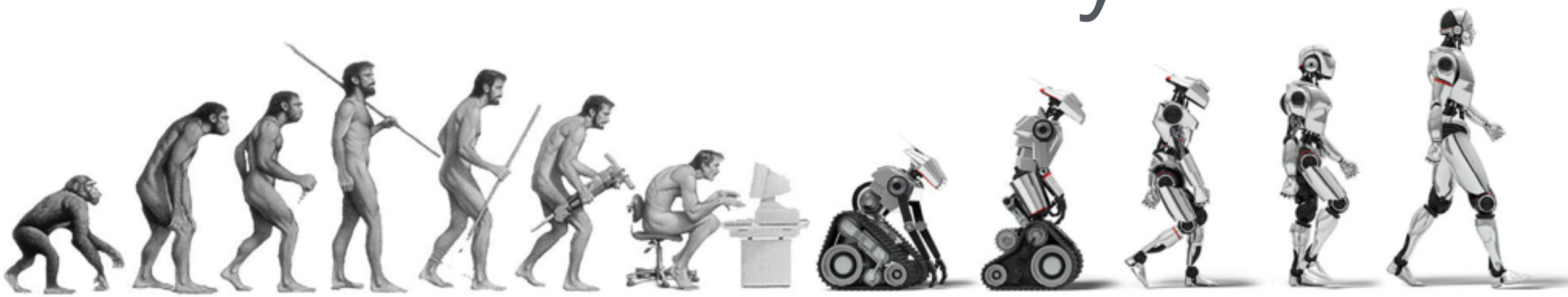
Introduction to Deep Learning and Applications

Fabio A. González
Univ. Nacional de Colombia

Some history



https://www.youtube.com/watch?v=cNxadbrN_aI

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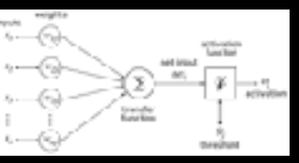
Rosenblatt's Perceptron (1957)

- Input: 20x20 photocells array
- Weights implemented with potentiometers
- Weight updating performed by electric motors

Neural networks time line

1943 1957 1969 1986 1995 2007 2012 2016

Neural networks time line



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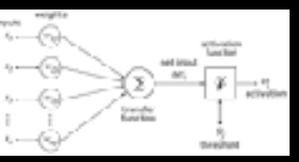
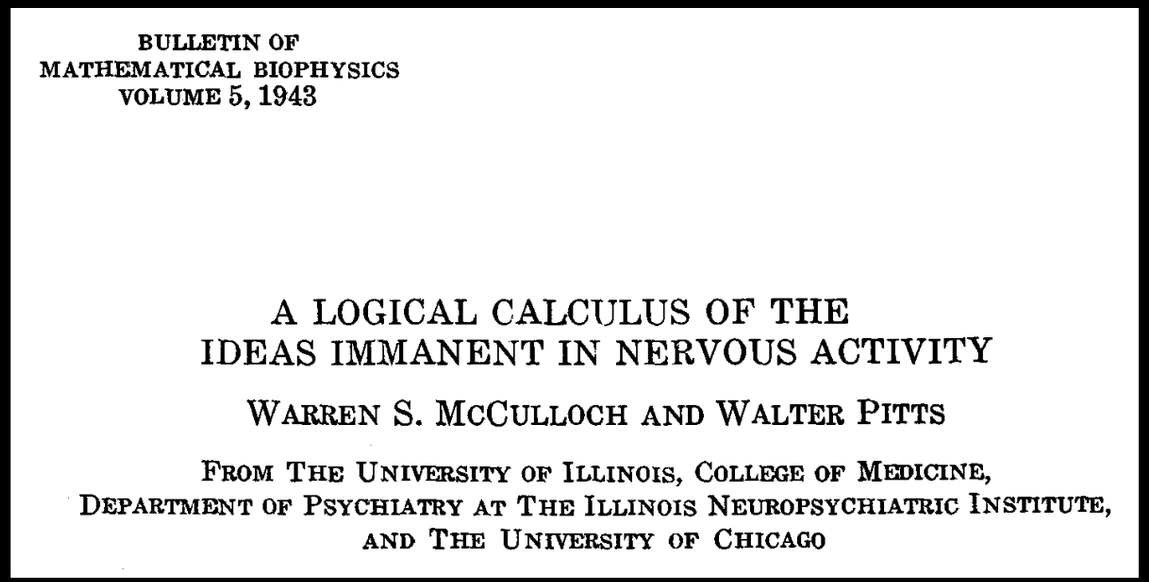
Neural networks time line



1943 1957 1969 1986 1995 2007 2012 2016

McCulloch & Pitts Artificial Neuron

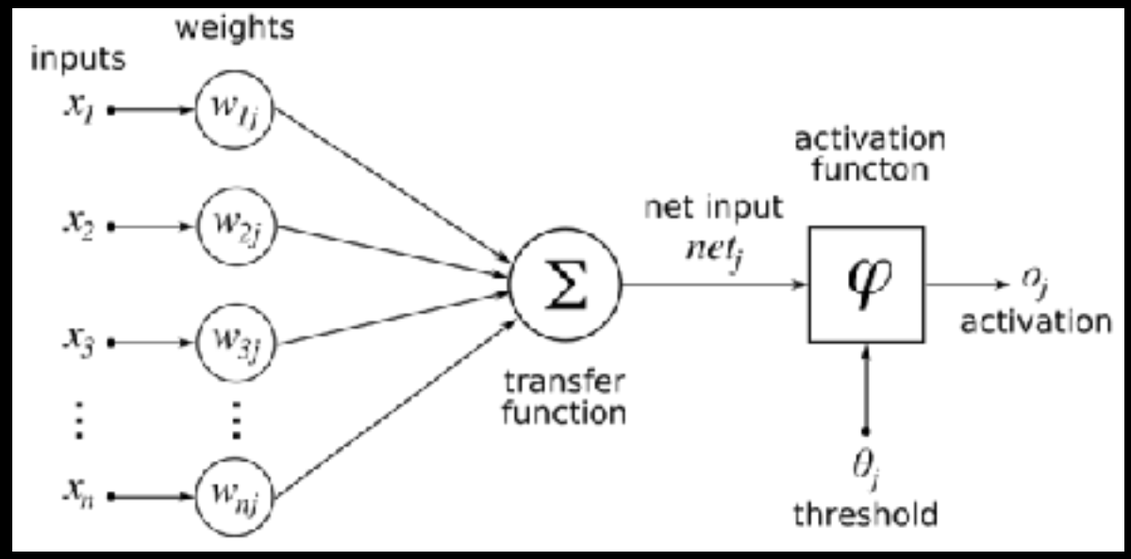


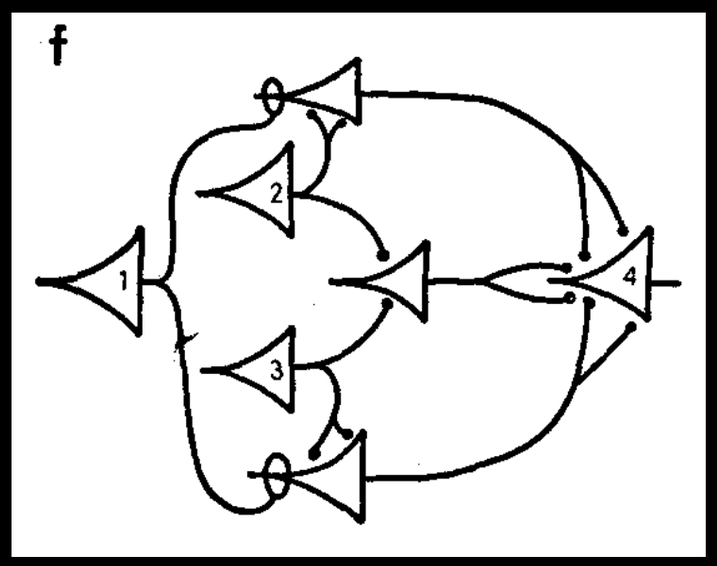
BULLETIN OF
MATHEMATICAL BIOPHYSICS
VOLUME 5, 1943

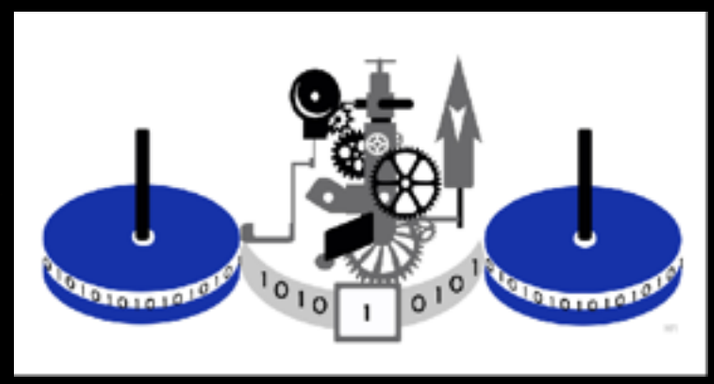
A LOGICAL CALCULUS OF THE
IDEAS IMMANENT IN NERVOUS ACTIVITY

WARREN S. MCCULLOCH AND WALTER PITTS

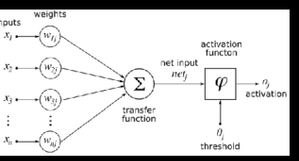
FROM THE UNIVERSITY OF ILLINOIS, COLLEGE OF MEDICINE,
DEPARTMENT OF PSYCHIATRY AT THE ILLINOIS NEUROPSYCHIATRIC INSTITUTE,
AND THE UNIVERSITY OF CHICAGO







Neural networks time line



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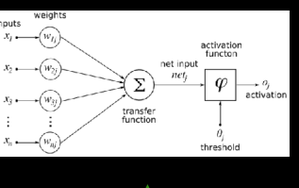
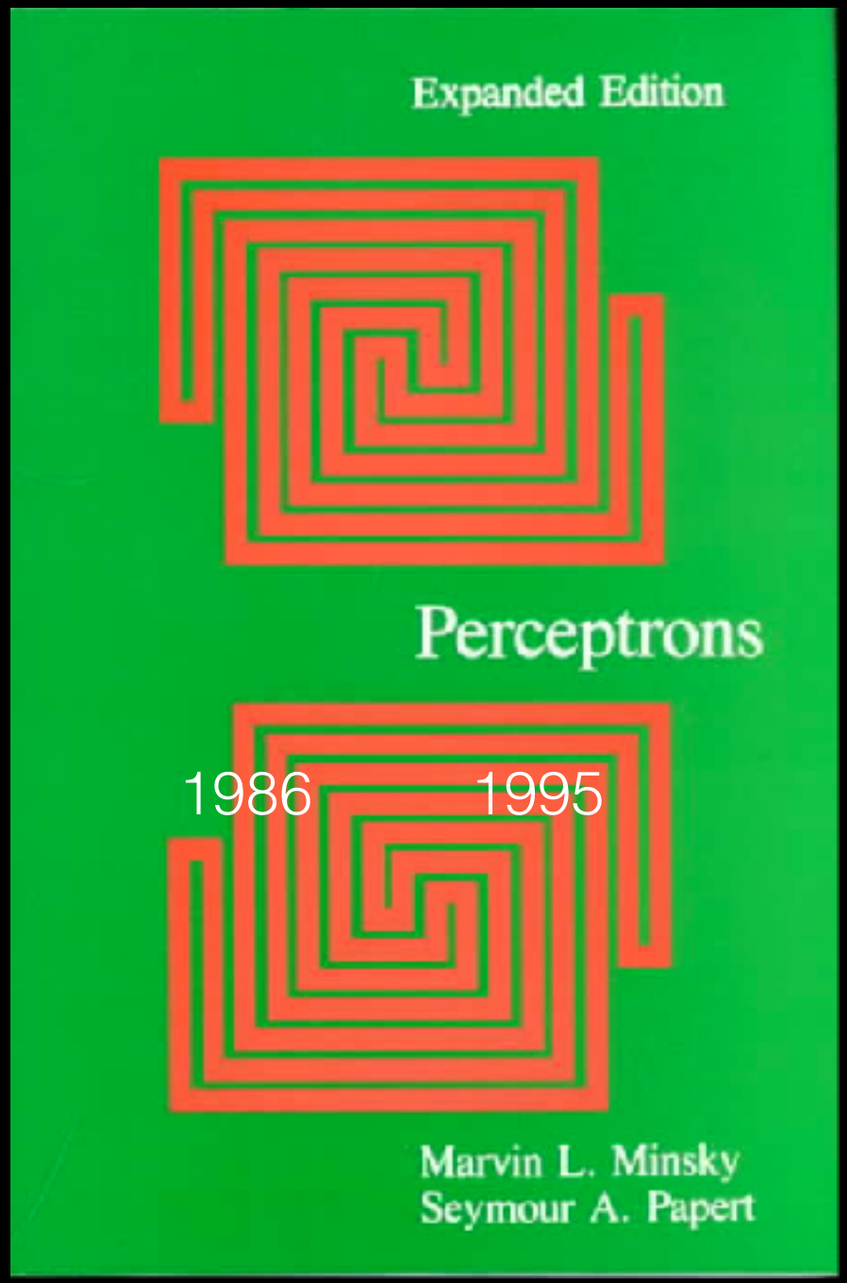
Neural networks time line





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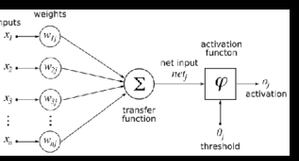
Neural networks time line



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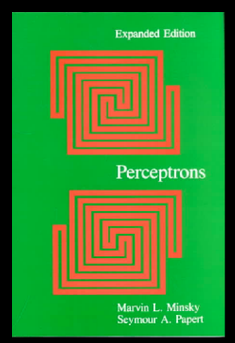

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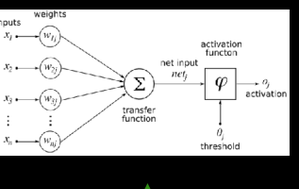
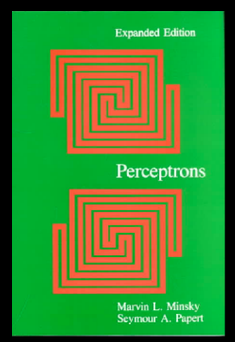
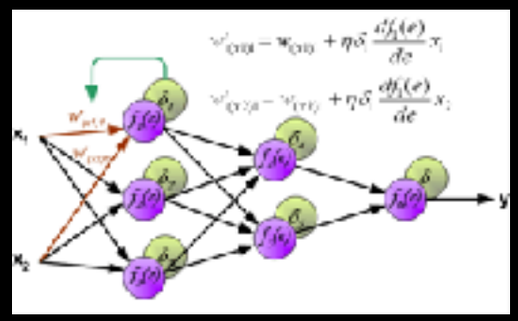
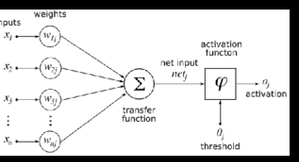


1943 1957 1969 1986 1995 2007 2012 2016



Neural networks time line





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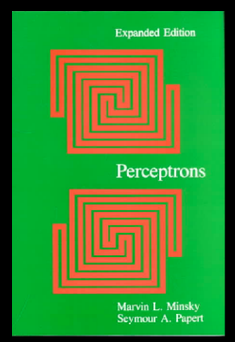
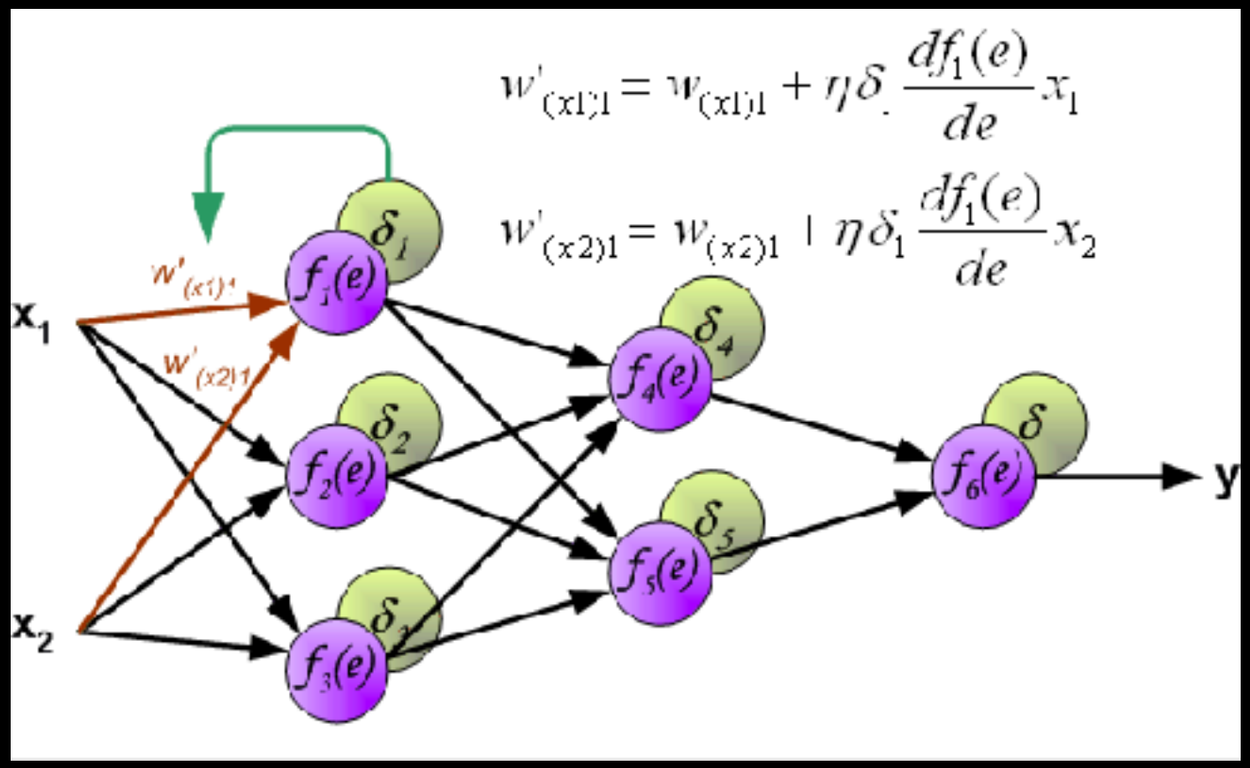
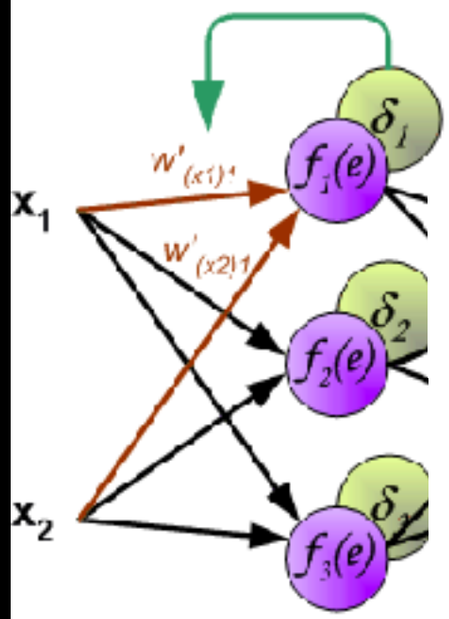


Backpropagation



Source: http://home.agh.edu.pl/~vlsi/AI/backp_t_en/backprop.html

Backpropagation



$$w'_{(x1)1} = w_{(x1)1} + \eta\delta_1 \frac{df_1(e)}{de} x_1$$

$$w'_{(x2)1} = w_{(x2)1} + \eta\delta_1 \frac{df_1(e)}{de} x_2$$

letters to nature

Nature **323**, 533 - 536 (09 October 1986); doi:10.1038/323533a0

nature

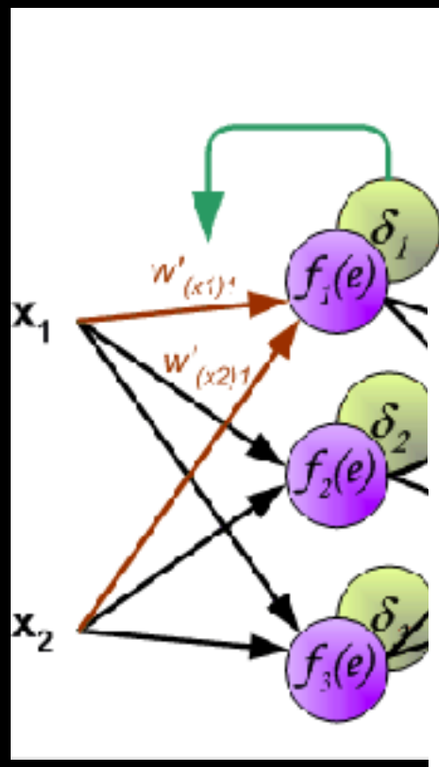
Learning representations by back-propagating errors

David E. Rumelhart*, Geoffrey E. Hinton† & Ronald J. Williams*

* Institute for Cognitive Science, C-015, University of California, San Diego, La Jolla, California 92093, USA
† Department of Computer Science, Carnegie-Mellon University, Pittsburgh, Philadelphia 15213, USA

Source: http://home.agh.edu.pl/~vlsi/AI/backp_t_en/backprop.html

Backpropagation



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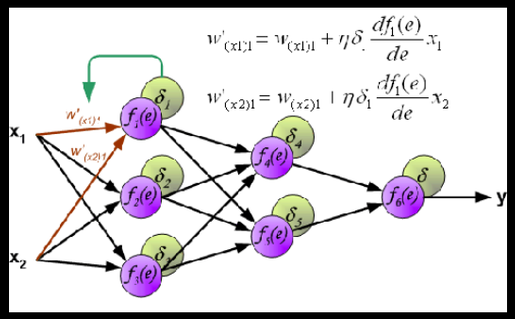
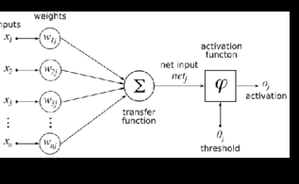
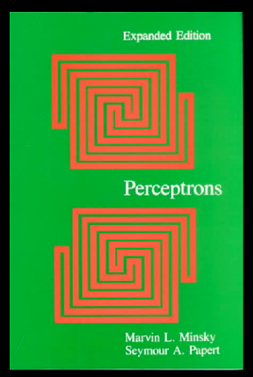
Neural networks time line

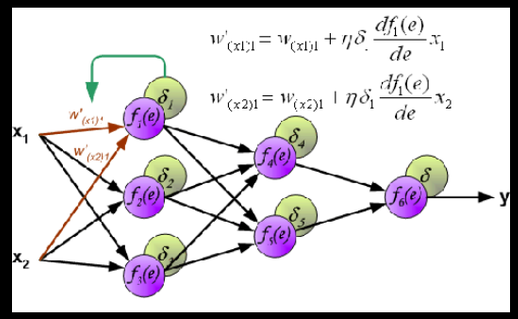


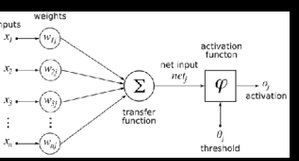


1943 1957 1969 1986 1995 2007 2012 2016

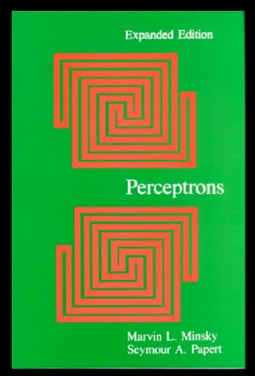


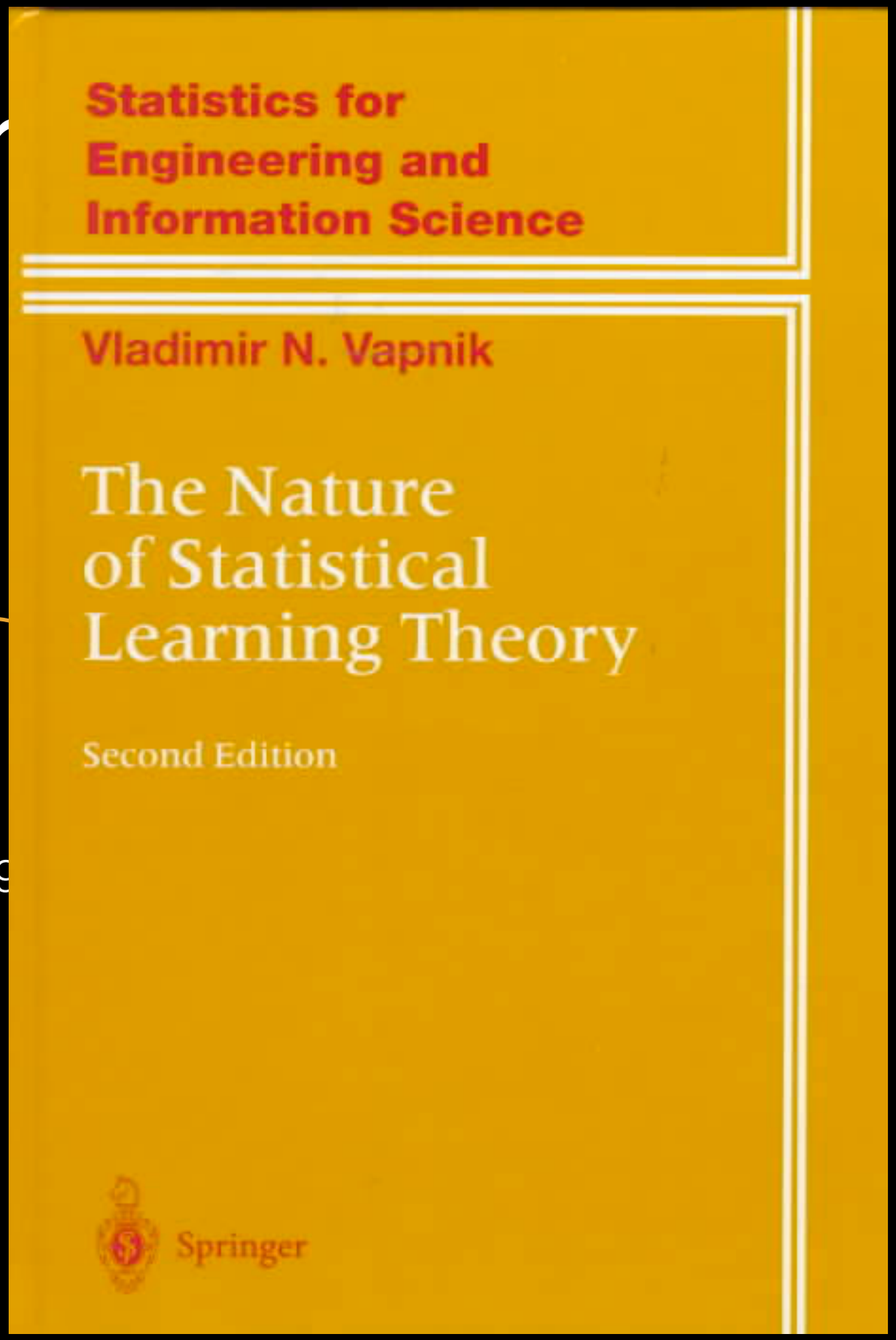
Neural networ



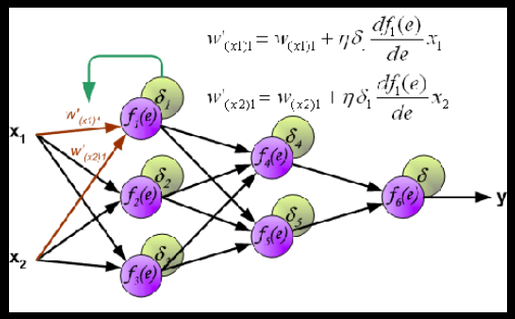


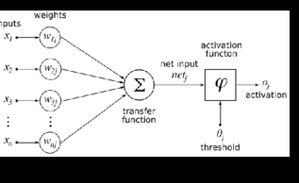
1943 1957 1969 1986 19





Neural networks time line





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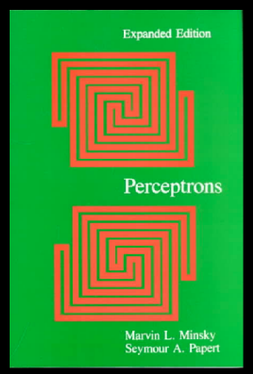
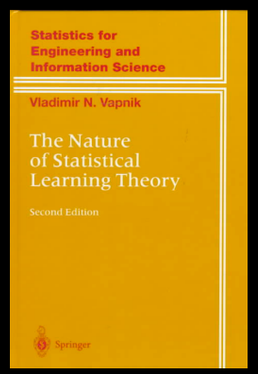
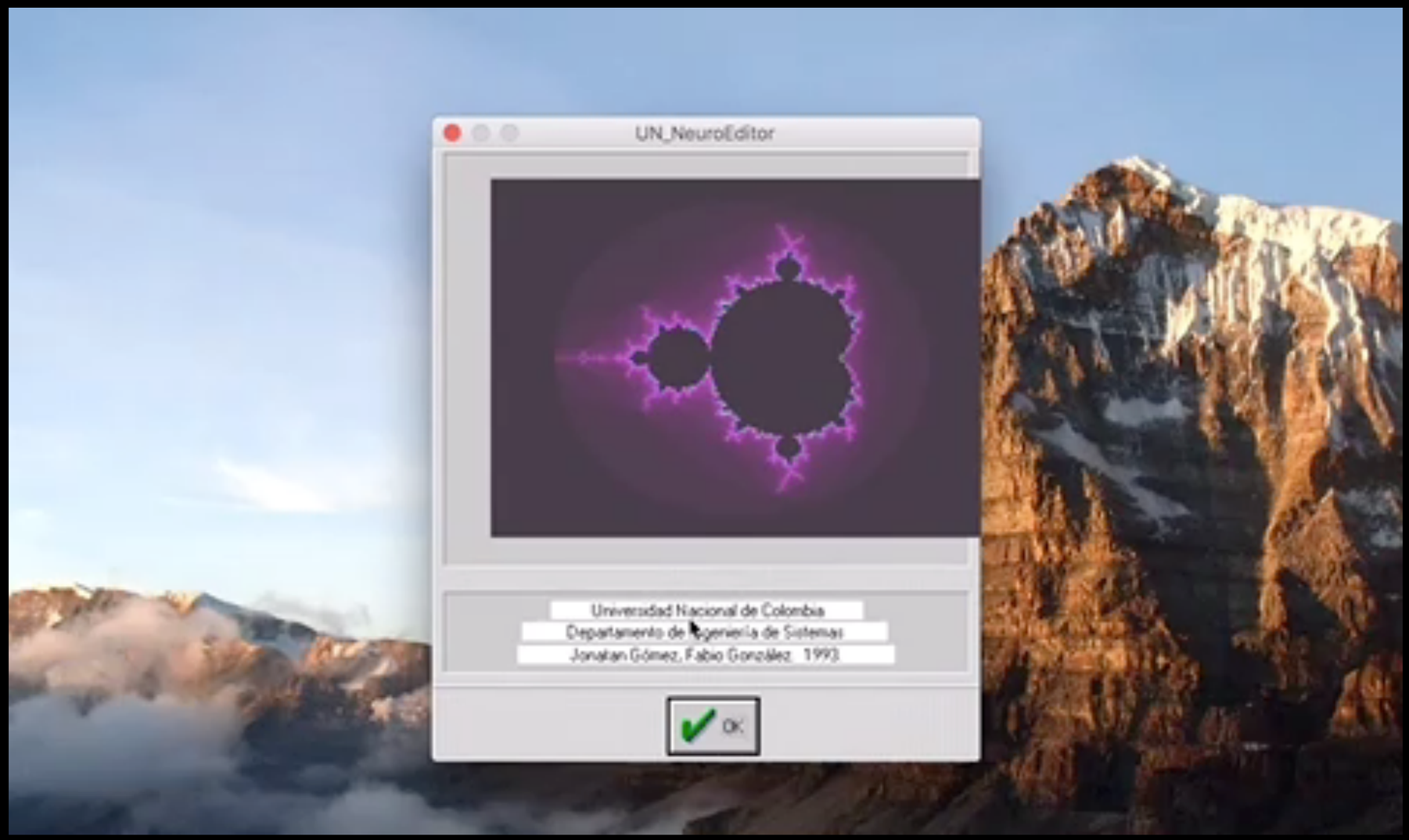




My own history with NN (circa 1993)



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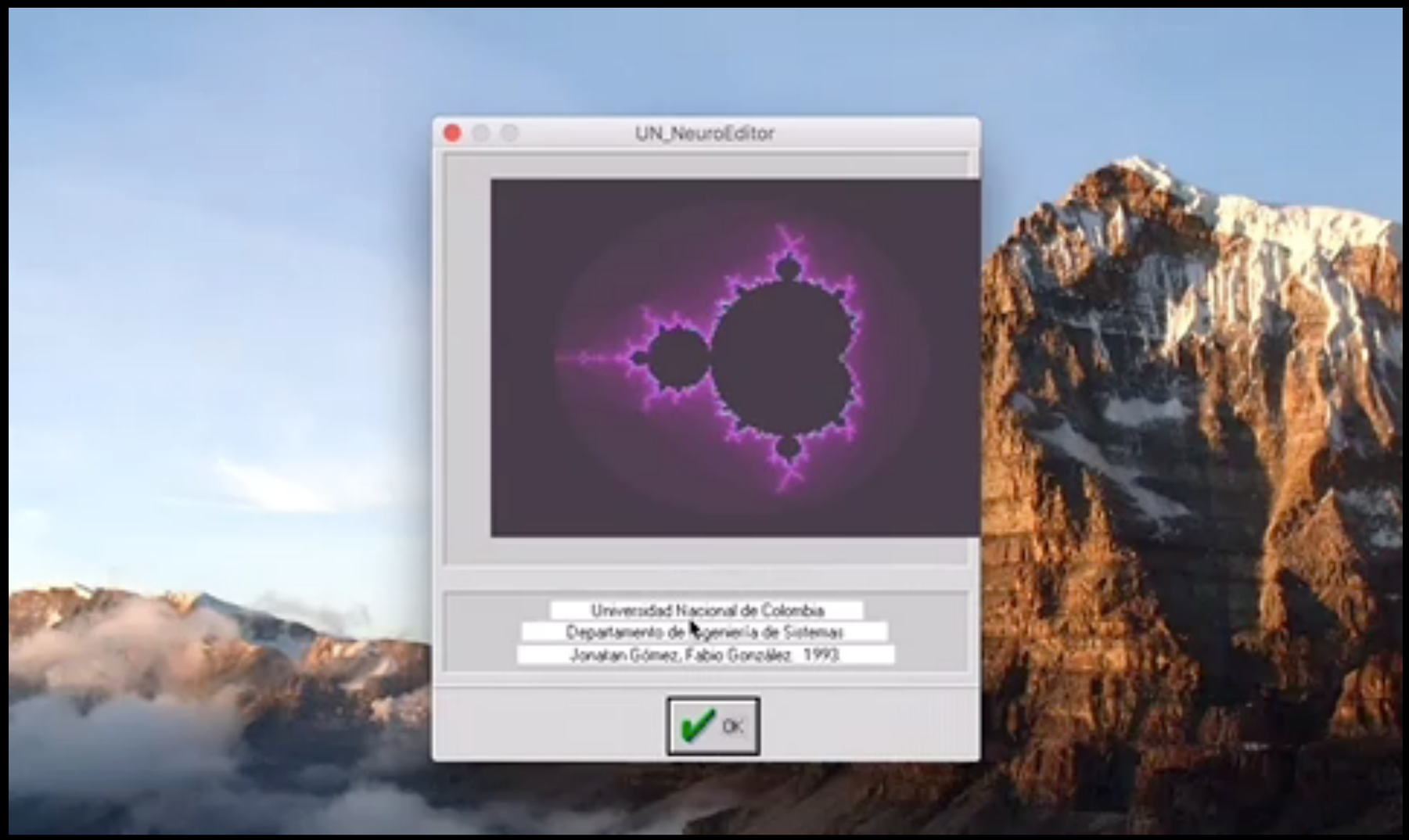
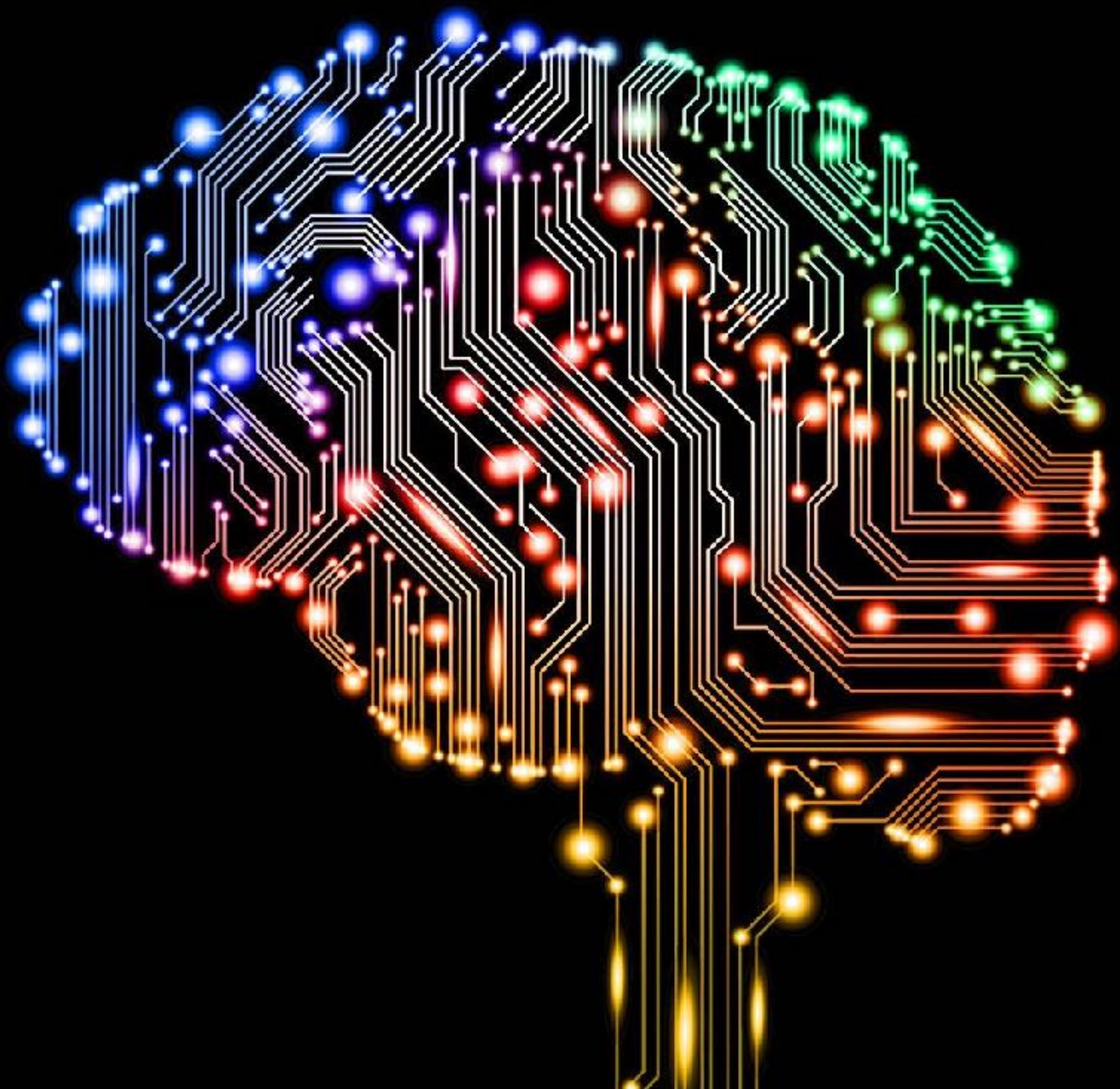


