

# Future Directions of Machine Intelligence

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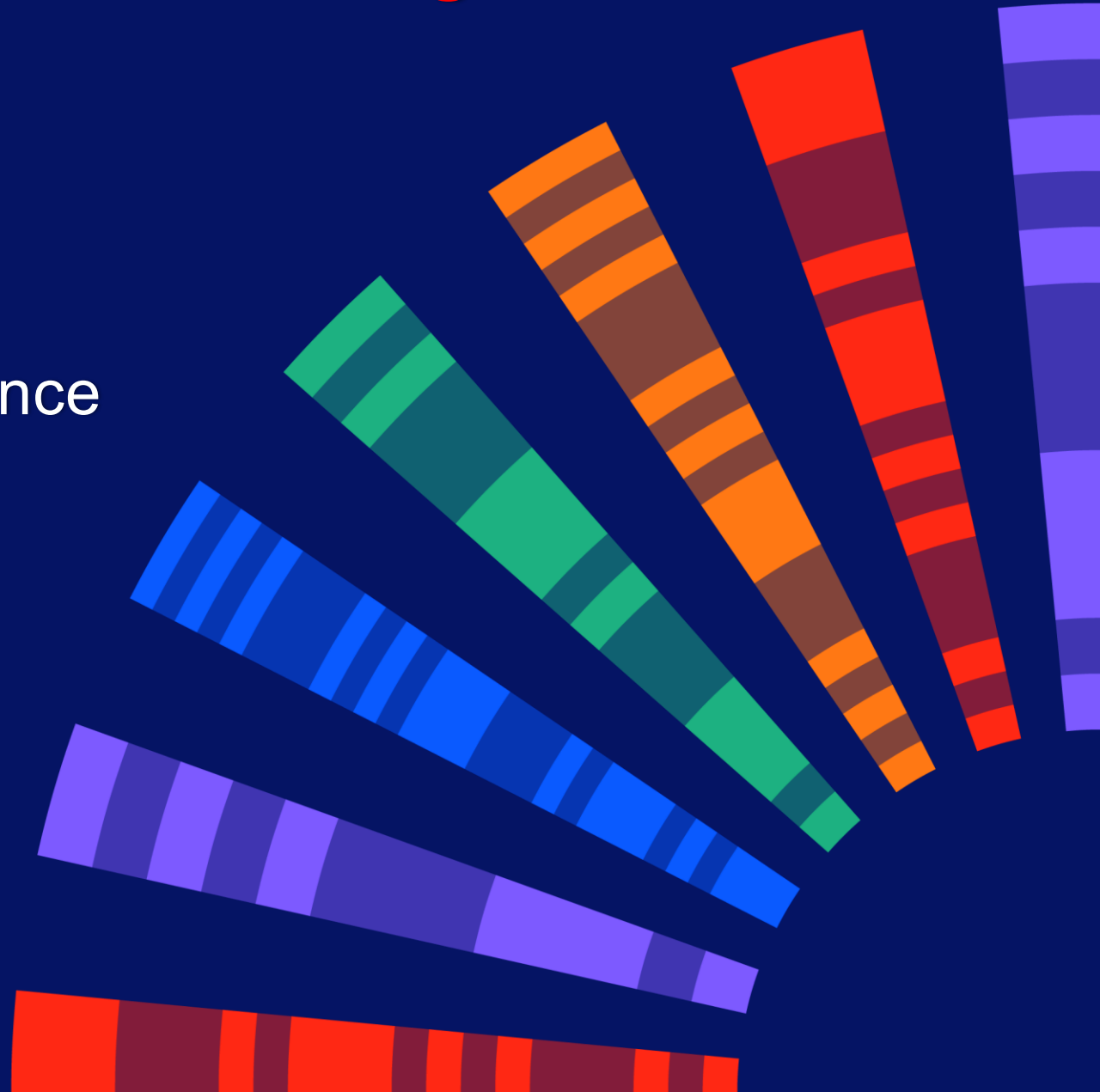
**Professor Yi Ma**

School of Computing and Data Science

The University of Hong Kong



SCHOOL OF  
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# Prologue

Seek a scientific and theoretical foundation for **Intelligence**:

- what to learn?
- how to learn?
- why correct?

*“What I cannot create, I do not understand.”*

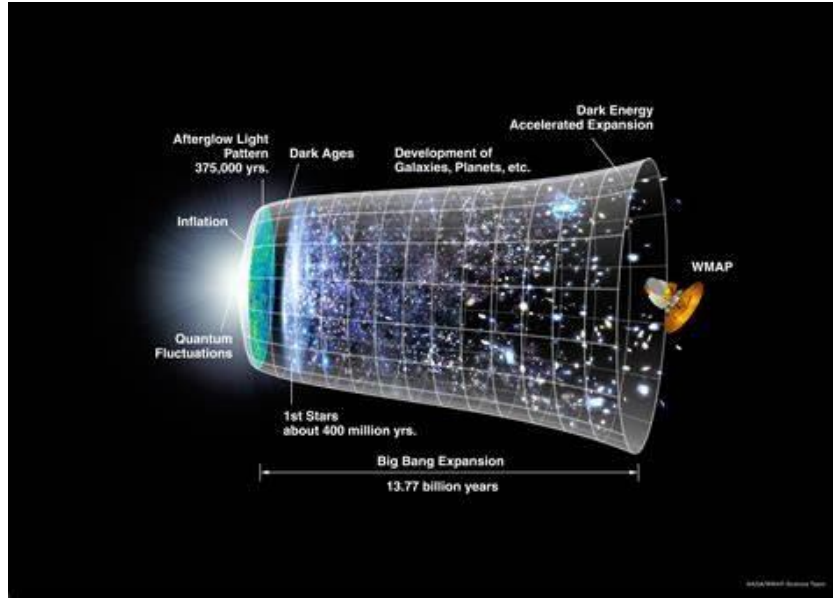
-- Richard Feynman

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# Evolution of Life and Intelligence

Evolution of the Universe is **Physics** at work



Evolution of Life is **Intelligence** at work



*“Just as the constant **increase of entropy** is the basic law of the universe, so it is the basic law of life to be ever more highly structured and to struggle **against entropy**.”*

-- Vaclav Havel

# Evolution of Life and Intelligence: From DNA to Brain

From the first DNA to the emergence of life with Brain: **3.6 Billion Years**

From the first Brain to the explosion of lives in the Cambrian period: **50 Million Years**

DNAs: Pretrained “Large Models”  
Random Mutation & Natural Selection  
**Reinforcement Learning**

Emergence of Brain & Senses  
Individual Models: Memory  
**Learn from Feedback**

Explosion of Lives

**The Cambrian period**

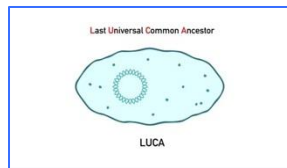
**DNA appeared** near  
some volcano in the  
ocean



**40B Years**

First DNA

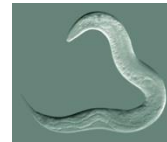
Common ancestor  
of all lives: **LUCA**



**3.5B Years**

First Life Form

First life form with a brain  
(**Nematode**)



**550M Years**

First Brain



**500M Years**

Cambrian Period

*A Brief History of Intelligence*, [Max Bennett, 2023](#)

# Evolution of Life and Intelligence: From Species to Individuals

**Emergence and evolution of life are mechanisms of intelligence at work!**

Life depends on intelligence to continuously acquire more knowledge to better predict the world.

