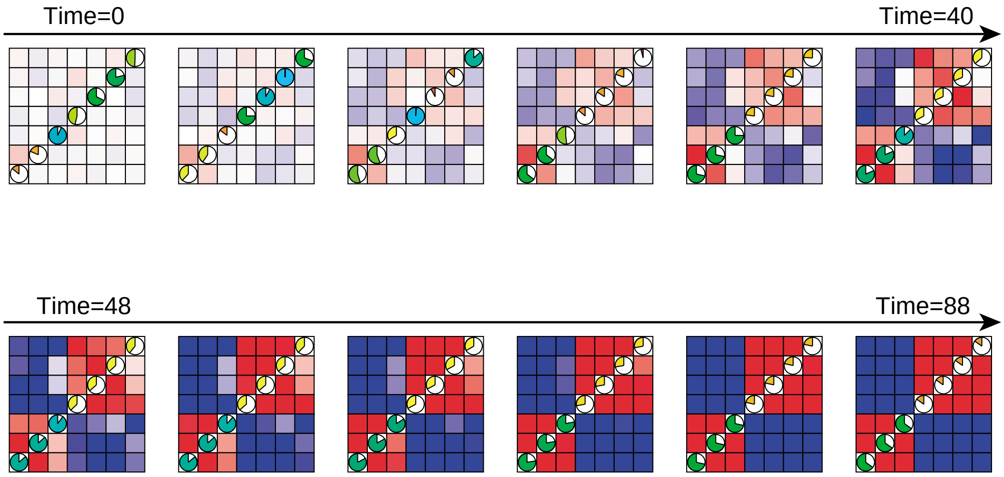

Fig. 2. The emergence of a two-cluster state. The sequence of the matrix graphs displays the time development of the state of the dynamical system, $\{\phi_i(t), k_{ij}(t)\}$. In this state, the phases of the oscillators, $\phi_i(t)$, are organized into two synchronized groups as shown in the diagonal blocks in the matrix graphs. The coupling weights among the oscillators, $k_{ij}(t)$, shown in the off-diagonal blocks, take positive couplings (red) within a synchronized group and negative couplings (blue) between the different groups. This two-cluster state emerges in the case of $\beta \sim -\pi/2$, with which the evolution rule of the coupling weight has a similar effect of like-and-like rule.

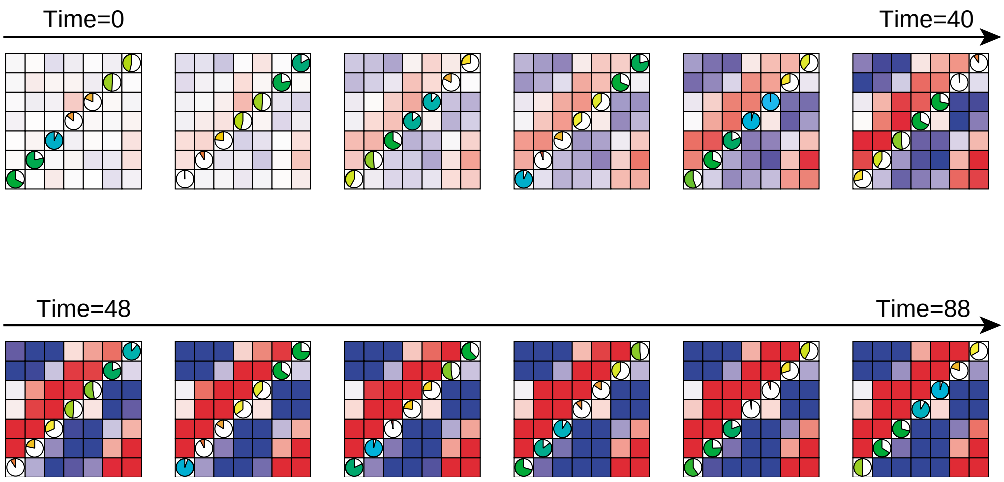

Fig. 3. The emergence of a coherent state with a fixed phase relation. A sequential pattern of the oscillators are organized, in which a fixed phase relationship is maintained over a long period. This state is observed for the parameter $\beta \sim 0$, with which the evolution rule of the coupling weight is strongly dependent on the order of the phases of oscillators, in a similar way as the spike-timing dependent plasticity in neural networks.

with frustration. These distinct dynamical behaviors can be characterized by mutual information between the initial and final phase patterns, and by entropy of the final phase pattern. In Fig. 5, the mutual information is largest for the coherent state. Since mutual information measures the information that the initial and final states share, the initial phase pattern can be most easily inferred from the final one in the coherent state. This suggests that the coherent state preserves a phase pattern through the co-evolving dynamics. A similar situation is observed for the case of the two-cluster state, except that the entropy is much smaller than that for the coherent state. This is because the possible phase patterns are restricted for the two-clustered state. For the chaotic state, the mutual information takes almost zero and the entropy is almost maximum. This fact implies that the information of the initial state is lost with time and the system is wandering over all possible phase patterns.

2. Firing Activity of Optimized Neuronal Networks

In the previous section, we descibed a simplified model of co-evolving dynamics. In this simple model, the behavior of the system is reduced to a few essential parameters. Thus this model allowed us to understand the behavior of the co-evolving systems without knowing the details of the systems. However, because this model is an abstract model, more specific models are needed to understand the detailed behavior of individual systems, such as our brain. As an example, here we describe a specific neuronal network model to explain the activity of the neuronal networks in the brain. This neuronal network model is a top-down model, whose dynamics we derived to maximize an objective function, which is the mutual information in this case. It is in a sharp contrast to the model in the previous section, which explained the behavior of the co-evolving systems by using two bottom-up rules (Eqs. (1) and (2)). The