Convolutional Neural Networks

HARVARD MEDICAL SCHOOL | BRIGHAM AND WOMEN'S HOSPITAL | DANA-FARBER CANCER INSTITUTE

SAM Joint Imaging-Therapy Scientific Symposium (Certificate Series Session 3) - Convolutional Neural Nets - Wednesday, 8/1/2018 1:45 PM - 3:45 PM

- Why do we need convolutions?
- CNN specifics
- CNN flavors
- Resources

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TensorFlow - MNIST For Beginners

https://www.tensorflow.org/versions/r1.1/get_started/mnist/beginners

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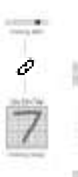

TensorFlow - MNIST For Beginners

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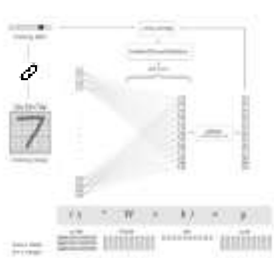
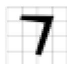
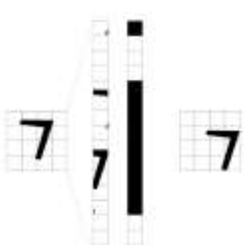


Translation Variance

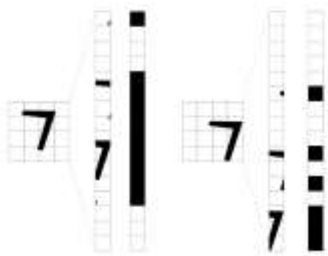


Translation Variance

Translation Variance

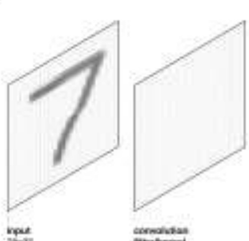


Translation Variance

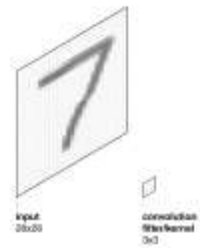


Weight Sharing

Convolutions

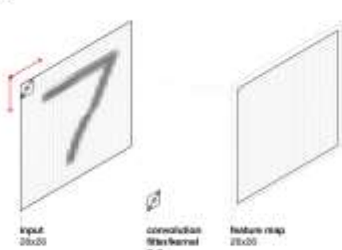


Convolutions

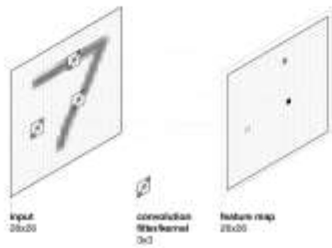


Convolutions

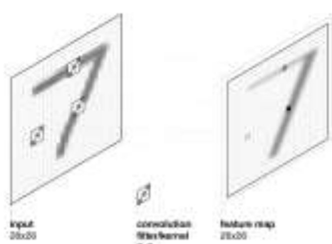
Convolutions



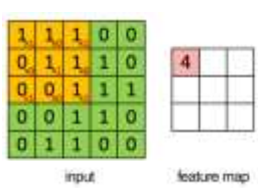
Convolutions



Convolutions

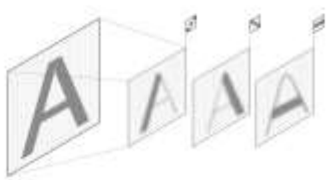


Convolutions

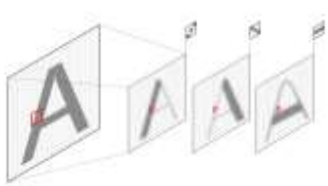


Convolutions

Convolutions



Convolutions



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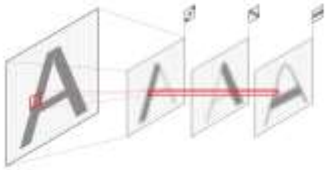
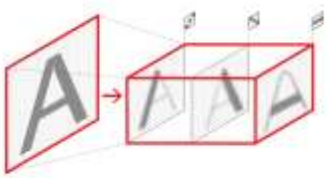
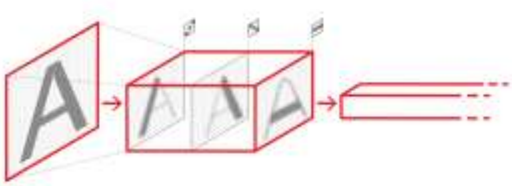


