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Bayesian Analyses of the Survivor Interaction Contrast

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



NEW CL



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

Outline

- 1 Introduction
- 2 Parametric Test
 - Model
 - Simulation
- 3 Nonparametric Test
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- 4 Comparisons Among SIC Tests
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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?

Saliency

- 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.

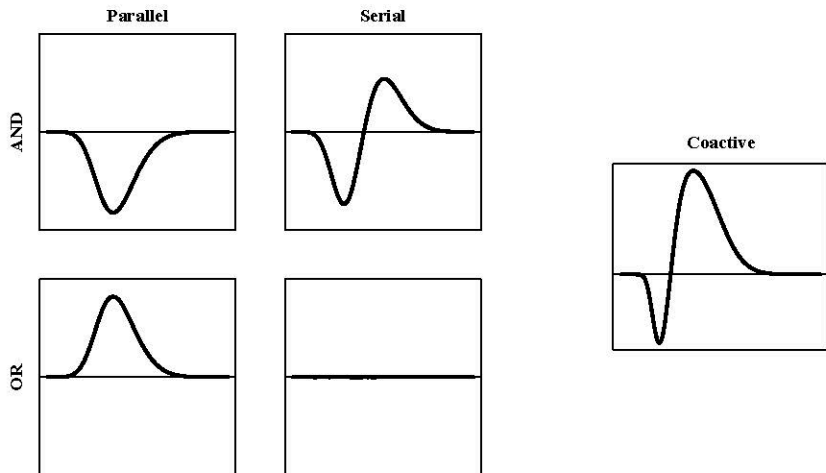
Survivor Interaction Contrast

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

$$\text{SIC}(t) = [S_{LL}(t) - S_{LH}(t)] - [S_{HL}(t) - S_{HH}(t)]$$

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

Survivor Interaction Contrast

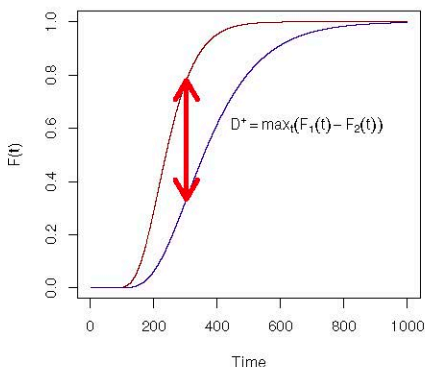


Townsend & Nozawa (1995)
 Schweickert, Giorgini & Dzhaferov
 (2000)

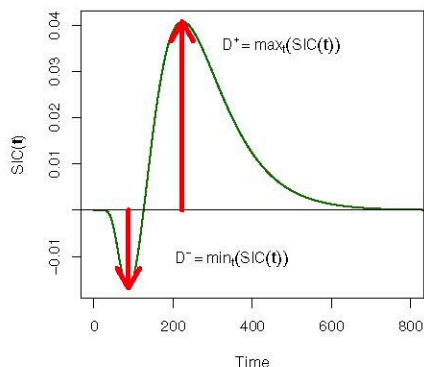
Dzhaferov, Schweickert & Sung (2004)
 Houpt & Townsend (2011)

Null Hypothesis Test

Kolmogorov–Smirnov Test



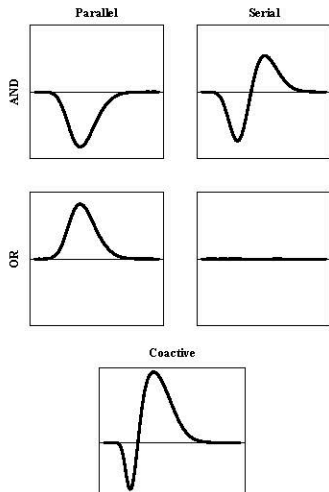
SIC Statistic



$$\lim_{N \rightarrow \infty} \Pr\{\sqrt{ND^+} \geq x\} = \Pr\{\sqrt{ND^-} \geq x\} = e^{-2x^2}$$

$$N_{KS} = \frac{1}{1/m + 1/n}$$

$$N_{SIC} = \frac{1}{1/k + 1/l + 1/m + 1/n}$$



Model	\hat{D}^+	\hat{D}^-	Mean Interaction
Serial-OR	\emptyset	\emptyset	\emptyset
Serial-AND	✓	✓	\emptyset
Parallel-OR	✓	\emptyset	✓
Parallel-AND	\emptyset	✓	✓
Coactive	✓	✓	✓

✓: Reject null hypothesis
 \emptyset : 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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Parallel-AND $f_{12}(t) = f_1(t)F_2(t) + f_2(t)F_1(t)$

