Deep Learning - COSC2779

Vision Application & CNN Architectures

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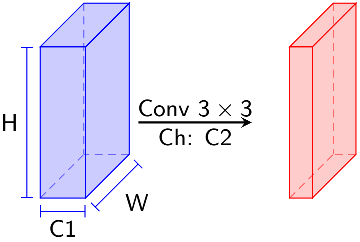
RMIT UNIVERSITY

Semester 2, 2022

Outline

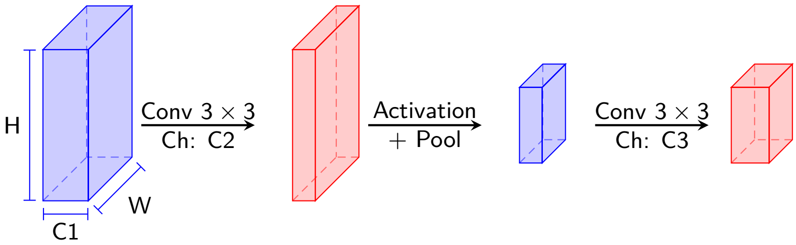
Last Week: Pooling & Convolutions



Convolutions can be combined with pooling to construct a chain of layers.

- Feature extraction usually happens locally - **sparse connectivity**.
- In feature extraction the same operation is applied at different locations - **parameter sharing.**
- Pooling help reduce redundant information and provide some level of *invariance to translations*.

Last Week: Pooling & Convolutions



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- Feature extraction usually happens locally - **sparse connectivity**.
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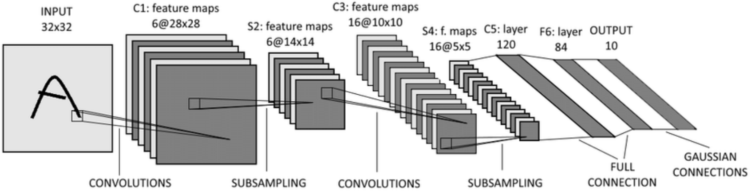
"*LeNet is a classic example of convolutional neural network to successfully predict handwritten digits.*" [LeNet]



How Can We Design the Architecture?

There are so many hyper parameter to choose in CNN:

- Number of convolutional layers, filter size, number of filters, stride, initialization . . .
- Pooling size, Number of pooling layers . . .
- Number of FC layers, units, . . .
- optimization type, lerning rate, . . .
- . . .

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- ...

Use classic networks like LeNet, AlexNet, VGG-16, VGG-19, ResNet etc. as inspiration (follow the trend used in those architectures).

Objectives of the Lecture

- Identify how deep networks are developed via case study: Image classification (IMAGENET).
- Understand the main trends in classic architectures and why they work.
- Identify the classic network architectures used for common computer vision problems:
  - Image Classification
  - Object Detection
  - Image Segmentation

Outline

Image Classification

The ImageNet Large Scale Visual Recognition Challenge (ILSVRC) is an annual competition helped between 2010 and 2017.

The datasets comprised approximately 1 million images and 1,000 object classes.

The annual challenge focuses on multiple tasks for image classification.

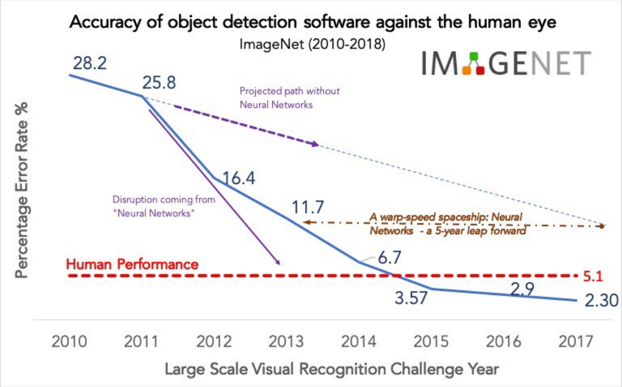
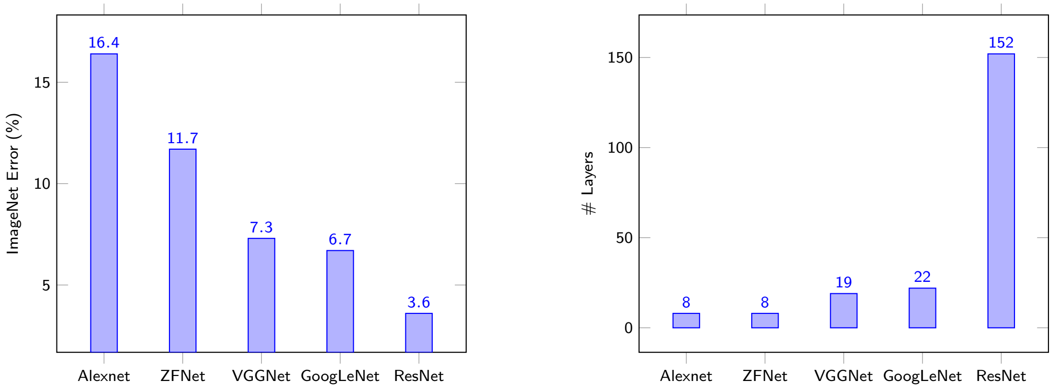


Image source: ImageNet
Alex Krizhevsky, et al. "ImageNet Classification with Deep Convolutional Neural Networks" developed a convolutional neural network that achieved top results on the ILSVRC-2010 and ILSVRC-2012 image classification tasks.

Outline



Supervised learning based image classification.

