神经拟态的类脑智能

中国科学院自动化研究所
吴高巍
gaowei.wu@ia.ac.cn
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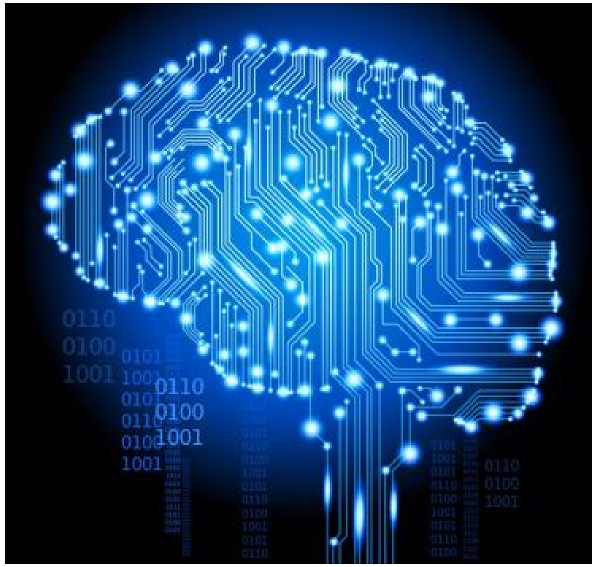
从“联结主义”到“类脑智能”

- 深度学习在视、听、说等方面取得的巨大成功掀起了类脑计算的新浪潮。

- 借助于 Deep Learning 算法，人类终于找到了如何处理 “抽象概念” 这个亘古难题的方法。



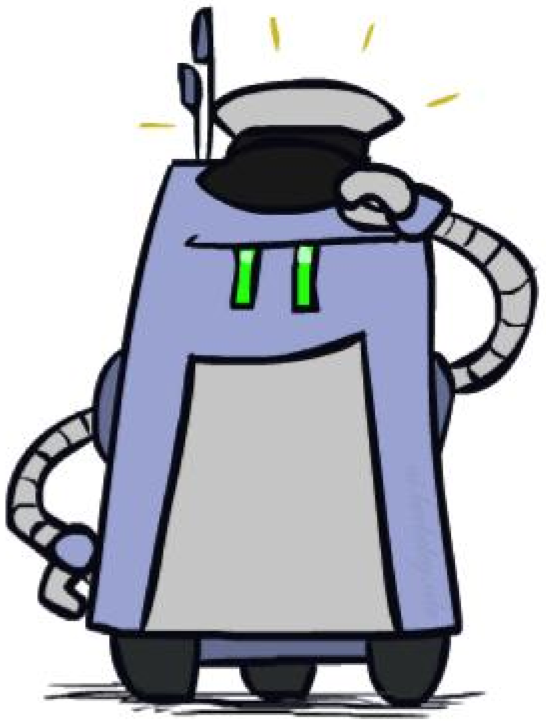
类脑智能的兴起

- 原由
  - 从计算机体系结构的角度
    - 由于传统半导体器件的尺寸逐渐接近其物理极限，摩尔定理难以为继，同时功耗问题也日渐突出。
  - 从智能信息处理的角度
    - 人工智能虽然取得了很大进展，并在许多特定领域得到了广泛应用，但智能程度依然极为有限，与人的智能依然相差甚远，理论与方法上亟待出现新思路与新突破。

类脑智能的兴起

- 现有智能的不足
  - 综合能力差
  - 自主学习能力弱
  - 理解能力弱，鲁棒性差

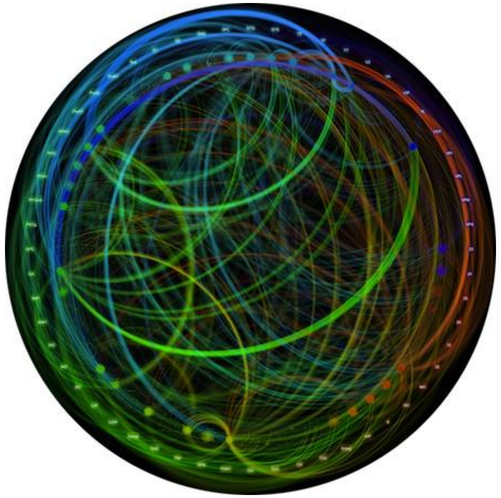
  - 深度神经网络依然有它的瓶颈
    - 训练效率问题
    - 不够鲁棒



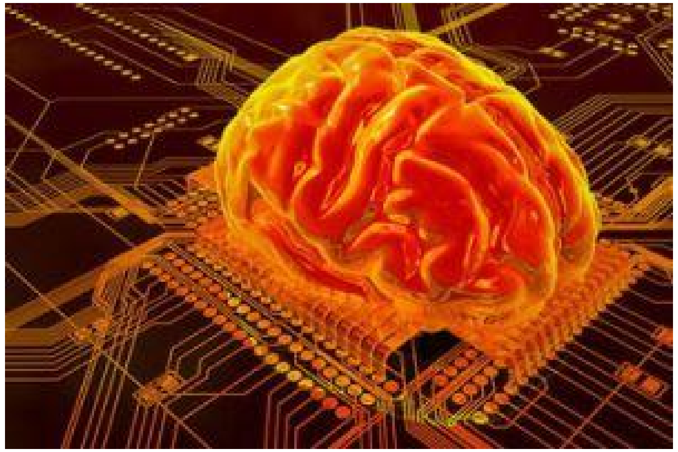
类脑智能的兴起

IBM 深蓝电脑

IBM 沃森(Watson)



