

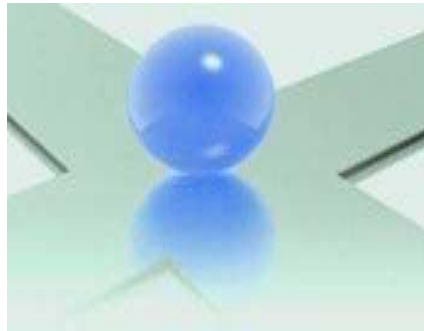
# The Paradox of Choice

## Why MORE is LESS

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Technion

Israel Institute of Technology



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# 1 *What Makes a Good Decision?*

§ Schwartz, Barry, 2004

*Paradox of Choice: Why More Is Less*



Figure 1: Barry Schwartz, 1946–.

§ Barry Schwartz, Yakov Ben-Haim, and Cliff Dacso, 2011, What Makes a Good Decision? Robust Satisficing as a Normative Standard of Rational Behaviour, *The Journal for the Theory of Social Behaviour*, 41(2): 209-227. Pre-print to be found on:

<http://info-gap.com/content.php?id=23>

## 1.1 *Choosing a College*

## § Decision problem:

- You've been accepted to several **good universities**.
- You must **choose one**.
- How to go about it?

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  - **Location.**
  - **Reputation.**
  - **Quality of physics program.**
  - **Electrical Engineering Dept.**
  - **Social life.**
  - **Housing.**

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## § Uncertainty: **severe.**

- **What is a good strategy?**
- **What are *attributes* of a good strategy?**

## 1.2 *Severe Uncertainty: Good Strategy? Good Attributes?*

## § Decision strategy: Outcome optimization

- Make best possible estimates.
- Choose school with best estimate.

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## § Decision strategy: 1-reason (lexicographic)

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## § Which strategy to use?

§ In order to choose a strategy we first discuss:  
Concepts of probability and uncertainty.

## 1.3 *Three Types of Probability*

### § Sources:

- Schwartz, Ben-Haim, Dacso, 2011.
- Jonathan Baron, 2008, *Thinking and Deciding*.

## § What is probability?

What do the following statements mean?

- The probability of throwing “7” with 2 dice is  $1/6$ .
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- The probability of developing prostate cancer is 0.03.
- The probability that Maccabee Tel Aviv will win championship is  $1/4$ .

## § Logical probability.

- 36 equi-probable outcomes with 2 dice.
- 6 outcomes sum to “7”.
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- The prob of “7” is a **logical deduction**.

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- Sample 10,000 healthy men, aged 45–70.
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- “Will Maccabee TA win?” ... “I think so.”  
“How sure are you?” ... “I’d give ‘em 25% chance.”
- **Personal judgment**.
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## § Do these concepts of probability differ?

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## § Logical & Personal probability overlap.

- **Personal:** judgment based on experience.
- **Logical:**
  - Deduction with rules of inference.
  - Pre-logical choice of rules of inference.  
E.g. reason by contradiction.

## § All three concepts of probability,

**Logical:** outcome of ideal dice,

**Empirical:** frequency of prostate cancer,

**Personal:** Maccabee's chances,

- Overlap but differ in meaning.
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**Logical:** outcome of ideal dice,

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- Overlap but differ in meaning.
- Are mathematically identical: Kolmogorov axioms.

## 1.4 *Severe Uncertainty*

§ We discussed **three types of probability**.

§ **Is all uncertainty probabilistic?**

§ In a previous lecture<sup>1</sup> we claimed that **ignorance is not probabilistic**:

- Monty Hall's 3-door problem.
- Pascal's wager about God.
- Lewis Carroll's 2-bag riddle.
- Keynes' new material.

§ We now introduce a **new distinction**.

---

<sup>1</sup>These examples are discussed in lecture “The Strange World of Human Decision Making”, [\lectures\decisions\lectures\foibles\foibles01.pdf](#).

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- *Risk, Uncertainty and Profit*, 1921.
- **Risk:**
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  - New innovation by competitor.
  - New consumer preferences.
  - Political upheaval.
  - Unforeseen natural disaster.
  - **Ambiguity**, which we now consider.

