Artificial Intelligence and the Singularity

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www.scaruffi.com

October 2014 - Revised 2016

"The person who says it cannot be done should not interrupt the person doing it" (Chinese proverb)
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Intelligence is not Artificial
Why the Singularity is not coming any time soon and other Meditations on the Peri-Human Condition and the Future of Intelligence
piero scaruffi

Thinking about Thought
the structure of life and the meaning of matter

BRAIN
Volume 1
In the "Thinking about Thought" series
piero scaruffi

A History of Silicon Valley
1900-2015

Almost a third edition 2015 update

Olivetti AI Center, 1987
Piero Scaruffi

- Cultural Historian
- Cognitive Scientist
- Blogger
- Poet
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This is Part 11

- See http://www.scaruffi.com/singular for the index of this Powerpoint presentation and links to the other parts
  1. Classic A.I. - The Age of Expert Systems
  2. The A.I. Winter and the Return of Connectionism
  3. Theory: Knowledge-based Systems and Neural Networks
  4. Robots
  5. Bionics
  6. Singularity
  7. Critique
  8. The Future
  9. Applications
  10. Machine Art
  11. The Age of Deep Learning
  12. Natural Language Processing
Modern A.I.
The Age of Deep Learning
Deep Learning

Deep Learning

MACHINE LEARNING

NEURAL NETWORKS

DEEP LEARNING

ARTIFICIAL INTELLIGENCE

COMPUTER SCIENCE
Deep Learning

Training multilayered networks

2006: Geoffrey Hinton's Deep Belief Networks

2007: Yoshua Bengio's Stacked Autoencoders
Deep Learning

2006: Hinton's Deep Belief Networks

Deep Belief Network

\[ P(v, h^1, h^2, h^3) = P(v|h^1)P(h^1|h^2)P(h^2, h^3) \]

\[ P(v|h^1) = \prod_i P(v_i|h^1) \]

\[ P(h^1|h^2) = \prod_j P(h_j^1|h^2) \]

\[ P(h^2, h^3) = \frac{1}{Z(W^3)} \exp(h^2W^3h^3) \]
Deep Learning

2007: Yoshua Bengio's Stacked Autoencoders

Auto-Encoders
- Multilayer neural nets with target output = input.
- Reconstruction = decoder(encoder(input))
- Objective is to minimize the reconstruction error.

$$\mathcal{L}(q) = -D_{KL}(q(z|x) \parallel p_{model}(z)) + E_{z \sim q(z|x)} \log p_{model}(x|z)$$

http://www.slideshare.net/KazukiNitta/variational-autoencoder-68765109

Stacked Auto-encoders
Deep Learning

2011: Yoshua Bengio's ReLu
Deep Learning

Geoffrey Hinton
1947, Google & U of T, BP
92.9-93.10 >200 papers

Michael I. Jordan
1956, UC Berkeley

Andrew Ng
1976, Stanford, Coursera
Google Brain → Baidu Brain

Yann LeCun
1960, Facebook & NYU,
CNN & LeNet

AT&T colleague

Yoshua Bengio
1964; UdeM, RNN & NLP

Michael Jordan
California, Berkeley

PhD

Postdoc

PhD

PhD

Nature (28 May 2015)
Trivia: The Stars of Deep Learning

Kunihiko Fukushima: Japan
Hava Siegelmann: Israel
Sepp Hochreiter: Germany
Juergen Schmidhuber: Switzerland
Yann LeCun: France
Geoffrey Hinton: Britain/ Canada
Yoshua Bengio: France/ Canada
Andrew Ng: China
Daniela Rus: Romania
Fei-fei Li: China
Sebastian Thrun: Germany
DeepMind: Britain/ New Zealand
Ilya Sutskever: Russia
Quoc Le: Vietnam
Trivia: The Stars of Deep Learning

Jitendra Malik: India
Dong Yu: China
Oriol Vinyals: Spain
Ian Goodfellow: Canada
Karen Simonyan: Armenia
Andrew Zisserman: Britain
Christian Szegedy: Germany
Aja Huang: China
Kaiming He: China
Jian Sun: China
Andrej Karpathy: Slovakia/ Canada
Pieter Abbeel: Belgium
Ronan Collobert: France
Yangqing Jia: China
Rajat Monga: India
Richard Socher: Germany
Trivia: The Stars of Deep Learning

Elon Musk: South Africa
Jen-Hsun Huang: Taiwan
Trivia: The Women of Deep Learning

Hava Siegelmann, Univ of Massachusetts
Fei-Fei Li, Stanford Univ
Daphne Koller, Calico Labs
Cynthia Breazeal, Jibo
Andrea Frome, Clarifai
Rana el Kaliouby, Affectiva
Hua Wu, Baidu
Angelica Lim, Simon Fraser Univ
Daniela Rus, MIT
Jane Wang, Google DeepMind
Rama Akkiraju, IBM Watson
Suzanne Gildert, KindredAI
Raia Hadsell, DeepMind
Raquel Urtasun, Univ of Toronto
Leslie Kaelbling, MIT
Jeannette Bohg, Max Planck Inst
The Homeland of Deep Learning
Deep Learning

2010: The ImageNet challenge (ILSVRC)

Large Scale Visual Recognition Challenge 2010

Winner team:
Yuanqing Lin
NEC Laboratories
Deep Learning

Annus mirabilis of Deep Learning: 2012

Error rates on the ILSVRC-2012 competition:
- Krizhevsky et al.: 16.4%
- University of Tokyo: 26.1%
- Oxford University Vision Group: 26.9%
- INRIA + XRCE: 27.0%
- University of Amsterdam: 29.5%

ImageNet: Image Classification Task

Classification Error (%)

- Deep CNN

5 Convolutional Layers

3 Fully Connected Layers
Deep Learning

AlexNet: 8 layers

Alex Krizhevsky, Ilya Sutskever, Geoffrey E. Hinton
Deep Learning

• Andrew Ng’s Google Brain (2012): 1.7 billion connections (and 16,000 processors) learn to recognize cats in YouTube videos
2010s

ICDAR OFFLINE CHINESE HANDWRITING RECOGNITION CONTEST

OCT 2013: NEAR-HUMAN PERFORMANCE

JÜRGEN SCHMIDHUBER, IDSIA
2010s

• 2015: Jun Sun's team at Fujitsu's Chinese laboratories surpasses human performance in handwritten Chinese character recognition

Fujitsu

Fujitsu Achieves 96.7% Recognition Rate for Handwritten Chinese Characters Using AI That Mimics the Human Brain

First time ever to be more accurate than human recognition, according to conference

Fujitsu R&D Center Co., Ltd., Fujitsu Laboratories Ltd.

Beijing, China and Kawasaki, Japan, September 17, 2015
Deep Learning

Region-based CNNs (Jitendra Malik’s team, 2013)
• Objection detection
Deep Learning

• Speech recognition
Deep Learning

Annus mirabilis of Deep Learning: 2012
Why did it take until 2012?
   Too many parameters to be learned from too few labeled examples
   Processing speed wasn’t there before Google paid for it
   Training datasets weren’t big enough earlier

Thus to the Eastern wealth through Storms we go,
But now, the Cape once doubled, fear no more:
   A constant Trade-wind will securely blow,
And gently lay us on the Spicy shore.
(John Dryden, Annus Mirabilis, 1667)
The real heroes of Deep Learning

Nvidia’s GPUs

Deep Learning is born
NVIDIA GPUs help Microsoft build record-breaking Image Recognition System

Thanks to the use of GPUs, Microsoft researchers achieved record results on ImageNet, a prestigious image-recognition benchmark. Compared to last year, Microsoft’s system cut the top-5 error rate by half, correctly classifying images within 1,000 pre-defined categories more than 96 percent of the time. Their system uses a 152-layer neural network, which is nearly five times deeper than the state of the art.

Nvidia’s CEO, Jen-Hsun Huang, delivers the first DGX-1 to Elon Musk’s OpenAI (2016)
The real heroes of Deep Learning

Google Tensor Processing Unit (2016)
Intel Nervana (2017)
Unsung Heroes: The datasets

1990: Switchboard-1 Telephone Speech Corpus (TI)
1991: Continuous Speech Recognition (CSR) Corpus
1993: FERET (Army Research Lab)
1994: ORL face dataset (Olivetti)
1996: Broadcast News corpus
1999: MNIST handwritten-digit dataset (NYU)
2000: PASCAL VOC
2007: Tiny Images Dataset (MIT)
2007: Labeled Faces in the Wild (University of Massachusetts)
2009: ImageNet
2013: dataset of Atari games (University of Alberta)
2014: COCO (Microsoft)
Unsung Heroes: The datasets

Videos:
- Human3.6m (2014, Romanian Academy)
- YouTube-8M (2016, Google)
- Kinetics-600 (2017, Oxford)

Human-machine interaction:
- SEMAINE (2007, Queen's University Belfast)
- Cam3D (2011, Cambridge)
- MAHNOB-HCI (2011, ICL)

Facial expressions:
- EAGER (2013, Binghamton Univ)
- FaceWarehouse (2014, Zhejiang Univ)
- CelebA (2015, Hong Kong)
- DCU (2014, Dublin City Univ)
Unsung Heroes: The datasets

**Scenes:**
- LSUN (2015, Princeton University)

**Human interactions:**
- DCU (2014, Dublin City Univ)

**Machine translation:**
- UM (2014, Macau Univ)
- Tvsub & Mvsub (2016, Dublin City Univ)

**Reading comprehension:**
- SNLI (2015, Stanford)
- SQuAD (2016, Stanford)
- MARCO (2016, Microsoft)
- WebText (2018, OpenAI)

**Sentiment analysis:**
- LMRD (2011, Stanford)
- SST (2013, Stanford)
Unsung Heroes: The Platforms

• Open-source platforms for deep learning
  – Torch (Ronan Collobert @ IDIAP, Switzerland, 2002)
  – Theano (Bengio’s group @ Univ of Montreal, Canada, 2010)
  – Caffe (Yangqing Jia @ UC Berkeley, 2013)
  – TensorFlow (Rajat Monga @ Google, 2015)
Deep Learning

- Scales well with memory/data/computation
- Solves the representation learning problem
- State-of-the-art for images, audio, language, ...
Deep Learning

Deep Learning mimics the workings of the brain: the audiovisual cortex works in multiple hierarchical stages.
Artificial Intelligence

Genealogy of Intelligent Machines

Hydraulic machines
  ↓
Steam engines
  ↓
Cybernetics
  ↓
Neural networks
  ↓
  ↓
Logic
  ↓
Hilbert
  ↓
Turing Machine
  ↓
Computers
  ↓
Expert Systems
Progress in Neural Networks

