Inferences from Causal Selection Explanation

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Explanations

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[1] Lombrozo (2012)

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- Product vs. process explanations

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  1. Billy ate the carrot cake because it is his favourite.

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  1. Billy ate the carrot cake because it is his favourite.
  2. Billy ate the carrot cake because it is his favourite *and* he was hungry.

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Causal Explanations

[2] Halpern (2016)

Causal Explanations

Actual Causation (*a cause*): Explanations that describe what causes were causally responsible for an outcome are typically referred to as actual causation[2].

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Causal Explanations

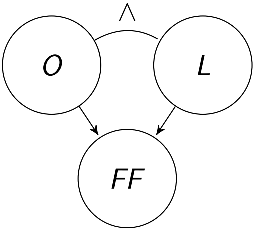
Actual Causation (*a cause*): Explanations that describe what causes were causally responsible for an outcome are typically referred to as actual causation[2].

Causal Selection (*the cause*): Selecting one set of causal variables that are considered the cause of an outcome. Depends on **counterfactual simulations** and on the **normality** of the variables.

[2] Halpern (2016)

Causal Example

Conjunction



Lightning strikes a forest (L) *and* with the oxygen in the air (O) a forest fire erupts (FF).

Causal Example

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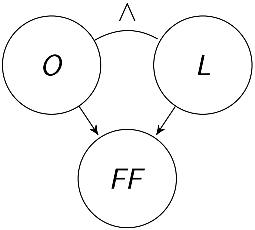
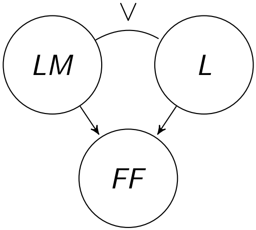


Lightning strikes a forest (L) *and* with the oxygen in the air (O) a forest fire erupts (FF).

If the lightning strikes the forest and oxygen is present in the atmosphere, **which one caused the forest fire?**

Causal Example

Disjunction



A forest fire may be caused by *either* a lightning strike (L) or an arsonist dropping a lit match (LM).

Causal Example

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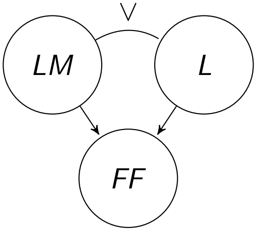

A forest fire may be caused by *either* a lightning strike (L) or an arsonist dropping a lit match (LM).
If the lightning strikes the forest and the arsonist drops the lit match, **which one caused the forest fire?**

Theories of Casual Selection

[3] Icard et al. (2017)
[4] Quillien and Lucas (2023)

Theories of Casual Selection

- Necessity and Sufficiency Model[3] (NSM)

$$\kappa_P(\vec{X}, Y) = P(\vec{X} = \vec{x}')P^{\nu}_{\vec{X} \leftarrow \vec{x}'}(Y \neq y) + P(\vec{X} = \vec{x}^*)P^{\sigma}_{Y \neq y, \vec{X} = \vec{x}', \vec{X} \leftarrow \vec{x}^*}(Y = y)$$

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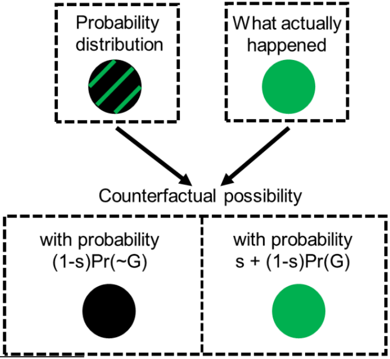
- Counterfactual Effect Size Model[4] (CESM)



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Causal Inference from Explanation

Previous Study

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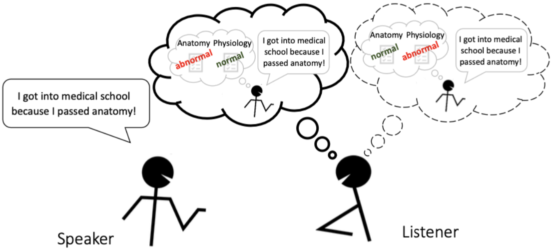

Causal Inference from Explanation

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Particularly that conjunctive and disjunctive causal structures can be disambiguated:

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Kirfel et al. (2022) demonstrate a three way interaction between the following properties:

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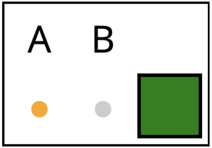
Two questions remain:

1. Do causal selection judgements help with complex causal inference?
2. Do effective causal selection judgements depend on normality?

