

# A REPRESENTATION THEOREM FOR CAUSAL DECISION MAKING

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## This talk

We provide a definition of **causal sophistication**:

- ◇ When are preferences over *interventions* consistent with a subjective causal model?
- ◇ We represent causality via *structural equations*
- ◇ In the paper, we provide:
  - ◇ An axiomatic characterization
  - ◇ An identification Theorem

## Causation and Counterfactuals

- ◇ Modern theories define causation through counterfactuals.
  - ◇ Requires evaluating worlds that do not exist
- ◇ We take a structural approach a la Pearl [2000]:
  - ◇ Equations directly encode causal mechanisms
  - ◇ Provide a succinct way of contemplating counterfactuals

## Variables

- ◇  $\mathcal{U}$  and  $\mathcal{V}$  denote **exogenous** and **endogenous** variables, resp.
- ◇  $\mathcal{R}(Z) \subset \mathbb{R}$  is the range of  $Z \in \mathcal{U} \cup \mathcal{V}$
- ◇ A **context** is a vector  $\vec{u}$  of values for all the exogenous variables  $\mathcal{U}$ .
  - ◇ Let  $\text{ctx} = \prod_{U \in \mathcal{U}} \mathcal{R}(U)$  collect all contexts
- ◇ A **resolution** is a vector  $\vec{r}$  of values for all variables  $\mathcal{U} \cup \mathcal{V}$ .
  - ◇ Let  $\text{res} = \prod_{Y \in \mathcal{U} \cup \mathcal{V}} \mathcal{R}(Y)$  collect all resolutions

The decision maker cares about the resolution and is uncertain about the context:

- ◇ Utility will be defined over **res**
- ◇ Beliefs will be defined over **ctx**

## Example

The US Federal Reserve is contemplating the economy.

The relevant variables are: the growth rate (gw), the prior interest rate (pr), the current interest rate (rate), inflation (inf), employment rate (emp):

$$\mathcal{U} = \begin{cases} U_{gw} \\ U_{pr} \end{cases} \quad \mathcal{V} = \begin{cases} Y_{rt} \\ X_{emp} \\ X_{inf} \end{cases}$$

## Example

- ◇ Utility is determined by the inflation rate and employment level:

- ◇  $u(\vec{r}) = 2X_{emp} - X_{inf}$ .

- ◇ Does not know the growth rate:

- ◇ believes  $U_{gw} = 1$  with prob  $\alpha$  and  $U_{gw} = 0$  with prob  $(1 - \alpha)$ .

- ◇ Contemplate interventions that set the interest rate:

- ◇ This will casually effect the resolution
  - ◇ But exactly how might depend on the context

## Causal Models

Given  $\mathcal{U}$  and  $\mathcal{V}$  with ranges  $\mathcal{R}$ , a **causal model**  $\mathbf{M}$  consists of:

- ◇  $\mathcal{F} = \{F_X\}_{X \in \mathcal{V}}$ , a set of **structural equations**, where

$$F_X: \prod_{Y \in \mathcal{U} \cup (\mathcal{V} - \{X\})} \mathcal{R}(Y) \rightarrow \mathcal{R}(X).$$

- ◇ Call  $\mathbf{M}$  *recursive* if there exists a partial order on  $\mathcal{V}$ :
  - ◇  $F_X$  is independent of the variables succeeding  $X$



## Example

The causal equations are

$$Y_{rt} = U_{pr}$$

$$(F_{Y_{rt}})$$

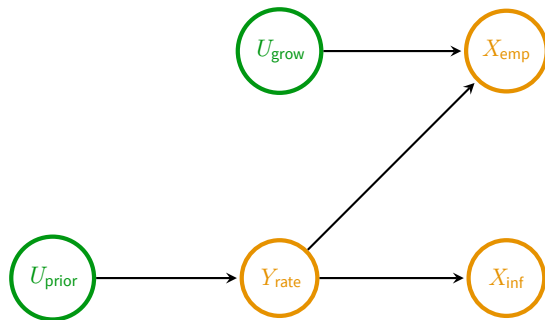
$$X_{inf} = 1 - Y_{rt}$$

$$(F_{X_{inf}})$$

$$X_{emp} = 1 - (Y_{rt} \times (1 - U_{gw}))$$

$$(F_{X_{inf}})$$

## Example



## Example

Given a recursive  $\mathbf{M}$ , each context  $\vec{u}$  induces a unique resolution  $\vec{r}$ :

$$U_{gw} = 0$$

$$U_{pr} = 0$$

$$Y_{rt} = U_{pr}$$

$$X_{inf} = 1 - Y_{rt}$$

$$X_{emp} = 1 - (Y_{rt} \times (1 - U_{gw}))$$

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$$U_{gw} = 0$$

$$U_{pr} = 0$$

$$Y_{rt} = 0$$

$$X_{inf} = 1$$

$$X_{emp} = 0$$

- ◇ When is decision making consistent causal reasoning via some model **M**?
- ◇ What kind of data is needed to answer this?
- ◇ Preferences over **interventions**

