Trustworthy AI Systems

-- Image Classification

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Trustworthy AI Systems

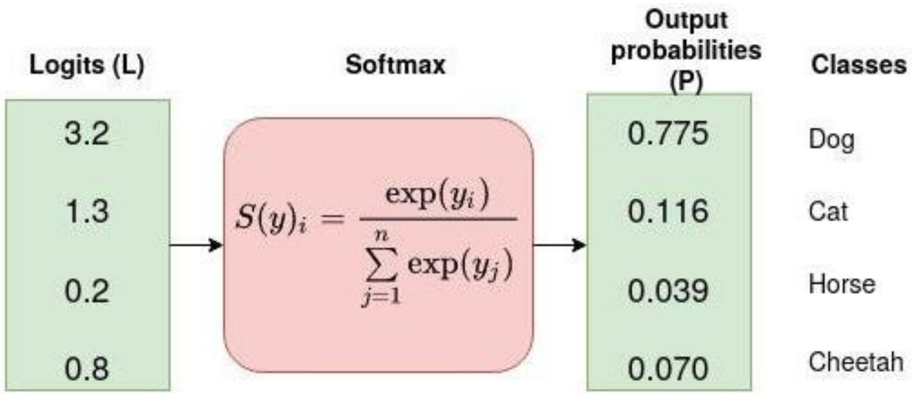
- This course is NOT the traditional…
  - Computer Vision
  - Natural Language Processing
  - Speech Recognition
  - Deep Learning
  - Machine Learning
  - Artificial Intelligence

- Last Lecture: an overview of Trustworthy AI Systems

Image Classification: a core task in CV

https://stock.adobe.com/search?k=panda

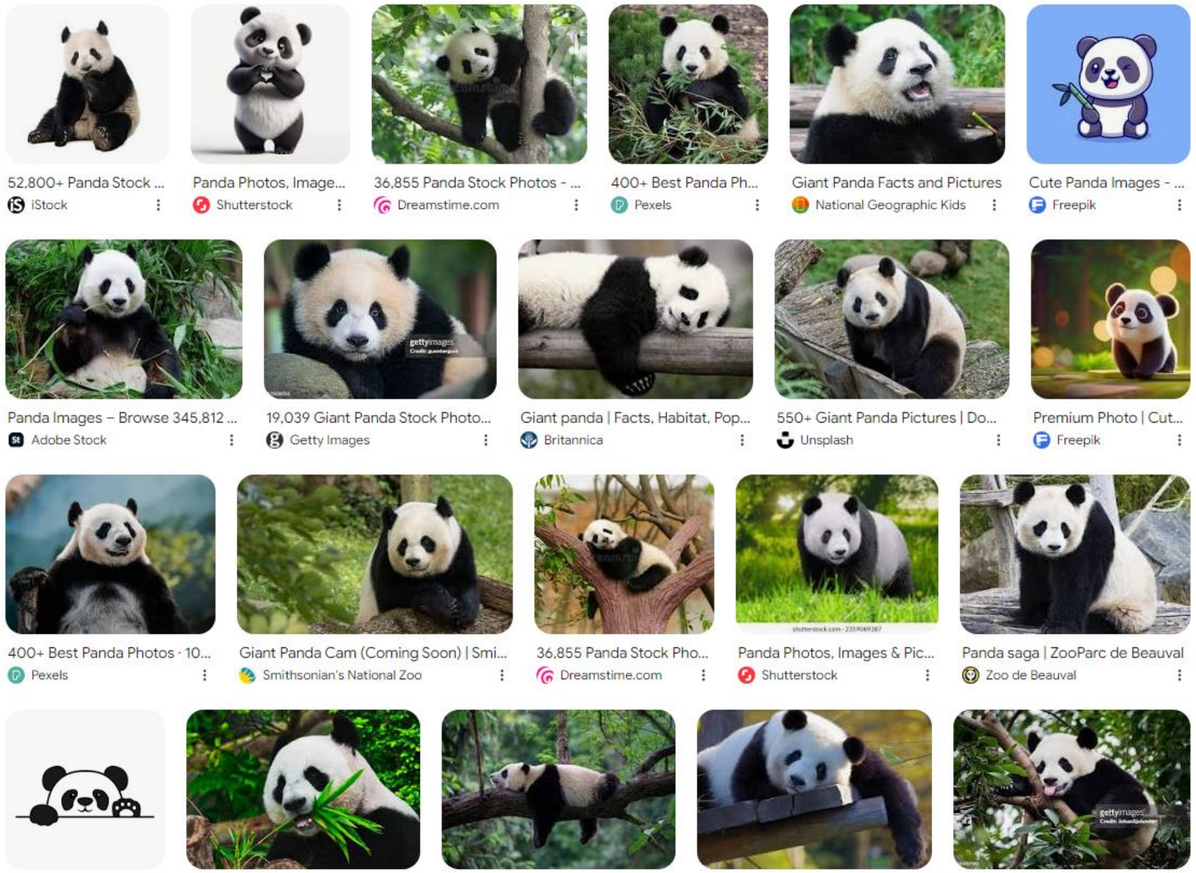
```python
import torch
import torch.nn as nn
class Model4_1(nn.Module):
    def __init__(self):
        super(Model4_1, self).__init__()
        self.lin1 = nn.Linear(784, 100)
        self.relu = nn.ReLU()
        self.lin2 = nn.Linear(100, 10)

    def forward(self, x):
        out = self.lin1(x)
        out = self.relu(out)
        out = self.lin2(out)
        return out

model4_1 = Model4_1()
```



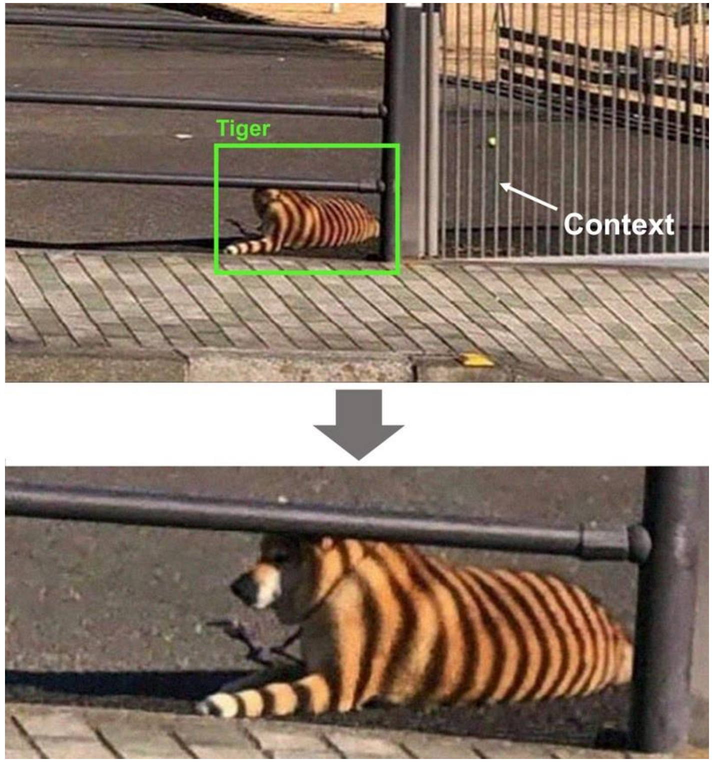
Challenges in Classification

Variations in the physical world

- Illumination
- Background Clutter
- Occlusion
- Deformation
- Intraclass variation

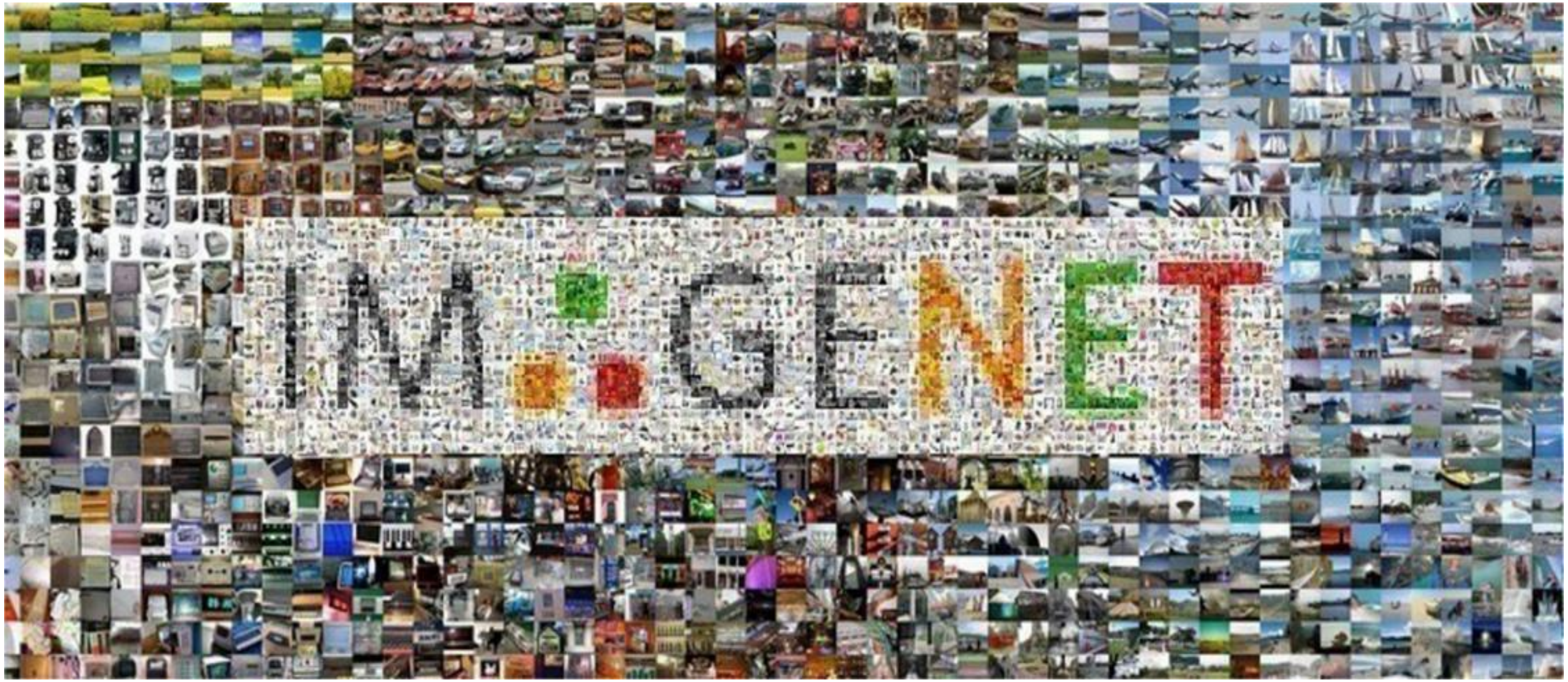


Classification Challenges: Context



https://www.linkedin.com/posts/ralph-aboujaoude-diaz-40838313_technology-artificialintelligence-computervision-activity-6912446088364875776-h-lq/?utm_source=linkedin_share&utm_medium=member_desktop_web

