Convolutional Neural Networks

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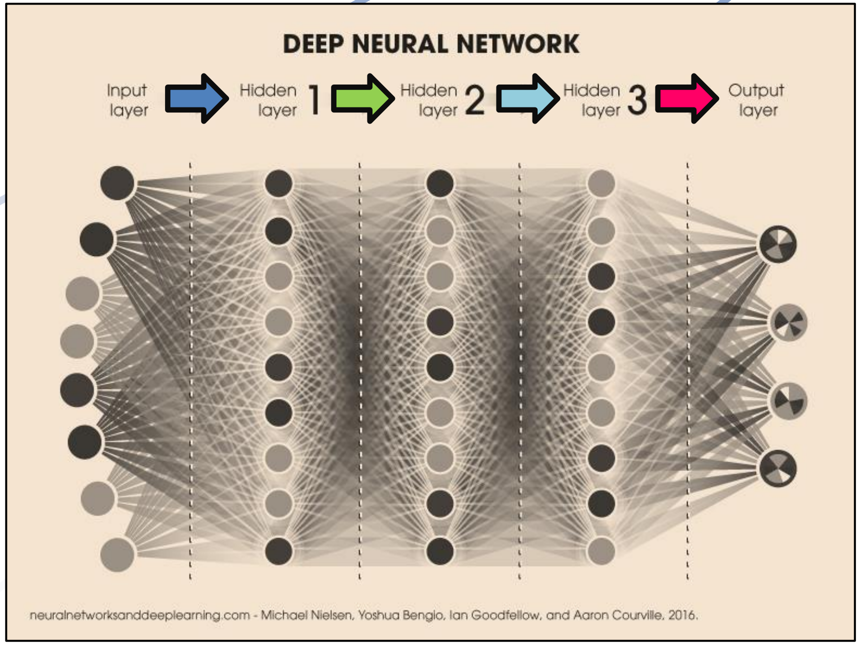
Deep Neural Networks

Definition

- *Deep Neural Networks (DNNs)* have a count of layers (depth) $L \geq 3$.
  - There are multiple hidden layers with regard to the MLP reference model.



Deep Neural Network with $L = 4$

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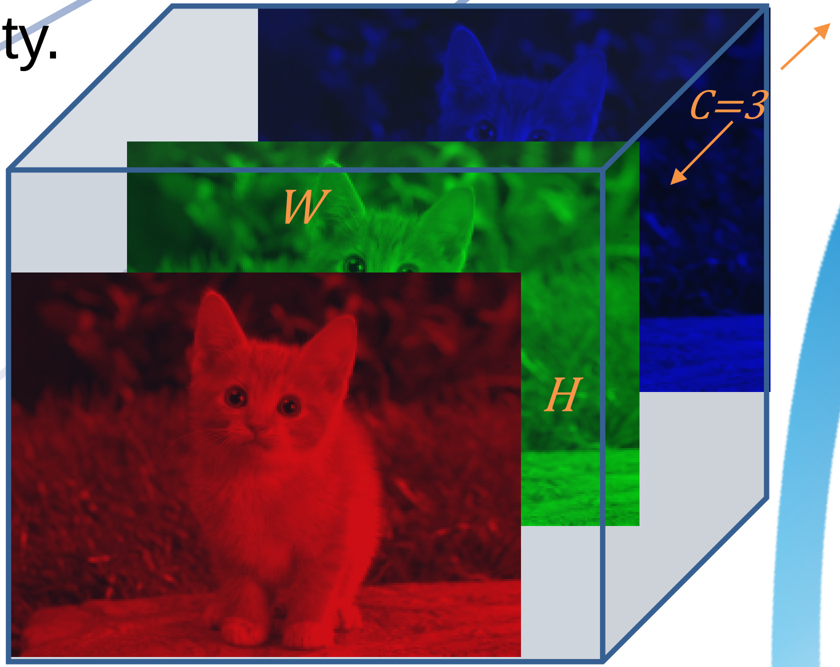
Deep Neural Networks

Applied for Computer Vision tasks

- There is a vast number of pixel features, e.g., $H \times W \times 3$ color image features for an $H \times W$ RGB image.
    - Problem: Increased computational complexity.
    - Solution: Convolutional Neural Networks (CNNs) that employ sparse connectivity and weight replication.



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Convolutional Neural Networks

Long history with recent success

- Foundations: Rummelhart, Hinton, Williams (1985) described a solution to the *T-C problem*.

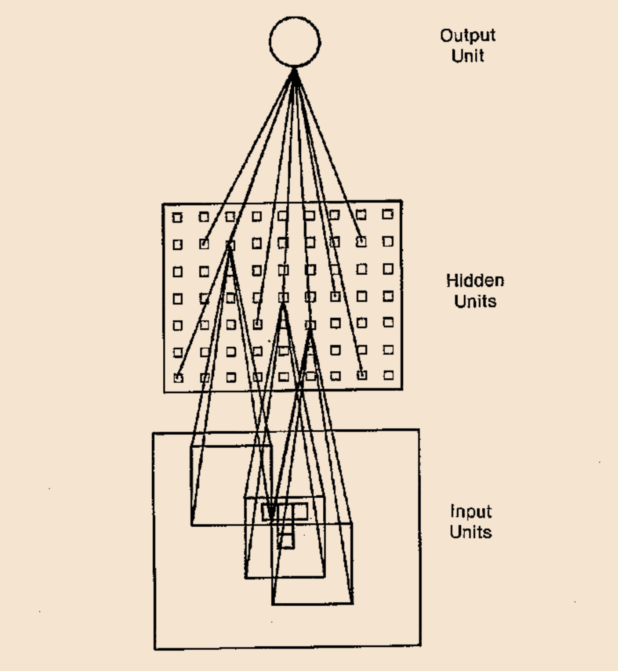

FIGURE 14. The network for solving the T-C problem. See text for explanation.

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Convolutional Neural Networks

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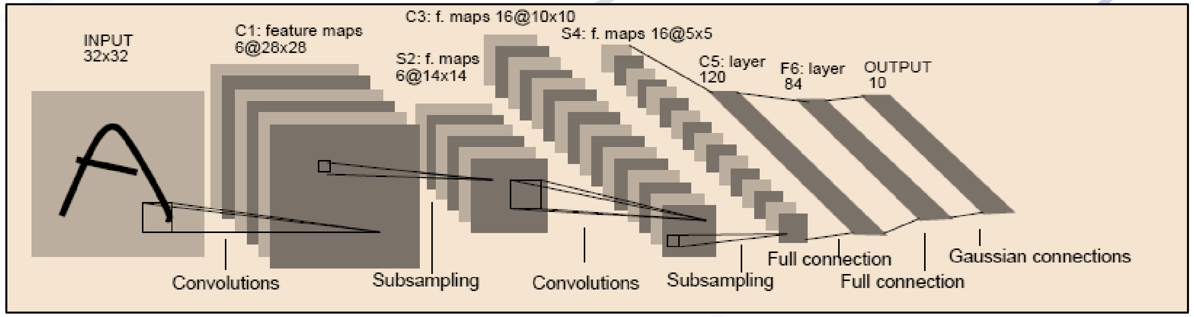
- First CNN: LeCun, Bottou, Bengio, Haffner (1989) proposed convolutional layer for character recognition.



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Convolutional Neural Networks

Long history with recent success

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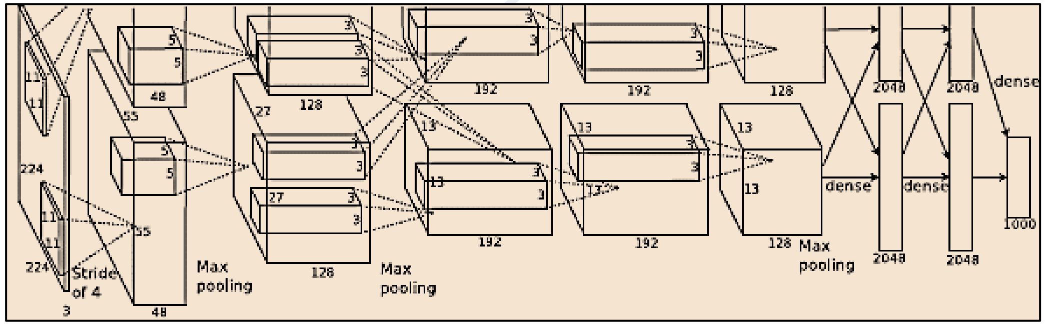
- Foundations: Rummelhart, Hinton, Williams (1985) described a solution to the *T-C problem*
- First CNN: LeCun, Bottou, Bengio, Haffner (1989) proposed convolutional layer for character recognition
- Success: Krizhevsky, Sutskever, Hinton (2012) significantly outperformed the state-of-the-art for image classification in the *ImageNet* competition.



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CNN Research Advances

The ImageNet competition

- The ImageNet Large Scale Image Recognition Challenge (ILSVRC) is an annual competition started in 2010.
- Large scale image datasets are used that have over a million images of natural scenes and objects.
- Since 2012, research in the CNN area produced significant advances, some through the ILSVRC competition.
  - The CNN that won the classification task (CLS) in 2015, surpassed the human classification accuracy on the same test set.

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Convolutional Neural Networks
Notations

- Standard CNN input is a $H \times W \times C$ multi-channel (color) image represented by 3D tensor $\boldsymbol{X}$.
- The multichannel image is a tensor $\boldsymbol{X}$ or a 3D signal $x(i,j,r): i = 1, \dots, H,\ j = 1, \dots, W, r = 1, \dots, C$.
  - The number of channels C is sometimes called *depth*.
- A multichannel image block of dimensions $h_1 \times h_2$: $h_1 = 2q_1 + 1, h_2 = 2q_2 + 1$ centered at $[i,j]^T$ is noted as the 3D tensor $\boldsymbol{X}_{ij}$.
- The 2D matrix $\boldsymbol{X}_{ij}(r)$ is a slice of $\boldsymbol{X}_{ij}$ that contains the values of channel r (e.g. intensity of red/green/blue) for the $h_1 \times h_2$ image block centered at $[i,j]^T$.

Matrix of feature (channel) r for the image block centered at $[i,j]^T$:

$$\boldsymbol{X}_{ij}(r) = [x(k_1,k_2,r): k_1 = i - q_1, \dots, i + q_1, k_2 = j - q_2, j + q_2]$$

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Reference CNN Classifier

The AlexNet CNN

Convolutional Module 1
- Convolutional Layer 1
- Max Pooling 1
- Local Response Normalization 1

Convolutional Module 2
- Convolutional Layer 2
- Max Pooling 2
- Local Response Normalization 2

Convolutional Module 3
- Convolutional Layer 3
- Local Response Normalization 3

Convolutional Module 4
- Convolutional Layer 4
- Local Response Normalization 4

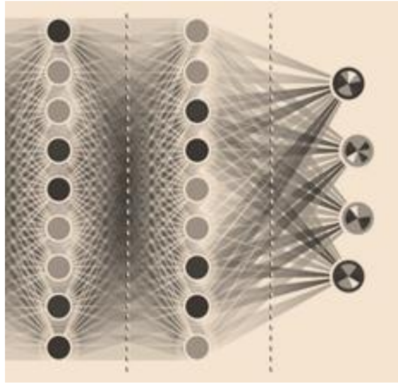
Convolutional Module 5
- Convolutional Layer 5
- Max Pooling 5
- Local Response Normalization 5

Fully Connected Module 1
- FC Layer 6
- Dropout

Fully Connected Module 2
- FC Layer 7
- Dropout

Softmax Output Module
- FC Layer 8
- Softmax Function

- There are several *convolutional layers.*
- There is a classifier that consists of 3 *fully connected* layers.
- Class prediction are given by *softmax* functions.



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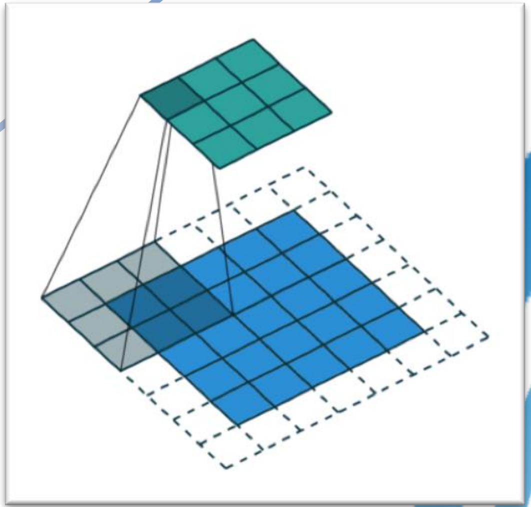
Convolutional Neural Networks

Characteristics: Sparse Connectivity

- A convolutional neuron implements *sparse connectivity* with a sliding window of dimensions $h_1 \times h_2$ operating locally on the input data.
  The step s of the window motion is called *stride*.
  - Simple notation for *convolutional kernels:* $[h_1 \times h_2/s]$
  - Extended notation for *convolutional kernels:* $[h_1 \times h_2/s|d_{in} \rightarrow d_{out}]$ where d_{in}, d_{out} are the input, output feature depths. For the first layer $d_{in} = C$.



- For 2D image data two different strides s_H, s_V may be used for the horizontal and the vertical sliding window motion.

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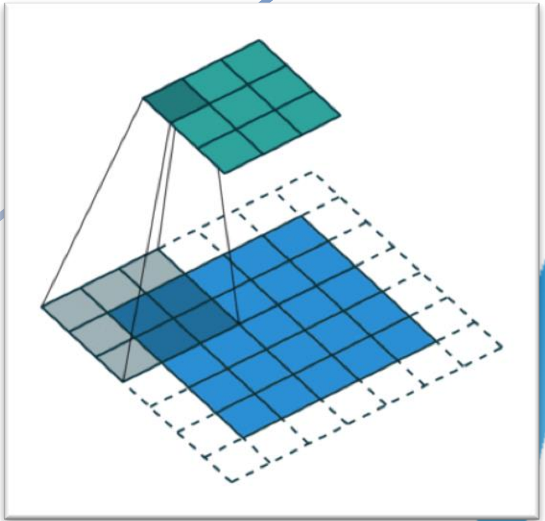
Convolutional Neural Networks

Characteristics: Local Receptive Fields

- Each neuron has a *local receptive field* that implements a dynamic mapping to a small local region $\mathbf{X}_{ij}$ of the input image $\mathbf{X}$ centered at $[i,j]^T$.



