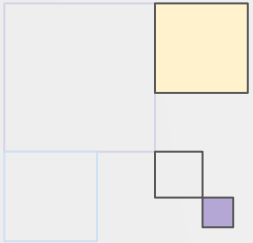
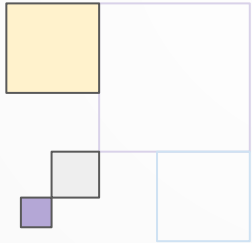
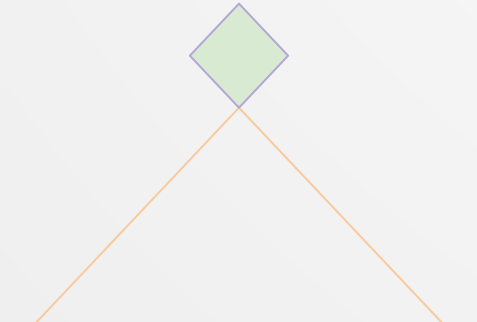




Deep Learning

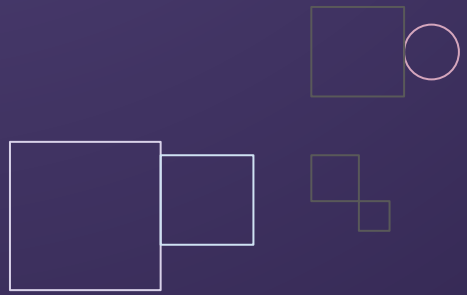
CNNs



Bryan Cardenas
Caspar van Leeuwen
Monica Rotulo
Robert Jan Schlimbach

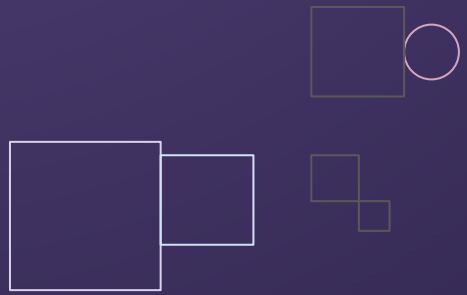
SURF

How do Computers see?



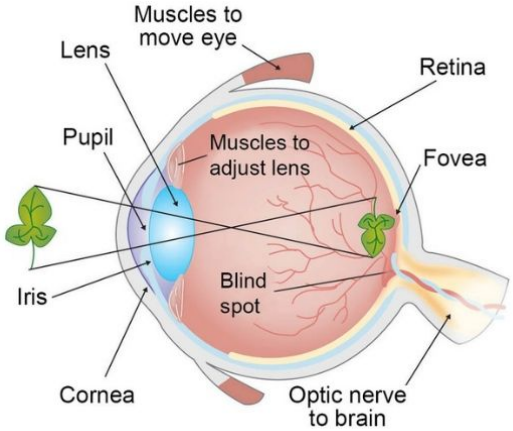
SURF

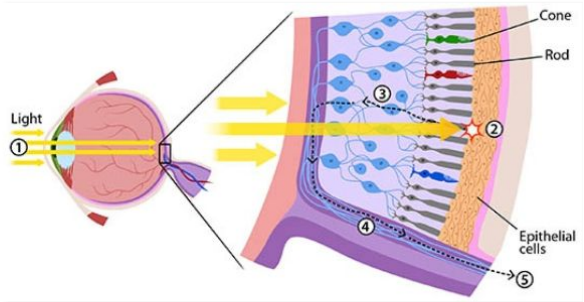
How do Humans see?

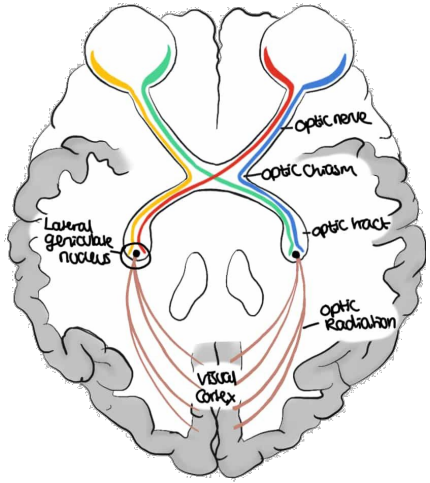


SURF

Mammalian Visual System



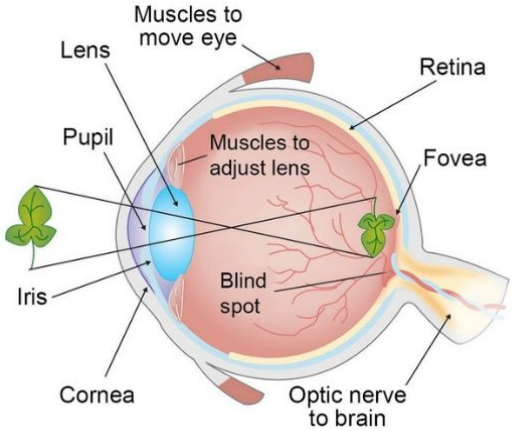


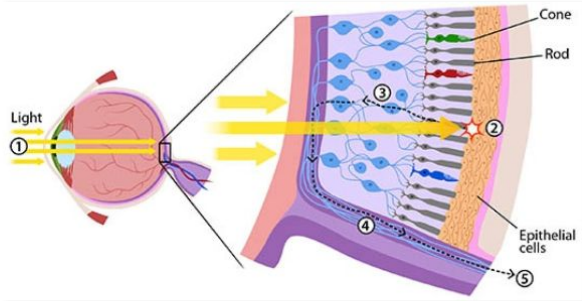


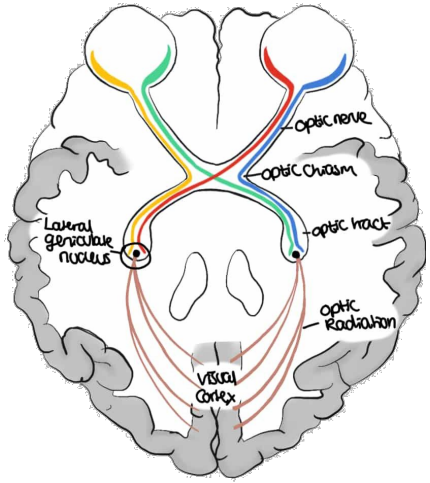
Mammalian Visual System

Cones and rods picks up photons and propagate the signal to the back of our brain

Along the way, the signal gets processed in stages





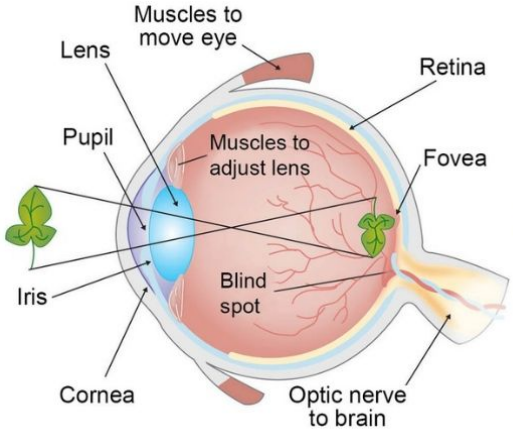


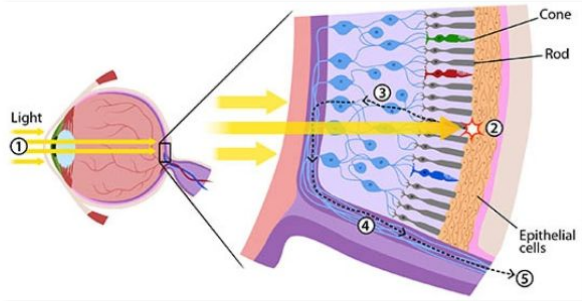
Mammalian Visual System

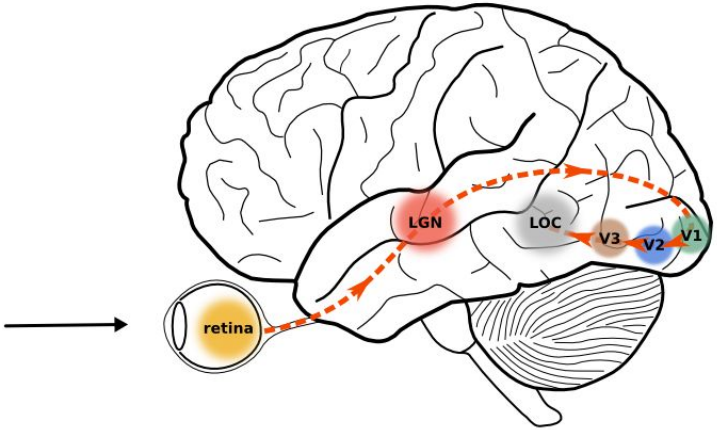
Cones and rods picks up photons and propagate the signal to the back of our brain

Along the way, the signal gets processed in stages

The extracted information gets aggregated and formed into an image





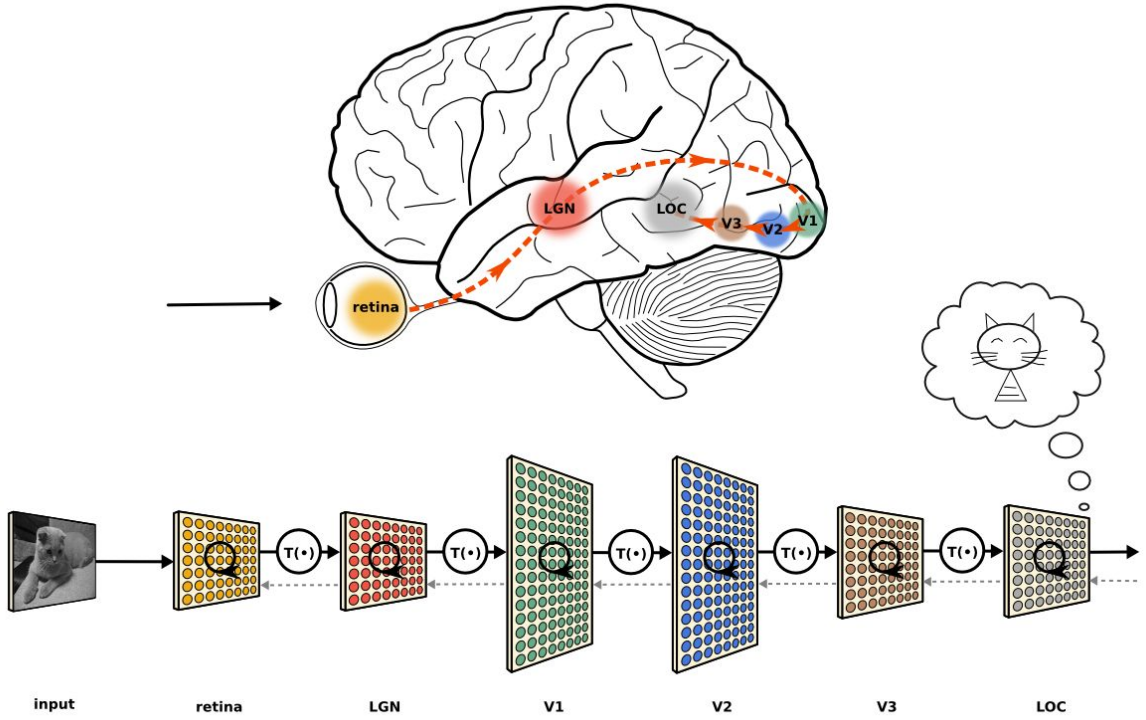


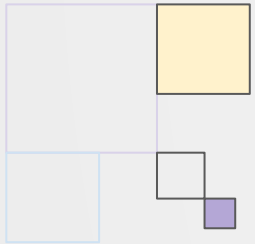
Mammalian Visual System

Cones and rods picks up photons and propagate the signal to the back of our brain

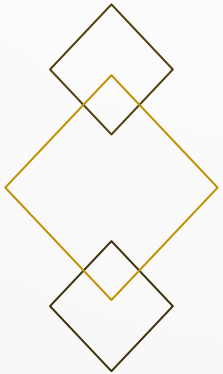
Along the way, the signal gets processed in stages

The extracted information gets aggregated and formed into an image





Convolutional Neural Networks



High Performance Machine Learning Group

SURF

Image Representation

01. Is a matrix or grid of intensity values

02. integers [0, 255] or float points [0,1]

03. Each element in the matrix is a **pixel**

04. Can have 1 greyscale channel or multiple colour **channels: RGB**

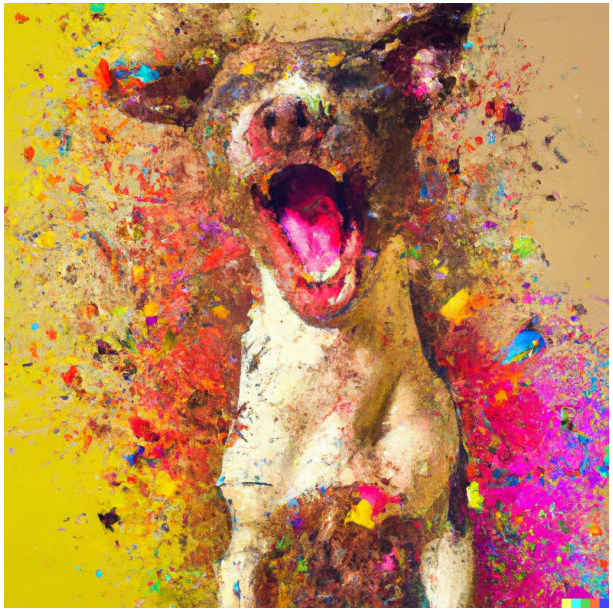


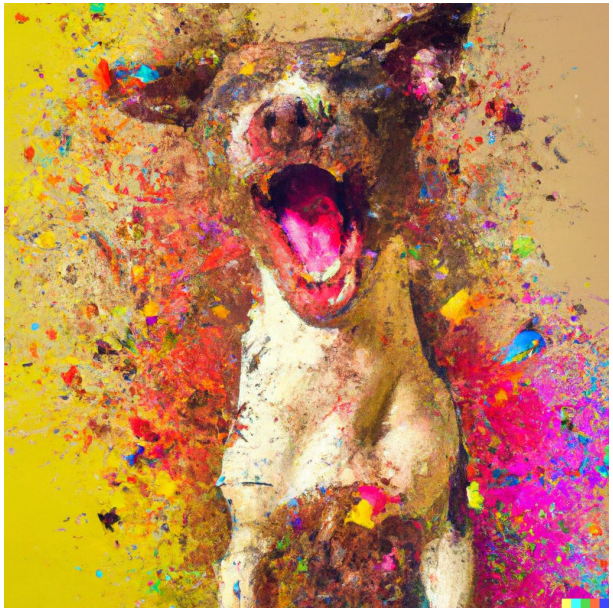
Image Representation

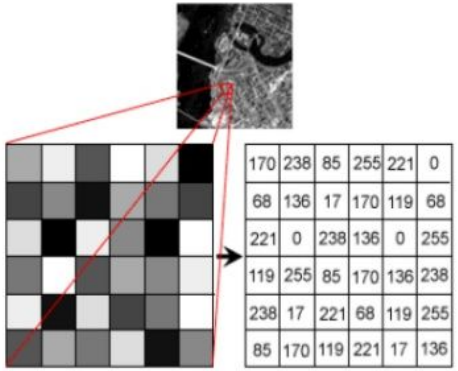
01. Is a matrix or grid of intensity values

