Introduction to Convolutional Neural Networks (CNNs)

Nojun Kwak
nojunk@snu.ac.kr
http://mipal.snu.ac.kr

Department of Transdisciplinary Studies
Seoul National University, Korea

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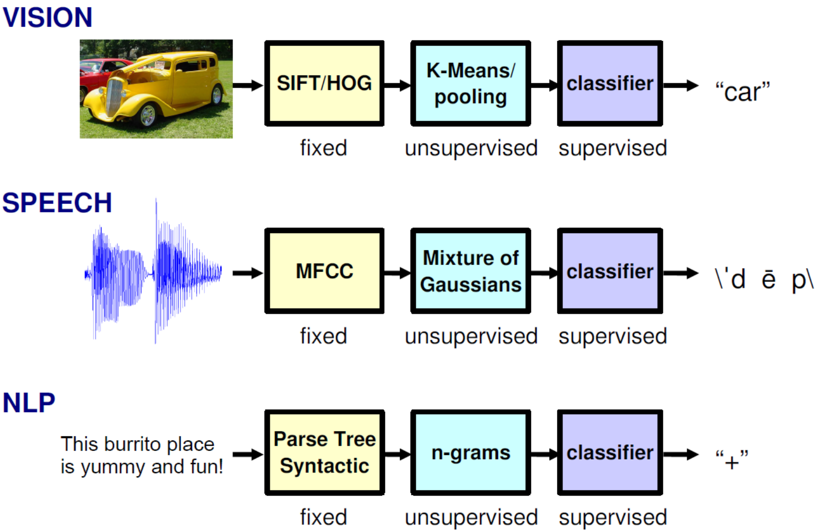
Many slides are from *Fei-Fei Li @Stanford*, *Raquel Urtasun @U. Toronto*, and *Marc'Aurelio Ranzato @Facebook*.

Traditional Pattern Recognition



Hierarchical Compositionality (DEEP)

VISION

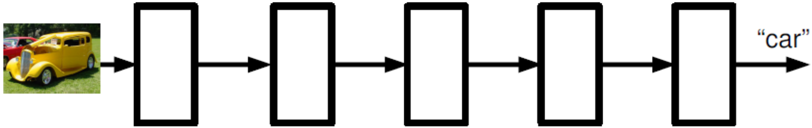
pixels → edge → texton → motif → part → object

SPEECH

sample → spectral band → formant → motif → phone → word

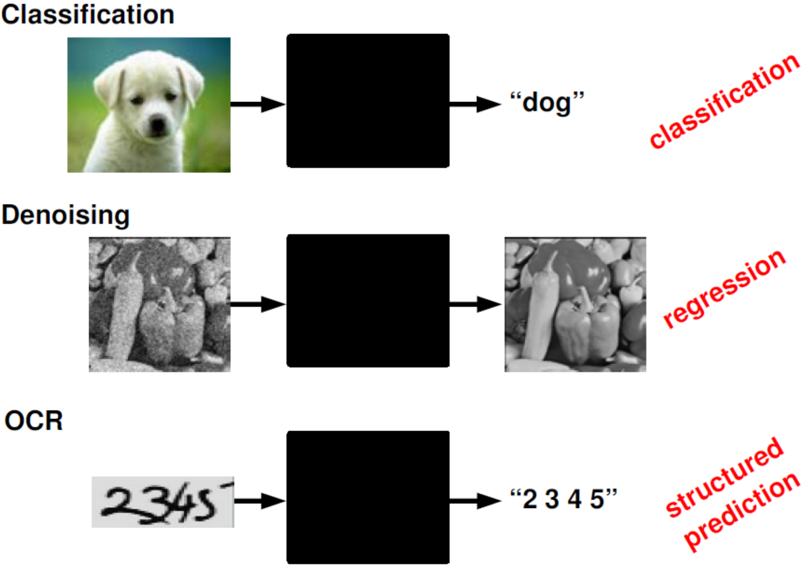
NLP

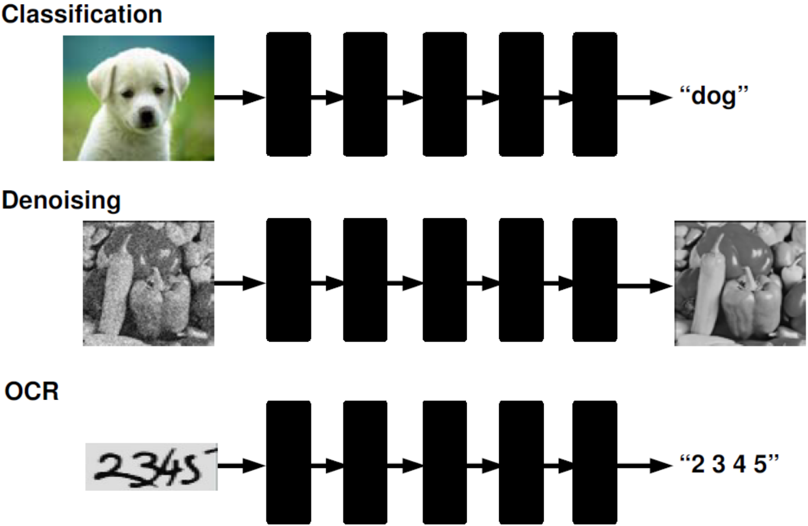
character → word → NP/VP/.. → clause → sentence → story



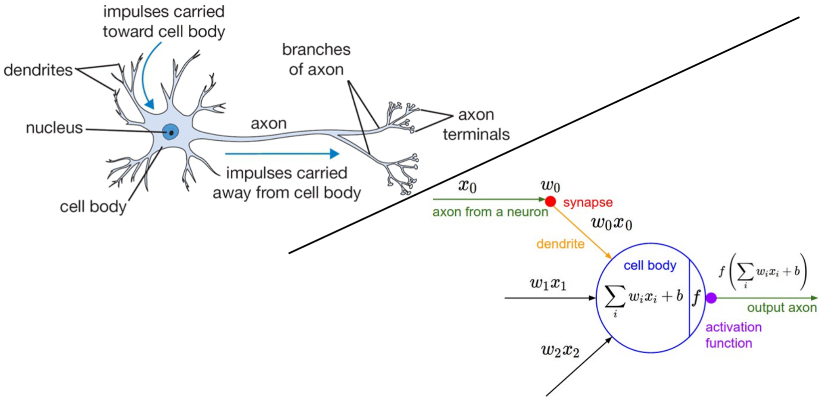
What is deep learning?

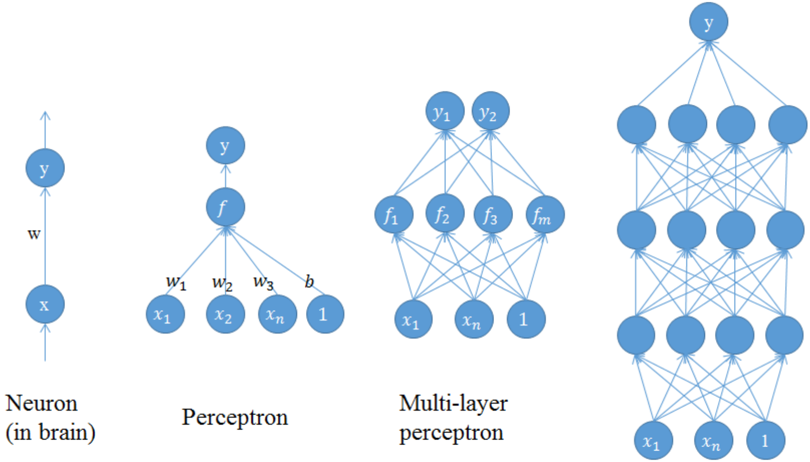
- Nothing new!
- (Many) cascades of nonlinear transformations
- End-to-end learning (no human intervention / no fixed features)


Classification
"dog"
classification
Denoising
regression
OCR
"2 3 4 5"
structured prediction


