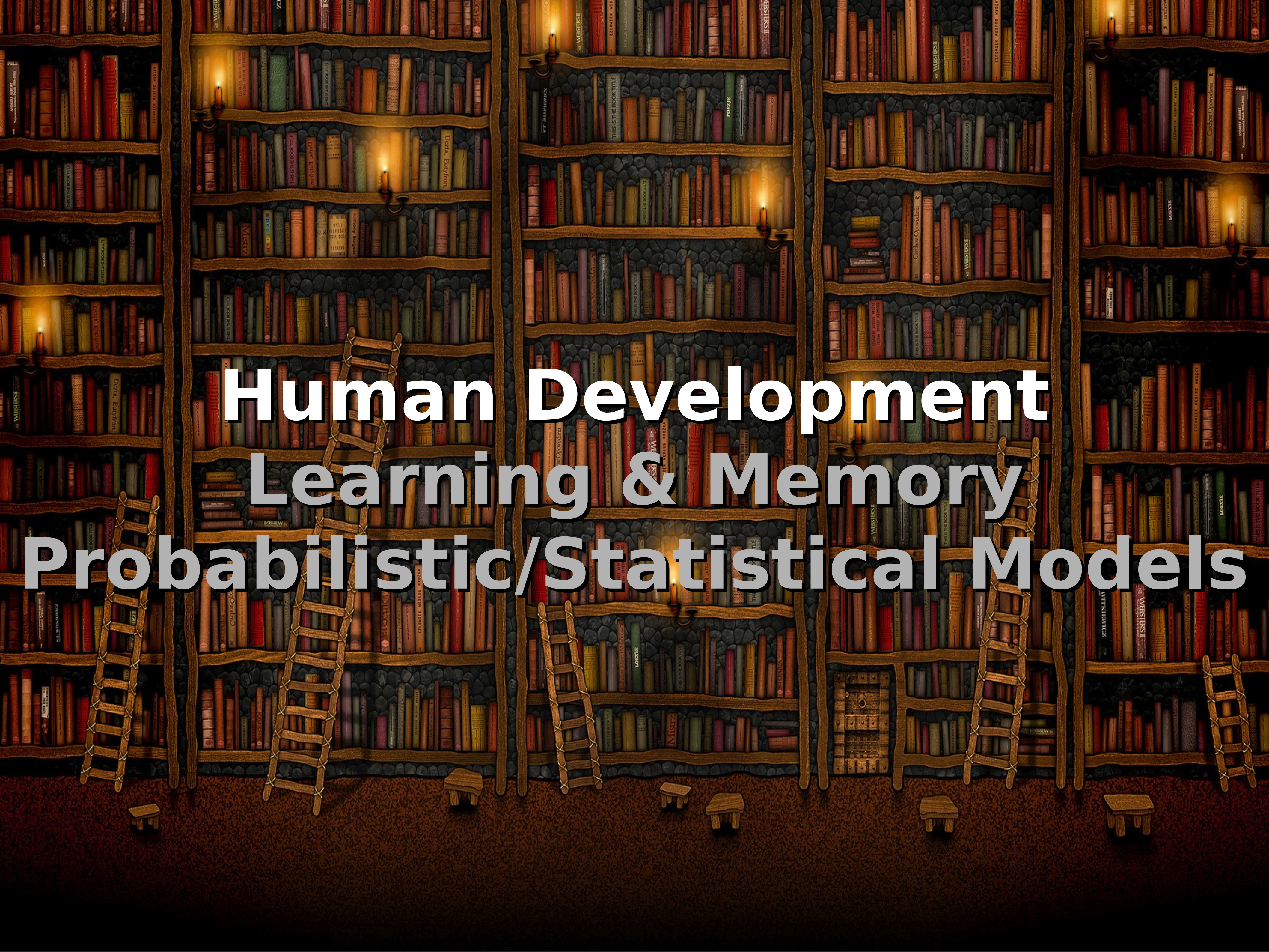
神經與行為模型建構
(Neural & Behavioral Modeling)