02. integers [0, 255] or float points [0,1]

03. Each element in the matrix is a **pixel**

04. Can have 1 greyscale channel or multiple colour **channels: RGB**





SURF

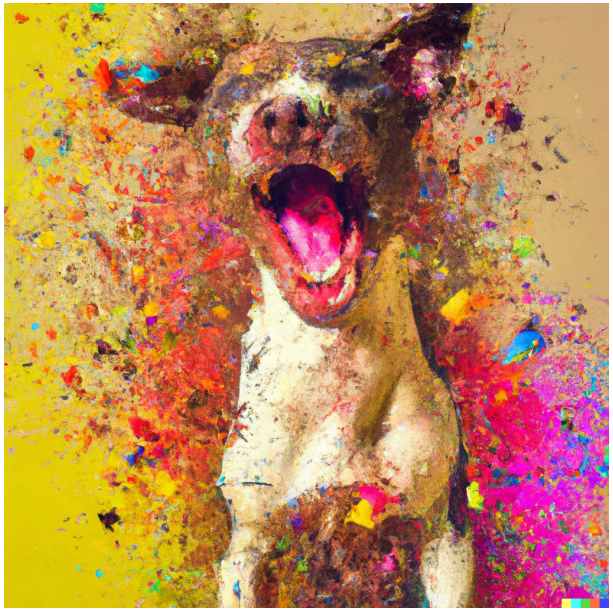
Image Representation

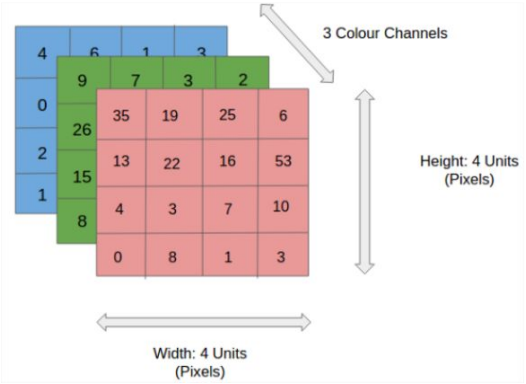
01. Is a matrix or grid of intensity values

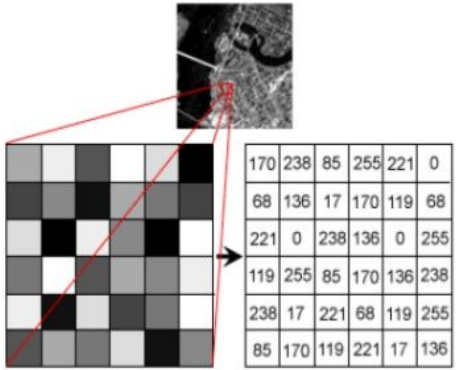
02. integers [0, 255] or float points [0,1]

03. Each element in the matrix is a **pixel**

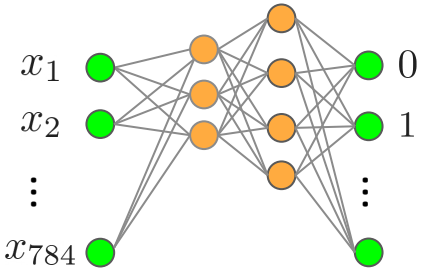
04. Can have 1 greyscale channel or multiple colour **channels: RGB**







Correlated structures

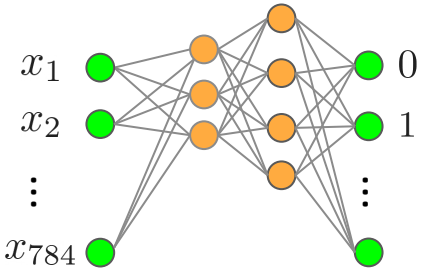


Images are **correlated spatially**

Strong correlation between neighbouring pixels

Shifting an object will not alter its essence

Correlated structures

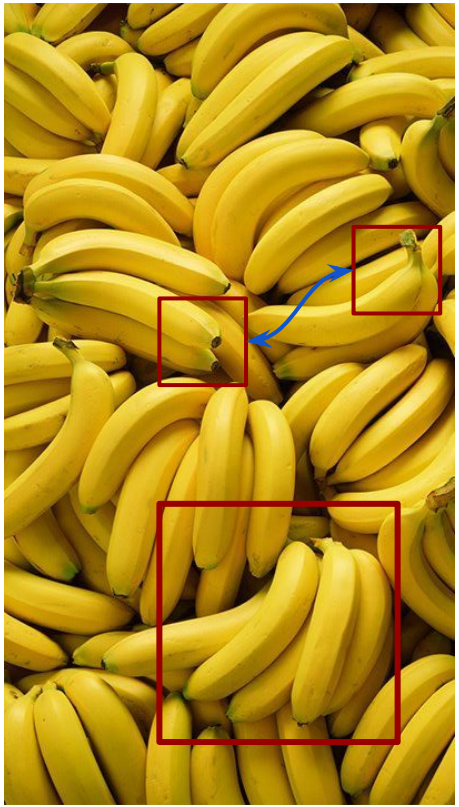


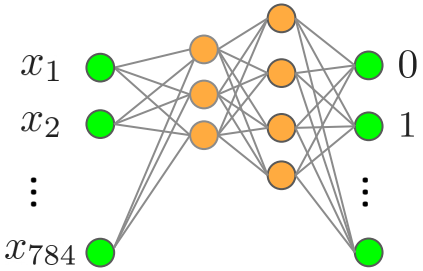
Images are **correlated spatially**

Strong correlation between neighbouring pixels

Shifting an object will not alter its essence

Correlated structures



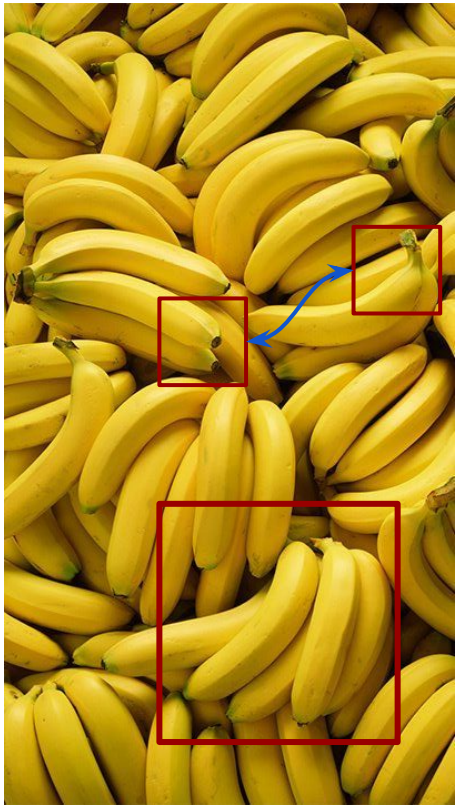


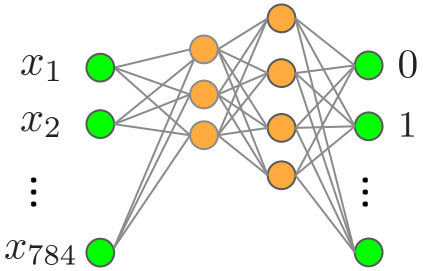
Images are **correlated spatially**

Strong correlation between neighbouring pixels

Shifting an object will not alter its essence

Correlated structures



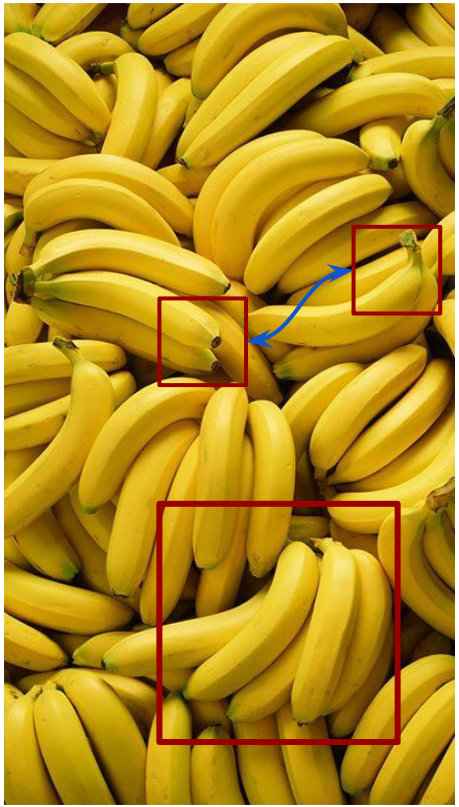


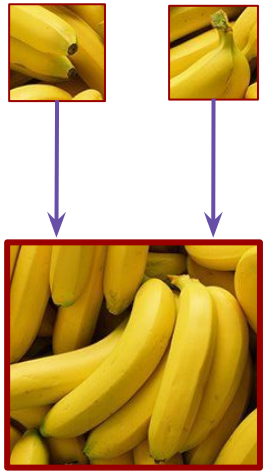
Images are **correlated spatially**

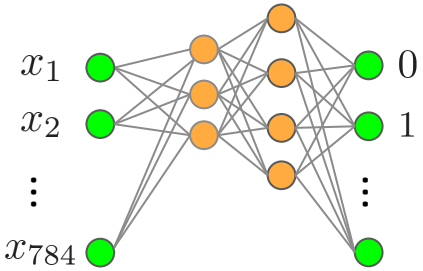
Strong correlation between neighbouring pixels

Shifting an object will not alter its essence

Correlated structures





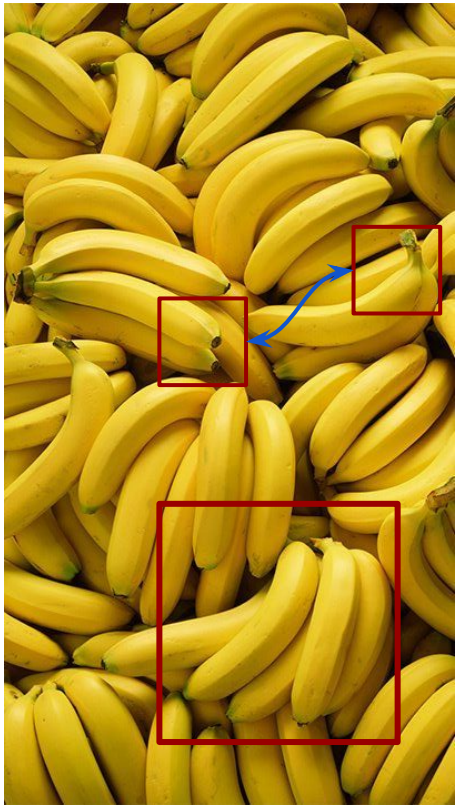


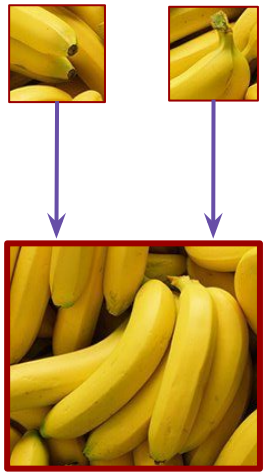
Images are **correlated spatially**

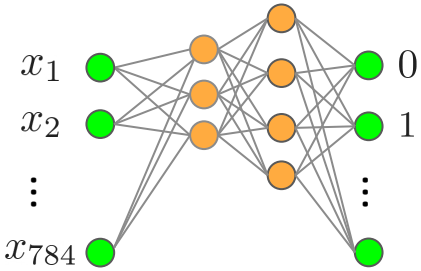
Strong correlation between neighbouring pixels

