

EE488 Special Topics in EE

<Deep Learning and AlphaGo>

Sae-Young Chung

Lecture 1

August 28, 2017

Contact Information

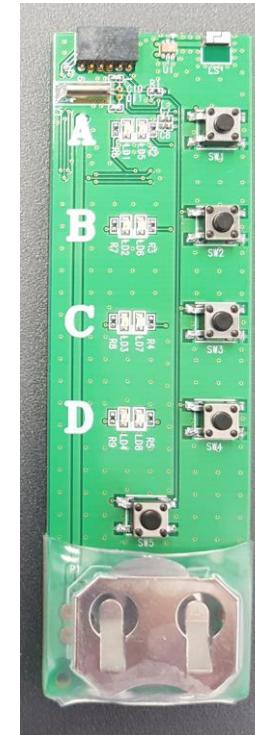
- Professor: Sae-Young Chung (정세영)
 - Email: schung@kaist.ac.kr
 - Homepage: <http://itml.kaist.ac.kr> (Information Theory & Machine Learning Lab)
 - Office: N1 Room 615, Tel: x3481
 - Office hours: Thu 10am-noon
- TA's
 - Jin Hak Kim (김진학), jinhakkim@kaist.ac.kr, 010-4597-6873
 - Balhae Kim (김발해), balhae92@kaist.ac.kr, 010-2624-2695
 - Jongmin Yoon (윤종민), jm.yoon@kaist.ac.kr, 010-2036-2651
 - Hwe Hee Chung (정희희), hwehee_chung@kaist.ac.kr, 010-5092-9170
 - Byeol Yi Han (한별이), byeolyihan@kaist.ac.kr, 010-3391-6513
 - Office: N1 Room 618, Tel: x5481

Syllabus

- Summary
 - This is an undergraduate-level introductory course on deep learning. In this course, students will learn history and theoretical background of deep learning. Some programming assignments will be given so that students can design, train, and test various deep learning architectures. Last few weeks will be devoted to design and implementation of a simple version of AlphaGo based on deep learning that can play Go on a small Go board. All assignments and projects will use Python and Tensorflow. Previous experience in Python and Tensorflow is not required.
- Prerequisites
 - Basic probability theory
 - (Multivariable calculus, linear algebra, basic programming)
- Textbook
 - “Deep Learning” by Ian Goodfellow, Yoshua Bengio, and Aaron Courville
 - Available freely at <http://www.deeplearningbook.org/>
 - “Reinforcement learning: An introduction” by R. Sutton and A. Barto
 - Draft available online at <http://incompleteideas.net/sutton/book/the-book-2nd.html>
 - Lecture notes and other handouts available at KLMS

Homeworks, Projects, Exams

- 3 homeworks
- 3 mini projects including
 - Deep reinforcement learning
 - AlphaGo
- Mid-term exam
- No final exam
- Instant quizzes during lectures using Clicker
 - Plus automated attendance check



Grading Policy

- Homework: 25%
- Projects: 35%
- Exam: 30%
- Quiz & attendance: 10%
- Separate grading for undergraduate and graduate students
- Late penalty: 10% per day
- Academic integrity
 - E.g., copying homework and projects strictly prohibited

Programming Tools

- Python 2.7 and Tensorflow

- Python tutorial
 - <https://docs.python.org/2/tutorial/>
 - <http://www.learnpython.org/>
 - Tensorflow tutorial
 - <https://www.tensorflow.org>

Computing Facilities

- 해동 라운지 (E3-4 room 1412): <https://ee.kaist.ac.kr/node/15074>

- 36 computers with Windows 10 & Ubuntu 16.04 dual boot
- Each machine has two GTX1070 GPU's
- User id/pw: your student id
- Change your password in Ubuntu when you first login, then your Windows password will also be changed automatically
- Do NOT change your password in Windows
- Use your student card key to enter the room



Computing Facilities

- In addition to computers in E3-4, you can also use the following via remote login (Ubuntu linux)
 - 25 computers in LG hall, each equipped with 4 GTX1070 GPU's
 - 24 computers in N5, each equipped with a GTX960 GPU (Exclusively for this course)
- Total # of GPU's available for this course: 196
 - 72 GPU's in E3-4
 - 100 GPU's in LG hall
 - 24 GPU's in N5
 - Computers in E3-4 and LG hall are shared with other students taking some other deep learning related courses.
- Never use computers for other purposes
 - E.g., mining bitcoin, ethereum
 - Severe penalty

Schedule

- Tentative schedule

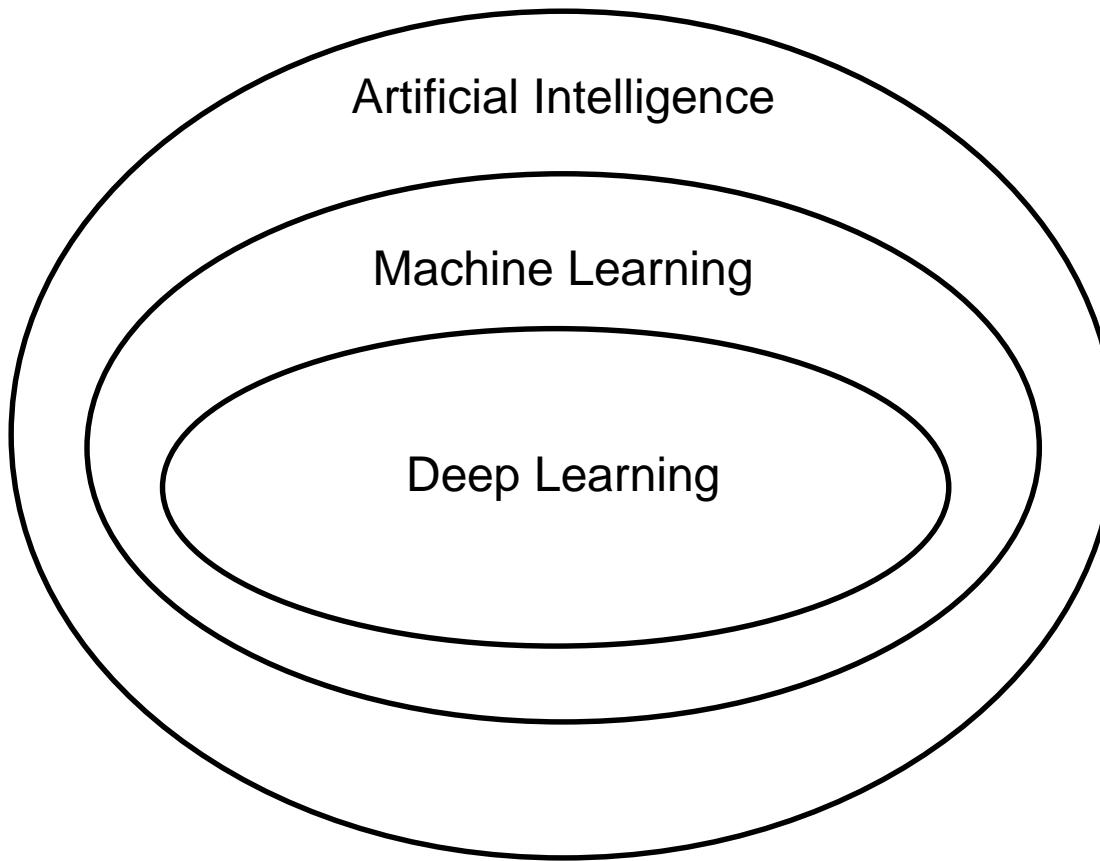
- Week 1: Introduction
- Week 2: Probability, information theory, and numerical optimization
- Week 3: Basic machine learning
- Week 4: Perceptron
- Week 5: Deep feedforward networks
- Week 6: Training methods
- Week 7: Convolutional networks
- Week 8: Mid-term exam
- Week 9: Reinforcement learning
- Week 10: Deep reinforcement learning
- Week 11: Monte Carlo tree search
- Week 12: AlphaGo
- Week 13: AlphaGo
- Week 14: AlphaGo
- Week 15: Misc. topics

Artificial Intelligence



Artificial Intelligence

- Learning
- Logical reasoning and problem solving
- Understanding
- Planning
- Creativity
- Natural language processing (NLP)
- Motion
- Artistic intelligence
- Social intelligence
- Emotional intelligence
- Artificial general intelligence
- Self awareness



Deep Learning – Wikipedia

- Deep learning (also known as deep structured learning or hierarchical learning) is part of a broader family of machine learning methods based on learning data representations, as opposed to task-specific algorithms. Learning can be supervised, partially supervised or unsupervised.
- Some representations are loosely based on interpretation of information processing and communication patterns in a ***biological nervous system***, such as neural coding that attempts to define a relationship between various stimuli and associated neuronal responses in the brain. Research attempts to create efficient systems to learn these representations from large-scale, unlabeled data sets.
- Deep learning architectures such as ***deep neural networks***, deep belief networks and recurrent neural networks have been applied to fields including computer vision, speech recognition, natural language processing, audio recognition, social network filtering, machine translation and bioinformatics where they produced results comparable to and in some cases superior[6] to human experts.