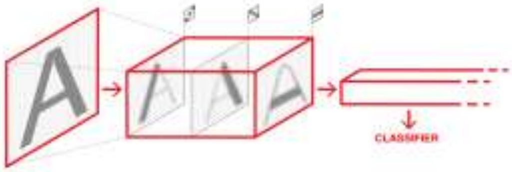
Convolutions



Convolutions

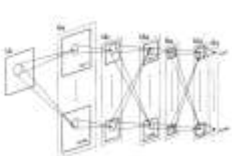


Convolutions



CNN specifics

Neocognitron



Neocognitron: A Self-organizing Neural Network Model for a Mechanism of Pattern Recognition Unaffected by Shift in Position
Biological Cybernetics - 1980

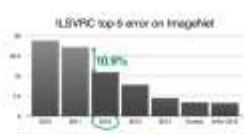
LeNet-5

Object Recognition with Gradient Based Learning
Shape, Contour and Grouping in Computer Vision - 1999

AlexNet

ImageNet Classification with Deep Convolutional Neural Networks
Advances in Neural Information Processing Systems - 2012

AlexNet @ ImageNet



Hyperparameters

# of filters

32, 64, 128 ...

Hyperparameters

filter size

11x11, 5x5, 3x3 ...

Hyperparameters

padding

pad the input image?

stride

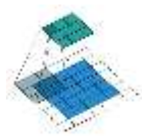
# of pixels to shift the filter

Hyperparameters

padding no
stride 2

Hyperparameters

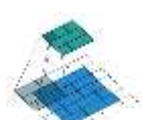
padding no
stride 2



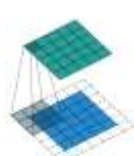
padding yes
stride 2

Hyperparameters

padding no
stride 2

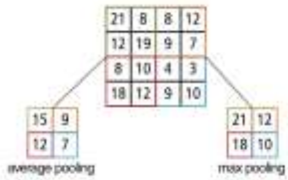


padding yes
stride 2

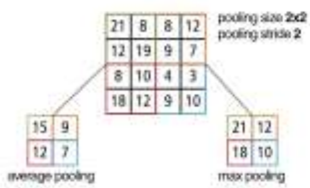


padding yes
stride 1

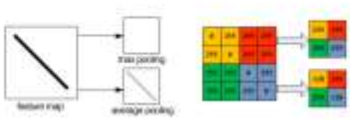
Pooling



Pooling

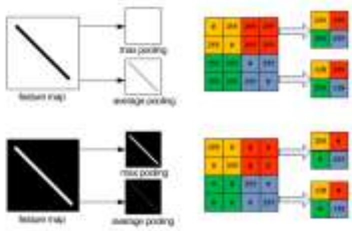


Pooling



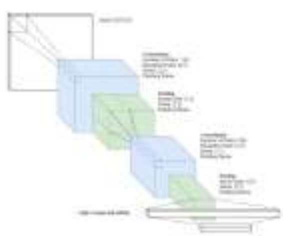
Mixed Pooling for Convolutional Neural Networks
International Conference on Rough Sets and Knowledge Technology - 2014

Pooling



Mixed Pooling for Convolutional Neural Networks
International Conference on Rough Sets and Knowledge Technology - 2014

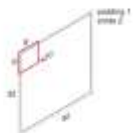
Convolutional Neural Networks



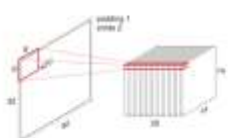
Data Augmentation

- rotate
- translate
- shear
- flip
- scale/zoom
- crop
- apply whitening
- apply noise
- shift channel
- shift brightness/contrast
- blur
- ...

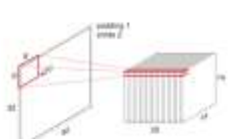
Number of Parameters



Number of Parameters

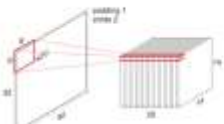


Number of Parameters



	filter		feature map				
without weight sharing	(8*8*1 + 1)	*	(14*14)	*	20	=	**254,800**

Number of Parameters



	filter		feature map				
without weight sharing	(8*8*1 + 1)	*	(14*14)	*	20	=	254,800
with weight sharing	(8*8*1 + 1)		*		20	=	1,300

Memory Management

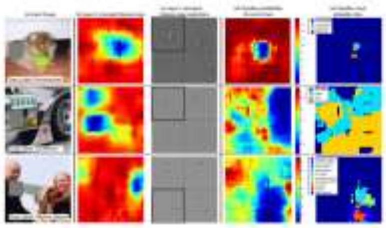
Very Deep Convolutional Networks for Large-Scale Image Recognition
International Conference on Rough Sets and Knowledge Technology - 2014

