Wright State University

From the SelectedWorks of Joseph W. Houpt

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Bayesian Approaches to Assessing Architecture and Stopping Rule

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J. T. Townsend, Indiana University - Bloomington



Bayesian Analyses of the Survivor Interaction Contrast

Joseph W. Houpt, Andrew Heathcote, Ami Eidels and James T. Townsend



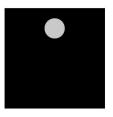


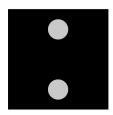


Society for Mathematical Psychology Annual Meeting Columbus, Ohio July 22, 2012

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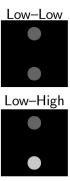


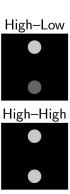


- How do different sources of information combine in mental processing?
 - Are both sources used concurrently, or do we use one at a time?
 - How many sources are enough to respond?

Salience

• To test architecture and stopping rule, without conflating them with workload capacity, factorially speed up and slow down the processing of each source of information.





Survivor Interaction Contrast

Indicates architecture and stopping rule.

Survivor Interaction Contrast

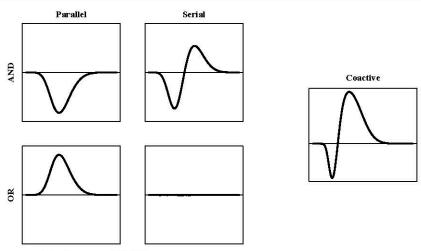
- Indicates architecture and stopping rule.
- The SIC is interaction between the salience manipulations.
 - Instead of just using the mean time, we use the survivor function:

$$S(t) = \Pr\{T > t\} = 1 - F(t).$$

$$\operatorname{SIC}(t) = \left[\operatorname{S}_{\operatorname{LL}}\left(t\right) - \operatorname{S}_{\operatorname{LH}}\left(t\right)\right] - \left[\operatorname{S}_{\operatorname{HL}}\left(t\right) - \operatorname{S}_{\operatorname{HH}}\left(t\right)\right]$$

Here, the subscripts indicate the salience of each source of information.

Survivor Interaction Contrast

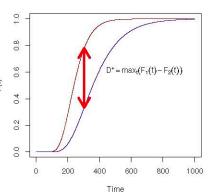


Townsend & Nozawa (1995) Schweickert, Giorgini & Dzhafarov (2000)

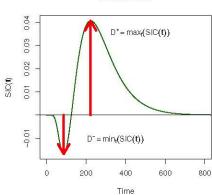
Dzhafarov, Schweickert & Sung (2004) Houpt & Townsend (2011)

Null Hypothesis Test

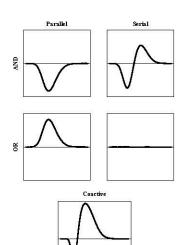




SIC Statistic



$$\begin{split} & \lim_{N \to \infty} \Pr\{\sqrt{N}D^+ \ge x\} = \Pr\{\sqrt{N}D^- \ge x\} = e^{-2x^2} \\ & N_{\rm KS} = \frac{1}{1/m + 1/n} \qquad N_{\rm SIC} = \frac{1}{1/k + 1/i + 1/m + 1/n} \end{split}$$



Model	\hat{D}^+	Ĵ−	Mean Interaction
Serial-OR	Ø		Ø
Serial-AND	V	√	Ø
Parallel-OR	√	Ø	\checkmark
Parallel-AND	Ø	\checkmark	\checkmark
Coactive	✓	\checkmark	\checkmark

✓: Reject null hypothesisØ: Fail to reject null hypothesis

Shortcomings

- Tests positive and negative deflections not SIC form.
 - · Requires two separate tests.
- Only can gain evidence against a lack of positive or negative deflection.
- Only get a yes/no answer, not relative evidence.