Machine Translation

- Deep learning (also known as deep structured learning or hierarchical learning) is part of a broader family of machine learning methods based on learning data representations, as opposed to task-specific algorithms. Learning can be supervised, partially supervised or unsupervised.
- 심층 학습 (심층 구조 학습 또는 계층 적 학습이라고도 함)은 작업 별 알고리즘과 달리 학습 데이터 표현을 기반으로하는 광범위한 학습 방법의 일부입니다. 학습은 감독, 부분 감독 또는 감독하지 않을 수 있습니다. [Google]
- 심층 학습(심층적 학습 또는 계층 학습)은 직무별 알고리즘과 달리 학습 데이터 표현에 기초한 광범위한 기계 학습 방법의 일부이다. 학습은 감독되거나 부분적으로 감독되거나 감독될 수 있다. [네이버 파파고]



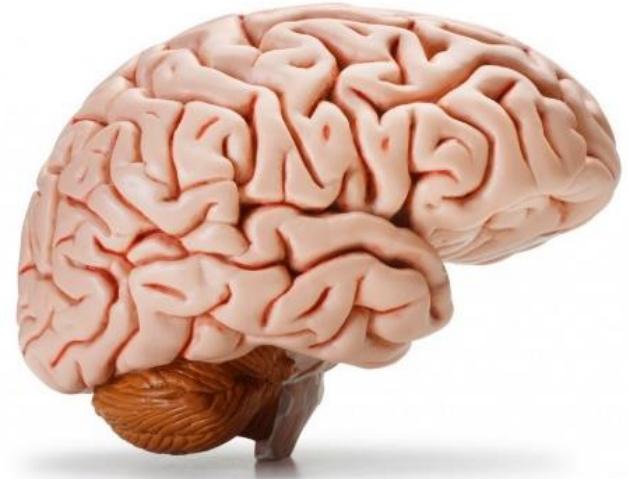
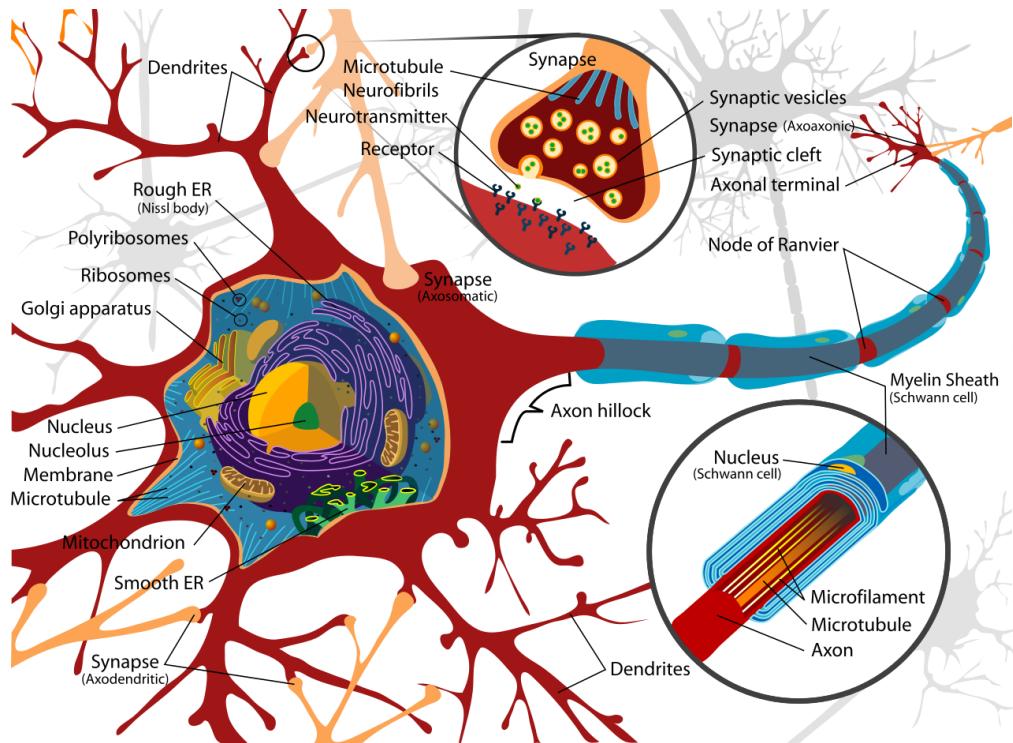
碁 (바둑 기)
Pronounced as
“Go” in Japan



Named after AlphaGo,
but has nothing to do
with the game of Go.

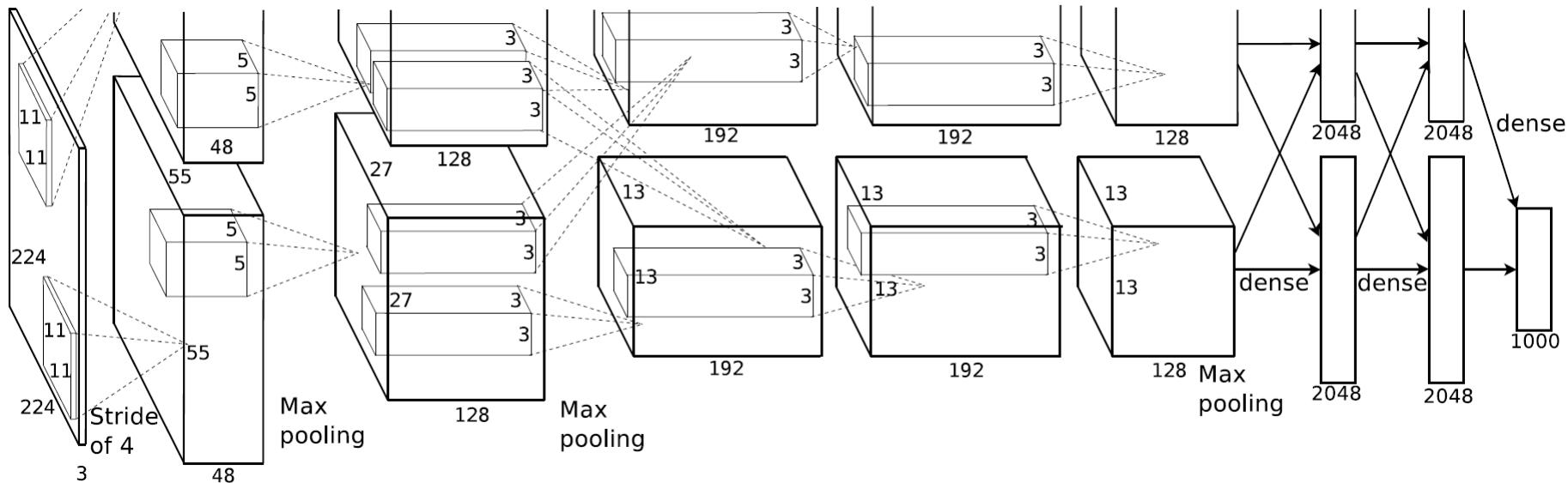
Deep Learning

- Machine learning using (deep) artificial neural network



Deep Convolutional Neural Network

- Alex Krizhevsky, Ilya Sutskever, Geoffrey Hinton, “ImageNet classification with deep convolutional neural networks”, NIPS 2012
- Winner of 1,000 category classification task (ImageNet Large Scale Visual Recognition Challenge (ILSVRC) 2012)
- Beat traditional approaches by ~40%
- AlexNet: 60 million parameters and 650,000 neurons



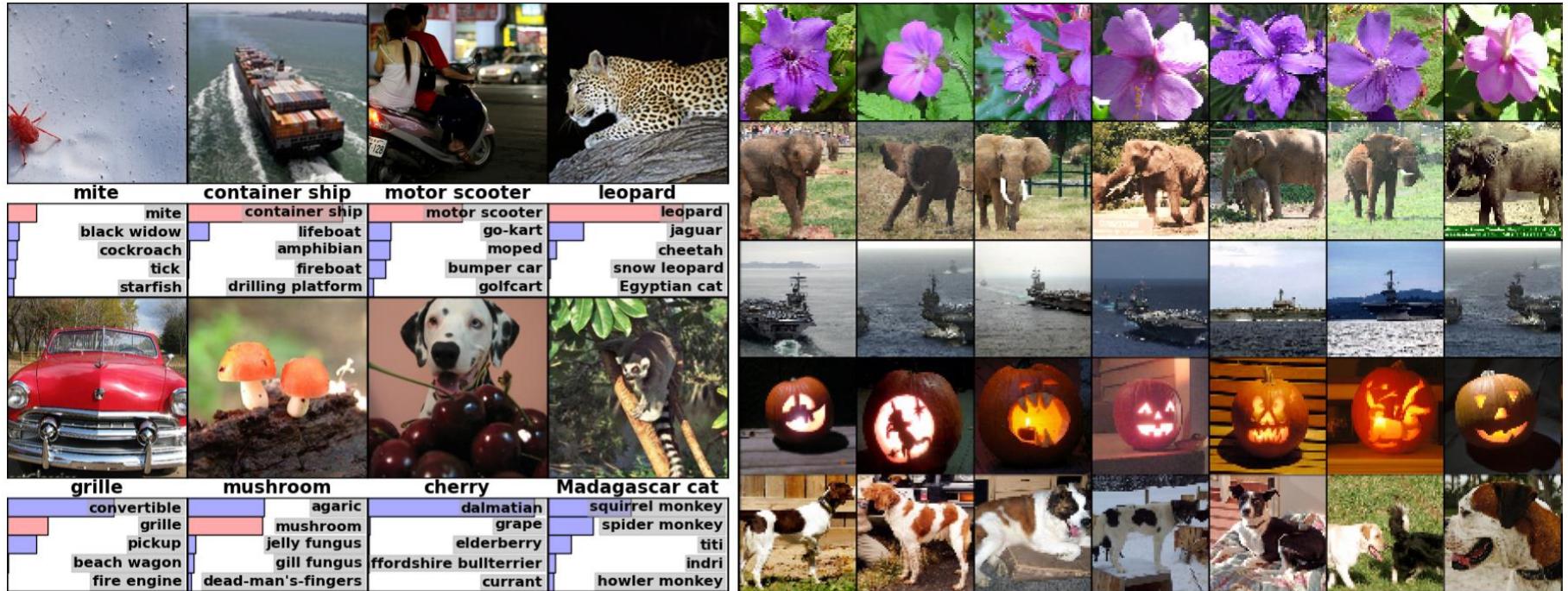
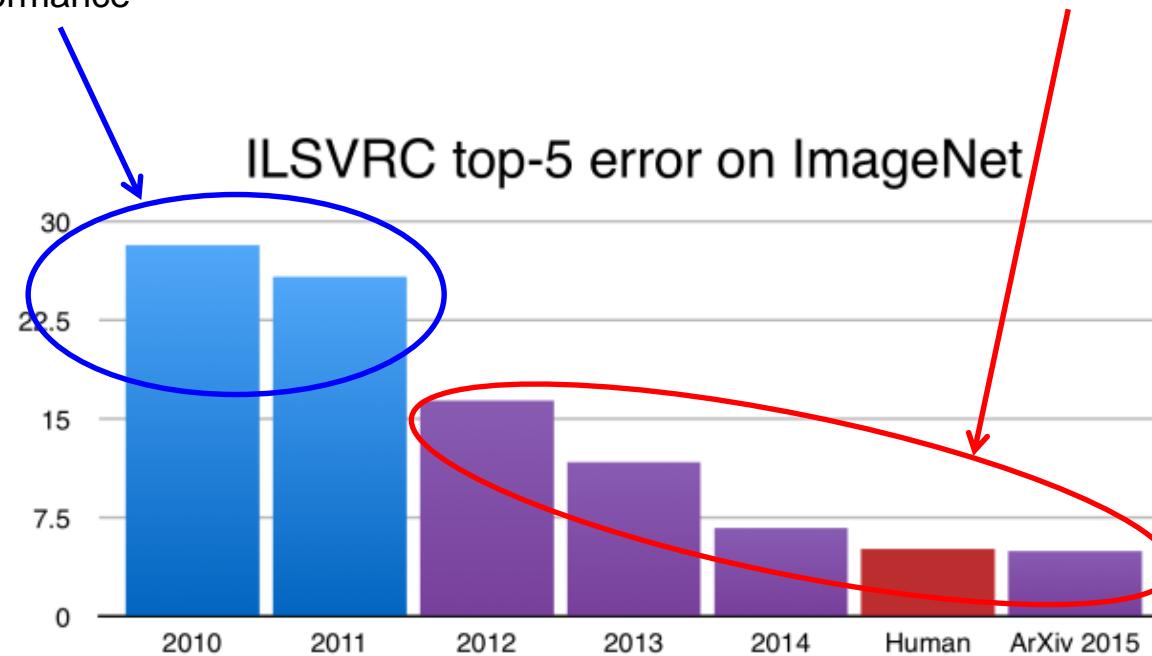


