Deep Learning - MAI

Convolutional neural networks

THEORY

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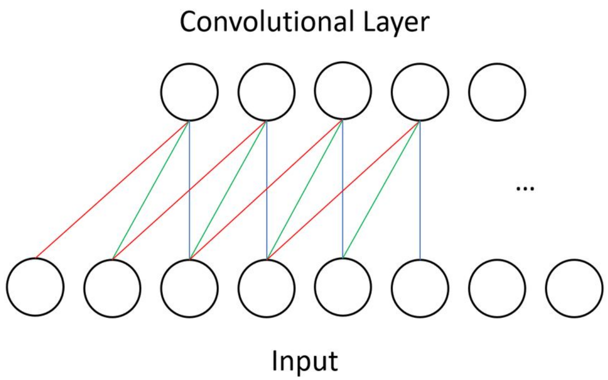
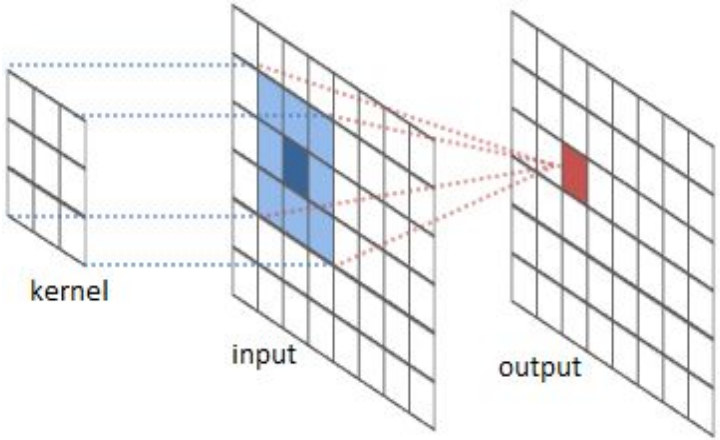
Spatial Connectivity

- Some data has spatial correlations that can be exploited
  - 1D, 2D, 3D, ...
- Near-by data points are more relevant than far-away.
- Sparsify connectivity to reduce complexity and ease the learning





Weight Sharing

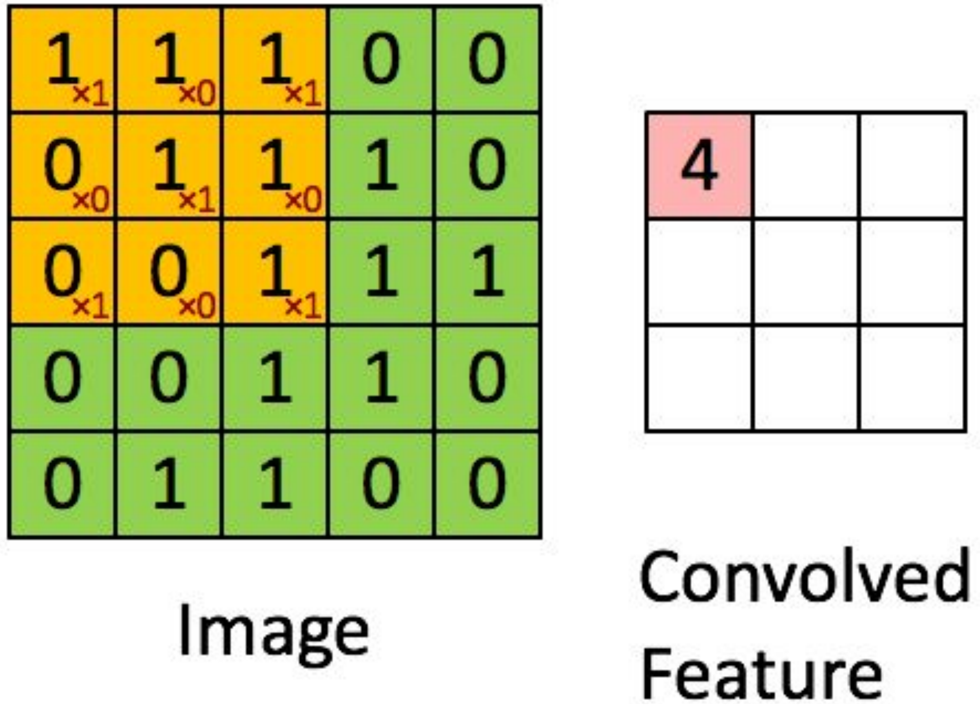
- Sparse connectivity is nice, but we want to apply filters everywhere.
- Each filter will get convolved all over the image: 2D activations matrix
- In static we have sets of neurons sharing weights
- In this context, what is a neuron?

Convolution in Action

Kernel size 3x3
(neuron input = 9)

1 0 1
0 1 0
1 0 1

Detect 'X'



Filter convolution process

Activations (pre-func.)

Image Transformations

- Convolving filters transform the image
- Let the model learn the kernels it needs

Edge detection	$\begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix}$	
Sharpen	$\begin{bmatrix} 0 & -1 & 0 \\ -1 & 5 & -1 \\ 0 & -1 & 0 \end{bmatrix}$	
Gaussian blur 3 × 3	$\frac{1}{16}\begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix}$	

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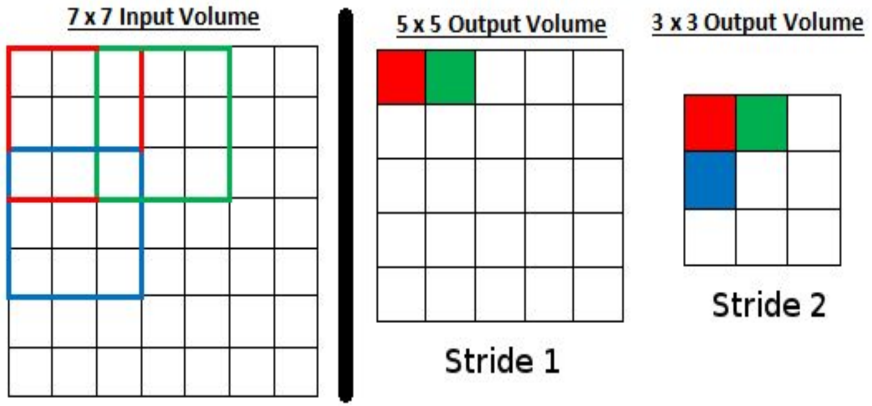
Convolution Details

