VISUAL COMPUTING
& SECURITY LAB

Deep Learning with Convolutional Neural Networks

Sebastian Hegenbart

November, 2015

Motivation

Did you ever wonder what that deep learning and CNN stuff everyone talks about is?!

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You might also wonder what this image is about!?

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Worry no more! You will know in approximately 5 hours!

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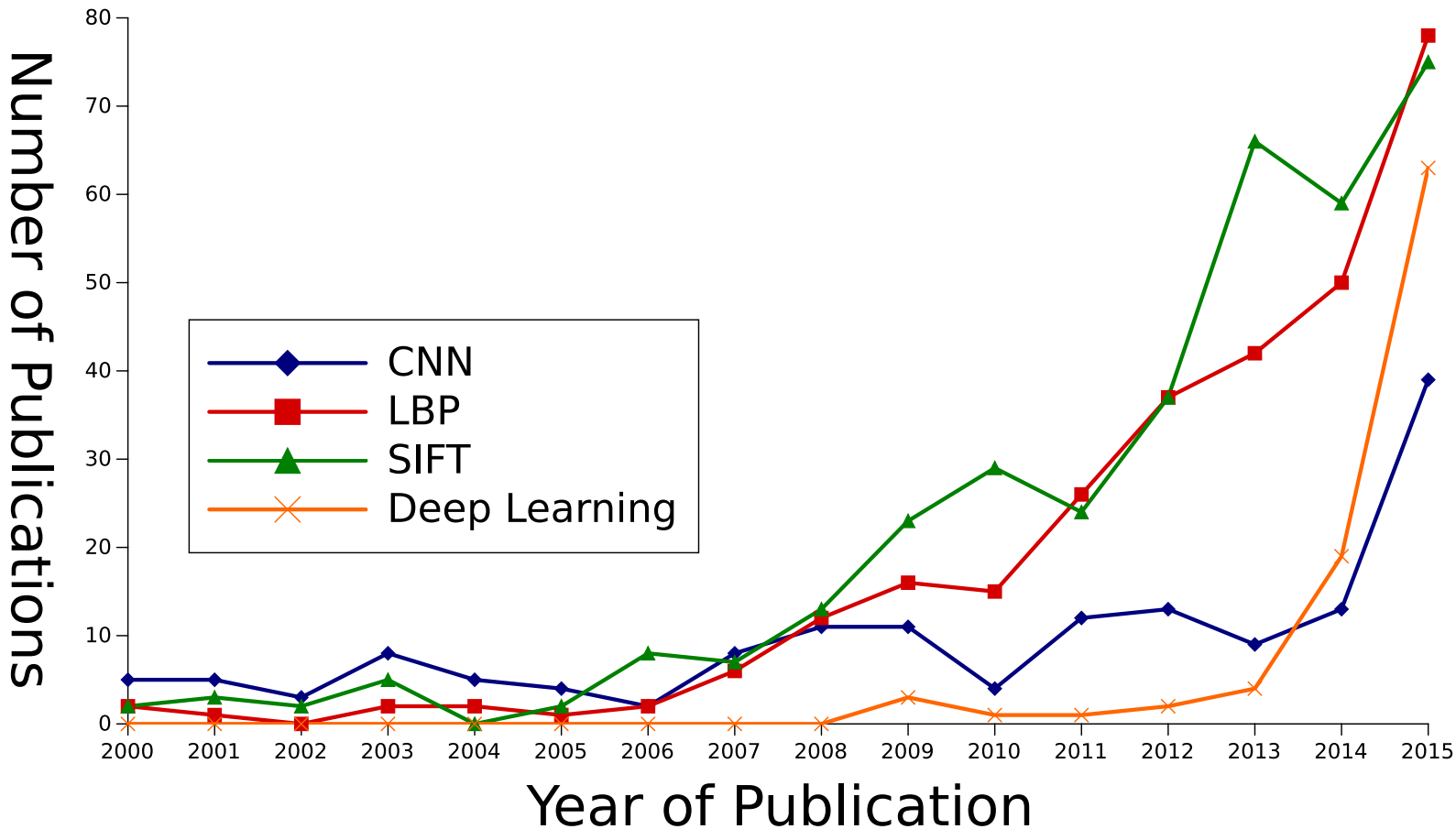
6. ConvNets are seeping into **industry** as well!

Motivation cont.

As quick search on **Science Direct** gives a raw estimate of the number of journal publications from 2000 to 2015. Deep learning and CNNs are **gaining** more and more **interest**.



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This talk should give you a head start getting into ConvNets and deep learning, even if you know little or nothing about ANNs.

From the Brain to Convolutional Neural Networks

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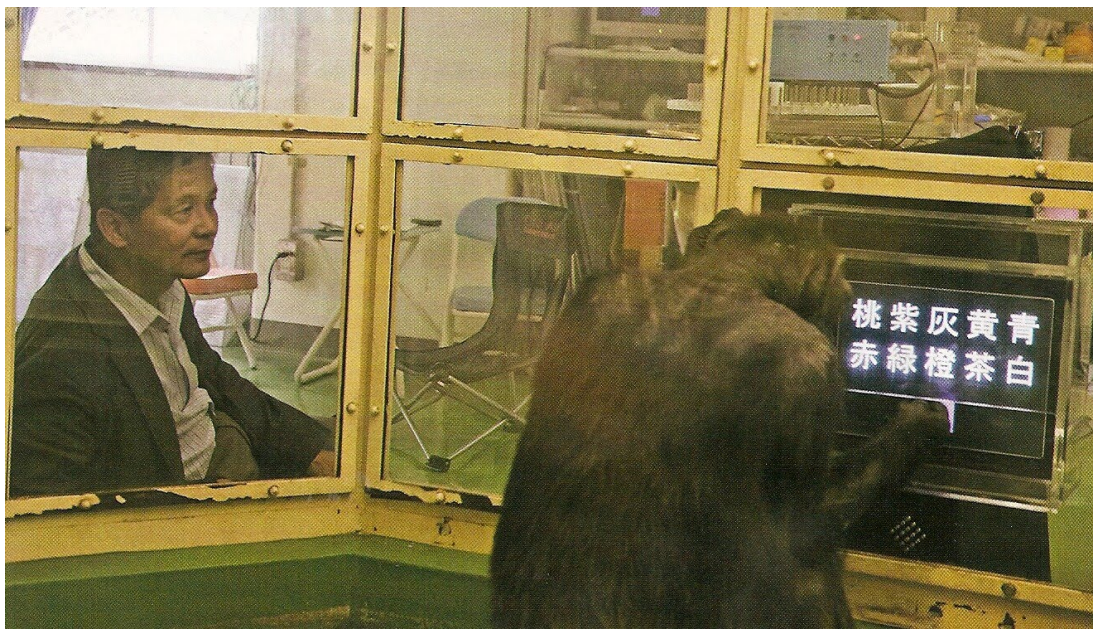

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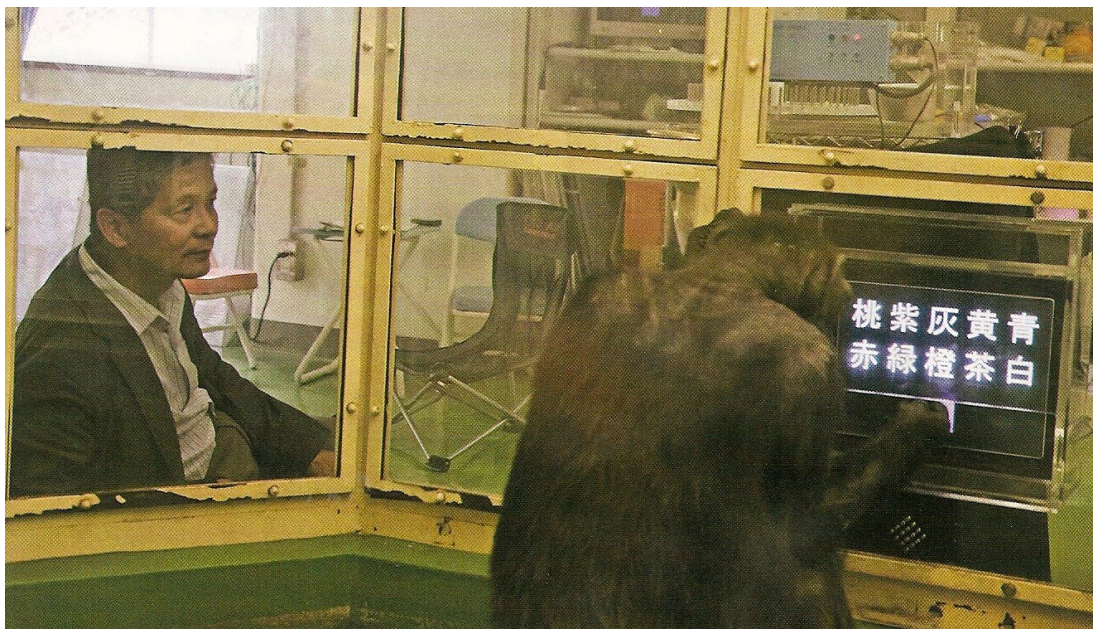

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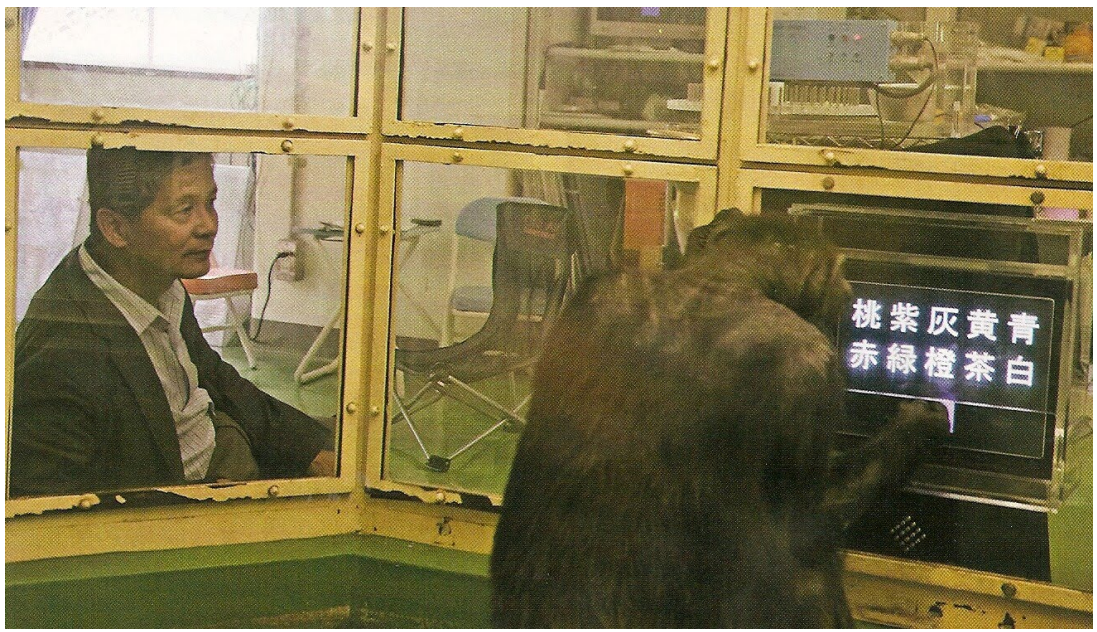
3. **Neural networks** are **inspired** by the mammal **brain** and are capable of "programming themselves" or "learn" to solve a problem



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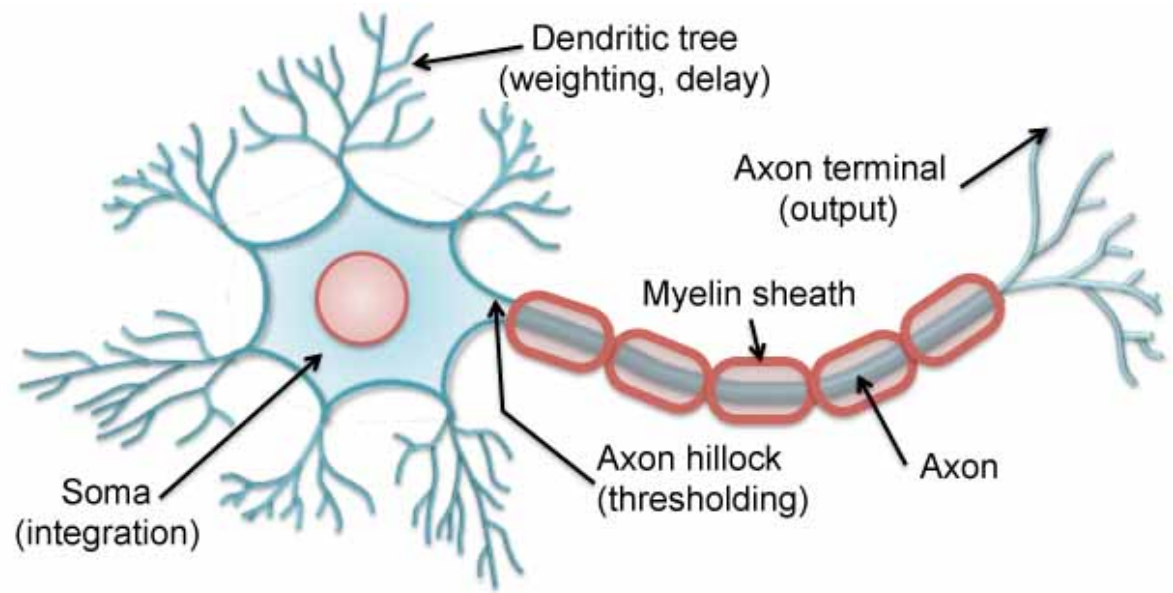

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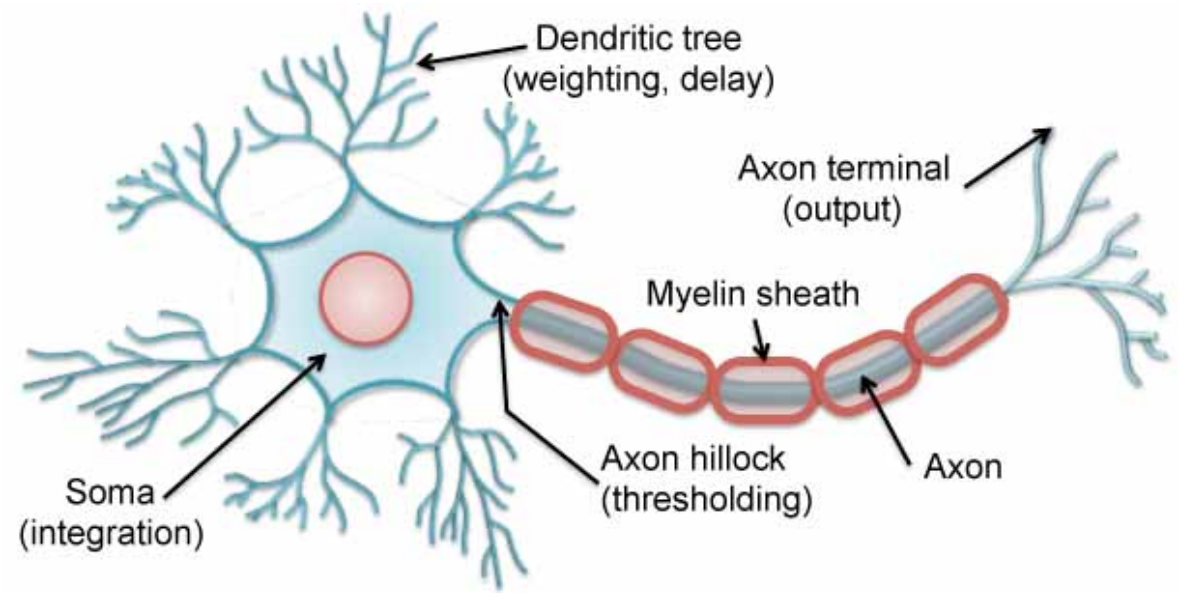

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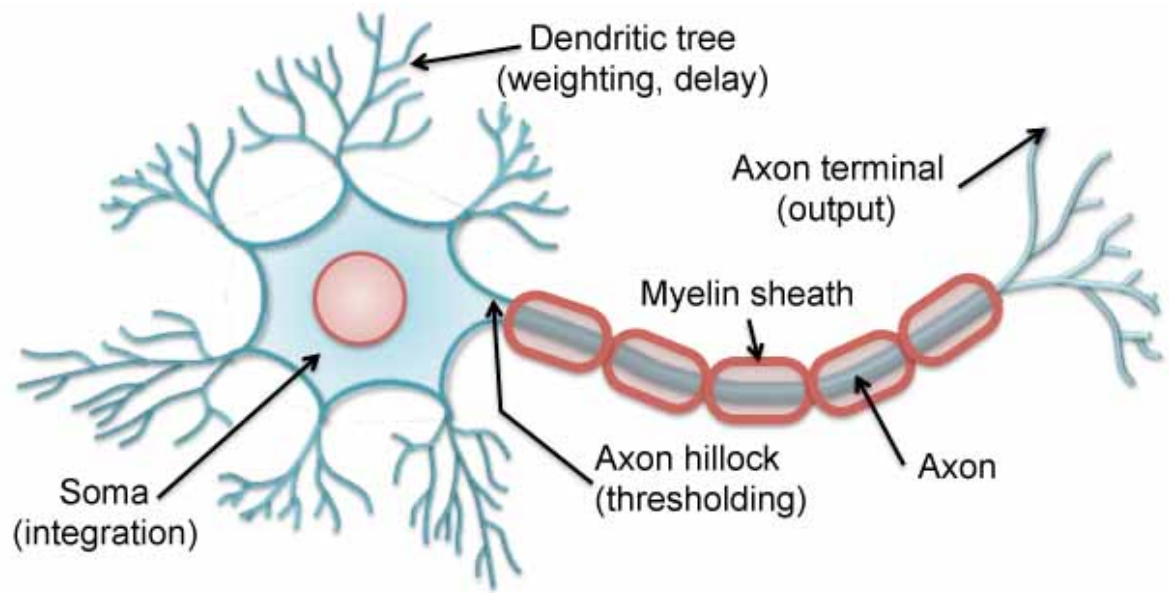
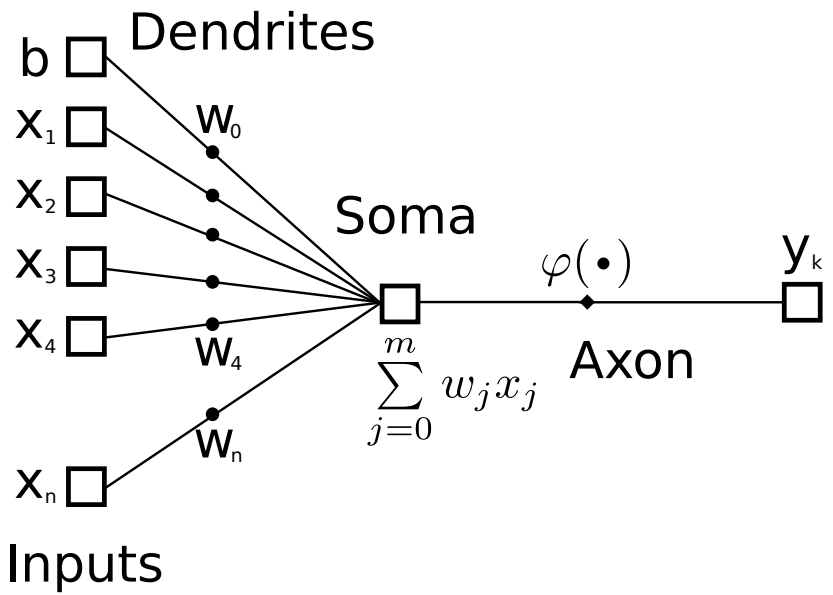
3. With the use of **synapses**, **neurons** form a **network sending signals** to specific target cells



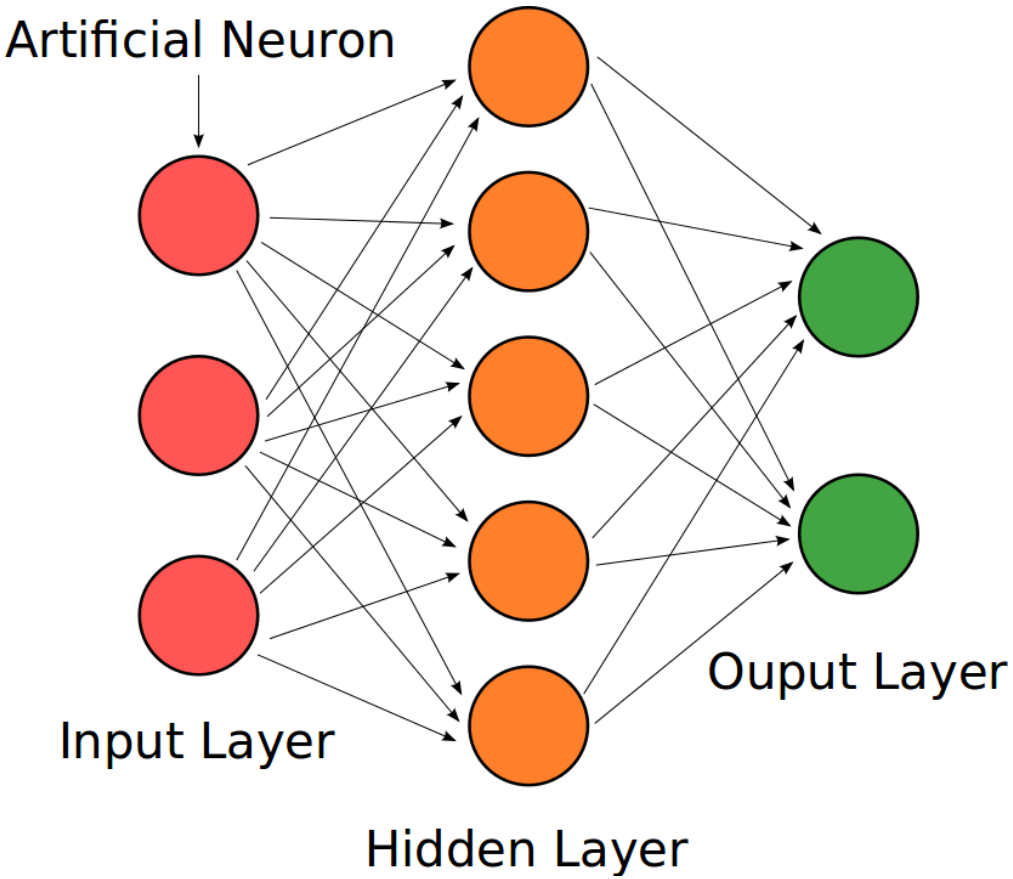
The **neurons modeled** in NN are a **simplification** of the biological counterpart.