Shifting an object will not alter its essence

Correlated structures







Detect the features across an image and aggregate them

Form complete features higher up in the **hierarchy**

Images are **correlated spatially**

Strong correlation between neighbouring pixels

Shifting an object will not alter its essence

ImageNet Challenge

Computer Vision Benchmark

1.4M Images, 1000 classes

Image Classification

Difficult until 2012

SURF

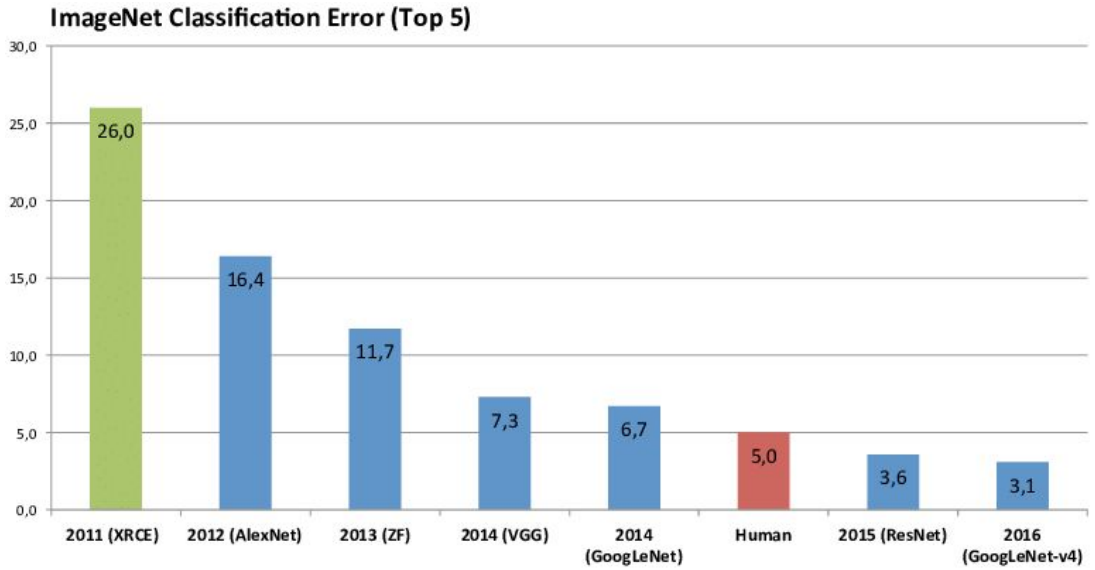
ImageNet Challenge

Computer Vision Benchmark

Image Classification

1.4M Images, 1000 classes

Difficult until 2012



SURF

The Convolution Operation

$$(f * g)(t) = \int_{-\infty}^{\infty} f(\tau)g(t-\tau)d\tau$$

The Convolution Operation

$$(f * g)(t) = \int_{-\infty}^{\infty} f(\tau) g(t - \tau) d\tau$$

$$S(t) = (E * R)(t) = \int_{-\infty}^{\infty} E(\tau) R(t - \tau) d\tau$$

The Convolution Operation

$$(f * g)(t) = \int_{-\infty}^{\infty} f(\tau) g(t - \tau) d\tau$$

Impulse Response

$$S(t) = (E * R)(t) = \int_{-\infty}^{\infty} E(\tau) R(t - \tau) d\tau$$

SURF

The Convolution Operation

$$(f * g)(t) = \int_{-\infty}^{\infty} f(\tau) g(t - \tau) d\tau$$

Source Signal

Impulse Response

$$S(t) = (E * R)(t) = \int_{-\infty}^{\infty} E(\tau) R(t - \tau) d\tau$$

SURF

The Convolution Operation

$$(f * g)(t) = \int_{-\infty}^{\infty} f(\tau) g(t - \tau) d\tau$$

Seismogram **Source Signal** **Impulse Response**

$$S(t) = (E * R)(t) = \int_{-\infty}^{\infty} E(\tau) R(t - \tau) d\tau$$

SURF

The Convolution Operation

$$(f * g)(t) = \int_{-\infty}^{\infty} f(\tau) g(t - \tau) d\tau$$

$$(f * g)[n] = \sum_{m=-\infty}^{\infty} f[m] g[n - m]$$

The Convolution Operation

Initial signal gets modified by the system's **response**

One signal **slides** across the other

$$(f * g)[n] = \sum_{m=-\infty}^{\infty} f[m]g[n-m]$$

Convolutions

Kernel (filter): small matrix that we use to convolve an image

Operation	Kernel	Image result
Identity	$\begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}$	
Edge detection	$\begin{bmatrix} 1 & 0 & -1 \\ 0 & 0 & 0 \\ -1 & 0 & 1 \end{bmatrix}$	
	$\begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix}$	
	$\begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix}$	
Sharpen	$\begin{bmatrix} 0 & -1 & 0 \\ -1 & 5 & -1 \\ 0 & -1 & 0 \end{bmatrix}$	
Box blur (normalized)	$\frac{1}{9}\begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$	

Convolutions

Kernel (filter): small matrix that we use to convolve an image

Convolution:

An operation that “blends” one function with another.

Operation	Kernel	Image result
Identity	$\begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}$	
Edge detection	$\begin{bmatrix} 1 & 0 & -1 \\ 0 & 0 & 0 \\ -1 & 0 & 1 \end{bmatrix}$	
	$\begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix}$	
	$\begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix}$	
Sharpen	$\begin{bmatrix} 0 & -1 & 0 \\ -1 & 5 & -1 \\ 0 & -1 & 0 \end{bmatrix}$	
Box blur (normalized)	$\frac{1}{9}\begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$	

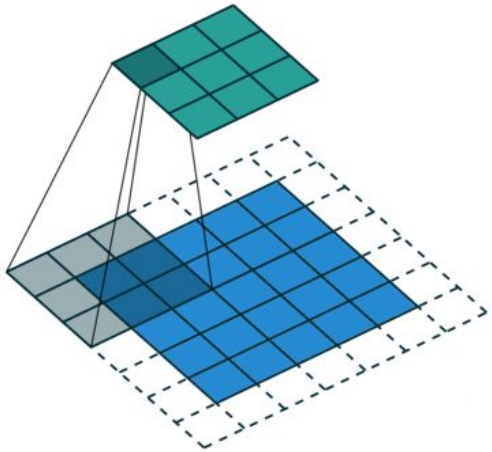
Convolutions

Kernel (filter): small matrix that we use to convolve an image

Convolution:

An operation that “blends” one function with another.

A filter applies a **convolution** operation on an image



Operation	Kernel	Image result
Identity	$\begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}$	
Edge detection	$\begin{bmatrix} 1 & 0 & -1 \\ 0 & 0 & 0 \\ -1 & 0 & 1 \end{bmatrix}$	
	$\begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix}$	
	$\begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix}$	
Sharpen	$\begin{bmatrix} 0 & -1 & 0 \\ -1 & 5 & -1 \\ 0 & -1 & 0 \end{bmatrix}$	
Box blur (normalized)	$\frac{1}{9}\begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$	

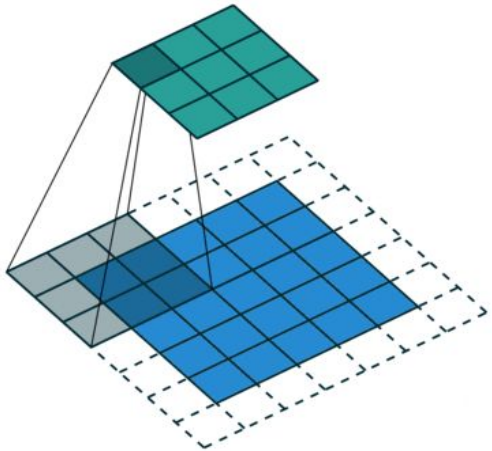
Convolutions

Kernel (filter): small matrix that we use to convolve an image

Convolution:

An operation that “blends” one function with another.

A filter applies a **convolution** operation on an image



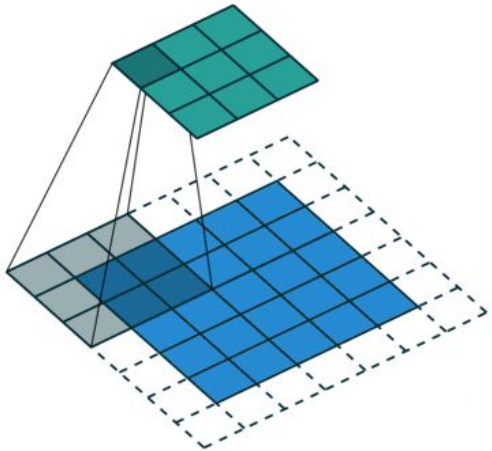
Convolutions

Kernel (filter): small matrix that we use to convolve an image

Convolution:

An operation that “blends” one function with another.

A filter applies a **convolution** operation on an image



Convolutions

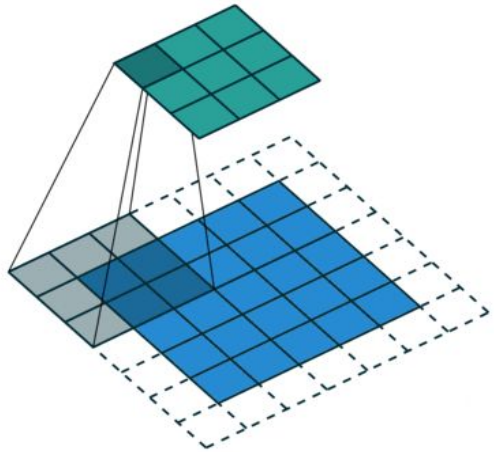
Kernel (filter): small matrix that we use to convolve an image

Convolution:

An operation that “blends” one function with another.

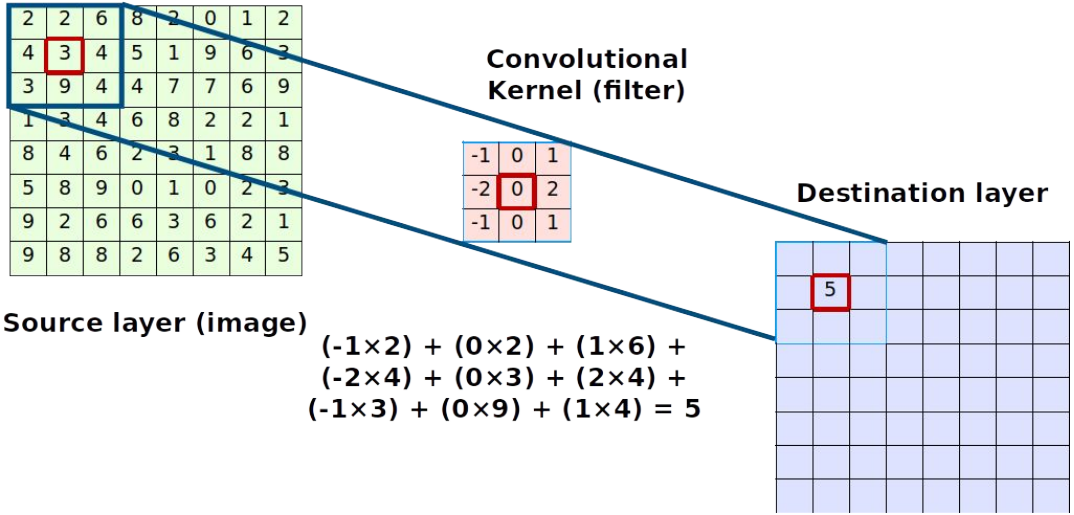
A filter applies a **convolution** operation on an image

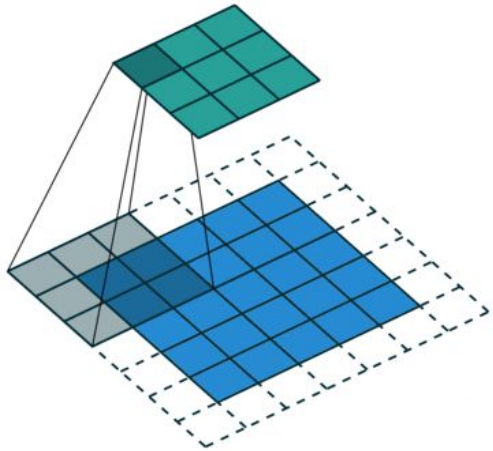
$$\sum_{i=-\infty}^{\infty} \sum_{j=-\infty}^{\infty} I(i,j) \cdot K(x-i, y-j)$$



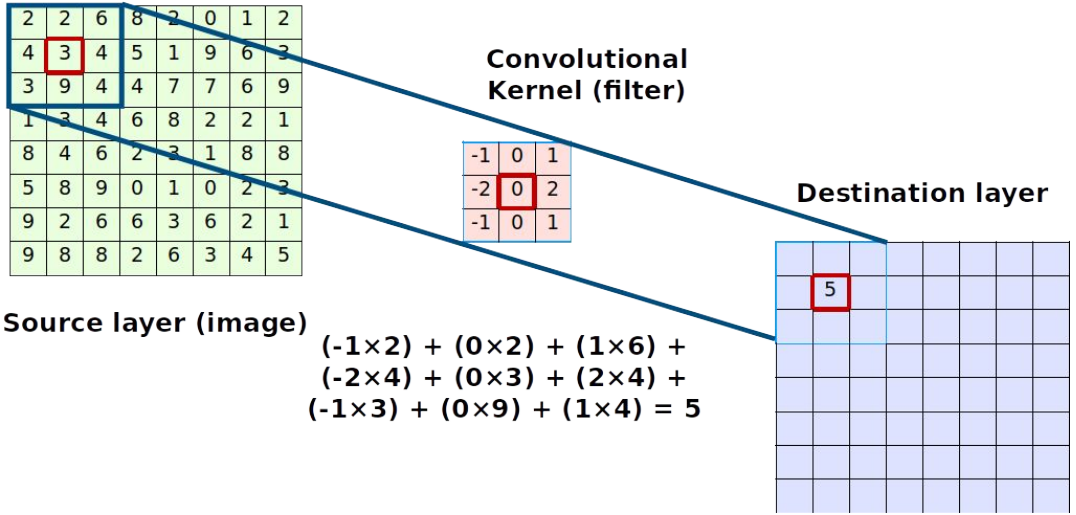
SURF

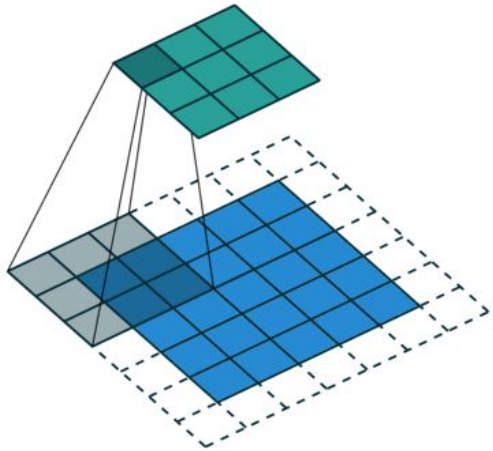
Convolutions Compute





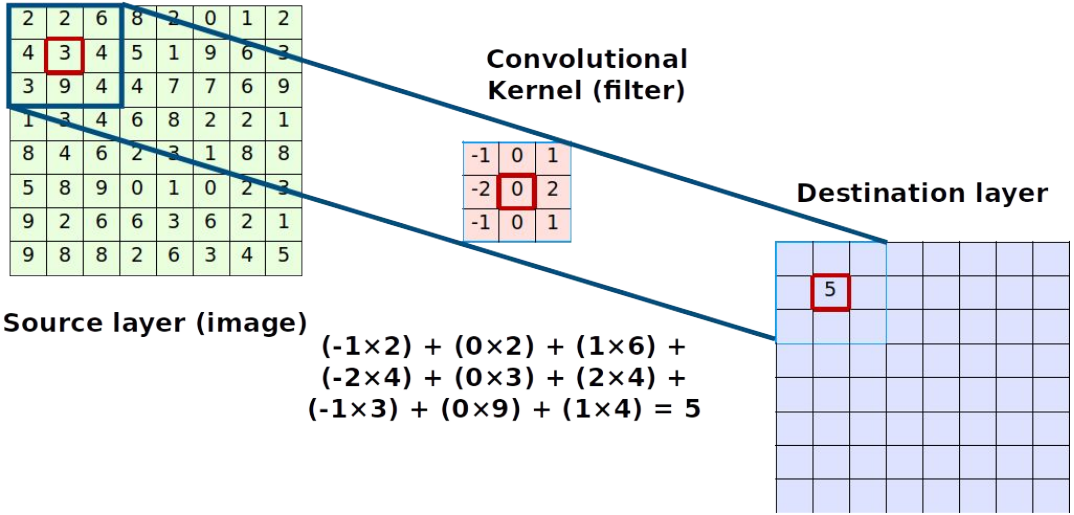
Convolutions Compute

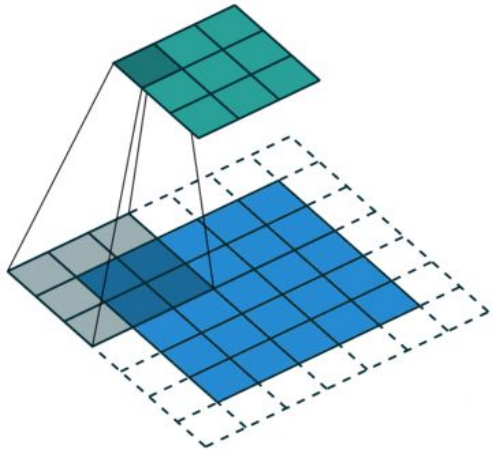




The kernel is **shifted** across the image and produces a point value
The step size in which it shifts is the **stride**
The output is always smaller, we use **padding** to preserve dimensions