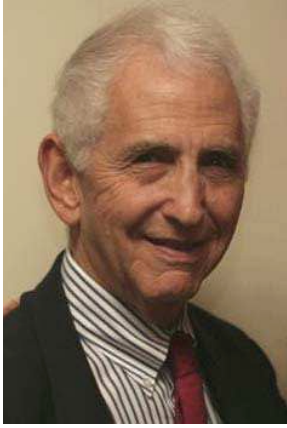


Figure 2: Ellsberg, 1931–.

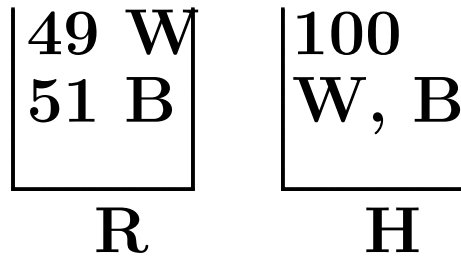


Figure 3: Ellsberg's Urns.

## § Ellsberg paradox:

- 1st experiment: win on black. Which urn?
-



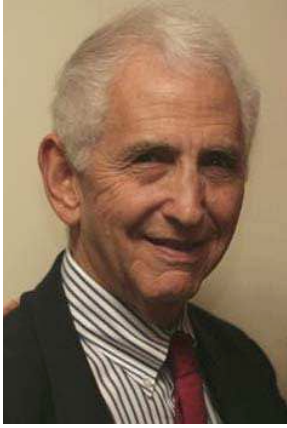


Figure 4: Ellsberg, 1931–.

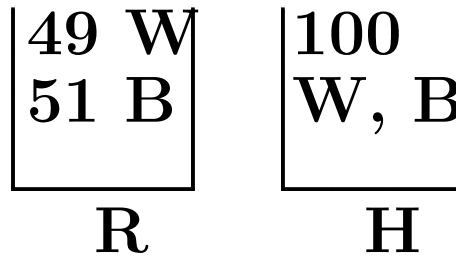


Figure 5: Ellsberg's Urns.

## § Ellsberg paradox:

- 1st experiment: win on black. Which urn?
- 2nd experiment: win on white. Which urn?
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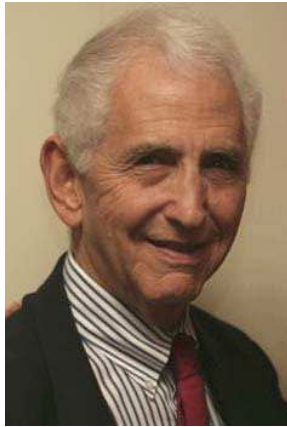


Figure 6: Ellsberg, 1931–.

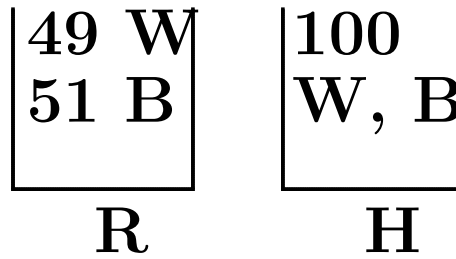


Figure 7: Ellsberg's Urns.

## § Ellsberg paradox:

- 1st experiment: win on black. Which urn?
- 2nd experiment: win on white. Which urn?
- Most folks stick with R. Sensible?
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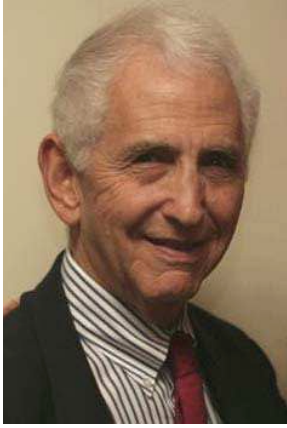


Figure 8: Ellsberg, 1931–.

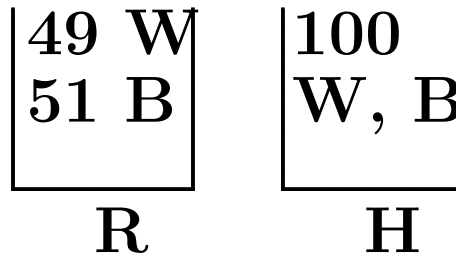


Figure 9: Ellsberg's Urns.