Kernel size: Size of the receptive field of convolutional neurons



Stride: Steps size of convolution

Padding: Allows focus on border

- Most common fill: Zeros
- Valid (no padding): Internal only. May skip data. Reduces dimensionality
- Same: Keep dimensionality with stride 1

$$OutputSize = \frac{InputSize - KernelSize + 2 * Padding}{Stride} + 1$$

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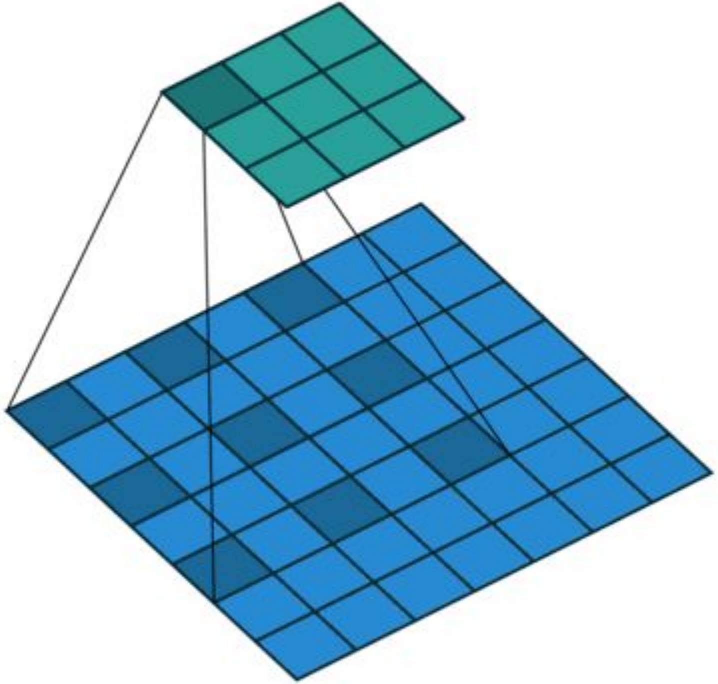
Dilated/Atrous Convolutions

Sparsify the kernel

- Increases perceptive field without added complexity
- Loses details, gains context
- Another hyperparam :(
- Used for
  - Down/Upsampling (segmentation)
  - High Resolution inputs



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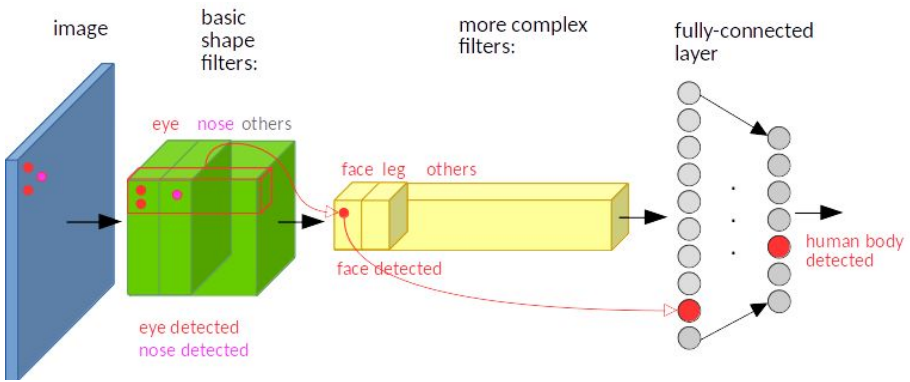
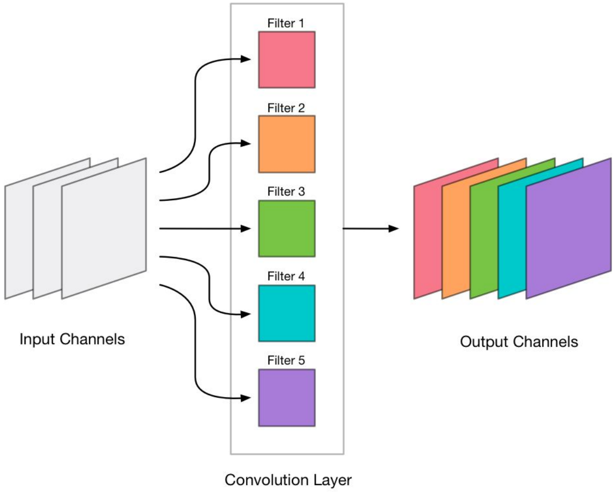
Output Volumes

- Typically, conv filters are full depth (**N*N*input_depth**)
- Each conv filter (often 3D) convolved generates a 2D plane of data
- Depth provides all the *views* on a part of the input
- Output volume: New representation of input with different dimensions





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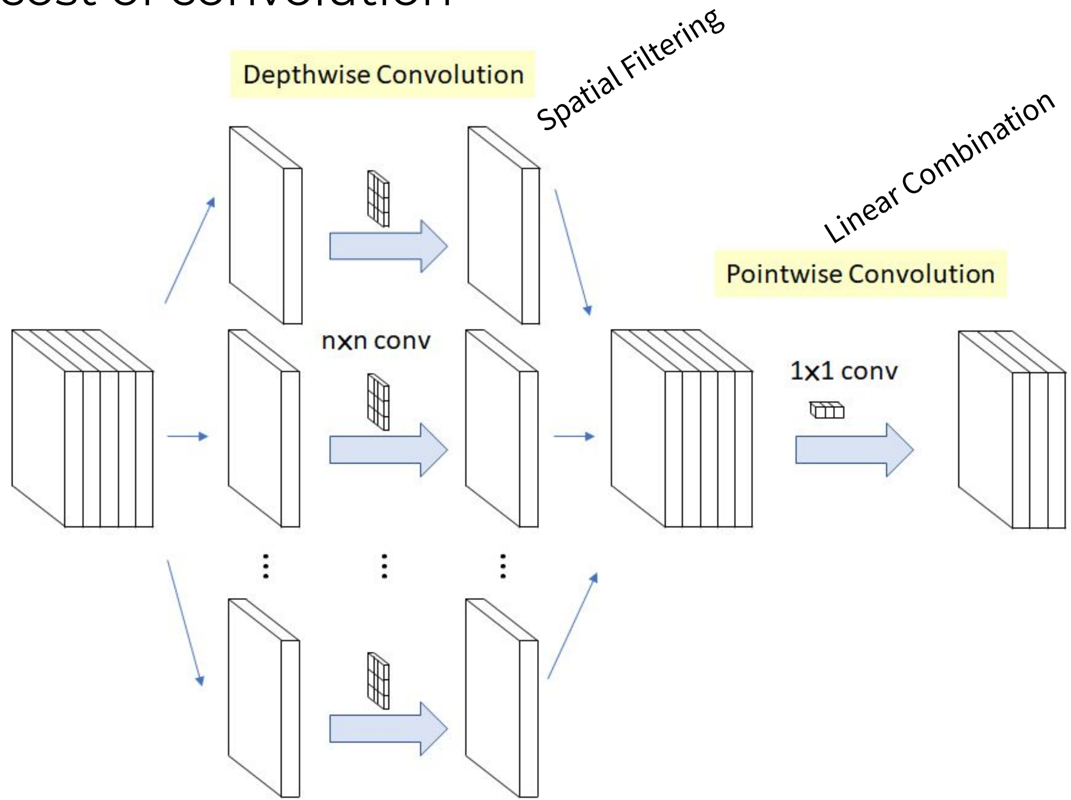
Depth-wise Separable Convolutions

