Lecture 1:
Introduction to Computer Vision and Deep Learning

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Face++ 旷视

Agenda

- What is Computer Vision
- A few milestones in Computer Vision
- Deep learning for Computer Vision
- Applications
- Course overview

Computer Vision in AI

Perceptual Cognitive

Speech

NLP

Vision

AGI：reasoning, self-learning, interacting…

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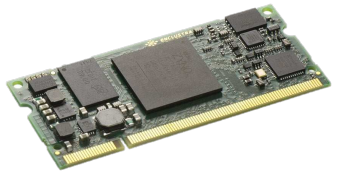
Speech UI
Image/Video Recognition
Autonomous Driving
Robotics

Language Understanding
Conversation/Chat
Personal Assistant
AlphaGo



，Finance，Medical，Education，…

技术领先 近十年唯一中国企业入选MIT Tech Review全球前沿技术

10 Breakthrough Technologies

2017

These technologies all have staying power. They will affect the economy and our politics, improve medicine, or influence our culture. Some are unfolding now; others will take a decade or more to develop. But you sho about all of them right now.

Paying with Your Face

Face-detecting systems in China now authorize payments, provide access to facilities, and track down criminals. Will other countries follow?

50 Smartest Companies 2017

1 Nvidia
2 SpaceX
3 Amazon
4 23andMe
5 Alphabet
6 iFlytek
7 Kite Pharma
8 Tencent
9 Regeneron
10 Spark Therapeutics
11 Face ++

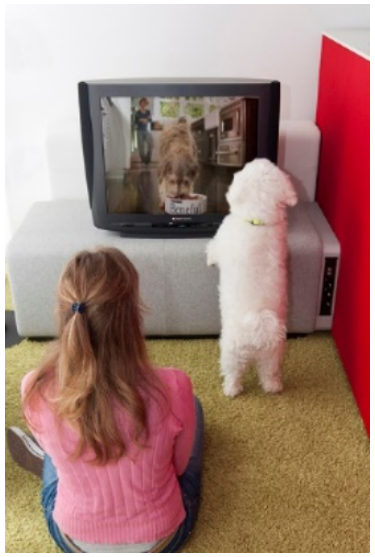
MIT Tech Review全球50最聪明的公司

A picture is worth a thousand words

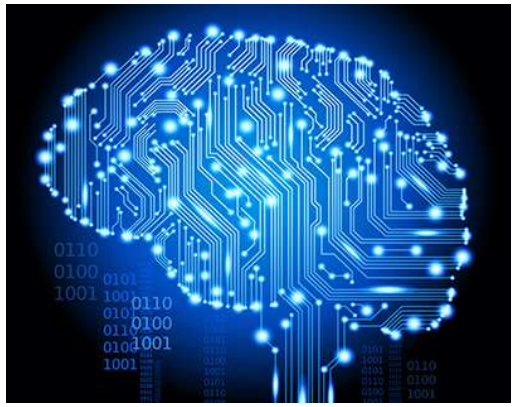
A picture is worth a thousand words

Computer Vision

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



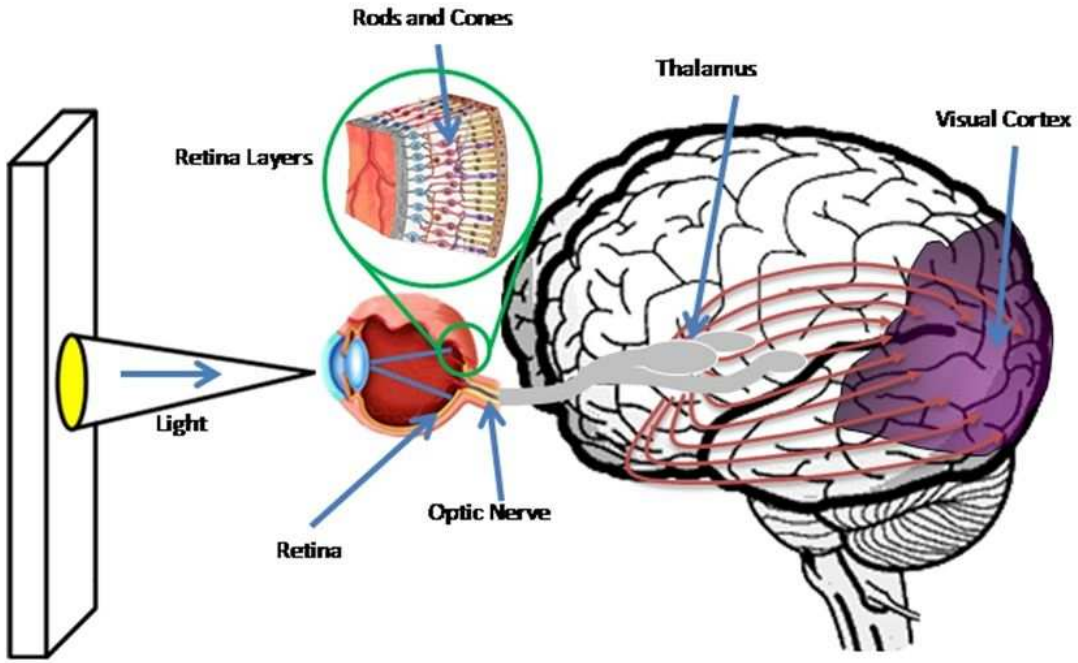
“Eyes”

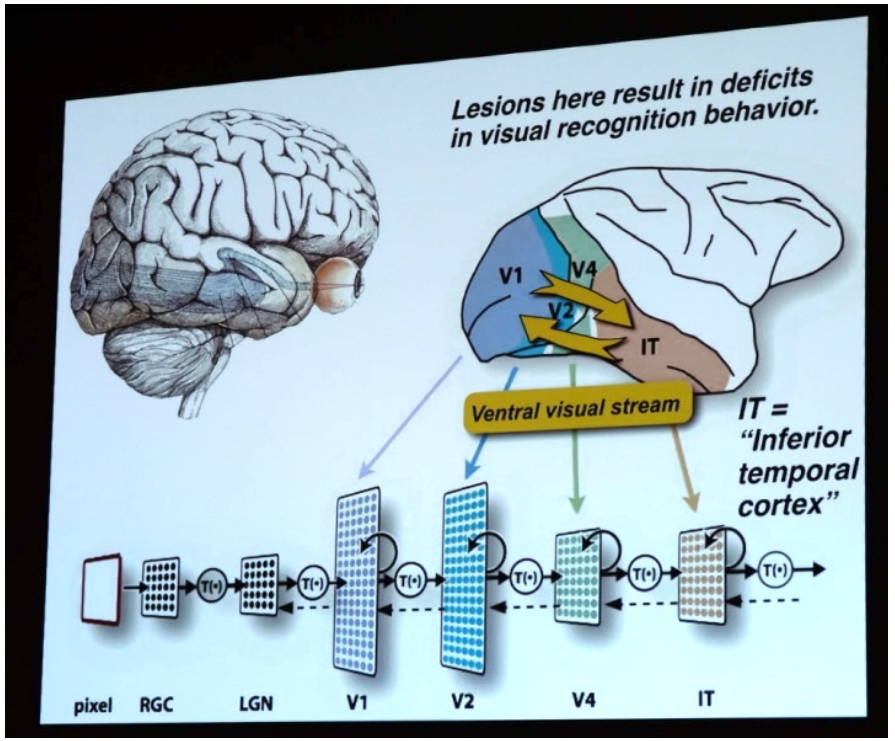


“Brain”

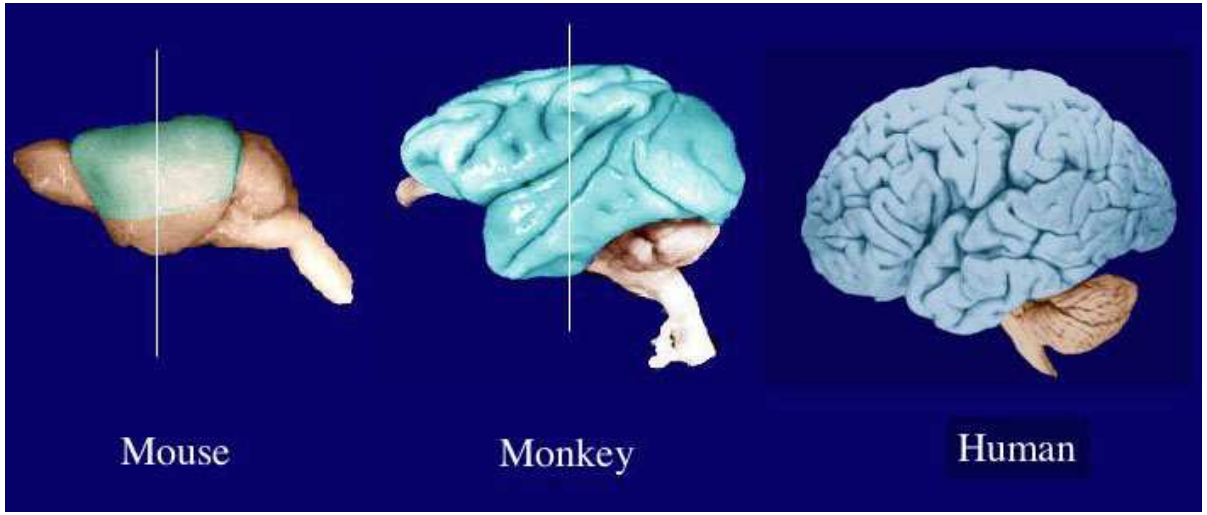
Objects
Activities
Scenes
Locations
Text
Faces
Gestures
Motions
Emotions…

Human Visual System





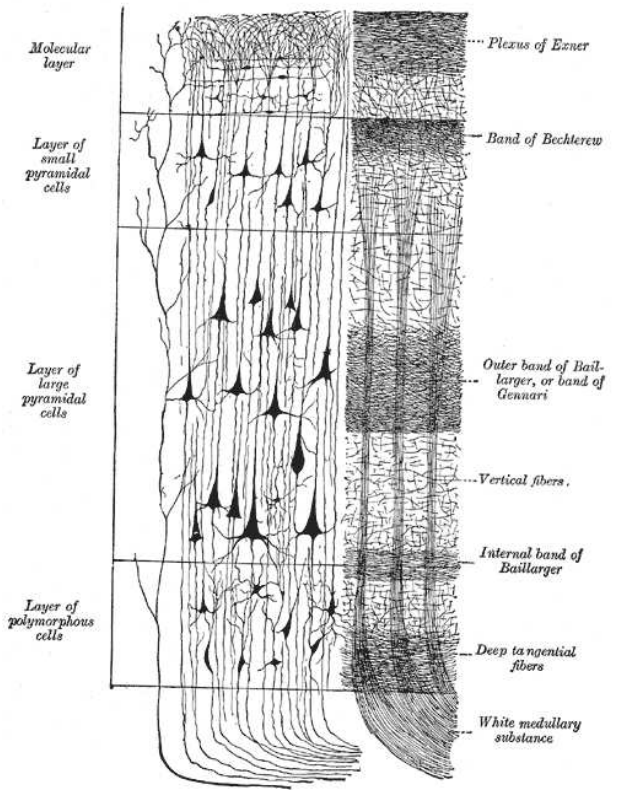
大脑皮层



- 6层，每层2毫米厚

- 300亿个神经元(neurons), 每个有几千个其他相连接。他们包含了我们所有的记忆，知识，技能，生活经验。物理上是毫无二至的表面，没有明显的边界和分区。

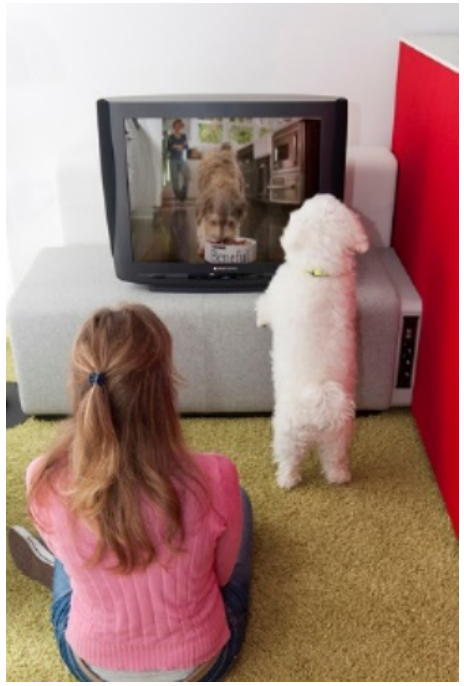
- 层级结构：视觉有V1，V2, V4，IT区，MT负责运动检测，A1的听觉区域，S1的初级体感。还有联合区域接受多个感官的输入。M1负责向脊髓传送指令驱动肌肉



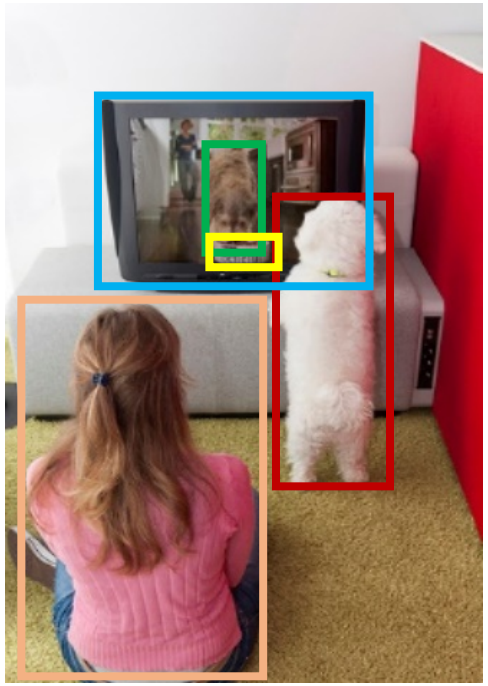
Computer Vision and AI

- A quest to AI
  - “ If we want our machines to think, we need to teach them to see.” – Feifei Li
- A driving force of AI
  - Convolutional Neural Network
  - Batch normalization, attention, residual learning
- Key application of AI

