Lecture 07 – CNN Applications and Tricks

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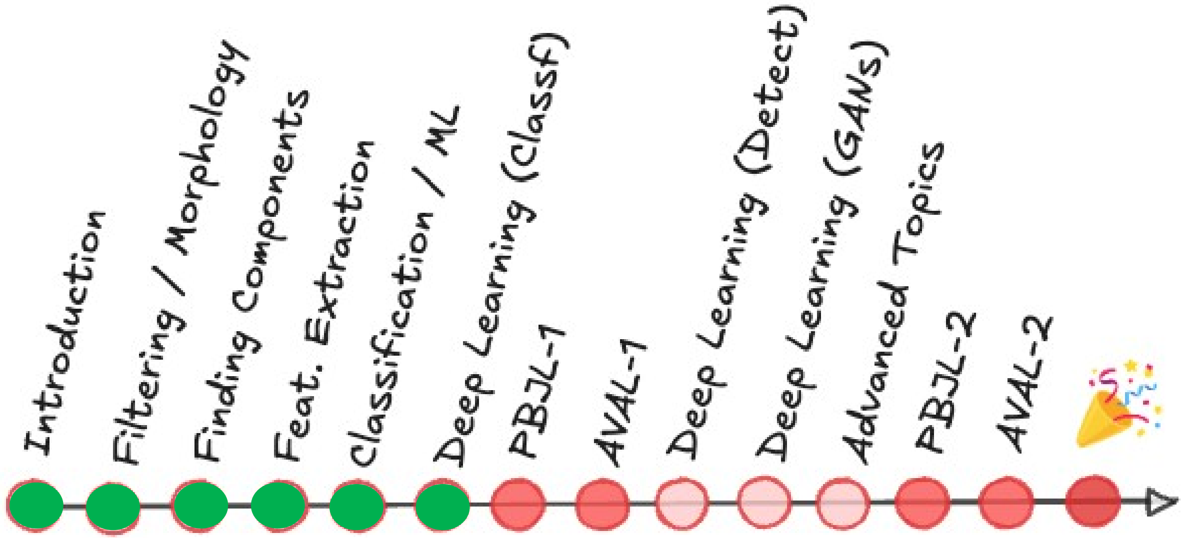
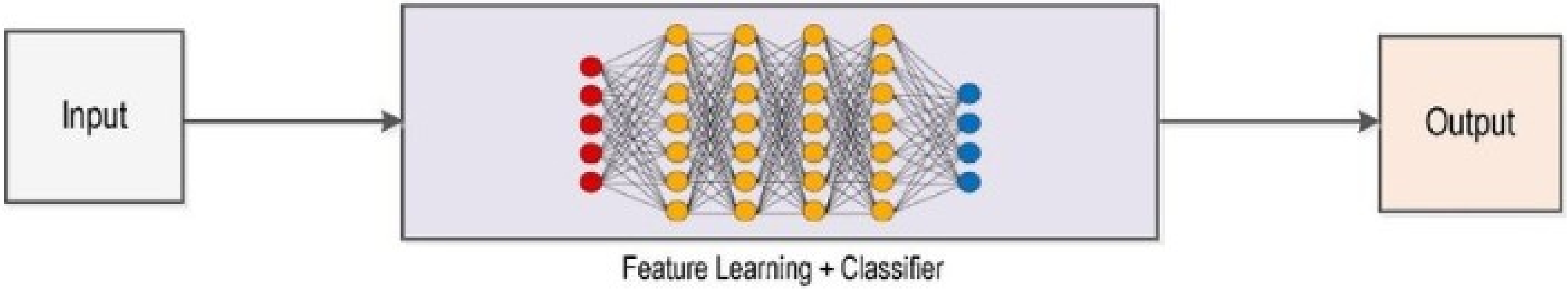
Topics

- Convolutional Neural Network
  - Basic Concepts
  - Archictetur and Hiper Parameters
  - Overfitting
  - Data Augmentation
  - Transfer-Learning
  - Applications
- State of The Art Architectures
- Practice