Artificial Neuron used in NN

From the Brain to Convolutional Neural Networks

Multiple **fully connected neurons** in multiple layers then **build** a full neural **network**.



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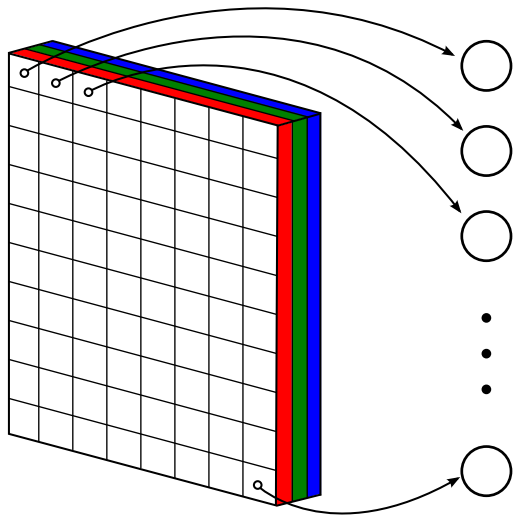

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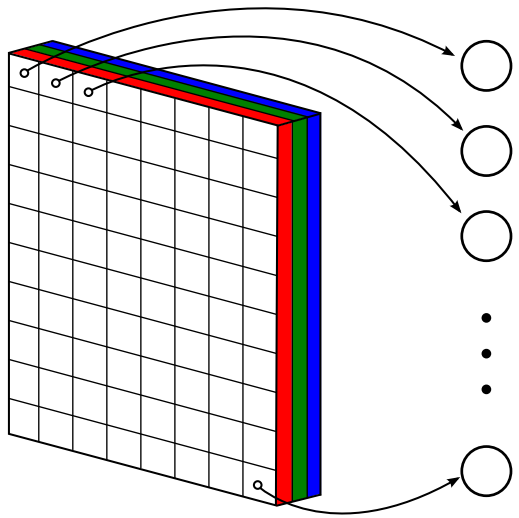

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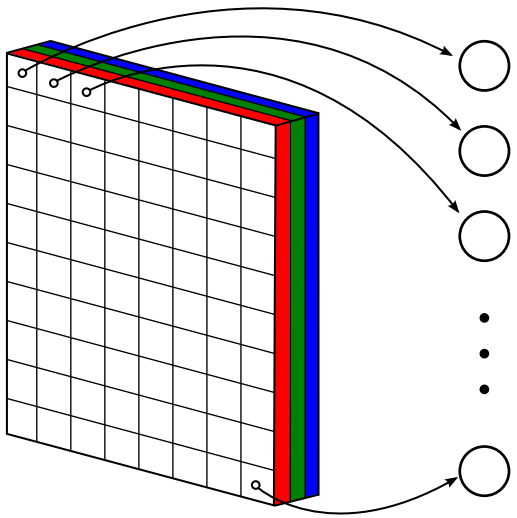

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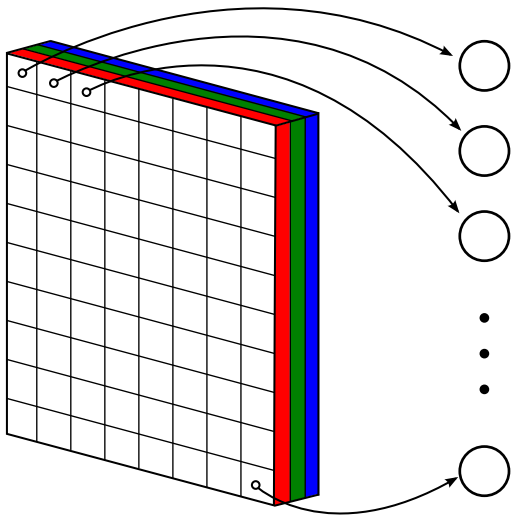

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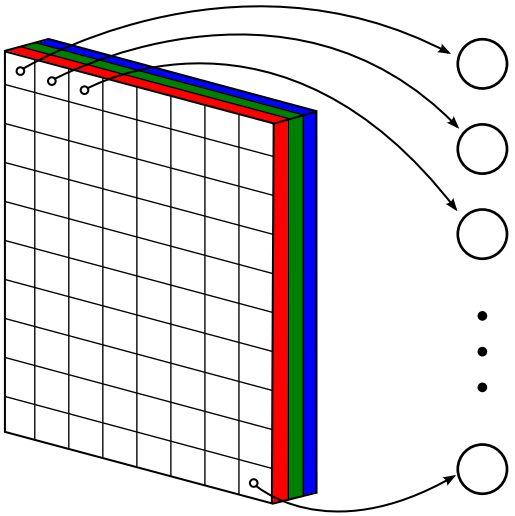

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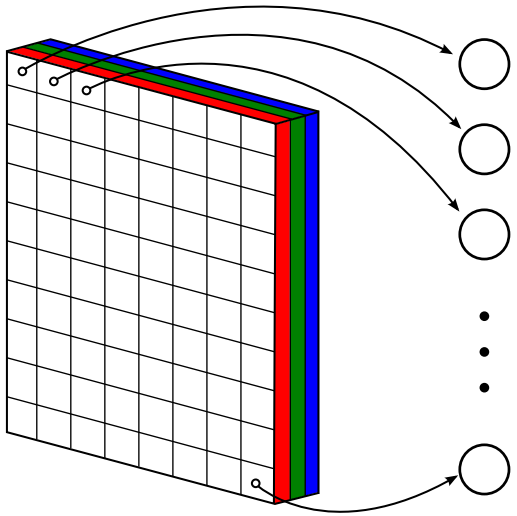

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SVMs and other simpler (and faster) methods gradually overtook ANNs in machine learning over the last 15 years

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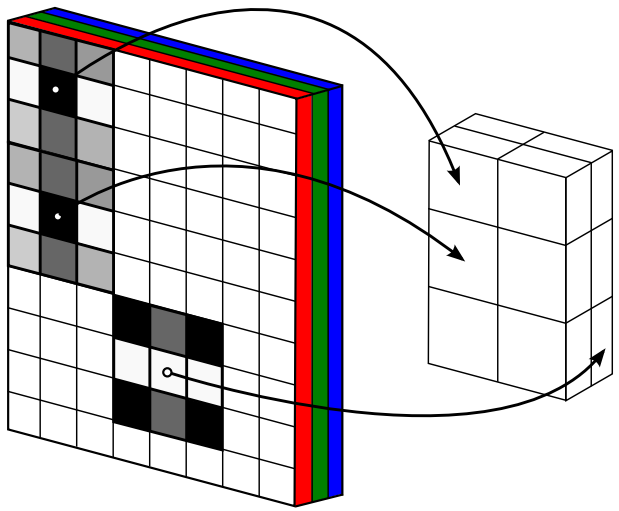

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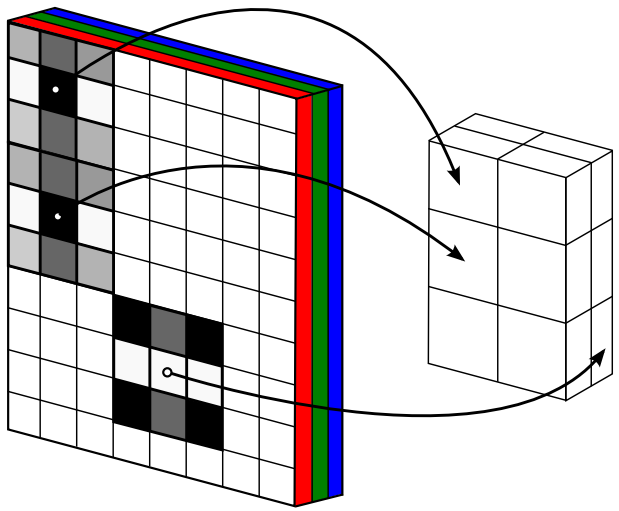

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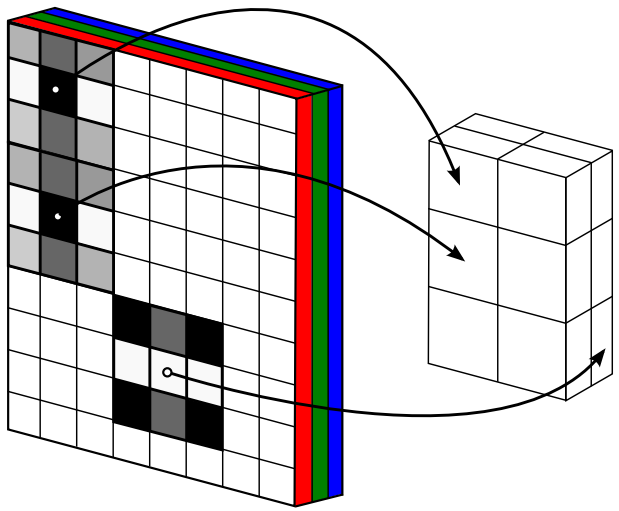

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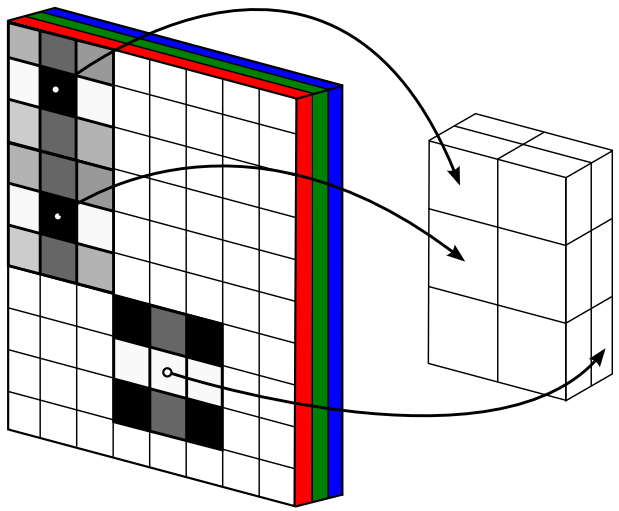

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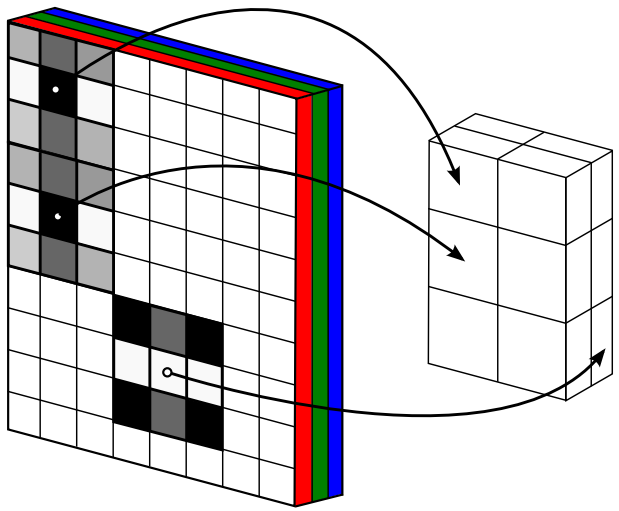

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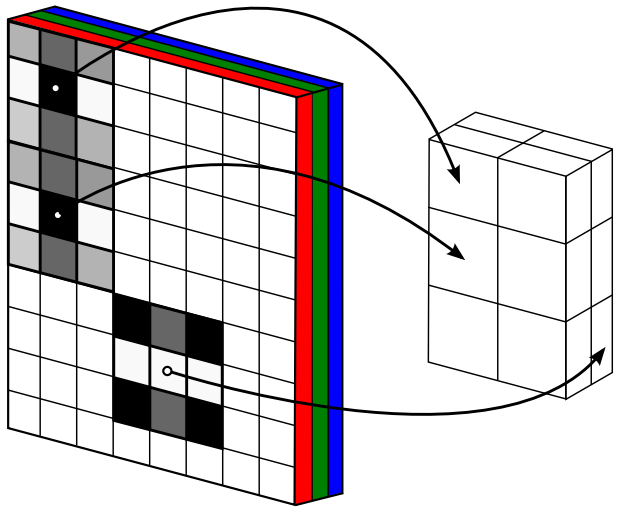

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CNNs no more require hand crafted features, they are capable of learning feature detectors!

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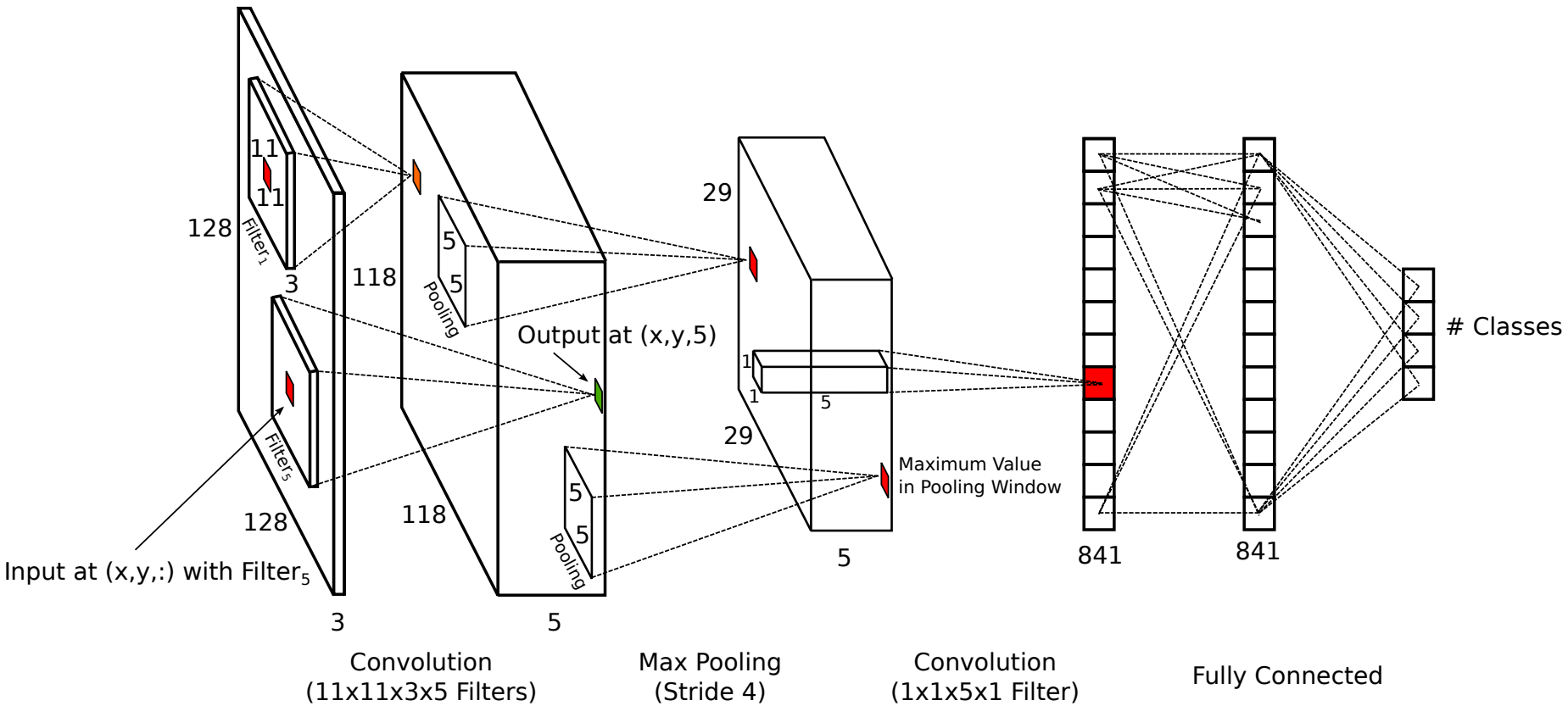
A standard CNN **architecture** is usually described in terms of **layer geometry**. The notion of using **neurons as single units** is split into multiple **layers** which are composed following the same abstraction as classical NNs.



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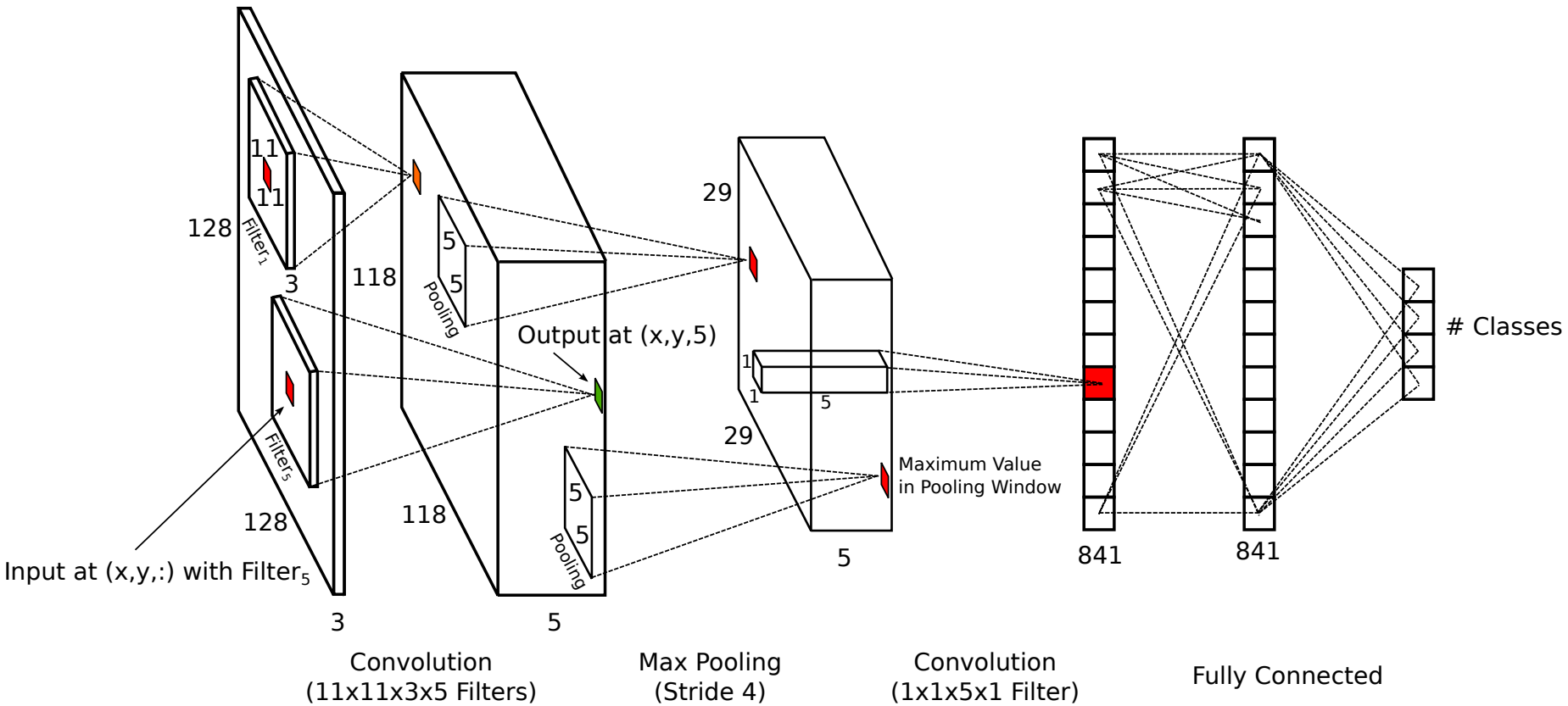

Do not worry, we will come back to this later again!

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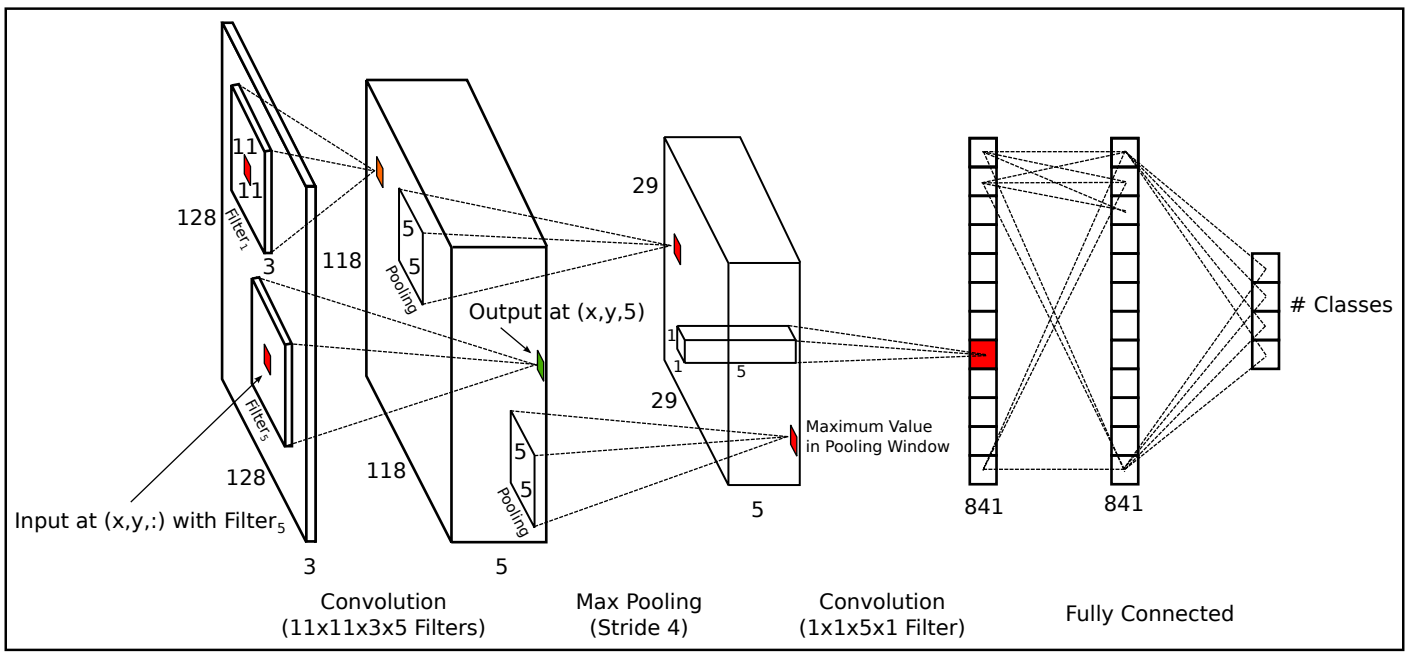
ConvNets are **trained** as classical neural networks are: Using the **back-propagation** algorithm.

