



香港中文大學
The Chinese University of Hong Kong

CMSC5743

L01 Introduction

Bei Yu

(Latest update: October 20, 2020)

Fall 2020



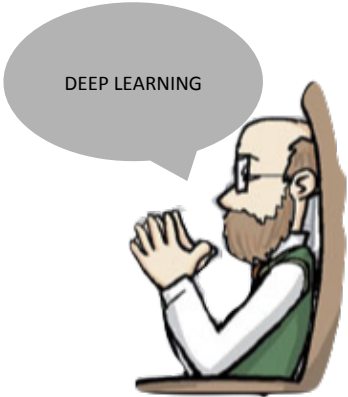


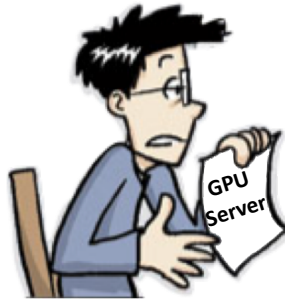
I want to research on a topic with DEAP LEARNING in it?



What should I learn to do well in computer vision research?





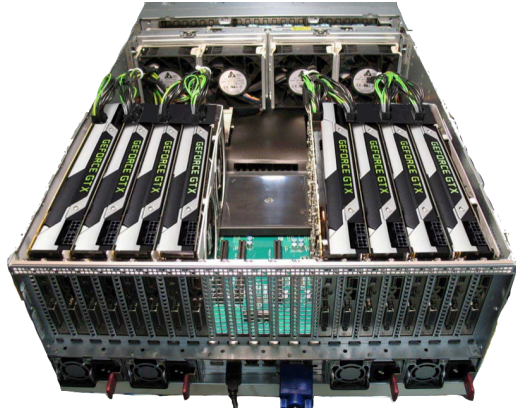






State of the art recognition methods

- Very Expensive
 - Memory
 - Computation
 - Power





What We Focus on?



What you expect to Learn?



How About the Workload?



Grading System?



CNN Architecture Overview

CNN Energy Efficiency

CNN on Embedded Platform



CNN Architecture Overview

CNN Energy Efficiency

CNN on Embedded Platform

What happened to Object Detection



Object Detection: PASCAL VOC mean Average Precision (mAP)

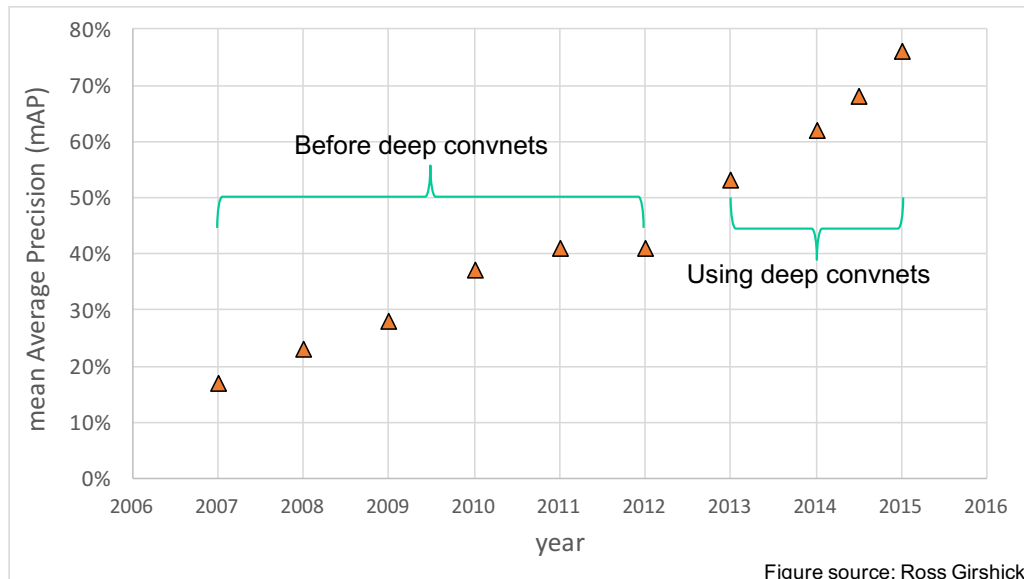


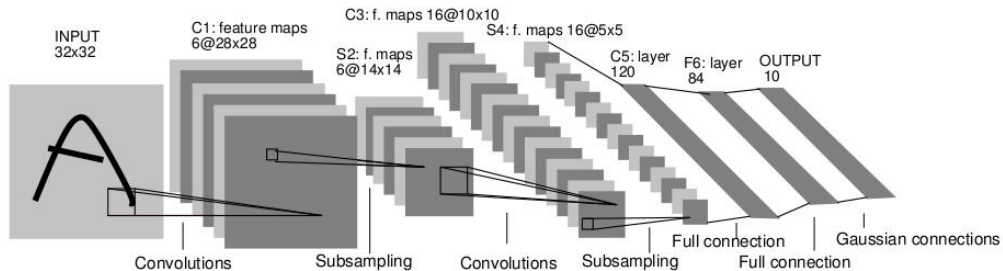
Figure source: Ross Girshick



Actually, it happened a while ago ...



LeNet 5

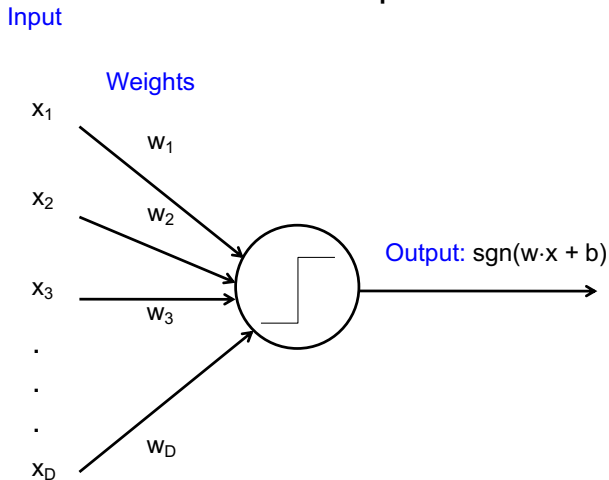


Y. LeCun, L. Bottou, Y. Bengio, and P. Haffner, [Gradient-based learning applied to document recognition](#), Proc. IEEE 86(11): 2278–2324, 1998.