Data-driven Computer Vision

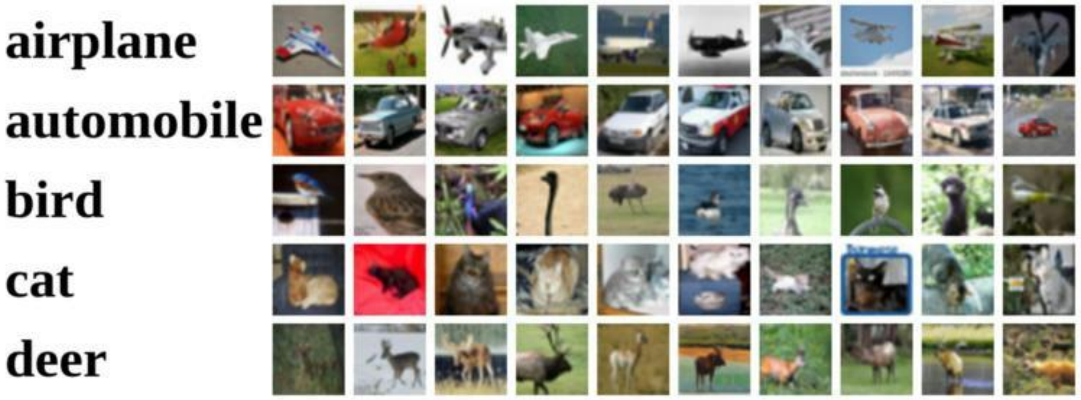


Data-driven Computer Vision

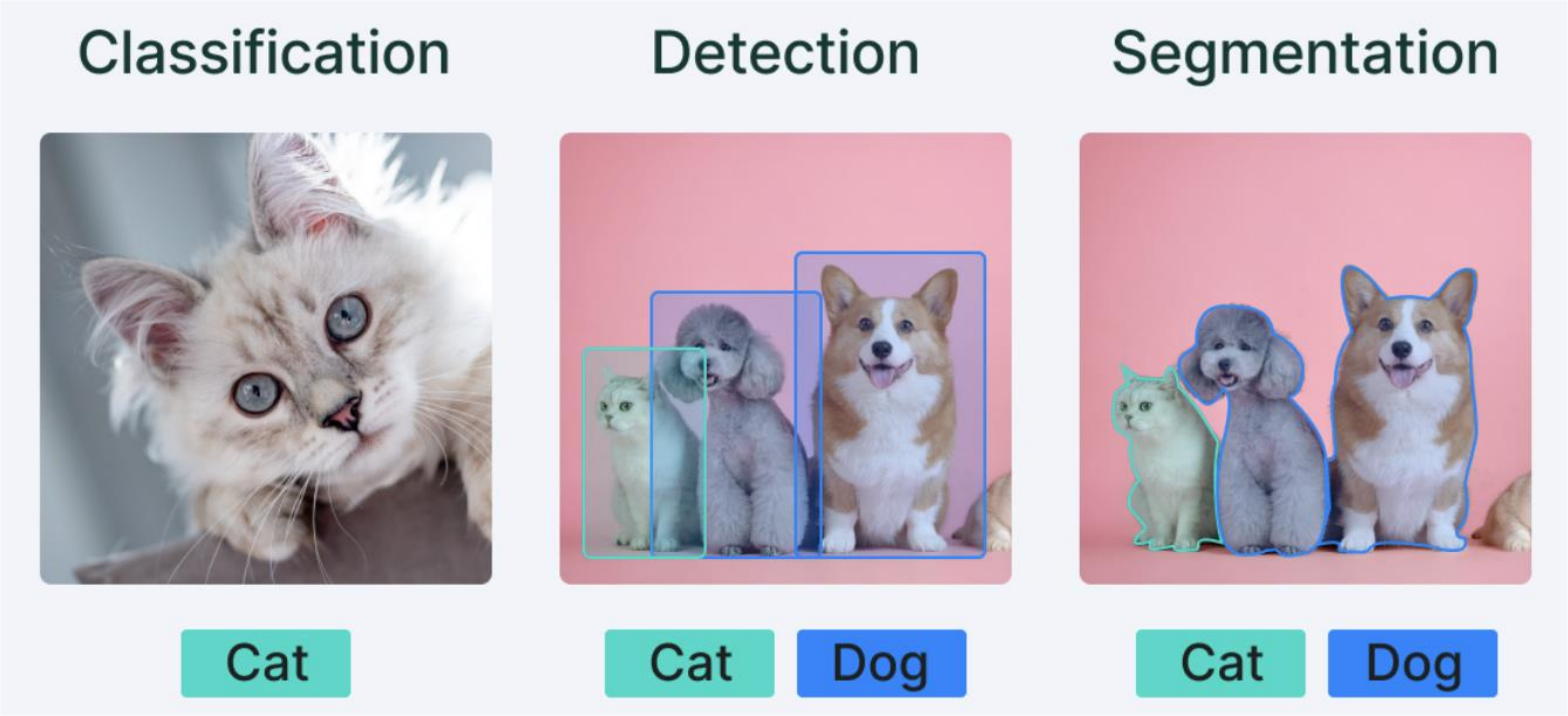
- Collect a dataset of images and labels
- Use Machine Learning algorithms to train a classifier
- Evaluate the classifier on new images

```
def train(images, labels):
  # Machine learning!
  return model
```

```
def predict(model, test_images):
  # Use model to predict labels
  return test_labels
```



Classical Computer Vision Tasks

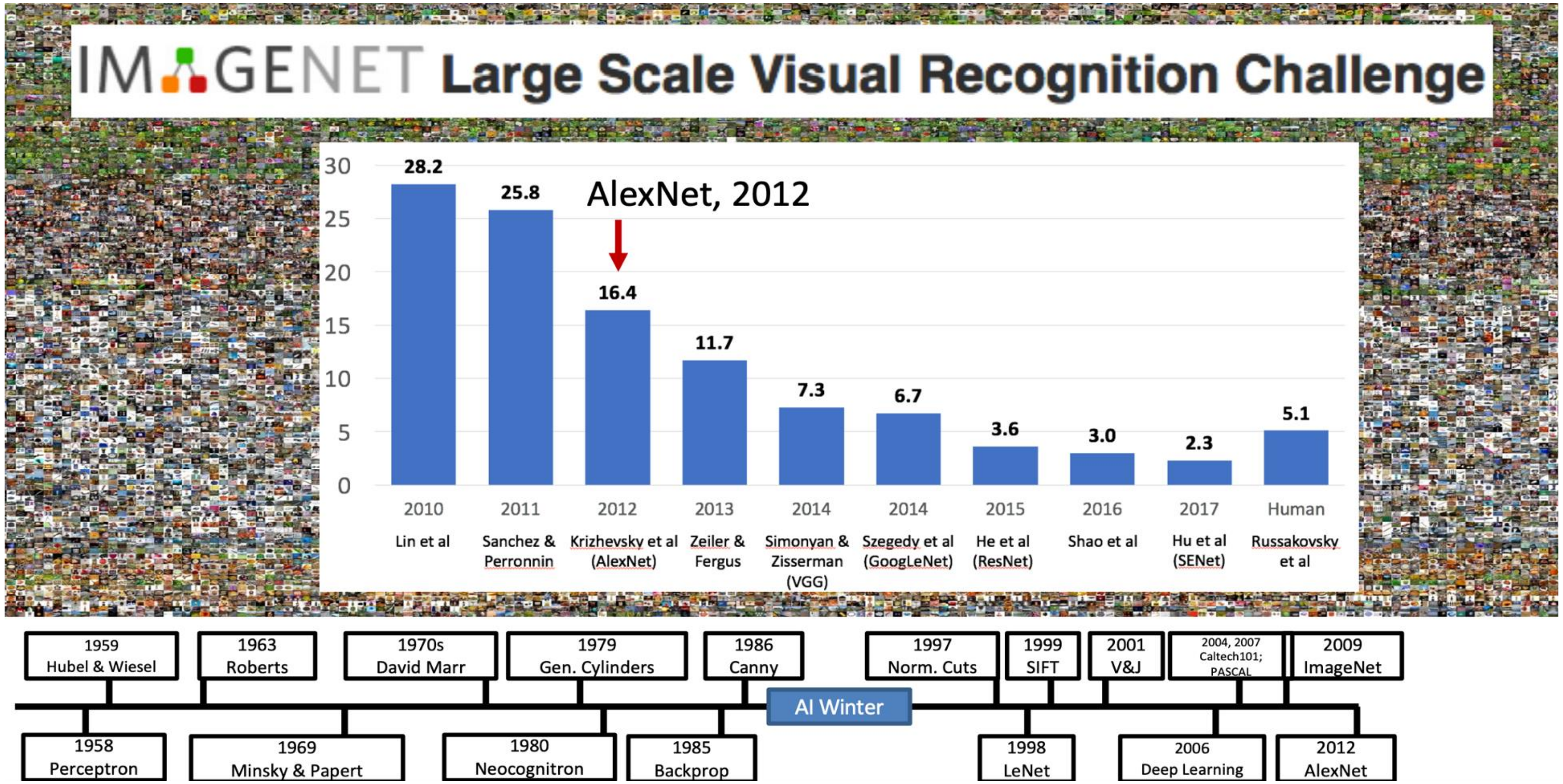


Localizing and label objects

Dividing images into regions

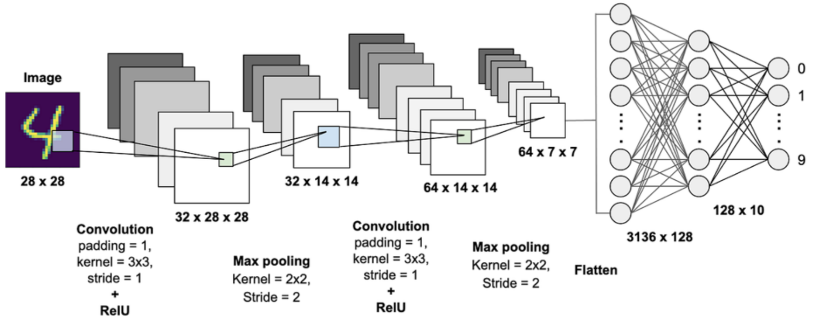
https://www.v7labs.com/blog/what-is-computer-vision