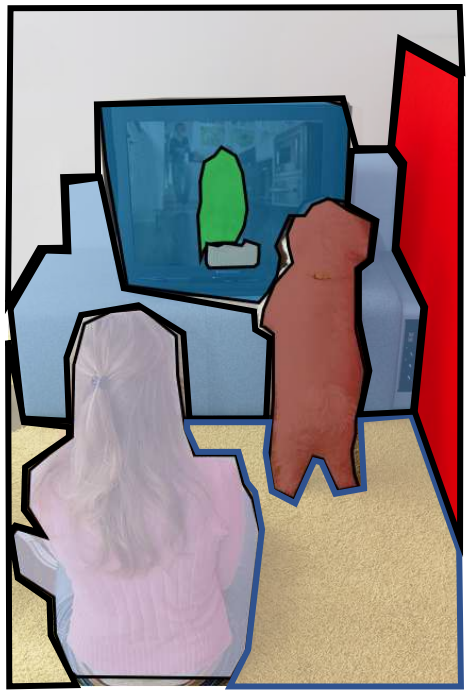
A Few Core Problems



Classification



Detection



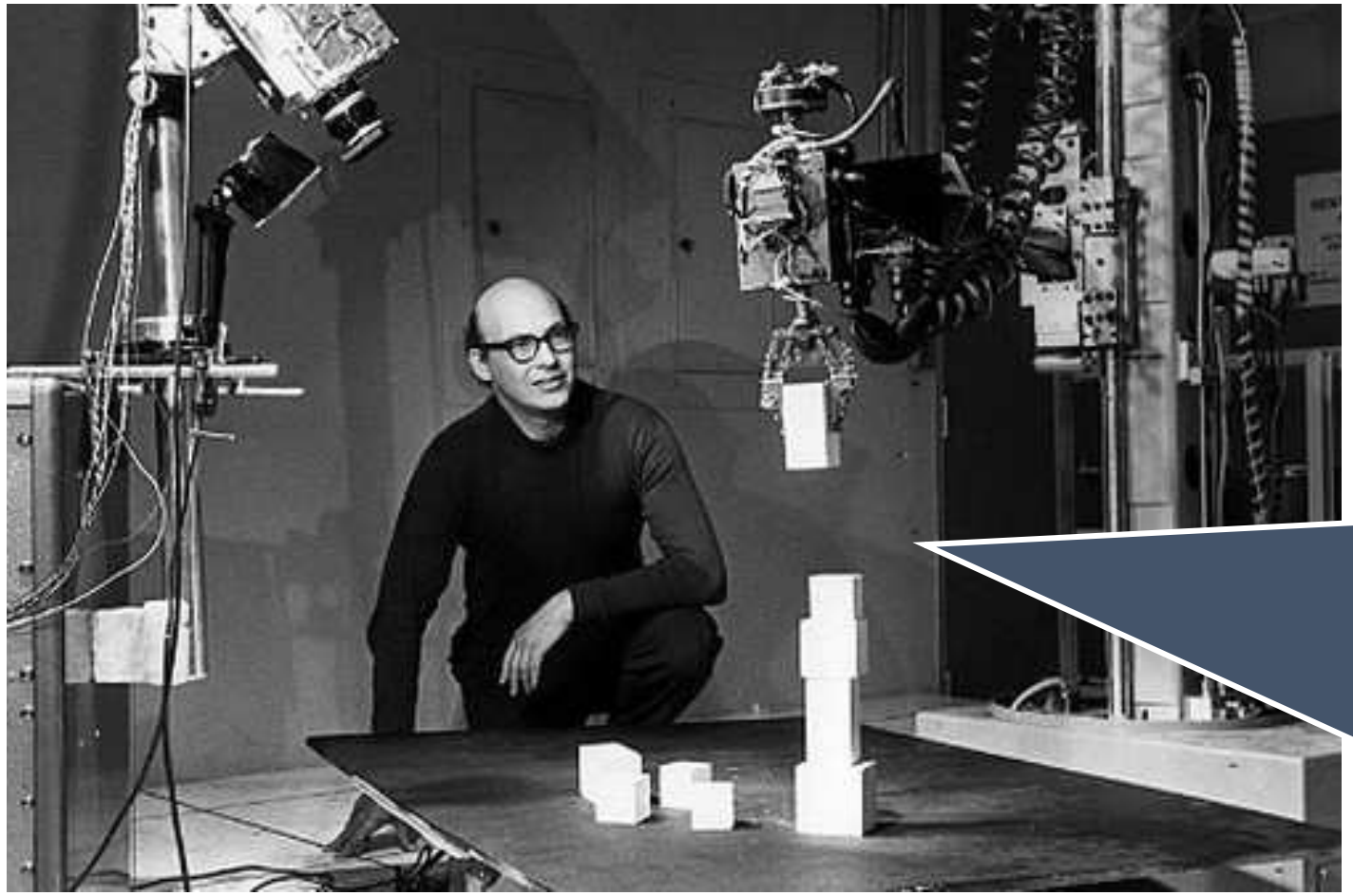
Segmentation

Sequence

Image → Region → Pixel

Video

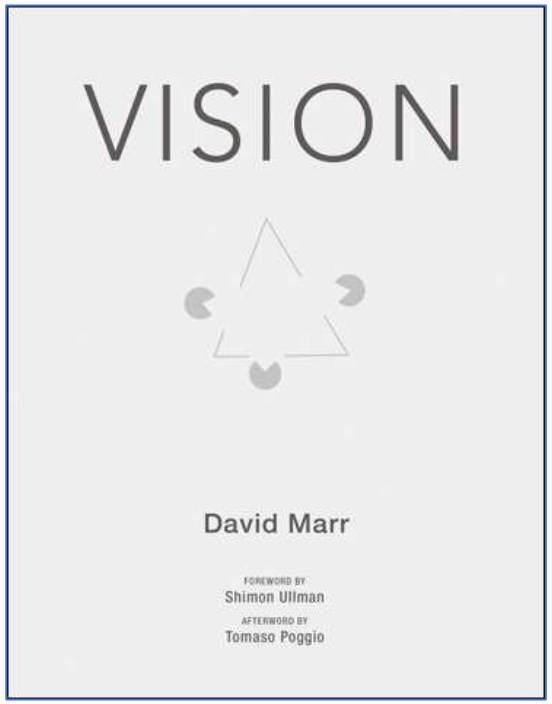
Computer Vision
Since the beginning of Artificial Intelligence



"Connect a television camera to a computer and get the machine to describe what it sees."

—Marvin Minsky (1966)

David Marr

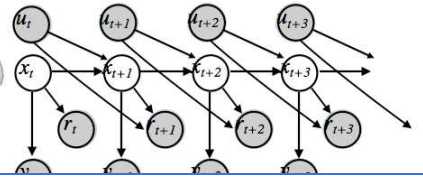


Three levels of description *(David Marr, 1982)*

Computational
Why do things work the way they do?
What is the goal of the computation?
What are the unifying principles?

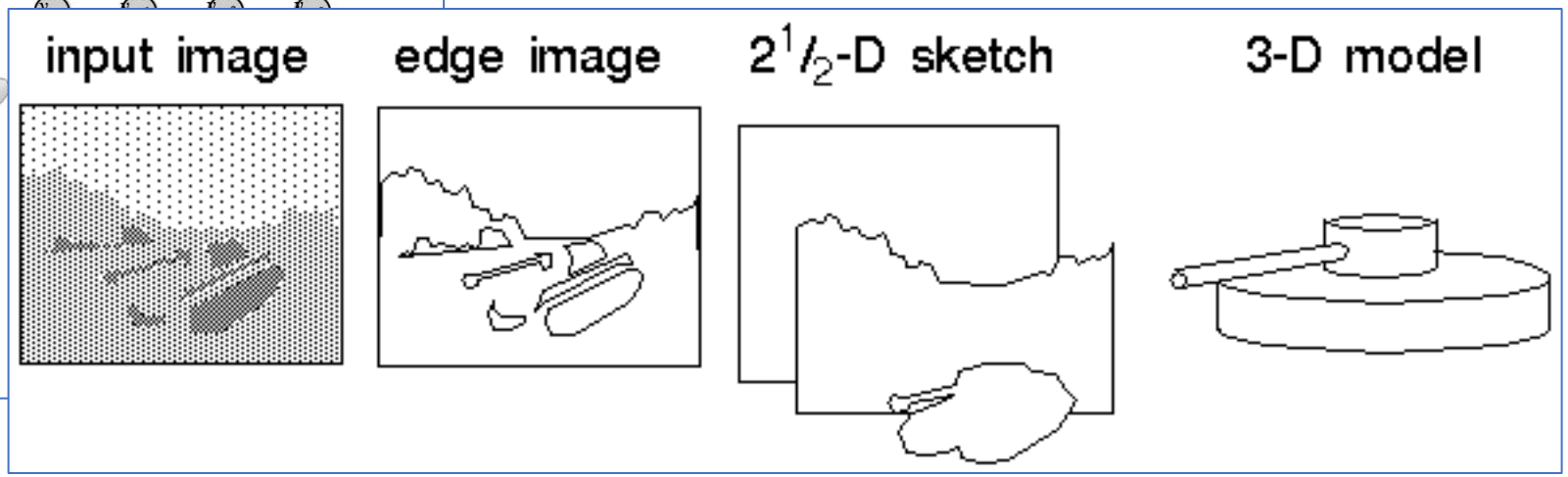
maximize:

$$R_t = r_{t+1} + r_{t+2} + \cdots + r_T$$



Algorthmic
What representations can implement such computations?
How does the choice of representations determine the algorithm?

Implementational
How can such a system be built in hardware?
How can neurons carry out the computations?

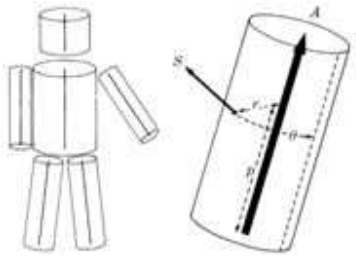


When David Marr at MIT moved into computer vision, he generated a lot of excitement, but he hit up against the problem of knowledge representation; he had no good representations for knowledge in his vision systems.

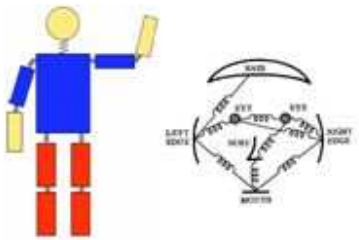
— Marvin Minsky —

AZ QUOTES

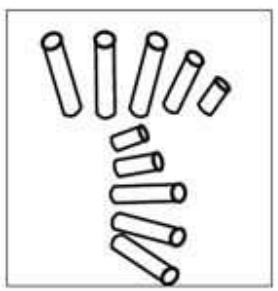
Part Representation



Marr & Nishihara 1978



Fischler & Elschlager 1973
Felzenszwalb & Huttenlocher 2005



Part Representation

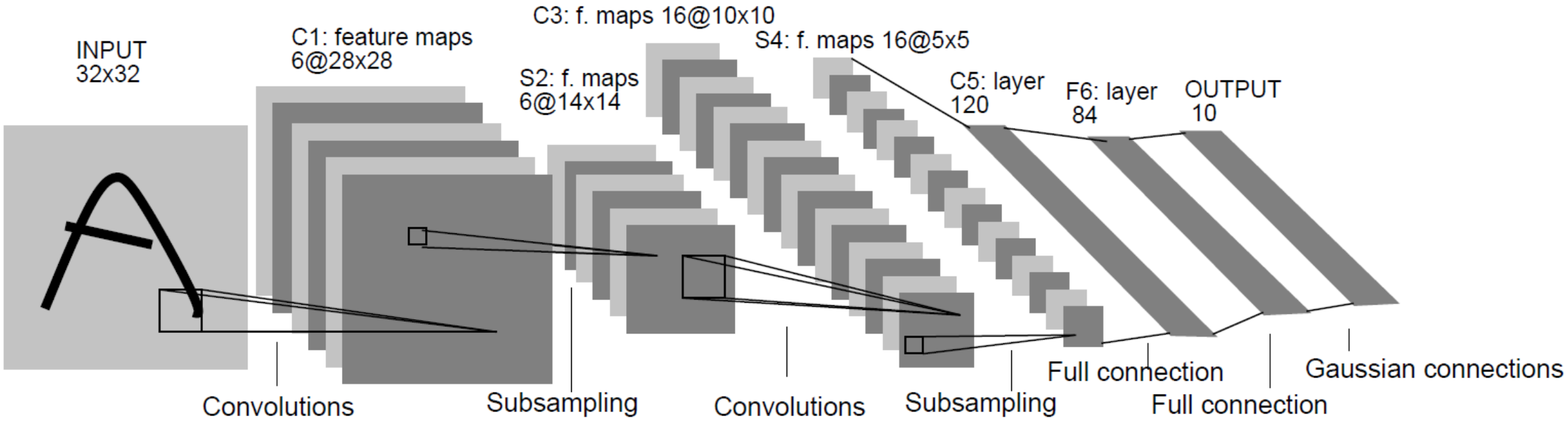
- Head, Torso, Arm, Leg
- Location, Rotation, Scale

Pictorial Structure

- Unary Templates
- Pairwise Springs

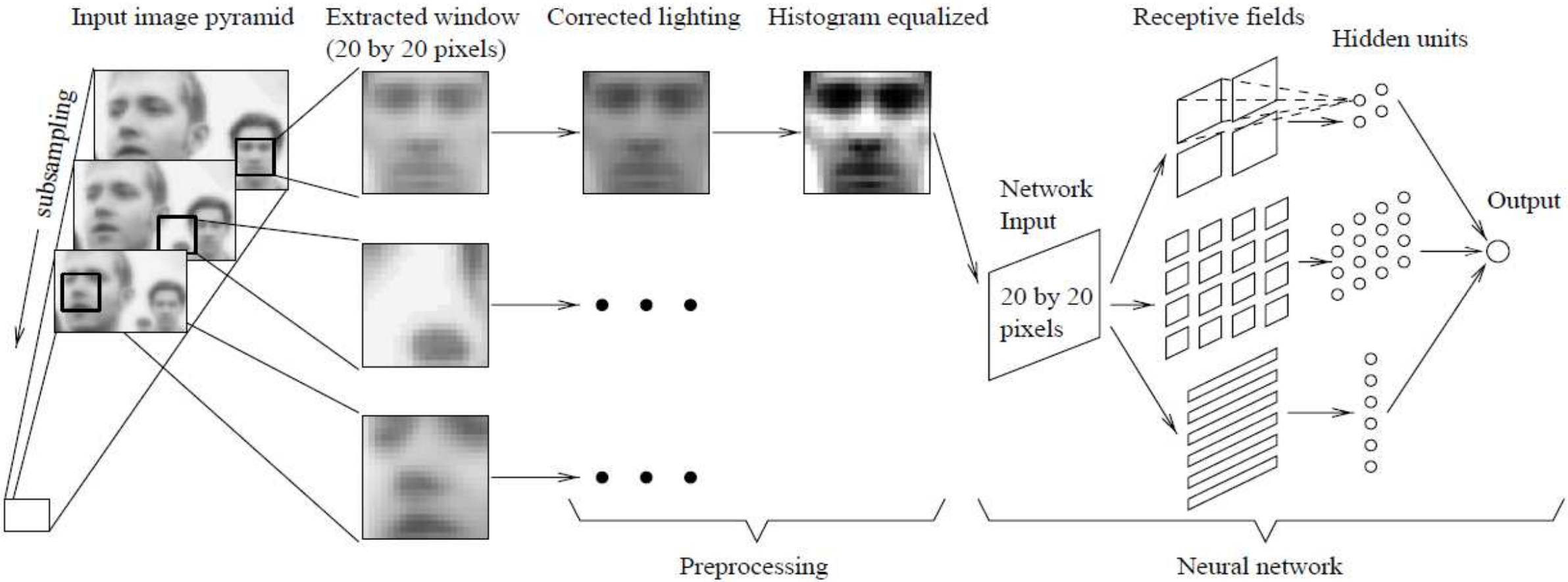
Lan & Huttenlocher 2005
Sigal & Black 2006
Ramanan 2007
Epshteian & Ullman 2007
Wang & Mori 2008
Ferrari etc. 2008
Andriluka etc. 2009
Eichner etc. 2009
Singh etc. 2010
Johnson & Everingham 2010
Sapp etc. 2010
Tran & Forsyth 2010

1989 Digits



Source: Backpropagation Applied to Handwritten Zip Code Recognition, Lecun et al., Neural Computation 1989

1998 Faces



Source: Neural Network-Based Face Detection, Rowley et. al., PAMI 1998

The fall of neural networks

Became unpopular in the mid 1990s

The rise of Support Vector Machines (SVMs)

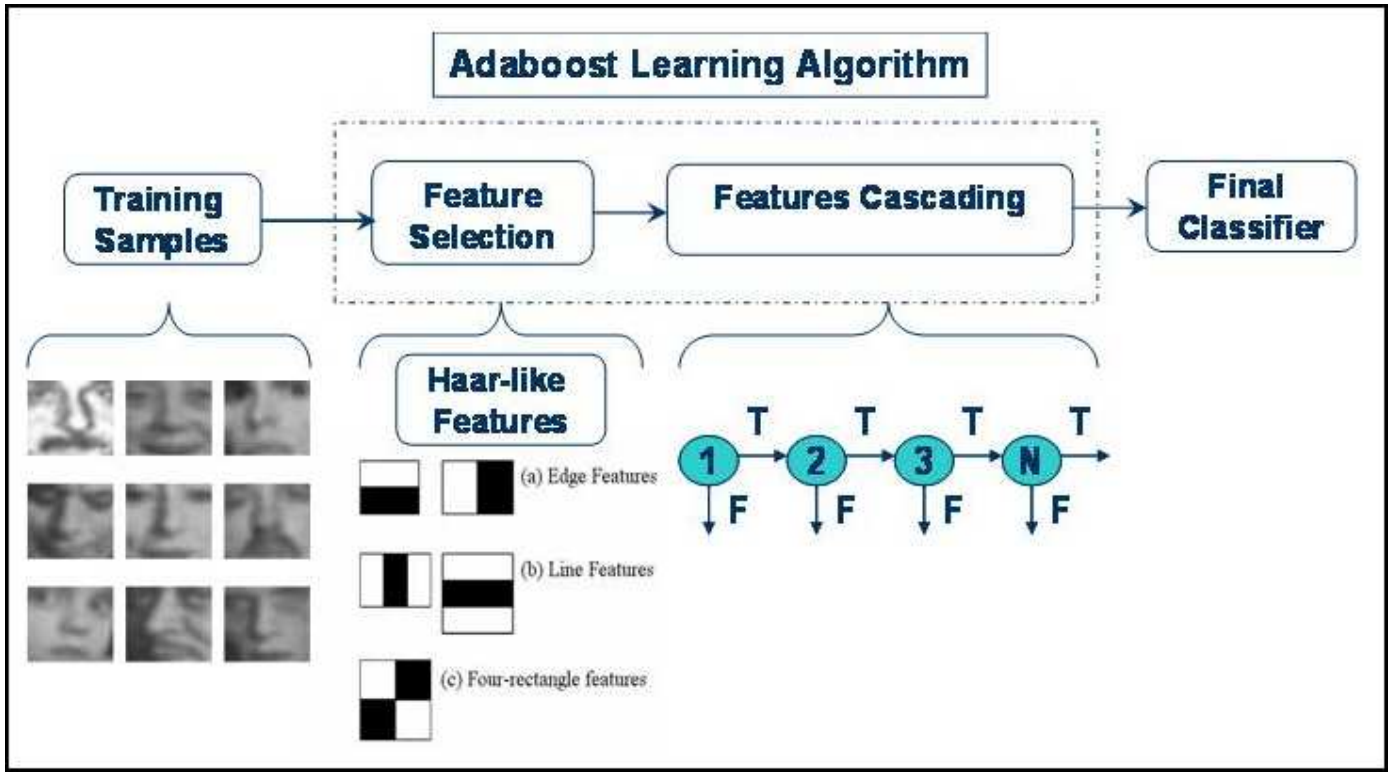
Mathematical advantages (theory, convex optimization)

