Machine Learning (CE 40477)

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CNNs Are Everywhere!

- The success of deep learning in image recognition is driven by two key factors:
  - Large-scale CNNs
  - Transfer learning

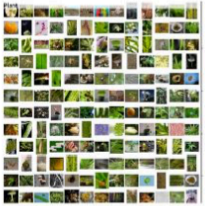
ImageNet Large-Scale Visual Recognition Challenge (ILSVRC)

2009: IMAGENET

- Dataset and benchmark for image classification
- 1 million images with ground truth class labels for training (hand-annotated) 1000 object categories

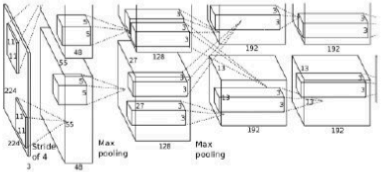
Deng et al., CVPR 2009

CNNs Are Old. Why Did It Work Eventually?



Big Data: ImageNet

+



Deep Convolutional Neural Network

+

Backprop on GPU

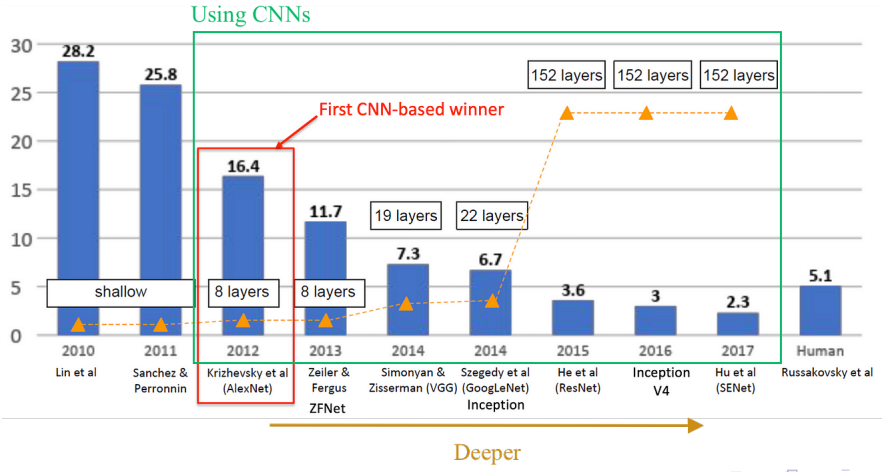
+ **A number of small tweaks**

Sigmoid □ ReLU, batch normalization, dropout

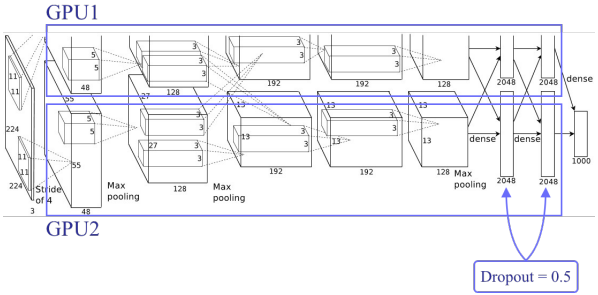
Image Source

AlexNet, First CNN Based Winner

- Reduced the error rate by 10%



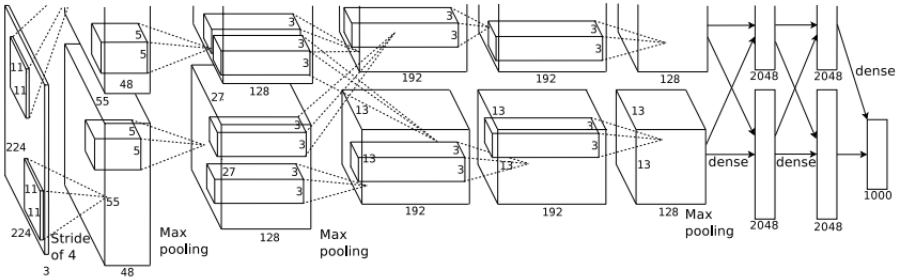
AlexNet [Krizhevsky, et al. NIPS (2012)]



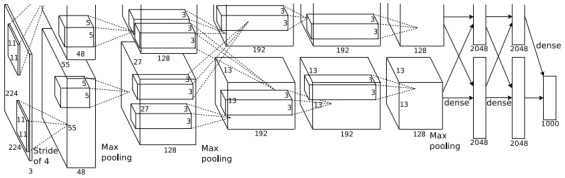
- Training: 6 days on 2 NVIDIA GTX 580 GPUs (3 GB RAM)
- 8 layers / 60 million parameters and 650,000 neurons
- 5 convolutional layers, some of which are followed by max-pooling layers
- 3 fully-connected layers
- Testing: Multi-crop
  - Classify different shifts of the image and vote over the lot!
  - Test-time data augmentation

AlexNet Architecture

CONV1
MAX POOL1
NORM1
CONV2
MAX POOL2
NORM2
CONV3
CONV4
CONV5
MAX POOL3
FC6
FC7
FC8



AlexNet Architecture



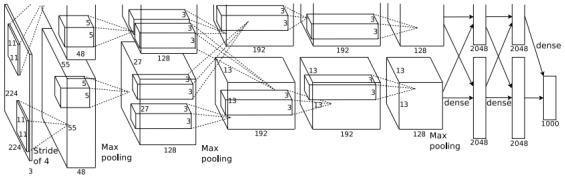
Input: $227 \times 227 \times 3$ images

First layer (CONV1): 96 11×11 filters applied at stride 4

$$W' = \frac{W-F+2P}{S+1}$$

$\Rightarrow$ Q: What is the output volume size? Hint: (227-11)/4+1 = 55

AlexNet Architecture



Input: $227 \times 227 \times 3$ images

First layer (CONV1): 96 11×11 filters applied at stride 4
$\Rightarrow$ Output volume $[55 \times 55 \times 96]$

$$W' = \frac{W-F+2P}{S+1}$$

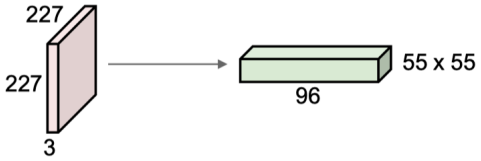
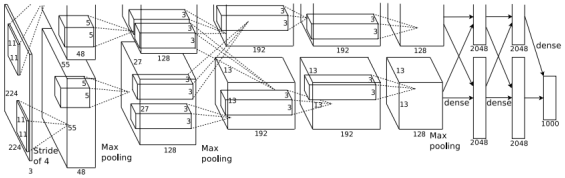


Figure: Alex Krizhevsky, et al., 2012

AlexNet Architecture



Input: $227 \times 227 \times 3$ images

First layer (CONV1): 96 11×11 filters applied at stride 4
$\Rightarrow$ Output volume $[55 \times 55 \times 96]$
Q: How many parameters are there in this layer?