Design

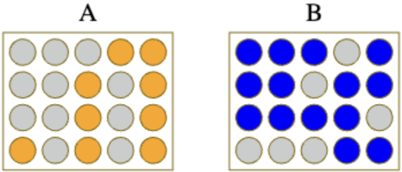
Observation Example



Push the button below to draw a new sample!

Remaining samples: 2

Draw sample



Design
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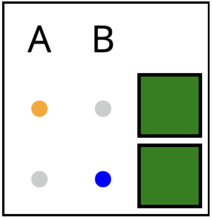
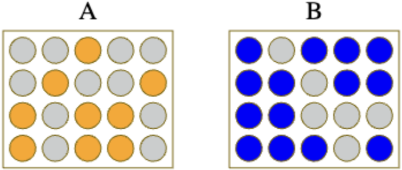


Push the button below to draw a new sample!

Remaining samples: 1

Draw sample



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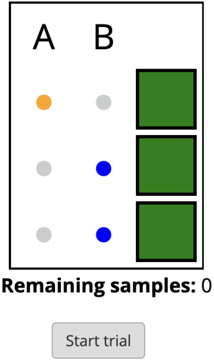

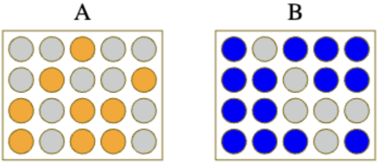

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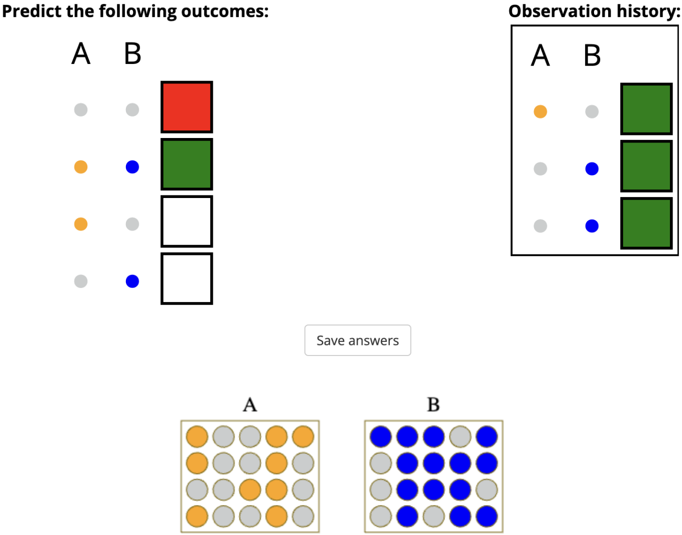

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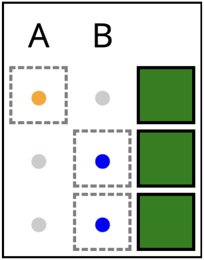
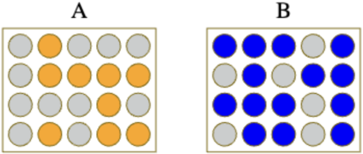
Explanation Example



Push the button below to continue

Next



Design

Explanations and Causal Structure

Three conditions for the kind of explanation:

- Causal inference from observations with no causal explanation (NE).
- Causal inference from observations with explanations of *a* cause (AC).
- Causal inference from observations with explanations of *the* cause (TC).