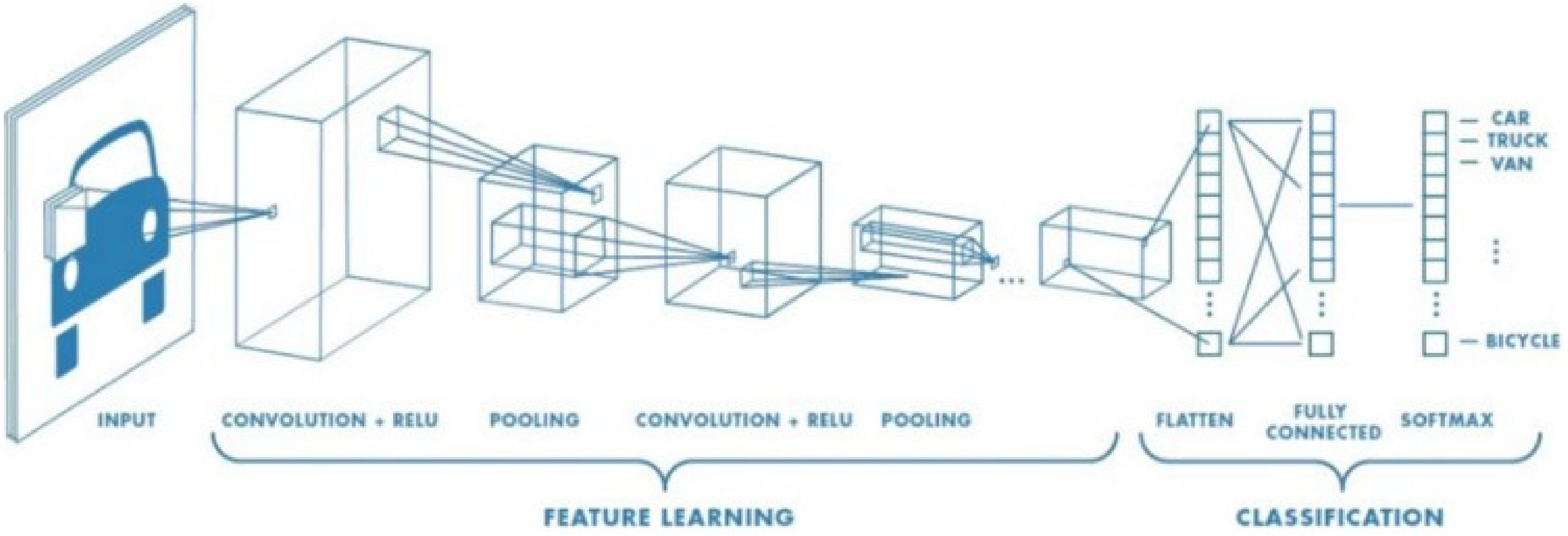


Deep Learning Pipeline



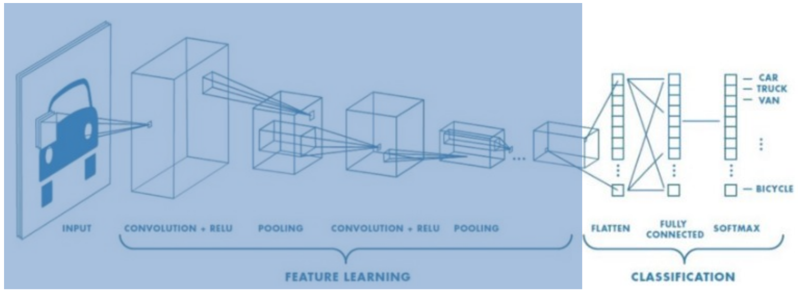
Convolutional Neural Network

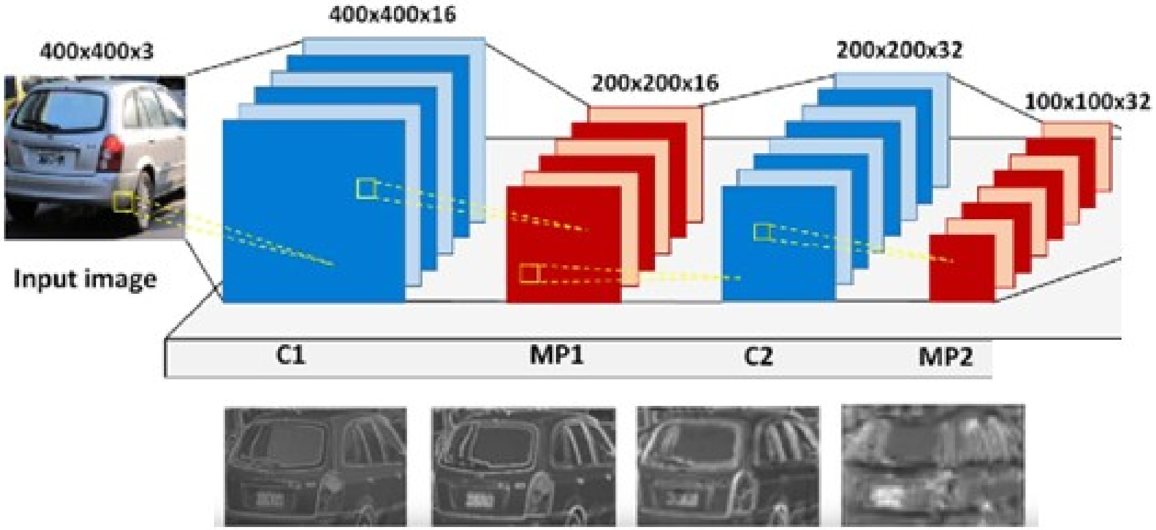
- CNN



Convolutional Neural Network

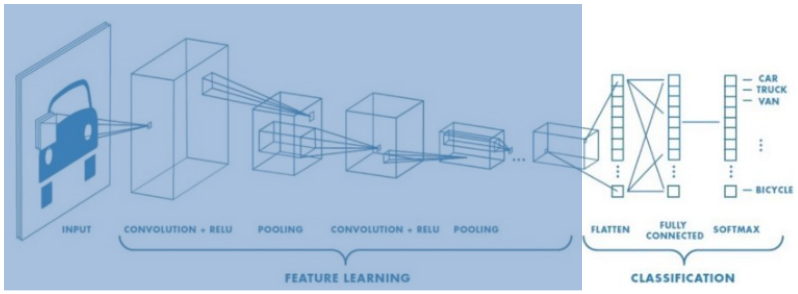
- Feature Extraction

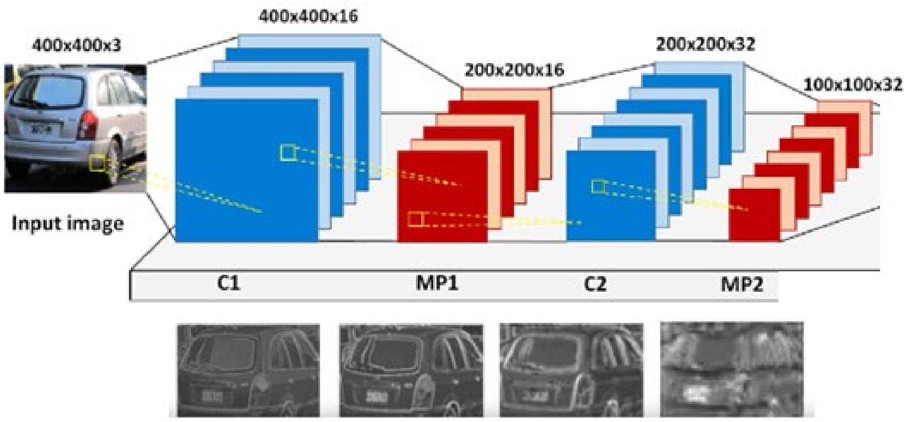


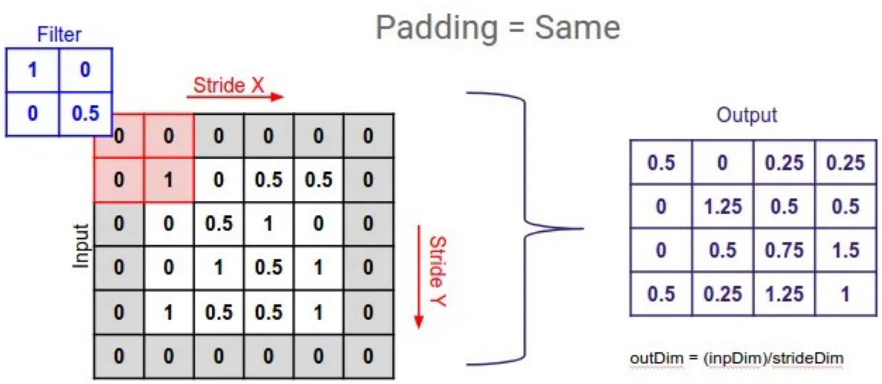


Convolutional Neural Network

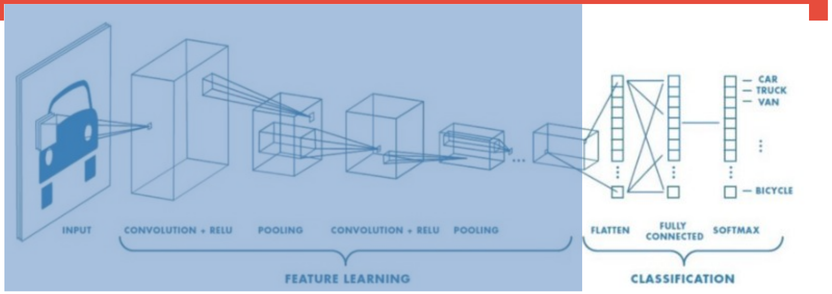
- Convolutional Layer (Learnable Filters)
  - Padding
  - Stride
  - Kernel Size
  - Number of Filters



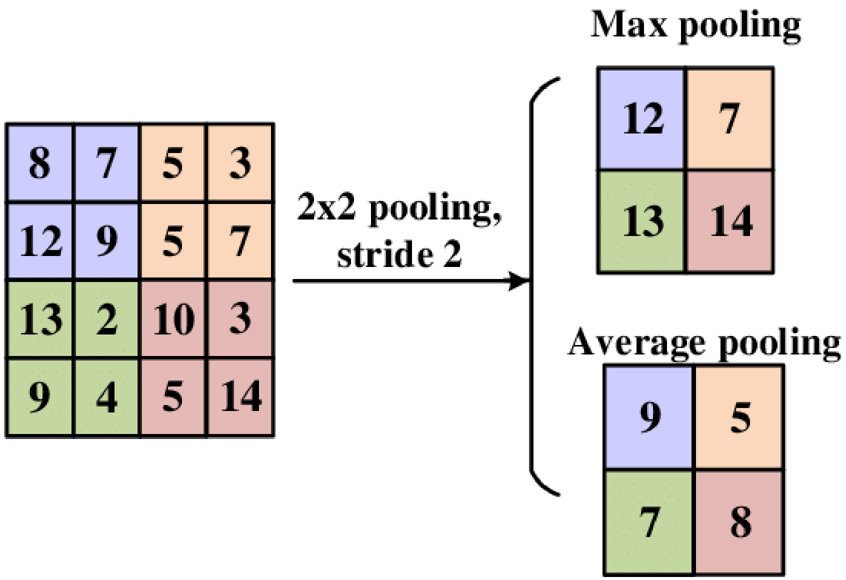




Convolutional Neural Network

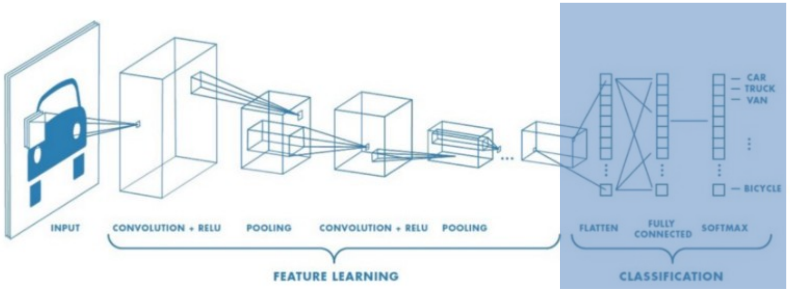


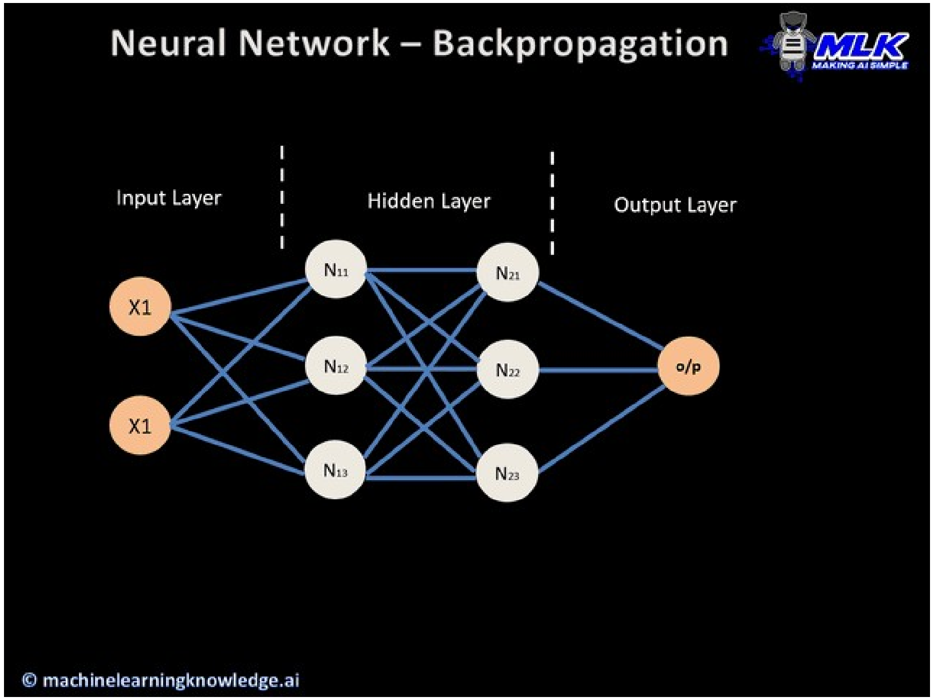
- Pooling Layer
  - Reduce Spatial Dimensions
  - Translation-Invariant
  - Common Filter
    - Max: Preserve the “strongest” features
    - Average: Smooth features, preserves general representations



Convolutional Neural Network

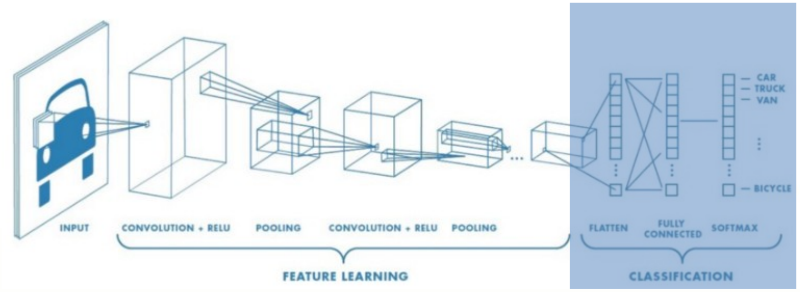
- Classification
  - Forward and Back Propagation

