Decision-making

吴思
心理与认知科学学院
IDG/McGovern 脑科学研究所
北大-清华联合生命科学中心
北京大学

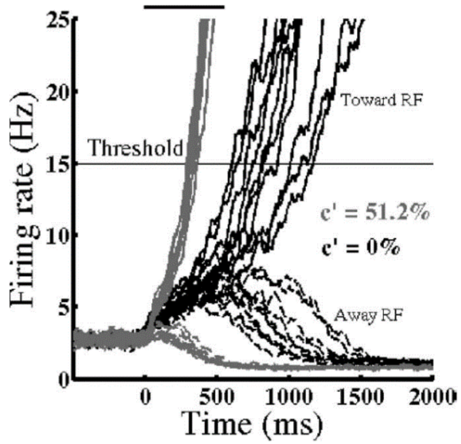
Decision-making

In psychology, **decision-making** (also spelled **decision making** and **decisionmaking**) is regarded as the cognitive process resulting in the selection of a belief or a course of action among several possible alternative options, it could be either rational or irrational.

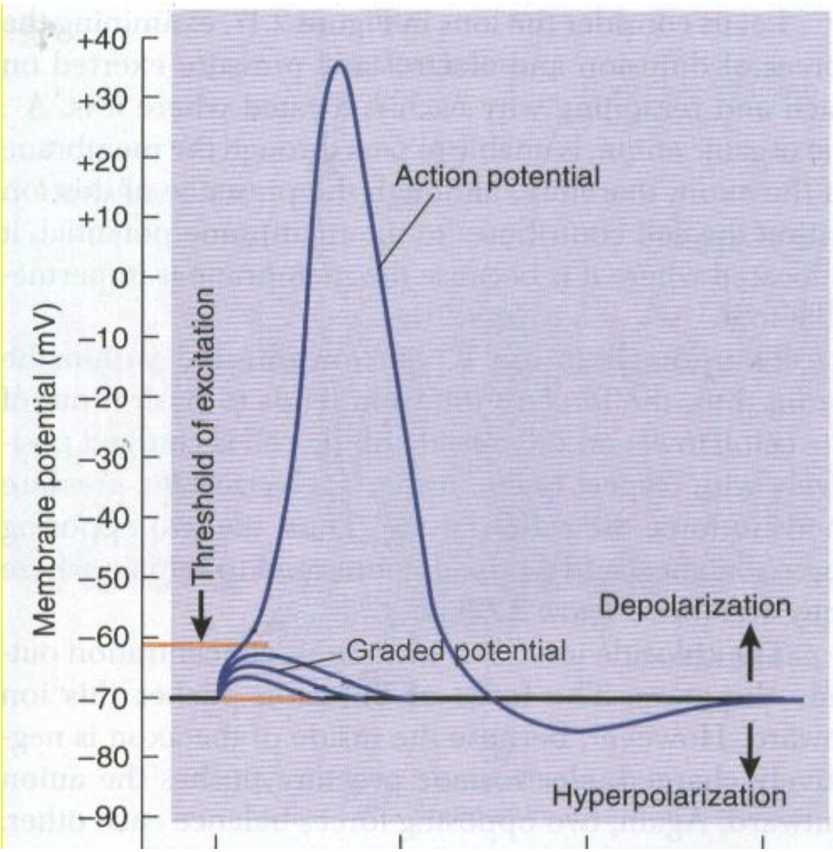
From Wikipedia

Spiking: event-based decision-making

- Spiking: an event-based decision-making
- "Spiking" : an abrupt change of the state
- Why event-based?



Spiking: Integrate & Firing



Integrating input and fire!

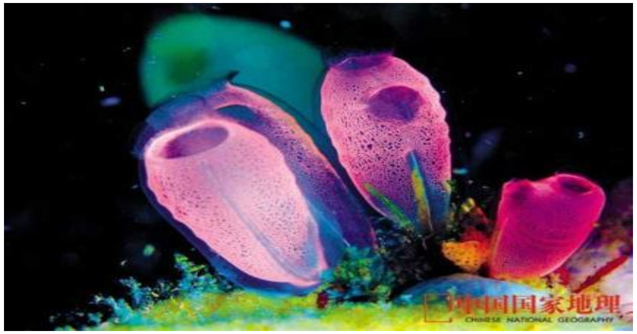
Integrating information and fire!

Spiking: event-based decision-making!

Brain is targeted for processing dynamical Information

- Baby sea squirt swim, having brain

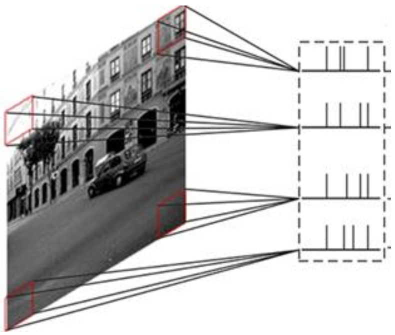
- Adult sea squirt no movement, without brain



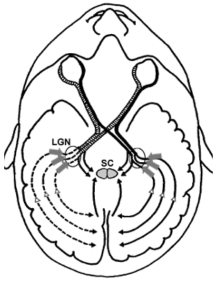
Brain is targeted for processing dynamical Information

◆The brain processes spatio-temporal pattern

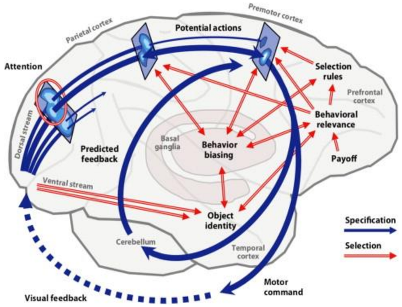
动态视觉光流信号



动态脉冲序列传播



动态交互的信息加工



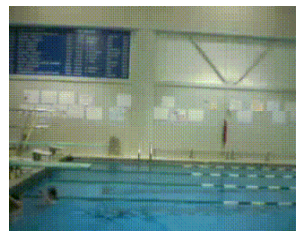
动态跨脑区信息整合

We never “see” a static image!