## § Ellsberg paradox:

- 1st experiment: win on black. Which urn?
- 2nd experiment: win on white. Which urn?
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- Types of uncertainty:
  - Probability vs ambiguity.
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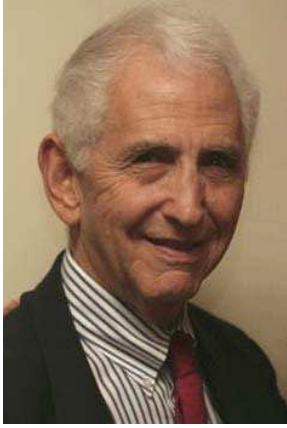


Figure 10: Ellsberg, 1931–.

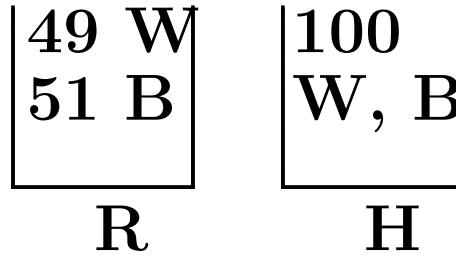


Figure 11: Ellsberg's Urns.

## § Ellsberg paradox:

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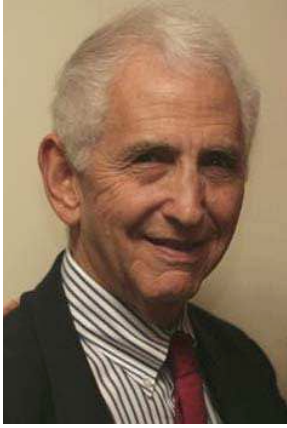


Figure 12: Ellsberg, 1931–.

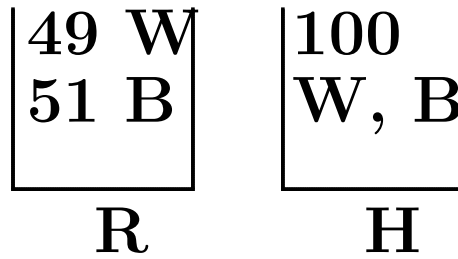


Figure 13: Ellsberg's Urns.

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  - Probabilistic risk vs Knightian uncertainty.

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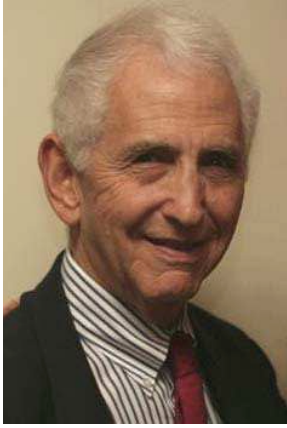


Figure 14: Ellsberg, 1931–.

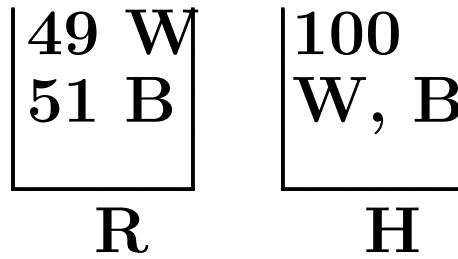


Figure 15: Ellsberg's Urns.

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§ Now consider a different aspect: **strategic interaction**.



Figure 16: Cuban missile crisis, Oct 1962. U-2 reconnaissance photograph of Soviet nuclear missiles in Cuba. Missile transports and tents for fueling and maintenance are visible. Courtesy of CIA. [http://en.wikipedia.org/wiki/Cuban\\_Missile\\_Crisis](http://en.wikipedia.org/wiki/Cuban_Missile_Crisis).

## § Strategic uncertainty.

- Outcomes depend on 2 or more agents.
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- Outcomes depend on 2 or more agents.
- “Your” info about “Them” very limited.
- Common knowledge: you know that they know ...
- Example: **Cuban missile crisis**.
  - US detects nuclear missiles on Cuba.
  - How many missiles? Russian intentions unclear.
  - What should US do?

## § Ignorance is **not** probabilistic:<sup>2</sup>

- Monty Hall's 3-door problem.
- Pascal's wager.
- Lewis Carroll's 2-bag riddle.
- Keynes' new material.

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<sup>2</sup>These examples are discussed in lecture “The Strange World of Human Decision Making”, [\lectures\decisions\lectures\foibles\foibles01.pdf](#).