Classification
"dog"
Denoising
OCR
2345
"2 3 4 5"

- Biologically inspired models





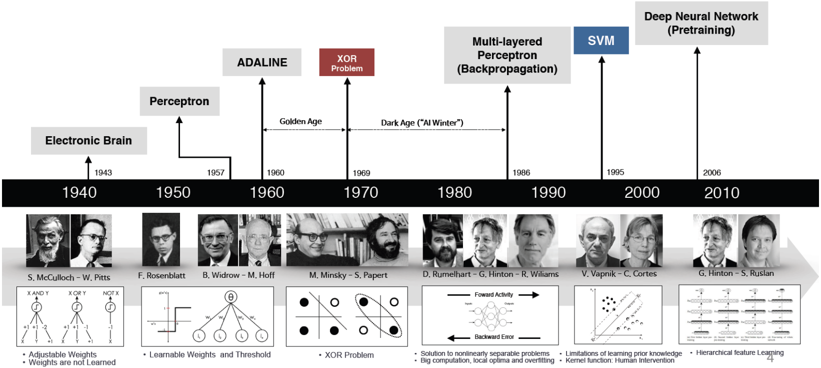
Neuron (in brain)

Perceptron

Multi-layer perceptron

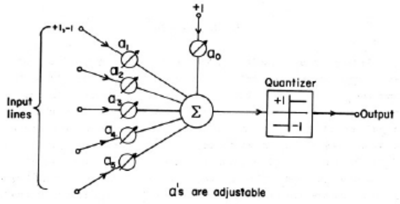
Deep neural network

A Brief History of ANNs



source of image: VUNO Inc.

- First Generation: 1957 ∼
  - Perceptron: Rosenblatt, 1957
  - Adaline: Widrow and Hoff, 1960



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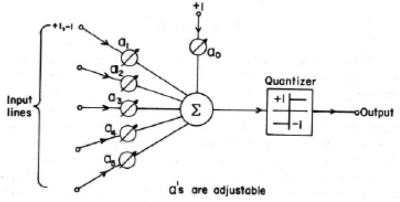
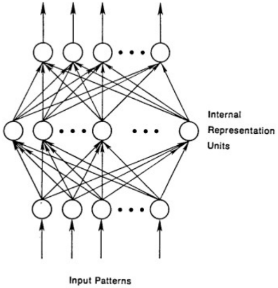
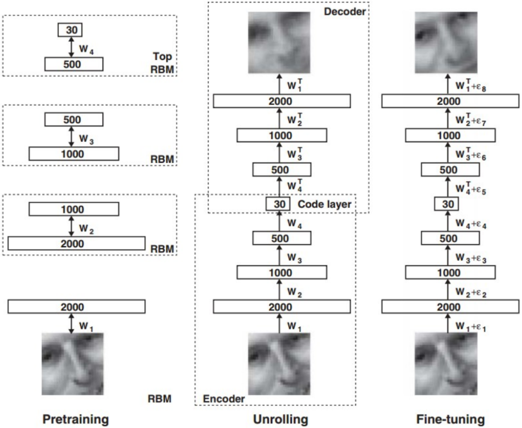


- Second Generation: 1986 ∼
  - MLP with BP: Rumelhart



- Third Generation: 2006 ~
  - RBM: Hinton and Salkhutdinov
  - Reinvigorated research in Deep Learning

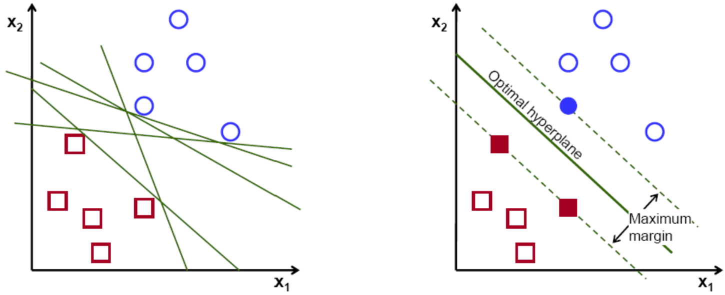


Classification problems

- Given inputs $\boldsymbol{x}$, and outputs $t \in \{-1, 1\}$
- Find a hyperplane that divides the space into half (binary classification)

$$y_* = \text{sign}(\boldsymbol{w}_*^T \boldsymbol{x} + \boldsymbol{w}_0)$$

$\Rightarrow$ SVM tries to maximize the margin.



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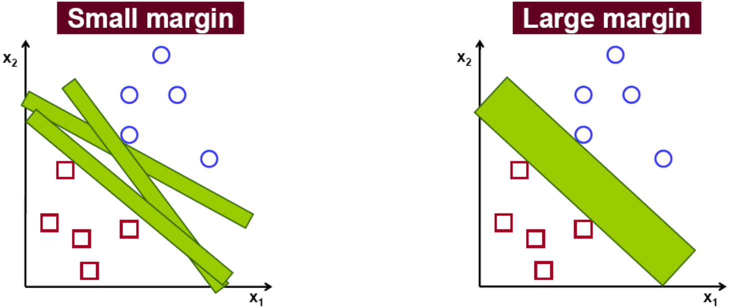

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Two types of widely used approaches

- Kernel Trick: Fixed functions and optimize linear parameters on nonlinear mappings $\phi(\boldsymbol{x})$

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Two types of widely used approaches

- Kernel Trick: Fixed functions and optimize linear parameters on nonlinear mappings $\phi(\boldsymbol{x})$

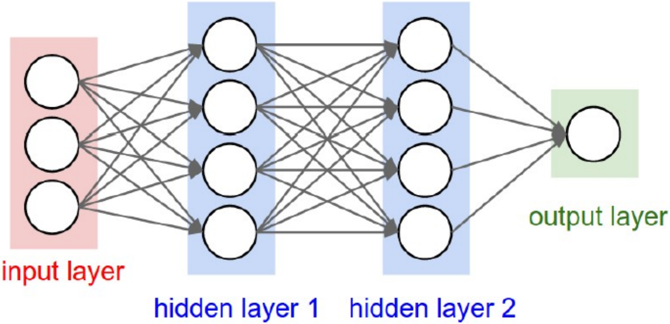
$$y = \mathsf{sign}(\boldsymbol{w}^T \phi(\boldsymbol{x}) + b)$$

- Deep Learning: Learn parametric nonlinear functions

$$y = F(\boldsymbol{x}, \boldsymbol{w}) = \cdots (\boldsymbol{h}_2(\boldsymbol{w}_2^T \boldsymbol{h}_1(\boldsymbol{w}_1^T \boldsymbol{x} + b_1) + b_2) \cdots$$

$\boldsymbol{h}_{1,2}$: activation function at layer 1 or 2

- Deep learning uses composite of simpler functions, e.g., ReLU, sigmoid, tanh, max
- Note: a composite of linear functions is linear!
- Example: 2 layer NNet (Convention: input and output layers are not taken as a layer)



Neural Networks

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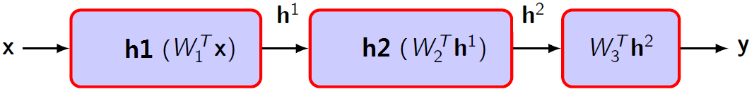
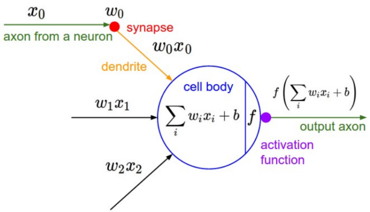


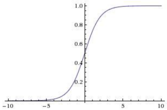
  - $\boldsymbol{x}$ is the input
  - $\boldsymbol{y}$ is the output
  - $\boldsymbol{h}^i$ is the i-th hidden layer output
  - W^i is the set of parameters of the i-th layer



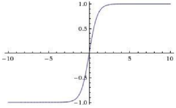
- A singlue neuron can be used as a binary linear classifier
- Regularization has the interpretation of gradual forgetting

Classical NNs used sigmoid or tanh function as an activation function.

