

# UNDERSTANDING INFORMATION ACQUISITION THROUGH F-INFORMATIVITY AND DUALITY

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Choice and Decision Workshop, BSE Summer Forum --- June 2025

~~UNDERSTANDING INFORMATION ACQUISITION THROUGH F-INFORMATIVITY AND DUALITY~~

MODELING THE MODELER:  
A NORMATIVE THEORY OF EXPERIMENTAL DESIGN

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- ◇ We propose three normative principles for experimental design
  - ◇ minimal rationality properties, independent of specific motivations
  - ◇ We will specifically think about revealed preference experiments
- ◇ We show that they imply a particular representation
  - ◇ Relates an experiment to the expected value of identification
  - ◇ Unifies many distinct models of experimentation
  - ◇ Axiomatic characterization for Bayesian Experimental Design
  - ◇ Test for analyst to make sure they do not have an “agenda”

## Normative Principles

**Structural Invariance:** Two experiments that identify the sets of parameters are equally valued

**Information Monotonicity:** Experiments that induce sharper identification are (weakly) better

**Identification Separability:** The value of identifying a set of parameters should *not* depend on counterfactuals



An analyst (she) wishes to infer a subject's (he) utility function over  $Z$ :

- ◇ Revealed Preference: she should offer a menu  $A \subseteq Z$  and observe the subject's choice
- ◇ Different menus offer different “inference” opportunities
- ◇ Ranking over menus will depend on the goals for the analyst

## Experimental Environment

- ◇  $Z$  set of alternatives
- ◇  $\mathcal{U} \subseteq \{u : Z \rightarrow \mathbb{R}\}$  set of utility functions over  $Z$
- ◇  $\Omega$  algebra of measurable sets of  $\mathcal{U}$
- ◇  $\mu$  prior over  $(\mathcal{U}, \Omega)$

The tuple  $(Z, \mathcal{U}, \Omega, \mu)$  constitutes a theory for a Bayesian experimenter

## Expected Identification Value

These principles characterize ranking according to *expected identification value*

- ◇ Exists some  $\tau$ : for  $W \subseteq \mathcal{U}$ ,  $\tau(W)$  is the value of identifying  $W$
- ◇ Let  $\mathcal{W}$  be the sets that might get identified
- ◇ Experiments are valued according to:

$$\sum_{W \in \mathcal{W}} \tau(W) \mu(W)$$

- ◇ where  $\mu$  is the (exogenous) prior probability



## Special Case: Entropy

$$\tau(W) = -\log(\mu(W))$$

- ◇ Value of experiment is expected reduction in entropy

## Special Case: Hypothesis Testing

$$\tau(W) = \begin{cases} 1 & \text{if } W \subseteq W^* \text{ or } W^* \subseteq W^c \\ 0 & \text{otherwise.} \end{cases}$$

- ◇ Hypothesis: the true utility lies in  $W^*$
- ◇ Value of exp is the probability the hypothesis can be accepted or rejected

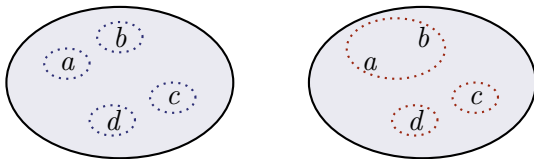
## Special Case: Actions

$$\tau(W) = \max_{a \in \mathbb{A}} \int_W \xi(a, u) d\mu.$$

- ◇ The analyst will take action  $a \in \mathbb{A}$
- ◇ Utility of outcome depends on the utility:  $\xi(a, u)$
- ◇ Value of exp is expected value of conditionally optimal action

An **experiment**  $e = (A, \mathcal{P})$  is a pair:

- ◇  $A \subseteq Z$  is finite decision problem
- ◇  $\mathcal{P}$  is a partition of  $A$



- ◇ Represents observability constraints
- ◇ Allows for dynamic experiments, non-lab settings, etc

