

# Identifying Optimal Sequential Decisions

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# Main Messages

To find an optimal sequential decision strategy must allow it to depend on all available information.

Conditions for identifying a decision strategy that depends on all available information are 'simple'.

Note: we use influence diagrams instead of causal DAGs.

# Data Situation

$A_1, \dots, A_N$  “action” variables  $\rightarrow$  can be ‘manipulated’

$L_1, \dots, L_N$  covariates  $\rightarrow$  (available) background information

$Y = L_{N+1}$  response variable

all measured over time,  $L_i$  before  $A_i$

$\mathbf{A}^{<i}$  =  $(A_1, \dots, A_{i-1})$  **past** up to before  $i$ ;  $\mathbf{A}^{\leq i}$ ,  $\mathbf{A}^{>i}$  etc. similarly

# Example

Consider patients receiving anticoagulant treatment  $\Rightarrow$  has to be monitored and adjusted.

$L_i$  = blood test results, other health indicators.

$A_i$  = dose of anticoagulant drug.

Plausibly, 'optimal' dose  $A_i$  will be a function of  $\mathbf{L}^{\leq i}$  (and poss.  $\mathbf{A}^{< i}$ ).

# Strategies

**Strategy**  $s = (s_1, \dots, s_N)$  set of functions assigning an action

$$a_i = s_i(\mathbf{a}^{<i}, \mathbf{l}^{\leq i}) \text{ to each history } (\mathbf{a}^{<i}, \mathbf{l}^{\leq i})$$

(Could be stochastic, then dependence on  $\mathbf{a}^{<i}$  relevant.)

Also called: **conditional** / **dynamic** / **adaptive** strategies.

# Evaluation

Let  $p(\cdot; \mathbf{s})$  be distribution under strategy  $\mathbf{s}$ .

Let  $k(\cdot)$  be a loss function. Want to evaluate  $E(k(Y); \mathbf{s})$ .

Define

$$f(\mathbf{a}^{\leq j}, \mathbf{l}^{\leq i}) := E\{k(Y) | \mathbf{a}^{\leq j}, \mathbf{l}^{\leq i}; \mathbf{s}\} \quad i = 1, \dots, N; j = i - 1, i.$$

Then obtain  $f(\emptyset) = E(k(Y); \mathbf{s})$  from  $f(\mathbf{a}^{\leq N}, \mathbf{l}^{\leq N})$  iteratively by:

$$f(\mathbf{a}^{< i}, \mathbf{l}^{\leq i}) = \sum_{a_i} \underbrace{p(a_i | \mathbf{a}^{< i}, \mathbf{l}^{\leq i}; \mathbf{s})}_{\text{known by } \mathbf{s}} \times f(\mathbf{a}^{\leq i}, \mathbf{l}^{\leq i})$$

$$f(\mathbf{a}^{< i}, \mathbf{l}^{< i}) = \sum_{l_i} p(l_i | \mathbf{a}^{< i}, \mathbf{l}^{< i}; \mathbf{s}) \times f(\mathbf{a}^{< i}, \mathbf{l}^{\leq i}).$$

(cf. extensive form analysis)

# Identifiability

Problem: doctors are following their 'gut feeling' (and not a specific strategy) in modifying the dose of anticoagulant drug.

**Identifiability:** *can* we find the optimal strategy from such data?

In particular:  $p(l_i | \mathbf{a}^{<i}, \mathbf{l}^{<i}; \mathbf{s})$  then not known.

But could *estimate*  $p(l_i | \mathbf{a}^{<i}, \mathbf{l}^{<i}; o)$  under **observational regime**.