Let's back up even more...

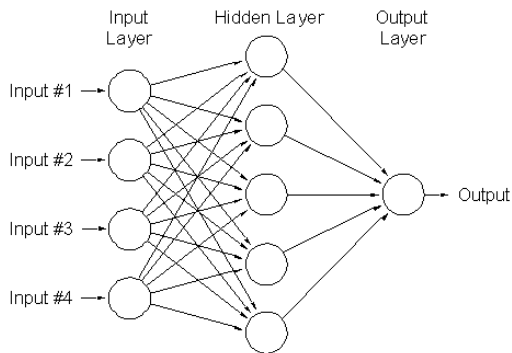


The Perceptron

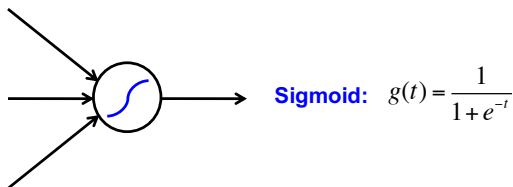


Rosenblatt, Frank (1958), The Perceptron: A Probabilistic Model for Information Storage and Organization in the Brain, Cornell Aeronautical Laboratory, Psychological Review, v65, No. 6, pp. 386–408.

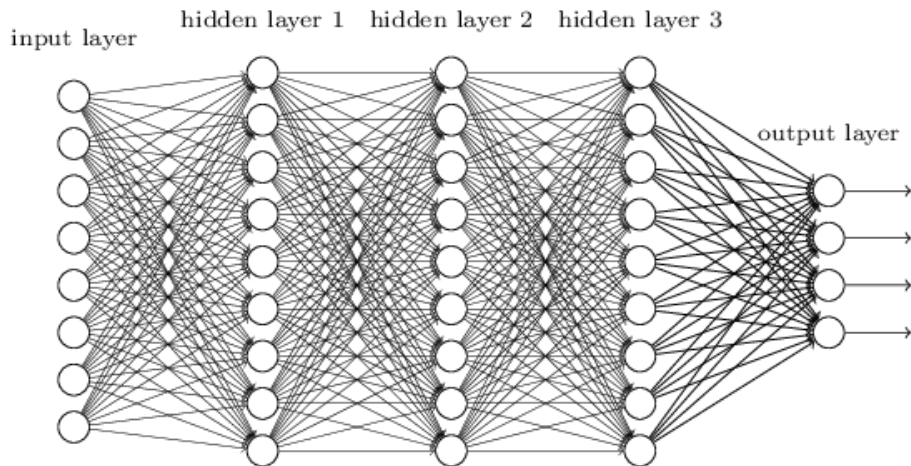
Two-layer neural network



- Can learn nonlinear functions provided each perceptron has a differentiable nonlinearity



Multi-layer neural network



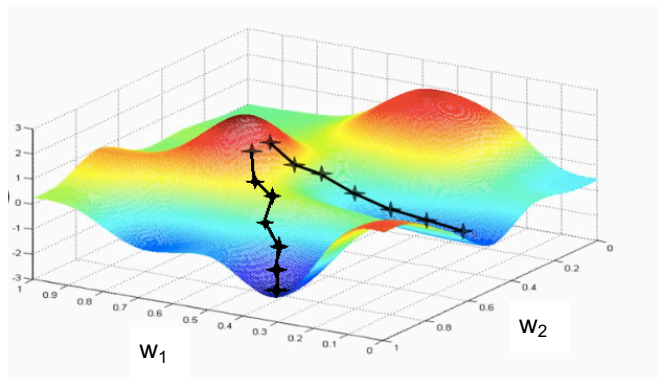


Training of multi-layer networks

- Find network weights to minimize the *training error* between true and estimated labels of training examples, e.g.:

$$E(\mathbf{w}) = \sum_{i=1}^N (y_i - f_{\mathbf{w}}(\mathbf{x}_i))^2$$

- Update weights by **gradient descent**: $\mathbf{w} \leftarrow \mathbf{w} - \alpha \frac{\partial E}{\partial \mathbf{w}}$



Training of multi-layer networks

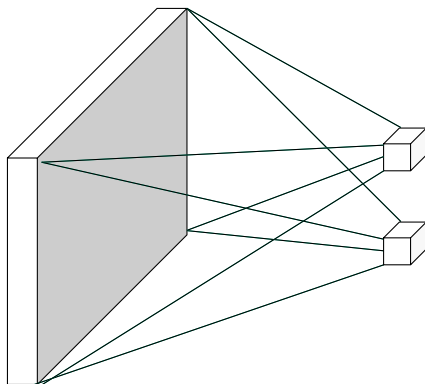


- Find network weights to minimize the *training error* between true and estimated labels of training examples, e.g.:

$$E(\mathbf{w}) = \sum_{i=1}^N (y_i - f_{\mathbf{w}}(\mathbf{x}_i))^2$$

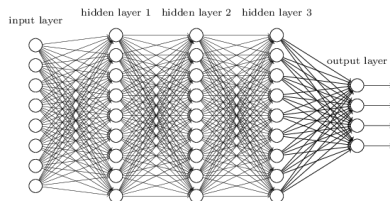
- Update weights by **gradient descent**: $\mathbf{w} \leftarrow \mathbf{w} - \alpha \frac{\partial E}{\partial \mathbf{w}}$
- Back-propagation**: gradients are computed in the direction from output to input layers and combined using chain rule
- Stochastic gradient descent**: compute the weight update w.r.t. one training example (or a small batch of examples) at a time, cycle through training examples in random order in multiple epochs