AI for Discriminating Spatio-temporal Patterns

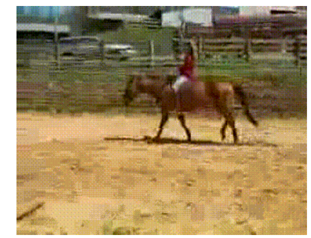
- Play basketball

- Biking



- Diving

- Golfing



- Horse riding

- Soccer juggling

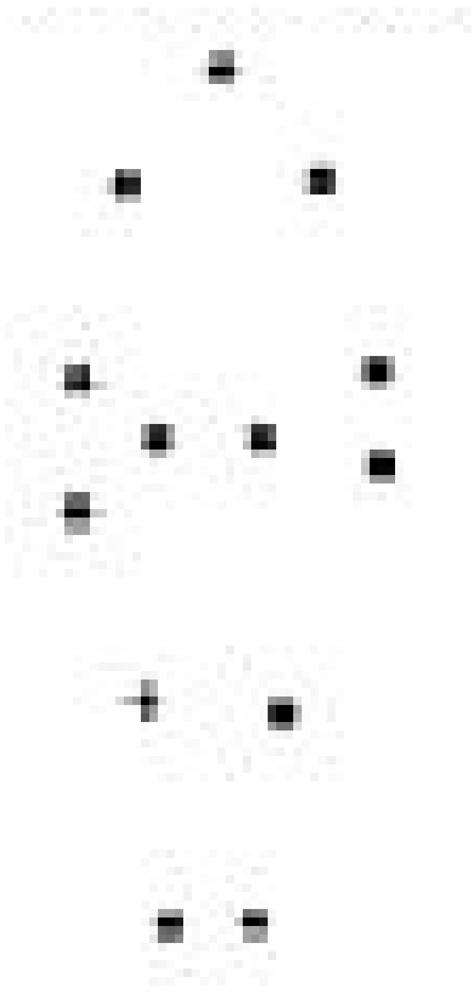
- Swing

- Tennis

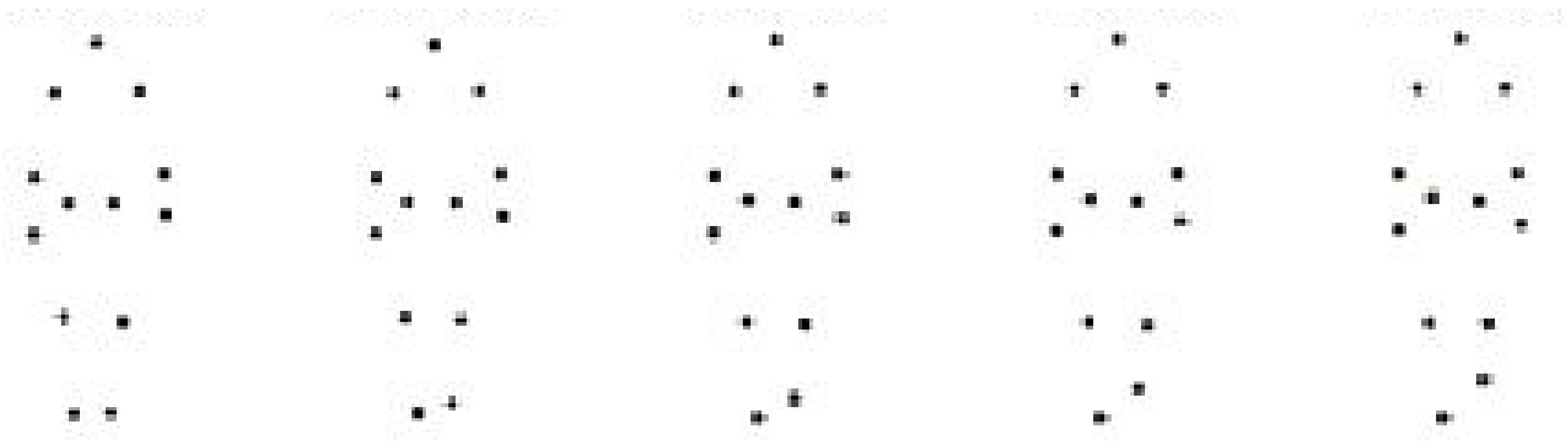
- Trampoline jumping

- Volleyball

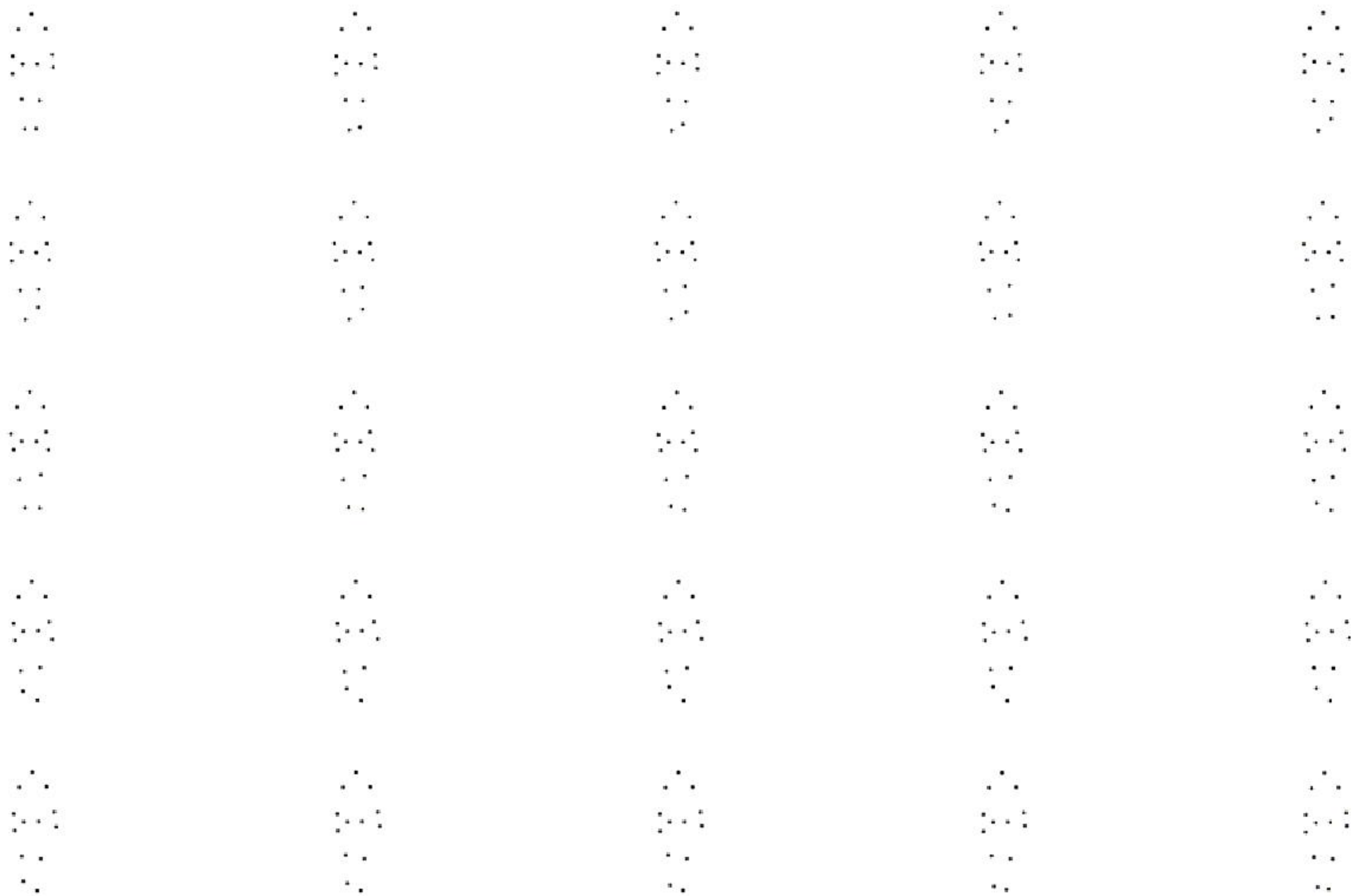
What is this?



What is this?

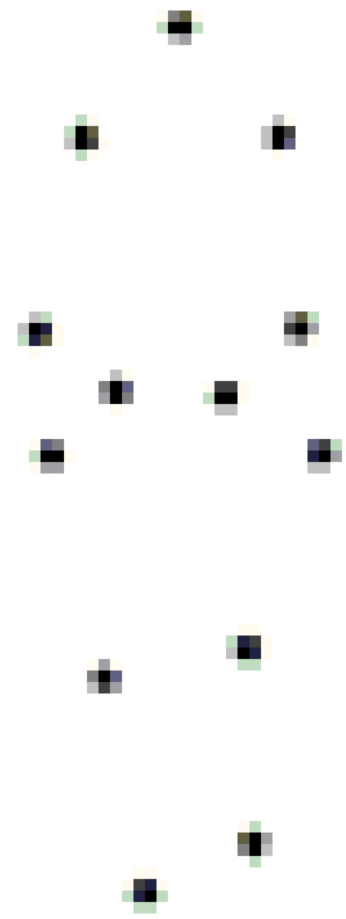


What is this?



The spatial-temporal structure of an image sequence defines the motion pattern

Extracting spatial-temporal structure is the key



Shuffled sequence

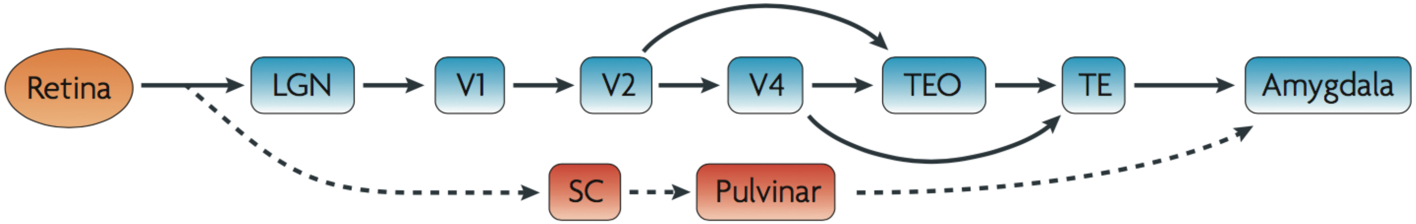
The challenge for processing spatio-temporal information

- Extracting spatial features frame by frame

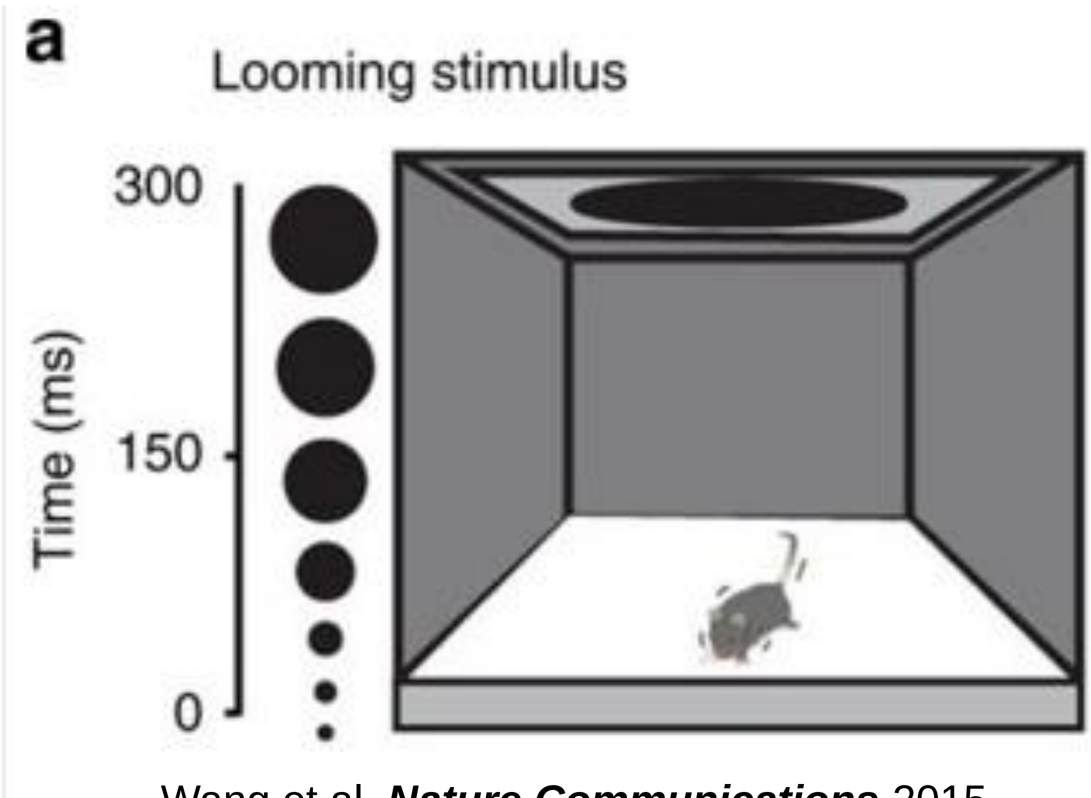
- Integrating information over time <u>and</u> in the right order