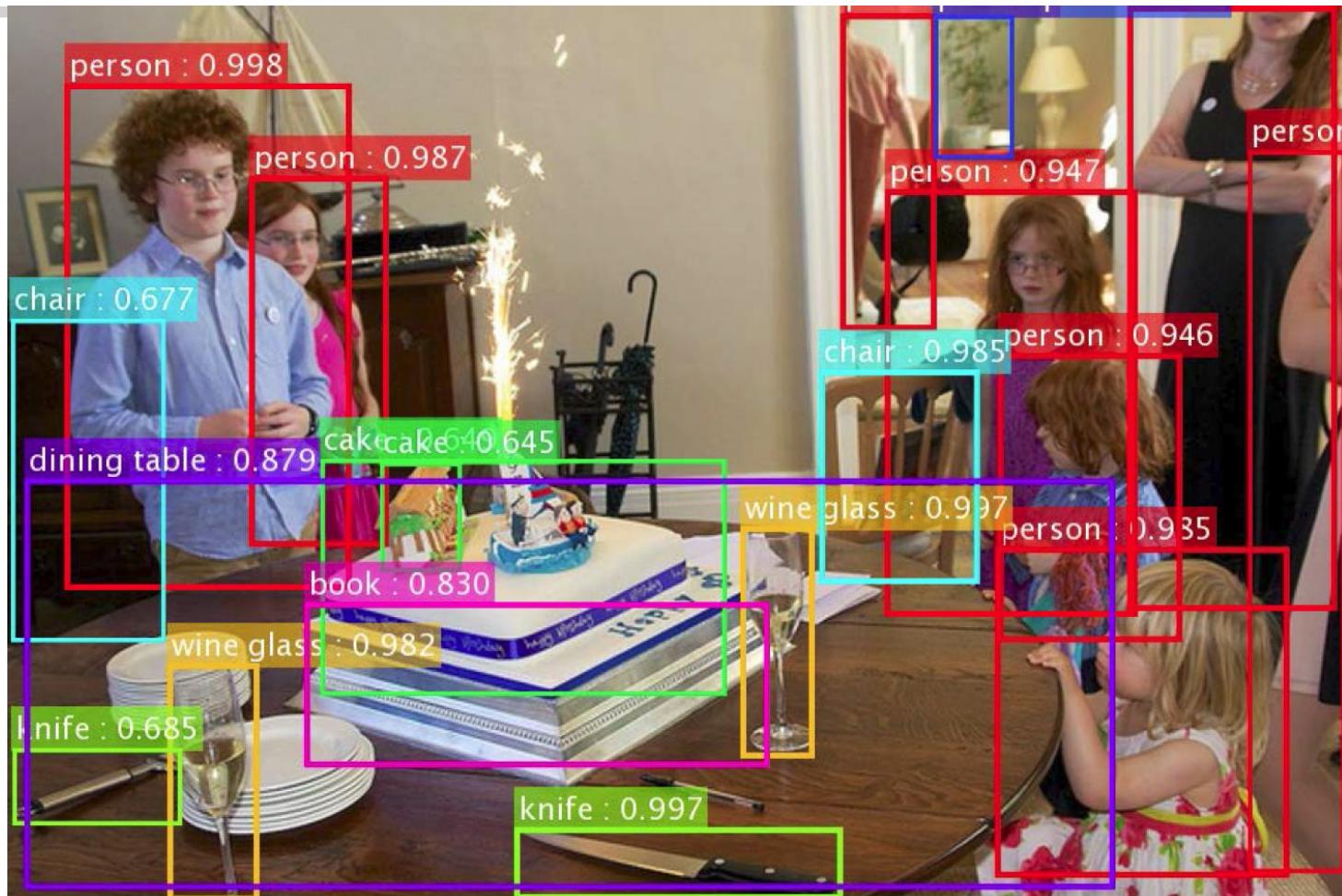
Figure 4: (**Left**) Eight ILSVRC-2010 test images and the five labels considered most probable by our model. The correct label is written under each image, and the probability assigned to the correct label is also shown with a red bar (if it happens to be in the top 5). (**Right**) Five ILSVRC-2010 test images in the first column. The remaining columns show the six training images that produce feature vectors in the last hidden layer with the smallest Euclidean distance from the feature vector for the test image.

- Hand-crafted algorithm by humans
- Very slow to develop (years)
- Very slow to code
- Poor performance

- “Algorithm” automatically learned from data
- Very fast to learn (days)
- No coding required during learning
- Better-than human performance

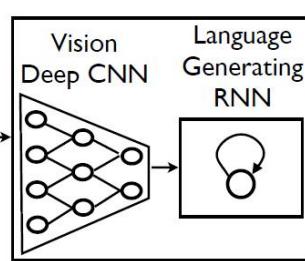


Object Localization



Kaiming He, et al. (MSRA), Deep residual learning for image recognition, arXiv 2015

Scene Description



A group of people shopping at an outdoor market.

There are many vegetables at the fruit stand.



“Two pizzas sitting on top of a stove top oven”

Oriol Vinyals, et al. (Google), Show and tell: A neural image caption generator, arXiv 2014

A person riding a motorcycle on a dirt road.



A group of young people playing a game of frisbee.



A herd of elephants walking across a dry grass field.



Two dogs play in the grass.



A skateboarder does a trick on a ramp.



A dog is jumping to catch a frisbee.



Two hockey players are fighting over the puck.



A little girl in a pink hat is blowing bubbles.



A refrigerator filled with lots of food and drinks.



A close up of a cat laying on a couch.



A red motorcycle parked on the side of the road.



A yellow school bus parked in a parking lot.



Describes without errors

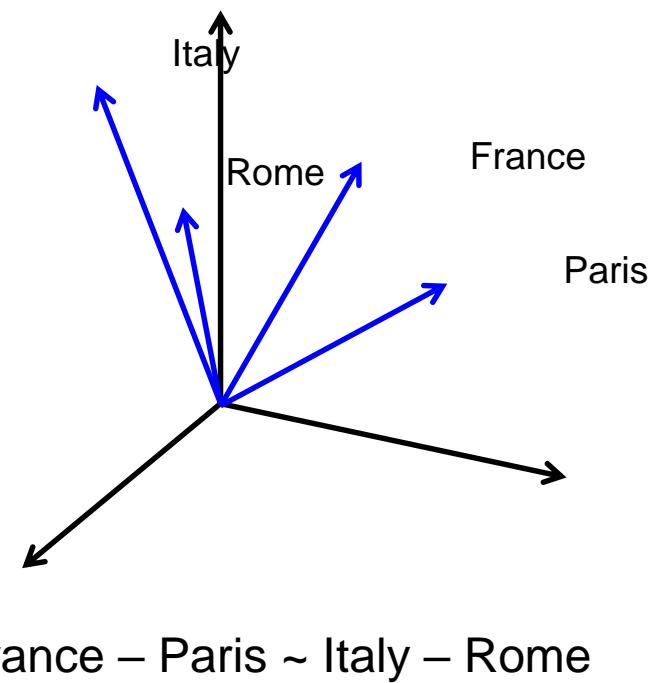
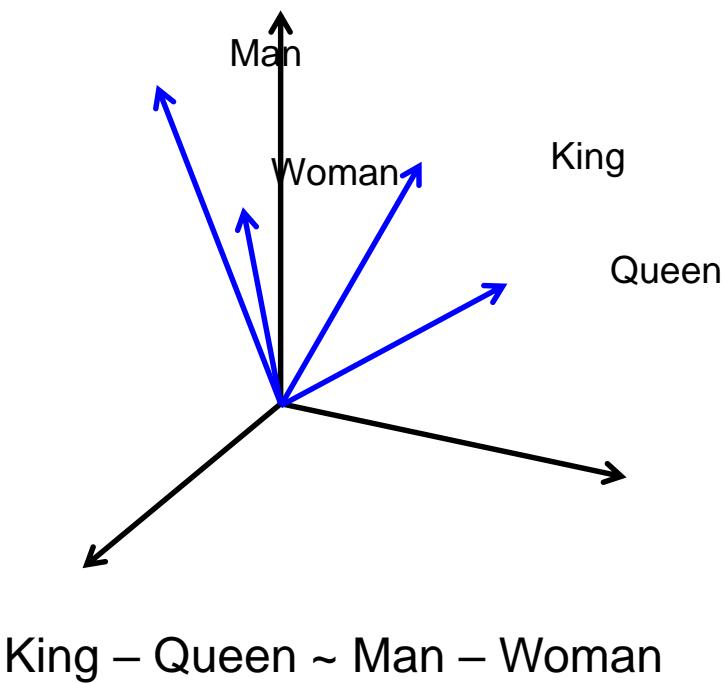
Describes with minor errors

