EXPLANATIONS IN THE FORM OF CAUSAL SELECTION JUDGEMENTS ASSIST WITH ABDUCTION OF COMPLEX CAUSAL STRUCTURES.

Nicolas Navarre[1], Can Konuk[2], Salvador Mascarenhas[2]

[1]School of Informatics, School of Philosophy, Psychology and Language Sciences, University of Edinburgh, Scotland, United Kingdom
[2]Ecole Normale Supérieure, Department of Cognitive Studies, Institut Jean-Nicod, ENS, EHESS, PSL University, CNRS, Paris France.

Summary

- Causal selection is a robust psychological phenomenon when giving causal explanations.
- State-of-the-art theories of causal selection model it through a process of counterfactual sampling.
- Existing accounts of inference from causal selection judgements do not consider complex causal structures.
- Explanations of any cause are not effective for abduction of causal structures unless they are coherent with the causal selection judgement.

Causal selection

- Humans have robust intuitions about which of the causally active variables were the real or the main causes.
- This psychological phenomenon is known as **causal selection**.
- Current computational theories of causal selection understand it as the result of a process of **counterfactual sampling**, where variables are sampled depending on their normality.
- Causal selection judgements are based on the **normality** of the active causal variables the **causal structure** relating the events to the outcome.

Examples

- **(A) Abnormal inflation:** *A forest catches fire after a storm in the dry season.*
  - **a. The forest caught fire because of the lightning bolt.**
  - b. The forest caught fire because of the dry weather.
  - c. The forest caught fire because there was oxygen in the air.
- **(B) Normal inflation:** *To get to medical school, Susan needs to pass at least one of two exams: Anatomy (a very easy exam) and Physiology (very hard). On the day of the results, she learns she passed both (Icard et al., 2017).*
  - a. She entered medical school because of Physiology.
  - **b. Susan entered medical school because of Anatomy.**

The experiment

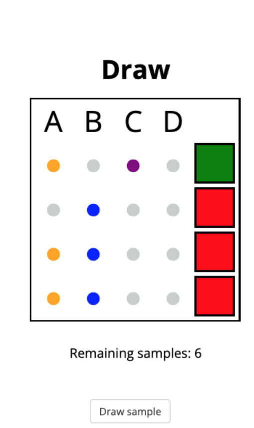

Figure 1: Screenshot from the experiment. Observations with no explanation.

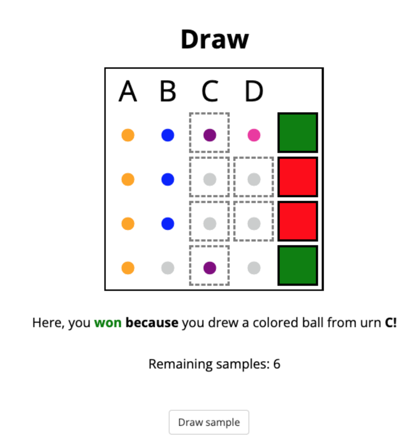

Figure 2: Screenshot from the experiment. Observations with causal selection judgements explanations.

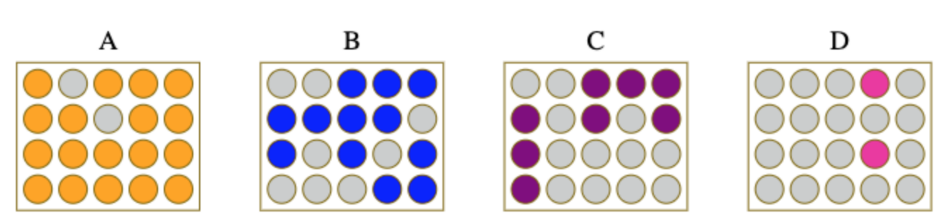

Figure 3: Urns from the experiment from which items were sampled. Normality of each urn is given by the proportion of coloured and uncoloured balls.

Causal structure

$$O \leftarrow (A \wedge D) \vee C \qquad (1)$$

- The boolean rule dictates the outcome of drawing balls from each of the urns.
  - Win (green)
  - Lose (red)
- The rule depends on whether the ball drawn from each urn is either coloured or uncoloured.
- The rule is complex as it combines both a disjunctive and conjunctive structure.

Design

- We present four urns, each with different proportions of coloured and uncoloured balls.
- A draw consists of taking a ball from each of the urns.
- Each draw is determined by a hidden boolean rule (1) where the outcome is presented as a green (win) or red (lose) square.
- Participants draw from the urns 10 times (with replacement), observing the outcome of each draw.
- Draws are controlled to ensure every participant sees the same draws.
- Three conditions:
  1. No causal explanation.
  2. Explanation given by **any** cause.
  3. Explanation given by **the** cause.
- Participants' understanding of the rule is tested by asking them to predict the outcome of all (16) possible draws from the four urns.

