模拟生物智能的神经形态认知计算

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脑机智能全国重点实验室

Is the Brain a Computer?

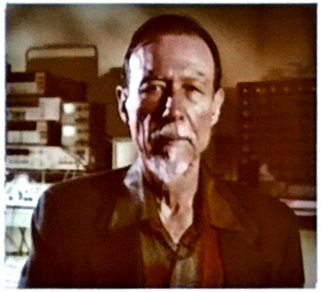
It is a long debate: Is the Brain a Computer?

Alan Turing

in 1950 predicted that by 2000 machine could think like human brains

John von Neumann

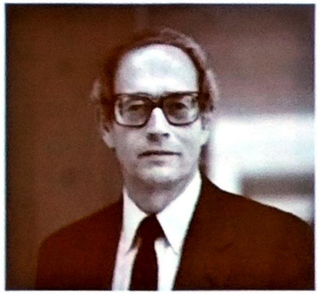
"brain is an arithmetic organ"



Carver Mead

A pioneer of modern microelectronics, creating "neuromorphic electronic systems"

"to synthesize it to fully understand it"



Gerald Edelman

1972 Nobel Prize in Physiology or Medicine

"brain is not a computer"

NCRC

Is the Brain a Computer?

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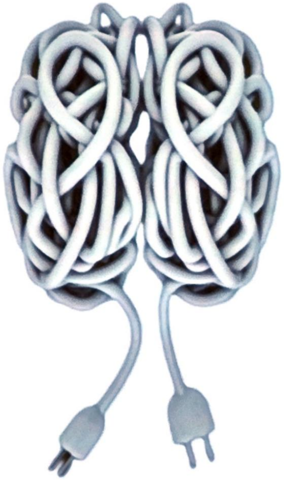
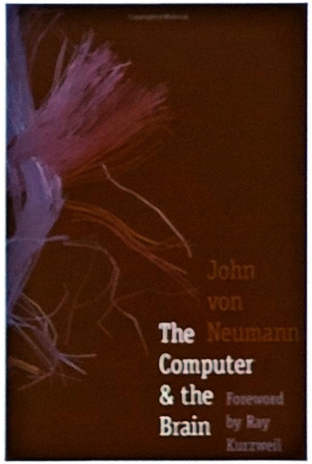




THE BRAIN IS A COMPUTER

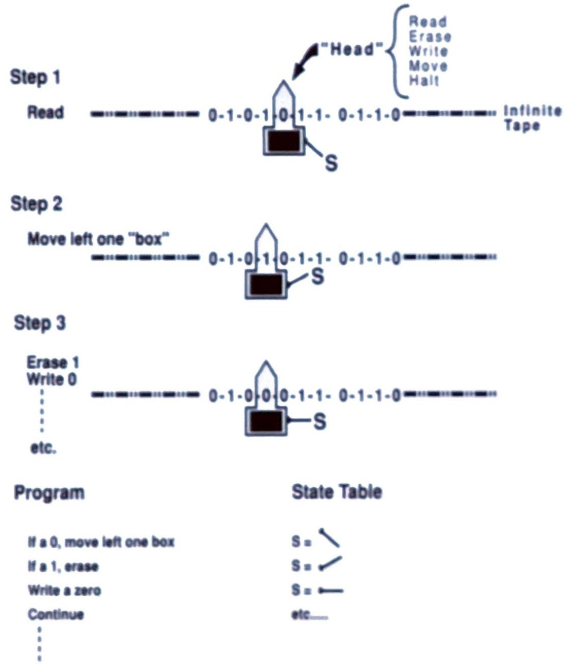
Von Neumann takes the fundamental operator of the brain to be the neuron, and he represents the neuron as a digital device (in spite of its evident analog electrochemical properties). "A neuron transmits a pulse. The nervous pulses can clearly be viewed as (two-valued) markers. The absence of a pulse then represents one value (say, the binary digit 0), and the presence of one represents the other (say, the binary digit 1). The nervous system has a prima facie digital character. "

The Computer and the Brain, John von Neumann

NCRC

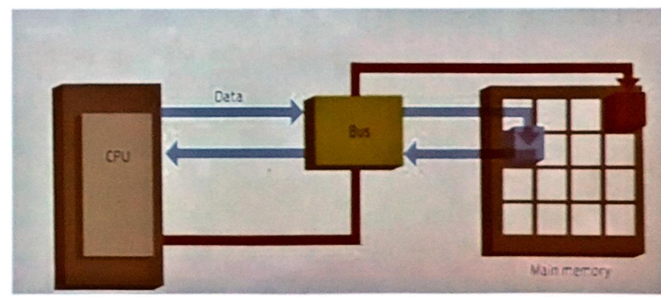
计算机算法与架构

Alan Turing



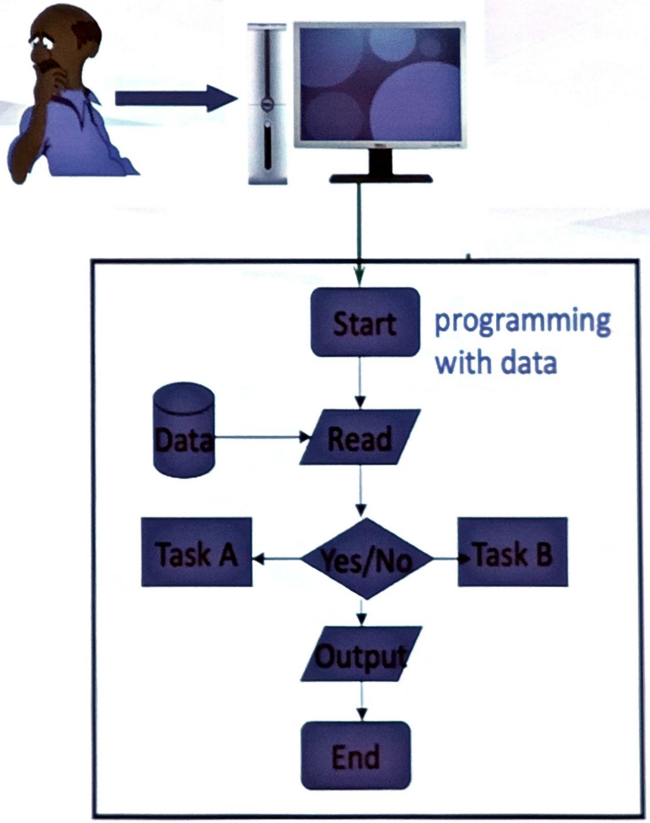
John von Neumann
冯·诺伊曼

ENIAC, the first electronic computer



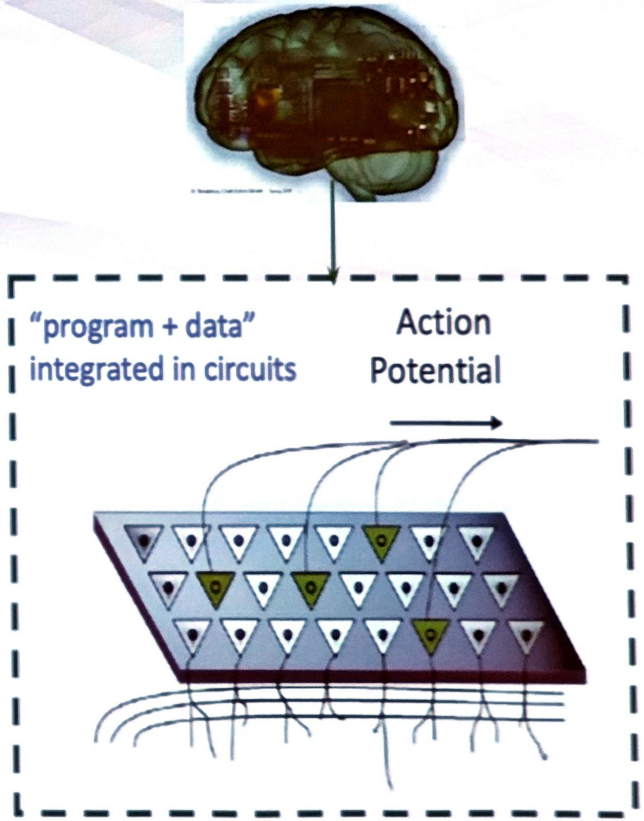
A computing substrate (von Neumann architecture) is completely detached from algorithms (Turing Machine framework)

AI Based



- Constructed by explicit programming
- Closed (designed)
- Centralized control

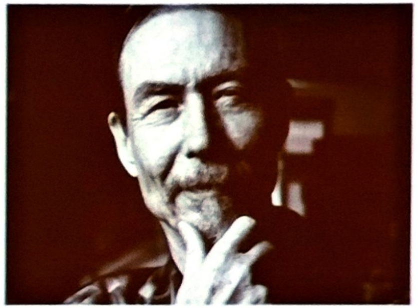
Brain



- Learn autonomously and process signals from the environment
- Open (situated)
- Distributed in nature

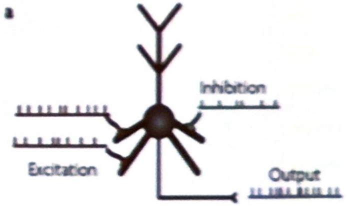
Neuromorphic Computing and Engineering

- Neuromorphic engineering is an interdisciplinary subject that takes inspiration from biology, physics, mathematics, computer science, and electronic engineering to design artificial neural systems, such as vision systems, head-eye systems, auditory processors, and autonomous robots, whose physical architecture and design principles are based on those of biological nervous systems. Neuromorphic engineering was first proposed by Carver Mead in the late 1980s.



Carver Mead, 加州理工教授

- Neuromorphic computing works by mimicking the physics of the human brain and nervous system by spiking neural networks, where spikes from individual electronic neurons activate other neurons down a cascading chain. It is analogous to how the brain sends and receives signals from biological neurons that spark or recognize movement and sensations in our bodies. As opposed to more traditional approaches, where systems orchestrate computation in rigid binary terms (1/0), neuromorphic chips compute more flexibly and broadly. Its spiking neurons operate without any prescribed order. (https://www.hpe.com/us/en/insights/articles/whats-this-neuromorphic-computing-youre-talking-about-2105.html)



Is the Brain a Computer?

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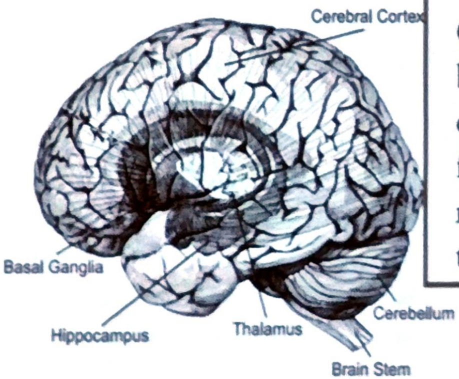
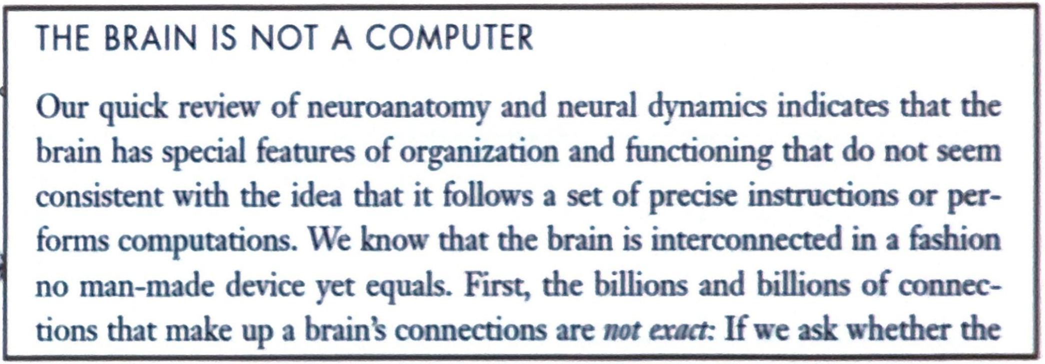




THE BRAIN IS NOT A COMPUTER

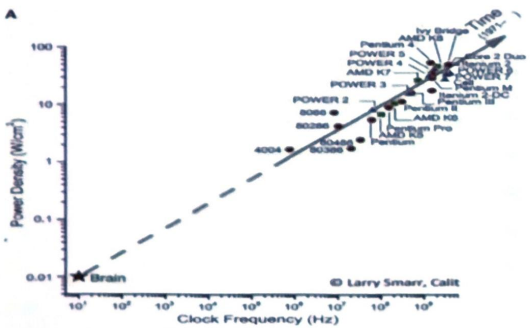
Our quick review of neuroanatomy and neural dynamics indicates that the brain has special features of organization and functioning that do not seem consistent with the idea that it follows a set of precise instructions or performs computations. We know that the brain is interconnected in a fashion no man-made device yet equals. First, the billions and billions of connections that make up a brain's connections are *not exact:* If we ask whether the

A universe of consciousness, G.E. Edelman and G. Tononi

- Is your brain a computer? https://www.technologyreview.com/2021/08/25/1030861/is-human-brain-computer/
- Why your brain is not a computer. https://www.theguardian.com/science/2020/feb/27/why-your-brain-is-not-a-computer-neuroscience-neural-networks-consciousness
- Why can't a computer be more like a brain? April 2007 | IEEE Spectrum