NN Demo

https://playground.tensorflow.org/



Deep Learning

Deep learning boom

Deep learning boom

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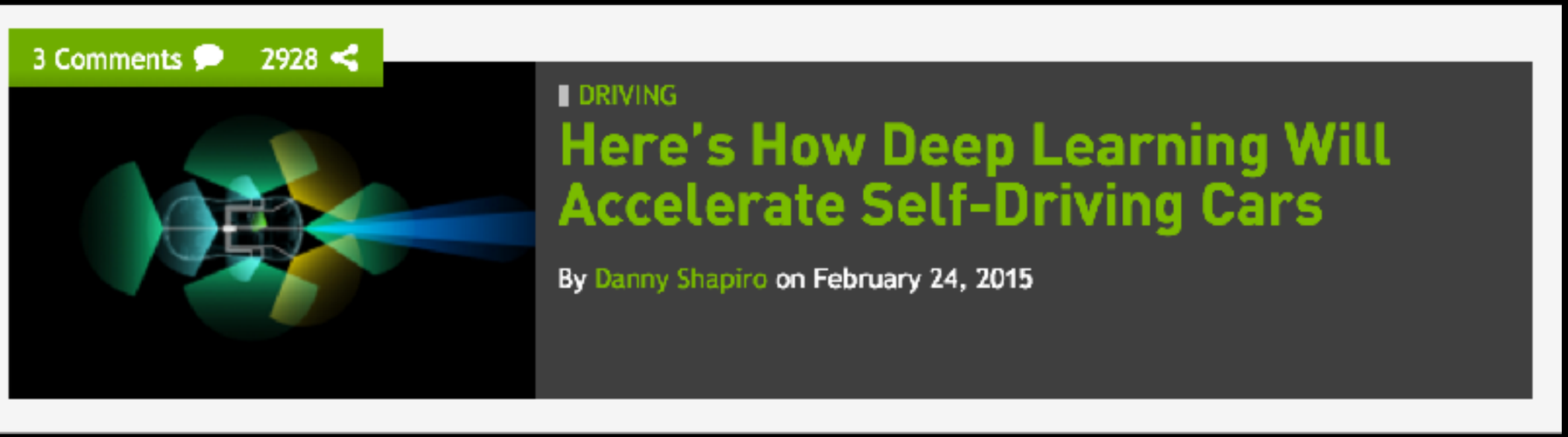
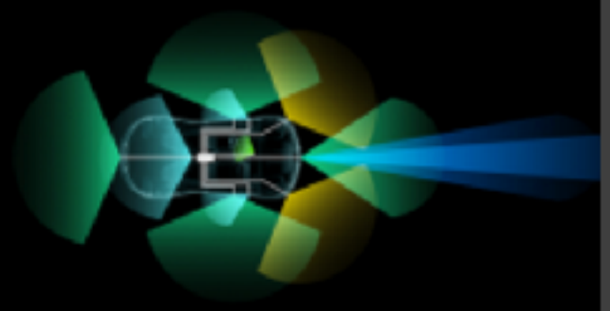


Deep learning boom

3 Comments 2928



DRIVING

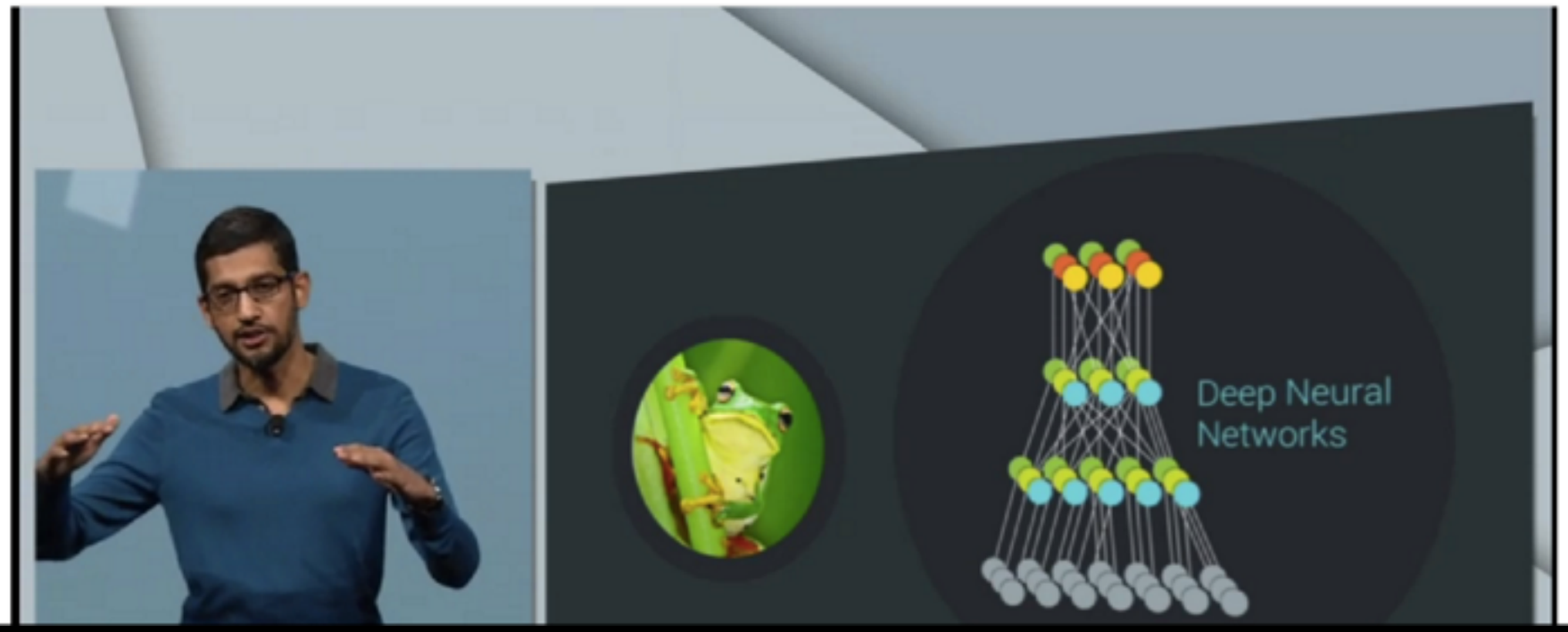
Here's How Deep Learning Will Accelerate Self-Driving Cars

By Danny Shapiro on February 24, 2015

Google says its speech recognition technology now has only an 8% word error rate

JORDAN NOVET MAY 28, 2015 10:40 AM

TAGS: ARTIFICIAL INTELLIGENCE, DEEP LEARNING, GOOGLE, GOOGLE I/O 2015, SUNDAR PICHAI



Deep learning boom

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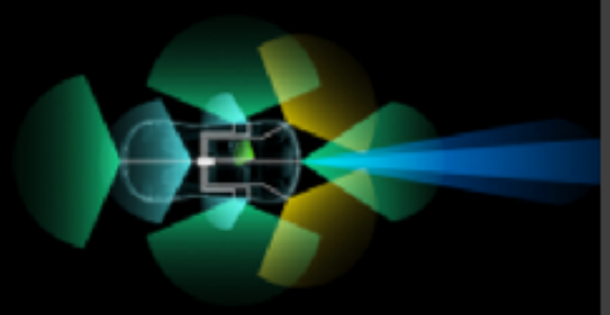

DRIVING

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By Danny Shapiro on February 24, 2015

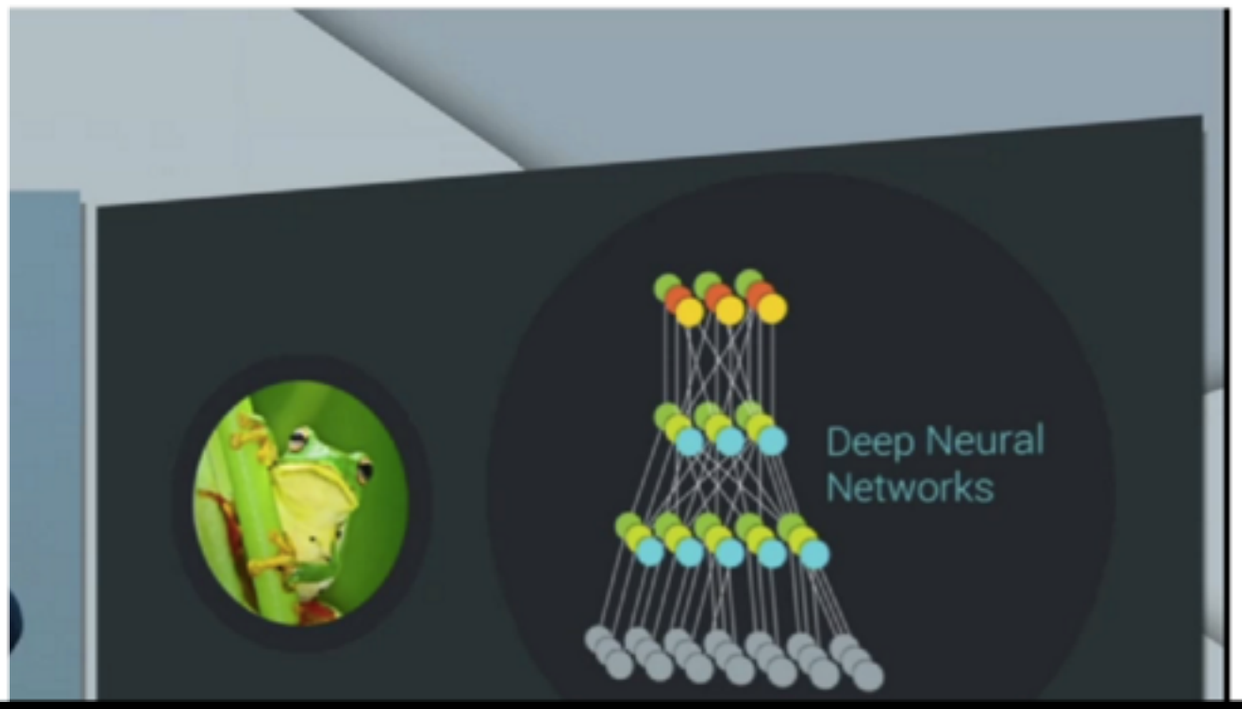
ROBERT MCMILLAN BUSINESS 03.13.13 6:30 AM

GOOGLE HIRES BRAINS THAT HELPED SUPERCHARGE MACHINE LEARNING

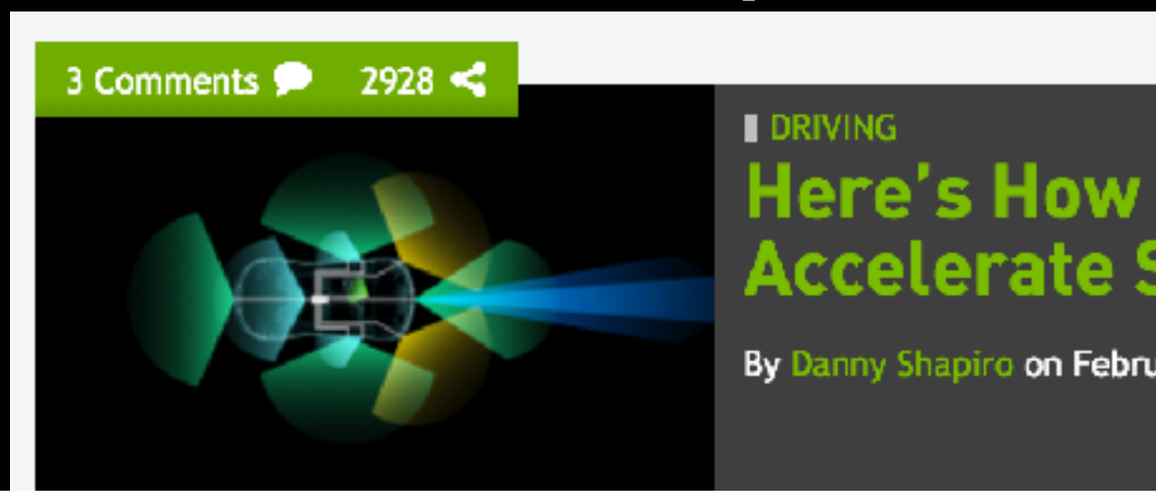
speech recognition technology now

word error rate

ING, GOOGLE, GOOGLE I/O 2015, SUNDAR PICHAI



Deep learning boom



ROBERT MCMILLAN BUSINESS 03.13.13 6:30 AM

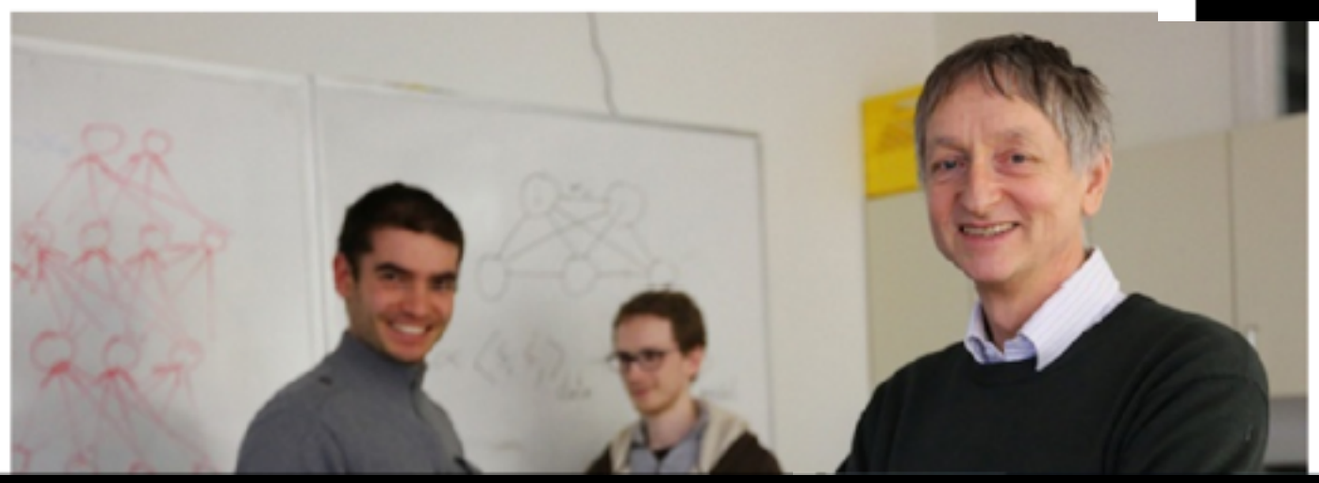
GOOGLE HIRES BRAINS THAT HELPED SUPERCHARGE MACHINE LEARNING

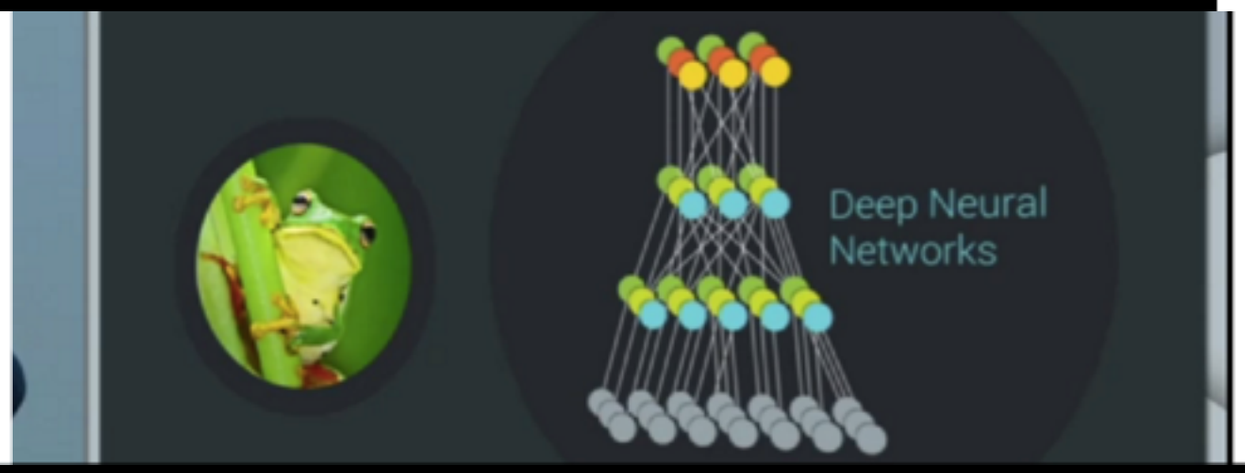
MIT Technology Review

Baidu 百度

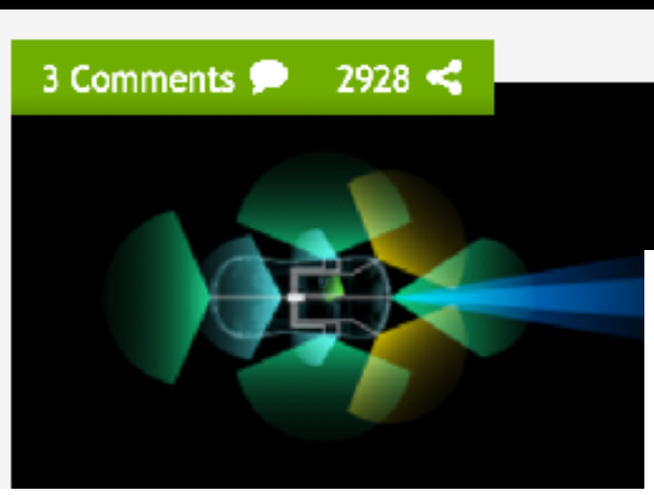
Computing

Chinese Search Giant Baidu Hires Man Behind the "Google Brain"





Deep learning boom



ROBERT MCMILLAN BUSINESS 03.13.13 6:30

GOOGLE HIRES B
HELPED SUPERC
MACHINE LEARN

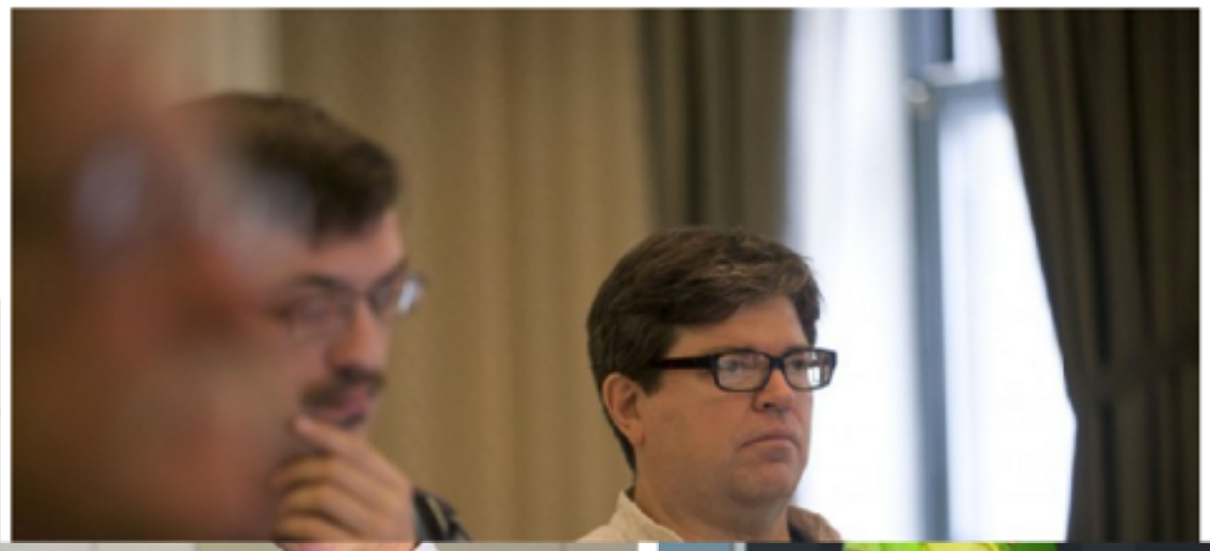
DRIVING
Here's How

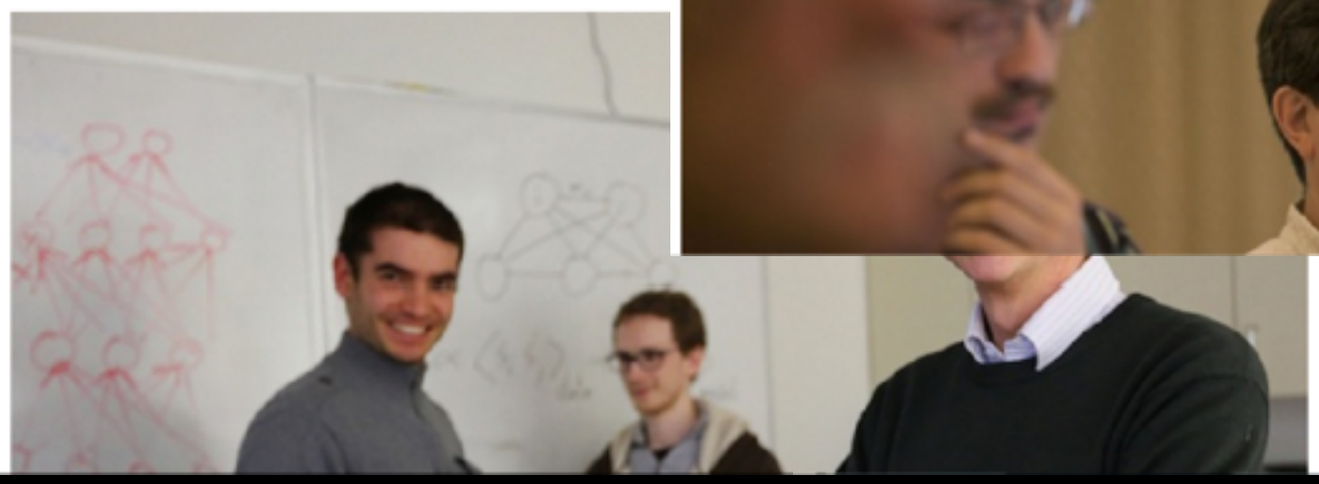
MIT
Technology
Review

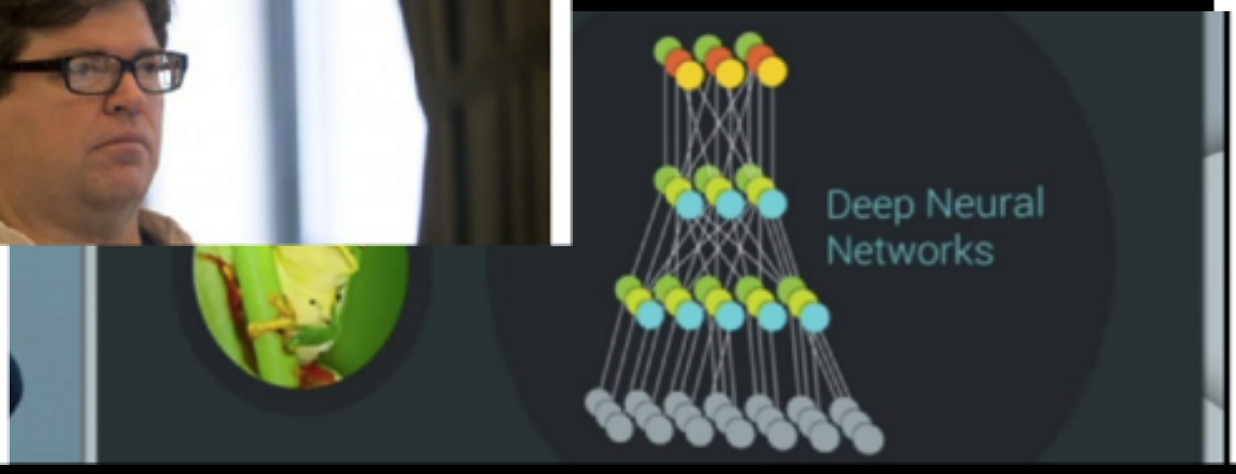
CADE METZ BUSINESS 12.09.13 3:14 PM

FACEBOOK TAPS 'DEEP LEARNING' GIANT FOR NEW AI LAB

rch Giant
Man Behind
Brain"



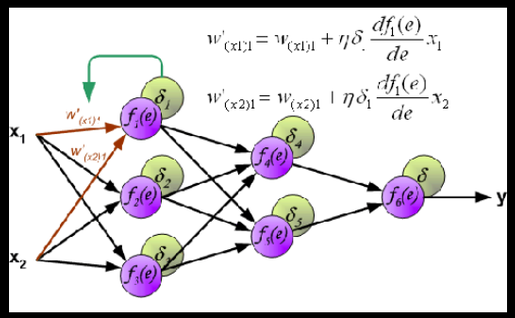


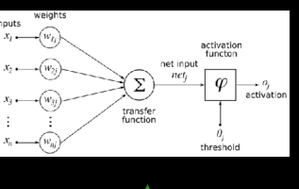


Google assistant calling to make a reservation

Google assistant calling to make a reservation

Deep learning time line





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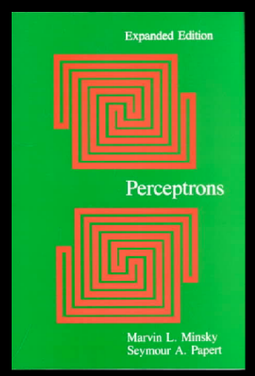
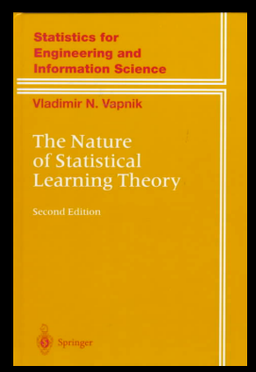
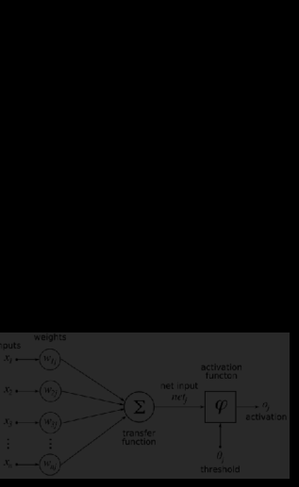
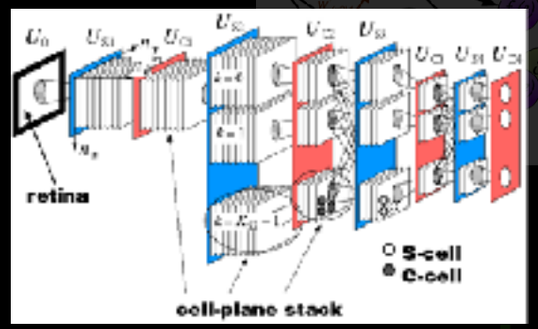
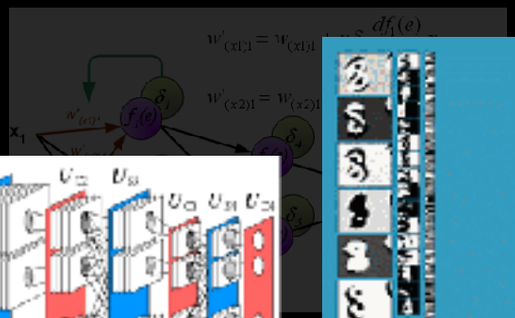


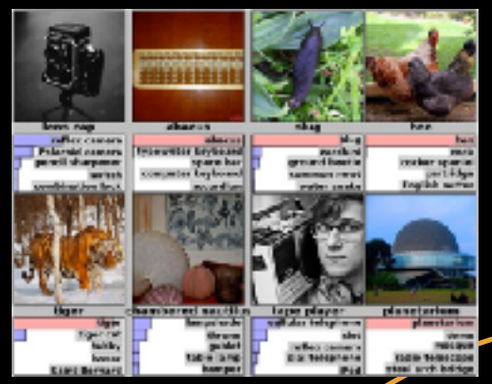


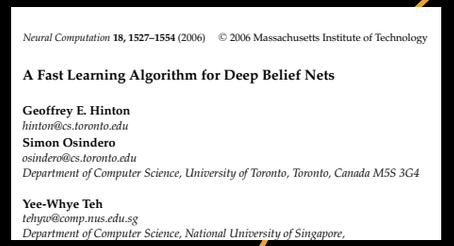
Deep learning time line











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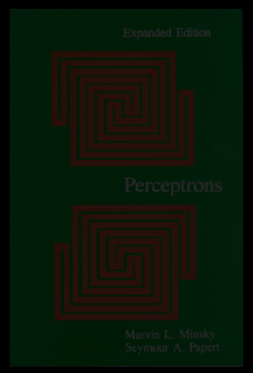
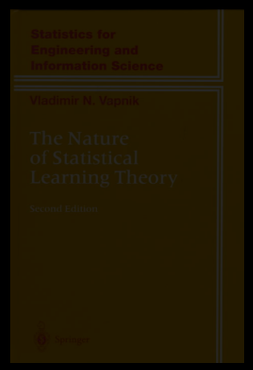
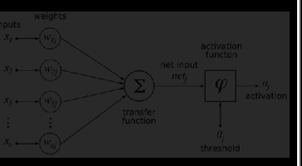




Deep learning time line



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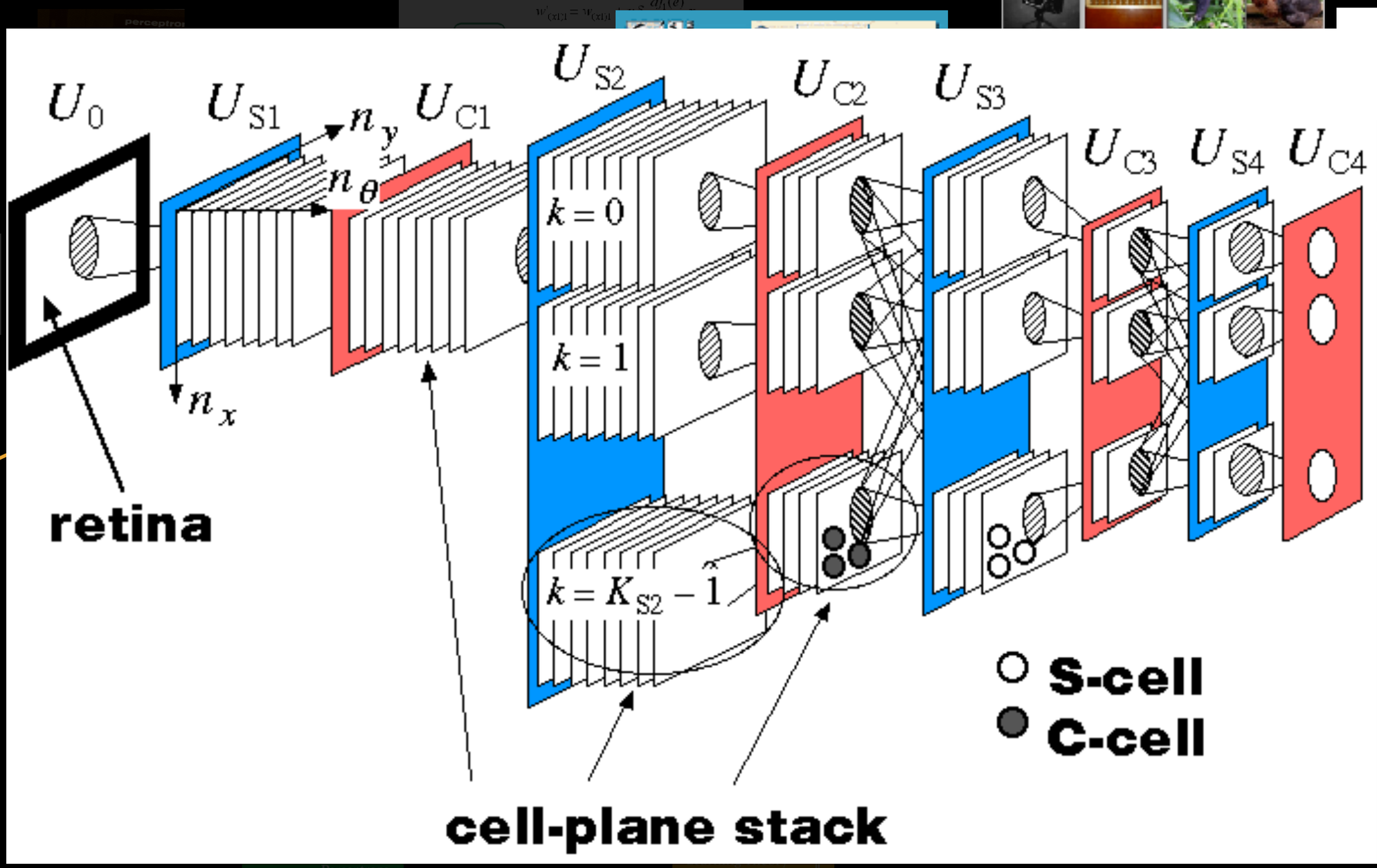

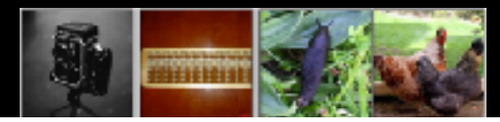

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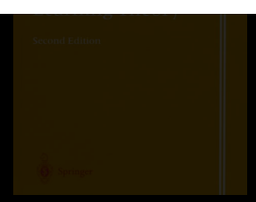
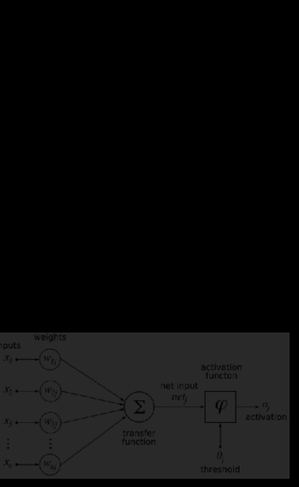
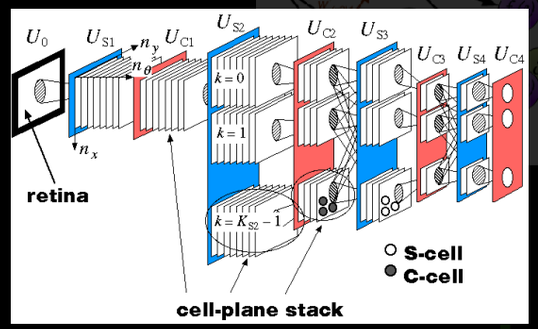
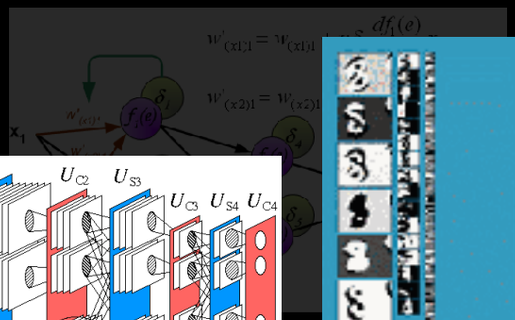
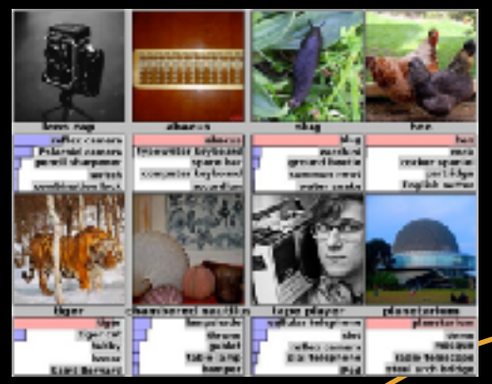


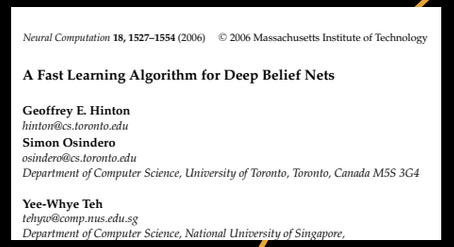
Deep learning time line







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A Fast Learning Algorithm for Deep Belief Nets

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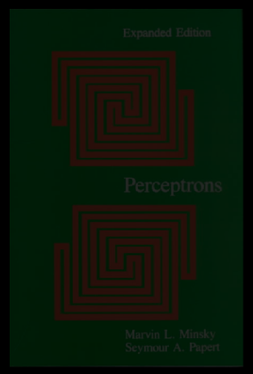
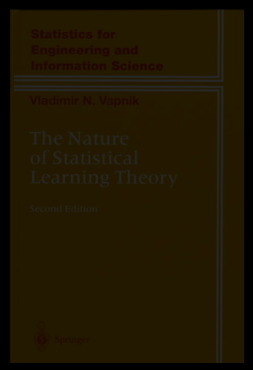
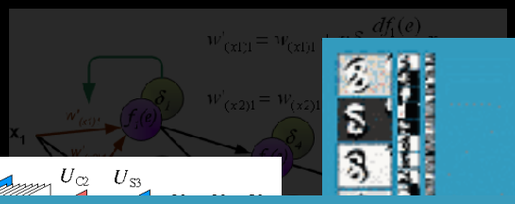




