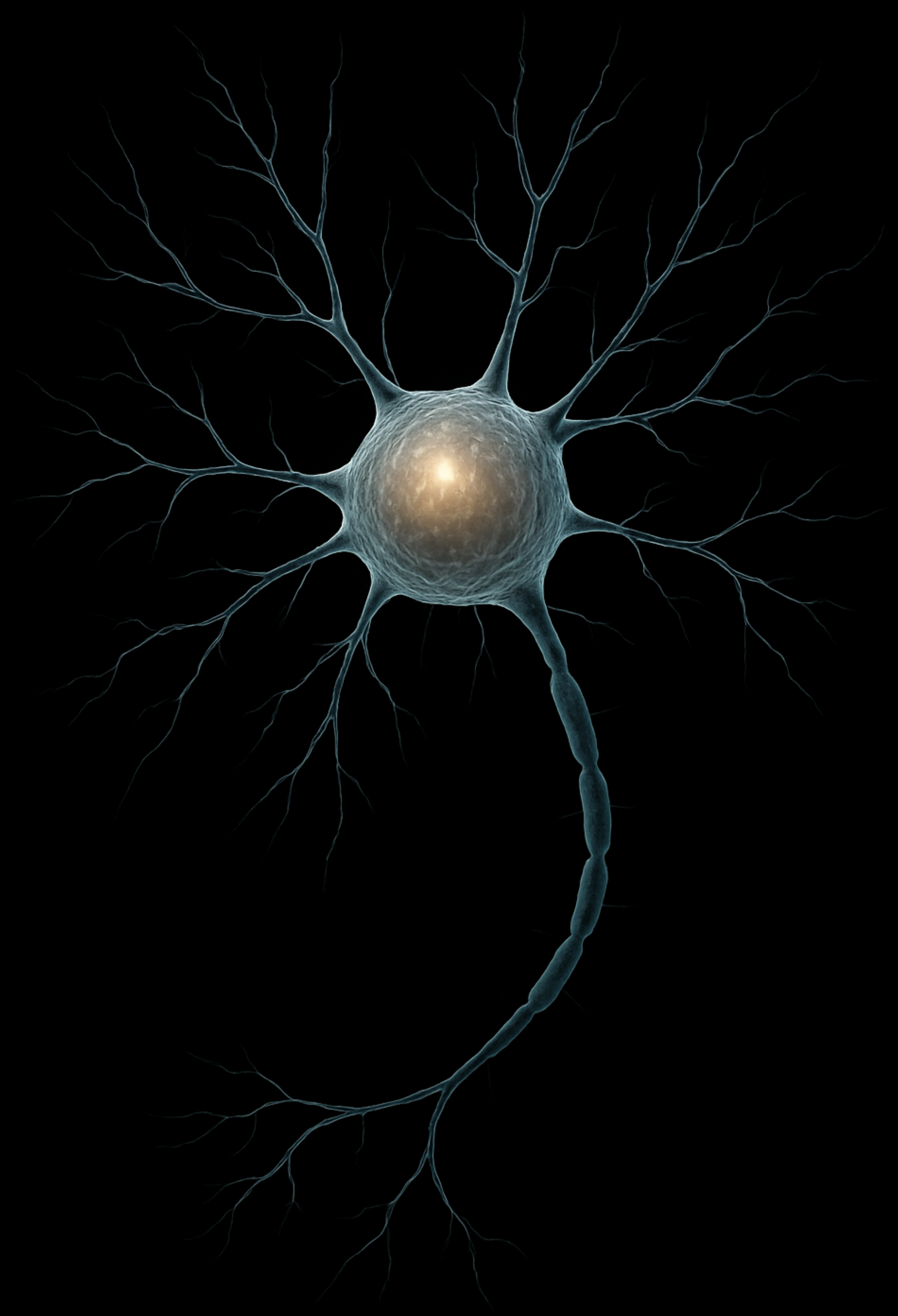
جامعة الملك عبدالله للعلوم والتقنية
King Abdullah University of Science and Technology

أكاديمية كاوست
KAUST ACADEMY

Biology in Artificial Intelligence

For Accurate Neural Modeling



Sattam J. Altuuaim, August 13th 2025

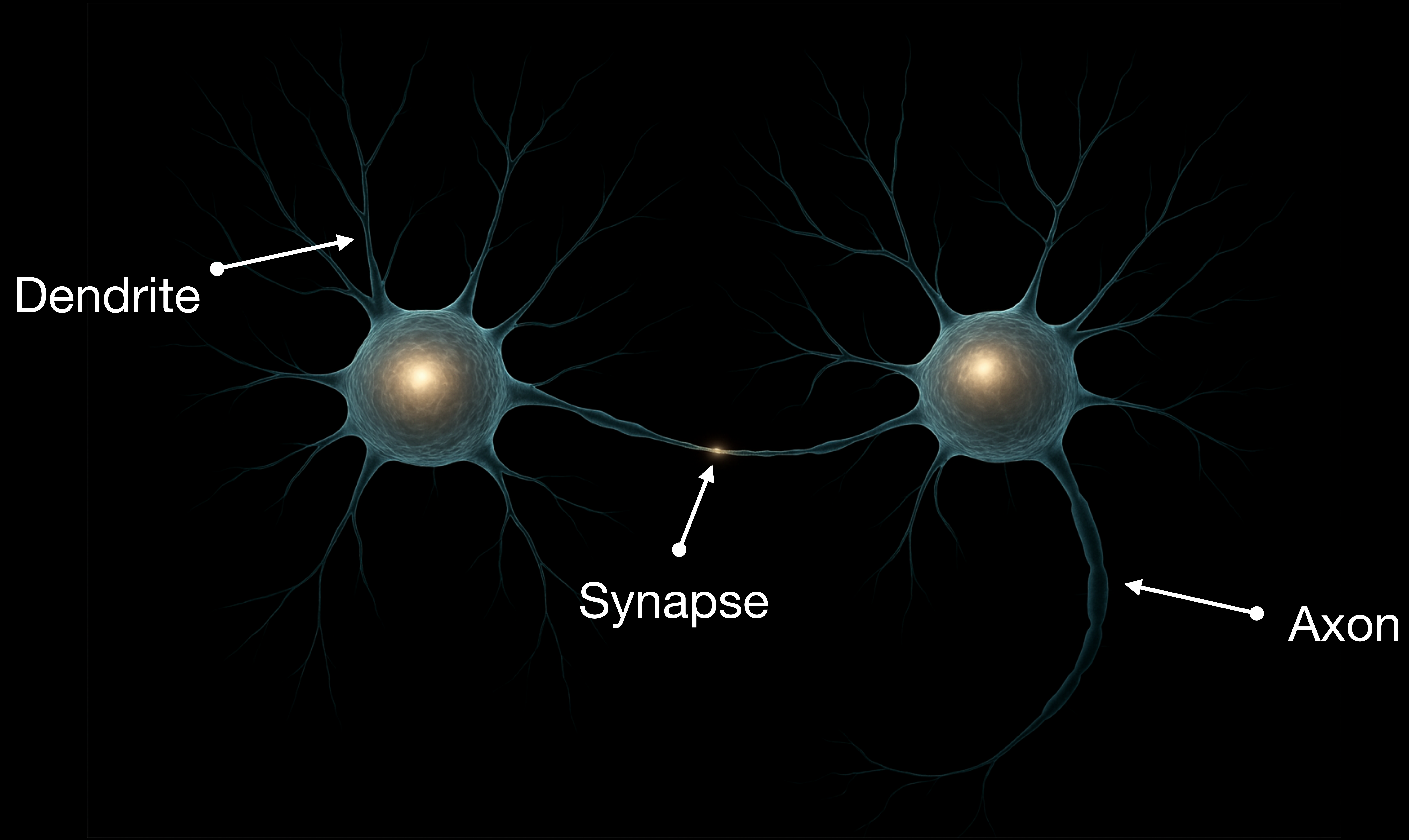
Why Biology?