Convolutions Compute





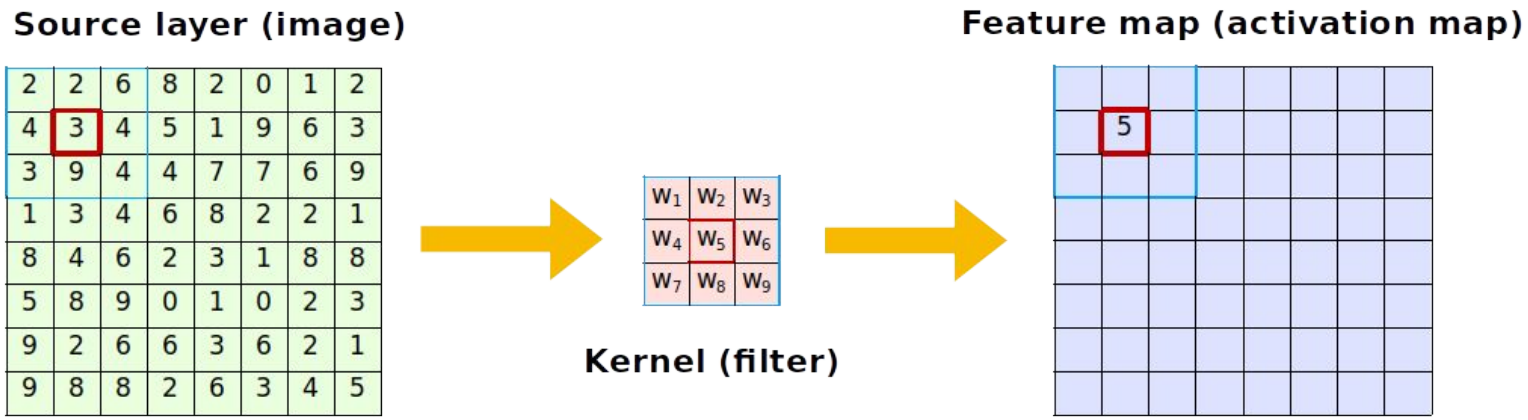
The kernel is **shifted** across the image and produces a point value
The step size in which it shifts is the **stride**
The output is always smaller, we use **padding** to preserve dimensions

The image shrinks according to

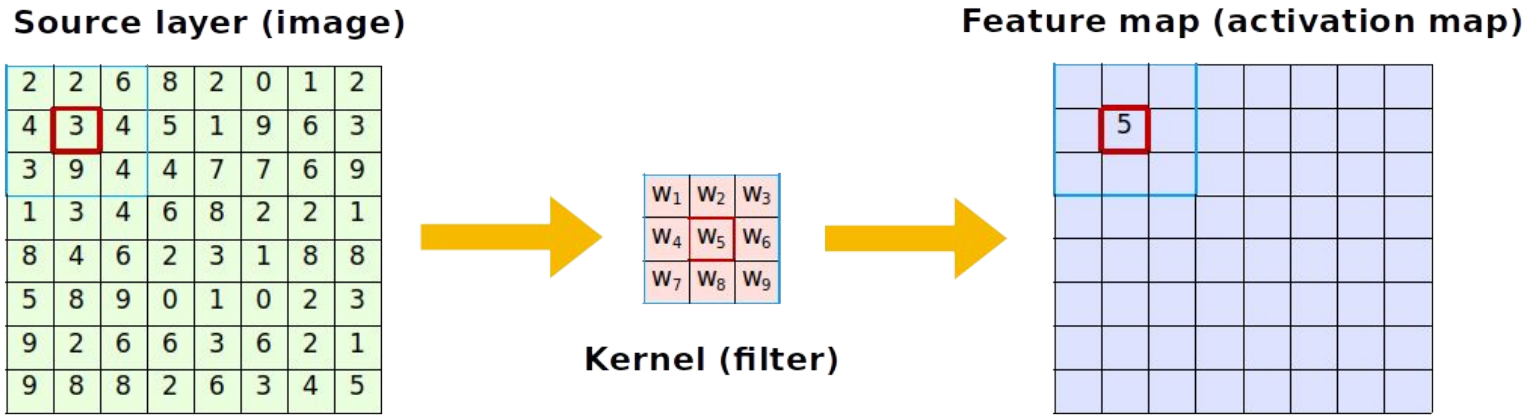
Output_size = inputSize -(KernelSize - 1)

SURF

Convolutions



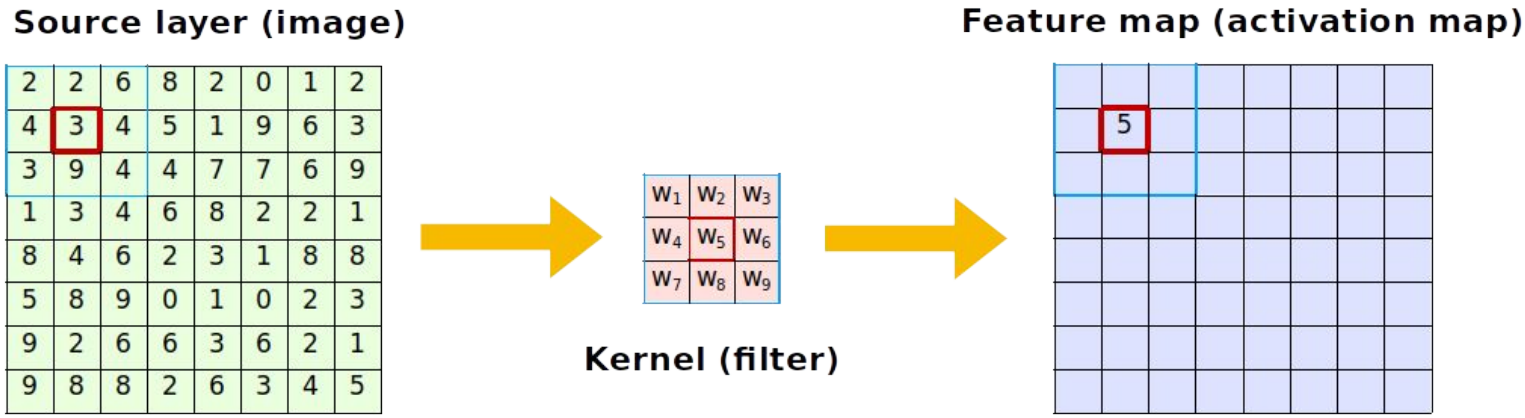
Convolutions



How do we know which kernels to use?

Kernels are learnt and initialized randomly
during training the CNN learns spatial features

Convolutions



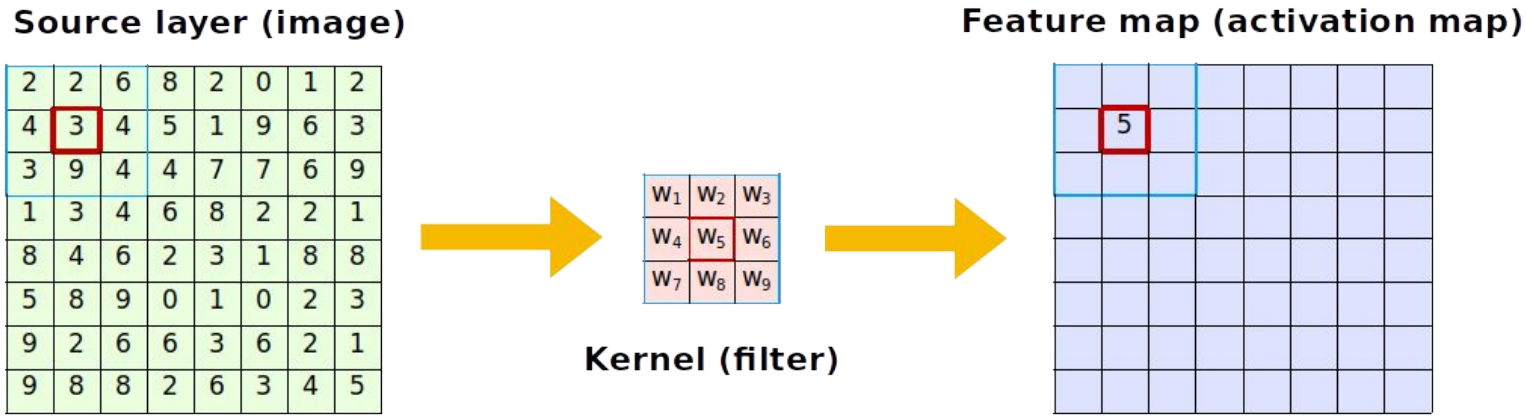
How do we know which kernels to use?

Kernels are learnt and initialized randomly during training the CNN learns spatial features

Fully connected

$$\sum_{i \in \text{image}}^{W \times H \times C} \mathbf{x}_i \mathbf{w}_i$$

Convolutions



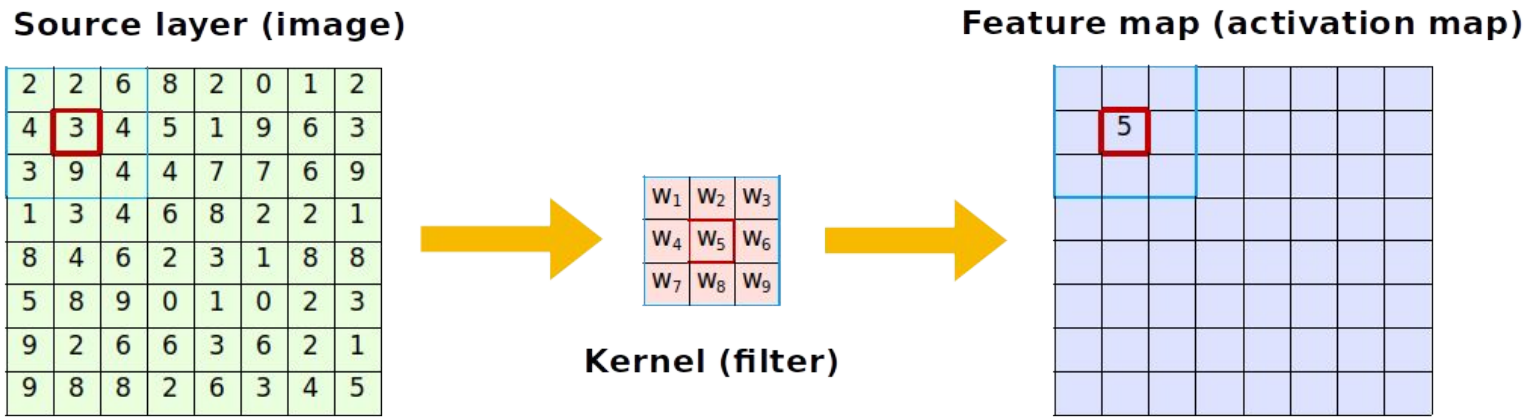
How do we know which kernels to use?

Kernels are learnt and initialized randomly during training the CNN learns spatial features

Fully connected

$$\sum_{i \in \text{image}}^{W \times H \times C} \mathbf{x}_i \mathbf{w}_i \rightarrow$$

Convolutions



How do we know which kernels to use?

Kernels are learnt and initialized randomly during training the CNN learns spatial features

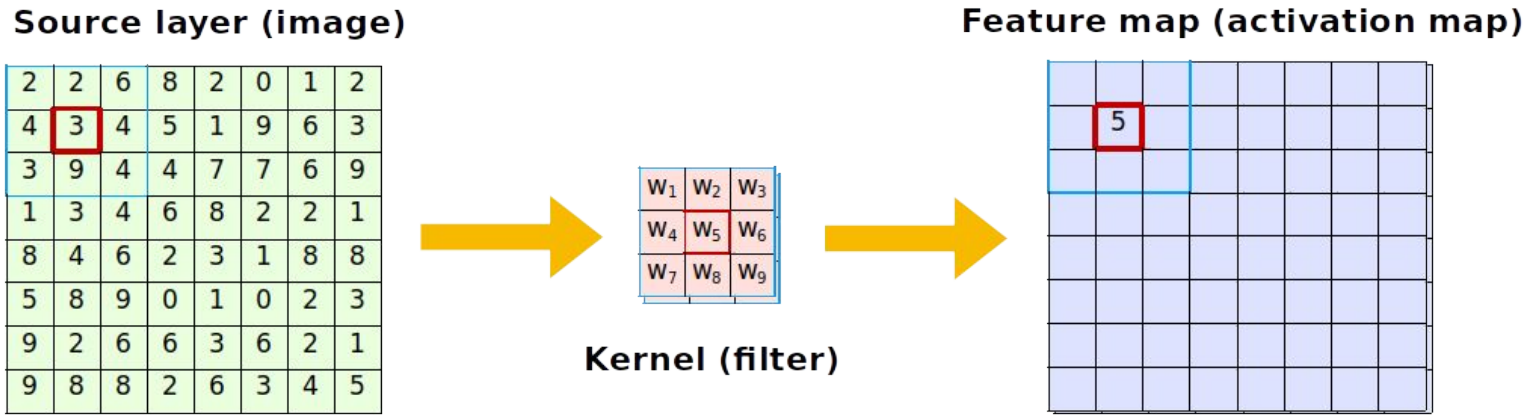
Fully connected

$$\sum_{i \in \text{image}}^{W \times H \times C} \mathbf{x}_i \mathbf{w}_i$$

Locally connected shared weights

$$\sum_{i \in 3 \times 3}^{W \times H \times C} \mathbf{x}_i \mathbf{w}_i$$

Convolutions



How do we know which kernels to use?

