Exploring Robotic Minds by Using the Frameworks of Predictive Coding and Active Inference

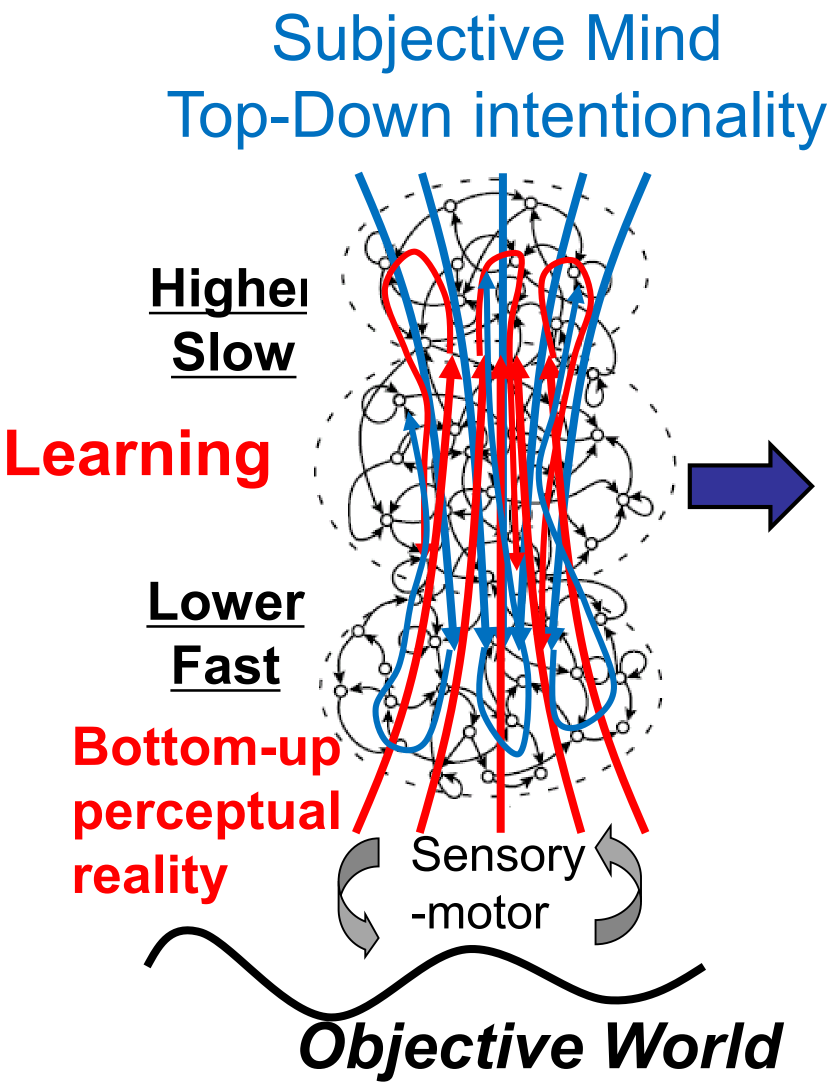
Jun Tani
Okinawa Institute of Science and Technology

Research Questions

- How can compositional knowledge of the world be attained through iterative learning of continuous sensory-motor flow experience?
- What are the essential mechanisms enabling social cognition?
- How can we explain the phenomena of self and consciousness?

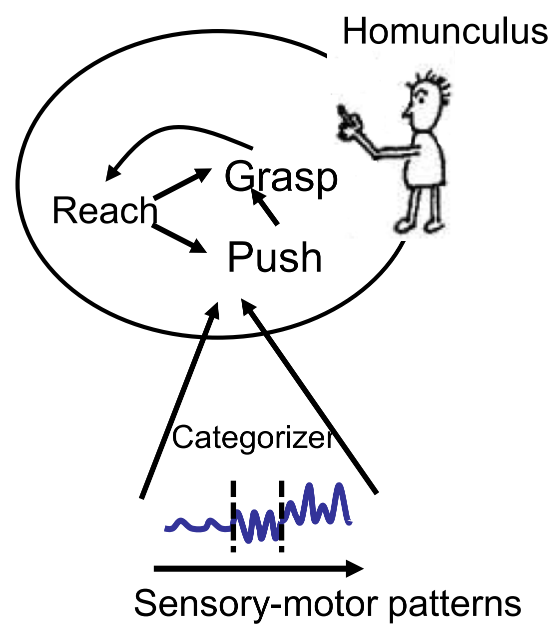
Understanding through synthesis → Synthetic Neurorobotics Study

Synthetic Neurorobotics Experiments



Emergence

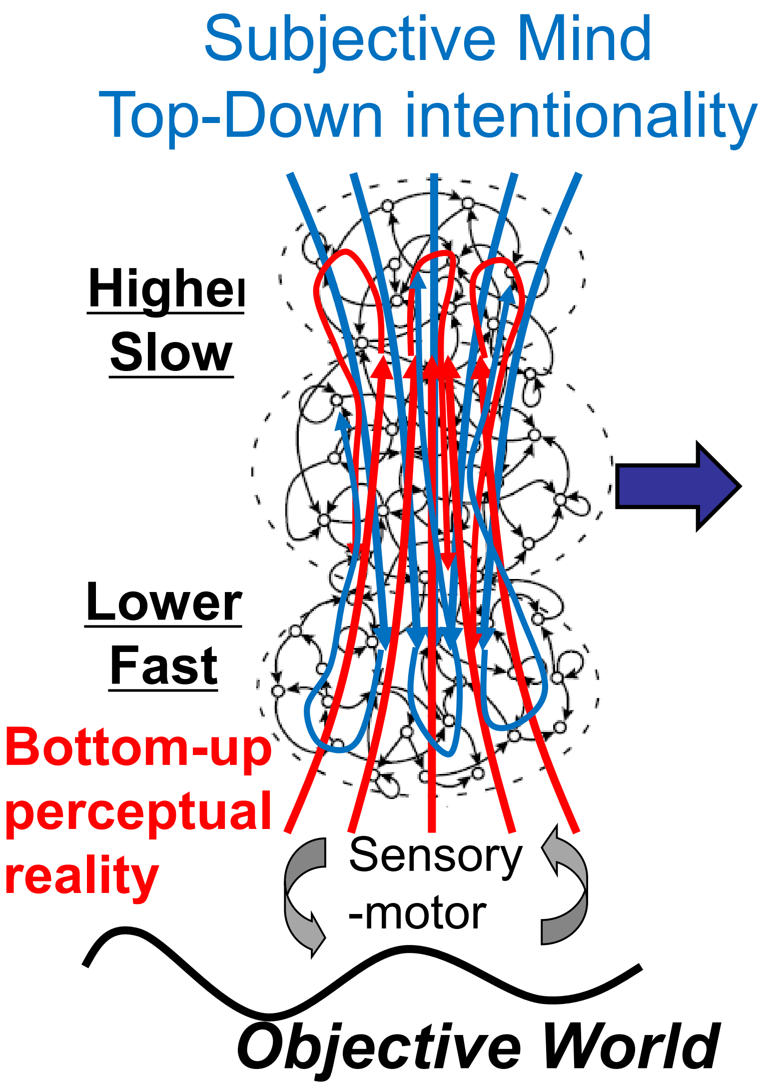
- Development of compositionality with functional hierarchy.



It looks like as if there were symbols to be manipulated by homunculus…

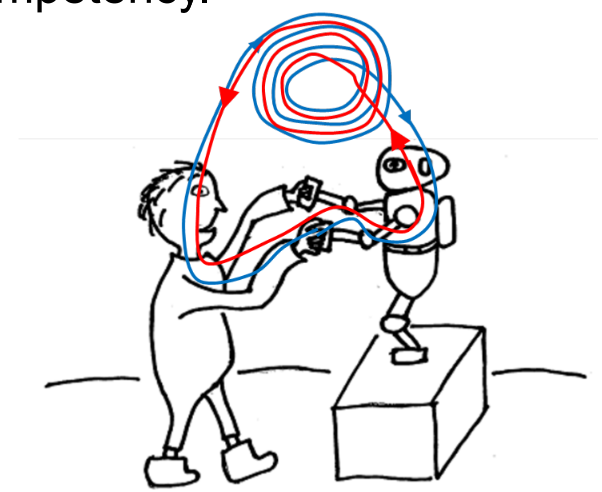
But, what are their reality?

Synthetic Neurorobotics Experiments



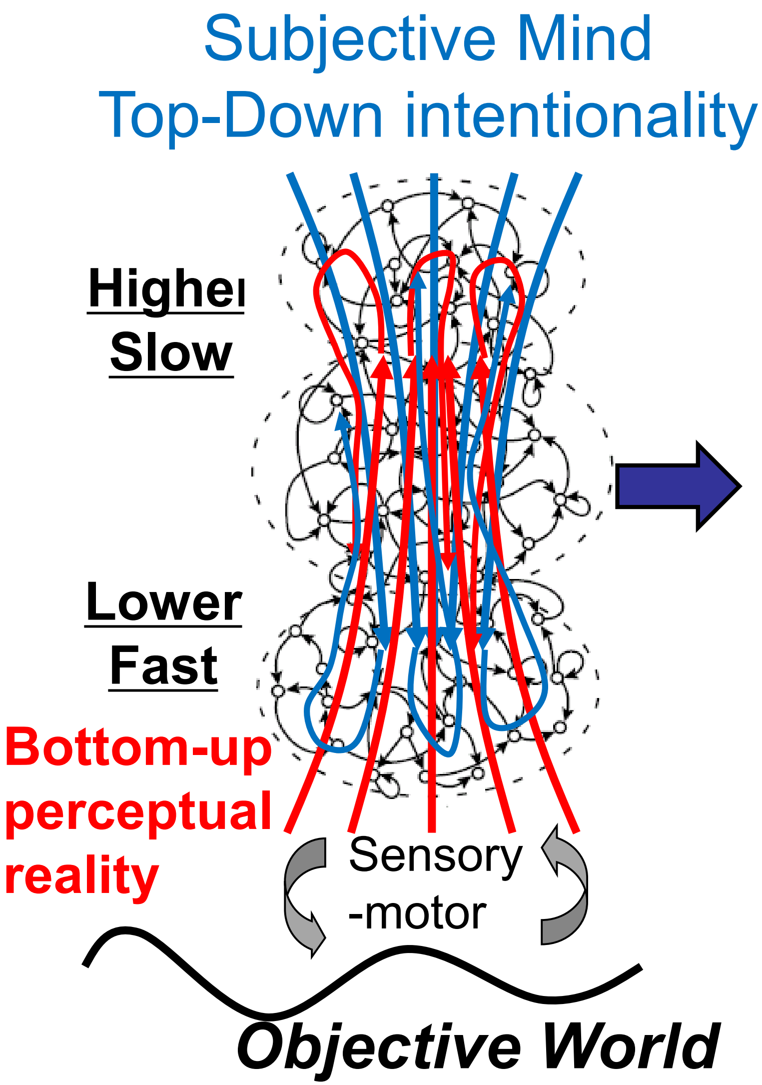
Emergence

Development of social cognitive competency.



- Spontaneous coupling and decoupling among agents.
- Autonomous switching from one social context to another.
- Failure cases due to developmental diseases including ASD.

Synthetic Neurorobotics Experiments



Emergence

Subjective experiences & their correspondence to phenomenology

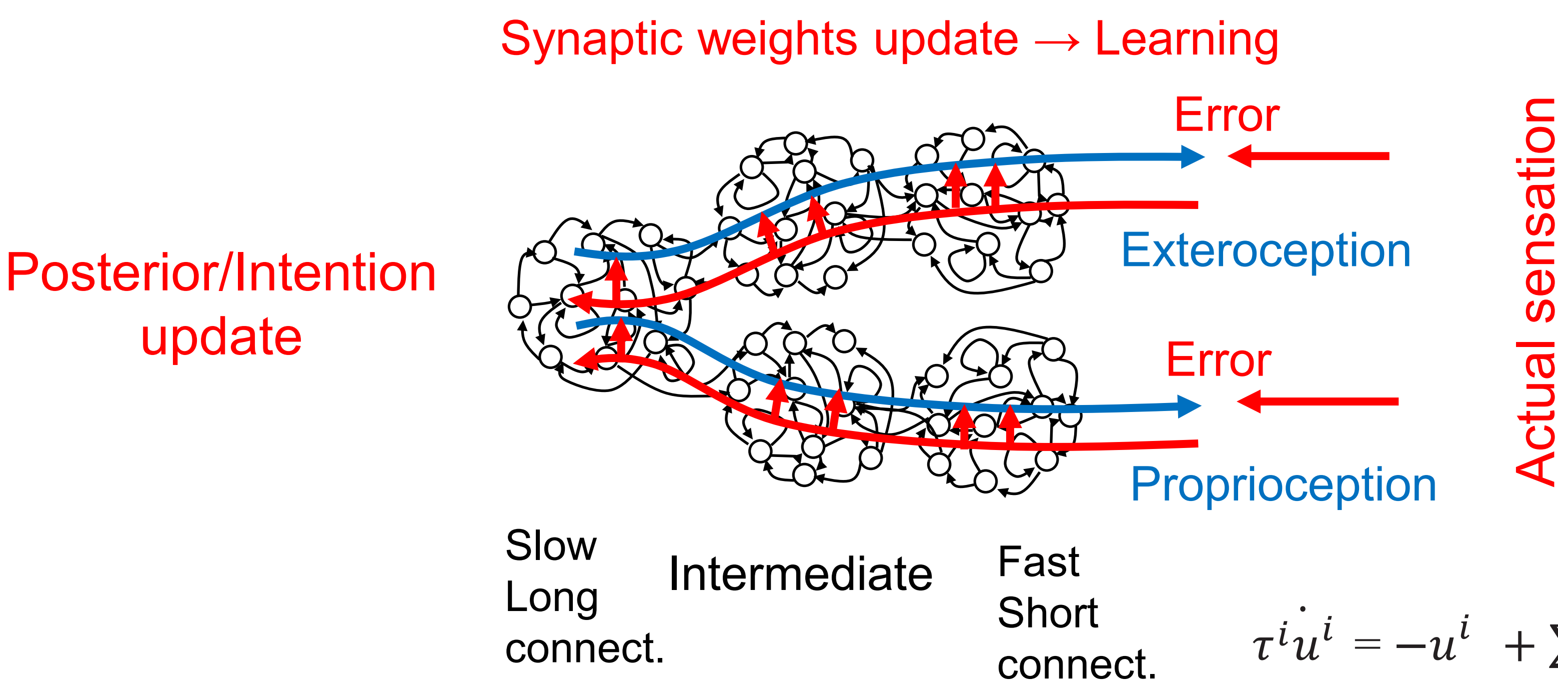
- The sense of minimal self and narrative self (Gallagher, 2001)
- Immanent time (Husserl)
- Free will and its delayed awareness (B. Libet)
- Autonomy of consciousness (William James)

Predictive-Coding Accounting by Error Min. Principle

(Rao & Ballard, 1999; Friston, 2005; Clark, 2015)