Decreasing the complexity and cost of convolution

1. Depth-wise convolutions
   - Filters: N*N*1
2. Point-wise convolution
   - Filters: 1*1*input_depth

Params: N*N+N

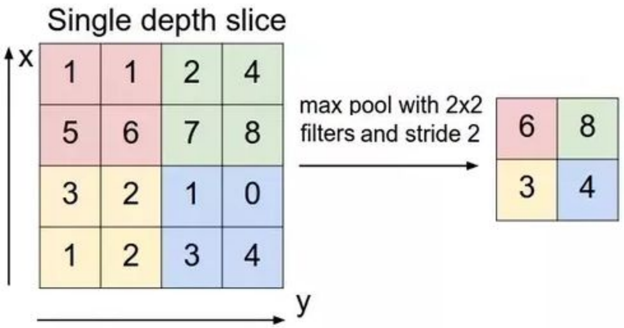


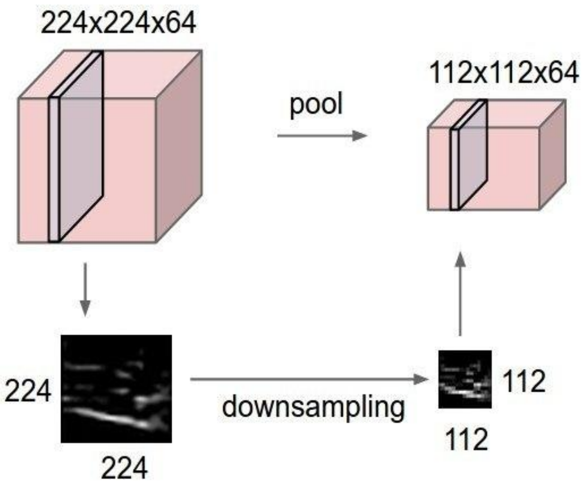
To Pool Or Not To Pool

- Operation: **Max** or Avg
- Dimensionality reduction (along *x* and *y* only)
- Rarely applied full depth
- Parameter free layer
- Hyperparams: Size & Stride
- Loss in spatial precision / Robust to invariance

Other means to reduce complexity

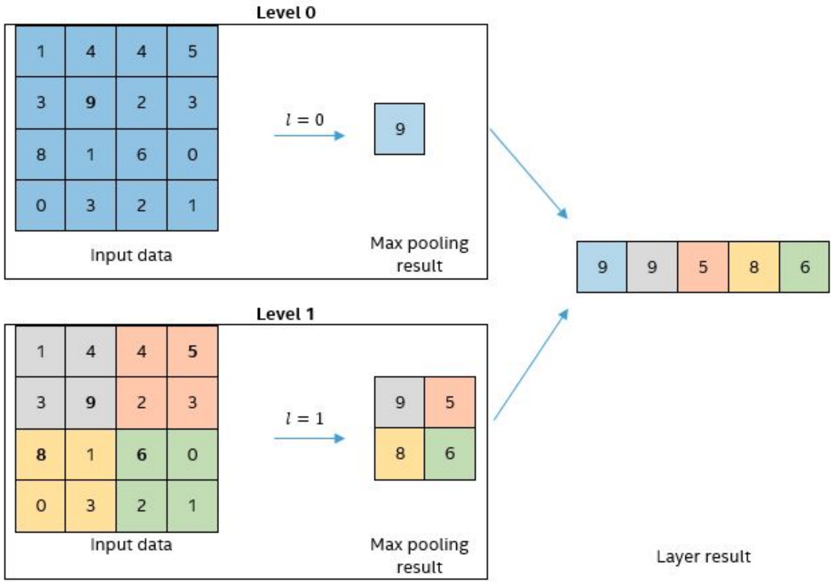
- Depth-wise separable convs, bigger conv. strides

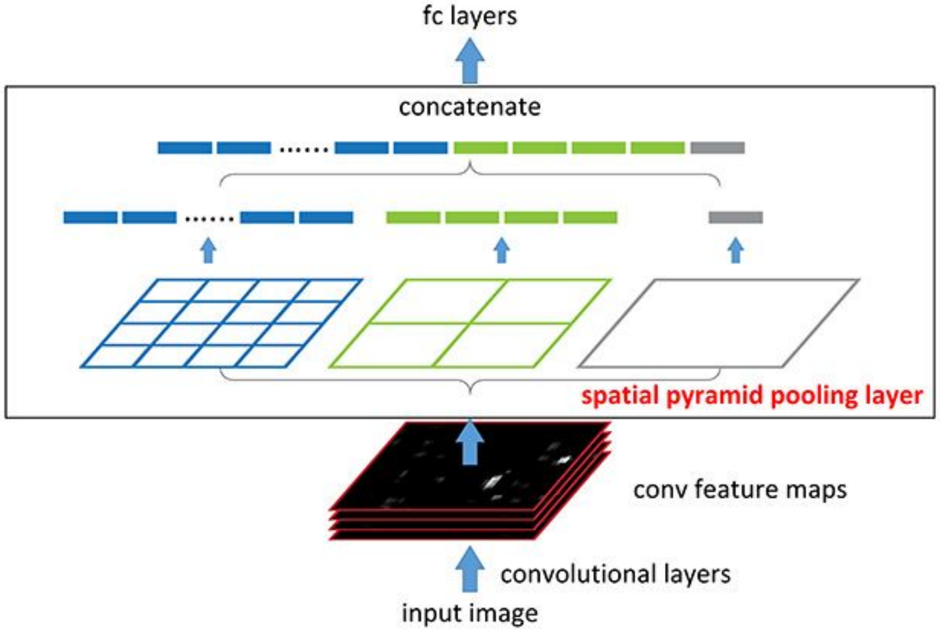




Spatial Pyramid Pooling (SPP)

- Multi-scale Pool (by powers of 2)
- Often used between conv and fc





More alternatives: Atrous spatial PP, Global average pooling, Pyramid pooling module, Adaptive PP

Practical Tips XI

Convolutional

- Small/big filters (**3x3**, 5x5, 7x7)
  - Cheap/Expensive
  - Local/General
  - Bigger/Smaller outputs (stride)
- Kernel Size = input size: fc
- Kernel size = 1x1: Alter depth)

Pooling

- 2x2, stride 1 is the least invasive

<u>Hyperparameters incomplete list</u> #4

- ❑ Kernel size (conv & pool)
- ❑ Stride (conv & pool)
- ❑ Padding (conv & pool)
- ❑ Num. filters
- ❑ Dilatation rate

The Challenge

ImageNet Large-Scale Visual Recognition Challenge 2012 (ILSVRC'12)

- Image Classification: 1,000 classes
- Training: 1.2M
- Living things + Human-made objects
  - 120 breeds of dogs

- DANGER! When using a new test set (2019) performance drops +10%

Data Augmentation for CNNs

Apply what is safe for each case

- Problem specific
- Limited impact
- Computation
- Train/Val/Test

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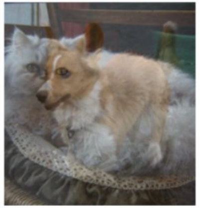
Advanced image regularization/augmentation

Increase training variance, attention to all input regions, noisy!



