Topics in AI (CPSC 532S):
Multimodal Learning with Vision, Language and Sound

Lecture 4: Introduction to Deep Learning (continued)

Course **Logistics**

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— **Assignment 2** will be out Thursday night

(note, it will take computation time)

Short **Review** … weight regularization

L2 Regularization: Learn a more (dense) distributed representation

$$R(\mathbf{W}) = ||\mathbf{W}||_2 = \sum_i \sum_j \mathbf{W}_{i,j}^2$$

L1 Regularization: Learn a sparse representation (few non-zero wight elements)

$$R(\mathbf{W}) = ||\mathbf{W}||_1 = \sum_i \sum_j |\mathbf{W}_{i,j}|$$

(others regularizers are also possible)

Example:

$$\mathbf{x} = [1, 1, 1, 1]$$

$$\mathbf{W}_1 = [1, 0, 0, 0]$$

$$\mathbf{W}_2 = \left[\frac{1}{4}, \frac{1}{4}, \frac{1}{4}, \frac{1}{4}\right]$$

$$\mathbf{W}_1 \cdot \mathbf{x}^T = \mathbf{W}_2 \cdot \mathbf{x}^T$$

two networks will have identical output

L2 Regularizer:

$$R_{L2}(\mathbf{W}_1) = 1$$
$$R_{L2}(\mathbf{W}_2) = 0.25$$

L1 Regularizer:

$$R_{L1}(\mathbf{W}_1) = 1$$
$$R_{L1}(\mathbf{W}_2) = 1$$

Short **Review** … batch normalization

Normalize each mini-batch (using Batch Normalization layer) by subtracting empirically computed mean and dividing by variance for every dimension -> samples are approximately unit Gaussian

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

In practice, also learn how to scale and offset:

$$y^{(k)} = \underbrace{\gamma^{(k)}\bar{x}^{(k)} + \beta^{(k)}}_{\text{BN layer parameters}}$$

Benefit:

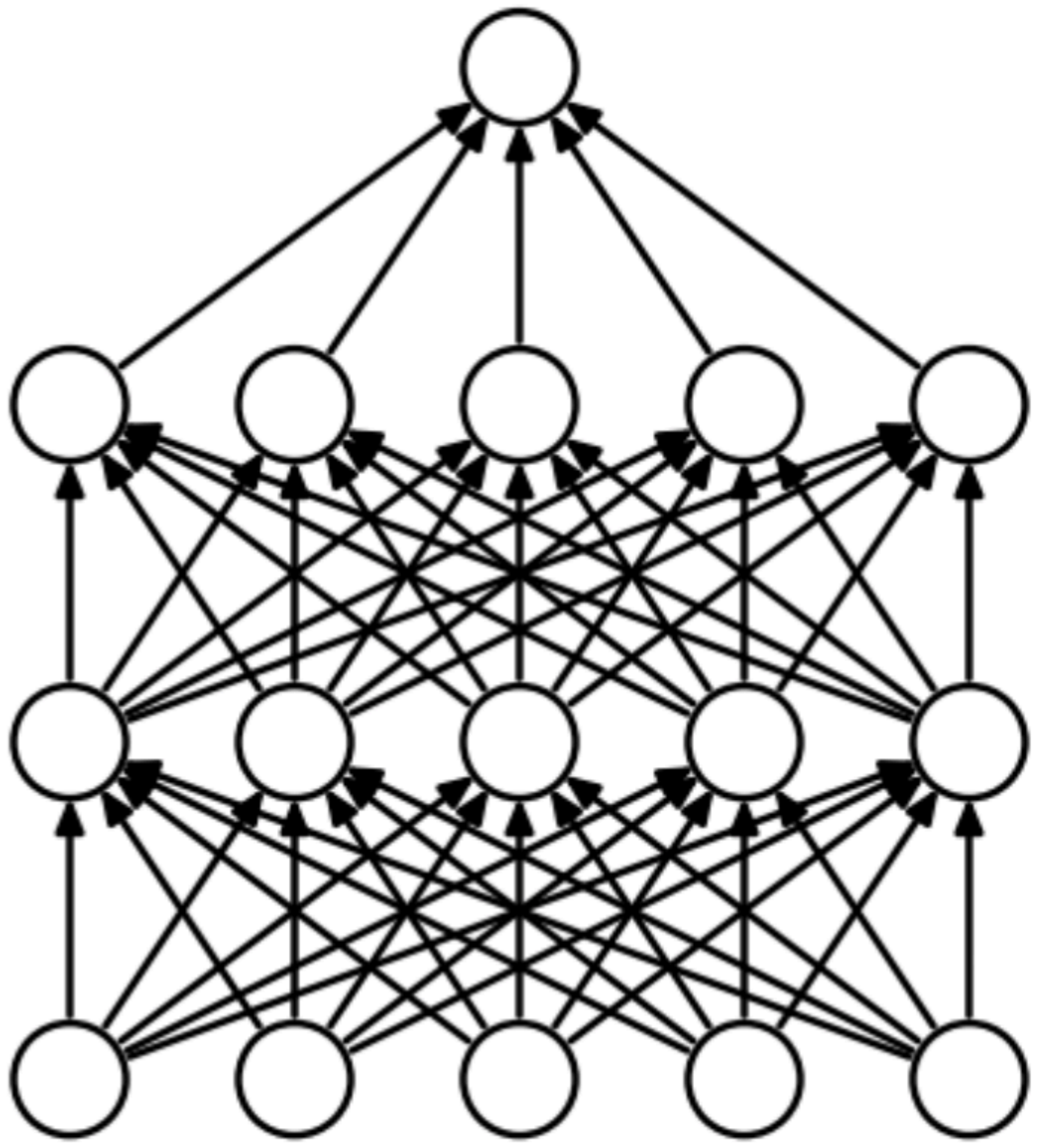
Improves learning (better gradients, higher learning rate, less reliance on initialization)

