Prospective coding in motor learning and motor decision making

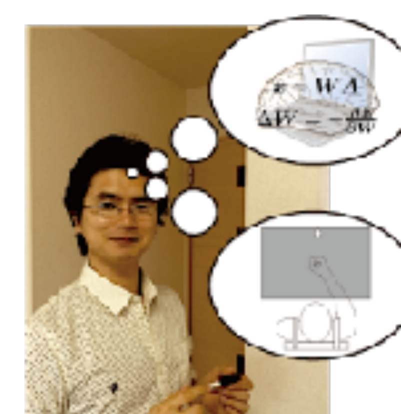
- I will succeed
- I will fail

Where to aim?

The keeper will move leftward.

Ken Takiyama

Tokyo University of Agriculture and Technology(TUAT)



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1. motor learning

2. motor decision making

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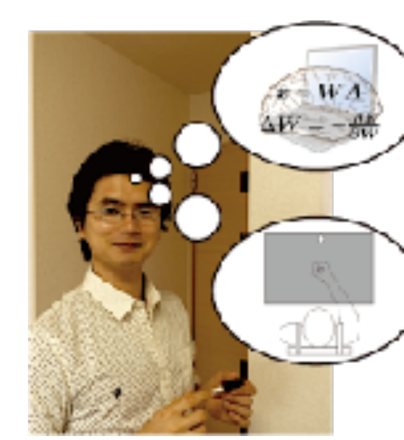

Prospective errors determine motor learning

- a step towards a unified model of motor learning -

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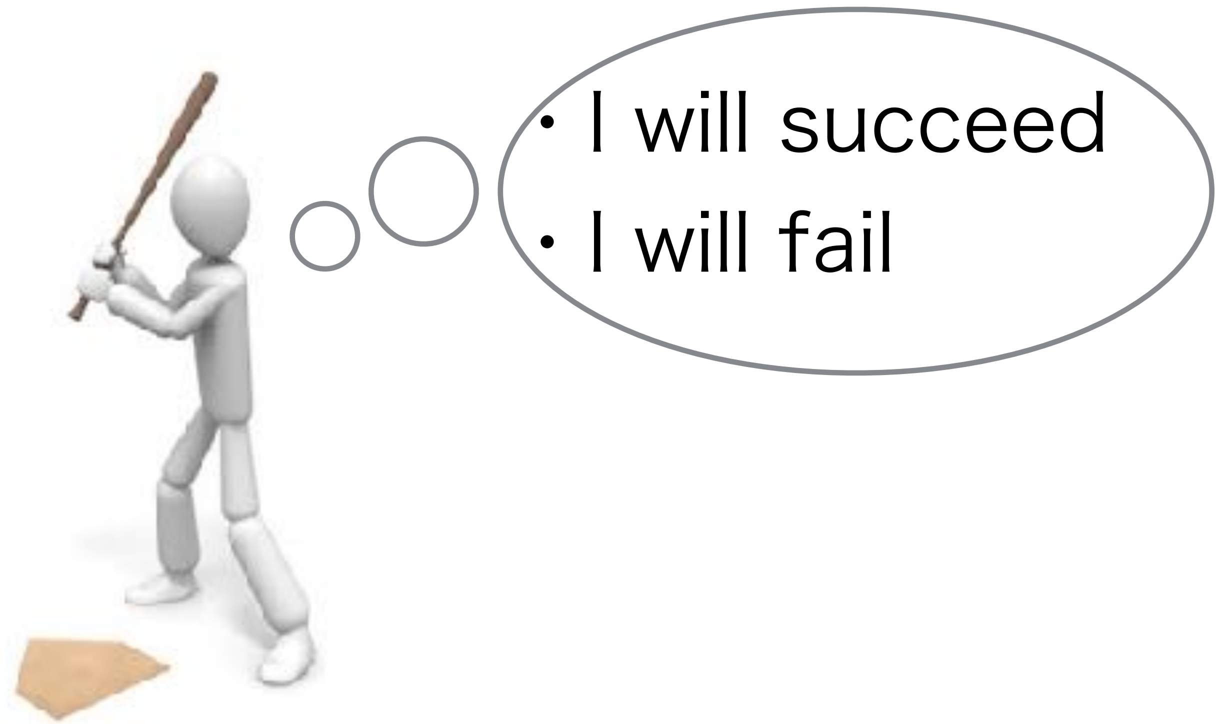
Prospective errors determine motor learning

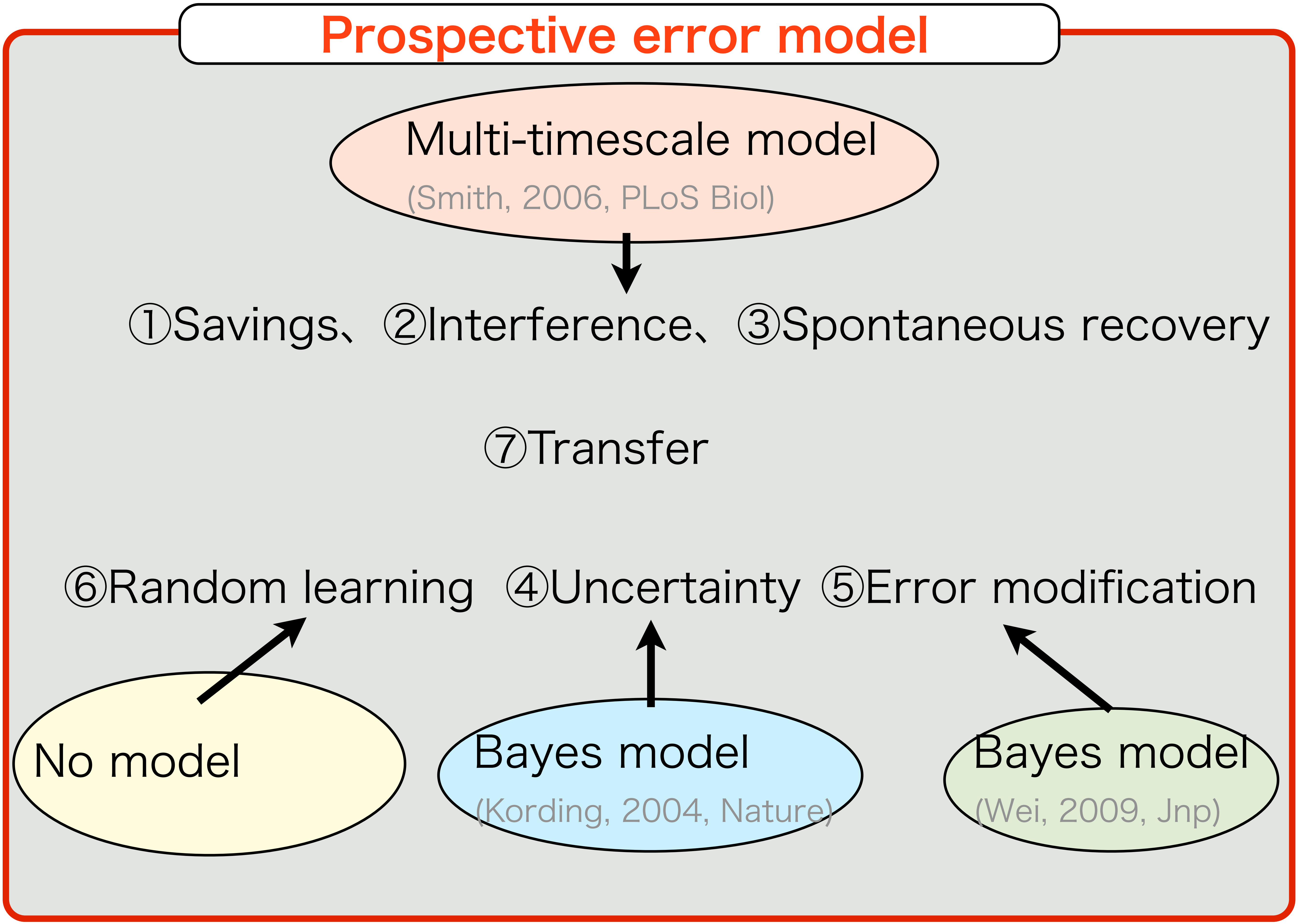
Ken Takiyama[1], Masaya Hirashima[2] & Daichi Nozaki[3]

Takiyama, Hirashima, Nozaki, Nature Comm, 2015

Our hypothesis



The predicted movement error, prospective error, determines neural activity and motor command in motor learning.


