Deep Learning
State of the Art Convolutional Architectures

Michaël Sdika [1]

[1] CNRS, CREATIS UMR 5220

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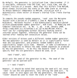
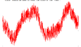
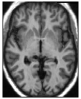
Machine learning



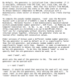


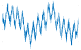


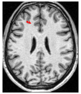
Unstructured data

...

Input $\longrightarrow$ $\boxed{\text{Mapping}}$ $\longrightarrow$ Answer







- physiological parameters
- Yes/No
- Category
- ...

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Supervized Deep Learning

- How to represent the mapping ?
  - Deep learning : Neural network
  - Which architecture for the network ?
- How to estimate the network coefficient ?
  - Loss functions ?
  - Optimization ?
  - Generalization ?

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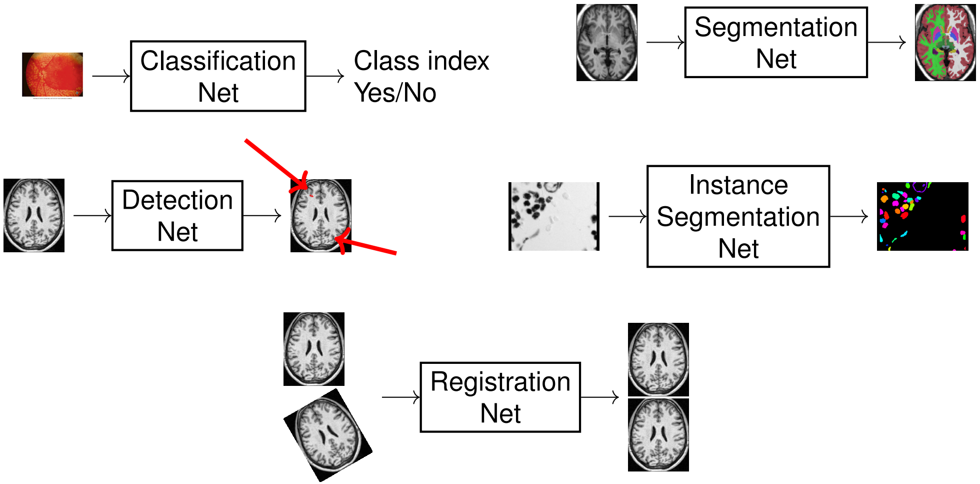
5 classes of architectures adressed in this course



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Outline

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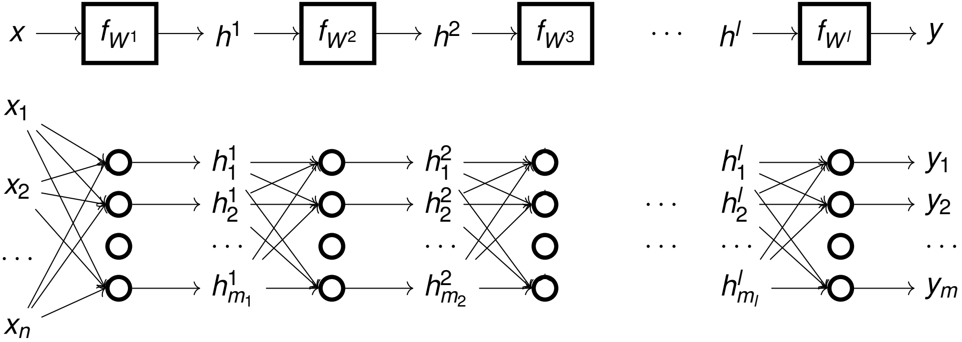
Deep Neural Network

$$x \longrightarrow \boxed{f_{W^1}} \longrightarrow h^1 \longrightarrow \boxed{f_{W^2}} \longrightarrow h^2 \longrightarrow \boxed{f_{W^3}} \quad \cdots \quad h^l \longrightarrow \boxed{f_{W^l}} \longrightarrow y$$

Basic Layers :

- Linear Layers : Fully Connected / Convolution : mixing features
- Activation layers : introducing nonlinearity
- Pooling layers : spatial aggregation, subsampling
- Normalization layers : stabilizing the training

Multi Layer Perceptron



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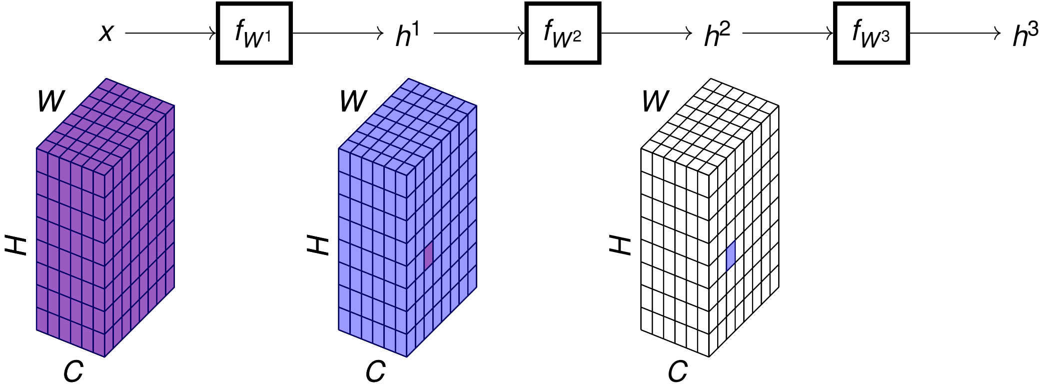
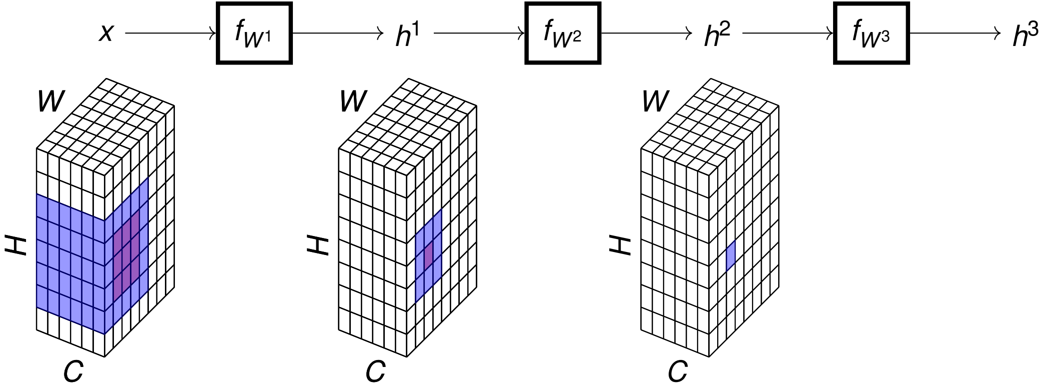
Multi Layer Perceptron



CNN



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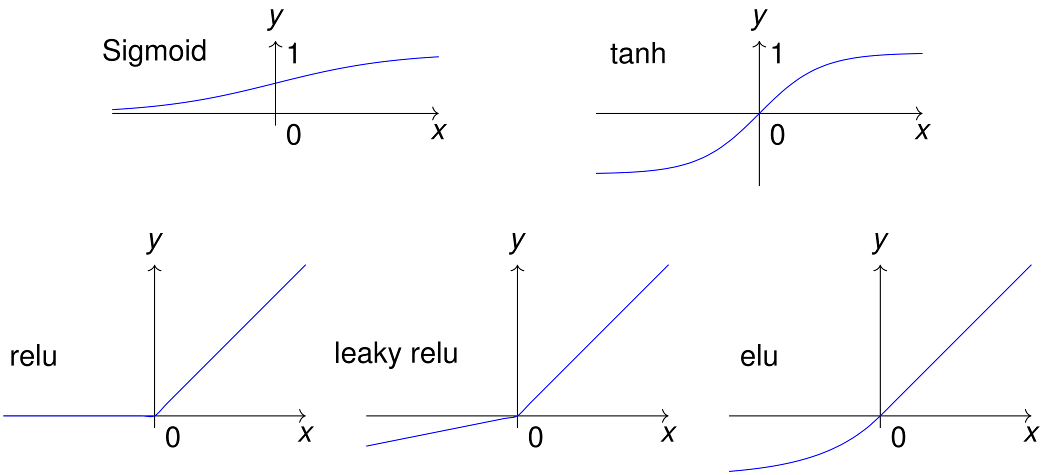
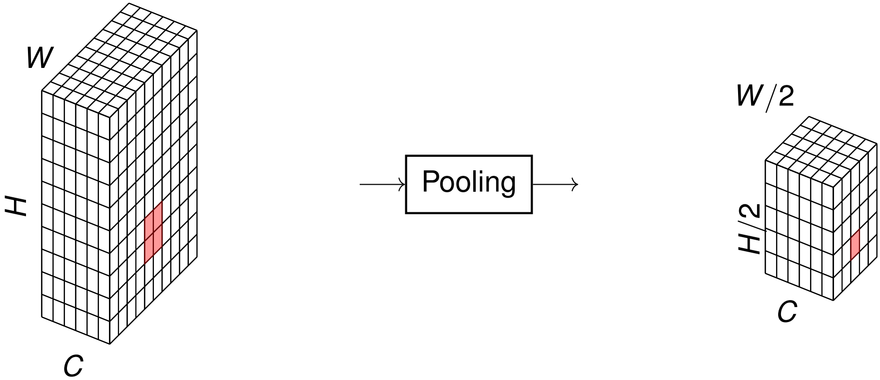
Activation functions



Pooling



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Normalization

- deep network : need to normalize input x such that x $N(0, 1)$
- Z-normalization
- what about features within the network ?

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Batch Normalization

$$x \longrightarrow \boxed{\text{BatchNorm}} \longrightarrow y = \gamma\hat{x} + \beta$$

with $\hat{x} = \frac{x-\mu}{\sigma}$

- μ, σ : mean, std of x over a minibatch
- γ, β : trainable parameters
- Inference : use average μ, σ from training

Ioffe & Szegedy, ICML 2015, Batch normalization : Accelerating deep network training by reducing internal covariate shift

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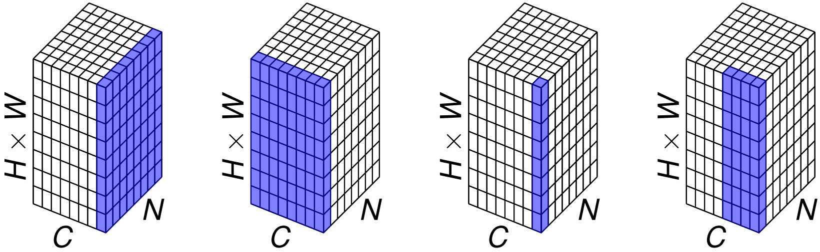
Related Normalization



Batch Norm — small minibatch

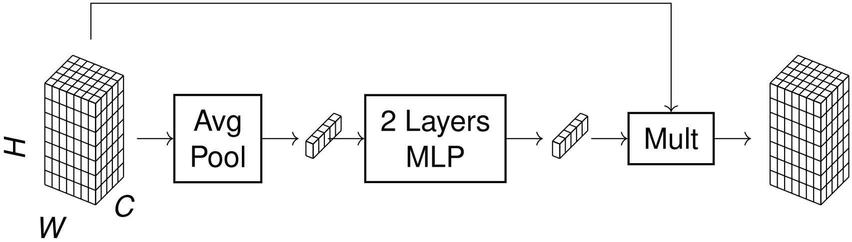
Layer Norm — small minibatch

Instance Norm — remove contrast, style transfer

Group Norm

Ulyanov et al arxiv 2016, Instance normalization : The missing ingredient for fast stylization
Ba et al, 2016, Layer Normalization
Wu & He 2018, Group Normalization

