

# **Introduction to Deep Learning and Convolutional Neural Networks**

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# Deep Learning???



deep learning



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JANUARY 25, 2017

## Deep learning algorithm does as well as dermatologists in identifying skin cancer

In hopes of creating better access to medical care, Stanford researchers have trained an algorithm to diagnose skin cancer.

BY TAYLOR KUBOTA

It's scary enough making a doctor's appointment to see if a strange mole could be cancerous. Imagine, then, that you were in that situation while also living far away from the nearest doctor, unable to take time off work and unsure you had the money to cover the cost of the visit. In a scenario like this, an option to receive a diagnosis through your smartphone could be lifesaving.

Universal access to health care was on the minds of computer scientists at Stanford when they set out to create an artificially intelligent diagnosis algorithm for skin cancer. They made a database of nearly 130,000 skin disease images and trained their algorithm to visually diagnose potential cancer. From the very first test, it performed with inspiring accuracy.

"We realized it was feasible, not just to do something well, but as well as a human dermatologist," said Sebastian Thrun, an adjunct professor in the Stanford Artificial Intelligence Laboratory. "That's when our thinking changed. That's



A dermatologist uses a dermatoscope, a type of handheld microscope, to look at skin. Computer scientists at Stanford have created an artificially intelligent diagnosis algorithm for skin cancer that matched the performance of board-certified dermatologists. (Image credit: Matt Young)

News

## Redwood City ready to debut futuristic delivery robots



## Amazon Go, deep learning, and a better retail experience

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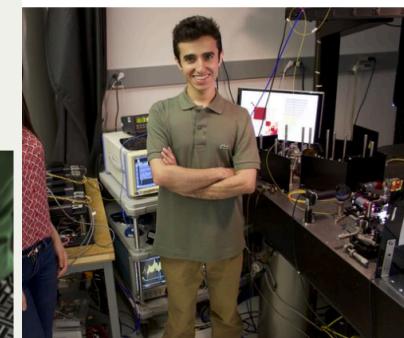


## Microscope uses artificial intelligence to find cancer cells more efficiently

Device invented by UCLA professor uses deep learning and photonic time stretch to analyze 10 million images per second

, 2016

TWEET in SHARE 177 EMAIL PRINT



Tunde Akinloye/CNSI

Atta Mahjoubfar with the new device, which can image cancer cells without damaging blood samples.

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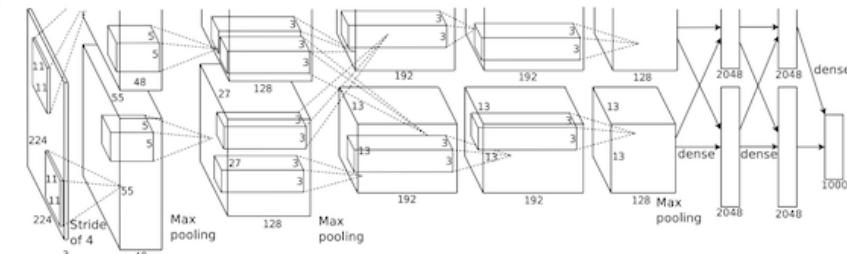
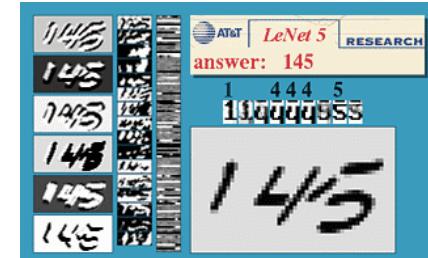
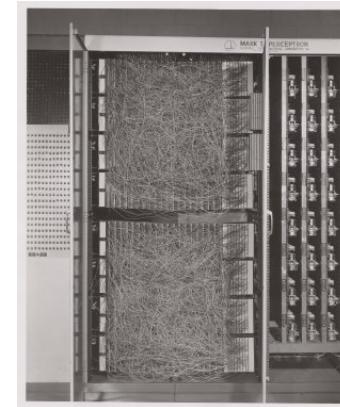
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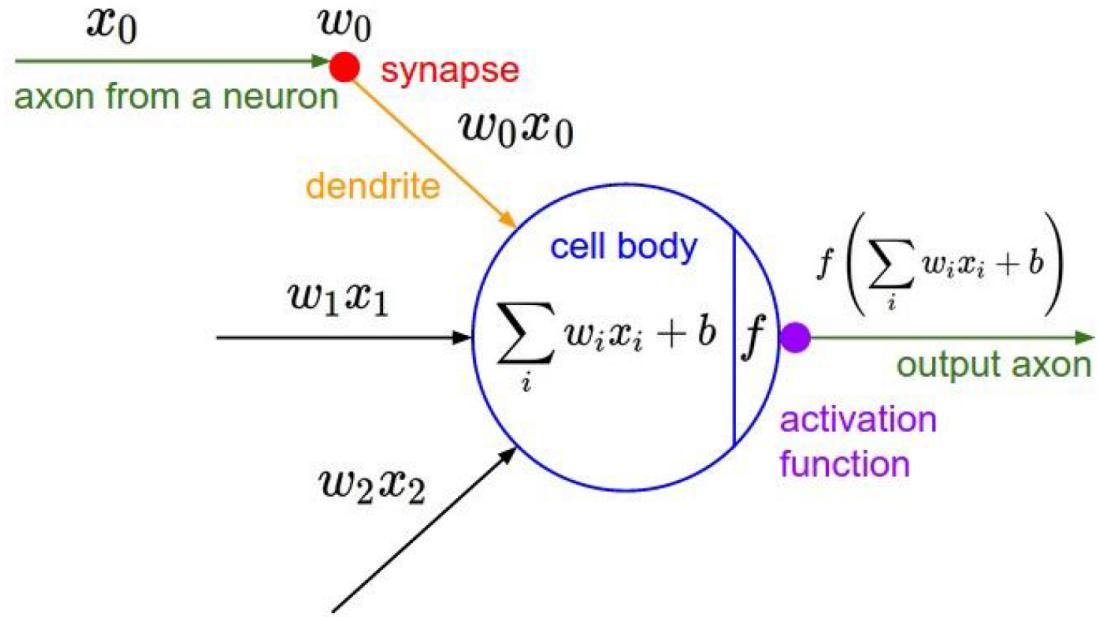
SCIENCE + TECHNOLOGY

# History

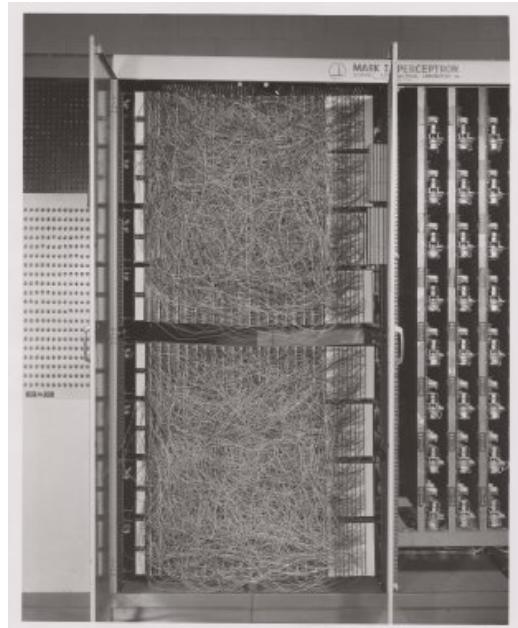
- **1957:** Perceptron
- **1960:** Adaline
- **1969:** Linear models  
can't learn XOR
- **70's:** not much
- **1980:** Neocognitron  
(based on V1)
- **80's:** Connectionism;  
first back propagation  
studies (modest results)
- **1998:** LeNet  
(convolutional)
- **2006:** Back propagation  
improvements
- **2012:** AlexNet