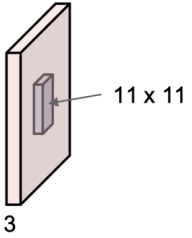
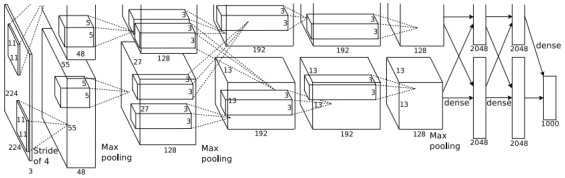


Figure: Alex Krizhevsky, et al., 2012

AlexNet Architecture



Input: $227 \times 227 \times 3$ images

First layer (CONV1): 96 11×11 filters applied at stride 4
$\Rightarrow$ Output volume $[55 \times 55 \times 96]$
Parameters: $(11 \times 11 \times 3 + 1) \times 96 = 35K$

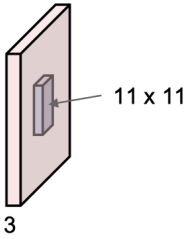
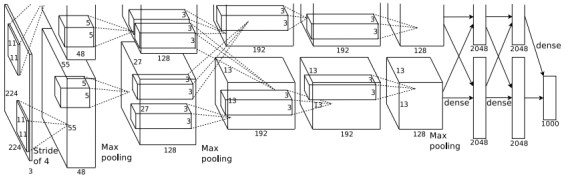


Figure: Alex Krizhevsky, et al., 2012

AlexNet Architecture



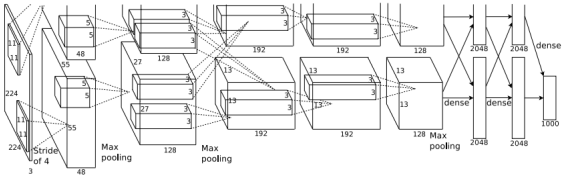
Input: $227 \times 227 \times 3$ images
After CONV1: $55 \times 55 \times 96$

Second layer (POOL1): 3×3 filters applied at stride 2

$$W' = \frac{W-F+2P}{S+1}$$

Q: What is the output volume size? Hint: (55-3)/2+1 = 27

AlexNet Architecture



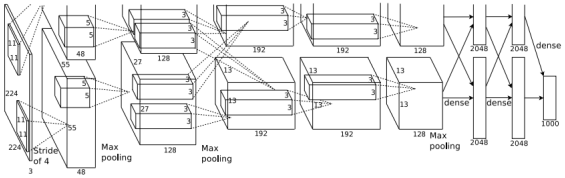
Input: $227 \times 227 \times 3$ images
After CONV1: $55 \times 55 \times 96$

Second layer (POOL1): 3×3 filters applied at stride 2
Output volume: $27 \times 27 \times 96$

$$W' = \frac{W-F+2P}{S+1}$$

Q: What is the number of parameters in this layer?

AlexNet Architecture

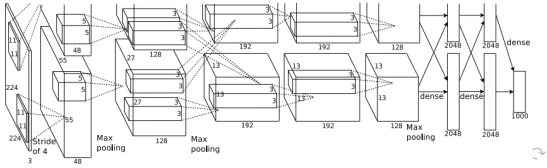


Input: $227 \times 227 \times 3$ images
After CONV1: $55 \times 55 \times 96$

Second layer (POOL1): 3×3 filters applied at stride 2
Output volume: $27 \times 27 \times 96$
Parameters: 0!

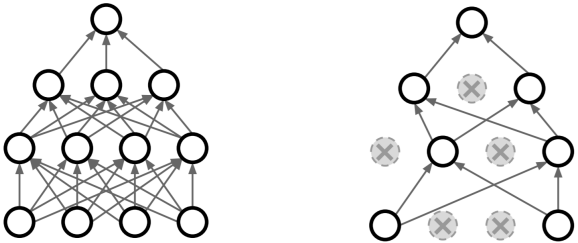
AlexNet Full Architecture

[227 × 227 × 3] INPUT
[55 × 55 × 96] CONV1: 96 11 × 11 filters at stride 4, pad 0
[27 × 27 × 96] MAX POOL1: MAX POOL1: 3 × 3 filters at stride 2
[27 × 27 × 96] NORM1: Normalization layer
[27 × 27 × 256] CONV2: 256 5 × 5 filters at stride 1, pad 2
[13 × 13 × 256] MAX POOL2: 3 × 3 filters at stride 2
[13 × 13 × 256] NORM2: Normalization layer
[13 × 13 × 384] CONV3: 384 3 × 3 filters at stride 1, pad 1
[13 × 13 × 384] CONV4: 384 3 × 3 filters at stride 1, pad 1
[13 × 13 × 256] CONV5: 256 3 × 3 filters at stride 1, pad 1
[6 × 6 × 256] MAX POOL3: 3 × 3 filters at stride 2
[4096] FC6 4096 neurons
[4096] FC7 4096 neurons
[1000] FC8 1000 neurons (class scores)



Dropout

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

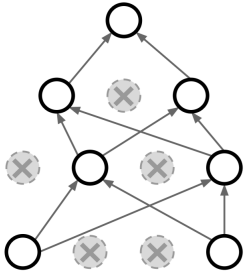


Srivastava et al., JMLR 2014

- Thus, a smaller network is trained for each sample
  → Smaller network provides a regularization effect

Dropout

- How can dropout be a good idea?

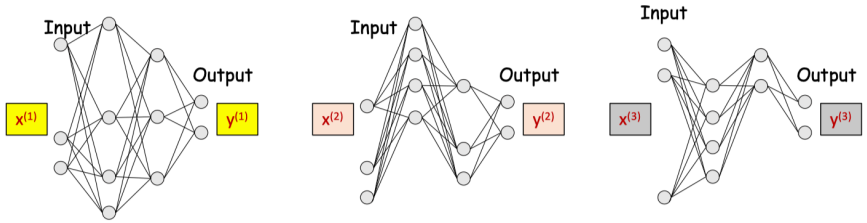


Forces the network to have a redundant representation;
Prevents co-adaptation of features

Hinton et al., 2012

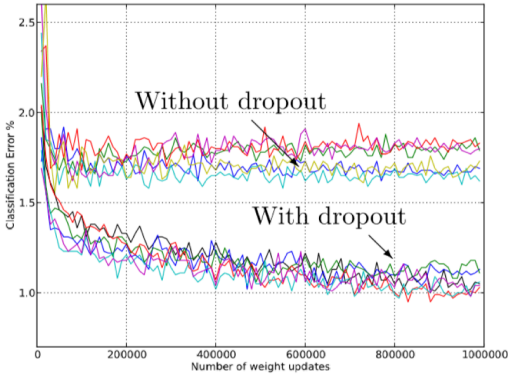
Dropout

- During training: Backpropagation is effectively performed only over the remaining network
  - → The effective network is different for different inputs
  - → Gradients are obtained only for the weights and biases from On nodes to On nodes
  - → For the remaining, the gradient is just 0



Dropout

- Test error of different architectures on MNIST with and without dropout
  - → 2-4 hidden layers with 1024-2048 units

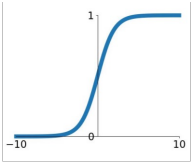


Srivastava et al., 2013

Flashback To Activation Functions

Sigmoid:

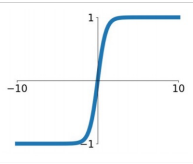
- $\sigma(x) = \frac{1}{1+e^{-x}}$
- Squashes numbers to range [0,1]
- Historically popular due to their interpretation as a neurons saturating firing rate
- **Problems:**
  - → Saturated neurons kill the gradients
  - → Sigmoid outputs are not zero-centered



Sigmoid

Tanh:

- $tanh(x) = \frac{1-e^{-2x}}{1+e^{2x}} = 1 - 2\sigma(2x)$
- Squashes numbers to range [-1,1]
- Zero centered (nice)
- Still kills gradients when saturated