- MixUp (merge two samples), AdaMixup (manifold intrusion)

- CutOut (remove a patch)
- CutMix (merge samples w/ patch)

- Auto/DeepAugment (learn <*op.,mag.*> from the data. Danger!)

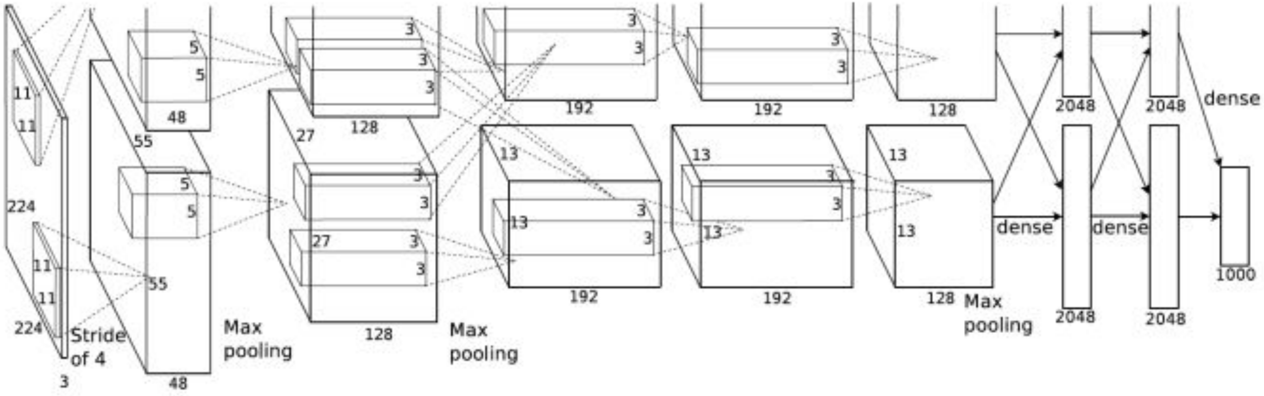
More data is always better than more augmentation!

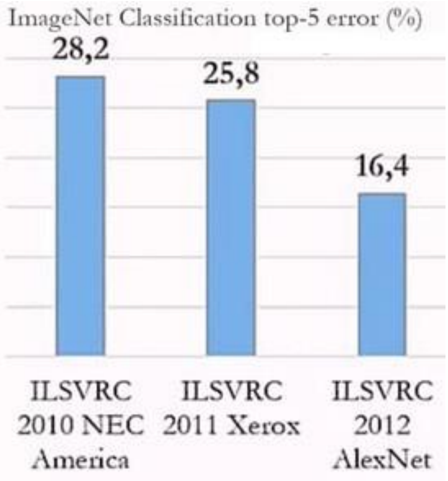
[40,41,42,43,44,50]

CNNs Big Bang

AlexNet (2012)

- Breakthrough in ILSVRC
- 5 convs+pools, ReLU, 2 dense, and dropout
- 62M parameters





On the shoulders of giants

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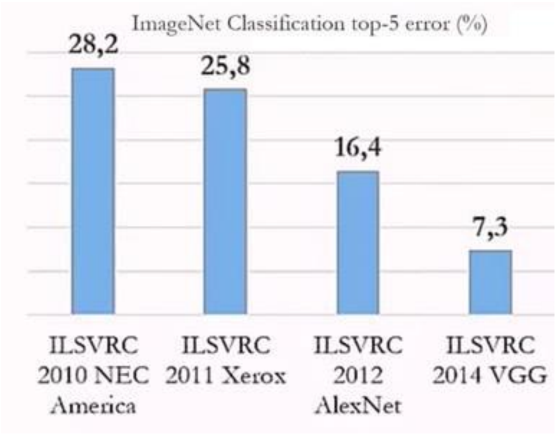
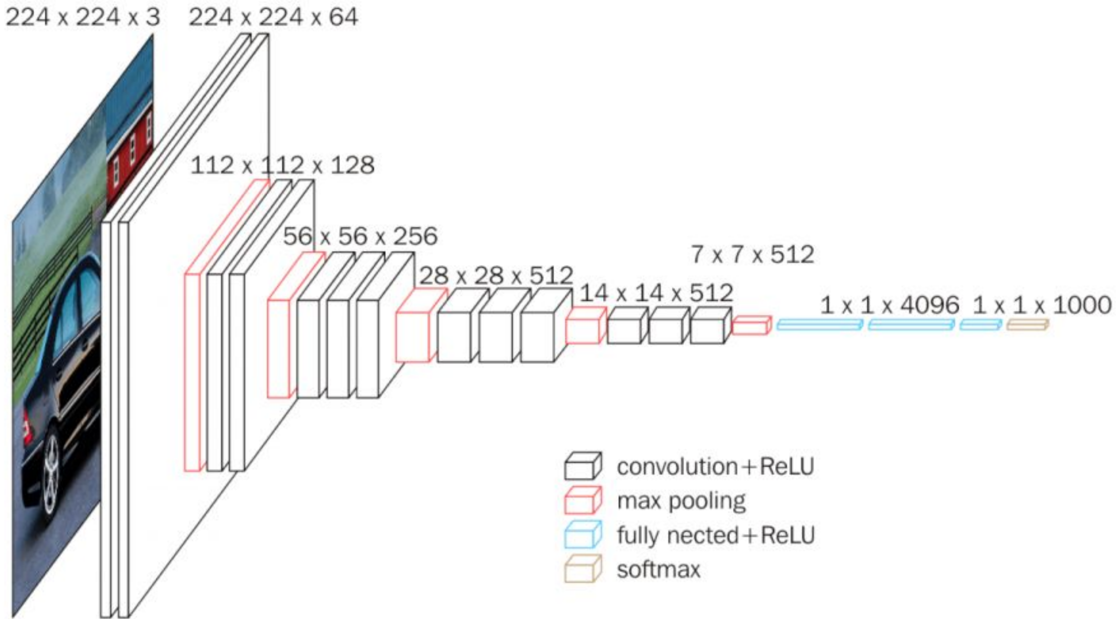
A new Standard for CNNs