Somewhat related to the image

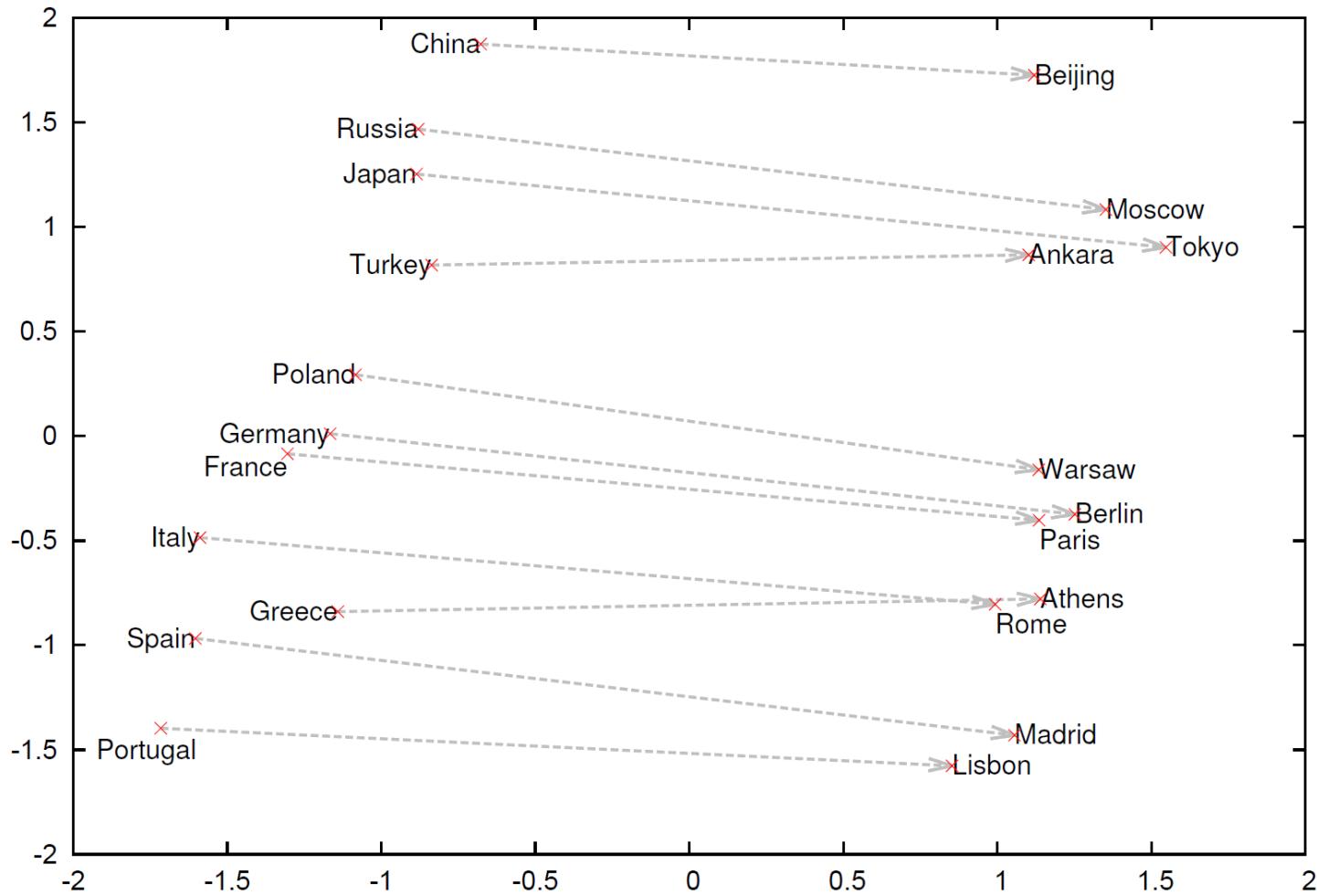
Unrelated to the image

Oriol Vinyals, et al. (Google), Show and tell: A neural image caption generator, arXiv 2014

Word Embedding



Country and Capital Vectors Projected by PCA



Tomas Mikolov, et al., Distributed representations of words and phrases and their compositionality, 2013

Neural Art

A



B



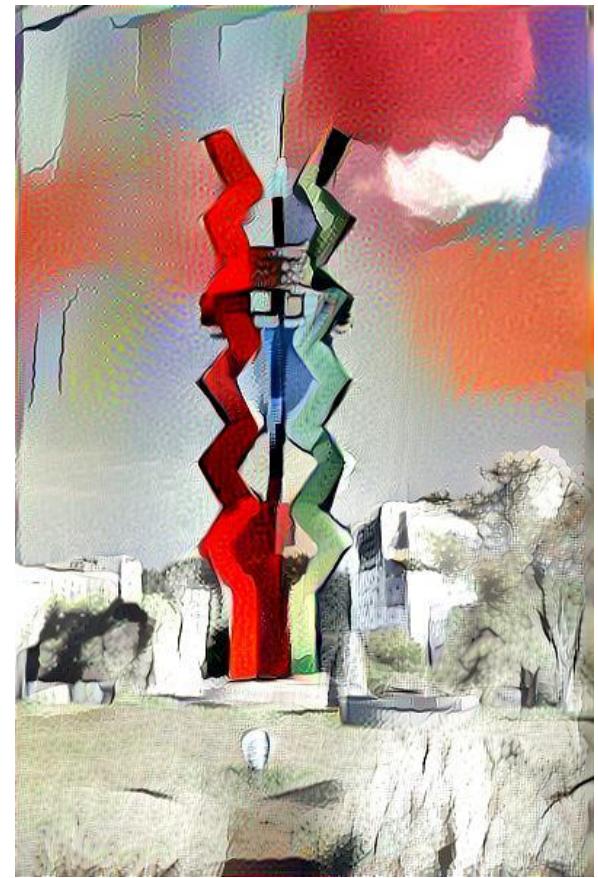
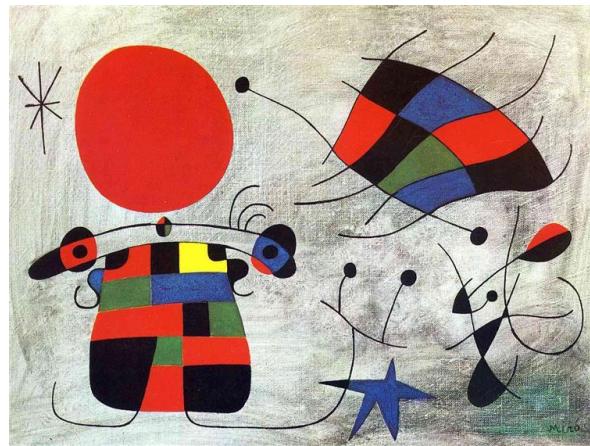
C



D



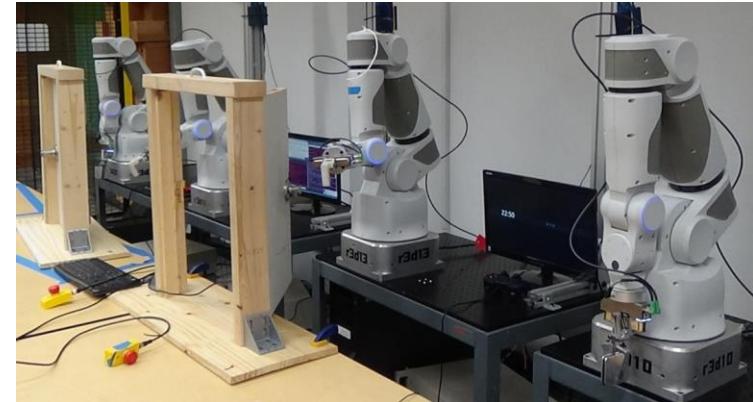
L. Gatys, et al., A neural algorithm of artistic style, arXiv 2015



Types of Machine Learning

- Machine learning
 - Supervised learning
 - Unsupervised learning
 - Reinforcement learning
- Supervised learning
 - Answers (or labels) are provided
- Unsupervised learning
 - Answers are not provided
- Reinforcement learning
 - Tries to maximize reward
 - Learns which action to take when
 - Environment has memory (state): agent's action affects future states

Reinforcement Learning Examples



<https://www.youtube.com/watch?v=TmPfTpjtdgg>

Reinforcement Learning Examples



<https://www.youtube.com/watch?v=5iZlrBqDYPM>



<https://www.youtube.com/watch?v=gn4nRCC9TwQ>



Challenge Match

8 - 15 March 2016



AlphaGo



AlphaGo

Lee Sedol



Google DeepMind

Challenge Match

8 - 15 March 2016

Before & After AlphaGo Match

- Before
 - How can a computer win against pro 9-dan?
 - Computers don't have intuition humans have
 - Computers only perform tasks programmed by humans and it is impossible to program all possible Go moves
- After
 - It's not fair due to lack of information about AlphaGo before the game
 - It's not fair since AlphaGo used 1202 CPU's

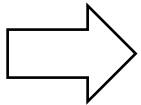
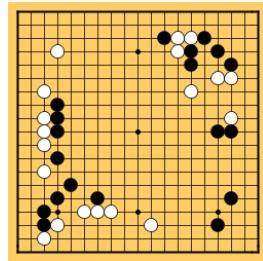
Humans have intuition

||

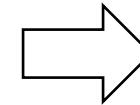
I have no idea how humans think

Intuition

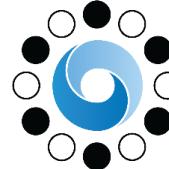
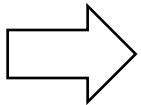
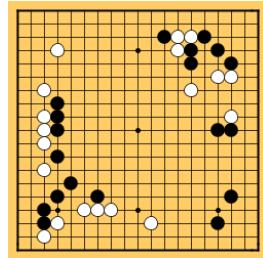
Input



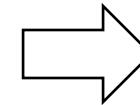
Output



Situation
analysis,
Best move,
...