課號：Psy5352
識別碼：227U2810

教室： 普 101
時間： 一 234


本週有更多美妙的例子
！



Human Development

Learning & Memory

Probabilistic/Statistical Models

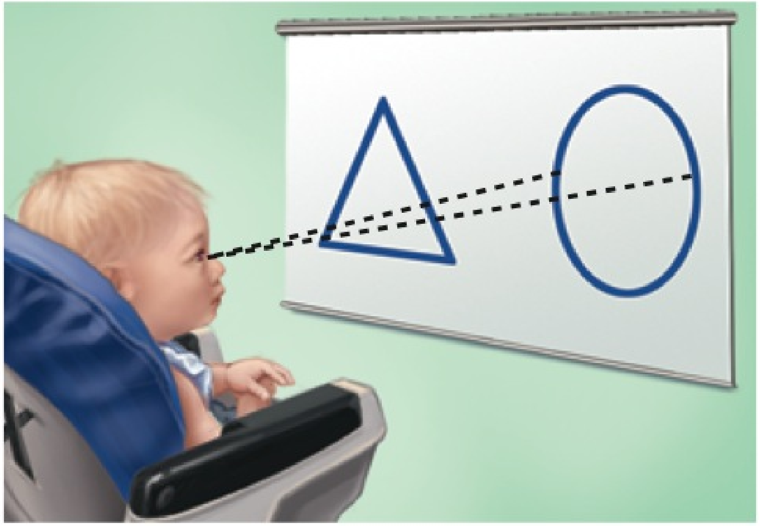
Superbaby Studies

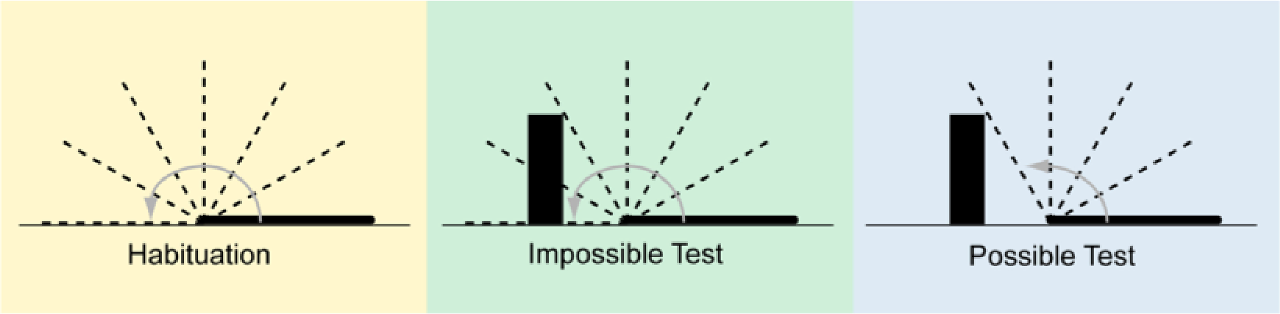
嬰兒有算數與道德能力，也了解物理規則

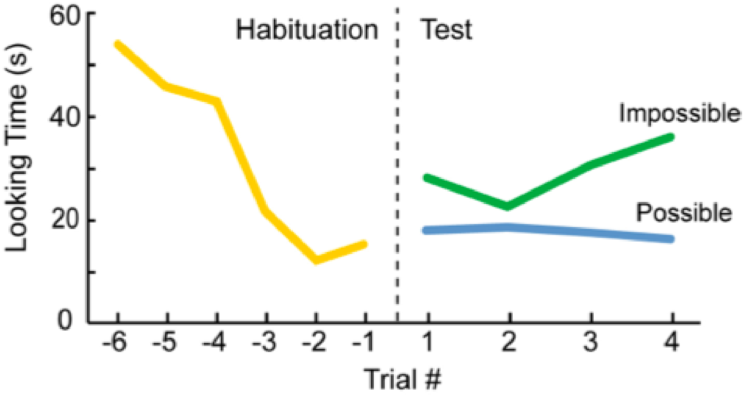
寶寶什麼都會，但寶寶不說

Preferential Looking Paradigm

嬰兒會對新奇或奇怪的事物注視更久







打臉文：動態模型可模擬

Drawbridge 實驗結果本該如此，和嬰兒知識無關

Using Dynamic Field Theory to Rethink Infant Habituation

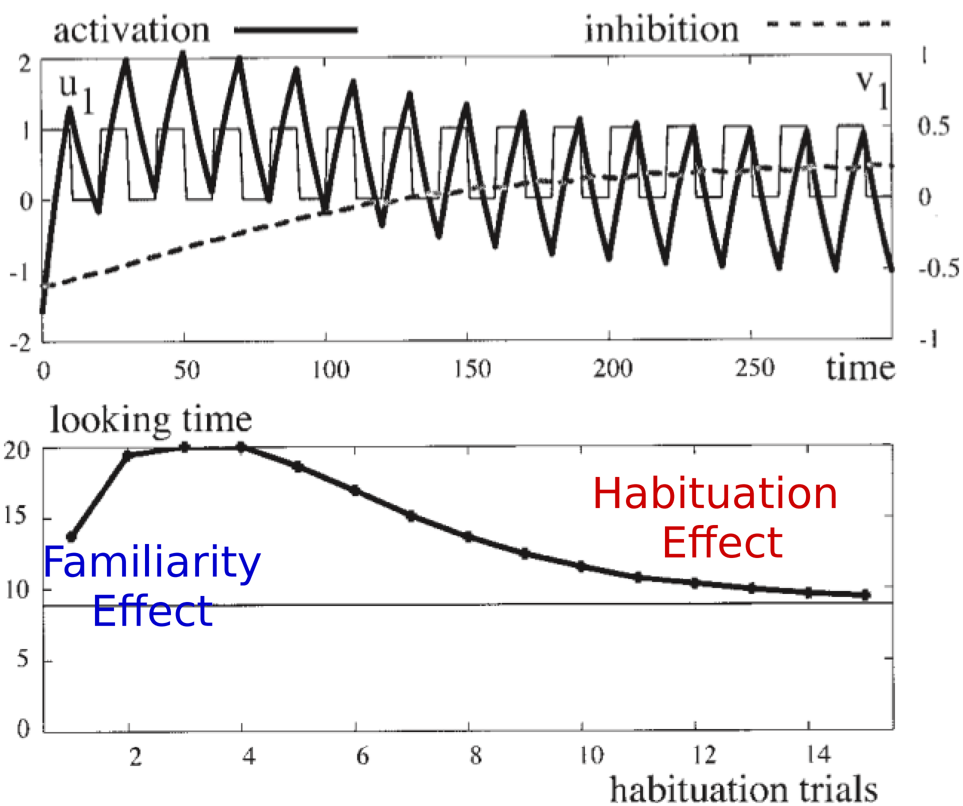
Gregor Schöner
Ruhr-Universität

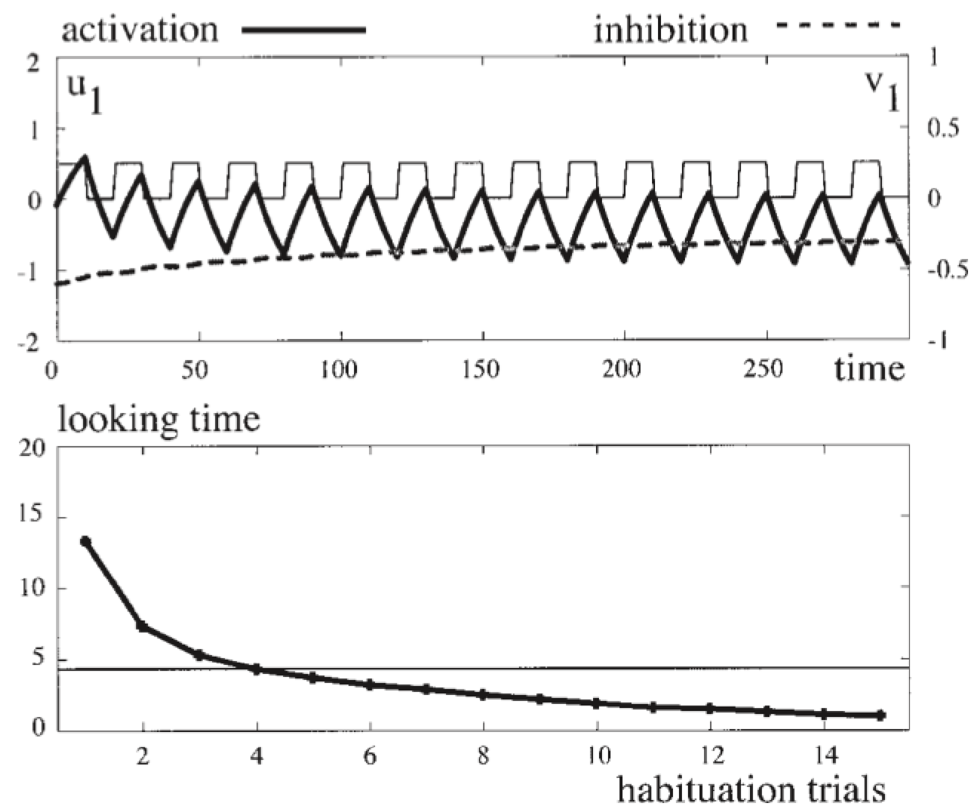
Esther Thelen
Indiana University

Much of what psychologists know about infant perception and cognition is based on habituation, but the process itself is still poorly understood. Here the authors offer a dynamic field model of infant visual habituation, which simulates the known features of habituation, including familiarity and novelty effects, stimulus intensity effects, and age and individual differences. The model is based on a general class of dynamic (time-based) models that integrate environmental input in varying metric dimensions to reach a single decision. Here the authors provide simulated visual input of varying strengths, distances, and durations to 2 coupled and interacting fields. The 1st represents the activation that drives "looking," and the 2nd, the inhibition that leads to "looking away," or habituation. By varying the parameters of the field, the authors simulate the time course of habituation trials and show how these dynamics can lead to different depths of habituation, which then determine how the system dishabituates. The authors use the model to simulate a set of influential experiments by R. Baillargeon (1986, 1987a, 1987b) using the well-known "drawbridge" paradigm. The dynamic field model provides a coherent explanation without invoking infant object knowledge. The authors show that small changes in model parameters can lead to qualitatively different outcomes. Because in typical infant cognition experiments, critical parameters are unknown, effects attributed to conceptual knowledge may be explained by the dynamics of habituation.

模型動態的模擬 (1/2)

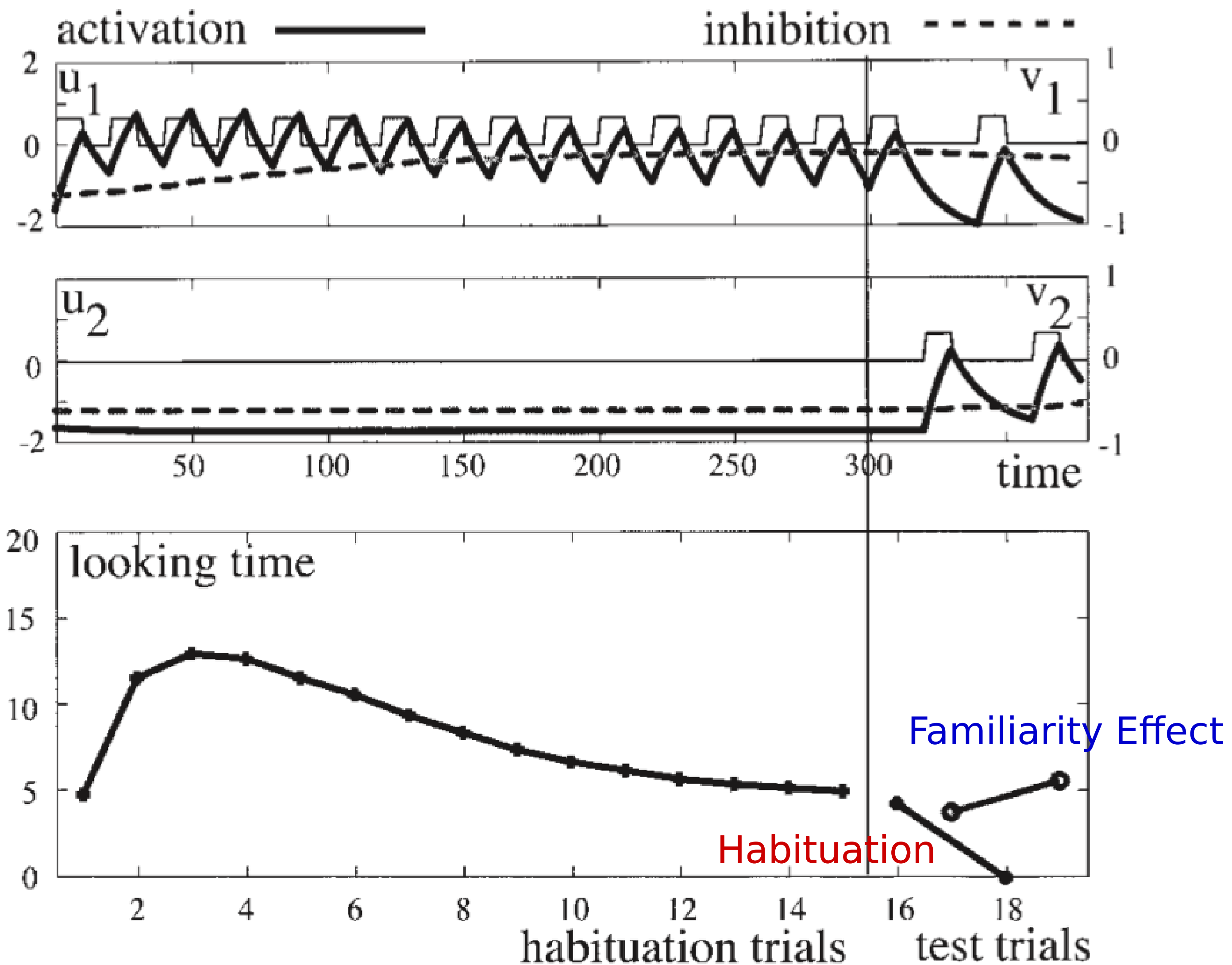
會根據模型參數的不同而變化





模型動態的模擬 (2/2)

新舊事物的測試結果：習慣效應 vs. 熟悉效應



動態模型方程式

簡單透過 v_1/v_2 累積 habituation 去抑制 u_1/u_2

$$\sigma(u) = \frac{1}{1 + \exp[-\beta u]}$$

$$\tau_u \dot{u}_1 = -u_1 + h_u + s_1(t) - c_u \sigma(v_1) + q_u \xi_1(t),$$

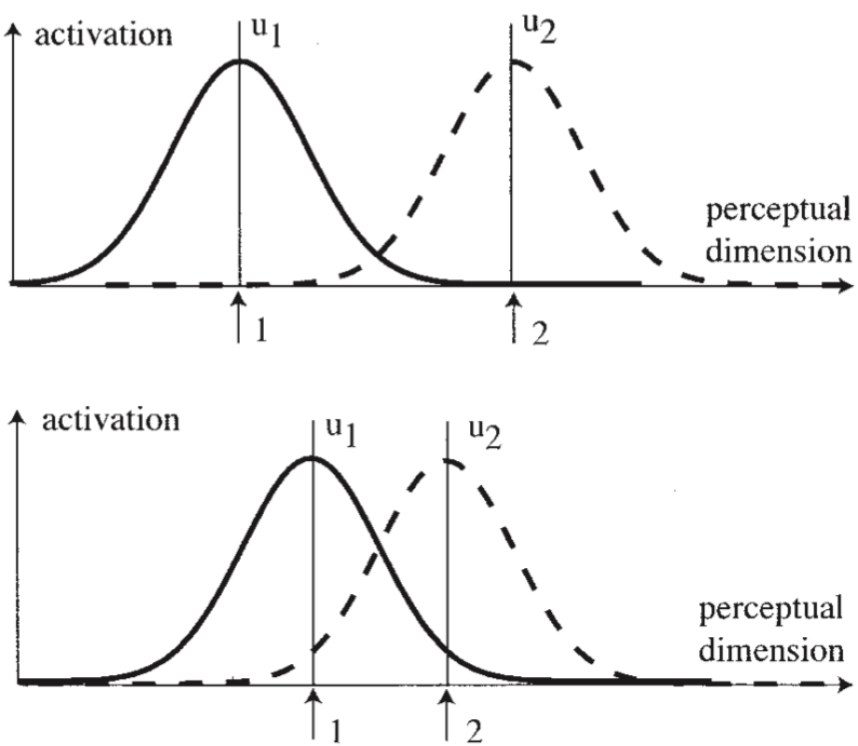
$$\tau_v \dot{v}_1 = -v_1 + h_v + c_v \sigma(u_1) + q_v \xi_2(t),$$