Kernels are learnt and initialized randomly during training the CNN learns spatial features

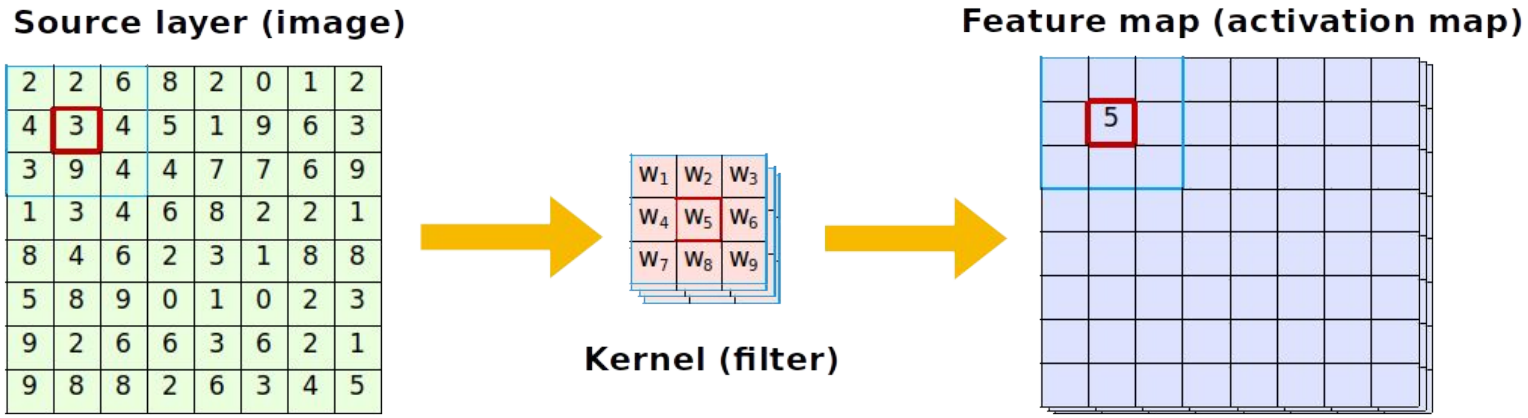
Fully connected

$$\sum_{i \in \text{image}}^{W \times H \times C} \mathbf{x}_i \mathbf{w}_i$$

Locally connected shared weights

$$\sum_{i \in 3 \times 3}^{W \times H \times C} \mathbf{x}_i \mathbf{w}_i$$

Convolutions



How do we know which kernels to use?

Kernels are learnt and initialized randomly during training the CNN learns spatial features

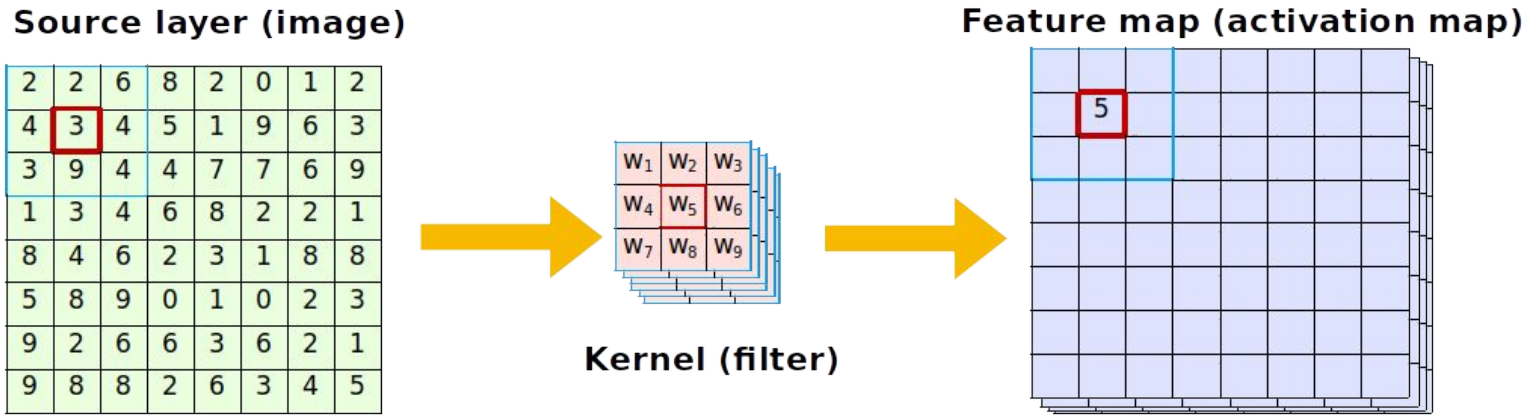
Fully connected

$$\sum_{i \in \text{image}}^{W \times H \times C} \mathbf{x}_i \mathbf{w}_i$$

Locally connected shared weights

$$\sum_{i \in 3 \times 3}^{W \times H \times C} \mathbf{x}_i \mathbf{w}_i$$

Convolutions



How do we know which kernels to use?

Kernels are learnt and initialized randomly during training the CNN learns spatial features

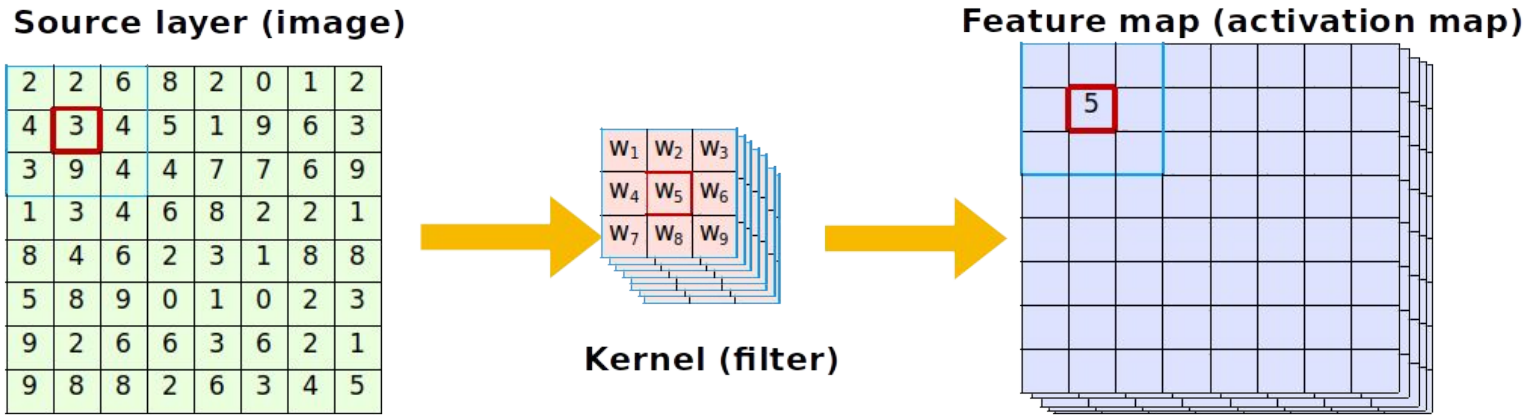
Fully connected

$$\sum_{i \in \text{image}}^{W \times H \times C} \mathbf{x}_i \mathbf{w}_i$$

Locally connected shared weights

$$\sum_{i \in 3 \times 3}^{W \times H \times C} \mathbf{x}_i \mathbf{w}_i$$

Convolutions



How do we know which kernels to use?

Kernels are learnt and initialized randomly during training the CNN learns spatial features

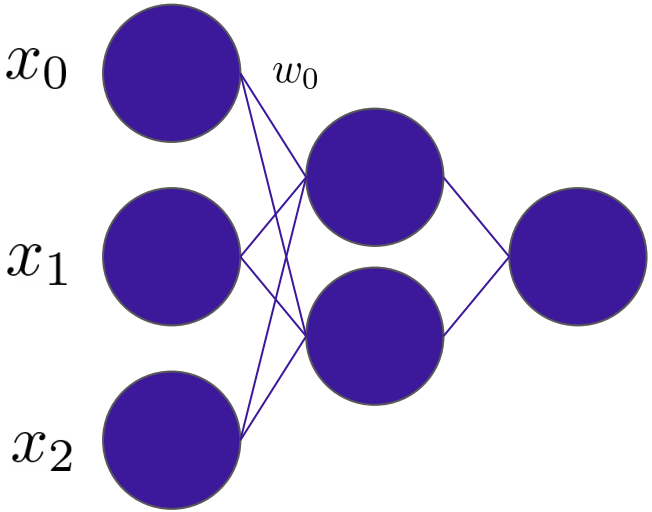
Fully connected

$$\sum_{i \in \text{image}}^{W \times H \times C} \mathbf{x}_i \mathbf{w}_i$$

Locally connected shared weights

$$\sum_{i \in 3 \times 3}^{W \times H \times C} \mathbf{x}_i \mathbf{w}_i$$

Anatomy of an Convolutional Neural Network

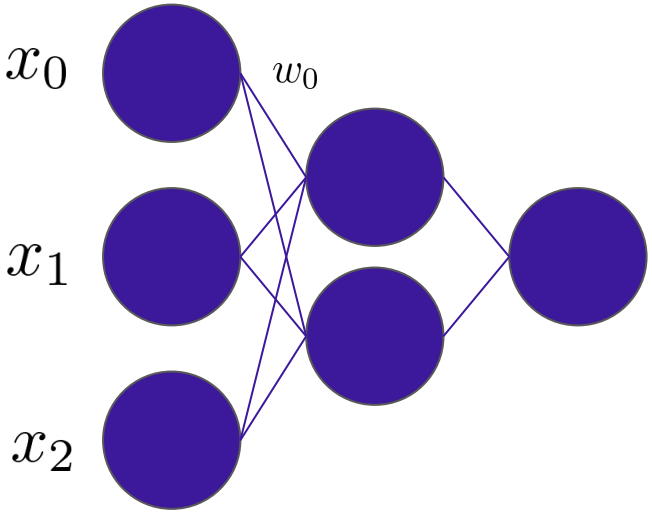


CNNs actually look a lot like normal Dense Neural Networks

Interpretation: Every node is a kernel

SURF

Anatomy of an Convolutional Neural Network



See the nodes as moving across the image!

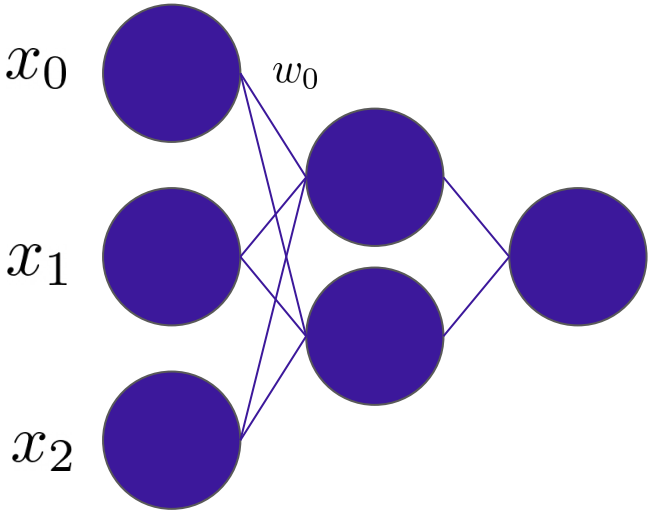
We say these are **shared weights**

CNNs actually look a lot like normal Dense Neural Networks

Interpretation: Every node is a kernel

SURF

Anatomy of an Convolutional Neural Network



Fully connected

$$\sum_{i \in \text{image}}^{W \times H \times C} \mathbf{x}_i \mathbf{w}_i$$

Locally connected shared weights

$$\sum_{i \in 3 \times 3}^{W \times H \times C} \mathbf{x}_i \mathbf{w}_i$$

See the nodes as moving across the image!

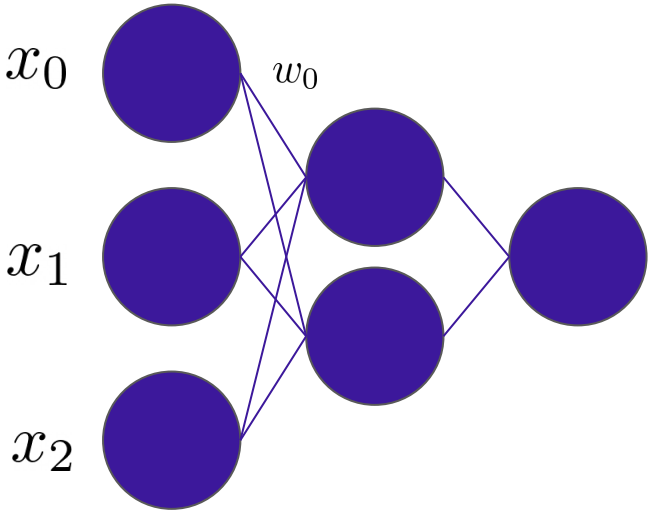
We say these are **shared weights**

CNNs actually look a lot like normal Dense Neural Networks

Interpretation: Every node is a kernel

SURF

Anatomy of an Convolutional Neural Network



Fully connected

$$\sum_{i \in \text{image}}^{W \times H \times C} \mathbf{x}_i \mathbf{w}_i$$

Locally connected shared weights

$$\sum_{i \in 3 \times 3}^{W \times H \times C} \mathbf{x}_i \mathbf{w}_i$$

w_1	w_2	w_3
w_4	w_5	w_6
w_7	w_8	w_9

See the nodes as moving across the image!