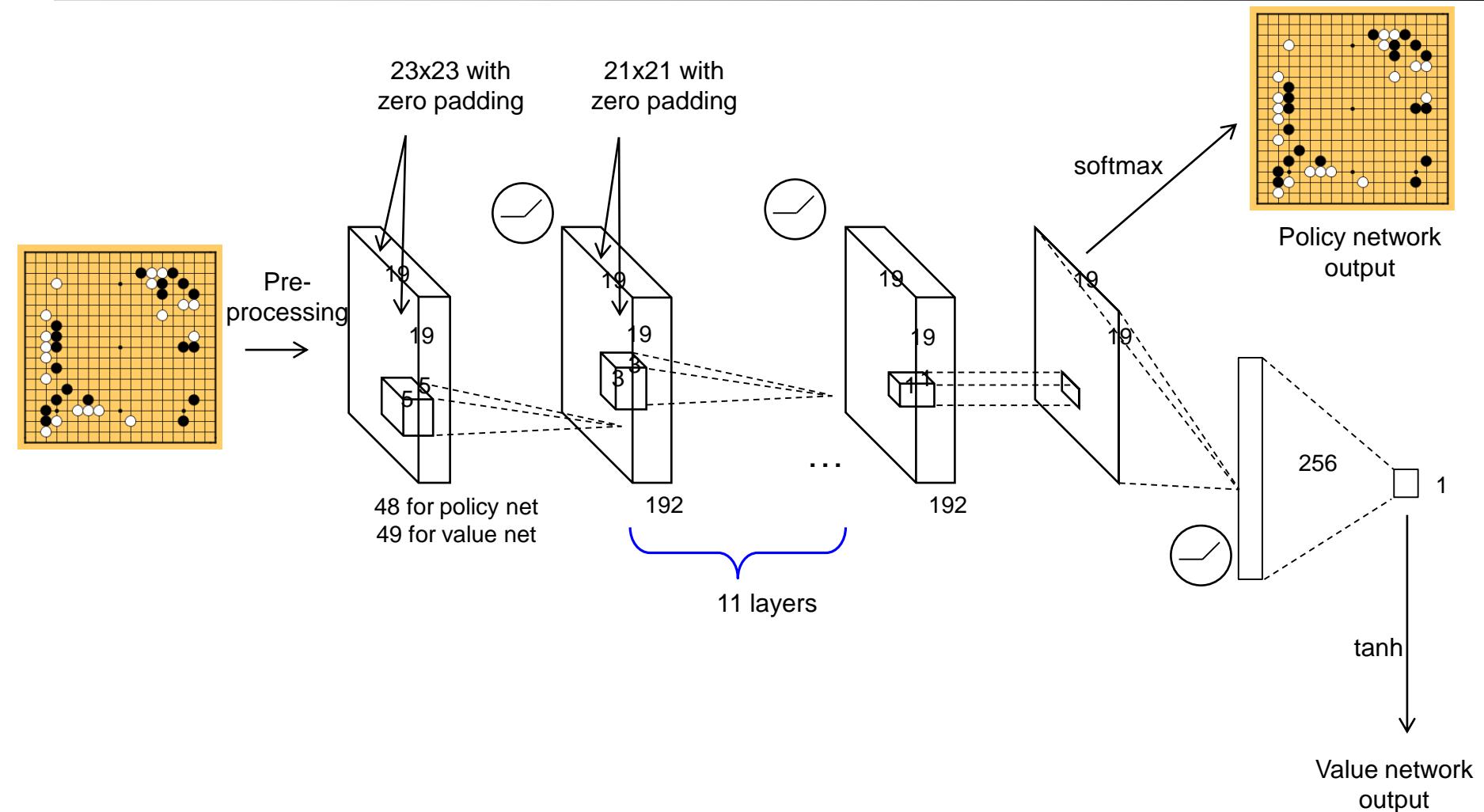


AlphaGo



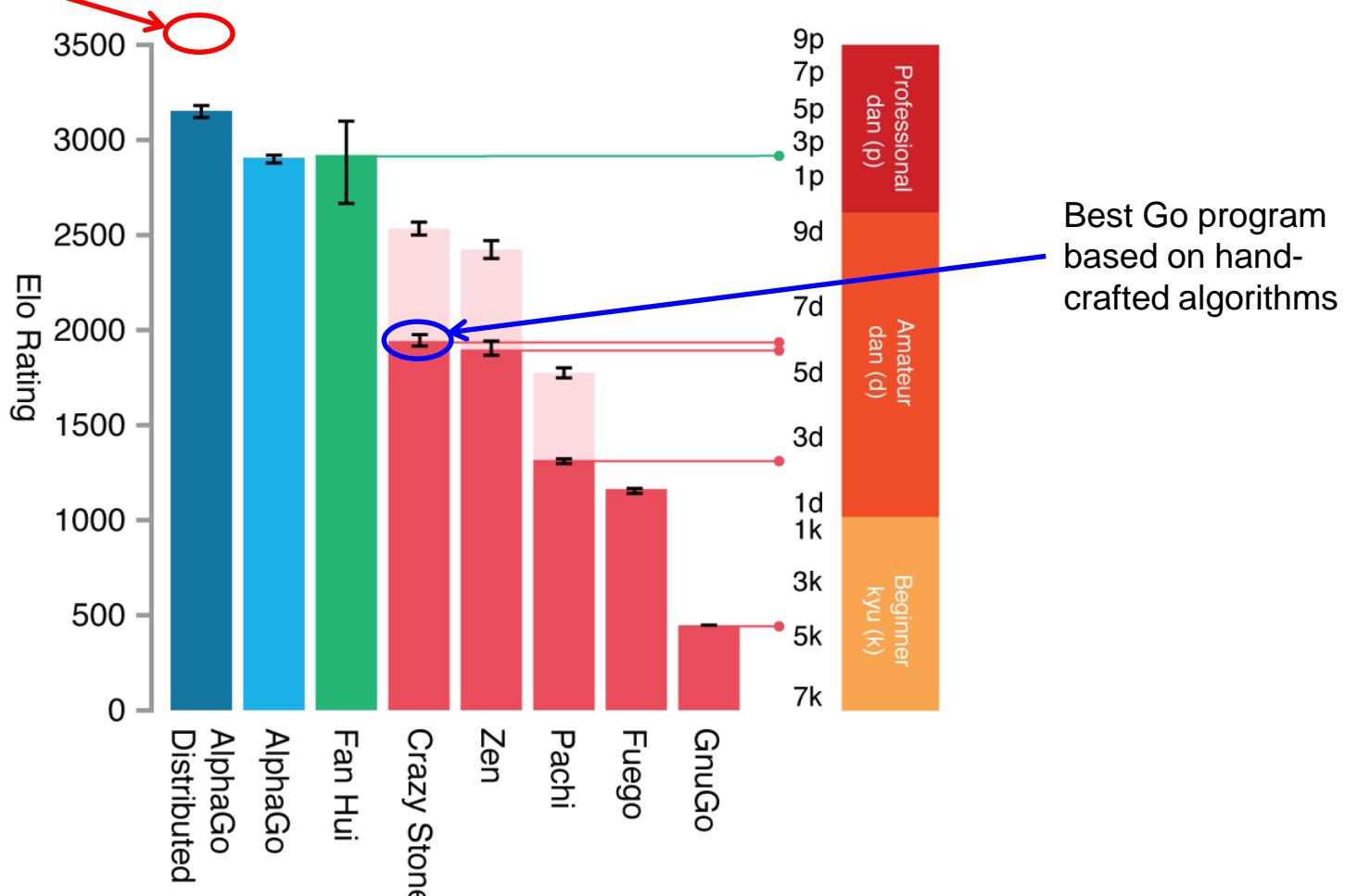
Situation
analysis,
Best move,
...