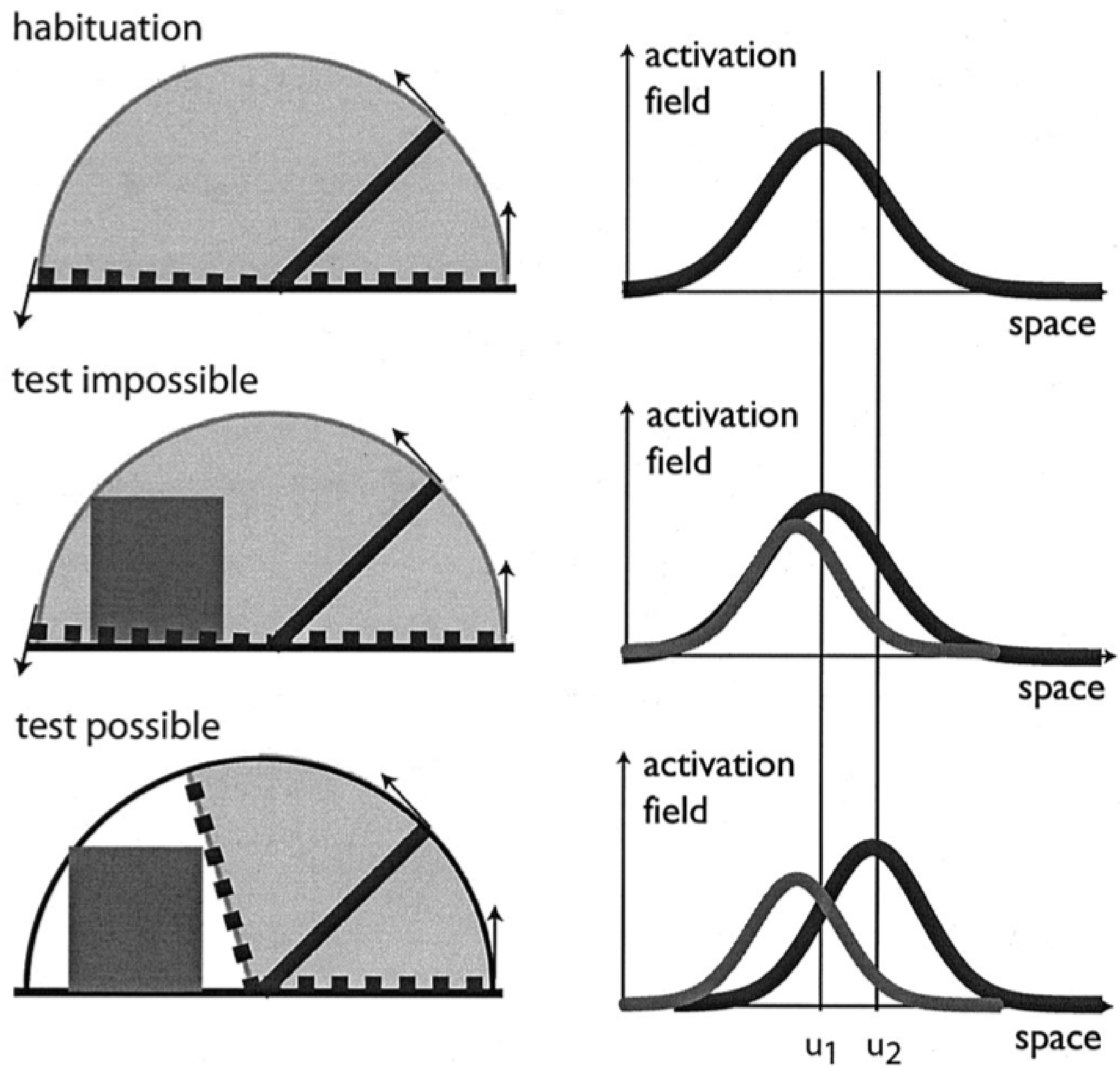
$$\tau_u \dot{u}_2 = -u_2 + h_u + s_2(t) - c_u \sigma(v_2) + q_u \xi_3(t),$$

$$\tau_v \dot{v}_2 = -v_2 + h_v + c_v \sigma(u_2) + q_v \xi_4(t),$$

吊橋實驗的刺激

處理左邊位置的神經元在 test impossible 中反應更大

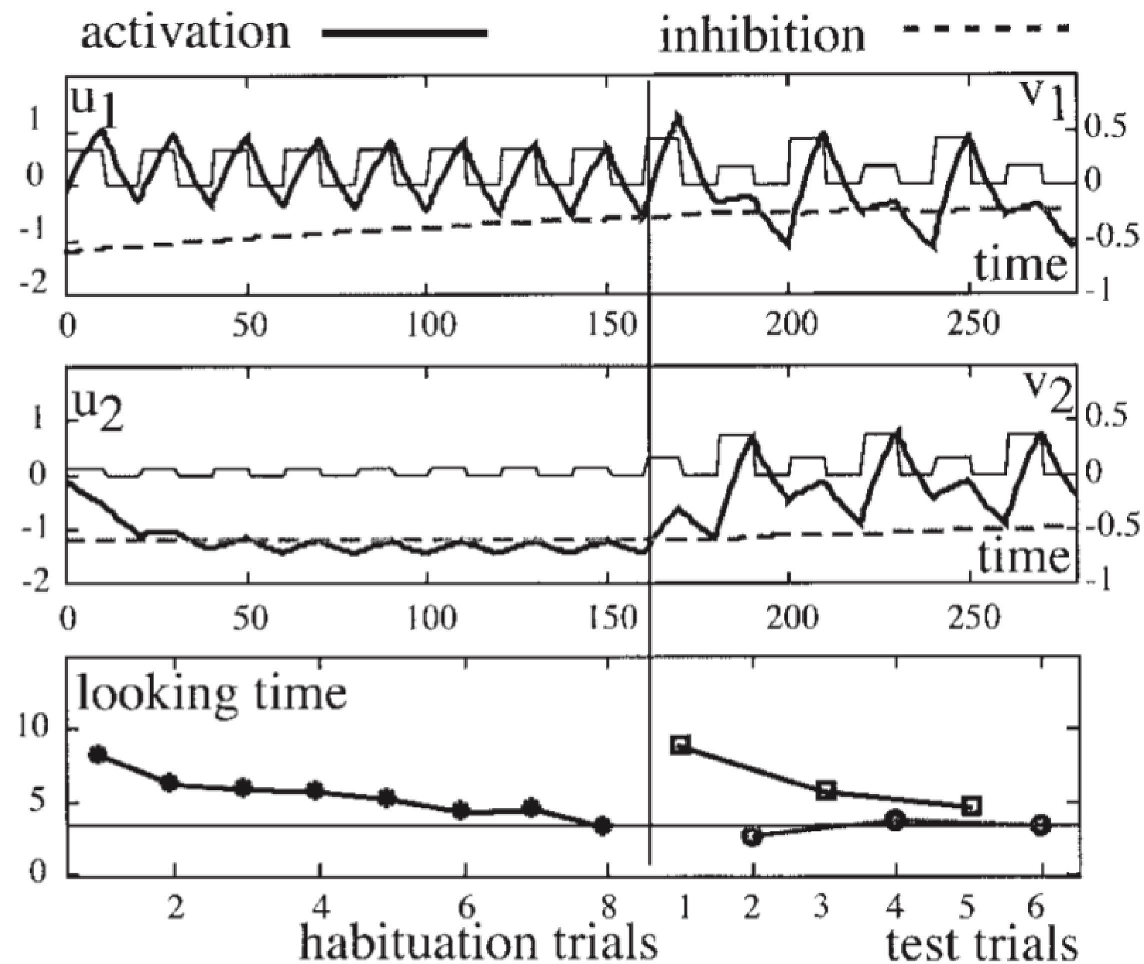




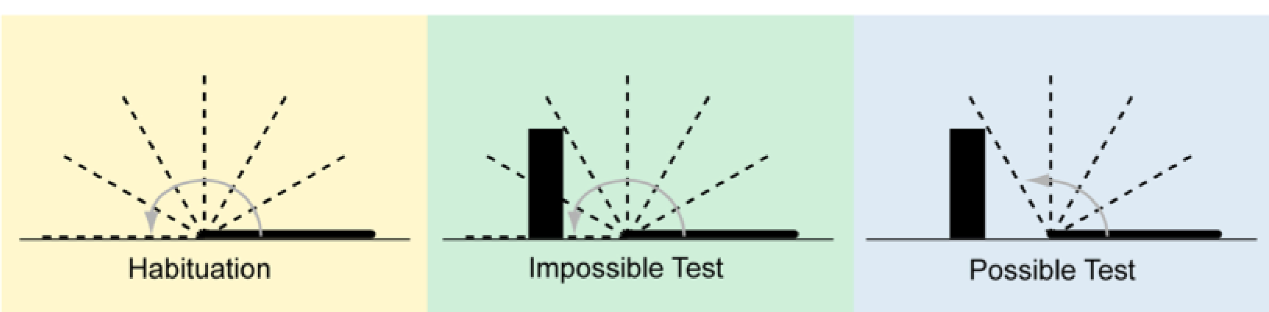
吊橋實驗的模擬：Motion Boost

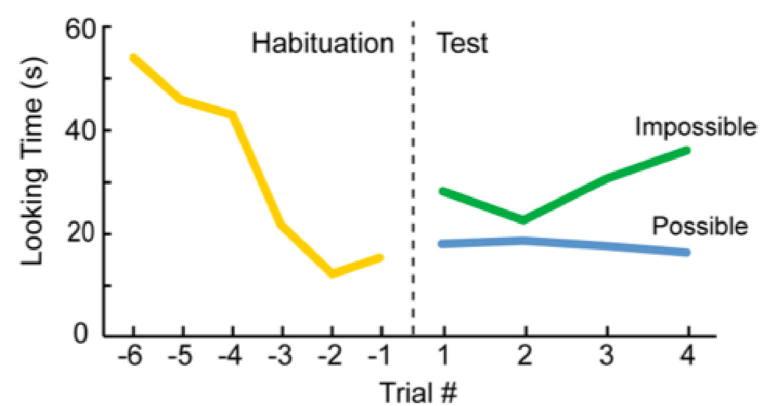
Impossible event:

Possible event:



模擬結果有幾分神似，
嚇死寶寶了！



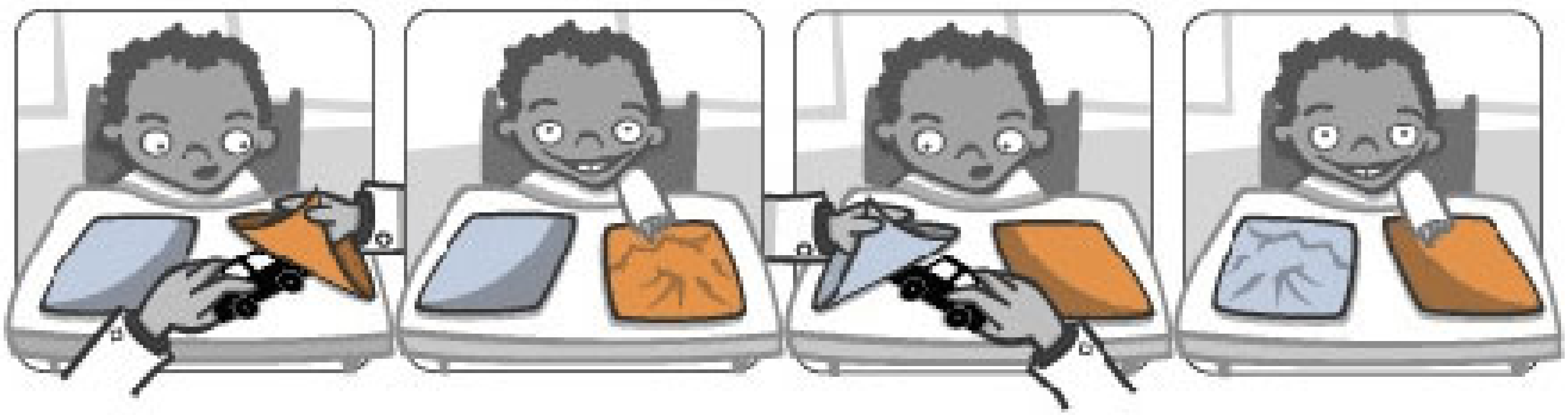


範例 2：A-not-B error

Why?

A trial:

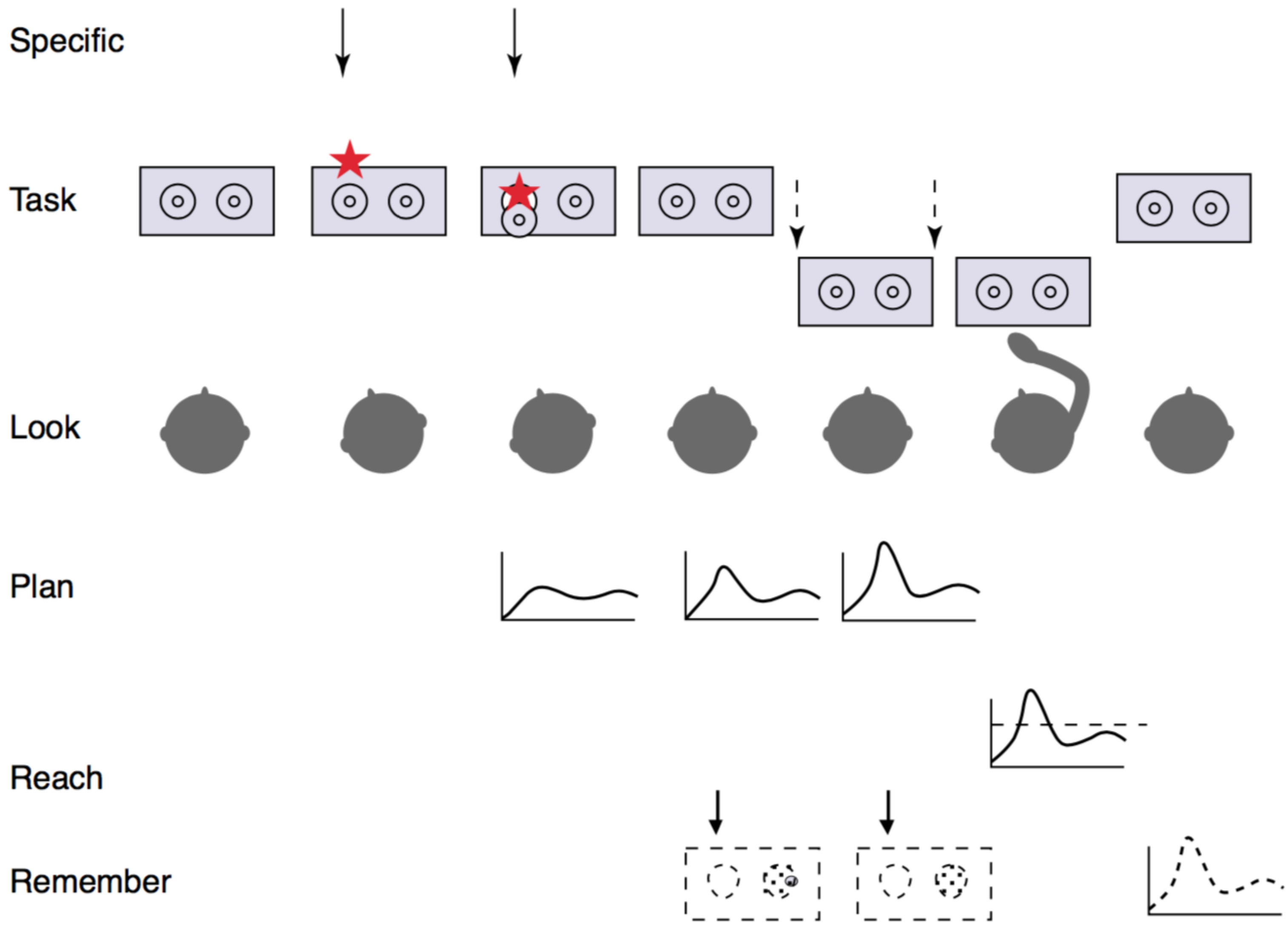
B trial:



皮亞傑：1 歲下的小孩沒有 " 物體恆存 " 觀念

打臉文：動態模型可模擬 (1/3)

A-not-B 實驗結果本該如此，和嬰兒知識無關



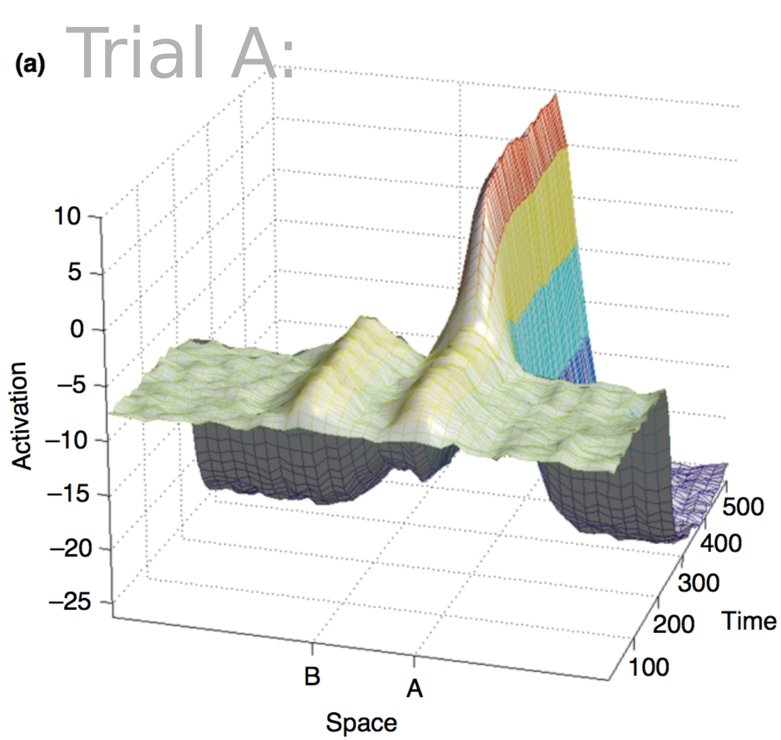
打臉文：動態模型可模擬 (2/3)

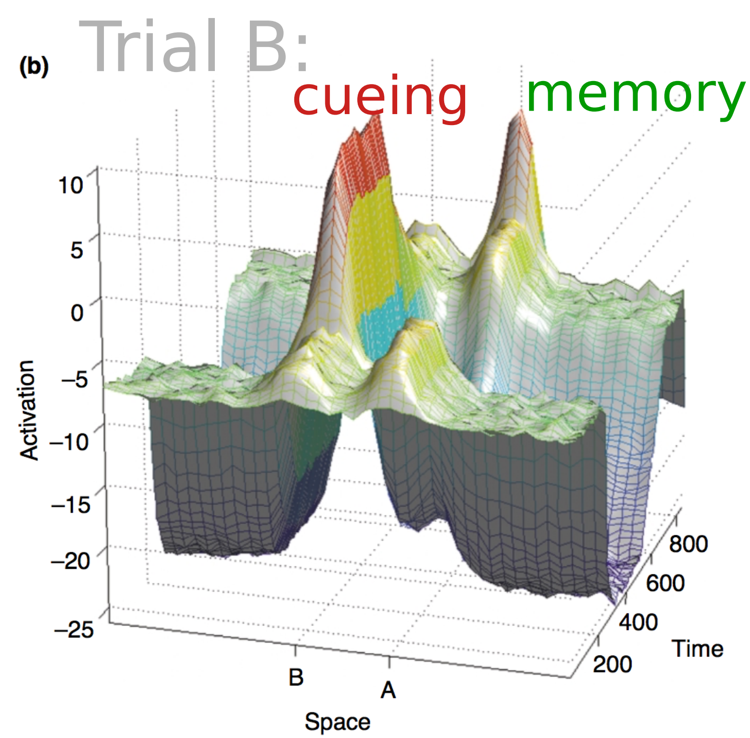
$$S(x,t) = S_{task}(x,t) + S_{specific}(x,t) + S_{memory}(x,t)$$