AlexNet [Krizhevsky et al. 2012]

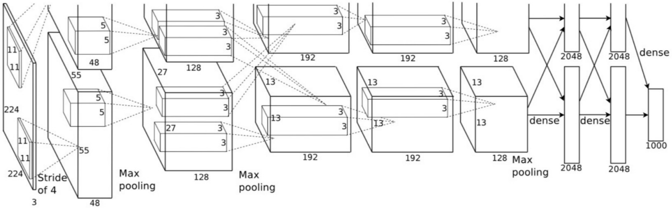


Image: ImageNet Classification with Deep Convolutional Neural Networks

Input: $227 \times 227 \times 3$

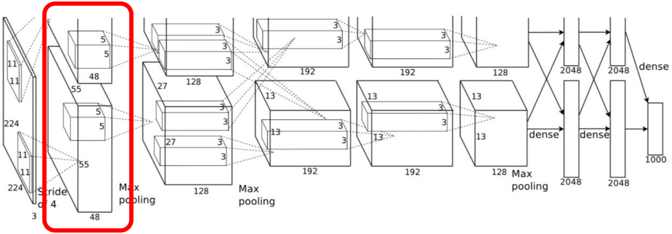


Image: ImageNet Classification with Deep Convolutional Neural Networks

Input: $227 \times 227 \times 3$

Layer 1: 2D Convolution with 96, $[11 \times 11]$ filters, with stride of 4. 'ReLU' activation. Output Shape ?

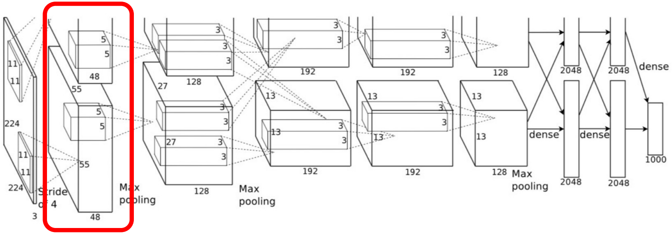
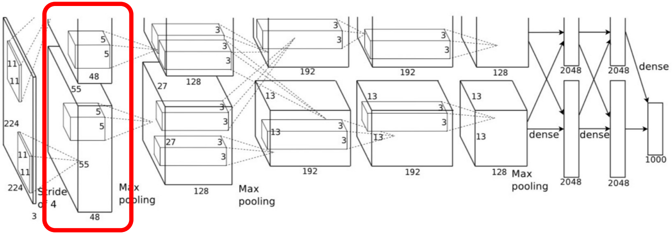


Image: ImageNet Classification with Deep Convolutional Neural Networks

Input: $227 \times 227 \times 3$

Layer 1: 2D Convolution with 96, $[11 \times 11]$ filters, with stride of 4. 'ReLU' activation.
Output Shape $(W - F + 2P)/S + 1 = (227 - 11 + 2 * 0)/4 + 1 = 55 \rightarrow [?, 55, 55, 96]$
Parameters ?



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Parameters $11 \times 11 \times 3 \times 96 + 96$

AlexNet [Krizhevsky et al. 2012]

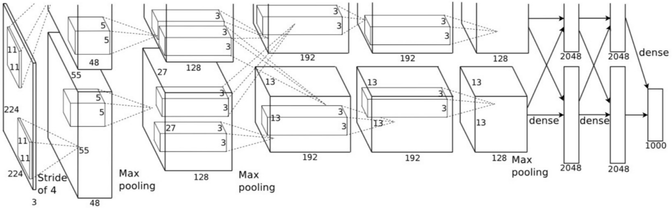

Image: ImageNet Classification with Deep Convolutional Neural Networks

Input: $227 \times 227 \times 3 \rightarrow$ **After Conv1**: $55 \times 55 \times 96$

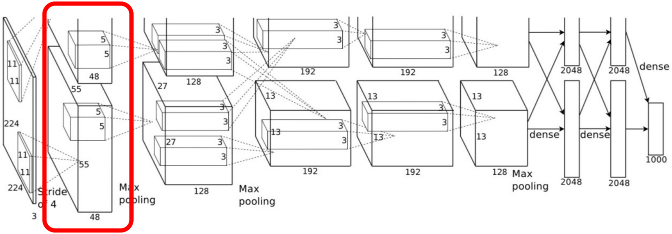

Image: ImageNet Classification with Deep Convolutional Neural Networks

Input: $227 \times 227 \times 3 \rightarrow$ **After Conv1**: $55 \times 55 \times 96$

Layer 2: Max Pooling with, $[3 \times 3]$, with stride of 2.
Output Shape ?

AlexNet [Krizhevsky et al. 2012]

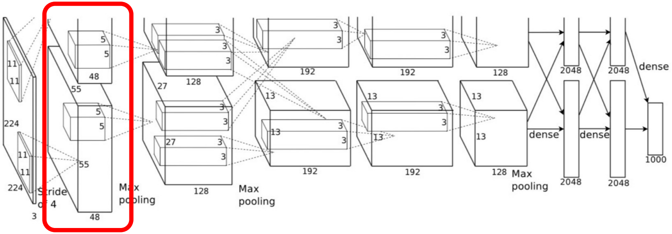

Image: ImageNet Classification with Deep Convolutional Neural Networks

Input: $227 \times 227 \times 3 \rightarrow$ **After Conv1**: $55 \times 55 \times 96$

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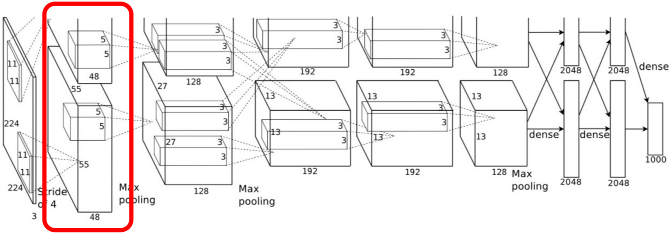
Output Shape $(W - F + 2P)/S + 1 = (55 - 3 + 2 * 0)/2 + 1 = 27 \rightarrow [?, 27, 27, 96]$
Parameters ?