Deep learning time line



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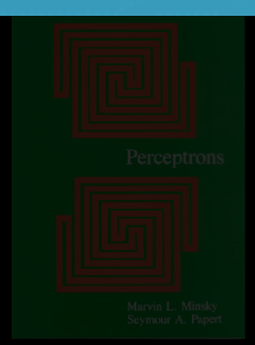
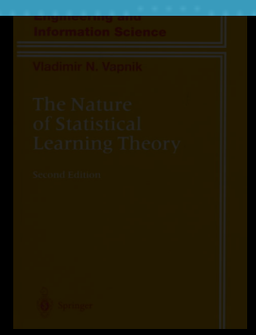
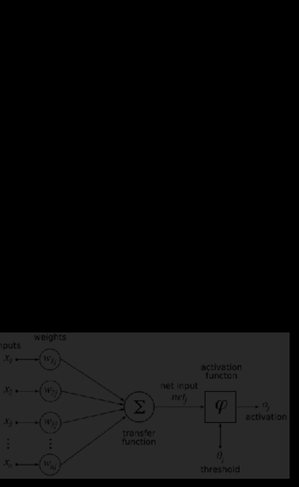
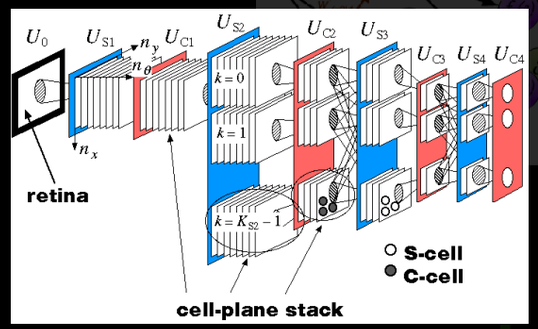
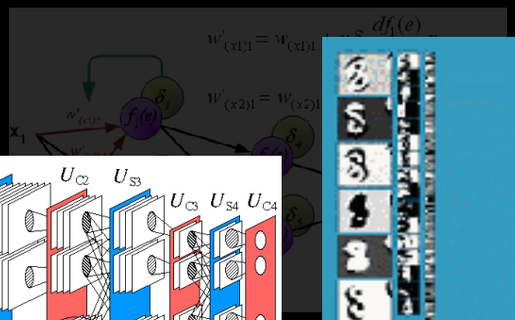


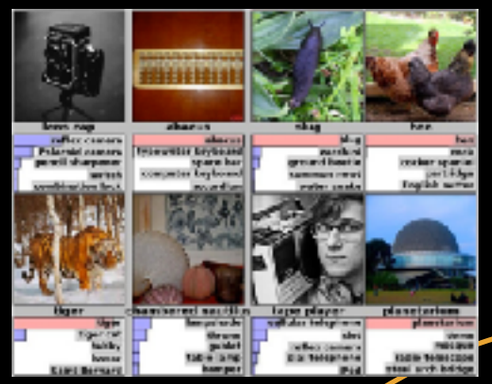


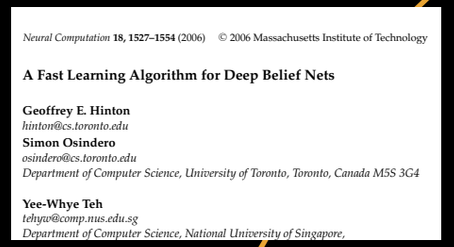
Deep learning time line







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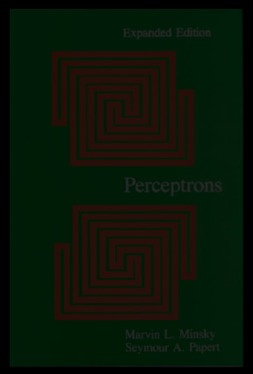

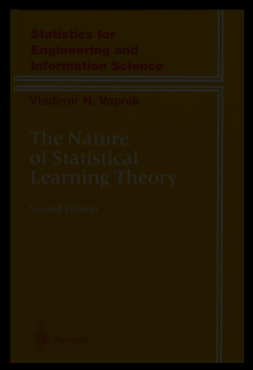

Deep Learning is Born

Neural Computation **18, 1527–1554** (2006)

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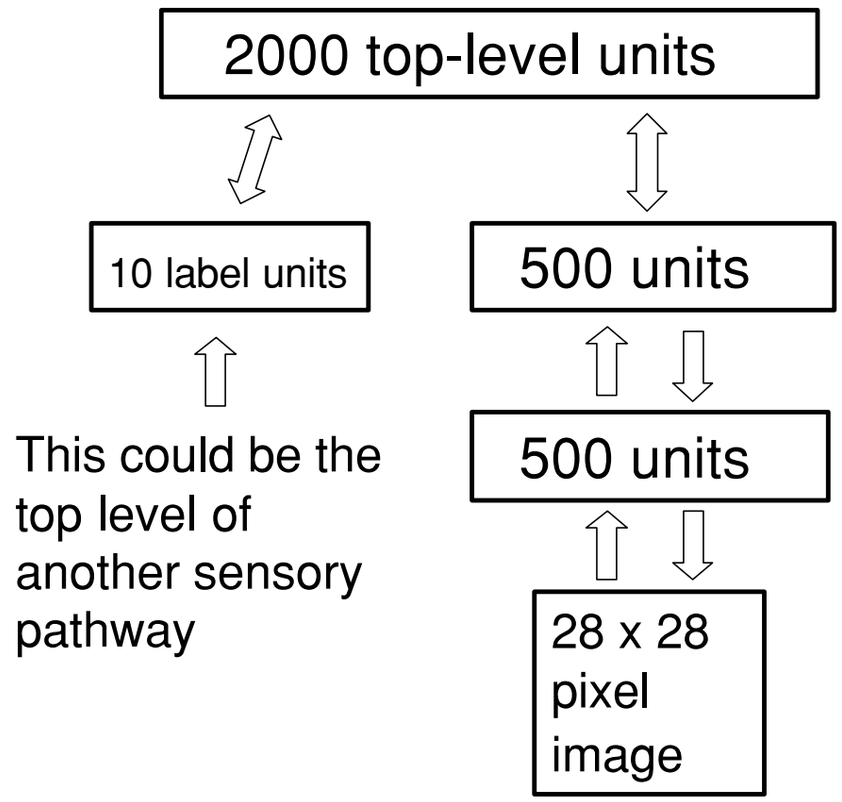

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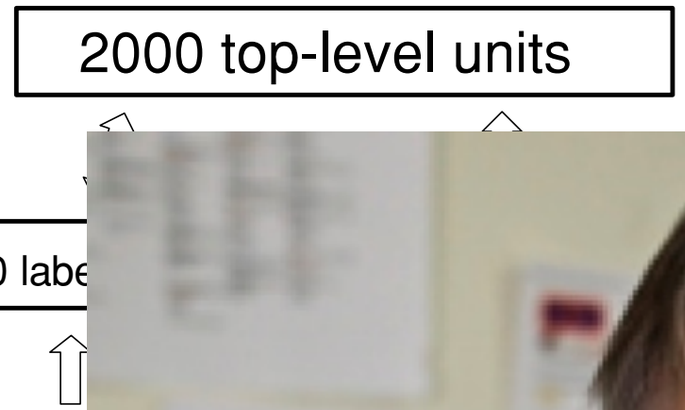
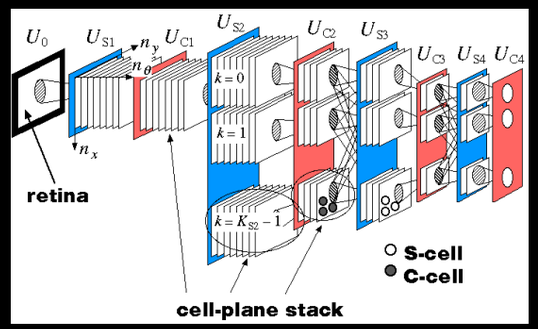
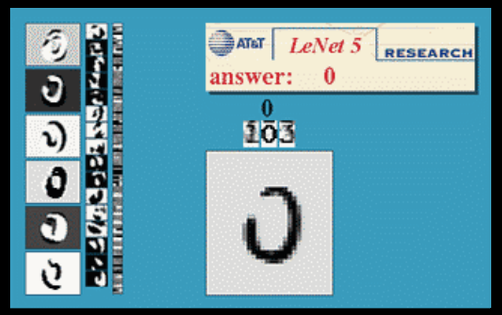
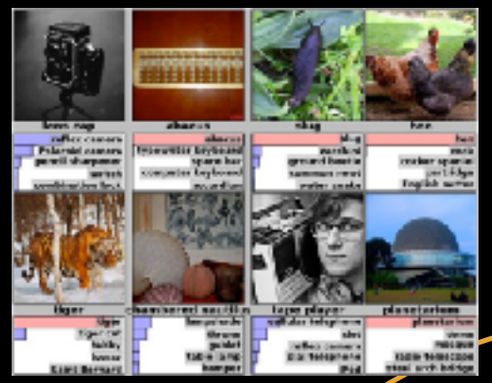
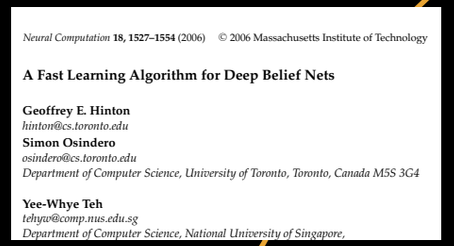


Deep learning time line









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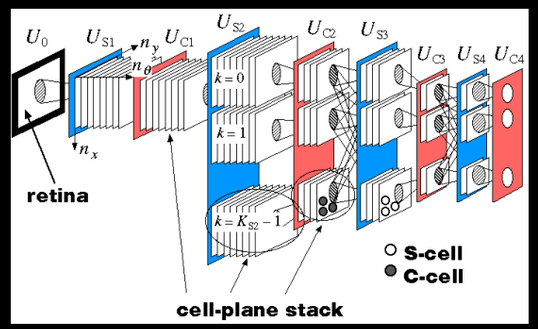
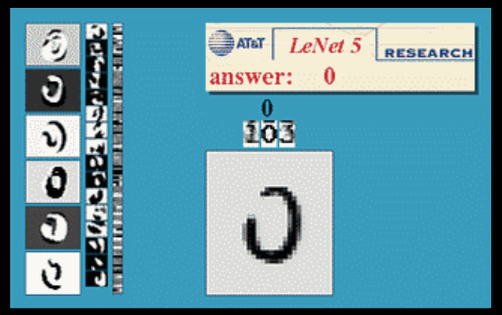
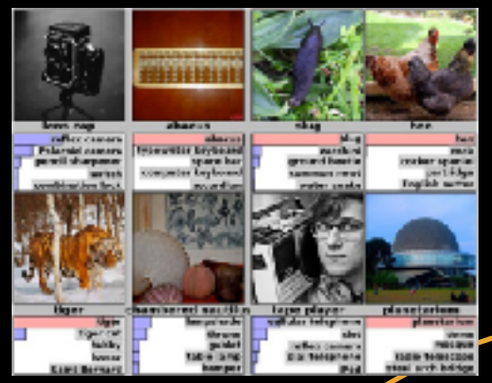
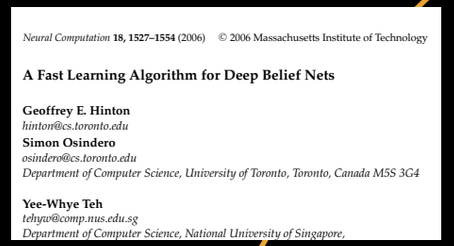
Deep learning time line









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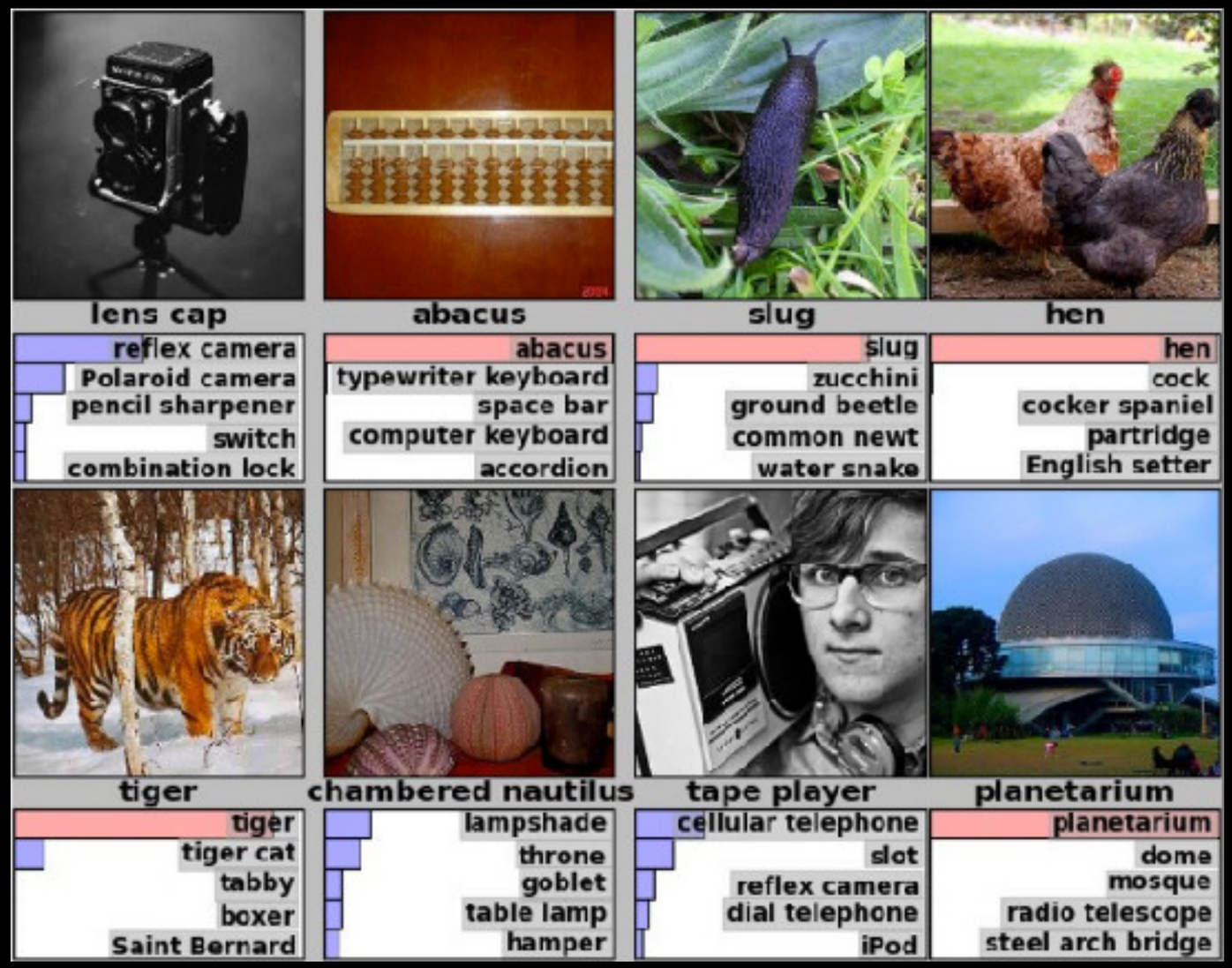
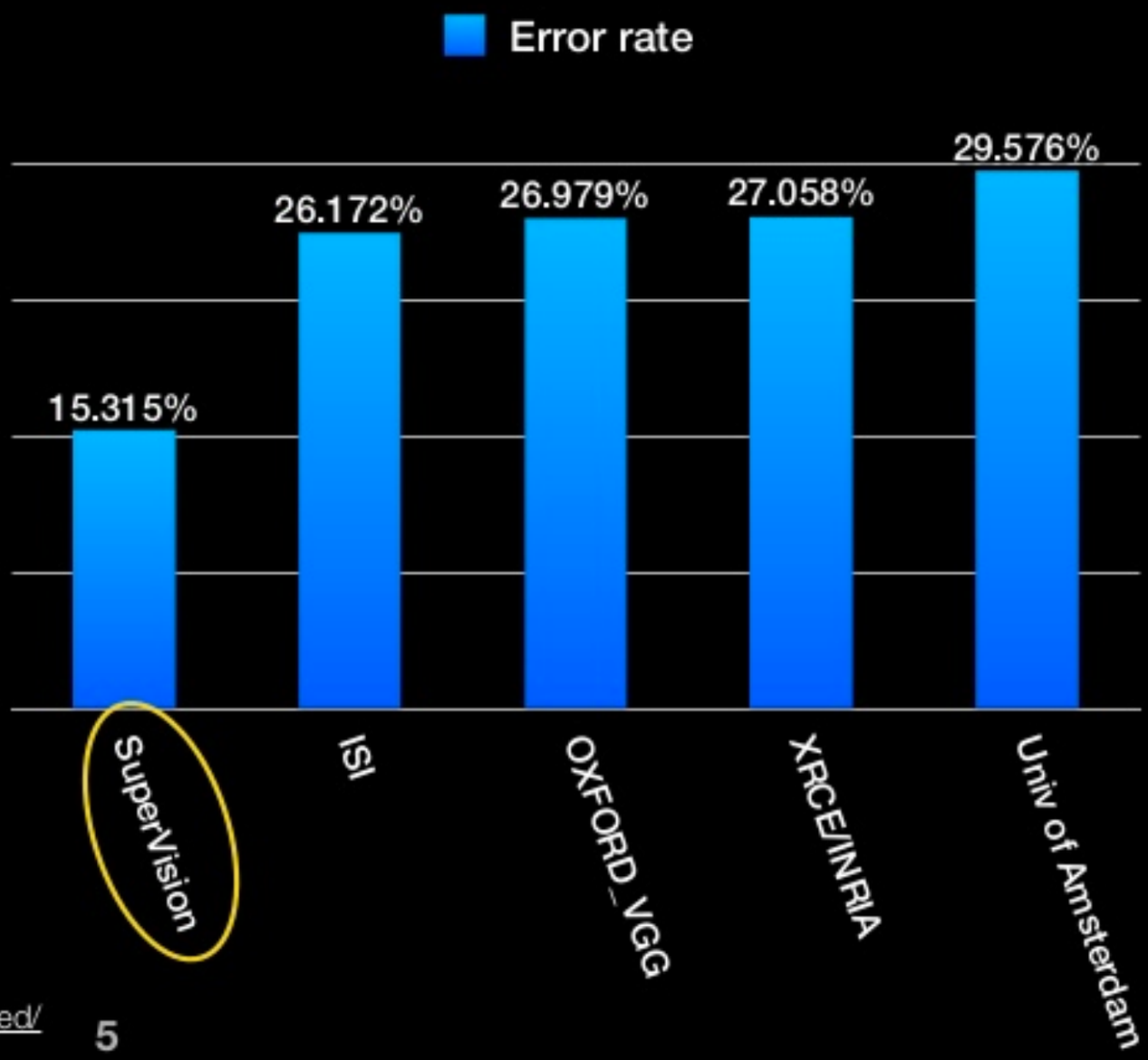
Deep learning model won ILSVRC 2012 challenge



Deep learning model won ILSVRC 2012 challenge

- ILSVRC 2012 (ImageNet Large Scale Visual Recognition)

Image source: http://cs.stanford.edu/people/karpathy/cnnembed/



Deep learning model won ILSVRC 2012 challenge

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  Larg
  Reco

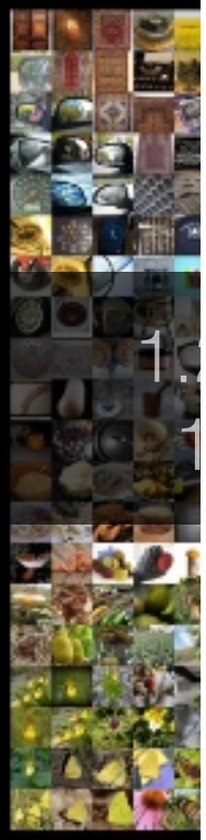
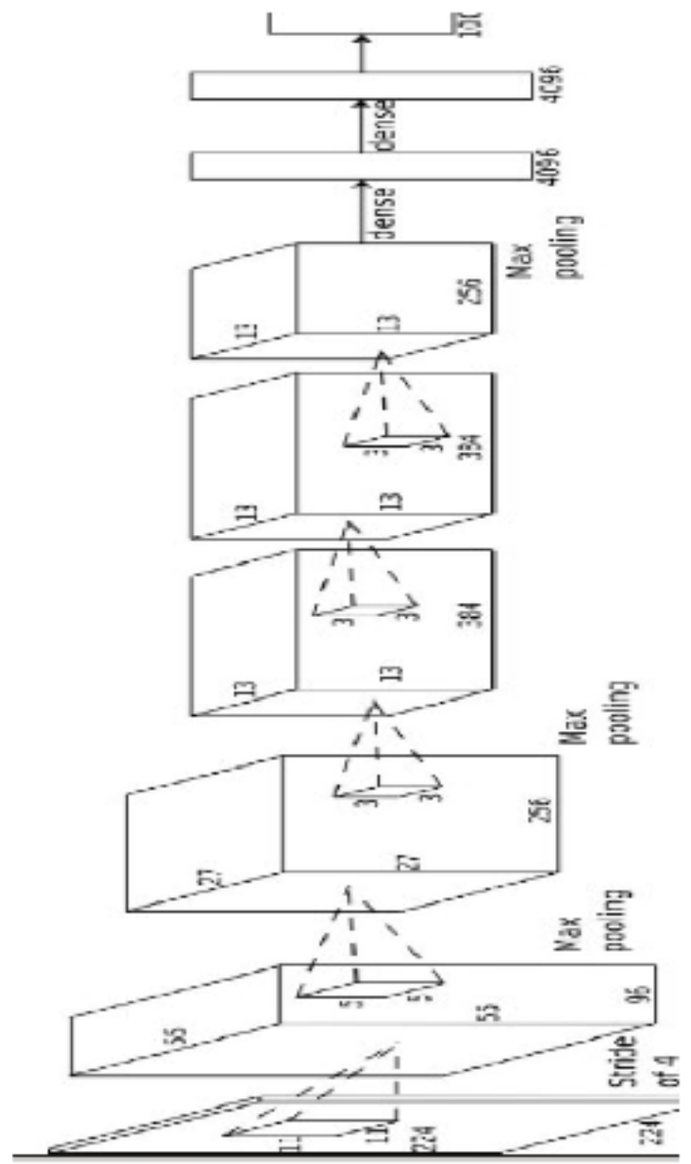


Image source

Won the 2012 ImageNet LSVRC. 60 Million parameters, 832M MAC ops

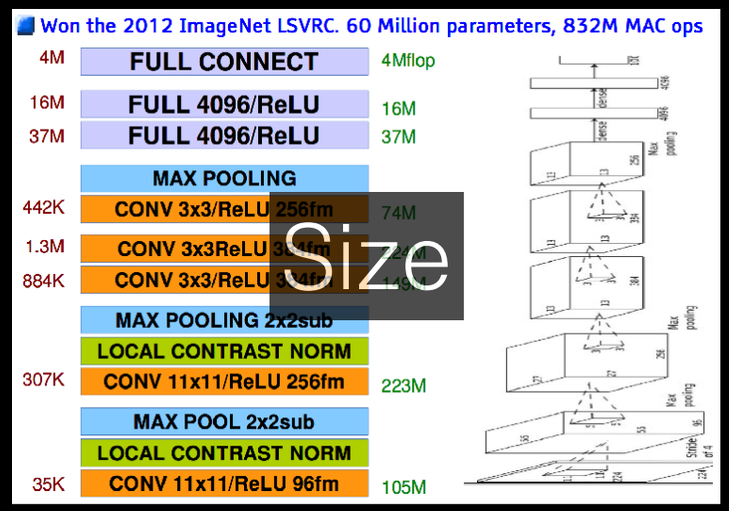
4M	FULL CONNECT	4Mflop
16M	FULL 4096/ReLU	16M
37M	FULL 4096/ReLU	37M
	MAX POOLING	
442K	CONV 3x3/ReLU 256fm	74M
1.3M	CONV 3x3ReLU 384fm	224M
884K	CONV 3x3/ReLU 384fm	149M
	MAX POOLING 2x2sub	
	LOCAL CONTRAST NORM	
307K	CONV 11x11/ReLU 256fm	223M
	MAX POOL 2x2sub	
	LOCAL CONTRAST NORM	
35K	CONV 11x11/ReLU 96fm	105M