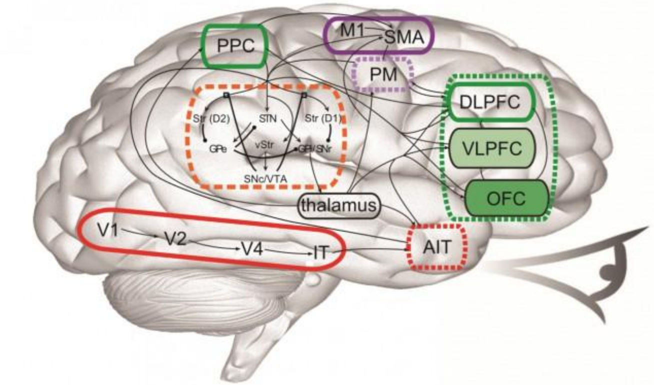
IBM 类脑模拟



谷歌大脑

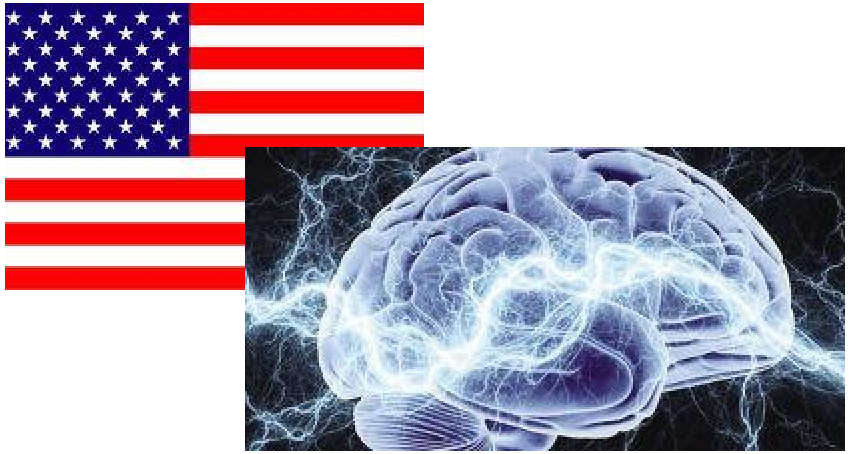
类脑智能的兴起

Deep Mind



SPAUN

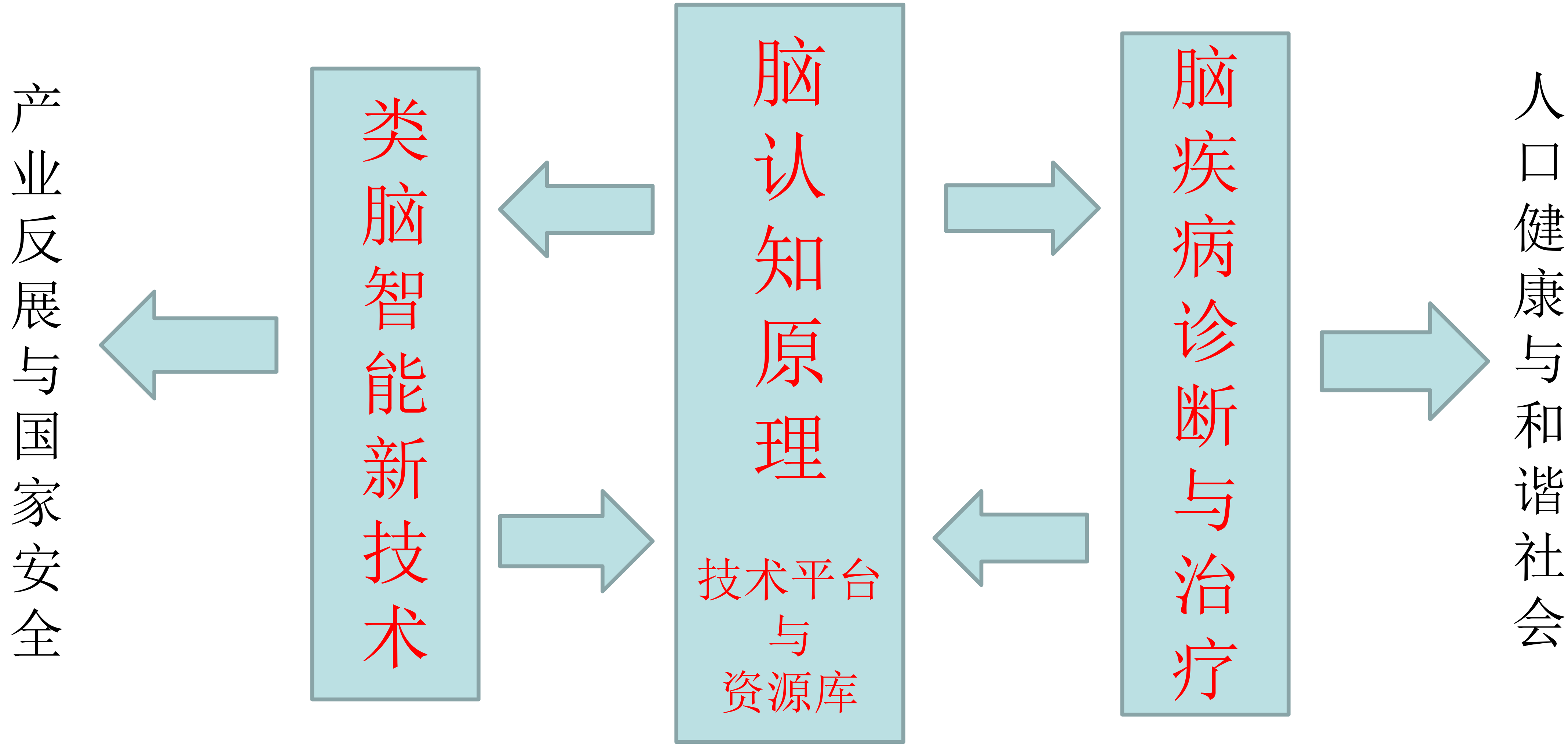
欧盟的“人类大脑计划”



美国的“大脑活动图谱计划”

中国脑计划

（十三五期间国家重大专项）



类脑智能研究

- 主要课题
  - 如何从对大脑可塑性相当粗浅的理解中，抽取对类脑智能技术有启发的内容
- 研究核心
  - 主要在于脑科学、计算科学、信息科学、医学等学科领域密集的交叉融合
- 技术支持
  - 脑认知科学等进展丰富了对大脑的认识；
  - 大数据提供了丰富的训练样本；
  - 计算能力的提升促进了大规模模拟；
  - 集成电路等领域突破奠定硬件基础。

人工智能的发展方向：类脑智能

- 通过类脑神经机理的模拟与实现达到类人行为上的机器智能
  - 从实现机理上采用类脑神经网络
  - 网络结构、脑区、神经元功能上模拟脑
  - 从单任务向多任务、多通道、多脑区协同处理发展

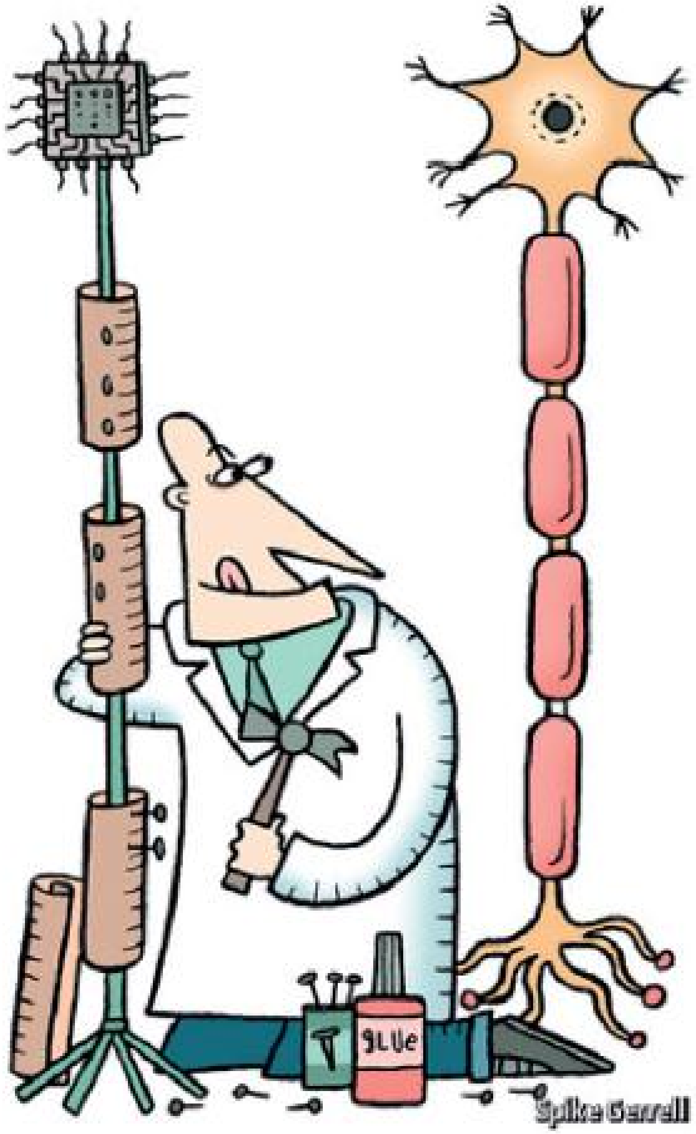
类脑机理

- 通过与现实世界持续交互、自主学习和演化，实现类人智能
  - 多模态协同和与非结构化数据的交互式学习自主能力
  - 复杂单任务能力到自主多任务协同演化的智能系统
  - 能自行解决问题

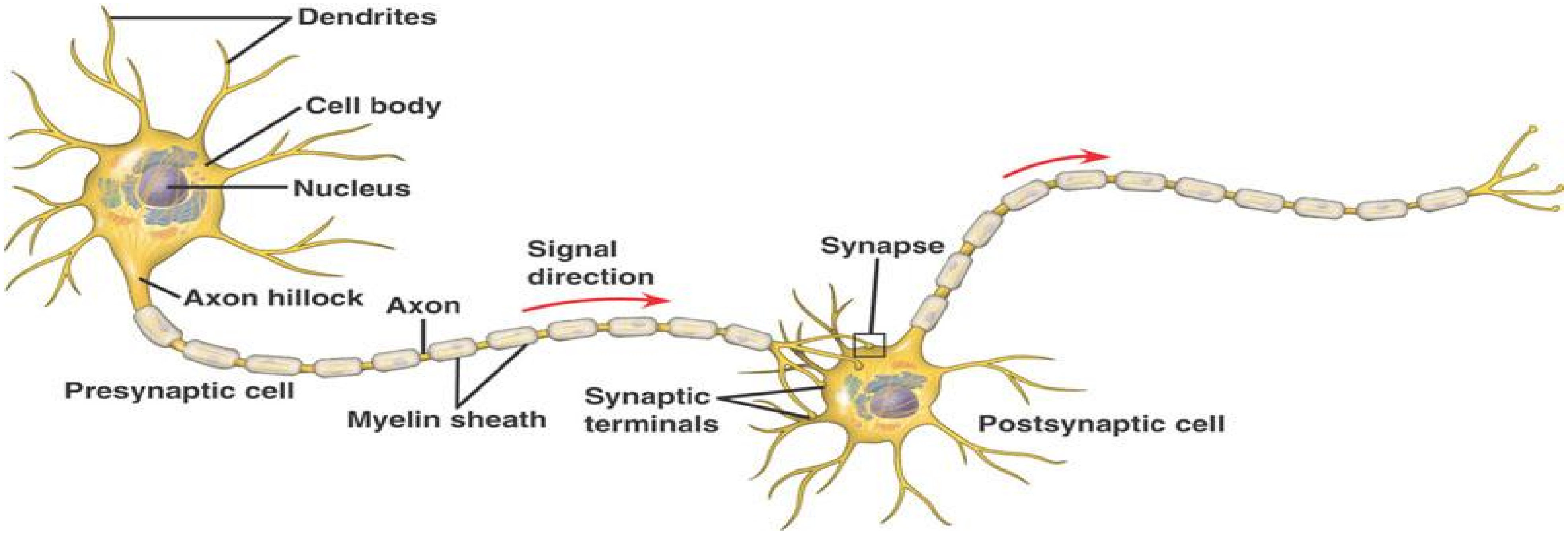
类人智能行为

类脑是手段，智能是目标

脉冲神经网络(Spiking neural networks)

