COMS E6998 010

Practical Deep Learning Systems Performance

Lecture 6 10/22/20

Logistics

- Homework 3 posted; due Nov 3 11:59 PM
- Project discussion slots
- Project proposal due 10/29
- Seminar dates: Nov 2, 4, and 6.

Recall from last lecture

- Downpour SGD and its scaling
- Ring all-reduce algorithm
- Distributed training scaling work
  - Goyal et al (Facebook)
  - Cho et al (IBM)
- Horovod and its benchmarking numbers
- Tensorflow and distribution support
- Tensor Processing Units
- Convolutional Neural Networks: convolution, padding, pooling, strides

LeNet (1998)

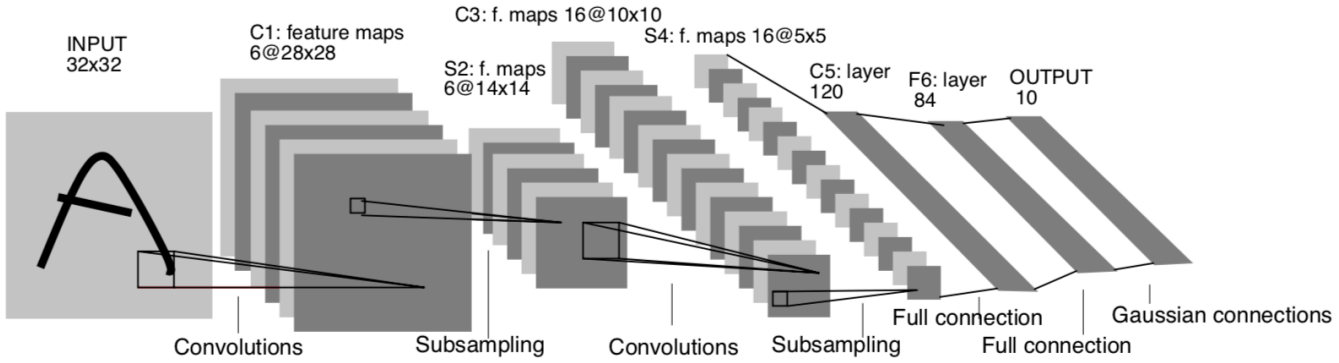


Fig. 2. Architecture of LeNet-5, a Convolutional Neural Network, here for digits recognition. Each plane is a feature map, i.e. a set of units whose weights are constrained to be identical.

- First convolutional layer: 6 filters, 5x5, stride 1; # parameters = 156
- First pooling layer: 6 filters, 2x2, stride 2; # parameters = 12
- Second convolutional layer: 16 filters, 5x5, stride 1; # parameters = 1516 (not a regular convolution layer, each unit in a feature map connected to a subset of input feature maps at identical locations, no weight sharing in same map)
- Second pooling layer: 16 filters, 2x2 stride, 2; # parameters = 32
- Third convolutional layer: 120 filters, 5x5, stride 1; # parameters = 25x16x120+120 = 48, 120. It is a fully connected layer
- Fully connected layer: #parameters = 84x120 +84 = 10,164

LeNet Questions

- How did we get number of parameters = 156 on first convolutional layer?
- How many connections in first convolutional layer ?
- Why number of trainable parameters is 12 for first pooling layer ?
- Why third convolutional layer is technically a fully connected layer ?
- What type of layers are contributing the maximum number of trainable parameters ?

Alexnet (2012)

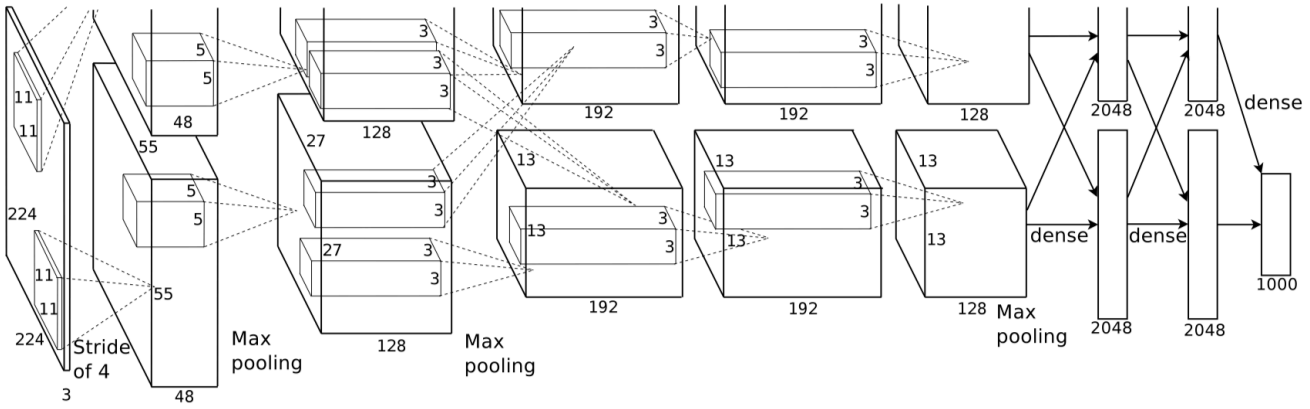


Figure 2: An illustration of the architecture of our CNN, explicitly showing the delineation of responsibilities between the two GPUs. One GPU runs the layer-parts at the top of the figure while the other runs the layer-parts at the bottom. The GPUs communicate only at certain layers. The network's input is 150,528-dimensional, and the number of neurons in the network's remaining layers is given by 253,440–186,624–64,896–64,896–43,264–4096–4096–1000.

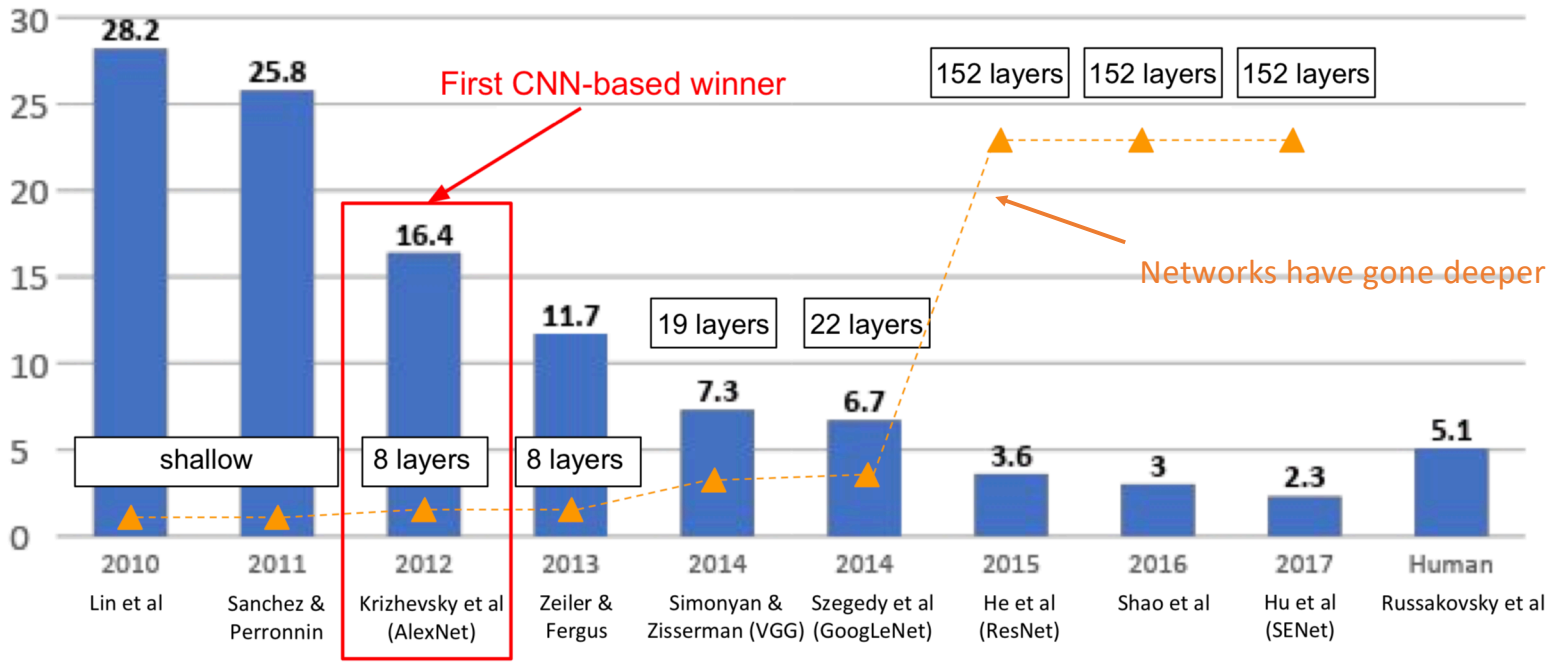
Alexnet architecture details

- ReLU activation functions (first to use in CNNs)
- Training on multiple GPUs
  - Single GTX 580 GPU has only 3GB
  - Network spread across two GPUs; Puts half of the kernels (or neurons) on each GPU
  - Inter-GPU communication only in certain layers
- Overlapping pooling – reduces overfitting
- 8 layers with weights
  - First five are convolutional, 3 max-pool (reduces output size by half)
  - Remaining three are fully- connected
  - Output of the last fully-connected layer is fed to a 1000-way softmax