物品吸引度　　位置線索強度　　動作慣性

$$\tau\dot{u}(x,t) = -u(x,t) + S(x,t) + \int w(x-x')f(u(x'))dx'$$

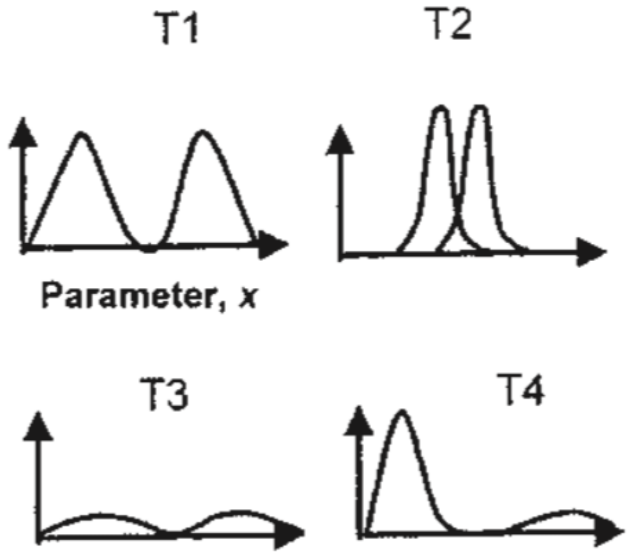
同一時間不同位置的交互作用



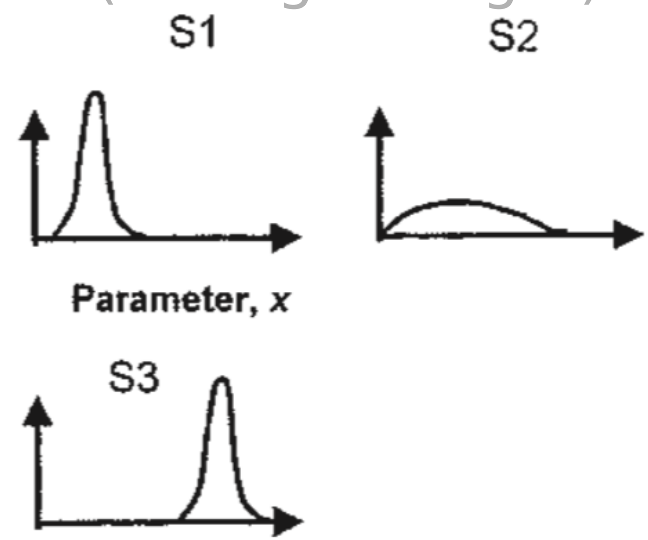


打臉文：動態模型可模擬 (3/3)

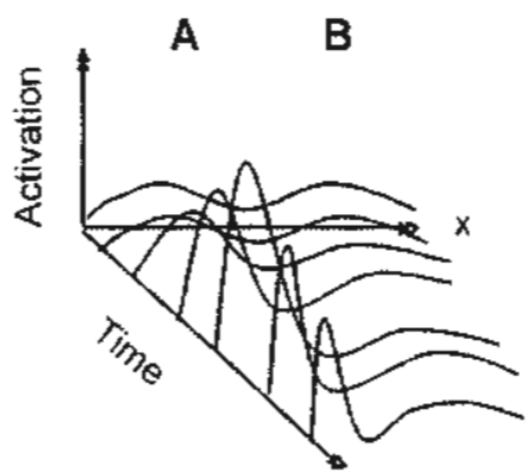
Task input (item saliency)



Specific input
(cueing strength)



T3+S1:



若 B trial 站起來看 (T1→T2),
因記憶影響消失可減少此錯誤 .


Human Development
Learning & Memory
Probabilistic/Statistical Models

可透過語言來快速學習別人的經驗

Where is the nearest café?

"At that traffic light, turn right."

S → **R**

範例 1: Instructed Learning

有點好棒棒

Computational Models for the Combination of Advice and Individual Learning

Guido Biele,[a] Jörg Rieskamp,[a,b] Richard Gonzalez[c]

[a]*Max Planck Institute for Human Development*
[b]*Department of Psychology, University of Basel*
[c]*Department of Psychology, University of Michigan, Ann Arbor*

Received 6 August 2007; received in revised form 2 June 2008; accepted 5 June 2008

Abstract

Decision making often takes place in social environments where other actors influence individuals' decisions. The present article examines how advice affects individual learning. Five social learning models combining advice and individual learning-four based on reinforcement learning and one on Bayesian learning-and one individual learning model are tested against each other. In two experiments, some participants received good or bad advice prior to a repeated multioption choice task. Receivers of advice adhered to the advice, so that good advice improved performance. The social learning models described the observed learning processes better than the individual learning model. Of the models tested, the best social learning model assumes that outcomes from recommended options are more positively evaluated than outcomes from nonrecommended options. This model correctly predicted that receivers first adhere to advice, then explore other options, and finally return to the recommended option. The model also predicted accurately that good advice has a stronger impact on learning than bad advice. One-time advice can have a long-lasting influence on learning by changing the subjective evaluation of outcomes of recommended options.

實驗作業：Iowa gambling task

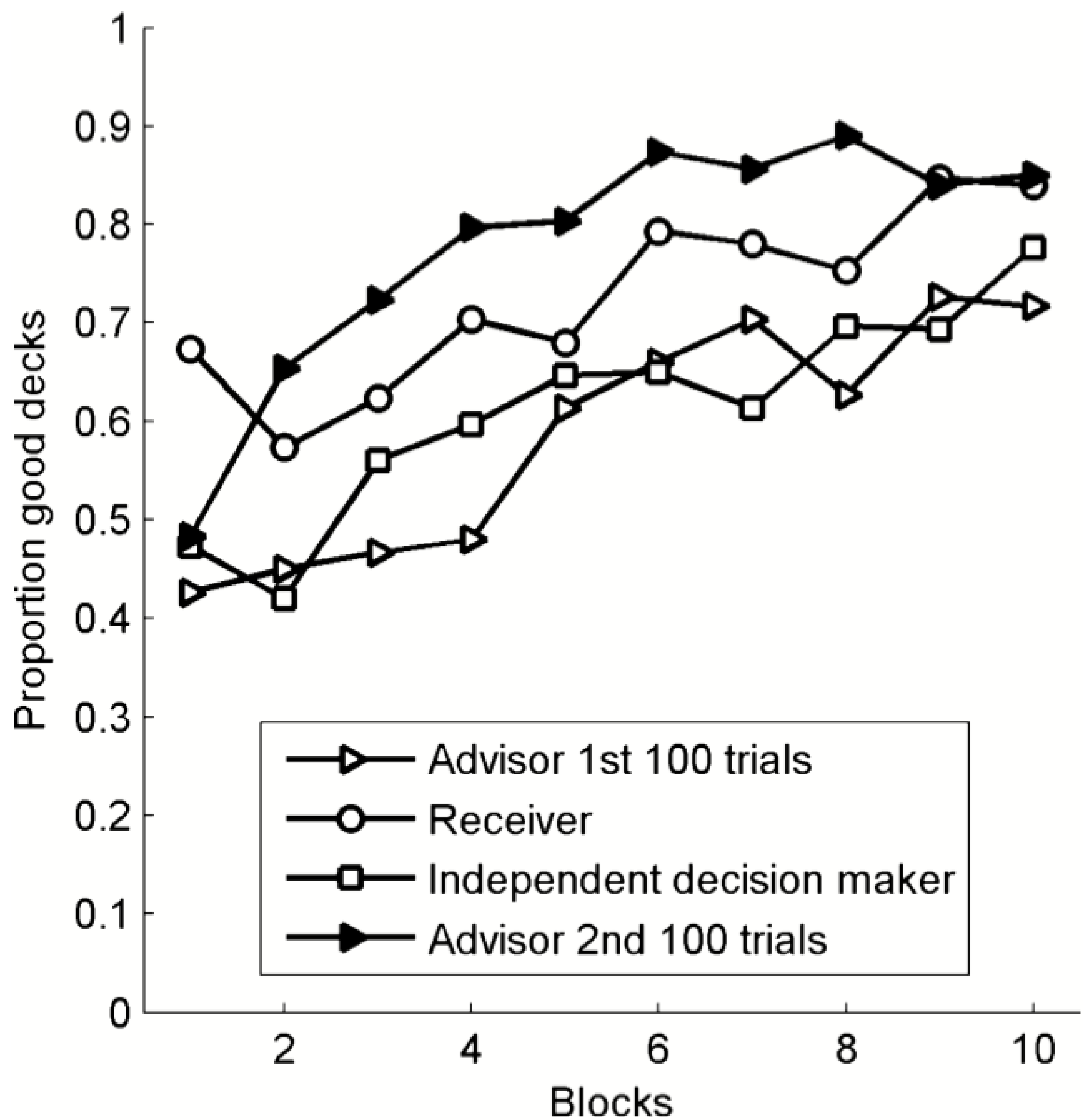
先玩的為前輩，需指引後輩

	Bad Decks		Good Decks	
	A	B	C	D
Gain/Deck:	$100	$100	$50	$50
Loss/10 cards:	$1250	$1250	$250	$250
Net/10 cards:	-$250	-$250	$250	$250

