Introduction to Deep Learning

Module 4

Ganapathy Krishnamurthi

IIT-Madras

Organization

- Introduction

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- Introduction
- CNN Operations

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- Introduction
- CNN Operations
- CNN Training

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- Illustrative Example ("Hello World") - MNIST digit classification

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- Image Recognition-SoTA model(s)

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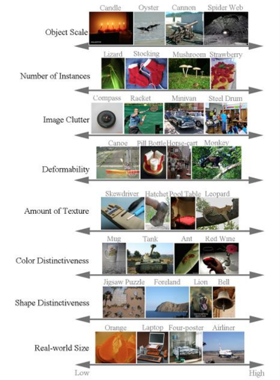
https://arxiv.org/pdf/1409.0575.pdf

ImageNet challenge



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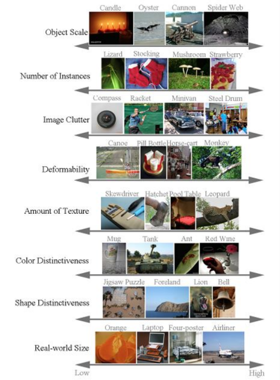

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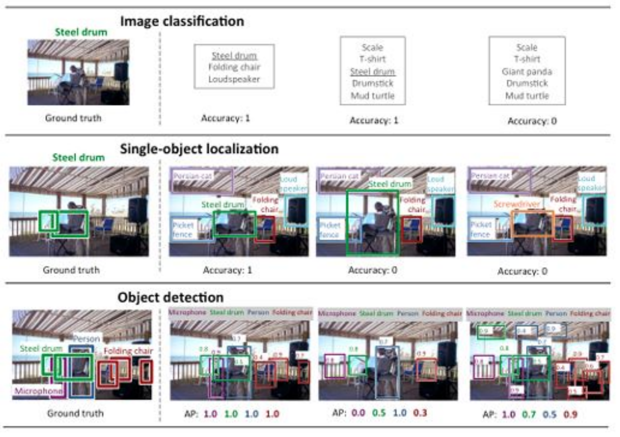

ImageNet challenge

ILSVRC 2010

Codename	CLS	**Insitutions**	**Contributors and references**
Hminmax	54.4	Massachusetts Institute of Technology	Jim Mutch, Sharat Chikkerur, Hristo Paskov, Ruslan Salakhutdinov, Stan Bileschi, Hueihan Jhuang
IBM	70.1	IBM research[†], Georgia Tech[‡]	Lexing Xie[†], Hua Ouyang[‡], Apostol Natsev[†]
ISIL	44.6	Intelligent Systems and Informatics Lab., The University of Tokyo	Tatsuya Harada, Hideki Nakayama, Yoshitaka Ushiku, Yuya Yamashita, Jun Imura, Yasuo Kuniyoshi
ITNLP	78.7	Harbin Institute of Technology	Deyuan Zhang, Wenfeng Xuan, Xiaolong Wang, Bingquan Liu, Chengjie Sun
LIG	60.7	Laboratoire d'Informatique de Grenoble	Georges Quénot
NEC	**28.2**	NEC Labs America[†], University of Illinois at Urbana-Champaign[‡], Rutgers[∓]	Yuanqing Lin[†], Fengjun Lv[†], Shenghuo Zhu[†], Ming Yang[†], Timothee Cour[†], Kai Yu[†], LiangLiang Cao[‡], Zhen Li[‡], Min-Hsuan Tsai[‡], Xi Zhou[‡], Thomas Huang[‡], Tong Zhang[∓] (Lin et al., 2011)
NII	74.2	National Institute of Informatics, Tokyo,Japan[†], Hefei Normal Univ. Heifei, China[‡]	Cai-Zhi Zhu[†], Xiao Zhou[‡], Shin'ichi Satoh[†]
NTU	58.3	CeMNet, SCE, NTU, Singapore	Zhengxiang Wang, Liang-Tien Chia
Regularities	75.1	SRI International	Omid Madani, Brian Burns
UCI	46.6	University of California Irvine	Hamed Pirsiavash, Deva Ramanan, Charless Fowlkes
XRCE	33.6	Xerox Research Centre Europe	Jorge Sanchez, Florent Perronnin, Thomas Mensink (Perronnin et al., 2010)

ILSVRC 2011

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ISI	36.0	-	Intelligent Systems and Informatics lab, University of Tokyo	Tatsuya Harada, Asako Kanezaki, Yoshitaka Ushiku, Yuya Yamashita, Sho Inaba, Hiroshi Muraoka, Yasuo Kuniyoshi
NII	50.5	-	National Institute of Informatics, Japan	Duy-Dinh Le, Shin'ichi Satoh
UvA	31.0	**42.5**	University of Amsterdam[†], University of Trento[‡]	Koen E. A. van de Sande[†], Jasper R. R. Uijlings[‡], Arnold W. M. Smeulders[†], Theo Gevers[†], Nicu Sebe[‡], Cees Snoek[†] (van de Sande et al., 2011b)
XRCE	**25.8**	56.5	Xerox Research Centre Europe[†], CIII[‡]	Florent Perronnin[†], Jorge Sanchez[†‡] (Sanchez and Perronnin, 2011)

ILSVRC 2012

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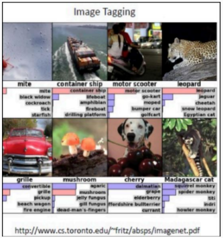
ISI	26.2	53.6	University of Tokyo[†], JST PRESTO[‡]	Naoyuki Gunji[†], Takayuki Higuchi[†], Koki Yasumoto[†], Hiroshi Muraoka[†], Yoshitaka Ushiku[†], Tatsuya Harada[†‡], Yasuo Kuniyoshi[†] (Harada and Kuniyoshi, 2012)
LEAR	34.5	-	LEAR INRIA Grenoble[†], TVPA Xerox Research Centre Europe[‡]	Thomas Mensink[†‡], Jakob Verbeek[†], Florent Perronnin[‡], Gabriela Csurka[‡] (Mensink et al., 2012)
VGG	27.0	50.0	University of Oxford	Karen Simonyan, Yusuf Aytar, Andrea Vedaldi, Andrew Zisserman (Arandjelovic and Zisserman, 2012; Sanchez et al., 2012)
SuperVision	**16.4**	**34.2**	University of Toronto	Alex Krizhevsky, Ilya Sutskever, Geoffrey Hinton (Krizhevsky et al., 2012)
UvA	29.6	-	University of Amsterdam	Koen E. A. van de Sande, Amir Habibian, Cees G. M. Snoek (Sanchez and Perronnin, 2011; Scheirer et al., 2012)
XRCE	27.1	-	Xerox Research Centre Europe[†], LEAR INRIA [‡]	Florent Perronnin[†], Zeynep Akata[†‡], Zaid Harchaoui[‡], Cordelia Schmid[‡] (Perronnin et al., 2012)

CNN-Applications



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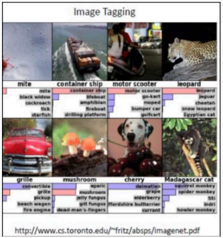

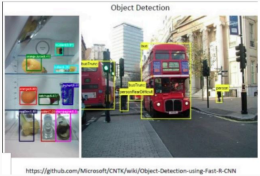

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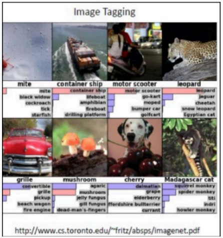

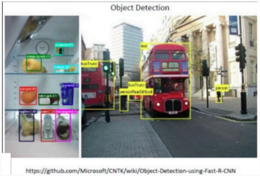

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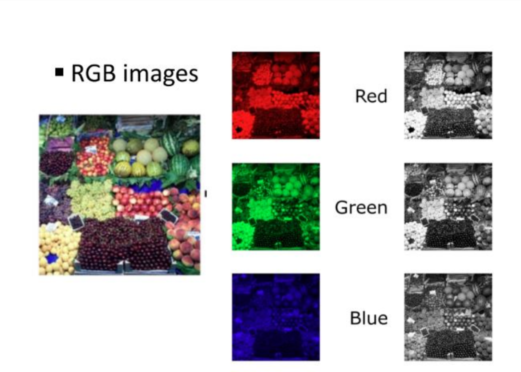
Introduction - Image Parametrization



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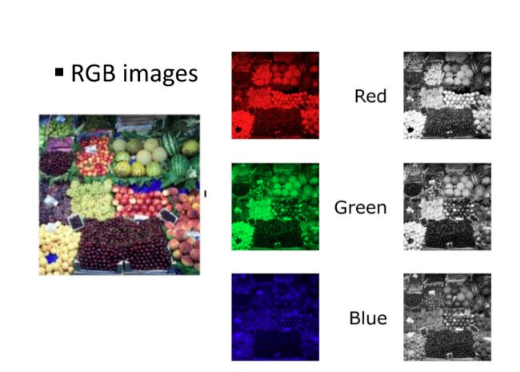

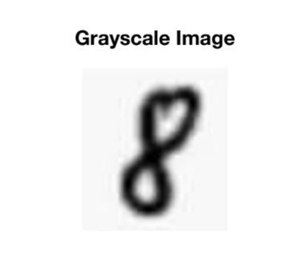

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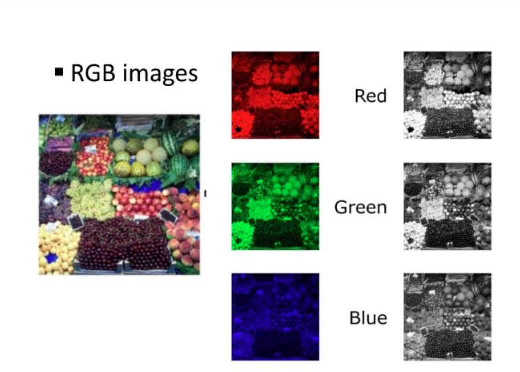