Deep learning recipe

Data

Algorithms



Size

Tricks

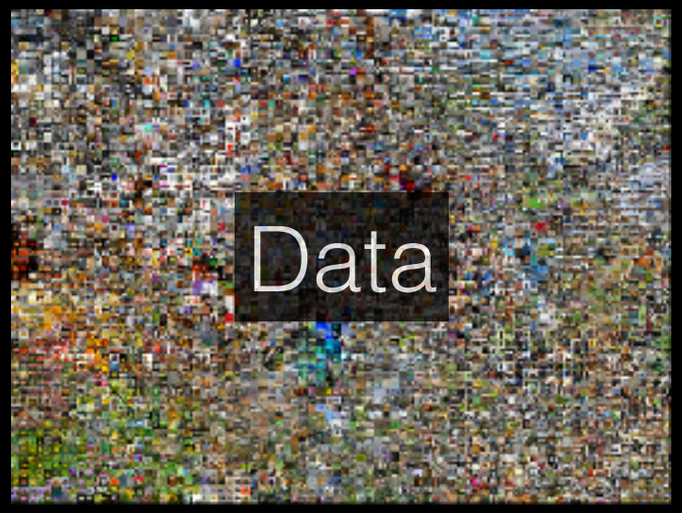
Feature learning

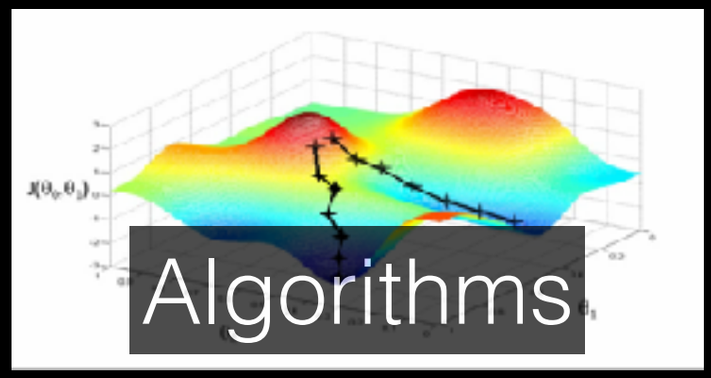
HPC

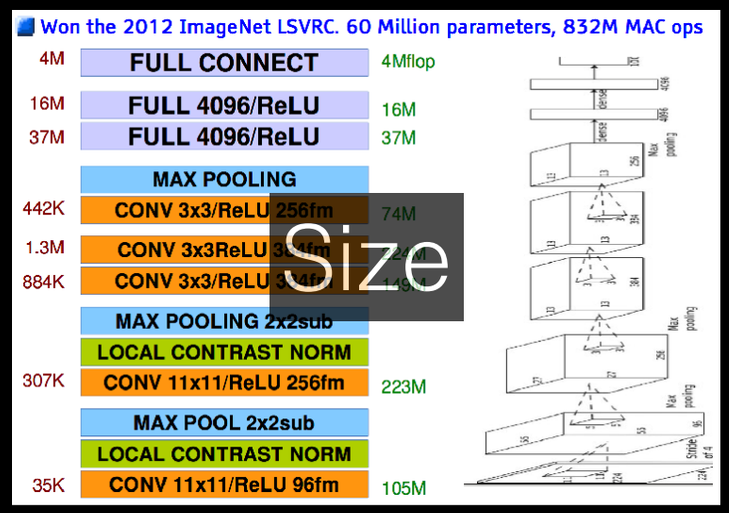
Fabio A. González

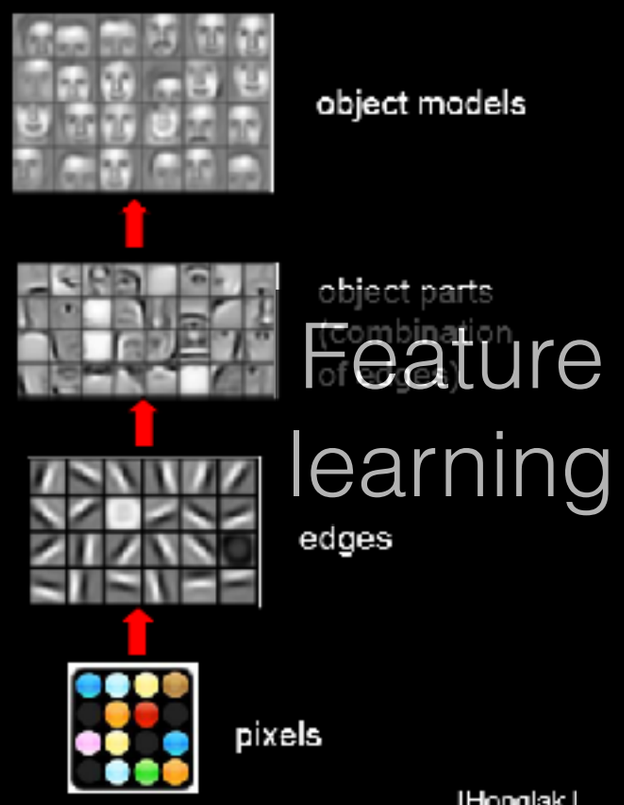
Universidad Nacional de Colombia

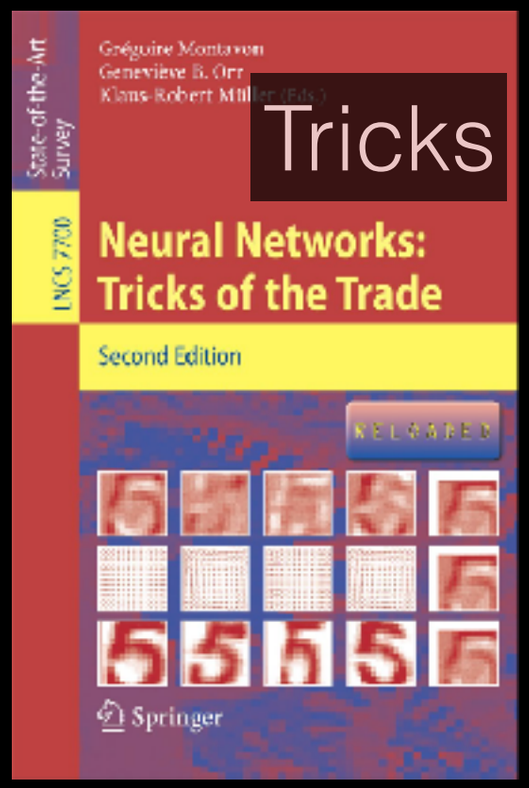
Deep learning recipe



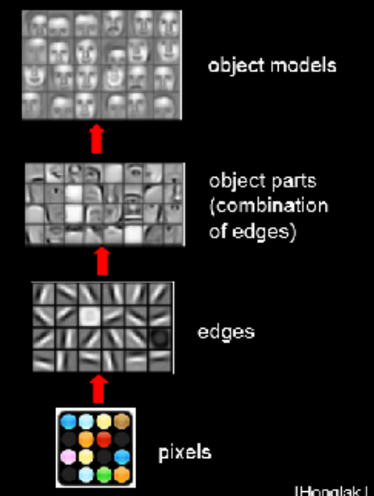




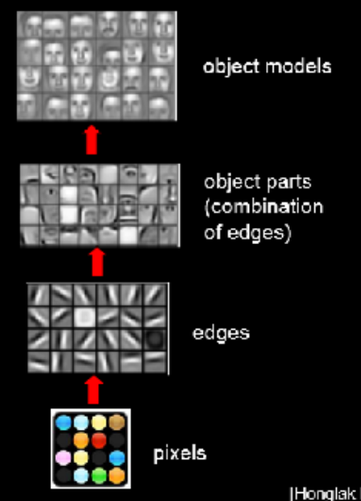


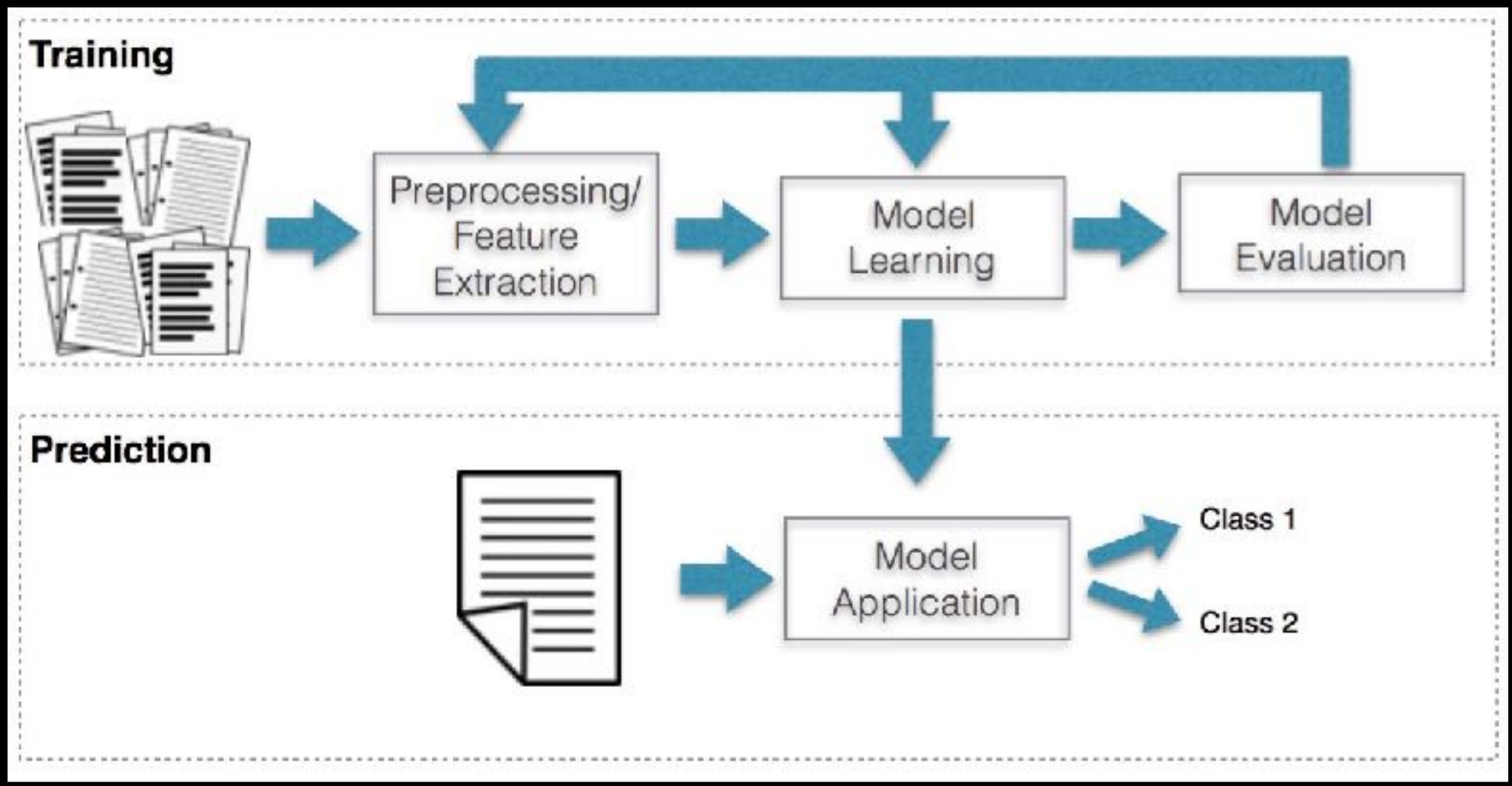


Feature learning

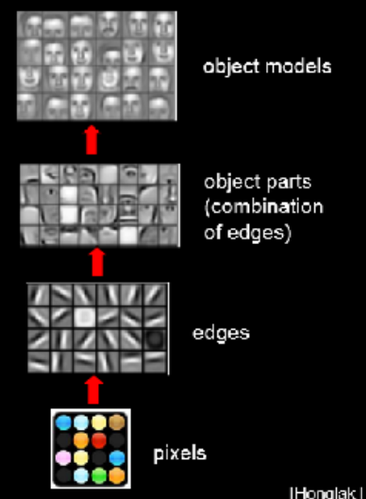


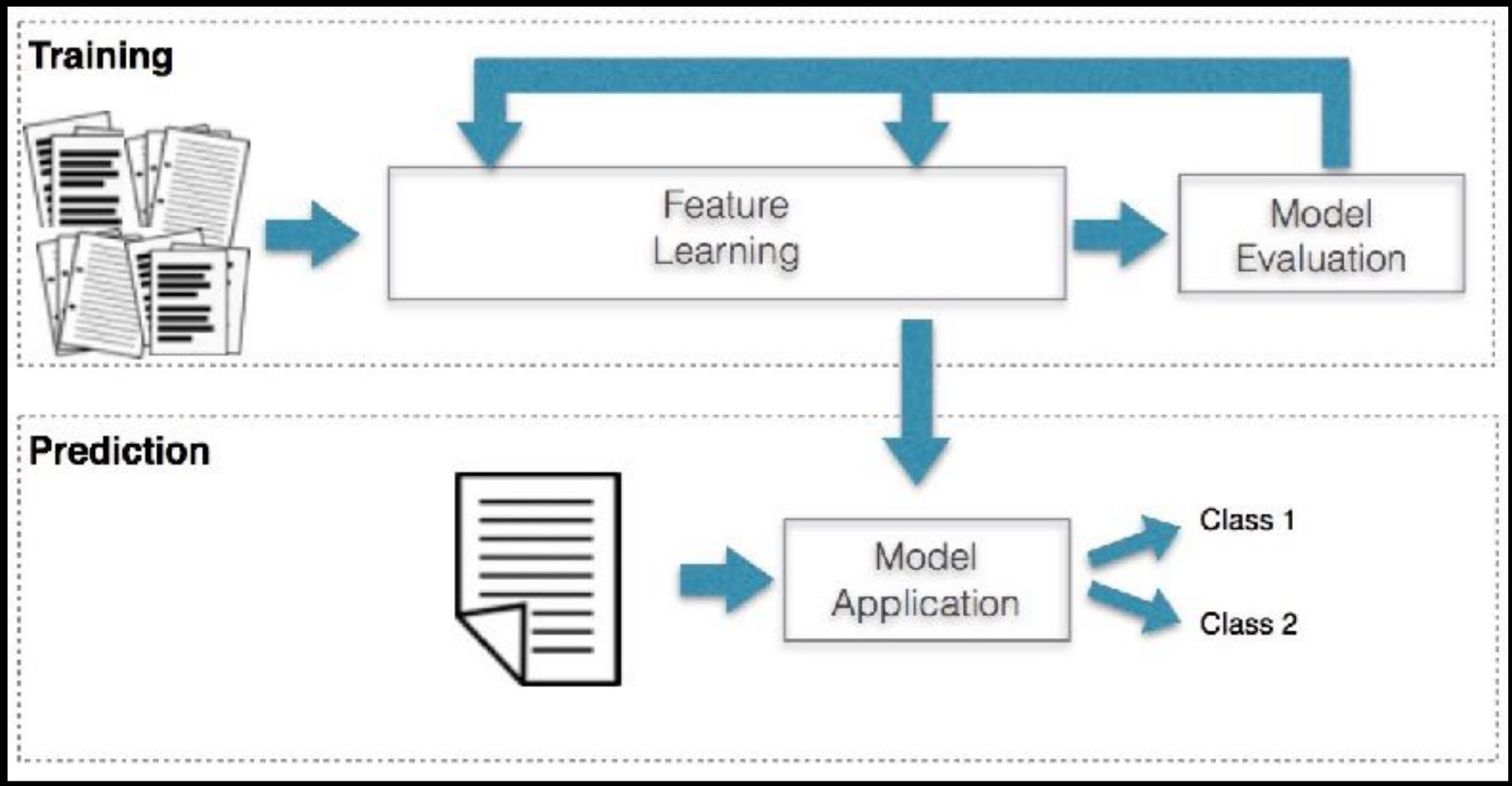
Feature learning



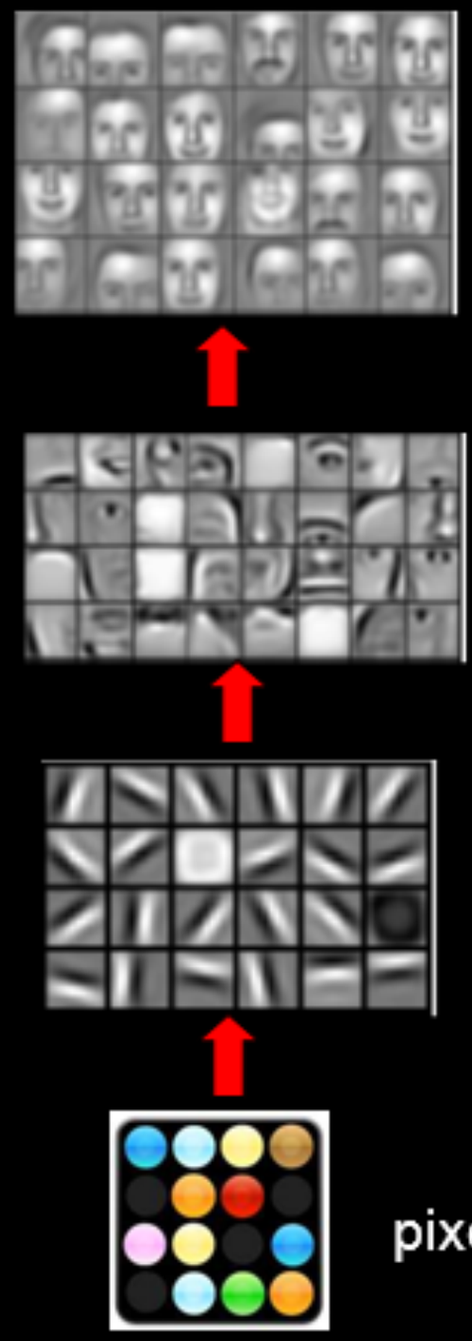


Feature learning



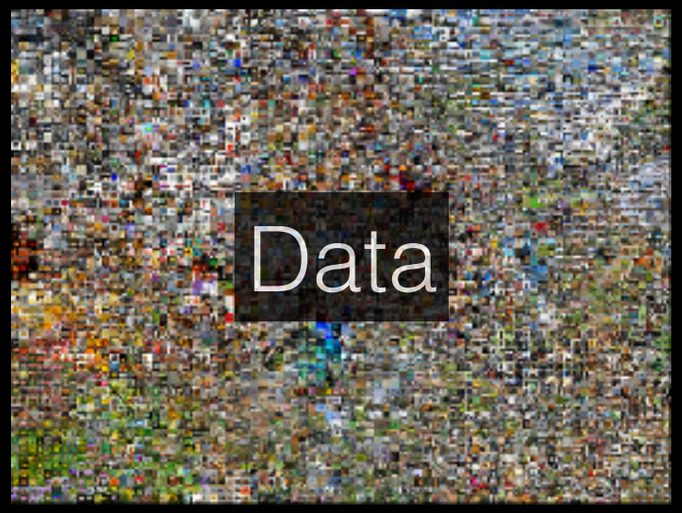


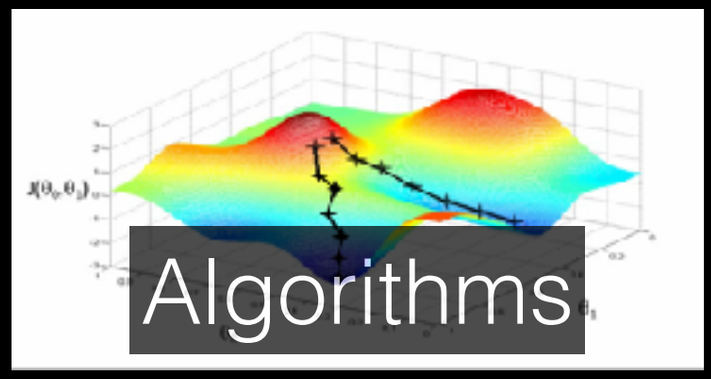
Feature learning

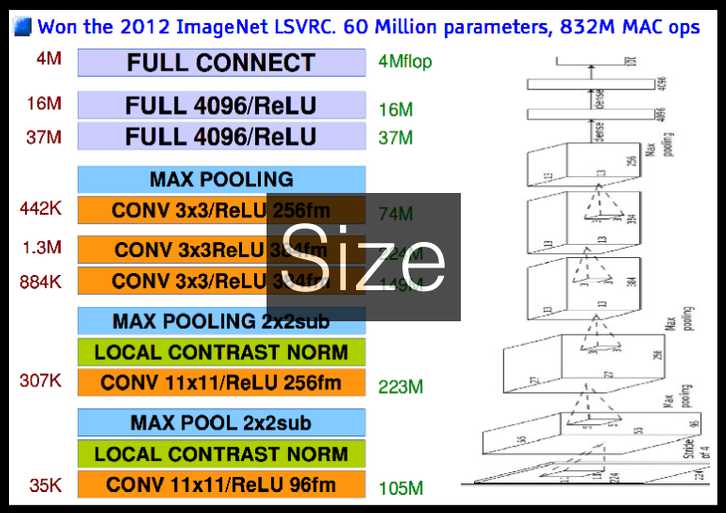


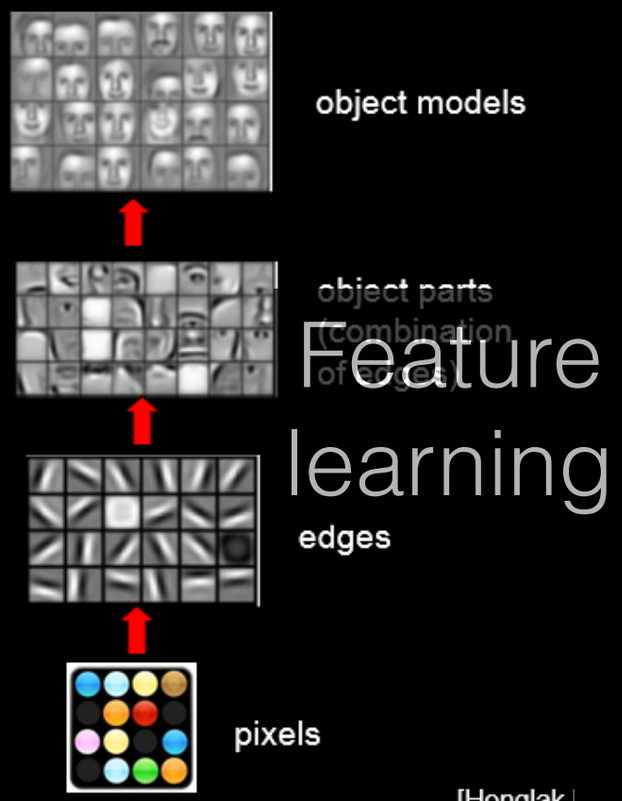
[Honglak

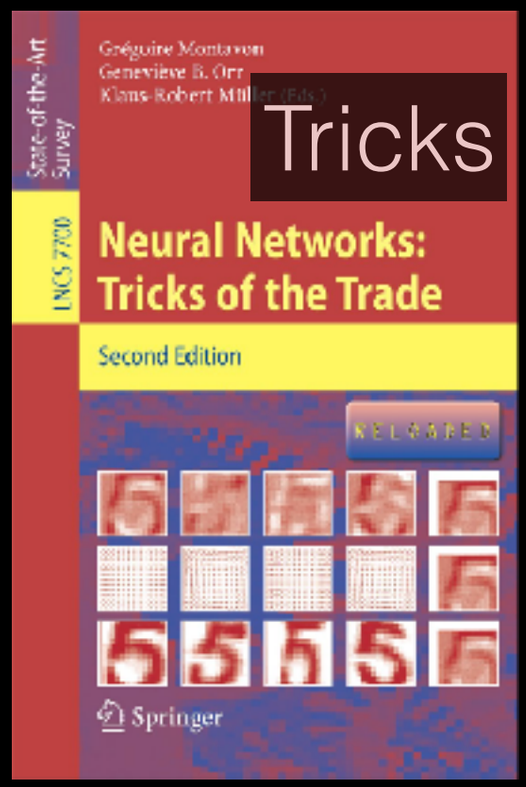
Deep learning recipe



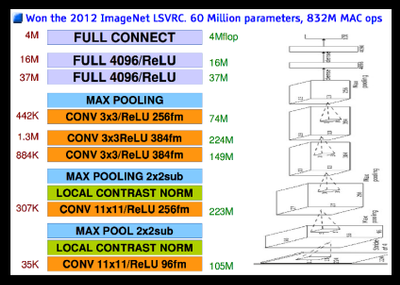






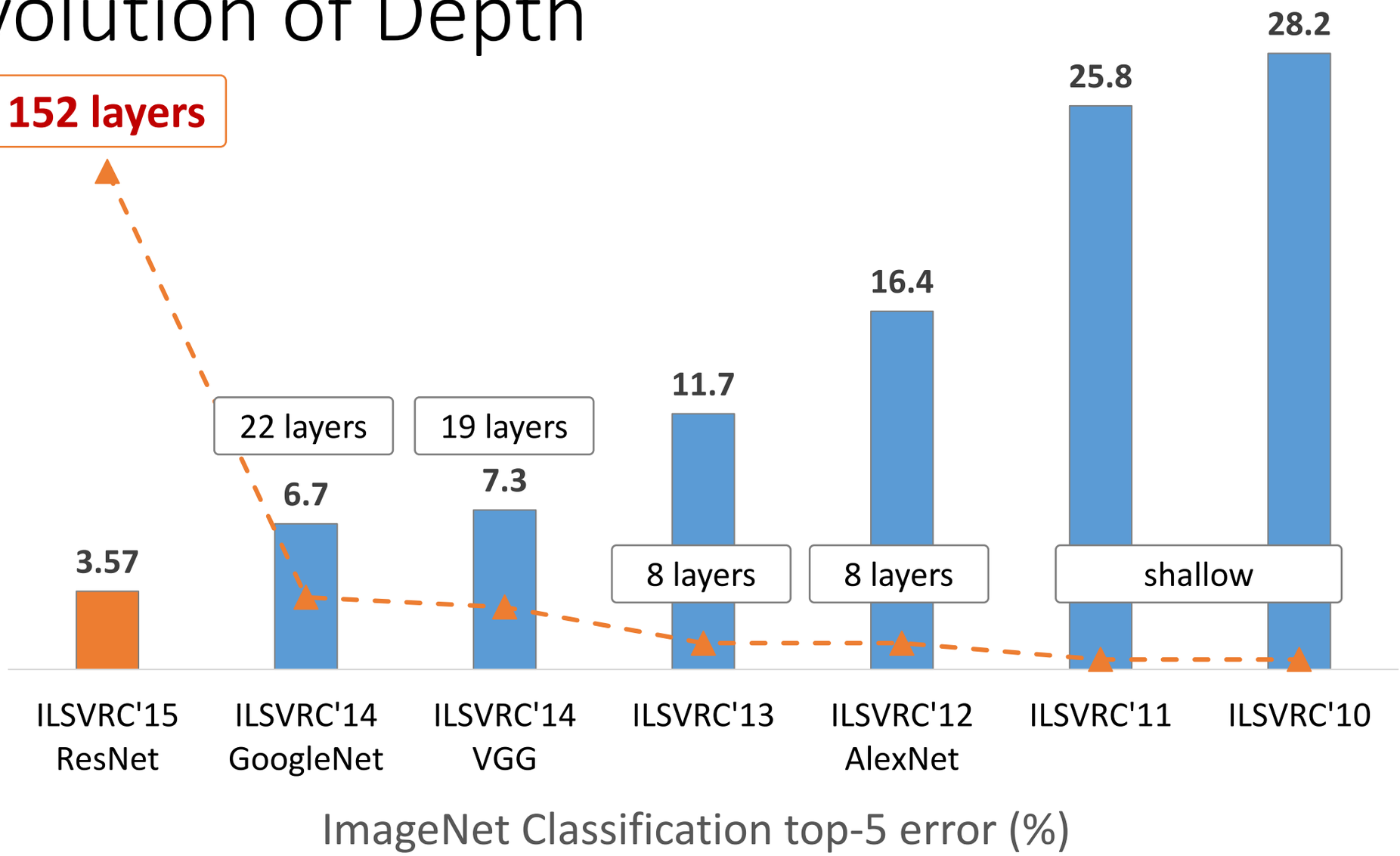


Deep —> Bigger

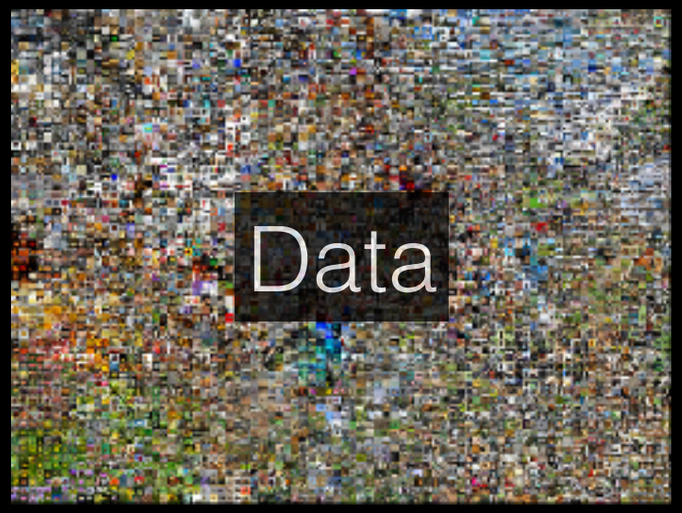


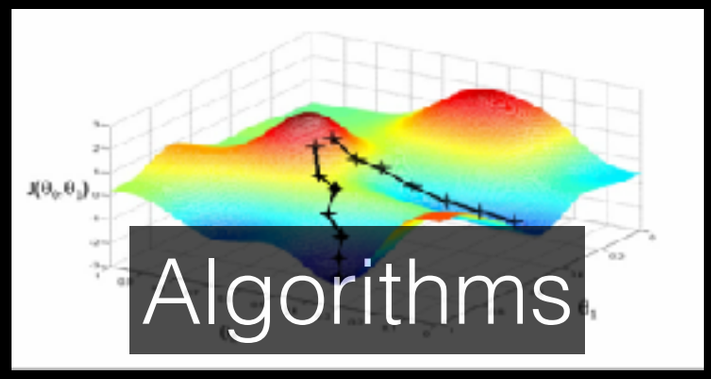
Microsoft Research

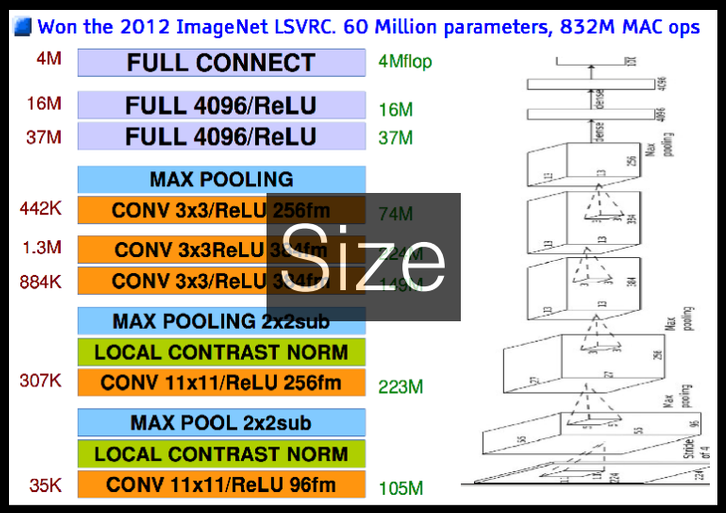
Revolution of Depth

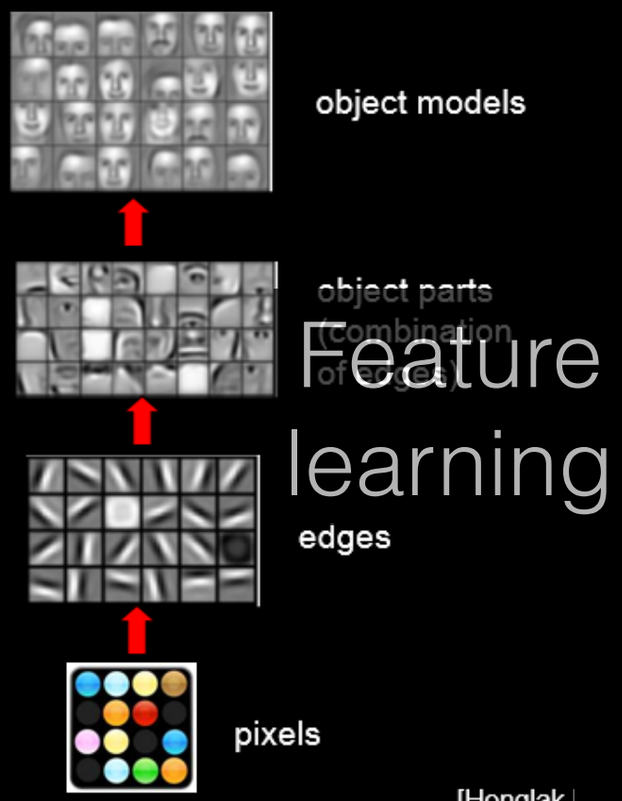


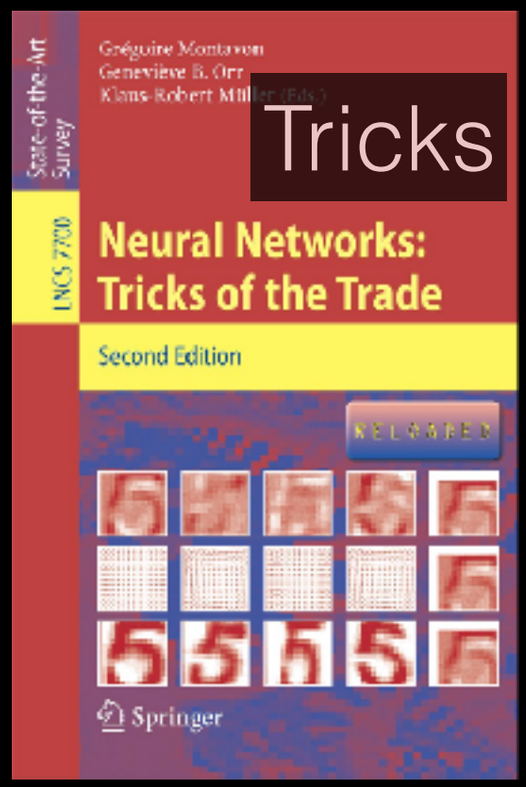
Deep learning recipe





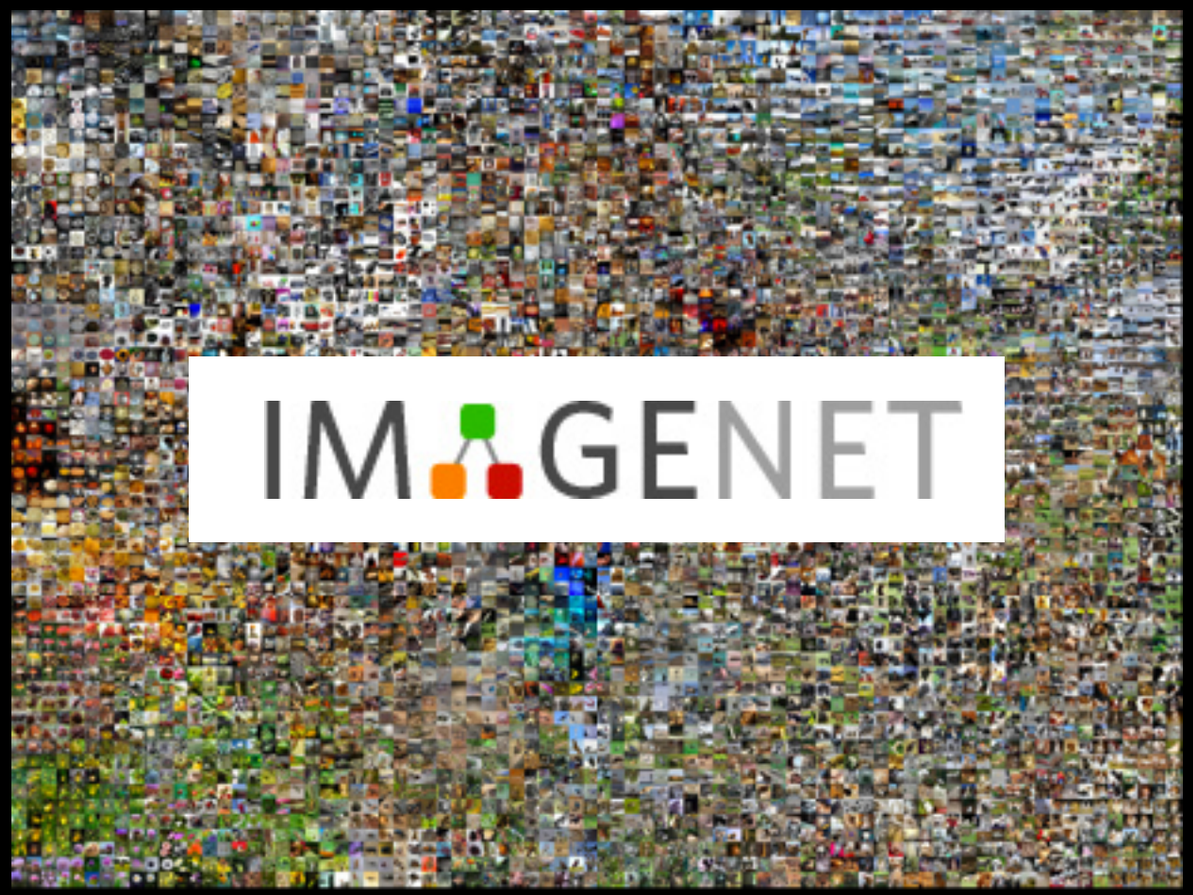




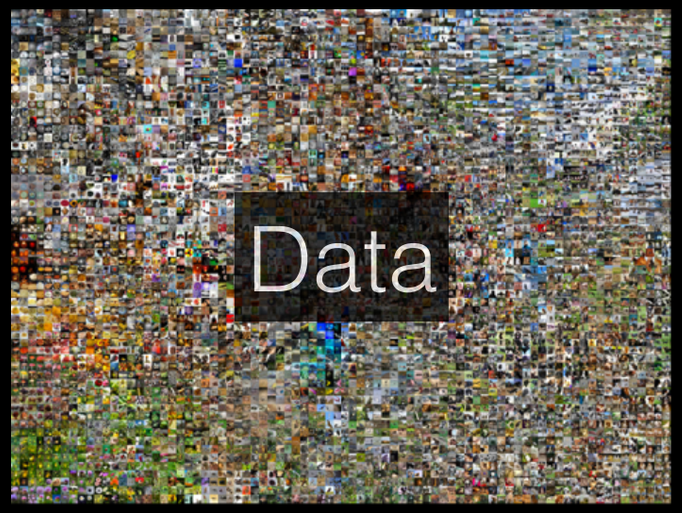


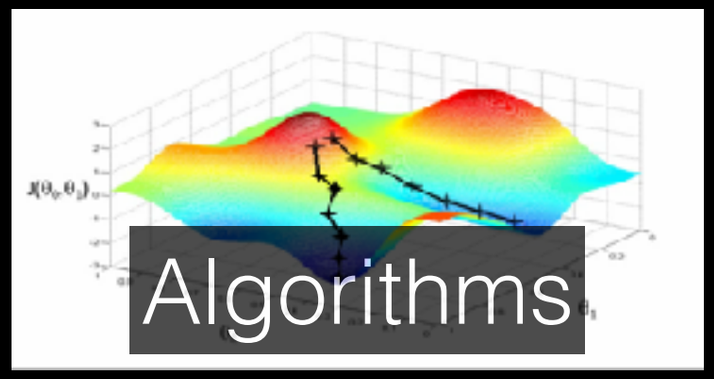
Data…

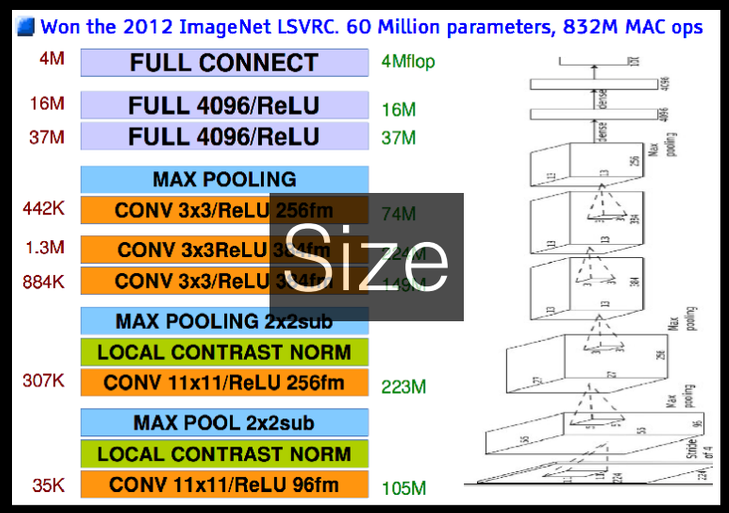
- Images annotated with WordNet concepts
- Concepts: 21,841
- Images: 14,197,122
- Bounding box annotations: 1,034,908
- Crowdsourcing

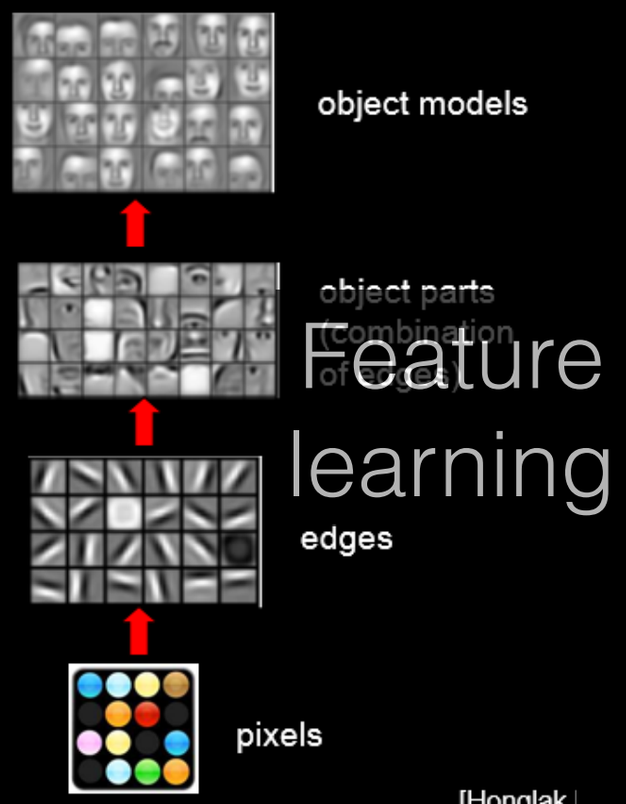


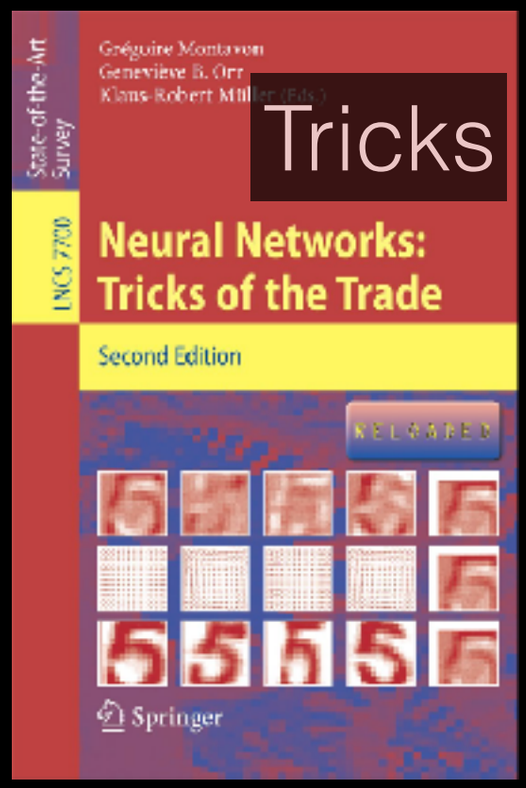
Deep learning recipe











HPC

Tesla K40

Larger datasets
Faster acceleration
Dynamic Power Scaling
Same power

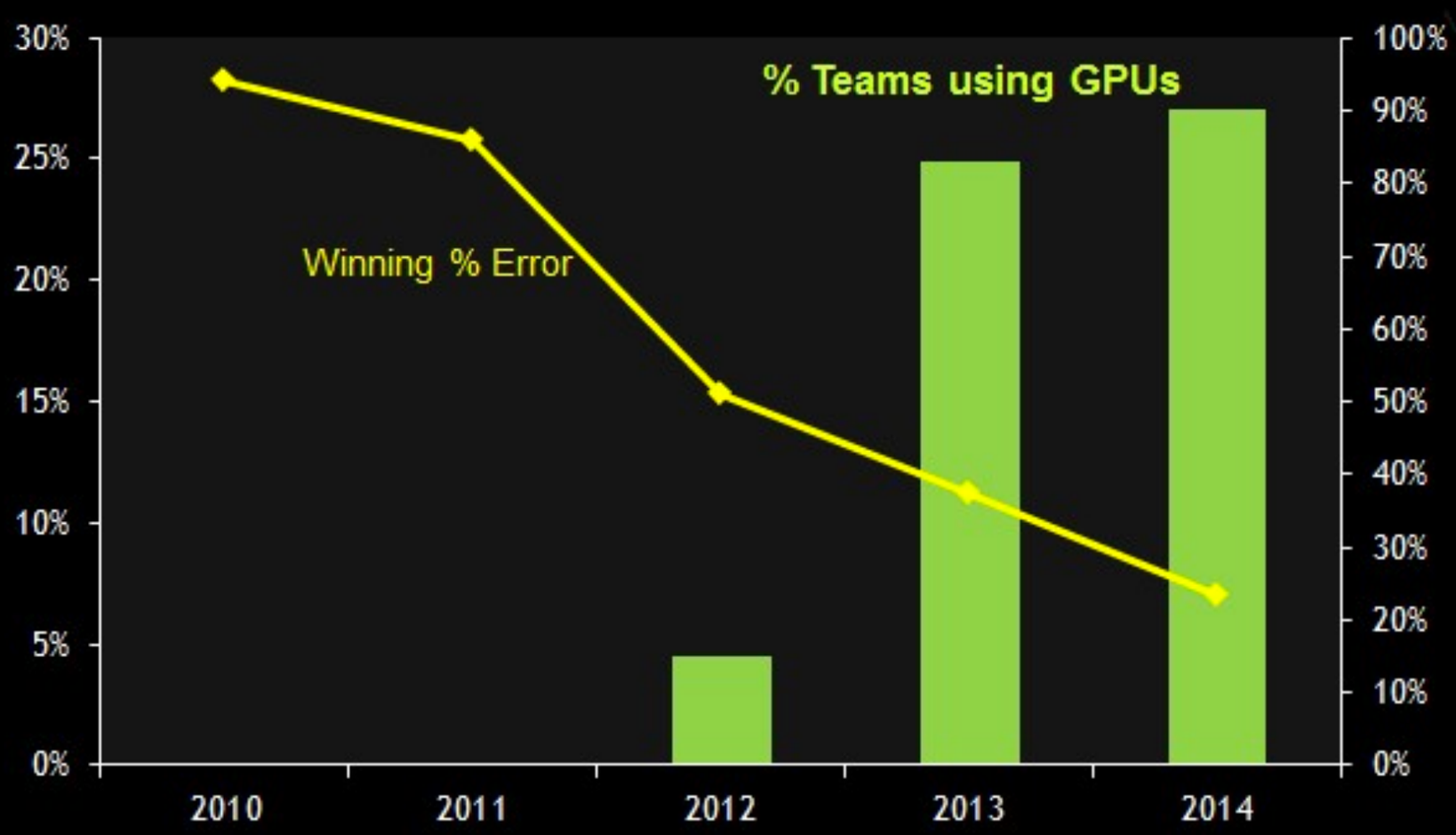
Expands GPU Opportunity &
Lead over Competition

K40 specs are preliminary

	K20X	K40 (Atlas)
GPU(s)	1x GK110	1x GK180
Peak Single Precision Peak SGEMM	3.95 TF 2.90 TF	>4.0 TF
Peak Double Precision Peak DGEMM	1.32 TF 1.22 TF	>1.4 TF
Memory size	6 GB	12 GB
Memory BW (ECC off)	250 GB/s	288 GB/s
Workload for Boost Clocks	-	AMBER, ANSYS
PCIe Gen	Gen 2	Gen 3
# CUDA Cores	2688	2880
Total Board Power	235W	235W (245W SXM)
Form factor	PCIe Passive, SXM	PCIe Passive, Active & TTP, SXM

HPC


TESLA


% Teams using GPUs
Winning % Error
30%
25%
20%
15%
10%
5%
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90%
80%
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10%
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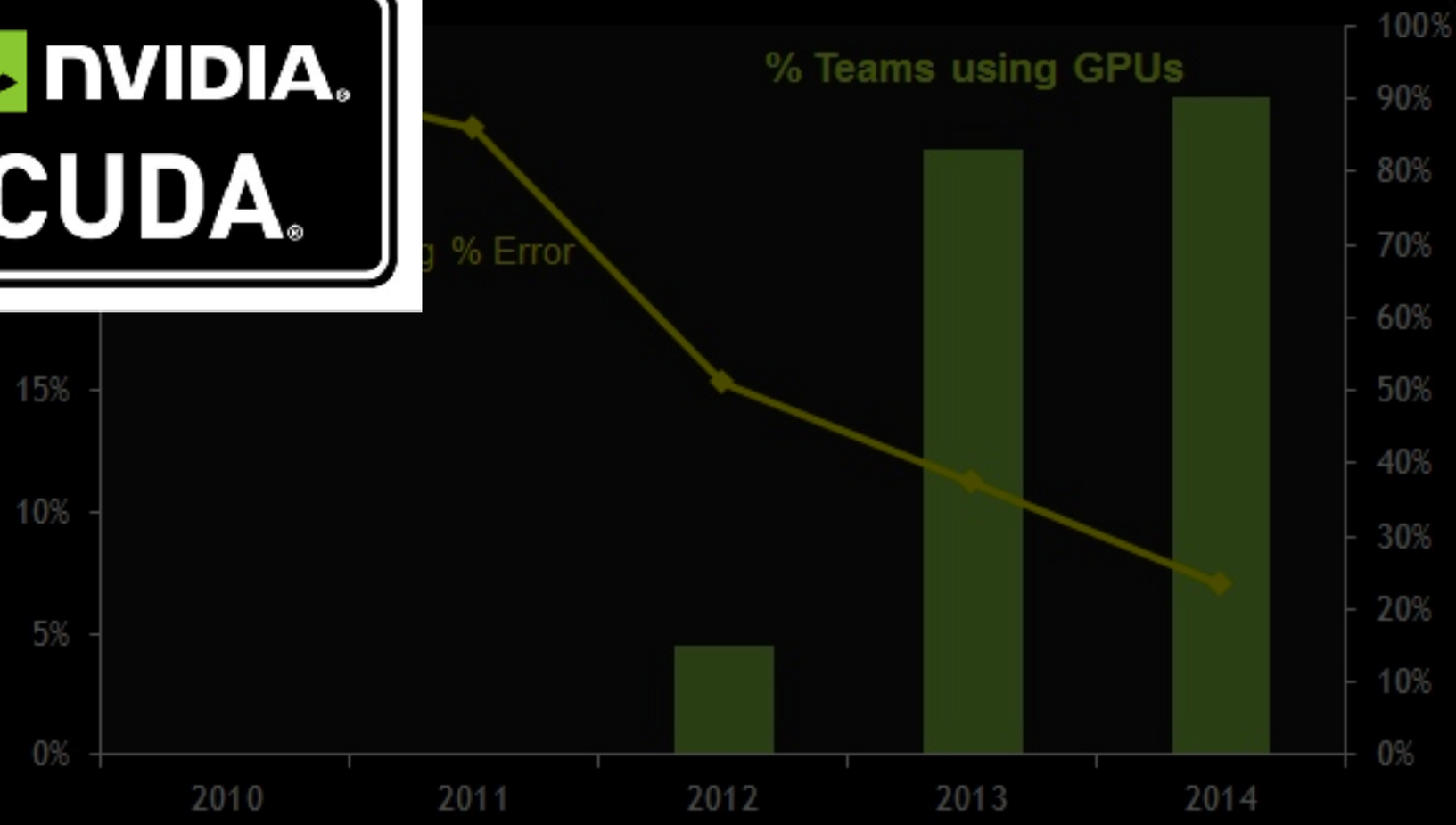
2010
2011
2012
2013
2014

