



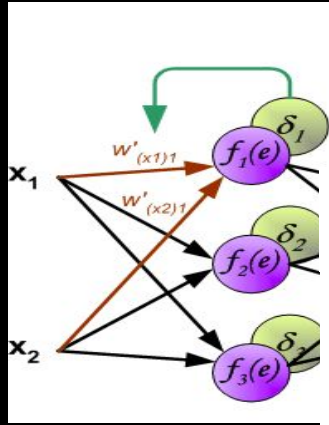


Instructors

	<p>Fabio Gonzalez Full Professor</p>  <p>UNIVERSIDAD NACIONAL DE COLOMBIA</p> <p>National University of Colombia Visiting Professor at UH Email: fagonzalezo@unal.edu.co Office: PGH 598</p>
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Intro to DL

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

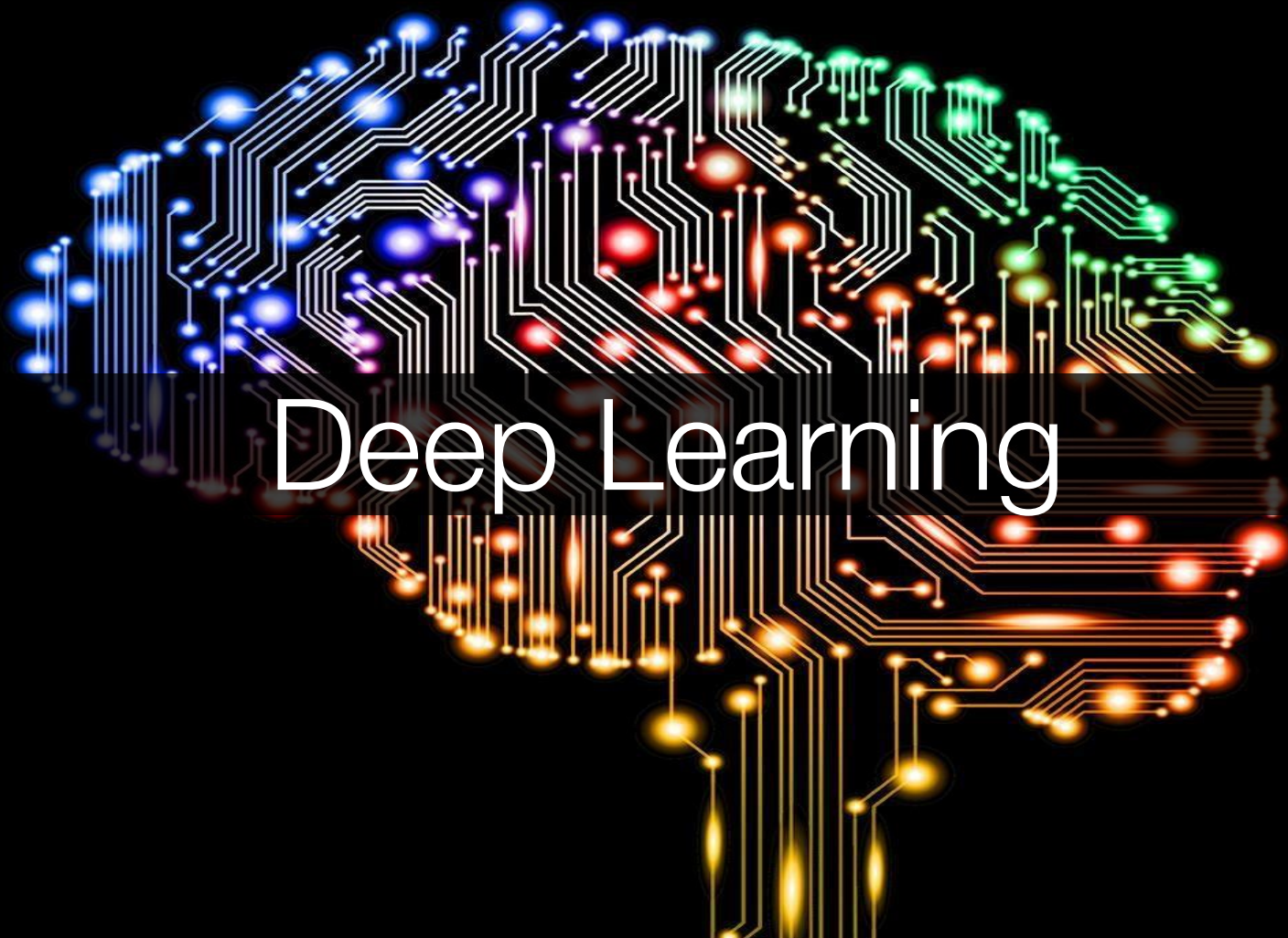
David E. Rumelhart*, Geoffrey E. Hinton† & Ronald J. Williams*