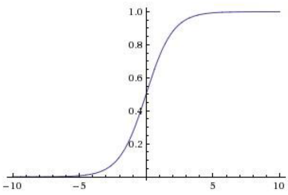
- sigmoid: $\sigma(x) = \frac{1}{1+e^{-x}}$
- tanh: $\tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$



Sigmoid

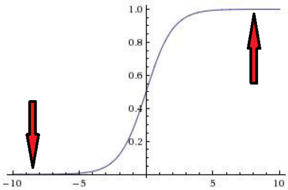


tanh(x)



Sigmoid

- Squashes numbers to range [0,1]
- Historically popular since they have nice interpretation as a saturating "firing rate" of a neuron



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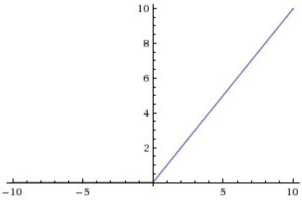
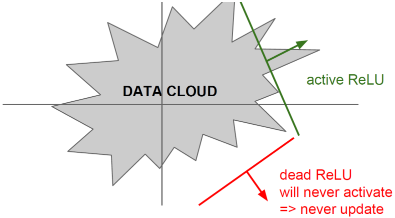
2 BIG problems:

1. Saturated neurons kill the gradients (cannot backprop further) $\Rightarrow$ Major bottleneck for the conventional NNs: not able to train more than 2 or 3 layers
2. Sigmoid outputs are not zero-centered $\Rightarrow$ Restriction on the gradient directions



ReLU

- $f(x) = \max(0, x)$
- Does not saturate
- Computationally very efficient
- Converges much faster than sigmoid/tanh in practice (e.g. 6x)



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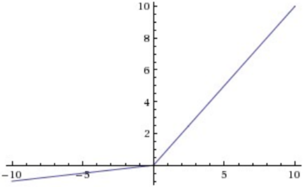
- One annoying problem $\Rightarrow$ Dead neurons



Leaky ReLU

- $f(x) = \max(0, x)$
- Does not saturate
- Computationally very efficient
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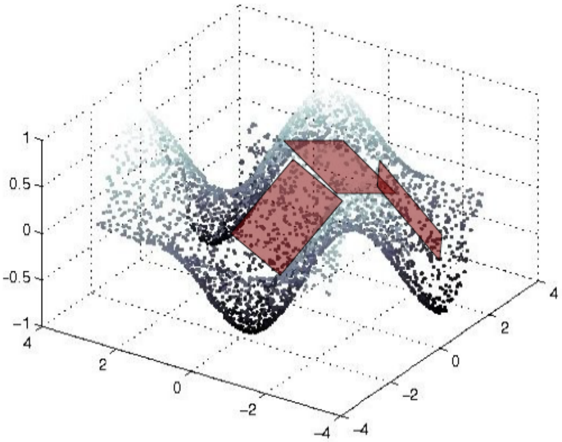
- One annoying problem ⇒ Dead neurons
- Solution: leaky ReLU (small slope for negative input)
  - Never dies.
  - However, almost the same performance in practice.

Why ReLU?

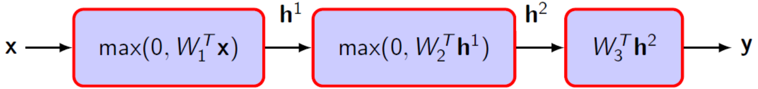


Piecewise linear tiling: mapping is locally linear

Montufar et al. "On the number of linear regions of DNNs", arXiv 2014

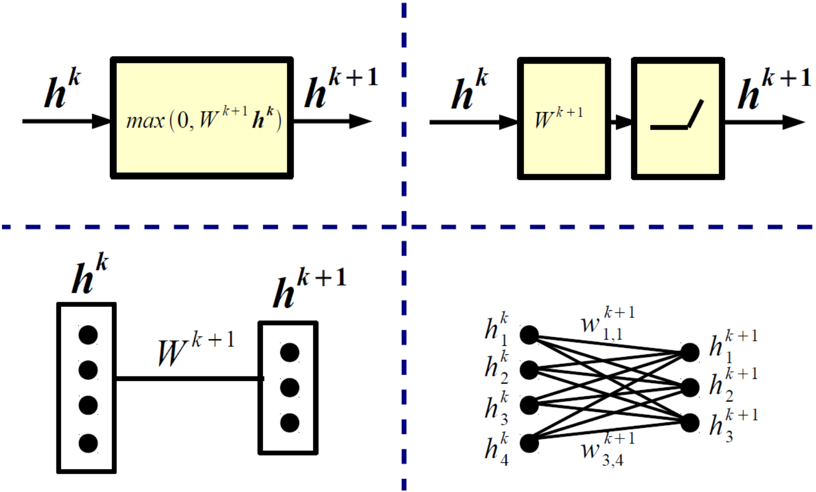
Forward Pass: Evaluating the function

- Forward propagation: compute the output $\boldsymbol{y}$ given the input $\boldsymbol{x}$



- Fully connected layer
- Nonlinearity comes from ReLU
- Do it in a compositional way

$$\boldsymbol{x} \Rightarrow \boldsymbol{h}^1 \Rightarrow \boldsymbol{h}^2 \Rightarrow \boldsymbol{y}$$



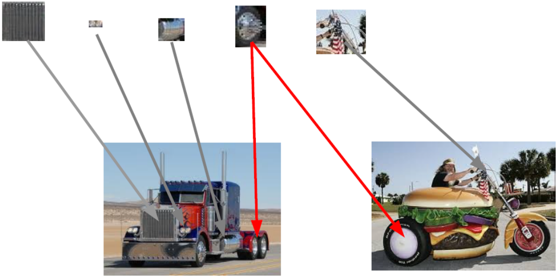
Slide from M. Ranzato

Why many layers?

Hierarchically distributed representations

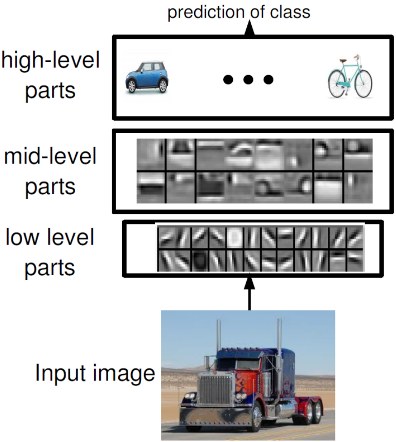
[1 1 0 0 0 1 0 **1** 0 0 0 0 1 1 0 1 . . .] motorbike

[0 0 1 0 0 0 0 **1** 0 0 1 1 0 0 1 0 . . .] truck



Lee et al. "Convolutional DBN's · · · " ICML 2009

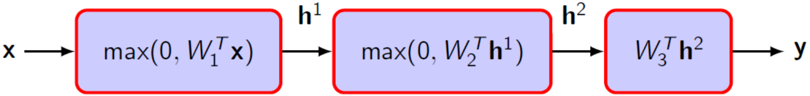
Hierarchically distributed representations



- distributed representations
- feature sharing
- compositionality

Lee et al. “Convolutional DBN's · · · ” ICML 2009

Training



- We want to estimate the parameters, biases and hyper-parameters (e.g., number of layers, number of neurons) for good predictions.
- Collect a training set of input-output pairs $\{\boldsymbol{x}_i, t_i\}_{i=1}^N$.
- Encode the output with 1-K encoding $t = [0, \cdots, 1, \cdots, 0]$.