**Phylogenetic Intelligence:** DNA inheritance, random mutation, and natural selection

**Ontogenetic Intelligence:** Individual memory, perception & feedback, and error correction.



3.7B years ago  
Life begins

500M years ago  
Cambrian period

400M years ago  
fish

360M years ago  
amphibian

250M years ago  
reptile

200M years ago  
bird and mammal

310T years ago  
neanderthal



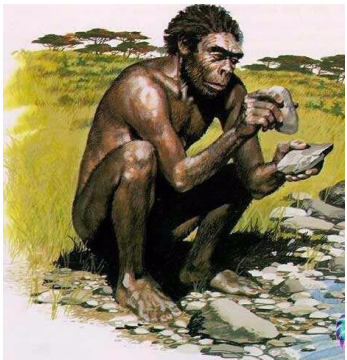
# Evolution of Intelligence: From Societal to Artificial Intelligence

Emergence and evolution of life are mechanisms of intelligence at work!

Life depends on intelligence to continuously acquire more knowledge to better predict the world.

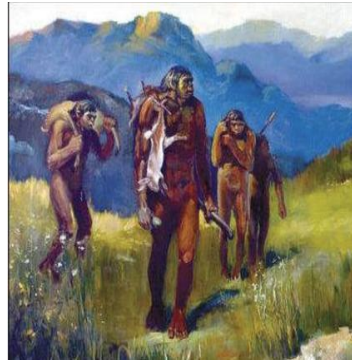
**Societal Intelligence:** Languages and texts, empirical knowledge, trial and error

**Artificial Intelligence:** Scientific facts, theorize, hypothesis testing & falsification.



310T years ago  
neanderthal

Tools and  
group hunting



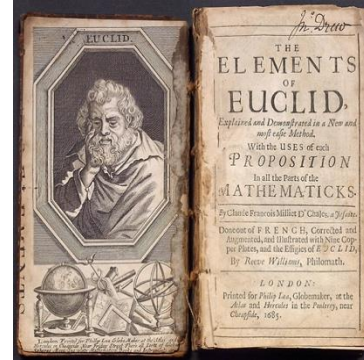
70T years ago  
**Societal intelligence**

Languages  
Information sharing



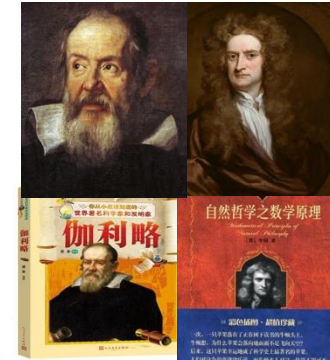
3500 BC  
written language

Knowledge  
accumulation



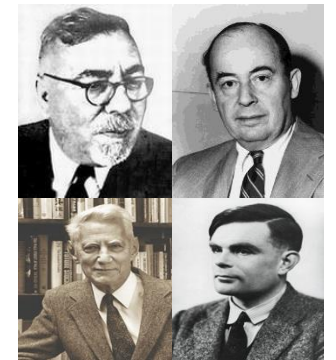
600-300 BC  
**Scientific Intelligence**

Abstraction, formal  
logic, and mathematics



14-18<sup>th</sup> Century  
Renaissance

Science  
Hypothesis Testing



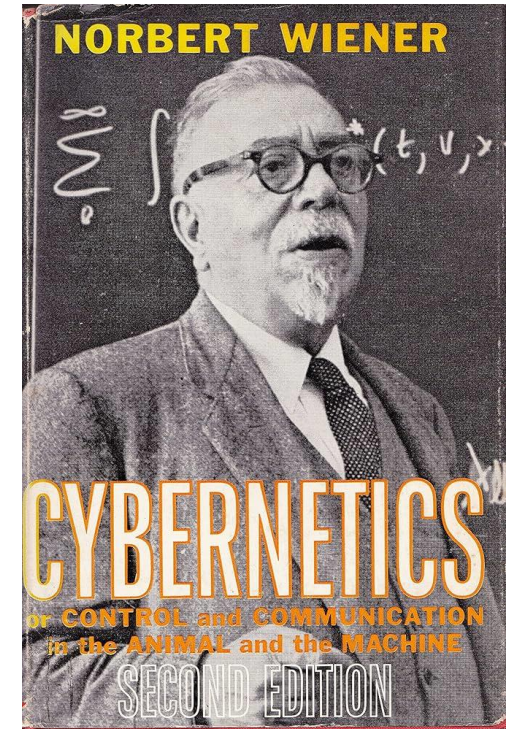
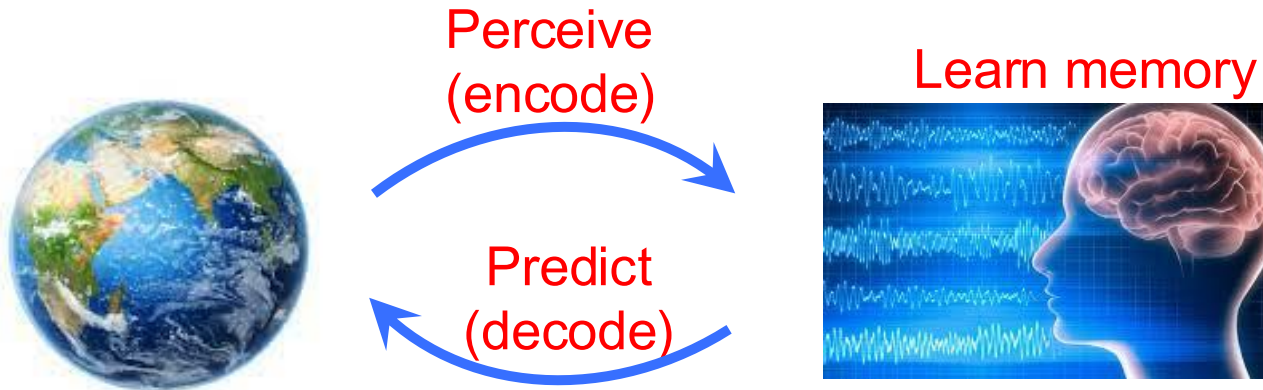
The 1940s  
**Machine Intelligence**