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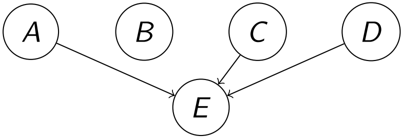
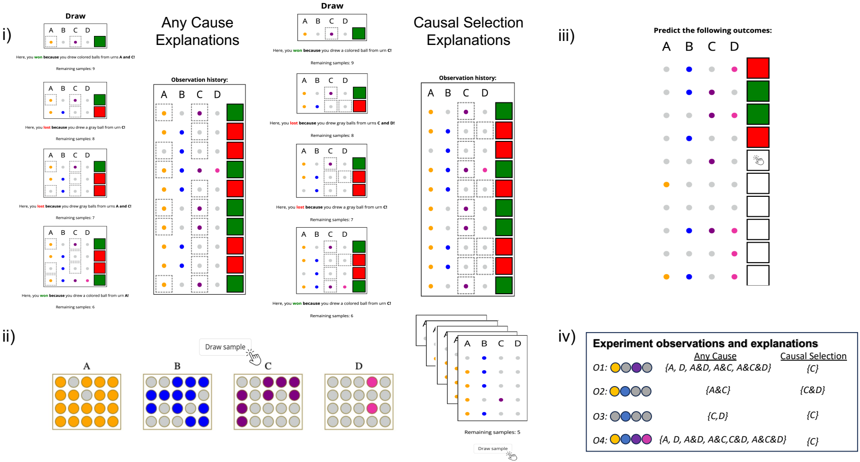
$$(A \wedge D) \vee C \tag{1}$$



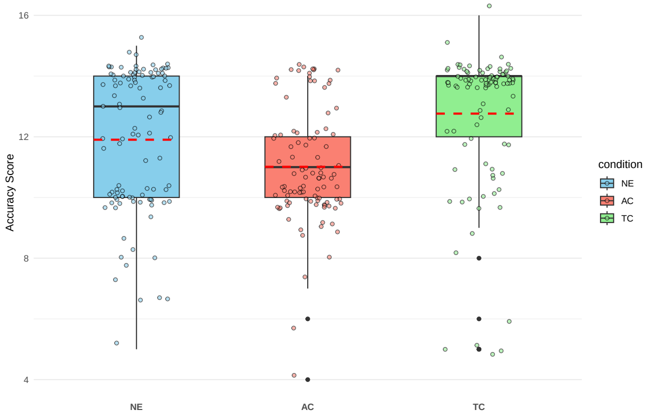
Design

Stimulus

Demo (NE) Demo (AC) Demo (TC)



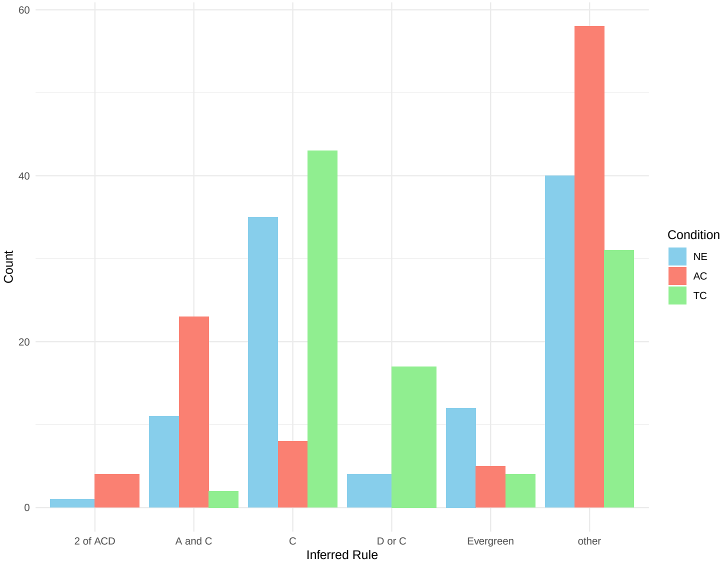
Results



Participants (N=298) in the TC condition were significantly better at accurately predicting world outcomes than those in the NE condition ($p < 0.005$). Participants in the AC condition were significantly worse at predicting the world outcomes than those in the NE condition ($p < 0.003$).