Recurrent Net Implementation

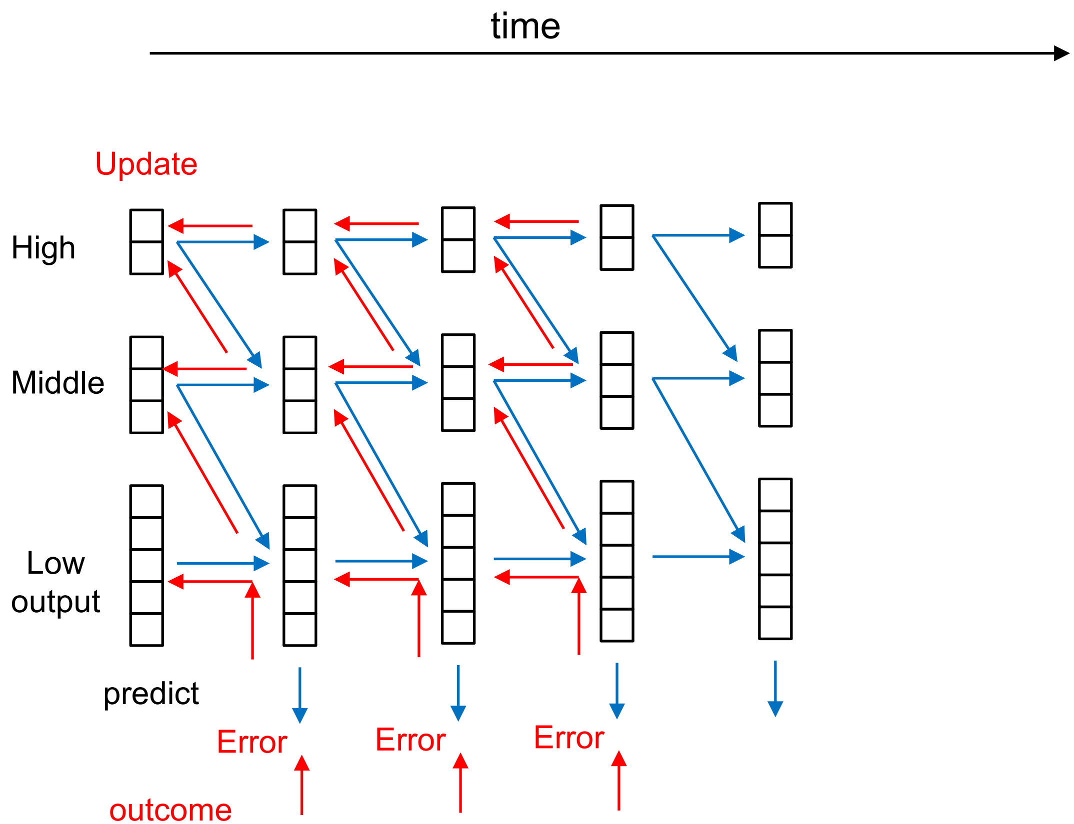
(Tani and colleagues, 1999 ~)



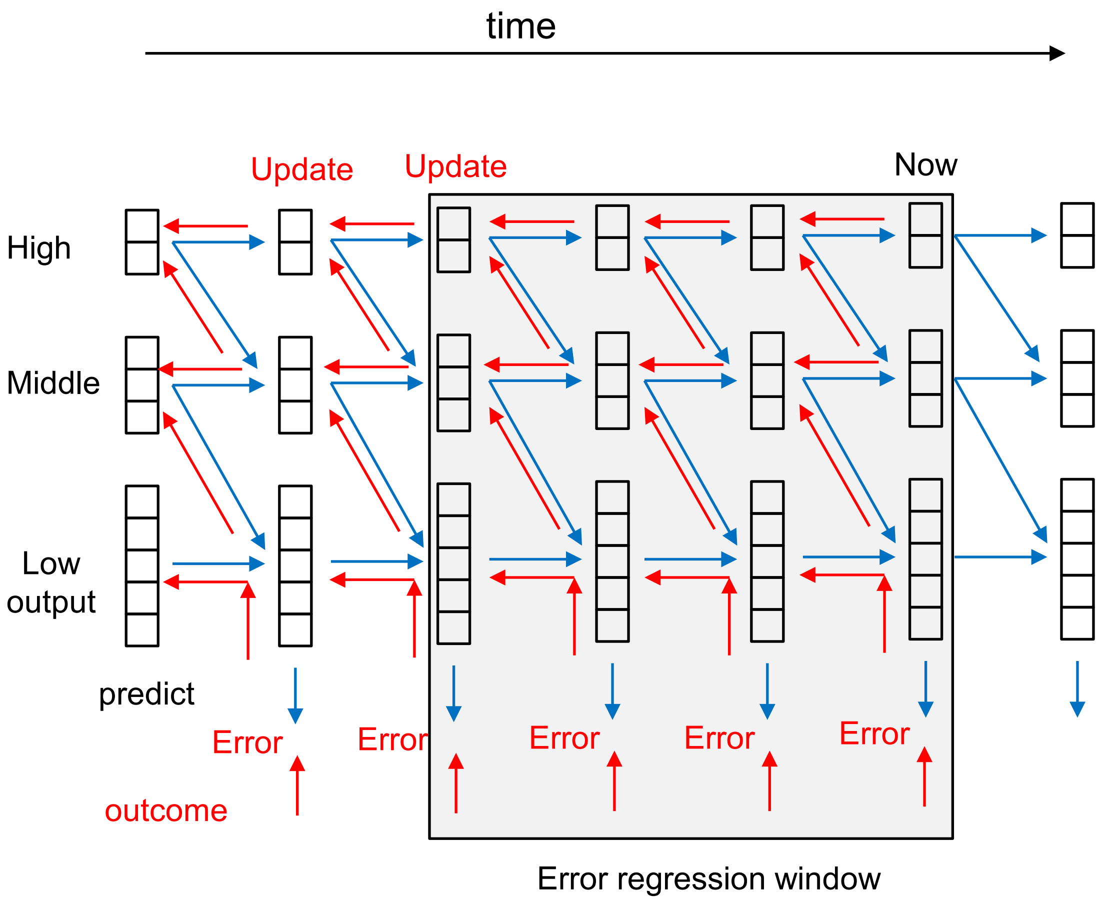
$$\tau^i \dot{u}^i = -u^i + \sum_j a^j w_{ij} + I^i$$

$$a^i = 1/(1 + e^{-u^i})$$

Temporary Extended by BPTT



Temporary Extended by BPTT



Hierarchical Predictive Coding RNN Models (1998~2018)

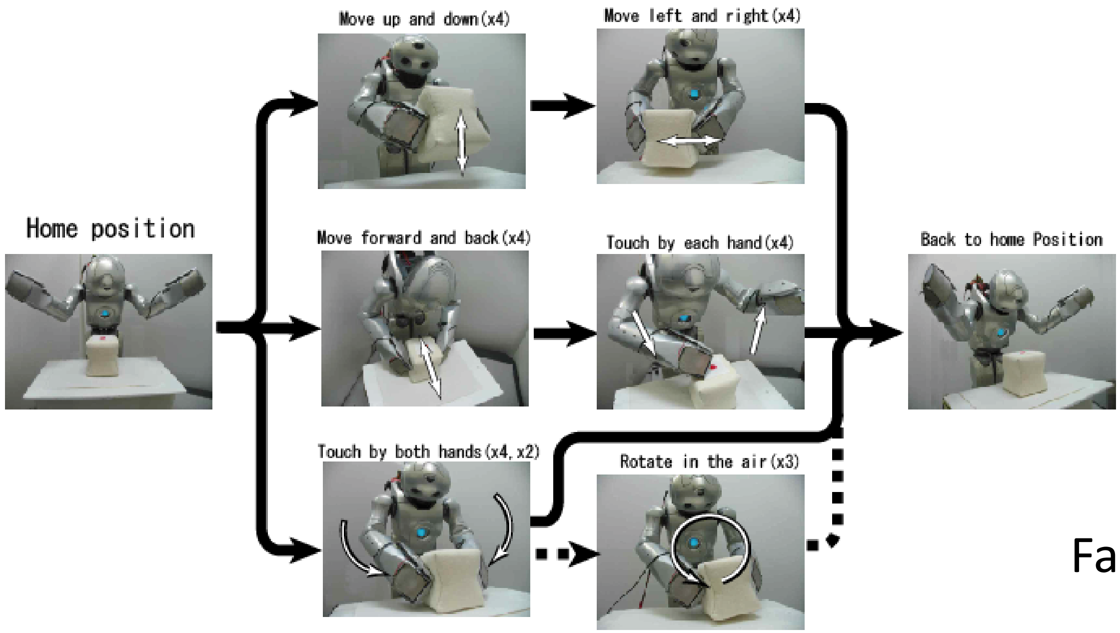
- Hierarchical Mixture of RNNs (Tani & Nolfi, 1998)
- RNN with Parametric Bias (Tani, 2003)
- Multiple Timescale RNN (Tani & Yamashita, 2008)
- Multiple Spatio-Temporal-Scale RNN for Visuo-Motor learning (Hwang et al; Choi et al, 2018)
- Predictive-Coding type Variational Bayes RNN (Ahmadi & Tani, 2018)

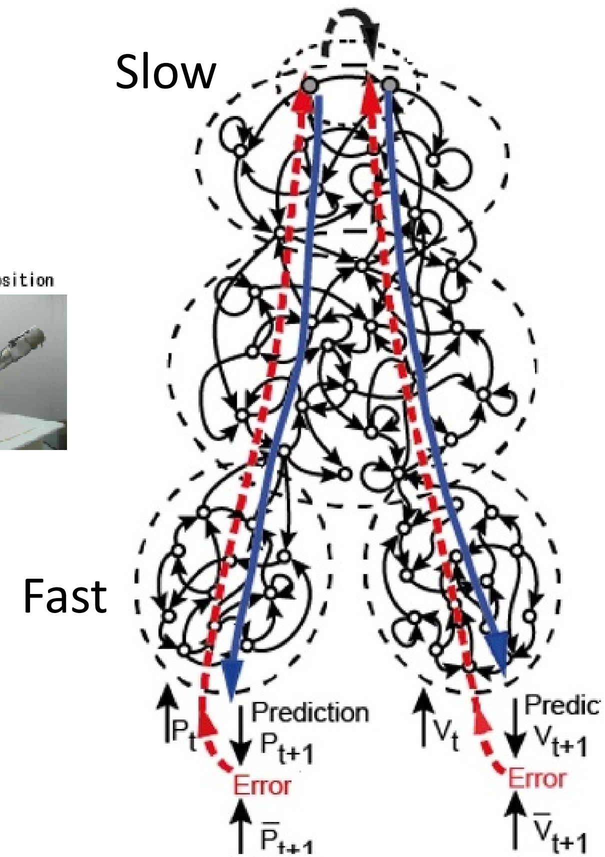
Developmental tutoring of object-manipulation tasks on a humanoid using MTRNN (Nishimoto & Tani 2009)

Task 1

Task 2

Task 3





MTRNN
(Yamashita &Tani, 2008)

