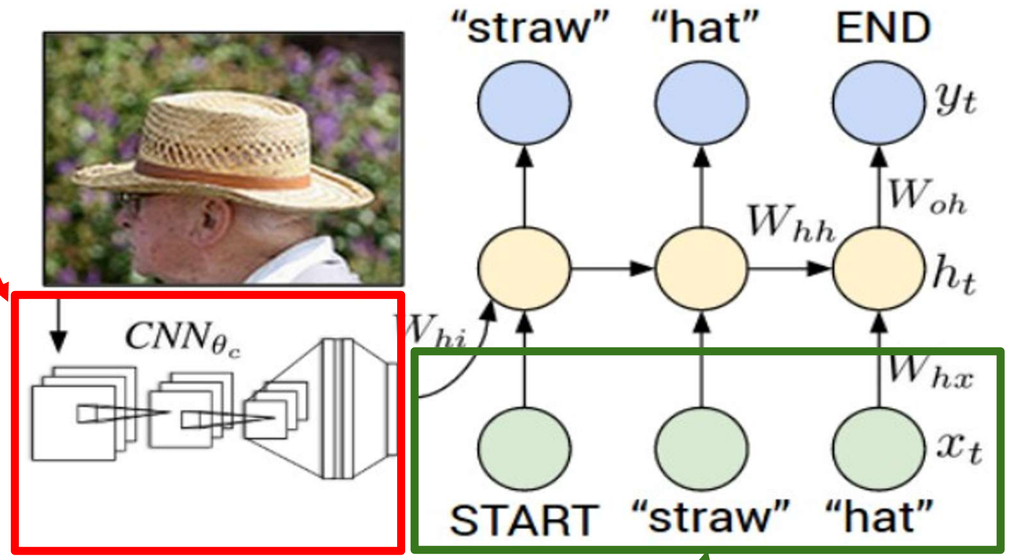
Karpathy and Fei-Fei, "Deep Visual-Semantic Alignments for Generating Image Descriptions", CVPR 2015

Transfer learning is pervasive!
It's the norm, not the exception

Object Detection (Fast R-CNN)



CNN pretrained on ImageNet



Word vectors pretrained with word2vec

Girshick, "Fast R-CNN", ICCV 2015
Figure copyright Ross Girshick, 2015. Reproduced with permission.

Karpathy and Fei-Fei, "Deep Visual-Semantic Alignments for Generating Image Descriptions", CVPR 2015

Convolutional Neural Networks (CNNs)

- A bit of CNN history
- CNN Layers
    - Convolutions, Pooling, Fully Connected Layers, Normalization
- Training CNNs
    - Advanced Optimization
    - Weight initialization
    - Regularization: Dropout
    - Extended training data: Augmentation, Transfer Learning
    - Sanity-checking the learning process; Hyperparameter tuning strategies
- Famous CNN architectures
- CNNs for image segmentation

Convolutional Neural Networks (CNNs)

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Babysitting the learning process

Double check that the loss is reasonable:

```
def init_two_layer_model(input_size, hidden_size, output_size):
  # initialize a model
  model = {}
  model['W1'] = 0.0001 * np.random.randn(input_size, hidden_size)
  model['b1'] = np.zeros(hidden_size)
  model['W2'] = 0.0001 * np.random.randn(hidden_size, output_size)
  model['b2'] = np.zeros(output_size)
  return model
```

```
model = init_two_layer_model(32*32*3, 50, 10) # input size, hidden size, number of classes
loss, grad = two_layer_net(X_train, model, y_train, 0.0)
print loss
```

disable regularization

What output would you expect?