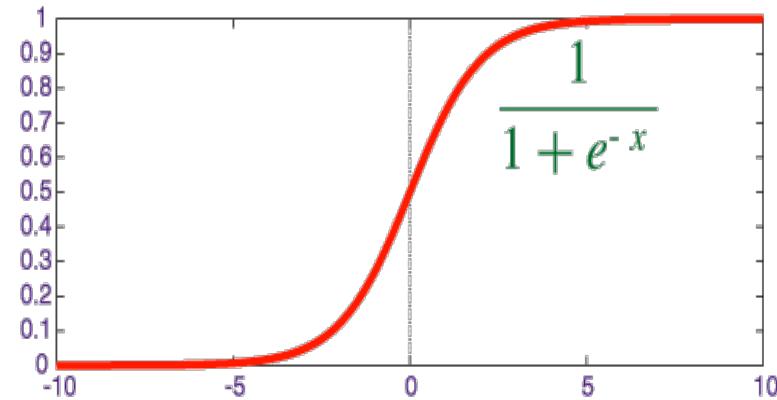
# The Perceptron



source: (Andrej, 2016)



- Simple mathematical model of a neuron
- Sigmoid was used to model the a neurons “firing rate”



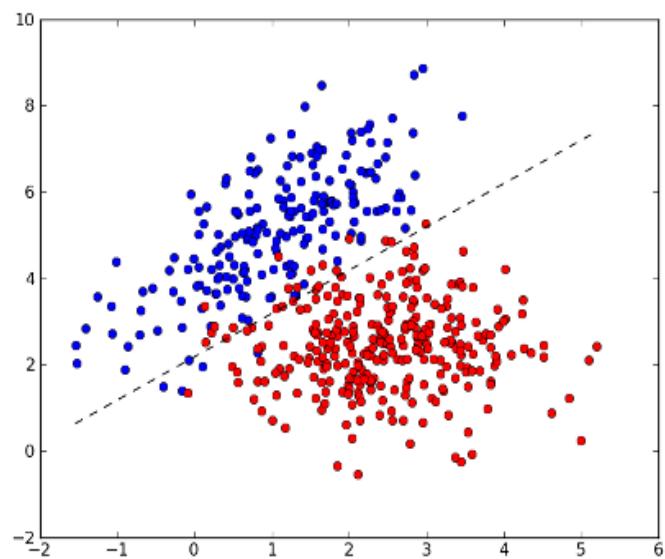
# Linear Classifier

- Linear classifier

$$f(x, W, b) = Wx + b$$

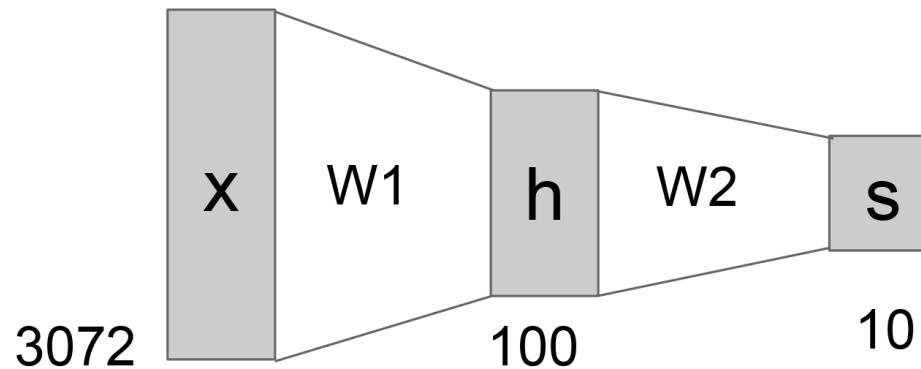
$$f = \sum_i (w_i x_i + b)$$

- $x$ : image
- $W$ : weights
- $b$ : bias, independent from data
- Parametric approach



# 2-Layer Neural Network

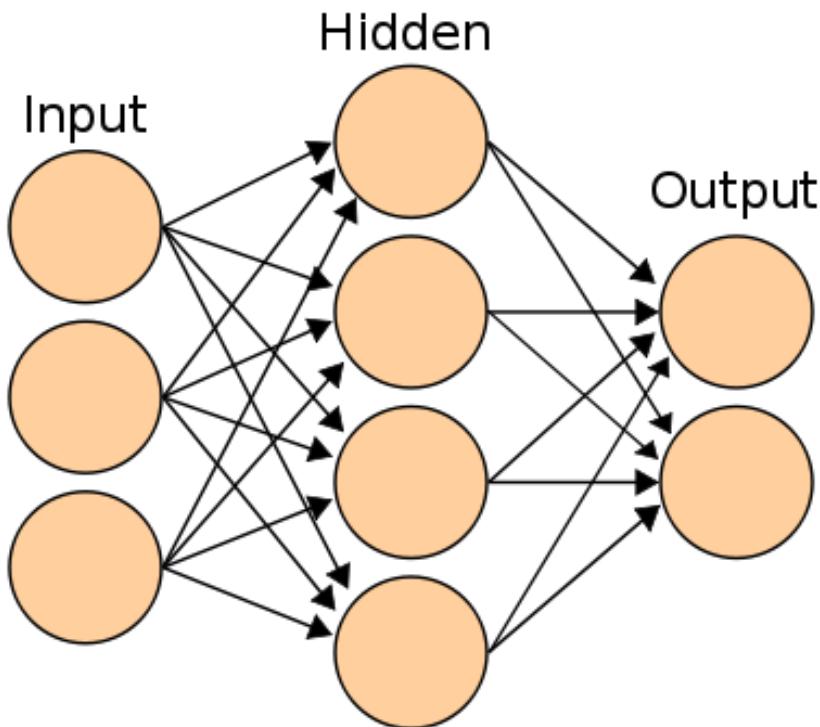
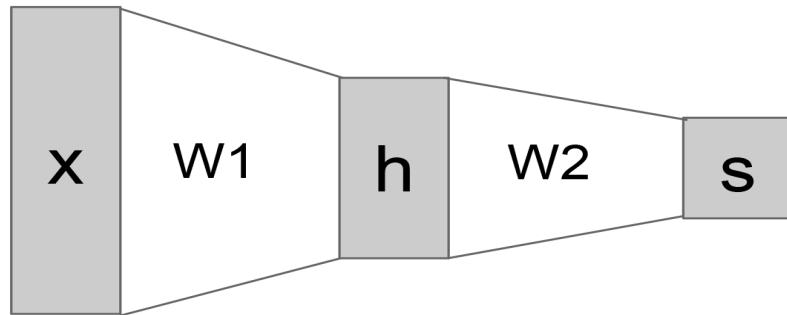
$$f = W_2 \max(0, W_1 x)$$



source: (Andrej, 2016)

$$f = W_3 \max(0, W_2 \max(0, W_1 x))$$

# 2-Layer Neural Network



- Neural nets are organized in layers
- Amenable to vectorization
- Can run in parallel
- More efficient

