

# ALM: An R Package for Simulating Associative Learning Models

Ching-Fan Sheu & Teng-Chang Cheng

National Cheng Kung University, Taiwan

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# Introduction & motivation

- Psychologists have been using a variety of experimental paradigms to study associative learning.
- A computer software is needed to implement models of associative learning for teaching and research.
  - Macho (2002) implemented the configural model of Pearce with Microsoft Excel.
  - Schultheis, Thorwart, & Lachnit (2008) implemented the elemental model of Harris with MATLAB.
  - Excel and MATLAB are commercial software.
  - Programming with spreadsheets is inefficient.

# Pavlovian conditioning (Pavlov, 1927)

- Theories of associative learning are concerned with the factors that govern the association formation when two stimuli are presented together (Pearce & Bouton, 2001).

Conditioning Before	Unconditioned Stimulus (US) Food Bell	Unconditioned Response (UCR) Salivation -
During	Conditioned Stimulus (CS) + US Bell + Food	UCR Salivation
After	CS Bell	Conditioned Response (CR) Salivation

# Blocking (Kamin, 1969)

Condition	Stage 1	Stage 2	Test
Treatment	Light Shock	Light+Tone Shock	Tone
Control	- -	Light+Tone Shock	Tone
Trial	16	8	

- Rats in the treatment group showed no fear of the tone, while rats in the control group were afraid of it.

# The Rescorla-Wagner model (1972)

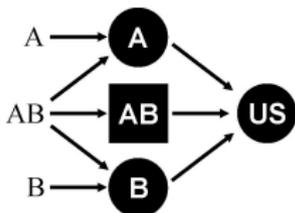
At each trial, the association strength between a given CS and the US changes in proportion to the discrepancy between the maximum strength supported by the US and the total strength of all conditioned stimuli present at the current trial:

$$\Delta V_{CS} = \alpha_{CS}\beta_{US}(\lambda_{US} - \sum_{i=1}^n V_i)$$

# Blocking Effect Explained

Conditioning				
End of stage 1	CS	Present	Weight	CR
	Light	1	1	1
	Tone	0	0	0
<hr/>				
During stage 2				
	Light	1	1	1
	Tone	1	0	0
<hr/>				
Test				
	Light	0	1	0
	Tone	1	0	0

# Configural or elemental associations



- Conditioning with a compound stimuli results in a unitary representation of the compound entering into association with the reinforcer.
- When two or more stimuli are presented for conditioning, each element may enter into association with the reinforcer.

# Human associative learning (Shanks, et al. 1998)

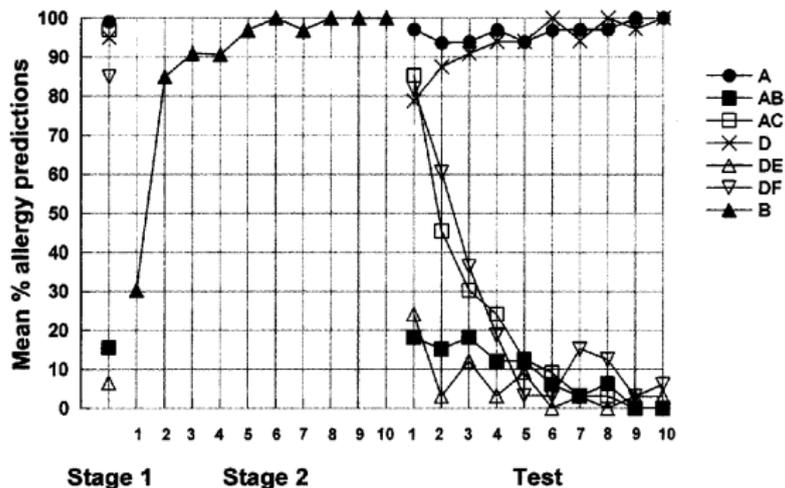
	Stage 1	Stage 2	Test
	A+	B+	A+
	AB-	GH+	AB-
	AC+	IJ-	AC-
	D+	-	D+
	DE-	-	DE-
	DF+	-	DF-
Trial	15	10	10

- Participants were asked to predict whether an allergy would occur (+) for the food (A) presented and received feedback trial by trial.
- Learning at stage 2 should lead to more positive responses for AB than for DE if patterns are learned elementwise.

