Intro
DQN In Theory
DQN In Practice
Beyond DQN
AI Revolution

Deep Reinforcement Learning

Deep Learning — Unit 10

Dr. Jon Krohn
jon@untapt.com

Slides available at jonkrohn.com/talks

April 7th, 2018

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DQN In Theory
DQN In Practice
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AI Revolution

Outline

1 Introduction
2 Deep Q-Learning Theory
3 Cart Pole Deep Q-Learning
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Categories of A.I.

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

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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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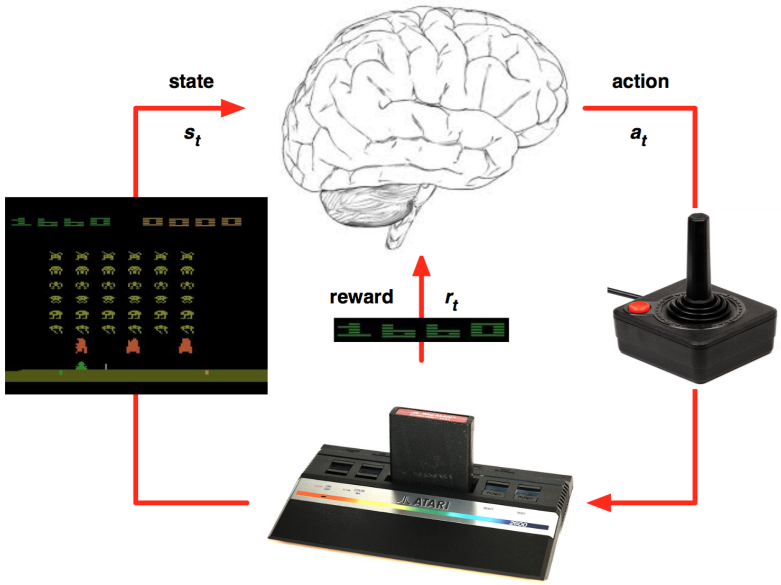
Reinforcement Learning



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

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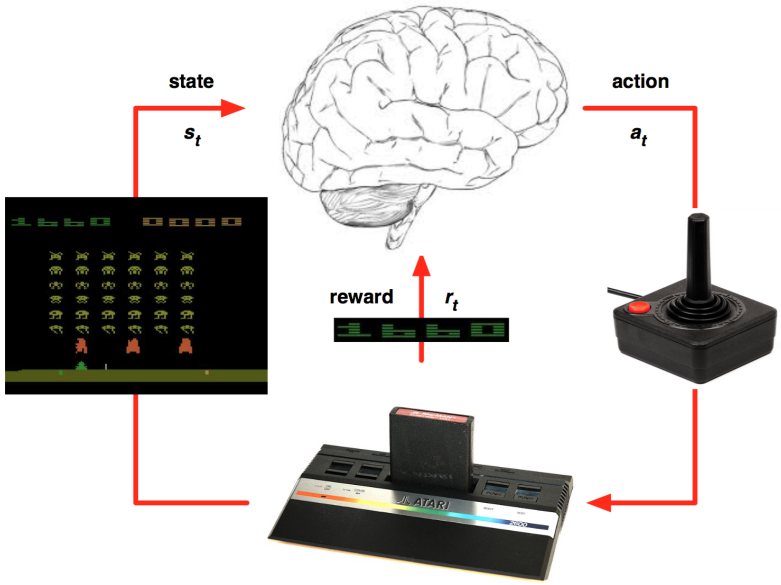
Reinforcement Learning



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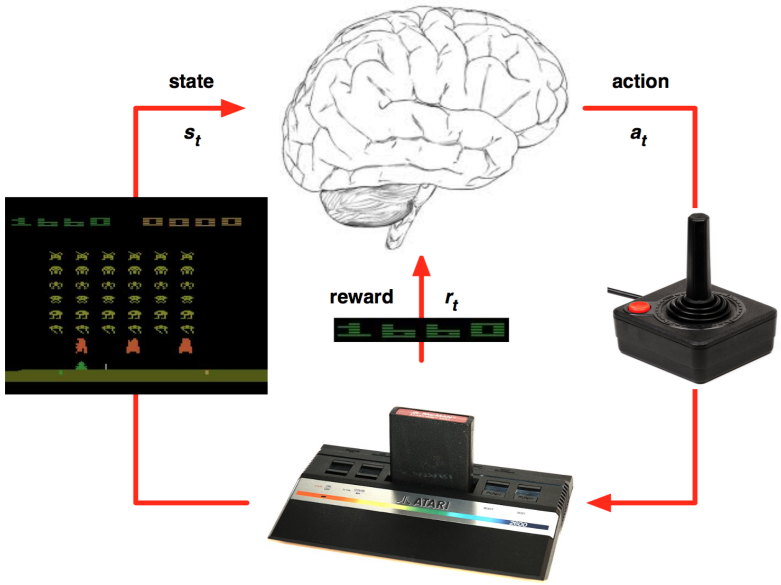

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Mnih et al. (2013)

- “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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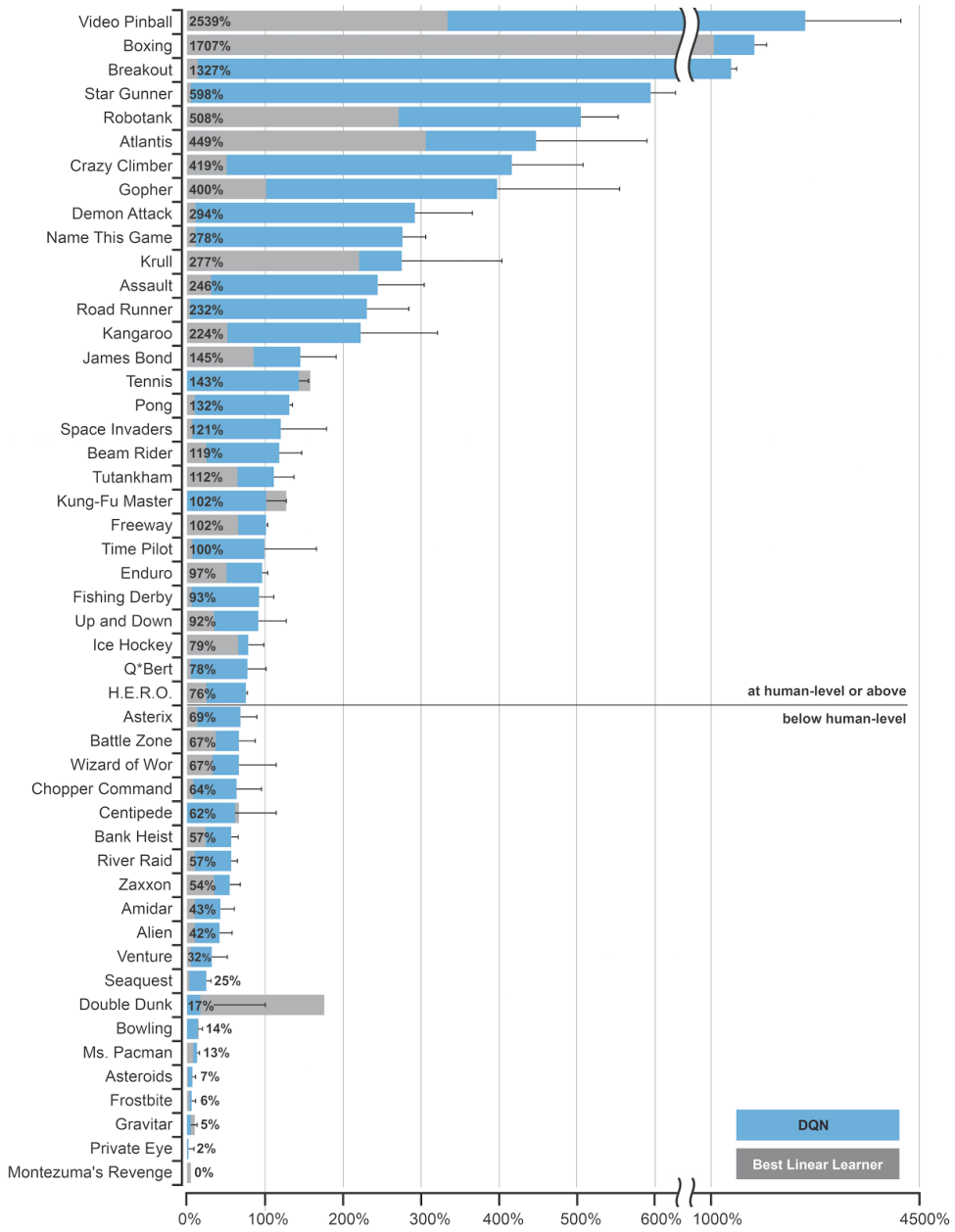

[Atari Games]

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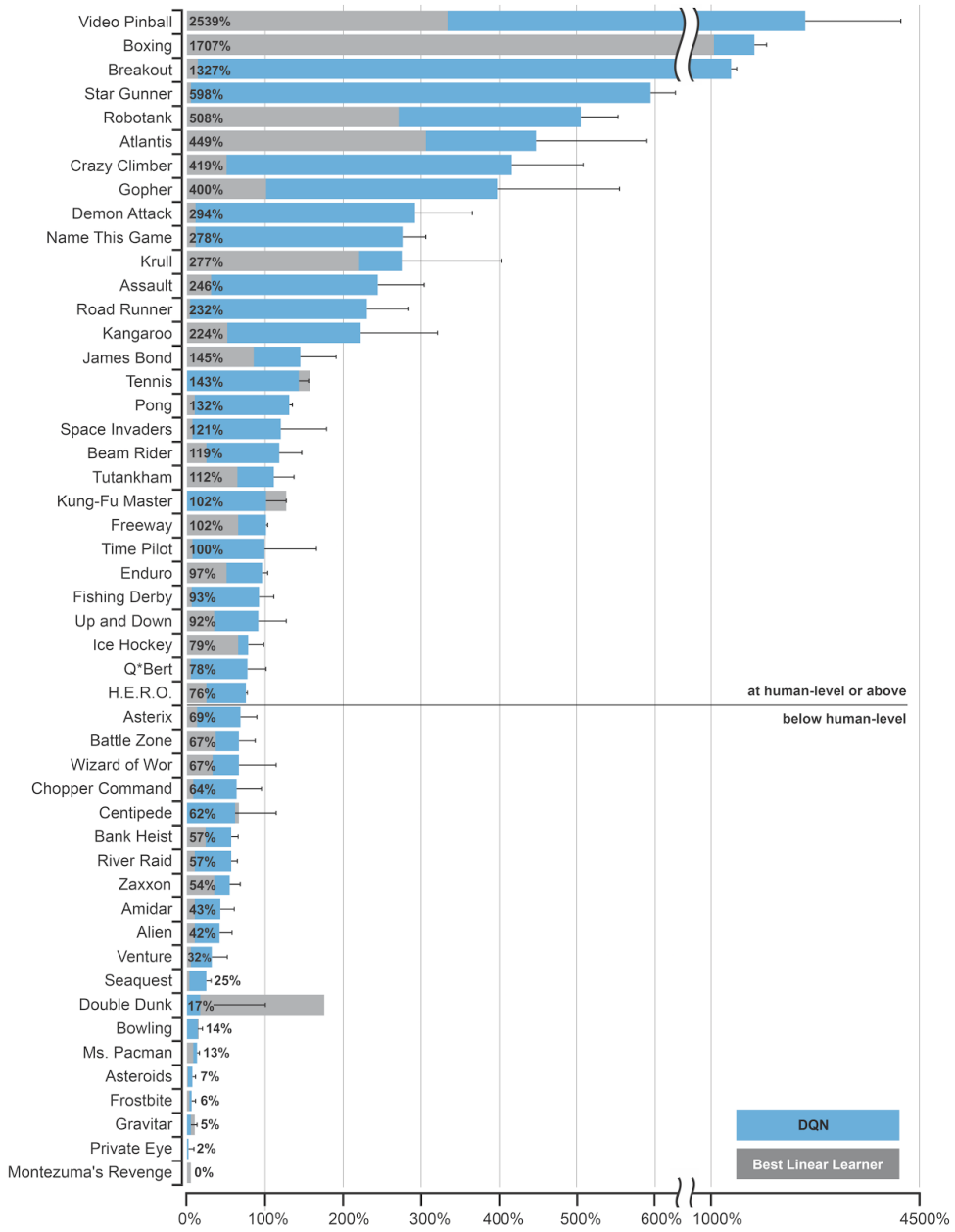

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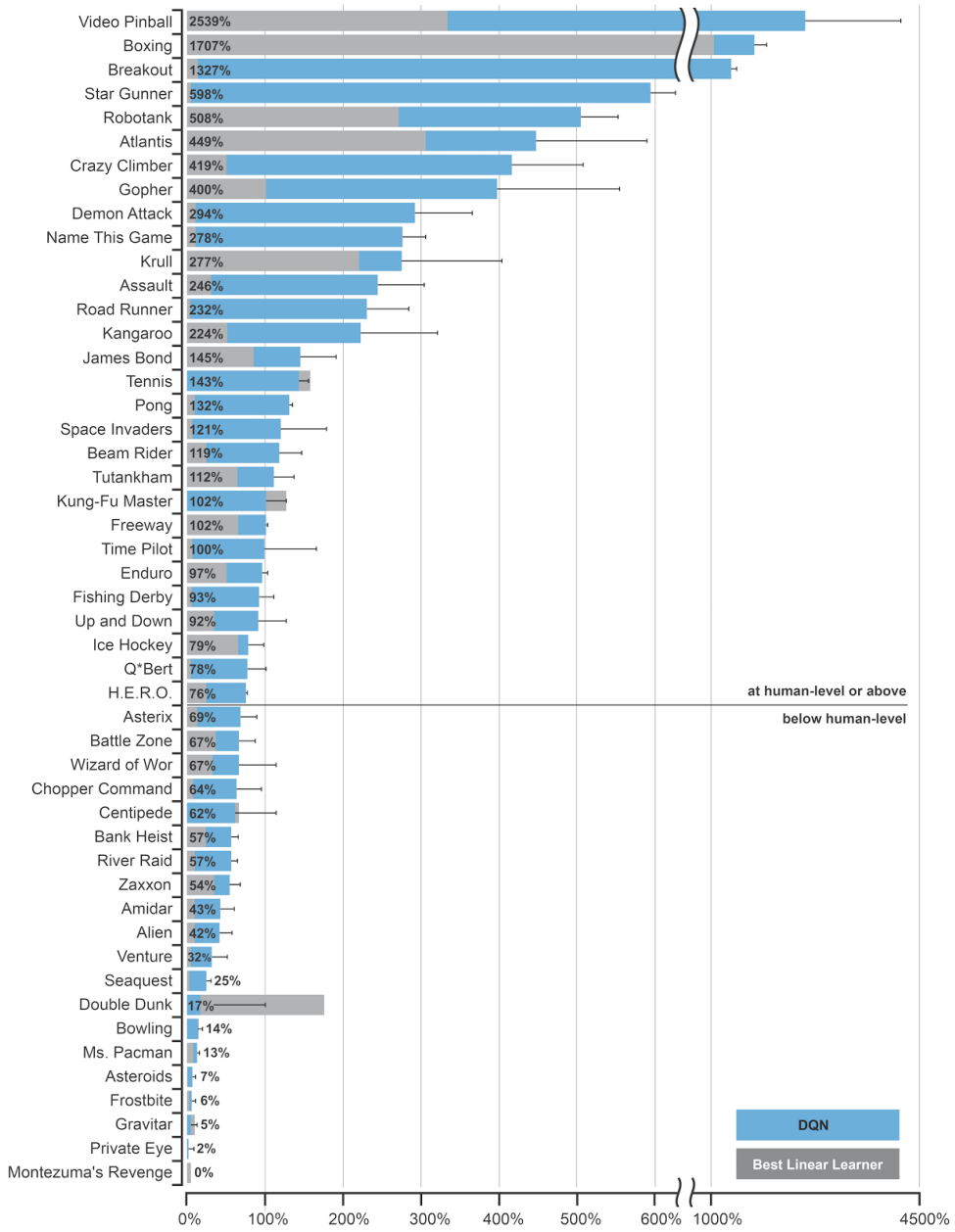