Alexnet Training

- 60 Million parameters to learn (how did we get this number ? Hw3 question)
- Techniques employed to reduce overfitting
  - Data augmentation (done on CPU) --- pipelined with training, no GPU required, done online
    - Artificially enlarge the dataset using label-preserving transformations
      - Random cropping (224x224 from 256x256) and horizontal reflections
      - Altering intensities of RGB channels in training images
  - Dropout
    - In first two fully connected layers with dropout probability 0.5
- Batch size: 128
- SGD with 0.9 momentum
- Learning rate 1e-2, reduced by 10 manually when validation accuracy plateaus
- L2 weight decay 0.0005
- Error rate: 18.2% (1 CNN)-> 16.4% (5 CNNs ensemble)

Imagenet Large Scale Visual Recognition (ILSVRC) Challenge Winners

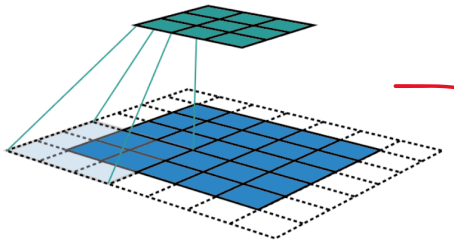


Receptive Field of a CNN

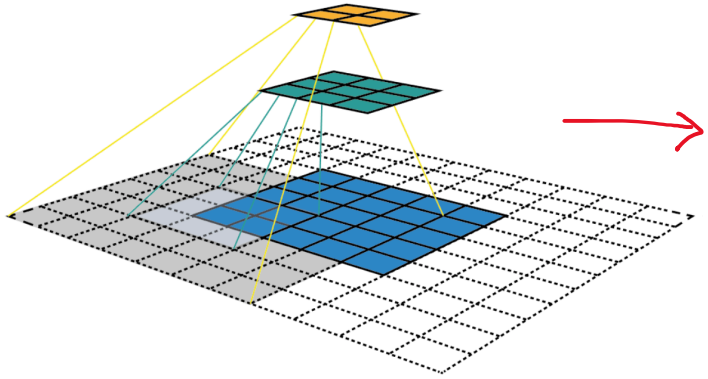
*The **receptive field** is defined as the region in the input space that a particular CNN's feature is looking at (i.e. be affected by)*

The common way to visualize a CNN feature map. Only looking at the feature map, we do not know where a feature is looking at (the center location of its receptive field) and how big is that region (its receptive field size). It will be impossible to keep track of the receptive field information in a deep CNN.

Convolution with kernel size k = 3x3, padding size p = 1x1, stride s = 2x2



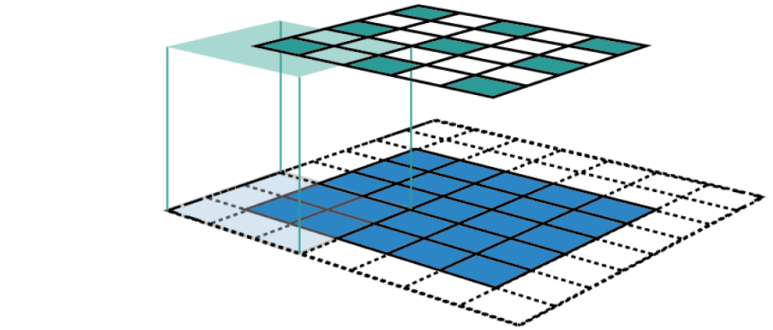
Applying the convolution on a 5x5 input map to produce the 3x3 green feature map

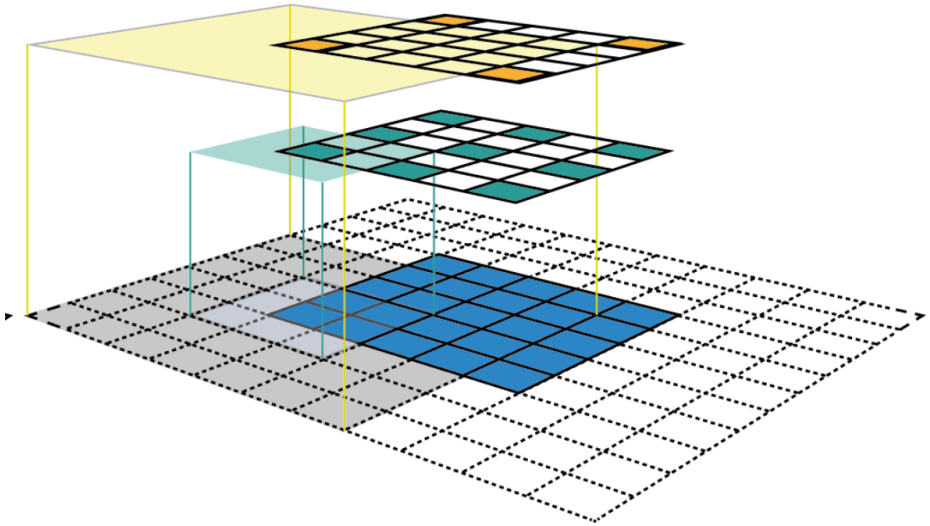


Applying the same convolution on top of the green feature map to produce the 2x2 orange feature map.

Fixed-size CNN feature map visualization

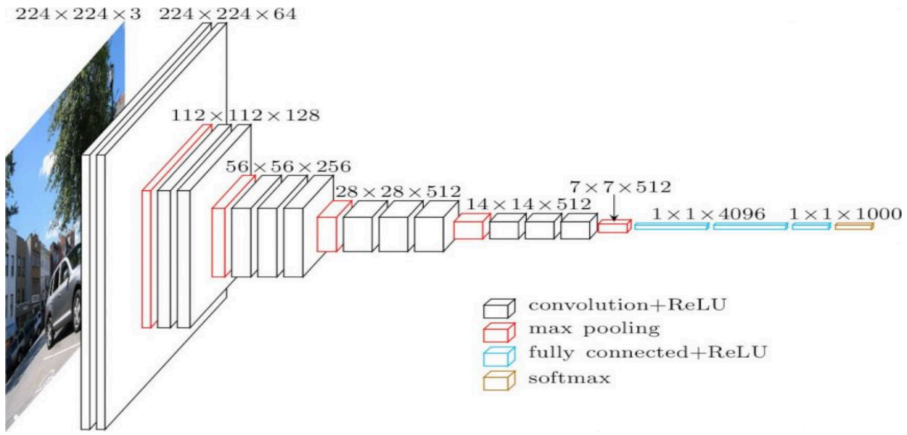
The fixed-sized CNN feature map visualization, where the size of each feature map is fixed, and the feature is located at the center of its receptive field.





VGG (2014)

ConvNet Configuration				VGG16	VGG19
A	A-LRN	B	C	D	E
11 weight layers	11 weight layers	13 weight layers	16 weight layers	16 weight layers	19 weight layers
input (224 × 224 RGB image)					
conv3-64	conv3-64 **LRN**	conv3-64 **conv3-64**	conv3-64 conv3-64	conv3-64 conv3-64	conv3-64 conv3-64
maxpool					
conv3-128	conv3-128	conv3-128 **conv3-128**	conv3-128 conv3-128	conv3-128 conv3-128	conv3-128 conv3-128
maxpool					
conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256 **conv1-256**	conv3-256 conv3-256 **conv3-256**	conv3-256 conv3-256 conv3-256 **conv3-256**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
FC-4096					
FC-4096					
FC-1000					
soft-max					



VGG16 Architecture

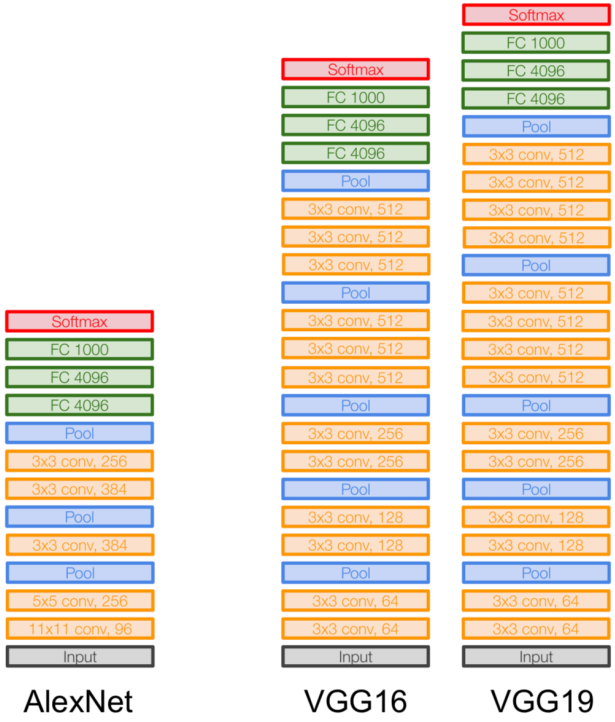
Table 2: **Number of parameters** (in millions).