# Softmax

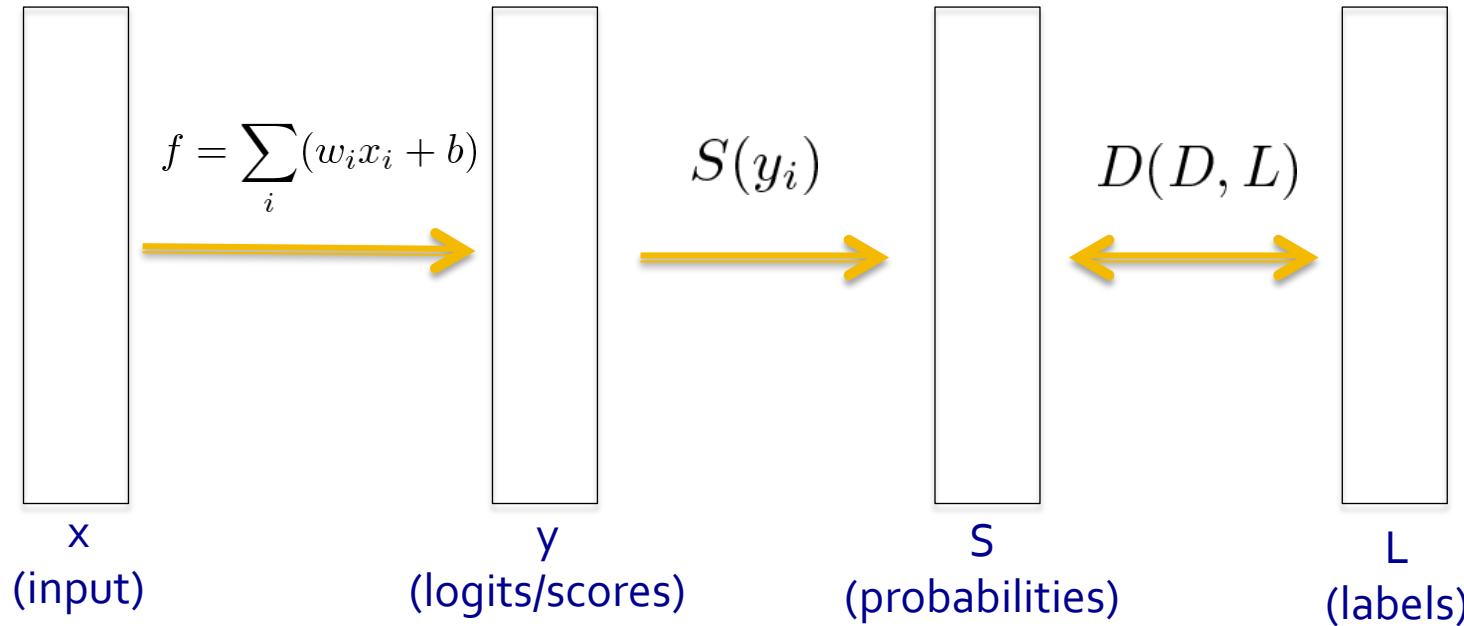
$$S(y_i) = \frac{\exp(y_i)}{\exp(\sum_j \exp(y_j))}$$

- Input: scores from the last layer
- Output: probability distribution over the  $j$  classes

# Loss Function

- Loss functions: compute the distance between classification and training **labels**
- Cross-entropy