[Atari Games]

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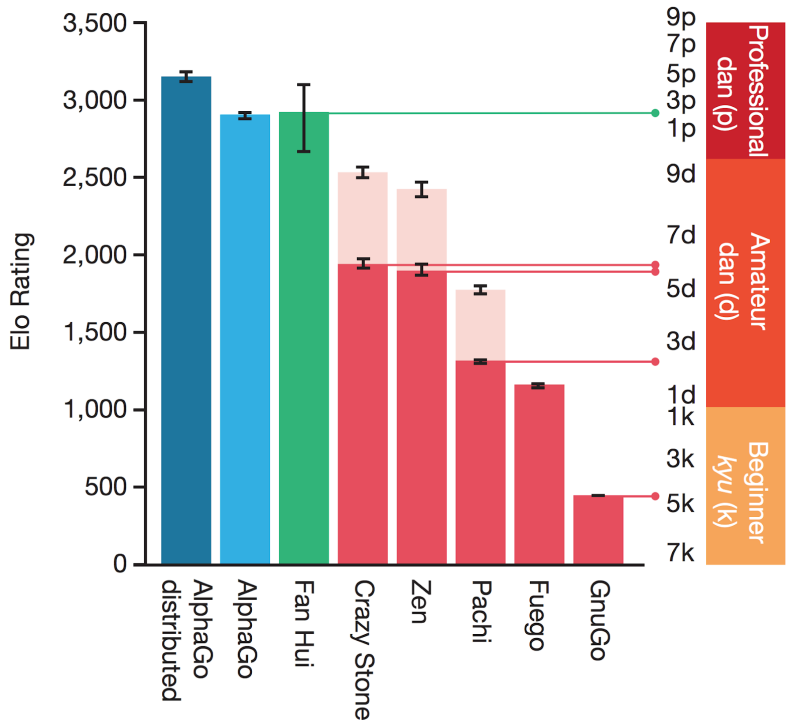
AlphaGo

Silver et al. (2016)



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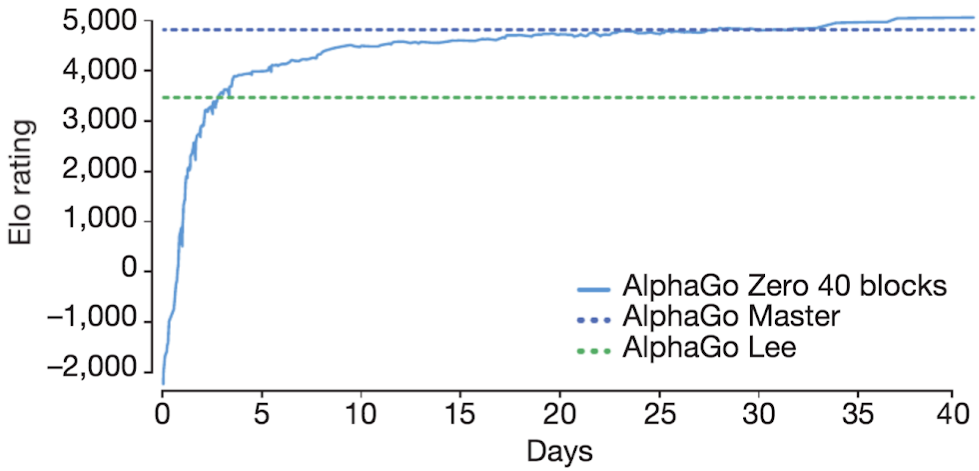
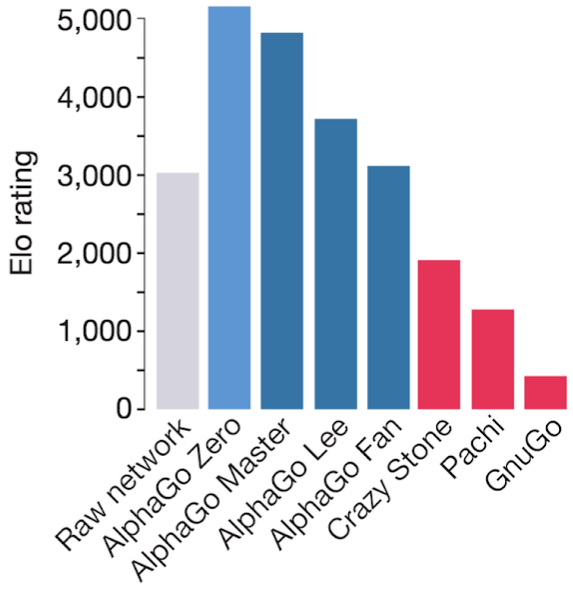
Silver et al. (2017a)





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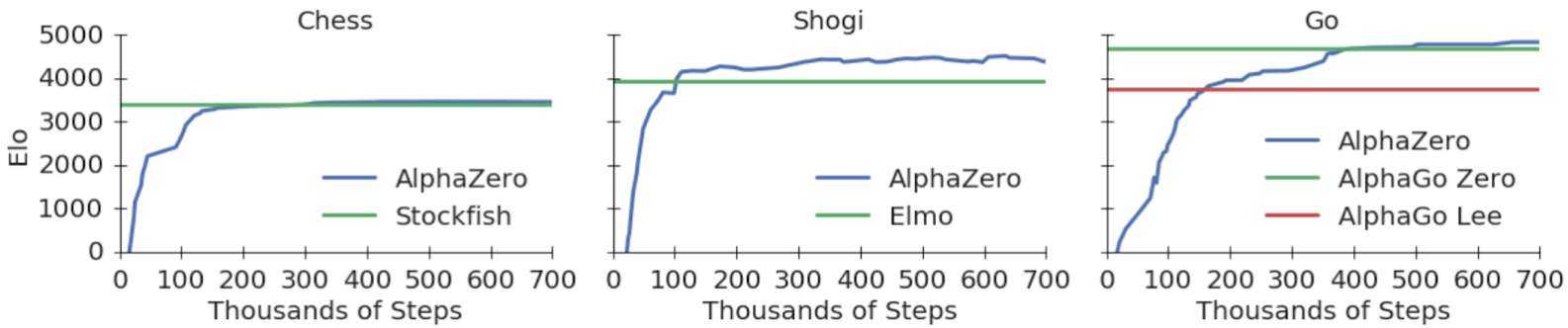
AlphaZero

Silver et al. (2017b)



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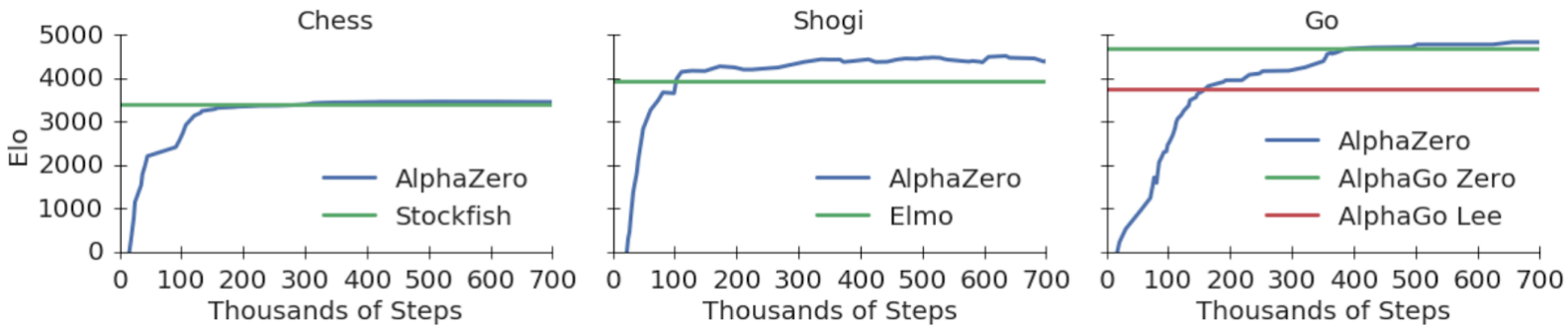

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Environments

1. OpenAI Gym
2. DeepMind Lab
3. Unity

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Essential Deep Q-Learning Theory

[whiteboarding]

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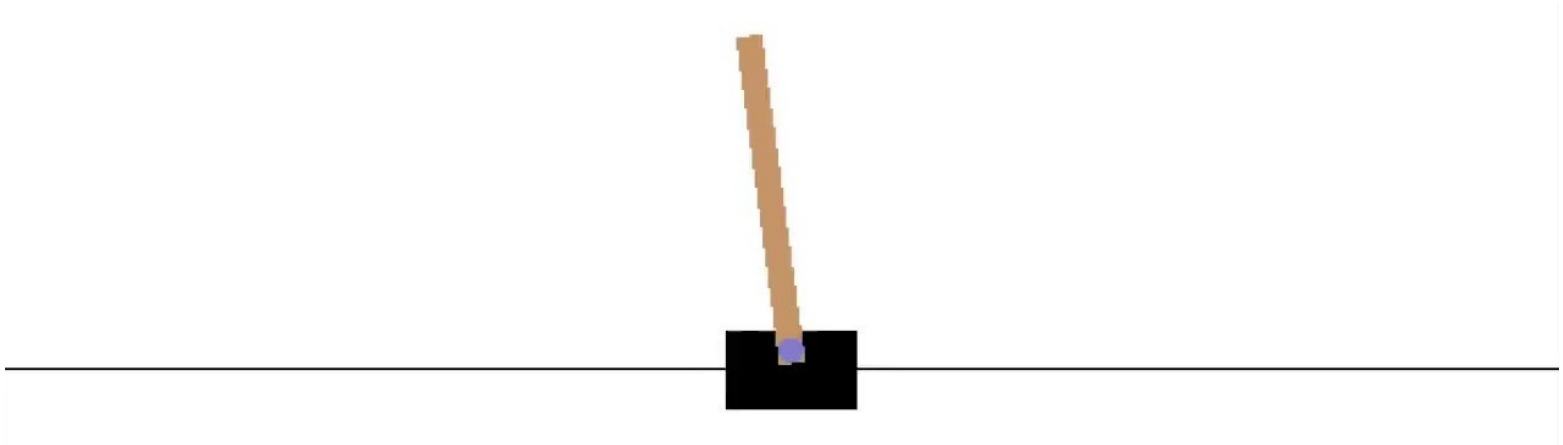
The Cartpole Game

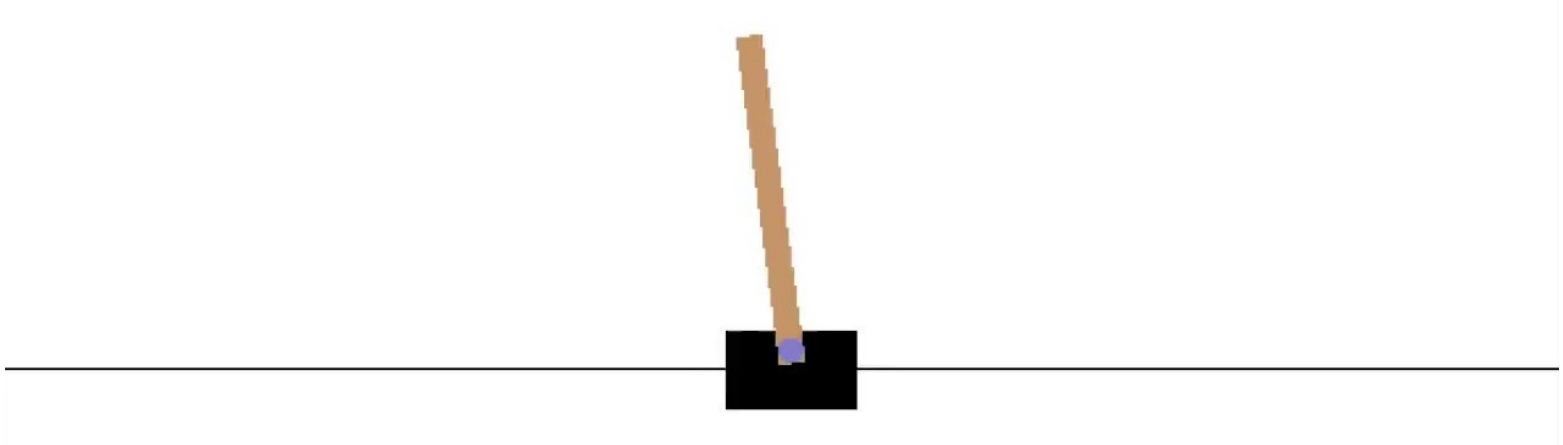
OpenAI



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

The Cartpole Game

OpenAI



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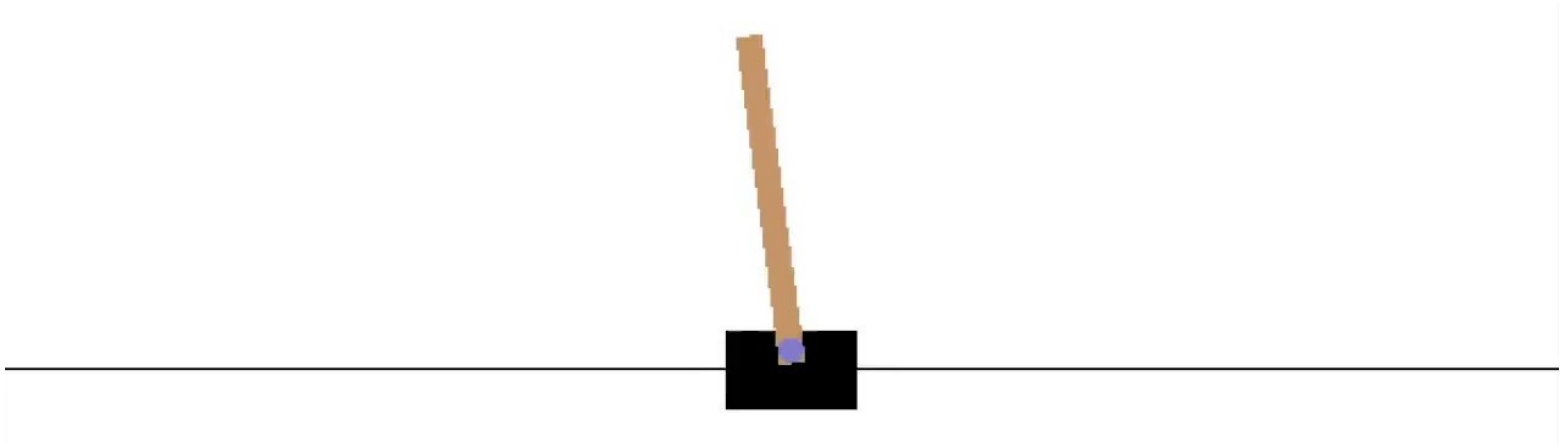