Network	A,A-LRN	B	C	D	E
Number of parameters	133	133	134	138	144

VGG memory and compute calculation

Layer	Number of Activations (Memory)	Parameters (Compute)
Input	$224 * 224 * 3 = 150K$	0
CONV3-64	$224 * 224 * 64 = 3.2M$	$(3 * 3 * 3) * 64 = 1728$
CONV3-64	$224 * 224 * 64 = 3.2M$	$(3 * 3 * 64) * 64 = 36{,}864$
POOL2	$112 * 112 * 64 = 800K$	0
CONV3-128	$112 * 112 * 128 = 1.6M$	$(3 * 3 * 64) * 128 = 73{,}728$
CONV3-128	$112 * 112 * 128 = 1.6M$	$(3 * 3 * 128) * 128 = 147{,}456$

VGG Architecture



- Smaller filters (3x3, stride 1) compared to 11x11 and 5x5 in Alexnet
- Deeper nets: more layers compared to Alexnet (8 vs 16 or 19)
- Why smaller filters ?
  - Receptive field of 3 3x3 stacked conv. layers is same as a single 7x7 conv layer
  - More non-linearities with stack of smaller conv layers => makes decision function more discriminative
  - Lesser number of parameters: $3 * (3^2C^2)$ vs. 7^2C^2 for C channels per layer (55% less)

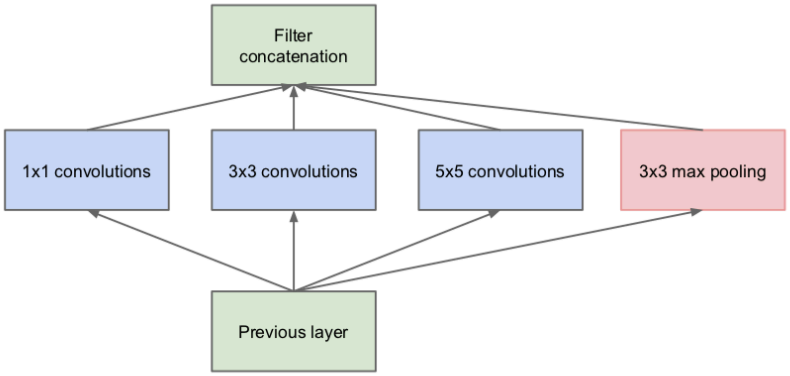
Receptive field equivalence

- Output activation map length: L-F+1
- Single 7x7 filter
  - Output activation map length: L-7+1 = L-6
  - Number of parameters (for input and output depth C): (7x7xC)XC = 7^2C^2
- 3 stacked 3x3 filters
  - Output activation map length after first conv layer: L-3+1 = L-2
  - Output activation map length after second conv layer: (L-2)-3+1=L-4
  - Output activation map length after third conv layer: L-4-3+1 = L-6
  - Number of parameters (for input and output depth C):
    - One conv layer: (3x3xC)XC=3^2C^2
    - 3 conv layers: 3.(3^2C^2)
- Parameter saving: 55% (27 vs 49) less with 3 stacked 3x3 vs a single 7x7

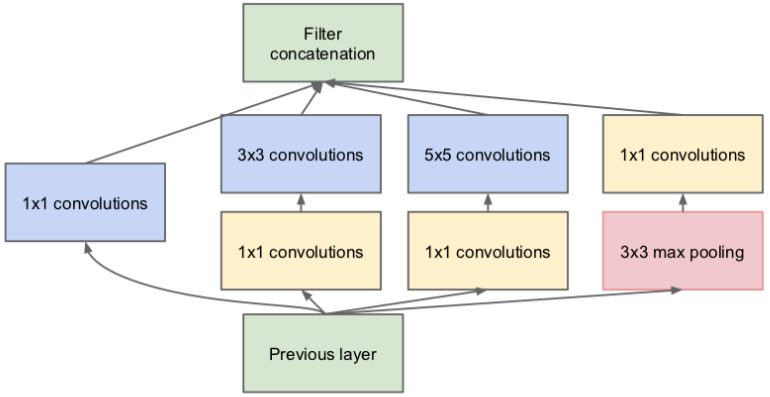
Stack of Small Convolution Layers

- A stack of three 3 × 3 conv. layers instead of a single 7 × 7 layer
  - Same receptive field
  - 3 non-linear rectification layers instead of one
  - Less number of parameters
- Imposing a regularisation on the 7 × 7 conv. filters, forcing them to have a decomposition through the 3 × 3 filters (with non-linearity injected in between)

GoogleNet (2014)



(a) Inception module, naïve version

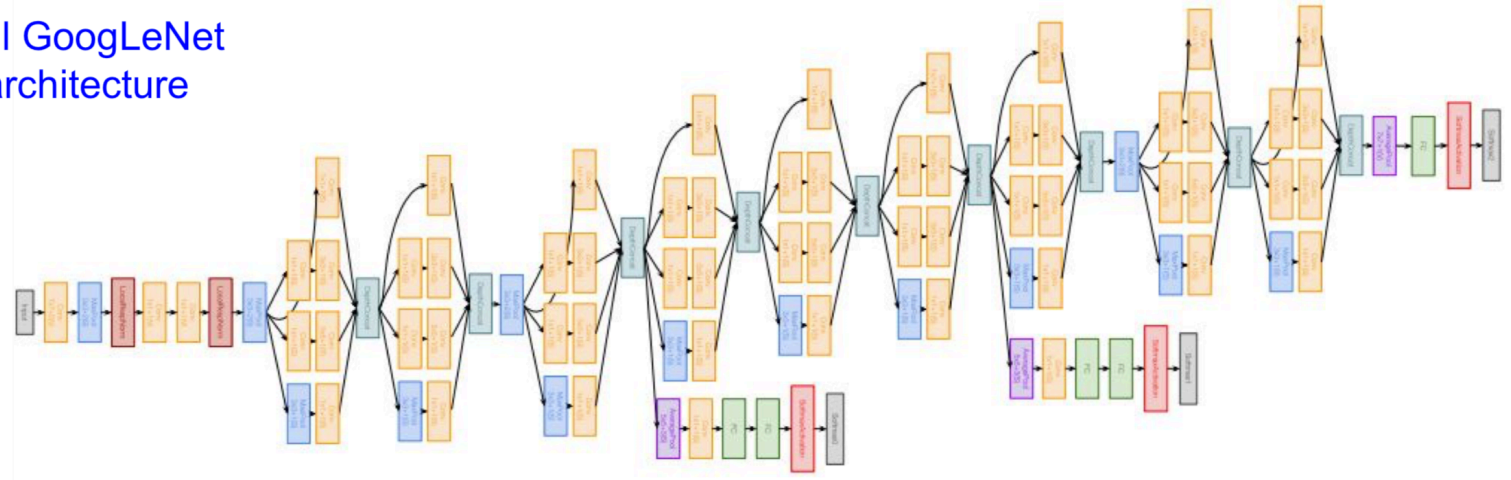


(b) Inception module with dimension reductions

- To preserve local and sparse correlations, parallel convolutional filters of different sizes
- Inception architecture: Inception modules stacked to create Googlenet
- Dimension reduction module has reduced computational complexity compared to naïve version

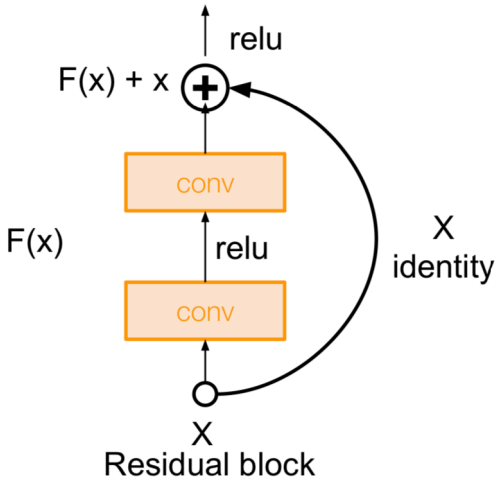
GoogleNet(2014)