Deep Learning and Image Classification

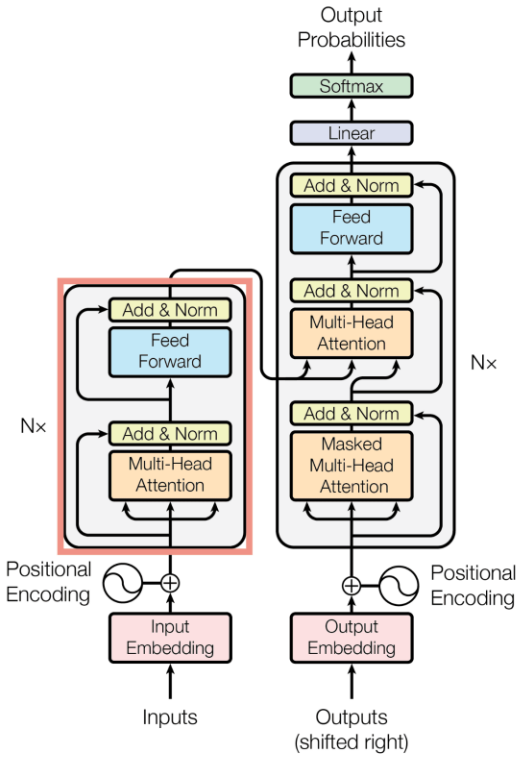


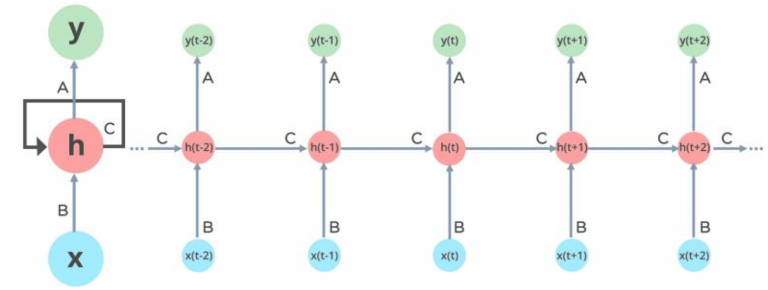
https://cs231n.stanford.edu/slides/2024/lecture_1_part_1.pdf

Main Deep Learning Models



https://becominghuman.ai/building-a-convolutional-neural-network-cnn-model-for-image-classification-116f77a7a236

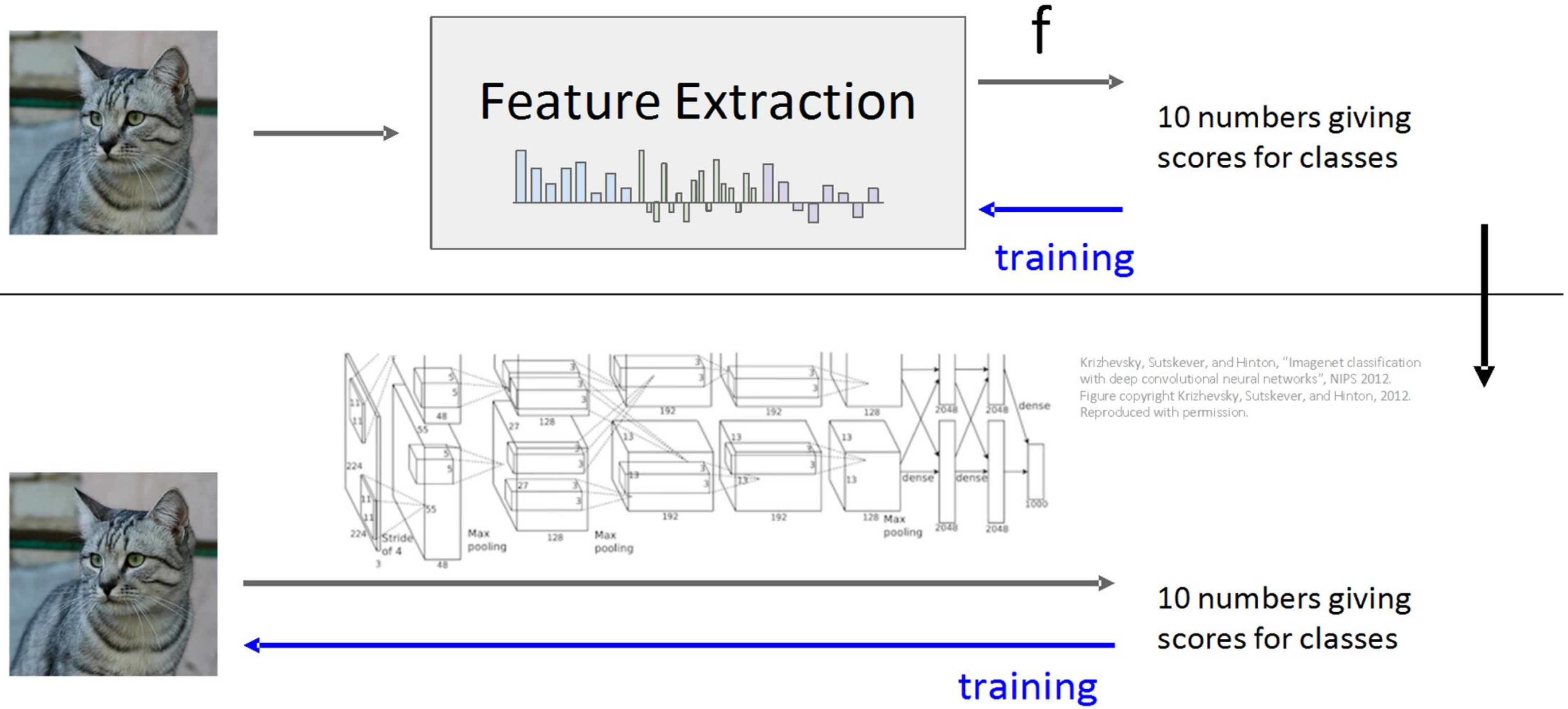




https://www.analyticsvidhya.com/blog/2022/03/a-brief-overview-of-recurrent-neural-networks-rnn/

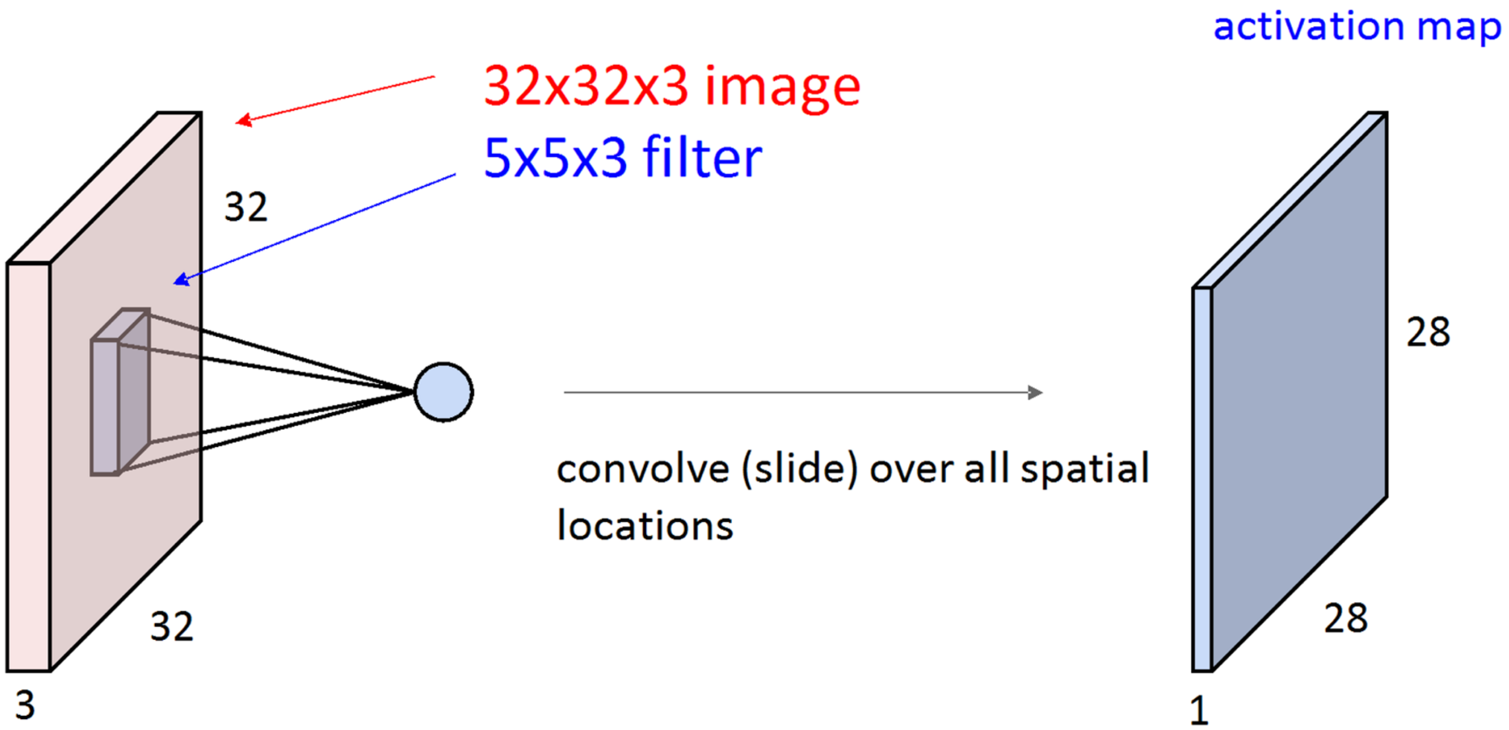
https://machinelearningmastery.com/the-transformer-model/

