Individual Differences in Causal Learning

Laila Johnston[1,3], Noah Hillman[2,3], David Danks[3,5]

[1] Department of Mathematics, UCF; [2] Department of Mathematics, Statistics, and Computer Science, St. Olaf College; [3] Center for the Neural Basis of Cognition, CMU; [4] Department of Psychology, CMU

ST. OLAF COLLEGE

CNBC CENTER FOR THE NEURAL BASIS OF COGNITION

Carnegie Mellon University

UCF Academic Advancement Programs UNIVERSITY OF CENTRAL FLORIDA

ACADEMIC ADVANCEMENT PROGRAMS McNAIR

Introduction

- **Goal:** Investigate how certain causal learning models could best describe the ways in which individuals make causal inferences

Data

Two experimental datasets from Danks & Schwartz (2005, 2006) were analyzed:

- Participants were presented with a sequence of binary cause-effect cases
- After each case, the participant estimates the strength of the relationship between the cause and effect on a scale from -100 to 100
- Sequences are non-stationary: at the halfway point in each trial, the causal relationship switches direction

Procedure

Generate Predictions

A grid search was employed to generate predictions for reasonable sets of parameter values for each model

Calculate SSE

For each participant in each condition, the sum of squared errors between the participant data and the model predictions was found

Find Best Fit Model

The causal learning model with the set of parameters that generated the lowest SSE is declared the model of best fit for that participant in that condition

Causal Learning Models

Existing Models

Augmented Rescorla-Wagner

$$\Delta V_i = \alpha_{i\gamma(C_i)}\beta_{\delta(E)}\left(\lambda\delta(E) - \textstyle\sum_{\delta(C_j)} V_j\right)$$

Proportion of Confirming Instances (PCI)

$$\Delta V_j^{i+1} = \beta((-1)^{|\delta(E)-\delta(C_j)|}\lambda - V_j^i)$$

Catena Belief Adjustment

$$J_i = J_{i-1} + \gamma(PCI - J_{i-1})$$

Causal Support

$$\text{support} = \log\left(\frac{P(D|\text{Graph }1)}{P(D|\text{Graph }0)}\right)$$

Power PC

$$\Delta V_i = \alpha_{i\gamma(i)}\beta_{\delta(E)}(\lambda\delta(E) - \textstyle\prod_{\delta(V_k)=1}(1-V_k)[1-\prod_{\delta(V_j)=1}(1-V_j)])$$

Sequential Bayesian Theory

$$P(\vec{w}_{t+1}|D_t,m) = \int P(\vec{w}_{t+1}|\vec{w}_t)P(\vec{w}_t|D_t,m)d\vec{w}_t$$

$$P(\vec{w}_{t+1}|D_{t+1},m) = \frac{P(D_{t+1}|\vec{w}_{t+1},m)*P(\vec{w}_{t+1}|D_t,m)}{P(D_{t+1}|D_t)}$$

Conditional Probabilistic Contrast

$$\Delta P_i = P(E|i\cap Q) - P(E|\neg i\cap Q)$$

Novel Models

Bayesian Correlation Optimization

$$Pr(\rho|W) = \frac{Pr(W|\rho)Pr(\rho)}{Pr(W)} \text{ where } W = X_1 + X_2$$

Moving k-Window

$$V = \tfrac{1}{k}(N(C,E) + N(\neg C,\neg E)) - \tfrac{1}{k}(N(\neg C,E) + N(C,\neg E))$$

Win-Stay, Lose Shift

$$V_{i+1} = \begin{cases} V_i + \frac{1-V_i}{2} & V_i \geq 0, \delta(E) = \delta(C) \\ -.5 & V_i \geq 0, \delta(E) \neq \delta(C) \\ V_i - \frac{1+V_i}{2} & V_i < 0, \delta(E) \neq \delta(C) \\ .5 & V_i < 0, \delta(E) = \delta(C) \end{cases}$$

Rescorla-Wagner with decay

$$\Delta V_i = \mu\alpha_{i\gamma(C_i)}\beta_{\delta(E)}(\lambda\delta(E) - \textstyle\sum_{\delta(C_j)} V_j)$$

where $\mu = e^{-\gamma n}$

Rescorla-Wagner with stability of beliefs

$$\Delta V_i = \mu\alpha_{i\gamma(C_i)}\beta_{\delta(E)}(\lambda\delta(E) - \textstyle\sum_{\delta(C_j)} V_j)$$

where $\mu = \max(\gamma\sigma, \frac{1}{\sqrt{n}})$

Power PC with decay

$$\Delta V_i = \mu\alpha_{i\gamma(C_i)}\beta_{\delta(E)}(\lambda\delta(E) - \textstyle\prod_{\delta(C_k)=1}(1-V_k)[1-\prod_{\delta(C_j)}(1-V_j)])$$

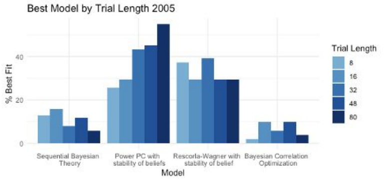
where $\mu = e^{-\gamma * n}$

Power PC with stability of beliefs

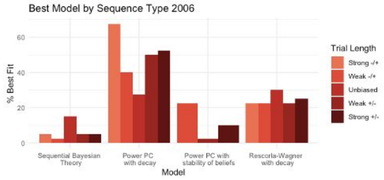
$$\Delta V_i = \mu\alpha_{i\gamma(C_i)}\beta_{\delta(E)}(\lambda\delta(E) - \textstyle\prod_{\delta(C_k)=1}(1-V_k)[1-\prod_{\delta(C_j)}(1-V_j)])$$

where $\mu = max(\gamma * \sigma, \frac{1}{\sqrt{n}})$

Results

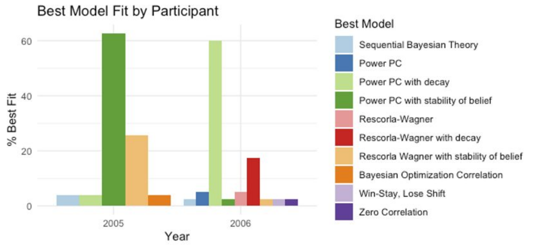


Left: Best-fitting models by trial length (2005)



Right: Best-fitting models by sequence type (2006)

Below: Distribution of best fit models



Conclusions

- No model was found to be of universal fit; this may be because theories of average causal learning behavior are simply not good theories of any particular individual's causal learning behavior
- The **Rescorla-Wagner** models and **Power PC** models (modified to increase stability of long-run judgments) seemed to be the best fit overall