§ Ignorance is **not** probabilistic:

- Monty Hall's 3-door problem.
- Pascal's wager.
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§ **Ignorance** is a **gap** between what we **do know** and what we **need to know** in order to make a good decision.

## 1.5 *Responses to Severe Uncertainty*

## § What decision strategy for severe uncertainty?

- Best-model optimization.
- 1-reason (lexicographic).
- Min-max (worst case).
- Robust satisficing.
- Opportune windfalling.

§

## § What decision strategy for severe uncertainty?

- Best-model optimization.
- 1-reason (lexicographic).
- Min-max (worst case).
- Robust satisficing.
- Opportune windfalling.

## § Paradox of choice (Barry Schwartz):

- Under severe uncertainty,  
aiming for **more** achieves **less**.
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## § Paradox of choice (Barry Schwartz):

- Under severe uncertainty,  
aiming for **more** achieves **less**.
- Do you agree? Always? Sometimes?

§ We will explore **robust satisficing**.

§



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§ **Response to ignorance: 2 questions.**

- What do you want/need? What is essential outcome?
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Choose option which:

- Satisfies requirements.
- Maximally robust to surprise.

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§ **Does rob-sat differ from outcome optimization?**



## § Foraging strategies.

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  - Satisfice caloric requirement.
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- Robust-satisficing **survives in evolution.**



## § Financial market strategies.

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- **Optimizing:** Maximize revenue.
- **Robust-satisficing:** beat the competition.
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  - Maximize robustness to uncertainty.
- Robust-satisficing **survives in competition.**
  - Equity premium puzzle.
  - Home bias paradox.

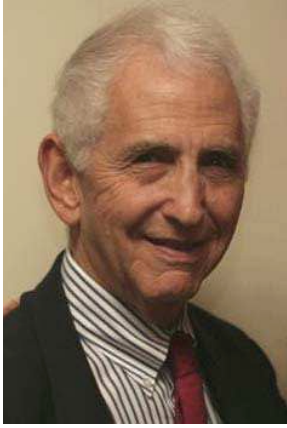


Figure 19: Ellsberg, 1931–.

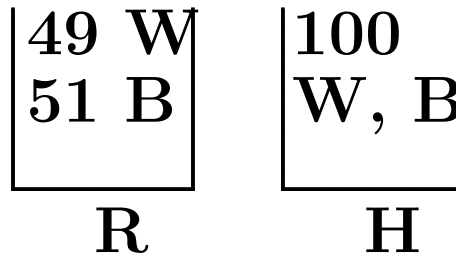


Figure 20: Ellsberg's Urns.

## § Humans and ambiguity: Ellsberg paradox.

- Probabilistic risk vs uncertainty.
- **Optimizing:** Maximize expected utility.
-

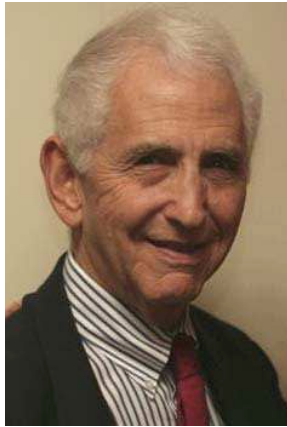


Figure 21: Ellsberg, 1931–.

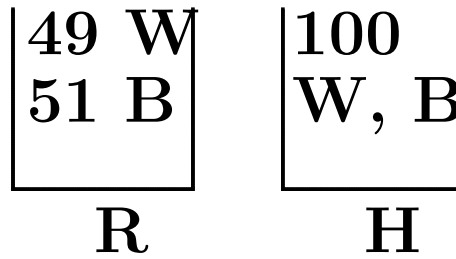


Figure 22: Ellsberg's Urns.

## § Humans and ambiguity: Ellsberg paradox.

- Probabilistic risk vs uncertainty.
- **Optimizing:** Maximize expected utility.
- **Robust-satisficing:** do good enough.
  - Satisfice expected utility.
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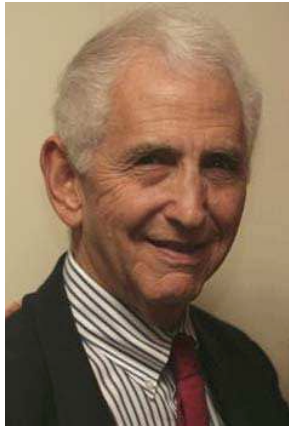


Figure 23: Ellsberg, 1931–.