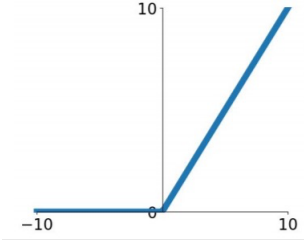


Tanh

ReLU

ReLU

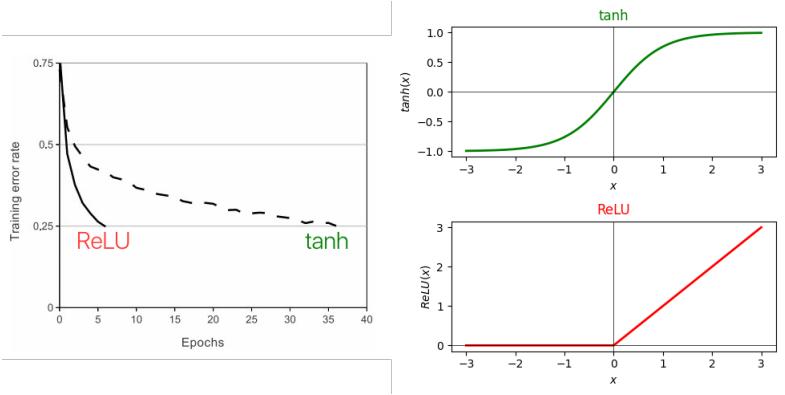
- Does not saturate (in +region)
- Very computationally efficient
- Converges much faster than sigmoid/tanh in practice (e.g. 6x)
- Actually more biologically plausible than sigmoid
- **Problems:**
  - → Not zero-centered output
  - → An annoyance:
    - ⋆ Hint: "what is the gradient when x < 0?"



ReLU

ReLU

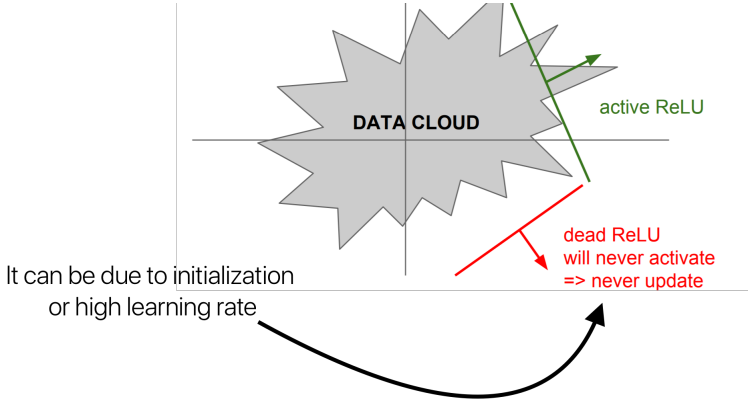
- ReLu trains faster than tanh



Krizhevsky, et al., 2012

ReLU Initialization

- It is common to initialize ReLU neurons with slightly positive biases (e.g. 0.01)
- It can be due initialization or high learning rate

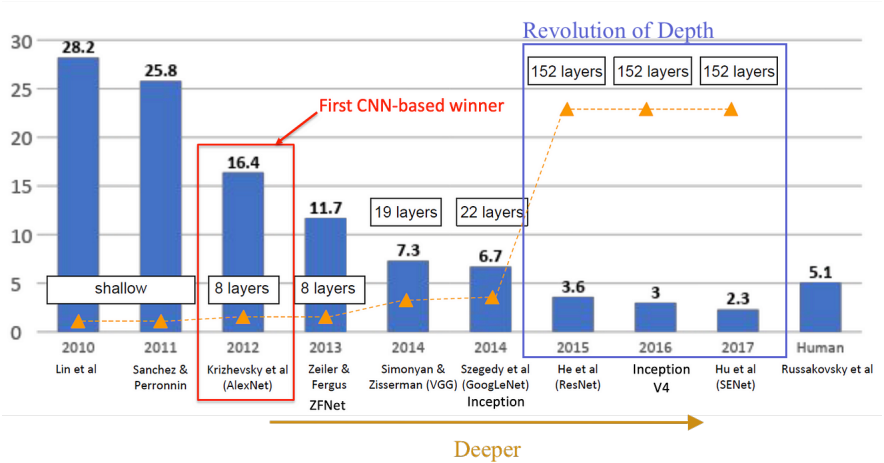


Learning Magic In Alexnet

- First use of ReLU
  - → Made a large difference in convergence
- "Dropout" 0.5 (in FC layers only)
- Heavy data augmentation
- SGD with momentum of 0.9 and a mini-batch size of 128
- L2 weight decay 5e-4
- Learning rate: 0.01, decreased by 10 every time validation accuracy plateaus
- Evaluated using: Validation accuracy
- **Final top-5 error: 18.2% with a single net, 15.4% using an ensemble of 7 networks**
  - → **Lowest prior error using conventional classifiers: > 25 %**

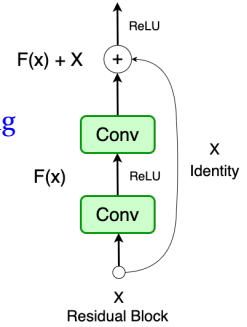

WE NEED TO GO
DEEPER
troll-face.ru

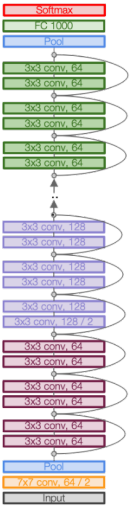
Revolution Of Depth



ResNet [He, et al., (2015)]

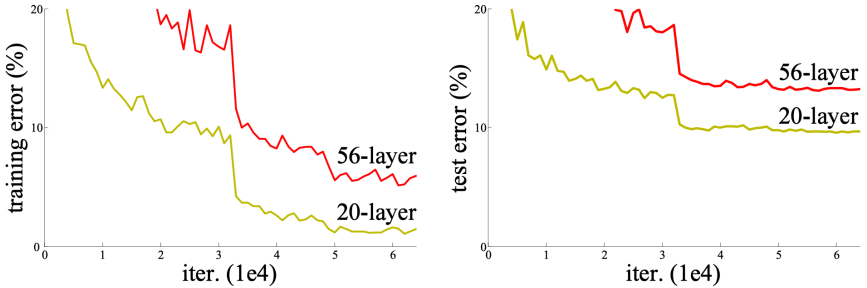
- Very deep networks using residual connections
- ResNet introduces the concept of skip connections (or residual connections) that allow the gradient to be directly backpropagated to earlier layers
- Skip connections helps overcoming gradient vanishing problem, where the accuracy saturates and then degrades rapidly as the network depth increases.
- 152-layer model for ImageNet
- ILSVRC15 classification winner (3.57 % top 5 error)
- Swept all classification and detection competitions in ILSVRC15 and COCO15!





ResNet [He, et al., (2015)]

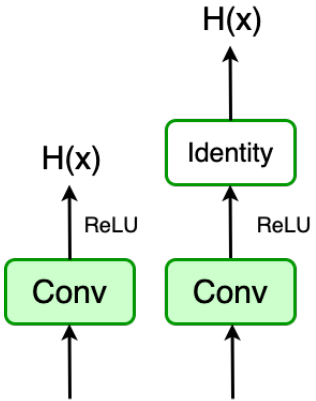
- What happens when we continue stacking deeper layers on a “plain” convolutional neural network?
- **Question**: Whats strange about these training and test curves?