$$D(D, L) = - \sum_i L_i \log(S_i)$$



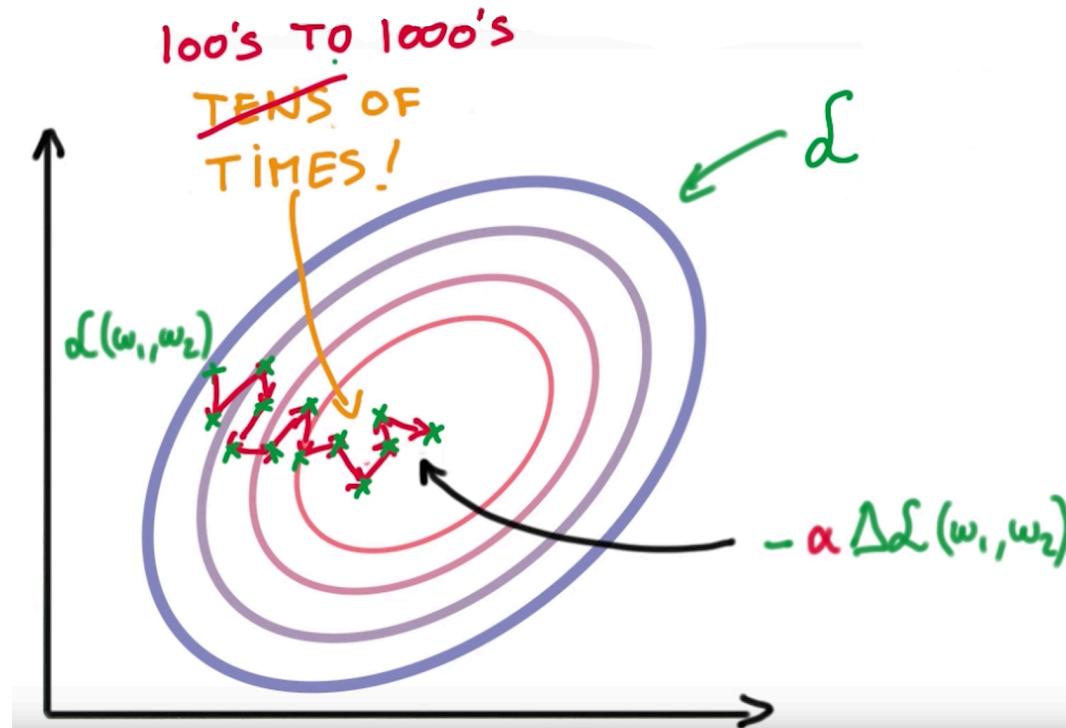
# Loss Function & Training

- Loss

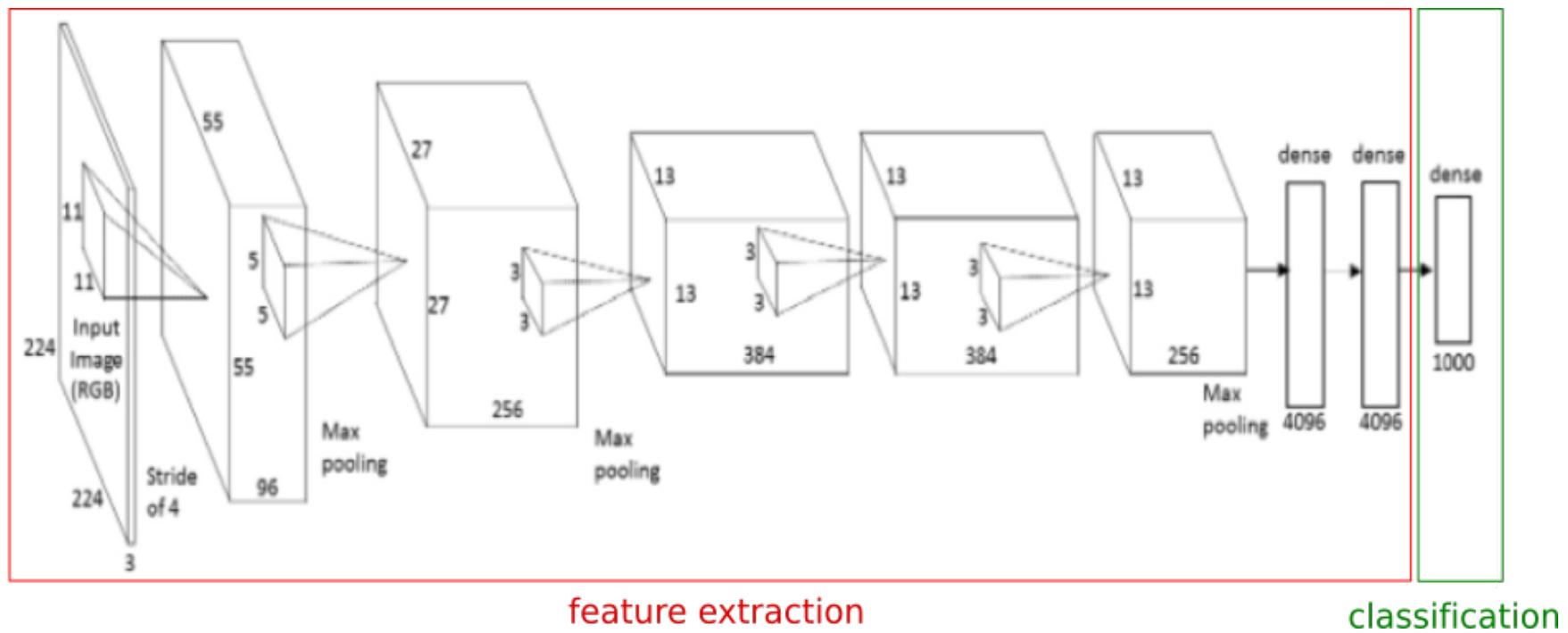
$$\mathcal{L} = \frac{1}{N} \sum_i D(S(Wx_i + b), L_i)$$

our network goes here

- Parameters **W** and **b** can be learned by optimization: **SGD**
- Gradients are computed by **Back Propagation**



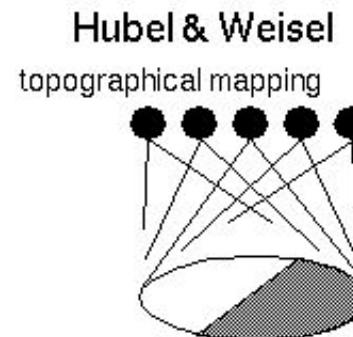
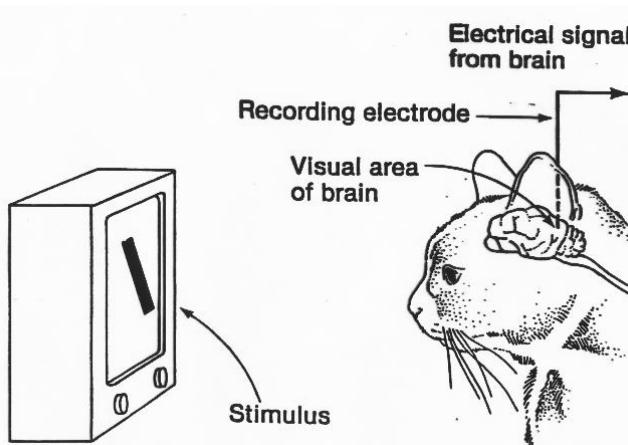
# Convolutional Network (ConvNet)



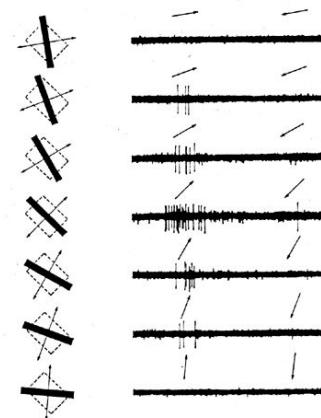
- Computer vision: detection, localization, segmentation
- Convolutional layers + fully connected layers work as a filter bank
  - Representations get more abstract in deeper layers
- Last layer outputs the class scores

# Biological Motivation

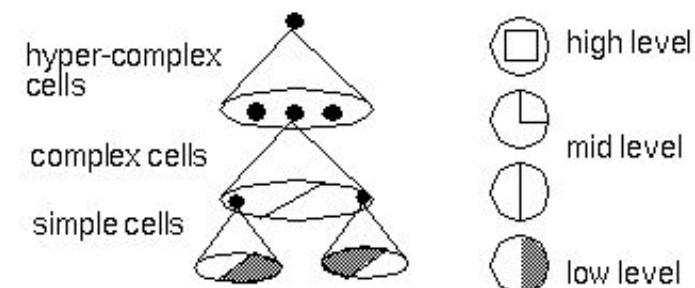
- Hubel & Weisel (late 50's)
  - Cat's neurons responded to images projected in specific locations
  - Early visual cortex responded strongly to oriented bars
  - Identified visual cortex hierarchical architecture
  - Nobel prize in 1981



V1 physiology:  
direction  
selectivity

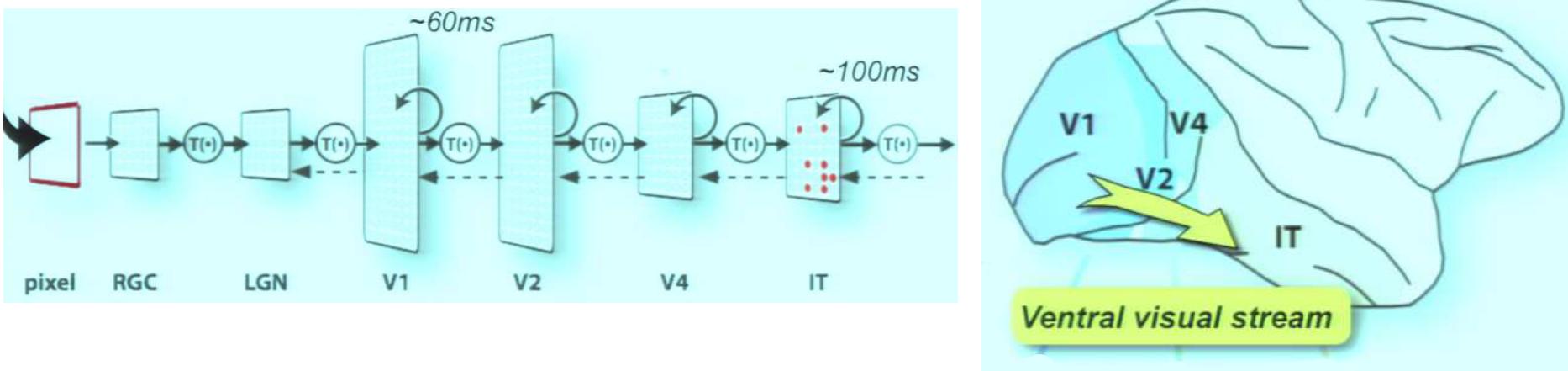


featural hierarchy



# Biological Motivation

- Simplified view of the visual system



source: (DiCarlo, 2013)