Training

$$\mathbf{x} \longrightarrow \boxed{\max(0, W_1^T\mathbf{x})} \xrightarrow{\mathbf{h}^1} \boxed{\max(0, W_2^T\mathbf{h}^1)} \xrightarrow{\mathbf{h}^2} \boxed{W_3^T\mathbf{h}^2} \longrightarrow \mathbf{y}$$

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- Collect a training set of input-output pairs $\{\boldsymbol{x}_i, t_i\}_{i=1}^N$.
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- Define a loss per training example and minimize the empirical loss

$$\mathcal{L}(\boldsymbol{w}) = \frac{1}{N}\sum_{i=1}^{N} l(\boldsymbol{w}, \boldsymbol{x}_i, t_i) + \mathcal{R}(\boldsymbol{w})$$

N: number of training examples

$\mathcal{R}$: regularizer

$\boldsymbol{w}$: set of all parameters

$$\mathcal{L}(\boldsymbol{w}) = \frac{1}{N}\sum_{i=1}^{N} l(\boldsymbol{w}, \boldsymbol{x}_i, t_i) + \mathcal{R}(\boldsymbol{w})$$

- Softmax (Probability of class k given input):

$$p(c_k = 1|\boldsymbol{x}) = \frac{\exp(y_k)}{\sum_{j=1}^{C}\exp(y_j)}$$

Loss functions

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- Cross entropy (most popular loss function for classification):

$$l(\boldsymbol{w}, \boldsymbol{x}, t) = -\sum_{k=1}^{C} t^{(k)} \log p(c_k|\boldsymbol{x})$$

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- Gradient descent to train the network

$$\boldsymbol{w}^* = \operatorname*{argmin}_{\boldsymbol{w}} \mathcal{L}(\boldsymbol{w})$$

- Efficient way of computing gradient (Chain rule)
- Partial derivatives and gradients

$$f(x,y) = xy \quad \rightarrow \quad \frac{\partial f}{\partial x} = y \quad \frac{\partial f}{\partial y} = x$$

$$\frac{df(x)}{dx} = \lim_{h \rightarrow 0} \frac{f(x+h) - f(x)}{h} \qquad f(x+h) = f(x) + h\frac{df(x)}{dx}$$

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- Example: $x = 4, y = -3 \Rightarrow f(x, y) = -12$

$$\frac{\partial f}{\partial x} = -3 \quad \frac{\partial f}{\partial x} = 4 \qquad \nabla f = \left[\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}\right]$$

Backpropagation

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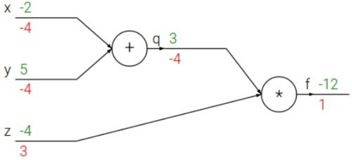
- Question: If I increase x by h, how would the output f change?

Compound expressions with graphics (example from F.F. Li)

$$q = x + y \quad \frac{\partial q}{\partial x} = 1, \frac{\partial q}{\partial x} = 1$$

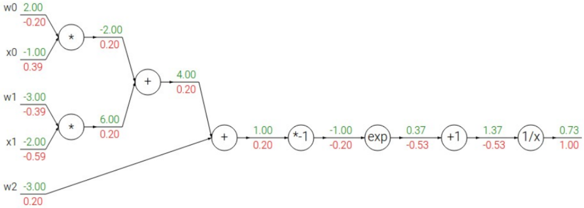
$$f = qz \quad \frac{\partial f}{\partial q} = z, \frac{\partial f}{\partial z} = q$$

Chain rule: $\frac{\partial f}{\partial x} = \frac{\partial f}{\partial q}\frac{\partial q}{\partial x}$



Backpropagation: Another Example

Another example: $$f(w,x) = \frac{1}{1+e^{-(w_0x_0+w_1x_1+w_2)}}$$



$f(x) = e^x$	$\rightarrow$	$\frac{df}{dx} = e^x$	$f(x) = \frac{1}{x}$	$\rightarrow$	$\frac{df}{dx} = -1/x^2$
$f_a(x) = ax$	$\rightarrow$	$\frac{df}{dx} = a$	$f_c(x) = c + x$	$\rightarrow$	$\frac{df}{dx} = 1$

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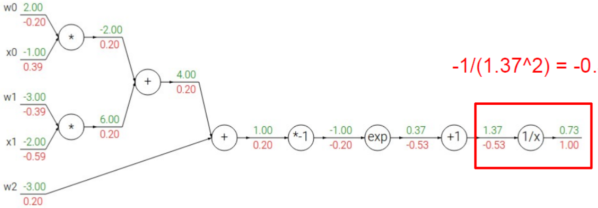

-1/(1.37^2) = -0.53

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Fei-Fei Li & Andrej Karpathy Lecture 5 - 15 21 Jan 2015

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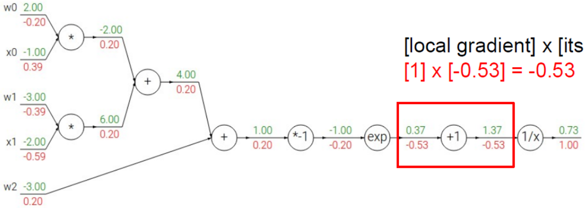

[local gradient] x [its gradient]

[1] x [-0.53] = -0.53

$$f(x) = e^x \quad \rightarrow \quad \frac{df}{dx} = e^x \qquad\qquad f(x) = \frac{1}{x} \quad \rightarrow \quad \frac{df}{dx} = -1/x^2$$

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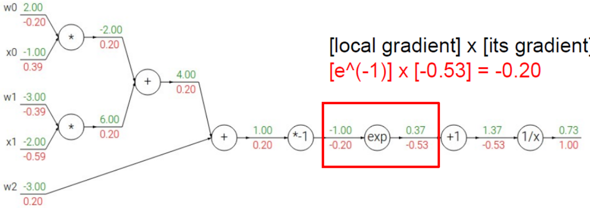

[local gradient] x [its gradient]
[e^(-1)] x [-0.53] = -0.20

$f(x) = e^x \quad \rightarrow \quad \frac{df}{dx} = e^x$	$f(x) = \frac{1}{x} \quad \rightarrow \quad \frac{df}{dx} = -1/x^2$
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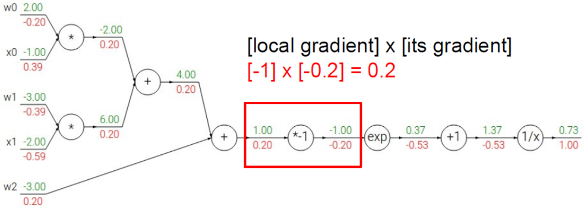

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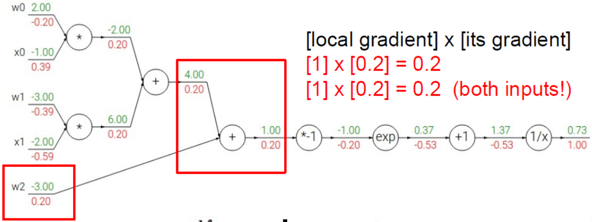


[local gradient] x [its gradient]

[1] x [0.2] = 0.2

[1] x [0.2] = 0.2 (both inputs!)