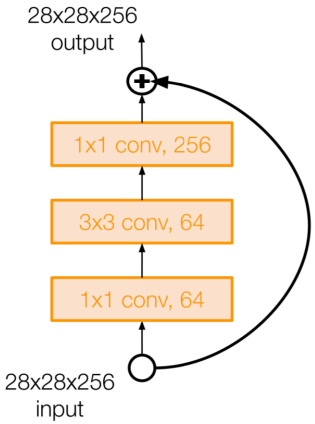
Full GoogLeNet architecture

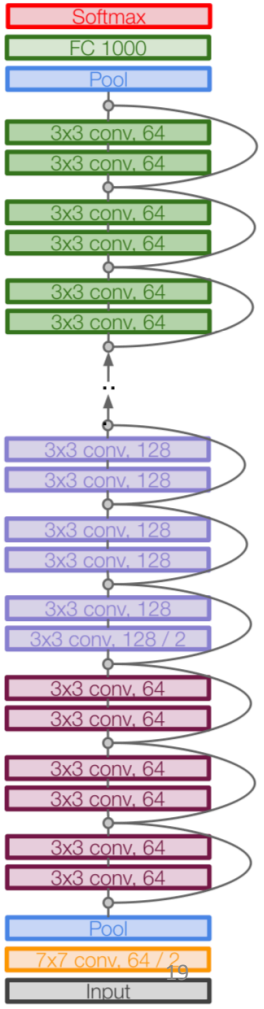


- Deeper network (22 layers)
- Computationally efficient “Inception” module
- Avoids expensive FC layers → uses average pooling
- 12x less params than AlexNet

ResNet

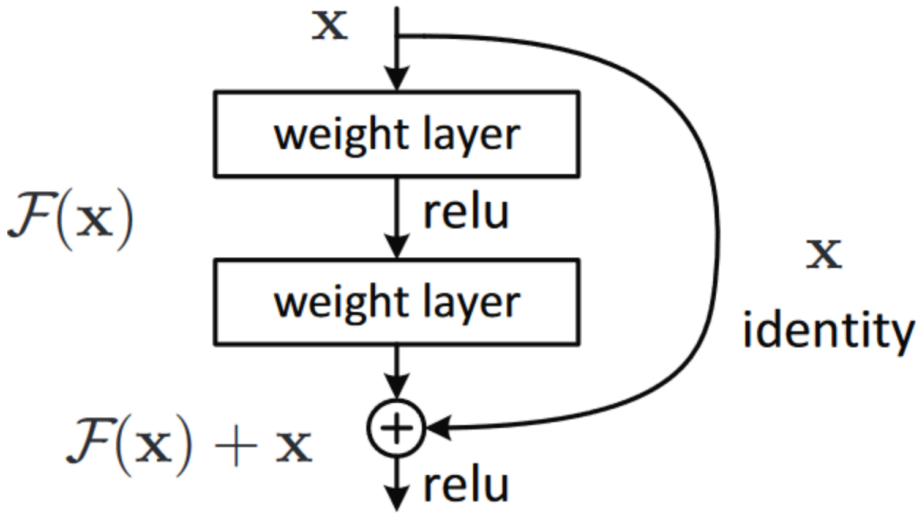






- Stack of residual blocks: each residual block has 2 3x3 conv layers; number of filters is doubled periodically
- Global average pooling layer after last conv layer
- Different depths: 34, 50, 101, 152
- Deeper network (ResNet50+) add 1x1 conv for computational efficiency

Residual connections prevents vanishing gradient



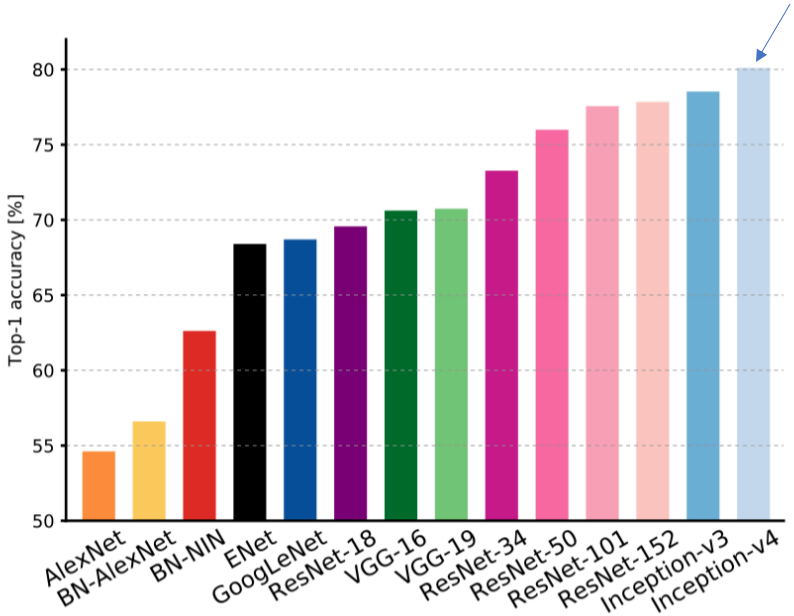
$$\frac{\partial L}{\partial x} = \frac{\partial L}{\partial H}\frac{\partial H}{\partial x} = \frac{\partial L}{\partial H}(\frac{\partial F}{\partial x} + 1) = \frac{\partial L}{\partial H}\frac{\partial F}{\partial x} + \frac{\partial L}{\partial H}$$

Combining Inception with Residual Connections (Inception V4)

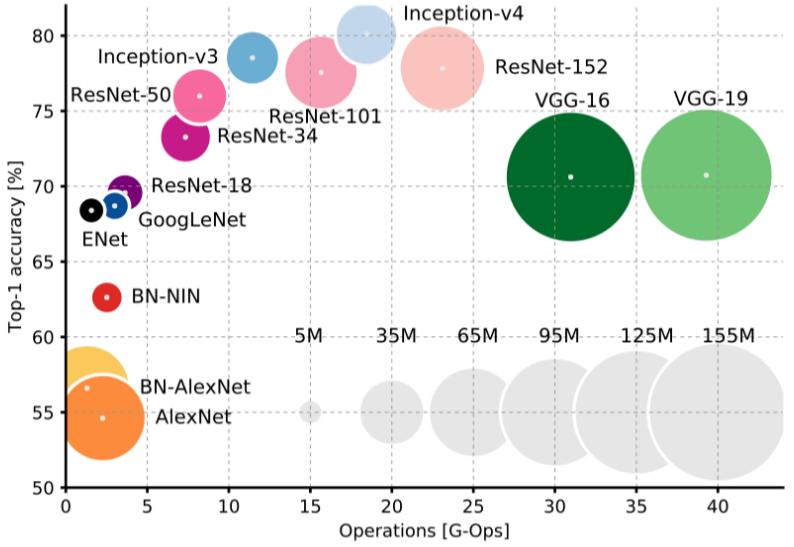
- Whether there are any benefit in combining the Inception architecture with residual connections ?
  - Training with residual connections accelerates the training of Inception networks significantly
  - Some evidence that residual Inception networks outperforms similarly expensive Inception networks without residual connections by a thin margin

Top1 Accuracy Comparison

Inception-v4: Resnet + Inception!

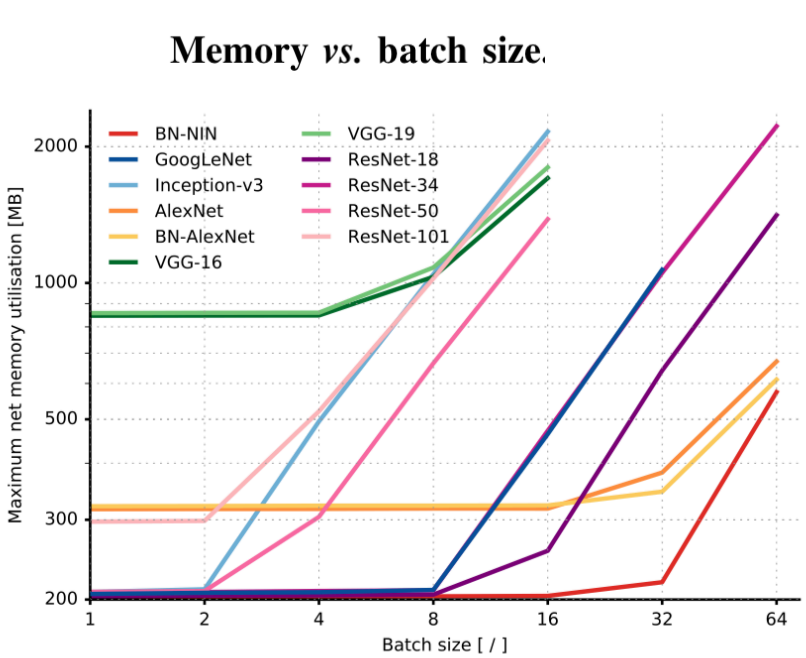


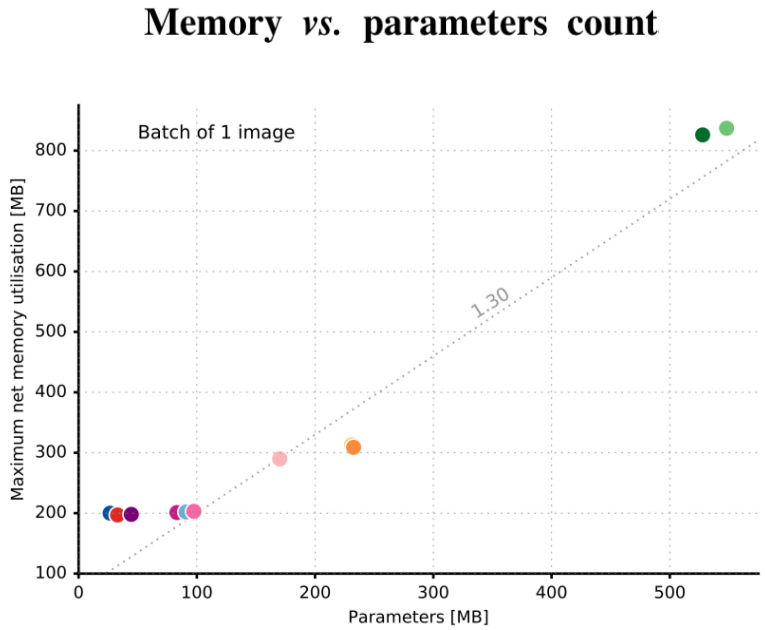
Top1 *vs.* network.