- Padding with zeros at the edges of input $\mathbf{X}$, so that the convolution operator can operate on the entire input image domain.

- Square receptive fields have $h_1 = h_2 = h$. They can overlap when the stride
of the convolution operation is $1 \leq s < h$.

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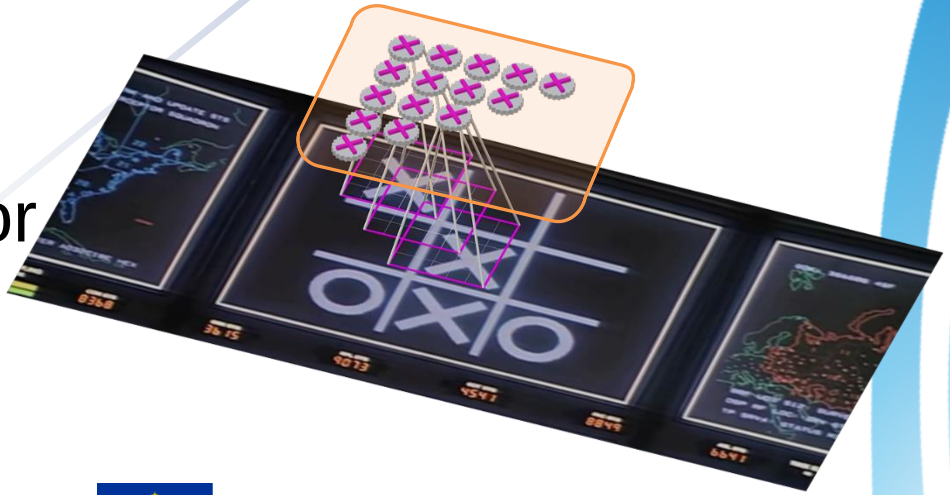
Convolutional Neural Networks
Characteristics: Weight sharing

- A convolutional layer abstracts multiple neurons that cover all regions of input and share the same synaptic weights.

- *Weight sharing* (or weight replication) is also implemented by the sliding window mechanism.

- The *convolutional kernel* is a 4D tensor of all shared weights noted as $\mathbf{W}$.



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Convolutional Neural Networks

Characteristics: Local Receptive Fields

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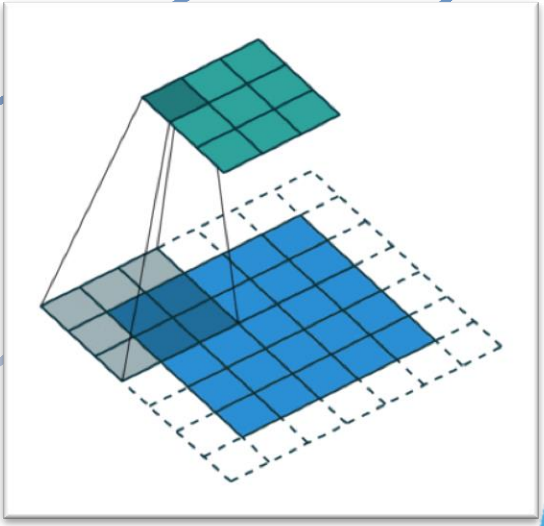
- The convolution kernel is given by the 4D tensor:

$$\boldsymbol{W} = [w_{k_1,k_2,r,o}: \quad k_1 = 1,\dots,h_1, k_2 = 1,\dots,h_2, \\ r = 1,\dots,d_{in}, o = 1,\dots,d_{out}]: \boldsymbol{W} \in \mathbb{R}^{h_1 \times h_2 \times d_{in} \times d_{out}}.$$



- For specific $r, o,$ the $h_1 \times h_2$ *convolution filters* $\boldsymbol{w}(r,o)$ contain the synaptic weights for the $h_1 \times h_2$ neuron receptive field.

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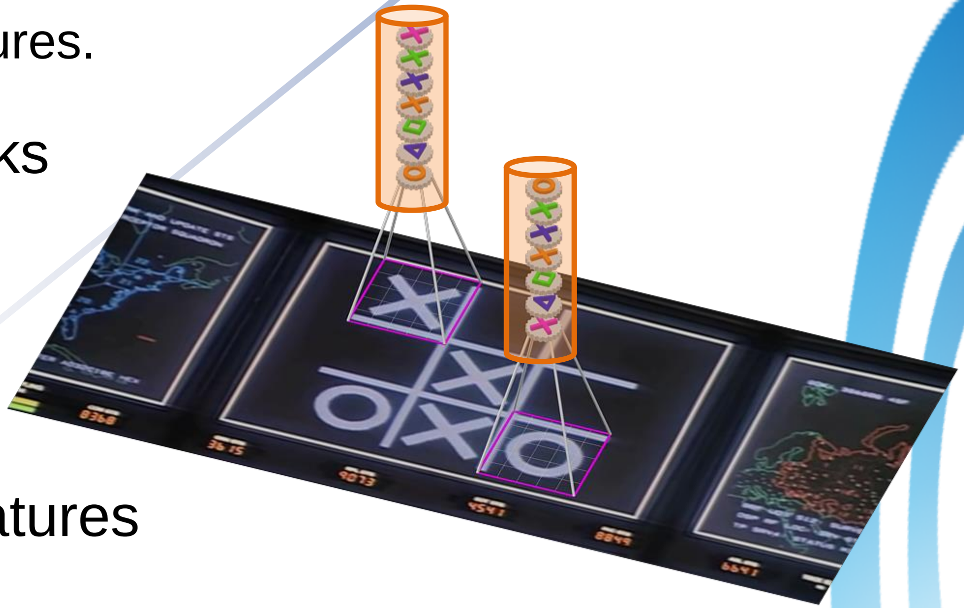
Convolutional Neural Networks

Characteristics: Multiple Local Feature Extractor

- A *convolutional layer* is an abstraction of a column of neurons, that share a common receptive field, operating on the same region of input $\boldsymbol{X}_{ij}$.
  - There are different 3D weight tensors $\boldsymbol{W}(o)$ for each neuron, extracting a different feature o from incoming features of $\boldsymbol{X}_{ij}$.
  - The input region $\boldsymbol{X}_{ij}$ has R,G,B intensities as features.
- In each layer, there are $n \times m$ local image blocks of size $h_1 \times h_2$, depending on stride *s*.
  - If $s = 1$ then $n = H, m = W$.
- A d_{out}-dimensional *feature descriptor* vector: $\boldsymbol{y}_{ij} = [y_{ij}(o): o = 1, \dots, d_{out}]^T$ holds all output features for an input local block $[i, j]^T$.



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Convolutional Layer

Activation map spatial dimensions

- For a centered convolution operation with squared input image dimensions $n_{in} \times n_{in}$, square filter window $h \times h$, stride s and padding n_{pad}, the dimension of the $n_{out} \times n_{out}$ output image (activation map) is:

$$\boxed{n_{out} = \frac{n_{in} - h + 2\, n_{pad}}{s} + 1\ , \qquad h = 2q + 1\,, \qquad n_{in}, n_{out}, q, n_{pad} \in \mathbb{N},}$$

- Specific input sizes are chosen due to this expression. Examples:
  1. AlexNet CNN with an input image resolution of 227×227 pixels and a convolutional filter

     $[11 \times 11/2]$ without zero padding $(\mathrm{n_{pad}} = 0\,)$ has $n_{out} = \frac{227-11+0}{4} + 1 = 55.$
  2. An input image resolution of 223×223 pixels can have $n_{out} = \frac{223-7+2}{2} + 1 = 110,$

     when a $[7 \times 7\ /2]$ convolutional filter is used with zero padding $n_{pad} = 1.$

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Inspiration from visual neurons

Biological V1 Hypercolumn

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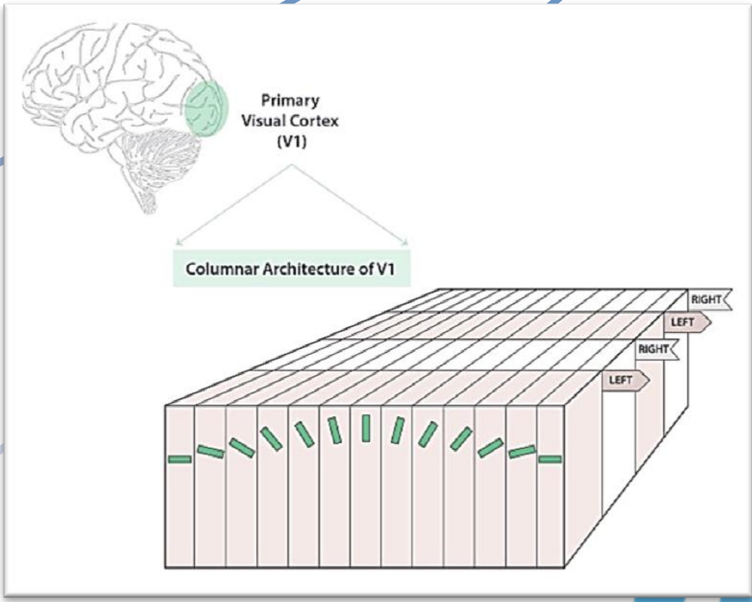
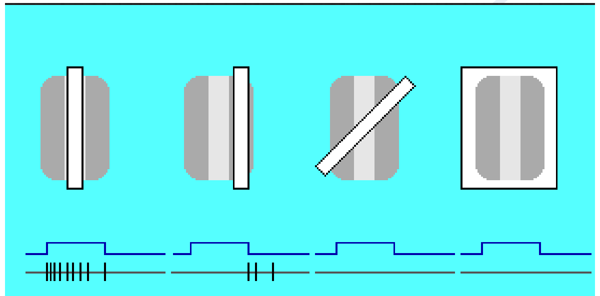
- CNNs were inspired by brain neurons in the mammalian primary visual cortex (V1).
- V1 cells are mapped to the same local region of the retina, forming *hypercolumns*.
- V1 simple cells detect image lines and are sensitive to orientation.





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Convolutional Layer

Synaptic summation

- The classic neurons have a weighted sum on vectors (1D) of features values.

Perceptron Neuron Summation

$$u = w_0 + \sum_{i=1}^{N} w_i x_i = w_0 + \boldsymbol{w}^T \boldsymbol{x}.$$

- Convolutional neurons implement the sum u with a *convolution operation* $\boldsymbol{W} * \boldsymbol{X}$ (or element-wise matrix multiplication $\boldsymbol{W} \odot \boldsymbol{X}_{ij}$) on 2D single feature image (matrix) $\boldsymbol{X}$, 2D kernel (coefficient matrix) $\boldsymbol{W}$ plus a scalar bias b:

Convolutional Neuron Summation

$$u(i,j) = b + \sum_{k_1=1}^{h_1} \sum_{k_2=1}^{h_2} w(k_1, k_2) x(i - k_1, j - k_2) = b + (\boldsymbol{W} * \boldsymbol{X})(i,j) = b + \boldsymbol{W} \odot \boldsymbol{X}_{ij}.$$

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Convolutional Layer

Synaptic summation centered on input

Convolutional Neuron Summation

$$u(i,j) = b + \sum_{k_1=1}^{h_1} \sum_{k_2=1}^{h_2} w(k_1,k_2)x(i-k_1, j-k_2) = b + (\boldsymbol{X} * \boldsymbol{W})(i,j).$$

- Using an odd convolution window with $h_1 = 2q_1 + 1$ and $h_2 = 2q_2 + 1$, the filter output is mapped to the filter window center at location $[i,j]^T$.

Convolutional Neuron Summation - Centered on Input:

$$u(i,j) = b + \sum_{k_1=-q1}^{q_1} \sum_{k_2=-q2}^{q_2} w(k_1,k_2)x(i-k_1, j-k_2) = b + (\boldsymbol{X} * \boldsymbol{W})(i,j).$$

For a convolutional filter $h_1 \times h_2$ where $h_1 = 2q_1 + 1$ and $h_2 = 2q_2 + 1$.

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Convolutional Layer

Single feature extracted from grayscale images

- For a convolutional layer l with an activation function $f_l(\cdot)$, a single input feature (e.g., grayscale image intensities) and a single feature output:

Output feature extracted from image block centered at $[i,j]^T$

$$y^{(l)}(i,j) = f_l\left(b^{(l)} + \sum_{k_1=1}^{h_1^{(l)}} \sum_{k_2=1}^{h_2^{(l)}} w^{(l)}(k_1,k_2)x^{(l)}(i-k_2, j-k_2)\right).$$

- The *activation map* $\boldsymbol{A}^{(l)}(o), = \boldsymbol{Y}^{(l)}, o = 1$ is a table of the output feature values for all $n \times m$ regions.

Convolutional Layer Activation Map (2D matrix) from single input feature

$$a_{ij}^{(l)}(1) = f_l\left(b^{(l)} + \boldsymbol{W}^{(l)}(1,1) * \boldsymbol{X}_{ij}^{(l)}(1)\right)$$

$\boldsymbol{W}^{(l)}(1,1)$: *2D filter for the 1st output feature,* $\boldsymbol{X}_{ij}$*(1): grayscale intensities of the local block at* $[i,j]^T$

$$\boldsymbol{A}^{(l)}(1) = \left[a_{ij}^{(l)}: i = 1,..,n^{(l)}, j = 1,..,m^{(l)}\right]$$

The activation map for the 1st output feature at layer l is the matrix $\boldsymbol{A}^{(l)}(1)$ that contains $a_{ij}^{(l)}$ across all regions.

