Training Aspects of Neural Networks

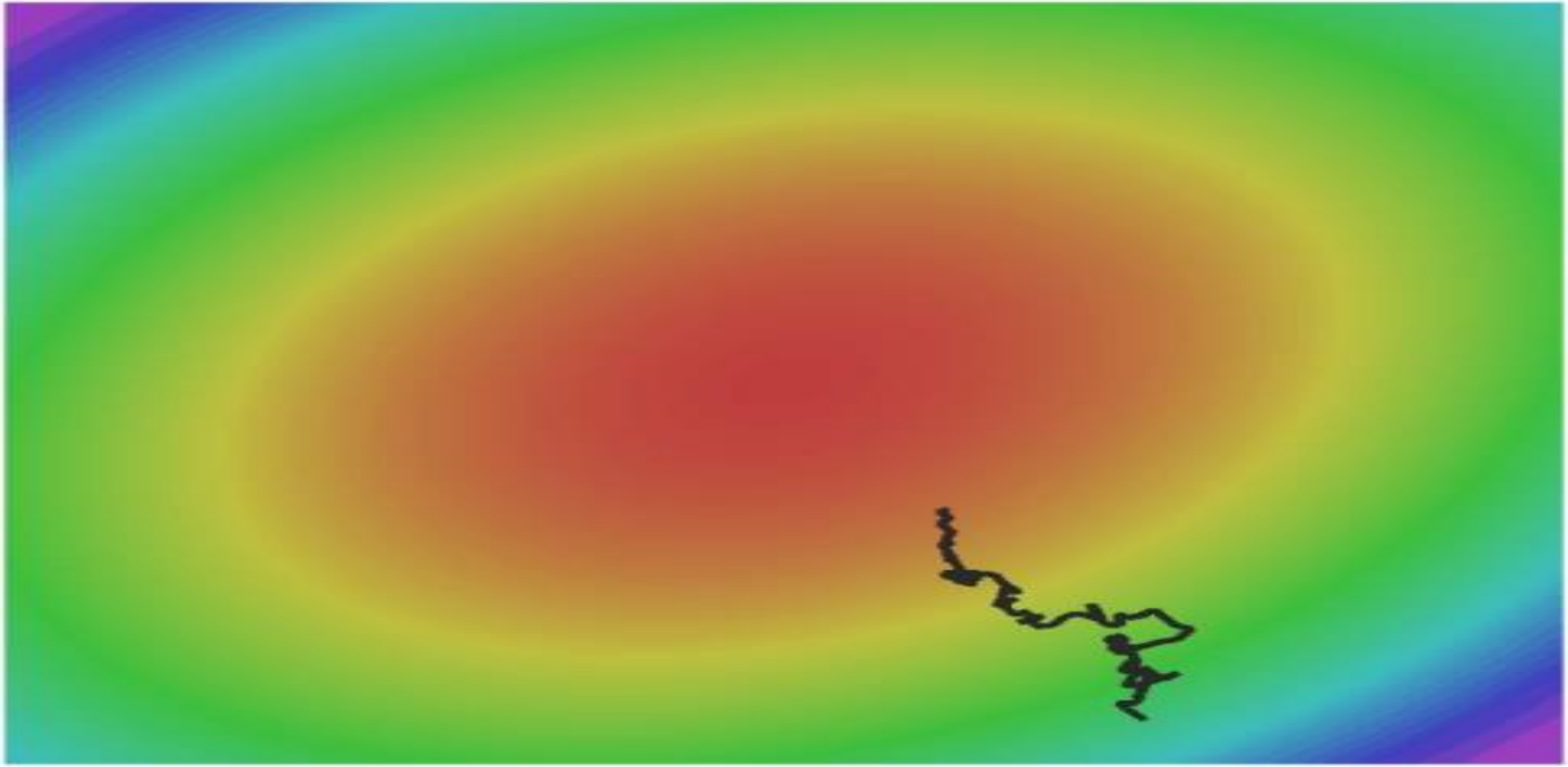
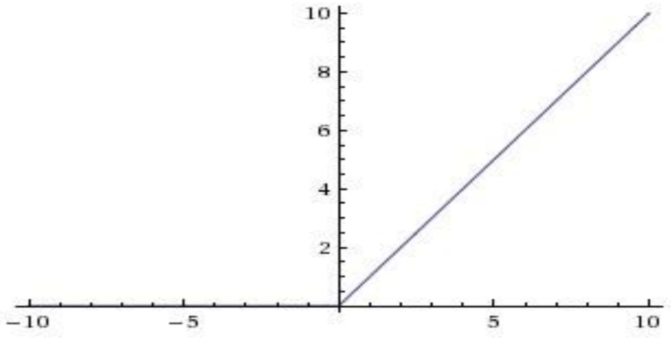


Image Source: cs231n, Stanford University

Previous Class

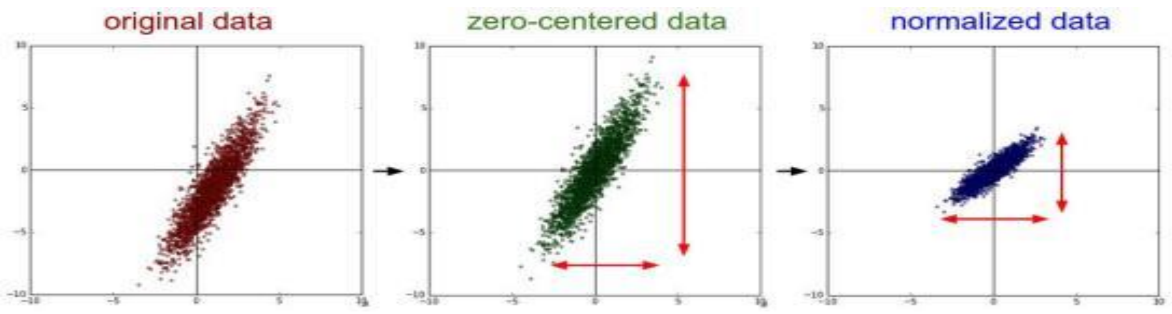
Training Aspects of CNN

- Activation Functions



- Dataset Preparation

- Data Preprocessing

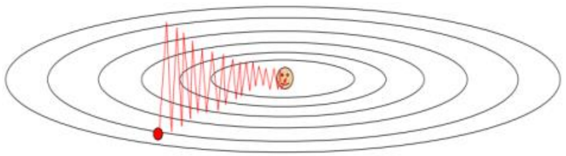


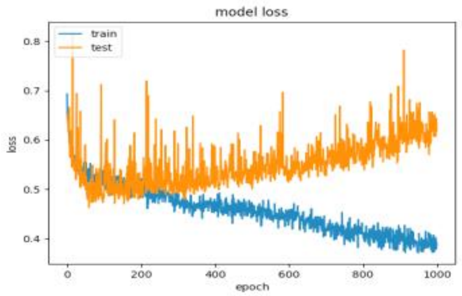
- Weight Initialization

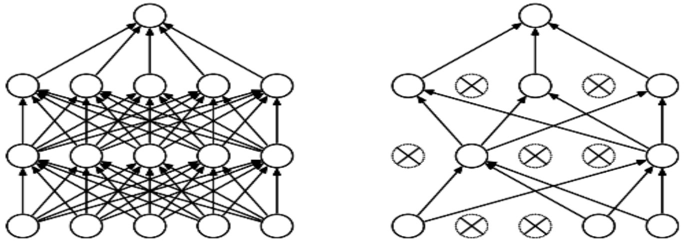
Next Few Classes

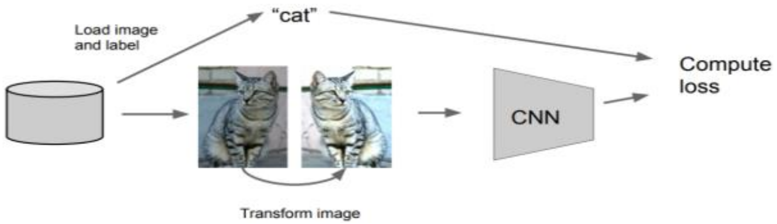
Training Aspects of CNN

- Optimization
- Learning Rate
- Regularization
- Dropout
- Batch Normalization
- Data Augmentation
- Transfer Learning
- Interpreting Loss Curve






(a) Standard Neural Net
(b) After applying dropout.



Optimization

Source: cs231n

Mini-batch SGD

Loop:
1. **Sample** a batch of data
2. **Forward** prop it through the graph (network), get loss
3. **Backprop** to calculate the gradients
4. **Update** the parameters using the gradient

Source: cs231n

Stochastic Gradient Descent (SGD)

The procedure of repeatedly evaluating the gradient of loss function and then performing a parameter update.

Vanilla (Original) Gradient Descent:

```
while True:
  dx = compute_gradient(x)
  x -= learning_rate * dx
```

Source: cs231n

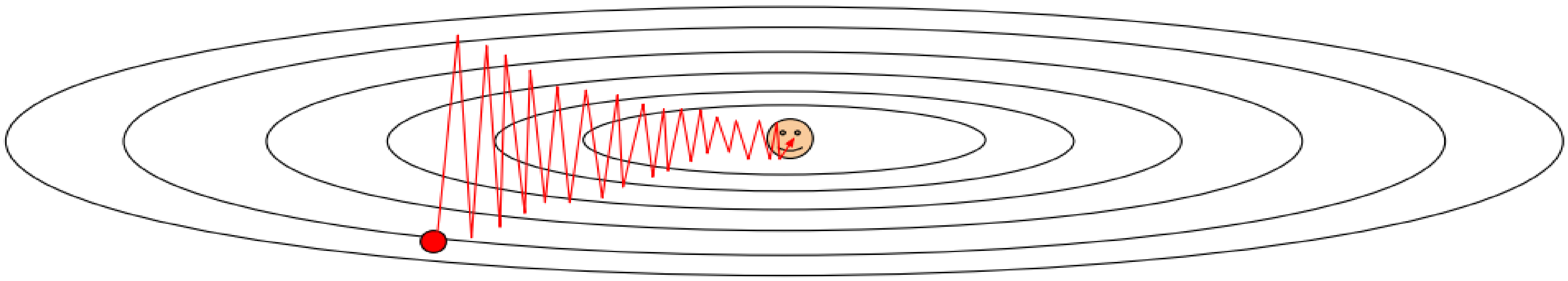
SGD: Problems

What if loss changes quickly in one direction and slowly in another?

SGD: Problems

What if loss changes quickly in one direction and slowly in another?

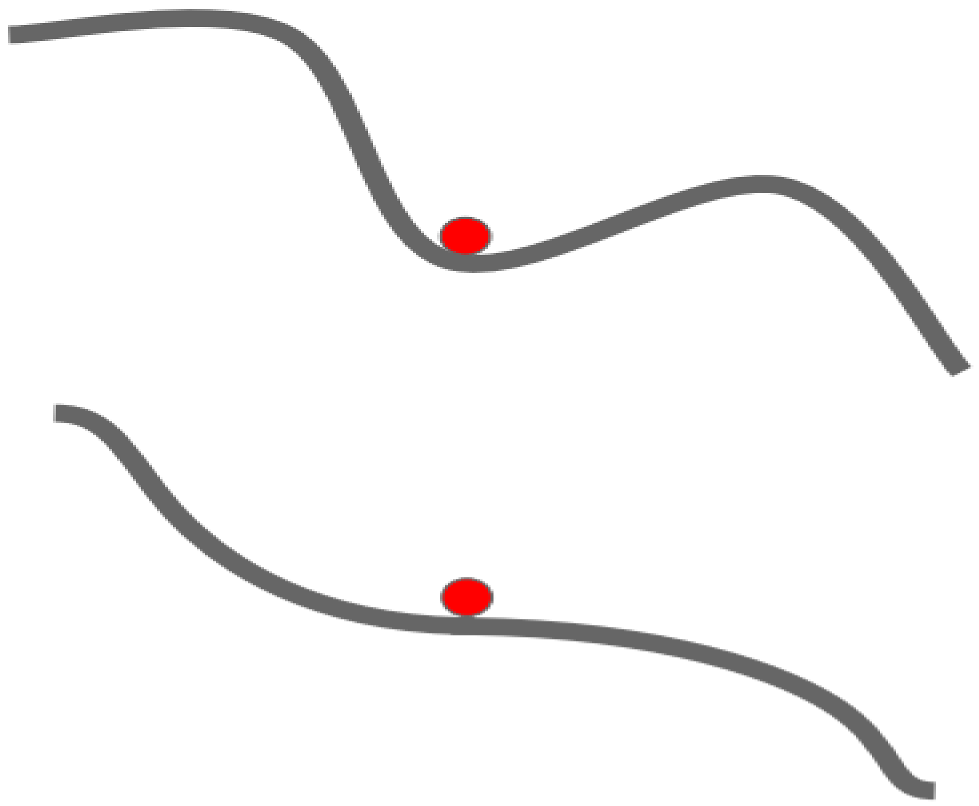
Very slow progress along shallow dimension, jitter along steep direction



Source: cs231n

SGD: Problems

What if the loss function has a **local minima** or **saddle point**?

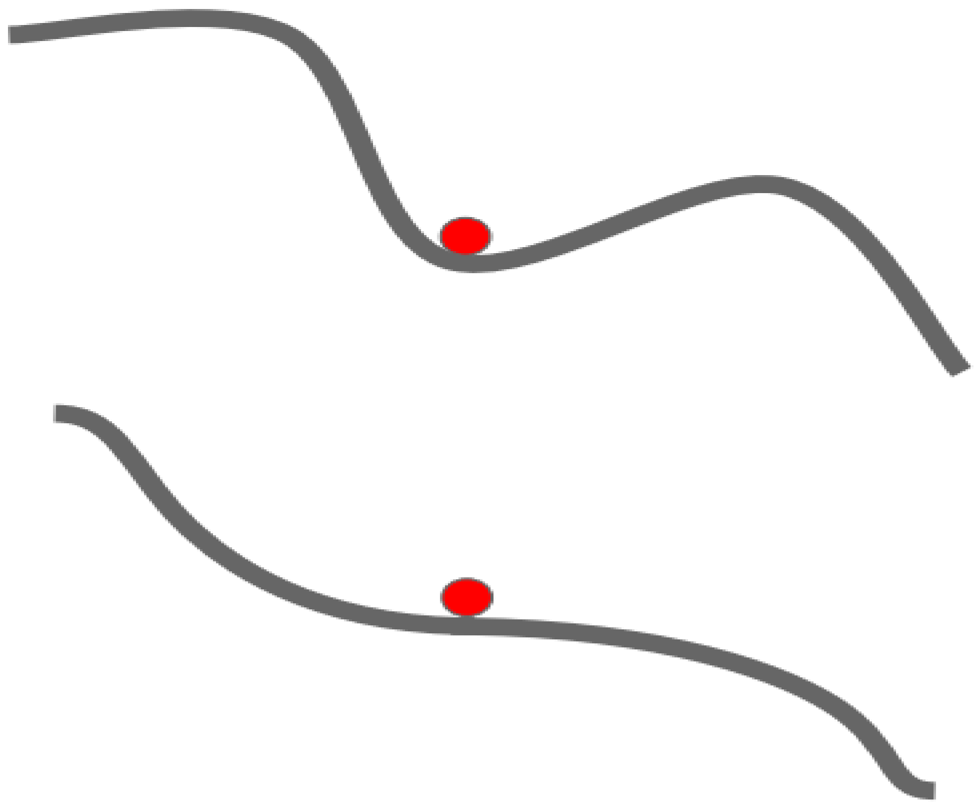


Source: cs231n

SGD: Problems

What if the loss function has a **local minima** or **saddle point**?

Zero gradient, gradient descent gets stuck



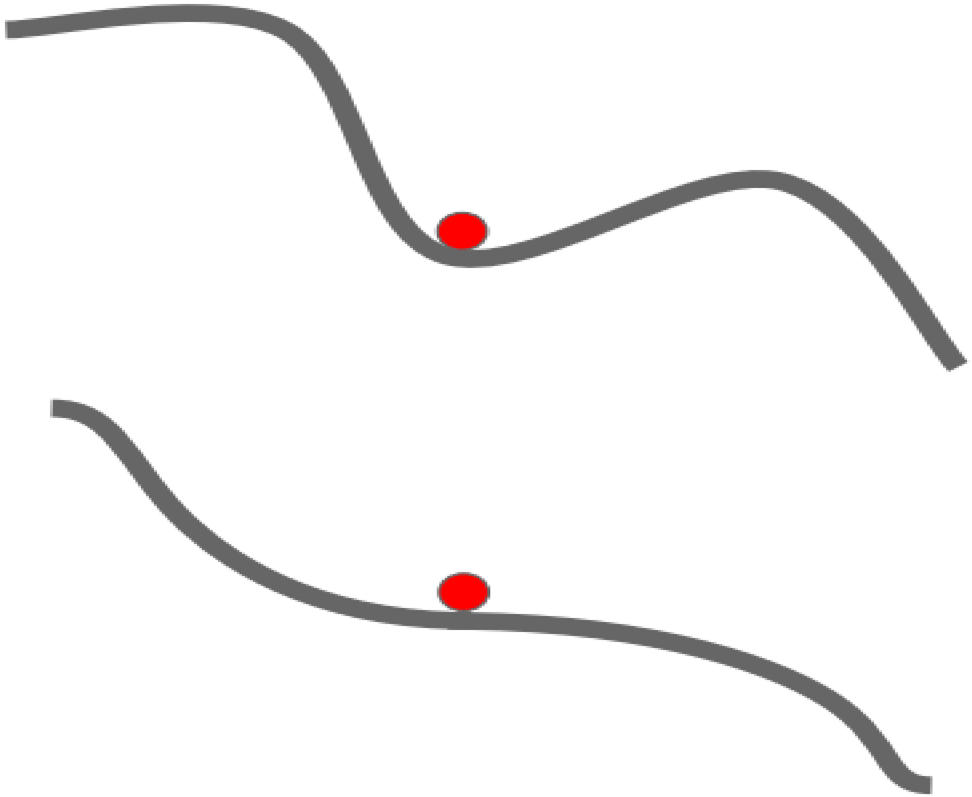
Source: cs231n

SGD: Problems

What if the loss function has a **local minima** or **saddle point**?