Typically inserted **before** activation layer

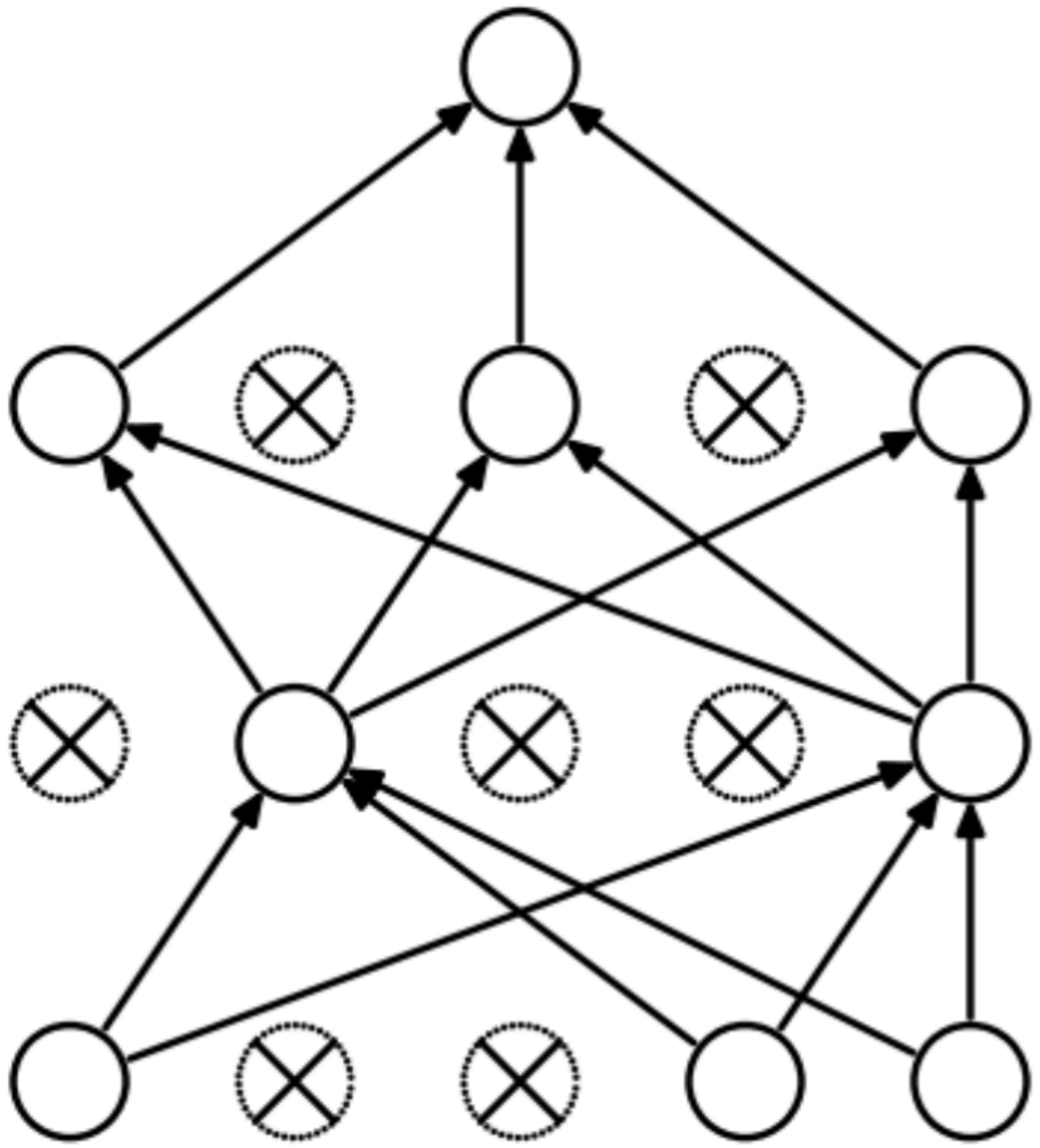
[Ioffe and Szegedy, NIPS 2015]

