

Spiegler (2016, QJE)

Bayesian Networks and Boundedly Rational Expectations

Kyohei Okumura*

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1 Motivation

- 限定合理性, 特に nonrational expectation が形成されるメカニズムを明らかにする.
- nonrational expectations の下で何が起こるかを分析する.

2 Approach

- DAG(directed acyclic graph) を人々が心の内に抱いている Causality model の表現と考える.
- 人々は, objective probability distributions $p(x_1, \dots, x_n)$ に DAG R を fit させることで subjective belief $p_R(x_1, \dots, x_n)$ を形成し, その上で意思決定を行う と考える.
- 定常状態 (i.e. $p_R(x) \equiv p(x)$ となっている状態) を分析する. そのために, 均衡概念 (personal equilibrium) を定義.

3 Contribution

1. Bayesian network factorization formula (bayesian network の記述する条件付独立性に基づいて, 確率分布を条件付確率分布の積に分解する公式) を, 意思決定の均衡モデルに統合させた初の試み.
 - 既存のモデルに容易に限定合理性を導入できる.
 - 限定合理的な因果関係を R を用いて記述した上で, $p(x_{-1} | x_1)$ を $p_R(x_{-1} | x_1)$ で置換.
2. Causal/Statistical reasoning の誤りを記述する簡便な枠組みを与える.
 - reverse causation (因果関係の勘違い): DAG で矢印を逆に張ることに対応.
 - removal of a link (変数間の関係の見落とし): DAG で枝を消去することに対応.
 - この2つは, 典型的な人々の勘違いを描写しているのでは? と考え, Illustrations と General Analysis の項で少し詳しく分析.
3. General characterizations of choice behavior
 - rational なときと irrational なときで行動が変わるための条件は?
 - ある causality model R が, 常に他の causality model R' より優れているといったことはあるのか? (答: ない.)
4. Bayesian networks as a unifying framework
 - nonrational expectation を分析した既存の議論をある程度整理して議論できそう?

*E-mail: kyohei.okumura@gmail.com

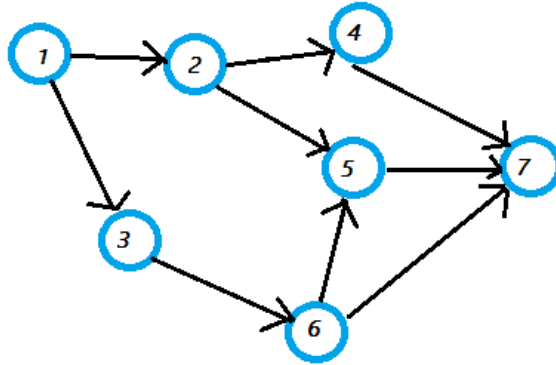
4 Model

- $X := X_1 \times \dots \times X_N$: a finite set of states. しばしば $X_1 = A$ と表す.
- $p \in \Delta(X_1, \dots, X_n)$: objective probability distribution
- X_i を値域に持つ確率変数 \tilde{X}_i ($i \in [n]$)
- causality model: DAG (N, R) , (しばしば, N を省略して R で DAG を表す.)
 - the set of nodes $N := \{1, \dots, n\}$ ($i \in N$ は, 確率変数 \tilde{X}_i に対応)
 - the set of edges $R := N \times N$.
 - $(i, j) \in R$ は, node i から node j の間に有向辺が存在することを表す. $i \rightarrow j$ と表すことも.
 - イメージ: 「 i が j の直接の原因」
 - $R(i) := \{j \in N \mid (j, i) \in R\}$: node i の親の集合.
 - $M \subseteq N$ のとき, $x_M := (x_i)_{i \in M}$.

e.g. 4.1 (DAG の例). $N := \{1, 2, \dots, 7\}$,

$R := \{(1, 2), (1, 3), (2, 4), (2, 5), (3, 6), (4, 7), (5, 7), (6, 5), (6, 7)\}$

$R(5) = \{2, 6\}$, $x_{R(5)} = (x_2, x_6)$, $\text{Descendants}(6) = \{5, 7\}$, $\text{NonDescendants}(6) = \{1, 2, 3, 4\}$



- DM は, p を元に, R を通して信念 (主観的確率) p_R を形成した上で, 最適化問題を解く.
- 一般には, $p = p_R$ とは限らず.

$$p_R(x) := \prod_{i=1}^n p(x_i \mid x_{R(i)})$$

$$\max_{p(x_1)} \sum_{x_{-1}} p_R(x_{-1} \mid x_1) u(x)$$

e.g. 4.2 (p_R の構成例). Fix $N := \{1, 2, 3\}$ and $p \in \Delta(X_1, X_2, X_3)$. Suppose that DM has his subjective DAG $R : 1 \rightarrow 2 \leftarrow 3$. Then, he constructs his subjective belief p_R as follows:

$$p_R(x_1, x_2, x_3) := p(x_1)p(x_3)p(x_2 \mid x_1, x_3)$$

Lem. 4.1 (p_R is a probability distribution). For any $p \in \Delta(X)$, the function $p_R : X \rightarrow [0, 1]$ is also a probability distribution, i.e., $p_R \in \Delta(X)$.

Proof. Assume w.l.o.g. that $(1, \dots, n)$ are topologically sorted.¹ Then,

$$\begin{aligned}
 \sum_x p_R(x) &= \sum_{x_1} \cdots \sum_{x_n} \prod_{i=1}^n p(x_i | x_{R(i)}) \\
 &= \sum_{x_1} \cdots \sum_{x_{n-1}} \prod_{i \leq n-1} p(x_i | x_{R(i)}) \underbrace{\sum_{x_n} p(x_n | x_{R(n)})}_{=1} \\
 &= \sum_{x_1} \cdots \sum_{x_{n-1}} \prod_{i \leq n-1} p(x_i | x_{R(i)}) \\
 &= \cdots \\
 &= 1
 \end{aligned}$$

□

Def. 4.1 (consistent). p is consistent with R , or p factorizes over R

$$\stackrel{\Delta}{\iff} p(x) = \prod_{i=1}^n p(x_i | x_{R(i)}) \iff p = p_R$$

- objective probability distribution p is consistent with the true DAG R^* .

Ass. 4.1. node 1 is ancestral in both R and R^* , i.e., $R(1) = R^*(1) = \emptyset$.

Def. 4.2 (Conditional Independence). $V := \{V_1, \dots, V_n\}$: a set of random variables, $X, Y, Z \subseteq V$.

$$X \perp Y | Z \stackrel{\Delta}{\iff} [p(Y = y, Z = z) > 0 \implies p(X = x | Y = y, Z = z) = p(X = x | Z = z)]$$

Lem. 4.2 (local independencies). p factorizes over R iff the following holds:

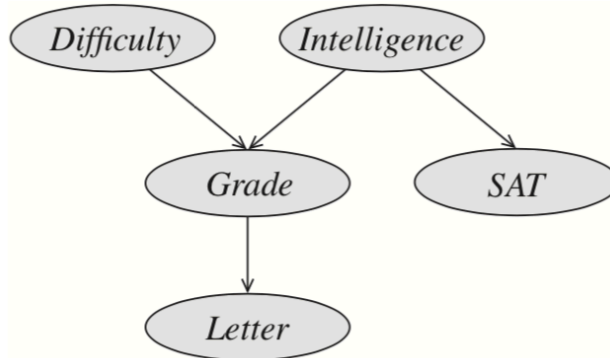
$$\tilde{X}_{\text{NonDescendants}(i)} \perp \tilde{X}_i | \tilde{X}_{R(i)}$$

Cor. 4.1. Let R be a DAG. Suppose that $R' \supseteq R$ and R' is also a DAG. If p is consistent with R , then p is also consistent with R' .