# Food Stimuli

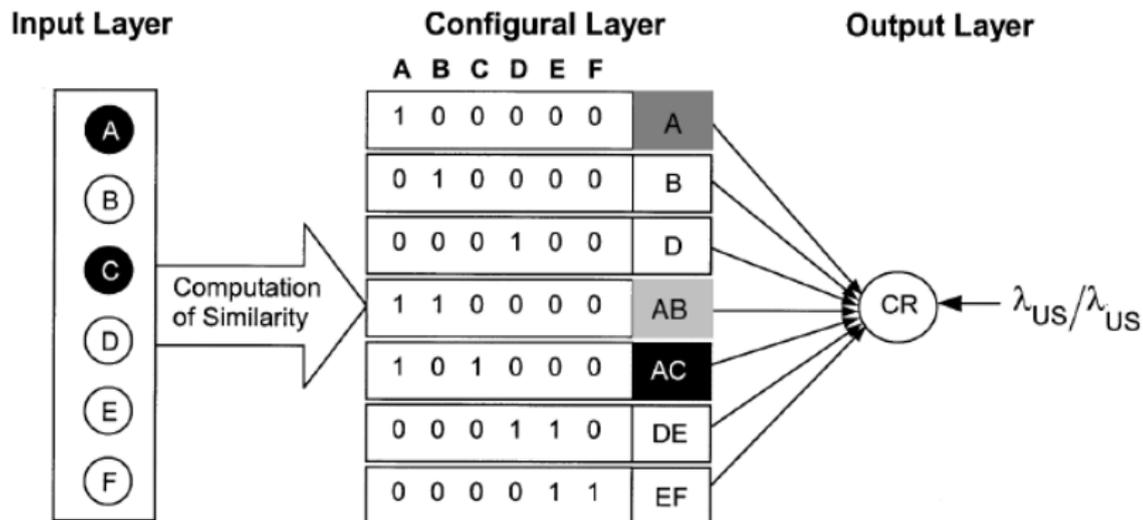
A	Cheese	Fromage
B	Chocolate	Chocolat
C	Milk	Lait
D	Cucumber	Concombre
E	Fish	Poisson
F	Banana	Banane
G	Olive oil	Huile d'olive
H	Vinegar	Vinaigre
I	Onion	Oignon

# Human associative learning (Shanks, et al. 1998)



- Responses to AB and DE at the test stage were virtually the same.

# The configural model of Pearce (1987)



# The configural model of Pearce

$$a^c_j = (a^{it} \cdot w^c_j)^\sigma$$

$$a^o = \sum_j w^o_j \cdot a^c_j$$

$$\Delta w^o_j = \alpha_j \beta_k (\lambda_k - a^o)$$

- $a^c_j$  is the activation of configural unit  $j$ .
- $a^i$  is the input vector.
- $w^c_j$  is the configural vector of configural unit  $j$ .
- $\sigma$  is the specificity parameter.
- $a^o$  is the activation of output unit.
- $\Delta w^o_j$  is the weight change between configural unit  $j$  to output.

# The elemental model of Harris (2006)

$$\Delta w_y = w_y - \sum_{j=i}^m w_j - V_{j-y}$$

$$\Delta V_{xy} = \begin{cases} w_x \beta_y \Delta w_y & \text{if } \Delta w_y \geq t \\ -w_x \beta_y |\Delta w_y| & \text{if } \Delta w_y < t \end{cases}$$

$$R(A) = \sum_{i=1}^n w A_i V A_i$$

- A stimulus activates a population of elements.
- Activated elements compete for entry to an attention buffer with capacity  $t$ .
- Each element has a fixed probability of being connected to any other elements.
- $\Delta V_{xy}$  is the change in association strength between element  $x$  and element  $y$ .
- $\Delta w_y$  is the difference between self-generated weight,  $w_y$ , and the activated weight of  $y$  by association.
- $R(A)$  is the response strength of  $A$ .