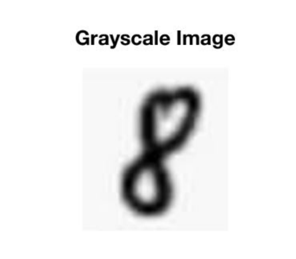

CNNs- From Fully connected to convolutional Layers

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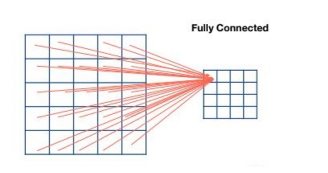

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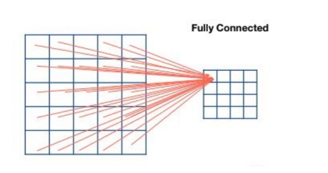

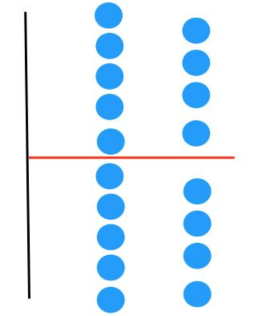

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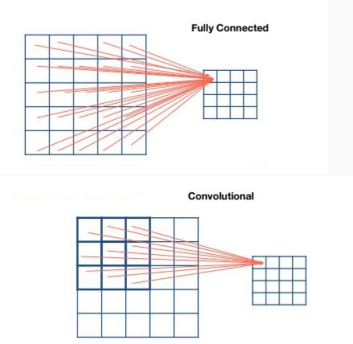

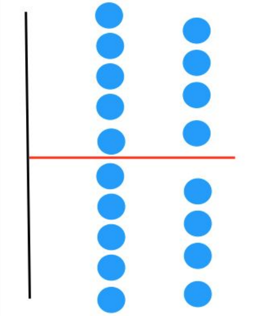

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- A ‘Volume’ image input like RGB images will lead to an explosion in the number of weights – Requires more memory, computations and data.

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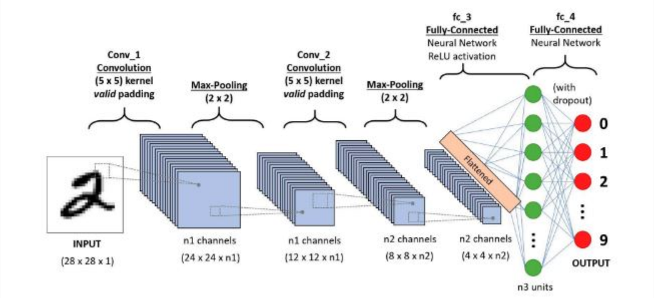

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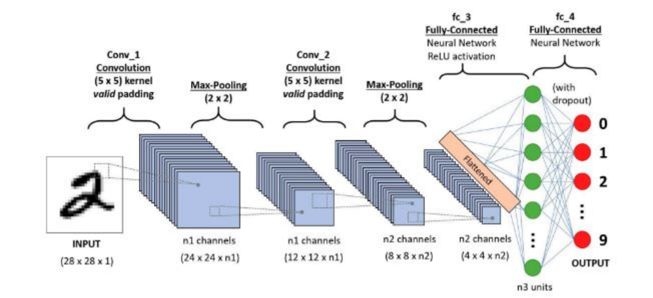
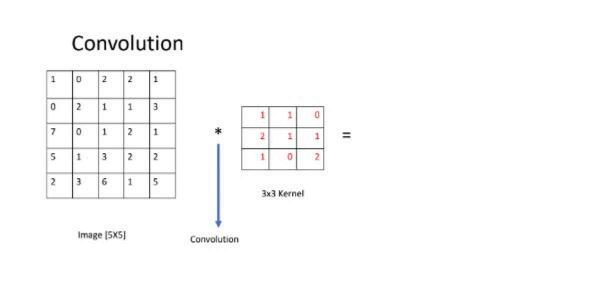


https://editor.analyticsvidhya.com/uploads/90650dnn2.jpeg

CNN- Convolution



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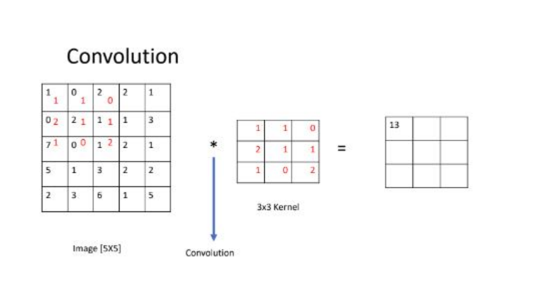

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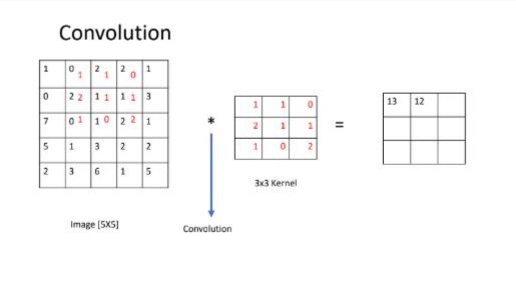

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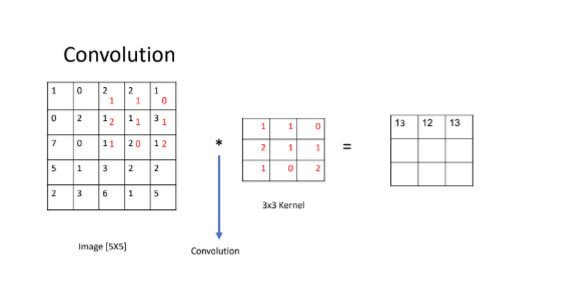

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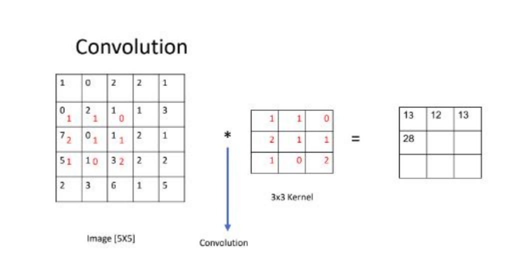

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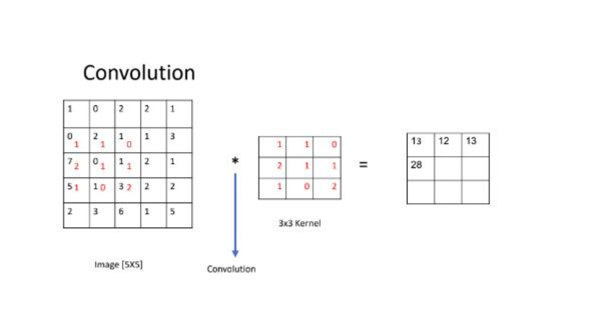

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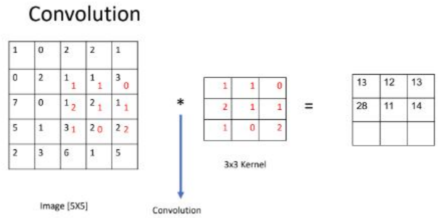

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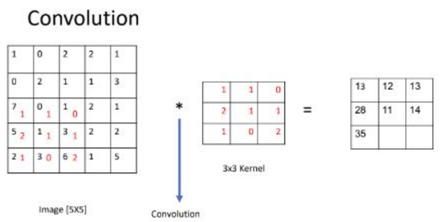

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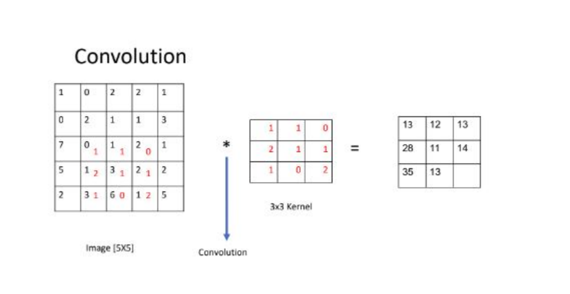

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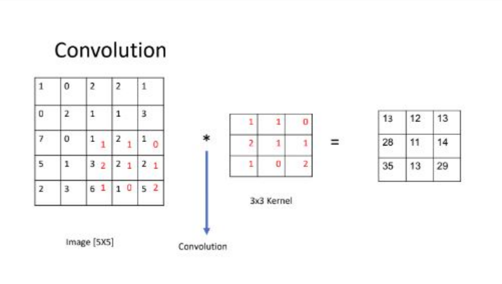
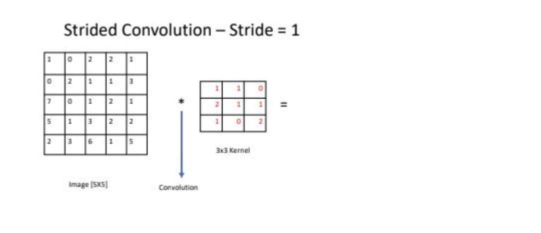


Strided Convolutions



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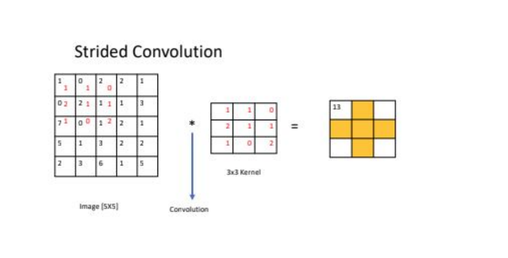

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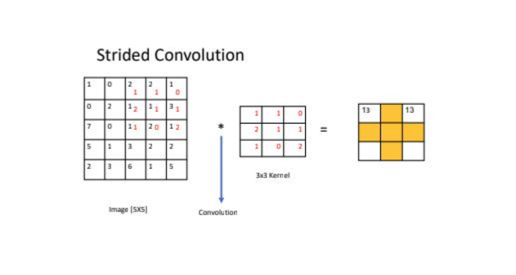