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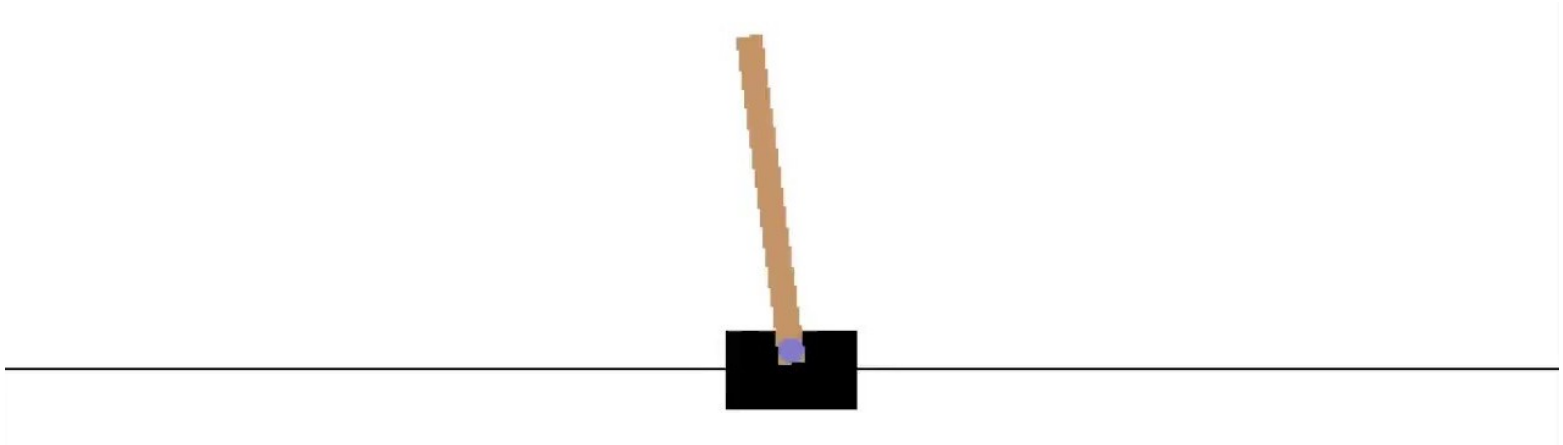

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[*cartpole* notebook]

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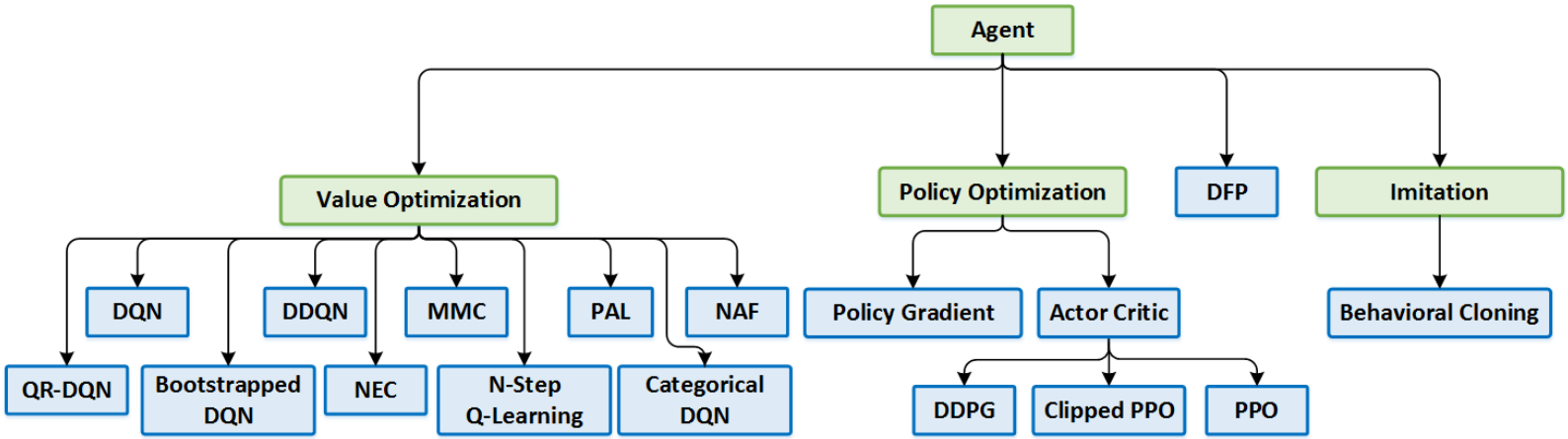
Genetic Algorithms

[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]

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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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Jeanne Calment

Jeanne Calment

(1875-1997 — i.e., 122 years)

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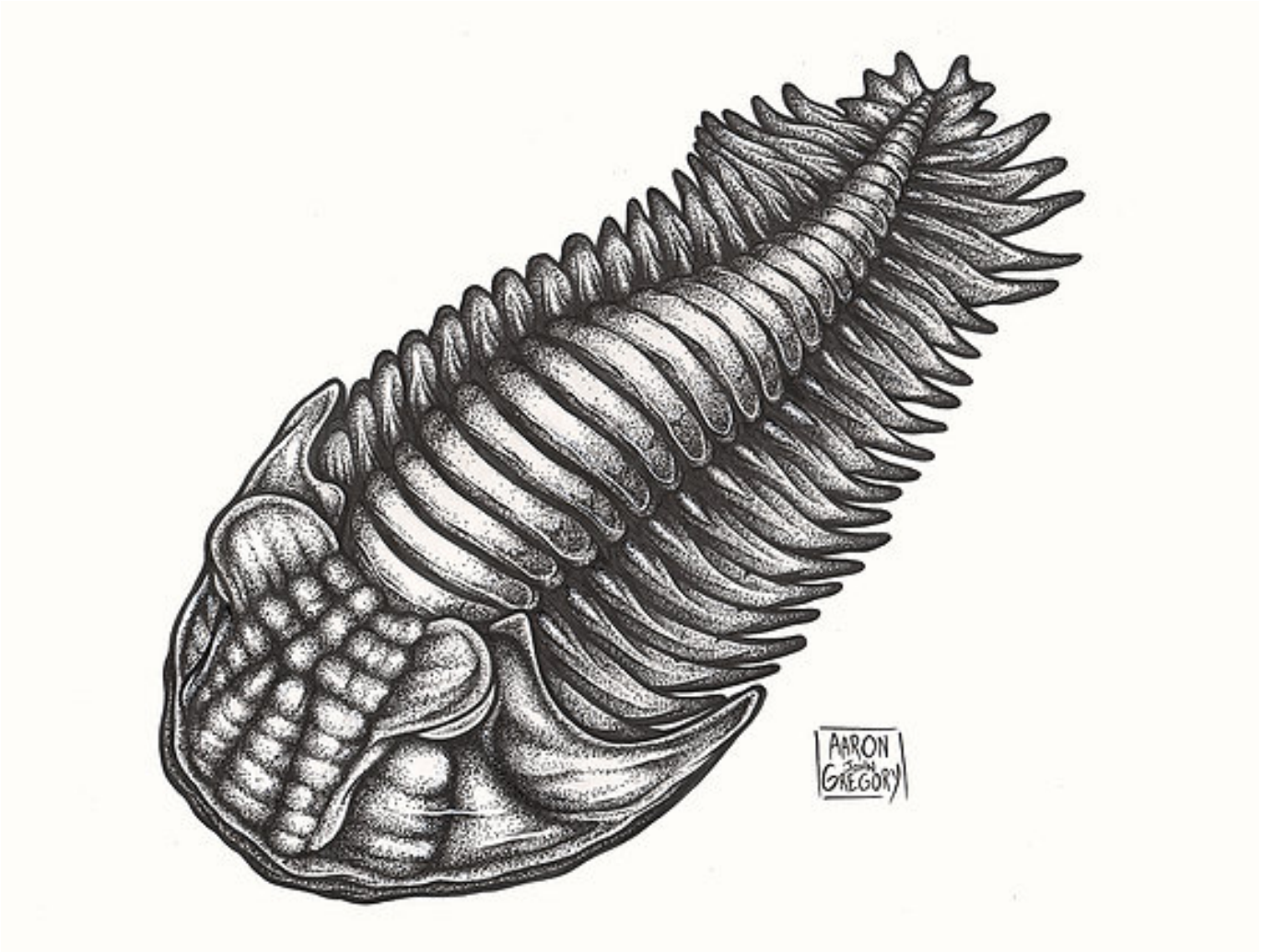
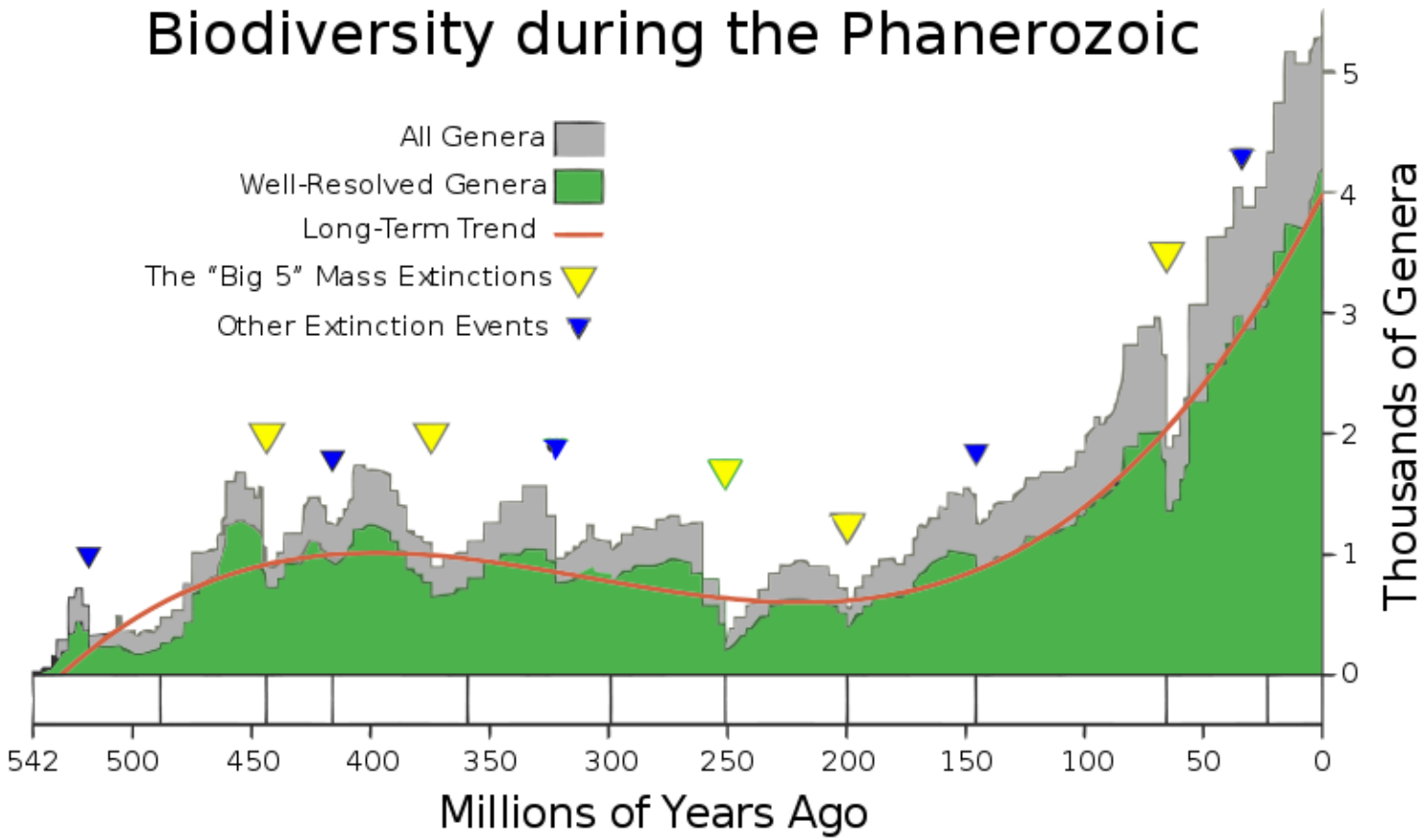
Life in the Year 2138

The AI Revolution

Hasn't Even Begun


AARON
GREGORY



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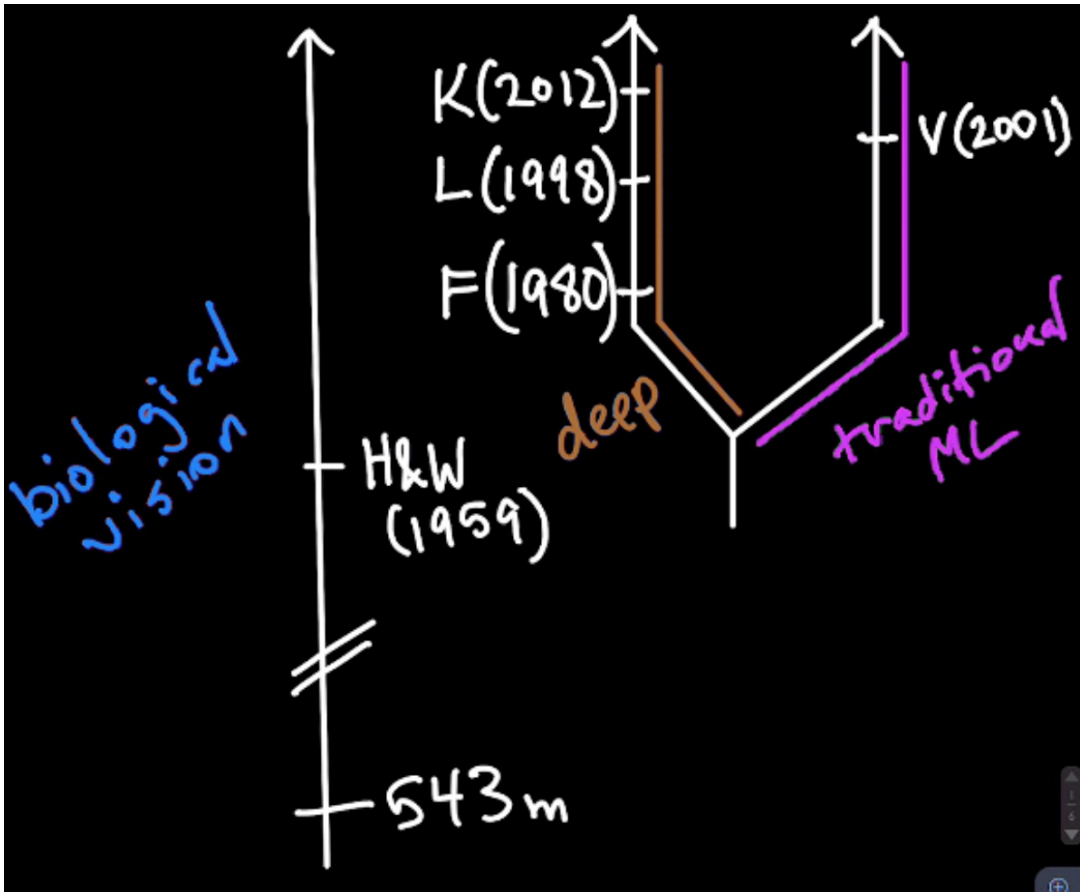

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Factors Driving A.I.