HPC

NVIDIA CUDA



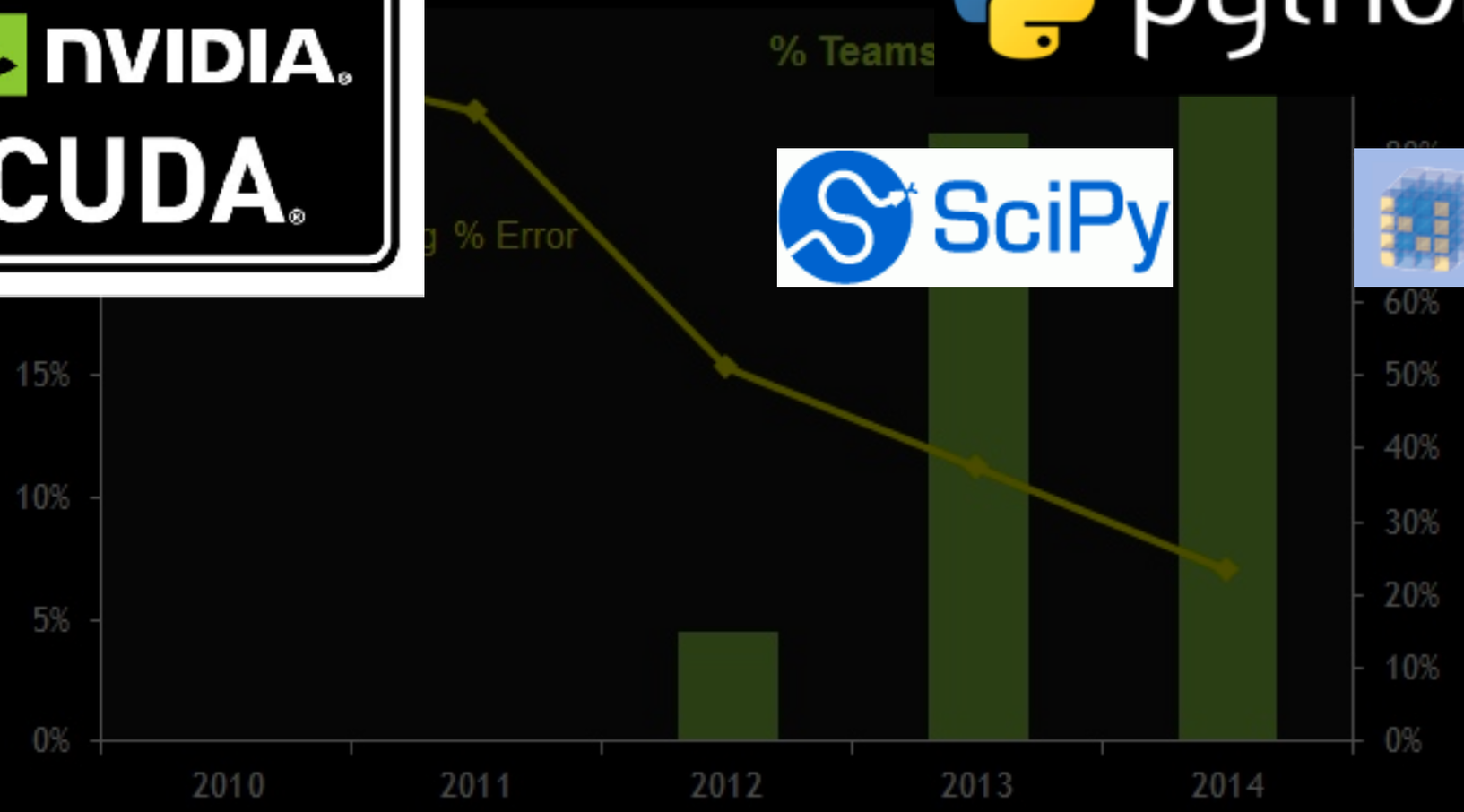
HPC

NVIDIA CUDA

python™

SciPy

NumPy



HPC

NVIDIA CUDA

python™

SciPy

NumPy

theano

CONTINUUM ANALYTICS

TensorFlow

HPC

NVIDIA CUDA

python™

SciPy

NumPy

CONTINUUM ANALYTICS

theano

torch

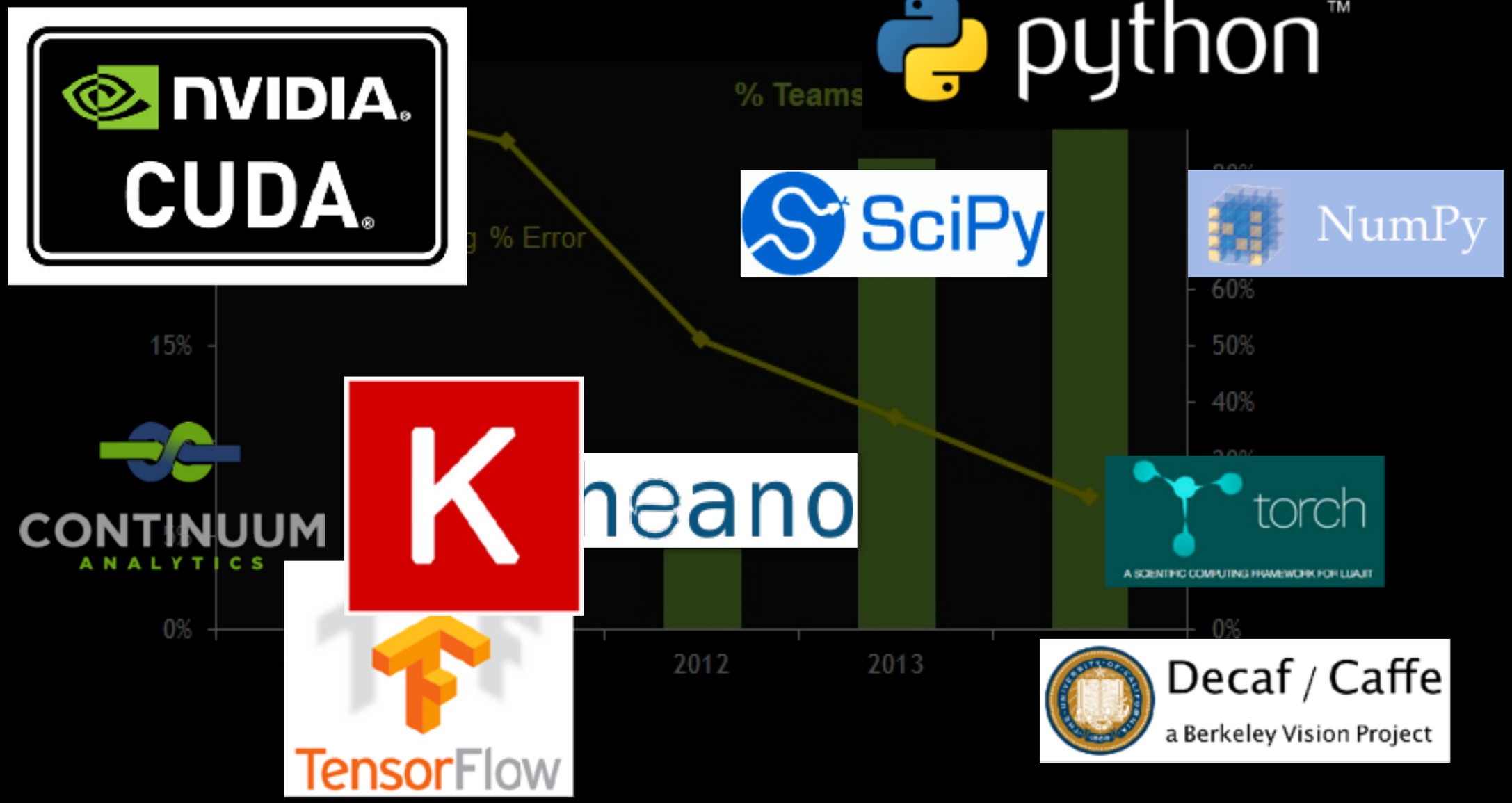
A SCIENTIFIC COMPUTING FRAMEWORK FOR LUAJIT

TensorFlow

Decaf / Caffe

a Berkeley Vision Project

HPC



NVIDIA CUDA

python™

SciPy

NumPy

CONTINUUM ANALYTICS

K

heano

torch

A SCIENTIFIC COMPUTING FRAMEWORK FOR LUAJIT

TensorFlow

Decaf / Caffe

a Berkeley Vision Project

HPC

HPC


```
int main( void ) {
    CPUBitmap bitmap( DIM, DIM );
    unsigned char     *dev_bitmap;

    HANDLE_ERROR( cudaMalloc( (void**)&dev_bitmap,
                              bitmap.image_size() ) );

    dim3    grid(DIM,DIM);
    kernel<<<grid,1>>>( dev_bitmap );

    HANDLE_ERROR( cudaMemcpy( bitmap.get_ptr(),
                              dev_bitmap,
                              bitmap.image_size(),
                              cudaMemcpyDeviceToHost ) );
    bitmap.display_and_exit();

    cudaFree( dev_bitmap );
}
```

NVIDIA CUDA

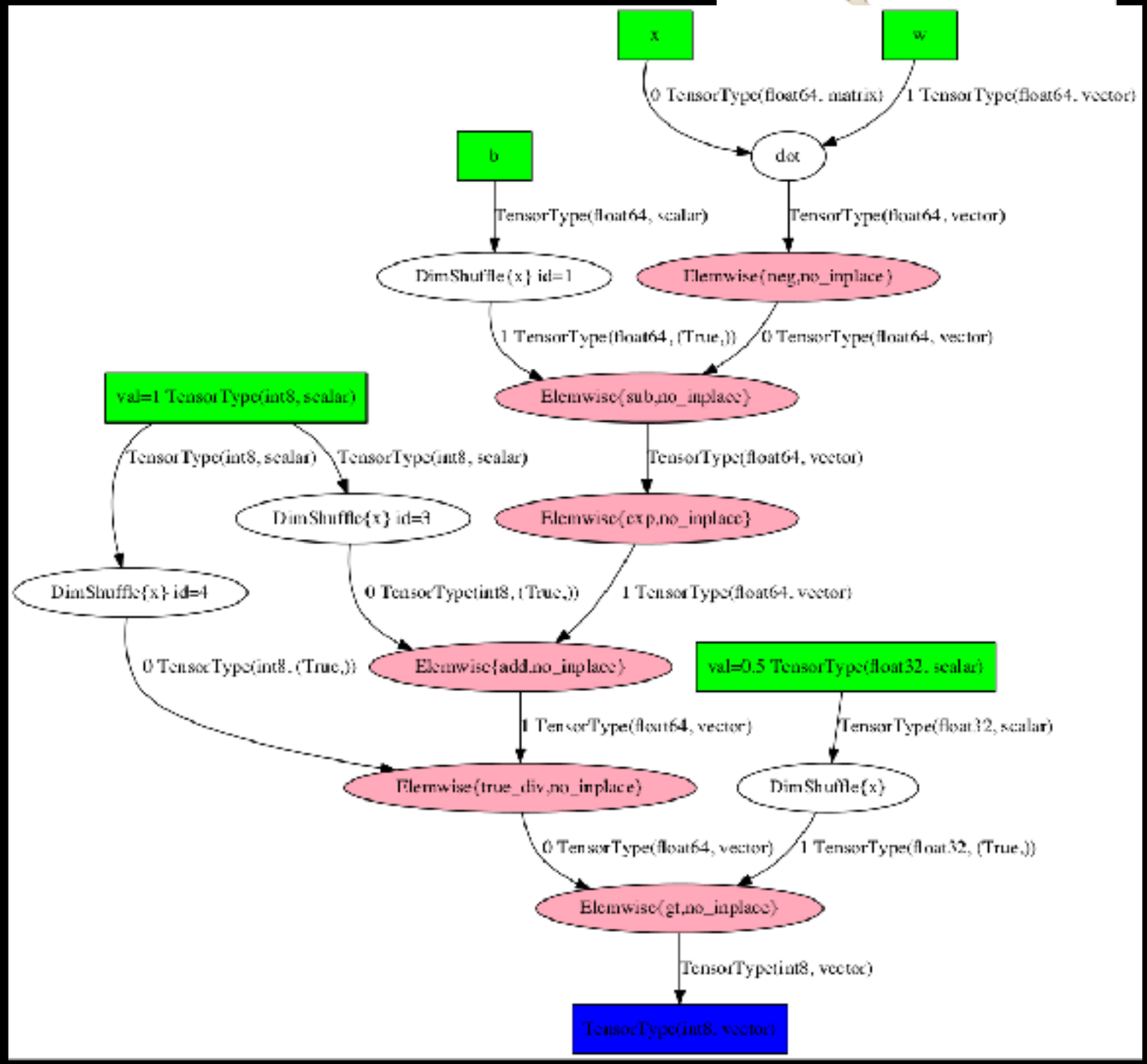
HPC


```
# Declare Theano symbolic variables
x = T.matrix("x")
y = T.vector("y")
w = theano.shared(rng.randn(feats).astype(theano.config.floatX), name="w")
b = theano.shared(numpy.asarray(0., dtype=theano.config.floatX), name="b")
x.tag.test_value = D[0]
y.tag.test_value = D[1]

# Construct Theano expression graph
p_1 = 1 / (1 + T.exp(-T.dot(x, w)-b)) # Probability of having a one
prediction = p_1 > 0.5 # The prediction that is done: 0 or 1
xent = -y*T.log(p_1) - (1-y)*T.log(1-p_1) # Cross-entropy
cost = xent.mean() + 0.01*(w**2).sum() # The cost to optimize
gw,gb = T.grad(cost, [w,b])

# Compile expressions to functions
train = theano.function(
            inputs=[x,y],
            outputs=[prediction, xent],
            updates=[(w, w-0.01*gw), (b, b-0.01*gb)],
            name = "train")
predict = theano.function(inputs=[x], outputs=prediction,
            name = "predict")
```

theano

NVIDIA CUDA

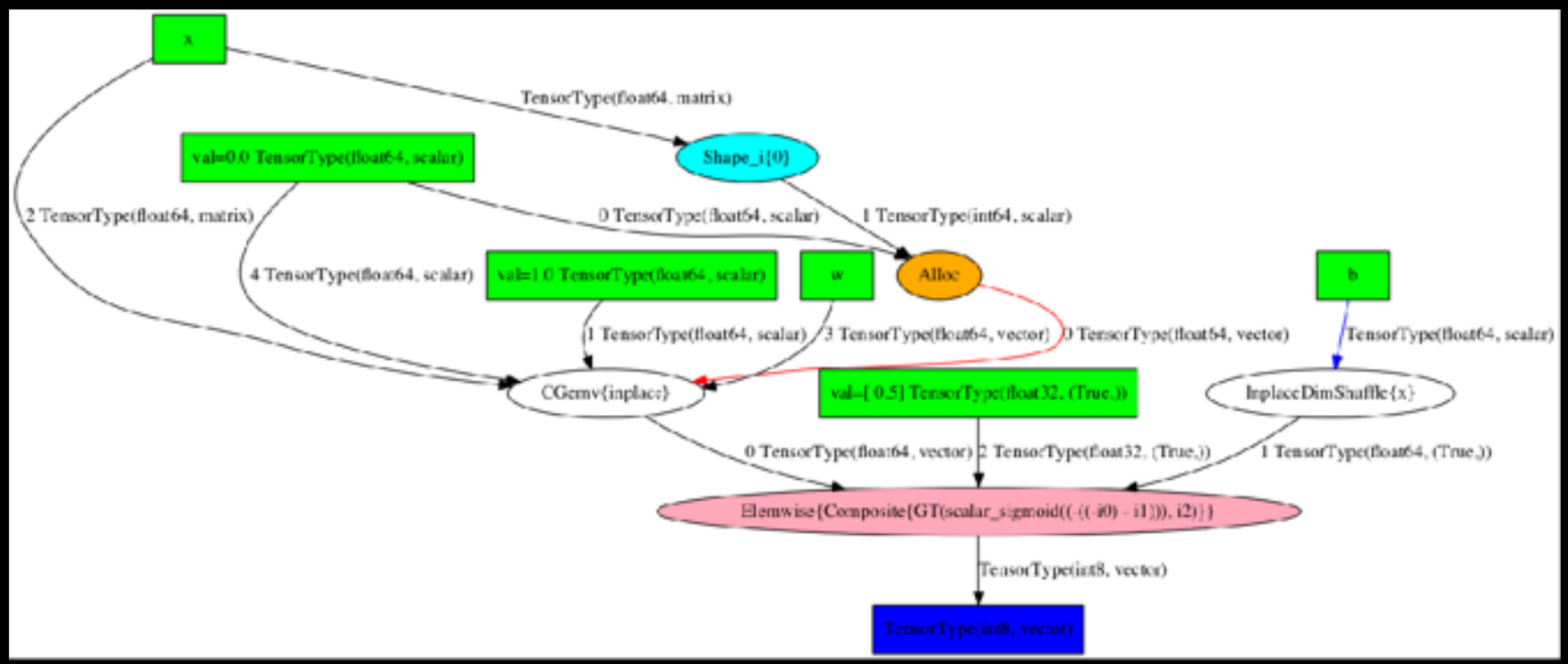
HPC



theano

NVIDIA CUDA

HPC



theano

NVIDIA CUDA

HPC

theano

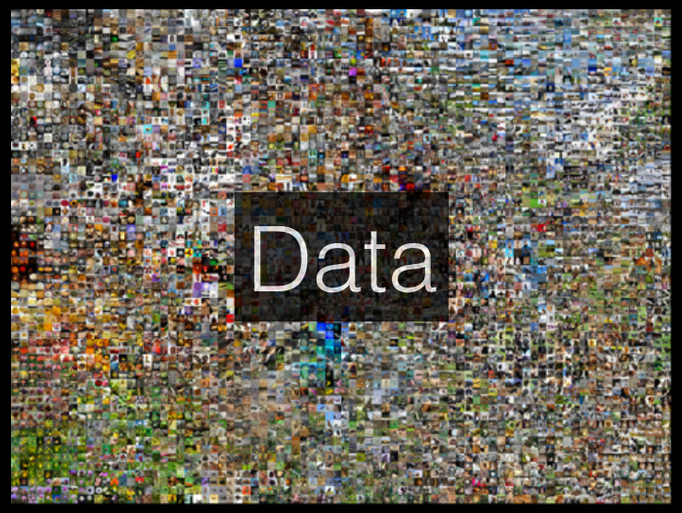

```python
# Parameters
learning_rate = 0.01
training_epochs = 25
batch_size = 100
display_step = 1

# tf Graph Input
x = tf.placeholder(tf.float32, [None, 784]) # mnist data image of shape 28*28=784
y = tf.placeholder(tf.float32, [None, 10]) # 0-9 digits recognition => 10 classes

# Set model weights
W = tf.Variable(tf.zeros([784, 10]))
b = tf.Variable(tf.zeros([10]))

# Construct model
pred = tf.nn.softmax(tf.matmul(x, W) + b) # Softmax

# Minimize error using cross entropy
cost = tf.reduce_mean(-tf.reduce_sum(y*tf.log(pred), reduction_indices=1))
# Gradient Descent
optimizer = tf.train.GradientDescentOptimizer(learning_rate).minimize(cost)

# Initializing the variables
init = tf.initialize_all_variables()
```

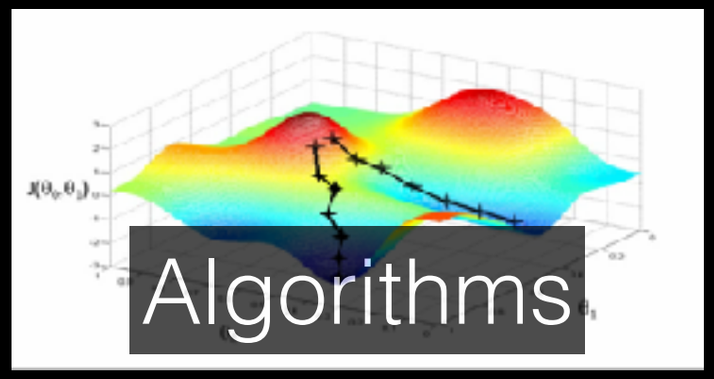
HPC

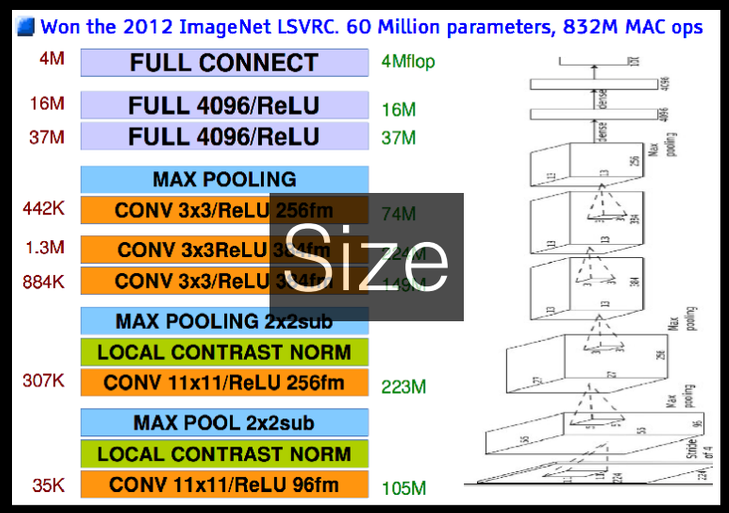
theano

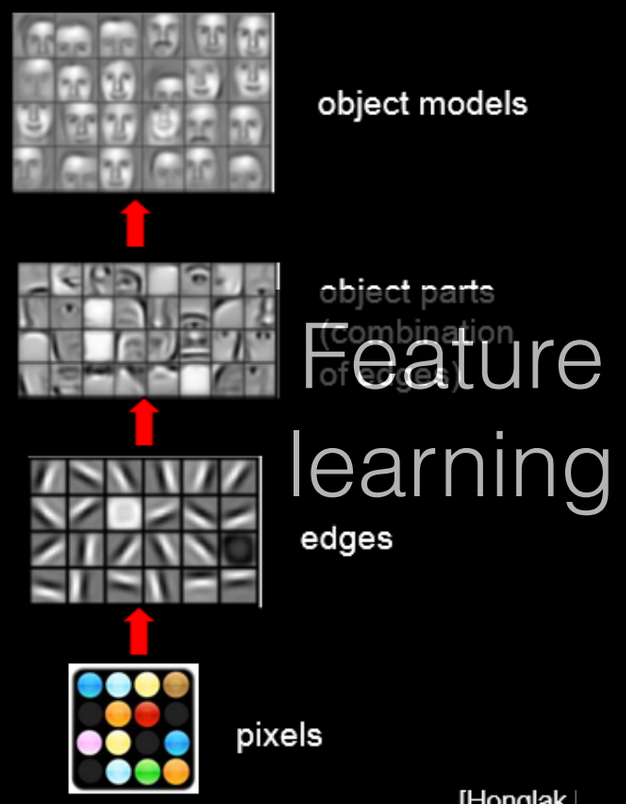

```
train_y_ohe = one_hot_encode_object_array(train_y)
test_y_ohe = one_hot_encode_object_array(test_y)

model = Sequential()
model.add(Dense(16, input_shape=(4,)))
model.add(Activation('sigmoid'))
model.add(Dense(3))
model.add(Activation('softmax'))
model.compile(loss='categorical_crossentropy', metrics=['accuracy'], optimizer='

# Actual modelling
model.fit(train_X, train_y_ohe, verbose=0, batch_size=1)
score, accuracy = model.evaluate(test_X, test_y_ohe, batch_size=16, verbose=0)
```

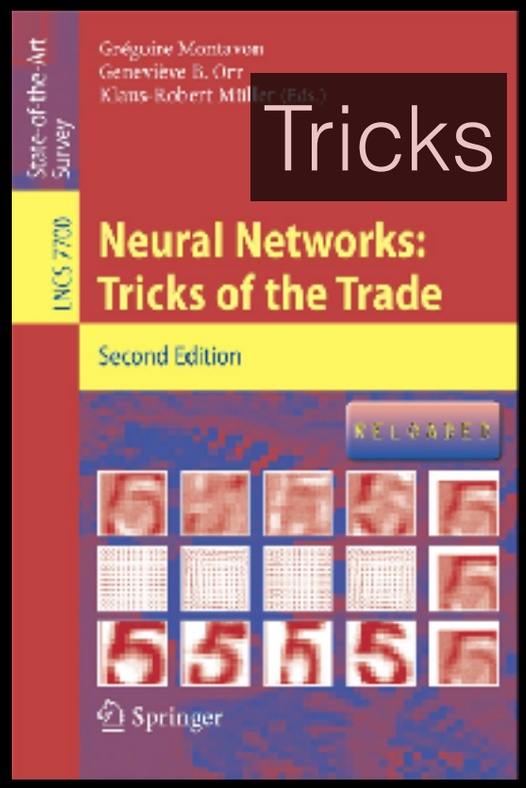
Deep learning recipe





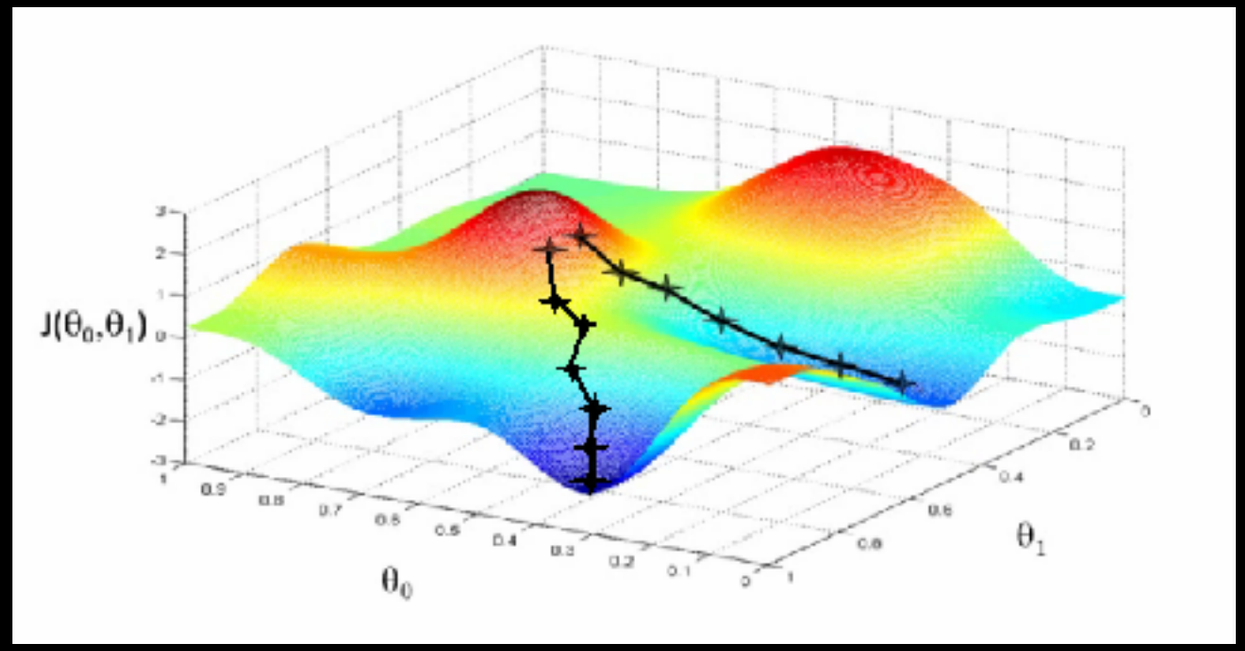




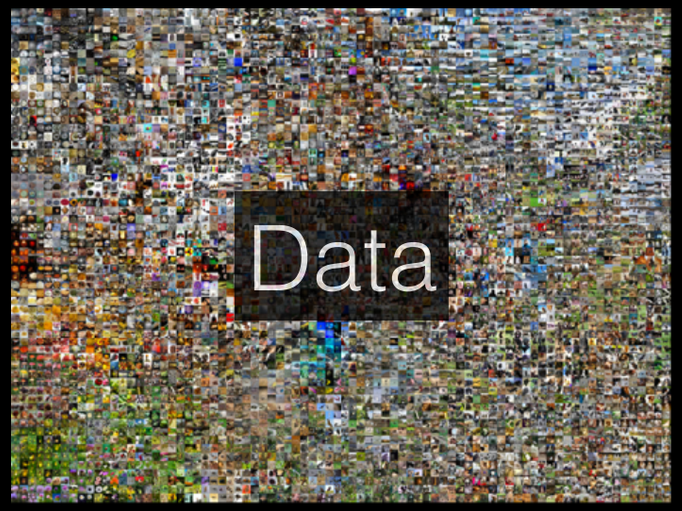


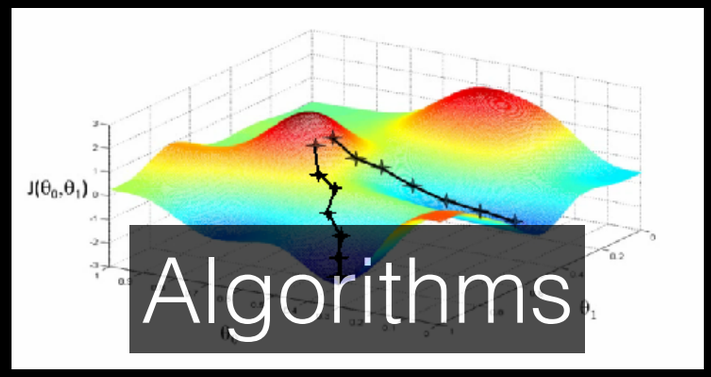
Algorithms

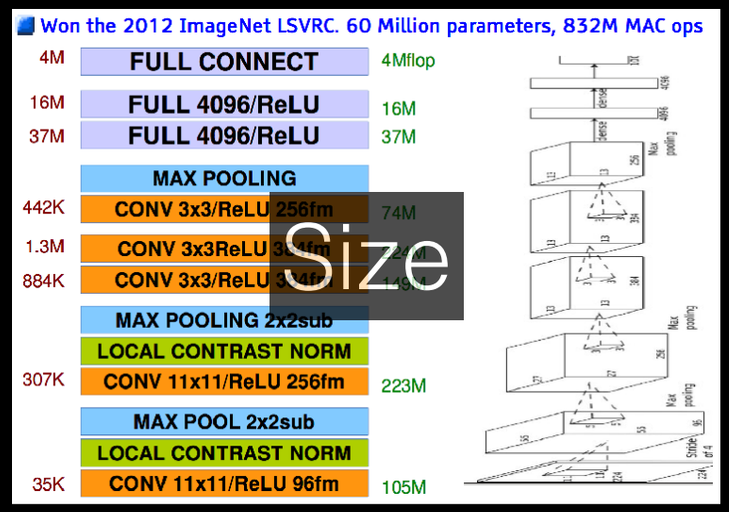
- Backpropagation
- Backpropagation through time
- Online learning (stochastic gradient descent)
- Softmax (hierarchical)

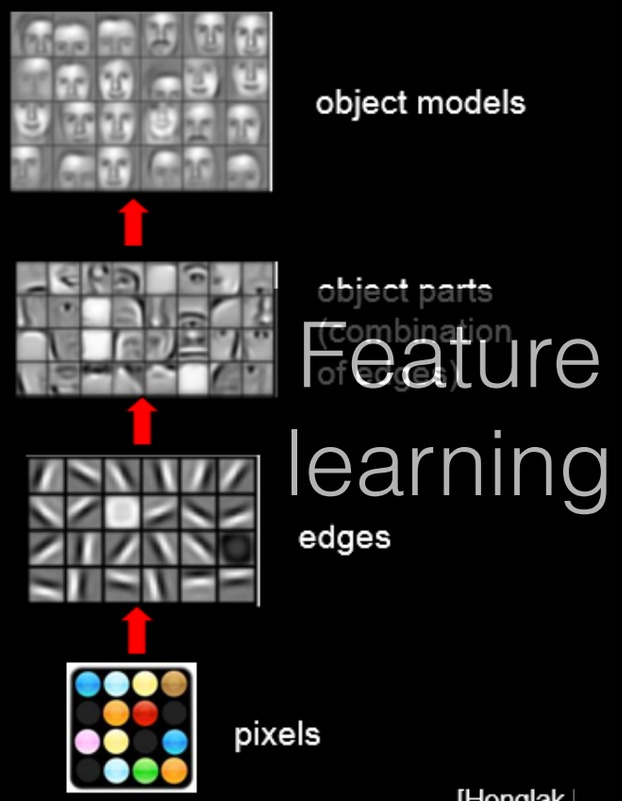


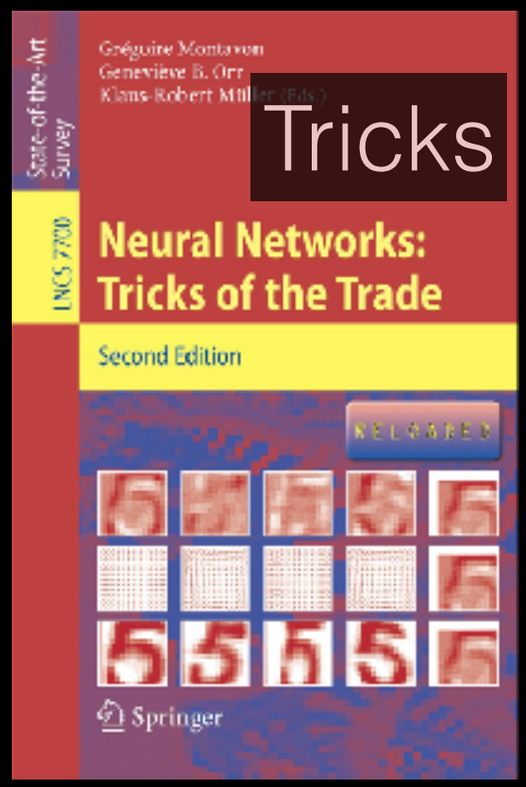
Deep learning recipe





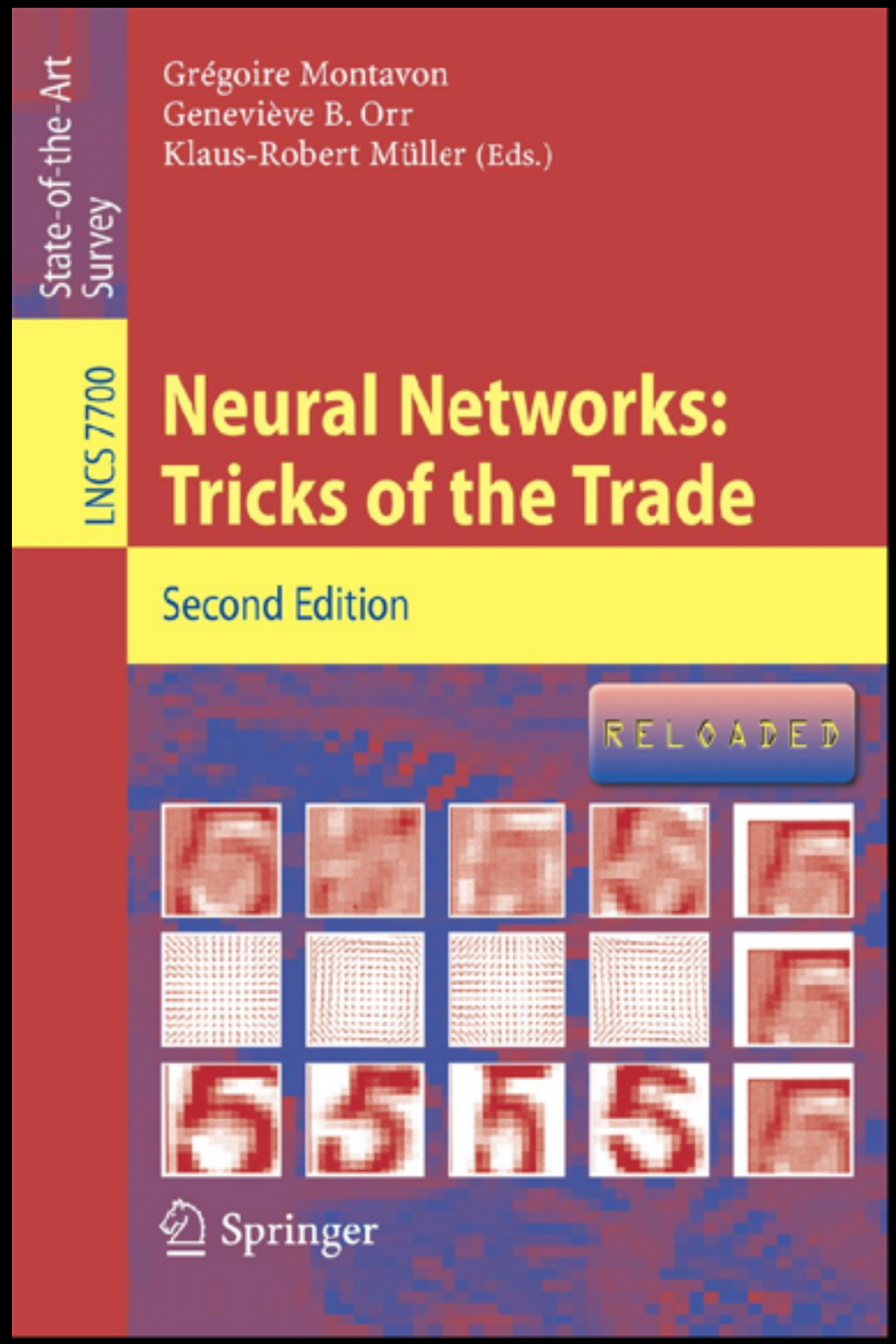




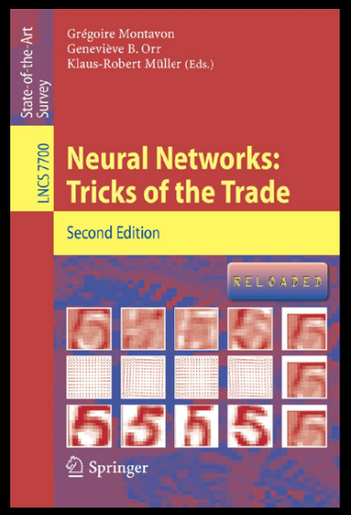


Tricks

- DL is mainly an engineering problem
- DL networks are hard to train
- Several tricks product of years of experience



