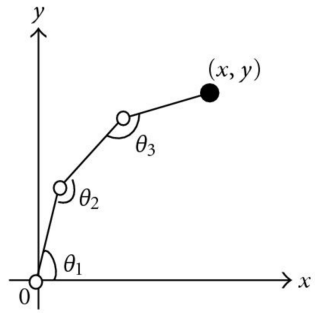
Neuromechanics of Human Motion

Motor Adaptation & Learning

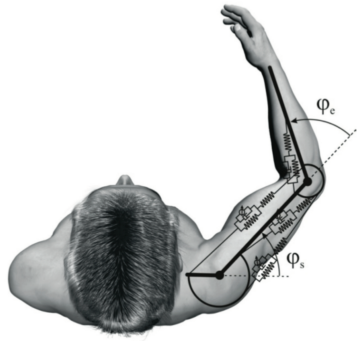
Joshua Cashaback, PhD

Recap — Cost Functions

Redundancy: Degrees-of-Freedom (DOF) > Task Space Dimensions

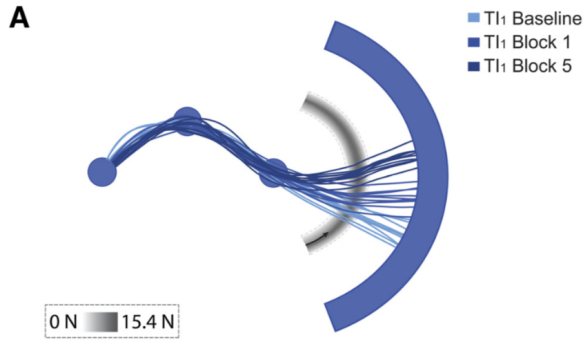


Joint Redundancy



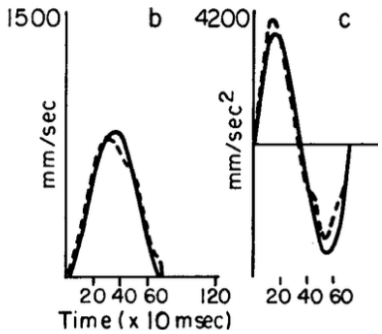
Schematic of "full-blown" musculoskeletal model described in Kistemaker et al. (2010).

Muscle Redundancy



Work-Space Redundancy

Recap — Cost Functions



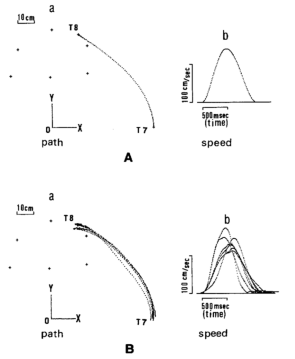
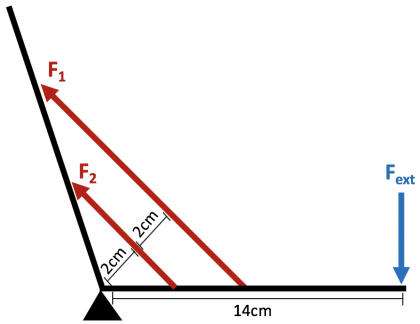
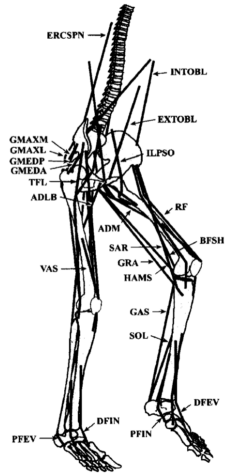


Fig. 4A and B. Large free movements between two targets (T7→T8); the starting posture is stretching an arm in the side direction and the end point is approximately in front of the body. **A** Hand trajectory predicted by the minimum torque-change model. **a** shows the path and **b** shows the corresponding speed profile. **B** Observed hand trajectories for the seven subjects. **a** shows the paths and **b** shows the corresponding speed profiles





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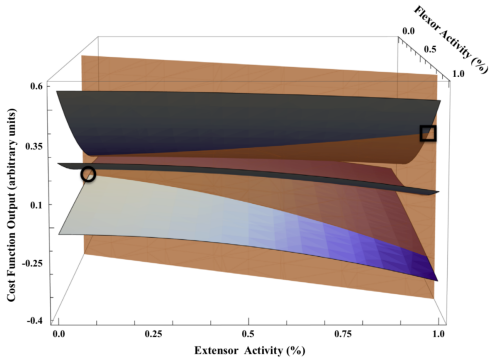
Recap — Cost Functions



Actions are the only way we can influence our world and determine whether we pass along genes

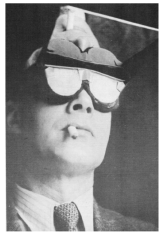
Lecture Objectives — Learning

1. Common Experimental Tasks
2. Adaptation Model (Smith et al, 2006)
   - Learning (and forgetting)
   - Spontaneous recovery
   - Savings
3. Generalization
4. Variability
5. Implicit vs. Explicit
6. Learning vs. Adaptation

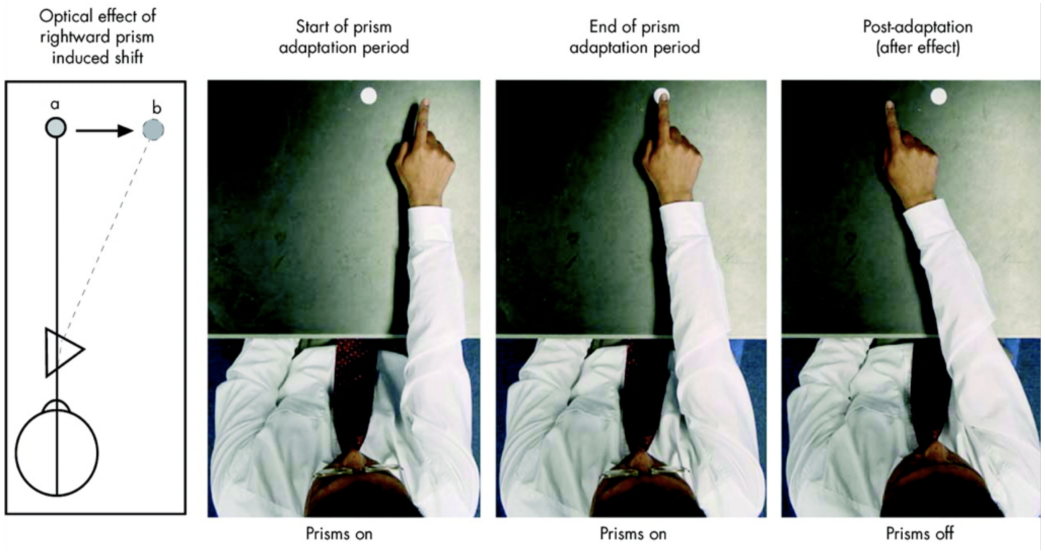
Experimental Tasks

Prism Adaptation

"Visuomotor Rotation"

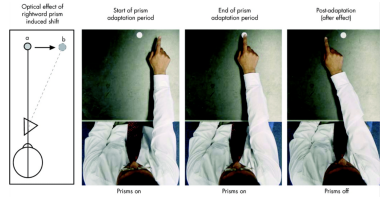


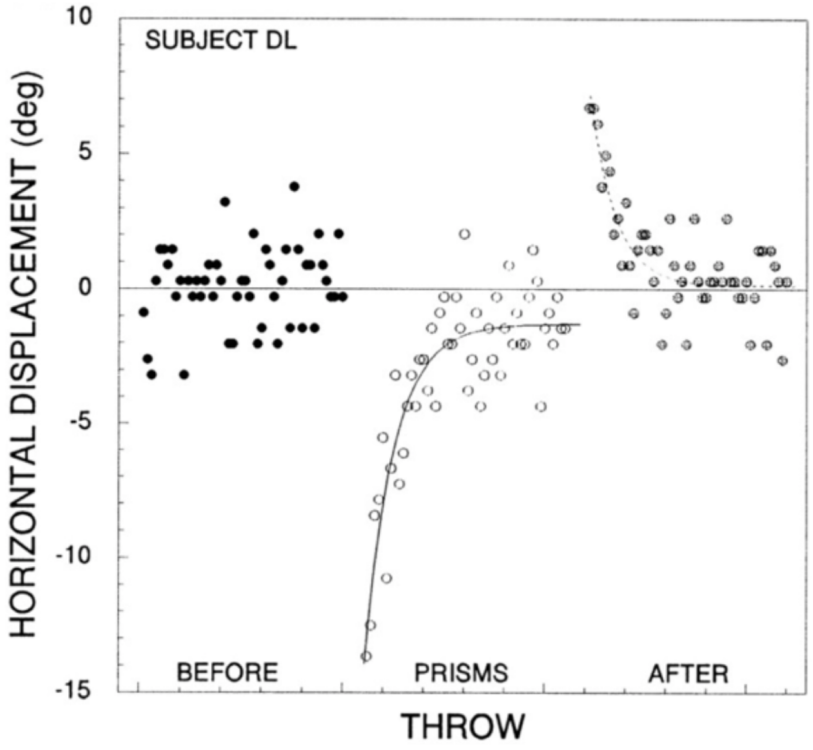
George Stratton (1896) Kohler (1951)



