ECG782: MULTIDIMENSIONAL DIGITAL SIGNAL PROCESSING

DEEP COMPUTER VISION USING CNNS

Géron Chapter 14

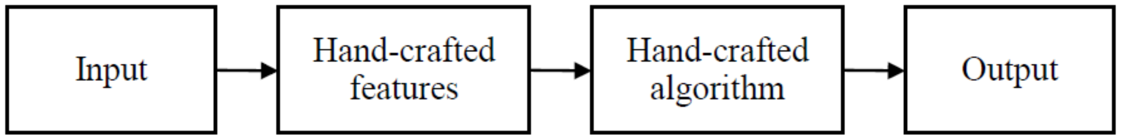
http://www.ee.unlv.edu/~b1morris/ecg782

OUTLINE

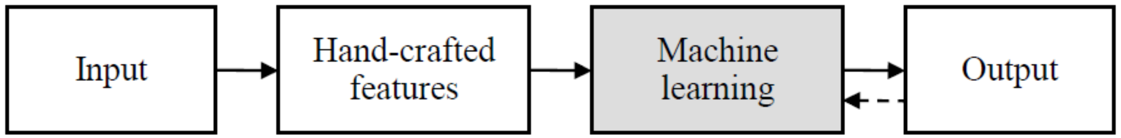
- Biological Inspiration
- Convolutional Layers
- Pooling Layers
- CNN Architectures
- Object Detection
- Semantic Segmentation

EVOLUTION OF COMPUTER VISION

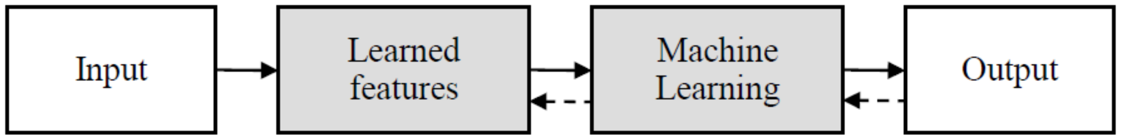
- Classical vision
  - Hand-crafted features and algorithm based on expert knowledge
- Classical machine learning
  - Hand-crafted features (pre-processing) but ML for classification
- Deep learning
  - Both features and classification are learned
  - End-to-end training (from pixels to output)



(a) Traditional vision pipeline

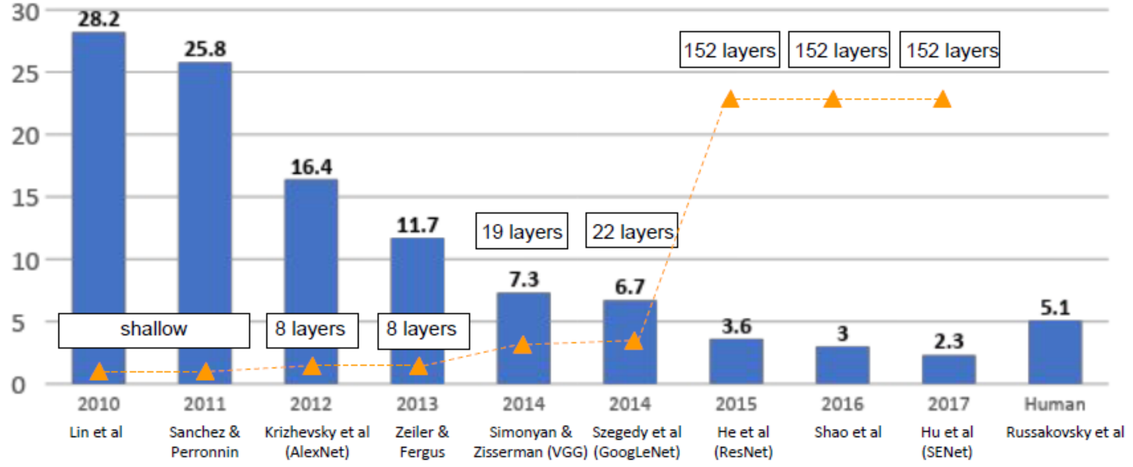


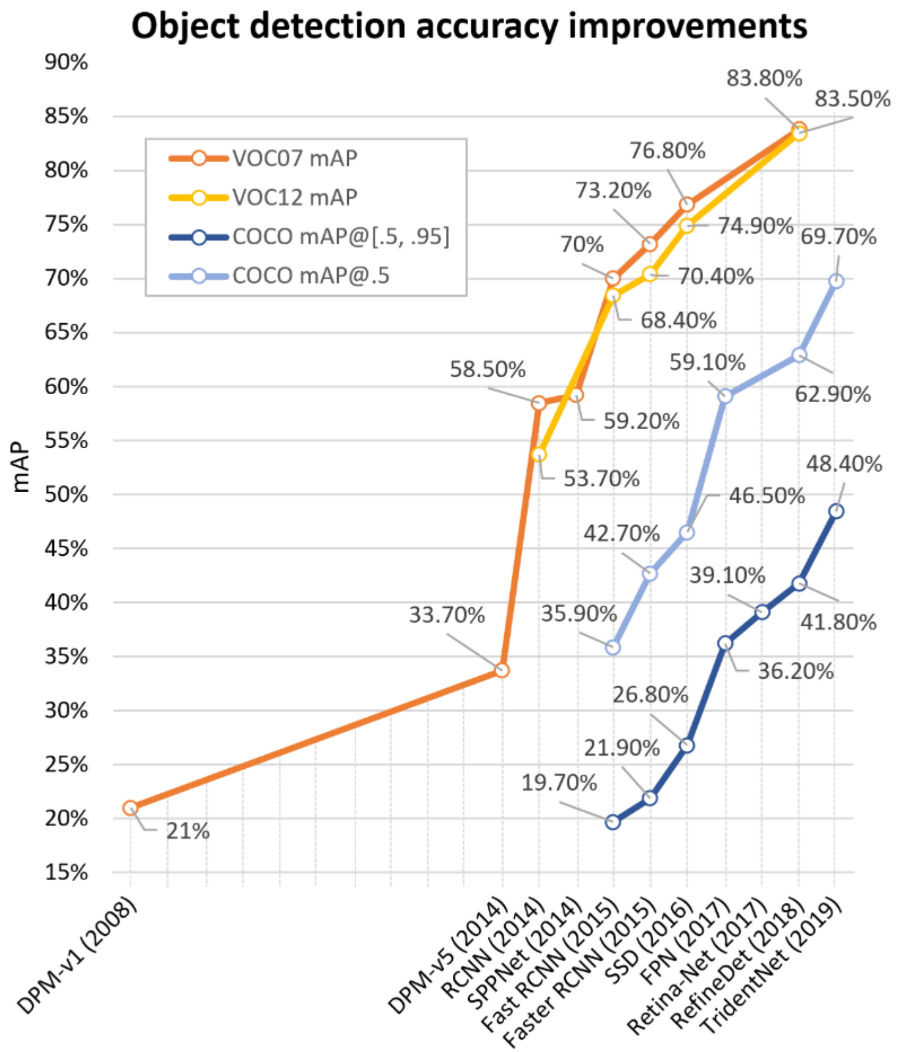
(b) Classic machine learning pipeline



(c) Deep learning pipeline

DEEP CNN DOMINANCE IN CV



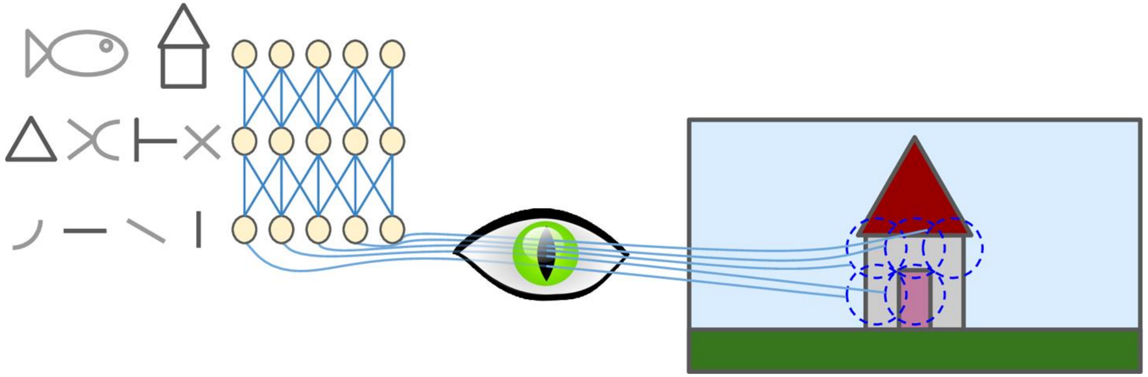


Li, Johnson, and Yeung, 2019

Zou et al., "Object Detection in 20 Years: A survey, 2019

ARCHITECTURE OF THE VISUAL CORTEX

- Modern CV is inspired by human vision (sensory modules)
- Hubel and Wiesel showed that neurons in the visual cortex had a small local receptive field
  - Only reacted to stimuli in a limited region of visual field (blue dashed circles)
- Lower-level neurons with simple pattern response (e.g. lines of specific orientation)
- Higher-level neurons with larger receptive field and combination of lower-level patterns
  - Neurons at higher-levels only connected to few at lower-level

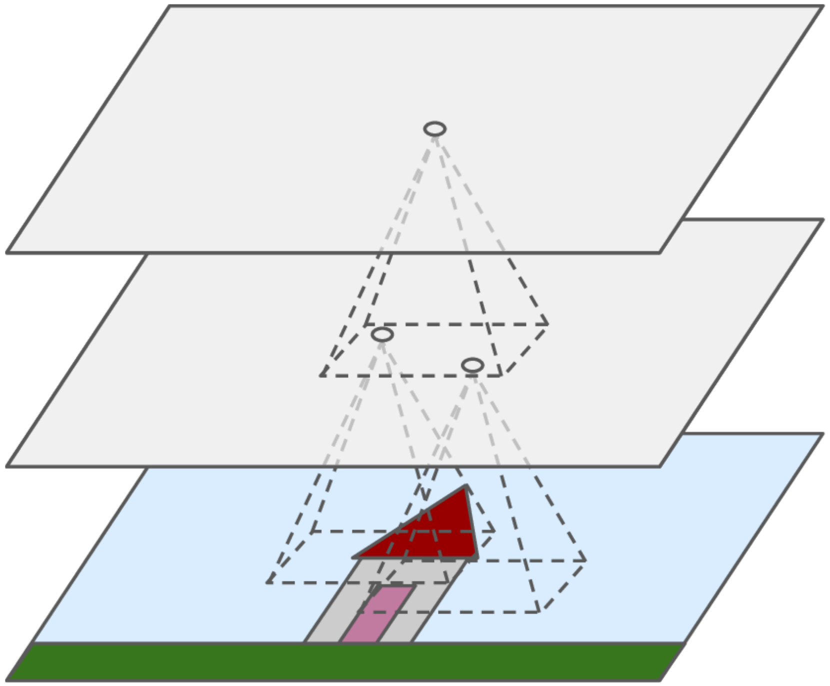


CONVOLUTIONAL NEURAL NETWORK

- Stacked neuron architecture enables detection of complex patterns in any area of the visual field → convolutional neural networks (CNNs)
- Led to LeNet-5 architecture by Yann LeCunn for handwritten number recognition (MNIST)
  - Fully connected layers and sigmoid activations
  - Convolutional layers and pooling layers
- Why not fully connected layers for images?
  - Even small images have large number of pixels resulting in huge networks
  - CNNs solve this with partial connected layers and weight sharing