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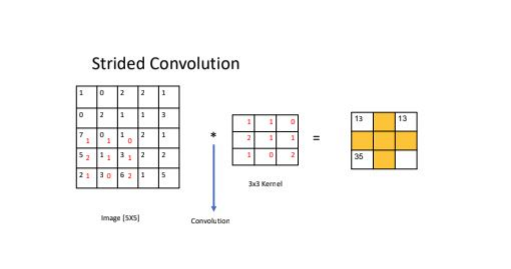

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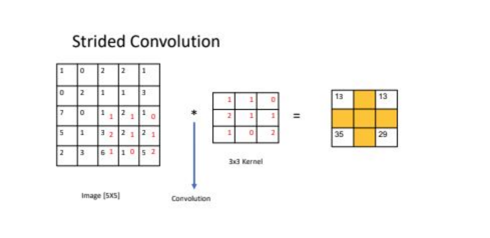

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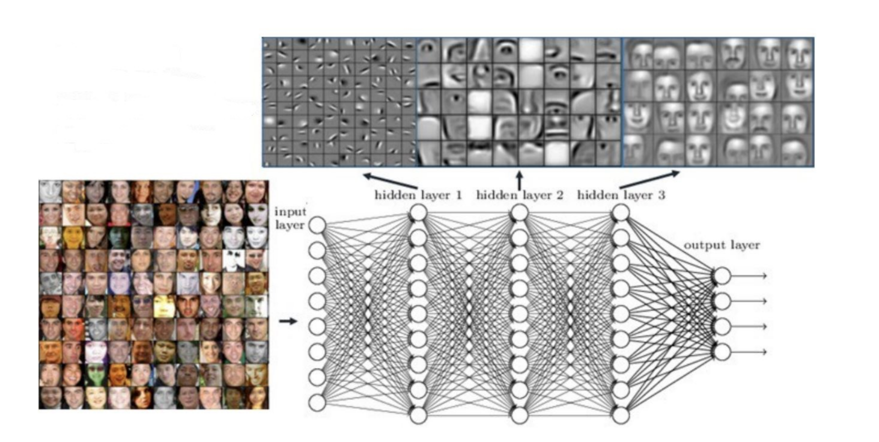

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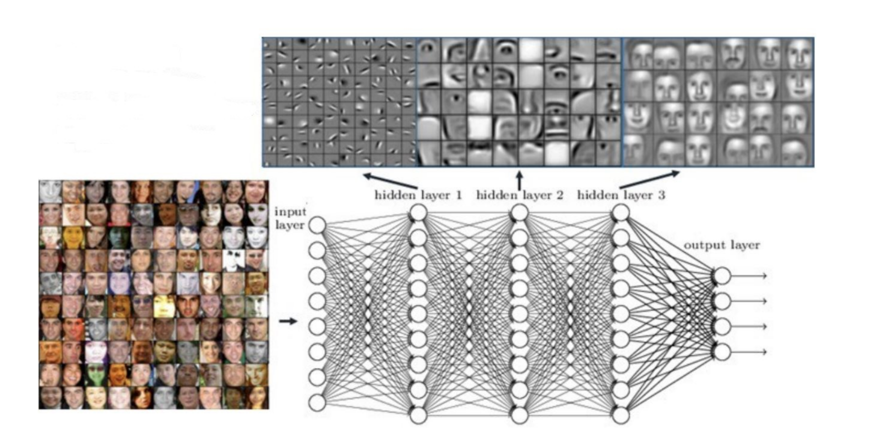

https://medium.com/@fenjiro/face-id-deep-learning-for-face-recognition-324b50d916d1

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  - The projection is accomplished using a matrix multiplication. A related example is Fourier transform where you project the signal into sinusoidal basis functions.

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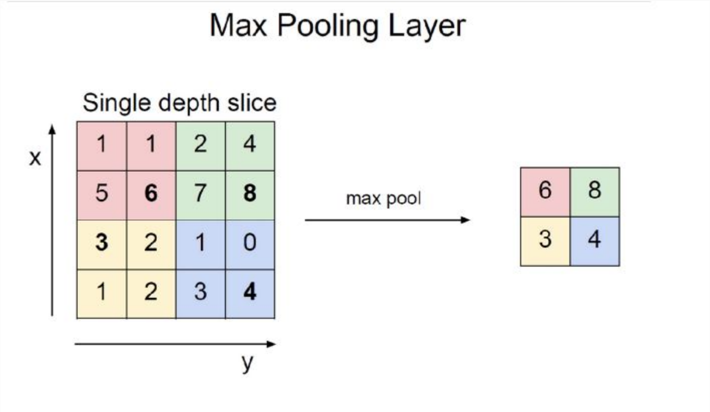
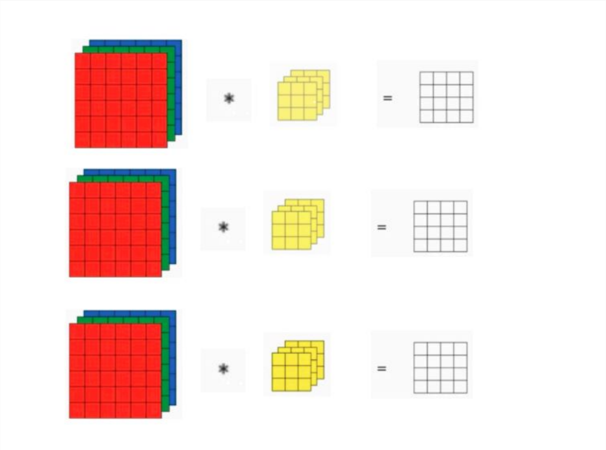
- Two ways to understand CNNs
  - CNNs autonomously learns filters that are typically either hand crafted or emerge as output of some optimisation criterion.
  - Advantage is that certain filters hard to formulate mathematically are learnt- problem dependent.
- Projection in to lower dimensional space
  - Consider N×N images as a point in N×N dimensional space.
  - Understanding and extracting features in this space becomes harder as N increases.
  - CNNs project these images into smaller dimensions and eventually in to a vector (for instance 1024 hidden units in a linear layer).
  - The projection is accomplished using a matrix multiplication. A related example is Fourier transform where you project the signal into sinusoidal basis functions.
  - In this case, the basis functions ie the weight matrices are learnt during training.

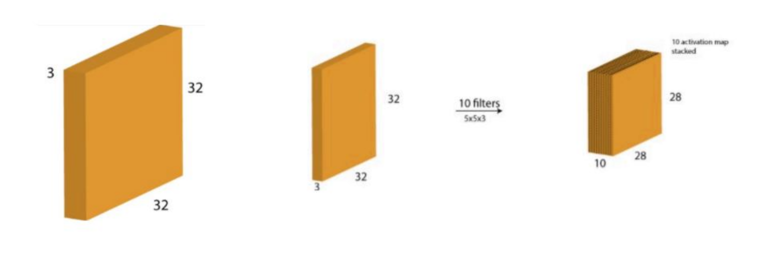
CNN Operations- Max Pooling



CNN Operations- Convolution Filters



CNN Operations- Convolution Filters



CNN Operations- Convolution Filters

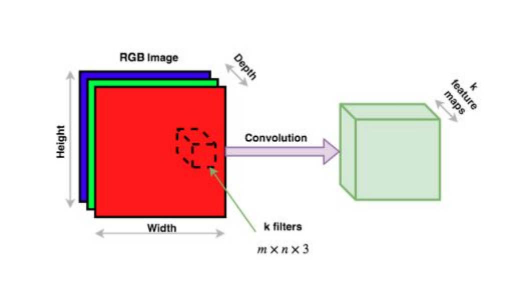
- Takes a 3D volume of numbers.

CNN Operations- Convolution Filters

- Takes a 3D volume of numbers.
- Outputs a 3D volume of numbers.

CNN Operations- Convolution Filters

- Takes a 3D volume of numbers.
- Outputs a 3D volume of numbers.



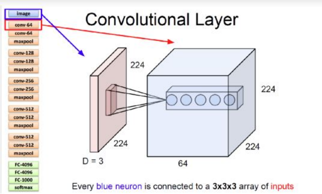
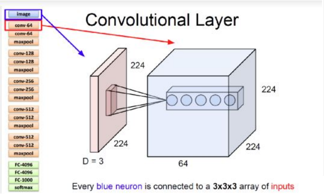
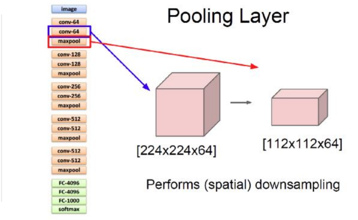


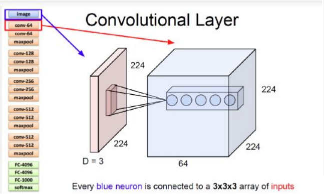
image
conv-64
conv-64
maxpool
conv-128
conv-128
maxpool
conv-256
conv-256
maxpool
conv-512
conv-512
maxpool
conv-512
conv-512
maxpool
FC-4096
FC-4096
FC-1000
softmax
Convolutional Layer
224
224
D = 3
224
224
64
Every blue neuron is connected to a 3x3x3 array of inputs



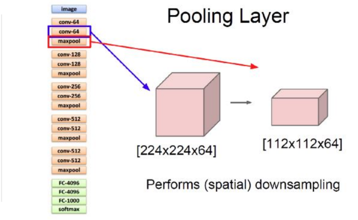
Convolutional Layer
image
conv-64
conv-64
maxpool
conv-128
conv-128
maxpool
conv-256
conv-256
maxpool
conv-512
conv-512
maxpool
conv-512
conv-512
maxpool
FC-4096
FC-4096
FC-1000
softmax
224
224
D = 3
224
224
64
Every blue neuron is connected to a 3x3x3 array of inputs



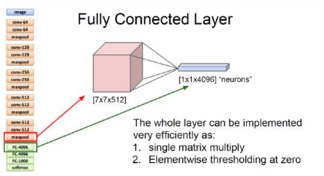
Pooling Layer
image
conv-64
conv-64
maxpool
conv-128
conv-128
maxpool
conv-256
conv-256
maxpool
conv-512
conv-512
maxpool
conv-512
conv-512
maxpool
FC-4096
FC-4096
FC-1000
softmax
[224x224x64]
[112x112x64]
Performs (spatial) downsampling