- RGC and LGN mainly carry signal to V1
- V1 is arranged in a spatial map.
- V1 (in our model) is composed of simple-cells and complex cells.
  - Simple cells: detect spatially localized features
  - Complex cells: detect spatially localized features, somewhat invariant to light changes and shifts in position

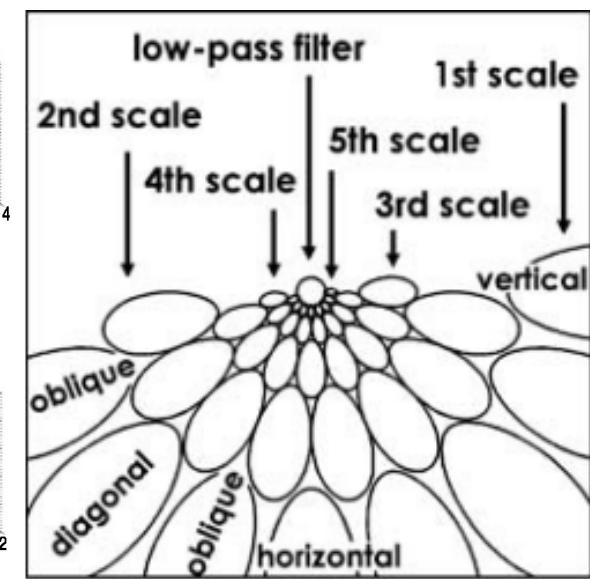
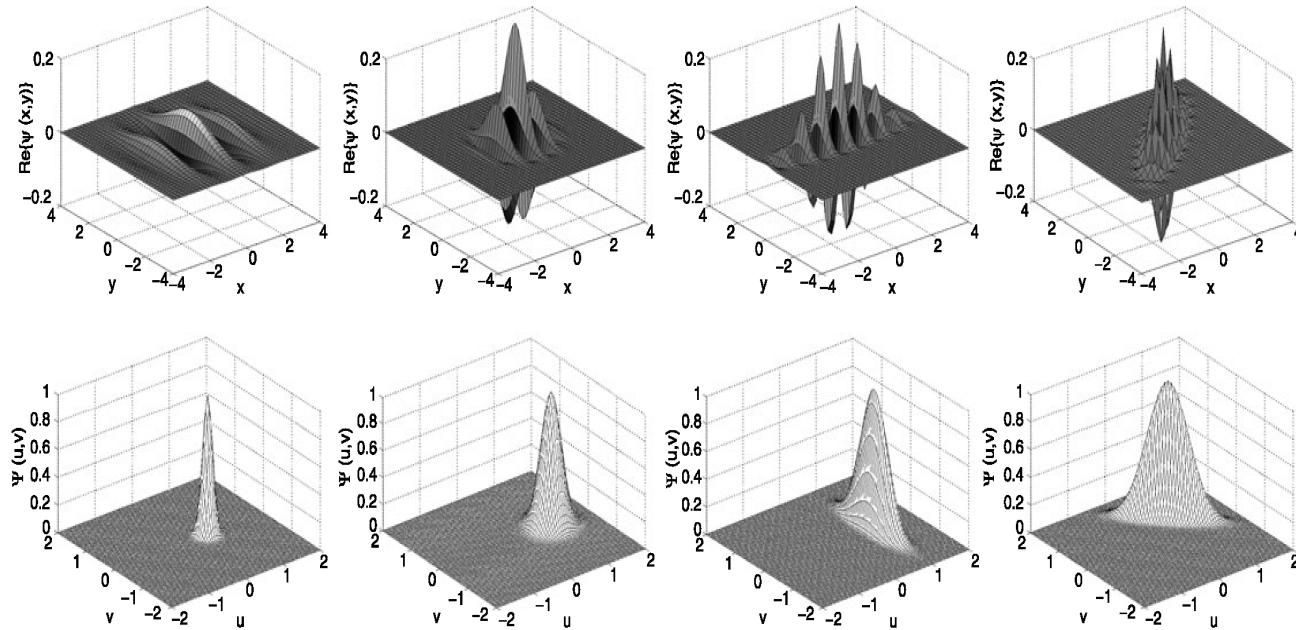
# Biological Motivation

- V1 cell responses can be modeled as Gabor filters

$$w(x, y, \alpha, \beta_x, \beta_y, f, \phi, x_0, y_0, \tau) = \alpha \exp(-\beta_x x'^2 - \beta_y y'^2) \cos(fx' + \phi)$$

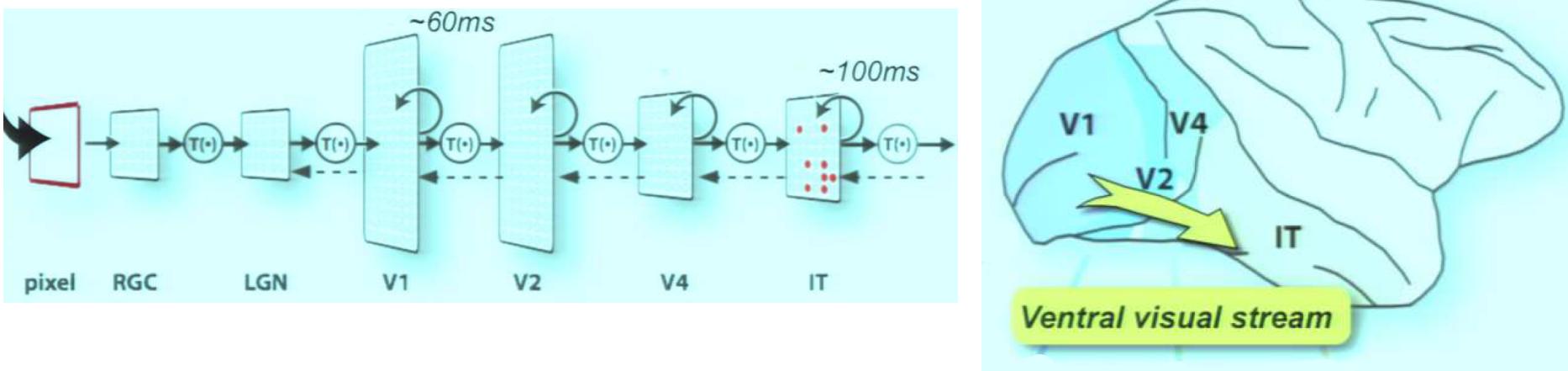
$$x' = (x - x_0)\cos(\tau) + (y - y_0)\sin(\tau)$$