C 與 D 期望值相同，若前輩說 C 後輩不受教則會選 D

實驗結果

被指導者比未被指導者賺更多錢



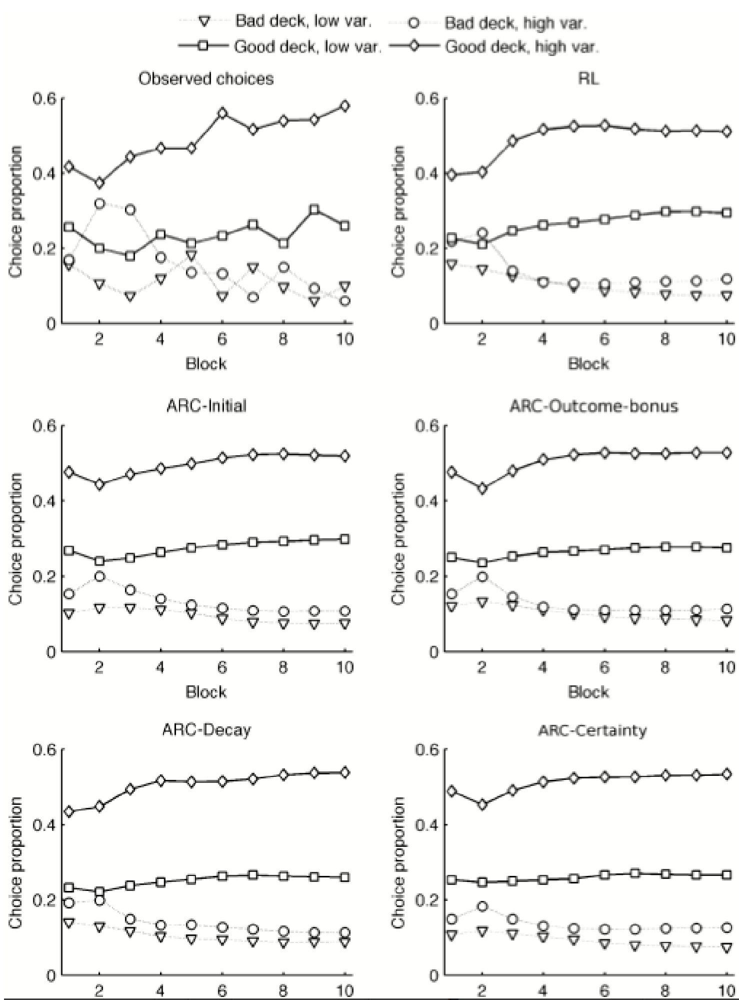
可能的模型：每個方程都有其它可能

Advice-Reinforcement Combination models

Mechanism	RL Model	ARC Models
First choice	$p(i\|i{\in}A) = 1/m$ and $p(i\|i{\notin}A) = 0$	No difference
Initial attraction	$q_1(i) = 0$	ARC-Initial: $q_1(i\|i{\in}A) = \|\mu\|{\cdot}\iota$ and $q_1(i\|i \notin A) = 0$
Reinforcement	$r_t(i) = \pi_t(i)$	ARC-Outcome-bonus: $r_t(i) = \begin{cases} i \in A \to \pi_t(i) + \|\mu\| \cdot \rho \\ i \notin A \to \pi_t(i) \end{cases}.$
Updating	$q_{t+1}(i) = (1-\phi) \cdot q_t(i) + r_t(i)$	ARC-Decay:$q_t(i) = \begin{cases} i \in A \to q_t(i) \cdot (1-\phi_{\text{advice}}) + r_t \\ i \notin A \to q_t(i) \cdot (1-\phi) + r_t \end{cases}.$
Choice rule	$p(i) = \mathrm{e}^{\lambda \cdot q(i)} / \sum_{j=1}^{n} \mathrm{e}^{\lambda \cdot q(j)}$	ARC-Certainty: $p(i) = \begin{cases} \sigma(\Pi) < \tau \wedge i \in A \to 1/m \\ \sigma(\Pi) < \tau \wedge i \notin A \to 0 \\ \sigma(\Pi) \geq \tau \to p \end{cases}.$

這邊的 RL model 只是簡單積 r 的 leaky integrator

模型參數估計與質性比較



質性上看起來都差不多！

所以要進一步做量化比較！

Model Fit or Parameter	RL	ARC Models			
		Initial	Outcome-Bonus	Decay	Certainty
Social learning parameter		ι = 21.18 (12.05, 23.22)	ρ = 3.89 (2.95, 3.88)	$\phi_{advised}$ = .17 (.08, .29)	τ = .16 (.13, .14)
Decay (ϕ)	.16 (.05, .26)	.18 (.05, .3)	.36 (.2, .32)	.52 (.57, .35)	.32 (.1, .36)
Sensitivity (λ)	3.26 (4.42, 2.09)	1.55 (1.63, 1.59)	3.1 (4, 2.05)	3.09 (3.93, 2.02)	2.44 (2.82, 2.3)

模型的量化比較

Outcome-Bonus Model 勝出

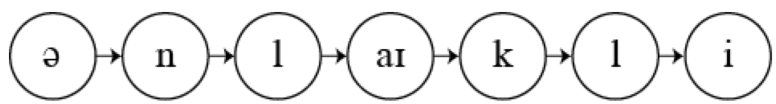
BIC=-2LL+k*log(N); Δ BIC=BIC(baseline)-BIC(model)

Model Fit or Parameter	RL	ARC Models			
		Initial	Outcome-Bonus	Decay	Certainty
ΔBIC	2.55 (1.59, 23.96)	7.08 (4.02, 21.69)	10.77 (3.99, 16.56)	8.13 (4.87, 18.66)	10.4 (7.06, 15.26)
Social learning parameter		ι = 21.18 (12.05, 23.22)	ρ = 3.89 (2.95, 3.88)	ϕ_{advised} = .17 (.08, .29)	τ = .16 (.13, .14)
Decay (ϕ)	.16 (.05, .26)	.18 (.05, .3)	.36 (.2, .32)	.52 (.57, .35)	.32 (.1, .36)
Sensitivity (λ)	3.26 (4.42, 2.09)	1.55 (1.63, 1.59)	3.1 (4, 2.05)	3.09 (3.93, 2.02)	2.44 (2.82, 2.3)
RMSD					
Good deck	.062	.055	.059	.056	.063
Adherence	.102	.048	.036	.036	.040
All choices	.048	.044	.045	.043	.046

此模型暗示指導語主要影響我們對酬賞價值的評估

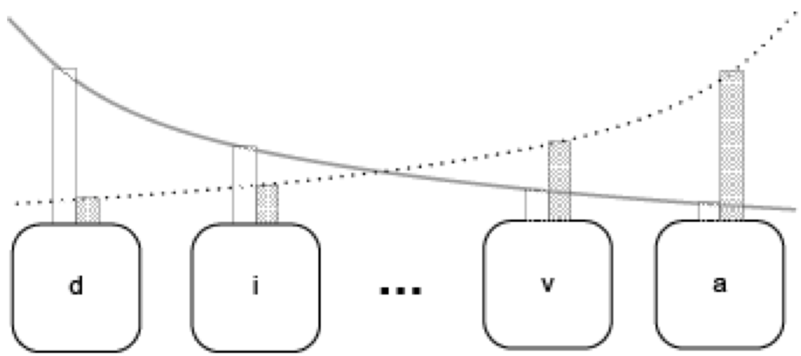
範例 2:Memory for Serial Order

文獻中共有三大類模型



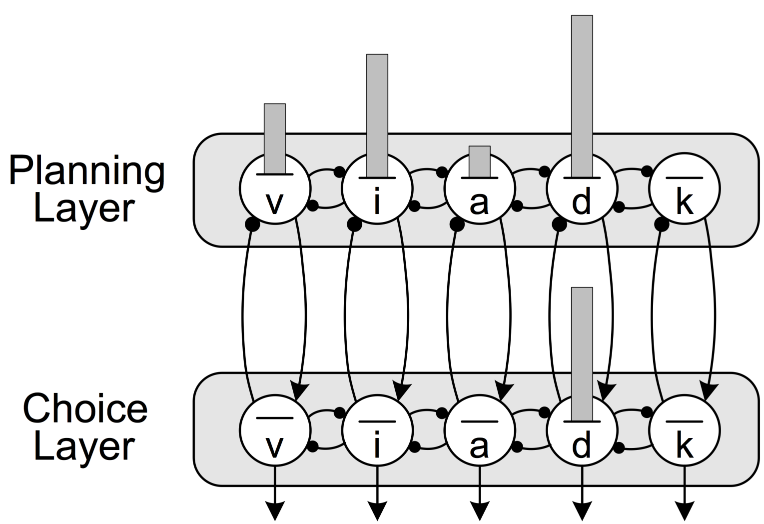
Associative chaining models

Represent order through item-item chaining



Positional models

Represent order by explicit association of item with "slot" or with a time-varying signal



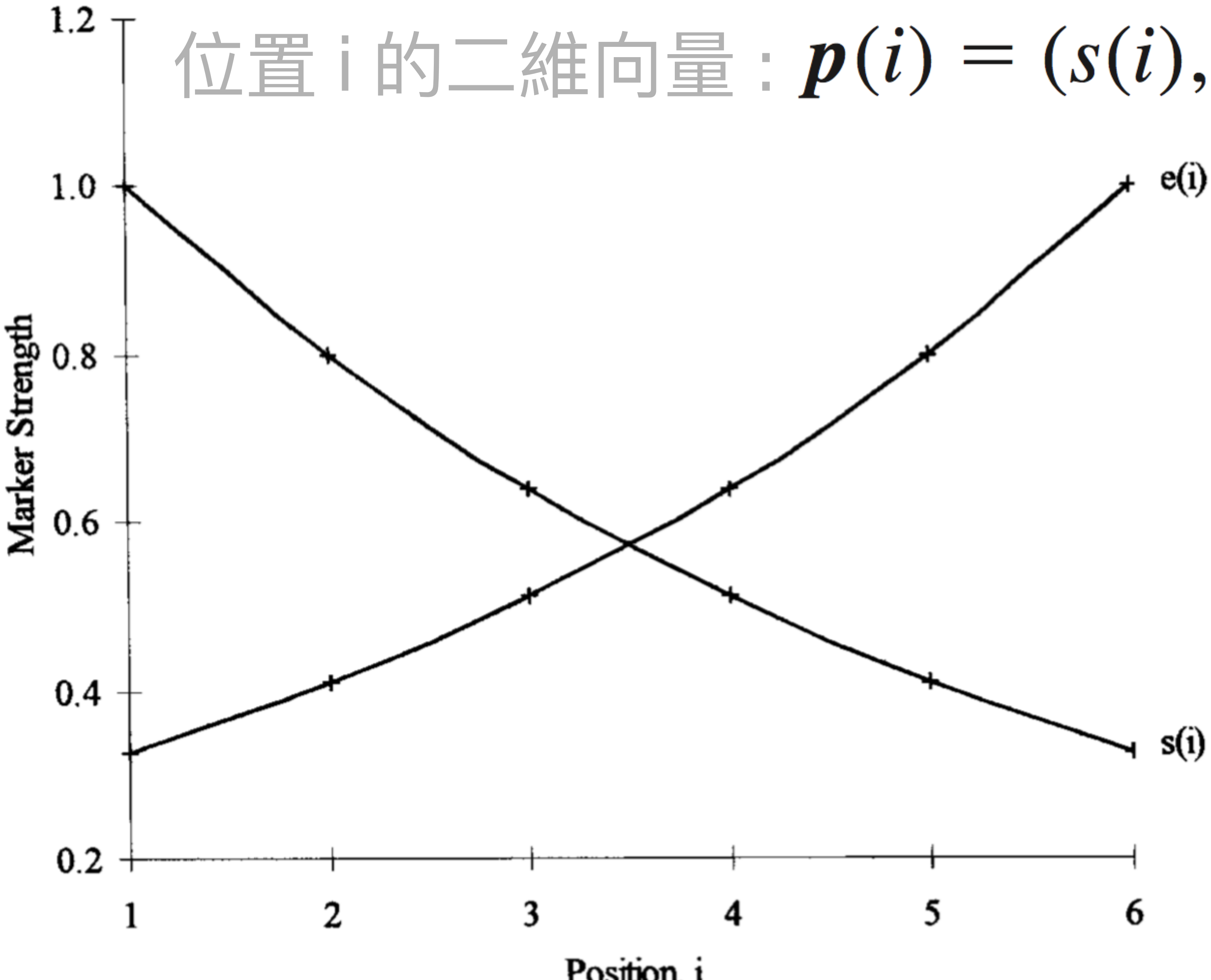
Ordinal models

Represent order by relative activation levels of representative units

位置模型 :Start-End Model (1/3)

