EECS 545: Machine Learning

Lecture 12: Optimization for Neural Networks, Convolutional Neural Network

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02/19/2025

Outline

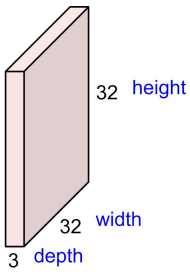
- Optimization
- CNN basics
- Examples of CNN Architectures
- Applications of CNN

Image Classification

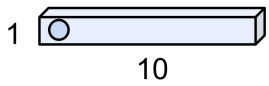
"airplane"

Image Classification

32x32x3 image



10-class output



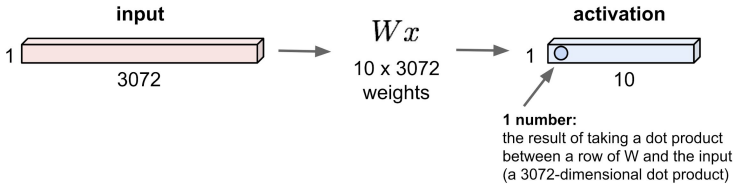
Note: in this lecture, we use vectors visualized as rows

Slide credit: Fei-Fei Li, Justin Johnson, Serena Yeung

Fully Connected Layer

Note: in this lecture, we use vectors visualized as rows

32x32x3 image -> stretch to 3072 x 1

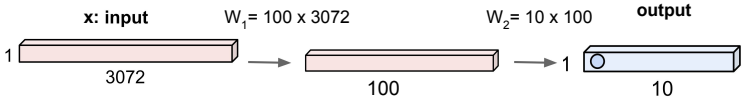


1 number:
the result of taking a dot product between a row of W and the input (a 3072-dimensional dot product)

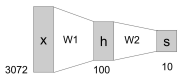
Note: k-th row of W is a transposed version of weight vector $\mathbf{w}_k \in \mathbb{R}^{3072}$ for the class k.

Slide credit: Fei-Fei Li, Justin Johnson, Serena Yeung

Neural Network with 1 hidden layer (with Rectified Linear Units)



Alternatively (diagram):



Alternatively (short notation): $f = W_2 \max(0, W_1 x)$

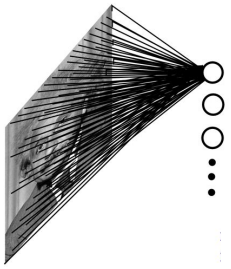
Deeper models: We can add more layers, etc.

Q. Have we solved the problem? Will this be applicable for larger-sized images?

Slide credit: Fei-Fei Li, Justin Johnson, Serena Yeung

Scaling to larger-sized images

Example: 200x200 image, 40k hidden units: Fully connected neural network would have ~2B parameters!



Slide credit: Russ Salakhutdinov

Motivation: Convolutional Neural Networks

- How can we design neural networks that are specifically adapted for classifying large-sized images?
  - Must deal with very **high-dimensional inputs**: 150 x 150 pixels = 22500 inputs, or 3 x 22500 if RGB pixels
  - Can exploit the **2D topology** of pixels (or 3D for video data)
  - Can build in **invariance** to certain variations: translation, illumination, etc.
- **Convolutional networks** leverage these ideas
  - Local connectivity
  - Convolution, parameter sharing
  - Pooling / subsampling hidden units

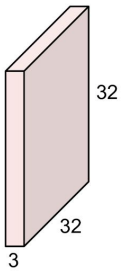
Slide credit: Russ Salakhutdinov

Convolution Layer

32x32x3 image

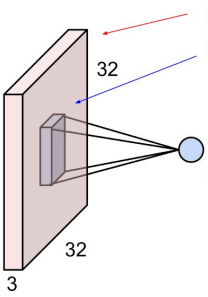
Filters always extend the full depth of the input volume

5x5x3 filter



Convolve the filter with the image
i.e. "slide over the image spatially, computing dot products"

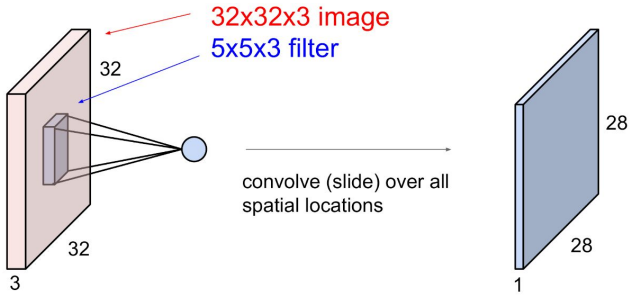
Convolution Layer



1 number:
the result of taking a dot product between the filter and a small 5x5x3 chunk of the image (i.e. 5*5*3 = 75-dimensional dot product + bias)