Rotate a cursor relative to movement (no vision of hand or arm)

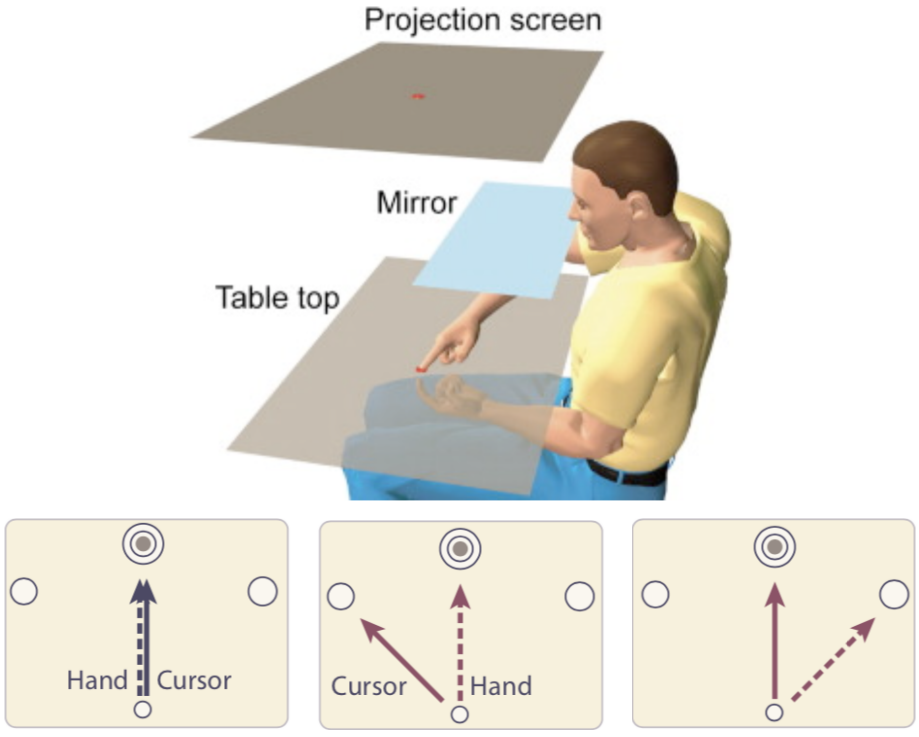
Prism Adaptation





Martin et al. (2002) J Neurophysiol 88: 1685-1694 7

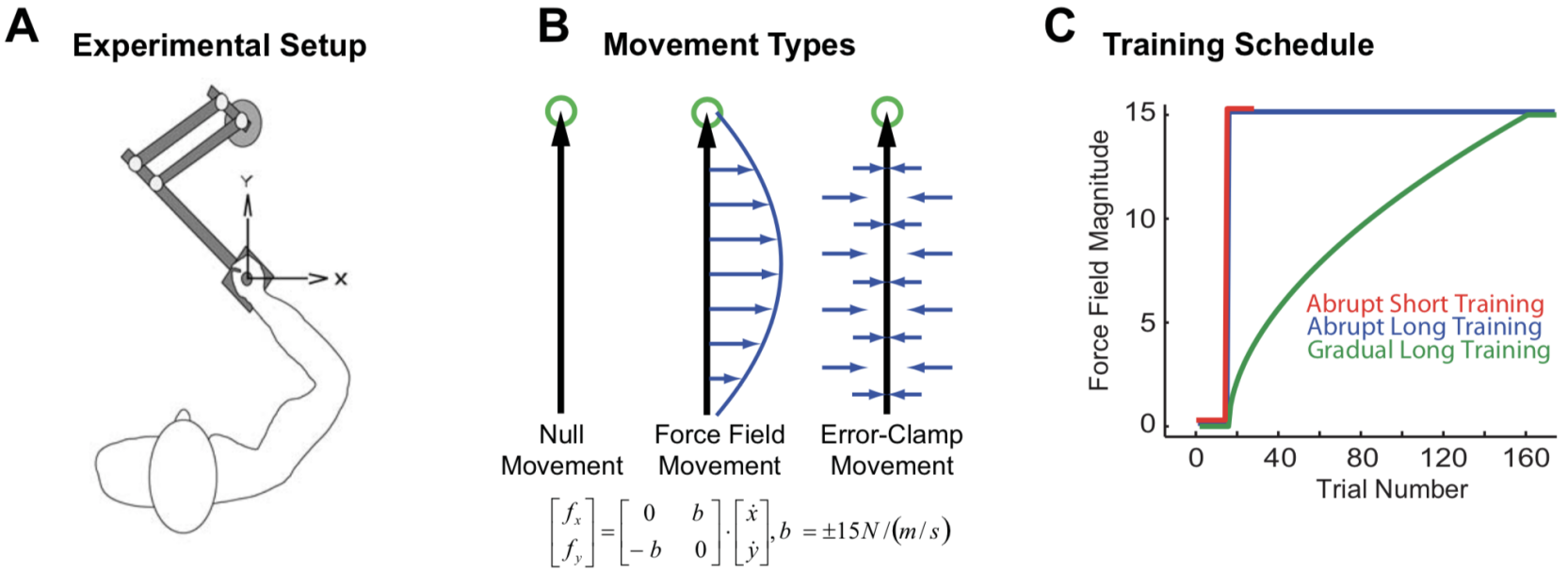
Visuomotor Rotation



van Beers (2015), Shadmehr et al (2010)

1. Virtual prism adaptation
2. Cursor rotates to create some error
3. Fast reaches or hand/arm blocked from vision

Force-Field Adaptation



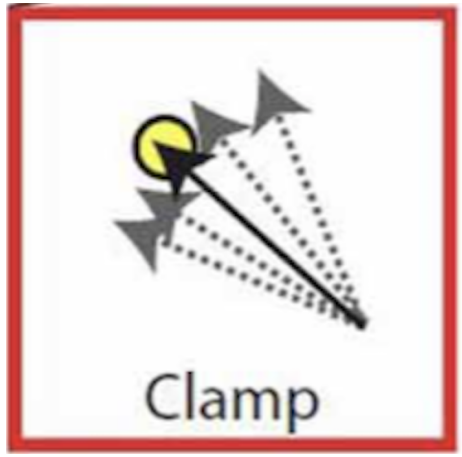
Joiner (2013)

Split-Belt Adaptation

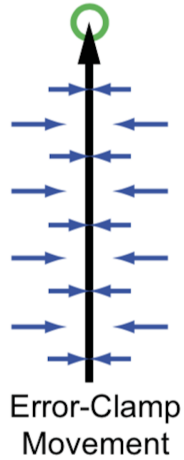
Belts move at independent speeds

$SL_{asym} = SL_{fast} - SL_{slow}$

Error Clamps



visuomotor rotation clamp



force-field clamp

1. Error Clamps artificially impose zero error allowing us to probe the current state
2. Visuomotor clamp: cursor goes to target regardless of movement (record hand position)
3. Force field clamp: movement is straight (record force acting on wall and compare to optimal value)

Error-Based Adaptation Models

One State Model — Adaptation Rate

$$x(i+1) = x(i) + Be(i)$$

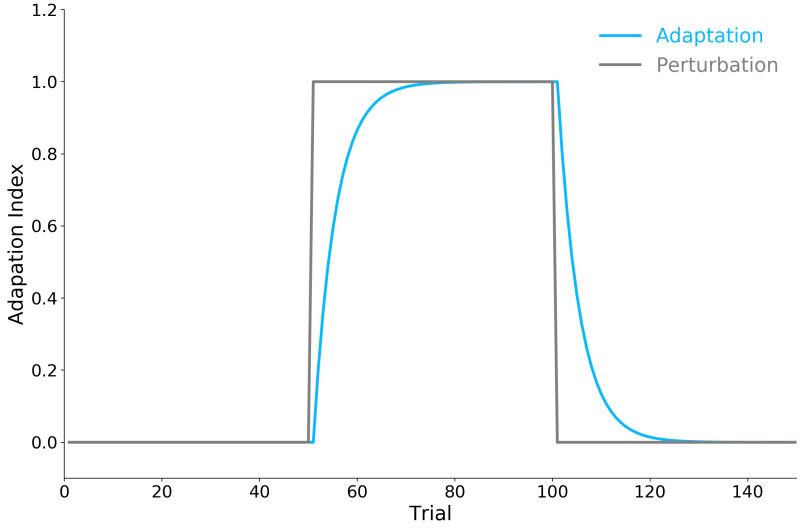
s.t.