CNN in AlphaGo



AlphaGo (2016)

AlphaGo as of 2016/03



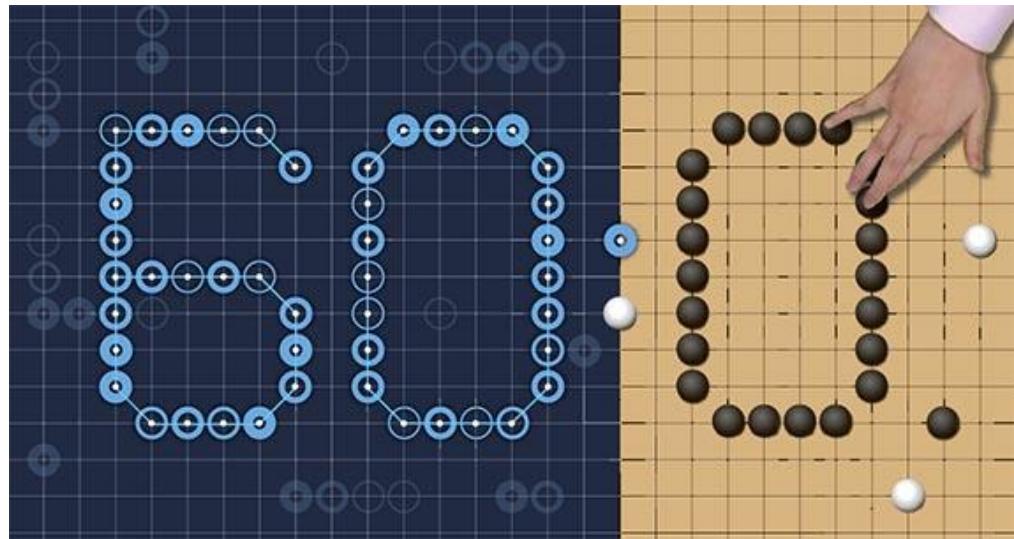
- As of 2016/03/15 (goratings.com after 5 matches with Lee Sedol)

Rank	Name	♂♀	Flag	Elo
1	Ke Jie	♂		3621
2	Google AlphaGo			3586
3	Park Jungwhan	♂		3569
4	Iyama Yuta	♂		3545
5	Lee Sedol	♂		3520

- As of 2016/07/18 (goratings.org)

Rank	Name	♂♀	Flag	Elo
1	Google DeepMind AlphaGo			3611
2	Ke Jie	♂		3608
3	Park Junghwan	♂		3588
4	Lee Sedol	♂		3556
5	Iyama Yuta	♂		3535

AlphaGo Master (2017)



알파고에 진 한·중·일 바둑기사들



이름: 박정환 9단
랭킹: 국내 랭킹 1위
전적:

5 패



안성준 9단
국내 랭킹 4위

1 패



커제 9단
중국 랭킹 1위

3 패



류자시 9단
중국 랭킹 2위

1 패



이야마 유타 9단
일본 랭킹 1위

1 패

AlphaGo Master (2017)



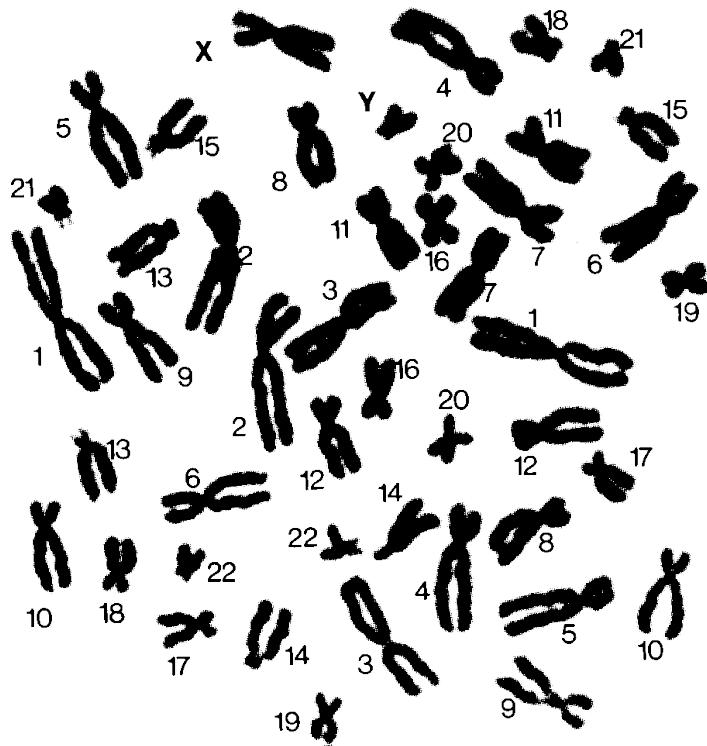
AlphaGo Master (2017)



Elo rating ~ 3,750
Distributed machines with 50 TPU's

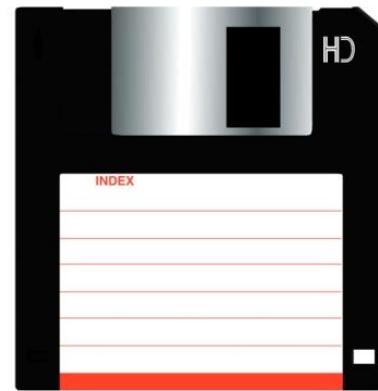
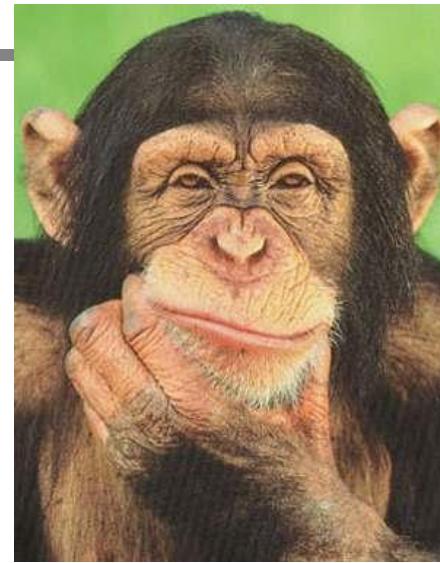
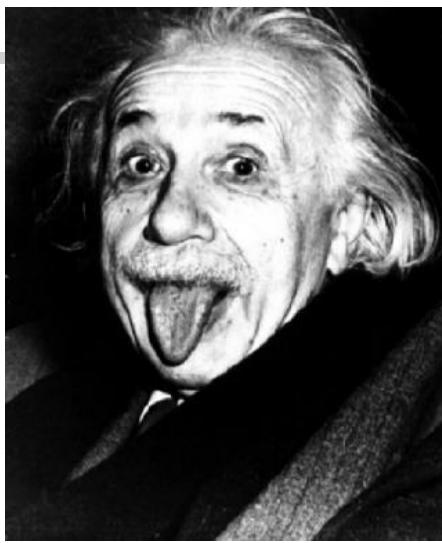
Elo rating ~ 4,750
Single machine with
TPU v2

Information Content in Human DNA



750MB

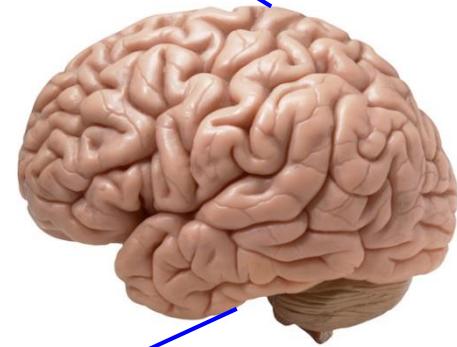
3 billion base pairs from mother, another 3 billion base pairs from father, but they are almost identical. 3 billion base pairs = 750MB



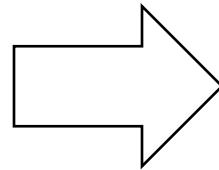
You Are What You Eat



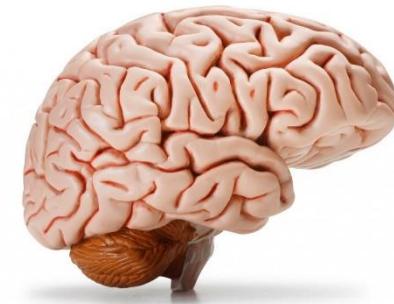
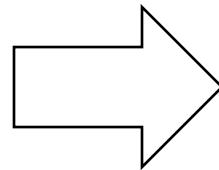
You Are What You Experience



750MB



xx MB



Amount of information needed to specify the learning algorithm of human brain



86 billion neurons
150 trillion synapses
Storage capacity ~2.5PB

xx MB to make
x PB from learning

Upper bound on the amount of
information a human brain can learn

86.1 \pm 8.1 billion neurons and 84.6 \pm 9.8 billion non-neuron cells (F. Azevedo, et al., Equal numbers of neuronal and nonneuronal cells make the human brain an isometrically scaled-up primate brain, J Comp Neurol. 2009)



- Training data for a human baby during the 1st year
 - 100 million frames of video
 - 1 million spoken words
- A lot of training data for low-level functions
 - Audio
 - Visual
 - Language
 - Motion
 - ...

Adult brain: 86 billion neurons and 150 trillion synapses.

86.1 ± 8.1 billion neurons and 84.6 ± 9.8 billion non-neuron cells (F. Azevedo, et al., Equal numbers of neuronal and nonneuronal cells make the human brain an isometrically scaled-up primate brain, J Comp Neurol. 2009)