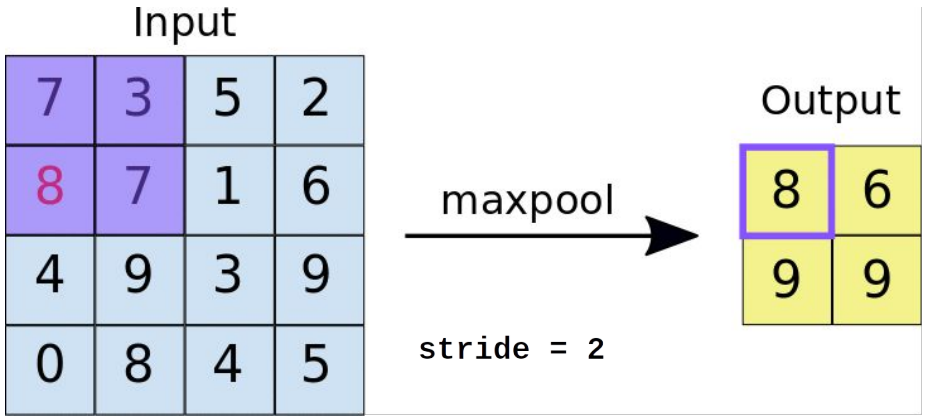
We say these are **shared weights**

CNNs actually look a lot like normal Dense Neural Networks

Interpretation: Every node is a kernel

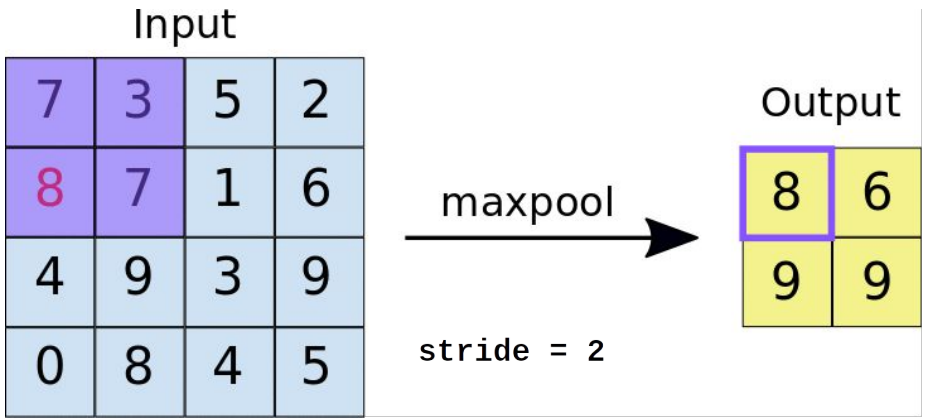
SURF

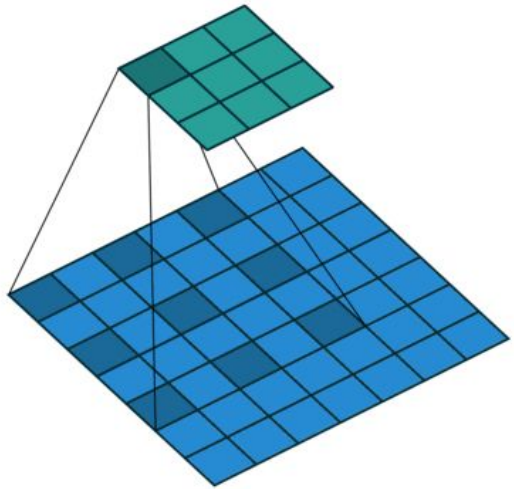
Pooling and dilated convolutions



We could discard information gradually by max pooling
Keep the strongest signal, works better than average pooling
Nowadays, we use a bigger stride for dimensionality reduction

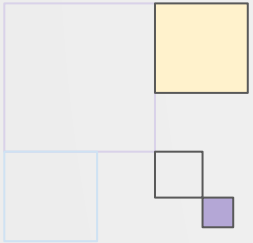
Pooling and dilated convolutions



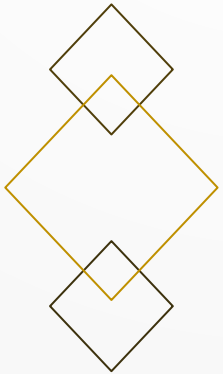


We could discard information gradually by max pooling
Keep the strongest signal, works better than average pooling
Nowadays, we use a bigger stride for dimensionality reduction

Dilated convolutions can be used if you expect your images to have information which are spatially far from each other

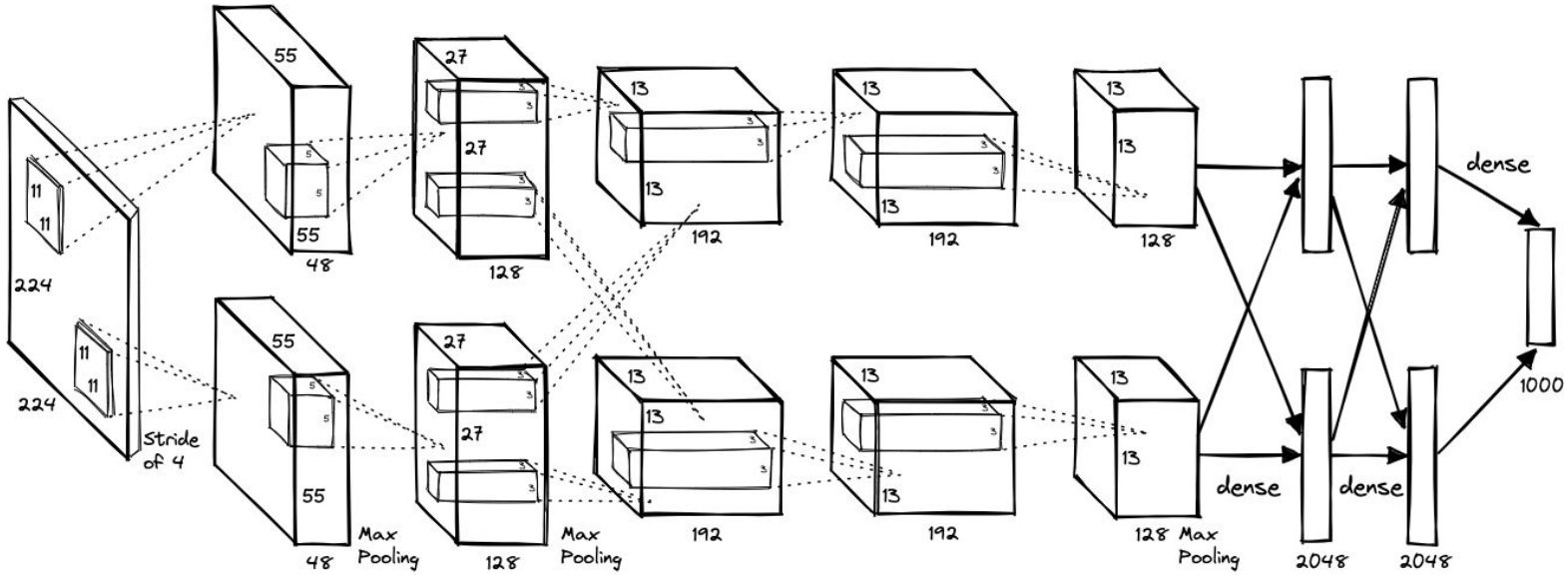


CNN Cases

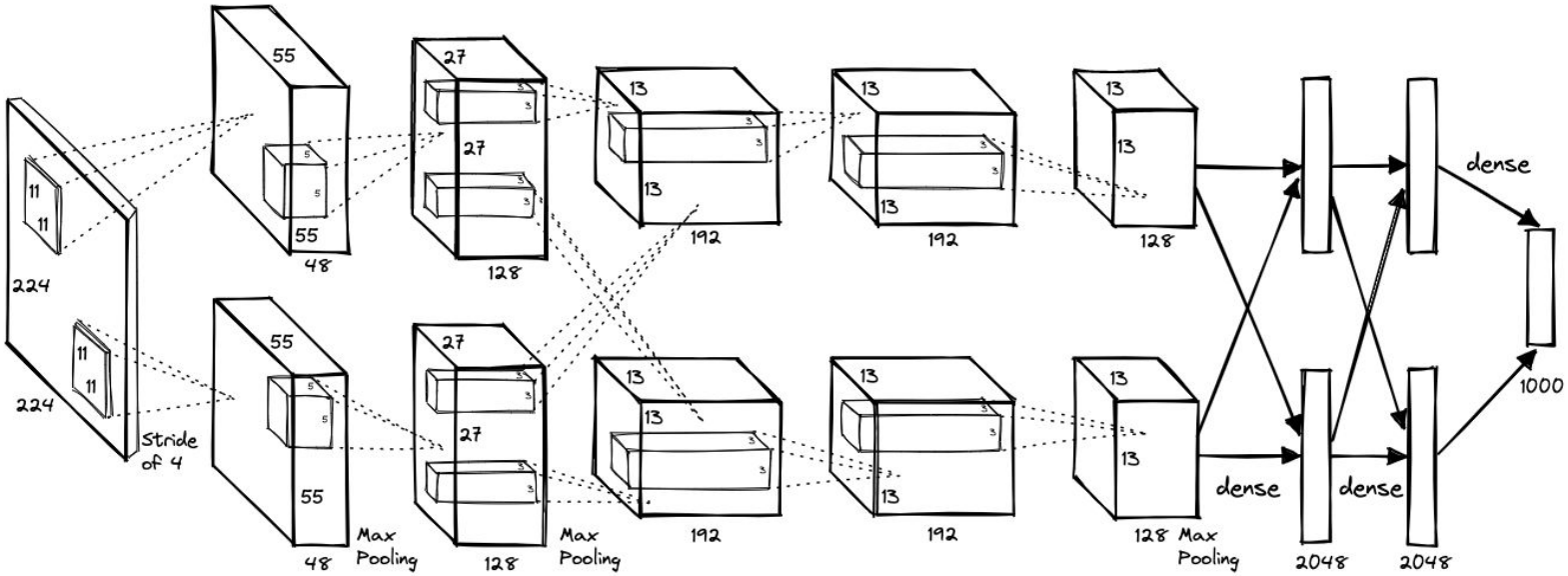


SURF

AlexNet (2012)



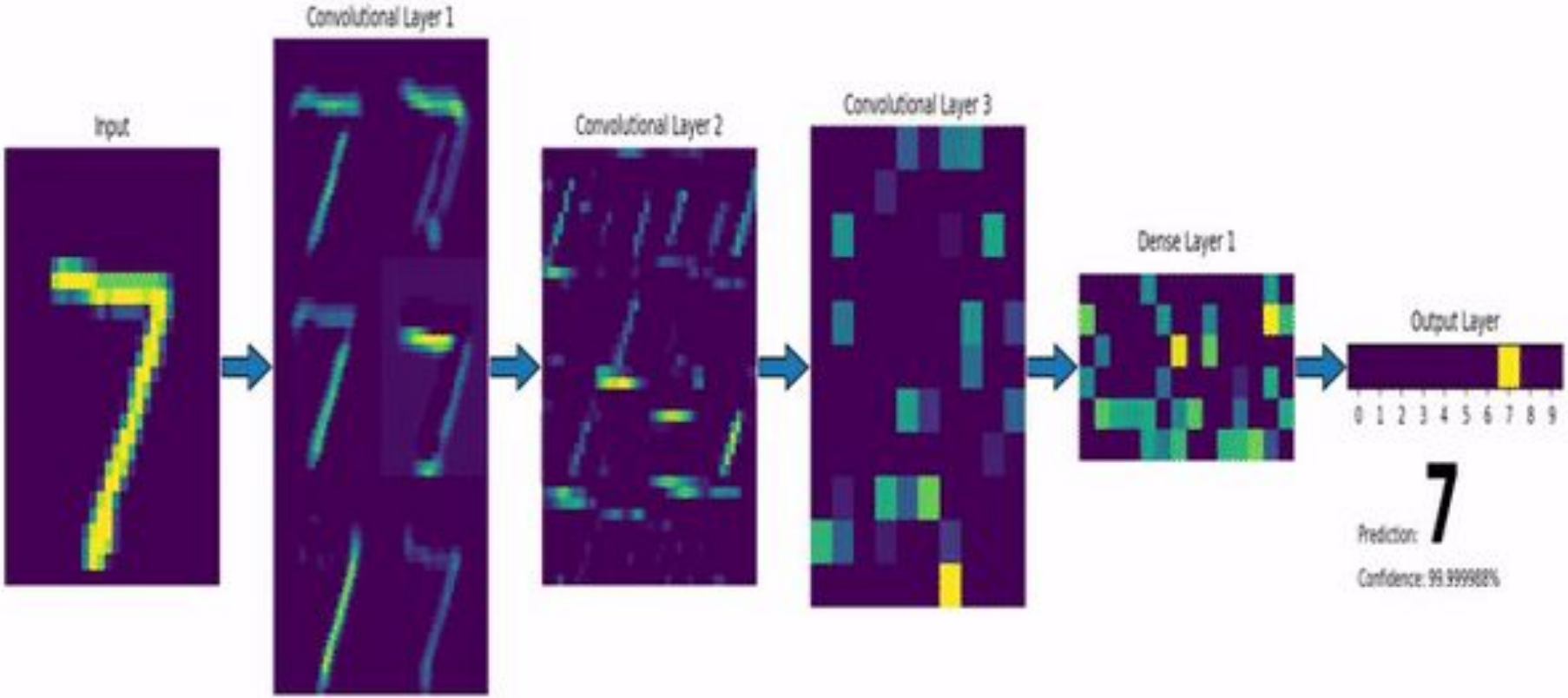
AlexNet (2012)



Images become smaller and number of filters increases as we go deeper

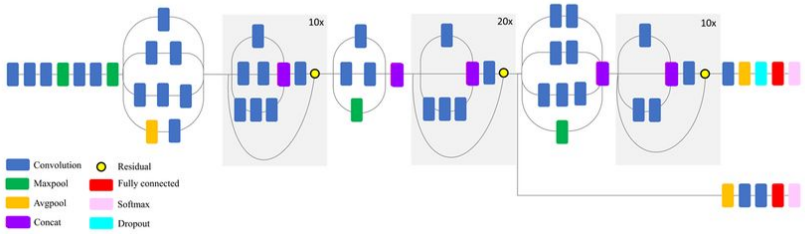
8 layers with **dropout** and **ReLU** activations trained for **6 days on 2 GPUs**

CNN with a Dense Layer output



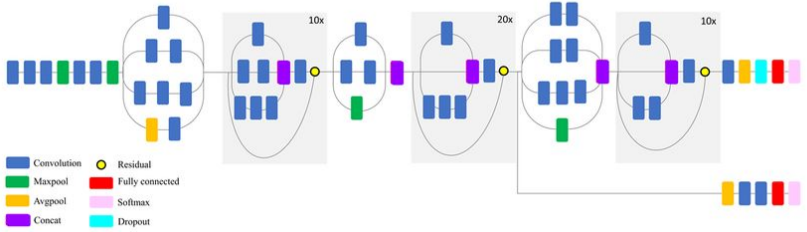
https://www.louisbouchard.ai/densenet-explained/