# Input file

Cue	A	B	C	D	E	F	US	Phase	Feedback	Iseval
A	1	0	0	0	0	0	1	1	1	1
AB	1	1	0	0	0	0	0	1	1	1
AC	1	0	1	0	0	0	1	1	1	1
D	0	0	0	1	0	0	1	1	1	1
DE	0	0	0	1	1	0	0	1	1	1
DF	0	0	0	1	0	1	1	1	1	1
B	0	1	0	0	0	0	1	2	1	1
AB	1	1	0	0	0	0	0	2	0	0
DE	0	0	0	1	1	0	0	2	0	0

# Configural model of Pearce in R

```
CMP=function(dat, itemlabel, items, phase, US, feedback, nb1=15,  
nb2=10, sigma=2, alpha=1, beta=0.15, lambda=c(0,100))
```

- dat: input dataframe
- itemlabel: column index for item label
- items: column indices for items
- phase: column index for phase
- US: column index for unconditioned stimulus
- feedback: column index for feedback
- nb1: number of learning trials in phase 1
- nb2: number of learning trials in phase 2
- sigma: specificity parameter
- alpha: salience parameter
- beta: learning rate parameter
- lambda: asymptotic value of the unconditioned stimulus

# Elemental model of Harris in R

```
EMH=function(dat, itemlabel, items, phase, feedback, nelements=20,  
nruns=20, ntrials=c(20,20), beta=2, gain=1, fraction=0, cdensity=.5)
```

- dat: input dataframe
- itemlabel: column index for item label
- items: column indices for items
- phase: column index for phase
- feedback: column index for feedback
- nelements: number of elements
- nruns: number of simulation runs
- ntrials: number of trials in each of two phases
- beta: learning rate parameter
- gain: gain parameter
- fraction: fraction parameter
- cdensity: connectivity density parameter

## An example script

```
> input=read.table("xp3data.asc", h=t)
> cmpOut=CMP(input[1:9,1:10],1,c(2:7),9,8,10,sigma=2);
> CMP.plot(cmpOut$sumdata,cmpOut$itemlabel, "sigma=2")
#
> emhOut=EMH(input[1:9,1:10],1,c(2:8),9,10,ntrial=c(30,20))
> EMH.plot(emhOut$sumdata,emhOut$evallabs, "EMH Plot")
```