Squeeze and Excitation



compute channel "amplitude"

compute channel rescaling factors

rescale input tensor

Hu et al CVPR 2018, Squeeze-and-excitation networks
Roy et al, MICCAI 2018, Concurrent Spatial and Channel Squeeze & Excitation in Fully Convolutional Networks

Outline

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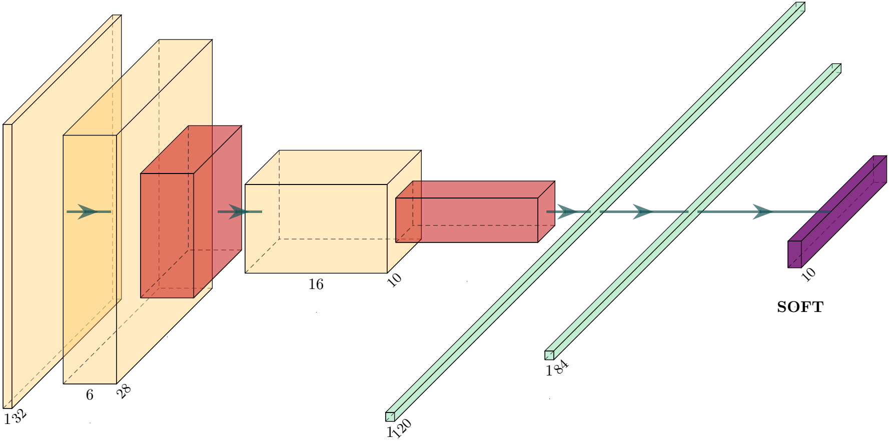
Le Net



LeCun et al., Neural Computation 1989, "Backpropagation Applied to Handwritten Zip Code Recognition"
LeCun et al., 1998, Proceedings of the IEEE, Gradient-based learning applied to document recognition.

Image Net

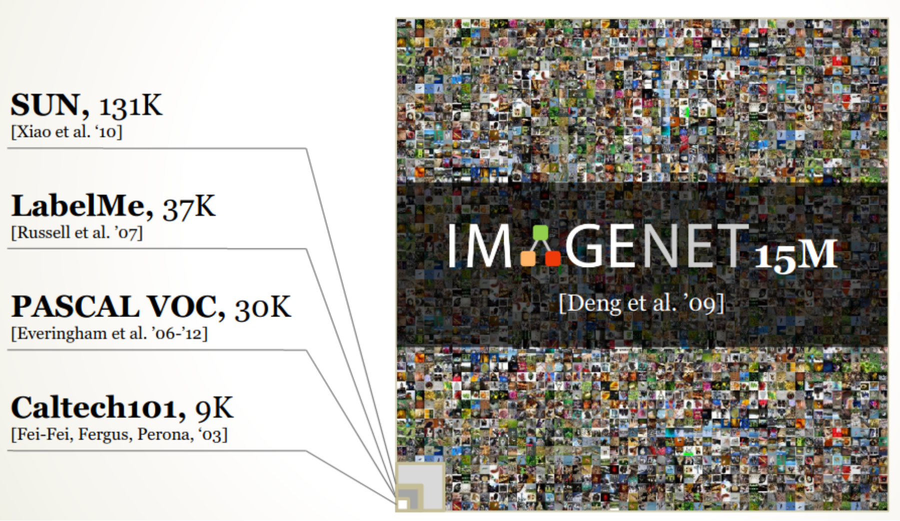
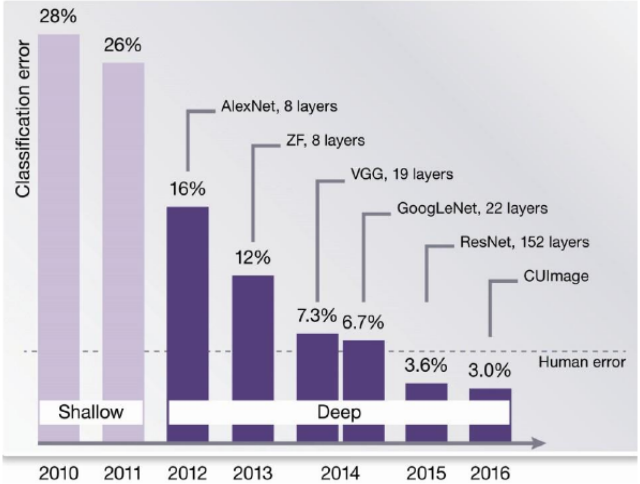

SUN, 131K
[Xiao et al. '10]
LabelMe, 37K
[Russell et al. '07]
PASCAL VOC, 30K
[Everingham et al. '06-'12]
Caltech101, 9K
[Fei-Fei, Fergus, Perona, '03]
IMAGENET 15M
[Deng et al. '09]

Image Net


Classification error
28%
26%
16%
12%
7.3%
6.7%
3.6%
3.0%
AlexNet, 8 layers
ZF, 8 layers
VGG, 19 layers
GoogLeNet, 22 layers
ResNet, 152 layers
CUImage
Human error
Shallow
Deep
2010
2011
2012
2013
2014
2015
2016

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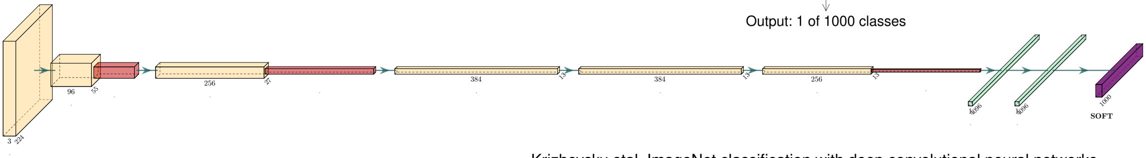
Alex Net

LeNet

Image: 28 (height) × 28 (width) × 1 (channel)
↓
Convolution with 5×5 kernel+2padding:28×28×6
↓ sigmoid
Pool with 2×2 average kernel+2 stride:14×14×6
↓
Convolution with 5×5 kernel (no pad):10×10×16
↓ sigmoid
Pool with 2×2 average kernel+2 stride: 5×5×16
↓ flatten
Dense: 120 fully connected neurons
↓ sigmoid
Dense: 84 fully connected neurons
↓ sigmoid
Dense: 10 fully connected neurons
↓
Output: 1 of 10 classes

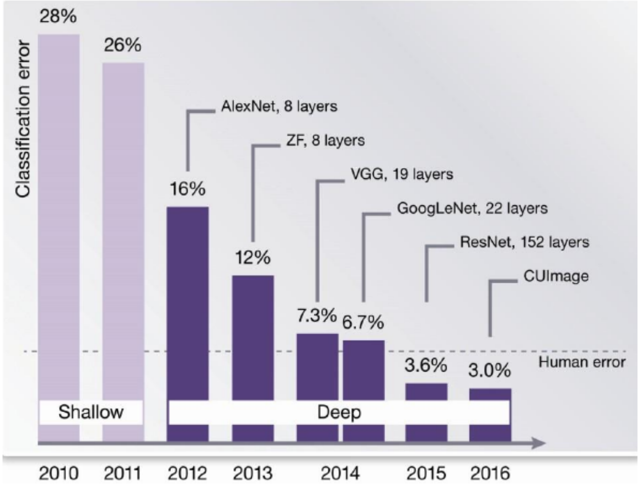
AlexNet

Image: 224 (height) × 224 (width) × 3 (channels)
↓
Convolution with 11×11 kernel+4 stride:54×54×96
↓ ReLu
Pool with 3×3 max. kernel+2 stride: 26×26×96
↓
Convolution with 5×5 kernel+2 pad:26×26×256
↓ ReLu
Pool with 3×3 max. kernel+2stride:12×12×256
↓
Convolution with 3×3 kernel+1 pad:12×12×384
↓ ReLu
Convolution with 3×3 kernel+1 pad:12×12×384
↓ ReLu
Convolution with 3×3 kernel+1 pad:12×12×256
↓ ReLu
Pool with 3×3 max. kernel+2stride:5×5×256
↓ flatten
Dense: 4096 fully connected neurons
↓ ReLu, dropout p=0.5
Dense: 4096 fully connected neurons
↓ ReLu, dropout p=0.5
Dense: 1000 fully connected neurons
↓
Output: 1 of 1000 classes



Krizhevsky etal. ImageNet classification with deep convolutional neural networks

Image Net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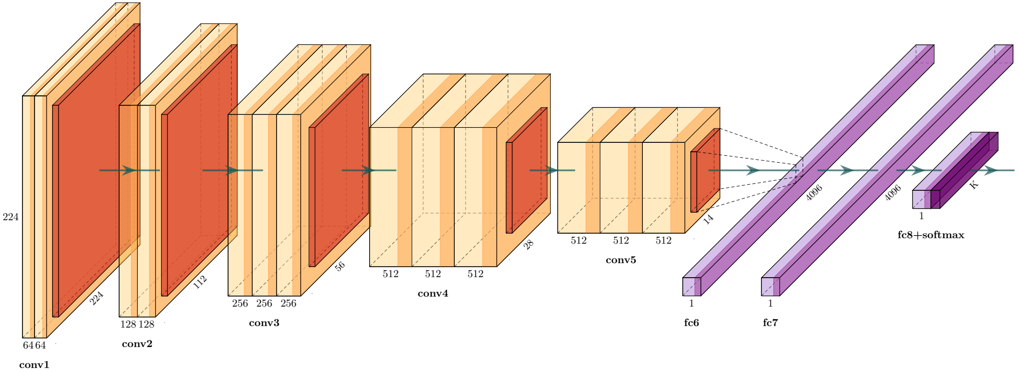
VGG

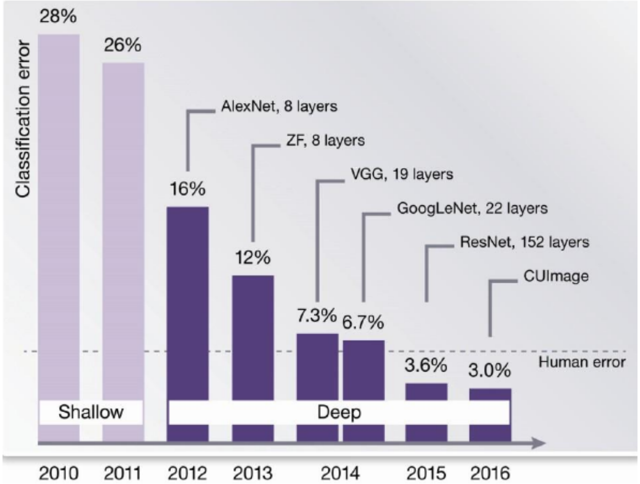
Deeper network

3x3 convolutions



Simonyan & Zisserman, ICLR 2015, Very Deep Convolutional Networks for Large-Scale Image Recognition