Success of Deep Learning

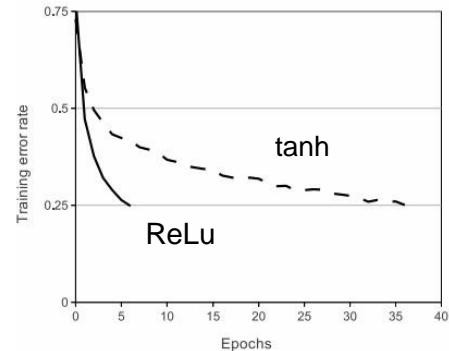
Moor's Law



Large amount
of data for
training



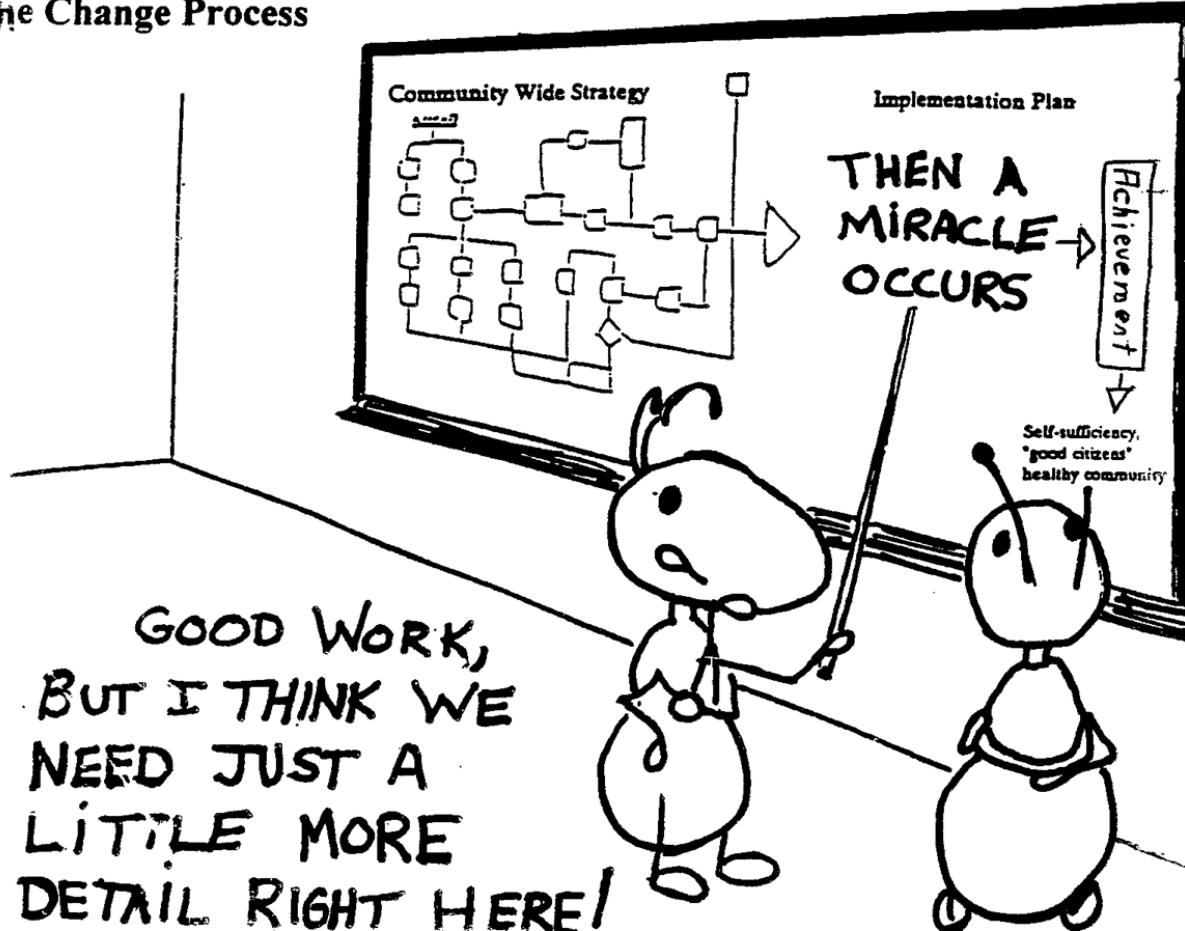
Better Architectures and Algorithms



Convolutional NN
Dropout
Max pooling
Autoencoder
DBN
Layer-wise training

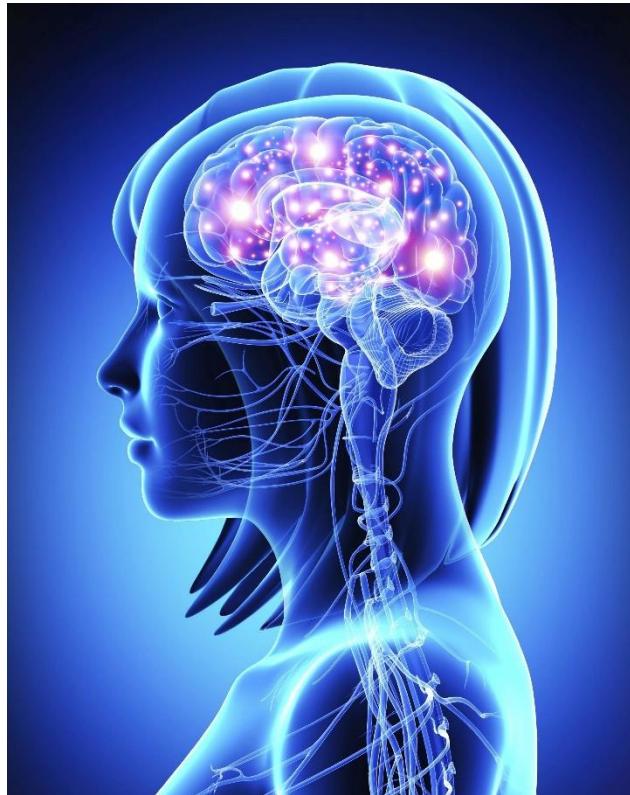
Why Deep Learning Works?

The Change Process



Working Example

- We always had a working example of deep learning, i.e., human brain.
- Thinking this way, it is not so surprising that deep learning works.



-
- But, we don't understand how our brain works.
 - Worse, we don't understand how deep learning works although we designed it.
 - For example, the developers of AlphaGo do not understand why it is so good at the game of Go. They can print out millions of neural network parameters, but they are just numbers. It is practically impossible to conclude why such a set of numbers give good performance.
 - Likewise, we can try to extract all information we can from a human brain, but it will be practically impossible to understand how human intelligence emerges.
 - Good news
 - Deep learning often just works whether or not we fully understand why it works
 - There's a possibility of having more progress even though we don't fully understand how deep learning works.
 - Perhaps even strong AI.
 - Designing without understanding is now possible!!!
 - Of course, we should try to apply our theoretical knowledge whenever possible and try to come up with new theories whenever possible.

Traditional Engineering

- We need to have FULL understanding when designing complicated machines like airplanes in traditional engineering



Lack of “Understanding”

- Lack of “understanding” often results in catastrophic failures in traditional engineering



Not Anymore

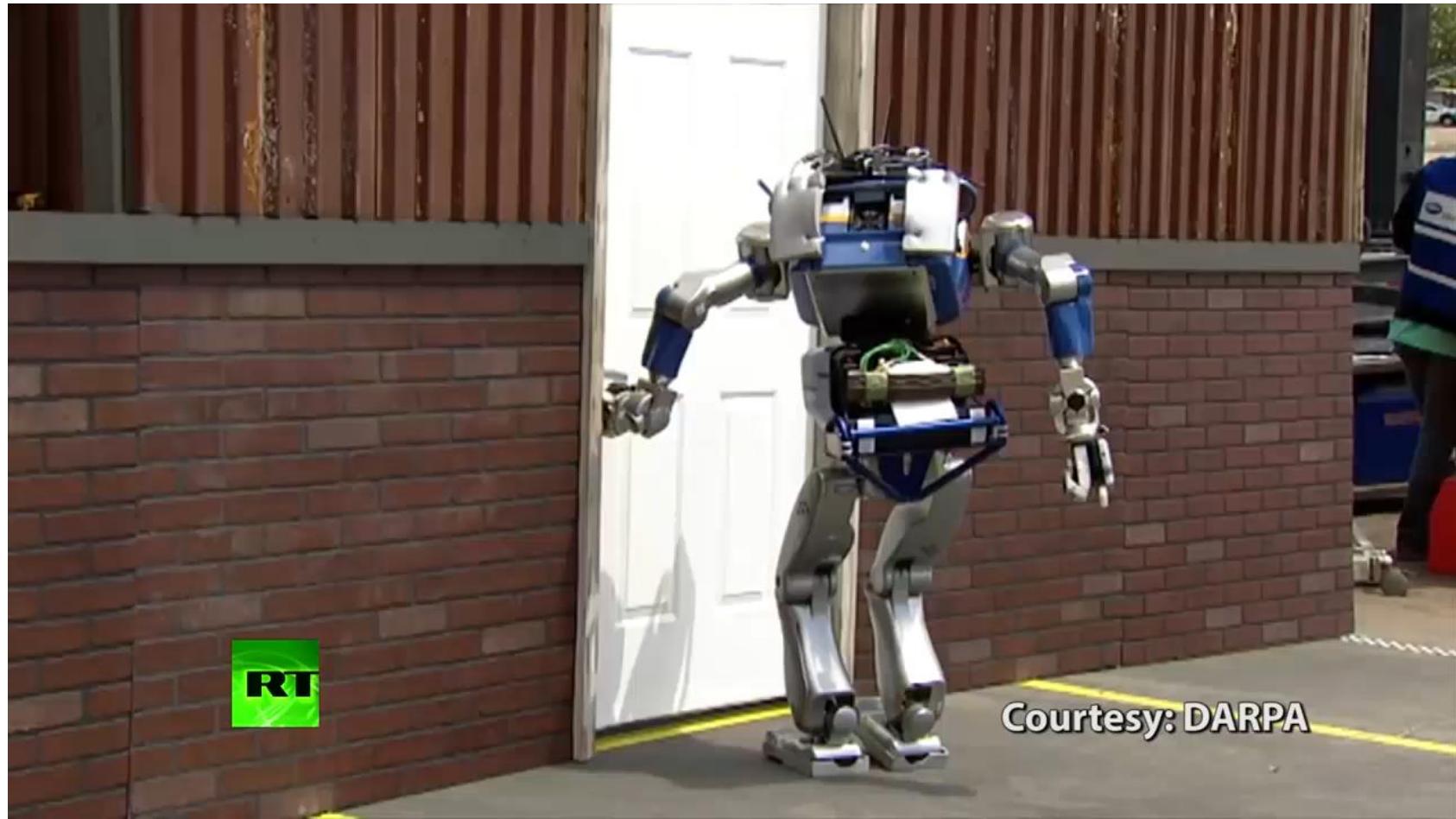
- Making AlphaGo only requires basic principles and algorithms
 - SGD, backpropagation, policy gradient method, MCTS, ...
- “Magic” happens after
 - A lot of training with random explorations



Welcome to the world of deep learning!

Now you can design things without full understanding!