Prospective error model
Multi-timescale model
(Smith, 2006, PLoS Biol)
①Savings、②Interference、③Spontaneous recovery
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④Uncertainty
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No model
Bayes model
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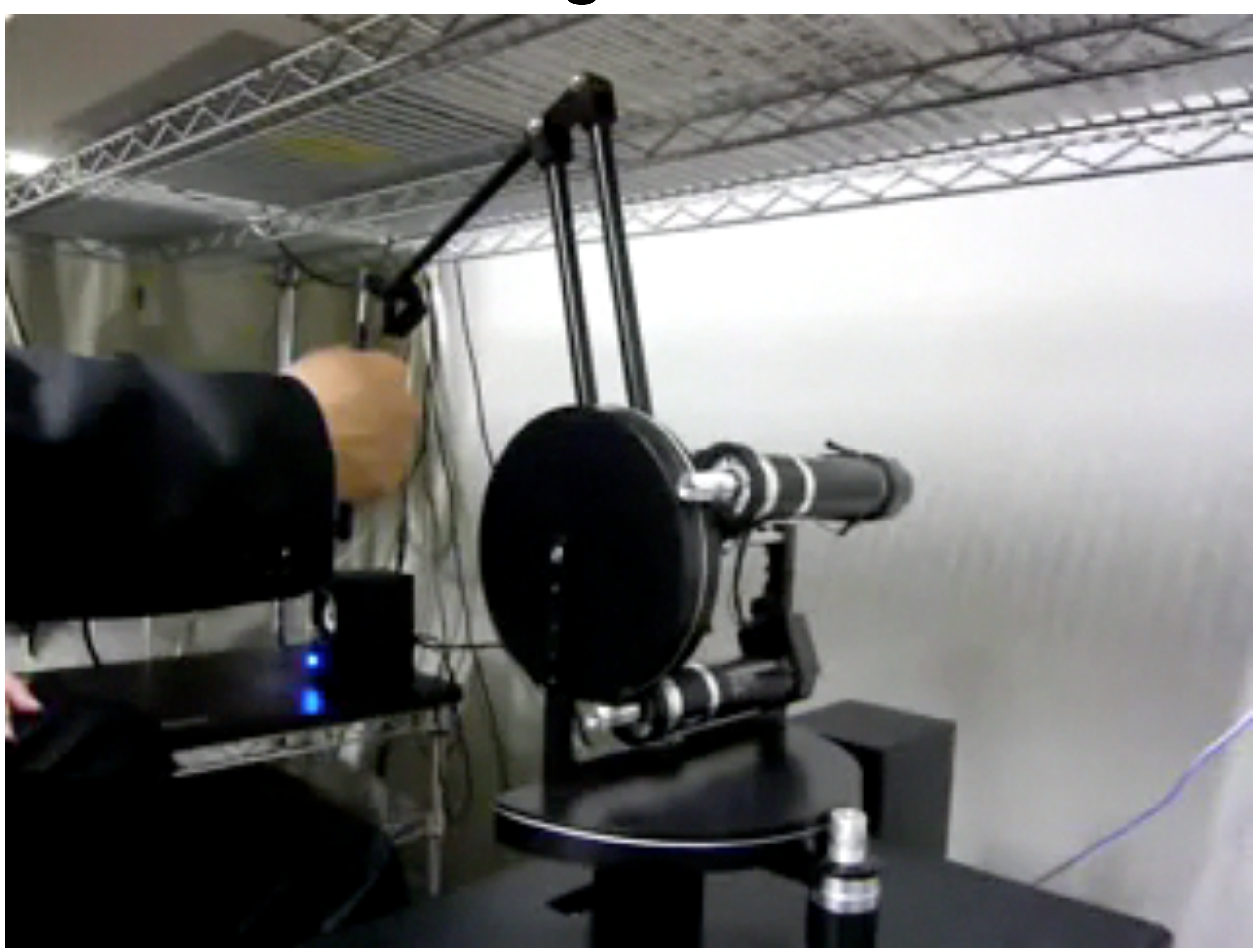
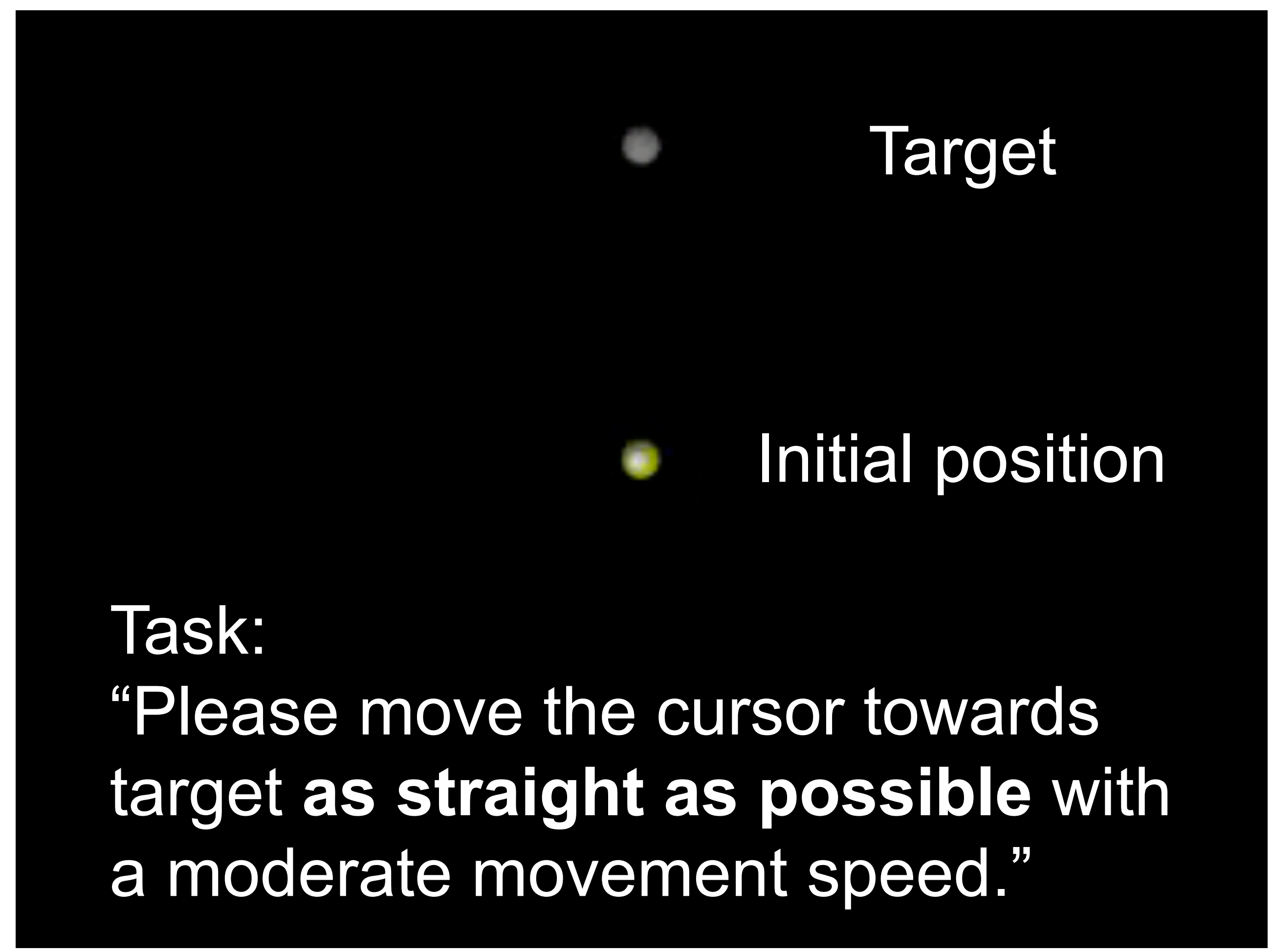
Experiment: reaching movements (unimanual) + Perturbation

These videos were offered by Yokoi-sensei.