Top1 *vs.* operations, size $\propto$ parameters

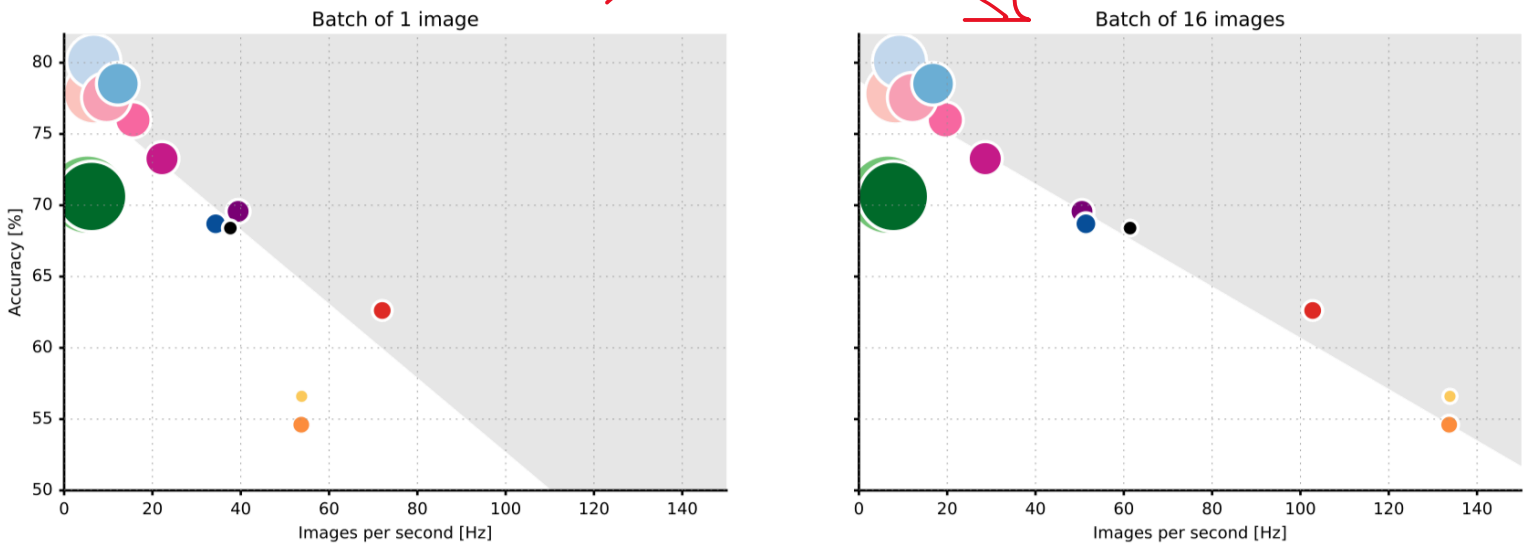
Memory Consumption





Accuracy vs Throughput : Inference ?

All models show improvement in throughput
Improvement in throughput is different for each model



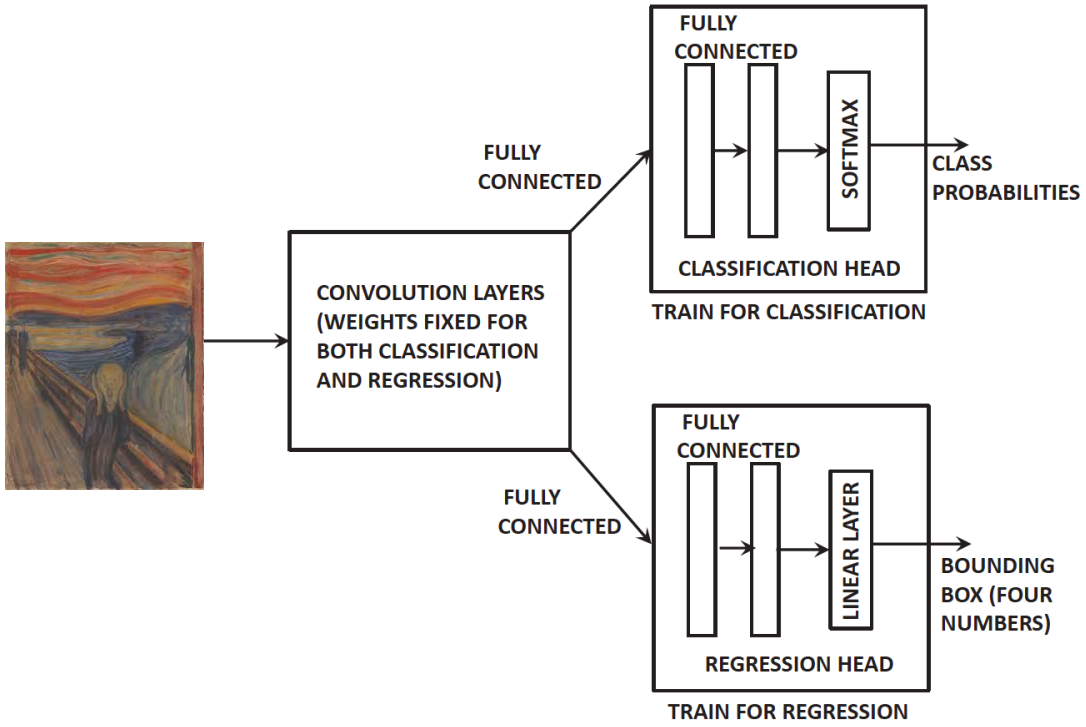
CNN Applications

- Image classification
- Object localization
- Object detection

Object Localization

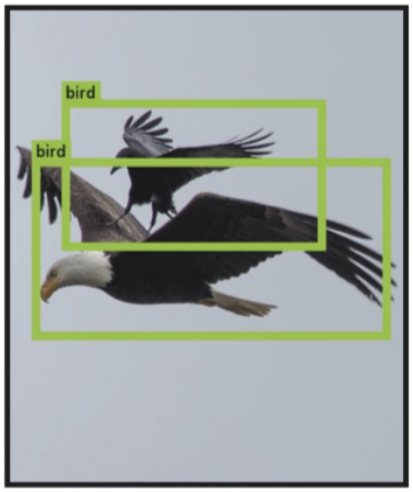
- Given a fixed set of objects in an image, identify rectangular regions in the image in which the object occurs
- Four numbers to identify a bounding box: coordinates of the top-left corner and two dimensions (length and width)
- Often integrated with classification of objects

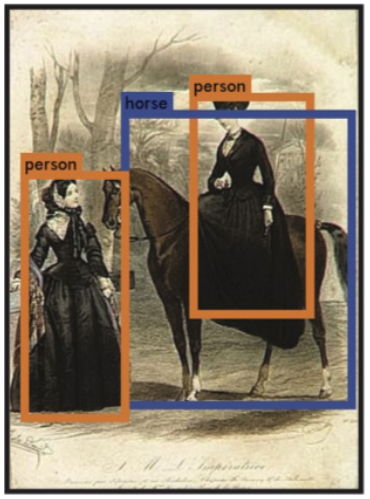
Object Localization

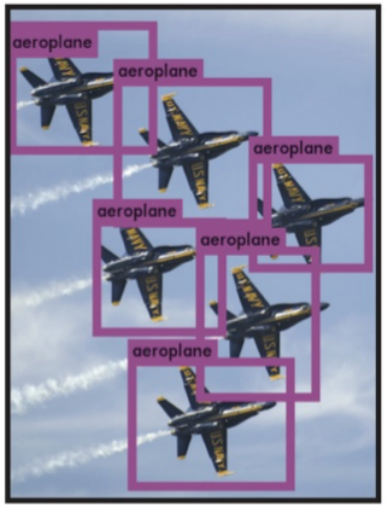


Object Detection

- Variable number of objects of different classes in an image
- Identify all the objects and their class