Forward Pass: Compute Neuron Activations



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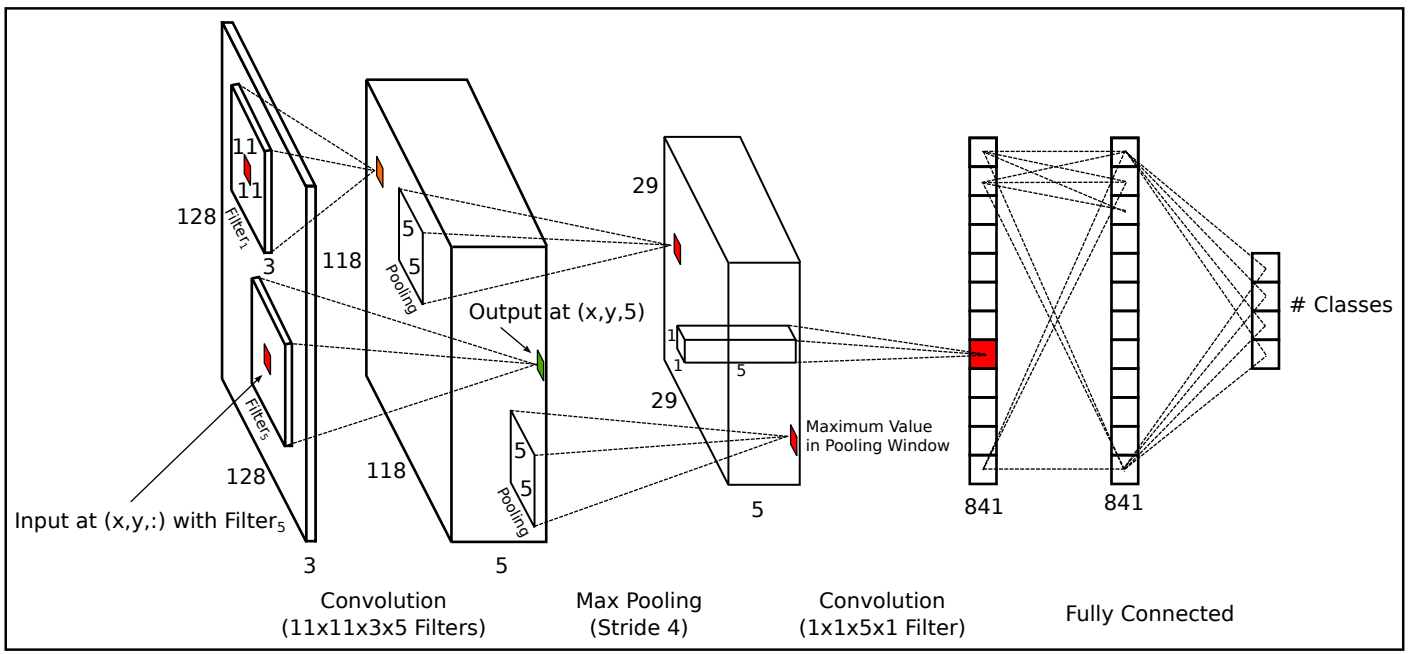
Backward Pass: Compute Derivative of the Loss w.r.t. each Parameter



Foward Pass
CNN Building Blocks: Layers

The Convolutional Layer

The Convolutional Layer: Kernel-Maps

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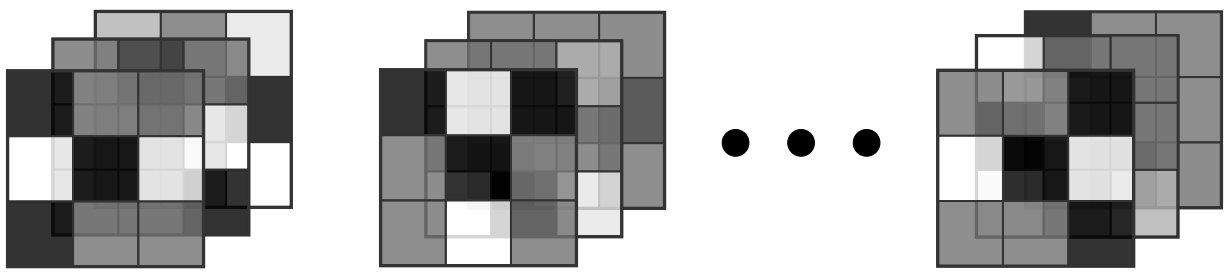

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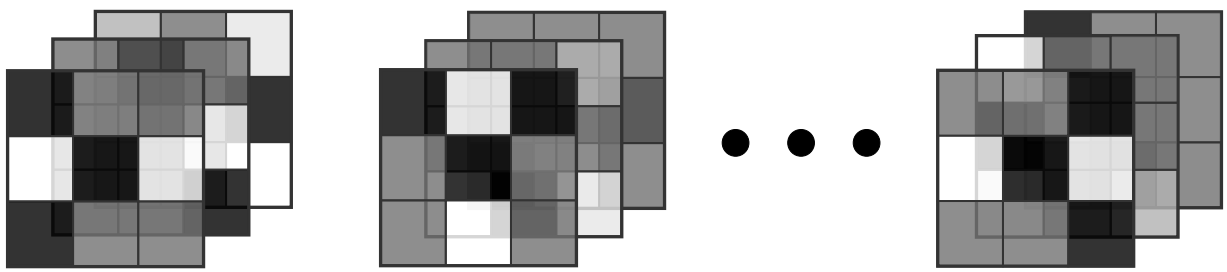

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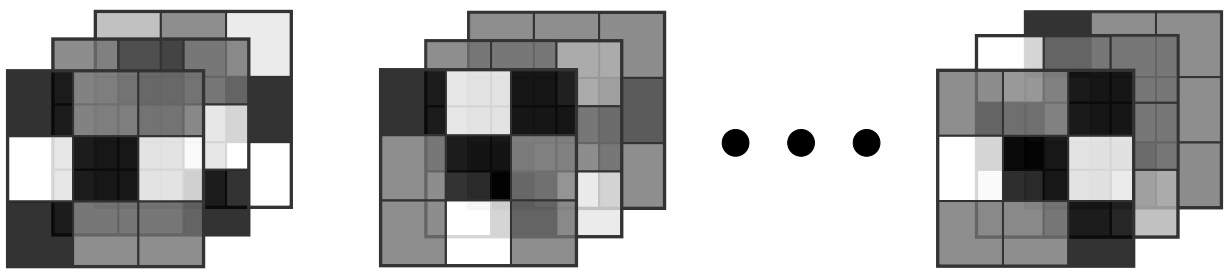

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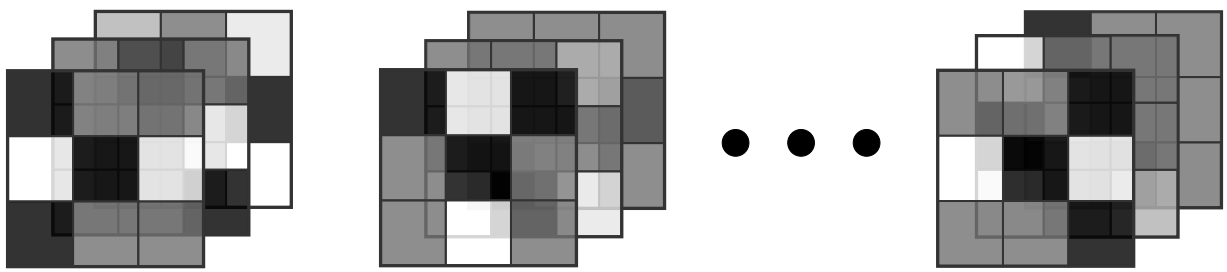
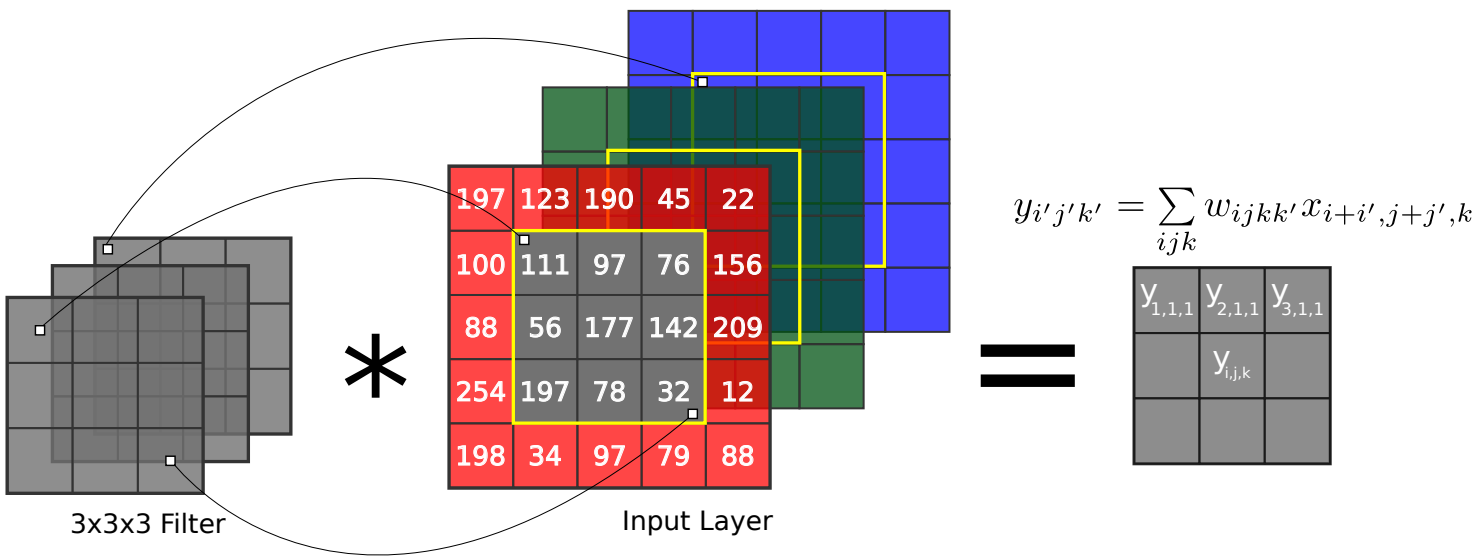
3. The **depth dimension** *D* of kernel-map and input must be **equal**
4. **Convolution** of each of the *HxWxD* filters in a kernel-map **gives a 2D-result** which is **concatenated** to a **3D-output**



3x3x3xN - Kernel Map

The Convolutional Layer: Forward Pass

1. A *HxWxDxN* **kernel-map** is **convolved** with a *XxYxD* **feature-map** to produce a $X'xY'xN$ output



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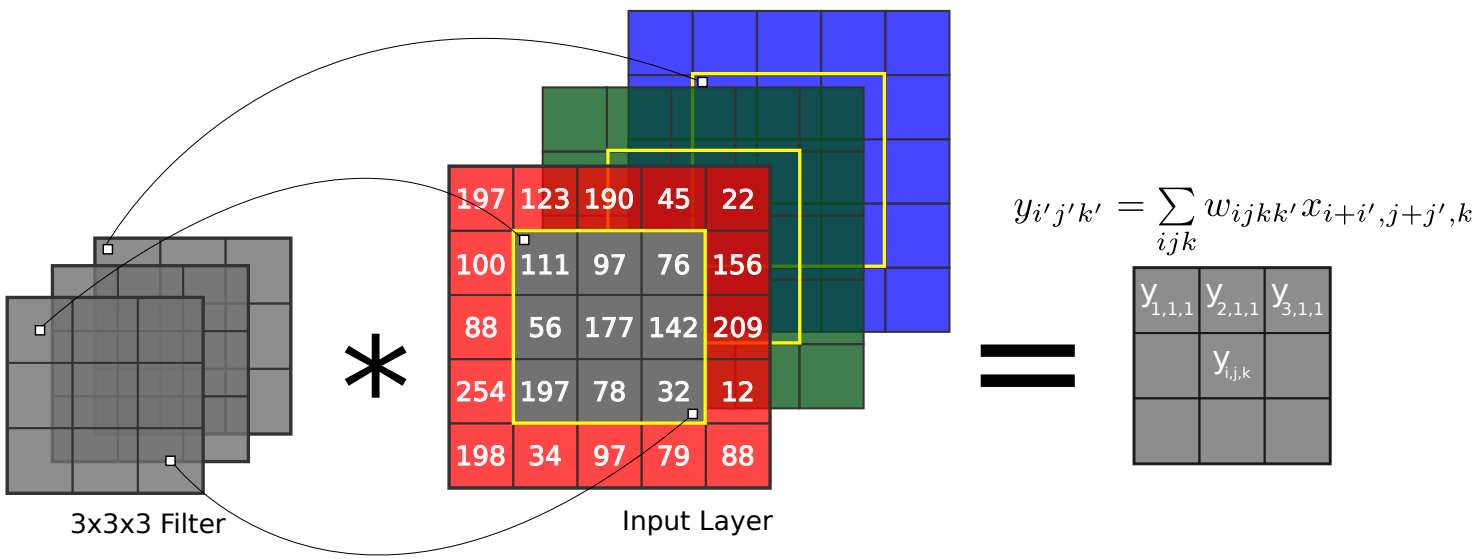

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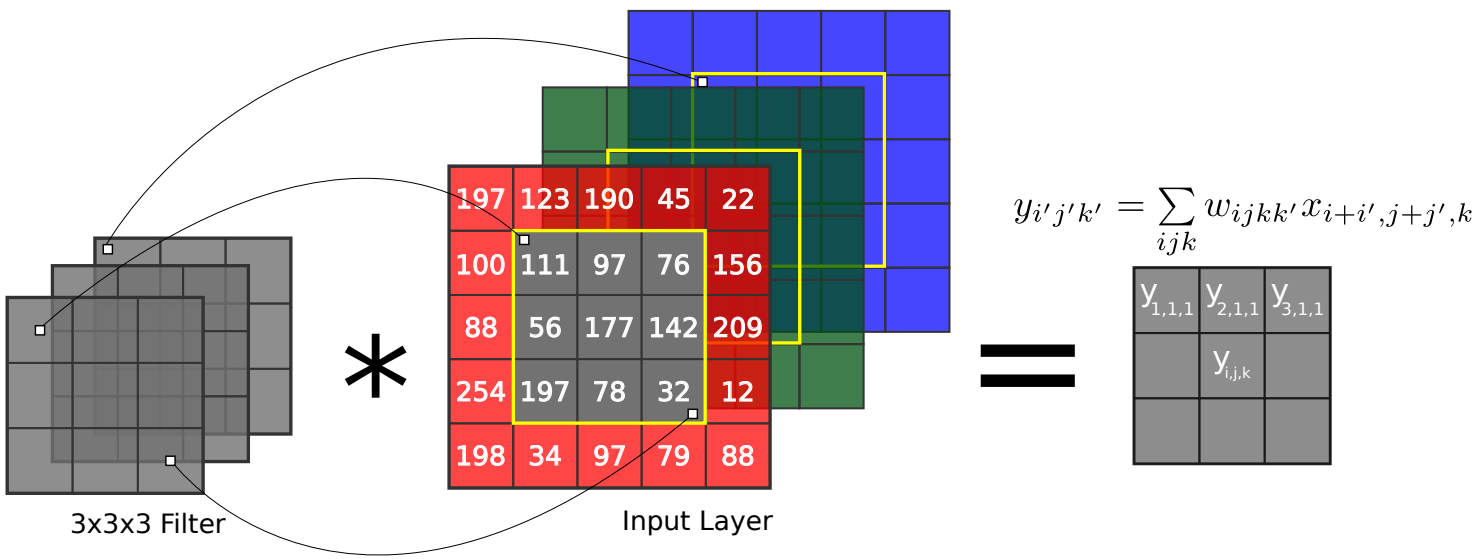
3. Note: The below charts actually performs **cross-correlation** instead of convolution (as implemented in MatConvNet and Caffe) which does not matter as the filters are initialized randomly



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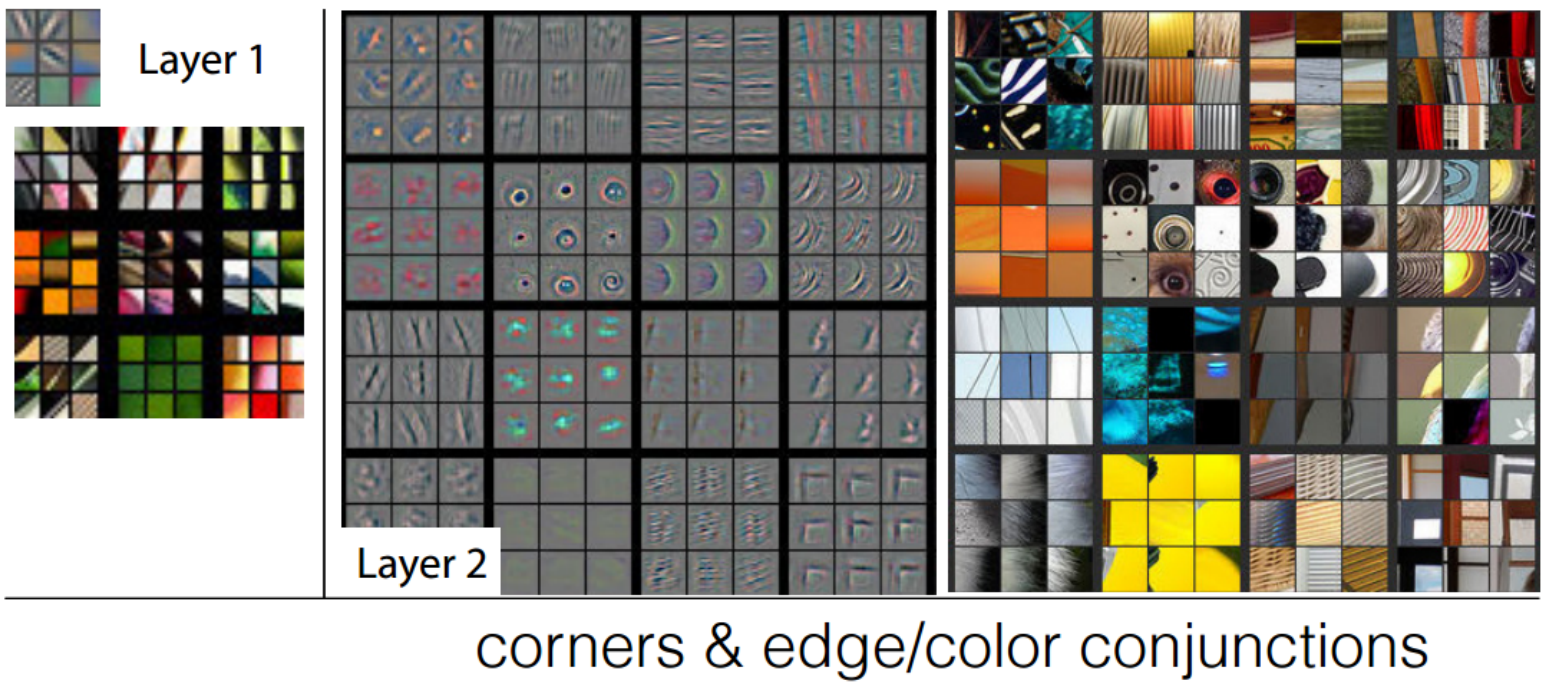

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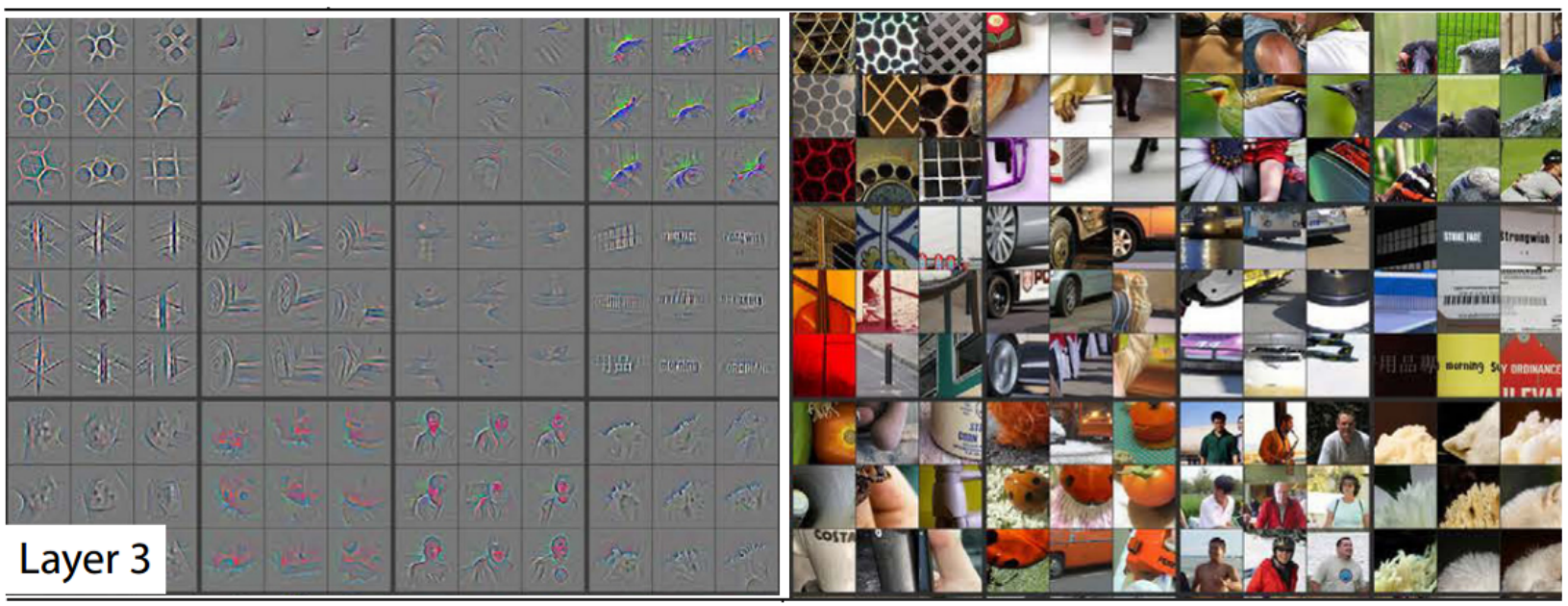