Proof. Suppose that $R' \supseteq R$, and p is consistent with R . Assume w.l.o.g that (N, R) is topologically sorted. Since p is consistent with R , $p(x) = \prod_i p(x_i | x_{R(i)})$. Consider the term $p(x_i | x_{R(i)})$ for each i . Since R' is a DAG, $x_{R'(i)} = x_{R(i)}$, or $x_{R'(i)} = x_{R(i)} \sqcup x_{N'}$, where $N' \subseteq \text{NonDescendants}(i)$; otherwise, R' has a cycle. Then, by Lem.4.2, $p(x_i | x_{R'(i)}) = p(x_i | x_{R(i)})$. □

e.g. 4.3 (local independencies). 下図のような *bayesian network structure* R (i.e. DAG) を考える。確率変数の従う分布を p とする。 *Difficulty*: 受けた授業の難易度, *Intelligence*: 生徒の賢さ, *Grade*: 生徒の成績, *SAT*: SAT の成績, *Letter*: 推薦状の強さ。

$R(\text{Letter}) = \{\text{Grade}\}$, $\text{NonDescendants}(\text{Letter}) = \{\text{Difficulty}, \text{Intelligence}, \text{SAT}\}$. いま, p is consistent with R とする.² このとき, 例えば, p は, $\text{Difficulty} \perp \text{Letter} | \text{Grade}$ という関係を満たすような分布になっている。つまり, 推薦状の強さは, 成績を所与としたとき, 授業の難易度とは独立に決まる。これは, 「成績が推薦状の強さの直接の原因である」ことを表している。



¹DAG において, node の順番をうまく並び替えて, $i \rightarrow j \implies i < j$ とできることが知られている。(i.e. ある関数 $f: N \rightarrow N$ が存在し, $(i, j) \in R \implies f(i) < f(j)$ となる。) このとき明らかに, 任意の i について, $j > i$ ならば, $j \notin R(i)$.

² p factorizes over (N, R) のとき, DAG と分布の組 $((N, R), p)$ を *bayesian network* と呼ぶ。

- historical database interpretation

- 新しい DM が、自分より前の DMs 達が生成した膨大なデータを元に意思決定することを考える。
- 膨大なデータは true distribution p に対応。
- DM は、自分の causal model に基づいて、各 i について、 $p_R(x_i | x_{R(i)})$ を学ぶ。
- その上で、真の分布を $p_R(x)$ だと思って戦略 $(p(a))_a$ をとる。その結果が、 $p_R \equiv p$ となっている。(定常状態)
- 定常状態においては、 $p = p_R$ が成立しており、おかしな causality model R に整合的な data(objective distrib.) が社会全体として実現してしまっている。

- 定常状態を考えるため、均衡概念を定義する必要。

- $p_R(y | a)$ が $(p(a))_a$ にも依存するため、 $p_R(y | a)$ を given として好き勝手に $(p(a))_a$ を動かすことはできない。
- “trembling” を用いた定義: 均衡である以上、最適でない行動と比較した結果の行動であってほしいが、他の行動と比較するためには、全ての行動 a について、条件付期待値 $p_R(y | a)$ が定義されている必要があり、そのためには $p(a) > 0$ が必要。

Def. 4.3 (ε -perturbed personal equilibrium). Fix R and $\varepsilon > 0$. A distribution $p \in \Delta(X)$ *with full support on A* is an ε -perturbed personal equilibrium

\Leftrightarrow

$$\forall a \in A; p(a) > \varepsilon \implies a \in \operatorname{argmax}_{a'} \sum_y p_R(y | a') u(a', y)$$

Def. 4.4 (personal eqm.). $p^* \in \Delta(X)$ is a personal eqm.

\Leftrightarrow

$$\exists (\varepsilon_k)_k \exists (p_k)_k; \varepsilon_k \rightarrow 0, p_k : \varepsilon_k\text{-perturbed personal equilibrium}, p_k \rightarrow p^*$$

Prop. 4.1 (Proposition 2). For any DAG R , there exists a personal equilibrium.

Proof. We show the following statement:

$$\forall (p(y | a))_{y,a} \exists (p(a))_a; p \text{ is PE, where } p(a, y) := p(y | a)p(a)$$

Fix $(p(y | a))_{y,a}$. Define $Q^\varepsilon \subseteq \Delta(A)$ as follows:

$$Q^\varepsilon := \{\pi \in \Delta(A) \subseteq R^{|A|} \mid \forall a \in A; \pi(a) \geq \varepsilon\}$$

For each $\pi \in Q^\varepsilon$, define $p^\pi, p_R^\pi(a, y)$ as

$$p^\pi(a, y) := \pi(a)p(y | a), p_R^\pi(a, y) := \prod_{i=1}^n p^\pi(x_i | x_{R(i)})$$

Next, define a correspondence $BR : Q^\varepsilon \rightrightarrows Q^\varepsilon$ as follows:

$$BR(\pi) := \operatorname{argmax}_{\rho \in Q^\varepsilon} \underbrace{\sum_a \rho(a) \sum_y p_R^\pi(y | a) u(a, y)}_{=: h(\rho, \pi)}.$$

Lem. 4.3 (Kakutani's theorem). Suppose the following conditions:

- $F : X \rightrightarrows X$ is convex-valued, nonempty-valued and has a closed graph.
- X is convex, compact, nonempty.

Then, there exists $x \in X$ such that $x \in F(x)$.

Lem. 4.4 (Berge's theorem). • $f : X \times \Theta \rightarrow \mathbb{R}$: continuous.

• $\Gamma : \Theta \rightrightarrows X$: compact-valued, continuous.

• $v(\theta) := \max_{x \in \Gamma(\theta)} f(x, \theta)$

• $x^*(\theta) := \operatorname{argmax}_{x \in \Gamma(\theta)} f(x, \theta)$

Then, v is continuous, and x^* is u.s.c.

Lem. 4.5 (Sufficient condition for the closed graph). $F : X \rightrightarrows X$ has a closed graph if F is closed-valued and F is u.s.c.

Step 1: BR has a fixed point. For sufficiently small $\varepsilon > 0$, Q^ε is convex, compact, and nonempty. $h(\rho) \equiv h(\rho, \pi)$ is linear in ρ ; hence, ρ is continuous and quasi-concave in ρ .

- Since h is continuous in ρ and Q^ε is compact, $\operatorname{BR}(\pi) \neq \emptyset$ for all $\pi \in Q^\varepsilon$.
- Since h is continuous, $\operatorname{BR}(\pi)$ is closed.
- Since h is quasi-concave, $\operatorname{BR}(\pi)$ is convex.

Then, we need to show that $\operatorname{BR}(\pi)$ has a closed graph. Since $\operatorname{BR}(\pi)$ is closed-valued, it is sufficient to show that $\operatorname{BR}(\pi)$ is u.s.c. Let $X \times \Theta := Q^\varepsilon \times Q^\varepsilon$ is the statement of Berge's theorem. Since $\Gamma(\theta) \equiv Q^\varepsilon$ (constant), Γ is continuous and compact. We can show that $h(\rho, \pi)$ is continuous not only in ρ but also in π . ($\because p^\pi(a, y)$ is continuous in π , and then $p_R^\pi(a, y)$ and $p^\pi(y | a)$ are also continuous in π .) As h is a function defined on a finite dimensional Euclidean space, h is continuous in (ρ, π) . By Berge's theorem, $\operatorname{BR}(\pi)$ is u.s.c. in π ; therefore, BR has a fixed point, i.e.,

$$\exists \pi \in Q^\varepsilon; \pi \in \operatorname{BR}(\pi).$$

Step 2: p^π is ε -PE. Note that

$$\pi \in \operatorname{argmax}_{\rho \in Q^\varepsilon} \sum_a \rho(a) \sum_y p_R^\pi(y | a) u(a, y).$$

Consider the slightly modified version of the definition of ε -PE:

Def. 4.5 (ε -PE (\star)). $p \in \Delta(X)$ s.t. $\forall a \in A; p(a) \geq \varepsilon$ is ε -PE (\star)

\Leftrightarrow^Δ

$$\forall a \in A; p(a) \geq \varepsilon \implies a \in \operatorname{argmax}_{a'} \sum_y p_R(y | a') u(a', y) \quad (1)$$

Lem. 4.6 (The set of PEs remains the same). Consider two sets of PEs: one is the set of PEs under the original definition of ε -PE, \mathcal{E} ; the other is the set of PEs under the original definition of ε -PE (\star) , \mathcal{E}' . Then, $\mathcal{E} = \mathcal{E}'$.

$\mathcal{E}' \subseteq \mathcal{E}$ clearly holds. Fix $p^* \in \mathcal{E}$ and a corresponding sequence $(\varepsilon_k, p_k)_k$. Let $\varepsilon'_k := \min\{\varepsilon_k, p_k(a)\}$. Then, $p'_k \rightarrow p^*$ and p'_k is ε'_k -PE. This completes the proof of Lem.4.6.

