Intro
DQN In Theory
DQN In Practice
Beyond DQN
AI Revolution
Jeanne Calment
Culture Dish
Enlightenment
The View From Here

Deep Reinforcement Learning

Deep Learning — Unit 10

Dr. Jon Krohn
jon@untapt.com

Slides available at jonkrohn.com/talks

April 13th, 2019

NYC DATA SCIENCE ACADEMY

Intro
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Intro
DQN In Theory
DQN In Practice
Beyond DQN
AI Revolution
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Culture Dish
Enlightenment
The View From Here

Outline

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Intro
DQN In Theory
DQN In Practice
Beyond DQN
AI Revolution
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The View From Here

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DQN In Practice
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DQN In Theory
DQN In Practice
Beyond DQN
AI Revolution
Jeanne Calment
Culture Dish
Enlightenment
The View From Here

Outline

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Intro
DQN In Theory
DQN In Practice
Beyond DQN
AI Revolution
Jeanne Calment
Culture Dish
Enlightenment
The View From Here

Outline

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Categories of A.I.

1. ANI: *Narrow*
2. AGI: *General*
3. ASI: *Super*

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Deep Learning Categories

1. supervised learning
2. unsupervised learning
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Supervised Learning

- have x and y
- goal is to approximate function that predicts y with x
- e.g.: classification (MNIST digits, IMDB sentiment), regression (sales of a product, future value of an asset)

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Unsupervised Learning

- have *x* without *y* labels
- goal is to learn data's underlying hidden structure
- e.g.: word vectors, GANs

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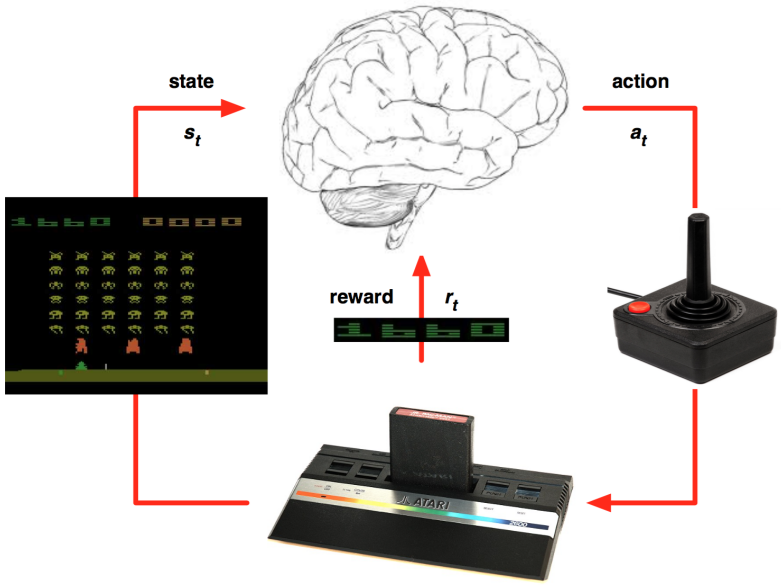
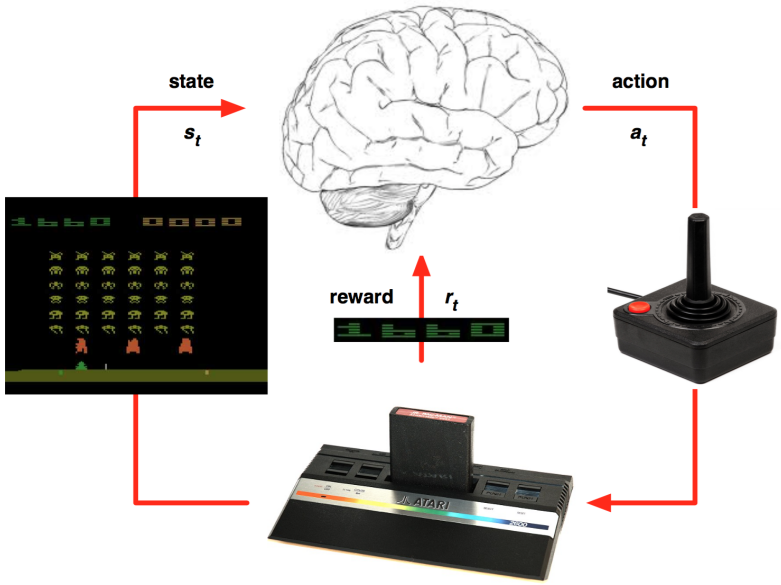
Reinforcement Learning



- an *agent* takes action in an *environment*
- environment returns *state*, i.e., *reward* at t, state at $t+1$
- repeat

Reinforcement Learning



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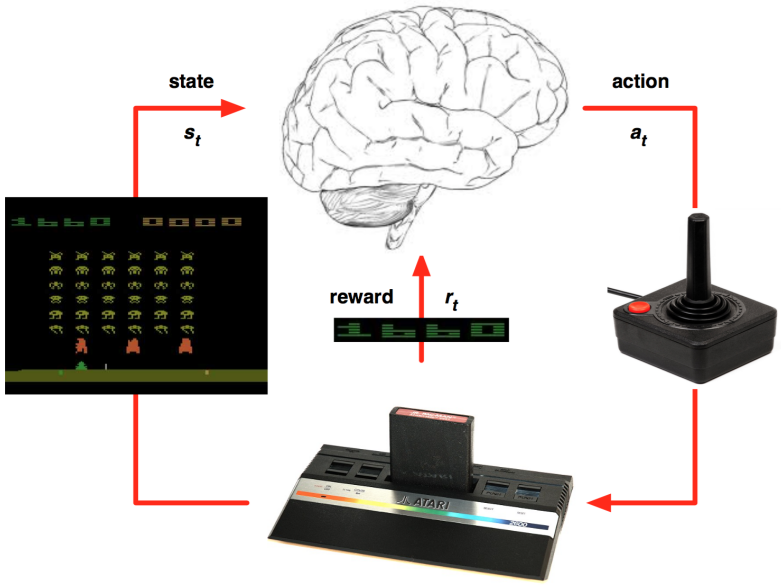

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Deep Q-Learning

Mnih et al. (2013)

- “Playing Atari with Deep RL”
- NIPS and arXiv paper
- played seven Atari 2600 games
- beat previous ML approaches on six
- beat human expert on three

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Intro
DQN In Theory
DQN In Practice
Beyond DQN
AI Revolution
Jeanne Calment
Culture Dish
Enlightenment
The View From Here

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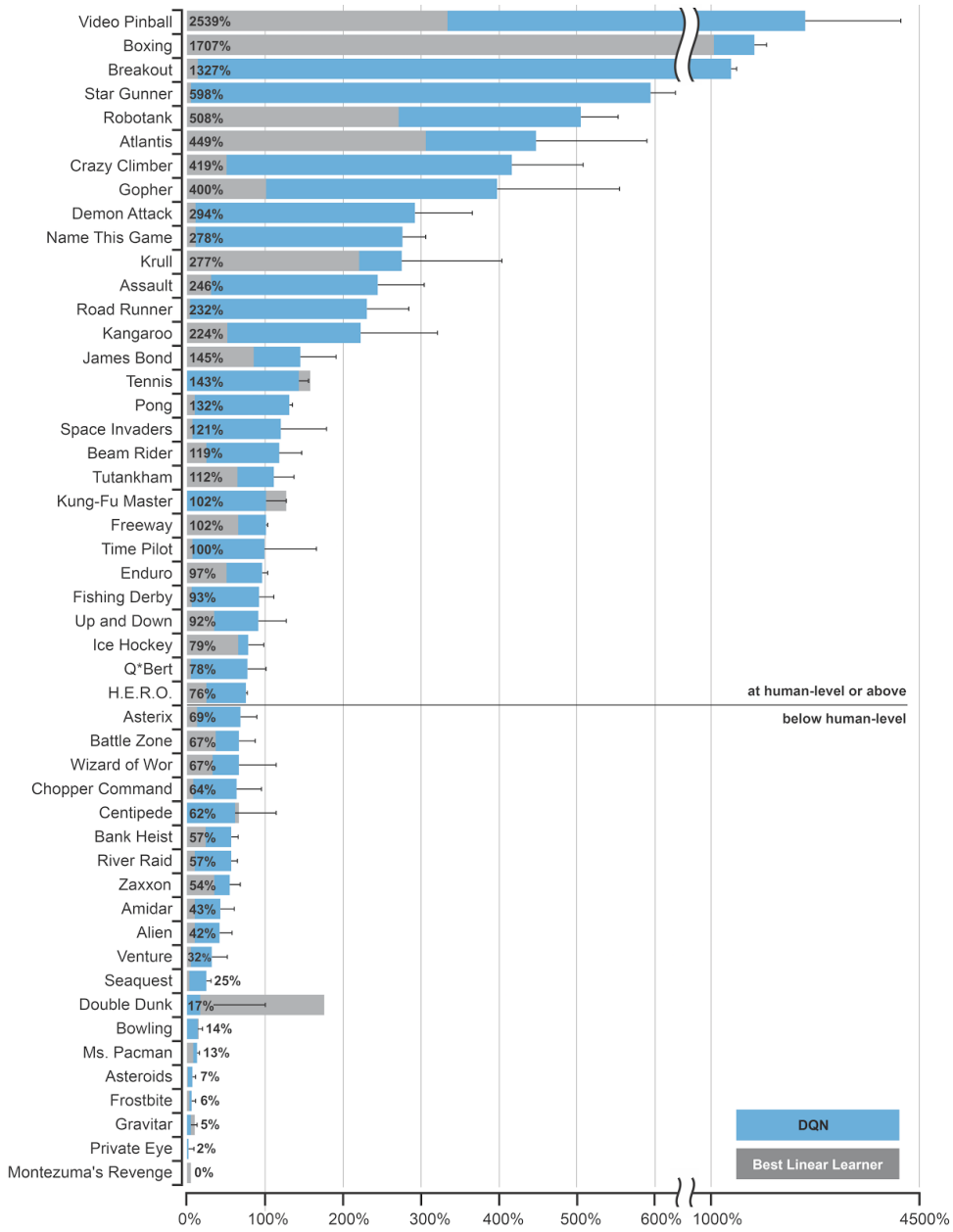

[Atari Games]

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Intro
DQN In Theory
DQN In Practice
Beyond DQN
AI Revolution
Jeanne Calment
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Enlightenment
The View From Here

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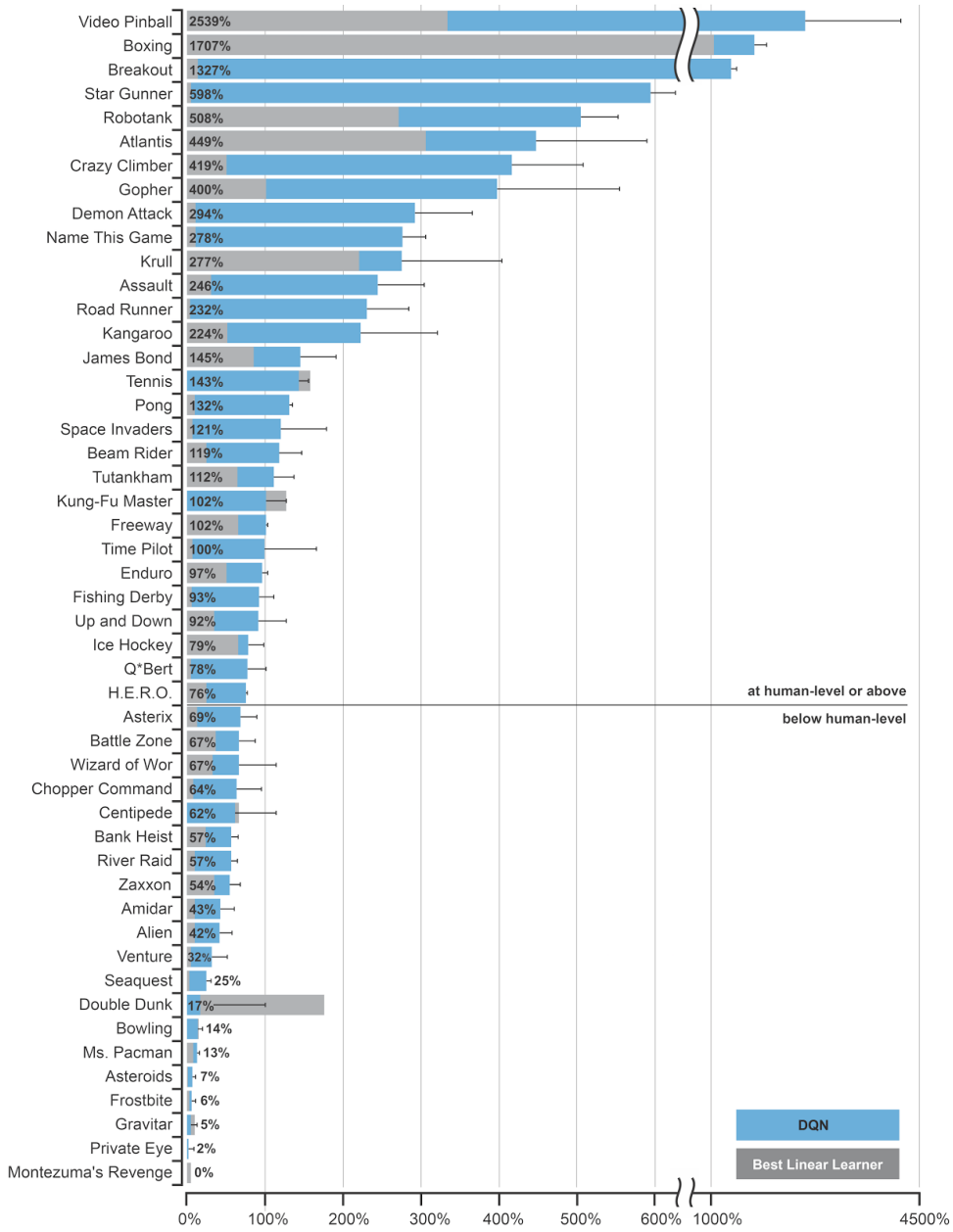

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NYC DATA SCIENCE ACADEMY

Intro
DQN In Theory
DQN In Practice
Beyond DQN
AI Revolution
Jeanne Calment
Culture Dish
Enlightenment
The View From Here

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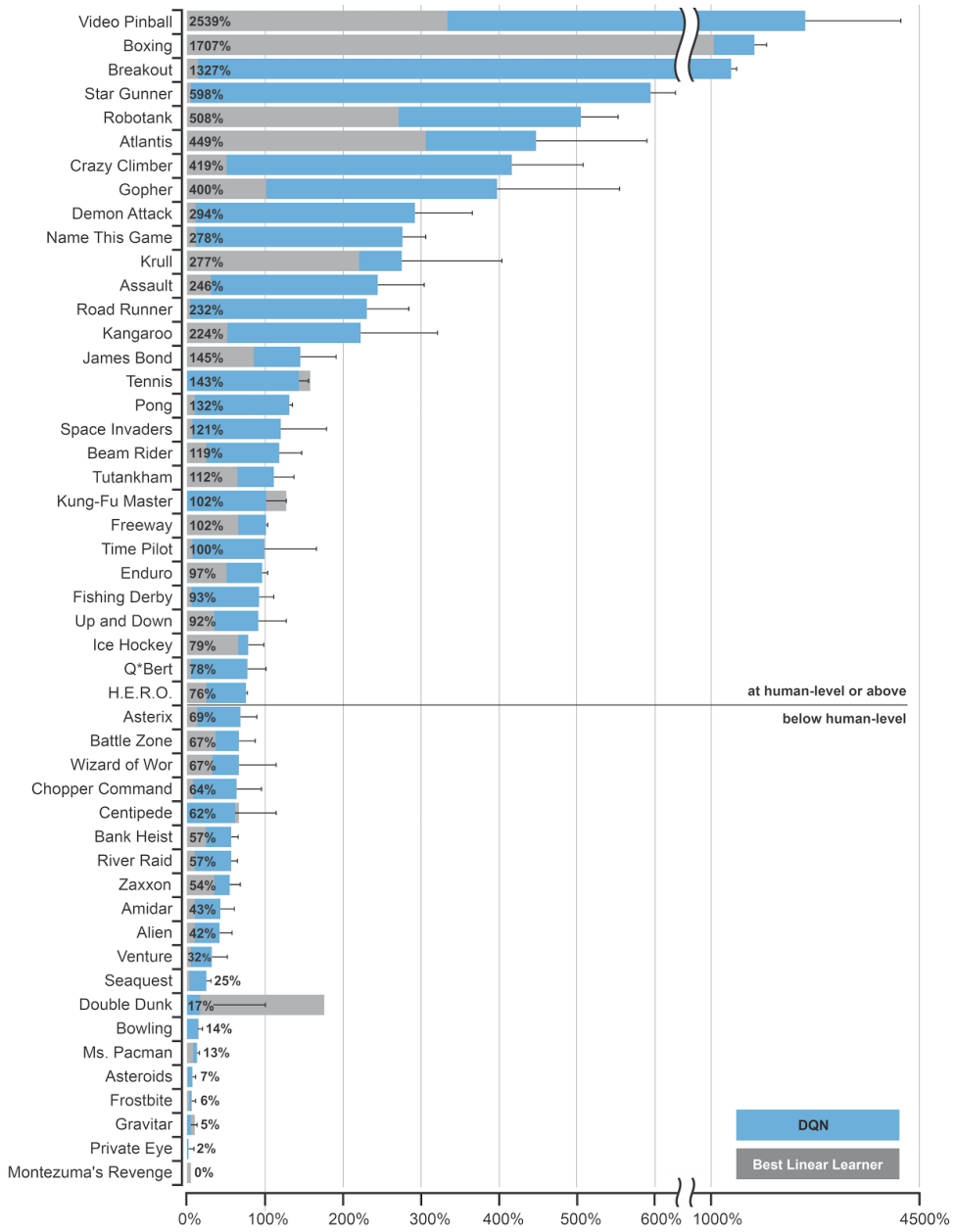