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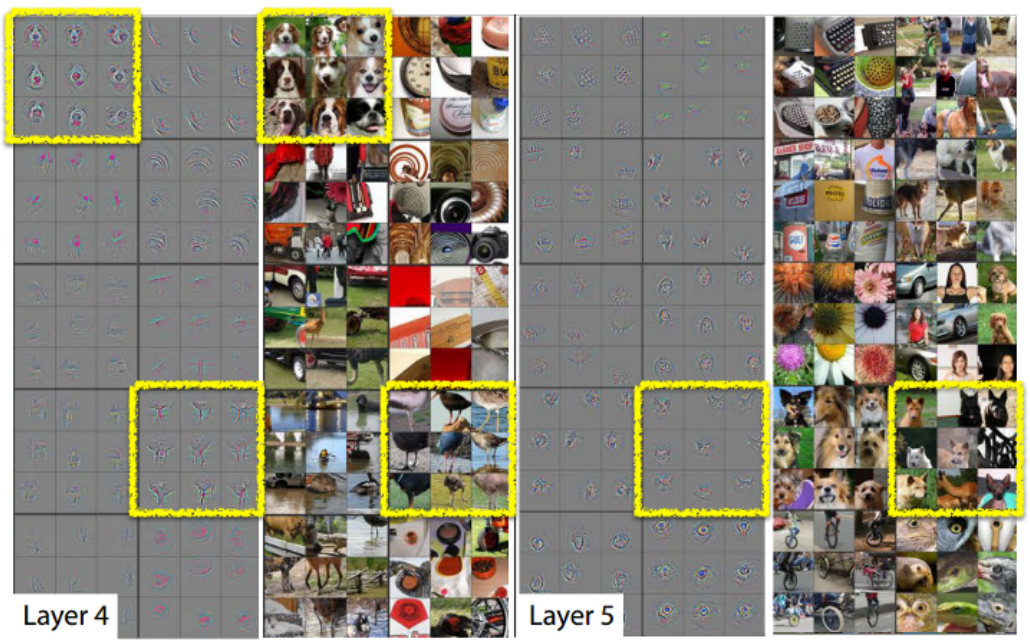

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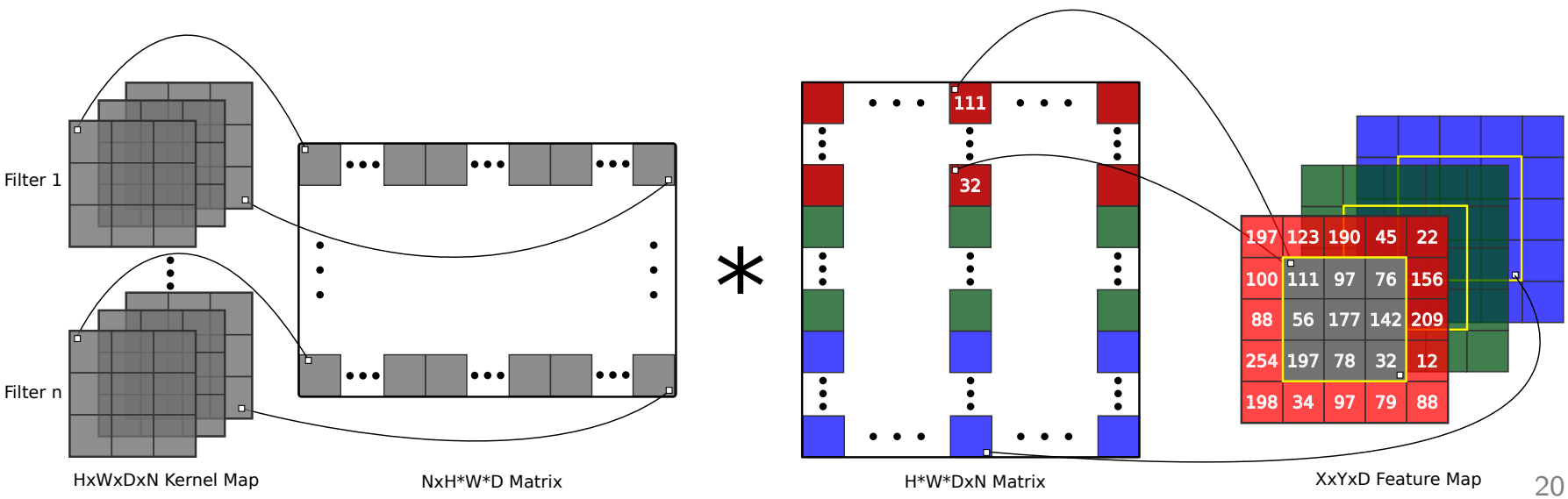

The Pooling Layer

The Pooling Layer: Max-pooling

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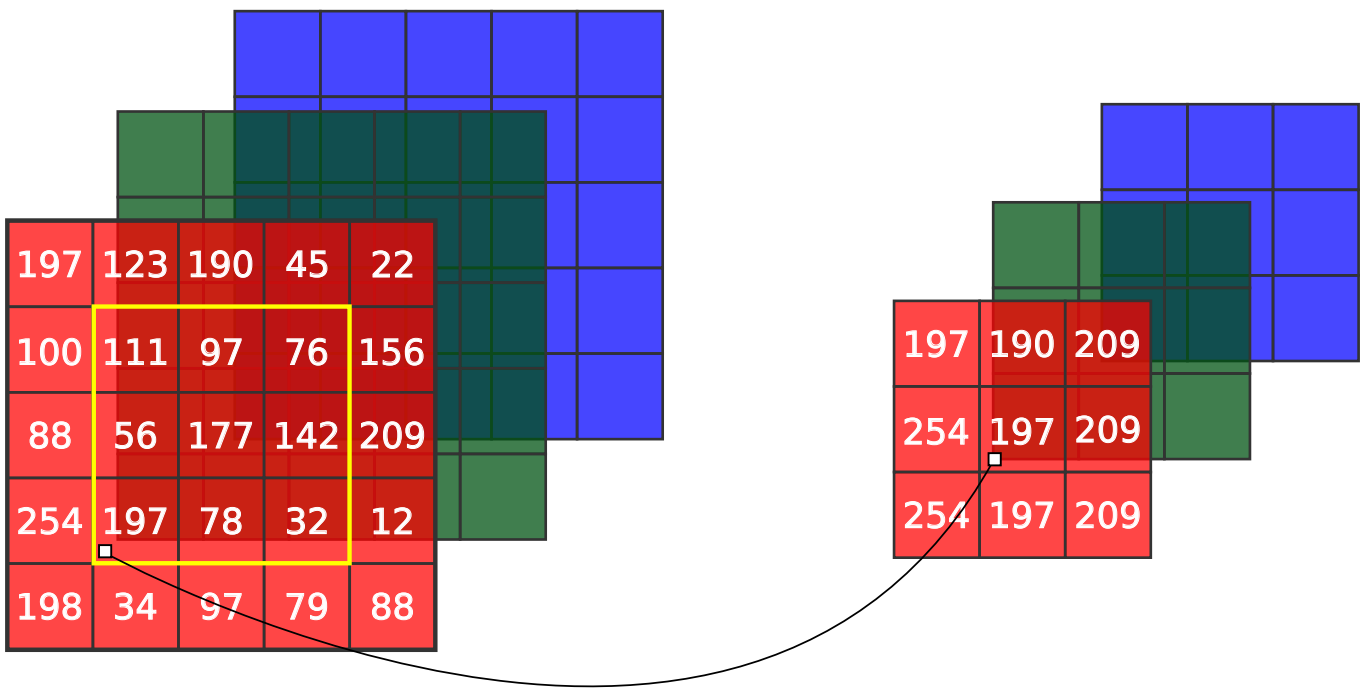

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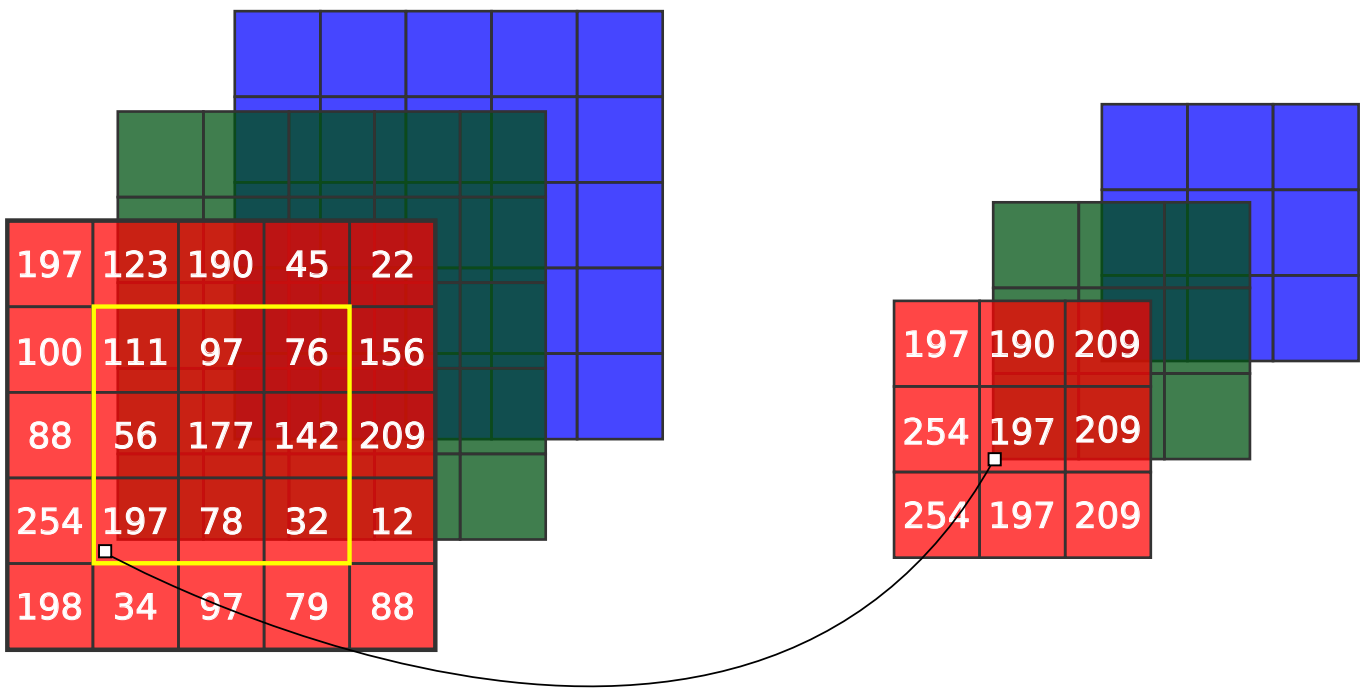

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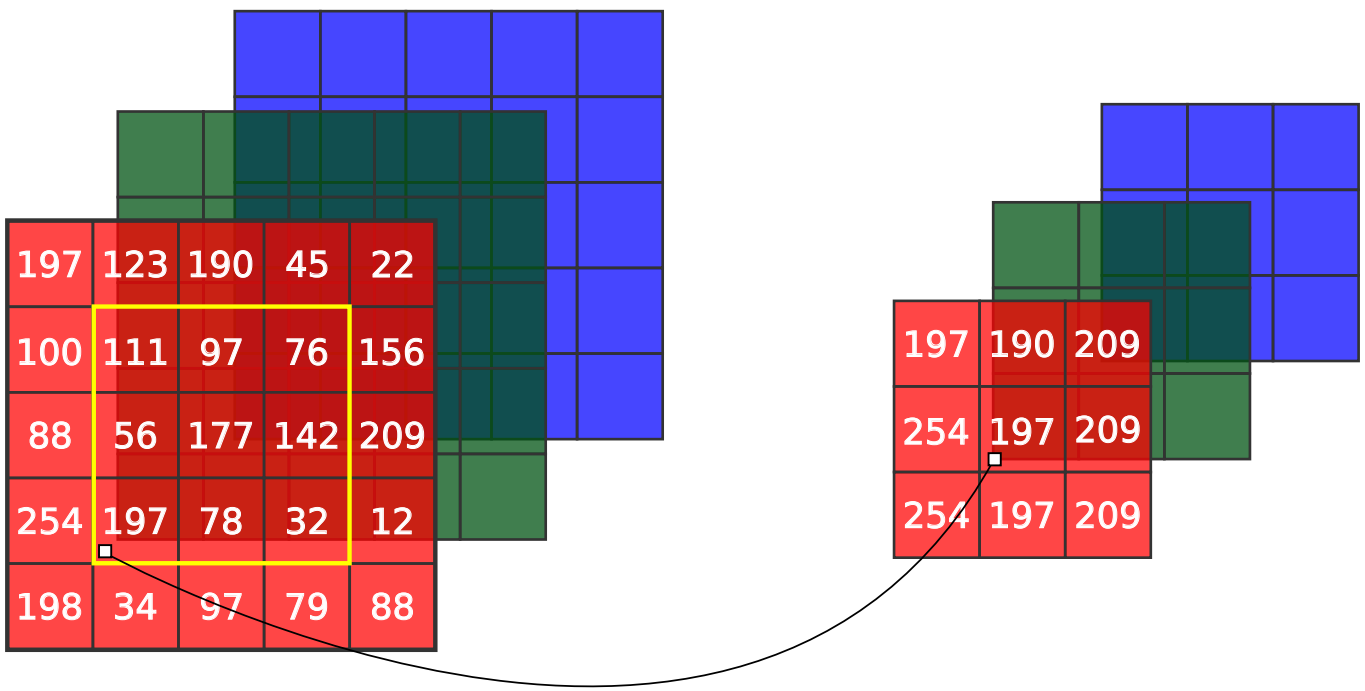

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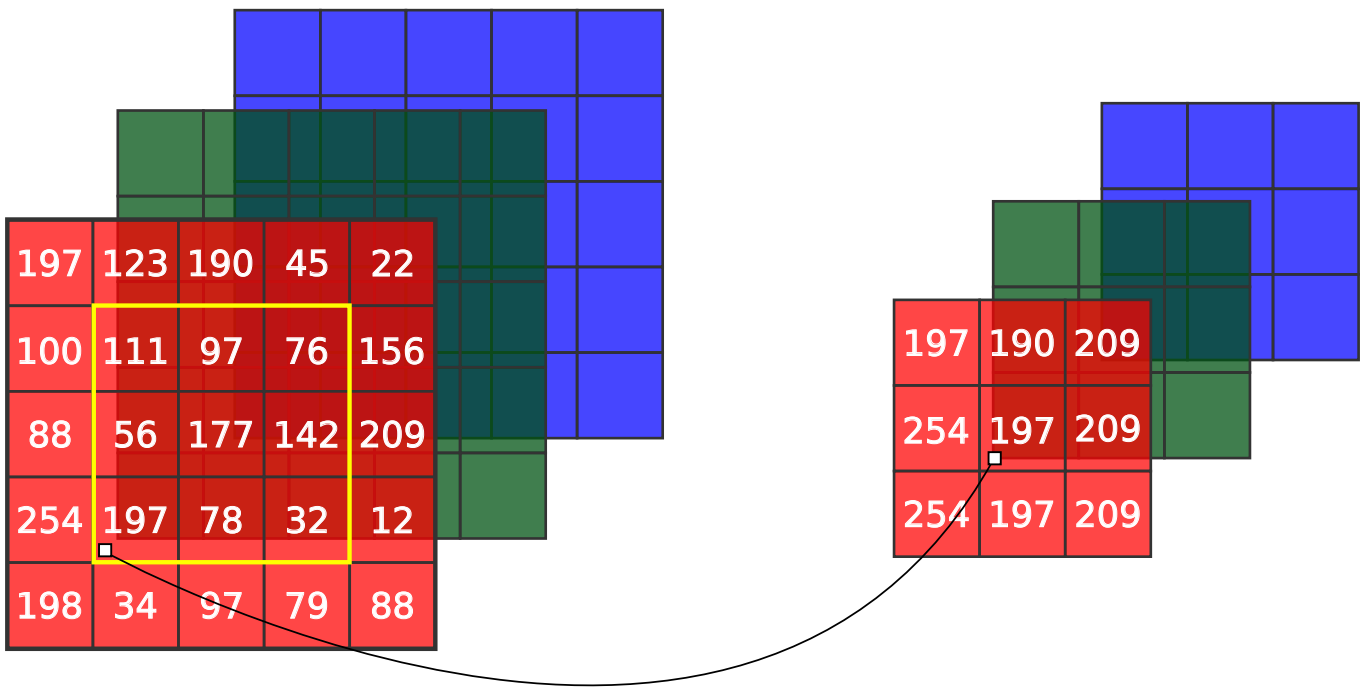

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$\varphi(\cdot)$: Hyperbolic Tangent

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$\varphi(\cdot)$: Rectified Linear Unit (ReLU)

$$y = max(0, x)$$

The Non-Linear Layer: Why does everybody use ReLU?

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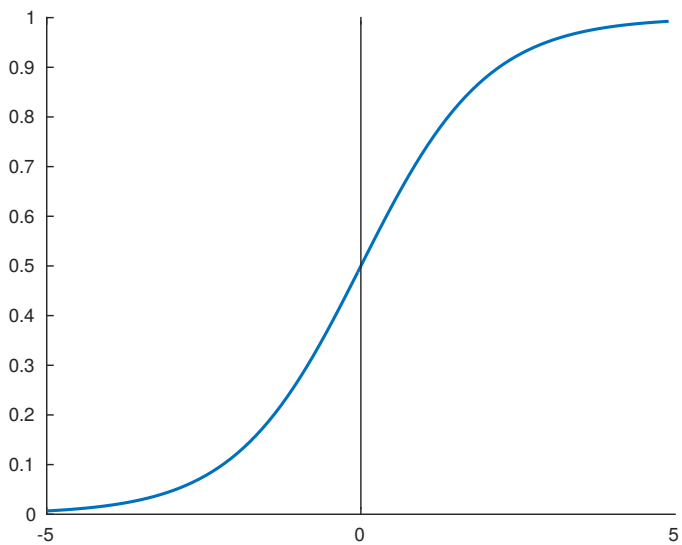
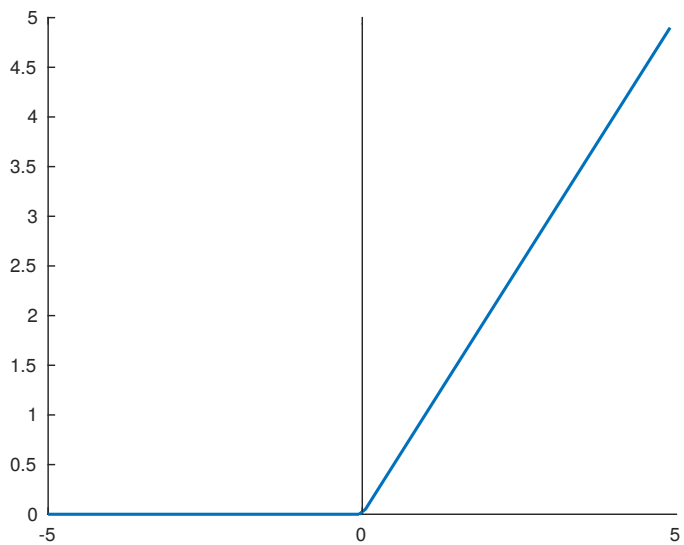


(a) Sigmoid



(b) ReLU

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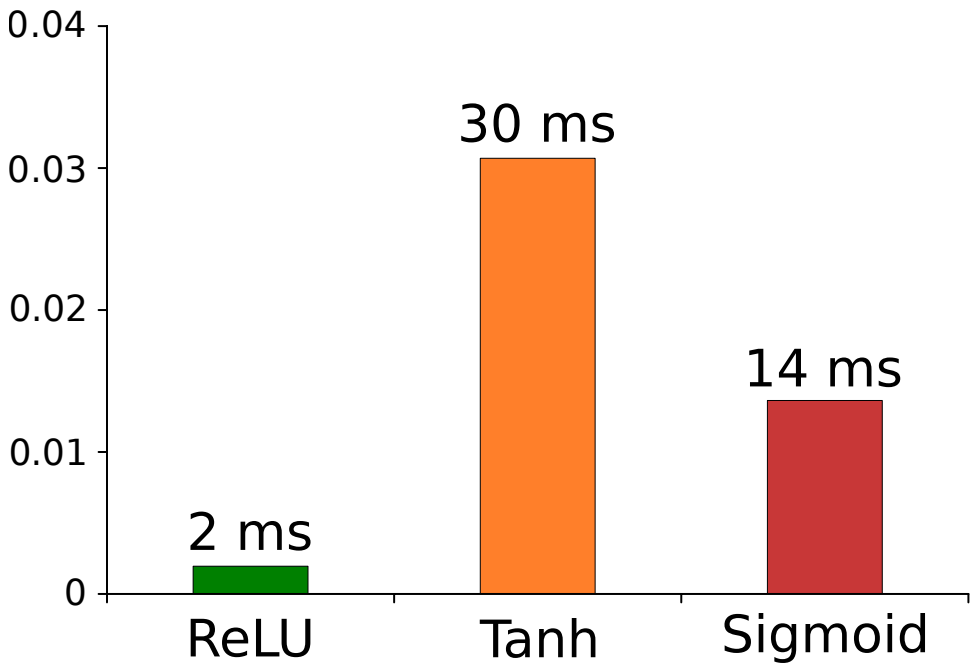

Computational Time for 1024*1024 neurons.