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

[Wait But Why]

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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

AGI

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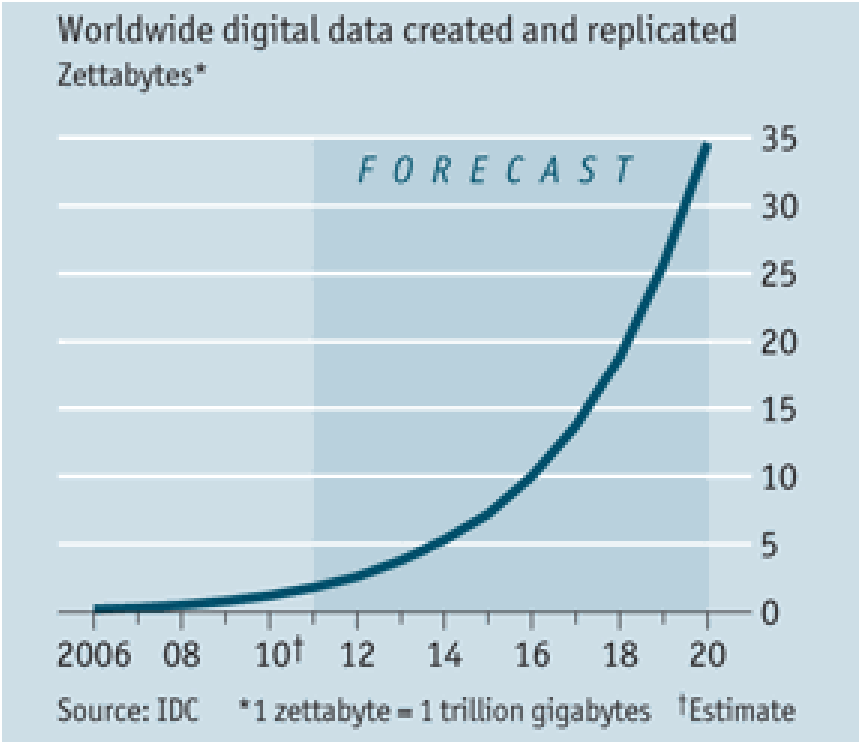

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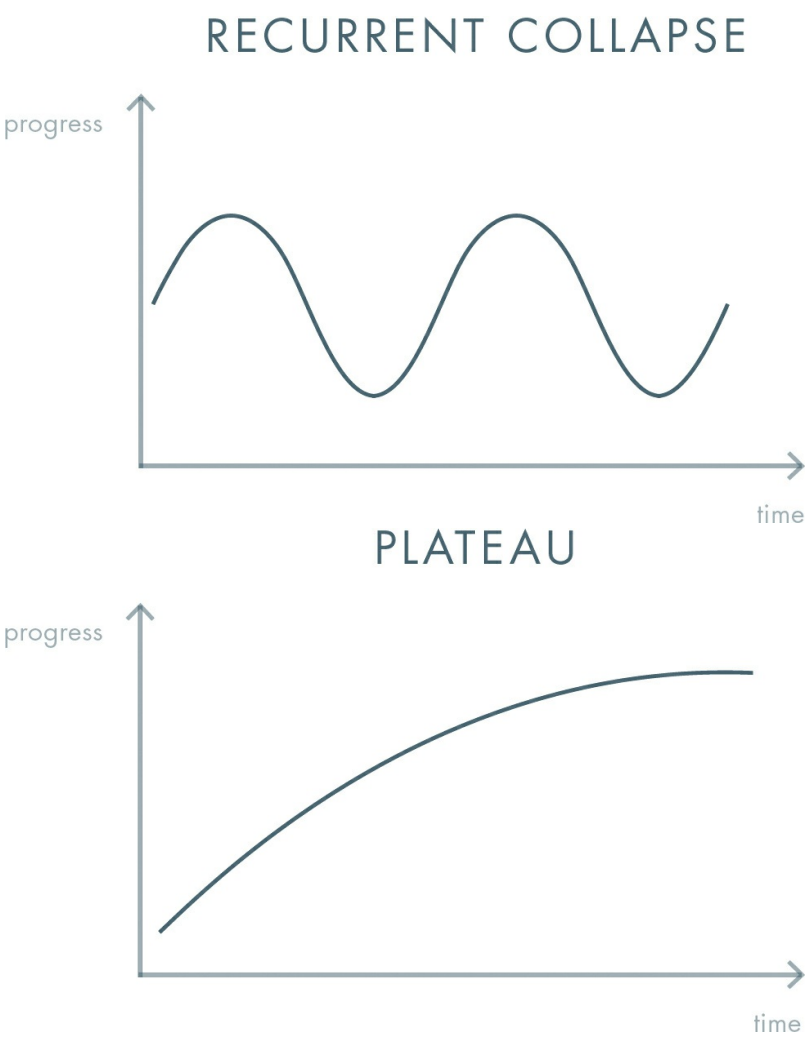
Jeanne Calment

Thiel & Masters (2014)



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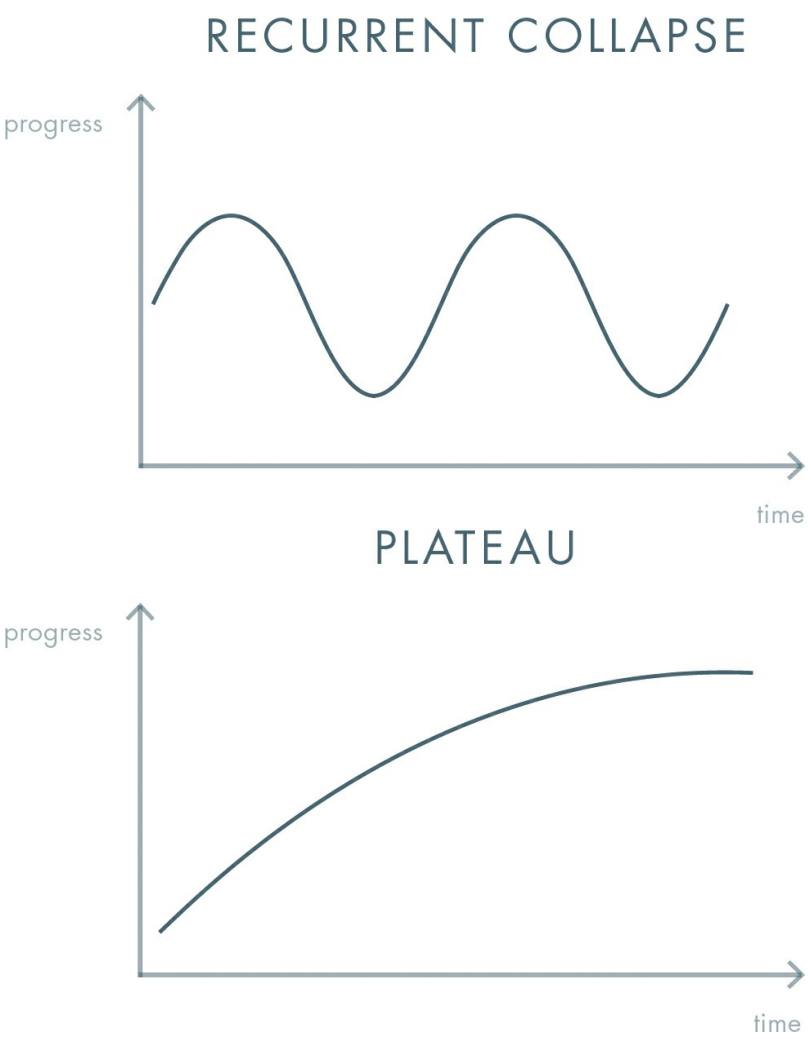

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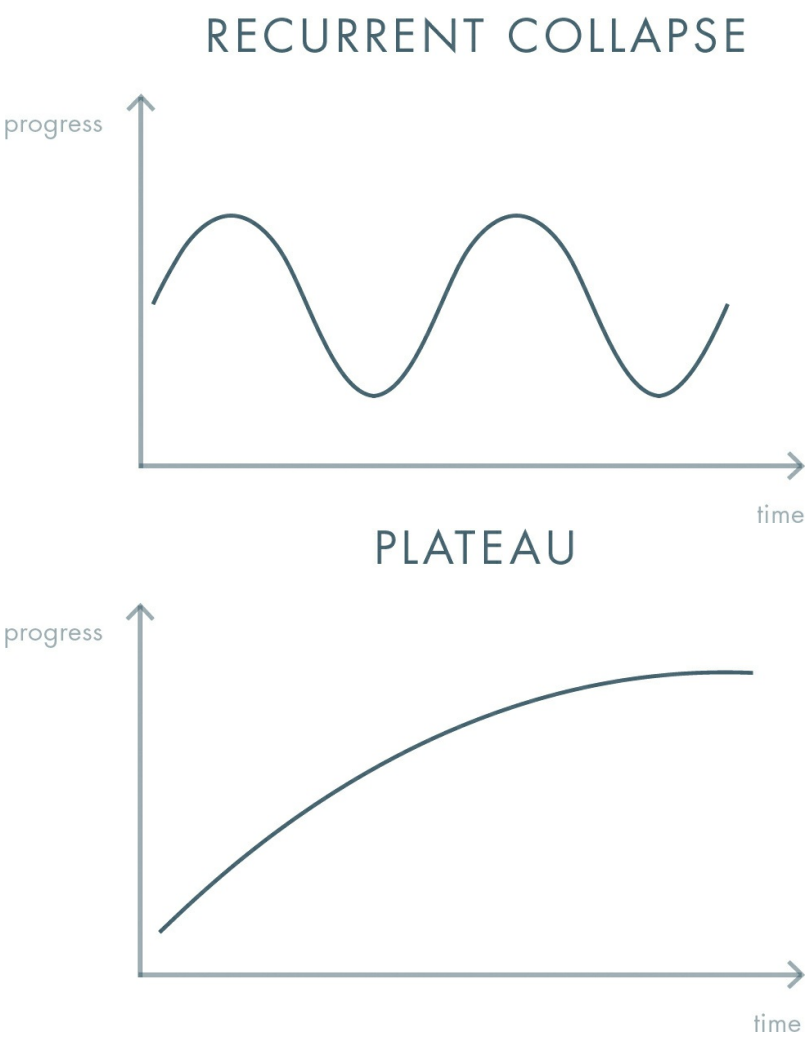
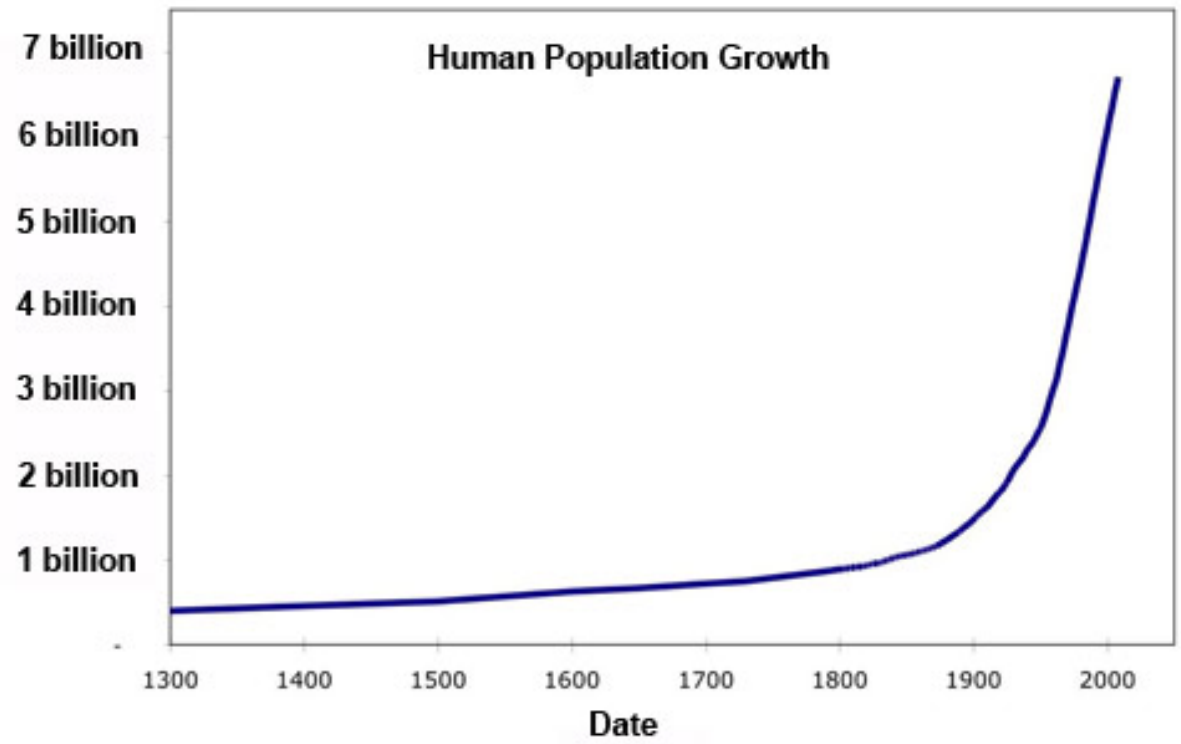
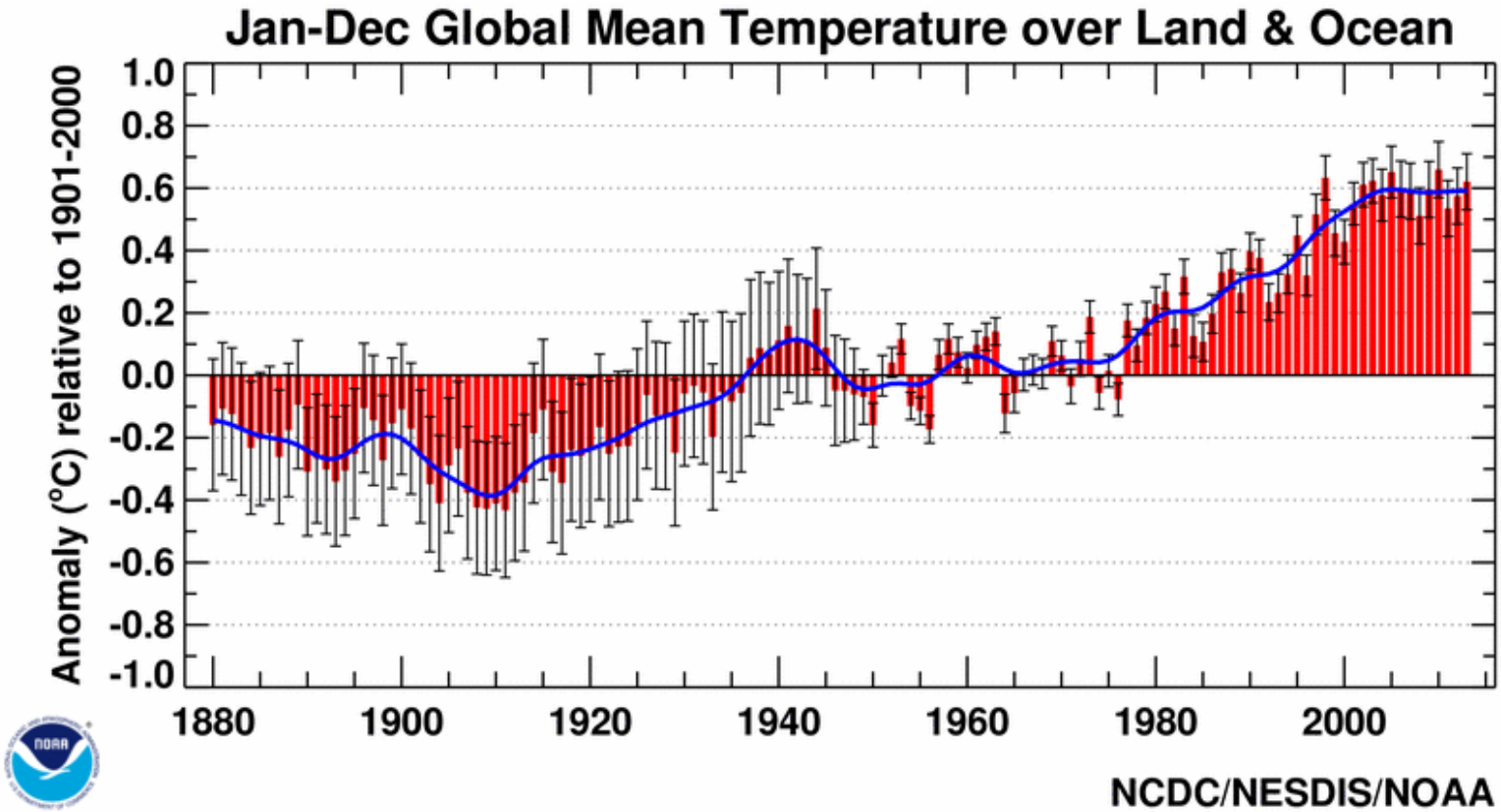
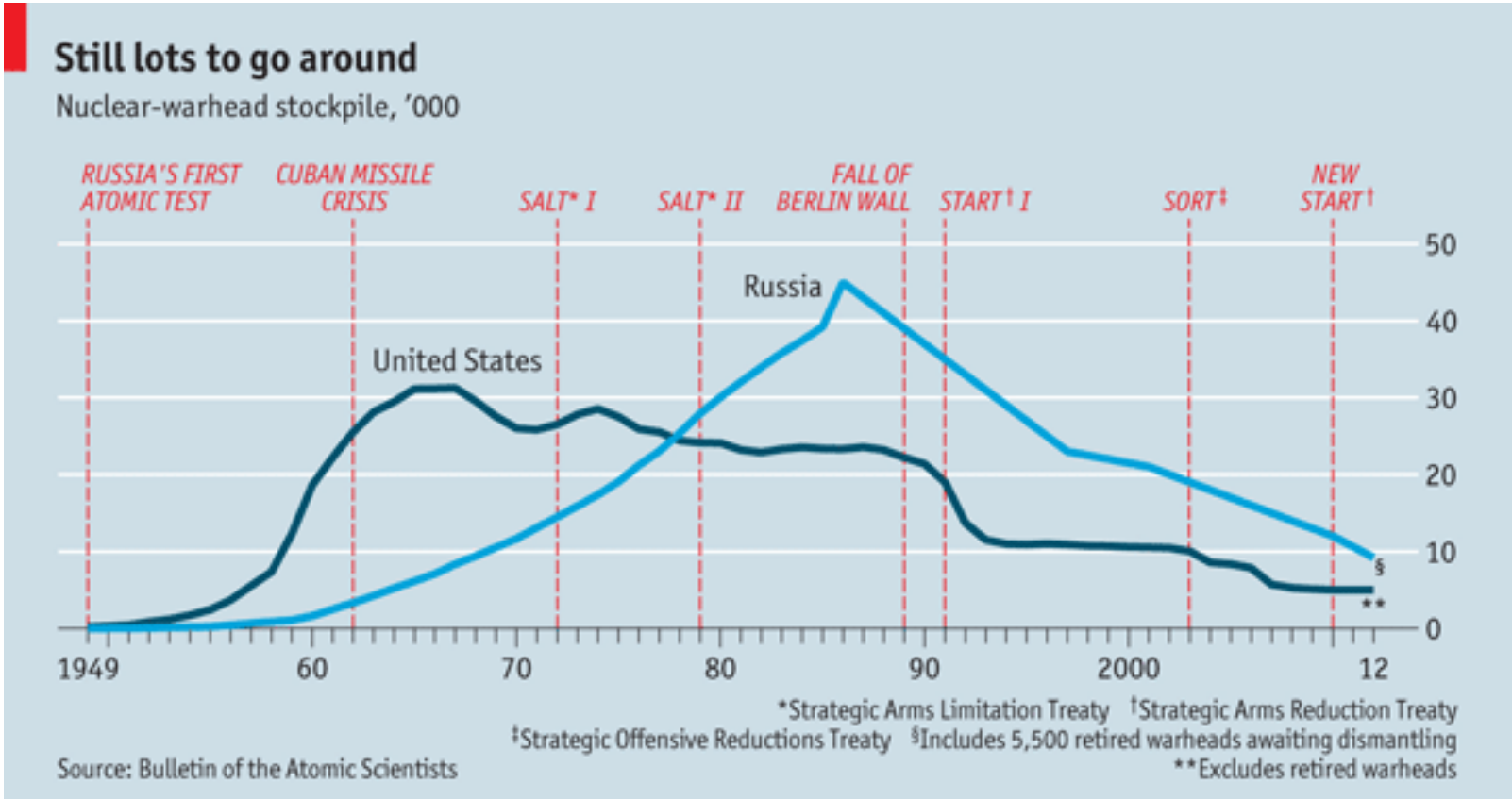



