IRTrees for eye tracking

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Based on research in collaboration with Sun-Joo Cho and Sarah Brown-Schmidt

Process data

- direct process data: data on *activities while working on a problem*
- indirect process data: data with relevance to inferences regarding activities while working on a problem often these are parallel data: response times, brain activation fMRI data, EEG data, introspective questions

Process models

Models fitting with a process narrative based on direct or indirect process data

The models to be presented are

- dynamic models for direct process data they are extremely intensive longitudinal data
- they fit with a process narrative because they are tree models

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- dynamic models for direct process data they are extremely intensive longitudinal data
- they fit with a process narrative because they are tree models

Which does not prove they capture real ongoing processes

we are stretching model complexity testing the limits

to isolate the gravity effect in the paths of for falling leafs on a windy November day

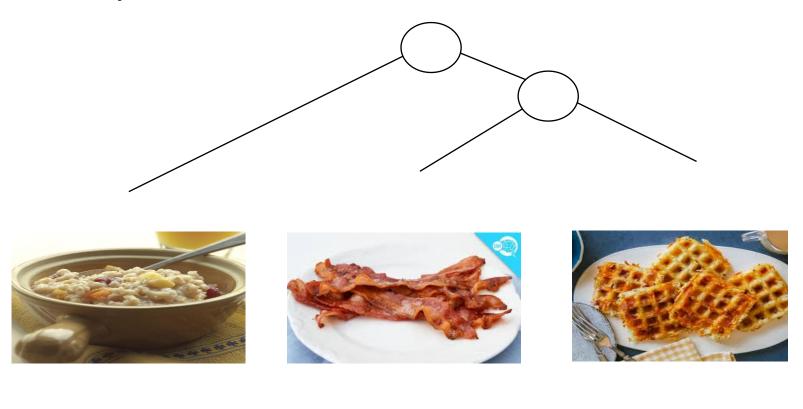


IRTree models

response tree models item response tree models

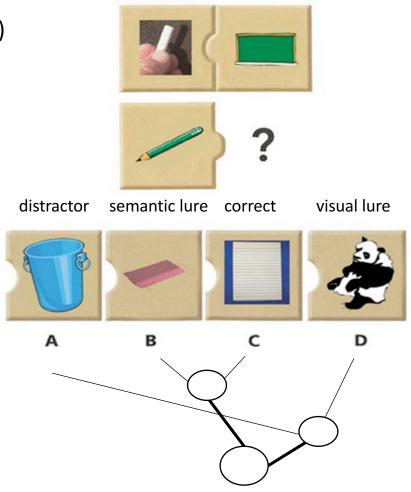
- extensions of discrete survival (frailty) models
- multinomial processing tree models from cognitive psychology, with random effects (Batchelder)
- have been used to model missing responses (Cees Glas)
- general formulation in psychometric literature Böckenholt (2012), De Boeck & Partchev (2012), Roe-Thissen & Thissen (2013)

Examples

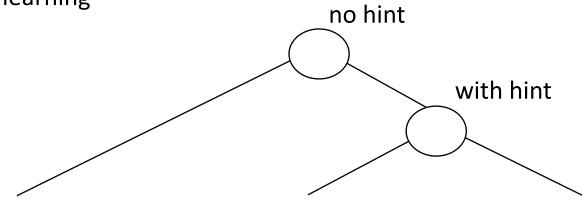


oatmeal bacon waffles

Wright, .., Bunge (2008) Neural correlates of fluid reasoning



Problem solving with and without a hint retry, learning



correct 1 incorrect 1 & 2

incorrect 1 correct 2

A <u>Node 1 response</u> is a subset of possible responses for example, "not oatmeal"

All <u>other Node responses</u> are <u>conditional responses</u>, responses given a condition is fulfilled for example, the Node 2 response "bacon" is a conditional response, a response conditional on "not oatmeal"

Trees can represent the response structure one is interested in Only binary trees are considered (can be extended)