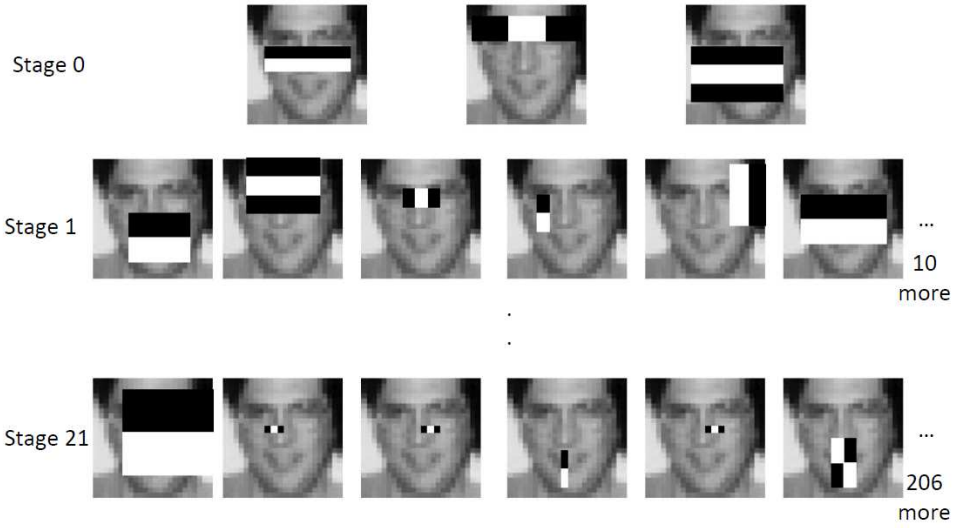
Insensitive datasets

Competitive performance on MNIST digit classification

All methods look competitive

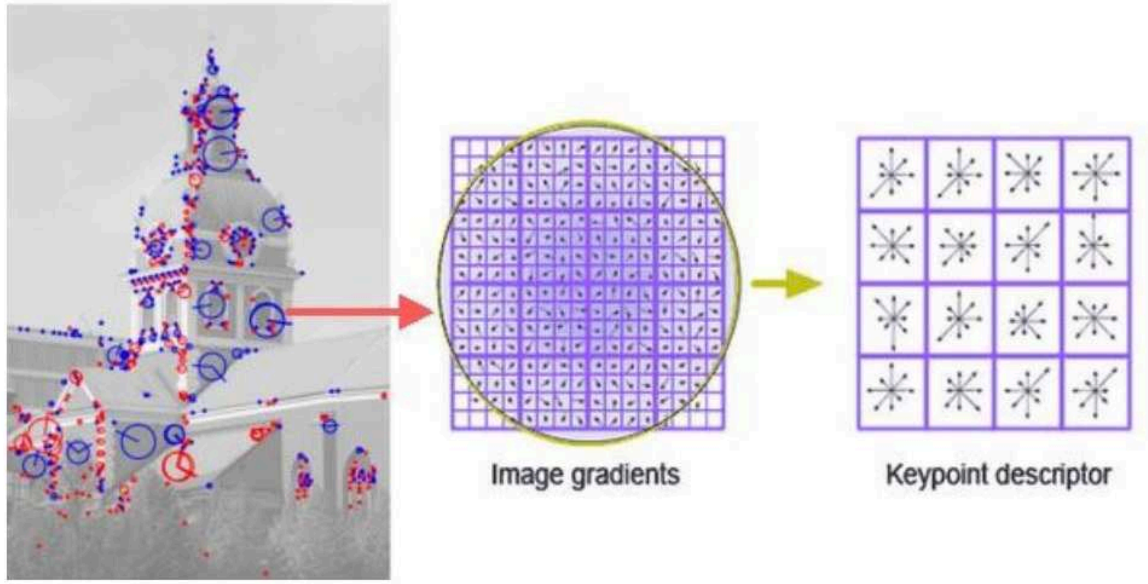
Learning-based Representation

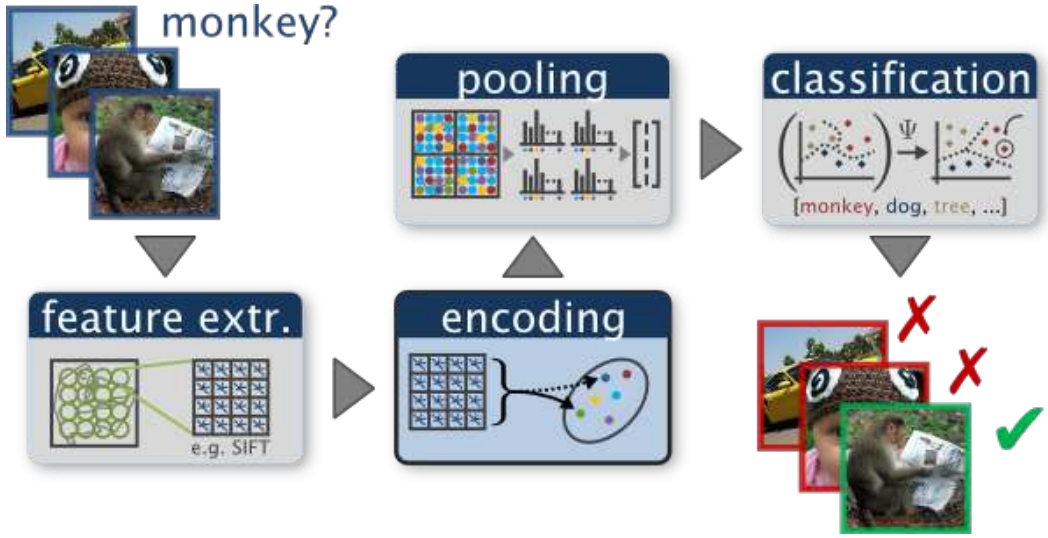




Viola & Jones. Robust Real-time Object Detection, IJCV 2001

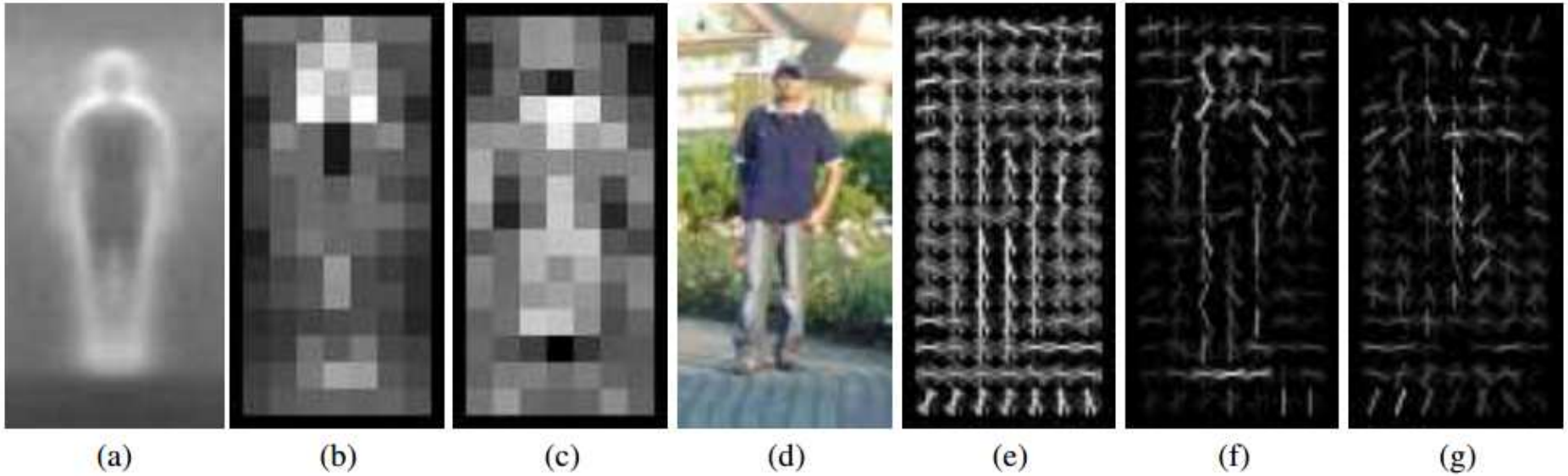
Feature-based Representation: SIFT/HOG





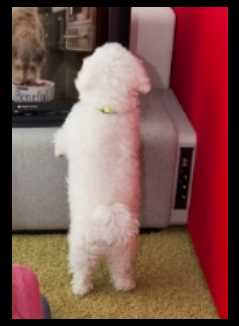
David Low. Distinctive Image Features from Scale-Invariant Keypoints. IJCV 2004.

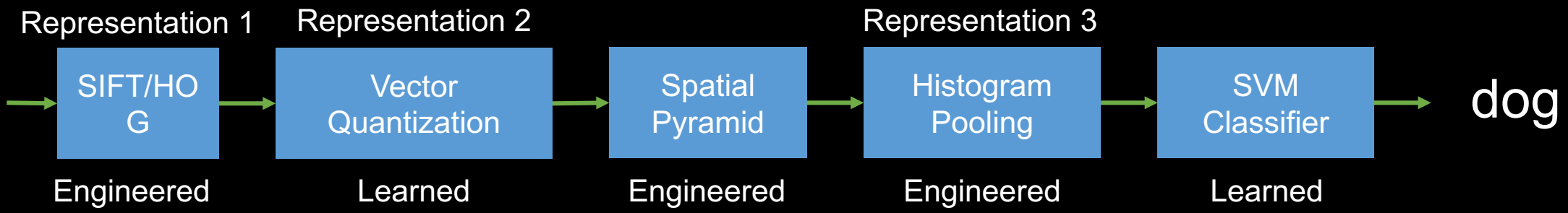
The key to SVM/Random Forest
It's all about having good features



Source: Histograms of Oriented Gradients for Human Detection, Dalal and Triggs, CVPR 2005 (**9.6k** citations)
Distinctive Image features from scale-invariant keypoints, Lowe, ICCV 1999, IJCV 2004 (**35k** citations)

Features Engineering + SVM/Random Forest

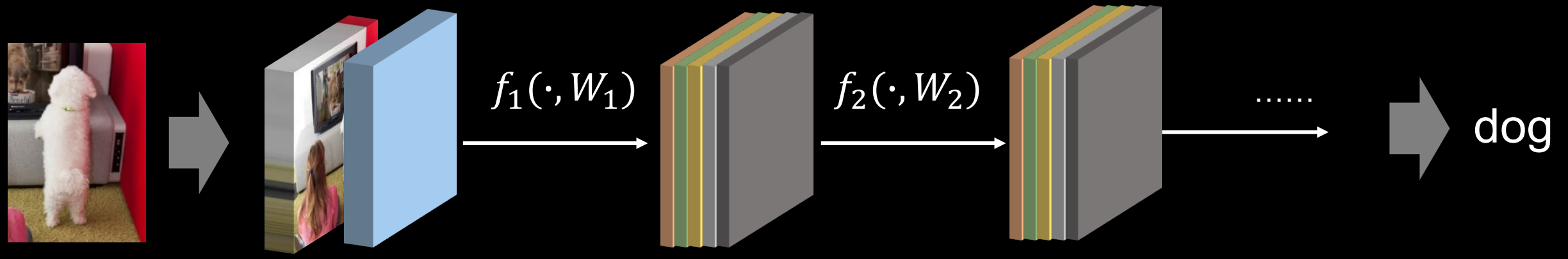




A short sequence of learned *non-linear* transformations

Too much "hand engineering" of features/parameters

Deep Convolutional Neural Networks



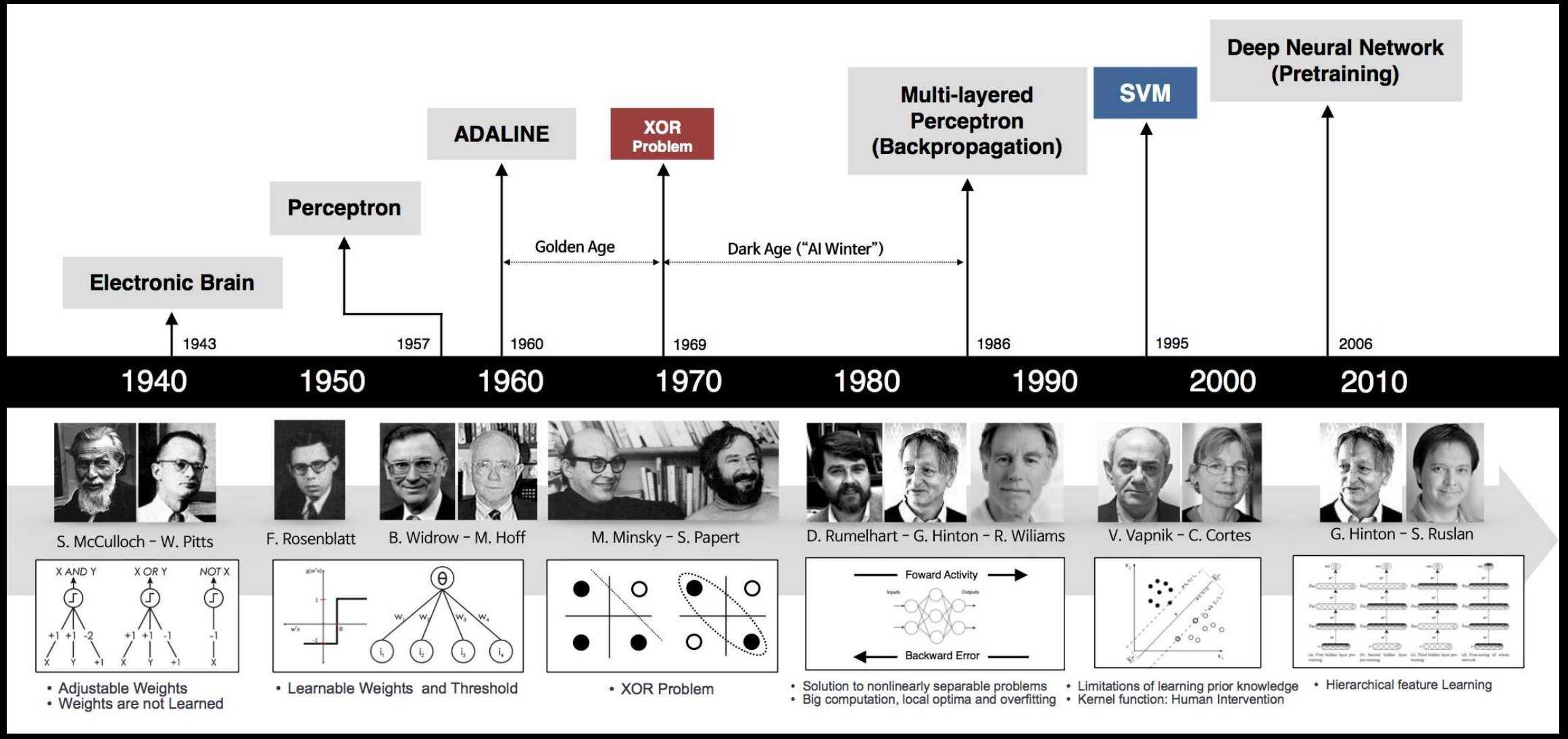
$$CNN(x) = f_5(f_4(f_3(f_2(f_1(\mathrm{x}, W_1), W_2), W_3), W_4), W_5)$$

A long sequence of learned *non-linear* transformations

End-to-end learning - all of the free parameters are jointly optimized

Krizhevsky, A., Sutskever, I. and Hinton, G. E. "ImageNet Classification with Deep Convolutional Neural Networks". NIPS 2012.