“The brain is a massively parallel processor that’s very good at doing things computers aren’t very good at, so it seemed sensible to try to mimic it.”

— **Geoffrey Hinton, Godfather of Deep Learning.**

The Neurons

The Building Blocks of The Brain



Artificial Neural Networks

The First Artificial Neuron

McCulloch & Pitch (1943)

- Warren McCulloch (neuroscientist) and Walter Pitts (logician) created the first *mathematical model* of a neuron.
- They showed that a simple on/off "neuron" could be connected in networks to compute logical functions.
- It was **biologically inspired**, but highly simplified.

Neumann Architecture

John von Neumann (1945–1949)

- Stored-Program Computer Architecture enables computers to store instructions and data together.
- Foundation for Neural Simulations using computational frameworks.
- This architecture is what we use now in our computers for AI.

Hebb's Rule

Donald Olding Hebb (1949)

- Proposed a theory for how biological neurons strengthen their synaptic connections.

- *"Neurons that fire together, wire together".*

- This was the seed for learning in Artificial Neural Networks.

Hebbian Learning Rule

In Artificial Neural Networks

$$\Delta w_{ij} = \eta \, x_i \, y_j$$

“Neurons that fire together, wire together”

The Preceptron

Frank Rosenblatt (1958)

- Built the perceptron, the first trainable neural network model.
- It could classify patterns using the Hebbian Rule.
- The U.S Navy funded it for potential applications like image recognition.

The AI Revolution

Backpropagation & Deep Learning

Dr. Geoffrey Hinton

Backpropagation

Dr. Fei-Fei Li

ImageNet

Dr. Ashish Vaswani

Transformers

Artificial Neural Networks

Are Just Tensor Transformations..

$$\mathbf{a}^{[l]} = f^{[l]}\left(\mathbf{W}^{[l]}\mathbf{a}^{[l-1]} + \mathbf{b}^{[l]}\right), \quad l = 1, 2, \ldots, L$$

They work great on Von Neumann Architecture..

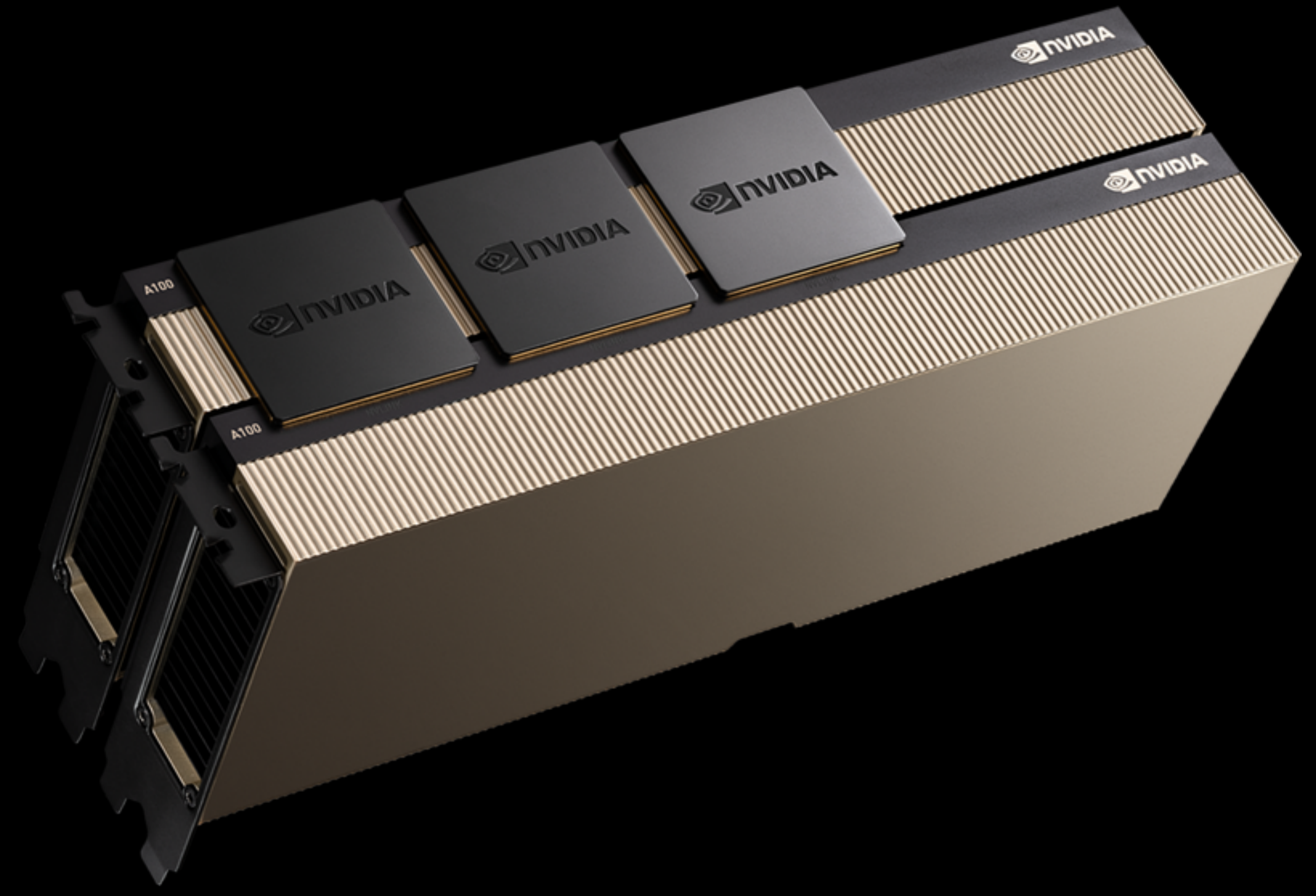
But are they really Bio-Accurate?