Subcortical visual pathway

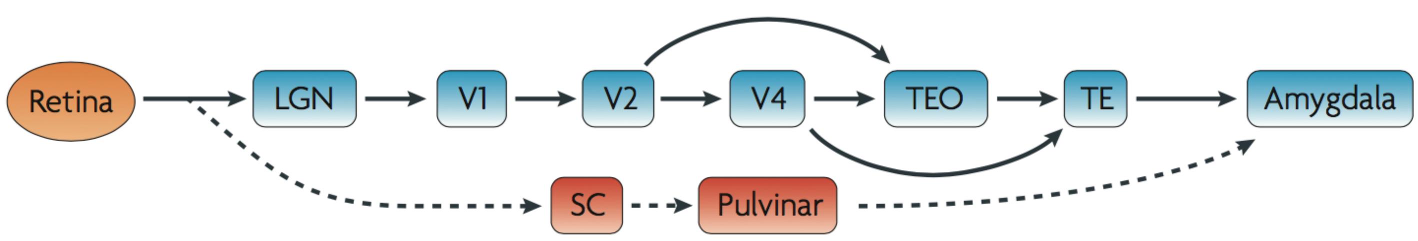
Gelder et al, ***Current Biology***, 2008



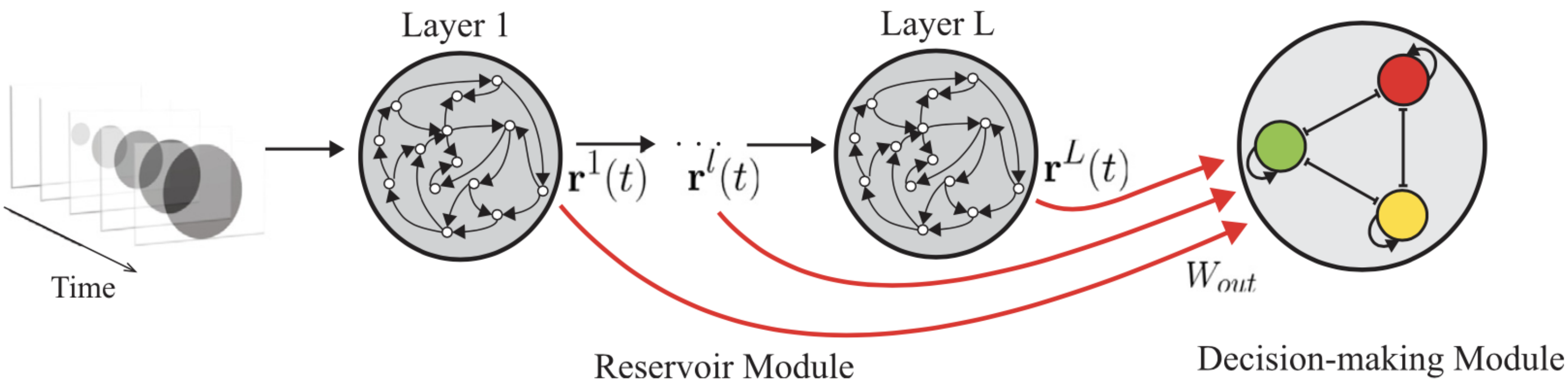
Subcortical pathway for rapid motion processing



Wang et al, ***Nature Communications*** 2015



A canonic spatio-temporal pattern recognition model



⇩ **Dimension expansion**

⇩ **Evidence accumulation**

Lin et al. Neural Networks 2021

The subcortical visual pathway

The first two stages of subcortical visual pathway:
Retina → superior colliculus

Dimension expansion: retinal network.

Decision making: Wide-field vertical cells in the superfical layers of SC integrate optical inputs over a large retinal area; Wide-acting inhibition has been recorded between wide-field vertical cells.

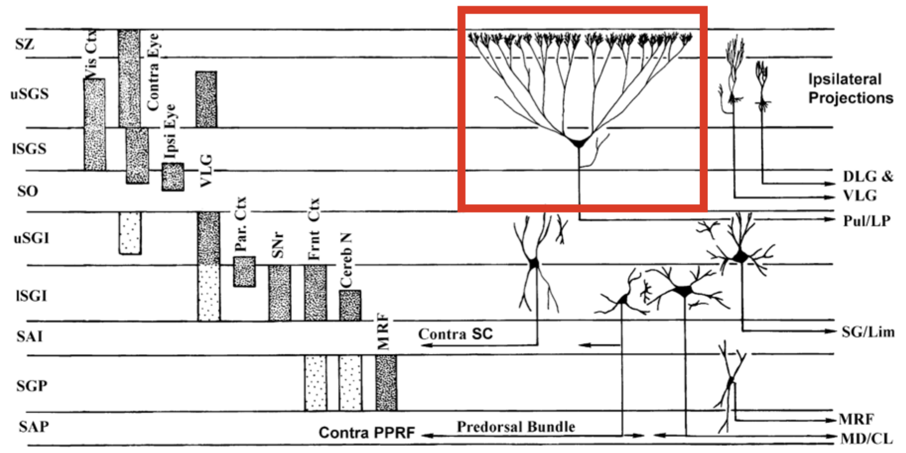


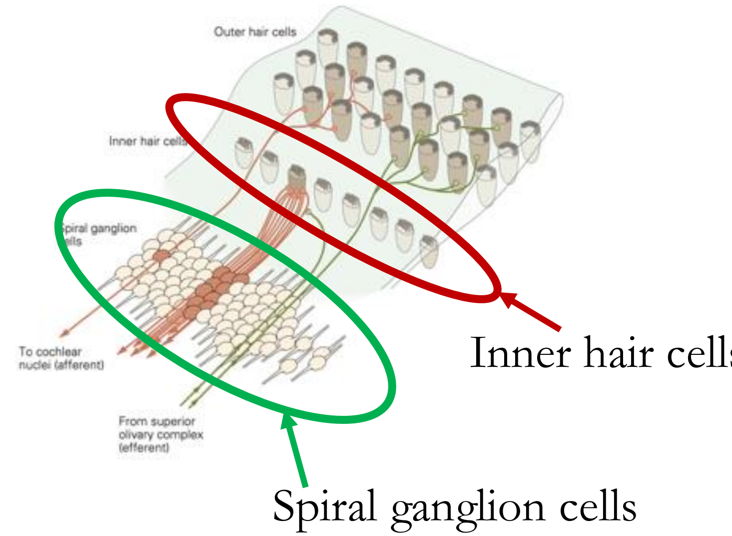
Fig. 24. Summary diagram illustrating inputs (on left) and output cells (on right) inhabiting the various layers of the gray squirrel superior colliculus (P.J. May and W.C. Hall, unpublished observations).

Primary cell types in SC

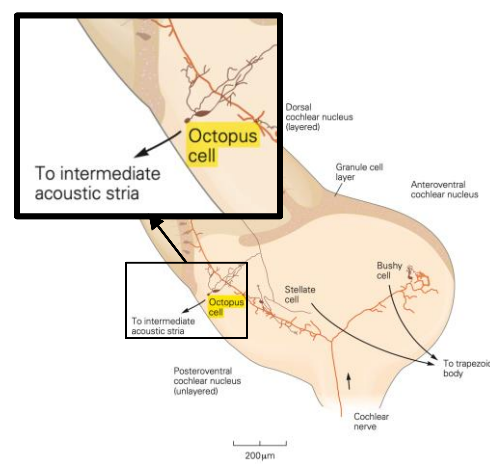
The auditory pathway

The first two stages of primary auditory pathway:
Inner Ear → Cochlear Nuclei

Dimension expansion: Each inner hair cell synapses on about 10 spiral ganglion cells; each spiral ganglion cell receives input from only 1 inner hair cell.



Decision-making: the octopus cell in the cochlear nuclei has large spaning of dendritic trees and very low input resistence. Therefore, it can detect specific sound with exceptional temporal precision.



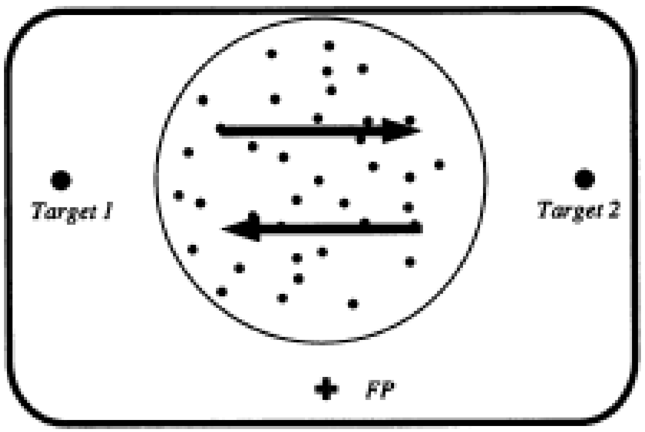
Evidence accumulation in decision-making

Three key elements:

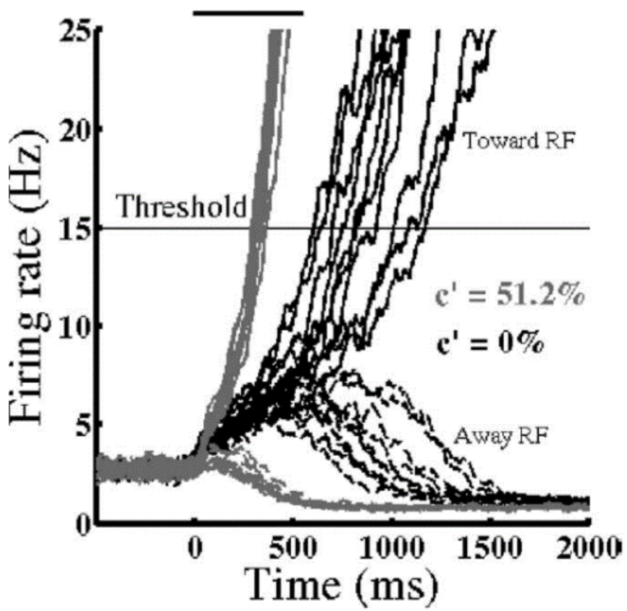
- Evidence favoring each choice is integrated over time
- Decision is reached when sufficient evidence has accumulated favoring one choice over others
- Decision made is robust to noises