Feature Engineering V.S. ConvNets



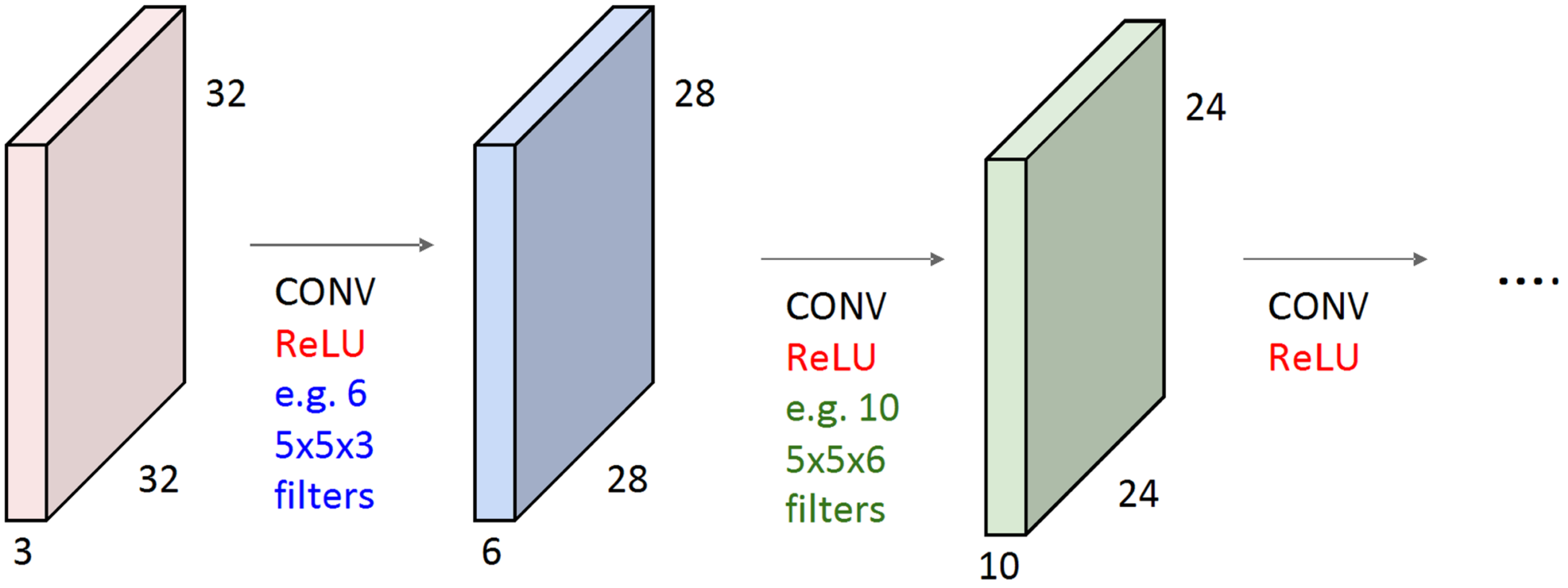
Krizhevsky, Sutskever, and Hinton, "Imagenet classification with deep convolutional neural networks", NIPS 2012. Figure copyright Krizhevsky, Sutskever, and Hinton, 2012. Reproduced with permission.

Convolutional Layer



Filter: a small matrix of weights

Convolutional Neural Network



Conv Layer in PyTorch

Conv2d

CLASS torch.nn.Conv2d(*in_channels*, *out_channels*, *kernel_size*, *stride=1*, *padding=0*, *dilation=1*, *groups=1*, *bias=True*, *padding_mode='zeros'*, *device=None*, *dtype=None*) [SOURCE]

Applies a 2D convolution over an input signal composed of several input planes.

In the simplest case, the output value of the layer with input size (N, C_{in}, H, W) and output $(N, C_{\text{out}}, H_{\text{out}}, W_{\text{out}})$ can be precisely described as:

$$\text{out}(N_i, C_{\text{out}_j}) = \text{bias}(C_{\text{out}_j}) + \sum_{k=0}^{C_{\text{in}}-1} \text{weight}(C_{\text{out}_j}, k) \star \text{input}(N_i, k)$$

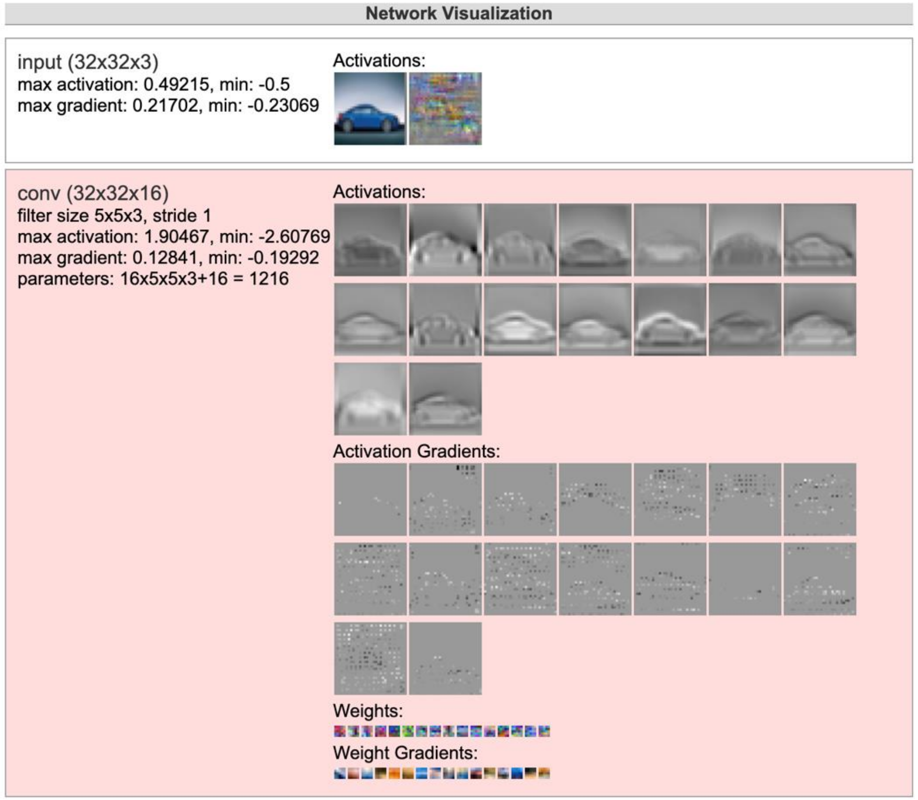
where $\star$ is the valid 2D cross-correlation operator, N is a batch size, C denotes a number of channels, H is a height of input planes in pixels, and W is width in pixels.

This module supports TensorFloat32.

On certain ROCm devices, when using float16 inputs this module will use different precision for backward.

- `stride` controls the stride for the cross-correlation, a single number or a tuple.
- `padding` controls the amount of padding applied to the input. It can be either a string {'valid', 'same'} or an int / a tuple of ints giving the amount of implicit padding applied on both sides.
- `dilation` controls the spacing between the kernel points; also known as the u00e0 trous algorithm. It is harder to describe, but this link has a nice visualization of what `dilation` does.

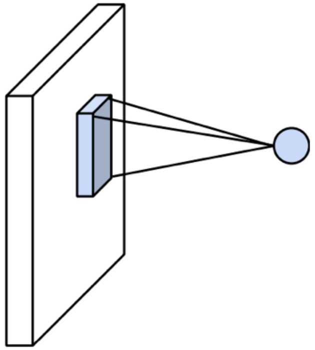
ConvNet JS Demo



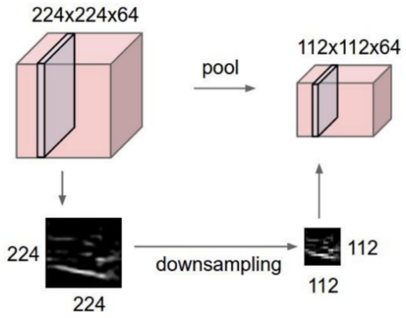
https://cs.stanford.edu/people/karpathy/convnetjs/demo/cifar10.html

Components of CNNs

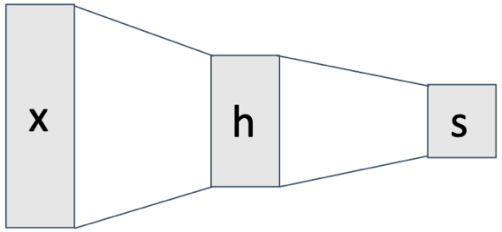
Convolution Layers



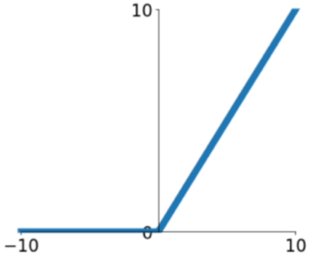
Pooling Layers



Fully-Connected Layers



Activation Function



Normalization

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

Batch Normalization (1)

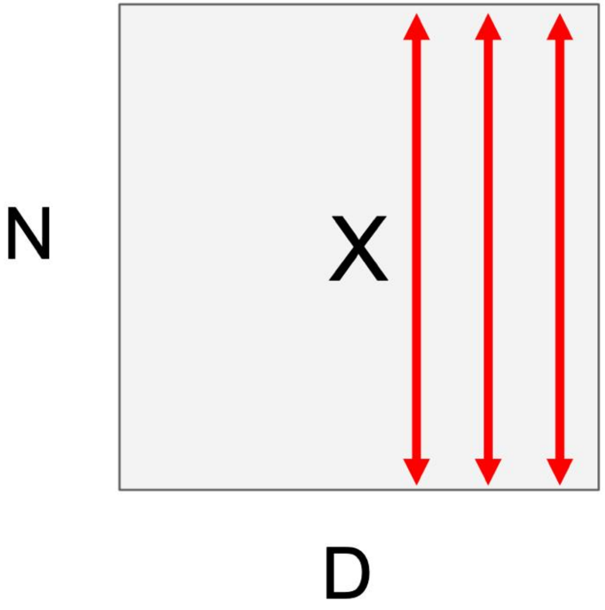
Consider a single layer $y = Wx$

The following could lead to tough optimization:
- Inputs x are not *centered around zero* (need large bias)
- Inputs x have different scaling per-element
  (entries in W will need to vary a lot)

Idea: force inputs to be “nicely scaled” at each layer!

Batch Normalization (2)

Input: $x : N \times D$



$$\mu_j = \frac{1}{N}\sum_{i=1}^{N} x_{i,j}$$

Per-channel mean, shape is D

$$\sigma_j^2 = \frac{1}{N}\sum_{i=1}^{N} (x_{i,j} - \mu_j)^2$$

Per-channel var, shape is D

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

Normalized x, Shape is N x D

Problem: What if zero-mean, unit variance is too hard of a constraint?