Zero gradient, gradient descent gets stuck

Saddle points much more common in high dimension



Dauphin et al, “Identifying and attacking the saddle point problem in high-dimensional non-convex optimization”, NIPS 2014

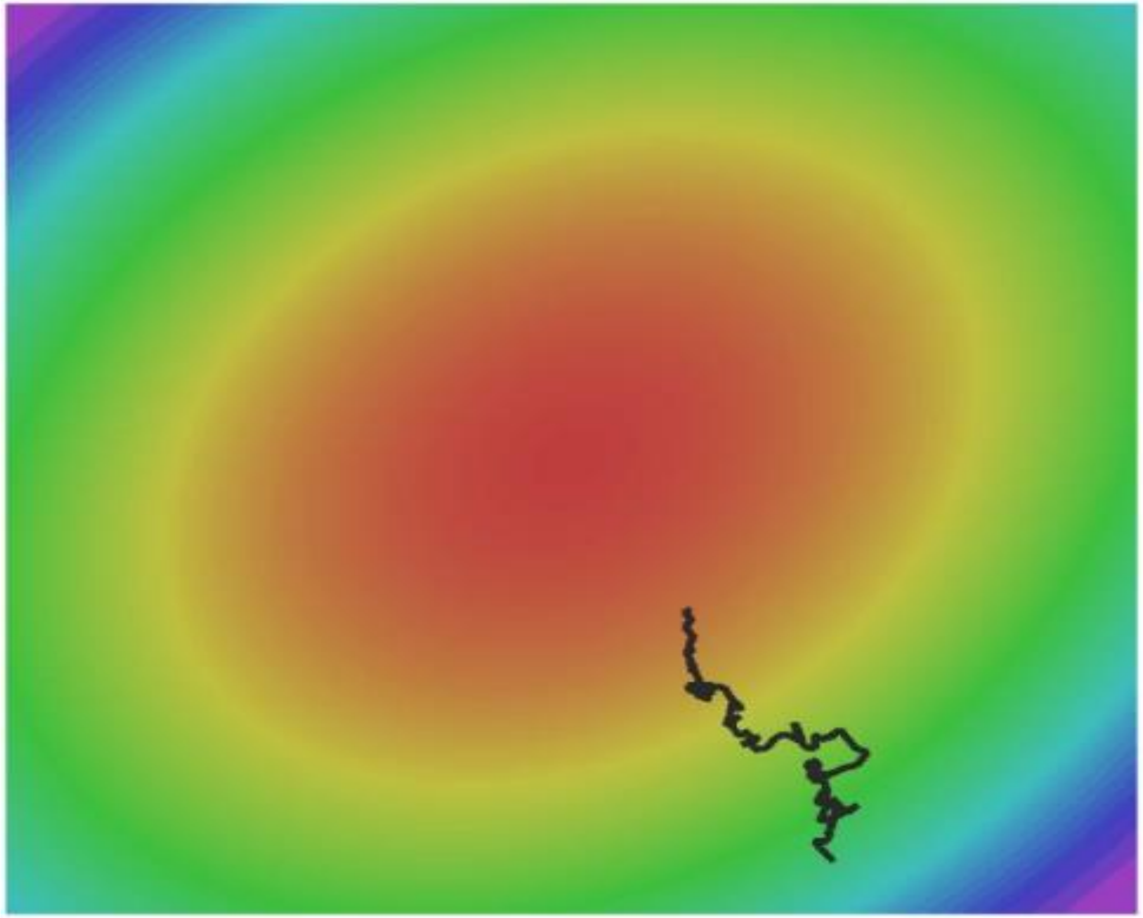
Source: cs231n

SGD: Problems

Our gradients come from **minibatches** so they can be **noisy!**

$$L(W) = \frac{1}{N} \sum_{i=1}^{N} L_i(x_i, y_i, W)$$

$$\nabla_W L(W) = \frac{1}{N} \sum_{i=1}^{N} \nabla_W L_i(x_i, y_i, W)$$



Source: cs231n

SGD + Momentum

SGD

$$x_{t+1} = x_t - \alpha \nabla f(x_t)$$

```
while True:
  dx = compute_gradient(x)
  x -= learning_rate * dx
```

Source: cs231n

SGD + Momentum

SGD

$$x_{t+1} = x_t - \alpha \nabla f(x_t)$$

```
while True:
  dx = compute_gradient(x)
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```

SGD+Momentum

$$v_{t+1} = \rho v_t + \nabla f(x_t)$$
$$x_{t+1} = x_t - \alpha v_{t+1}$$

Source: cs231n

SGD + Momentum

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SGD+Momentum

$$v_{t+1} = \rho v_t + \nabla f(x_t)$$
$$x_{t+1} = x_t - \alpha v_{t+1}$$

```
vx = 0
while True:
  dx = compute_gradient(x)
  vx = rho * vx + dx
  x -= learning_rate * vx
```

Source: cs231n

SGD + Momentum

SGD

$$x_{t+1} = x_t - \alpha \nabla f(x_t)$$

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```
vx = 0
while True:
  dx = compute_gradient(x)
  vx = rho * vx + dx
  x -= learning_rate * vx
```

- Build up “velocity” in any direction that has consistent gradient
- Rho gives “friction”; typically rho=0.9 or 0.99

Source: cs231n

SGD + Momentum

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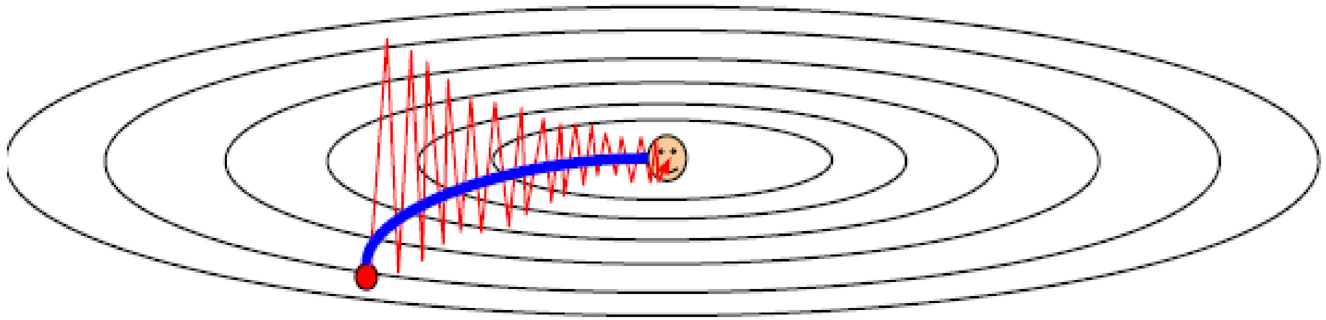

Source: cs231n

AdaGrad

```
grad_squared = 0
while True:
  dx = compute_gradient(x)
  grad_squared += dx * dx
  x -= learning_rate * dx / (np.sqrt(grad_squared) + 1e-7)
```

Added element-wise scaling of the gradient based on the historical sum of squares in each dimension

Duchi et al, “Adaptive subgradient methods for online learning and stochastic optimization”, JMLR 2011

Source: cs231n

AdaGrad

```
grad_squared = 0
while True:
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What happens to the step size over long time?

Duchi et al, “Adaptive subgradient methods for online learning and stochastic optimization”, JMLR 2011

Source: cs231n

AdaGrad

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```

What happens to the step size over long time?

Effective learning rate diminishing problem

Duchi et al, “Adaptive subgradient methods for online learning and stochastic optimization”, JMLR 2011

Source: cs231n

RMSProp

AdaGrad

```
grad_squared = 0
while True:
  dx = compute_gradient(x)
  grad_squared += dx * dx
  x -= learning_rate * dx / (np.sqrt(grad_squared) + 1e-7)
```

RMSProp

```
grad_squared = 0
while True:
  dx = compute_gradient(x)
  grad_squared = decay_rate * grad_squared + (1 - decay_rate) * dx * dx
  x -= learning_rate * dx / (np.sqrt(grad_squared) + 1e-7)
```

Tieleman and Hinton, 2012

Source: cs231n

Adam

Kingma and Ba, “Adam: A method for stochastic optimization”, ICLR 2015

```
first_moment = 0
second_moment = 0
while True:
  dx = compute_gradient(x)
  first_moment = beta1 * first_moment  + (1 - beta1) * dx
  second_moment = beta2 * second_moment + (1 - beta2) * dx * dx
  x -= learning_rate * first_moment / (np.sqrt(second_moment) + 1e-7))
```

Source: cs231n

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```

Sort of like RMSProp with Momentum

Source: cs231n

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

Sort of like RMSProp with Momentum

Problem:

Initially, second_moment=0 and beta2=0.999

After 1st iteration, second_moment -> close to zero

So, very large step for update of x

Source: cs231n

Adam (with Bias correction)

Kingma and Ba, “Adam: A method for stochastic optimization”, ICLR 2015

```
first_moment = 0
second_moment = 0
for t in range(num_iterations):
  dx = compute_gradient(x)
  first_moment = beta1 * first_moment  + (1 - beta1) * dx
  second_moment = beta2 * second_moment + (1 - beta2) * dx * dx
  first_unbias = first_moment / (1 - beta1 ** t)
  second_unbias = second_moment / (1 - beta2 ** t)
  x -= learning_rate * first_unbias / (np.sqrt(second_unbias) + 1e-7))
```

AdaGrad/ RMSProp

Bias Correction

Momentum

Bias correction for the fact that first and second moment estimates start at zero

Source: cs231n

Adam (with Bias correction)

Kingma and Ba, “Adam: A method for stochastic optimization”, ICLR 2015

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first_moment = 0
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for t in range(num_iterations):
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  first_moment = beta1 * first_moment  + (1 - beta1) * dx
  second_moment = beta2 * second_moment + (1 - beta2) * dx * dx
  first_unbias = first_moment / (1 - beta1 ** t)
  second_unbias = second_moment / (1 - beta2 ** t)
  x -= learning_rate * first_unbias / (np.sqrt(second_unbias) + 1e-7))
```

AdaGrad/ RMSProp

Bias Correction

Momentum

Bias correction for the fact that first and second moment estimates start at zero

Adam with **beta1 = 0.9**, **beta2 = 0.999**, and **learning_rate = 1e-3 or 5e-4** is a **great starting point** for many models!

Source: cs231n

Major Problem with Adam

- Does not the optimization trajectory information such as short term gradient behavior

- Overshoots the optima

- Oscillates near the optima

diffGrad Optimizer

Solves the previously mentioned problems by incorporating the local gradient change as friction in effective learning rate.

High local gradient change → low friction → high learning rate

Small local gradient change → high friction → slow learning rate

S.R. Dubey et al. (2020), diffGrad: An Optimization Method for Convolutional Neural Networks, IEEE Transactions on Neural Network and Learning Systems.

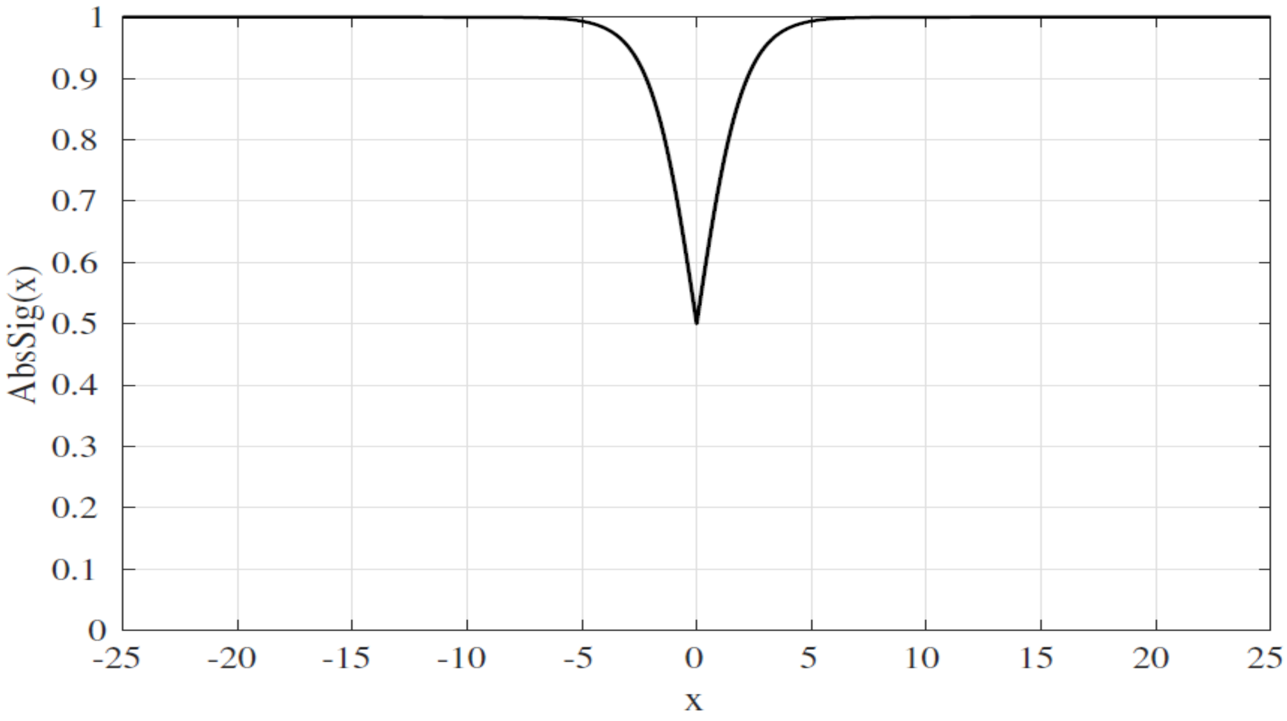
diffGrad Optimizer

$$\theta_{t+1,i} = \theta_{t,i} - \frac{\alpha_t \times \xi_{t,i} \times \hat{m}_{t,i}}{\sqrt{\hat{v}_{t,i}} + \epsilon}$$

$$\xi_{t,i} = AbsSig(\Delta g_{t,i})$$

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

$$\Delta g_{t,i} = g_{t-1,i} - g_{t,i}$$



S.R. Dubey et al. (2020), diffGrad: An Optimization Method for Convolutional Neural Networks, IEEE Transactions on Neural Network and Learning Systems.

Recent SGD Based Optimizers

- Rectified Adam (RADAM)
- AdaBelief
- AngularGrad (Under Review) – by us
- AdaInject (Under Review) – by us

and many more.... still a challenging problem.

https://pythonawesome.com/a-collection-of-optimizers-for-pytorch/

Which optimizer to use in practice?

- Adaptive methods tend to reduce initial training error faster than SGD and are "safer"
  - Andrej Karpathy: *"In the early stages of setting baselines I like to use Adam with a learning rate of 3e-4. In my experience Adam is much more forgiving to hyperparameters, including a bad learning rate. For ConvNets a well-tuned SGD will almost always slightly outperform Adam, but the optimal learning rate region is much more narrow and problem-specific."*
  - Use Adam at first, then switch to SGD?

- However, some literature reports problems with adaptive methods, such as failing to converge or generalizing poorly (Wilson et al. 2017, Reddi et al. 2018)

Optimizer

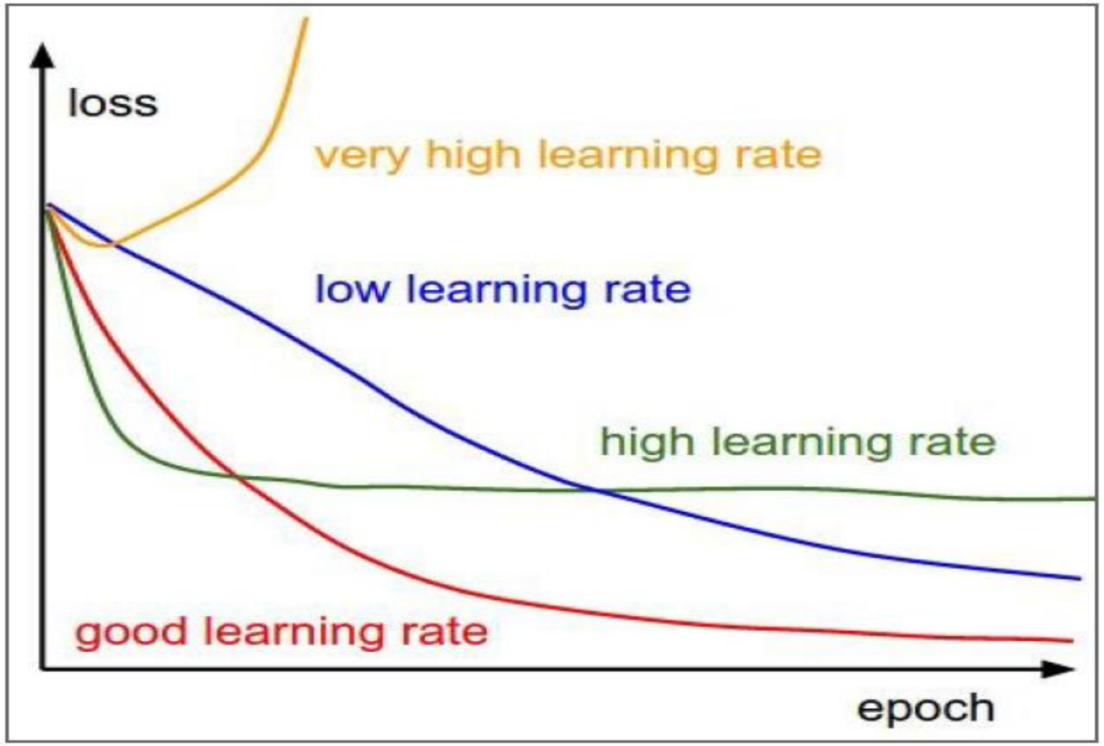
In Practice:

- **Adam** is a good default choice in most cases
    - Try out RADAM, diffGrad and AdaBelief

More Optimizer: http://ruder.io/optimizing-gradient-descent/

Learning Rate

SGD, SGD+Momentum, Adagrad, RMSProp, Adam all have **learning rate** as a hyperparameter.