The Essence of the Current AI

◆Feats and Defeats: 数据、算力、算法



Conventional computing is moving away from the brain

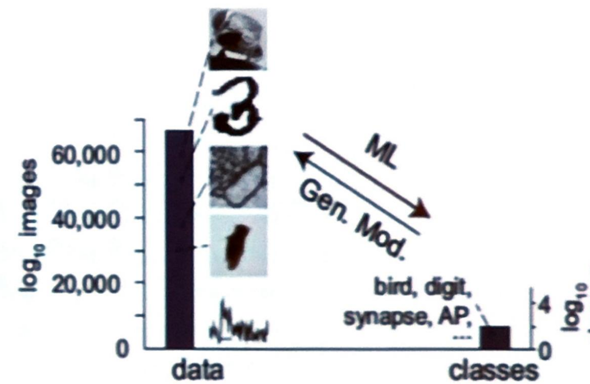

MENU nature

EDITORIAL · 06 FEBRUARY 2018

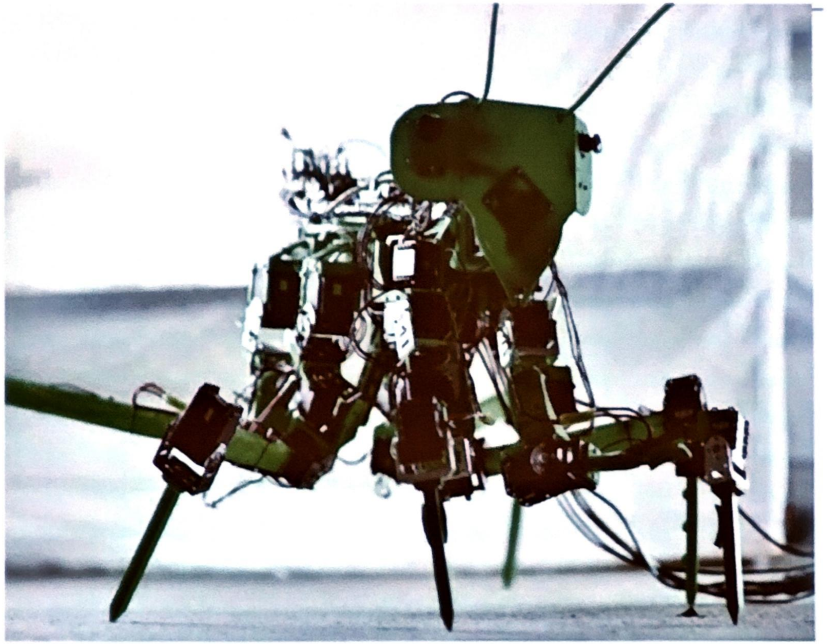
Big data needs a hardware revolution

Artificial intelligence is driving the next wave of innovations in the semico

Software companies make headlines but research on computer hardware could bring bigger rewards.



- Big data
- High computation cost,
- Single, small tasks…



NEUROSCIENCE

Robots with insect brains

A literal approach to mechanistic explanation provides insight in neuroscience

By **Barbara Webb**

robot's control program). Despite the vast

"Despite the vast range of insect body types, behaviors, habitats, and lifestyles, there are many surprising consistencies across species in brain organization, suggesting that these might be effective, efficient, and general-purpose solutions."

Number of neurons:

- fruit fly brain (~135,000)
- mouse (70 million)
- human (86 billion).

Barbara Webb. 2020 • VOL 368 ISSUE 6488, Science

Spiking Neuron Model

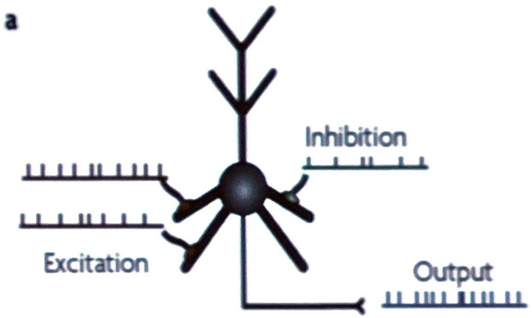
- Leaky Integrate and Fire (LIF)

$$\tau_{\mathrm{m}} \frac{du(t)}{dt} = -[u(t) - u_{rest}] + R_{\mathrm{m}} I(t)$$

τ_{m} : Membrane time constant
$u(t)$: Membrane potential
u_{rest}: Resting potential
R_{m}: Membrane resistance
$I(t)$: Total input current

脉冲神经元的动力学特性 Temporal Dynamics:
膜电位积分、漏电、不应期、脉冲发放

a



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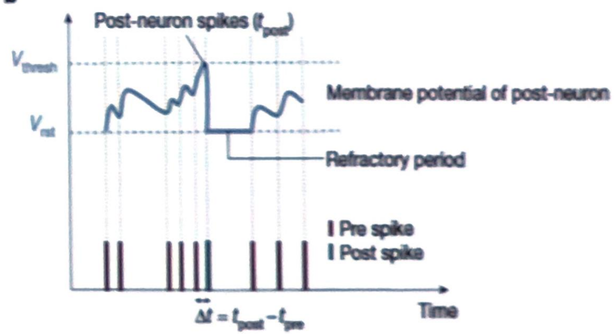
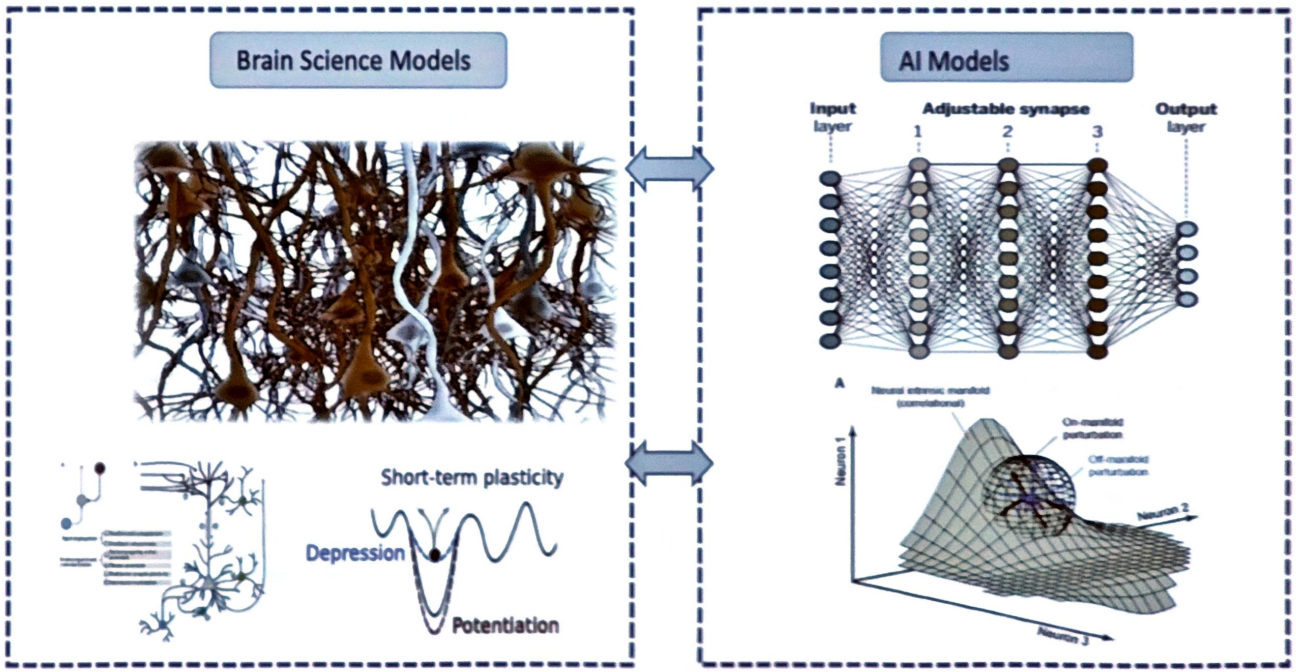


可塑性与网络结构

- Synaptic plasticity vs back propogation;
- Local learning vs global loss function;
- Hierarchical, parallel vs feedforward, lay-wise.



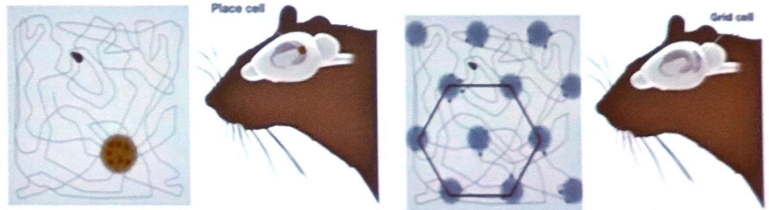
Lillicrap et al, Nature Reviews Neuroscience 2020
Ullman, Science 2019; Leng et al, Scientific reports 2018

内嗅-海马环路模拟

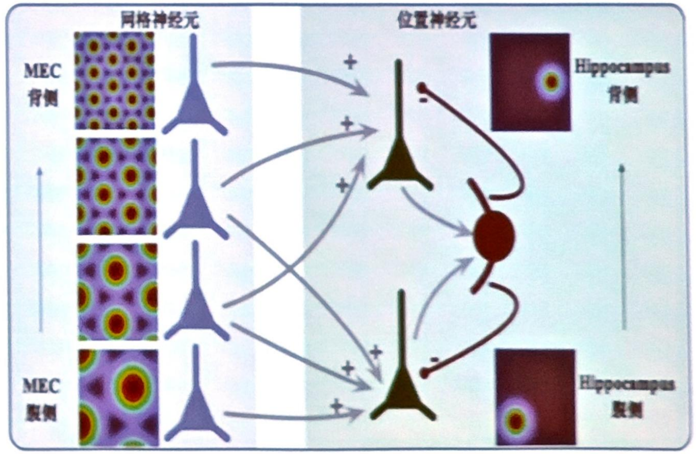
2014诺贝尔生理学或医学奖

John O'Keefe, May-Britt Moser, and Edvard I. Moser

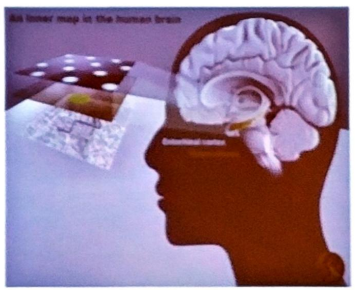
位置神经元　　网格神经元



从网格神经元到位置神经元的连接



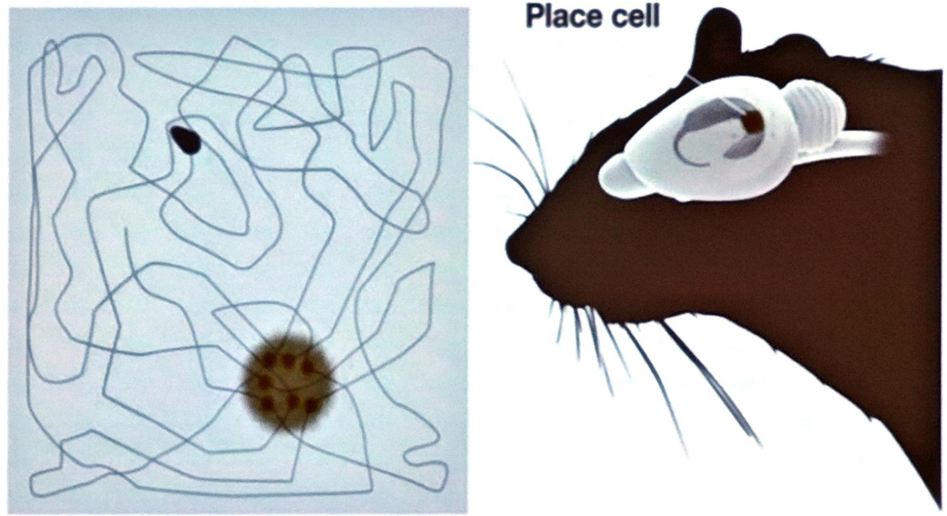
大脑内部GPS系统：认知地图



“这三位诺贝尔奖获得者在此领域做出的贡献代表了人类在理解自身高级认知功能方面的巨大进步，人类逐渐开始了解神经元如何通过集群活动实现导航、记忆和规划等高级活动。”

Nature vol 514, 2014.

Place cells

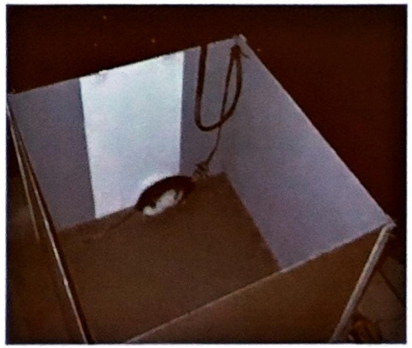


The hippocampus, where the place cells are located is highlighted. The grey square depicts the open field the rat is moving over. Place cells fire when the animal reaches a particular location in the environment. The dots indicate the rat's location in the arena when the place cell is active. Different place cells in the hippocampus fire at different places in the arena.