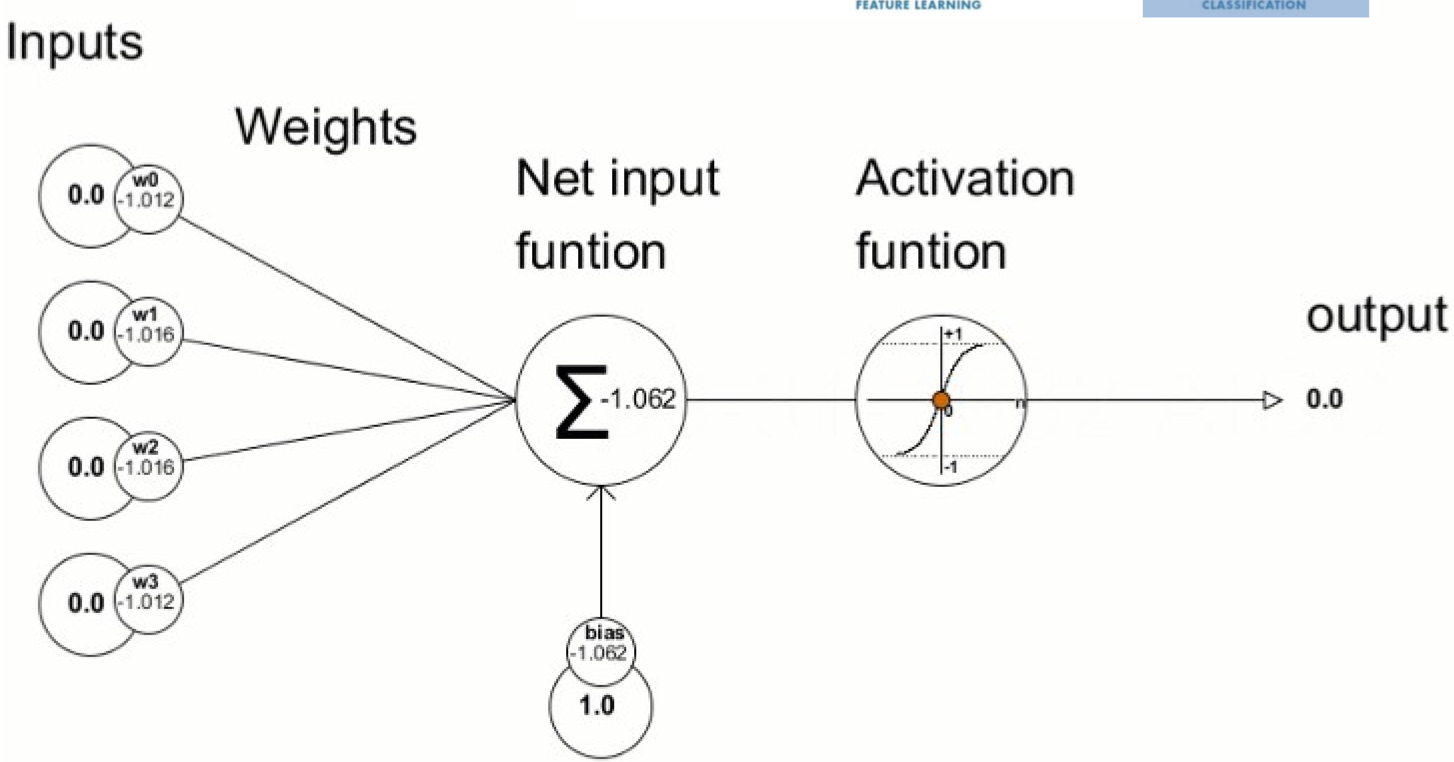




Convolutional Neural Network

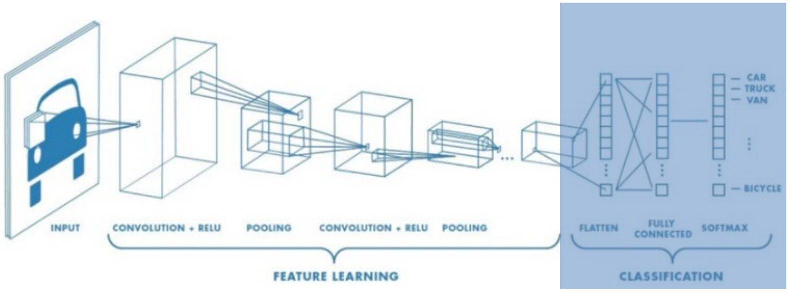
- Forward and Back Propagation

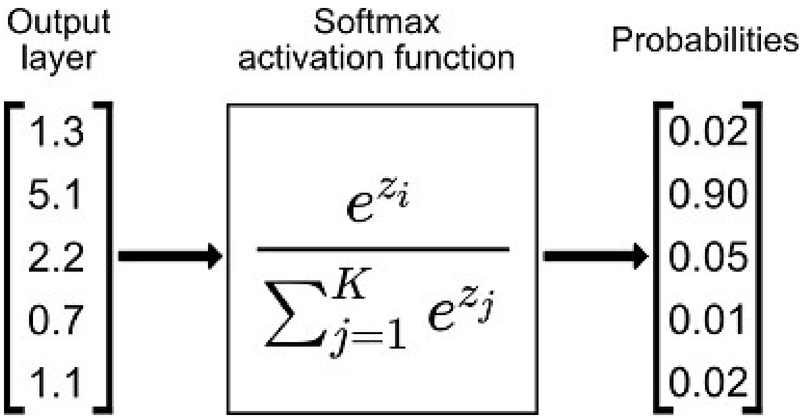


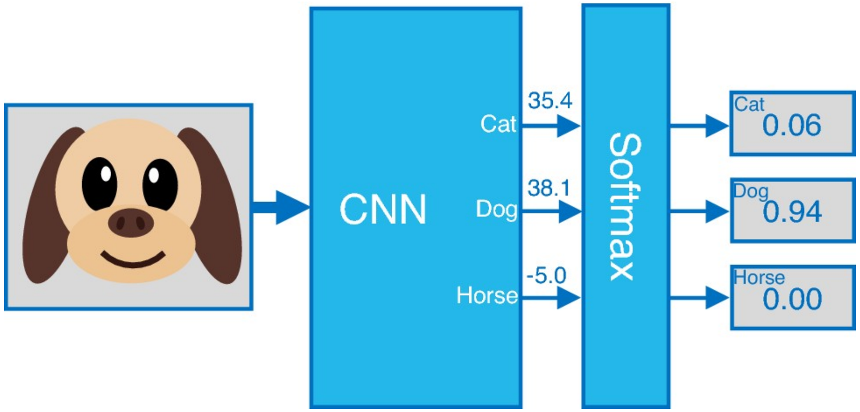


Convolutional Neural Network

- Softmax







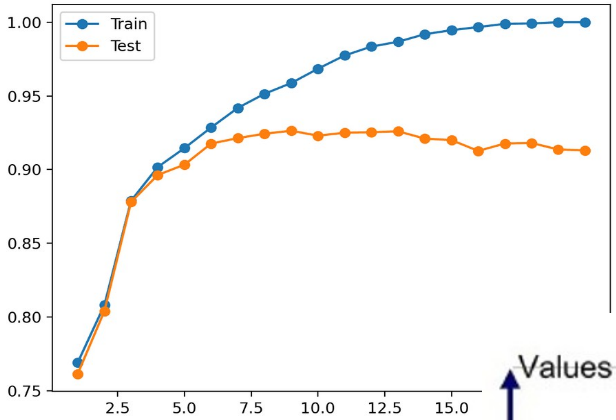
Convolutional Neural Network

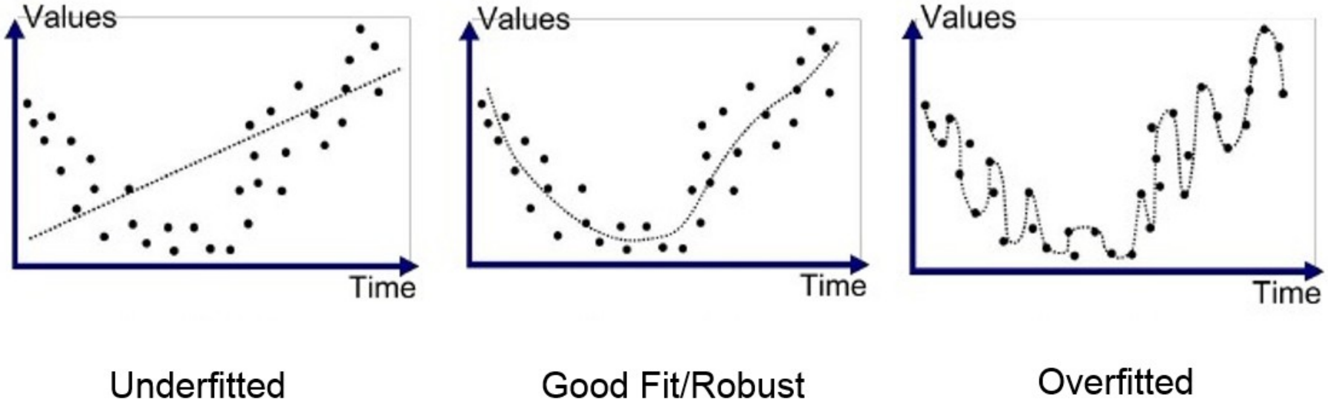
- Lets code our first CNN from scratch

Lecture 07 - CNN Architecture

Overfitting

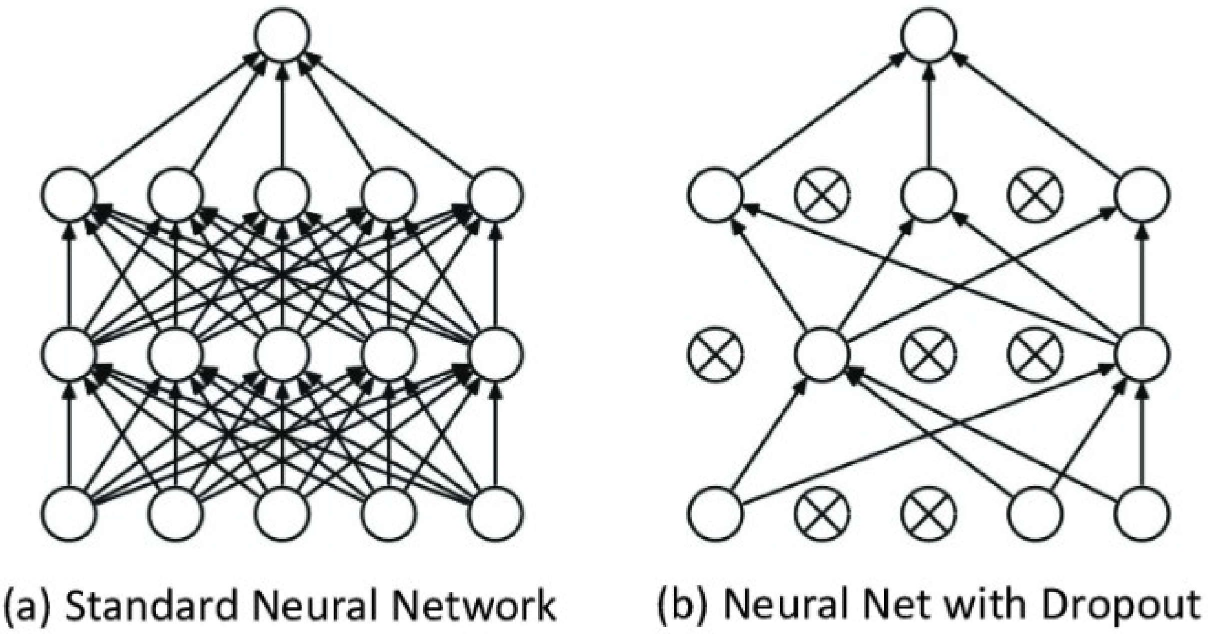
- Overfitting occurs when a model captures noise or specific patterns in the training data, impairing its ability to generalize to unseen data. Strategies such as regularization, dropout, data augmentation, and transfer learning help mitigate this by controlling model complexity and leveraging pre-learned features.





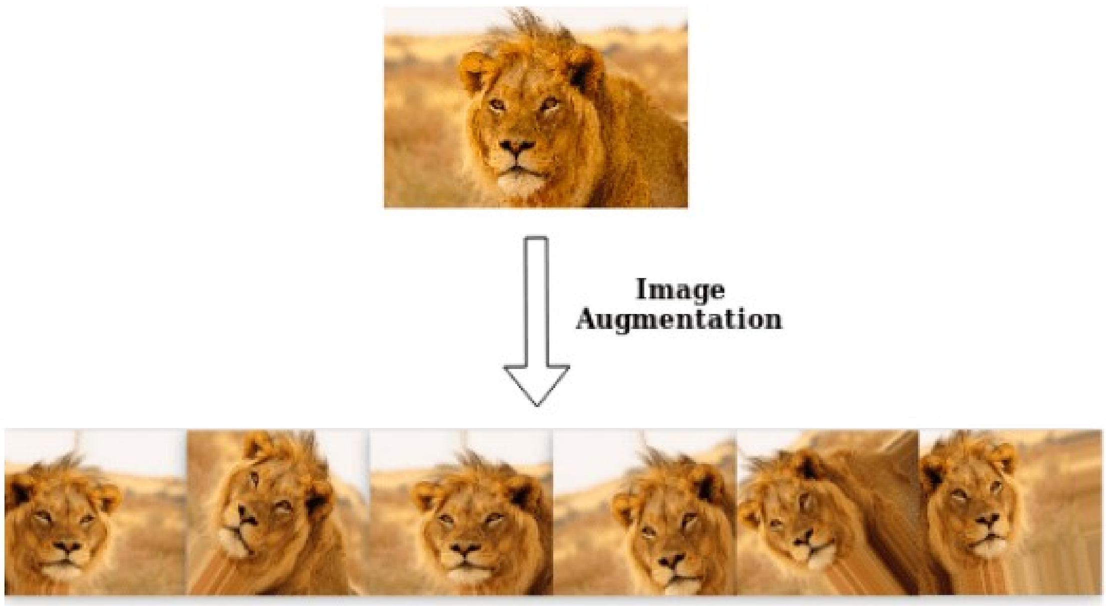
Dropout

- Dropout is a regularization technique that randomly deactivates a fraction of neurons during training, forcing the model to learn redundant representations and reducing overfitting.