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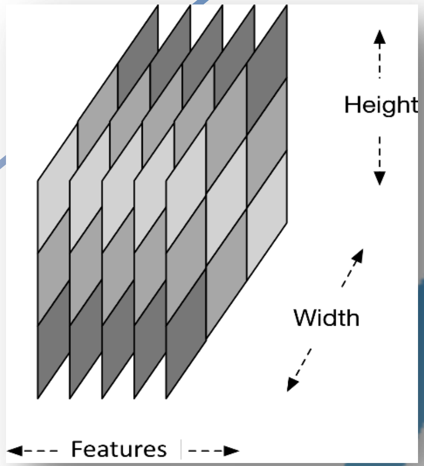
Convolutional Layer

For RGB images

- For a convolutional layer l with an activation function $f_l(\cdot)$, multiple incoming features d_{in} and one single output feature



Multiple input features to single feature o transformation

$$y^{(l)}(i,j,o) = f_l\left(b^{(l)} + \sum_{r=1}^{d_{in}} \sum_{k_1=-q_1}^{q_1^{(l)}} \sum_{k_2=-q_2}^{q_2^{(l)}} w^{(l)}(k_1,k_2,r,o)\, x^{(l)}(i-k_1, j-k_2, r) \right)$$

Convolutional Layer Activation Volume (3D tensor)

$$a_{ij}^{(l)}(o) = f_l\left(b^{(l)}(o) + \sum_{r=1}^{d_{in}} \boldsymbol{W}^{(l)}(r,o) * \boldsymbol{X}_{ij}^{(l)}(r)\right) \qquad \boldsymbol{A}^{(l)} = \left[a_{ij}^{(l)}(o): i = 1,..,n^{(l)}, j = 1,..,m^{(l)}, o = 1,\dots,d_{out}\right]$$

where $\boldsymbol{A}^{(l)}$ is the activation volume for the convolutional layer l, $\boldsymbol{W}^{(l)}(r,o)$ is a 2D slice of the convolutional kernel $\boldsymbol{W}^{(l)} \in \mathbb{R}^{h_1 \times h_2 \times d_{in} \times d_{out}}$ for input feature r and output feature o, $b^{(l)}(o)$ a scalar bias and

$\boldsymbol{X}_{ij}^{(l)}(r)$ a region of input feature r centered at $[i,j]^T$, e.g. $\boldsymbol{X}^{(1)}(1)$ the R channel of an image $d_{in} = C = 3$.

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Convolutional Layer

As many-to-many feature transformation

- The convolutional layer is a feature transformation operation $\boldsymbol{A}^{(l-1)} \rightarrow \boldsymbol{A}^{(l)}$ $(d_{in} \rightarrow d_{out})$ that extracts multiple output features from multiple input features.
- The convolutional kernel is a 4D tensor of weights. It can be considered a collection of 2D filters for each input-to-output feature correspondence.

Convolutional Layer

$$a^{(l)}(i,j,o) = f_l\left(b^{(l)}(o) + \sum_{r=1}^{d_{in}} \boldsymbol{W}^{(l)}(r,o) * \boldsymbol{A}_{ij}^{(l-1)}(r)\right)$$

$\boldsymbol{A}^{(l)}= [\, a^{(l)}(i,j,o), i = 1, \dots, n^{(l)}, j = 1, \dots, m^{(l)}, o = 1, .., d_{out}^{(l)} \,],\ \boldsymbol{A}^{(l)} \in \mathbb{R}^{n^{(l)} \times m^{(l)} \times d_{out}^{(l)}}$,

$\boldsymbol{A}_{ij}^{(l-1)}(r) \in \mathbb{R}^{n^{(l-1)} \times m^{(l-1)} \times d_{in}^{(l)}}$ where $\boldsymbol{A}_{ij}^{(l-1)}(r) = \boldsymbol{X}^{(l)}(r)$ is a 2D slice of previous layer activation volume for feature r at region $[i,j]^T$ used as input to the layer, $\boldsymbol{W}^{(l)}(r,o)$ is the 2D slice of the convolutional kernel $\boldsymbol{W}^{(l)} \in \mathbb{R}^{h_1^{(l)} \times h_2^{(l)} \times d_{in}^{(l)} \times d_{out}^{(l)}}$ for input feature r and output feature o and $b^{(l)}(o)$ is the scalar bias.

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Convolutional Layer

Basic Activation Functions

- Sigmoid and hyperbolic tangent function are not proper for CNNs, because they lead to the *vanishing gradients* problem.

- Rectifiers are more suitable for activation functions.
  - **ReLU** - Rectified Linear Unit

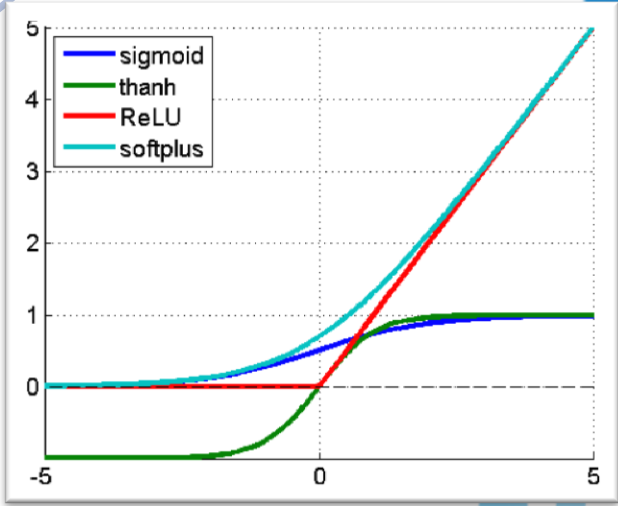
    $y = ReLU(u) = \max\{u, 0\} \quad : \mathbb{R} \rightarrow [0, +\infty)$

  - **ReLU6** - Rectified Linear Unit Bounded by 6

    $y = min\ \{ReLU(u), 6\} = \min\{\max\{u, 0\}, 6\} \quad : \mathbb{R} \rightarrow [0,6]$

  - **Softplus**

    $y = softplus(u) = log(1 + e^u) \quad : \mathbb{R} \rightarrow [0, +\infty)$



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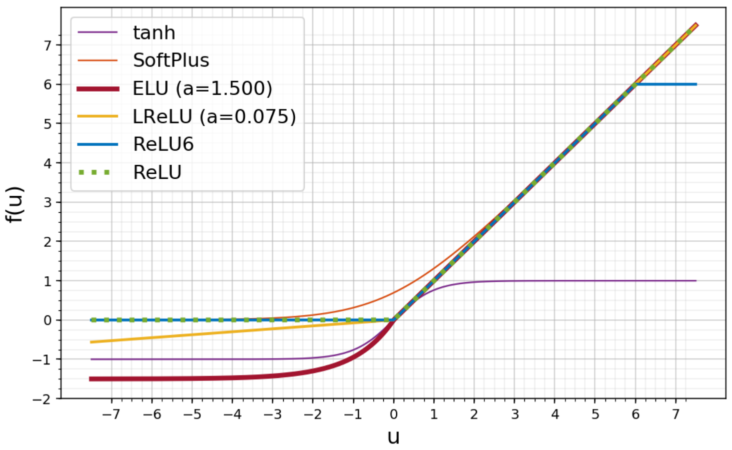
Convolutional Layer

Advanced Activation Functions

- Activation functions with positive range of values have mean activation larger than zero, leading to the *bias shift* problem.
  - Activations of neurons should be capable of cancelling each other at the next layer.
- Advanced activation functions try to mitigate the negative effects of ReLU.
  - **LReLU** - Leaky Rectified Linear Unit (2013)

$$y = LReLU(u) = \begin{cases} ReLU(u) & , u \geq 0 \\ -a \cdot ReLU(-u) & , u < 0 \end{cases} : \mathbb{R} \rightarrow (-\infty, +\infty)$$

  - **PReLU** - Parametric Rectified Linear Unit) (2015)
  - **RReLU** - Randomized Leaky Rectified Linear Unit (2015)



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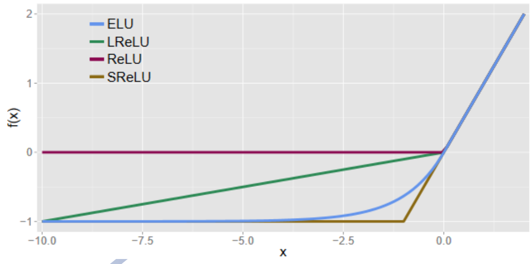
Convolutional Layer

ELU - Exponential Linear Unit (2015)

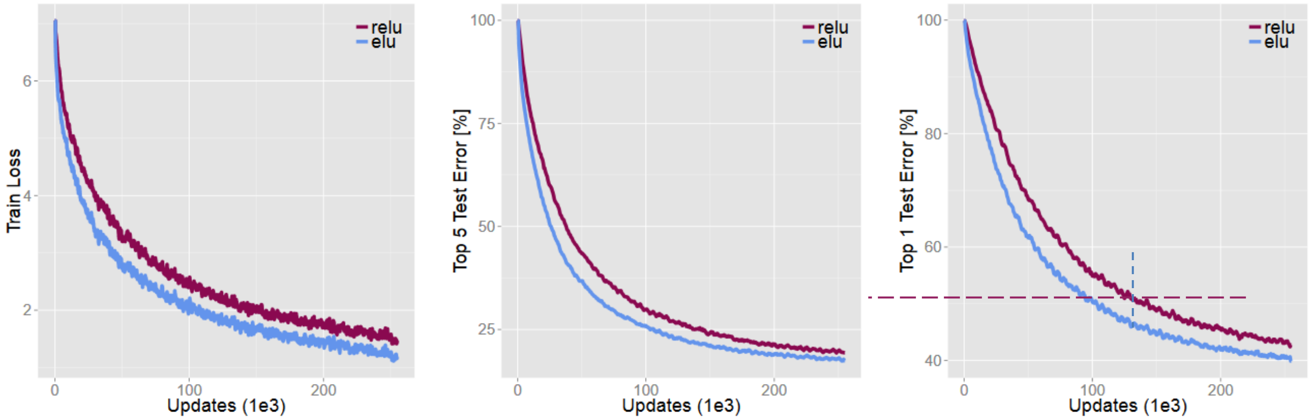
- The ELU activation function aims to mitigate the bias shift problem:

$$y = ELU(u) = \begin{cases} ReLU(u) = \max\{u, 0\} & , u \geq 0 \\ a \cdot (e^{u} - 1) & , u < 0 \end{cases} \quad : \mathbb{R} \rightarrow (-a, +\infty)$$

$$0 < a \leq 1$$



- It achieves better training convergence in shorter amount of time.



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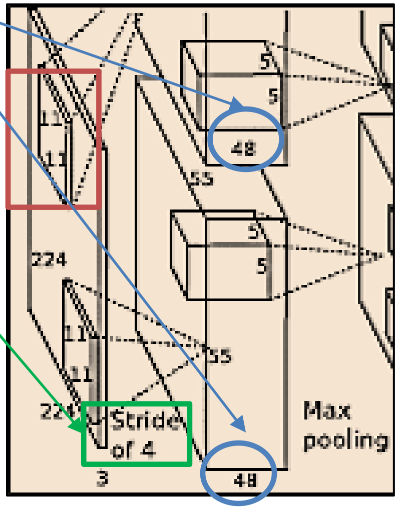
Convolutional Neural Networks

As many-to-many feature transformation

- For RGB images there is $d_{in} = 3$ and $d_{out} > 1$ features which are extracted by the first layer with the use of the 4D convolutional kernel.

- The notation for a convolutional layer can be augmented to indicate the input and output features as $[h_1 \times h_2 / s \mid d_{in} \rightarrow d_{out}]$
  - E.g.: AlexNet 1st convolutional layer is $[\mathbf{11 \times 11} \; /\mathbf{4} \mid 3 \rightarrow \mathbf{96}]$



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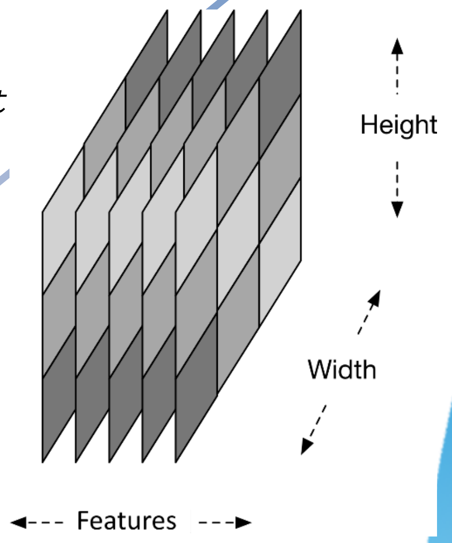
Convolutional Neural Networks

Neural Features Representation

- An input image is an RGB representation of a natural scene.
- An activation volume of a convolutional layer $\boldsymbol{A}^{(l)} \in \mathbb{R}^{n^{(l)} \times m^{(l)} \times d_{out}^{(l)}}$ is a multi-dimensional *neural feature representation* of the input image $\boldsymbol{A}^{(0)} = \boldsymbol{X} \in \mathbb{R}^{H \times W \times 3}$ at layer l.
- Feature depth increases as resolution decreases.
  - First convolutional layer represents *local features.*

    e.g. First convolutional layer in AlexNet outputs 96 features in a 55×55 map.
  - Last convolutional layer represents *global features.*

    e.g. Last convolutional layer in AlexNet output 256 features in 6×6 map.



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Convolutional Neural Networks

Neural Features Representation

- Image is downsampled but feature descriptors become more discriminative than original RGB pixel features.

- The features are optimized through gradient descent, in contrast to handcrafted feature extractors like SIFT, HOG, SURF.
  - Performance of learned CNN features has shown superiority in experiments, with a formal explanation.
  - Robustness of learned features is an open research issue.