Computing machines

# True Origin of Machine Intelligence (the magic era!)

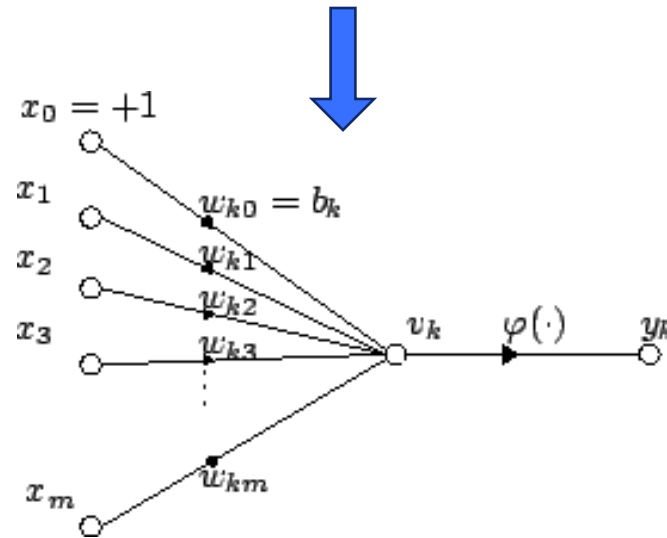
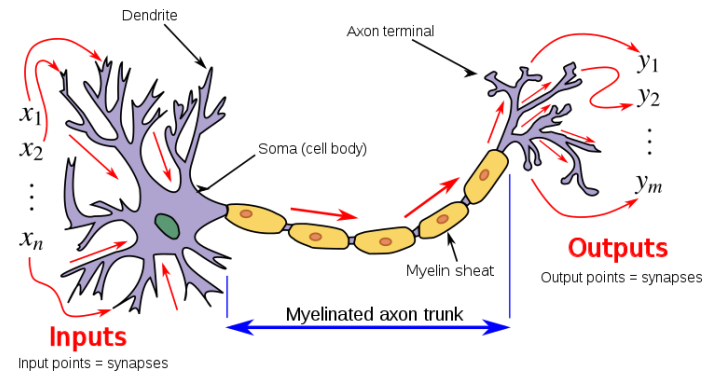
1940s, people started to make machines **imitate intelligence** (of animals).

- 1948, **Cybernetics & System Theory**, **Nobert Wiener**
- 1943, **Artificial Neural Networks**, Warren McCulloch and Walter Pitts
- 1948, **Information Theory**, Claude Shannon
- 1944, **Game Theory**, John von Neumann
- 1940's, **Turing Machine and Turing Test**, Alan Turing



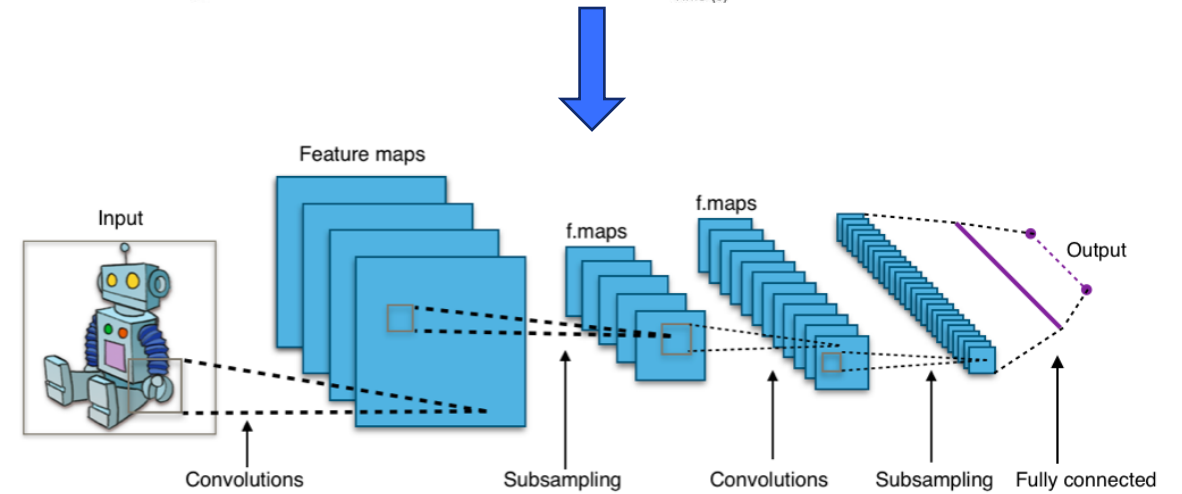
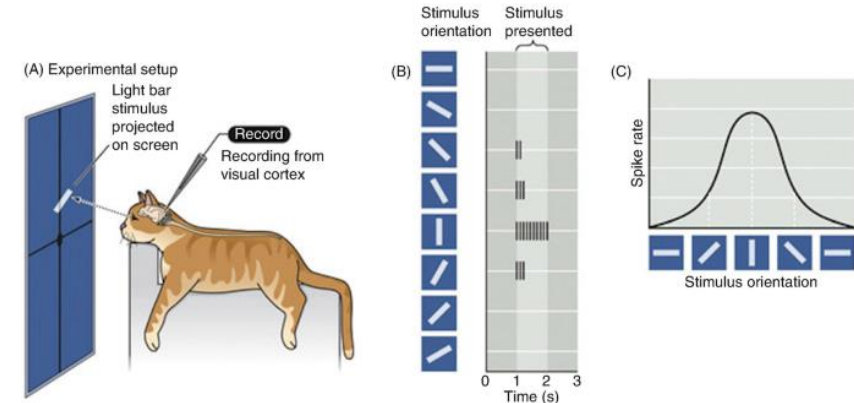
# Artificial Neurons and Neural Networks: Learn from Nature

Golgi and Cajal 1888 (1901 Nobel Prize)



Warren McCulloch & Walter Pitts 1948

Hubel and Wiesel 1959 (1981 Nobel Prize)



Fukushima 1980 & LeCun 1989 (Turing Award)



# Learning Deep Representations of Low-Dim Distributions

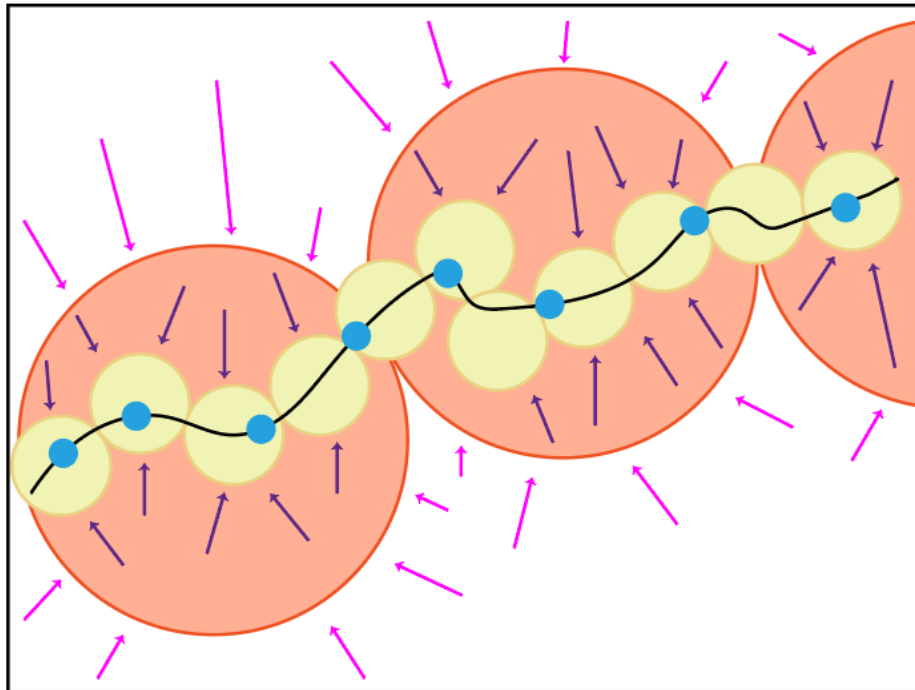
How to measure information in a distribution with a low-dimensional support?