Interactive Tutoring Video

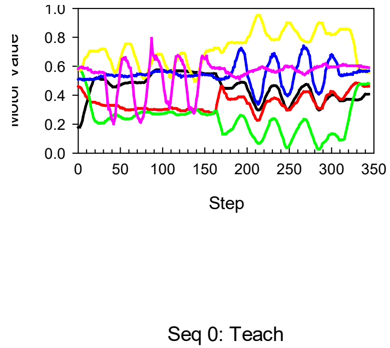
Developmental Interactive Tutoring

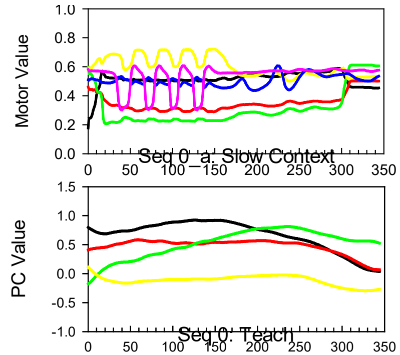
VIDEO

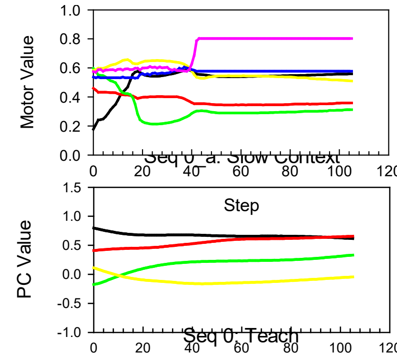
Developmental Learning Process

Teaching | Mental Imagery | Actual Action

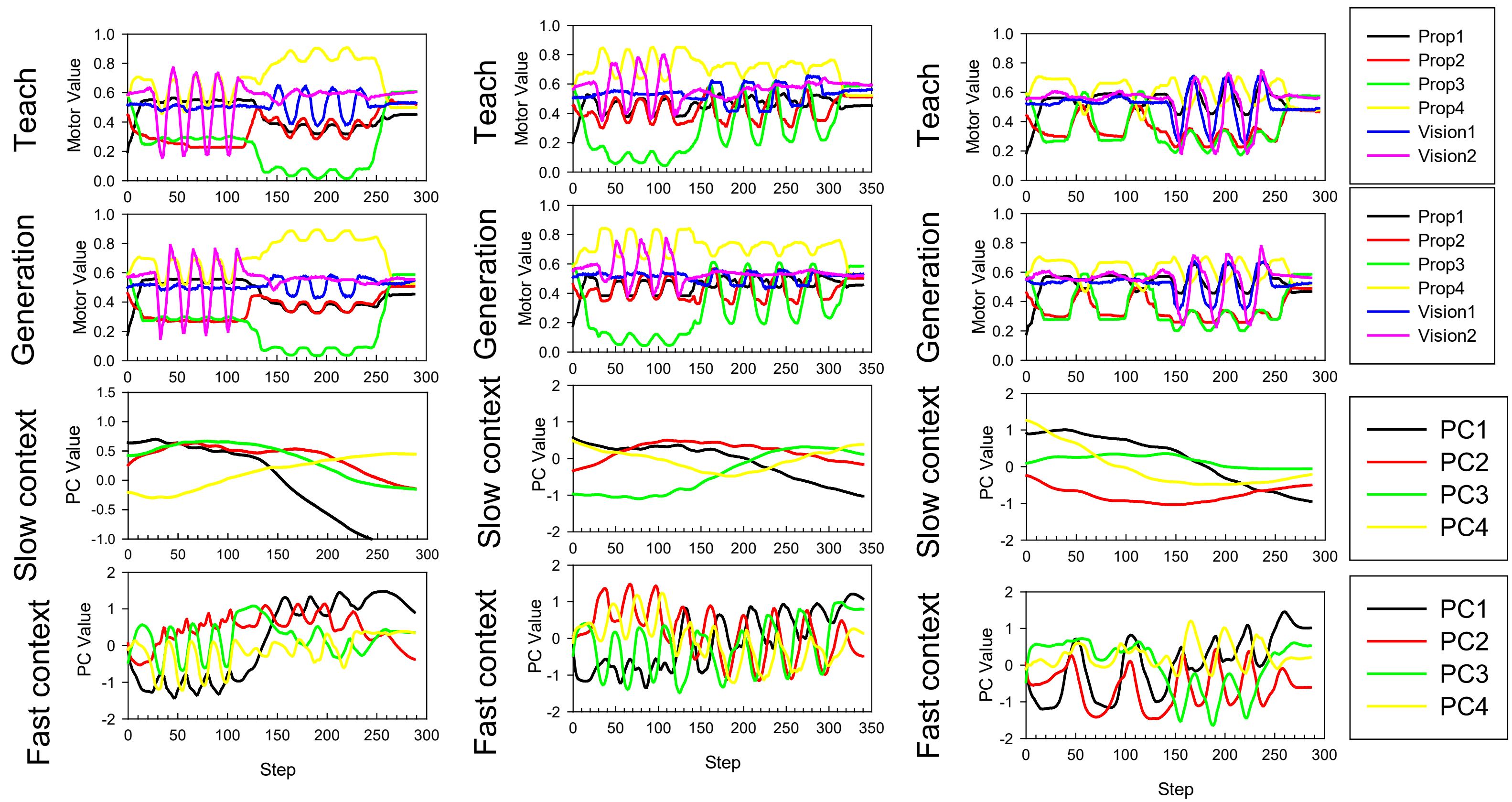
Session1







All 3 task sequences at the end of the final tutoring session

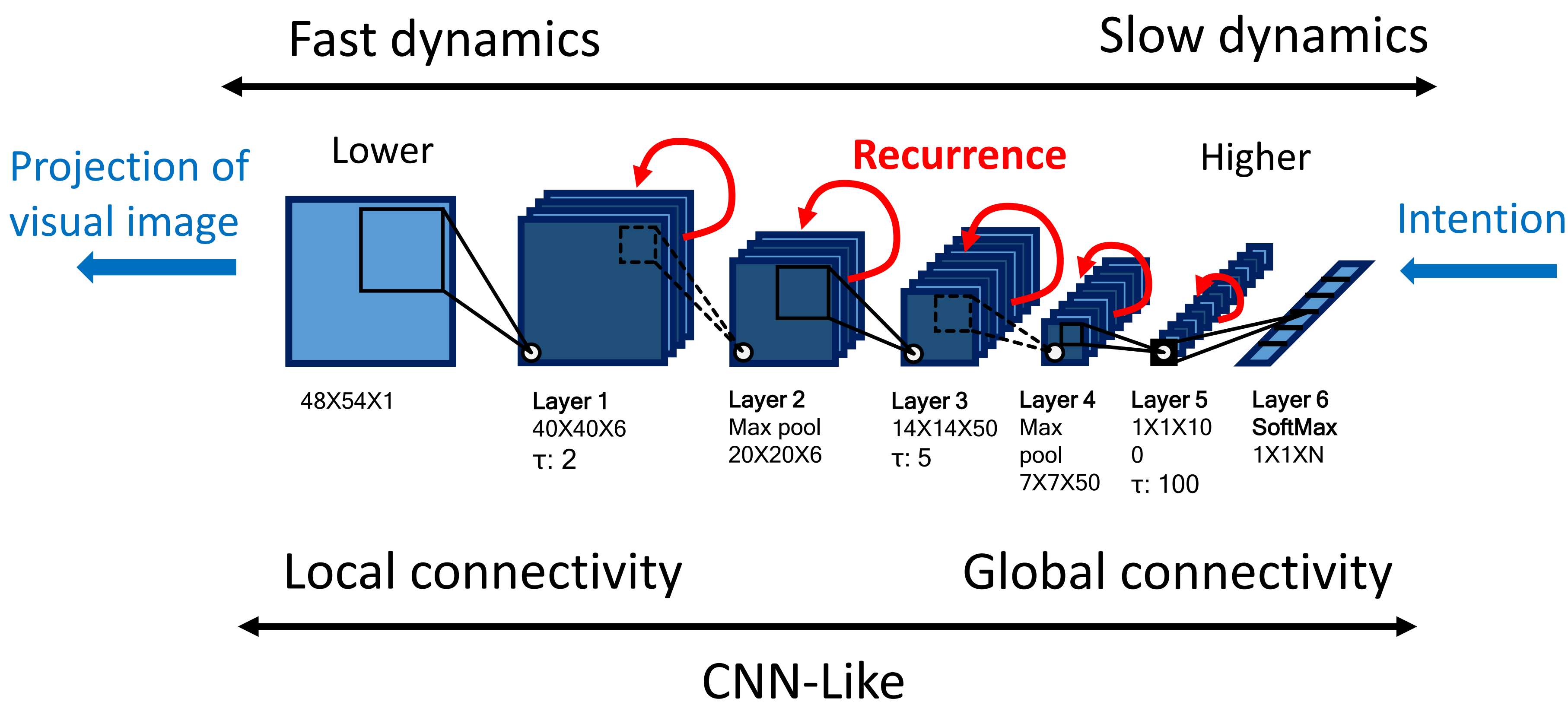


(a) Task 1　　(b) Task 2　　(c) Task 3

“Kinetic Melody” by Luria

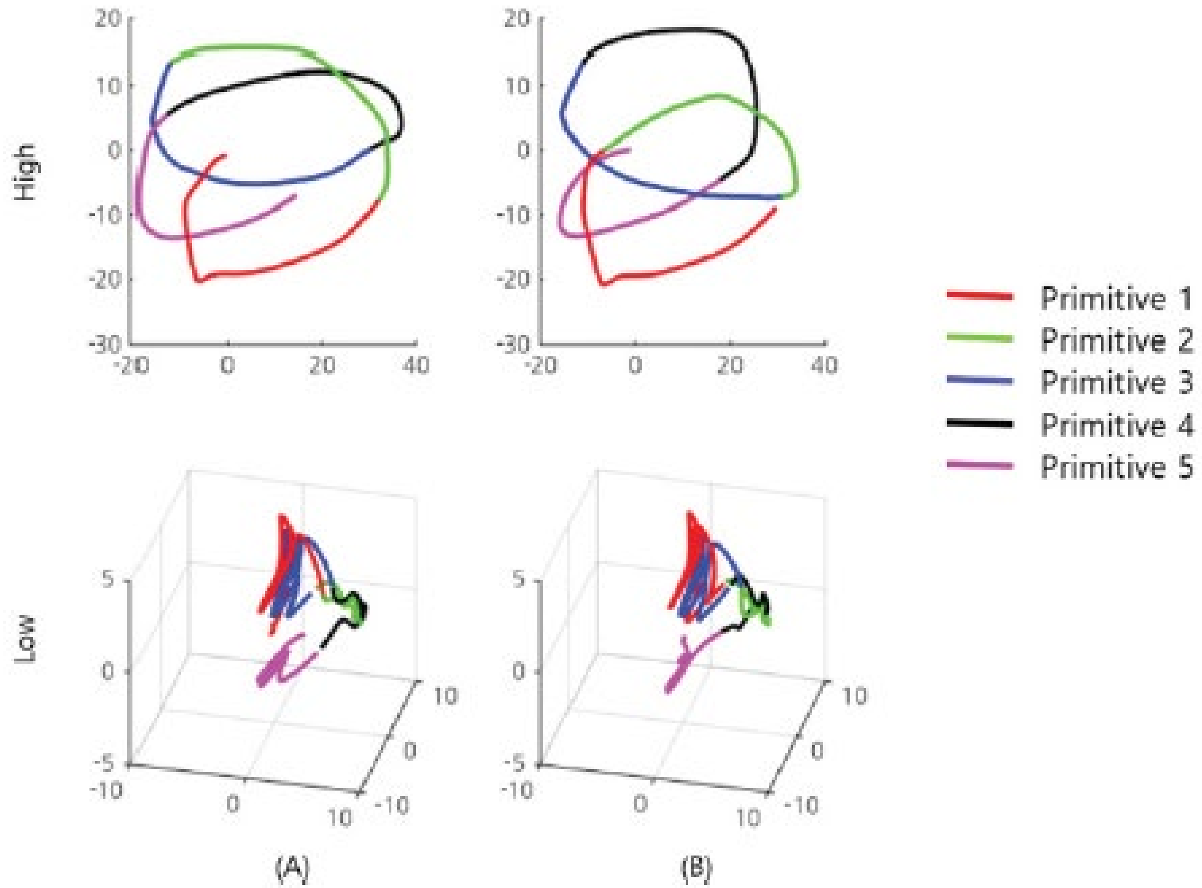
Multiple Spatio-Temporal Scales RNN (MSTRNN) Generation and Recognition of Video by Predictive Coding

(Choi & Tani, 2017)



Test-2: Learning Concatenated Sequences of 5 Subjects

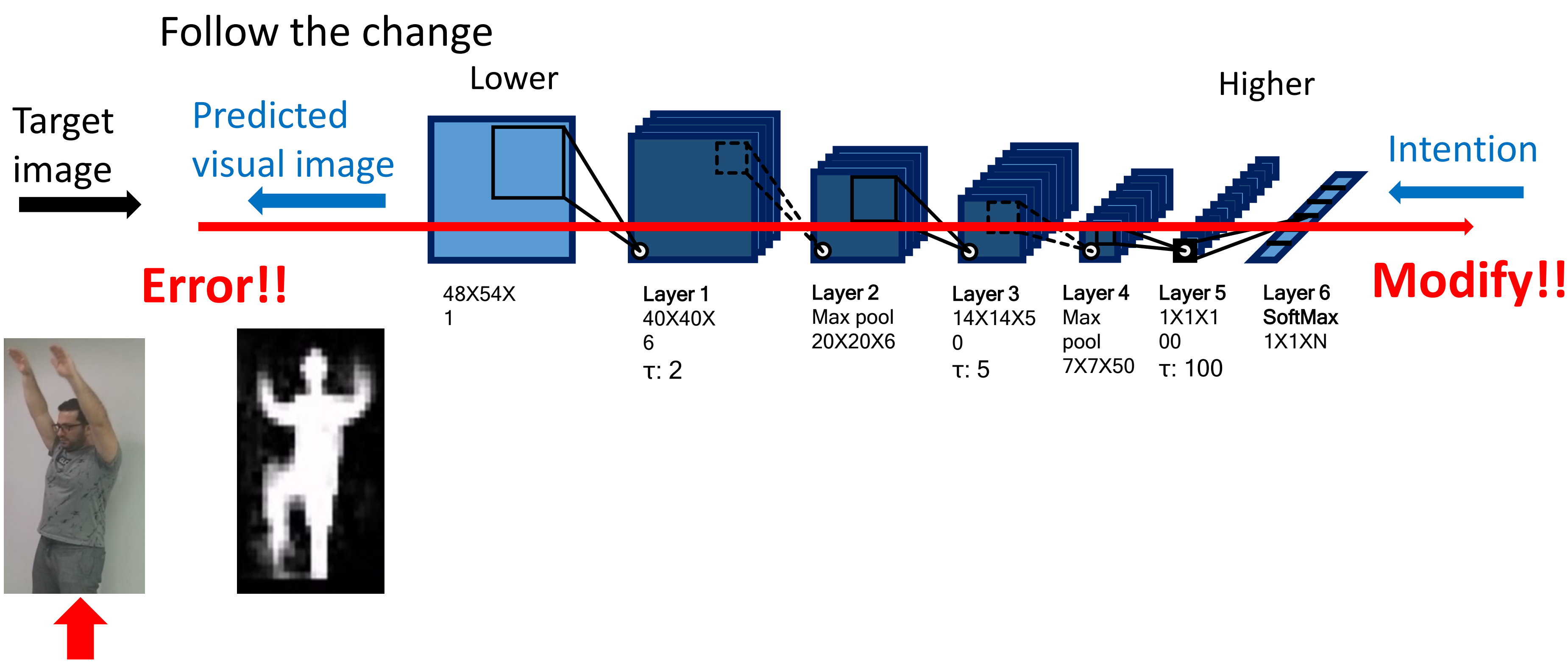
Forward concatenated sequence video



P1-P2-P3-P4-P5 P5-P4-P3-P2-P1

Recognition by Error Regression Imitative Synchronization with Target

(Choi & Tani, 2017)

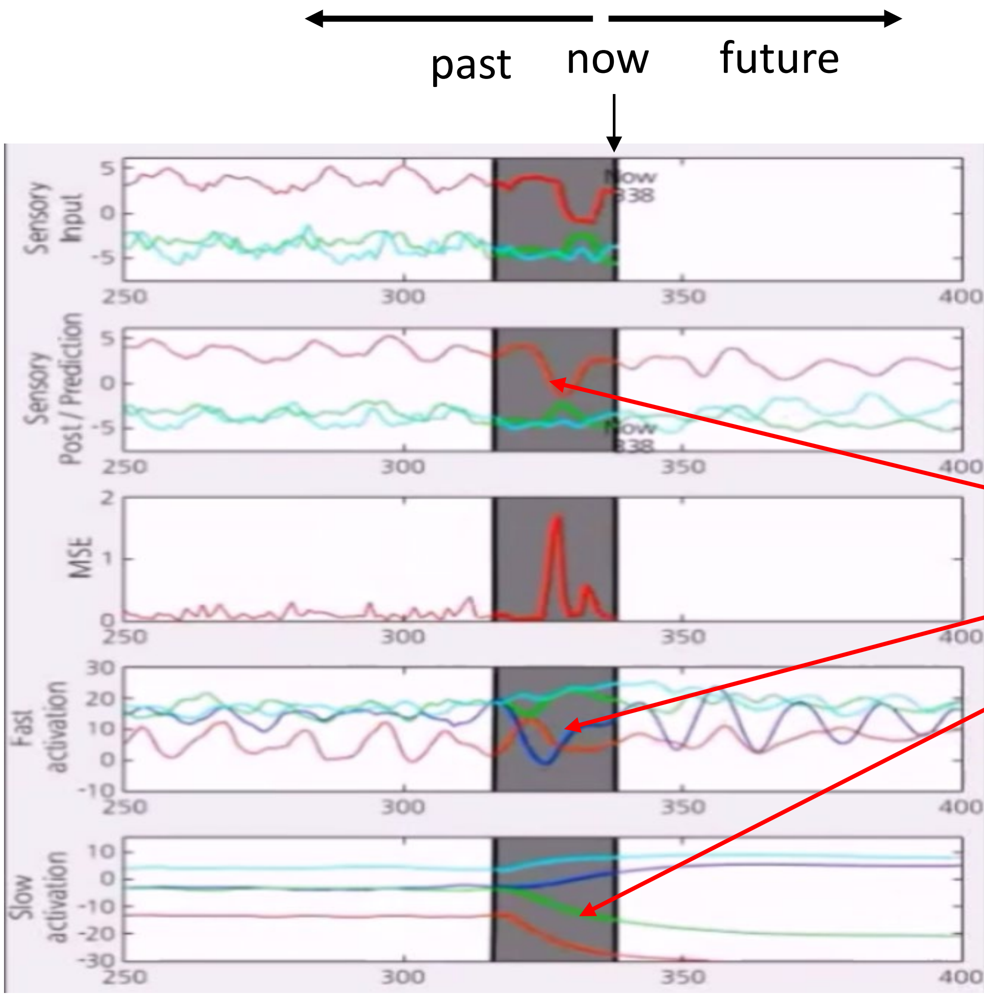


Sudden change from a trained pattern to another

Imitation of Target Visual Inputs by Bottom-Up Error Regression

(Choi & Tani, 2016)