Batch Normalization (3)

Input: $x : N \times D$

$$\mu_j = \frac{1}{N}\sum_{i=1}^{N} x_{i,j}$$

Per-channel mean, shape is D

Learnable scale and shift parameters:

$\gamma, \beta : D$

$$\sigma_j^2 = \frac{1}{N}\sum_{i=1}^{N}(x_{i,j} - \mu_j)^2$$

Per-channel var, shape is D

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

Normalized x, Shape is N x D

Learning $\gamma = \sigma$, $\beta = \mu$ will recover the identity function!

$$y_{i,j} = \gamma_j \hat{x}_{i,j} + \beta_j$$

Output, Shape is N x D

Batch Normalization: Test Time

Input: $x : N \times D$

Learnable scale and shift parameters:

$\gamma, \beta : D$

During testing batchnorm becomes a linear operator! Can be fused with the previous fully-connected or conv layer

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

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

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

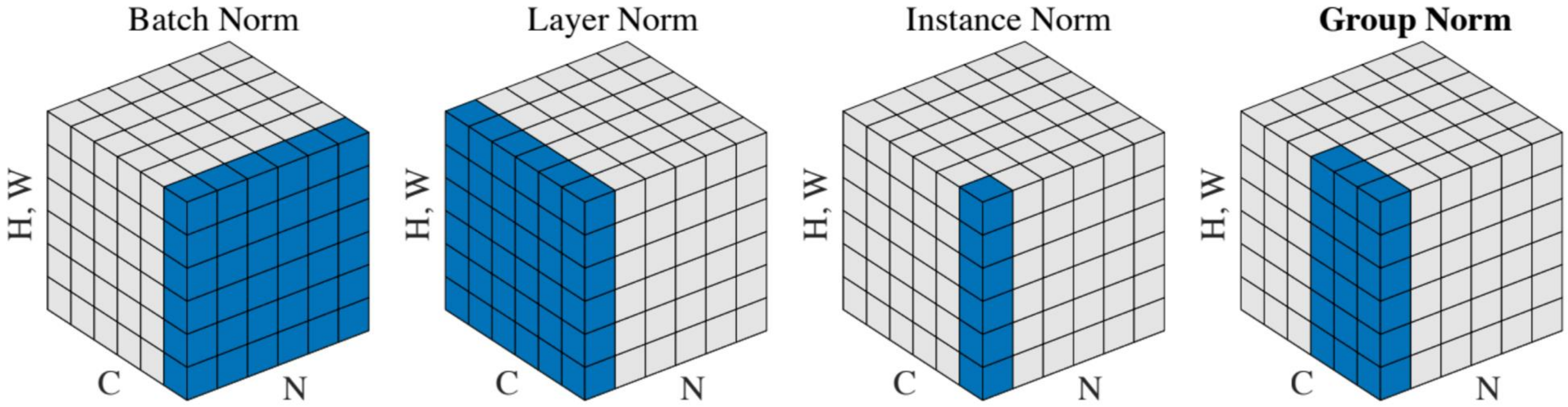
Normalized x, Shape is N x D

$$y_{i,j} = \gamma_j \hat{x}_{i,j} + \beta_j$$

Output, Shape is N x D

Not homework… but read papers to learn

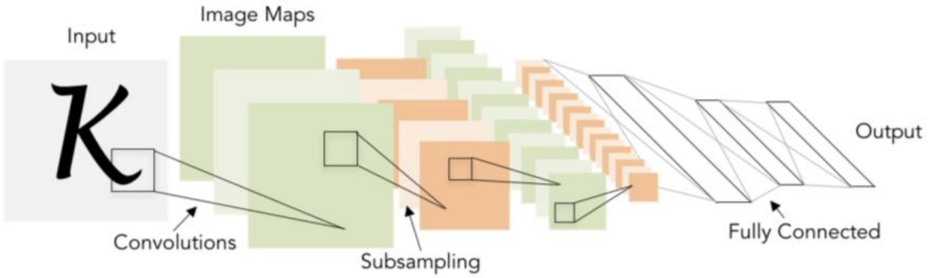
- Why using normalization?
- Other normalization techniques?

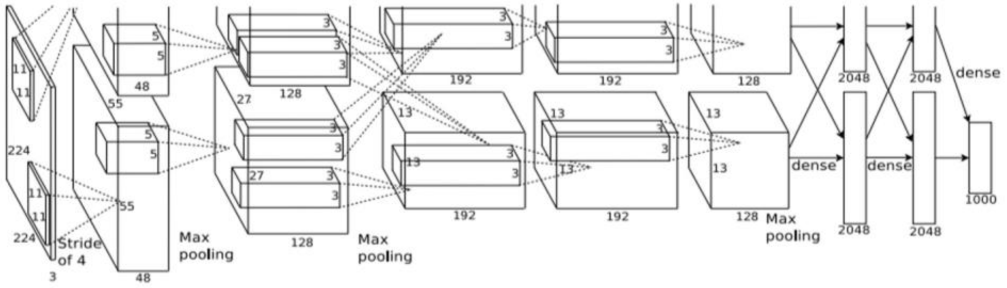


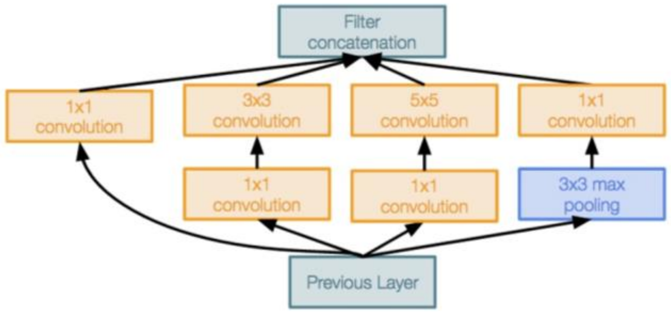
$\boldsymbol{\mu}, \boldsymbol{\sigma}$: 1×C×1×1

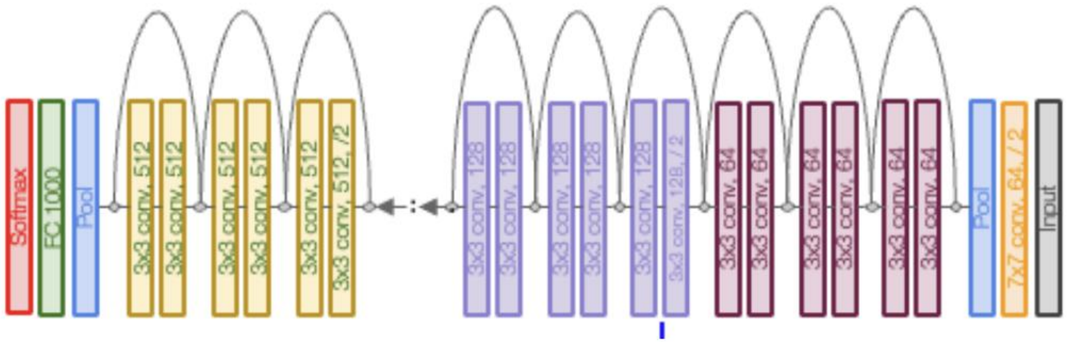
$\boldsymbol{\mu}, \boldsymbol{\sigma}$: N×C×1×1

CNN Architectures





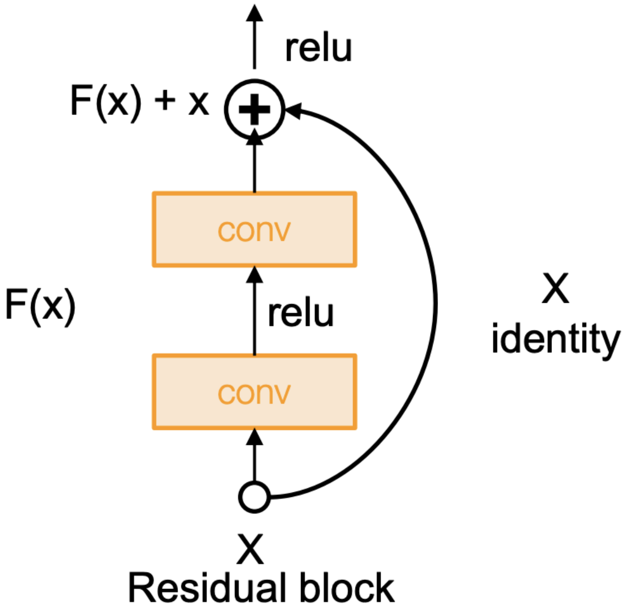


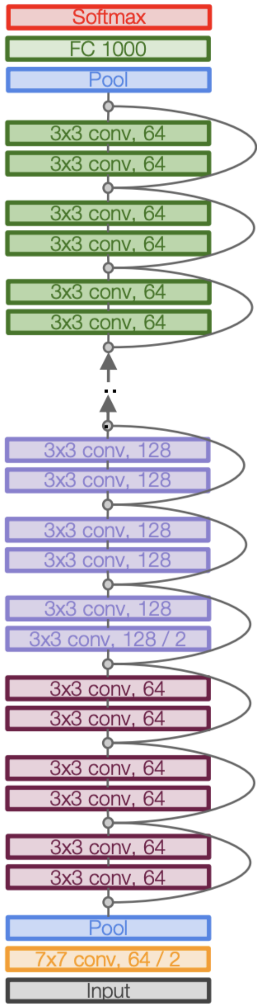


ResNet (1)

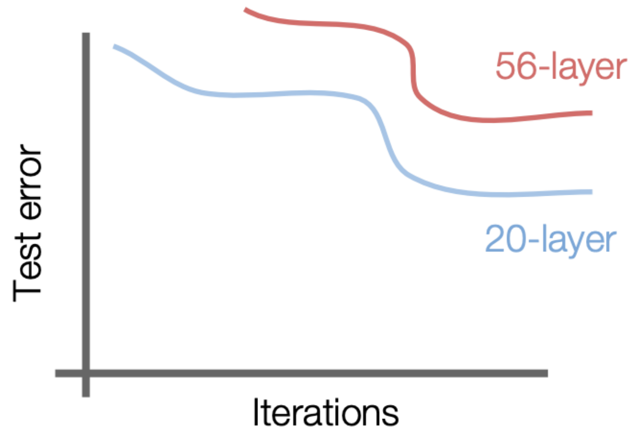
Very deep networks using residual connections:

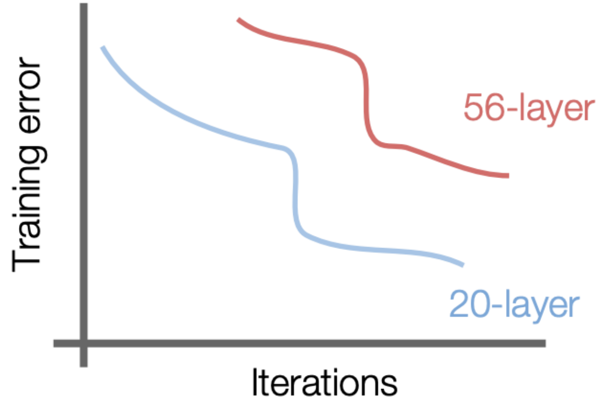
- 152-layer model for ImageNet
- ILSVRC'15 classification winner (3.57% top 5 error) - Swept all classification and detection competitions in ILSVRC'15 and COCO'15!