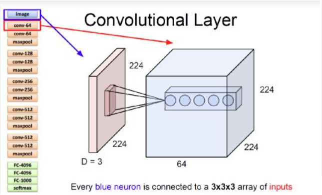
Convolutional Layer
image
conv-64
conv-64
maxpool
conv-128
conv-128
maxpool
conv-256
conv-256
maxpool
conv-512
conv-512
maxpool
conv-512
conv-512
maxpool
FC-4096
FC-4096
FC-1000
softmax
224
224
D = 3
224
224
64
Every blue neuron is connected to a 3x3x3 array of inputs

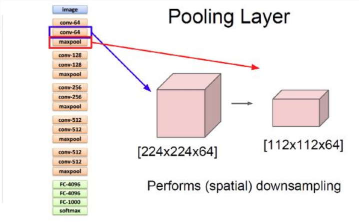


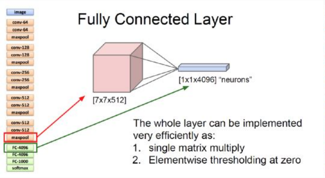
Pooling Layer
image
conv-64
conv-64
maxpool
conv-128
conv-128
maxpool
conv-256
conv-256
maxpool
conv-512
conv-512
maxpool
conv-512
conv-512
maxpool
FC-4096
FC-4096
FC-1000
softmax
[224x224x64]
[112x112x64]
Performs (spatial) downsampling



Fully Connected Layer
image
conv-64
conv-64
maxpool
conv-128
conv-128
maxpool
conv-256
conv-256
maxpool
conv-512
conv-512
maxpool
conv-512
conv-512
maxpool
FC-4096
FC-4096
FC-1000
softmax
[1x1x4096] "neurons"
[7x7x512]
The whole layer can be implemented very efficiently as:
1. single matrix multiply
2. Elementwise thresholding at zero


Convolutional Layer
image
conv-64
conv-64
maxpool
conv-128
conv-128
maxpool
conv-256
conv-256
maxpool
conv-512
conv-512
maxpool
conv-512
conv-512
maxpool
FC-4096
FC-4096
FC-1000
softmax
224
224
224
224
D = 3
64
Every blue neuron is connected to a 3x3x3 array of inputs


Pooling Layer
image
conv-64
conv-64
maxpool
conv-128
conv-128
maxpool
conv-256
conv-256
maxpool
conv-512
conv-512
maxpool
conv-512
conv-512
maxpool
FC-4096
FC-4096
FC-1000
softmax
[224x224x64]
[112x112x64]
Performs (spatial) downsampling


Fully Connected Layer
[7x7x512]
[1x1x4096] "neurons"
The whole layer can be implemented very efficiently as:
1. single matrix multiply
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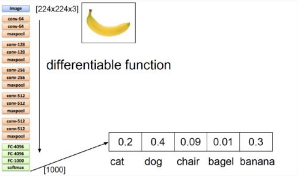
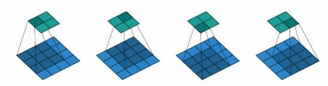

[224x224x3]
differentiable function
[1000]
0.2
0.4
0.09
0.01
0.3
cat
dog
chair
bagel
banana

Types of Convolutions

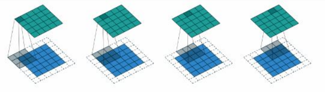
- Valid Convolutions



(No padding, unit strides) Convolving a 3×3 kernel over a 4×4 input using unit strides (i.e., i=4, k=3, s=1 and p=0).

Types of Convolutions

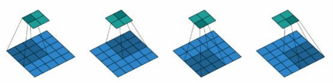
- Valid Convolutions
- Same Convolutions



(Half padding, unit strides) Convolving a 3×3 kernel over a 5×5 input using unit strides (i.e., i=5, k=3, s=1 and p=1).

Types of Convolutions

- Valid Convolutions
- Same Convolutions
- Strided Convolutions

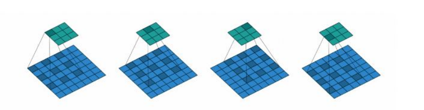


(No zero padding, arbitrary strides) Convolving a 3×3 kernel over a 5×5 input using 2×2 strides (i.e., i=5, k=3, s=2 and p=0).

A guide to convolution arithmetic for deep learning, Vincent Dumoulin and Francesco Visina, January 12, 2018

Types of Convolutions

- Valid Convolutions
- Same Convolutions
- Strided Convolutions
- Dilated Convolutions

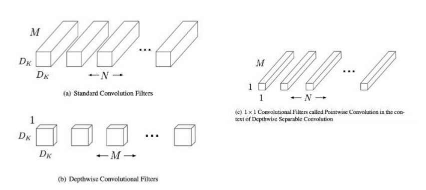


(Dilated Convolution) Convolving a 3×3 kernel over a 7×7 input with a dilated factor of 2 (i.e., i=7, k=3, d=2, s=1 and p=0).

A guide to convolution arithmetic for deep learning, Vincent Dumoulin and Francesco Visina, January 12, 2018

Types of Convolutions

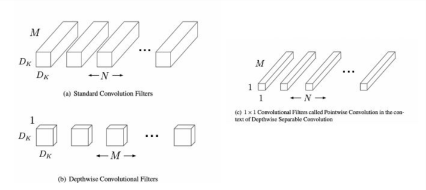
- Valid Convolutions
- Same Convolutions
- Strided Convolutions
- Dilated Convolutions
- Depthwise Convolutions



A guide to convolution arithmetic for deep learning, Vincent Dumoulin and Francesco Visina, January 12, 2018

Types of Convolutions

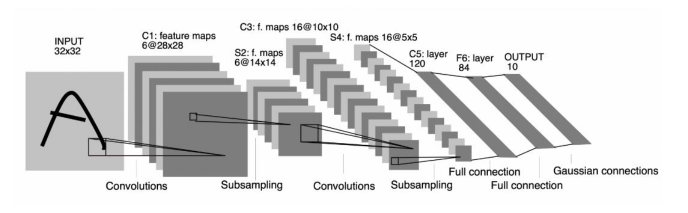
- Valid Convolutions
- Same Convolutions
- Strided Convolutions
- Dilated Convolutions
- Depthwise Convolutions
- Depthwise Separable Convolutions



A guide to convolution arithmetic for deep learning, Vincent Dumoulin and Francesco Visina, January 12, 2018

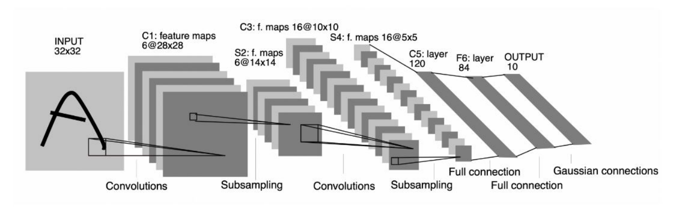
MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications, Andrew G. Howard, Weijun Wang, Menglong Zhu, Tobias Weyand, Bo Chen, Marco Andreetto, Dmitry Kalenichenko, Hartwig Adam, Google Inc

MNIST Digit Classification- LeNet



Gradient-Based Learning Applied to Document Recognition, YANN LECUN. MEMBER, IEEE, LEON BOTTOU, YOSHUA BENGIO, AND PATRICK HAFFNER

MNIST Digit Classification- LeNet

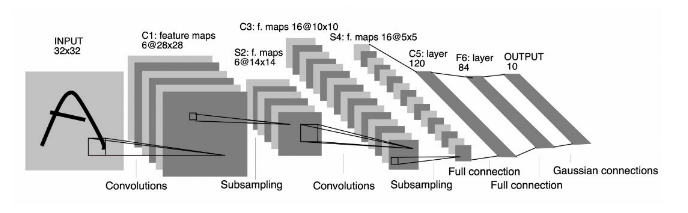


C1 is convolutional layer with 6 feature maps output by 6 filter kernels. Each filter kernel is of size 5×5.

$32 \times 32 \rightarrow$ output size of 28×28

Gradient-Based Learning Applied to Document Recognition, YANN LECUN. MEMBER, IEEE, LEON BOTTOU, YOSHUA BENGIO, AND PATRICK HAFFNER

MNIST Digit Classification- LeNet

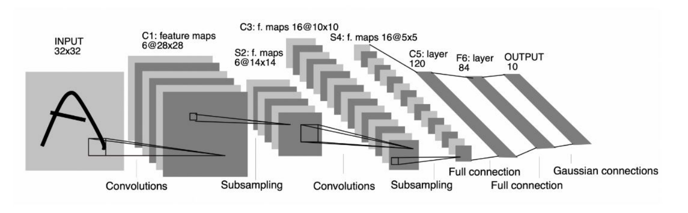


S2 is the sampling layer with 6 feature maps.

2×2 max pooling $\rightarrow$ different in the original paper which as trainable parameters.

Gradient-Based Learning Applied to Document Recognition, YANN LECUN. MEMBER, IEEE, LEON BOTTOU, YOSHUA BENGIO, AND PATRICK HAFFNER

MNIST Digit Classification- LeNet

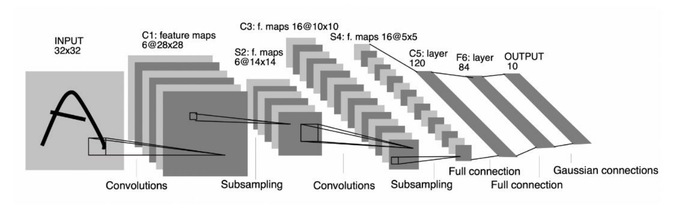


Layer C3 is the convolutional layer with 16 feature maps . Each filter kernel is 5×5.

Input $14 \times 14 \rightarrow$ output 10×10.