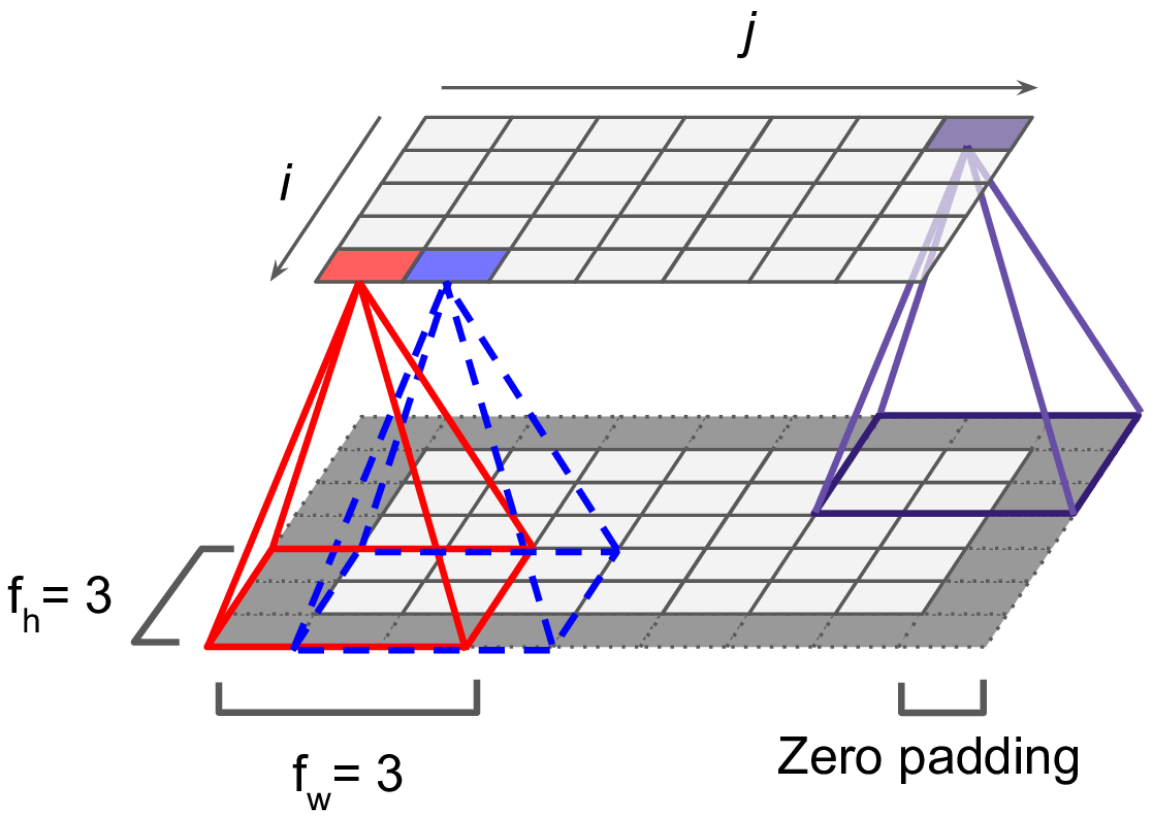
CONVOLUTIONAL LAYERS

- Neurons in the first layer are not connected to every single pixel in input image
  - Connected to receptive field
  - Stacked receptive field approach
- Hierarchical structure
  - First layer – small low-level features
  - Higher-levels – assemble lower-level features into higher-level features
  - Structure is common in real-world images



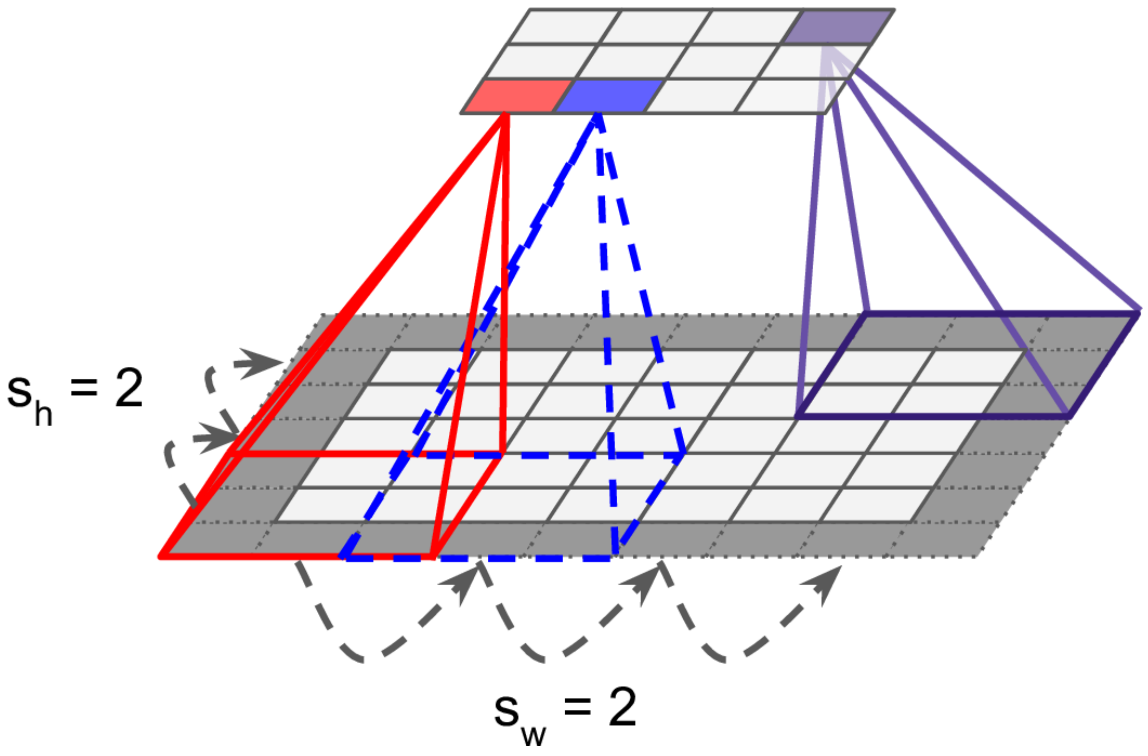
CONVOLUTIONAL LAYER CONNECTIONS

- Note: the actual operation performed is cross-correlation (no-flipping)
- Neuron (row, column) (i, j) is connected to neurons in previous layer within receptive field
  - Row $[i, i + f_h - 1]$
    - f_h - height of receptive field
  - Column $[j, j + f_w - 1]$
    - f_w - width of receptive field
  - Note: this is a causal filter though shown as symmetric
- Zero padding used to keep output/input layers of same size



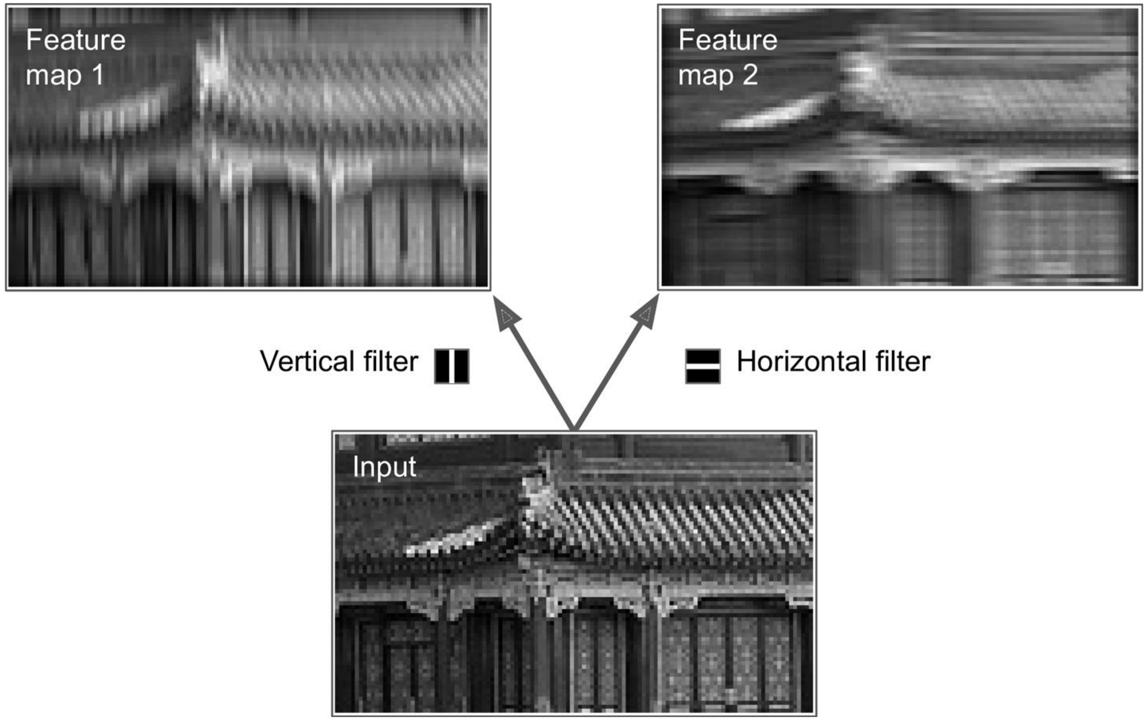
CONVOLUTIONAL LAYERS STRIDE

- Stride can be used to connect a large input layer to smaller output layer
- Change the spacing the of the receptive field
- Dramatically reduce model computational complexity (squared)
  - Height and width stride can be different

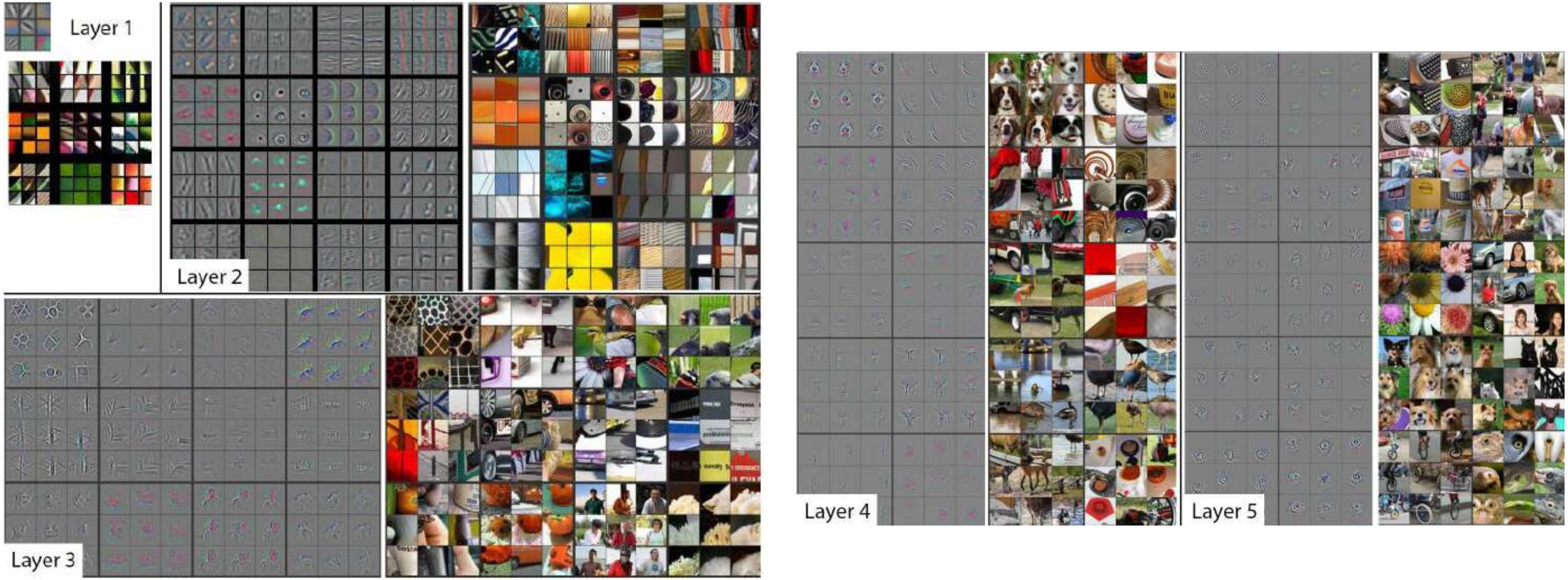


FILTERS

- Filters = convolutional kernels
- Size of the kernel is the receptive field for the neuron
- Feature map – output of the "convolution" operation
  - Highlights areas in an image that activate the filter most
- For CNNs, the filters are not defined manually!
  - Learn most useful filters for a task
  - Higher layers will learn to combine into more complex patterns



