#### モデル化とシミュレーション特論 2021 年度前期 佐賀大学理工学研究科 只木進一



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Introduction

#### Introduction

- neural network with mutual interaction
  - memory and retrieval
- Non-deterministic motion
- Hopfield model
- Boltzmann machine

- N neurons: state  $s_i = \{-1, 1\}$
- Interaction (symmetric because of theoretical reason)

$$w_{ij} = w_{ji}, \quad w_{ii} = 0 \tag{1}$$

- Asynchronous update
  - Select one neuron randomly and update its state
  - One time step consists of N updates (one Monte Carlo step)

$$s_i = \begin{cases} 1 & \text{if } h_i = \sum_j w_{ij} s_j \ge 0\\ -1 & \text{otherwise} \end{cases}$$
(2)

# Energy

Energy

$$E = -\frac{1}{2} \sum_{i} \sum_{j} w_{ij} s_i s_j \tag{3}$$

• Energy varies by update of one neuron

$$\delta E = -\sum_{j} w_{ij} s_j \delta s_i \le 0 \tag{4}$$

•  $\delta s_i$  always has the same sign of  $h_i = \sum_j w_{ij} s_j$ 

- Energy monotonously decreases
  - Monotonously degreasing functions are called Lyapunov

• For 
$$h_i = \sum_j w_{ij} s_j \ge 0$$

$$\delta s_i = \begin{cases} 2 & \text{if } s_i = -1 \\ 0 & \text{otherwise} \end{cases}$$

• For 
$$h_i = \sum_j w_{ij} s_j \le 0$$

$$\delta s_i = \begin{cases} -2 & \text{if } s_i = 1\\ 0 & \text{otherwise} \end{cases}$$

(5)

(6)

# Hebb's learning rule

• For learning pattern  $\vec{\xi}$ 

$$w_{ij} = \lambda \xi_i \xi_j, \qquad i \neq j$$
 (7)

•  $\lambda$  is  $O(N^{-1})$  quantity

- Energy must be extensive (示量変数): proportional to system size
- Energy is extensive for ordinary physical systems
- cf: intensive variables (示強変数)(independent of system size) temperature, pressure, etc.

$$E = -\frac{1}{2} \sum_{i} \sum_{j \neq i} \lambda \xi_i \xi_j s_i s_j$$
$$= -\frac{\lambda}{2} \left[ \left( \sum_{i} \xi_i x_i \right)^2 - \sum_{i} \xi_i^2 s_i^2 \right] = -\frac{\lambda}{2} \left[ \left( \sum_{i} \xi_i x_i \right)^2 - N \right]$$
(8)

- Two energy minima:  $\vec{s} = \pm \vec{\xi}$
- Same as ferromagnetic (強磁性) systems

P patterns

• Hebb' rule

$$w_{ij} = \lambda \sum_{\mu=0}^{P-1} \xi_i^{\mu} \xi_j^{\mu}$$
 (9)

• Overlapping with  $\mu$ -th pattern

$$m_{\mu} = \frac{1}{N} \sum_{i} \xi_i^{\mu} s_i \tag{10}$$

$$E = -\frac{\lambda}{2}N^2 \sum_{\mu} (m_{\mu})^2 + \frac{\lambda}{2}NP$$
(11)

- Each pattern is indicated by energy minima, if they are orthogonal
- There may be energy minima not indicating memory patterns

## Dynamics at finite temperature

At finite temperature T, transition probability is given by

$$P(\delta s_{i} = \pm 2) = \frac{1}{1 + e^{\pm 2\beta h_{i}}}$$
(12)  
$$h_{i} = \sum_{j} w_{ij} s_{j}, \quad \beta = 1/T$$
(13)

- probability of  $\delta s_i = -2$  ( $s_i = 1$ )
  - low temperature limit( $\beta \to \infty$ )

$$P\left(\delta s_i = -2\right) \to \begin{cases} 1 & h_i > 0\\ 0 & h_i < 0 \end{cases}$$
(14)

• high temperature limit (  $\beta \rightarrow 0$  )

$$P\left(\delta s_i = -2\right) \to 1/2 \tag{15}$$

- probability of  $\delta s_i = 2$  ( $s_i = -1$ )
  - low temperature limit( $\beta \to \infty$ )

$$P\left(\delta s_i = 2\right) \to \begin{cases} 1 & h_i < 0\\ 0 & h_i > 0 \end{cases}$$
(16)

high temperature limit

$$P\left(\delta s_i = 2\right) \to 1/2 \tag{17}$$

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# Equilibrium



$$\frac{P_{\mu}}{P_{\nu}} = \frac{w_{\uparrow}}{w_{\downarrow}} = \frac{1 + e^{-2\beta h_i}}{1 + e^{2\beta h_i}} = e^{-2\beta h_i} = \frac{e^{-\beta h_i}}{e^{\beta h_i}}$$

$$= \frac{e^{-\beta E(\mu)}}{e^{-\beta E(\nu)}}$$

$$P_{\mu} \propto e^{-\beta E(\mu)}$$
(18)
(19)

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$$h_{i} = \sum_{j \neq i} w_{ij} 1 \times s_{j}$$

$$= \frac{1}{2} \sum_{j \neq i} w_{ij} 1 \times s_{j} + \frac{1}{2} \sum_{j \neq i} w_{ij} s_{j} \times 1 + \frac{1}{2} \sum_{j \neq i} \sum_{k \neq i} w_{jk} s_{j} s_{k}$$

$$= E(\mu)$$

$$-h_{i} = \sum_{j \neq i} w_{ij} (-1) \times s_{j}$$

$$= \frac{1}{2} \sum_{j \neq i} w_{ij} (-1) \times s_{j} + \frac{1}{2} \sum_{j \neq i} w_{ij} s_{j} \times (-1) + \frac{1}{2} \sum_{j \neq i} \sum_{k \neq i} w_{jk} s_{j} s_{k}$$

$$= E(\nu)$$

$$(20)$$

Simulation

# Simulation

- Setting 10 Kanji patterns: not orthogonal!
- Change the number of patterns
- Zero or finite temperature
- Observe how the system find one of patterns

#### model package

- Neuron class:states of a neuron
- Hopfield class
  - generate weight vectors from patterns
  - update states at zero and finite temperature
  - evaluate overlapping with patterns
  - evaluate the energy
- AbstractPatterns

Simulation

#### Zero temperature

#### Overlapping with patterns



zero temperature (10 patterns)

Temporal variation of energy at  ${\cal T}=0$ 



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