Limitations of ANNs

Energy-Hungry

Human Brain

Around 20 Watts

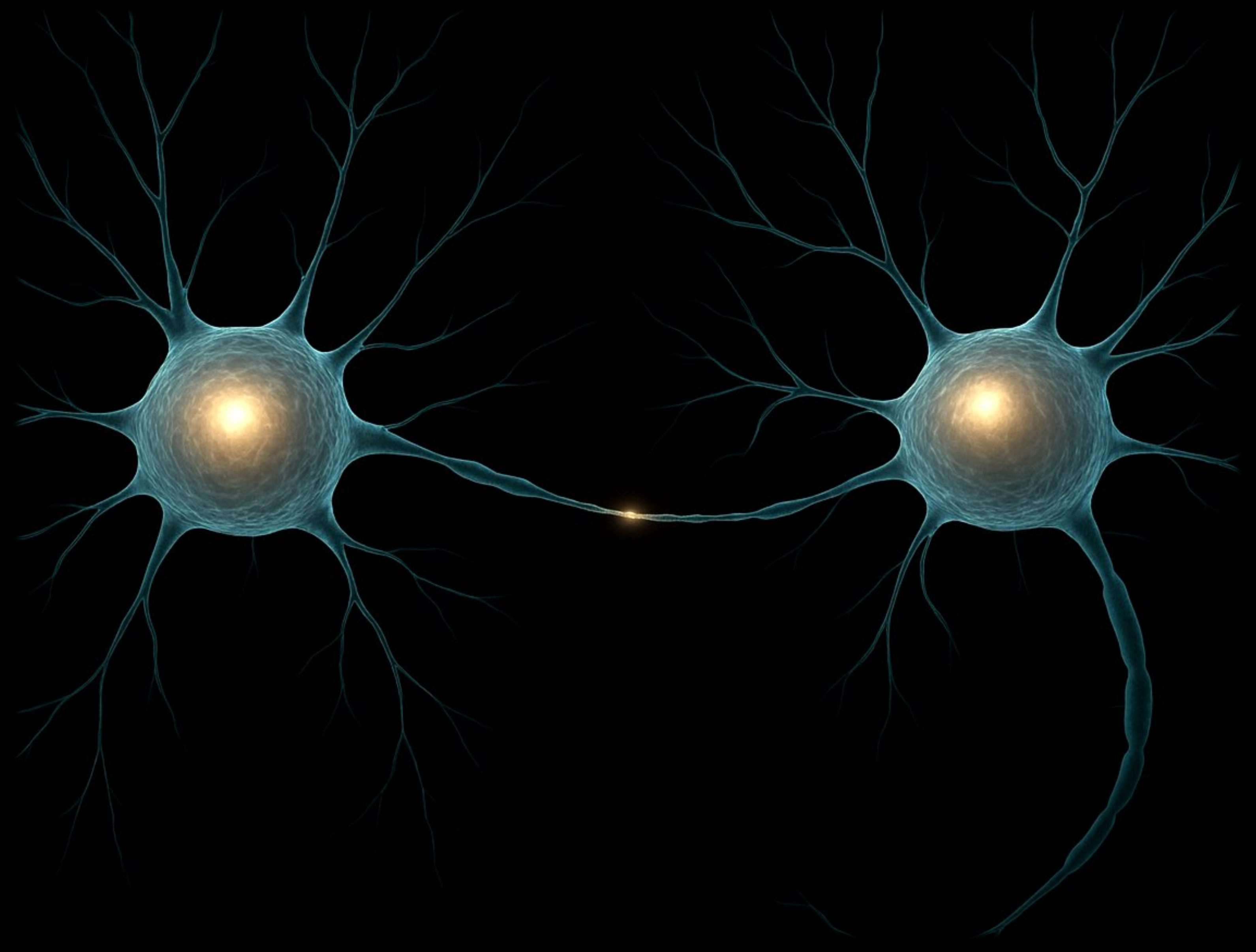


Neumann Based GPUs

Hundreds of Watts

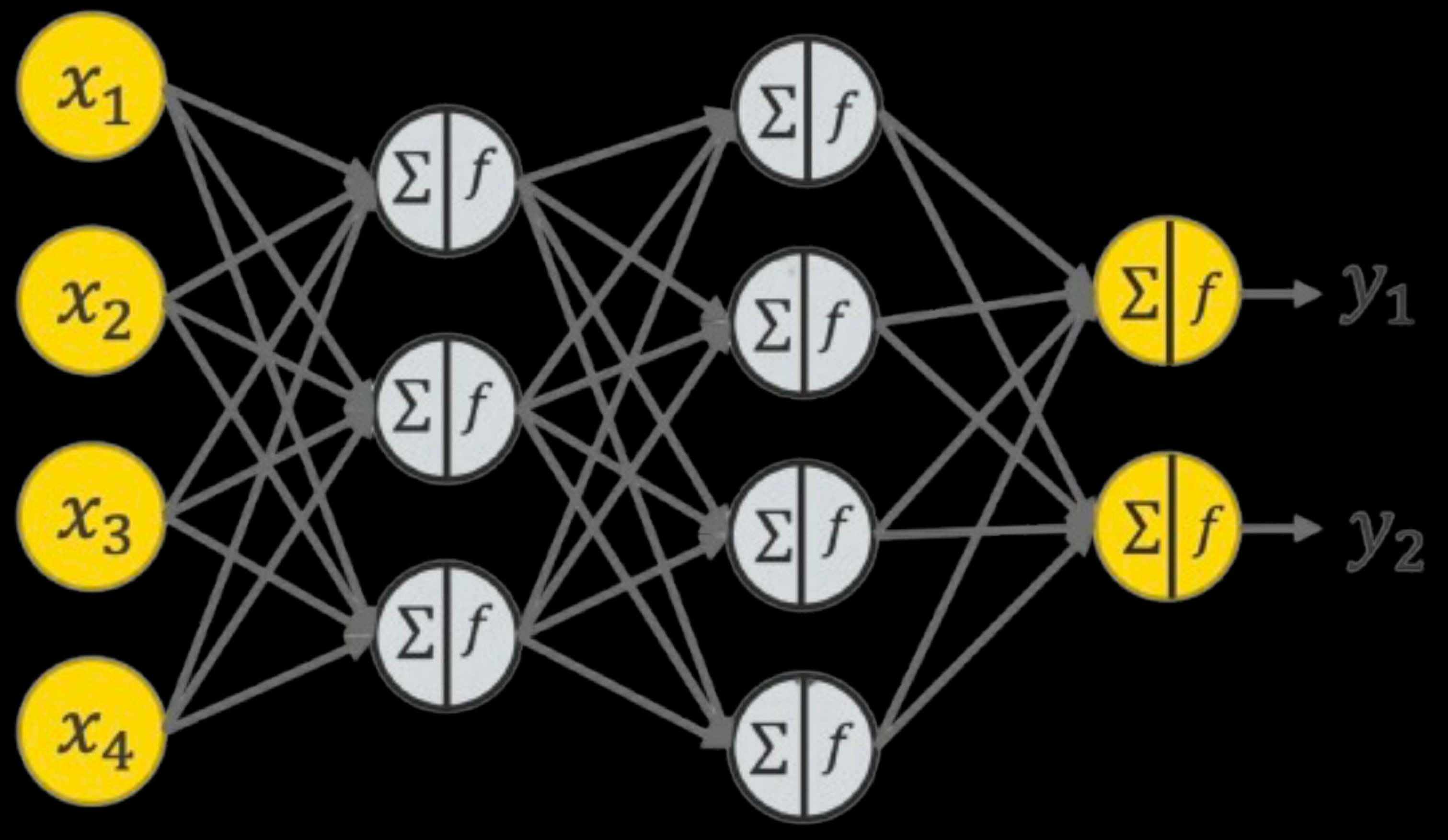
Limitations of ANNs

Inefficient for Temporal Data



Biological Nervous System

Event Driven Activations

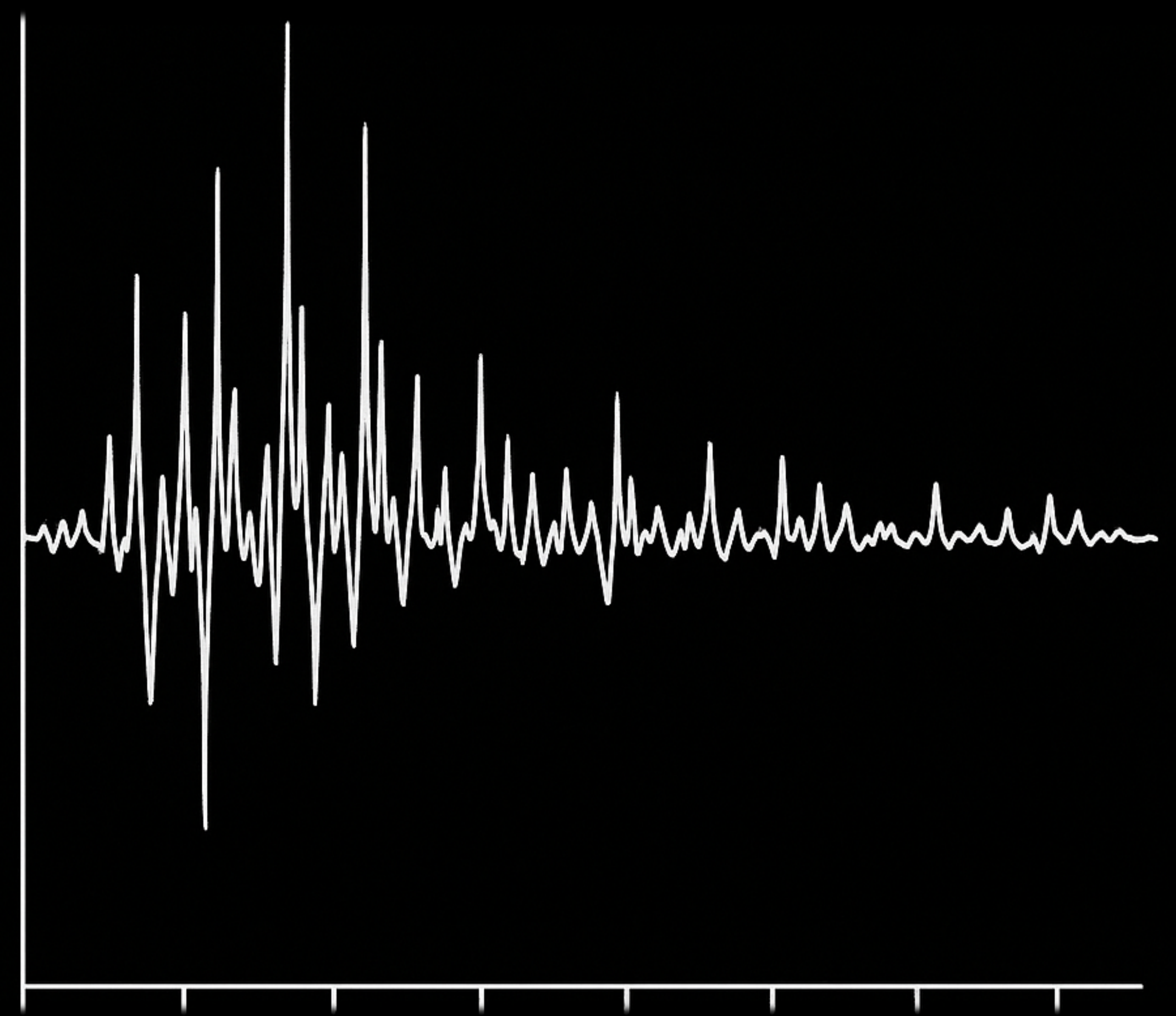


Artificial Neural Networks

Redundant Computations

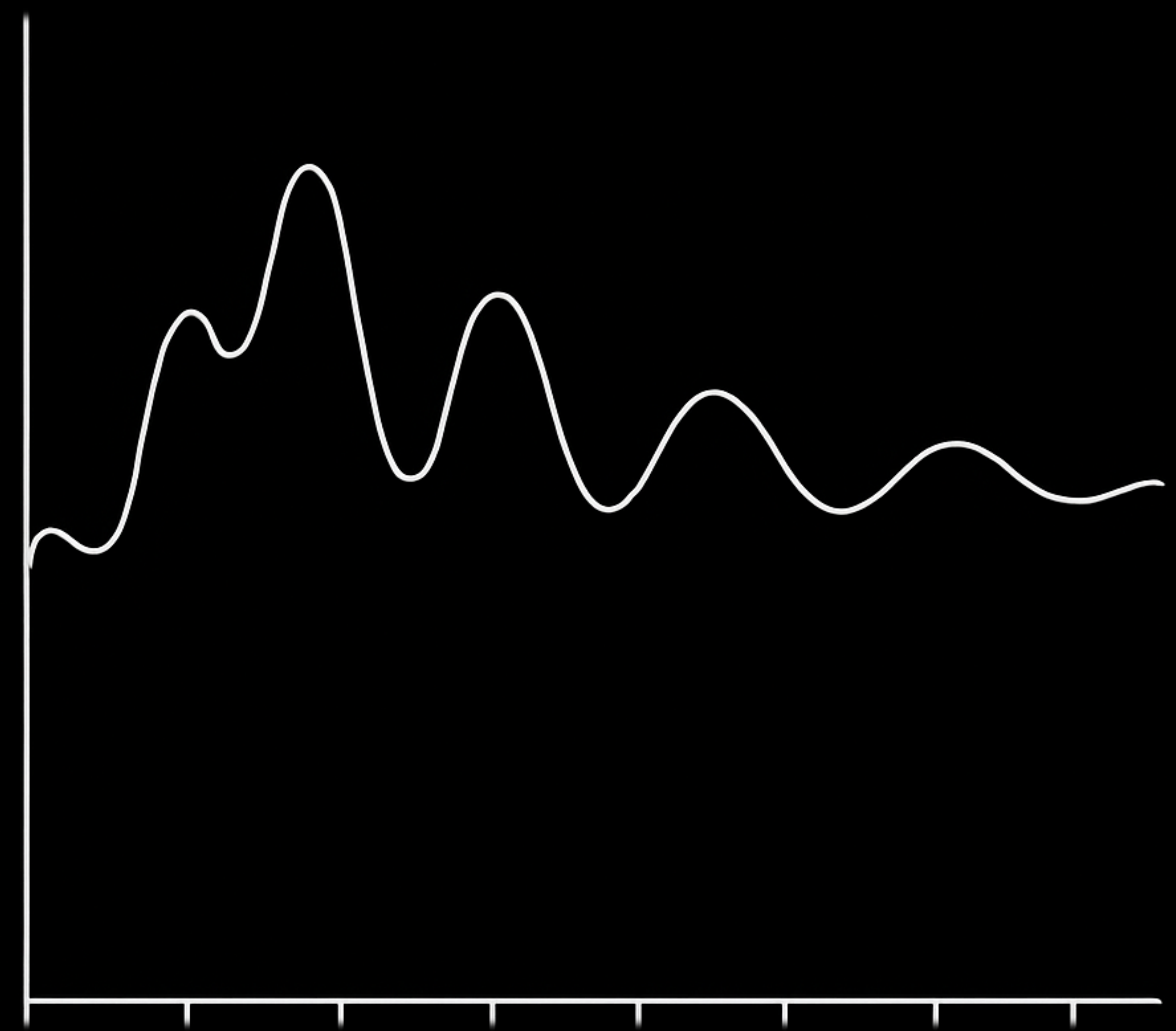