- Physics: Hopfield’s recurrent neural networks mimic annealing
- Neuroscience: Fukuyama’s convolutional neural networks mimic the cat’s visual system
- Rediscovery of old mathematics (mainly optimization and control methods)
2010s

2014: Microsoft’s Skype Translator, a real-time spoken language translation system

2014: IBM’s TrueNorth processor

Lawrence Livermore National Laboratory and IBM Collaborate to Build Brain-Inspired Supercomputer

LIVERMORE, Calif. and ARMONK, N.Y. - 29 Mar 2016
The 2010s

- Widespread adoption of image recognition
  - Facebook’s DeepFace (2015)
  - Deep Face (2014) claims 97% accuracy… but mysteriously disappears
  - Microsoft's CaptionBot (2016)
2010s

- Facebook (2010): face recognition
- FindFace (2016): identify the pictures of strangers
- Face++: pay with your face
The 2010s

- Face-reading algorithms: detecting human emotion (eg Emotient)
The 2010s

- Gadgets for
  - Speech Recognition
  - Image Recognition
State of the Art in Deep Learning

- Perceptron
- CNN = Convolutional Neural Networks (face recognition, object identification, disease detection)
- RNN/LSTM = Recurrent Neural Networks (speech recognition, translation, caption generation)
- GAN = Generative Adversarial Networks (image generation, style transfer)
- DRL = Deep Reinforcement Learning (robot training, game playing)
Evolution of Neural Networks

- Perceptrons (1960s)
- Reinforcement Learning (1970s)
- Recurrent Neural Networks (1970s)
- Convolutional Neural Networks (1990s)
- Deep Learning (2000s)
- Generative Adversarial Networks (2010s)
Evolution of Neural Networks

1960’s

\[ u = \sum_{i} w_i x_i \]

\[ y = g(u) \]

1980’s

\[ u = \sum_{i} w_i x_i \]

\[ y = g(u) \]

2000’s

\[ u = \sum_{i} w_i x_i \]

Not much has changed...
The 5 years that changed A.I. 2013-17

1. Very Deep Learning
2. Reinforcement Learning
3. Recurrent Neural Nets
4. Generative Adversarial Networks
5. Recursive Cortical Networks
6. Capsule Nets
7. Development Platforms
8. Automatic Machine Learning
9. Explainable Deep Networks
10. Machine Creativity
Very Deep Learning

Most influential architectures:

- AlexNet (2012)
- R-CNN (2013)
- VGGNet or VGG-16 (2014)
- GoogleNet or Inception (2014)
- DeepFace (2014)
- Conditional networks (2016)
- Inception v4 and Inception-ResNet (2016)
- SqueezeNet (2016)
- ResNeXt (2017)
Very Deep Learning

Most influential architectures:
• AlexNet (2012)
Very Deep Learning

Most influential architectures:
- R-CNN (2013) – Ross Girshick and Jitendra Malik
Very Deep Learning

Most influential architectures:
- VGGNet or VGG-16 (2014) Karen Simonyan & Andrew Zisserman
Very Deep Learning

Most influential architectures:

- GoogleNet or Inception (2014) – Christian Szegedy
  - The first layers is a “depthwise separable convolution” (Laurent Sifre, 2013)
Very Deep Learning

Most influential architectures:

- GoogLeNet (Inception)

9 Inception modules
Very Deep Learning

Most influential architectures:
• DeepFace (2014) – Lior Wolf
Very Deep Learning

Most influential architectures:

- Network-in-Network/ NiN (2014) – Shuicheng Yan
Very Deep Learning

Most influential architectures:

- Another “network-in-network architectures” like Inception
Very Deep Learning

Most influential architectures:
- ResNet with identity mappings (2016) – Kaiming He – 1001 layers

\[
y_l = h(x_l) + \mathcal{F}(x_l, \mathcal{W}_l), \\
x_{l+1} = f(y_l),
\]

\[
f \equiv \text{ReLU}
\]

2015

2016 with identity mappings

identity mapping:
\[
h(x_l) = x_l
\]

\[
f \text{ is also an identity mapping: } x_{l+1} = y_l
\]

\[
x_L = x_l + \sum_{i=l}^{L-1} \mathcal{F}(x_i, \mathcal{W}_i)
\]

for any deeper unit \(L\) and any shallower unit \(l\)
Very Deep Learning

2016: Microsoft’s conditional networks – Antonio Criminisi

Decision Forests, Convolutional Networks and the Models in-Between
Microsoft Research Technical Report 2015-58
Yani Ioannou\textsuperscript{1} Duncan Robertson\textsuperscript{2} Darko Zikic\textsuperscript{2} Peter Kontschieder\textsuperscript{2}
Jamie Shotton\textsuperscript{2} Matthew Brown\textsuperscript{3}

Antonio Criminisi\textsuperscript{2}

Our automatically-optimized conditional architecture is \(~5\) times faster and \(~6\) times smaller than NiN, with same accuracy.
Very Deep Learning

Object detection (improving R-CNN):
- SPPnet (2014)
- Fast RCNN (2014)

Figure 3: A network structure with a spatial pyramid pooling layer. Here 256 is the filter number of the conv5 layer, and conv8 is the last convolutional layer.
Very Deep Learning

Object detection (improving R-CNN):

- Faster RCNN (2015)
- Yolo (2016)
Very Deep Learning

Batch Normalization (Sergey Ioffe and Christian Szegedy at Google, 2015)

A way to accelerate the training of a deep network

**Input:** Values of $x$ over a mini-batch: $\mathcal{B} = \{x_1, \ldots, x_m\}$; Parameters to be learned: $\gamma, \beta$

**Output:** $\{y_i = \text{BN}_{\gamma, \beta}(x_i)\}$

\[
\begin{align*}
\mu_B & \leftarrow \frac{1}{m} \sum_{i=1}^{m} x_i & \quad \text{// mini-batch mean} \\
\sigma_B^2 & \leftarrow \frac{1}{m} \sum_{i=1}^{m} (x_i - \mu_B)^2 & \quad \text{// mini-batch variance} \\
\hat{x}_i & \leftarrow \frac{x_i - \mu_B}{\sqrt{\sigma_B^2 + \epsilon}} & \quad \text{// normalize} \\
y_i & \leftarrow \gamma \hat{x}_i + \beta \equiv \text{BN}_{\gamma, \beta}(x_i) & \quad \text{// scale and shift}
\end{align*}
\]
Most influential architectures:

- Inception-v4 (2016)
- Inception-ResNet (2016)
Very Deep Learning

Most influential architectures:

- Inception v1 - Introduced inception blocks and one “depthwise separable convolution”
- Inception v2 - Added batch normalization (Dec 2015)
- Inception v3 - Factorized the inception blocks further
- Inception v4 - Adds residual connections (2016)
Very Deep Learning

Most influential architectures:
- SqueezeNet (2016) – Kurt Keutzer
Very Deep Learning

Most influential architectures:

• Xception (2016, Francois Chollet) replaces all Inception modules with “depthwise separable convolutions”
Very Deep Learning

Most influential architectures:

- ResNeXt (2017) – Ross Girshick, Kaiming He

Figure 1. Left: A block of ResNet [14]. Right: A block of ResNeXt with cardinality = 32, with roughly the same complexity. A layer is shown as (# in channels, filter size, # out channels).
Very Deep Learning

Most influential architectures:

- **R-net (2017)** – Microsoft China
  - Bidirectional RNN for reading comprehension (Mikolov et al., 2010) (Wang & Jiang, 2016)
Very Deep Learning

Most influential architectures:
- FractalNet (Chicago, 2017)
- PolyNet (Hong Kong, 2017)
Very Deep Learning

Most influential architectures:
• Tsung-wei Ke’s Multigrid networks (2017)
Very Deep Learning

Most influential architectures:
- Gao Wang’s MSDNet (2018)
Very Deep Learning

The Power of Depth

Ronen Eldan and Ohad Shamir prove that "depth can be exponentially more valuable than width" (2016).

The Power of Depth for Feedforward Neural Networks

May 2016

Ronen Eldan
Weizmann Institute of Science

Ohad Shamir
Weizmann Institute of Science

all known activation functions, including rectified linear units, sigmoids and thresholds, and formally demonstrates that depth – even if increased by 1 – can be exponentially more valuable than width for standard feedforward neural networks. Moreover, compared to related results in the context of Boolean...
Huang’s Law

"Nvidia’s GPUs today are 25 times faster than 5 years ago" (Nvidia CEO Jensen Huang, April 2018)

2012: It took six days on two Nvidia GTX 580s to train AlexNet

2018: It takes 18 minutes with the Nvidia DGX-2

Move Over, Moore’s Law: Make Way for Huang’s Law

Graphics processors are on a supercharged development path that eclipses Moore’s Law, says Nvidia’s Jensen Huang
Huang’s Law

2016: Nvidia’s Volta
2016: Nvidia’s DGX-1: 8 GPUs + software to train neural networks

Nvidia’s Tesla P100 for deep learning

640 TENSOR CORES
An Exponential Leap in Performance
Volta delivers over 100 Teraflops per second
Huang’s Law

Google’s TPU (programmed via TensorFlow and offered via Google Cloud)

Internal search ranking model training (2018):
~9 hours on 1/4 pod vs. ~132 hours on 275 high end CPU machines (14.2 times faster)

Internal image model training:
~22 hours on 1/4 pod vs. ~216 hours on previous production setup (9 times faster)
A.I. for Makers

Let’s start with the easy part: how can a maker build A.I. systems?
Luckily, this is increasingly easy.
A.I. for Makers

Arduino & Raspberry

- Google TensorFlow available for Raspberry Pi
- Dobot’s Arduino A.I. Suite
A.I. for Makers

Google Coral

GOOGLE LAUNCHES AI PLATFORM THAT LOOKS REMARKABLY LIKE A RASPBERRY PI

by: Brian Benchoff  80 Comments

March 5, 2019
A.I. for Makers

Nvidia Jetson

Nvidia announces $99 AI computer for developers, makers, and researchers

Mar 18, 2019,
The Jetson Nano
A.I. for Makers

HiKey
Sipeed
Horned Sungem
Intel
A.I. for Makers

Free resources

• Google’s AI Education site https://ai.google/education
• Free online book "Neural Networks and Deep Learning“ http://neuralnetworksanddeeplearning.com/
• David Silver's course on Reinforcement Learning on YouTube https://www.youtube.com/watch?v=2pWv7GOvuf0
A.I. for Makers

Udemy's 14-hour video course
“Deep Learning with Python”

Complete Guide to TensorFlow for Deep Learning with Python
Learn how to use Google’s Deep Learning Framework - TensorFlow with Python! Solve problems with cutting edge techniques!