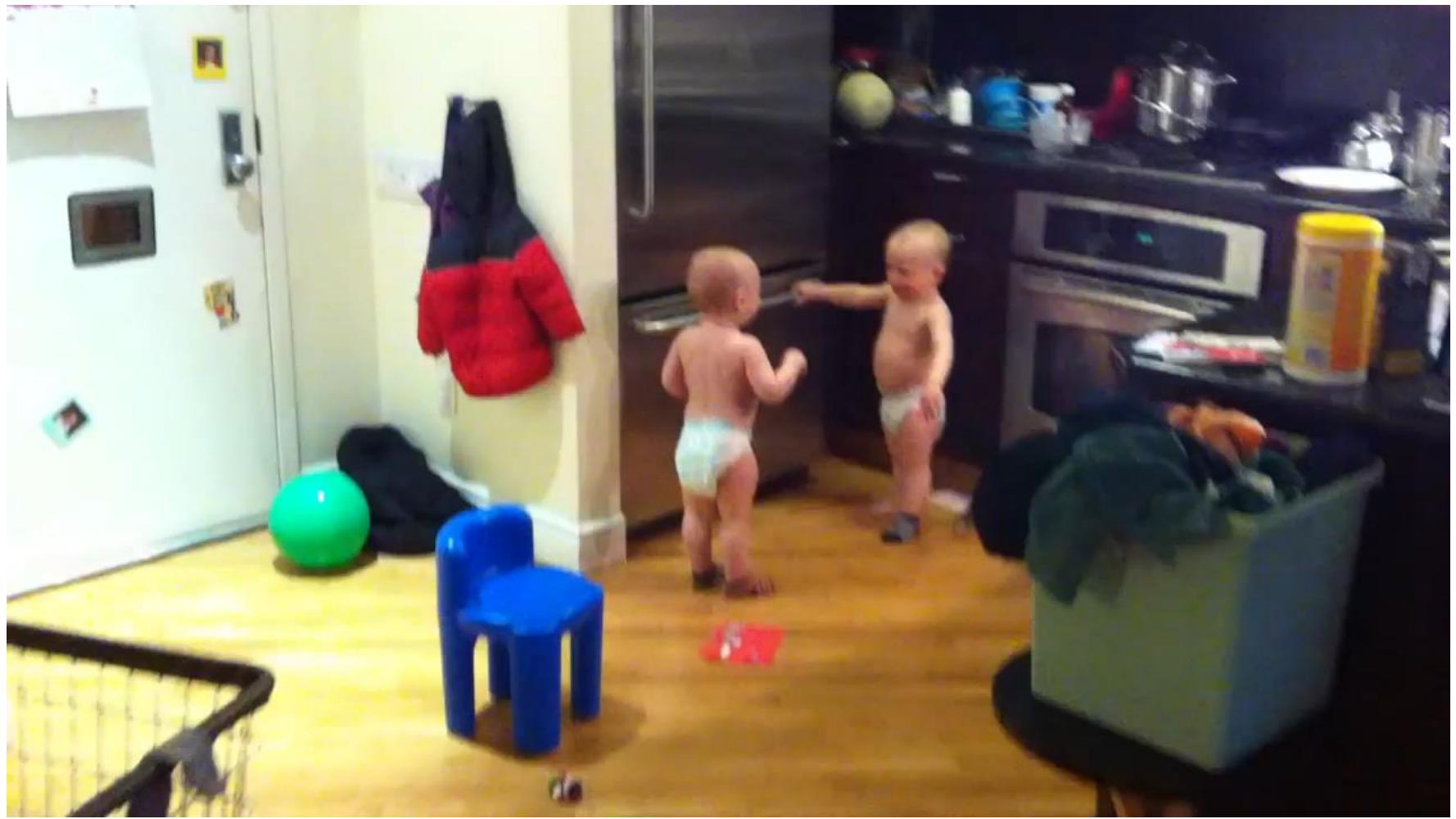
But, still a long way to go to reach
human-level AI for general tasks
Artificial General Intelligence (AGI)







-
- “Facebook shuts down robots after they invent their own language” –
The Telegraph (UK) 2017/08/01
 - Bob: i can i i everything else
 - Alice: balls have zero to me to me
 - Bob: you i everything else
 - Alice: balls have a ball to me to me to me to me to me to me to me
 - Bob: i i can i i i everything else
 - Alice: balls have a ball to me to me to me to me to me to me to me
 - Bob: i
 - “Facebook AI researcher slams 'irresponsible' reports about smart bot experiment” – CNBC 2017/08/01



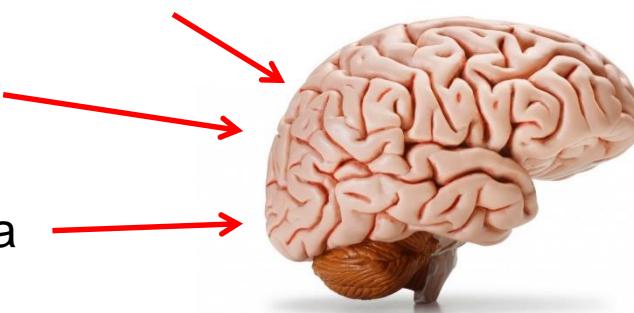
Practice Makes Perfect



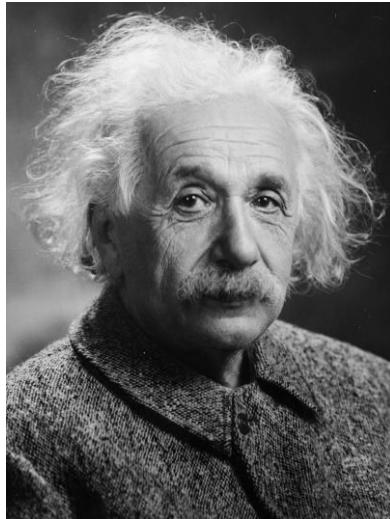
A lot of training data

A lot of training data

A lot of training data



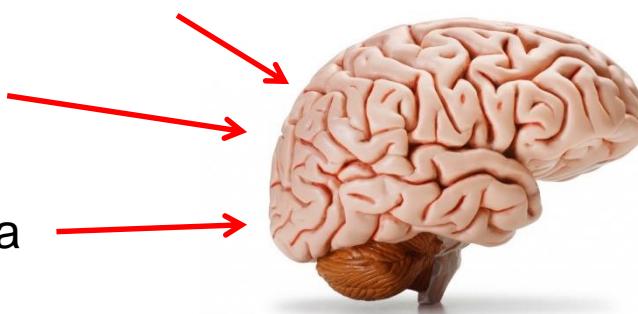
Practice Makes Perfect



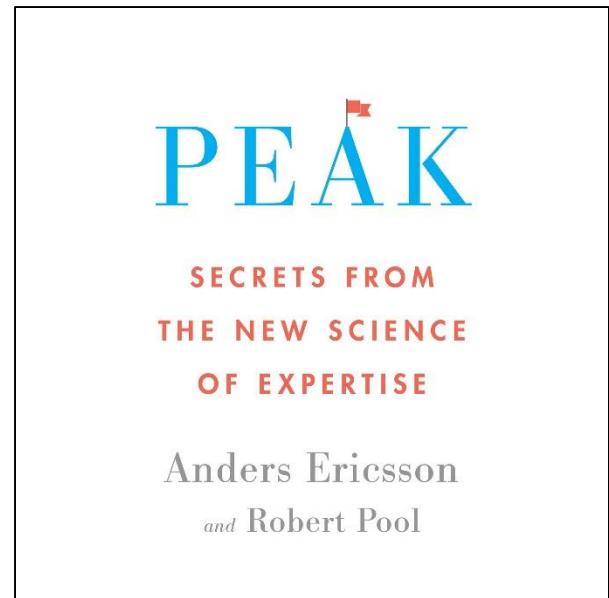
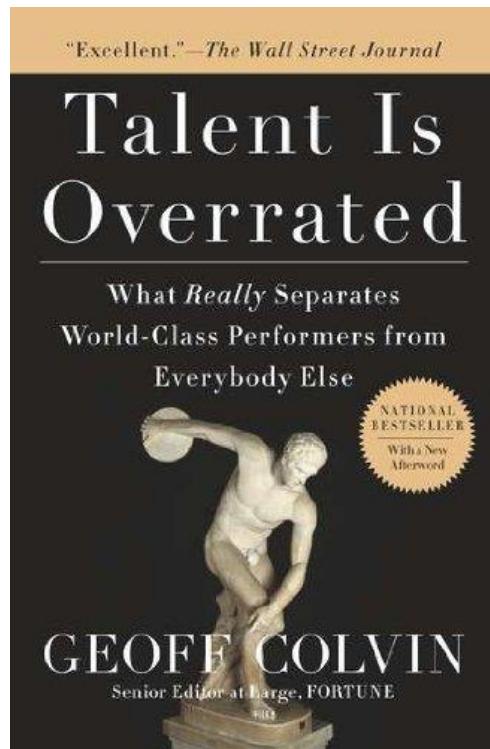
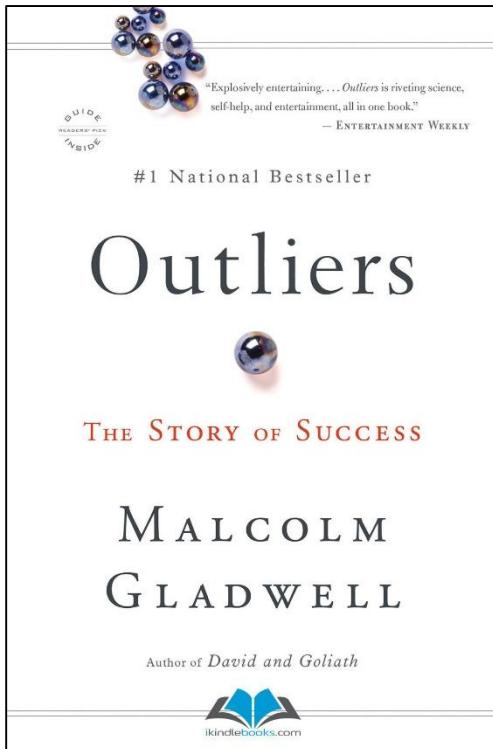
A lot of training data

A lot of training data

A lot of training data



How to Practice Well (For Humans)?



How to Practice Well (For AI)?



To be continued in Lecture 2