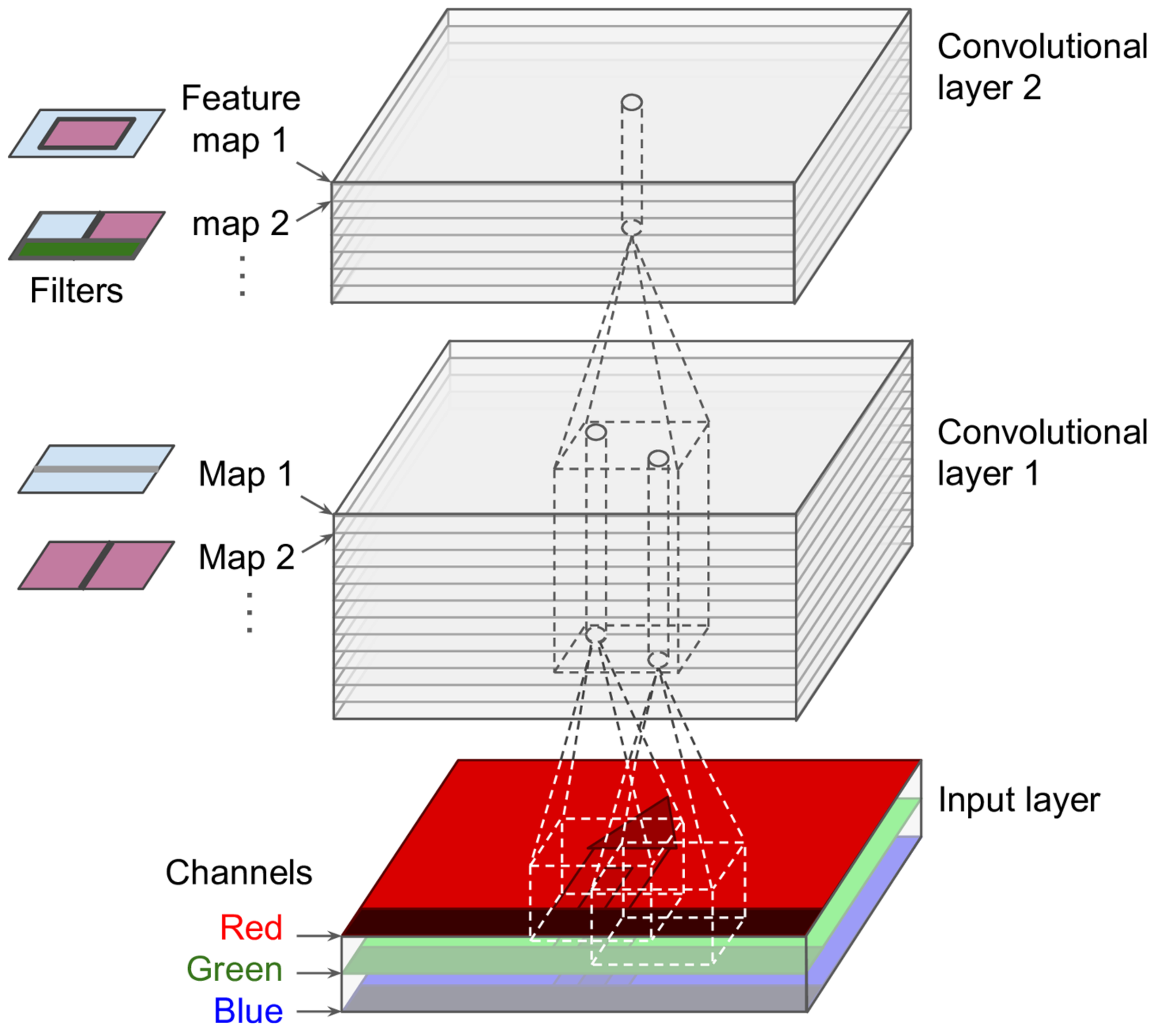
VISUALIZING WEIGHTS AND FEATURES



See Szeliski 2e, Ch 5.4.5

STACKING MULTIPLE FEATURE MAPS I

- Each convolution layer has multiple filters
  - Stacked 3D output (1 feature map for each filter)
- Each neuron in a feature map shares the same parameters (weights and bias)
- Neurons in different feature maps use different parameters
- Neuron's receptive field applies to all feature maps of previous layer
- Note input images often have multiple sublayers (channels)



STACKING MULTIPLE FEATURE MAPS II

- Output of a neuron in a convolutional layer

$$z_{i,j,k} = b_k + \sum_{u=0}^{f_h-1} \sum_{v=0}^{f_w-1} \sum_{k=0}^{f_{n'}-1} x_{i',j',k'} \times w_{u,v,k',k}$$

$$\begin{cases} i' = i \times s_h + u \\ j' = j \times s_w + v \end{cases}$$

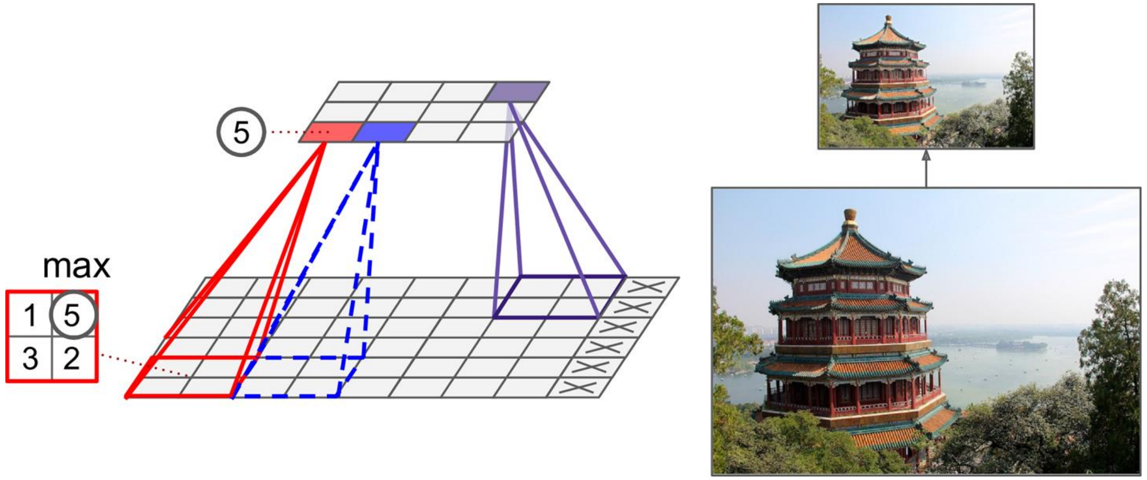
- $z_{i,j,k}$ - output of neuron in row i, column, j, in feature map k of the convolutional layer l
- b_k - bias term for feature map k (in layer l)
  - Tweaks overall brightness of feature map k
- s_h, s_w - vertical and horizontal strides
- f_h, f_w - height and width of receptive field (kernel)
- $f_{n'}$ - number of feature maps in previous (lower layer)
- $x_{i',j',k'}$ - output of neuron located in layer $l-1$, row i', column j', feature map k
- $w_{u,v,k',k}$ - connection weight between any neuron in feature map k of the layer l and its input located at row u, column v (relative to the neuron's receptive field), and feature map k'

MEMORY REQUIREMENTS

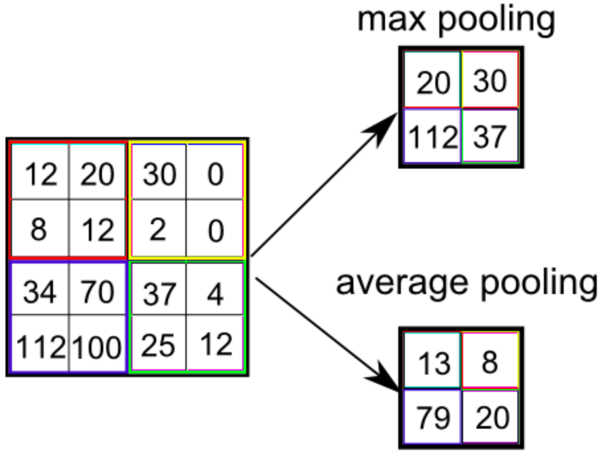
- Though much smaller the fully connected networks, CNNs still use significant amount of RAM
- During training, the reverse pass of backpropagation requires all the intermediate values computed during the forward pass
  - Need to have enough for all layers in the network
  - Forward pass can release memory after each layer is computed (only two consecutive layers required)
- Out-of-memory error
  - Reduce mini-batch size, increase stride, remove layers, change precision (16-bit vs 32-bit floats or use int), or distribute the CNN across devices

POOLING LAYERS

- Subsample input in order to reduce computational load, memory usage, and number of parameters (reduce risk of overfitting)
- Aggregate over the receptive field
  - Aggregate functions such as max (most popular) or mean
  - Max tends to work better by preserving only the strongest feature → cleaner signal, more invariance, less compute
- Stride gives downsampling
- Pooling kernel size can be even