Training error (left) and test error (right) on CIFAR-10 with 20-layer and 56-layer plain networks

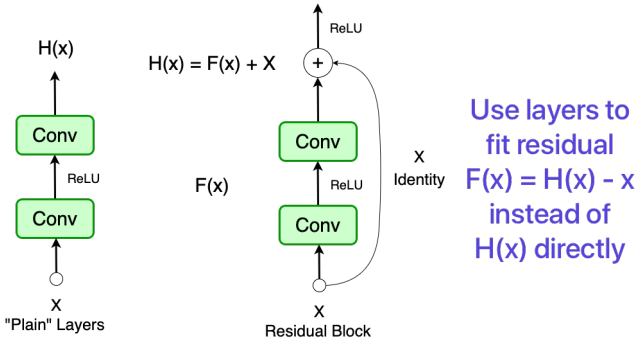
ResNet [He, et al., (2015)]

- **Fact:** Deeper models have more representation power (more parameters) than shallower models.
- But **56-layer model performs worse** on both training and test error and its not caused by overfitting!
- **Hypothesis:** The issue is related to optimization, deeper models are harder to optimize
- What should the deeper model learn to be at least as good as the shallower model?
- A solution by construction is copying the learned layers from the shallower model and setting additional layers to identity mapping.



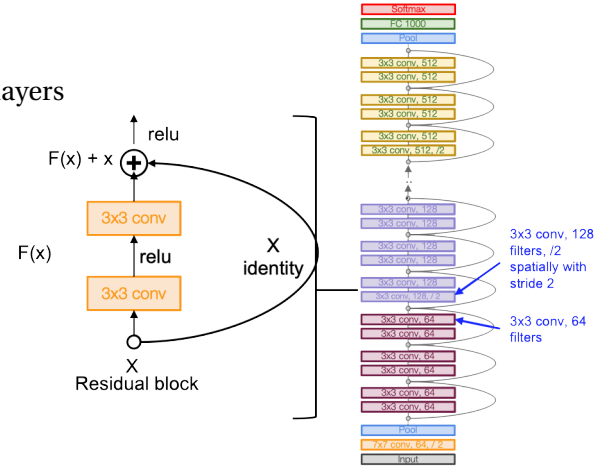
ResNet [He, et al., (2015)]

- Solution: Use network layers to fit a residual mapping rather than directly fitting the desired underlying mapping
- Identity mapping: $H(x) = x$ if $F(x) = 0$



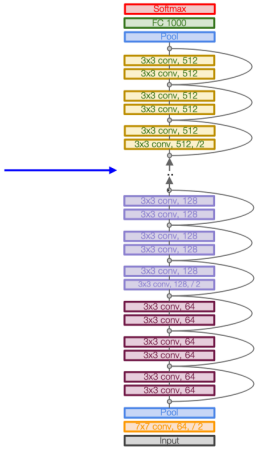
Full ResNet Architecture

- Stack residual blocks
- Every residual block has two 3x3 conv layers
- Periodically, double number of filters and downsample spatially using stride 2 (/2 in each dimension) Reduce the activation volume by half
- Additional conv layer at the beginning
- No FC layers at the end (only FC 1000 to output classes)
- (In theory, you can train a ResNet with input image of variable sizes)



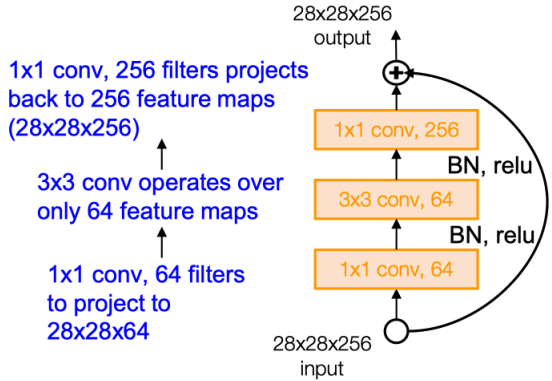
Full ResNet Architecture

- Total depths of 18, 34, 50, 101, or 152 layers for ImageNet



Full ResNet Architecture

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

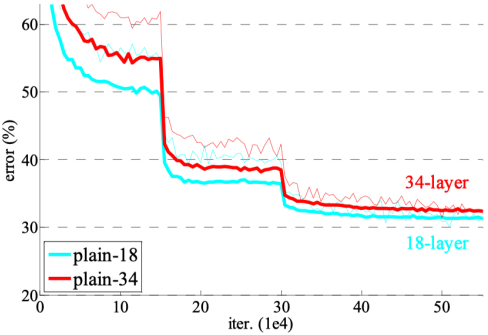


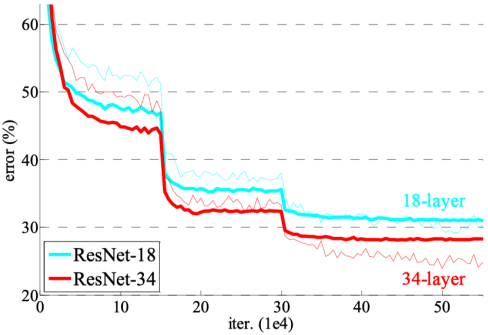
Experimental Results

- Able to train very deep networks without degrading (152 layers on ImageNet, 1202 on CIFAR)
- Deeper networks now achieve lower training error as expected
- Swept 1st place in all ILSVRC and COCO 2015 competitions

ILSVRC 2015 classification winner (3.6% top 5 error) -- better than "human performance"! (Russakovsky 2014)

ResNet Experiments





Thin curves represent training error, and bold curves represent validation error [He, et al. 2015]

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

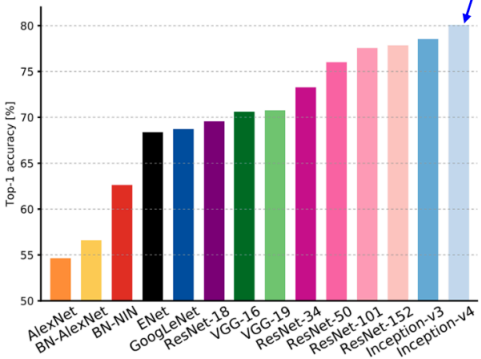
Key Points

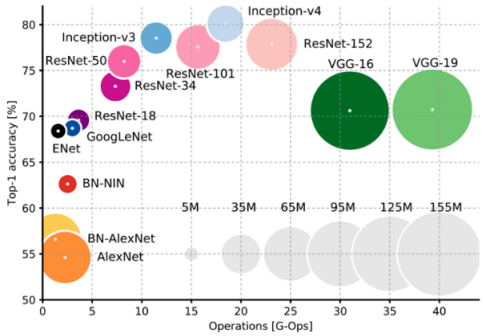
- **AlexNet** showed that you can use CNNs to train Computer Vision models.
- **ResNet** showed us how to train extremely deep networks
  - → Limited only by GPU & memory!
  - → Showed diminishing returns as networks got bigger
- After ResNet: CNNs were better than the human metric and focus shifted to other topics:
  - ⋆ Efficient Networks: **MobileNet, ShuffleNet**
  - ⋆ **Neural Architecture Search** can now automate architecture design

Model Comparison

Comparing complexity...

Inception-v4: Resnet + Inception!