Image Net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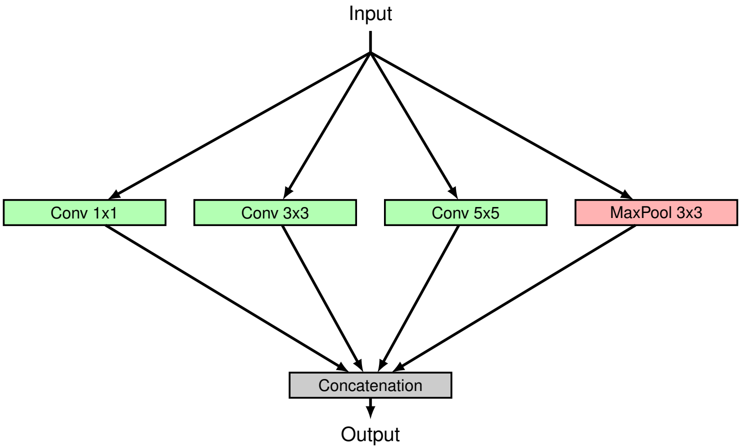
Inception Block



Szegedy et al, CVPR 2015, Going Deeper With Convolutions

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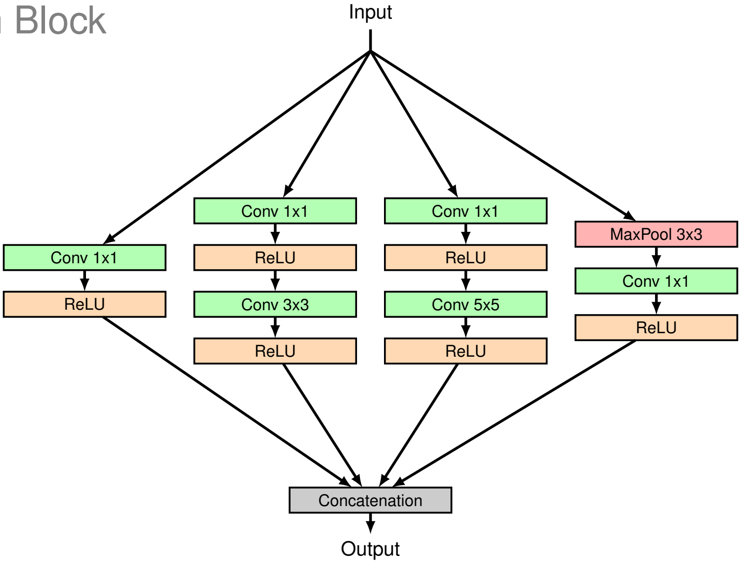
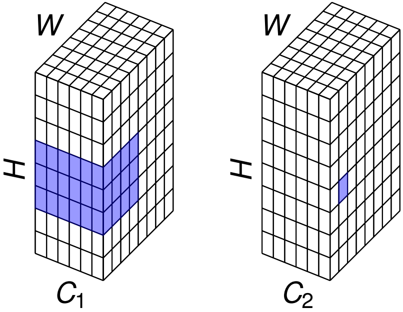
Inception Block

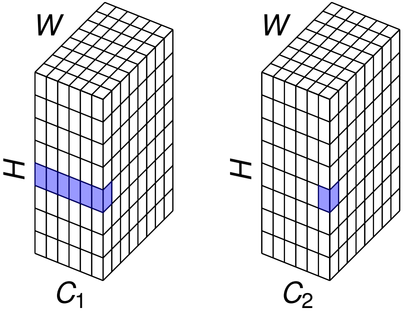


Szegedy et al, CVPR 2015, Going Deeper With Convolutions

1x1 Convolution



3x3 convolution
receptive field



1x1 convolution
receptive field

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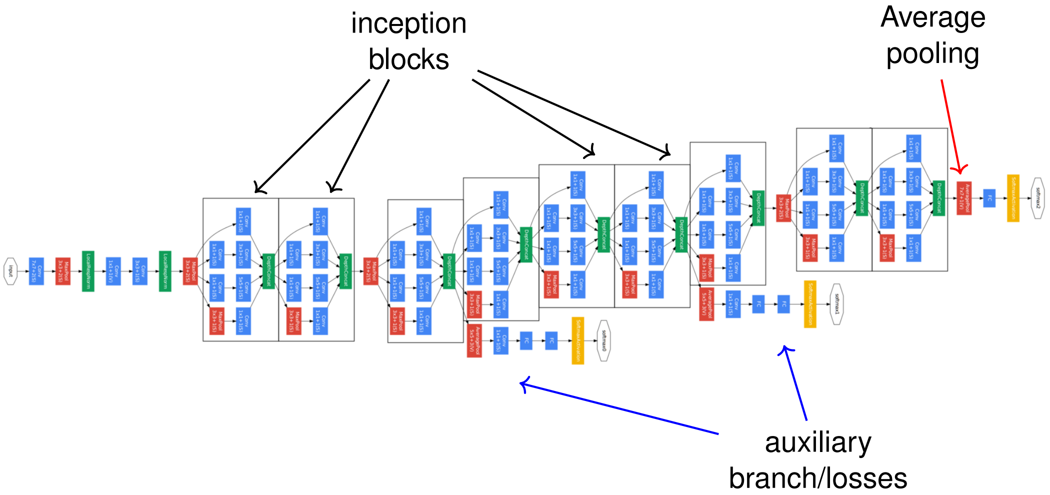
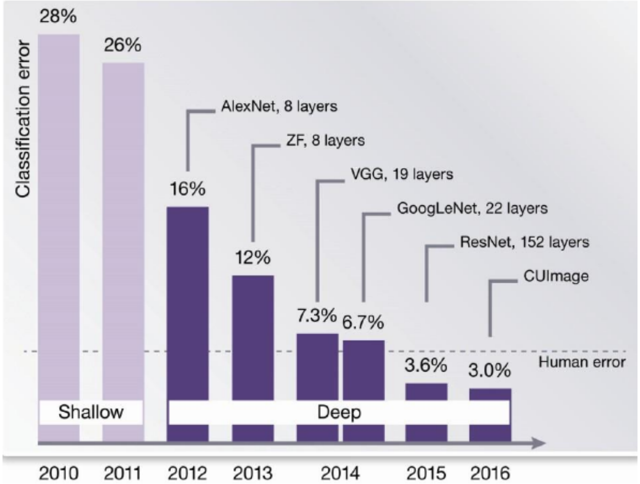
GoogLe Net



Szegedy et al, CVPR 2015, Going Deeper With Convolutions

Image Net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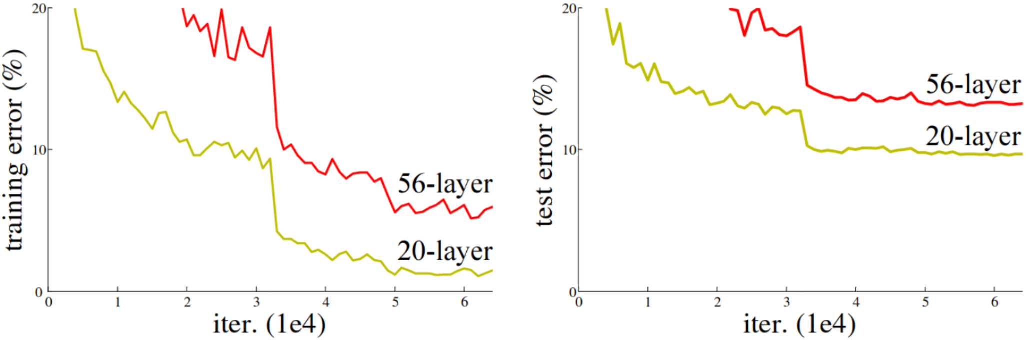
Going Deeper ? ?



He et al, CVPR 2016, Deep Residual Learning for Image Recognition

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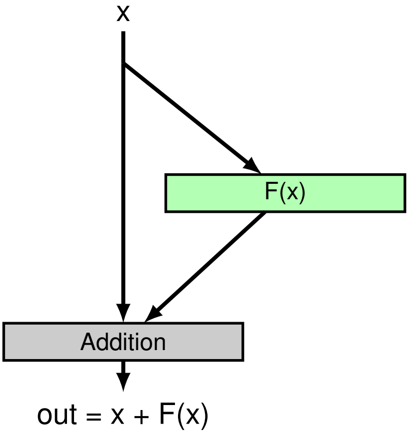
Residual Block

observation :

- more layers $\Rightarrow$ higher train errors
- Problem is training

Architecture easier to train

Vanishing gradient



He etal, CVPR 2016, Deep Residual Learning for Image Recognition.

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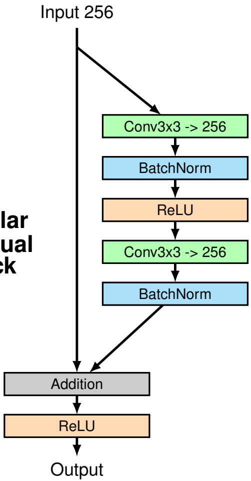
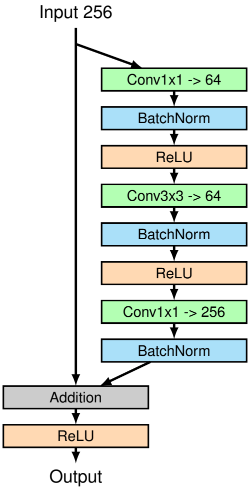
Residual Block



Regular Residual Block



Bottleneck

He et al, CVPR 2016, Deep Residual Learning for Image Recognition

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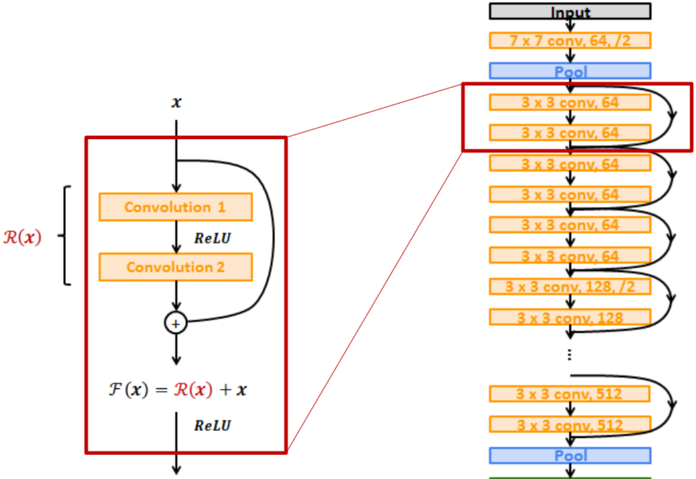
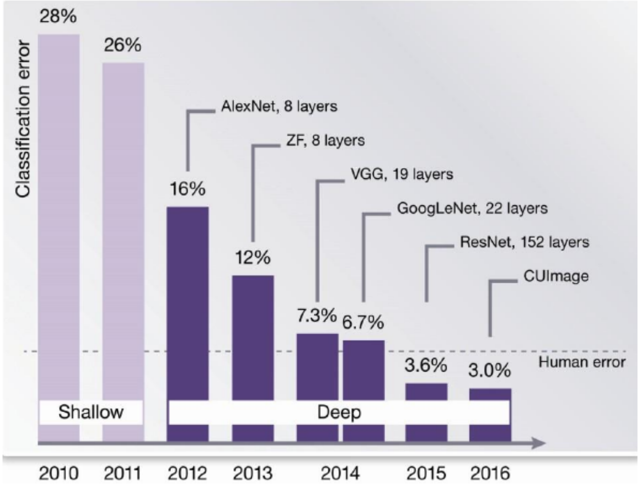
Res Net