Dimension  
 $\dim(\mathbf{x}) = 0$

Volume  
 $\text{vol}(\mathbf{x}) = 0$

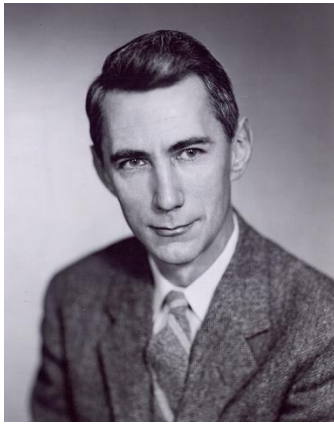
Differential entropy  
 $h(\mathbf{x}) = -\infty$

Construct *a finite codebook* by packing the support of the distribution with  $\epsilon$ -balls.



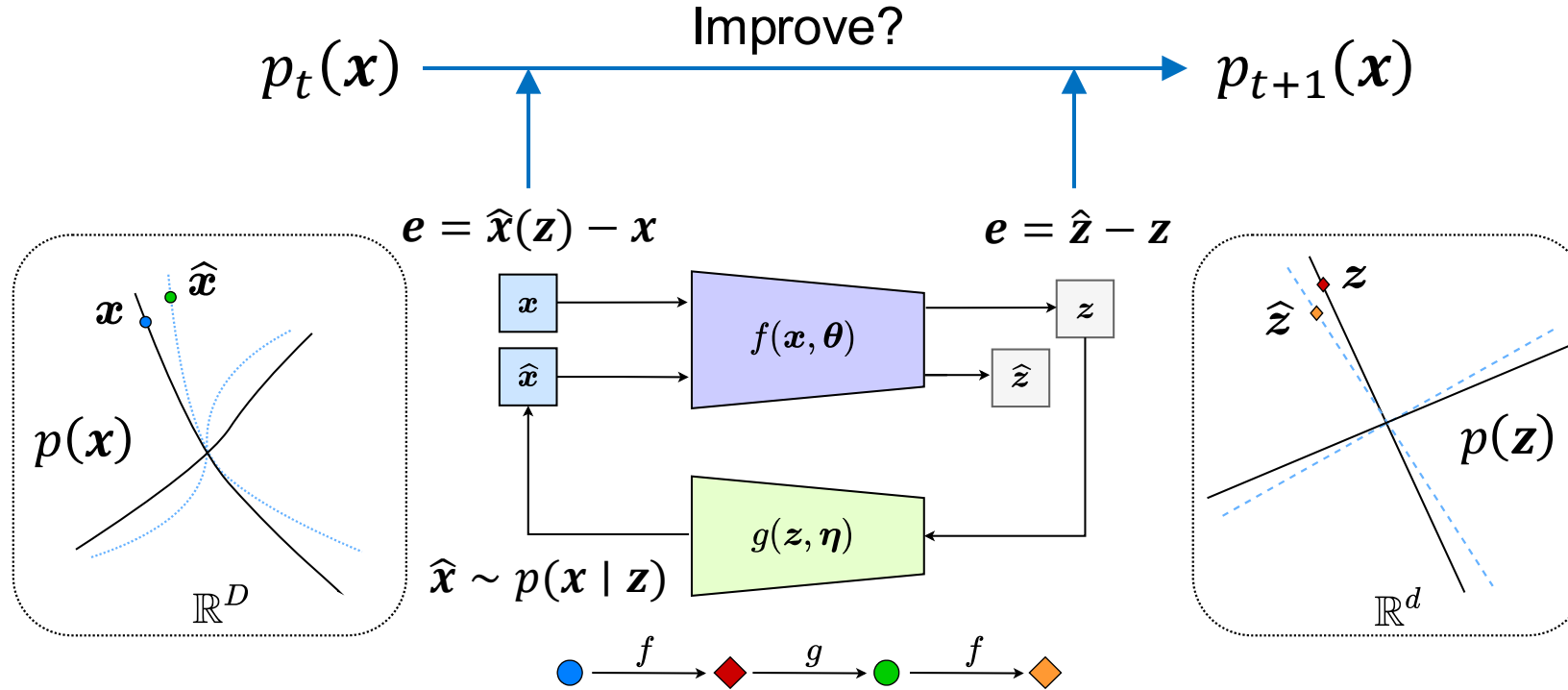
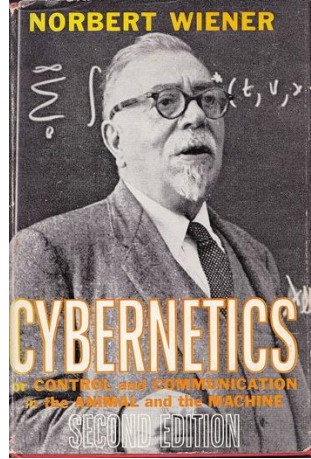
rate distortion

$$R(\mathbf{x}, \epsilon) = \min_{\mathbb{E} \|\hat{\mathbf{x}} - \mathbf{x}\| \leq \epsilon} h(\hat{\mathbf{x}}) - h(\hat{\mathbf{x}} | \mathbf{x})$$



# Towards Autonomous Intelligence (AI 2.0)

How to self-learn a more consistent representation, continuously?



In nature, **all intelligent systems learn from closed-loop feedback!** (Cybernetics)

# Towards AI 2.0: Close the Loop via Minimax Game

Closed-loop systems learnt via **minimax game** do not forget catastrophically!



Incremental Learning via Closed-Loop [TDWLY+Ma, ICLR 2023]

Unsupervised Learning of Structured Memory: one sample at a time<sup>11</sup>

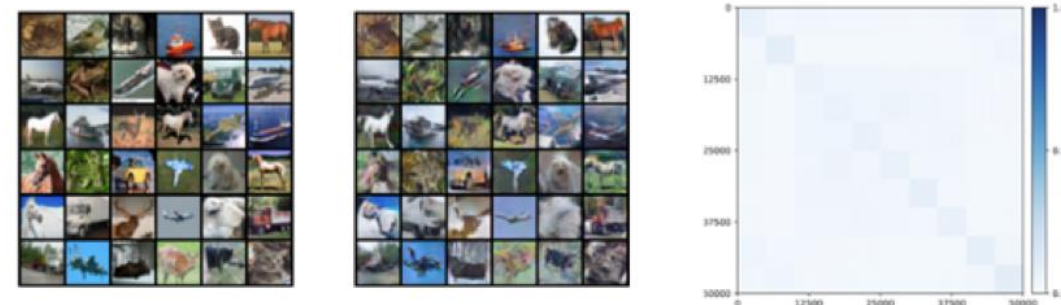
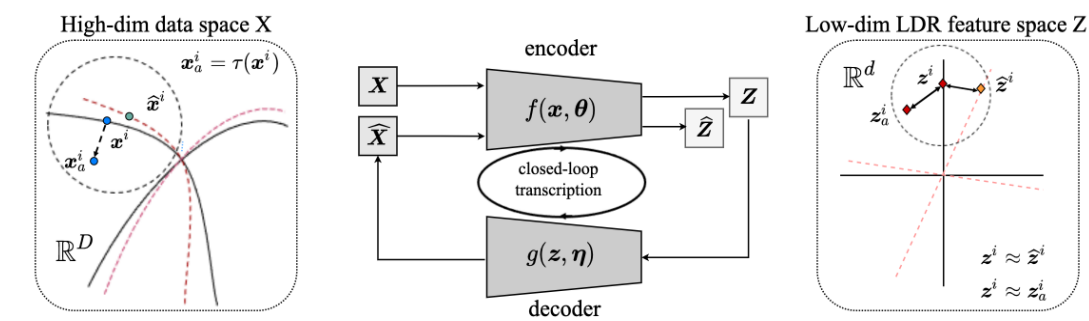


Figure: Sample-wise self-consistency and block-diagonal structures.