ResNet (2)

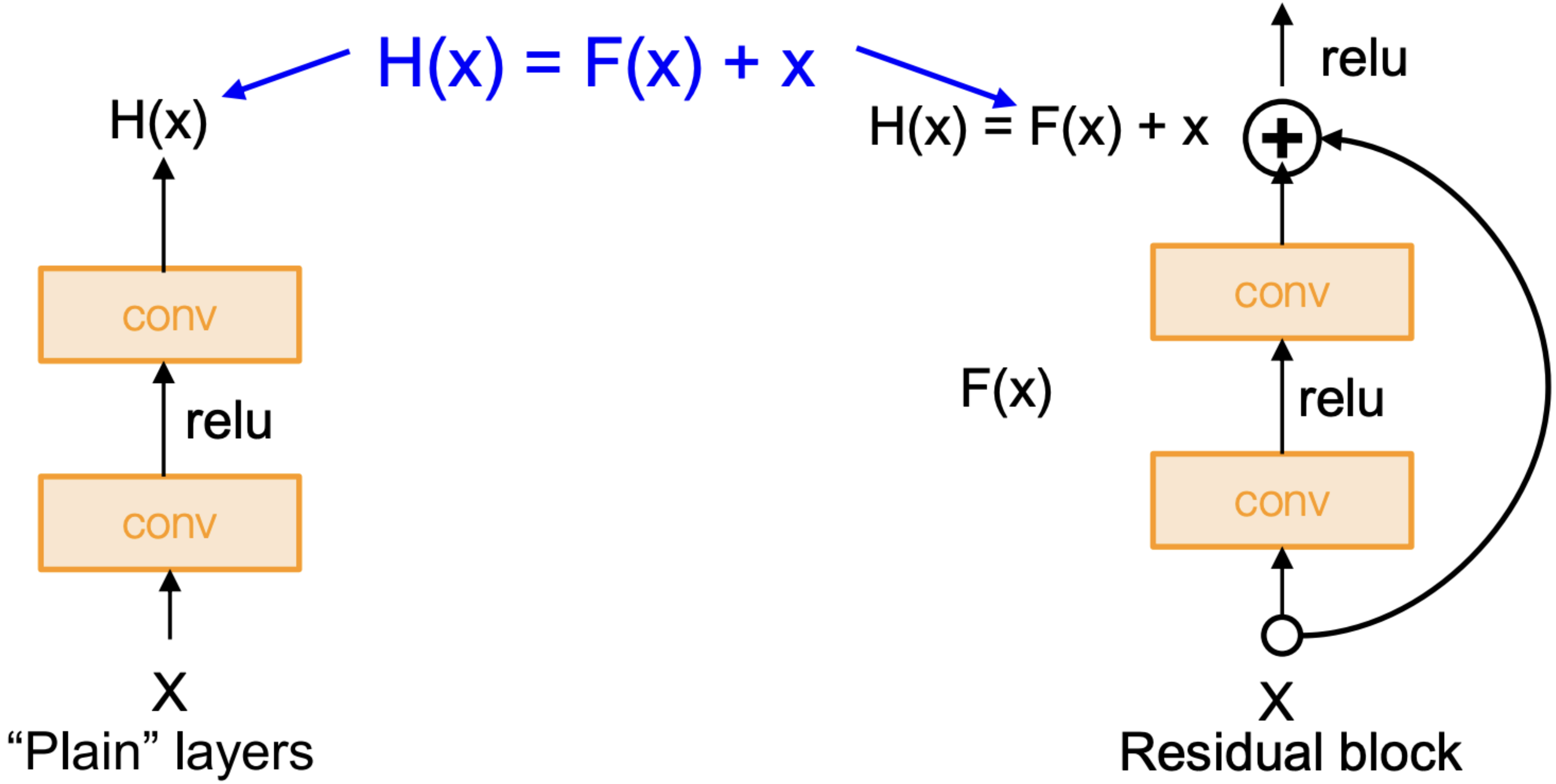




Problem: Deeper models are harder to optimize

Solution: Copying the learned layers from the shallower model and setting additional layers to identity mapping

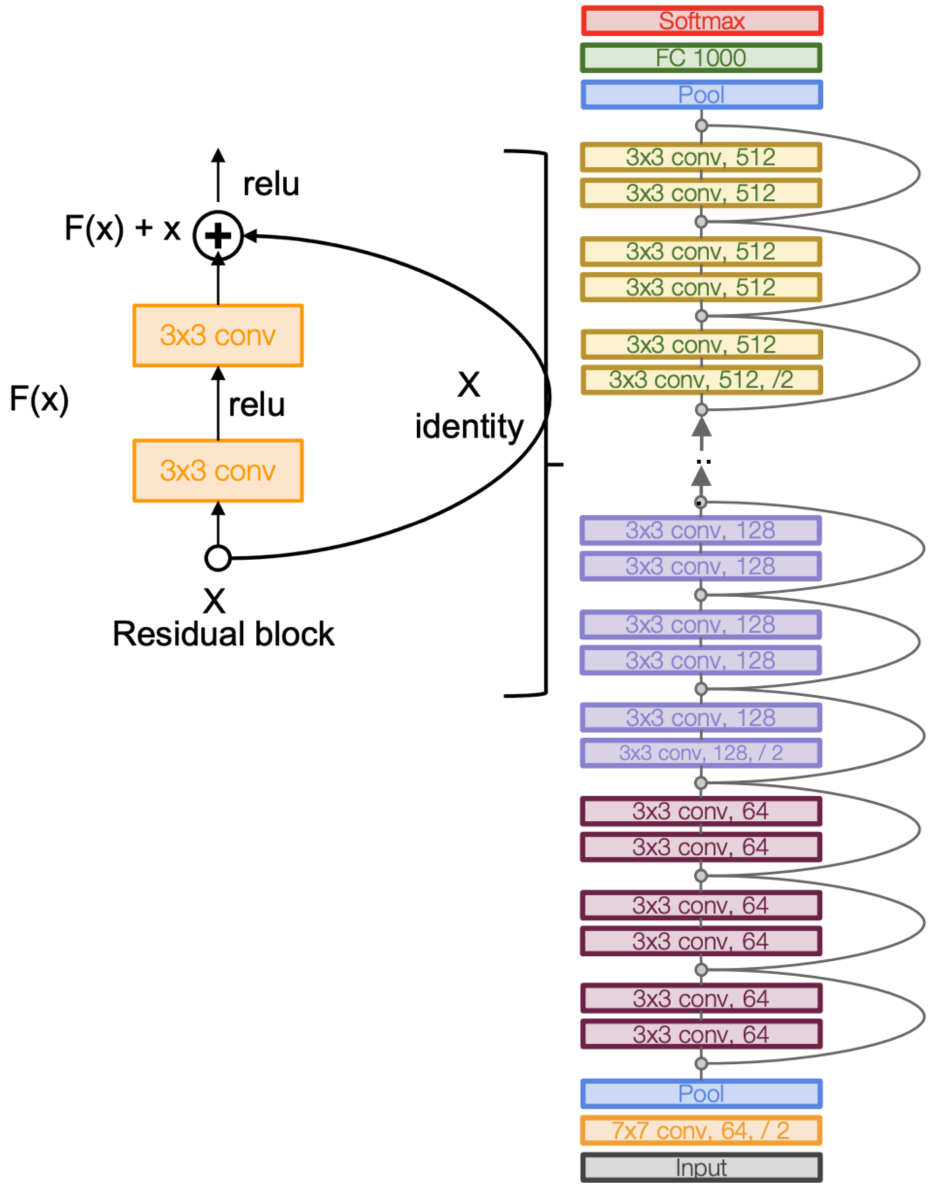
ResNet (3)



H(x) = F(x) + x
H(x)
conv
relu
conv
X
"Plain" layers
relu
H(x) = F(x) + x
conv
F(x)
relu
conv
X
Residual block

ResNet (4)

- Total depths of 18, 34, 50, 101, or 152 layers for ImageNet
- Stack residual blocks
- Every residual block has two 3x3 conv layers
- Periodically, double # of filters and down sample spatially using stride 2 (/2 in each dimension)
- Additional conv layer at the beginning (stem)
- No FC layers at the end (only FC 1000 to output classes)



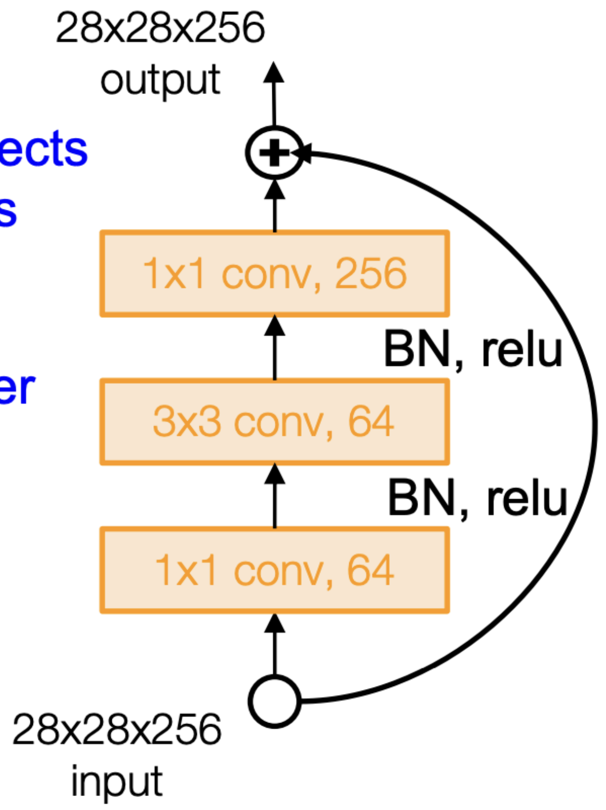
ResNet (5)

For deeper networks (ResNet-50+), use “bottleneck” layer to improve efficiency (similar to GoogLeNet)

1x1 conv, 256 filters projects back to 256 feature maps (28x28x256)