He et al, CVPR 2016, Deep Residual Learning for Image Recognition

Image Net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Dense Block

$$x_0 \rightarrow \boxed{H_1} \rightarrow x_1 \rightarrow \boxed{H_2} \rightarrow x_2 \rightarrow \boxed{H_3} \rightarrow x_3 \rightarrow \boxed{H_4} \rightarrow x_4 \qquad \cdots$$

Res block :
$x_l = x_{l-1} + H_l(x_{l-1})$

Dense block :
$x_l = H_l\left([x_0, x_1, \ldots, x_{l-1}]\right)$

Gao, et al. CVPR 2017, Densenet : densely connected convolutional networks

Dense Block

$$x_0 \to \boxed{H_1} \to x_1 \to \boxed{H_2} \to x_2 \to \boxed{H_3} \to x_3 \to \boxed{H_4} \to x_4 \quad \cdots$$

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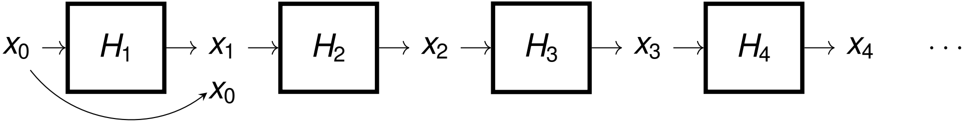
Dense Block



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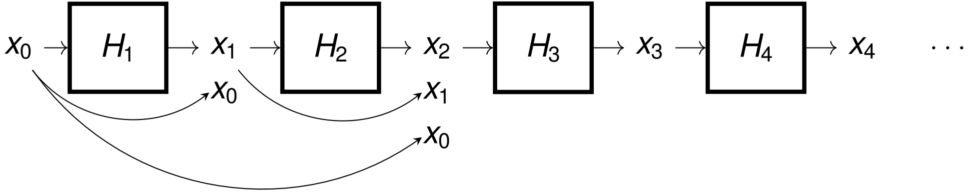

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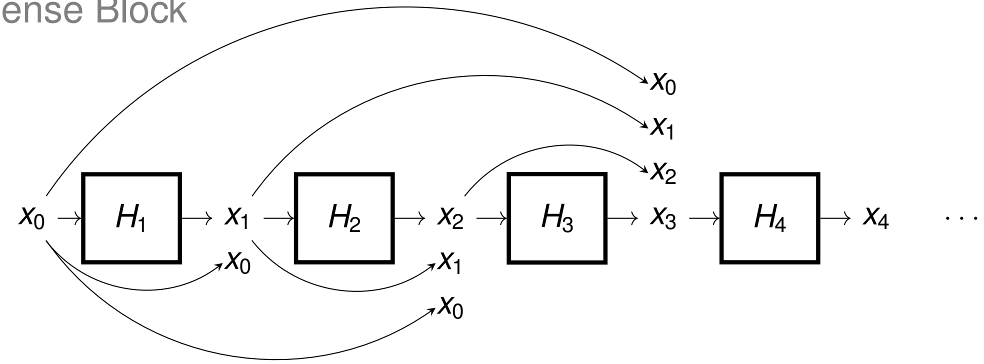
Dense Block



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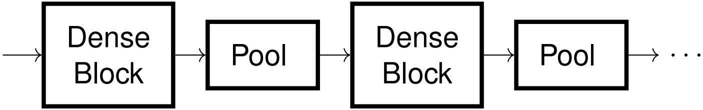
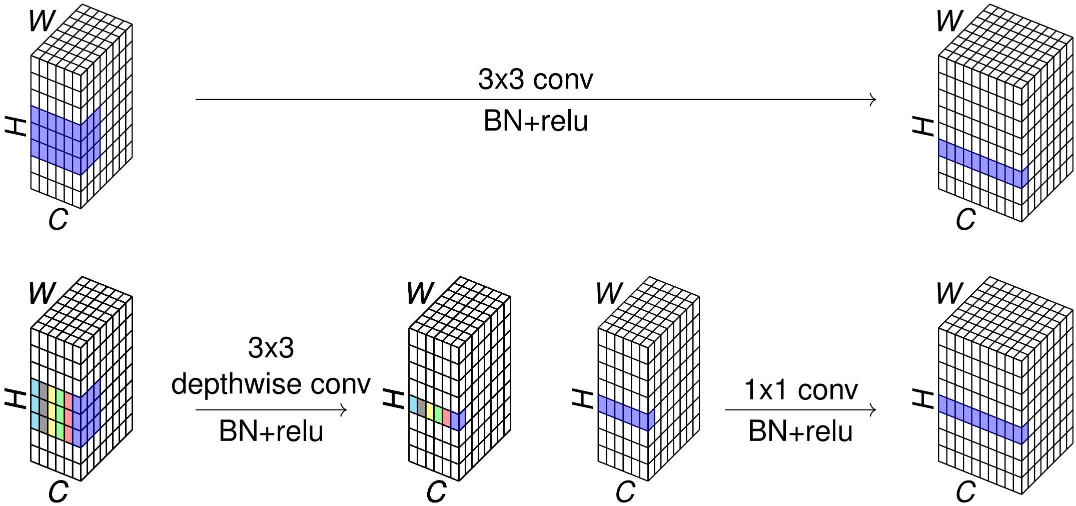
Gao, et al. CVPR 2017, Densenet : densely connected convolutional networks

Dense Net



Gao, et al. CVPR 2017, Densenet : densely connected convolutional networks

Mobile Net V1 : depthwize conv



L. Sifre. Rigid-motion scattering for image classification. PhD thesis, Ph. D. thesis, 2014. 1, 3
Howard et al, arxiv 2017, MobileNets : Efficient Convolutional Neural Networks for Mobile Vision Applications

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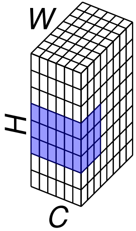
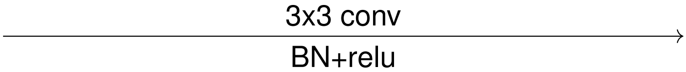
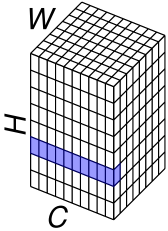
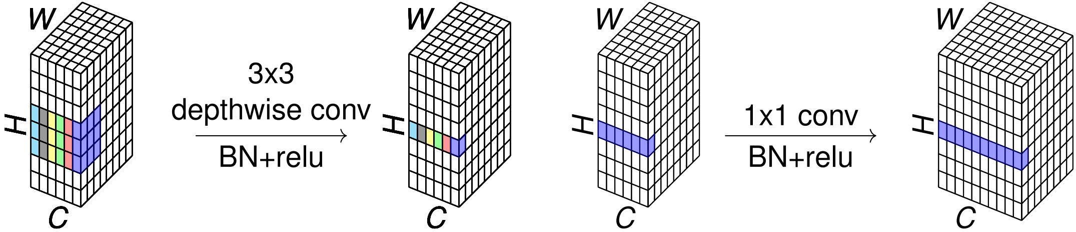
Mobile Net V1 : depthwize conv







More layers : more nonlinearity
less FLOPS, less parameters
slower than conv3x3 on modern GPU!



L. Sifre. Rigid-motion scattering for image classification. PhD thesis, Ph. D. thesis, 2014. 1, 3
Howard et al, arxiv 2017, MobileNets : Efficient Convolutional Neural Networks for Mobile Vision Applications

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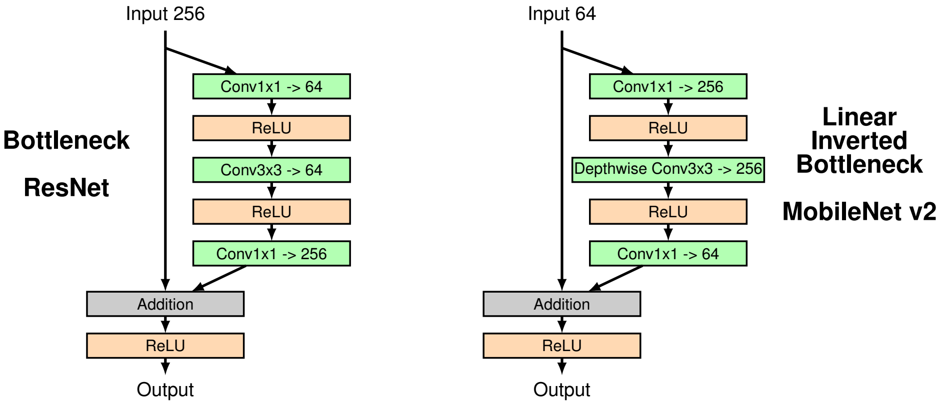
Mobile Net V2 : inverted bottleneck



Sandler et al, CVPR 2018, MobileNetV2 : Inverted Residuals and Linear Bottlenecks

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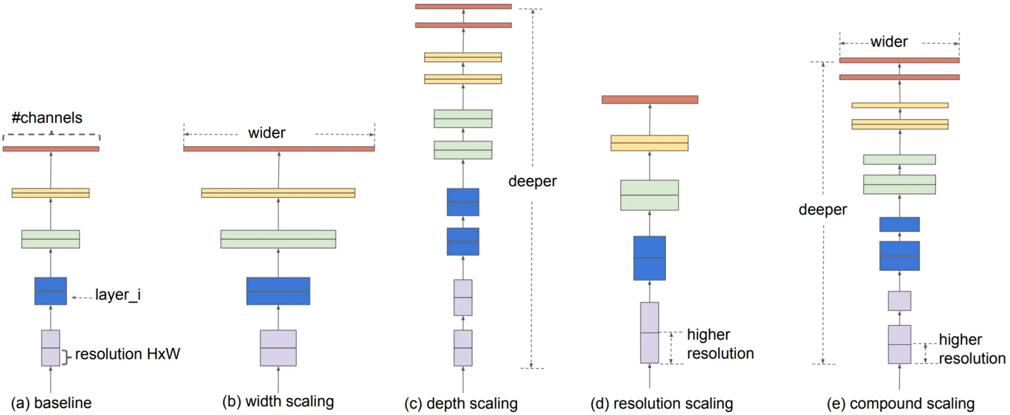
Efficient Net : compound scaling of networks



Tan and Le. PMLR 2019, Efficientnet : Rethinking model scaling for convolutional neural networks

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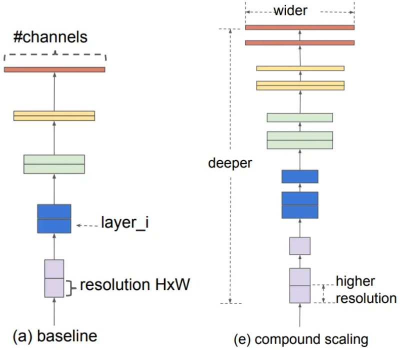
Efficient Net : compound scaling of networks



- depth, width, resolution for B1
  - $d_1 = \alpha d_0$
  - $w_1 = \beta w_0$
  - $r_1 = \gamma r_0$
- grid search for α, β, γ
- Bk : α^k, β^k, γ^k