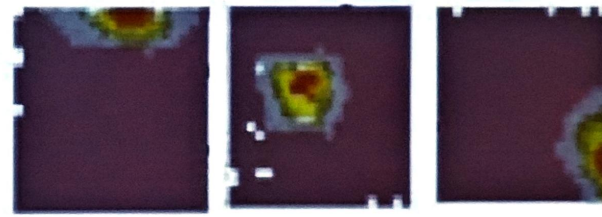
http://www.nobelprize.org/nobel_prizes/medicine/laureates/2014/

Place cells

Box



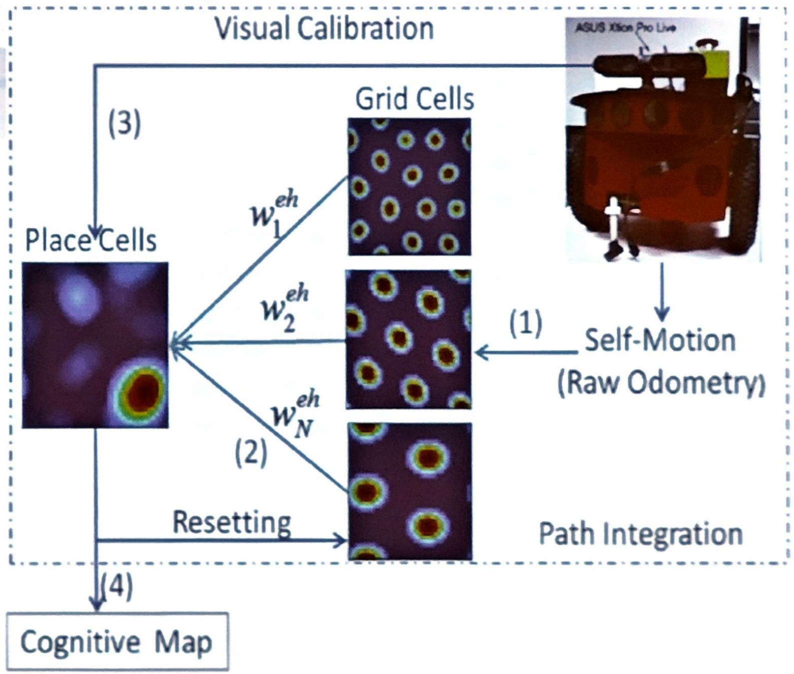
Hippocampal Place Fields



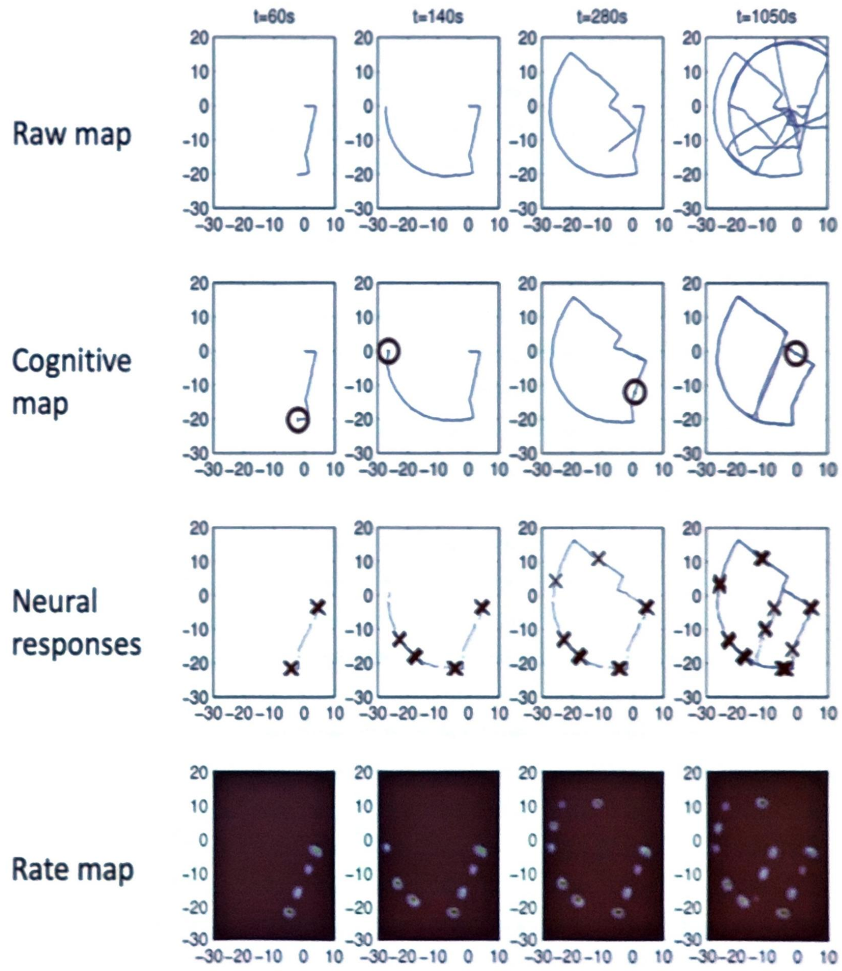
Circular Track

http://krieger.jhu.edu/mbi/knierimlab/research/index.html

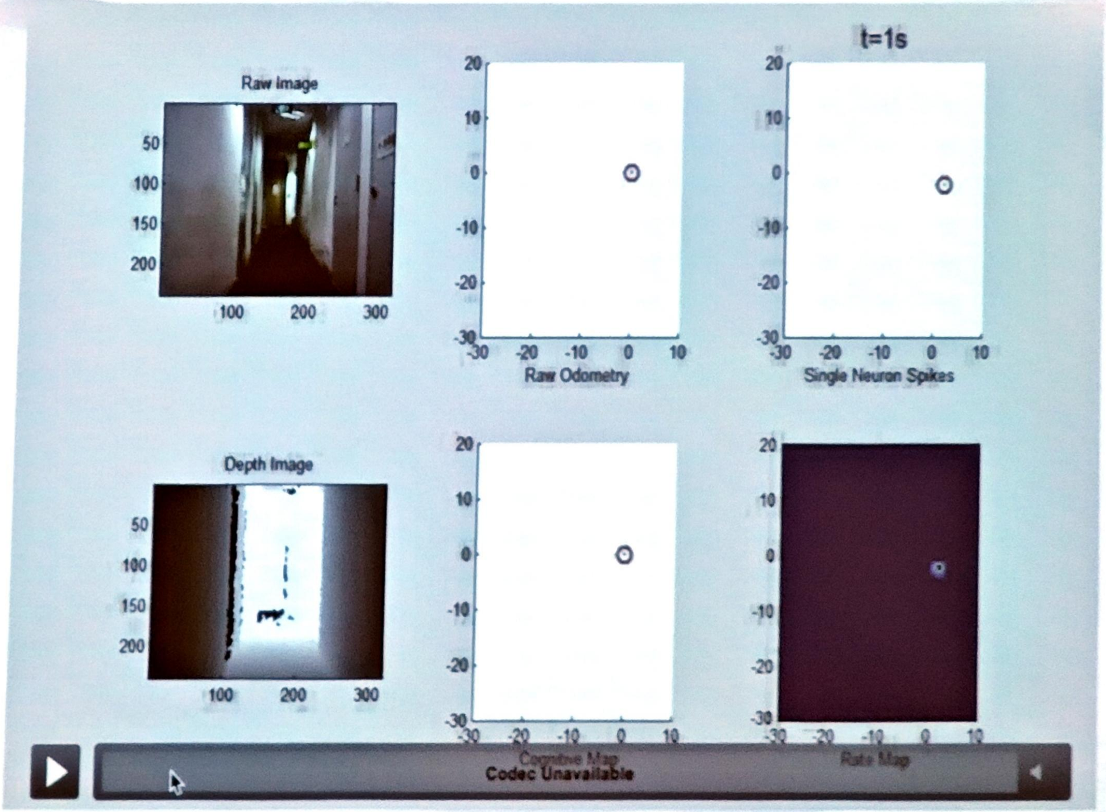
机器人的空间感知系统gSLAM



Yuan et al. An Entorhinal-Hippocampal Model for Simultaneous Cognitive Map Building. AAAI 2015.


t=60s
t=140s
t=280s
t=1050s
Raw map
Cognitive map
Neural responses
Rate map

机器人的空间感知系统gSLAM



MIT Technology Review

ROBOTICS NEWS

2 COMMENTS

A Robot Finds Its Way Using Artificial "GPS" Brain Cells

One robot has been given a simulated version of the brain cells that let animals build a mental map of their surroundings.

By Will Knight on October 19, 2015

The behavior and interplay of two types of neurons in the brain helps give humans and other animals an uncanny ability to navigate by building a mental map of their surroundings. Now one robot has been given a similar cluster of virtual cells to help it find its own way around.

WHY IT MATTERS

Mimicking the functioning of the brain could help make machines more efficient and capable.

Researchers in Singapore simulated two types of cells known to be used for navigation in the brain – so-called "place" and "grid" cells – and showed they could enable a small-wheeled robot to find its way around. Rather than simulate the cells physically, they created a simple two-dimensional model of the cells in software. The work was led by Haizhou Li, a professor at the Agency for Science, Technology and Research (A*STAR).

Science | DOI:10.1145/3231168

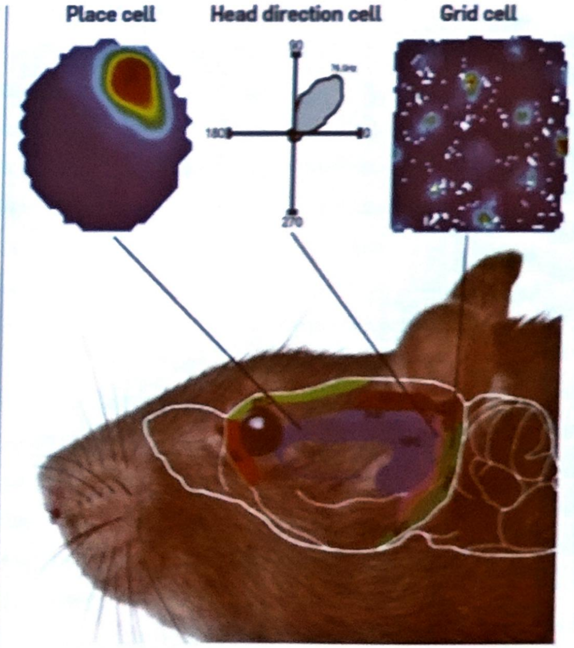
Chris Edwards

Animals Teach Robots to Find Their Way

Navigation research demonstrates bio-machine symbiosis.

A DEMONSTRATION VIDEO that veteran University College, London neuroscientist John O'Keefe often presents in lectures shows a rat moving around the inside of a box. Every time the rat heads for the top-left corner, loud pops play through a speaker; those sounds are the result of the firing of a specific neuron attached to an electrode. The neuron only fires when the rat moves to the same small area of the box. This connection of certain neurons to locations led O'Keefe and student Jonathon Dostrovsky to name those neurons "place cells" when they encountered the phenomenon in the early 1970s.

Today, researchers such as Huajin Tang, director of the Neuromorphic Computing Research Center at Sichuan University, China, are using maps of computer memory to demonstrate how simulated neurons fire in much the same way inside one of their wheeled robots. As it moves around a simple cruciform maze, the machine associates places with pictures of milk cartons, cheese, and apples that it encounters. When asked to find those objects, the same neurons fire. Although the robot looks in the direction of each object when



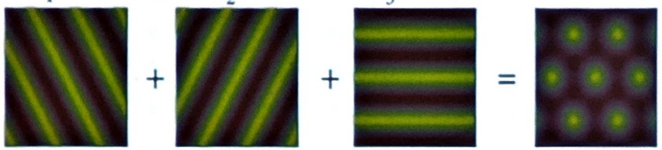
Example cells and a graphic representation of their anatomical distribution in the rat brain. At top left, the firing rate heat map of a place cell recorded as a rat explored a circular arena. Top center, a head direction cell firing rate plot. Top right, firing rate map of a grid cell.

Today, researchers such as Huajin Tang, director of the Neuromorphic Computing Research Center at Sichuan University, China, are using maps of computer memory to demonstrate how simulated neurons fire in much the same way inside one of their wheeled robots.

Communications of ACM, Aug 2018.

Do Grid Cells Form A Metric for Space?

$$c_1 e^{\omega_1' \mathbf{x}} + c_2 e^{\omega_2' \mathbf{x}} + c_3 e^{\omega_3' \mathbf{x}} = g(\mathbf{x})$$



Theorem 1. *Let shift-invariant kernel function $k(\mathbf{x}, \mathbf{y}) = k(\mathbf{x} - \mathbf{y})$ is the Fourier transform of probability distribution function p, we have*

1. *Let $\mathrm{diam}(\mathcal{M})$ be the diameter of $\mathcal{M}$. Then, for the grid cell codes, we have*

$$\Pr\left[\sup_{\mathbf{x},\mathbf{y}\in\mathcal{M}}\left|\sum_{g\in\mathbf{g}} g(\mathbf{x})g(\mathbf{y})^* - k(\mathbf{y}, \mathbf{x})\right| \geq \epsilon\right] \leq 2^8 \left(\frac{\sigma_p \,\mathrm{diam}(\mathcal{M})}{\epsilon}\right)^2 \exp\left(-\frac{N\epsilon^2}{4(m+2)}\right) \quad (2)$$

where $\sigma_p^2 \equiv E_p[\omega^*\omega]$ is the second moment of p, and m is the dimension of $\mathcal{M}$. Further,

$$\sup_{\mathbf{x},\mathbf{y}\in\mathcal{M}}\left|\sum_{g\in\mathbf{g}} g(\mathbf{x})g(\mathbf{y})^* - k(\mathbf{y}, \mathbf{x})\right| \leq \epsilon$$

with any constant probability when

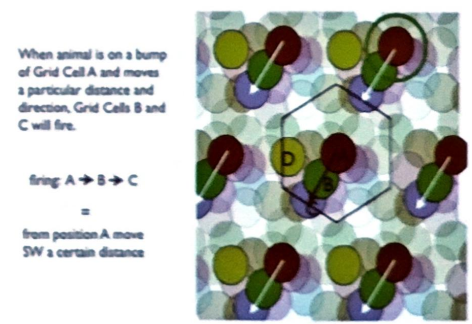
$$N = \Omega\left(\frac{m}{\epsilon^2}\log\frac{\sigma_p \,\mathrm{diam}(\mathcal{M})}{\epsilon}\right)$$

2. *Let $d^2(\mathbf{x}, \mathbf{y}) = k(\mathbf{x}, \mathbf{x}) + k(\mathbf{y}, \mathbf{y}) - 2k(\mathbf{x}, \mathbf{y})$. The kernel distance d embeds isometrically in the Euclidean space $\mathcal{M}$.*

- Grid cells code the space with a spatial resolution that is set by the animal's behavioral requirements, and the supremum of ϵ is a constant with the given resolution.
- The capacity of grid cells grows exponentially with their number.
- As a position encoding method, grid cell population codes "linearize" the metric by mapping the positions to a vector space.