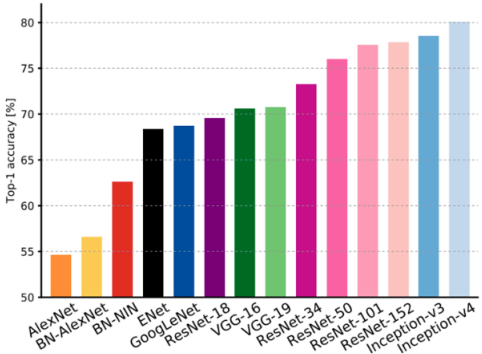




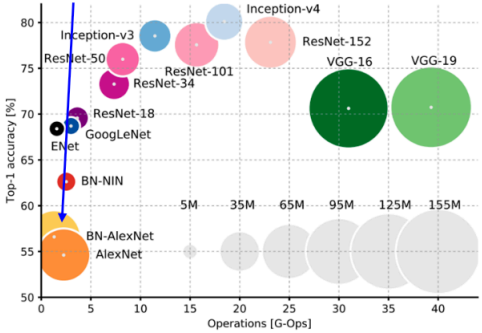
An Analysis of Deep Neural Network Models for Practical Applications, 2017.

Model Comparison

Comparing complexity...



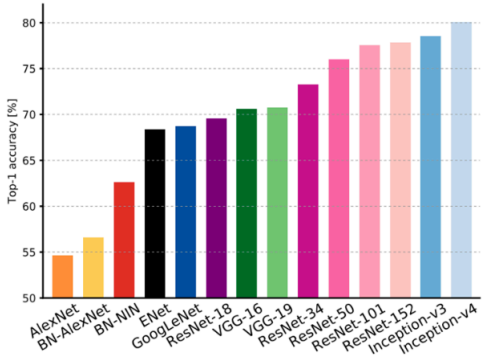
AlexNet:
Smaller compute, still memory heavy, lower accuracy



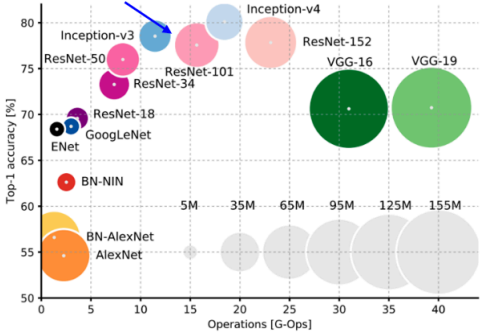
An Analysis of Deep Neural Network Models for Practical Applications, 2017.

Model Comparison

Comparing complexity...



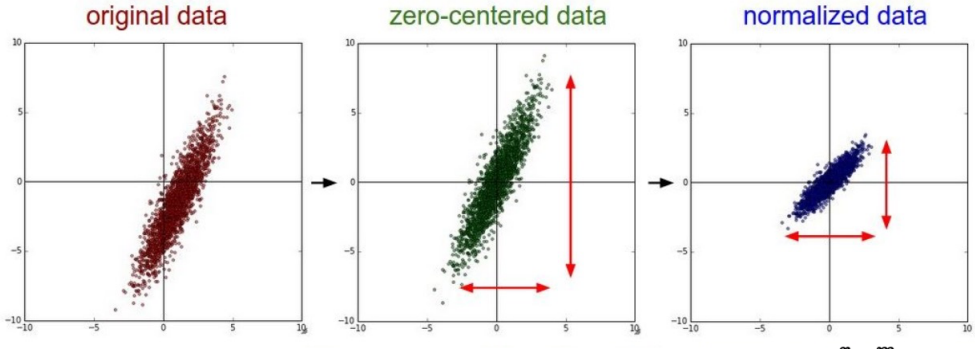
ResNet:
Moderate efficiency depending on model, highest accuracy



An Analysis of Deep Neural Network Models for Practical Applications, 2017.

Normalizing The Data

- Assume $X_{n\times d}$ is data matrix, with each sample in a row
- i is the index of dimension ($i = 1, \dots d$)

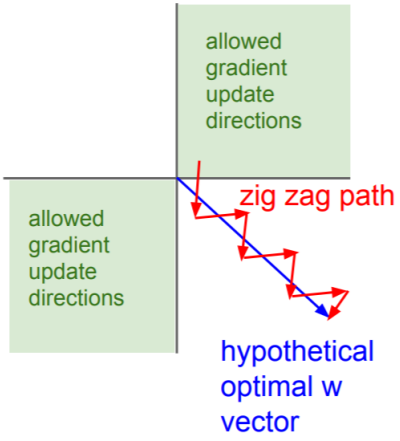


TLDR: In Practice For Images: Center Only

- Example: consider CIFAR-10 example with $[32, 32, 3]$ images
- 3 different approaches:
  1. Subtract the mean image (e.g. AlexNet)
     - mean image = $[32, 32, 3]$ array
  2. Subtract per-channel mean (e.g. VGGNet)
     - mean along each channel = 3 numbers
  3. Subtract per-channel mean and divide by per-channel std (e.g. ResNet)

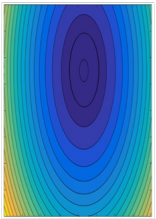
Why Zero-Mean The Input?

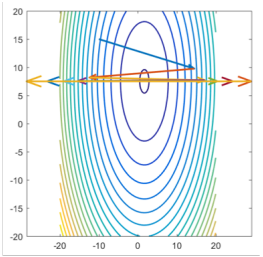
- Reminder: sigmoid
- Consider what happens when the input to a neuron is always positive...
- What can we say about the gradients on w? Always all positive or all negative
  - This is also why zero-mean data is preferable!



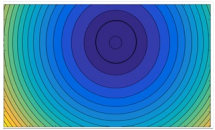
Why Normalize The Input?

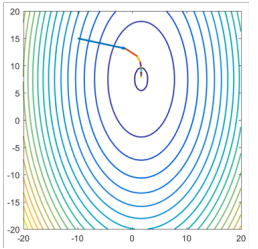
- Very different range of input features
- i.e. poor conditioning
- Causes noisy movement of gradient



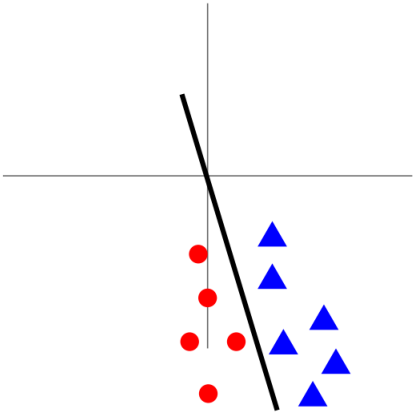


- Normalized data:
  - Improves loss landscape (alleviate poor conditioning)
  - Faster optimization (training)