Created by Jose Portilla  Last updated 11/2018
English  English [Auto-generated], French [Auto-generated], 9 more

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A.I. for Makers

The tools are the easy part… the problem is what to do with the tools…

You can do simple things like robots that say “hello” and recognize objects…

… but A.I. wants to do much more

What is A.I. studying now?
Very Deep Learning

ImageNet 2012-15
BinaryConnect: Training Deep Neural Networks with binary weights during propagations

Matthieu Courbariaux
École Polytechnique de Montréal

Yoshua Bengio
Université de Montréal, CIFAR Senior Fellow

Binary weights, i.e., weights which are constrained to only two possible values (e.g. -1 or 1), would bring great benefits to specialized DL hardware by replacing many multiply-accumulate operations.
Ternary Networks

Ternary Networks (2016)

Ternary weight networks

Fengfu Li and Bo Zhang
Institute of Applied Math., AMSS, CAS
Beijing, China

Bin Liu
Moshanghua Tech Co., Ltd.
Beijing, China

A. Trends in DNN accuracies on ImageNet

- Ternary ResNet-50 used in Intel study offers top accuracy (13%+ better than AlexNet)
- State-of-the-art "human-level" accuracy
- AlexNet accuracy is used for reference in many studies

CMU + Intel study (2016)

*Ternary ResNet is the first sparse and very low precision (2bit) DNN to offer comparable accuracy to ResNet-152
Reinforcement Learning

Types of Machine Learning

- Supervised
  - Classification
- Unsupervised
  - Clustering
- Reinforcement
  - Performance
Reinforcement Learning

Supervised learning: learning from a dataset of positive instances (e.g., object recognition).

Unsupervised learning: clustering objects together by similarity (e.g., concept formation)

Reinforcement learning: improving performance by direct interaction with the environment
Reinforcement Learning

Edward Thorndike (1911): "The greater the satisfaction or discomfort, the greater the strengthening or weakening of the bond."

Ivan Pavlov (1926): “The magnitude and timing of the conditioned response changes as a result of the contingency between the conditioned stimulus and the unconditioned stimulus”.

Burrhus Skinner (1938): “The only differences between the behavior of rat and man lie in the field of verbal behavior.”

Donal Hebb (~1946): Neurons that fire together wire together
Reinforcement Learning

Claude Shannon (1949): use an evaluation function to help a computer learn how to play chess

Marvin Minsky’s thesis (1954)

Richard Bellman (1957): dynamic programming/ optimal control

Arthur Samuel (1959): checkers program

Donald Michie (1961): MENACE program

Harry Klopf (1972): neurons actively seek "excitatory" signal and avoid "inhibitory" signals.
Reinforcement Learning

Ian Witten (1977): actor-critic method
John Holland (1977): classifier systems
Bart Kosko (1986): differential Hebbian learning
Chris Watkins (1989): Q Learning
Reinforcement Learning

Gerald Tesauro (1992): reinforcement learning to play backgammon
Wulfram Gerstner (1996): neuronal dynamics
David Fogel (1996): evolutionary algorithm to learn checkers

... DeepMind (2013): deep reinforcement learning to play Atari games
DeepMind (2016): deep reinforcement learning for continuous action
Reinforcement Learning

• Unsupervised learning
• A computational approach to goal-directed learning from interaction between an active decision-making agent and its environment
• Learning what to do so as to maximize a reward
• The four pillars of reinforcement learning: a policy, a reward function, a value function, and a model of the environment
• Learning by self-play

Andrew Barto
Richard Sutton
Reinforcement Learning

- Policy-based RL. Search directly for the policy achieving maximum future reward
- Value-based RL. Estimate the maximum value achievable under any policy
- Model-based RL. Build a transition model of the environment
Reinforcement Learning

• Markov Decision Process:
  – Set of states, \( S \)
  – Set of actions, \( A \)
  – Reward function, \( R \)
  – Policy, \( \pi \)
  – Value, \( V \)

• Action (\( A \)) transitions from start state to end state (\( S \)) and is assigned a (positive or negative) reward (\( R \))
  – Policy: set of actions
  – Value: set of rewards

• Goal: choose policy that maximizes value
Reinforcement Learning

• Markov Decision Process:
  – Richard Bellman’s "value iteration" method (1957)
  – Ronald Howard’s "policy iteration" method 1960)
Reinforcement Learning

- Q-learning
- Sarsa
- TD-learning
Reinforcement Learning

Deep Reinforcement Learning

• Applying DL to RL
• Use a deep network to represent value function and/or policy and/or model
• Optimise the value function and/or policy and/or model
• Combines CNN and RL
Deep Reinforcement Learning

Deep Q-Networks (DQN) provide a stable solution to deep value-based RL (Volodymyr Mnih, 2013)

Figure 1. The DQN algorithm is composed of three main components, the Q-network \((Q(s, a; \theta))\) that defines the behavior policy, the target Q-network \((Q(s, a; \theta^-))\) that is used to generate target Q values for the DQN loss term and the replay memory that the agent uses to sample random transitions for training the Q-network.

Source: Arun Nair (2015)
The Limitations of Reinforcement Learning

Andrey Kurenkov
https://thegr gradient.pub/why-rl-is-flawed/

DQN fails at Montezuma Revenge
Deep Reinforcement Learning

Arun Nair’s GORILA (2015)
First massively distributed architecture for deep reinforcement learning
A lot faster implementation of DQN

Four main components: parallel actors that generate new behavior; parallel learners that are trained from stored experience; a distributed neural network to represent the value function or behavior policy; and a distributed store of experience.
Reinforcement Learning

• Computer go/weiqi
  – 2009: Fuego Go (Monte Carlo program by Univ. of Alberta) beats Zhou Junxun
  – 2010: MogoTW (Monte Carlo program developed in 2008 by a Euro-Taiwanese team) beat Catalin Taranu
  – 2012: Tencho no Igo/ Zen (Monte Carlo program developed by Yoji Ojima in 2005) beat Takemiya Masaki
  – 2013: Crazy Stone (Monte Carlo program by Remi Coulom in 2005) beat Yoshio Ishida
  – Pachi (open-source Monte Carlo program by Petr Baudis)
Reinforcement Learning

2016: Google/DeepMind’s AlphaGo beats the weiqi champion Se-dol Lee

Google AlphaGo computer beats professional at 'world's most complex board game' Go

Milestone in AI research likened to defeat of world chess champion Garry Kasparov in 1997 by IBM’s Deep Blue computer
Reinforcement Learning

2017: AlphaGo beats the Go champion Ke Jie
Reinforcement Learning

AlphaGo (2016)
Reinforcement Learning

AlphaGo Overview

Policy Network
- Expert Games
  - 130 000 Games
  - 30 M Positions
- Supervised Learning
  - SL Policy
  - Position $\rightarrow$ Next Move
  - Accuracy: 56%

Fast Policy Network
- Expert Games
  - 140 000 Patterns
  - 120 000 Games
  - 30 M Positions
- Supervised Learning
  - Fast Policy
  - Pattern $\rightarrow$ Next Move
  - Accuracy: 24%

Reinforcement Learning Policy Network
- Self-Play Games
  - 1.3 M Games by various versions of RL Policy
- Reinforcement Learning
  - RL Policy
  - Position $\rightarrow$ Next Move
  - Wins 80% vs. SL Policy

Value Network
- Self-Play Games
  - 30 M Positions by fixed version of RL Policy
- Reinforcement Learning
  - Position $\rightarrow$ Win Probability
  - 15 000 times faster than MCTS Rollouts evaluations

AlphaGo

Monte Carlo Tree Search

© Bob van den Hoek
Reinforcement Learning

AlphaGo architecture
Training policy and value networks
Reinforcement Learning

AlphaGo architecture
Planning with an environment model and Monte Carlo Tree Search

Figure 3 | Monte Carlo tree search in AlphaGo. a, Each simulation traverses the tree by selecting the edge with maximum action value $Q$, plus a bonus $u(P)$ that depends on a stored prior probability $P$ for that edge. b, The leaf node may be expanded; the new node is processed once by the policy network $p_\pi$ and the output probabilities are stored as prior probabilities $P$ for each action. c, At the end of a simulation, the leaf node is evaluated in two ways: using the value network $v_\theta$, and by running a rollout to the end of the game with the fast rollout policy $p_\pi$, then computing the winner with function $r$. d, Action values $Q$ are updated to track the mean value of all evaluations $r(\cdot)$ and $v_\theta(\cdot)$ in the subtree below that action.
Deep Reinforcement Learning

Fanuc/ Preferred Networks robot (2015)
Toyota’s self-teaching car (2016)
Deep Reinforcement Learning

AlphaGo Zero (2017)

Mastering the game of Go without human knowledge


40 days
AlphaGo Zero surpasses all other versions of AlphaGo and, arguably, becomes the best Go player in the world. It does this entirely from self-play, with no human intervention and using no historical data.
Deep Reinforcement Learning

AlphaGo Zero (2017)
Playing go without human knowledge

Figure 1 | Self-play reinforcement learning in AlphaGo Zero.
Deep Reinforcement Learning

AlphaGo Zero (2017)
Playing go without human knowledge

Figure 2 | MCTS in AlphaGo Zero
Deep Reinforcement Learning

AlphaGo Zero (2017)
Playing go without human knowledge
Deep Reinforcement Learning

AlphaGo Zero (2017)
- Learns the rules of go in three hours
- Consumes 12 times less power than AlphaGo

3 hours
AlphaGo Zero plays like a human beginner, forgoing long term strategy to focus on greedily capturing as many stones as possible.