Find which place cell will fire: $\arg\max_{\mathbf{x}\in\mathcal{X}} \sum_{g\in\mathbf{g}} g(\varsigma)g^*(\mathbf{x})$

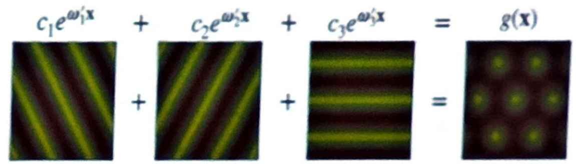
Grid Cell firing patterns in a module code movement distance and direction



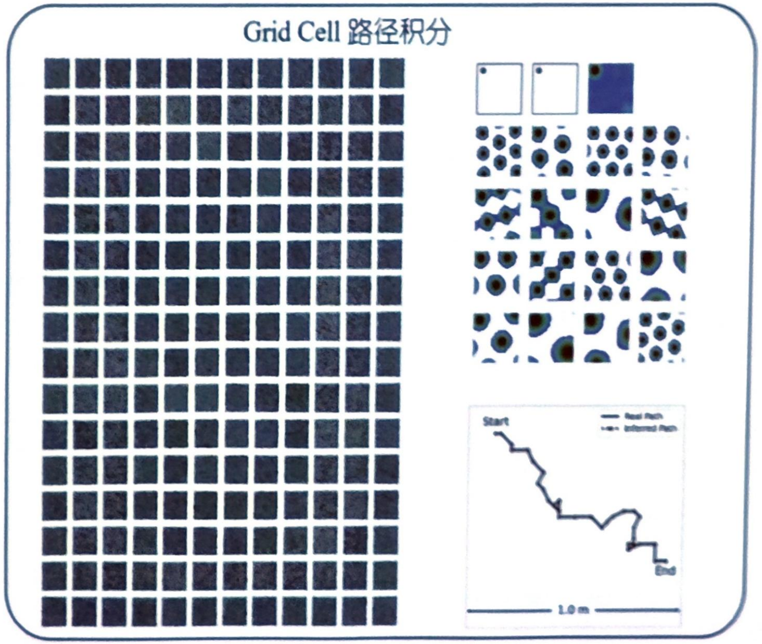
Dang S, Wu Y, Yan R, et al. Why grid cells function as a metric for space[J]. Neural Networks, 2021, 142: 128-137.

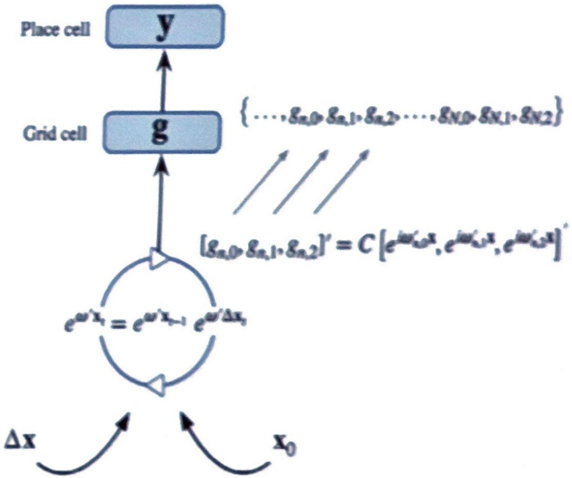
EC-Hippocampus Based Navigation Model

The navigation based on the grid-cell space coding

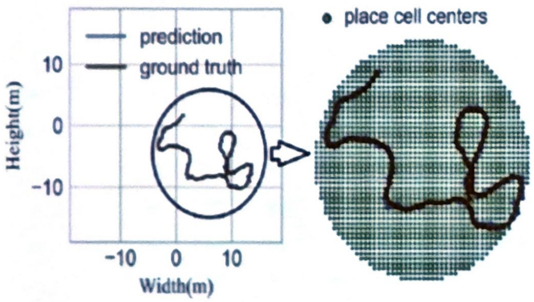


The firing pattern of the grid cell

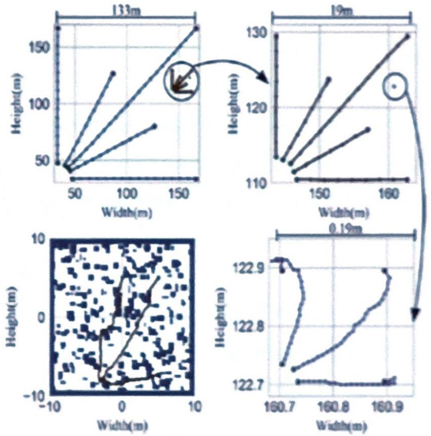




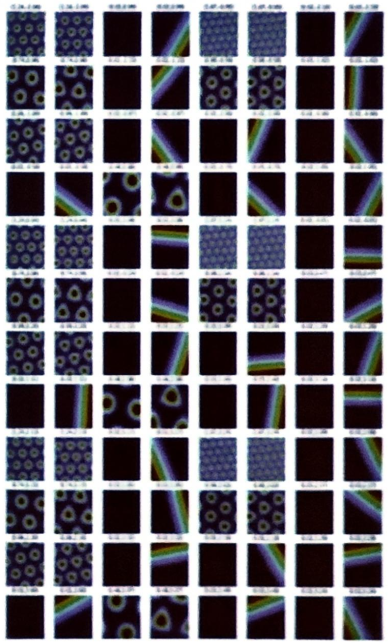
The neural network model to learn the parameters of grid cells。



Accurate path integration



Goal directed navigation



The activities of the grid cells in 19m×19m square area. The upper titles on each image are the scale and orientation of the grid cell.

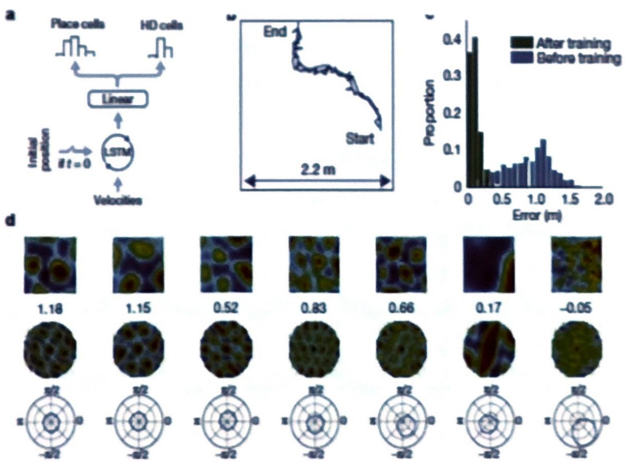
Dang S, Wu Y, Yan R, et al. Why grid cells function as a metric for space[J]. Neural Networks, 2021, 142: 128-137

LETTER Deepmind, NATURE | https://doi.org/10.1038/d41586-018-04992-7

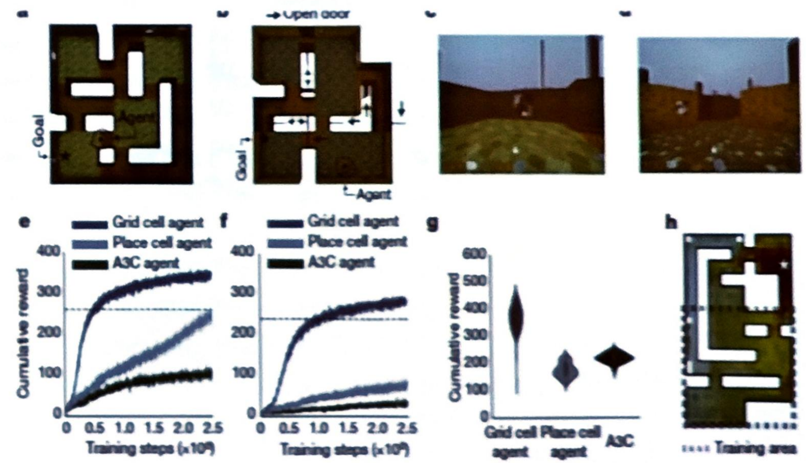
https://doi.org/10.1038/s41586-018-0102-6

Vector-based navigation using grid-like representations in artificial agents

Andrea Banino[1,2,3,5]*, Caswell Barry[2,5]*, Benigno Uria[1], Charles Blundell[1], Timothy Lillicrap[1], Piotr Mirowski[1], Alexander Pritzel[1], Martin J. Chadwick[1], Thomas Degris[1], Joseph Modayil[1], Greg Wayne[1], Hubert Soyer[1], Fabio Viola[1], Brian Zhang[1], Ross Goroshin[1], Neil Rabinowitz[1], Razvan Pascanu[1], Charlie Beattie[1], Stig Petersen[1], Amir Sadik[1], Stephen Gaffney[1], Helen King[1], Koray Kavukcuoglu[1], Demis Hassabis[1,4], Raia Hadsell[1] & Dharshan Kumaran[1,3]*



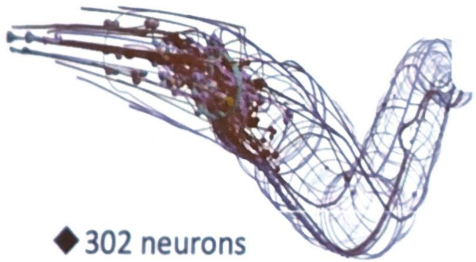
LSTM 和强化学习训练生成网格细胞发放模式



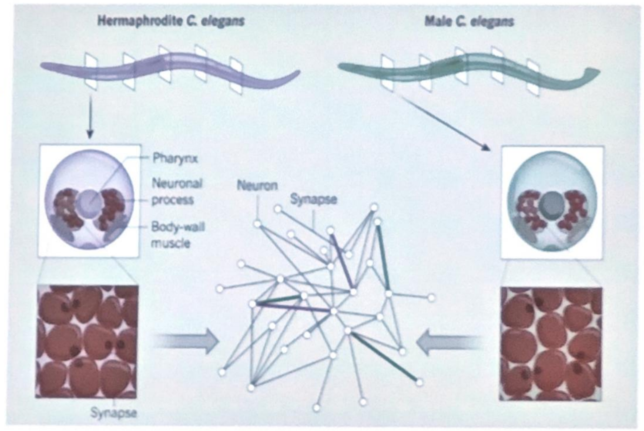
仿真环境下位置细胞和网格细胞的空间表达性能对比

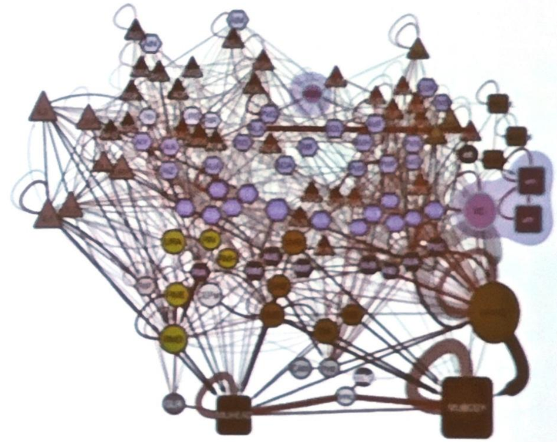
Neural Systems Modeling

C. Elegans



- 302 neurons
- 95 muscle cells
- 5000 chemical synapses
- 6000 electric synapses

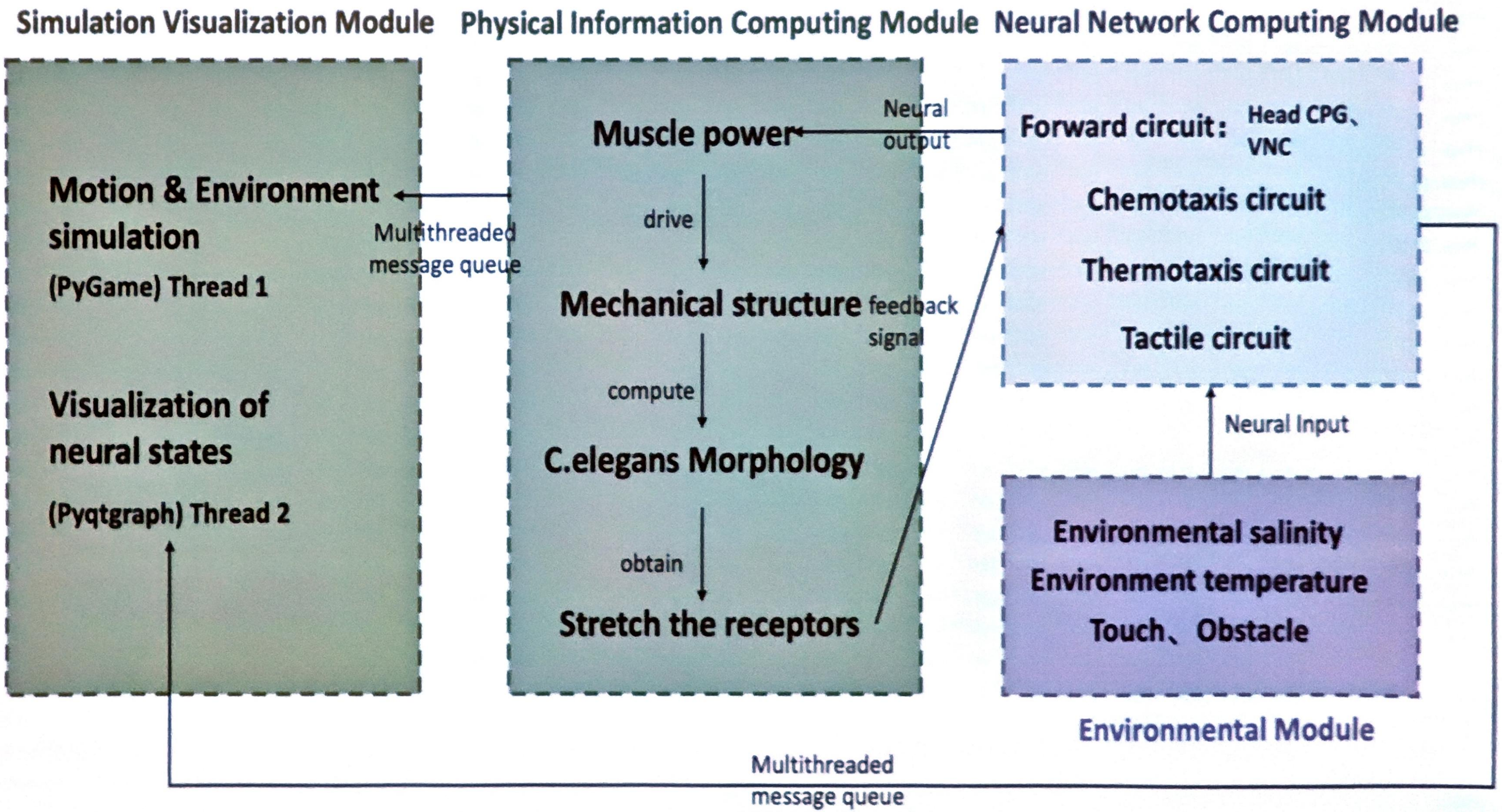




The connections

- 3 times Nobel prizes: 2002 and 2006 (Physiology or Medicine)， 2008 (Chemistry)

