Causality: A Decision Theoretic Foundation

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Overview

- Savage (1972) derives probability beliefs from preferences
- Similarly, this paper derives causality beliefs from preferences
 - ► Introduce the framework
 - ▶ Agent behavior *as if* the relation between two variables is causal
 - Axioms on preferences and representation
 - Existence and uniqueness of a DAG [directed acyclic graph]

Motivating Example

- Consider a random US citizen with college degree: would you guess she earns more or less than \$50K a year?
- 2. Consider a random US citizen **without** college degree: would you guess she earns more or less than \$50K a year?
- 3. Would you encourage the US government to make college education compulsory?
- Correlation does not mean causation

Introduction: Subjective Causation

- Consider the relation between Ability, Education, and Income
- Savage: we can reveal subjective probability beliefs
 - Consider again a randomly drawn citizen with high school/college degree
 - Accept a safe bet (\$0 for sure) or a risky bet (+\$1 if income>\$50K, -\$1 otherwise)
 - Possible pattern: accept the risky bet conditional on college degree, accept the safe bet conditional on high school degree [correlation]
- Schenone: we can also reveal subjective causality beliefs
 - Accept a safe bet (\$0 for sure) or a risky "policy+bet" (college education becomes compulsory, +\$1 if income>\$50K, -\$1 otherwise)
 - Possible pattern: accept the risky bet conditional on college degree, accept the safe bet in the policy case [no causation]

Introduction: Subjective Causation

- Definition of causation: a variable subjectively causes another variable if, holding all other variables constant, policy interventions on the first variable affects subjective beliefs about the second
- We may believe that education policies are useless to affect income (holding fixed intellectual ability), i.e. believe that education levels do not cause income levels
- The definition includes correlation and policy recommendation
- ► This paper: foundation for selecting models with which empirical researchers can estimate causal effects

Preview of Results

- Decision problem similar to Savage's [set of states, set of acts mapping states into monetary amounts, the DM chooses among acts based on a preference relation]
- Additionally, we accommodate for the possibility of choosing policies that affect the states
- Axioms necessary and sufficient for a numerical representation of beliefs
- Bayesian networks as main tool to represent preferences
- ► Additional axiom to identify causal effects (useful for empirical applications) not discussed today [section 5]

Model (DAG - Notation)

- \triangleright Directed graph (V, E)
- ▶ V set of nodes and $E \subset V \times V$ set of edges
- A directed graph is acyclic [DAG] iff for all v ∈ V, v is not a descendant of v [i.e. there is no directed path from v to itself]
- ► *D*(*v*) and *ND*(*v*) are the sets of descendants and non-descendants of *v*
- ▶ Pa(v) is the set of parents of v: $Pa(v) = \{v' \in V : (v', v) \in E\}$

Model (Acts and Policies)

- ► State space $S = \prod_{i=1}^{N} X_i$, where each X_i is finite
- ▶ Each $i \in \mathcal{N}$ indicates a variable
- ► Set of Savage acts $A = \mathbb{R}^S$
- ▶ Preferences \succ over \mathcal{A}
- ► Set of intervention policies $\mathcal{P} = \prod_{i}^{N} (X_i \cup \{\emptyset\})$
- ▶ Policies with $p_i = \emptyset$ leave i unaffected
- ▶ Policies with $p_j = x_j \in X_j$ forces j value to be x_j
- Each policy implies a collection of interventions over states
- Precise definition: no "reduced spaces", yes "impossible policy"

Model (Preferences over Policies)

- ▶ Given a policy $p \in \mathcal{P}$:
- \triangleright $\mathcal{N}(p)$ is the set of variables that p leaves unaffected
- ▶ A(p) is the set of acts over variables that p leaves unaffected
- ▶ The primitive domain is the set $\{(p, a) : p \in \mathcal{P}, a \in \mathcal{A}\}$
- ► The DM has a preference relation > over the set above

Savage vs. Schenone (again)

- ➤ The preference relation is defined over pairs of policies and acts over unaffected variables
- ► Given $\bar{\succ}$, each p induces an intervention preference on A(p)
- ▶ $f, g \in A(p)$, we say $f \succ_p g \iff (p, f) \bar{\succ} (p, g)$
- In Savage model the DM chooses an act, and Nature select a value for the state
- ▶ In this model Nature is replaced by the DM active choice of *p*
- Savage conditional preferences correspond to a special case where $p = (\emptyset, ..., \emptyset)$

Causal Effect

- A variable j causes a variable i when policies that intervene j at different levels have a ceteris paribus effect on the DM beliefs about i
- ▶ If the choices of acts over *i* is insensitive to whether *j* was intervened, *j* does not cause *i*
- ► Based on this definition, subjective causation is a correlation that is sufficient for policy recommendations
- We separate direct and indirect effects by defining intervention independence
- ▶ Consider a set of variables K, and two variables $i, j \notin K$
- ▶ i is K-independent of j if, after eliminating mediation effect through K, the choice of acts over i is insensitive to interventions of j

\mathcal{K} -Independence (Formal definition)

▶ *i* is K-independent of *j* if the following holds for every f , g , x_j , x_j'

$$f \succ_{x_j, x_{\mathcal{K}}} g \iff f \succ_{x'_j, x_{\mathcal{K}}} g$$
$$f \succ_{x_j, x_{\mathcal{K}}} g \iff \mathbb{1}_{X_j} f \succ_{x_{\mathcal{K}}} \mathbb{1}_{X_j} g$$

- ▶ Line 1: conditional on K intervention, *intervening* on j has no effect on choices of acts
- ► Line 2: conditional on *K* intervention, the *ability* to intervene on *j* has no effect on choices
- The second line implies the first (so we use the second as formal definition)