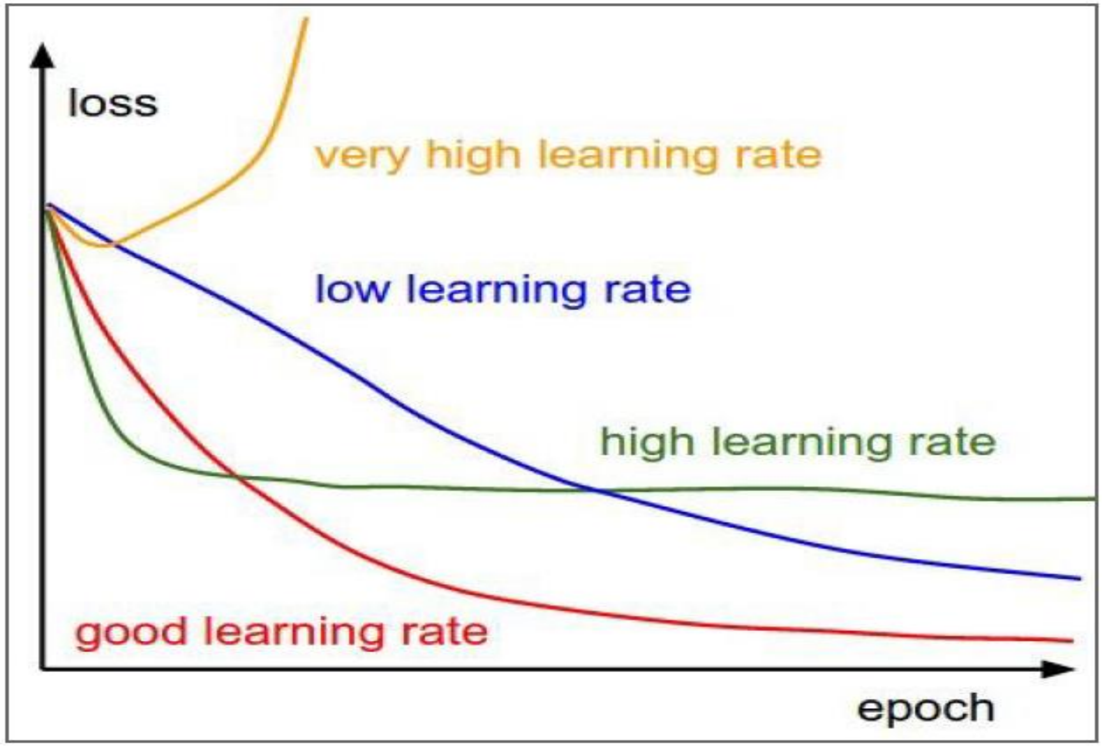


Q: Which one of these learning rates is best to use?

Source: cs231n

Learning Rate

SGD, SGD+Momentum, Adagrad, RMSProp, Adam all have **learning rate** as a hyperparameter.



=> Learning rate decay over time!

step decay:
e.g. decay learning rate by half every few epochs.

exponential decay:

$$\alpha = \alpha_0 e^{-kt}$$

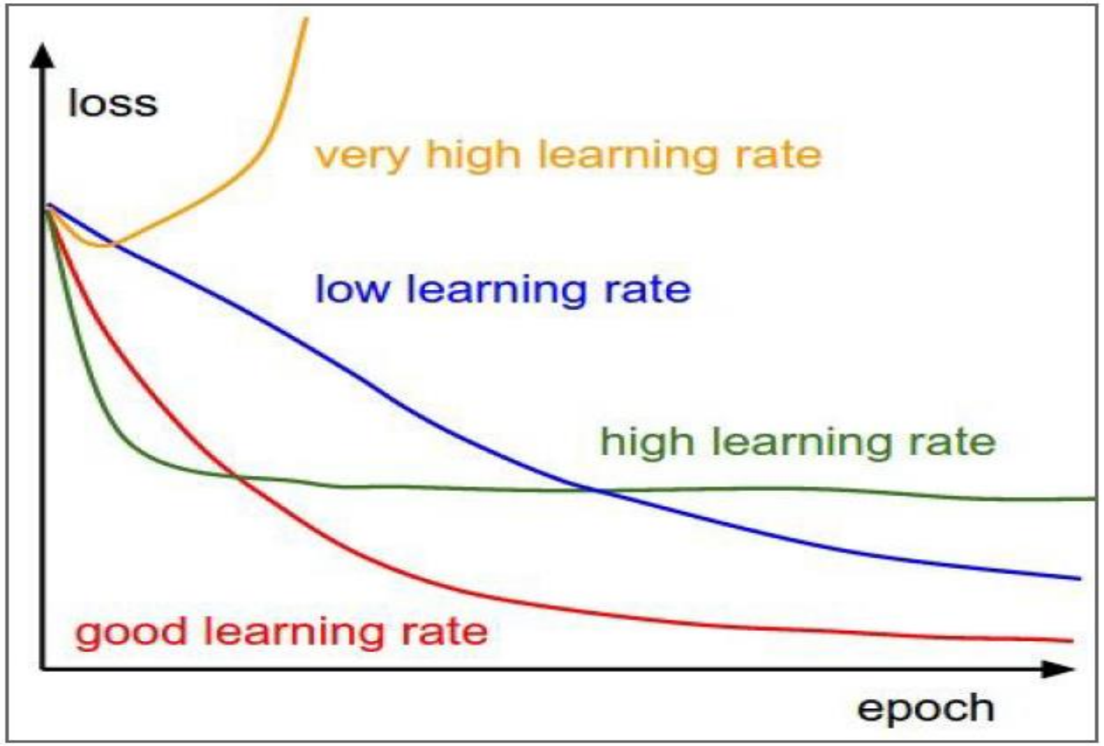
1/t decay:

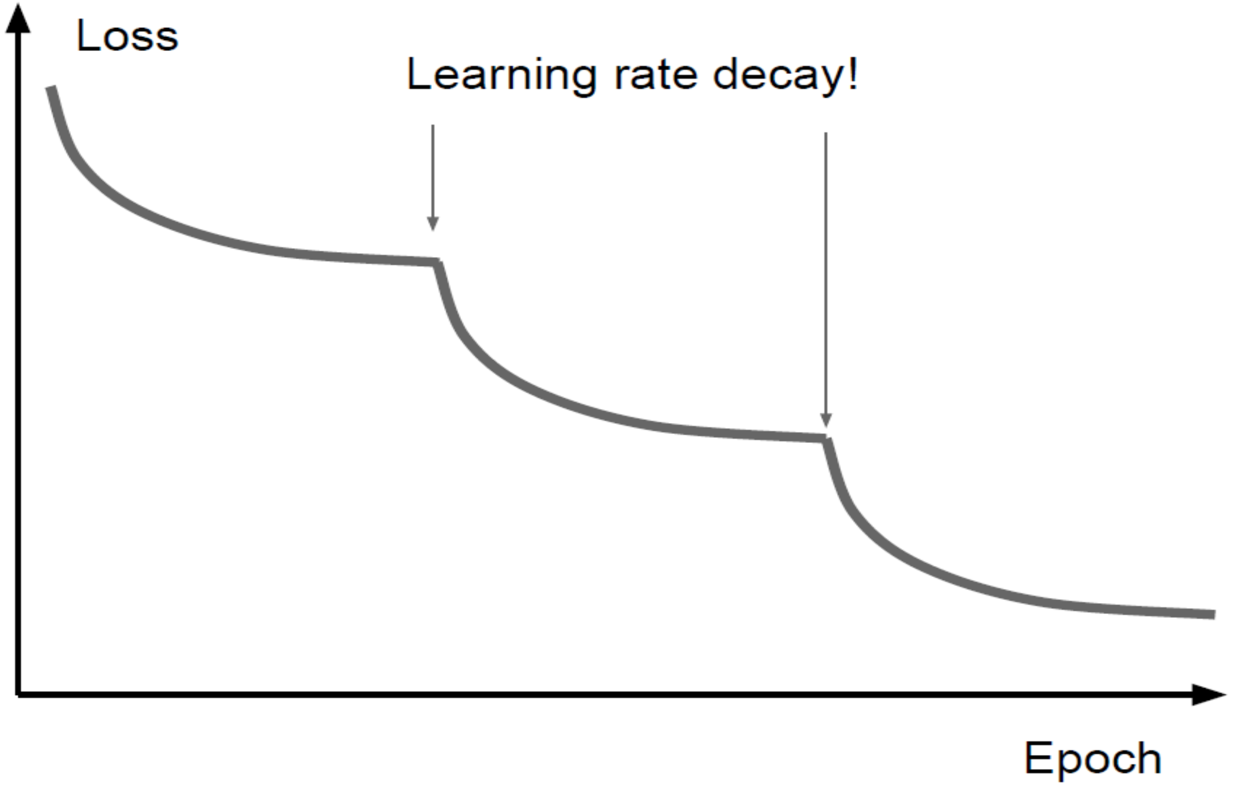
$$\alpha = \alpha_0 / (1 + kt)$$

Source: cs231n

Learning Rate

SGD, SGD+Momentum, Adagrad, RMSProp, Adam all have **learning rate** as a hyperparameter.

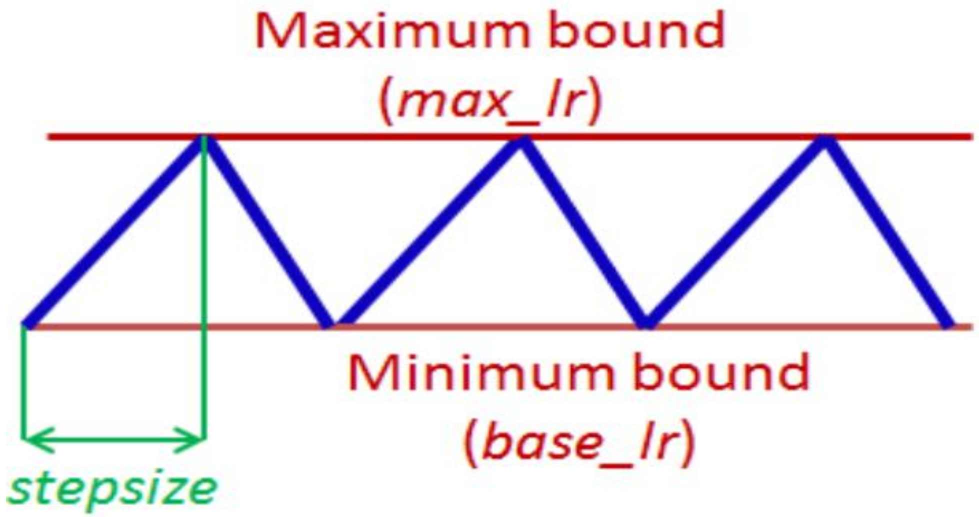


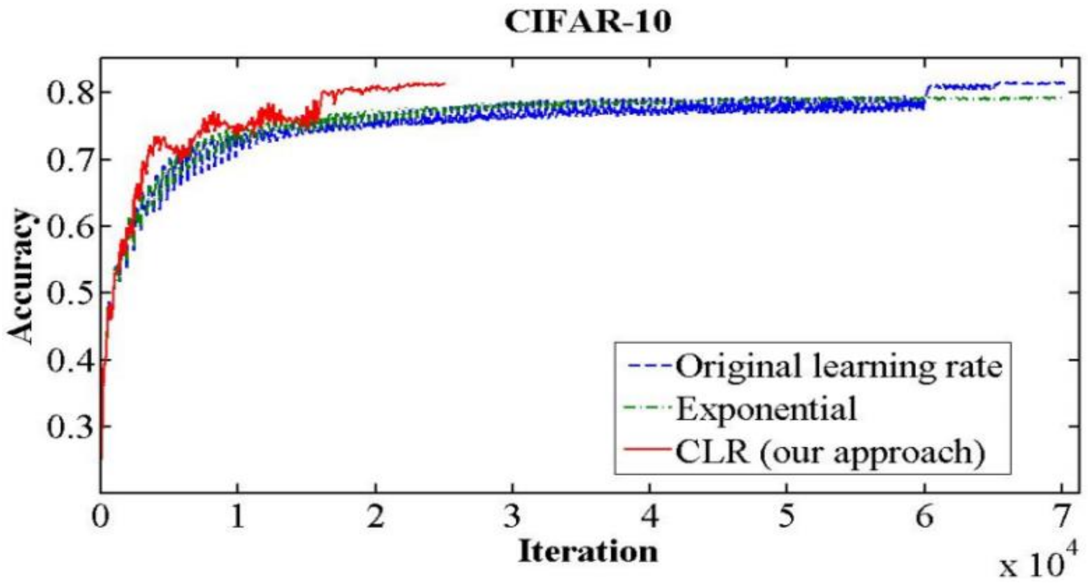


Source: cs231n

Learning Rate

Cyclic Learning Rate





Smith, Leslie N. "Cyclical learning rates for training neural networks." *WACV 2017*.

Learning Rate

In Practice:

- **Learning rate** with step decay is commonly used
  - **Step decay:** reduce rate by a constant factor every few epochs, e.g., by 0.5 every 5 epochs, 0.1 every 20 epochs
  - **Manual:** watch validation error and reduce learning rate whenever it stops improving
    - “Patience” hyperparameter: number of epochs without improvement before reducing learning rate

- **Warmup:** train with a low learning rate for a first few epochs, or linearly increase learning rate before transitioning to normal decay schedule (Goyal et al., 2018)

Setting the mini-batch size

- Larger mini-batches: more expensive and less frequent updates, lower gradient variance, more parallelizable
- SGD with larger batches may generalize more poorly (e.g., Keskar et al., 2017)
- But can be made to work well by carefully controlling learning rate and addressing other optimization issues (Goyal et al., 2018)

When to stop training?

- Monitor validation error to decide when to stop
  - "Patience" hyperparameter: number of epochs without improvement before stopping
  - *Early stopping* can be viewed as a kind of regularization

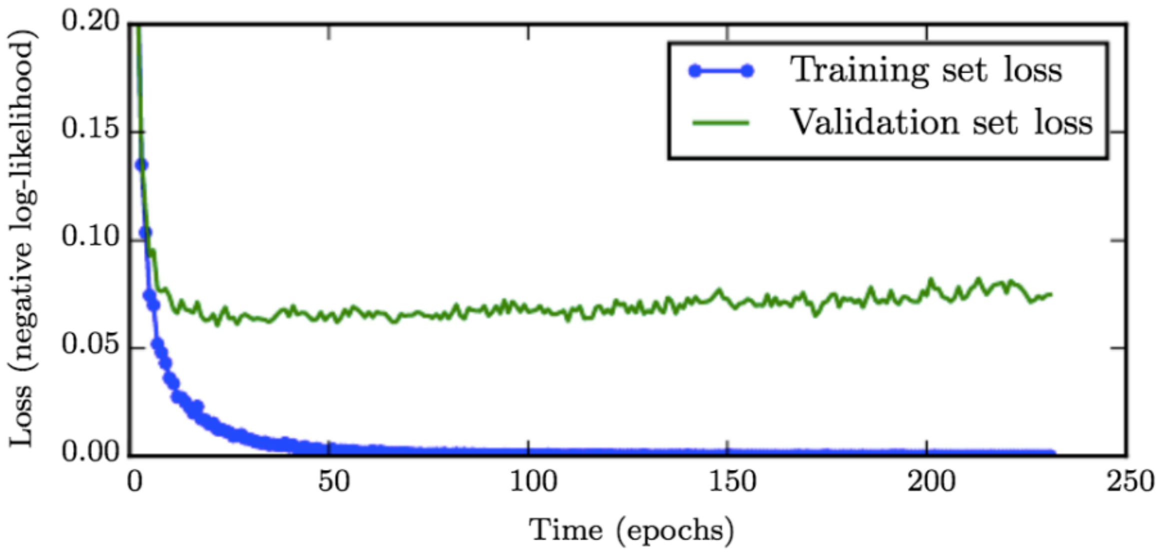
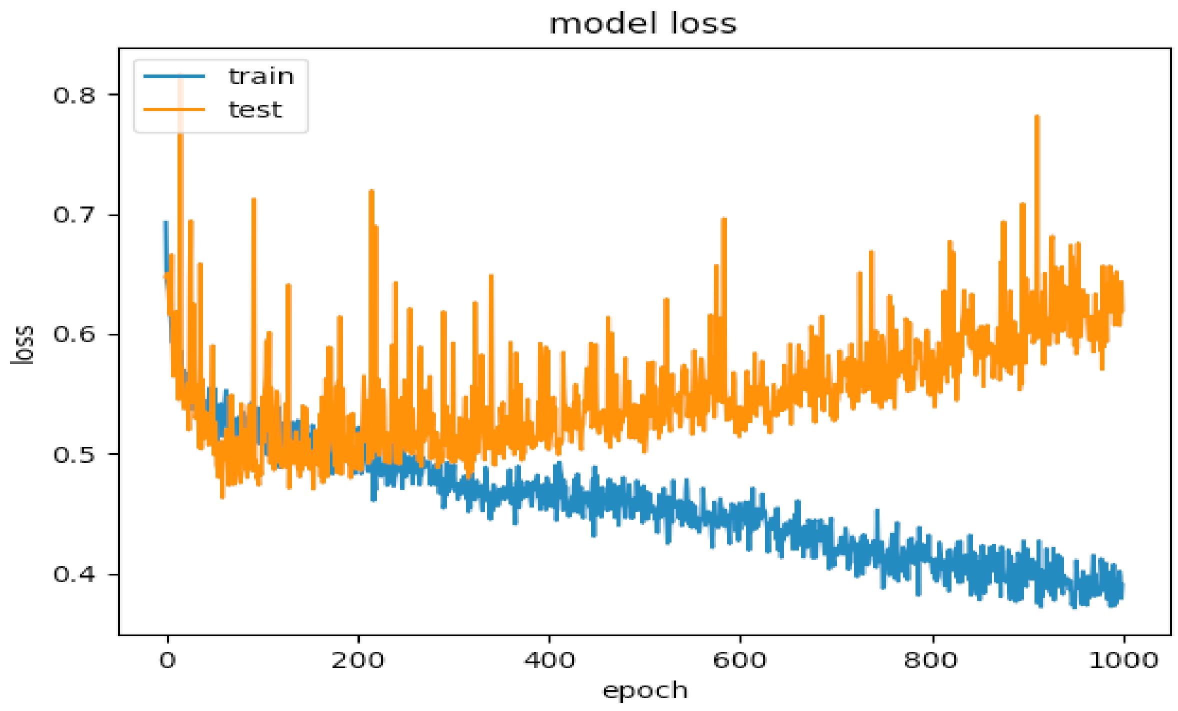


Figure from [Deep Learning Book]