The framework of C.elegans simulation system

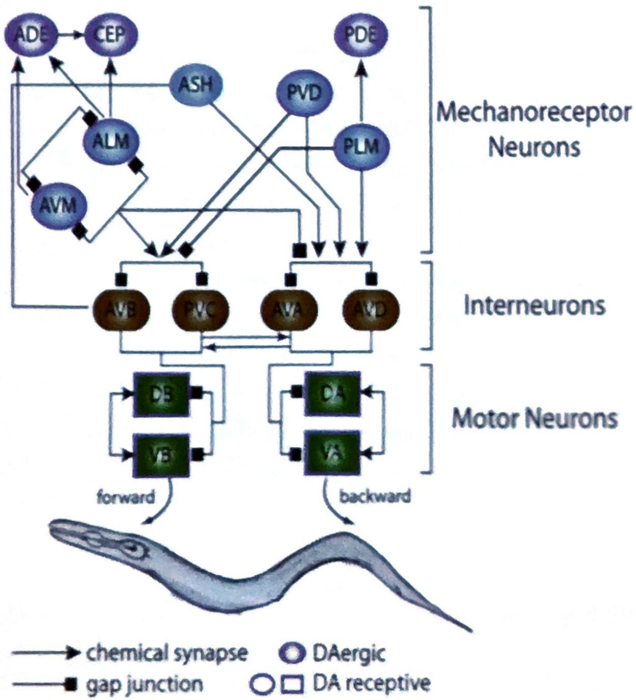


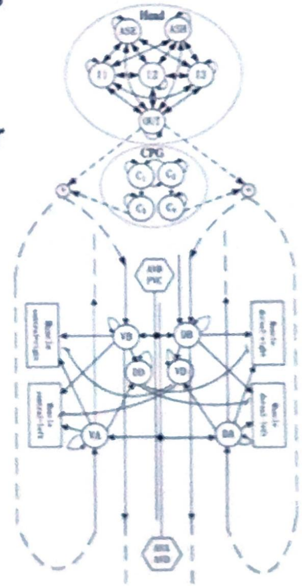
Tactile Escape Circuit

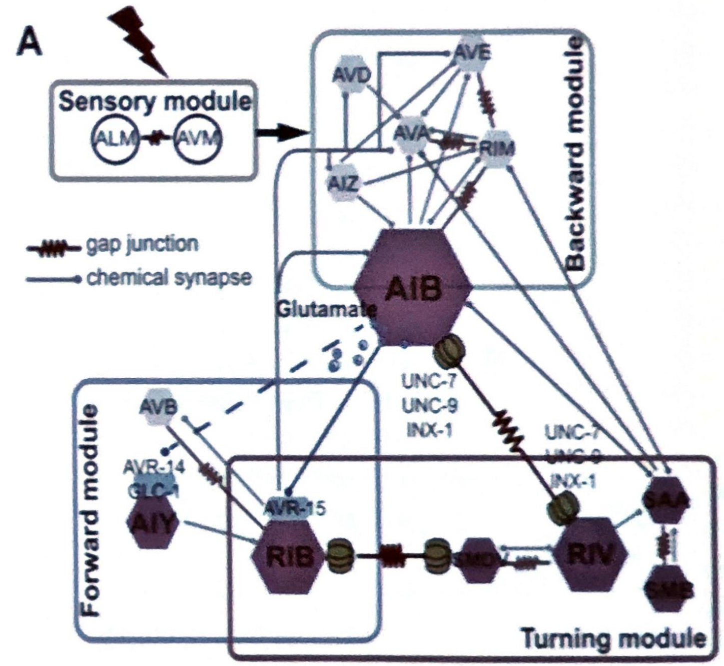
Touch -> activates tactile sensing neurons -> drives nematodes to retreat

Step 1：

- Tactile perception neurons and related dynar
- Interneurons: AVB, PVC, AVA, AVD
- Backward neural circuits: DA, VA

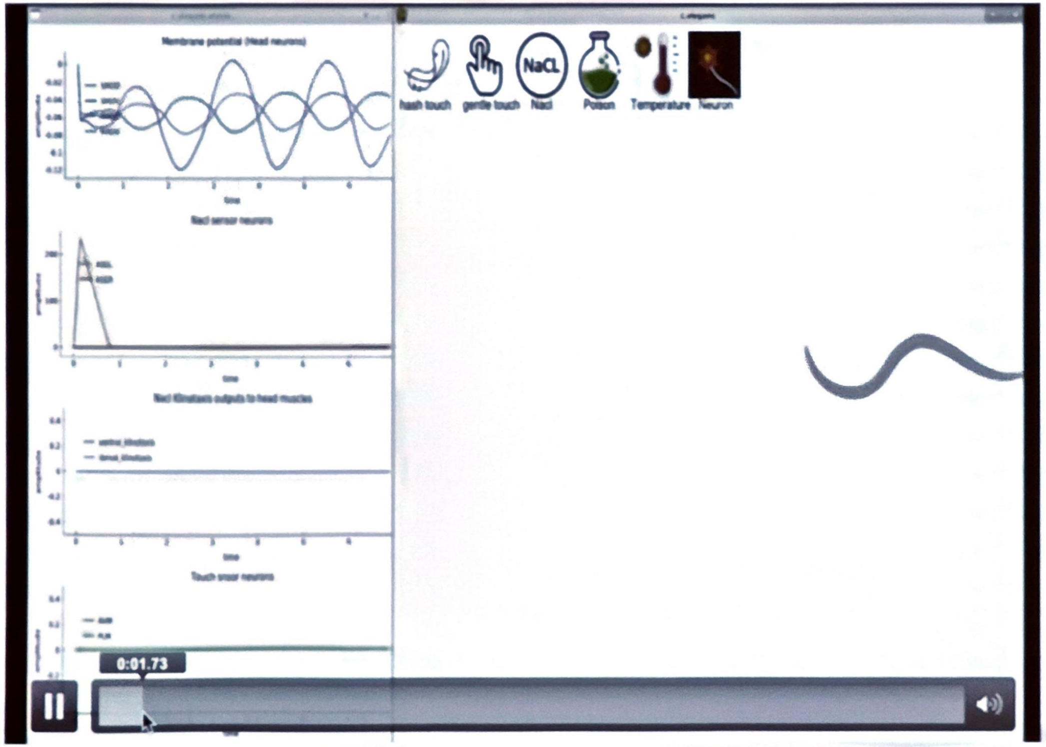


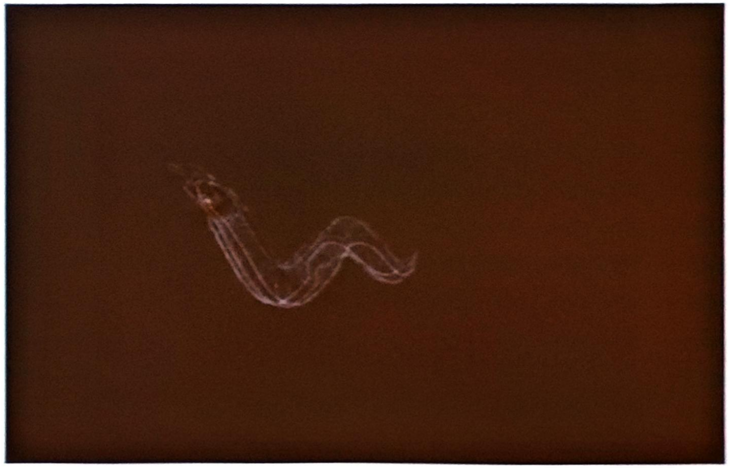




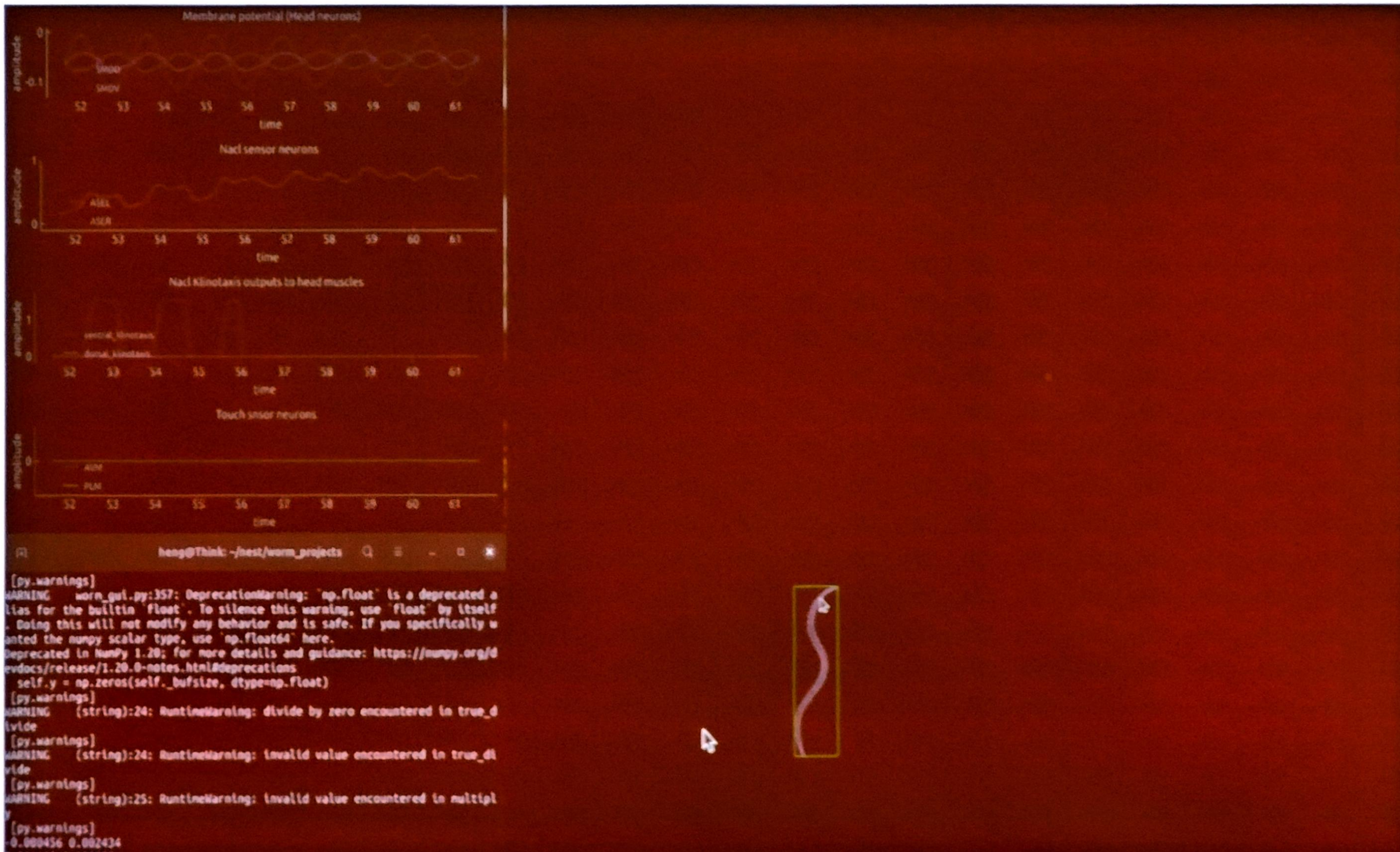
- Tactile perception neurons and related dynamics
- Interneurons: AVB, PVC, AVA, AVD
- Backward neural circuits: DA, VA
- Omega turn circuit
- pause loop
- regulatory circuit

C. elegans simulation Demo





Demonstration of forward, touch and chemotaxis behaviors of C.elegans

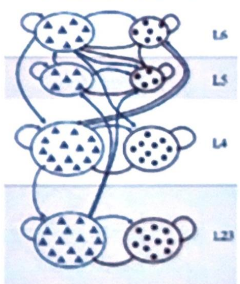


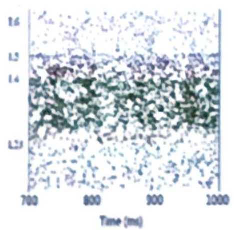
类脑系统的软硬件体系构建

技术路线

思路：构建基于**SPAIC框架的算法模型**到类脑硬件系统的映射与运行，支撑本项目重点研究的基于脉冲信号的感知与决策、**多脑区调控与协同两大类算法模型的部署与应用。**