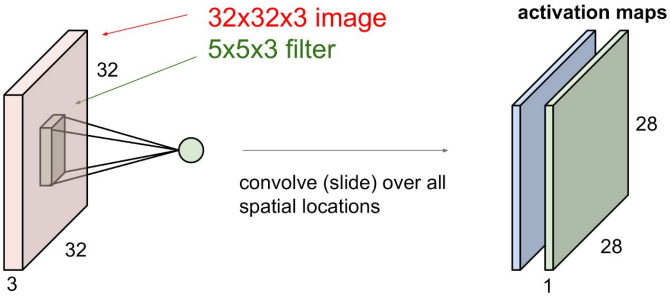
$$w^T x + b$$

Convolution Layer



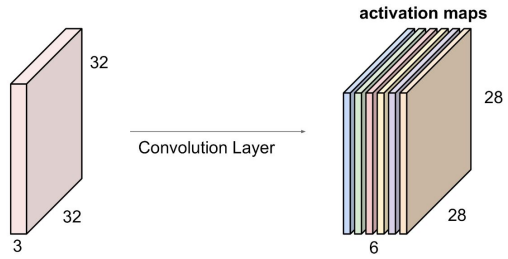
Convolution Layer

consider a second filter



Convolution Layer

For example, if we had 6 5x5 filters, we'll get 6 separate activation maps:



We stack these up to get a "new image" of size 28x28x6!

Discrete Convolution

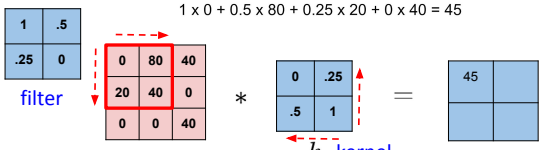
- Applying filter to an image via "sliding window" can be efficiently computed as a convolution of an image x with kernel k as follows

$$(\mathbf{x} *_{\text{valid}} \mathbf{k})_{i,j} = \sum_{m=i}^{i+H_k-1} \sum_{n=j}^{j+W_k-1} x_{m,n} k_{i-m+H_k,j-n+W_k}$$

- Example

1 x 0 + 0.5 x 80 + 0.25 x 20 + 0 x 40 = 45

kernel is a flipped version of a filter



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Discrete Convolution

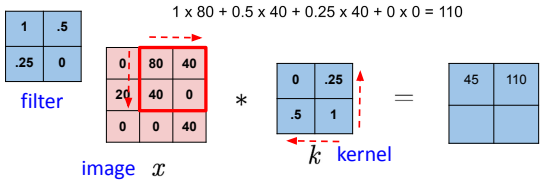
- Applying filter to an image via "sliding window" can be efficiently computed as a convolution of an image x with kernel k as follows

$$(\mathbf{x} *_{\text{valid}} \mathbf{k})_{i,j} = \sum_{m=i}^{i+H_k-1} \sum_{n=j}^{j+W_k-1} x_{m,n} k_{i-m+H_k,j-n+W_k}$$

- Example

1 x 80 + 0.5 x 40 + 0.25 x 40 + 0 x 0 = 110

kernel is a flipped version of a filter



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Discrete Convolution

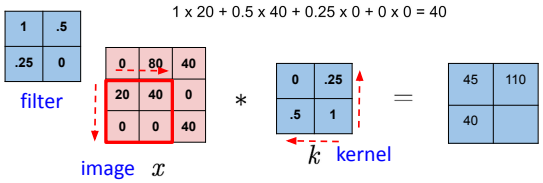
- Applying filter to an image via "sliding window" can be efficiently computed as a convolution of an image x with kernel k as follows

$$(\mathbf{x} *_{\text{valid}} \mathbf{k})_{i,j} = \sum_{m=i}^{i+H_k-1} \sum_{n=j}^{j+W_k-1} x_{m,n} k_{i-m+H_k,j-n+W_k}$$

- Example

1 x 20 + 0.5 x 40 + 0.25 x 0 + 0 x 0 = 40

kernel is a flipped version of a filter



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Discrete Convolution

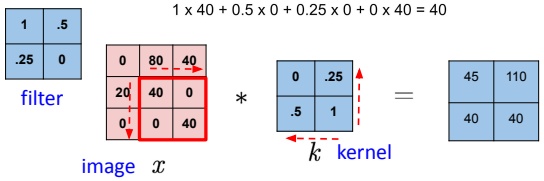
- Applying filter to an image via "sliding window" can be efficiently computed as a convolution of an image x with kernel k as follows

$$(\mathbf{x} *_{\text{valid}} \mathbf{k})_{i,j} = \sum_{m=i}^{i+H_k-1} \sum_{n=j}^{j+W_k-1} x_{m,n} k_{i-m+H_k, j-n+W_k}$$