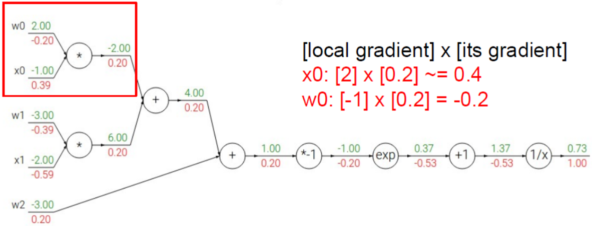
$f(x) = e^x \quad \rightarrow \quad \frac{df}{dx} = e^x$

$f_a(x) = ax \quad \rightarrow \quad \frac{df}{dx} = a$

$f(x) = \frac{1}{x} \quad \rightarrow \quad \frac{df}{dx} = -1/x^2$

$f_c(x) = c + x \quad \rightarrow \quad \frac{df}{dx} = 1$

Another example: $f(w,x) = \frac{1}{1+e^{-(w_0x_0+w_1x_1+w_2)}}$



[local gradient] x [its gradient]
x0: [2] x [0.2] ~= 0.4
w0: [-1] x [0.2] = -0.2

$$f(x) = e^x \quad \rightarrow \quad \frac{df}{dx} = e^x \qquad\qquad f(x) = \frac{1}{x} \quad \rightarrow \quad \frac{df}{dx} = -1/x^2$$

$$f_a(x) = ax \quad \rightarrow \quad \frac{df}{dx} = a \qquad\qquad f_c(x) = c + x \quad \rightarrow \quad \frac{df}{dx} = 1$$

Fei-Fei Li & Andrej Karpathy Lecture 5 - 20 21 Jan 2015

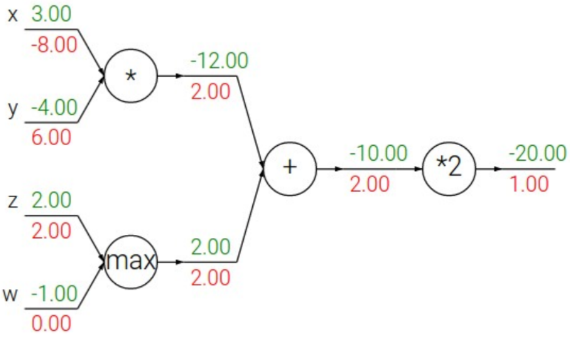
Every gate during backprop computes, for all its inputs:

[LOCAL GRADIENT] x [GATE GRADIENT]

Can be computed right away, even during forward pass

The gate receives this during backpropagation

- Add: gradient distributor
- Max: gradient router
- Mul: gradient switcher



- Gradient descent to train the network

$$\boldsymbol{w}^* = \operatorname*{argmin}_{\boldsymbol{w}} \frac{1}{N} \sum_{i=1}^{N} l(\boldsymbol{w}, \boldsymbol{x}_i, t_i) + \mathcal{R}(\boldsymbol{w})$$

- At each iteration, we need to compute

$$\boldsymbol{w}_{n+1} = \boldsymbol{w}_n - \gamma_n \nabla \mathcal{L}(\boldsymbol{w}_n)$$

- Use the backward pass to compute $\nabla \mathcal{L}(\boldsymbol{w}_n)$ efficiently
- Recall that the backward pass requires the forward pass first

- At each iteration, we need to compute

$$\boldsymbol{w}_{n+1} = \boldsymbol{w}_n - \gamma_n \nabla \mathcal{L}(\boldsymbol{w}_n)$$

with

$$\nabla \mathcal{L}(\boldsymbol{w}_n) = \frac{1}{N} \sum_{i=1}^{N} \nabla l(\boldsymbol{w}_n, \boldsymbol{x}_i, t_i) + \nabla \mathcal{R}(\boldsymbol{w}_n)$$

- Too expensive when having millions of training examples

- At each iteration, we need to compute

$$\boldsymbol{w}_{n+1} = \boldsymbol{w}_n - \gamma_n \nabla \mathcal{L}(\boldsymbol{w}_n)$$

with

$$\nabla \mathcal{L}(\boldsymbol{w}_n) = \frac{1}{N} \sum_{i=1}^{N} \nabla l(\boldsymbol{w}_n, \boldsymbol{x}_i, t_i) + \nabla \mathcal{R}(\boldsymbol{w}_n)$$

- Too expensive when having millions of training examples
- Instead, approximate the gradient with a mini-batch (subset of examples: 100 $\sim$ 1,000) - called stochastic gradient descent

$$\frac{1}{N} \sum_{i=1}^{N} \nabla l(\boldsymbol{w}_n, \boldsymbol{x}_i, t_i) \approx \frac{1}{|S|} \sum_{i \in S} \nabla l(\boldsymbol{w}_n, \boldsymbol{x}_i, t_i)$$

SGD with momentum

- Stochastic Gradient Descent update

$$\boldsymbol{w}_{n+1} = \boldsymbol{w}_n - \gamma_n \nabla \mathcal{L}(\boldsymbol{w}_n)$$

with

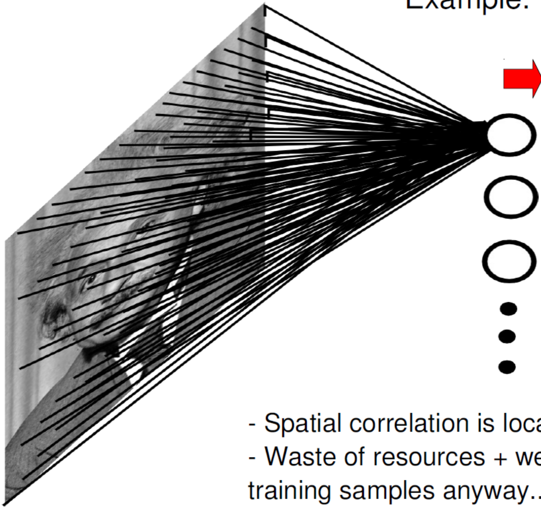
$$\nabla \mathcal{L}(\boldsymbol{w}_n) = \frac{1}{|S|} \sum_{i \in S} \nabla l(\boldsymbol{w}_n, \boldsymbol{x}_i, t_i)$$

- We can use momentum

$$\boldsymbol{w} \longleftarrow \boldsymbol{w} - \gamma \Delta$$

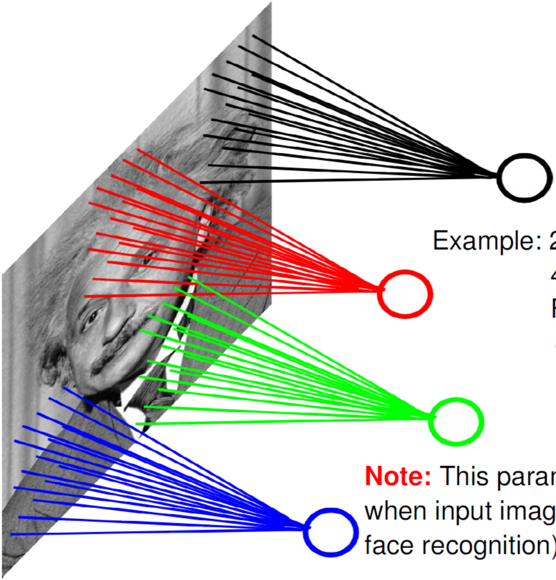
$$\Delta \longleftarrow \kappa \Delta + \nabla \mathcal{L}$$

- We can also decay learning rate γ as iterations goes on



Example: 200x200 image
40K hidden units
~2B parameters!!!

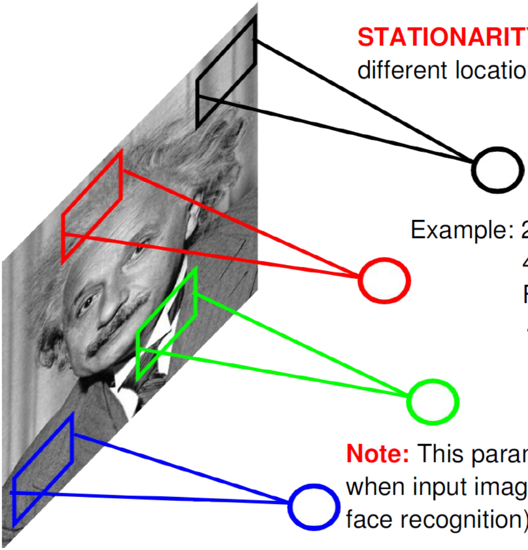
- Spatial correlation is local
- Waste of resources + we have not enough training samples anyway..



Example: 200x200 image
40K hidden units
Filter size: 10x10
4M parameters

Note: This parameterization is good when input image is registered (e.g., face recognition).