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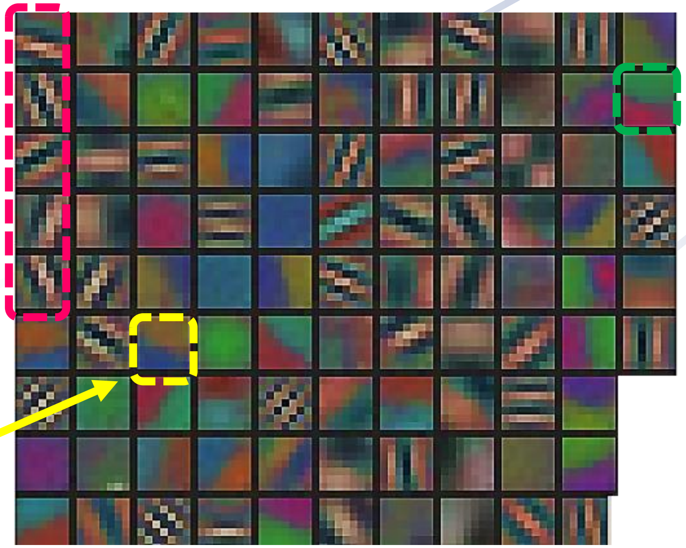
Convolutional Neural Networks
Visualization

- Visualizing the $d_{out} = 96$ features learned from RGB pixels in the 1st layer of the Zeiler & Fergus CNN (ZFNet) shows characteristics of biological vision.
  - ZFNet is an improvement of AlexNet with 1st layer: $[7 \times 7\ /2|\ 3 \rightarrow 96]$
  - Feature visualization indicated poorly trained convolutional kernels in AlexNet.

orientation selectivity found in V1 simple cells



green/red color opponency observed in retinal neurons and human visual perception

blue/yellow color opponency observed in retinal neurons and human visual perception

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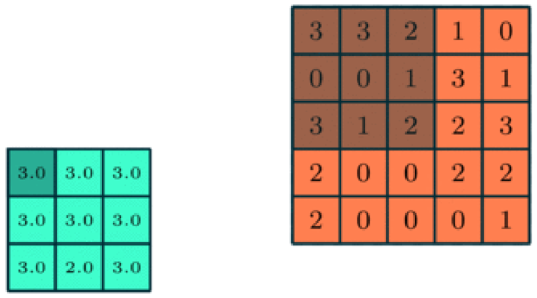
Convolutional Neural Networks
Pooling Layers

- Pooling layers are added inside a CNN architecture primarily for downsampling, aiming to reduce the computational cost. Secondarily helps on translation invariance.
  - The pooling window is moved over an activation map $\boldsymbol{A}_{ij}^{(l)}(o)$ along i, j with stride s.
  - Typical pool window sizes 2×2, 3×3.
  - Downsampling usually with $s = 2$.
  - Pools could overlap, e.g., $[3 \times 3 \ / \ 2]$



- Ad-hoc decision to use pooling or not.
- No formal justification for the effect of overlapping on pooling regions.

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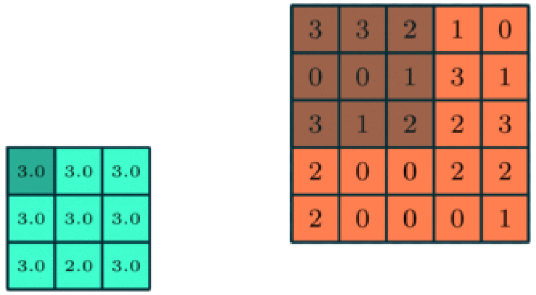
Convolutional Neural Networks

Max Pooling Layer

- Max pooling keeps the strongest activation in a $n \times m$ region of an activation map.
  - Edges between high and low activations could be lost.
  - Downsampling is preferred to be done in max pooling layers and not in convolutional layers.

- No formal justification for the benefits of keeping the strongest activation.



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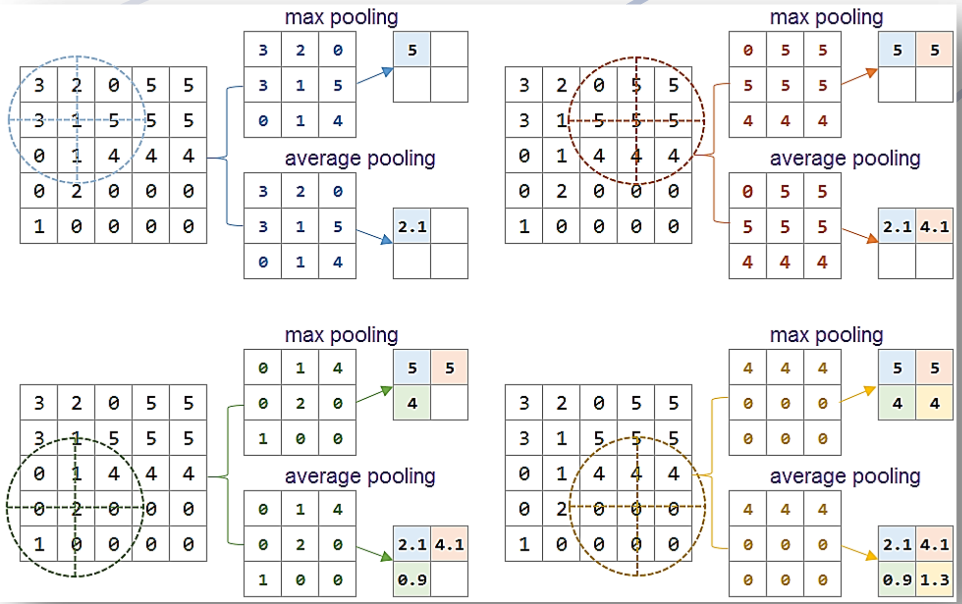
Convolutional Neural Networks
Max Pooling vs Average Pooling

- Local max pooling is preferred over local *average pooling*.
  - Average pooling is a smoothing operation, i.e. a low-pass filter.
  - Average pooling represents better the regions that have small total activation.



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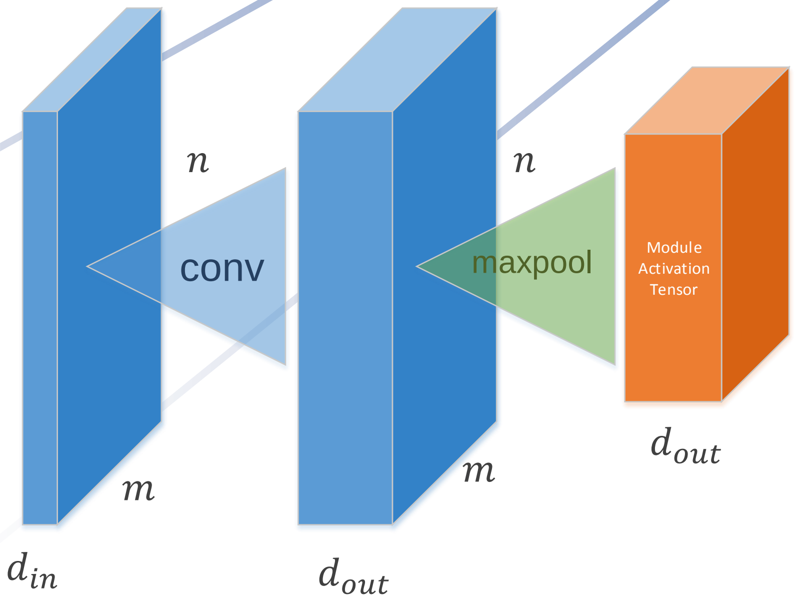
Convolutional Neural Networks

Simple Convolutional Module

- The simplest convolutional module has one convolutional layer with stride $s = 1$ and one max pooling layer with stride $s_{pool} = 2$ for downsampling.

  - Input has $n \times m$ spatial regions and d_{in} features.



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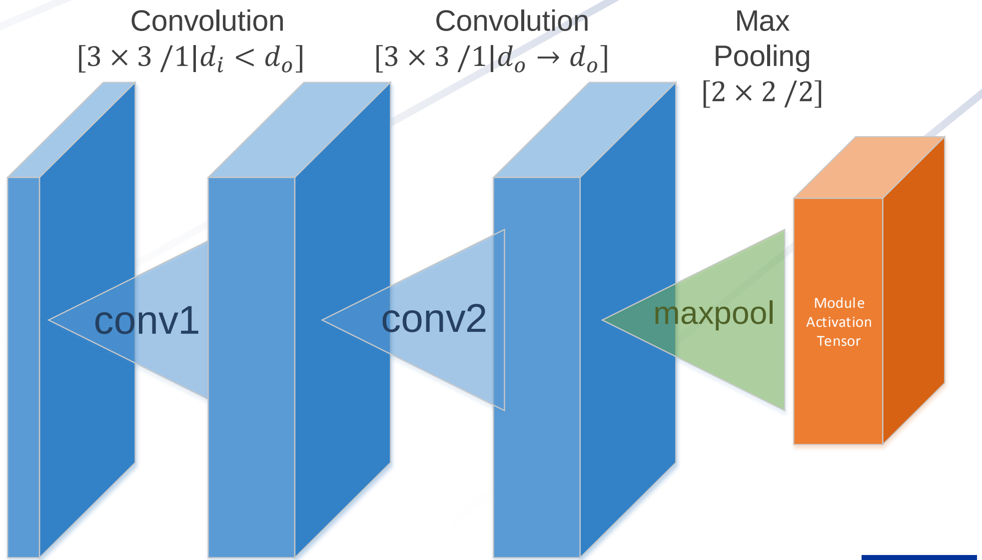
Convolutional Neural Networks

VGG Convolutional Module

- A stack of two 3×3 convolutional layers has an effective spatial size of 5×5.
- Uses consecutive $[3 \times 3/1]$ convolutional layers with the same d_{out} followed by 2×2 non-overlapping max pooling for downsampling.



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Classification and Regression

- **Classification:** If we have a class label set $\boldsymbol{C}=\{c_1,\ldots,c_L\}$, train a NN model to assign a class label vector $\hat{\boldsymbol{y}} \in [0,1]^L$ to an object $\boldsymbol{x}$: $\hat{\boldsymbol{y}} = f_{NN}(\boldsymbol{x}, \boldsymbol{\theta})$, where $\boldsymbol{\theta}$ are the CNN trainable parameter vector.
  - Essentially, we assign (predict) probabilities $P(\hat{\boldsymbol{y}} \mid \boldsymbol{x})$ that an object $\boldsymbol{x}$ belongs to each of the L classes.
  - **Training:** Given $N_{training}$ ground truth pairs $\{\boldsymbol{x}_\mathrm{i}, \boldsymbol{y}_\mathrm{i}\}$, $i = 1, \ldots, N_{training}$, estimate $\boldsymbol{\theta}$ by minimizing an error function $\min_{\boldsymbol{\theta}} J(\boldsymbol{y}\text{-}\,\hat{\boldsymbol{y}})$.
  - **Testing:** Given N_{test} ground truth validation pairs $\{\boldsymbol{x}_i, \boldsymbol{y}_i\}, i = 1, \ldots, N_{test}$ calculate (*predict*) $\hat{\boldsymbol{y}}_I$, $i = 1, \ldots, N_{test}$ and calculate *a performance metric*.

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Classification and Regression

- **Classification:**
  - Two class (*L*=2) and multiple class (*L*>2) classification.
  - **Example:** *Face detection* (two classes), *face recognition* (many classes).

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Classification and Regression

- **Regression:** If we have a function $\boldsymbol{y} = \boldsymbol{f}(\boldsymbol{x})$, train a NN model to predict **real-valued quantities** (vector $\boldsymbol{y}$ entries), $\hat{\boldsymbol{y}} = f_{NN}(\boldsymbol{x}, \boldsymbol{\theta})$, so that an error function $\min_{\boldsymbol{\theta}} J(\boldsymbol{y} - \hat{\boldsymbol{y}})$ is minimized.
  - **Training:** Given $N_{training}$ ground truth pairs $\{\boldsymbol{x}_i, \boldsymbol{y}_i\}, i = 1, \ldots, N_{training}$, estimate $\boldsymbol{\theta}$ by minimizing an error function $\min_{\boldsymbol{\theta}} J(\boldsymbol{y} - \hat{\boldsymbol{y}})$.
  - **Testing:** Given N_{test} ground truth validation pairs $\{\boldsymbol{x}_i, \boldsymbol{y}_i\}, i = 1, \ldots, N_{test}$ calculate (*predict*) $\hat{\boldsymbol{y}}_i, i = 1, \ldots, N_{test}$ and calculate an error function $J(\boldsymbol{y} - \hat{\boldsymbol{y}})$, e.g. MSE.

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Classification and Regression

- **Regression:**
  - **Example:** In object detection, regress object ROI parameters (width *W*, height *H*, offsets *X*, *Y*).
  - **Function approximation:** it is essentially regression, when the function $\mathbf{y} = \mathbf{f}(\mathbf{x})$ is known.

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Training CNNs

Gradient descent on a large number of images

- CNNs are trained with the same gradient descent methods as multilayer perceptron.
  - Convolution is a differentiable operation.
  - Mini-batch Stochastic Gradient Descent methods are used for image batches.
- Optimization methods:
  - *Learning rate decay* are scheduled changes to the learning rate at the various training epochs. For non-adaptive mini-batch SGD methods, e.g. *Momentum*.
  - *ADAM* is an optimization method with an adaptive learning rate.
- Large scale datasets are needed to adequately train a CNN.
  - CNNs are prone to over-fitting.
  - Training images count in the magnitude of 10 or 100 thousands.

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Training CNNs

The ILSVRC2012 dataset

- State-of-the-art CNNs are trained on this dataset
  - The de-facto benchmark to evaluate the state-of-the-art in image classification.
- Ground Truth Set
  - Training Set: 1.28 million images that are labeled with 1000 classes
  - Validation Set: 50.000 images that are labeled with 1000 classes. Used to check the training quality at the end of a training epoch.
- Unknown Test Set:
  - 100.000 images that are used for testing a trained network.
  - Labels remain unknown until the end of the competition.