70 hours
AlphaGo Zero plays at super-human level. The game is disciplined and involves multiple challenges across the board.
Deep Reinforcement Learning

AlphaGo Zero (2017)
– Combines policy and value into just one neural network
– Monte-Carlo tree search with policy-iteration
Deep Reinforcement Learning

AlphaZero (2017)
- Learns multiple games (eg chess)

A general reinforcement learning algorithm that masters chess, shogi, and Go through self-play

David Silver1,2,*, Thomas Hubert1,*, Julian Schrittwieser1,*, Ioannis Antonoglou1, Matthew Lai1, Arthur Guez1, Marc Lanctot1, Laurent Sifre1, Dharshan Kumaran1, Thore Graepel1, Timothy Lillicrap1, Karen Simonyan1, Demis Hassabis1†

The game of chess is the longest-studied domain in the history of artificial intelligence. The strongest programs are based on a combination of sophisticated search techniques, domain-specific adaptations, and handcrafted evaluation functions that have been refined by human experts over several decades. By contrast, the AlphaGo Zero program recently achieved superhuman performance in the game of Go by reinforcement learning from self-play. In this paper, we generalize this approach into a single AlphaZero algorithm that can achieve superhuman performance in many challenging games. Starting from random play and given no domain knowledge except the game rules, AlphaZero convincingly defeated a world champion program in the games of chess and shogi (Japanese chess), as well as Go.
Deep Reinforcement Learning

AlphaZero (2017)
   – Hassabis at MIT (2019)
Deep Reinforcement Learning

AlphaZero (2017)
– Hassabis at MIT (2019)
Deep Reinforcement Learning

Tools

2016 OpenAI Gym, a toolkit for research on reinforcement learning,

2017 OpenAI Roboschool, a software environment to create real-world simulations for training robots.
Deep Reinforcement Learning

Methods

John Schulman's proximal policy optimization (PPO, 2017)

Proximal Policy Optimization

\[ L_{CLIP}(\theta) = \hat{E}_t \left[ \min(r_t(\theta)\hat{A}_t, \text{clip}(r_t(\theta), 1 - \varepsilon, 1 + \varepsilon)\hat{A}_t) \right] \]

- \( \theta \) is the policy parameter
- \( \hat{E}_t \) denotes the empirical expectation over timesteps
- \( r_t \) is the ratio of the probability under the new and old policies
- \( \hat{A}_t \) is the estimated advantage at time \( t \)
- \( \varepsilon \) is a hyperparameter, usually 0.1 or 0.2
Deep Reinforcement Learning

Methods

Deep Mind’s Rainbow (2017)

Rainbow: Combining Improvements in Deep Reinforcement Learning

Matteo Hessel
Will Dabney
Joseph Modayil
Dan Horgan
Hado van Hasselt
Bilal Piot
Tom Schaul
Mohammad Azar
Georg Ostrovski
David Silver

Oct 2017

Median human-normalized score

0%
200%

0
44
100
200

 Millions of frames

DQN
DDQN
Prioritized DDQN
Dueling DDQN
A3C
Distributional DQN
Noisy DQN
Rainbow
Deep Reinforcement Learning

Challenging Environments

PPO to train a robot in Roboschool environments

E.g. an agent tries to reach a target (the pink sphere), learning to walk, run, turn, recover from being hit by objects, and get up again when knocked over.
Deep Reinforcement Learning

Challenging Environments

PPO to train a robot in Roboschool environments

Agents trained with PPO develop flexible movement policies that let them improvise turns and tilts as they head towards a target location.
Deep Reinforcement Learning

Challenging Environments
PPO to teach complicated, simulated robots to walk, like the ‘Atlas’ model from Boston Dynamics: the model has 30 distinct joints, versus 17 for the bipedal robot
Deep Reinforcement Learning

Reinforcement Learning: Issues
1. Reinforcement learning is highly unnatural: humans don’t need thousands of examples
Deep Reinforcement Learning

Reinforcement Learning: Issues

2. Simpler algorithms can solve the same problems

– Jeff Clune's team at Uber AI Labs ("Deep Neuroevolution: Genetic Algorithms Are a Competitive Alternative for Training Deep Neural Networks for Reinforcement Learning", 2017),

– Tim Salimans at OpenAI ("Evolution Strategies as a Scalable Alternative to Reinforcement Learning", 2017)

– Aravind Rajeswaran at the University of Washington ("Towards Generalization and Simplicity in Continuous Control", 2017)

Deep Reinforcement Learning

3. Designing the correct reward function is extremely difficult in the real world

4. Balancing exploration and exploitation ("the multi-armed bandit problem"): DQN could play Atari games so well but not Montezuma Revenge, a game that requires more exploration.
Deep Reinforcement Learning

Go belongs to the simplest category of A.I. problems:
• deterministic,
• fully observable and known,
• discrete
• static

2018: OpenAI Five learns from scratch the multiplayer videogame Dota 2 (neither fully observable/known nor discrete nor static)
   Note: OpenAI Five uses proximal policy optimization

2018: and then applies to robotic hand Dactyl to learn to manipulate cubes
Deep Reinforcement Learning

2018: … and then applies to robotic hand Dactyl to learn to manipulate cubes

An AI-driven robot hand spent a hundred years teaching itself to rotate a cube

July 30, 2018

A reinforcement-learning algorithm allows Dactyl to learn physical tasks by practicing them in a virtual-reality environment.
Deep Reinforcement Learning

OpenAI Five (2018)

Optimizer + Connected Rollout Workers (x256)

- **Rollout Workers**
  - ~500 CPUs
  - Run episodes
    - 80% against current bot
    - 20% against mixture of past versions
- **Randomized game settings**
  - Push data every 60s of gameplay
  - Discount rewards across the 60s using generalized advantage estimation

Optimizer

- 1 p100 GPU
- Compute Gradients
  - Proximal Policy Optimization with Adam
  - Batches of 4096 observations
  - BPTT over 16 observations

Model Parameters

- (10M floats)

Eval Workers

- ~2500 CPUs
- Play in various environments for evaluation
  - vs hardcoded "scripted" bot
  - vs previous similar bots (used to compute Trueskill)
  - vs self (for humans to watch and analyze)

<table>
<thead>
<tr>
<th>OPENAI FIVE</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>CPUs</strong></td>
</tr>
<tr>
<td><strong>GPUs</strong></td>
</tr>
<tr>
<td><strong>Experience collected</strong></td>
</tr>
</tbody>
</table>
Deep Reinforcement Learning

OpenAI Five (2018)

OpenAI Five trains by playing 180 years worth of games against itself every day, running on 256 GPUs and 128,000 CPU cores, using a separate LSTM for each hero.

<table>
<thead>
<tr>
<th></th>
<th>Details</th>
</tr>
</thead>
<tbody>
<tr>
<td>CPUs</td>
<td>128,000 preemptible CPU cores on GCP</td>
</tr>
<tr>
<td>GPUs</td>
<td>256 P100 GPUs on GCP</td>
</tr>
<tr>
<td>Experience collected</td>
<td>~180 years per day (~900 years per day counting each hero separately)</td>
</tr>
</tbody>
</table>
Deep Reinforcement Learning

OpenAI Five (2018)
OpenAI Five contest
Deep Reinforcement Learning

OpenAI Five (2018)
but...

OpenAI bots smashed in their first clash against human Dota 2 pros
AI can react faster than humans, but don't play well enough to beat the masters yet
October 2019

OpenAI's robotic arm solves the Rubik’s Cube using OpenAI Five's reinforcement learning algorithm + Josh Tobin's Automatic Domain Randomization (ADR) which endlessly generates progressively more difficult environments in simulation. This frees us from having an accurate model of the real world (2017)

ADR generates endlessly more complicated simulation environments which help train the robotic arm.

Similarly Rui Wang's Paired Open-Ended Trailblazer (POET) at Uber endlessly generates increasingly complex learning environments (2019)
Deep Reinforcement Learning

OpenAI's robotic arm solves the Rubik’s Cube (2019)
Deep Reinforcement Learning

Microsoft investment in OpenAI (2019)

Microsoft to invest $1 billion in OpenAI

Sam Altman, CEO of OpenAI (left), and Microsoft CEO Satya Nadella
Deep Reinforcement Learning

Deep Reinforcement Learning

DeepMind AlphaStar (2018)
Deep Reinforcement Learning

DeepMind AlphaStar (2018)
Deep Reinforcement Learning

DeepMind AlphaStar (2018)
Deep Reinforcement Learning

DeepMind AlphaStar (2018)
Deep Reinforcement Learning

DeepMind AlphaStar (2018)

Many key challenges remain

- Unsupervised Learning
- Memory and one-shot learning
- Imagination-based Planning with Generative Models
- Learning Abstract Concepts
- Transfer Learning
- Language understanding
Deep Reinforcement Learning

DeepMind AlphaStar plays StarCraft (2019)

Grandmaster level in StarCraft II using multi-agent reinforcement learning

Oriol Vinyals1,2, Igor Babuschkin1, Wojciech M. Czarnecki1, Michele Mathieu1, Andrew Duthie1, Junyoung Chung1, David H. Choi1, Richard Powell1, Timo Ewaldis1, Petko Georgiev1, Junhyuk Oh1, Dan Horgan1, Manuel Kroiss1, Ivo Danilevsky1, Aja Huang1, Laurent Sifre1, Trevor Cat1, John P. Agapiou1, Max Jaderberg1, Alexander S. Vezhinovets1, Rémi Leblond1, Tobias Pföhl1, Valentin Dalibard1, David Buckden1, Yury Bulatsky1, James Molloy1, Tom L. Palais1, Casiglar Gul(.)1, Ziyu Wang1, Tobias Pföhl1, Yuhuai Wu1, Roman Ring1, Davi Yogatama1, Dario Wünsch1, Kotriya McKinney1, Oliver Smith1, Tom Schaul1, Timothy Lillicrap1, Konstantinos Kavukcuoglu1, Demis Hassabis1, Chris Apps1,2 & David Silver1,2


https://doi.org/10.1038/s41586-019-1724-2
Received: 30 August 2019
Accepted: 8 October 2019
Published online: 30 October 2019

DeepMind’s StarCraft 2 AI is now better than 99.8 percent of all human players.
Deep Reinforcement Learning

Robot training

DQN works well for videogames, which have a discrete action space, but it cannot be used for the continuous spaces of robot movement. DDPG for continuous action spaces (DeepMind, 2016)

Published as a conference paper at ICLR 2016

CONTINUOUS CONTROL WITH DEEP REINFORCEMENT LEARNING

Timothy P. Lillicrap; Jonathan J. Hunt; Alexander Pritzel, Nicolas Heess, Tom Erez, Yuval Tassa, David Silver & Daan Wierstra
Google Deepmind

Lillicrap  Hunt

DeepMind

David Silver & Daan Wierstra

Update critic by minimizing the loss: 

\[ L = \frac{1}{N} \sum_i (y_i - Q(s_i, a_i | \theta^Q))^2 \]

Update the actor policy using the sampled policy gradient:

\[ \nabla_{\theta^\mu} J \approx \frac{1}{N} \sum \nabla_a Q(s, a | \theta^Q)|_{s=s_i, a=\mu(s_i)} \nabla_{\theta^\mu} \mu(s | \theta^\mu)|_{s_i} \]
Deep Reinforcement Learning

Robot training

Train the visual system and the motor system at the same time
The visual system adapts to the motor system, i.e. to the goal
Turning policy search into supervised learning
Deep Reinforcement Learning

Robot vision and manipulation

Kalashnikov & Levine (UC Berkeley + Google, 2018)

Scalable Deep Reinforcement Learning for Vision-Based Robotic Manipulation

Dmitry Kalashnikov, Alex Irpan, Peter Pastor, Julian Ibarz, Alexander Herzog, Eric Jang, Deirdre Quillen, Ethan Holly, Mrinal Kalakrishnan, Vincent Vanhoucke, Sergey Levine

Google Brain, Berkeley, Google

![Diagram of reinforcement learning process](image)
Deep Reinforcement Learning

Robot training

Reinforcement Learning in Robotics: A Survey

Jens Kober†
J. Andrew Bagnell‡
Jan Peters§

Figure 5: Boston Dynamics

(a) OBELIX robot
(b) Zebra Zero robot
(c) Autonomous helicopter
(d) Sarcos humanoid
Deep Reinforcement Learning

Chemical industry: optimizing chemical reactions
Deep Reinforcement Learning

Resource management (like Skynet in “Terminator”!)
Deep Reinforcement Learning

Multi-agent reinforcement learning
E.g. OpenAI Five: Dota 2 AI agents are trained to coordinate with each other to compete against humans
UC Berkeley: Rlib (2018)

Scaling Multi-Agent Reinforcement Learning

Eric Liang and Richard Liaw
Dec 12, 2018

RLlib: Abstractions for Distributed Reinforcement Learning
29 Jun 2018

Eric Liang, Richard Liaw, Philipp Moritz, Robert Nishihara, Roy Fox, Ken Goldberg, Joseph E. Gonzalez, Michael I. Jordan, Ion Stoica

RLlib is an open-source library for reinforcement learning that offers both a collection of reference algorithms and scalable primitives for composing new ones.