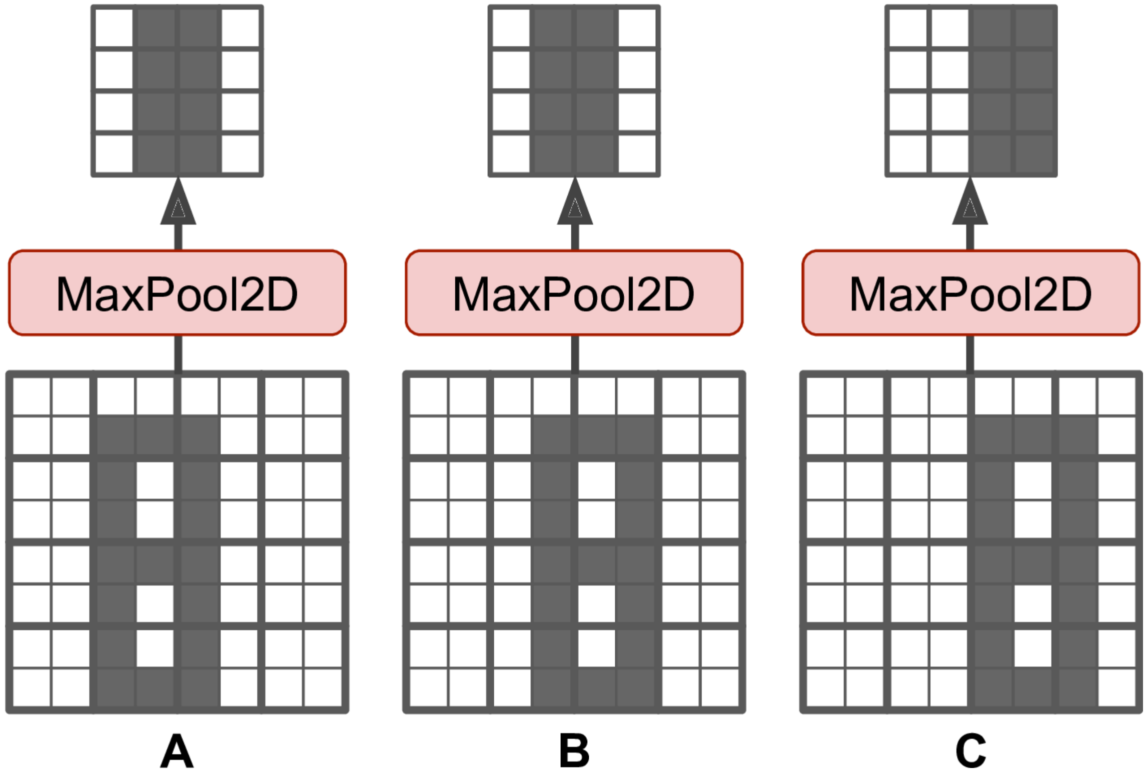


Max pooling layers (2x2 kernel, stride=2, no padding)



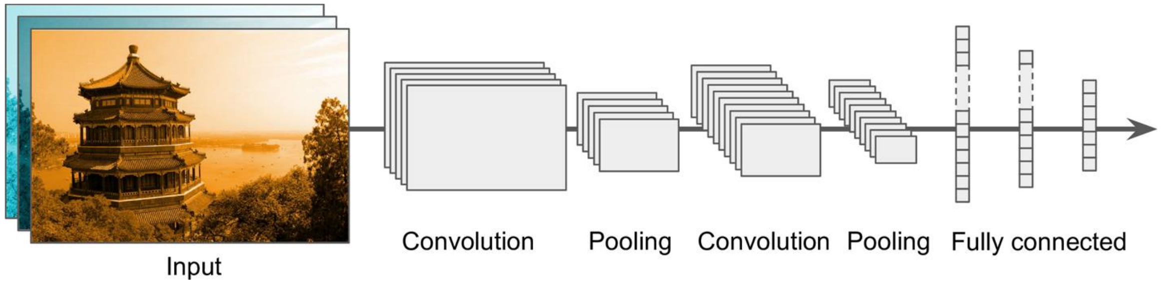
POOLING LAYERS INVARIANCE

- Introduces some level of invariance to small translations
  - Small image shifts result in same response
  - Additionally small invariance to rotation and scale with max pool
- Max pool every few CNN layers for invariance at larger scale
  - Useful when task should be invariant (e.g. image classification)
- Drawbacks
  - Destructive – 2x2, stride 2 drops 75% of input values
  - Invariance not always desirable (e.g. semantic segmentation should have equivariance)



CNN ARCHITECTURES

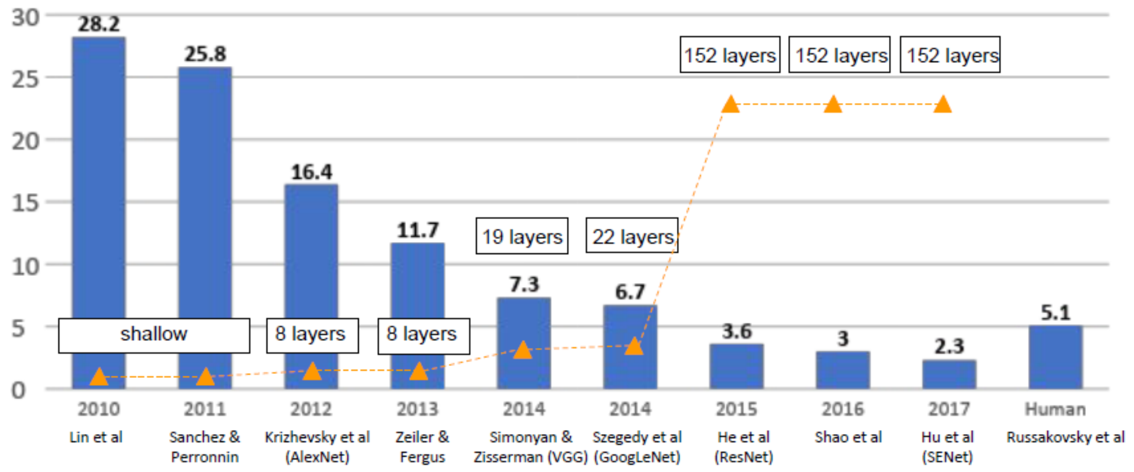
- Typical CNN architecture
  - Stack a few convolutional layers (each followed by ReLU layer for non-linearity)
  - Pooling layer
  - Repeat Conv + ReLU + Pool
  - Top layers are regular feedforward neural network which is usually fully connected layers (+ReLUs)
  - Final layer outputs the prediction (e.g. softmax for class probabilities)



- Input kernel can be larger since generally only 3 sublayers (RGB channels)
- Conv layers use stacked small 3x3 kernels since it is more computationally efficient and perform better than larger
- Number of filters increases at higher layers
  - Few low-level patterns, but more ways to combine
  - Double #filters after pooling (stride 2)
- Flatten conv output before fully connected dense layer
  - Add dropout to avoid overfitting

ILSVRC IMAGENET CHALLENGE

- Variants of basic CNN architecture have been developed
- Benchmark with ImageNet Challenge
  - Large scale with 1M images and 1000 classes
  - Much more complicated than any benchmark at the time (~2010)
- Dramatic drop in top-five error from 26% to 2.3% in 6 years
  - Bigger is better



LENET-5

- Network of Yann LeCun (1998) [NYU] designed for handwritten digit recognition (MNIST)
- Images normalized at input
- No padding → smaller size each layer
- Average pool has learnable coefficient and bias term
- Limited C3-S2 map connections
- Output square Euclidean distance
  - Similar cross-entropy

Table 14-1. LeNet-5 architecture

Layer	Type	Maps	Size	Kernel size	Stride	Activation
Out	Fully connected	–	10	–	–	RBF
F6	Fully connected	–	84	–	–	tanh
C5	Convolution	120	1 × 1	5 × 5	1	tanh
S4	Avg pooling	16	5 × 5	2 × 2	2	tanh
C3	Convolution	16	10 × 10	5 × 5	1	tanh
S2	Avg pooling	6	14 × 14	2 × 2	2	tanh
C1	Convolution	6	28 × 28	5 × 5	1	tanh
In	Input	1	32 × 32	–	–	–

http://yann.lecun.com/exdb/lenet/index.html

ALEXNET

- 2013 ImageNet winner
  - 17% top-5 error rate (26% for 2nd place)
  - Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton [U Toronto]
- Similar to LeNet-5 but larger and deeper
- First to stack convolutional layers directly on top of one another (no pooling in between)
- To reduce overfitting
  - 50% dropout of layers F9 and F10
  - Data augmentation
- Local response normalization used to inhibit neighboring feature maps
  - Encourage different feature maps to specialize, push neighbors apart, and improve generalization

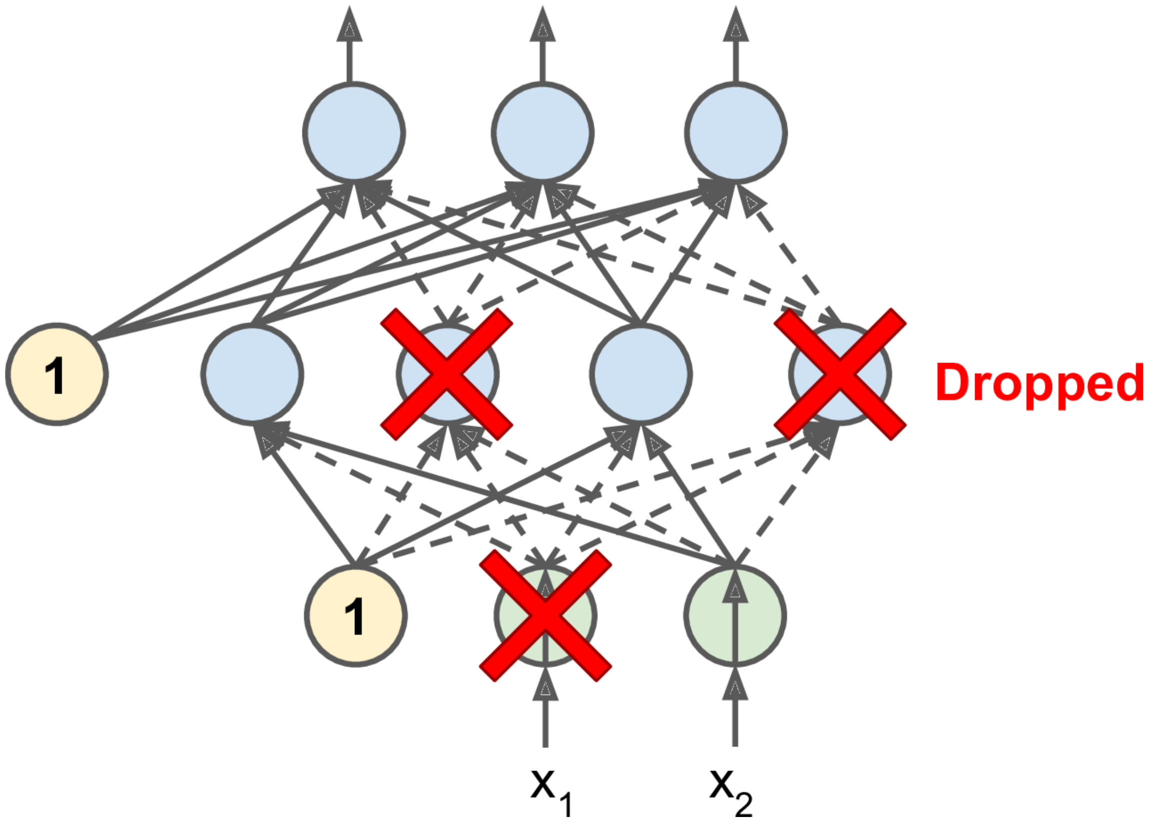
Table 14-2. AlexNet architecture

Layer	Type	Maps	Size	Kernel size	Stride	Padding	Activation
Out	Fully connected	–	1,000	–	–	–	Softmax
F10	Fully connected	–	4,096	–	–	–	ReLU
F9	Fully connected	–	4,096	–	–	–	ReLU
S8	Max pooling	256	6 × 6	3 × 3	2	valid	–
C7	Convolution	256	13 × 13	3 × 3	1	same	ReLU
C6	Convolution	384	13 × 13	3 × 3	1	same	ReLU
C5	Convolution	384	13 × 13	3 × 3	1	same	ReLU
S4	Max pooling	256	13 × 13	3 × 3	2	valid	–
C3	Convolution	256	27 × 27	5 × 5	1	same	ReLU
S2	Max pooling	96	27 × 27	3 × 3	2	valid	–
C1	Convolution	96	55 × 55	11 × 11	4	valid	ReLU
In	Input	3 (RGB)	227 × 227	–	–	–	–