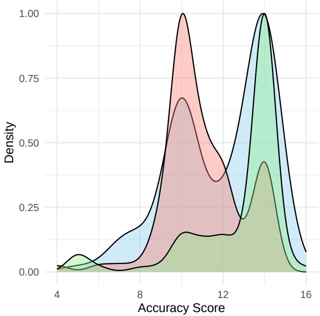
Results

Rules inferred

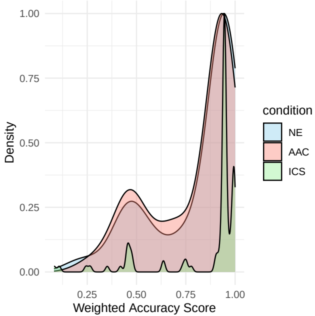


Results

Normality in inference accuracy



(a) Accuracy score distribution by condition.



(b) Weighted accuracy score by condition

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Thank you!

Bibliography

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Inference from Causal Explanation

Possible Worlds

Table

A	B	C	D	Times Seen in Observation	Probability ($*10^{-4}$)
0	0	0	0	0	216
0	0	0	1	0	24
0	0	1	0	0	144
0	0	1	1	0	16
0	1	0	0	1	324
0	1	0	1	0	36
0	1	1	0	0	216
0	1	1	1	0	24
1	0	0	0	0	1944
1	0	0	1	0	216
1	0	1	0	4	1296
1	0	1	1	0	144
1	1	0	0	4	2916
1	1	0	1	0	324
1	1	1	0	0	1944
1	1	1	1	1	216

Table: List of all possible worlds and their prior probabilities.

Causal Inference from Explanation

Causal Selections

A	B	C	D	Actual causes	Causal Selection
0	1	0	0	[A], [D], [A,D], [A,C], [A,C,D]	[C]
1	0	1	0	[A,C]	[C]
1	1	0	0	[C], [D]	[C,D]
1	1	1	1	[A], [D], [A,C], [A,D], [D,C] [A,C,D]	[C]

Table: List of actual causes for each sample, as well as the intuitive causal selection given the normality of variables A,B,C,and D.

HP-Definition of Actual Cause

Definition (HP Actual Cause)

$\vec{X} = \vec{x}$ is an actual cause of φ in the causal setting $\langle \mathcal{M}, \vec{u} \rangle$ if the following three conditions hold:

1. $\langle \mathcal{M}, \vec{u} \rangle \models (\vec{X} = \vec{x})$ and $\langle \mathcal{M}, \vec{u} \rangle \models \varphi$.
2. There is a set $\vec{W}$ of variables in $(\mathbf{V} \cup \mathbf{U}) \backslash \vec{X}$ and a setting $\vec{x}'$ of the variables in $\vec{X}$ such that if $\langle \mathcal{M}, \vec{u} \rangle \models \vec{W} = \vec{w}^*$, then $\langle \mathcal{M}, \vec{u} \rangle \models [\vec{X} \leftarrow \vec{x}', \vec{W} \leftarrow \vec{w}^*](\neg\varphi)$.
3. $\vec{X}$ is minimal; there is no strict subset $\vec{X}'$ of $\vec{X}$ such that $\vec{X}' = \vec{x}'$ satisfies conditions 1. and 2., where $\vec{x}'$ is the restriction of $\vec{x}'$ to variables in $\vec{X}'$.

The superscript in $\vec{w}^*$ represents that $\vec{w}$ should take on the actual value of $\vec{W}$. The prime in $\vec{x}'$ represents $\vec{x}$ should be something other than the actual world value of $\vec{X}$. Lastly, if $\vec{X}$ is an actual cause of φ, then every part of $\vec{X}$ is also an actual cause of φ.

Structural Causal Model

A Structural Causal Model (SCM) is typically a tuple of the form $\mathcal{M} = \langle \mathbf{U}, \mathbf{V}, \mathcal{F}, \mathbf{P} \rangle$[5].

1. A set of exogenous variables denoted by $\mathbf{U} = \{U_1, U_2, \ldots, U_n\}$.
2. A set of endogenous variables denoted by $\mathbf{V} = \{V_1, V_2, \ldots, V_m\}$.
3. A set of structural equations denoted by $\mathbf{F} = \{F_1, F_2, \ldots, F_n\}$, where each equation relates an endogenous variable to a function involving other endogenous variables and exogenous variables.
4. A set of probability distributions denoted by $\mathbf{P} = \{P_1, P_2, \ldots, P_n\}$, where each probability distribution corresponds to one of the exogenous variables.

[5] Bareinboim et al. (2022)