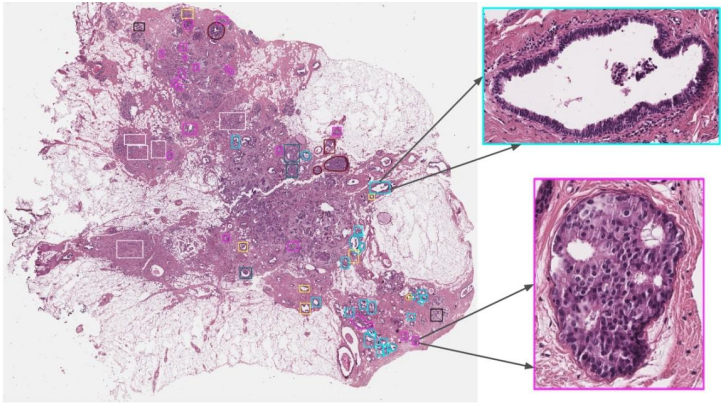
Transfer Learning

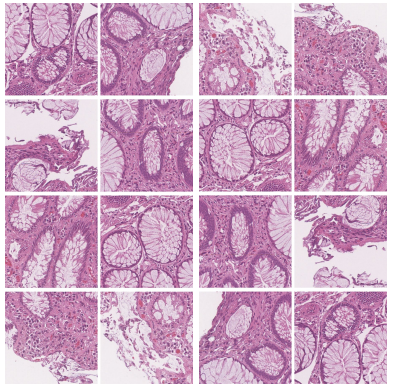


SURF

Transfer Learning

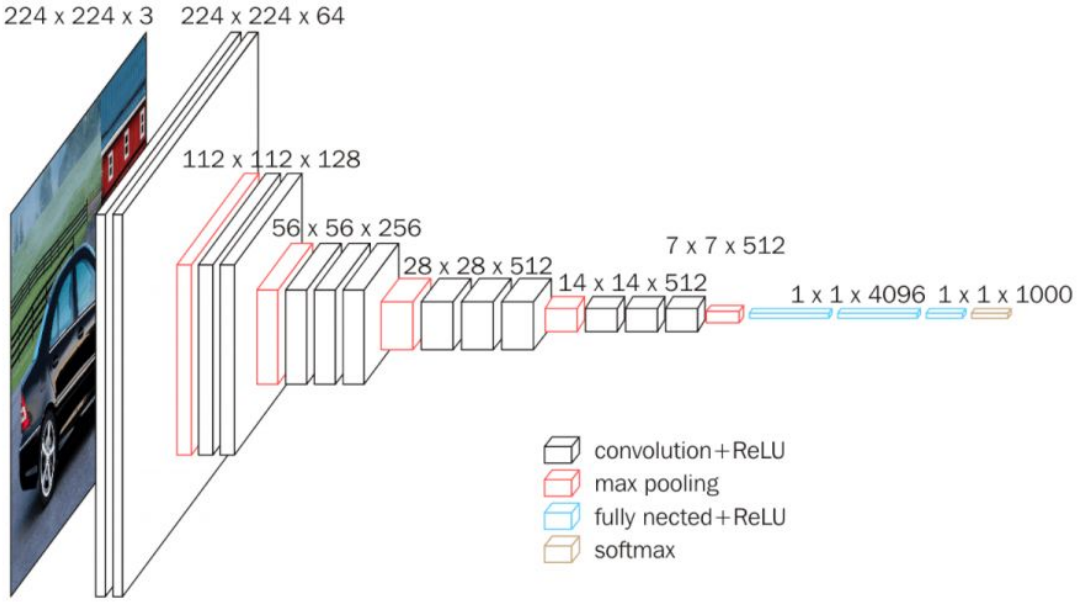






SURF

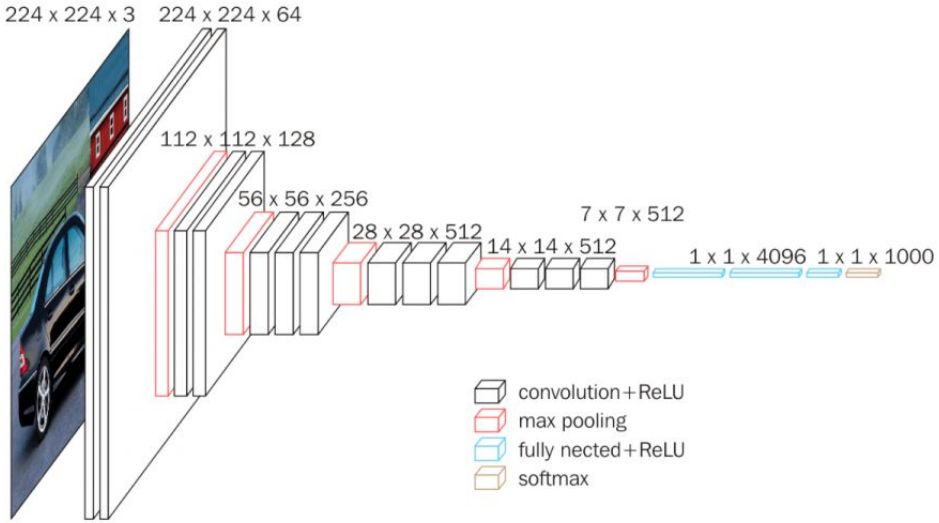
VGG16 and ResNet (2014, 2015)

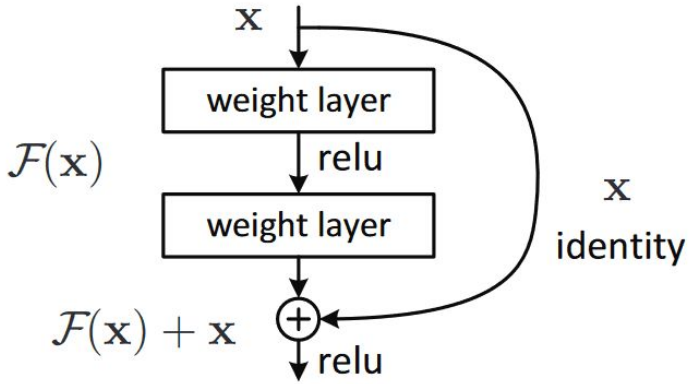


VGG16: construct large and deep models (120M params)

Vanishing gradient problem

VGG16 and ResNet (2014, 2015)

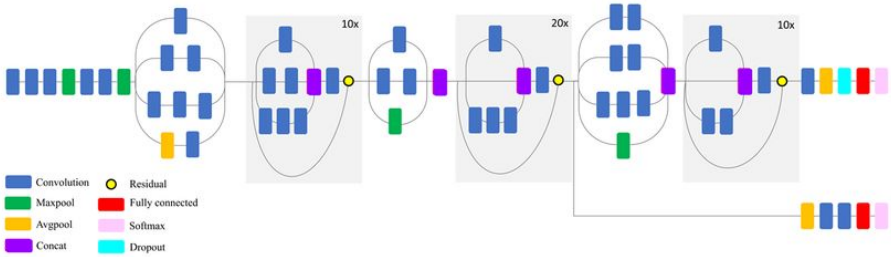


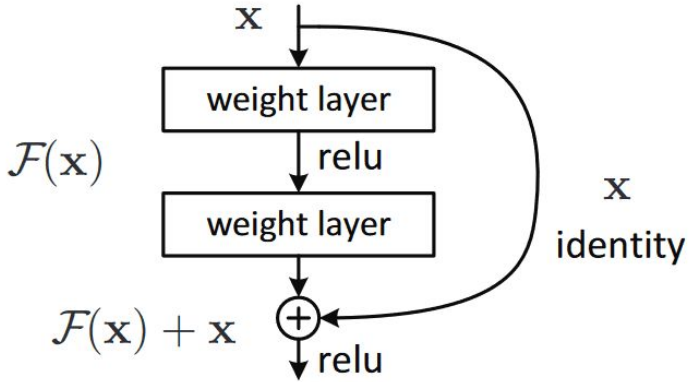


VGG16: construct large and deep models (120M params)

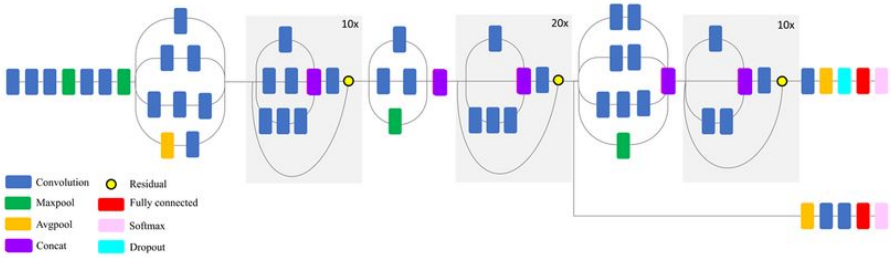
Vanishing gradient problem

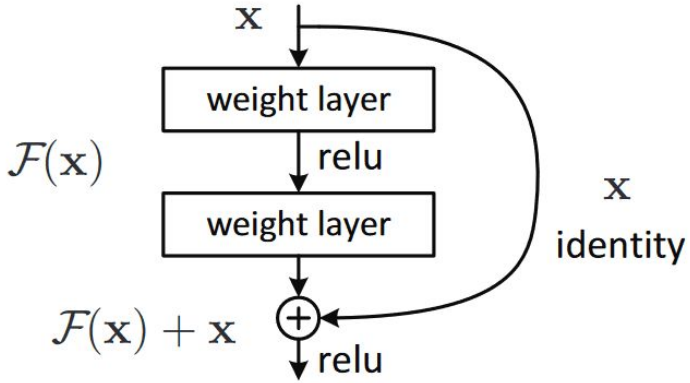
ResNet (2015)


10x
20x
10x
Convolution
Maxpool
Avgpool
Concat
Residual
Fully connected
Softmax
Dropout


x
weight layer
$\mathcal{F}(\mathbf{x})$
relu
weight layer
x
identity
$\mathcal{F}(\mathbf{x}) + \mathbf{x}$
relu

ResNet (2015)

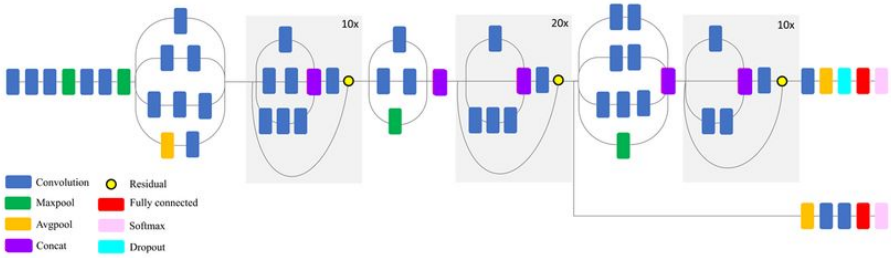


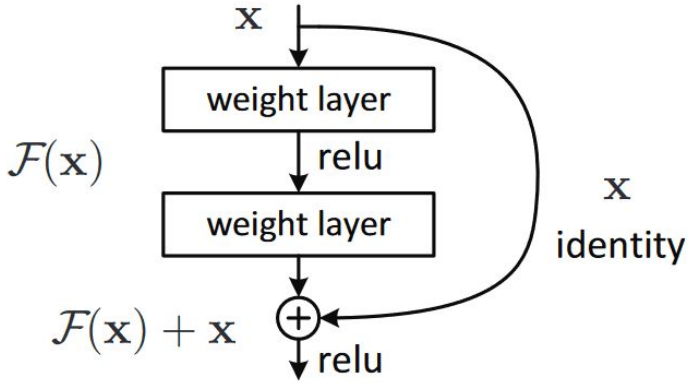


ResNets: construct large and deep models with **skip connections**, able to train up to **152 layers** (!)

Higher abstraction and less nuisance from vanishing or exploding gradients

ResNet (2015)



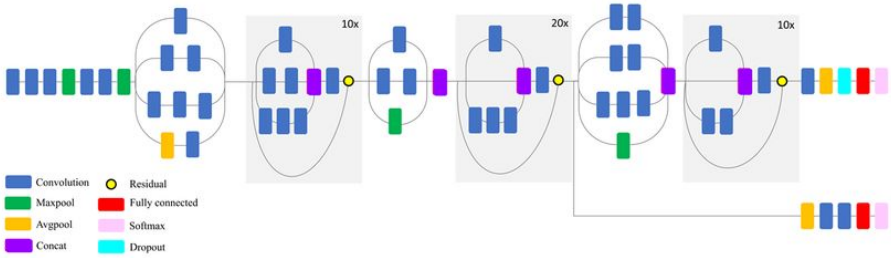


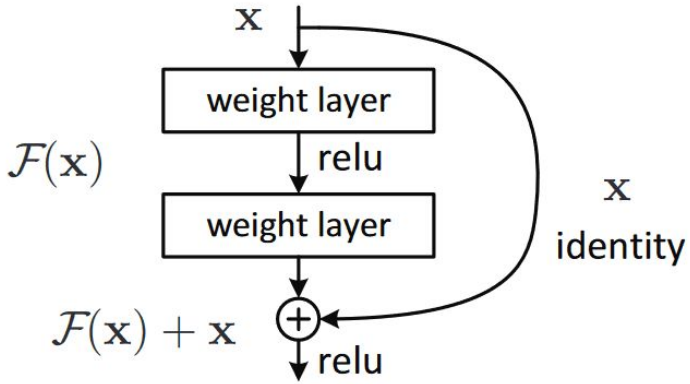
ResNets: construct large and deep models with **skip connections**, able to train up to **152 layers** (!)