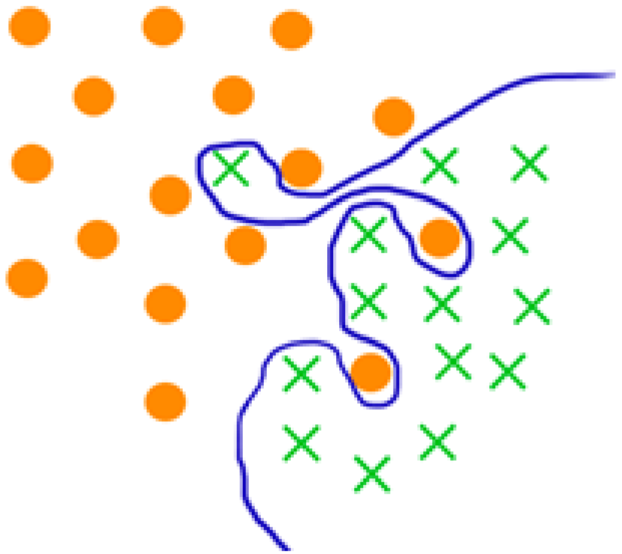


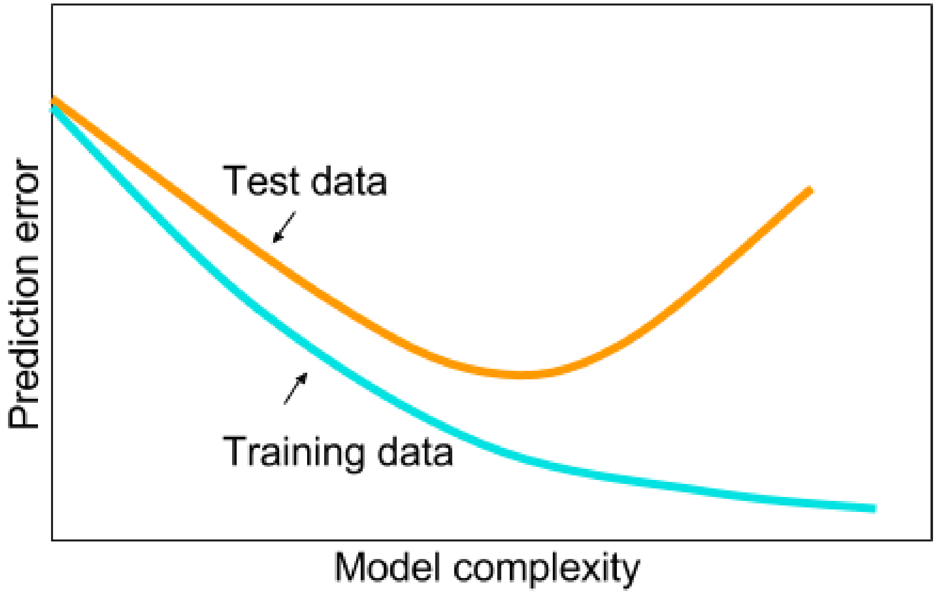
Regularization

Image Source: https://stackoverflow.com/questions/44909134/how-to-avoid-overfitting-on-a-simple-feed-forward-network/44985765

Recall: Regularization

- Techniques for controlling the capacity of a neural network to prevent overfitting





Regularization

$$\underbrace{L(W) = \frac{1}{N}\sum_{i=1}^{N} L_i(f(x_i, W), y_i)}$$

Data loss: Model predictions should match training data

Source: cs231n

Regularization

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

Source: cs231n

Regularization

λ = regularization strength (hyperparameter)

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

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

Source: cs231n

Regularization

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

Why regularize?

- Express preferences over weights
- Make the model *simple* so it works on test data
- Improve optimization by adding curvature

Source: cs231n

Regularization

$$x = [1,1,1,1]$$

$$w_1 = [1,0,0,0]$$

$$w_2 = [0.25,0.25,0.25,0.25]$$

Source: cs231n

Regularization

$$x = [1,1,1,1]$$

$$w_1 = [1,0,0,0]$$

$$w_2 = [0.25,0.25,0.25,0.25]$$

$$w_1.x = w_2.x = 1$$

Source: cs231n

Regularization

$$x = [1,1,1,1]$$

$$w_1 = [1,0,0,0]$$

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$$w_1 . x = w_2 . x = 1$$

Which W to consider?

Source: cs231n

Regularization

$$x = [1,1,1,1]$$

$$w_1 = [1,0,0,0]$$

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$$w_1.x = w_2.x = 1$$

L2 Regularization

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

Source: cs231n

Regularization

$$x = [1,1,1,1]$$

$$w_1 = [1,0,0,0]$$

$$\boxed{w_2 = [0.25,0.25,0.25,0.25]}$$

$$w_1 . x = w_2 . x = 1$$

L2 regularization likes to "spread out" the weights

L2 Regularization

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

Source: cs231n

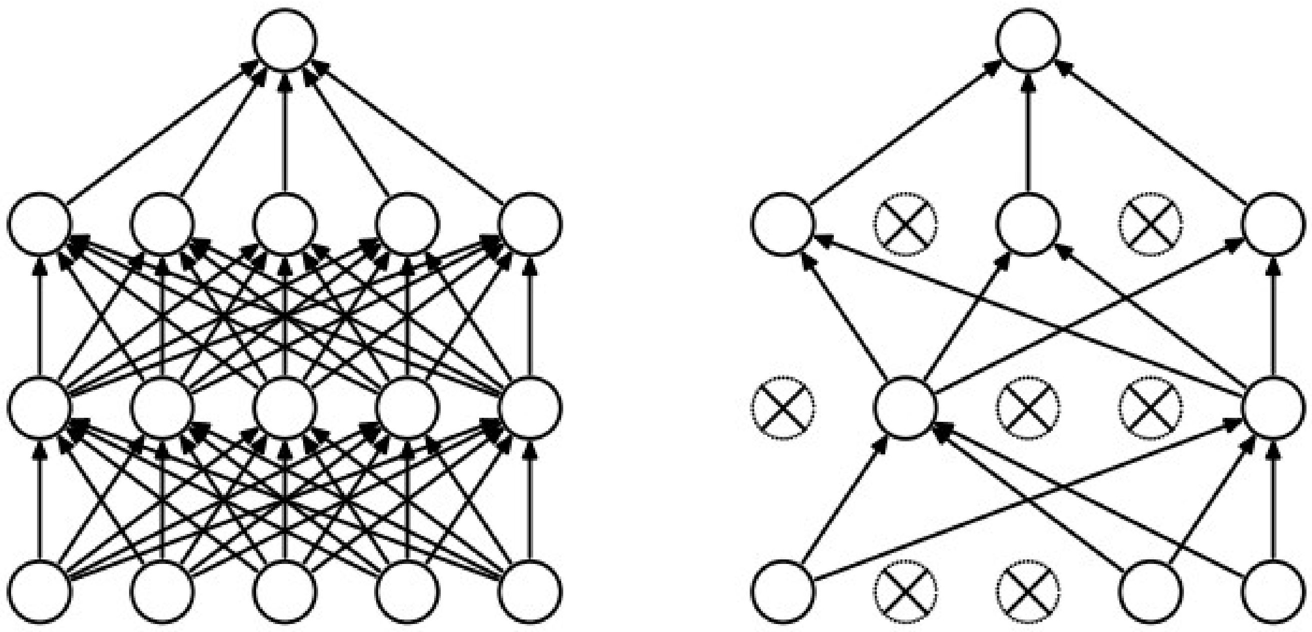
Other types of regularization

- Dropout
- Dropconnect
- Batch Normalization
- Data Augmentation
  - Adding noise to the inputs
  - Recall motivation of max margin criterion
- Adding noise to the weights (Excluded in this course)

Dropout

Dropout

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

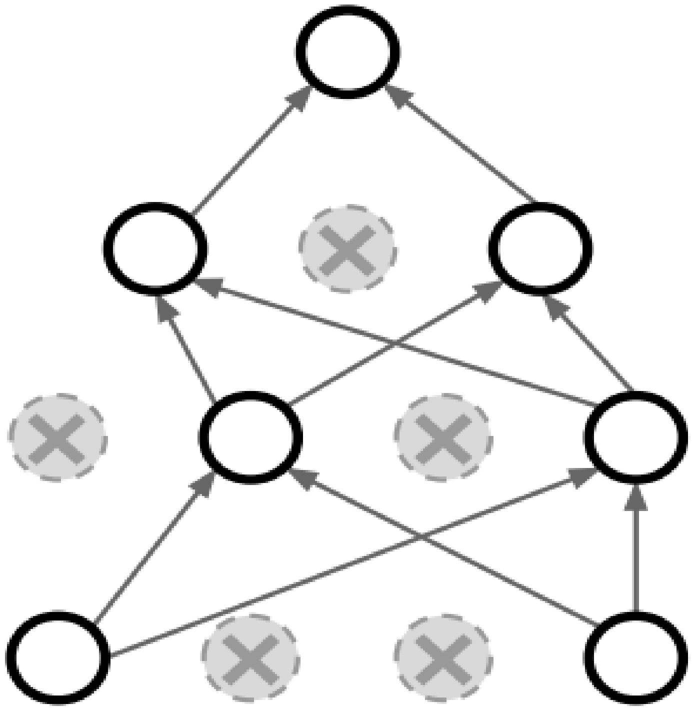


(a) Standard Neural Net (b) After applying dropout.

Dropout: A simple way to prevent neural networks from overfitting [Srivastava JMLR 2014]

Dropout

How can this possibly be a good idea?



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Dropout

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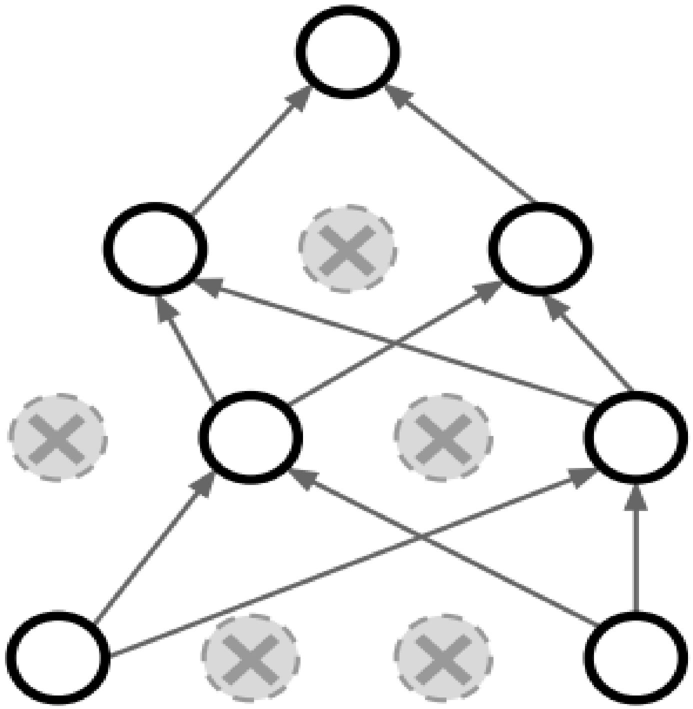
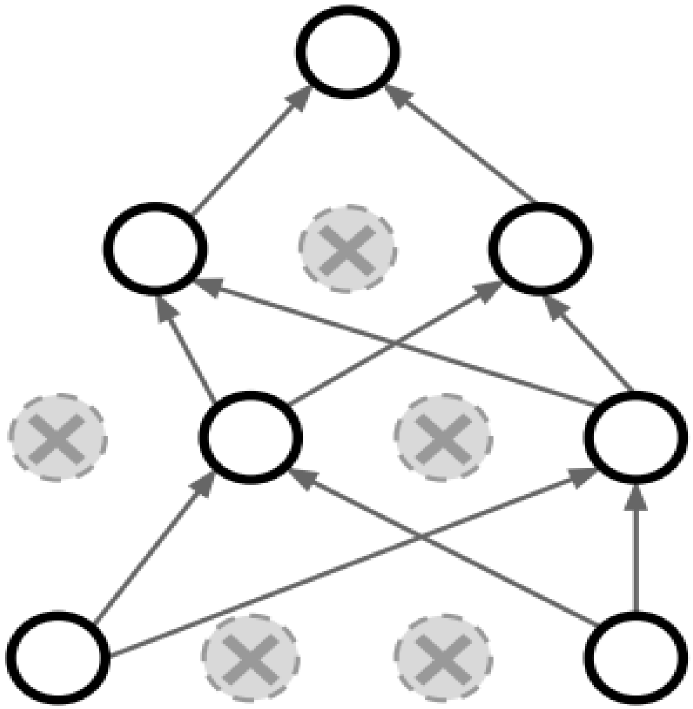


- Intuitions
  - Prevent “co-adaptation” of units, increase robustness to noise
  - Train *implicit ensemble*

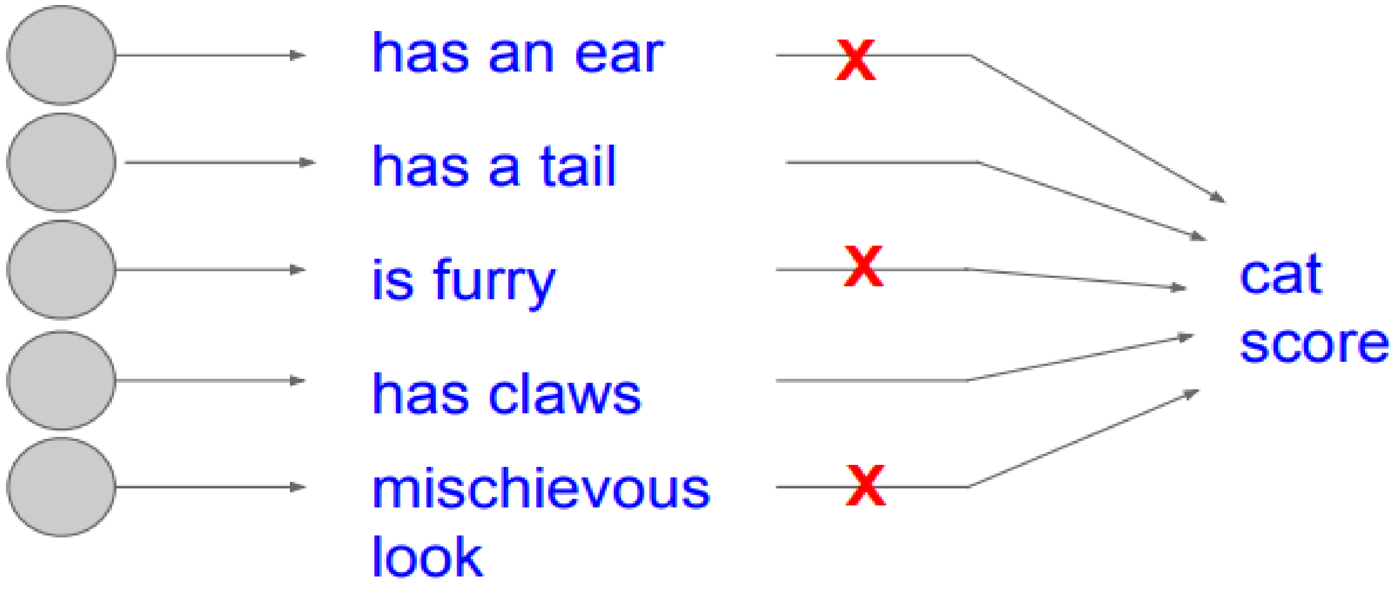
Source: cs231n

Dropout

How can this possibly be a good idea?



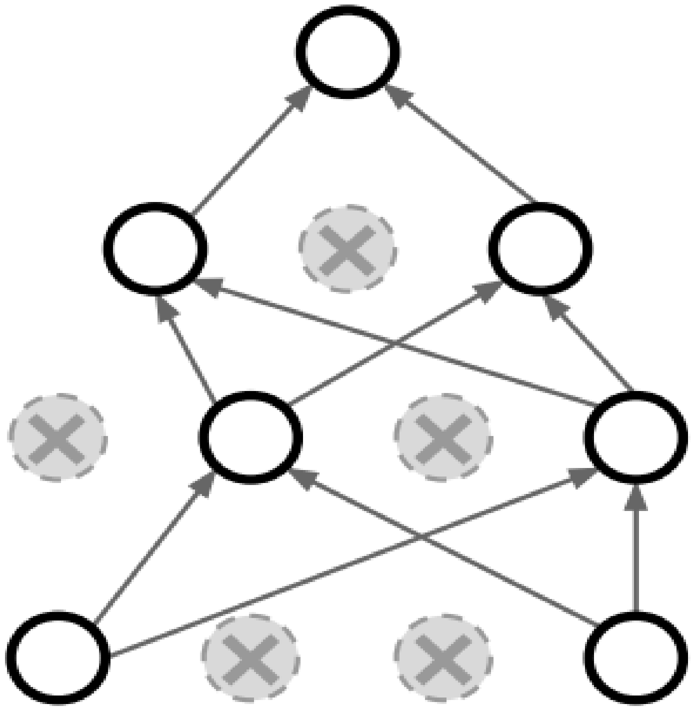
Forces the network to have a redundant representation;
Prevents co-adaptation of features



Source: cs231n

Dropout

How can this possibly be a good idea?



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

Intuition: successful conspiracies

- 50 people planning a conspiracy

- Strategy A: plan a big conspiracy involving 50 people
  - Likely to fail. 50 people need to play their parts correctly.

- Strategy B: plan 10 conspiracies each involving 5 people
  - Likely to succeed!

Source: cs231n

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:
<u>output at test time</u> = <u>expected output at training time</u>

More common: "Inverted dropout"

Source: cs231n

Dropout: More common: “Inverted dropout”

We drop and scale at train time and don't do anything at test time.

```
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
```

test time is unchanged!