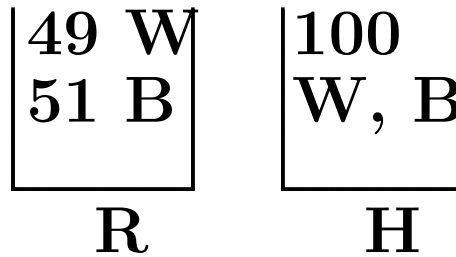


Figure 24: Ellsberg's Urns.

## § Humans and ambiguity: Ellsberg paradox.

- Probabilistic risk vs uncertainty.
- **Optimizing:** Maximize expected utility.
- **Robust-satisficing:** do good enough.
  - Satisfice expected utility.
  - Maximize robustness to uncertainty.
- Robust-satisficers are **happier**. (Schwartz)

## 1.6 *Does Robust Satisficing Use Probability?*

§ **Source:** Schwartz, Ben-Haim, Dacso, 2011.

§ It might be argued that:

Robust-satisficing implicitly uses probability:

- “Choose the more robust option.”  
is the same as
- “Choose the option more likely to succeed.”

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- How wrong can our estimates be  
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## § Robustness question:

- How wrong can our estimates be  
and outcome of choice still acceptable?
- The answer does not use probability.  
(More on this later.)

## § Example of robust thinking in choosing university.

- Attribute: number of great physicists
- Requirement: At least 2 great physicists.
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- **Uni 2 is more robust** if all else the same.

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- Note: this is both a **bug** and a **feature**.

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- Note: this is both a **bug** and a **feature**.

## § Judgment of robustness is not judgment of likelihood.

§ **A common confusion: description vs prescription.**

- **Describe** behavior of decision makers.

This **can** always be done probabilistically (or robustly).

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- **Describe** behavior of decision makers.

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This **cannot** always be done probabilistically:

- Probabilistic strategy **requires** pdfs.
- Robust satisficing **does not require** pdfs.

(But R-S does have requirements.)

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## § Probability and Robustness are:

- **Descriptively interchangeable.**
- **Prescriptively distinct.**

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## § Probability and Robustness are:

- **Descriptively interchangeable.**
- **Prescriptively distinct.**

## § Robust satisficing does not use probability.



## 1.7 *Does Robust Satisficing Use Probability? (cont.)*

### § Sources:

- Yakov Ben-Haim, 2010, Uncertainty, Probability and Robust Preferences, working paper.<sup>3</sup>
- Yakov Ben-Haim, 2011, Robustness and Locke's Wingless Gentleman.<sup>4</sup>

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<sup>3</sup><http://info-gap.com/content.php?id=23>

<sup>4</sup><http://decisions-and-info-gaps.blogspot.com/2011/09/robustness-and-lockes-wingless.html>

§ **Conflicting views on uncertainty and probability.**  
**Keynes and Carnap vs Knight and Wald.**

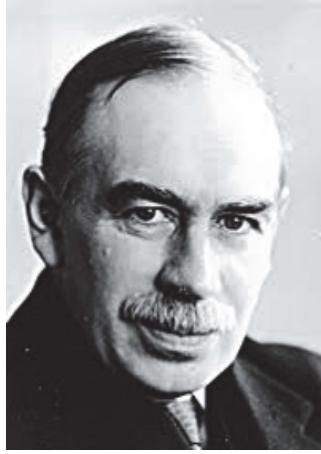


Figure 25: John Maynard Keynes, 1883–1946.

§ **Probability is fundamental to uncertainty.**

**John Maynard Keynes** asserts:<sup>5</sup> “Part of our knowledge we obtain direct; and part by argument. The Theory of Probability is concerned with that part which we obtain by argument, and it treats of the different degrees in which the results so obtained are conclusive or inconclusive. . . .

“The method of this treatise has been to regard subjective probability as fundamental and to treat all other relevant conceptions as derivative from this.”