Reaching movement

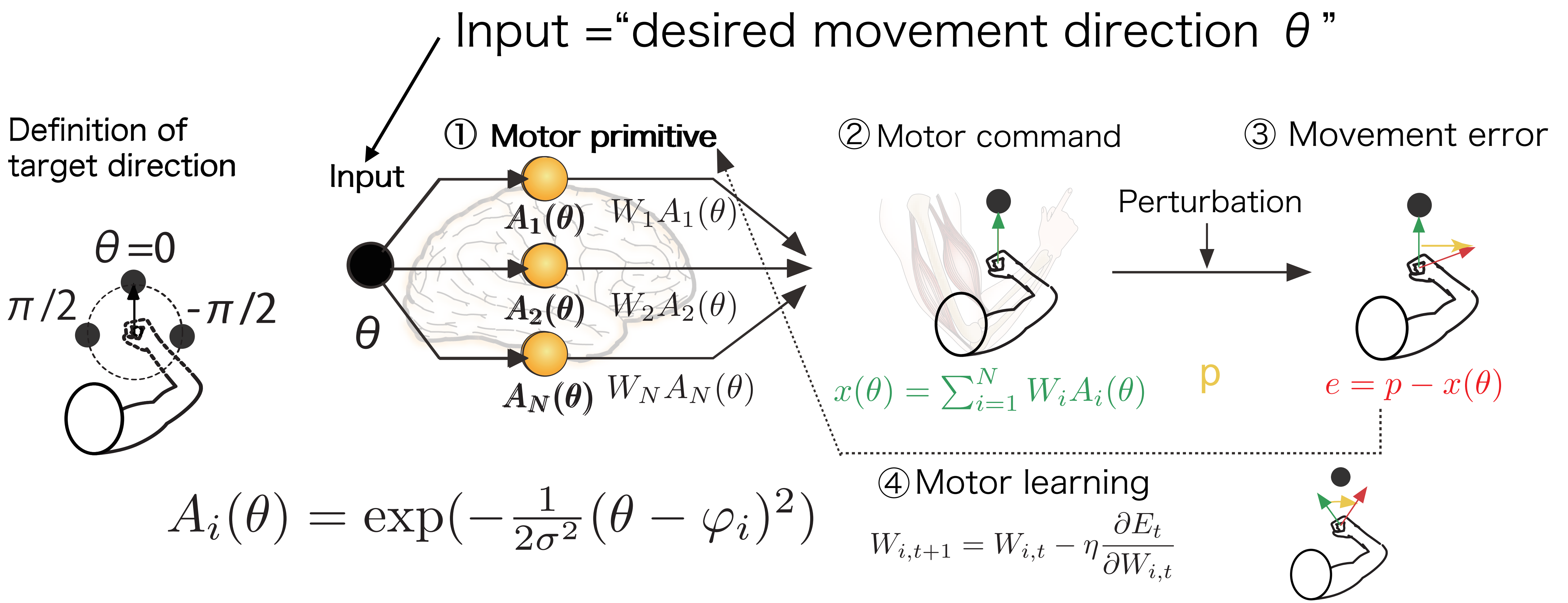


30° **visuomotor rotation**



Compatibility of simplicity in learning and complexity in control: Motor primitive

(Thoroughman & Shadmehr, 2000, Nature).



Simplicity in learning ··· linear learning equation of W

Complexity in learning ··· linear combination of A (nonlinear function)

What determines neural activity in motor learning? … No consensus.

1. Force (Evarts, 1964, Jnp)
2. Desired movement direction (Georgopoulos et al., 1984, JNS)
3. Desired movement speed & position (Moran et al., 2007, Jnp)
4. Actual movement (Gonzalez-Castro et al., 2011, PLoS Compt Biol)
5. Aiming movement direction (Taylor & Ivry, 2011, PLoS Compt Biol)
6. Reward (Huang et al., 2009, Neuron)
7. Uncertainty (Kording & Wolpert, 2004, Nature)
8. Visual and proprioceptive information (Brayanov et al., 2011, JNS)

Our hypothesis: predicted errors in the upcoming movement determine neural activity

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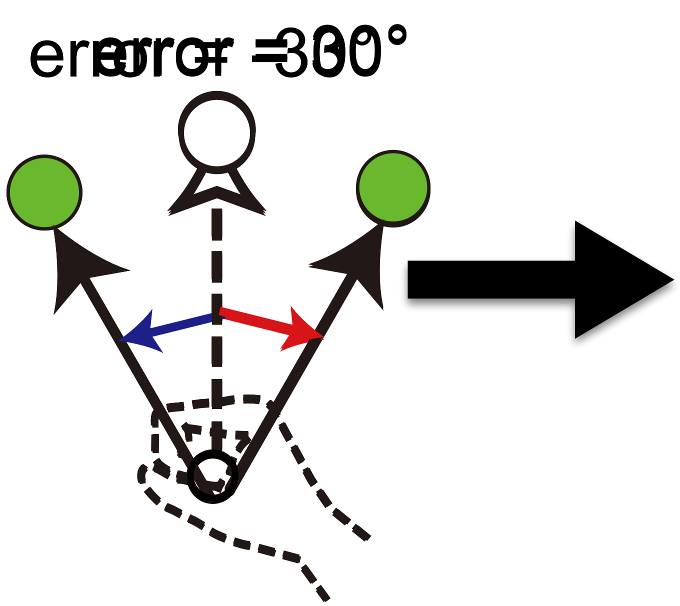
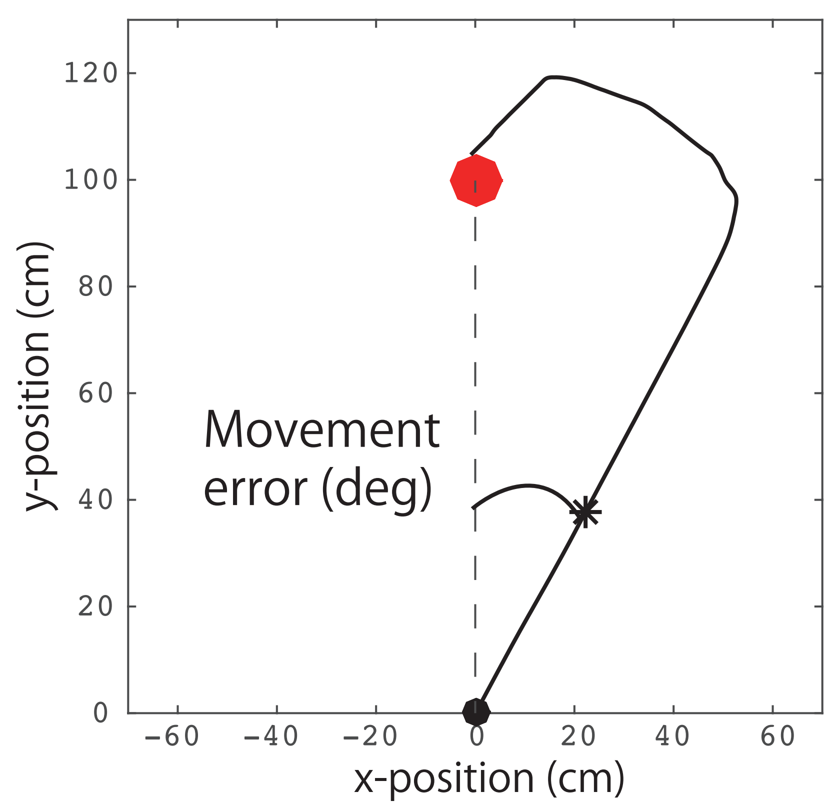
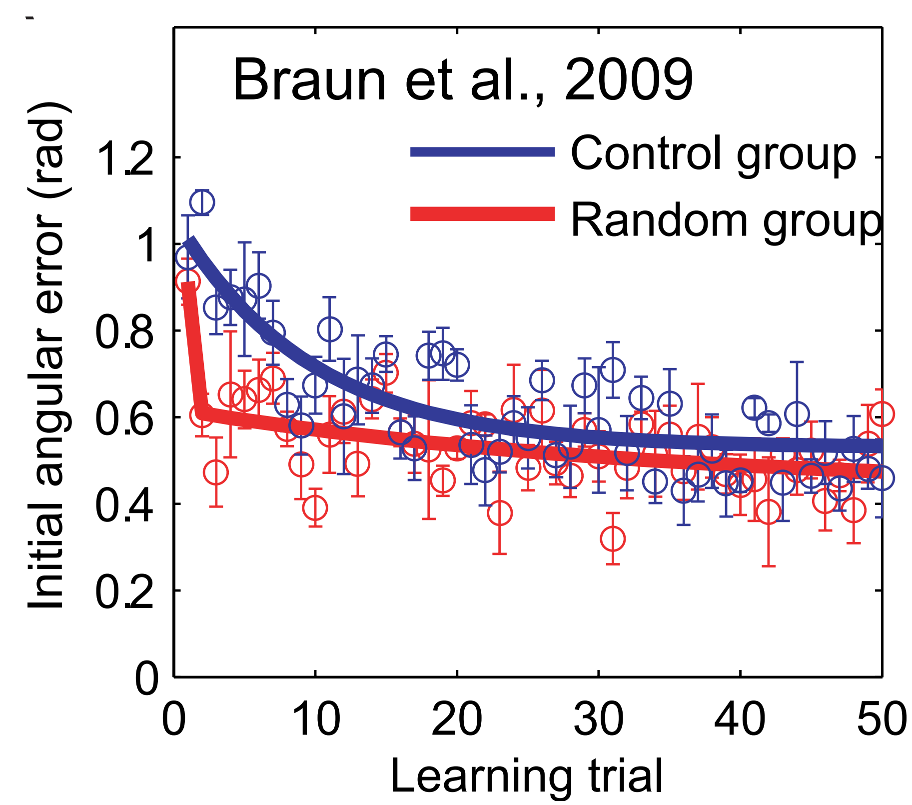
Prediction of conventional models:
<u>When movement error is 0 on average ($\langle e_t \rangle = 0$), no motor learning is facilitated</u>.

