**Report of Discussion in Session 2**

Session Theme: World Model Learning and Inference

Chair: Hiroaki Gomi (NTT Communication Science Laboratories)

Discussant: Mitsuo Kawato (ATR)

Session 2 Speakers:

Ila Fiete (Massachusetts Institute of Technology)

Karl Friston (University College London)

Yukie Nagai (The University of Tokyo International Research Center for Neurointelligence)

Maneesh Sahani (Gatsby Computational Neuroscience Unit)

Tadahiro Taniguchi (Ritsumeikan University)

Reporter: Tatsuya Matsushima (The University of Tokyo)

URL: <https://vimeo.com/471415258>

**Report**

Mitsuo Kawato first provided four points of discussions according to the speakers talk:

* How can achievements of the speakers contribute to neuroscience & AI?
* How do humans achieve learning motor-control from a small sample?
* Finding the essential low-dimensional space for sensorimotor control
* How psychiatric and developmental disorders are related to sensorimotor learning?

In the discussion, the panelists talked about them, which I report in this article.

**Learning Generative Models and Model-based Reinforcement Learning**

Tadahiro Taniguchi mentioned their achievements on multi-modal concept formulation and language acquisition with generative models described in the talk have been focused on the perception of the cognitive system. However, Taniguchi thinks these models can be meaningful in motor learning as well. For example, humans seem to generate goals with languages for motor control. In this line of research, Taniguchi argues that the key idea is “control as probabilistic inference”, which can be a way of reinterpreting model-based reinforcement learning.

Kawato indicated that it would be extremely difficult to acquire a good internal model from a limited number of samples if there are huge degrees of freedom in the body, although Kawato admits the idea of model-based reinforcement learning itself is notable. Kawato instead pointed out the possibility that the cognitive functionalities help reduce dimensionality drastically and are essential for learning internal models.

Maneesh Sahani mentioned that unsupervised data contribute to learning from a small number of trials and the same underlying schemes can work both for unsupervised learning and reinforcement learning built on the probabilistic inference. Kawato agreed with the idea that reinforcement learning and unsupervised learning take place simultaneously, but added that acquiring a brand new skill requires finding a new trajectory, which the agent has never experienced, and therefore it is the most difficult part of learning. Sahani suggested that causal structure allows agents to generalize to new environments and trajectories.

Yukie Nagai, who has been working on developmental robotics, mentioned the importance of the limitation of bodies and environments in child learning. Nagai suggested that these limitations can work as good constraints in motor and sensor capabilities. Nagai also pointed out social environments can also be a scaffold for child learning.

**Learning Hierarchy**

Ila Fiete suggested that learning a new motor action is associated with compositionality and decomposition of representations in the internal cortex and hippocampus. The low dimensional metric variables can be combined to represent a new kind of relationship flexibly. Fiete raised questions about how the brain breaks a problem into the appropriate hierarchies, and how much data is needed to recognize the hierarchical structure.

Karl Friston proposed a view of treating hierarchy as a way of simplifying generative models by minimizing complexity. Friston mentioned that it has a seamless connection with program learning mentioned in the keynote lecture from Josh Tenenbaum, when we see finding a good simple structure having factored representation as a structure learning problem. Friston also added that the framework can be applied to algorithm learning or meta reinforcement learning from the perspective of trying to find the right kinds of structures.

**Finding a Good Representation and Neural Structure**

Gomi then raised a question on the relationship between finding the essential low dimensional space for sensory-motor control and the neural mechanisms like cerebrum, basal ganglia, and prefrontal cortex. Sahani gave the opinion that distributed representations like successor representations can be well-suited for hierarchical structure because they represent occupancy over the future and linked to policies. Sahani pointed out that these representations that fit with the inferential view of planning and perception would give us a foundation to work with.

Sahani also mentioned recurrent circuits are necessary to map learning algorithms to neural substrates. The key observation here is that the inferential process around a single variable can be written in a very general form that depends basically on the feedback term in a recurrent network. From the perspective of learning, this scheme can potentially contribute to learning different timescales to find a sensible decomposition of the world.

**Sensory-Motor Learning and Psychiatric or Developmental Disorders**

Lastly, the discussion goes to relationships between psychiatric or developmental disorders and sensory-motor learning. Nagai introduced their experiments with representational drawing and suggested that hypo- or hyperpriors and difficulties in making hierarchical structures are one of the reasons why persons with these disorders have difficulties in controlling motors and generalizing acquired abilities. Nagai added that modification of certain genes results in an imbalance between excitatory and inhibitory neurons, which is often observed in brains of autism. Nagai supposes that the imbalance also causes hypo- or hyperpriors, which produces too strong or too weak reliance on the predictions.

Friston pointed out that Nagai’s idea is consistent with the formulation of the “free-energy principle”: if we contrast false inference in these disorders and the view of motor control as “planning as inference”, the balance of the prior belief against the sensory evidence can be the reason for wrong inference. These formulations, Friston supposes, can provide explanations on a wide range of disorders like autism, schizophrenia, hallucinations and illusions, and mechanisms for unintentional movement seen in Parkinson's disease. He then stressed that, in this way, insights from machine learning and artificial intelligence can provide useful perspectives on abnormal belief update and psychiatric and developmental disorders.

My Thought

In this session, various concepts, ideas, algorithms, and phenomena were discussed around world-model learning. The main theme of the discussion was “how to learn” the world model, especially, how to learn low dimensional and hierarchical representations essential for sensory-motor control. The unified view for model-learning ranging from bayesian formulation to neural mechanisms and psychiatric disorders introduced by each speaker inspired me a lot.

However, in my opinion, issues on “how to utilize” the learned world model for motor control has also a lot of points to be discussed. Recently, in my research area, the intersection of robot control and machine learning (i.e. robot learning), studies on modeling data in an unsupervised manner using deep generative models become very popular like VAE or GAN, but I feel the utilization of learned models for robot control is less explored. In concrete, one can think of multiple options for using learned models for motor control, for example regarding the model as a simulator that rolls out future prediction of observations or leveraging for trajectory optimization. Therefore, I suppose that discussions and methodologies on model utilization as well as world-model learning are needed for realizing artificial intelligence in the real world. In the discussion session, the topic on “control as inference” introduced by Taniguchi and “active inference” from Friston is potentially related to the model utilization, but not covered so much. I hope I can participate in the discussion about the model utilization at another opportunity.

From the algorithmic perspective of world-model learning, I expect that advances in structure learning would be a key for the next several years. That is because most recent advances on deep generative models are based on engineered graphical models using inductive biases of humans. In order to acquire appropriate graphical models from the data itself, I think we can leverage insights from causal inference or meta-learning. At this point, I agree with the idea of Sahani about mathematical formulation for learning hierarchies and structures behind data streams, and the idea of Friston that minimizing complexity can be a unified formulation.

Lastly, interpreting the cause of psychiatric or developmental disorders as an imbalance in internal computation for sensory-motor control seemed novel and interested me. I suppose that these insights on mechanisms of the disorders from mathematical formulation may also be useful for discovering a new way of treatment from theoretical aspects. However, since regions of the brain are interconnected with each other, I imagine that careful contrast between clinical evidence and theoretical results of the hypothesis would be required to prevent too much simplification.

In conclusion, I believe this session showed the possibility that the disciplines of different strategies, artificial intelligence and neuroscience, can be contrasted under a unified notion of “world model”. I hope that the content of this session will enhance communications among the panelists, participants, and readers of this article, and lead to a better understanding of intelligence.