$$y' = -(x - x_0)\sin(\tau) + (y - y_0)\cos(\tau)$$



# Biological Motivation

- Simplified view of the visual system

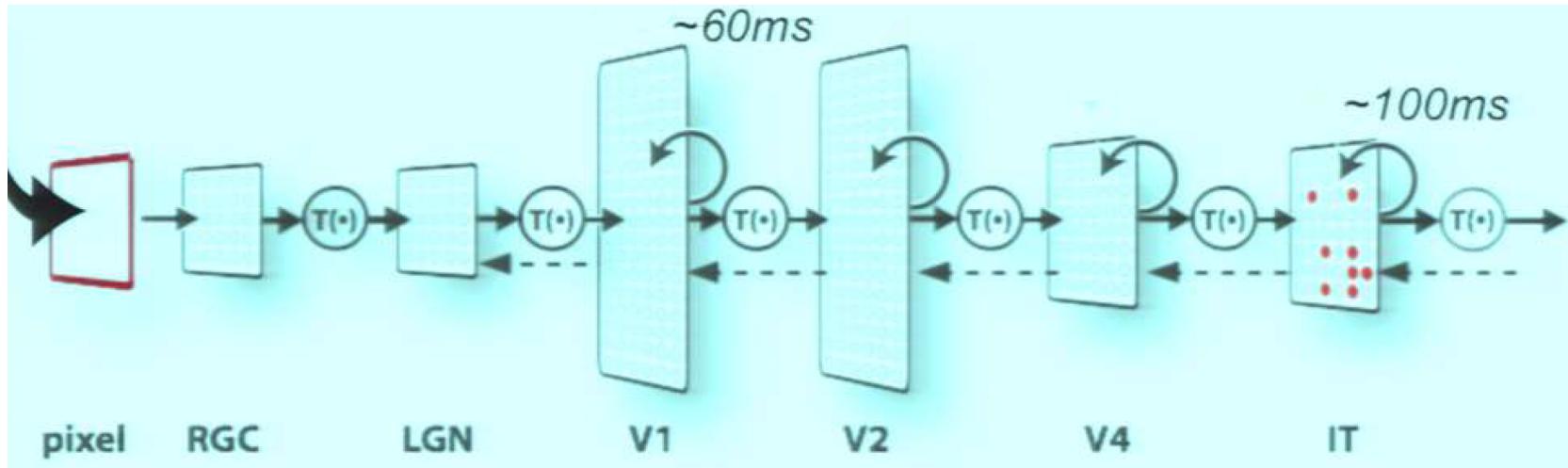


source: (DiCarlo, 2013)

- ConvNet are designed to capture 3 V1 properties:
  - Simple cells: ConvNet detectors (kernels) simulate simple cells
  - Complex cells: Pooling units simulate complex cells
  - Spatial mapping: ConvNets also consider input information as 2D maps

# Biological Motivation

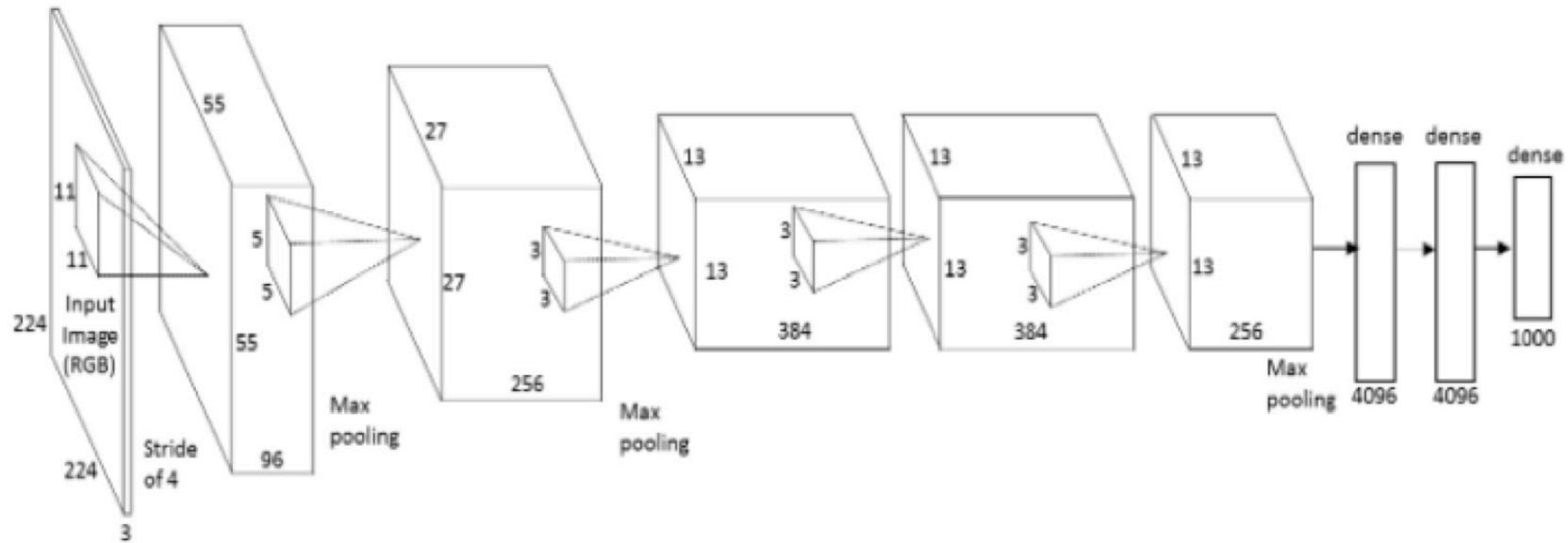
- Simplified view of the visual system



source: (DiCarlo, 2013)

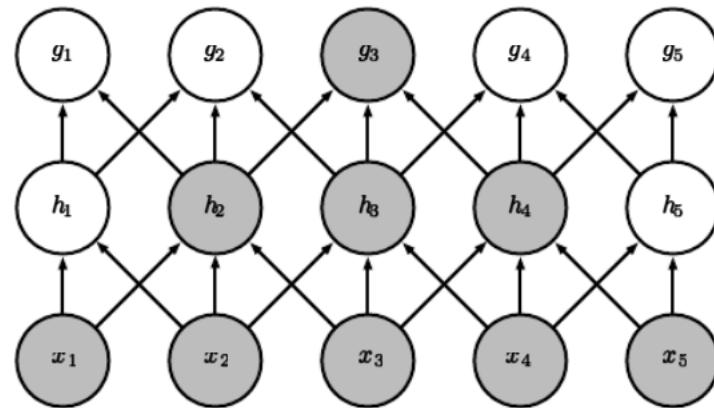
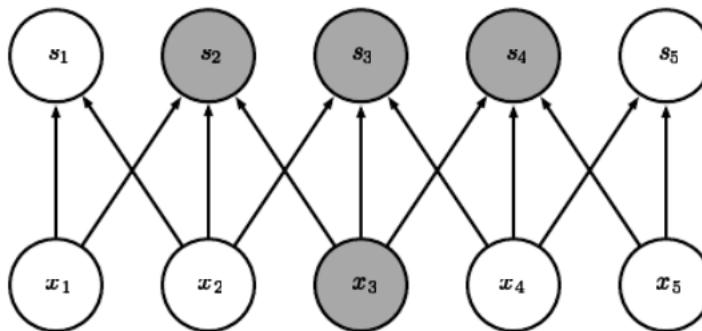
- Convolution + pooling is repeated through the visual cortex layers
- “grandmother cells” fire for specific concepts, located in the medial temporal lobe (in humans).
  - Invariant to input transformations
- Inferotemporal cortex (IT) layer is similar to a ConvNet last layer