ZF Net is an AlexNet variant with tweaked hyperparameters

DROPOUT

- Popular technique from Hinton 2012 and Srivastava et al. 2014
  - 1-2% accuracy boost (even SOTA)
- At each training step, a neuron has a probability of being ignored (dropped out)
  - Neuron can be active during next training step
- Dropout rate generally between 10-50%
  - 20-30% for recurrent neural networks
  - 40-50% for CNNs
- Forces networks to diversify
  - Neurons cannot co-adapt with neighbors
  - Cannot rely only an a few input neurons
  - Less sensitive to slights changes in input
  - ~Average of many networks



DATA AUGMENTATION

- Artificially increase training dataset size by generating realistic variants of training instances
  - Ideally, shouldn't be able to distinguish real from augmented example
- Reduces overfitting (regularization technique)
- Common augmentations
  - Small shifts, rotation, resize (scaling)
  - Horizontal flip – orientation invariance
  - Vary contrast – lighting condition invariance

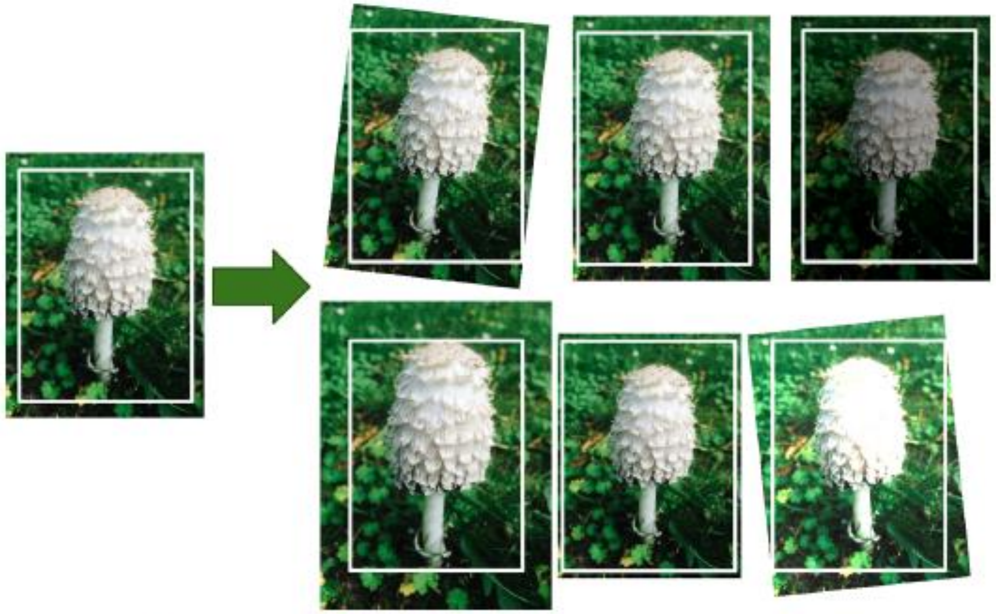
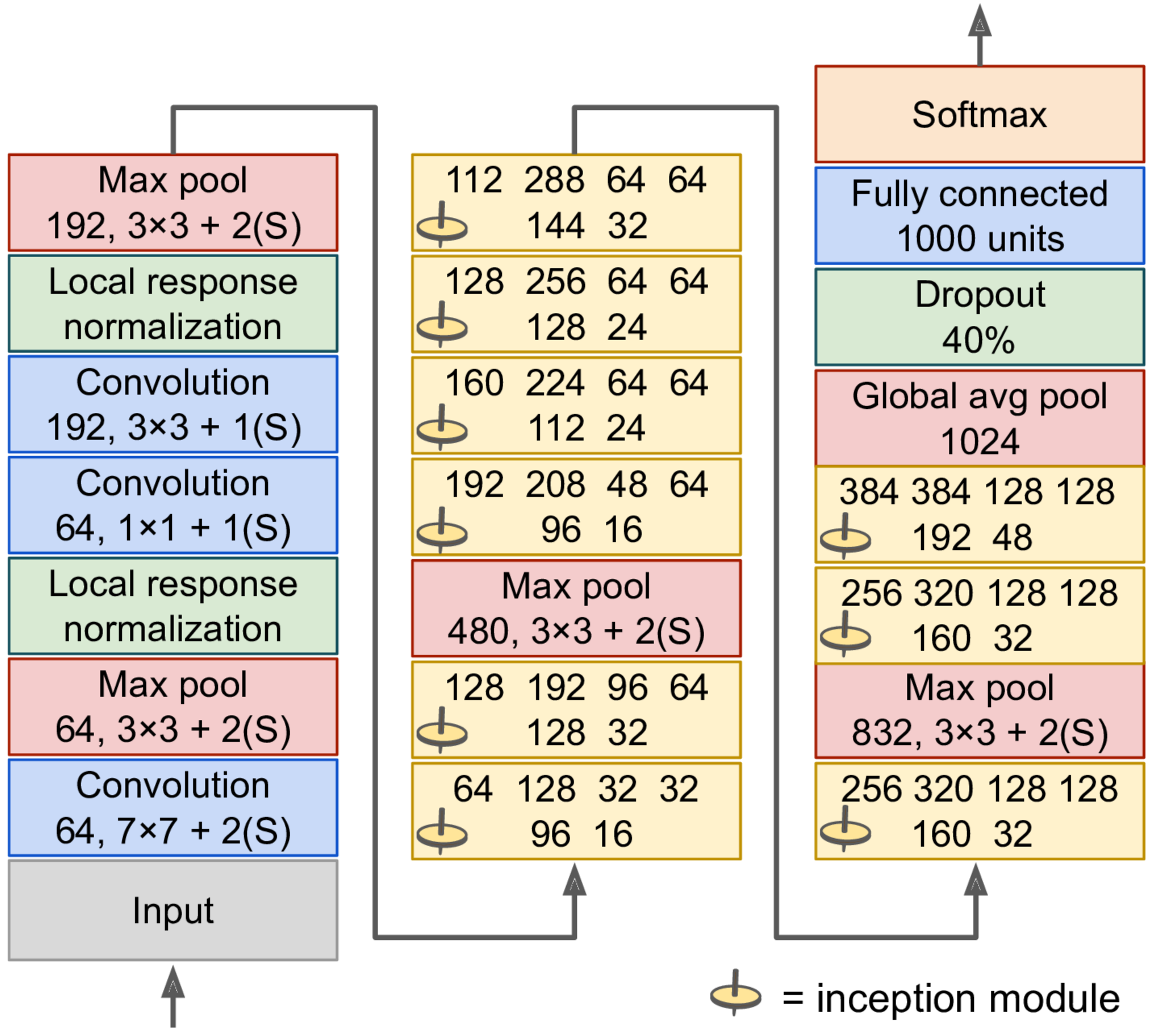


Figure 14-12. Generating new training instances from existing ones

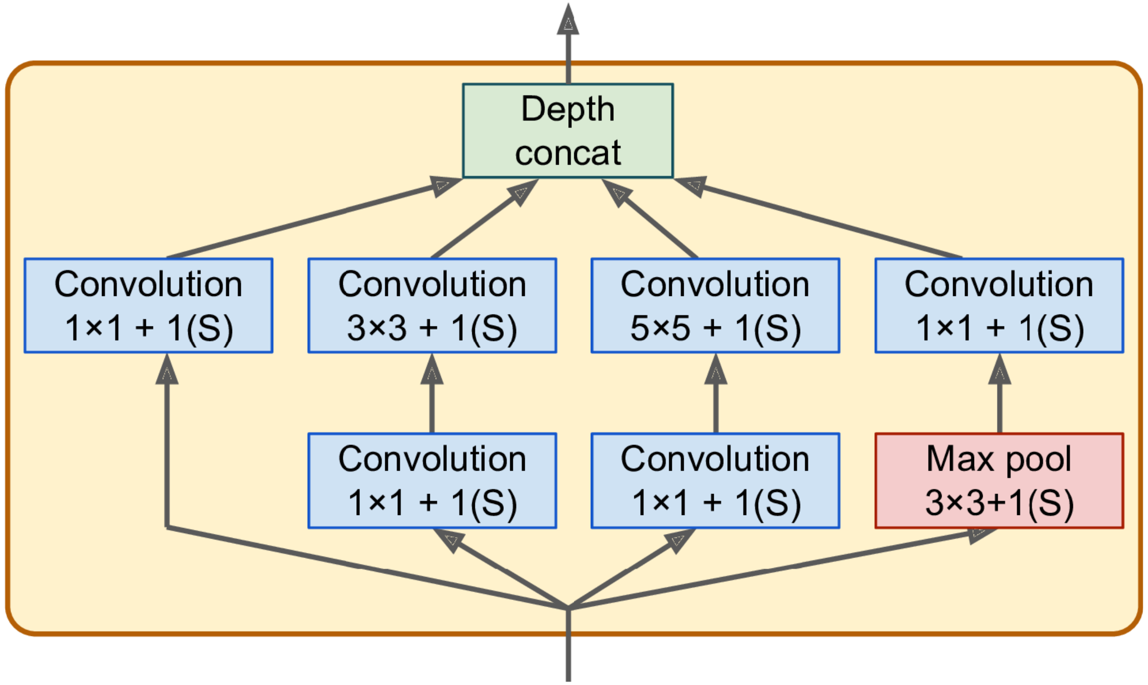
GOOGLENET (INCEPTION)

- 2014 ILSVRC Winner
  - <7% top-5 error rate
  - Christian Szegedy et al. [Google]
  - Current versions Inception-v3 and Inception-v4 (GoogLeNet + ResNet)
- Much deeper architecture than previous CNN (large stack)
  - Much fewer parameters (6M vs. 60M AlexNet)
- Inception layers for parameter efficiency
- Use of 1x1 convolutions as a bottleneck layers
- Local response normalization to learn a wide variety of features
- Classification task with multiple (max) pool to reduce size (avg. final 7x7 map)
  - No need for multiple fully connected (FC) layers to save parameters