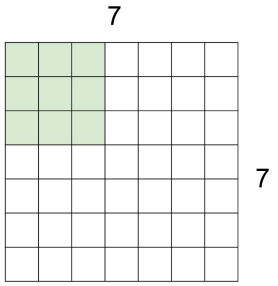
- Example

1 x 40 + 0.5 x 0 + 0.25 x 0 + 0 x 40 = 40

kernel is a flipped version of a filter

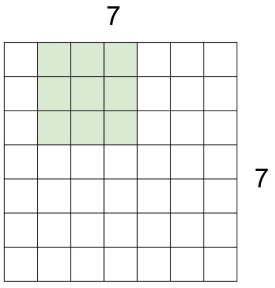


Closer look at spatial dimensions



7x7 input (spatially)
assume 3x3 filter

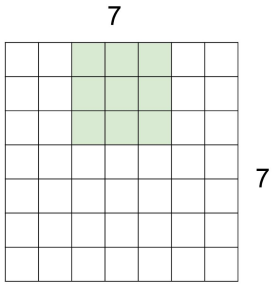
Closer look at spatial dimensions



7x7 input (spatially)
assume 3x3 filter

Stride is convolutional "step size": here, = 1

Closer look at spatial dimensions



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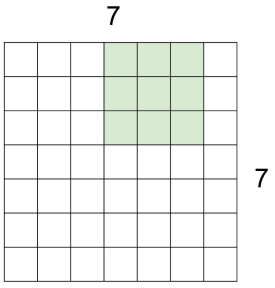
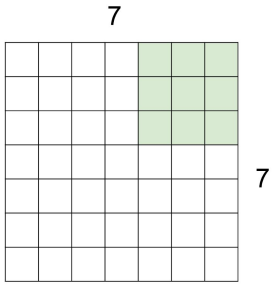
Closer look at spatial dimensions



7x7 input (spatially)
assume 3x3 filter

Stride is convolutional "step size": here, = 1

Closer look at spatial dimensions

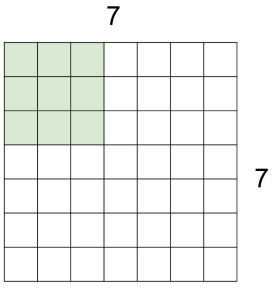


7x7 input (spatially)
assume 3x3 filter

Stride is convolutional "step size": here, = 1

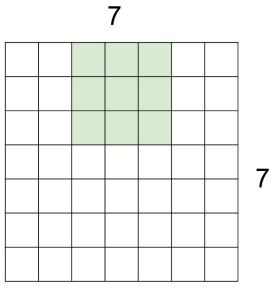
=> 5x5 output

Closer look at spatial dimensions



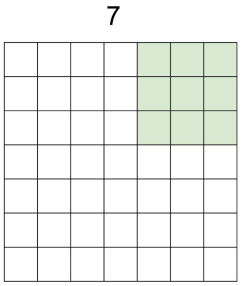
7x7 input (spatially)
assume 3x3 filter
applied **with stride 2**

Closer look at spatial dimensions



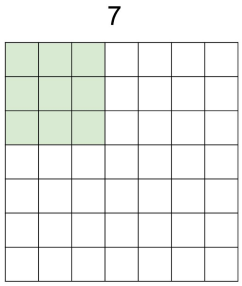
7x7 input (spatially)
assume 3x3 filter
applied **with stride 2**

Closer look at spatial dimensions



7x7 input (spatially)
assume 3x3 filter
applied **with stride 2**
=> 3x3 output!

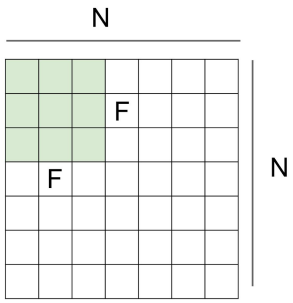
Closer look at spatial dimensions



7x7 input (spatially)
assume 3x3 filter
applied **with stride 3?**

doesn't fit!
cannot apply 3x3 filter on
7x7 input with stride 3.

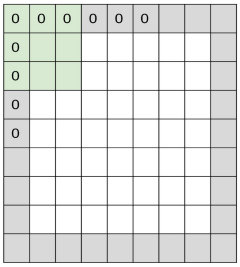
Closer look at spatial dimensions



Output size:
(N - F) / stride + 1

e.g. N = 7, F = 3:
stride 1 => (7 - 3)/1 + 1 = 5
stride 2 => (7 - 3)/2 + 1 = 3
stride 3 => (7 - 3)/3 + 1 = 2.33 :\

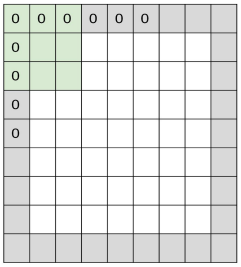
In practice: Common to zero pad the border



e.g. input 7x7
3x3 filter, applied with **stride 1**
pad with 1 pixel border => what is the output?

(recall:)
(N - F) / stride + 1

In practice: Common to zero pad the border



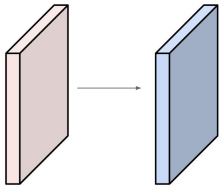
e.g. input 7x7
3x3 filter, applied with **stride 1**
pad with 1 pixel border => what is the output?