$$\text{Learning rule: } \langle W_{t+1} \rangle = \lambda \langle W_t \rangle + \frac{\eta}{N} \langle e_t \rangle \langle A^T(\theta_t) \rangle = \lambda \langle W_t \rangle$$



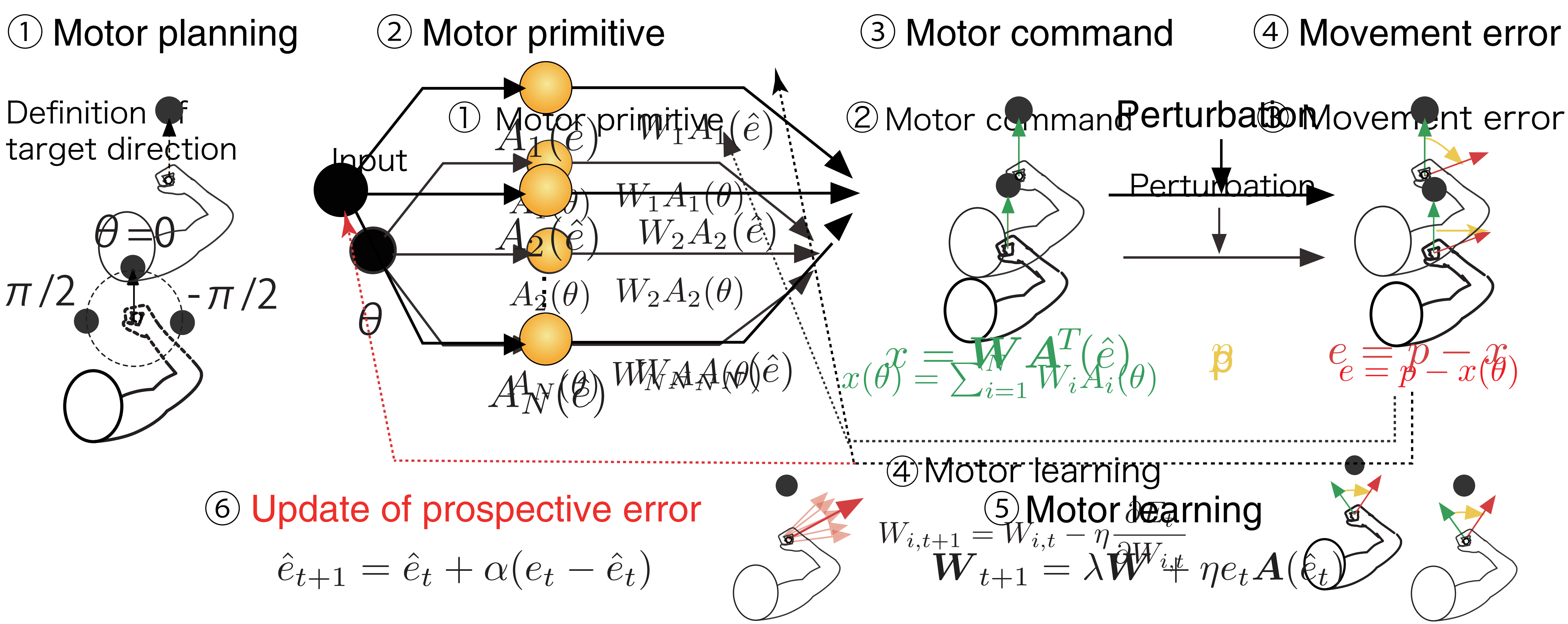




However, this prediction contradicts ***<u>random learning</u>***<u>, *or structural learning*</u> (Braun, 2009, Curr Biol).

To reproduce random learning, *A* should be correlated to ***e***.

$$\langle W_{t+1}\rangle = \lambda\langle W_t\rangle + \frac{\eta}{N}\langle e_t A(\theta_t)\rangle = \lambda\langle W_t\rangle + \frac{\eta}{N}\boxed{\mathrm{Cov}(e_t A(\theta_t))}$$