[Atari Games]

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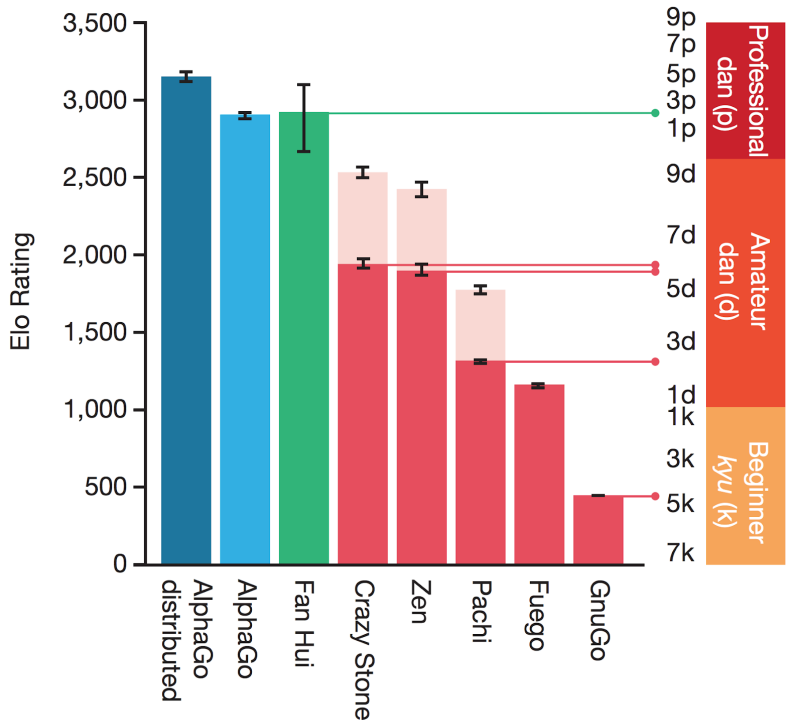
AlphaGo

Silver et al. (2016)



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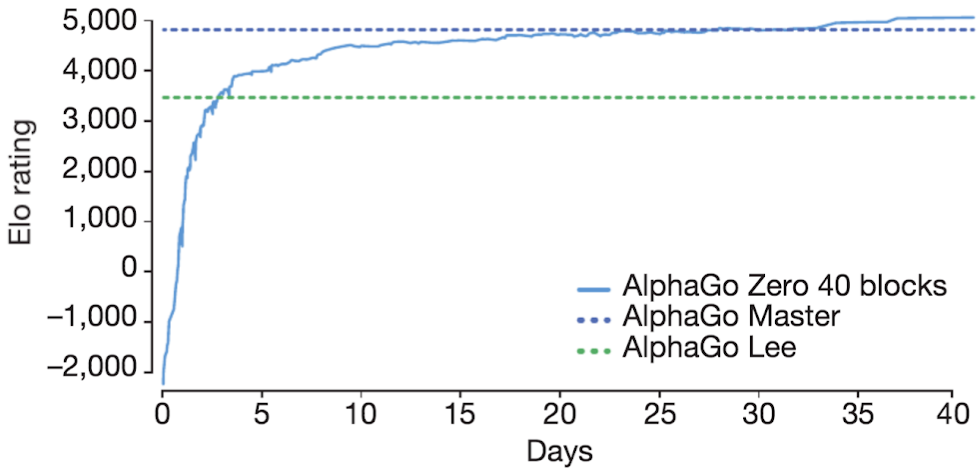
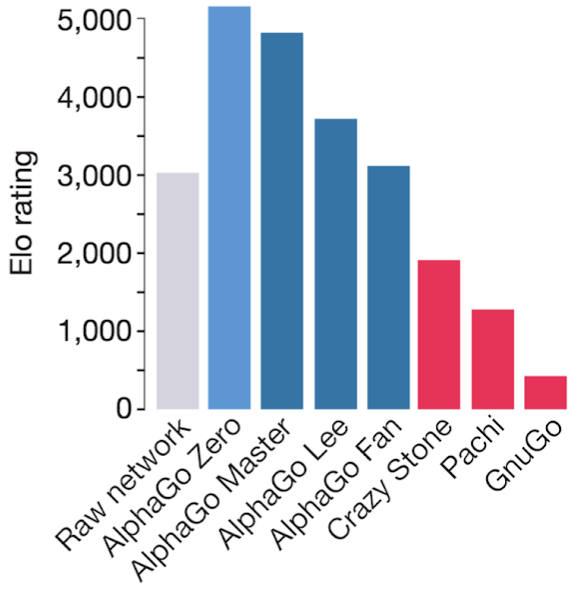
AlphaGo Zero

Silver et al. (2017a)





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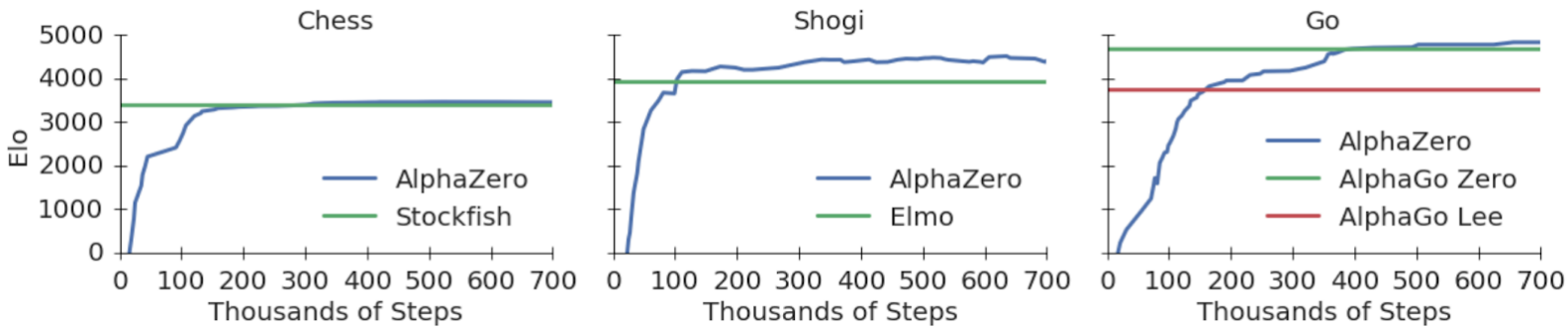
AlphaZero

Silver et al. (2017b)



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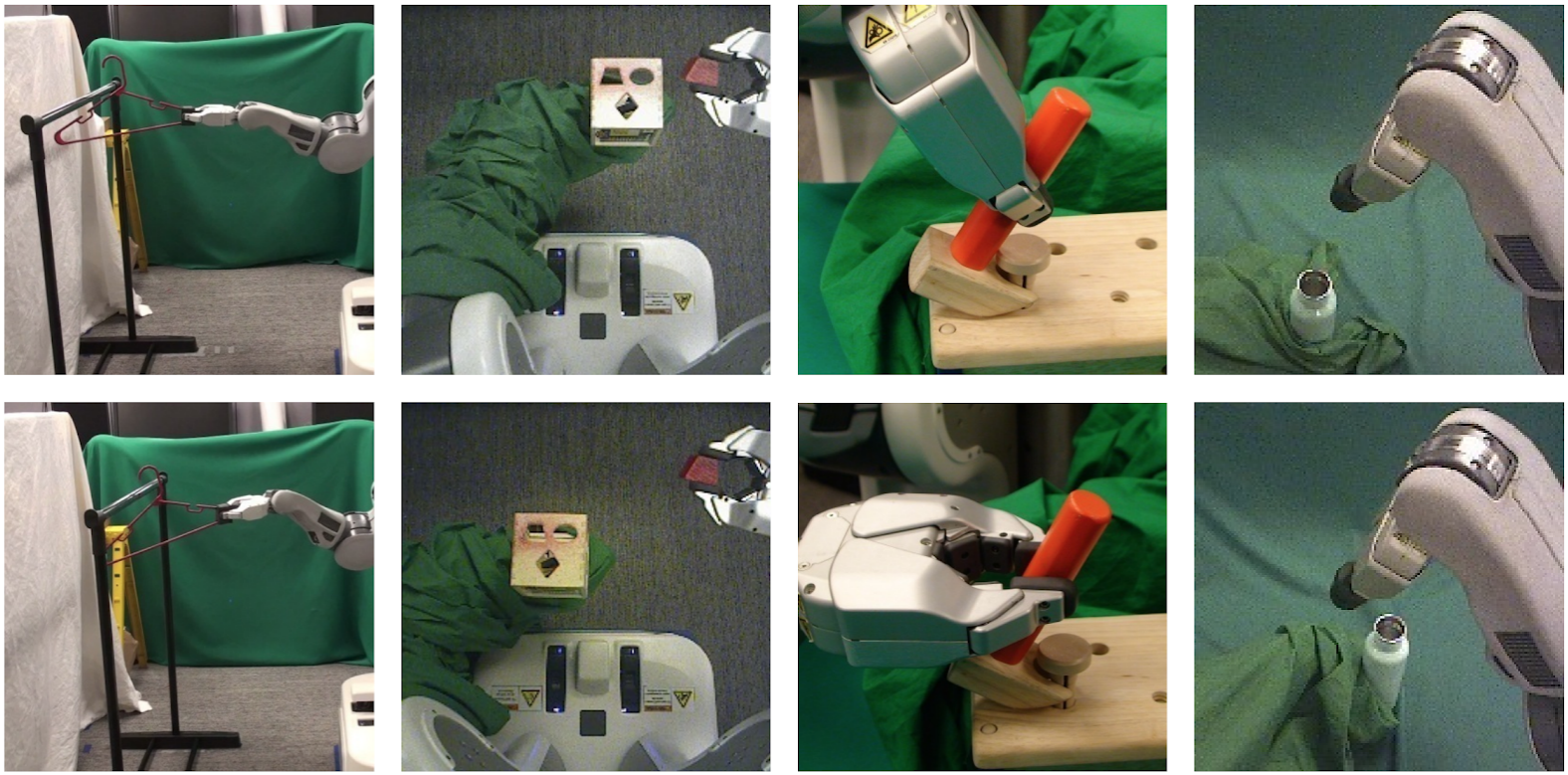
Real-World End-to-End

Levine et al. (2016)



(a) hanger (b) cube (c) hammer (d) bottle

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Environments

1. OpenAI Gym
2. DeepMind Lab
3. Unity

...or create your own with, e.g., the PyGame Learning Environment

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Intro
DQN In Theory
DQN In Practice
Beyond DQN
AI Revolution
Jeanne Calment
Culture Dish
Enlightenment
The View From Here

Outline

1 Introduction

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Essential Deep Q-Learning Theory

[whiteboarding]

Intro
DQN In Theory
DQN In Practice
Beyond DQN
AI Revolution
Jeanne Calment
Culture Dish
Enlightenment
The View From Here

Outline

1 Introduction

2 Deep Q-Learning Theory

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- Jeanne Calment
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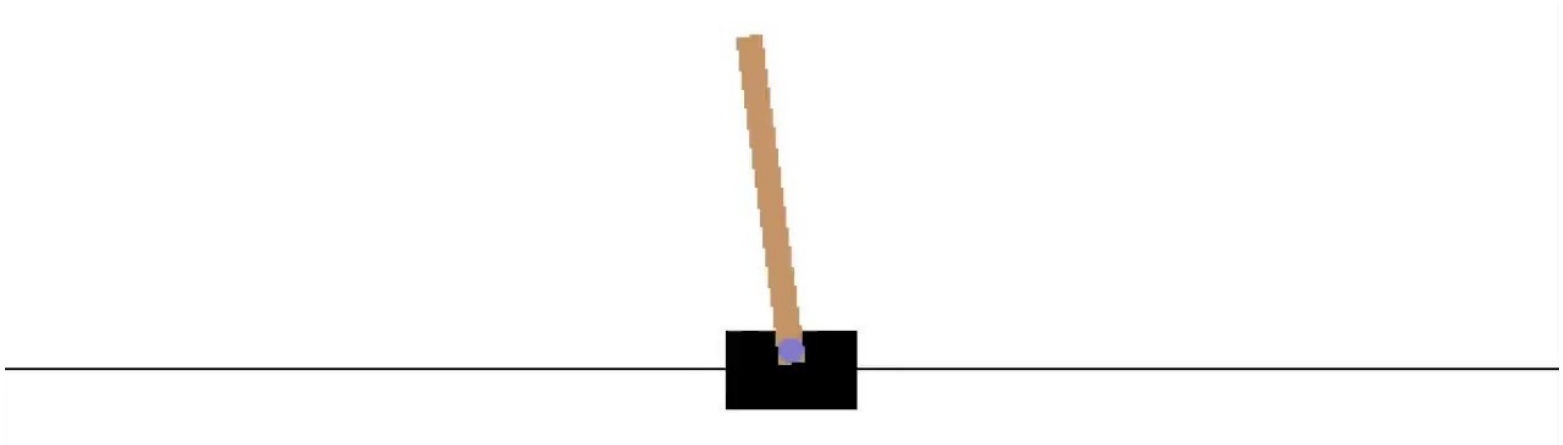
The Cartpole Game

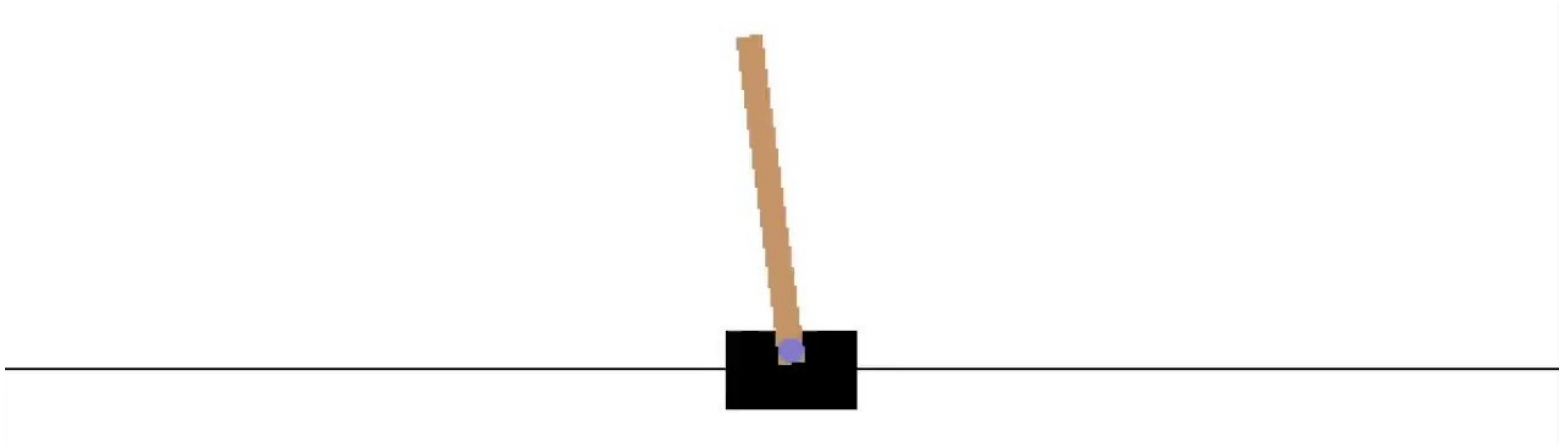
OpenAI



1. cart position
2. cart velocity
3. pole angle
4. pole angular velocity

The Cartpole Game

OpenAI



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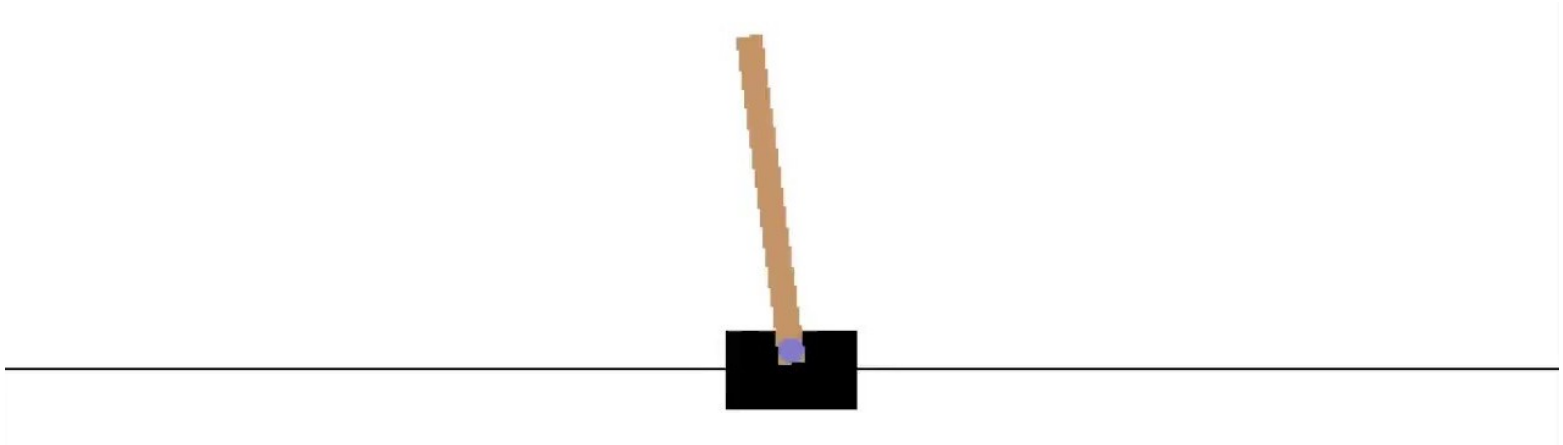