Human Population Growth
7 billion
6 billion
5 billion
4 billion
3 billion
2 billion
1 billion
1300
1400
1500
1600
1700
1800
1900
2000
Date


Jan-Dec Global Mean Temperature over Land & Ocean
Anomaly (°C) relative to 1901-2000
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
-0.4
-0.6
-0.8
-1.0
1880
1900
1920
1940
1960
1980
2000
NCDC/NESDIS/NOAA



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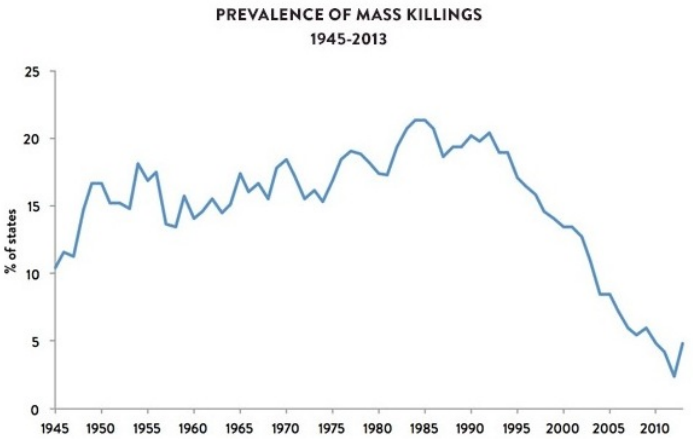
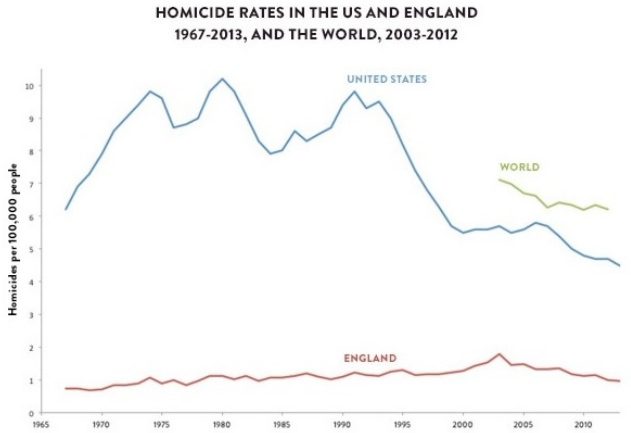
Pinker & Mack (2014)



Source: Early Warning Project, https://cpgearlywarning.wordpress.com/; Ulfelder, Jay and Valentino, Benjamin, "Assessing Risks of State-Sponsored Mass Killing" (Feb. 1, 2008). Available at SSRN: http://ssrn.com/abstract=1703426 or http://dx.doi.org/10.2139/ssrn.1703426



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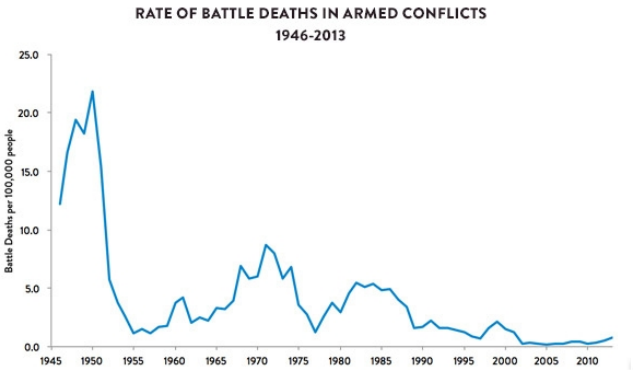

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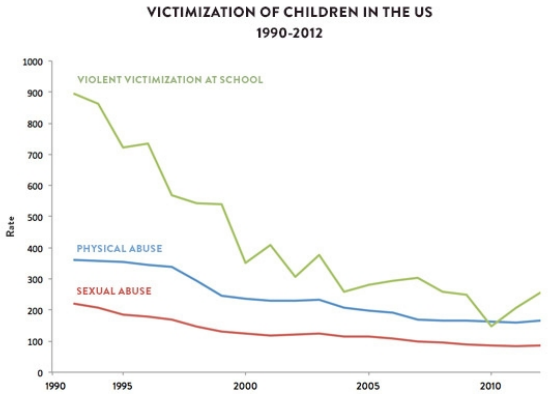

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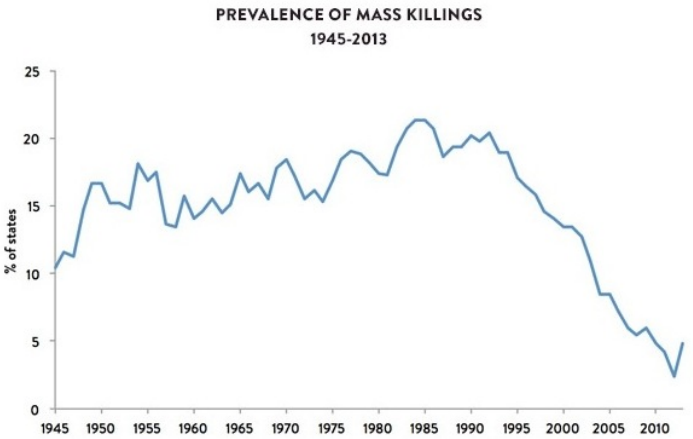
Pinker & Mack (2014)



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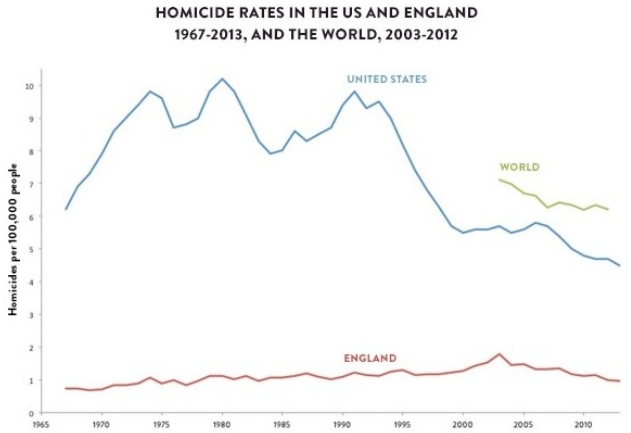

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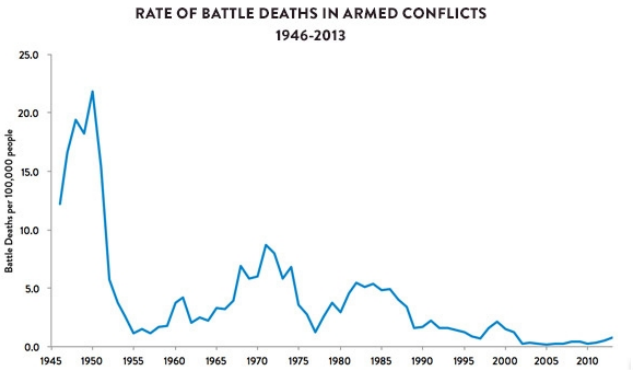

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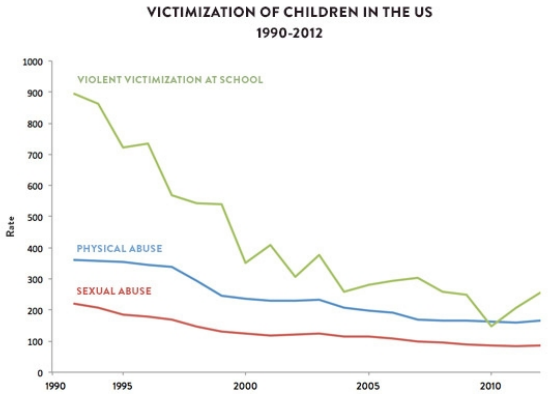

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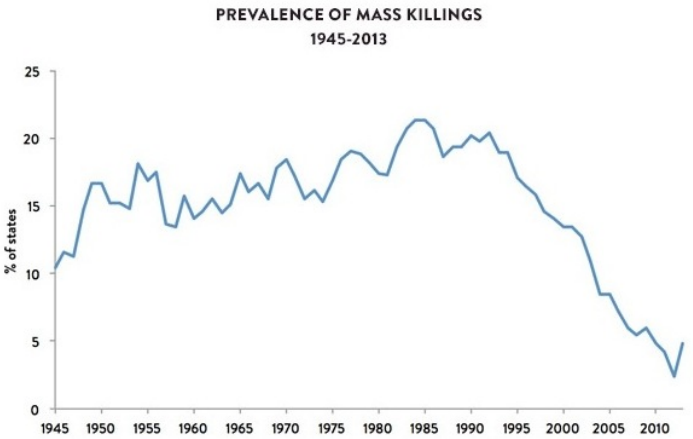

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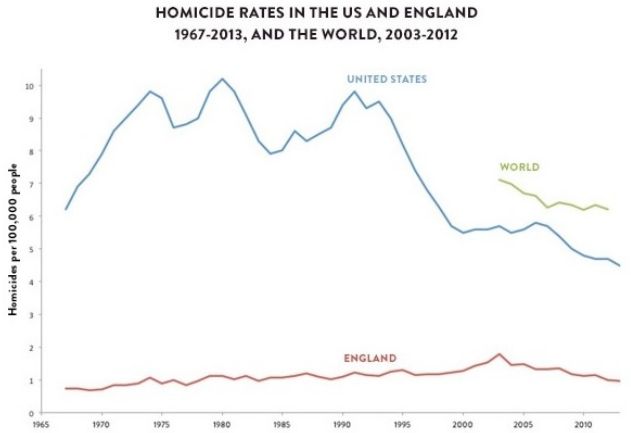