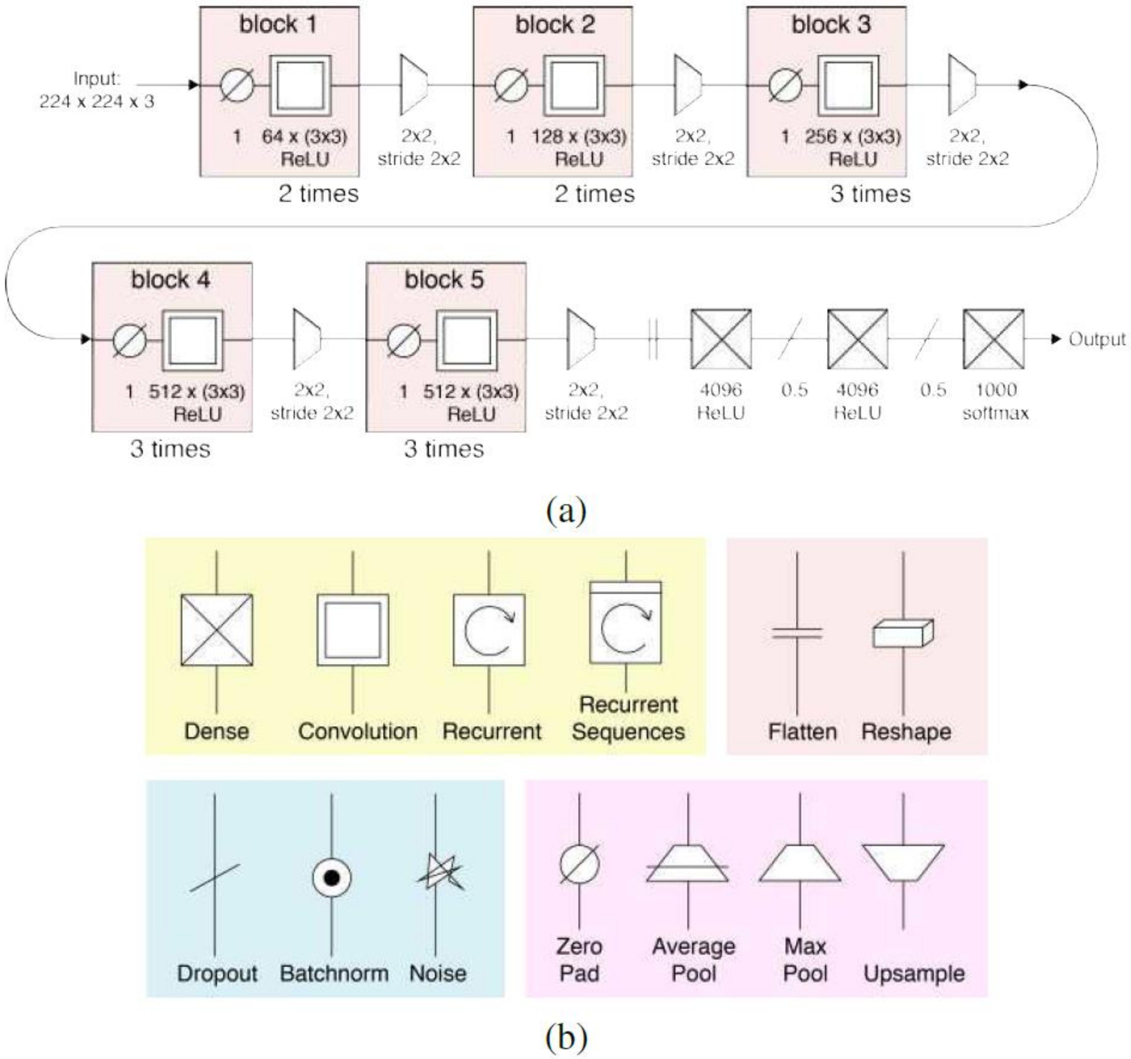
INCEPTION MODULE

- Parallel convolutions
  - 3x3+1(S) = 3x3 kernel, stride 1, “same” padding
  - All use ReLU activation
- 2nd convolution layer
  - Different kernel size for patterns at different scale
  - Stacked conv for more complex patterns than single linear convolution
- Depth concat
  - All layers have the same outputs size
  - Stack 2nd layer outputs depthwise
- 1x1 bottleneck layers
  - Fewer output than input dimension
  - Fewer parameters, faster training, improved generalization
  - Not spatial but depth patterns



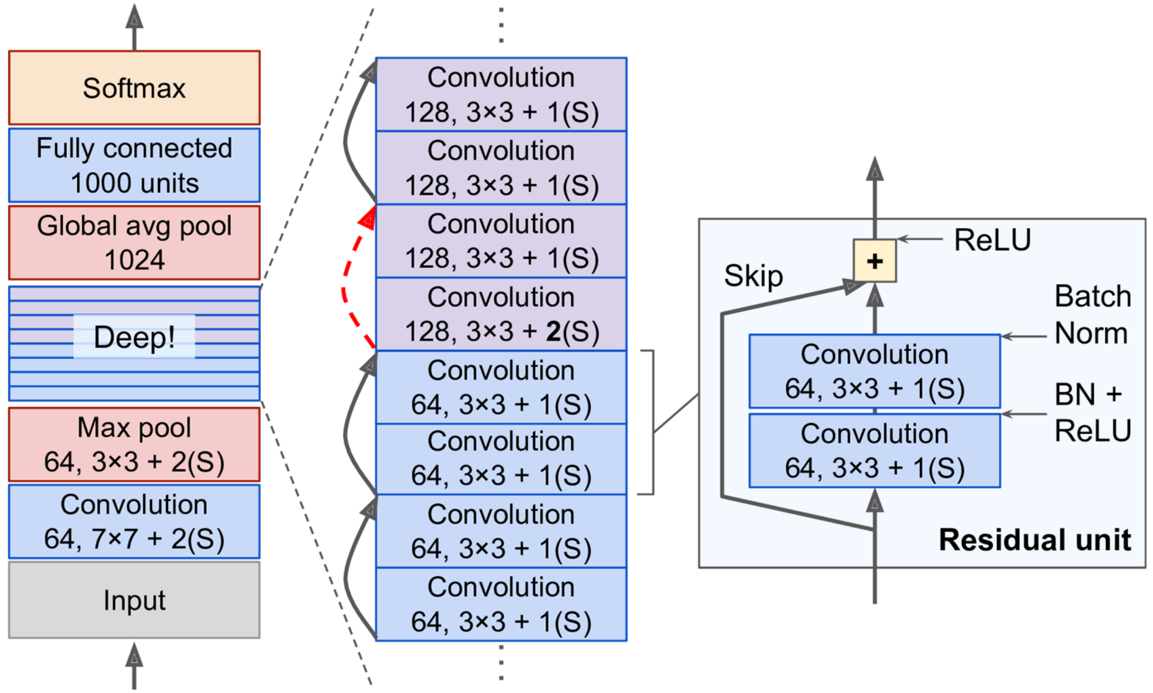
VGGNET

- 2014 ILSVRC runner-up
  - Simonyan and Zisserman [Oxford]
- Classical architecture
  - Stacked 2-3 conv + pool layers
  - Variants of 16 or 19 conv layers
  - 3 FC classification layers
- Used many 3x3 filters



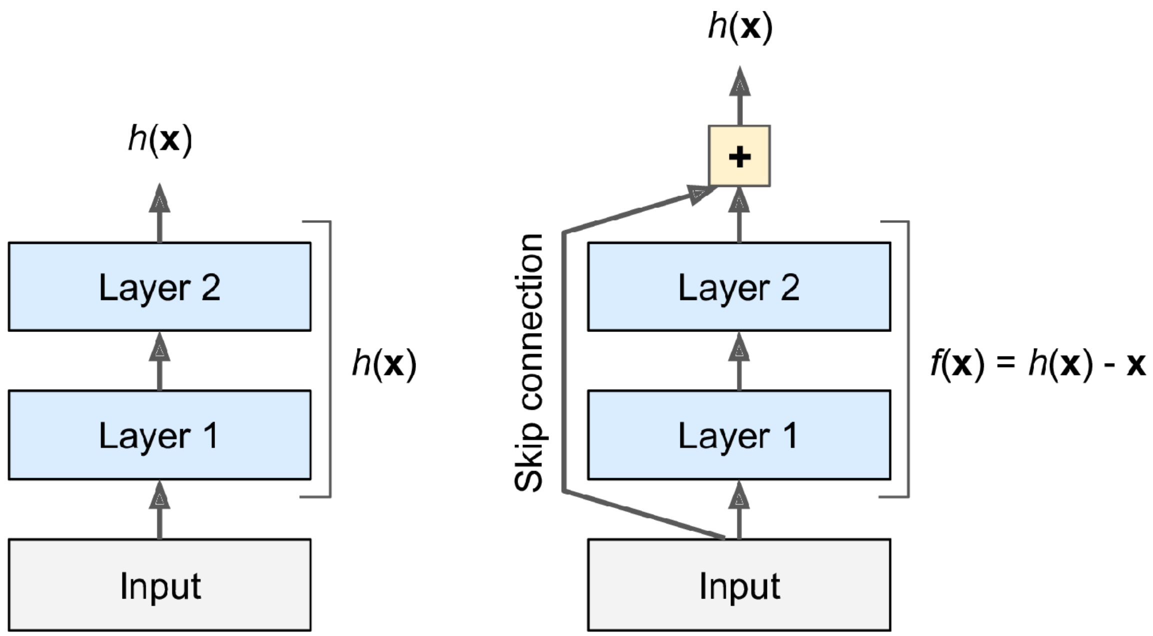
RESNET

- 2015 ILSVRC winner
  - <3.6% top-5 error rate
  - Kaiming He et. Al [Microsoft]
- Deeper with fewer parameters
  - 152 layer winner
  - Variants of 34, 50, and 101 layers
- Skip (shortcut) connections
  - Signal passed into up one layer and a further layers ahead
  - Build network on residual units (RUs)
- Batch normalization (pg 338)
  - Better gradient conditioning (vanishing gradient)
  - Standardize inputs then rescales and offsets
  - Acts as a regularizer (e.g. no need for dropout)



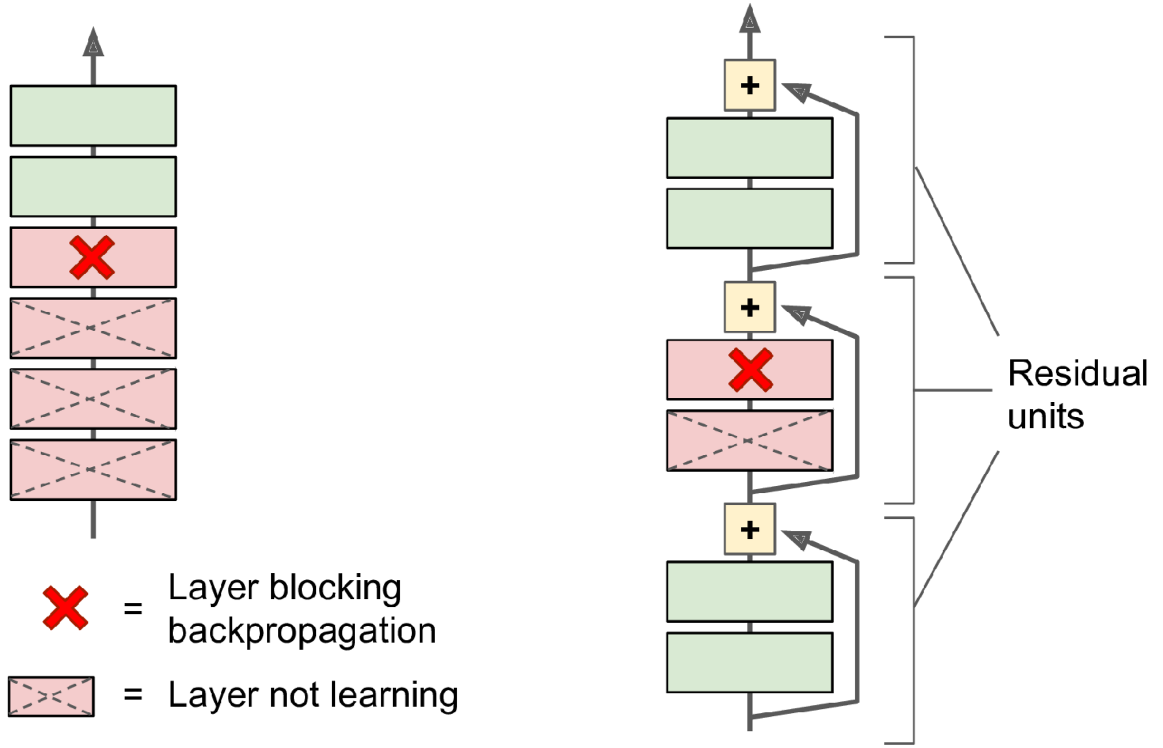
RESIDUAL LEARNING I

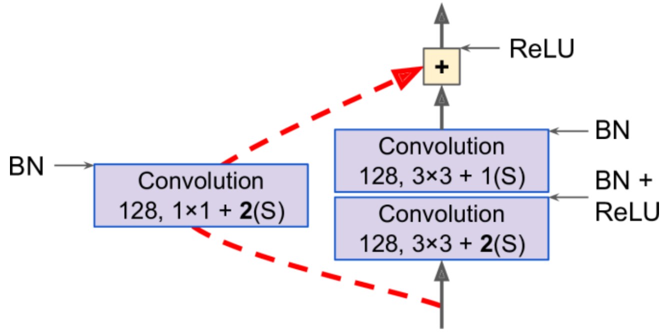
- Signal feeding layer is also added to the output of a layer higher in the stack
- Instead of modeling function $h(x)$, it models $f(x) = h(x) - x$
- Faster weight update (0 initialization)
  - Regular networks output 0
  - Skip connection copies input (identity function)