Tricks



- DL is mainly an engineering problem
- DL networks are hard to train
- Several tricks product of years of experience

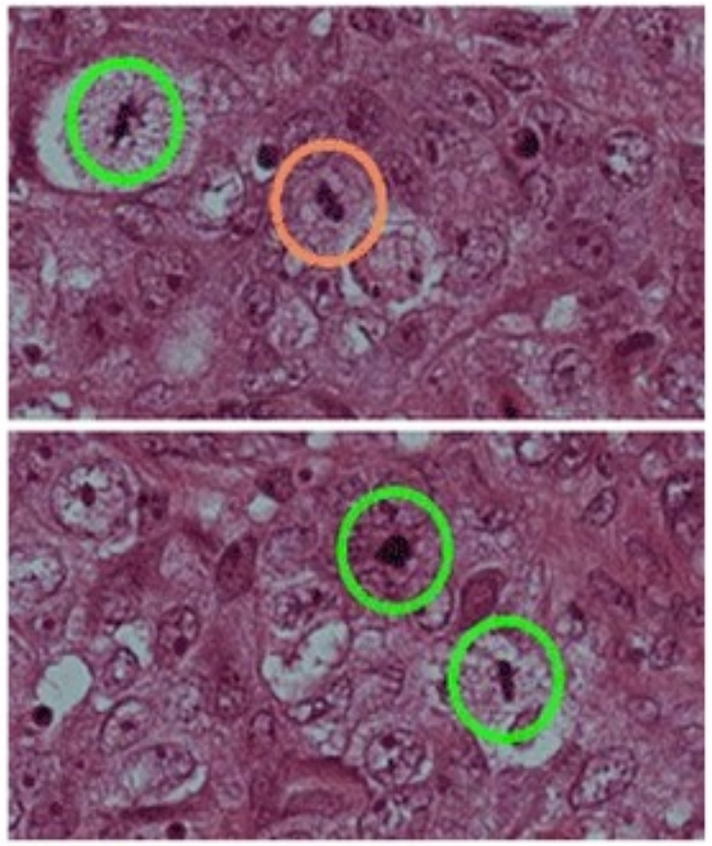
- Layer-wise training
- RELU units
- Dropout
- Adaptive learning rates
- Initialization
- Preprocessing
- Gradient norm clipping

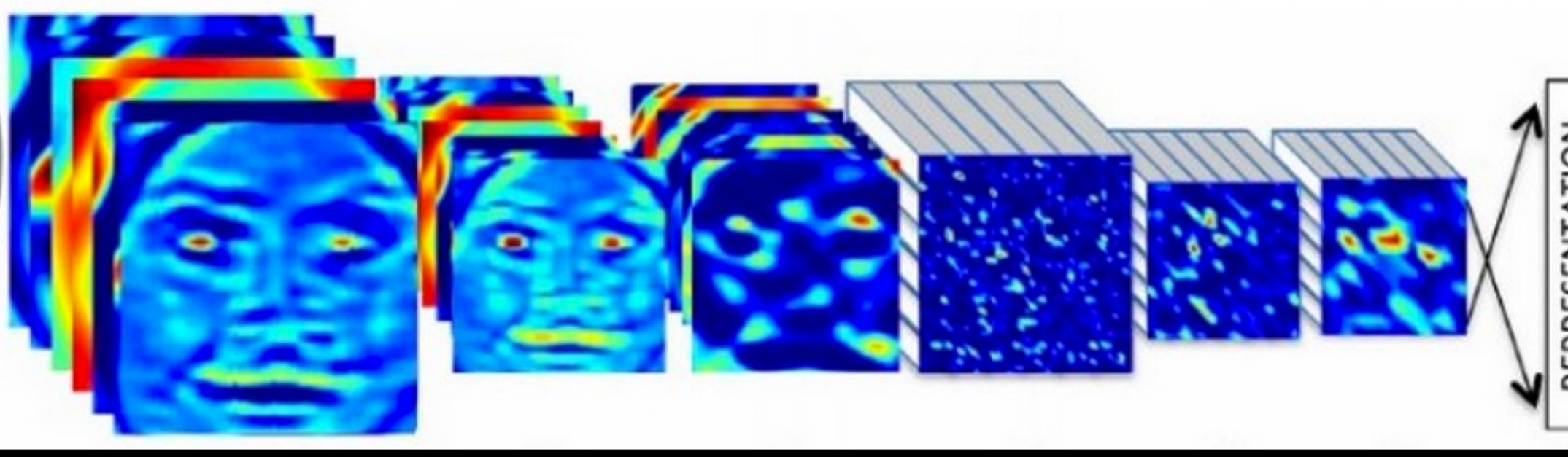
Applications

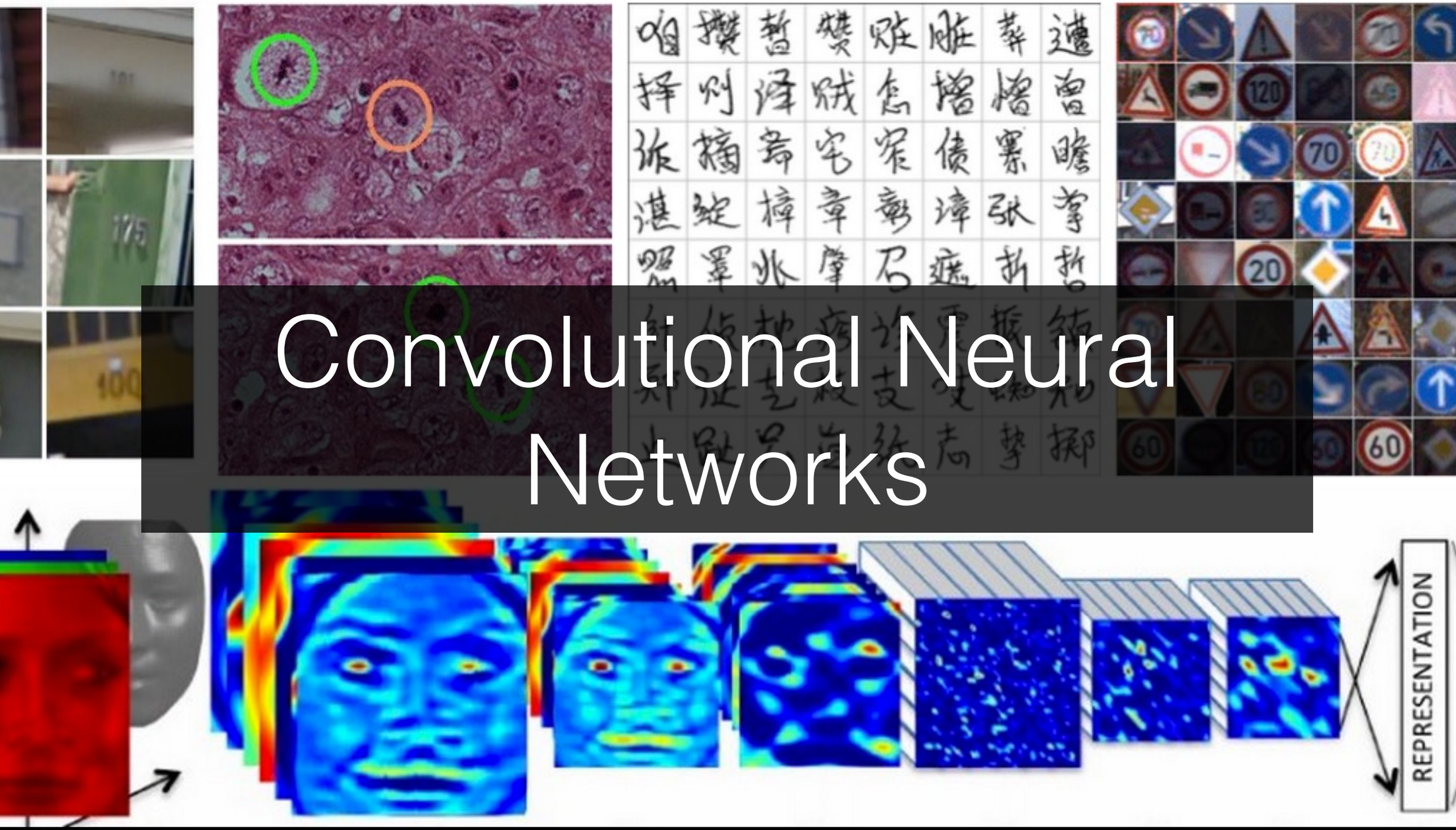
- Computer vision:
  - Image: annotation, detection, segmentation, captioning
  - Video: object tracking, action recognition, segmentation
- Speech recognition and synthesis
- Text: language modeling, word/text representation, text classification, translation
- Biomedical image analysis

Autoencoder Demo

https://cs.stanford.edu/people/karpathy/convnetjs/demo/autoencoder.html




REPRESENTATION

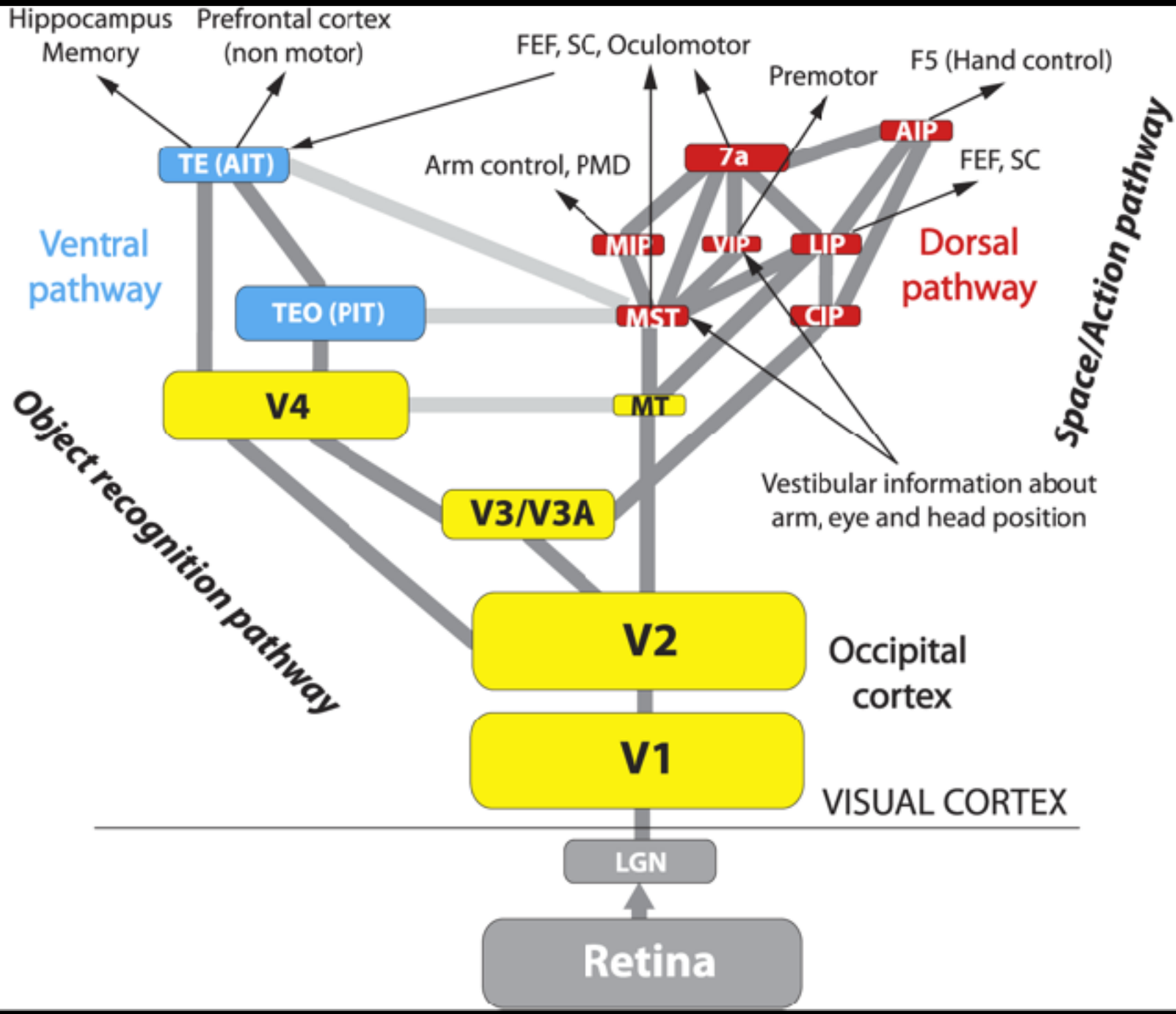


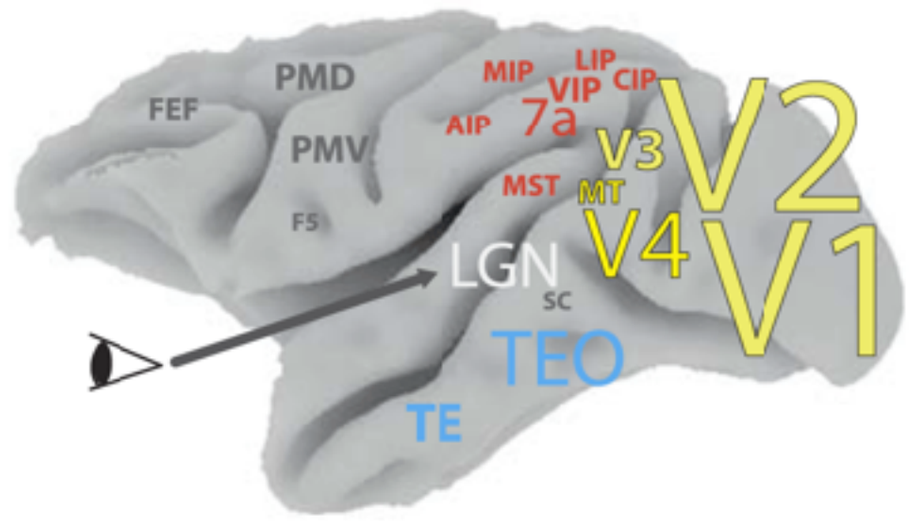
Convolutional Neural Networks

Fabio A. González

Universidad Nacional de Colombia

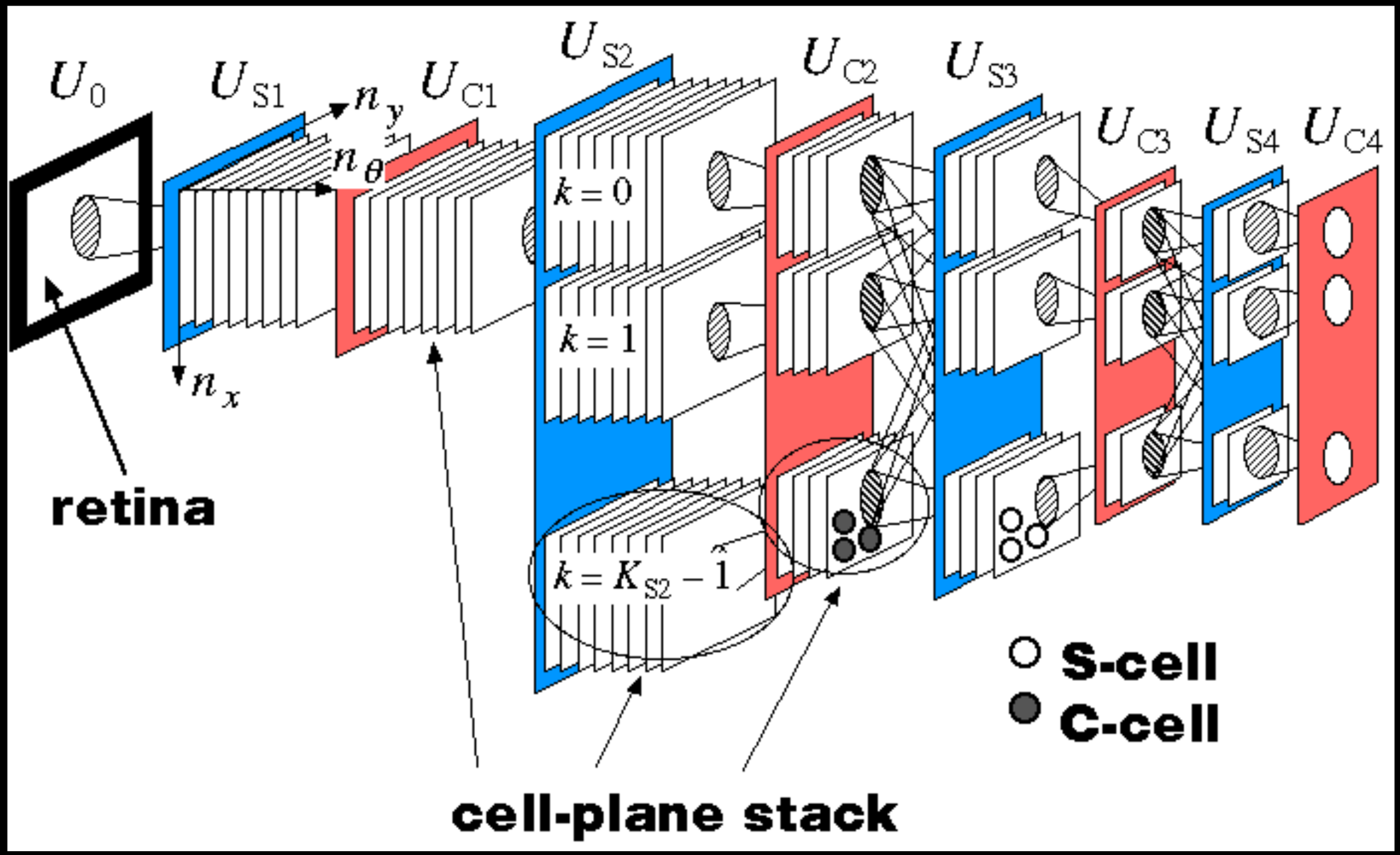
Visual Cortex





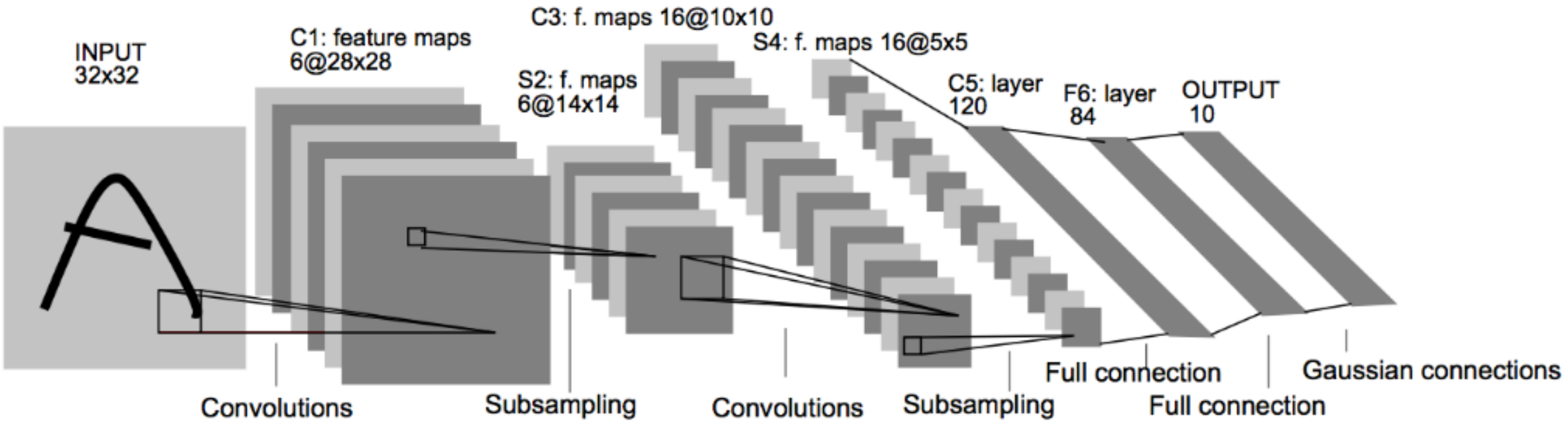
Neocognitron

(Fukushima, 1980)

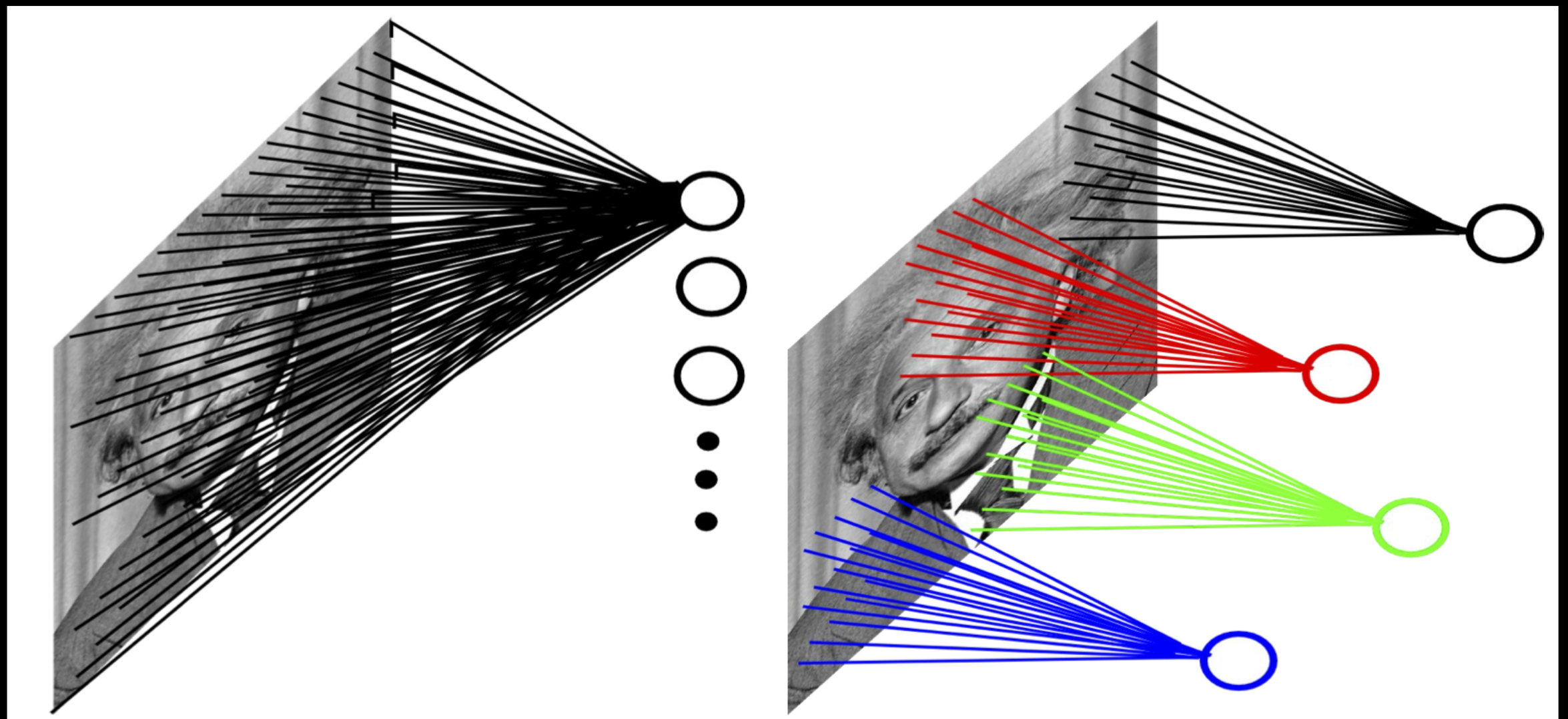


LeNet

(LeCun, 1998)



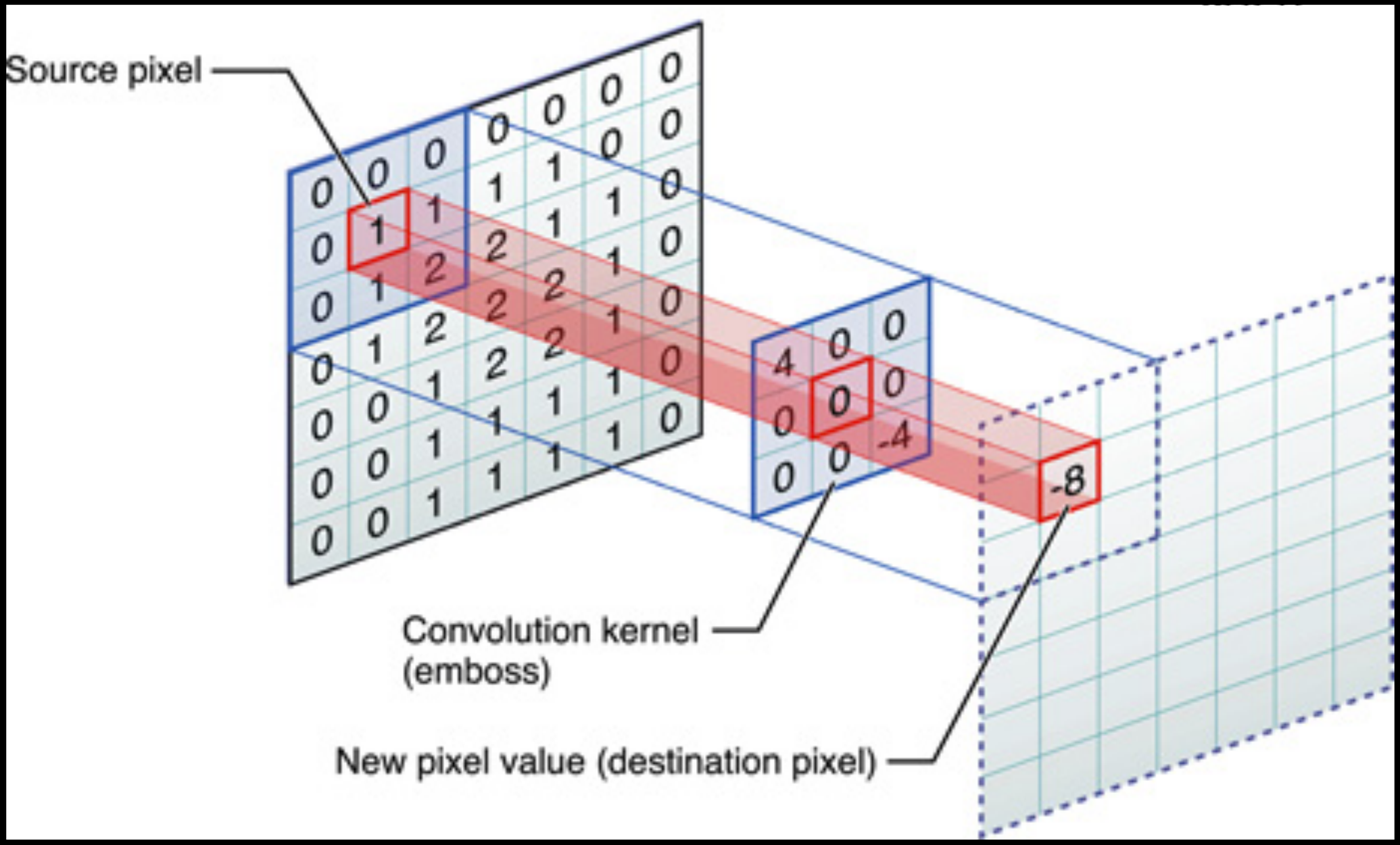
Convolution



(source: ICML2013 Deep Learning Tutorial, Yan LeCun et al.)

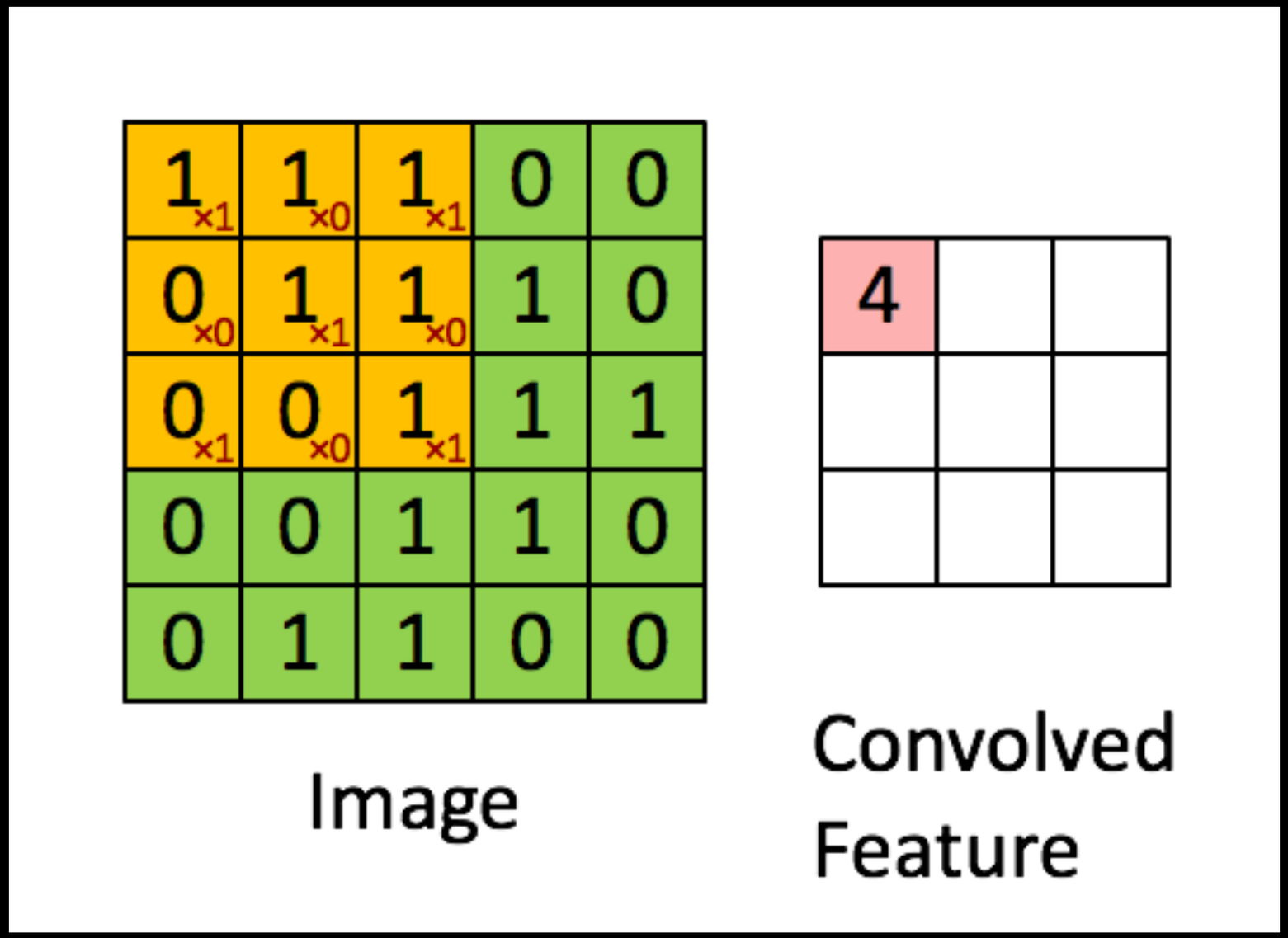
(sources: ICML2013 Deep Learning Tutorial, Yan LeCun et al.
Feature extraction using convolution, Stanford Deep Learning Wiki)

Convolution



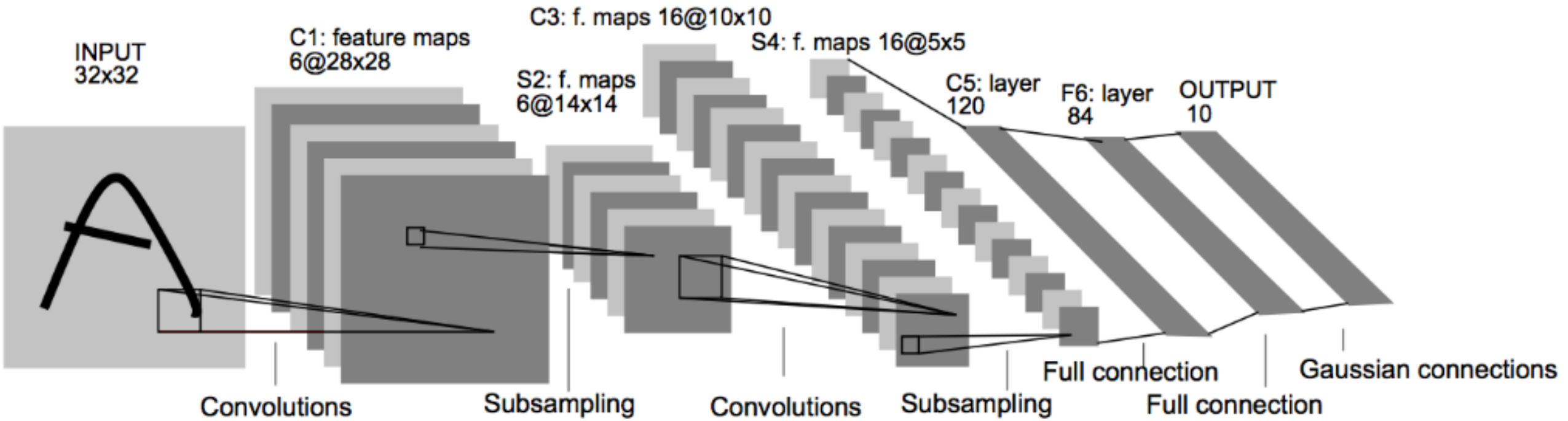
(sources: ICML2013 Deep Learning Tutorial, Yan LeCun et al.
Feature extraction using convolution, Stanford Deep Learning Wiki)

Convolution



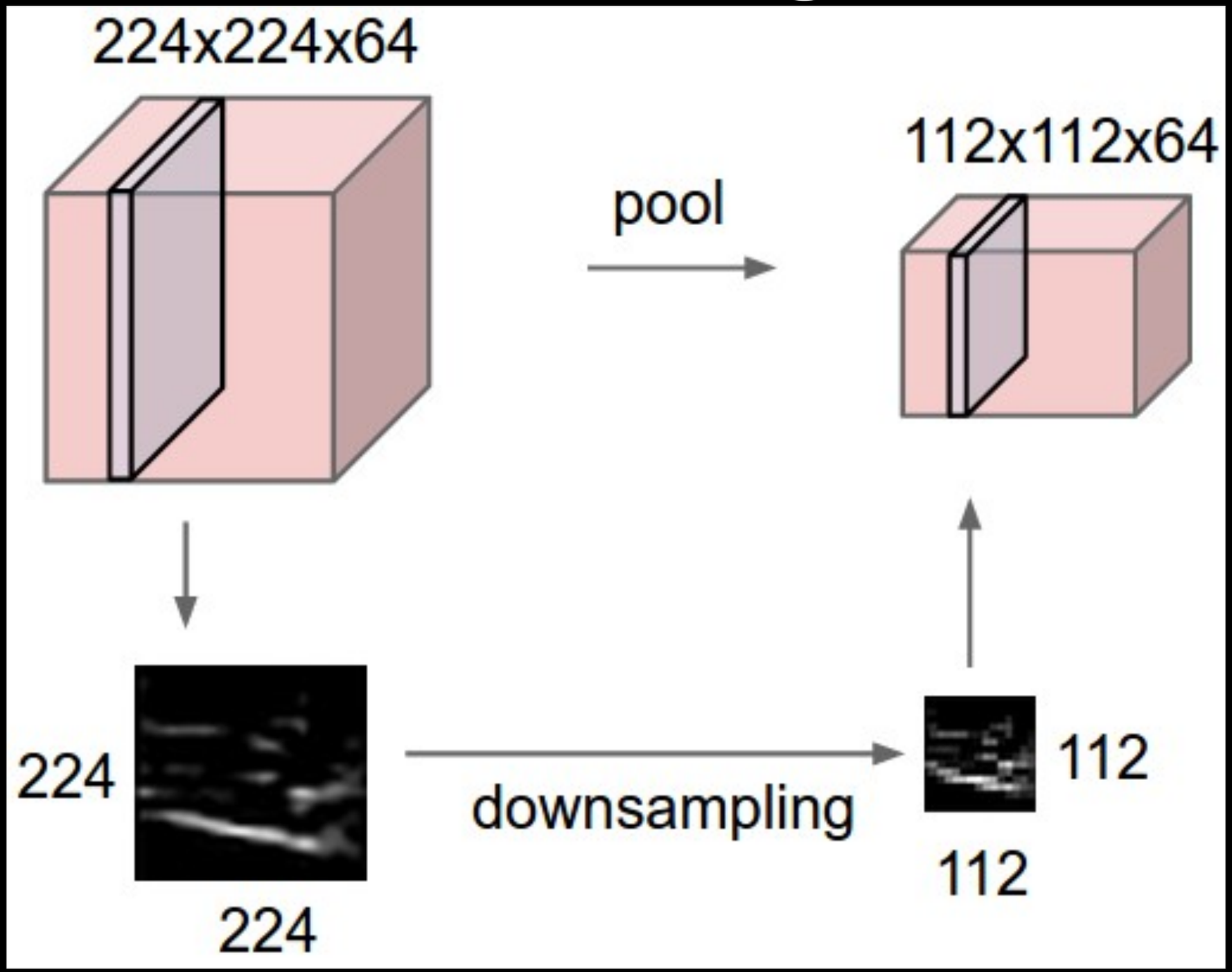
(sources: ICML2013 Deep Learning Tutorial, Yan LeCun et al.
Feature extraction using convolution, Stanford Deep Learning Wiki)