VIDEO VIDEO2



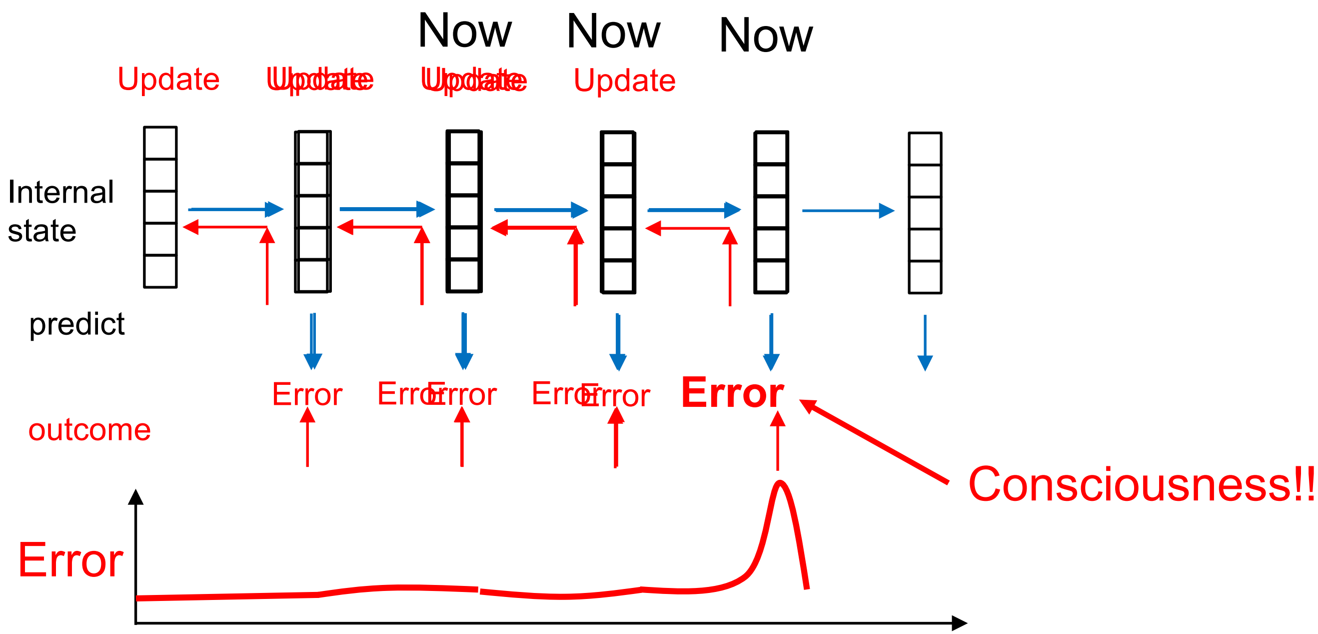
Rewrite the past.
Postdiction!!

Prediction for Future and Postdiction for Reflecting Past

(Tani, 2003)

time

The minimal self becomes consciously aware as triggered by the prediction error

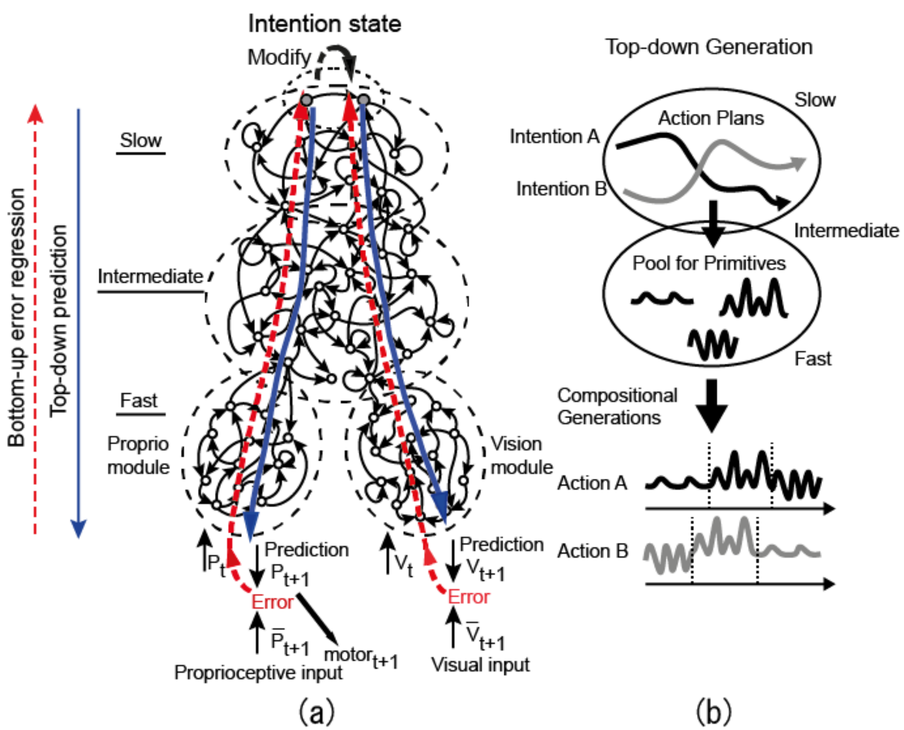


- The minimal self as the causality between intention and perceptual outcome at each momentary step.
- Such minimal self in terms of the causality becomes consciously aware when encountering with its break-down accompanied by the error.

Development of the Narrative Self by Objectifying Own Experience

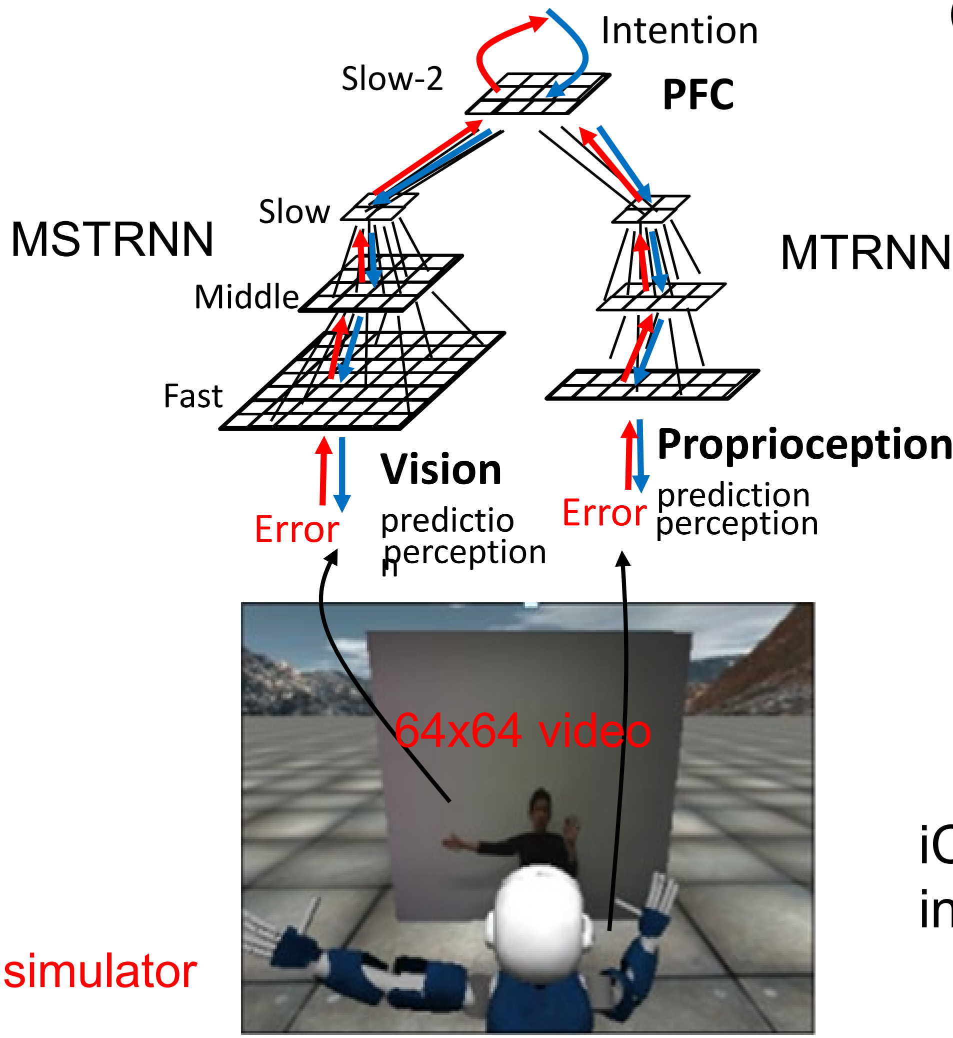
- A set of primitives are developed as manipulable objects.
- Time-extended experience is compositionally represented by using such primitives.
- Therefore, the experience is memorized not as a pure experience but as objectified or narrative one after consolidative learning.

Development of Compositionality



Predictive Visuo-Motor Deep Dynamic Neural Network for Robot

(Hwang et al., ICDL2017)



iCub simulator

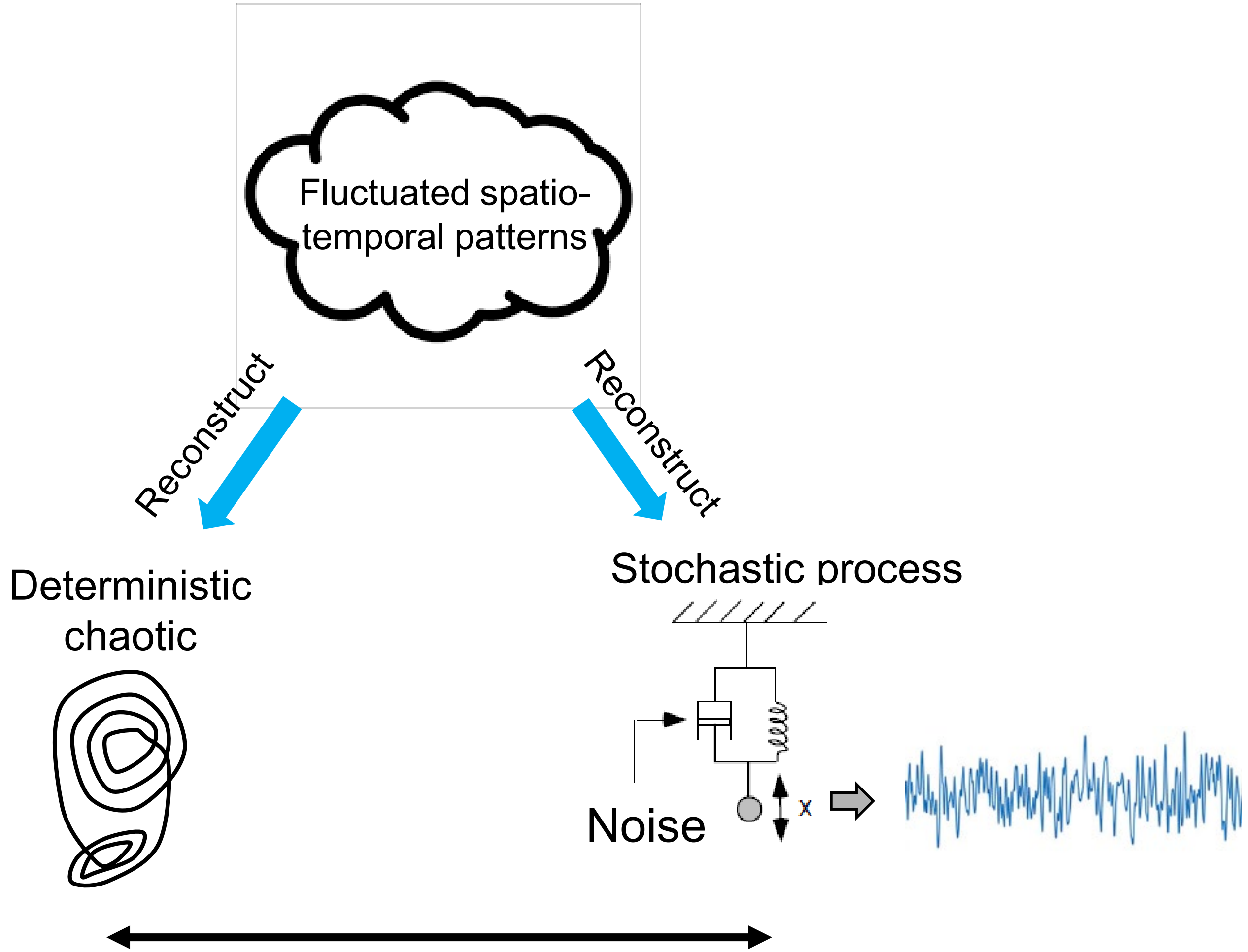
ER-Video

MentalSimVideo

OP2-DanceVideo

iCub-human imitative interaction task

Deterministic or Probabilistic?
(Ahmadi & Tani, 2017)



What are the theories connecting between these two?