VGG 11/13/16/19 (2014)

- ❖ Prototype of **(conv-pool)*+dense*** architecture
- ❖ 133-144M parameters
- ❖ 3x3 convs only

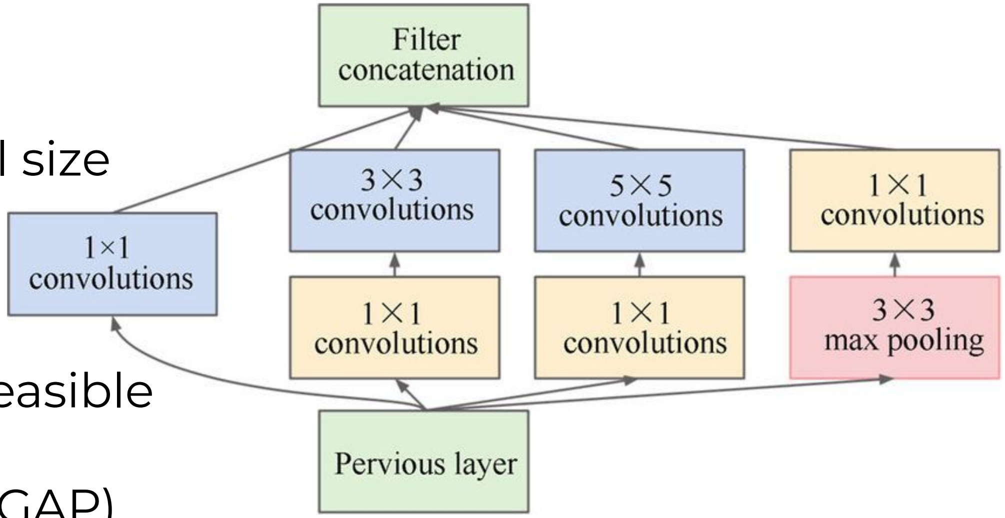




The Inception Family

GoogLeNet (2014)

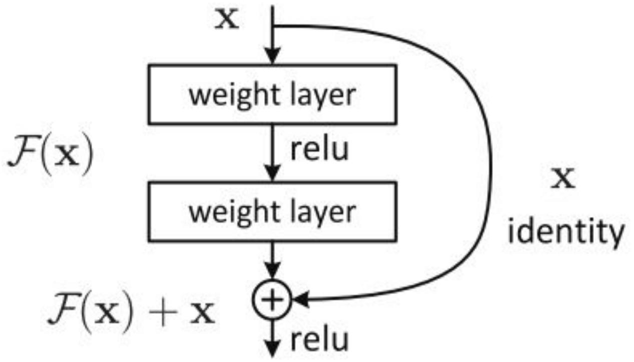
- The Inception block
- Let the model decide the kernel size
- Better scale adaptation
- Bottleneck 1x1 conv to make it feasible
- No FC: Global Average Pooling (GAP)

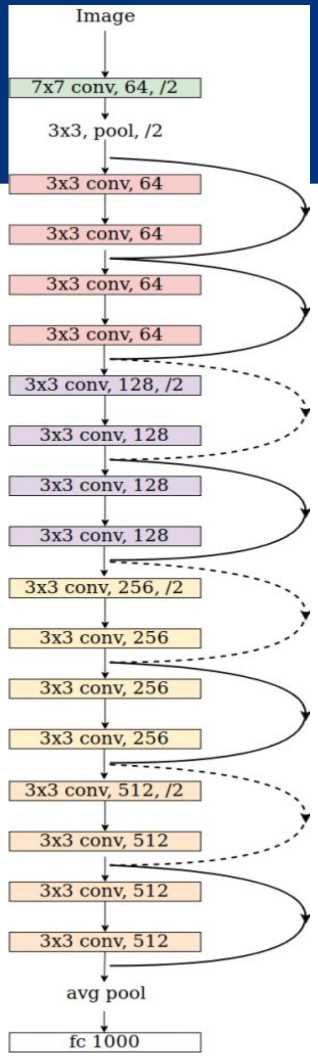


The Skipped Connection

ResNet (2015)

- ❖ Residual blocks / Skip connections
- ❖ Deeper should never be worse
  - ▪ Learning the identity is hard
  - ▪ Learning to cancel out is easy
- ❖ Shallow ensemble of nets
- ❖ Train up to 1K layers (do not!)
- ❖ ILSVRC'12 human level





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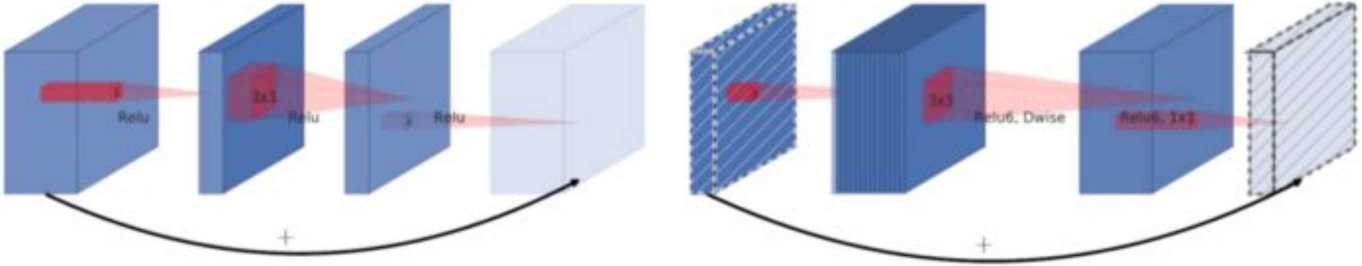
Inverted Residuals and Linear Bottlenecks