Here, we show that p^π is a ε -PE (\star) . Note that π satisfies the condition that $\pi(a) \geq \varepsilon$ for all $a \in A$. Suppose toward contradiction that

$$\exists a \in A; \pi(a) > \varepsilon, a \notin \underbrace{\operatorname{argmax}_{a'} \sum_y p_R^\pi(y | a') u(a', y)}_{=: U(a')}$$

Pick some $a^* \in \operatorname{argmax}_{a'} U(a')$. (Since A is finite, we can pick such a^* .) Define $\tilde{\pi} \in Q^\varepsilon$ as follows:

$$\tilde{\pi}(a') = \begin{cases} \pi(a') + \frac{\pi(a) - \varepsilon}{2} & (a' = a^*) \\ \pi(a') - \frac{\pi(a) - \varepsilon}{2} & (a' = a) \\ \pi(a') & \text{o.w.} \end{cases}$$

Note that $\tilde{\pi} \in Q^\varepsilon$ certainly holds. It suffices to check $\tilde{\pi}(a) \geq \varepsilon$:

$$\tilde{\pi}(a) = \frac{2\pi(a) - \pi(a) + \varepsilon}{2} = \frac{\pi(a) + \varepsilon}{2} \geq \varepsilon \quad (\because \pi \in Q^\varepsilon)$$

Observe that $\sum_a \tilde{\pi}(a)U(a) > \sum_a \pi(a)U(a)$. This contradicts $\pi \in \operatorname{BR}(\pi)$. Therefore, p^π is a ε -PE (\star).

Step 3: At least one PE p^* exists. So far, we have shown that ε -PE exists (as long as ε is small enough.) Fix some sequence $(\varepsilon^k)_k \subseteq \mathbb{R}$ such that $\varepsilon^k \rightarrow 0$. Let p^k be a ε -PE for each k . Note that $(p^k)_k \subseteq \Delta(X) \subseteq \mathbb{R}^{|X|}$. Since $(p^k)_k$ is a sequence in a compact subset of a finite dimensional Euclidean space, $(p^k)_k$ has a convergent subsequence $(p^{k_m})_m$ such that $(p^{k_m})_m \rightarrow p^* \in \Delta(X)$. This p^* is PE. \square

5 Illustrations

- Reverse causation: Dieter's dilemma
- Coarseness I: Demand for Education
- Coarseness II: Public Policy

5.1 Reverse causation: Dieter's dilemma

- Three variables: a, h, c :
 - DM's choice(diet or not), health outcome(good or bad), chemical level(high or low)
- DM は意思決定する時点では c, h の実現値については知らない.

5.1.1 Rational DM の場合

- True DAG: $R^* : a \rightarrow c \leftarrow h$
 - このとき, p は $p(a, h, c) = p(a)p(h)p(c | a, h)$ を満たす.
 - もし DM が rational(i.e. causality を正しく認識している) なら, 彼が解く問題は,

$$\max_a \sum_h \sum_c p(h)p(c | a, h)u(a, h, c)$$

5.1.2 Irrational DM の場合

- DM の causality model が $R : a \rightarrow c \rightarrow h$ の場合を考える.
- p が personal eqm. なら, $p(a') > 0$ となる a' は以下の式を満たす.

$$a' \in \operatorname{argmax}_a \sum_h \sum_c p(h | c)p(c | a)u(a, h, c)$$

5.1.3 Solving for the personal eqm.

- R の下での personal eqm. を求めている。
- もう少し構造を入れて考える。
 - $a, c, h \in \{0, 1\}$
 - $u(a, h, c) = u(a, h) := h - \kappa a$
 - $p(h = 1) = p(h = 0) = 1/2, h \perp a, c = (1 - h)(1 - a)$
- DM が rational な場合は, $p_{R^*}(h | a) = p(h)$ なので, 常に $a^* := 0$ を選択することに注意。

Prop. 5.1 (personal eqm. in Dieter's dilemma). *In this case, there is a unique personal eqm p :*

$$p(a = 0) = \begin{cases} 0 & (\kappa \leq 1/4) \\ 2 - \frac{1}{2\kappa} & (\kappa \in (1/4, 1/2)) \\ 1 & (\kappa \geq 1/2) \end{cases}$$

Proof. personal eqm. p を任意にとり, $\beta := p(a = 0) \in [0, 1]$ とする。まず, p についての specification より,

$$p(c = 0 | a = 1) = 1, p(c = 0 | a = 0) = \frac{1}{2}, p(h = 1 | c = 1) = 0, p(h = 1 | c = 0) = \frac{1}{2 - \beta}$$

がわかる。

$$\begin{aligned} p_R(h = 1 | a = 0) &= p(h = 1 | c = 0)p(c = 0 | a = 0) + p(h = 1 | c = 1)p(c = 1 | a = 0) \\ &= \frac{1}{2} \frac{1}{2} \end{aligned}$$

$$\begin{aligned} p_R(h = 1 | a = 1) &= p(h = 1 | c = 0)p(c = 0 | a = 1) + p(h = 1 | c = 1)p(c = 1 | a = 1) \\ &= \frac{1}{2 - \beta} \end{aligned}$$

であり, また, $\sum_h p(h | a)u(a, h)$ の値は, a の取りうる各値についてそれぞれ以下のようになる。

$$\begin{aligned} \sum_h p_R(h | a' = 0)u(a' = 0, h) &= p_R(h = 1 | a' = 0) \cdot 1 \\ &= \frac{1}{2} \frac{1}{2 - \beta} \end{aligned} \tag{E0}$$

$$\begin{aligned} \sum_h p_R(h | a' = 1)u(a' = 1, h) &= \frac{1}{2 - \beta}(1 - \kappa) + \left(1 - \frac{1}{2 - \beta}\right) \\ &= \frac{1}{2 - \beta} - \kappa \end{aligned} \tag{E1}$$

Case (i): $\beta \in (0, 1)$ のとき $\beta > \varepsilon, 1 - \beta > \varepsilon$ を満たすような十分小さい $\varepsilon > 0$ を一つとり固定する。personal eqm. の定義より, このとき, (E0) = (E1) が必要。

$$\therefore \beta = 2 - \frac{1}{2\kappa}$$

これが personal eqm. になることは, $\varepsilon_k \rightarrow 0$ となるような点列を任意にとり, $p_k := (\beta, 1 - \beta)$ とすれば, 十分大きい k について p_k は ε_k -perturbed personal eqm であり, $p_k \rightarrow p$ となることより ok。

Case (ii): $\beta = 0$ のとき $1 - \beta > \varepsilon$ となるような ε を任意にとり固定する. このとき, $(E0) \leq (E1)$ が必要. $(E0) \leq (E1) \iff \kappa \leq 1/4$. これが **personal eqm.** になることは, $\kappa \leq 1/4$ のとき, $\varepsilon_k \rightarrow 0$ となるような点列を任意にとり, $p_k := (0, 1)$ とすれば, 十分大きい k について p_k は ε_k -perturbed personal eqm であり, $p_k \rightarrow p$ となることより ok.

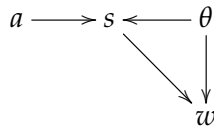
Case (iii): $\beta = 1$ のとき Case (ii) のときと同様に示せる. □

Interpretation:

- diet のコストが高すぎない限り, 定常状態において, irrational DM は正の確率で diet をしてしまう. なぜか?
- 仮にいま DM が $a = 0$ を選んでいたとする. このとき, DM は c, h の間に negative correlation があることに気づく.
- 彼は今 $a \rightarrow c \rightarrow h$ だと思っているので, $a \uparrow \rightarrow c \downarrow \rightarrow h \uparrow$ とできると勘違いしてしまう.
- その結果, $p(a = 1) > 0$ となってしまう.
- $a = 1$ の頻度が下がると c, h 間の負の相関を強く認識. $(p(h = 1 | c = 0) = \frac{1}{2-\beta})$

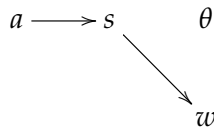
5.2 Coarseness I: Demand for Education

- a, θ, s, w : parent's investment, child's innate ability, school performance, wage
- true DAG R^* :



$$\max_a \sum_{\theta} p(\theta) \sum_s p(s | a, \theta) \sum_w p(w | \theta, s) u(a, w)$$

- DM's subjective DAG R :



$$\max_a \sum_s p(s | a) \sum_w p(w | s) u(a, w)$$

- 「目に見えない変数 θ の影響を無視してしまう」ような間違い.
- $a \in [0, 1], s, \theta, w \in \{1, 0\}$
- $u(a, w) := w - \kappa(a)$
- κ : twice-differentiable, increasing, weakly convex. (i.e. $\kappa' > 0, \kappa'' \leq 0$), $\kappa'(0) = 0, \kappa'(1) \geq 1$.
- $p(s = 1 | a, \theta) = a\theta, p(w = 1 | s, \theta) = \theta\beta_s$ ($\beta_1 > \beta_0$), $p(\theta = 1) = \delta > 0$.

5.2.1 rational DM's choice

$$\max_a \{\delta[a\beta_1 + (1-a)\beta_0] - \kappa(a)\}$$

- $\kappa'(a^*) = \delta(\beta_1 - \beta_0)$ を満たす a^* が optimal.