From fully connected to convolutional networks

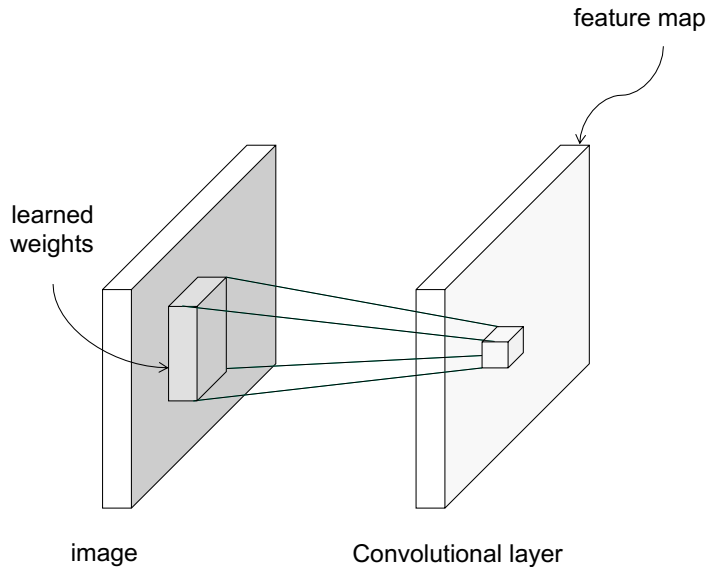


image

Fully connected layer



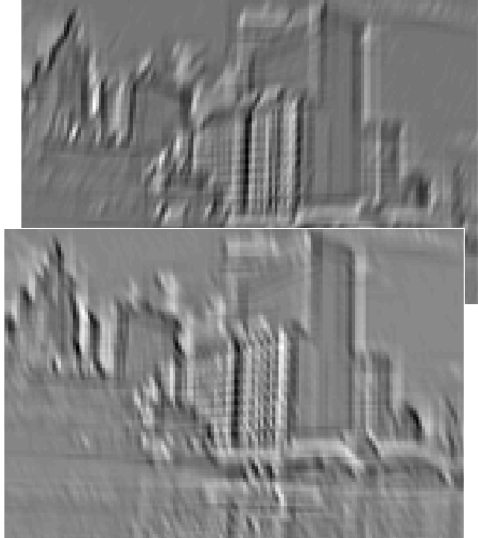
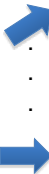
From fully connected to convolutional networks



Convolution as feature extraction



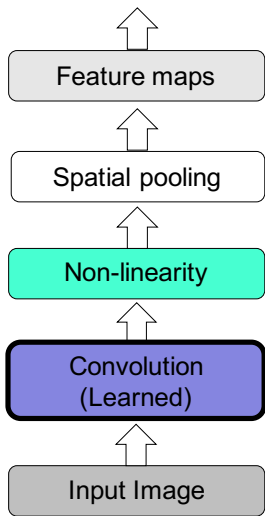
Input



Feature Map



Key operations



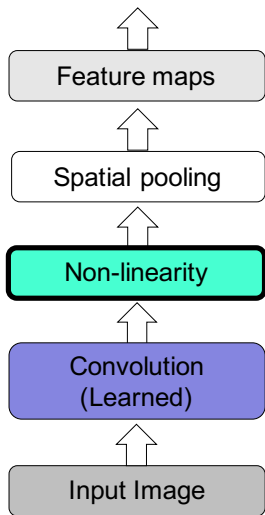
Input



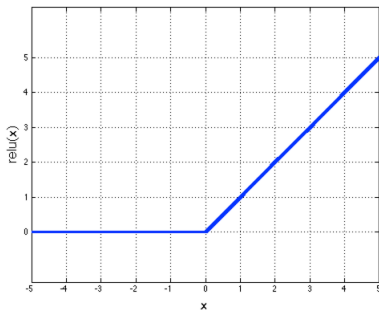
Feature Map

Source: R. Fergus, Y. LeCun

Key operations

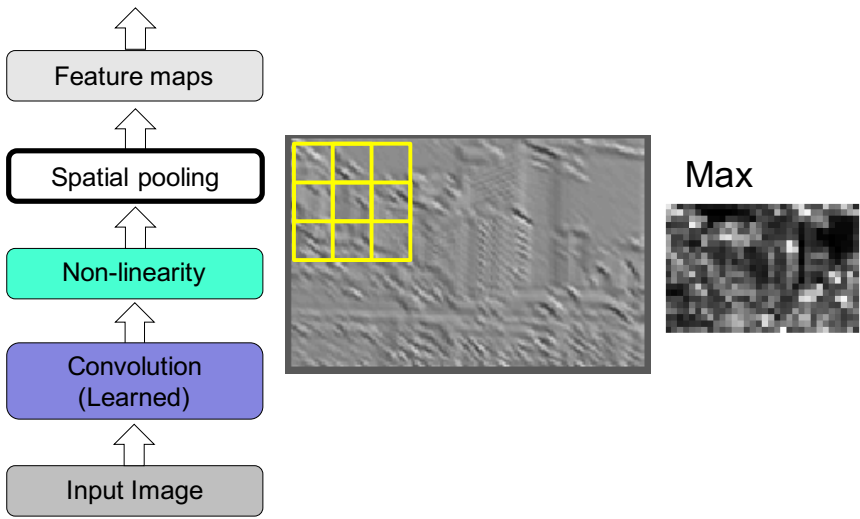


Rectified Linear Unit (ReLU)