Efficient Net v2 :
architecture grid search fo B0

Tan and Le. PMLR 2019, Efficientnet : Rethinking model scaling for convolutional neural networks
Tan and Le. ICML 2021, EfficientNetV2 : Smaller Models and Faster Training

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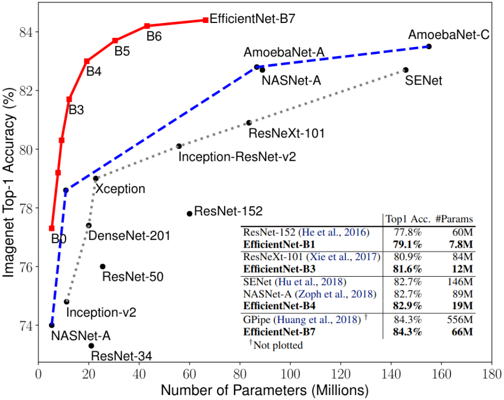
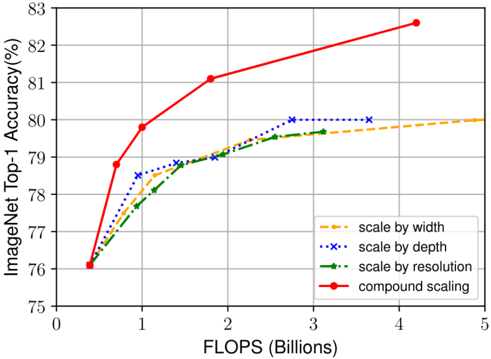
Efficient Net



	Top1 Acc.	#Params
ResNet-152 (He et al., 2016)	77.8%	60M
EfficientNet-B1	**79.1%**	**7.8M**
ResNeXt-101 (Xie et al., 2017)	80.9%	84M
EfficientNet-B3	**81.6%**	**12M**
SENet (Hu et al., 2018)	82.7%	146M
NASNet-A (Zoph et al., 2018)	82.7%	89M
EfficientNet-B4	**82.9%**	**19M**
GPipe (Huang et al., 2018) †	84.3%	556M
EfficientNet-B7	**84.3%**	**66M**

† Not plotted



Tan and Le. PMLR 2019, Efficientnet : Rethinking model scaling for convolutional neural networks

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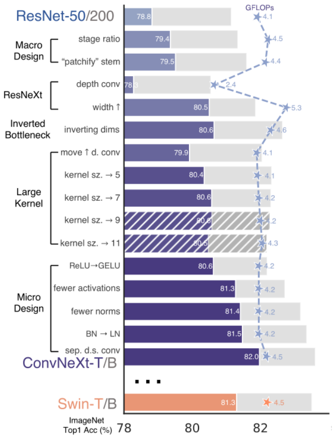
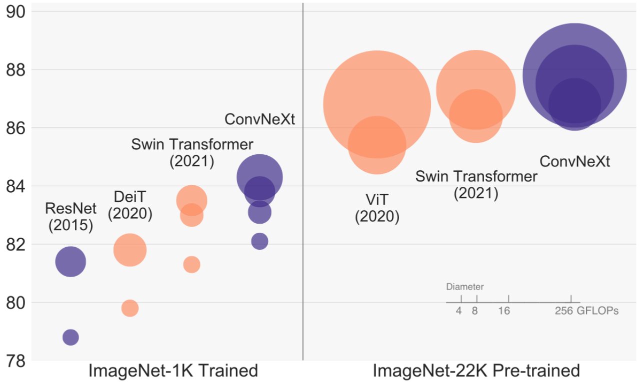
ConvNext





Liu etal, CVPR 2022, A ConvNet for the 2020s

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Outline

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Encoder/Decoder architecture

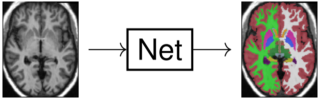


Image Segmentation

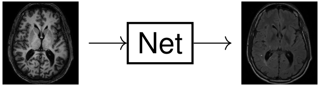
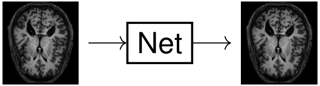


Image Synthesis, Domain adaptation



Denoising

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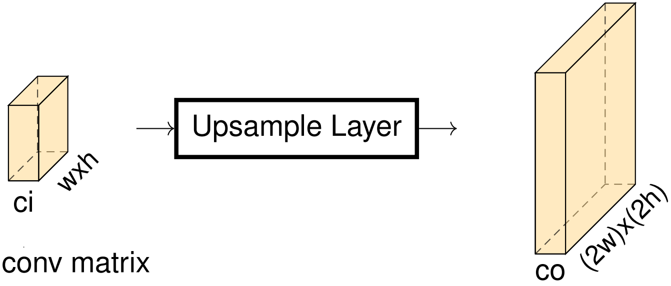
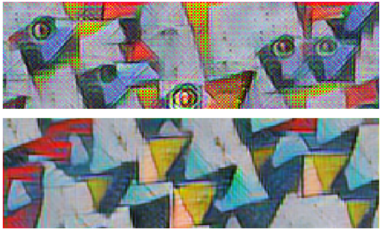
Upsampling Layer

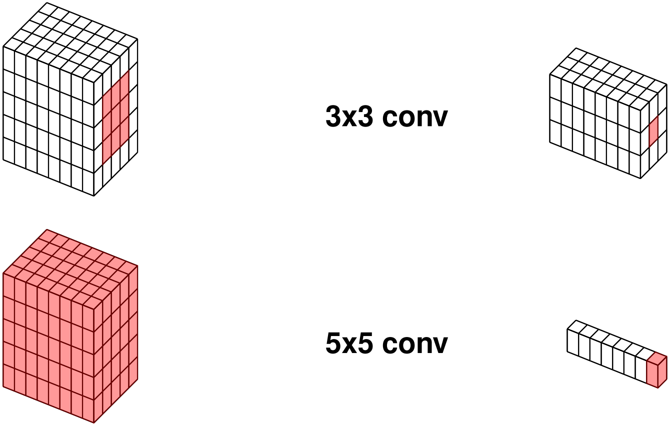


- deconv
  - transpose of strided conv matrix
  - learn the upsampling coefficient
- unpool :
  - upsample on maxpool indices
- interpolation
  - bi/tri linear
  - no chessboard artifact

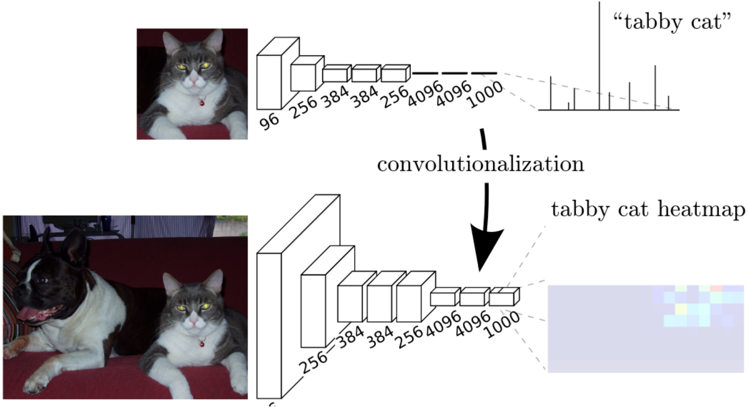


distill.pub/2016/deconv-checkerboard

Fully Convolutional Network : FC as convolution



Fully Convolutional Network : FC as convolution



- use kernels that cover their entire input regions

Long et al., CVPR 2015, Fully convolutional networks for semantic segmentation

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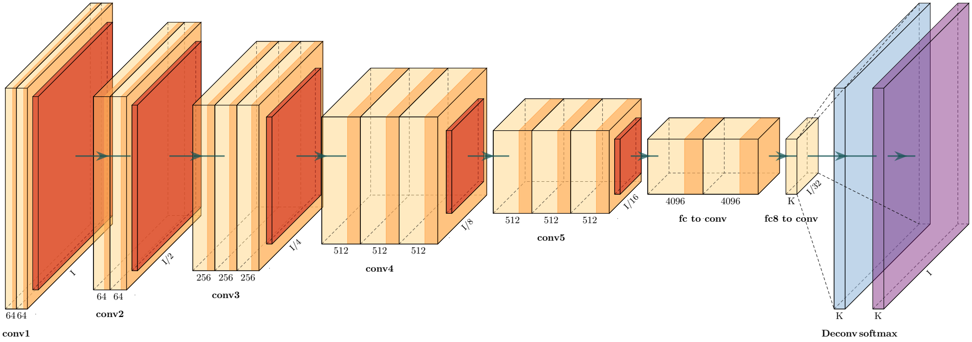
Fully Convolutional Network



- deconv layer + pixelwize cross entropy

Long et al., CVPR 2015, Fully convolutional networks for semantic segmentation

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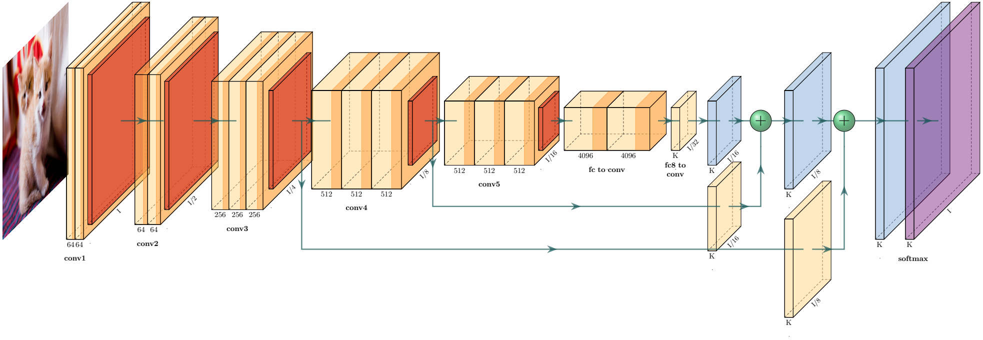
Fully Convolutional Network



- progressive upsampling + reuse fine scale features

Long et al., CVPR 2015, Fully convolutional networks for semantic segmentation

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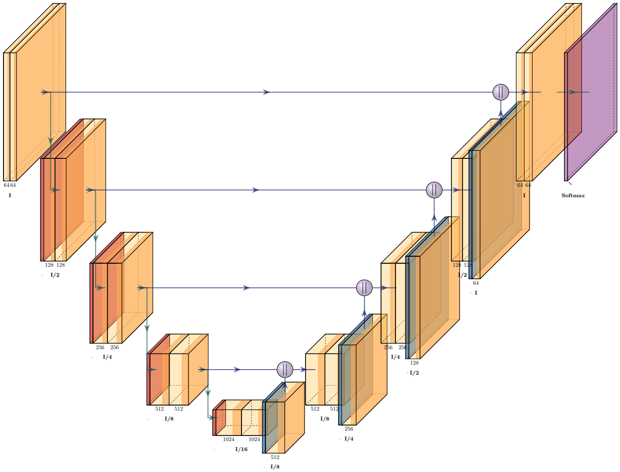
Unet



Ronneberger et al, MICCAI 2015. U-net : Convolutional networks for biomedical image segmentation