Predictive Coding type Variational Bayes RNN (PV-RNN)

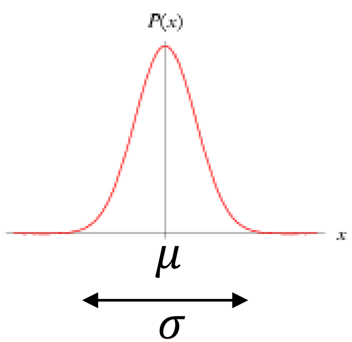
(Ahmadi & Tani, 2018)

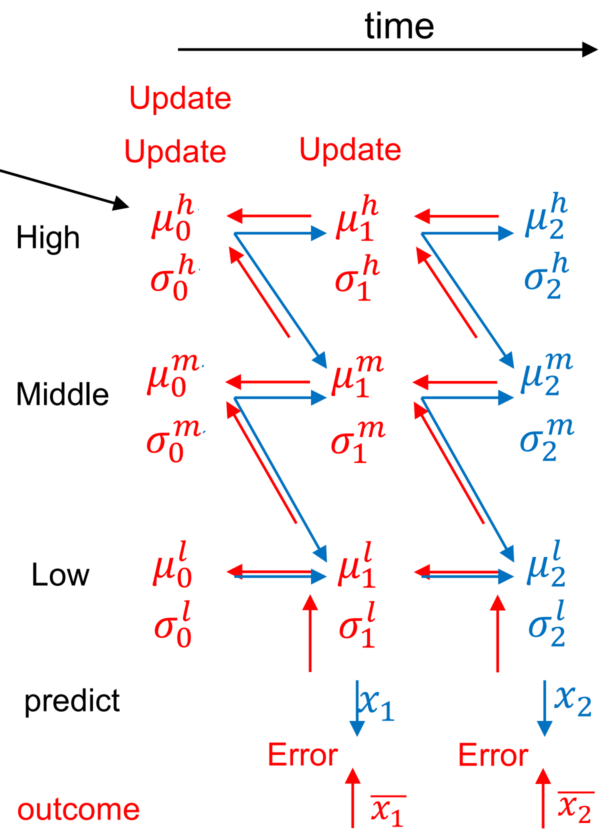
Min. Reconstruction error   Min. KL div. between posterior and prior

$$L(\theta,\emptyset) = \sum_{t=1}^{T} E_{q_{\emptyset}(Z_t|\bar{d}_{t-1},x_{1:T})}\left[lnP_{\theta,x}(x_t|\bar{d}_{t-1},Z_t)\right] - w \cdot KL\left[q_{\emptyset}\left(Z_t\middle|\bar{d}_{t-1},x_{1:T}\right)||P_{\theta,z}(Z_t|\bar{d}_{t-1})\right]$$

Maximizing the lower bound is equal to minimizing free energy (Friston, 2005)

The first order statistics



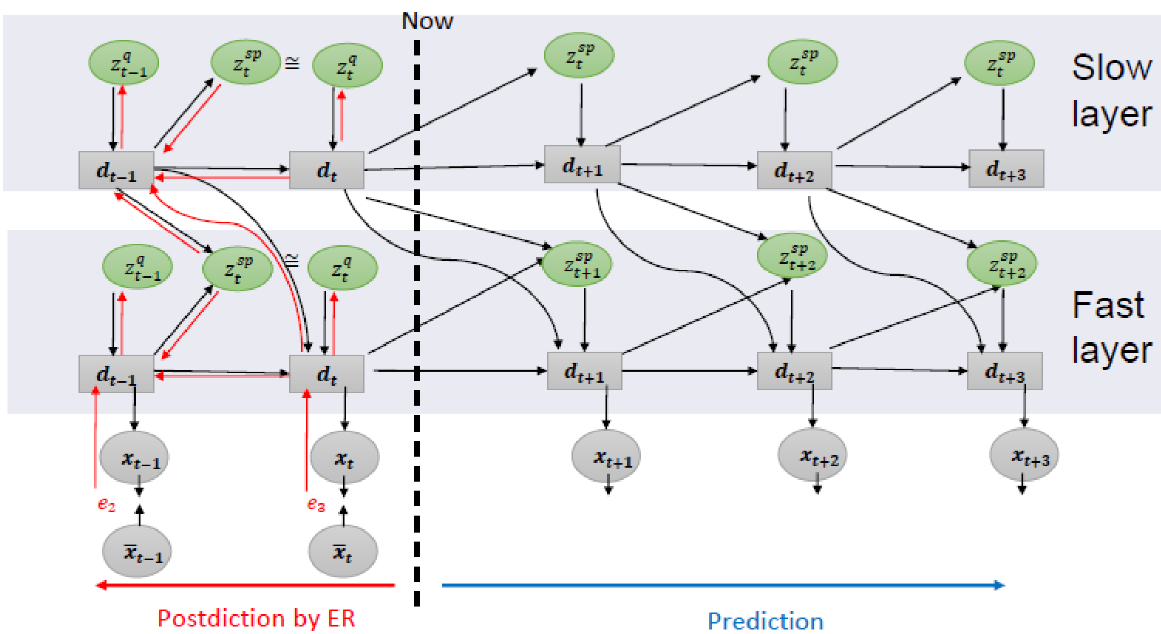


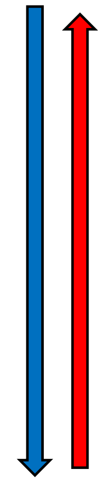
PV-RNN with Hierarchical Organization

Min. Reconstruction error

Min. KL div. between posterior and prior

$$L(\theta, \emptyset) = \sum_{t=1}^{T} E_{q_{\emptyset}(Z_t|\bar{d}_{t-1}, x_{1:T})}[lnP_{\theta,x}(x_t|\bar{d}_{t-1}, Z_t)] - w \cdot KL[q_{\emptyset}(Z_t|\bar{d}_{t-1}, x_{1:T})||P_{\theta,z}(Z_t|\bar{d}_{t-1})]$$

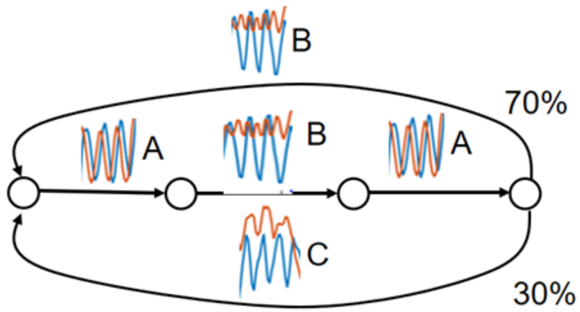




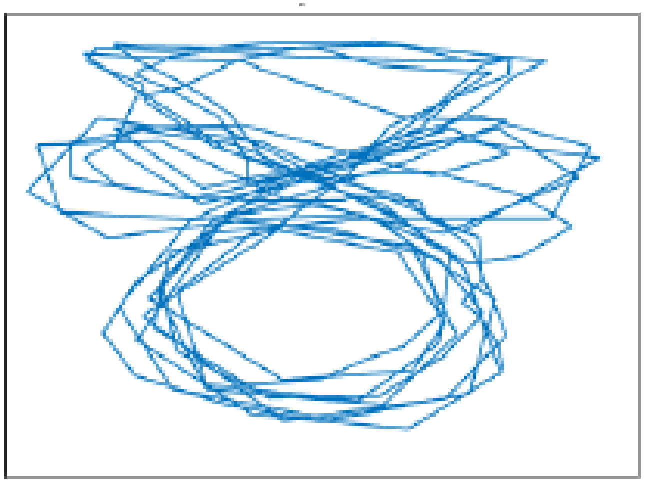
Top-down strength modulated by the meta-prior in the higher layer.

Bottom-up strength modulated by the meta-prior in the lower layer.

Training of PV-RNN using 2-D Hand-Drawing patterns



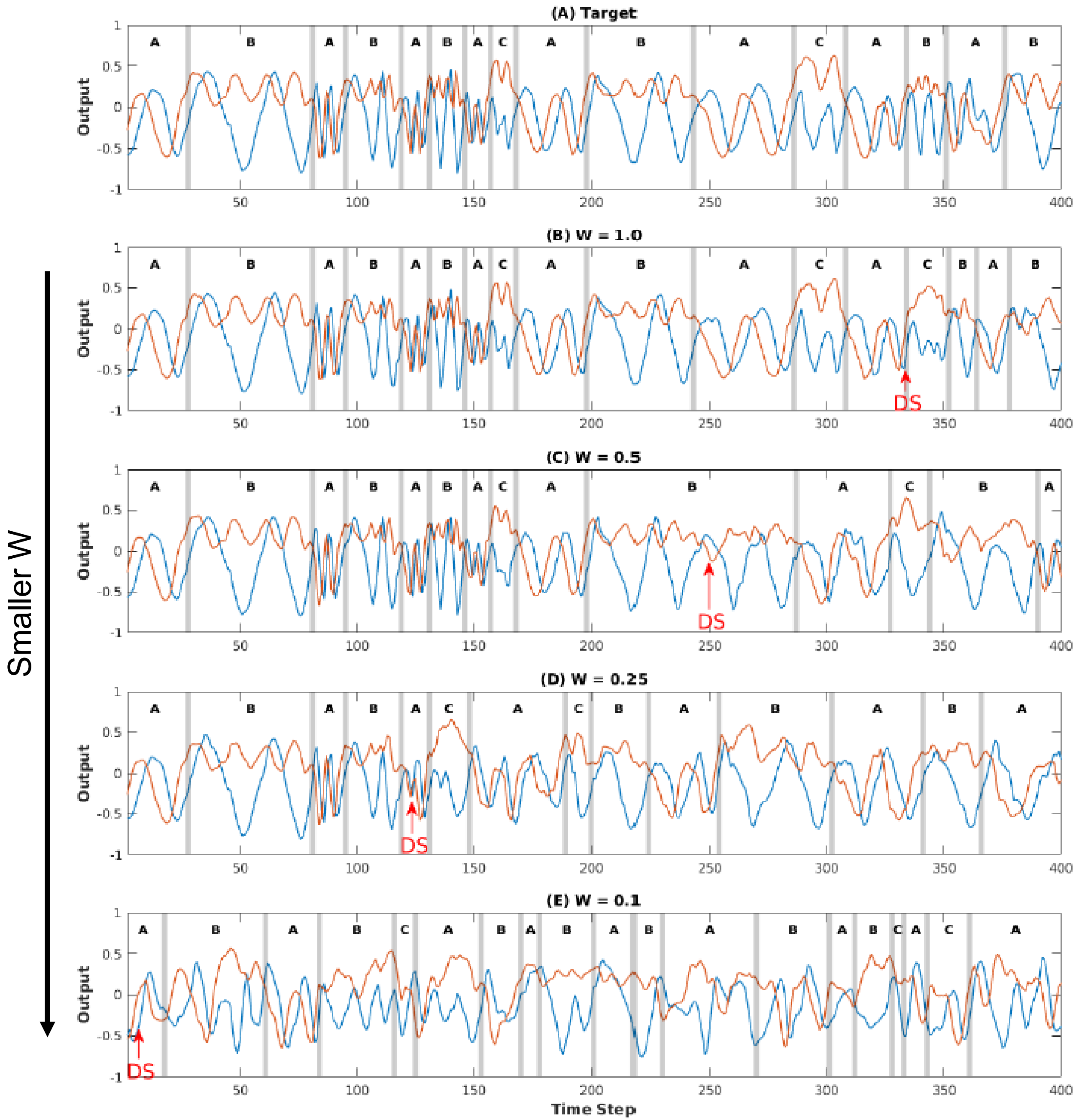
A S-FSM instructed

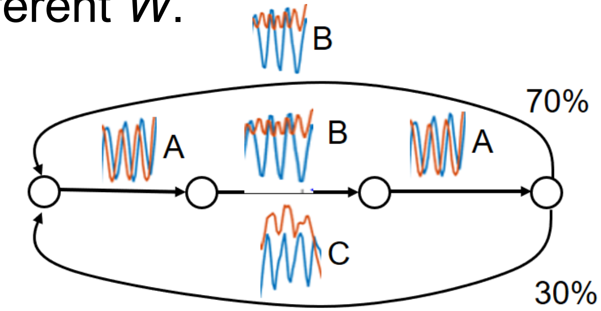


2-D Hand drawing by following the S-FSM

400 steps X 16 sequences are generated for training data

Regeneration of a training target sequence pattern with different *W*.

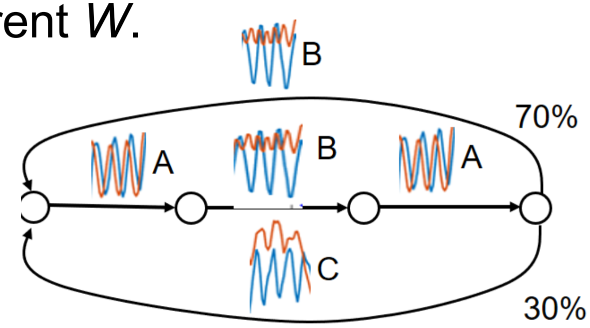




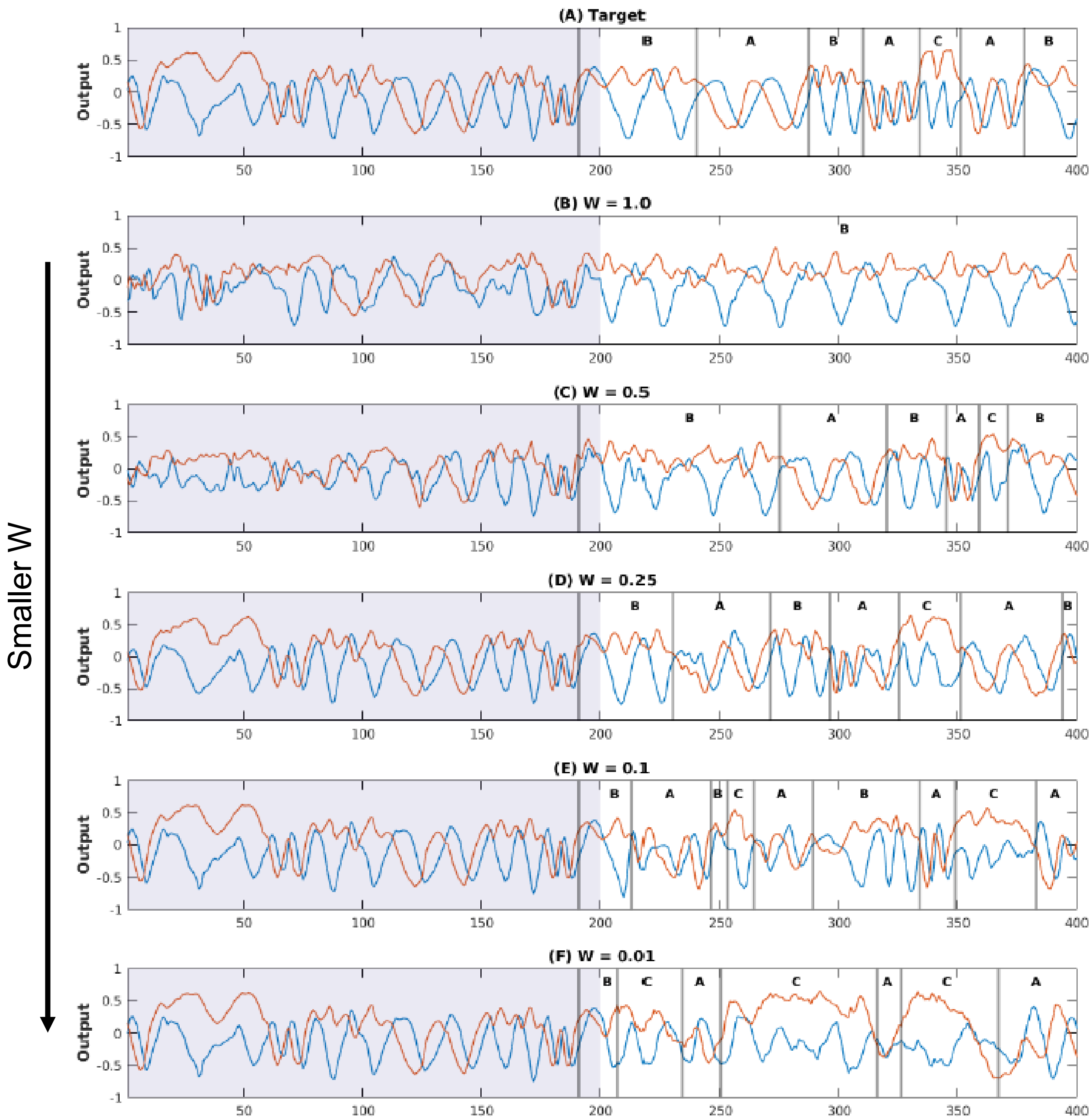
Stochastic-FSM to generate target 2D sequence patterns to be learned.