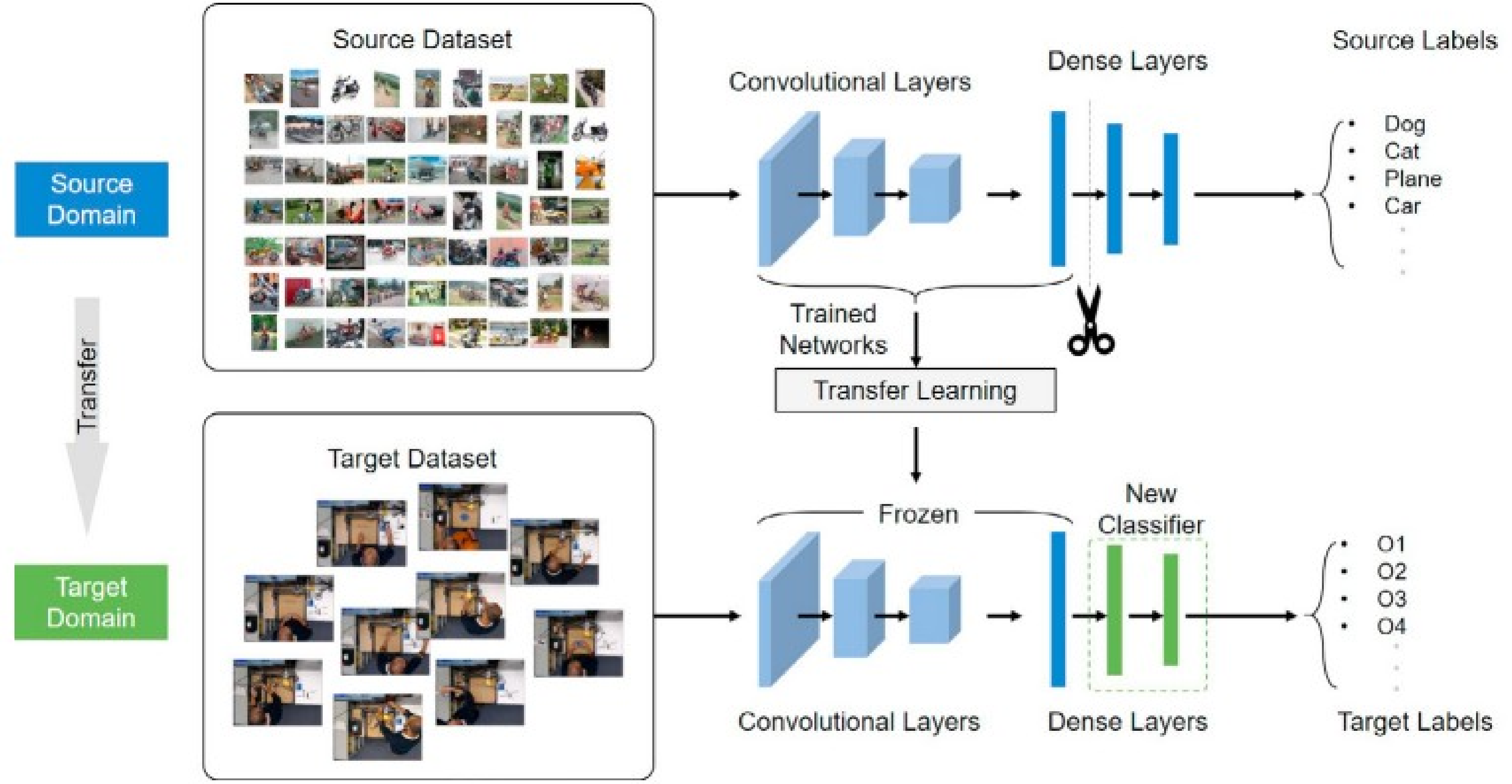
Data Augmentation

- Enlarge the dataset with synthetic samples
  - Rotation
  - Crop
  - Brightness



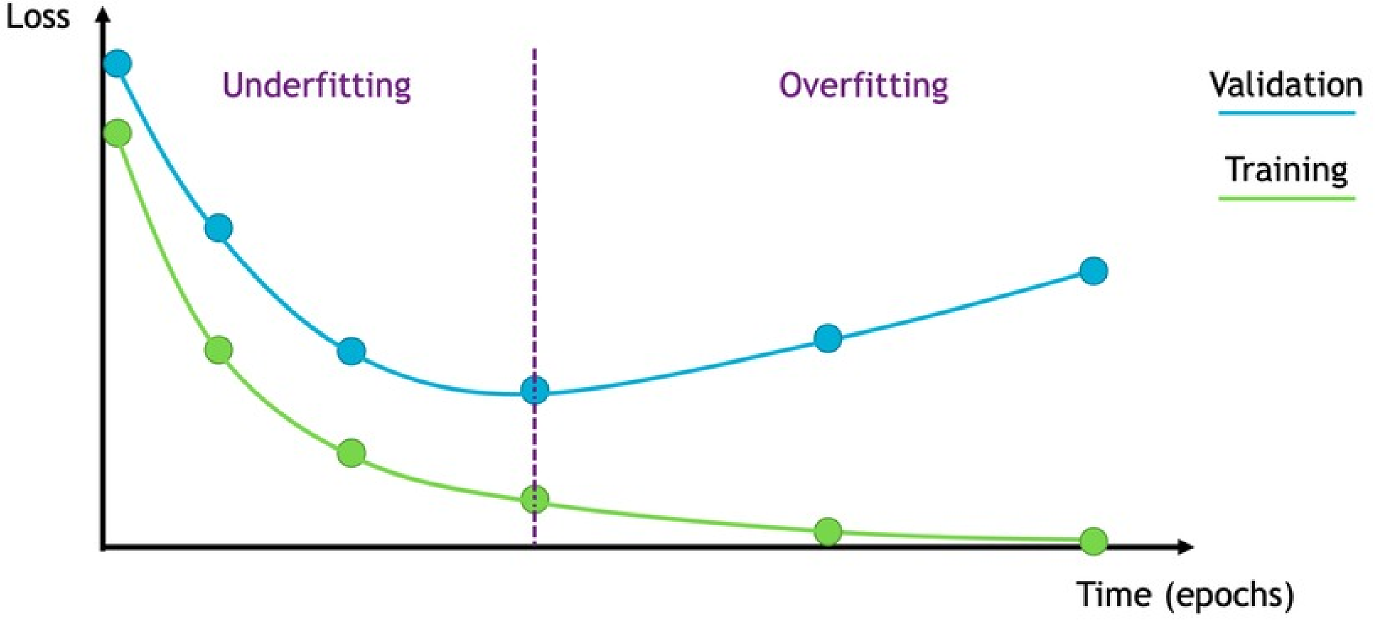
Transfer Learning

- Weight Sharing
- Feature Extraction weights are frozen (or not...) during learning



