

Experiments, decision rules, and costly information acquisition

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MOTIVATION

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$$\begin{array}{cc} \text{maximize} & [\text{benefit} - \text{cost}] \\ \text{(decision rule, experiment)} & \end{array}$$

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- Decision rule: signal-dependent actions
- Experiment: state-dependent signal distributions
- Benefit: ex ante expected payoff w/ information
- Cost: money/time/fatigue to generate/process information

OBJECTIVE

- Axiomatic model of costly information acquisition
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- Axiomatic model of costly information acquisition
 - Bayesian DM + information cost
- Primitive: \succsim over (decision rule, experiment)
- Characterize several models that differ in cost structures:
 - **Today:** 1. general 2. posterior separable

1 MODEL

2 CHARACTERIZATION

3 SUMMARY

PRIMITIVES

- \mathcal{E} : set of *experiments* $e: \Omega \rightarrow \Delta(S)$, $\omega \mapsto e_\omega$
 - Ω : finite set of *states*
 - S : Polish space of *signals*
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- \mathcal{D} : set of **decision rules** $\delta: \mathcal{E} \times S \rightarrow \mathcal{H}$, $(e, s) \mapsto \delta_s^e$
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 - Identify $h \in \mathcal{H}$ with constant decision rule $(e, s) \mapsto h$
- \succsim : preference over **strategies** $(\delta, e) \in \mathcal{D} \times \mathcal{E}$

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4. A state is resolved & DM receives a payoff

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$$r_\omega^u(\delta, e) = \int u(\delta_s^e(\omega)) \, de_\omega(s) = u\left(\int \delta_s^e(\omega) \, de_\omega(s)\right) = u((\delta * e)_\omega)$$

where

$$\delta * e \equiv \left(\int \delta_s^e(\omega) \, de_\omega(s) \right)_{\omega \in \Omega}$$

(the ***induced act by*** (δ, e))

COST OF INFORMATION

Definition

An (*information*) *cost function* is any continuous $c: \mathcal{E} \rightarrow \mathbb{R}_+$ s.t.

1. $e \succcurlyeq_B f \implies c(e) \geq c(f)$;
2. $c(e^0) = 0$ for each uninformative $e^0 \in \mathcal{E}$.

- Topology over experiments is induced by distr. over posteriors
 - Topology is prior-independent
- \succcurlyeq_B : *Blackwell order* on \mathcal{E}
- e^0 is *uninformative* $\stackrel{\text{def}}{\iff} e^0_\omega = e^0_{\omega'}, \quad \forall (\omega, \omega') \in \Omega^2$

AGGREGATORS

Definition

An **aggregator** is any continuous $W: T \times K \rightarrow \mathbb{R}$ s.t.

- T and K are real intervals;
 - $W(\cdot, k)$ is increasing for each $k \in K$;
 - $W(t, \cdot)$ is decreasing for each $t \in T$.
-
- Additive aggregator: $(t, k) \mapsto t - k$
 - Multiplicative aggregator: $(t, k) \mapsto e^{-k}t$

UTILITY REPRESENTATION

Definition

A **costly information acquisition representation of \succsim** is $\langle u, \mu, c, W \rangle$ s.t.

- u is a vNM function;
- μ is a full support prior;
- c is a cost function;
- W is an aggregator;
- \succsim is represented by

$$V(\delta, e) = W\left(\int r_{\omega}^u(\delta, e) d\mu(\omega), c(e)\right).$$

POSTERIOR SEPARABILITY

Definition

A **posterior separable representation of \succsim** is $\langle u, \mu, H \rangle$ s.t.

- u is a vNM function;
- μ is a full support prior;
- H is a convex function on $\Delta(\Omega)$;
- \succsim is represented by

$$V(\delta, e) = \int r_{\omega}^u(\delta, e) d\mu(\omega) - c(e),$$
$$c(e) = \int H(\mu_s^e) de_{\mu}(s) - H(\mu).$$

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AXIOMS

A1—Regularity

\succsim is nondegenerate, complete, transitive, and continuous.

- Topology over strategies:

Two strategies are “close” \iff

the induced acts and experiments are “close”

A2—Statewise dominance

For each $((\delta, \gamma), e) \in \mathcal{D}^2 \times \mathcal{E}$,

1. $\delta \geq_D^e \gamma \implies (\delta, e) \succeq (\gamma, e)$;
2. $\delta >_D^e \gamma \implies (\delta, e) \succ (\gamma, e)$.

- $\delta \geq_D^e \gamma \iff ((\delta * e)_\omega, e) \succeq ((\gamma * e)_\omega, e) \quad \forall \omega \in \Omega$
- $\delta >_D^e \gamma \iff \delta \geq_D^e \gamma \text{ \& } ((\delta * e)_\omega, e) \succ ((\gamma * e)_\omega, e) \quad \exists \omega \in \Omega$

A3—Information monotonicity

For each $((\delta, \gamma), (e, f)) \in \mathcal{D}^2 \times \mathcal{E}^2$, if

$$\delta * e = \gamma * f \quad \text{and} \quad f \succcurlyeq_B e,$$

then $(\delta, e) \precsim (\gamma, f)$.