Gradient-Based Learning Applied to Document Recognition, YANN LECUN. MEMBER, IEEE, LEON BOTTOU, YOSHUA BENGIO, AND PATRICK HAFFNER

MNIST Digit Classification- LeNet

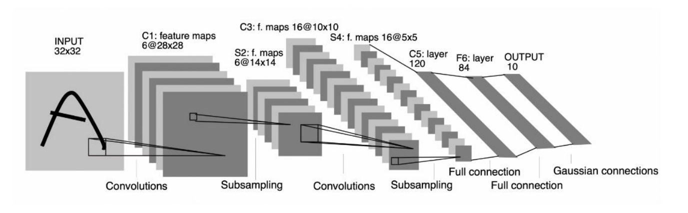


	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
0	X				X	X	X			X	X	X	X		X	X
1	X	X				X	X	X			X	X	X	X		X
2	X	X	X				X	X	X			X		X	X	X
3		X	X	X			X	X	X	X			X		X	X
4			X	X	X			X	X	X	X		X	X		X
5				X	X	X			X	X	X	X		X	X	X

Each column indicates which feature map in S2 are combined by the units in a particular feature map of C3.

Gradient-Based Learning Applied to Document Recognition, YANN LECUN. MEMBER, IEEE, LEON BOTTOU, YOSHUA BENGIO, AND PATRICK HAFFNER

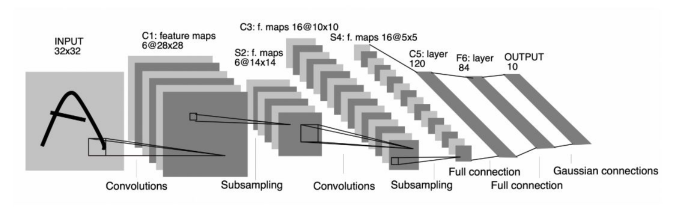
MNIST Digit Classification- LeNet



Layer S4 is a sub sampling layer with 16 feature maps of size 5×5. Every feature map is obtained using 2×2 pooling from C3.

Gradient-Based Learning Applied to Document Recognition, YANN LECUN. MEMBER, IEEE, LEON BOTTOU, YOSHUA BENGIO, AND PATRICK HAFFNER

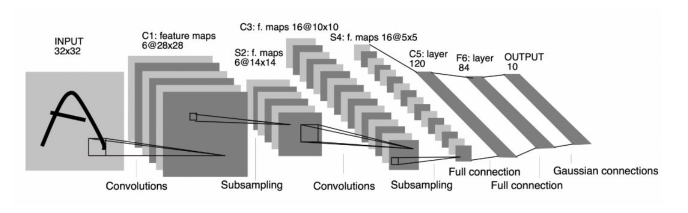
MNIST Digit Classification- LeNet



Layer C5 is a convolutional layer with 120 feature maps. Each filter kernel is of size $5 \times 5 \times 16$. Output is of size 1×1.

Gradient-Based Learning Applied to Document Recognition, YANN LECUN. MEMBER, IEEE, LEON BOTTOU, YOSHUA BENGIO, AND PATRICK HAFFNER

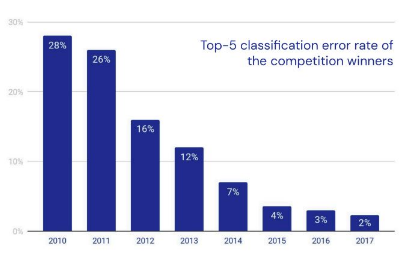
MNIST Digit Classification- LeNet



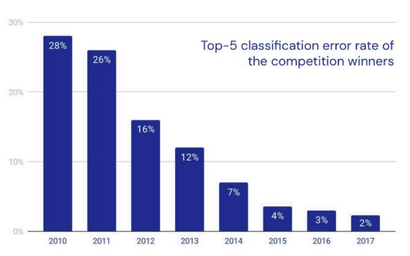
Layer F6 contains 84 units And is fully connected to C5.

Gradient-Based Learning Applied to Document Recognition, YANN LECUN. MEMBER, IEEE, LEON BOTTOU, YOSHUA BENGIO, AND PATRICK HAFFNER

ImageNet Challenge

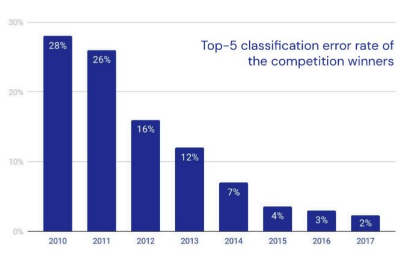


ImageNet Challenge



1. **Training set of 1.4 Million Images**
2. **1000 classes**
3. **Image recognition challenge**
4. **Top 5 prediction error rates**

ImageNet Challenge



1. **Training set of 1.4 Million Images**
2. **1000 classes**
3. **Image recognition challenge**
4. **Top 5 prediction error rates**

1. 2010 and 2011 best results are computer vision techniques- Conventional
2. Alexnet was 16%
3. VGGNet and Inception got 7%
4. Resnet dropped to 4%

CNN Architectures

- AlexNet

CNN Architectures

- AlexNet
- VGG

CNN Architectures

- AlexNet
- VGG
- ResNet

CNN Architectures

- AlexNet
- VGG
- ResNet
- DenseNet

CNN Architectures

- AlexNet
- VGG
- ResNet
- DenseNet
- MobileNet

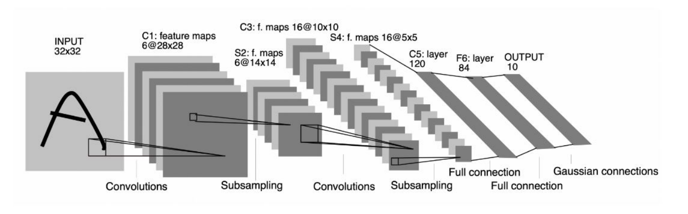
CNN Architectures

- AlexNet
- VGG
- ResNet
- DenseNet
- MobileNet
- ShuffleNet

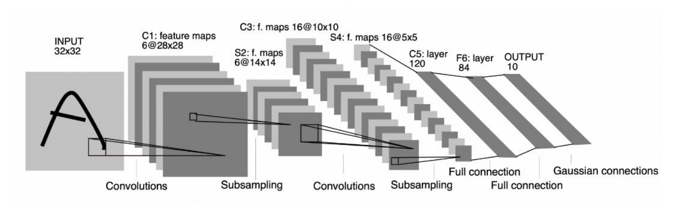
CNN Architectures

- AlexNet
- VGG
- ResNet
- DenseNet
- MobileNet
- ShuffleNet
- NAS

LeNet Architecture

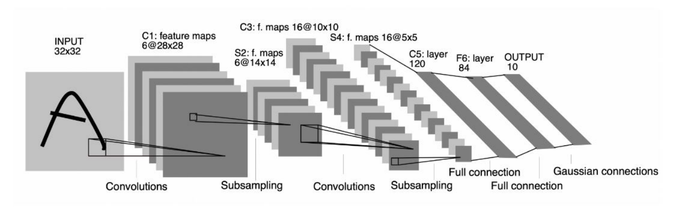


LeNet Architecture



Architecture of LeNet-5, a convolutional NN, here used for digital recognition. Each plane is a feature map, i.e., a set of units whose weights are constrained to be identical.

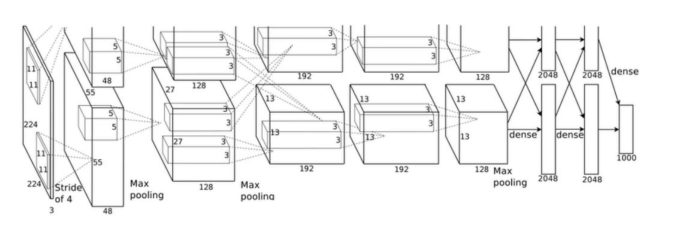
LeNet Architecture



Architecture of LeNet-5, a convolutional NN, here used for digital recognition. Each plane is a feature map, i.e., a set of units whose weights are constrained to be identical.

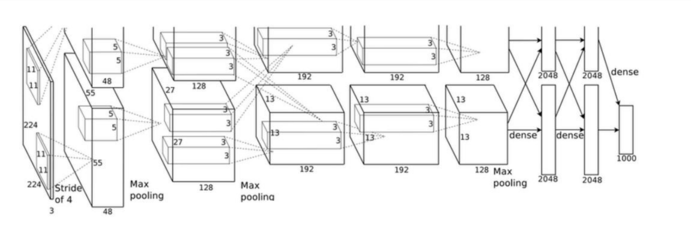
Gradient-Based Learning Applied to Document Recognition, YANN LECUN. MEMBER, IEEE, LEON BOTTOU, YOSHUA BENGIO, AND PATRICK HAFFNER

AlexNet



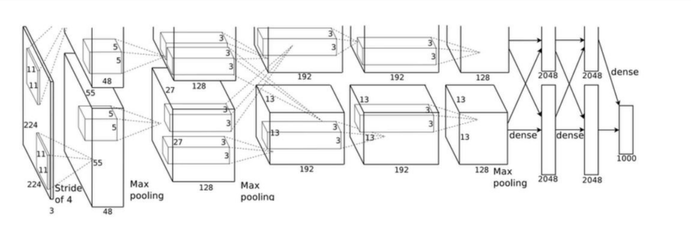
An illustration of the architecture of our CNN, explicitly showing the delineation of responsibilities between the two GPUs. One GPU runs the layer-parts at the top of the figure while the other runs the layer-parts at the bottom. The GPUs communicate only at certain layers. The network's input is 150,528-dimensional, and the number of neurons in the network's remaining layers is given by 253,440-186,624-64,896-64,896-43,264-4096-4096-1000.

AlexNet



The second convolutional layer takes as input the (response-normalized and pooled) output of the first convolutional layer and filters it with 256 kernels of size 5 x 5 x 48. The third, fourth, and fifth convolutional layers are connected to one another without any intervening pooling or normalization layers. The third convolutional layer has 384 kernels of size $3 \times 3 \times 256$ connected to the (normalized, pooled) outputs of the second convolutional layer. The fourth convolutional layer has 384 kernels of size 3 x 3 x 192, and the fifth convolutional layer has 256 kernels of size 3 x 3 x 192. The fully-connected layers have 4096 neurons each.