AlexNet [Krizhevsky et al. 2012]



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Parameters 0

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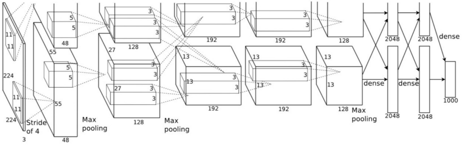


Image: Krizhevsky et al. 2012

227x227x3	Input
55x55x96	Conv1: 96 11x11 filters at stride 4, pad 0
27x27x96	Max-pool1: 3x3 filters at stride 2
27x27x96	Norm1: Normalization layer
27x27x256	Conv2: 256 5x5 filters at stride 1, pad 2
13x13x256	Max-pool2: 3x3 filters at stride 2
13x13x256	Norm2: Normalization layer
13x13x384	Conv3: 384 3x3 filters at stride 1, pad 1
13x13x384	Conv4: 384 3x3 filters at stride 1, pad 1
13x13x256	Conv5: 256 3x3 filters at stride 1, pad 1
6x6x256	Max-pool3: 3x3 filters at stride 2
4096	FC6: 4096 neurons
4096	FC7: 4096 neurons
1000	FC8: 1000 neurons (class scores)

AlexNet [Krizhevsky et al. 2012]

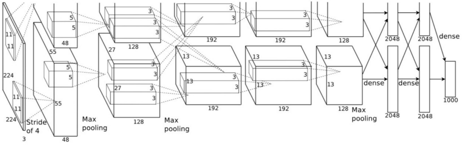
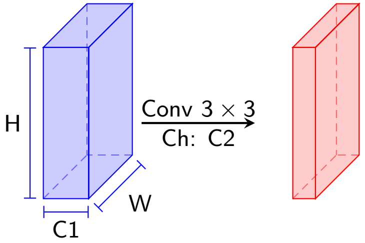


Image: Krizhevsky et al. 2012

What happens if we change the input tensor height & width to conv layer?



Can we change the input to AlexNet?
No, This will change the dimensions of the input tensor to FC layers.

AlexNet [Krizhevsky et al. 2012]

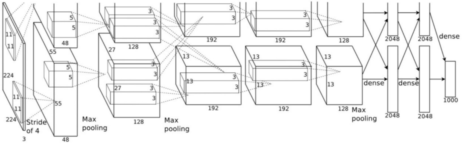


Image: Krizhevsky et al. 2012

- **Number of Parameters**: Overall, AlexNet has about 61M parameters.
- Use of ReLU
- Norm layers - not common anymore
- Data augmentation
- Dropout 0.5 in FC layers.
- Batch size 128
- SGD Momentum 0.9
- Initial learning rate 1e-2, reduced by 10x manually when val accuracy plateaus.
- RegularizationL2 weight decay 5e-4
- 7 CNN ensemble: 18.2% to 15.4%

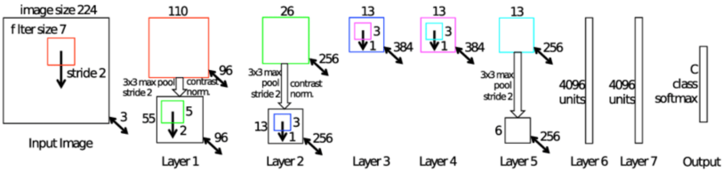


Image: Visualizing and Understanding Convolutional Networks

Similer to AlexNet:

- Conv1: Change from 11x11 stride 4 to 7x7 stride 2.
- Conv3,4,5: Change from 384, 384, 256 filters to 512, 1024, 512.
- ImageNet top 5 error improved from 16.4% to 11.7%

Outline

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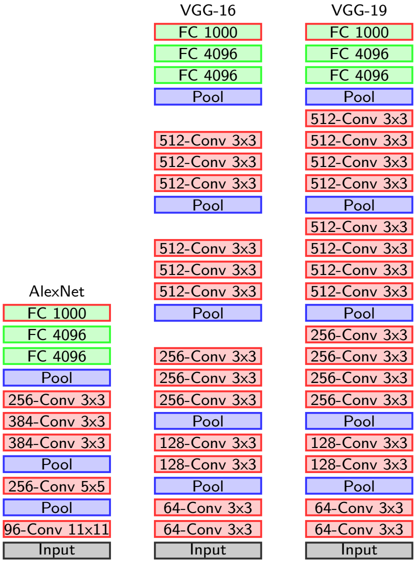


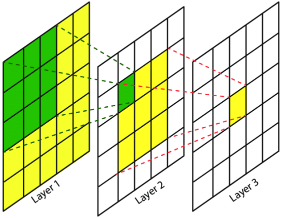
Convolution layers: 3x3, stride 1, pad 1.
Pooling layers: 2x2 max-pool stride 2.