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3. Faster **convergence** hence **less iterations** in training are **required**

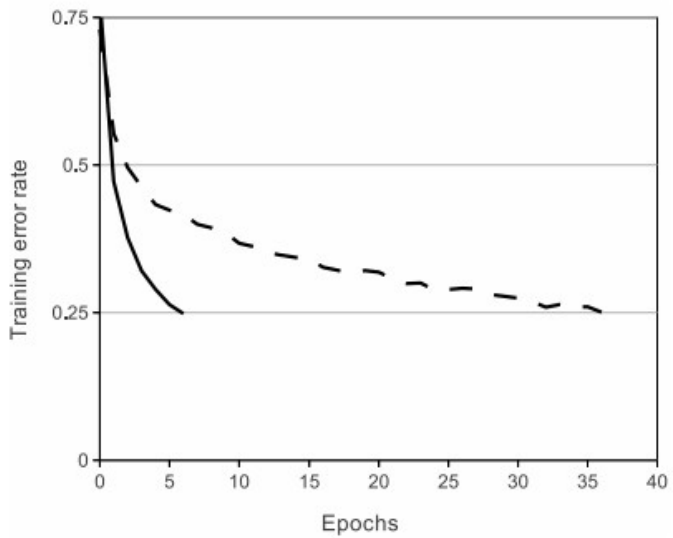

Figure : Krizhevsky et al.: ReLU (solid line) convergence compared to tanh (dashed line) in a 4-layer ConvNet on the CIFAR-10 dataset

The Non-Linear Layer: More about ReLUs

ReLUs are **not the holy grail** however. There are still some other **problems** that should be considered:

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1. **Dying ReLU problem**: ReLUs outputs always 0, neurons can not learn
2. **Leaky ReLUs** can help to recover: $y = \begin{cases} x & \text{if } x > 0 \\ 0.01x & \text{otherwise} \end{cases}$

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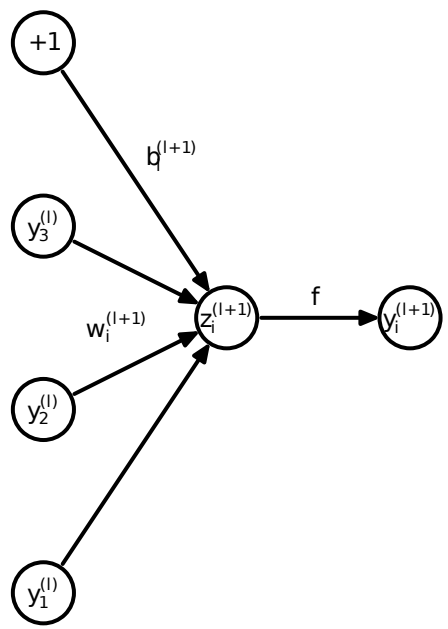
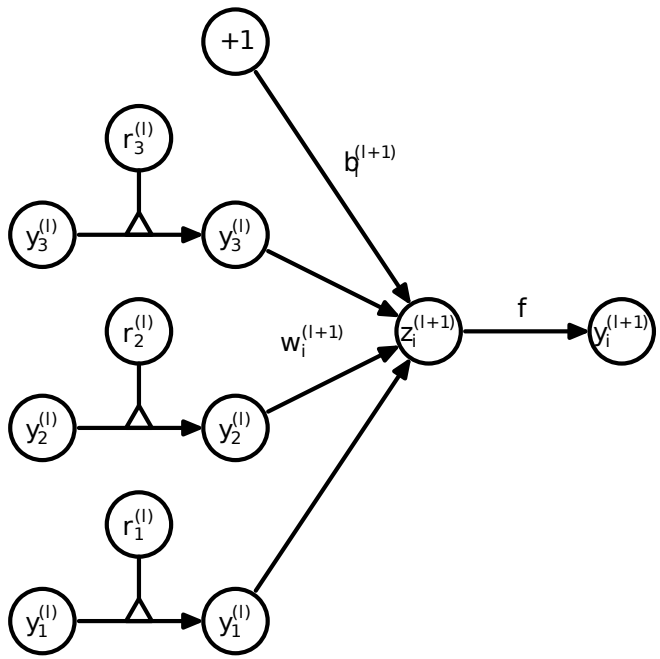


Standard Network



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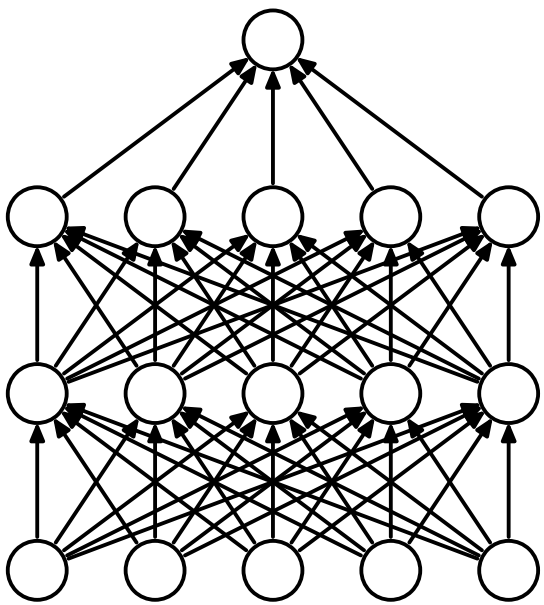

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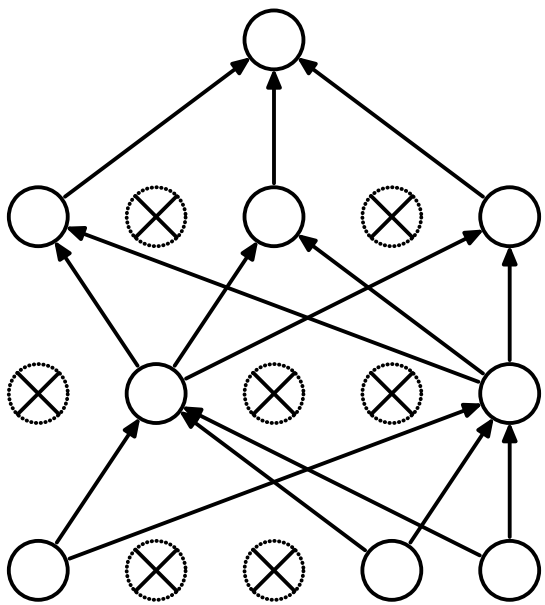

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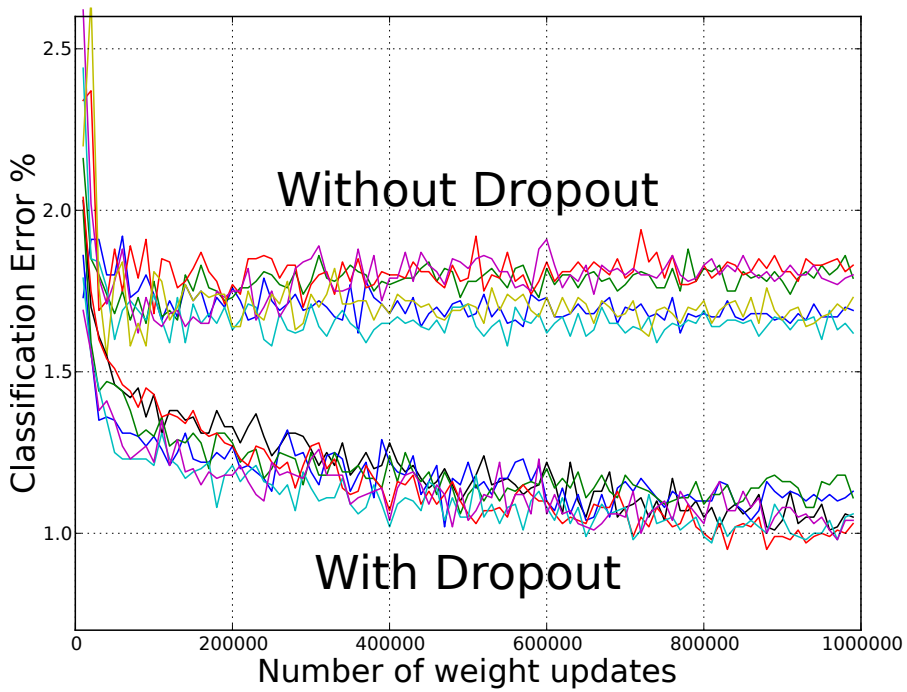

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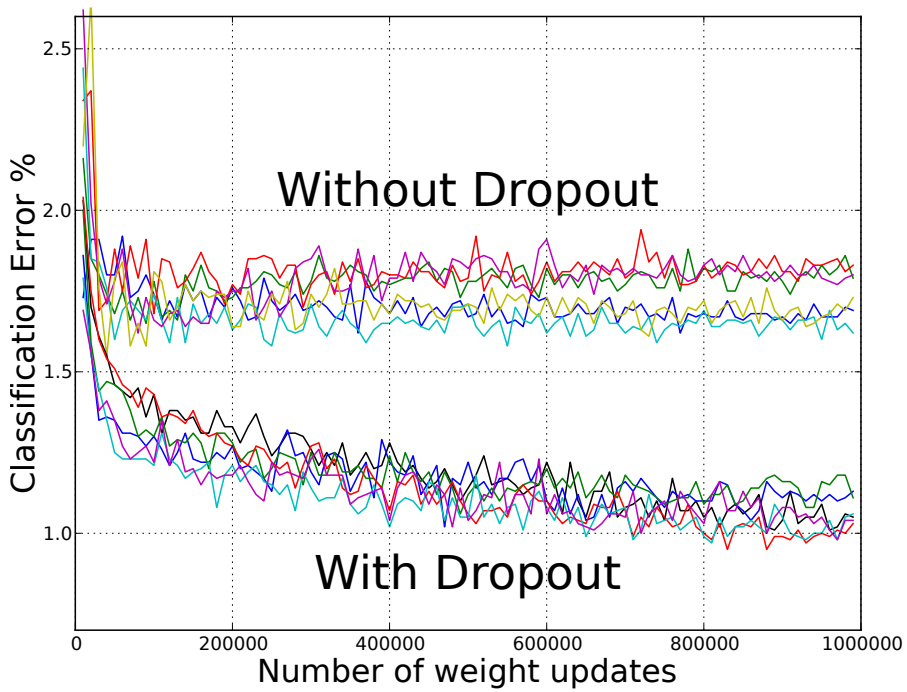

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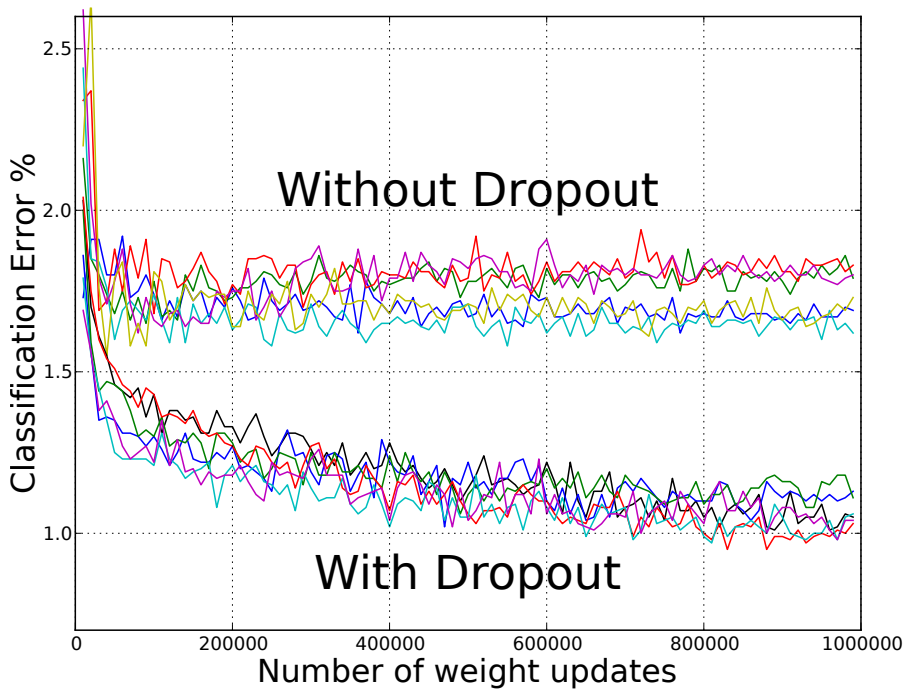

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The softmax function maps a K-dimensional vector of real numbers to a K-dimensional vector between 0 and 1.

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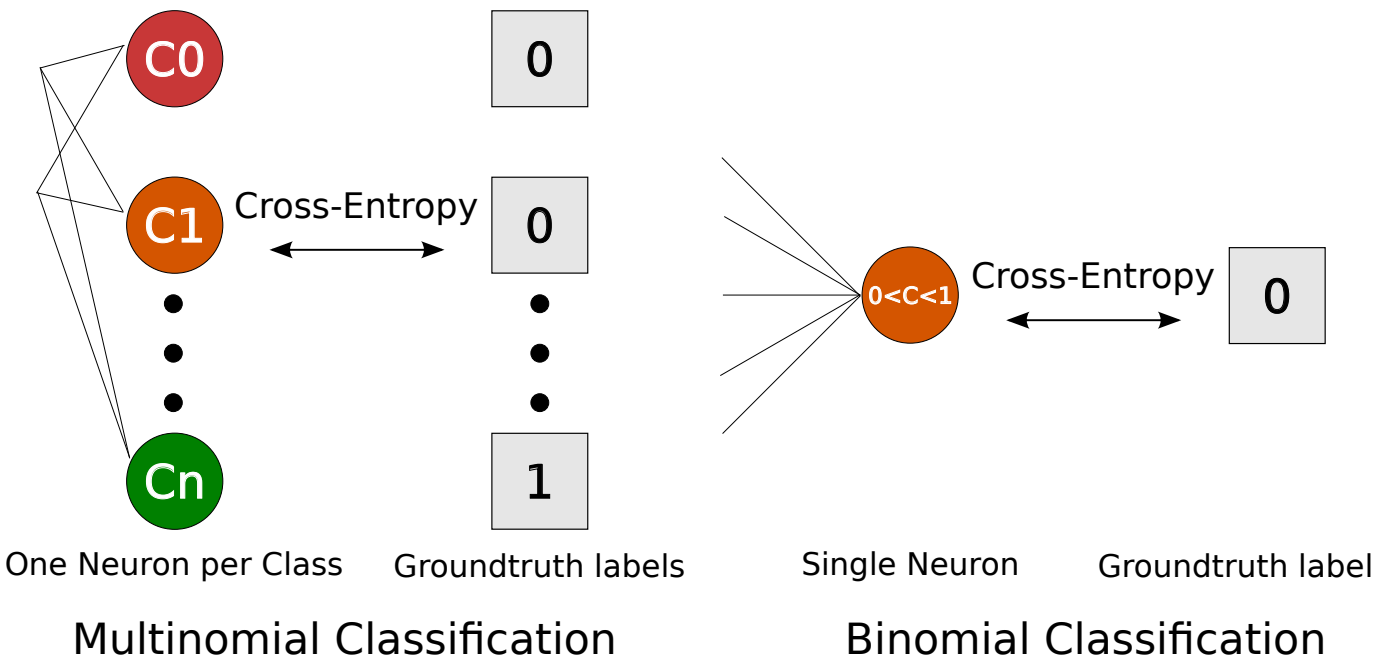
5. Each output can be interpreted as **posterior probability of a class** given the input

The Loss Layer

The Loss Layer: Output Encoding

1. A **binomial problem** can be solved using a network with a **single logistic output neuron**



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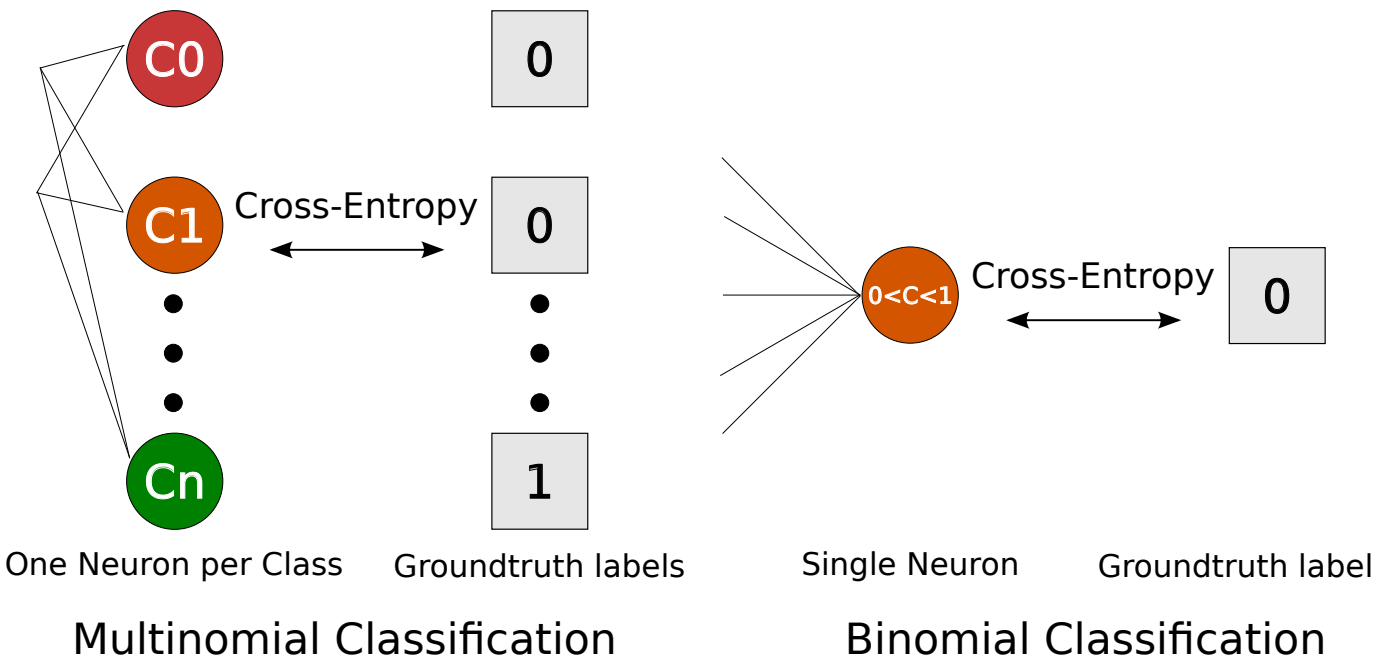

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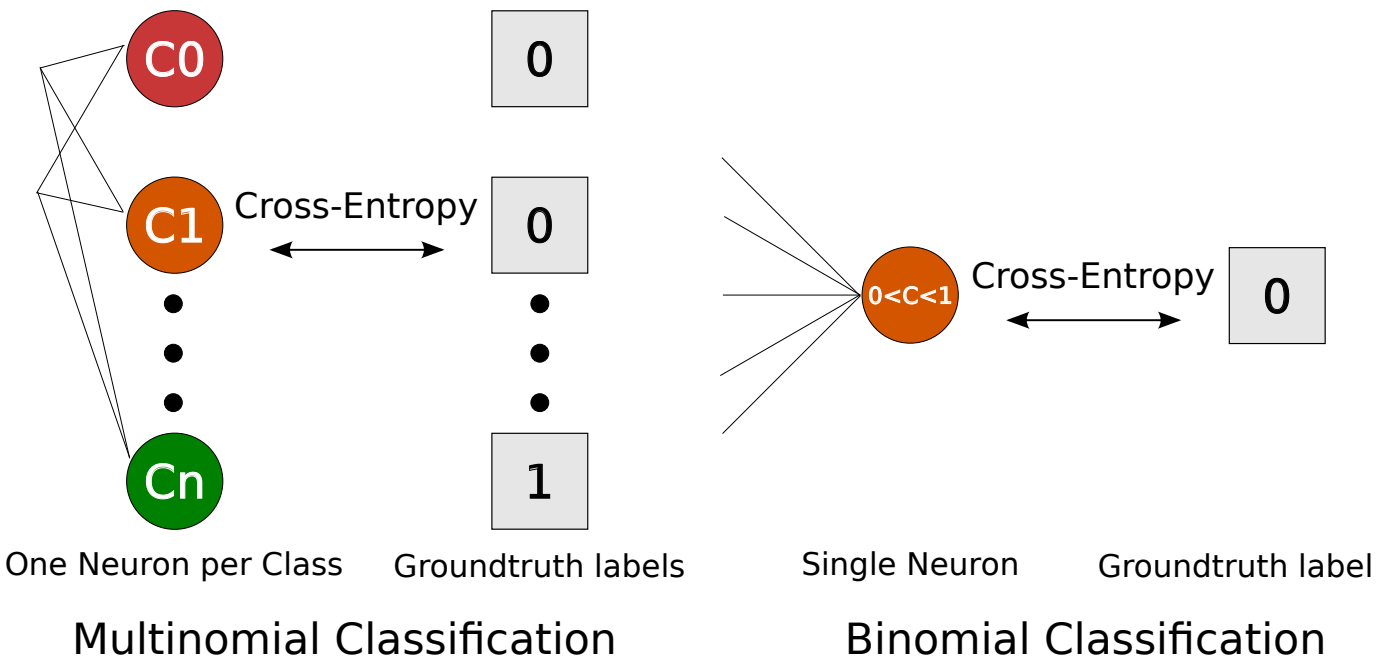
3. In both cases the **cross-entropy loss** can be used to compute the **network error**



The Loss Layer: Computing the Loss

The loss layer is where the **groundtruth** (l) is used to compute **how well the network performed** in predicting the class labels (z) of the input for a C-class problem.