AlexNet



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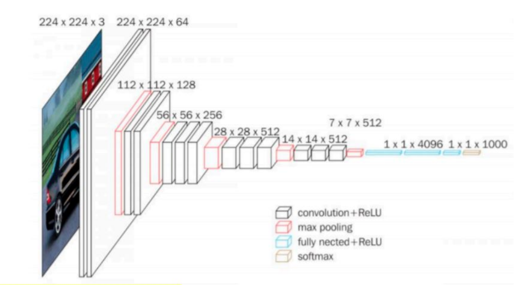
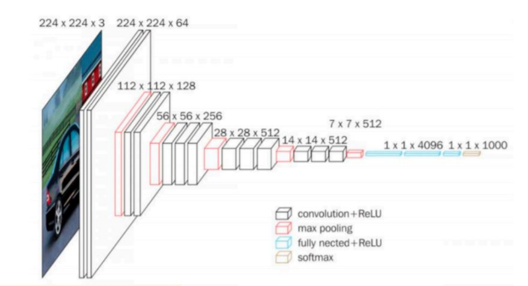
ImageNet Classification with Deep Convolutional Neural Networks, Alex Krizhevsky, Ilya Sutskever, Geoffrey E. Hinton

VGGNet



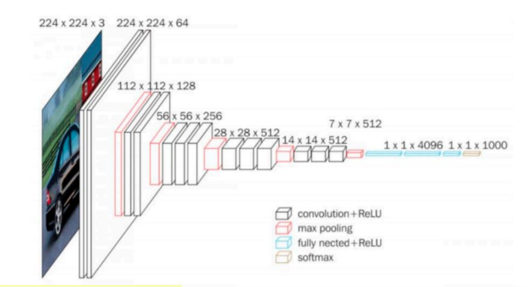
224 x 224 x 3
224 x 224 x 64
112 x 112 x 128
56 x 56 x 256
28 x 28 x 512
14 x 14 x 512
7 x 7 x 512
1 x 1 x 4096
1 x 1 x 1000
convolution+ReLU
max pooling
fully nected+ReLU
softmax

VGGNet



11,13 ,16 and 19 layers. The best result is for 16 layers. It actually slightly worsens for 19 layers.

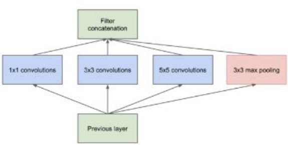
VGGNet



11,13 ,16 and 19 layers. The best result is for 16 layers. It actually slightly worsens for 19 layers.

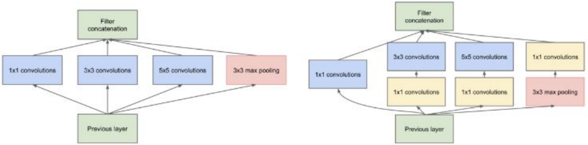
VERY DEEP CONVOLUTIONAL NETWORKS FOR LARGE-SCALE IMAGE RECOGNITION, Karen Simonyan & Andrew Zisserman, Visual Geometry Group, Department of Engineering Science, University of Oxford karen, az@robots.ox.ac.uk

GoogleNet



(a) Inception module, naïve version (b) Inception module with dimension reductions

GoogleNet



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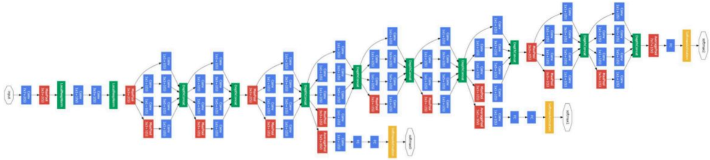
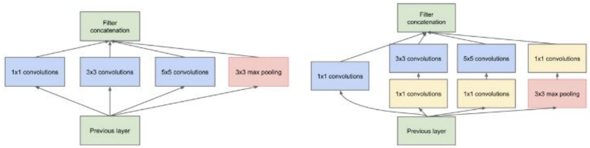


GoogleNet



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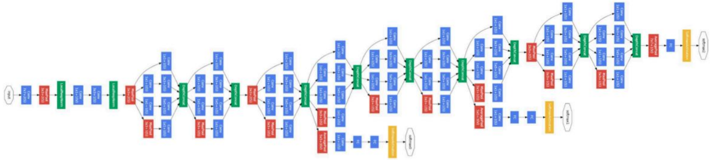
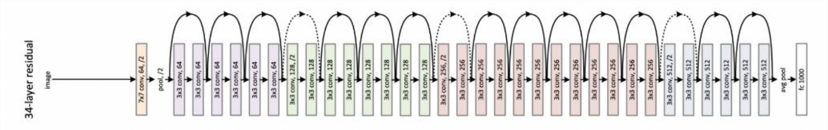


Going deeper with convolutions, Christian Szegedy, Pierre Sermanet, Vincent Vanhoucke, Wei Liu, Scott Reed, Dragomir Anguelov, Andrew Rabinovich, Yangqing Jia and Dumitru Erhan

ResNet (ResNet -34 architecture)



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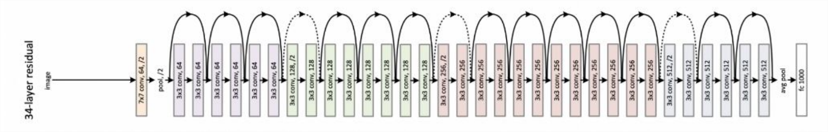

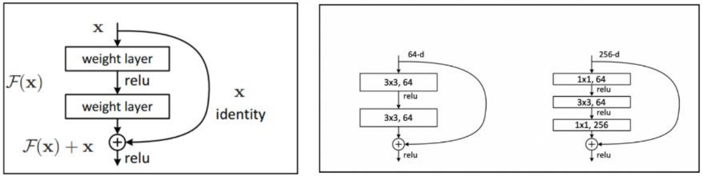

Skip (Shortcut) connection

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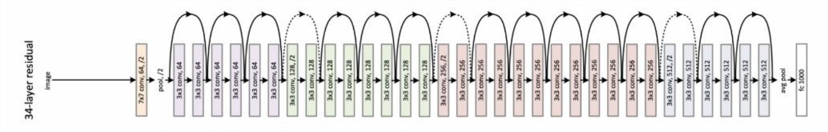

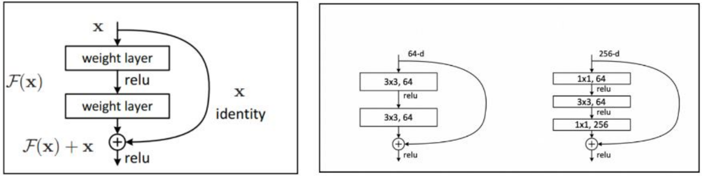

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Deep Residual Learning for Image Recognition, Kaiming He, Xiangyu Zhang, Shaoqing Ren, Jian Sun, Microsoft Research, kahe, v-xiangz, v-shren, jiansun@microsoft.com

DenseNet

A 5-layer dense block with a growth rate of $k = 4$. Each layer takes all preceding feature-maps as input

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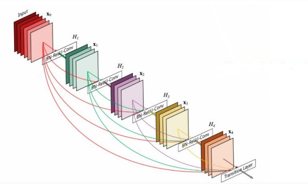

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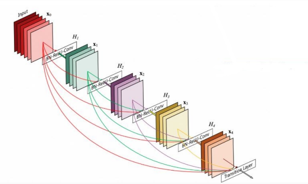

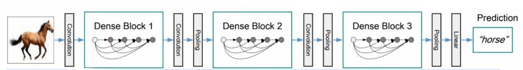

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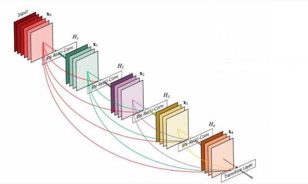

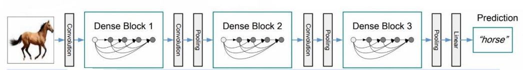

A deep DenseNet with three dense blocks. The layers between two adjacent blocks are referred to as transition layers and change feature-map sizes via convolution and pooling.

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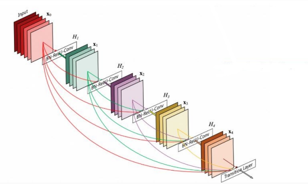

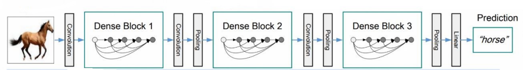

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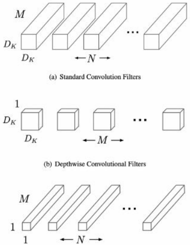
Figures from , DOI: 10.1109/CVPR.2017.243

MobileNet

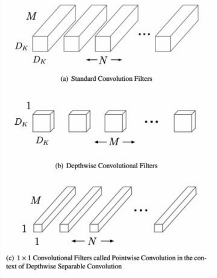


(a) Standard Convolution Filters

(b) Depthwise Convolutional Filters

(c) 1×1 Convolutional Filters called Pointwise Convolution in the context of Depthwise Separable Convolution

MobileNet



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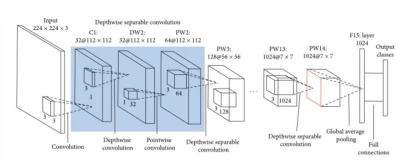
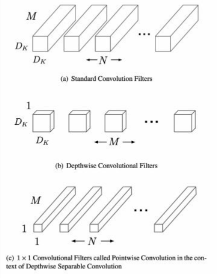


MobileNet



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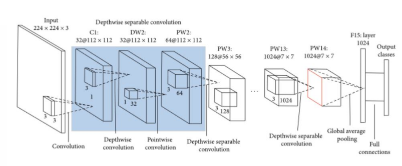
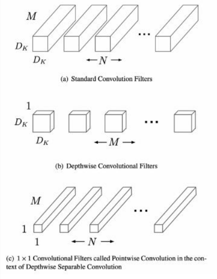
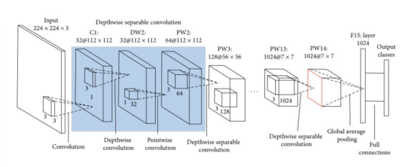


The standard convolutional filters in (a) are replaced by two layers: depthwise convolution in (b) and pointwise convolution in (c) to build a depthwise separable filter.