VGGNet [Simonyan and Zisserman, 2014]

AlexNet	VGG-16	VGG-19
	FC 1000	FC 1000
	FC 4096	FC 4096
	FC 4096	FC 4096
	Pool	Pool
		512-Conv 3x3
	512-Conv 3x3	512-Conv 3x3
	512-Conv 3x3	512-Conv 3x3
	512-Conv 3x3	512-Conv 3x3
	Pool	Pool
		512-Conv 3x3
	512-Conv 3x3	512-Conv 3x3
	512-Conv 3x3	512-Conv 3x3
	512-Conv 3x3	512-Conv 3x3
FC 1000	Pool	Pool
FC 4096		256-Conv 3x3
FC 4096	256-Conv 3x3	256-Conv 3x3
Pool	256-Conv 3x3	256-Conv 3x3
256-Conv 3x3	256-Conv 3x3	256-Conv 3x3
384-Conv 3x3	Pool	Pool
384-Conv 3x3	128-Conv 3x3	128-Conv 3x3
Pool	128-Conv 3x3	128-Conv 3x3
256-Conv 5x5	Pool	Pool
Pool	64-Conv 3x3	64-Conv 3x3
96-Conv 11x11	64-Conv 3x3	64-Conv 3x3
Input	Input	Input

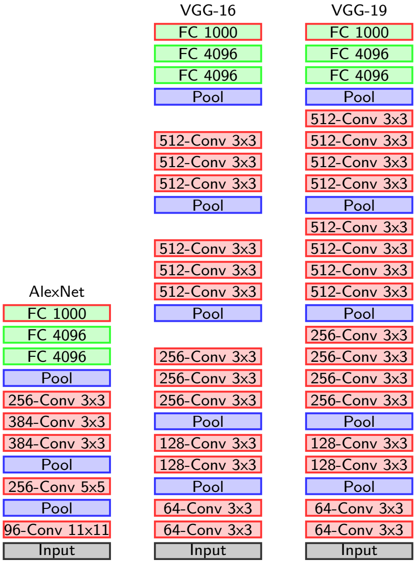
Images: from Unsplash

What will happen when objects are at different scales?



Stack of three 3x3 convolution (stride 1) layers has same effective receptive field as one 7x7 convolution layer.

VGGNet [Simonyan and Zisserman, 2014]



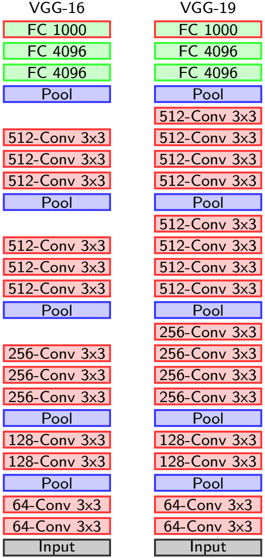
Convolution layers: 3x3, stride 1, pad 1.
Pooling layers: 2x2 max-pool stride 2.

Stack of three 3x3 convolution (stride 1) layers has same effective receptive field as one 7x7 convolution layer.

Deeper structure allows more non-linearities.

Still have fewer parameters: 3x(3x3xC_ixC_o) Vs. (7x7xC_ixC_o)

VGGNet [Simonyan and Zisserman, 2014]



Memory: 96MB per image (forward pass)

Number of Parameters: 138M parameters

- Similar training procedure as AlexNet.
- Use ensembles for best results.
- FC7 features generalize well to other tasks.
- Large amount of parameters at the last FC layers (80%).

Main idea: Smaller filters and deeper networks.

GoogLeNet [Szegedy et al., 2014]

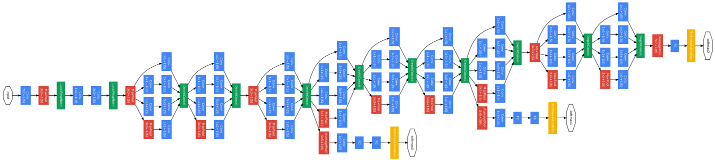


Image: Going deeper with convolutions

Computationally efficient deeper network:

- **Number of parameters**: 5M (12x less that AlexNet, 27x less than VGG-16)
- No fully connected layers at the end. Average pooling across channels.
-

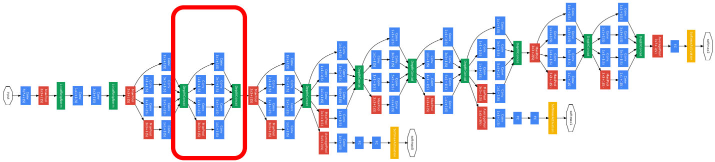


Image: Going deeper with convolutions

Computationally efficient deeper network:

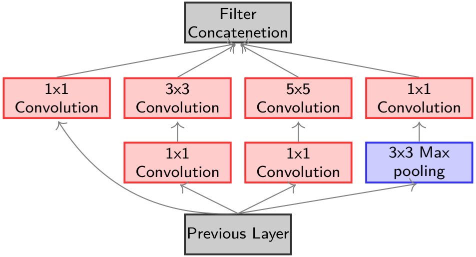
- **Number of parameters**: 5M (12x less that AlexNet, 27x less than VGG-16)
- No fully connected layers at the end. Average pooling across channels.
- 22 layers (with efficient "Inception module")

GoogLeNet [Szegedy et al., 2014]

Images: from Unsplash

Inception module:

- Design a good local network topology
- Apply filters with different size receptive fields to the input form previous layer (1x1, 3x3, 5x5, 3x3 pooling). Then Concatenate all filter outputs together in channel diminution.
- ‘ReLU’ activation or convolution modules.
- Why use 1x1 convolutions?



