Training Deep Learning Models

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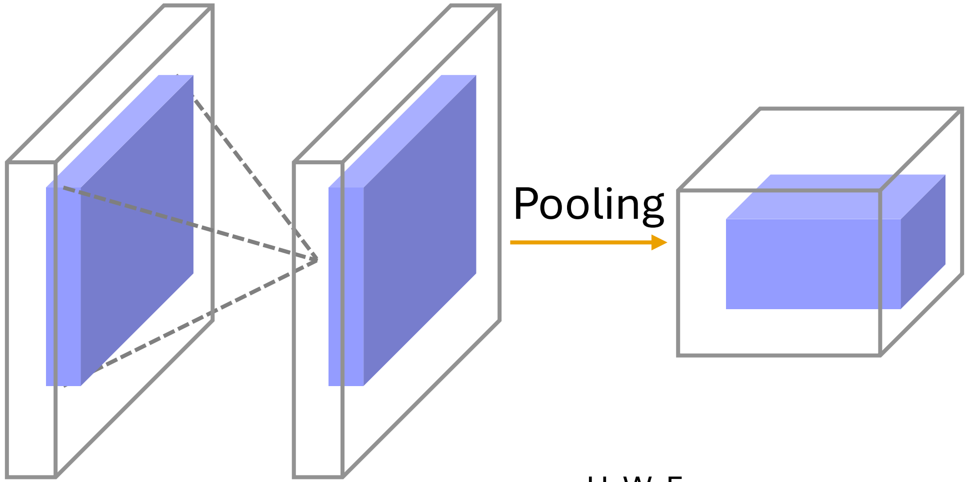
UCF

How to build and train *Deep* CNNs?

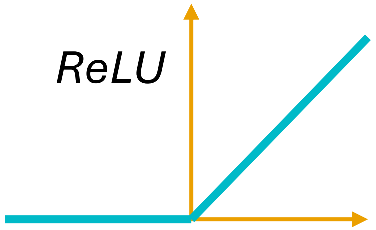
- Normalizations & Dropout
- Activation Functions
- Model Architectures
- Data Preprocessing
- Data Augmentation
- Transfer Learning
- Hyperparameter Tuning
- Code Practice

Training Deep Neural Networks

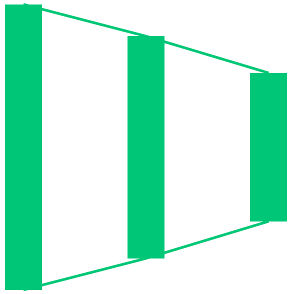
Convolution layers

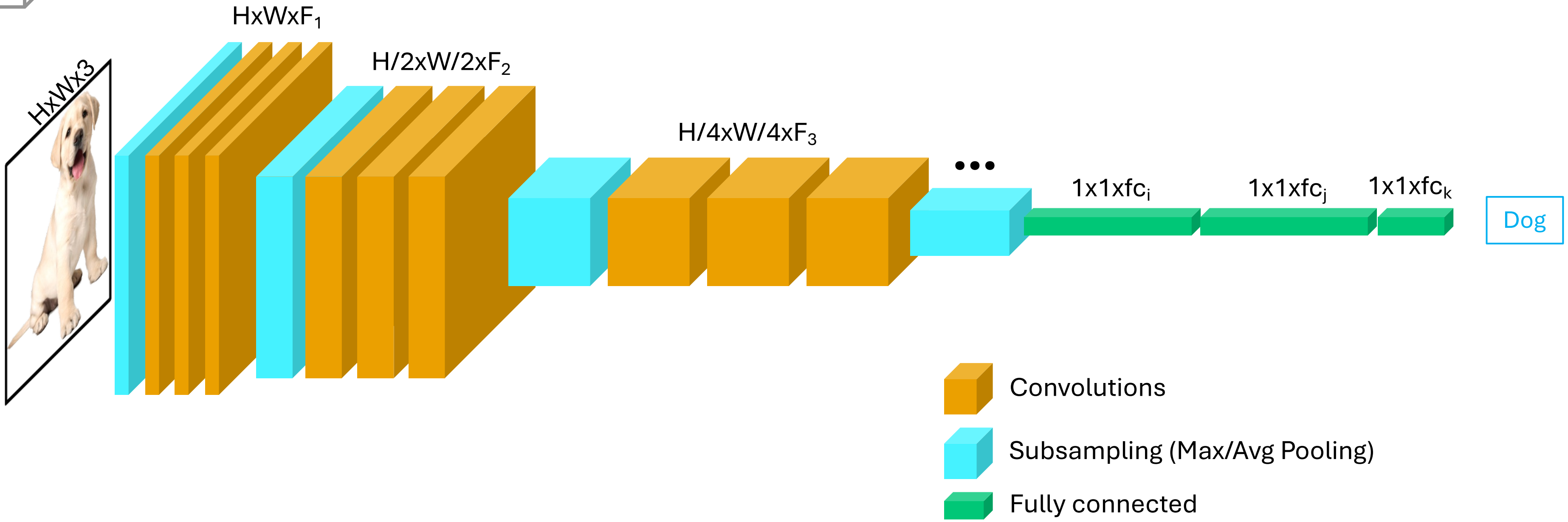


Activation function



Fully-Connected (FC)





Training Deep Neural Networks

- Normalize input tensors/features
- *Scale/shift* by trainable parameters

Normalize per batch

$x: N \times D$

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

Trainable parameters

$\beta: \ 1 \times D$

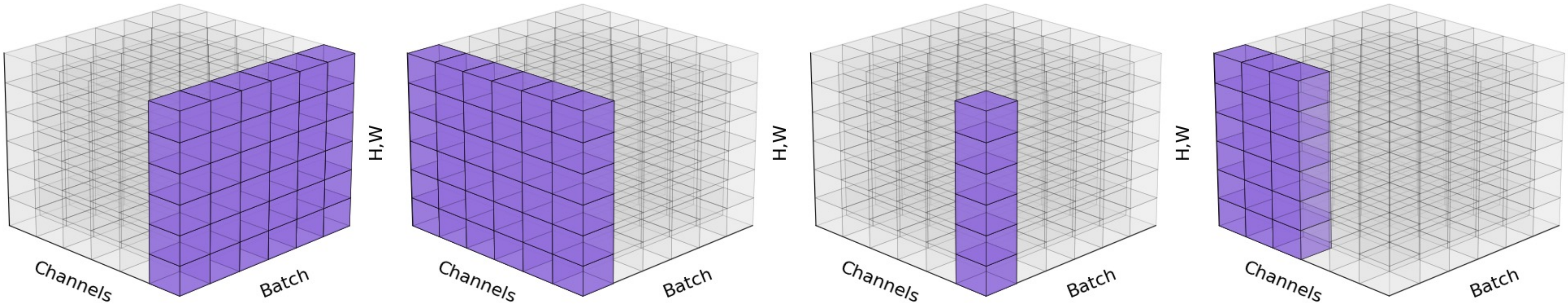
$$y = \frac{\gamma(x-\mu)}{\sigma} + \beta\gamma$$