The conditional coding is the only one that does not induce dependency between the response options

Conditional coding

option 1	0 -	option 1	0 0 -
option 2	1 0	option 2	0 1 -
option 3	1 1	option 3	1 - 0
		option 4	1 - 1

missingness is MAR

Speaker instructs listener "Click on the small ... envelope"

N= 152 (listeners)
96 items in 3 conditions
112 time points
(intervals of 10 millisec
between 180 and 1300ms
following the onset

pipe	large envelope	dog
balloon	X	car
small envelope	house	small elephant

large dog pipe envelope balloon X car house

Node 1 = 0

Node 2 = NA

Speaker instructs listener "Click on the small ... envelope"

small small envelope elephant

Node 1 = 1 Node 2 = 0 or 1

Speaker instructs listener

"Click on the small ... envelope"

small elephant

Node 1 = 1

Node 2 = 0

Speaker instructs listener "Click on the small ... envelope"

small envelope

Node 1 = 1

Node 2 = 1

Conditions in experiment

- One contrast
- Two contrasts shared
- Two contrasts privileged

One contrast

N C L

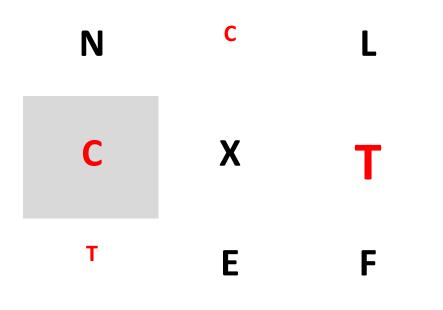
D X T

T E F "Click on the small ... T"

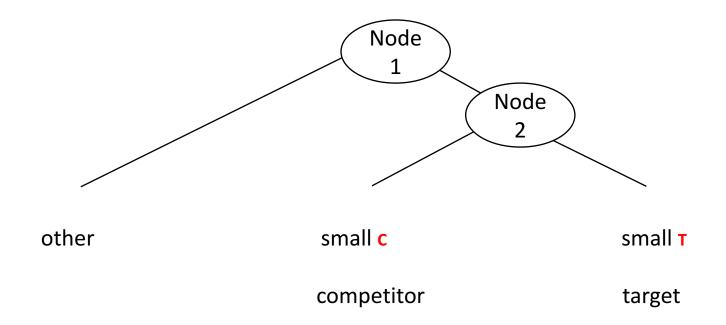
Two contrasts shared

N C L
C X T
T E F "Click on the small ... T"

Two contrasts privileged



"Click on the small ... T" listener is told that speaker does not see the large C



Coding of eye fixation on

		conditional response
	Node 1	Node 2
other	0	_
competitor	1	0
target	1	1

Main interest are the fixed effects of condition coding of conditions:

- one contrast (-1) vs two contrasts shared (0.5) & two contrasts privileged (0.5)
- one contrast (0) and two con (-0.5) vs two con privileged (0.5)

Additional fixed effects

- trend
- autoregressive effects to avoid bias in main interest estimates and standard errors

Random effects for persons and items

Three important aspects

- Node specificity of effects
 Everything can be different between the nodes including multidimensionality across nodes
- 2. Nodes combined with random effects issue of selecting random effects
- 3. Nodes combined with time series two parallel series: *Node 1* and *Node 2* missing observations for *Node 2*

1. Node specificity of effects

- Stronger positive trend for Node 2?
- Multidimensionality: a different dimension per node?
- Do condition effects depend on the node?