* 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



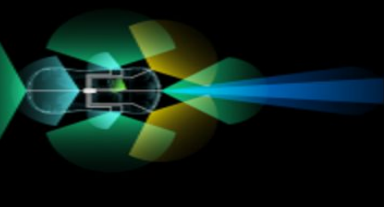
Source: http://home.agh.edu.pl/~vlsi/AI/backp_t_en/backprop.html



Deep Learning

Deep learning boom

ents 2928



DRIVING
**Here's How Deep
Acc**

By Danny

MIT
**Technology
Review**

FACEBOOK TAPS 'DEEP
LEARNING' GIANT FOR NEW AI
LAB

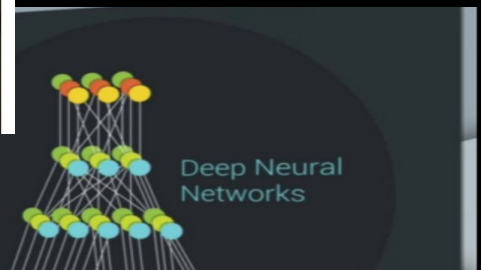
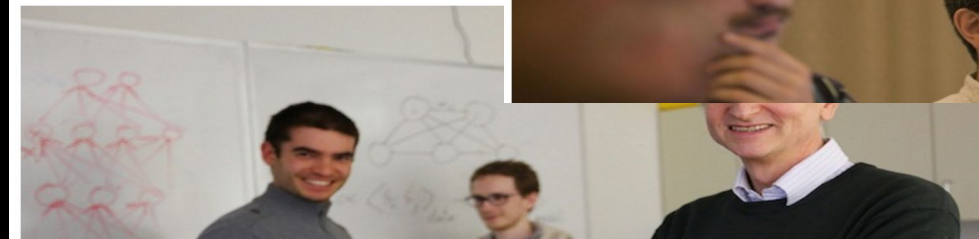
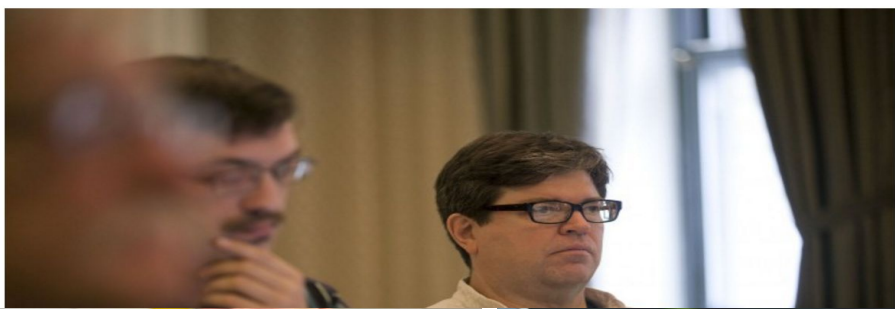
CADE METZ BUSINESS 12.09.13 3:14 PM



Research Giant
Man Behind
Brain"

ROBERT MCMILLAN BUSINESS 03.13.13 6:3

GOOGLE HIRES I
HELPED SUPERC
MACHINE LEARN



Deep Learning is Born

Neural Computation 18, 1527–1554 (2006) © 2006 Massachusetts Institute of Technology

A Fast Learning Algorithm¹⁵²⁸

G. Hinton, S. Osindero, and Y.-W. Teh

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Department of Computer Science

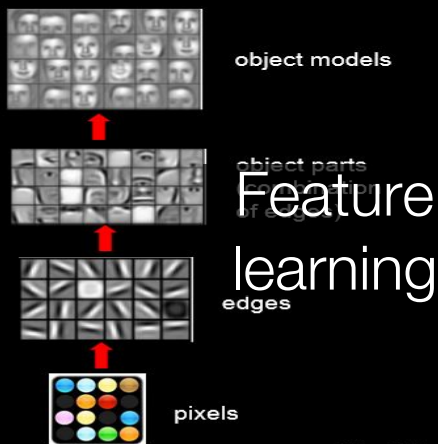
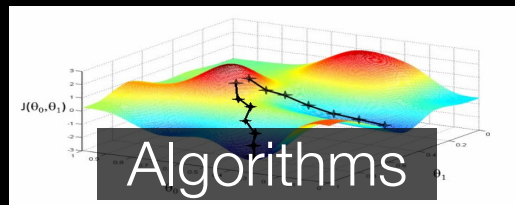
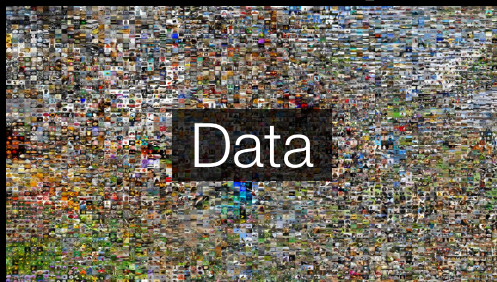
Yee-Whye Teh