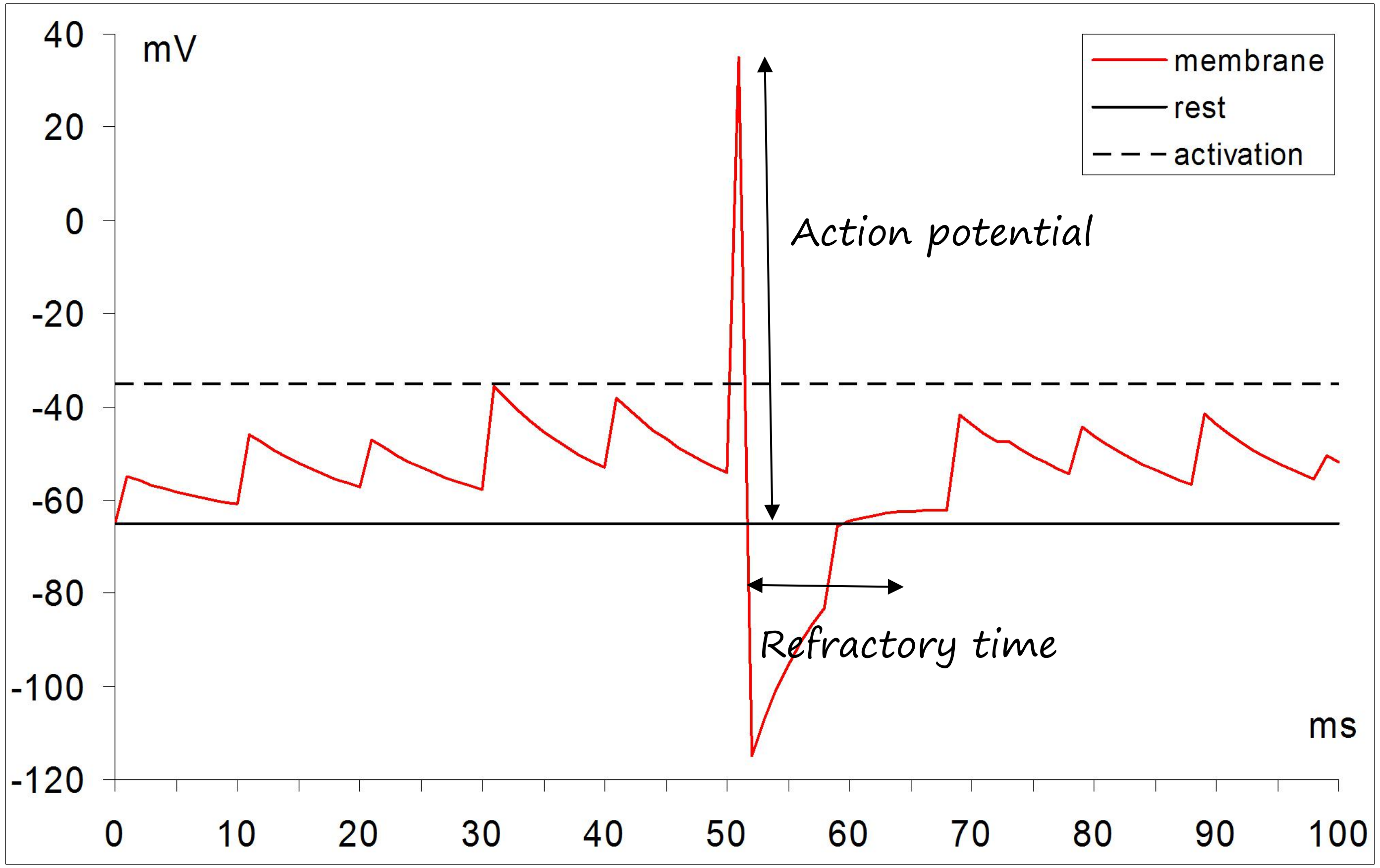


生物神经元



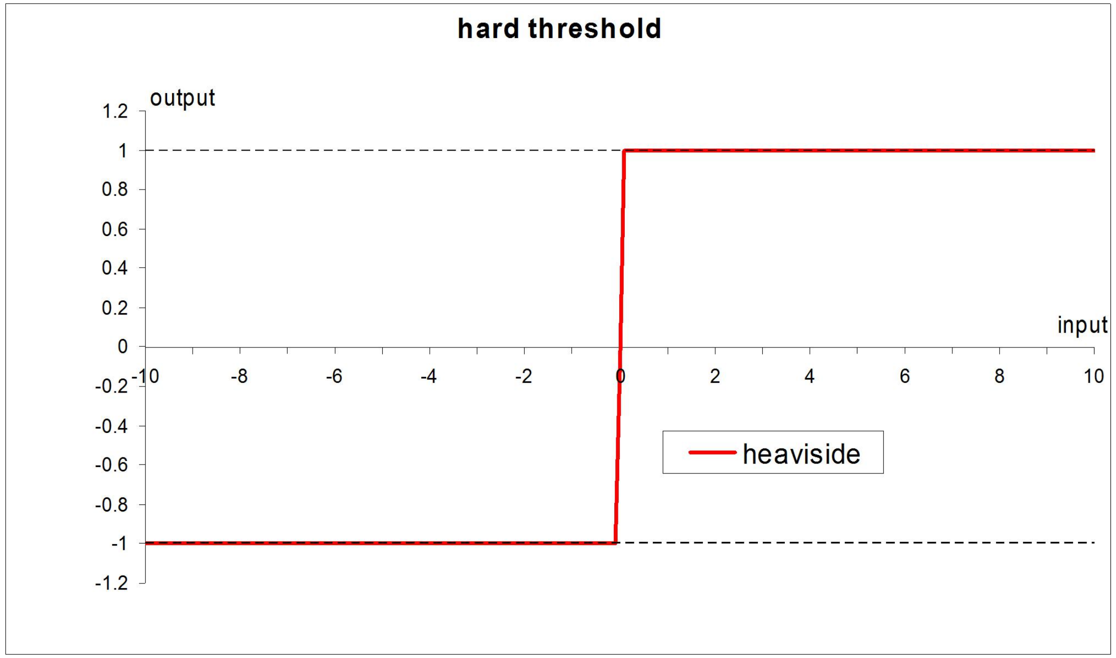
- 神经元组成：细胞体，轴突，树突，突触
- 神经元之间通过突触两两相连。信息的传递发生在突触。
- 突触记录了神经元间联系的强弱。
- 只有达到一定的兴奋程度，神经元才向外界传输信息。

Neural Dynamics



Action potential ≈ 100mV
Activation threshold ≈ 20-30mV
Rest potential ≈ -65mV
Spike time ≈ 1-2ms
Refractory time ≈ 10-20ms

Binary Neurons



Stimulus

$$u_i = \sum_j w_{ij} \cdot x_j$$

Response

$$y_i = f\left(u_{rest} + u_i\right)$$

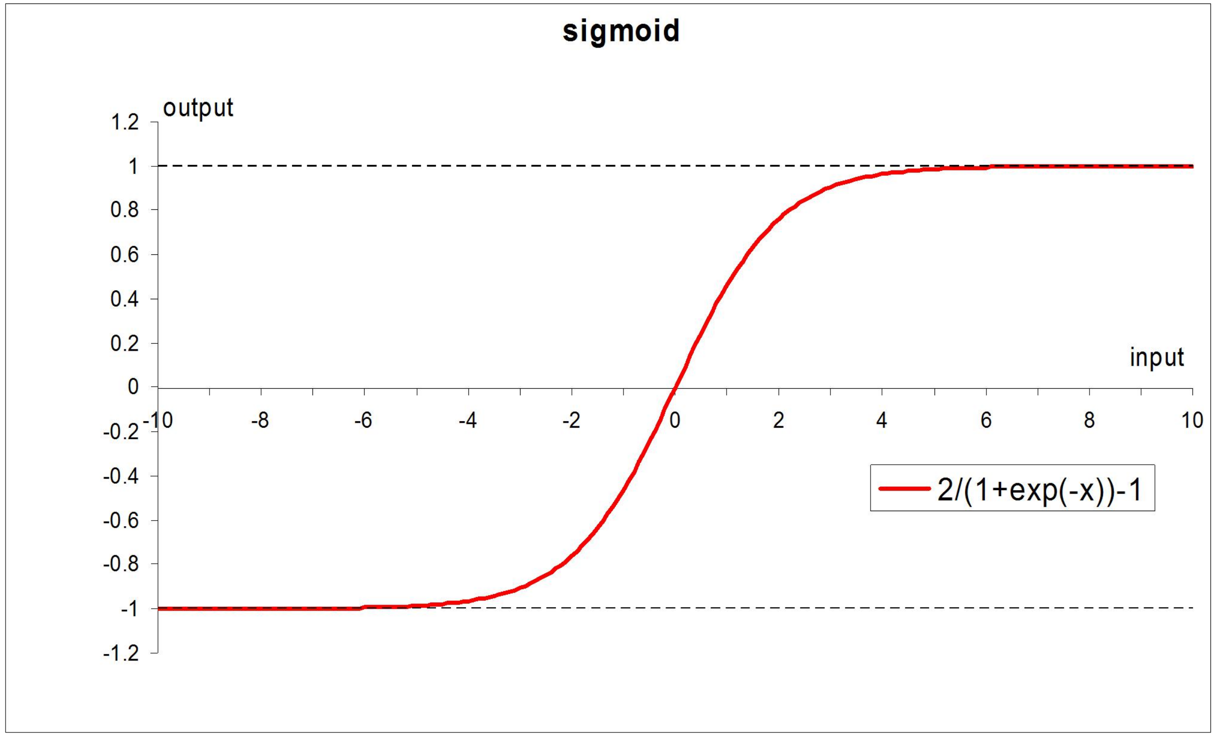
"Hard" threshold

$$f(z) = \begin{cases} z \geq \Theta \Rightarrow ON \\ else \Rightarrow OFF \end{cases}$$

Θ= threshold

- ex: Perceptrons, Hopfield NNs, Boltzmann Machines
- Main drawbacks: can only map binary functions, biologically implausible.