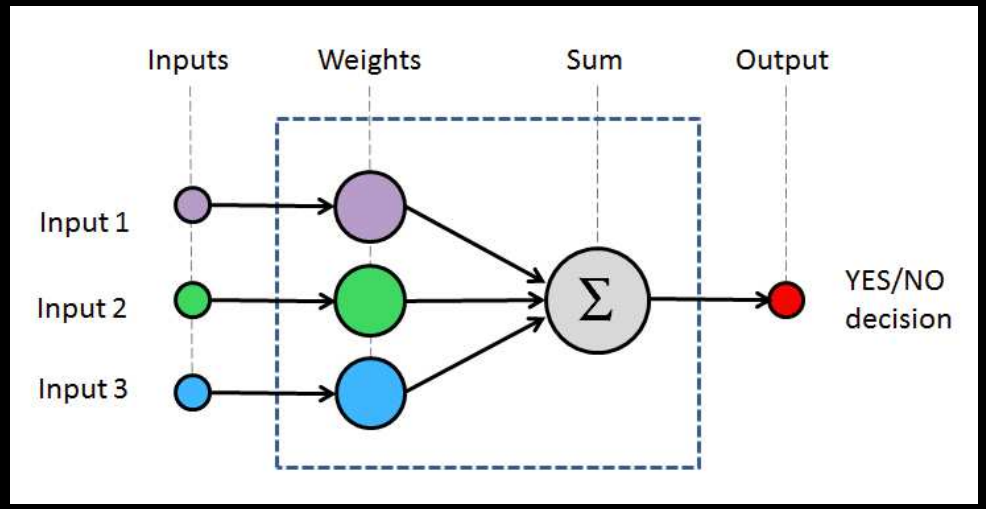
A Bit of History



The Perceptron (1957)

- "*The Navy revealed the embryo of an electronic computer today that it expects will be able to walk, talk, see, write, reproduce itself an be conscious of its existence*"

  – The New Yorker Times



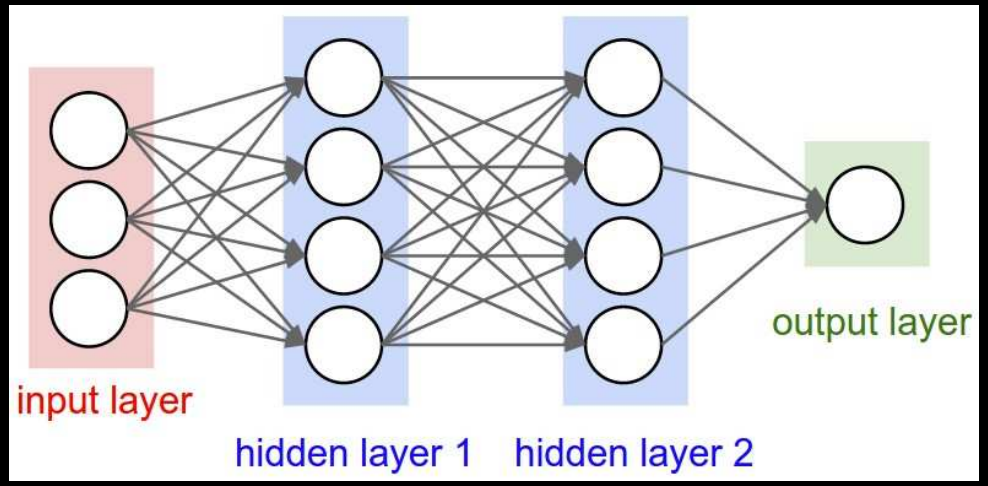
"Neuron"

A	B	
0	0	0
0	1	1
1	0	1
1	1	0

Rosenblatt, Frank. The Perceptron--A Perceiving and Recognizing Automaton. Technical Report, Cornell 1957.

MultiLayer Perceptron (MLP)

- “Any function can be approximated arbitrarily closed by a MLP.”

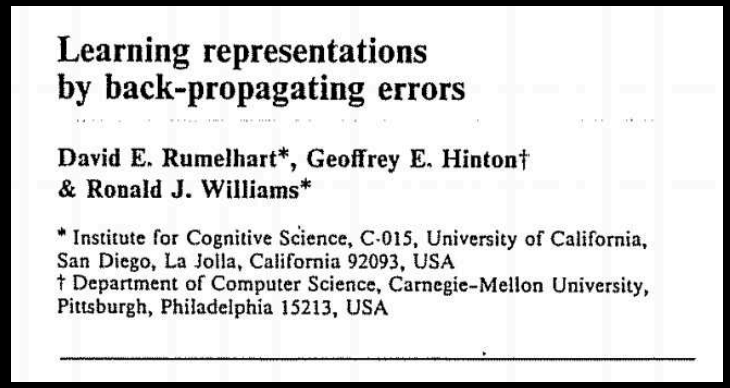


- A visual proof: http://neuralnetworksanddeeplearning.com/chap4.html

Marvin Minsky and Seymour Papert. Perceptrons: An Introduction to Computational Geometry. MIT Press 1969.

Backpropagation (BP)

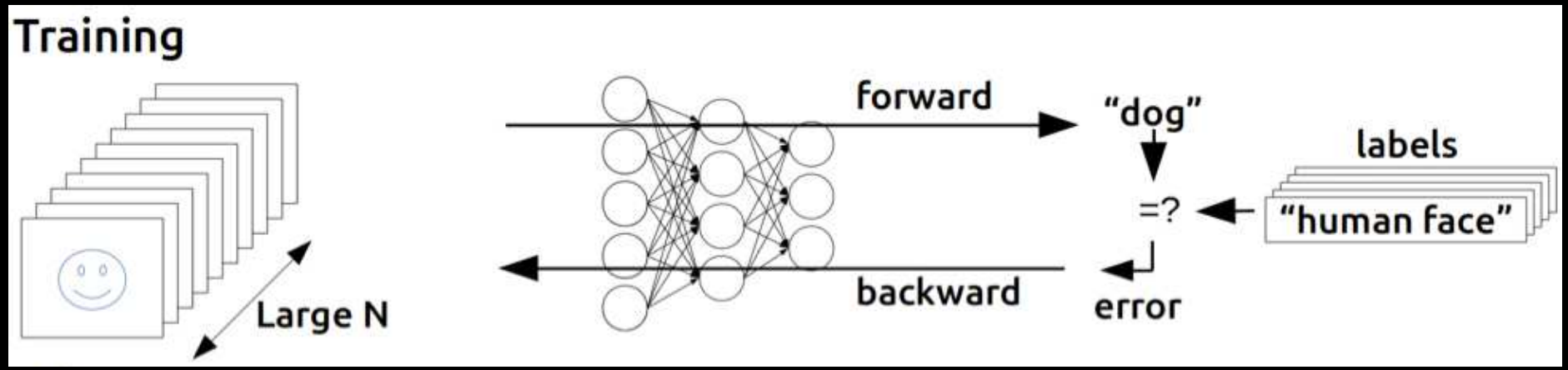
- Discovered multiple times (1968,1982,1986)



Learning representations
by back-propagating errors

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

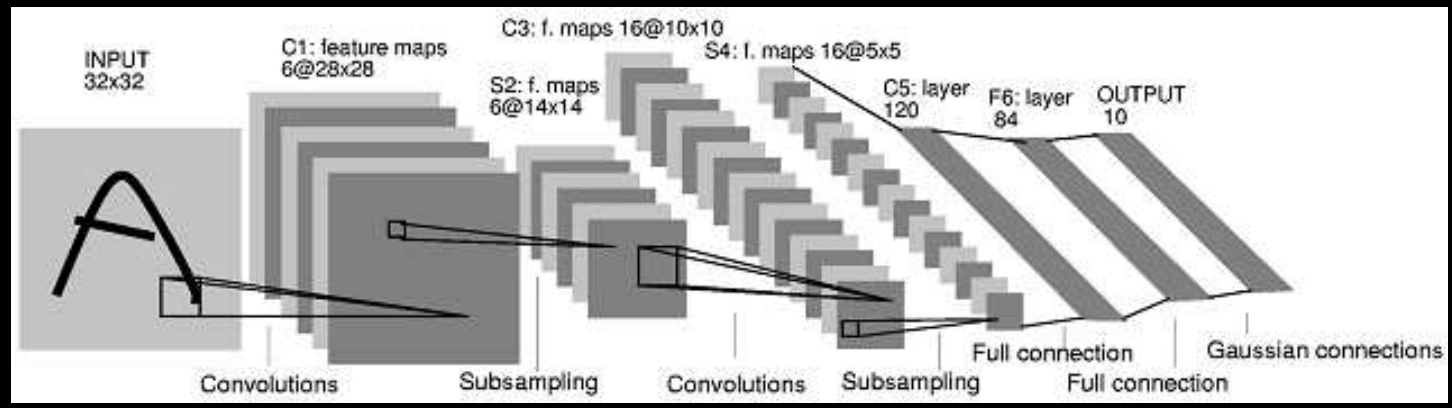
* Institute for Cognitive Science, C-015, University of California, San Diego, La Jolla, California 92093, USA
† Department of Computer Science, Carnegie-Mellon University, Pittsburgh, Philadelphia 15213, USA



David E. Rumelhart, Geoffrey Hinton, Ronald J. Willians. Learning Representations by Back-propagating Errors. *Nature*, 1986.

Neural Networks in 90’

- Convolutional Neural Networks [LeCun et.al. 1989]



- Autoencoder
- Boltzmann Machine
- Belief Nets
- Recurrent Neural Networks (RNNs)

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

魔咒：

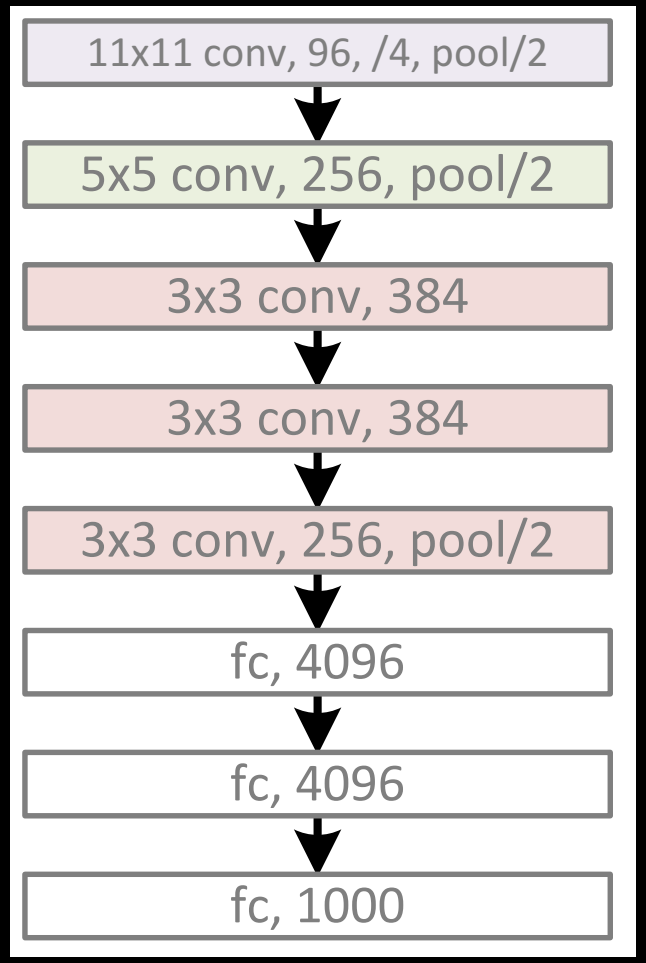
“Deep neural networks are no good and could never be trained.”

Renaissance of Deep Learning (2006-)

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

Revolution of depth

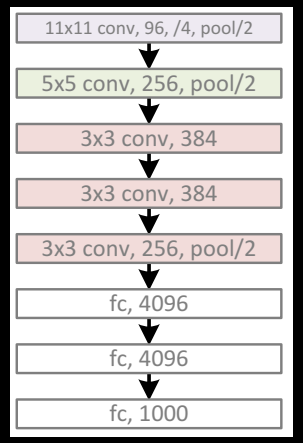
AlexNet, 8 layers
(ILSVRC 2012)



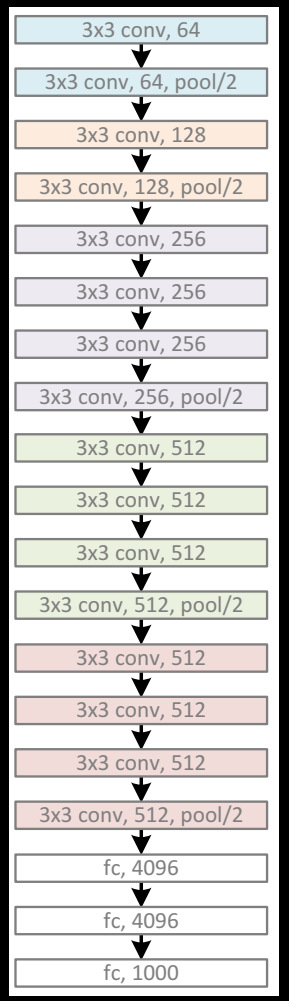
ILSVRC (ImageNet Large Scale Visual Recognition Challenge)

Revolution of depth

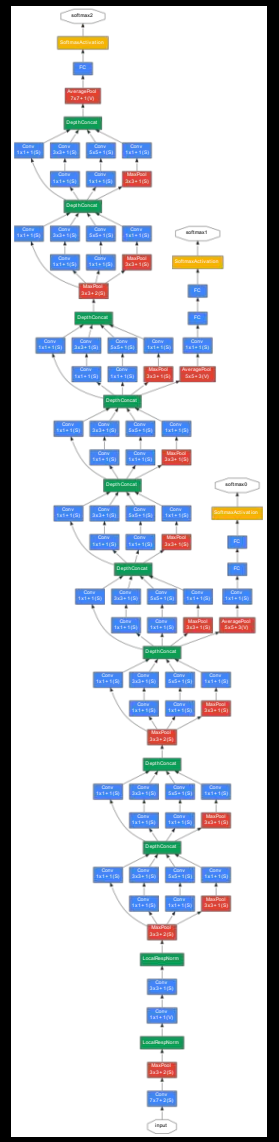
AlexNet, 8 layers
(ILSVRC 2012)



VGG, 19 layers
(ILSVRC 2014)



GoogleNet, 22 layers
(ILSVRC 2014)



ILSVRC (ImageNet Large Scale Visual Recognition Challenge)

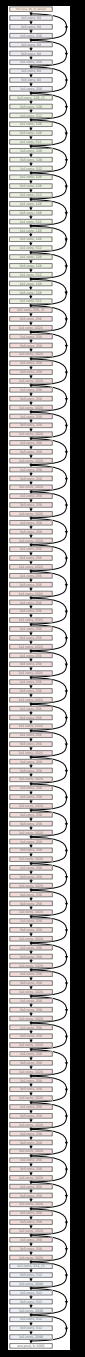
Revolution of depth

AlexNet, 8 layers
(ILSVRC 2012)

VGG, 19 layers
(ILSVRC 2014)