Decision-making in neural system

Two-alternative forced choice



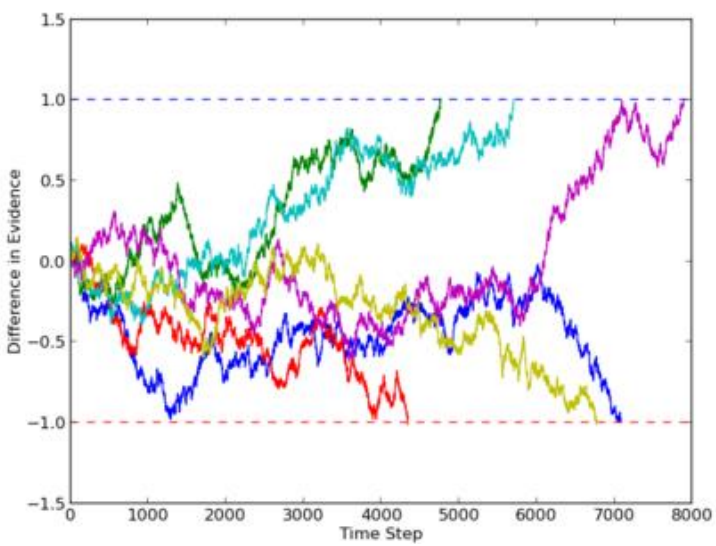
LIP neuron



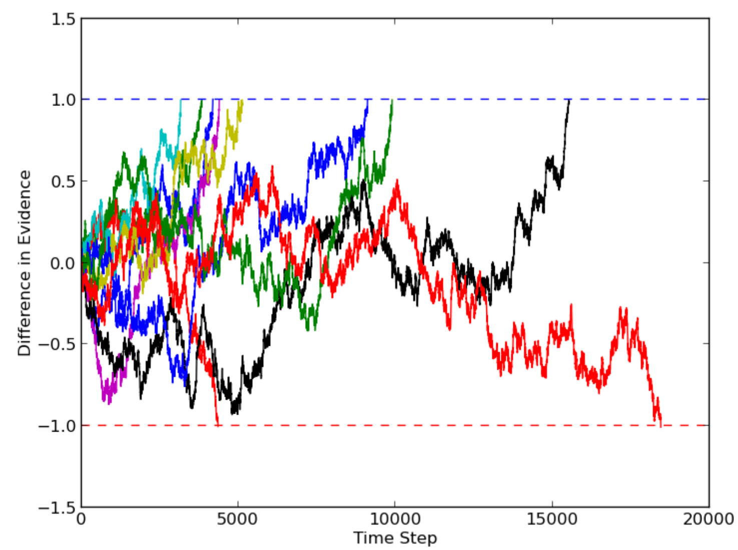
The standard drift-diffusion model

$$dx = Adt + cdW \ , \ x(0) = 0$$

A: the drift term, related to evidence
dW： the noise term, related to input ambiguity



A=0



A>0

Other decision-making models

- **Ornstein – Uhlenbeck model**

$$dx = (\lambda x + A)dt + cdW$$

- **Race model**

$$\begin{aligned} dy_1 &= I_1 dt + cdW_1 \\ dy_2 &= I_2 dt + cdW_2 \end{aligned}, \quad y_1(0) = y_2(0) = 0$$

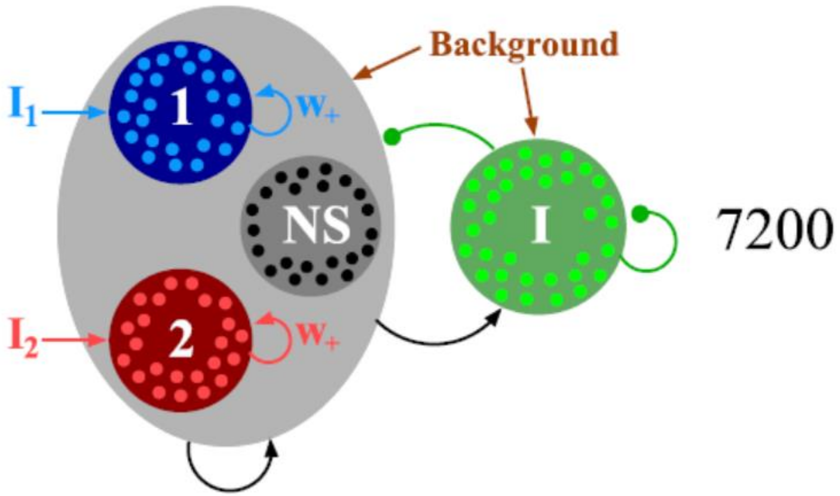
- **Mutual inhibition model**

$$\begin{aligned} dy_1 &= (-ky_1 - wy_2 + I_1)dt + cdW_1 \\ dy_2 &= (-ky_2 - wy_1 + I_2)dt + cdW_2 \end{aligned}, \quad y_1(0) = y_2(0) = 0$$

A neural decision-making model

Probabilistic Decision-making by Slow Reverberation in Cortical Circuits

Spiking neuronal network model



$$I_{syn}(t) = I_{ext,AMPA}(t) + I_{rec,AMPA}(t) + I_{rec,NMDA}(t) + I_{rec,GABA}(t)$$

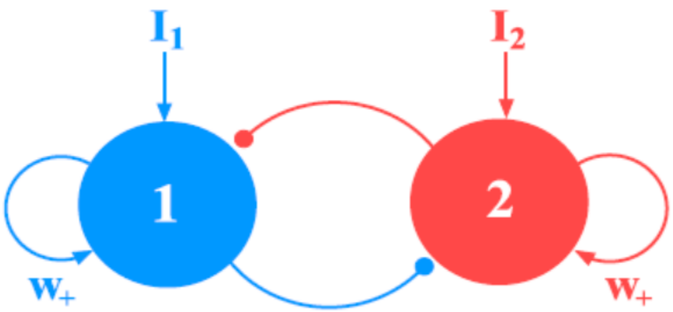
$$I_{rec,NMDA}(t) = \frac{g_{NMDA}(V(t) - V_E)}{(1 + [Mg^{2+}]\exp(-0.062V(t))/3.57)} \sum_{j=1}^{C_E} w_j s_j^{NMDA}(t)$$

Features:

- Self-excitation
- Slow dynamics

Wang, *Neuron*, 2002

The working mechanism



Mean field Model

$$\frac{dS_i}{dt} = -\frac{S_i}{\tau_S} + (1 - S_i)\gamma H_i$$

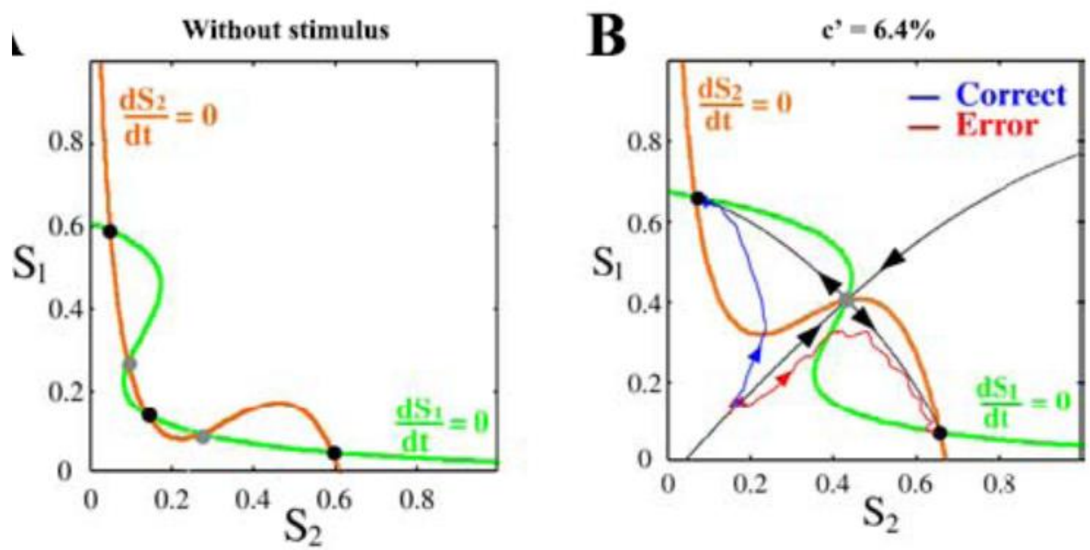
$$H_i = \frac{ax_i - b}{1 - \exp[-d(ax_i - b)]}$$

$$x_1 = J_{N,11}S_1 - J_{N,12}S_2 + I_0 + I_1 + I_{\text{noise},1}$$

$$x_2 = J_{N,22}S_2 - J_{N,21}S_1 + I_0 + I_2 + I_{\text{noise},2}$$

$$I_i = J_{A,\text{ext}}\mu_0\left(1 \pm \frac{c'}{100\%}\right)$$

$$\tau_{\text{AMPA}}\frac{dI_{\text{noise},i}(t)}{dt} = -I_{\text{noise},i}(t) + \eta_i(t)\sqrt{\tau_{\text{AMPA}}\sigma^2_{\text{noise}}},$$