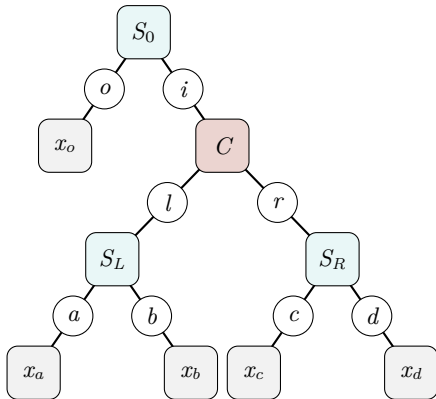
## Example: Dynamic Games

Consider a dynamic game:

- ◇ Computer randomizes 50-50
- ◇ Subject's strategies:

$$A = \left\{ \begin{array}{l} (i, a, c), (i, b, c), (i, a, d), (i, b, d), \\ (o, a, c), (o, a, d), (o, b, c), (o, b, d) \end{array} \right\}$$

- ◇ There are observable paths:  
 $(o)$ ,  $(i, a)$ ,  $(i, b)$ ,  $(i, c)$ , and  $(i, d)$

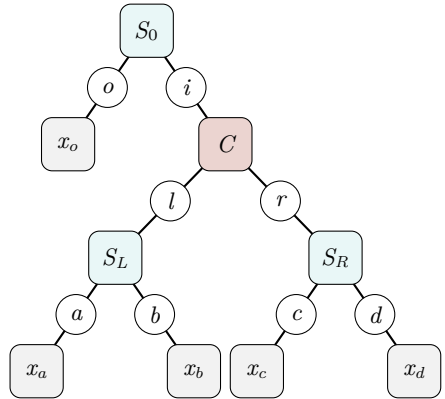


## Example: Dynamic Games

Now consider the following partitions of  $A$

$$\mathcal{P}_L = \left\{ \begin{array}{l} \left\{ (o, a, c), (o, b, c), \right. \\ \left. (o, a, d), (o, b, d) \right\}, \\ \left\{ (i, a, c), (i, a, d) \right\}, \\ \left\{ (i, b, c), (i, b, d) \right\} \end{array} \right\}$$

$$\mathcal{P}_R = \left\{ \begin{array}{l} \left\{ (o, a, c), (o, b, c), \right. \\ \left. (o, a, d), (o, b, d) \right\}, \\ \left\{ (i, a, c), (i, b, c) \right\}, \\ \left\{ (i, a, d), (i, b, d) \right\} \end{array} \right\}$$



Given an experiment,  $(A, \mathcal{P})$ , define the *identified set*:

$$W_{A,P} = \{u \in \mathcal{U} \mid P \cap \operatorname{argmax}_{x \in A} u(x) \neq \emptyset\}$$

- ◇ Observing  $P \in \mathcal{P}$  identifies that the subject's utility is in  $W_{A,P}$
- ◇ We require for an experiment  $(A, \mathcal{P})$  that for any  $P, Q \in \mathcal{P}$ 
  - (1)  $W_{A,P} \in \Omega$  — measurability
  - (2)  $\mu(W_{A,P} \cap W_{A,Q}) = 0$  — zero  $\mu$ -prob of ties