Best reconstruction

Prediction of a test (unlearned) sequence pattern with different *W*.



Stochastic-FSM to generate target 2D sequence patterns to be learned.

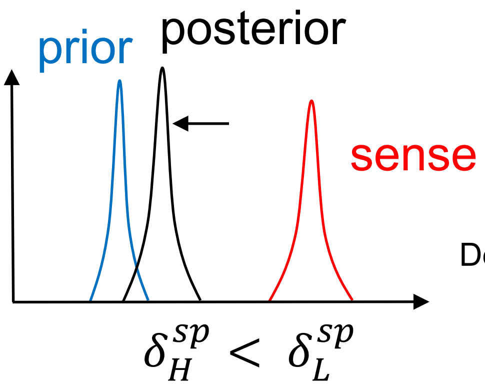


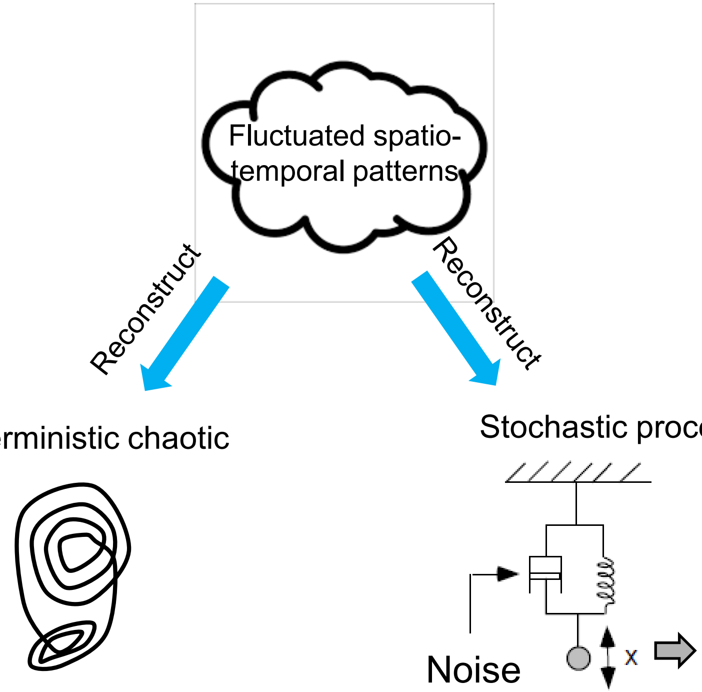
Best predictability

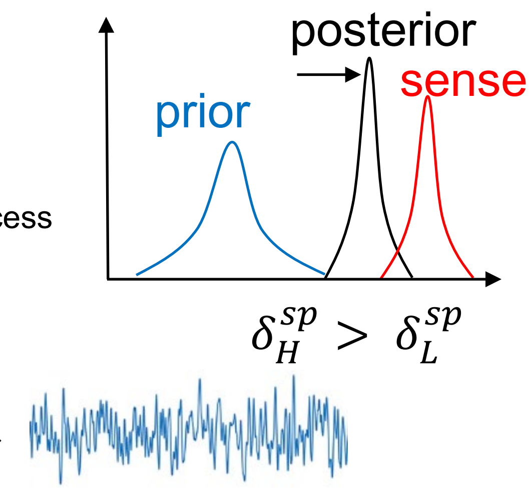
Min. Reconstruction error   Min. KL div. between posterior and prior

$$L(\theta,\emptyset) = \sum_{t=1}^{T} E_{q_{\emptyset}(Z_t|\bar{d}_{t-1},x_{1:T})}\left[lnP_{\theta,x}(x_t|\bar{d}_{t-1},Z_t)\right] - w \cdot KL\left[q_{\emptyset}(Z_t|\bar{d}_{t-1},x_{1:T})||P_{\theta,z}(Z_t|\bar{d}_{t-1})\right]$$

(Ahmadi & Tani, 2018)







Large $\xleftarrow{\quad w \quad}$ Small

Strong top-down prior
High precision

Weak top-down prior
Low precision

Over-fitting   Generalization   Random

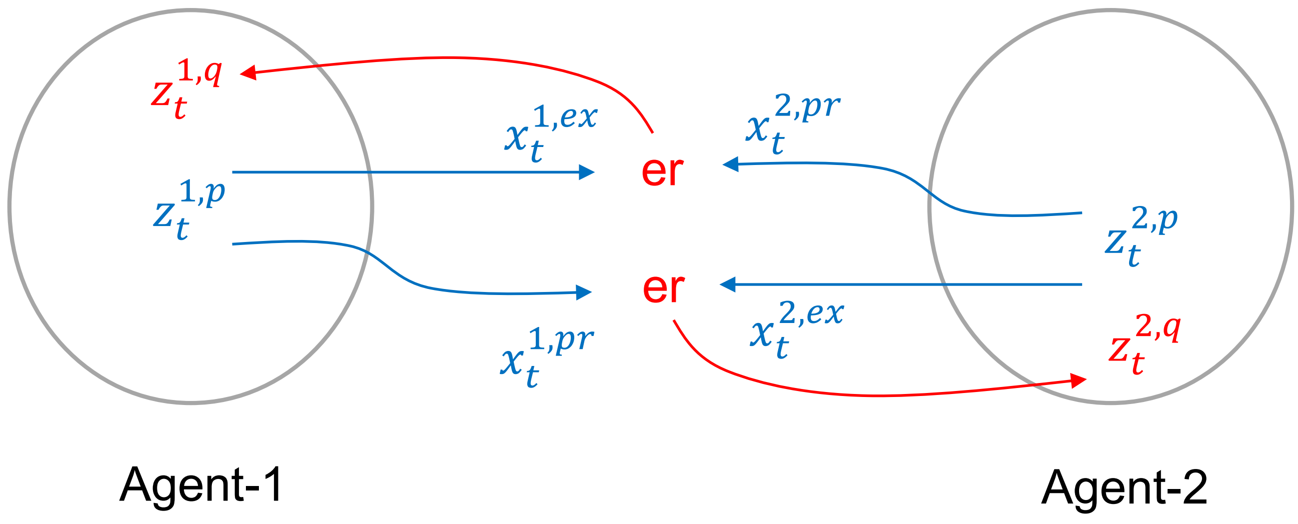
ASD? (Van de Cruys, 2014)

(Nagai CREST project)

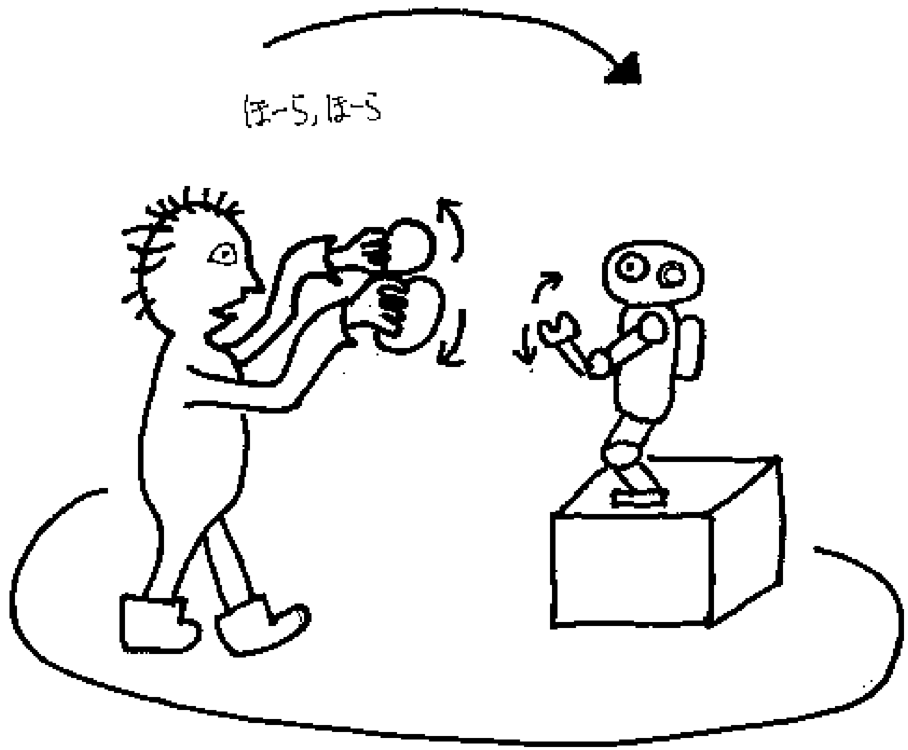
Deficits in low-level sensory processing may cascade into those in higher-order cognitive competency in ASD (Stevenson et al., 2014).

Social Cognition

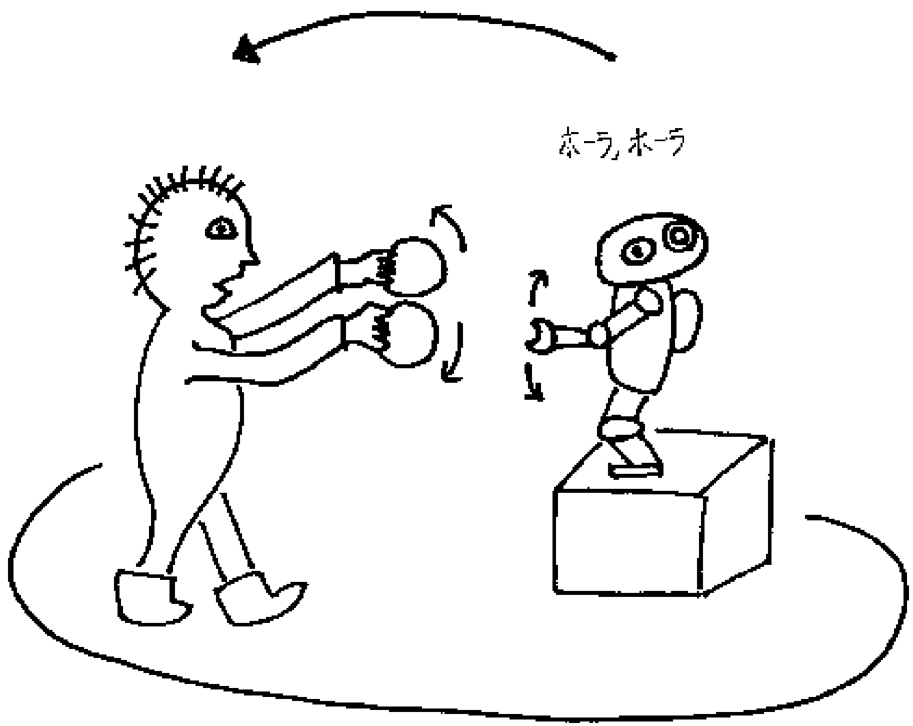
- Examine mutual interactions.
  - Robot vs robot
  - Robot vs human