start: $s(i) = S_0 S^{i-1}$ end: $e(i) = E_0 E^{N-i}$

位置 i 的二維向量 : $\boldsymbol{p}(i) = (s(i), e(i))$

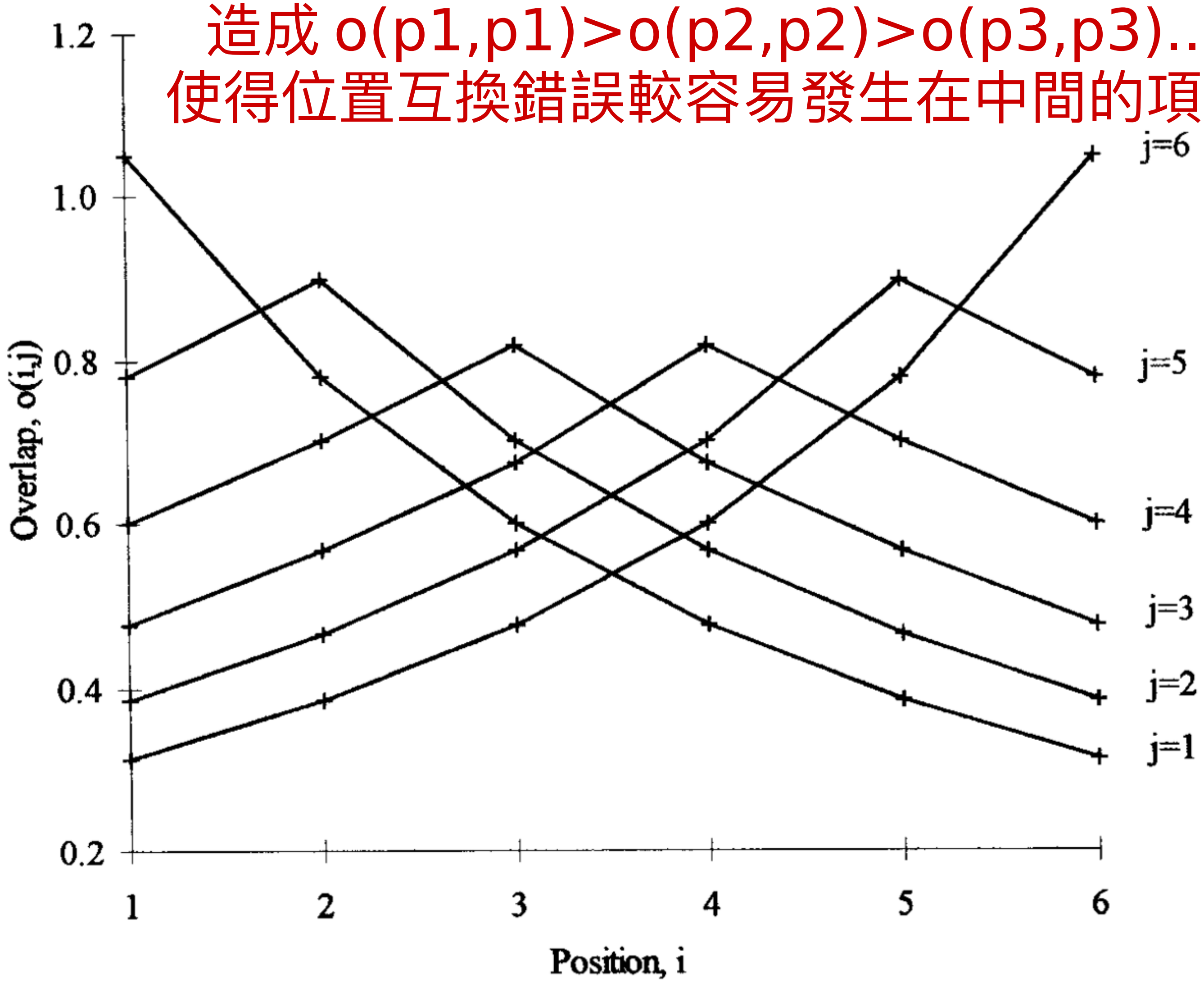


位置模型 :Start-End Model (2/3)

overlap:

$$o(\boldsymbol{p}(i), \boldsymbol{p}(j)) = \underline{\{\boldsymbol{p}(i) \cdot \boldsymbol{p}(j)\}^{1/2}} \exp\left\{-\left(\sum_k (p_k(i) - p_k(j))^2\right)^{1/2}\right\}$$

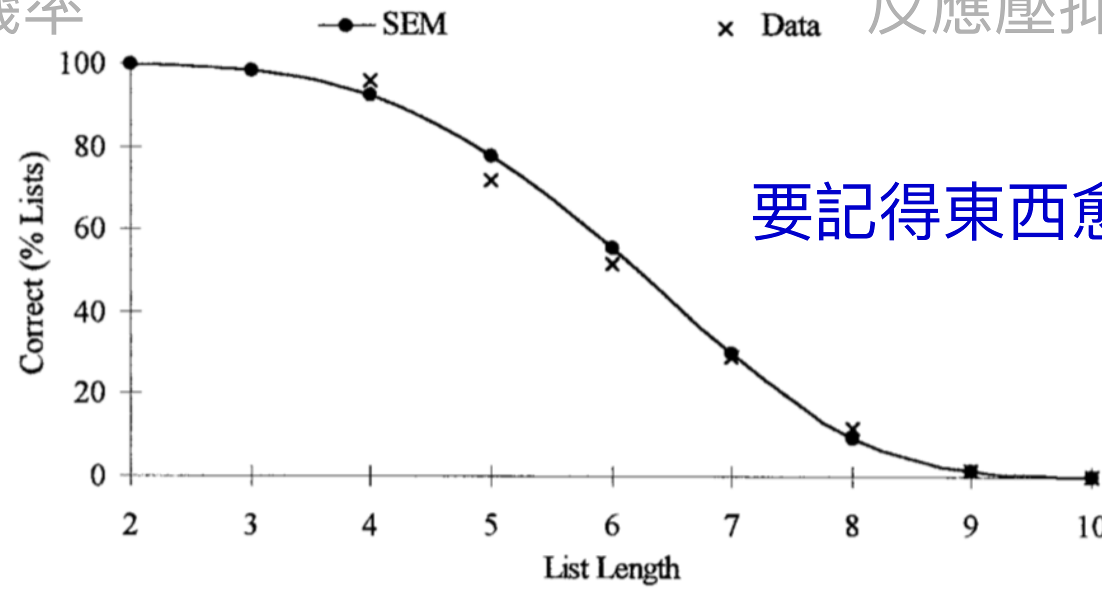
造成 o(p1,p1)>o(p2,p2)>o(p3,p3)...
使得位置互換錯誤較容易發生在中間的項目



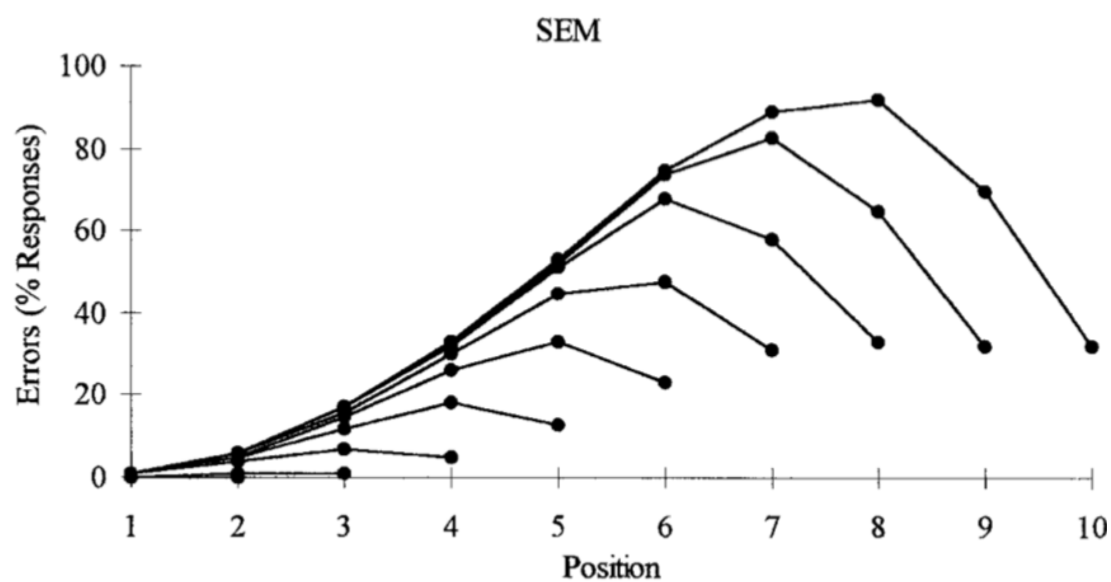
位置模型 :Start-End Model (3/3)