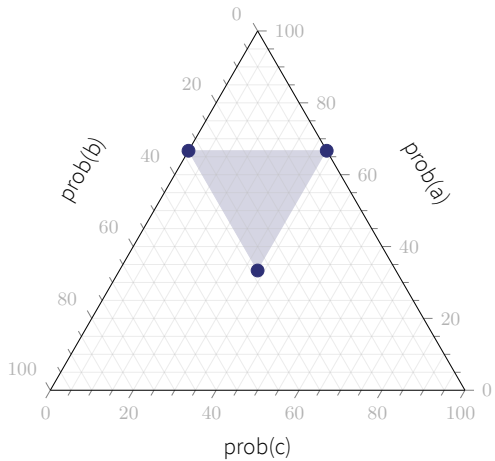
## Example: EU Preferences

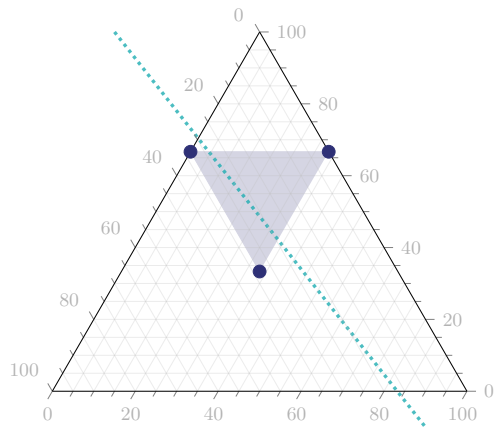
We can example identifying EU preferences as an example:

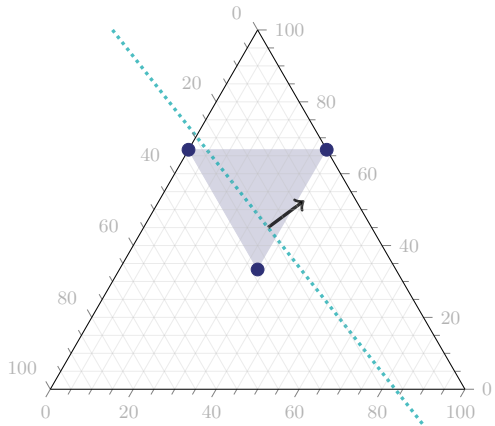
- ◇  $Z$  is lotteries over  $\{a, b, c\}$
- ◇  $\mathcal{U}$  is affine functions

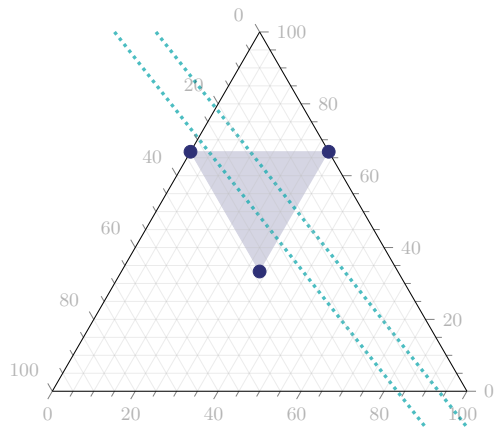


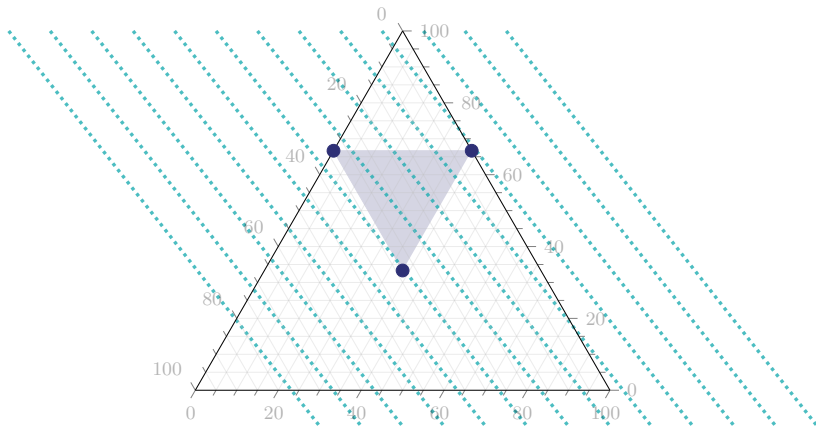
$$\{\frac{2}{3}a + \frac{1}{3}b, \frac{2}{3}a + \frac{1}{3}c, \frac{1}{3}a + \frac{1}{3}b + \frac{1}{3}c\}$$