Batch Normalization

Layer Normalization
Ba, Kiros, & Hinton, arXiv 2016

Instance Normalization

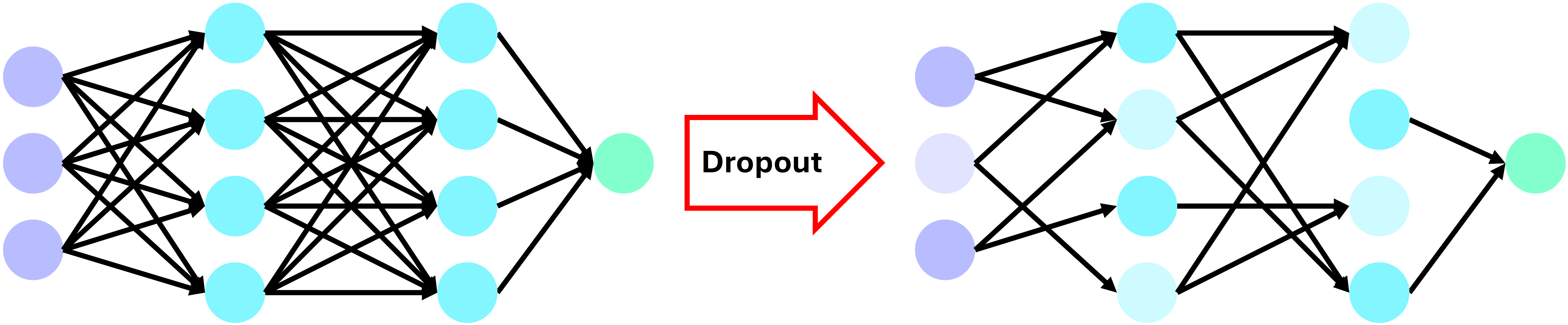
Group Normalization
Wu & He, ECCV 2018



Training Deep Neural Networks

"Dropout: A simple way to prevent neural networks from overfitting",

Srivastava et al, JMLR 2014



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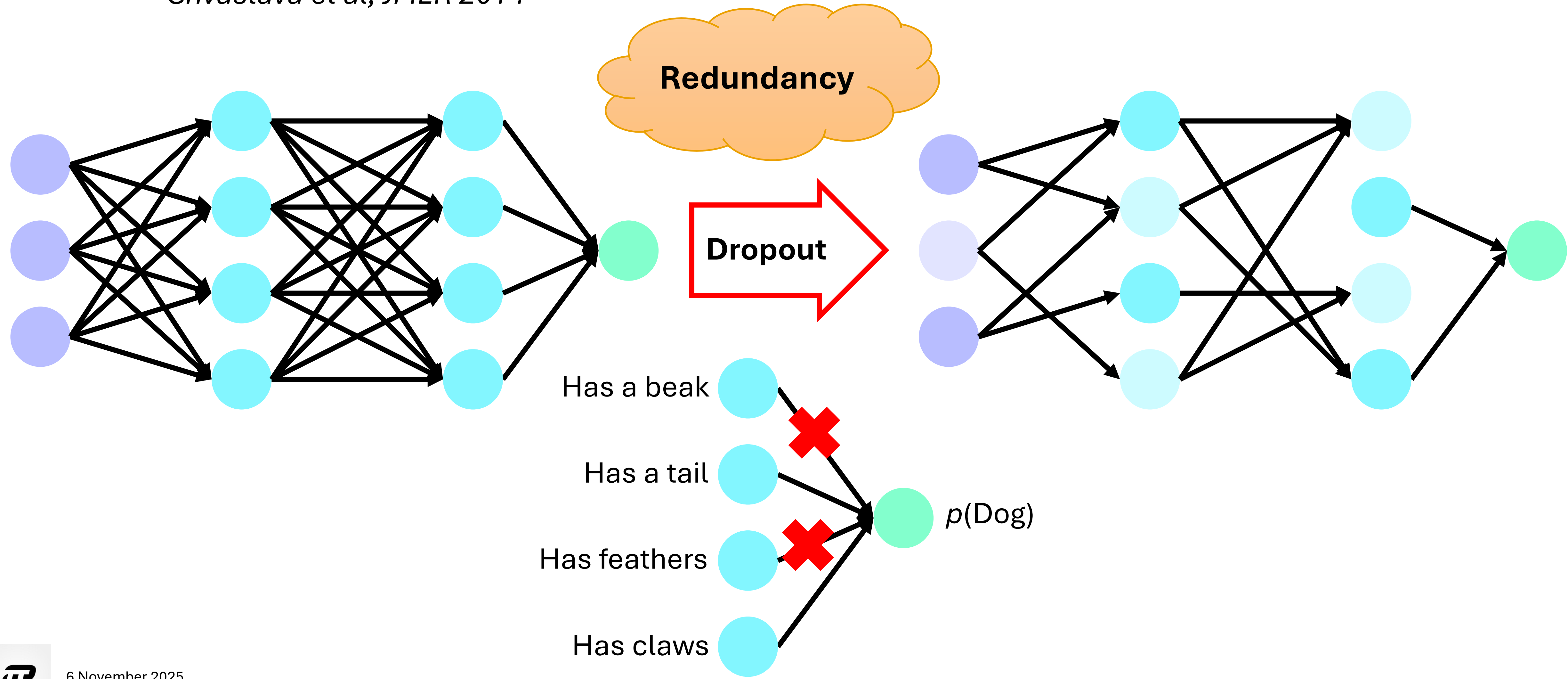


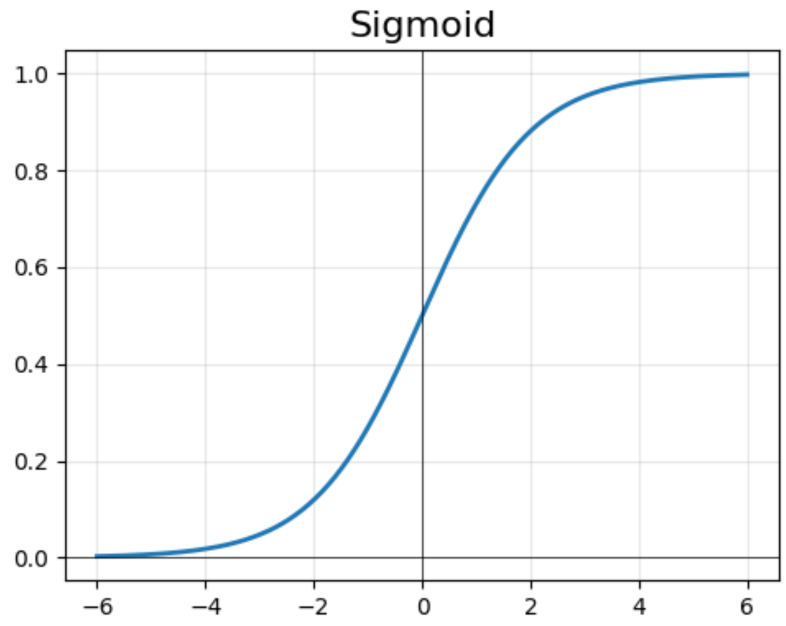
- Dropout: ensemble of several models that share parameters!
- At test (inference) all neurons and connections are active!
  - Each neuron's activation *MUST* be scaled!

```
def classify(x):
    H1 = torch.relu(torch.matmul(W1, x) + b1) * p
    H2 = torch.relu(torch.matmul(W2, H1) + b2) * p
    output = torch.matmul(W3, H2) + b3
    return output
```