7x7 output!
in general, common to see CONV layers with stride 1, filters of size FxF, and zero-padding with (F-1)/2. (will preserve size spatially)
e.g. F = 3 => zero pad with 1
F = 5 => zero pad with 2
F = 7 => zero pad with 3

Example

Convolution layer requires 4 hyper-parameters:
number of filters, their spatial dimension, stride, pad

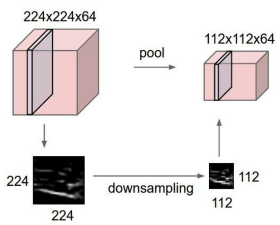
Input volume: **32x32x3**
10 5x5 filters with stride 1, pad 2



Output volume size:
(32+2*2-5)/1+1 = 32 spatially, so
32x32x10

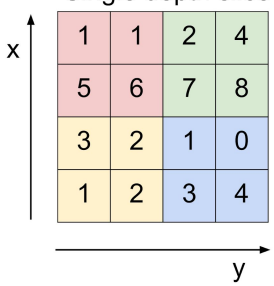
Pooling

- Makes the representations smaller and more manageable
- Operates over each activation map independently

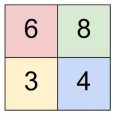


Max Pooling

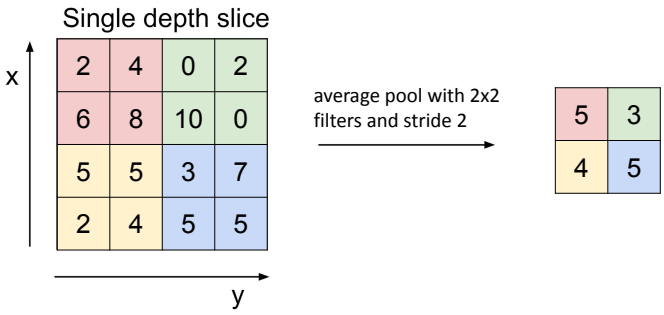
Single depth slice



max pool with 2x2 filters
and stride 2



Average Pooling



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Classic ConvNet Architecture

Input

Conv blocks

- Convolution + non-linear activation (relu)
- Convolution + non-linear activation (relu)
- ...
- Maxpooling 2x2

Output layer (e.g. for classification)

- Fully connected layers
- Softmax

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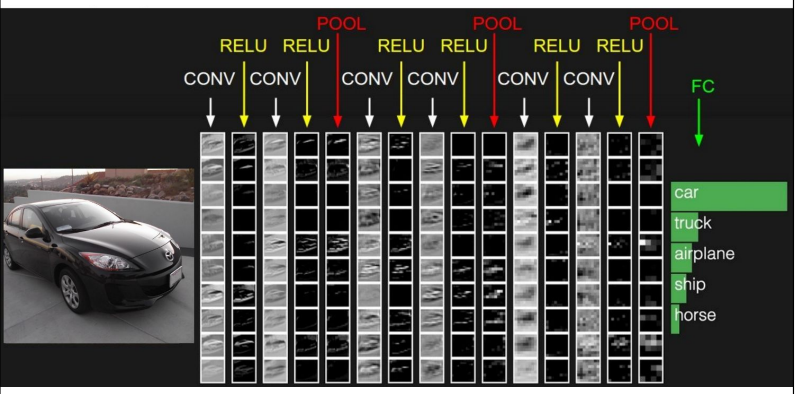

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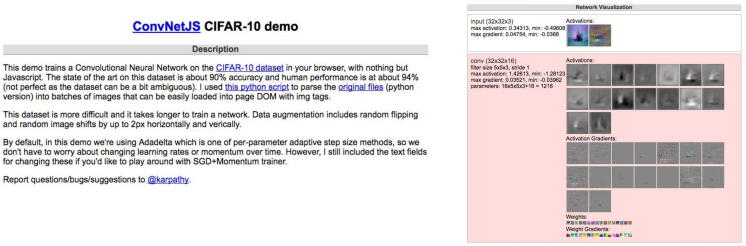
ConvNetJS demo: training on CIFAR-10



http://cs.stanford.edu/people/karpathy/convnetjs/demo/cifar10.html

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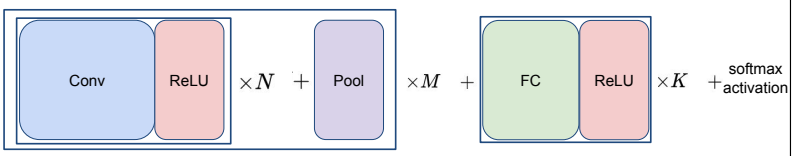
Summary

- ConvNets stack CONV, POOL, FC layers
- Trend towards smaller filters and deeper architectures
- Trend towards getting rid of POOL/FC layers (just CONV)
- Typical architectures look like



where N is usually up to ~5, M is large, 0 <= K <= 2.