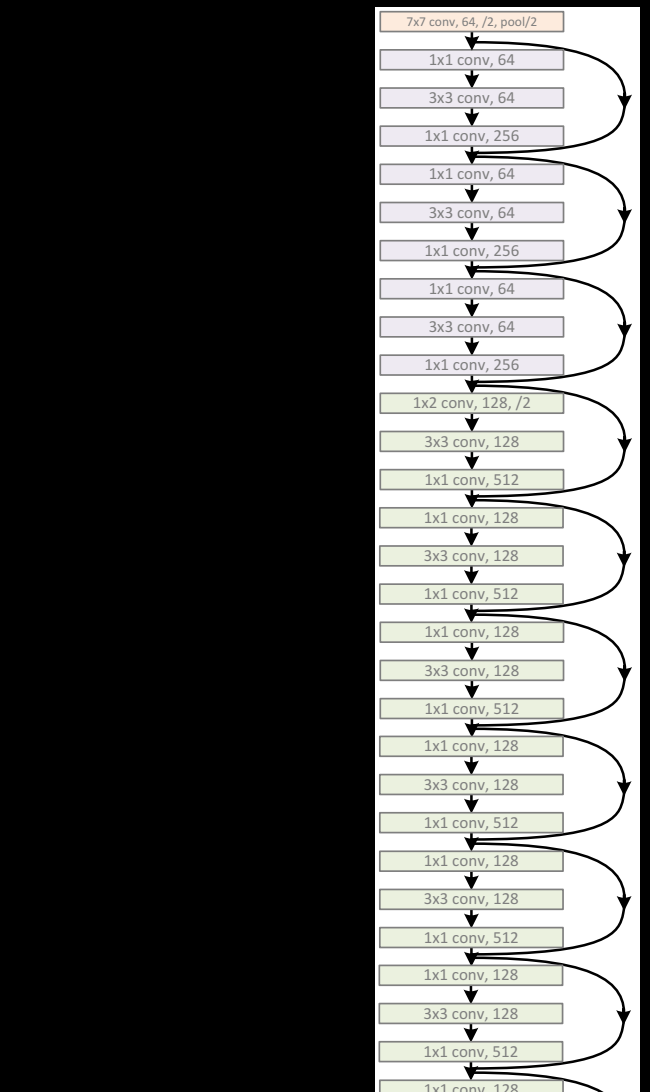
ResNet, 152 layers
(ILSVRC 2015)

Microsoft



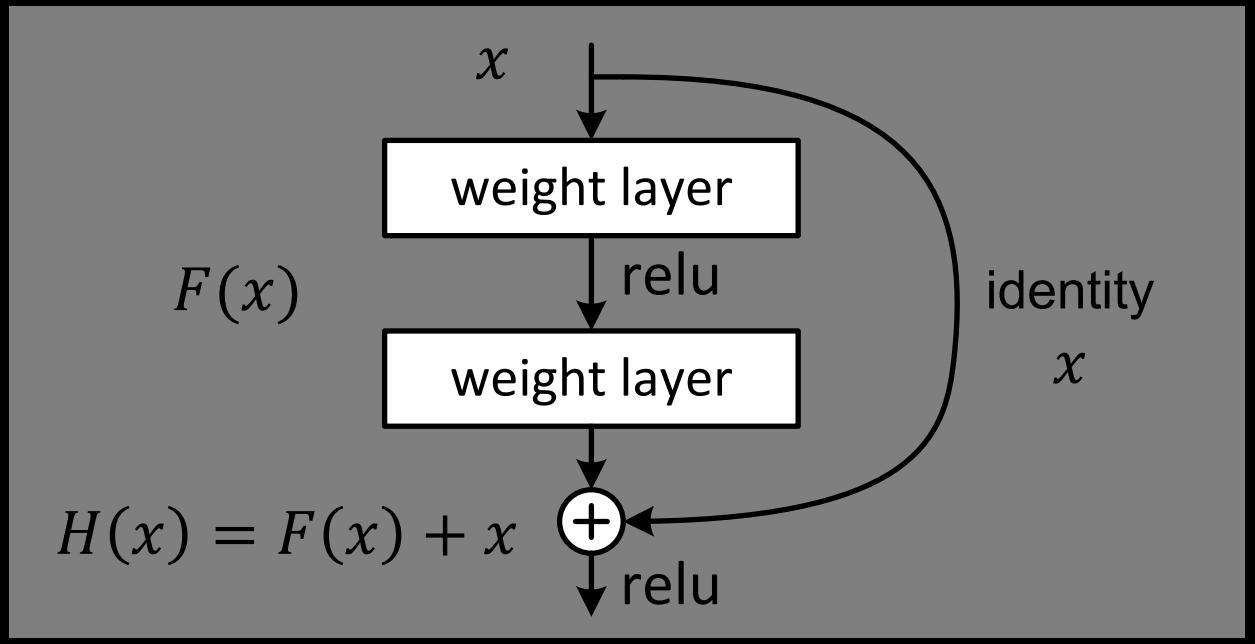
ILSVRC (ImageNet Large Scale Visual Recognition Challenge)

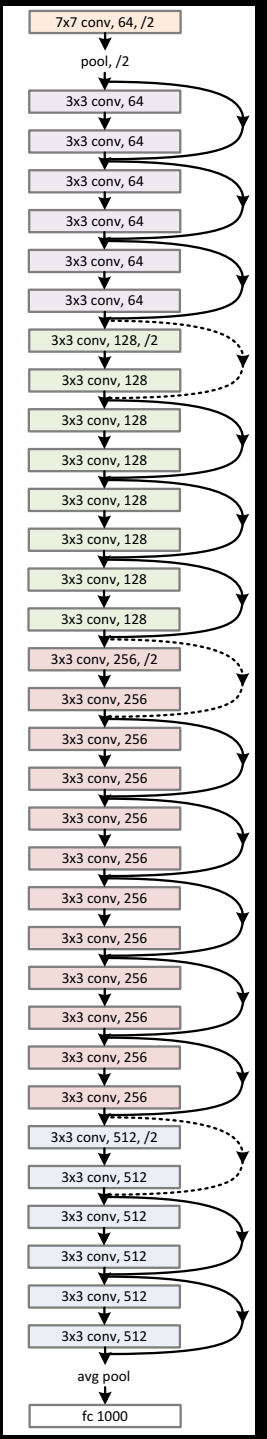
ResNet (152 layers)



Design of ResNet

- Key ideas:
  - skip connection = “residual function”
  - the shortest path contains only a few layers

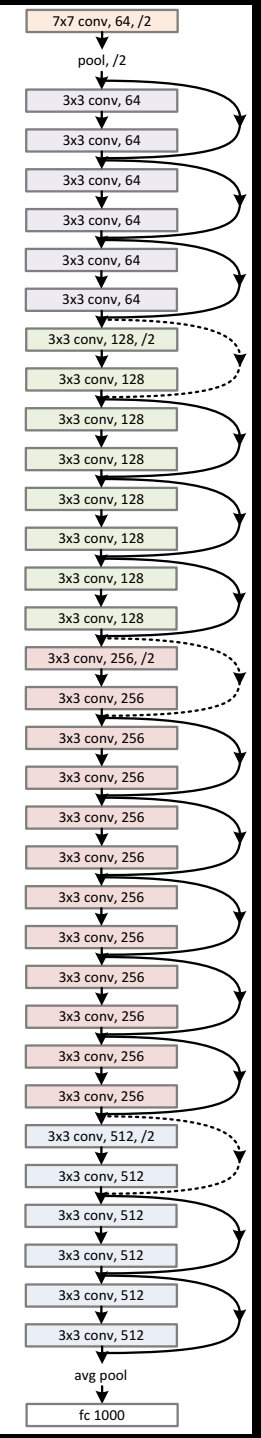




Design of ResNet

- Key ideas:
  - skip connection = “residual function”
  - the shortest path contains only a few layers

- Forward view: “shallow-to-deep” dynamics in training
  - Early stage – train shallow networks
  - Later stage – train deep networks

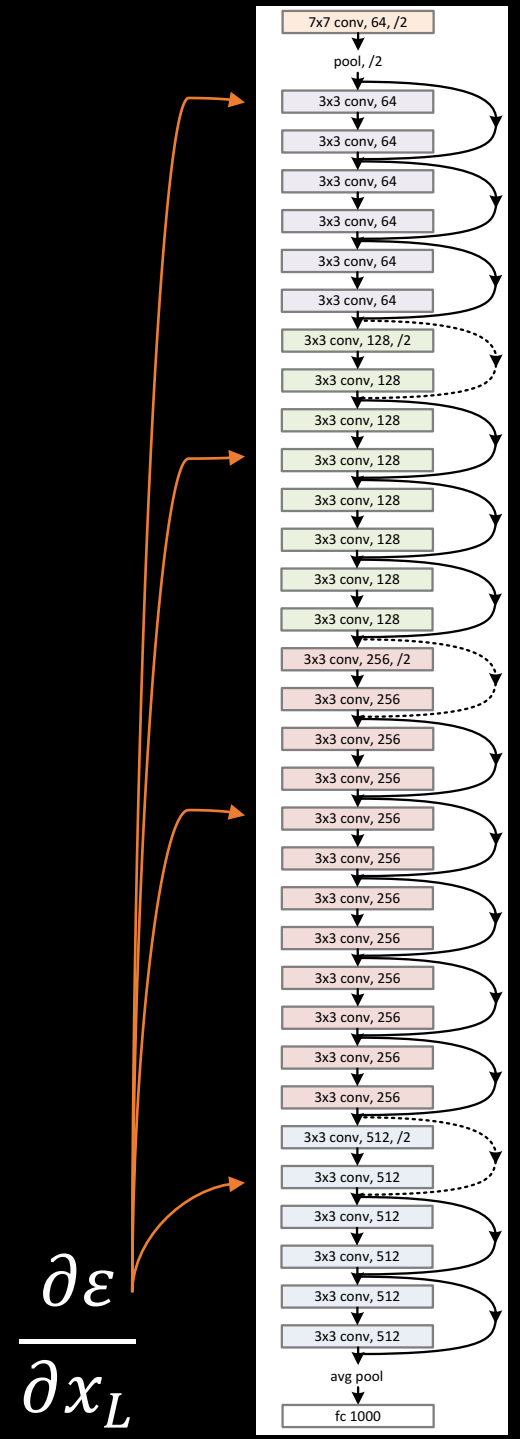


Design of ResNet

- Key ideas:
  - skip connection = “residual function”
  - the shortest path contains only a few layers

- Backward view: identity gradient path

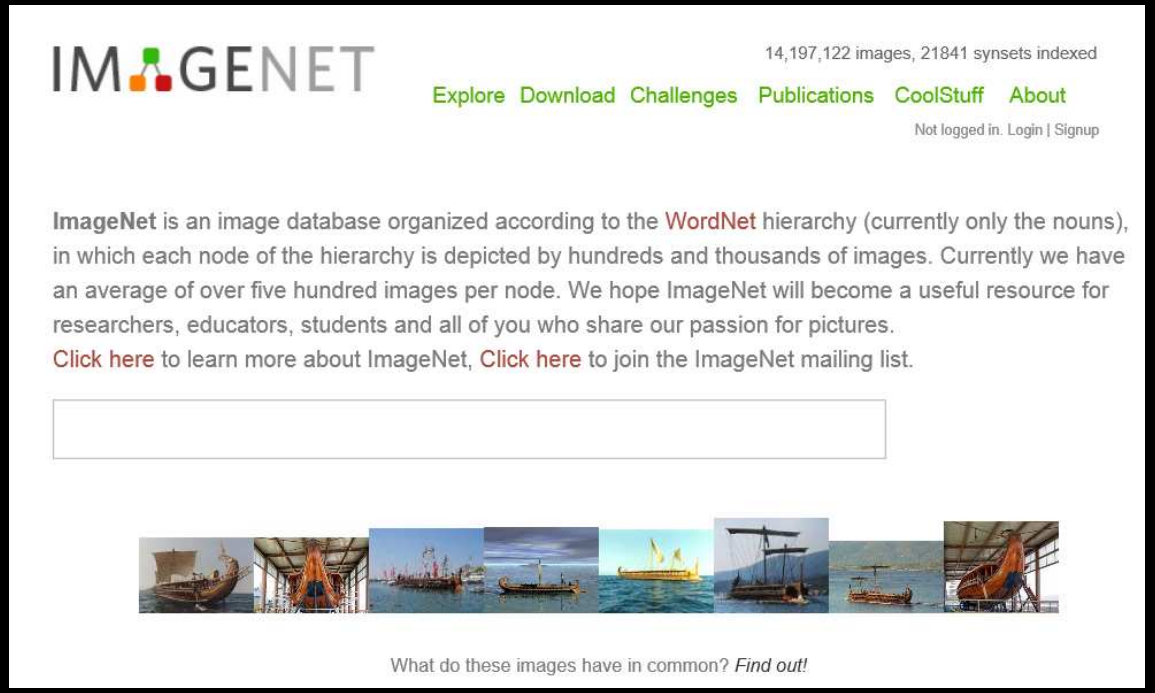
$$\frac{\partial \varepsilon}{\partial x_l} = \frac{\partial \varepsilon}{\partial x_L}\frac{\partial x_L}{\partial x_l} = \frac{\partial \varepsilon}{\partial x_L}\left(1 + \frac{\partial}{\partial x_l}\sum_{i=1}^{L-1} F(x_i, W_i)\right)$$



$$\frac{\partial \varepsilon}{\partial x_L}$$

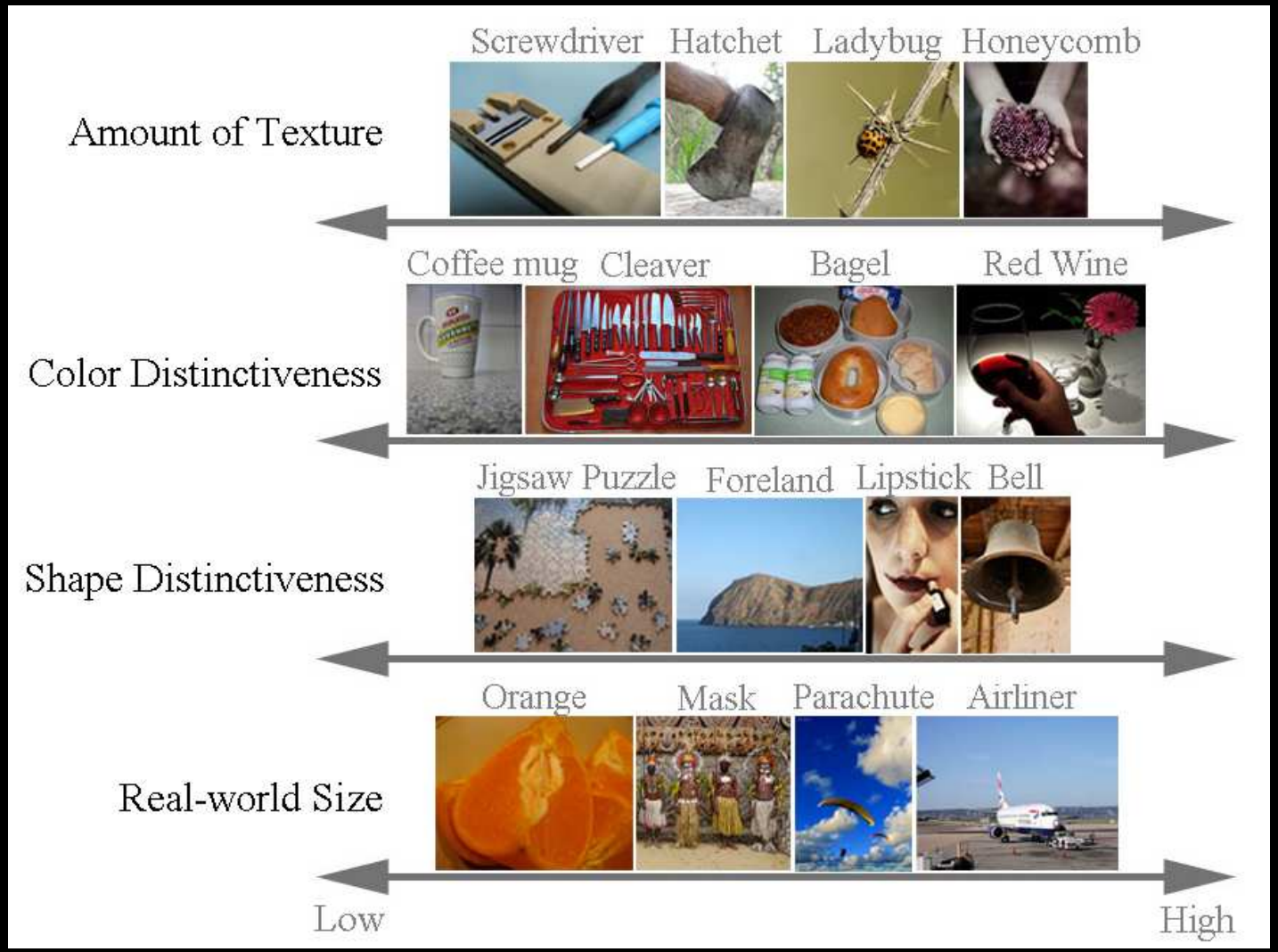
ImageNet Large Scale Visual Recognition Challenge

Dataset – ImageNet



- An image dataset organized according to the WordNet hierarchy.
- 14 M images, 22K synsets
  - Synset - multiple words for the same visual concept
  - majority of them are nouns
- Images of each concept are quality-controlled and human-annotated

Variety of Object Classes in ILSVRC



ILSVRC Classification Task (top-5 error)

Steel drum

Output:
Scale
T-shirt
<u>Steel drum</u>
Drumstick
Mud turtle

✔

Output:
Scale
T-shirt
Giant panda
Drumstick
Mud turtle

✗

Top-5 error is to allow an algorithm to identify multiple objects in an image and not be penalized if one of the objects identified was in fact present, but not included in the ground truth.