Wong, *J. Neurosci.*, 2006

A further simplified decision-making model

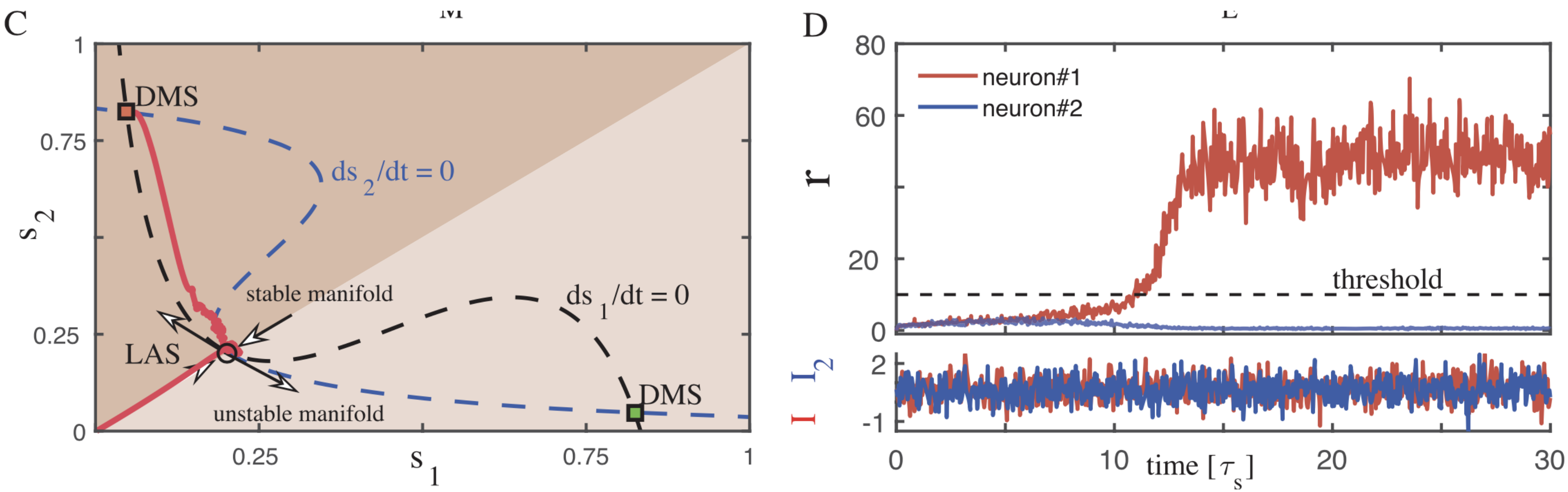
Denote x_i the synaptic input received by the ith neuron, r_i the corresponding neuronal activity, and s_i the synaptic current due to NMDA receptors. The dynamics of the module is written as,

$$x_i(t) = J_E s_i + \sum_{j \neq i}^{N_{dm}} J_M s_j + I_i$$

$$r_i(t) = \frac{\beta}{\gamma} \ln[1 + \exp(\frac{x_i - \theta}{\alpha})]$$

$$\tau_s \frac{ds_i}{dt} = -s_i + \gamma(1 - s_i) r_i$$

Accumulating evidence over time

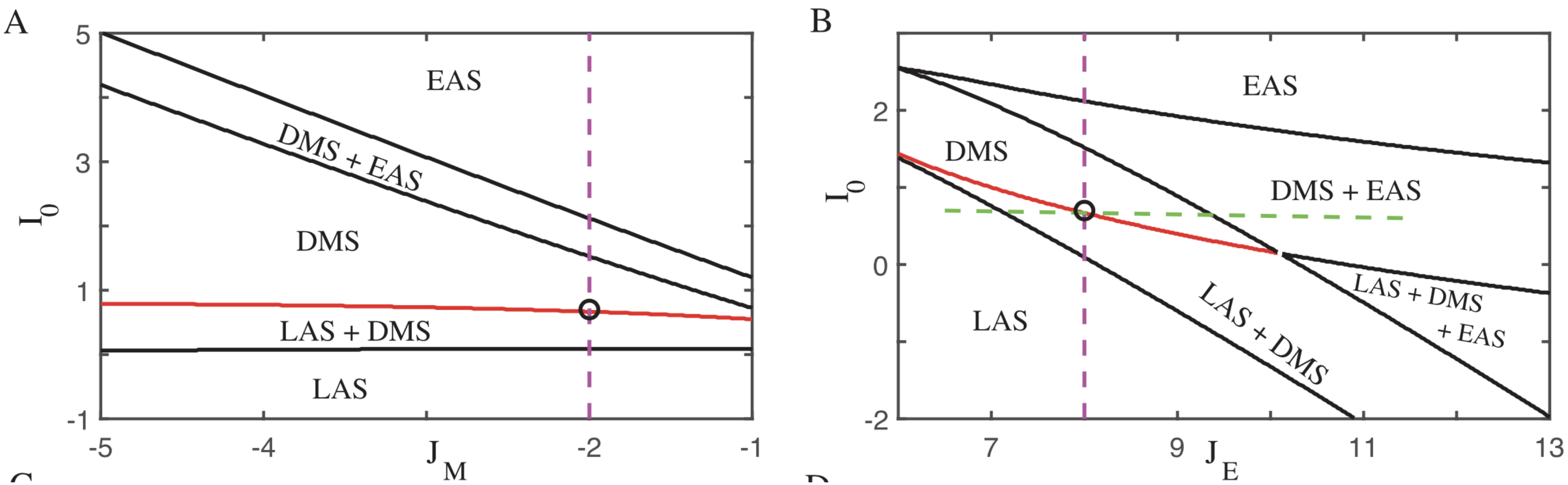


$$I_1(t) = 6.65 + 0.9 * \zeta_1(t),$$

$$I_2(t) = 6.6 + 0.9 * \zeta_2(t),$$

$\zeta_1(t), \zeta_2(t)$ are Gaussian white noise

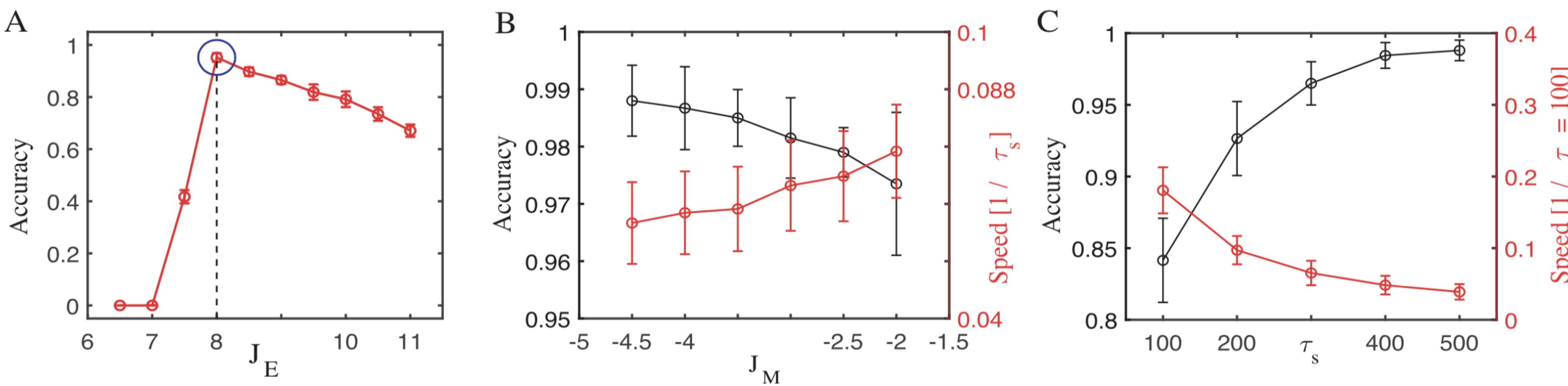
Phase diagram of a decision-making model



- LAS: all neurons are at a low firing rate;
- DMS: only one neuron is at a high firing rate and others at low firing rate, and the network makes a decision;
- EAS: all neurons are at a high firing rate.

Parameter setting in the decision-making module

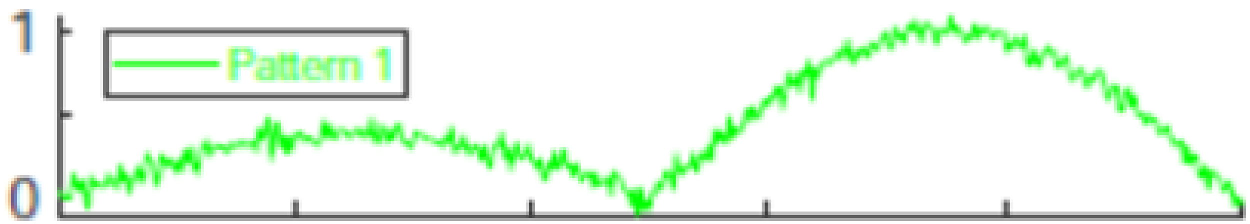
Speed-accuracy tradeoff



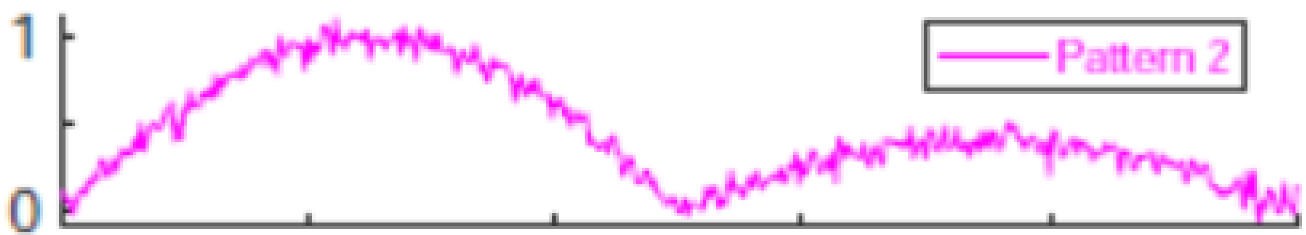
The optimal parameter regime for decision-making should be on the DM-boundary