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Object detection: Definitions

Object Detection

- Object detection consists of:
- Object classification:
  - Find the object class out of *C* classes.
- Object localization:
  - Find object ROI (bounding box) *A* parameters $[H_A, W_A, X_A, Y_A]$ through (CNN) regression.
- Ground truth used in training: Object class labels C_i and Bounding boxes (ROIs) B_i, $i=1,\ldots,N_{training}$.

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Performance metrics

Classification: Top-5 Error

- Given the ground truth object class label C_i and top 5 predicted class labels $c_{i1}, \dots, c_{i5}$ the prediction is correct when there is $c_{ij} = C_i$. The error of a single prediction is:

$$e_{CLS}(c_{ij}, C_i) = \begin{cases} 1, & c_{ij} \neq C_i, \quad j = 1, \dots, 5 \\ 0, & otherwise. \end{cases}$$

- The top-5 error is the fraction of N_{test} test images on which the prediction is wrong:

$$top5error_{CLS} = \frac{1}{N_{test}} \sum_{i=1}^{N_{test}} \min_j \{e_{CLS}(c_{ij}, C_i)\}, j = 1, \dots, 5.$$

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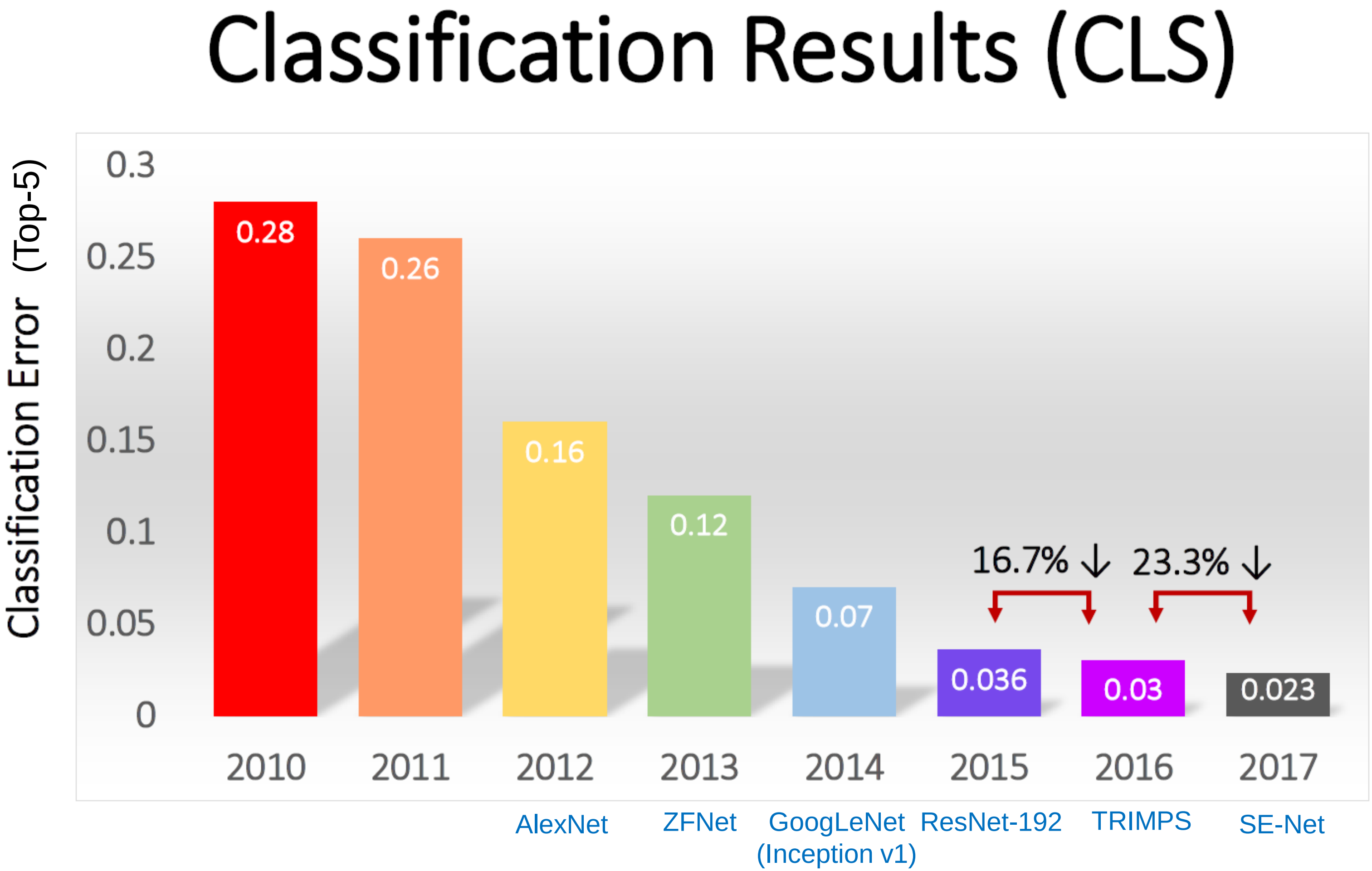
CNN Advances

Image Classification



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Performance metrics

Single Object Localization: Top-5 Localization Error

- Let us have a pair of ground truth a) label C_i and b) bounding box B_{ik}, a set of classification/localization predictions $\{(c_{ij}, A_{ij})\}_{j=1}^{5}$ of class labels c_{ij} with corresponding bounding boxes A_{ij}.
- Localization error $e_{LOC}(A_{ij}, B_{ik}) = \begin{cases} 1, & J(A_{ij}, B_{ik}) \leq 0.5 \\ 0, & J(A_{ij}, B_{ik}) > 0.5 \end{cases}$, where *intersection over union* or *Jaccard similarity coefficient* $J(\cdot)$ is defined for sets $\hat{Y}, Y$ as $J(\hat{Y}, Y) = \frac{|\hat{Y} \cap Y|}{|\hat{Y} \cup Y|}$.

$$top5error_{LOC} = \frac{1}{N_{test}} \sum_{i=1}^{N_{test}} \min_j \{e_{LOC}(A_{ij}, B_{ik})\}, j = 1, \dots, 5.$$

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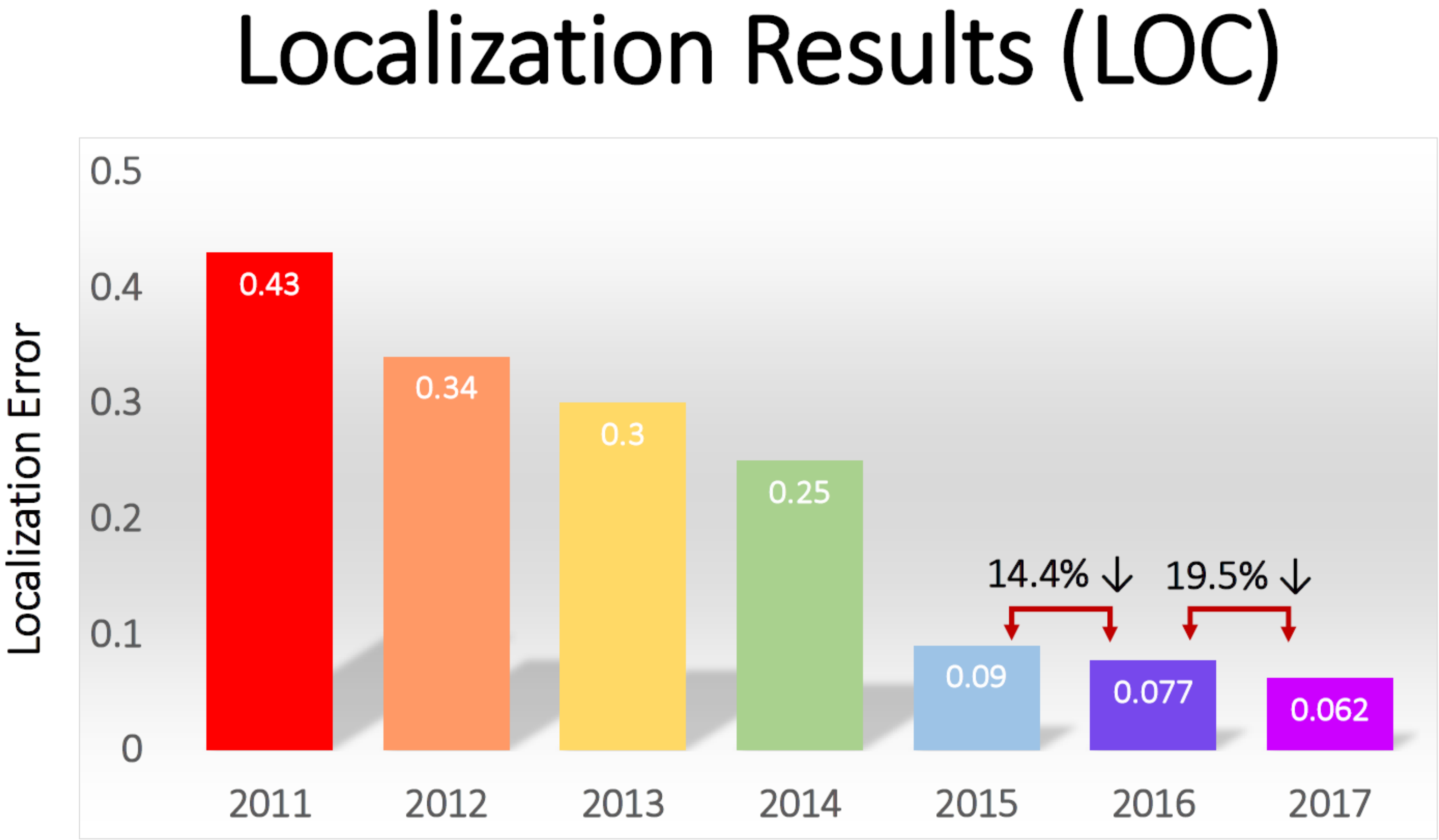
CNN Advances

Object Localization



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Performance metrics

Object Detection

- Object detection consists of:
- Object classification
  - Performance measured by e.g., top5error
- Object localization
  - find object ROI (bounding box) parameters [*H*,*W*, *X*,*Y*] through (CNN) regression.
  - Performance measured by the *Jaccard similarity coefficient* or *Intersection-over-Union (IoU)* ratio.

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Performance metrics

Object Detection: Mean Average Precision (mAP)

- Object detection predicts pairs of bounding boxes A_{ij} and confidence score s_{ij} for each detection j on image $i = 1, \dots, Ntest$. If A_{ij} is matched to the ground truth box B_{ik} according to $J(A_{ij}, B_{ik}) > T(B_{ik})$ then $z_{ij} = 1$. The matching threshold depends on dimensions $H \times W$ of the ground truth box $T(B) = min\left(0.5, \frac{HW}{(W+1)(H+1)}\right)$.

- For a confidence threshold t: $Recall(t) = \frac{\sum_{ij} 1[s_{ij} \geq t] z_{ij}}{C}$ and *Precision*$(t) =$ $\frac{\sum_{ij} 1[s_{ij} \geq t] z_{ij}}{\sum_{ij} 1[s_{ij} \geq t]}$,
  C *total number of* ground truth objects instances in the dataset.

- *Mean Average Precision* (mAP) is calculated for M levels of recall achieved by varying the confidence threshold t: $mAP_{DET} = \frac{1}{M} \sum_{i=1}^{M}$ *Precision*(t_i).

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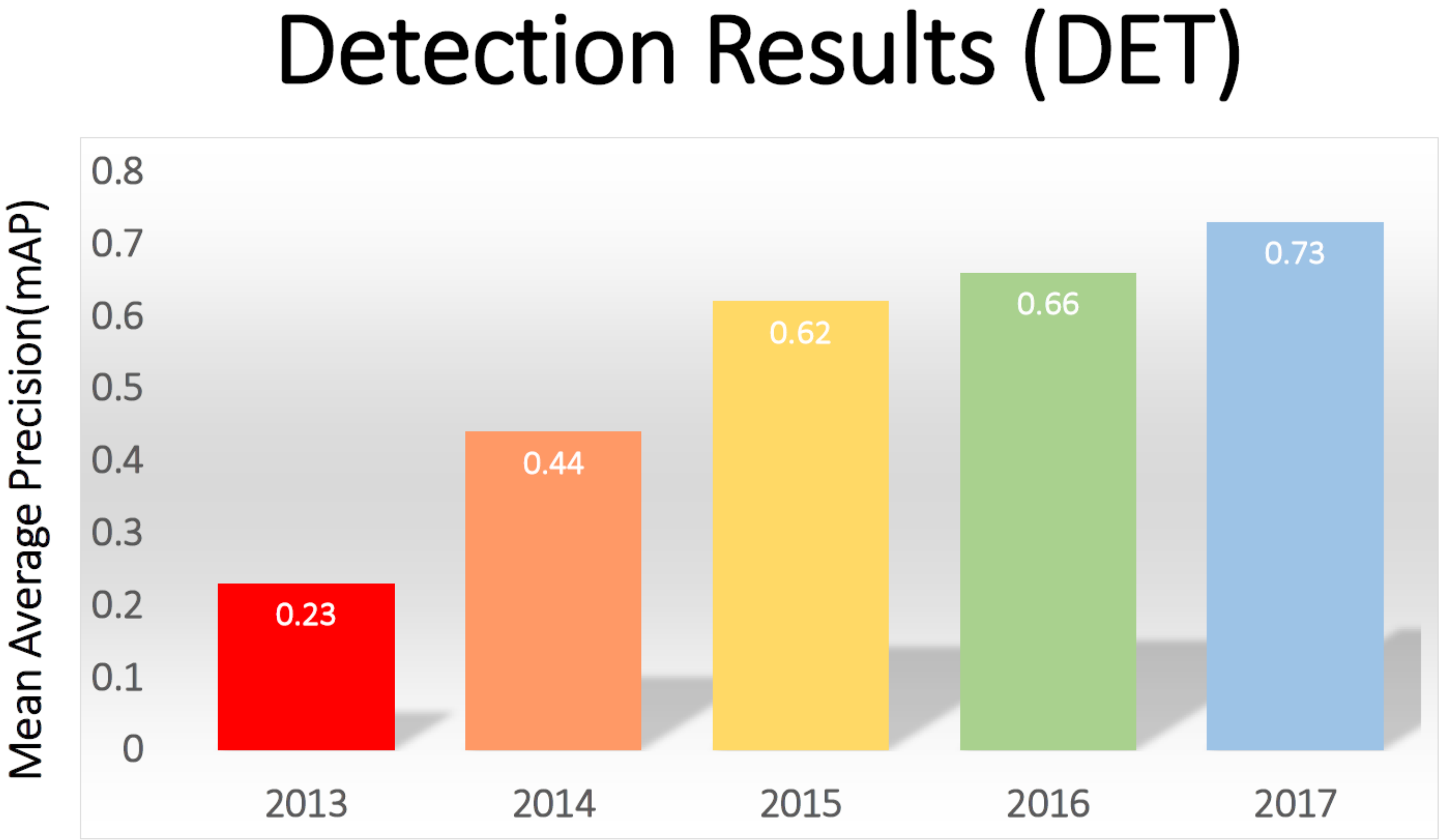
CNN Advances