类脑抽象化模型





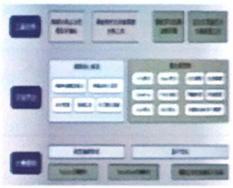
SPAIC 仿真脉冲神经网络

人工大脑

SPAIC

模型框架：脉冲神经网络仿真平台

SPAIC功能模块架构

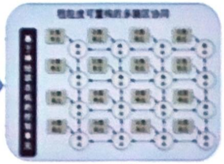


编译器前端

编译器后端

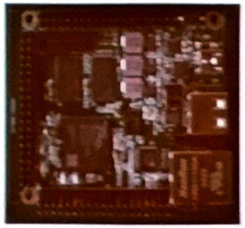
编译器：算法模型到硬件资源的映射

arm

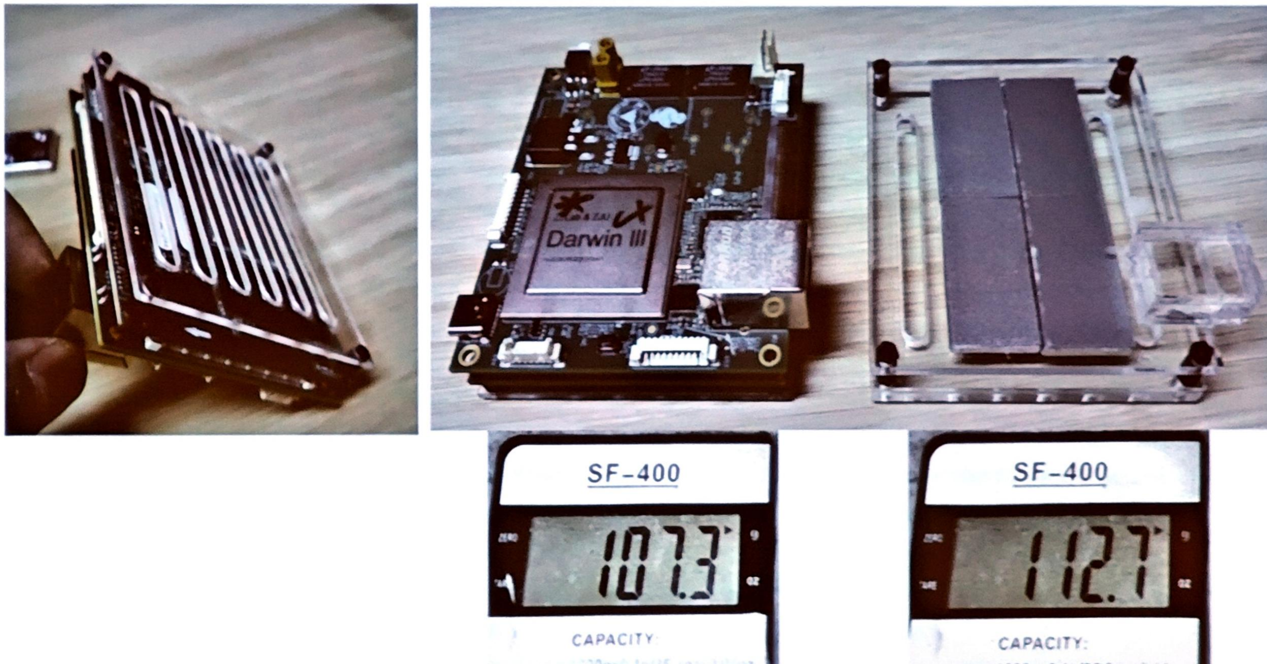


运行时　　固件

硬件：自适应可重构的神经形态硬件



◆ 仿生飞鸟



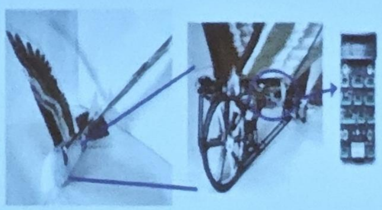
新机型搭载配重板进行试飞，总配重重量为112.7+20=132.7g

✓ 112.7g配重：参照浙大与之江实验室联合研制的搭载达尔文芯片的机载计算板的重量；

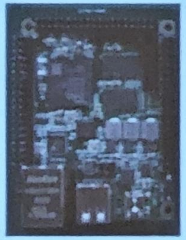
✓ 20g配重：参照摄像头模块的重量。

仿生飞鸟系统

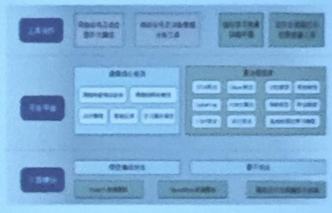
类脑软硬件平台



仿生飞鸟平台

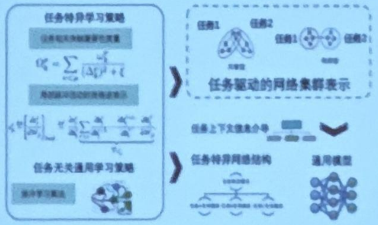


类脑嵌入式计算平台

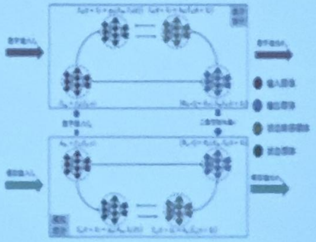


脉冲神经网络仿真平台（SPAIC）

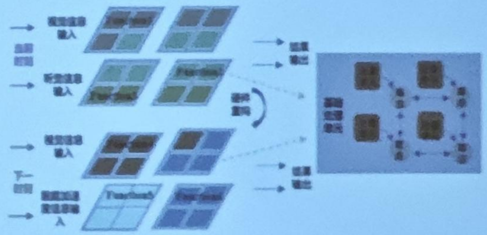
类脑系统



1. 多任务学习模型



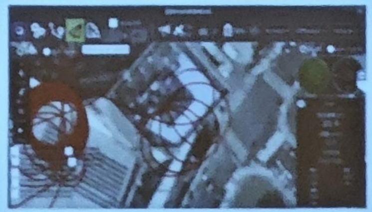
2. 混合感知与决策



3.类脑系统架构

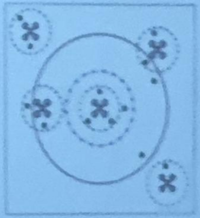
应用验证

基于单目视觉的地面目标定位



旋翼机视觉跟随前方扑翼机飞行

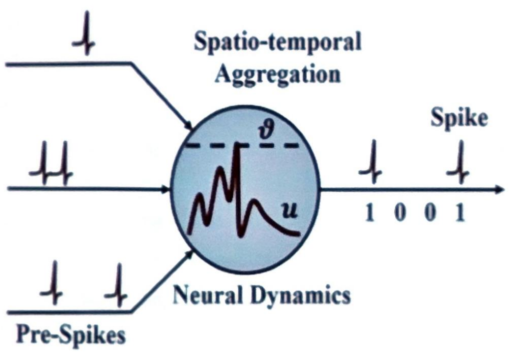
扑翼飞行器路径规划

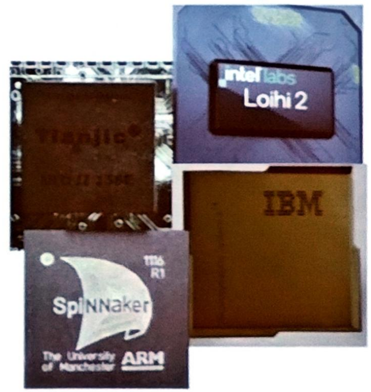


多机协作任务决策

Training Large Scale, Energy Efficient SNNs

- Spiking neural networks (SNNs), composed of biologically plausible spiking neurons, operate with **discrete spikes asynchronously, enabling sparse accumulation** calculation in the **spatial-temporal** domain.





- ✓ Event-driven Computation
- ✓ Runtime Spike Sparsity

- ✓ Energy Efficiency
- ✓ Local/Online Learning

- ✓ Edge Application
- ✓ Dynamic Event Stream

Method

Correctability: Finally evolves to SNN

$$\ell_{\text{noise}}(\boldsymbol{F}, \boldsymbol{s}) \triangleq \mathbb{E}_{\hat{\boldsymbol{m}}}[\boldsymbol{\ell}(\boldsymbol{F}_{\text{noise}}(\boldsymbol{s}))] = \mathbb{E}_{\hat{\boldsymbol{m}}}[\boldsymbol{\ell}(\boldsymbol{F}_{\text{snn}}(\boldsymbol{s}, \hat{\boldsymbol{m}}))]$$

Approx. 4.1 *Minimizing the loss of noisy network $\ell_{noise}(\mathbf{F}, \mathbf{s})$ is equivalent to minimizing the loss of the embedded SNN $\ell_{snn}(\mathbf{F}, \mathbf{s})$ regularized by the layerwise distance between $\Theta(\hat{\mathbf{u}}^l)$ and $H_\alpha(\hat{\mathbf{u}}^l)$.*

$$\ell_{\text{noise}}(\boldsymbol{F}, \boldsymbol{s}) \approx \ell_{\text{snn}}(\boldsymbol{F}, \boldsymbol{s}) + \frac{1-p}{2p}\sum_{l=1}^{L}\left\langle \boldsymbol{C}^l, \operatorname{diag}\left(H_\alpha\left(\hat{\mathbf{u}}^l\right) - \Theta\left(\hat{\mathbf{u}}^l\right)\right)^{\odot 2}\right\rangle$$

$$\boldsymbol{C}^l = D^2\left(\boldsymbol{\ell} \circ \mathbb{E}_{\hat{\boldsymbol{m}}}\left[\boldsymbol{G}^l\right]\right)\left[\boldsymbol{s}^l\right] \quad \text{(Nagel et al., 2020)}$$

Iterative Alternate Optimization

(1) fix weights $\boldsymbol{W}$, optimize width $\boldsymbol{\alpha}$: we have $H_\alpha(x) \to \Theta(x)$ for each layer suppose the spike injection always increase the loss

$$\ell_{noise}(\boldsymbol{F}, \boldsymbol{s}) \to \ell_{snn}(\boldsymbol{F}, \boldsymbol{s})$$

(2) fix width $\boldsymbol{\alpha}$, optimize weights $\boldsymbol{W}$:

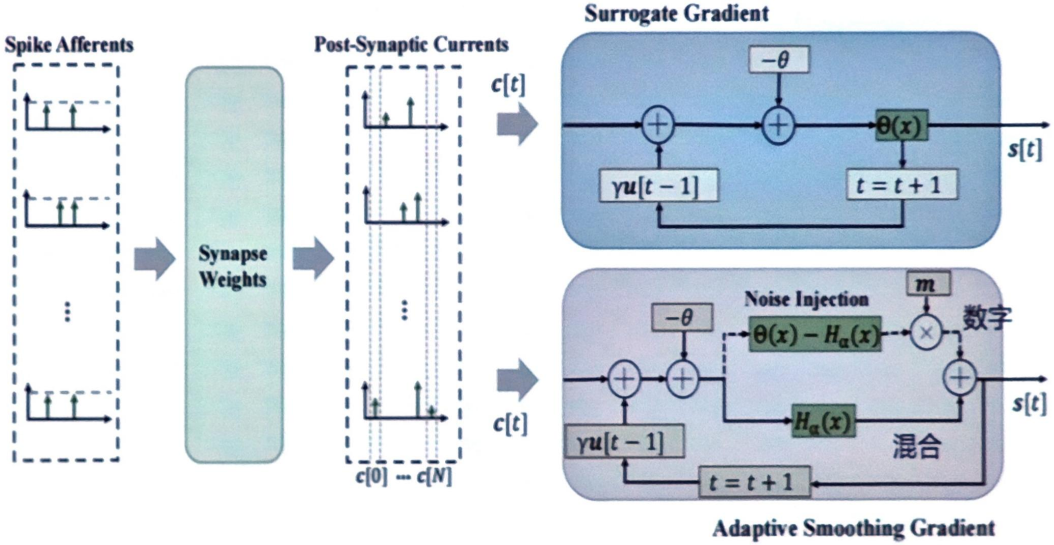
$$\textbf{\textit{minimize}} \quad \ell_{noise}(\boldsymbol{F}, \boldsymbol{s})$$

Table 6. The symbols and corresponding definitions (explanations).

Symbol	Defination
$\boldsymbol{\ell}$	loss function
$\boldsymbol{s}$ or $\boldsymbol{s}^0$	input spike pattern
$\boldsymbol{f}^l$	the l-th spiking layer with $\Theta(\hat{\mathbf{u}}^l)$
$\boldsymbol{F}^l$	$\boldsymbol{f}^l \circ \boldsymbol{f}^{l-1} \circ \ldots \circ \boldsymbol{f}^1$
$\boldsymbol{s}^l$	the output of $\boldsymbol{F}^l$ with fully spike propagation
$\boldsymbol{g}^l$	the l-th noise spiking layer with random mask $\hat{m}^l$
$\boldsymbol{G}^l$	$\boldsymbol{g}^L \circ \boldsymbol{g}^{L-1} \circ \ldots \circ \boldsymbol{g}^{l+1}$
p	noise probability controlling the percent of spike mode

数模信号混合计算

◆多模态混合神经状态机信号整合与决策的基础：混合模态神经网络学习



✓ 构造一个具有脉冲神经元动态（漏电，积分）但采用模拟编码函数$H_\alpha(x)$的代理神经网络

✓ 在训练过程中随机的选择一部分模拟代理神经元置换为使用阶跃函数$\Theta(x)$ 数字脉冲神经元

✓ 平滑度α表征模拟函数$H_\alpha(x)$对阶跃函数$\Theta(x)$平衡程度，可以随混合模态代理网络一起训练

✓ 引入支持混合模态自适应学习算法，代理网络最终可以趋向于内嵌的脉冲神经网络

Wang Z, Jiang, R., Lian, S., Yan, R., and Tang, H. "Adaptive smoothing gradient learning for spiking neural networks." ICML2023

◆混合模态神经网络：实现脉冲神经网络的高效学习

Wang, Z., Jiang, R., Lian, S., Yan, R., and Tang, H. Adaptive smoothing gradient learning for spiking neural networks. In ICML 2023, pp. 35798–35816.