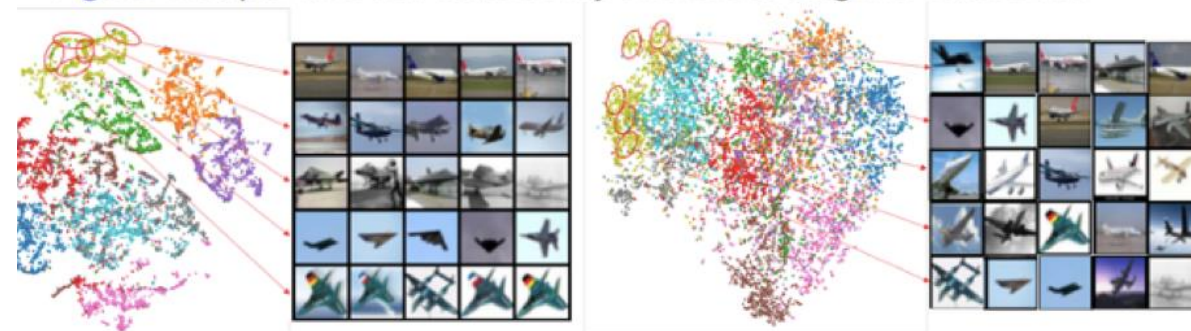


Figure: t-SNE of learned features . Left: U-CTRL and Right: MoCoV2.

$$\begin{aligned} & \max_{\checkmark} \min_{\mathcal{H}} R(Z) + \Delta R(Z, \hat{Z}) \\ & \text{subject to } \bigwedge_{i \in [2N]} \Delta R(z^i, \hat{z}^i) = 0, \text{ and } \bigwedge_{i \in [2N]} \Delta R(z^i, z_a^i) = 0. \end{aligned}$$

<sup>11</sup>Unsupervised Learning of Structured Representations via Closed-Loop Transcription, S. Tong, Yann LeCun, and Yi Ma, [arXiv:2210.16782](https://arxiv.org/abs/2210.16782), 2022.

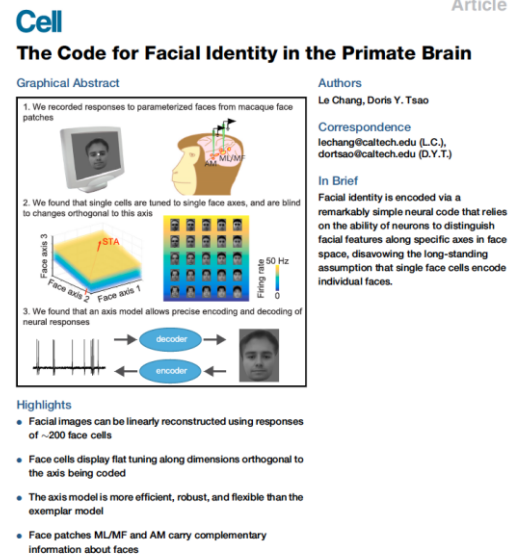
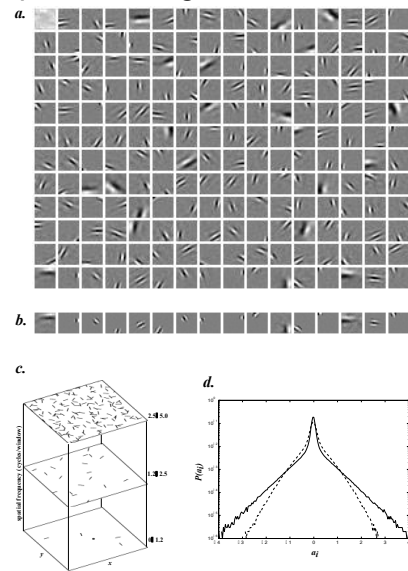
EMP-SSL: Towards Self-Supervised Learning in One Training Epoch, Shengbang Tong, Yubei Chen, Yi Ma, Yann Lecun, [arXiv:2304.03977](https://arxiv.org/abs/2304.03977)

# Towards AI 2.0: Time to Learn from Nature Again?

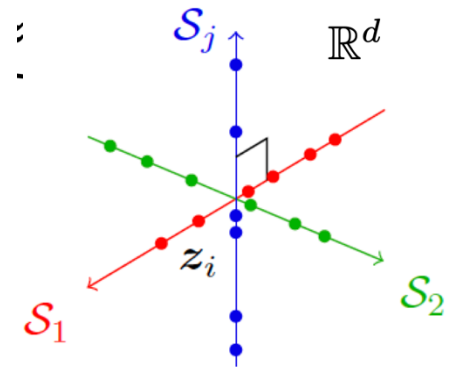
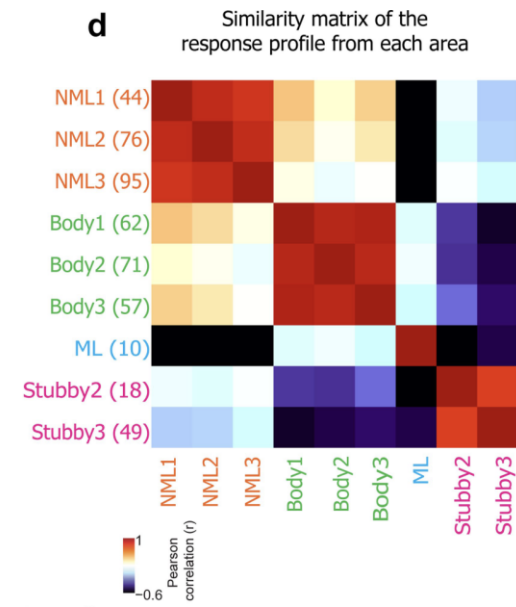
Similar characteristics and mechanisms are ubiquitous in nature!

- Sparse coding in visual cortex (Olshausen, Nature 1996)<sup>12</sup>.
- Subspace embedding (Tsao, Cell 2017, Nature 2020).<sup>13</sup>
- Predictive coding in visual cortex (Rao, Nature Neuroscience 1999).

sparse coding in visual cortex



Article





# Towards AI 2.0 (Neural Science)

**A position paper about Intelligence in 2022:**

## **On the Principles of Parsimony and Self-Consistency for the Emergence of Intelligence**

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*<sup>2</sup>Department of Molecular & Cell Biology and Howard Hughes Medical Institute, University of California, Berkeley, CA 94720, USA*

*<sup>3</sup>International Digital Economy Academy, Shenzhen 518045, China*

<sup>†</sup>E-mail: yima@eecs.berkeley.edu; dortsao@berkeley.edu; hshum@idea.edu.cn

# Towards AI 2.0 (Neural Science)

- **Parsimony:** what's in neuroscience to verify this principle?
- **Self-consistency:** what's in neuroscience to verify this principle?
- **Forward optimization** versus backward propagation?
- **Closed-loop** versus open-loop?
- **Self-correcting** or self-improving mechanisms?