Convolution



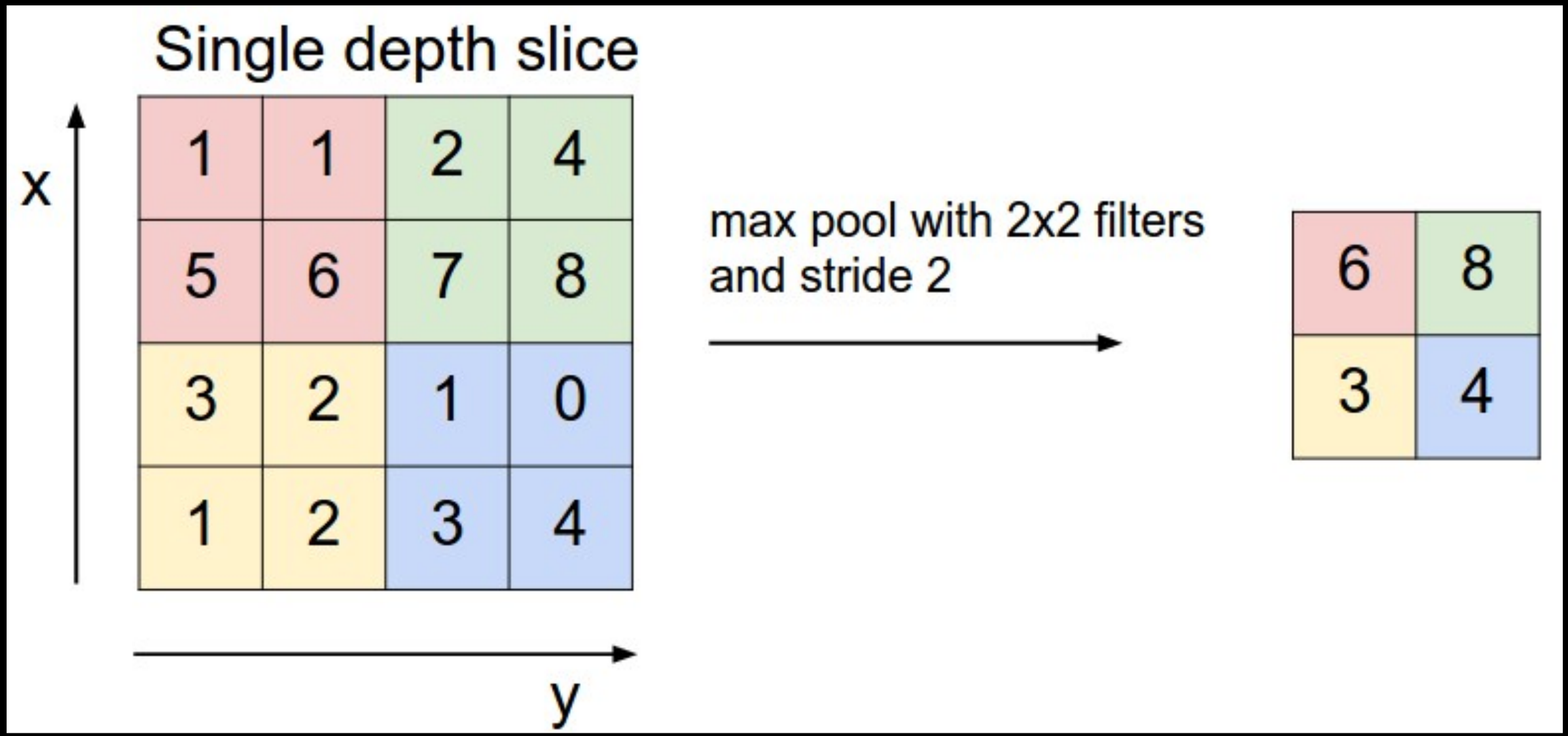
(sources: ICML2013 Deep Learning Tutorial, Yan LeCun et al.
Feature extraction using convolution, Stanford Deep Learning Wiki)

Pooling



(source: Karpathy, CS231n Convolutional Neural Networks for Visual Recognition)

Pooling



(source: Karpathy, CS231n Convolutional Neural Networks for Visual Recognition)

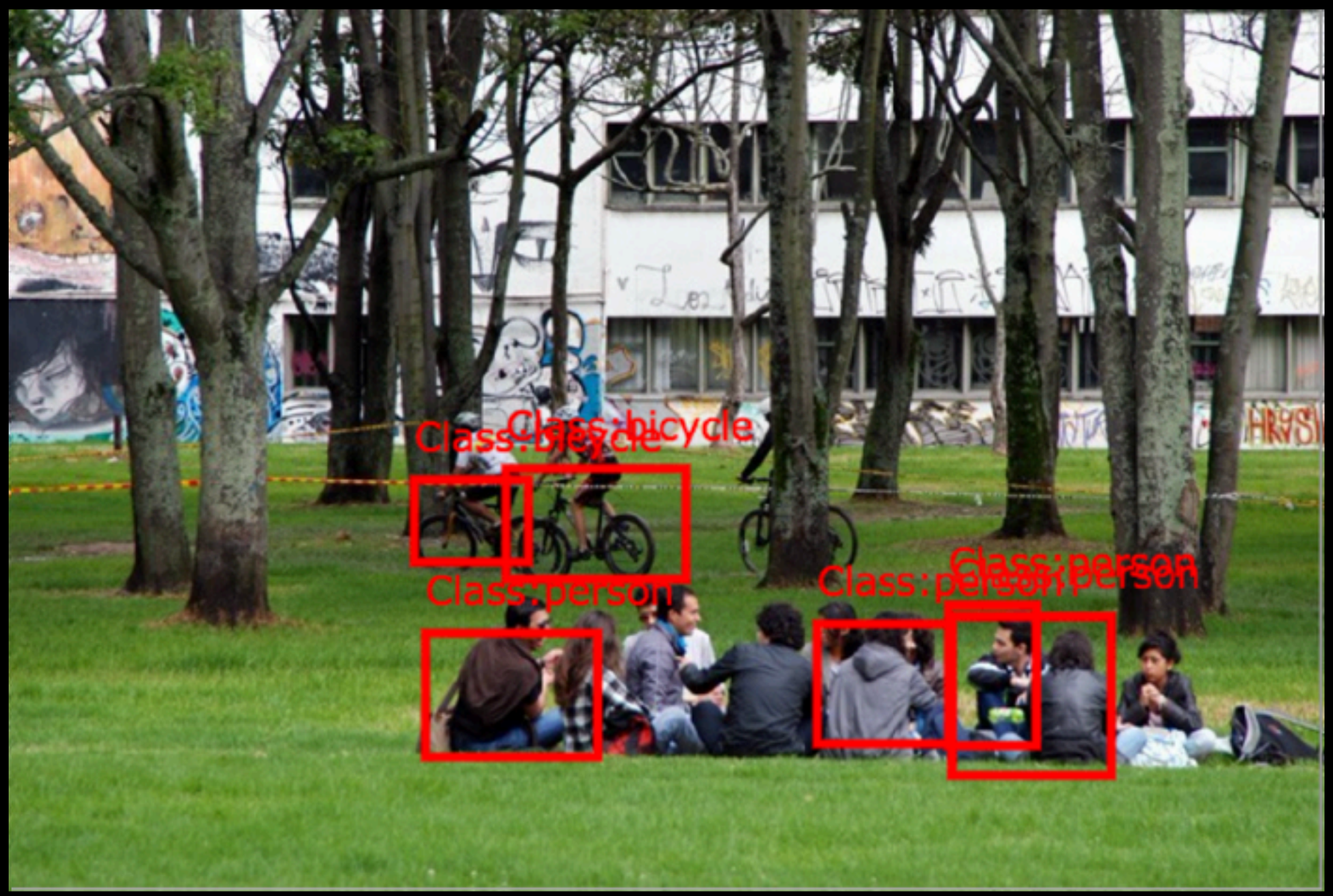
CNN Demo

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

Object Detection

http://silverpond.com.au/object-detector

Object Detection

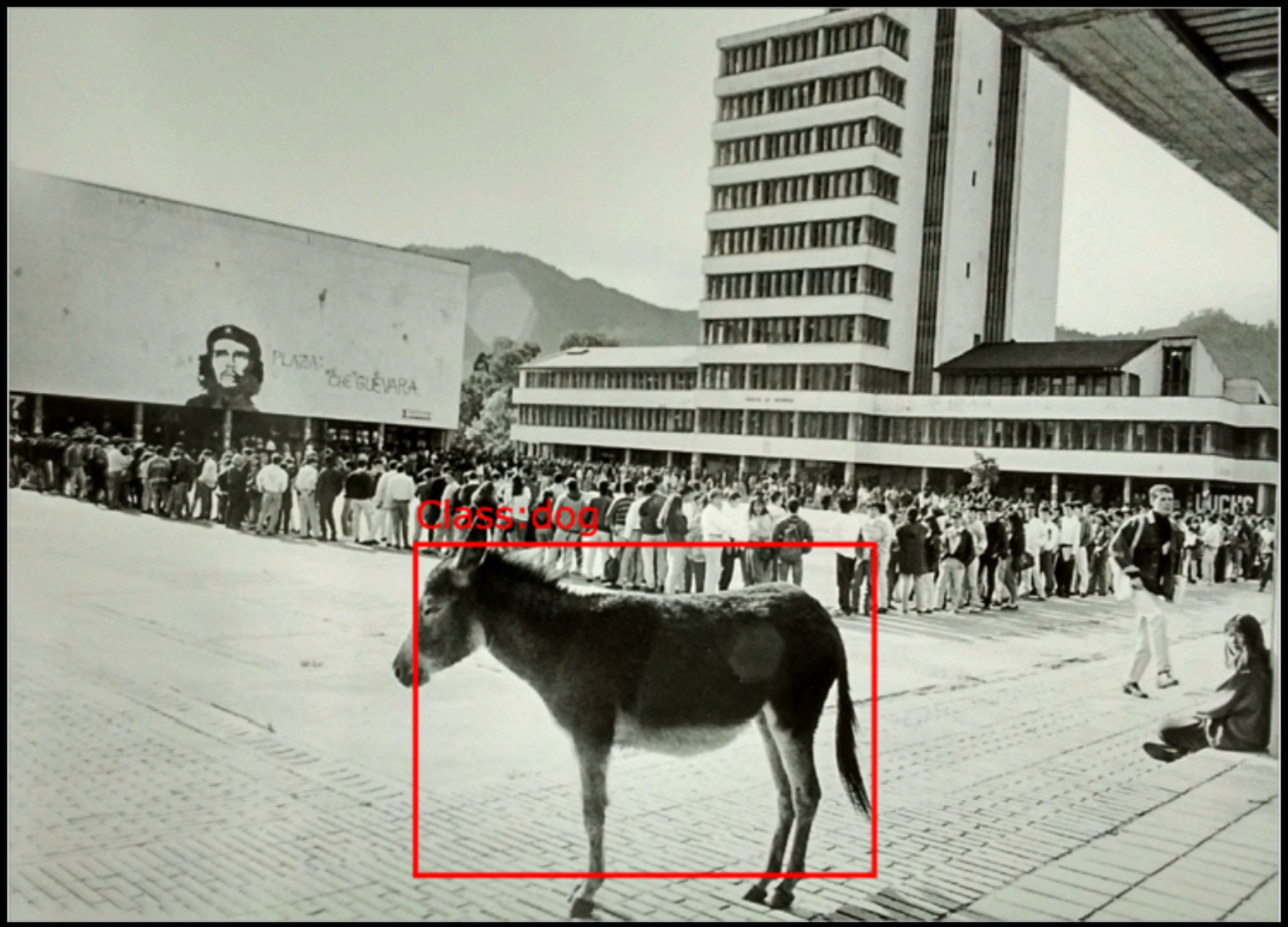


http://silverpond.com.au/object-detector

Object Detection

http://silverpond.com.au/object-detector

Object Detection



http://silverpond.com.au/object-detector

Image Captioning

I think it's a group of people sitting at a park.

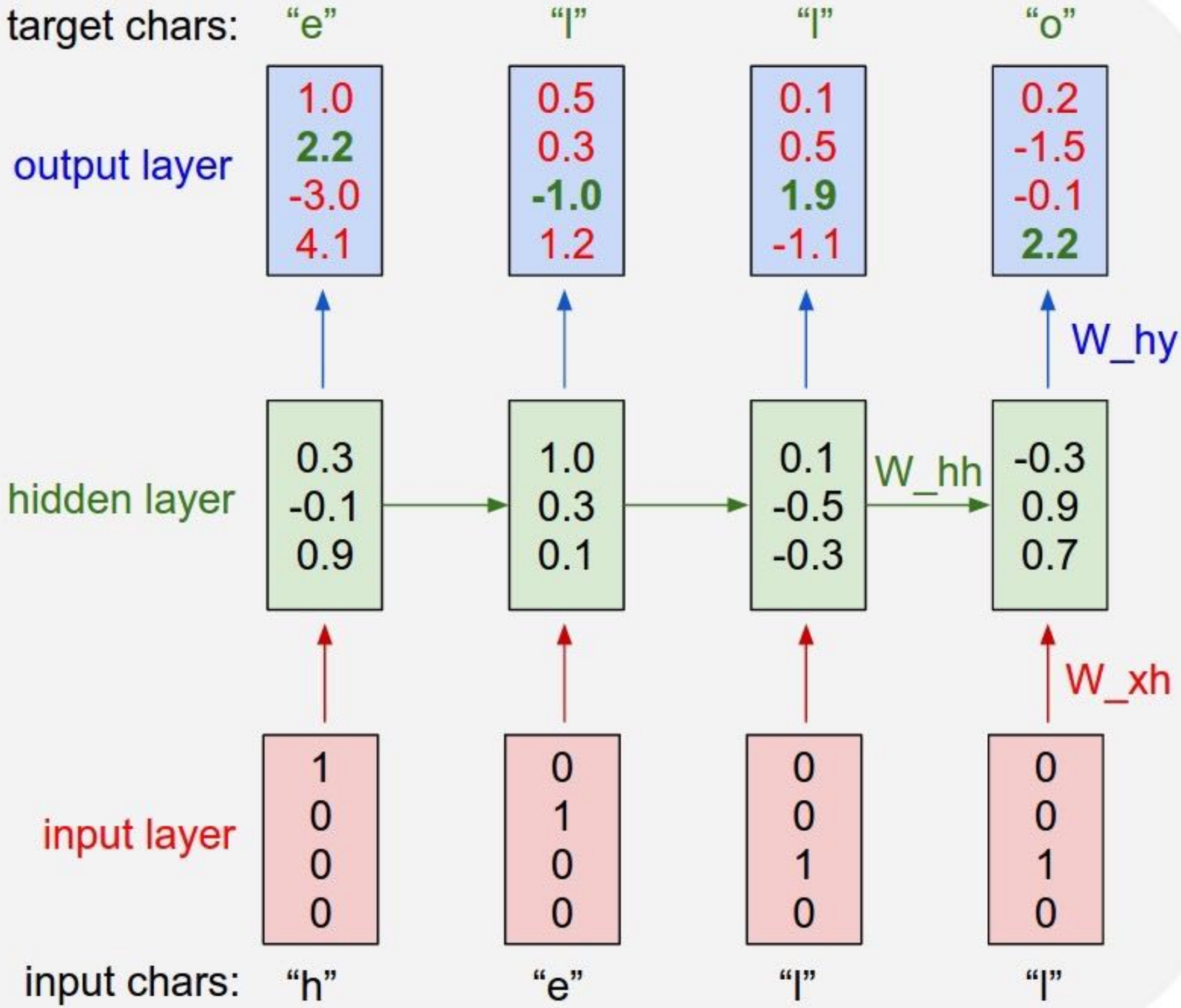
Image Captioning

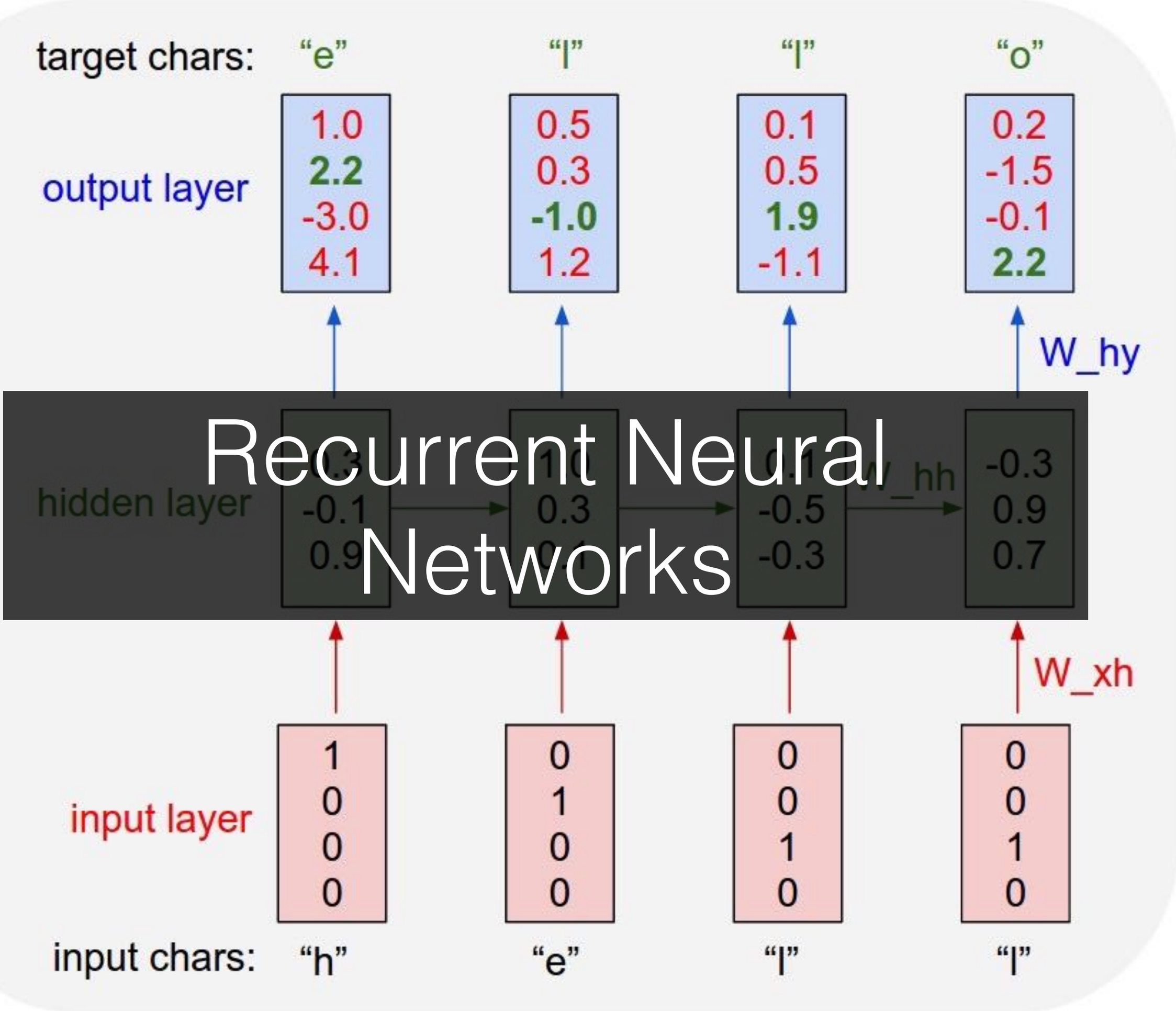
I think it's a horse standing in front of a building and he seems 😐.

Style Transfer

Style Transfer

Style Transfer

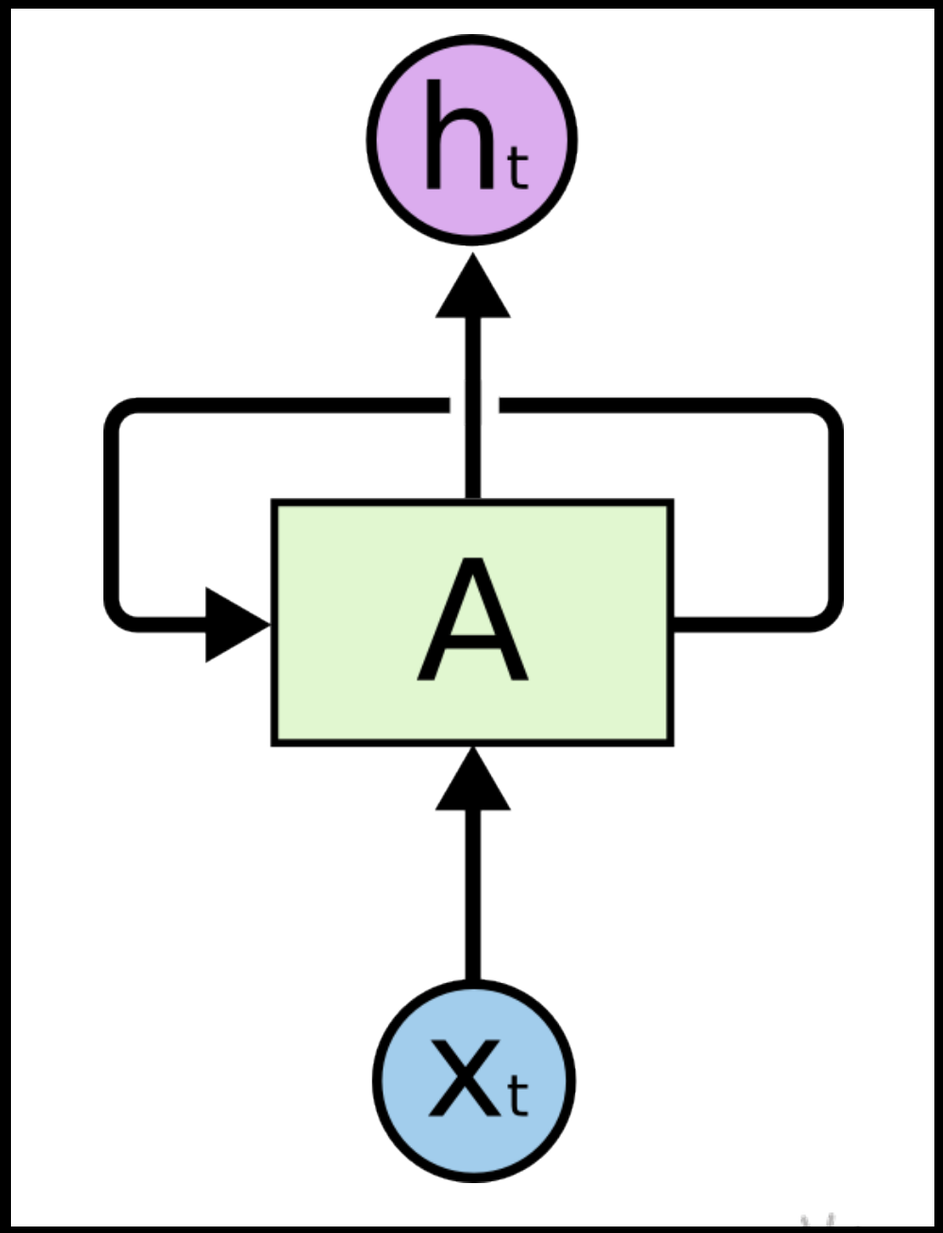

target chars:
“e”
“l”
“l”
“o”
output layer
1.0
2.2
-3.0
4.1
0.5
0.3
-1.0
1.2
0.1
0.5
1.9
-1.1
0.2
-1.5
-0.1
2.2
W_hy
hidden layer
0.3
-0.1
0.9
1.0
0.3
0.1
0.1
-0.5
-0.3
W_hh
-0.3
0.9
0.7
W_xh
input layer
1
0
0
0
0
1
0
0
0
0
1
0
0
0
1
0
input chars:
“h”
“e”
“l”
“l”



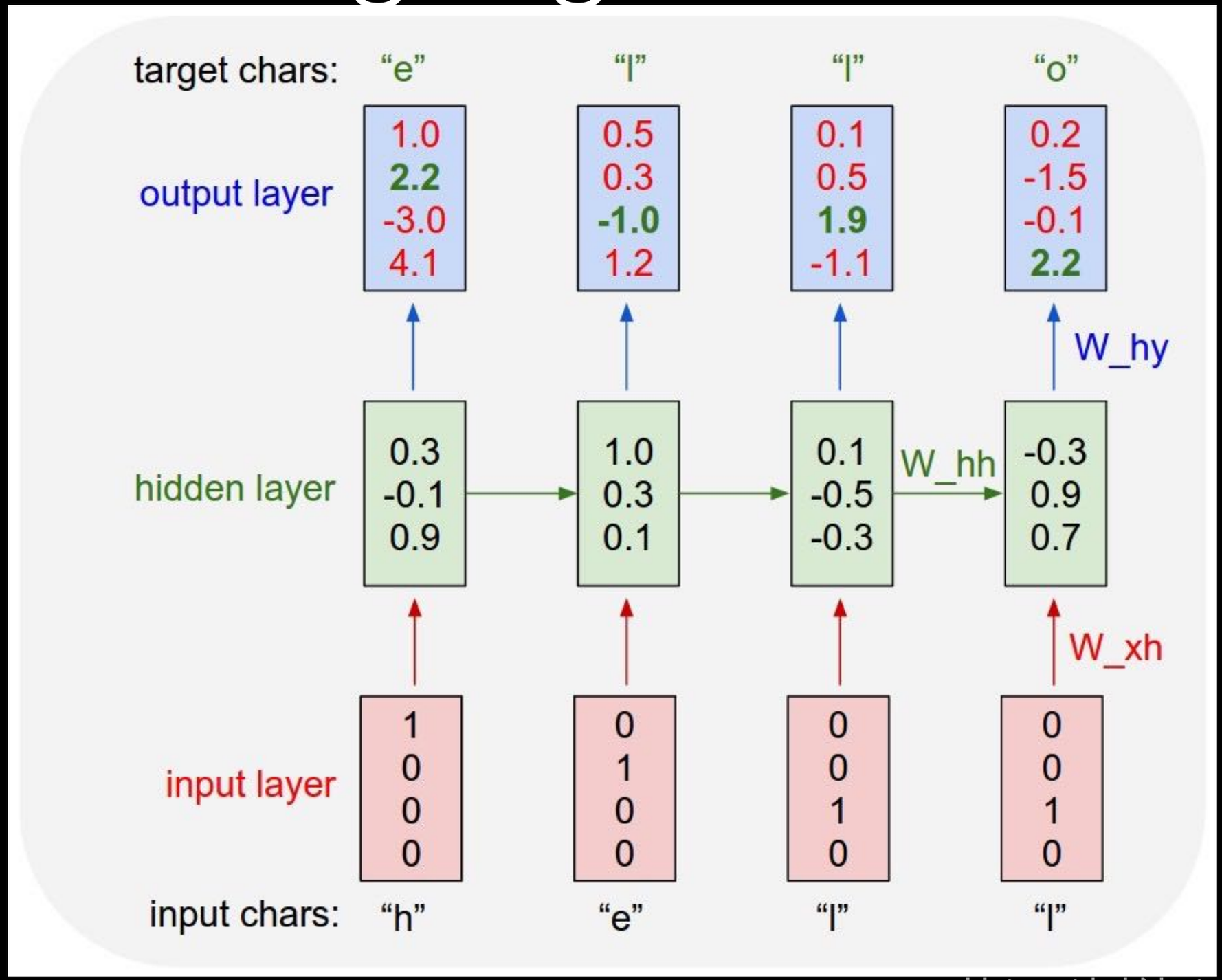
Recurrent Neural Networks

Recurrent NN

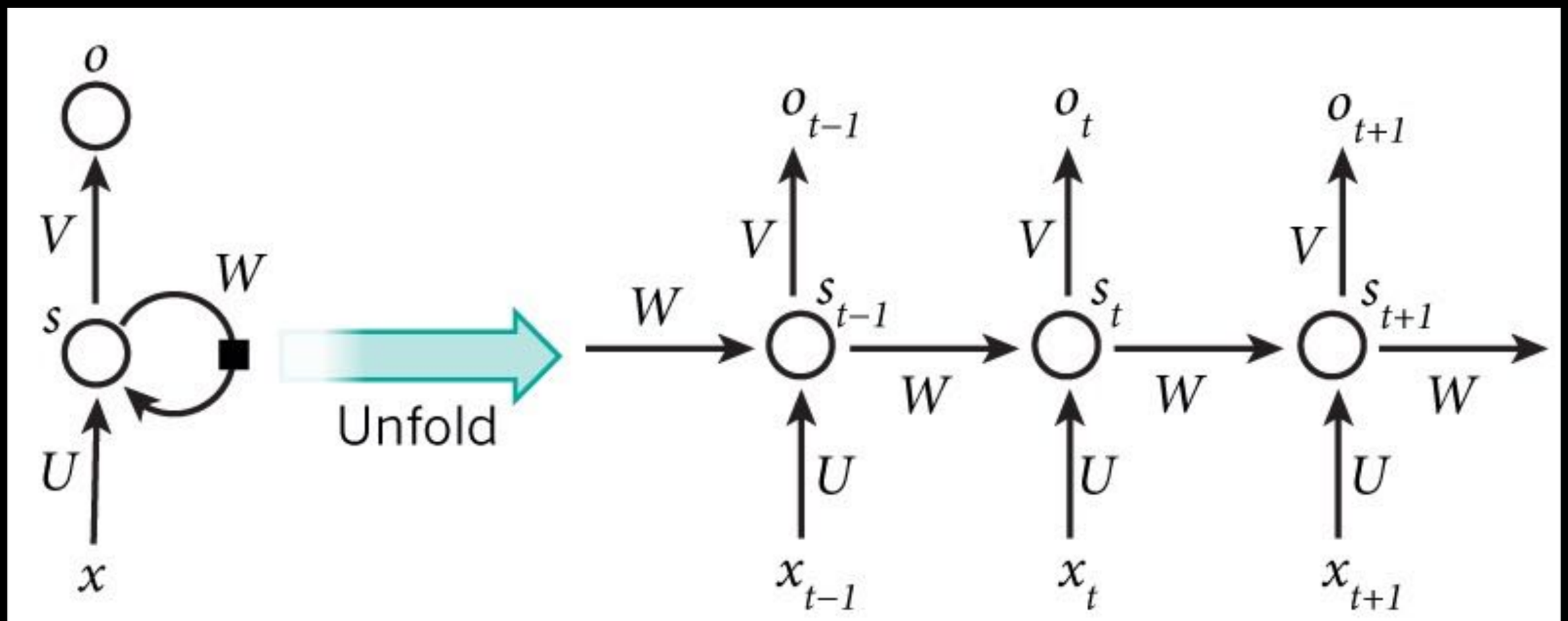
- Neural networks with memory
- Feed-forward NN: output exclusively depends on the current input
- Recurrent NN: output depends on current and previous states
- This is accomplished through lateral/backward connections which carry information while processing a sequence of inputs



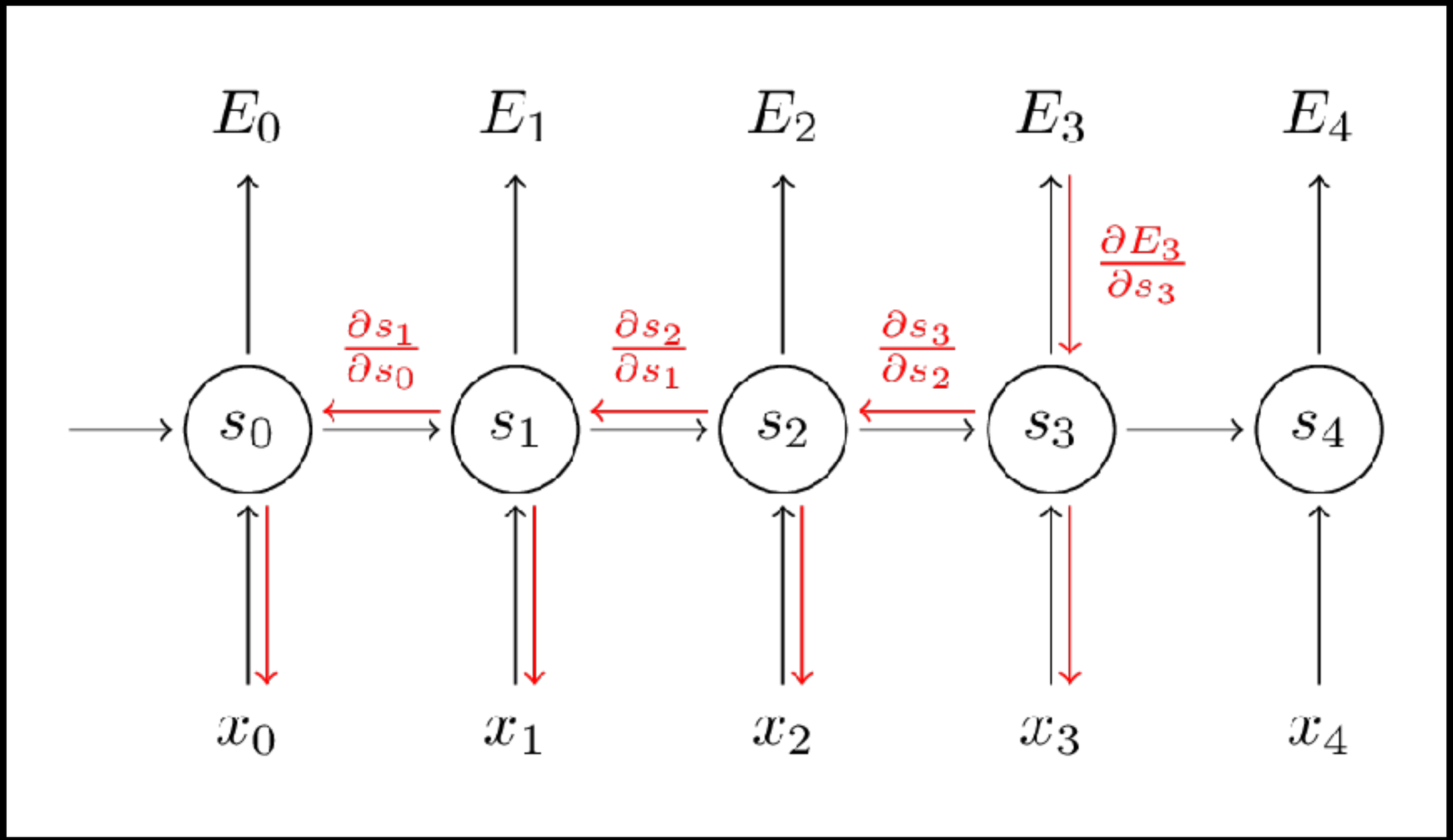
Character-level language model



Network unrolling

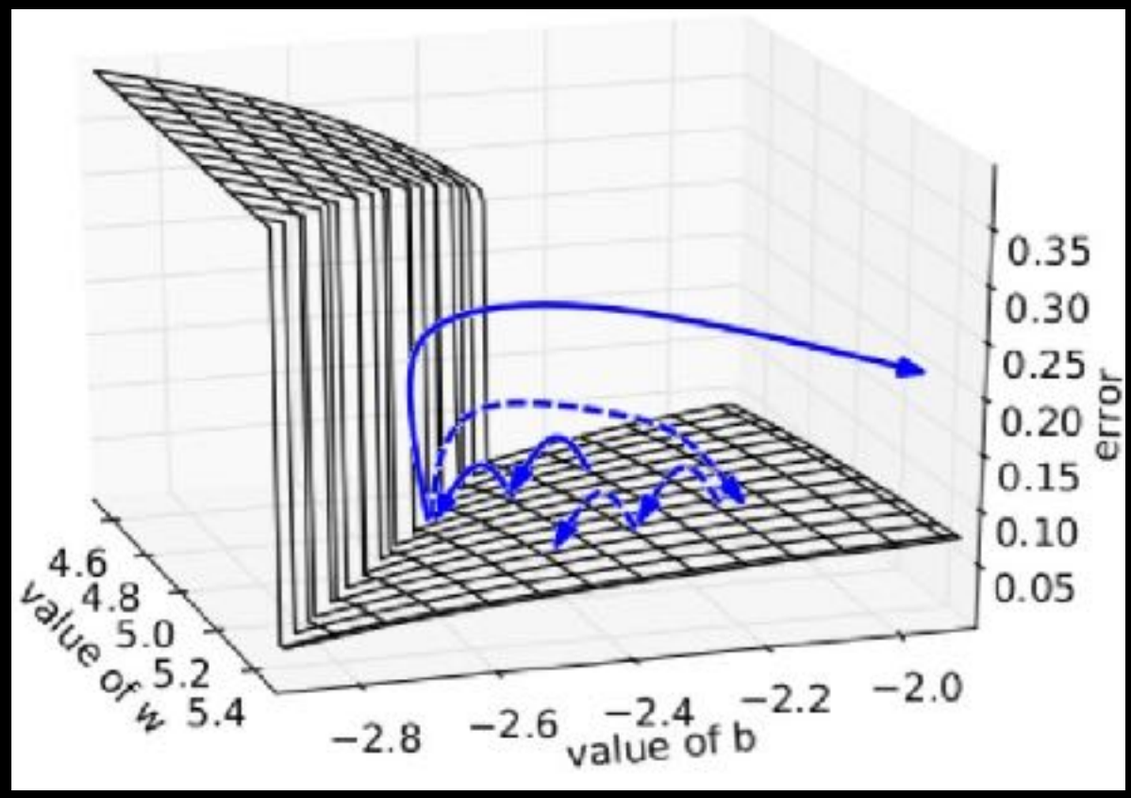


Backpropagation through time (BPTT)

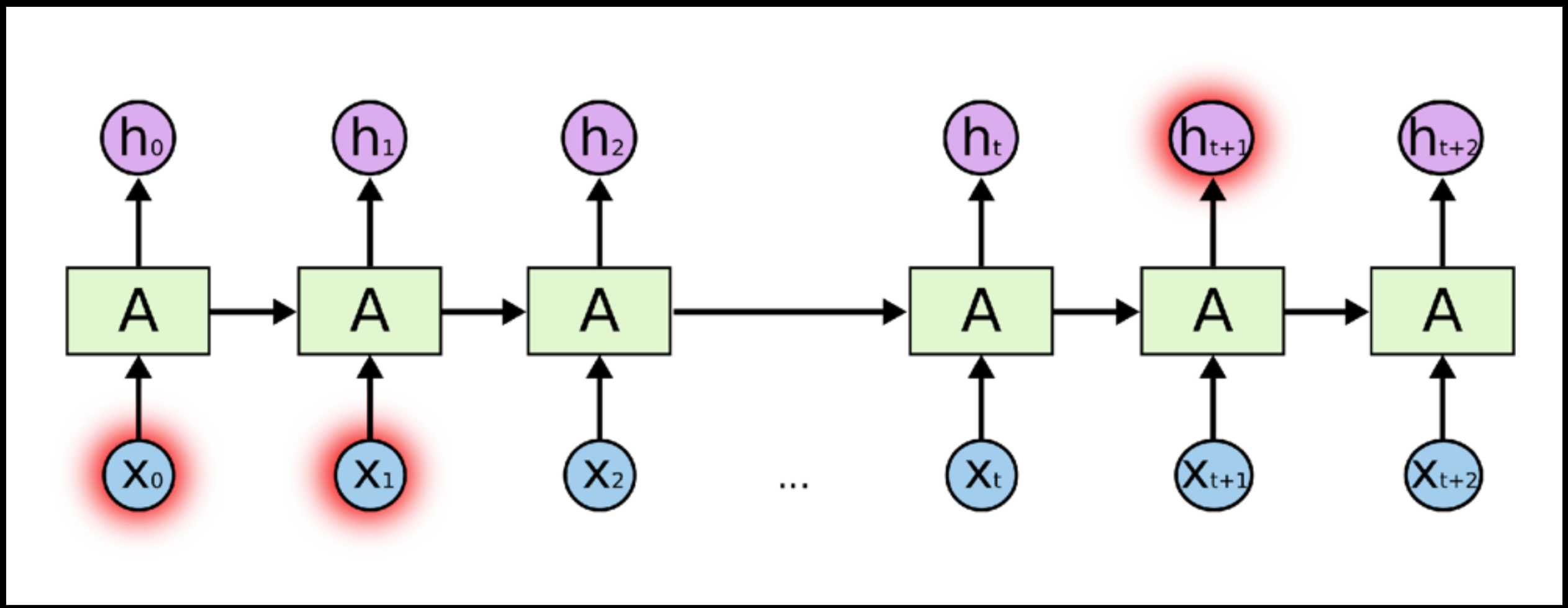


BPTT is hard

- The *vanishing* and the *exploding* gradient problem
- Gradients could vanish (or explode) when propagated several steps back
- This makes difficult to learn long-term dependencies.
- Razvan Pascanu, Tomas Mikolov, and Yoshua Bengio. 2013. *On the difficulty of training Recurrent Neural Networks*. Proc. of ICML, abs/1211.5063.