Limitations of ANNs

Biological Mismatch



Brain Signals

Discrete Spikes



Artificial Neural Networks

Continuous Activations

Spiking Neural Networks

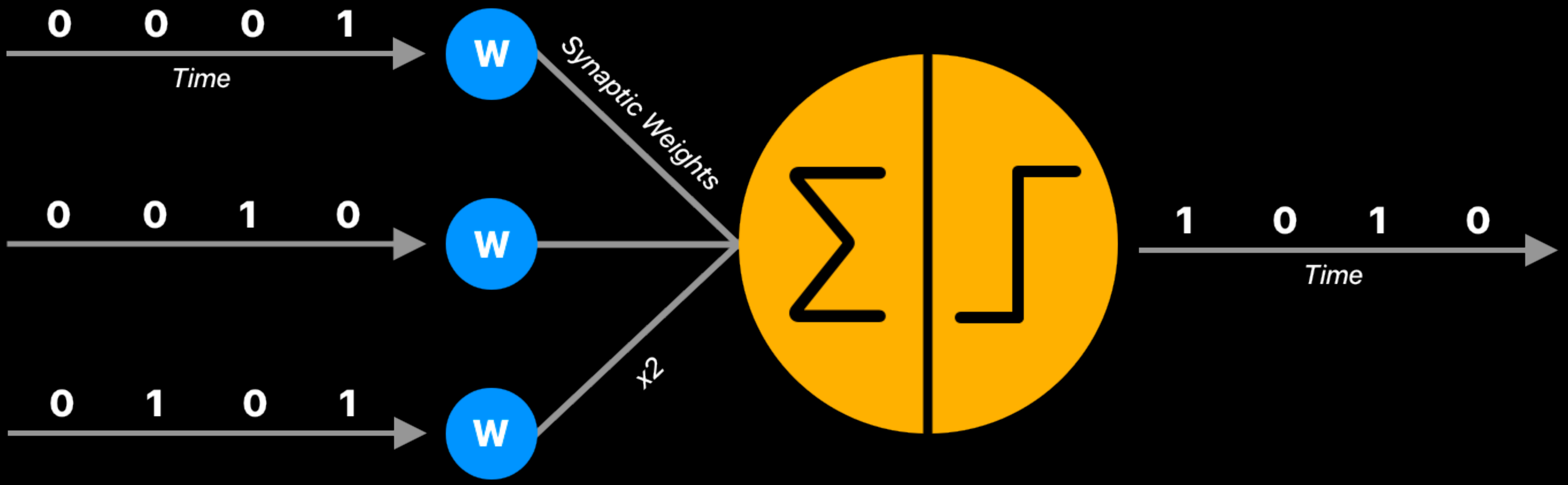
The Birth of SNNs

Wolfgang Maass (1997)

- Third-Generation Networks, after Perceptrons and ANNs.
- Temporal coding with spike timing encodes information.
- Closer to Biology, where they model actual neuron communication patterns.