- but recent advances such as ResNet/GoogLeNet challenge this paradigm

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Outline

- Optimization
- CNN basics
- Examples of CNN Architectures
- Applications of CNN

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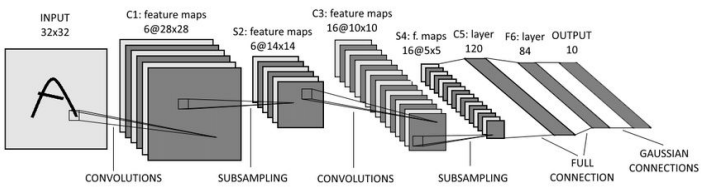
LeCun et al. 1989

Gradient-based learning applied to document recognition [LeCun, Bottou, Bengio, Haffner, 1989]



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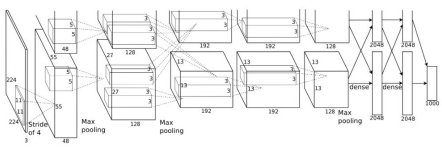
AlexNet



First conv layer: kernel 11x11x3x96 stride 4

- Kernel shape: (11,11,3,96)
- Output shape: (55,55,96)
- Number of parameters: 34,944
- Equivalent MLP parameters: 43.7 x 1e9

Simplified version of Krizhevsky, Alex, Sutskever, and Hinton. "Imagenet classification with deep convolutional neural networks." NIPS 2012

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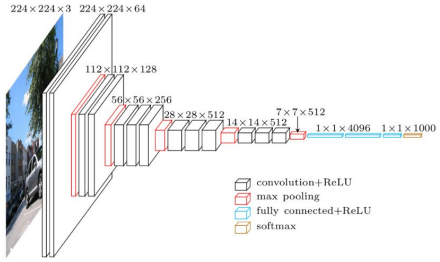
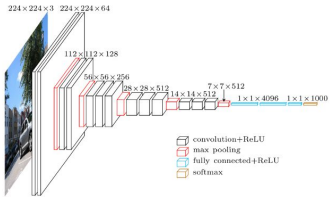
VGG-16



Simonyan, Karen, and Zisserman. "Very deep convolutional networks for large-scale image recognition." (2014)

VGG-16



ConvNet Configuration					
A	A-LRN	B	C	D	E
11 weight layers	11 weight layers	13 weight layers	16 weight layers	16 weight layers	19 weight layers
input (224 × 224 RGB image)					
conv3-64	conv3-64 **LRN**	conv3-64 **conv3-64**	conv3-64 conv3-64	conv3-64 conv3-64	conv3-64 conv3-64
maxpool					
conv3-128	conv3-128	conv3-128 **conv3-128**	conv3-128 conv3-128	conv3-128 conv3-128	conv3-128 conv3-128
maxpool					
conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256 **conv1-256**	conv3-256 conv3-256 **conv3-256**	conv3-256 conv3-256 conv3-256 **conv3-256**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
FC-4096					
FC-4096					
FC-1000					
soft-max					

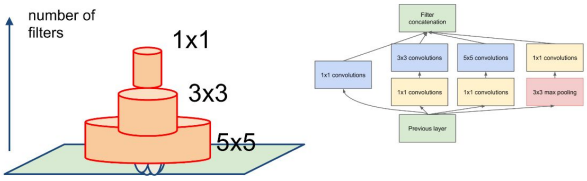
Lots of 3x3 convolution layers: more non-linearity than a single 7x7 conv layer

Very Deep Models

Going deep with convolutions, Szegedy et al.

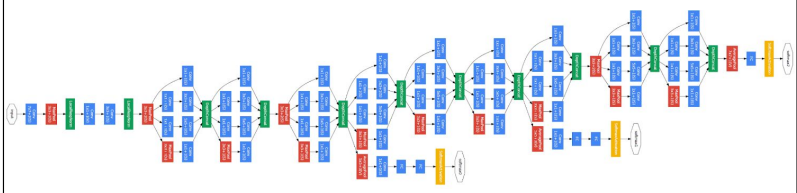
GoogLeNet inception module:

1. Multiple filter scales at each layer
2. Dimensionality reduction to keep computational requirements down



Very Deep Models

Going deep with convolutions, Szegedy et al.

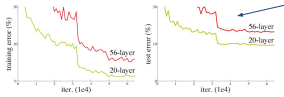


Residual Networks

[He, Zhang, Ren, Sun, CVPR 2016]

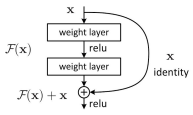
Really, really deep convnets don't train well, E.g. CIFAR10:

deeper networks perform worse due to vanishing gradient



Key idea: introduce "pass through" into each layer

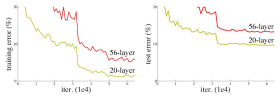
Thus only residual now needs to be learned



Residual Networks

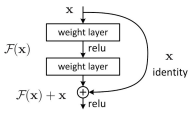
[He, Zhang, Ren, Sun, CVPR 2016]

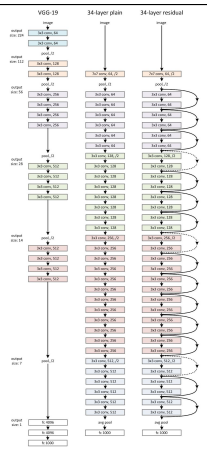
Really, really deep convnets don't train well, E.g. CIFAR10:



Key idea: introduce "pass through" into each layer

Thus only residual now needs to be learned

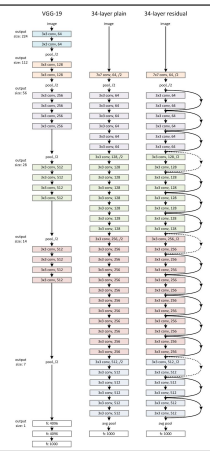




Residual Networks

ResNet50 Compared to VGG:

- Superior accuracy in all vision tasks
  5.25% top-5 error vs 7.1%
- Less parameters
  25M vs 138M
- Computational complexity
  3.8B Flops vs 15.3B Flops
- Fully convolutional until the last layer



Deeper is better

ImageNet Large Scale Visual Recognition Challenge (ILSVRC)

- Dramatically outperformed traditional methods.
- The first time a deep learning method CNN was used.

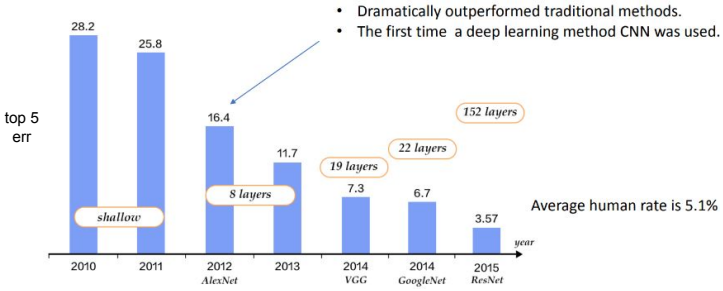
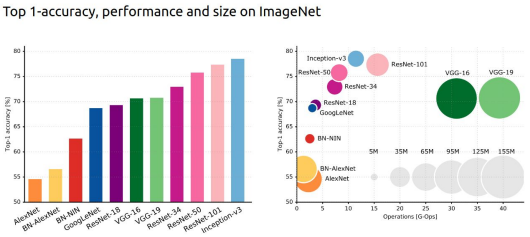


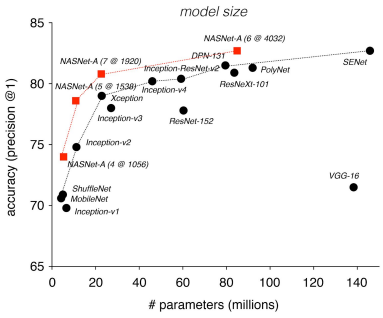
Figure source: http://www.rt-rk.uns.ac.rs/sites/default/files/materijali/predavanja/DL_5.pdf

ImageNet classification



Canziani, Paszke, and Culurciello. "An Analysis of Deep Neural Network Models for Practical Applications." (May 2016).

Learned architectures surpass human-invented



Red: architectures found by Neural Architecture Search

Black: Human-designed neural network architectures

Learning Transferable Architectures for Scalable Image Recognition
B Zoph, V Vasudevan, J Shlens, Q Le (2017)

Outline

- Optimization
- CNN basics
- Examples of CNN Architectures
- Applications of CNN

Pre-trained models

- Training a model on ImageNet from scratch takes **days or weeks**.
- Many models trained on ImageNet and their weights are publicly available!

Transfer learning

- Use pre-trained weights, remove last layers to compute representations of images
- Train a classification model from these features on a new classification task
- The network is used as a generic feature extractor
- Better than handcrafted feature extraction on natural images

Pre-trained models

- Training a model on ImageNet from scratch takes **days or weeks**.
- Many models trained on ImageNet and their weights are publicly available!

Fine-tuning

Retraining the (some) parameters of the network (given enough data)

- Truncate the last layer(s) of the pre-trained network
- Freeze the remaining layers weights
- Add a (linear) classifier on top and train it for a few epochs
- Then fine-tune the whole network or the few deepest layers
- Use a smaller learning rate when fine tuning

Applications of CNN

- **Case study 1: image classification**
- Case study 2: object detection
- Case study 3: segmentation

Object classification

- Given an input image, classify the object within it
- Input?

- Output? "Cat" (class probability): $\hat{y} = (\hat{p_1}, \hat{p_2}, \cdots, \hat{p_C})$
- Loss? $\mathcal{L}(y, \hat{y}) = -y \log(\hat{y}) = -\sum_{c=1}^{C} p_c \log(\hat{p_c})$

Object classification

- Imagenet dataset
- Very large dataset of many object classes
- Enable learning models capable to identify many object features

Object Classification: Deeper is better

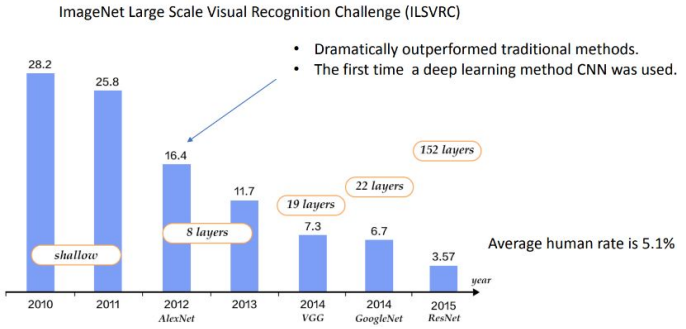


Figure source: http://www.rt-rk.uns.ac.rs/sites/default/files/materijali/predavanja/DL_5.pdf