The Cross-Entropy Loss:

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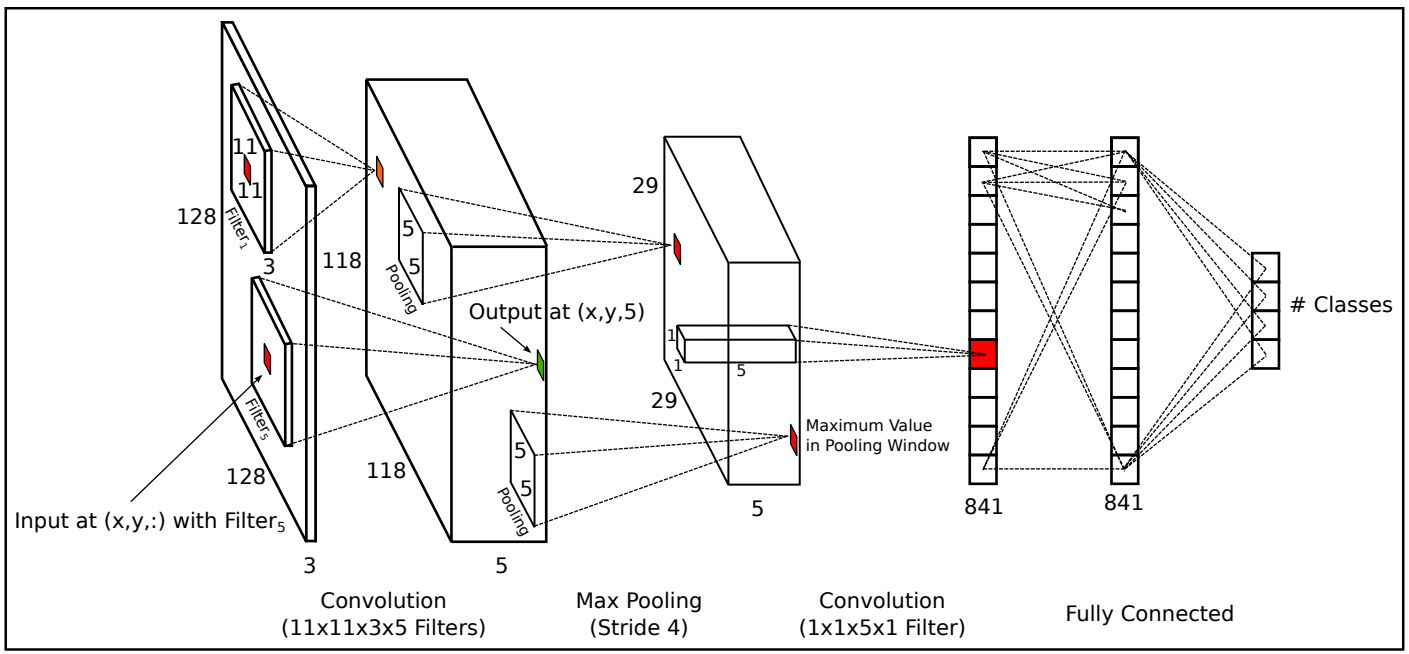
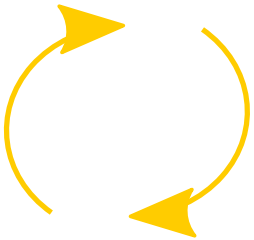
3. A **large loss is bad**, a **small loss is good**

Backward Pass
CNN Building Blocks: Layers

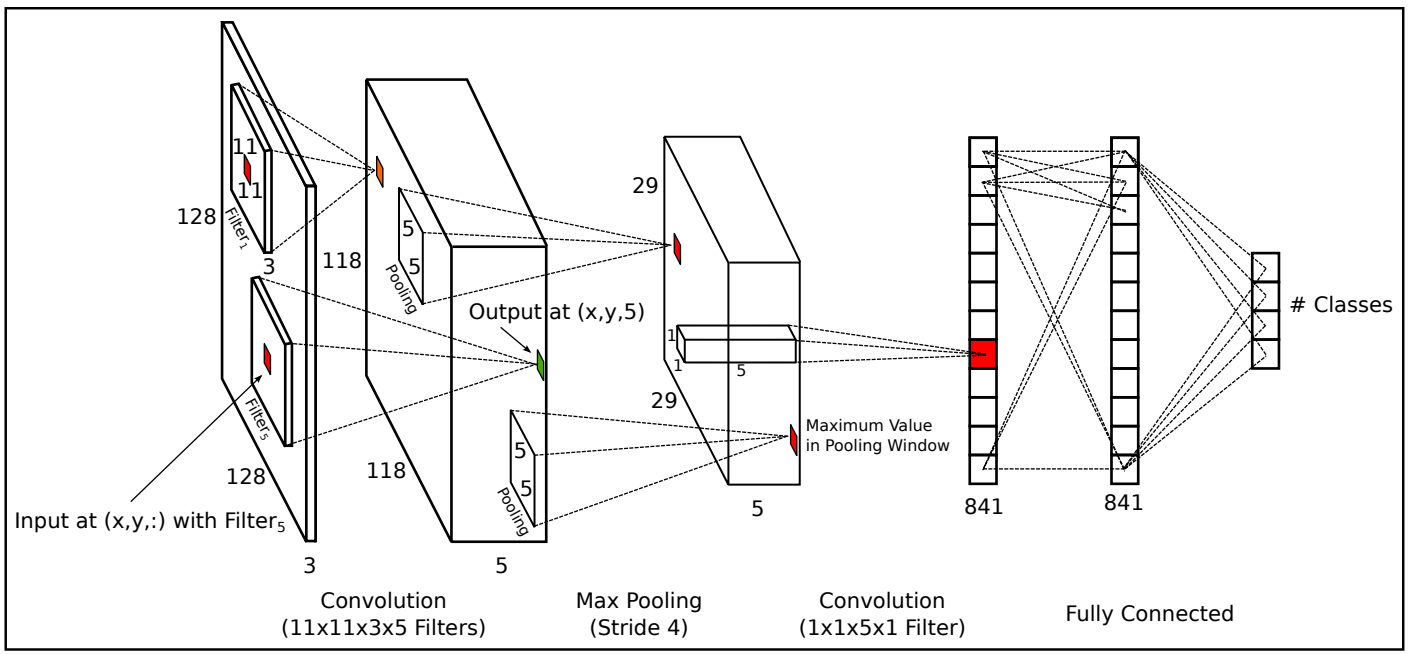
Backward Pass: Compute Derivative of the Loss w.r.t. each Parameter



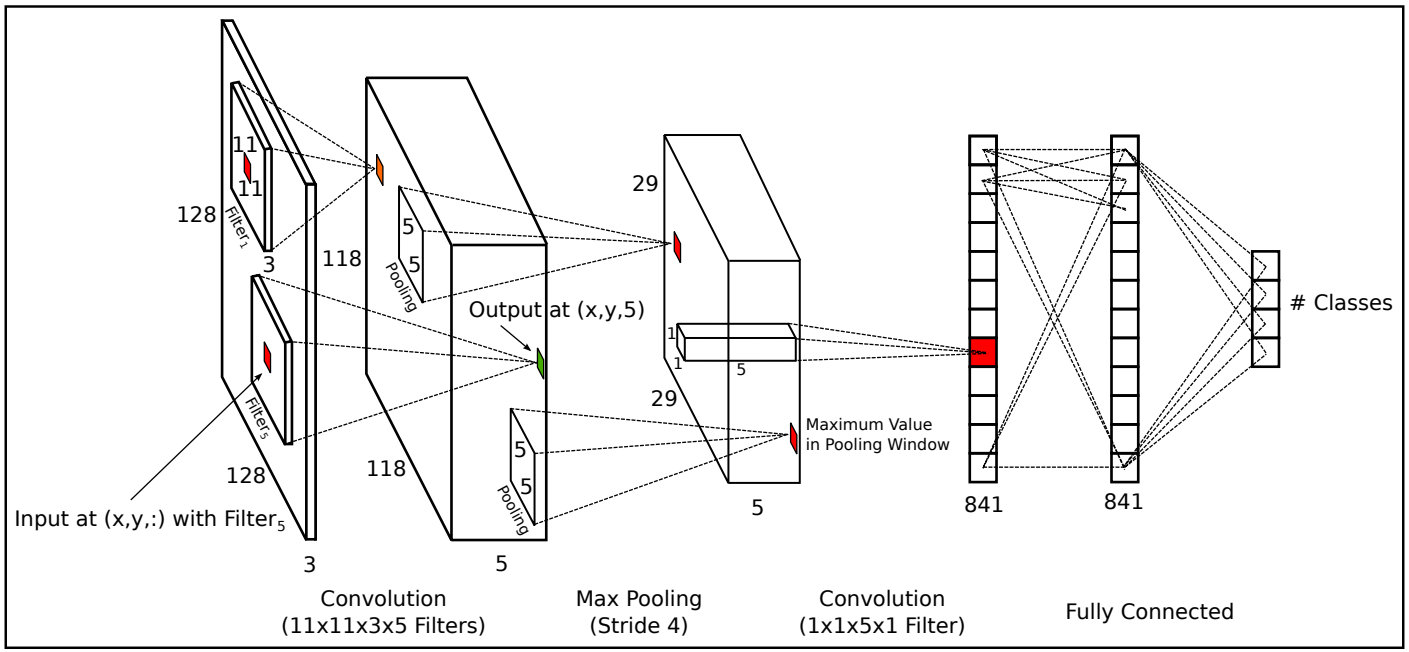
CNN Building Blocks: Layers - Backward Pass



Update Weights to minimize Loss.



Forward Pass: Compute Neuron Activations



Learning: Stochastic Gradient Descent

Stochastic Gradient Descent (SGD) is used to Optimize the Loss:

$$w_{i+1} \leftarrow w_i - \eta_i \frac{\partial L}{\partial w_i} + \alpha \Delta w_i - \eta_i \lambda w_i$$

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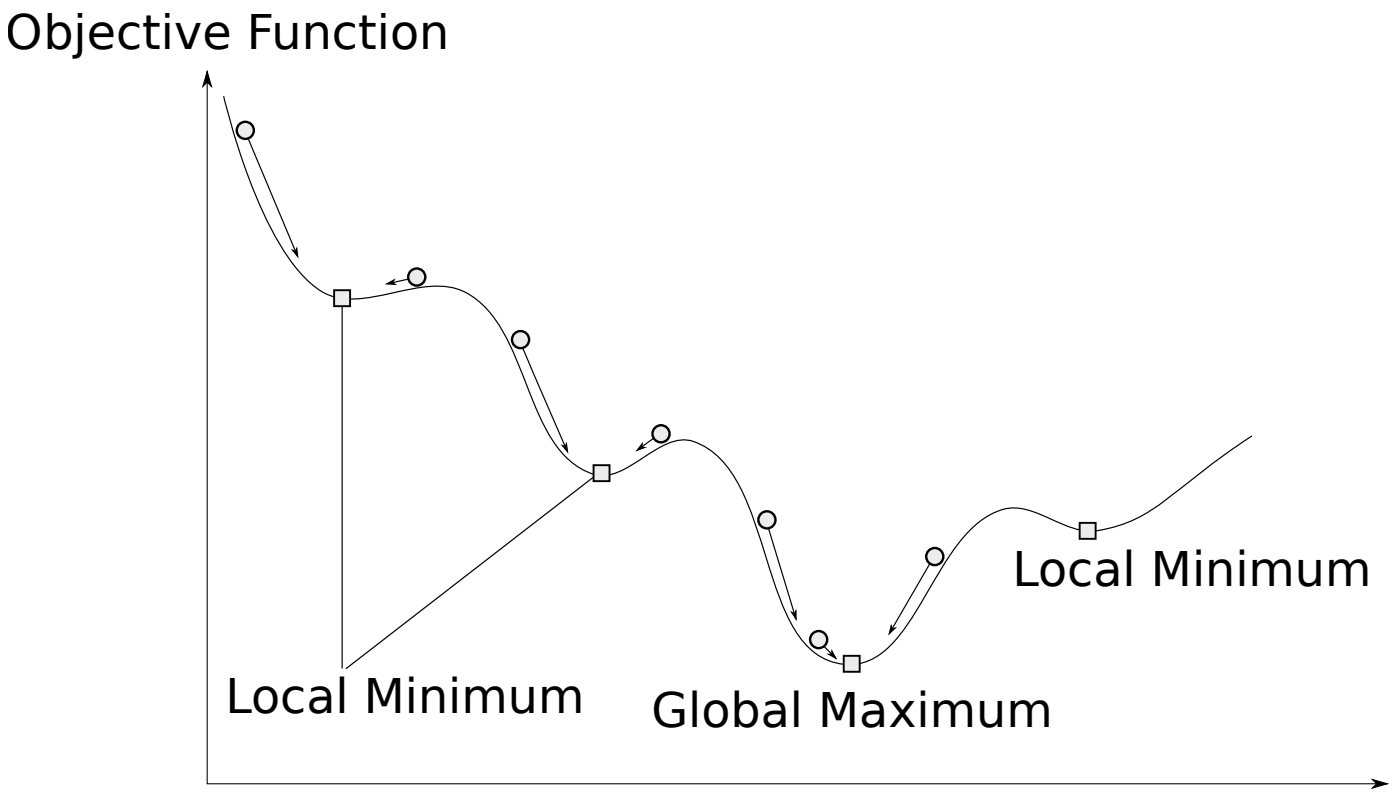

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To learn the weights for a problem we have to compute the derivative of the loss function w.r.t. each parameter in the NN.

Backward Pass: Backpropagation

Backpropagation Sketch

A feed-forward network can be seen as a **composition of functions**:

$$f(x) = f_L(\dots f_2(f_1(x; w_1); w_2)\dots); w_L);$$

Using the **chain-rule** this allows to **compute the derivatives layer by layer**.

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Total Derivative

The **total or full derivative** of a function $y = f(t, u_1(t), \dots, u_m(t))$ of **several variables that depend on each other** is computed as:

$$\frac{\partial y}{\partial t} = \frac{\partial f}{\partial t} + \frac{\partial f}{\partial u_1}\frac{\partial u_1}{\partial t} + \dots + \frac{\partial f}{\partial u_m}\frac{\partial u_m}{\partial t}$$

Backward Pass: The Loss Layer

Loss Layer

$$\begin{aligned} \frac{\partial y}{\partial z_i} &= \frac{\partial}{\partial zi}\left(-\sum_{c=1}^{C} l_c \; log(z_c)\right) \\ &= -\frac{l_i}{z_i} \end{aligned}$$

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1. Most implementations assume that the class probabilities are $\in \{0, 1\}$ and only **compute the gradient for the correct class**
2. The **net only adapts parameters** (learns) that **contributed to the activation** of the corresponding neuron

Backward Pass: The Softmax Layer

Softmax Layer: Backward Pass

Softmax Layer

$$y_j = \frac{e^{x_j}}{\sum_{k=1}^{K} e^{x_k}}, \qquad \text{for } j = 1, \ldots, K$$

The **total derivative** of output y_i w.r.t. a parameter x_j is:

$$\frac{\partial y_i}{\partial x_j} = \frac{\partial y_i}{\partial x_1} + \frac{\partial y_i}{\partial x_2} + \cdots + \frac{\partial y_i}{\partial x_K} \tag{1}$$

Softmax Layer: Backward Pass

Case $i = j$:

$$\frac{\partial y_i}{\partial x_i} = \frac{e^{x_i}\left(\sum_j e^{x_j}\right) - e^{x_i}e^{x_i}}{\left(\sum_j e^{x_j}\right)^2} = \frac{e^{x_i}\sum_j e^{x_j}}{\left(\sum_j e^{x_j}\right)^2} - \frac{e^{2x_i}}{\left(\sum_j e^{x_j}\right)^2}$$

$$= \underbrace{\frac{e^{x_i}}{\sum_j e^{x_j}}}_{=y_i} - \left(\underbrace{\frac{e^{x_i}}{\sum_j e^{x_j}}}_{=y_i}\underbrace{\frac{e^{x_i}}{\sum_j e^{x_j}}}_{=y_i}\right)$$

$$= y_i\left(1 - y_i\right)$$

Softmax Layer: Backward Pass

Case $i \neq j$:

$$\frac{\partial y_i}{\partial x_j} = \frac{-e^{x_j} e^{x_i}}{\left(\sum_j e^{x_j}\right)^2} = -\underbrace{\frac{e^{x_j}}{\sum_j e^{x_j}}}_{=y_j} \underbrace{\frac{e^{x_i}}{\sum_j e^{x_j}}}_{=y_i} = -y_j \, y_i$$

The derivatives of the softmax layer are then **multiplied** with the **derivatives of the previous layer**. Note how the output of the forward pass can be re-used.

Backward Pass: The Dropout Layer

Dropout Layer: Backward Pass

The dropout operation $y = x \circ d$ is a **point-wise multiplication** of n independent random variables D following a Bernoulli distribution with the activations produced by n neurons x.

Dropout Layer

$$\frac{\partial y}{\partial x_i} = \begin{cases} 1, & \text{if } d_n = 1 \\ 0, & \text{otherwise} \end{cases}$$

Backward Pass: The Non-Linear Layer

Non-Linear Layer: Backward Pass (ReLU)

Note that the **ReLU function** $y = max(0, x)$ is not **differentiable in 0**. But it has **subdifferential** $\partial f(0) \in [0, 1]$. Therefore any value in $[0, 1]$ can be used as **subderivative** in SGD (which is then actually sub-gradient stochastic descent).

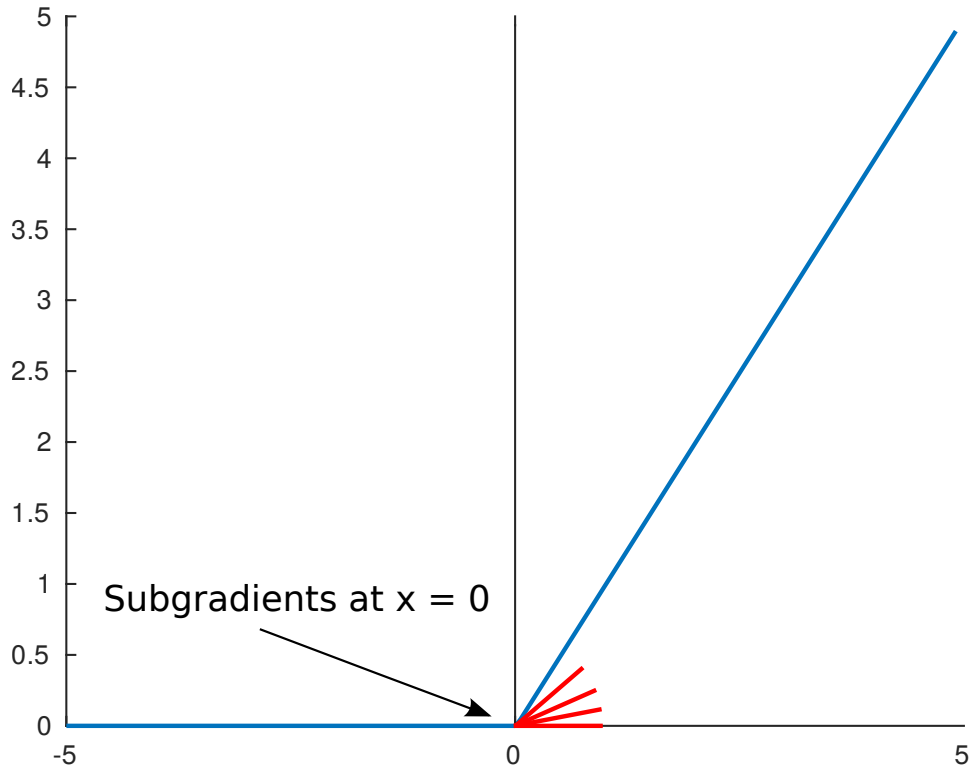

Figure : Subgradients of the ReLU function at x = 0

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ReLU Derivative

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Backward Pass: The Pooling Layer

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The derivative of the max-pooling layer $y = max\{x_1, \ldots, x_n\}$ is again computed using **sub-gradients**.

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And it should be fast!

Convolution Layer: Backward Pass

Cross-Correlation Derivative

$$y_{i'j'k'} = \sum_{ijk} w_{ijkk'} x_{i+i',j+j',k}$$

The **derivative** w.r.t. an **input parameter** x_{lmn} is $\frac{\partial y_{i'j'k'}}{\partial x_{lmn}} = w_{lmnk'}$.