Introduce indicator

$$\sigma = \begin{cases} o, & \text{observational regime} \\ s, & \mathbf{s} \in \mathcal{S} = \text{set of strategies} \end{cases}$$

# Simple Stability

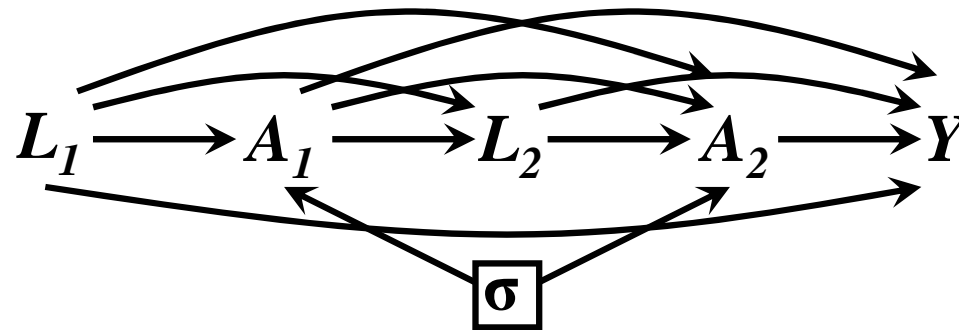
Sufficient for identifiability is

$$p(l_i | \mathbf{a}^{<i}, \mathbf{l}^{<i}; \mathbf{s}) = p(l_i | \mathbf{a}^{<i}, \mathbf{l}^{<i}; \mathbf{o}) \quad \text{for all } i = 1, \dots, N + 1$$

or (via intervention indicator)

$$L_i \perp\!\!\!\perp \sigma | (\mathbf{A}^{<i}, \mathbf{L}^{<i}) \quad \text{for all } i = 1, \dots, N + 1$$

Or graphically:



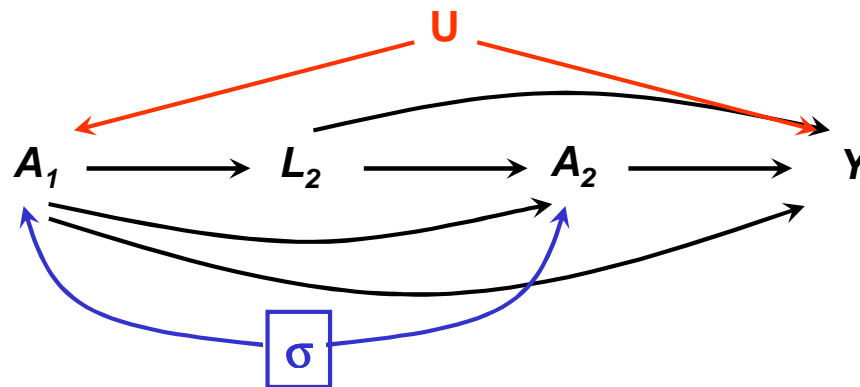


# Extended Stability

Might not be able to assess simple stability without taking unobserved variables into account.

$\Rightarrow$  extend covariates  $\mathbf{L}$  to include unobserved / hidden variables  $\mathbf{U} = (U_1, \dots, U_N)$  and check if simple stability can be deduced.

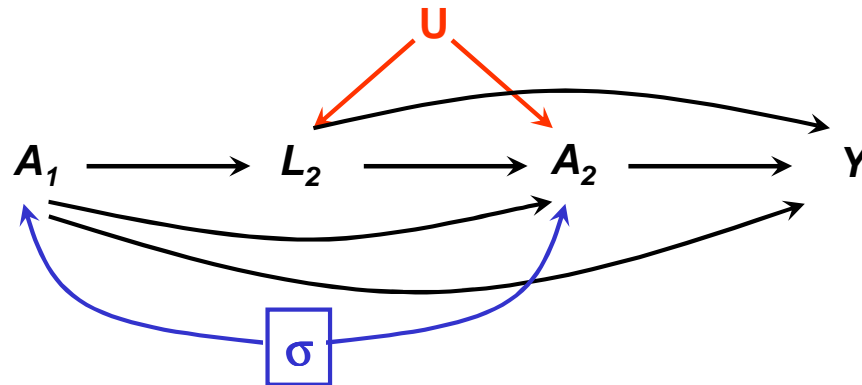
**Example 1:** particular underlying structure (note:  $L_1 = \emptyset$ )



Simple stability violated as  $Y \not\perp\!\!\!\perp \sigma \mid (A_1, A_2, L_2)$ .