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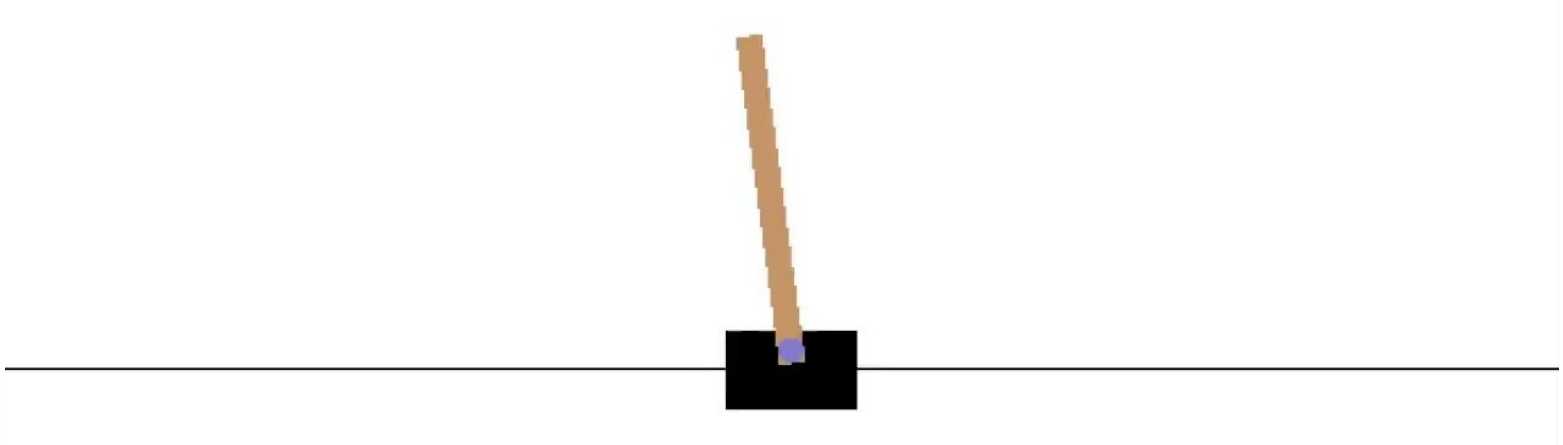

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[*cartpole* notebook]

Intro
DQN In Theory
DQN In Practice
Beyond DQN
AI Revolution
Jeanne Calment
Culture Dish
Enlightenment
The View From Here

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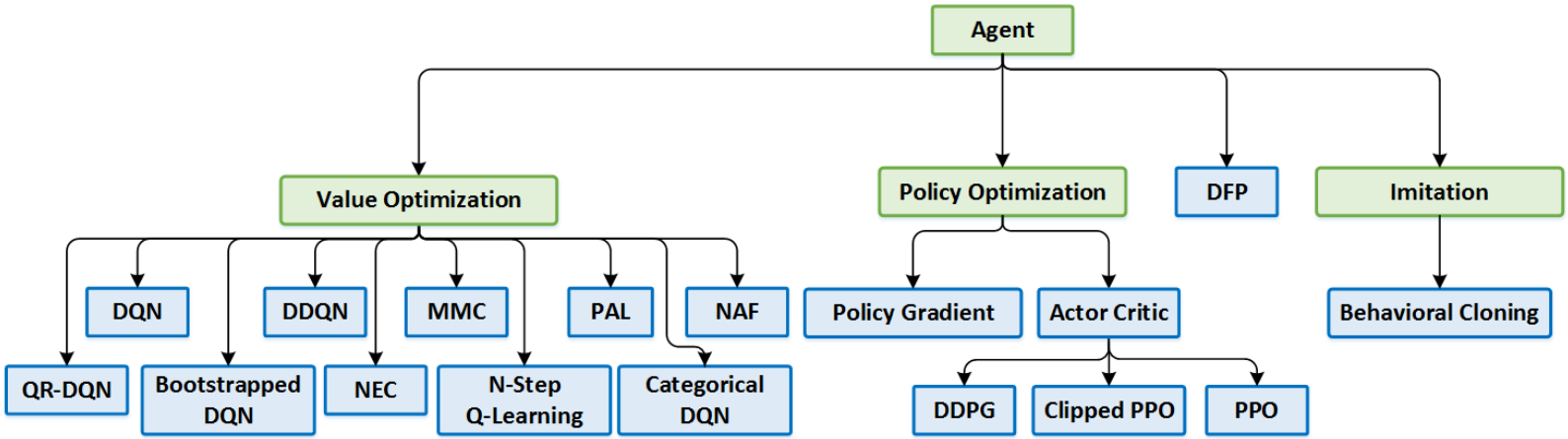
Genetic Algorithms

[Mar/I/O]

Ready-Made Agents



[Coach]

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Automated Experimentation

[OpenAI Lab]

Human Imitation Learning

Warneken & Tomasello (2006)

[videos]

Machine Imitation Learning

Finn, Levine & Abbeel

[videos]

Software 2.0 Pros

Karpathy (2017)

1. Computational Homogeneity
2. Constant Running Time
3. Constant Memory Use
4. Portable Across Devices
5. Easy
6. Superior

[Medium]

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DQN In Theory
DQN In Practice
Beyond DQN
AI Revolution
Jeanne Calment
Culture Dish
Enlightenment
The View From Here

Outline

1 Introduction

2 Deep Q-Learning Theory

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5 The AI Revolution
- Jeanne Calment
- Culture Dish
- Enlightenment
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Intro
DQN In Theory
DQN In Practice
Beyond DQN
AI Revolution
Jeanne Calment
Culture Dish
Enlightenment
The View From Here

Outline

1 Introduction

2 Deep Q-Learning Theory

3 Cart Pole Deep Q-Learning

4 Beyond DQN

5 The AI Revolution
- Jeanne Calment
- Culture Dish
- Enlightenment
- The View From Here

Intro
DQN In Theory
DQN In Practice
Beyond DQN
AI Revolution
Jeanne Calment
Culture Dish
Enlightenment
The View From Here

Jeanne Calment

Jeanne Calment

(1875-1997 — i.e., 122 years)

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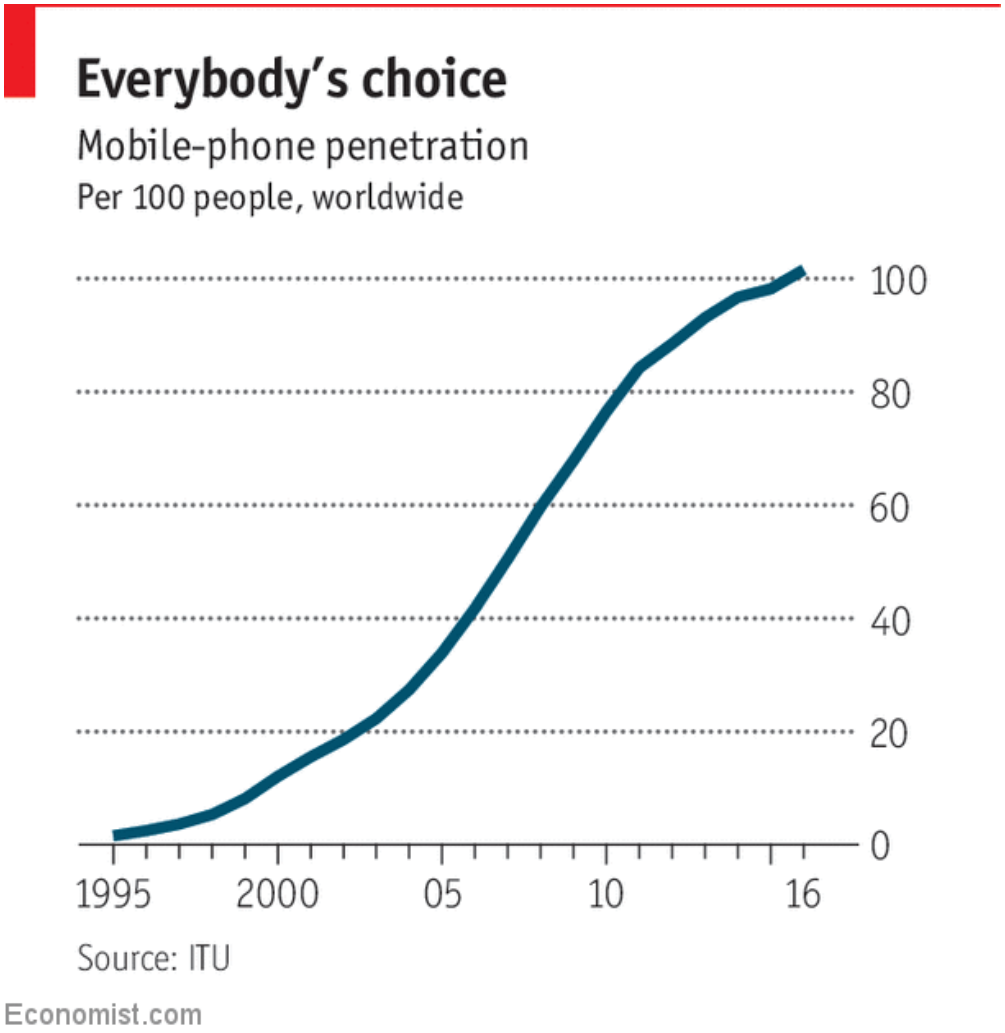
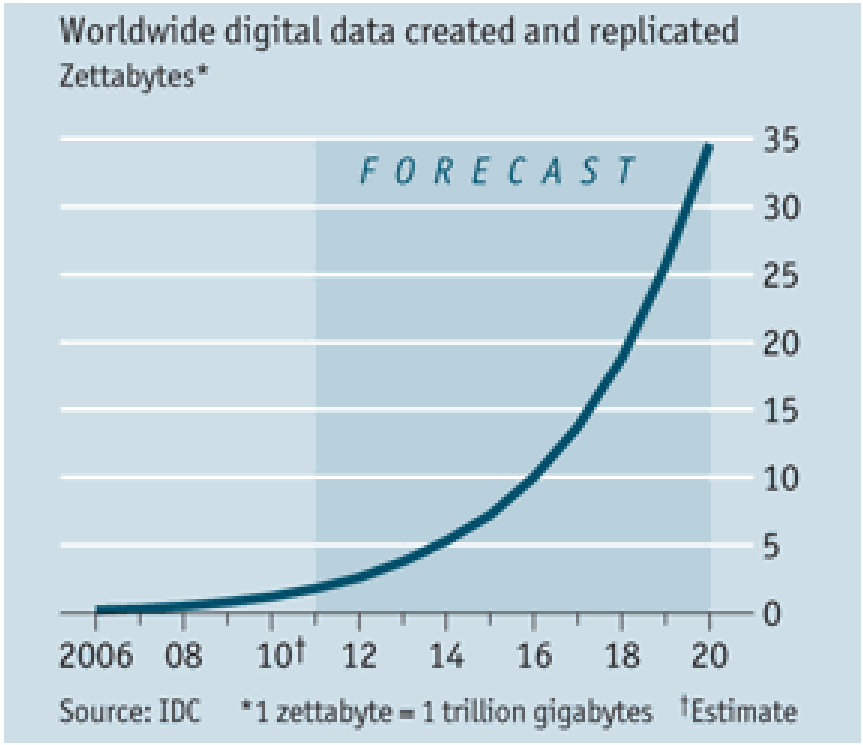
Intro
DQN In Theory
DQN In Practice
Beyond DQN
AI Revolution
Jeanne Calment
Culture Dish
Enlightenment
The View From Here

Life in the Year 2140


Everybody's choice
Mobile-phone penetration
Per 100 people, worldwide
100
80
60
40
20
0
1995
2000
05
10
16
Source: ITU
Economist.com



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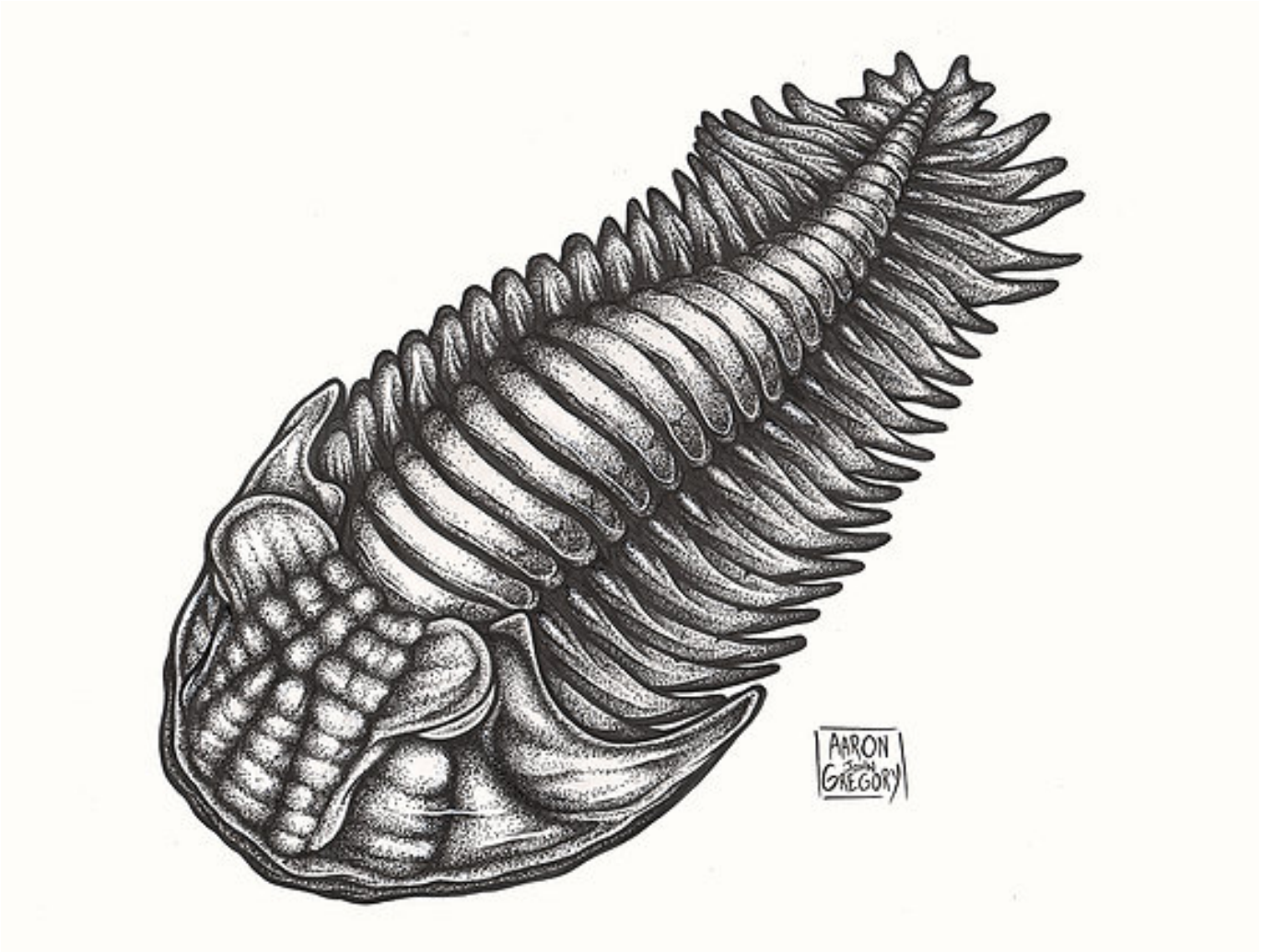
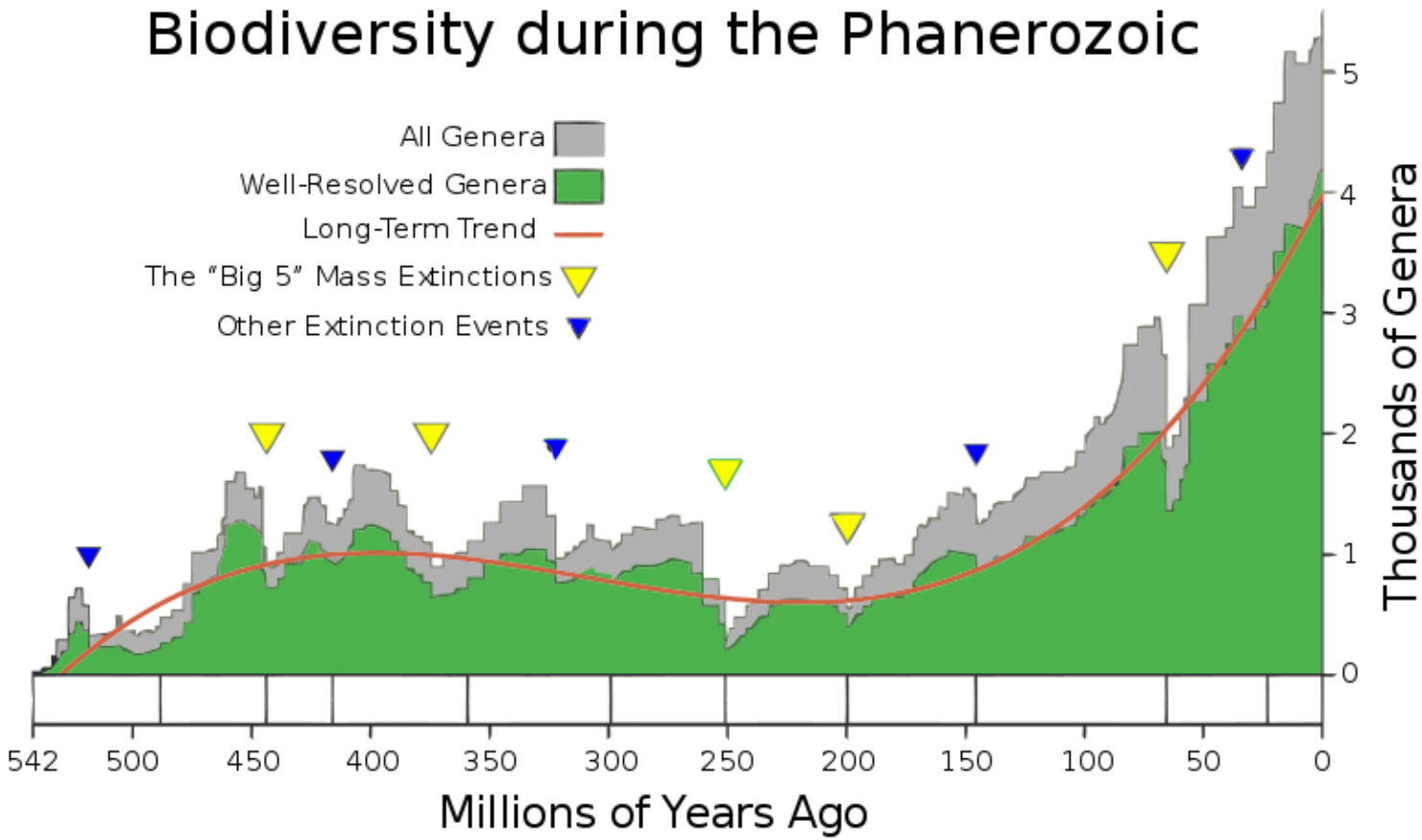
The AI Revolution