Object Detection



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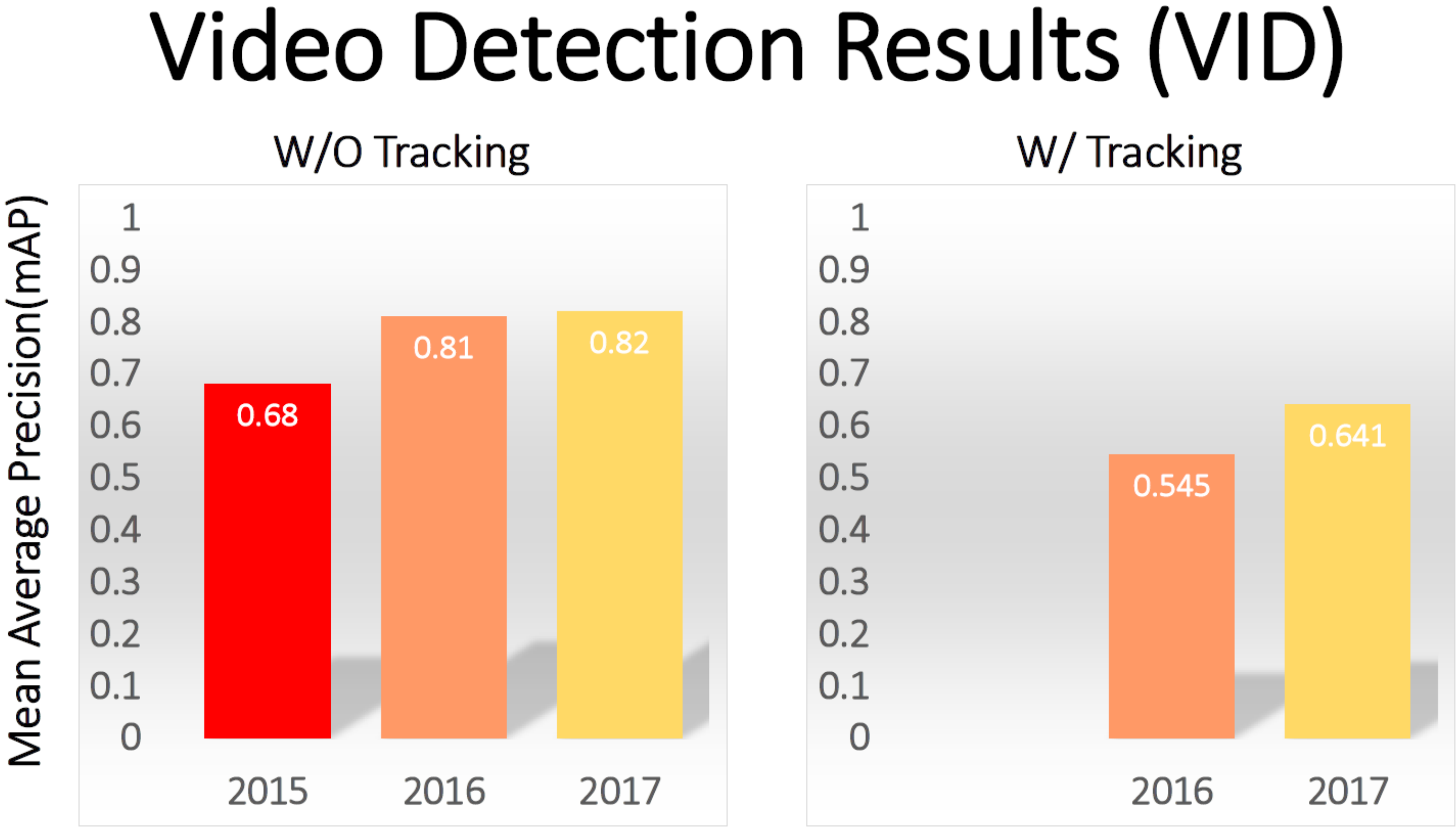
CNN Advances

Object Detection from Video



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Training CNNs???

Data Preprocessing

- Images are preprocessed before the training process.
  - Mean centering by subtraction of mean R,G,B values from n images with $W \times H = m$ pixels: $\boldsymbol{X} = \boldsymbol{X}_R, \boldsymbol{X}_G, \boldsymbol{X}_B$: $\boldsymbol{X} \in \mathbb{R}^{\boldsymbol{n} \times \boldsymbol{m}}$

$$\boldsymbol{X}_{MEAN\_CENTERED} = \boldsymbol{X} - \overline{\boldsymbol{X}}$$

  - Apply *a whitening* filter $\boldsymbol{W}$ using the eigendecomposition $\boldsymbol{X}\boldsymbol{X}^{\boldsymbol{T}} = \boldsymbol{P}\boldsymbol{D}\boldsymbol{P}^T$, where $\boldsymbol{D}$ has the eigenvalues on the diagonal:

$$\boldsymbol{X}_{WHITENED} = \boldsymbol{W}\,\boldsymbol{X}_{MEAN\_CENTERED}$$

  - PCA Whitening: $\boldsymbol{W} = \boldsymbol{W}_{PCA} = \boldsymbol{D}^{-1/2}\boldsymbol{P}^T$
  - ZCA Whitening: $\boldsymbol{W} = \boldsymbol{W}_{\boldsymbol{ZCA}} = \boldsymbol{P}\boldsymbol{D}^{-1/2}\boldsymbol{P}^T$. ZCA is preferred for natural images.
- Preprocessing helps illumination invariance and convergence on certain visual features distribution, e.g. natural images of ILSVRC2012.

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Training CNNs

Weight initialization

- Completely random initialization of weights has experimentally proven ineffective to train deep CNNs.
- Values are chosen from a uniform distribution and restricted in an interval that relates to the layer input/output feature depths

$$\boxed{\left[-\sqrt{\frac{3\ \cdot a\ \cdot \beta}{d_{in} + (a-1)\cdot d_{out}}}, \sqrt{\frac{3\ \cdot a\ \cdot \beta}{d_{in} + (a-1)\cdot d_{out}}}\right]}$$

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Training CNNs

Xavier initialization (2010)

$$\left[-\sqrt{\frac{3 \cdot a \cdot \beta}{d_{in} + (a-1) \cdot d_{out}}}, \sqrt{\frac{3 \cdot a \cdot \beta}{d_{in} + (a-1) \cdot d_{out}}}\right]$$

- Two intervals for the respective initialization methods:
  - Glorot initialization uses $\beta = 1, a = 2$, $\sqrt{\frac{6}{d_{in} + d_{out}}}$.
  - Xavier initialization is simplified as $\frac{2}{d_{in} + d_{out}}$.

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Training CNNs

Data Augmentation

- It is used to avoid overfitting.
- The training image set is augmented during training with label-preserving transformation of the samples:
  - Image translations and random image crops.
  - Photometric distortions, i.e. altering the intensities of RGB channels.
  - Scaling and rotation, e.g. at $\leq 90^o$
  - Vertical reflections, e.g. mirror.
  - Addition of Salt and Pepper noise.
- Data augmentation can be done with minimal computation cost inside the training process.

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Training CNNs

Normalization Layers

- Level the intermediate activations to a desired range.

- Prevent the *exploding gradients problem,* during gradient descent training of CNNs, when using activation functions that have no upper bound.
  - **LCN** - Local Contrast Normalization is both a subtractive and divisive normalization (2009).
  - **LRN** - Local Response Normalization resembles LCN (2012).

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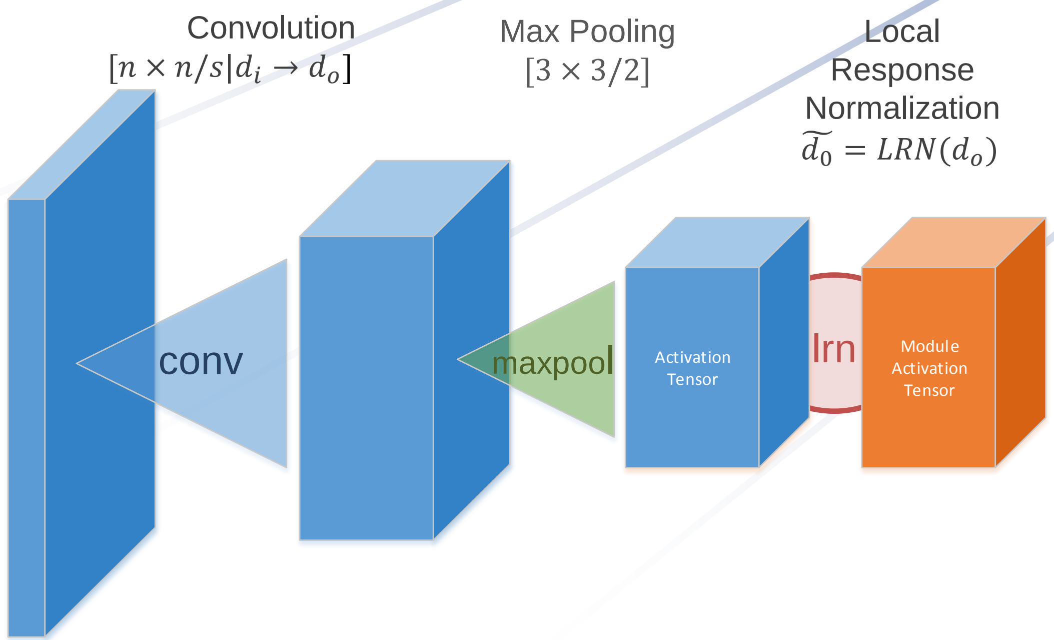
CNN Modules

AlexNet / ZFNet Convolutional Module

- It contains one convolutional layer, followed by a max pooling layer, followed by a local response normalization layer.



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Training CNNs

In-layer normalization

- When using mini-batches, the probability distribution of the input for a CNN layer constantly changes during training. This causes a shift in the probability distribution of learned weights, and thus, of the CNN activations.
- The root cause is the change in the training data distribution between training mini-batches. This has been studied as the *internal covariate shift problem.*
- In-layer batch normalization fixes the distribution of the input samples.
  - BN - Batch normalization (2015)
  - BRN - Batch renormalization (2017)

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Training CNNs

Batch Normalization

- Batch normalization introduces extra parameters γ and β that scale and shift the normalized values for the mini-batches of images. These are learned together with network weights via gradient descent.

Batch Normalization

$$BN_{\gamma,\beta,\varepsilon}(x_i) = \gamma \frac{(x_i - \bar{x})}{\sqrt{s^2 + \varepsilon}} + \beta:\ i = 1,..,\mathrm{C}$$

N training samples and C minibatch size

$k = \frac{C}{N},\ \ k \in \mathbb{N}$ count of mini-batches

Mean and Sample Standard Deviation

$$\bar{x} = \frac{1}{C}\sum_{n=1}^{C} x_i$$

$$s^2 = \frac{1}{C}\sum_{n=1}^{C} (x_i - \bar{x})^2$$

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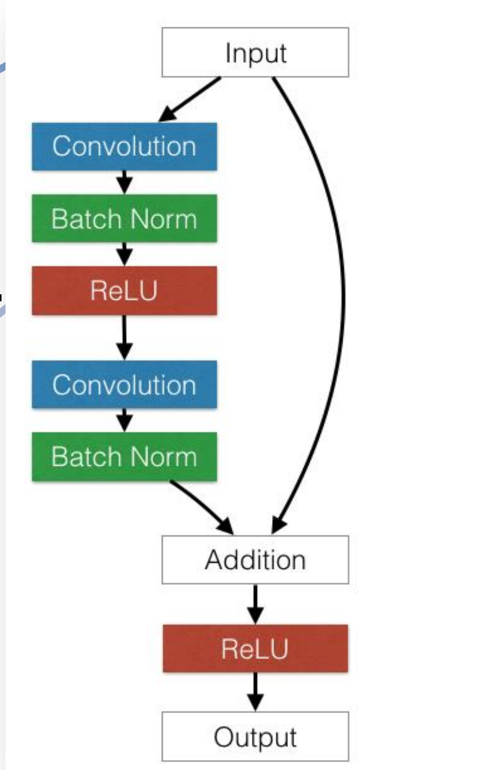
Advanced CNN modules

Residual Convolutional Module

- The basic module of *ResNets.*
- A *shortcut connection* bypasses layers. BN is used before the activation function. These implement *identity mapping*.

$$\mathbf{A}^{(l+2)} = f_{l+2}(\mathbf{A}^{(l)} + BN_{l+2}\big(\mathbf{b}^{(l+2)} + \mathbf{W}^{(l+2)} * f_{l+1}(BN_{l+1}(\mathbf{b}^{(l+1)} + \mathbf{W}^{(l+1)} * \mathbf{A}^{(l)}))\big)$$

- *Residual learning* makes possible to train extremely deep CNNs up to 192 layers.