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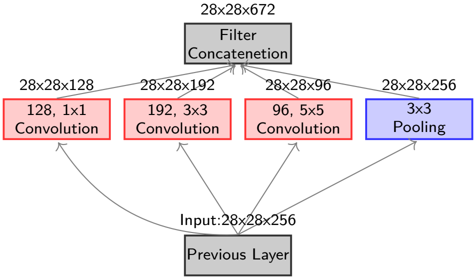
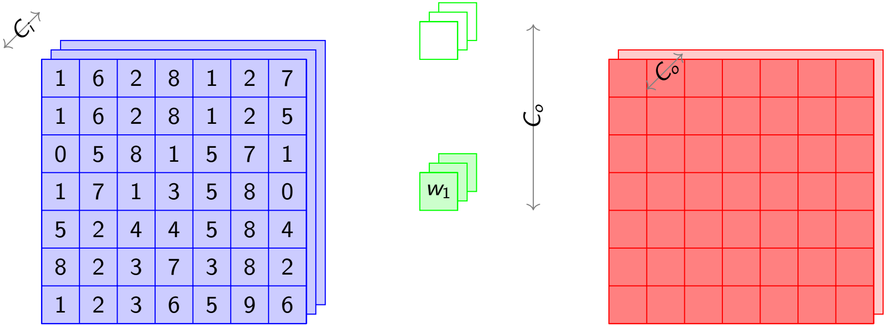


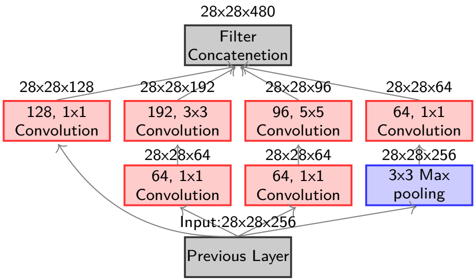
Inception module:

- The channel dimension grows with depth of the network.
- Very expensive to compute.
- Path [3x3] has $3 \times 3 \times 192 \times 256 = 442368$ parameters.



We can do channel dimensionality reduction (increase) with 1x1 convolutions.

GoogLeNet [Szegedy et al., 2014]



- "Bottleneck" modules [1x1] reduce computational cost and output shape.
- Path [3x3] originally had $3 \times 3 \times 192 \times 256 = 442,368$ parameters.
- Path [3x3] how has $1 \times 1 \times 64 \times 256 + 3 \times 3 \times 192 \times 64 = 126,976$ parameters.

GoogLeNet [Szegedy et al., 2014]

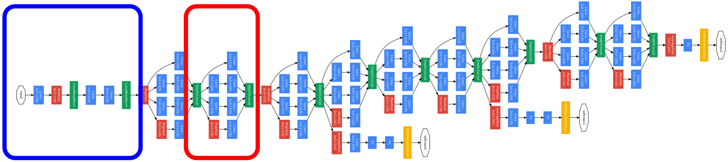


Image: Going deeper with convolutions

- Some convolution + max pooling at start.
- Stack "Inception module" on top of each other.
- Some intermediate stacking will have max-pooling.

GoogLeNet [Szegedy et al., 2014]

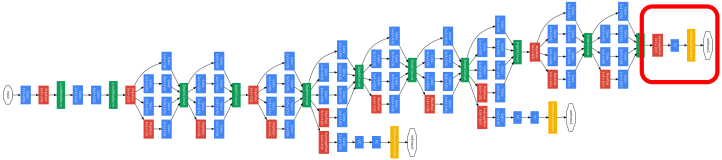


Image: Going deeper with convolutions

- No FC layers at the end. The output of last inception module is subjected to **global average pooling** and then the final “softmax” layer with 1000 classes.

Gobal Average Pooling (GAP)

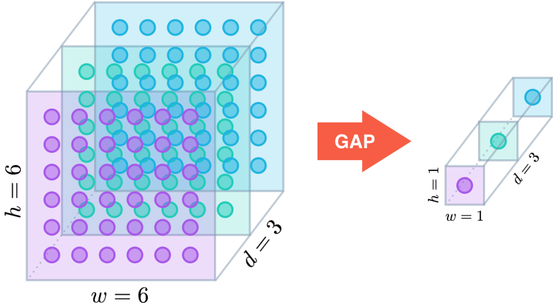


Image: Global Average Pooling Layers for Object Localization

- Normal pooling does each channel independently with 2D masks.
- In GAP, all the pixels in each channel is averaged (or max in global max-pooling) independently to produce a vector.
- If the input to GAP is [B, H, W, C] the output will be [B, 1, 1, C].
- Allows different input shapes at train and test times.
- First paper to use GAP-Network In Network

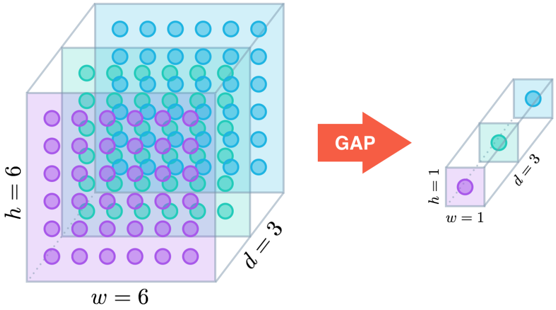
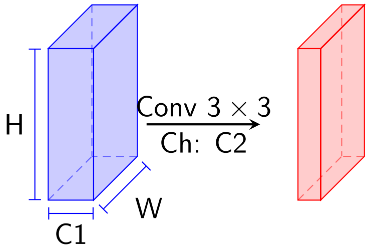


Image: Global Average Pooling Layers for Object Localization

What happens if we change the input tensor height & width to conv layer?