ILSVRC Classification Task (top-5 error)

Steel drum

Output:
Scale
T-shirt
<u>Steel drum</u>
Drumstick
Mud turtle

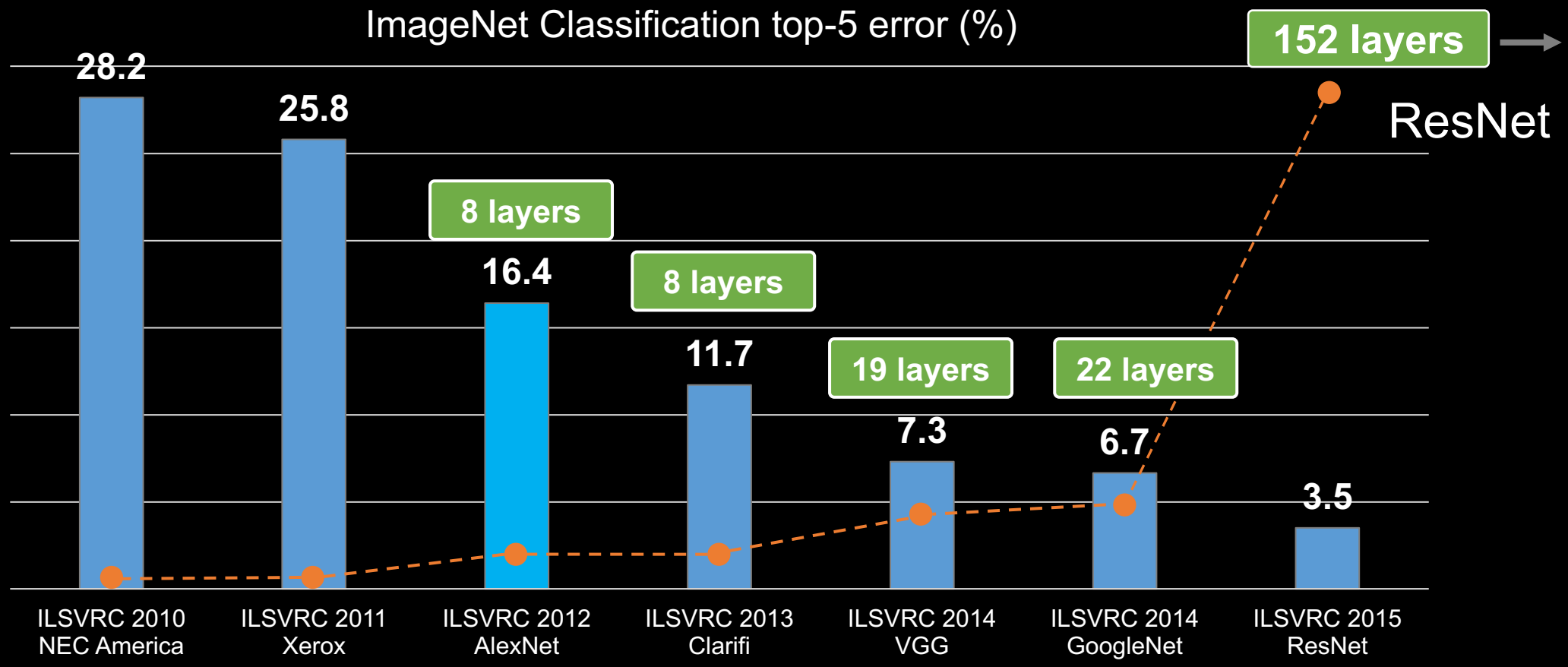
✔

Output:
Scale
T-shirt
Giant panda
Drumstick
Mud turtle

✗

$$\text{Accuracy} = \frac{1}{100{,}000} \sum_{\substack{100{,}000 \\ \text{images}}} 1[\text{correct on image i}]$$

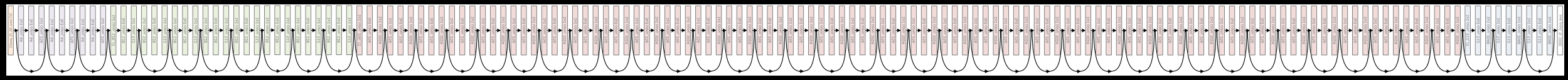
ImageNet Classification: Surpassed Human

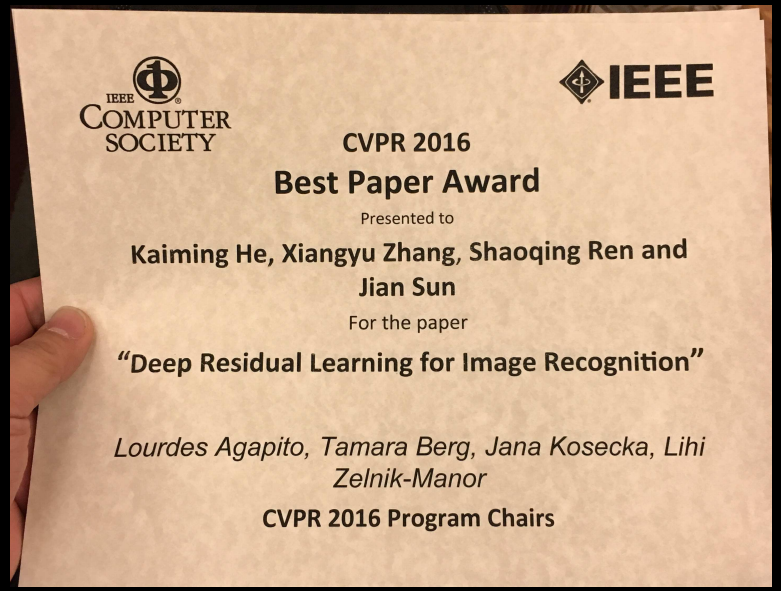


Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. “Deep Residual Learning for Image Recognition”. ArXiv 2015 / CVPR 2016.

152层网络意味着什么？解决了什么问题？

ResNet, 152 layers





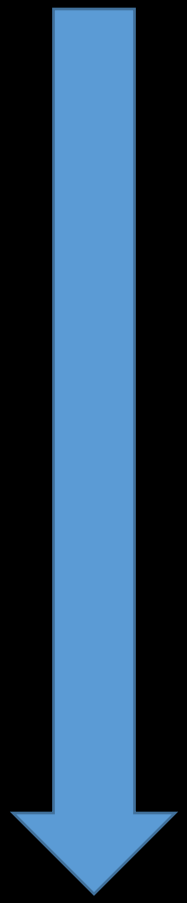
Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. “Deep Residual Learning for Image Recognition”. ArXiv 2015 / CVPR 2016.

深度学习：破除魔咒之旅

- Geoffrey Hinton’s points:
  - Our labeled datasets were thousands of times too small.
  - Our computers were millions of times too slow.
  - We initialized the weights in a stupid way.
  - We used the wrong type of non-linearity.

- ResNets imply:
  - Our network architectures were optimization-unfriendly.

Architecture Design



2012
- AlexNet [Krizhevsky et.al. 2012]

2013
- Maxout Networks [Goodfellow. et.al. 2013]
- Network in Network [Lin et.al. 2014]

2014
- Deeply-supervised Nets [Lee et al. 2014]
- VGG [Simonyan et al. 2014]
- GoolgeNet [Szegedy et al. 2014]

2015
- Residual Networks [He et al. 2015]
- Highway networks [Srivastava et al., 2015]
- FitNets [Romero et al., 2015]

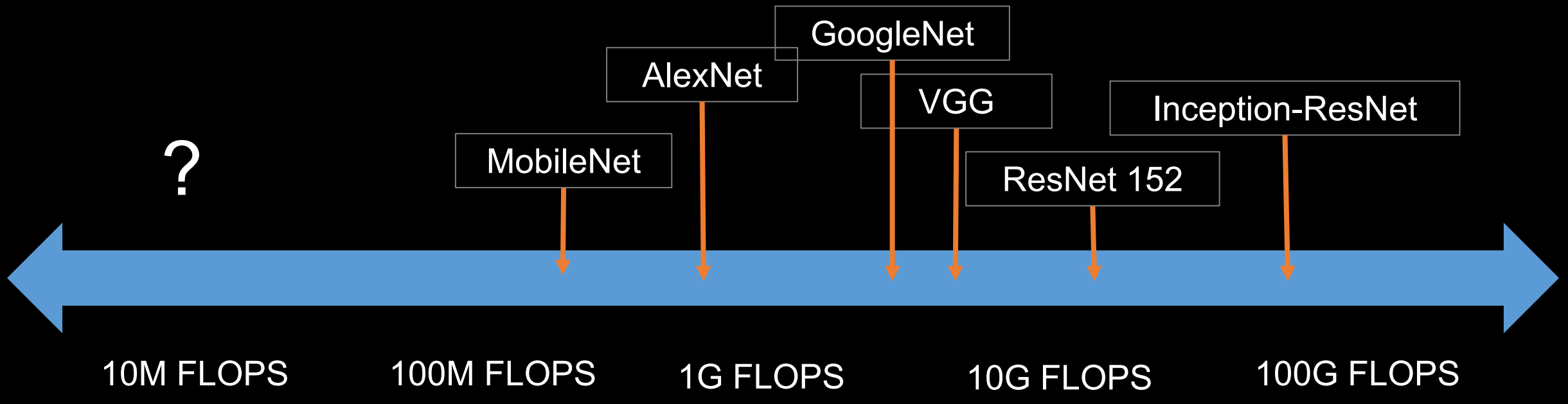
2016
- Inception-ResNet [Szegedy et al. 2016]
- Residual Networks with pre-activation [He et al. 2016] 1001 layers

2016

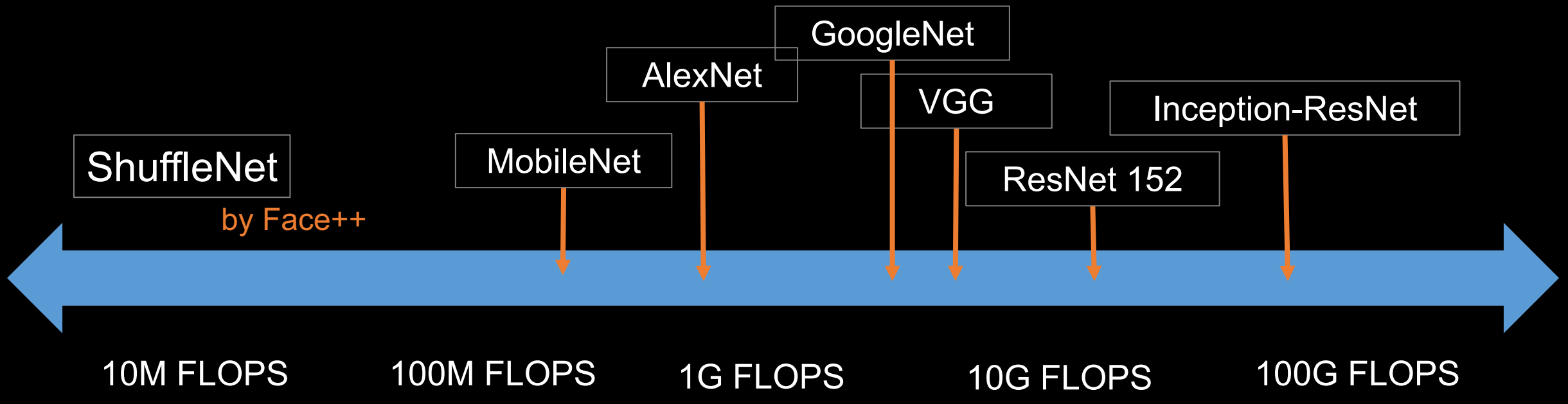
2017

- SqueezeNet[Forrest N. Iandola et.al. 2016]
- FractalNet[Larsson et al. 2016]
- DenseNet [Huang et al. 2016]
- ResNet in ResNet [Targ el al. 2016]
- Wide Residual Networks [Zagoruyko el al. 2016]
- Stochastic Depth [Huang et al. 2016]
- PolyNet [Zhang et al. 2016]
- ResNeXt [He et al. 2016]
- Xception [Chollet et al. 2016]
- BinaryNet [Matthieu et al. 2016]
- XNOR-Net [Rastegari et al. 2016]
- DeReFa-Net [Zhou et al. 2016]
- MobileNets [Howard et al. 2017]