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

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

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

Serial-AND $f_{12}(t) = f_1(t) * f_2(t)$

$$T_{i;H} \sim \text{IG} \left(\frac{\alpha}{\nu_H}, \alpha^2 \right)$$

$$\eta \sim \text{Exponential}(100)$$

$$T_{i;L} \sim \text{IG} \left(\frac{\alpha}{\nu_L}, \alpha^2 \right)$$

$$\nu_L \sim \Gamma(4, 0.1)$$

$$\alpha \sim \Gamma(4, 0.1)$$

$$\nu_H = \nu_L + \eta$$

$$T_{i;H} \sim \text{IG} \left(\frac{\alpha}{\nu_H}, \alpha^2 \right) \quad \eta \sim \text{Exponential}(100)$$

$$T_{i;L} \sim \text{IG} \left(\frac{\alpha}{\nu_L}, \alpha^2 \right) \quad \nu_L \sim \Gamma(4, 0.1)$$

$$\alpha \sim \Gamma(4, 0.1) \quad \nu_H = \nu_L + \eta$$

$$f_i(t; \nu_i, \alpha) = \sqrt{\frac{\alpha^2}{2\pi t^3}} \exp \left[\frac{-(t\nu_i - \alpha)^2}{2t} \right]$$

$$F_i(t; \nu_i, \alpha) = \Phi \left[\sqrt{\frac{\alpha^2}{t}} \left(\frac{t\nu_i}{\alpha} - 1 \right) \right] + \exp[2\alpha\nu_i] \Phi \left[-\sqrt{\frac{\alpha^2}{t}} \left(\frac{t\nu_i}{\alpha} + 1 \right) \right]$$

Simulation Parameters

$$T_i = \inf\{t : X_i(t) \geq \alpha\}$$

$$T_i \sim \mathcal{IG}\left(\frac{\alpha}{\nu_i}, \frac{\alpha}{\sigma^2}\right)$$

$$\alpha = 30$$

$$\nu_H = 0.3$$

$$\sigma^2 = 1$$

$$\nu_L = 0.1$$

$$p = 0.5$$

Simulation Results

	Serial OR	Serial AND	Parallel OR	Parallel 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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$$\alpha_I \sim DP(\beta)$$

$$RT_{I(i)} \sim \alpha_I.$$

Simulation

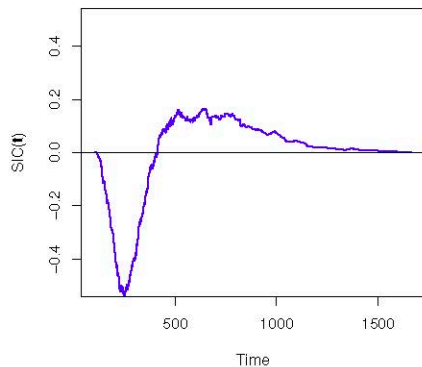
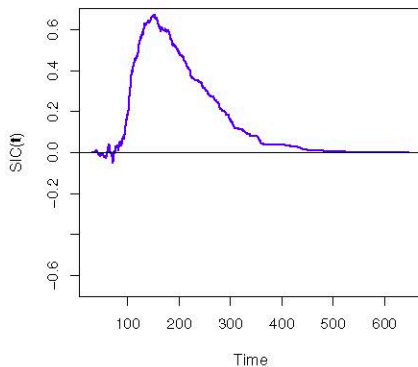
- Tested on same models as parametric-Bayesian test (but with 1000 rounds rather than 100).
 - Used region of probabilistic equivalence ± 1 for SIC and ± 3 for MIC.

Simulation

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	Serial OR	Serial AND	Parallel OR	Parallel 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

Serial AND**Parallel OR**

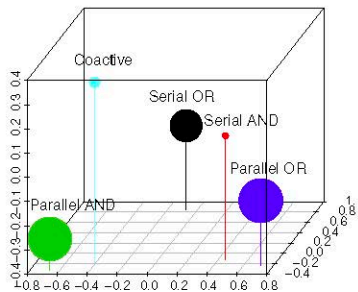
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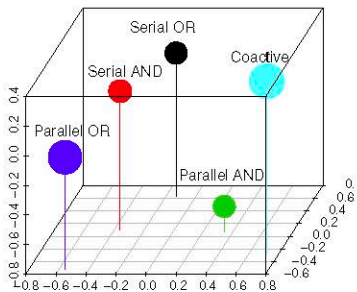
		Serial OR	Serial AND	Parallel OR	Parallel AND	Coactive
Serial OR	KS	0.96	0	0	0.04	0
	DP	1.00	0	0	0	0
	BUGS	1.00	0	0	0	0
Serial AND	KS	0	0.80	0	0.15	0.05
	DP	0	0.79	0	0.21	0
	BUGS	0	0.99	0	0.01	0
Parallel OR	KS	0	0	1.00	0	0
	DP	0	0	0.93	0	0.07
	BUGS	0	0	0.98	0	0.02
Parallel AND	KS	0	0	0	1.00	0
	DP	0	0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

Participant	OR Task		AND Task	
	\sqrt{ND}^+	\sqrt{ND}^-	\sqrt{ND}^+	\sqrt{ND}^-
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				
	Serial		Parallel		Coactive
	OR	AND	OR	AND	
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

Parametric Bayes

	AND Task				
	Serial		Parallel		Coactive
	OR	AND	OR	AND	
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					
	Serial		Parallel		Coactive	Np
	OR	AND	OR	AND		
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					
	Serial		Parallel		Coactive	Np
	OR	AND	OR	AND		
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.
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Thank you.