5.2.2 irrational DM's choice

Prop. 5.2. In this case, the parent assigns probability one to some action a^{**} such that

$$\kappa'(a^{**}) = \delta \left[\delta\beta_1 - \beta_0 \cdot \frac{\delta(1 - a^{**})}{\delta(1 - a^{**}) + 1 - \delta} \right]$$

If κ' is either weakly convex or weakly concave, then a^{**} is unique.

Note that since $\kappa'(a^{**}) < \kappa'(a^*)$, we have $a^{**} > a^*$: the parent overinvests in personal eqm.

Interpretation:

- The parent overinvests because he overly estimates the positive correlation b/w a and w :
 - DM は s と w の間には pure causal effect しかないと考えているが、実際は θ が影響.
 - 投資が効くときは、 θ が高いときであり、そのとき、 w は高くなりやすくなっている。(しかしそのことに気づいていない.)
 - 投資の効果を過大評価.
- the perceived marginal benefit of investment $\kappa'(a^{**})$ が, eqm. investment a^{**} の関数に.
 - DM は常に $w \perp_R a \mid s$ だと思っているが、実際はそうではない.
 - perceived causal effect of s on w は、 a の分布に依存する.
 - i.e. true DAG に consistent な p について、一般には $p(w \mid s, a) \neq p(w \mid s)$
 - 例えば、 $s = 0$ を所与としたとき、 $a = 1$ であったとすると、そこから $\theta = 0$ の確率が高いことが推測される.
 - $\mathbb{E}[w \mid s = 1] - \mathbb{E}[w \mid s = 0]$ increases in long-run investment. (a が大きいことを given にすると、 $s = 0$ のとき、 $\theta = 0$ の確率が高まるので、 $\mathbb{E}[w \mid s = 0]$ は a が低いときと比べて小さくなる.)
 - 以上の議論は true distribution の下で考えている. personal eqm. では、true DAG, subjective DAG 両方の性質が満たされることに注意.

Proof of Prop.5.2.

$$\begin{aligned} \sum_s p(s \mid a) \sum_w p(w \mid s) u(a, w) &= \sum_s p(s \mid a) p(w = 1 \mid s) - \kappa(a) \\ p(s = 1 \mid a) &= \sum_{\theta} p(\theta) p(s = 1 \mid a, \theta) = \delta a \\ p(s = 1 \mid a) &= \sum_{\theta} p(\theta) p(s = 1 \mid a, \theta) = \delta a \\ p(w = 1 \mid s = 1) &= \delta\beta_1 \\ p(w = 1 \mid s = 0) &= \frac{p(w = 1, s = 0)}{p(s = 0)} \end{aligned}$$

$$\begin{aligned}
p(w = 1, s = 0) &= \sum_{\theta} \sum_a p(w = 1, s = 0, a, \theta) \\
&= \sum_{\theta} \int_a p(\theta) p(w = 1 \mid s = 0, \theta) p(s = 0 \mid \theta, a) d\mu(a) \\
&= (1 - \delta) \int_a \underbrace{p(w = 1 \mid s = 0, \theta = 0)}_0 p(s = 0 \mid \theta = 0, a) d\mu(a) \\
&\quad + \delta \int_a \underbrace{p(w = 1 \mid s = 0, \theta = 1)}_{(\beta_0)} \underbrace{p(s = 0 \mid \theta = 1, a)}_{(1-a)} d\mu(a) \\
&= \delta \beta_0 \int_a (1 - a) d\mu(a)
\end{aligned}$$

$$\begin{aligned}
p(s = 0) &= \sum_{\theta} \sum_a p(a, s = 0, \theta) \\
&= \sum_{\theta} \sum_a p(\theta) p(a) p(s = 0 \mid a, \theta) \\
&= (1 - \delta) \int_a \underbrace{p(s = 0 \mid a, \theta = 0)}_1 d\mu(a) + \delta \int_a \underbrace{p(s = 0 \mid a, \theta = 1)}_{(1-a)} d\mu(a) \\
&= (1 - \delta) + \delta \int_a (1 - a) d\mu(a)
\end{aligned}$$

Then,

$$p(w = 1 \mid s = 0) = \frac{\delta \int_a (1 - a) d\mu(a)}{\underbrace{(1 - \delta) + \delta \int_a (1 - a) d\mu(a)}_{=:\gamma}} \beta_0$$

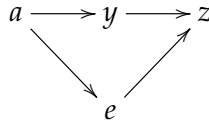
Note that $\gamma < \delta$. Hence,

$$\sum_s p(s \mid a) p(w = 1 \mid s) - \kappa(a) = \delta a \cdot \delta \beta_1 + (1 - \delta a) \gamma \beta_0 - \kappa(a)$$

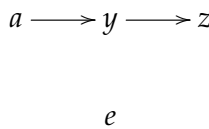
FOC is $\kappa'(a) = \delta(\delta \beta_1 - \gamma \beta_0) \in (0, 1)$. □

5.3 Coarseness II: Public Policy

- a, y, e, z : policy, two macro variables, private sector's expectation of y .
- true DAG R^* :



- DM's DAG R :



6 General Analysis

6.1 Consequentialist Rationality

- personal equilibrium が最適化問題の解として記述できるための条件は？
- (そもそもなんでこんなことを議論したいの?)

6.1.1 Preliminaries

Def. 6.1 (skeleton). Fix a DAG $\mathcal{G} := (N, R)$. The skeleton of \mathcal{G} , $\tilde{\mathcal{G}} := (N, \tilde{R})$, is an undirected version of \mathcal{G} : formally, $\tilde{R} := \{(i, j) \in N \times N \mid (i, j) \in R, \text{ or } (j, i) \in R\}$. $(i, j) \in \tilde{R}$ is sometimes denoted by $i\tilde{R}j$, or $i - j$.

e.g. 6.1 (skeleton). $R : i \rightarrow j \rightarrow k, \tilde{R} : i - j - k$.

Def. 6.2 (clique, ancestral clique). Fix a DAG (N, R) . $M \subseteq N$ is a clique in R

\iff

$$\forall i, j \in M; i \neq j \implies i\tilde{R}j.$$

A clique M in R is an ancestral clique when $\forall i \in M; R(i) \subseteq M$.

e.g. 6.2 (clique). • $M_1 := \{5, 6, 7\}$: clique, but not ancestral clique.

• $M_2 := \{2, 4, 5, 7\}$: not clique.

• $M_3 := \{1, 3\}$: ancestral clique.

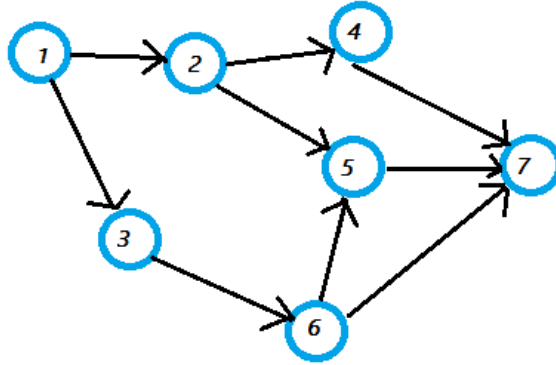


Figure 1: DAG

Def. 6.3 (equivalent). Fix N . Two DAGs R and Q are equivalent, denoted as $R \sim Q$,

\iff

$$\forall p \in \Delta(X); p_R(x) = p_Q(x)$$

We sometimes denote the equivalence class of R as $[R]$.

e.g. 6.3 (equivalent). $R : 1 \rightarrow 2$ and $Q : 2 \rightarrow 1$ are equivalent: For any $p \in \Delta(X)$,

$$p(x_1, x_2) = p(x_2 \mid x_1)p(x_1) = p(x_1 \mid x_2)p(x_2).$$

Def. 6.4 (v-structure). The v-structure of a DAG R , $v(R)$, is defined as follows:

$$v(R) := \{(i, j, k) \mid i \rightarrow j, j \rightarrow k, i \nrightarrow j, j \nrightarrow i\}$$

e.g. 6.4 (v-structure). Consider the DAG R in Figure 1. $(2, 5, 6)$ is a v-structure of R ; $(5, 7, 6)$ is not a v-structure in R .

Prop. 6.1 (Verma and Pearl, 1991). $R \sim Q \iff [\tilde{R} = \tilde{Q} \text{ and } v(R) = v(Q)]$.

e.g. 6.5. $R : 1 \rightarrow 2 \rightarrow 3$ and $Q : 3 \rightarrow 2 \rightarrow 1$ are equivalent: $\tilde{R} = \tilde{Q} = 1 - 2 - 3$ and $v(R) = v(Q) = \emptyset$. However, $S : 1 \rightarrow 2 \leftarrow 3 \not\sim R$ because $v(S) = \{(1, 2, 3)\} \neq \emptyset$.