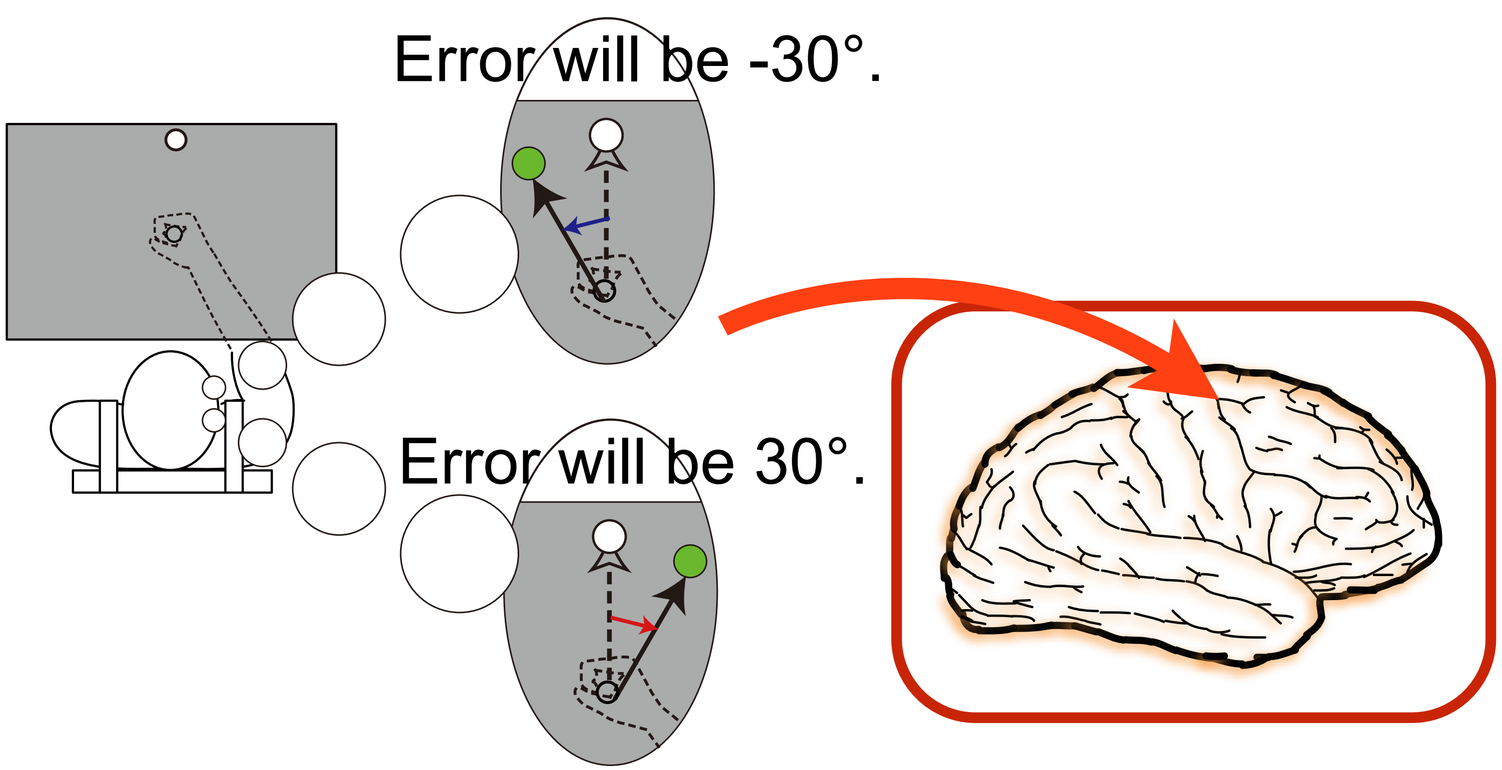


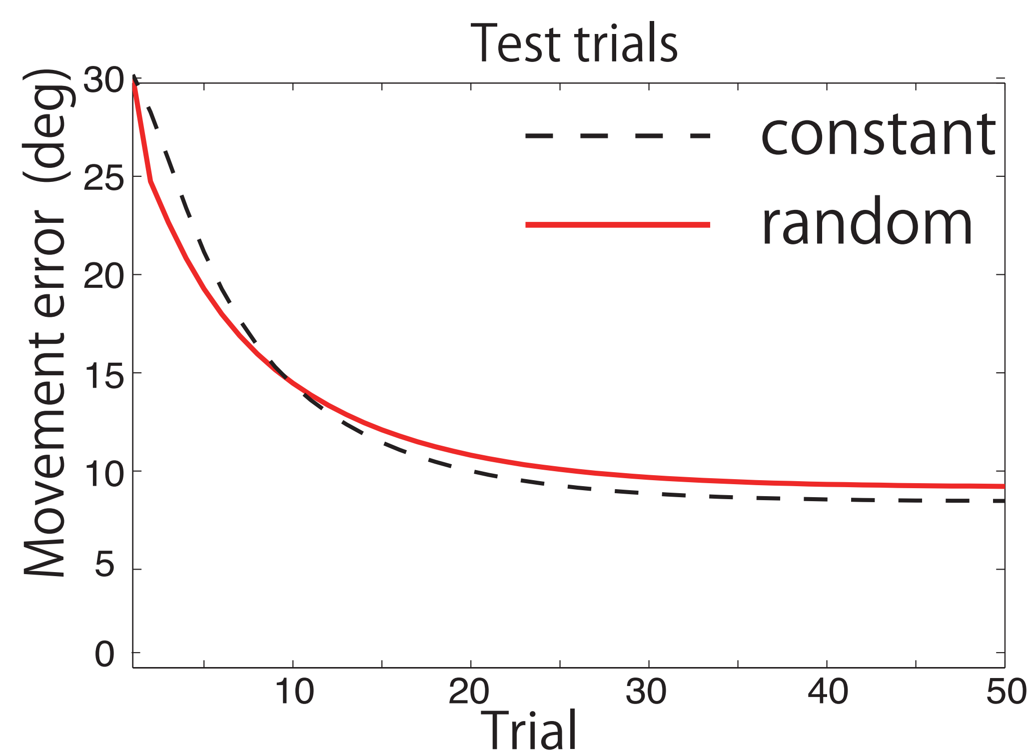
Note: *A* → before the initiation of movement.

e → after the end of movement. *A* cannot be correlated to ***e***.

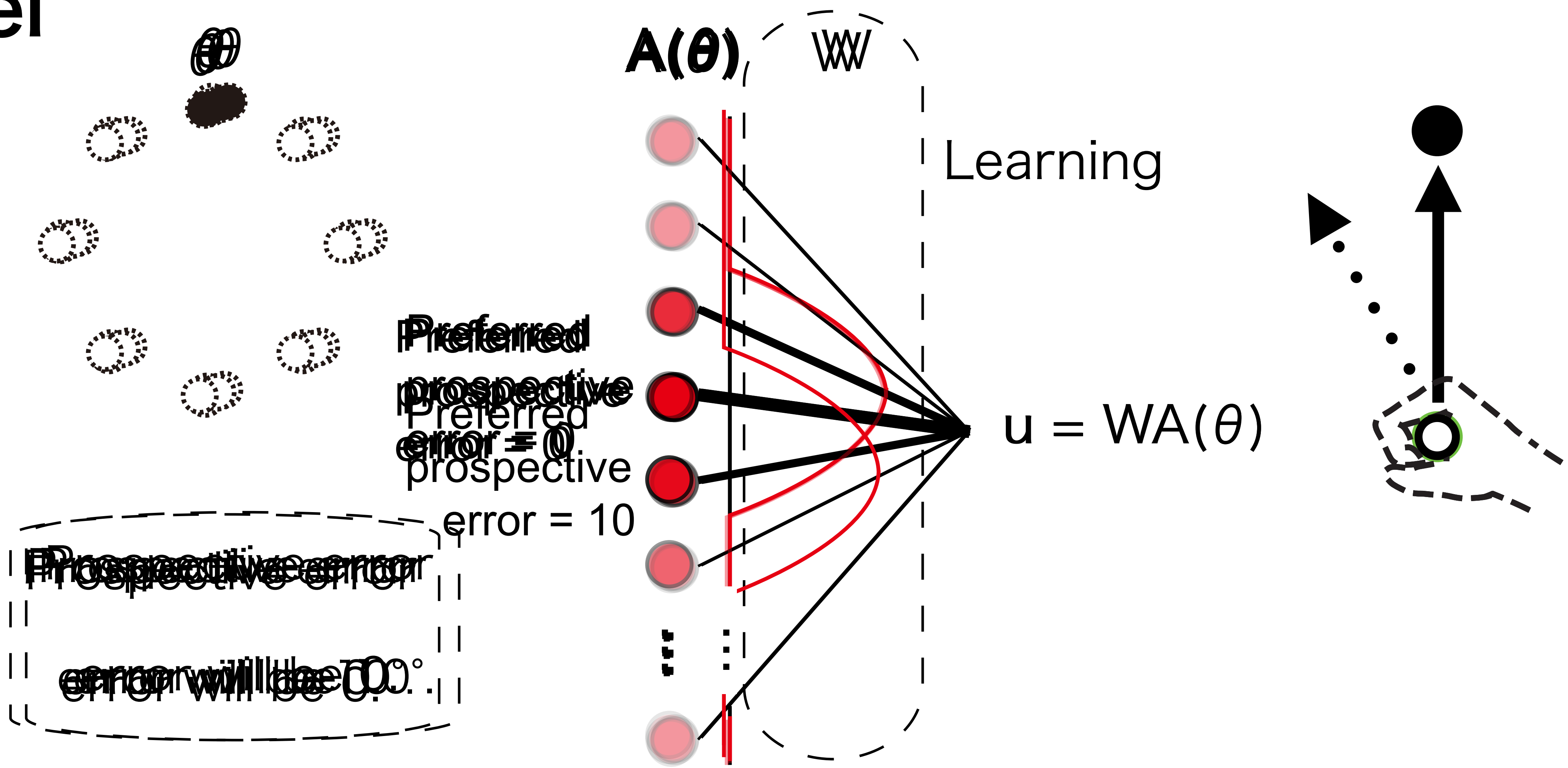
What are inputs x in motor learning ?

Our proposal: We predict movement error before the initiation of movement and the predicted movement error (**prospective error**) affects neural activity and motor learning.





Model



1. Desired movement direction & prospective error.
2. Neural activities **A**. (e.g., A···Gaussian)
3. Motor command: $u = \sum_{i=1}^{N} W_i A_i(\theta)$
4. Modify **W** to minimize prediction error.
5. Update prospective error. $\hat{e}_{t+1} = \hat{e}_t + \alpha(e_t - \hat{e}_t)$

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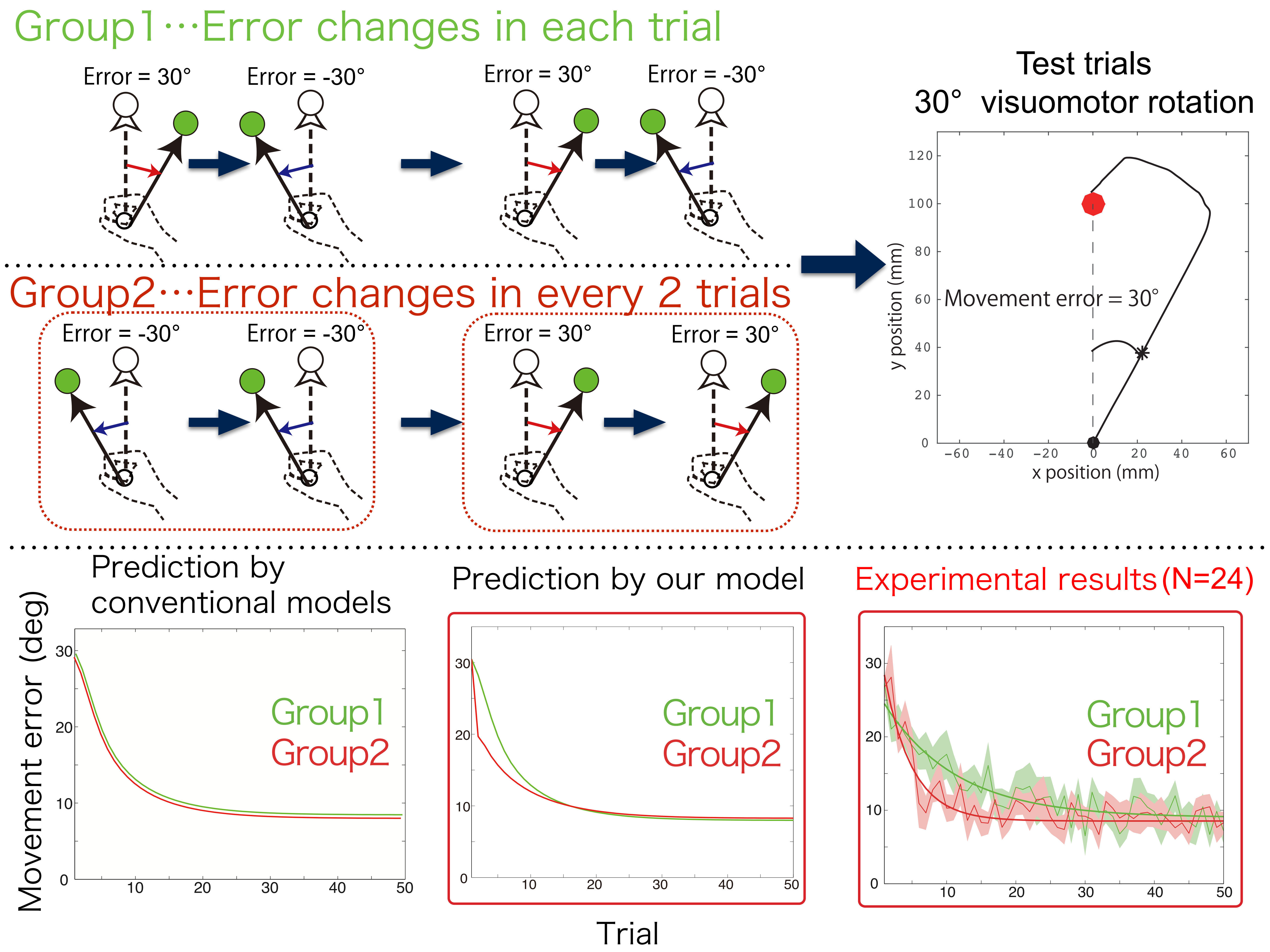