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Training CNNs

Regularization

- Regularizers aim to reduce over-fitting during training of deep CNNs on image data:
  - *Weight decay* is a well-known approach that adds norms of the networks weights, like the L_2 (Euclidean norm), as terms of the loss function.
  - *Dropout* randomly excludes a set of neurons from a certain training epoch with a constant keep out probability p_{keep}.

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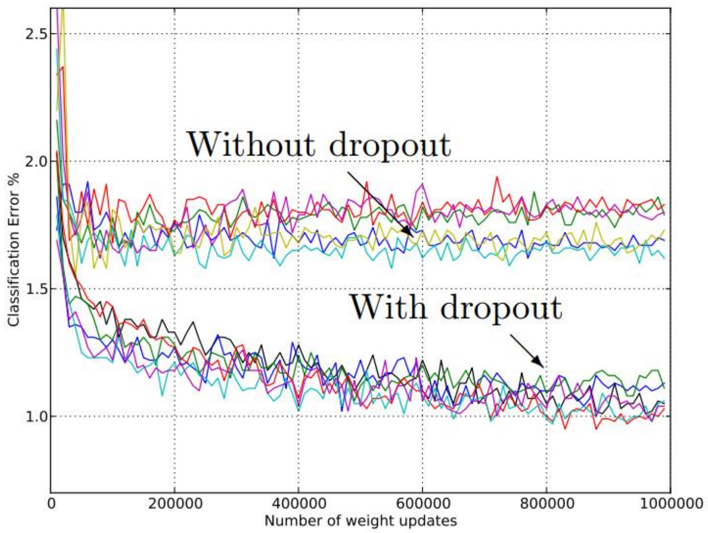
Training CNNs

Dropout

- Activations of dropped out neurons are set to zero.
  - They do not participate in the loss, thus excluded from back-propagation.
  - Dropout was initially used in AlexNet after each fully connected layer.
  - During testing a trained model, all neurons are used with their already learned weights.
- Induces dynamic sparsity during training.
- Prevents complex co-adaptations of the synaptic weights, that may lead to correlated activations of neurons.



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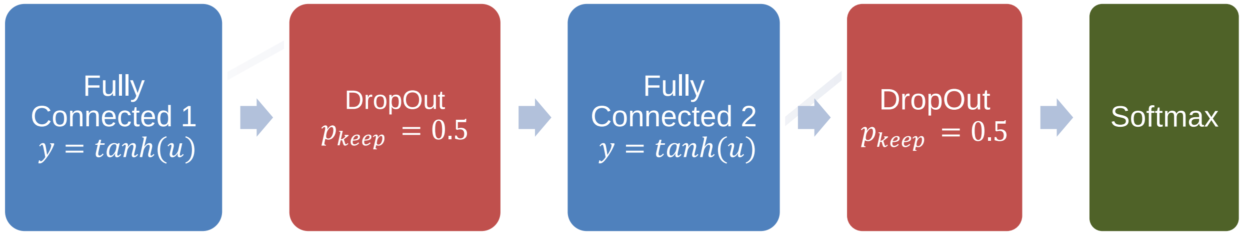
CNN Classifiers

AlexNet / ZFNet Fully Connected Classifier

- Dropout of 50% of neurons is used during classifier training.

- There are 2 fully connected layers with $d_{out} = 4096$ neurons and a Softmax output layer with N neurons for N classes.



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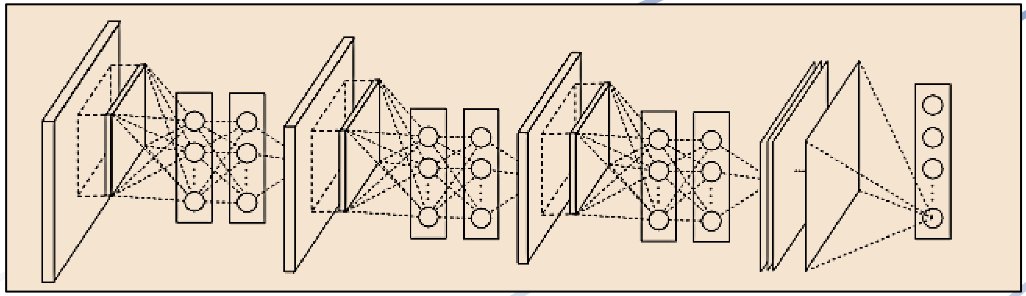
CNN methods

Network-In-Network (NiN)

- A micro neural network is placed between two neural network layers.



- This idea is extensively used by the state-of-the-art CNNs as a 1×1 convolutional layer $(h_1 = 1, h_2 = 1)$.
- Output features are weighted averaged (plus activation functions) of the input features.
- Operating at a single region of input, increases the representation power its feature descriptor.
  - Feature dimensionality can increase or decrease.

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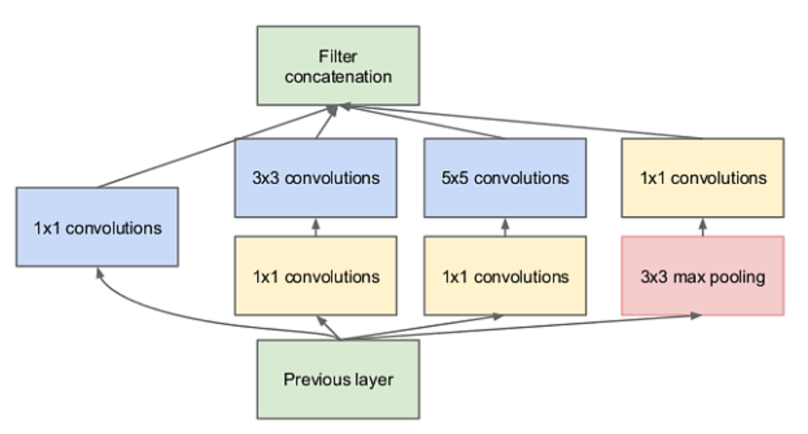
Advanced CNN modules

Inception Convolutional Module

- Basic idea is to have multiple window sizes for convolutions that operate over the same input region.
  - Building block of GoogleLeNet (Inception v1) CNN.
  - Latest upgrade to the model is Inception v4.



- The activation volumes are concatenated in the module output along the feature dimension.
  - $d_{out} = d_{1\times1} + d_{3\times3} + d_{5\times5} + d_{maxpool}$
- The 1×1 convolutional layers are used before the computationally intensive 3×3 and 5×5 convolution operations.

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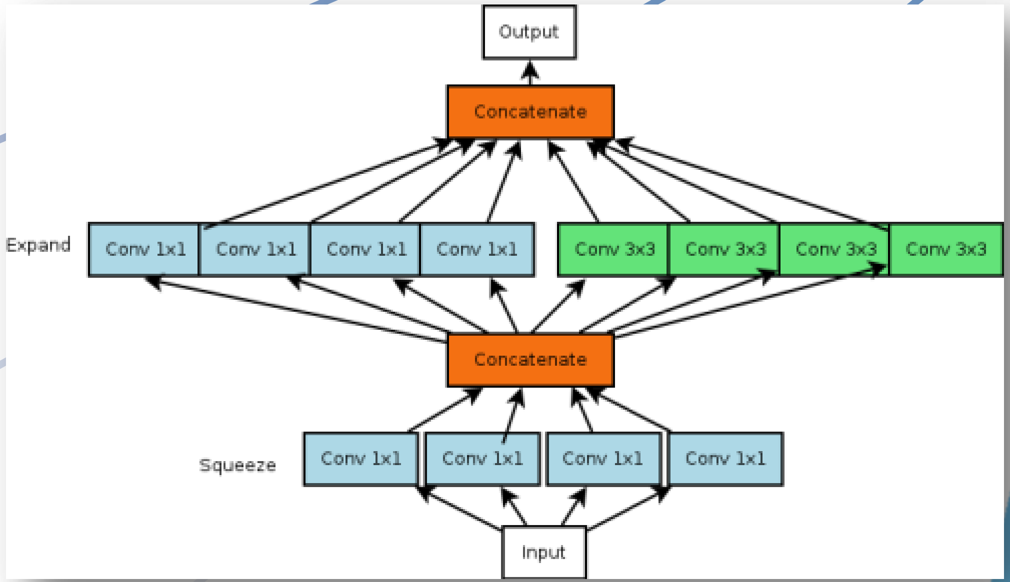
Lightweight CNN Modules

Fire Module

- Dimensionality of features is reduced by parallel 1×1 layers.
  - "Squeezed" activations are concatenated.
- Dimensionality of features is increased by multiple and 3×3 and 1×1 layers.
  - "Expanded" activations are concatenated.



- Building block of SqueezeNet that achieves AlexNet classification accuracy with $50\times$ fewer parameters. This research area is *model compression.*

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CNN methods

Global Average Pooling

- In the NiN paper, a *Global Average Pooling* layer is proposed, which averages the values of each activation map.

Global Average Pooling Operation

$$y^{(l)}(o) = \frac{1}{n_{out}^{(l-1)} \times m_{out}^{(l-1)}} \sum_{i=1}^{n_{out}^{(l-1)}} \sum_{j=1}^{m_{out}^{(l-1)}} y_{ij}^{(l-1)}(o)$$

on $n_{out} \times m_{out}$ activation map for feature o of previous layer $l-1$

- It is used in a CNN classifier before the softmax layer.
- It links feature activations with class predictions.
  - Feature activation maps become confidence maps for the predicted classes.
  - Global Average Pooling can replace computationally expensive fully connected layers.

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CNN Classifiers

Inception Output Classifier

- It contains a global average pooling, 40% dropout and a fully connected (FC) layer of $d_{out} = 1024$ neurons with a linear activation function before the Softmax layer.
  - It replaces the memory demanding classifier that uses two FC layers of $d_{out} = 4096$ each.

Global Average Pooling → DropOut $p_{keep} = 0.6$ → Fully Connected Linear $y = f(u)$ → Softmax

- There are two auxiliary classifiers in the Inception v1 (GoogleLeNet) CNN for two additional gradient flows.

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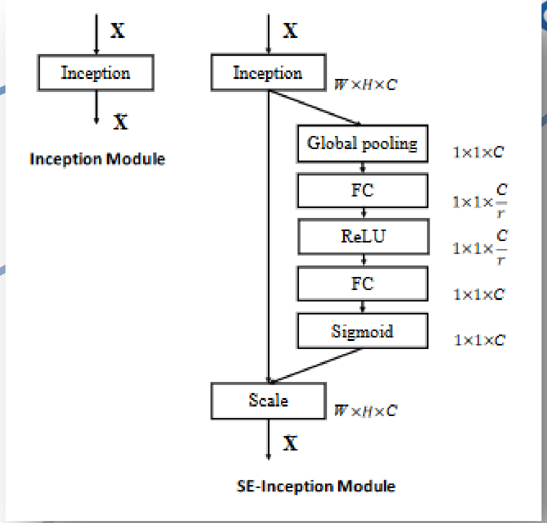
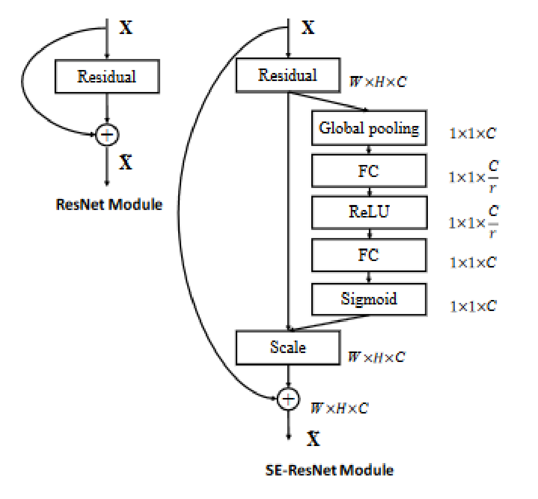
Current state-of-the-art CNN

Squeeze and Excitation Module

- Global spatial information is “squeezed” into one feature descriptor with global average pooling.
- A bottleneck mini-network implements a gating mechanism.
  - First fully connected (FC) layer reduces dimensionality before the ReLU non-linearity.
  - Second FC layer increases dimensionality before the Sigmoid gating function. Output is $s^{(l)} \epsilon [0,1]$
- Convolutional activations are scaled $\boldsymbol{Z}^{(l)} = \boldsymbol{A}^{(l)} s^{(l)}$.





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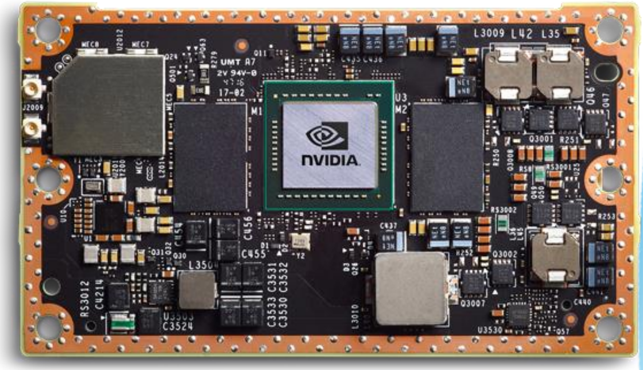
Convolutional Neural Networks

Computational Cost

- Current research aims to reduce the number of CNN model parameters, thus reducing the complexity.
  - Less parameters means less memory and faster recall of patterns.
  - Prediction accuracy of models should be competitive or the same.

- Lightweight CNNs need to fit in the memory of mobile accelerators, like the *NVIDIA Jetson TX2* that is used in MultiDrone.
  - Less computations means less energy consumption.
  - Better models may lead to increased flight time.