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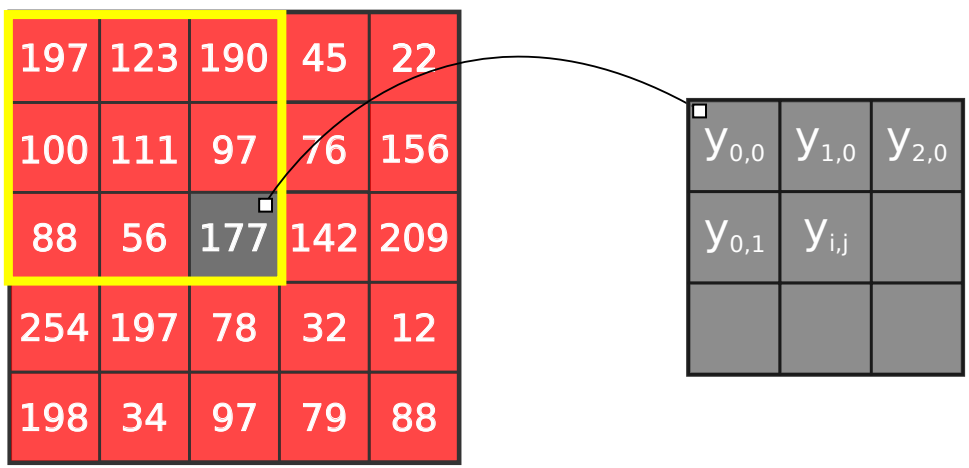

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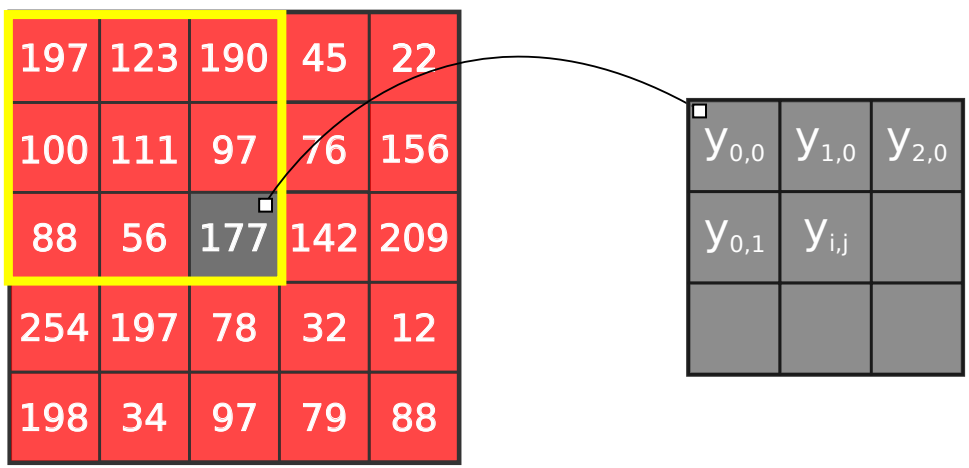

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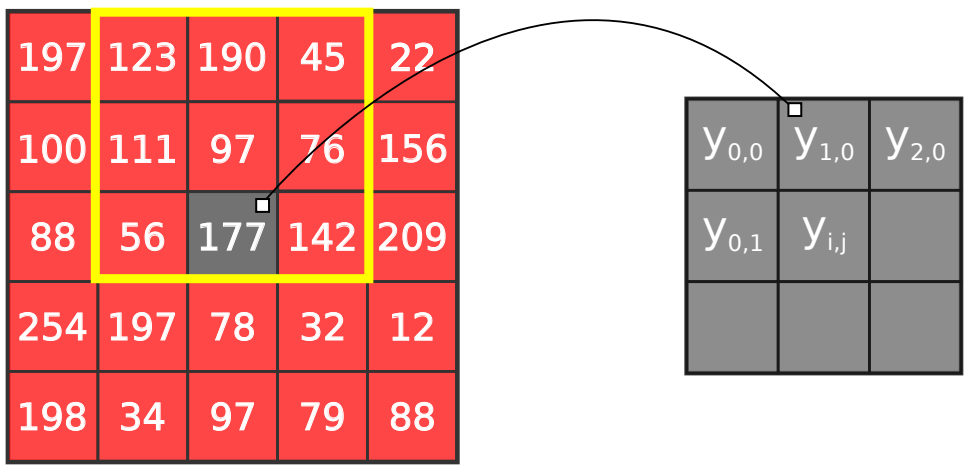

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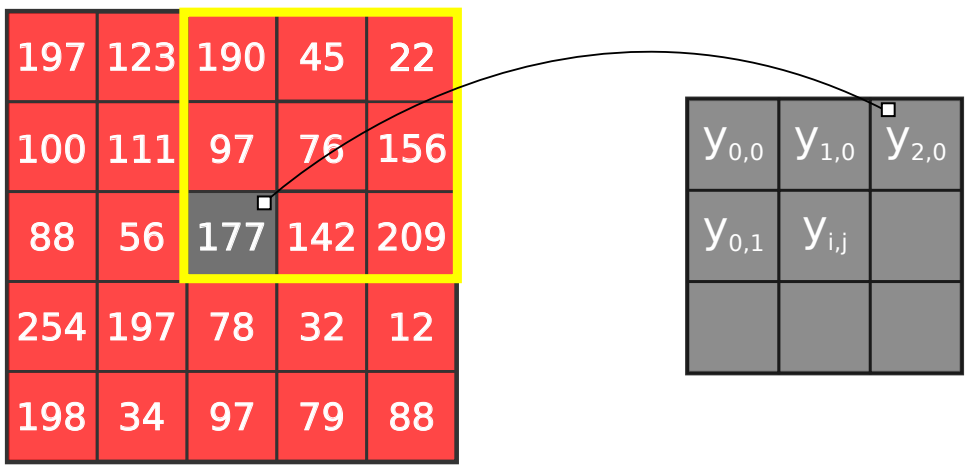

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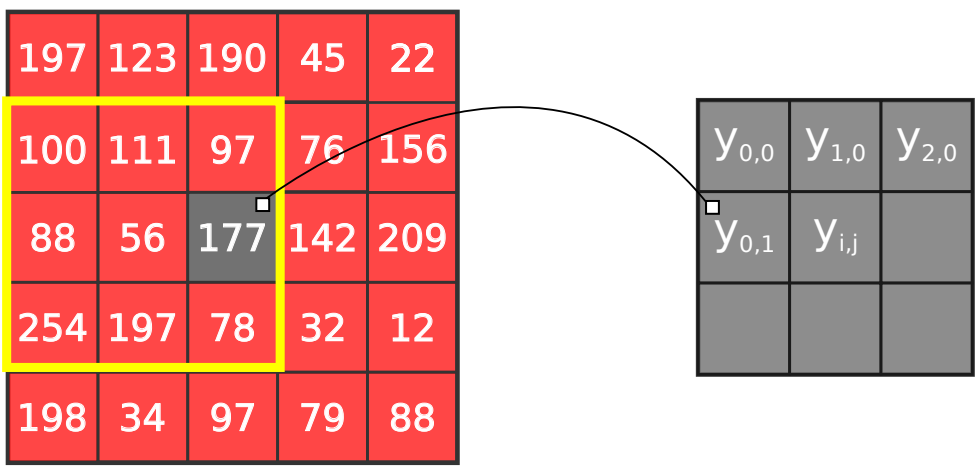

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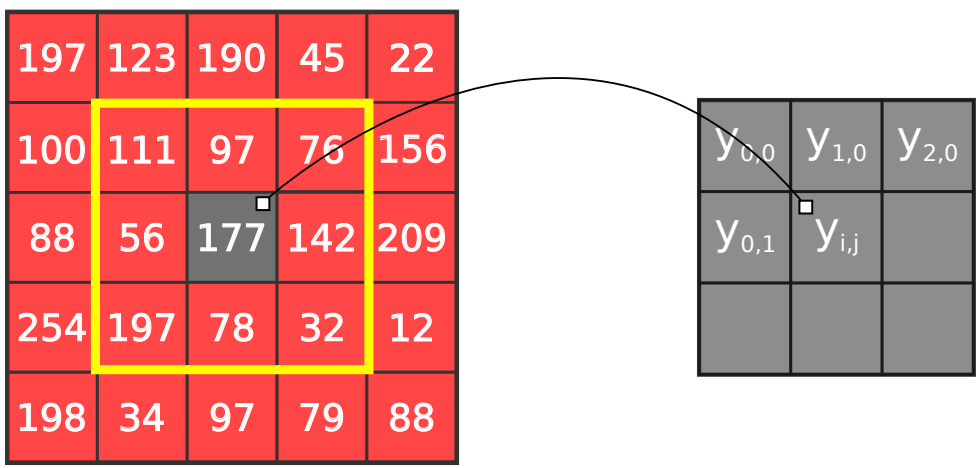

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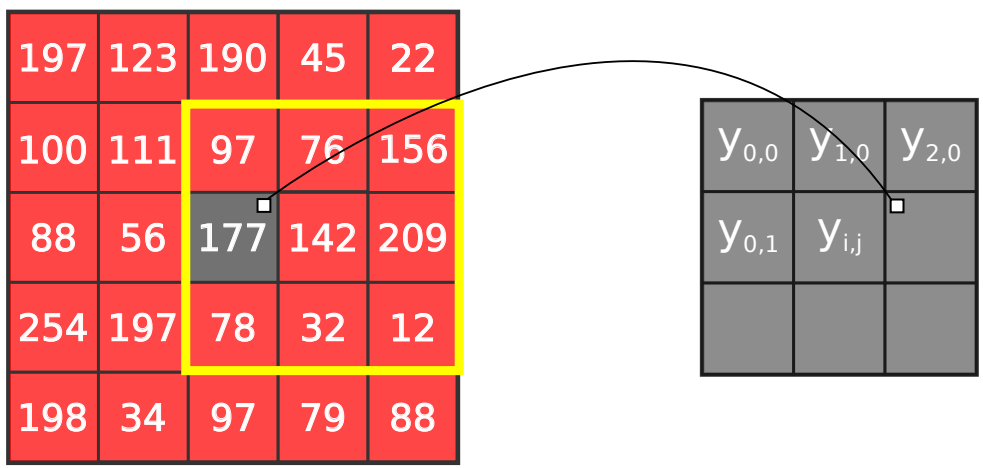

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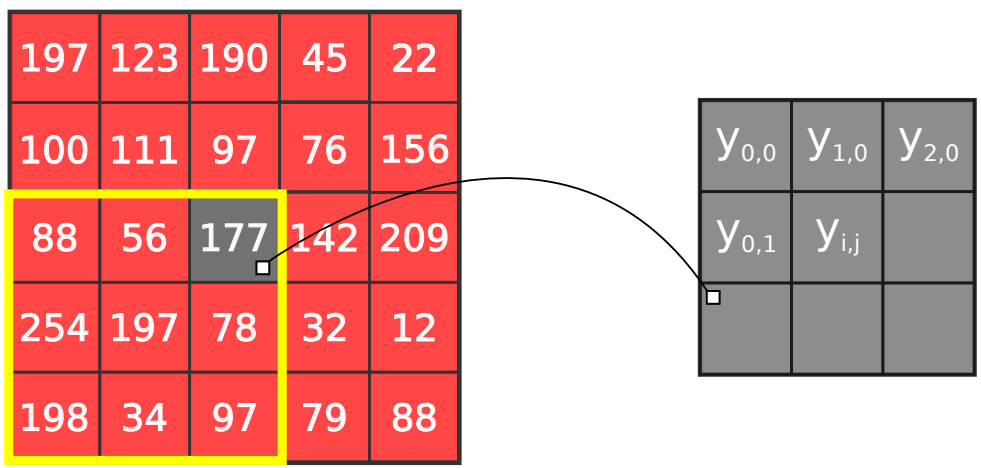

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Convolution Layer: Backward Pass

Cross-Correlation Derivative

$$y_{i'j'k'} = \sum_{ijk} w_{ijkk'} x_{i+i',j+j',k}$$

The **derivative** w.r.t. an **input parameter** x_{lmn} is $\frac{\partial y_{i'j'k'}}{\partial x_{lmn}} = w_{lmnk'}$.

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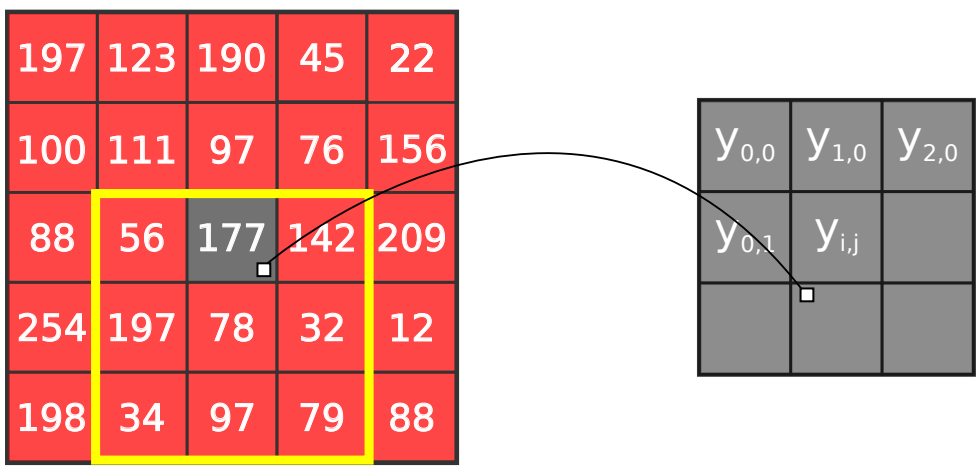

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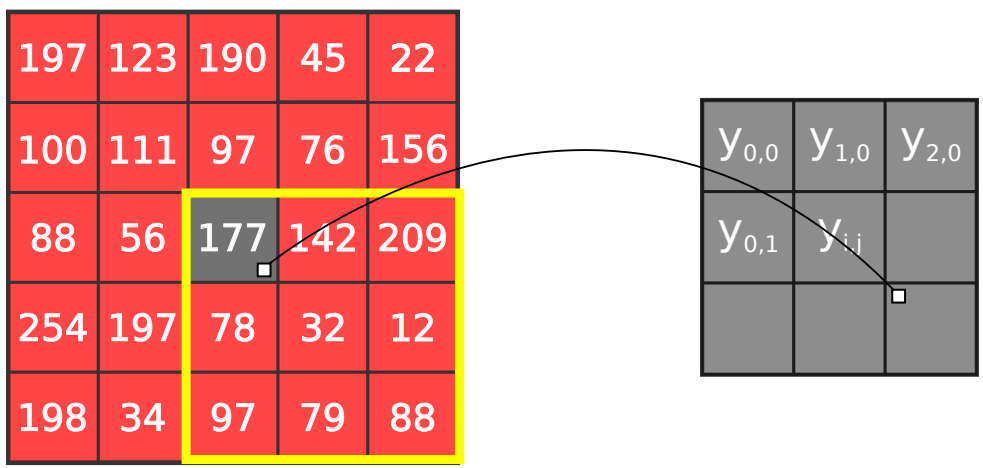

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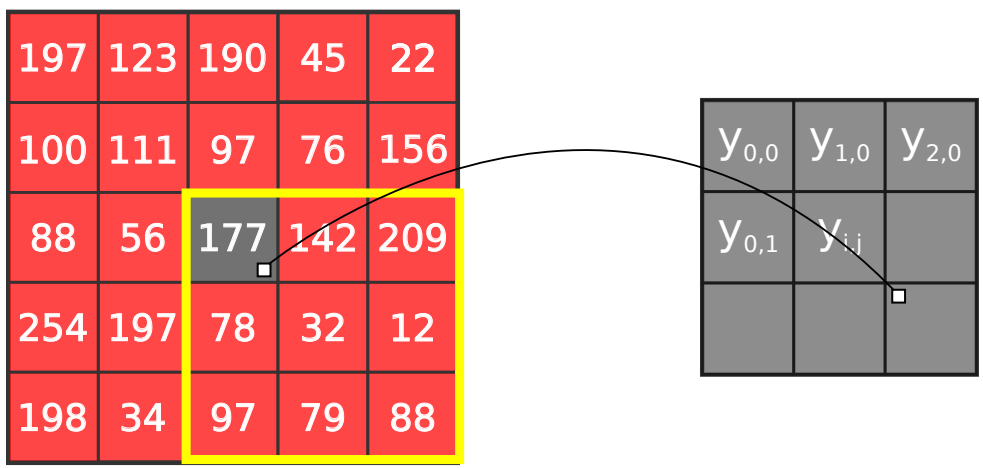

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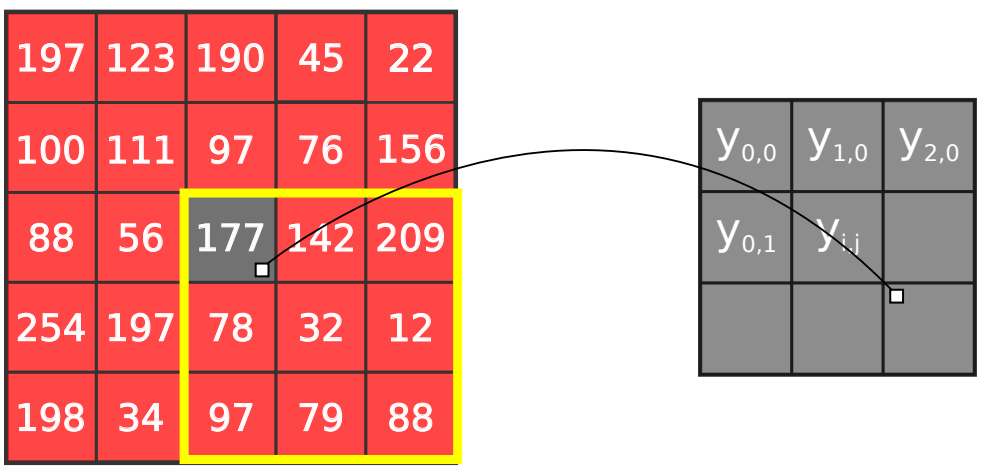

It's a convolution!

Back to the Beginning

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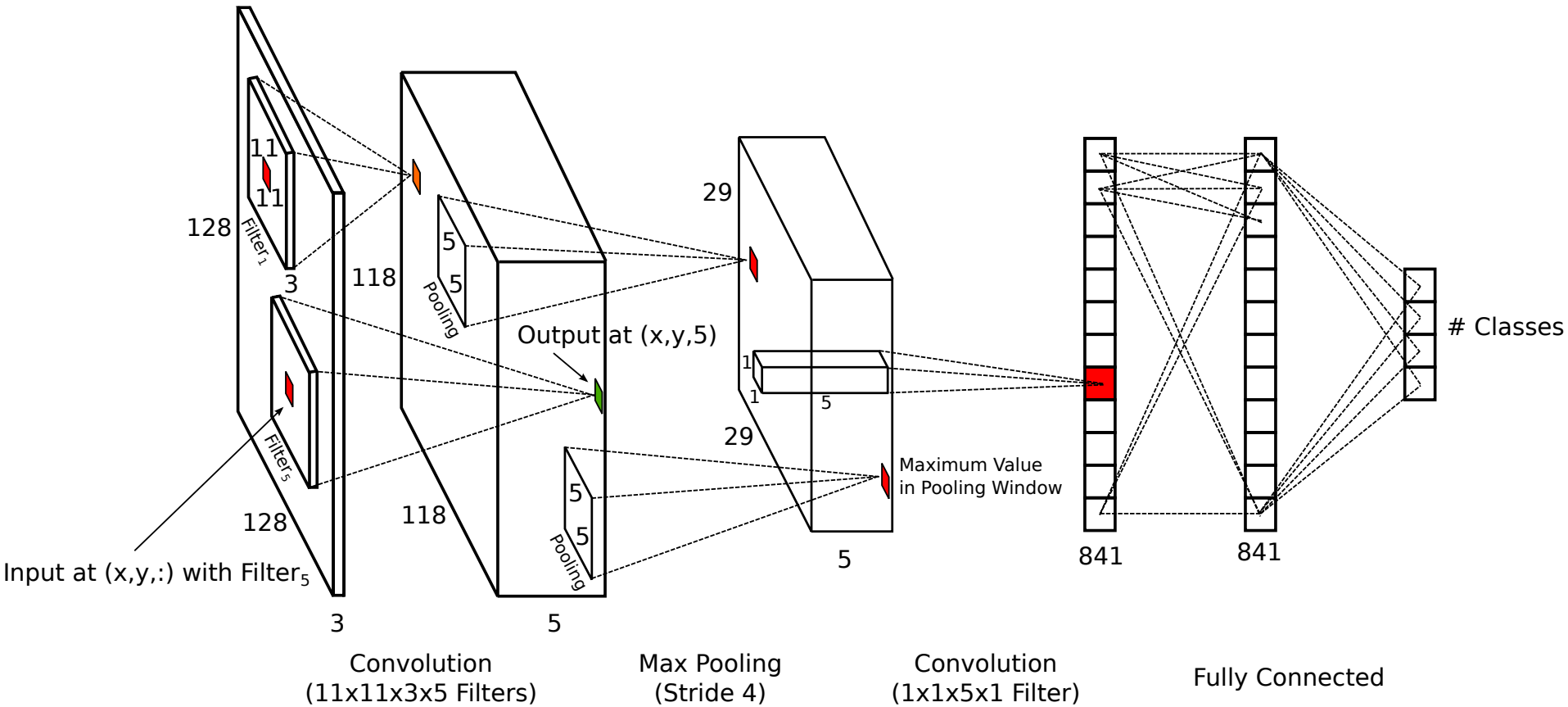

ConvNets in the Wild: Again Performance!

Performance in the Wild

The winning architecture of the LSVRC-2010 challenge (**AlexNet**) comes with **60 million parameters and 500 000 neurons**. It is trained on **1.3 million high-resolution images** in a **1000 class** problem.

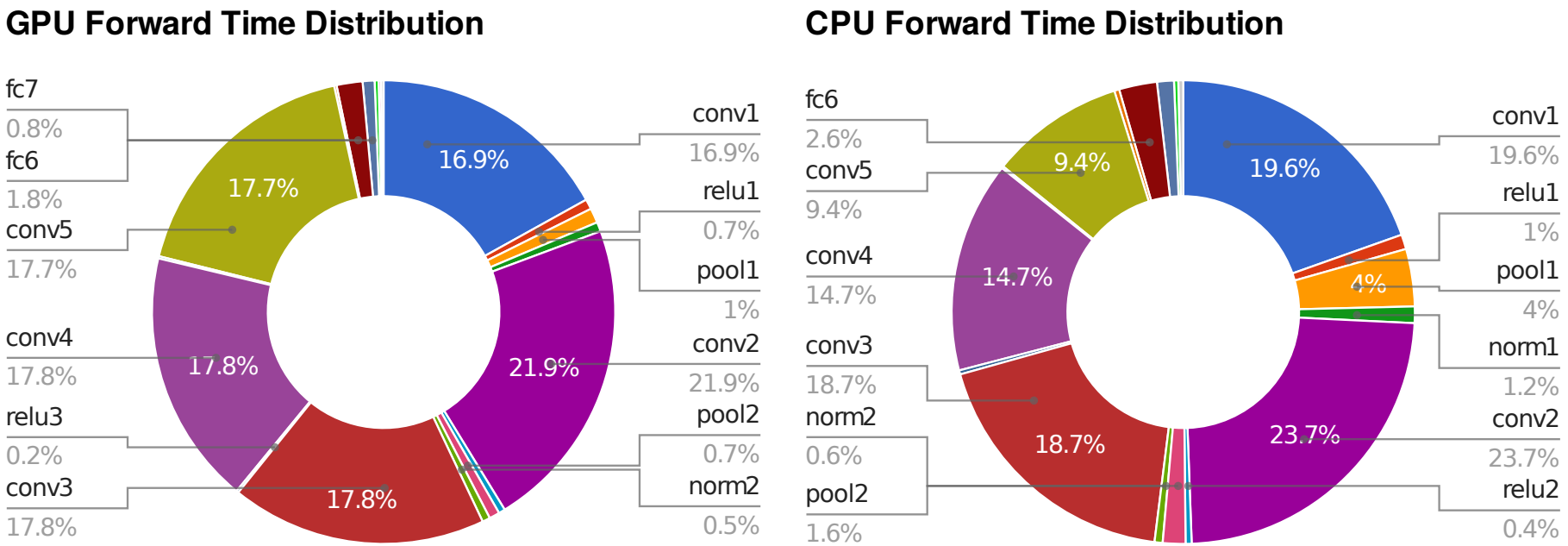

Figure : Jia: Time distribution of CNN layers in the AlexNet architecture. 95% GPU and 89% CPU of time is spent in convolution layers.