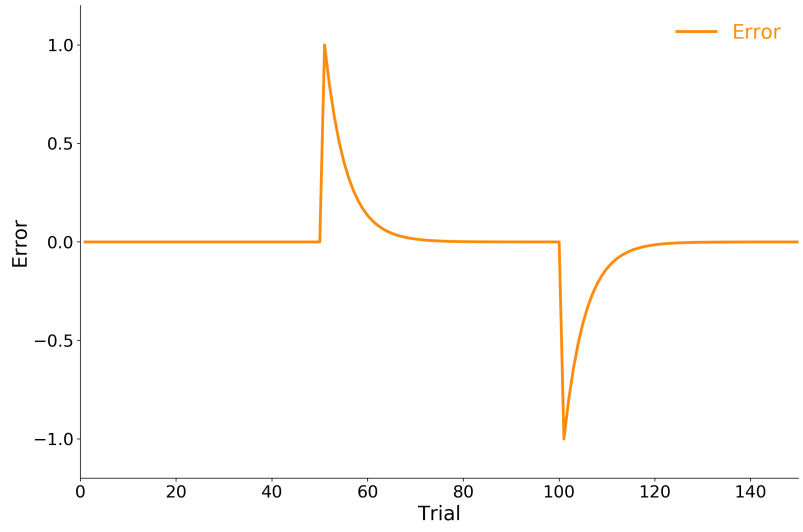
$$e(i) = t(i) - x(i)$$

$$x(1) = 0$$

1. $x(i)$: movement direction or force in movement i
2. $e(i)$: movement error or force error in movement i
3. B: adaptation rate (proportion of error correction)
4. $t(i)$: target (e.g., target position or optimal force)