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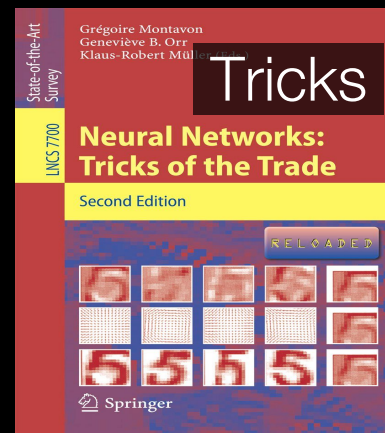
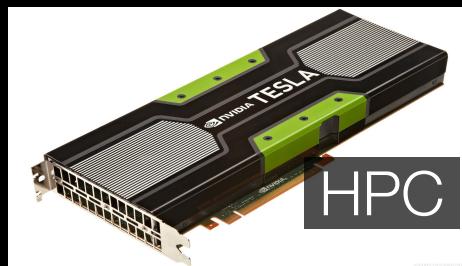
Deep learning recipe



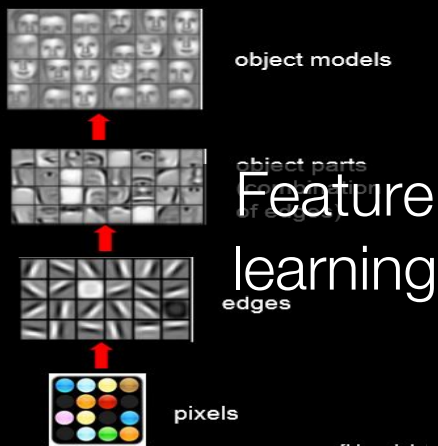
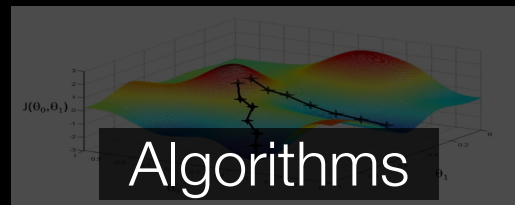
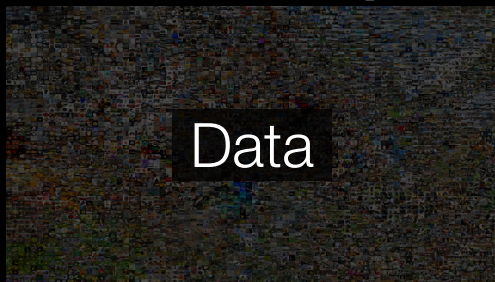
Won the 2012 ImageNet LSVRC. 60 Million parameters, 832M MAC ops

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 3x3/ReLU 384fm	
884K	CONV 3x3/ReLU 384fm	
	MAX POOLING 2x2sub	
	LOCAL CONTRAST NORM	
307K	CONV 11x11/ReLU 256fm	223M
	MAX POOL 2x2sub	
	LOCAL CONTRAST NORM	
35K	CONV 11x11/ReLU 96fm	105M

Size



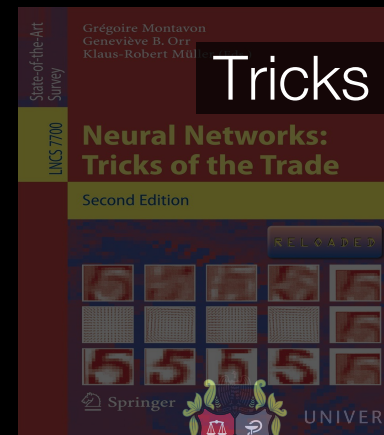
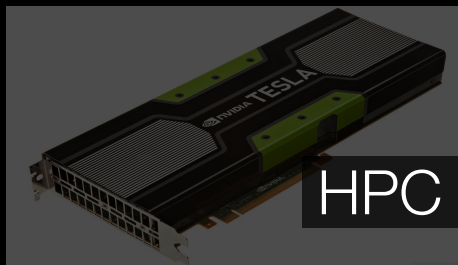
Deep learning recipe