RESIDUAL LEARNING II

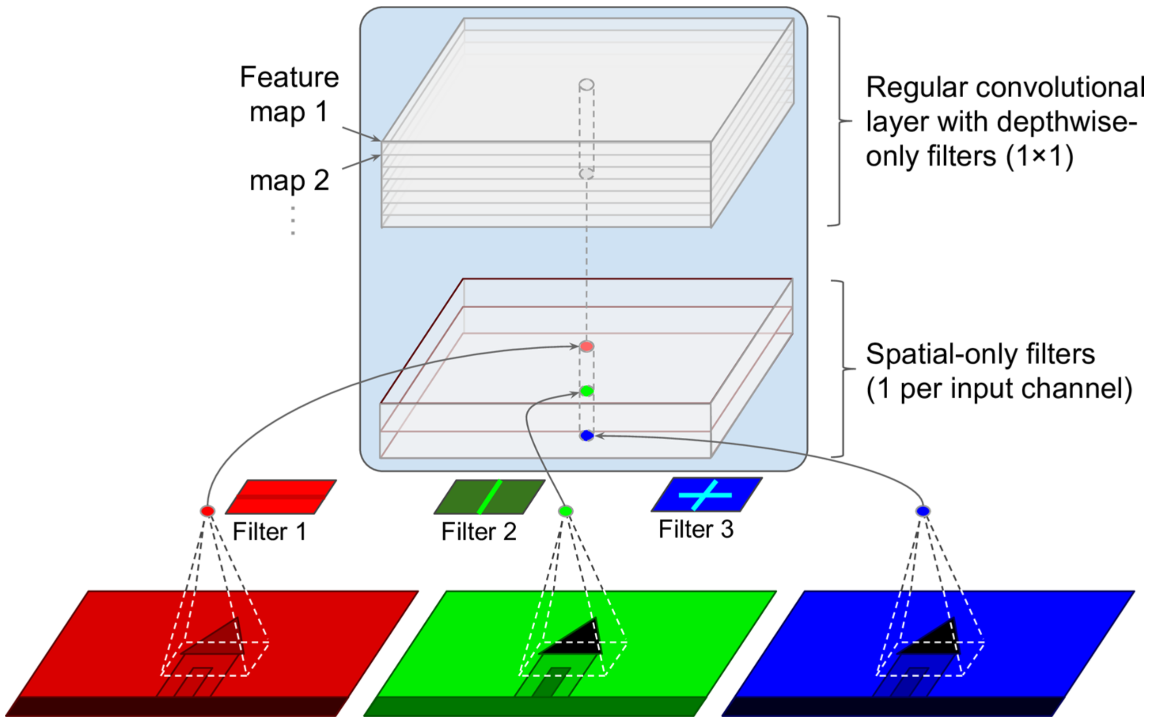
- Skip connection bypass layer blocking
  - Input signal can propagate to higher levels
  - Can train layers even if lower layers have not started learning yet
- Feature map size and depth change
  - Skip connection prevents direct addition after resize
  - 1x1 convolution, stride 2, and output matched kernel size





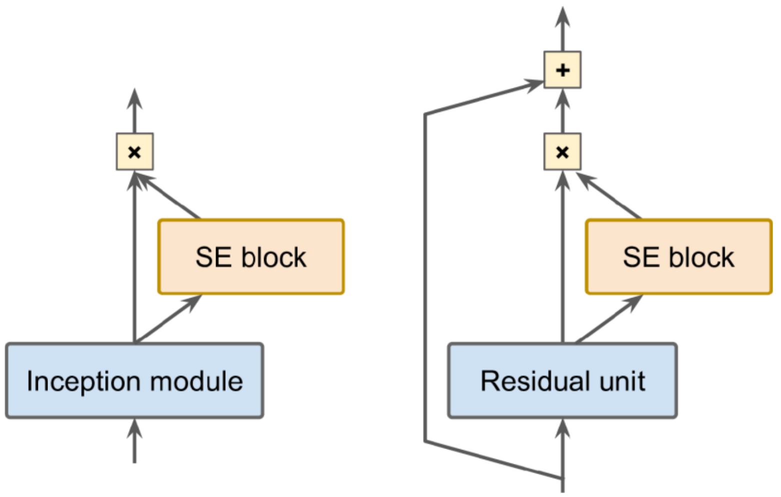
XCEPTION

- GoogLeNet variant
  - Combines GoogLeNet + ResNet
  - Inception modules replaced with depthwise separable convolution layer
  - Chollet 2016 (Keras author)
- Separable convolution layer
  - Separate spatial and depth
  - 1 spatial filter per input channel
  - Use on layers with many feature channels (not on input/early layers)
  - Fewer parameters, less memory, fewer computations, and generally perform better

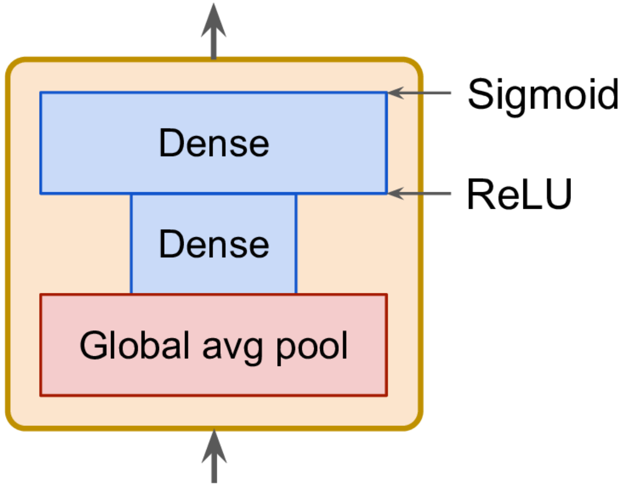


SENET

- 2018 ILSVRC winner
  - Squeeze-and-Excitation Network
  - 2.25% top-5 error rate
  - Built on Inception (SE-Inception) and ResNets (SE-ResNet)

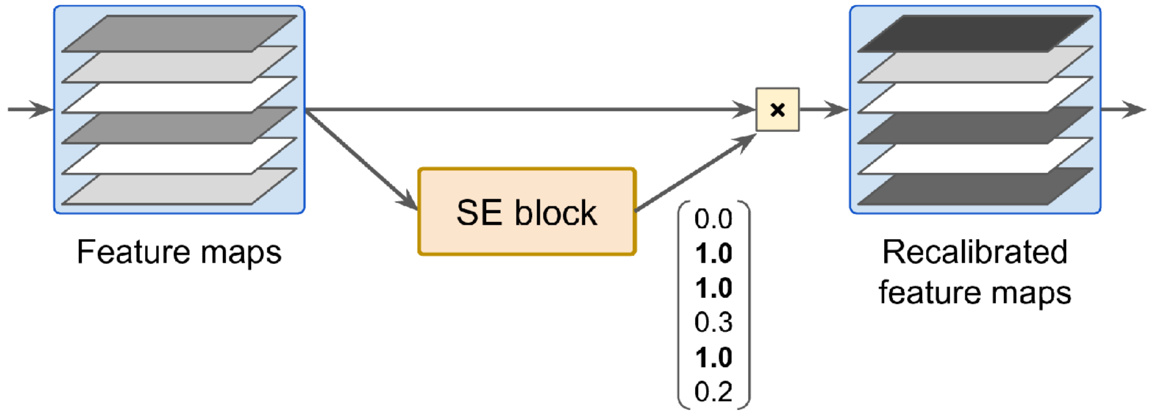


- SE block
  - Global average pool: mean of each feature map
  - "Squeeze" (bottleneck)
    - Dramatically reduce number of maps for low dimensional embedding of feature distribution
    - Force SE block to learn general representations of feature combinations
  - Output: recalibration vector (boost normally co-occurring features)



SE BLOCK

- Analyze output of attached unit to learn features that are usually most active together (depth search)
- Recognizes features that respond together (mouth, nose, eyes) and boosts features that are missing/low response (e.g. eyes)
- Recalibration steps solves ambiguity when feature is confused with something else



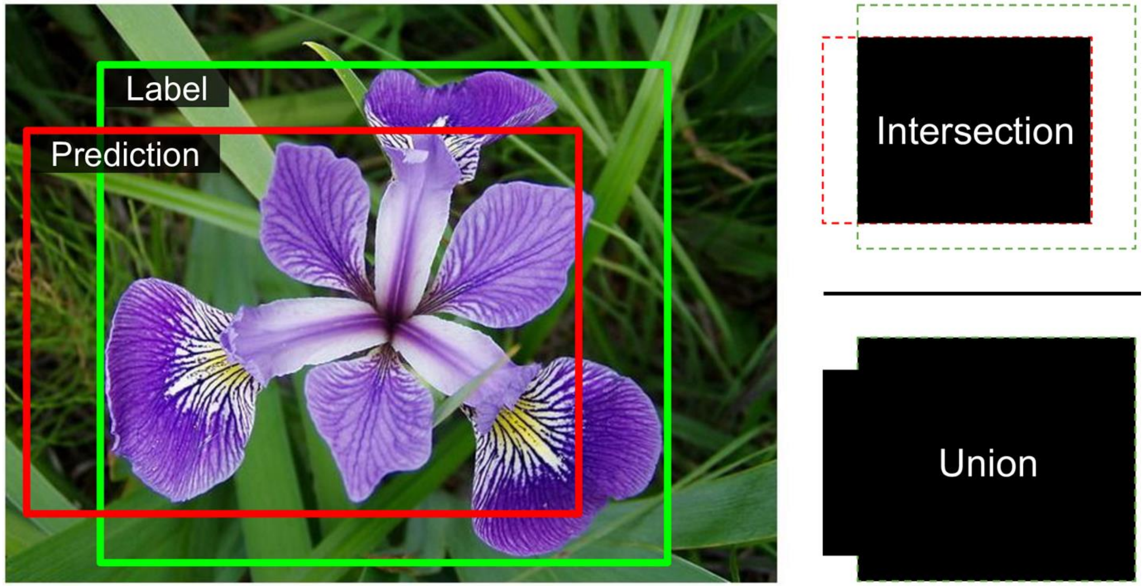
PRETRAINED MODELS AND TRANSFER LEARNING

- Don't implement models from scratch by hand, use existing implementations
  - Known as backbone network
- Models pretrained on ImageNet
  - Good general features
  - Models expect specific size and pre-processing (e.g. normalization)
- Only requires a few lines of code