(1) Application Support
(2) Abstractions for RL
(3) Distributed Execution
Deep Reinforcement Learning

Multi-agent reinforcement learning

• Most successes of RL are in single-agent scenarios

• Multi-agent (multiple players interacting)
  – imperfect information
  – joint action space
  – large state space
  – delayed credit assignment

Note: the probability of taking a gradient step in the correct direction decreases exponentially with the number of agents (Lowe et al., 2017)

Note: the “LazyAgent Problem” (Sunehag et al., 2017)
Deep Reinforcement Learning

Multi-agent reinforcement learning

• Challenge: SC2LE1 (StarCraft II Learning Environment)
Deep Reinforcement Learning

Multi-agent reinforcement learning
Decentralized Actor Centralized Critic
(Ryan Lowe & Yi Wu, OpenAI, 2017)

Multi-Agent Actor-Critic for Mixed Cooperative-Competitive Environments

16 Jan 2018

OpenAI
McGill

Figure 2: Illustrations of the experimental environment and some tasks we consider, including a) Cooperative Communication b) Predator-Prey c) Cooperative Navigation d) Physical Deception.
Deep Reinforcement Learning

Multi-agent reinforcement learning
Counterfactual Multi-agent or COMA
(Jakob Foerster & Gregory Farquhar, Oxford Univ, 2017)
QMIX (Oxford, 2018)
Deep Reinforcement Learning

Multi-agent reinforcement learning

Social Influence as Intrinsic Motivation (MIT + DeepMind, 2019)

Figure 6: The Model of Other Agents (MOA) architecture learns both an RL policy $\pi_e$, and a supervised model that predicts the actions of other agents, $\alpha_{t-1}$.

Figure 3: The communication model has two heads, which learn the environment policy, $\pi_e$, and a policy for emitting communication symbols, $\pi_m$. Other agents’ communication messages $m_{t-1}$ are input to the LSTM.
Deep Reinforcement Learning

DRL for continuous action spaces (e.g. robot behavior)

D4PG (Timothy Lillicrap, DeepMind, 2018)

Figure 9: Control Suite domains used for benchmarking. Top: acrobot, cartpole, cheetah, finger, fish, hopper. Bottom: humanoid, manipulator, pendulum, reacher, swimmer6, swimmer15, walker.

Published as a conference paper at ICLR 2018

DISTRIBUTED DISTRIBUTIONAL DETERMINISTIC POLICY GRADIENTS

Gabriel Barth-Maron, Matthew W. Hoffman, David Budden, Will Dabney, Dan Horgan, Dhruva TB, Alistair Muldal, Nicolas Heess, Timothy Lillicrap
DeepMind
Figure 1: Our method (PE-TS): **Model:** Our probabilistic ensemble (PE) dynamics model is shown as an ensemble of two bootstraps (bootstrap disagreement far from data captures epistemic uncertainty: our subjective uncertainty due to a lack of data), each a probabilistic neural network that captures aleatoric uncertainty (inherent variance of the observed data). **Propagation:** Our trajectory sampling (TS) propagation technique uses our dynamics model to re-sample each particle (with associated bootstrap) according to its probabilistic prediction at each point in time, up until horizon $T$. **Planning:** At each time step, our MPC algorithm computes an optimal action sequence, applies the first action in the sequence, and repeats until the task-horizon.
Deep Reinforcement Learning

Model-based DRL
PETS (Kurtland Chua, UC Berkeley, 2019)

Figure 2: Tasks evaluated.

(a) Cartpole  (b) 7-dof Pusher  (c) 7-dof Reacher  (d) Half-cheetah

Cartpole

7-DOF Pusher

7-DOF Reacher

Half-cheetah

Reward vs Number of Timesteps for different tasks and methods.
Deep Reinforcement Learning

Model-based DRL
Google Brain’s SimPLe (Finn, Levine, etc 2019)
Deep Reinforcement Learning

Model-based DRL
Google Brain’s SimPLe (Finn, Levine, etc, 2019)
Deep Reinforcement Learning

Model-based DRL

Performance of Simple

Figure 3: Comparison with Rainbow. Each bar illustrates the number of interactions with environment required by Rainbow to achieve the same score as our method (SimPLe).

Figure 4: Comparison with PPO
Deep Reinforcement Learning

Model-based DRL

DeepMind’s Deep Planning Network (PlaNet, Danijar Hafner & Timothy Lillicrap, 2019)

Learning Latent Dynamics for Planning from Pixels

Deterministic

Stochastic

Deterministic and stochastic

(a) Deterministic model (RNN)

(b) Stochastic model (SSM)

(c) Recurrent state-space model (RSSM)

Too slow

Latent overshooting

(a) Standard variational bound

(b) Observation overshooting

(c) Latent overshooting
Deep Reinforcement Learning

Model-based DRL

DeepMind’s PlaNet (2019)

Training time:

<table>
<thead>
<tr>
<th>Method</th>
<th>Modality</th>
<th>Episodes</th>
<th>Cartpole Balance</th>
<th>Cartpole Swingup</th>
<th>Finger Spin</th>
<th>Cheetah Run</th>
<th>Ball in cup</th>
<th>Walker Walk</th>
</tr>
</thead>
<tbody>
<tr>
<td>A3C</td>
<td>proprioceptive</td>
<td>100,000</td>
<td>952</td>
<td>558</td>
<td>129</td>
<td>214</td>
<td>105</td>
<td>311</td>
</tr>
<tr>
<td>D4PG (ours)</td>
<td>pixels</td>
<td>100,000</td>
<td>993</td>
<td>862</td>
<td>985</td>
<td>524</td>
<td>980</td>
<td>968</td>
</tr>
<tr>
<td>PlaNet (ours)</td>
<td>pixels</td>
<td>2,000</td>
<td>986</td>
<td>831</td>
<td>744</td>
<td>650</td>
<td>914</td>
<td>890</td>
</tr>
<tr>
<td>CEM + true simulator</td>
<td>simulator state</td>
<td>0</td>
<td>998</td>
<td>850</td>
<td>825</td>
<td>656</td>
<td>993</td>
<td>994</td>
</tr>
</tbody>
</table>

Data efficiency gain PlaNet over D4PG (factor) | 100 | 180 | 16 | 50+ | 20 | 11
Deep Reinforcement Learning

Model-based DRL
DeepMind’s PlaNet (2019)
Deep Reinforcement Learning

DRL & Evolutionary algorithms
Shauharda Khadka & Kagan Tumer: Collaborative Evolutionary Reinforcement Learning (2019)

Figure 1. High level schematic of CERL. A portfolio of policy gradient learners operate in parallel to neuroevolution.
Deep Reinforcement Learning

Distributed DRL:

- R2D2 (DeepMind, 2018): model-free RL
- MuZero (DeepMind, 2019): model-based RL
- Agent 57 (DeepMind, 2020), based on NGU, which is based on R2D2

Mastering Atari, Go, Chess and Shogi by Planning with a Learned Model

Julian Schrittwieser, Ioannis Antonoglou, Thomas Hubert, Karen Simonyan, Laurent Sifre, Simon Schmitt, Arthur Guez, Edward Lockhart, Demis Hassabis, Thore Graepel, Timothy Lillicrap, David Silver

1DeepMind, 6 Paneras Square, London N1C 4AG.
2University College London, Gower Street, London WC1E 6BT.
*These authors contributed equally to this work.

<table>
<thead>
<tr>
<th>Agent</th>
<th>Median</th>
<th>Mean</th>
<th>Env. Frames</th>
<th>Training Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ape-X</td>
<td>434.1%</td>
<td>1695.6%</td>
<td>22.8B</td>
<td>5 days</td>
</tr>
<tr>
<td>R2D2</td>
<td>1920.6%</td>
<td>4024.9%</td>
<td>37.5B</td>
<td>5 days</td>
</tr>
<tr>
<td>MuZero</td>
<td>2041.1%</td>
<td>4999.2%</td>
<td>20.0B</td>
<td>12 hours</td>
</tr>
<tr>
<td>IMPALA</td>
<td>191.8%</td>
<td>957.6%</td>
<td>200M</td>
<td>–</td>
</tr>
<tr>
<td>Rainbow</td>
<td>231.1%</td>
<td>–</td>
<td>200M</td>
<td>10 days</td>
</tr>
<tr>
<td>UNREAL*</td>
<td>250%</td>
<td>880%</td>
<td>250M</td>
<td>–</td>
</tr>
<tr>
<td>LASER</td>
<td>431%</td>
<td>–</td>
<td>200M</td>
<td>–</td>
</tr>
<tr>
<td>MuZero Reanalyze</td>
<td>731.1%</td>
<td>2168.9%</td>
<td>200M</td>
<td>12 hours</td>
</tr>
</tbody>
</table>

Table 1: Comparison of MuZero against previous agents in Atari.
Deep Reinforcement Learning

Distributed DRL:

RL Algorithms

Model-Free RL

Policy Optimization

Policy Gradient
A2C / A3C
PPO
TRPO

DDPG
TD3
SAC

Q-Learning

DQN
C51
QR-DQN
HER

Model-Based RL

Learn the Model

World Models

I2A
MBMF
MBVE

Given the Model

AlphaZero

R2D2 -> NGU -> Agent57
MuZero
Deep Reinforcement Learning

Distributed DRL:

Image Credit: DeepMind
Recurrent Neural Nets

- Using RNNs to guess the next word
- Using RNNs for machine translation
- Using RNNs for scene analysis
Recurrent Neural Nets

- Using RNNs to generate sequences
  - Alex Graves (2014)
Recurrent Neural Nets

- Using RNNs for machine translation

Google Translate now provides live translation of Japanese text

Posted 10 hours ago by Darrell Etherington (@etherington)
Zappa's intervention in the traditional melody begins with the exaggeration, until exasperation, of the most frustrating elements, such as the ruthless corrections taken a bit from the doo-wop a bit from the beat (the vocals of Ray Collins are Perhaps the most distinctive trait of parodism, especially when they are countered by the fecal cranial faeces repellent of the leader, such as the idiotic middle class high school or commercials; And triumphs for geniality that is devious in the mad reel of sound events, in the perfect twist that leads from a theme to its opposite, smooth, discontinuous or harmonious fractures, with the absurd coherence that is just crazy and genes.
Recurrent Neural Nets

- Using RNNs for scene analysis (Oriol Vinyals)
Recurrent Neural Nets

- Scene analysis (Karpathy & Fei-fei Li)

**Deep Visual-Semantic Alignments for Generating Image Descriptions**

Andrej Karpathy  Li Fei-Fei
Department of Computer Science, Stanford University
Recurrent Neural Nets

2014: Image captioning
Fei-Fei Li's on algorithm to annotate photos
Recurrent Neural Nets

2014: Google’s Scene Analysis system (Vinyals)
Recurrent Neural Nets

Google Research Blog
November 17, 2014
Posted by Google Research Scientists Oriol Vinyals

Descriptions of images:
- A person riding a motorcycle on a dirt road.
- Two dogs play in the grass.
- A skateboarder does a trick on a ramp.
- A dog is jumping to catch a frisbee.
- A group of young people playing a game of 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 herd of elephants walking across a dry grass field.
- 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.

https://research.googleblog.com/2014/11/a-picture-is-worth-thousand-coherent.html
Recurrent Neural Nets

But note…

Google Research Blog
November 17, 2014
Posted by Google Research Scientists Oriol Vinyals,

A refrigerator filled with lots of food and drinks.
Recurrent Neural Nets

Using RNNs and variational autoencoders to generate images (DeepMind, 2015)
Deep Learning

- Supervised Learning:
  - AlexNet (2012)
  - VGGNet or VGG-16 (2014)
  - GoogleNet or Inception (2014)
  - DeepFace (2014)
  - Inception-ResNet (2016)
  - ResNeXt (2017)
  - …
Variational Autoencoders

2013: Max Welling and Diederik Kingma
2014: Danilo Rezende, Shakir Mohamed, Daan Wierstra

Application: generate images that are similar to the ones in the training dataset
Variational Autoencoders

Continuous-time neural networks
• Barak Pearlmutter (1995)
• Ricky Chen’s Neural ordinary differential equations (2018)
Generative Adversarial Networks

Ian Goodfellow (2014)
Alex Radford (2015)

The game between the generator $G$ and the discriminator $D$ is the minimax objective

$$\min_G \max_D \mathbb{E}_{x \sim \mathcal{P}_r} [\log(D(x))] + \mathbb{E}_{\tilde{x} \sim \mathcal{P}_g} [\log(1 - D(\tilde{x}))],$$
Generative Adversarial Networks

Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks

Alec Radford, Luke Metz, Soumith Chintala

All images in this paper are generated by a neural network. They are NOT REAL.
Generative Adversarial Networks

Conditional GAN (Mehdi Mirza @ Univ Montreal, 2014)
Generative Adversarial Networks

GANs of 2016

- InfoGAN (Xi Chen @ UC Berkeley, 2016)
- Semi-supervised GAN (Augusto Odena @ Google, 2016)
- Auxiliary Classifier GAN (Augusto Odena @ Google)
Generative Adversarial Networks

- More than 100 variants of GANs are introduced in 2017.
Generative Adversarial Networks

Text to image synthesis

Figure 1. Examples of generated images from text descriptions. Left: captions are from zero-shot (held out) categories. Right: captions are from training set categories.
Generative Adversarial Networks

Caption generation

Generative Adversarial Text to Image Synthesis
Scott Reed, Zeynep Akata, Xinchen Yan, Lajanugen Logeswaran
Honglak Lee, Bernt Schiele

This small bird has a pink breast and crown, and black primaries and secondaries.
This magnificent fellow is almost all black with a red crest, and white cheek patch.
The flower has petals that are bright pinkish purple with white stigma.
This white and yellow flower have thin white petals and a round yellow stamen.

Figure 1. Examples of generated images from text descriptions.
Left: captions are from zero-shot (held out) categories. Right: captions are from training set categories.
Generative Adversarial Networks

Video generation

Vondrick & Torralba (MIT)
Generative Adversarial Networks

Video generation

Clark & Simonyan (DeepMind, 2019)
Generative Adversarial Networks

Video Generation

A set of four-second synthesized video clips
Generative Adversarial Networks

• Image-to-image translation
  – Alexei Efros (UC Berkeley) – Pix2pix
  – Ming-yu Liu (Nvidia)

Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks

Jun-Yan Zhu*  Taesung Park*  Phillip Isola  Alexei A. Efros
UC Berkeley
In ICCV 2017
Generative Adversarial Networks

- Image-to-image translation
  - Alexei Efros (UC Berkeley)
Generative Adversarial Networks

- Image-to-image translation
  - Ming-yu Liu (Nvidia)
Generative Adversarial Networks

- Photorealistic faces of fake celebrities (Jaakko Lehtinen, 2017)

Figure 5: 1024 × 1024 images generated using the CELEBA-HQ dataset.

Figure 10: Top: Our CELEBA-HQ results
Generative Adversarial Networks

- Photorealistic faces of fake celebrities (Tero Karras, 2018)
Generative Adversarial Networks

- **WGAN-GP** (Aaron Courville, 2017)

  Improved Training of Wasserstein GANs

  Dec 2017

  Ishaan Gulrajani, Faruk Ahmed, Martin Arjovsky, Vincent Dumoulin, Aaron Courville

  1 Montreal Institute for Learning Algorithms
Generative Adversarial Networks

- BEGAN (Google Brain, 2017)
Generative Adversarial Networks

• SAGAN (Rutgers, 2018)

Figure 2: The proposed self-attention mechanism. The $\otimes$ denotes matrix multiplication. The softmax operation is performed on each row.
Generative Adversarial Networks

- BigGAN (DeepMind, 2018): details generated based on long-range dependencies (using Xiaolong Wang’s self-attention)
Generative Adversarial Networks

Visually-Aware Fashion Recommendation and Design with Generative Image Models

Wang-Cheng Kang
UC San Diego

Chen Fang
Adobe Research

Zhaowen Wang
Adobe Research

Julian McAuley
UC San Diego

CNN + GAN = Learn a person's favorite style of fashion and generate personalized clothing

(a)Generated Images
Generative Adversarial Networks

Nvidia GauGAN (2018)

Stroke of Genius: GauGAN Turns Doodles into Stunning, Photorealistic Landscapes
Generative Adversarial Networks

Video-to-video

- Dongdong Chen: COVST (Microsoft Research Asia, 2017)
Generative Adversarial Networks

Video-to-video

- Ting-Chun Wang (Nvidia, 2018)
Generative Adversarial Networks

Leon Gatys and Alexander Ecker’s "A Neural Algorithm of Artistic Style“ (2015): style and content (Neural Style Transfer)

Leonid Afremov

Neural Network
Generative Adversarial Networks

Multi-style transfer
Xinyuan Chen (Jiao Tong Univ, 2019)

Gated-GAN: Adversarial Gated Networks for Multi-Collection Style Transfer
Xinyuan Chen, Chang Xu, Xiaokang Yang, Li Song, and Dacheng Tao
Generative Adversarial Networks

Artificially intelligent painters invent new styles of art
Generative Adversarial Networks

- Cornell Univ’s style-transfer network (2017)
Generative Adversarial Networks

- Nvidia’s face generator (2018)
Platforms

• Open-source platforms for deep learning
  – Torch (Ronan Collobert @ IDIAP, Switzerland, 2002): flexible
  – Theano (Bengio’s group @ Univ of Montreal, Canada, 2010): easiest to install
  – Caffe (Yangqing Jia @ UC Berkeley, 2013)
  – TensorFlow (Rajat Monga @ Google, 2015): scalable
  – Chainer (Seiya Tokui @ Preferred Networks, Japan, 2015): RNNs with LSTM
Platforms

• Open-source platforms for deep learning
  – Pytorch (Soumith Chintala @ Facebook, 2016)
  – Keras (Francois Chollet @ Google, 2015) which (in 2018) ships out-of-the-box with 5 CNNs pre-trained on the ImageNet dataset
    • VGG16
    • VGG19
    • ResNet50
    • Inception V3
    • Xception
Platforms

- Open-source platforms for deep learning
  - MXNet (UW, NYU, NUS, MIT, CMU, 2015)
  - ONNX (Facebook and Microsoft, 2017)
  - Gluon (Microsoft and Amazon, 2017)
Platforms

- Open-source platforms of 2018
  - Fast.ai library for training of neural nets
  - Facebook: Detectron for object detection
  - Google: Dopamine for fast prototyping of reinforcement learning algorithms
  - Nvidia: vid2vid for video-to-video synthesis
Platforms

- Google TensorFlow
- Apple CoreML
Platforms

Machine Learning for Developers.

Nexosis makes it easy to start building machine learning applications.
Hardware Platforms

2017: DT42's BerryNet released on GitHub: multiple deep-learning methods on a $35 Raspberry Pi
Aids for Machine Learning

- Open-source platforms for deep learning
  - CUDA Convnet
  - cuDNN
  - Deeplearning4j
  - PyBrain
  - PyLearn2
  - SINGA
  - ...