Source: R. Fergus, Y. LeCun

Key operations

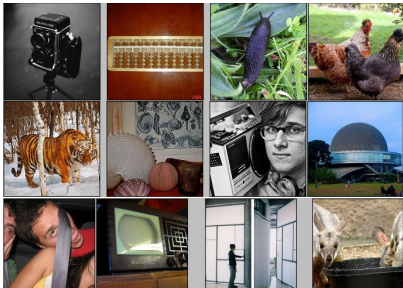


Source: R. Fergus, Y. LeCun

Fast forward to the arrival of big visual data



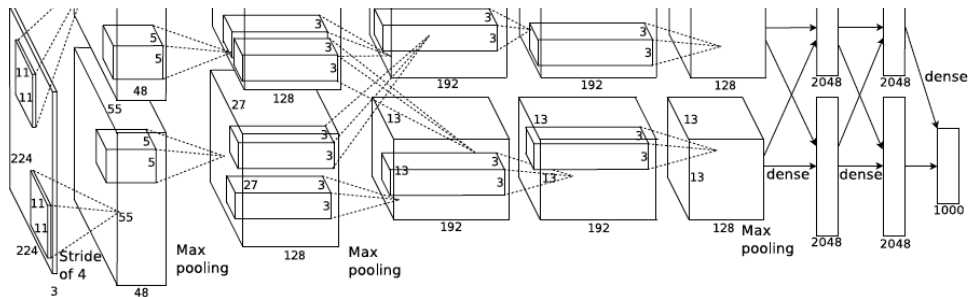
IMAGENET



- ~14 million labeled images, 20k classes
- Images gathered from Internet
- Human labels via Amazon MTurk
- ImageNet Large-Scale Visual Recognition Challenge (ILSVRC): 1.2 million training images, 1000 classes

www.image-net.org/challenges/LSVRC/

AlexNet: ILSVRC 2012 winner



- Similar framework to LeNet but:
 - Max pooling, ReLU nonlinearity
 - More data and bigger model (7 hidden layers, 650K units, 60M params)
 - GPU implementation (50x speedup over CPU)
 - Trained on two GPUs for a week
 - Dropout regularization

A. Krizhevsky, I. Sutskever, and G. Hinton, [ImageNet Classification with Deep Convolutional Neural Networks](#), NIPS 2012

Overview



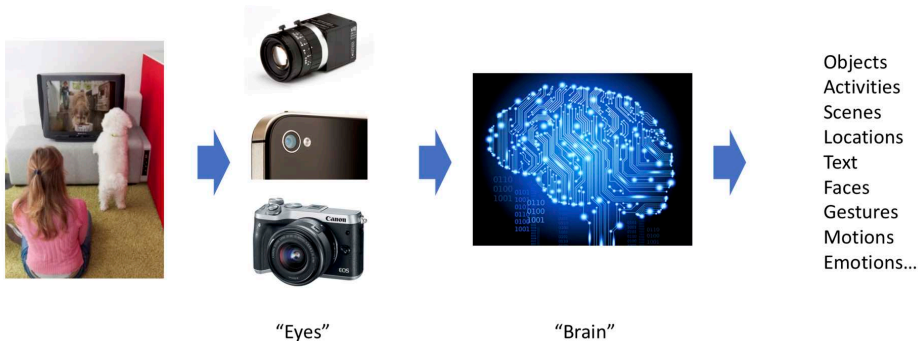
CNN Architecture Overview

CNN Energy Efficiency

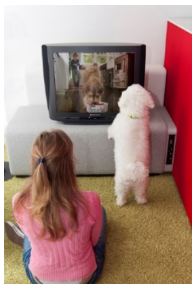
CNN on Embedded Platform



- ▶ Humans use their **eyes** and their **brains** to visually sense the world.
- ▶ Computers use their **cameras** and **computation** to visually sense the world

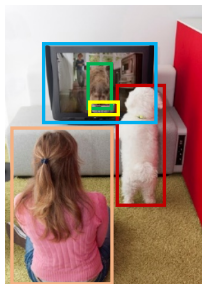


Few More Core Problems



Classification

Image



Detection

Region



Segmentation

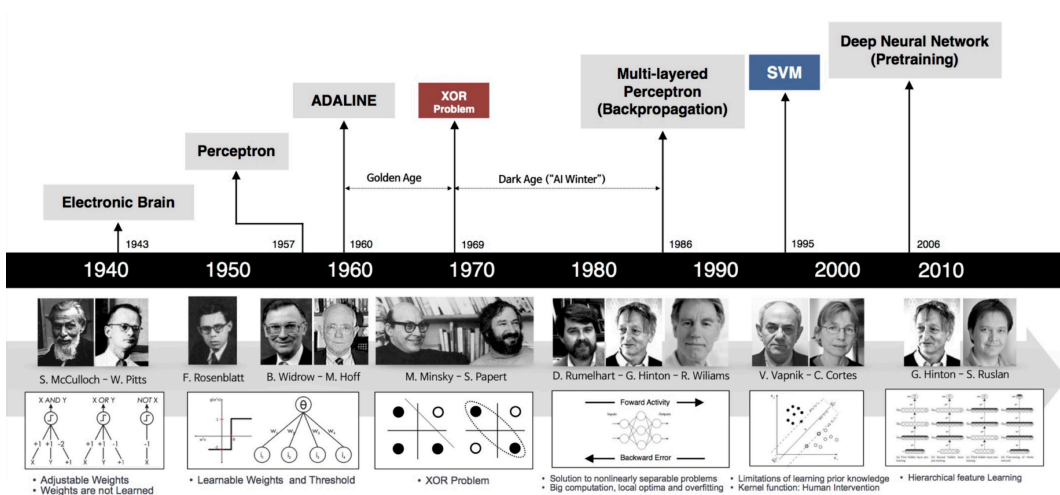
Pixel



Sequence

Video

A Bit of History



Jian Sun, "Introduction to Computer Vision and Deep Learning".