A human drives a robot



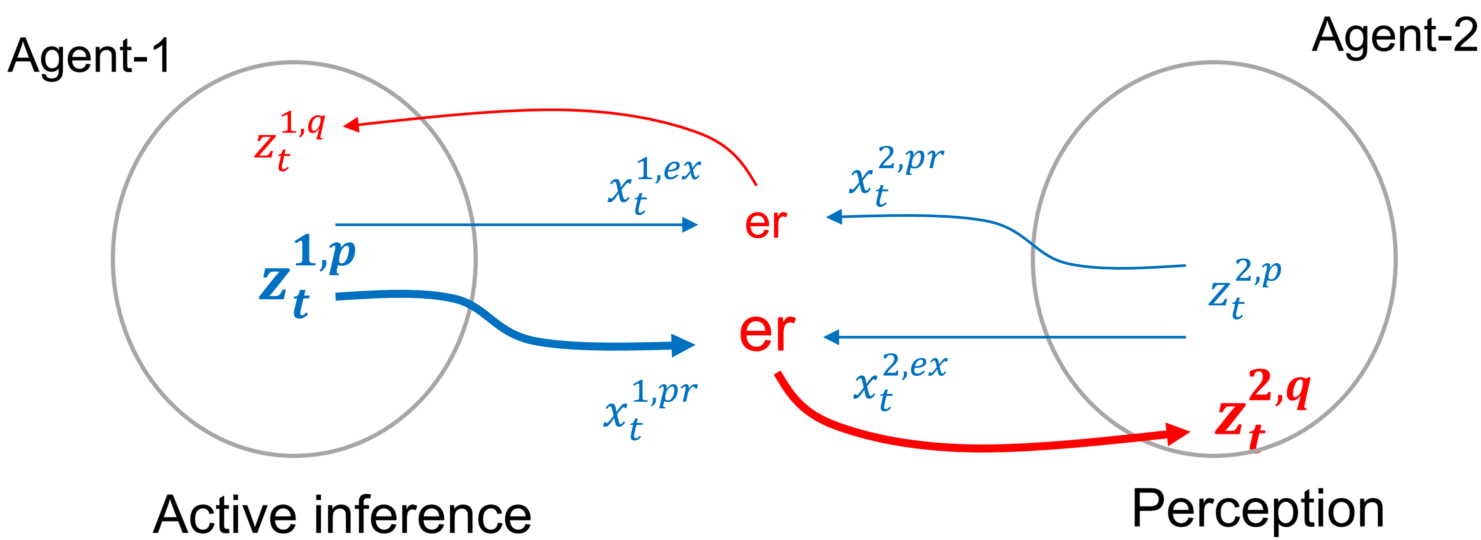
A robot drives a human



Perception and Active Inference

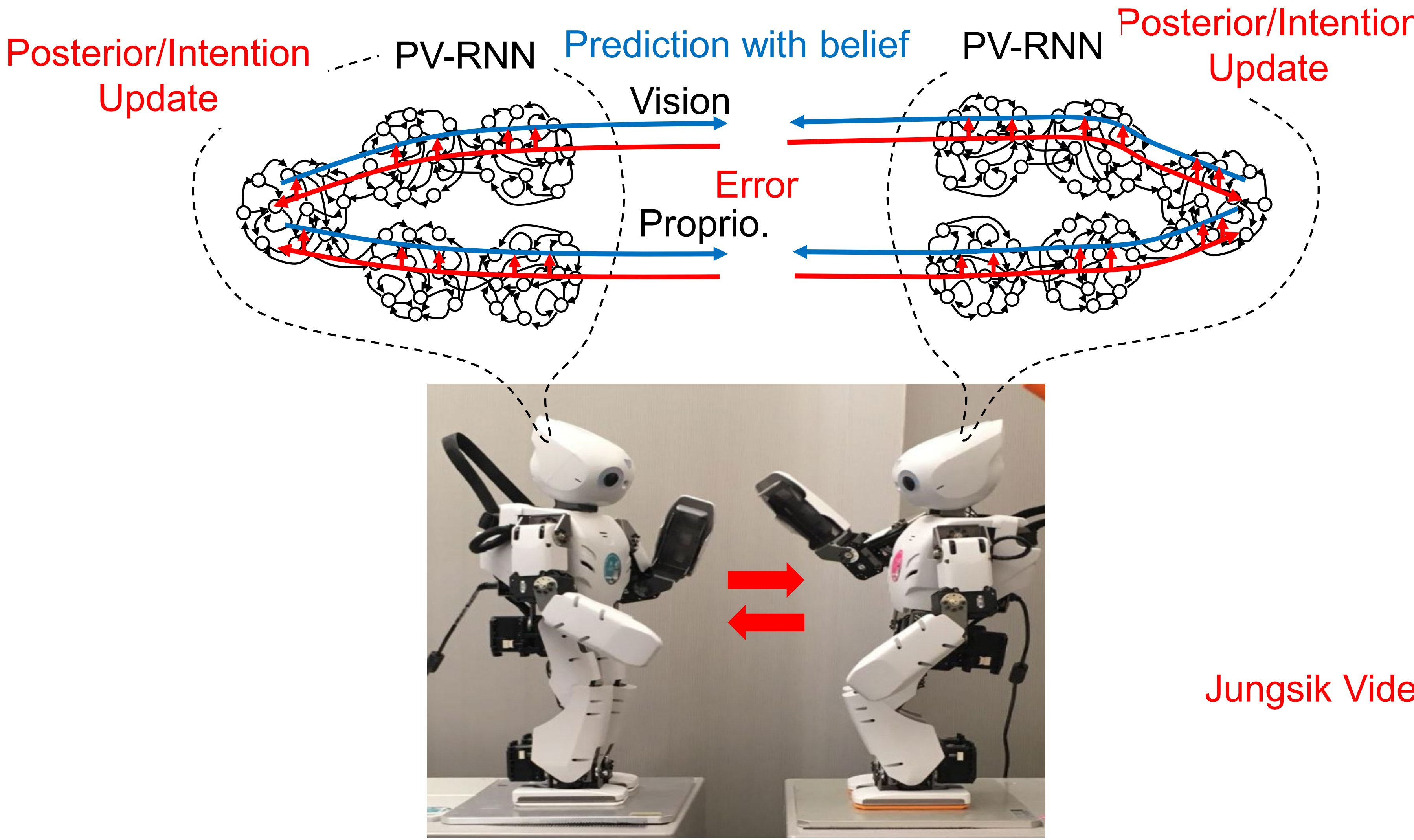
(Friston et al., 2010)

- Perception
  - Minimizing the prediction error by changing own internal state.
- Active Inference
  - Minimizing the prediction error by changing the sensory inputs by acting on the environment.



Imitative Interaction between Two Humanoid Robots with Mirror Neuron Mechanism

(Hwang, Wirkuttis, & Tani, in press)

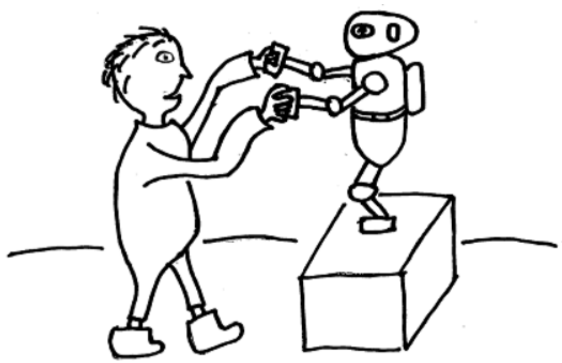


Jungsik Video

Co-developmental tutoring between robots and human

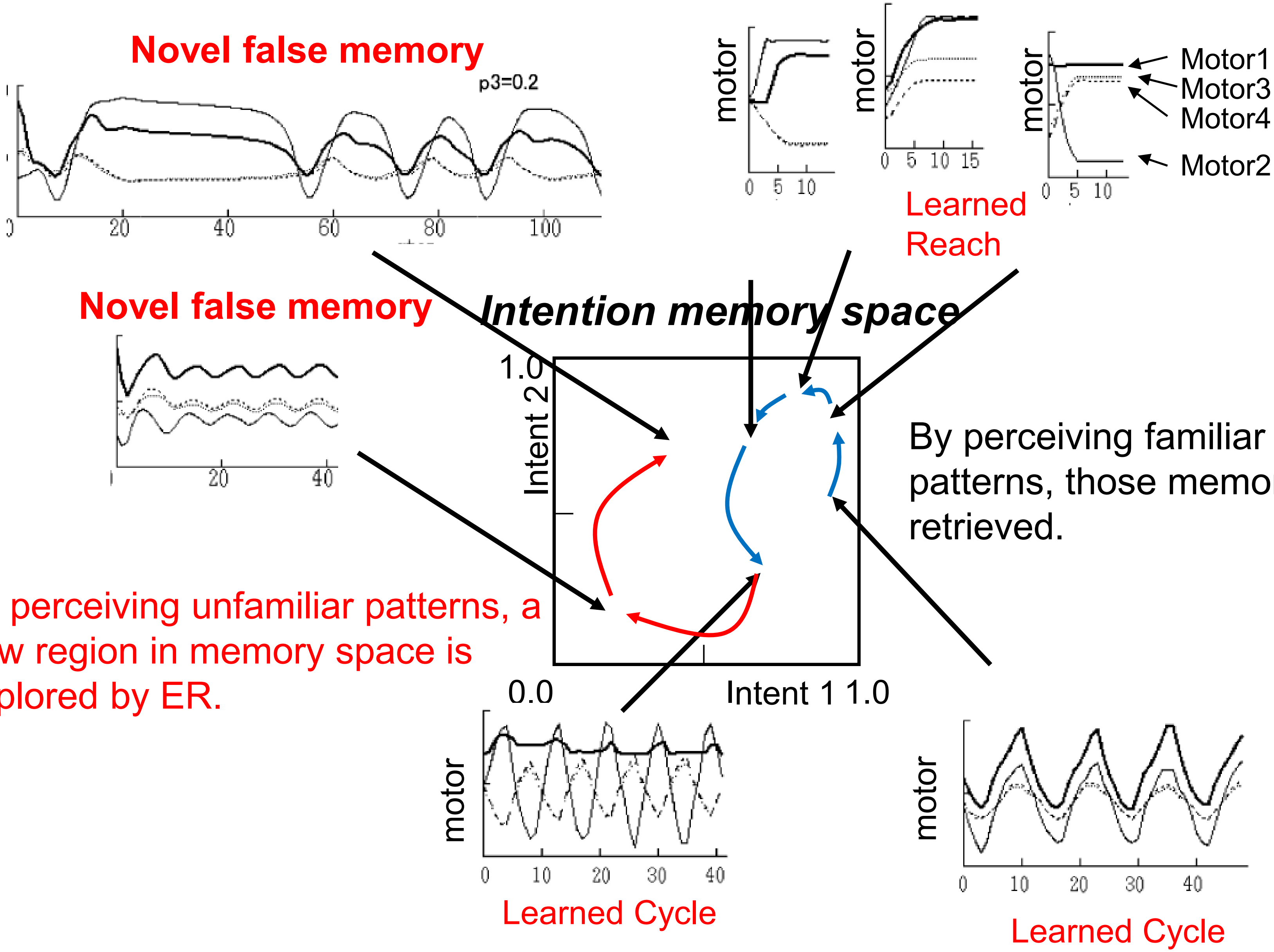
(Hendry & Tani, ongoing)

1. A robot has been trained for a set of behavior patterns by a tutor.
2. The robot can generate those behaviors by itself.
3. Then, the human tutor interacts with the robot by sometime suggesting new patterns.



Torobo-VIDEO

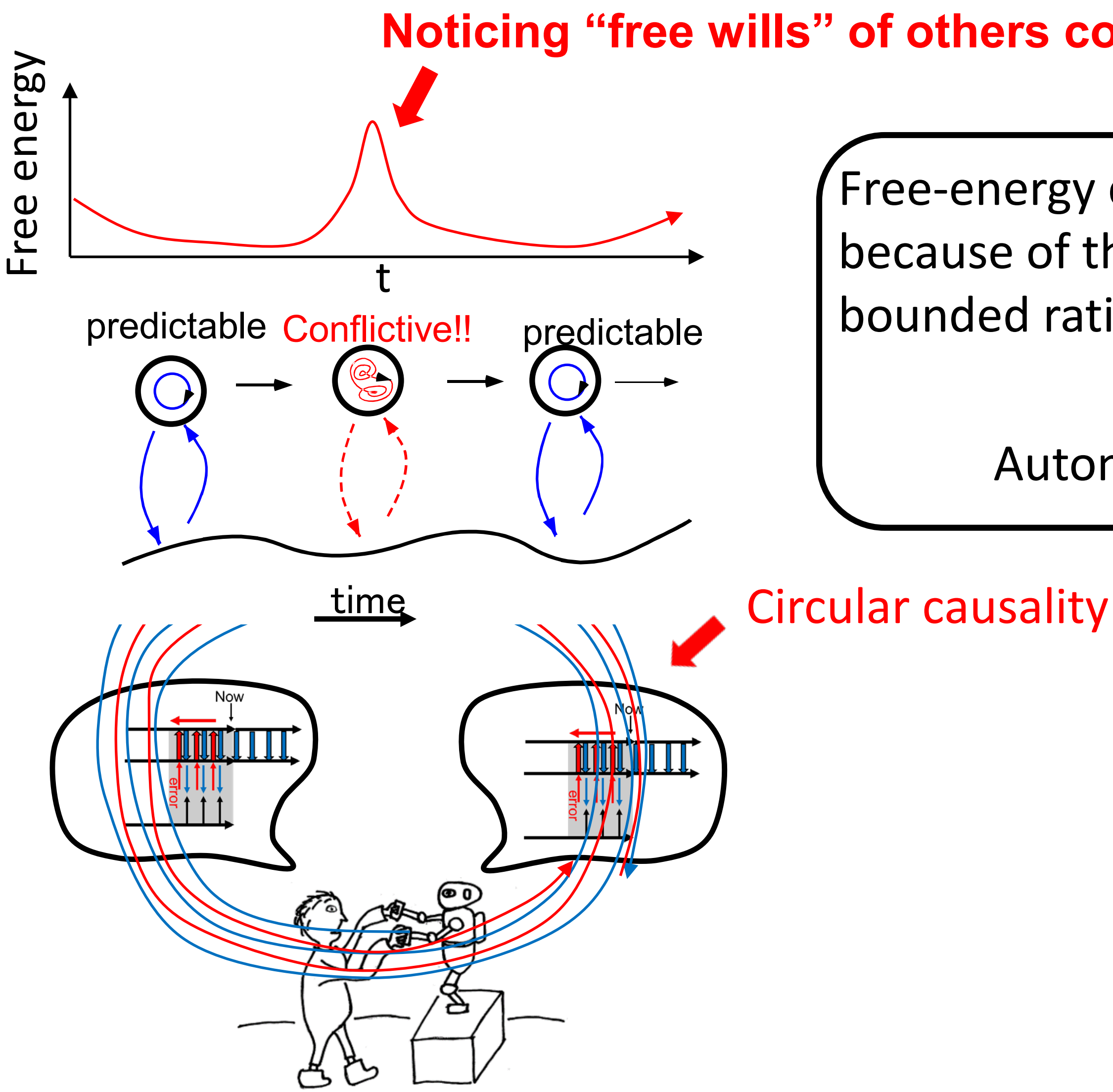
Spontaneous creation of novel patterns through exploration of memory space (Tani, 2003)



By perceiving familiar patterns, those memory are retrieved.

By perceiving unfamiliar patterns, a new region in memory space is explored by ER.

Exploration of new experience of human by putting human in the robotic-loop



Free-energy cannot be simply minimized because of the circular causality and the bounded rationality due to embodiment.

Autonomy of consciousness

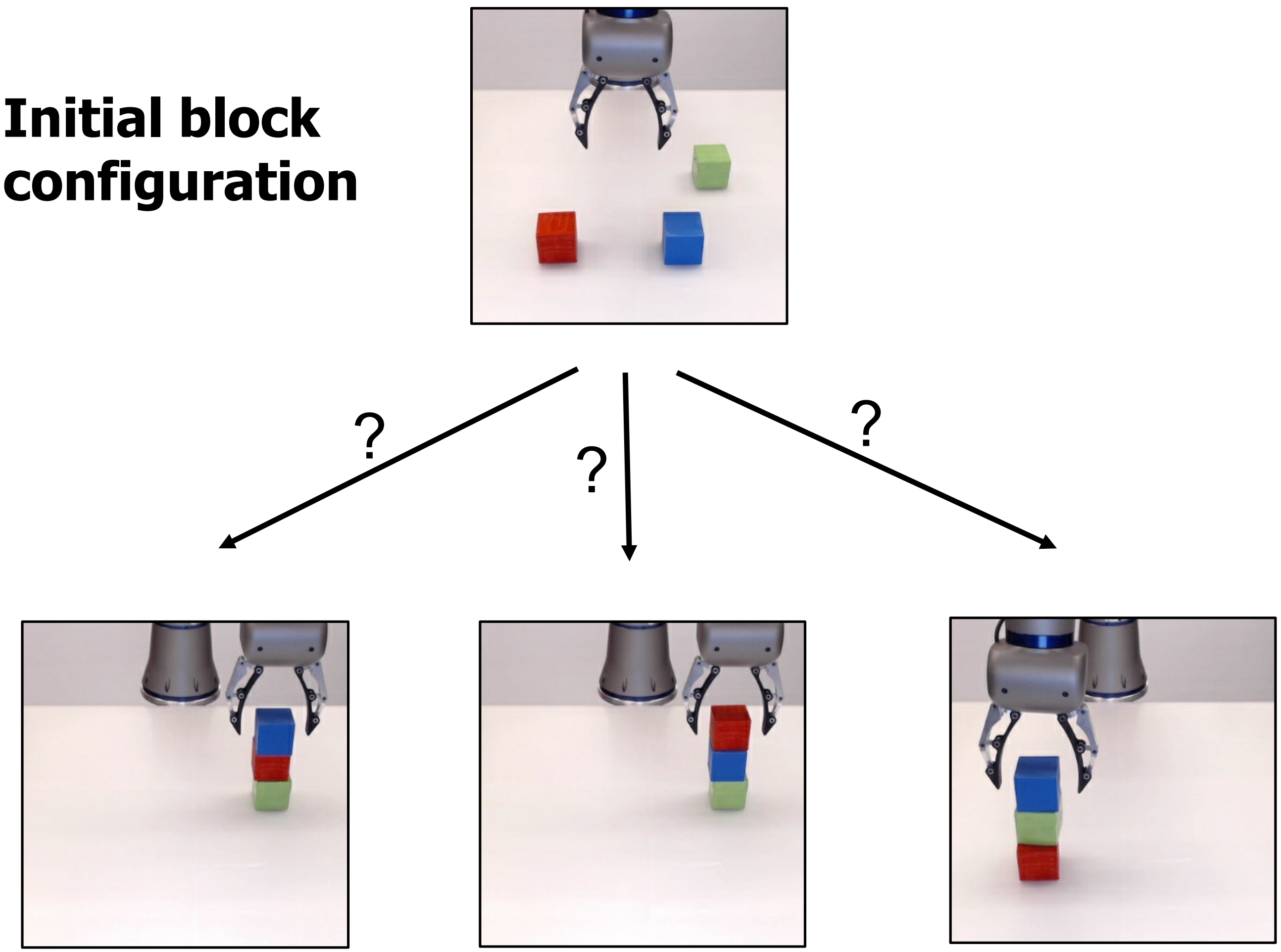
Goal-Directed Planning by Active Inference
(Development of Adequate Use of Visual Attention and WM)

(Jung, Matsumoto, & Tani, 2019)

- Generating visual mental image for achieving specified goals by active inference.
- Development of autonomous visual attention mechanism.
  - Learning to know what to look at.
- Development of adequate use of visual working memory.
  - Learning to know what to memorize in V-WM.