Locally Connected Layer

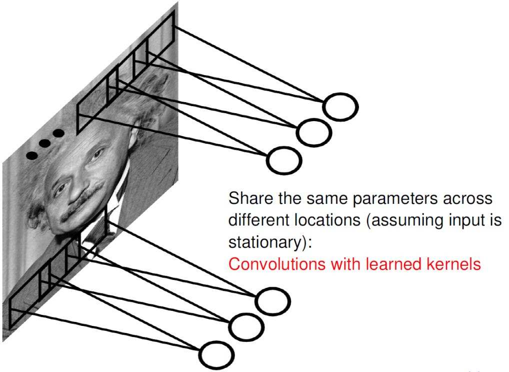


STATIONARITY? Statistics is similar at different locations

Example: 200x200 image
40K hidden units
Filter size: 10x10
4M parameters

Note: This parameterization is good when input image is registered (e.g., face recognition).

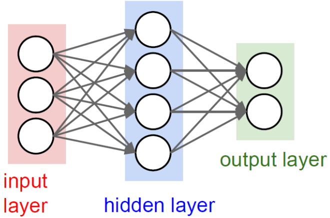
- Idea: statistics are similar at different locations (Lecun 1998)
- Connect each hidden unit to a small input patch and share the weight across space
- This is called convolution layer and the network is a convolutional neural network



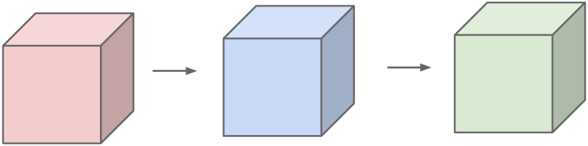
- Number of filters (neurons) is considered as a new dimension (depth)

  $\Rightarrow$ Volumetric representation

before:

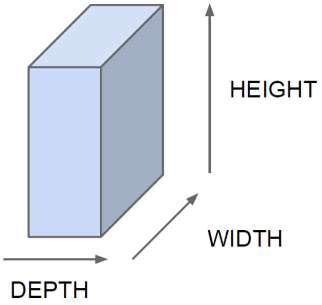


now:



- Number of filters (neurons) is considered as a new dimension (depth)
  $\Rightarrow$ Volumetric representation

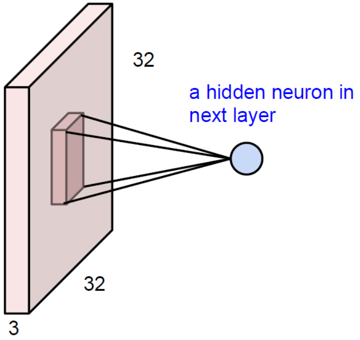
All Neural Net activations arranged in **3 dimensions:**



For example, a CIFAR-10 image is a 32x32x3 volume
32 width, 32 height, 3 depth (RGB channels)

CNNs are just neural nets BUT:

1. Local connectivity



CNNs are just neural nets BUT:

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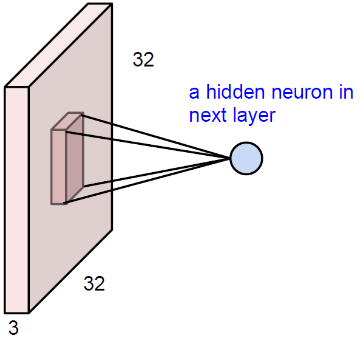


image: 32x32x3 volume

before: fully connected: 32x32x3 weights

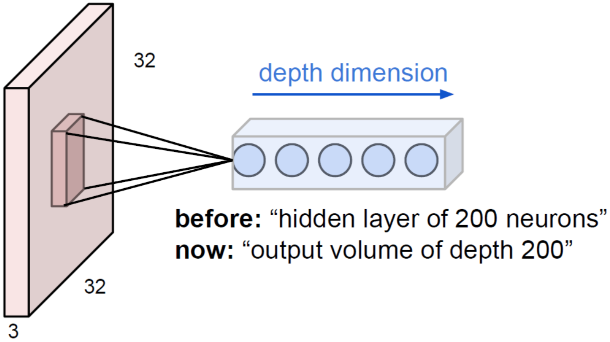
now: one neuron will connect to, e.g., 5x5x3 chunk (receptive field) and only have 5x5x3 weights

connectivity is:

- local in space (5x5 instead of 32x32)
- but full in depth (all 3 depth channels)

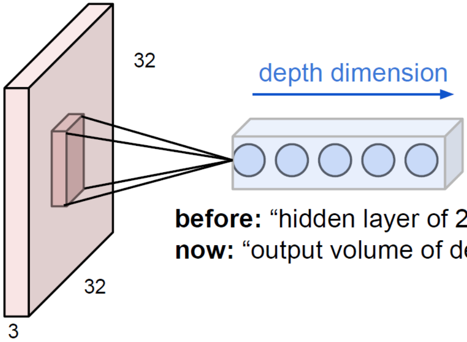
CNNs are just neural nets BUT:

1. Local connectivity



CNNs are just neural nets BUT:

1. Local connectivity

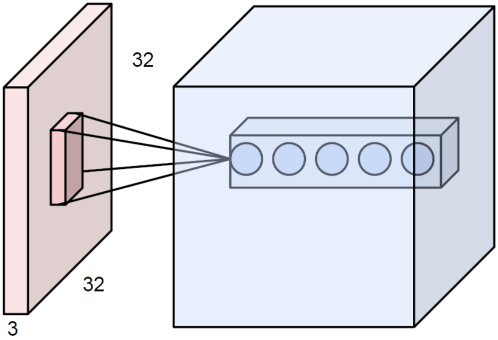


Multiple neurons all looking at the same region of the input volume, stacked along depth.

before: "hidden layer of 200 neurons"
now: "output volume of depth 200"

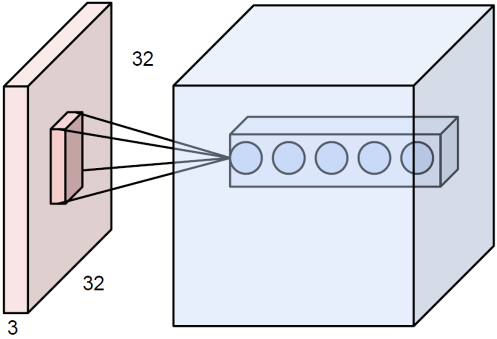
CNNs are just neural nets BUT:

2. Weight sharing



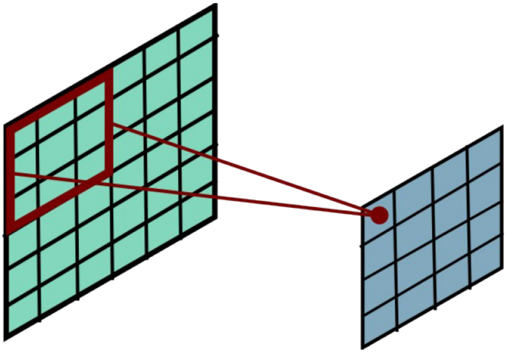
CNNs are just neural nets BUT:

2. Weight sharing

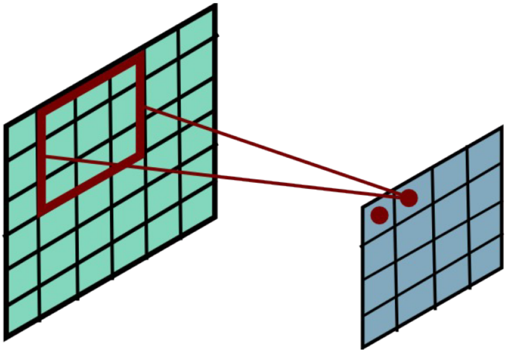


- Weights are shared across different locations
- Each depth slice is called one feature map