returns the loss and the gradient for all parameters

Double check that the loss is reasonable:

```
def init_two_layer_model(input_size, hidden_size, output_size):
  # initialize a model
  model = {}
  model['W1'] = 0.0001 * np.random.randn(input_size, hidden_size)
  model['b1'] = np.zeros(hidden_size)
  model['W2'] = 0.0001 * np.random.randn(hidden_size, output_size)
  model['b2'] = np.zeros(output_size)
  return model
```

```
model = init_two_layer_model(32*32*3, 50, 10) # input size, hidden size, number of classes
loss, grad = two_layer_net(X_train, model, y_train, 0.0)
print loss
```

disable regularization

```
2.30261216167
```

loss ~2.3.
"correct " for
10 classes

returns the loss and the
gradient for all parameters

Double check that the loss is reasonable:

```
def init_two_layer_model(input_size, hidden_size, output_size):
  # initialize a model
  model = {}
  model['W1'] = 0.0001 * np.random.randn(input_size, hidden_size)
  model['b1'] = np.zeros(hidden_size)
  model['W2'] = 0.0001 * np.random.randn(hidden_size, output_size)
  model['b2'] = np.zeros(output_size)
  return model
```

```
model = init_two_layer_model(32*32*3, 50, 10) # input size, hidden size, number of classes
loss, grad = two_layer_net(X_train, model, y_train, 1e3)
print loss
```

crank up regularization

```
3.06859716482
```

loss went up, good. (sanity check)

Let’s try to train now…

1st check: Make sure that you can overfit very small portion of the training data

```
model = init_two_layer_model(32*32*3, 50, 10) # input size, hidden size, number of classes
trainer = ClassifierTrainer()
X_tiny = X_train[:20] # take 20 examples
y_tiny = y_train[:20]
best_model, stats = trainer.train(X_tiny, y_tiny, X_tiny, y_tiny,
                                  model, two_layer_net,
                                  num_epochs=200, reg=0.0,
                                  update='sgd', learning_rate_decay=1,
                                  sample_batches = False,
                                  learning_rate=1e-3, verbose=True)
```

The above code:

- take the first 20 examples from CIFAR-10
- turn off regularization (reg = 0.0)
- use standard “sgd”

Let’s try to train now…

1st check: Make sure that you can overfit very small portion of the training data

Very small loss, train accuracy 1.00, nice!

```
model = init_two_layer_model(32*32*3, 50, 10) # input size, hidden size, number of classes
trainer = ClassifierTrainer()
X_tiny = X_train[:20] # take 20 examples
y_tiny = y_train[:20]
best_model, stats = trainer.train(X_tiny, y_tiny, X_tiny, y_tiny,
                                  model, two_layer_net,
                                  num_epochs=200, reg=0.0,
                                  update='sgd', learning_rate_decay=1,
                                  sample_batches = False,
                                  learning_rate=1e-3, verbose=True)
```

```
Finished epoch 1 / 200: cost 2.302603, train: 0.400000, val 0.400000, lr 1.000000e-03
Finished epoch 2 / 200: cost 2.302258, train: 0.450000, val 0.450000, lr 1.000000e-03
Finished epoch 3 / 200: cost 2.301849, train: 0.600000, val 0.600000, lr 1.000000e-03
Finished epoch 4 / 200: cost 2.301196, train: 0.650000, val 0.650000, lr 1.000000e-03
Finished epoch 5 / 200: cost 2.300044, train: 0.650000, val 0.650000, lr 1.000000e-03
Finished epoch 6 / 200: cost 2.297864, train: 0.550000, val 0.550000, lr 1.000000e-03
Finished epoch 7 / 200: cost 2.293595, train: 0.600000, val 0.600000, lr 1.000000e-03
Finished epoch 8 / 200: cost 2.285096, train: 0.550000, val 0.550000, lr 1.000000e-03
Finished epoch 9 / 200: cost 2.268094, train: 0.550000, val 0.550000, lr 1.000000e-03
Finished epoch 10 / 200: cost 2.234787, train: 0.500000, val 0.500000, lr 1.000000e-03
Finished epoch 11 / 200: cost 2.173187, train: 0.500000, val 0.500000, lr 1.000000e-03
Finished epoch 12 / 200: cost 2.076862, train: 0.500000, val 0.500000, lr 1.000000e-03
Finished epoch 13 / 200: cost 1.974090, train: 0.400000, val 0.400000, lr 1.000000e-03
Finished epoch 14 / 200: cost 1.895885, train: 0.400000, val 0.400000, lr 1.000000e-03
Finished epoch 15 / 200: cost 1.820876, train: 0.450000, val 0.450000, lr 1.000000e-03
Finished epoch 16 / 200: cost 1.737430, train: 0.450000, val 0.450000, lr 1.000000e-03
Finished epoch 17 / 200: cost 1.642356, train: 0.500000, val 0.500000, lr 1.000000e-03
Finished epoch 18 / 200: cost 1.535239, train: 0.600000, val 0.600000, lr 1.000000e-03
Finished epoch 19 / 200: cost 1.421527, train: 0.600000, val 0.600000, lr 1.000000e-03
...
Finished epoch 195 / 200: cost 0.002694, train: 1.000000, val 1.000000, lr 1.000000e-03
Finished epoch 196 / 200: cost 0.002674, train: 1.000000, val 1.000000, lr 1.000000e-03
Finished epoch 197 / 200: cost 0.002655, train: 1.000000, val 1.000000, lr 1.000000e-03
Finished epoch 198 / 200: cost 0.002635, train: 1.000000, val 1.000000, lr 1.000000e-03
Finished epoch 199 / 200: cost 0.002617, train: 1.000000, val 1.000000, lr 1.000000e-03
Finished epoch 200 / 200: cost 0.002597, train: 1.000000, val 1.000000, lr 1.000000e-03
finished optimization. best validation accuracy: 1.000000
```