Aids for Machine Learning

- Facebook’s FBLearner Flow and Asimo, that allow to optimize neural networks (i.e. automate the job of neural-network engineers).
Aids for Machine Learning

- MOA http://moa.cs.waikato.ac.nz/
- Neurokernel http://neurokernel.github.io/
- NuPic https://github.com/numenta/nupic
- Orange http://orange.biolab.si/
- RapidMiner http://rapidminer.com
- Spark http://spark.apache.org/mllib/
- TunedIT http://tunedit.org/
- Vahara https://github.com/thedatachef/varaha
- Viv http://viv.ai/
- Vowpal Wabbit https://github.com/JohnLangford/vowpal_wabbit/wiki
- Weka http://www.cs.waikato.ac.nz/ml/weka/
- Dlib http://dlib.net/ml.html
- MADLib http://madlib.net/
- Mahout http://mahout.apache.org/
- MCMLL http://mcmll.sourceforge.net/
- MLC++ http://www.sgi.com/tech/mlc/
- mloss http://mloss.org/software/
- mlpack http://mlpack.org/
- Shogun http://www.shogun-toolbox.org/
- Stan http://mc-stan.org/
Aids for Machine Learning

• Not open-source:
  – Ayasdi http://www.ayasdi.com/
  – BigML https://bigml.com/
  – H2O http://h2o.ai
  – IBM Watson
  – Nutonian http://www.nutonian.com/
  – Prediction.io http://prediction.io/
  – Rocketfuel http://rocketfuel.com/
  – Skytree http://www.skytree.net/
  – Trifacta http://www.trifacta.com/
  – Wolfram Alpha http://www.wolframalpha.com/
  – Yhat https://yhathq.com/
Info about Machine Learning

• Conferences
  – Intl Joint Conference on Artificial Intelligence (IJCAI)
  – ICML icml.cc/
  – NIPS
  – Machine Learning Conference mlconf.com
  – AAAI aaai.org
  – Machine Intelligence Summit re-work.co
  – Artificial Intelligence and Applications (AIAPP)
  – AI Summit theaisummit.com
  – The AI Conference aiconference.ticketleap.com
  – The O’Reilly Artificial Intelligence Conference
  – Intl Joint Conference on Computational Intelligence ijcci.org
Info about Machine Learning

• Journals
  – ML Journal http://www.springer.com/computer/ai/journal/10994
  – JMLR http://jmlr.org/papers/
  – Pattern Recognition http://www.jprr.org/index.php/jprr
  – gitXiv http://gitxiv.com

• Blogs
  – FastML http://fastml.com/
  – Chris Olah http://colah.github.io/
  – Andrej Karparthy http://karpathy.github.io
  – DeepLearning.net http://deeplearning.net/
Info about Machine Learning

• Books
  – Murphy, Kevin: Machine Learning: A Probabilistic Perspective (2012)
Automatic Machine Learning

- Kevin Leyton-Brown’s Auto-Weka (2013) based on Bayesian optimization
- Frank Hutter's Auto-Sklearn (2015) based on Bayesian optimization
Automatic Machine Learning

- Randy Olson’s TPOT (2015) based on genetic programming.
Automatic Machine Learning

- Quoc Le’s & Barret Zoph’s AutoML (2017) based on reinforcement learning
Automatic Machine Learning

Texas A&M University (2018): Auto-Keras

- automatically search for the best architecture and hyperparameters
Automatic Machine Learning

Amazon SageMaker for automatic model tuning (2017)

• BUILD
  – Collect & prepare training data
  – Data labeling & pre-built notebooks for common problems
  – Choose & optimize your ML algorithm
  – Model & algorithm marketplace
  – Built-in, high-performance algorithms

• TRAIN
  – Setup & manage environments for training
  – One-click training on the highest performing infrastructure
  – Train & tune model

• DEPLOY
  – Deploy model in production
  – Scale & manage the production environment
  – Fully managed with auto-scaling for 75% less
Automatic Machine Learning

Google MorphNet (2019) takes an existing neural network as input and produces a new neural network that is smaller and faster.
XAI (Explainable AI)

• The mystery of deep networks
  – Nobody quite understands why they work so well.
  – The workings of a nonlinear algorithm are, to a large extent, inscrutable.
XAI

- Carlos Guestrin
- Wojciech Samek
- DARPA’s XAI

**Explaining Recurrent Neural Network Predictions in Sentiment Analysis**

Leila Arras¹, Grégoire Montavon², Klaus-Robert Müller²,³,⁴, and Wojciech Samek¹

"Why Should I Trust You?" Explaining the Predictions of Any Classifier

Marco Tulio Ribeiro
University of Washington

Sameer Singh
University of Washington

Carlos Guestrin
University of Washington

DARPA

DEPARTMENT OF DEFENSE ADVANCED RESEARCH PROJECTS AGENCY

Explainable Artificial Intelligence (XAI)

Mr. David Gunning

Machine Learning System

This is a cat:
- It has fur, whiskers, and claws.
- It has this feature:

Current Explanation

XAI Explanation
XAI

Zeiler & Fergus (2013)
XAI

• Naftali Tishby

“Optimal Deep Learning” and the Information Bottleneck method

ICRI-CI retreat, Haifa, May 2015

Naftali Tishby
Noga Zaslavsky

School of Engineering and Computer Science
The Edmond & Lily Safra Center for Brain Sciences
Hebrew University, Jerusalem, Israel
XAI

- Google Brain (2018)

The Building Blocks of Interpretability

March 6, 2018
The #GANpaint app works by directly activating and deactivating sets of neurons in a deep network trained to generate images. Each button on the left ("door", "brick", etc) corresponds to a set of 20 neurons. The app demonstrates that, by learning to draw, the network also learns about objects such as trees and doors and rooftops. By switching neurons directly, you can observe the structure of the visual world that the network has learned to model.
XAI

Deep Learning

Warning: Deep Learning is NOT the only kind of A.I., it is NOT always the best, it is NEVER precise, it is NOT a brain

For example:
Explainable Artificial Intelligence (XAI)

Mr. David Gunning

Machine Learning System

This is a cat:
- It has fur, whiskers, and claws.
- It has this feature:

This is a cat.

Current Explanation

XAI Explanation
Danger of A.I.

Stephen Hawking
Bill Gates
Elon Musk (OpenAI, 2016)
Danger of A.I.

Elon Musk Urges U.S. Governors to Regulate AI Before “It’s Too Late”

This famous roboticist doesn’t think Elon Musk understands AI

Zuckerberg blasts Musk warnings against artificial intelligence as 'pretty irresponsible'

Artificial intelligence pioneer says we need to start over
Danger of A.I.

An Artificial Intelligence Developed Its Own Non-Human Language

Researchers shut down AI that invented its own language

Facebook engineers panic, pull plug on AI after bots develop their own language

‘Terminator’ Come To Life? – Facebook Shuts Down Artificial Intelligence After It Developed Its Own Language
Danger of A.I.

How the Enlightenment Ends
Philosophically, intellectually—in every way—human society is unprepared for the rise of artificial intelligence.

HENRY A. KISSINGER  JUNE 2018 ISSUE

Kissinger falls prey to a very commonly-held erroneous belief, following the AlphaZero results: "On its own, in just a few hours of self-play, it achieved a level of skill that took human beings 1,500 years to attain. Only the basic rules of the game were provided to AlphaZero. Neither human beings nor human-generated data were part of its process of self-learning. If AlphaZero was able to achieve this mastery so rapidly, where will AI be in five years?"
Danger of A.I.

Allen Institute
Asilomar Conference (2017)
AI for Good Global Summit (2017)
Danger of A.I.

Electronic Frontier Foundation
https://www.eff.org/ai/metrics

Atari 2600 Bank Heist
Human performance

Score

-250 250 500 750 1000 1250 1500

2013 2014 2015 2016 2017

0 20000

Nature DQN DQN (tuned) noop SARSA

DQN noop DQN+Pop-Art noop

QQQ noop

SARSA

Nature DQN

SARSA

DQN (tuned) hs

DQN hs

DQNN (tuned) hs

SARSA

DQN+Pop-Art noop

QQQ noop

SARSA

DQN noop

DQN+Pop-Art noop

QQQ noop

SARSA

DQN noop

DQN+Pop-Art noop

QQQ noop

SARSA

DQN noop

DQN+Pop-Art noop

QQQ noop

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DQN+Pop-Art noop

QQQ noop

SARSA

DQN noop

DQN+Pop-Art noop

QQQ noop

SARSA

DQN noop

DQN+Pop-Art noop

QQQ noop

SARSA

DQN noop

DQN+Pop-Art noop

QQQ noop

SARSA

DQN noop

DQN+Pop-Art noop
The Real Danger

• Software to create alternative realities
• Face morphing
  – Project VoCo (Adobe, 2016)
  – Face2Face (Stanford, 2017)
• Voice cloning
  – CandyVoice
  – VivoText
  – Festvox (CMU)
Face Morphing

Face Morphing

Matthias Niessner’s Face2Face (2016): real-time face capture and reenactment
Face Morphing

AMAZING NEW VIDEO TWEAKING PROGRAM LETS USERS EDIT A PERSON'S LIP MOVEMENTS IN REAL TIME

By Chloe Olewitz — March 21, 2016 1:08 PM

Face2Face: Real-time Face Capture and Reenactment of RGB Videos (CVPR 2016 Oral)

Face Morphing

Deepfakes/ Fakeapp (2018)

Fake celebrity porn is blowing up on Reddit, thanks to artificial intelligence
Face Morphing

Deep video portraits (Christian Theobalt, 2018)

Deep Video Portraits

HYEONGWOO KIM, Max Planck Institute for Informatics, Germany
PABLO GARRIDO, Technicolor, France
AYUSH TEWARI and WEIPENG XU, Max Planck Institute for Informatics, Germany
JUSTUS THIES and MATTHIAS NIESSNER, Technical University of Munich, Germany
PATRICK PÉREZ, Technicolor, France
CHRISTIAN RICHARDT, University of Bath, United Kingdom
MICHAEL ZOLLHÖFER, Stanford University, United States of America
CHRISTIAN THEOBALT, Max Planck Institute for Informatics, Germany

Input
Output
Input
Output
Voice Morphing

Adobe Voco (2017)
Lyrebird (2017)
Adobe is working on an audio app that lets you add words someone never said
Voice Morphing

- Voice cloning

We create virtual speech with the voices you love

CUSTOMIZE A TEXT-TO-SPEECH SYNTHETIC VOICE IS VERY EASY!