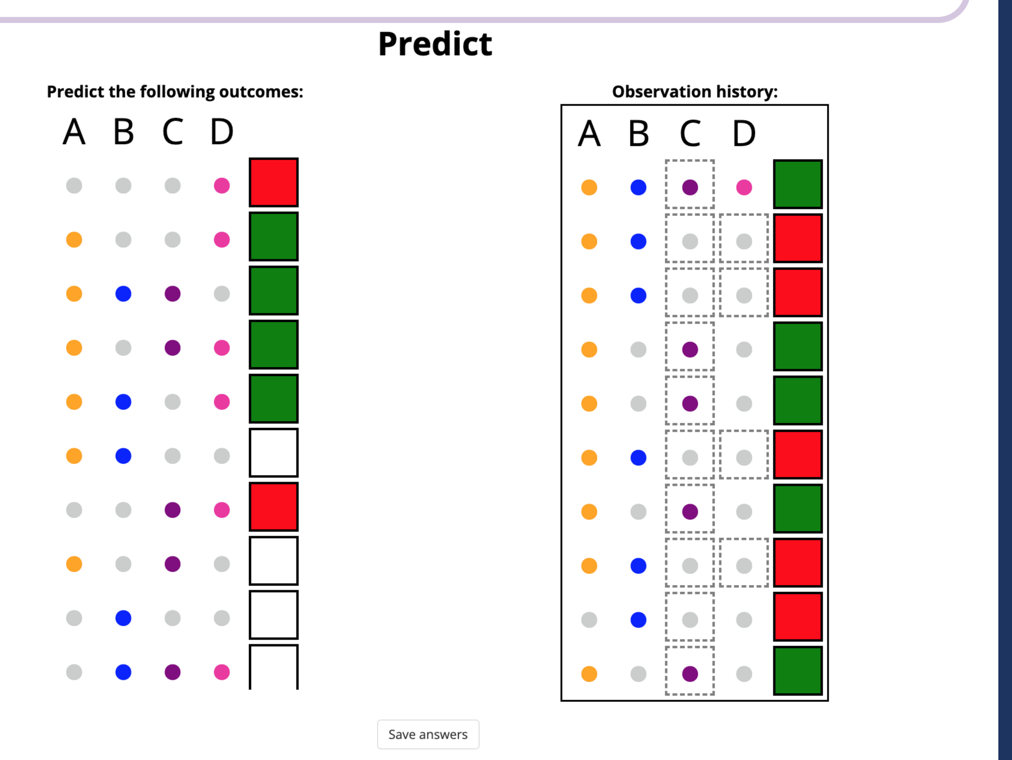

Figure 4: Screenshot of the prediction stage. Participants fill in the blank outcomes with either green of red outcomes. Previously seen observations and outcomes from the sampling phase are shown to participants on the right.

Results

Predictions and results

Predictions:

- Participants will come closer to inferring the right causal structure when they get causal explanations of some form or another.
- Causal selection judgements may be equally or more informative than any other causal explanation.

Results:

- Causal selection explanations significantly increased prediction accuracy from no explanations.
- Causal explanations of any other causally active component significantly decreased the prediction accuracy from no explanation.
- Explanations in general made participants much more certain in inferring a rule.
- Inferred rules are representative of the process of abductive inference given different pieces of evidence (observation and explanation).