$$c(i, j) = o(p(i), p(j))\,(1 - r(i)) + n$$

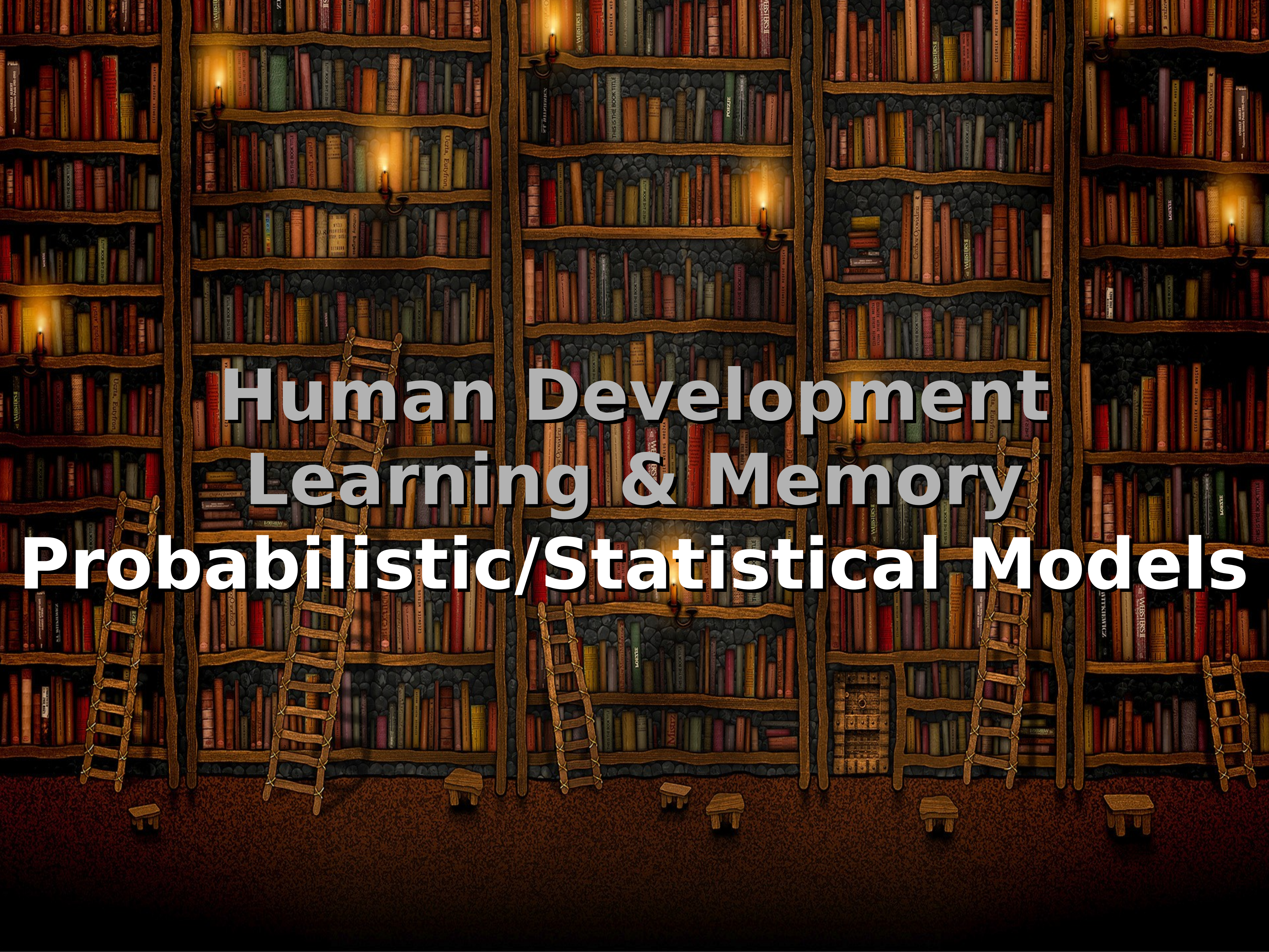
i 在第 j 個回答的“機率”　　　　　　　　　　　　　反應壓抑　noise



要記得東西愈多愈記不住



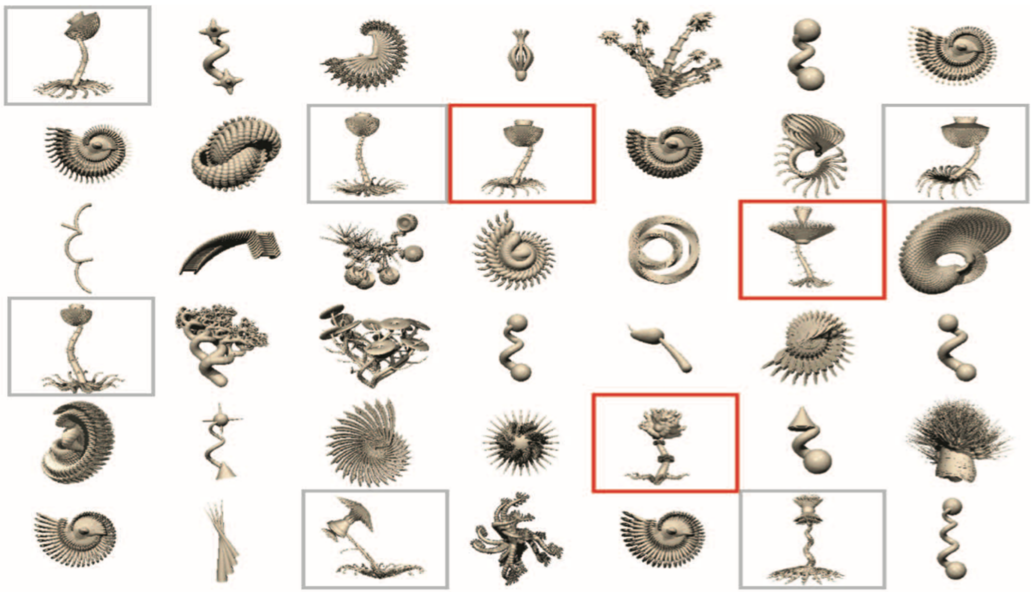
Primacy Effect
&
Recency Effect



Human Development
Learning & Memory
Probabilistic/Statistical Models

機率模型範例 1: 類別的小數據學習

$$P(h|d)=\frac{P(d|h)P(h)}{\sum_{h'\in H}P(d|h')P(h')}\propto P(d|h)P(h)$$



若紅色框起來的叫 tufas,
多數人會認為灰色框的也是 tufas.
But why?

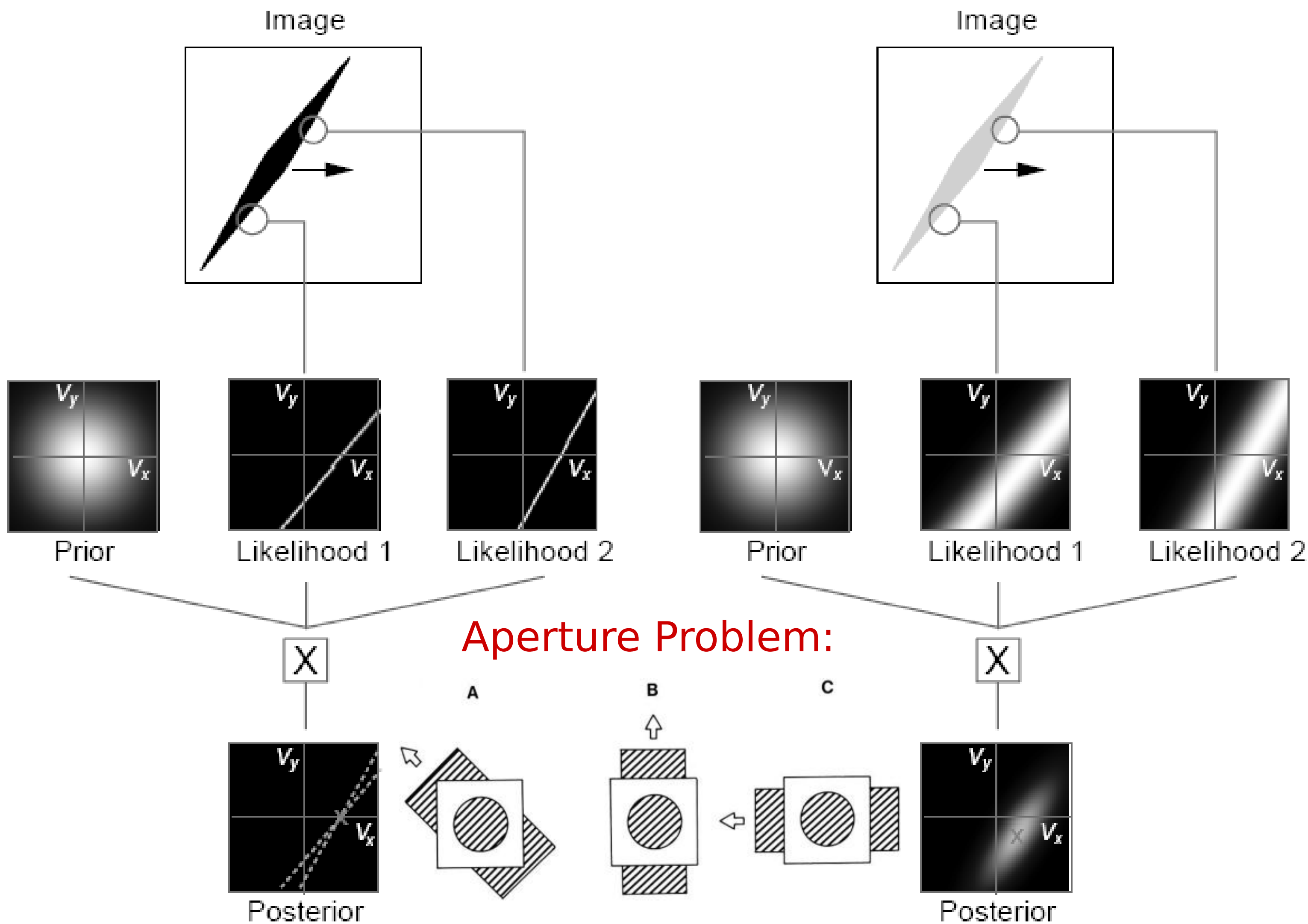
在階層架構下，若紅框的都叫 tufas,
則最有可能的是灰框的整群應該都是
tufas.(cf. K-NN or
semi-supervised learning)

Tenenbaum et al., 2011, *Science*

機率模型範例 2: 視錯覺

$$p\left(Stimulus \middle| Percept\right) \propto p\left(Percept \middle| Stimulus\right) p\left(Stimulus\right)$$

Posterior **Likelihood** **Prior**



單一神經元對速度估計有些不確定性

Weiss et al., 2002, Nature Neuroscience

統計模型範例：腹語術

怎麼 model 跨感官整合不一致的音源位置估計？

$$\hat{S}_{VA} = W_V \hat{S}_V + W_A \hat{S}_A$$

權重和估計變異（不可信賴度）成反比：

$$W_A = \frac{1/\sigma_A^2}{1/\sigma_A^2 + 1/\sigma_V^2} = \frac{\sigma_V^2}{\sigma_A^2 + \sigma_V^2}$$

$$\sigma_{VA}^2 = \frac{\sigma_V^2 \sigma_A^2}{\sigma_A^2 + \sigma_V^2} \leq min\left(\sigma_V^2, \sigma_A^2\right)$$

Alias & Burr, 2004, *Current Biology*


Game Over