The effect of information constraints on decision-making and economic behaviour

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Paradoxes of Expected Utility

Optimisation of Information Utility

Results

Example: SPB Lottery References106

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Introduction: Choice under Uncertainty

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Learning Systems



• Performance and information have orders, and the relation between them is monotonic.



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- Complete partial orders, domain theory.



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- Complete partial orders, domain theory.
- Utility theory, information theory



- Performance and information have orders, and the relation between them is monotonic.
- Complete partial orders, domain theory.
- Utility theory, information theory
- Allows for treating both deterministic and non-deterministic case:

$$x = f(\omega), \qquad x = f(\omega) + rand()$$

Expected Utility Theory

• $f: \Omega \to \mathbb{R}$ a utility function.

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• Choice under uncertainty

$$q \lesssim p \quad \Longleftrightarrow \quad \mathbb{E}_q\{f\} \le \mathbb{E}_p\{f\}$$

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Question (Why expected utility?)

•
$$\mathbb{E}_{y}\{f\} = f(\omega) \text{ if } y(\Omega') = \delta_{\omega}(\Omega').$$

• $x \leq y \iff \lambda x \leq \lambda y, \forall \lambda > 0$
• $x \leq y \iff x + z \leq y + z, \forall z \in Y.$

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St. Petersburg lottery

Due to Nicolas Bernoulli (1713)

• The lottery is played by tossing a fair coin repeatedly until the first head appears.

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- $\bullet\,$ To enter the lottery, you must pay a fee of $\pounds X$
- How much is $\pounds X$?

Why is it a paradox?

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- Let p(n) be the probability of $n \in \mathbb{N}$

head	1	2	3	4	• • •	n	• • •
win	£2	£4	£8	£16		2^n	•••
p(n)	$\frac{1}{2}$	$\frac{1}{4}$	$\frac{1}{8}$	$\frac{1}{16}$	• • •	$\frac{1}{2^n}$	• • •

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• It is easy to see that

$$\mathbb{E}_p\{\mathsf{win}\} = 2 \cdot \frac{1}{2} + 4 \cdot \frac{1}{4} + 8 \cdot \frac{1}{8} + 16 \cdot \frac{1}{16} + \dots = \sum_{n=1}^{\infty} \frac{2^n}{2^n} = \infty$$

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• One cannot buy what is not for sale.

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• Some suggest to use only f such that

$$\|f\|_{\infty} := \sup |f(\omega)| < \infty$$

Northern Rock lottery

Due to unknown author (2008)

 \bullet You can borrow a mortgage of any amount $\pounds X$

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• How much would you borrow? ($\pounds X = ?$)

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The Allais (1953) paradox

Consider two lotteries:

A :
$$p(\pounds 300) = \frac{1}{3}$$
 (and $p(\pounds 0) = \frac{2}{3}$)
B : $p(\pounds 100) = 1$

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$$\mathbb{E}_{A}\{x\} = 300 \cdot \frac{1}{3} + 100 \cdot 0 + 0 \cdot \frac{2}{3} = 100$$

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Remark

Safety is preferred (i.e. risk averse).

The Allais (1953) paradox (2)

Consider two lotteries:

C :
$$p(-\pounds 300) = \frac{1}{3}$$
 (and $p(\pounds 0) = \frac{2}{3}$)
D : $p(-\pounds 100) = 1$

The Allais (1953) paradox (2)

Consider two lotteries:

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- $\bullet\,$ Most of the people seem to prefer $C\gtrsim D$
- Note that

$$\mathbb{E}_C\{x\} = -300 \cdot \frac{1}{3} - 100 \cdot 0 - 0 \cdot \frac{2}{3} = -100$$

$$\mathbb{E}_D\{x\} = -300 \cdot 0 - 100 \cdot 1 - 0 \cdot 0 = -100$$

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Remark

Risk is preferred (i.e. risk taking).

Why is it a paradox?



Remark

Any linear functional (e.g. $\mathbb{E}_p\{x\}$) has parallel level sets. If people use expected utility to make choices, then they are either risk-averse or risk-taking, but not both.

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Prospect theory

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• It was proposed that the utility is convex, when the choice is among gains, and concave when the choice is among losses.

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Remark

This theory is not normative (i.e. it is not derived using rational approach).

The Ellsberg (1961) paradox

Consider two lotteries:

A :
$$p(\pounds 100) = \frac{1}{2}$$
 (and $p(\pounds 0) = \frac{1}{2}$)

$$\mathsf{B} : p(\pounds 100) = \mathsf{unknown}$$

The Ellsberg (1961) paradox

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- Note that

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Remark

More information is preferred.

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Extreme Value Problems

Unconditional extremum

• Maximise f(y):

 $\sup f(y)$

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• Maximise f(y) subject to $g(y) \leq \lambda$:

 $\overline{f}(\lambda) := \sup\{f(y) : g(y) \le \lambda\}$

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$$\partial f(\bar{y}) - \alpha \partial g(y) \ni 0$$
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- Necessary condition $\partial f(\bar{y}) \alpha \partial g(y) \ni 0$.
- Sufficient if $K(y, \alpha) := f(y) + \alpha[\lambda g(y)]$ is concave.