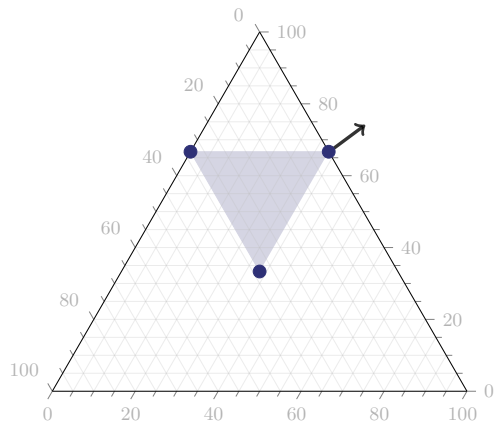


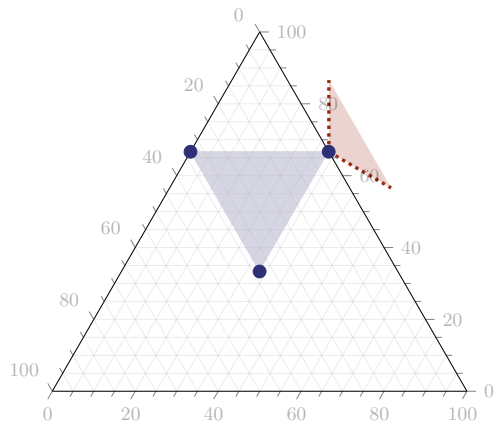


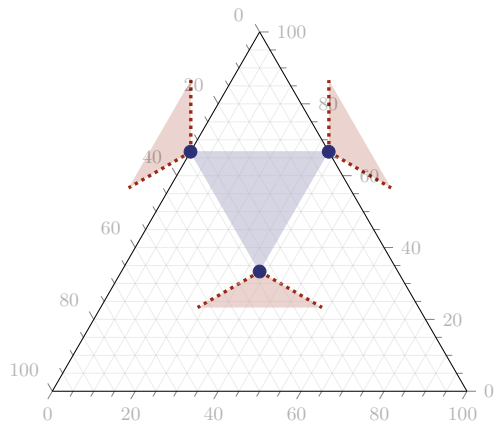






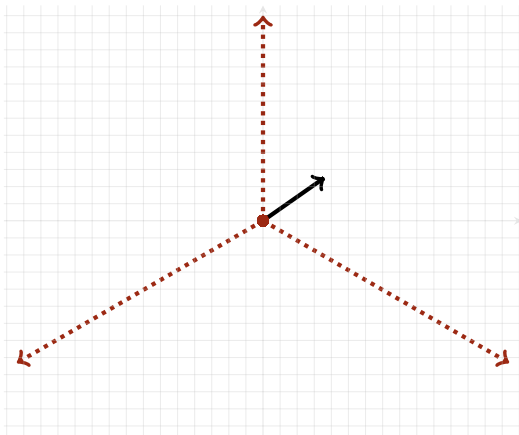








$$\mathcal{U} \cong \mathbb{R}^2$$



## $\mu$ -equivalence

Call  $\{W_1, \dots, W_n\}$  and  $\{V_1, \dots, V_m\}$ , families of subsets of  $\mathcal{U}$ ,  $\mu$ -*equivalent* if for all  $W_i$  and  $V_j$ :

$$\begin{aligned}\mu(W_i) &= \mu(W_i \cap V_j) \text{ for some } j \quad \text{and,} \\ \mu(V_j) &= \mu(W_i \cap V_j) \text{ for some } i\end{aligned}$$