Group1…Error changes in each trial
Error = 30°
Error = -30°
Error = 30°
Error = -30°
Group2…Error changes in every 2 trials
Error = -30°
Error = -30°
Error = 30°
Error = 30°
Test trials
30° visuomotor rotation
Movement error = 30°
y position (mm)
x position (mm)
Prediction by conventional models
Prediction by our model
Experimental results (N=24)
Movement error (deg)
Trial
Group1
Group2

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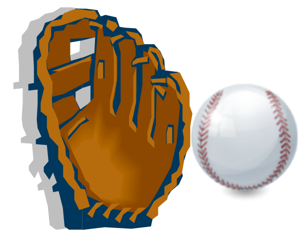
Theory 1: Bayesian (Kording, Wolpert, 2004, Nature)

Low uncertainty

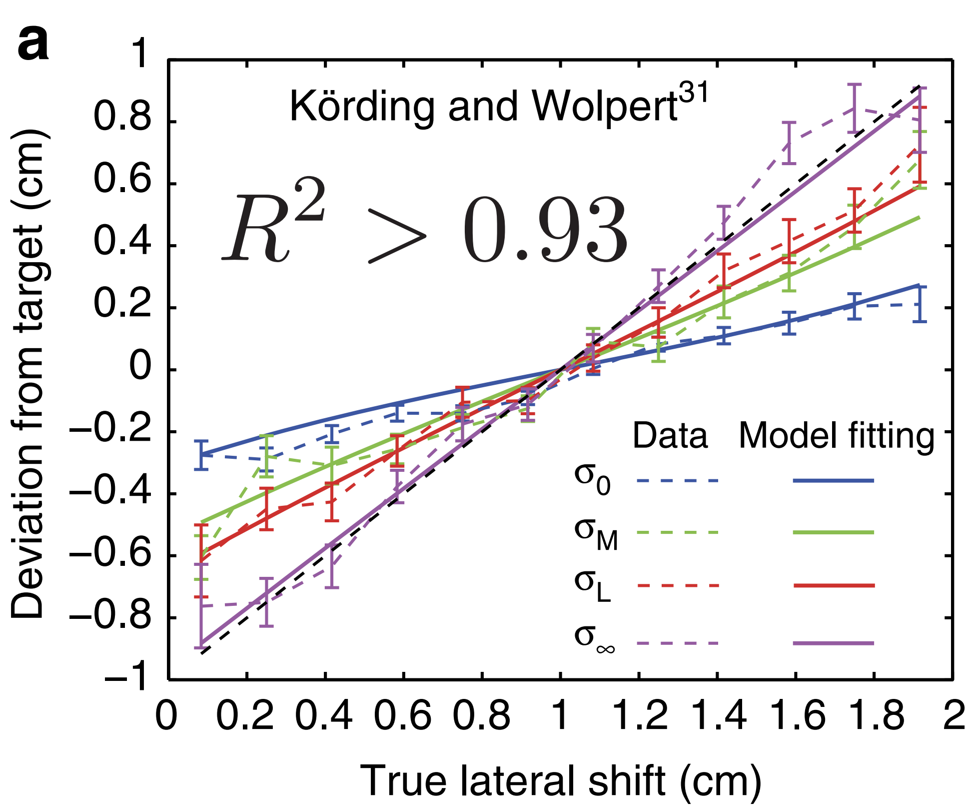


Fast learning

High uncertainty

Slow learning

Mathematical model: $$x_{\text{estimated}} = \frac{\sigma^2_{\text{sensed}}}{\sigma^2_{\text{sensed}} + \sigma^2_{\text{prior}}}[1\text{cm}] + \frac{\sigma^2_{\text{prior}}}{\sigma^2_{\text{sensed}} + \sigma^2_{\text{prior}}} x_{\text{sensed}}$$



Prospective error hypothesis:
＊Higher uncertainty causes difficulty in predicting error, resulting in slower learning.

Theory 2: non-quadratic error (Kording, Wolpert, 2004, PNAS)

Probable error

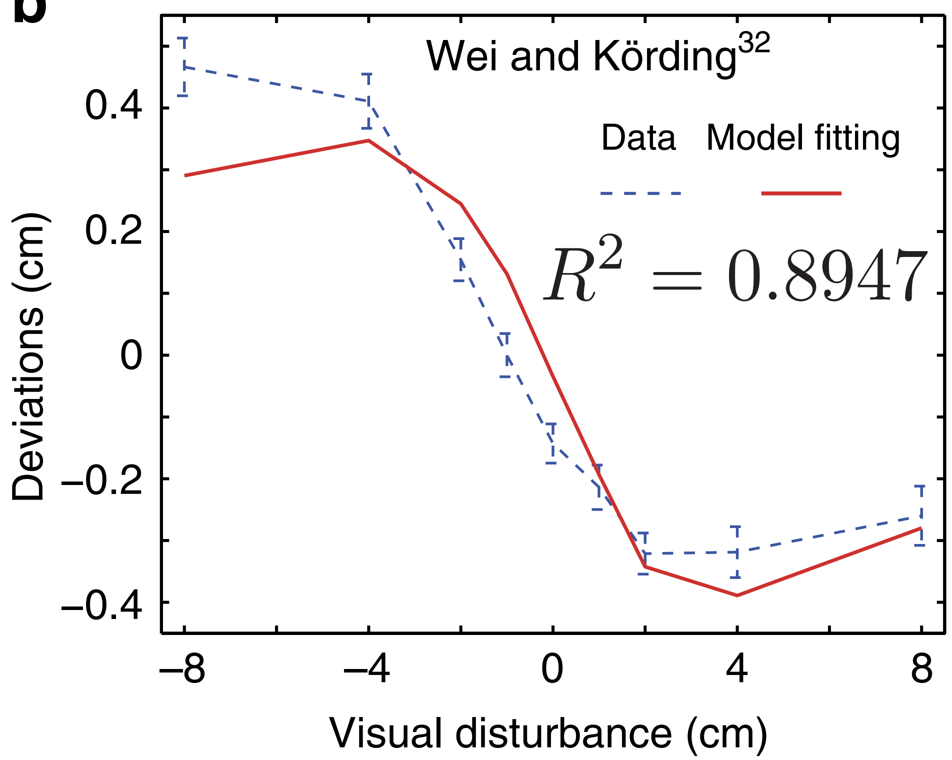
Fast learning

Improprobable error ！？

Slow learning

Mathematical model: $\hat{x}_{hand} = x_{vis}\, S\, \dfrac{N(x_{vis},\ \sigma^2)}{N(x_{vis},\ \sigma^2) + c}$

b



Wei & Kording, 2008, Jnp

Larger error results in slower learning.

Prospective error hypothesis:

＊Large error causes difficulty in predicting error, resulting in slower learning.