Training Deep Neural Networks

- ✓ Squashes to range [0,1]
- ✓ Well-known as neuron firing rate
- x Large values ***kill*** the gradient
- x Too many layers of sigmoid results in ***gradient-vanishing***!

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



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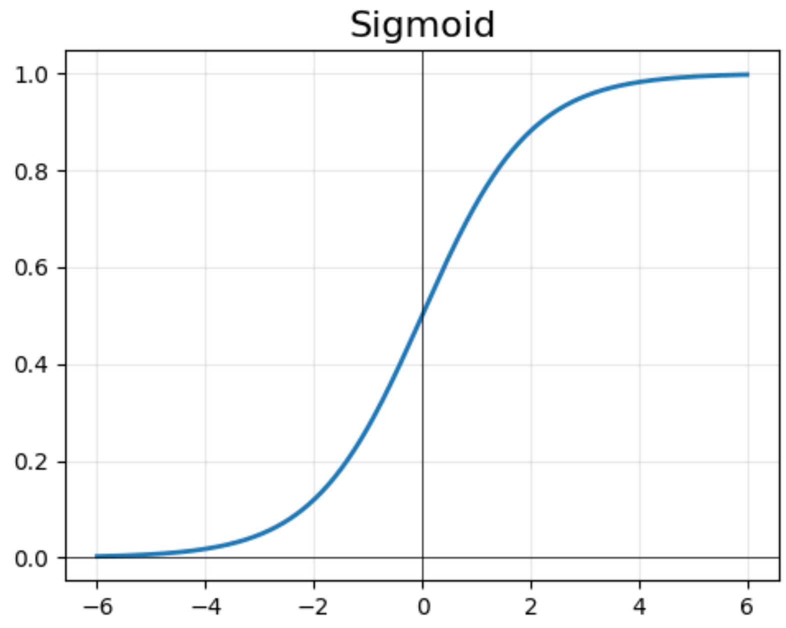
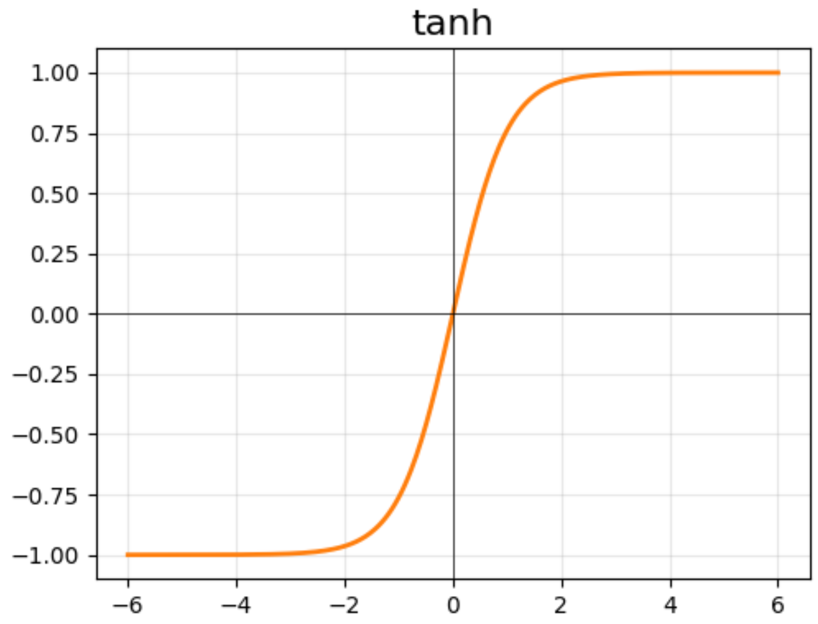


- Between [-1,1] and zero-centered
- Slightly slower gradient-vanishing
- Still saturates like Sigmoid does