Long term dependencies



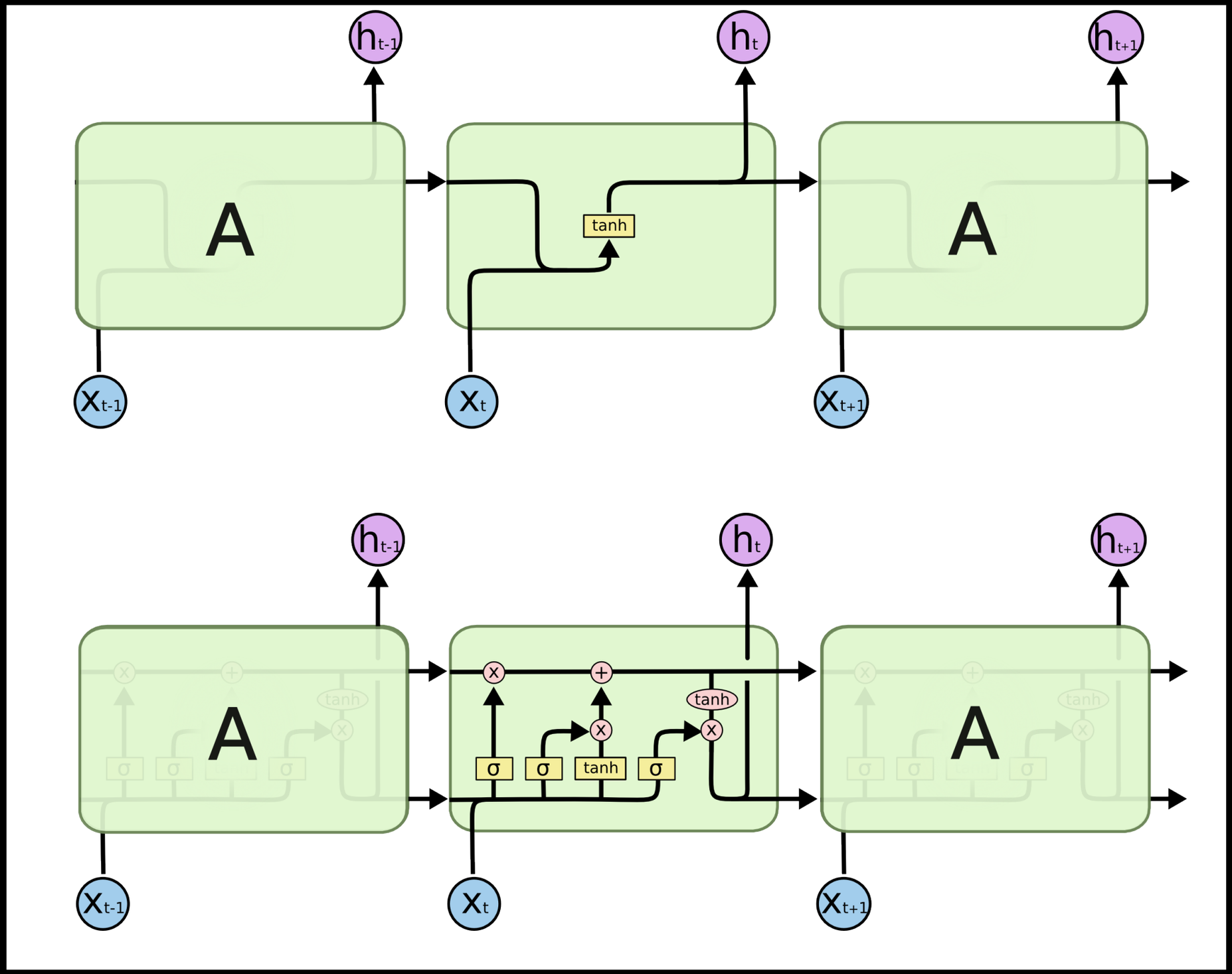
Long short-term memory (LSTM)

- LSTM networks solve the problem of long-term dependency problem.

- They use gates that allow to keep memory through long sequences and be updated only when required.

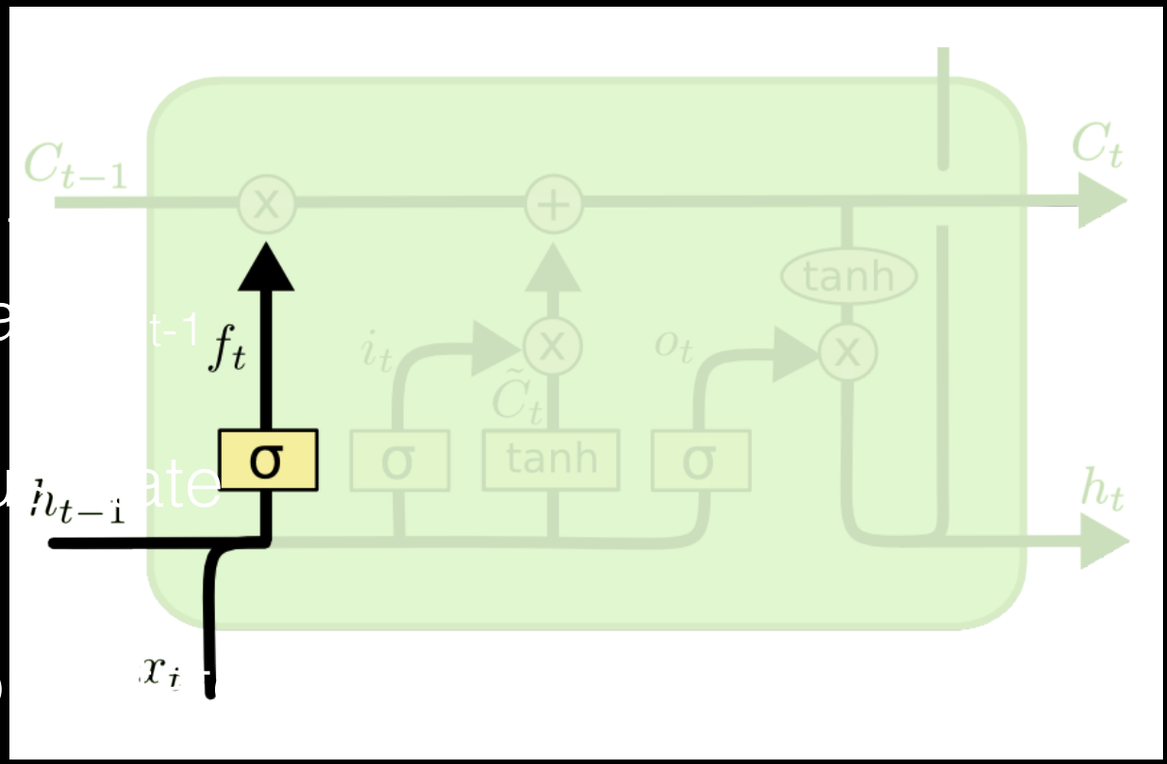
- Hochreiter, Sepp, and Jürgen Schmidhuber. "*Long short-term memory*." Neural computation 9, no. 8 (1997): 1735-1780.

Conventional RNN vs LSTM



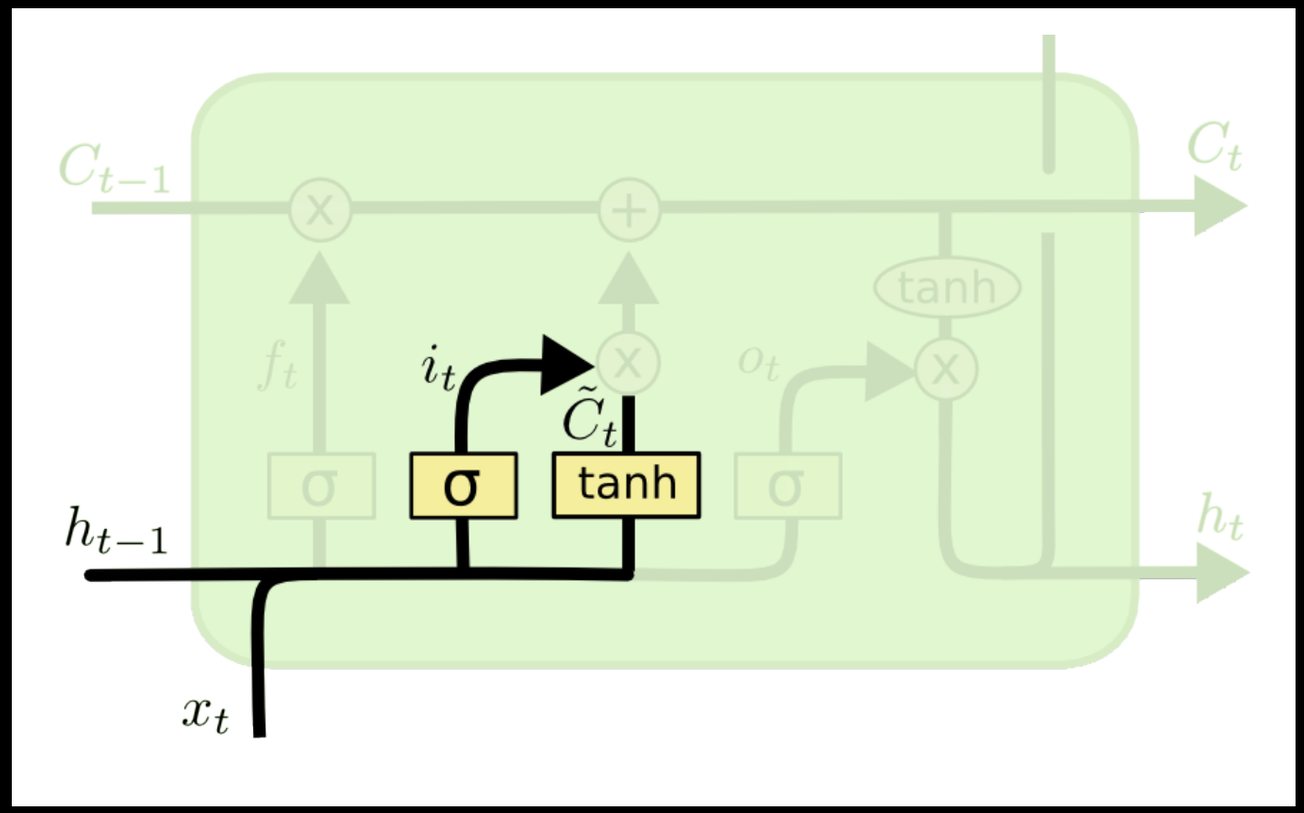
Forget gate

- Controls the flow of t
  previous internal sta
- f_t=1 ⇒ keep previou
- f_t=0 ⇒ forget previo

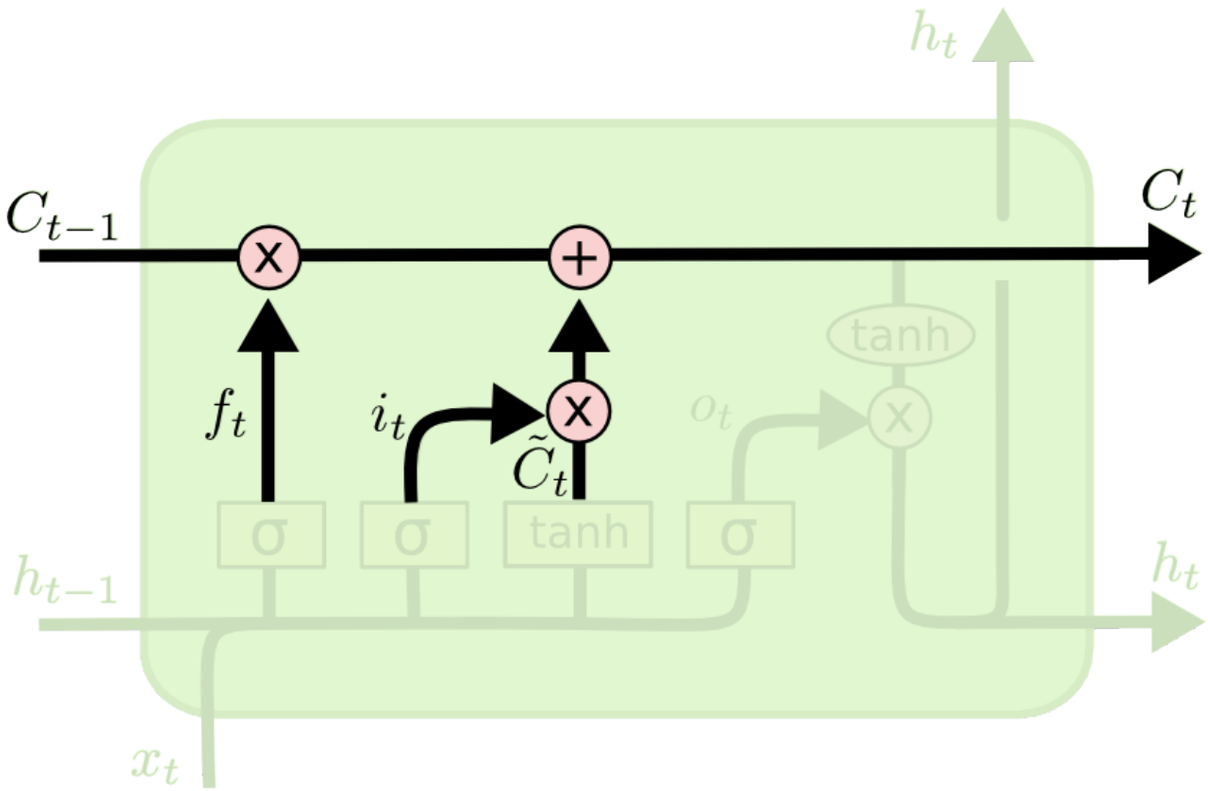


Input gate

- Controls the flow of the input state x_t
- i_t=1 ⇒ take input into account
- i_t=0 ⇒ ignore input

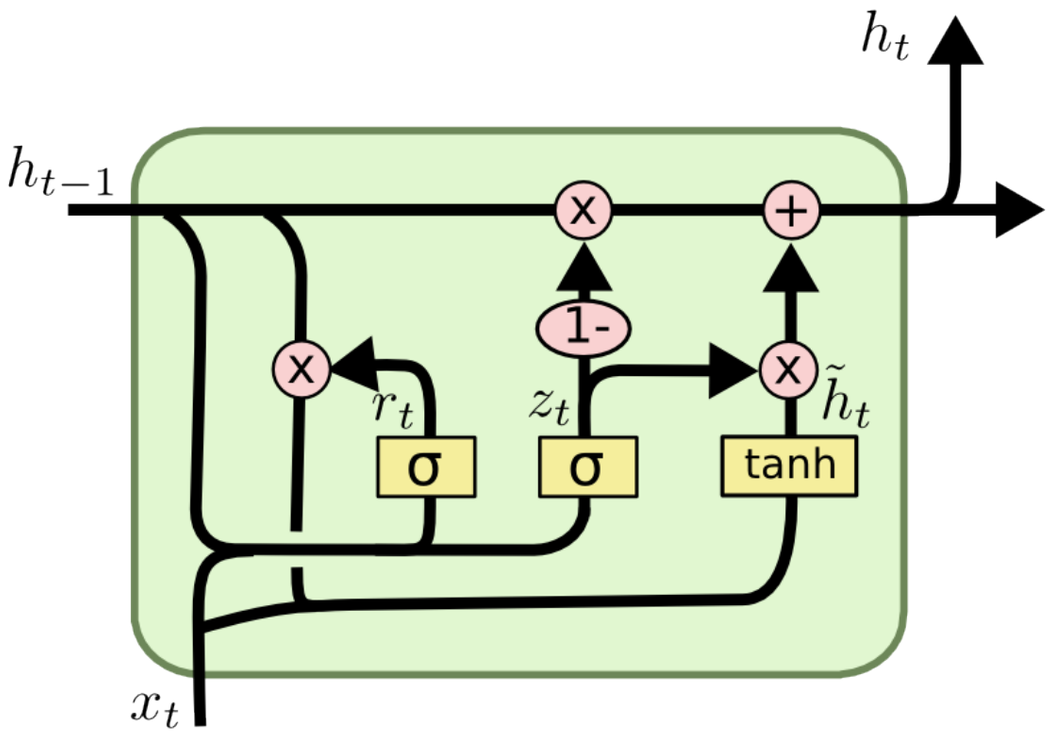


Current state calculation



$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$$

Gated recurrent units



$$z_t = \sigma\left(W_z \cdot [h_{t-1}, x_t]\right)$$

$$r_t = \sigma\left(W_r \cdot [h_{t-1}, x_t]\right)$$

$$\tilde{h}_t = \tanh\left(W \cdot [r_t * h_{t-1}, x_t]\right)$$

$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t$$

Cho, K., Van Merriënboer, B., Gulcehre, C., Bahdanau, D., Bougares, F., Schwenk, H., & Bengio, Y. (2014). ***Learning phrase representations using rnn encoder-decoder for statistical machine translation***. arXiv preprint arXiv:1406.1078.

Playing With LSTMs for Language Modeling

Interactive Demo

The Unreasonable Effectiveness of Recurrent Neural Networks

- Famous blog entry from Andrej Karpathy (UofS)
- Character-level language models based on multi-layer LSTMs.
- Data:
  - Shakspare plays
  - Wikipedia
  - LaTeX
  - Linux source code

Algebraic geometry book in LaTeX

Proof. Omitted. □

Lemma 0.1. *Let $\mathcal{C}$ be a set of the construction.*

Let $\mathcal{C}$ be a gerber covering. Let $\mathcal{F}$ be a quasi-coherent sheaves of $\mathcal{O}$-modules. We have to show that

$$\mathcal{O}_{\mathcal{O}_X} = \mathcal{O}_X(\mathcal{L})$$

.

Proof. This is an algebraic space with the composition of sheaves $\mathcal{F}$ on $X_{\acute{e}tale}$ we have

$$\mathcal{O}_X(\mathcal{F}) = \{morph_1 \times_{\mathcal{O}_X} (\mathcal{G}, \mathcal{F})\}$$

where $\mathcal{G}$ defines an isomorphism $\mathcal{F} \to \mathcal{F}$ of $\mathcal{O}$-modules. □

Lemma 0.2. *This is an integer Z is injective.*

Proof. See Spaces, Lemma ??. □

Lemma 0.3. *Let S be a scheme. Let X be a scheme and X is an affine open covering. Let $\mathcal{U} \subset \mathcal{X}$ be a canonical and locally of finite type. Let X be a scheme. Let X be a scheme which is equal to the formal complex.*

The following to the construction of the lemma follows.

Let X be a scheme. Let X be a scheme covering. Let

$$b : X \to Y' \to Y \to Y \to Y' \times_X Y \to X.$$

be a morphism of algebraic spaces over S and Y.

Proof. Let X be a nonzero scheme of X. Let X be an algebraic space. Let $\mathcal{F}$ be a quasi-coherent sheaf of $\mathcal{O}_X$-modules. The following are equivalent

(1) $\mathcal{F}$ is an algebraic space over S.
(2) If X is an affine open covering.

Consider a common structure on X and X the functor $\mathcal{O}_X(U)$ which is locally of finite type. □

This since $\mathcal{F} \in \mathcal{F}$ and $x \in \mathcal{G}$ the diagram

$$\begin{array}{ccc} \mathcal{S} & \longrightarrow & \\ \downarrow & & \\ \xi & \longrightarrow & \mathcal{O}_{X'} \\ & & \uparrow \\ \mathrm{gor}_s & & \end{array} \qquad \begin{array}{ccc} = \alpha' & \longrightarrow & \\ \updownarrow & & \\ = \alpha' & \longrightarrow & \alpha \end{array} \qquad \begin{array}{c} X \\ \downarrow \\ \end{array}$$

$$\mathrm{Spec}(K_\psi) \qquad \mathrm{Mor}_{Sets} \quad \mathrm{d}(\mathcal{O}_{X_{\acute{e}t}}, \mathcal{G})$$

is a limit. Then $\mathcal{G}$ is a finite type and assume S is a flat and $\mathcal{F}$ and $\mathcal{G}$ is a finite type f_*. This is of finite type diagrams, and

- the composition of $\mathcal{G}$ is a regular sequence,
- $\mathcal{O}_{X'}$ is a sheaf of rings.

□

Proof. We have see that $X = \mathrm{Spec}(R)$ and $\mathcal{F}$ is a finite type representable by algebraic space. The property $\mathcal{F}$ is a finite morphism of algebraic stacks. Then the cohomology of X is an open neighbourhood of U. □

Proof. This is clear that $\mathcal{G}$ is a finite presentation, see Lemmas ??.
A *reduced above* we conclude that U is an open covering of $\mathcal{C}$. The functor $\mathcal{F}$ is a "field

$$\mathcal{O}_{X,x} \longrightarrow \mathcal{F}_{\overline{x}} \quad \text{-1}(\mathcal{O}_{X_{\acute{e}tale}}) \longrightarrow \mathcal{O}_{X_i}^{-1}\mathcal{O}_{X_\lambda}(\mathcal{O}_{X_n}^{\mathbb{V}})$$

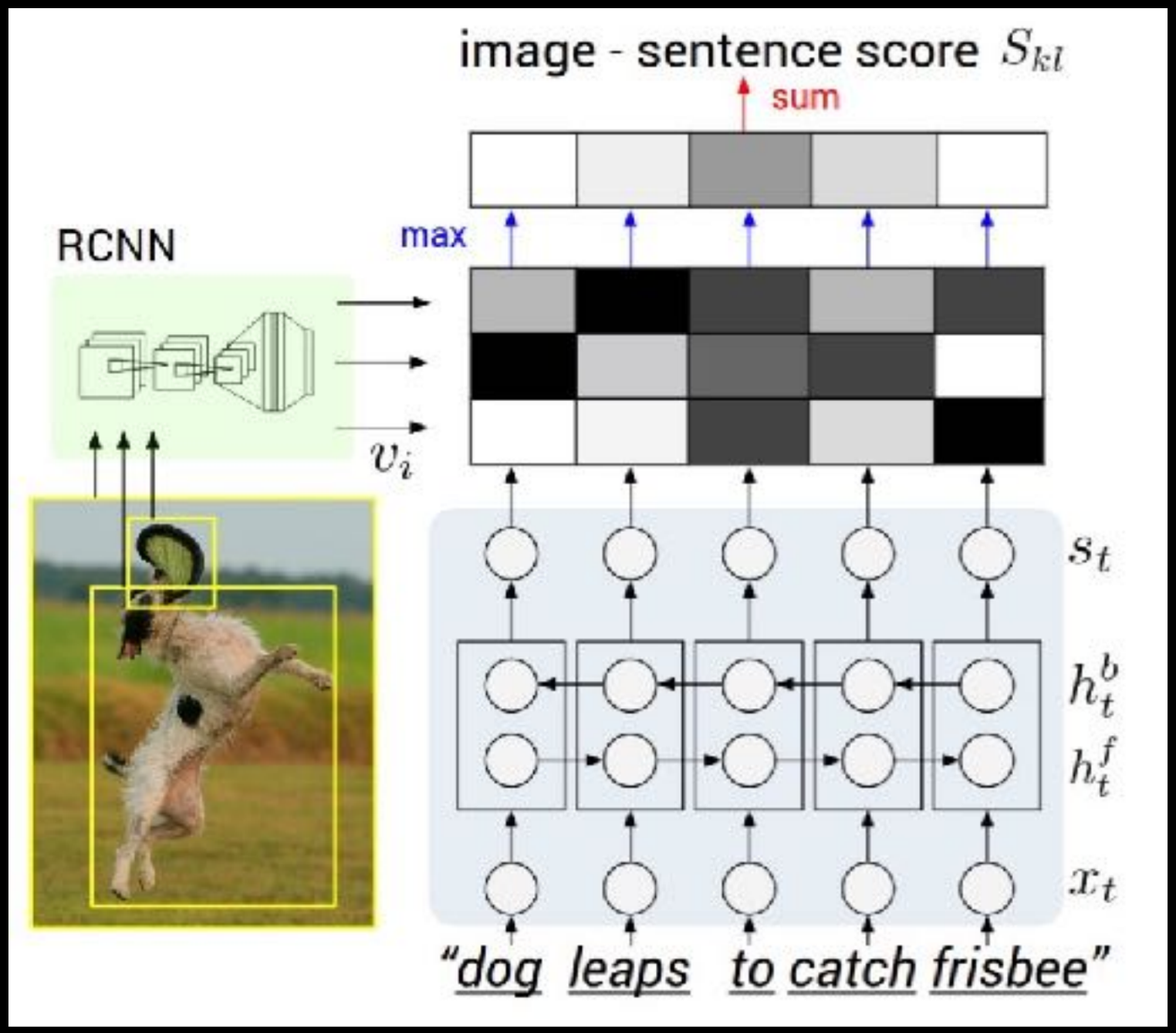
is an isomorphism of covering of $\mathcal{O}_{X_i}$. If $\mathcal{F}$ is the unique element of $\mathcal{F}$ such that X is an isomorphism.
The property $\mathcal{F}$ is a disjoint union of Proposition ?? and we can filtered set of presentations of a scheme $\mathcal{O}_X$-algebra with $\mathcal{F}$ are opens of finite type over S.
If $\mathcal{F}$ is a scheme theoretic image points. □

If $\mathcal{F}$ is a finite direct sum $\mathcal{O}_{X_\lambda}$ is a closed immersion, see Lemma ??. This is a sequence of $\mathcal{F}$ is a similar morphism.

Linux source code

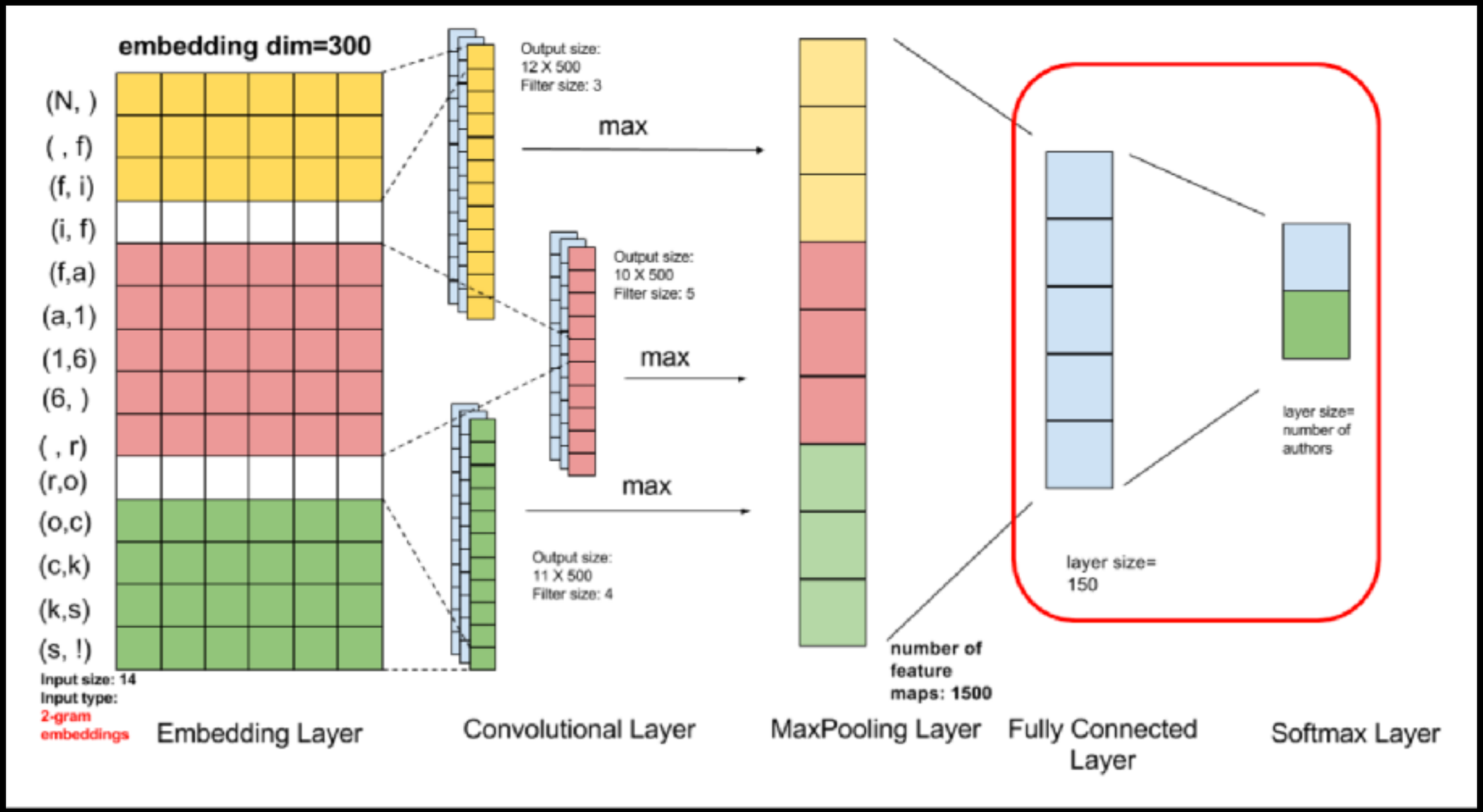
```
/*
 * Increment the size file of the new incorrect UI_FILTER group information
 * of the size generatively.
 */
static int indicate_policy(void)
{
  int error;
  if (fd == MARN_EPT) {
    /*
     * The kernel blank will coeld it to userspace.
     */
    if (ss->segment < mem_total)
      unblock_graph_and_set_blocked();
    else
      ret = 1;
    goto bail;
  }
  segaddr = in_SB(in.addr);
  selector = seg / 16;
  setup_works = true;
  for (i = 0; i < blocks; i++) {
    seq = buf[i++];
    bpf = bd->bd.next + i * search;
    if (fd) {
      current = blocked;
```

Multimodal models



Karpathy, Andrej, and Li Fei-Fei. "***Deep visual-semantic alignments for generating image descriptions***." CVPR2015. arXiv preprint arXiv:1412.2306 (2014).

CNN for text


embedding dim=300
(N,)
(, f)
(f, i)
(i, f)
(f,a)
(a,1)
(1,6)
(6,)
(, r)
(r,o)
(o,c)
(c,k)
(k,s)
(s, !)
Input size: 14
Input type:
2-gram
embeddings
Embedding Layer
Output size:
12 X 500
Filter size: 3
max
Output size:
10 X 500
Filter size: 5
max
Output size:
11 X 500
Filter size: 4
max
Convolutional Layer
number of
feature
maps: 1500
MaxPooling Layer
layer size=
150
layer size=
number of
authors
Fully Connected
Layer
Softmax Layer

Additional Resources on RNN

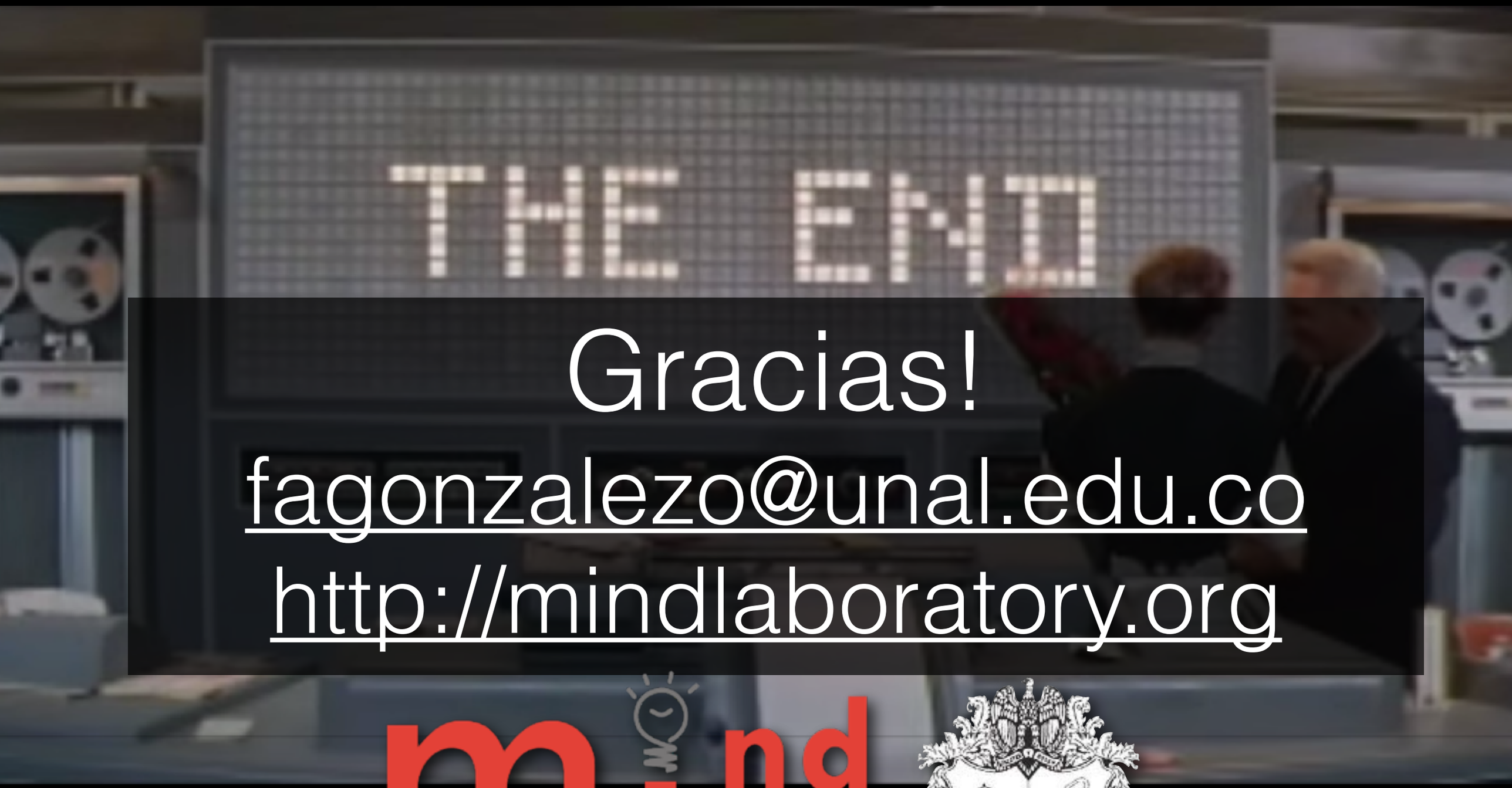
- Christopher Olah, Understanding LSTM Networks, [http://colah.github.io/posts/2015-08-Understanding-LSTMs/]

- Denny Britz, Recurrent Neural Networks Tutorial, [http://www.wildml.com/2015/09/recurrent-neural-networks-tutorial-part-1-introduction-to-rnns/]

- Andrej Karpathy, The Unreasonable Effectiveness of Recurrent Neural Networks, [http://karpathy.github.io/2015/05/21/rnn-effectiveness/]

- Jürgen Schmidhuber, Recurrent Neural Networks, [http://people.idsia.ch/~juergen/rnn.html]


THE END



Gracias!

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machine learning
perception and discovery