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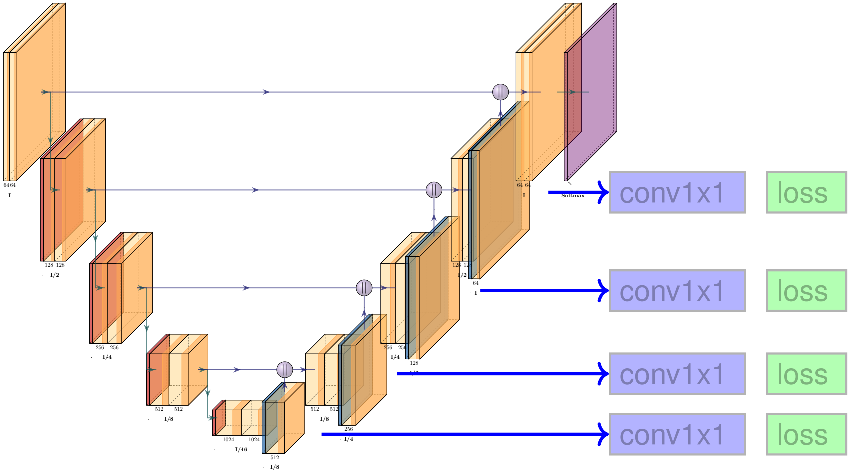
Unet



Ronneberger et al, MICCAI 2015. U-net : Convolutional networks for biomedical image segmentation

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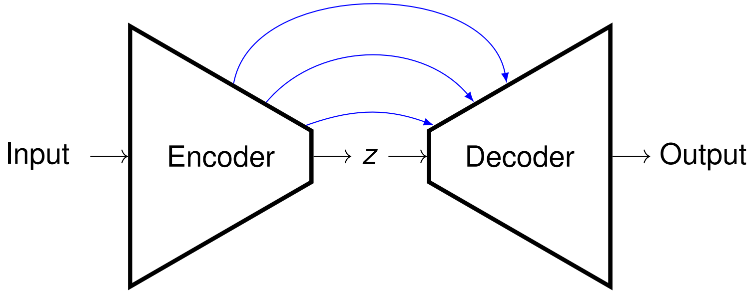
Encoder / Decoder



Tiramisu Net :
* conv → dense block

Unet+ / Unet++ :
* add skip connection across scale

Eff-UNet :
* Encoder is efficient net
* standard unet Decoder

Jegou et al, CVPR 2017, The One Hundred Layers Tiramisu : Fully Convolutional DenseNets for Semantic Segmentation

Baheti et al, CVPR 2020, Eff-UNet : A Novel Architecture for Semantic Segmentation in Unstructured Environment

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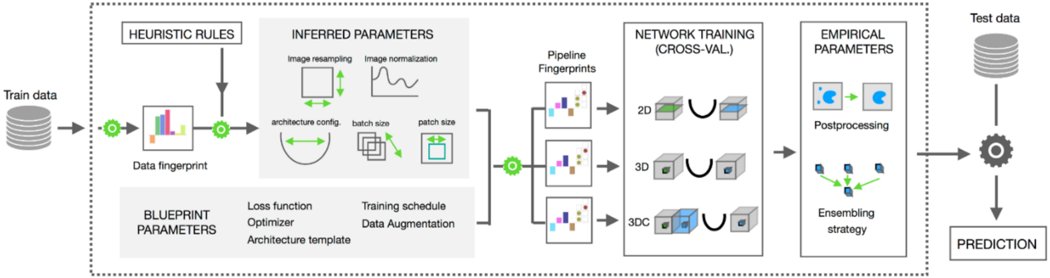
nn-Unet : self configuration



Isensee, et al. Nature 2021, nnU-Net : a self-configuring method for deep learning-based biomedical image segmentation

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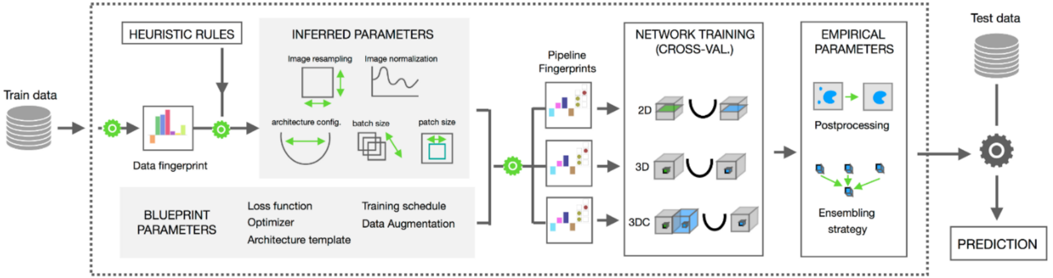
nn-Unet : self configuration



Isensee, et al. Nature 2021, nnU-Net : a self-configuring method for deep learning-based biomedical image segmentation

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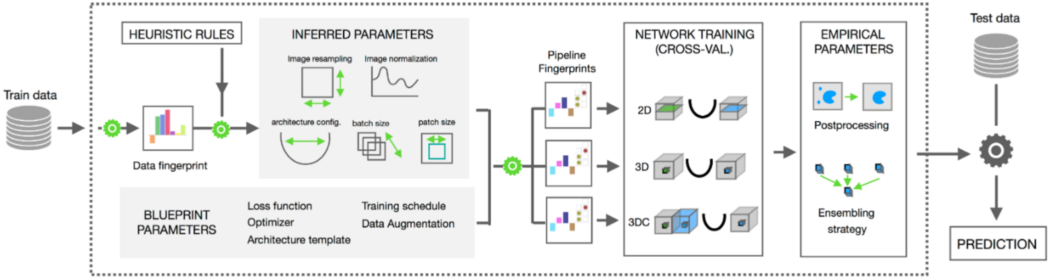
nn-Unet : self configuration



Isensee, et al. Nature 2021, nnU-Net : a self-configuring method for deep learning-based biomedical image segmentation

Outline

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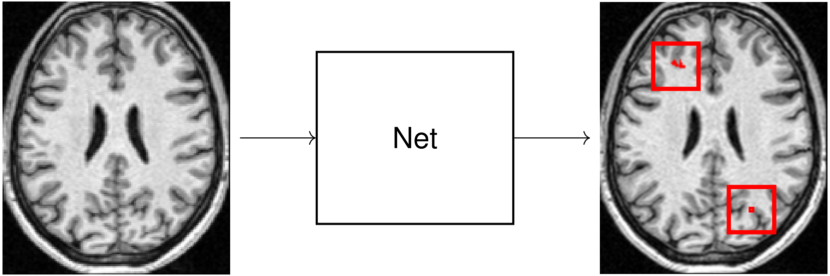
Object Detection



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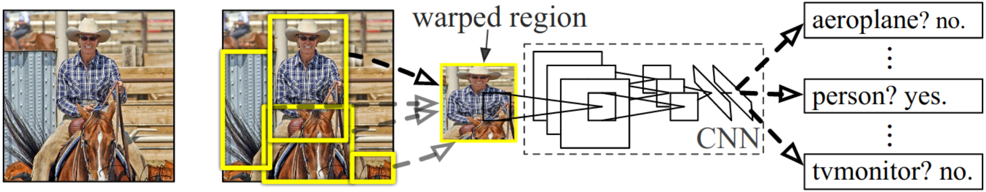
R-CNN



- regions extractor (non deep)
- for each region $\rightarrow$ **very slow**
  - deep feature
  - classif + box regression

Girshick, et al. CVPR 2015, Rich feature hierarchies for accurate object detection and semantic segmentation

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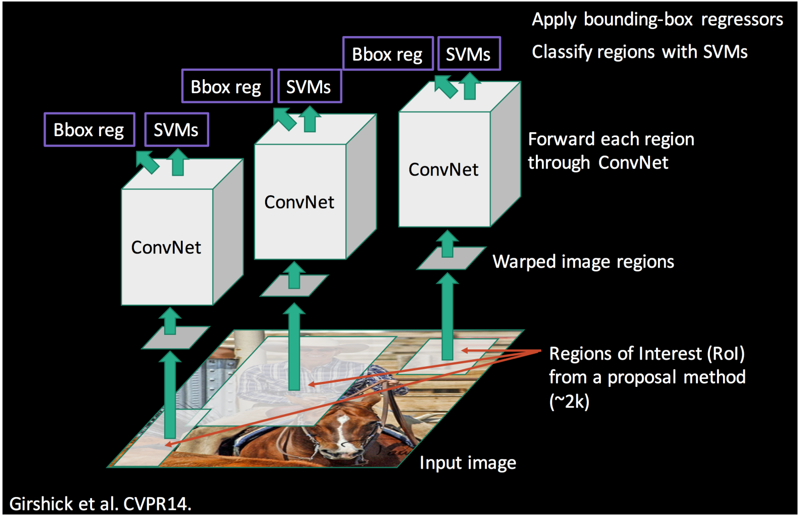
R-CNN



Girshick, et al. CVPR 2015, Rich feature hierarchies for accurate object detection and semantic segmentation
(credit : jhui.github.io/2017/03/15/Fast-R-CNN-and-Faster-R-CNN)

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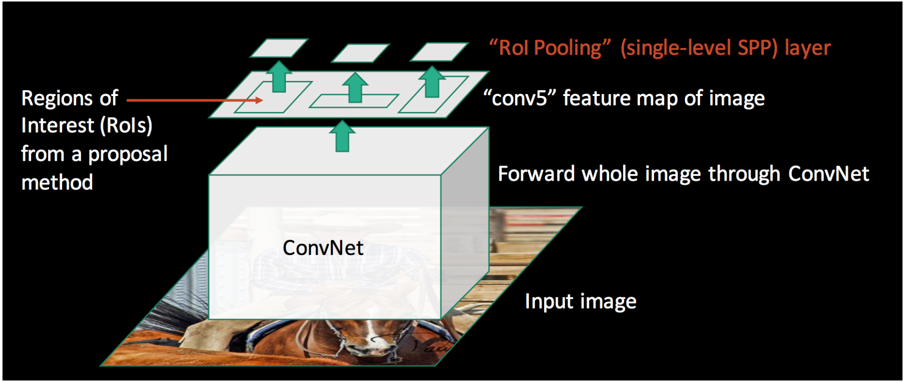
Fast RCNN



- all the feature computed at once

Girshick, ICCV 2015, Fast r-cnn
(credit : jhui.github.io/2017/03/15/Fast-R-CNN-and-Faster-R-CNN)