Winter of Neural Networks (mid 90' – 2006)



- ▶ The rises of SVM, Random forest
- ▶ No theory to play
- ▶ Lack of training data
- ▶ Benchmark is insensitive
- ▶ Difficulties in optimization
- ▶ Hard to reproduce results

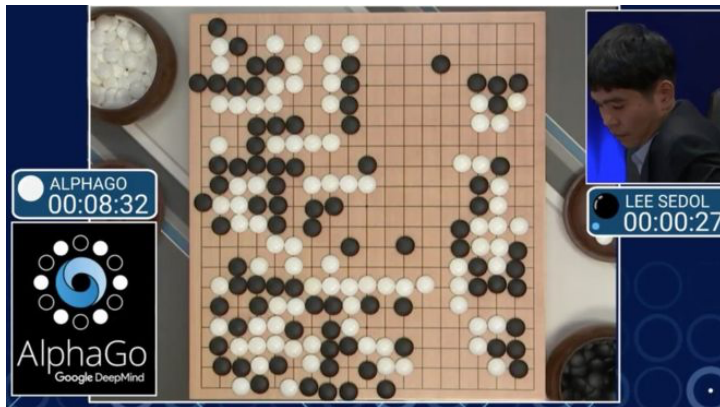
Curse

“Deep neural networks are no good and could never be trained.”



Renaissance of Deep Learning (2006 –)

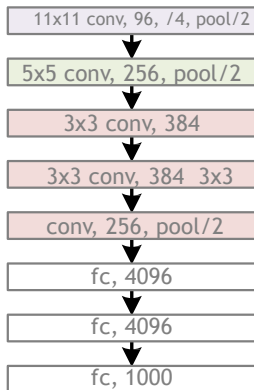
- ▶ A fast learning algorithm for deep belief nets. [Hinton et.al 1996]
- ▶ Data + Computing + Industry Competition
- ▶ NVidia's GPU, Google Brain (16,000 CPUs)
- ▶ **Speech**: Microsoft [2010], Google [2011], IBM
- ▶ **Image**: AlexNet, 8 layers [Krizhevsky et.al 2012] (26.2% -> 15.3%)





Revolution of Depth

AlexNet, 8
layers
(ILSVRC 2012)

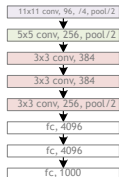


Slide Credit: He et al. (MSRA)

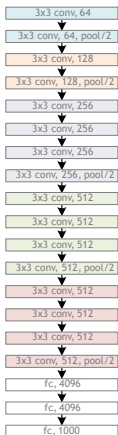


Revolution of Depth

AlexNet, 8
layers
(ILSVRC 2012)



VGG, 19
layers
(ILSVRC
2014)



GoogleNet, 22
layers
(ILSVRC 2014)



Slide Credit: He et al. (MSRA)



Revolution of Depth

AlexNet, 8
layers
(ILSVRC 2012)



VGG, 19
layers
(ILSVRC
2014)



ResNet, 152
layers
(ILSVRC 2015)



Slide Credit: He et al. (MSRA)

Some Recent Classification Architectures

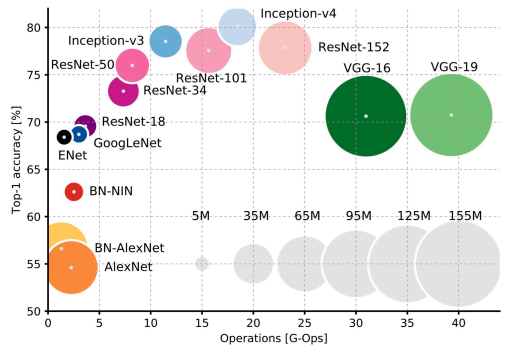
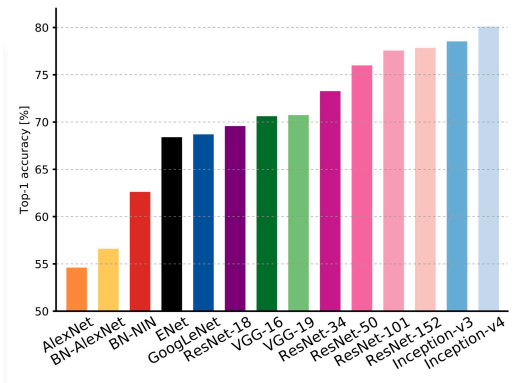


- ▶ AlexNet (Krizhevsky, Sutskever, and E. Hinton 2012) 233MB
- ▶ Network in Network (Lin, Chen, and Yan 2013) 29MB
- ▶ VGG (Simonyan and Zisserman 2015) 549MB
- ▶ GoogleNet (Szegedy, Liu, et al. 2015) 51MB
- ▶ ResNet (He et al. 2016) 215MB
- ▶ Inception-ResNet (Szegedy, Vanhoucke, et al. 2016)
- ▶ DenseNet (Huang et al. 2017)
- ▶ Xception (Chollet 2017)
- ▶ MobileNetV2 (Sandler et al. 2018)
- ▶ ShuffleNet (Zhang et al. 2018)

Some Recent Classification Architectures



- ▶ AlexNet (Krizhevsky, Sutskever, and E. Hinton 2012) 233MB
- ▶ Network in Network (Lin, Chen, and Yan 2013) 29MB
- ▶ VGG (Simonyan and Zisserman 2015) 549MB
- ▶ GoogleNet (Szegedy, Liu, et al. 2015) 51MB
- ▶ ResNet (He et al. 2016) 215MB
- ▶ Inception-ResNet (Szegedy, Vanhoucke, et al. 2016) 23MB
- ▶ DenseNet (Huang et al. 2017) 80MB
- ▶ Xception (Chollet 2017) 22MB
- ▶ MobileNetV2 (Sandler et al. 2018) 14MB
- ▶ ShuffleNet (Zhang et al. 2018) 22MB



1

¹Alfredo Canziani, Adam Paszke, and Eugenio Culurciello (2017). "An analysis of deep neural network models for practical applications". In: *arXiv preprint*.