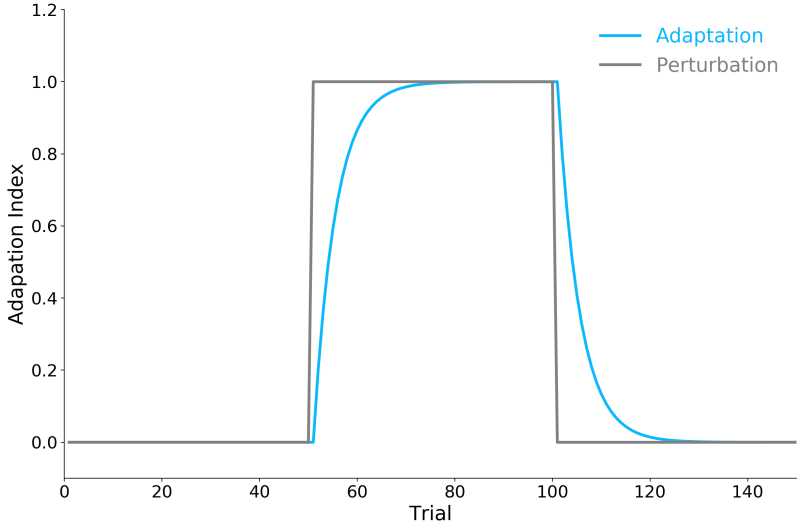
One State Model — Adaptation Rate

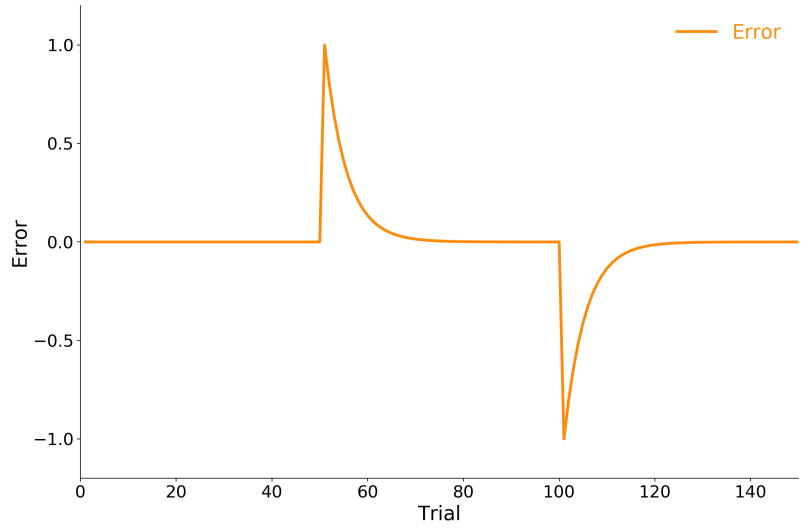




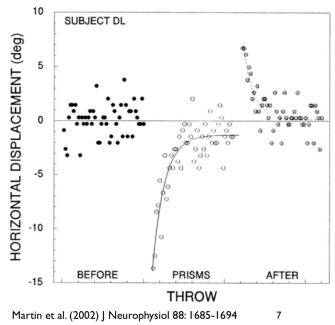
$$B = 0.2$$

One State Model — Adaptation Rate



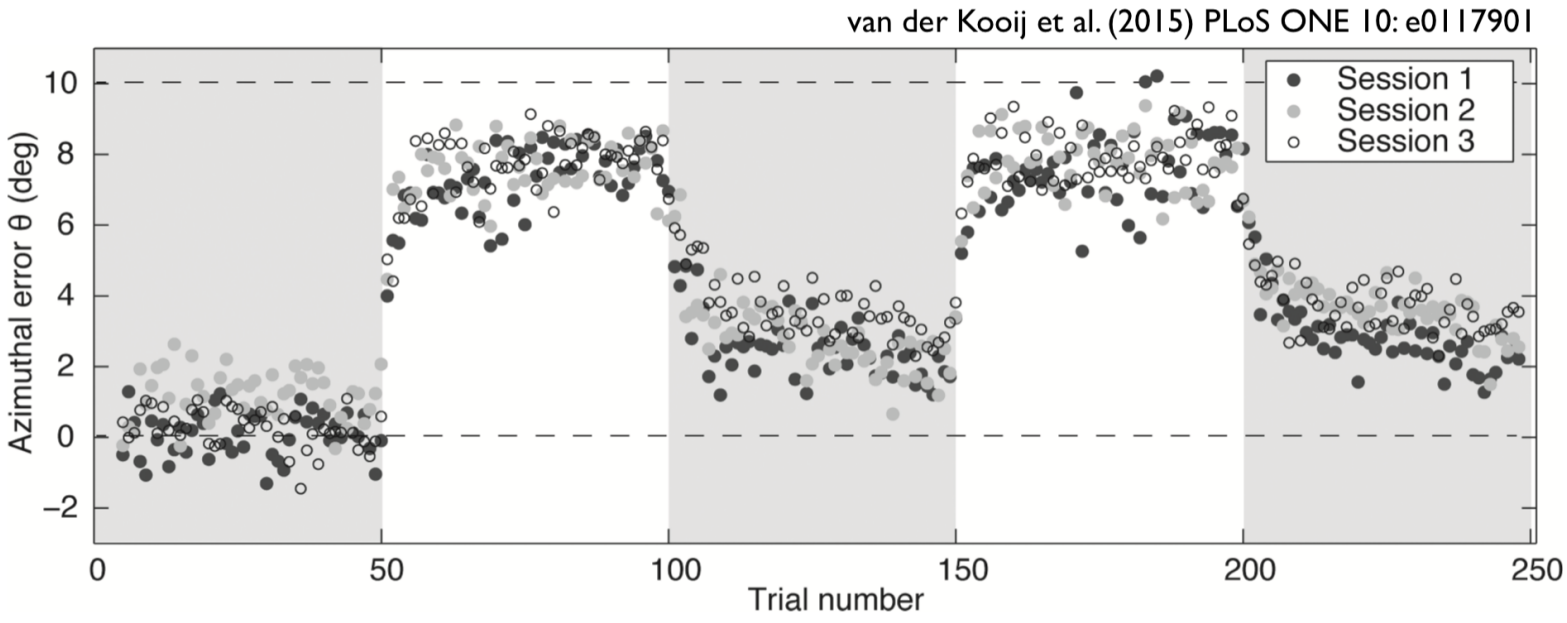


$$B = 0.2$$



Martin et al. (2002) J Neurophysiol 88: 1685-1694 7

Adaptation Not Complete



One State Model — Retention Rate

$$x(i+1) = Ax(i) + Be(i)$$

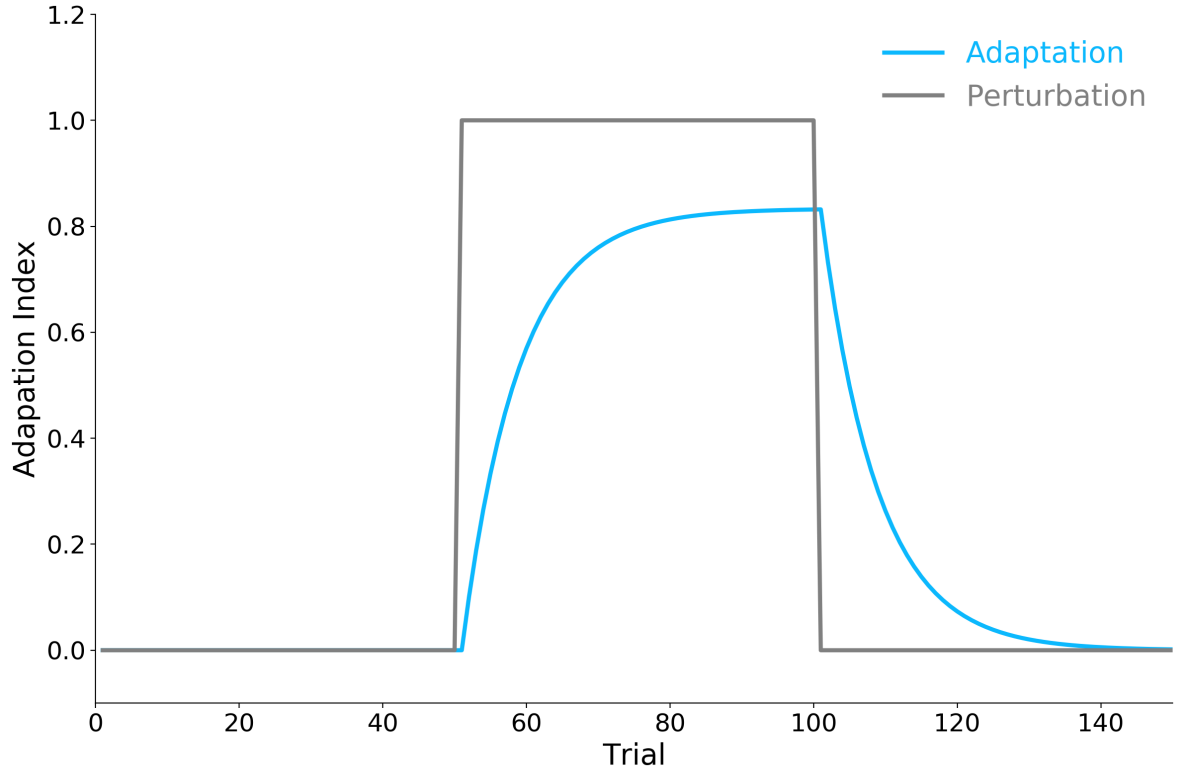
s.t.

$$e(i) = t(i) - x(i)$$

$$x(1) = 0$$

1. A: retention rate (or forgetting what you previously learning)

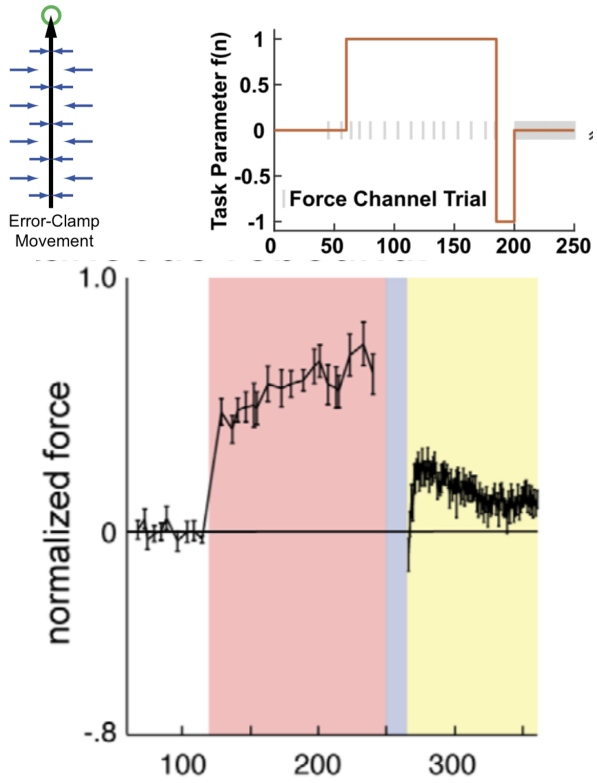
One State Model — Retention Rate



$$A = 0.98, B = 0.1$$

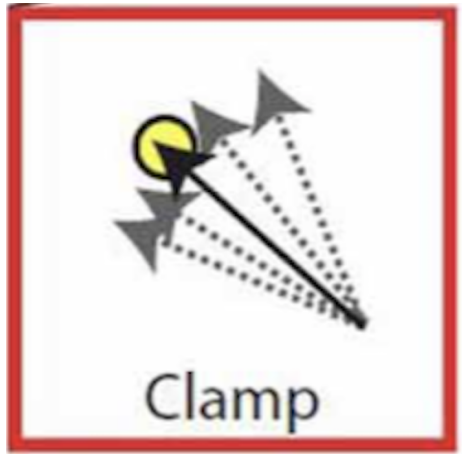
We can capture incomplete learning by including a retention rate

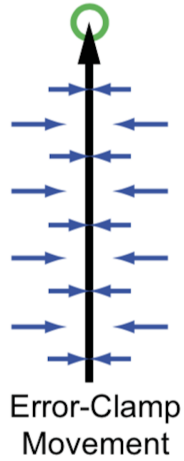
Spontaneous Recovery



1. Clamp trials in a force-field task
2. Baseline (intermittent clamps), CW force-field (intermittent clamps), CCW force-field, clamps
3. Notice in the last phase the spontaneous recovery (rebound) to pre-CCW levels

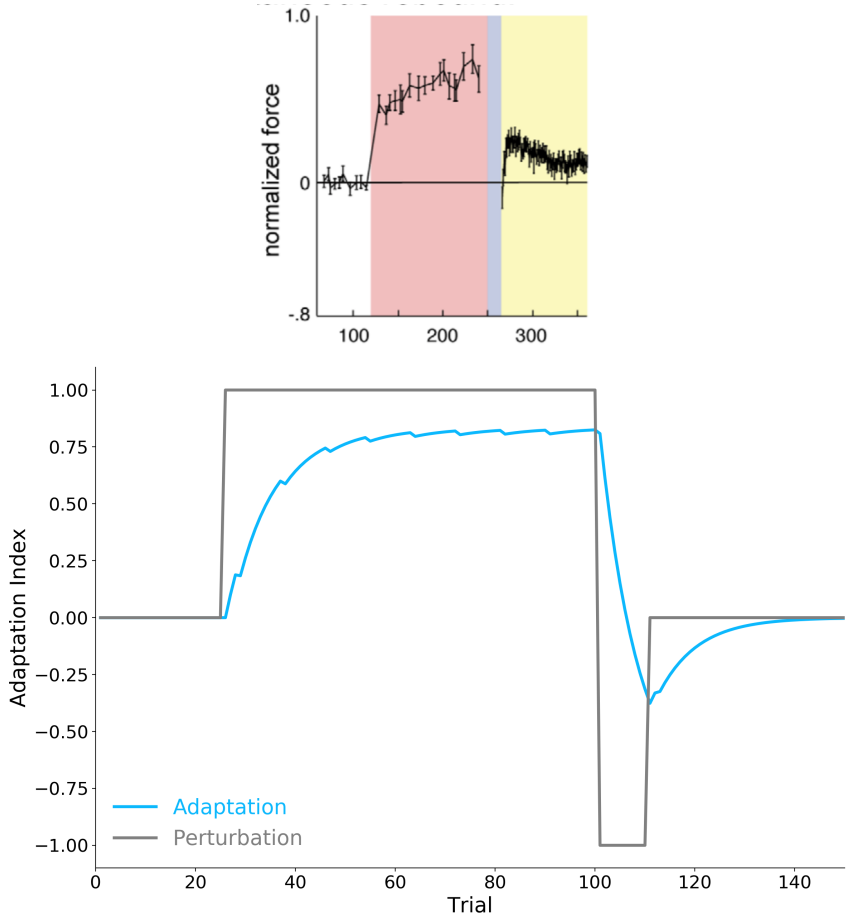
Modelling Clamp Trials





1. $e(i) = 0$
2. Clamp trials make the error to be zero.
3. The idea is to probe the state of the system when there is no error signal [t = x(i)].