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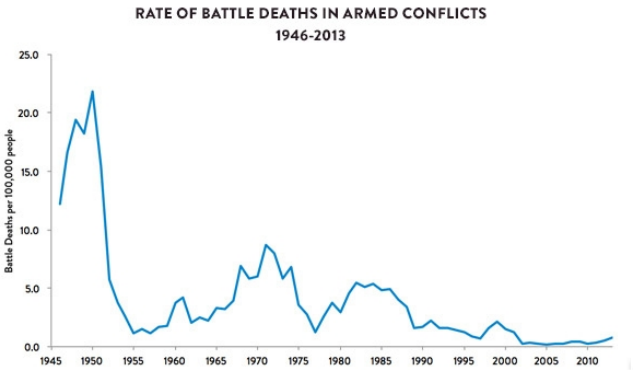

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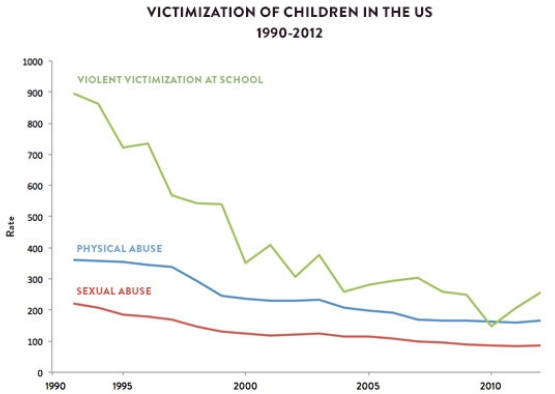

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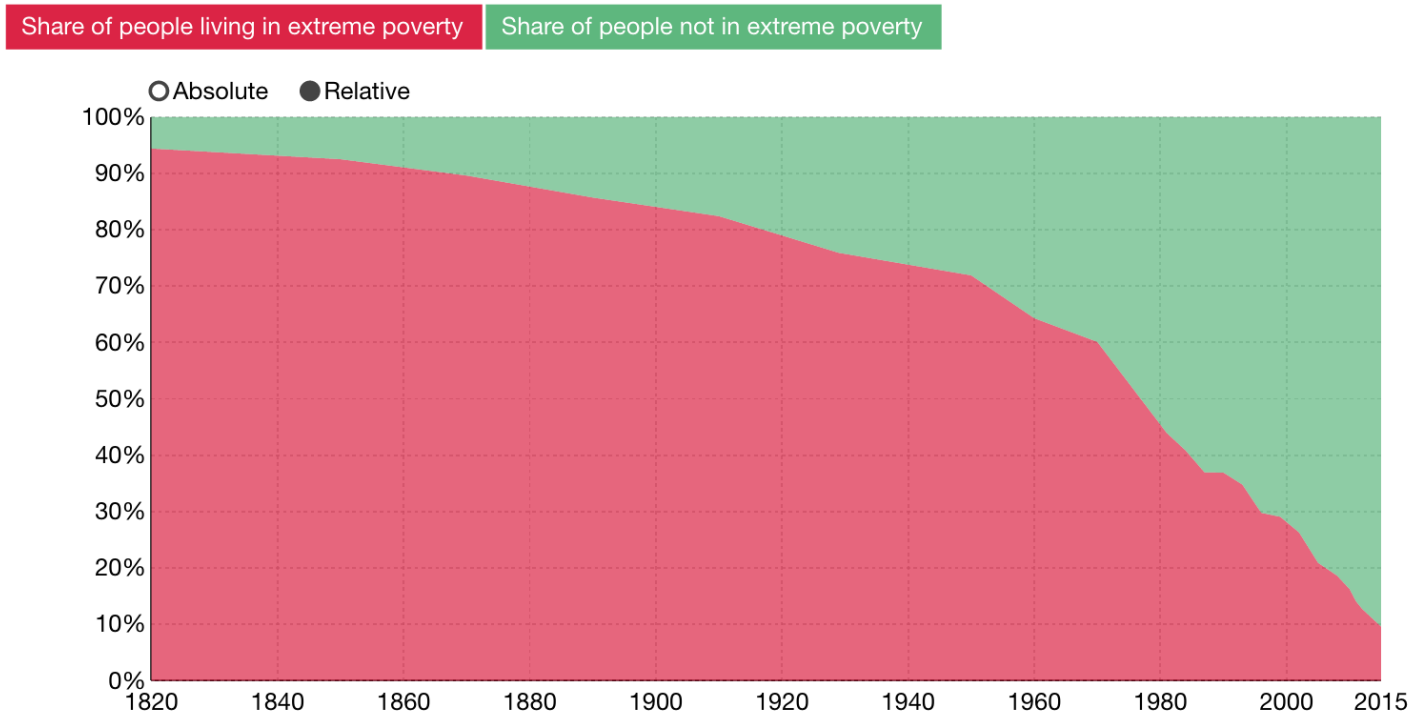
World population living in extreme poverty, 1820 to 2015

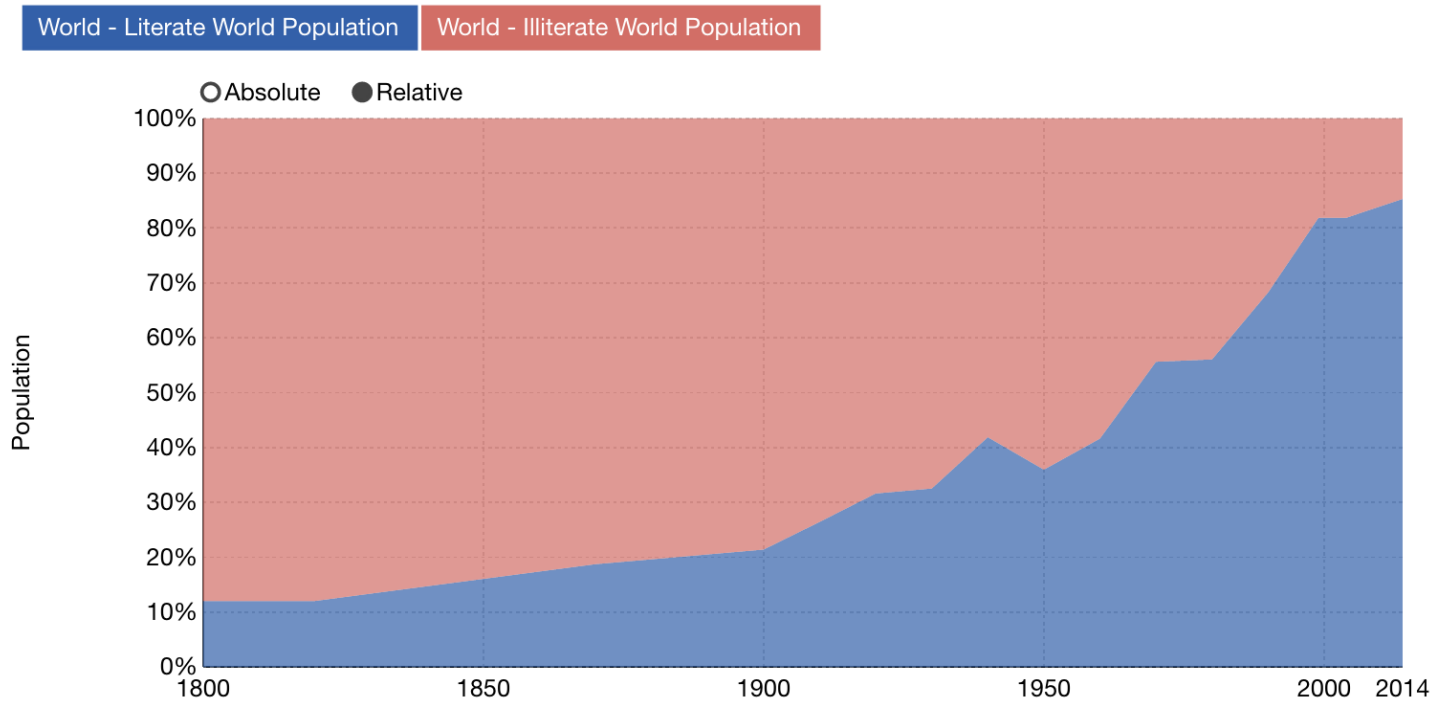
Our World in Data



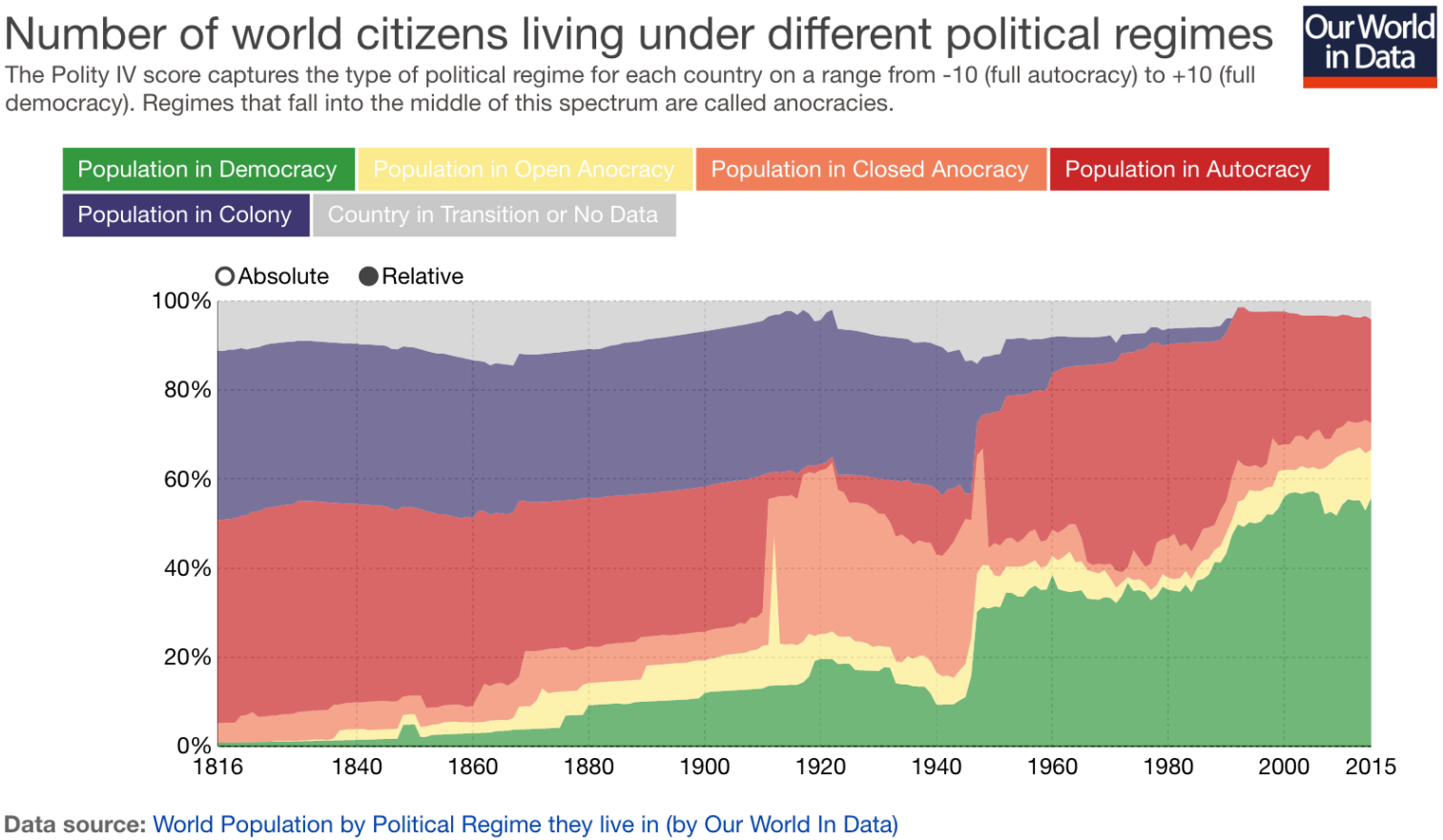
Data source: World Poverty in absolute numbers (Max Roser based on World Bank and Bourguignon and Morrisson (2002))

Literate and illiterate world population, 1800 to 2014

Our World in Data



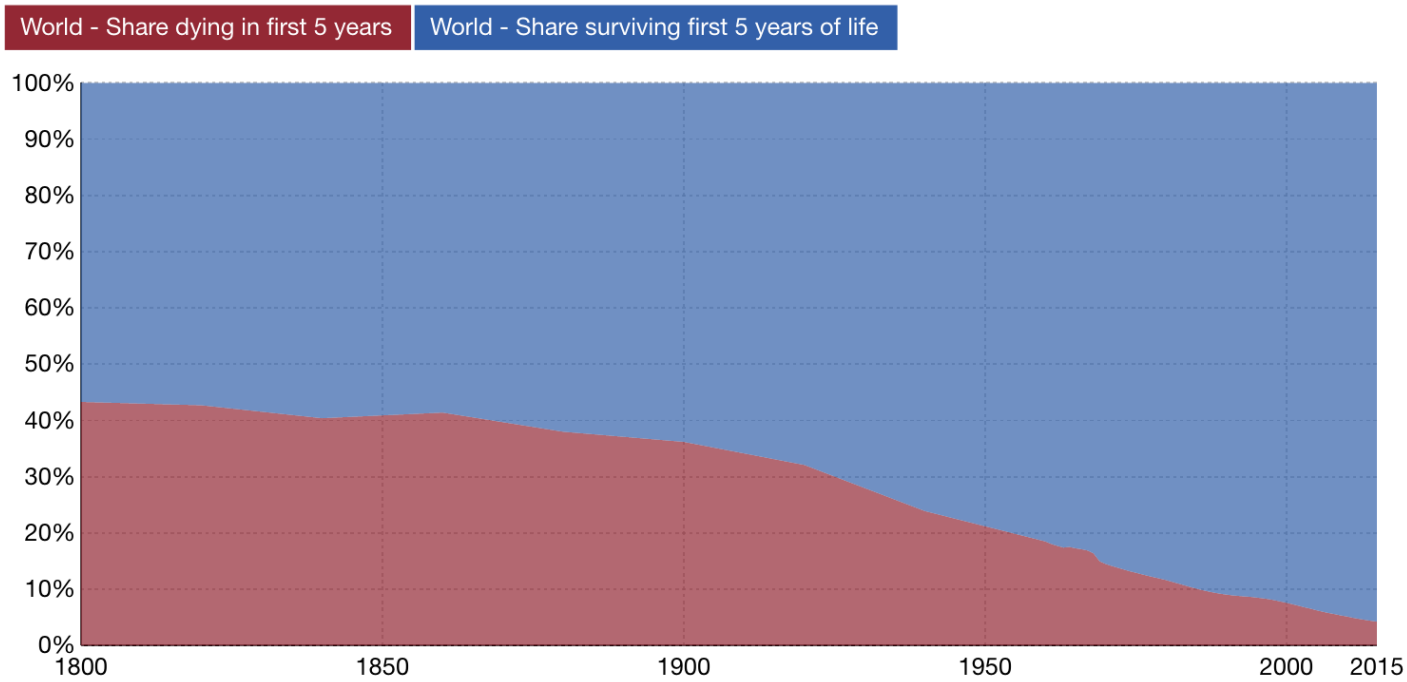
Data source: Literate World Population (Our World In Data based on OECD and UNESCO)


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.
Our World in Data
Population in Democracy
Population in Open Anocracy
Population in Closed Anocracy
Population in Autocracy
Population in Colony
Country in Transition or No Data
Absolute
Relative
100%
80%
60%
40%
20%
0%
1816
1840
1860
1880
1900
1920
1940
1960
1980
2000
2015
Data source: World Population by Political Regime they live in (by Our World In Data)