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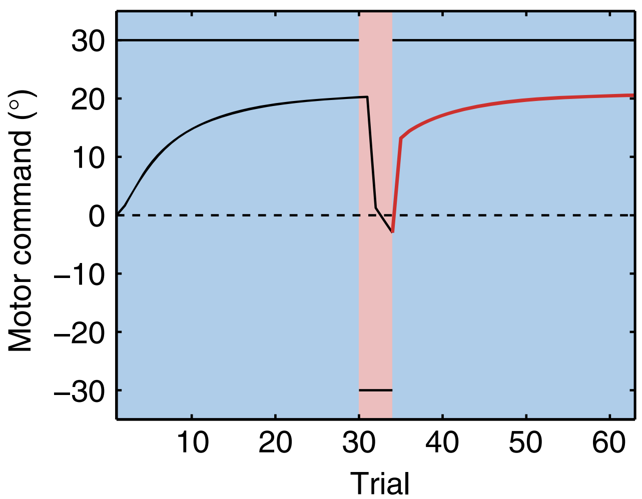
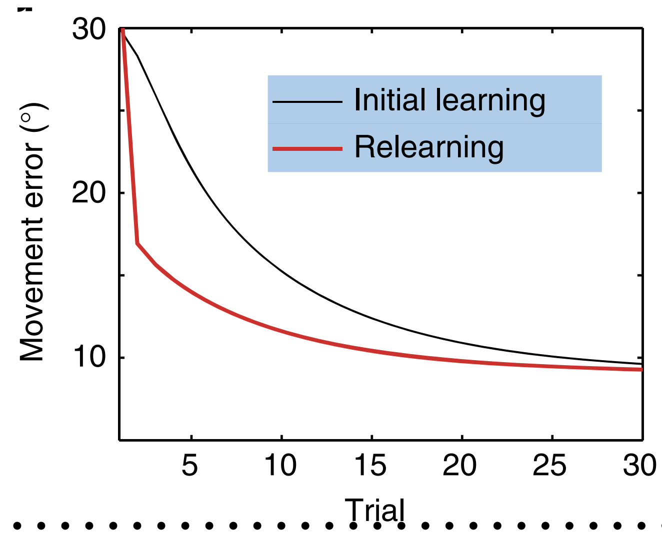
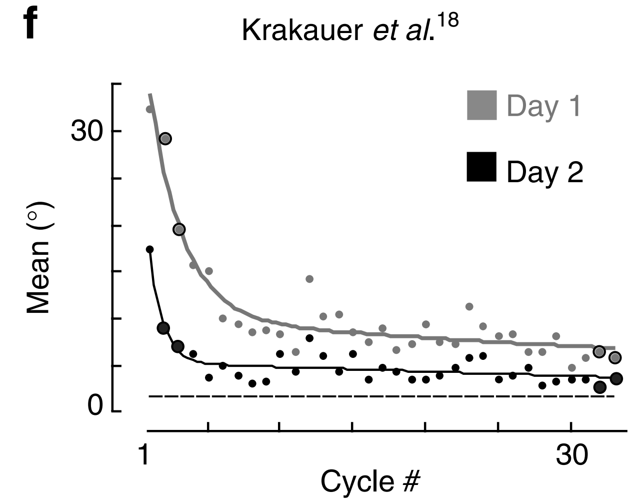
Theory 3: Multiple timescale model (Smith, 2006, PLoS Biol)