# Examples

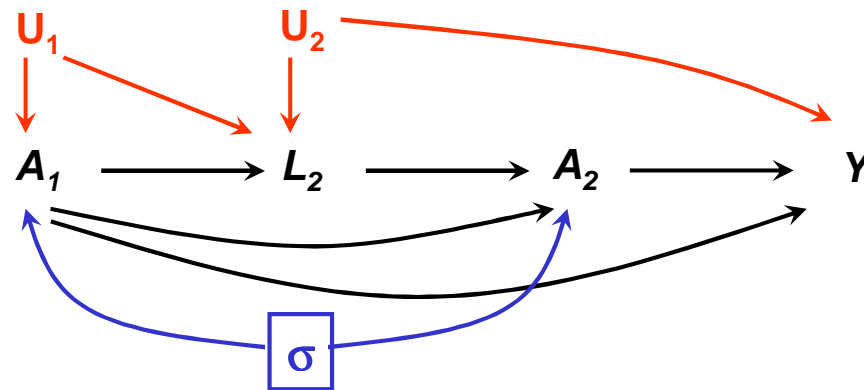
**Example 2:** different underlying structure



Simple stability satisfied.

# Examples

**Example 3:** another different underlying structure



Simple stability violated:  $L_2 \not\perp\!\!\!\perp \sigma \mid A_1$  and  $Y \not\perp\!\!\!\perp \sigma \mid (A_1, A_2, L_2)$

# Relax Simple Stability?

For given strategy  $\mathbf{s}$  can relax conditions for identifiability.

Assume extended stability holds wrt.  $\mathbf{A}, \mathbf{L}, \mathbf{U}, Y$ , and define 'new' joint distributions  $p_i(\mathbf{A}, \mathbf{L}, \mathbf{U}, Y) =$

$$p(\mathbf{A}^{\leq i}, \mathbf{L}^{\leq i}, \mathbf{U}^{\leq i}; o) \times p(\mathbf{A}^{> i}, \mathbf{L}^{> i}, \mathbf{U}^{> i}, Y | \mathbf{A}^{\leq i}, \mathbf{L}^{\leq i}, \mathbf{U}^{\leq i}; \mathbf{s})$$

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$$\underbrace{p(\mathbf{A}^{\leq i}, \mathbf{L}^{\leq i}, \mathbf{U}^{\leq i}; \mathbf{o})}_{\text{obs. for } \leq i} \times p(\mathbf{A}^{> i}, \mathbf{L}^{> i}, \mathbf{U}^{> i}, Y | \mathbf{A}^{\leq i}, \mathbf{L}^{\leq i}, \mathbf{U}^{\leq i}; \mathbf{s})$$

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**Theorem 1:** sufficient condition for identifiability of  $s$  is

$$p_{i-1}(y | \mathbf{a}^{\leq i}, \mathbf{l}^{\leq i}) = p_i(y | \mathbf{a}^{\leq i}, \mathbf{l}^{\leq i}), \quad i = 1, \dots, N.$$

(Simple stability implies the above.)

# Comments

## Theorem 1, in words:

once we know  $a_i$  and the observable past variables the distribution of  $Y$  does not depend on *how*  $a_i$  was generated, when  $\mathbf{a}^{<i}$  is observational and  $\mathbf{a}^{>i}$  follows the strategy.

## Note:

Essentially same as Pearl & Robins (1995) for *unconditional* strategies.