Convolutional Neural Network (CNN)



Autonomous drive

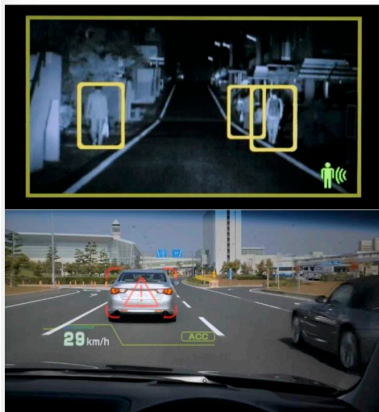
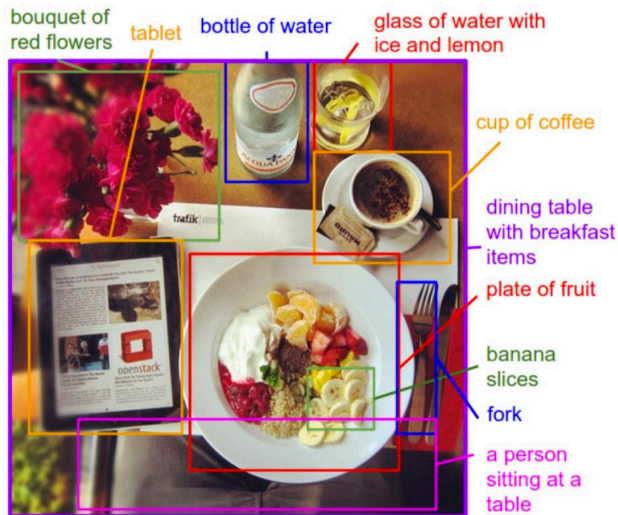
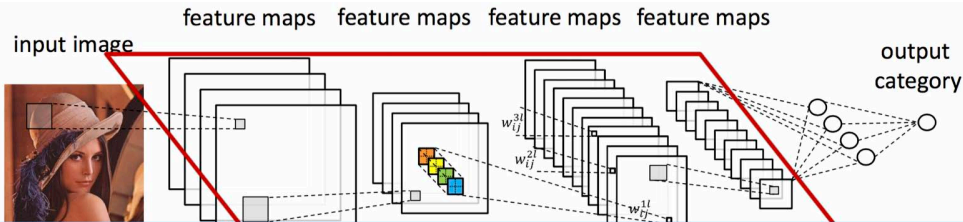


Image recognition



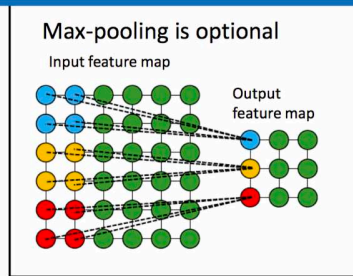
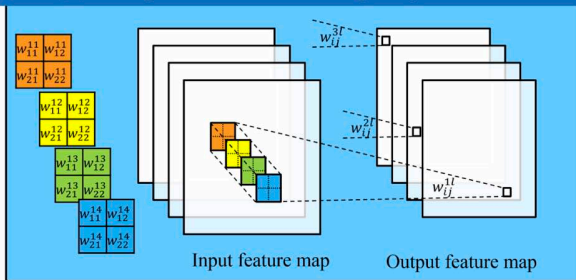
Convolutional Neural Network (CNN)



Convolutional layers account for over 90% computation

[1] A. Krizhevsky, etc. Imagenet classification with deep convolutional neural networks. NIPS 2012.

[2] J. Cong and B. Xiao. Minimizing computation in convolutional neural networks. ICANN 2014





Example: Hisense ADAS



Hisense core|photonics

Start Video

Overview



CNN Architecture Overview

CNN Energy Efficiency

CNN on Embedded Platform

When Machine Learning Meets Hardware

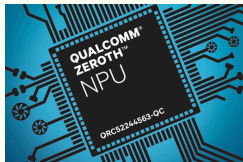
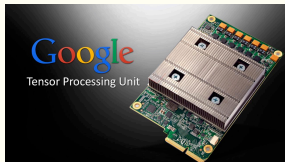


Convolution layer is one of the most expensive layers

- ▶ Computation pattern
- ▶ **Emerging** challenges

More and more end-point devices with limited memory

- ▶ Cameras
- ▶ Smartphone
- ▶ Autonomous driving



1st Challenge: Model Size

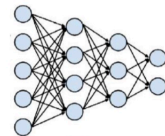


Hard to distribute large models through over-the-air update



This item is over 100MB.
Microsoft Excel will not download until you connect to Wi-Fi.