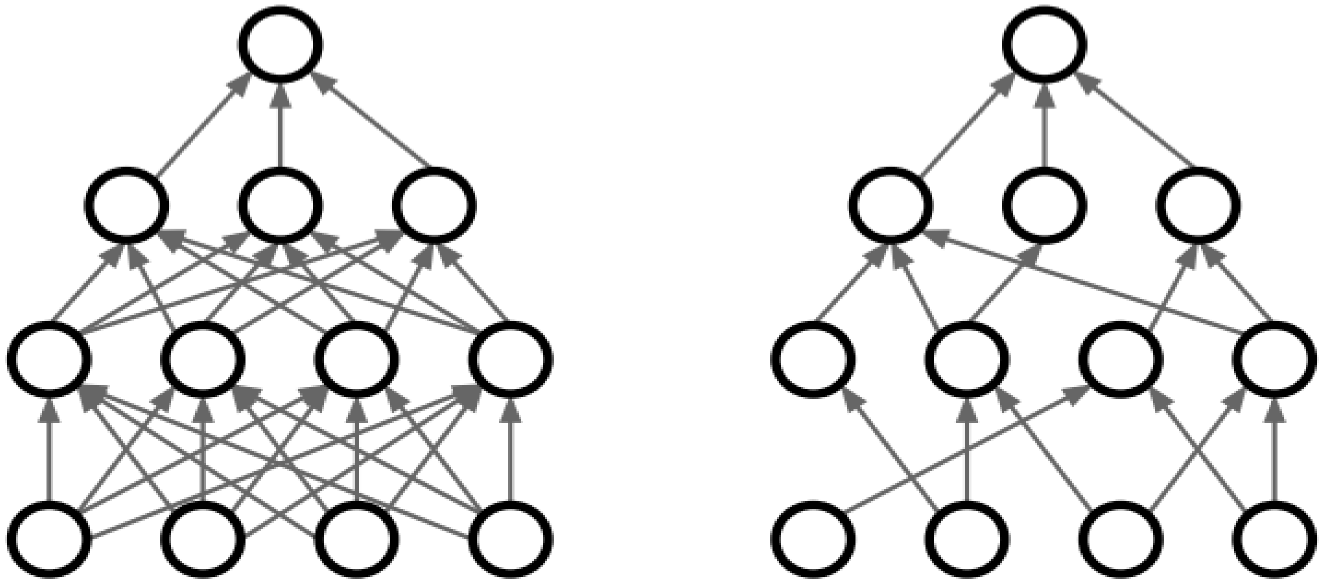
Source: cs231n

Current status of dropout

- Against
  - Slows down convergence
  - Made redundant by batch normalization or possibly even clashes with it
  - Unnecessary for larger datasets or with sufficient data augmentation
- In favor
  - Can still help in certain situations: e.g., used in Wide Residual Networks
  - Helpful in RNNs

DropConnect

Dropping some connections



Wan et al, “Regularization of Neural Networks using DropConnect”, ICML 2013

Source: cs231n

Batch Normalization

Batch Normalization

“We want zero-mean unit-variance activations? lets make them so.”

Batch Normalization: Accelerating Deep Network Training by
Reducing Internal Covariate Shift [Ioffe and Szegedy 2015]

Source: cs231n

Batch Normalization

“We want zero-mean unit-variance activations? lets make them so.”

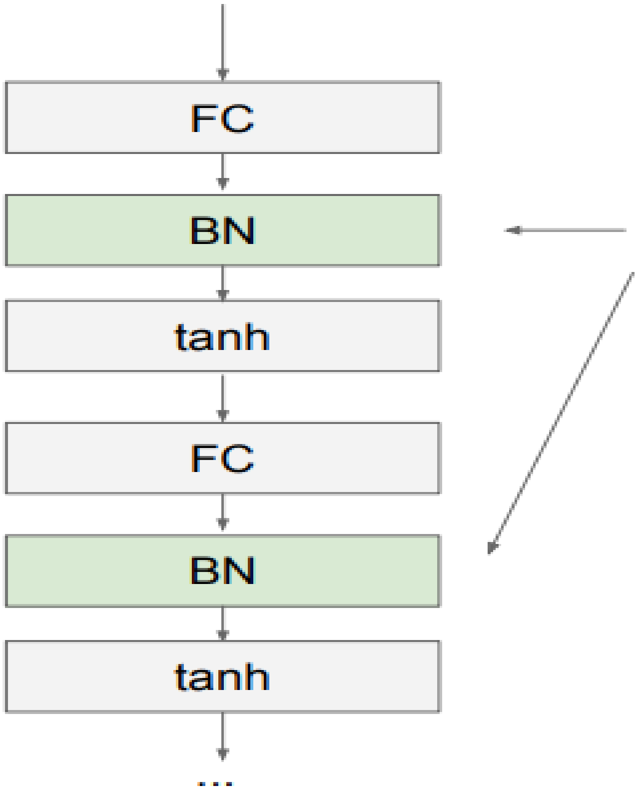
consider a batch of activations at some layer. To make each dimension zero-mean unit-variance, apply:

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

Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift [Ioffe and Szegedy 2015]

Source: cs231n

Batch Normalization

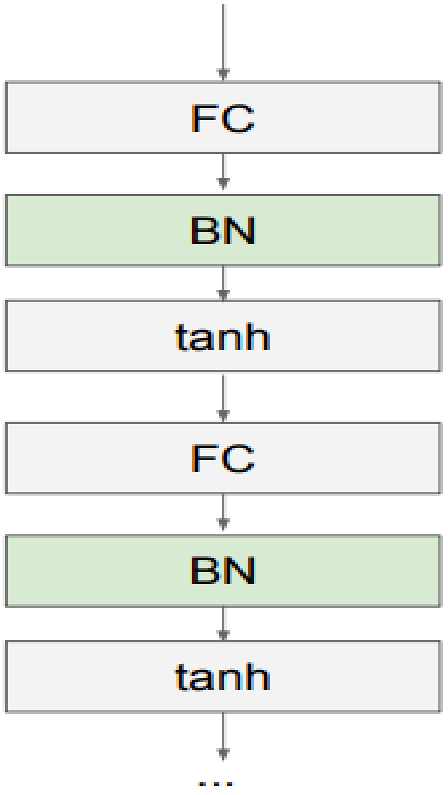


Usually inserted after Fully Connected or Convolutional layers, and before nonlinearity.

Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift [Ioffe and Szegedy 2015]

Source: cs231n

Batch Normalization



Usually inserted after Fully Connected or Convolutional layers, and before nonlinearity.

Problem:
do we necessarily want a zero-mean unit-variance input?

Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift [Ioffe and Szegedy 2015]

Source: cs231n

Batch Normalization

Normalize:

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

And then allow the network to squash
the range if it wants to:

$$\boxed{y^{(k)} = \gamma^{(k)} \widehat{x}^{(k)} + \beta^{(k)}}$$

Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift [Ioffe and Szegedy 2015]

Source: cs231n

Batch Normalization

Normalize:

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

And then allow the network to squash
the range if it wants to:

$$y^{(k)} = \gamma^{(k)}\widehat{x}^{(k)} + \beta^{(k)}$$

Note, the network can learn:

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

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

to recover the identity mapping.

Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift [Ioffe and Szegedy 2015]

Source: cs231n

Batch Normalization

Input: Values of x over a mini-batch: $\mathcal{B} = \{x_{1...m}\}$;
Parameters to be learned: γ, β

Output: $\{y_i = \mathrm{BN}_{\gamma,\beta}(x_i)\}$

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

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

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

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

Batch Normalization: Accelerating Deep Network Training by
Reducing Internal Covariate Shift [Ioffe and Szegedy 2015]

Source: cs231n

Batch Normalization

Note: at test time BatchNorm layer functions differently:

The mean/std are not computed based on the batch.

Instead, a single fixed empirical mean of activations during training is used.

(e.g. can be estimated during training with running averages)

Batch Normalization: Accelerating Deep Network Training by
Reducing Internal Covariate Shift [Ioffe and Szegedy 2015]

Source: cs231n

Batch Normalization

Input: Values of x over a mini-batch: $\mathcal{B} = \{x_{1\ldots m}\}$;
Parameters to be learned: γ, β

Output: $\{y_i = \mathrm{BN}_{\gamma,\beta}(x_i)\}$

At test time (usually):

$$\xcancel{\mu_{\mathcal{B}} \leftarrow \frac{1}{m}\sum_{i=1}^{m} x_i}$$ // ~~mini-batch~~ training set mean

$$\xcancel{\sigma_{\mathcal{B}}^2 \leftarrow \frac{1}{m}\sum_{i=1}^{m} (x_i - \mu_{\mathcal{B}})^2}$$ // ~~mini-batch~~ training set variance

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

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

Batch Normalization: Accelerating Deep Network Training by
Reducing Internal Covariate Shift [Ioffe and Szegedy 2015]

Source: cs231n

Batch Normalization

Benefits

- Improves gradient flow through the network
- Allows higher learning rates and Accelerates convergence of training
- Reduces the strong dependence on initialization
- Acts as a form of regularization

Pitfalls

- Behavior depends on composition of mini-batches, can lead to hard-to-catch bugs if there is a mismatch between training and test regime (example)
- Doesn't work well for small mini-batch sizes
- Cannot be used in recurrent models

Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift [Ioffe and Szegedy 2015]

Source: cs231n

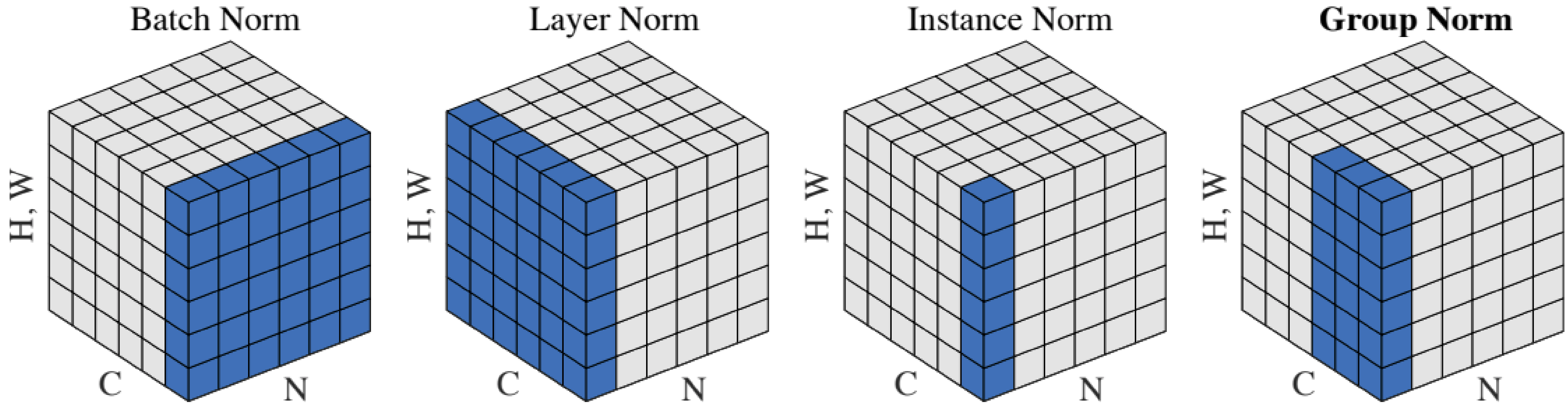
Why does BatchNorm *really* work? **Optional**

- It may have to do not with internal covariate shift (ICS), but with making the optimization problem much smoother (Santurkar et al., 2018)
- *Is ICS even a thing?* (Lipton and Steinhardt, 2018)

Other types of normalization

Optional

- [Layer normalization](#) (Ba et al., 2016)
- [Instance normalization](#) (Ulyanov et al., 2017)
- [Group normalization](#) (Wu and He, 2018)
- [Weight normalization](#) (Salimans et al., 2016)



Y. Wu and K. He, [Group Normalization](#), ECCV 2018

Batch Normalization: Recent Trends

Layer Normalization:
Ba, Kiros, and Hinton, “Layer Normalization”, arXiv 2016

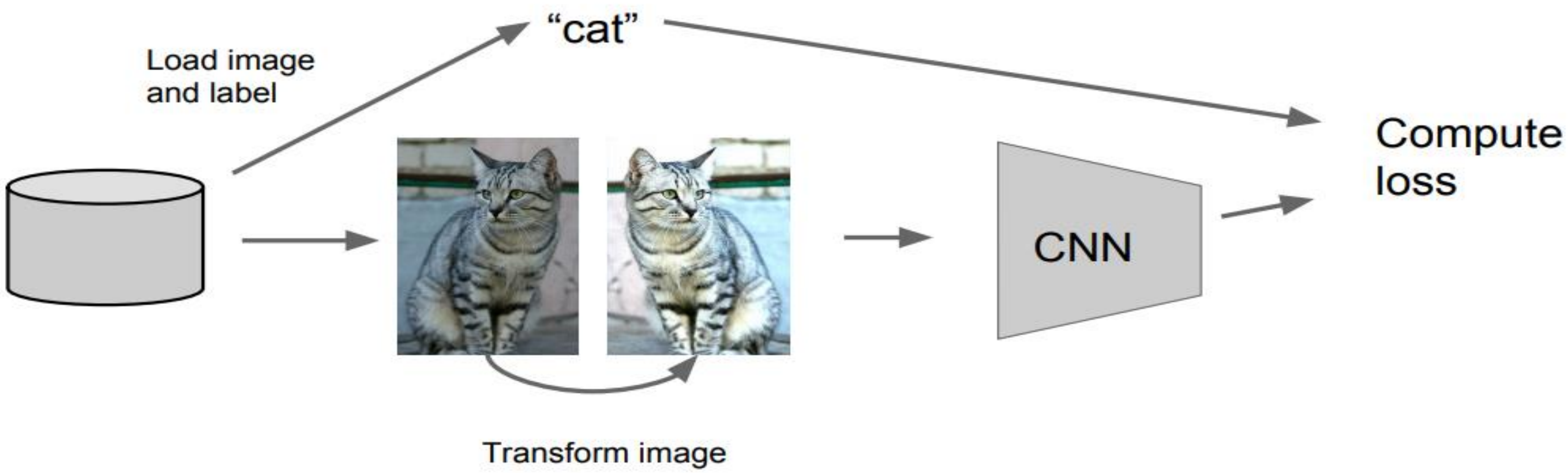
Instance Normalization:
Ulyanov et al, Improved Texture Networks: Maximizing Quality and Diversity in Feed-forward Stylization and Texture Synthesis, CVPR 2017

Group Normalization:
Wu and He, “Group Normalization”, arXiv 2018
(Appeared 3/22/2018)

Decorrelated Normalization:
Huang et al, “Decorrelated Batch Normalization”, arXiv 2018 (Appeared 4/23/2018)

Data Augmentation

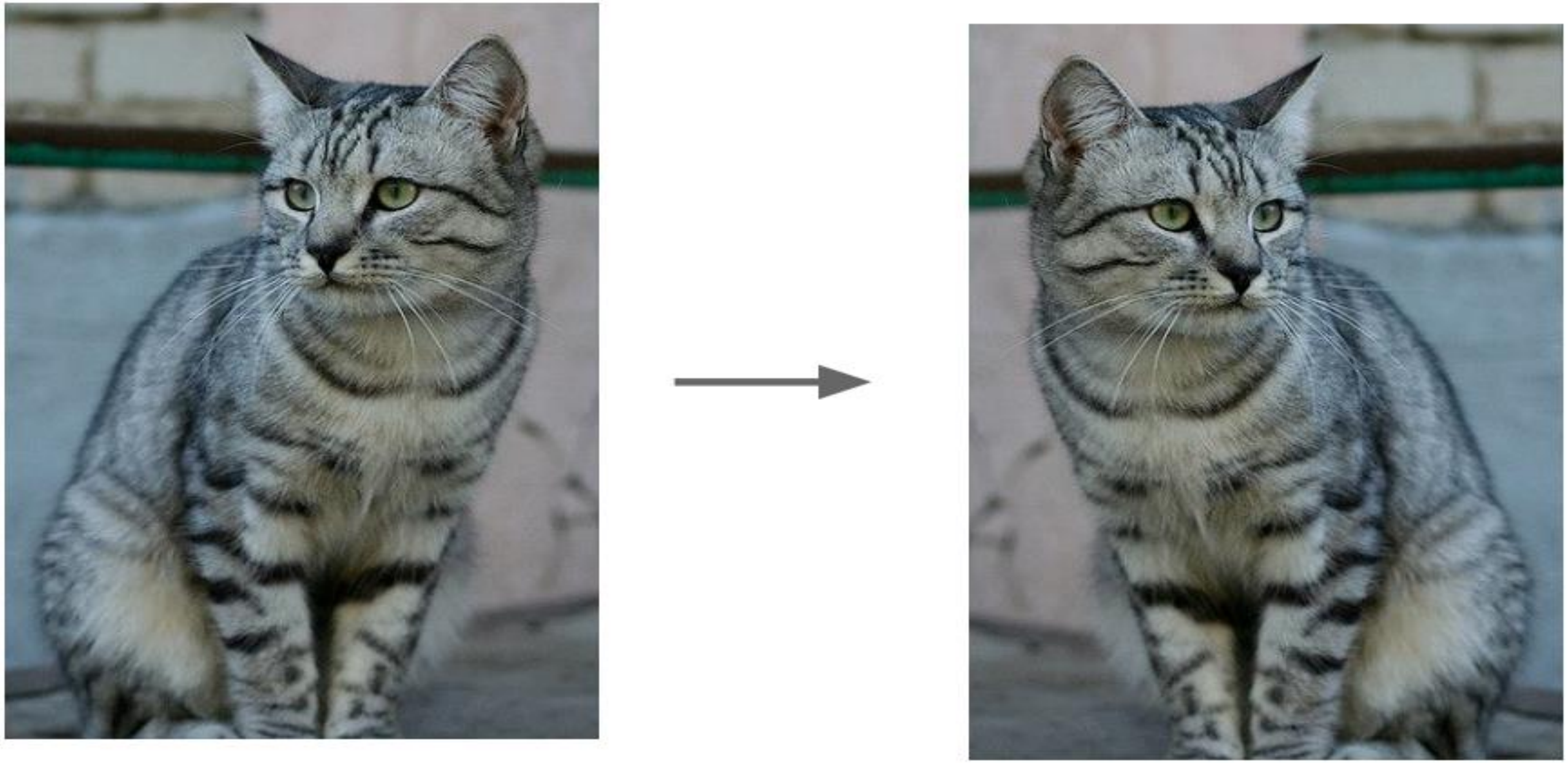
Data Augmentation (Jittering)



Source: cs231n

Data Augmentation (Jittering)