- Transfer learning
  - Utilize strong backbone and adjust last layers for a specific task
- Useful when not working with ImageNet classes (all the time) and with limited training data
- Initialize network with ImageNet weights and only train higher layers (e.g. classification or minimal conv)

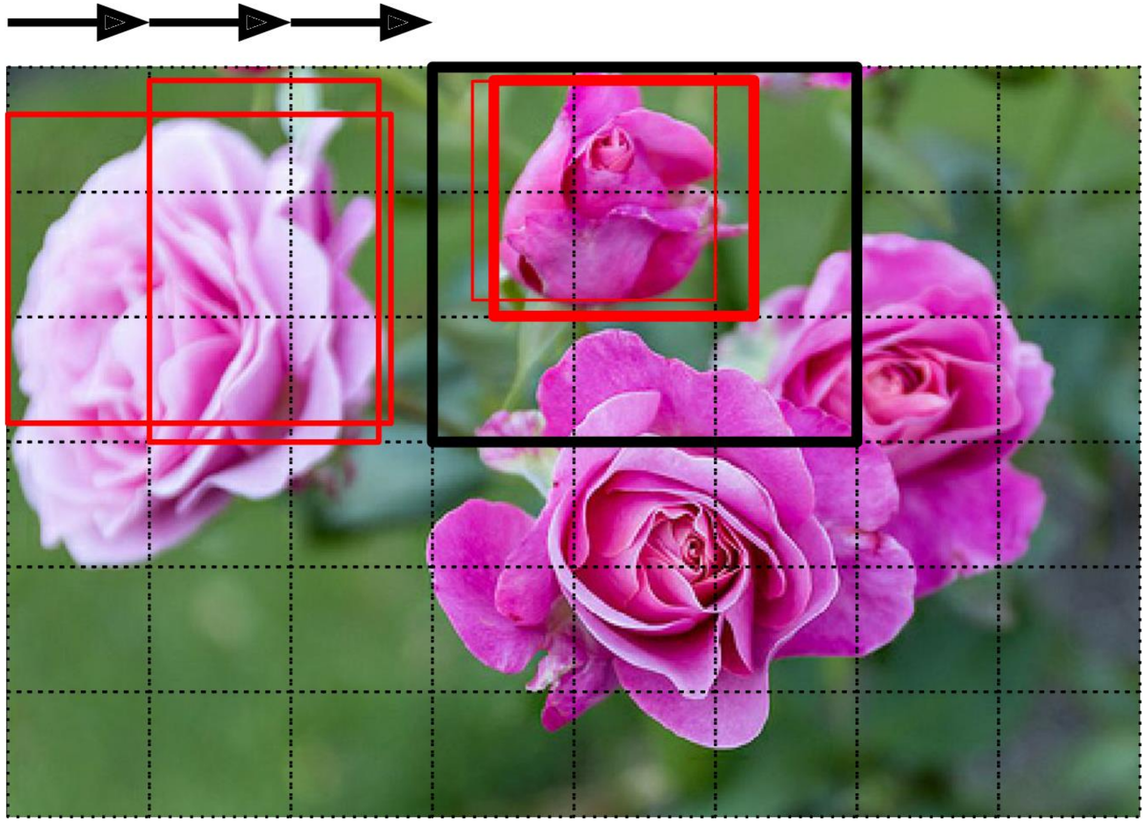
CLASSIFICATION AND LOCALIZATION

- Classification – identify the image class
- Localization – provide a bounding box for the image class
  - Expressed as a regression task [x, y, w, h]
  - Assumption of a single object per image
  - Much of the work is in labeling the data with bounding boxes
    - Many tools exist (e.g. VGG Image Annotator, LabelImg, OpenLabeler, ImgLab, LabelBox, Suervisely)
  - Evaluated with intersection over union (IoU) the overlap



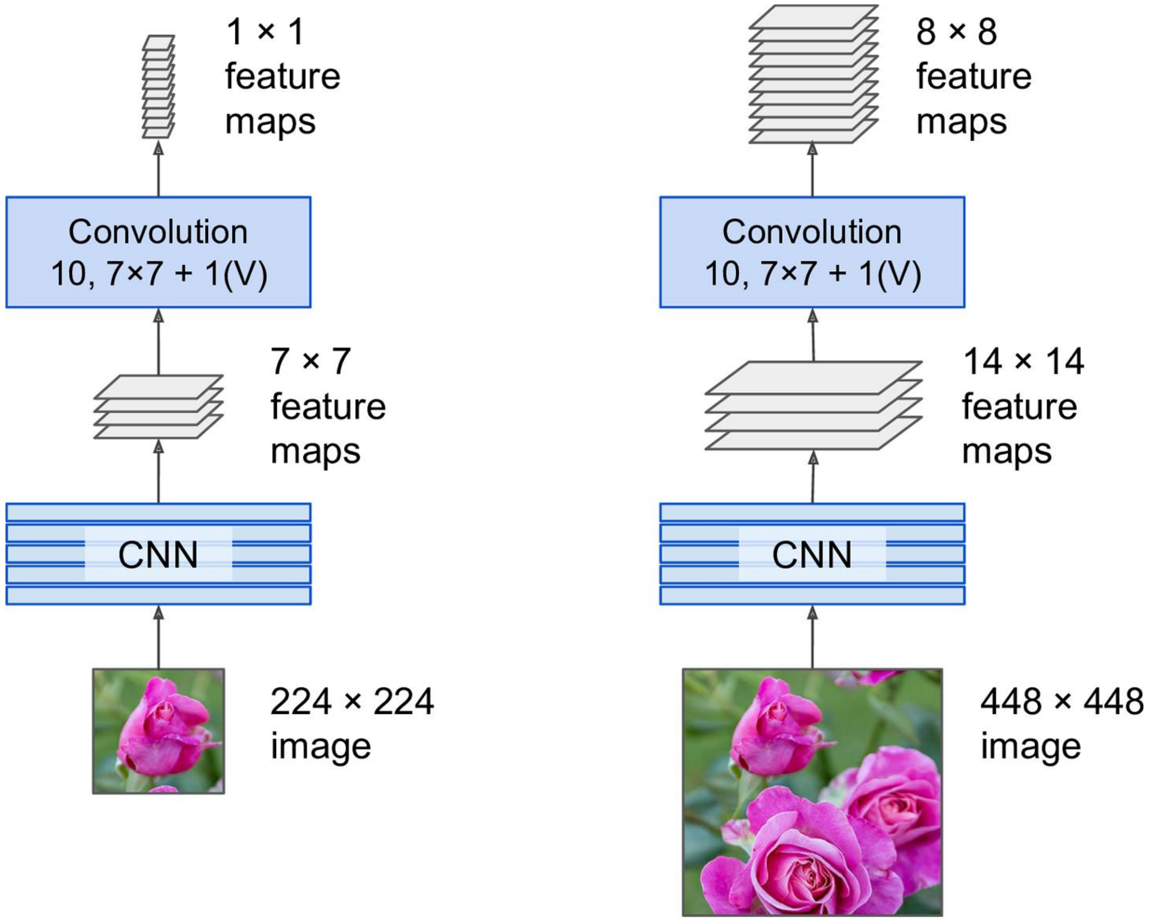
OBJECT DETECTION

- Task of classifying and localizing multiple objects in an image
- Early attempts used a sliding window
  - Run classification CNN over each window in the image
  - Need search at scale (multiple passes)
  - Get multiple responses to same object → NMS
    - Objectness score to remove responses
    - Merge responses with high IoU



FULLY CONVOLUTIONAL NETWORKS

- Introduced by Long CVPR 2015 for semantic segmentation
- Replace dense classification with convolutional layers
  - Same number of operations but with different output tensor shape
  - Allows processing input of any size (unlike dense layer with fixed input size)
- For larger image, equivalent to sliding CNN across image in blocks

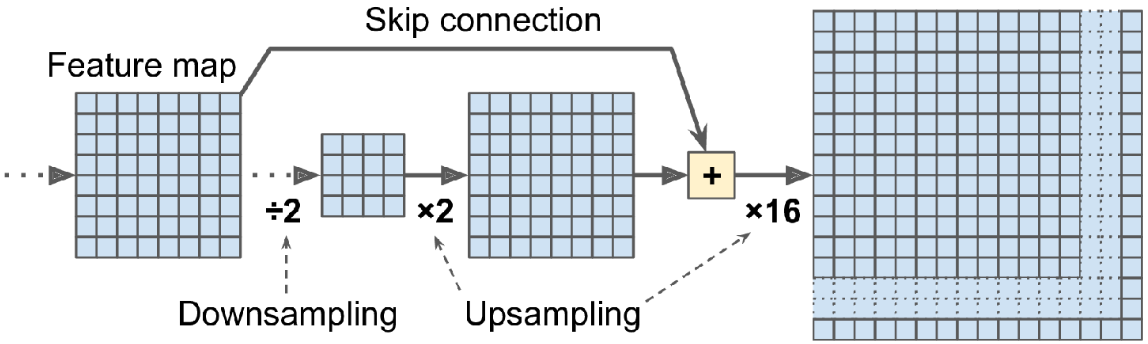


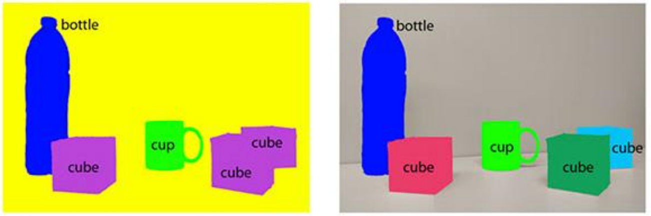
OBJECT DETECTION ARCHITECTURES

- Fast(er) R-CNN
  - Apply FCN approach with region proposals
  - Fast R-CNN uses Selective Search
  - Faster R-CNN uses a small region proposal network to predict bounding boxes
- YOLO (you only look once) – major shift in approach with a single CNN pass
  - Divide image into cells and predict 5 bounding boxes per cell
  - Predicts bbox offset rather than absolute location (smaller range)
  - Use of anchor boxes (bounding box priors) as prototypical object dimensions
  - Trained with images of different scale → detect different scale
- SSD (single shot detector)
  - Better accuracy than YOLO
  - Use of MultiBox with decreasing convolutional layers for detection scales
  - More bounding box predictions than YOLO

SEMANTIC SEGMENTATION

- Each pixel is classified according to the class of the object it belongs
  - Different objects of same class are not distinguished (panoptic segmentation)
- Traditional CNNs lose spatial resolution due to layer stride
  - Need to "upsample" coarse feature map
  - Use transposed convolutional layer
  - Add skip connections for better resolution
- Instance segmentation – each object is distinguished from each other
  - Mask R-CNN, Kaiming He 2017 as extension of Faster R-CNN to produce pixel mask for each bounding box





(c) Semantic segmentation (d) Instance segmentation