The Forward-Forward  
Algorithm for  
Training Deep Neural  
Networks

Invited Talk at NeurIPS 2022  
Thurs 01 Dec  
02:30 PM CST [ Hall H ]



Geoffrey Hinton

# Towards AI 2.0: How to Implement (Computer Science)



To understand intelligence, one must understand computational complexity:

**Incomputable  $\Rightarrow$  computable  $\Rightarrow$  tractable  $\Rightarrow$  scalable  $\Rightarrow$  natural**

Kolmogorov  
complexity

Turing & Shannon

NP vs P

DNN & BP

Closed-loop  
& feedback?

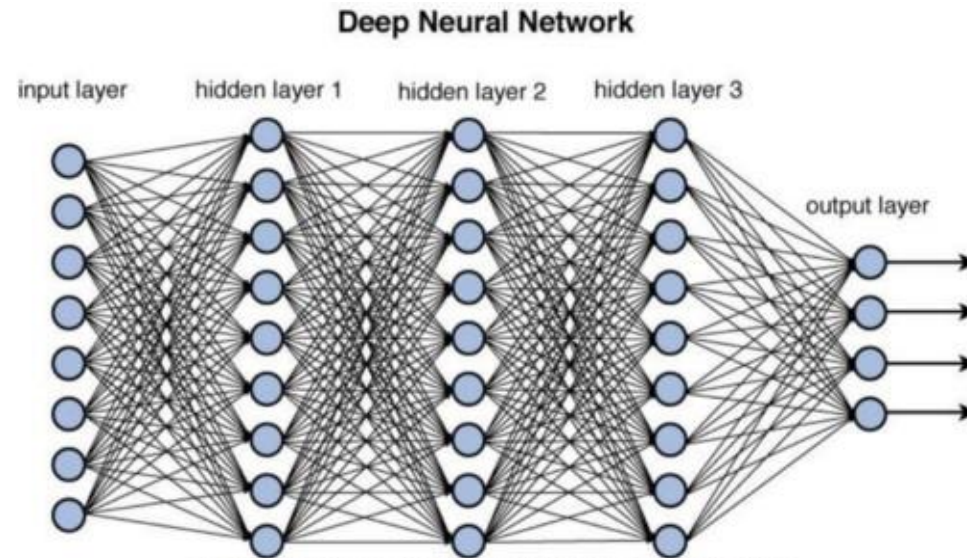
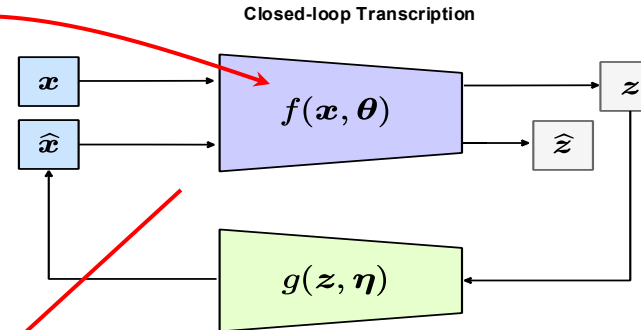
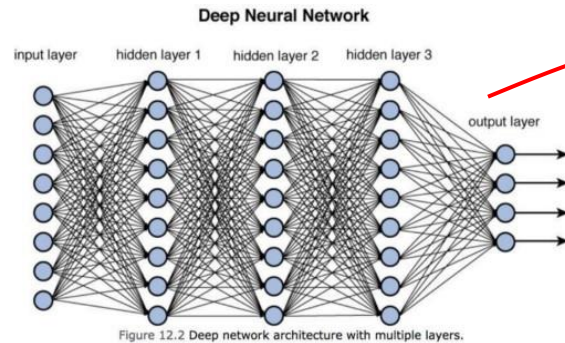


Figure 12.2 Deep network architecture with multiple layers.

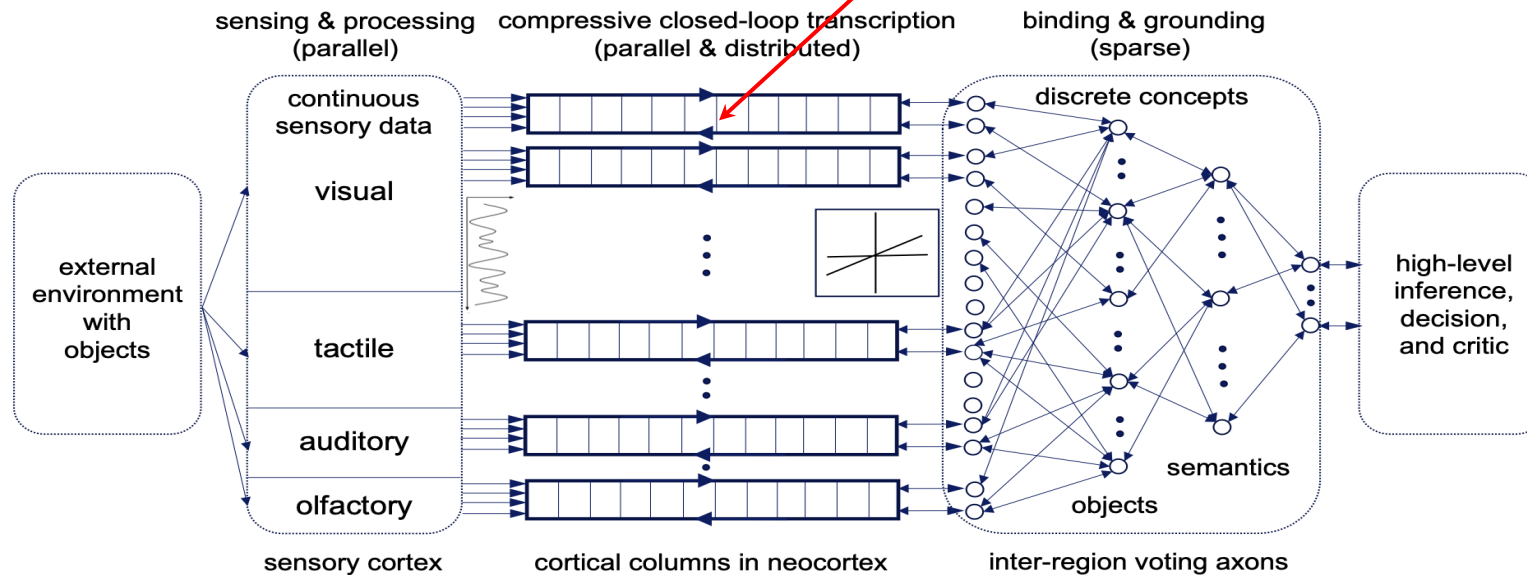
End to end open loop systems

# Towards AI 2.0: Time to Learn from Nature Again?

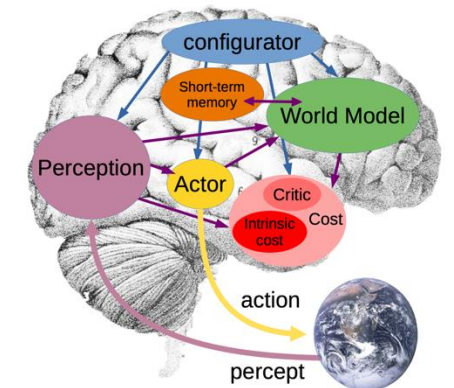
Neural networks are nature's **optimization** algorithms that maximize information gain.