6.1.2 Consequentialist Rationality

- $\Delta_R(X) := \{p \in \Delta(X) \mid p \text{ is consistent with } R\}$ とする.

Def. 6.5 (Consequentialistically rational). *A DAG R is C-rational w.r.t. true DAG R^**

\Leftrightarrow

$$\forall p, q \in \Delta_{R^*}(X); [\forall x; p(x_{-1} \mid x_1) = q(x_{-1} \mid x_1) \implies \forall x; p_R(x_{-1} \mid x_1) = q_R(x_{-1} \mid x_1)]$$

- R : C-rational であれば, true distrib. p の $p(x_1)$ を $p(x_{-1} \mid x_1)$ を変えないようにいじっても, $p_R(x_{-1} \mid x_1)$ は変化しない.
- つまり, $p(x_{-1} \mid x_1)$:given として $p(x_1)$ を最適化問題の解として選んでも $p(x_{-1} \mid x_1)$ には無影響.

e.g. 6.6 (C-rationality in dieter's dilemma). 例えば $p_R(h = 1 \mid a = 0) = \frac{1}{2-\beta} \frac{1}{2}$ といった結果からわかるように, *dieter's dilemma* においては, R は C-rational ではない: いまある p を所与とし, $p_R(h \mid a)$ の下で最適化問題を解いて $p^*(a)$ を求めると, $p'(a, h, c) := p(h, c \mid a)p^*(a) \neq p(a, h, c)$ であり, $p'_R(h \mid a) \neq p_R(h \mid a)$ となる.

- R^* itself is C-rational w.r.t. R^* .

\therefore Fix $p, q \in \Delta_{R^*}(X)$ s.t. $p(x_{-1} \mid x_1) = q(x_{-1} \mid x_1)$ for all x . Fix x .

$$p_{R^*}(x) = p(x_1)p(x_{-1} \mid x_1). \quad p_{R^*}(x_1) = p(x_1) \sum_{x_{-1}} p(x_{-1} \mid x_1) = p(x_1).$$

$$\text{Then, } p_{R^*}(x_{-1} \mid x_1) = p(x_{-1} \mid x_1). \text{ Similarly, } q_{R^*}(x_{-1} \mid x_1) = q(x_{-1} \mid x_1). \quad \square$$

- From now on, assume that $R \neq R^*$.

Prop. 6.2 (characterization of C-rationality (Proposition 6)). *R is C-rational w.r.t. R^**

\Leftrightarrow

$$\forall i > 1; 1 \notin R(i) \implies x_i \perp_{R^*} x_1 \mid x_{R(i)}$$

e.g. 6.7 (Dieter's dilemma). • True DAG: $R^* : 1 \rightarrow 3 \leftarrow 2$

- Subjective DAG: $R : 1 \rightarrow 2 \rightarrow 3$ について考える.
- $i := 3$ として考える. このとき, $1 \notin R(3), x_3 \not\perp_{R^*} x_1 \mid x_2$.
- よって, R is not C-rational w.r.t. R^* .
- 次に, $R' : 1 \rightarrow 3 \rightarrow 2$ について考えてみる. (fully coarsed/cursed)
- R' is C-rational w.r.t. $R^* : x_2 \perp_{R^*} x_1$.

- DAG のサイズが大きいと, 独立性の条件を調べるのは大変
- d-separation という概念を用いた効率的な判定アルゴリズムが存在.

Proof of Prop.6.2. [細部よくわからず.]

$$\begin{aligned} p_R(x_{-1} | x_1) &= \frac{p_R(x_1, x_{-1})}{p_R(x_1)} = \frac{p(x_1) \prod_{i \geq 2} p(x_i | x_{R(i)})}{\sum_{x'_{-1}} p(x_1) \prod_{i \geq 2} p(x'_i | x_{R(i) \cap \{1\}}, x'_{R(i) - \{1\}})} \\ &= \frac{\prod_{i \geq 2} p(x_i | x_{R(i)})}{\sum_{x'_{-1}} \prod_{i \geq 2} p(x'_i | x_{R(i) \cap \{1\}}, x'_{R(i) - \{1\}})} \end{aligned} \quad (2)$$

今、示したいのは次のような命題であることに注意する.

$$\begin{aligned} &p(x_{-1} | x_1) \text{ を保ちながら } p(x_1) \text{ を変えたときに } p_R(x_{-1} | x_1) \text{ が変化しない} \\ \iff \forall i > 1; 1 \notin R(i) \implies x_i \perp_{R^*} x_1 | x_{R(i)} \end{aligned}$$

\Leftarrow) (2)において、分母の部分は、 $p(x_1)$ に依存していない。よって、任意の $i \geq 2$ について、

$$p(x'_i | x_{R(i) \cap \{1\}}, x'_{R(i) - \{1\}}) \quad (\star)$$

の部分が変わるかを見ればよい.

$1 \in R(i)$ であれば、

$$(\star) = p(x'_i | x_1, x'_{R(i)})$$

であるので、 (\star) は $p(x_1)$ には依存しない. (???)

$1 \notin R(i)$ の場合、仮定より、 $x_i \perp_{R^*} x_1 | x_{R(i)}$ であるので、

$$\begin{aligned} (\star) &= p(x'_i | x'_{R(i)}) = \sum_{x''_1} p(x''_1) p(x'_i | x''_1, x'_{R(i)}) \\ &= \sum_{x''_1} p(x''_1) p(x'_i | x'_{R(i)}) \\ &= p(x'_i | x'_{R(i)}) \end{aligned}$$

であるので、この場合も (\star) は $p(x_1)$ に依存しない. 以上より、 $p(x_1)$ を変えても $p_R(x_{-1} | x_1)$ が変化しないことが示された.

\Rightarrow) $i > 1, 1 \notin R(i)$ をなる i を任意にとる. $1 \notin R(i)$ より、

$$(\star) = p(x'_i | x'_{R(i)}) = \sum_{x''_1} p(x''_1) p(x'_i | x''_1, x'_{R(i)})$$

いま、仮に $x_i \not\perp_{R^*} x_1 | x_{R(i)}$ だとする. このとき、 $p(x'_i | x''_1, x'_{R(i)})$ は x''_1 に依存して変化する. (???) このとき、 (\star) は $p(x''_1)$ に依存して変化する. よって、 $(?)p_R(x_{-1} | x_1)$ も $p(x''_1)$ に依存して変化する. \square

6.2 Behavioral Rationality

- DAG R がどういう性質を満たしているとき, DM は rational な場合に最適である行動を選ぶか? – all payoff-relevant variables are causally linked and have no other causes.
- よくある因果関係の勘違い (ここでは特に, link を一本逆にすることを考える) が behavioral rationality を violate するのはどういうときか?

6.2.1 Preliminaries

Def. 6.6 (fully connected). A directed graph (N, R) is fully connected if $i \rightarrow j$ or $j \rightarrow i$ holds for all $i, j \in N$.

Lem. 6.1 (fully connected DAG). A DAG (N, R) is fully connected $\iff R$ is consistent for all $p \in \Delta(X)$.

Proof. Assume w.l.o.g that $\{1, 2, \dots, n\}$ are topologically sorted.

\Rightarrow) Fix any x . Then,

$$p(x) = \prod_i p(x_i \mid x_1, \dots, x_{i-1}) = p_R(x)$$

\Leftarrow) We show contraposition. Suppose that R is not fully connected. Then, since R does not have enough its degree of freedom, we can construct p that is not consistent with R . For example, consider $R : 1 \rightarrow 2 \rightarrow 3$. R is not fully connected because $1 \nrightarrow 3$. Then, we can construct p such that

$$p(x) = p(x_1)p(x_2 \mid x_1)p(x_3 \mid x_2, x_1) \neq p(x_1)p(x_2 \mid x_1)p(x_3 \mid x_2) = p_R(x)$$

□

Def. 6.7 (d -separation). Let R be a DAG, and $X, Y, Z \subseteq N$.

A directed path P is d -separated by Z

$\stackrel{\Delta}{\iff}$

- P contains a chain $i \rightarrow m \rightarrow j$ or a fork $i \leftarrow m \rightarrow j$ such that $m \in Z$.
- P contains an inverted fork $i \rightarrow m \leftarrow j$ such that m and the descendants of m are not in Z .