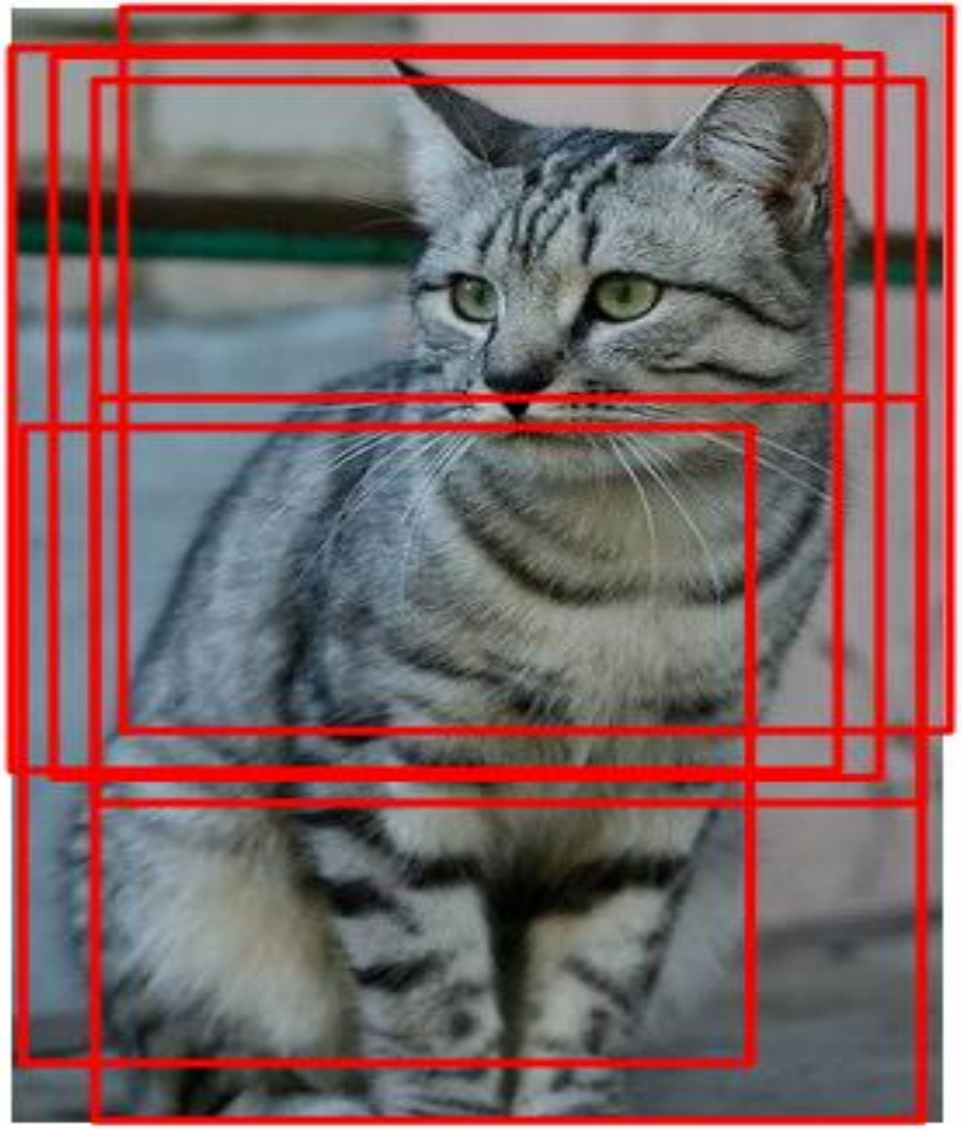
Horizontal Flips



Source: cs231n

Data Augmentation (Jittering)

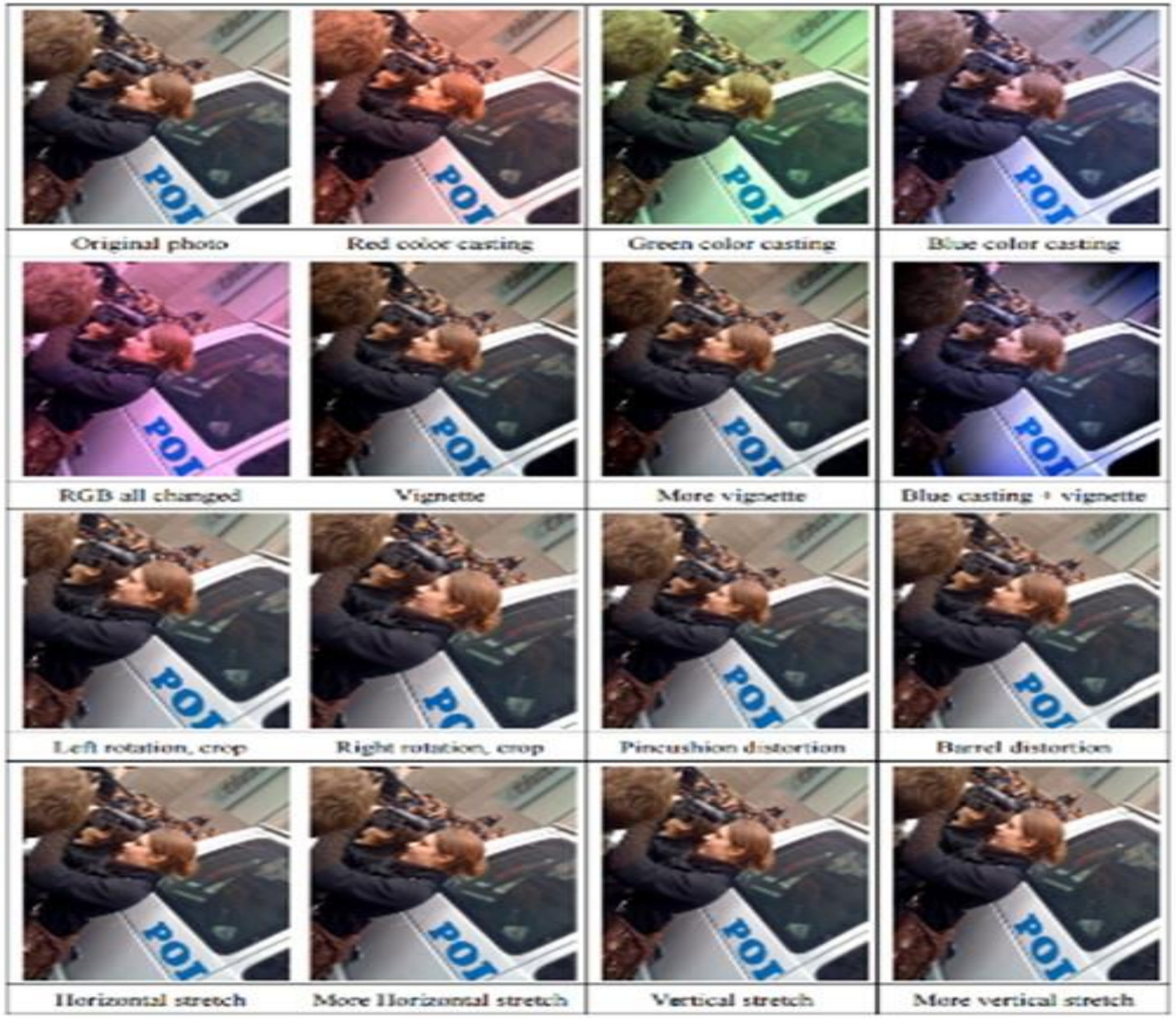
Random crops and scales



Source: cs231n

Data Augmentation (Jittering)

- Create *virtual* training samples
- Get creative for your problem!
  - Horizontal flip
  - Random crop
  - Color casting
  - Randomize contrast
  - Randomize brightness
  - Geometric distortion
  - Rotation
  - Photometric changes

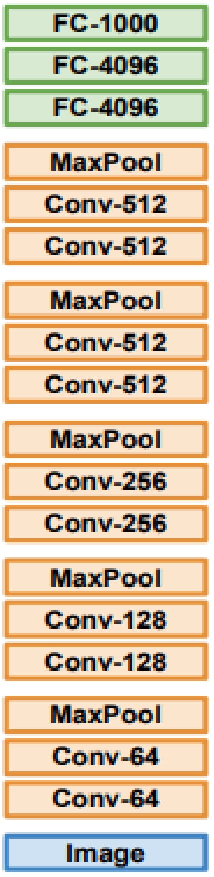


Deep Image [Wu et al. 2015]

Transfer Learning

Transfer Learning with CNNs

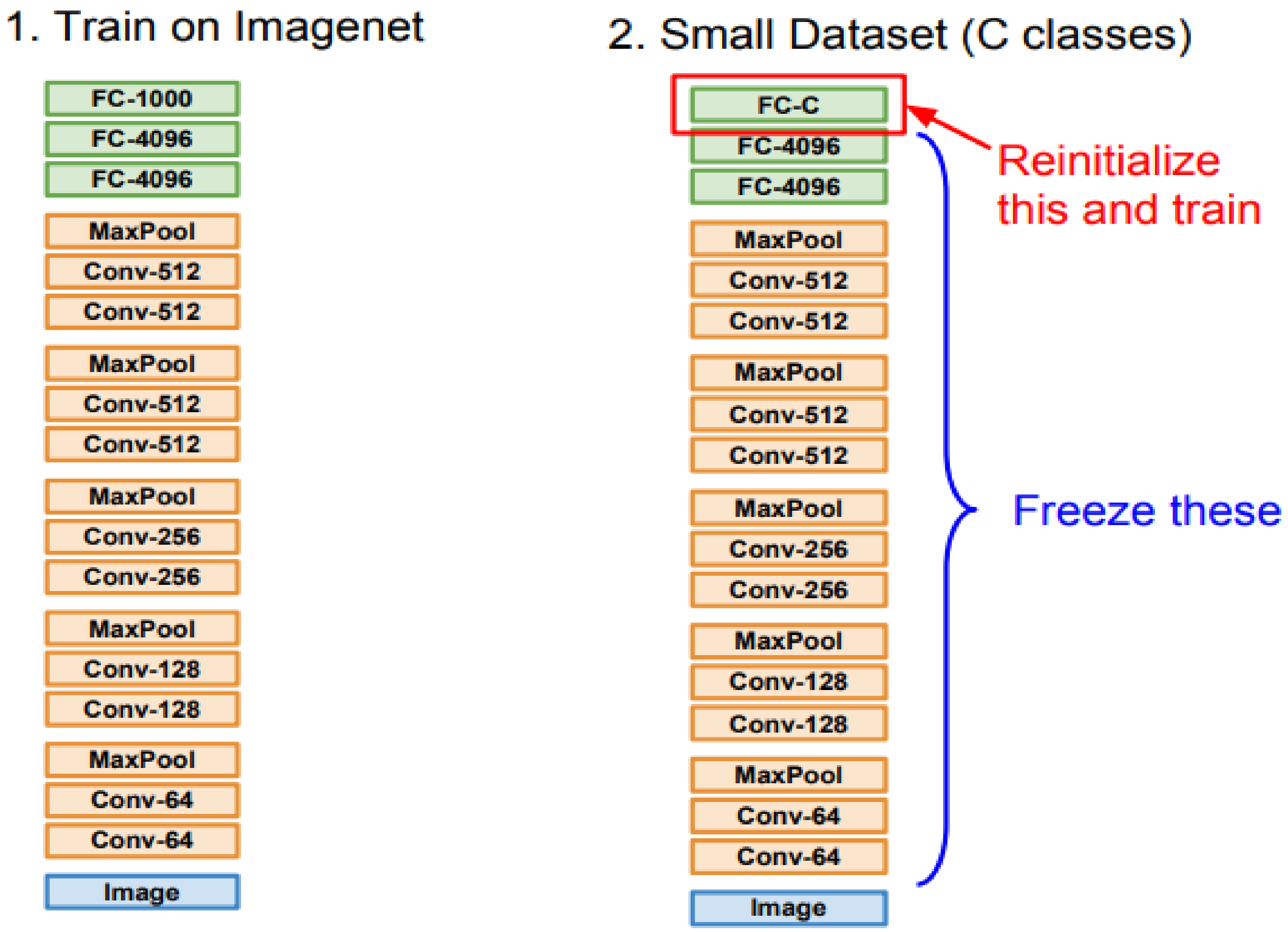
1. Train on Imagenet



Donahue et al, “DeCAF: A Deep Convolutional Activation Feature for Generic Visual Recognition”, ICML 2014
Razavian et al, “CNN Features Off-the-Shelf: An Astounding Baseline for Recognition”, CVPR Workshops 2014

Source: cs231n

Transfer Learning with CNNs



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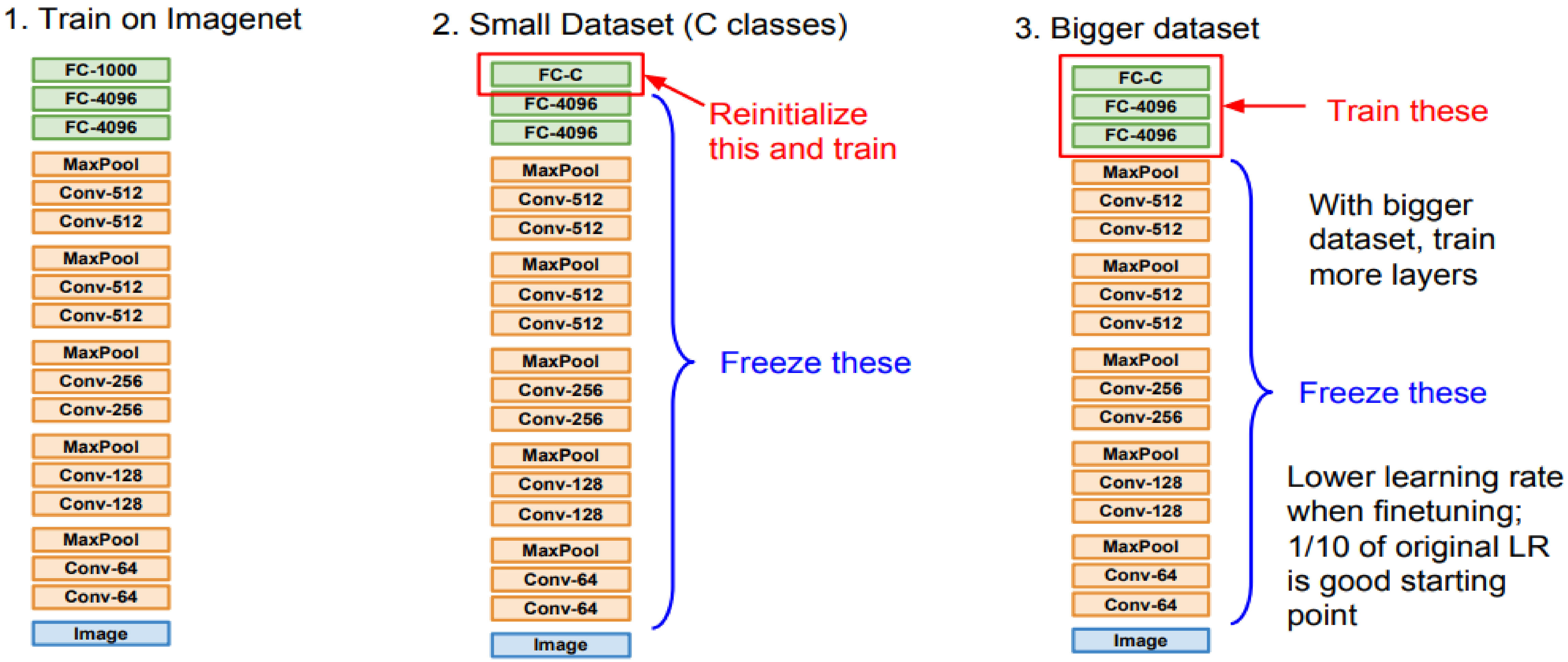
Transfer Learning with CNNs



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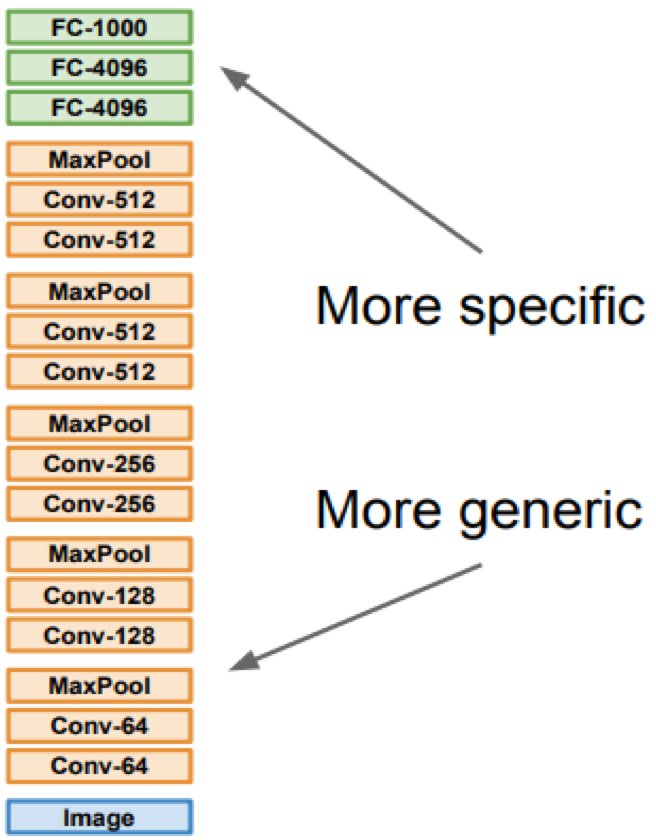
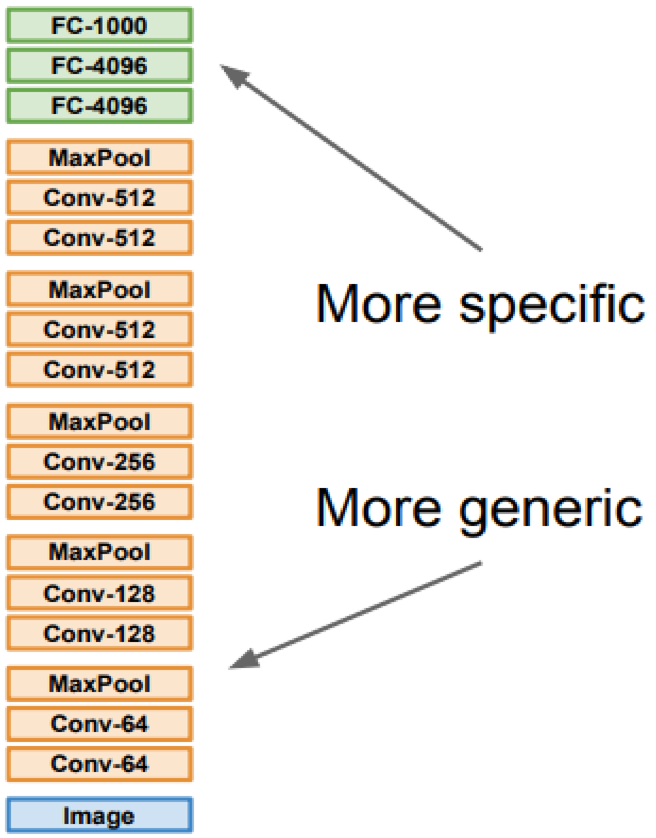
Transfer Learning with CNNs