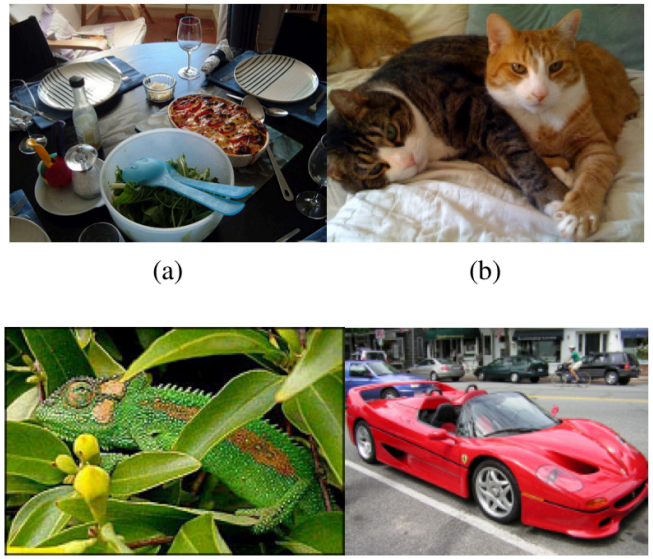






Cannot use object localization architecture as the number of classification and regression heads needed is not known

Identify region in image containing an object

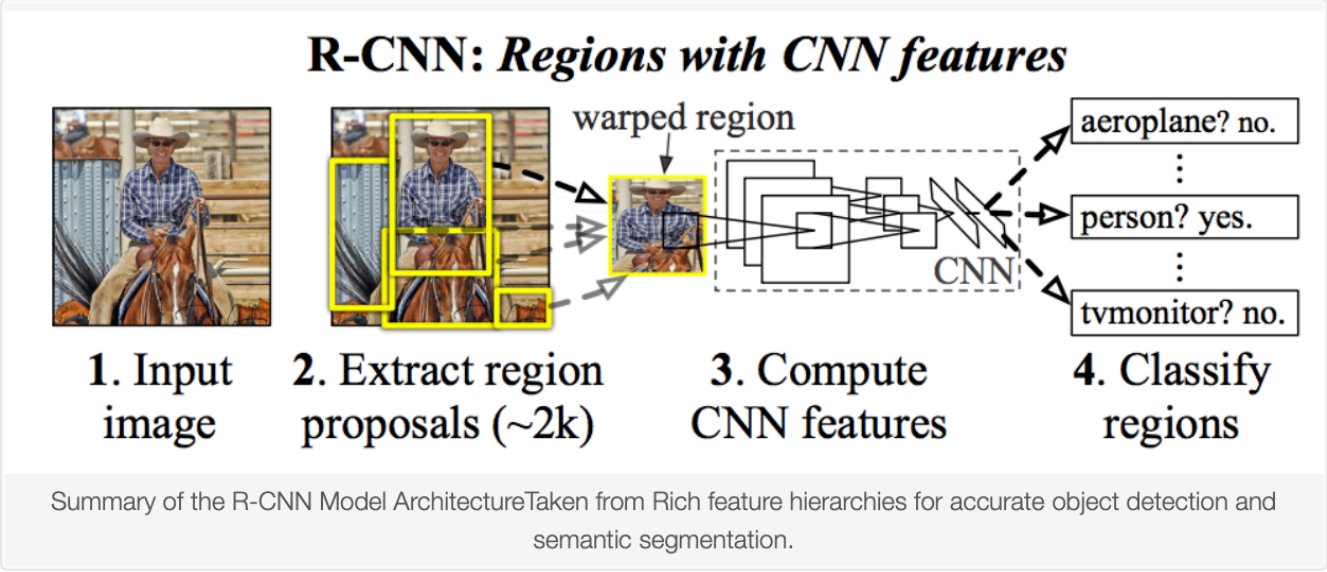


(a) (b)

(c) (d)

Figure 1: There is a high variety of reasons that an image region forms an object. In (b) the cats can be distinguished by colour, not texture. In (c) the chameleon can be distinguished from the surrounding leaves by texture, not colour. In (d) the wheels can be part of the car because they are enclosed, not because they are similar in texture or colour. Therefore, to find objects in a structured way it is necessary to use a variety of diverse strategies. Furthermore, an image is intrinsically hierarchical as there is no single scale for which the complete table, salad bowl, and salad spoon can be found in (a).

R-CNN (Region Based Convolutional Neural Network)



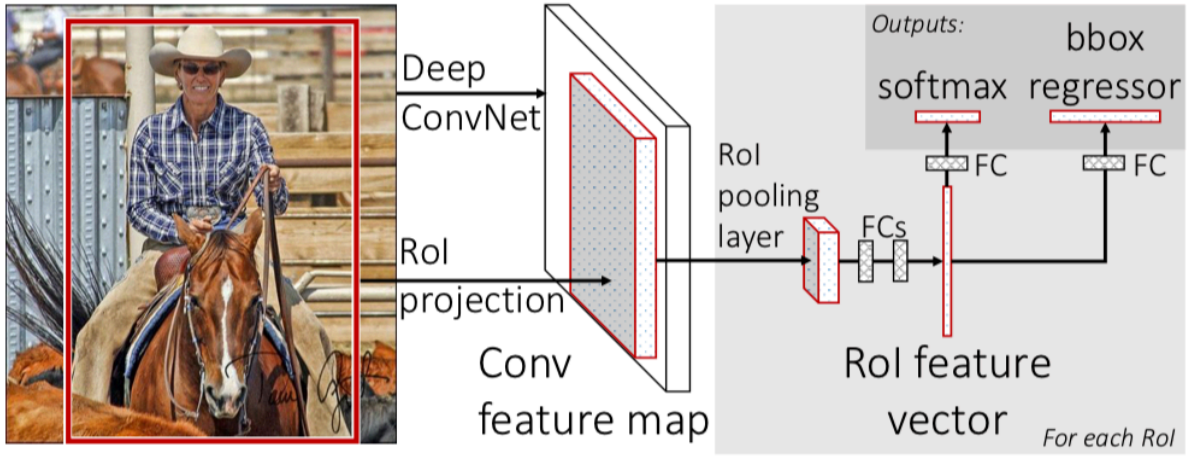
Summary of the R-CNN Model ArchitectureTaken from Rich feature hierarchies for accurate object detection and semantic segmentation.

Three main modules:

1. **Region Proposal**. Generate and extract category independent region proposals, e.g. candidate bounding boxes.
2. **Feature Extractor**. Extract feature from each candidate region, e.g. using a deep convolutional neural network.
3. **Classifier**. Classify features as one of the known class, e.g. linear SVM classifier model.

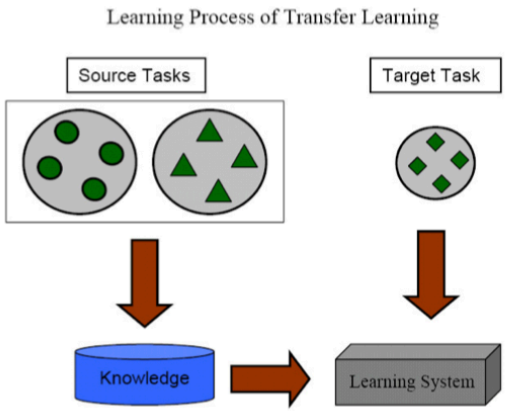
Fast R-CNN

- R-CNN is slow
  - CNN-based feature extraction pass on each of the candidate regions, no sharing of computation
  - ~2,000 proposed regions per image at test-time



Transfer Learning

- Building good machine learning models require lot of training data
  - To capture robust representation of unknown input distribution
- Small training jobs are common and labeled data is scarce in many domains
  - In commercial VR service (Bhatta et al. 2019), average number of images submitted is 250 and average number of classes are 5; ~50 images per class
- Can we leverage knowledge learnt from related tasks for target task ?
- Transfer learning is a class of techniques to reuse knowledge gathered from “source” tasks (with sufficiently rich set of labeled data) for a “target task (with few labeled data)