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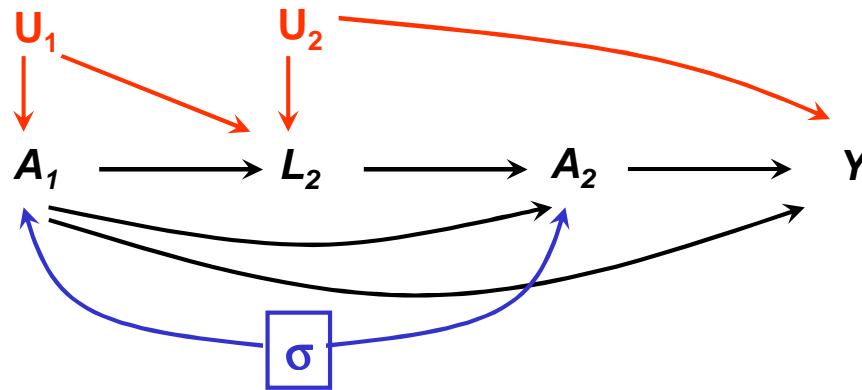
**Graphical check:** draw graphs  $D_i$  with

- $\text{pa}(A_k)$  as under observational regime for  $k < i$
- $\text{pa}(A_k)$  as under strategy for  $k > i$
- $\text{pa}(A_i)$  union of both regimes and  $\sigma$ .

$\Rightarrow$  check separation  $Y \perp\!\!\!\perp \sigma \mid (\mathbf{A}^{\leq i}, \mathbf{L}^{\leq i})$  in  $D_i$ ,  $i = 1, \dots, N$

## Example 3 ctd.

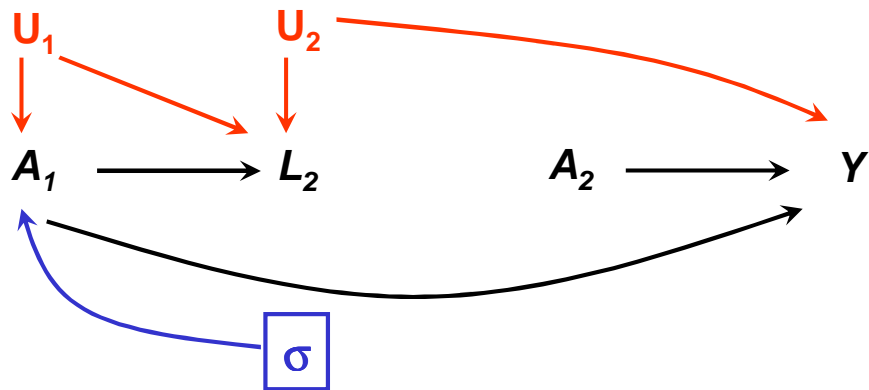
Assumed underlying structure (note:  $L_1 = \emptyset$  here)



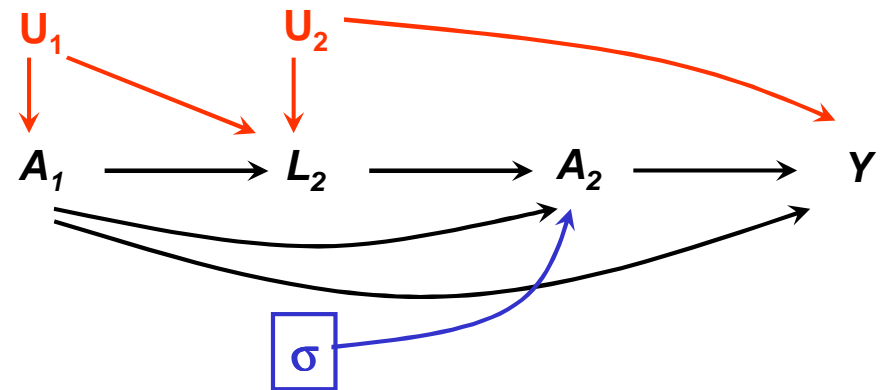
**Now:** also assume that  $s_2$  is **unconditional**, i.e. choice of action  $A_2$  in our strategy does not depend on past observations.