Let’s try to train now…

Start with small regularization and find learning rate that makes the loss go down.

```
model = init_two_layer_model(32*32*3, 50, 10) # input size, hidden size, number of classes
trainer = ClassifierTrainer()
best_model, stats = trainer.train(X_train, y_train, X_val, y_val,
                                  model, two_layer_net,
                                  num_epochs=10, reg=0.000001,
                                  update='sgd', learning_rate_decay=1,
                                  sample_batches = True,
                                  learning_rate=1e-6, verbose=True)
```

Let’s try to train now…

Start with small regularization and find learning rate that makes the loss go down.

loss not going down:
learning rate too low

```
model = init_two_layer_model(32*32*3, 50, 10) # input size, hidden size, number of classes
trainer = ClassifierTrainer()
best_model, stats = trainer.train(X_train, y_train, X_val, y_val,
                                  model, two_layer_net,
                                  num_epochs=10, reg=0.000001,
                                  update='sgd', learning_rate_decay=1,
                                  sample_batches = True,
                                  learning_rate=1e-6, verbose=True)
```

```
Finished epoch 1 / 10: cost 2.302576, train: 0.080000, val 0.103000, lr 1.000000e-06
Finished epoch 2 / 10: cost 2.302582, train: 0.121000, val 0.124000, lr 1.000000e-06
Finished epoch 3 / 10: cost 2.302558, train: 0.119000, val 0.138000, lr 1.000000e-06
Finished epoch 4 / 10: cost 2.302519, train: 0.127000, val 0.151000, lr 1.000000e-06
Finished epoch 5 / 10: cost 2.302517, train: 0.158000, val 0.171000, lr 1.000000e-06
Finished epoch 6 / 10: cost 2.302518, train: 0.179000, val 0.172000, lr 1.000000e-06
Finished epoch 7 / 10: cost 2.302466, train: 0.180000, val 0.176000, lr 1.000000e-06
Finished epoch 8 / 10: cost 2.302452, train: 0.175000, val 0.185000, lr 1.000000e-06
Finished epoch 9 / 10: cost 2.302459, train: 0.206000, val 0.192000, lr 1.000000e-06
Finished epoch 10 / 10: cost 2.302420, train: 0.190000, val 0.192000, lr 1.000000e-06
finished optimization. best validation accuracy: 0.192000
```

Loss barely changing:
Learning rate is probably too low

Notice train/val accuracy goes to 20% though, what’s up with that? (remember this is softmax)

Let’s try to train now…

Start with small regularization and find learning rate that makes the loss go down.

loss not going down:
learning rate too low

```
model = init_two_layer_model(32*32*3, 50, 10) # input size, hidden size, number of classes
trainer = ClassifierTrainer()
best_model, stats = trainer.train(X_train, y_train, X_val, y_val,
                                  model, two_layer_net,
                                  num_epochs=10, reg=0.000001,
                                  update='sgd', learning_rate_decay=1,
                                  sample_batches = True,
```

Now let’s try learning rate 1e6.