One State Model — Spontaneous Recovery



One state model cannot capture spontaneous recovery

Two State Model

$$x_f(i+1) = A_f x_f(i) + B_f e(i)$$

$$x_s(i+1) = A_s x_s(i) + B_s e(i)$$

$$x_{net}(i) = x_f(i) + x_s(i)$$

s.t.

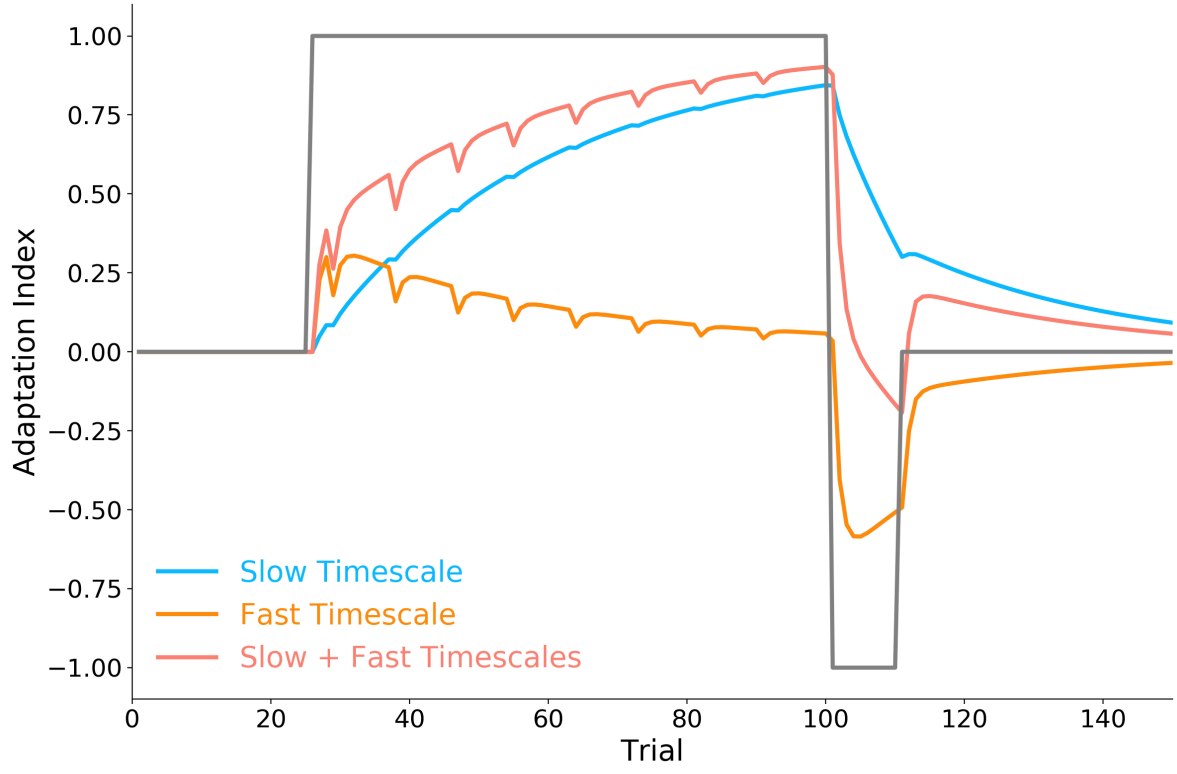
$$e(i) = t(i) - x_{net}(i)$$

$$A_s \geq A_f; B_f \geq A_s$$

$$x_f(1) = 0, x_s(1) = 0$$

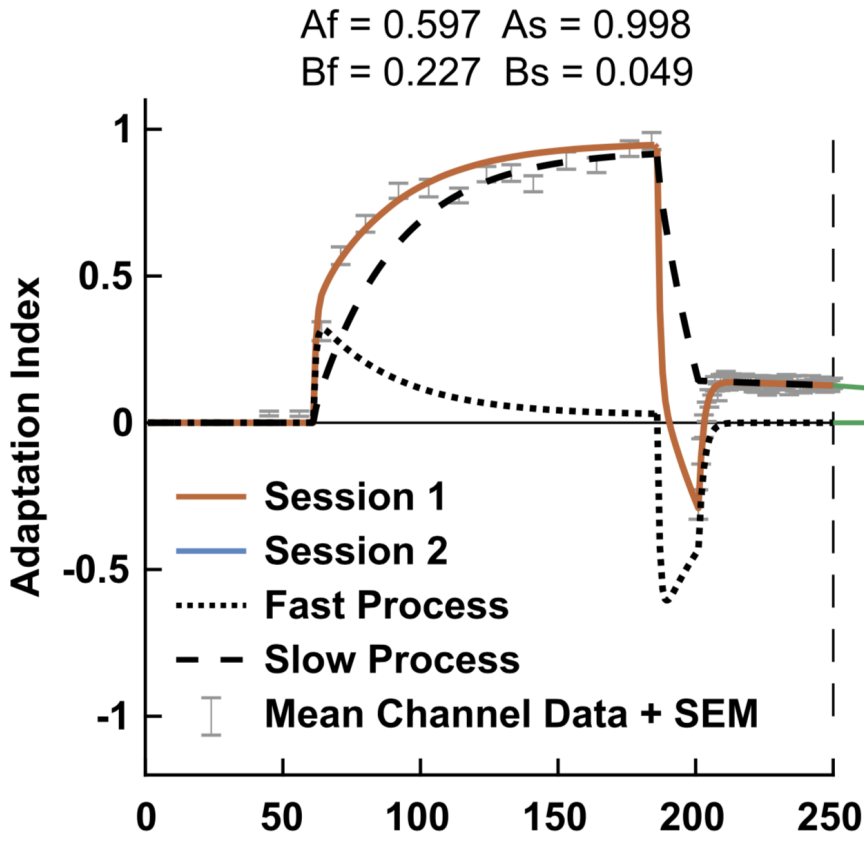
Smith et al (2006). PLoS biology, 4(6).

Two State Model — Spontaneous Recovery



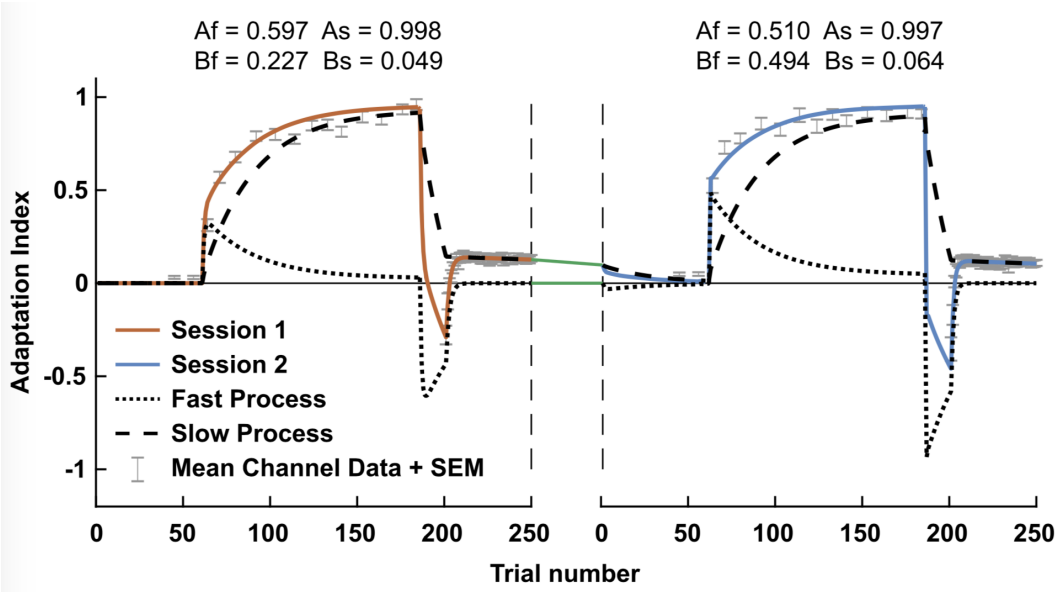
Two-state model can capture spontaneous recovery (‘rebound’)