Memory Management

Nvidia GeForce GTX 980 4GB

Very Deep Convolutional Networks for Large-Scale Image Recognition
International Conference on Rough Sets and Knowledge Technology - 2014

Visualizing Attention

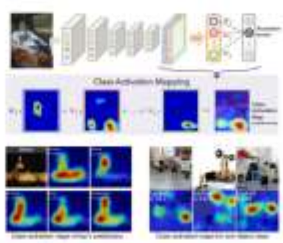


Matthew Zeiler & Rob Fergus

Visualizing and Understanding Convolutional Networks

European Conference on Computer Vision - 2014

Visualizing Attention



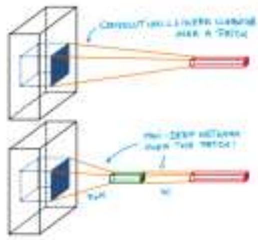
Bolei Zhou, Aditya Khosla, Agata Lapedriza, Aude Oliva & Antonio Torralba

Learning Deep Features for Discriminative Localization

Conference on Computer Vision and Pattern Recognition - 2016

CNN flavors

1x1 Convolutions



1x1 Convolutions
Udacity Deep Learning Nanodegree Program

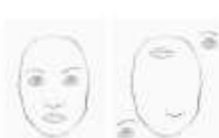
Inception Module

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

Figure 2: Inception module

Christian Szegedy, Wei Liu, Yangqing Jia, et al.
Going Deeper with Convolutions (GoogleNet/Inception)
CVPR - 2015

Capsule Networks



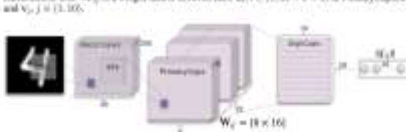
Capsule Networks

Capsule Networks

"The pooling operation used in convolutional neural networks is a big mistake and the fact that it works so well is a disaster." – **Geoffrey Hinton**

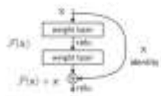
Capsule Networks

Figure 1: A simple CapsNet with 3 layers. This model gives comparable results to deep convolutional networks (such as Chang and Chen [2015]). The length of the activity vector of each capsule in DigitCaps layer indicates presence of an instance of each class and is used to calculate the classification loss. W_{ij} is a weight matrix between each u_i, $i \in (1, 32 \times 6 \times 6)$ in PrimaryCapsules and v_j, $j \in (1, 10)$.



Dynamic Routing Between Capsules
Conference on Neural Information Processing Systems - 2017

ResNets



Deep Residual Learning for Image Recognition
Conference on Computer Vision and Pattern Recognition - 2016

Figure 1: Residual Networks are conventionally shown as (a), which is a natural representation of Equation (1). When we expand this formulation to Equation (6), we obtain an unraveled view of a 3-block residual network (b). Circular nodes represent additions. From this view, it is apparent that residual networks have $O(2^n)$ implicit paths connecting input and output and that adding a block doubles the number of paths.

Residual Networks Behave Like Ensembles of Relatively Shallow Networks
Conference on Computer Vision and Pattern Recognition - 2016

Fully Convolutional Networks

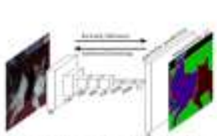
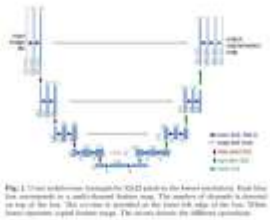


Figure 1: Fully convolutional networks can efficiently learn to make dense predictions for per-pixel tasks like semantic segmentation.

Fully Convolutional Networks for Semantic Segmentation
CVPR - 2015

Fully Convolutional Networks

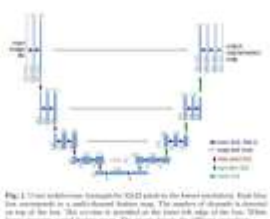


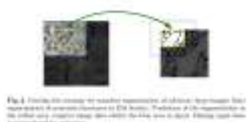
Olaf Ronneberger, Philipp Fischer & Thomas Brox

U-Net: Convolutional Networks for Biomedical Image Segmentation

MICCAI - 2015

Fully Convolutional Networks





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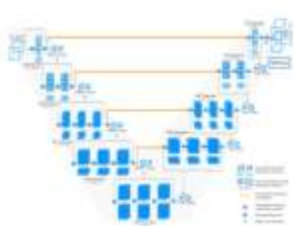
U-Net: Convolutional Networks for Biomedical Image Segmentation