Let’s try to train now…

Start with small regularization and find learning rate that makes the loss go down.

loss not going down:
learning rate too low

loss exploding:
learning rate too high

```
model = init_two_layer_model(32*32*3, 50, 10) # input size, hidden size, number of classes
trainer = ClassifierTrainer()
best_model, stats = trainer.train(X_train, y_train, X_val, y_val,
                                  model, two_layer_net,
                                  num_epochs=10, reg=0.000001,
                                  update='sgd', learning_rate_decay=1,
                                  sample_batches = True,
                                  learning_rate=1e6, verbose=True)
```

```
/home/karpathy/cs231n/code/cs231n/classifiers/neural_net.py:50: RuntimeWarning: divide by zero en
countered in log
  data_loss = -np.sum(np.log(probs[range(N), y])) / N
/home/karpathy/cs231n/code/cs231n/classifiers/neural_net.py:48: RuntimeWarning: invalid value enc
ountered in subtract
  probs = np.exp(scores - np.max(scores, axis=1, keepdims=True))
Finished epoch 1 / 10: cost nan, train: 0.091000, val 0.087000, lr 1.000000e+06
Finished epoch 2 / 10: cost nan, train: 0.095000, val 0.087000, lr 1.000000e+06
Finished epoch 3 / 10: cost nan, train: 0.100000, val 0.087000, lr 1.000000e+06
```

loss: NaN often means learning rate too high…

Let’s try to train now…

Start with small regularization and find learning rate that makes the loss go down.

loss not going down: learning rate too low

loss exploding: learning rate too high

```
model = init_two_layer_model(32*32*3, 50, 10) # input size, hidden size, number of classes
trainer = ClassifierTrainer()
best_model, stats = trainer.train(X_train, y_train, X_val, y_val,
                                  model, two_layer_net,
                                  num_epochs=10, reg=0.000001,
                                  update='sgd', learning_rate_decay=1,
                                  sample_batches = True,
                                  learning_rate=3e-3, verbose=True)
```

```
Finished epoch 1 / 10: cost 2.186654, train: 0.308000, val 0.306000, lr 3.000000e-03
Finished epoch 2 / 10: cost 2.176230, train: 0.330000, val 0.350000, lr 3.000000e-03
Finished epoch 3 / 10: cost 1.942257, train: 0.376000, val 0.352000, lr 3.000000e-03
Finished epoch 4 / 10: cost 1.827868, train: 0.329000, val 0.310000, lr 3.000000e-03
Finished epoch 5 / 10: cost inf, train: 0.128000, val 0.128000, lr 3.000000e-03
Finished epoch 6 / 10: cost inf, train: 0.144000, val 0.147000, lr 3.000000e-03
```

3e-3 is still too high. Cost explodes…

➡ Rough range for learning rate we should be validating is somewhere [1e-3 … 1e-5]