Emotion Classification

- Given an input human face, label the emotion
- Input? 
- Output? "fear"
- Loss? Multi-class cross entropy

Examples of emotion categories

Figure from: https://www.youtube.com/watch?v=wlaR5F30hiU

Emotion Classification

Figure credit: https://github.com/oarriaga/face_classification

Emotion Classification

- Pipeline:
  - Input preprocessing (alignment, normalization, etc)
  - Given the preprocessed data, pass it to a CNN and get output
  - Output label with highest probability is the assigned emotion

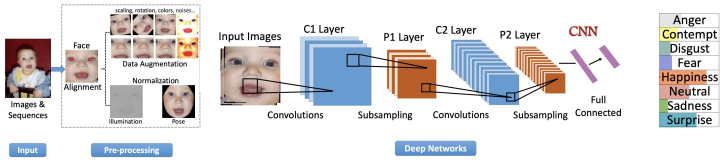


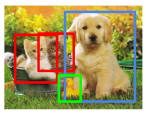
Figure credit: Shan Li and Weihong Deng. Deep Facial Expression Recognition: A Survey.

Applications of CNN

- Case study 1: Image Classification
- **Case study 2: Object Detection**
- Case study 3: Segmentation

Object Detection

- Given an image, detect all objects and classify
- Input?
- Output?
- Loss?



CAT, DOG, DUCK

Error in bounding box position?
Bounding box scale? Class label?

Object Detection

Classes = [cat, dog, duck]

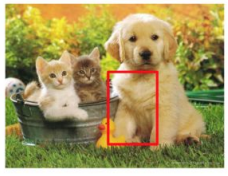
Cat ? YES

Dog ? NO

Duck? NO

Slide credit: Amaia Salvador

Object Detection



Classes = [cat, dog, duck]

Cat ? NO

Dog ? NO

Duck? NO

Slide credit: Amaia Salvador

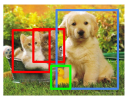
Object Detection

Problem:
Too many positions & scales to test

Solution: If your classifier is fast enough, go for it

Slide credit: Amaia Salvador

Object Detection



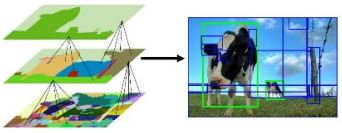
- Two sub-problems:
  - Object locations/size: localize each object with a tight bounding box in the image
  - Object classification: classify the object in each bounding box

CAT, DOG, DUCK

- Typically solved by **"proposing candidate bounding boxes"** and **"classifying them"**
- Two main families:
  - A grid in the image where each cell is a proposal (YOLO)
  - Region proposal (Fast RCNN, Faster RCNN)

Bounding Box Proposals

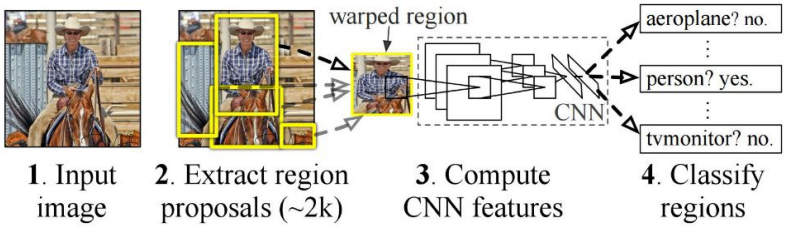
- Instead of having a predefined set of box proposals, find them on the image:
  - Selective Search (from pixels, not learnt)
  - Region Proposal Network (RPN, learnt)



Uijlings, J. R., Van De Sande, K. E., Gevers, T., & Smeulders, A. W. (2013). Selective search for object recognition. *IJCV*, *104*(2), 154-171.

Region-CNN (RCNN)

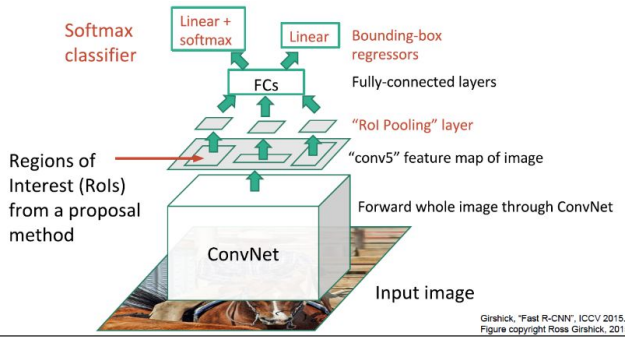
For each region proposal, use CNN to predict the categories (with confidence)



Girshick, R., Donahue, J., Darrell, T., & Malik, J. (2014). Rich feature hierarchies for accurate object detection and semantic segmentation. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 580-587).