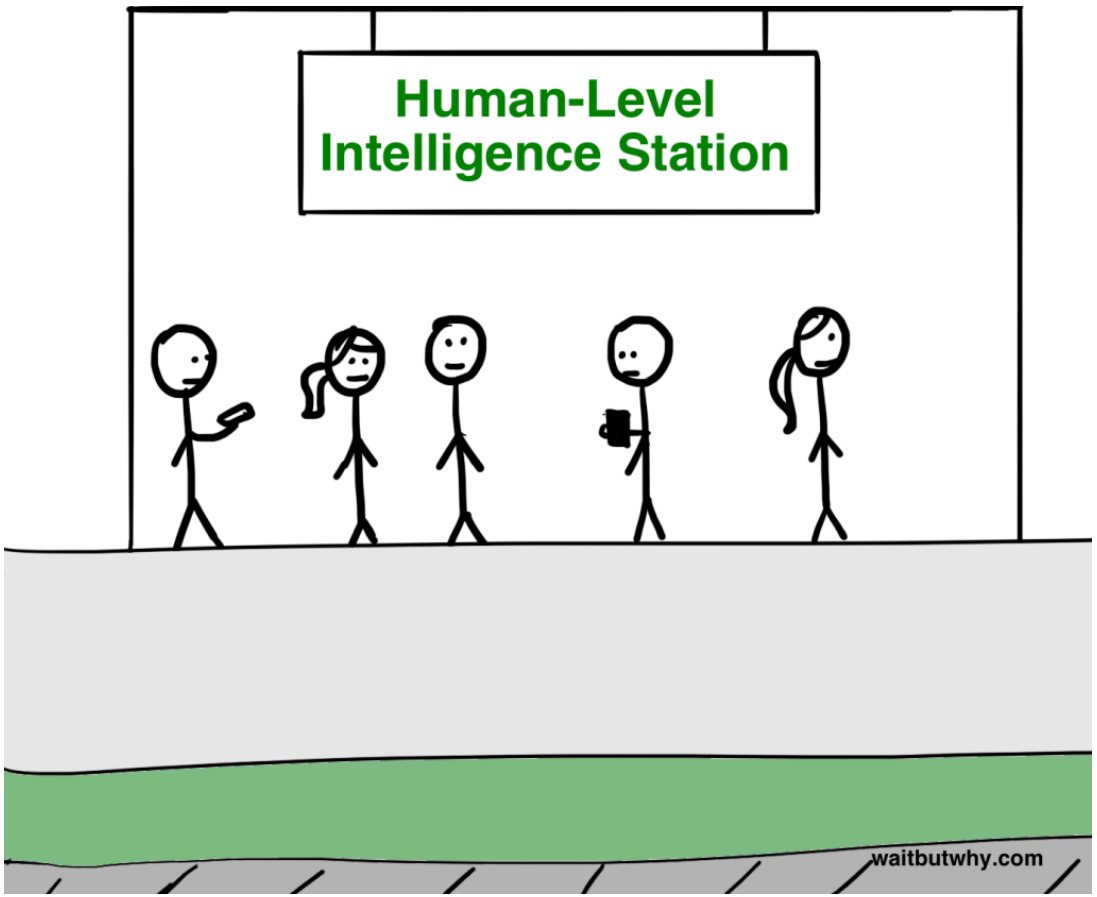
Global child mortality, 1800 to 2015

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

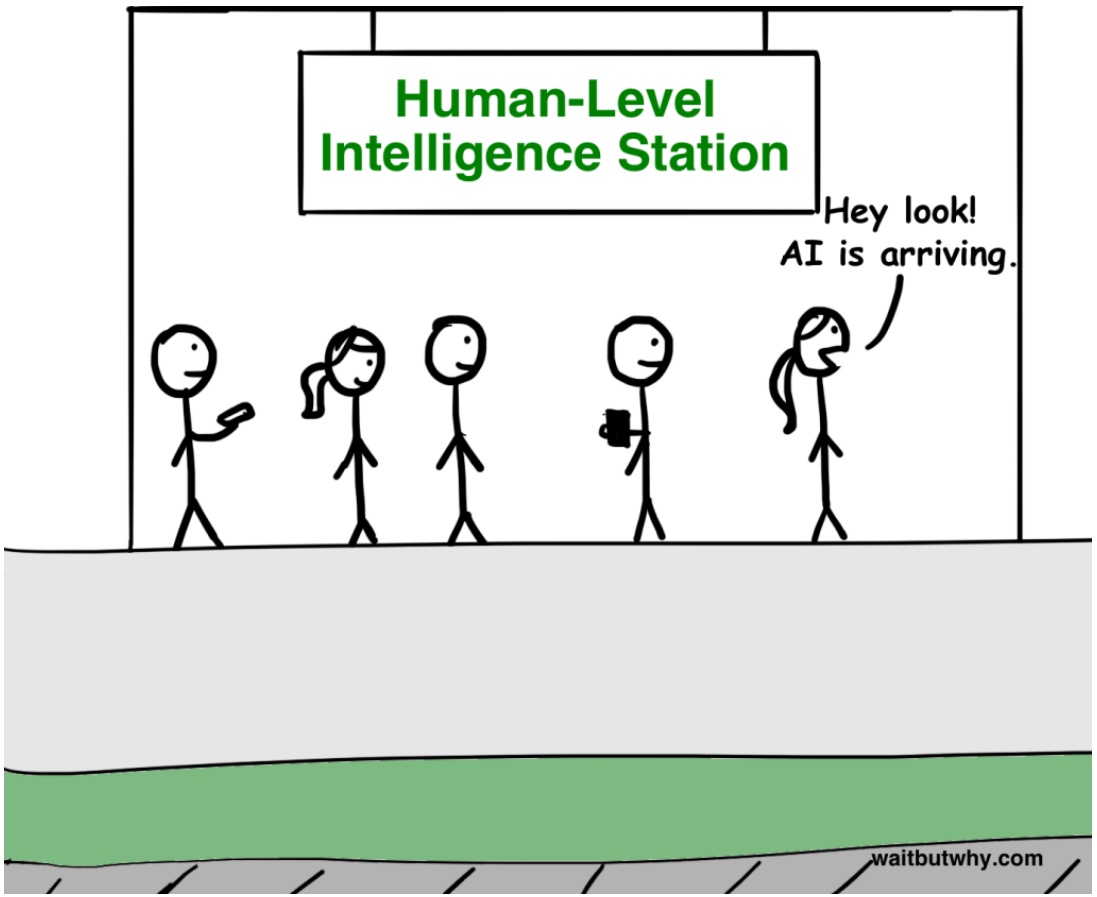
Our World in Data



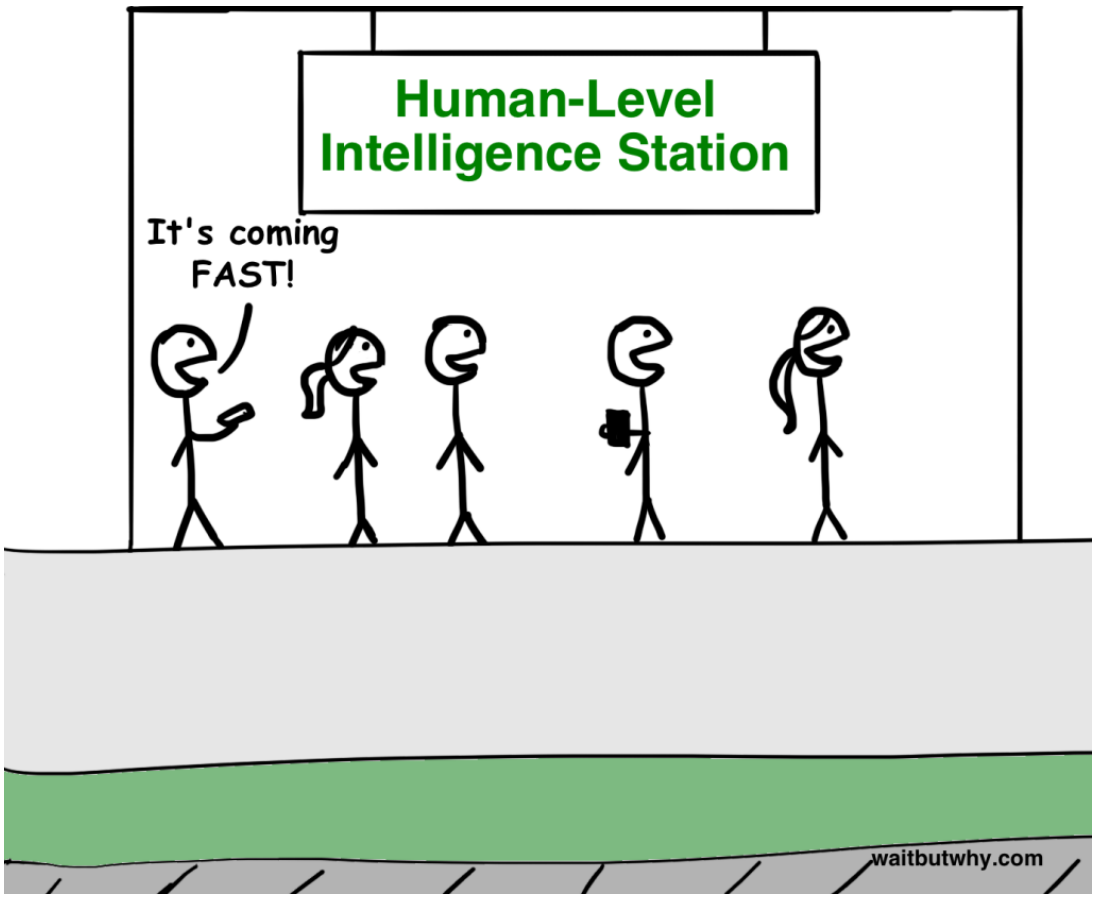
Data source: Global child mortality (since 1800) based on Gapminder and World Bank


Human-Level Intelligence Station
waitbutwhy.com

Intro
DQN In Theory
DQN In Practice
Beyond DQN
AI Revolution



NYC DATA SCIENCE ACADEMY


Human-Level Intelligence Station
It's coming FAST!
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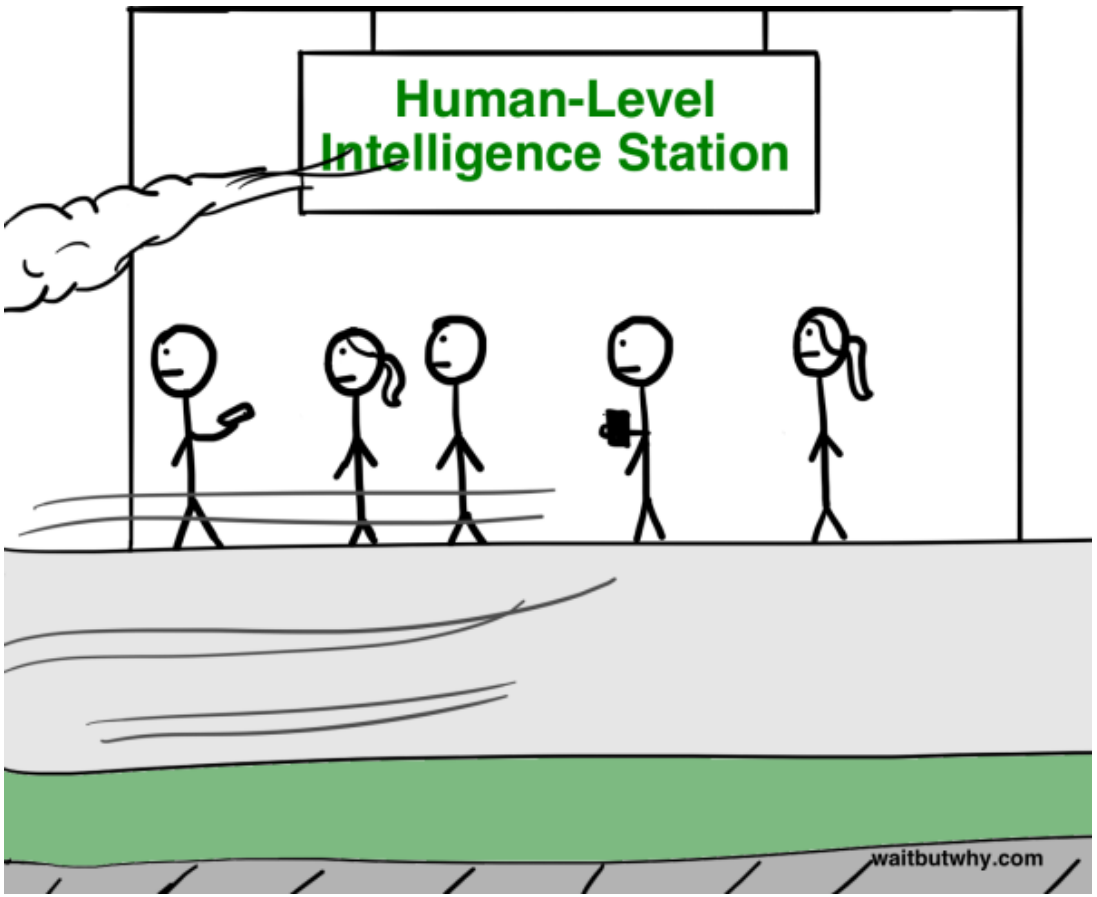
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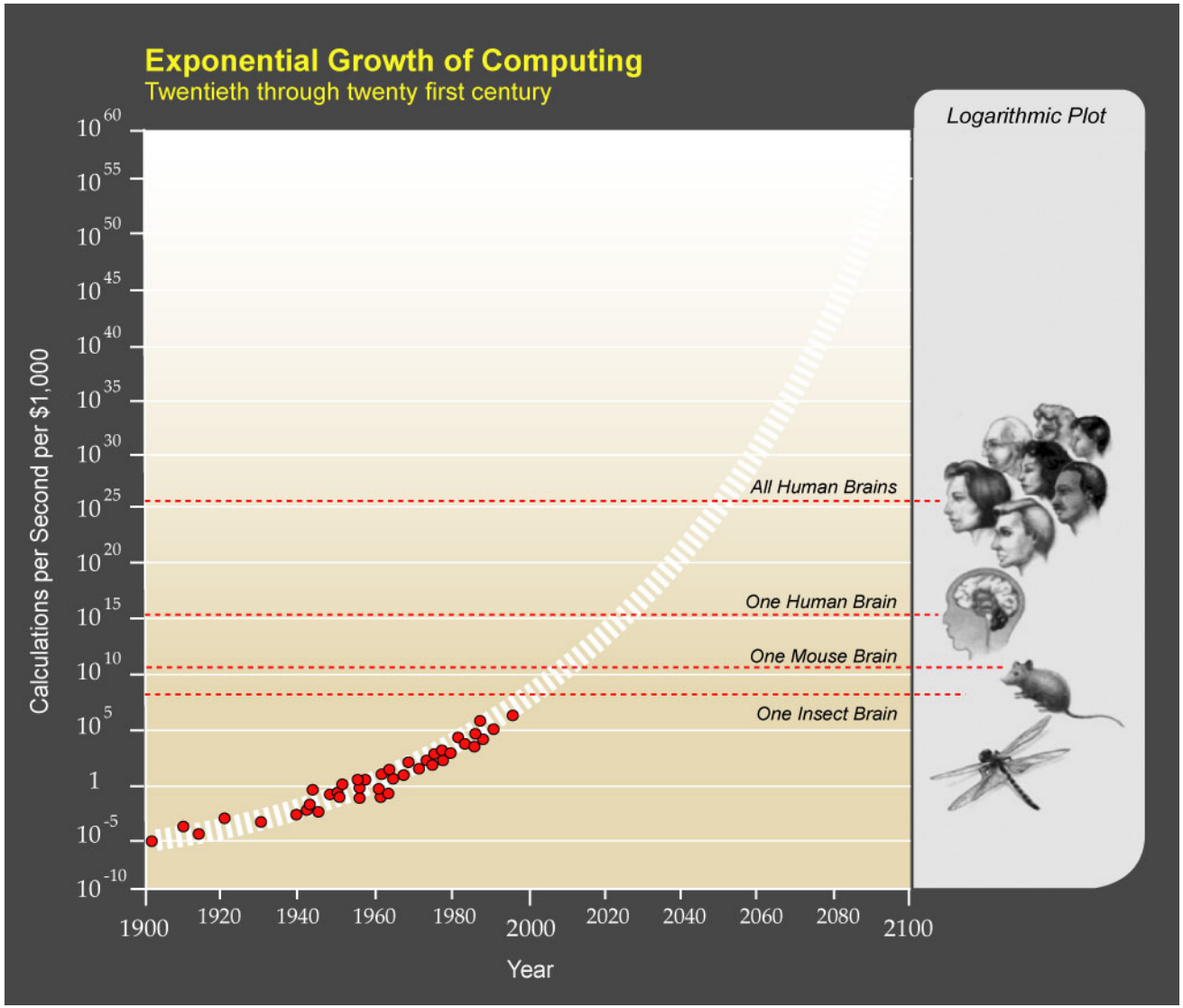