Hasn't Even Begun


AARON
GREGORY



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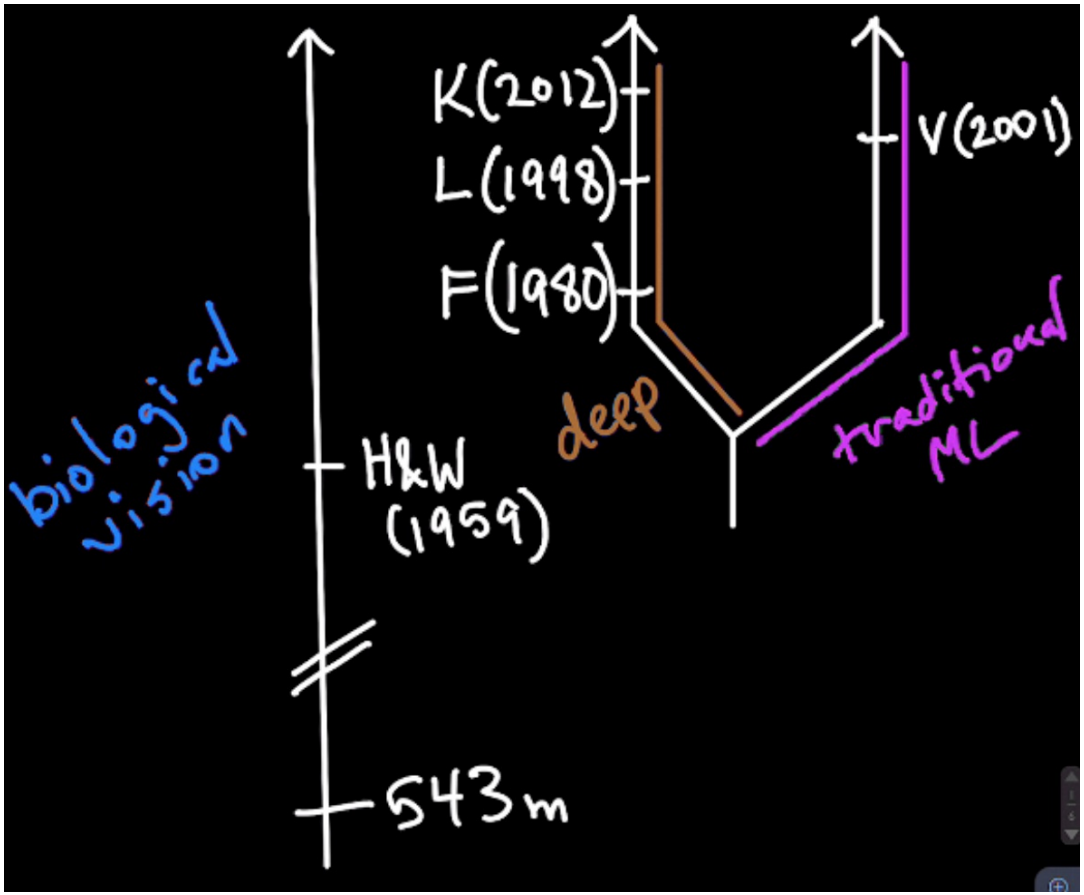

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Factors Driving A.I.

1. Data, incl. Sensors Everywhere
2. Computing Power
3. Algorithms
4. Infrastructure

[Wait But Why]

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AGI

Deep Learning Barriers

1. Requires Many, Many Samples
2. Black Box
3. Doesn't Leverage Knowledge of the World
4. Correlation = Causation
5. Unintuitive / Embarrassing / Adversarial Failures

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DQN In Practice
Beyond DQN
AI Revolution
Jeanne Calment
Culture Dish
Enlightenment
The View From Here

Outline

1 Introduction

2 Deep Q-Learning Theory

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4 Beyond DQN

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- Jeanne Calment
- Culture Dish
- Enlightenment
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DQN In Practice
Beyond DQN
AI Revolution
Jeanne Calment
Culture Dish
Enlightenment
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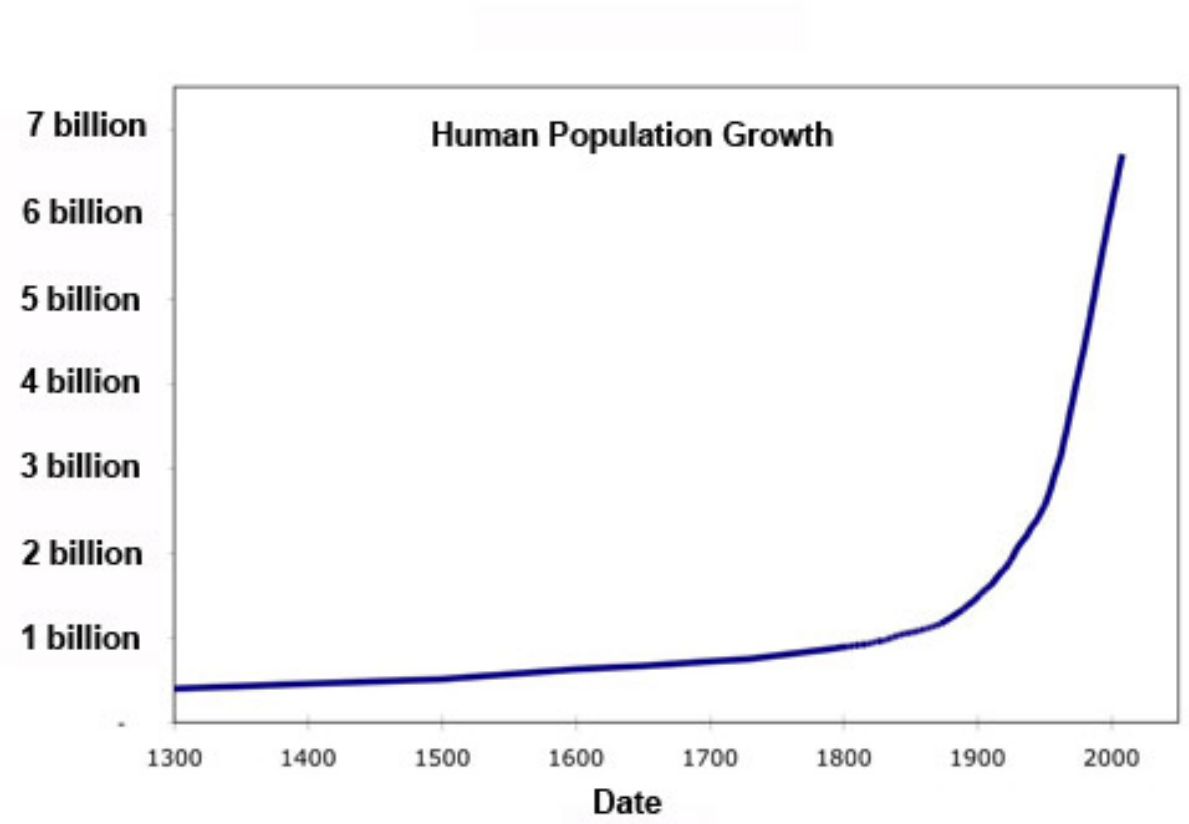
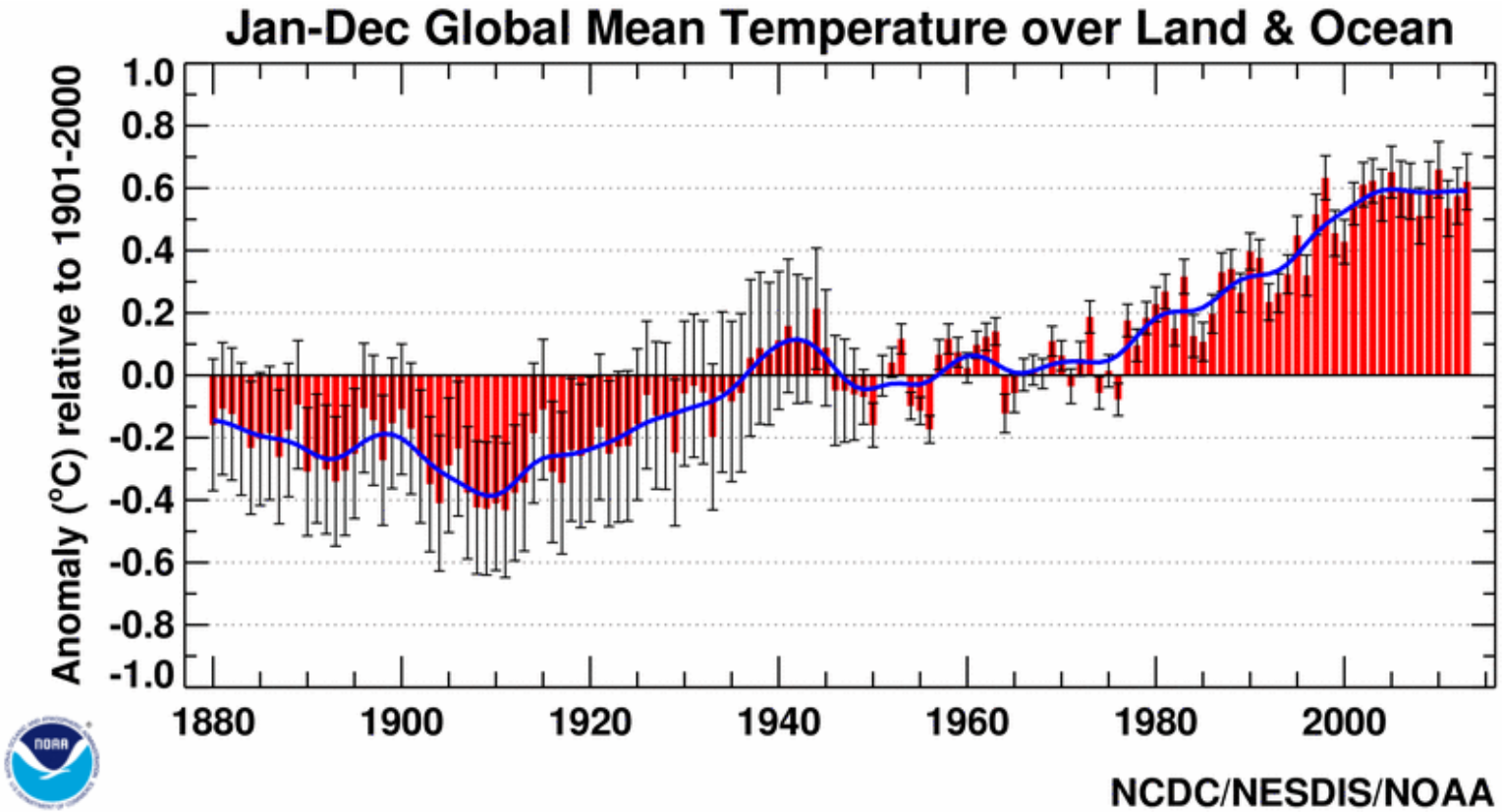
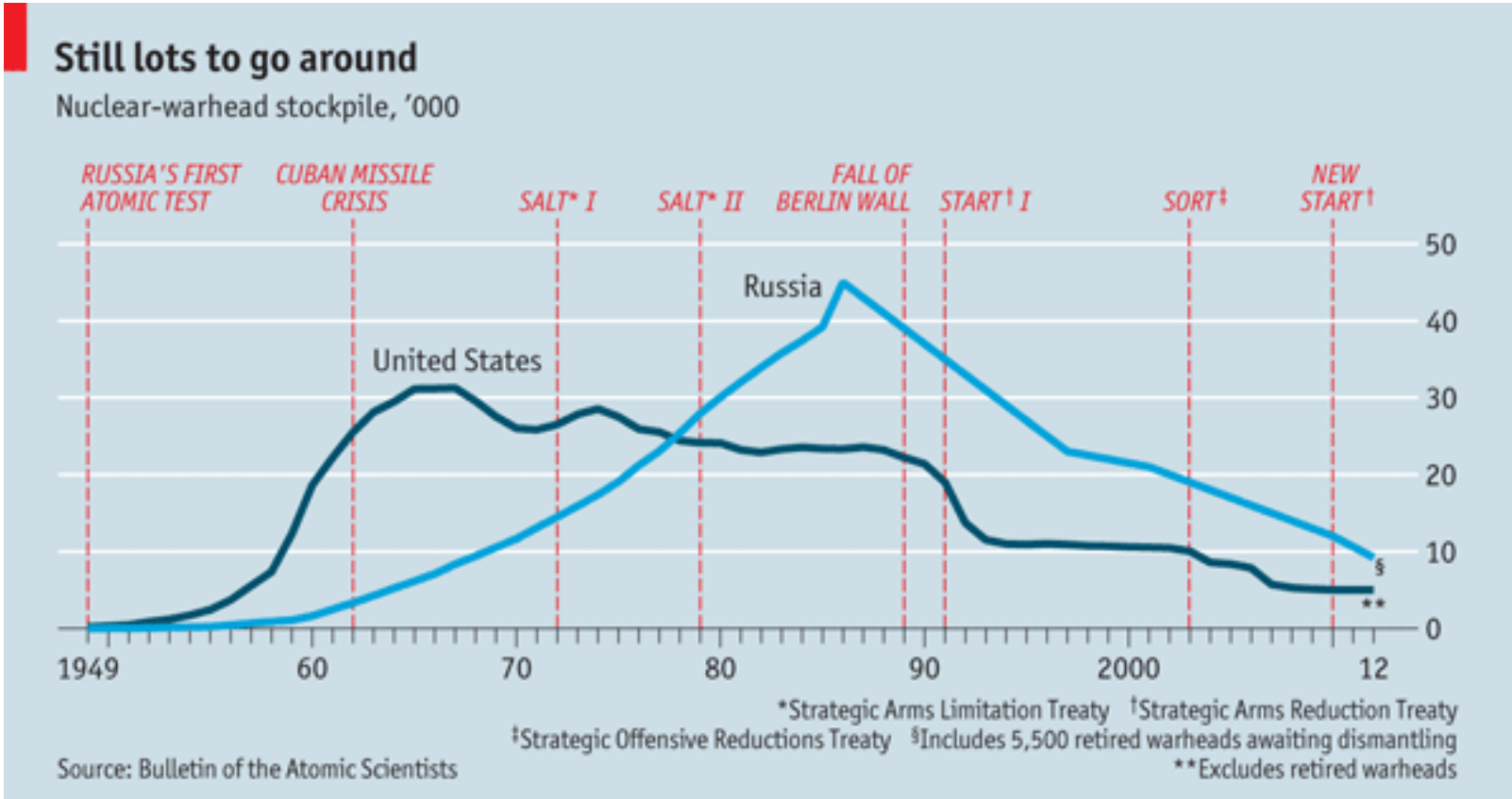