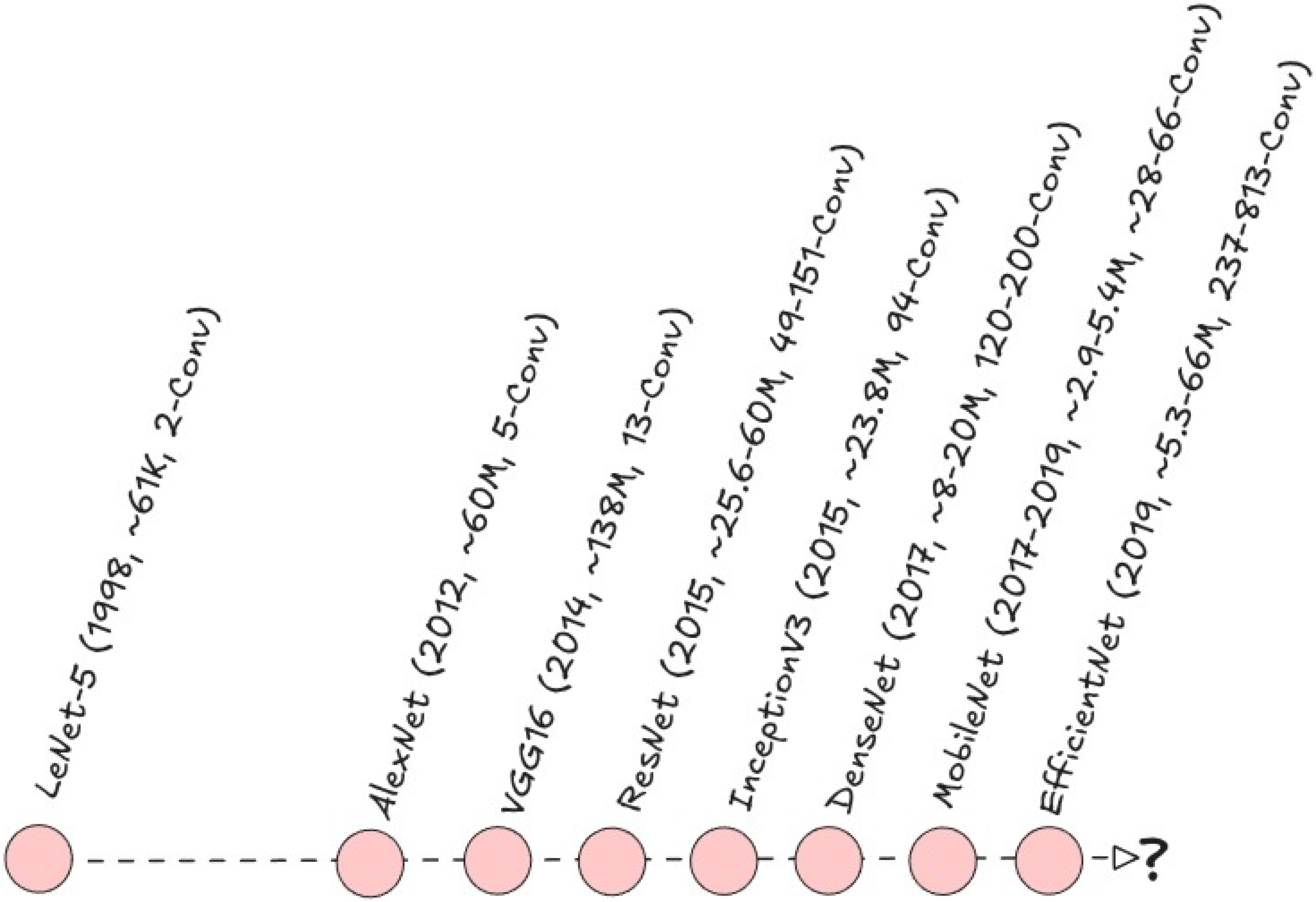
Miscellaneous

- Save and Load Weights
- Model Checkpoint
- Resuming Training
- Early Stopping

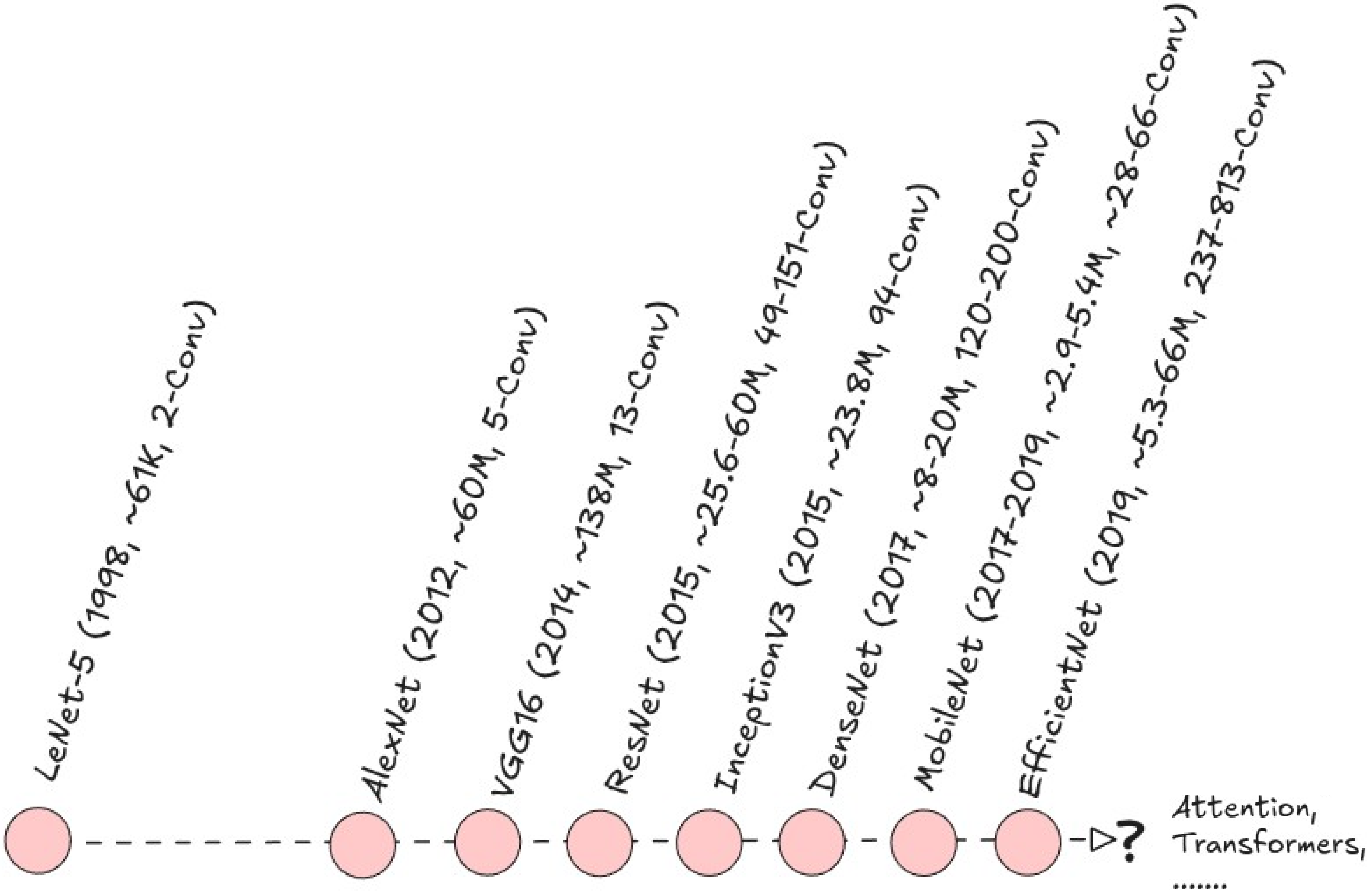


State of The Art Architectures

CNN Architectures Timeline



CNN Architectures Timeline

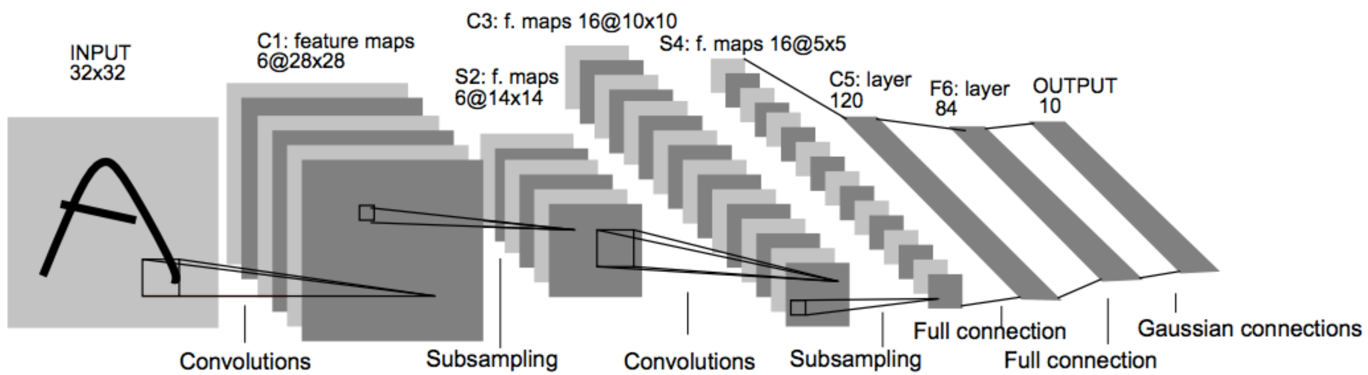


Lenet-5

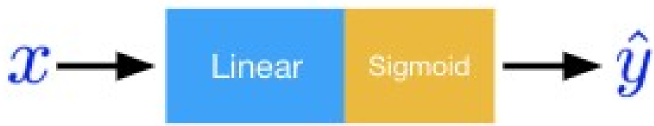
Gradient-Based Learning Applied to Document Recognition

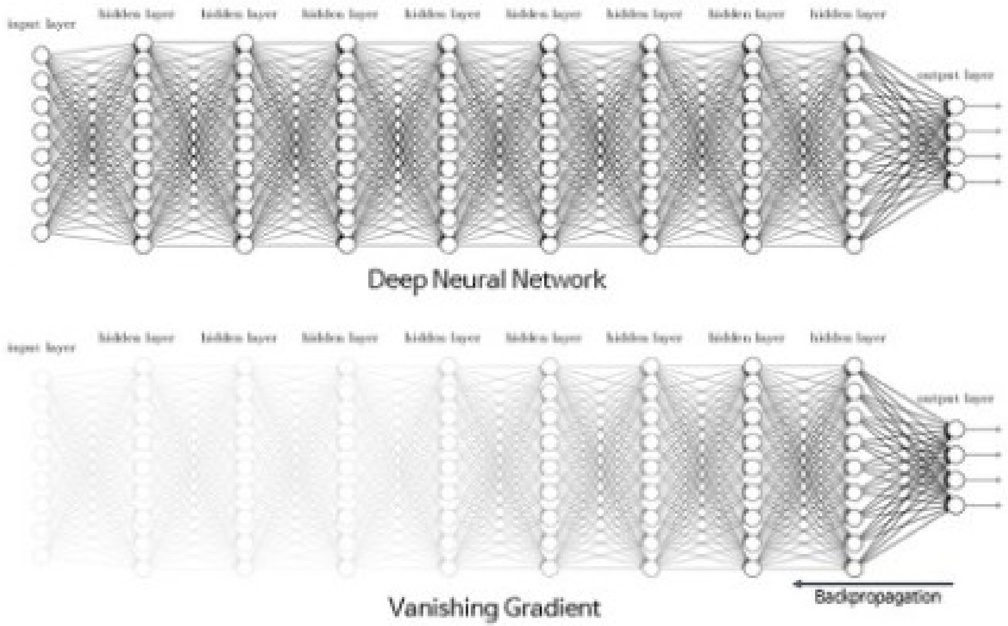
YANN LECUN, MEMBER, IEEE, LÉON BOTTOU, YOSHUA BENGIO, AND PATRICK HAFFNER

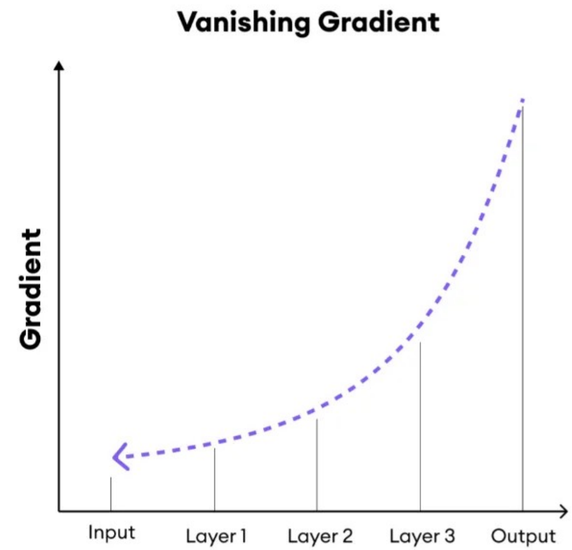
- Architecture: 2 Conv + Pool layers + 3 Fully Connected layers.
- MNIST digit recognition.
- Learned convolutional filters for feature extraction.
- Parameters: ~60k trainable weights.
- First widely cited CNN demonstrating effectiveness for vision tasks.