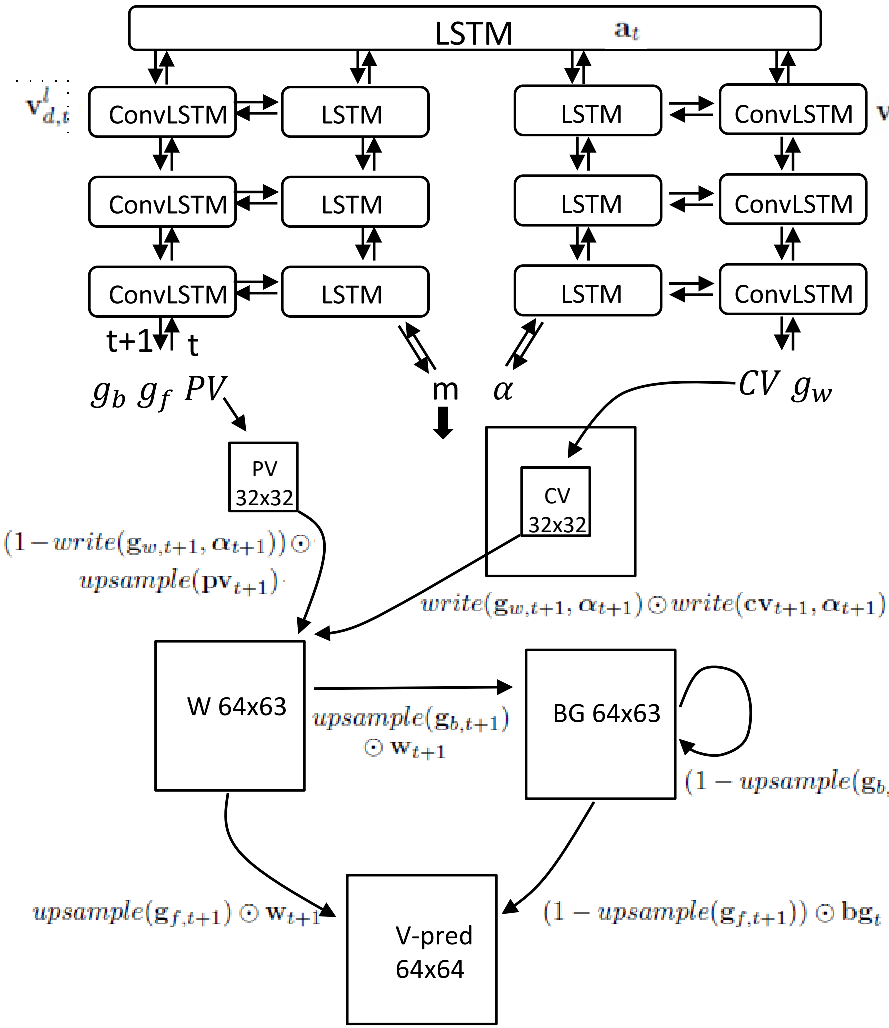
Goal-Directed Planning

Initial block configuration



Goal block configurations

Minju Model 2018



$$\mathbf{v}^0_{d,t} = downsample([\mathbf{v}^0_t, \mathbf{r}_t])$$

$$\mathbf{pv}_{t+1} = \tanh(deconv(\mathbf{v}^1_{d,t}))$$

$$\mathbf{v}^l_{d,t} = \begin{cases} ConvLSTM(\mathbf{v}^{l-1}_{d,t}, \mathbf{m}^l_{d,t-1}, \mathbf{a}_{t-1}), & \text{if } l = L \\ ConvLSTM(\mathbf{v}^{l-1}_{d,t}, \mathbf{m}^l_{d,t-1}, \mathbf{v}^{l+1}_{d,t-1}), & \text{otherwise} \end{cases}$$

$$\mathbf{g}_{f,t+1} = \sigma(deconv(\mathbf{v}^1_{d,t}))$$

$$\mathbf{g}_{b,t+1} = \sigma(deconv(\mathbf{v}^1_{d,t}))$$

$$\mathbf{m}^l_{d,t} = \begin{cases} LSTM(\mathbf{m}^{l-1}_{d,t}, \mathbf{v}^l_{d,t-1}, \mathbf{a}_{t-1}), & \text{if } l = L \\ LSTM(\mathbf{m}^{l-1}_{d,t}, \mathbf{v}^l_{d,t-1}, \mathbf{m}^{l+1}_{d,t-1}), & \text{otherwise} \end{cases}$$

$$\mathbf{v}^0_{v,t} = read([\mathbf{v}^0_t, \mathbf{r}_t], \boldsymbol{\alpha}_t)$$

$$\mathbf{v}^l_{v,t} = \begin{cases} ConvLSTM(\mathbf{v}^{l-1}_{v,t}, \mathbf{m}^l_{v,t-1}, \mathbf{a}_{t-1}), & \text{if } l = L \\ ConvLSTM(\mathbf{v}^{l-1}_{v,t}, \mathbf{m}^l_{v,t-1}, \mathbf{v}^{l+1}_{v,t-1}), & \text{otherwise} \end{cases}$$

$$\mathbf{cv}_{t+1} = \tanh(deconv(\mathbf{v}^1_{v,t}))$$

$$\mathbf{g}_{w,t+1} = \sigma(deconv(\mathbf{v}^1_{v,t}))$$

$$\mathbf{m}^l_{v,t} = \begin{cases} LSTM(\mathbf{m}^{l-1}_{v,t}, \mathbf{v}^l_{v,t-1}, \mathbf{a}_{t-1}), & \text{if } l = L \\ LSTM(\mathbf{m}^{l-1}_{v,t}, \mathbf{v}^l_{v,t-1}, \mathbf{m}^{l+1}_{v,t-1}), & \text{otherwise} \end{cases}$$

$$\mathbf{a}_t = LSTM(\mathbf{v}^L_{d,t}, \mathbf{v}^L_{v,t}, \mathbf{m}^L_{d,t}, \mathbf{m}^L_{v,t})$$

$$\boldsymbol{\alpha}_{t+1} = MLP(\mathbf{m}^1_{d,t}, \mathbf{m}^1_{v,t})$$

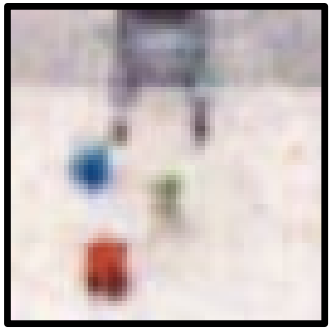
$$\mathbf{m}_{t+1} = MLP(\mathbf{m}^1_{d,t}, \mathbf{m}^1_{v,t})$$

α: attention, CV: central v, PV: peripheral V, m: motor, W: write image,
BG: background memory, g_w: *write mask* g_f: *fore mask*, g_b: *background mask*

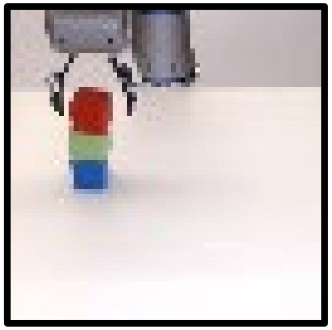
Visual prediction

Target video

Visual prediction

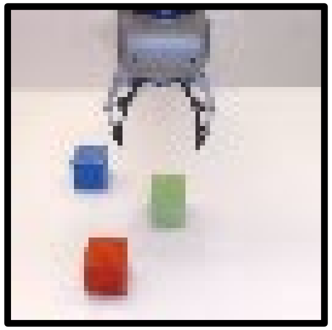


PV prediction

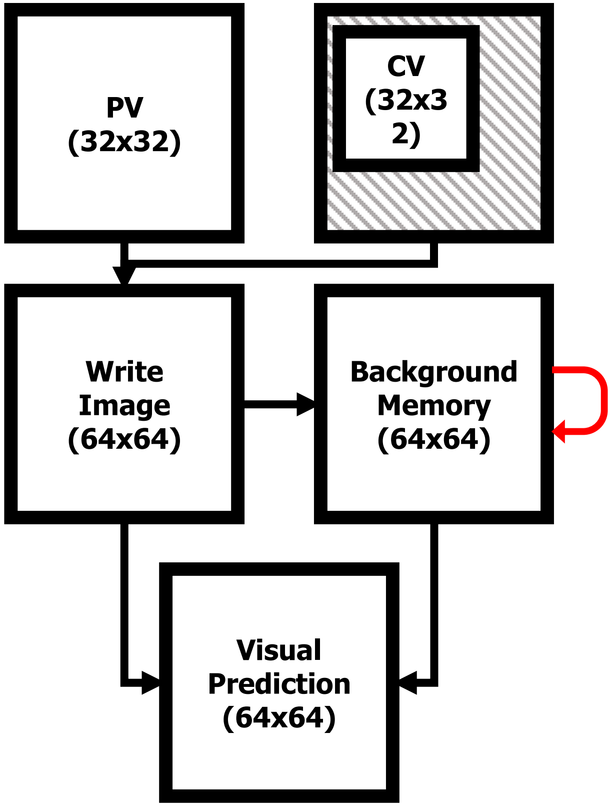


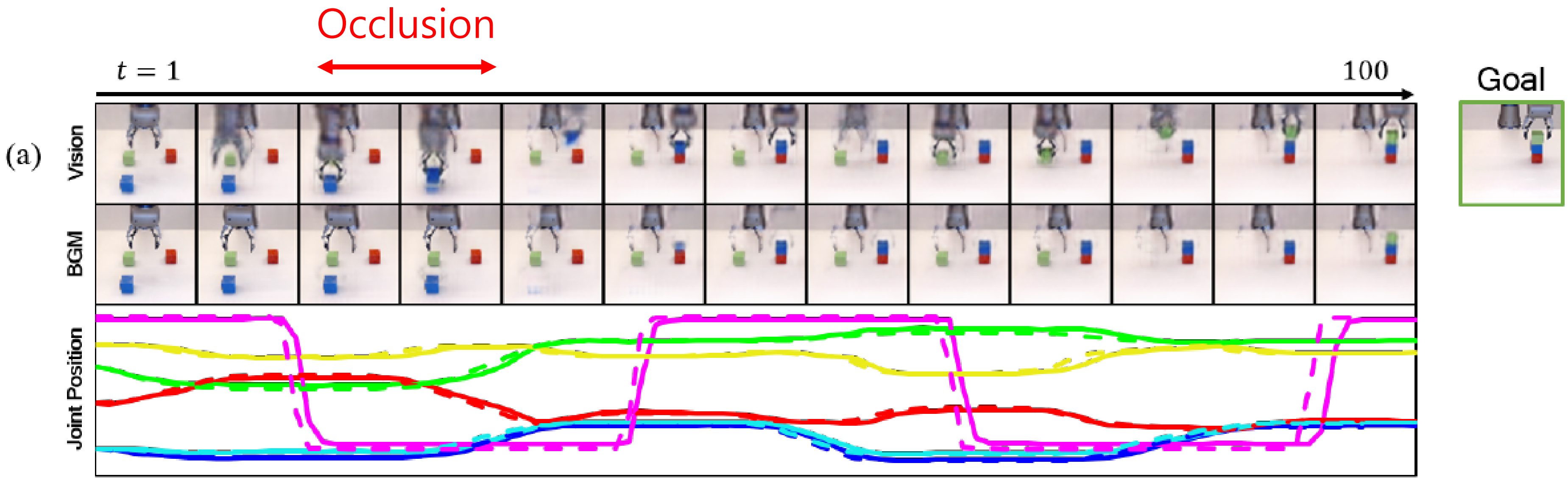
Goal image

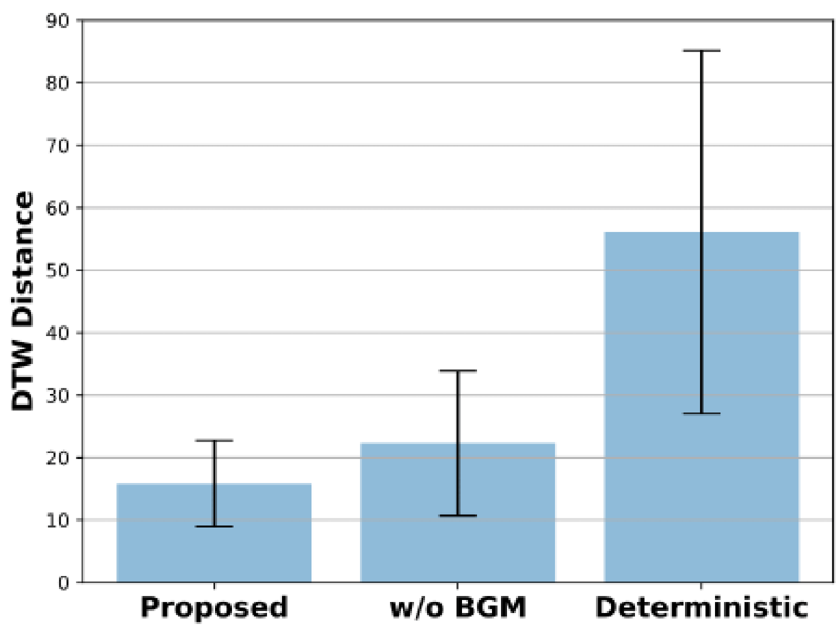
CV prediction



Background memory







Performance comparison

Discussions

- Competency without understanding ("Bacteria to Bach and Back", by Daniel Dennett, 2017).
  - Reverse engineering from phenomena to mechanism.
- Do we need furthermore meta-levels?
  - Prediction → prediction of predictability→meta-prior→???
- Free energy minimization principle (FEP) drives systems toward equilibrium state (biological death).
  - Can FEP + circular causality + embodiment avoid this?
    - How to theorize it?

Advertisement
New Book from Oxford!!

Thank you!!


Nadine Wirkuttis
Jungsik Hwang
Minju Jung
Hendry
Reza Ahmadi

Social Cognition