NYC DATA SCIENCE ACADEMY

Intro
DQN In Theory
DQN In Practice
Beyond DQN
AI Revolution
Jeanne Calment
Culture Dish
Enlightenment
The View From Here

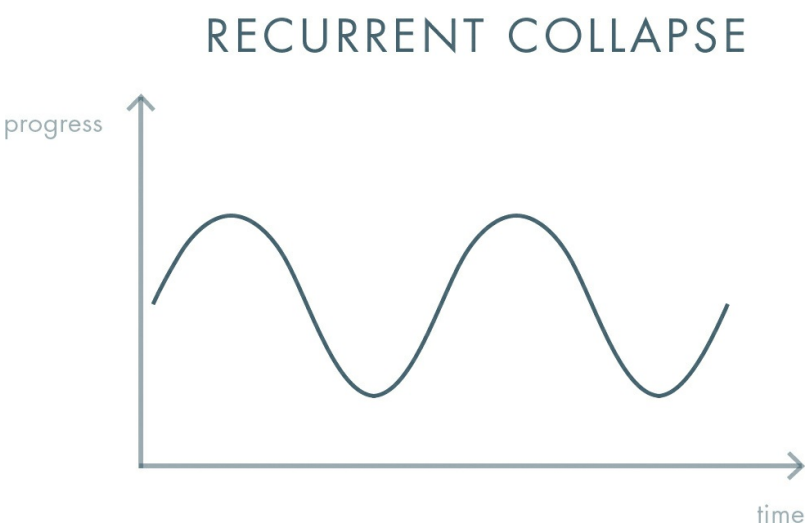


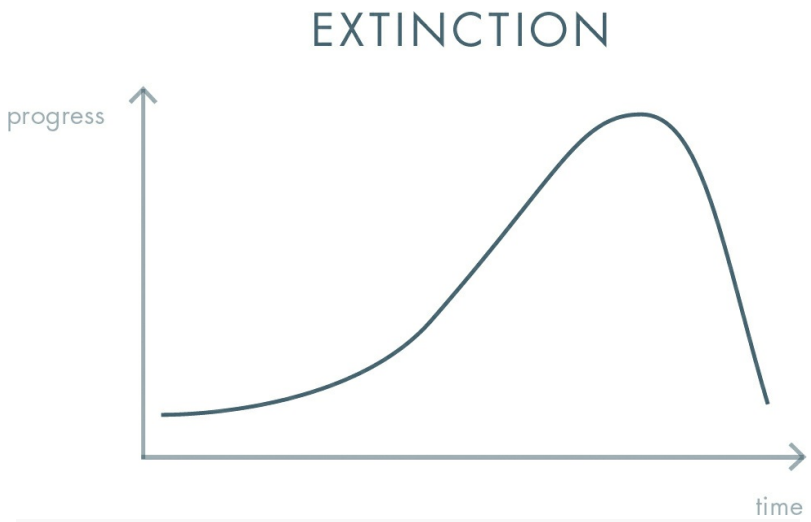
Intro
DQN In Theory
DQN In Practice
Beyond DQN
AI Revolution
Jeanne Calment
Culture Dish
Enlightenment
The View From Here

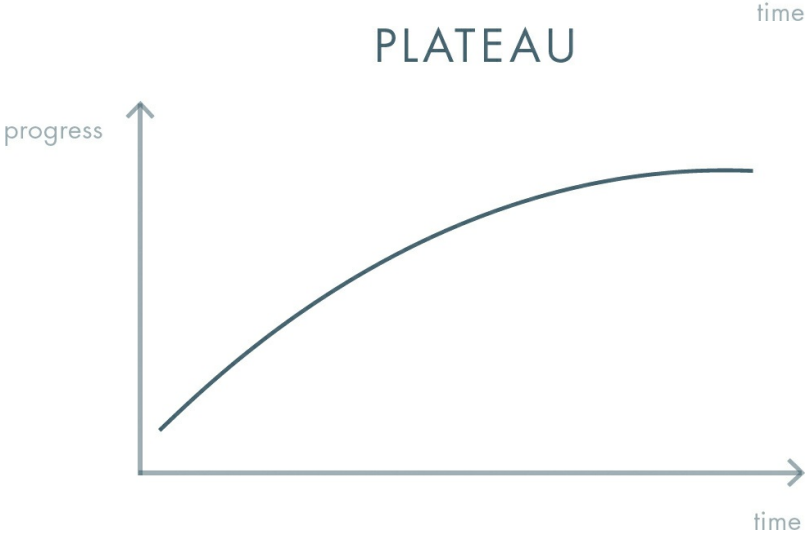


NYC DATA SCIENCE ACADEMY

Thiel & Masters (2014)







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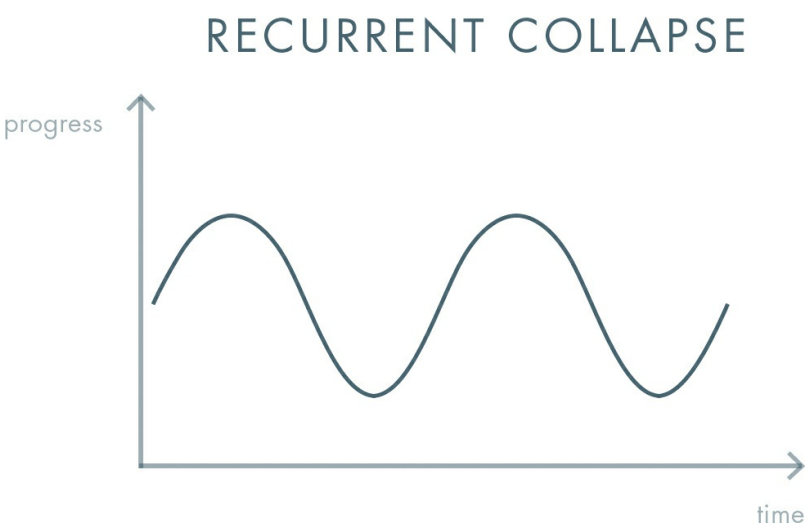

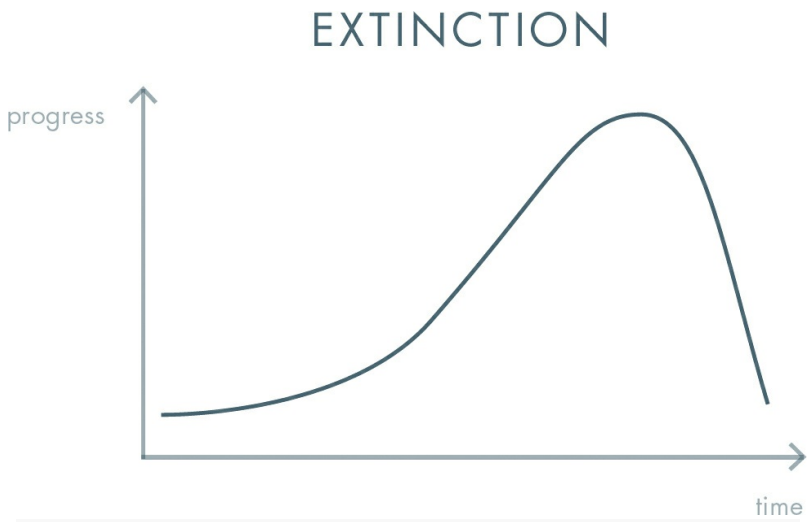

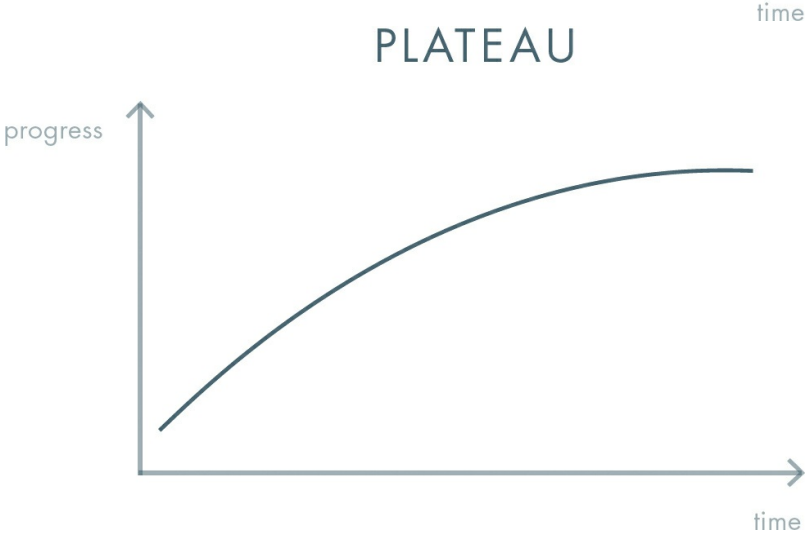

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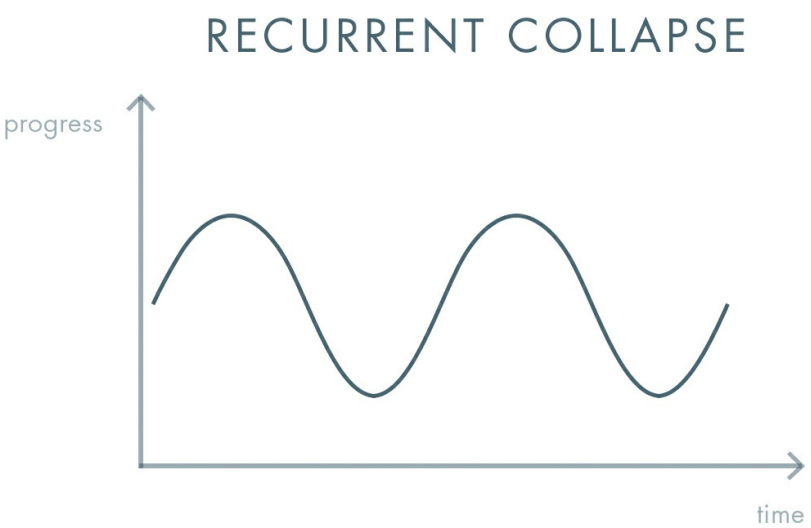

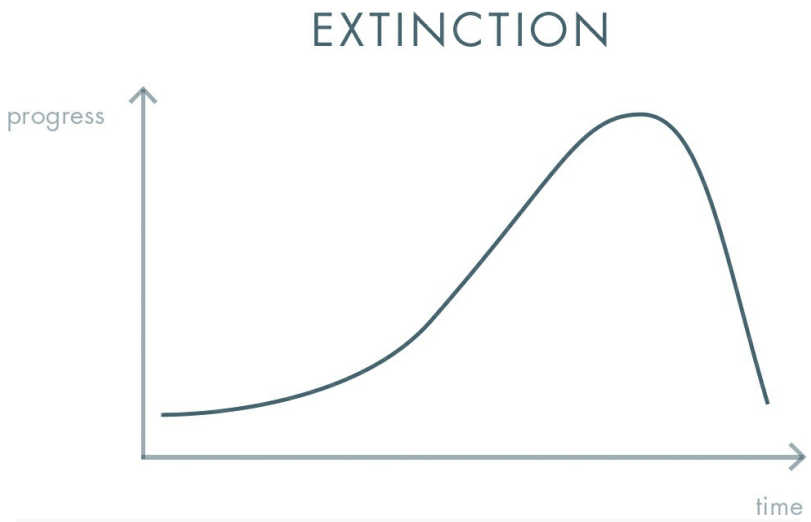

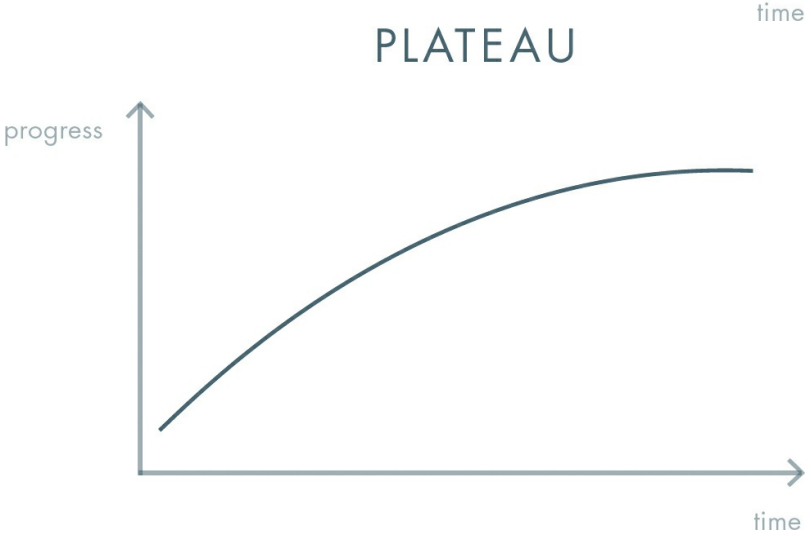

NYC DATA SCIENCE ACADEMY

Intro
DQN In Theory
DQN In Practice
Beyond DQN
AI Revolution
Jeanne Calment
Culture Dish
Enlightenment
The View From Here

Outline

1 Introduction

2 Deep Q-Learning Theory

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5 The AI Revolution
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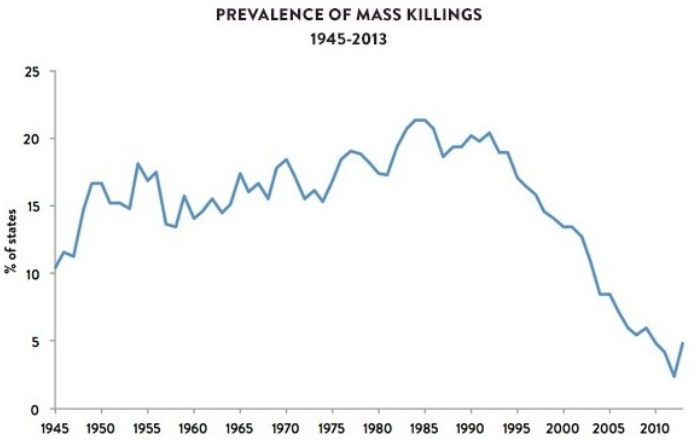

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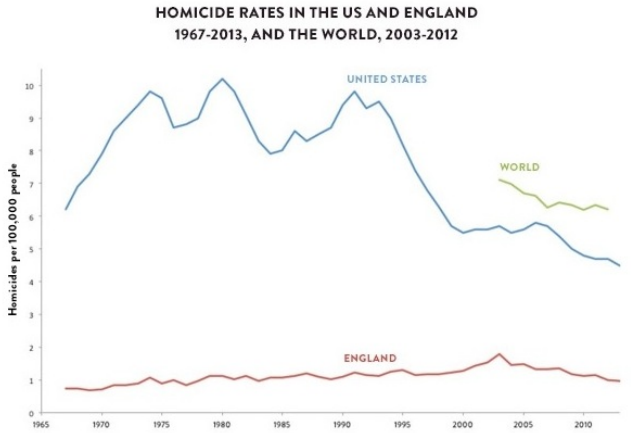

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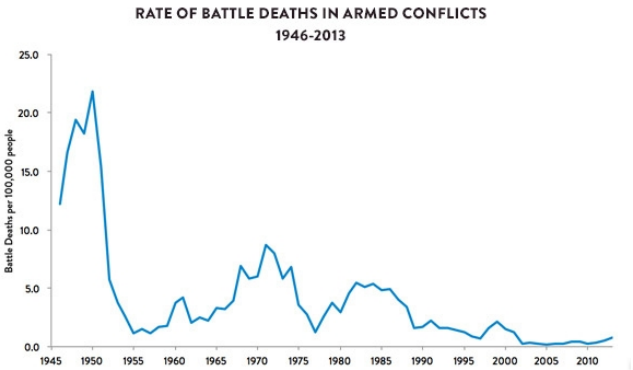

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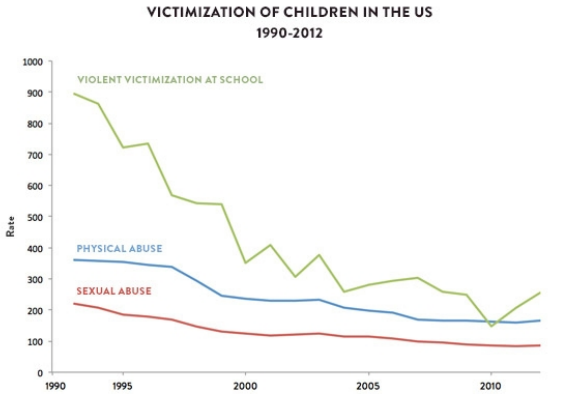