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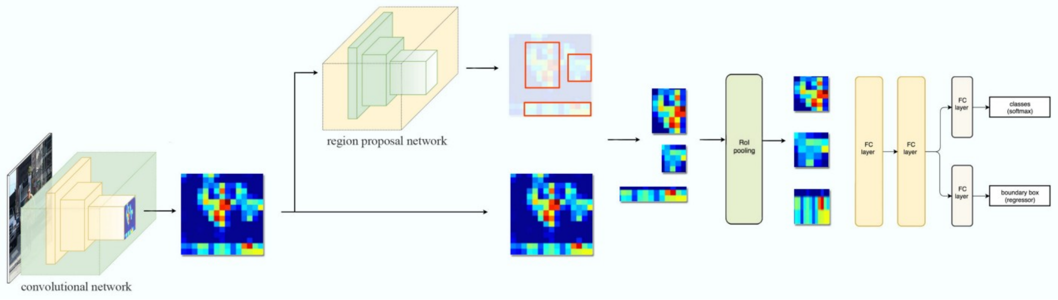
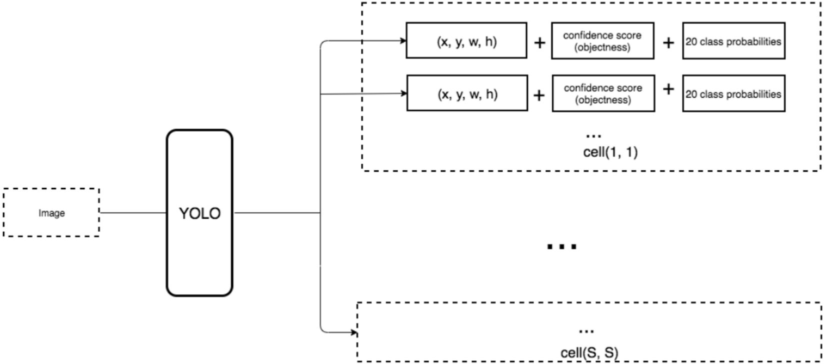
Faster RCNN



- DEEP region proposal network :
  for each position in the feature map, output
  - k proba : object vs non object
  - k offset for bounding box proba

, Shaoqing, et al. INIPS 2015. Faster r-cnn : Towards real-time object detection with region proposal networks
(credit : jhui.github.io/2017/03/15/Fast-R-CNN-and-Faster-R-CNN)

YOLO (You Only Look Once)



- yolo V1 : CNN $\rightarrow$ pb with small object
- yolo V2, V3 : Unet

Redmon et al, CVPR 2016, You Only Look Once : Unified, Real-Time Object Detection
Redmon, YOLOv3 : An Incremental Improvement

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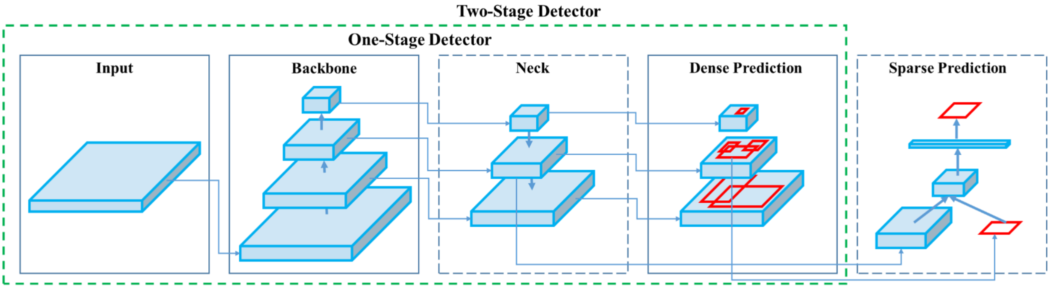
YOLO (You Only Look Once)



Bochkovskiy et al, arxiv 2020, Yolov4 : Optimal speed and accuracy of object detection

Outline

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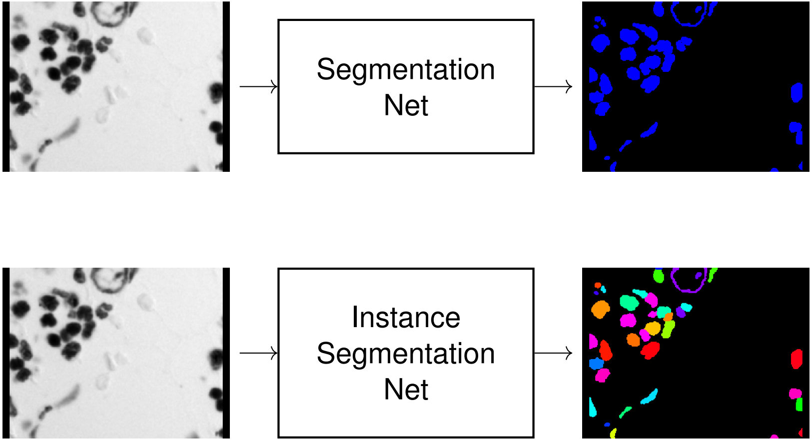
Instance Segmentation



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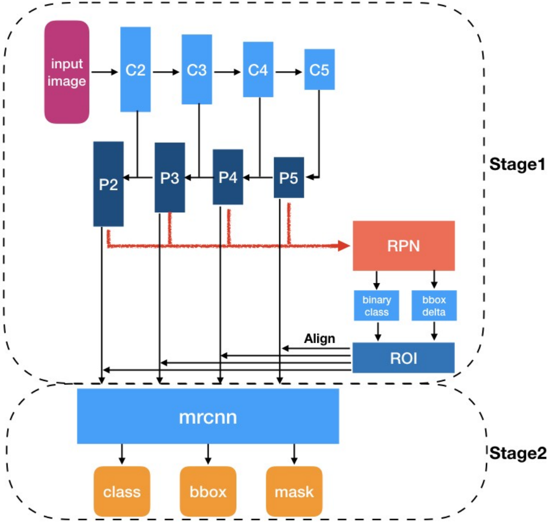
Mask R-CNN



He, Kaiming, et al, ICCV 2017, Mask r-cnn
https ://alittlepain833.medium.com/simple-understanding-of-mask-rcnn-134b5b330e95

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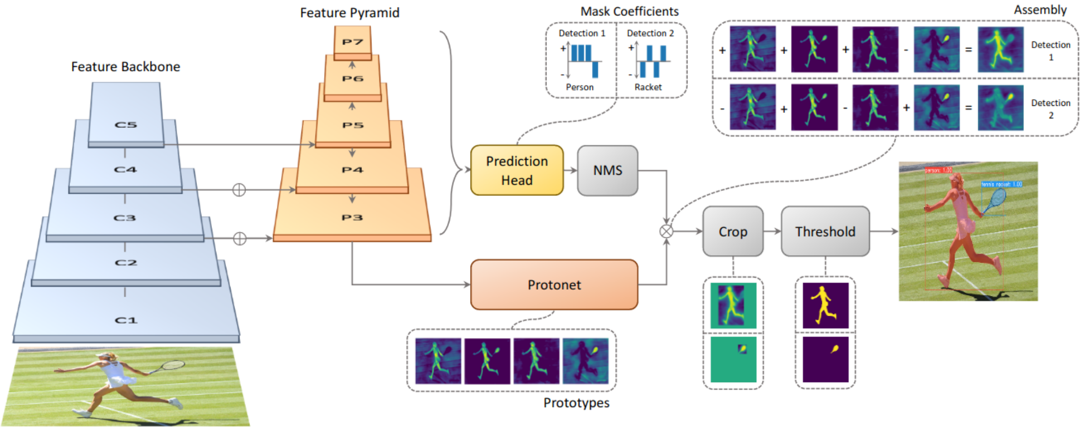
Yolact



Bolya et al, ICCV 2019, YOLACT, Real-time Instance Segmentation
Bolya et al, IEEE PAMI 2019, YOLACT++, Better Real-time Instance Segmentation

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Outline

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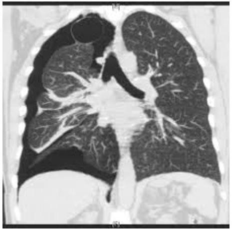
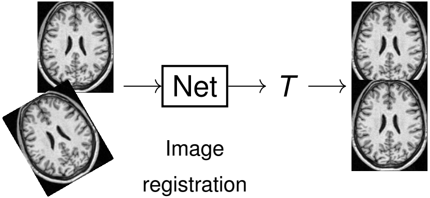
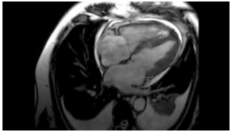
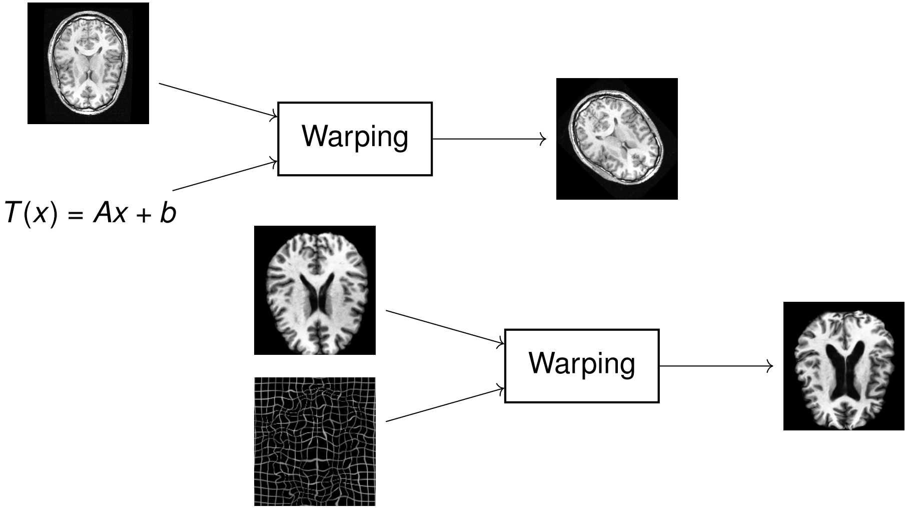
Motion/Registration



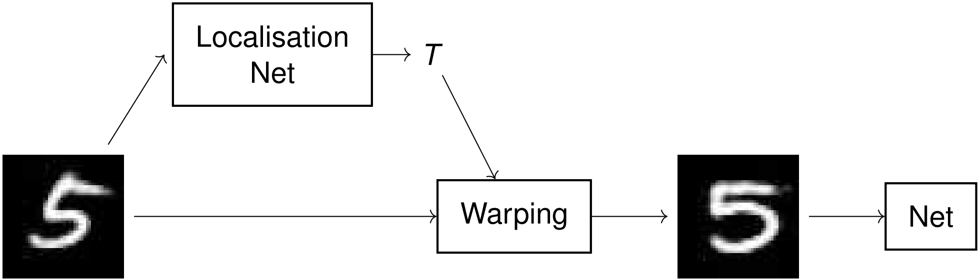




Warping Layer



Spatial Transformer Networks



Jaderberg et al, NIPS 2015, Spatial Transformer Networks

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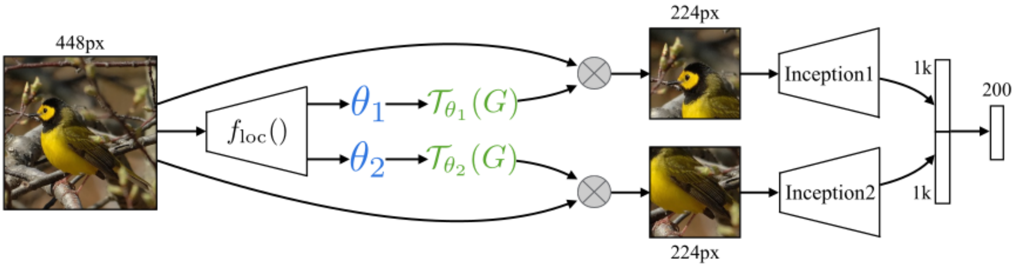
Spatial Transformer Networks