MobileNet

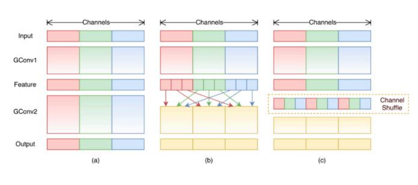




The standard convolutional filters in (a) are replaced by two layers: depthwise convolution in (b) and pointwise convolution in (c) to build a depthwise separable filter.

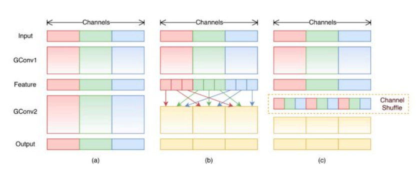
https://doi.org/10.48550/arXiv.1704.04861

ShuffleNet



Channel shuffle with two stacked group convolutions. GConv stands for group convolution. a) two stacked convolution layers with the same number of groups. Each output channel only relates to the input channels within the group. No cross talk; b) input and output channels are fully related when GConv2 takes data from different groups after GConv1; c) an equivalent implementation to b) using channel shuffle

ShuffleNet



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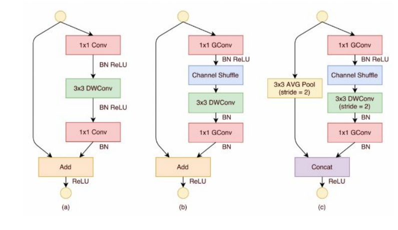
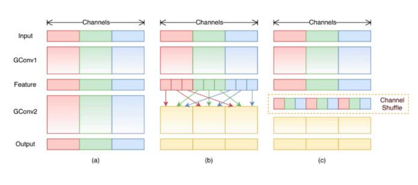


ShuffleNet Units. a) bottleneck unit [9] with depthwise convolution (DWConv) b) ShuffleNet unit with pointwise group convolution (GConv) and channel shuffle; c) ShuffleNet unit with stride = 2

ShuffleNet



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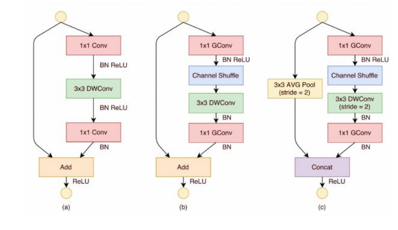

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https://doi.org/10.48550/arXiv.1707.01083

Layer	Output size	KSize	Stride	Repeat	Output channels (g groups)				
					$g = 1$	$g = 2$	$g = 3$	$g = 4$	$g = 8$
Image	224×224				3	3	3	3	3
Conv1	112×112	3×3	2	1	24	24	24	24	24
MaxPool	56×56	3×3	2						
Stage2[1]	28×28		2	1	144	200	240	272	384
	28×28		1	3	144	200	240	272	384
Stage3	14×14		2	1	288	400	480	544	768
	14×14		1	7	288	400	480	544	768
Stage4	7×7		2	1	576	800	960	1088	1536
	7×7		1	3	576	800	960	1088	1536
GlobalPool	1×1	7×7							
FC					1000	1000	1000	1000	1000
Complexity[2]					143M	140M	137M	133M	137M

ShuffleNet Architecture

https://doi.org/10.48550/arXiv.1707.01083

CNN Training

- Dropouts

CNN Training

- Dropouts
- Normalisation Layers

CNN Training

- Dropouts
- Normalisation Layers
- Hyperparameter optimisation

CNN Training

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CNN Training

- Dropouts
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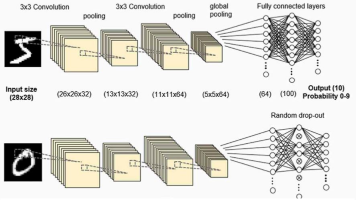
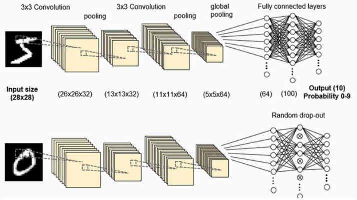
- Weight Initialization
- Data Augmentation

CNN Training-Dropouts



https://www.frontiersin.org/files/Articles/571894/fnagi-12-00273-HTML-r1/image_m/fnagi-12-00273-g001.jpg

CNN Training-Dropouts



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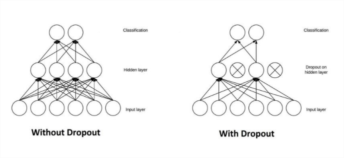


https://www.baeldung.com/wp-content/uploads/sites/4/2020/05/2-1-2048x745-1.jpg

CNN Training- Addressing Covariate Shift

- Batch Norm

CNN Training- Addressing Covariate Shift

- Batch Norm
- Layer Norm

CNN Training- Addressing Covariate Shift

- Batch Norm
- Layer Norm
- Instance Norm

CNN Training- Addressing Covariate Shift

- Batch Norm
- Layer Norm
- Instance Norm
- Group Norm

CNN Training- Addressing Covariate Shift

- Batch Norm
- Layer Norm
- Instance Norm
- Group Norm

Input: Values of x over a mini-batch: $B = \{x_{1...m}\}$;

Parameters to be learned: γ, β

Output: $\{y_i = BN_{\gamma,\beta}(x_i)\}$

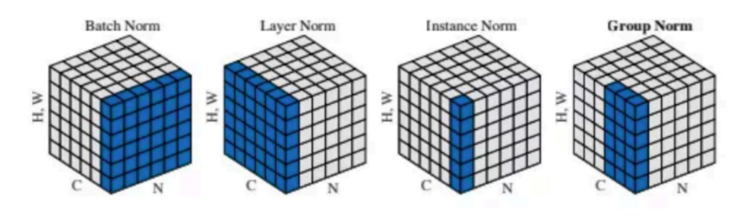
$$\mu_B \leftarrow \frac{1}{m}\sum_{i=1}^{m} x_i \text{ //mini-batch mean}$$

$$\sigma_B^2 \leftarrow \frac{1}{m}\sum_{i=1}^{m}(x_i - \mu_B)^2 \text{ // mini-batch variance}$$

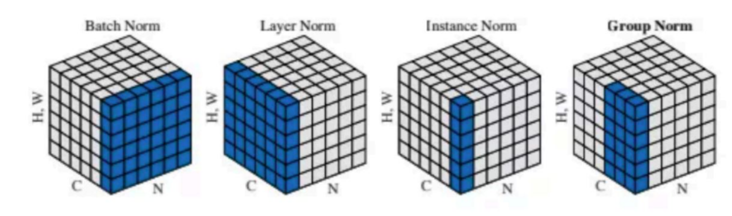
$$\hat{x}_i \leftarrow \frac{x_i - \mu_B}{\sqrt{\sigma_B^2 + \epsilon}} \text{// normalize}$$

$$y_i \leftarrow \gamma\hat{x}_i + \beta \equiv BN_{\gamma,\beta}(x_i) \text{ // scale and shift}$$

https://arxiv.org/abs/1502.03167v3

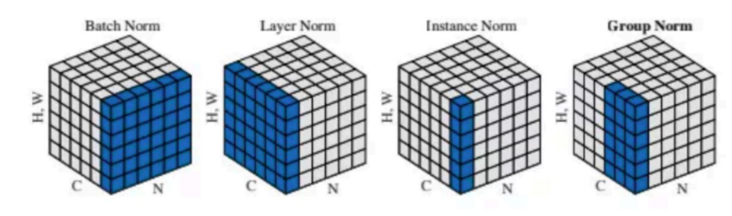


A visual comparison of various normalization methods



A visual comparison of various normalization methods

There has also been work on alternative normalization techniques, and in particular Layer Normalization (LN), proposed by (Ba et al., 2016). LN normalizes across the channel/feature dimension as shown in Figure 1. This could be extended to Group Norm (GN) (Wu & He, 2018), where the normalization is performed across a partition of the features/channels with different predefined groups. Instance Normalization (IN) (Ulyanov et al., 2016) is another technique, where per-channel statistics are computed for each sample.



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Power Norm: Rethinking Batch Normalization in Transformers, Sheng Shen, Zhewei Yao, Amir Gholami, Michael W. Mahoney, Kurt Keutzer

$$\mu_i = \frac{1}{m} \sum_{k \epsilon S_i} x_k,$$

$$\sigma_i = \sqrt{\frac{1}{m} \sum_{k \epsilon S_i} (x_k - \mu_i)^2 + \epsilon}, \ S_i \text{ defined below.}$$

$$S_i = \{k | k_N = i_N, \lfloor \frac{k_C}{C/G} \rfloor = \lfloor \frac{i_C}{C/G} \rfloor\}$$

$$\hat{x_i} = \frac{1}{\sigma_i}(x_i - \mu_i)$$

$$y_i = \gamma \hat{x_i} + \beta$$

Group Norm

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x is the feature computed by a layer, and i is an index. In the case of 2D images, **i** = (**i**N, **i**C, **i**H, **i**W) is a 4D vector indexing the features in (N, C, H, W) order, where **N** is the batch axis, **C** is the channel axis, and **H** and **W** are the spatial height and width axes. **G** is the number of groups, which is a pre-defined hyper-parameter. C/G is the number of channels per group. $\lfloor \rfloor$ is the floor operation, and "$\lfloor kC/(C/G) \rfloor = \lfloor ic/(C/G) \rfloor$" means that the indexes **i** and **k** are in the same group of channels, assuming each group of channels are stored in a sequential order along the C axis. GN computes μ and σ along the (H, W) axes and along a group of C/G channels.