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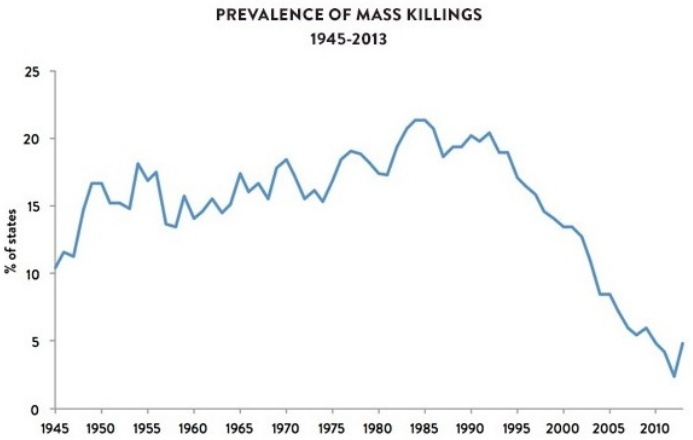

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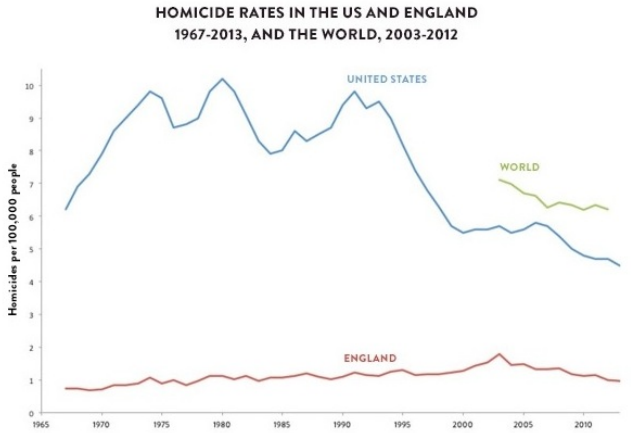

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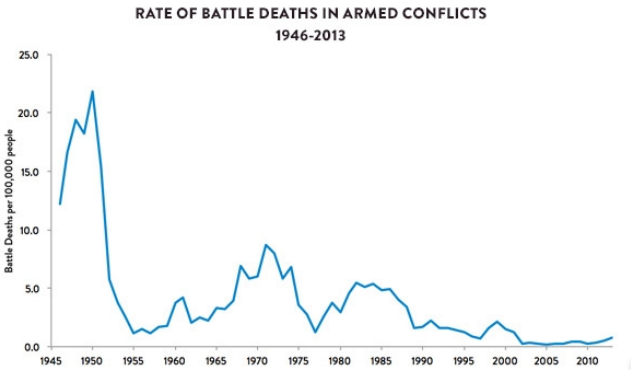

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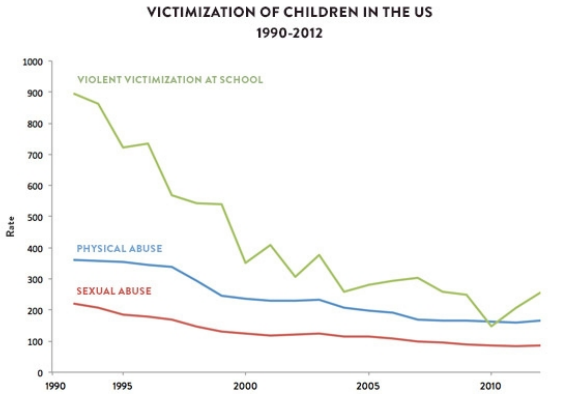

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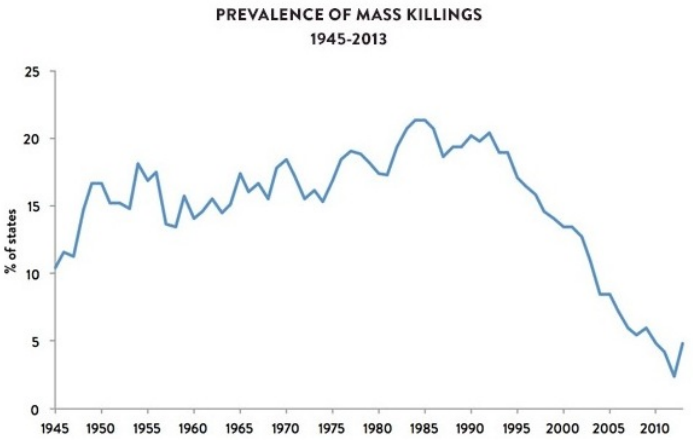

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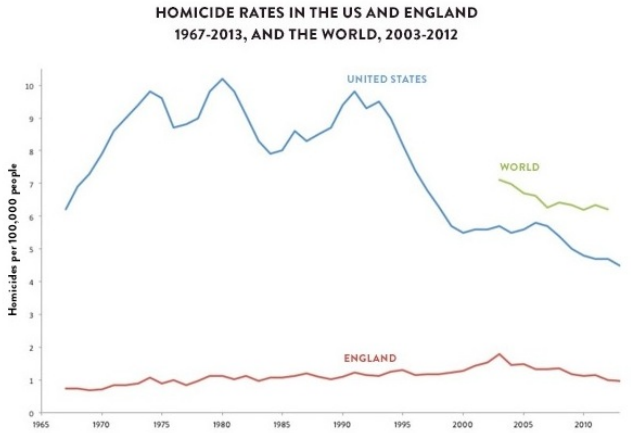

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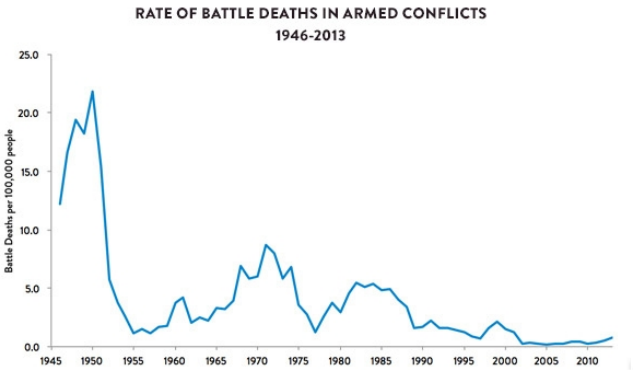

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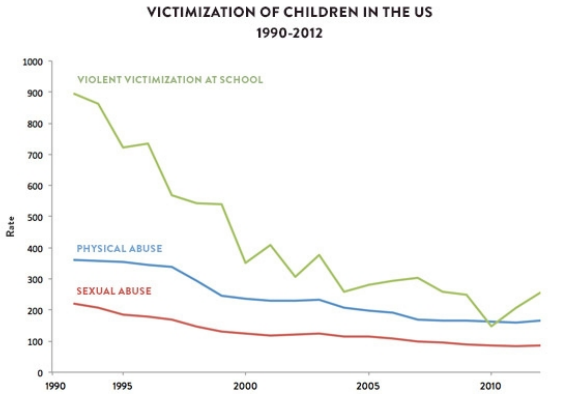

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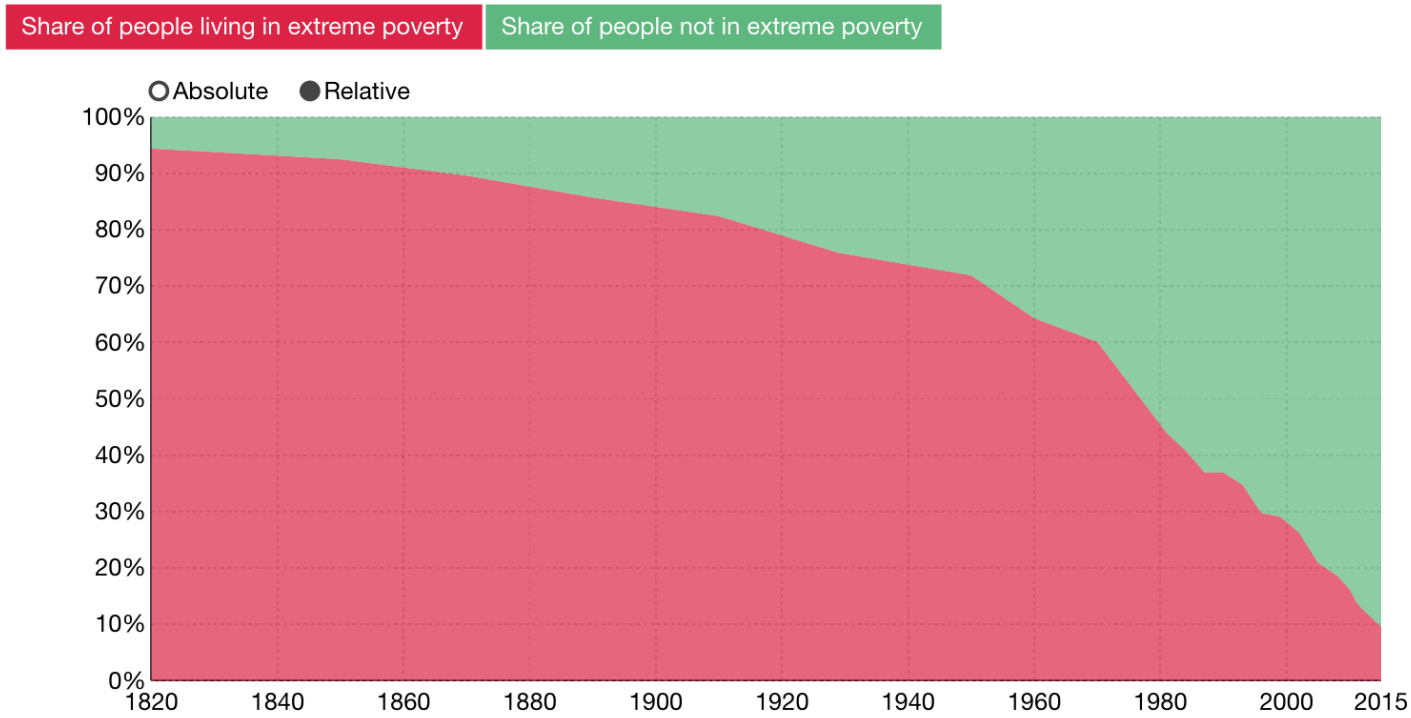
World population living in extreme poverty, 1820 to 2015

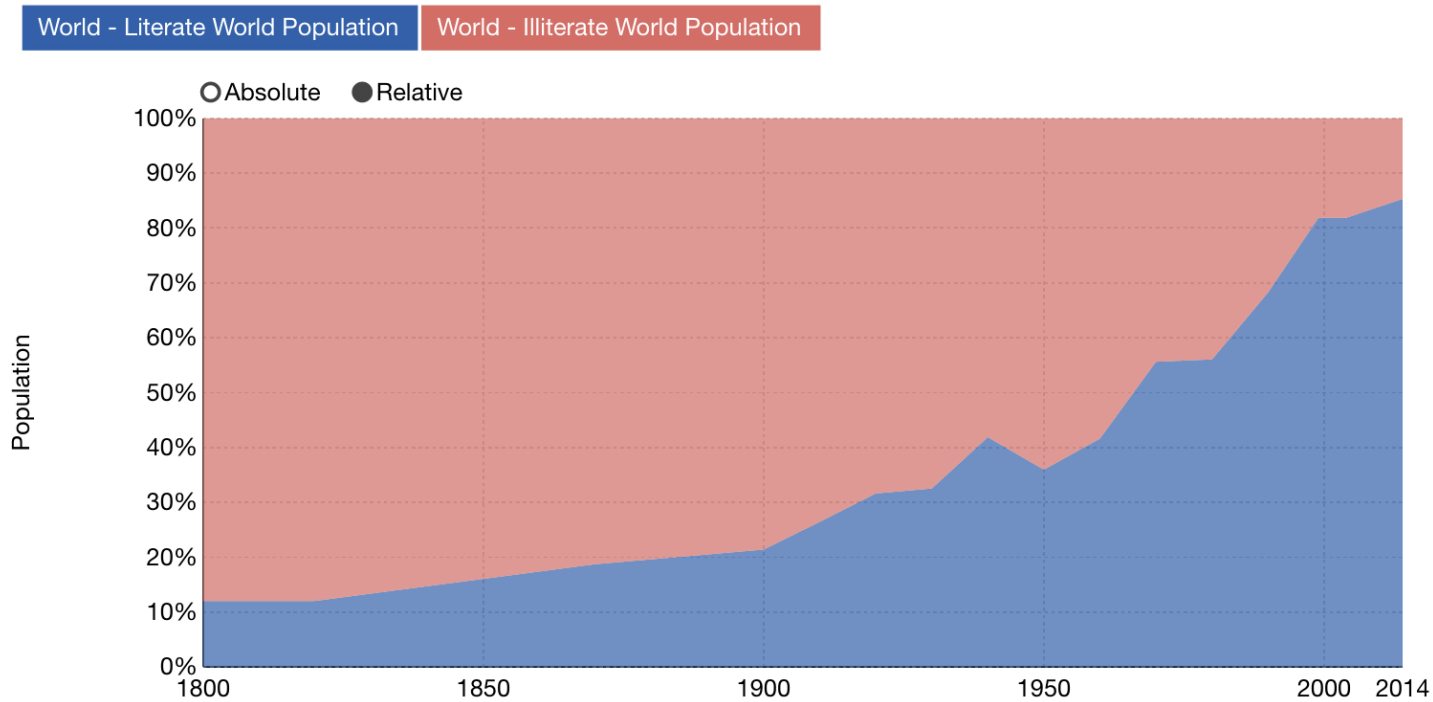
Our World in Data



Data source: World Poverty in absolute numbers (Max Roser based on World Bank and Bourguignon and Morrisson (2002))

Literate and illiterate world population, 1800 to 2014

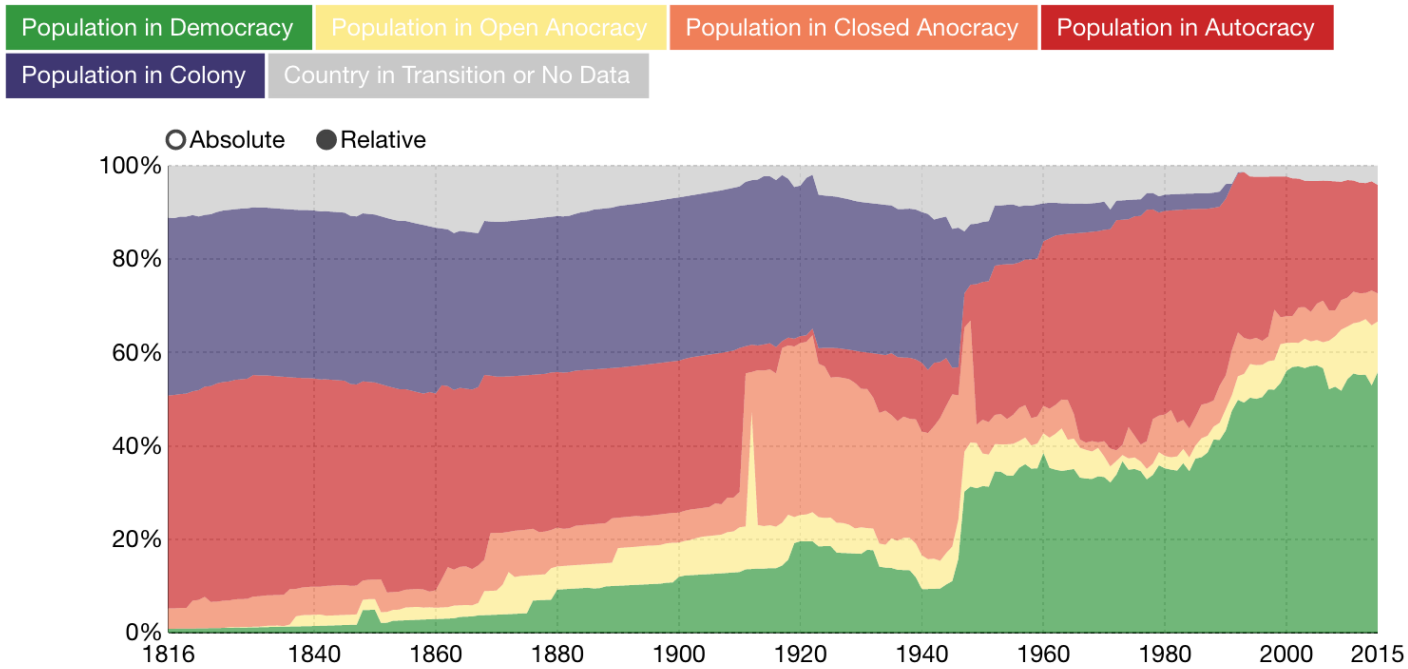
Our World in Data



Data source: Literate World Population (Our World In Data based on OECD and UNESCO)

Number of world citizens living under different political regimes

The Polity IV score captures the type of political regime for each country on a range from -10 (full autocracy) to +10 (full democracy). Regimes that fall into the middle of this spectrum are called anocracies.