Closed-loop transcription is a basic unit for **autonomously** learn consistent knowledge.



Parallel, distributed, hierarchical autoencoders **efficiently** learn knowledge of the external world.



**A unified purpose of intelligence: maximize “information gain” with every unit, at every stage!**



# What is Intelligence?

**Definition [Intelligence]:** an intelligent system is one that has the mechanisms for **self-correcting** and **self-improving** its existing knowledge (or information).

$$\begin{aligned}\text{Knowledge} &= \int_0^t \text{Intelligence}, \\ \text{Intelligence} &= \frac{d}{dt} \text{Knowledge}.\end{aligned}$$

Any system without such mechanisms, however large, does not have any intelligence!

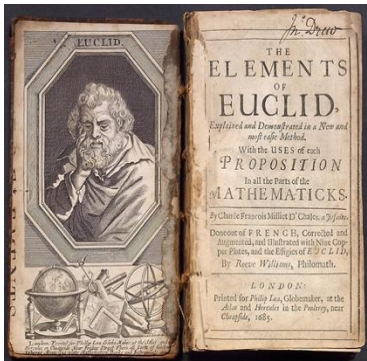
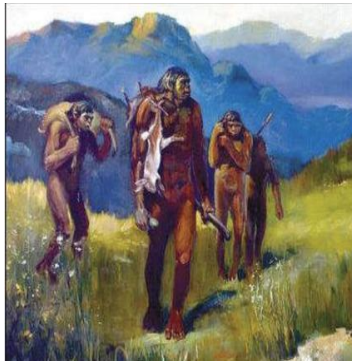


vs



**Who has intelligence,  
who has knowledge?**

# Evolution of Intelligence in Nature: Four Stages



Phylogenetic

Ontogenetic

Societal

Artificial

Intelligence is all about how to **encode and improve information** for better prediction of the world!

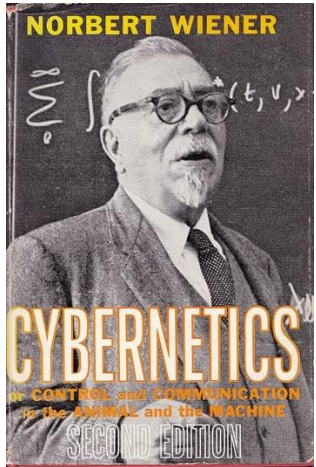
	Phylogentic	Ontogenetic	Societal	Artificial
Codebook	Amino Acids	Neural Networks	Alphabet & Words	Mathematics/Logic
Information	Genes/DNAs	Memory	Natural Languages	Scientific Facts
Improvement	Natural Selection	Continuous Feedback	Trial & Error	Hypothesis Testing

# Today's “Artificial Intelligence” is not that Artificial Intelligence!

A quote from the 1956 Dartmouth proposal: “*An attempt will be made to find how to make machines use language, form abstractions and concepts, solve kinds of problems now **reserved for humans**, and **improve themselves***”.

## 1940s (animal intelligence)

- Signal processing
- Information Rep.
- Prediction
- Error correction
- Optimal control
- Game theory

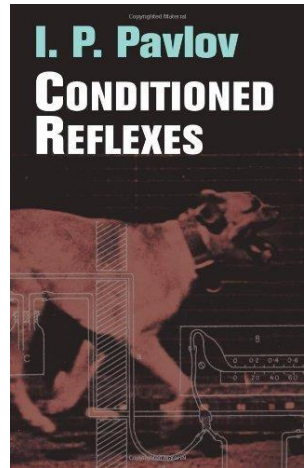


## 1956 (unique to human)

- Abstraction
- Logic deduction
- Causality
- Hypothesis forming & testing
- Problem solving

## Today's AI (animal or human?)

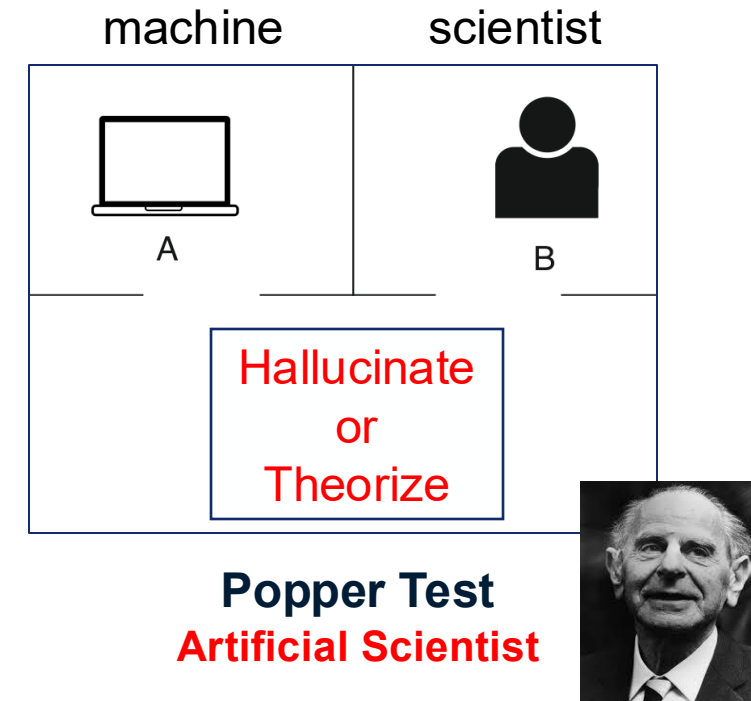
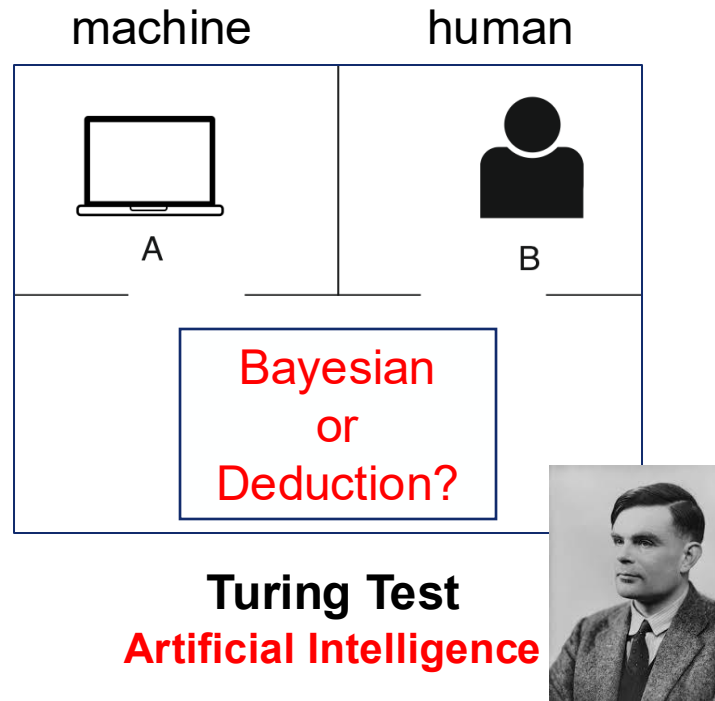
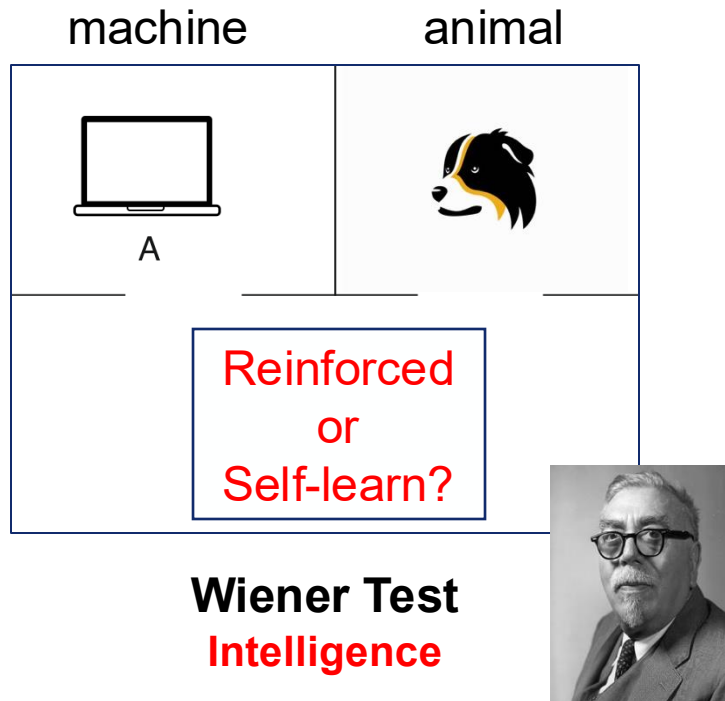
- Denoising
- Compression
- Object recognition
- Image generation
- Text generation
- Reinforce learning