Short **Review** … dropout

Randomly **set some neurons to zero** in the forward pass, with probability proportional to `dropout rate` (between 0 to 1)



Standar Neural Network

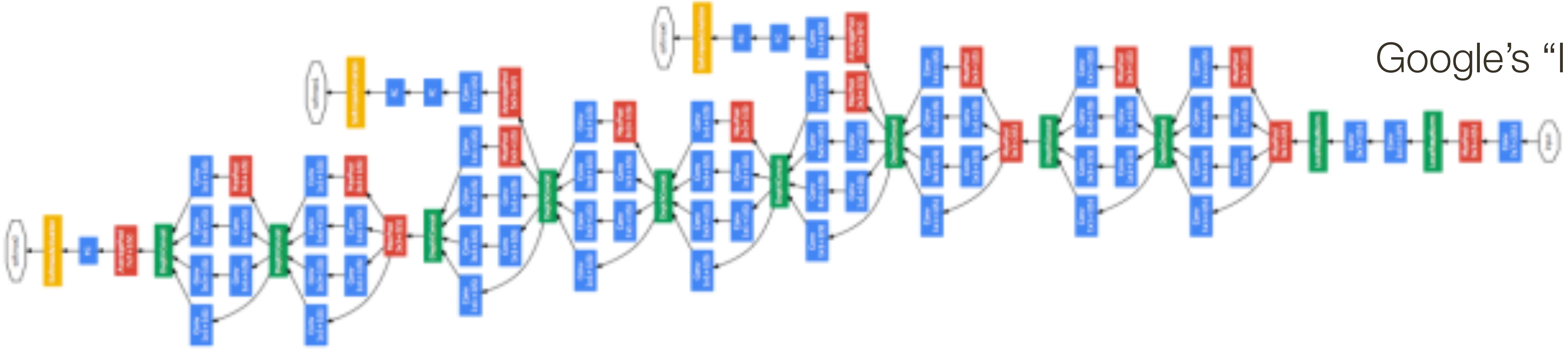


After Applying **Dropout**

[Srivastava et al, JMLR 2014]