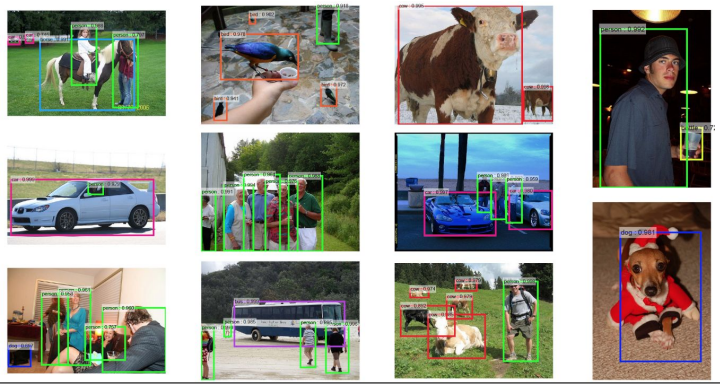
Fast RCNN

Main idea: calculate convolutional feature map only once and reuse it!



Girshick, "Fast R-CNN", ICCV 2015.
Figure copyright Ross Girshick, 2015;

Faster RCNN



Applications of CNN

- Case study 1: Image Classification
- Case study 2: Object Detection
- **Case study 3: Segmentation**

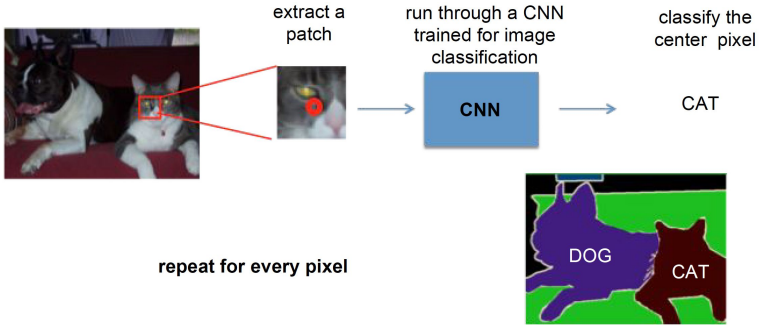
Semantic Segmentation

- Given an image, partition the image into coherent parts
- Input?

- Output? Pixel-level class map

- Loss? Pixel level classification loss

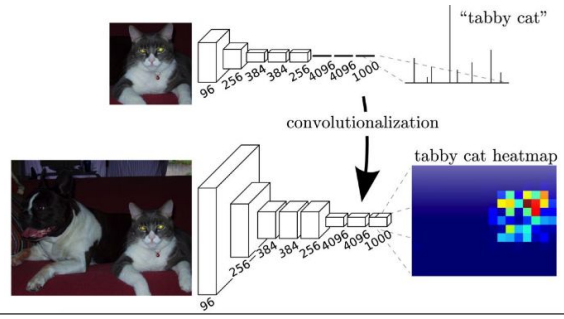
From Classification to Semantic Segmentation



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

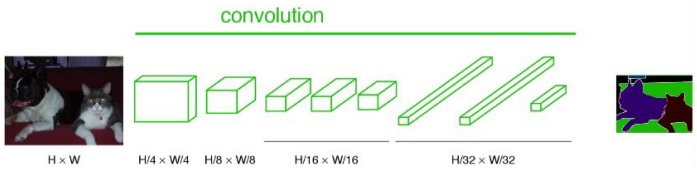
From Classification to Semantic Segmentation

- A classification network becoming fully convolutional



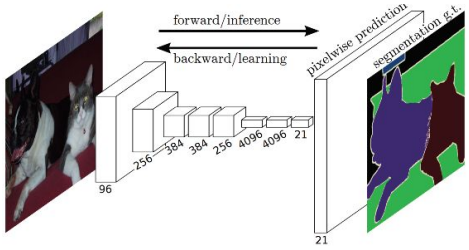
From Classification to Semantic Segmentation

- Dense prediction: fully convolutional, end to end, pixel-to-pixel network
- Problems
  - Output is smaller than input → Add upsampling layers



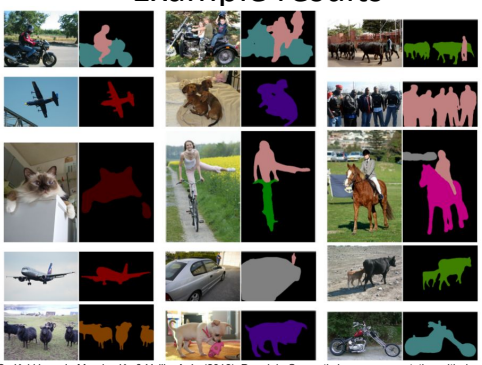
From Classification to Semantic Segmentation

- Dense prediction: fully convolutional, end to end, pixel-to-pixel network
- Learnable upsampling



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

Example results



Chen, L. C., Papandreou, G., Kokkinos, I., Murphy, K., & Yuille, A. L. (2018). Deeplab: Semantic image segmentation with deep convolutional nets, atrous convolution, and fully connected crfs. *IEEE transactions on pattern analysis and machine intelligence*, *40*(4), 834-848.