Two State Model — Spontaneous Recovery



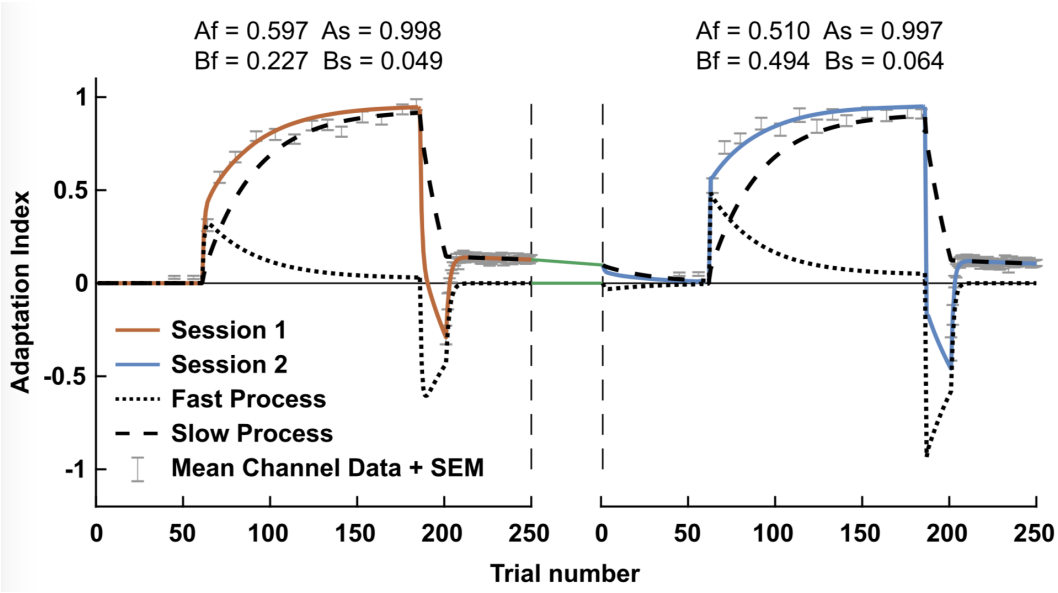
Two state model can capture spontaneous recovery ('rebound')

Two State Model — Savings



1. Savings: significantly faster learning the second time you perform the same task
2. The two-state model cannot capture 'savings' when there is a sufficiently large number of washout trials.

How to Capture Savings?



Capturing Savings

1. Multiple slow states
2. History of errors

Savings — Multiple Slow States

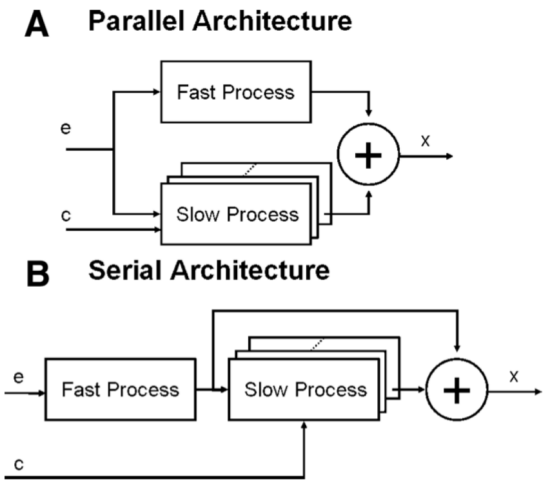


Figure 2. The two possible architectures of the 1-fast *n*-slow model: parallel (***A***) and serial (***B***). e is a motor error, c is a contextual cue, and x is a motor output. Multiple boxes in the slow process represent internal states switched by the contextual cue input.

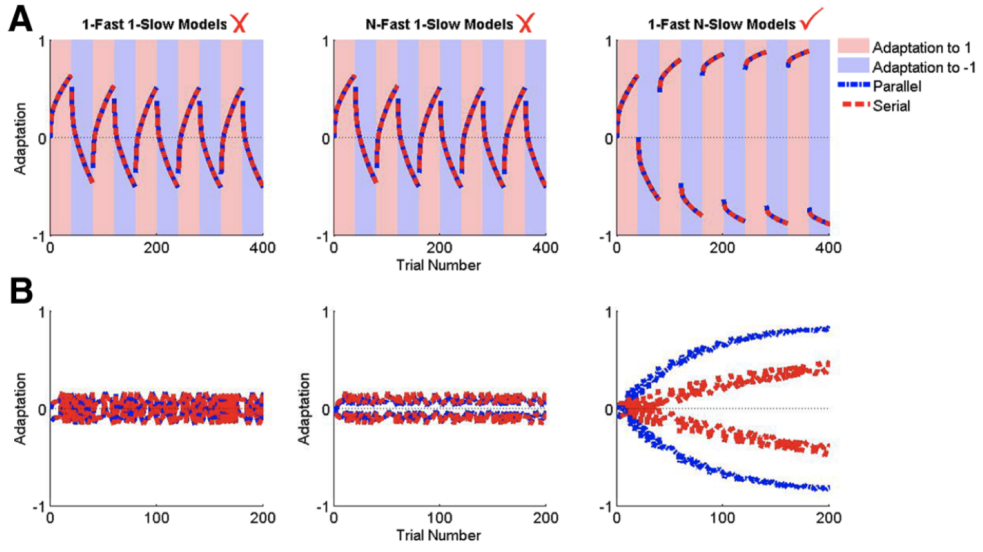
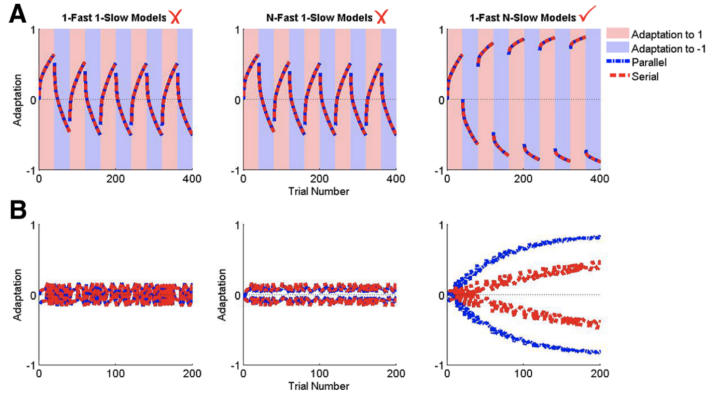


Figure 5. Simulations of two dual-adaptation experiments for the remaining six models considered: serial and parallel 1-fast 1-slow models, serial and parallel *n*-fast 1-slow models, and serial and parallel 1-fast *n*-slow models. The parallel and serial models are superimposed in all panels. ***A***, ***B***, Intermittent alternation of two tasks (***A***) and random alternation between two tasks (***B***). For each model, the same parameters are used in ***A*** and ***B***. Only the serial and parallel 1-fast *n*-slow models can reproduce dual adaptations in both intermitted and random conditions. Note that the parallel and serial 1-fast *n*-slow models behave identically in ***A*** but differently in ***B***: the parallel 1-fast *n*-slow model shows faster adaptation rates than the serial 1-fast *n*-slow model in random dual adaptation.

Lee & Schweighofer (2009) JNeurosci, 29(33), 10396-10404.

Savings — Multiple Slow States



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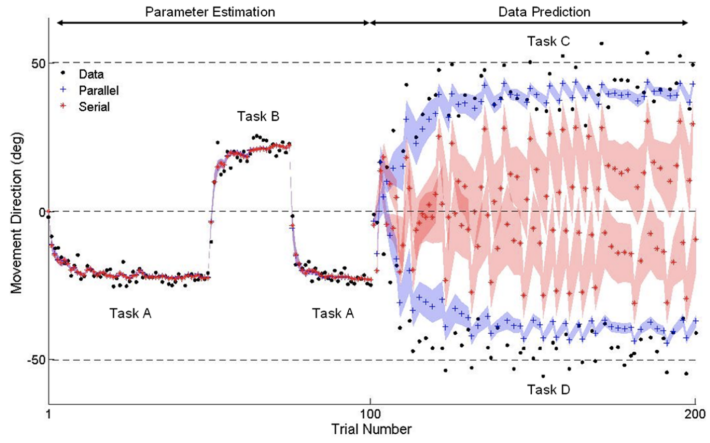