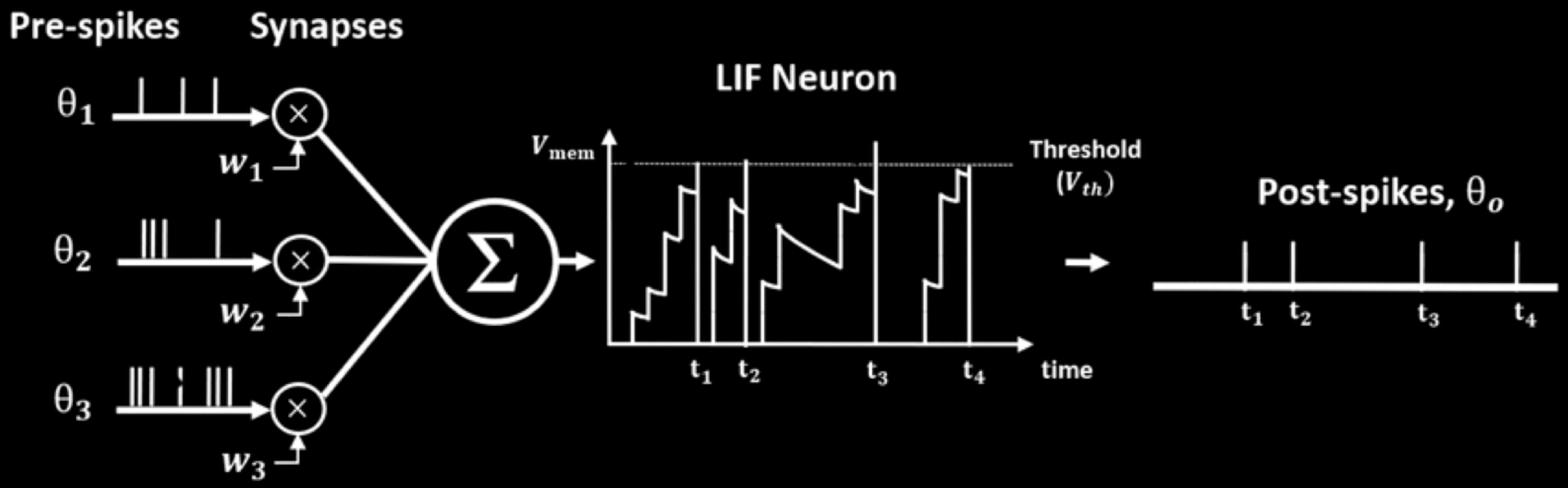
Spiking Neuron

How does it work?



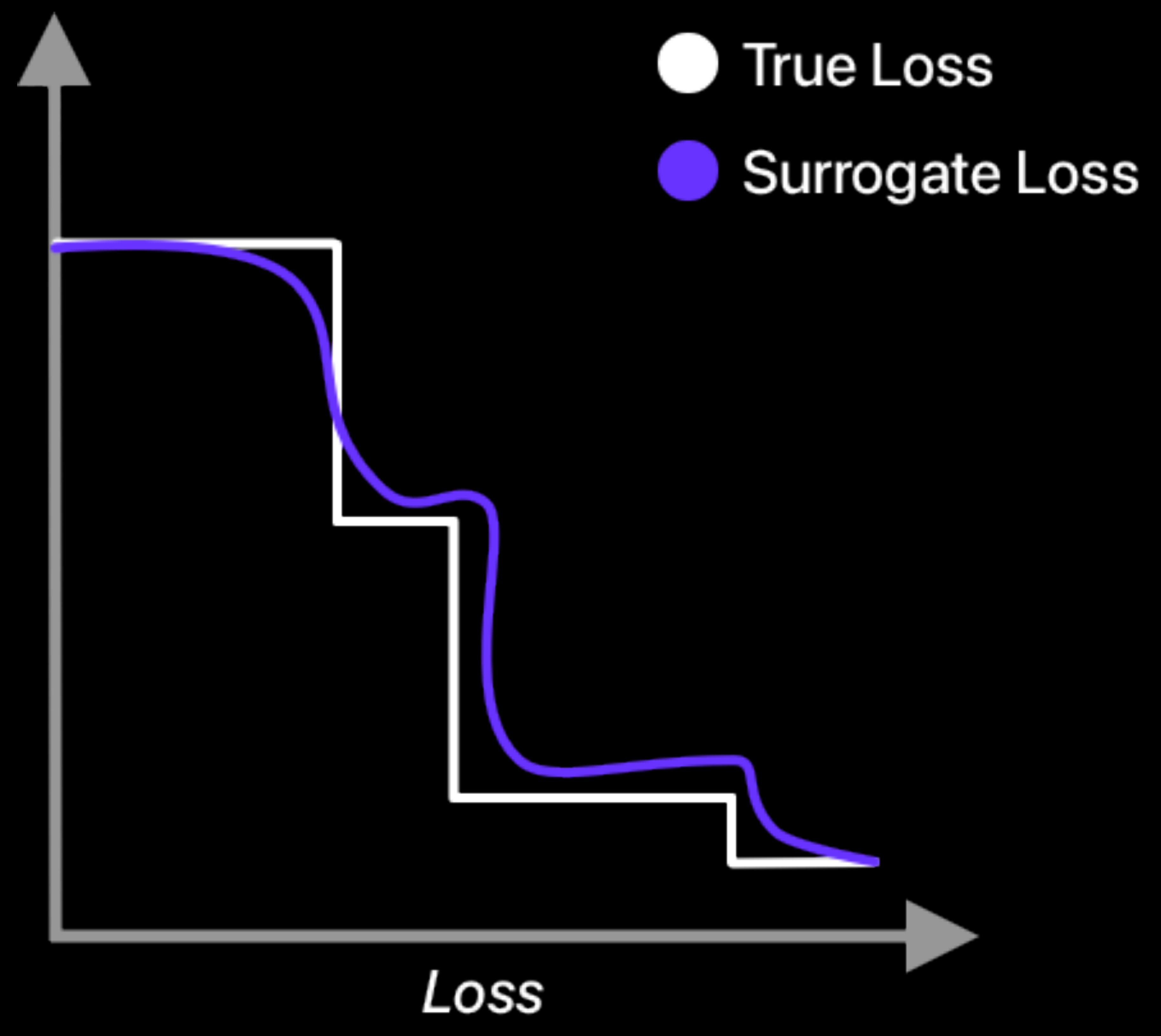
Leaky-Integrate & Fire (LIF)

In Spiking Neural Networks



How to train them?