3x3 conv operates over only 64 feature maps

1x1 conv, 64 filters to project to 28x28x64

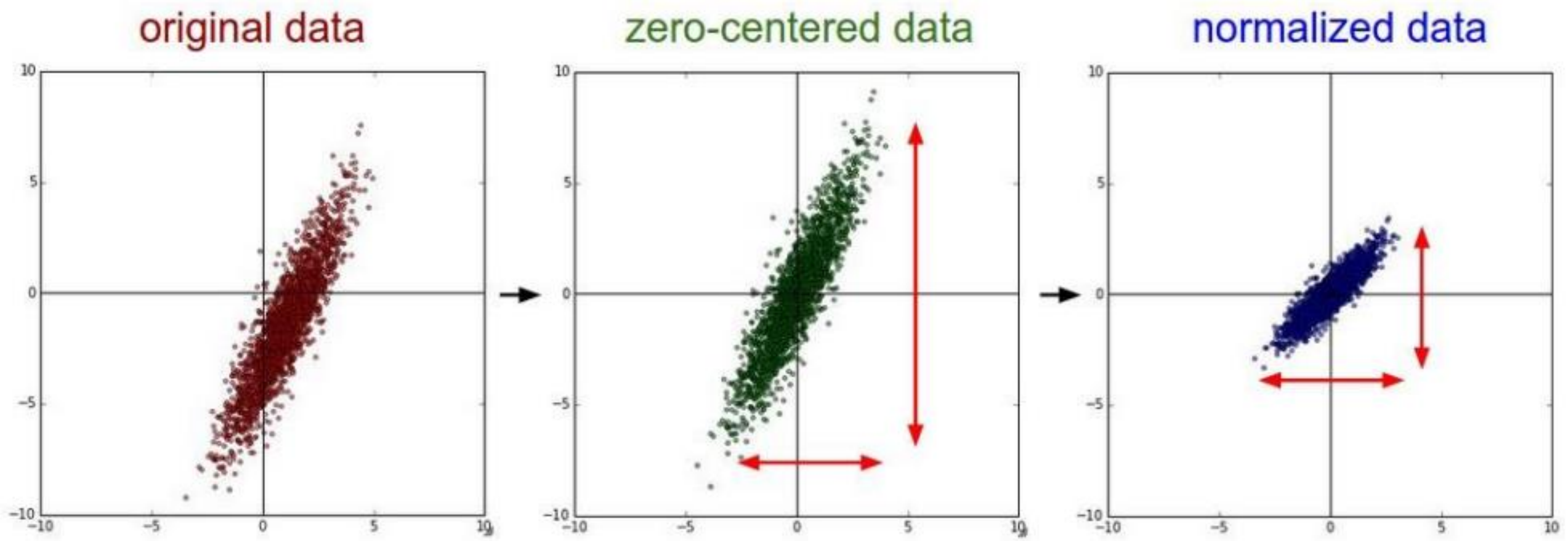


ResNet (6)

Training ResNet in practice:

- Batch Normalization after every CONV layer
- Xavier initialization from He et al.
- SGD + Momentum (0.9)
- Learning rate: 0.1, divided by 10 when validation error plateaus
- Mini-batch size 256
- Weight decay of 1e-5
- No dropout used

For your project: Data Preprocessing



`X -= np.mean(X, axis = 0)`

`X /= np.std(X, axis = 0)`

For your project: Transfer Learning

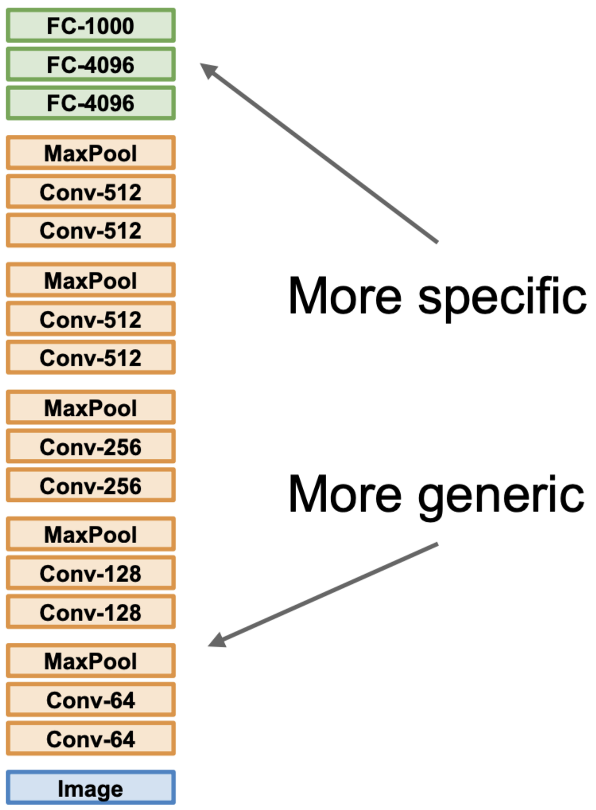
Have some dataset of interest but it has < ~1M images?

- Find a very large dataset that has similar data, train a big model there
- Transfer learn to your dataset

Deep learning frameworks provide a "Model Zoo" of pretrained models so you don't need to train your own

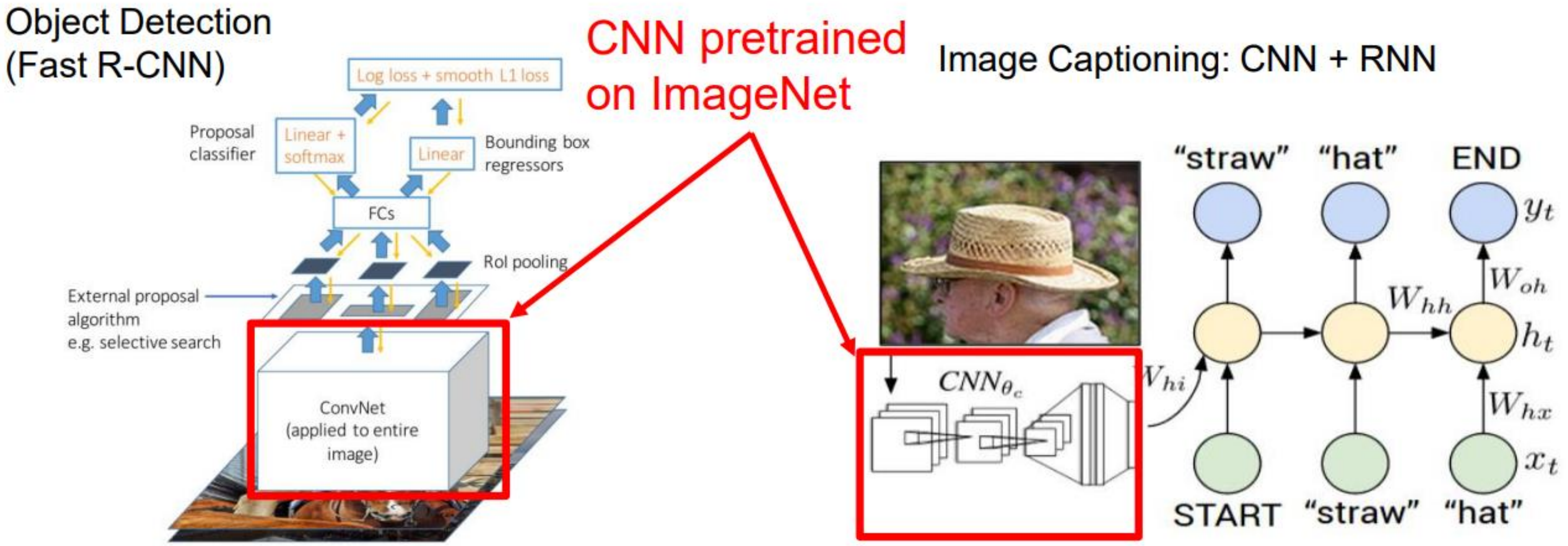
- https://github.com/tensorflow/models
- https://github.com/pytorch/vision

For your project: Transfer Learning



	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 or start from scratch!

For your project: Transfer Learning

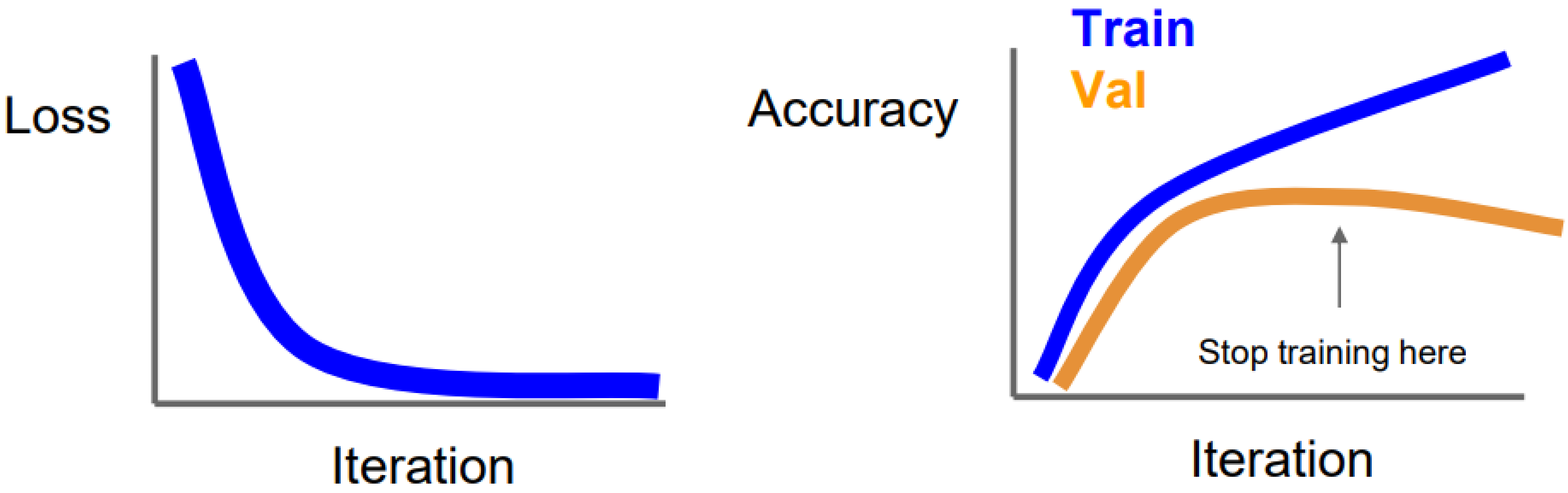


For your project: Some Practices

Consider CIFAR-10 example with [32,32,3] images:

- Data Preprocessing:
  - Subtract the mean image (e.g. AlexNet) (mean image = [32,32,3] array)
  - Subtract per-channel mean (e.g. VGGNet) (mean along each channel = 3 numbers)
  - Subtract per-channel mean and Divide by per-channel std (e.g. ResNet and beyond) (mean along each channel = 3 numbers)
- Weight Initialization: Kaiming / MSRA Initialization
- Use ReLU. Be careful with your learning rates
- Try out Leaky ReLU / PReLU / GELU (Check them out by yourself)

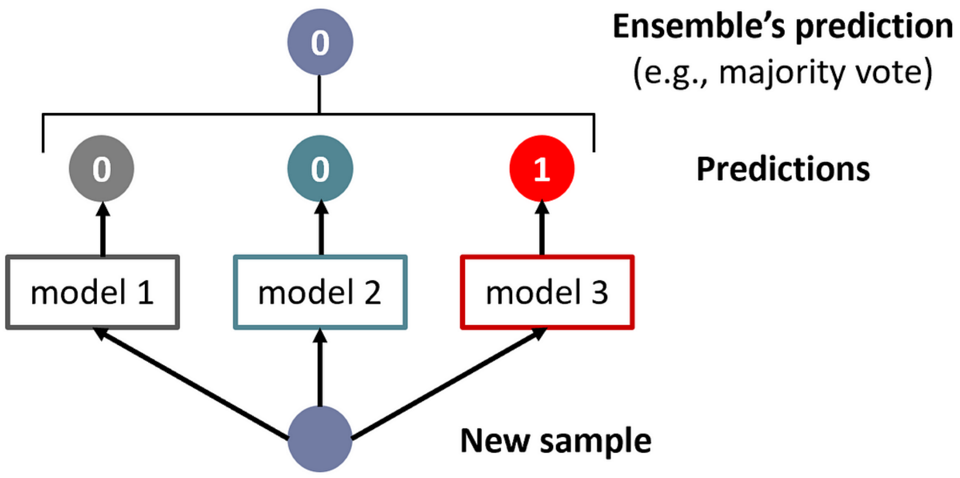
For your project: Early Stopping



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

For your project: Model Ensembles

- Train multiple independent models
- At test time average their results



https://pub.towardsai.net/introduction-to-ensemble-methods-226a5a421687

For your project: Regularization (1)

- Add a term to a loss:

$$L = \frac{1}{N}\sum_{i=1}^{N}\sum_{j\neq y_i}\max(0, f(x_i;W)_j - f(x_i;W)_{y_i} + 1) + \boxed{\lambda R(W)}$$

In common use:

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

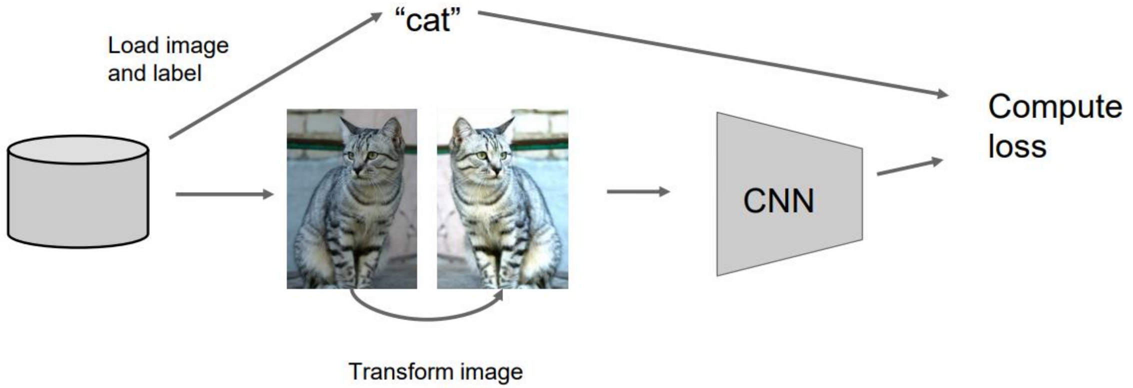
L1 regularization $R(W) = \sum_k \sum_l |W_{k,l}|$

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

- Random Dropout, 0.5 is common

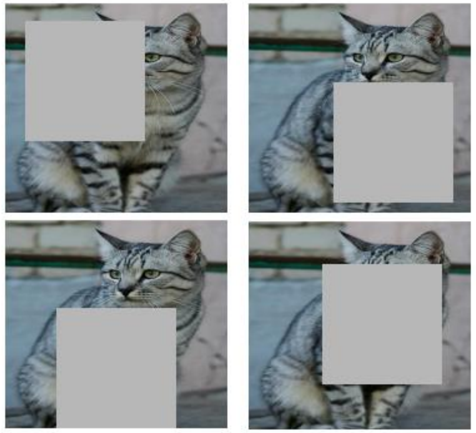
For your project: Regularization (2)

- Data Augmentation
  - Horizontal Flips
  - Random crops and scales
  - Color Jitter
  - Rotation
  - Shearing
  - ....



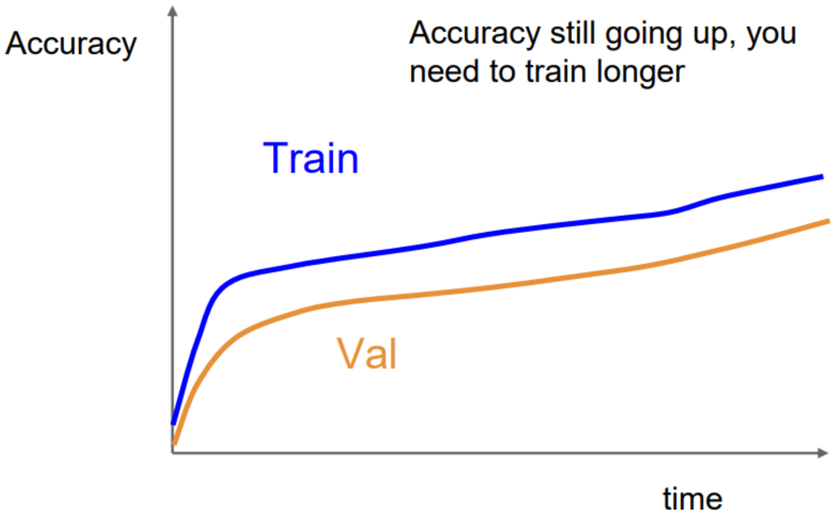
For your project: Regularization (3)

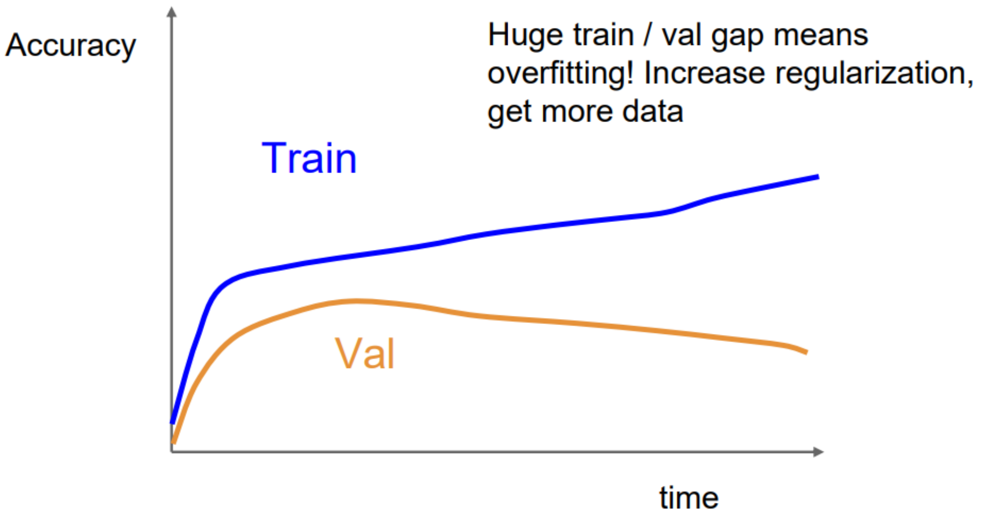
- Training: Add random noise
  - Dropout: Consider dropout for large fully connected layers
  - Batch Normalization
  - Data Augmentation
  - Cutout / Random Crop :Try cutout especially for small classification datasets

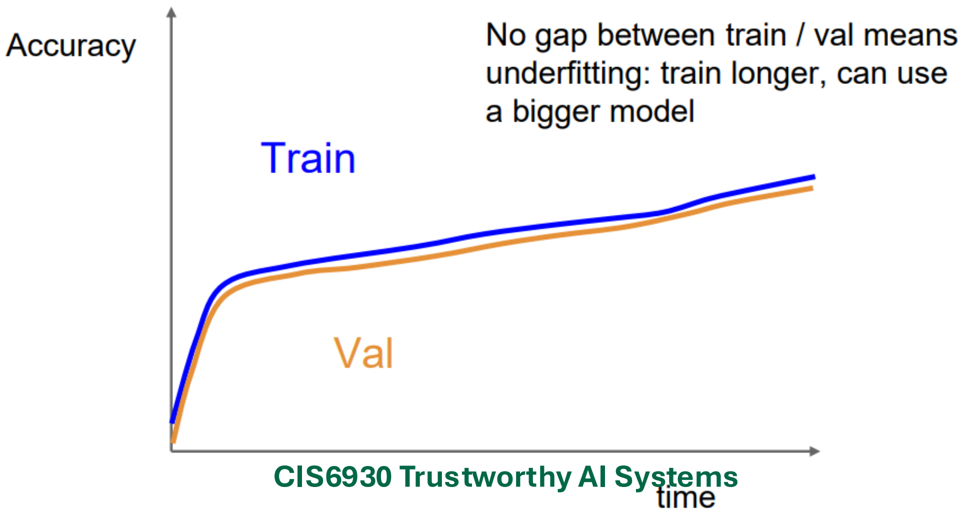


- Testing: Marginalize over the noise

For your project: Look at the Learning Curve







Homework 1 is released

- Paper Review Quality Instructions
- Questions on Homework 1?
- We will cover Image Detection and Segmentation next lecture

Reference: Stanford Spring 2024 cs231n

- https://cs231n.stanford.edu/schedule.html
- https://cs231n.stanford.edu/slides/2024/lecture_5.pdf
- https://cs231n.stanford.edu/slides/2024/lecture_6_part_1.pdf
- https://cs231n.stanford.edu/slides/2024/lecture_6_part_2.pdf