Mathematical Modelling of Meso-Scale Information Processing in the Brain

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1 Introduction

Meso-scale approach focuses on how meso-scale modules such as columns, areas, or dynamically formed clusters interact with each other, and try to understand and utilise the underlying computational principles.

Recently, the predictive coding theory and its related works have provided new aspects on how higher-order areas and lower-order areas interact in cerebral cortex. On the other hand, non-hierarchical systems have not been paid much attention.

To understand the meso-scale information processing, especially in non-hierarchical systems, four mathematical models are proposed at four different viewpoints.

2 Potential Network Model

The first model describes the dynamics of meso-scale modules at the landscape viewpoint. In general, the function of an neural assembly can be characterised by attractor states, and each attractor corresponds to a local minimum of the potential function. Here, the interaction between such neural assemblies are modelled as deformation of the potential landscape:

$$\begin{aligned}\frac{\mathrm{d}\boldsymbol{x}_i}{\mathrm{d}t} &= -\alpha \nabla U_i(\boldsymbol{x}_i, X_i) + \xi_i,\\ U_i(\boldsymbol{x}_i, X_i) &= U_i^0(\boldsymbol{x}_i) + \sum_{e_{ji}\in E} \sum_{k=1}^{L_j} w_j^k(\boldsymbol{x}_j)\, U_{ji}^k(\boldsymbol{x}_i).\end{aligned}$$

To investigate the usefulness of this model to describe meso-scale phenomena, a path-planning task by Mushiake et al. was simulated numerically, and the characteristics of neurons' activities in monkeys' brains were reproduced.

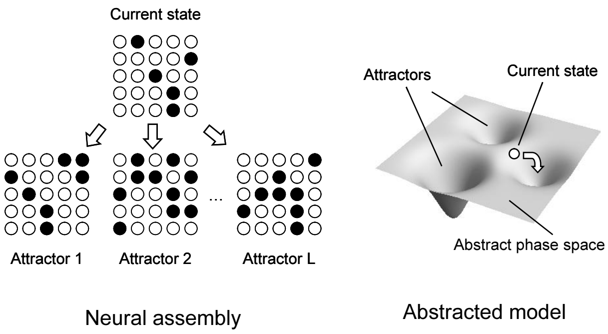

Fig 1: Attractors and potential landscape of a meso-scale module that corresponds to a neural assembly.

3 Networked Reinforcement Learning

The second model regards meso-scale modules as autonomous agents. To update their policies, reinforcement learning (RL) is used. In practice, it is problematic how to assign reward to the agents. Here, a new variable 'payment' is introduced.

This model is a generalisation of hierarchical RL and modular RL in the topological sense. By numerical simulations, this model was shown to work appropriately at least some simple situations.

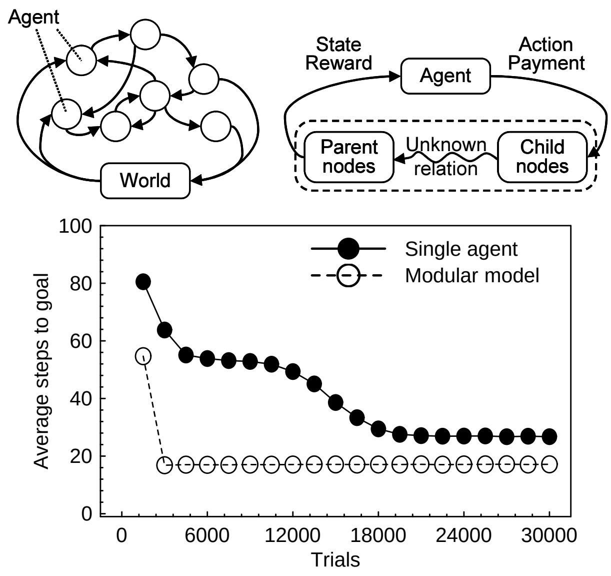

Fig 2: (Top) Schematic diagram of networked RL. (Bottom) Averaged learning curves for the task in Singh (1992).

4 Alternate Sampling

The third model is about the interaction between neocortex and hippocampus. Here the two systems are regarded as two generative models $\mathcal{M}_k = P(x, y \mid \theta_k)$ $(k = 1, 2)$, where y is a latent variable. By tuning the parameters θ_k, we attempt to fit the models to the given data set $D = \{x^1, \ldots, x^m\}$.

Under the assumption that neocortex and hippocampus may alternately learn during REM sleep and SWS, the alternate sampling method is derived:

1. Update $\mathcal{M}_1$ and $\mathcal{M}_2$ by using D (Wake phase),
2. Update $\mathcal{M}_1$ by using new samples D_2^l generated by $\mathcal{M}_2$ (SWS phase), and
3. Update $\mathcal{M}_2$ by using new samples D_1^l generated by $\mathcal{M}_1$ (REM phase).

By numerical simulations, this method was shown to be beneficial to avoid the local optima traps.

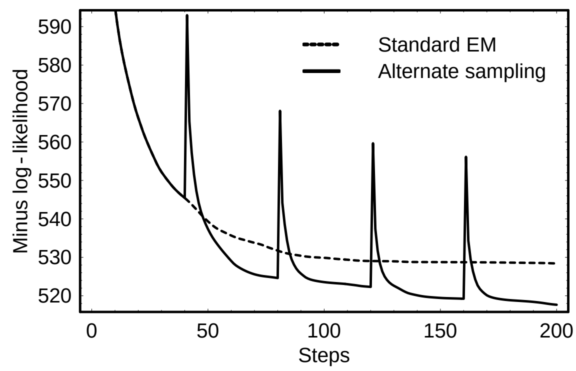

Fig 3: Averaged learning curves for the parameter estimation of a mixture of normal distributions.

5 Switching of Neuronal Clusters

In the fourth model, locally formed neuronal clusters are regarded as functional units at the meso-scale level. Similar to the traditional manner, learning pattern vectors $s^1, \ldots, s^M$ are embedded to a recurrent neural network as self-sustained attractors, and asymmetrical connections that determine cluster-to-cluster interaction are added:

$$W = \sum_{\alpha=1}^{M} s^\alpha.(s^\alpha)^{\mathrm{T}} + \lambda \sum_{(\alpha,\beta)\in A} s^\beta.(s^\alpha)^{\mathrm{T}}.$$

With proper initial condition and the rule set A, this model exhibits stepwise state transitions, which may be interpreted as a mechanism of multi-step computation in the brain.

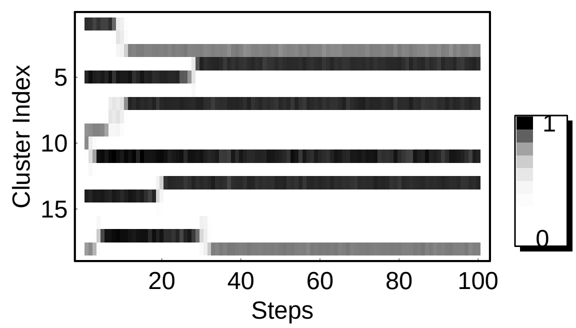

Fig 4: Time sequences of the activities of the clusters.