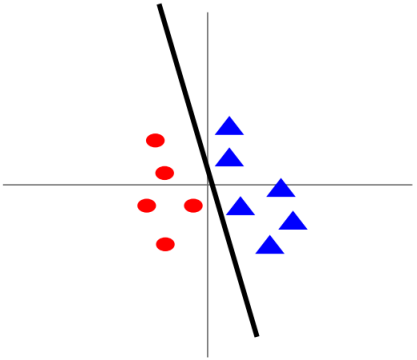




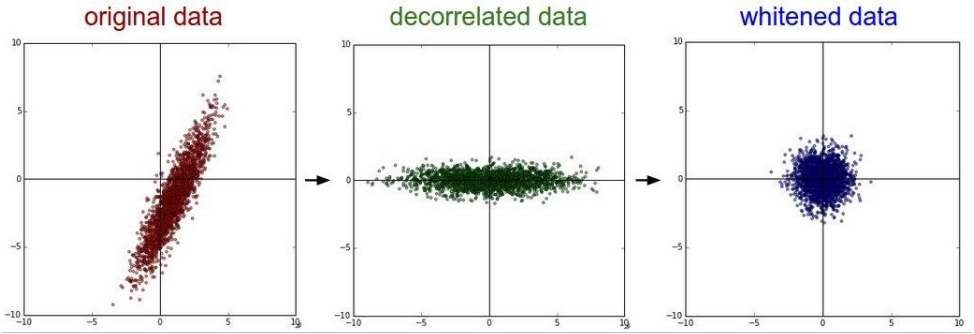
Before Normalization: classification loss very sensitive to changes in weight matrix; hard to optimize



After Normalization: loss is less sensitive to small changes in weight matrix; easier to optimize



Not Common To Normalize Variance, To Do PCA Or Whitening

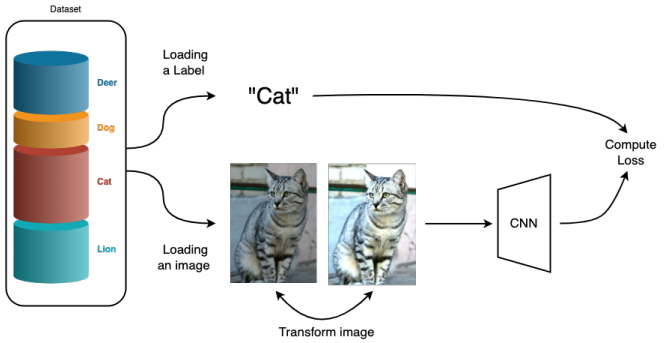


Data has diagonal covarianve matrix

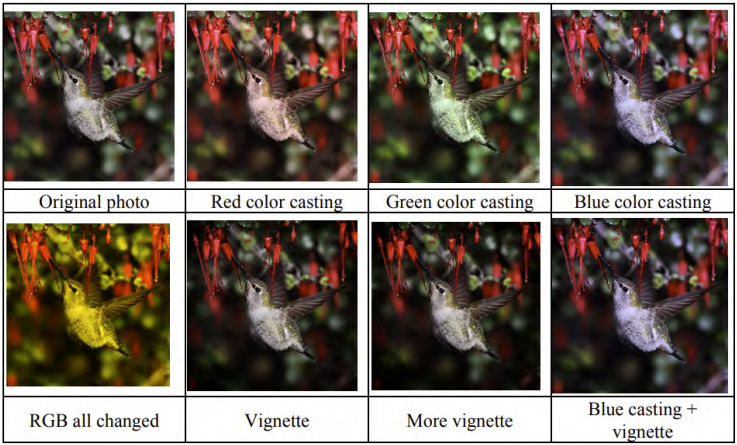
Covarianve matrix is identity matrix

Motivation

- Getting more training data can be expensive
- But, we can often generate additional training examples from existing datasets
- Transform each input data example in such a way that the label stays the same
- Benefits:
  - Reduces overfitting
  - Improves generalization
  - Acts as a regularization
- Examples of data augmentations
  - Translation
  - Flip (Horizental/Vertical)
  - Rotation
  - Stretching
  - Shearing
  - Lens distortions, (go crazy)



Examples of Data Augmentations



Wu, R., et al. “Deep image: Scaling up image recognition” (2015)

Augmentations In Action

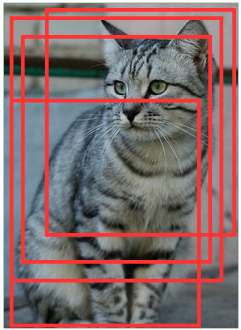
- Simple
  - Randomize contrast and brightness
- Complex
  1. Apply PCA to all [R, G, B] pixels in training set
  2. Sample a color offset along principal component directions
  3. Add offset to all pixels of a training image
     (As seen in AlexNet, ResNet, etc)

Color Jitter

Augmentations In Action

- **Training:** randomly sample crops and scales
  ResNet:
  1. Pick random L in range [256, 480]
  2. Resize training image, short side = L
  3. Sample random 224 x 224 patch
- **Testing:** average a fixed set of crops
  ResNet:
  1. Resize image at 5 scales: 224, 256, 384, 480, 640
  2. For each size, use 10 224 x 224 crops:
     4 corners + center, + flips

Random Crops and Scales



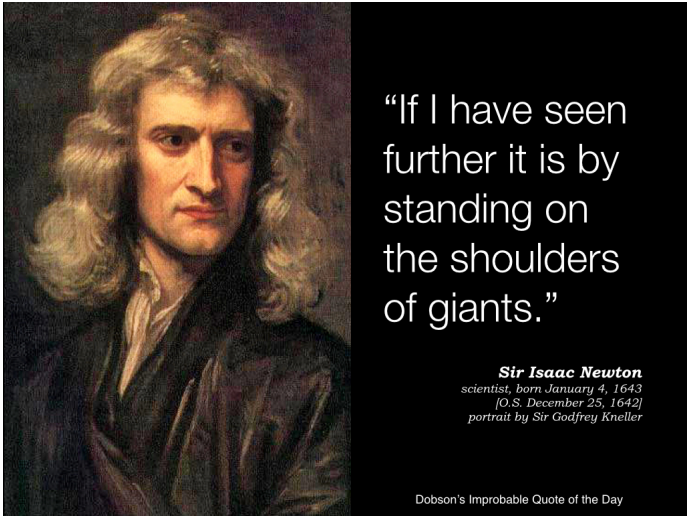
Augmentations In Action

- **Training:** Randomly set image regions to zero
- **Testing:** Use the full image
- Works very well for small datasets like CIFAR, less common for large datasets like ImageNet

Cutout

DeVries and Taylor, "Improved Regularization of Convolutional Neural Networks with Cutout", arXiv 2017

Motivation


“If I have seen further it is by standing on the shoulders of giants.”
Sir Isaac Newton
scientist, born January 4, 1643
[O.S. December 25, 1642]
portrait by Sir Godfrey Kneller
Dobson’s Improbable Quote of the Day

Motivation

- You need a lot of a data if you want to train/use CNNs
- Suppose you want to build an app to recognize flowers

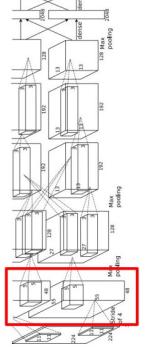
https://www.robots.ox.ac.uk/ vgg/data/flowers/102

Transfer learning

- However, by transfer learning you can use the learned features for a task (using a large amount of data) in another related task (for which you dont have enough data)
- **What should we train?**
- Option 1: Train only classification layer, freeze backbone
  - → Often referred to as the “linear evaluation protocol"
  - → Fast & simple
- Option 2: Train classification layer, fine-tune backbone at the same time
  - → Slower, but can adapt feature extraction to dataset statistics