- ◇ Such collections identify the same sets of utilities up to a measure zero
- ◇ Take  $[0, 1]$  with  $\lambda$  the Lebesgue measure. The following are  $\lambda$ -equivalent:
  - ◇  $\{[0, \frac{1}{2}), (\frac{1}{2}, 1]\}; \quad \{[0, \frac{1}{2}), \{\frac{1}{2}\}, (\frac{1}{2}, 1]\}, \quad \{[0, \frac{1}{2}], [\frac{1}{2}, 1]\}$

## Rich Experimental Settings

We say a set of experiments  $\mathbb{E}$  is *rich* if

- (1)  $(A, \mathcal{P}) \in \mathbb{E} \rightarrow (A, \mathcal{Q}) \in \mathbb{E}$  whenever  $\mathcal{Q}$  is a coarsening of  $\mathcal{P}$
- (2) For any finite  $\Omega$ -measurable partition of  $\mathcal{U}$ , there exists an experiment  $(A, \mathcal{P})$  such that  $\{W_{A,P}\}_{P \in \mathcal{P}}$  is  $\mu$  equivalent
  - ◇ Any partition can be approximated up to 0 probability events
  - ◇ For the EU model, the set of all experiments is rich for any “regular”  $\mu$

## Primitive

- ◇ Our primitive is a ranking  $\succsim$  over the set of all random experiments
- ◇ A *random experiment* is a lottery over some (fixed) rich set  $\mathbb{E}$



❖ *Normative Principles* ❖

“Two experiments that identify the sets of parameters are equally valued”

### (P1) - Structural Invariance

If  $\{W_{A,P} | P \in \mathcal{P}\}$  is  $\mu$ -equivalent to  $\{W_{B,Q} | Q \in \mathcal{Q}\}$  then  $(A, \mathcal{P}) \sim (B, \mathcal{Q})$ .

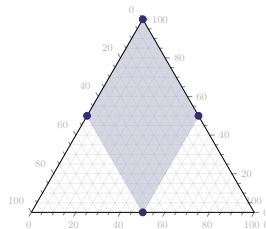
- ◇ Structural properties of experiments are irrelevant
- ◇ Also, 0-probability events are irrelevant

Consider our EU maximizing subject choosing lotteries over  $\{a, b, c\}$ .

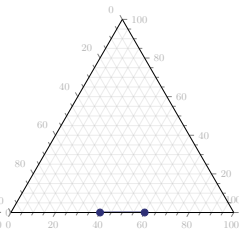
$$\begin{aligned}\text{EXP A : } A &= \{a, \tfrac{1}{2}a + \tfrac{1}{2}b, \tfrac{1}{2}a + \tfrac{1}{2}c, \tfrac{1}{2}b + \tfrac{1}{2}c\} \\ A' &= \{\tfrac{6}{10}b + \tfrac{4}{10}c, \tfrac{4}{10}b + \tfrac{6}{10}c\}.\end{aligned}$$

$$\begin{aligned}\text{EXP B : } B &= \{a, b, c\} \\ B' &= \{\tfrac{2}{3}a + \tfrac{1}{3}b, \tfrac{2}{3}a + \tfrac{1}{3}c, \tfrac{1}{3}a + \tfrac{1}{3}b + \tfrac{1}{3}c\}.\end{aligned}$$

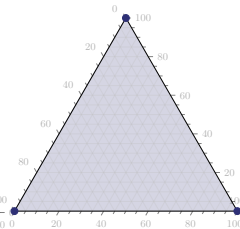
$$A = \{a, \frac{1}{2}a + \frac{1}{2}b, \frac{1}{2}a + \frac{1}{2}c, \frac{1}{2}b + \frac{1}{2}c\}$$



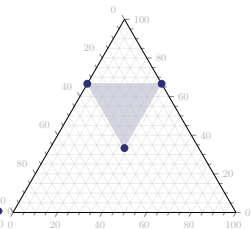
$$A' = \{\frac{6}{10}b + \frac{4}{10}c, \frac{4}{10}b + \frac{6}{10}c\}$$



$$B = \{a, b, c\}$$



$$B' = \{\frac{2}{3}a + \frac{1}{3}b, \frac{2}{3}a + \frac{1}{3}c, \frac{1}{3}a + \frac{1}{3}b + \frac{1}{3}c\}$$