Z d -separates X and Y $\stackrel{\Delta}{\iff} Z$ d -separates every path from a node in X to a node in Y . This is denoted by $(X \perp Y \mid Z)_R$.³

Prop. 6.3 (Probabilistic Implications of d -Separation). For any three disjoint subsets of nodes X, Y, Z in a DAG R , and for all probability distributions p ,

1. If p is consistent with R , then $(X \perp Y \mid Z)_R \implies (X \perp Y \mid Z)_p$
2. $(X \not\perp Y \mid Z)_R \implies \exists p; (X \not\perp Y \mid Z)_p$.

6.2.2 Behavioral Rationality

- no restriction on $p \in \Delta(X)$, i.e., assume that true DAG R^* is fully connected.
- Impose some restriction on the set of possible utility functions.

Ass. 6.1 (Restriction on u). $\exists M \subsetneq N$; $1 \in M$, and u is purely a function of x_M .

³For a probability distribution p , $(X \perp Y \mid Z)_p$ denotes that X and Y are independent conditional on Z .

Def. 6.8 (Behaviorally Rational). A DAG R is B-rational if in every personal eqm. p ,

$$p(x_1) \implies x_1 \in \operatorname{argmax}_{x'_1} \sum_{x_{-1}} p(x_{-1} \mid x_1) u(x'_1, x_{-1})$$

Prop. 6.4 (Spiegler(2017), Proposition 2). Let R be a DAG and let $C \subseteq N$.

$$[\forall p \in \Delta(X) \forall x; p_R(x_C) = p(x_C)] \iff [\exists Q \in [R]; C \text{ is an ancestral clique in } Q].$$

[2018/07/16: \Leftarrow is correct; \Rightarrow is not sure.]

e.g. 6.8. $R : 1 \rightarrow 2 \leftarrow 3$. By Prop.6.1, we can see that $[R] = \{R\}$. Since $\{x_2\}$ is not an ancestral clique in R , by Prop.6.4, $\exists p \exists x_2; p_R(x_2) \neq p(x_2)$.

Proof of Prop.6.4. See Appendix. よくわからず.

□

Prop. 6.5. *The DM is behaviorally rational $\iff \exists Q \in [R]; M$ is an ancestral clique in Q .*

Proof. [Prop.6.4 を修正しない限り, \Rightarrow は不成立.]

Note that, by assumption, node 1 is an ancestral node in both R and R^* .

\Leftarrow) Assume that there exists $Q \in [R]$ such that M is an ancestral clique in Q . By Prop.(6.4), $p_R(x_M) = p(x_M)$. Fix any personal eqm. p . We need to show that p satisfies the following:

$$\forall x_1; p(x_1) > 0 \implies x_1 \in \operatorname{argmax}_{x'_1} \sum_{x_{-1}} p(x_{-1} | x'_1) u(x).$$

Fix x_1 such that $p(x_1) > 0$. Since u depends only on x_M ,

$$\begin{aligned} \operatorname{argmax}_{x'_1} \sum_{x_{-1}} p(x_{-1} | x'_1) u(x) &= \operatorname{argmax}_{x'_1} \sum_{x_{M-\{1\}}} p(x_{M-\{1\}} | x'_1) u(x_M) \\ &= \operatorname{argmax}_{x'_1} \sum_{x_{M-\{1\}}} p_R(x_{M-\{1\}} | x'_1) u(x_M) (\because p_R(x_M) = p(x_M)) \\ &= \operatorname{argmax}_{x'_1} \sum_{x_{-1}} p_R(x_{-1} | x'_1) u(x) \end{aligned}$$

Since p is personal eqm., $x_1 \in \operatorname{argmax}_{x'_1} \sum_{x_{-1}} p_R(x_{-1} | x'_1) u(x)$. Therefore, R is B-rational.

\Rightarrow) Assume that R is B-rational. By Prop.(6.4), we have $p_R(x_1) = p(x_1)$. Then,

$$p_R(x_{M-\{1\}} | x_1) = \frac{p_R(x_M)}{p_R(x_1)} = \frac{p_R(x_M)}{p(x_1)}, \quad p(x_{M-\{1\}} | x_1) = \frac{p(x_M)}{p(x_1)}.$$

Hence, $p_R(x_{M-\{1\}} | x_1) = p(x_{M-\{1\}} | x_1)$ holds if and only if $p_R(x_M) = p(x_M)$ holds.

By Prop.(6.4)[要修正], it is sufficient to show that $p(x_M) \equiv p_R(x_M)$; it suffices to show that $p_R(x_{M-\{1\}} | x_1) = p(x_{M-\{1\}} | x_1)$. Suppose toward contradiction that $p_R(x_{M-\{1\}} | x_1) \neq p(x_{M-\{1\}} | x_1)$. Then, we can construct the utility function u under which DM does not choose the optimal action w.r.t. p . (??) \square

Interpretation:

- (1) all payoff-relevant variables are causally linked, (2) they have no other causes のときに, DM は rational な場合の最適行動を選択できる.
- ((1),(2) のどちらかが満たされなければ, ある p と u の下で suboptimal な行動をしてしまう. [要修正])
- 「簡単な operation が behavioral rationality を損なうか否か」 みたいな議論も面白いかも?

Prop. 6.6 (Proposition 9). *Suppose that R departs from R^* , which is fully connected, by omitting one link $i \rightarrow j$. Then,*

$$DM \text{ is B-rational. } \iff j = n, i \neq 1.$$

e.g. 6.9. • $R : 1 \rightarrow 3 \leftarrow 2$. $1 \rightarrow 2$ omitted from R^* . DM is not B-rational. – double-counting.

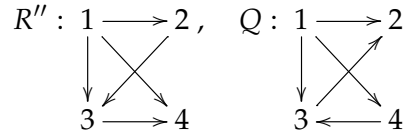
- $R : 1 \rightarrow 2 \rightarrow 3$. $1 \rightarrow 3$ omitted from R^* . DM is not B-rational. – failed to perceive any effect of x_1
- $R : 2 \leftarrow 1 \rightarrow 3$. $2 \rightarrow 3$ omitted from R^* . DM is B-rational. – not distinguish direct and indirect effect.

6.3 Payoff ranking of DAGs

- 矢印を一本増やす \approx より賢くなる
- より賢い DAG を持つ人は、常に良い利得を達成できるか？ – No

e.g. 6.10. • R : fully connected DAG, $1 \rightarrow 2 \rightarrow 3 \rightarrow 4$; u is purely a function of x_1 and x_4 .

- R' : $2 \rightarrow 3$ removed from R
- By Prop.6.6, R' is not B-rational: R' is weakly dominated by R in terms of expected performance.
- R'' : $2 \rightarrow 4$ removed from R' .



- $Q \sim R''$ (the same skeleton and v-structure). $\{1, 4\}$ is an ancestral clique in Q .
- R'' is B-rational w.r.t. R^* ; R' is weakly dominated by R'' .

Ass. 6.2 (For simplicity?). 1 is an isolated node in all relevant true and subjective DAGs.

Def. 6.9 (Ranking of DAGs). R is more rational than R'

$$\iff \forall p, u, a, a';$$

$$\sum_y p_R(y)u(a, y) > \sum_y p_R(y)u(a', y), \quad (3)$$

$$\sum_y p_{R'}(y)u(a', y) > \sum_y p_{R'}(y)u(a, y) \quad (4)$$

$$\implies \sum_y p(y)u(a, y) > \sum_y p(y)u(a', y) \quad (5)$$

- 「2 つの DAG で意見が割れたときは、常に片方が正しい」
- R : fully connected, R' : not fully connected のときは正しい。

Prop. 6.7 (Proposition 10). Suppose both R and R' are not fully connected. Then, neither DAG is more rational than the other.

Proof. Assume that both R and R' are not fully connected. If $R \sim R'$, the claim holds. Assume $R \succ R'$.

Suppose toward contradiction that R is more rational than R' . Fix any $p \in \Delta(X)$. Let $q := (p_R(y))_y$ and $r := (p_{R'}(y))_y$. Note that q and r are $k := |Y|$ -length probability vectors. Fix any u, a, a' . Let $z^y := u(a, y) - u(a', y)$, $z := (z^y)_y$, and $D := [q \quad -r \quad -p]$. Note that D is a $k \times 3$ matrix. Fix any $\varepsilon > 0$. Let $b := (\varepsilon, \varepsilon, \varepsilon)^\top$.