Surrogate Gradient Descent



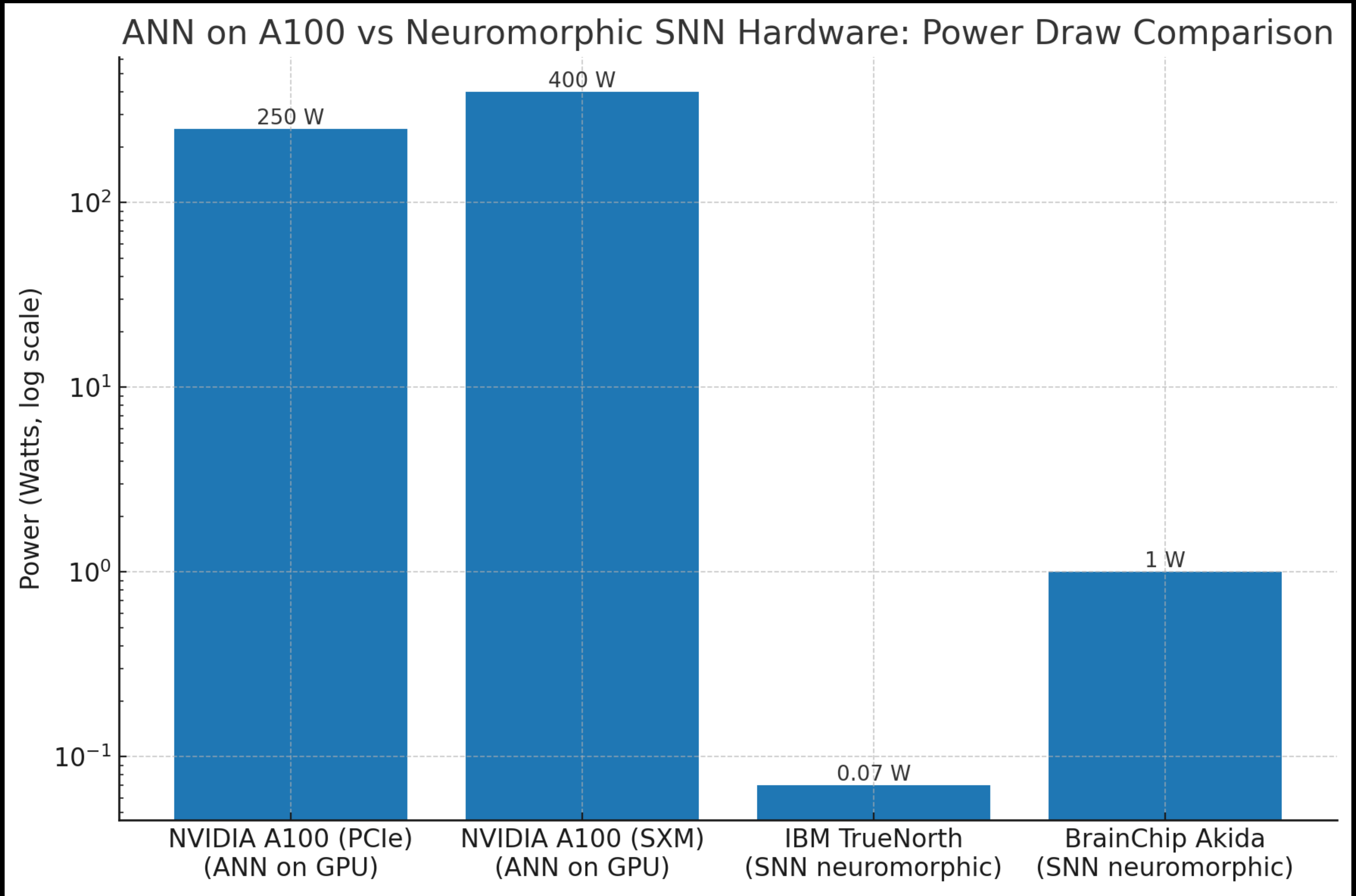
Neuromorphic Computing

Brain-Like Processors

- Have the structure and function of Biological Neural Networks.
- Examples: IBM TrueNorth, Intel Loihi, SpiNNaker.
- Processes spikes like neurons, idle when unneeded, saving power.

Super Energy Efficient

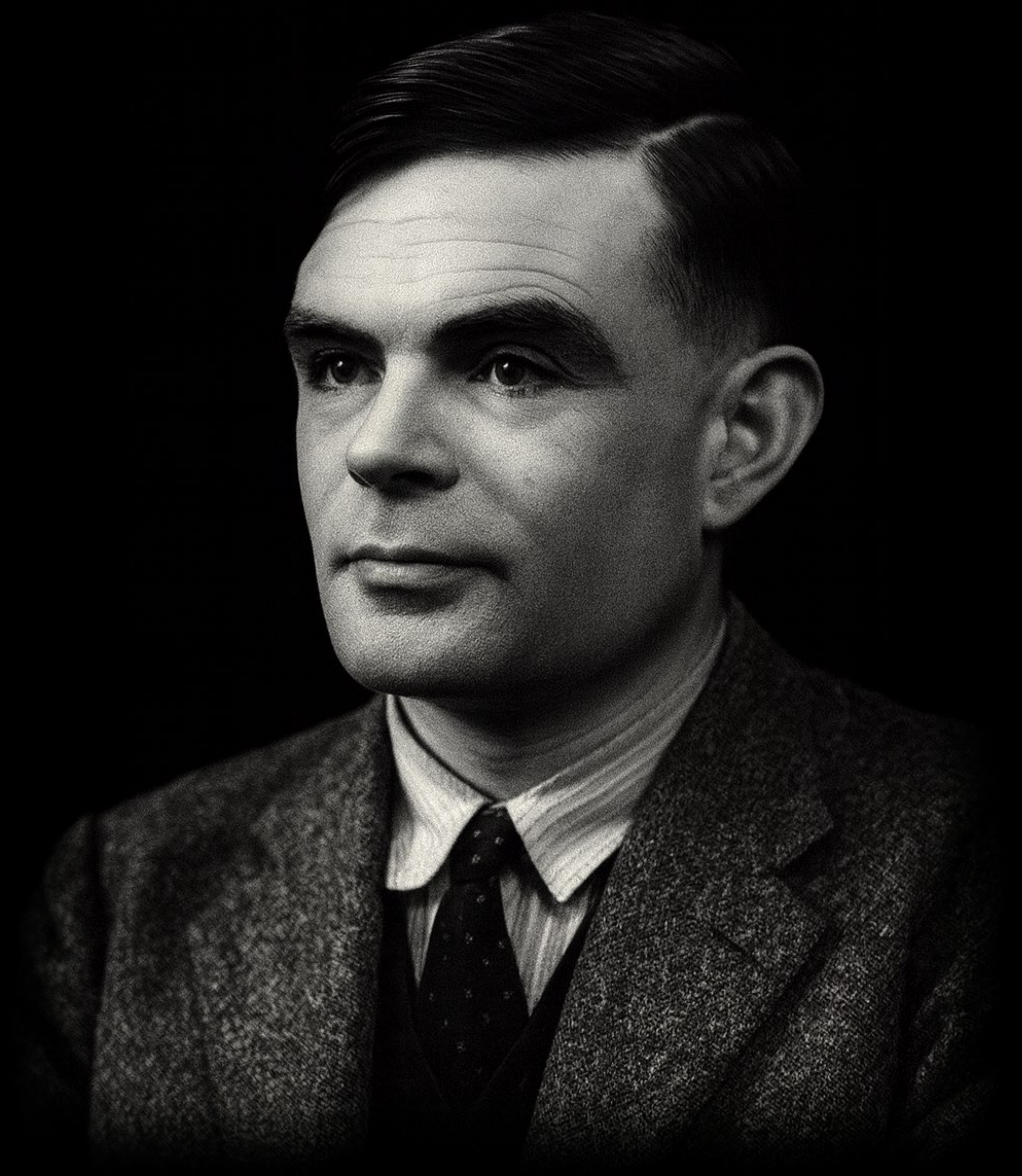
No Redundant Computations



Evolving Neural Networks

“Instead of trying to produce a program to simulate the adult mind, why not rather try to produce one which simulates the child’s?”

— Alan Turing, Godfather of CS & AI.



Genetic Algorithms

Nature's Optimization Blueprint

- **Initialization**: Create a population of candidate solutions (organisms).
- **Evaluation**: Assign fitness scores based on performance.
- **Selections**: Choose the fittest to reproduce.
- **Crossover**: Combine genetic material from parents.
- **Mutation**: Introduce small random changes to maintain diversity
- **Replacement**: Form a new generation and repeat.

Goal: Incrementally improve solutions until optimal or near-optimal performance is reached

Where It All Began

Kenneth O. Stanley (2002)

- Invented NEAT: NeuroEvolution of Augmenting Topologies.
- Builds on GAs, evolves both the weights and network topology over generations.
- Enabled more complex behaviors without predefining the architecture.