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https://arxiv.org/abs/1803.08494

CNN Training- Hyper parameter Optimisation

- Grid Search

CNN Training- Hyper parameter Optimisation

- Grid Search
- Random Search

CNN Training- Hyper parameter Optimisation

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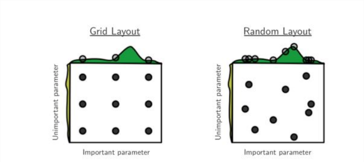

Grid and random search of nine trials for optimizing a function $f(x, y) = g(x) + h(y) \approx g(x)$ with low effective dimensionality. Above each square g(x) is shown in green, and left of each square h(y) is shown in yellow. With grid search, nine trials only test g(x) in three distinct places. With random search, all nine trials explore distinct values of g. This failure of grid search is the rule rather than the exception in high dimensional hyper-parameter optimization.

CNN Training- Hyper parameter Optimisation

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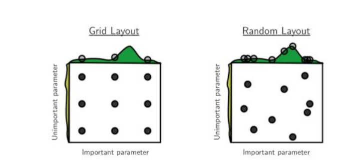
- Random Search
- Hand Tuning



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Random Search for Hyper-Parameter Optimization, James Bergstra, Yoshua Bengio, Département d'Informatique et de recherche opérationnelle, Université de Montréal, Montréal, QC, HBC 3J7, Canada

CNN Training-Non-Linearities & Loss functions

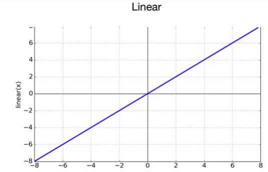
- Non-
  Linearities

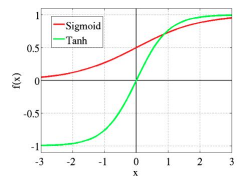
CNN Training-Non-Linearities & Loss functions

- Non-Linearities
- Loss Functions

CNN Training-Non-Linearities & Loss functions

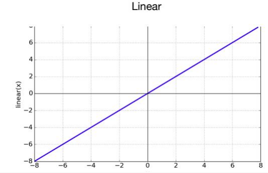
- Non-Linearities
- Loss Functions

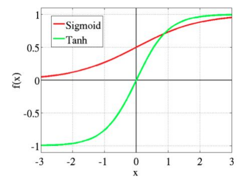


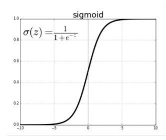


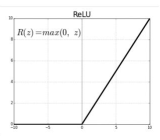
CNN Training-Non-Linearities & Loss functions

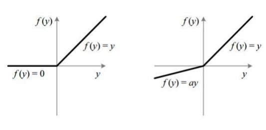
- Non-Linearities
- Loss Functions



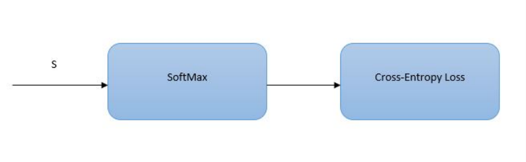


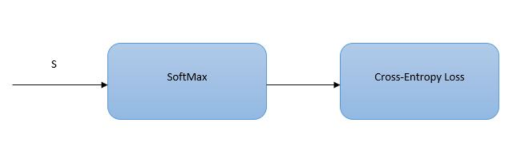






ReLU v/s Leaky ReLU

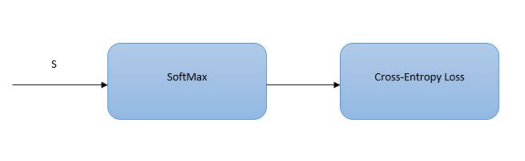

S
SoftMax
Cross-Entropy Loss



$$f(S)_i = \frac{e^{s_i}}{\sum_j^C ee^{s_j}}$$

$$CE = -\sum_i^C t_i \log(f(s)_i)$$

https://gombru.github.io/assets/cross_entropy_loss/softmax_CE_pipeline.png



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$$CE = -\sum_i^C t_i \log(f(s)_i)$$

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2$$

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https://gombru.github.io/assets/cross_entropy_loss/softmax_CE_pipeline.png

https://miro.medium.com/max/808/1*-e1QGatrODWpJkEwqP4Jyg.png

Visualising CNNs - Saliency Maps

More formally, let $S_c(I)$ be the score of the class c, computed by the classification layer of the ConvNet for an image I. We would like to find an L_2-regularised image, such that the score S_c, is high:

$$arg\ max S_c(I) - \lambda||I||_2^2$$

where λ is the regularisation parameter. A locally-optimal I can be found by the back-propagation method. The procedure is related to the ConvNet training procedure, where the back-propagation is used to optimise the layer weights. The difference is that in our case the optimisation is performed with respect to the input image, while the weights are fixed to those found during the training stage. We initialised the optimisation with the zero image (in our case, the ConvNet was trained on the zero-centred image data), and then added the training set mean image to the result. The class model visualisations for several classes are shown in Fig.1

Visualising CNNs - Saliency Maps

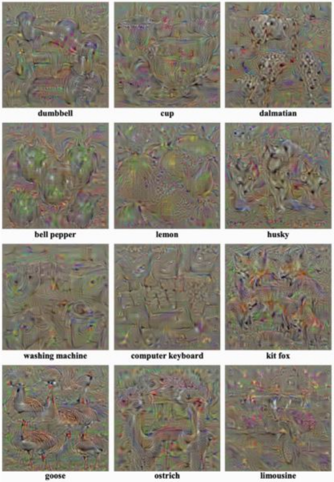


Figure 1: **Numerically computed images, illustrating the class appearance models, learnt by a ConvNet, trained on ILSVRC-2013.** Note how different aspects of class appearance are captured in a single image. Better viewed in colour.

Visualising CNNs - Saliency Maps

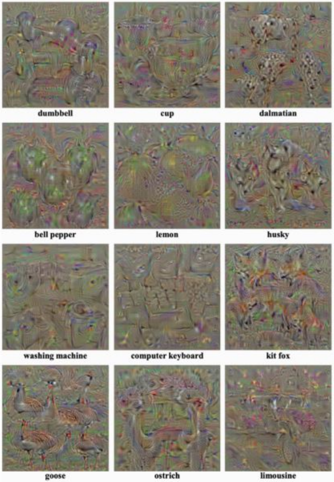


Figure 1: **Numerically computed images, illustrating the class appearance models, learnt by a ConvNet, trained on ILSVRC-2013.** Note how different aspects of class appearance are captured in a single image. Better viewed in colour.

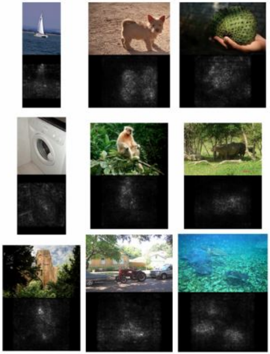
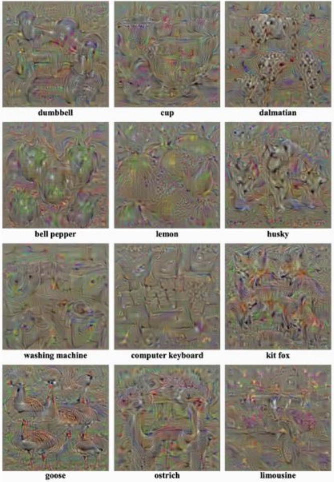


Figure 2: **Image-specific class saliency maps for the top-1 predicted class in ILSVRC-2013 test images.** The maps were extracted using a single back-propagation pass through a classification ConvNet. No additional annotation (except for the image labels) was used in training.

Visualising CNNs - Saliency Maps



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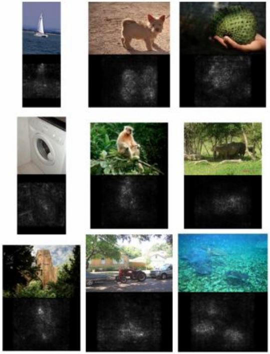

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Deep Inside Convolutional Networks: Visualising Image Classification Models and Saliency Maps, Karen Simonyan, Andrea Veduldi, Andrew Zisserman, Visual Geometry Group, University of Oxford (karen, vedaldi, az) @robots.ox.ac.uk

Visualising CNNs Gradient weighted Class Activated Maps

$$\alpha_k^c = \overbrace{\frac{1}{Z}\sum_i \sum_j}^{\text{global average pooling}} \underbrace{\frac{\partial y^c}{\partial A_{ij}^k}}_{\text{gradients via backprop}}$$

$$L_{\text{Grad-CAM}}^c = ReLU \underbrace{\left(\sum_k \alpha_k^c A^k\right)}_{\text{linear combination}}$$

Visualising CNNs Gradient weighted Class Activated Maps

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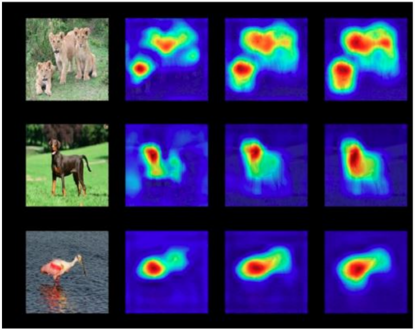

Visualising CNNs Gradient weighted Class Activated Maps

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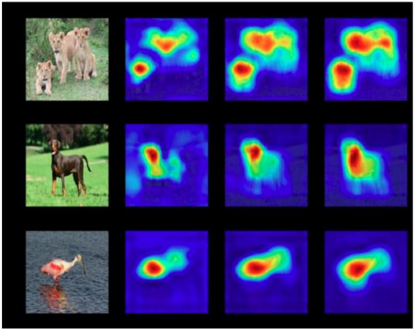

Grad-CAM: Visual Explanations from Deep Networks via Gradient-based Localization, Ramprasaath R. Selvaraju, Michael Cogswell, Abhishek Das, Ramakrishna Vedantam, Devi Parikh, Dhruv Batra