# Scientific Tests for Intelligence?

How to **scientifically certify** different types of ability of an “self-claimed intelligent” system:

- **Memorize:** simply having memorized a large amount of knowledge-carrying data and regenerating them;
- **Self-Learn:** being able to autonomously and continuously develop better knowledge from new observations;
- **Understand:** having truly understood existing knowledge and knowing how to deduce and apply it correctly;
- **Theorize:** being able to generate new scientific hypotheses and mathematical theories and verify them.





# Epilogue

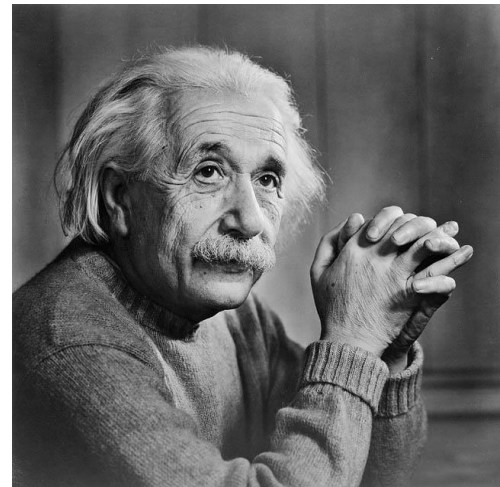
Seek a scientific and theoretical foundation for **Intelligence**:

- **what to learn?** *parsimony*
- **how to learn?** *compression*
- **why correct?** *consistency*

大道至简

*“Everything should be made as simple as possible,  
but not any simpler.”*

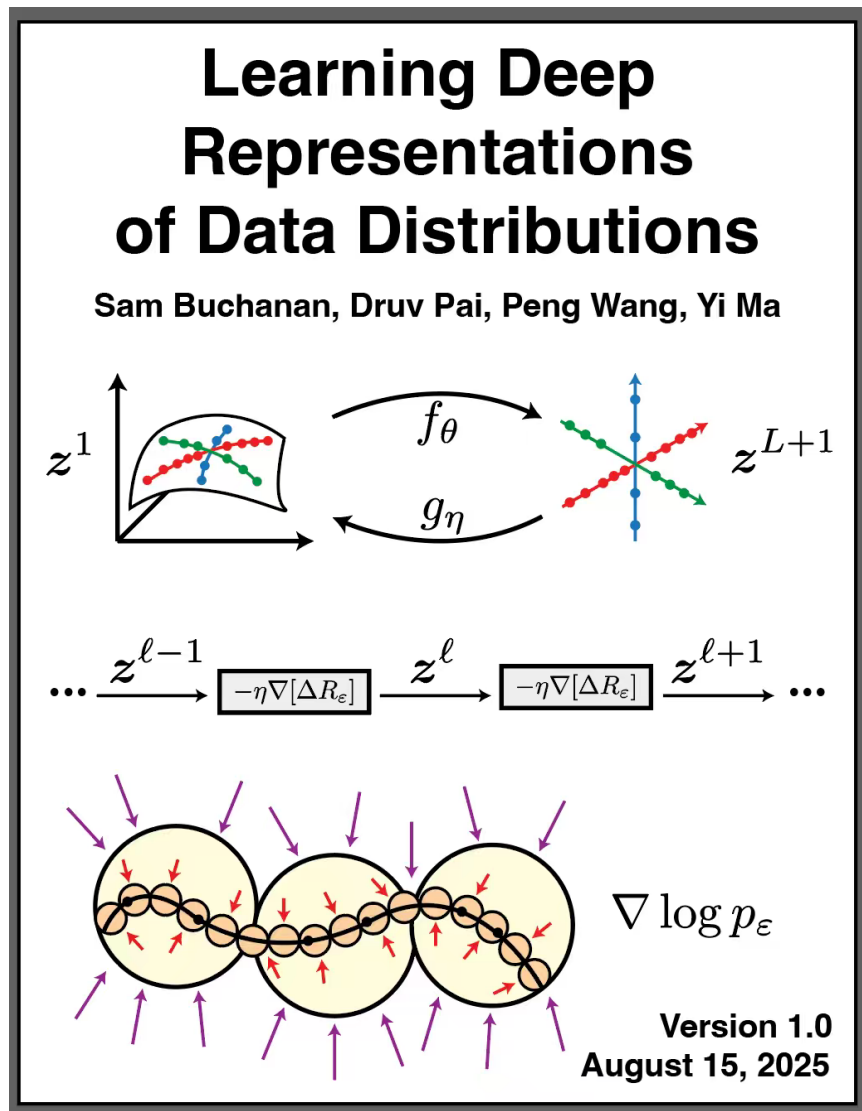
-- Albert Einstein



# Epilogue

## A new open-source online textbook!

<https://ma-lab-berkeley.github.io/deep-representation-learning-book/>



# Acknowledgement

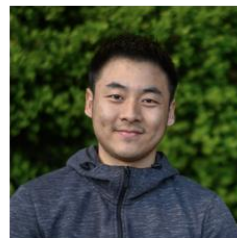
## A Truly Multi-University and Multi-Disciplinary Effort from Academia!



Druv Pai  
UC Berkeley



Sam Buchanan  
TTI Chicago



Yaodong Yu  
OpenAI, U. Maryland



Ziyang Wu  
UC Berkeley



Shengbang Tong  
New York University



Tianzhe Chu  
Hong Kong University



Benjamin Haeffele  
Johns Hopkins



Peng Wang  
UMichigan



Simon Zhai  
UC Berkeley, DeepMind



Jack Bai  
UIUC



Ryan Chan  
UPenn



HKU Musketeers Foundation  
**Institute of Data Science**  
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# Pursuing the Nature of Intelligence

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## Thanks



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