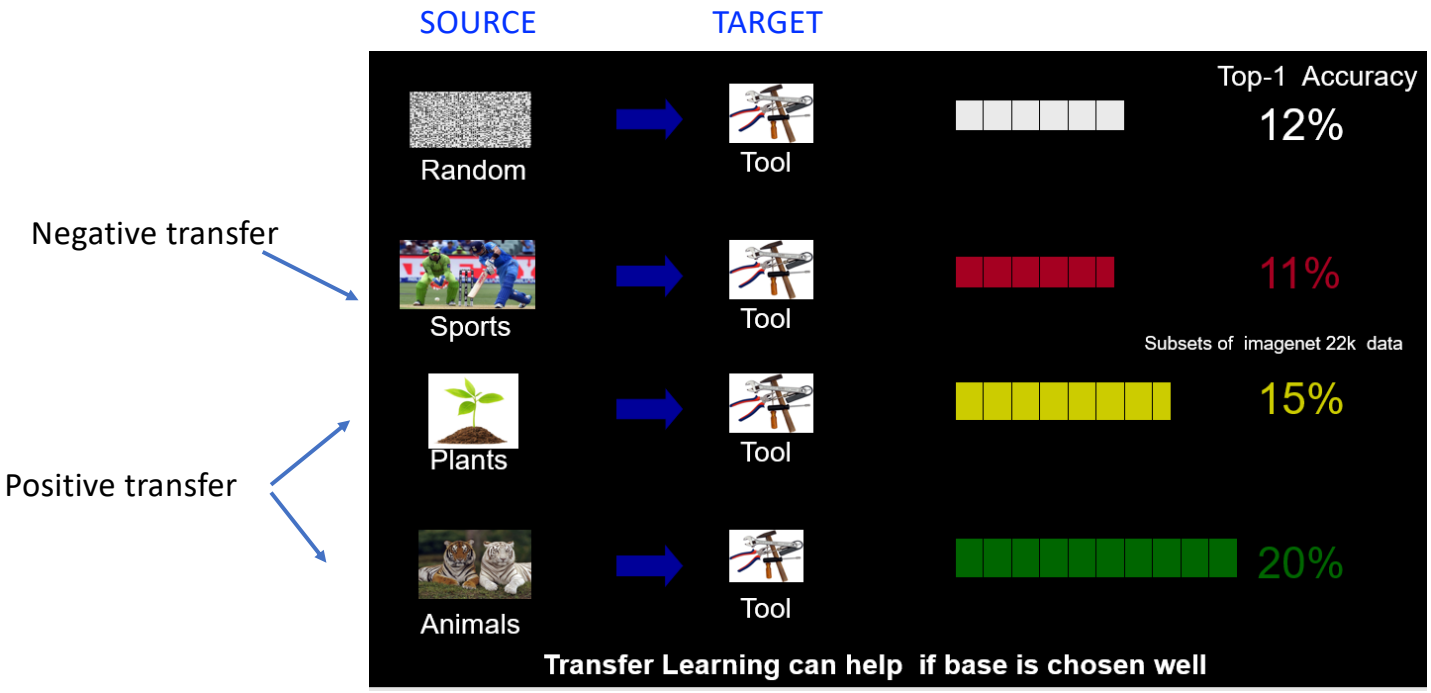
Transfer Learning Approaches

- *Common intuition*: Networks which have learned compact representations of a "source" task, can reuse these representations to achieve higher performance on a related "target" task.
- *Instance based* approaches attempt to identify appropriate data used in the source task to supplement target task training
- *Feature representation based* approaches attempt to leverage source task weight matrices
  - Trained weights in source network have captured a representation of the input that can be transferred by fine-tuning the weights or retraining the final dense layer of the network on the new task.

Improving Transferability in Transfer Learning

- **Selection of source model:** What is the best ”source” task/model to transfer knowledge for a “target” task ?
  - How to measure “similarity” between source and target task ?
    - Develop similarity measures between source and target datasets in feature space
  - Does size always matter ?
    - Will a source model trained on huge datasets will always outperform source models trained on smaller but more related datasets ?
  - Improper choice of a base dataset/model for a target could result in degraded performance compared to not using transfer learning (negative transfer)
- **Degree of finetuning**
  - Which layers to finetune and which to freeze ?
  - What should be the learning rate of layers to be finetuned ?
    - Higher learning rate ➔ loose information from source task

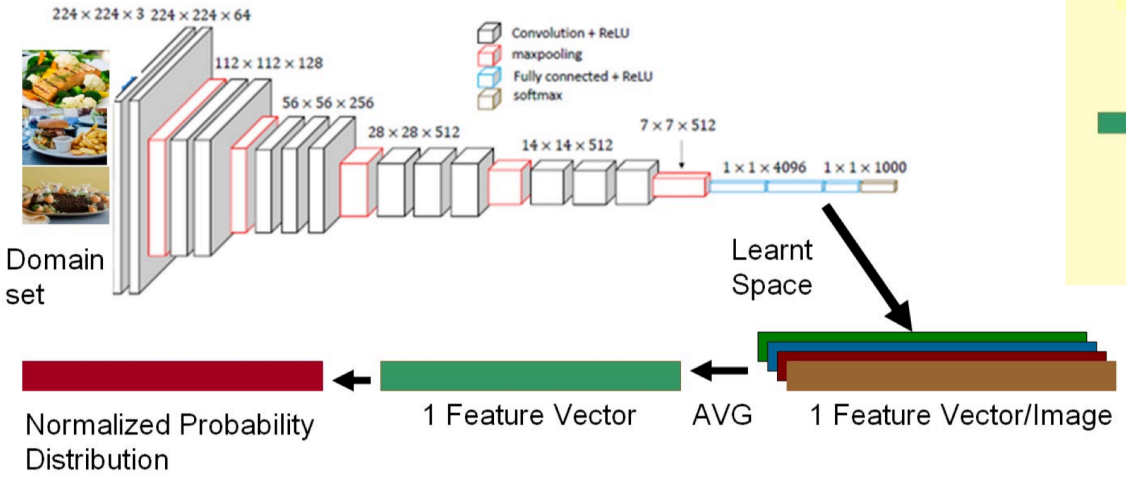
Good and bad sources

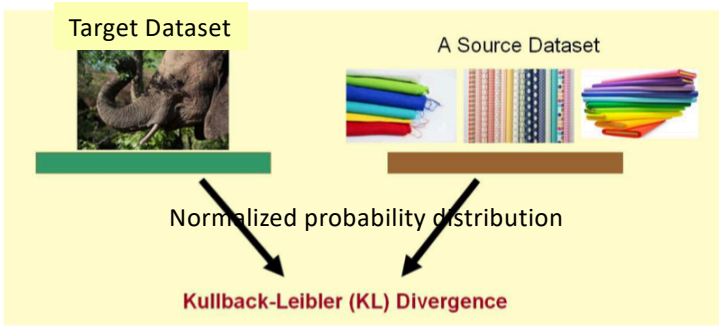


Efficient Selection of Source Models

- Training consumes valuable time / compute resources, we do not want to do a lengthy optimization process or train many candidate models per task
- Predict to Learn (P2L) approach (Bhatta et al 2019)
  - An efficient method to estimate the appropriateness of a previously trained model for use with a new learning task
  - Precludes the exhaustive approach of fine-tuning all existing source models to search for the best fit.
  - P2L only requires a single forward pass of the target data set through a single reference model to identify the most likely candidate for fine-tuning.
- P2L accounts for two attributes:
  - Similarity between source and target dataset: source dataset which is similar to a target dataset in feature space is most likely to have a higher degree of transferability and hence a better candidate for fine-tuning
  - Size of source dataset

P2L Approach: dataset similarity in feature space





P2L Performance

Target Dataset t_i	P2L Picked Best Dataset ?	Random Dataset Selection (OP-RDS)/RDS	No Transfer Learning (OP-Aϕ)/Aϕ
Fruit	**Yes**	0.59	1.00
Fabric	**Yes**	0.32	0.67
Building	**Yes**	0.36	0.63
Music	**Yes**	0.25	0.53
Nature	**Yes**	0.21	0.42
Food	**Yes**	0.37	0.31
Tool	**Yes**	0.12	0.25
Furniture	**Yes**	0.22	0.22
Person	**Yes**	0.13	0.25

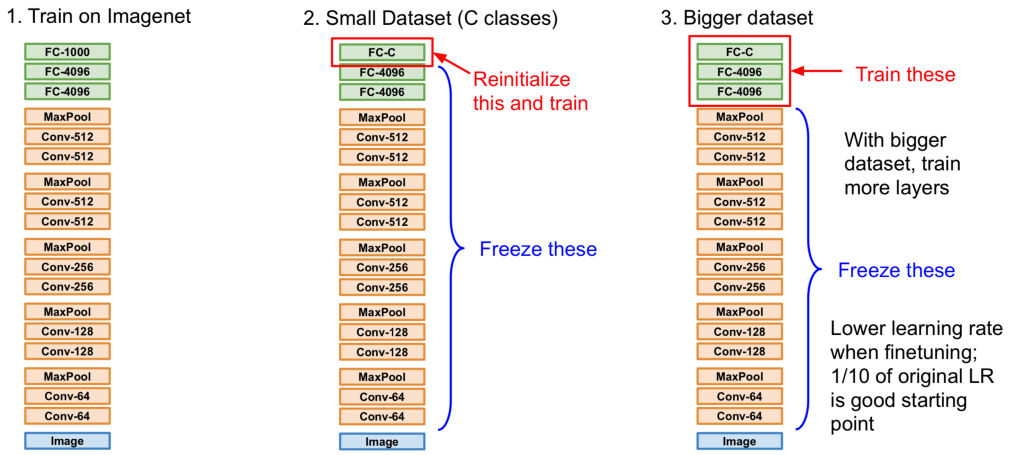
OP = Accuracy using P2L RDS = Avg accuracy of randomly picked source dataset