Real-time imitation of various voices from Microsoft Azure TTS (Text-To-Speech) voice

 festvox

CMU Speech Software | CMU Speech Group

The Festvox project aims to make the building of new synthetic voices more systemic and better documented, making it possible for anyone to build a new voice.
Voice Morphing

Google WaveNet (2016)
Voice Morphing

Supasorn Suwajanakorn (2017): given the audio, create the video of a speech

Synthesizing Obama: Learning Lip Sync from Audio

Supasorn Suwajanakorn
SIGGRAPH 2017

Output Obama Video
Voice and Face Morphing

Peter Cushing stars in a “Star Wars” movie… 22 years after dying

Paul Debevec

The Guardian
Rogue One: A Star Wars Story  Opinion
Peter Cushing is dead. Rogue One’s resurrection is a digital indignity  Catherine Shoard

How ‘Rogue One’ Brought Back Familiar Faces
Scene Understanding

Jiajun Wu (MIT, 2017): Neural scene de-rendering
Scene Understanding

Lukasz Romaszko (University of Edinburgh, 2017)

Vision-as-Inverse-Graphics:
Obtaining a Rich 3D Explanation of a Scene from a Single Image

Lukasz Romaszko¹  Christopher K.I. Williams¹,²  Pol Moreno¹  Pushmeet Kohli³,*
Scene Understanding

Ali Eslami and Danilo Rezende: understand the layout of a room
Scene Understanding

Roei Herzig and Moshiko Raboh (Tel Aviv University, 2018)
Variational Inference

David Duvenaud (University of Toronto):
Neural Ordinary Differential Equations (2018)
When to use Deep Learning

• When to use Deep Learning
  – Large dataset
  – Clean/balanced data
  – Modeling time-series data
  – Statistical methods don’t work

• When NOT to use Deep Learning
  – Small dataset
  – Data not balanced
  – The goal is insight
  – Your boss told you to do it because it’s popular
When to use Deep Learning

• A good example: NASA + Google (2017): discover patterns hidden in a large dataset of astronomical observations.
Deep Learning

Warning: Deep Learning is NOT the only kind of A.I., it is NOT always the best, it is NEVER precise, it is NOT a brain.
ARTIFICIAL INTELLIGENCE

MACHINE LEARNING

NEURAL NETWORKS

DEEP LEARNING

RNN

CNN

LSTM

RL

GAN
Business

- Multi-billion dollar investments in artificial intelligence and robotics in the 2010s
  - Amazon (Kiva, 2012; Angel.ai, 2016; Harvest.ai, 2017)
  - IBM (AlchemyAPI, 2015; Watson project)
  - Microsoft (Project Adam, 2014; Swifftkey, 2016; Genee and Maluuba, 2017)
  - Apple (Siri, 2011; Perceptio and VocalIQ, 2015; Emotient, Turi and Tuplejump, 2016; RealFace, 2017)
  - Facebook (Face.com, 2012; Wit.ai, 2015; Masquerade, 2017; Zurich Eye, 2017; Ozlo, 2017)
  - Yahoo (LookFlow, 2013; Incredible Labs, 2014)
  - Twitter (WhetLab, 2015; Magic Pony, 2016)
  - Salesforce (TempoAI, 2015; MetaMind, 2016; PredictionIO
  - Samsung (Viv Labs, 2016)
  - Intel (Nervana and Itseex in 2016)
  - General Electric (Wise.io, 2017)
Business

Venture Funding Into US Artificial Intelligence, Machine Learning, And Related Startups

2008 through 2017. Dollar volume based on deals of known size; round counts are for all deals.

- Total $ Invested
- Number of Deals

- $5.00B
- $3.33B
- $1.67B
- $0.00B


Number of Deals
Business

• Venture Scanner November 2017 and 2019
Business

- A.I. startups by country

![Pie chart showing A.I. startups by country](image)
Business

• DeepMind (2010, acquired by Google in 2014)
• Vicarious
• Sentient
• ...
Business

• Startups
  – AlchemyAPI
  – Clarifai
  – Ersatz Labs
  – Memkite
  – Nervana
  – Skymind
  – Wise.io
  – Saffron
  – Narrative Science
  – CrowdAI
  – …

Mostly acquired by big corporations
Business

- Investment in AI startups in 2014: $230 million
- Investment in AI startups in 2015: $128 million

*Artificial Intelligence, Real Money*

Total venture capital money for pure AI startups, by year

Data: CB Insights
What is counted as A.I.? 

https://www.venturescanner.com/blog/tags/artificial_intelligence
Business

- Between 2010 and 2015 over 45 companies and corporate VC arms have invested in AI startups (top of the list: Bloomberg, Samsung, Rakuten)
- Investment in AI startups in 2014: $230 million
- Investment in AI startups in 2015: $128 million
Business

Figure 1: Journal articles mentioning “deep learning” or “deep neural network”.
Business

Artificial Intelligence VC Funding by Country

Venture Scanner

Number of AI startups

Source: CBI Insights

Data from April 2017
Business

• Element
• Gradient
• Andre Ng

Element AI, a platform for companies to build AI solutions, raises $102M

AI visionary Andrew Ng is raising $150m for a new fund
Business

• But most A.I. startups were still losing money in 2020…
Centers of A.I. Research

Univ of Toronto: Geoffrey Hinton, Brendan Frey, Radford Neal
Univ of Montreal: Yoshua Bengio, Pascal Vincent, Aaron Courville, Roland Memisevic

New York Univ: Yann Lecun, Rob Fergus
Stanford Univ: Sebastian Thrun, Andrew Ng, Christopher Manning, Fei-fei Li
UC Berkeley: Bruno Olshausen, Trevor Darrell, Pieter Abbeel, Alexei Efros, Michael Jordan
University of Washington: Pedro Domingos, Ali Farhadi
Carnegie Mellon: Chris Dyer, Tom Mitchell, James Kuffner
Northwestern Univ: Ronald Williams
MIT: Tomaso Poggio, Cynthia Breazeal, Joshua Tenenbaum, Daniel Rus, Antonio Torralba
CalTech: Pietro Perona
Centers of A.I. Research

Oxford Univ: Nando de Freitas, Andrew Zisserman
Cambridge Univ: Carl-Edward Rasmussen
Univ of London: Christopher Watkins

IDSIA (Switzerland): Jurgen Schmidhuber, Dan Ciresan
IDIAP (Switzerland): Ronan Collobert
EPFL (Switzerland): Boi Faltings
Univ of Amsterdam: Max Welling

Tel Aviv Univ: Lior Wolf – Technion: Ran El-Yaniv

National Univ of Singapore: Shuicheng Yan

Australia: Marcus Hutter
Centers of A.I. Research

New York Univ: Yann Lecun, Rob Fergus
Stanford Univ: Sebastian Thrun, Andrew Ng, Christopher Manning, Fei-fei Li
UC Berkeley: Bruno Olshausen, Trevor Darrell, Pieter Abbeel, Alexei Efros, Michael Jordan, Jitendra Malik, Sergey Levine
University of Washington: Pedro Domingos
Carnegie Mellon: Chris Dyer, Tom Mitchell
Northwestern Univ: Ronald Williams
MIT: Antonio Torralba
Centers of A.I. Research

OpenAI: Ilya Sutskever, Ian Goodfellow, Durk Kingma
DeepMind: Alex Graves, Karol Gregor, Koray Kavukcuoglu, Andriy Mnih, Shane Legg, Christian Szegedy, Volodymyr Mnih, Daan Wierstra, Matthew Lai
Facebook: Yann Lecun, Rob Fergus, Jason Weston, Leon Bouttou, Ronan Collobert, Tomas Mikolov, Ross Girshick, Kaiming He
Twitter: Hugo Larochelle
Microsoft: Li Deng, Dong Yu, Antonio Criminisi
Tesla: Andrej Karpathy
Salesforce: Richard Socher
Indico: Alec Radford
Nvidia: Ming-yu Liu, Raquel Urtasun
A.I. in China

- Microsoft chatbot Xiaoce: 100 million users
- News recommendation: Toutiao
- Voice recognition: iFlytek
- Face recognition: Face++
- Several A.I. unicorns
- Cambricon AI chip
A.I. in China

- Cambricon AI chip (2016)
Artificial Intelligence in China

- Tencent Dream Writer (2015)
- Toutiao Xiaomingbot (2016)
A.I. in China

• The B.A.T.
  – Alibaba: ET City Brain (traffic optimization based on visual recognition), ET Medical Brain (medical image analysis)
  – Baidu: open software platform Apollo for self-driving cars (the “Android” of self-driving cars)
  – Tencent has data about social media (Wechat), payments (Wechat Pay) and games
A.I. in China

- A simple definition of A.I.: computational mathematics
A.I. in China

- 2015: China builds the equivalent of nearly one university per week
- 2015: China has more STEM graduates than the USA (78 million vs 67 million)
- 2016: China STEM graduates 4.7 million; USA 568,000.
A.I. in China

• 2016: China publishes more paper than the USA on Deep Learning

• 2017: China generates more data than the rest of the world combined
A.I. in China

• A.I. sponsored by local and national governments

• July 2017: National A.I. program for China to become the leading A.I. power by 2030

China's Artificial Intelligence Revolution

A new AI development plan calls for China to become the world leader in the field by 2030.

On July 20, China’s State Council issued the “Next Generation Artificial Intelligence Development Plan” (新一代人工智能发展规划).

Wan Gang, the minister of science and technology
Artificial Intelligence in China

- 2015: Ministry of Public Security launches a project to build the world’s most powerful facial recognition system with the power to identify any one of China’s 1.3 billion citizens within three seconds
- SeetaTech, a start-up established by several researchers from the Institute of Computing Technology at the Chinese Academy of Sciences in Beijing
- 2017: SeetaTech’s face recognition deployed at Public Security Departments in at least 15 provinces
Artificial Intelligence in China

- May 2017: Tsinghua Univ wins million-dollar Arnold Foundation’s challenge
- Aug 2017: Nanjing Univ wins ILSVRC2017 (ImageNet)
- Oct 2017: Harbin & iFlyted win first Stanford reading comprehension test (SQuAD)
- Nov 2017: Yitu wins first Face Recognition Prize Challenge
Artificial Intelligence in China

• October 2017: The robot Xiaoyi (Tsinghua University & iFlyTek) passes the medical licensing examination

• October 2017: Megvii beats Facebook and Google at Microsoft COCO object recognition challenge

• 2018: iFlytech offline speech translator
Artificial Intelligence in China

Baidu

• 2017: Xiaoyu Zaijia/ Little Fish voice-controlled family robot powered by Baidu's DuerOS AI platform
• 2017: Project Apollo for autonomous vehicle technology (with Microsoft and others)
• 2017: Partnership with Nvidia
• 2017: Acquisition of smart-home startup Raven Tech
• 2017: Acquisition of computer-vision startup xPerception
Artificial Intelligence in China

- Anuhi A.I. hospital (2017)
Artificial Intelligence in China

- Medical robot (2017)

For the First Time, a Robot Passed a Medical Licensing Exam

Chinese AI-powered robot Xiaoyi took the country's medical licensing examinations. It got a score of 456 points, 96 points above the required.
A.I. in China

China to add AI courses in primary education
The next breakthrough

• National projects that changed the world
  – Apollo Program (1963)
  – Arpanet (1969)
  – Human Genome Project (1990)
The next breakthrough

• National projects
  – USA: BRAIN Initiative (2013)
The next breakthrough

• National projects
  – Machine Intelligence from Cortical Networks (Microns) to map a cubic millimeter of cortex (about 10 million synapses for 100,000 neurons)
Next...

• See http://www.scaruffi.com/singular for the index of this Powerpoint presentation and links to the other parts