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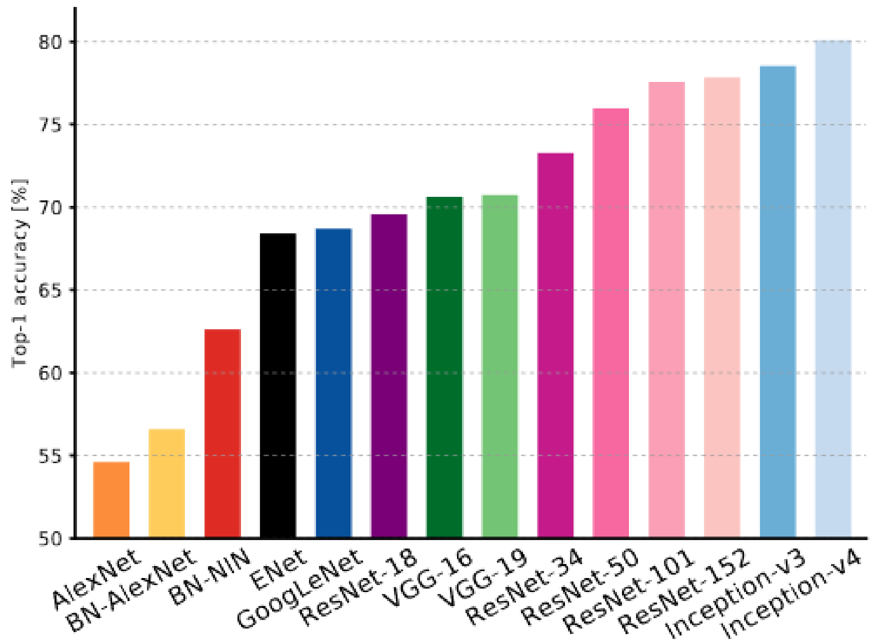
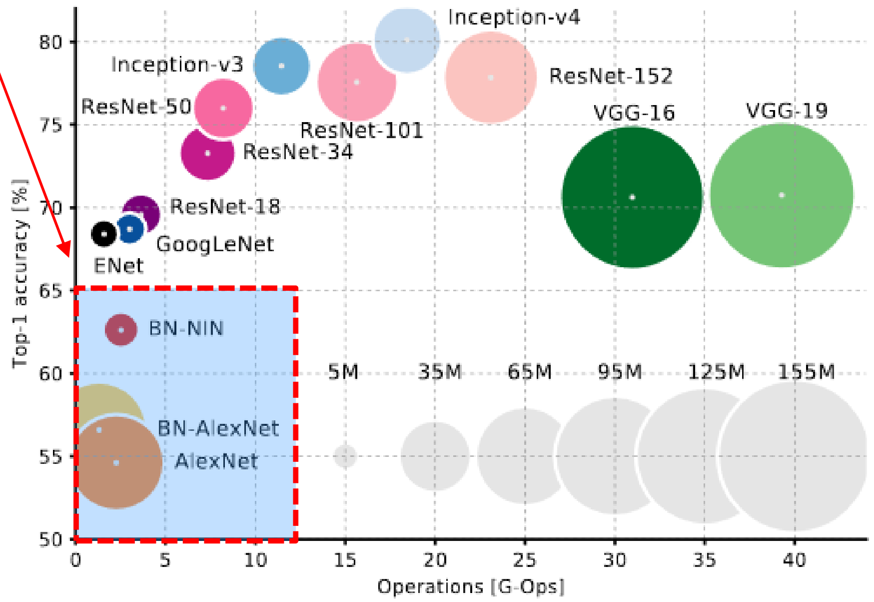
CNN Computational Cost

Early CNN models

Low performing models





A. Canziani, A. Paszke, and E. Culurciello, “An Analysis of Deep Neural Network Models for Practical Applications,” *arXiv:1605.07678 [cs]*, May 2016.

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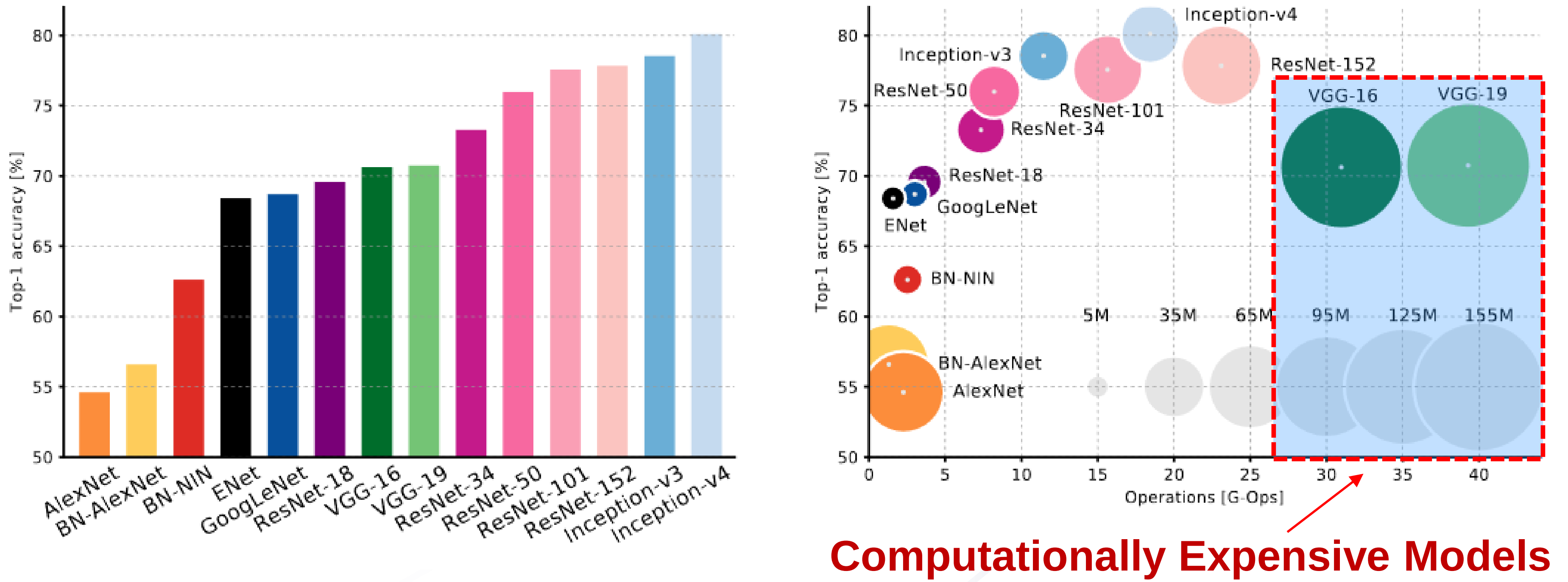
CNN Computational Cost

Heavy memory demands



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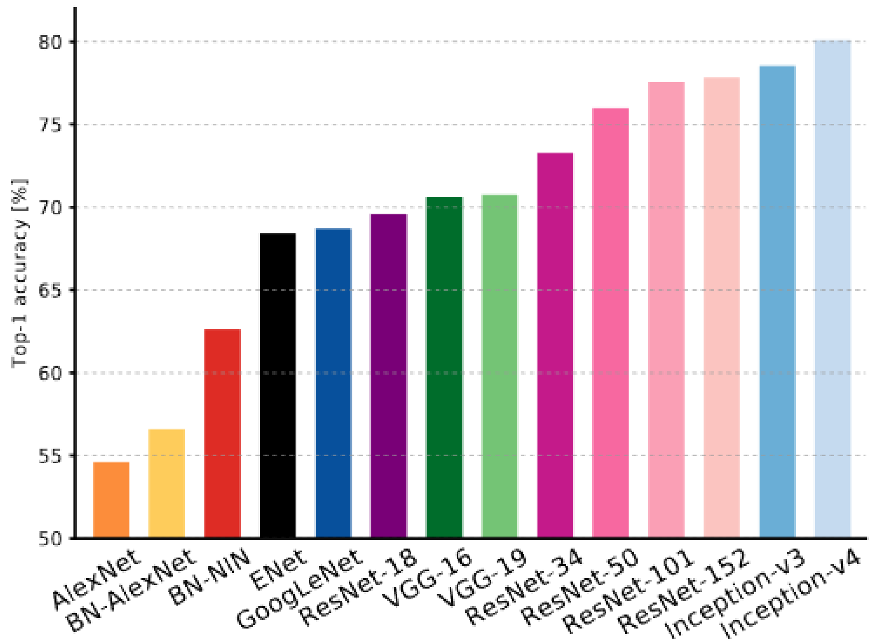
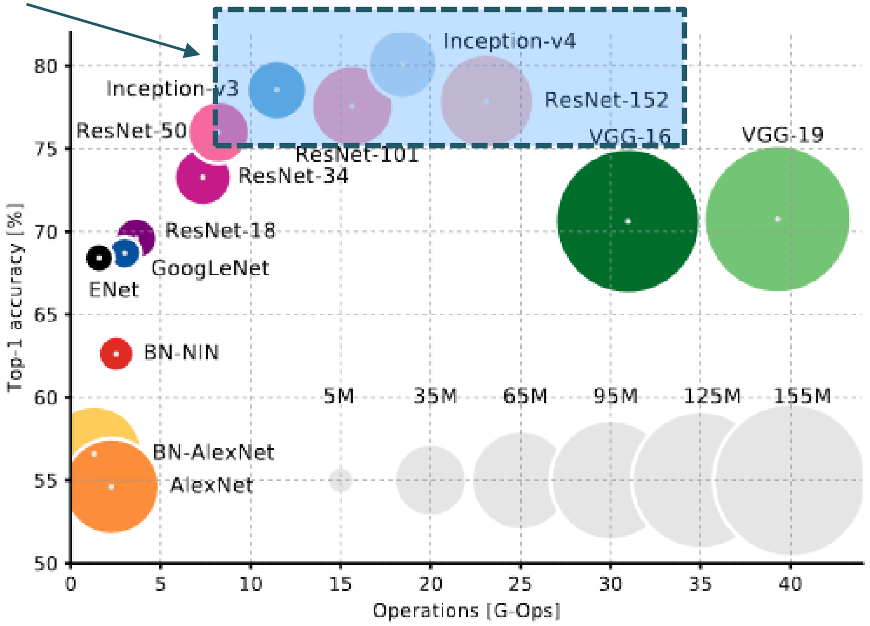
CNN Computational Cost

State-of-the-art

Best performance but increased complexity





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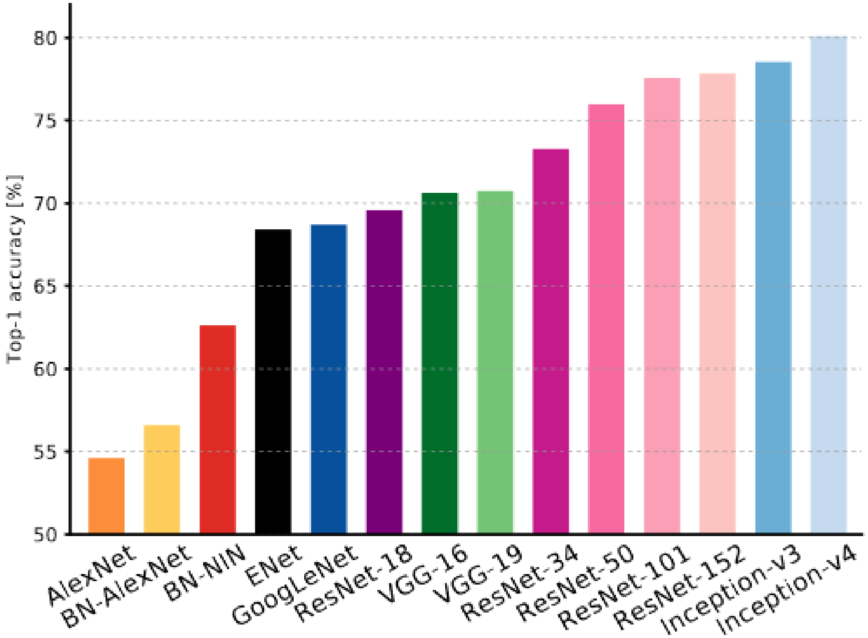
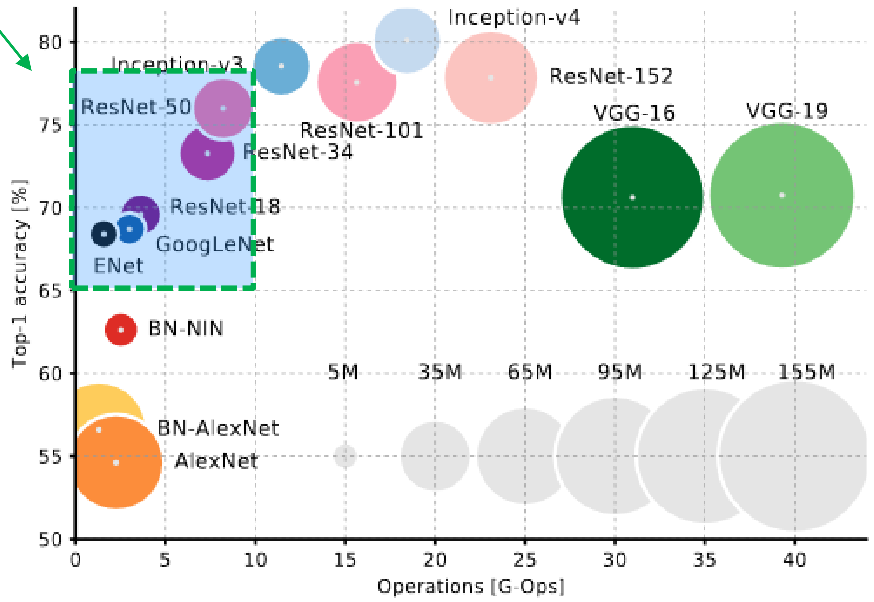
CNN Computational Cost

Candidates for real-world applications

"Goldilocks" zone of CNN models





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Q & A

Thank you very much for your attention!

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