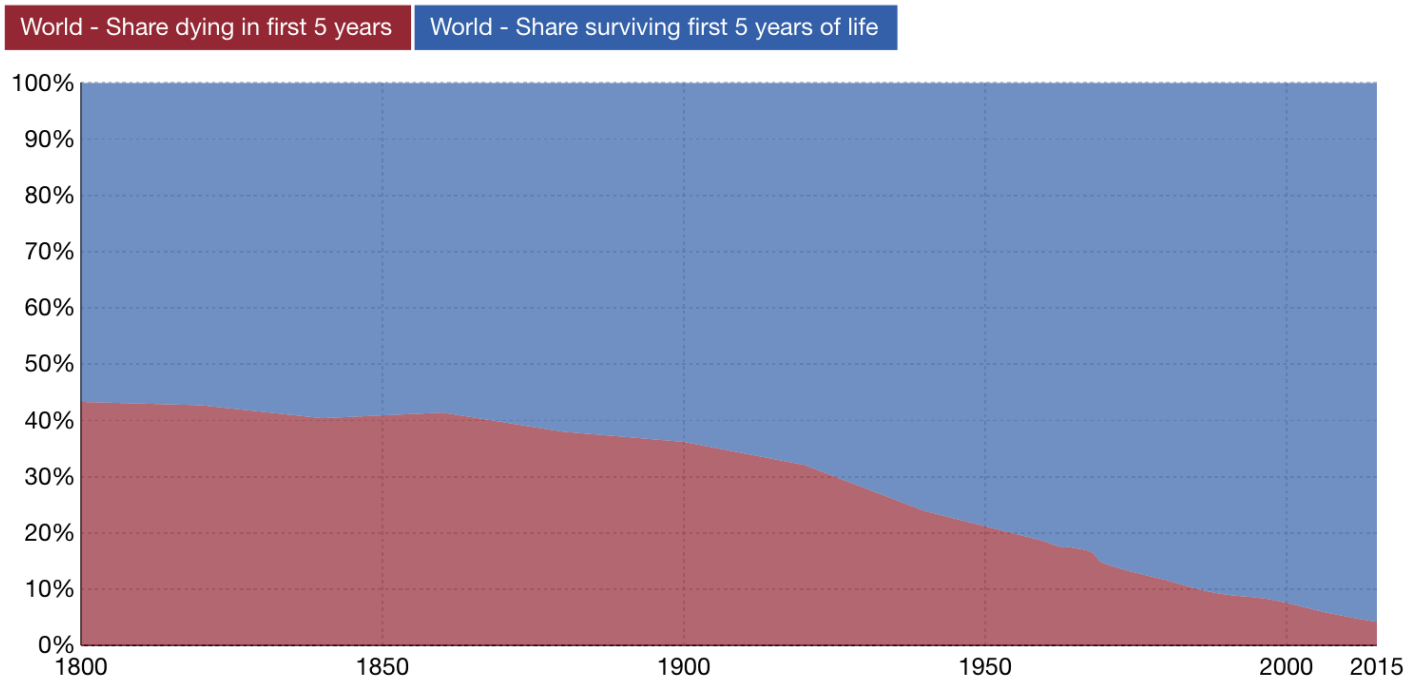


Data source: World Population by Political Regime they live in (by Our World In Data)

Global child mortality, 1800 to 2015

Share of the world population dying and surviving the first 5 years of life.

Our World in Data



Data source: Global child mortality (since 1800) based on Gapminder and World Bank

Intro
DQN In Theory
DQN In Practice
Beyond DQN
AI Revolution
Jeanne Calment
Culture Dish
Enlightenment
The View From Here

Outline

1 Introduction

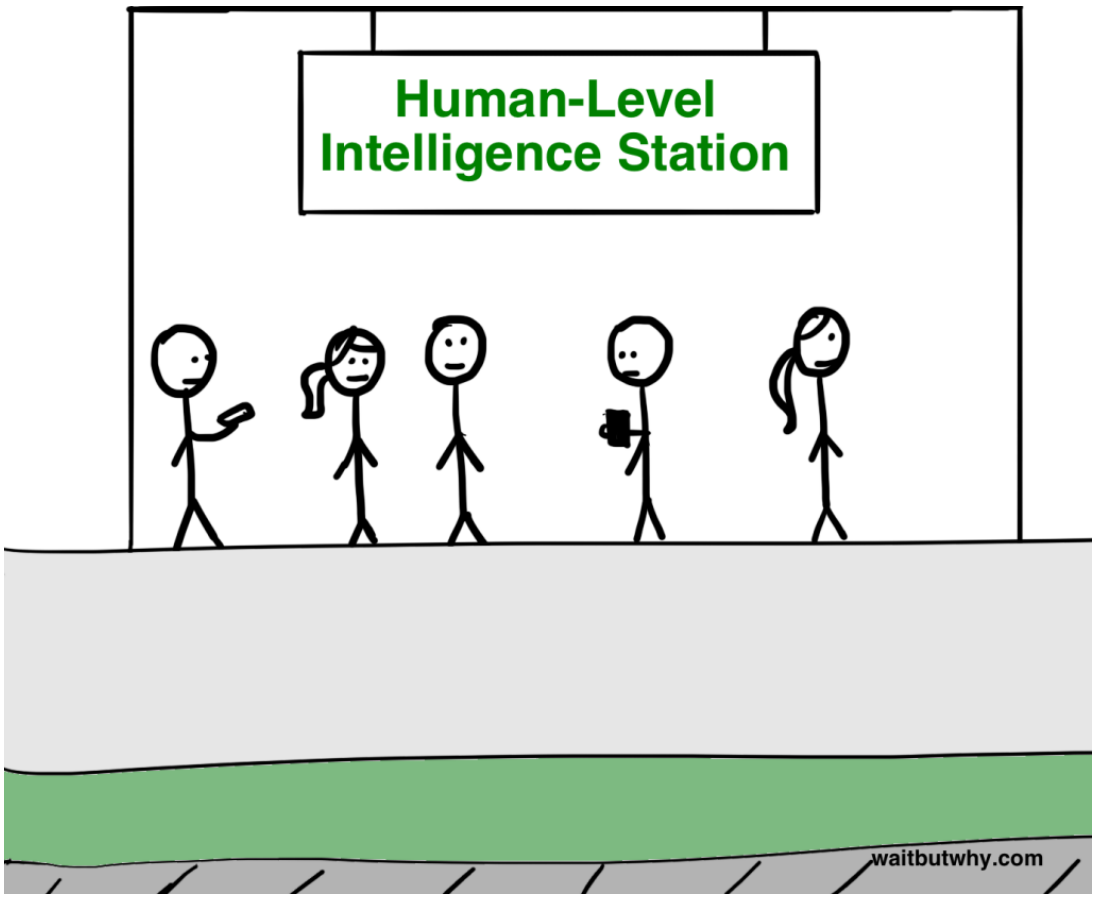
2 Deep Q-Learning Theory

3 Cart Pole Deep Q-Learning

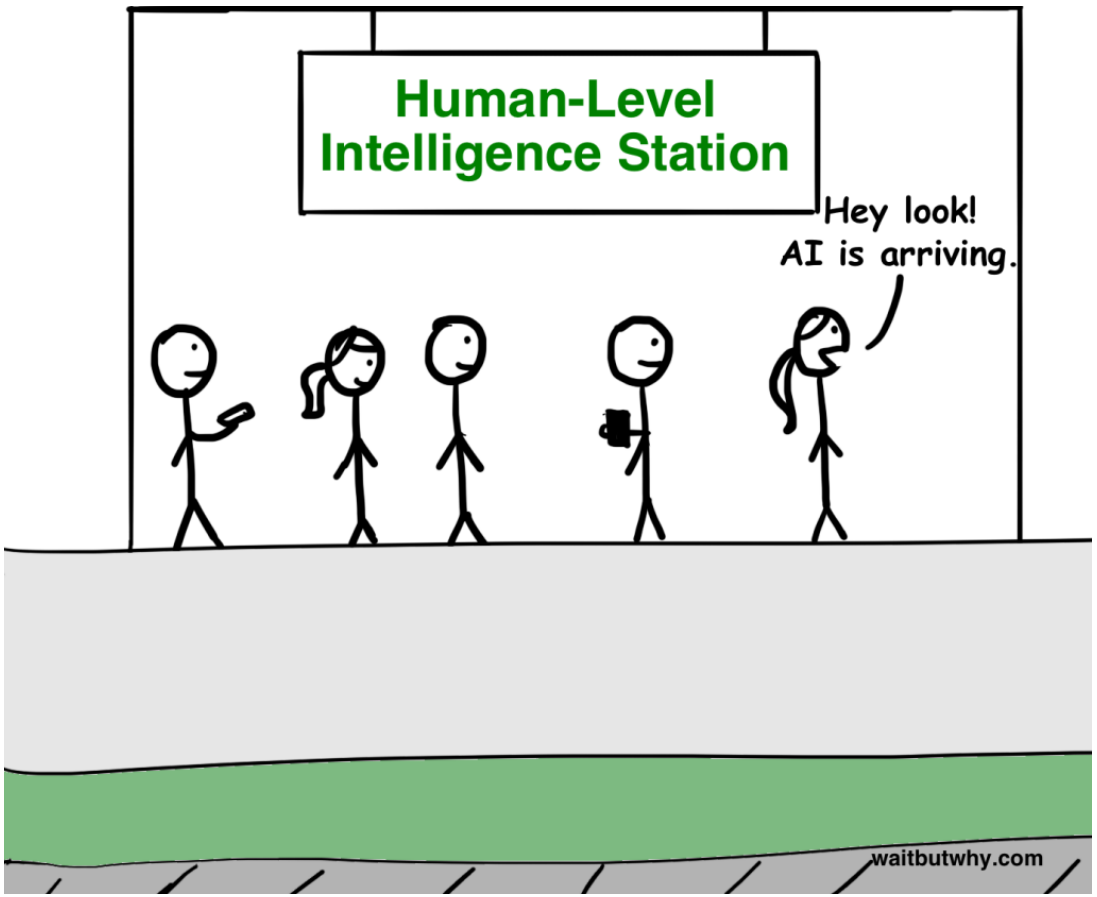
4 Beyond DQN

5 The AI Revolution
- Jeanne Calment
- Culture Dish
- Enlightenment
- The View From Here

Intro
DQN In Theory
DQN In Practice
Beyond DQN
AI Revolution
Jeanne Calment
Culture Dish
Enlightenment
The View From Here

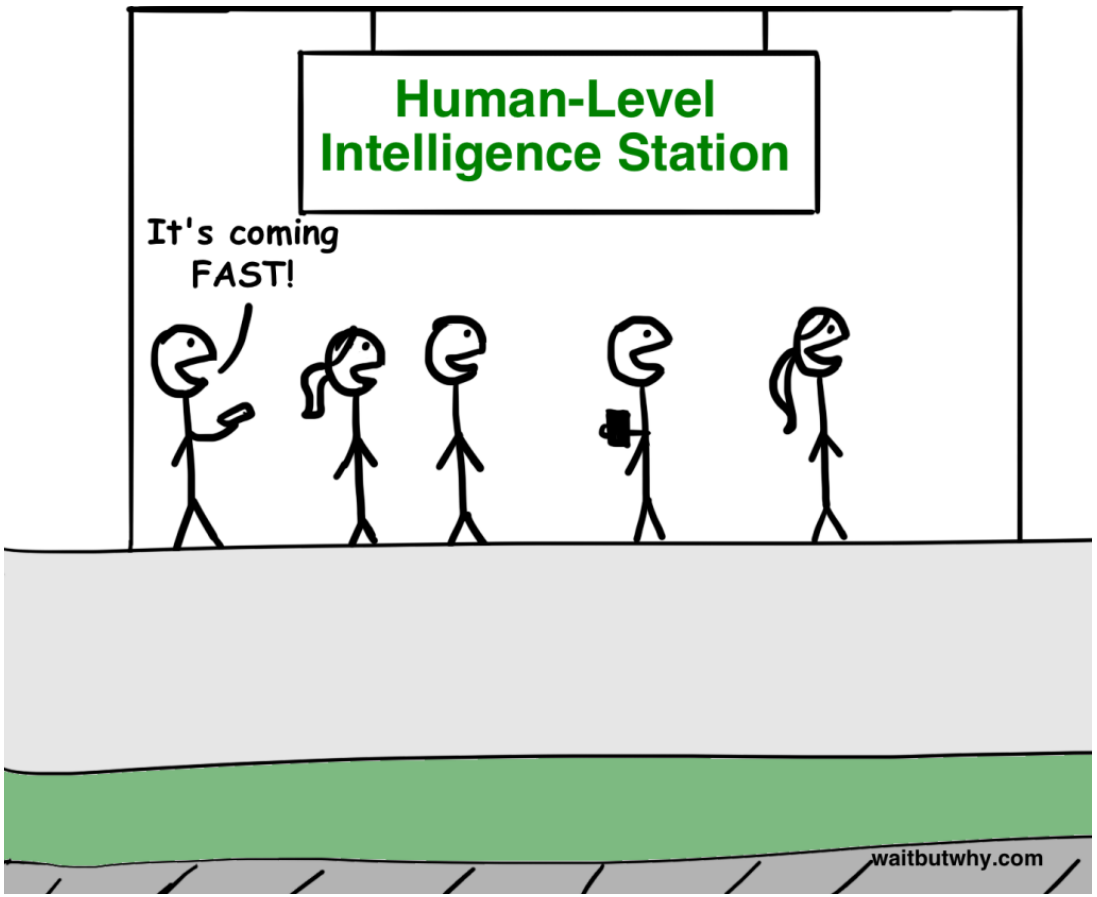


Intro
DQN In Theory
DQN In Practice
Beyond DQN
AI Revolution
Jeanne Calment
Culture Dish
Enlightenment
The View From Here



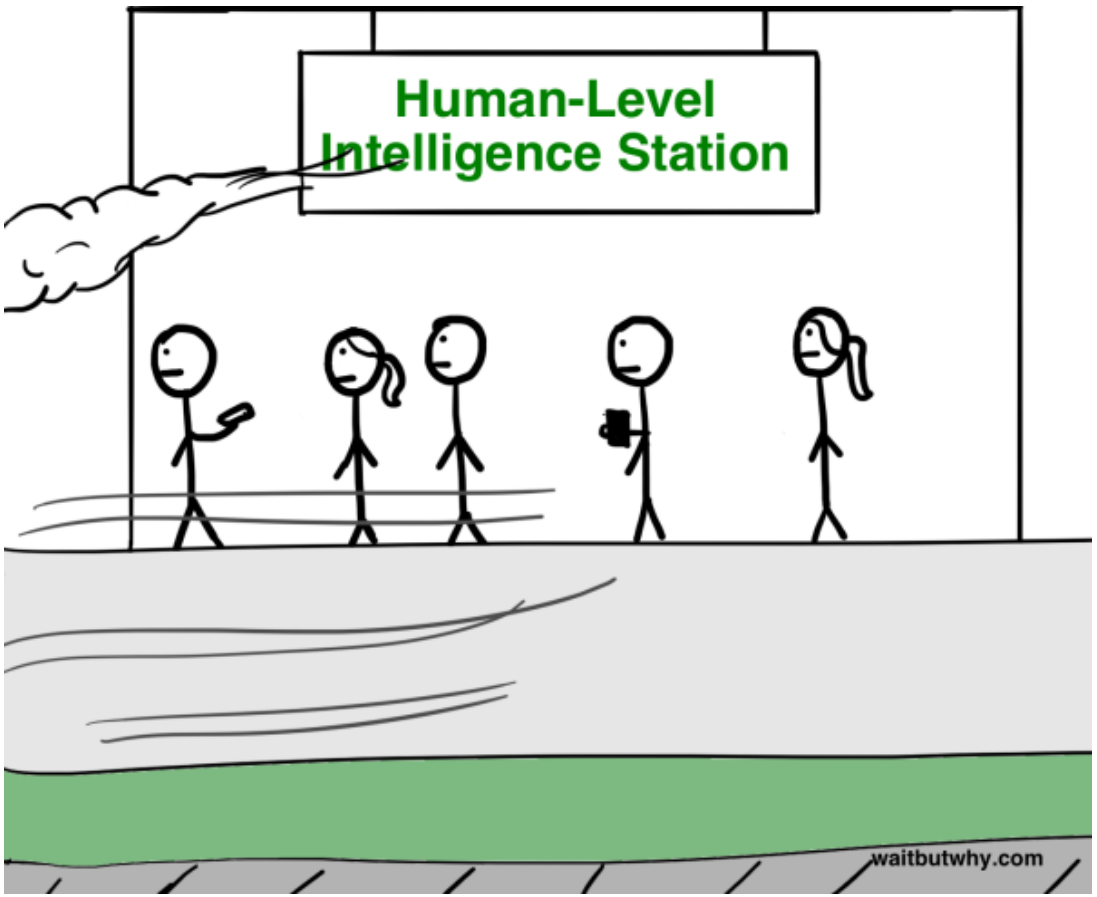
NYC DATA SCIENCE ACADEMY

Intro
DQN In Theory
DQN In Practice
Beyond DQN
AI Revolution
Jeanne Calment
Culture Dish
Enlightenment
The View From Here