1. Upsample depth
2. Depth-wise conv
3. Point-wise conv

(a) Residual block

(b) Inverted residual block



- ❖ Linear act at end
- ❖ Non-linear mid
- ❖ Residual link
- ❖ Efficient

Sponsored by:
The manifold hypothesis

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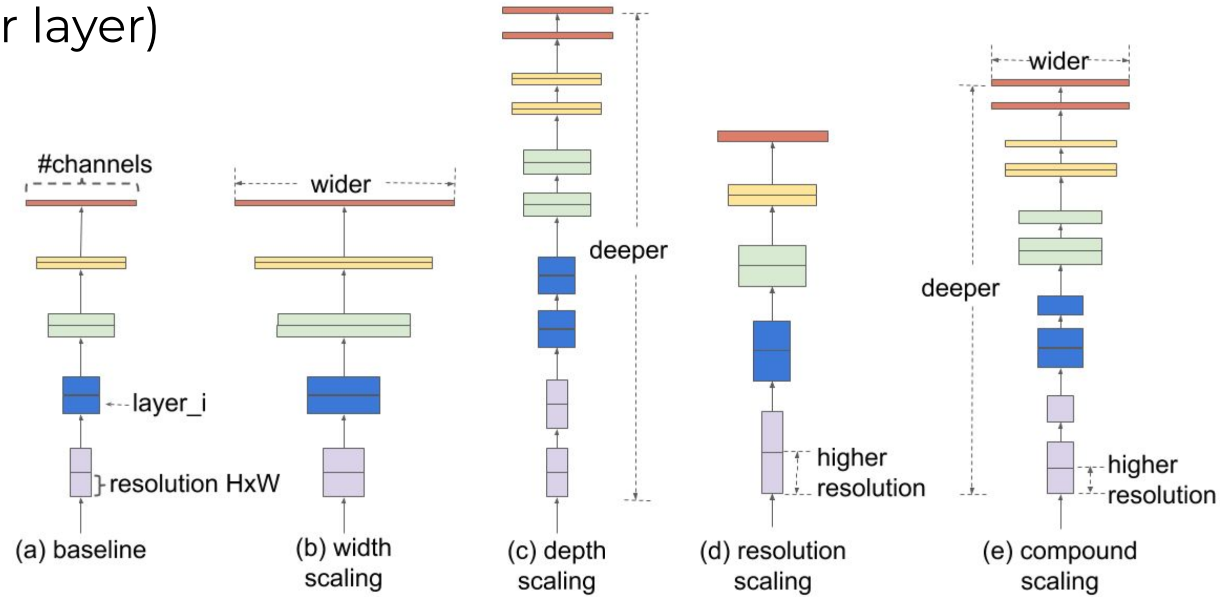
[38]

EfficientNet

Should I go deeper, wider or bigger?

- ❖ Find a balance between them (they are all related!)
  - ■ Width (neurons per layer)
  - ■ Depth (layers)
  - ■ Resolution (input)
- ❖ Choose a size
  - ■ EfficientNetB0-B7



Noisy Student

A semi-supervised training paradigm

1. Train model A (teacher) with the labeled data
2. Use A to generate pseudo-labels for an unlabeled data set
3. Train model B (student) with both labeled and pseudo-labeled data

- Iterate, re-labeling the unlabeled data each time
- Highly regularized (noise!) student to guarantee improvement
- Each student has more capacity than the previous

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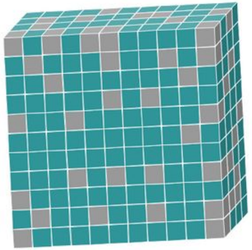
Spatial Dropout

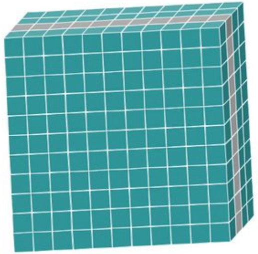
Standard Dropout is suboptimal for spatially related data

- ❖ Consecutive inputs can be strongly redundant



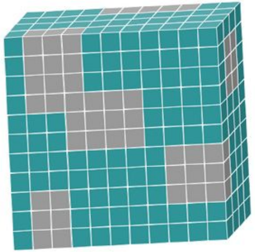
Spatial Dropout

- ❖ Drop entire feature maps, aka channels



Cutout

- ❖ Drop connected components along width, height and/or depth



[45,46,47]

Visualizing CNNs

Biases everywhere

The Basics

- NN are representation learning techniques
- CNNs build hierarchically complex features
  - From Gabor filters to dog faces
  - Induced by convolution
  - Tend to focus on the “non obvious for humans”
    - Backgrounds, textures
- The closer to the loss, more classifier (task) and less representation (data)

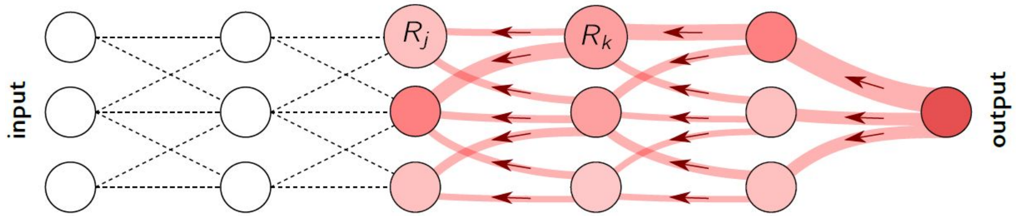
[25,26]

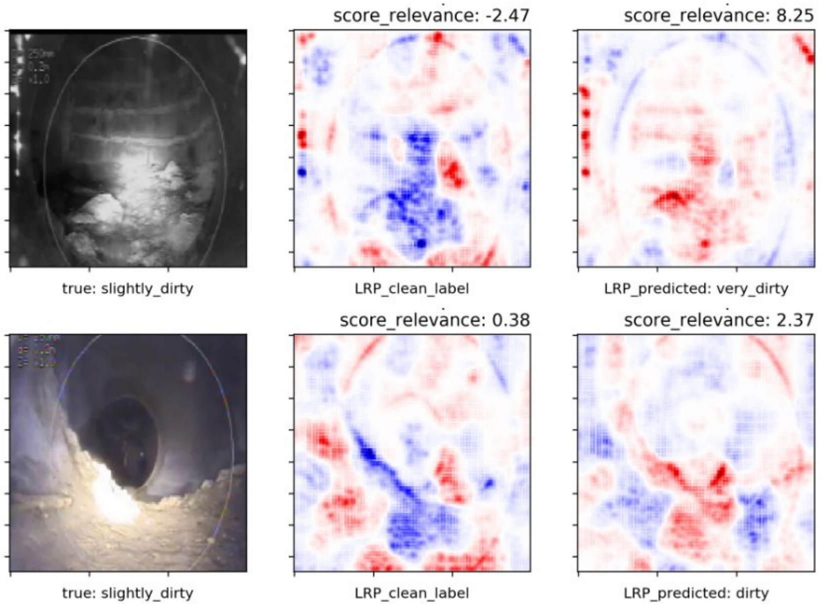
Ways of Looking at CNNs

- *Attribution*: **Where** is the network looking?
  - Grounded. Instance based.
  - Explainability in practice.
- *Feature Visualization*: **What** is the network seeing?
  - Uncontextualized. Maximization based.
  - Diagnosys & Insight
- *Exemplification*: **Which** samples cause a maximum activation?
  - Samples from a distribution