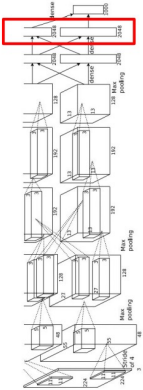
Transfer Learning: The idea

Earlier Layers -> more local features

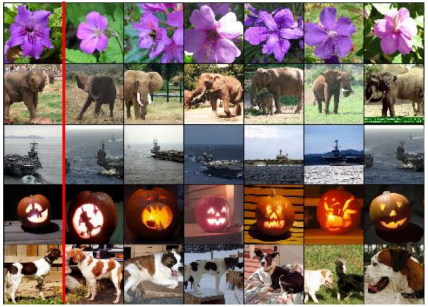


AlexNet:
64 x 3 x 11 x 11

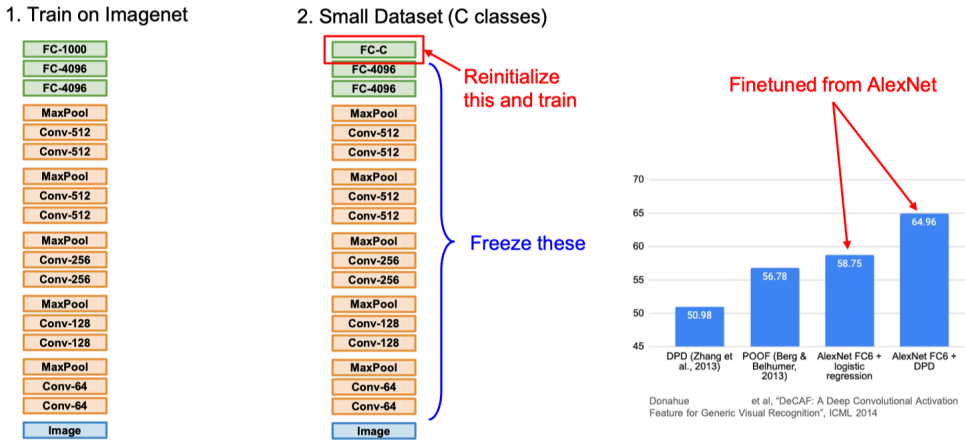
Final Layers -> more global features



Test image L2 Nearest neighbors in feature space

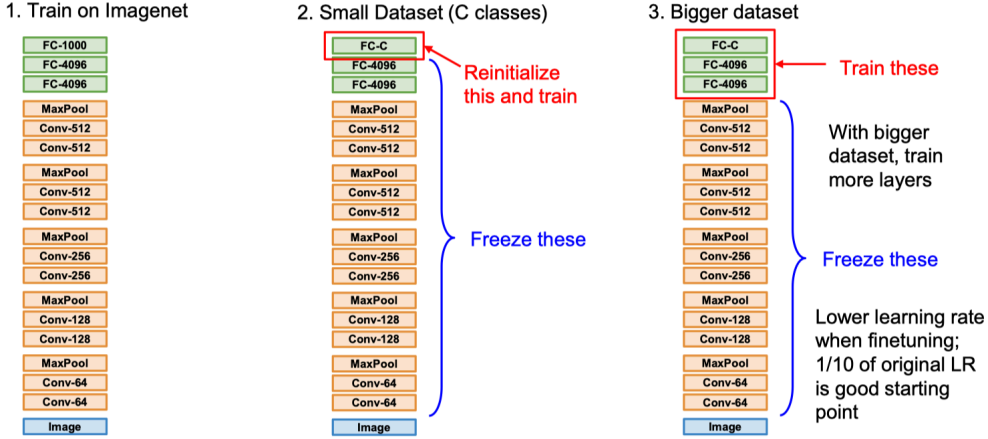


Transfer Learning With CNNs

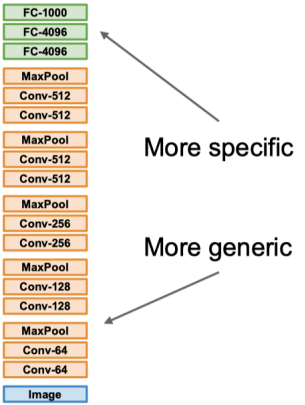


Donahue et al, DeCAF: A Deep Convolutional Activation Feature for Generic Visual Recognition, ICML 2014
Razavian et al, CNN Features Off-the-Shelf: An Astounding Baseline for Recognition, CVPR Workshops 2014

Transfer Learning With CNNs

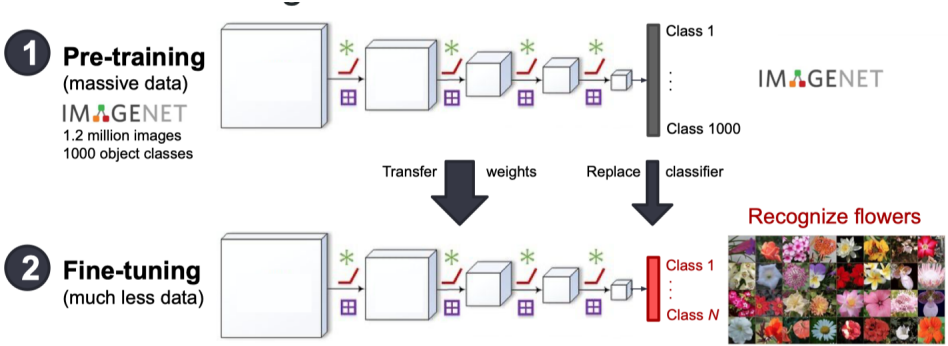


Transfer Learning With CNNs

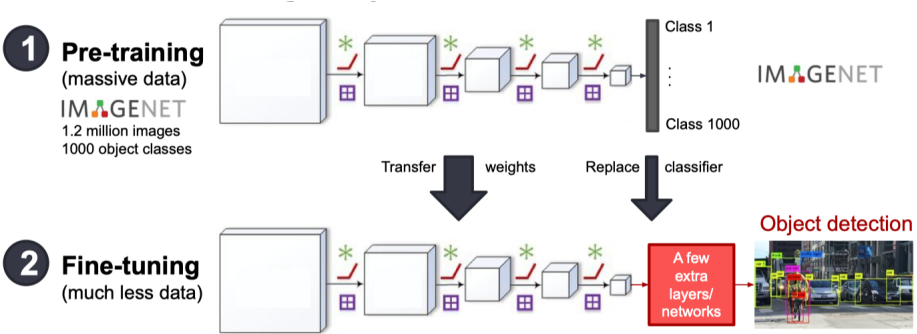


	very similar dataset	**very different dataset**
very little data	Use Linear Classifier on top layer	You're in trouble… Try linear classifier from different stages
quite a lot of data	Finetune a few layers	Finetune a larger number of layers or start from scratch!