* adopted from slides of **CS231n at Stanford**

Deep Learning **Terminology**



Google's "Inception" network

- **Network structure:** number and types of layers, forms of activation functions, dimensionality of each layer and connections (defines computational graph)

generally kept fixed, requires some knowledge of the problem and NN to sensibly set

deeper = better

- **Loss function:** objective function being optimized (`softmax`, `cross entropy`, *etc.*)

requires knowledge of the nature of the problem

- **Parameters:** trainable parameters of the network, including weights/biases of linear/fc layers, parameters of the activation functions, *etc.*

optimized using SGD or variants

- **Hyper-parameters:** parameters, including for optimization, that are not optimized directly as part of training (*e.g.*, `learning rate`, `batch size`, `drop-out rate`)

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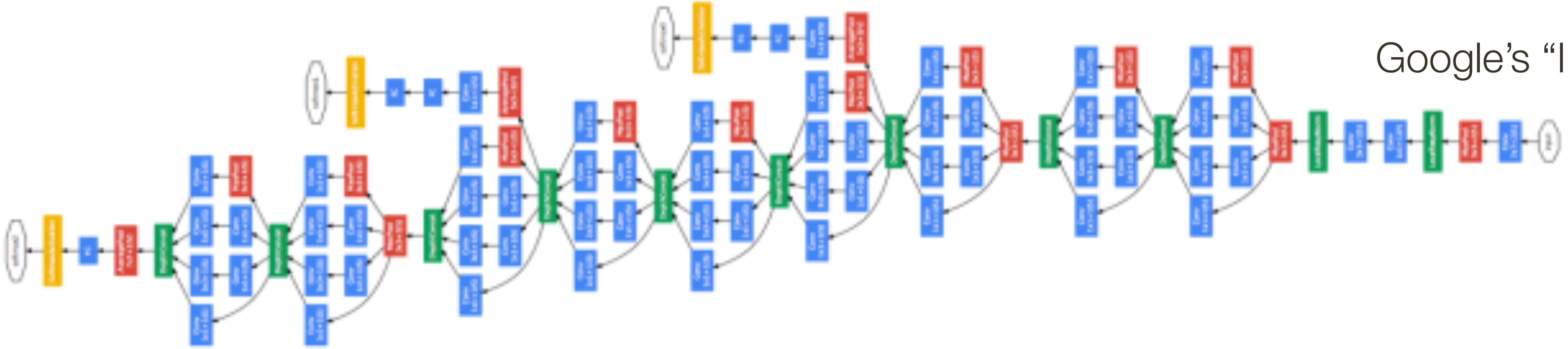

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grid search

Multivariate **Regression**

Input: feature vector $\mathbf{x} \in \mathbb{R}^n$

Output: output vector $\mathbf{y} \in \mathbb{R}^m$

Neural Network (input + intermediate hidden layers) $f(\mathbf{x};\Theta) : \mathbb{R}^n \rightarrow \mathbb{R}^k$

with **sigmoid** activations: $\mathbf{0} \leq f(\mathbf{x};\Theta) \leq \mathbf{1}$

with **Tanh** activations: $-\mathbf{1} \leq f(\mathbf{x};\Theta) \leq \mathbf{1}$

with **ReLU** activations: $\mathbf{0} \leq f(\mathbf{x};\Theta)$

Neural Network (output): linear layer

$$\hat{\mathbf{y}} = g(\mathbf{x};\mathbf{W},\mathbf{b}) = \mathbf{W}f(\mathbf{x};\Theta) + \mathbf{b} : \mathbb{R}^k \rightarrow \mathbb{R}^m$$

Loss: $\mathcal{L}(\mathbf{y},\hat{\mathbf{y}}) = ||\mathbf{y} - \hat{\mathbf{y}}||^2$

Binary Classification (Bernoulli)

Input: feature vector $\mathbf{x} \in \mathbb{R}^n$

Output: binary label $y \in \{0, 1\}$

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Neural Network (output): interpret sigmoid output as probability

$$p(y = 1) = f(\mathbf{x}; \Theta)$$

can interpret the score as the log-odds of $y = 1$ (a.k.a. the **logits**)

Loss:

$$\mathcal{L}(y, \hat{y}) = \begin{cases} -log[1 - f(\mathbf{x}; \Theta)] & y = 0 \\ -log[f(\mathbf{x}; \Theta)] & y = 1 \end{cases}$$

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Minimizing this **loss** is the same as maximizing **log likelihood** of data