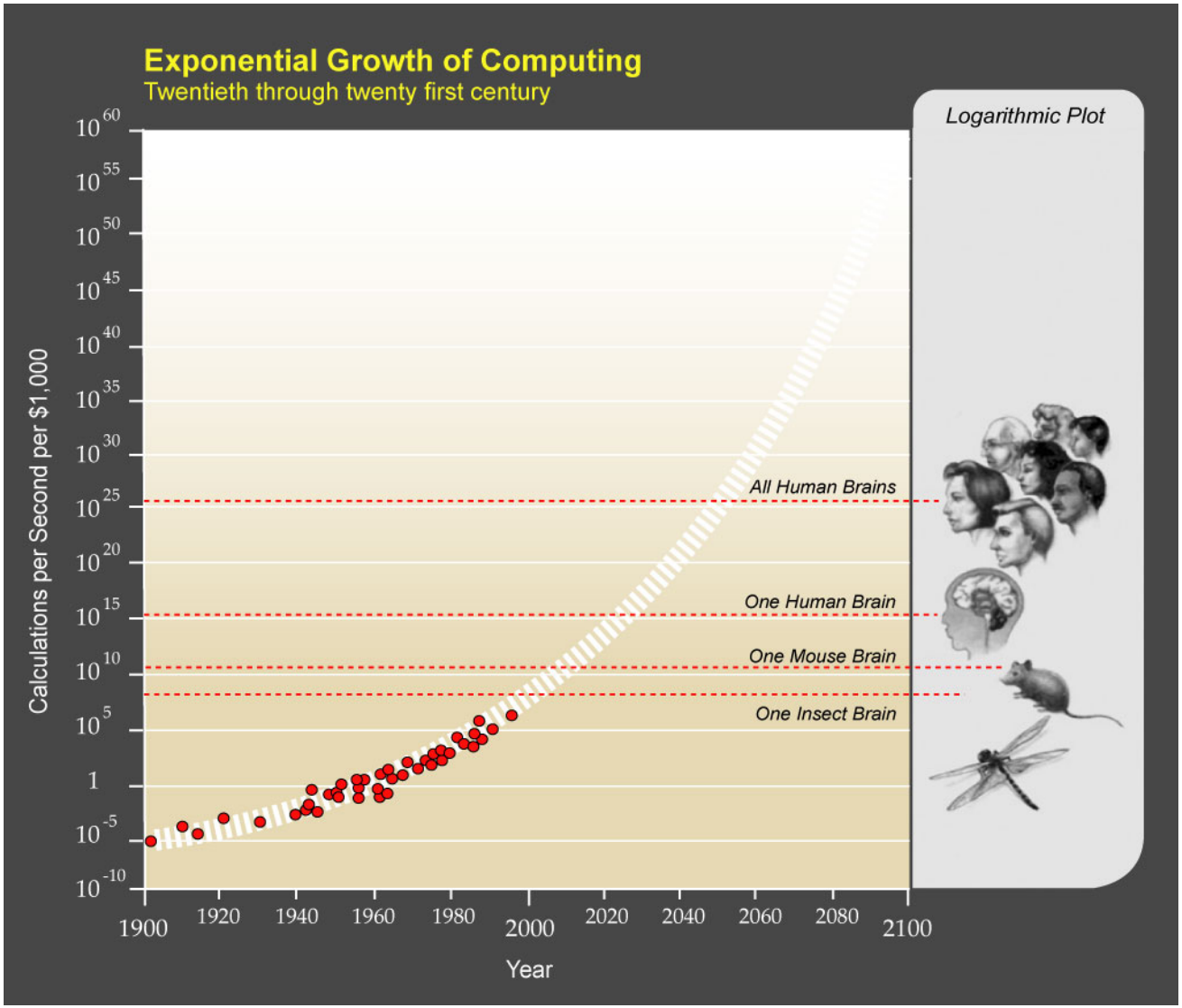


NYC DATA SCIENCE ACADEMY

Intro
DQN In Theory
DQN In Practice
Beyond DQN
AI Revolution
Jeanne Calment
Culture Dish
Enlightenment
The View From Here

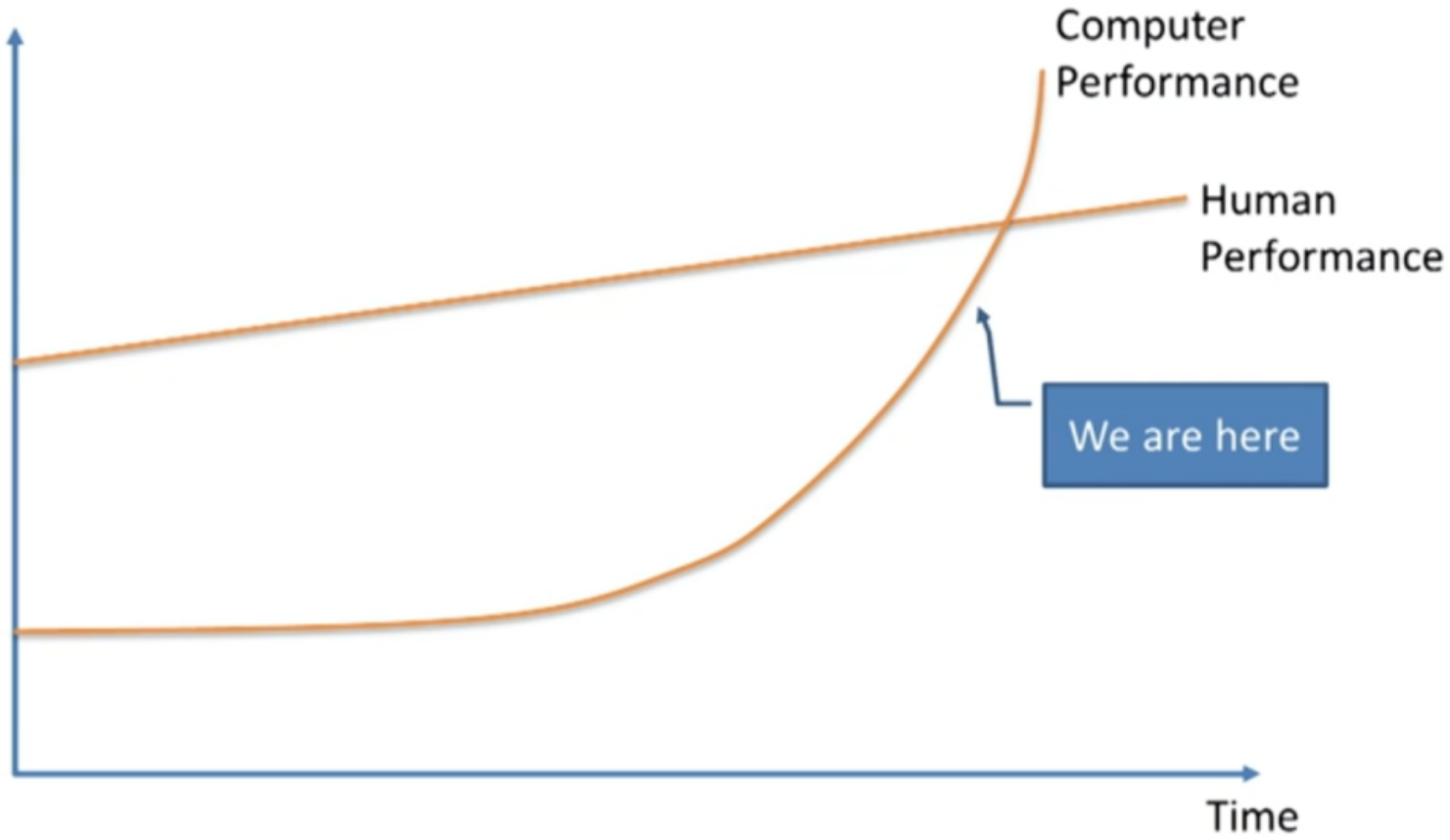


Intro
DQN In Theory
DQN In Practice
Beyond DQN
AI Revolution
Jeanne Calment
Culture Dish
Enlightenment
The View From Here



NYC DATA SCIENCE ACADEMY

Intro
DQN In Theory
DQN In Practice
Beyond DQN
AI Revolution
Jeanne Calment
Culture Dish
Enlightenment
The View From Here



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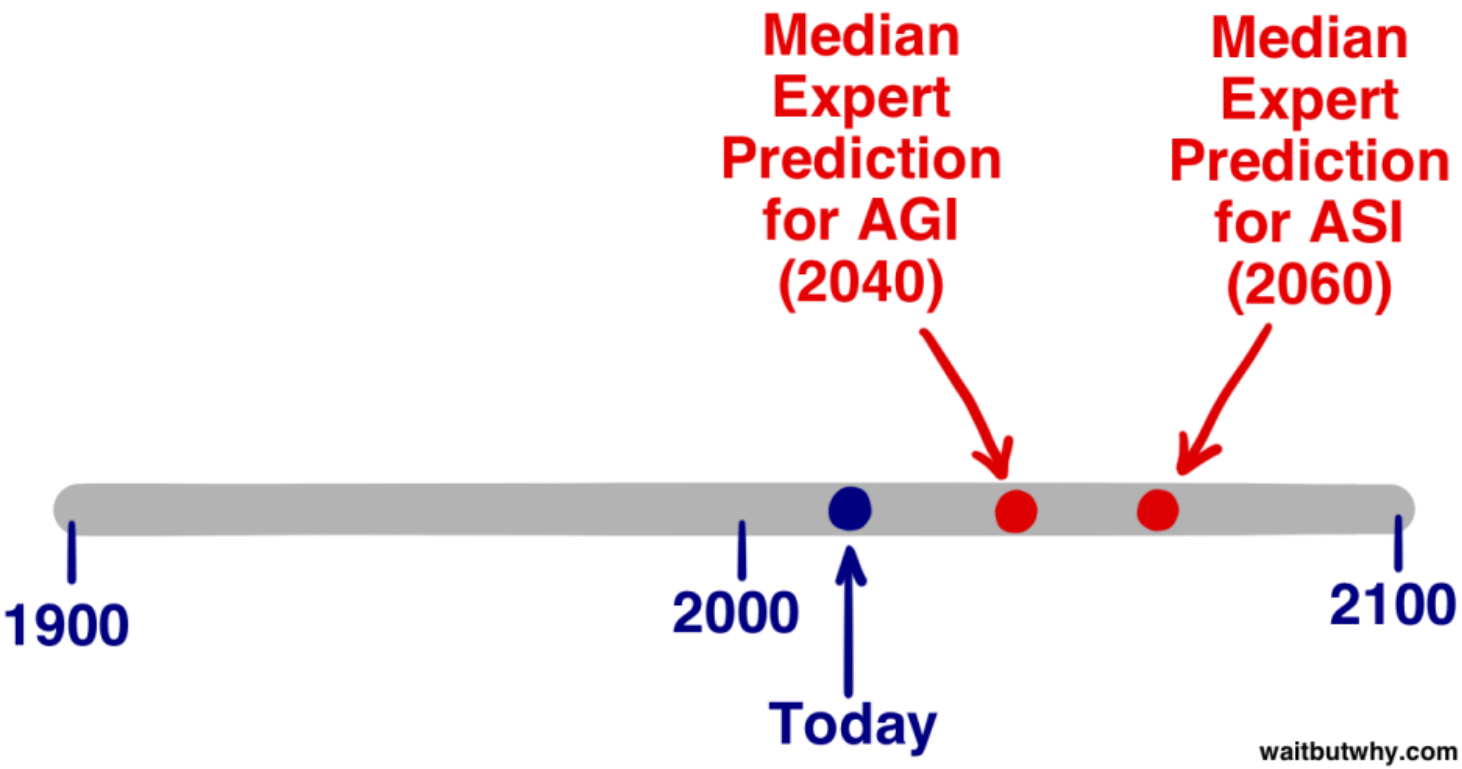

NYC DATA SCIENCE ACADEMY

Unit 10 — Deep RL

Intro

DQN In Theory

DQN In Practice

Beyond DQN

AI Revolution

Jeanne Calment

Culture Dish

Enlightenment

The View From Here

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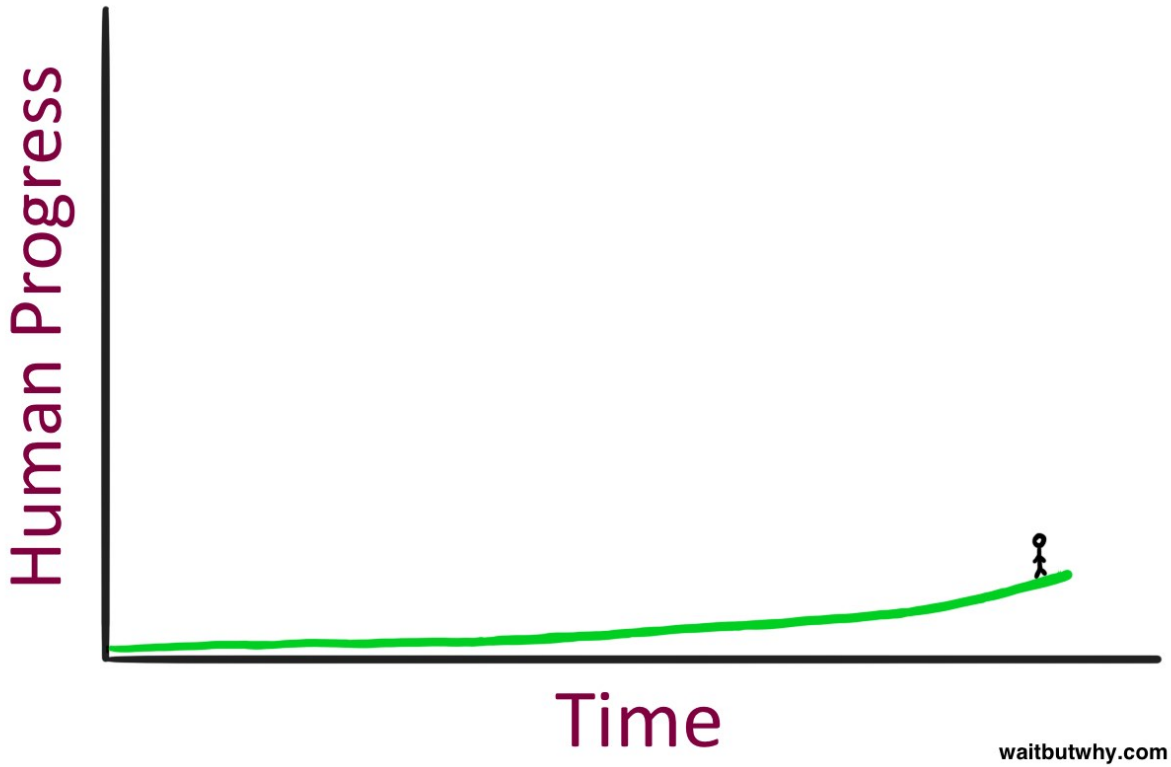
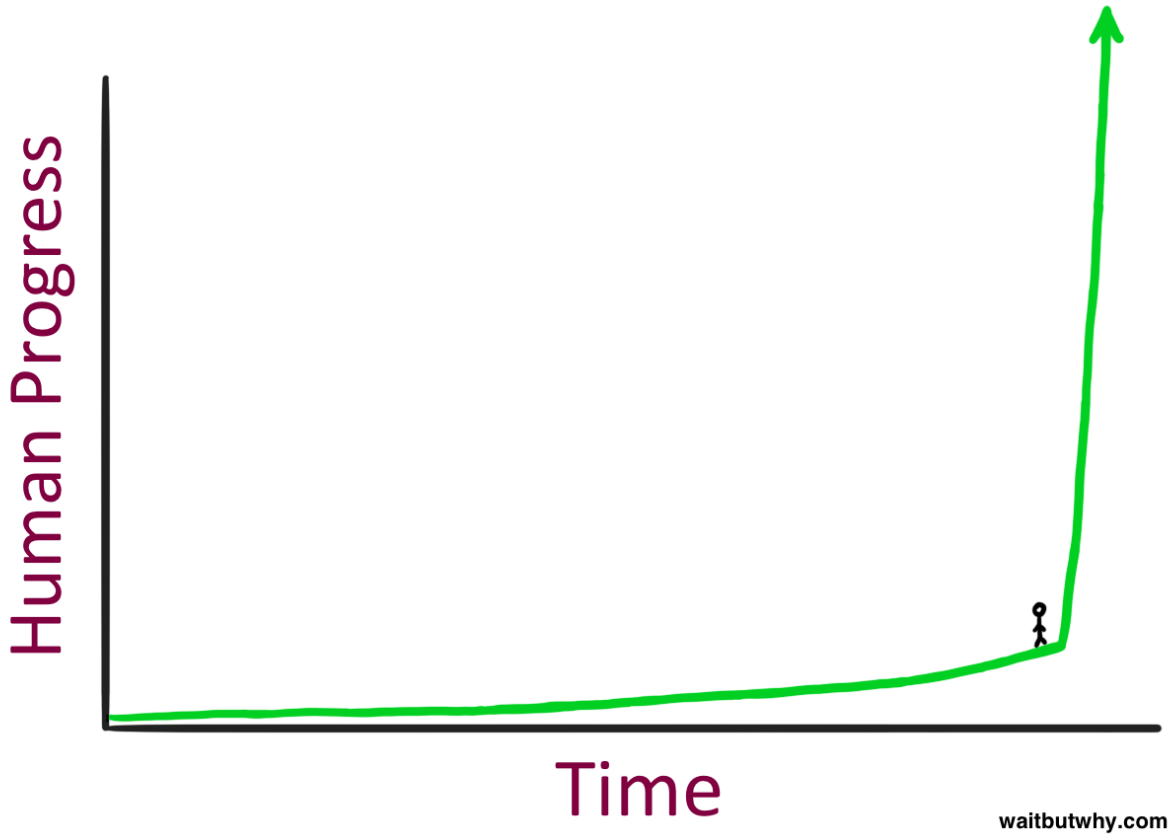

Human Progress
Time
waitbutwhy.com

Intro
DQN In Theory
DQN In Practice
Beyond DQN
AI Revolution
Jeanne Calment
Culture Dish
Enlightenment
The View From Here