Source: cs231n

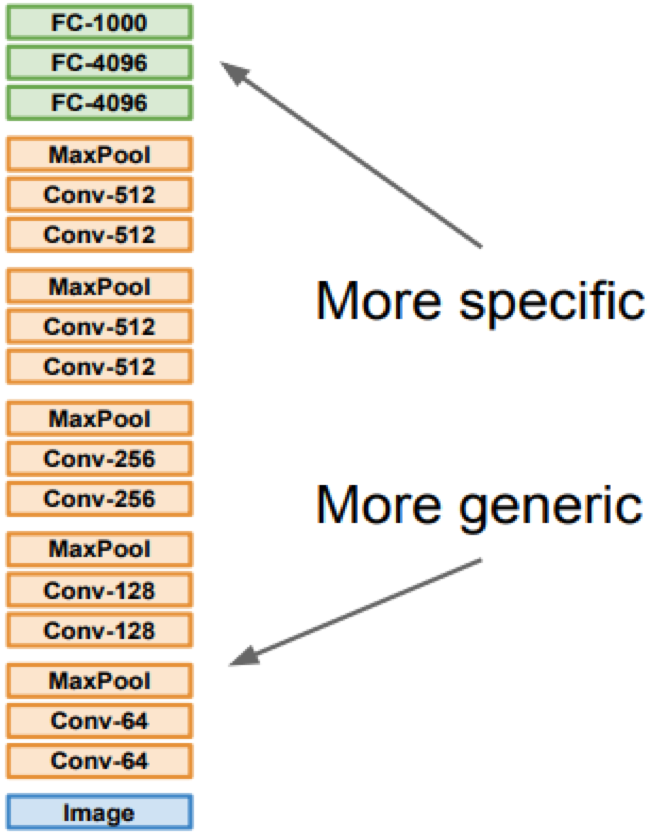
Transfer Learning with CNNs



	very similar dataset	very different dataset
very little data		
quite a lot of data		

Source: cs231n

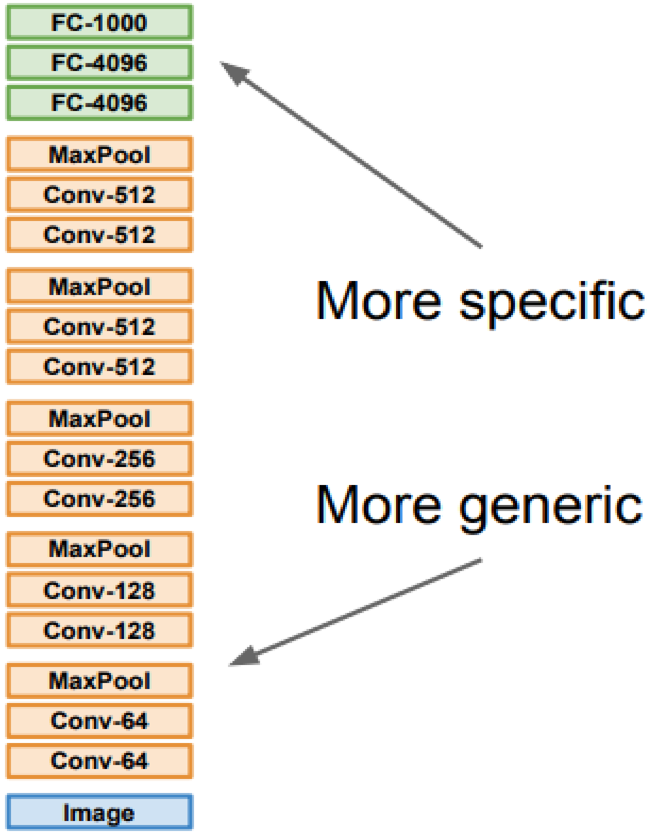
Transfer Learning with CNNs



	very similar dataset	**very different dataset**
very little data	Use Linear Classifier on top layer	
quite a lot of data		

Source: cs231n

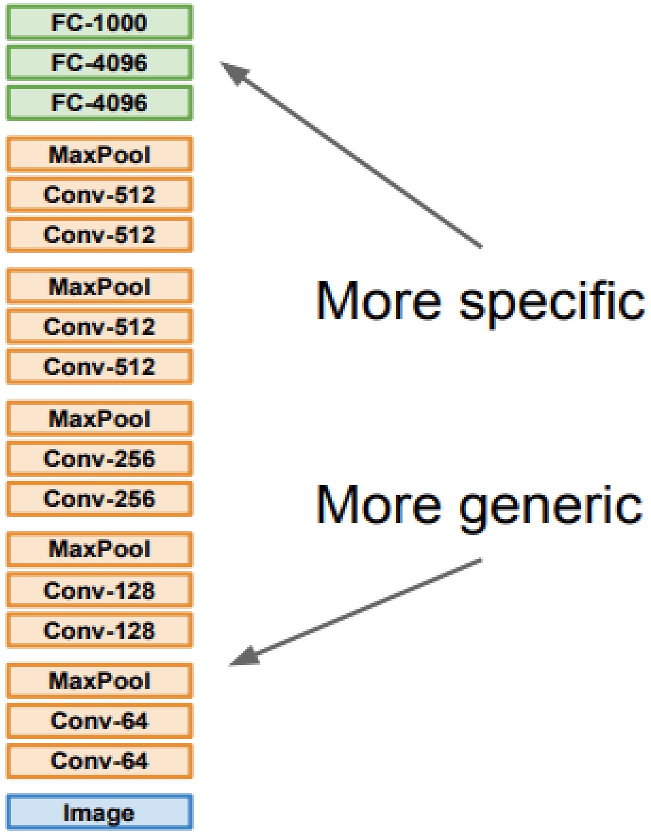
Transfer Learning with CNNs



	very similar dataset	**very different dataset**
very little data	Use Linear Classifier on top layer	
quite a lot of data	Finetune a few layers	

Source: cs231n

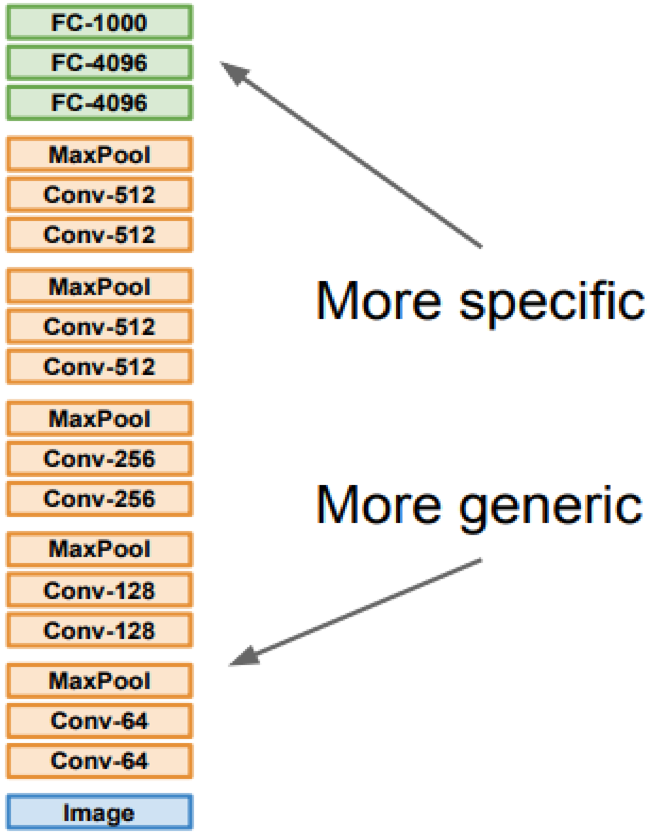
Transfer Learning with CNNs



	very similar dataset	**very different dataset**
very little data	Use Linear Classifier on top layer	
quite a lot of data	Finetune a few layers	Finetune a larger number of layers

Source: cs231n

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

Source: cs231n

Transfer Learning with CNNs

Takeaway for your projects and beyond:

Have some dataset of interest but it has < ~1M images?

1. Find a very large dataset that has similar data, train a big ConvNet there
2. Transfer learn to your dataset

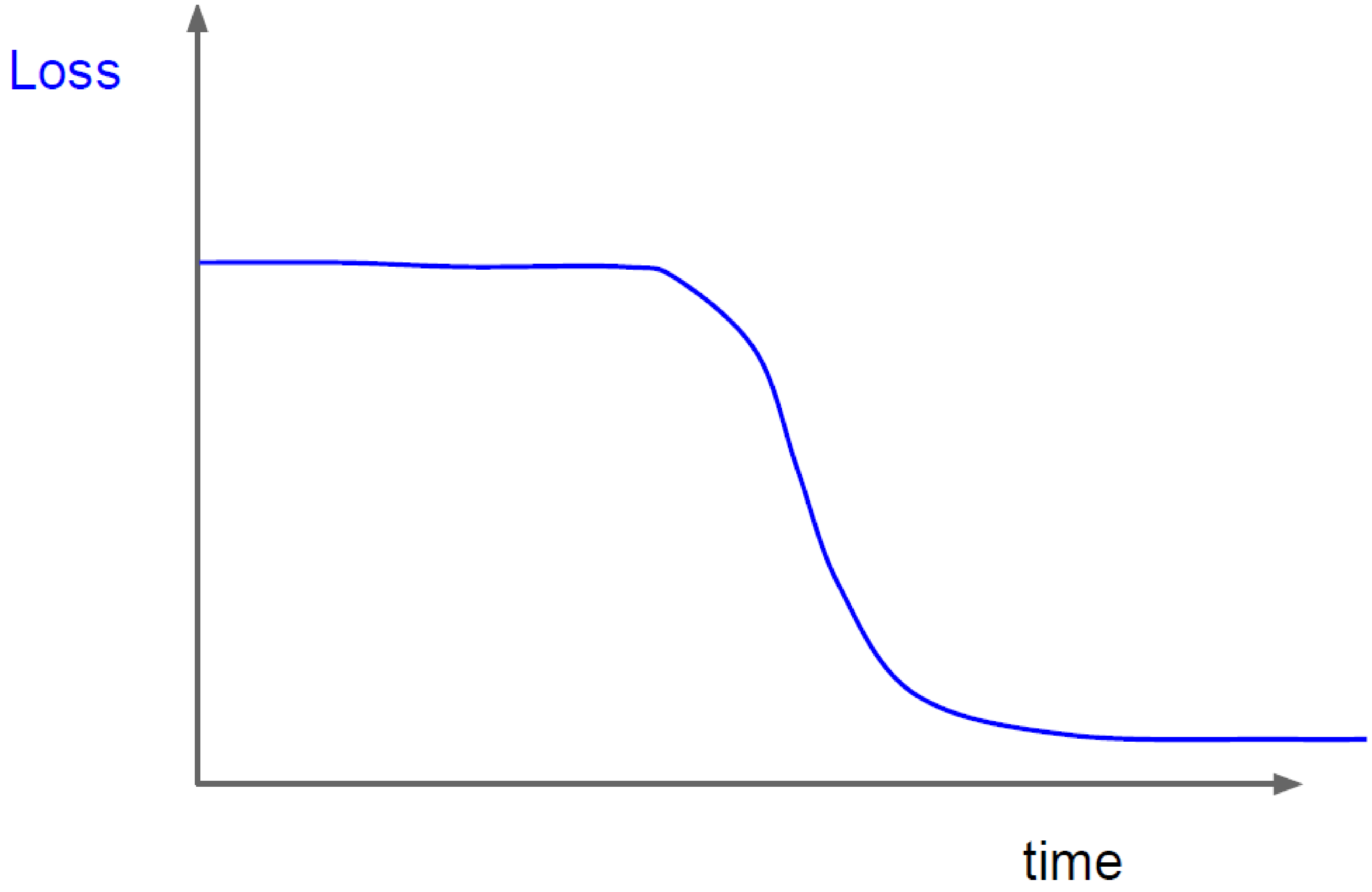
Deep learning frameworks provide a “Model Zoo” of pretrained models so you don’t need to train your own

Caffe: https://github.com/BVLC/caffe/wiki/Model-Zoo
TensorFlow: https://github.com/tensorflow/models
PyTorch: https://github.com/pytorch/vision
Matconvnet: http://www.vlfeat.org/matconvnet/pretrained/