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Multiclass Classification (e.g, ImageNet)

Input: feature vector $\mathbf{x} \in \mathbb{R}^n$

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(**one-hot** encoding)

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convert score into **probability**

normalize to sum up to 1 across classes

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Special case for multi-class single label

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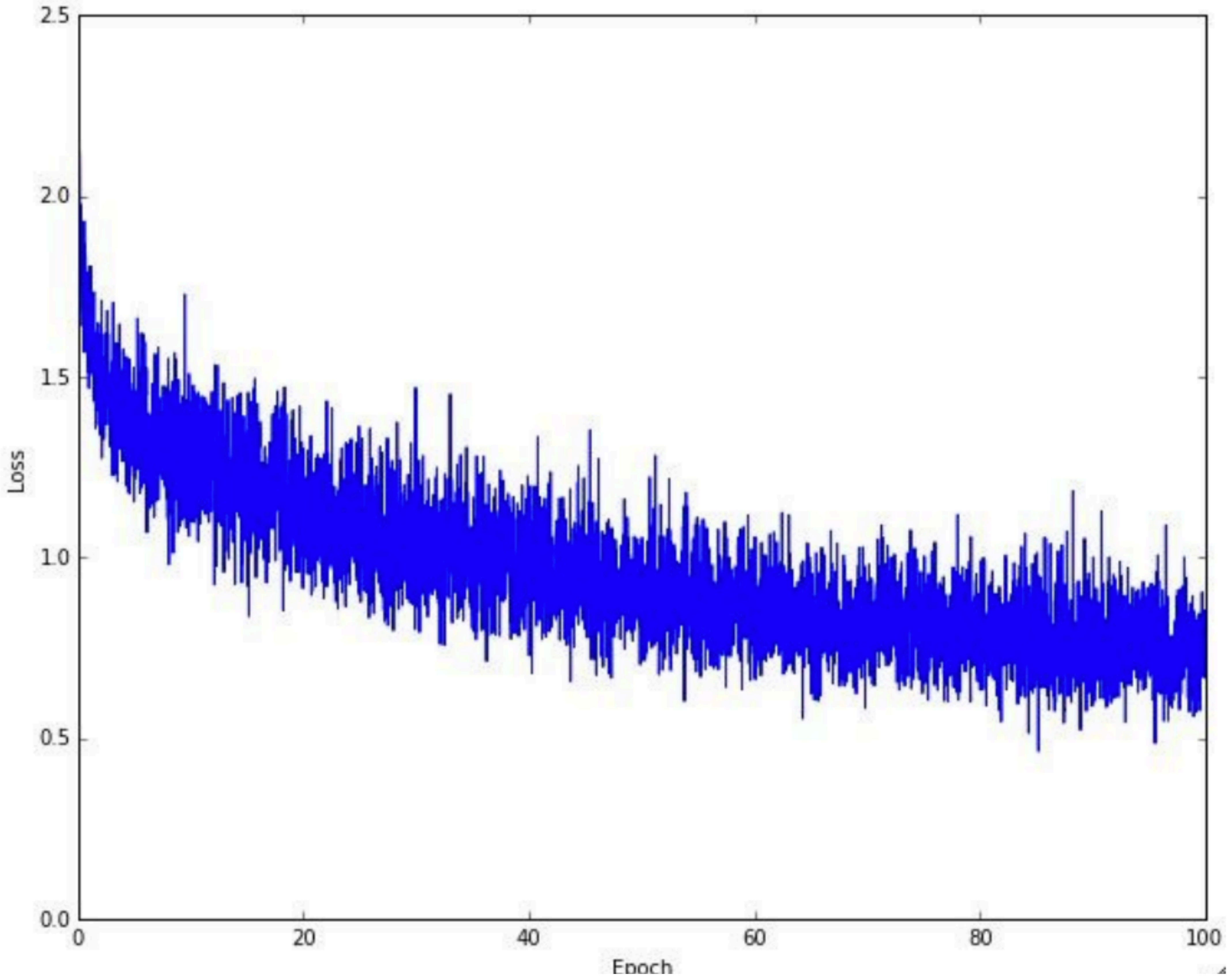
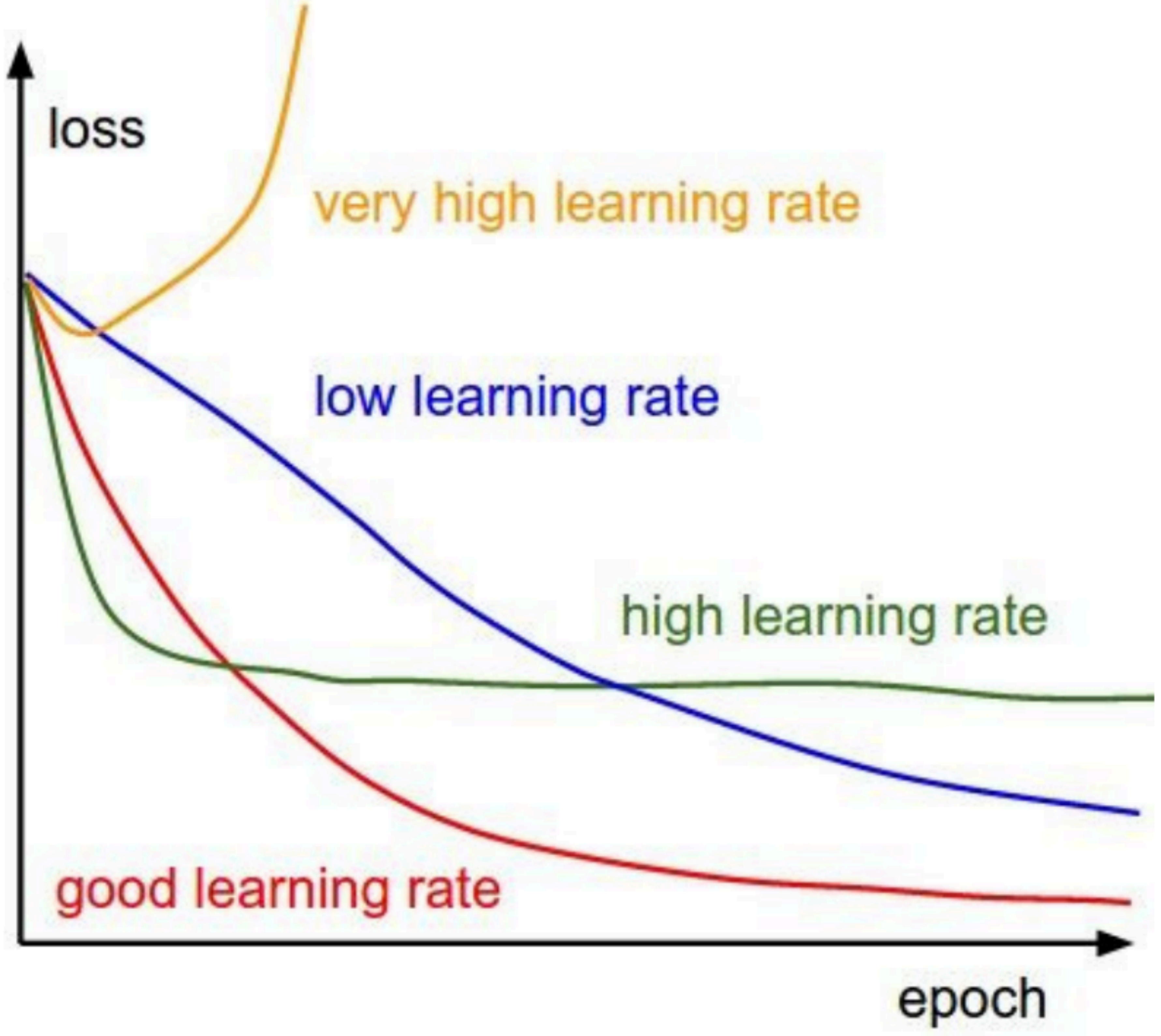
6. Use **Tensorboard** or **Weights & Biases** to keep track of experiments and visualize training & validation/testing loss and accuracy curves as you are training.