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



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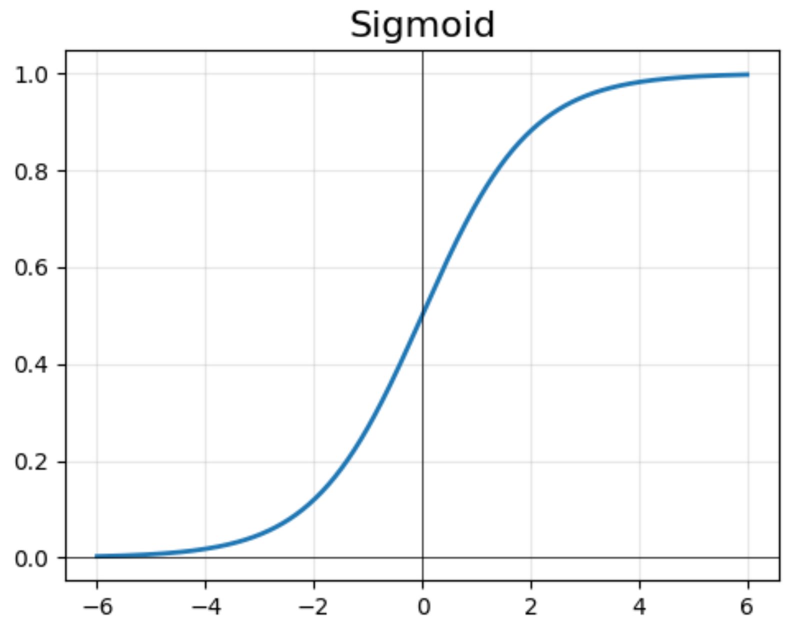
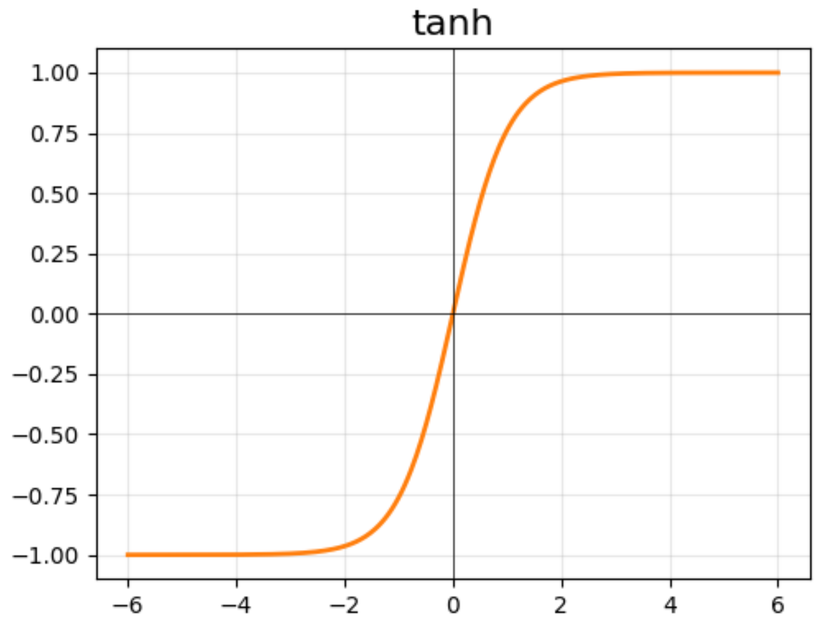
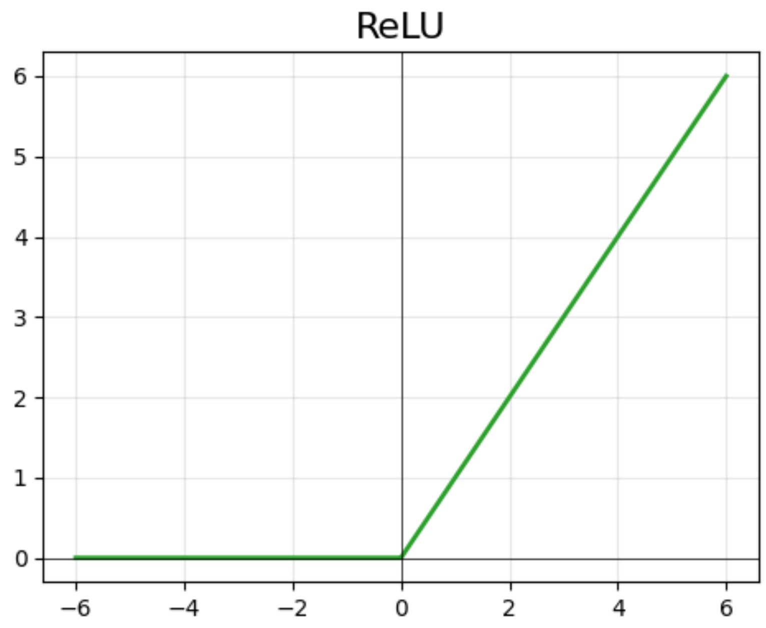
$$\tanh(x) = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}}$$

- ✓ Does not saturate
- ✓ Computationally efficient
- ✓ Converges much faster (~6x)
- x Not zero-centered
- x Dead zone for negatives

$$\mathrm{ReLU}(x) = \max(0, x)$$

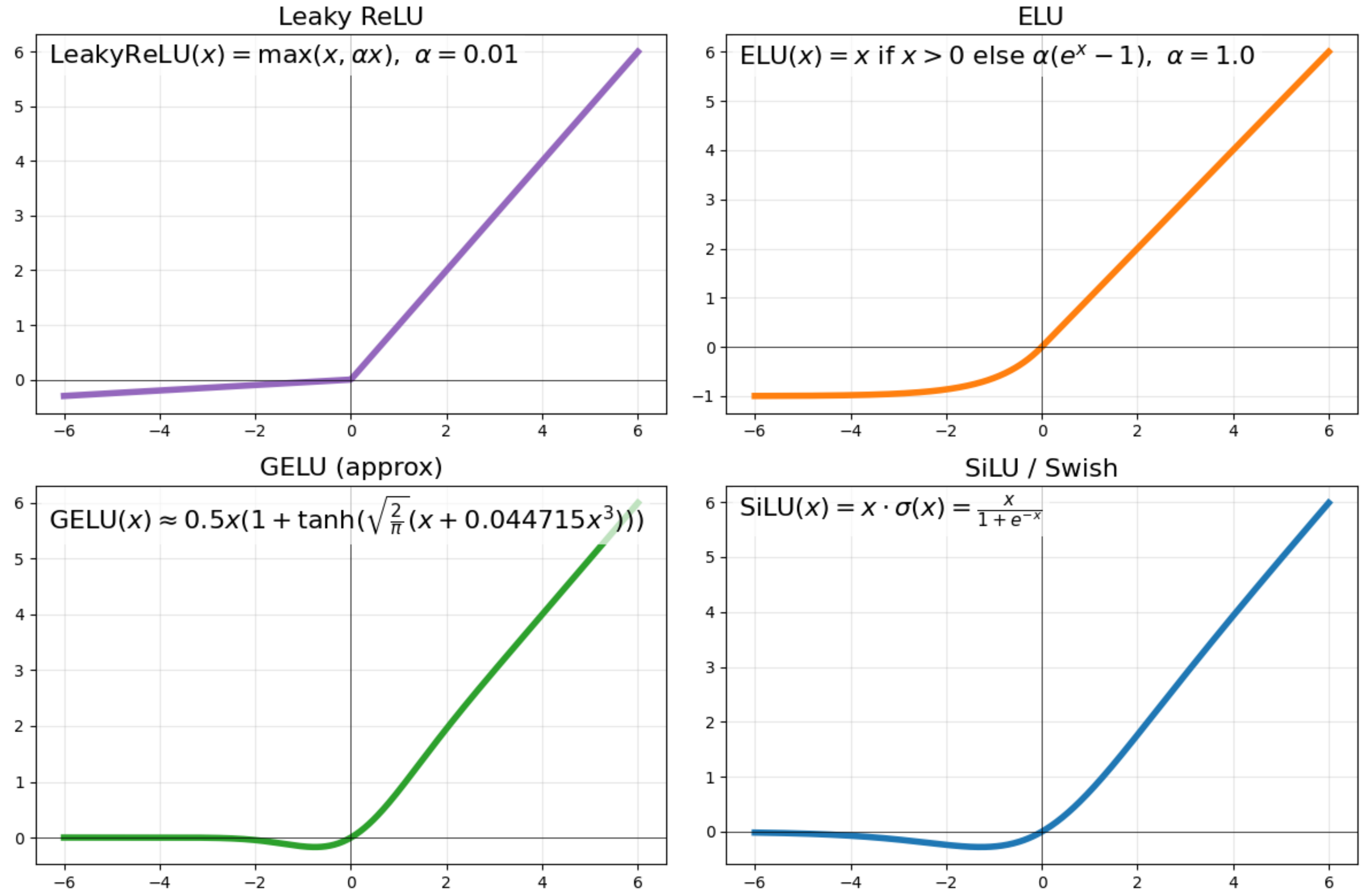






Training Deep Neural Networks

Activation Functions (Non-linearity)



ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners (2012-present):
AlexNet, VGG, GoogleNet, ResNet, DenseNet, AllConvNet, etc.