1. Savings - A-B-A paradigm, faster learning speed in relearning phase -

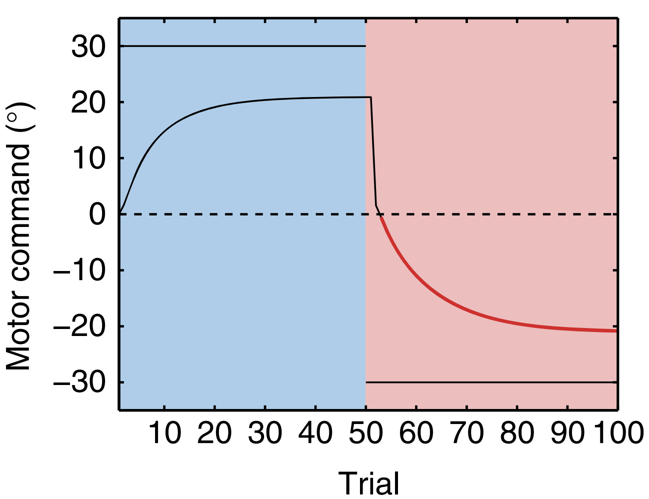


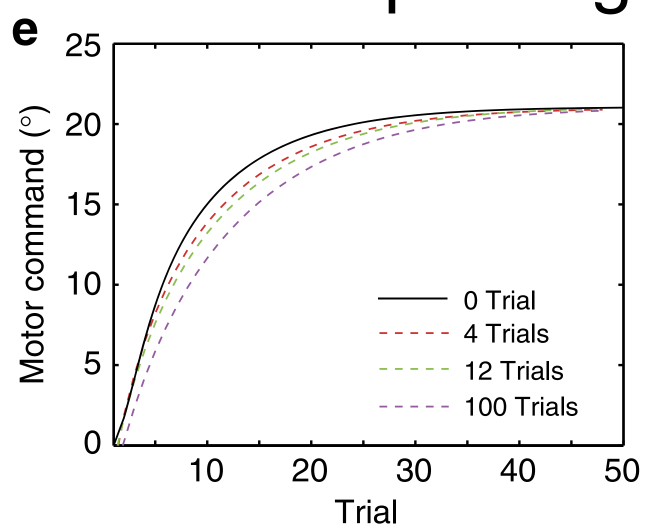


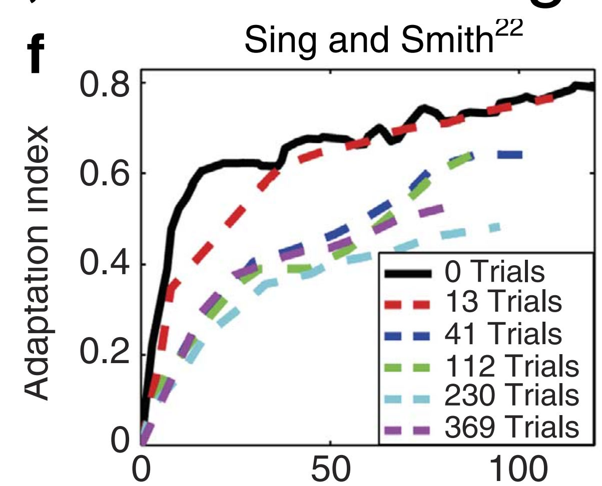


Krakauer+, 2000, Nat Neurosci

2. Anterograde interference - A-B paradigm, slower learning speed in B phase-

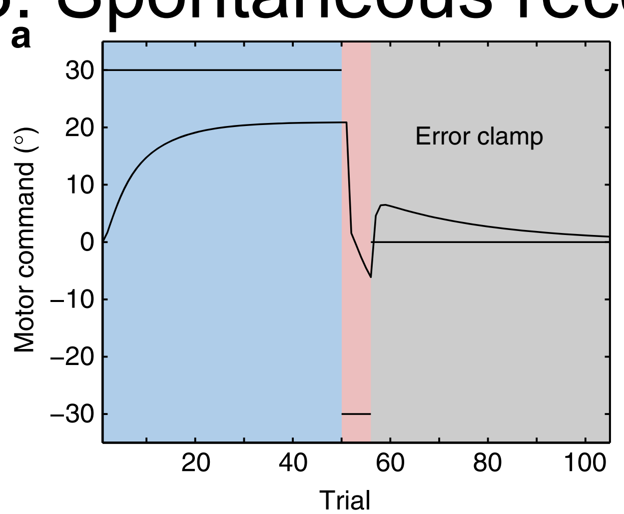


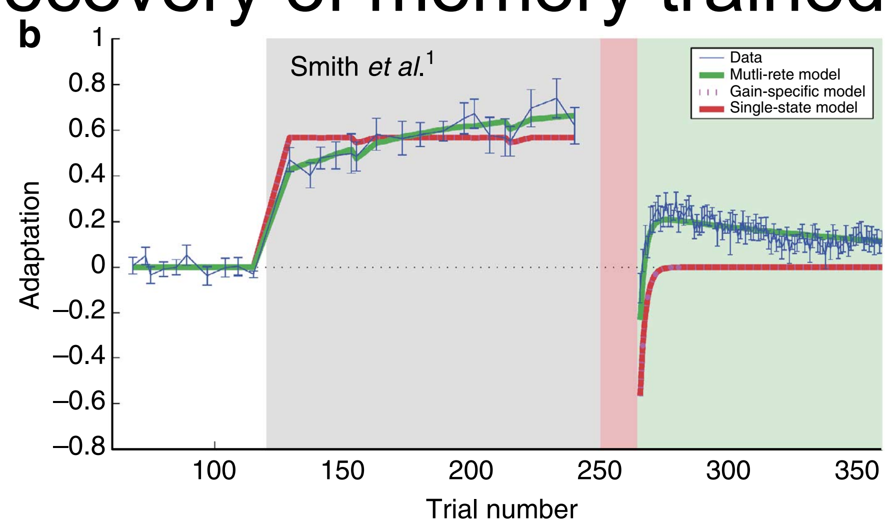




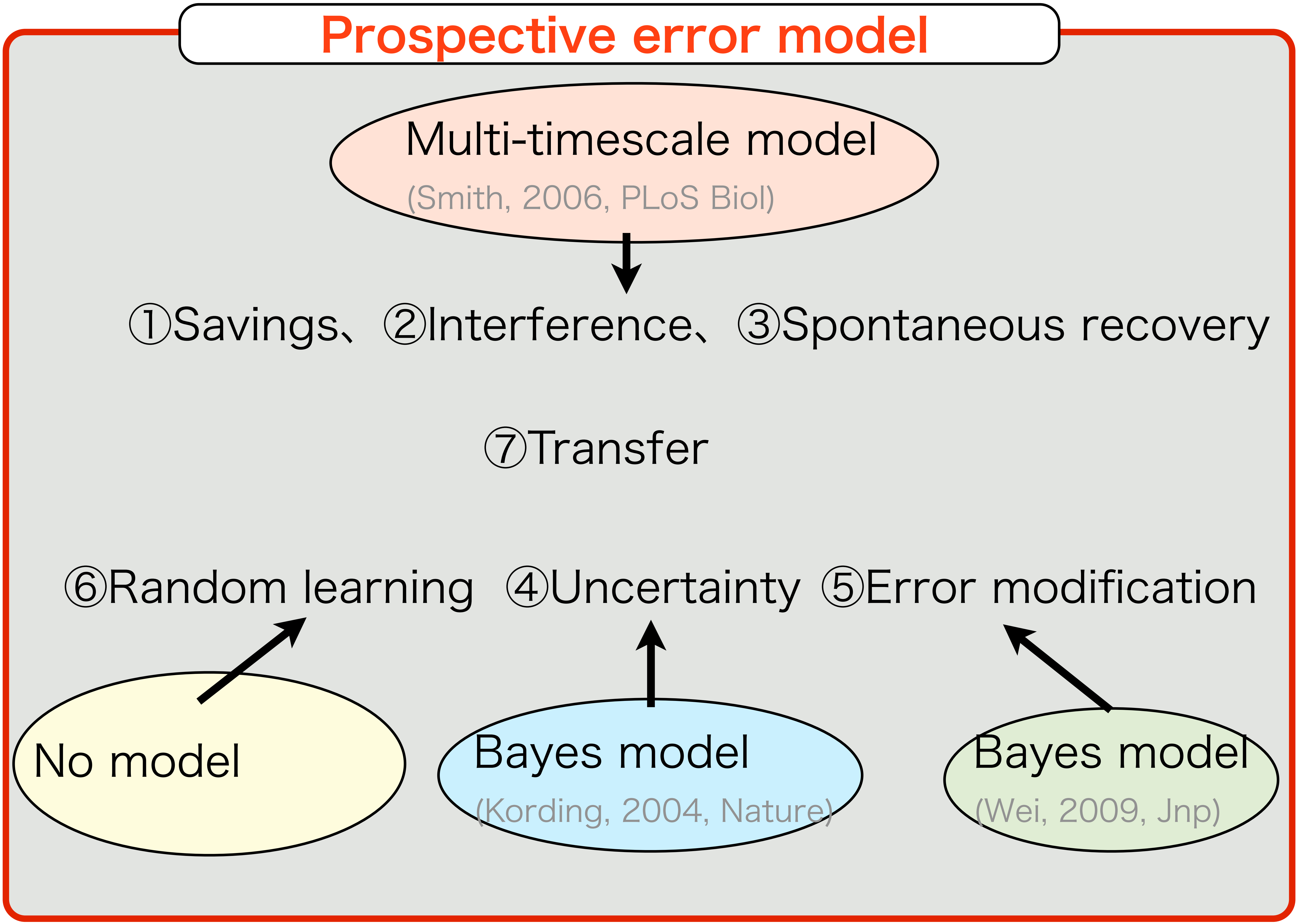
Sing+, 2010, PLoS Compt Biol

3. Spontaneous recovery - recovery of memory trained for a long time -





Smith+, 2006, PLoS Biol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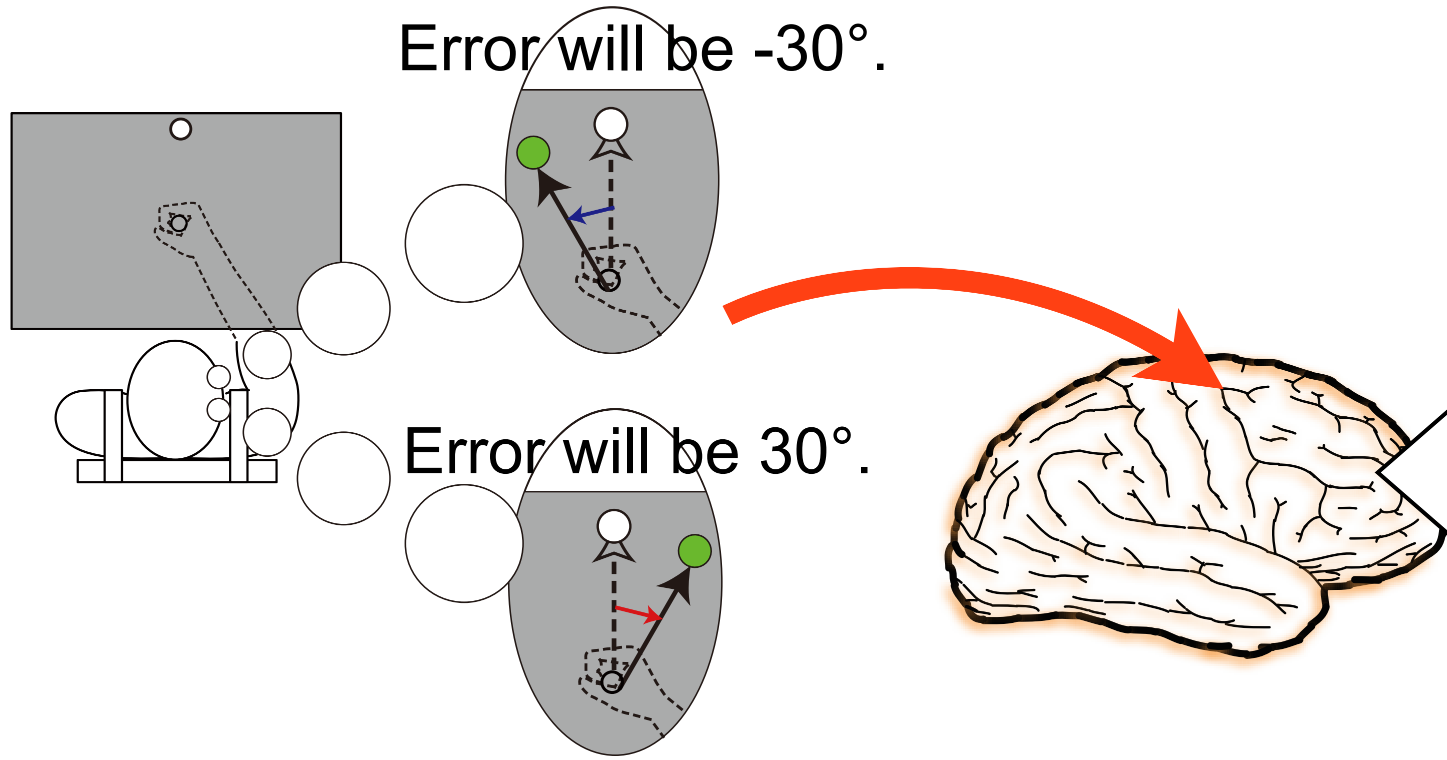

Prospective error model

1. anterograde intereference (Sing, 2010, PLoS CB)
2. spontaneous recovery (Smith, 2006, PLoS Biol)
3. relevance of error (Wei, 2009, Jnp)
4. short-term savings (Krakauer, 2000, Nat Neurosci)
5. long-term savings (Zarahn, 2008, Jnp)
6. Kalman filter (Kording, 2004, Nature)
7. structural learning (Braun, 2009, Curr Biol)

1. Based on math to reproduce random learning, we propose a novel hypothesis: ***the prospective error is encoded in motor planning***.

2. Based on our behavioral experiment, we validated our prediction which any conventional model never predicts ***- strong prediction power -***.

3. Our model can explain several phenomena which were separately explained by different computational models ***- a step towards a unified model of motor learning -***.

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Keiji Ota
(TUAT / NYU)

Is prospective coding effective
when there are other players?

- I will succeed
- I will fail

Ota & Takiyama, in preparation, Ota & Takiyama, 2017, SfN

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