Attribution

- Finding the importance of pixels
- Layerwise Relevance Propagation (LRP)
  - Backpropagate *an* output. Find the relevance of each neuron
    - Weighted by CNN parameters





[29]

Feature Visualization

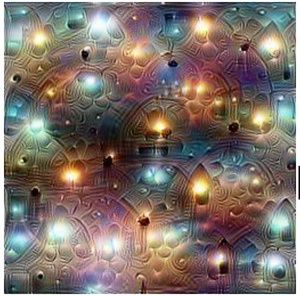
❖ Optimizing the input to maximize the output

- A neuron

  - A channel

- A layer (DeepDream)

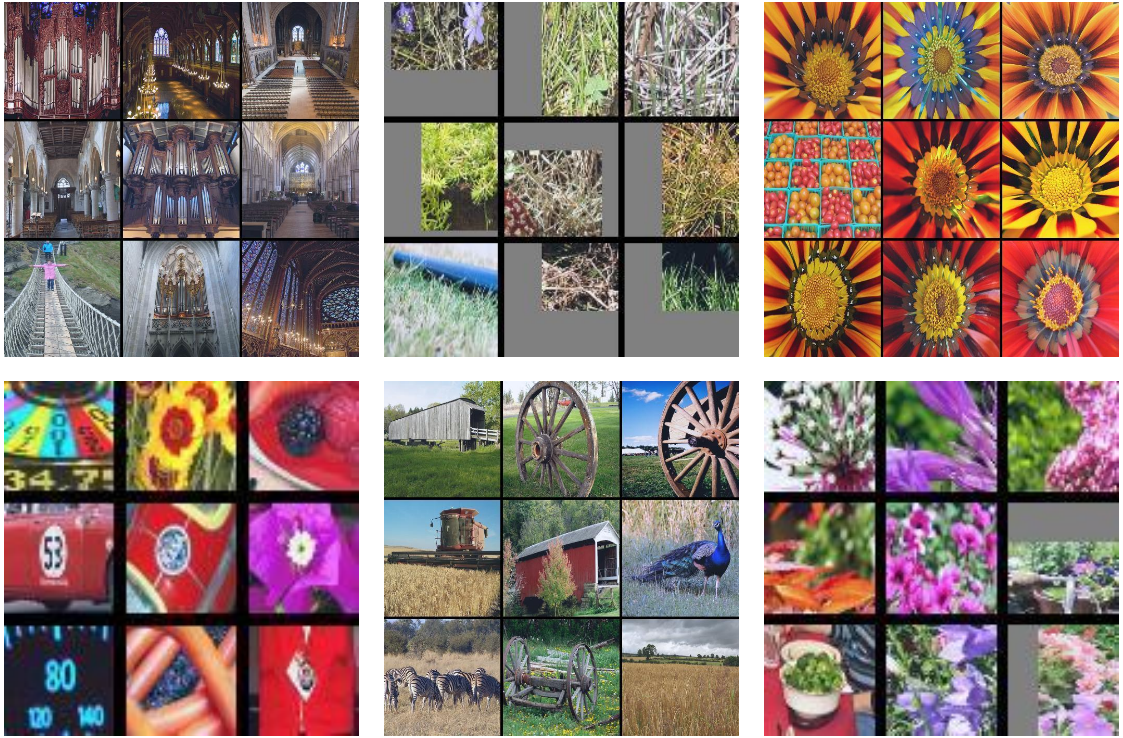
Low level



High level

Exemplification

- Finding images within a dataset maximizing outputs
  - Subjective
  - Partial
  - Stochastic



Bias in DL

"All models are wrong, some are useful" - George Box

-

"All DL models are biased, some are usefully biased"

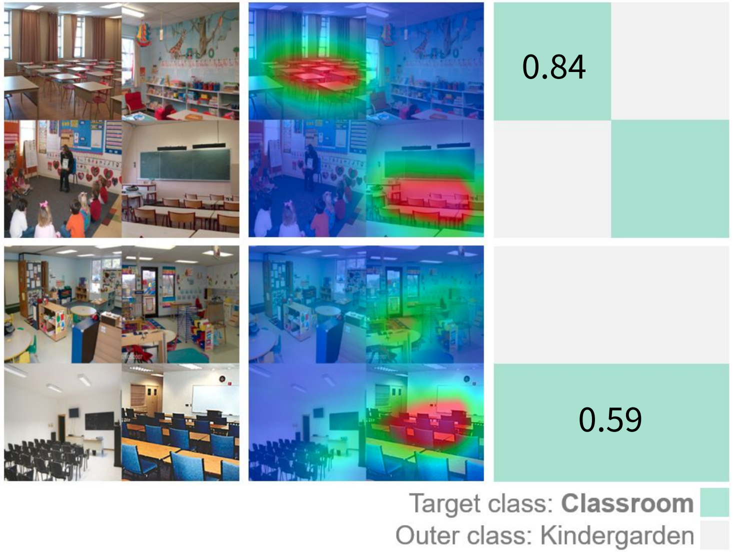
- Bias is what makes ML work. Is a form of generalization.
    - *Identification*: What bias?
        - Bonus track: Human bias (Pareidolia)
    - *Appreciation*: Desirable bias?
    - *Mitigation*: Altering dataset or model?

Bias Detection through XAI Attribution

Focus & Mosaics: An eye-tracking game

Why is this mosaic of class "cat"?

- ❖ Identification: Many examples needed
- ❖ Appreciation: Expert decision
- ❖ Mitigation:
  - ■ Shared bias:
    - ○ + target samples without bias
    - ○ + non-target samples with bias
  - ■ Missing bias: + target samples with bias