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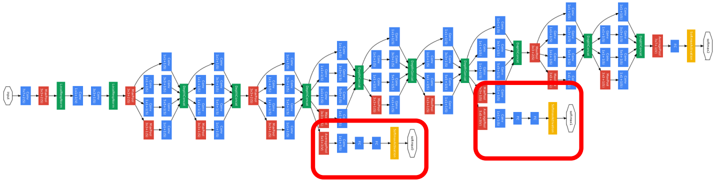


Image: Going deeper with convolutions

- Deep networks has the issue of vanishing gradients.
- Auxiliary classification outputs to inject additional gradient at lower layers.

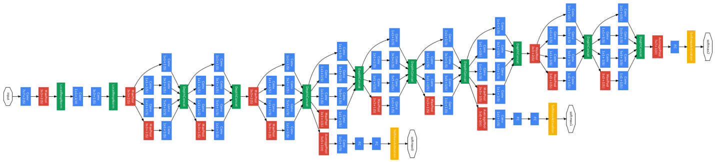


Image: Going deeper with convolutions

- Stochastic gradient descent with 0.9 momentum.
- Fixed learning rate schedule: decreasing the learning rate by 4% every 8 epochs.
- Data Augmentation and dropout (last layer) for preventing over-fitting.

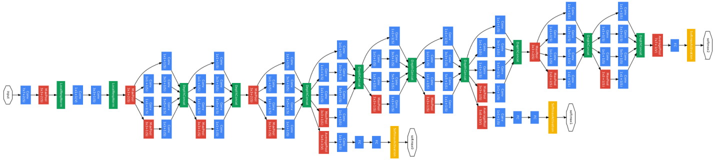
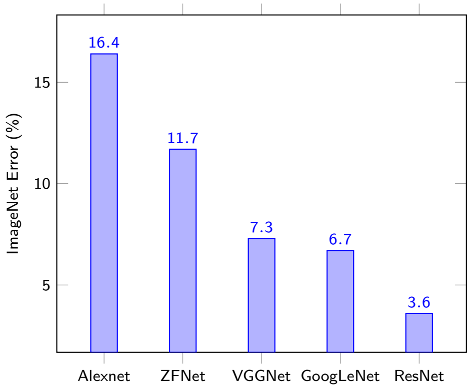


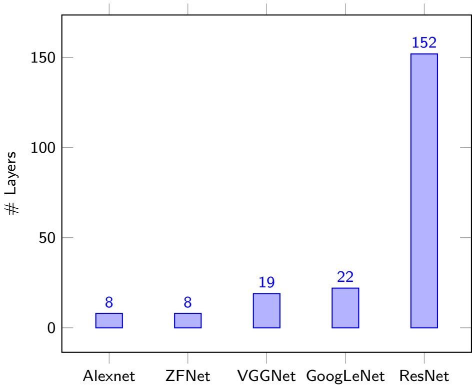
Image: Going deeper with convolutions

Main ideas:

- Efficient "Inception" module integrates information at multiple receptive fields.
- No FC at the end (use GAP instead) which will reduce the number of parameters significantly.
- Auxiliary classification outputs to inject additional gradient at lower layers.
- ILSVRC 2014 classification winner with 6.7% top 5 error.

Outline





Make the network more and more deep to increase performance?

What happens if we increase the depth?

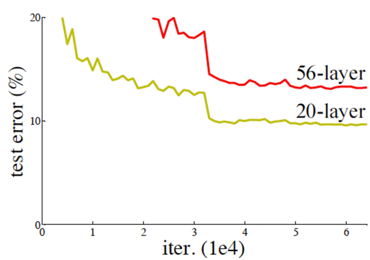


Image: Deep Residual Learning for Image Recognition

Deeper model performs worse than he shallow model. Maybe over-fitting?

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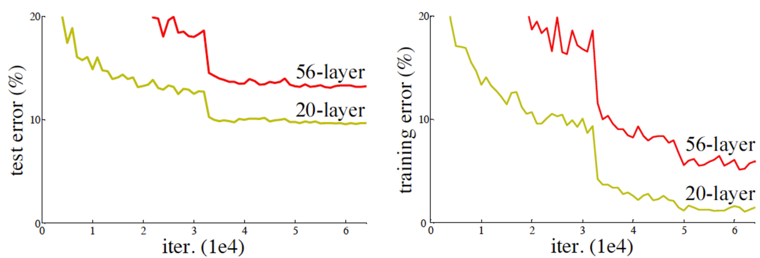


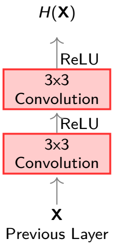
Image: Deep Residual Learning for Image Recognition

Deeper model performs worse than he shallow model. Maybe over-fitting?

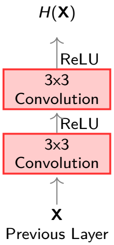
The training error of deeper model is also worse. Not over-fitting.
Hypothesis - Training (optimizing) deeper models is harder.

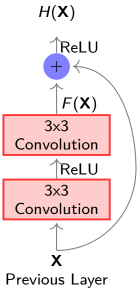
ResNet [He et al., 2015]

Learn a residual mapping at each layer, instead of trying to learn the underlying mapping.



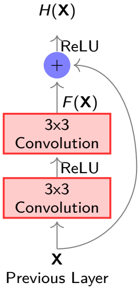
Learn a residual mapping at each layer, instead of trying to learn the underlying mapping.