Analog Neurons



Stimulus

$$u_i = \sum_j w_{ij} \cdot x_j$$

Response

$$y_i = f\left(u_{rest} + u_i\right)$$

"Soft" threshold

$$f(z) = \frac{2}{1 + e^{-z}} - 1$$

- ex: MLPs, Recurrent NNs, RBF NNs...
- Main drawbacks: difficult to process time patterns, biologically implausible.

Spiking Neurons

Stimulus

$$u_i(t) = \sum_j w_{ij} \cdot x_j(t)$$

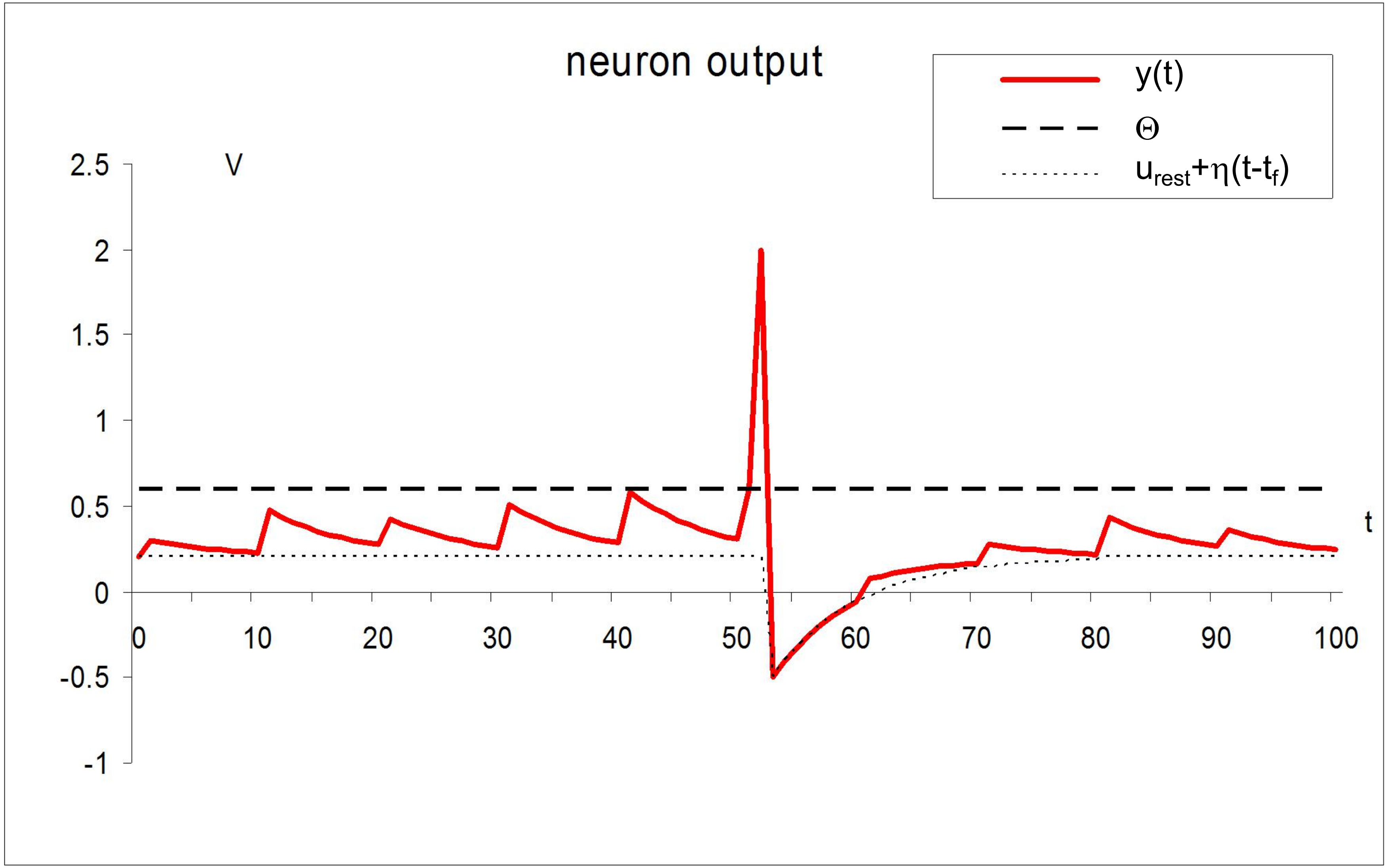
Response

$$y_i(t) = f\left(u_{rest} + \eta(t - t_f) + \sum_{\tau=0}^{t} \varepsilon(t, u_i(\tau))\right)$$

$$f(z) = \begin{Bmatrix} z \geq \Theta \;\&\; \dfrac{dz}{dt} > 0 \Rightarrow ON \\ else \Rightarrow OFF \end{Bmatrix}$$

η = *spike and afterspike potential*
u_{rest} = *resting potential*
$\varepsilon(t,u(\tau))$ = *trace at time t of input at time τ*
Θ= *threshold*
$x_j(t)$ = *output of neuron j at time t*
w_{ij} = *efficacy of synapse from neuron i to neuron j*
$u(t)$ = *input stimulus at time t*

Spiking Neuron Dynamics



spike response model, SRM

- the spike-train of a neuron

$$F = \{t^{(1)}, \dots, t^{(n)}\} = \{t \mid u_i(t) = \Theta \wedge u_i'(t) > 0\}$$

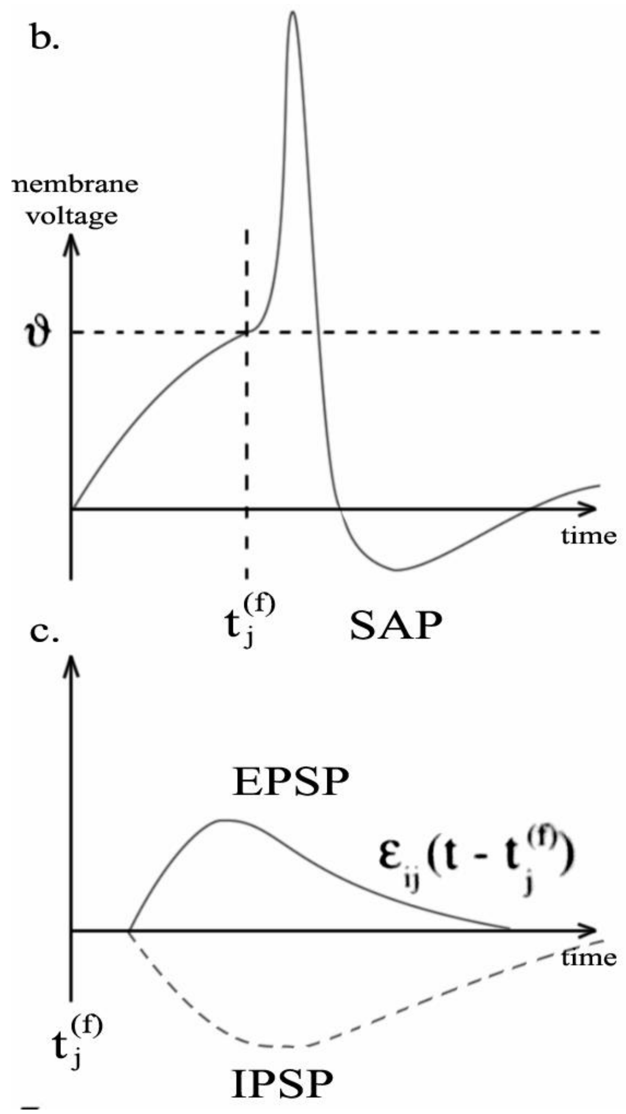
- model the refractoriness

$$\eta(s) = -n_0 \exp\left(-\frac{s-\delta^{abs}}{\tau}\right) H(s-\delta^{abs}) - K H(s) H(\delta^{abs} - s)$$

$$H(s) = \begin{cases} 1 & \text{if } s > 0 \\ 0 & \text{if } s \leq 0 \end{cases}$$

- effect of incoming postsynaptic potentials

$$\varepsilon_{ij}(s) = \left[\exp\left(-\frac{s-\Delta^{ij}}{\tau_s}\right) - \exp\left(-\frac{s-\Delta^{ij}}{\tau_f}\right)\right] H(s-\Delta^{ij})$$