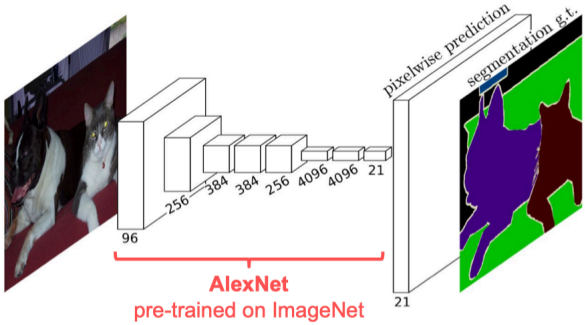
Transfer Learning With CNNs



Transfer Learning: Domain Shift

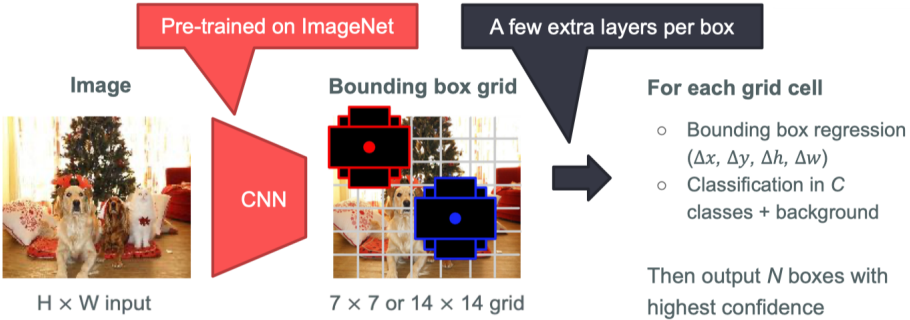


Example: Semantic Segmentation



Long, Shelhamer, Darrell, CVPR 2015

Example: Single-Stage Object Detectors: SSD, YOLO,



Liu et al., ECCV 2016 | Redmon et al., CVPR 2016 | Lin et al., CVPR 2017

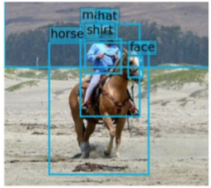
Transfer Learning With CNNs Is Pervasive

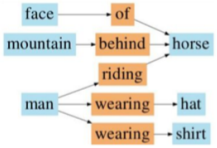
Pose estimation

Image captioning

"two young girls are playing with lego toy."

Scene graph prediction

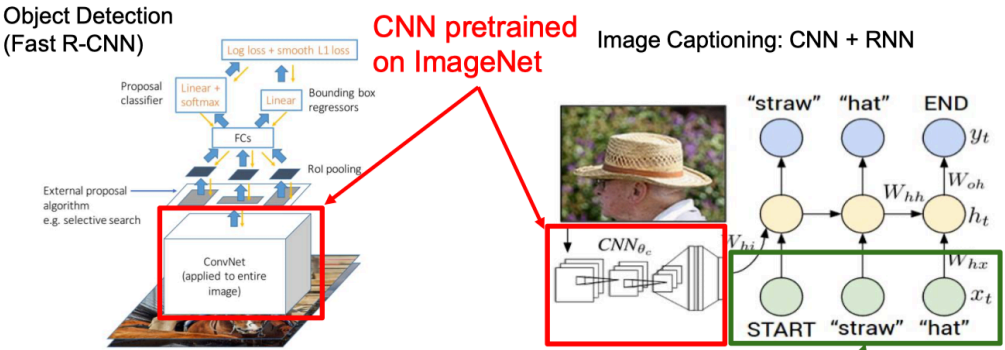




...

Many, many more

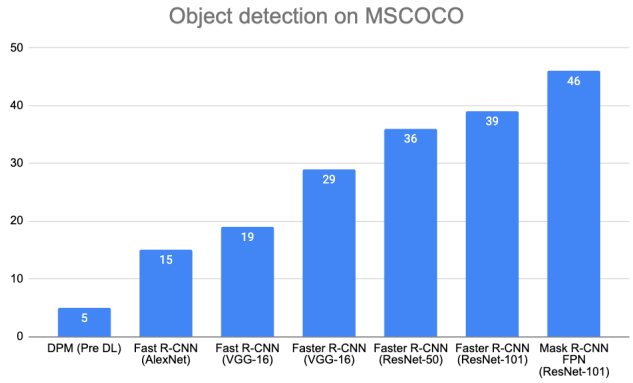
Transfer Learning With CNNs Is Pervasive



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
Figure copyright IEEE, 2015. Reproduced for educational purposes.

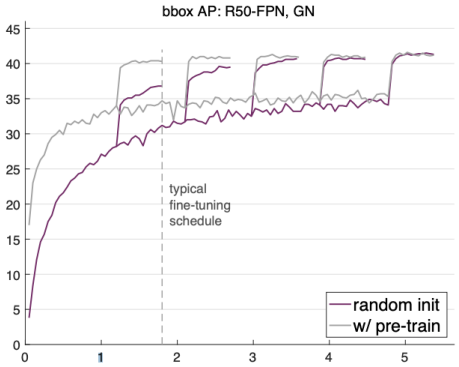
Architecture Matters In TL!



Girshick, The Generalized R-CNN Framework for Object Detection, ICCV 2017

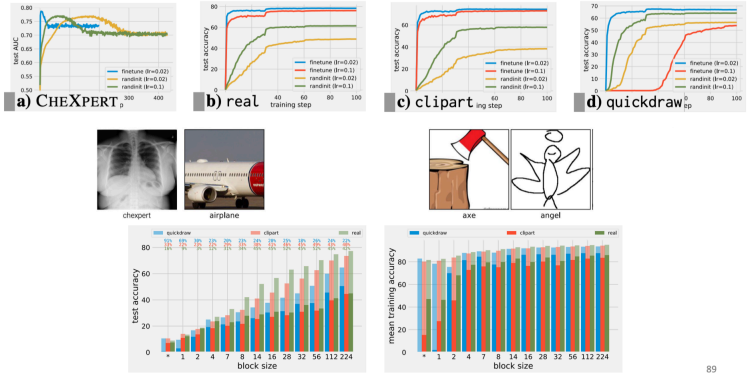
Transfer Learning Might Not Always Be Necessary!

- Training from scratch can work just as well as training from a pretrained ImageNet model for object detection
- But it takes 2-3x as long to train.
- They also find that collecting more data is better than finetuning on a related task



He et al, Rethinking ImageNet Pre-training, ICCV 2019 Figure copyright Kaiming He, 2019. Reproduced with permission.

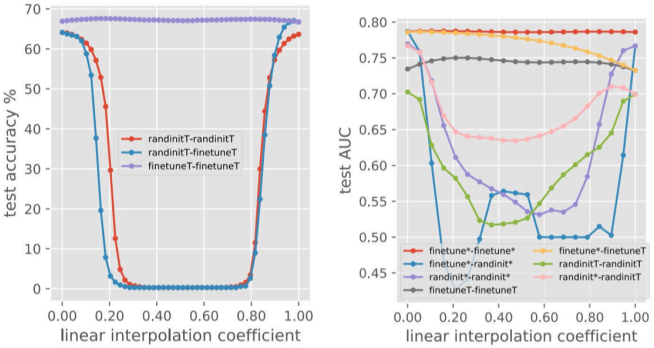
What Is Being Transferred?



Neyshabour et al, What is being transferred in transfer learning?, NeurIPS 2020

Performance Barrier Between Different Solutions

- There are no performance barriers between finetune models
- Finetune models reside in the same basin
- Random initializations end up in different basins, even for the same random seed



He et al, Rethinking ImageNet Pre-training, ICCV 2019

Takehome Message

- Have some dataset of interest but it has fewer than ~ 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 offer a "Model Zoo" of pretrained models so you don't need to train your own
  - **Pytorch:** https://github.com/pytorch/vision
  - **TensorFlow:** https://github.com/tensorflow/models

[1] Fei Fei Li, “Stanford University cs231n.” Lecture slides.

[2] M. Soleymani Baghshah, “Machine learning.” Lecture slides.

[3] B. Raj, “Carnegie Mellon University 11-785.” Lecture slides.

[4] Alexander Ecker, “Neuromatch Academy.” Lecture slides.

Any Questions?