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227x227x3 **8** Layers: 5 Conv, 3 FC 96x11x11 256x5x5 384x3x3 (2) 256x3x3 4096 4096 1000 ReLU + Softmax Dropout 0.5 ~60M trainable 2 branches, 2 GPUs		

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5 Conv, 3 FC	8 Conv, 3 FC	10 Conv, 3 FC	13 Conv, 3 FC	16 Conv, 3 FC
96x11x11	64x3x3	64x3x3 (2)	64x3x3 (2)	64x3x3 (2)
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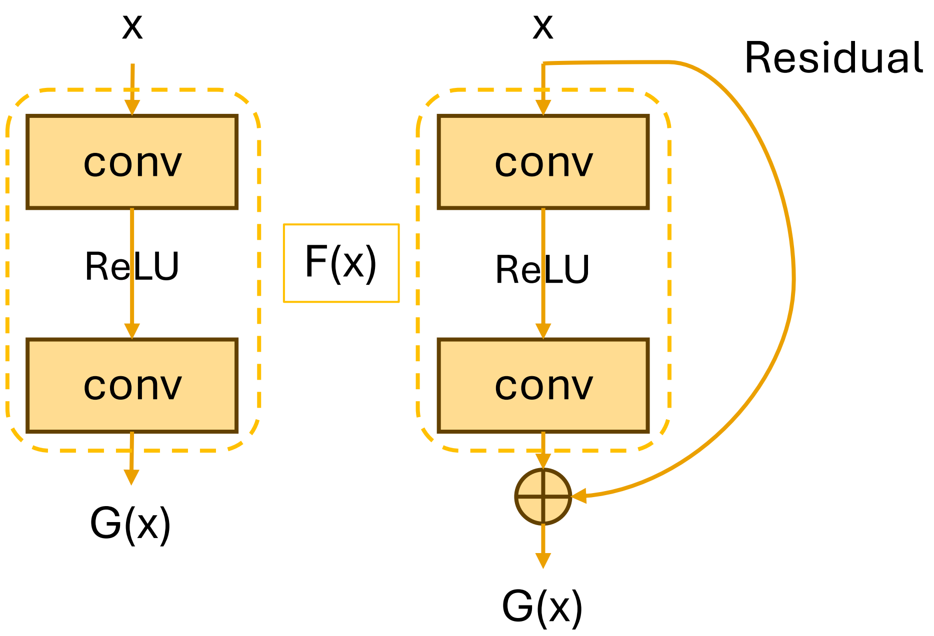
256x3x3	512x3x3 (2)	512x3x3 (2)	512x3x3 (3)	512x3x3 (4)
4096	512x3x3 (2)	512x3x3 (2)	512x3x3 (3)	512x3x3 (4)
4096	4096	4096	4096	4096
1000	4096	4096	4096	4096
ReLU + Softmax	1000	1000	1000	1000
Dropout 0.5	ReLU, Softmax	ReLU, Softmax	ReLU, Softmax	ReLU, Softmax
~60M trainable	Dropout 0.5	Dropout 0.5	Dropout 0.5	Dropout 0.5
2 branches, 2 GPUs	<133M trainable	>133M trainable	~138M trainable	~144M trainable

ResNet (18, 34, 50, 101, 152)

He et al. 2015

ResNet architecture:
- Stack residual blocks
- Every residual block has two 3x3 conv layers



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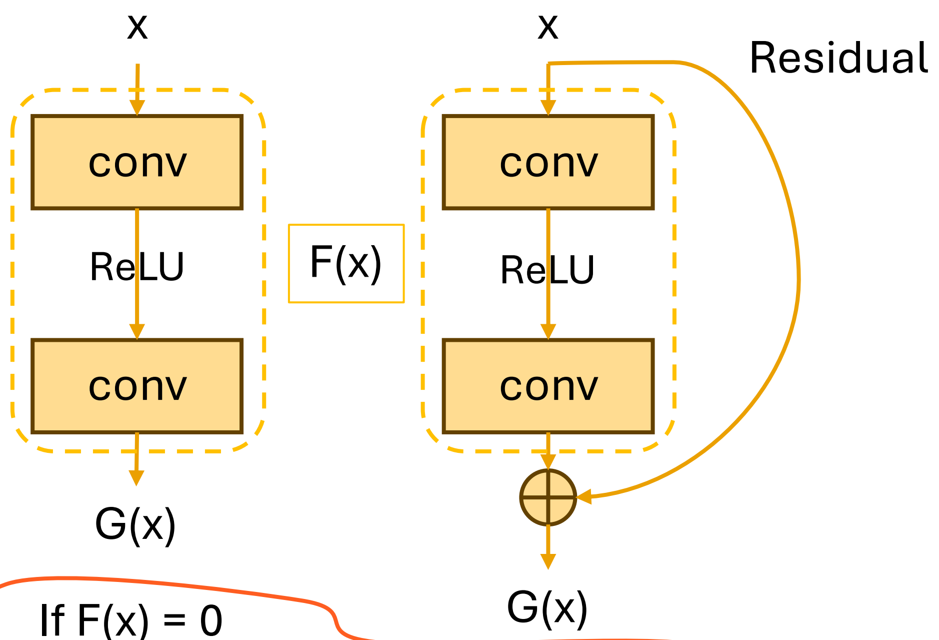

If F(x) = 0
→ G(x) = 0

G(x) = F(x) + x

Image (input) Normalization: Center and scale for each channel

- Subtract per-channel mean and divide by per-channel std
- Requires pre-calculation of mean and std for each pixel channel

```
import numpy as np
for pixel in images: # dataset
    for i in range(pixel.shape[0]):
        for j in range(pixel.shape[1]):
            for c in range(pixel.shape[2]):
                norm_pixel[i,j,c] = (pixel[i,j,c] - np.mean(pixel[:,:,c])) / np.std(pixel[:,:,c])
```

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```

Image (input) Resizing/Cropping:

- Deep learning models expect fixed input sizes: e.g. 224x224

```python
import torch
from torchvision import transforms
transforms.Resize((224, 224))
```

Regularization: A common pattern

- While training: add some randomness $y = fw(x, z)$
- At test: average out randomness $y = f(x) = E_z[f(x, z)] = \int p(x) f(x, z) dz$

Dropout: randomly drop activations

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Augmentation:

Training Deep Neural Networks

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Augmentation:

- Random contract and brightness

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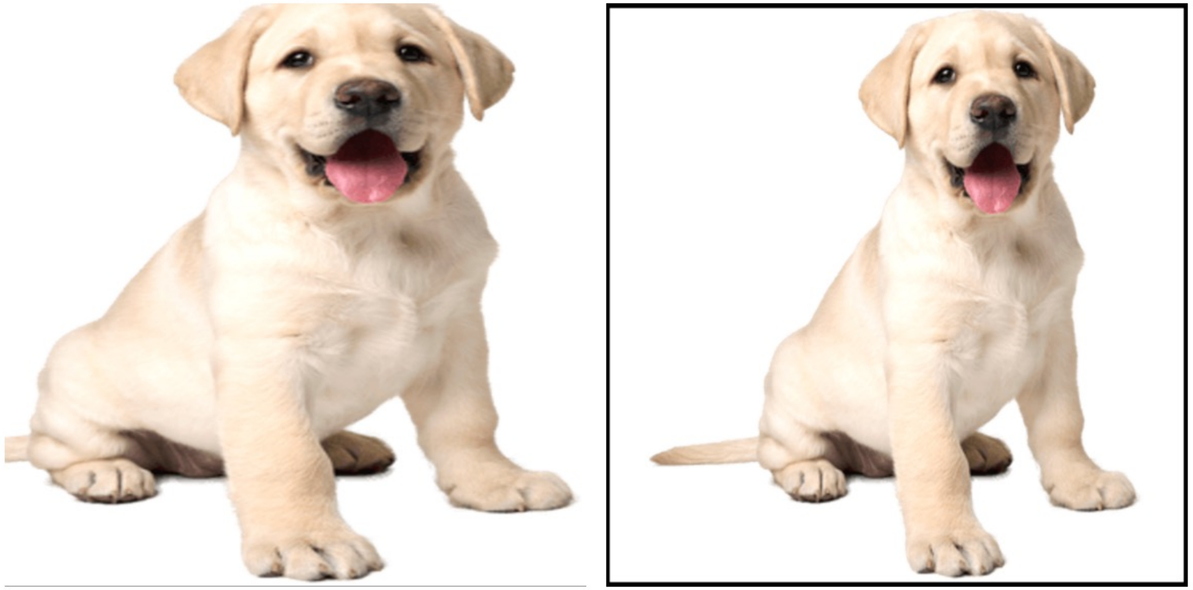

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Augmentation:

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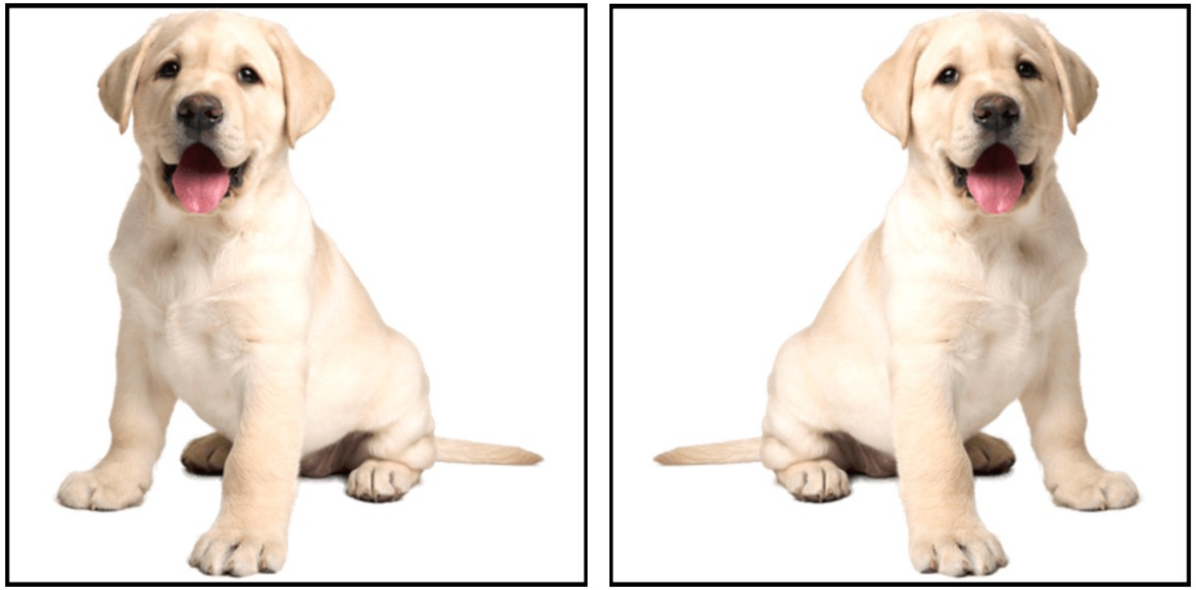

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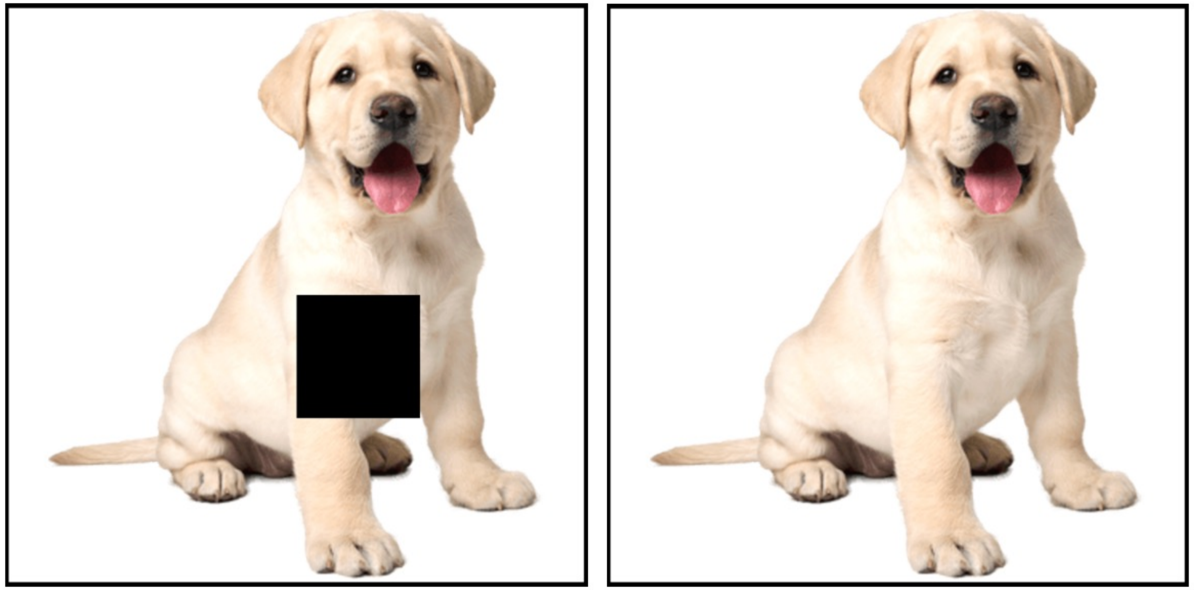
Use all activations and average with *p*