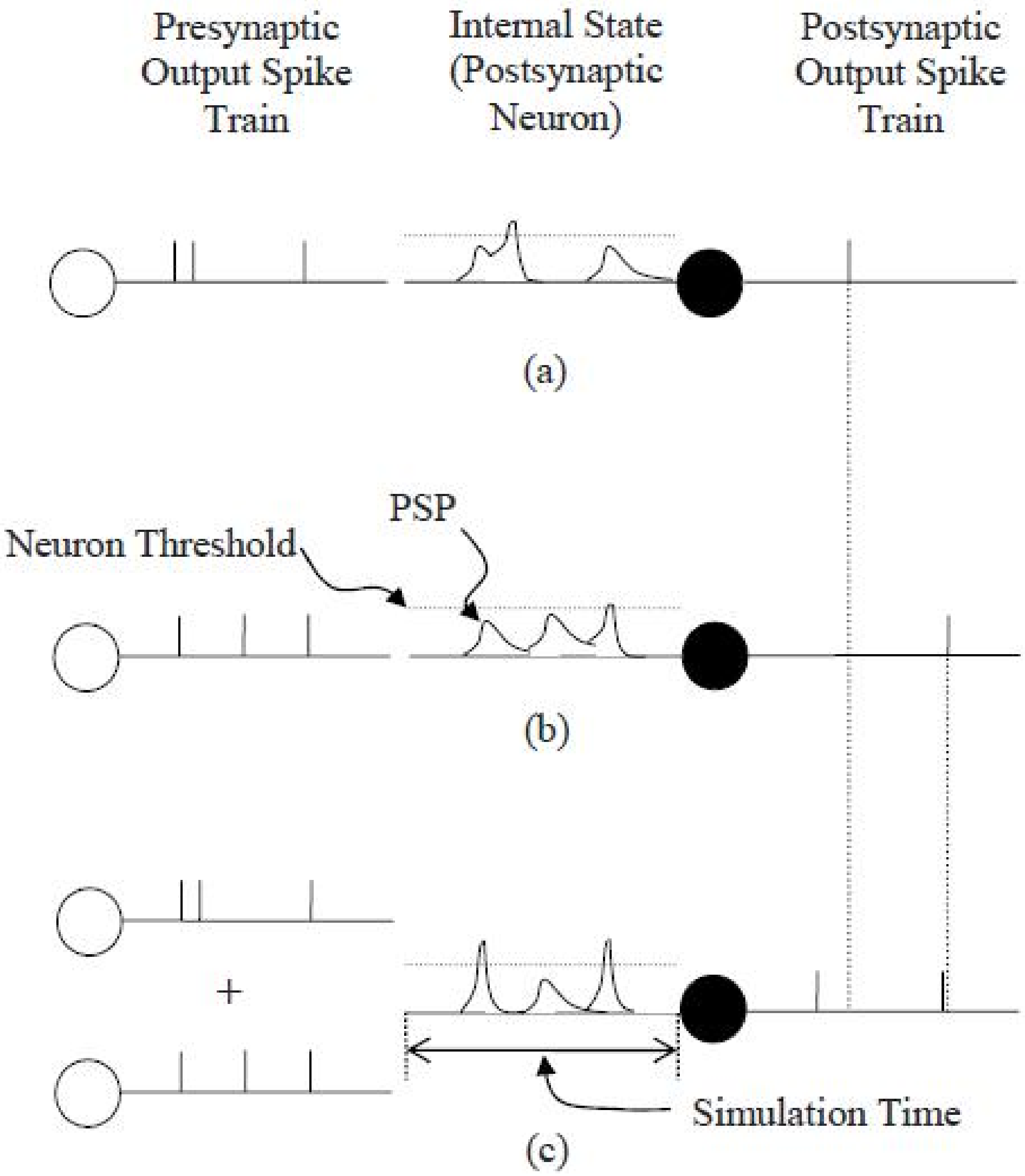
spike response model, SRM

- The current excitation of a neuron

$$u_i(t) = \sum_{t_i^{(f)} \in F_i} \eta(t - t_i^{(f)}) + \sum_{j \in \Gamma_i} \sum_{t_j^{(f)} \in F_j} w_{ij} \varepsilon(t - t_j^{(f)})$$

- Short-term memory neurons
  - only takes the refractory effects of the last pulse sent into account.

$$u_i(t) = \eta(t - t_i') + \sum_{j \in \Gamma_i} \sum_{t_j^{(f)} \in F_j} w_{ij} \varepsilon(t - t_j^{(f)})$$


Presynaptic Output Spike Train
Internal State (Postsynaptic Neuron)
Postsynaptic Output Spike Train
(a)
Neuron Threshold
PSP
(b)
+
Simulation Time
(c)

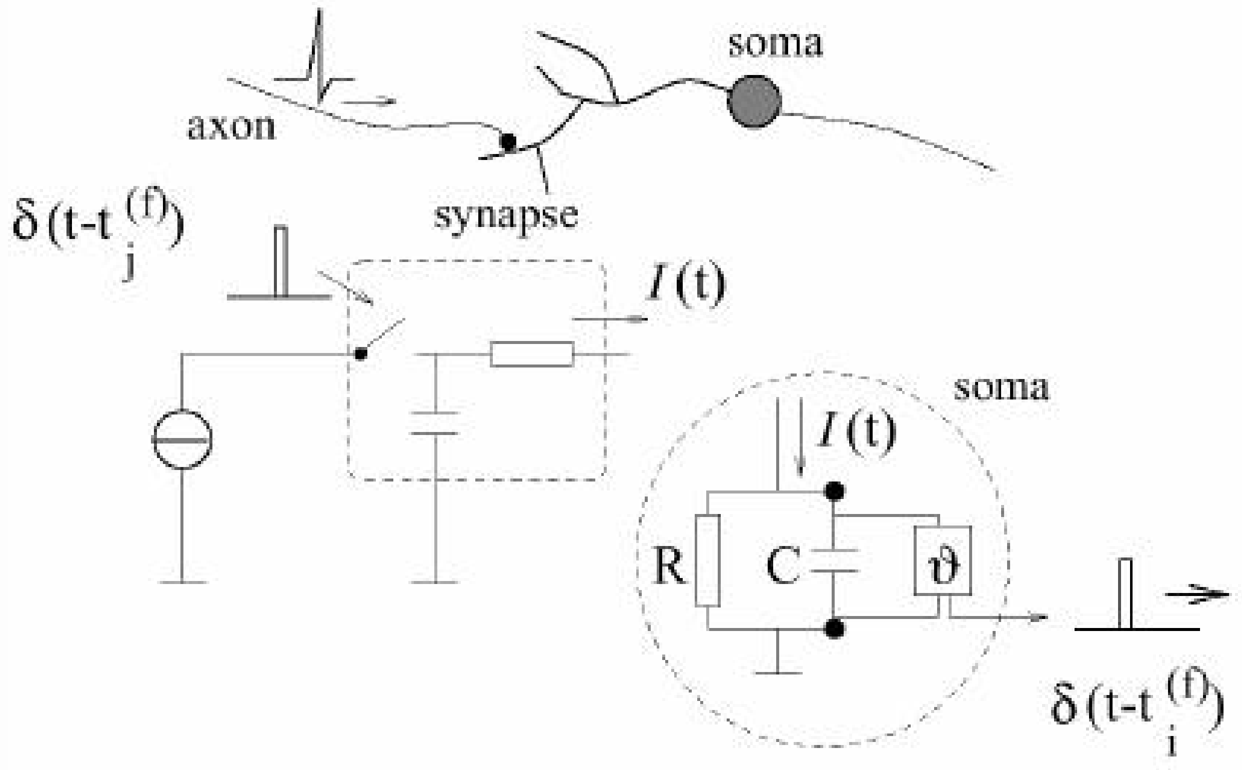
Leaky Integrate-and-Fire (LIF) Model

$$I(t) = \frac{u(t)}{R} + C\frac{du}{dt}$$

$$\tau_m \frac{du}{dt} = -u(t) + RI(t)$$

a 'firing-time' $t^{(f)} : u(t^{(f)}) = \vartheta$

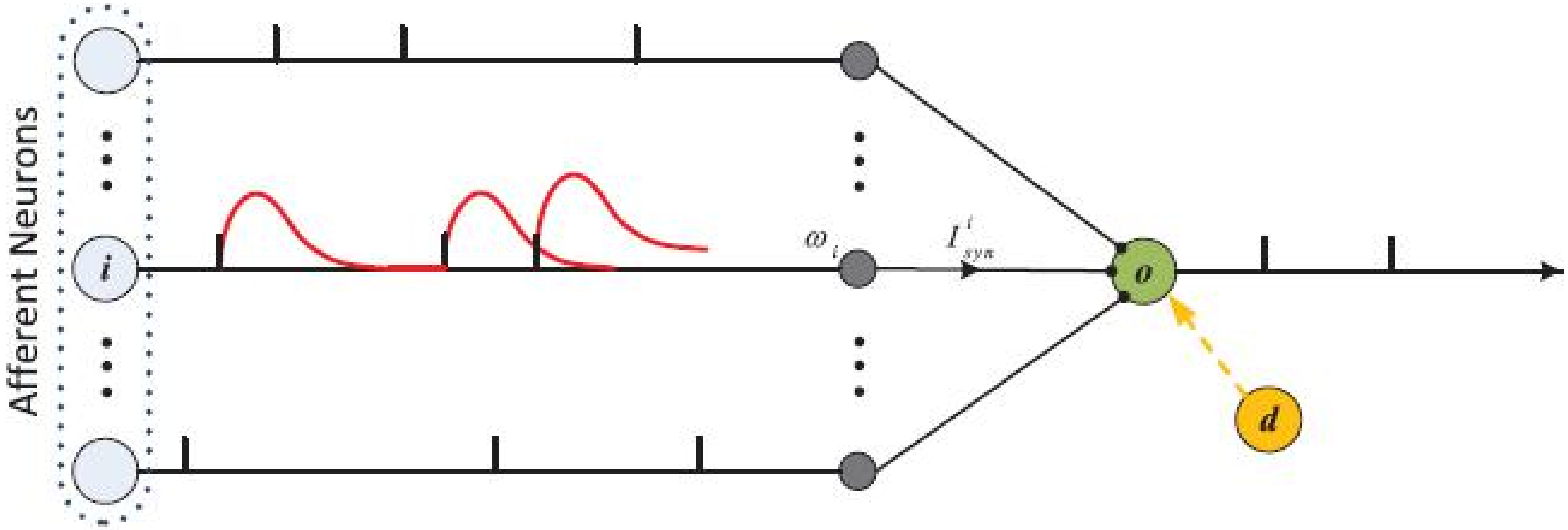
$$\lim_{t \to t^{(f)}, t > t^{(f)}} u(t) = u_{rest}$$