# Interventions

## An intervention

$$\text{do}[Y_1 \leftarrow y_1, \dots, Y_n \leftarrow y_n]$$

is a mediation that sets the values of  $Y_1 \dots Y_n \in \mathcal{V}$ :

- ◇  $y_i \in \mathcal{R}(Y_i)$
- ◇ abbreviated as  $\text{do}[\vec{Y} \leftarrow \vec{y}]$
- ◇ interventions only on endogenous variables.



A **conditional intervention** is of the form:

**if  $\phi$  then  $A$  else  $B$**

- ◇  $\phi$  is a true/false valued question about the variable values
  - ◇ such as “the value of  $X$  is positive”, etc
- ◇  $A$  and  $B$  are conditional interventions
- ◇ These is constructed recursively starting with interventions
- ◇ **if  $\phi$  then  $A$**  shorthand for when  $B = \emptyset$

# Preference

Observable: preference relation  $\succsim$  over conditional interventions:

- ◇ Interventions allow the DM to change the resolution
- ◇ Conditioning allows contracting away uncertainty about context

A **causally sophisticated** decision maker would understand the effect of conditional interventions via a causal model

## Interventions and Causal models

Given the model  $\mathbf{M}$ , the intervention

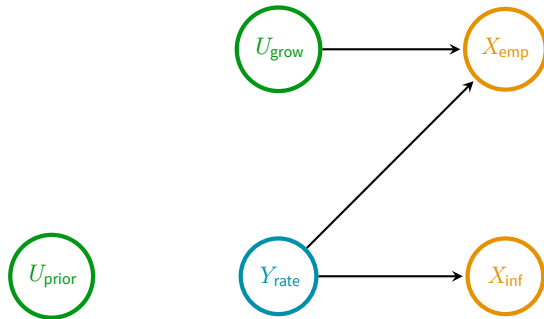
$$\text{do}[Y_1 \leftarrow y_1, \dots, Y_n \leftarrow y_n]$$

induces a *counterfactual model*,  $\mathcal{F}_{\text{do}[\vec{Y} \leftarrow \vec{y}]}$  where

$F_{Y_i}$  is replaced by the constant function  $F'_{Y_i} = y_i$

## Example

The intervention  $\text{do}[Y_{rt} \leftarrow 1]$  sets the current rate to 1:



## Example

$$U_{gw} = 0$$

$$U_{pr} = 0$$

$$Y_{rt} = 1$$

$$X_{inf} = 1 - Y_{rt}$$

$$X_{emp} = 1 - (Y_{rt} \times (1 - U_{gw}))$$

## Example

$$U_{gw} = 0$$

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## Example

$$U_{gw} = 0$$

$$U_{pr} = 0$$

$$Y_{rt} = 1$$

$$X_{inf} = 0$$

$$X_{emp} = 0$$



Given a (recursive) model **M** and conditional intervention *A*, let

$$\beta_A^M : \text{ctx} \rightarrow \text{res}$$

transform contexts into resolutions in the obvious way:

- ◇ **M** plus context determines ex-ante resolution
- ◇ This resolution determines the ‘clause’ of *A* in force, hence an intervention
- ◇ This intervention determines a (recursive) counterfactual model
- ◇ Along with context, this determines the ex-post resolution

# Representation

A causally sophisticated agent's preferences are parameterized by

- ◇  $\mathbf{M}$  — a recursive model capturing causal relationships
- ◇  $\mathbf{u} : \mathbf{res} \rightarrow \mathbb{R}$  — value of a resolution of all uncertainty
- ◇  $\mathbf{p} \in \Delta(\mathbf{ctx})$  — belief capturing uncertainty about the values of exogenous (hence endogenous) variables

# Representation

## Subjective Causal Utility

$(\mathbf{M}, \mathbf{p}, \mathbf{u})$  is a **subjective causal utility representation** of  $\succsim$ :

$$A \succsim B$$

if and only if

$$\sum_{\vec{u} \in \text{ctx}} \mathbf{u}(\beta_A^{\mathbf{M}}(\vec{u})) \mathbf{p}(\vec{u}) \geq \sum_{\vec{u} \in \text{ctx}} \mathbf{u}(\beta_B^{\mathbf{M}}(\vec{u})) \mathbf{p}(\vec{u}).$$