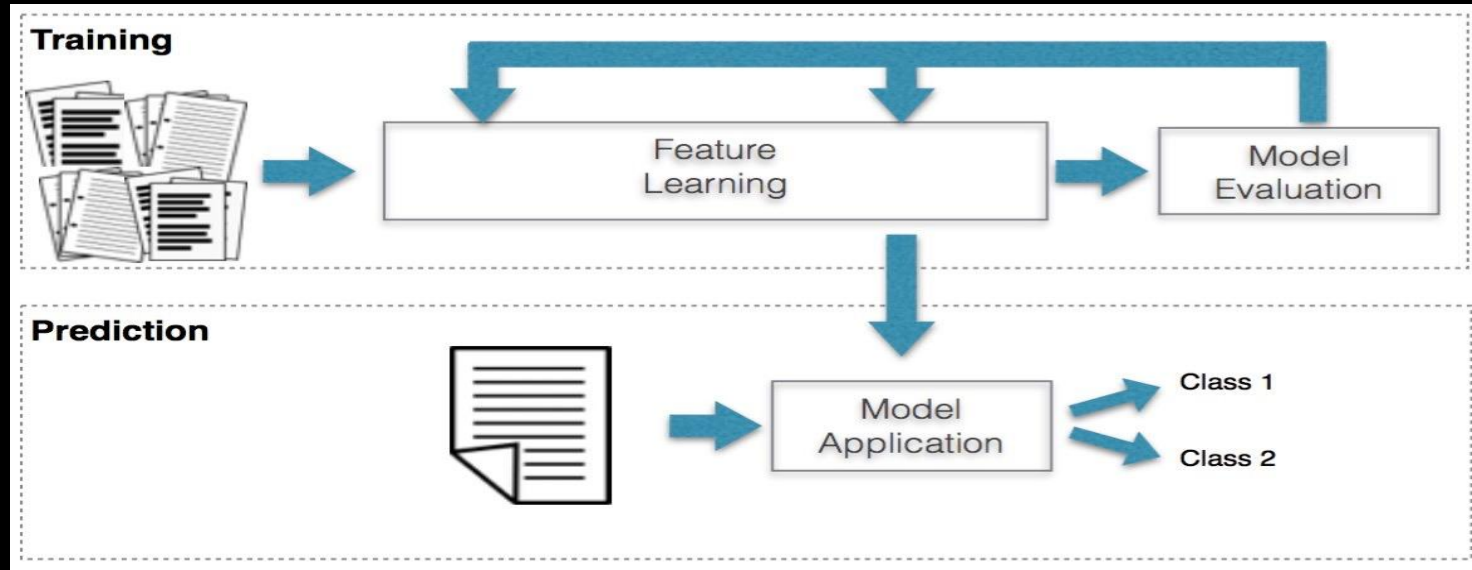
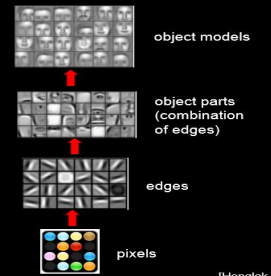
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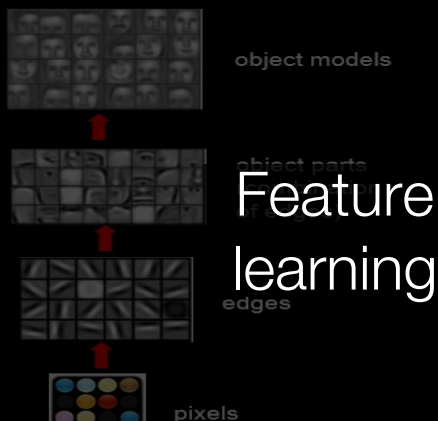
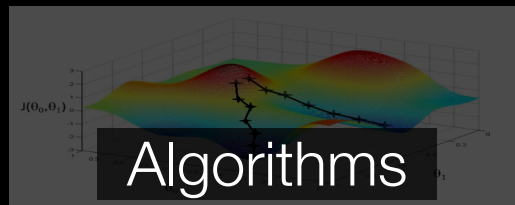
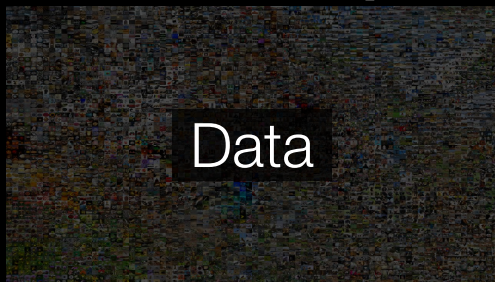
Size



Feature learning

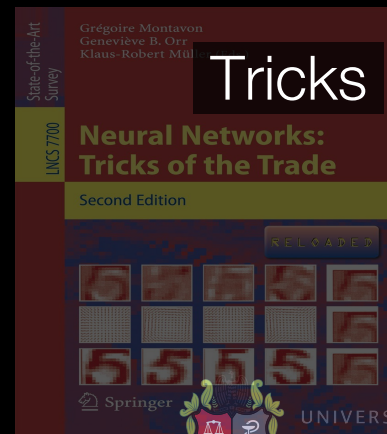
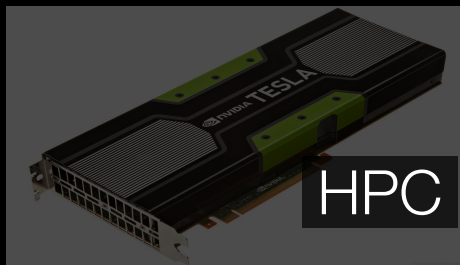