- More informative \implies more costly

A4—Cost consistency

For each $((\delta, \tilde{\delta}, \gamma, \tilde{\gamma}), (e, f)) \in \mathcal{D}^4 \times \mathcal{E}^2$, if

$$\delta * e = \gamma * f \quad \text{and} \quad \tilde{\delta} * e = \tilde{\gamma} * f \quad \text{and} \quad (\delta, e) \succeq (\gamma, f),$$

then $(\tilde{\delta}, e) \succeq (\tilde{\gamma}, f)$.

- Cost does not depend on decision rules

MATRIX NOTATION OF EXPERIMENTS

Let $\Omega = \{1, \dots, m\}$

If $e \in \mathcal{E}$ satisfies $\text{supp } e = \{s_1, \dots, s_n\}$, then

$$e \simeq \begin{bmatrix} e_1(s_1) & \cdots & e_1(s_n) \\ \vdots & \ddots & \vdots \\ e_m(s_1) & \cdots & e_m(s_n) \end{bmatrix}, \quad \sum_{i=1}^n e_\omega(s_i) = 1, \quad e_\omega(s_i) \geq 0$$

- e is identified w/ a row stochastic matrix

CONCATENATION OF EXPERIMENTS

- If $\text{supp } e \cap \text{supp } f = \emptyset$,

λ -mixture of e and f = " λ -concatenation of e and f "

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- In matrix notation, if $\text{supp } e = \{s_1, \dots, s_n\}$ and $\text{supp } f = \{\tilde{s}_1, \dots, \tilde{s}_k\}$,

$$\begin{aligned} \lambda e + (1 - \lambda)f &\simeq \left[\lambda e \mid (1 - \lambda)f \right] \\ &= \left[\begin{array}{ccc|ccc} \lambda e_1(s_1) & \cdots & \lambda e_1(s_n) & (1 - \lambda)f_1(\tilde{s}_1) & \cdots & (1 - \lambda)f_1(\tilde{s}_k) \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ \lambda e_m(s_1) & \cdots & \lambda e_n(s_n) & (1 - \lambda)f_m(\tilde{s}_1) & \cdots & (1 - \lambda)f_m(\tilde{s}_k) \end{array} \right] \end{aligned}$$

A5—Equivalent concatenation independence

For each $(\lambda, \delta, (e, e', f)) \in (0, 1] \times \mathcal{D}_{\text{inv}} \times \mathcal{E}^3$ w/

$e \sim_B e'$ and $(\text{supp } e \cup \text{supp } e') \cap \text{supp } f = \emptyset$,

$$(\delta, e) \succeq (\delta, e') \iff (\delta, \lambda e + (1 - \lambda)f) \succeq (\delta, \lambda e' + (1 - \lambda)f).$$

- \mathcal{D}_{inv} : set of *invariant* decision rules
 - $\delta_s^e = \delta_s^f$ for each $((e, f), s) \in \mathcal{E}^2 \times S$
- $e \sim_B e' \implies \lambda e + (1 - \lambda)f \sim_B \lambda e' + (1 - \lambda)f$ under support disjointness
- Mixture affects only on induced acts

Theorem 1

\succsim satisfies A1–A5 \iff

\succsim has a costly information acquisition representation.

- A1—*Regularity*
- A2—*Statewise dominance*
- A3—*Information monotonicity*
- A4—*Cost consistency*
- A5—*Equivalent concatenation independence*

POSTERIOR SEPARABLE REPRESENTATION

Theorem 3

\succsim satisfies A1–A3 & A6 $\iff \succsim$ has a posterior separable representation.

A6—Concatenation independence

For each $(\lambda, \delta, (e, e', f)) \in (0, 1] \times \mathcal{D}_{\text{inv}} \times \mathcal{E}^3$ w/

$e \sim_B e'$ and $(\text{supp } e \cup \text{supp } e') \cap \text{supp } f = \emptyset$,

$$(\delta, e) \succsim (\delta, e') \iff (\delta, \lambda e + (1 - \lambda)f) \succsim (\delta, \lambda e' + (1 - \lambda)f).$$

- A6 says signal-wise separability + separability of benefit and cost
- *Cost consistency* is implied by the other axioms

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SUMMARY

This paper characterizes

- Bayesian DM + costly information acquisition
- Bayesian DM + a posterior separable cost

LITERATURE

- **Preference over menus:**

menu choice → signal arrival → choice from menu

- de Oliveira (2014), de Oliveira · Denti · Mihm · Ozbek (2018),
Higashi · Hyogo · Takeoka (2025)

- **Stochastic choice:**

signal arrival → choice from a menu → stochastic choice

- Caplin · Dean (2015), Chambers · Liu · Rehbeck (2020), Denti (2022)

- **Statistical decision:**

- Furtado (2024)—same domain · no cost of information