$$I_{syn}(t) = \sum_i w_i I_{PSC}^i(t)$$

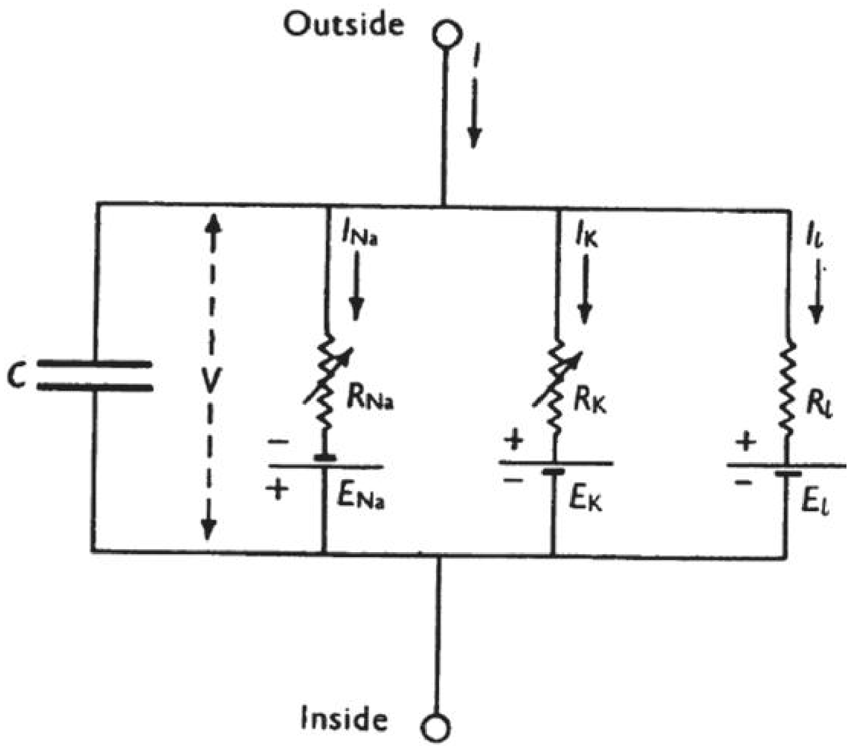
$$I_{PSC}^i(t) = \sum_{t^j} V_0 \left[\exp(-\frac{t-t^j}{\tau_s}) - \exp(-\frac{t-t^j}{\tau_f}) \right] H(t-t^j)$$