First, we show the following:

$$\nexists z \in \mathbb{R}^k; D^\top z > b \quad (6)$$

Suppose not. Then there exists $z \in \mathbb{R}^k$ such that

$$D^\top z = \begin{bmatrix} q^\top z \\ -r^\top z \\ -p^\top z \end{bmatrix} = \begin{bmatrix} \sum_y p_R(y)(u(a, y) - u(a', y)) \\ -\sum_y p_{R'}(y)(u(a, y) - u(a', y)) \\ -\sum_y p(y)(u(a, y) - u(a', y)) \end{bmatrix} > b$$

This implies

$$\begin{aligned}\sum_y p_R(y)u(a, y) &> \sum_y p_R(y)u(a', y) \\ \sum_y p_{R'}(y)u(a', y) &> \sum_y p_{R'}(y)u(a, y) \\ \sum_y p(y)u(a', y) &> \sum_y p(y)u(a, y)\end{aligned}$$

This contradicts the assumption that R is more rational than R' . Therefore, (6) must hold.

Next, we apply Gale's theorem:

Lem. 6.2 (Gale's Theorem). *Let $A \in \mathbb{R}^{M \times N}$ and $b \in \mathbb{R}^N$. The following two statements are equivalent:*

1. $\exists x \in \mathbb{R}^M; A^\top x \leq b$
2. $\forall y \in \mathbb{R}^N; y \geq 0, Ay = 0 \implies b^\top y \geq 0$

By (6) and Gale's theorem, we have

$$\exists w \in \mathbb{R}^3; w \geq 0, Dw = 0, b^\top w < 0$$

[Spiegler(2016) では $w > 0$ になっているがなぜ?]

Since $b^\top w < 0$, there exists $j \in \{1, 2, 3\}$ such that $w_j > 0$. Since $Dw = 0$, for all $i \in [k]$, $w_1 q^i = w_2 r^i + w_3 p^i$, or

$$w_1 p_R(y) = w_2 p_{R'}(y) + w_3 p(y)$$

By summing up w.r.t. i , we have $w_1 = w_2 + w_3$. Hence,

$$w_1 > 0, (w_2 > 0 \text{ or } w_3 > 0)$$

Since $w_1 > 0$, for all y ,

$$p_R(y) = \frac{w_2}{w_1} p_{R'}(y) + \frac{w_3}{w_1} p(y)$$

Let $\alpha := w_2/w_1$ and $\beta := w_3/w_1$. Then, by summing up w.r.t. y , we have $\alpha + \beta = 1$. Therefore, we have the following:

$$\forall p \exists \alpha \in [0, 1]; p_R = \alpha p + (1 - \alpha) p_{R'} \quad (7)$$

In case $\alpha < 1$, the proof is done: If p is consistent with R , or $p_R = p$, by (7), we have $p_R = p_{R'}$, and then $p = p_{R'}$; Similarly, if p is consistent with R' , then p is also consistent with R : we have the following relationship:

$$p = p_R \iff p = p_{R'}$$

In addition, for any $p \in \Delta(X)$, p_R is consistent with R . Replace p with p_R and apply the procedure to p_R ; we have $p_R = \alpha p_R + (1 - \alpha) p_{R'}$, and then $p_R = p_{R'}$.

[$\alpha < 1$ for all p , or, $w > 0$ が言えれば ok だが ...?, fully-connected の条件を用いていない.]

□

7 Variations and Relations to Other Concepts

7.1 Variations

- 複数の DAG を確率的に持つ (Partial cursedness)
- 社会に, 異なる DAG を持つ主体が混在している. (e.g. Dieters' dilemma)

7.2 Relations to Other Concepts

- Jehiel (2005) Analogy-based expectations
- Esponda (2008) Naive Behavioral Equilibrium
- Eyster and Rabin (2005) Partial cursedness
- Osborne and Rubinstein (1998) S(K) equilibrium

8 Concluding Remarks

8.1 Alternative interpretations of DAG

- Data limitations (cf: Spiegler (2017) Data Monkeys)
- Limited ability to ask the right questions

9 Appendix

Proof of Prop.6.4. [There is an error in the proof in Spiegler(2017).]

If C is empty, the proposition clearly holds; from now on, we assume $C \neq \emptyset$.

First, note that for any DAG R , the following holds:

$$\begin{aligned} p_R(x_C) &= \sum_{x'_{N-C}} p_R(x_C, x'_{N-C}) \\ &= \sum_{x_{N-C}} \prod_{i \in C} p(x_i | x_{R(i) \cap C}, x'_{R(i)-C}) \prod_{i \notin C} p(x'_i | x_{R(i) \cap C}, x'_{R(i)-C}) \end{aligned} \quad (8)$$

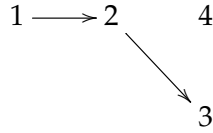
\Leftarrow) Fix C such that C is an ancestral clique in some $Q \in [R]$. Note that $R(i) - C = \emptyset$ for all $i \in C$. Then,

$$\prod_{i \in C} p(x_i | x_{R(i) \cap C}, x'_{R(i)-C}) = \prod_{i \in C} p(x_i | x_{R(i) \cap C}) = p(x_C) \quad (\because \text{topological sort})$$

Hence, by (8),

$$p_R(x_C) = p_Q(x_C) = p(x_C) \underbrace{\sum_{x_{N-C}} \prod_{i \notin C} p(x'_i | x_{R(i) \cap C}, x'_{R(i)-C})}_1 = p(x_C).$$

e.g. 9.1. For example, consider the following DAG:



Let $C := \{1, 2\}$. Then,

$$p_R(x_1, x_2) = \sum_{x'_3, x'_4} p_R(x_1, x_2, x'_3, x'_4) = p(x_1, x_2) \sum_{x'_3, x'_4} p(x'_4) p(x'_3 | x_2) = p(x_1, x_2)$$

\Rightarrow) [We need to make some fix in this direction.]

We show contrapositive: we show the following:

$$[\forall Q \in [R]; C \text{ is not an ancestral clique in } Q] \implies [\exists p \exists x; p_R(x_C) \neq p(x_C)]$$

Assume that C is not an ancestral clique in any $Q \in [R]$. Fix any $Q \in [R]$. We divide the proof into two cases:

Case (i): In case C is not a clique in Q . In this case, C is not a clique in any $R' \in [R]$. There must be two distinct nodes $i_0, i_1 \in C$ such that $(i_0, i_1) \notin Q$ and $(i_1, i_0) \notin Q$. Consider $p \in \Delta(X)$ such that for every $i \in C \setminus \{i_0, i_1\}$, x_i is independently distributed, whereas x_{i_0} and x_{i_1} are mutually correlated. Then,

$$\begin{aligned} \prod_{i \in C} p(x_i | x_{R(i) \cap C}, x'_{R(i)-C}) &= \prod_{i \in C} p(x_i) \quad (\because \text{there is no edge b/w } i_0 \text{ and } i_1) \\ \prod_{i \notin C} p(x'_i | x_{R(i) \cap C}, x'_{R(i)-C}) &= \prod_{i \notin C} p(x'_i) \\ p_R(x_C) &= (8) = \prod_{i \in C} p(x_i) \sum_{i \notin C} \prod_{i \notin C} p(x'_i) = \prod_{i \in C} p(x_i) \end{aligned}$$

However,

$$p(x_C) = p(x_{i_0}) p(x_{i_1} | x_{i_0}) \prod_{i \in C \setminus \{i_0, i_1\}} p(x_i)$$

Therefore, for some p , $p_R(x_C) \neq p(x_C)$.

Case (ii): C is a clique, but not an ancestral clique in Q . For a DAG R , denote the set of the all v -structures in R as $v(R)$, i.e.,

$$v(R) := \{(i, j, k) \mid i \rightarrow j, k \rightarrow j, i \nrightarrow k, k \nrightarrow i\}$$

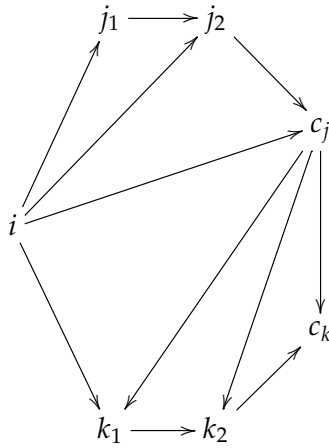
In the original proof, there is a lemma like the following, but the lemma is wrong:

Lem. 9.1. *Let R be a DAG and C be a clique in R . Assume the following two:*

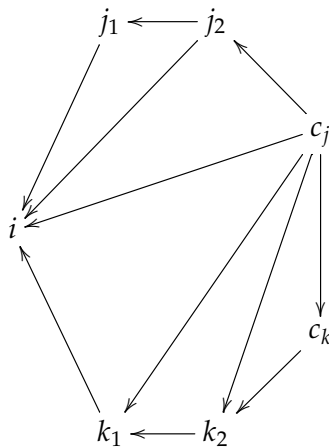
1. $\forall j \in C; j$ has no unmarried parents in R .
2. $\forall i \notin C$; if there is a directed path from i to some node $j \in C$ in R , then i has no unmarried parents in R .