Deep learning recipe

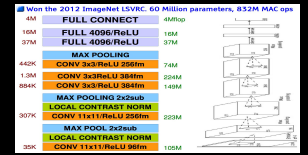


Won the 2012 ImageNet LSVRC. 60 Million parameters, 832M MAC ops

Size	Layer	Parameters	MAC ops
4M	FULL CONNECT	4M	4M flops
16M	FULL 4096/ReLU	16M	
37M	FULL 4096/ReLU	37M	
	MAX POOLING		
442K	CONV 3x3/ReLU 256fm		74M
1.3M	CONV 3x3/ReLU 384fm		
884K	CONV 3x3/ReLU 384fm		
	MAX POOLING 2x2sub		
307K	LOCAL CONTRAST NORM		223M
	CONV 11x11/ReLU 256fm		
	MAX POOL 2x2sub		
	LOCAL CONTRAST NORM		
35K	CONV 11x11/ReLU 96fm		105M



Deep \rightarrow Bigger



Revolution of Depth

Microsoft Research

152 layers

3.57
ILSVRC'15
ResNet

22 layers
6.7
ILSVRC'14
GoogleNet

19 layers
7.3
ILSVRC'14
VGG

11.7
8 layers
ILSVRC'13

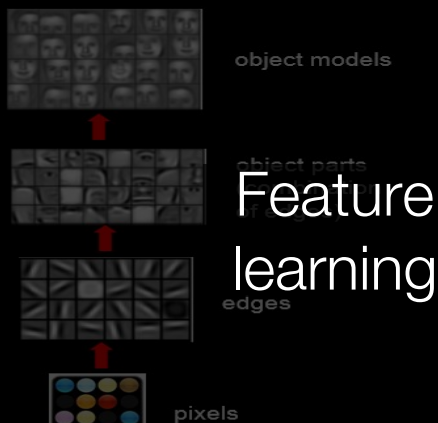
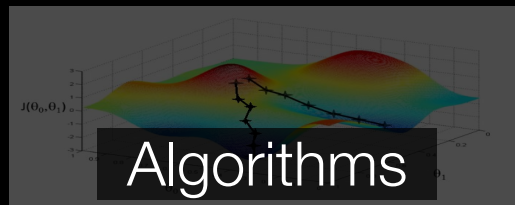
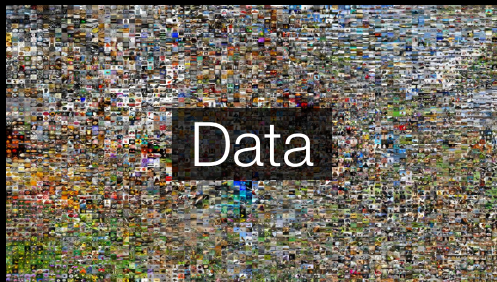
16.4
8 layers
ILSVRC'12
AlexNet

25.8
shallow
ILSVRC'11

28.2
shallow
ILSVRC'10

ImageNet Classification top-5 error (%)

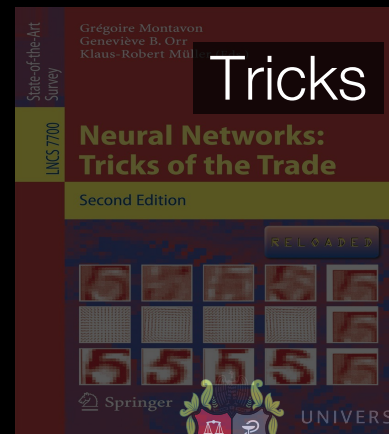
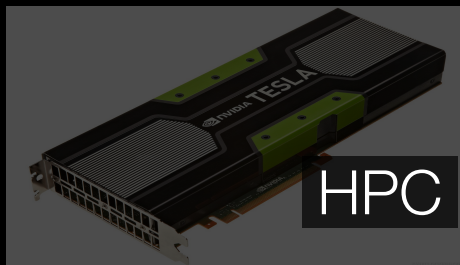
Deep learning recipe