Cancel OK



2nd Challenge: Energy Efficiency



AlphaGo: 1920 CPUs and 280 GPUs,
\$3000 electric bill per game



on mobile: **drains battery**
on data-center: **increases TCO**



Application Category



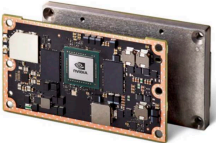
Both	Datacenter	Edge
Intel, Nvidia, IBM, Xilinx, HiSilicon, Google, Baidu, Alibaba Group, Cambricon, DeePhi, Bitmain, Wave Computing	AMD, Microsoft, Apple, Tencent Cloud, Aliyun, Baidu Cloud, HUAWEI Cloud, Fujitsu, Nokia, Facebook, HPE, Thinkforce, Cerebras, Graphcore, Groq, SambaNova Systems, Adapteva, PEZY	Qualcomm, Samsung, STMicroelectronics, NXP, MediaTek, Rockchip, Amazon_AWS, ARM, Synopsys, Imagination, CEVA, Cadence, VeriSilicon, Videantis, Horizon Robotics, Chipintelli, Unisound, AISpeech, Rokid, KnuEdge, Tenstorrent, ThinCI, Koniku, Knowm, Mythic, Kalray, BrainChip, Almotive, DeepScale, Leepmind, Krtkl, NovuMind, REM, TERADEEP, DEEP VISION, KAIST DNP, Kneron, Esperanto Technologies, Gyrfalcon Technology, GreenWaves Technology, Lightelligence, Lightmatter, ThinkSilicon, Innogrit, Kortiq, Hailo, Tachyum

Source: <https://basicmi.github.io/Deep-Learning-Processor-List/>

Flexibility vs. Efficiency



CPU
(Raspberry Pi3)



GPU
(Jetson TX2)

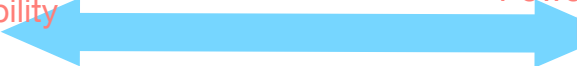


FPGA
(UltraZed)



ASIC
(Movidius)

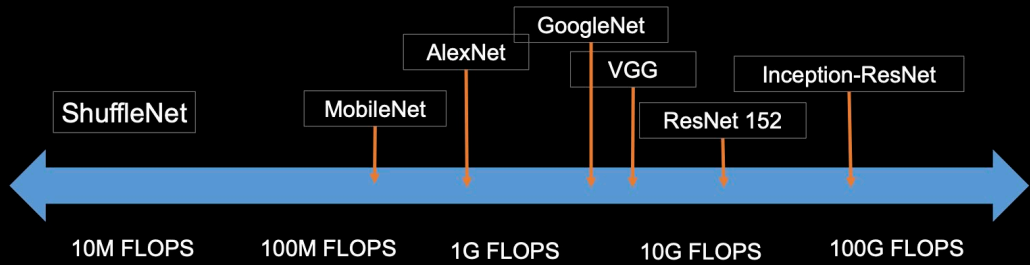
Flexibility



Power/Performance
Efficiency



Computing Spectrum





In-Datacenter Performance Analysis of a Tensor Processing Unit™

Norman P. Jouppi, Cliff Young, Nishant Patil, David Patterson, Gaurav Agrawal, Raminder Bajwa, Sarah Bates, Suresh Bhatia, Nan Boden, Al Borchers, Rick Boyle, Pierre-luc Cantin, Clifford Chao, Chris Clark, Jeremy Coriell, Mike Daley, Matt Dau, Jeffrey Dean, Ben Gelb, Tara Vazir Ghaemmaghami, Rajendra Gottipati, William Gulland, Robert Hagmann, C. Richard Ho, Doug Hogberg, John Hu, Robert Hundt, Dan Hurt, Julian Ibarz, Aaron Jaffey, Alek Jaworski, Alexander Kaplan, Harshit Khaitan, Daniel Killebrew, Andy Koch, Naveen Kumar, Steve Lacy, James Laudon, James Law, Diemthu Le, Chris Leary, Zhuyuan Liu, Kyle Lucke, Alan Lundin, Gordon MacKean, Adriana Maggiore, Maire Mahony, Kieran Miller, Rahul Nagarajan, Ravi Narayanaswami, Ray Ni, Kathy Nix, Thomas Norrie, Mark Omernick, Narayana Penukonda, Andy Phelps, Jonathan Ross, Matt Ross, Amir Salek, Emad Samadiani, Chris Severn, Gregory Sizikov, Matthew Snelham, Jed Souter, Dan Steinberg, Andy Swing, Mercedes Tan, Gregory Thorson, Bo Tian, Horia Toma, Erick Tuttle, Vijay Vasudevan, Richard Walter, Walter Wang, Eric Wilcox, and Doe Hyun Yoon

Google, Inc., Mountain View, CA USA

Email: {jouppi, cliffy, nishantpatil, davidpatterson}@google.com

To appear at the 44th International Symposium on Computer Architecture (ISCA), Toronto, Canada, June 26, 2017.

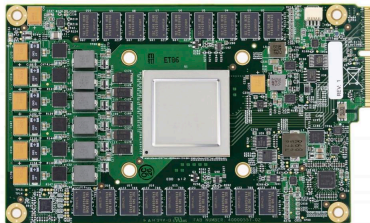


Figure 3. TPU Printed Circuit Board. It can be inserted in the slot for an SATA disk in a server, but the card uses PCIe Gen3 x16.

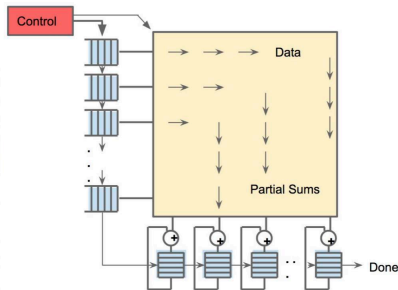


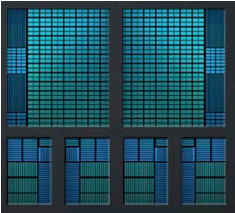
Figure 4. Systolic data flow of the Matrix Multiply Unit. Software has the illusion that each 256B input is read at once, and they instantly update one location of each of 256 accumulator RAMs.