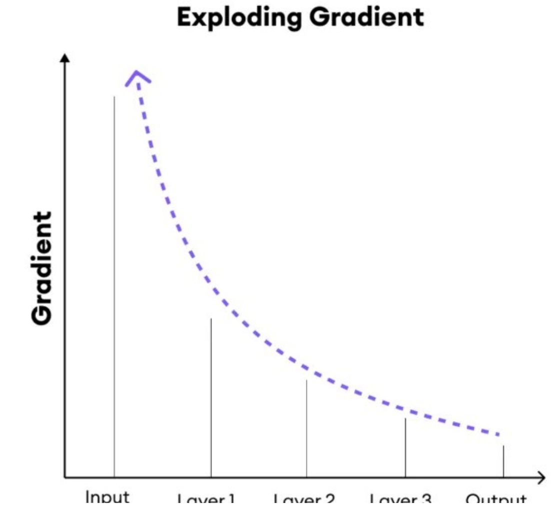


Vanish Gradient









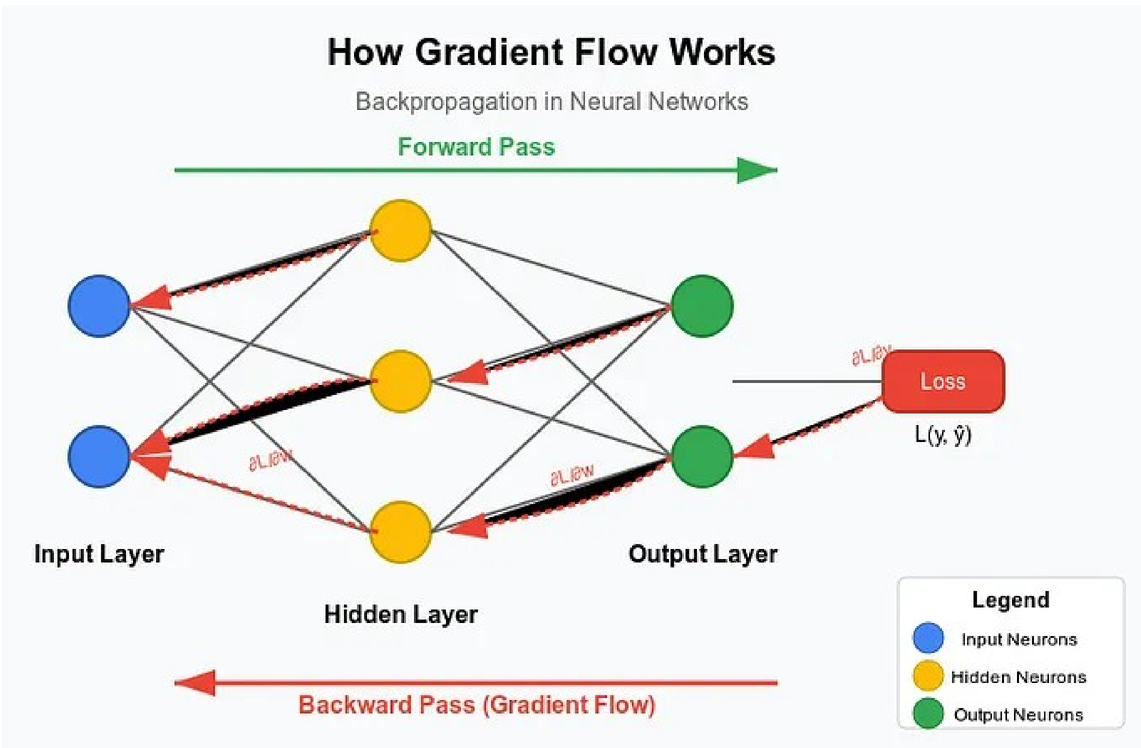
Vanish Gradient

Letter | Published: 09 October 1986

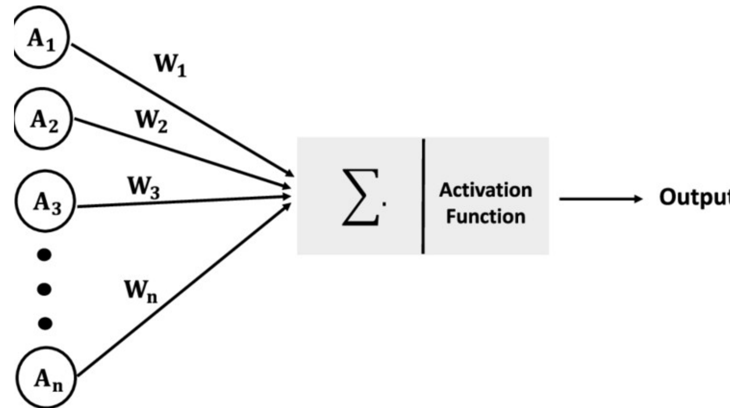
Learning representations by back-propagating errors

David E. Rumelhart, Geoffrey E. Hinton & Ronald J. Williams

- Backpropagation multiplies gradients layer by layer using the chain rule.



$$\frac{d}{dx}\left[f\big(g(x)\big)\right] = f'\big(g(x)\big)g'(x)$$



Artificial Neuron

$$z = \sum_{i=1}^{n} w_i x_i + b$$

Activation

$$y = f(z) = f\left(\sum_{i=1}^{n} w_i x_i + b\right)$$

Vanish Gradient

Letter | Published: 09 October 1986

Learning representations by back-propagating errors

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Backpropagation multiplies gradients layer by layer using the chain rule.

$$\frac{\partial \mathcal{L}}{\partial w} = \frac{\partial \mathcal{L}}{\partial a} * \frac{\partial a}{\partial z} * \frac{\partial z}{\partial w}$$

Gradient of the loss with respect to the weights

$$\frac{\partial \mathcal{L}}{\partial b} = \frac{\partial \mathcal{L}}{\partial z} * \frac{\partial z}{\partial b} = \frac{\partial \mathcal{L}}{\partial z} = a - y$$

Gradient of the loss with respect to the bias

$$\frac{\partial \mathcal{L}(y,a)}{\partial a} = \frac{\partial \mathcal{L}}{\partial a} = \frac{\partial}{\partial a}\left[-(y * log(a) + (1-y) * log(1-a))\right] =$$
$$= -\frac{\partial}{\partial a}\left(y * log(a)\right) - \frac{\partial}{\partial a}\left((1-y) * log(1-a)\right) =$$
$$= -\left(0 * log(a) + \frac{y}{a}\right) - \left(0 * log(1-a) - \frac{(1-y)}{(1-a)}\right) = -\frac{y}{a} + \frac{1-y}{1-a}$$

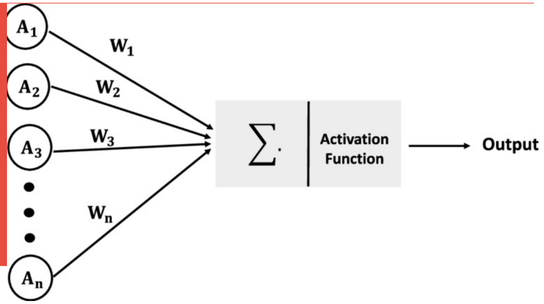
Gradient of the lost function with respect to the predicted value

$$w := w - \alpha\frac{\partial \mathcal{L}}{\partial w} = w - \alpha * (a-y)x$$

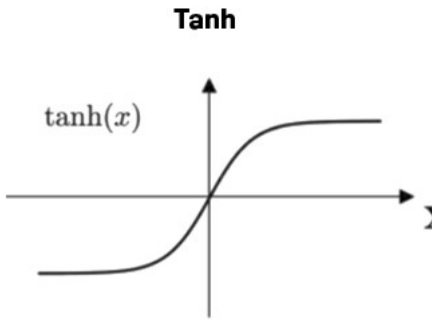
$$b := b - \alpha\frac{\partial \mathcal{L}}{\partial b} = w - \alpha * (a-y)$$

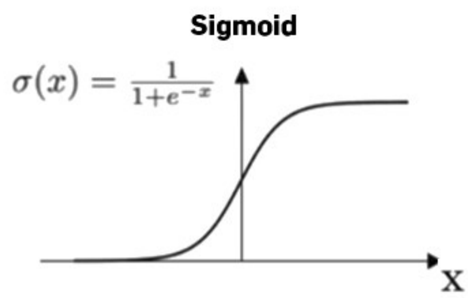
Weight and bias update

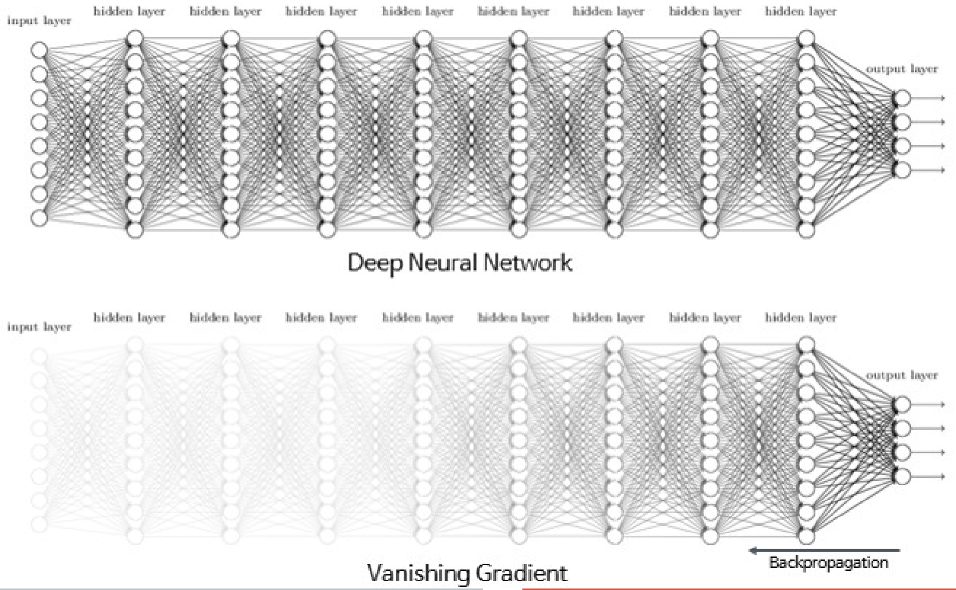
Vanish Gradient



- Backpropagation multiplies gradients layer by layer using the chain rule.
  - If activation functions (like sigmoid or tanh) squash inputs into small ranges, their derivatives are less than 1.
  - Multiplying many numbers less than 1 across deep layers causes the gradient to shrink exponentially toward zero.
  - As a result, weight updates in early layers vanish, preventing effective training.