## Example 3 ctd.

Then  $D_1$  and  $D_2$  are given by



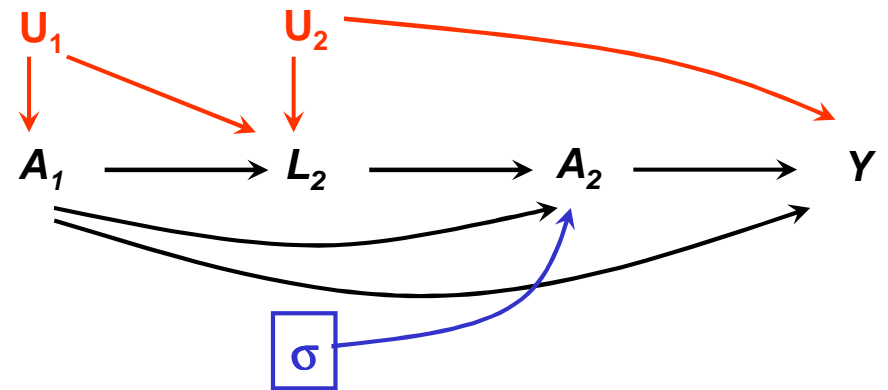
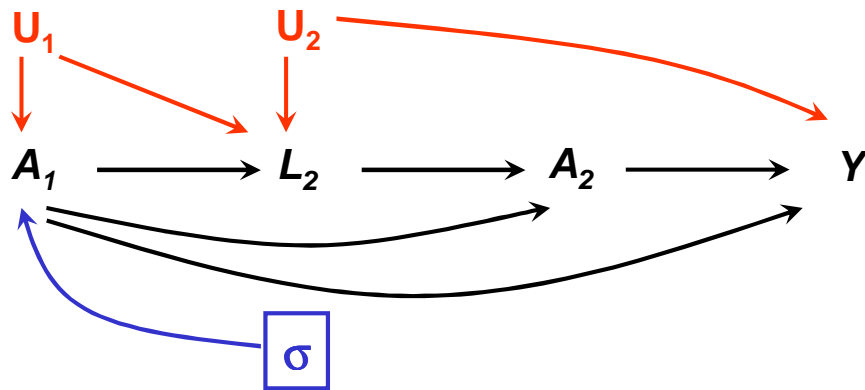
Can see that  $Y \perp\!\!\!\perp \sigma | A_1$  in  $D_1$



and  $Y \perp\!\!\!\perp \sigma | (A_1, A_2, L_2)$  in  $D_2$ .

## Example 3 ctd.

However, if  $s_2$  is conditional, i.e.  $A_2$  depends on past observations in our strategy, then  $D_1$  and  $D_2$  are given by



**Now**  $Y \not\perp\!\!\!\perp \sigma | A_1$  in  $D_1$ .

This suggests that the ‘relaxed’ conditions are not so ‘relaxed’ for conditional interventions.

# Result

**Assumption 1:**  $\text{pa}_s(A_i) \subset \text{pa}_o(A_i)$  for all  $i = 1, \dots, N$ .

**Assumption 2:** each  $L_1, \dots, L_N$  is an ancestor of  $Y$  in  $D_0$  (as under strategy  $s$ ),  $i = 1, \dots, N$ .

**Theorem 2:** With these assumptions, if the graphical check of [Theorem 1](#) succeeds then we also have [simple stability](#).

**Optimal strategies:** Assumption 2 satisfied because

- actions  $A_i$  must be allowed to depend on past  $\mathbf{L}^{\leq i}$
- and  $A_i$  ancestors of  $Y$ .

# Conclusions and Outlook

- A given strategy  $s$  can be identified using simple stability or Theorem 1 as criteria.  
⇒ latter is cumbersome to check.
- When we aim at searching for an optimal strategy, we need to be able to identify strategies that are conditional on all available information.  
⇒ only need to check simple stability criterion.
- For the same graphical structure, an unconditional strategy may be identified while a conditional one is not.