# Human associative learning - CMP

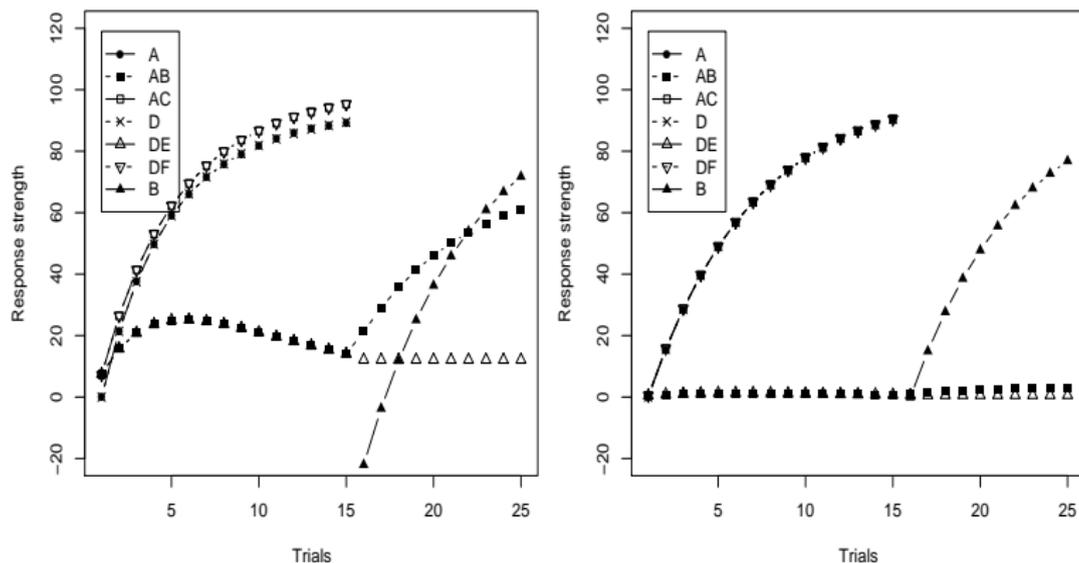


Figure:  $\sigma=2$  vs.  $\sigma=10$

# Human associative learning

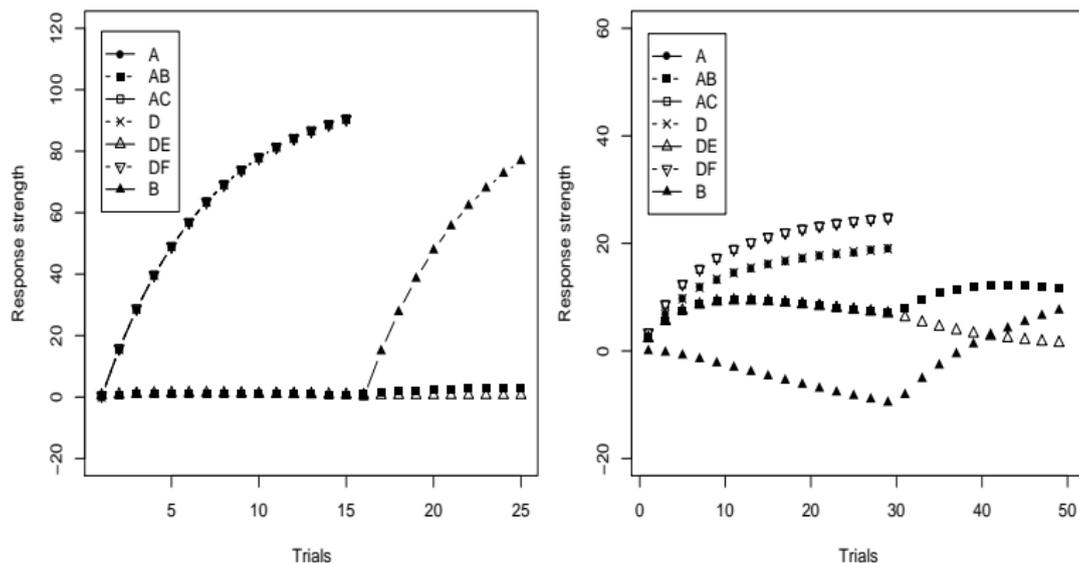


Figure: CMP vs. EMH

# Two discrimination problems

- In positive patterning, two stimuli are not reinforced when each is presented alone ( $A^-$ ,  $B^-$ ), but a US follows when the two are presented together ( $AB^+$ ).
- In negative patterning, a US is presented after each of two stimuli when they are presented alone ( $A^+$ ,  $B^+$ ), but not when they are presented together ( $AB^-$ ).