Source: cs231n

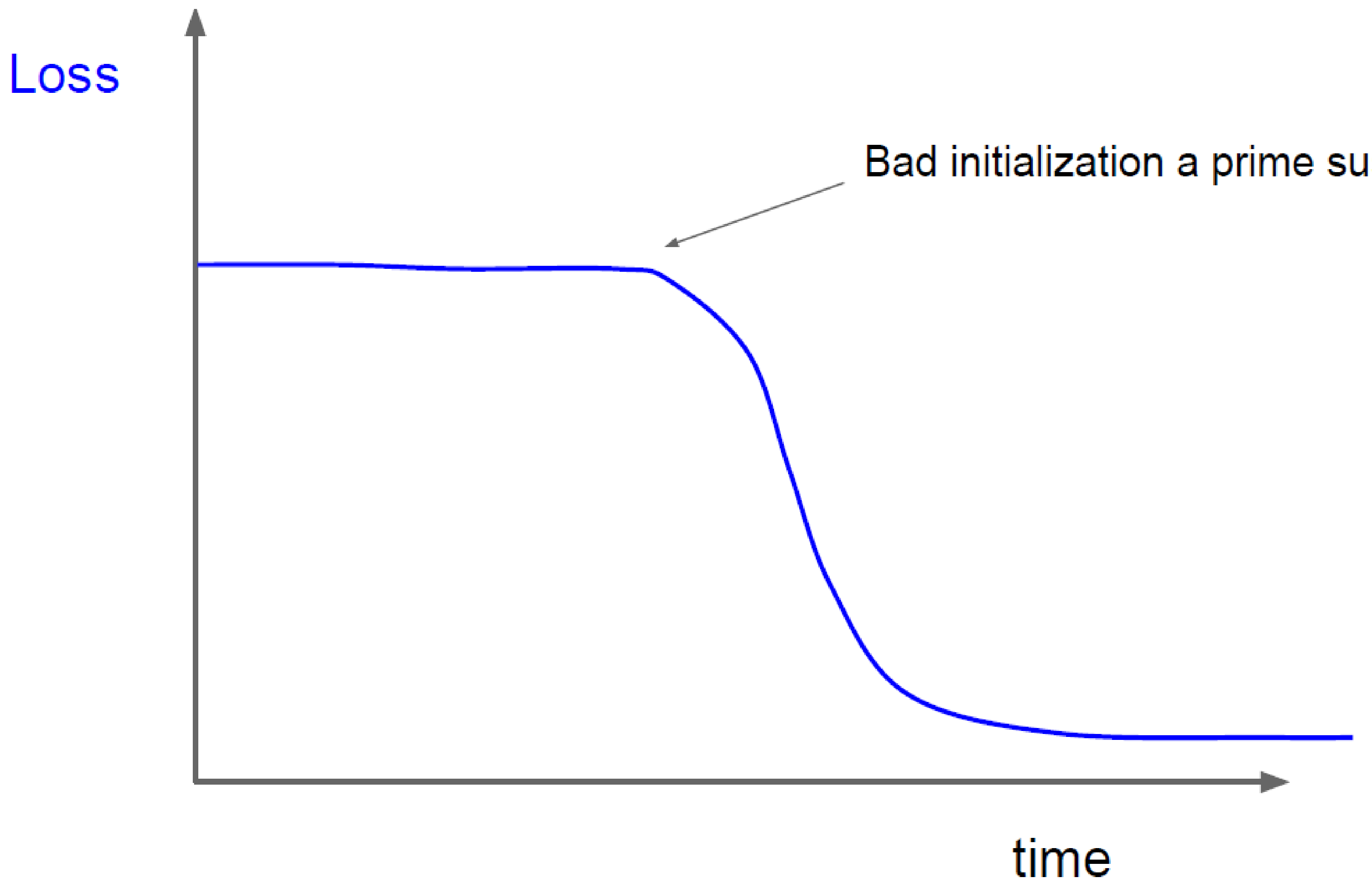
Monitor and Visualize the Loss Curve

Monitor and visualize the loss curve



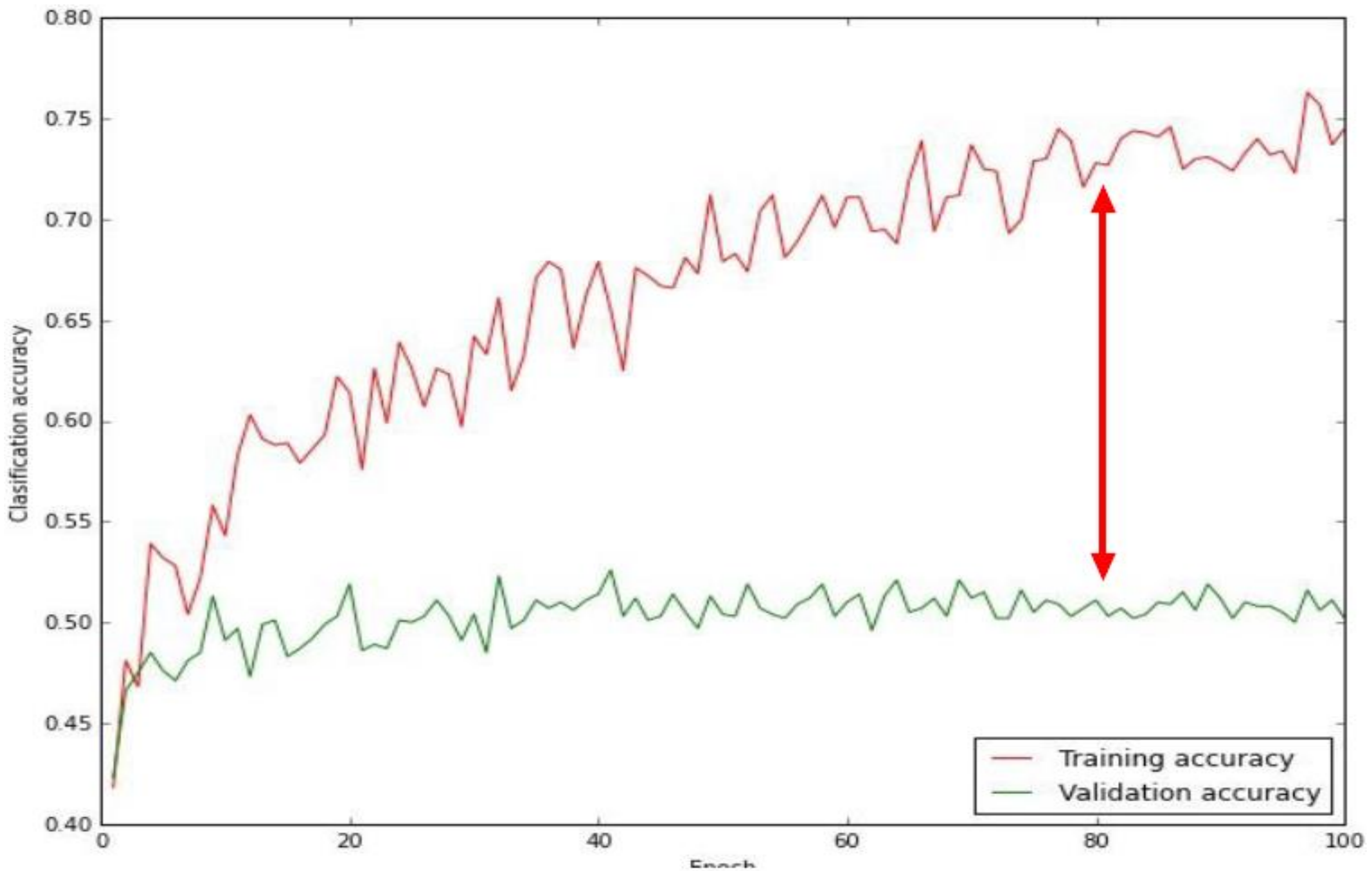
Source: cs231n

Monitor and visualize the loss curve



Source: cs231n

Monitor and visualize the loss curve

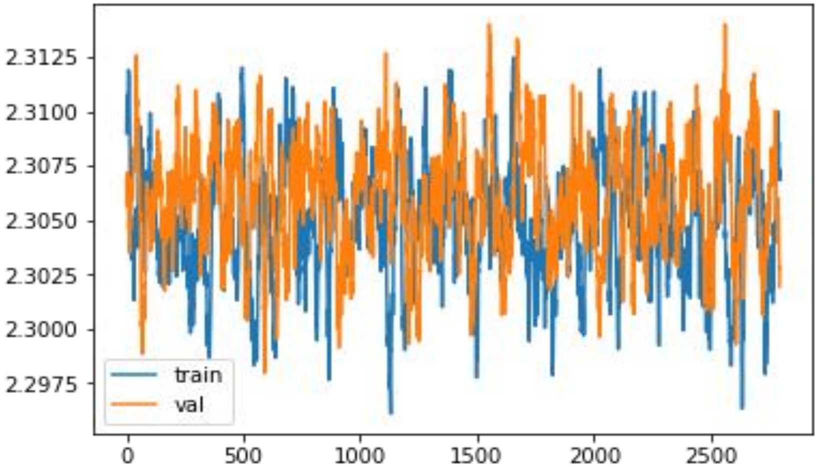


big gap = overfitting
=> increase regularization strength?

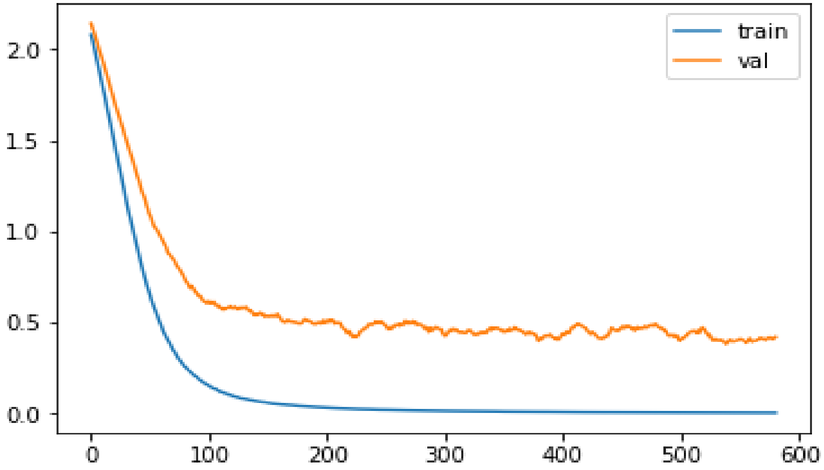
no gap
=> increase model capacity?

Source: cs231n

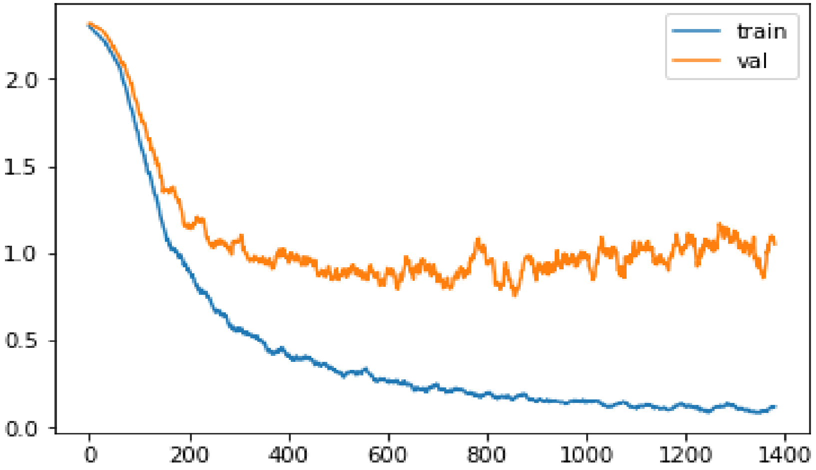
Monitor and visualize the loss curve



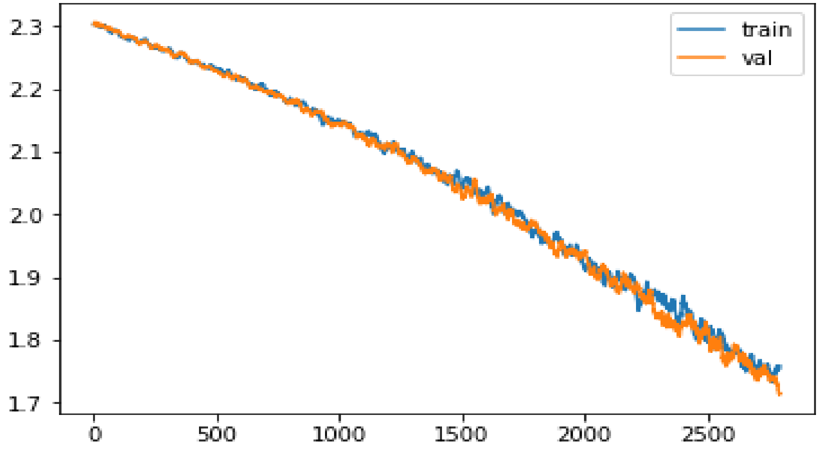
Not learning: gradients not applied to weights



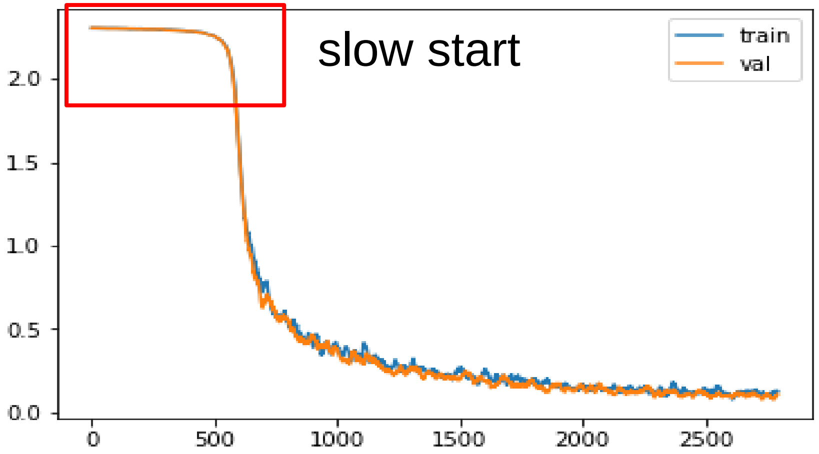
Overfit: model too large/dataset too small



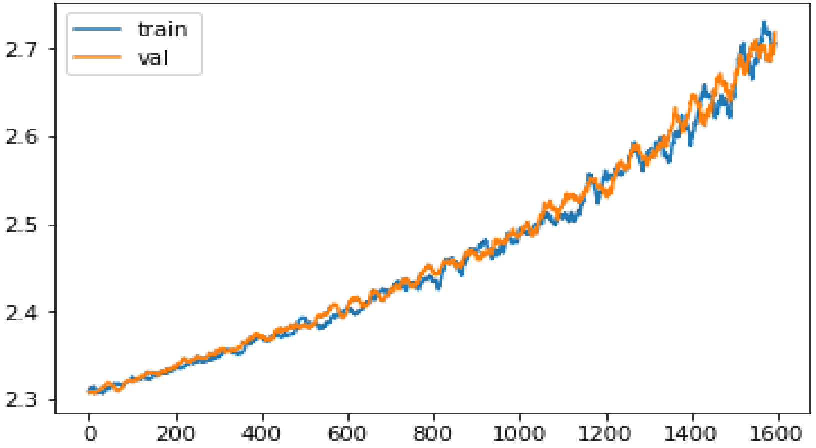
More extreme case of overfitting



Not converged yet: need longer training



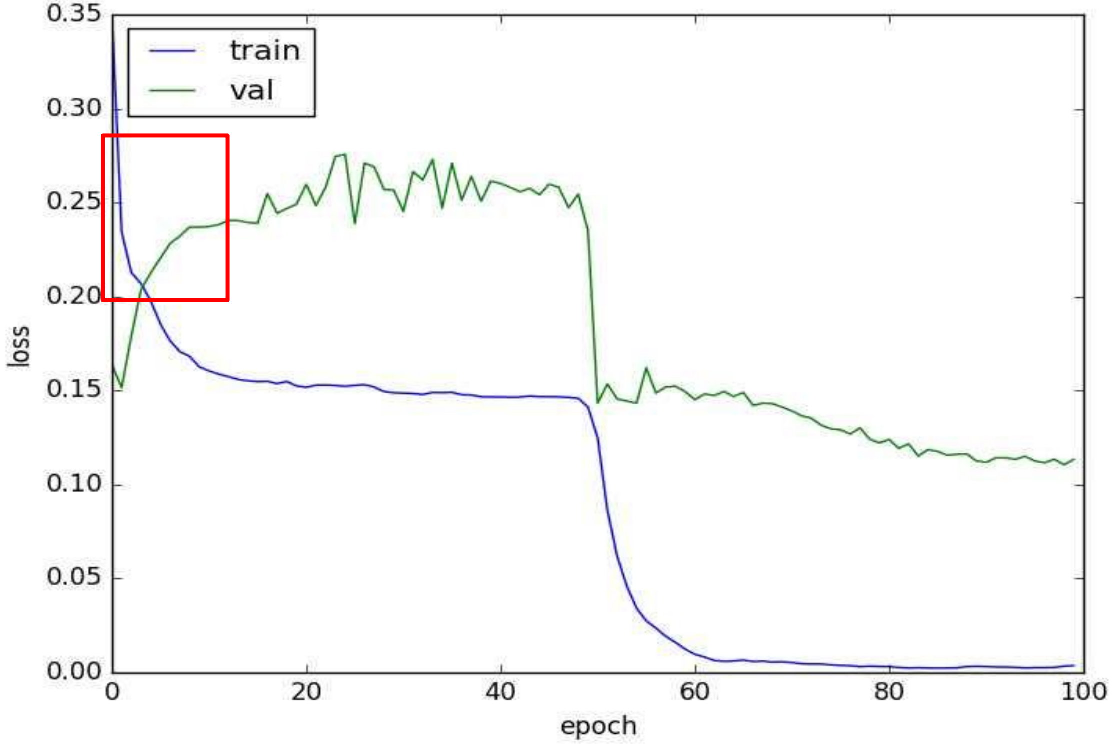
Slow start: initialization weights too small



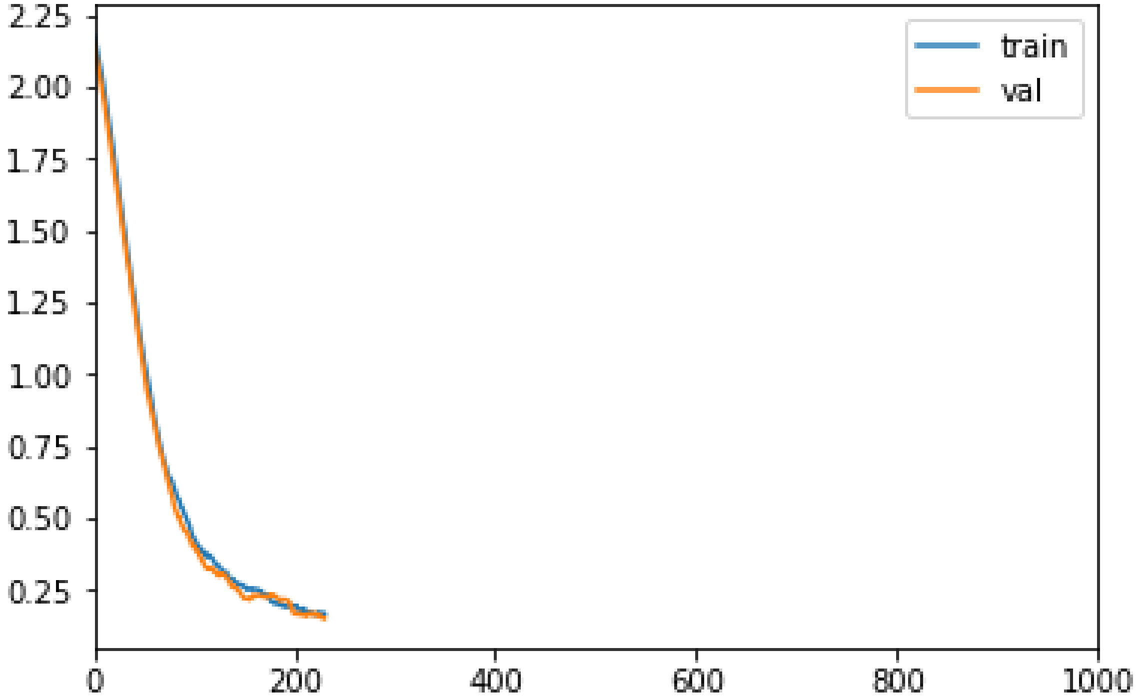
Applied the negative of gradients

Source: cs231n

Monitor and visualize the loss curve



Problem: val set too small, statistics not meaningful

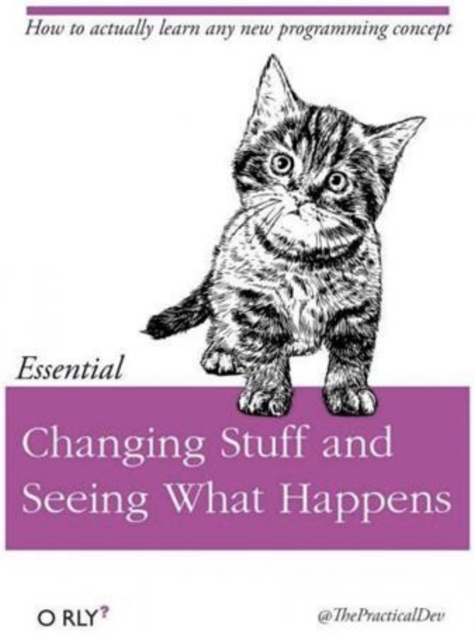


Get nans in the loss after a number of iterations: caused by high learning rate and numerical instability in models

Source: cs231n

Attempt at a conclusion

- Training neural networks is still a black art
- Process requires close "babysitting"
- For many techniques, the reasons why, when, and whether they work are in active dispute – read everything but don't trust anything
- It all comes down to (principled) trial and error
- Further reading: A. Karpathy, [A recipe for training neural networks]



Things to remember

- Training CNN
  - Adam is common (AMSGrad can be tried)
  - Learning rate: Step decay, Cyclic learning rate
  - Transfer learning, Fine tuning
- Regularization
  - L2/L1/Elastic regularization
  - Dropout and Dropconnect
  - Batch Norm
  - Data Augmentation: Flip, Crop, Contrast, etc.
- Interpreting Loss
  - Bad initialization
  - Overfitting
  - Slow/High learning rates
  - Update in wrong direction
  - Etc.

Acknowledgement

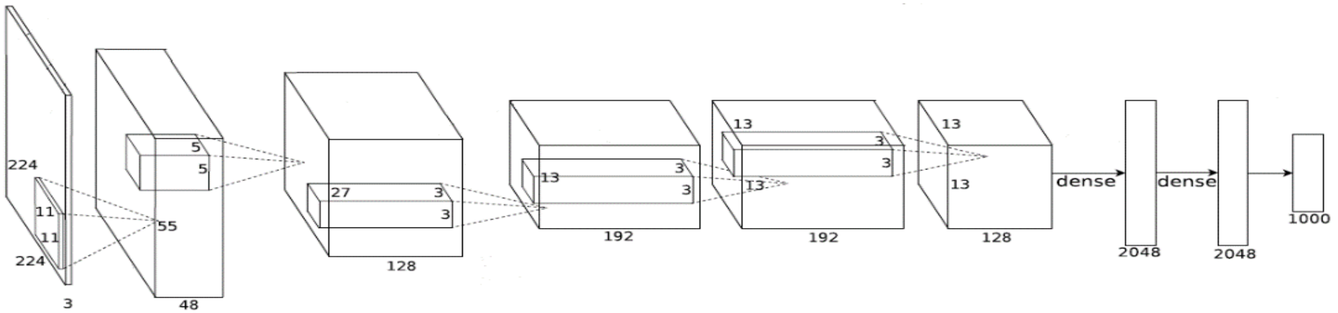
Thanks to the following courses and corresponding researchers for making their teaching/research material online

- Deep Learning, Stanford University
- Introduction to Deep Learning, University of Illinois at Urbana-Champaign
- Introduction to Deep Learning, Carnegie Mellon University
- Convolutional Neural Networks for Visual Recognition, Stanford University
- Natural Language Processing with Deep Learning, Stanford University
- And Many More ......

Next Class

CNN Architectures: Plain Models

- LeNet
- AlexNet
- ZFNet
- VggNet
- Network in Network



CNN Architectures: DAG Models

- GoogLeNet
- ResNet
- Pre-act ResNet
- SENet
- DenseNet
- ResNetXt
- Etc.