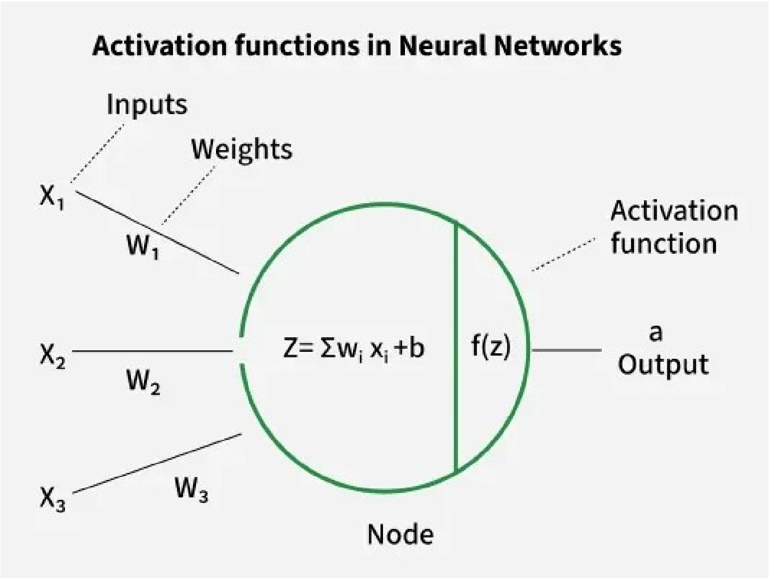


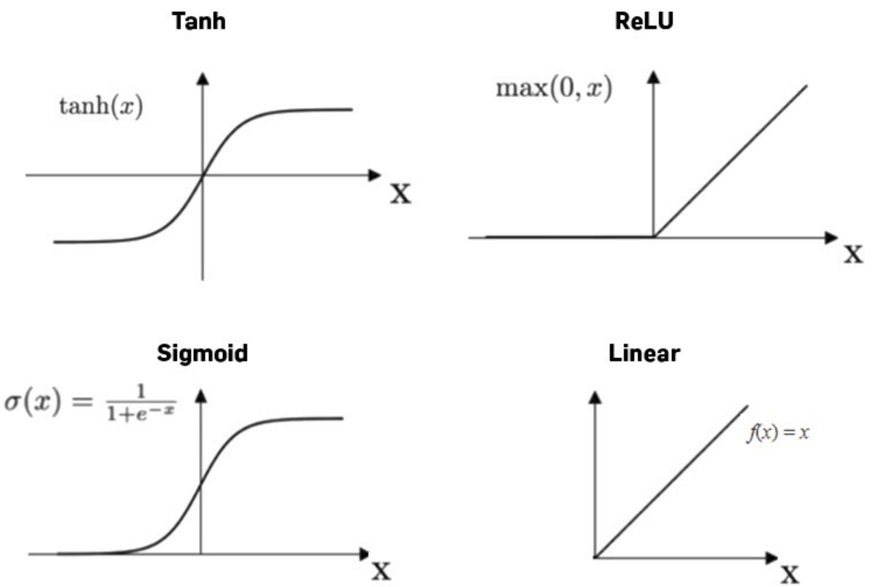




Mitigating The Vanish

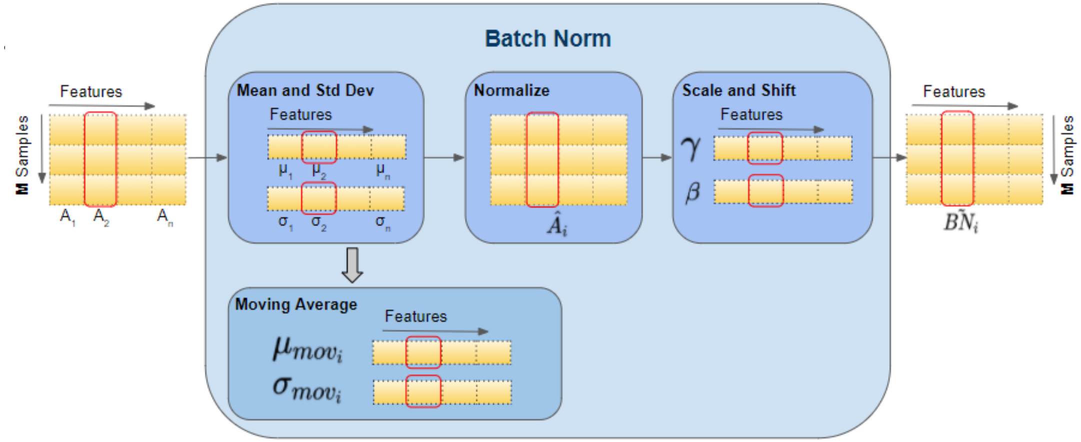
- ReLu Activation
  - Prevents saturation: Sigmoid/tanh saturate (gradient ≈ 0) for large or small values; ReLU does not.
  - Maintains gradient flow: Constant derivative (1) for x>0 preserves the backpropagation signal.
  - Computational simplicity: Direct calculation, no exponentials required.

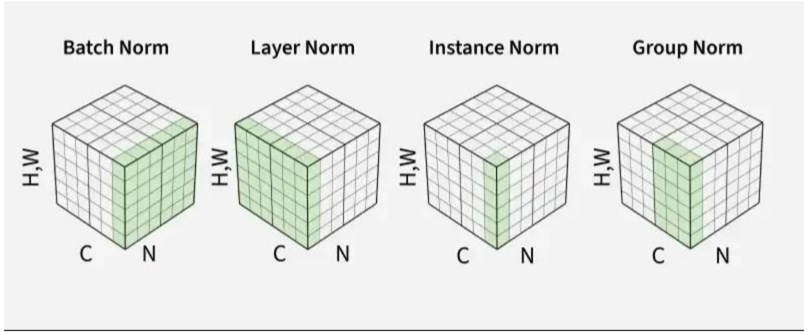




Mitigating The Vanish

- Batch Normalization (BN)
  - BN normalizes the output of a layer before applying the activation function
  - For a given mini-batch, it computes the mean and variance of each feature/channel and scales the activations to have zero mean and unit variance.
  - BN keeps the distribution of activations stable, which prevents gradients from shrinking too much in deep networks.
  - It reduces the dependency of gradient magnitude on the scale of previous layers’ weights.
  - Helps gradients propagate more effectively.





AlexNet

ImageNet Classification with Deep Convolutional Neural Networks

Alex Krizhevsky
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Ilya Sutskever
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Geoffrey E. Hinton
University of Toronto
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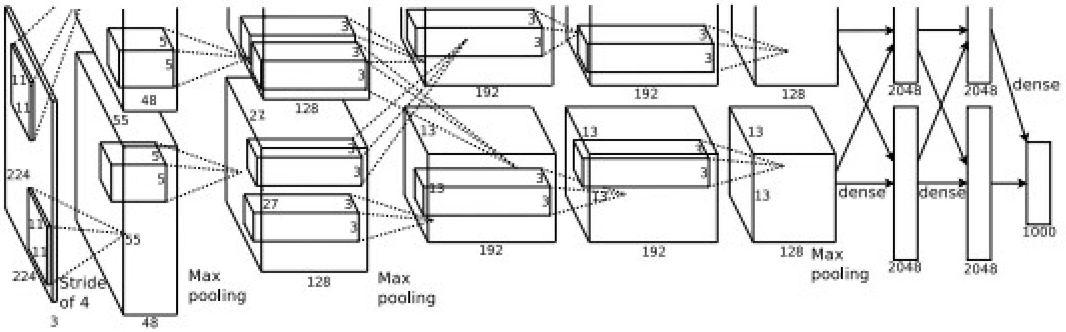
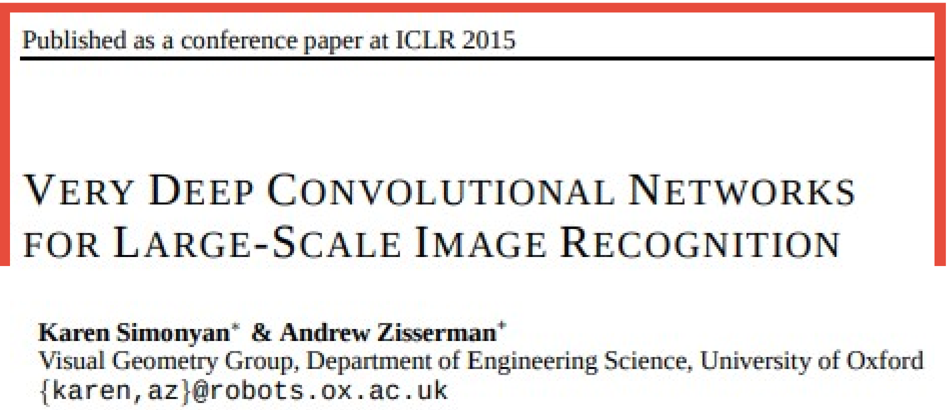
- Architecture: 5 Conv layers + 3 Fully Connected layers, ReLU activations, Dropout.
- IMAGENET Challenge 2012 – Error 16.4%
- Introduced ReLU, GPU training, data augmentation, and dropout.
- Parameters: ~61M.
- Sparked modern deep learning revolution in computer vision.



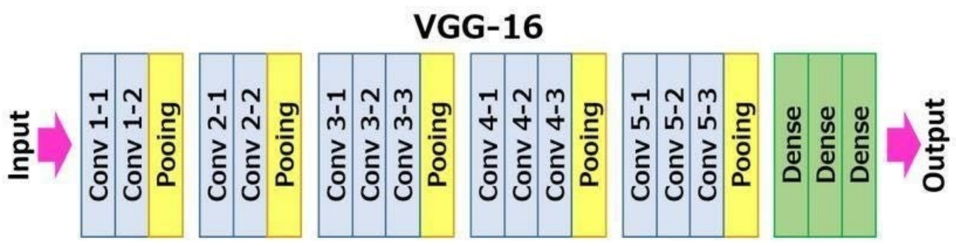
VGG16

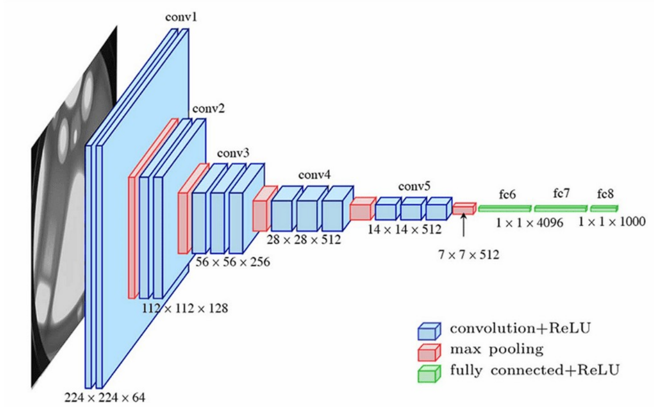

Published as a conference paper at ICLR 2015

VERY DEEP CONVOLUTIONAL NETWORKS FOR LARGE-SCALE IMAGE RECOGNITION

Karen Simonyan* & Andrew Zisserman+
Visual Geometry Group, Department of Engineering Science, University of Oxford
{karen,az}@robots.ox.ac.uk

- Architecture: 13 Conv layers + 3 Fully Connected layers, small 3×3 filters.
- IMAGENET Challenge 2012 – Error 6.7%
- Key Features: Deep network using uniform architecture with small filters.
- Parameters: ~138M.
- Showed depth improves performance; standard baseline for many tasks.



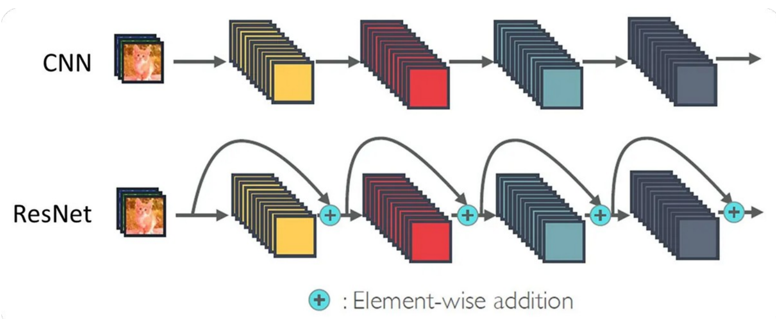


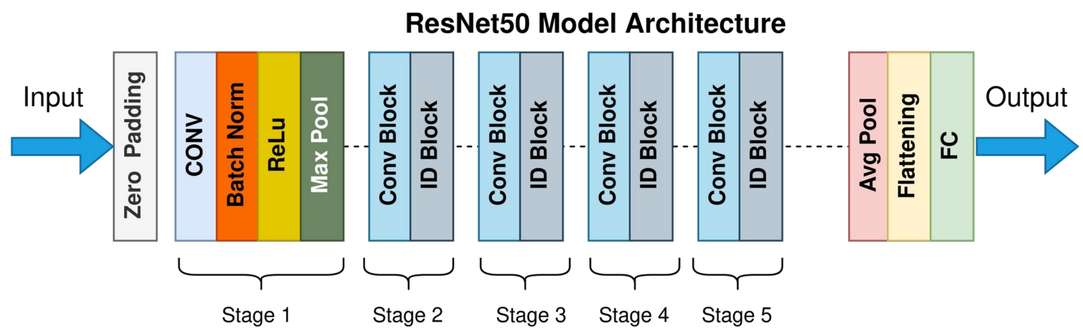
ResNet

Deep Residual Learning for Image Recognition

Kaiming He Xiangyu Zhang Shaoqing Ren Jian Sun
Microsoft Research
{kahe, v-xiangz, v-shren, jiansun}@microsoft.com

- Architecture: 50~152 layers with residual (skip) connections.
- IMAGENET Challenge 2012 – Error 3.6%
- Residual blocks enable training very deep networks (*).
- Parameters: ~25M to ~60M.
- Mitigates vanishing gradient problem; enabled ultra-deep networks.