# Positive Patterning: A-, B-, AB+

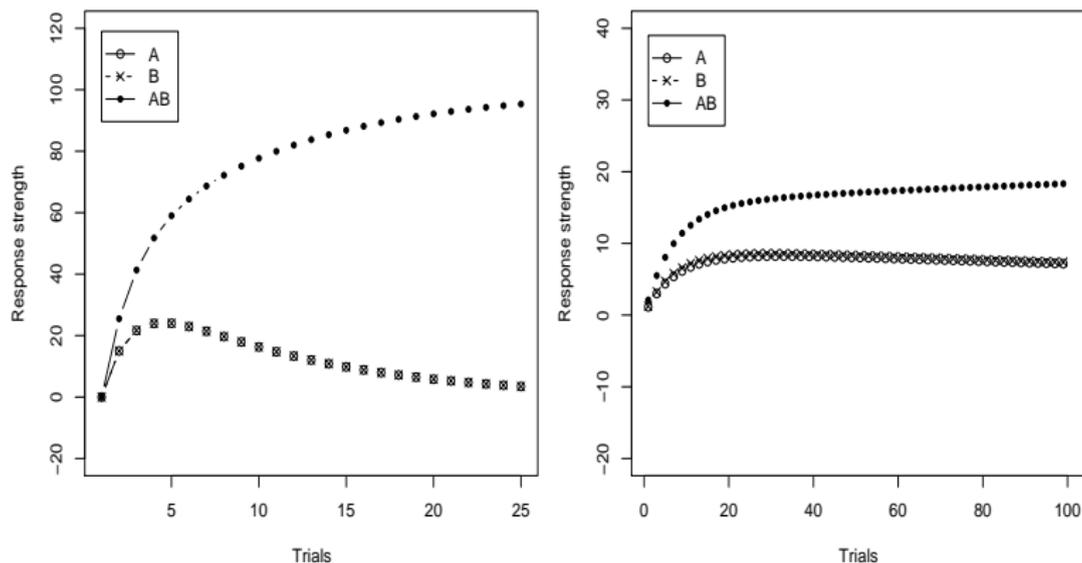


Figure: CMP vs. EMH

# Negative Patterning: A+, B+, AB-

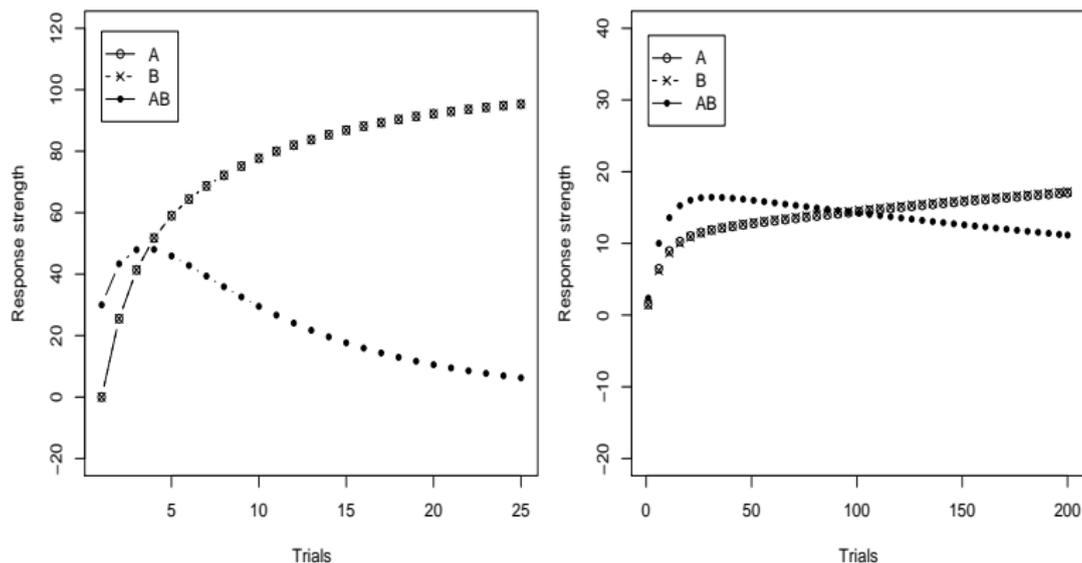


Figure: CMP vs. EMH

# Summary

- We implemented in R two models for associative learning.
- The unique cue theory and the replaced elements model are yet to be implemented.
- The ALM R package enables users to easily reproduce, modify, and extend these models for teaching and research.