Pure evidence accumulation over time is not enough

Temporal order is indistinguishable by pure temporal integration

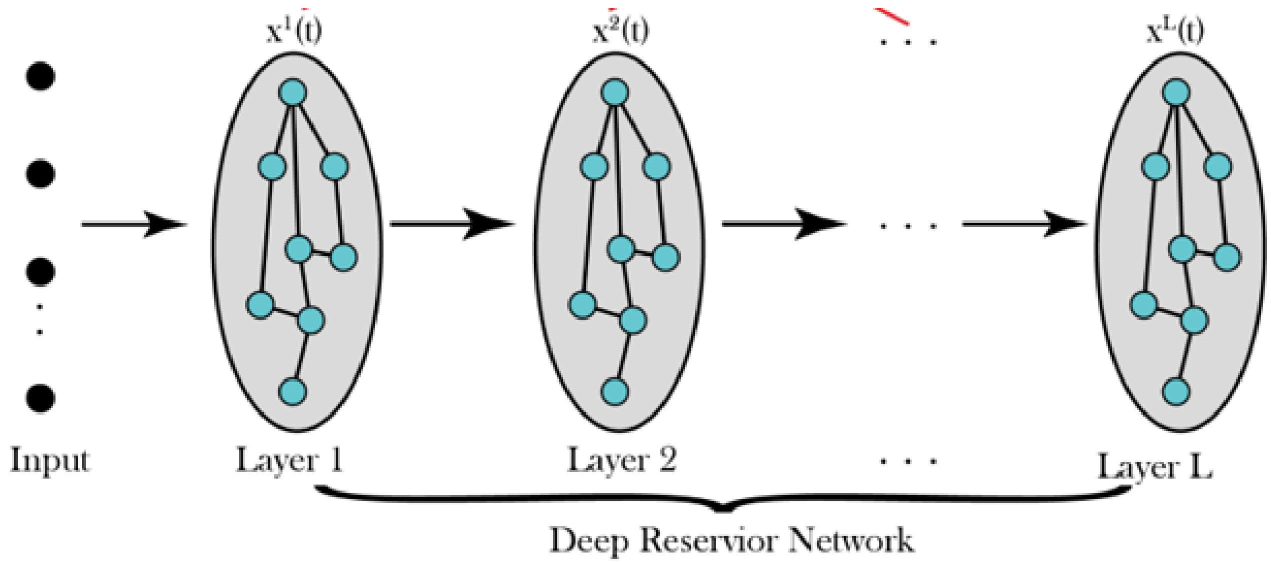


time



time

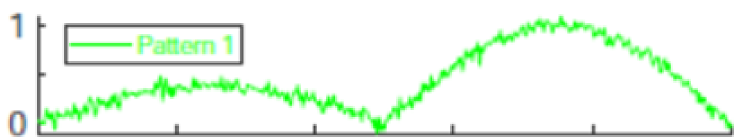
A reservoir network module



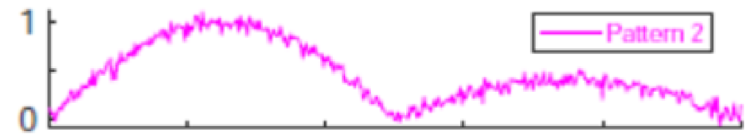
$$\tau_l \frac{dx_i^l}{dt} = -x_i^l + \sum_{j=1}^{N_{l-1}} W_{i,j}^{l,l-1} r_j^{l-1} + \sum_{j \neq i}^{N_l} W_{i,j}^{l,l} r_j^l + \sum_{j=1}^{N_{in}} W_{i,j}^{l,0} I_j^{ext} \delta_{l,1},$$

From temporal to spatial

Two temporal patterns of different orders are indistinguishable by temporal integration



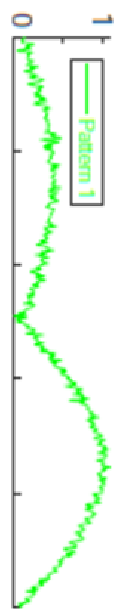
time



time

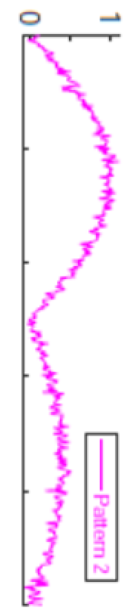
Processed by reservoir network

Space

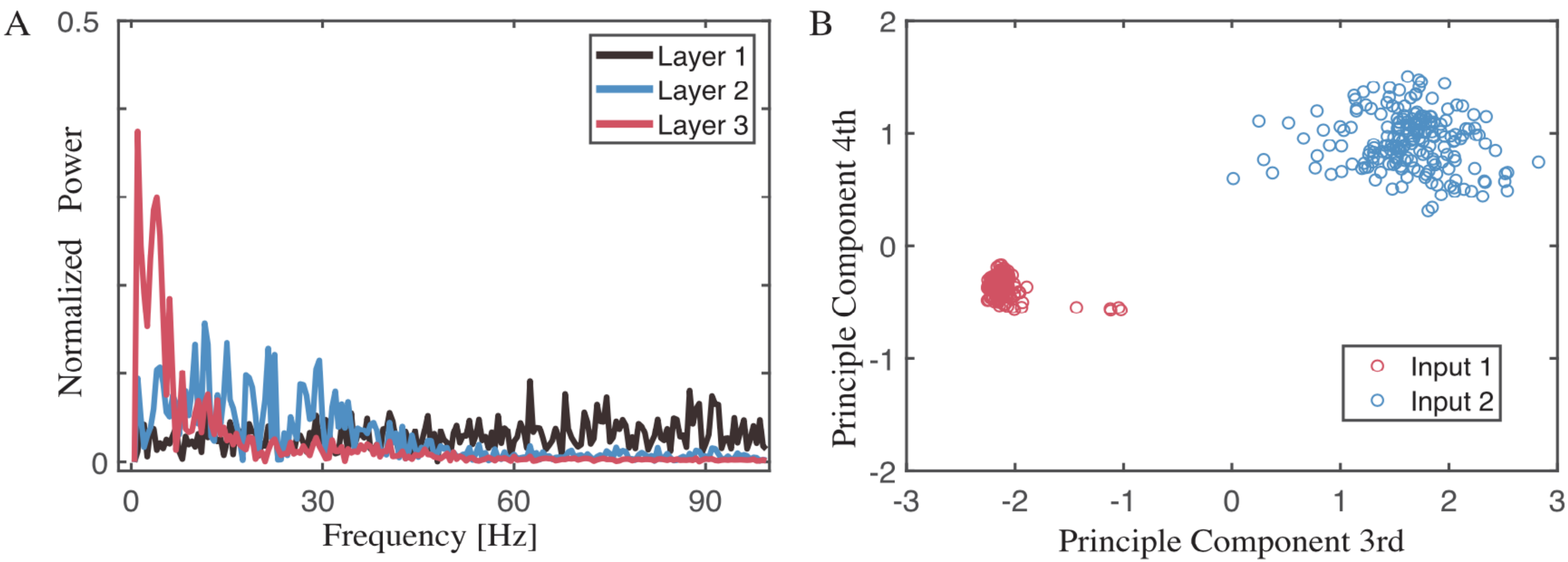


Two spatial patterns
becomes distinguishable!

Space



Neural representation in the reservoir module



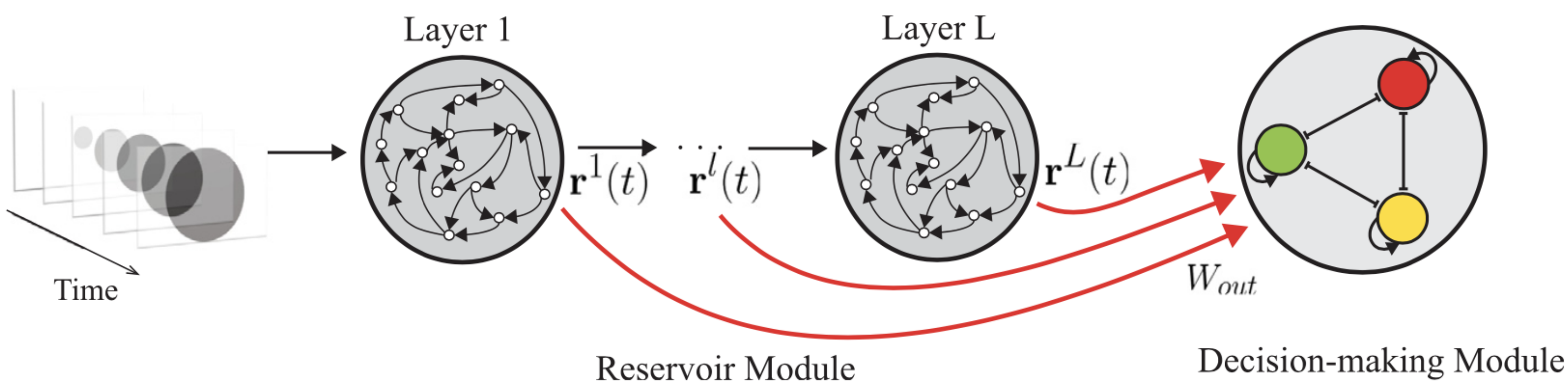
Response to Gaussian white noises

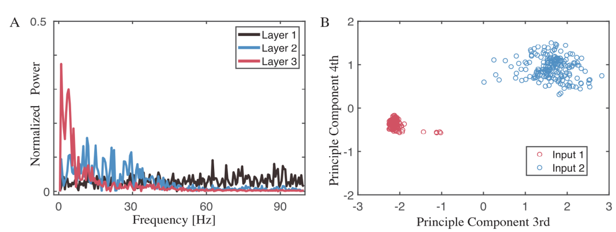
$$I^{ext,1}(t) = \sin(20\pi t) + \sin(200\pi t) + 0.1\xi_1(t)$$

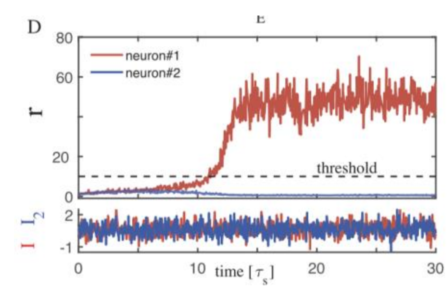
$$I^{ext,2}(t) = \sin(40\pi t) + \sin(160\pi t) + 0.1\xi_2(t).$$

Along the layer hierarchy, the dominating components of neuronal responses progress from high to low frequencies, indicating that the frequency information of temporal inputs is separated across layers.