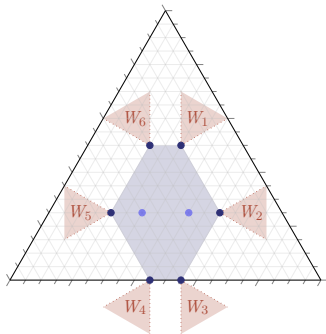


- ◇ Linearity states that

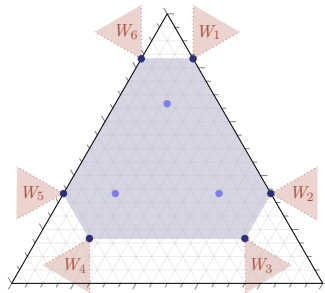
$$\left. \begin{array}{l} x \in \arg \max_A u(\cdot) \\ y \in \arg \max_B u(\cdot) \end{array} \right\} \quad \text{if and only if} \quad \alpha x + (1 - \alpha)y \in \arg \max_{\alpha A + (1 - \alpha)B} u(\cdot)$$

- ◇ Therefore, observing  $A$  followed by  $A'$  is equivalent to observing  $\frac{1}{2}A + \frac{1}{2}A'$

$$\frac{1}{2}A + \frac{1}{2}A'$$



$$\frac{1}{2}B + \frac{1}{2}B'$$



- ◇ Structural invariance reflects the symmetries of the given domain
- ◇ With linear utility, the symmetry is *translation invariance*:

### Structural Invariance for Expected Utility

$$(A, \{P_1, \dots, P_n\}) \sim (A + B, \{P_1 + B, \dots, P_n + B\})$$

- ◇ This isn't exactly correct, since  $\{P_1 + B, \dots, P_n + B\}$  might have overlaps....

“Experiments that induce sharper identification are (weakly) better”

(P2) - Information Monotonicity

If  $\mathcal{P}$  refines  $\mathcal{Q}$  then  $(A, \mathcal{P}) \succsim (A, \mathcal{Q})$ .

- ◇ Preference respects Blackwell order

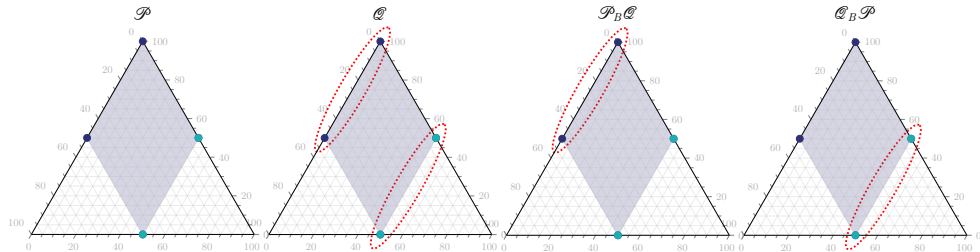
“The value of identification not depend on counterfactuals”

### (P3) - Identification Separability

$$\frac{1}{2}(A, \mathcal{P}) + \frac{1}{2}(A, \mathcal{Q}) \sim \frac{1}{2}(A, \mathcal{P}_B \mathcal{Q}) + \frac{1}{2}(A, \mathcal{Q}_B \mathcal{P}).$$

- ◇  $\mathcal{P}$  and  $\mathcal{Q}$  partitions of  $A$  and  $B \subseteq A$ , then  $\mathcal{P}_B \mathcal{Q}$  denotes the partition that coincides with  $\mathcal{P}$  over  $B$  and with  $\mathcal{Q}$  over  $A \setminus B$

Consider decision problem  $A$  (from before) with the following partitions



- ◇ The set  $B$  is the two south-east lotteries (in teal)

## Theorem

Let  $\succsim$  be an expected utility preference, represented by index  $F : \mathbb{E} \rightarrow \mathbb{R}$ .