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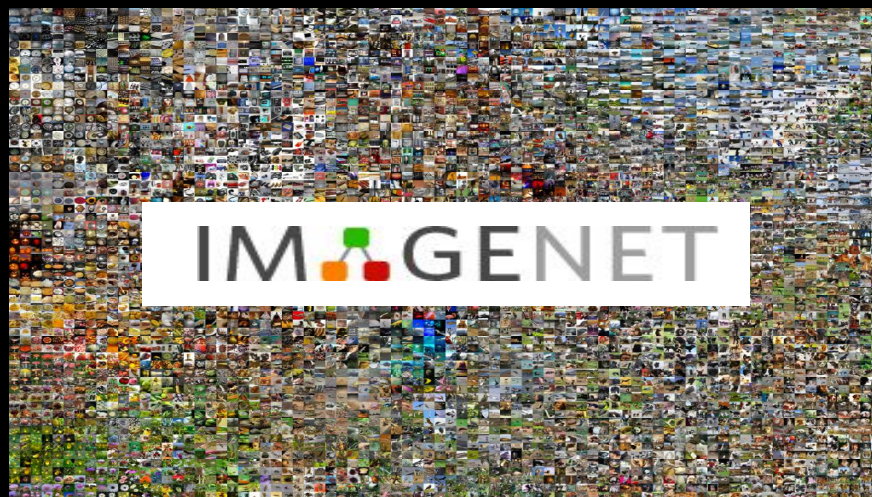
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Size

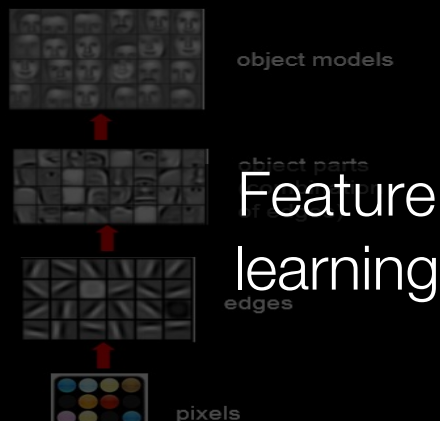
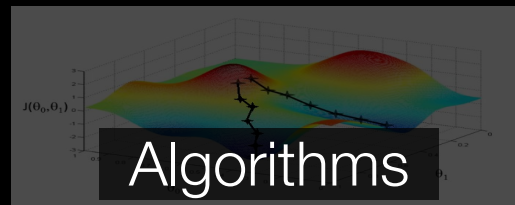
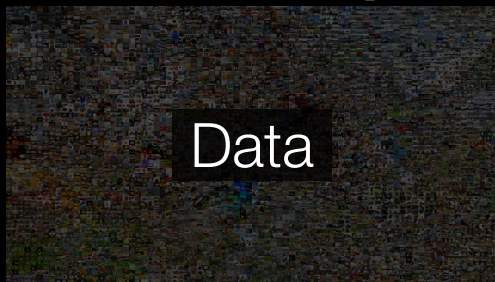


Data...

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



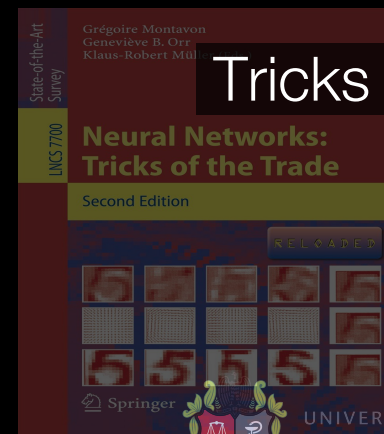
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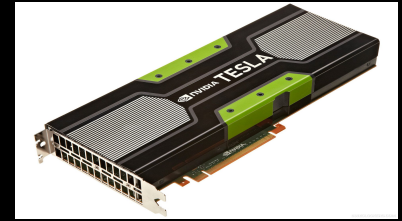
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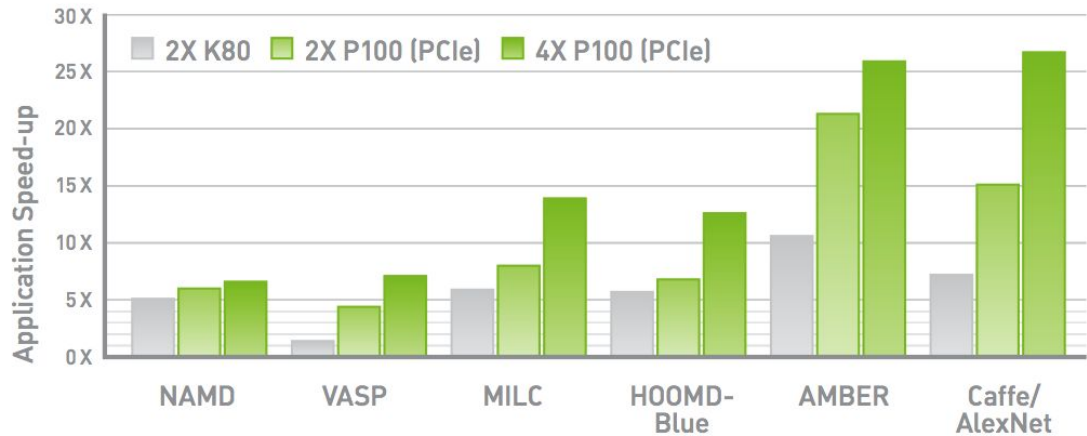
HPC