## Example

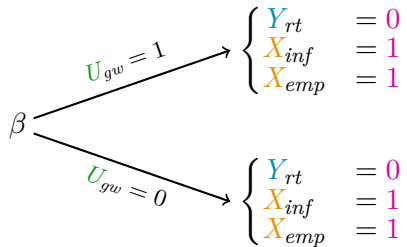
The utility of the Federal Reserve is determined by the inflation rate and employment level, and is given by

$$\mathbf{u}(\vec{r}) = 2X_{emp} - X_{inf}.$$

## Example

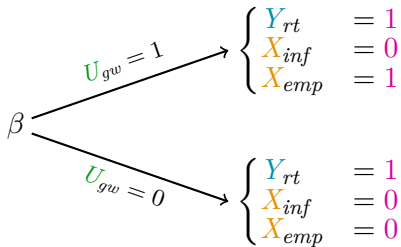
$\text{do}[Y_{rt} \leftarrow 0]$

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$\text{do}[Y_{rt} \leftarrow 1]$

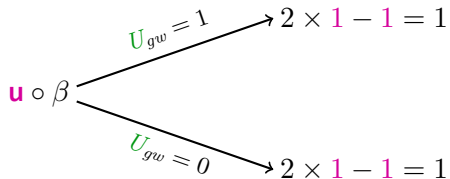
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## Example

$$\text{do}[Y_{rt} \leftarrow 0]$$

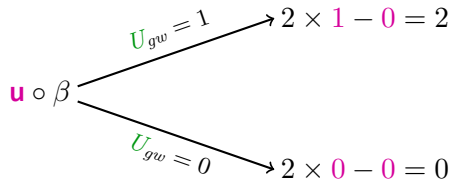
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Utility is 1

$$\text{do}[Y_{rt} \leftarrow 1]$$

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Utility is  $2\alpha$

## Example

- ◇ Preference between setting interest rate at 1 or 0 depends on belief about  $U_{gw}$ .
- ◇ The conditional intervention

**if** ( $U_{gw} = 1$ ) **then do** [ $Y_{rt} \leftarrow 1$ ] **else do** [ $Y_{rt} \leftarrow 0$ ]

dominates

From preference to causality:



For a resolution  $\vec{u} \in \text{ctx}$  let

if  $\vec{u}$  then  $A$  else  $B$

denote the conditional intervention on  $\vec{u}$  being true.

- ◇ i.e., do  $A$  if all variables coincide with  $\vec{u}$ , else do  $B$

Conditional on  $\vec{u}$ : if setting  $\vec{Y}$  to  $\vec{y}$  yields  $X = x$ , then the agent is indifferent from making such a further intervention on  $X$ :

$$\text{if } \vec{u} \text{ then do}[\vec{Y} \leftarrow \vec{y}, X \leftarrow x] \sim \text{if } \vec{u} \text{ then do}[\vec{Y} \leftarrow \vec{y}].$$

## Example

No Intervention

$$U_{gw} = 0$$

$$U_{pr} = 0$$

$$Y_{rt} = U_{pr}$$

$$X_{inf} = 1 - Y_{rt}$$

$$X_{emp} = 1 - (Y_{rt} \times (1 - U_{gw}))$$

**do** $[Y_{rt} \leftarrow 1]$

$$U_{gw} = 0$$

$$U_{pr} = 0$$

$$Y_{rt} = 1$$

$$X_{inf} = 1 - Y_{rt}$$

$$X_{emp} = 1 - (Y_{rt} \times (1 - U_{gw}))$$

**do** $[Y_{rt} \leftarrow 1, X_{emp} \leftarrow 0]$

$$U_{gw} = 0$$

$$U_{pr} = 0$$

$$Y_{rt} = 1$$

$$X_{inf} = 1 - Y_{rt}$$

$$X_{emp} = 0$$

## Example

No Intervention

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No Intervention

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$$\text{do}[Y_{rt} \leftarrow 1, X_{emp} \leftarrow 0]$$

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No Intervention

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$$X_{emp} = 1$$

$$\text{do}[Y_{rt} \leftarrow 1]$$

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$$X_{inf} = 0$$

$$X_{emp} = 0$$

$$\text{do}[Y_{rt} \leftarrow 1, X_{emp} \leftarrow 0]$$

$$U_{gw} = 0$$

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$$Y_{rt} = 1$$

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**Thank You!**