Then  $\succsim$  satisfies **P1-3** if and only if there exists a  $\tau : \Omega \rightarrow \mathbb{R}$  such that:

$$F(A, \mathcal{P}) = \sum_{P \in \mathcal{P}} \tau(W_{A,P}) \mu(W_{A,P})$$

with  $W \subseteq V$  implies

- ◇  $\tau(W) \mu(W|V) + \tau(V \setminus W) (1 - \mu(W|V)) \geq \tau(V)$
- ◇  $\mu(V \setminus W) = 0$  implies  $\tau(W) = \tau(V)$

Representation reflects our normative principles:

$$F(A, \mathcal{P}) = \sum_{P \in \mathcal{P}} \tau(W_{A,P}) \mu(W_{A,P})$$

- ◇ Only depends on  $W_{A,P} \rightarrow$  Structural Invariance
- ◇ Additive  $\rightarrow$  Identification Separability
- ◇  $\tau(W) \mu(W|V) + \tau(V \setminus W) (1 - \mu(W|V)) \geq \tau(V) \rightarrow$  Monotonicity





- ◇ Entropy is a common measure of information
- ◇ Entropy of a probability measure is

$$- \sum_{x \in \text{supp}(\mu)} \log(\mu(x)) \mu(x)$$

- ◇ The experimenter's value for an experiment is the (expected) entropy of the induced identification

$$F(A, \mathcal{P}) = - \sum_{P \in \mathcal{P}} \log(\mu(W_{A,P})) \mu(W_{A,P})$$

We can specialize each of the normative principals to this context

## Structural Invariance for Entropy: Symmetry

Fix  $(A, \{P_1, \dots, P_n\})$  and  $(B, \{Q_1, \dots, Q_n\})$ . Then if for all  $i \leq n$ ,

$$|\mu(W_{B, Q_i}) - \frac{1}{n}| \geq |\mu(W_{A, P_i}) - \frac{1}{n}|$$

it follows that

$$(A, \{P_1 \dots P_n\}) \succcurlyeq (B, \{Q_1 \dots Q_n\}).$$

- ◇ implies structural invariance:

- ◇ Fix  $(A, \mathcal{P} = \{P_1, \dots, P_n\})$  and let  $\mathcal{P}^1 = \{P_1^1, \dots, P_k^1\}$  partition  $P_1$ .
- ◇ Then  $\mathcal{P}^\dagger = \{P_1^1, \dots, P_k^1, P_2, \dots, P_n\}$  is also partition of  $A$ .
  - ◇ As if observing  $\mathcal{P}$  and then if  $P_1$  is realized, further observing  $\mathcal{P}^1$
  - ◇  $\mathcal{P}$  observed with prob 1,  $\mathcal{P}^1$  observed with probability  $\mu(W_{A, \mathcal{P}^1})$
- ◇ Let  $(B, \mathcal{Q} = \{Q_1, \dots, Q_k\})$  with  $\mu(W_{B, Q_i}) = \mu(W_{A, P_i^1} \mid W_{A, P_1})$ 
  - ◇ Observing  $\mathcal{Q}$  has same ‘informational content’ as observing  $\mathcal{P}^1$  conditional on realization of  $P_1$