Theorem 4.1 *Minimizing the loss of noisy network $\ell_{noise}(\boldsymbol{F}, \boldsymbol{s})$ is equivalent to minimizing the loss of the embedded SNN $\ell_{snn}(\boldsymbol{F}, \boldsymbol{s})$ regularized by the layerwise distance between $\Theta(\hat{\mathbf{u}}^l)$ and $H_\alpha(\hat{\mathbf{u}}^l)$.*

$$\ell_{noise}(\boldsymbol{F}, \boldsymbol{s}) = \ell_{snn}(\boldsymbol{F}, \boldsymbol{s}) + \frac{1-p}{2p}\sum_{l=1}^{L}\langle C^l, diag(H_\alpha(\hat{\mathbf{u}}^l) - \Theta(\hat{\mathbf{u}}^l))^{\odot 2}\rangle$$

$$C^l = D^2\left(\ell \circ \mathbb{E}_{\hat{m}}[G^l]\right)[s^l] \quad \text{(Nagel et al., 2020)}$$

Iterative Alternate Optimization

(1) fix weights W, optimize width α: we have $H_\alpha(x) \rightarrow \Theta(x)$ for each layer suppose the spike injection always increase the loss

$$\ell_{noise}(\boldsymbol{F}, \boldsymbol{s}) \rightarrow \ell_{snn}(\boldsymbol{F}, \boldsymbol{s})$$

(2) fix width α, optimize weights W:

$$minimize \qquad \ell_{noise}(\boldsymbol{F}, \boldsymbol{s})$$

Exploiting Noise as a Resource for Computation and Learning in Spiking Neural Networks

Gehua Ma, Rui Yan, Huajin Tang*

College of Computer Science and Technology, Zhejiang University
&
College of Computer Science and Technology, Zhejiang University of Technology

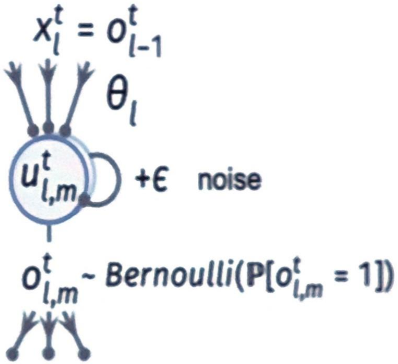
Gehua Ma, Rui Yan, and Huajin Tang*. "Exploiting Noise as a Resource for Computation and Learning in Spiking Neural Networks". Cell Press, *Patterns*, 2023. (In press)

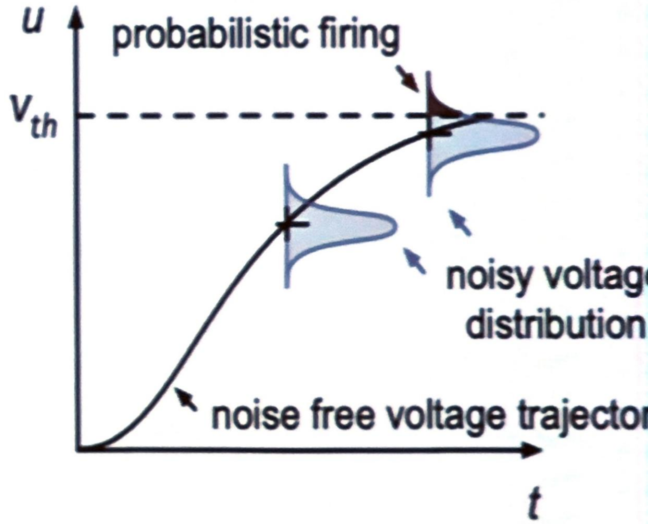
研究方法
Methodologies

➢ Noisy Leaky-Integrate & Fire (LIF) Neuron

我们考虑一种经典的基于扩散近似的LIF模型，其阈下动态收到一个扩散过程（Diffusion Process）的干扰。

$$\mathrm{d}u = -(u - u_{\mathrm{reset}})\frac{\mathrm{d}t}{\tau_m} + RI(t)\frac{\mathrm{d}t}{\tau_m} + \underbrace{\sigma \mathrm{d}W^t}_{\text{噪声项}},$$





离散化：$u^t = \tau u^{t-1} + \phi_\theta(x^t) + \epsilon,$

随机脉冲发放：$o^t \sim Bernoulli\left(CDF_\epsilon(u^t - v_{th})\right)$

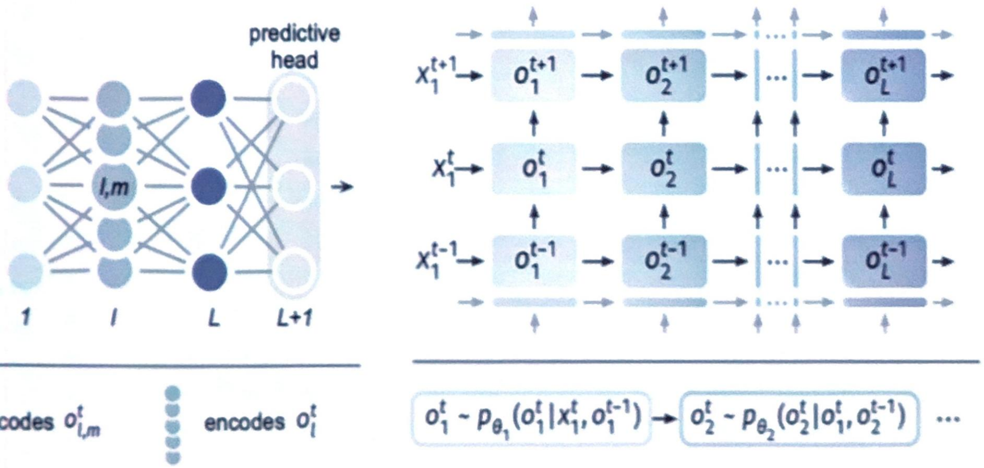
噪声作用下的神经元动力学可以诱导出一个
脉冲发放机制。其中发放概率由膜噪声(ϵ)的
分布函数(CDF)给出，膜电压(u)高出发放
(V_{th})越多，发放脉冲(o)概率越大。

H. Plesser, W. Gerstner. "Noise in integrate-and-fire neurons: from stochastic input to escape rates". MIT Press, *Neural Computation*, 1999.
W. Gerstner, WM Kistler, et al. *Neuronal dynamics: from single neurons to networks and models of cognition. 2014.*
Gehua Ma, Rui Yan, and Huajin Tang*. "Exploiting Noise as a Resource for Computation and Learning in Spiking Neural Networks". Cell Press, *Patterns*, 2023. (In press)

研究方法
Methodologies

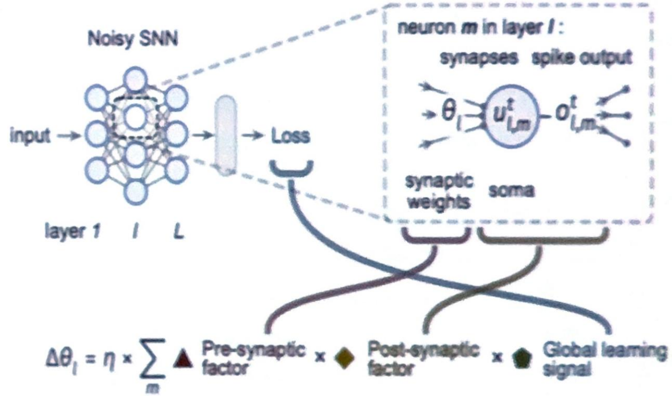
etworked Noisy LIF Neurons

一步地，我们提出了一种Noisy LIF 网络(Noisy SNN)的
般性建模，并推导出了用于更新其突触权重的噪声驱动学
(NDL)规则



Noisy SNN的结构化函数模型(Functional model)示意；（右）概率模型
babilistic model）示意。 其中脉冲发放状态 o 的双下标 (l, m) 表示 l^{th}-
m^{th}-neuron, 只有单下标则表示集合。

- Noise-driven Learning (NDL) Rule



Noise-driven Learning (NDL)

▲ $\partial u^t_{l,m} / \partial \theta_l$

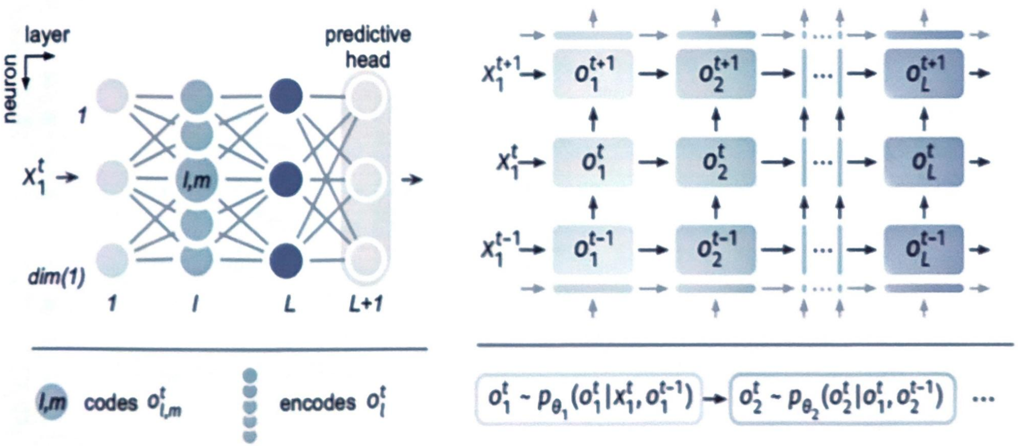
◆ acquired from noise statistics: $CDF'_{\epsilon}(u^t_{l,m} - v_{th})$

⬟ approximated by $\partial L^t / \partial o^t_{l,m}$

Ma, Rui Yan, and Huajin Tang*. “Exploiting Noise as a Resource for Computation and Learning in Spiking Neural Networks”. Cell Press,
s, 2023. (In press)

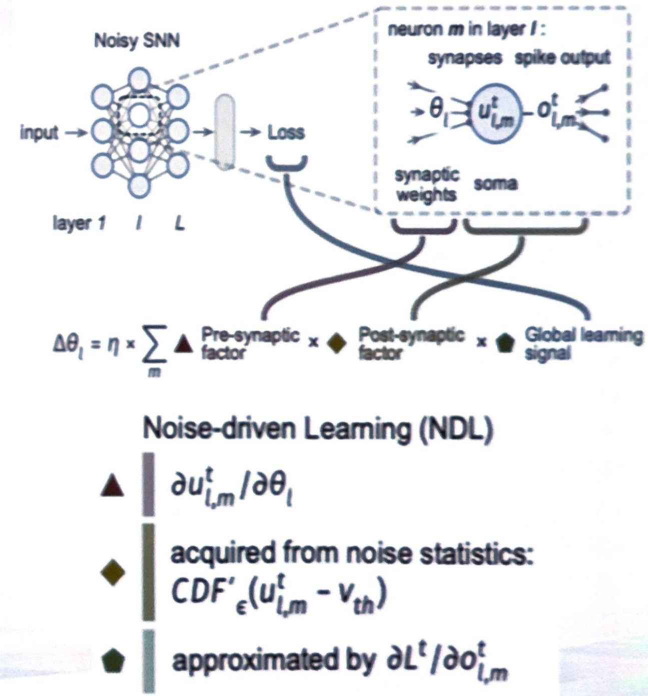
➢ Networked Noisy LIF Neurons

- 进一步地，我们提出了一种Noisy LIF 网络(Noisy SNN)的一般性建模，并推导出了用于更新其突触权重的噪声驱动学习(NDL)规则



（左）Noisy SNN的结构化函数模型(Functional model)示意；（右）概率模型(Probabilistic model)示意。其中脉冲发放状态 o 的双下标 (l, m) 表示 l^{th}-layer, m^{th}-neuron, 只有单下标则表示集合。

- Noise-driven Learning (NDL) Rule

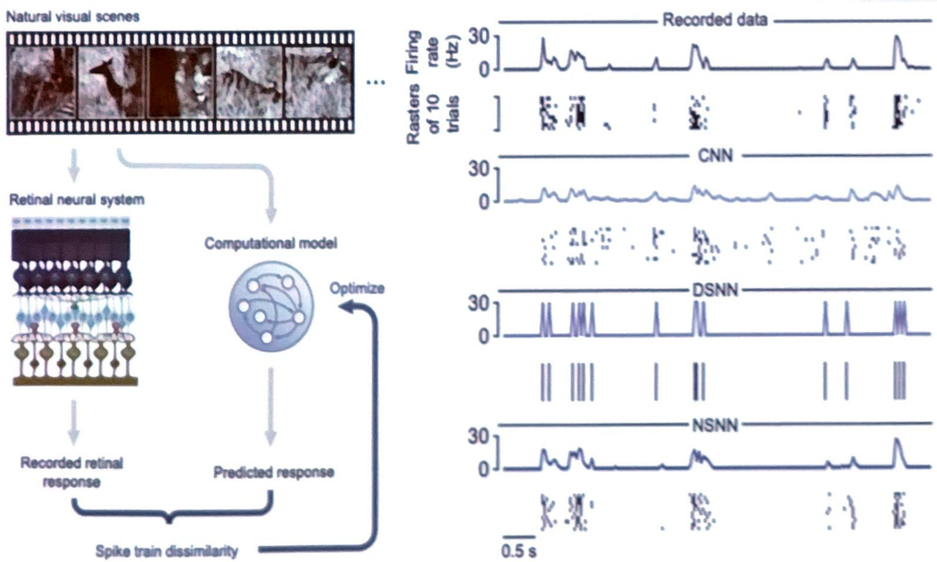


Gehua Ma, Rui Yan, and Huajin Tang*. "Exploiting Noise as a Resource for Computation and Learning in Spiking Neural Networks". Cell Press, *Patterns*, 2023. (In press)