- Stronger positive trend for Node 2? YES
- Multidimensionality: a different dimension per node? YES, but ...
- Do condition effects depend on the node? YES

- Upward trend is steeper for within-category disambiguation than for category identification 0.031 vs 0.005
- Node 2 is a different ability compared with Node 1 r = 0.414

Condition effects

Preliminary on semantics and pragmatics

Two effects based on *semantics*

- commonality
- contrast

One effect based on *pragmatics*

 knowing the conversation context and given perspective taking The two-contrasts conditions favor Node 1

T C

T

"small" is a

<u>common contrast</u>

feature of the two bottom

letters

	Node 1	Node 2
two vs one two priv vs shared	0.074 (0.014) -0.006 (0.021)	-0.370 (0.035) 0.066 (0.048)

The *one-contrast condition* favors Node 2

T

"small" is a unique contrast feature of the left bottom letter

T

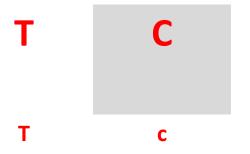
Node 1

Node 2

two vs one two priv vs shared $0.074 (0.014) \leftrightarrow -0.370 (0.035)$

-0.006 (0.021) 0.066 (0.048)

The privileged two-contrast condition favors Node 2



"small" is a

common contrast
feature of two letters

but unique in the conversation
context if perspective taking

two vs one two priv vs shared Node 1 0.074 (0.014) -0.006 (0.021) Node 2

-0.370 (0.035)

0.066 (0.048)

remember

2. Nodes combined with random effects

Even more random effects

Random effect selection issues: power, bias

- Minimal approach plus forward strategy
- Maximal approach plus backward strategy
- Structured search
- Sensitivity analysis focused on effects of interest

- Step 1: are nodes multidimensional?
- Step 2: if they are, then investigate model fit for random AR for persons, items, persons & items per node
- Step 3: test effects of interest with different choices for random effects

3. Nodes combined with time series

Autoregression and cross-lagged relationships for

- two time series
- missingness in the second time series

two times two series

Nodes 1 and 2

 X_1 : binary variable for N1 response $X_1 = 1$ if T or C fixation (Node 1), 0 otherwise

 X_2 : binary variable for conditional response (Node 2) $X_2 = 1$ if T fixation, 0 if C fixation, missing if other

 X_T : binary variable for target fixation, $X_T = 1$ for T fixation, 0 otherwise X_C : binary variable for competitor fixation,

 $X_C = 1$ for C fixation, 0 otherwise

 X_T 0 1 0 0 1 0 1 1 0 0 0 X_C 0 0 0 0 0 1 0 1 1 1 0 1 X_{N1} 0 1 0 0 1 1 1 1 1 1 1 1 1 1 X_{N2} - 1 - - 1 0 1 1 0 - 0

dynamic modeling which captures same information as AR1 and cross-lagged dependencies:

 $AR1_{T\to N1(t)}$: regression of $X_{N1(t-1)}$ on $X_{T(t-1)}$

 $AR1_{C \to N1 (t)}$: regression of $X_{N1(t-1)}$ on $X_{C(t-1)}$

 $AR1_{T\to N2 (t)}$: regression of $X_{N2(t-1)}$ on $X_{T(t-1)}$

 $AR1_{C \to N2 (t)}$: regression of $X_{N2(t-1)}$ on $X_{C(t-1)}$

Fixed effects

 $AR1_{T \rightarrow N1 (t)} \qquad 4.347$

 $AR1_{C \rightarrow N1 (t)} \qquad 4.024$

 $AR1_{T \rightarrow N2 (t)} \qquad 2.648$

 $AR1_{C \rightarrow N2 (t)} -2.629$

Random effects

 $AR1_{T\rightarrow N1 (t)} \qquad 0.114$

 $AR1_{C \to N1 (t)}$ 0.340

 $AR1_{T\to N2 (t)}$ 0.140 0.004 0.131

 $AR1_{C \to N2 (t)}$ -0.464 -0.515 <u>0.788</u> **0.247**

Afterthoughts

- A case study of complex modeling of complex data
- A conditional response approach can be helpful to extract information/effects one wants to focus on controlling for less relevant effects in the the background
- Remember the effect of two contrast privileged vs two contrast shared on Node 2 effect
 - Suppose there are individual difference in the effect (random person effects) ?
 - -- they would reflect a perspective taking ability



Complex can still be beautiful