$(A, \mathcal{P})$

$P_1$	$P_2$	$P_3$	$P_4$
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$(A, \mathcal{P})$	$P_1$	$P_2$	$P_3$	$P_4$
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$(A, \mathcal{P}^\dagger)$	$P_1^1$	$P_2^1$	$P_3^1$	$P_2$	$P_3$	$P_4$
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$(A, \mathcal{P})$	$P_1$	$P_2$	$P_3$	$P_4$
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$(A, \mathcal{P}^\dagger)$	$P_1^1$	$P_2^1$	$P_3^1$	$P_2$	$P_3$	$P_4$
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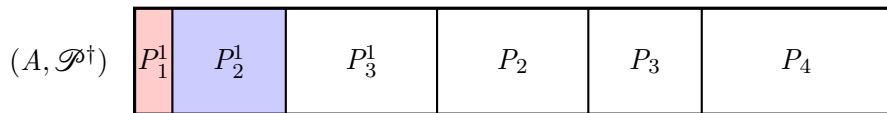
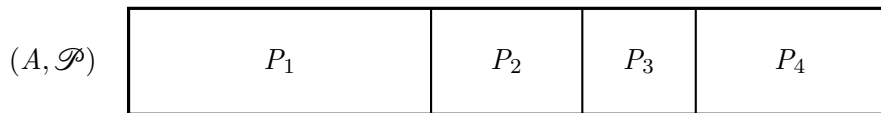
$(B, \mathcal{Q})$	$Q_1$	$Q_2$	$Q_3$
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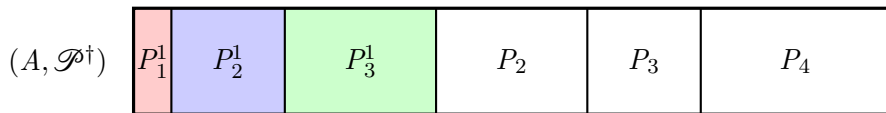
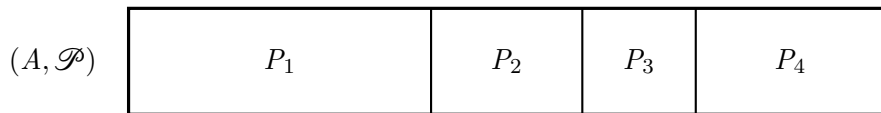


$(A, \mathcal{P})$	$P_1$	$P_2$	$P_3$	$P_4$
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$(A, \mathcal{P}^\dagger)$	$P_1^1$	$P_2^1$	$P_3^1$	$P_2$	$P_3$	$P_4$
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$(B, \mathcal{Q})$	$Q_1$	$Q_2$	$Q_3$
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### Option 1

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- ◇ Observe  $\mathcal{P}^\dagger$  with prob  $\alpha$
- ◇ Observe nothing with prob  $(1-\alpha)$

### Option 2

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- ◇ Observe  $\mathcal{P}$  with prob  $\alpha$
- ◇ Observe  $\mathcal{Q}$  with prob  $(1-\alpha)$

- ◇ To be indifferent  $\alpha$  must capture the likelihood of reviving extra information
- ◇ This is  $\alpha = \frac{1}{1+\mu(W_{A,P_1})}$

## Identification Separability for Entropy

Fix  $(A, \mathcal{P} = \{P_1, \dots, P_n\})$  and  $\mathcal{P}^\dagger = \{P_1^1, \dots, P_k^1, P_2, \dots, P_n\}$ .

Set  $\alpha = \frac{1}{1 + \mu(W_{A, P_1})}$ .

Then if  $(B, \{Q_1, \dots, Q_k\})$  is such that  $\mu(W_{B, Q_i}) = \mu(W_{A, P_i^1} \mid W_{A, P_1})$ , it follows that

$$\alpha(A, \mathcal{P}^\dagger) + (1 - \alpha)(A, \{A\}) \sim \alpha(A, \mathcal{P}) + (1 - \alpha)(B, \mathcal{Q})$$

- ◇ implies identification separability

## Theorem

Let  $\succsim$  be an expected utility preference.

Then  $\succsim$  satisfies the entropic versions of **P1-3** if and only if

$$F(A, \mathcal{P}) = - \sum_{P \in \mathcal{P}} \log(\mu(W_{A,P})) \mu(W_{A,P})$$

is an utility index for  $\succsim$