ASIC Example: Intel Movidius

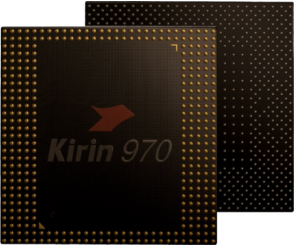


- ▶ [Start Video](#)
- ▶ [Introduction Link 2](#)

Other ASIC Examples



(a) A11



(b) Kirin970



(c) Snapdragon845



Microsoft: FPGA Wins Versus Google TPUs For AI



Moor Insights and Strategy Contributor

GUEST POST WRITTEN BY

Karl Freund

Karl Freund

Karl Freund is Sr. Analyst, Machine Learning and HPC, Moor Insights & Strategy



The Microsoft Brainwave mezzanine card extends each server with an Intel Altera Stratix 10 FPGA accelerator, synthesized to act as a "Soft DNN Processing Unit," or DPU, and a fabric interconnect that enables datacenter-scale persistent neural networks. MICROSOFT



FPGA云服务器

FPGA 云服务器 (FPGA Cloud Computing) 是基于FPGA (Field Programmable Gate Array) 现场可编程阵列的计算服务, 您只需单击几下即可在几分钟内轻松获取并部署您的FPGA计算实例。您可以在FPGA实例上编程, 为您的应用程序创建自定义硬件加速。我们为您提供可重编程的环境, 您可以在FPGA实例上多次编程, 而无需重新设计硬件, 让您更加专注于业务发展。

[立即申请](#)

🔔 申请使用资格, 将有专人为您提供服务与报价

[了解更多 >>](#)



[产品介绍](#)

[产品优势](#)

[产品功能](#)

[应用场景](#)

[产品文档](#)



百度云 产品 解决方案 云市场 合作与生态 帮助与支持 登录 注册 备案 论坛 管理控制台

FPGA云服务器

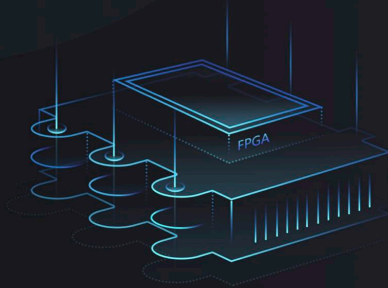
FPGA Cloud Compute

配备现场可编程门阵列 (Field Programmable Gate Array) 的高性能云计算服务。同时具备开发、模拟、调试和编译硬件代码所需的各种资源, 您可以基于FPGA云服务器为您的应用程序创建自定义的硬件加速能力。

[申请公测](#) [帮助文档 >](#)

[产品概述](#) [产品功能](#) [产品优势](#) [应用场景](#) [相关产品](#) [使用指南](#)

产品概述





News Byte

October 12, 2017

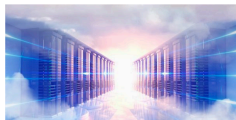
Share this Article



Contact Intel PR

INTEL FPGAS POWER ACCELERATION-AS-A-SERVICE FOR ALIBABA CLOUD

Intel today announced that Intel® field programmable gate arrays (FPGAs) are now powering the Acceleration-as-a-Service of Alibaba Cloud*, the cloud computing arm of Alibaba Group. The acceleration service, which can be launched from the Alibaba Cloud website, enables customers to develop and deploy accelerator solutions in the cloud for Artificial Intelligence inference, video streaming analytics, database acceleration and other fields where intense computing is required.



Xilinx Selected by Alibaba Cloud for Next-Gen FPGA Cloud Acceleration

Xilinx FPGAs are accelerating machine learning and other critical compute workloads for one of the world's largest cloud providers

Oct 12, 2017

HANGZHOU, China, Oct. 12, 2017 /PRNewswire/ -- Xilinx, Inc. (NASDAQ: XLNX) today announced at the Computing Conference that Alibaba Cloud, the cloud computing arm of Alibaba Group, has chosen Xilinx for next generation FPGA acceleration in their public cloud. As the largest cloud provider in China, Alibaba Cloud offers high-performance, elastic computing power to over two million customers. Based on Xilinx® FPGAs, the new "F2" instances give Alibaba Cloud customers access to acceleration for data analytics, genomics, video processing, and machine learning workloads.






NVIDIA CEO Says "FGPA is Not the Right Answer" for Accelerating AI



<https://medium.com/syncedreview/nvidia-ceo-says-fgpa-is-not-the-right-answer-for-accelerating-ai-83c810969edd>

CPU Example: Arduino



	Arduino	FPGA	ASIC
Shortcut	---	Field Programmable Gate Array	Application Specific Integrated Circuit
Shape			
Size	Medium	Medium	Very Tiny

CPU Example: Arduino



Arduino	FPGA	ASIC
		
		

CPU Example: Arduino



	Arduino	FPGA	ASIC
Cost	Sheap	Expensive	Expensive
Programing	Re-programmable	Re-programmable	Not-programmable
Design speed	Normal	Fast	FAST
Security	No	Yes	Yes
Sequential	Yes	No	No
Con-current	No	Yes	Yes
Source	Open source	----	----

Arduino + FPGA board



Arduino MKR Vidor 4000: combines a fast ARM microcontroller, WiFi, Bluetooth, and an FPGA.

Comparisons: FPGA, ASIC, GPU⁵



	Xilinx ZCU102	Xilinx ZCU104	Huawei Atlas 200	nVIDIA Jetson TX2	Cambricon MLU 270
price	3K RMB	2K RMB	4K RMB	2.8K RMB	12K RMB
MobileNet-V1	1.14 ms	1.37 ms	1.8 ms	12.44 ms	1.85 ms
ResNet50	5.23 ms	6.81 ms	3.6 ms	24.70 ms	2.54 ms
Inception_v2	2.68 ms	3.35 ms	6.0 ms	10.81 ms	5.12 ms
Inception_v3	6.44 ms	8.53 ms	5.7 ms	32.53 ms	4.71 ms
Inception_v4	11.87 ms	17.06 ms	9.3 ms	44.37 ms	11.33 ms

⁵price is NOT accurate – reference purpose.