A motion-pattern recognition model

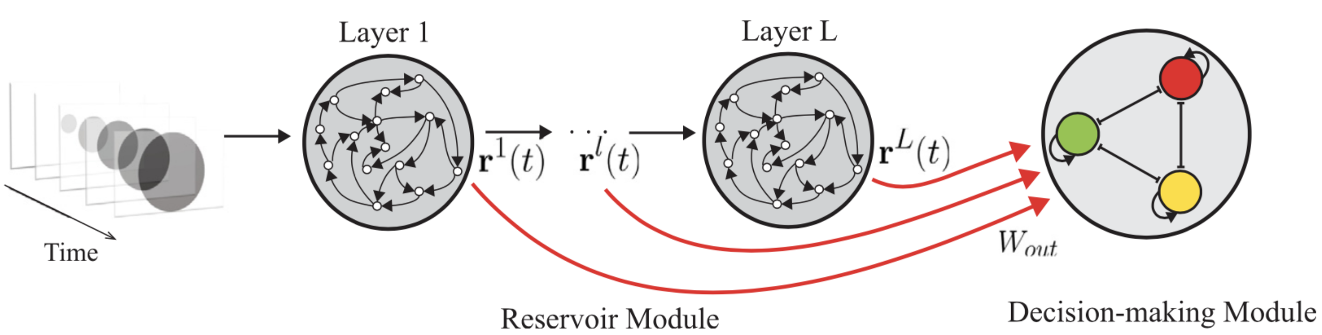






In summary

- ➢ Building up a reservoir module (no training, by theory).
- ➢ Building up a decision-making module (no training, by theory).
- ➢ Learning the connection weights from reservoir to decision-making modules via supervised training.



Supervised learning

Denote the input from the reservoir module to a decision- making neuron as,

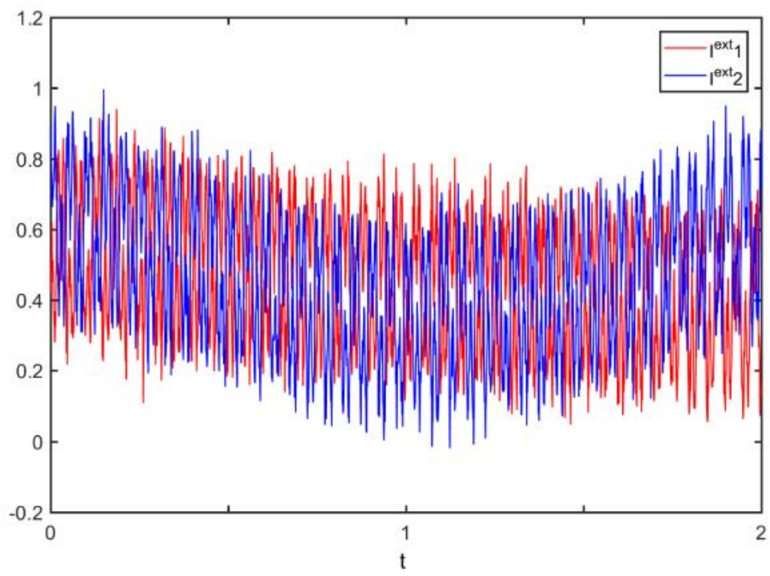
$$I_i = I_0^* + \sum_{l=1}^{L} \sum_{j=1}^{N^l} W_{lj}^{dm,i} r_j^l$$

We optimize the read-out matrix $\mathbf{W}^{dm} = \{W_{lj}^{dm,i}\}$ through minimizing the discrepancy between the actual inputs received by decision-making neurons and the target inputs, which is written as,

$$E = \frac{1}{2} \sum_{i=1}^{N_{dm}} \sum_{k=1}^{N_k} \int_0^T dt \left[f_i^k(t) - I_i^k(t)\right]^2$$

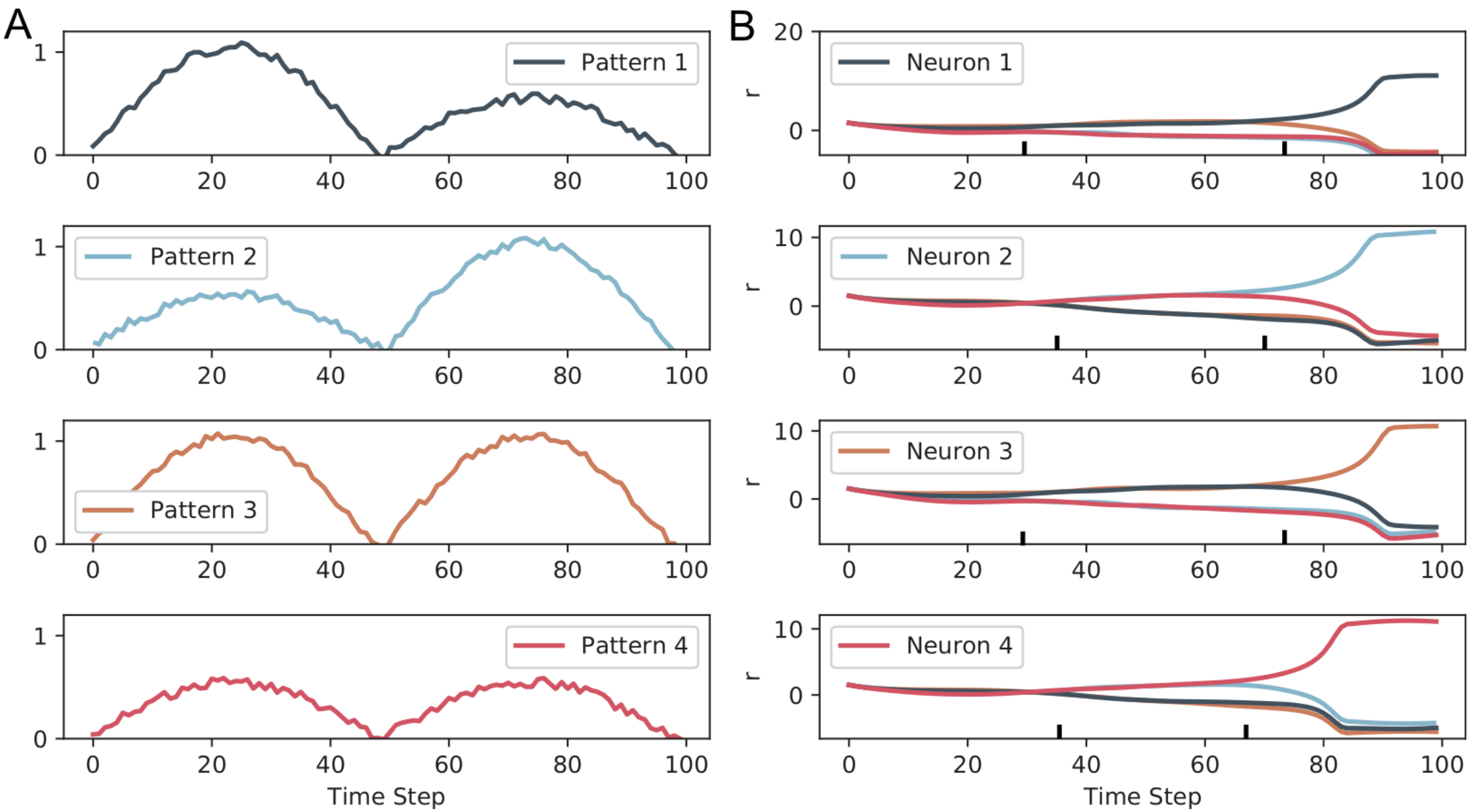
Discriminating temporal frequency

$$I_1^{ext} = \sum_{i=1}^{3} \sin\left[2\pi a_i^1 \left(t+\xi_1\right)\right] \Big/ 3+1; \quad I_2^{ext} = \sum_{i=1}^{3} \sin\left[2\pi a_i^2 \left(t+\xi_2\right)\right] \Big/ 3+1;$$

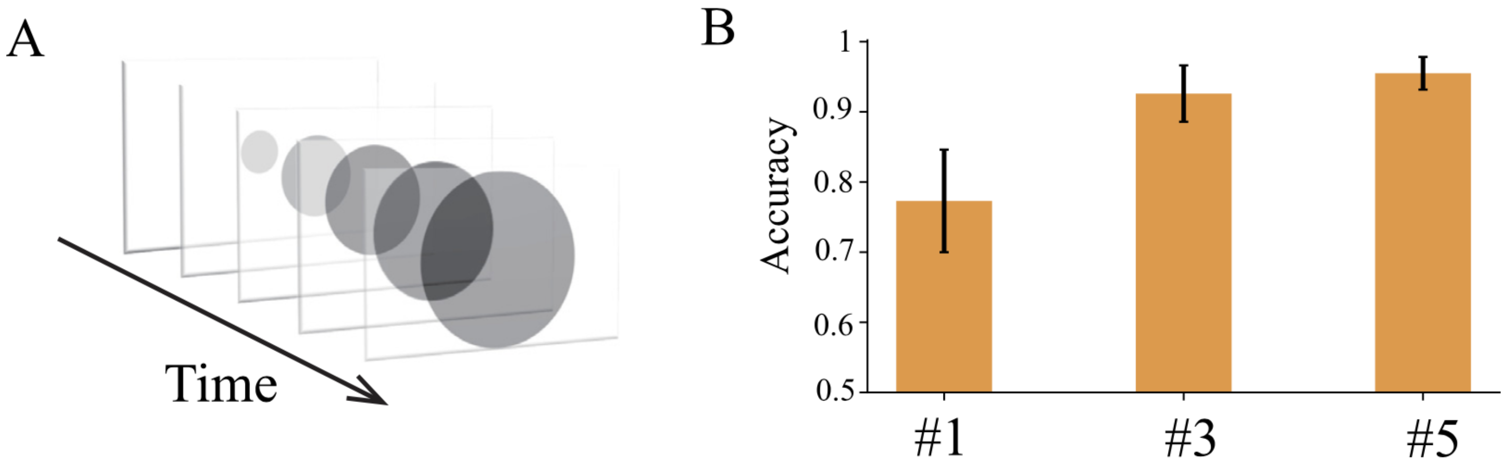


	Task A	Task B
1 Layer N = 180	51.91% τ_c = 1	69.47% τ_c = 0.25
3 Layer N = 60, 60, 60	61.90% τ_c = 5, 5, 5	90.35% τ_c = 0.25, 0.25, 0.25
3 Layers (Last) N = 60, 60, 60	86.37% τ_c = 0.25, 1, 12	91.43% τ_c = 0.25, 1, 7
3 Layer (All) N = 60, 60, 60	88.75% τ_c = 0.25, 1, 12	97.25% τ_c = 0.25, 1, 7
3 Layer (All) N = 80, 80, 80	94.55% τ_c = 0.25, 1, 12	99.62% τ_c = 0.25, 1, 7
3 Layer (All) N = 130, 130, 130	96.19% τ_c = 0.25, 1, 12	99.75% τ_c = 0.25, 1, 7
3 Layer (All) N = 130, 130, 130	45.9% τ_c = 12, 1, 0.25	40.35% τ_c = 7, 1, 0.25