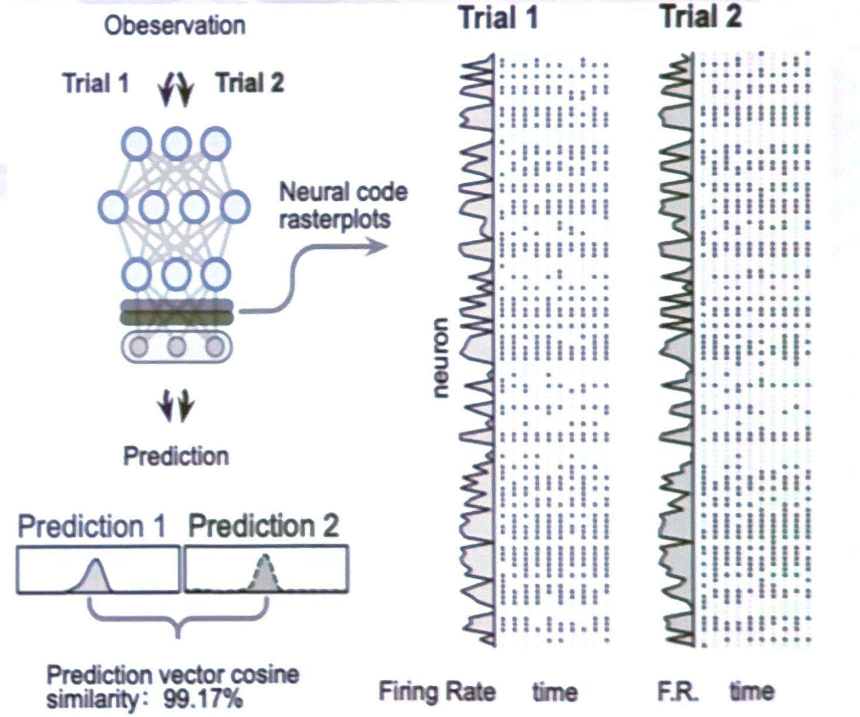
Noisy SNN重现了神经信息处理中的可靠性-可变性

NSNNs Account for Reliability-Variability in Spike-based Neural Processing

Noisy SNN的计算重现了神经信息处理中可靠性-可变性的特征，从而能够在更多的神经计算模拟任务上发挥作用。



(例）使用 Noisy SNN进行神经处理过程建模任务。



NSNN的决策-编码分析。用于事件序列识别任务的Noisy SNN模型除了展现出了决策层面的可靠性外（图左下），很好地再现了编码层面的可变性（图右）。

Gehua Ma, Rui Yan, and Huajin Tang*. "Exploiting Noise as a Resource for Computation and Learning in Spiking Neural Networks". Cell Press, *Patterns*, 2023. (In press)
G. Ma, R. Jiang, R. Yan, H. Tang*. "Temporal Conditioning Spiking Latent Variable Models of the Neural Response to Natural Visual Scenes". *arXiv*, 2023.

SPAIC framework

Github:

https://github.com/ZhejianglabNCRC/SPAIC

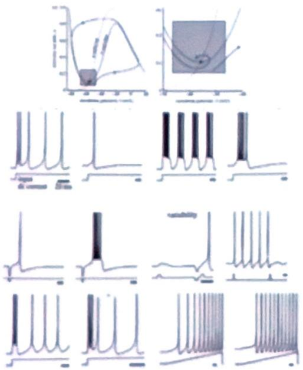
SPAIC

Spike-based Artificial Intelligent Computing Framework

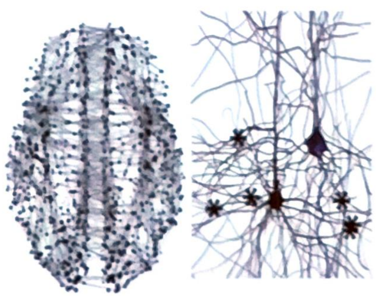
Needs from Neuroscience Computational Research

Needs from Brain-inspired Artificial Intelligent Application

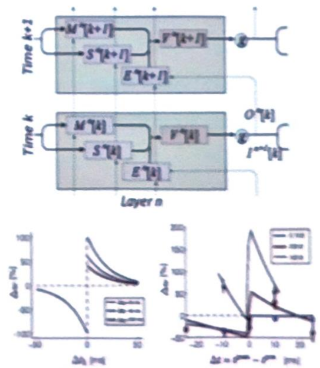
Modeling complex neural dynamics



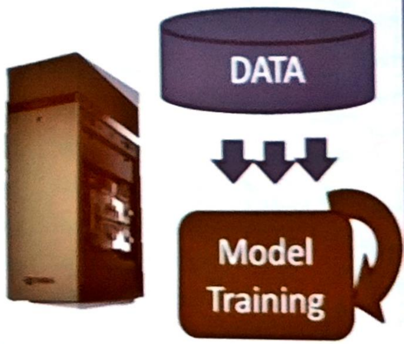
Modeling multiscale and complex structure



Fast developing various learning algorithms

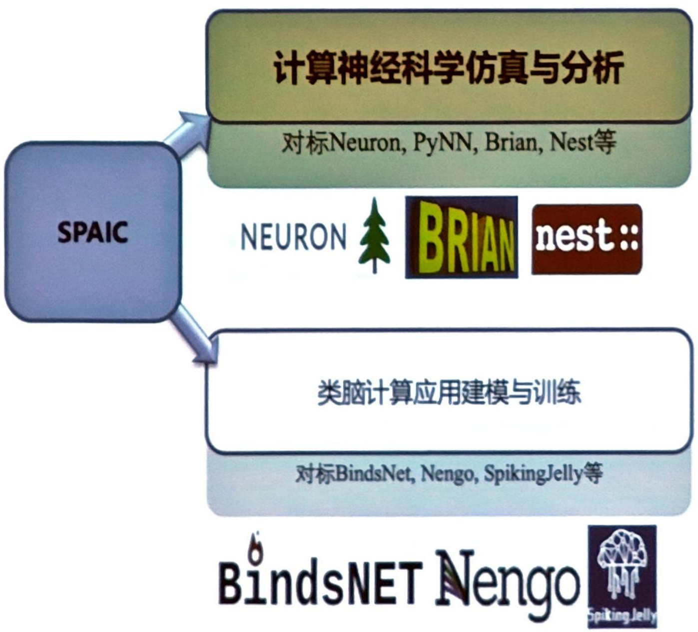


Support efficient training with big dataset on devices



* Figure partially adapted from [1] doi:10.1098/rsta.2010.0130; [2] doi.org/10.1038/nrn.2017.149;[3]doi.org/10.1073/pnas.1202128109;[4] DOI:10.24963/ijcai.2019/189; [5] doi/10.1073/pnas.1105933108;

SPAIC 功能介绍



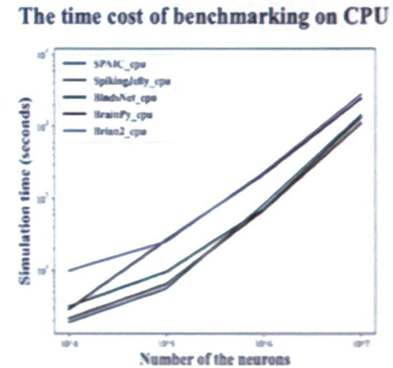
- 精确的单神经元建模
- 网络动力学建模
- 多尺度网络结构、复杂连接形式构建

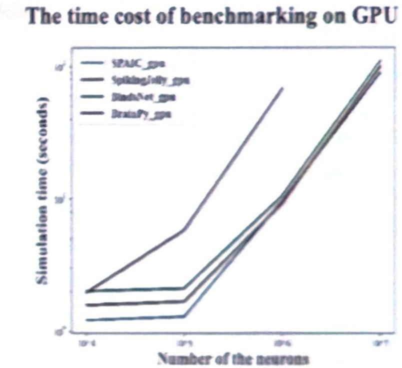
- 支持多种类型SNN学习算法
- 大规模网络高效训练与应用数据交互
- 提供开发、调试、软硬件部署工具链

Performance

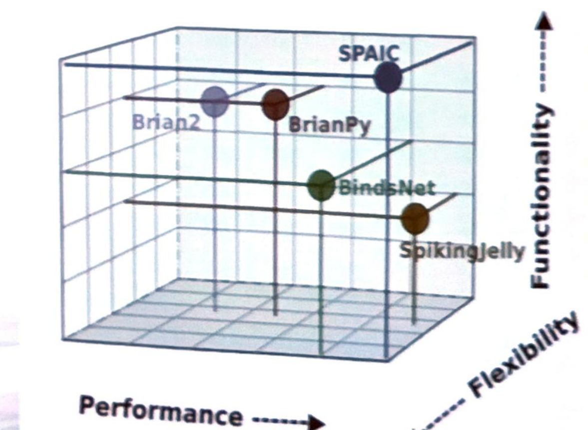
NEURON BRIAN nest:: BindsNET Nengo SpikingJelly SPAIC

	TensorFlow	PyTorch	NEURON	GENSIS	CARLsim	NEST	Brian2	BrainPy	Nengo	BindsNET	SpikingJelly	SPAIC
Neuron model												
LIF			✓		✓	✓	✓	✓	✓	✓	✓	✓
aEIF						✓	✓	✓				✓
IZH					✓	✓	✓	✓	✓			✓
HH			✓	✓		✓	✓	✓	✓	✓		✓
Synaptic type												
Chemical			✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Electrical			✓		✓	✓	✓	✓	✓			✓
Connection property												
Convolution	✓	✓								✓	✓	✓
Sparse	✓	✓	✓			✓	✓	✓		✓		✓
Loop			✓	✓	✓	✓	✓	✓	✓			✓
Delay			✓	✓	✓	✓	✓	✓	✓			✓
Learning algorithm												
STDP			✓		✓	✓	✓	✓	✓	✓		✓
Gradient	✓	✓								✓	✓	✓
Computing hardware												
CPU	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
GPU	✓	✓			✓			✓	✓	✓	✓	✓





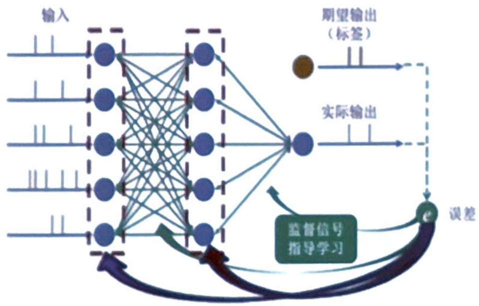
- ☐ SPAIC is a fusion of neuroscience model theory and deep learning algorithm
- ☐ SPAIC can perform both deep learning and computational neuroscience simulation tasks
- ☐ The performance of SPAIC is tested by running a fully connected network with a flexed number neuron in the input layer and an increased size of neurons in the output layer.
  - When the neuron size n ≤ 10^5, compared with BindsNet, BrainPy, Brian2 and SpikingJelly, SPAIC consumed the least time.
  - When the neuron size n ≥ 10^6 , comparable performance with SpikingJelly was also achieved.



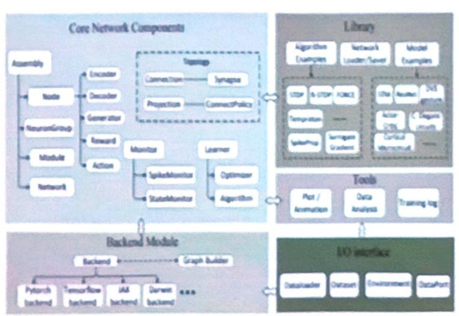
类脑算法及应用实现

SPAIC: A Spike-Based Artificial Intelligence Computing Framework.
IEEE Computational Intelligence Magazine，2024. DOI:
10.1109/MCI.2023.3327842

深度脉冲神经网络算法库



支持类脑应用的SPAIC类脑仿真训练平台



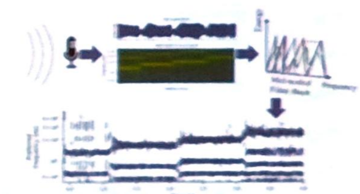
边缘端类脑智能

目标跟踪

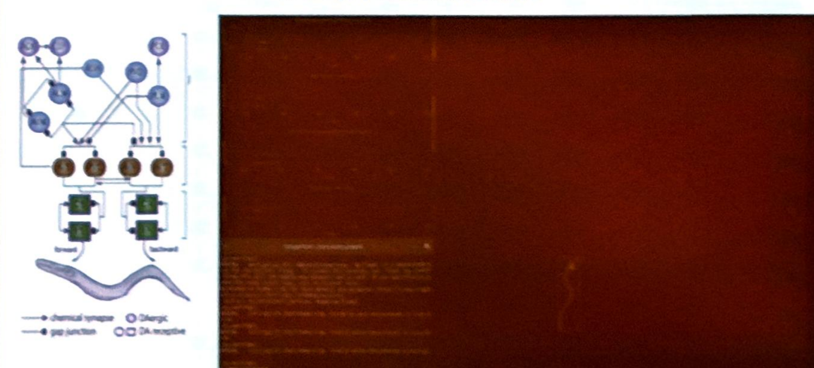
机器人导航

目标检测

语音识别



线虫神经系统模拟



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