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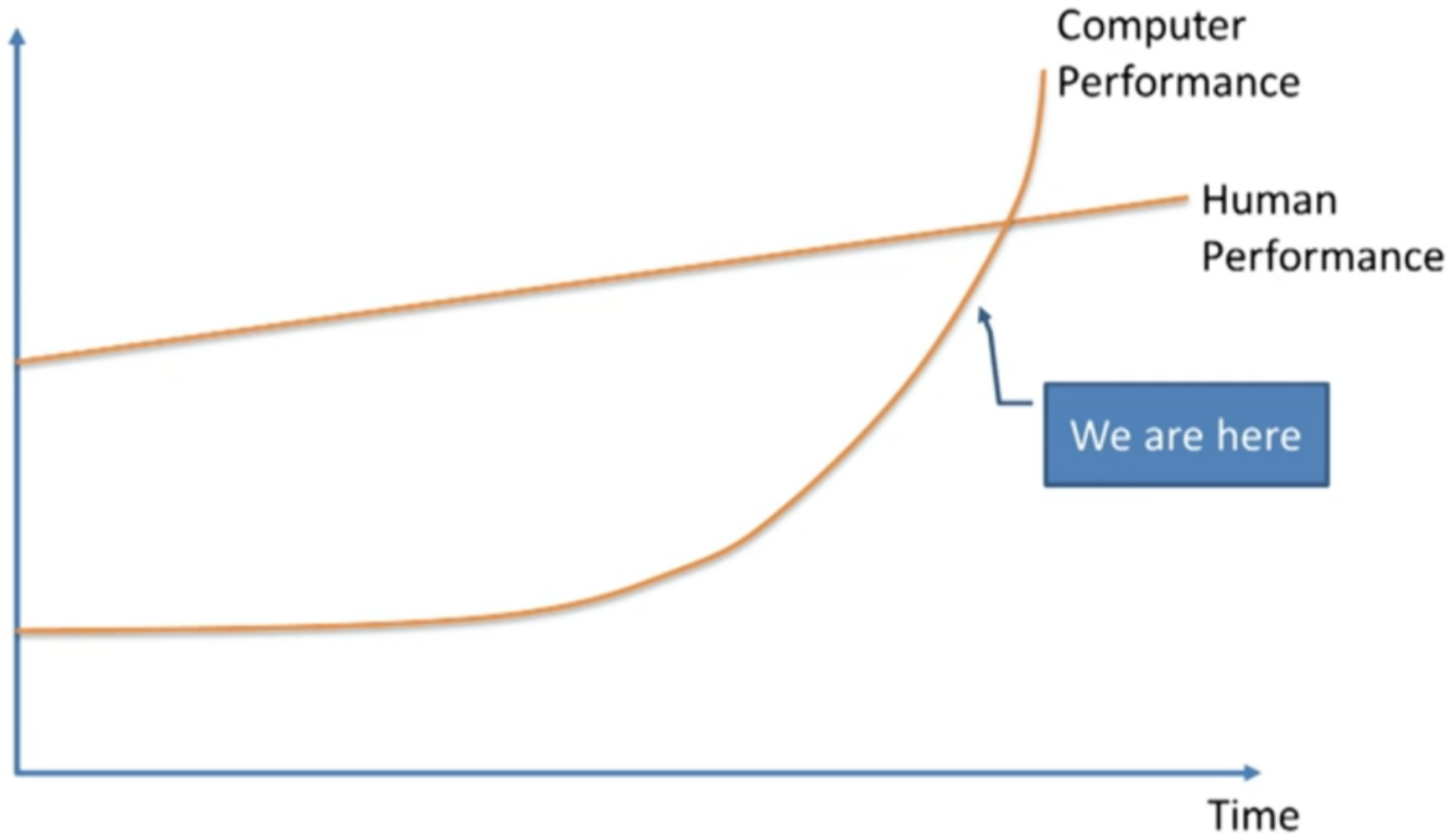
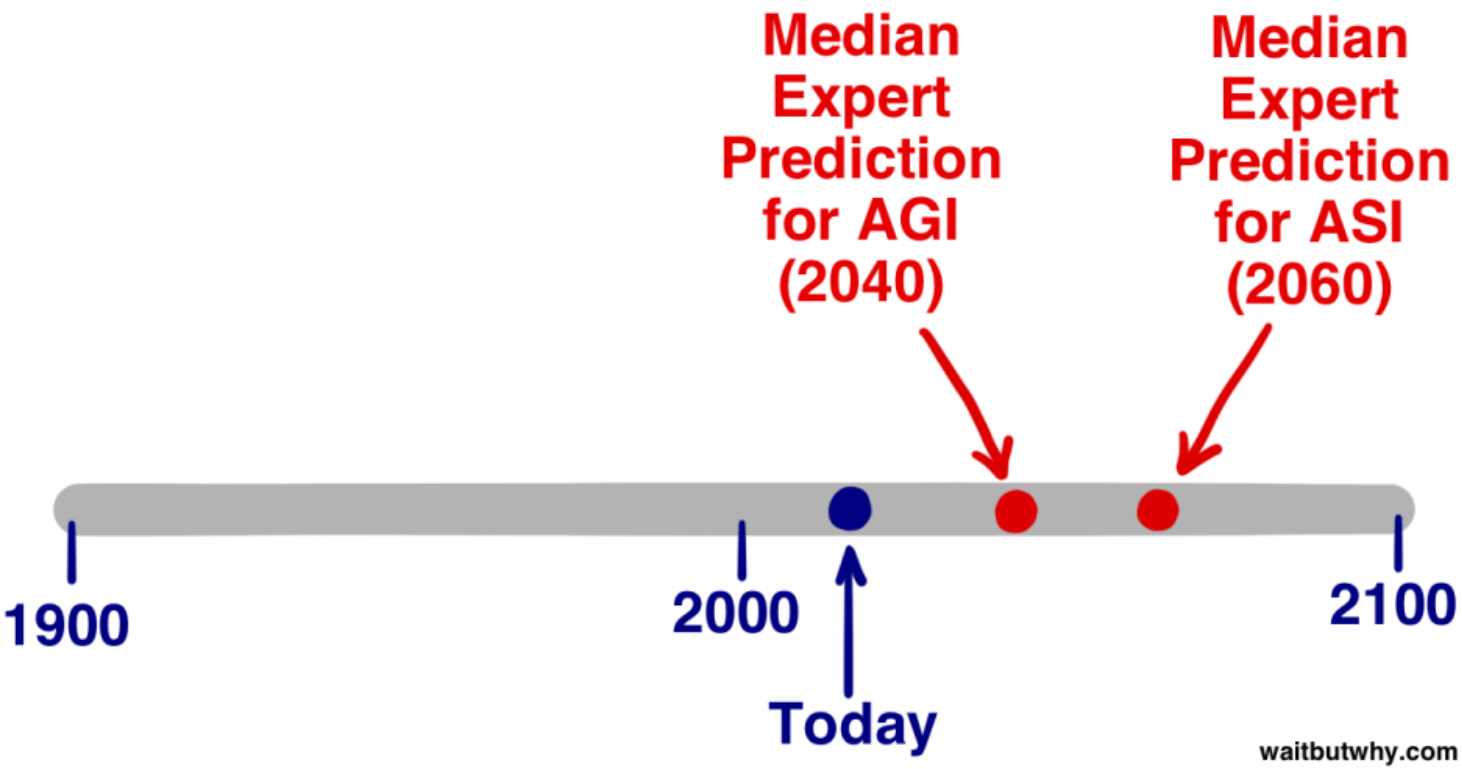

Computer Performance
Human Performance
We are here
Time



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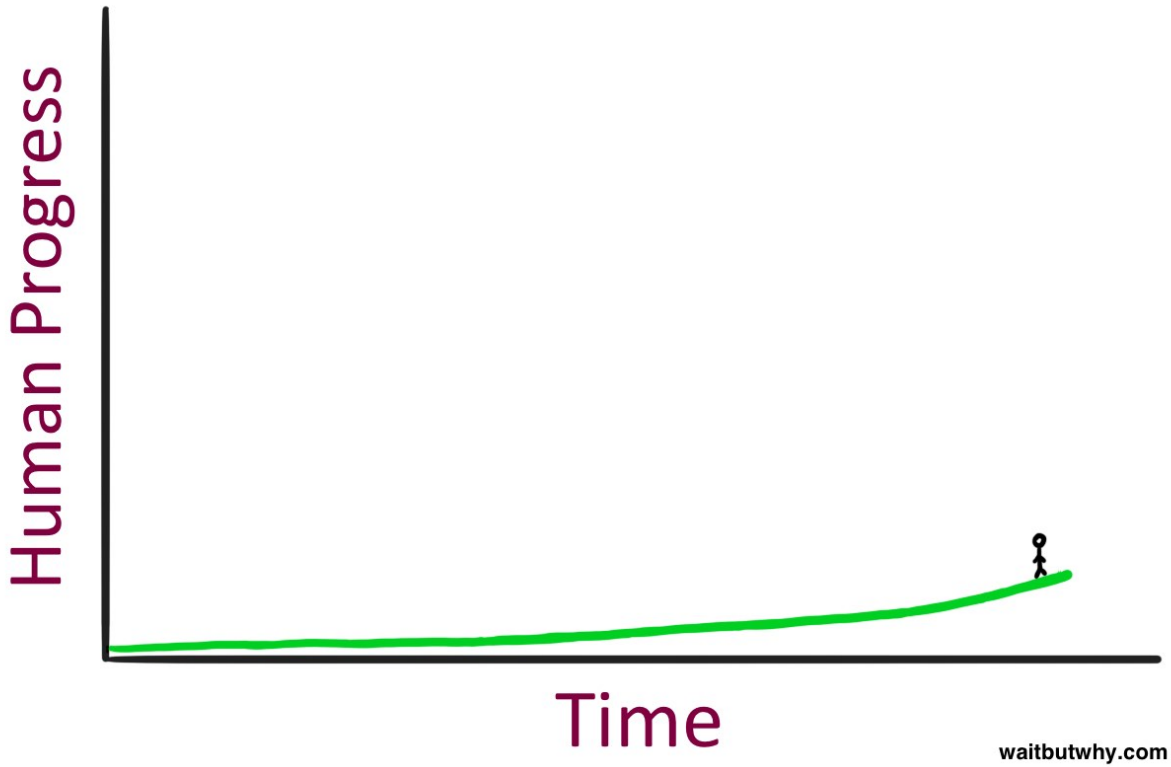
Human Progress
Time
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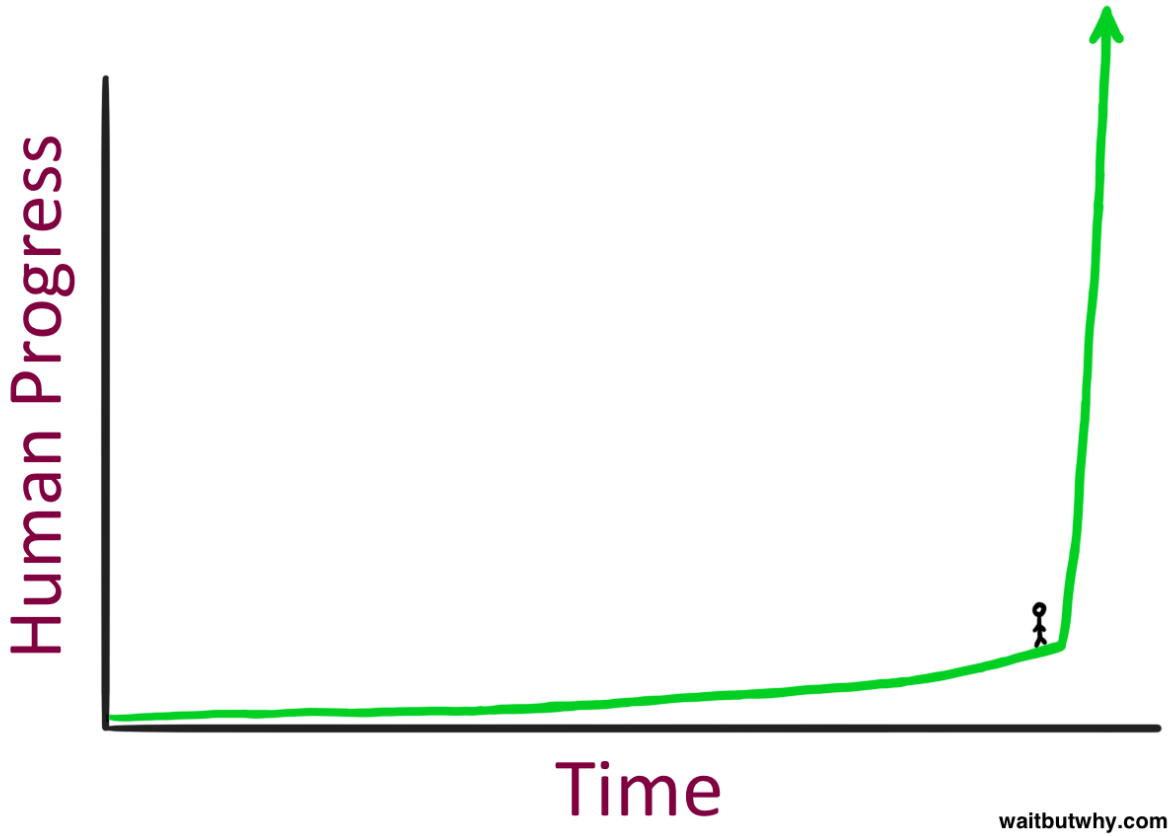
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