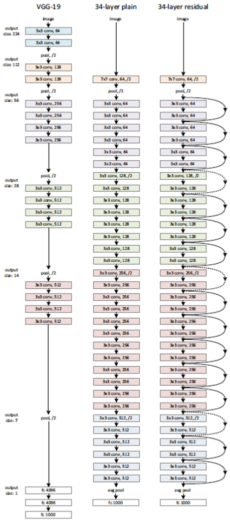




$$H(\mathbf{X}) = F(\mathbf{X}) + \mathbf{X}$$

$$F(\mathbf{X}) = H(\mathbf{X}) - \mathbf{X} \quad \triangleright \text{Residual}$$

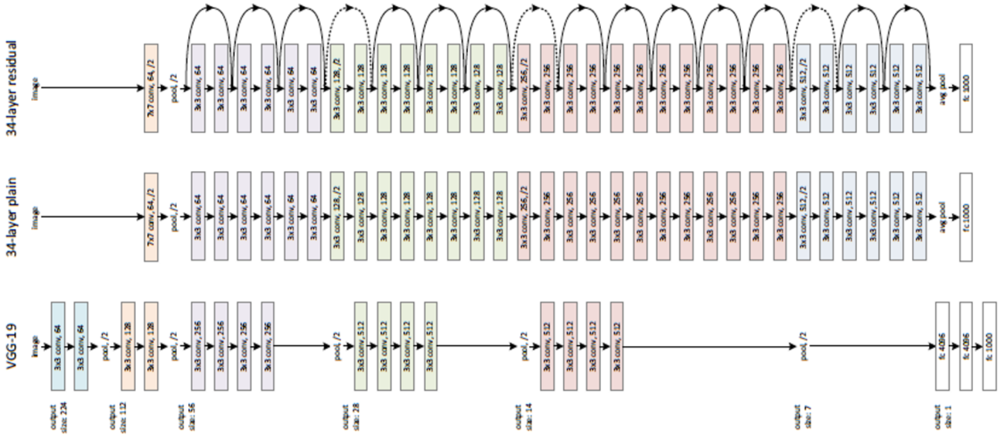




Full ResNet architecture:

- Stack residual blocks. Every residual block has two 3x3 conv layers.
- Periodically, double # of filters and downsample spatially using stride 2 (/2 in each dimension)

ResNet [He et al., 2015]



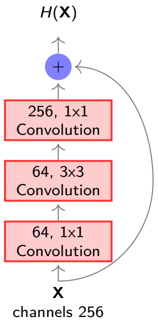
ResNet [He et al., 2015]

For very deep networks use "bottleneck" blocks to reduce computations.

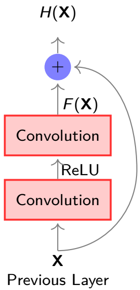
If $F(\mathbf{X}) = 0$ then only identify: $H(\mathbf{X}) = \mathbf{X}$.

Combined with weight decay we can get some layers to be identify.

Skip connections also provide a direct path for gradients to the bottom layer (close to input).



ResNet [He et al., 2015]



ILSVRC 2015 classification winner (3.6% top 5 error)

- Many layers: 152 layers on ImageNet, 1202 on Cifar.
- Additional conv layer at the beginning.
- No FC layers at the end (only FC 1000 to output classes)

Training ResNet in practice:

- Batch Normalization after every Convolution layer.
- He normal initialization from He et al.
- SGD + Momentum (0.9)
- Learning rate: 0.1, divided by 10 when validation error plateaus
- Mini-batch size 256
- Weight decay of 1e-5
- No dropout used

Improvements/Modifications to ResNet

- Improve residual block: Identity Mappings in Deep Residual Networks
- Wide residual blocks not only deep: Wide Residual Networks
- Residual blocks that share multi scale convolutions from GoogleLeNet: Aggregated Residual Transformations for Deep Neural Networks (ResNeXt)
- Dropout layers in residual block: Deep Networks with Stochastic Depth (dropout layers)
- All convolutions in a residual block also gets skip connections: Densely Connected Convolutional Networks.

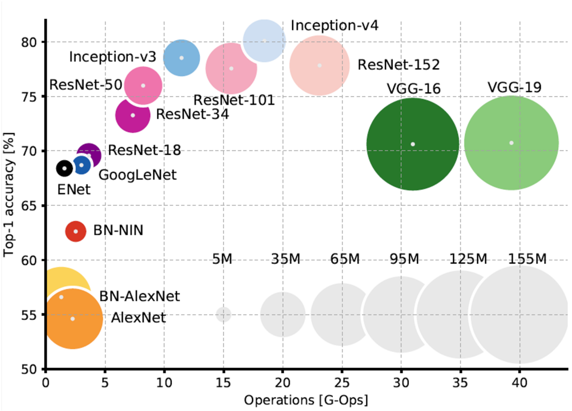


Image: An Analysis of Deep Neural Network Models for Practical Applications.

The size of the blobs is proportional to the number of network parameters

- AlexNet low accuracy, high computational cost.
- VGG Higest number of parameters.
- ResNet: Best accuracy, moderate complexity.

Efficient Networks for Mobile Applications

- Mobilenets: MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications.
- Squeeze Net: SqueezeNet: AlexNet-level accuracy with 50x fewer parameters and $<$0.5MB model size
- ShuffleNet: ShuffleNet: An Extremely Efficient Convolutional Neural Network for Mobile Devices

Outline

Image Segmentation

Image: SegNet: Road Scene Segmentation

Predict a category label (class) for each pixel of the image.

Crop patch and do classification of the center pixel using classification CNN?

Image Segmentation

Image: SegNet: Road Scene Segmentation

Predict a category label (class) for each pixel of the image.

Crop patch and do classification of the center pixel using classification CNN?

Image Segmentation

Image: SegNet: Road Scene Segmentation

Predict a category label (class) for each pixel of the image.

Crop patch and do classification of the center pixel using classification CNN? Very expensive to do inference. Not feasible.