---

<sup>5</sup>Keynes, John Maynard, 1929, *A Treatise on Probability*, Macmillan and Co., London, pp.3, 281–282

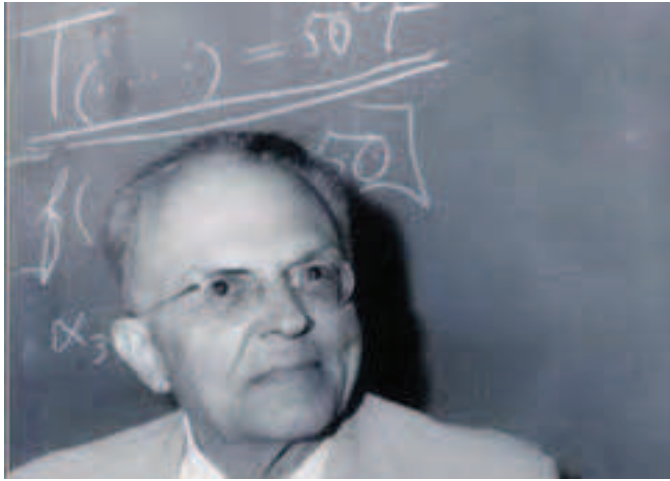


Figure 26: Rudolph Carnap, 1891–1970.

§ Probability is fundamental to uncertainty.

Among Rudolf Carnap's<sup>6</sup> “basic conceptions” is the contention that “all inductive reasoning, in the wide sense of nondeductive or nondemonstrative reasoning, is reasoning in terms of probability.”

---

<sup>6</sup>Carnap, Rudolf, 1962, *Logical Foundations of Probability*, 2nd ed., University of Chicago Press, p.v



Figure 27: Frank Knight, 1885–1972.

§ Probability is not fundamental to uncertainty.

**Frank Knight:**<sup>7</sup> “Business decisions . . . deal with situations which are far too unique, generally speaking, for any sort of statistical tabulation to have any value for guidance. The conception of an objectively measurable probability or chance is simply inapplicable. . . .

“It is this *true uncertainty* which by preventing the theoretically perfect outworking of the tendencies of competition gives the characteristic form of ‘enterprise’ to economic organization as a whole and accounts for the peculiar income of the entrepreneur.”

---

<sup>7</sup>Knight, Frank H., 1921, *Risk, Uncertainty and Profit*. Houghton Mifflin Co. Re-issued by University of Chicago Press, 1971, pp.231–232



Figure 28: Abraham Wald, 1902–1950.

§ **Probability is not fundamental to uncertainty.**

**Abraham Wald**<sup>8</sup> wrote that “in most of the applications not even the existence of ... an a priori probability distribution [on the class of distribution functions] ... can be postulated, and in those few cases where the existence of an a priori probability distribution ... may be assumed this distribution is usually unknown.”

---

<sup>8</sup>Wald, A., 1945. Statistical decision functions which minimize the maximum risk, *Annals of Mathematics*, 46(2), 265–280, p.267

§ We consider 3 questions:

(1) Does non-probabilistic  
robust preference between options  
need to assume a uniform probability distribution  
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(1) Does non-probabilistic robust preference between options need to assume a uniform probability distribution on underlying uncertain events?

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- (3) Are any probabilistic assumptions needed in order to justify robust preferences?
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## § Non-probabilistic robust preferences:

- Based on set-theory representation of uncertainty:  
Sets, or families of sets, of events.
- E.g. min-max (worst case) or info-gap.

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Sets, or families of sets, of events.
- E.g. min-max (worst case) or info-gap.

## § Robust preference between options $B$ and $C$ :

- $B$  more robust than  $C$ .
- Hence  $B$  “robust preferred” over  $C$ :  $B \succ_r C$ .

### 1.7.1 *First Question*

§ Does a non-probabilistic robust preference between options **need to assume** a uniform probability distribution on the underlying uncertain events?

§



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§ **Uniform distribution nonexistent if event space unbounded.**

- Thus uniform distribution **cannot underlie** robust preference.
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§ Does a non-probabilistic robust preference between options **need to assume** a uniform probability distribution on the underlying uncertain events?

§ **Uniform distribution nonexistent if event space unbounded.**

- Thus uniform distribution **cannot underlie** robust preference.
- Robust preference may be unjustified.

§ Does a non-probabilistic robust preference between options **need to assume** a uniform probability distribution on the underlying uncertain events?

§ **If uniform distribution exists:**

- It justifies robust preference if it implies  $B$  more likely than  $C$ .
-

§ Does a non-probabilistic robust preference between options **need to assume** a uniform probability distribution on the underlying uncertain events?