1. Data - black dots; parallel model = blue; serial model = red
2. Data significantly closer to parallel model

Savings — History of Errors

Typical learning model

$x(i+1) = Ax(i) + Be(i)$

Learning rate sensitive to error size

$x(i+1) = Ax(i) + B(e(i))e(i)$

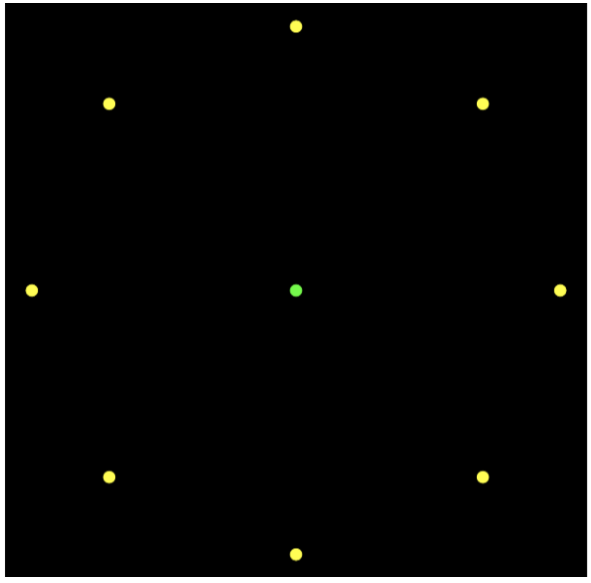
1. Error sensitivity decreases in a random environment
2. The nervous system stores a history of error
3. Will remember large and infrequent errors (cache): can explain savings

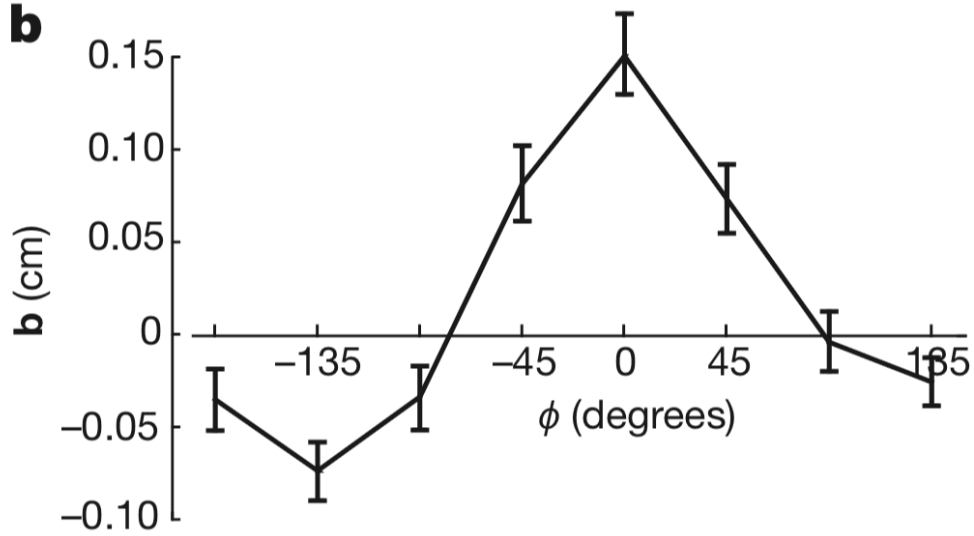
Herzfeld et al (2014). Science, 345(6202), 1349-1353.

Other Considerations of Learning

1. Generalization
2. Variability
3. Implicit vs. Explicit
4. Learning vs. Adaptation

Generalization

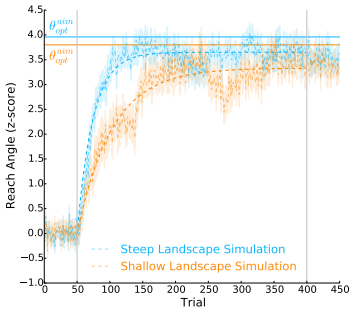




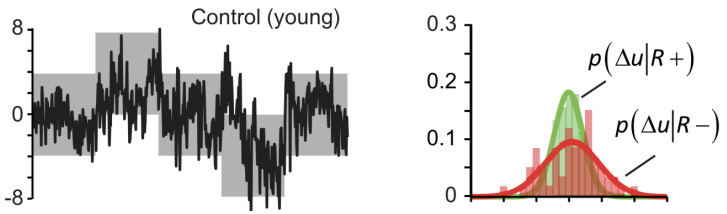
Thoroughman & Shadmehr (2000) Nature 407: 742-747

1. How does force-field learning when reaching to some target transfer when reaching to the current target?
2. Two state model version (Tanaka 2012, Neural Comput 24: 939-966)

Variability



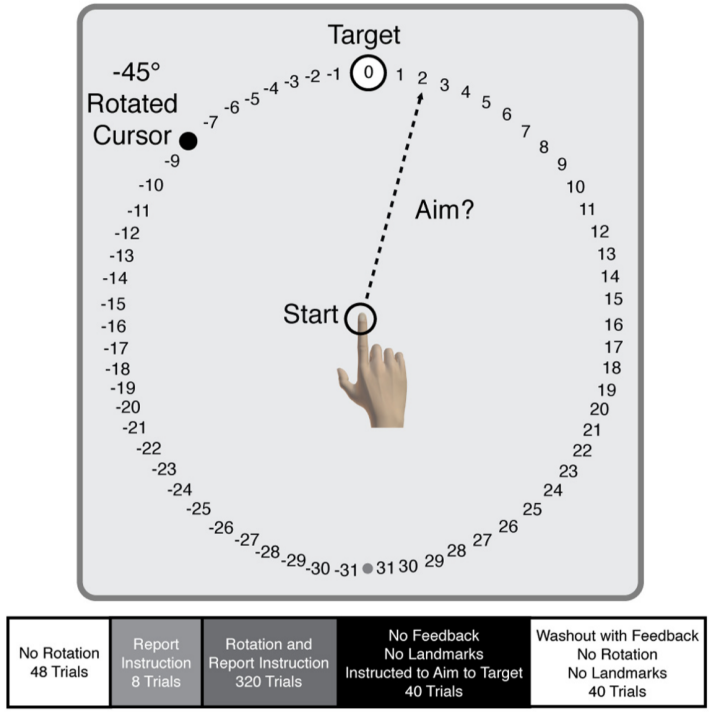
Cashaback et al. (2019)



Pekny et al. (2015)

1. Variability may or may not benefit error-based learning.
   . He et al. (2016). Wu et al (2014).
2. Seems necessary to explore in reinforcement-based learning.
   . Wu et al (2014).

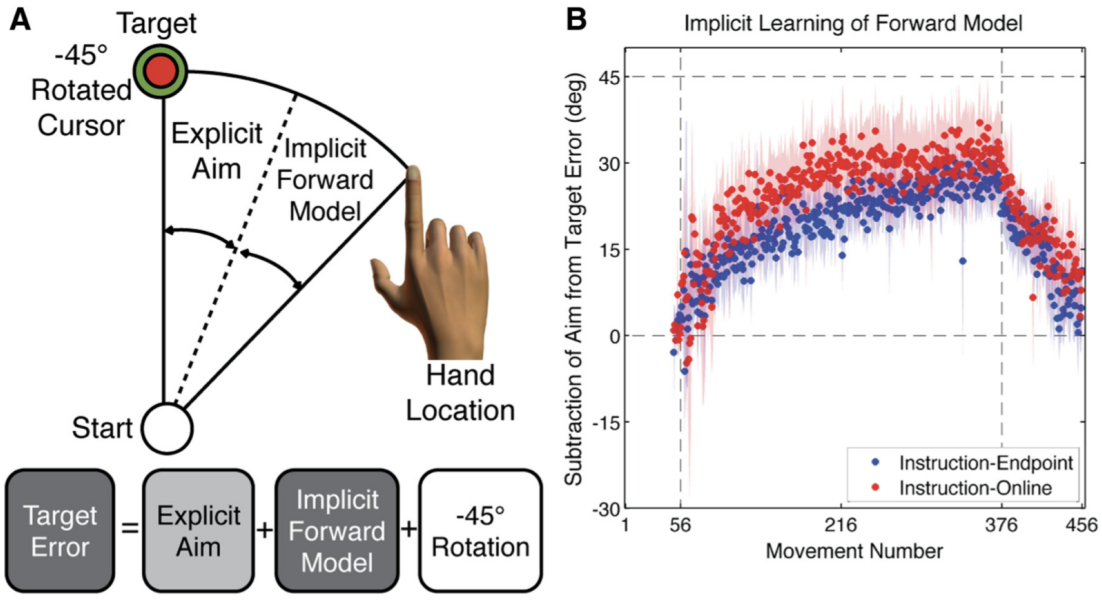
Implicit vs. Explicit



Taylor et al (2014) JNeurosci, 34(8), 3023-3032.