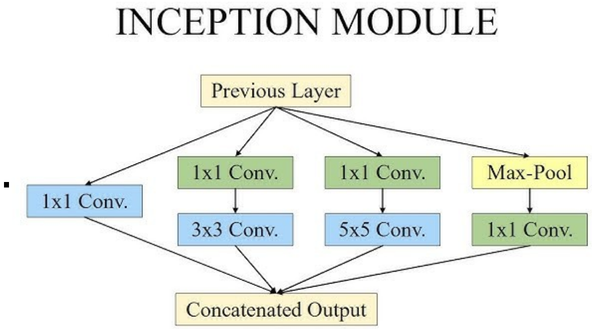


(*) At this point the focus shifts from parameter-heavy networks to efficient architectures with better feature representation.

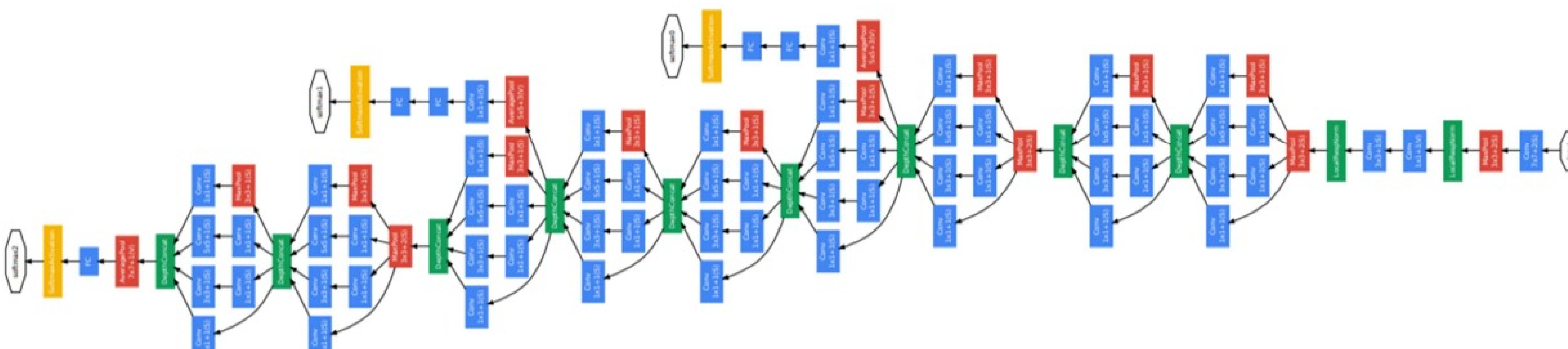
Inception


Going Deeper with Convolutions

Christian Szegedy[1], Wei Liu[2], Yangqing Jia[1], Pierre Sermanet[1], Scott Reed[3], Dragomir Anguelov[1], Dumitru Erhan[1], Vincent Vanhoucke[1], Andrew Rabinovich[4]
[1]Google Inc. [2]University of North Carolina, Chapel Hill
[3]University of Michigan, Ann Arbor [4]Magic Leap Inc.
[1]{szegedy,jiayq,sermanet,dragomir,dumitru,vanhoucke}@google.com
[2]wliu@cs.unc.edu, [3]reedscott@umich.edu, [4]arabinovich@magicleap.com



- Architecture: Inception modules with multi-scale convolutions.
- ImageNet classification
- **Efficient computation** via factorized convolutions and dimension reduction.
- Parameters: ~23.9M.
- Combines depth and width efficiently; high accuracy with moderate compute



DenseNet

Densely Connected Convolutional Networks

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Laurens van der Maaten
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Kilian Q. Weinberger
Cornell University
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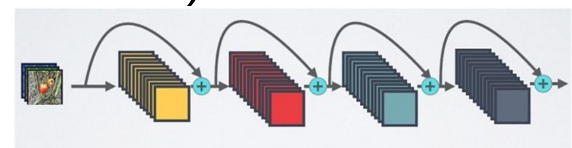
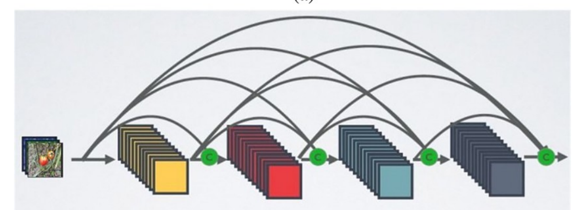
- Architecture: 121 ~201 layers with dense connections (feature reuse). 1X1 Convs
- ImageNet classification.
- Each layer receives inputs from **all previous layers.**
- Parameters: ~8M ~20M.
- Significance: Reduces parameters while maintaining high performance; encourages feature reuse.



(a)



(b)

Layers	Output Size	DenseNet-121 ($k=32$)	DenseNet-169 ($k=32$)	DenseNet-201 ($k=32$)	DenseNet-161 ($k=48$)
Convolution	112 × 112	7 × 7 conv, stride 2			
Pooling	56 × 56	3 × 3 max pool, stride 2			
Dense Block (1)	56 × 56	[1 × 1 conv, 3 × 3 conv] × 6	[1 × 1 conv, 3 × 3 conv] × 6	[1 × 1 conv, 3 × 3 conv] × 6	[1 × 1 conv, 3 × 3 conv] × 6
Transition Layer (1)	56 × 56	1 × 1 conv			
	28 × 28	2 × 2 average pool, stride 2			
Dense Block (2)	28 × 28	[1 × 1 conv, 3 × 3 conv] × 12	[1 × 1 conv, 3 × 3 conv] × 12	[1 × 1 conv, 3 × 3 conv] × 12	[1 × 1 conv, 3 × 3 conv] × 12
Transition Layer (2)	28 × 28	1 × 1 conv			
	14 × 14	2 × 2 average pool, stride 2			
Dense Block (3)	14 × 14	[1 × 1 conv, 3 × 3 conv] × 24	[1 × 1 conv, 3 × 3 conv] × 32	[1 × 1 conv, 3 × 3 conv] × 48	[1 × 1 conv, 3 × 3 conv] × 36
Transition Layer (3)	14 × 14	1 × 1 conv			
	7 × 7	2 × 2 average pool, stride 2			
Dense Block (4)	7 × 7	[1 × 1 conv, 3 × 3 conv] × 16	[1 × 1 conv, 3 × 3 conv] × 32	[1 × 1 conv, 3 × 3 conv] × 32	[1 × 1 conv, 3 × 3 conv] × 24
Classification Layer	1 × 1	7 × 7 global average pool			
		1000D fully-connected, softmax			

MobileNet

MobileNetV2: Inverted Residuals and Linear Bottlenecks

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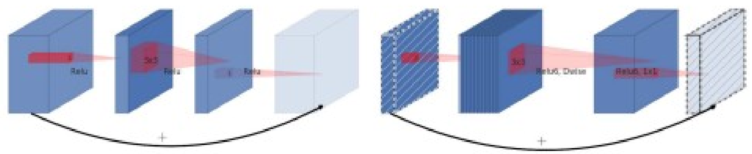
- Architecture: 53 depthwise separable convolutions.
- Mobile/embedded vision applications.
- **Inverted residual blocks, linear bottlenecks.**
- Parameters: ~3.4M.
- Optimized for low-latency and low-memory devices.

Input	Operator	Output
$h \times w \times k$	1x1 conv2d , ReLU6	$h \times w \times (tk)$
$h \times w \times tk$	3x3 dwise s=s, ReLU6	$\frac{h}{s} \times \frac{w}{s} \times (tk)$
$\frac{h}{s} \times \frac{w}{s} \times tk$	linear 1x1 conv2d	$\frac{h}{s} \times \frac{w}{s} \times k'$

Table 1: *Bottleneck residual block* transforming from k to k' channels, with stride s, and expansion factor t.

(a) Residual block (b) Inverted residual block



Input	Operator	t	c	n	s
$224^2 \times 3$	conv2d	-	32	1	2
$112^2 \times 32$	bottleneck	1	16	1	1
$112^2 \times 16$	bottleneck	6	24	2	2
$56^2 \times 24$	bottleneck	6	32	3	2
$28^2 \times 32$	bottleneck	6	64	4	2
$14^2 \times 64$	bottleneck	6	96	3	1
$14^2 \times 96$	bottleneck	6	160	3	2
$7^2 \times 160$	bottleneck	6	320	1	1
$7^2 \times 320$	conv2d 1x1	-	1280	1	1
$7^2 \times 1280$	avgpool 7x7	-	-	1	-
$1 \times 1 \times 1280$	conv2d 1x1	-	k	-	

EfficientNet

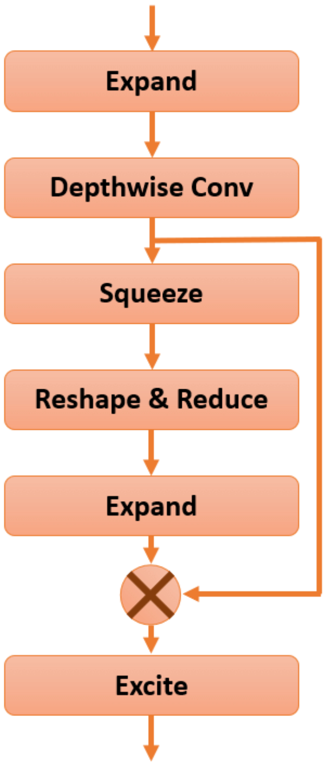
EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks

Mingxing Tan [1] Quoc V. Le [1]

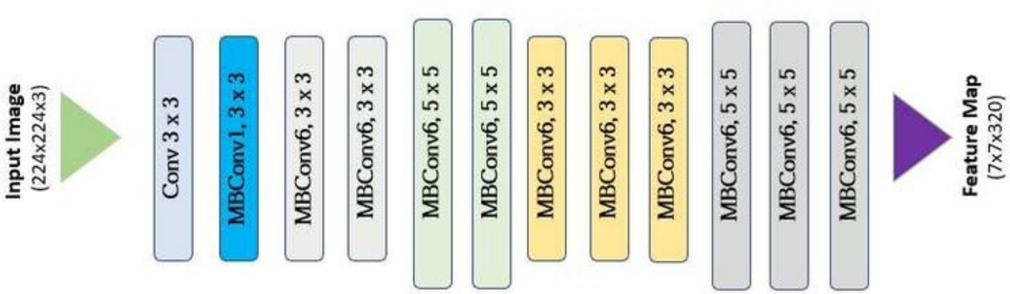
[1]Google Research, Brain Team, Mountain View, CA. Correspondence to: Mingxing Tan <tanmingxing@google.com>.

Proceedings of the 36th International Conference on Machine Learning, Long Beach, California, PMLR 97, 2019.

- Architecture: 16 ~81(*) MBConv blocks (depthwise + pointwise convs).
- Dataset/Application: ImageNet classification.
- Compound **scaling of depth, width, and resolution.**
- Parameters: ~5.3M ~ 66M .
- State-of-the-art efficiency; high accuracy with minimal compute.



EfficientNet Architecture



Let’s Code

[Lecture 07 - CNN Architecture]