Monitoring Learning: Visualizing the (training) loss





* slide from Li, Karpathy, Johnson's **CS231n at Stanford**

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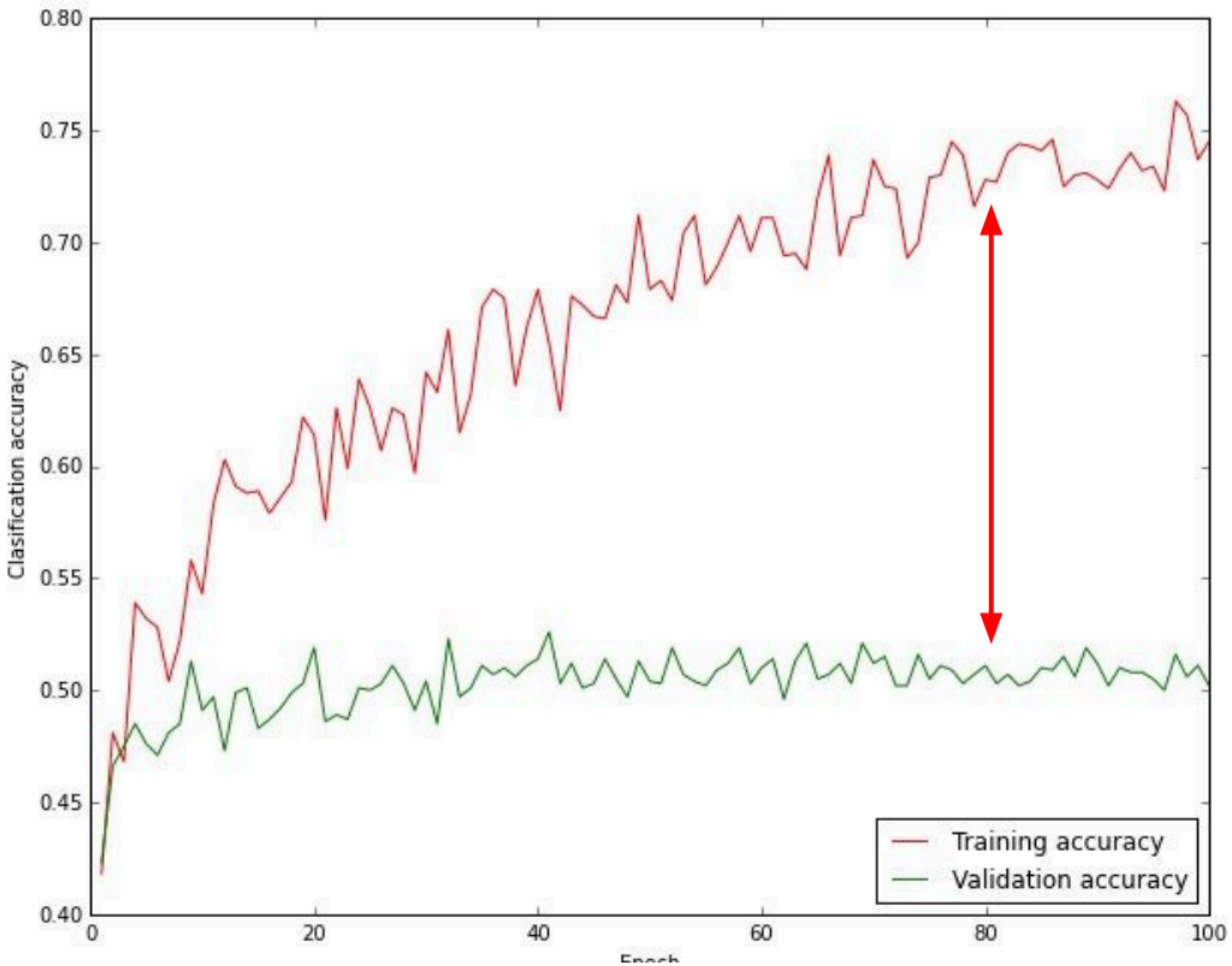

Big gap = overfitting

Solution: increase regularization

No gap = undercutting

Solution: increase model capacity

Small gap = **ideal**