1. Participants reported their aim
2. Reported aim = explicit (cognitive) strategy

Implicit vs. Explicit



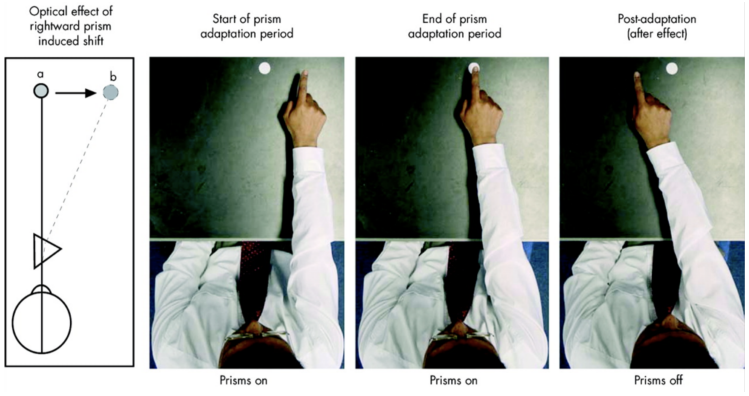
Taylor et al (2014) JNeurosci, 34(8), 3023-3032.

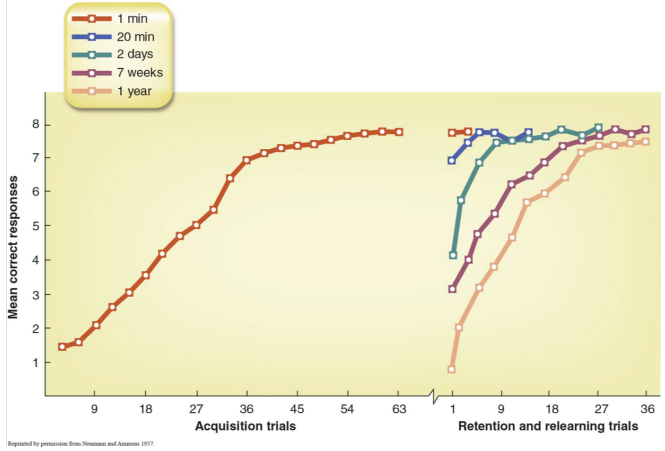
1. Implicit = Target error - explicit - (-45°)
2. Implicit maps onto slow process
3. Explicit strategy maps onto fast process

Learning vs. Adaptation

Adaptation

A set of processes associated with modulating the sensorimotor system for relatively temporary gains in task performance





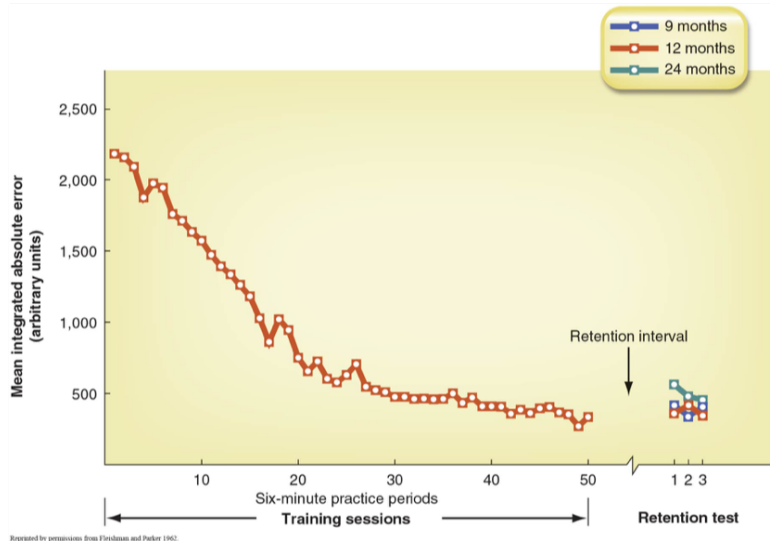
Often associated with discrete, lab-based tasks.

Acquired quickly and more fleeting

Learning vs. Adaptation

Learning

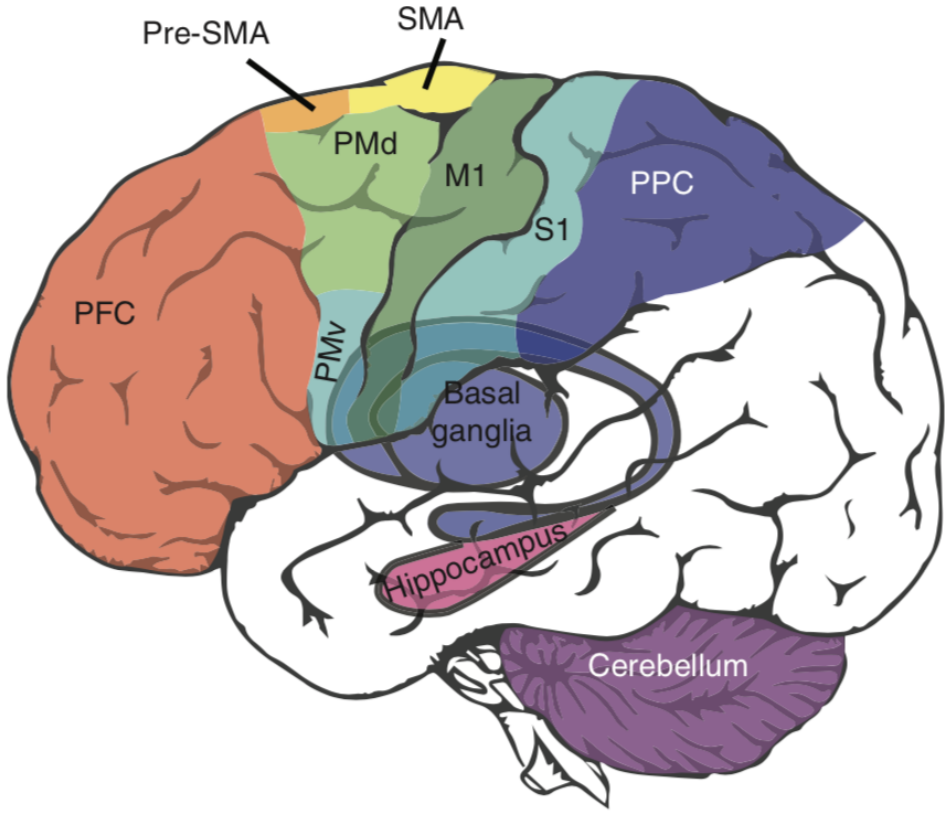
A set of processes associated with practice or experience causing relatively permanent gains to produce skilled performance.



Often associated with continuous, skill-based, real-world tasks.

Can take a very long time to aquire

Neural Basis of Learning



Krakauer et al (2019) Comprehensive Physiology 9 (2), 613-663

Two State Fitting — Sample Python Code

```
from pylab import *
import numpy as np
from scipy.optimize import minimize
# p = perturbation vector, eclamp = clamp trial vector
# data = fake data | Xnet(i) from forward model with known parameters
def find_coeff(IC, data, p, eclamp):
        As, Bs, Af, Bf = IC[0], IC[1], IC[2], IC[3]
        # two_state() below is the two state model function
        E, XS, XF, X = two_state(As, Bs, Af, Bf, p, eclamp)
        if Bf <= Bs or Af >= As or Bf <= 0.0 or Bf >= 1.0 or Bs <= 0.0 or Bs >= 1.0 or A
                mindiff = 1000.0
        else:
                mindiff = np.sum(abs(data-X) ** 1.0) * 1.0
        print(mindiff, As, Bs, Af, Bf)
        axis([0,150,-0.5,1])
        plt.ion()
        plot(data, linewidth = 5.0, color = 'blue')
        plot(X, linewidth = 2.0, color = 'orange')
        show()
        plt.pause(0.0001)
        plt.clf()
        return mindiff
As0, Bs0, Af0, Bf0 = 0.994, 0.025, 0.521, 0.268 # initial guess
IC = [As0, Bs0, Af0, Bf0]
results = minimize(find_coeff, IC, args = (data, p, eclamp), method = 'nelder-mead')
As1, Bs1, Af1, Bf1 = results.x
```

Summary

1. Understand multiple states of adaptation
2. Two state model can capture many features of learning
3. Many factors to consider (e.g., generalization, variability, etc.)
4. Model Fitting

Questions???

Assignment

see handout

Next Class

Presentations!

Acknowledgements

Robert van Beers (CoSMo lecture)

Michael Carter