# Convolutions



- $m(t) = (x * k)(t)$
- **m = feature map**
- $x$  = input: multidimensional array (aka **tensor**) of data (image)
- $k$  = **kernel**: multidimensional filter, tuned by the learning algorithm
- Convolution can be seen as a weighted sum

# Convolutions



source: (Goodfellow, 2016)

- **Receptive field:** portion of a lower layer that affects a neuron on the upper layer
- Parameter sharing and sparse connectivity
  - Less parameters to store (less memory)
  - Smaller number of computations
  - Better statistical efficiency
- Equivariance to translation
  - If the input is translated, the output is translated in the same way

# Convolutions

- Activation map size

$$A = \left[ \frac{N - F}{S} \right] + 1$$

N: input size

F: filter size

S: stride

- Padding size

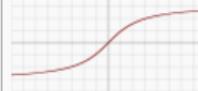
$$P = \frac{(F - 1)}{2}$$

F: filter size

```
def conv_relu(bottom, ks, nout, stride=1, pad=0, group=1,
              param=learned_param,
              weight_filler=dict(type='gaussian', std=0.01),
              bias_filler=dict(type='constant', value=0.1)):
    conv = L.Convolution(bottom, kernel_size=ks, stride=stride,
                         num_output=nout, pad=pad, group=group,
                         param=param, weight_filler=weight_filler,
                         bias_filler=bias_filler)
    return conv, L.ReLU(conv, in_place=True)

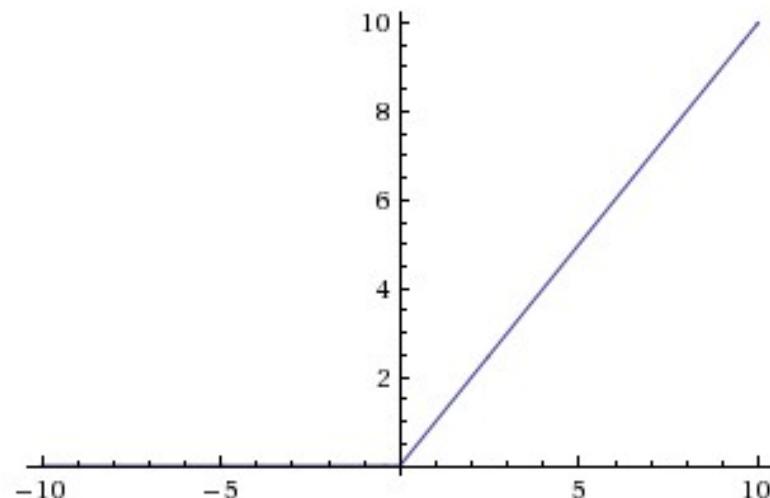
n.convl, n.relu1 = conv_relu(n.data, 11, 96, stride=4, param=param)
```

# Activation Functions

Name	Plot	Equation	Derivative
Identity		$f(x) = x$	$f'(x) = 1$
Binary step		$f(x) = \begin{cases} 0 & \text{for } x < 0 \\ 1 & \text{for } x \geq 0 \end{cases}$	$f'(x) = \begin{cases} 0 & \text{for } x \neq 0 \\ ? & \text{for } x = 0 \end{cases}$
Logistic (a. k. a Soft step)		$f(x) = \frac{1}{1 + e^{-x}}$	$f'(x) = f(x)(1 - f(x))$
TanH		$f(x) = \tanh(x) = \frac{2}{1 + e^{-2x}} - 1$	$f'(x) = 1 - f(x)^2$
ArcTan		$f(x) = \tan^{-1}(x)$	$f'(x) = \frac{1}{x^2 + 1}$
Rectified Linear Unit (ReLU) [2]		$f(x) = \begin{cases} 0 & \text{for } x < 0 \\ x & \text{for } x \geq 0 \end{cases}$	$f'(x) = \begin{cases} 0 & \text{for } x < 0 \\ 1 & \text{for } x \geq 0 \end{cases}$
Parameteric Rectified Linear Unit (PReLU) [2]		$f(x) = \begin{cases} \alpha x & \text{for } x < 0 \\ x & \text{for } x \geq 0 \end{cases}$	$f'(x) = \begin{cases} \alpha & \text{for } x < 0 \\ 1 & \text{for } x \geq 0 \end{cases}$
Exponential Linear Unit (ELU) [3]		$f(x) = \begin{cases} \alpha(e^x - 1) & \text{for } x < 0 \\ x & \text{for } x \geq 0 \end{cases}$	$f'(x) = \begin{cases} f(x) + \alpha & \text{for } x < 0 \\ 1 & \text{for } x \geq 0 \end{cases}$
SoftPlus		$f(x) = \log_e(1 + e^x)$	$f'(x) = \frac{1}{1 + e^{-x}}$

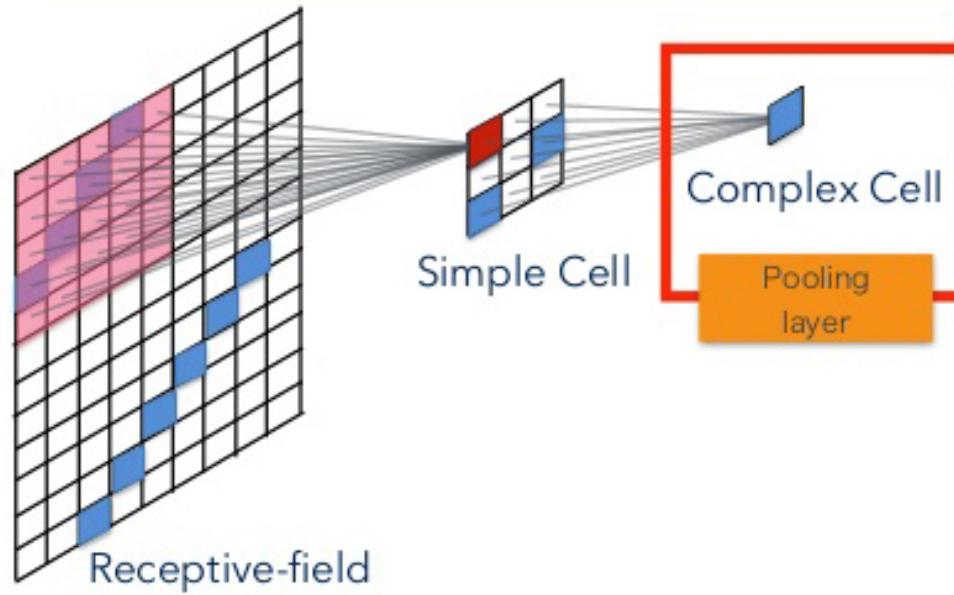
# ReLU (Rectified Linear Unit)