Augmentation:

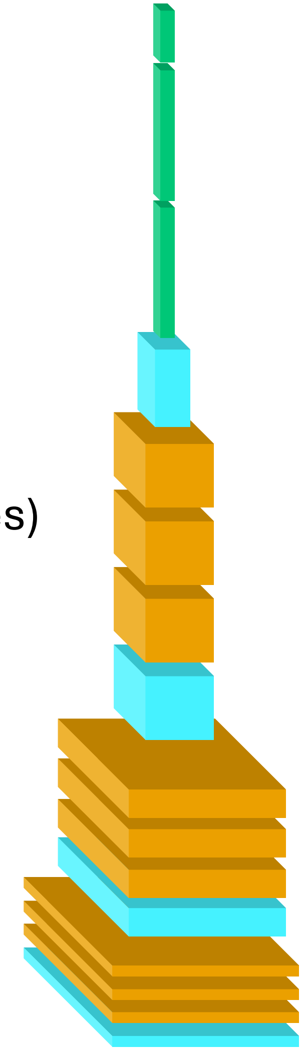
- Random contract and brightness
- Random cropping and scaling
- Random flipping
- Random cutouts (small datasets)



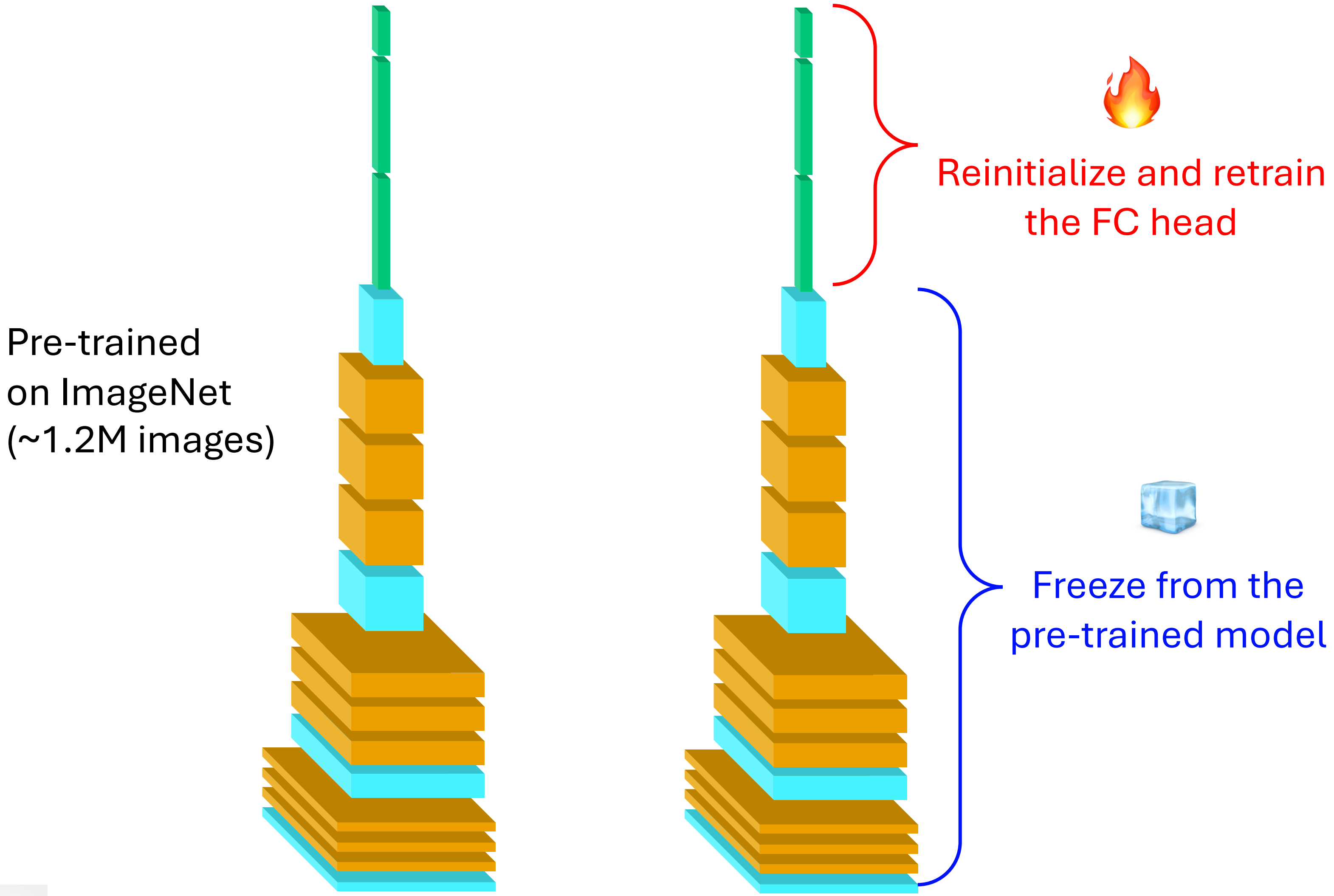
Training Deep Neural Networks

Training a ***deep*** network on a ***smaller*** dataset!

Pre-trained
on ImageNet
(~1.2M images)



Training a <u>*deep*</u> network on a <u>*smaller*</u> dataset!



Training Deep Neural Networks

Training a *deep* network on a *smaller* dataset! But if a *large* dataset ...