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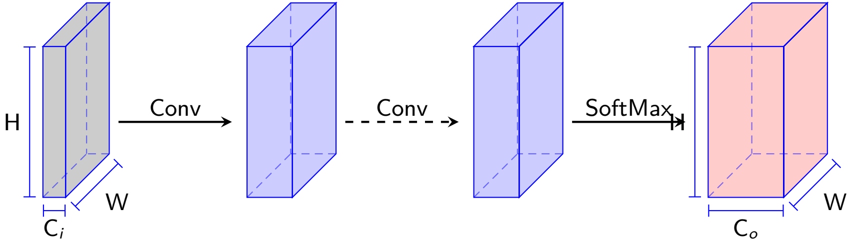


Design a network with only convolutional layers without downsampling operators to make predictions for pixels all at once. C_o is the number of classes in the classification problem. Very expensive, large memory requirement.

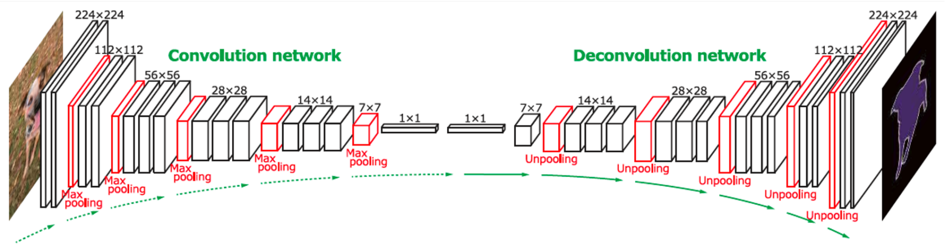


Image: SegNet: A Deep Convolutional Encoder-Decoder Architecture for Image Segmentation

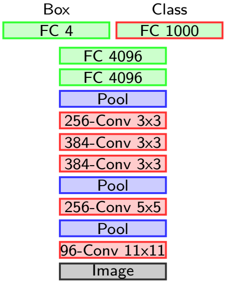
Encoder decoder architecture for segmentation.

- Encoder First part of the network with convolution and pooling (strided convolutions).
- Decoder Second part with convolution and upsampling (transpose convolutions).

- Fully Convolutional Networks for Semantic Segmentation
- SegNet: A Deep Convolutional Encoder-Decoder Architecture for Image Segmentation
- Learning Deconvolution Network for Semantic Segmentation
- U-Net: Convolutional Networks for Biomedical Image Segmentation

Need to predict the location as well as the object class. The location is usually defined by a bounding box.

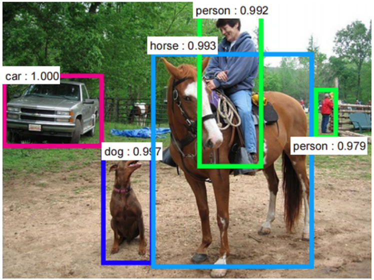
What if there is only one object?



Problem compose to two sub problems:

- Predict object class
- Object location (quantified by $[B_x, B_y, H, W]$)

Can use any CNN (discussed in classification section) and change the last layer to accommodate the two predictions.



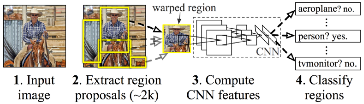
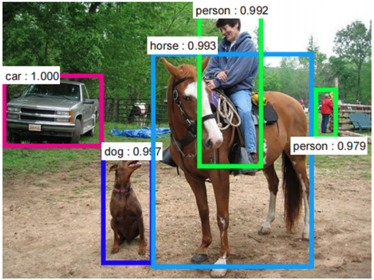


Image: RCNN

- Use a Region proposal algorithm (in traditional CV) to get initial bounding box proposals.
- Resize each proposed region to fixed size.
- Treat each proposal as a single object detection problem and follow the procedure in last slide.

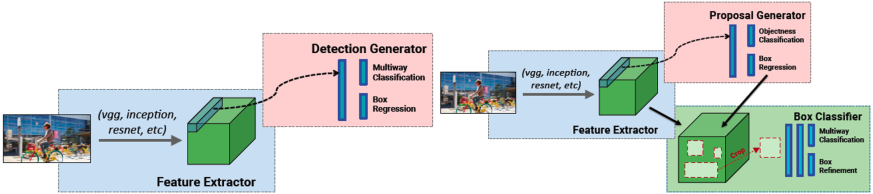
Initial part subject to errors. Technical difficulties when objects overlap. Need non minimal suppression.

Multi Object Detection



- ~~Use a Region proposal algorithm (in traditional CV) to get initial bounding box proposals.~~
- Use a CNN based Region proposal algorithm.
- Treat each as a single object detection and follow the procedure in last slide.

End-to-End network for object detection.



(a) SSD. (b) Faster RCNN.

- Use a back-borne network for CNN based region proposal algorithms.

- Faster RCNN
- SSD: Single Shot MultiBox Detector
- You Only Look Once: Unified, Real-Time Object Detection (YOLO)
- Speed/accuracy trade-offs for modern convolutional object detectors

Summary

Famous networks for image classification, segmetation and object detection.

- **AlexNet**: showed that you can use CNNs to train Computer Vision models.
- **VGG**: shows that bigger networks with smaller conv work better.
- **GoogLeNet**: Focus on efficiency using 1x1 bottleneck convolutions and global avg pool instead of FC layers.
- **ResNet**: showed us how to train extremely deep networks.
- **After ResNet**: CNNs were better than the human metric and focus shifted to Efficient networks:
- Lots of tiny networks aimed at **mobile devices**: MobileNet, ShuffleNet
- *ResNet is currently a good defaults to use.*