Representation in Paired Spaces

•
$$x \in X, y \in Y, \langle \cdot, \cdot \rangle : X \times Y \to \mathbb{R}$$

 $\langle x, y \rangle := \int_{\Omega} x(\omega) \, dy(\omega)$

Representation in Paired Spaces

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$$x \in X$$
, $y \in Y$, $\langle \cdot, \cdot \rangle : X \times Y \to \mathbb{R}$
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• Separation:

$$\begin{split} \langle x,y\rangle &= \mathsf{0}\,, \quad \forall \, x \in X \quad \Rightarrow \ y = \mathsf{0} \in Y \\ \langle x,y\rangle &= \mathsf{0}\,, \quad \forall \, y \in Y \quad \Rightarrow \ x = \mathsf{0} \in X \end{split}$$

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Expected value

$$\mathbb{E}_p\{x\} = \langle x, y \rangle|_{\mathcal{M}}$$

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Information

Definition (Information resource)

a closed functional $F: Y \to \mathbb{R} \cup \{\infty\}$ with $\inf F = F(z)$.

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Example (Relative Information (Belavkin, 2010b))

• For z > 0, let

$$F(y) := \left\{ egin{array}{ll} \left\langle \ln rac{y}{z}, y
ight
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• The dual $F^*: X \to \mathbb{R} \cup \{\infty\}$ is

$$F^*(x) := \langle 1, e^x z \rangle$$

Utility of Information

• If $x \in X$ is utility, then the value of event y relative to z is

$$\langle x, y - z \rangle = \mathbb{E}_y \{x\} - \mathbb{E}_z \{x\}$$

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Related functions

$$\begin{array}{rcl} -U_{-x}(I) &:=& \inf\{\langle x, y \rangle : F(y) \leq I\} \\ I_x(U) &:=& \inf\{F(y) : U_0 \leq U \leq \langle x, y \rangle\} \\ I_x(U) &:=& \inf\{F(y) : \langle x, y \rangle \leq U < U_0\} \end{array}$$

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Information Bounded Utility

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A function $f : \Omega \to \mathbb{R}$ that admits a solution to the utility of information problem $U_f(I)$ for $I \in (\inf F, \sup F)$
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Theorem

A solution to $U_f(I)$ and $I_f(U)$ exists if and only if set $\{x : F_q^*(x) \le I^*\}$ absorbs function f:

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Remark (Separation of information)

For all $I \in (\inf F, \sup F)$ there exist β_1^{-1} , $\beta_2^{-1} > 0$:

 $F_q(\partial F_q^*(\beta_1 f)) < I < F_q(\partial F^*(\beta_2 f))$

Information Topology (Belavkin, 2010a)

• The topology is defined using an information resource:

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Parametrisation by the Expected Utility



Let F(y) be negative entropy (i.e. F(y) is minimised at $y_0(\omega) = \text{const}$)

$$\begin{aligned} x: \Omega &\to \{c-d, c+d\} \qquad U(\beta) = \Psi'(\beta) = c + d \tanh(\beta d) \\ x: \Omega &\to [c-d, c+d] \qquad U(\beta) = \Psi'(\beta) = c + d \coth(\beta d) - \beta^{-1} \end{aligned}$$

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Parametrisation by Information



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Parametric Dependency



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A Solution of the SPB Paradox

• $f : \mathbb{N} \to \mathbb{R}$ is information bounded iff for some $\beta^{-1} > 0$:

$$F^*(\beta f) = \sum_{n=1}^{\infty} q(n) e^{\beta f(n)} < \infty$$

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• Let $q(n) = (e-1)e^{-n}$ (i.e. 2^{-n}).
• For $f(n) = n$, we have $\beta < 1$.

A Solution of the SPB Paradox

• Using $U = \Psi'_f(\beta)$ obtain

$$U = \frac{1}{1 - e^{\beta - 1}} \,, \qquad U_0 = \frac{1}{1 - e^{-1}}$$

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- Using $I = \beta (\ln \Psi(\beta))' \ln \Psi(\beta)$:

$$I_f(U) = (1 + \ln(1 - U^{-1}))U - \ln(e - 1) - \ln(U - 1)$$

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A Solution of the SPB Paradox

• Using $U = \Psi'_f(\beta)$ obtain

$$U = \frac{1}{1 - 2^{\beta - 1}}, \qquad U_0 = 2$$

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• Change e to 2 (In to \log_2).

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$$I_f(U) = (1 + \log_2(1 - U^{-1}))U - \log_2(U - 1)$$

- Change e to 2 (In to \log_2).
- For the information amount of 0 bits, the optimal entrance fee is $c \leq U_0 = 2$.

SPB Lottery



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- Allais, M. (1953). Le comportement de l'homme rationnel devant le risque: Critique des postulats et axiomes de l'École americaine. *Econometrica*, *21*, 503–546.
- Belavkin, R. V. (2010a). Information trajectory of optimal learning. In
 M. J. Hirsch, P. M. Pardalos, & R. Murphey (Eds.), *Dynamics of information systems: Theory and applications* (Vol. 40). Springer.
 Belavkin, R. V. (2010b). Utility and value of information in cognitive science, biology and quantum theory. In L. Accardi, W. Freudenberg, & M. Ohya (Eds.), *Quantum Bio-Informatics III* (Vol. 26). World

Scientific.

- Ellsberg, D. (1961, November). Risk, ambiguity, and the Savage axioms. *The Quarterly Journal of Economics*, *75*(4), 643–669.
- Stratonovich, R. L. (1965). On value of information. *Izvestiya of USSR Academy of Sciences, Technical Cybernetics, 5,* 3–12. (In Russian)
 Tversky, A., & Kahneman, D. (1981). The framing of decisions and the psychology of choice. *Science, 211,* 453–458.