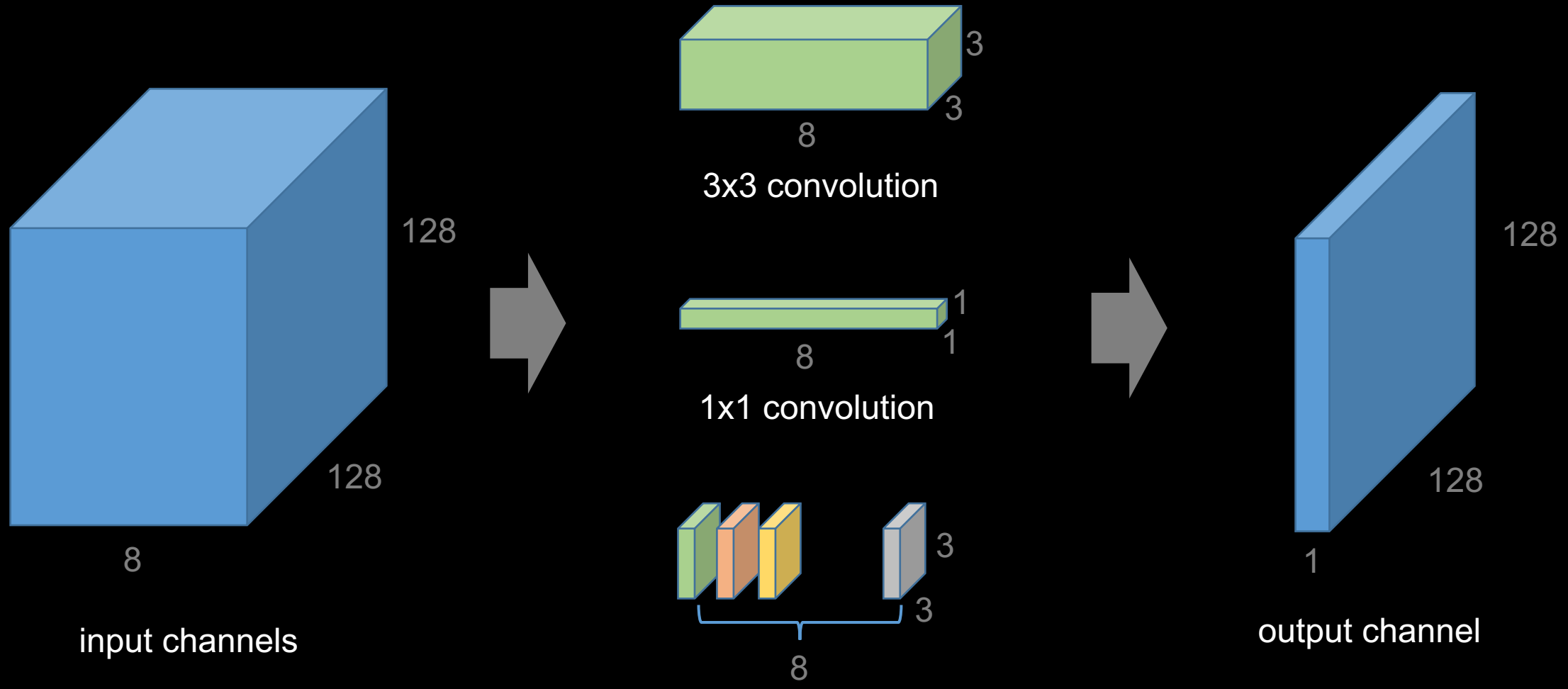
Computing Spectrum

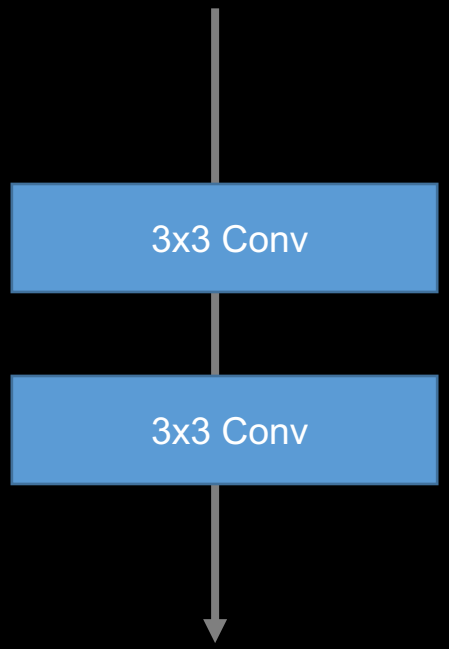


Computing Spectrum

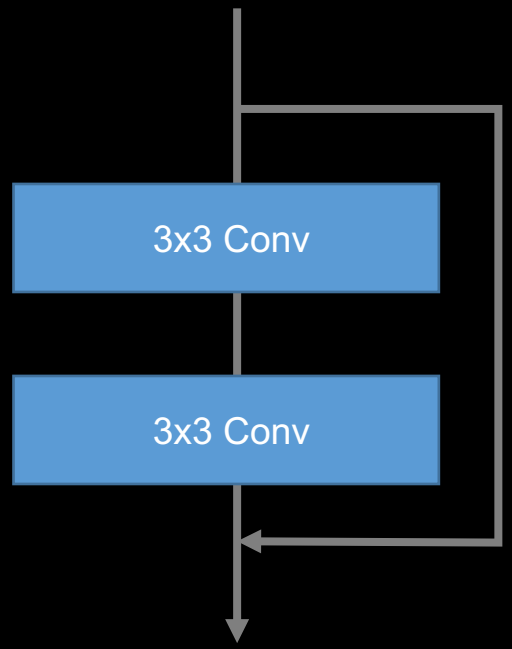


Convolution: 3x3, 1x1, depthwise 3x3



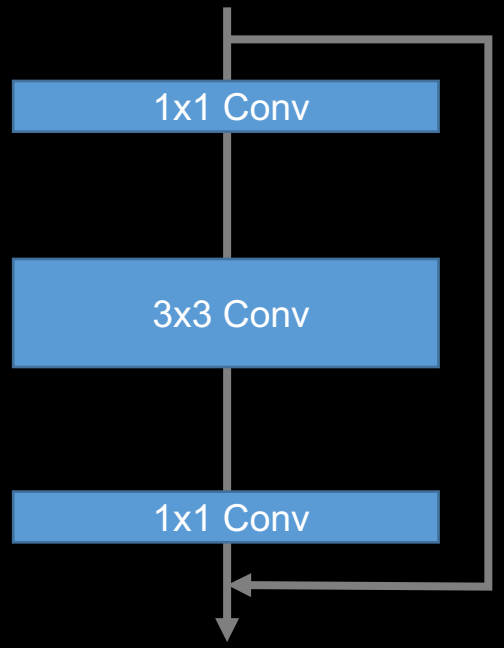


Plain Net



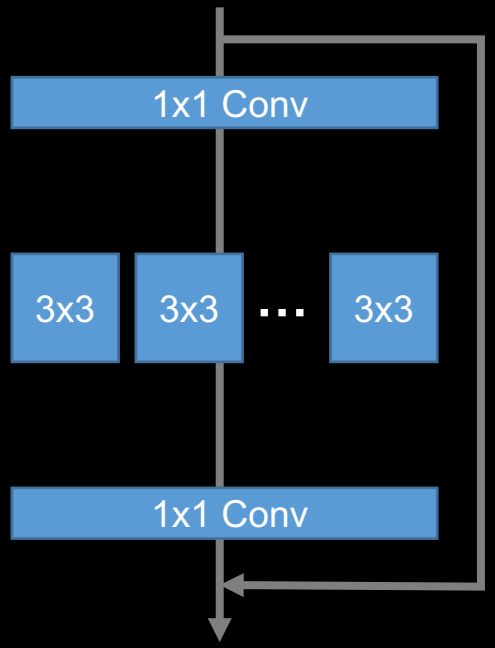
ResNet

[He et al. 2015]



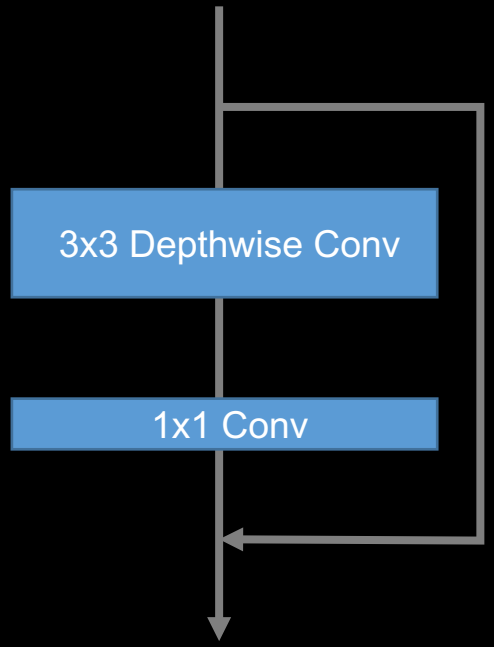
Bottleneck

[He et al. 2015]



ResNeXt

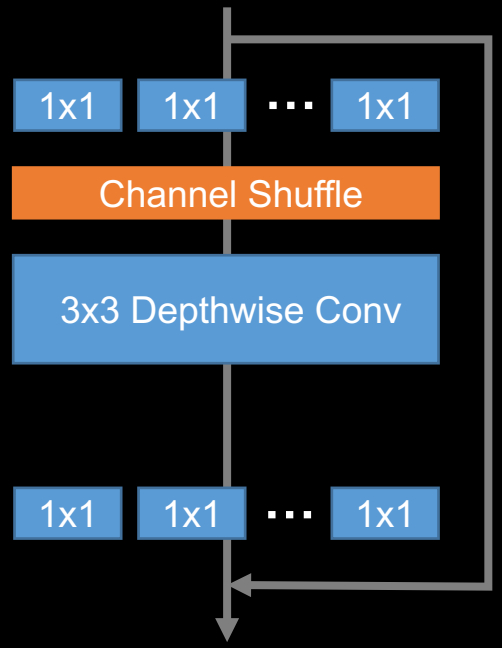
[Xie et al. 2017]



Xception/MobileNets

[Francois Chollet. 2017]

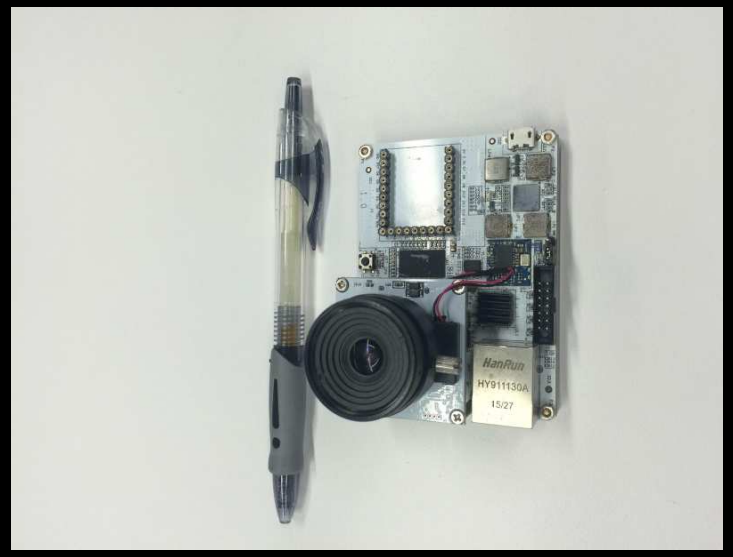
[Howard et al. 2017]



ShuffleNet

[Zhang et al. 2017]