Hyperparameter Optimization

Random Search vs. Grid Search

Random Search for
Hyper-Parameter Optimization
Bergstra and Bengio, 2012

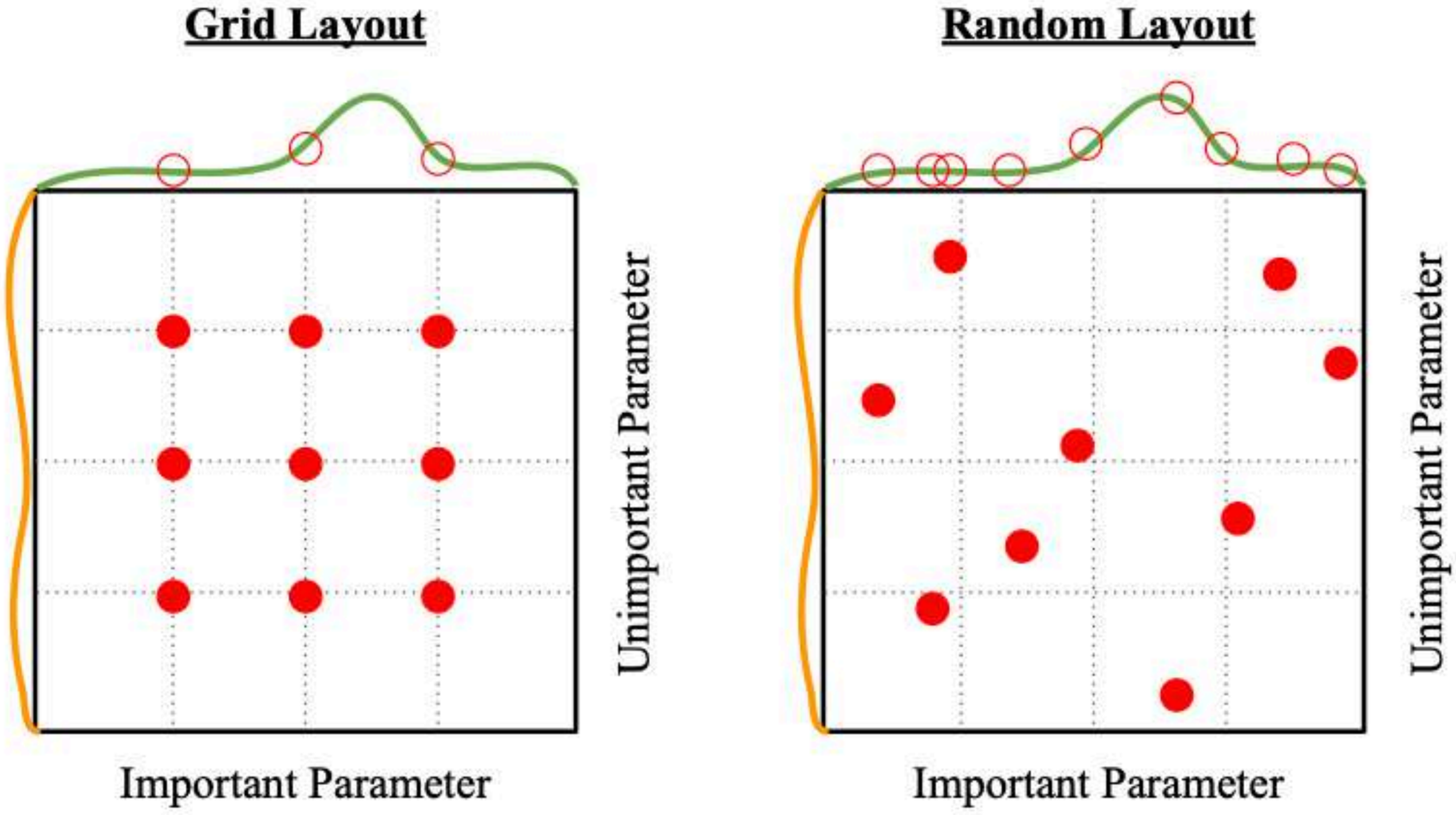

Illustration of Bergstra et al., 2012 by Shayne Longpre, copyright CS231n 2017

Validation strategy

coarse → fine validation in stages

First stage: only a few epochs to get rough idea of what params works

Second stage: longer running time, finer search

… (repeat as necessary)

For example: run coarse search for 5 epochs

```
max_count = 100
for count in xrange(max_count):
      reg = 10**uniform(-5, 5)
      lr = 10**uniform(-3, -6)

      trainer = ClassifierTrainer()
      model = init_two_layer_model(32*32*3, 50, 10) # input size, hidden size, number of classes
      trainer = ClassifierTrainer()
      best_model_local, stats = trainer.train(X_train, y_train, X_val, y_val,
                                              model, two_layer_net,
                                              num_epochs=5, reg=reg,
                                              update='momentum', learning_rate_decay=0.9,
                                              sample_batches = True, batch_size = 100,
                                              learning_rate=lr, verbose=False)
```