Phenotype & Genotype

In Nature

Phenotype

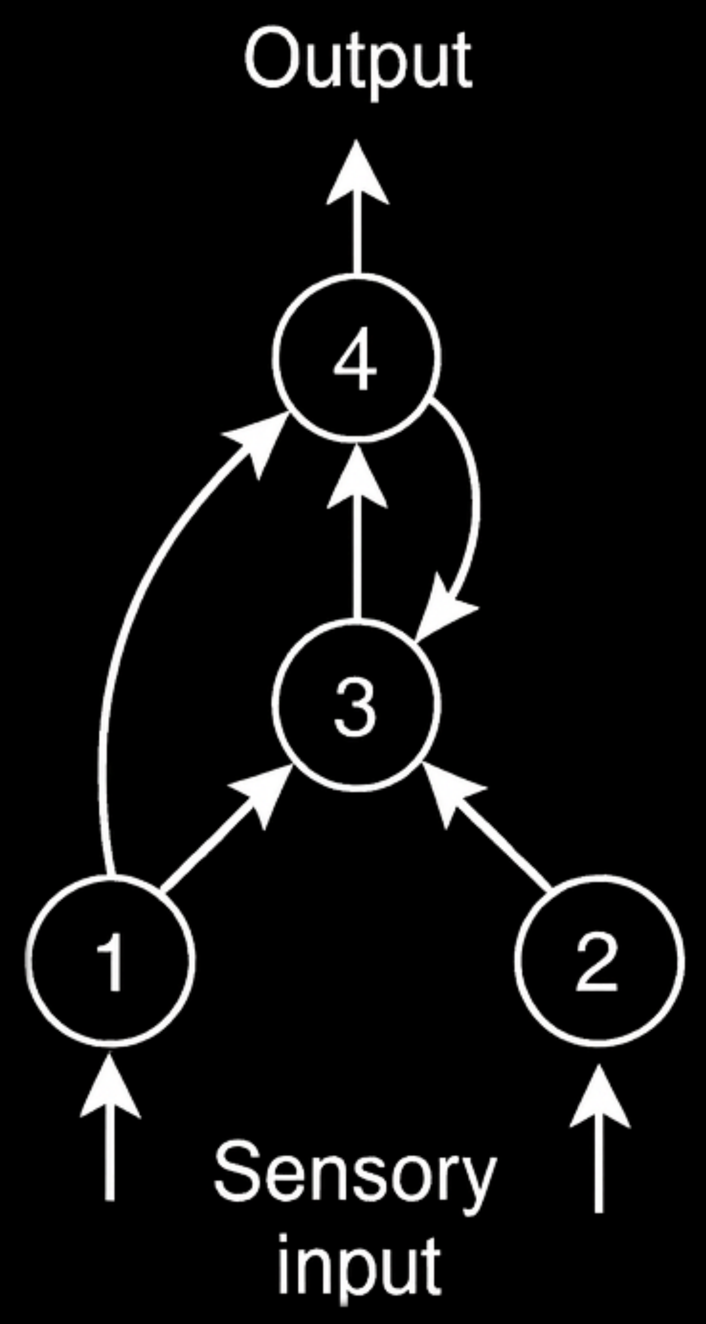
Body, Traits, & Behaviour

Genotype

The Genetic Blueprint

Phenotype & Genotype

In NEAT



Phenotype

The Actual Neural Network

Node genes

Node 1 Sensor	Node 2 Sensor	Node 3 Hidden	Node 4 Output

Connection genes

In 3 Out 4 Weight 0.2 Enabled Innov 1	In 1 Out 4 Weight 0.2 Enabled Innov 5	In 2 Out 4 Weight −1 DISABLED Innov 3
In 2 Out 2 Weight 0.3 Enabled Innov 4	In 4 Out 3 Weight 0.5 Enabled Innov 9	In 1 Out 3 Weight 0.5 Enabled Innov 10