Transform R into another DAG R' by inverting every link along every such path; R and R' has the same v -structure.

e.g. 9.2 (Counter example for Lem.9.1). *Let R be the graph below:*



Let $C := \{c_j, c_k\}$. Note that for all $k \in N \setminus C$ such that k has a path to some $c \in C$, k has no unmarried parents. R' is as follows:



Though $v(R) = \emptyset$, we have $v(R') = \{(j_1, i, k_1), (j_1, i, c_j), (j_2, i, k_1)\}$. Therefore, Lem.9.1 does not hold.

We can consider the modified version of the above lemma:

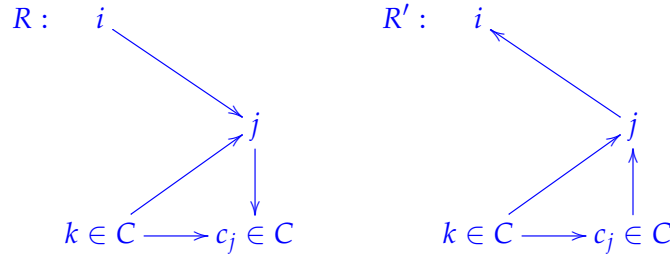
Lem. 9.2. Let R be a DAG and C be a clique in R . Assume the following two:

1. $\forall j \in C; j$ has no unmarried parents in R .
2. $\forall i, j \in N$; if there is a directed path from i to some node $c_i \in C$ and a path from j to some node $c_j \in C$ in R , then $i \rightarrow j$ or $j \rightarrow i$.

Transform R into another DAG R' by inverting every link along the every path $i \rightsquigarrow c$ such that $i \notin C$ and $c \in C$; then, R and R' has the same v -structure.

For the moment, let us admit Lem.9.2. (I prove it later.)

[I tried to modified the condition in assumption 2 from $\forall i, j \in N$ to $\forall i, j \notin C$, but this does not hold: Below, $(i, j, k) \in v(R)$, but $(i, j, k) \notin v(R')$]



The modified proof for Case (ii) By Lem.9.2, if the two assumptions in Lem.9.2 hold, there should exists $R' \in [R]$ such that C is an ancestral clique in R' ; this contradicts the assumption we made at the beginning of the proof.

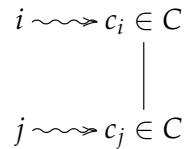
Hence, one of the following propositions holds:

$$\exists j \in C; j \text{ has an unmarried parents in } Q. \quad (P1)$$

$$\exists i, j \in N \exists c_i, c_j \in C; i \rightsquigarrow_Q c_i, j \rightsquigarrow_Q c_j, i \not\rightarrow_Q j, j \not\rightarrow_Q i \quad (P2)$$

In case of (P1), the original proof works. From now on, we assume (P1) does not hold and (P2) holds.

First of all, $i \notin C$ or $j \notin C$; otherwise there is an edge between them because C is a clique. Assume w.l.o.g. that $i \notin C$; Q contains the structure as below:



Let $P_i \subseteq N$ and $P_j \subseteq N$ are the set of nodes contained in the directed paths from i to c_i and from j to c_j respectively.

Observations:

- $|P_i| \geq 2$. ($\because i \notin C$.)
- $|P_j| \geq 1$. (j may be a member of C .)
- c_i and c_j may coincide.
- If $|P_j| = 1$, then $j \neq c_i$; otherwise, $i \rightarrow j$.

Consider $p \in \Delta(X)$ and a DAG R^* that satisfy

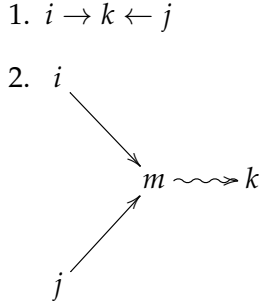
- p is consistent with R^* .
- $i \notin P_i \cup P_j \implies i$ is an isolated node in R^* .

Consider the subgraph of Q restricted on $P_i \cup P_j$. We name the subgraph Q' .

Case (ii-1): In case $Q'(j) = \emptyset$: Since C is a nonempty clique, $j \notin C$. Since $i \not\leftrightarrow j$, for all $p \in \Delta(X)$, we have $i \not\perp_{p_Q} j$. Consider $p \in \Delta(X)$ such that $i \perp_p j$. **Then, we can apply the same logic in the original proof in this case; we can show the existence of p such that $p(x_C) \neq p_Q(x_C)$ for some x_C .**

Case (ii-2): In case $Q'(j) \neq \emptyset$: Fix $k \in Q'(j)$. Since Q' is a DAG, k is not a descendant of j in Q' . We also have $k \neq i$. Since all the nodes in Q' is either the descendant of node i or that of node j , node k is a descendant of node i . Assume w.l.o.g that there is no node along the path from i to k such that the node is a parent of j . (If $|Q'(j)| \geq 2$, then we can take the node k that is closest to i .)

$(i \perp j \mid k)_{Q'}$ **holds:** \therefore First, take any path $i \rightsquigarrow j$, by the construction of k , k is on that path. Next, we need to check that neither of the following structure is contained in Q' :



However, since Q' is a DAG and $k \rightarrow_{Q'} j$, neither of them holds.

cont. Therefore, there exists $p' \in \Delta(X_{P_i \cup P_j})$ such that $(x_i \not\perp x_j \mid x_k)_{p'}$. Consider the following probability distribution p :

$$p(x) := p'(x_{P_i \cup P_j}) \prod_{l \notin P_i \cup P_j} p(x_l)$$

p_R should satisfy $(x_i \perp x_j \mid x_k)_Q$. This implies

$$\exists p \exists x_C; p(x_C) = p_{Q'}(x_C)$$

□

もしかしたら, Spiegelger が論文中でいっている主張は Lem.9.1 とは違うものかも.

Lem. 9.3. Let R be a DAG and C be a non-ancestral clique in any $R' \in [R]$. Assume the following two:

1. $\forall j \in C; j$ has no unmarried parents in R .
2. $\forall i \notin C$; if there is a directed path from i to some node $j \in C$ in R , then i has no unmarried parents in R .

Transform R into another DAG R' by inverting every link along every such path; R and R' has the same v -structure.

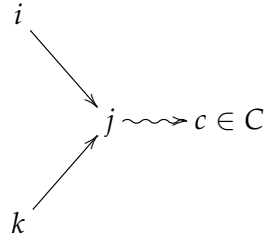
しかし, この証明の仕方もよくわからず.

Proof of Lem.9.2. We show $v(R) = v(R')$.

Step 1: $v(R) \subseteq v(R')$ Fix any v-structure $(i, j, k) \in v(R)$, $i \rightarrow j \leftarrow k$. By assumption 1 in Lem.9.2, we can assume that $j \notin C$. We can also assume that $i \notin C$ or $k \notin C$; otherwise there is an edge between i and k because C is a clique. Assume w.l.o.g that $i \notin C$.

It is sufficient to show that (i, j, k) remains as a v-structure after the inversion. Suppose toward contradiction that (i, j, k) is not a v-structure any more after the inversion. It is necessary that at least one of the edges $i \rightarrow j$ and $k \rightarrow j$ should be inverted.

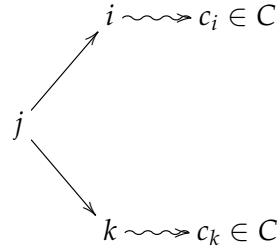
Case (1-1): In case $k \notin C$: Assume w.l.o.g that $i \rightarrow j$ is inverted. Then, there exists some node $c \in C$ such that $i \rightsquigarrow_R c$ ⁴; this implies that $i \rightsquigarrow_R c$, and $k \rightsquigarrow_R c$. The graph below summarizes the relationships:



However, by assumption 2 in Lem.9.2, there should be an edge between node i and node k ; this contradicts the assumption that (i, j, k) is a v-structure in R .

Case (1-2) In case $k \in C$: In this case, $k \rightarrow j$ is not inverted; then, $i \rightarrow j$ should be inverted. Then, by the same logic as in Case (1-1), this leads to a contradiction.

Step 2: $v(R) \supseteq v(R')$ We show that the inversion does not create a new v-structure. Suppose toward contradiction that there exists a triple $(i, j, k) \in v(R) \setminus v(R')$. In this case, the structure as in the below graph should hold in R (c_i and c_k may be the same node.):



However, by assumption 2 in Lem.9.2, there should be an edge between node i and node k . A contradiction. \square

⁴ $i \rightsquigarrow_R j$ denotes that there is a directed path from node i to node j in a DAG R .