MICCAI - 2015

Fully Convolutional Networks

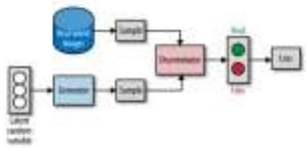


Fausto Milletari, Nassir Navab & Seyed-Ahmad Ahmadi

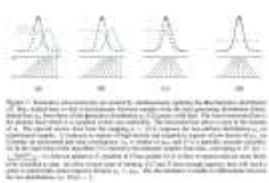
V-Net: Fully Convolutional Neural Networks for Volumetric Medical Image Segmentation

https://arxiv.org/abs/1606.04797

Generative Adversarial Networks (GAN)



Generative Adversarial Networks (GAN)

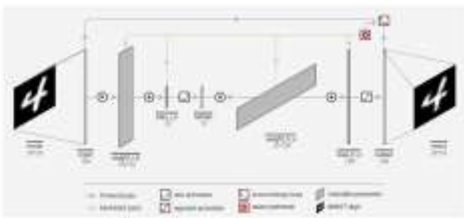


Generative Adversarial Nets
Advances in Neural Information Processing Systems - 2014

Deep Convolutional Generative Adversarial Networks (DCGAN)

Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks
International Conference on Learning Representations - 2016

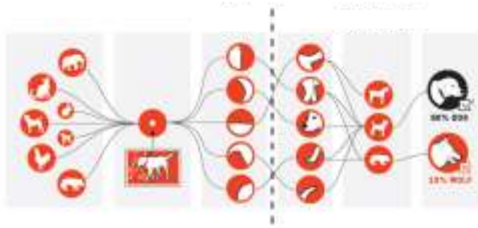
Variational Autoencoders



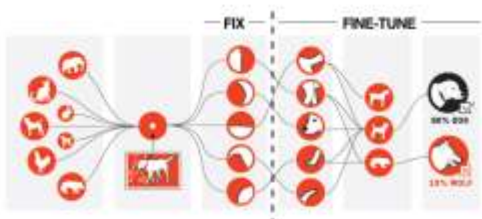
Resources

Transfer Learning

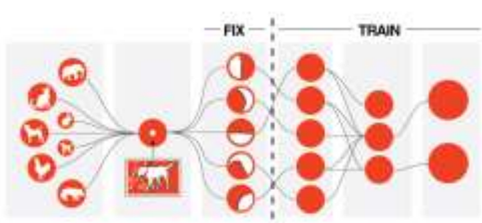
Transfer Learning



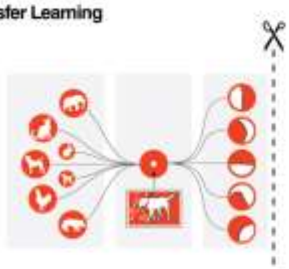
Transfer Learning



Transfer Learning



Transfer Learning



[illegible]

Transfer Learning

[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
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[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
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[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	

[illegible]

Online Resources

Deep Learning Book

[illegible]

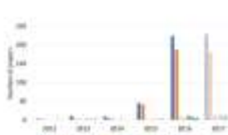
Neural Networks and Deep Learning

[illegible]

Online Resources

Online Resources

Reproducibility



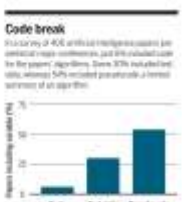
A Survey on Deep Learning in Medical Image Analysis
Medical Image Analysis · 2017

Deep Learning

Keras DL4J Caffe2 PYTORCH torch Caffe CNTK TensorFlow theano mxnet

Open-Source Deep Learning Tools
github.com

Reproducibility



Artificial Intelligence Faces Reproducibility Crisis
Science · 2018

Existing Solutions

Caffe: Convolutional Architecture for Fast Feature Embedding
arxiv.org/abs/1408.5093

Existing Solutions

GitXiv—Collaborative Open Computer Science
gitxiv.com

Existing Medical Imaging Solutions

MODELHUB
www.modelhub.ai

Components

ModelHub: Plug & Predict Solutions for Reproducible AI Research
modelhub.ai

How it Works

ModelHub: Plug & Predict Solutions for Reproducible AI Research
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For Contributors

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Community Outreach

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co-authorship through model contributions

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Thank you