Aϕ = Accuracy of ϕ

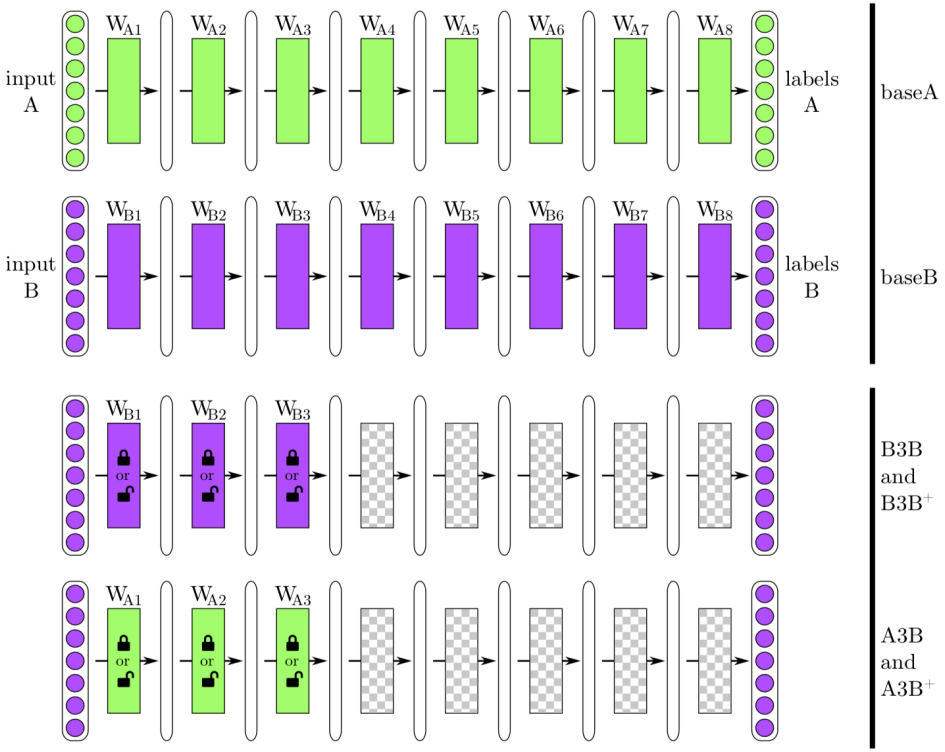
Transfer Learning: Basic Finetuning

- Take almost any deep network pre-trained on a large dataset of your choice
- Model zoo of pretrained models
  - TensorFlow: https://github.com/tensorflow/models
  - PyTorch: https://github.com/pytorch/vision
- Replace the last (classification) layer with a randomly initialized one
- Train only the new layer's weights, using the "frozen" embedding

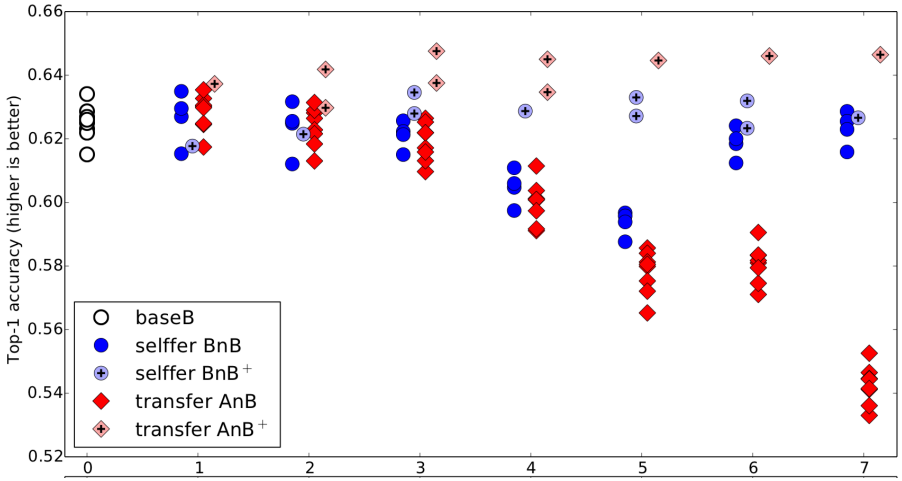
- This baseline method works well in many settings…
- …. Can we improve on it?



Transferability



Transferability



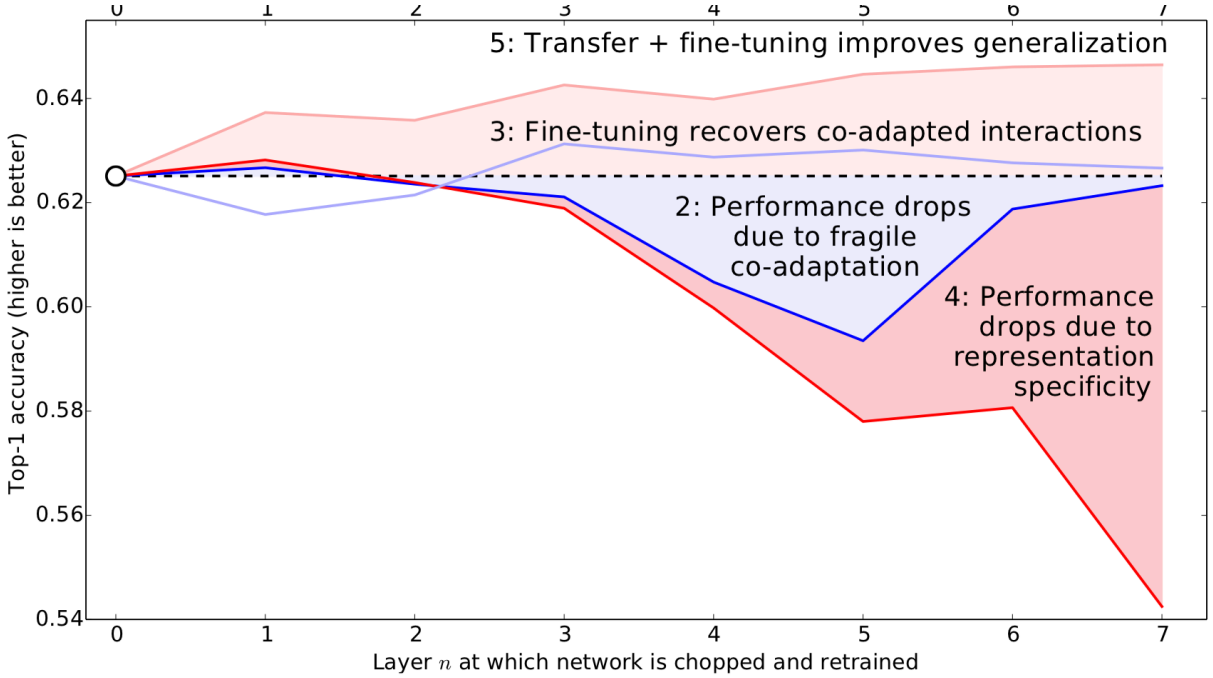
Layer n at which network is chopped and retrained

Each marker in the figure represents the average accuracy over the validation set for a trained network. The white circles above n = 0 represent the accuracy of baseB. There are eight points, because we tested on four separate random A/B splits. Each dark blue dot represents a BnB network. Light blue points represent BnB+ networks, or fine-tuned versions of BnB. Dark red diamonds are AnB networks, and light red diamonds are the fine-tuned AnB+ versions.

Questions

- The white baseB circles show that a network trained to classify a random subset of 500 classes attains a top-1 accuracy of 0.625, or 37.5% error. This error is lower than the 42.5% top-1 error attained on the 1000-class network. Why ?

Transferability



Lines connecting the means of each treatment.

IBM Visual Recognition Service

- IBM Watson Visual Recognition Service
- Cloud based service
- Supports both image classification and object detection
  - Use of pre-trained models or developing custom models
- Video: Visual Recognition in Watson Studio
- Custom object detection
- Visual recognition with CoreML
  - Source code and instructions for yourself to try: https://github.com/bourdakos1/visual-recognition-with-coreml
  - Tutorial http://ibm.biz/coremlworkshop

Seminar Reading List

- **Convolutional Neural Networks**
  - Yann LeCun et al. Gradient-Based Learning Applied to Document Recognition.1998
  - Alex Krizhevsky et al. ImageNet Classification with Deep Convolutional Neural Networks.2012
  - Karen Simonyan et al. VERY DEEP CONVOLUTIONAL NETWORKS FOR LARGE-SCALE IMAGE RECOGNITION .2015
  - Christian Szegedy et al. Going Deeper with Convolutions .2014
  - Christian Szegedy et a. Inception-v4, Inception-ResNet and the Impact of Residual Connections on Learning .2016
- **Object Detection**
  - Ross Girshick et al. Rich feature hierarchies for accurate object detection and semantic segmentation .2015
  - Ross Girshick. Fast R-CNN .2015
- **Transfer Learning in Vision**
  - Yosinski et al. How transferable are features in deep neural networks?. 2014
  - Bhatta et al. P2L: Predicting Transfer Learning for Images and Semantic Relations .2019

Suggested Reading

- Adrian Rosebrock. ImageNet: VGGNet, ResNet, Inception, and Xception with Keras 2017
- Dang Ha The Hien A guide to receptive field arithmetic for convolutional neural networks 2017