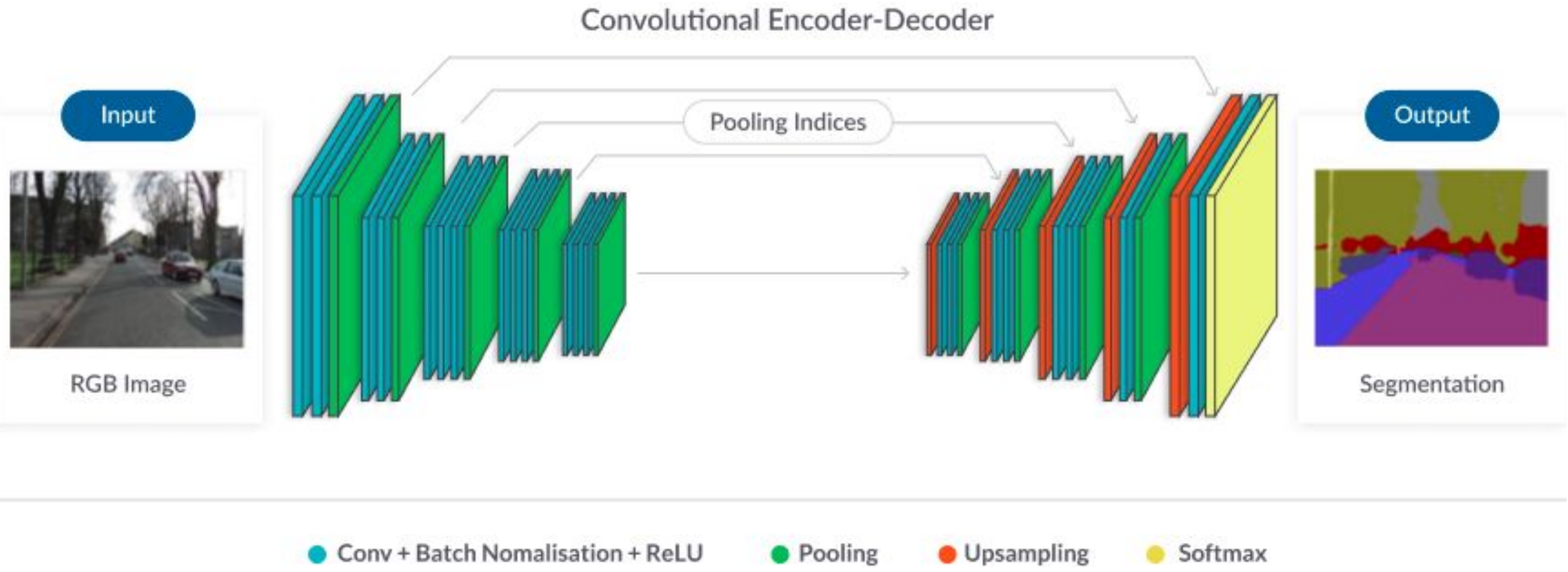


[48]

Playing with CNNs

Encoder-Decoder CNNs

- Pixel-wise classification task (image reconstruction loss)
- Bottlenecking makes it cheaper



[14]

Automatic Image Colorization

- Another pixel-wise classification application

(a) Colorado National Park, 1941 (b) Textile Mill, June 1937 (c) Berry Field, June 1909 (d) Hamilton, 1936

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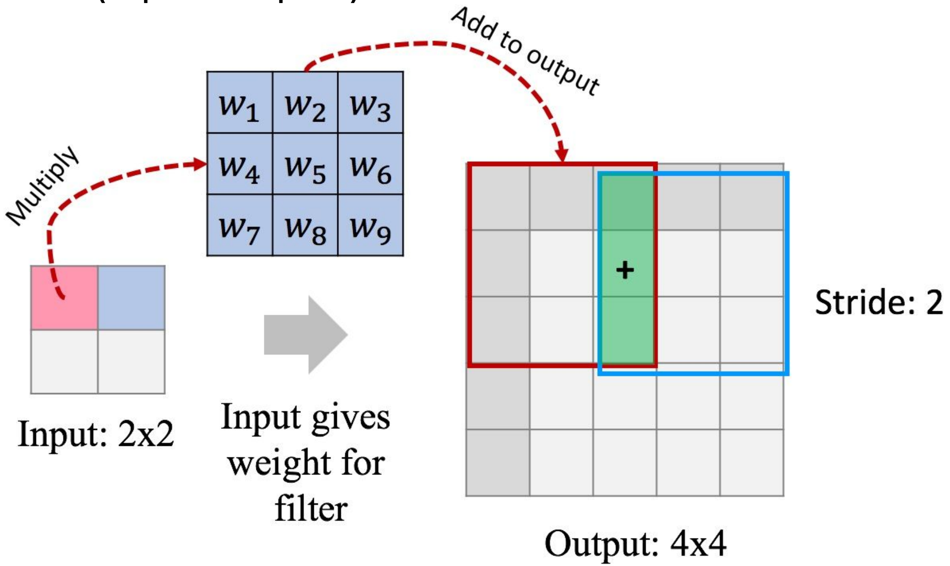
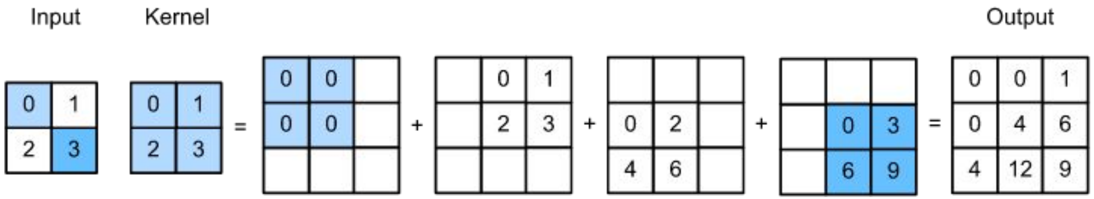
[15,16]

Transposed Convolution ~~Deconvolution~~

- Reverse effect of regular convolution (upsample)
- Learnt interpolation
- Applications
  - Segmentation
  - GANs
  - Super-Resolution
  - Conv. Autoencoders





Faster Segmentation

- ~~Pixel-wise classification~~ Object detection (bounding box)
  - Can be done with a “regular” CNN
- R-CNN: Propose crops (SVM). Extract features (CNN). Classify crops (SVM)
- Fast R-CNN: Extract features. Propose crops. Classify/Bounding Box (CNN)
- Faster R-CNN: Propose crops through a specific sub-net (RPN)
- YOLO v? (no regions, faster, less accurate)
  - Divide into grid. Predict class and bounding box for each cell.

Better Segmentation

- Mask R-CNN
  - Faster R-CNN for object detection
  - FCN for instance segmentation (pixel classification)
- Xception
  - Depth-wise separable Convs (inverted order & w/o non-linearity)
  - Skip connections
  - Atrous SPP

[17,18]

Style Transfer

- What do the correlation of activations intra-layer tell us?
  - What if we force it on another image?

- Gram matrix represents the *style*
  - Channel-wise (cXc)
  - Several mid layers

- Activations represents the *content*
  - One mid layer

- Optimize the **input** to minimize 2 losses
- Use a pre-trained net frozen
- Improved and extended

[19,20,21,22]

Image Generation

- StyleGAN2 + pix2pixHD
  - Pixel-wise generative models
- Flow-edge Guided Video Completion
- https://colab.research.google.com/drive/1KznIbRyNdiNBrrVbD7uolccdf9rngVUE?usp=sharing

[34,35,36,37]

Handwritten Generation

- https://github.com/sjvasquez/handwriting-synthesis
- https://arxiv.org/abs/1308.0850
- https://www.calligrapher.ai/

[34,35,36,37]

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