Jaderberg et al, NIPS 2015, Spatial Transformer Networks

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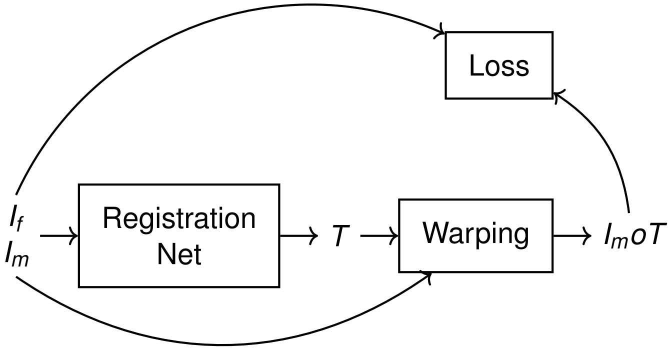
Image registration with deep learning



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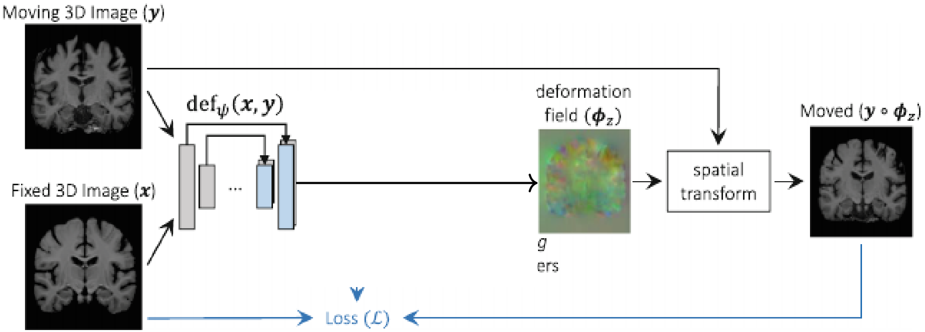
Unsupervized learning, VoxelMorph



- registration loss : no reference warp needed

Balakrishnan et al. IEEE TMI 2019, VoxelMorph : a learning framework for deformable medical image registration
Dalca et al, MICCAI 2018, Unsupervised learning for fast probabilistic diffeomorphic registration

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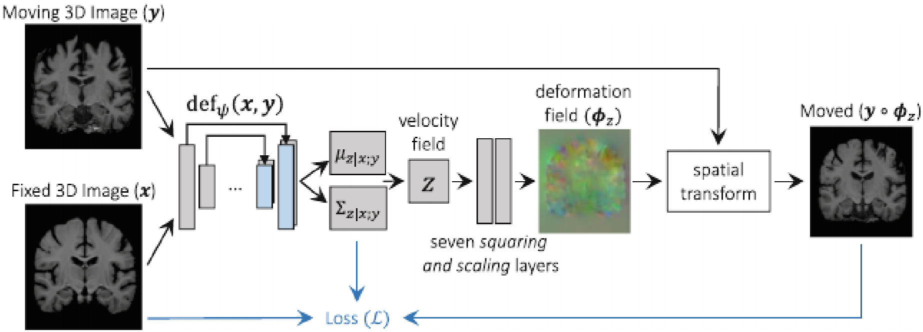
Unsupervized learning, VoxelMorph



- registration loss : no reference warp needed
- $T(x) = Exp(v)$: diffeomorphic $\longleftarrow$ scaling and squaring layers

Balakrishnan et al. IEEE TMI 2019, VoxelMorph : a learning framework for deformable medical image registration
Dalca et al, MICCAI 2018, Unsupervised learning for fast probabilistic diffeomorphic registration

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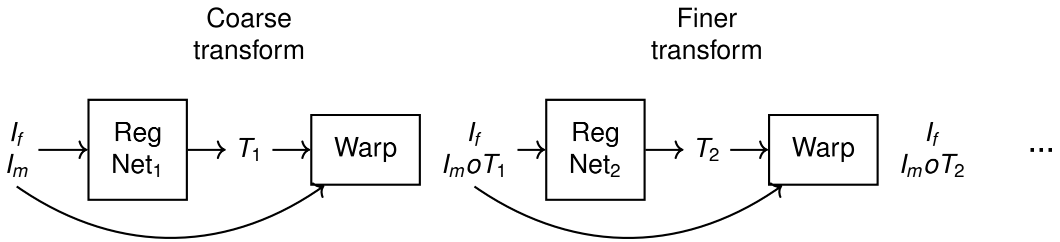
Coarse to fine registration



Bob D. de Vos et al, MEDIA 2019, A Deep Learning Framework for Unsupervised Affine and Deformable Image Registration

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Outline

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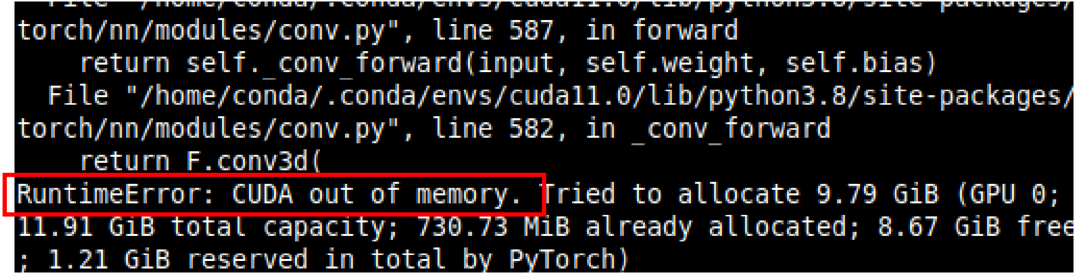
What about memory ?



Where is the memory ?

$$x \longrightarrow \boxed{f^1_{w_1}} \longrightarrow h^1 \longrightarrow \boxed{f^2_{w_2}} \longrightarrow h^2 \longrightarrow \boxed{f^3_{w_3}} \longrightarrow h^3 \longrightarrow \boxed{f^4_{w_4}} \longrightarrow y$$

$$\frac{\partial f^4}{\partial w_4}(h^3, w_4)$$

$$\frac{\partial f^3}{\partial w_3}(h^2, w_3) \longleftarrow \frac{\partial f^4}{\partial h_3}(h^3, w_4)$$

$$\frac{\partial f^2}{\partial w_2}(h^1, w_2) \longleftarrow \frac{\partial f^3}{\partial h_2}(h^2, w_3)$$

$$\frac{\partial f^1}{\partial w_1}(x, w_1) \longleftarrow \frac{\partial f^2}{\partial h_1}(h^1, w_2)$$

$$\frac{\partial f^1}{\partial x}(x, w_1)$$

First Trick

Reduce the batch size ! ! !

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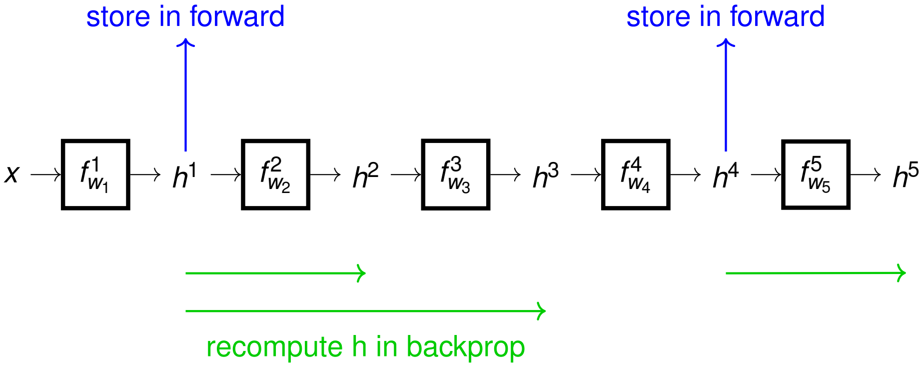
Second Trick : Checkpointing



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Third Trick : Revertible Networks

do no store h_l in forward

$$x \longrightarrow \boxed{f^1_{w_1}} \longrightarrow h^1 \longrightarrow \boxed{f^2_{w_2}} \longrightarrow h^2 \longrightarrow \boxed{f^3_{w_3}} \longrightarrow h^3 \longrightarrow \boxed{f^4_{w_4}} \longrightarrow h^4 \longrightarrow \boxed{f^5_{w_5}} \longrightarrow h^5$$

recompute h_l in backprop

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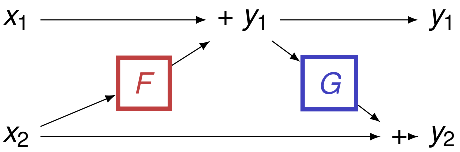
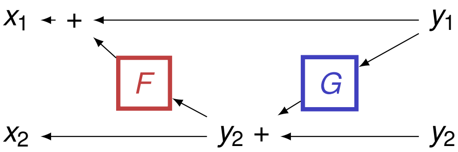
Third options : Revertible Networks

$$y_1 = x_1 + F(x_2)$$
$$y_2 = x_2 + G(y_1)$$

$$x_2 = y_2 - G(y_1)$$
$$x_1 = y_1 - F(x_2)$$





Gomez et al, Neurips 2017, The reversible residual network : Backpropagation without storing activations

Conclusion

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Take home message

Do not start your new network from scratch !

Thank you!!

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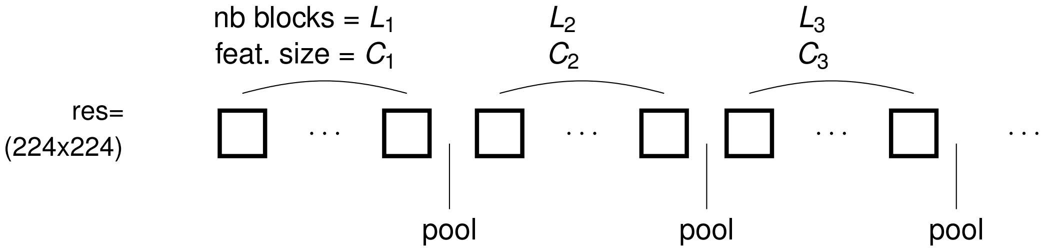
Efficient Net : compound scaling of networks



Tan and Le. PMLR 2019, Efficientnet : Rethinking model scaling for convolutional neural networks

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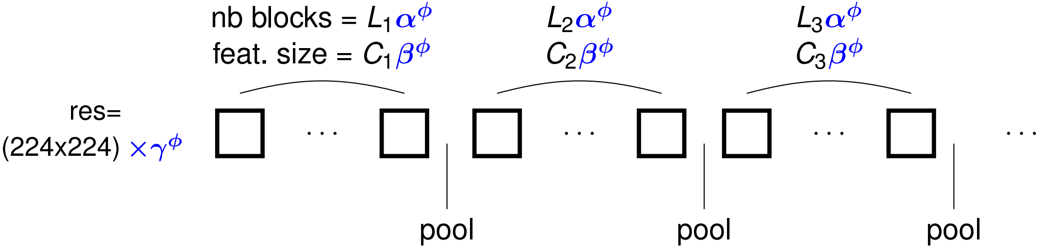
Efficient Net : compound scaling of networks



- base network EffNet$_1$, (ϕ = 1)
- find α, β, γ :
  - ϕ = 1
  - optimize accuracy/flops s.t. $\alpha\beta^2\gamma^2 \approx 2$

- More Capacity : change ϕ : EffNet$_{\phi}$
- flops = flops$_1$ $\times$ $(\alpha\beta^2\gamma^2)^{\phi}$

Tan and Le. PMLR 2019, Efficientnet : Rethinking model scaling for convolutional neural networks