- $f(x) = \max(0, x)$



- Nice mathematical properties
  - Easier to optimize
- Final function remains approximately linear
- Large derivatives
- Avoids vanishing gradients
- Not trainable (doesn't have weights)

# Pooling



source: (Matsui, 2015)

- Computes some kind of summary statistics of the output
- More common: **max pooling**
- Helps make representation invariant to small translations
- Improves network statistical efficiency
- Not trainable

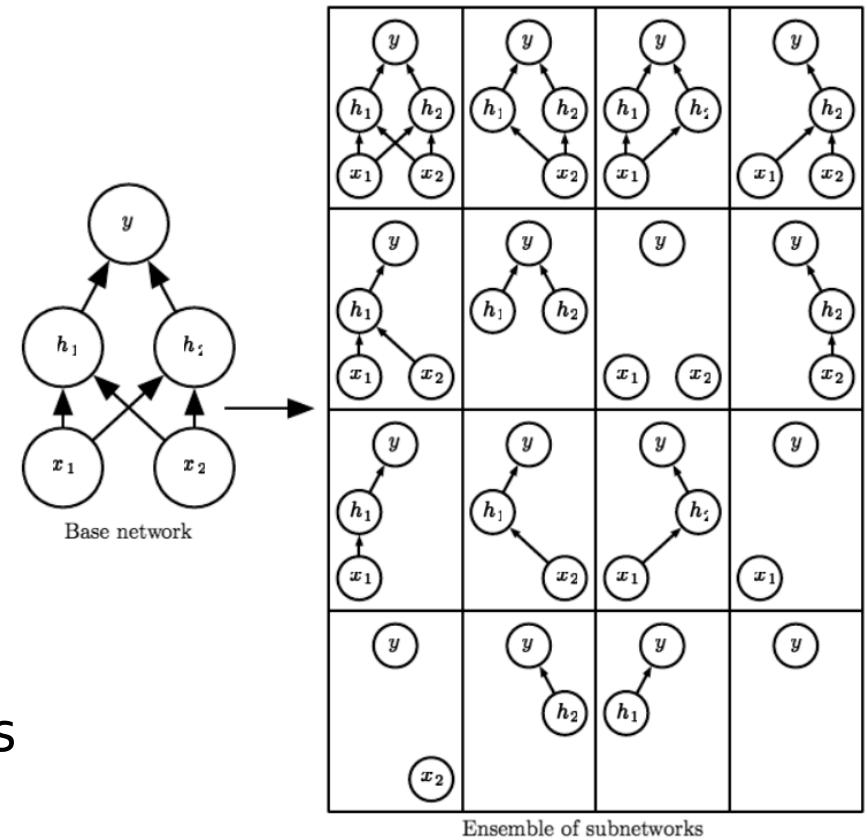
# Pooling

- Kernel size
- Stride
- Pooling function

```
def max_pool(bottom, ks, stride=1):
    return L.Pooling(bottom, pool=P.Pooling.MAX, kernel_size=ks, stride=stride)
```

# Dropout

- Inexpensive regularization
- Only used in training
- Works by randomly “muting” some connections during training
- Trains ensemble of “subnetworks”
- Computes average of the results
- Not effective for small networks



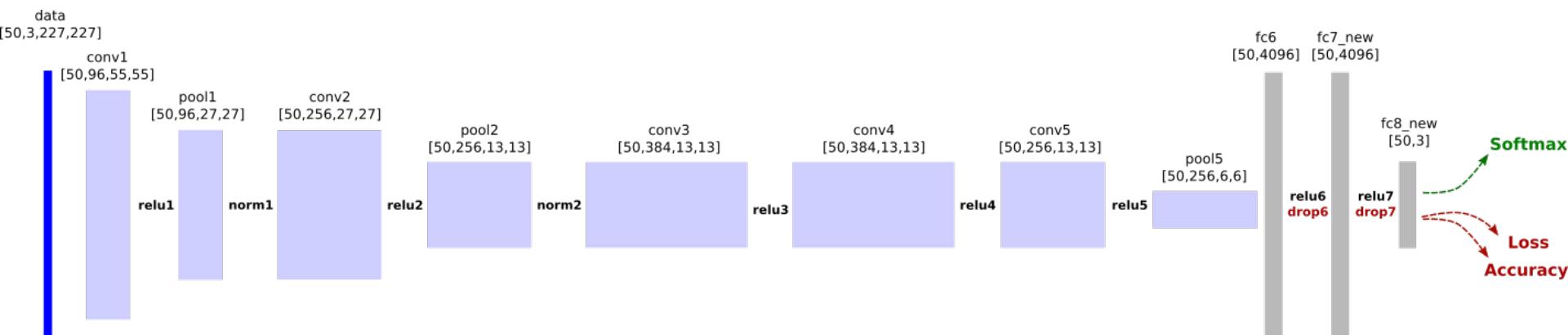
source: (Goodfellow, 2016)

```
fc7input = L.Dropout(n.relu6, in_place=True)
```

# Architectures

- There's no "best architecture" but several successful ones
- Empirical
- Standard combination of layers:

```
INPUT -> [ [CONV -> RELU]*N -> POOL?] *M -> [FC -> RELU]*K -> FC
```



# Deep Learning Frameworks

	Caffe	Torch	Theano	TensorFlow
Language	C++, Python	Lua	Python	Python
Pretrained	Yes ++	Yes ++	Yes (Lasagne)	Inception
Multi-GPU: Data parallel	Yes	Yes DataParallelTable	Yes platoon	Yes
Multi-GPU: Model parallel	No	Yes fbcunn.ModelParallel	Experimental	Yes (best)
Readable source code	Yes (C++)	Yes (Lua)	No	No
Good at RNN	No	Mediocre	Yes	Yes (best)

source: (Andrej, 2016)

# References

- (Goodfellow, 2016)**: Goodfellow, I.; Bengio, Y.; Courville, A. Deep Learning (book). MIT Press, 2016. (Free online: <http://www.deeplearningbook.org/>)
- (Andrej, 2016)**: Stanford class notes (<http://cs231n.stanford.edu/>)
- (DiCarlo, 2013)**: NIPS 2013 Tutorial (<https://www.youtube.com/watch?v=yDvfm7nzIV8>)
- (Matsui, 2015)**: Presentation slides (  
<http://www.slideshare.net/matsukenbook/deep-learning-chap6-convolutional-neural-net>)
- (Google, 2015)**: Google's Deep Learning course (<https://www.udacity.com/course/deep-learning--ud730>)
- Caffe**: <http://caffe.berkeleyvision.org/>
- Tensorflow**: <https://www.tensorflow.org/>
- Torch**: <http://torch.ch/>
- Theano**: <http://deeplearning.net/software/theano/#>