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$$f(t)$$
: Density (PDF) $F(t)$: Cumulative Distribution (CDF)

Parallel-OR
$$f_{12}(t) = f_1(t)[1 - F_2(t)] + f_2(t)[1 - F_1(t)]$$

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Parallel-OR
$$f_{12}(t) = f_1(t)[1 - F_2(t)] + f_2(t)[1 - F_1(t)]$$

Parallel-AND
$$f_{12}(t) = f_1(t)F_2(t) + f_2(t)F_1(t)$$

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Serial-OR
$$f_{12}(t) = pf_1(t) + (1-p)f_2(t)$$

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$$f_{12}(t) = f_1(t)[1 - F_2(t)] + f_2(t)[1 - F_1(t)]$$

Parallel-AND $f_{12}(t) = f_1(t)F_2(t) + f_2(t)F_1(t)$
Serial-OR $f_{12}(t) = pf_1(t) + (1 - p)f_2(t)$
Serial-AND $f_{12}(t) = f_1(t) * f_2(t)$

$$egin{align} \mathcal{T}_{i;H} &\sim \mathcal{IG}\left(rac{lpha}{
u_H}, lpha^2
ight) & \eta &\sim \mathrm{Exponential} \ \mathcal{T}_{i;L} &\sim \mathcal{IG}\left(rac{lpha}{
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u_L &\sim \Gamma(4, 0.1) \ & lpha &\sim \Gamma(4, 0.1) &
u_H &=
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u_H &=
u_I + \eta \end{split}$$

$$\begin{split} f_i(t;\nu_i,\alpha) &= \sqrt{\frac{\alpha^2}{2\pi t^3}} \exp\left[\frac{-(t\nu_i-\alpha)^2}{2t}\right] \\ F_i(t;\nu_i,\alpha) &= \Phi\left[\sqrt{\frac{\alpha^2}{t}}\left(\frac{t\nu_i}{\alpha}-1\right)\right] + \exp\left[2\alpha\nu_i\right] \Phi\left[-\sqrt{\frac{\alpha^2}{t}}\left(\frac{t\nu_i}{\alpha}+1\right)\right] \end{split}$$

Simulation Parameters

$$T_i = \inf\{t : X_i(t) \ge \alpha\}$$
 $T_i \sim \mathcal{IG}\left(\frac{\alpha}{\nu_i}, \frac{\alpha}{\sigma^2}\right)$

$$lpha=30$$
 $u_H=0.3$ $\sigma^2=1$ $u_L=0.1$ $u_L=0.1$

Parametric Test Simulation

Simulation Results

	Serial	Serial	Parallel	Parallel	
	OR	AND	OR	AND	Coactive
Serial-OR	1.00	0	0	0	0
Serial-AND	0	0.99	0	0.01	0
Parallel-OR	0	0	0.98	0	0.02
Parallel-AND	0	0	0	1.00	0
Coactive	0	0	0	0	1.00

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- Approach: Model the response time distributions
 - (as opposed to the RT generating process).
- Assume each RT distribution is an independent sample from a Dirichlet process prior.
- Compare the Bayes factor of each SIC form in the posterior relative to encompassing prior.

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$$lpha_I \sim \mathcal{DP}(eta) \ ext{RT}_{I(i)} \sim lpha_I.$$

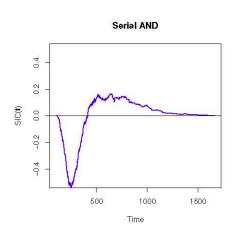
- Tested on same models as parametric-Bayesian test (but with 1000 rounds rather than 100).
 - ullet Used region of probabilistic equivalence $\pm .1$ for SIC and $\pm .3$ for MIC.

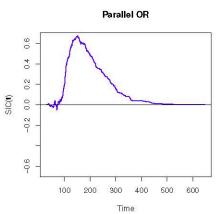
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	Serial	Serial	Parallel	Parallel	
	OR	AND	OR	AND	Coactive
Serial OR	1.00	0	0	0	0
Serial AND	0	0.79	0	0.21	0
Parallel OR	0	0	0.93	0	0.07
Parallel AND	0	0	0	1.00	0
Coactive	0	0	0	0	1.00