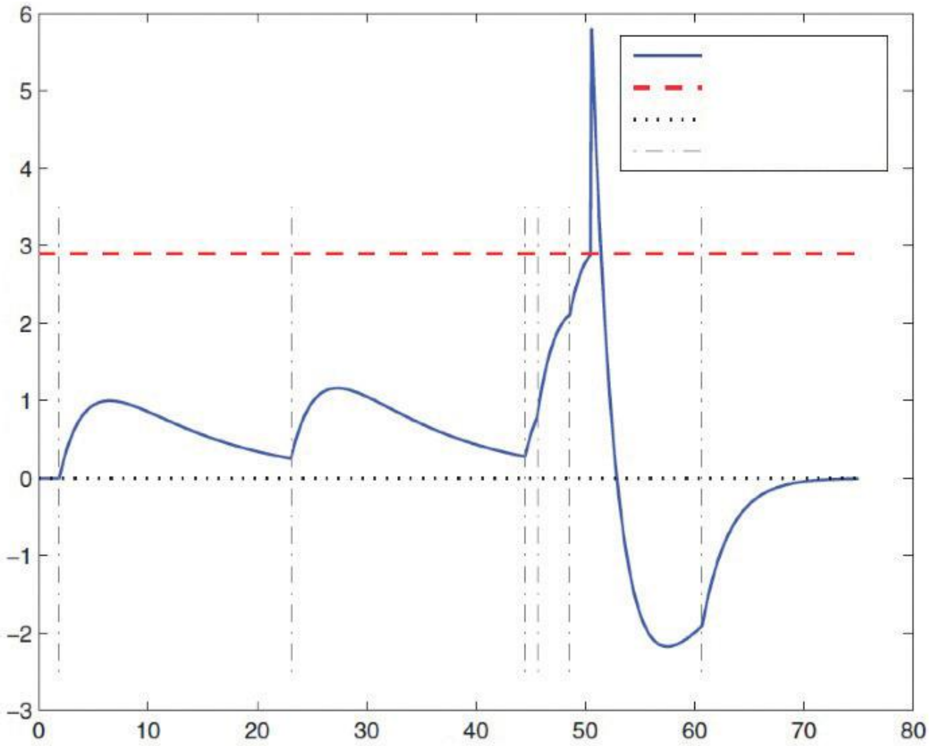
LIF



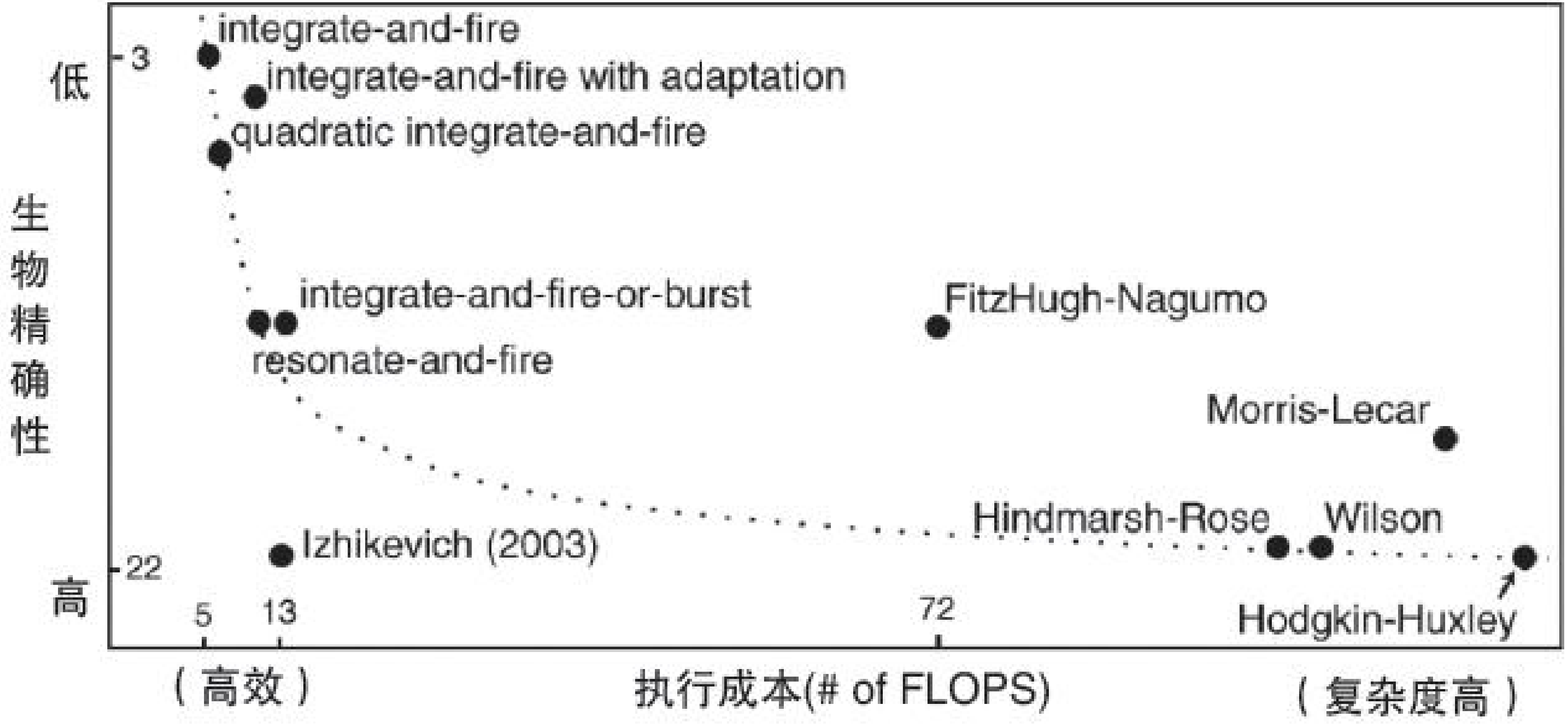
Hodgkin-Huxley(HH)模型

- HH 模型是一组描述神经元细胞膜的电生理现象的非线性微分方程





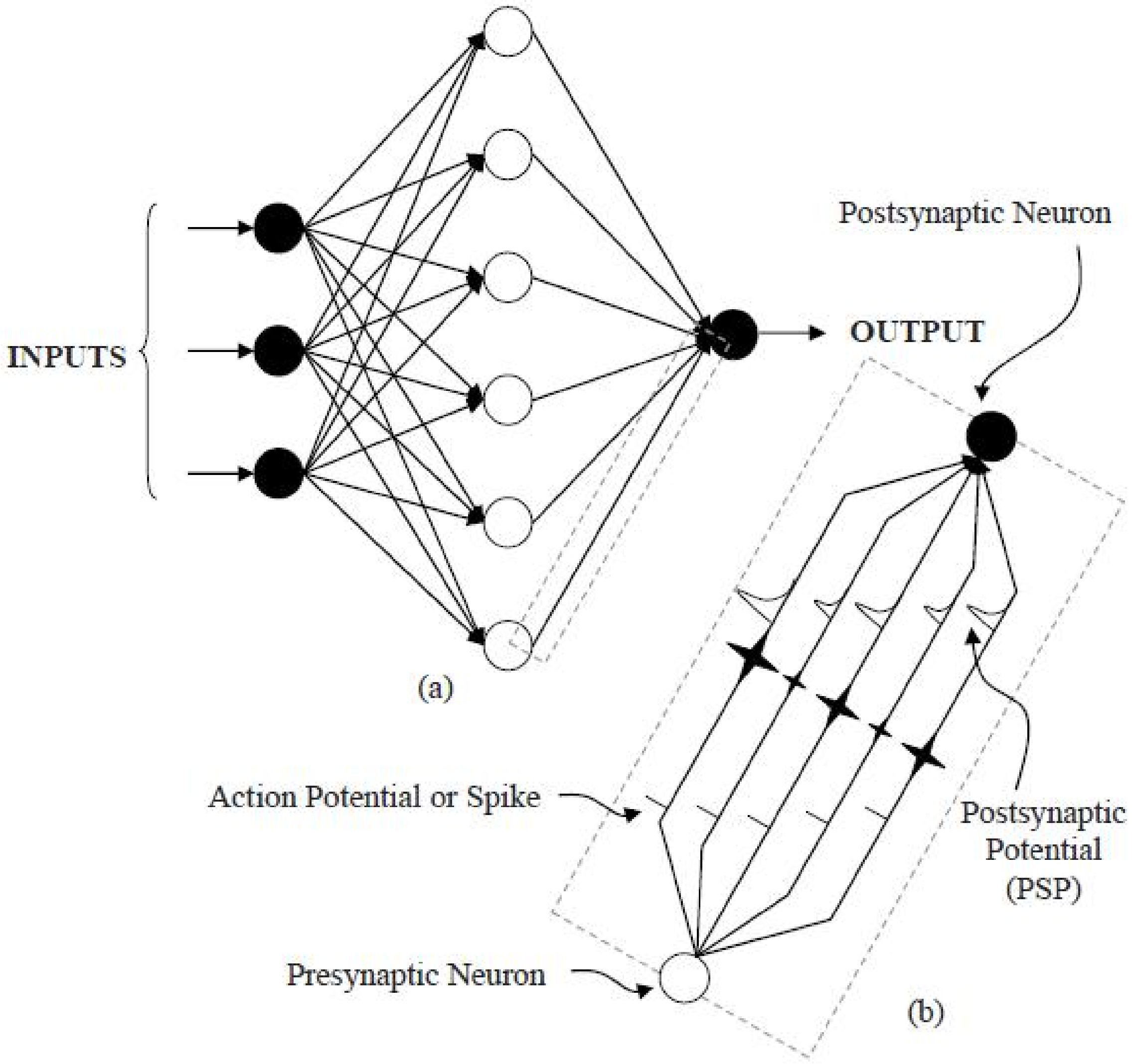
脉冲神经元模型



integrate-and-fire
integrate-and-fire with adaptation
quadratic integrate-and-fire
integrate-and-fire-or-burst
resonate-and-fire
FitzHugh-Nagumo
Morris-Lecar
Hindmarsh-Rose
Wilson
Izhikevich (2003)
Hodgkin-Huxley
3
22
低
生物精确性
高
5
13
72
（高效）
执行成本(# of FLOPS)
（复杂度高）

Spiking Neural Networks (SNNs)

- 由脉冲神经元构成的网络
  - The connection between two SNN neurons is modeled by multiple (K) synapses



脉冲神经网络的学习算法

- 非监督学习
  - 基于赫布法则(Hebbian Rule)而设，STDP(Spike Timing Dependent Plasticity)
  - “同时激发的神经元连接在一起”
- 监督学习
  - 基于反向传播训练算法的思想，从所犯的错误中学习
  - Precise-Spike-Diven Synaptic Plasticity (PSD)

  - 将传统的人工神经网络转化为脉冲神经网络的算法。

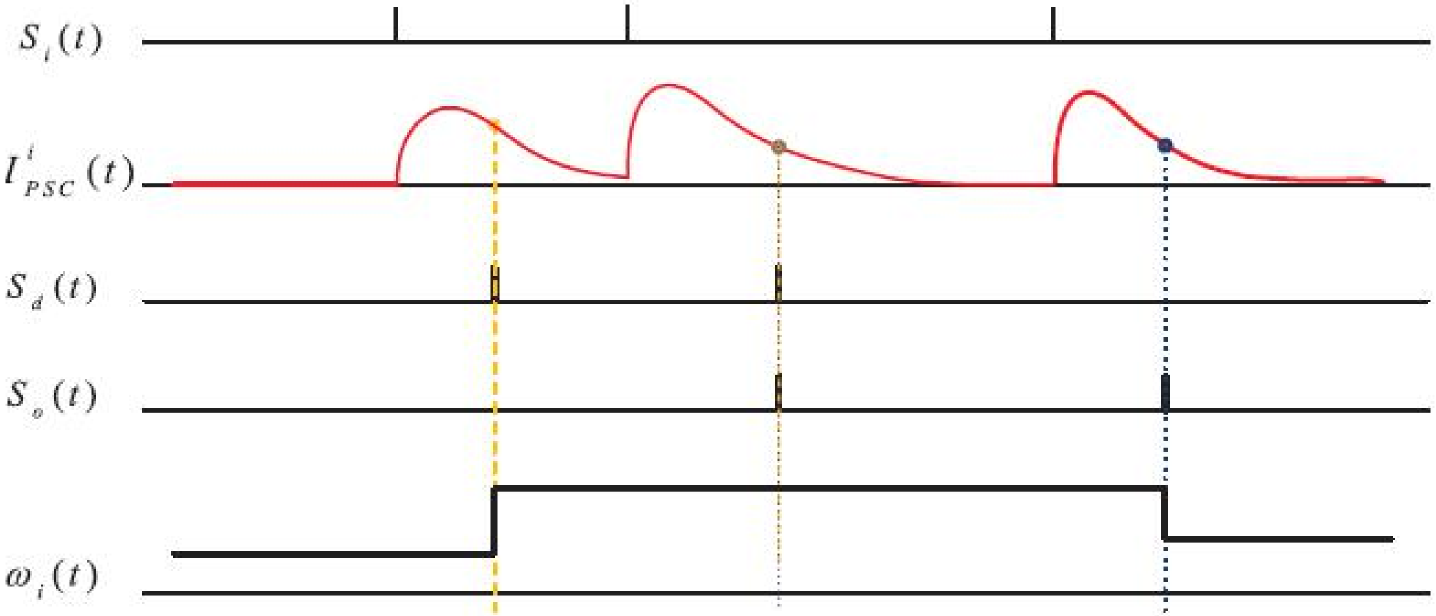
Precise-Spike-Diven Synaptic Plasticity (PSD)