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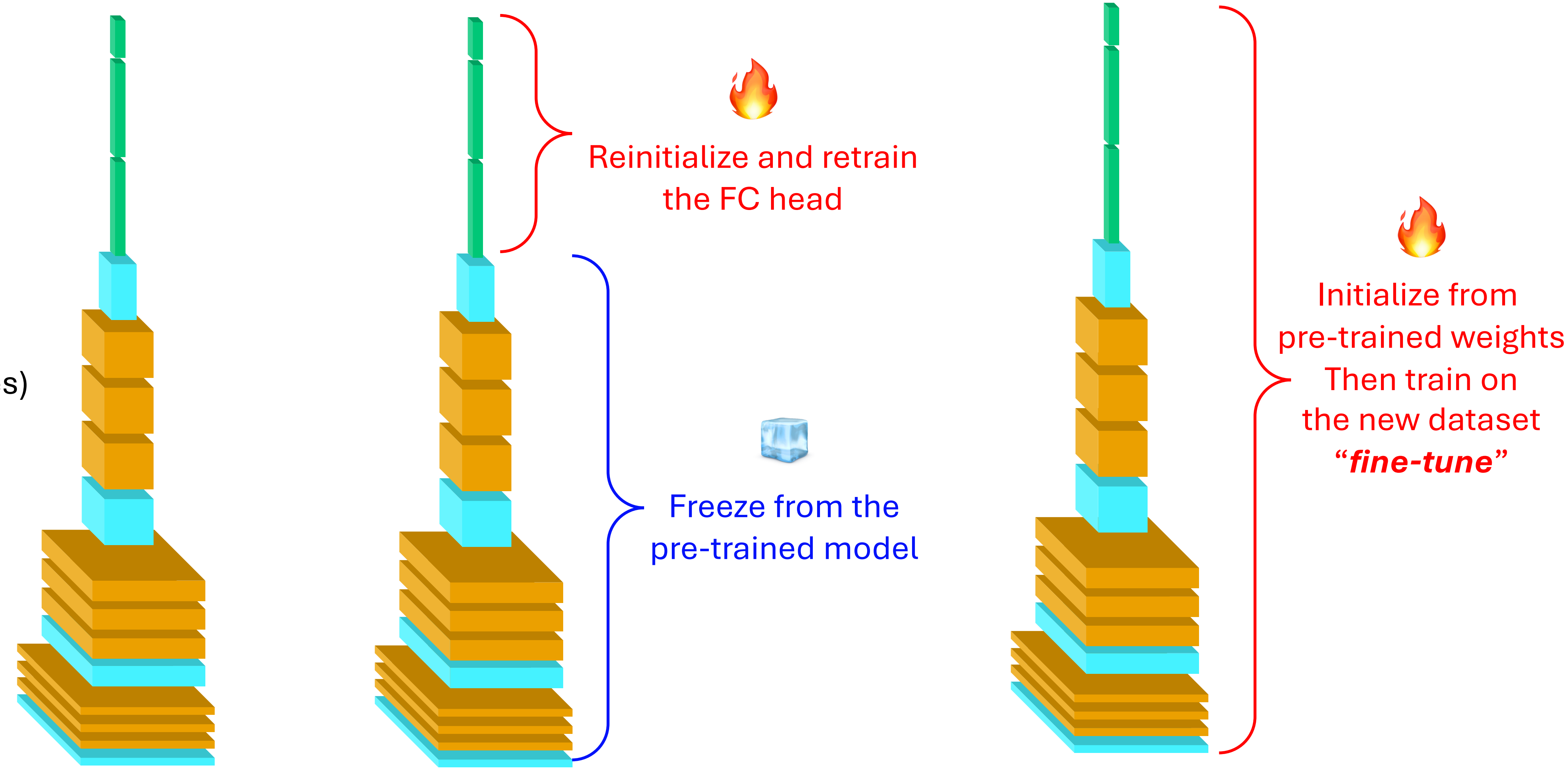
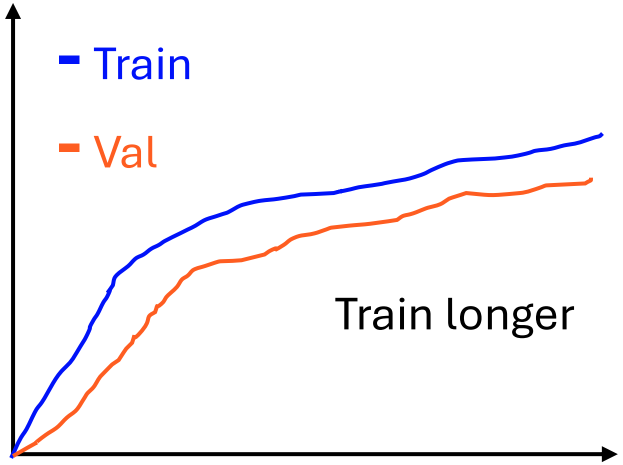
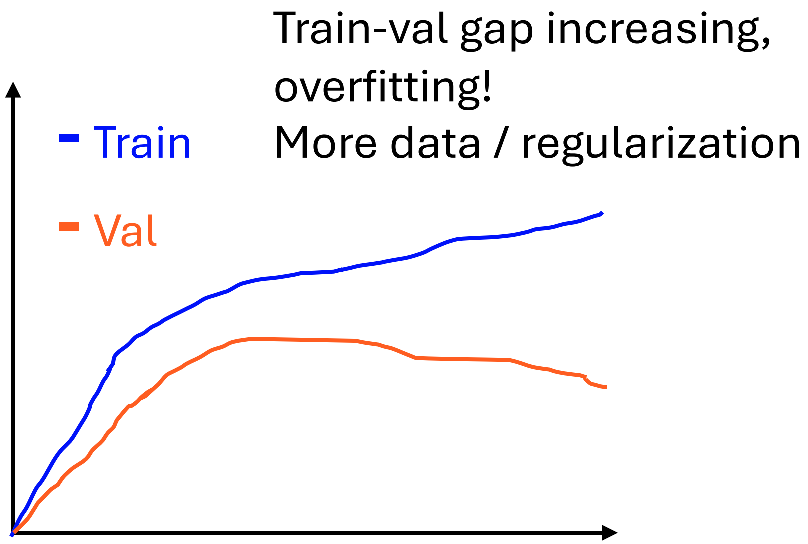
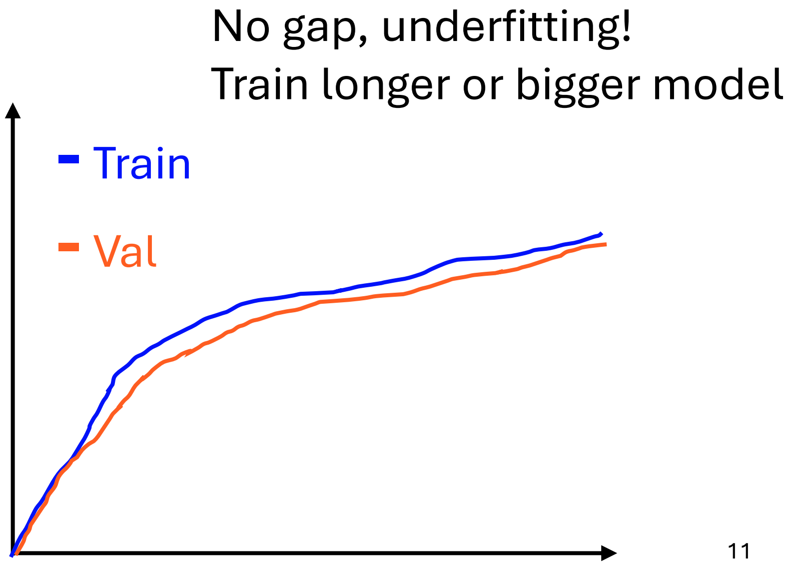


1. Check initial loss
2. Overfit a small sample
3. *Find a learning-rate that makes loss decrease significantly*
    1. Common rates: 1e-1, … , 1e-5
4. Try a broad set of hyperparameters, and train for 1~5 epochs
5. Refine your selection set and train longer
6. Always keep an eye on loss and accuracy curves→Step 5.







Training Deep Neural Networks

(Q&A)