Example SICs



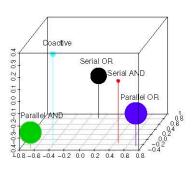


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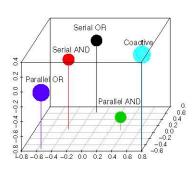
		Serial OR	Serial AND	Parallel OR	Parallel AND	Coactive
Serial OR	KS	0.96	0	0	0.04	0
	DP	1.00	0	0	0	0
	BUGS	1.00	0	0	0	0
Serial AND	KS	0	0.80	0	0.15	0.05
	DP	0	0.79	0	0.21	0
	BUGS	0	0.99	0	0.01	0
Parallel OR	KS	0	0	1.00	0	0
	DP	0	0	0.93	0	0.07
	BUGS	0	0	0.98	0	0.02
Parallel AND	KS	0	0	0	1.00	0
	DP	0	0	0	1.00	0
	BUGS	0	0	0	1.00	0
Coactive	KS	0	0	0.02	0	0.98
	DP	0	0	0	0	1.00
	BUGS	0	0	0	0	1.00

		Serial OR	Serial AND	Parallel OR	Parallel AND	Coactive
Serial OR	KS	0.93	0	0.05	0.02	0
	DP	0.79	0.18	0.02	0.01	0
Serial AND	KS	0	0.41	0	0.56	0.03
	DP	0	0.77	0	0.23	0
Parallel OR	KS	0	0	1.00	0	0
	DP	0	0	0.79	0	0.21
Parallel AND	KS	0	0	0	1.00	0
	DP	0	0.04	0	0.96	0
Coactive	KS	0	0	0.50	0	0.50
	DP	0	0	0	0	1.00

KS Test



DP Test



KS Test

	OR 7	Task	AND Task	
Participant	$\sqrt{N}\hat{D^+}$	$\sqrt{N}\hat{D^-}$	$\sqrt{N}\hat{D^+}$	$\sqrt{N}\hat{D}^-$
1	4.86***	0.11	0	4.65***
2	1.11	0.04	0.04	2.73***
3	4.87***	0.14	0	3.61***
4	2.12***	0.77	0.07	3.30***
5	2.59***	0.22	0.21	4.24***
6	3.52***	0.04	0.16	2.79***
7	1.44*	0.11	0.04	2.04***
8	3.64***	0.24	0.11	2.10***
9	3.86***	0.07	0.07	4.98***

Parametric Bayes

	OR Task							
	Se	rial	Par	allel				
	OR	AND	OR	AND	Coactive			
1	7991	7985	7869	8012	7964			
2	8489	8489	8394	8486	8488			
3	7831	7792	7623	7920	7746			
4	9480	9504	9530	9464	9505			
5	9347	9351	9274	9352	9335			
6	8870	8875	8885	8830	8867			
7	9210	9216	9192	9201	9214			
8	8624	8636	8531	8638	8620			
9	8830	8850	8828	8837	8837			

	AND Task							
	Se	rial	Par	allel				
	OR	AND	OR	AND	Coactive			
1	7861	7863	7872	7817	7890			
2	7832	7833	7791	7871	7836			
3	7246	7249	7242	7297	7265			
4	8883	8880	8922	8789	8890			
5	9390	9370	9350	9360	9380			
6	7434	7426	7441	7374	7426			
7	7853	7857	7815	7858	7861			
8	8272	8269	8229	8250	8273			
9	8011	7998	7968	8009	8010			

Nonparametric Bayes

	OR Task						
	Se	rial	Par	allel			
	OR	AND	OR	AND	Coactive	Np	
1	1	0.17	7.26	0	0.05	0	
2	160	2.57	7.24	0.03	0.15	0.02	
3	1	0.20	6.98	0	0.31	0	
4	1	0.12	3.19	0	0	0	
5	1	0.25	7.02	0	0.70	0	
6	1	0.25	7.45	0	0	0	
7	72	0.29	7.25	0	0.01	0	
8	1	0.25	7.19	0	0.13	0	
9	1	0.25	7.22	0	0.01	0	

Nonparametric Bayes

		AND Task						
	Se	Serial Parallel						
	OR	AND	OR	AND	Coactive	Np		
1	1	0.50	0	7.41	0	0		
2	1	0.25	0	7.51	0	0		
3	1	0.17	0	7.69	0	0		
4	1	0.50	0	7.26	0	0		
5	1	1.00	0	7.36	0	0		
6	1	0.17	0	7.37	0	0.24		
7	1	0.50	0	7.22	0	0.04		
8	1	0.25	0	7.37	0	0.48		
9	1	0.50	0	7.31	0	0		

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- Tested each of these approaches on both simulated data and experimental data.
 - Both did quite well on simulated data.
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Thank you.