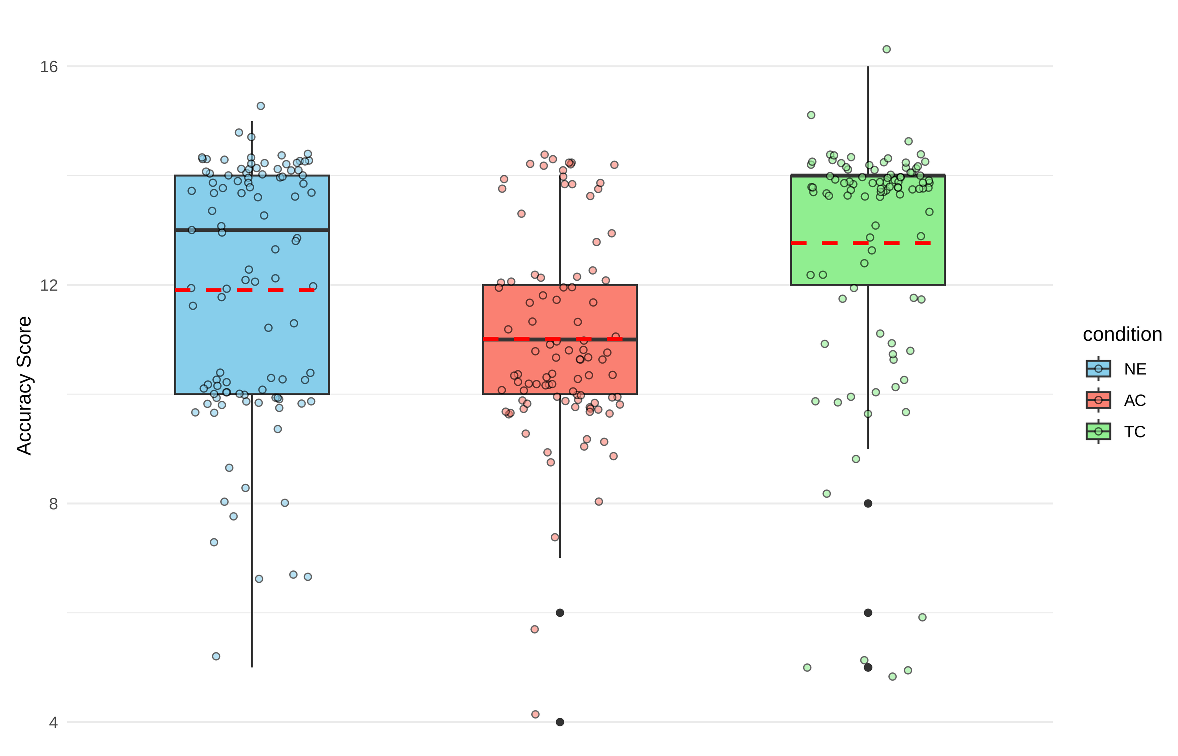

Figure 5: Total accuracy of outcome predictions in the three conditions (N=298): No explanation (NE), any cause (AC), and the cause (TC) which corresponds to the causal selection.

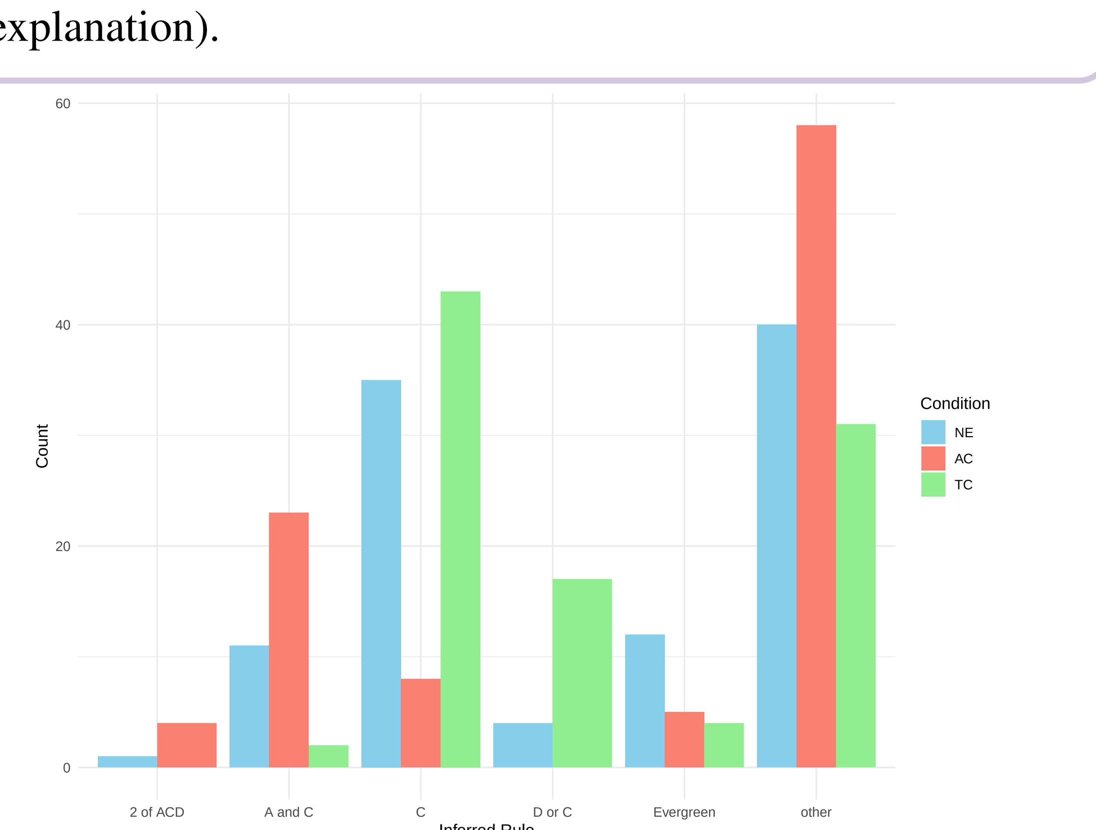

Figure 6: Most common inferred rules across conditions. "Evergreen" is a prediction strategy where all predictions were marked green.

Table 1: Statistical analysis of the prediction accuracy as a function of the condition and participant random effects.
Mixed-Effects model: `Accuracy ~ 1 + Condition + (1| Participant)`

Fixed Effects	Estimate	Standard Error	p-value
Intercept (NE)	1.11562	0.07304	$< 2e{-}16$
AC	-0.29284	0.10178	0.00401
TC	0.31959	0.10707	0.00284

Random Effects	Variance	Std. Deviation
Participant	0.1972	0.4441

Future directions

Open questions

- What model prediction can we generate about the inference if we make use of a semantics of "**because**"?
- What kinds of inferences would we observe in other complex rules?
- How effective are causal explanations when two agents are both uncertain about the causal structure?

Future projects

- Introducing interventions into the causal inference task, allowing cor all forms of causal inference from (observation, intervention and explanation).
- Multiple agent inference by exchange of explanations.

Selected references and acknowledgments

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Try it yourself!

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