- PSD Learning Rule

$$\Delta w_i = \eta x_i (y_d - y_o)$$

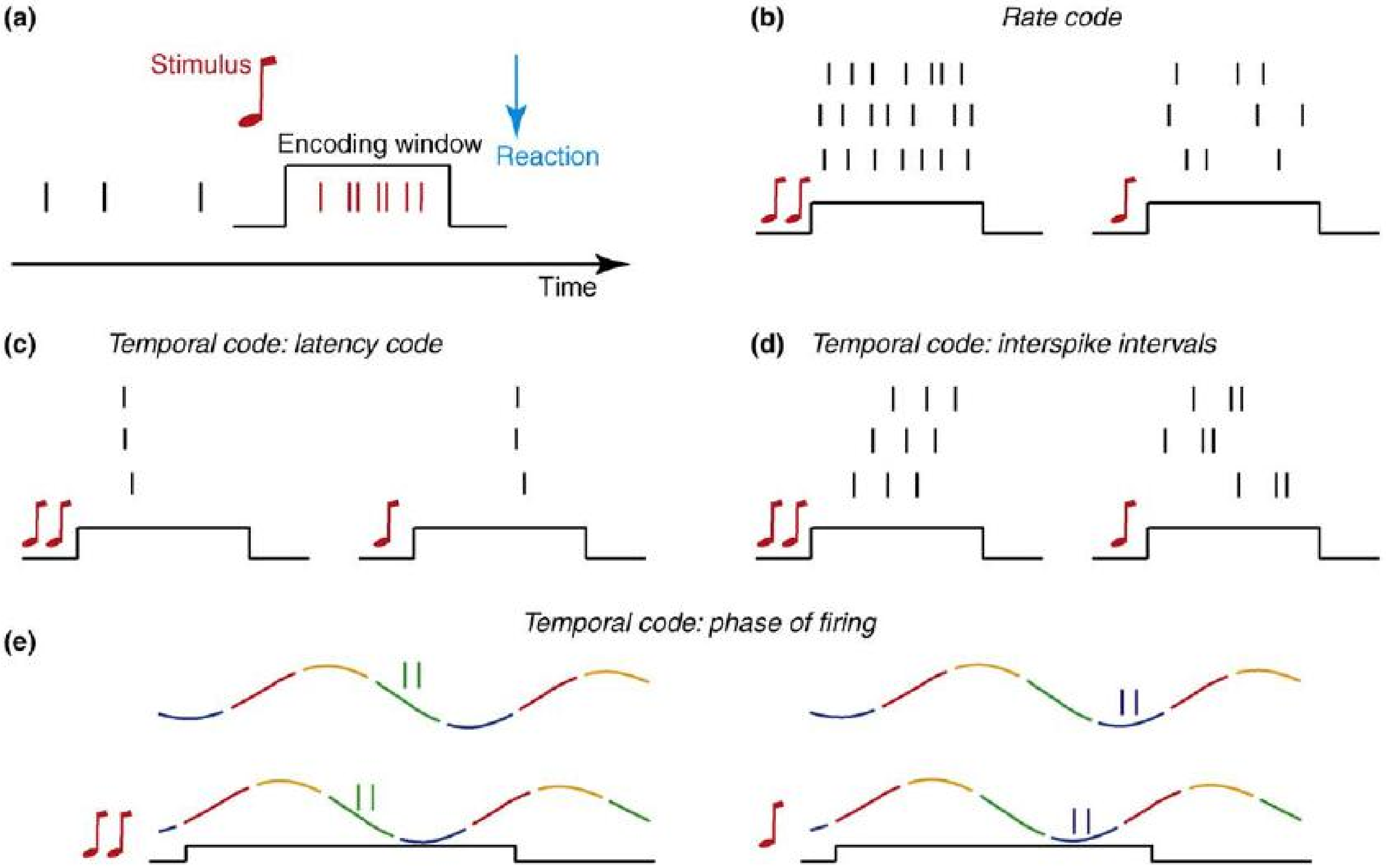
$$\begin{cases} s_i(t) = \Sigma_f \delta(t - t_i^f) \\ s_d(t) = \Sigma_g \delta(t - t_d^g) \\ s_o(t) = \Sigma_h \delta(t - t_o^h) \end{cases}$$

$$\frac{dw_i(t)}{dt} = \eta [s_d(t) - s_o(t)] I_{PSC}^i(t)$$



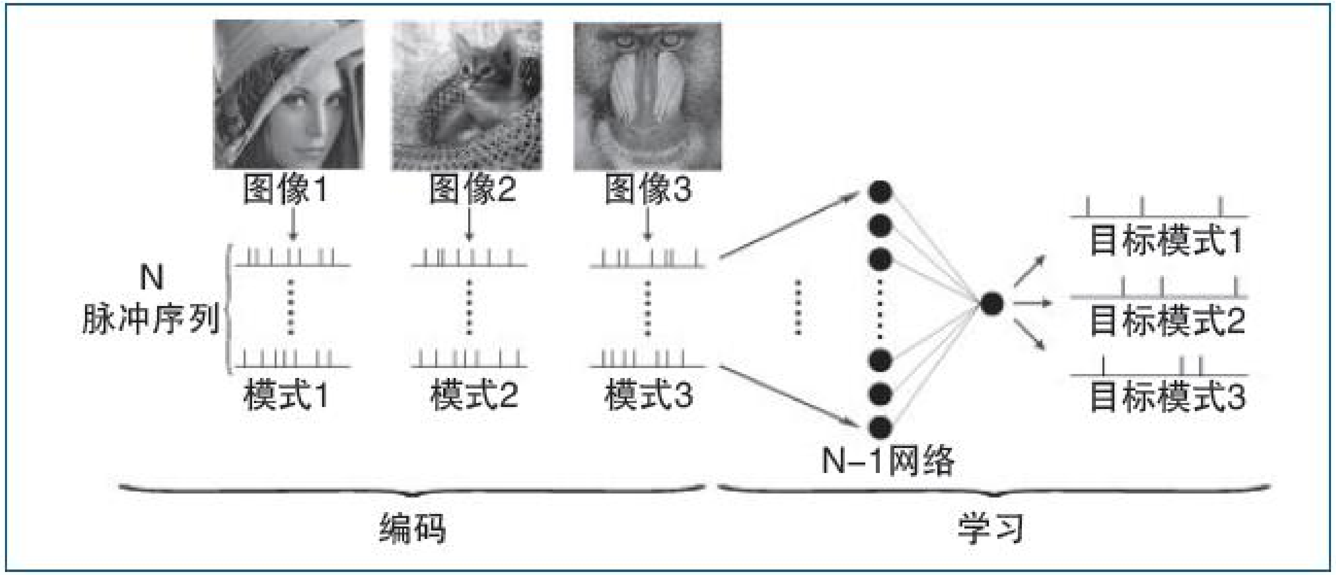
神经编码

- 神经脉冲序
  - 频率编码
    - 泊松过
  - 时间编码
  - 群体编码



应用：模式识别

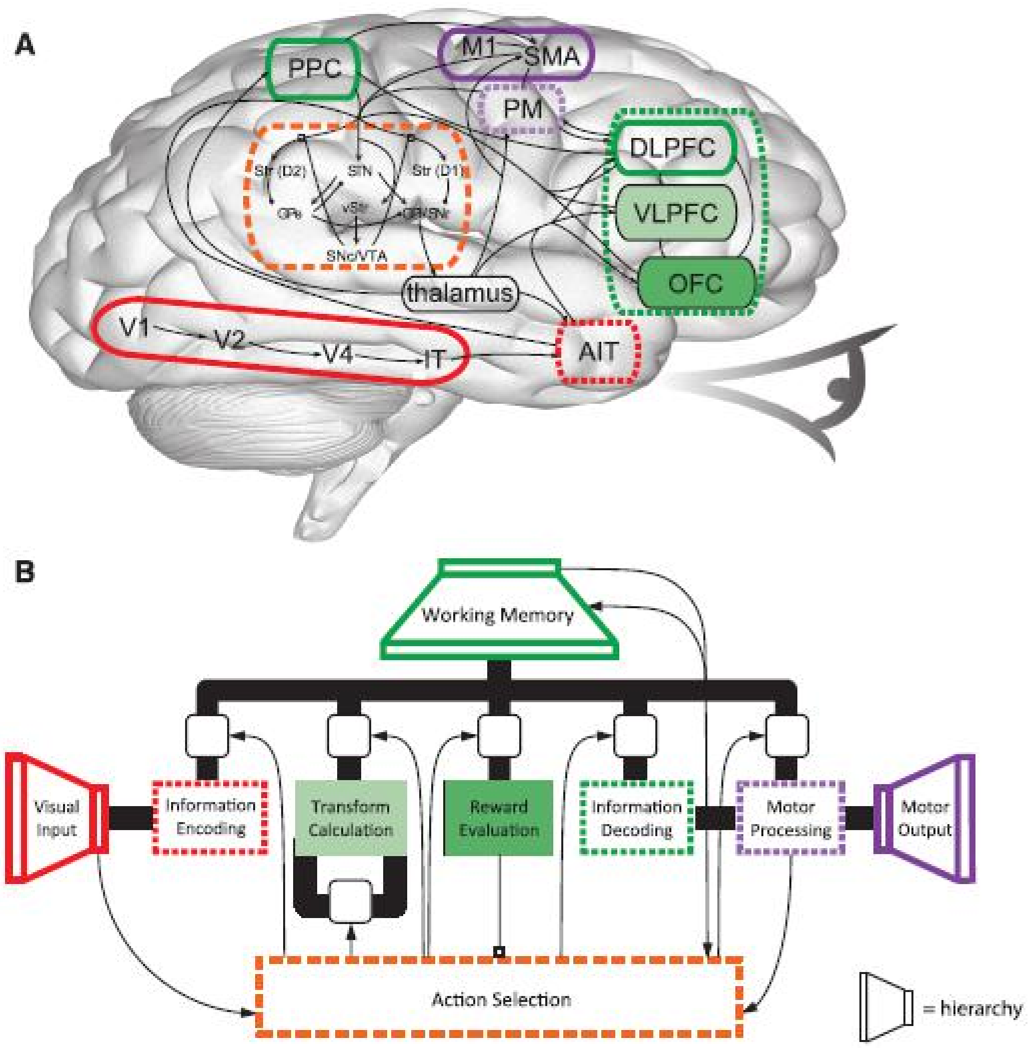
- 基于脉冲时间的模式识别模型
  - 主要由编码和学习网络两个部分组成
  - 编码部分采用将时滞编码和相位编码相结合的方法，以将图像信息转化为由神经脉冲序列组成的时空斑图(spatiotemporal pattern)。
  - 一个单层脉冲神经网络，用来学习识别不同的输入



J. Hu et al, 2013

应用：SPAUN

- Spaun（Semantic Pointer Architecture Unified Network，语义指针架构统一网络）
  - 人类大脑模拟系统
  - 拥有250万只虚拟神经元，可以执行8项不同的任务。



小结

- 美国和欧盟启动脑科学和类脑工程项目使得“类脑智能”成为热门话题。
- 目前所谓的“类脑智能”与人脑相距甚远。
- 人工智能目前的重点是探索使机器体现智能行为的各种途径，研究开发智能化的设备和各种智能应用软件。
  - 智能是目标，类脑是手段

How to design computers?

Biological computer

Mathematical computer

- Which model to emulate : brain or mathematical logic ?
- Which will win?

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Thanks !