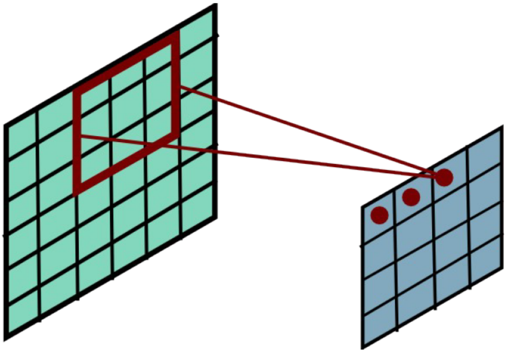
Convolutional Layer



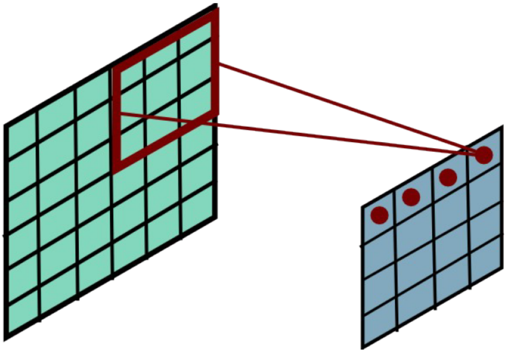
Convolutional Layer



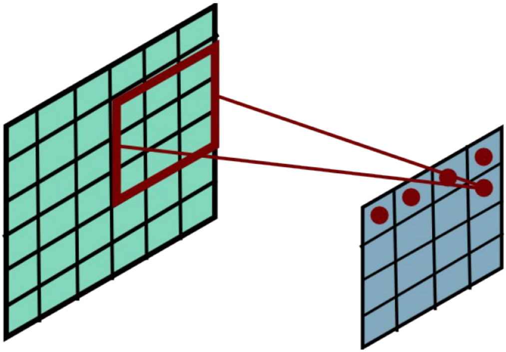
Convolutional Layer



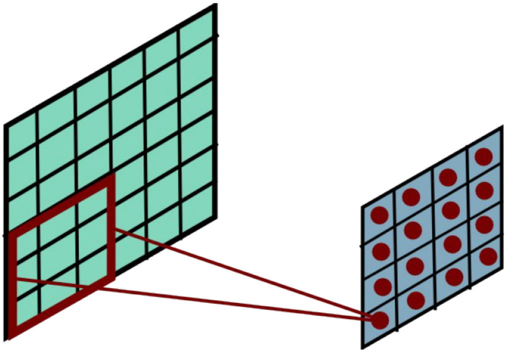
Convolutional Layer



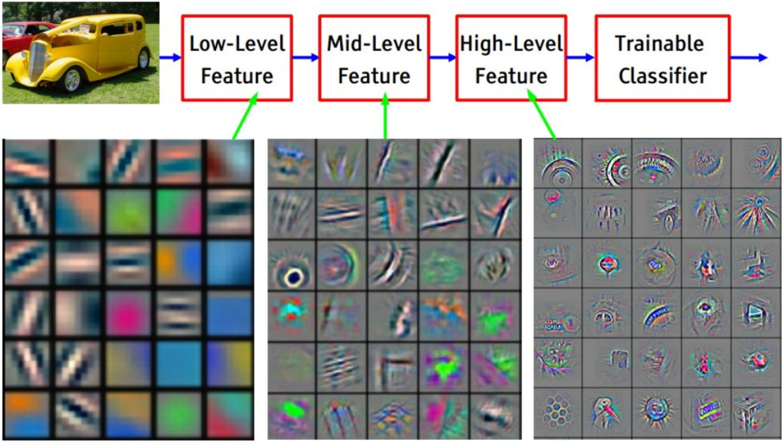
Convolutional Layer



Convolutional Layer



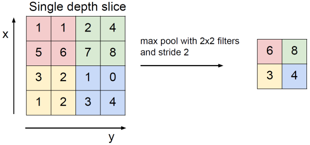
- Input volume of size [W1 x H1 x D1]
- using K neurons with receptive fields F x F
- and applying them at strides of S gives
- Output volume: [W2, H2, D2]
  W2 = (W1-F)/S+1,
  H2 = (H1-F)/S+1,
  D2 = K

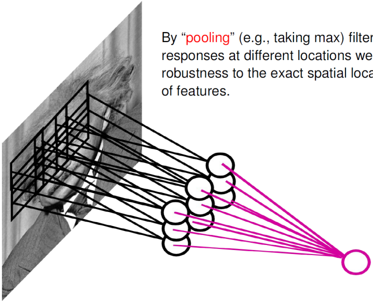


Feature visualization of convolutional net trained on ImageNet from [Zeiler & Fergus 2013]

In CNNs, Conv layers are often followed by Pool layers

- Pooling layer: makes the representations smaller and more manageable without losing too much information
- Increased receptive field
- Most common: MAX pooling
- Others: average, L2 pooling $\cdots$

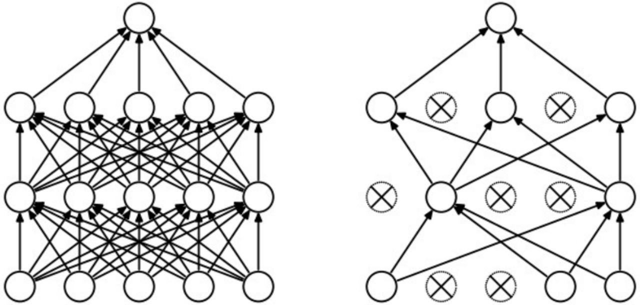




By "pooling" (e.g., taking max) filter responses at different locations we gain robustness to the exact spatial location of features.

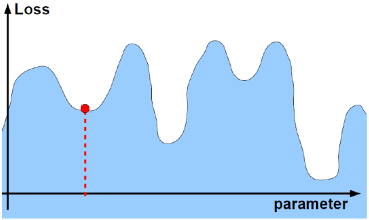
- Weight sharing (Reduce the number of parameters)
- Data augmentation (e.g., jittering, noise injection, tranformations)
- Dropout [Hinton et al.]: randomly drop units (along with their connections) from the neural network during training. Use for the fully connected layers only
- Regularization: Weight decay (L2, L1)
- Sparsity in the hidden units
- Multi-task learning
- Transfer learning

- Dropout [Hinton et al.]: randomly drop units (along with their connections) from the neural network during training. Use for the fully connected layers only

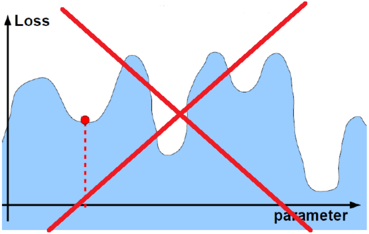


(a) Standard Neural Net (b) After applying dropout.

- Common knowledge: for non-convex problems, training does not work because we get stuck to local minima



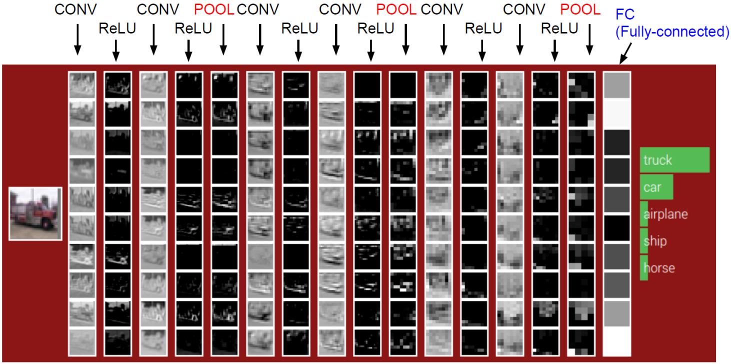
- Common knowledge: for non-convex problems, training does not work because we get stuck to local minima