Higher abstraction and less nuisance from vanishing or exploding gradients

Early layers learn features that get progressively more abstract, we can **preserve** and **control** the flow of information with **skip connections**

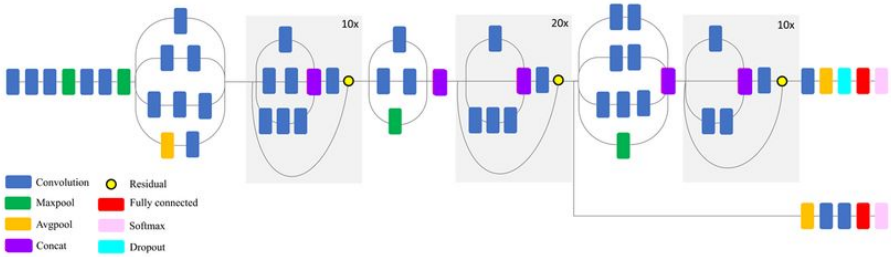
ResNet (2015)

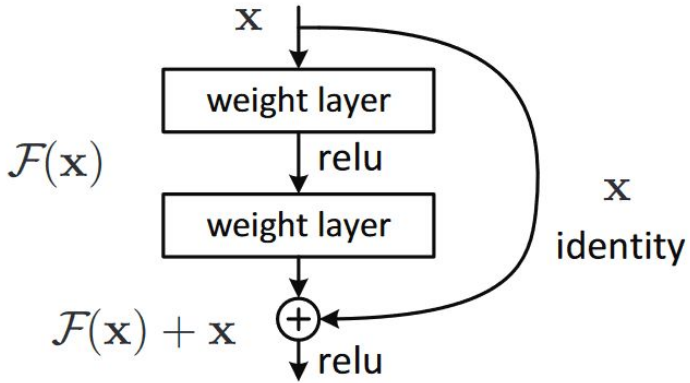




$$G(x) = \mathcal{F}(\mathbf{x}) + \mathbf{x}$$

ResNet (2015)

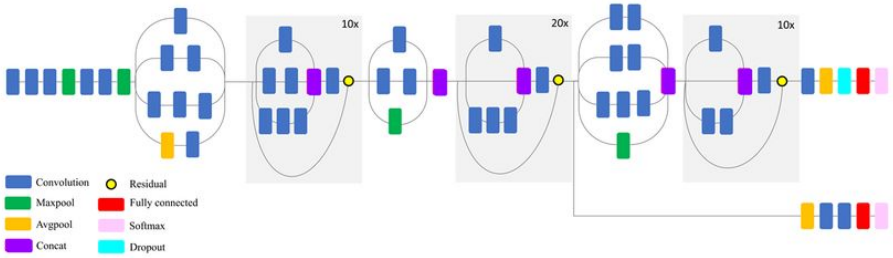


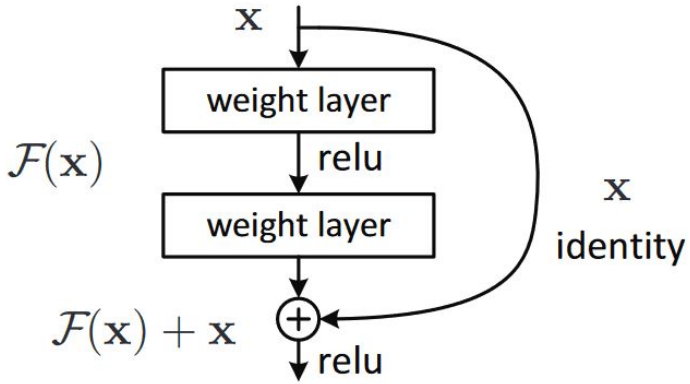


$$G(x) = \mathcal{F}(\mathbf{x}) + \mathbf{x}$$

$$\frac{\partial \mathcal{L}}{\partial G} \frac{\partial F(\mathbf{x}) + \mathbf{x}}{\partial \mathbf{x}}$$

ResNet (2015)



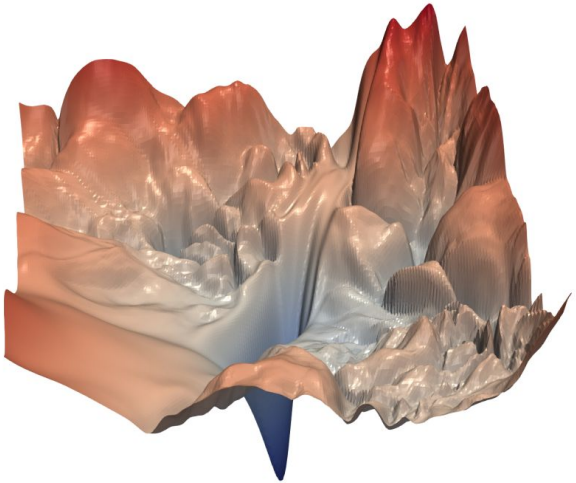


$$G(x) = \mathcal{F}(\mathbf{x}) + \mathbf{x}$$

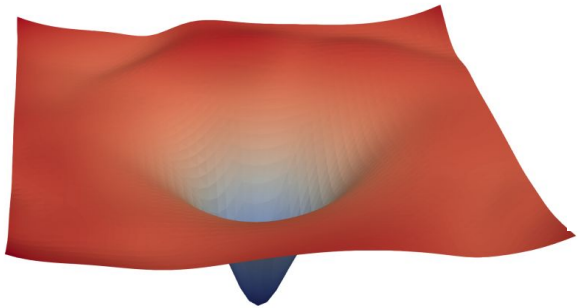
$$\frac{\partial \mathcal{L}}{\partial G}\frac{\partial F(\mathbf{x}) + \mathbf{x}}{\partial \mathbf{x}} = \frac{\partial \mathcal{L}}{\partial G}\frac{\partial F}{\partial \mathbf{x}} + \frac{\partial \mathcal{L}}{\partial G}$$

Li, H., Xu, Z., Taylor, G., & Goldstein, T. (2017). Visualizing the Loss Landscape of Neural Nets. *NIPS*

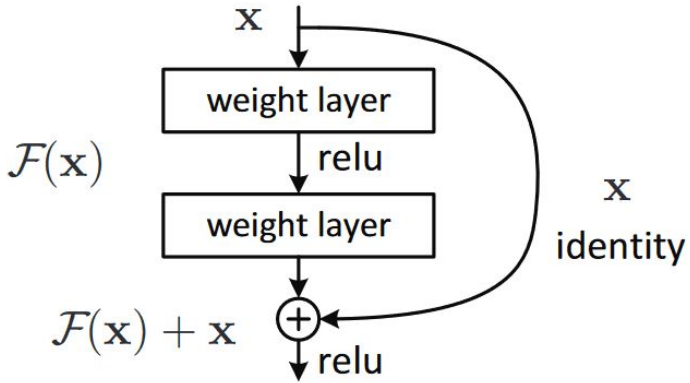
ResNet (2015)



(a) without skip connections

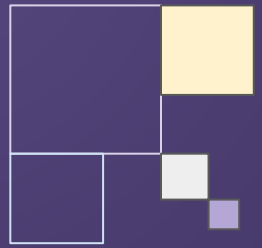


(b) with skip connections

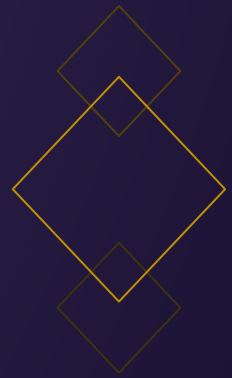


$$\frac{\partial \mathcal{L}}{\partial G}\frac{\partial F(\mathbf{x}) + \mathbf{x}}{\partial \mathbf{x}} = \frac{\partial \mathcal{L}}{\partial G}\frac{\partial F}{\partial \mathbf{x}} + \frac{\partial \mathcal{L}}{\partial G}$$

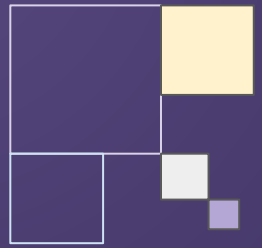
SURF



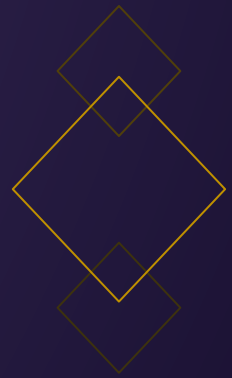
Thank You



09/11/2022



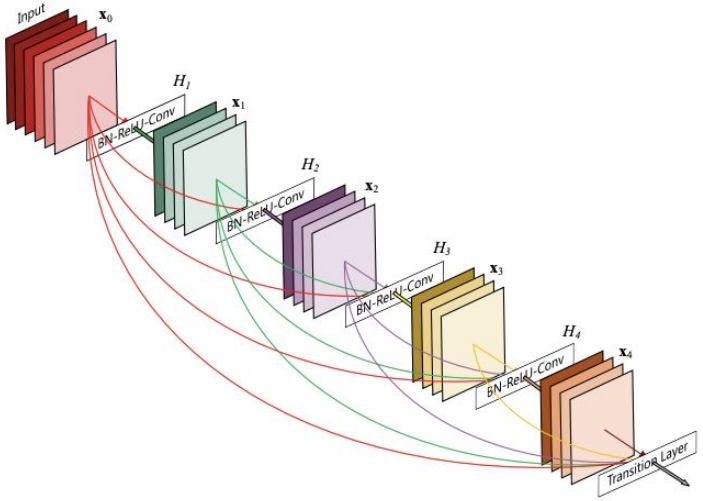
Slides Graveyard

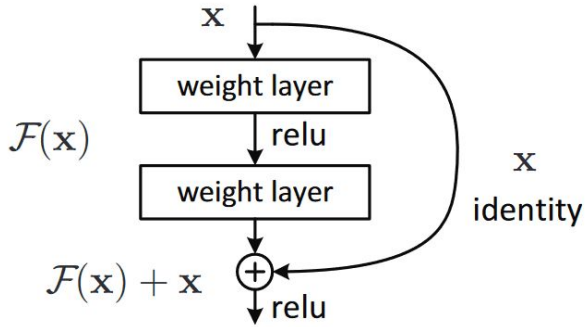


High Performance Machine Learning Group

SURF

DenseNet (2016)



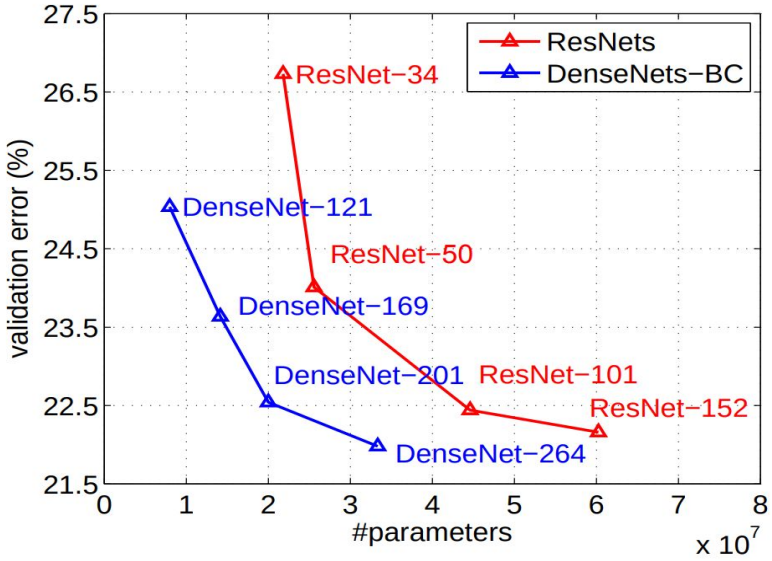


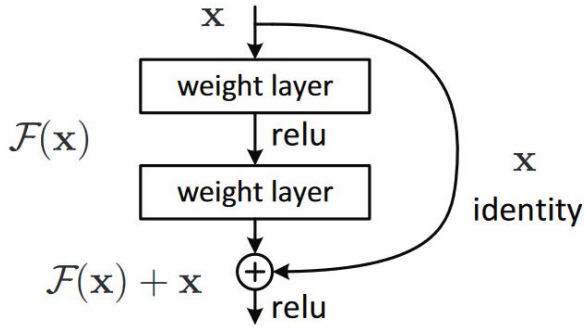
ResNets: construct large and deep models with skip connections, able to train up to 152 layers (!)

Higher abstraction and less nuisance from vanishing or exploding gradients

Early layers learn features that get progressively more abstract, we can **preserve** and **control** the flow of information with **skip connections**

DenseNet (2016)

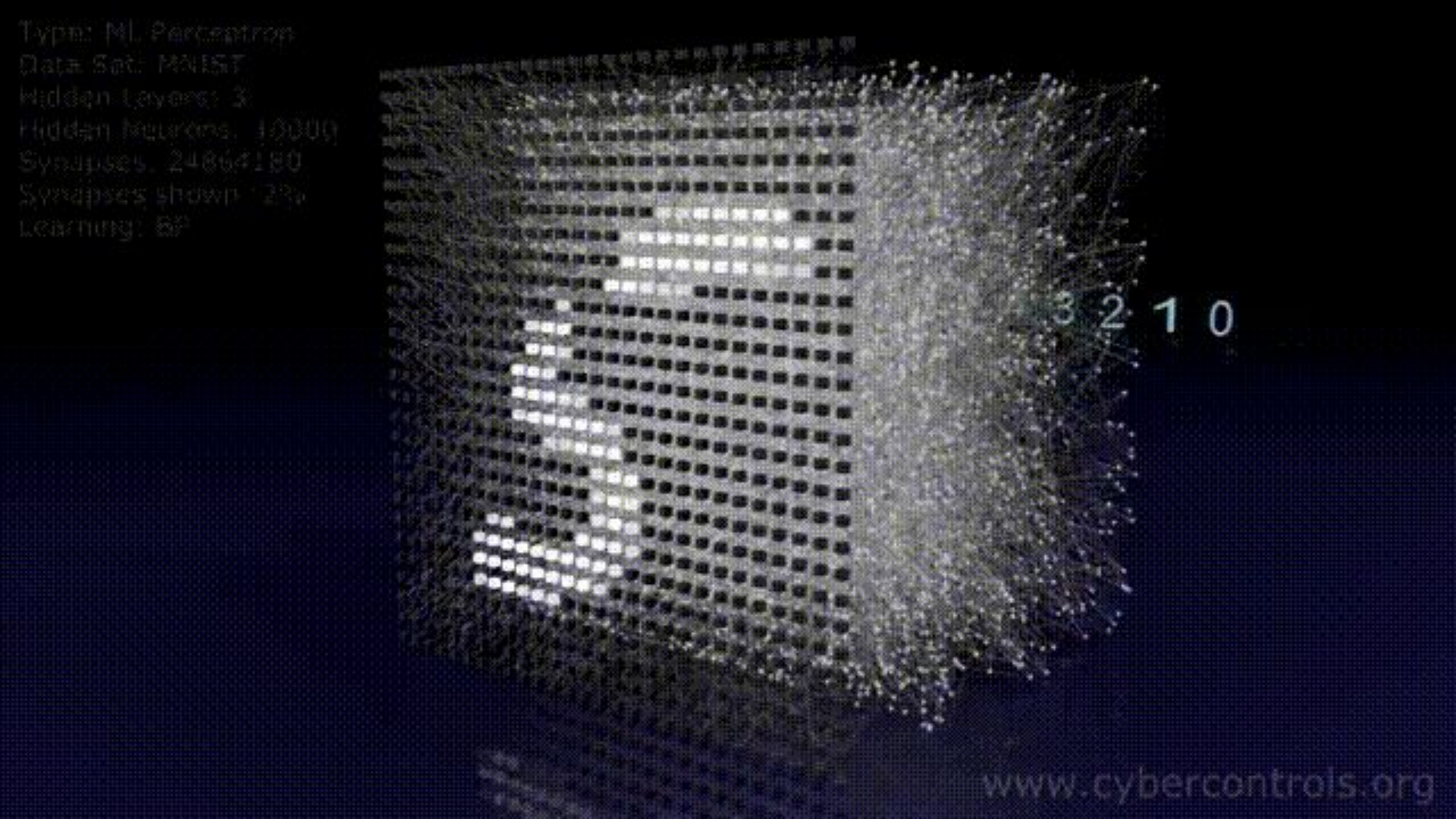




ResNets: construct large and deep models with skip connections, able to train up to 152 layers (!)

Higher abstraction and less nuisance from vanishing or exploding gradients

Early layers learn features that get progressively more abstract, we can **preserve** and **control** the flow of information with **skip connections**


Type: NL Perceptron
Data Set: MNIST
Hidden Layers: 3
Hidden Neurons: 10000
Synapses: 24864180
Synapses shown: 2%
Learning: 6P
3 2 1 0
www.cybercontrols.org