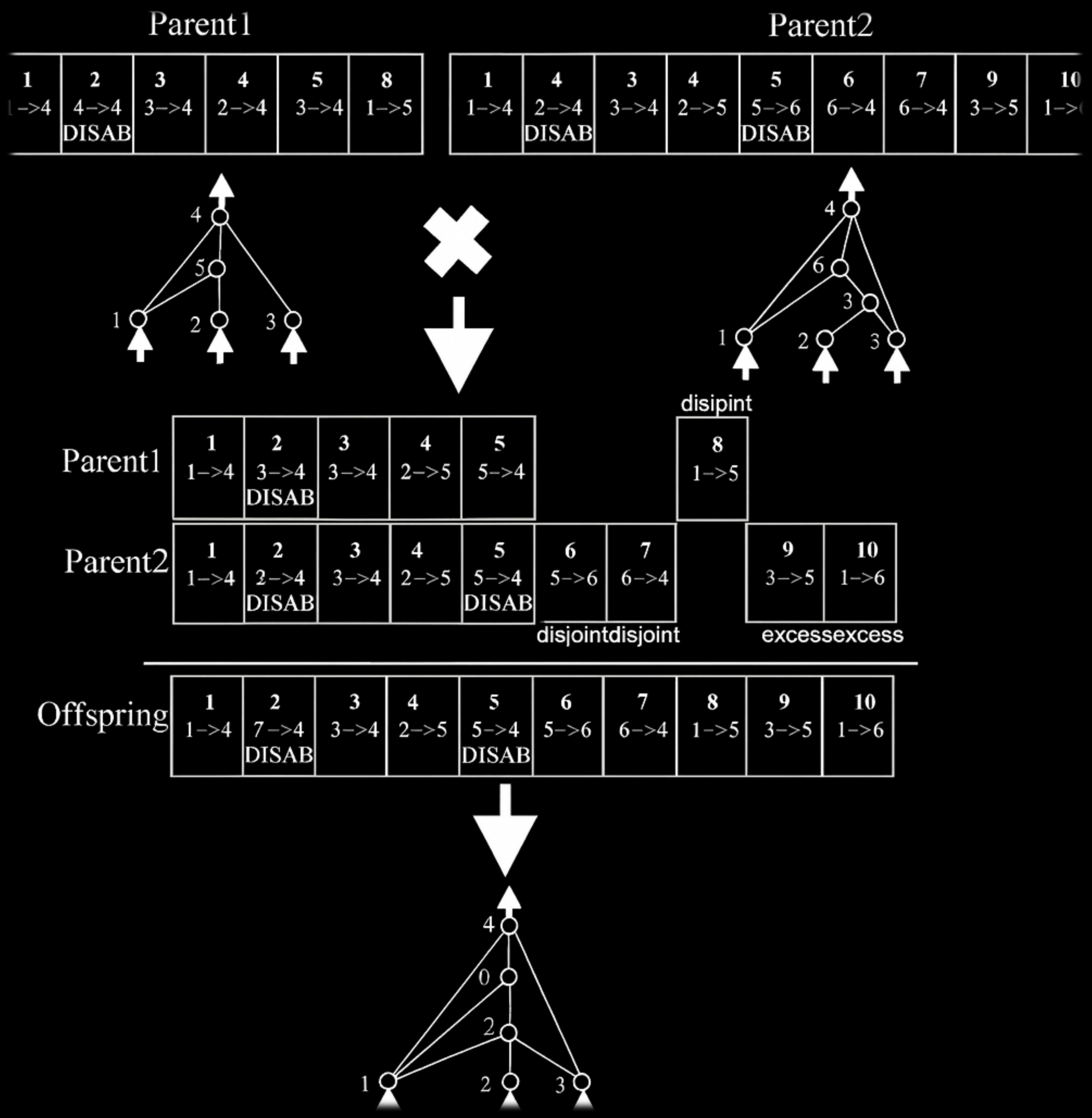
Genotype

The Encoded NN Structure

Evolving Neural Nets

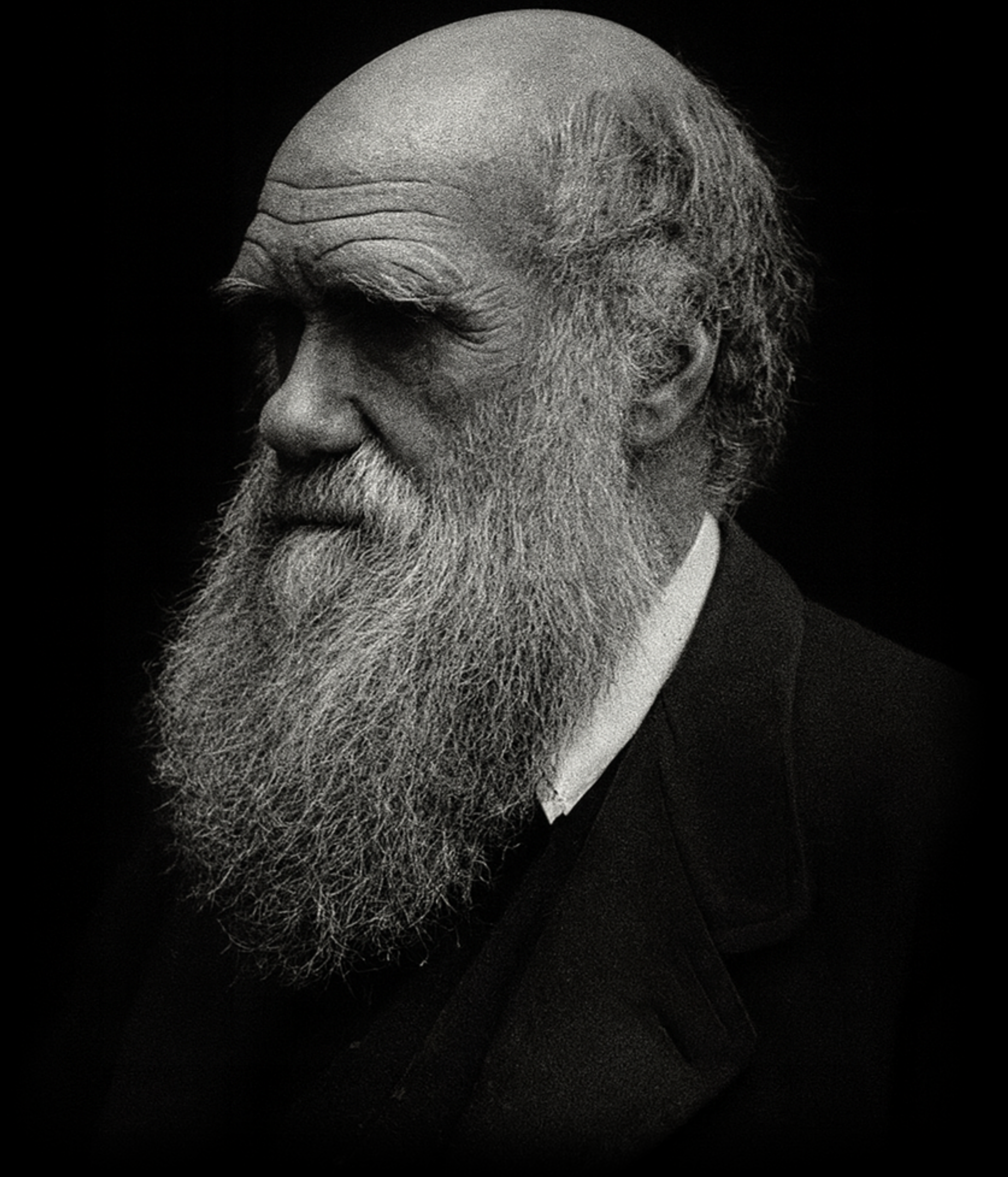
Crossover in NEAT

- Select the elite NNs to be parents.
- Align genes from parents using innovation numbers.
- Randomly copy matched genes; in case of a mismatch, take from the fittest parent.
- Perform random mutations; each new mutation gets an innovation number.



“It is not the strongest of the species that survive, nor the most intelligent, but the one most responsive to change.”

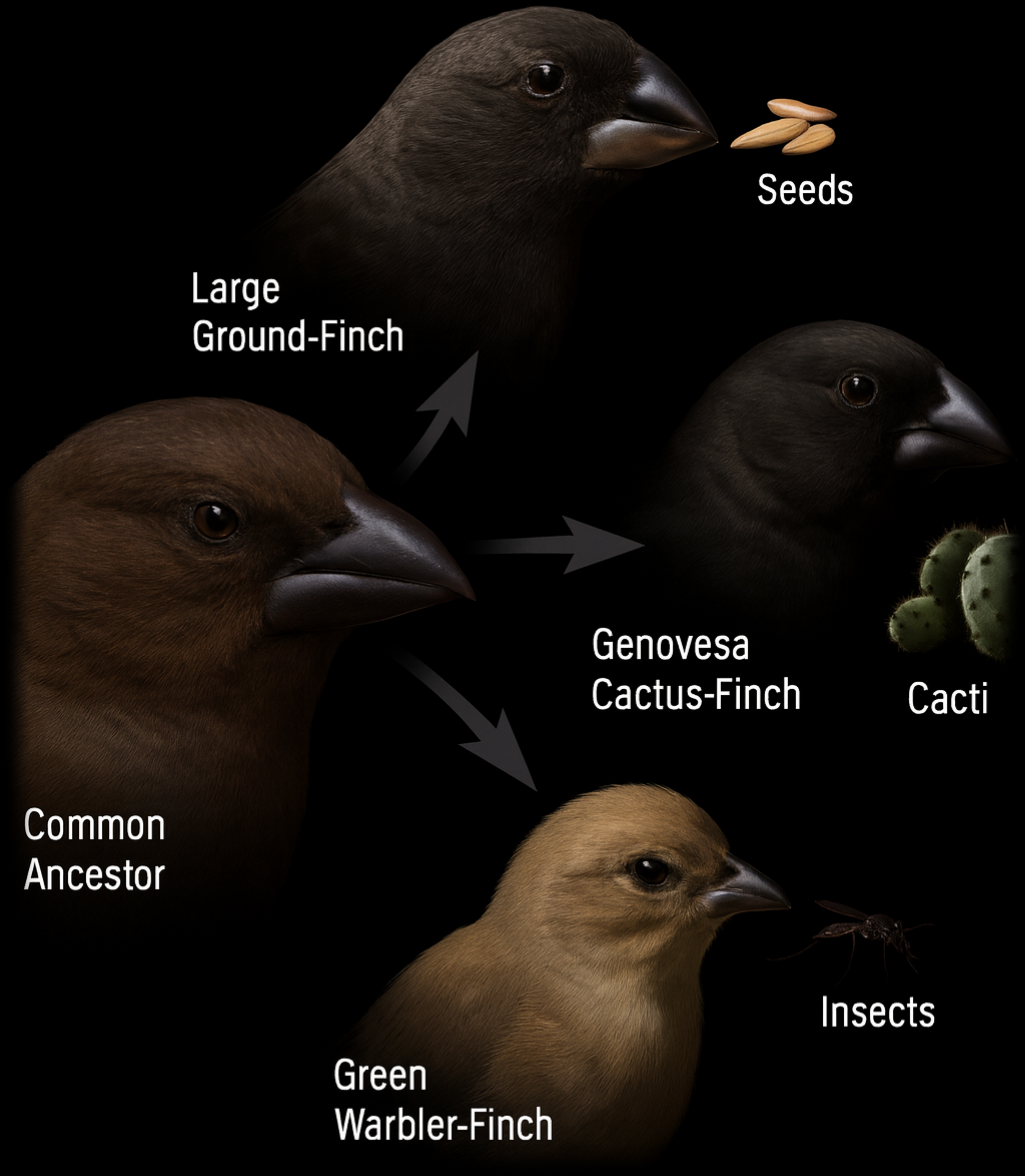
— Charles Darwin, Father of Evolution.



Protecting Innovation

By speciation

- Why? Novel structures might start weak, but they may be into something…
- In NEAT, calculate genetic similarity between organisms.
- Group similar organisms into species.
- Assign fitness sharing so no single species dominates too soon.



Q&A and Discussion

What’s missing?

Thank You!