note it's best to optimize in log space!

```
val_acc: 0.412000, lr: 1.405206e-04, reg: 4.793564e-01, (1 / 100)
val_acc: 0.214000, lr: 7.231888e-06, reg: 2.321281e-04, (2 / 100)
val_acc: 0.208000, lr: 2.119571e-06, reg: 8.011857e+01, (3 / 100)
val_acc: 0.196000, lr: 1.551131e-05, reg: 4.374936e-05, (4 / 100)
val_acc: 0.079000, lr: 1.753300e-05, reg: 1.200424e+03, (5 / 100)
val_acc: 0.223000, lr: 4.215128e-05, reg: 4.196174e+01, (6 / 100)
val_acc: 0.441000, lr: 1.750259e-04, reg: 2.110807e-04, (7 / 100)
val_acc: 0.241000, lr: 6.749231e-05, reg: 4.226413e+01, (8 / 100)
val_acc: 0.482000, lr: 4.296863e-04, reg: 6.642555e-01, (9 / 100)
val_acc: 0.079000, lr: 5.401602e-06, reg: 1.599828e+04, (10 / 100)
val_acc: 0.154000, lr: 1.618508e-06, reg: 4.925252e-01, (11 / 100)
```

nice

Now run finer search …

```
max_count = 100
for count in xrange(max_count):
      reg = 10**uniform(-5, 5)
      lr = 10**uniform(-3, -6)
```

adjust range →

```
max_count = 100
for count in xrange(max_count):
      reg = 10**uniform(-4, 0)
      lr = 10**uniform(-3, -4)
```

```
val_acc: 0.527000, lr: 5.340517e-04, reg: 4.097824e-01, (0 / 100)
val_acc: 0.492000, lr: 2.279484e-04, reg: 9.991345e-04, (1 / 100)
val_acc: 0.512000, lr: 8.680827e-04, reg: 1.349727e-02, (2 / 100)
val_acc: 0.461000, lr: 1.028377e-04, reg: 1.220193e-02, (3 / 100)
val_acc: 0.460000, lr: 1.113730e-04, reg: 5.244309e-02, (4 / 100)
val_acc: 0.498000, lr: 9.477776e-04, reg: 2.001293e-03, (5 / 100)
val_acc: 0.469000, lr: 1.484369e-04, reg: 4.328313e-01, (6 / 100)
val_acc: 0.522000, lr: 5.586261e-04, reg: 2.312685e-04, (7 / 100)
val_acc: 0.530000, lr: 5.808183e-04, reg: 8.259964e-02, (8 / 100)
val_acc: 0.489000, lr: 1.979168e-04, reg: 1.010889e-04, (9 / 100)
val_acc: 0.490000, lr: 2.036031e-04, reg: 2.406271e-03, (10 / 100)
val_acc: 0.475000, lr: 2.021162e-04, reg: 2.287807e-01, (11 / 100)
val_acc: 0.460000, lr: 1.135527e-04, reg: 3.905040e-02, (12 / 100)
val_acc: 0.515000, lr: 6.947668e-04, reg: 1.562808e-02, (13 / 100)
val_acc: 0.531000, lr: 9.471549e-04, reg: 1.433895e-03, (14 / 100)
val_acc: 0.509000, lr: 3.140888e-04, reg: 2.857518e-01, (15 / 100)
val_acc: 0.514000, lr: 6.438349e-04, reg: 3.033781e-01, (16 / 100)
val_acc: 0.502000, lr: 3.921784e-04, reg: 2.707126e-04, (17 / 100)
val_acc: 0.509000, lr: 9.752279e-04, reg: 2.850865e-03, (18 / 100)
val_acc: 0.500000, lr: 2.412048e-04, reg: 4.997821e-04, (19 / 100)
val_acc: 0.466000, lr: 1.319314e-04, reg: 1.189915e-02, (20 / 100)
val_acc: 0.516000, lr: 8.039527e-04, reg: 1.528291e-02, (21 / 100)
```

53% - relatively good for a 2-layer neural net with 50 hidden neurons.

← But this best cross-validation result is worrying. Why?

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- Famous CNN architectures
- CNNs for image segmentation

Course Outline

- Introduction to Image Analysis
- Basics: Neural Networks
- **Convolutional Neural Networks**
- Transformers
- Model Interpretability
- Self-supervised Learning
- Generative Models (GANs, Diffusion)