SPECIFICATIONS

GPU Architecture	NVIDIA Pascal
NVIDIA CUDA® Cores	3584
Double-Precision Performance	4.7 TeraFLOPS
Single-Precision Performance	9.3 TeraFLOPS
Half-Precision Performance	18.7 TeraFLOPS
GPU Memory	16GB CoWoS HBM2 at 732 GB/s or 12GB CoWoS HBM2 at 549 GB/s
System Interface	PCIe Gen3
Max Power Consumption	250 W
ECC	Yes
Thermal Solution	Passive
Form Factor	PCIe Full Height/Length

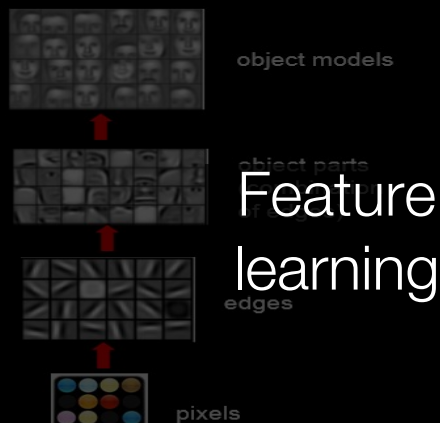
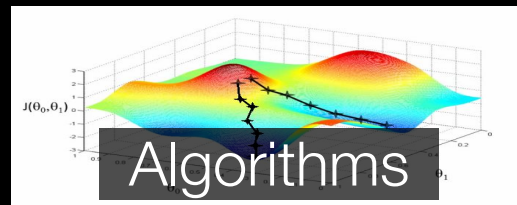
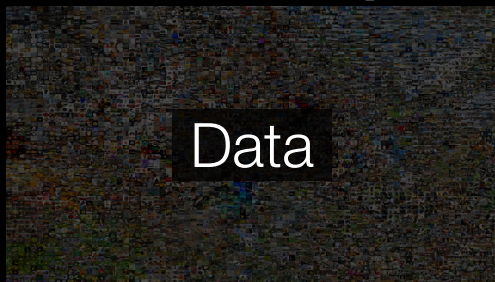
NVIDIA Tesla P100 for PCIe Performance



Dual CPU server, Intel E5-2698 v3 @ 2.3 GHz, 256 GB System Memory, Pre-Production Tesla P100



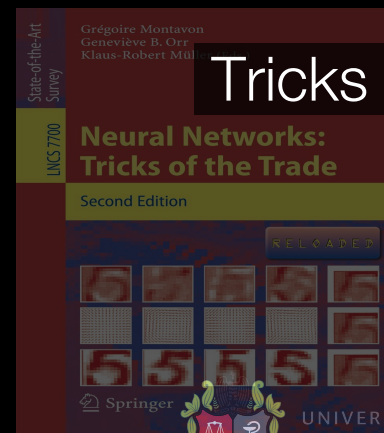
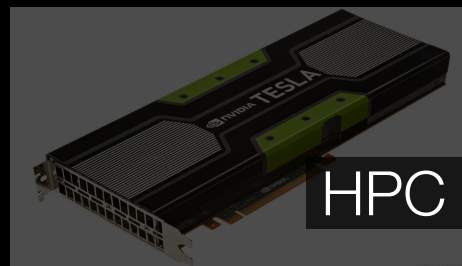
Deep learning recipe