Performance in the Wild

Processing performance is usually measured in floating-point operations per second (FLOPS). All mathematical **operations** in ConvNets are **memory bound** hence memory bandwidth is the **most important factor**.

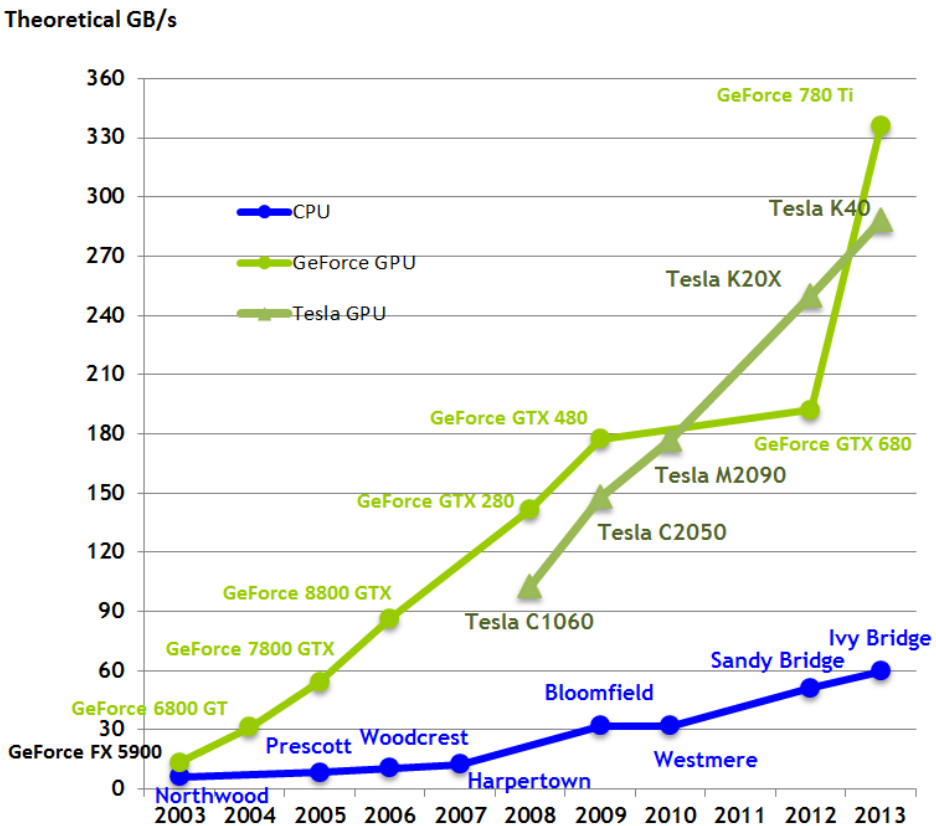

Figure : Dettmers: Memory bandwidth in GB/s for CPUs and GPUs over time

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4. Adapt the **learning rates**: Low for lower layers, high for higher layers
5. This potentially **reduces the required time** for training and **amount of data** significantly

ConvNets in the Wild: Software

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ConvNets in the Wild: MatConvNet

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MatConvNet: Feature-maps and Kernel-maps

MatConvNet makes heavy used of MATLAB's **array data type**.

Feature-maps in MatConvNet

Feature-maps come as **4-dimensional** arrays (Height x Width x Depth x #Feature-maps).

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A **Kernel-map** (or filter) is defined as a **4-dimensional** (Height x Width x Depth x #Filters) array. Filters for a convolution layer can simply be initialized as:

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Note that the **depth dimension** of kernel-maps and feature-maps have to be **equal** (except for filter-groups which I do not cover here).

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Convolution Layer in MatConvNet

For a given kernel-map w and an input batch x, the **forward pass** of the **convolution layer** can be computed as:

```
y = vl_nnconv(x, w, []);
```

To compute the **backward pass** we have to **supply the gradient** of the previous layer (or ones if there was no previous layer):

```
[DZDX, DZDW] = vl_nnconv(x, w, [], ones(size(y), 'single'));
```

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For a full API reference visit:
`http://www.vlfeat.org/matconvnet/functions`

MatConvNet: SimpleCNN Wrapper

There is a **wrapper** that let's us **define** a CNN **architecture** and does the **forward and backward passes**: `vl_simplenn`.

Defining a Convolution Layer in MatConvNet

A layer is defined as a **structure array** with an entry for each layer:

```
net.layers{end+1} = struct('type', 'conv', ...
                           'weights', {{w, b}}, ...
                           'stride', 1, 'pad', 0, ...
                           'learningRate', [1 2], ...
                           'weightDecay', [0.0001 0]);
```

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Each layer requires specific parameters. There are many examples to learn (or steal) from in MatConvNet.

MatConvNet: SimpleCNN Wrapper

For a defined ConvNet `vl_simplenn` can be called to **compute an iteration of forward and backward passes**.

Evaluating a ConvNet

```
res = vl_simplenn(x, net)
```

1. `res` is a **structure array** with one element per network layer plus one representing the input to the net
2. `res(i+1).x` is the **output of layer** `i`
3. `res(i+1).dzdx` is the **derivative of the network output** w.r.t. `res(i+1).x`

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7. Use **batch-sizes appropriate** for your hardware and problem

ConvNets in the Wild: Visualizing and Analyzing Deep Architectures

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Figure : The MNIST dataset.

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4. Consequently **inputs** can be **constructed** that will **fool a ConvNet**

Fooling ConvNets

Created images that **fool a ConvNet** but would **never be interpreted** as a certain class by a human observer:

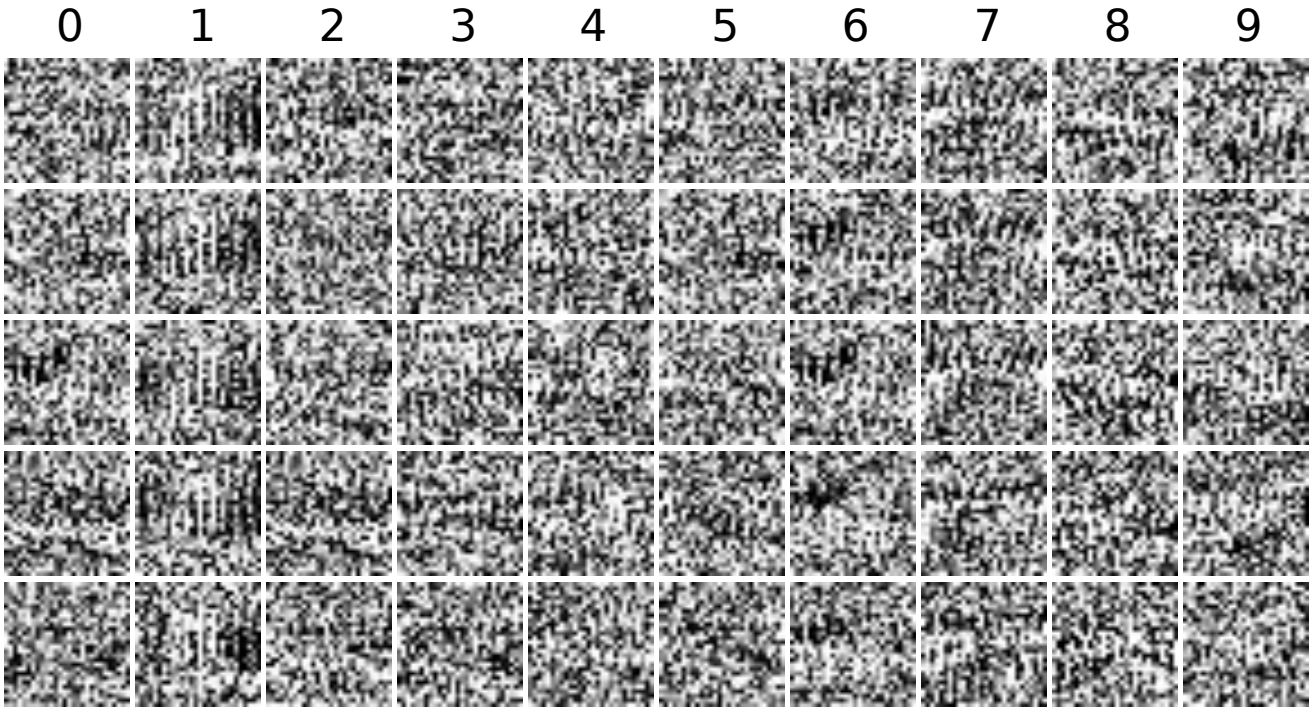

Figure : Nguyen et al.: Evolutionary optimized images that MNIST CNNs believe with 99.99% confidence are digits 0-9

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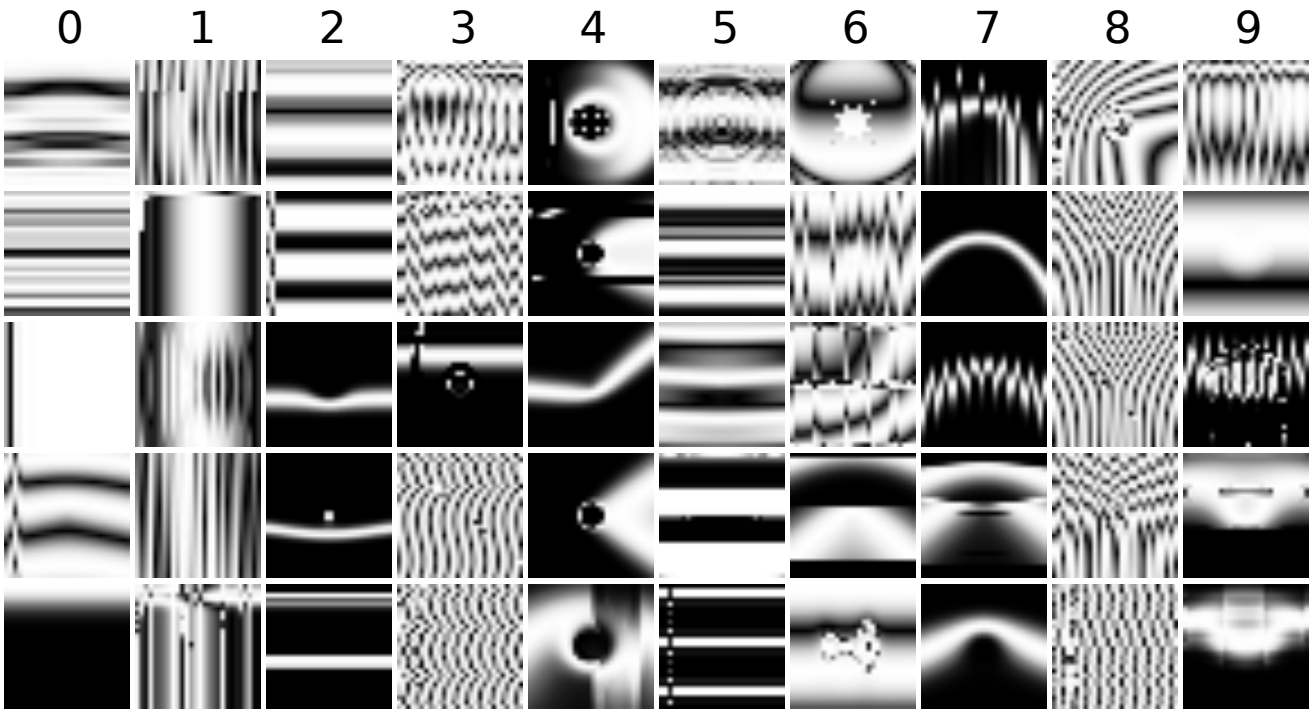

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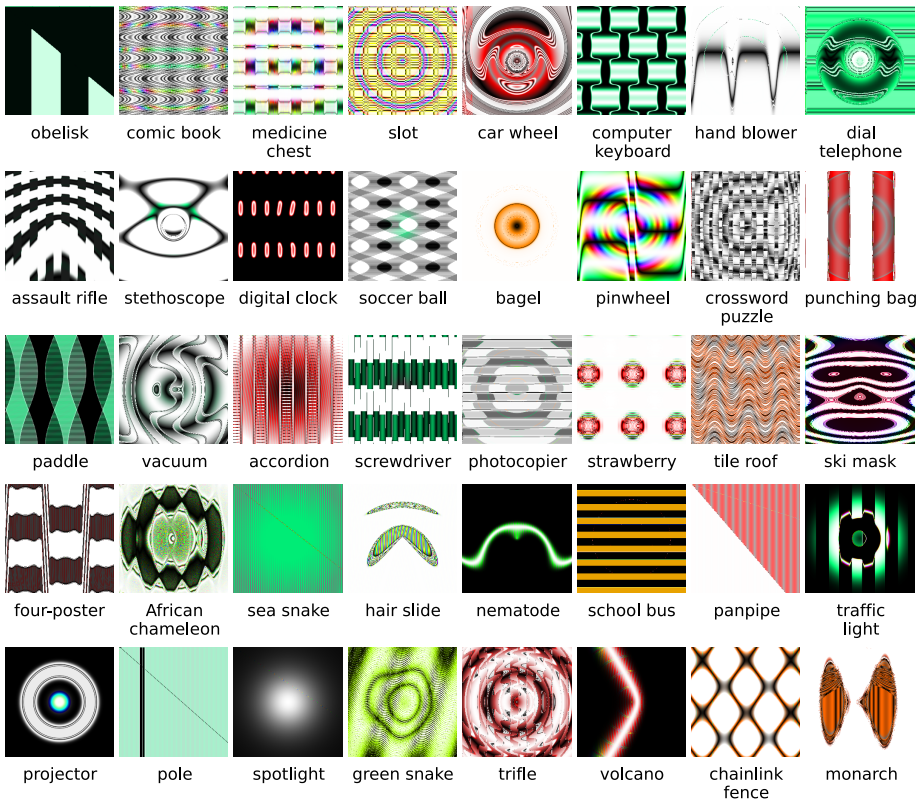

Figure : Nguyen et al.: Evolutionary optimized images for ImageNet CNNs with mean confidence score of 99.12%

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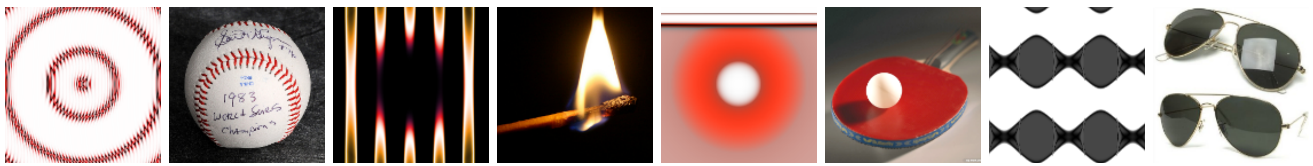

Figure : Nguyen et al.: Evolved images resembling target class.

ConvNets in the Wild: Deep Dreaming

Deep Dreaming

Another way of **visualizing what a ConvNets sees** is called **Inceptionism** and was invented by Google Research.

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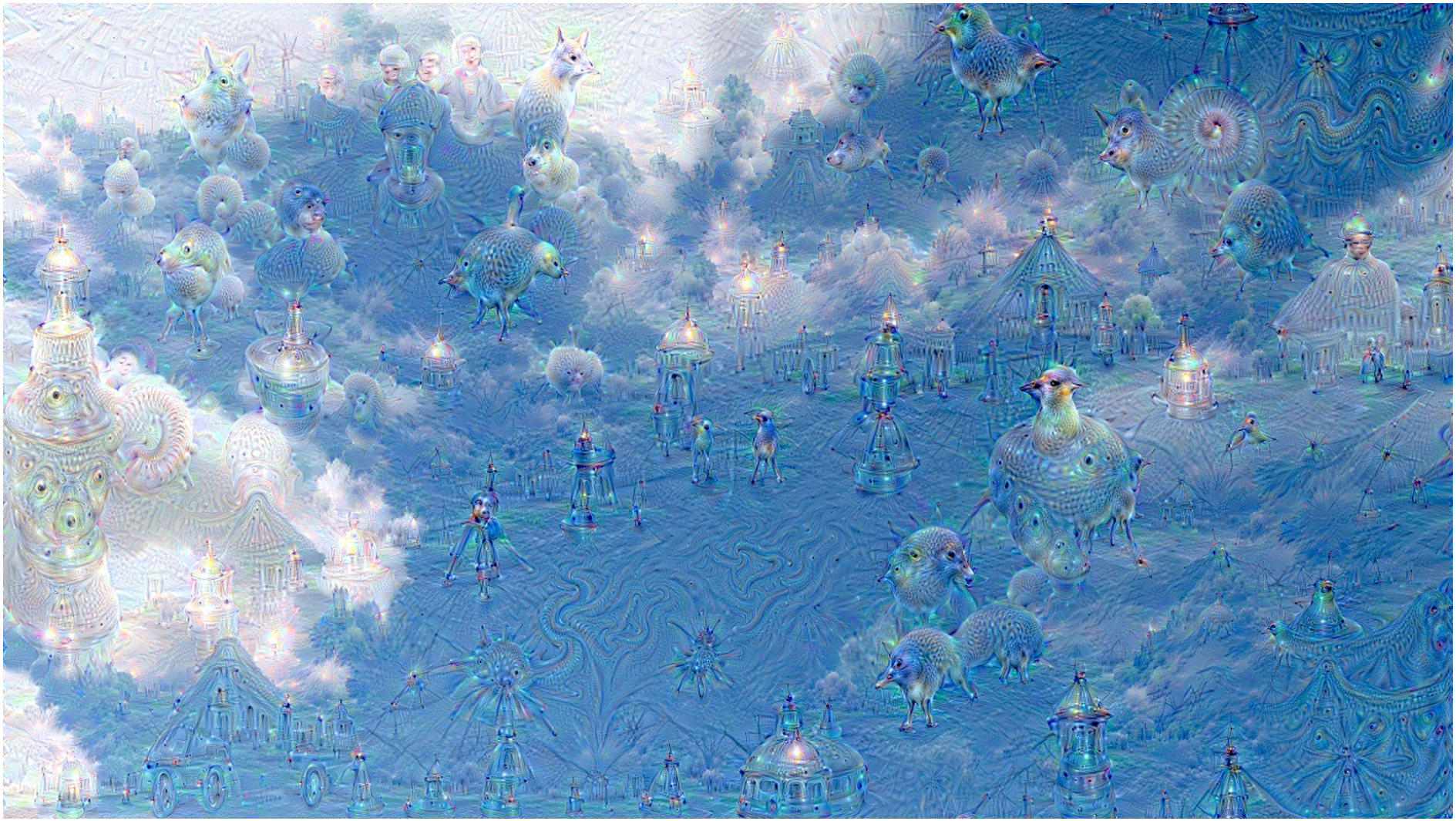
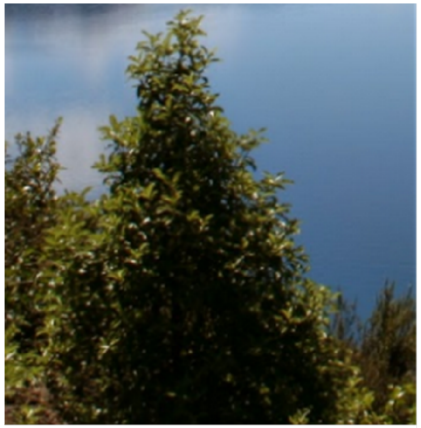
2. **Gradient ascent** with L^2 regularization **maximizing the activation** of a certain unit
3. Instead of weights, the **activations** in a layer are **optimized**
4. This is **iterated multiple times feeding the maximized output into the net** and leads to very interesting results

Deep Dreaming



Deep Dreaming

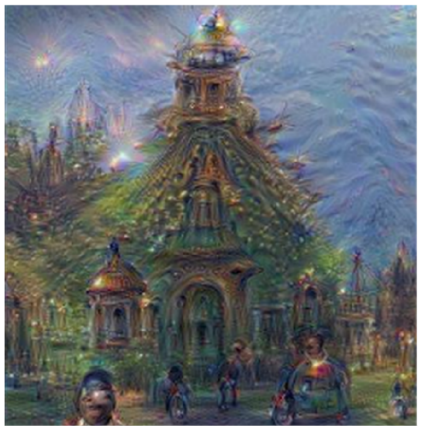
Horizon



Trees

Leaves

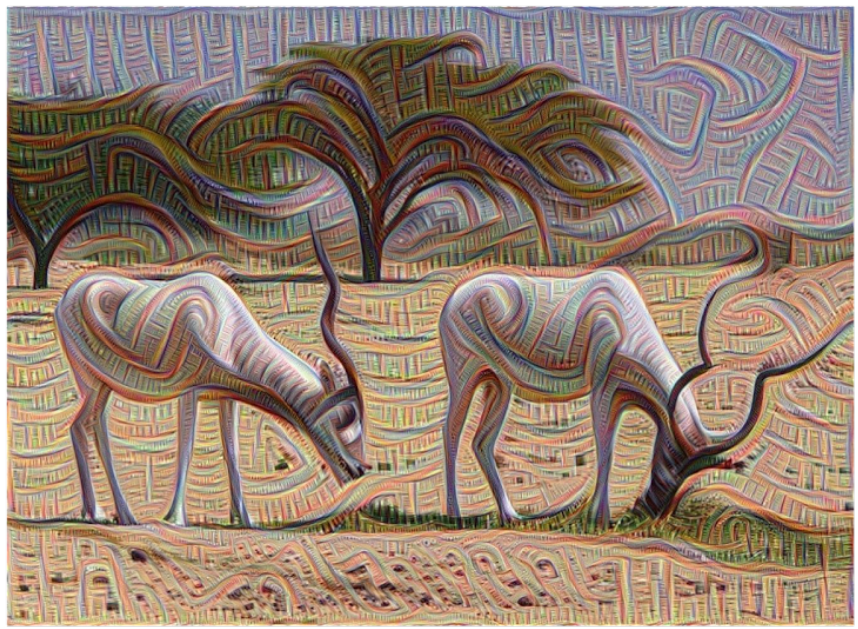
Towers & Pagodas



Buildings

Birds & Insects

Deep Dreaming



Deep Dreaming

Deep Dreaming

I am (finally) done!