ShuffleNet on FGPA



MegEye-C3S

智能人像抓拍机

Face Detection on FGPA, 1080p, 30fps, No Tracking

ShuffleNet on 手机

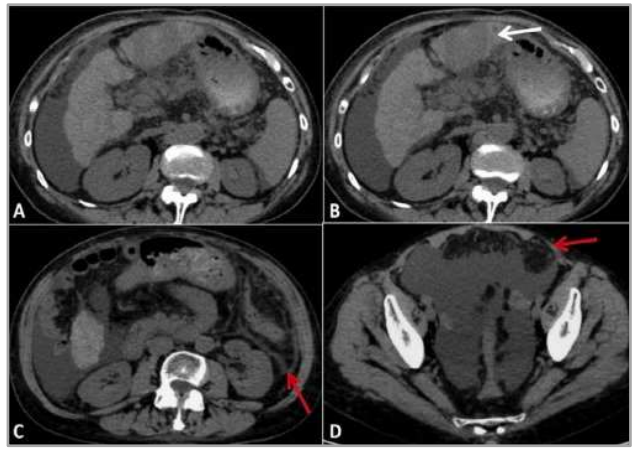
Vivo V7+ 第一款上市搭载完整人脸识别技术的国产手机

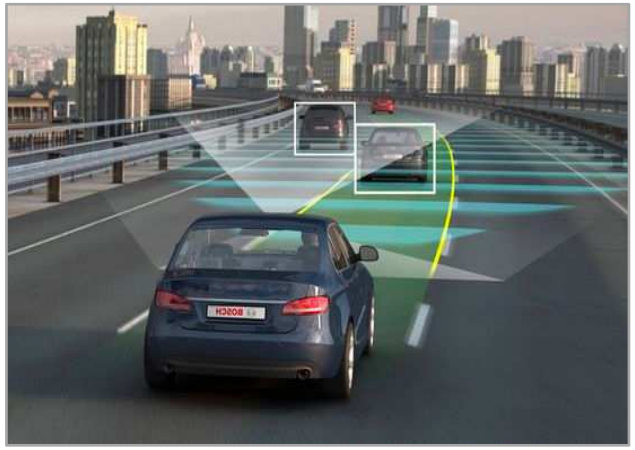
ShuffleNet on 手机

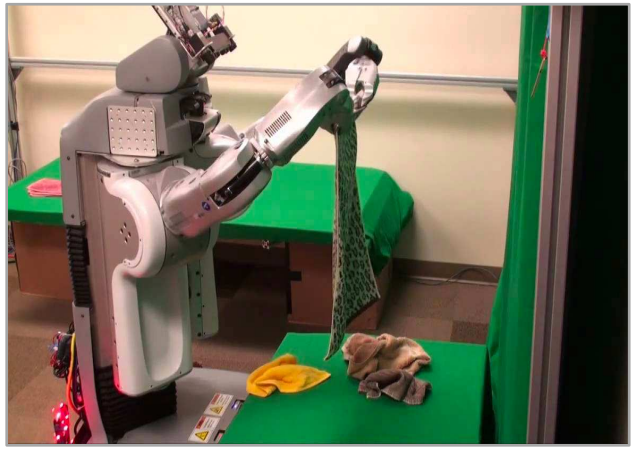
小米 Note 3 成为在国内发行的首款会“人脸解锁”的国产智能手机

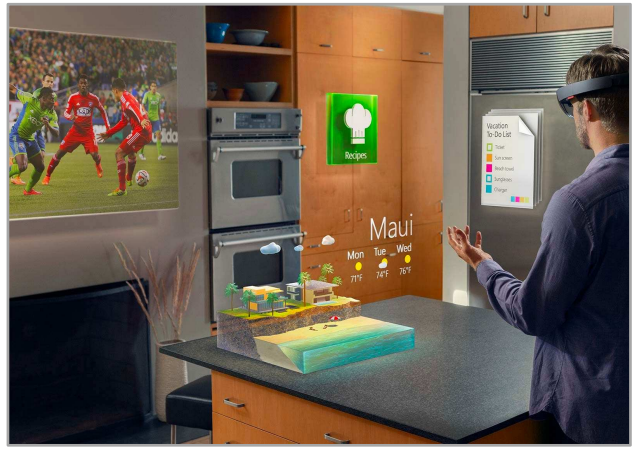

DOT PROJECTOR
7MP CAMERA
MICROPHONE
SPEAKER
AMBIENT LIGHT SENSOR
FLOOD ILLUMINATOR
PROXIMITY SENSOR
INFRARED CAMERA

Applications





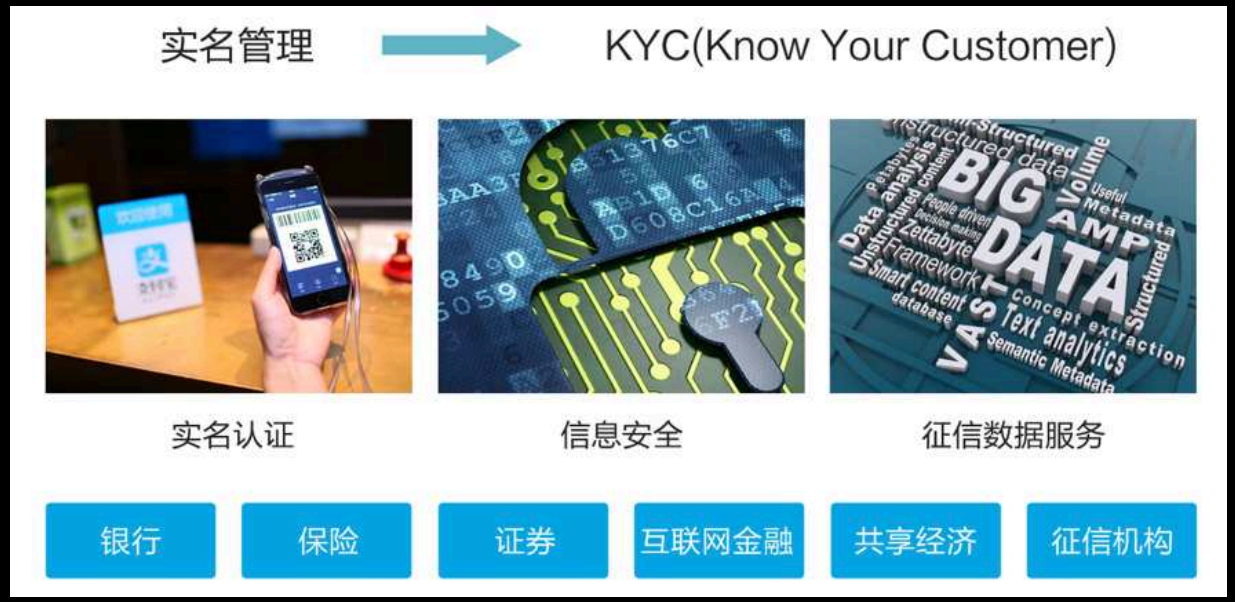




Face Recognition：Beyond Human

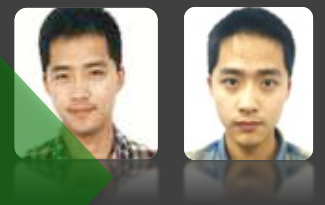
Face Verification in LFW Benchmark

FaceID 在线身份认证服务



典型客户

FaceID 在线身份认证服务

采集身份证照片	活体检测	照片处理	假脸检测	人脸比对
				
OCR读取信息 提取人脸照片	活体检测 采集人脸照片	质量检测 保存合格照片	判定面具、屏幕翻拍、合成脸等攻击	活体照片、身份证照片与底图交叉对比返回相似度

SDK

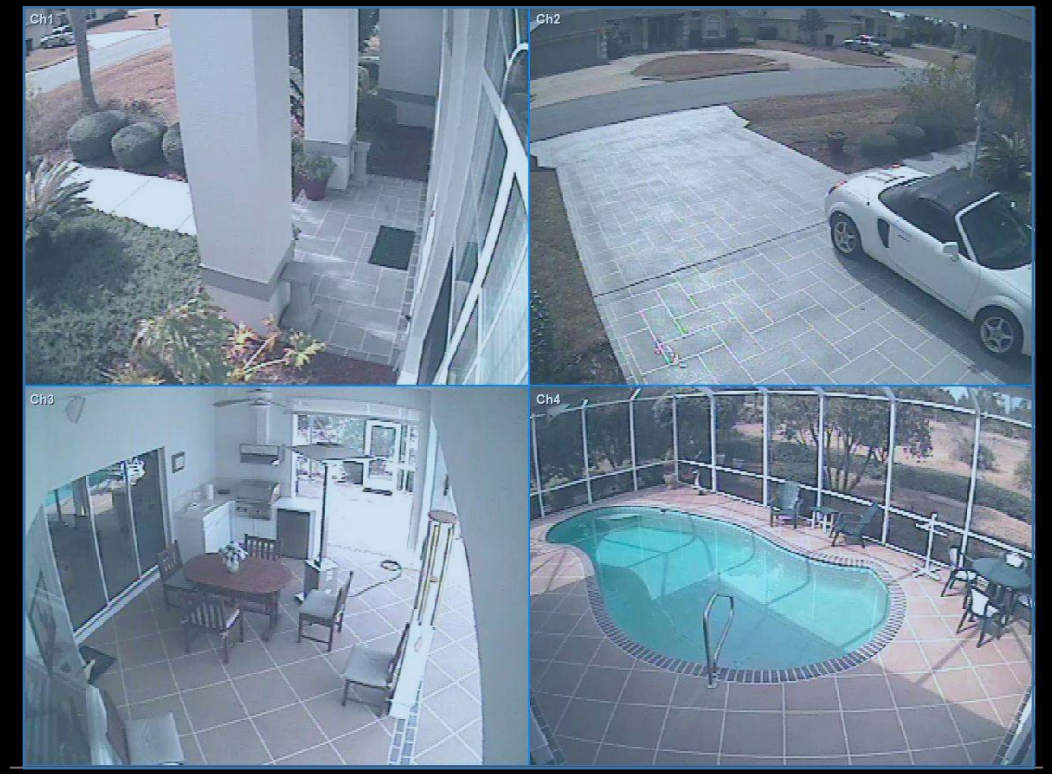
Cloud

世界最大的身份验证平台
2016年实现2.1亿人身份验证

智能城市

Top1 accuracy >90% , in 100M database

智能城市


Ch1
Ch2
Ch3
Ch4


旷视人像卡口大数据应用系统
卡口实况
智能查询
人员布控
数据研判
库管理
系统管理
GO
1
4
9
16
V
P
海淀区
科学院南路
苏州街
海淀南路
石景山区
王泉路
阜石路
莲石路
实时告警
查看历史
75
抓拍时间：2015-03-16-09-09-09
抓拍位置：A120-101-110
姓名：
身份证：
95
抓拍时间：2015-03-16-09-09-12
抓拍位置：A120-101-110
姓名：
身份证：

Video Analytics (Vehicle/Person Detection & Tracking)

Week 1	Intro to Deep Learning and Computer Vision
Week 2	Deep Learning Toolkits, Math Revisit, Dataset
Week 3	Neural Network Basis & Architecture Design
Week 4	Deep Learning Platform: from Theano to Tensorflow/Megbrain
Week 5	Neural Network Approximation: Pruning, Factorization, and Low-bit Representation
Week 6	Morden Object Detection: SSD, Faster-RCNN, R-FCN
Week 7	Semantic Image Segmentation
Week 8	Invited Talk
Week 9	Text Detection and Recognition
Week 10	Recurrent Neural Network (RNN) and LSTM
Week 11	Generative Models and GANs
Week 12	3D Reconstruction: Conventional and Modern (Deep Learning based) Approaches
Week 13	Visual Object Tracking
Week 14	Human Understanding: ReID and Pose and Attributes
Week15	Engineering in Deep Learning Research/System
Week 16	Student Spotlight Talk

http://szeliski.org/Book/

Computer Vision: Algorithms and Applications

Stanford University
CS 131 Computer Vision: Foundations and Applications
Fall 2016-2017

Course home | Syllabus, lectures and assignments | Discussion | FAQ

Announcements:

- Welcome to CS131!
- Schedule information may change during the quarter; please visit the Syllabus page regularly to stay up to date.
- **Lecture location has changed to 370-370 due to the high volume of student enrollment.**

Course Instructor:

Prof. Fei-Fei Li
Office: Room 246, Gates Building
Office hours: Tuesday, 3-4pm

CS231n: Convolutional Neural Networks for Visual Recognition

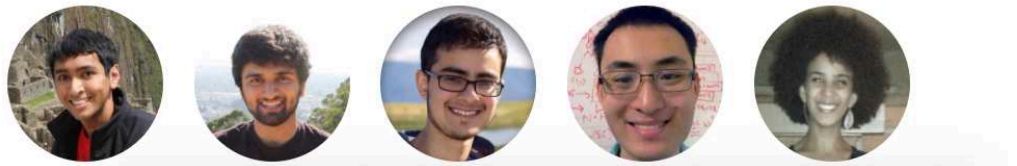
Spring 2017

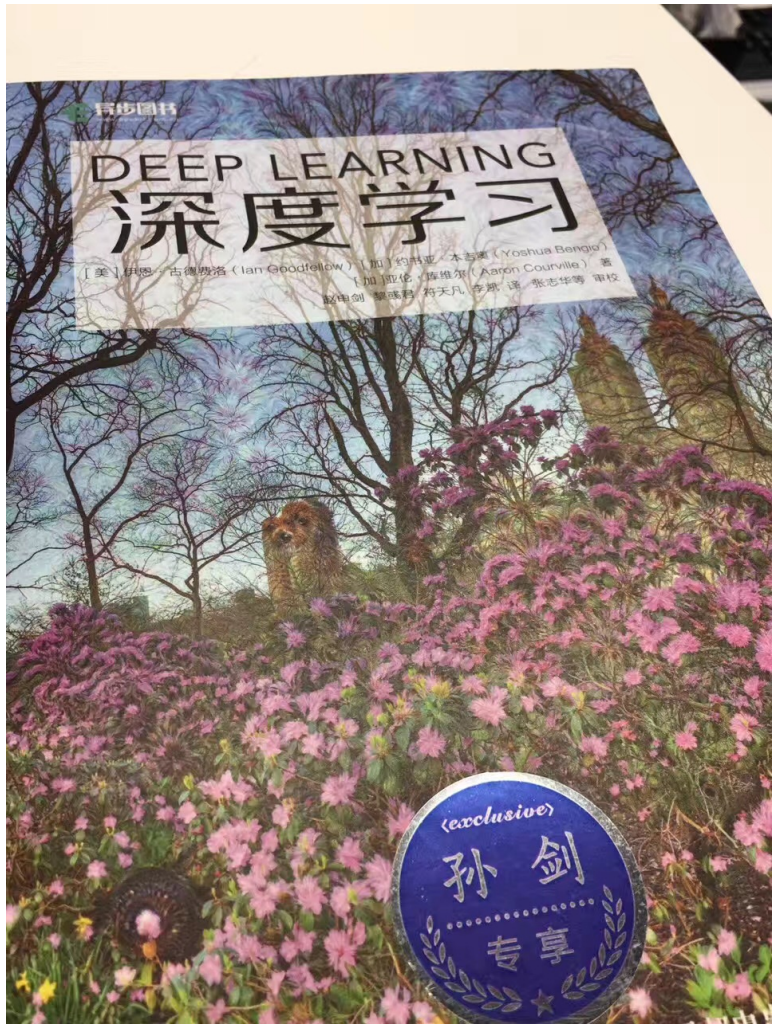
Course Description

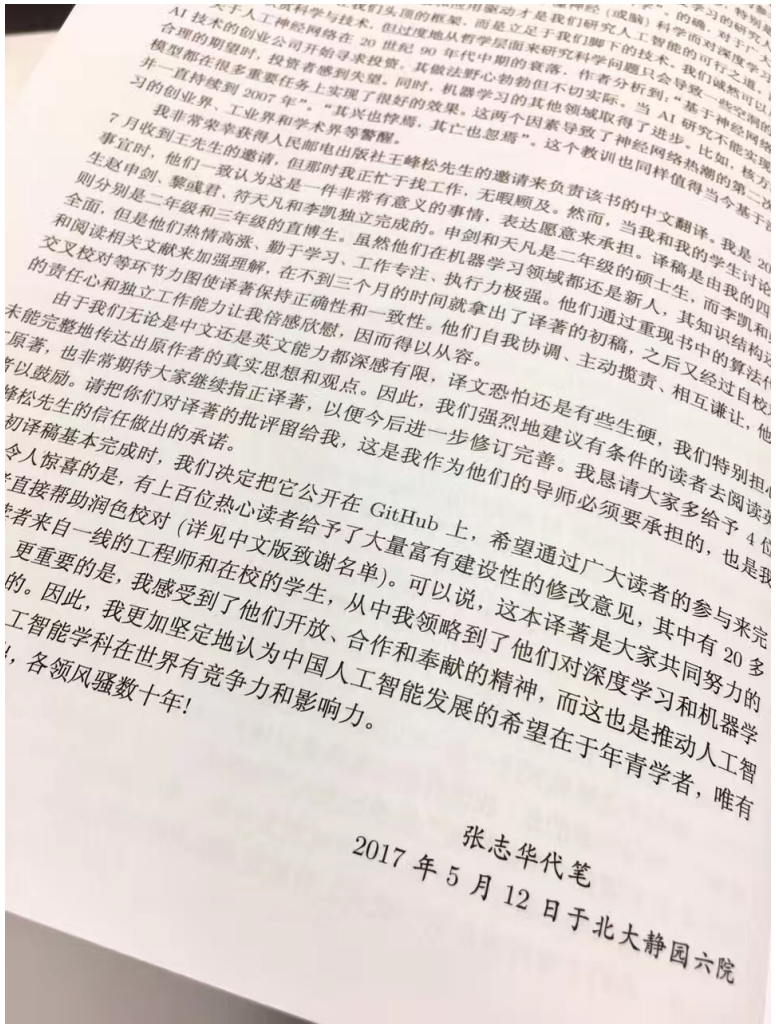
Computer Vision has become ubiquitous in our society, with applications in search, image understanding, apps, mapping, medicine, drones, and self-driving cars. Core to many of these applications are visual recognition tasks such as image classification, localization and detection. Recent developments in neural network (aka "deep learning") approaches have greatly advanced the performance of these state-of-the-art visual recognition systems. This course is a deep dive into details of the deep learning architectures with a focus on learning end-to-end models for these tasks, particularly image classification. During the 10-week course, students will learn to implement, train and debug their own neural networks and gain a detailed understanding of cutting-edge research in computer vision. The final assignment will involve training a multi-million parameter convolutional neural network and applying it on the largest image classification dataset (ImageNet). We will focus on teaching how to set up the problem of image recognition, the learning algorithms (e.g. backpropagation), practical engineering tricks for training and fine-tuning the networks and guide the students through hands-on assignments and a final course project. Much of the background and materials of this course will be drawn from the ImageNet Challenge.

Instructors

Teaching Assistants







AI 技术的创业公司开始寻求投资，其做法野心勃勃但不切实际。当 AI 研究不能实现
合理的期望时，投资者感到失望。同时，机器学习的其他领域取得了进步。比如，核方
模型都在很多重要任务上实现了很好的效果。这两个因素导致了神经网络热潮的第二次
并一直持续到 2007 年”。“其兴也悖焉，其亡也忽焉”。这个教训也同样值得当今基于
习的创业界、工业界和学术界等警醒。

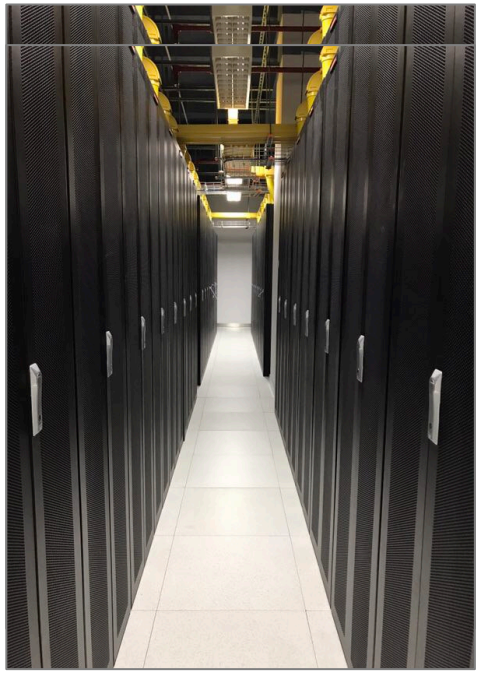
我非常荣幸获得人民邮电出版社王峰松先生的邀请来负责该书的中文翻译。我是 20
7 月收到王先生的邀请，但那时我正忙于找工作，无暇顾及。然而，当我和我的学生讨论
事宜时，他们一致认为这是一件非常有意义的事情，表达愿意来承担。译稿是由我的四
生赵申剑、黎彧君、符天凡和李凯独立完成的。申剑和天凡是二年级的硕士生，而李凯和
则分别是二年级和三年级的直博生。虽然他们在机器学习领域都还是新人，其知识结构
全面，但是他们热情高涨、勤于学习、工作专注、执行力极强。他们通过重现书中的算法
和阅读相关文献来加强理解，在不到三个月的时间就拿出了译著的初稿，之后又经过自校
交叉校对等环节力图使译著保持正确性和一致性。他们自我协调、主动揽责、相互谦让，他
的责任心和独立工作能力让我倍感欣慰，因而得以从容。

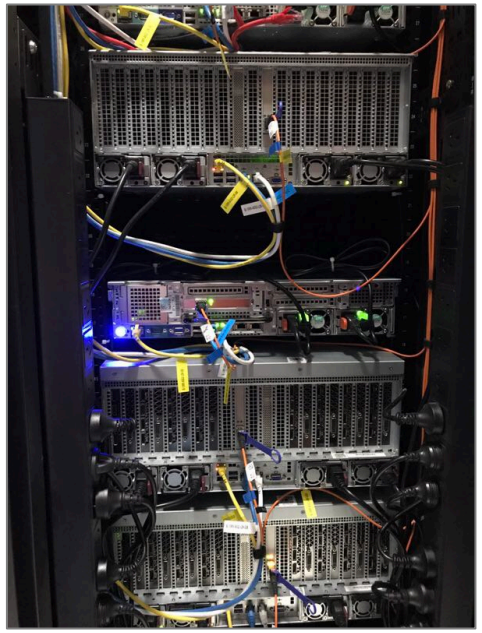
由于我们无论是中文还是英文能力都深感有限，译文恐怕还是有些生硬，我们特别担
未能完整地传达出原作者的真实思想和观点。因此，我们强烈地建议有条件的读者去阅读英
原著，也非常期待大家继续指正译著，以便今后进一步修订完善。我恳请大家多给予 4 位
者以鼓励。请把你们对译著的批评留给我，这是我作为他们的导师必须要承担的，也是我
锋松先生的信任做出的承诺。

初译稿基本完成时，我们决定把它公开在 GitHub 上，希望通过广大读者的参与来完
令人惊喜的是，有上百位热心读者给予了大量富有建设性的修改意见，其中有 20 多
直接帮助润色校对（详见中文版致谢名单）。可以说，这本译著是大家共同努力的
者来自一线的工程师和在校的学生，从中我领略到了他们对深度学习和机器学
更重要的是，我感受到了他们开放、合作和奉献的精神，而这也是推动人工智
的。因此，我更加坚定地认为中国人工智能发展的希望在于年青学者，唯有
工智能学科在世界有竞争力和影响力。
，各领风骚数十年！

张志华代笔

2017 年 5 月 12 日于北大静园六院





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