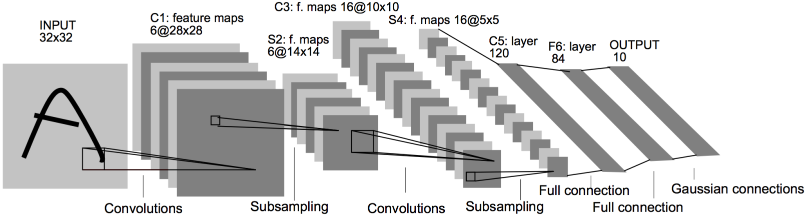


- Not true!!!
- If the size of the network is large enough, local descent can reach a global minimizer from any initialization

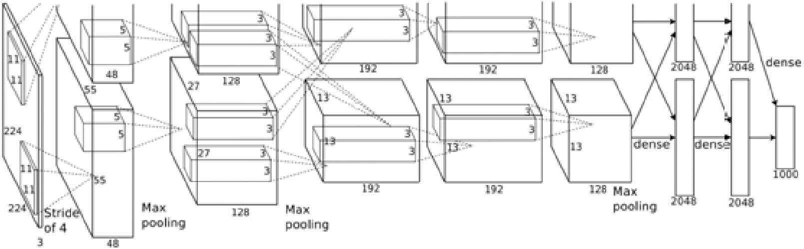
Haeffele, Vidal. Global Optimality in Tensor Factorization, Deep Learning and Beyond, arXiv'15

Typical ConvNet:
Image $\rightarrow$ [Conv - ReLU] $\rightarrow$ (Pool) $\rightarrow$ [Conv - ReLU] $\rightarrow$ (Pool) $\rightarrow$ FC (fully-connected) $\rightarrow$ Softmax



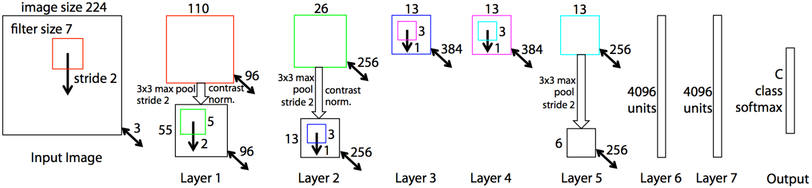


Lenet5 (Yann Lecun 1998)

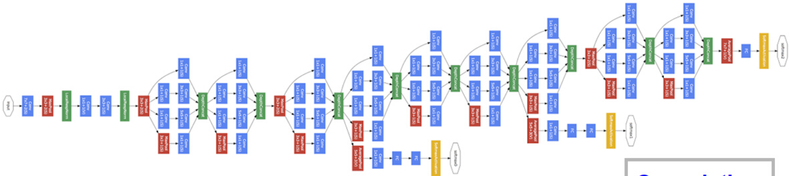


Alexnet (Alex Krizhevsky et. al., 2012)

ConvNets - Flavours



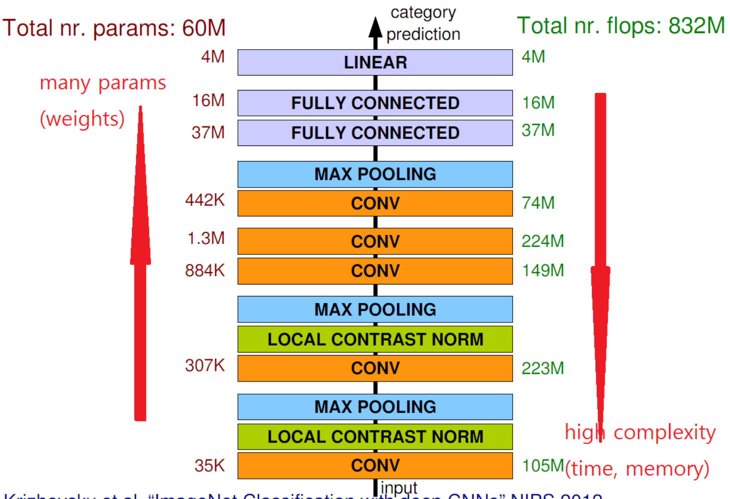
ZFnet: Clarifai (Matt Zeiler and Rob Fergus, 2013)



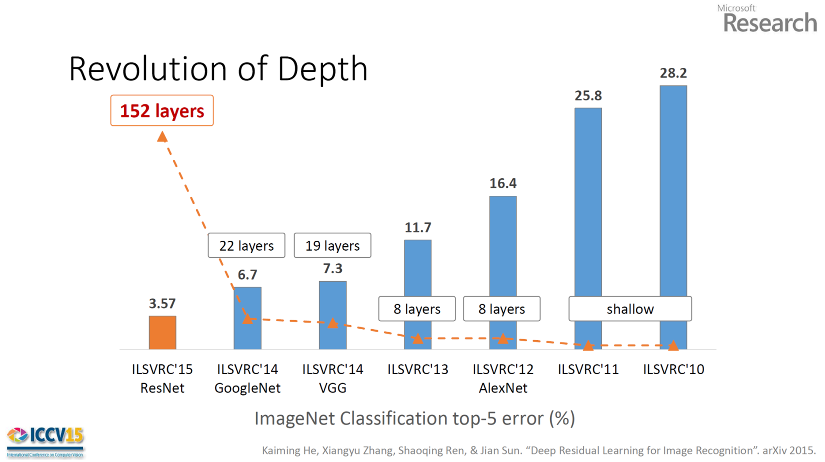
Googlenet (Google, 2014)

Convolution
Pooling
Softmax
Other

Complexity (Alexnet)



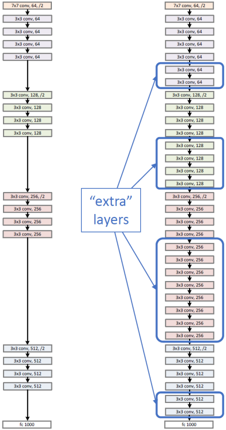
Krizhevsky et al. "ImageNet Classification with deep CNNs" NIPS 2012



- Human: 5.1% (Karpathy), Baidu cheating (2015.05) - 4.58%

Recent Trend

a shallower model (18 layers)



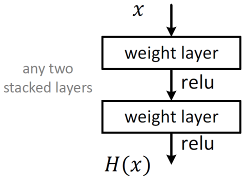
a deeper counterpart (34 layers)

- A deeper model should not have **higher training error**
- A solution *by construction*:
  - original layers: copied from a learned shallower model
  - extra layers: set as identity
  - at least the same training error
- Optimization difficulties: solvers cannot find the solution when going deeper...

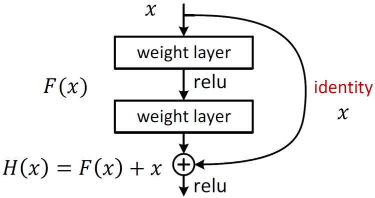
Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. “Deep Residual Learning for Image Recognition”. arXiv 2015.

Recent Trend

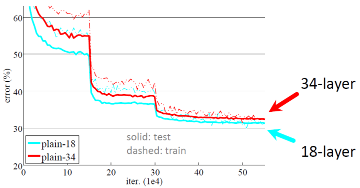
- Plaint net



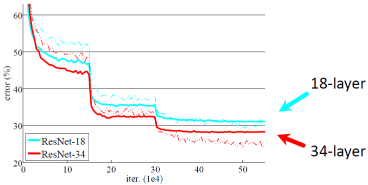
- Residual net



ImageNet plain nets



ImageNet ResNets



- Deep ResNets can be trained without difficulties
- Deeper ResNets have **lower training error**, and also lower test error

Conclusions

- Deep Learning = learning hierarhical models.
- ConvNets are the most successful example. Leverage large labeled datasets.
- Optimization
  - Don't we get stuck in local minima? No, they are all the same!
  - In large scale applications, local minima are even less of an issue.
- Scaling
  - GPUs
  - Distributed framework (Google)
  - Better optimization techniques
- Generalization on small datasets (curse of dimensionality):
  - data augmentation
  - weight decay
  - dropout
  - unsupervised learning
  - multi-task learning