Directed and Indirected Causality

- ▶ Variable j causes variable i if i is not $\{i, j\}^C$ -independent of j [complementary set of variables]
- Ca(i) is the causal set of i
- ▶ Variable j is an **indirect cause** of i if there is a sequence $j_0, ..., j_T$ such that for all t we have j_t causes j_{t+1} , with $j_0 = j$ and $j_T = i$
- ▶ Variable *i* is an **exogenous primitive** if $Ca(i) = \emptyset$
- Definition of causal graph
- ▶ Let $\bar{\succ}$ be a preference and $\{Ca(i): i \in \mathcal{N}\}$ be the collection of causal sets derived from it. Define $G(\bar{\succ}) = (V, E)$ with $V = \mathcal{N}$ and $E = \{(j, i): j \in Ca(i)\}$

Representation Theorem (Preview)

Theorem 1. Let $\bar{\succ}$ satisfy Axiom 1, and let μ_p be the intervention beliefs elicited from \succ_p . The following statements are equivalent:

- Axioms 2 and 3 hold
- ▶ Exists a unique G such that G is a DAG and G represents $\bar{\succ}$ in the following sense:
 - Unconditional beliefs are equal to the product of conditional beliefs (conditional on non-descendant variables)
 - ► The set of parents nodes is the smallest set with the above property
 - ▶ If *i* causes *j*, then $\mu_{x_{\{i,j\}}^C}(x_j) = \mu_{x_{\{i,j\}}^C}(x_j|x_i)$

Axioms

- **Axiom 1.** For each $\mathcal{J} \subset \mathcal{N}$ the followings are true
 - ► For each p, \succ_p satisfy Gul '95 axioms [completeness, transitivity, independence, monotonicity, continuity]
 - If $j \in Ca(i)$, then $f \succ_{x_{\{i,j\}^C}} g \iff \mathbb{1}_{x_j} f \succ_{x_{\{i,j\}^C}} \mathbb{1}_{x_j} g$
 - ▶ There are no null states: $\mathbb{1}_x \succ \mathbb{1}_X 0$ for all $x \in X$
 - ▶ Policies do not affect preferences (Bernoulli utility indexes)
- **Axiom 2.** For all $i \in \mathcal{N}$, i is not an indirect cause of i
- ▶ **Axiom 3.** $Ca(i) \subset \mathcal{I}$ iff the set $\mathcal{I} \subset \{i\}^C$ satisfies

$$\mathbb{1}_{x_{\mathcal{J}}}\mathbb{1}_{x_{\mathcal{T} \setminus \mathcal{K}}} f \succ_{x_{\mathcal{K}}} \mathbb{1}_{x_{\mathcal{J}}}\mathbb{1}_{x_{\mathcal{T} \setminus \mathcal{K}}} g \iff \mathbb{1}_{x_{\mathcal{T} \setminus \mathcal{K}}} f \succ_{x_{\mathcal{K}}} \mathbb{1}_{x_{\mathcal{T} \setminus \mathcal{K}}} g$$

Representation (DAG - 1)

- Definition of a DAG representing a probability distribution (from Lauritzen et al. 1990)
- ▶ Let $p \in \Delta(\Pi_i X_i)$. A DAG represents p iff

$$p(x) = \prod_{i} p(x_{i} | Pa(i))$$

$$p(x) = \prod_{i} p(x_{i} | \mathcal{T}_{i}) \Rightarrow \mathcal{T}_{i} = Pa(i) \quad \forall i \in \mathcal{N}$$

- ► Line 1: the DAG summarizes the conditional independence properties of *p*
- ► Line 2: the set of parents is the smallest possible set (minimality requirement)
- New preferences $\bar{\succ}$ are associated with a *collection* of beliefs (one for each induced \succ_p), so we need to define how a DAG represents a *collection* of probability distributions

Representation (DAG - 2)

- ▶ Let G be a DAG and $W \subset V$
- ► Truncation of a DAG: the W-truncated DAG G_W is the DAG obtained by eliminating all nodes in W and their arrows in both directions
- ▶ A truncated DAG is a representation of intervention beliefs: after intervening in all the variables in *W*, they are removed from the statistical model
- ▶ G represents $\bar{\succ}$ if these two conditions hold:
 - $G_{\mathcal{K}}$ represents $\mu_{\mathbf{x}_{\mathcal{K}}} \quad \forall \mathcal{K} \subset \mathcal{N}$ [correlation]
 - ▶ If $(i, j) \in E$, then $\mu_{x_{\{i,j\}}c}(x_j) = \mu_{x_{\{i,j\}}c}(x_j|x_i)$ [direction of causality]

Representation (DAG - 3)

- Proposition 1. Let ∑ be a DM's preferences, and let G(∑) = (N, E) be the directed graph defined by setting Pa(i) = Ca(i) ∀i. If ∑ satisties Axiom 1, then the following are true:
 - ▶ If $G = (\mathcal{N}, F)$ is a directed graph that represents $\bar{\succ}$, then $(j, i) \in F \Rightarrow j \in Ca(i)$
 - ▶ If $G = (\mathcal{N}, F)$ is a directed graph that represents $\bar{\succ}$, then $j \in Ca(i) \Rightarrow (j, i) \in F$ or $i \in Ca(j)$
- ▶ **No 2-cycles.** A graph has no 2-cycles if, for each pair i, j, $(i, j) \in E \Rightarrow (j, i) \notin E$. Axiom 2 implies G has no 2-cycles.
- ▶ **Corollary 1.** Under the assumptions of Proposition 1, if $G(\bar{\succ})$ has no 2-cycles, then $G(\bar{\succ}) = G$.

Representation Theorem (again)

Theorem 1. Let $\bar{\succ}$ satisfy Axiom 1, and let μ_p be the intervention beliefs elicited from \succ_p . The following statements are equivalent:

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