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

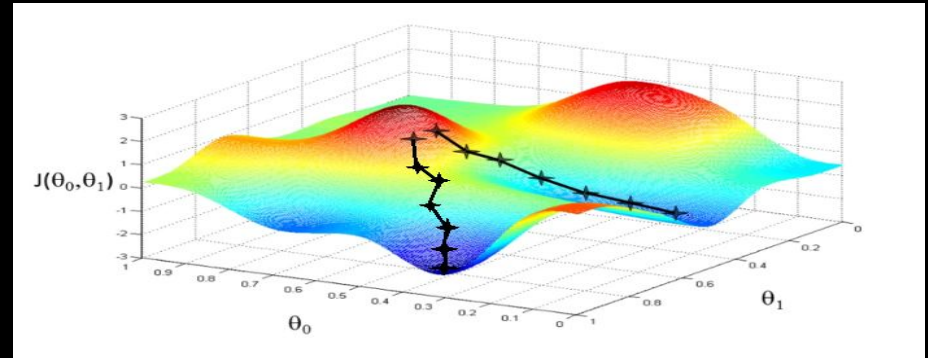
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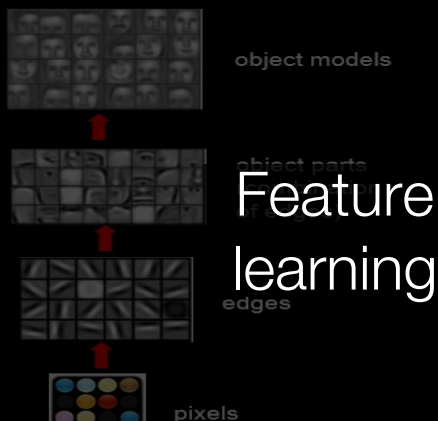
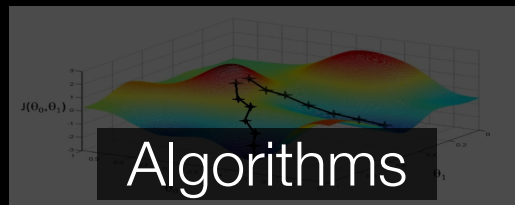
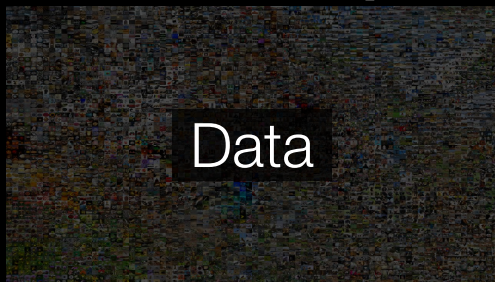


Algorithms

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



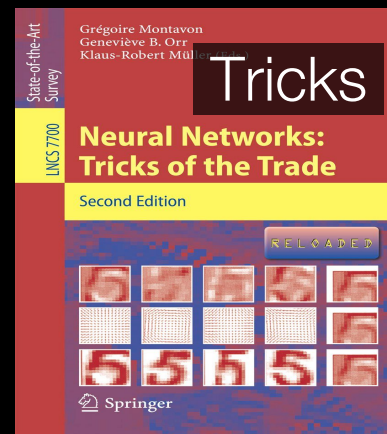
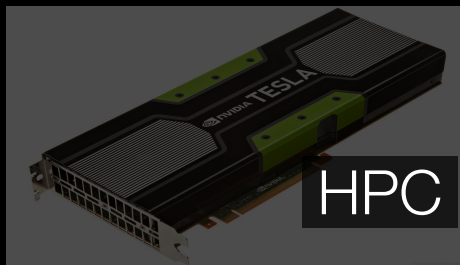
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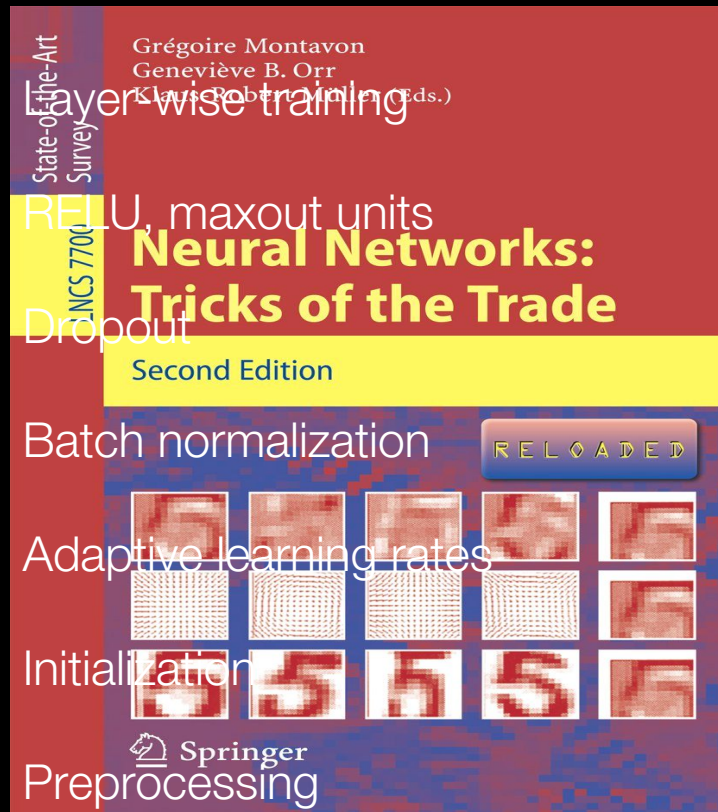
Size



Tricks

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

- Layer-wise training
- RELU, maxout units
- Dropout
- Batch normalization
- Adaptive learning rates
- Initialization
- Preprocessing



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