Discriminating temporal order



Looming pattern discrimination



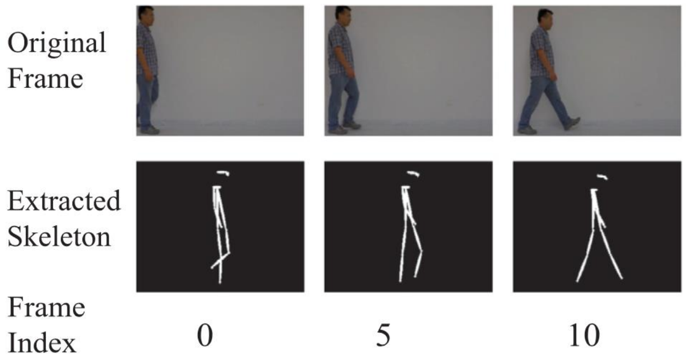
- Three categories of looming patterns with varying sizes and speeds are constructed.
- Good classification accuracies are archived with few labeled sequences.

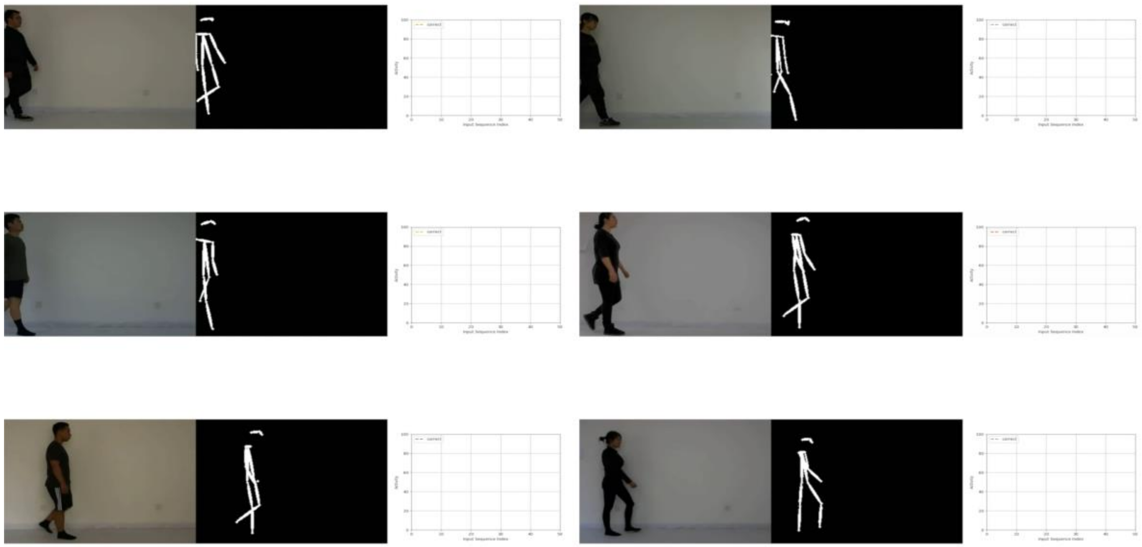
Gait Recognition

Model	5 classes	10 classes	15 classes
1-LSTM(20)	58.1%±6.2%	45.7%±6.0%	39.0%±4.4%
1-LSTM(50)	60.0%±7.9%	46.4%±6.3%	42.5%±5.0%
1-RDMN	**69.0% ± 5.5%**	**56.8% ± 2.4%**	**51.2% ± 4.0%**
5-LSTM(20)	81.8%±5.6%	77.5%±3.3%	73.8%±4.2%
5-LSTM(50)	81.9%±4.3%	79.9%±5.4%	80.3%±2.1%
5-RDMN	**93.0% ± 3.1%**	**83.9% ± 2.7%**	**83.0% ± 1.7%**

全国大学生类脑竞赛一等奖

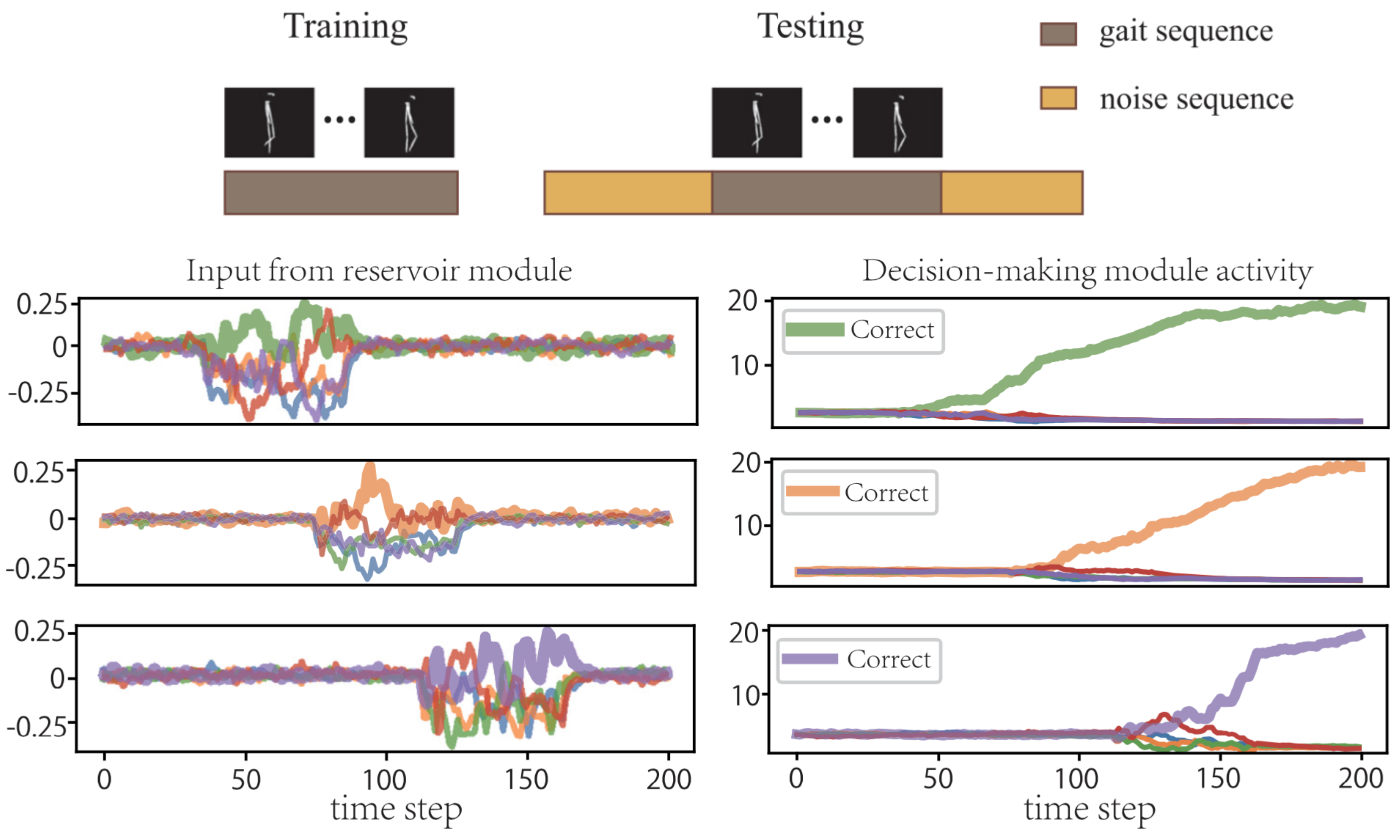
Gait recognition





Model	5 classes	10 classes	15 classes
LSTM(20)	92.4 ± 3.9	83.9 ± 3.3	79.5 ± 3.9
LSTM(50)	94.3 ± 2.0	85.7 ± 2.9	81.5 ± 3.1
LSTM(100)	90.6 ± 3.6	79.5 ± 3.2	76.6 ± 2.1
GRU(20)	92.4 ± 2.5	82.2 ± 3.7	81.3 ± 2.9
GRU(50)	95.4 ± 2.1	88.2 ± 3.2	85.7 ± 1.8
GRU(100)	96.4 ± 2.0	90.5 ± 2.1	89.7 ± 1.9
RDMN	**98.3** ± **1.0**	**93.4** ± **2.2**	**92.4** ± **2.5**

Event-based gait recognition



Model	5 classes	10 classes	15 classes
Linear	93.3 ± 3.0	79.6 ± 2.7	76.4 ± 2.5
RDMN	**98.3** ± **0.7**	**93.2** ± **2.4**	**92.3** ± **2.7**

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