§ **If uniform distribution exists:**

- It justifies robust preference if it implies  $B$  more likely than  $C$ .
- Many **other** distributions may imply  $B$  more likely than  $C$ .  
E.g. 3-door problem.
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E.g. 3-door problem.
- Uniform dist not necessary to justify robust pref.
- Robust pref may still require **some** distribution.

## 1.7.2 *Second Question*

§ Does a robust preference assume *some* probability distribution on the uncertain events?

§



§ Does a robust preference assume *some* probability distribution on the uncertain events?

§ Assuming a pdf *could justify* robust preferences.  
Such an assumption is *not necessary*.

## § Notation:

- $u$  is an underlying uncertain event.

There is a set-model of uncertain  $u$ .

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There is a set-model of uncertain  $u$ .

- $p(u)$  is a pdf on the  $u$ 's.
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- $S_B \subseteq S$ .  $S_B$  is set of all  $p(u)$ 's for which  $B$  is more likely to succeed than  $C$ .
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- $p_T(u)$  true pdf.

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- $u$  is an underlying uncertain event.

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- $p_T(u)$  true pdf.

## § Our question:

Is it **necessary** to assume  $p_T \in S_B$  to justify robust pref?

§  $p_T(u) \in S_B$  implies

robust pref is justified probabilistically:

$$p_T \in S_B \implies B \succ_r C \quad (1)$$

The ' $\implies$ ' means 'justifies' or 'warrants' or 'motivates'.

§



§  $p_T(u) \in S_B$  implies

robust pref is justified probabilistically:

$$p_T \in S_B \implies B \succ_r C \quad (2)$$

The ' $\implies$ ' means 'justifies' or 'warrants' or 'motivates'.

§ **Converse not true:**

Reasonable DM can accept  $\succ_r$   
without believing  $p_T \in S_B$ .

§

§  $p_T(u) \in S_B$  implies

robust pref is justified probabilistically:

$$p_T \in S_B \implies B \succ_r C \quad (3)$$

The ' $\implies$ ' means 'justifies' or 'warrants' or 'motivates'.

§ **Converse not true:**

Reasonable DM can accept  $\succ_r$   
without believing  $p_T \in S_B$ .

§ **Accept  $\succ_r$  if**

$p_T \in S_B$  *more likely* than  $p_T \notin S_B$ :

$$\mathbf{Prob}(p_T \in S_B) > \frac{1}{2} \implies B \succ_r C \quad (4)$$

§

§  $p_T(u) \in S_B$  implies

robust pref is justified probabilistically:

$$p_T \in S_B \implies B \succ_r C \quad (5)$$

The ‘ $\implies$ ’ means ‘justifies’ or ‘warrants’ or ‘motivates’.

§ **Converse not true:**

Reasonable DM can accept  $\succ_r$   
without believing  $p_T \in S_B$ .

§ **Accept  $\succ_r$  if**

$p_T \in S_B$  *more likely* than  $p_T \notin S_B$ :

$$\mathbf{Prob}(p_T \in S_B) > \frac{1}{2} \implies B \succ_r C \quad (6)$$

§ **Lower warrant** of “ $\implies$ ” in eq.(6) than in eq.(5),  
but still relevant.

§ **Accept  $\succ_r$  if**

$$\mathbf{Prob}(p_T \in S_B) > \frac{1}{2} \implies B \succ_r C \quad (7)$$

§ **Converse of (7) need not hold.**

§ **Accept  $\succ_r$  if**

$\mathbf{Prob}(p_T \in S_B) > \frac{1}{2}$  *more likely* than

$\mathbf{Prob}(p_T \in S_B) \leq \frac{1}{2}$ :

$$\mathbf{Prob}\left(\mathbf{Prob}(p_T \in S_B) > \frac{1}{2}\right) > \frac{1}{2} \implies B \succ_r C \quad (8)$$

§

§ **Accept  $\succ_r$  if**

$$\mathbf{Prob}(p_T \in S_B) > \frac{1}{2} \implies B \succ_r C \quad (9)$$

§ **Converse of (9) need not hold.**

§ **Accept  $\succ_r$  if**

$\mathbf{Prob}(p_T \in S_B) > \frac{1}{2}$  *more likely* than  
 $\mathbf{Prob}(p_T \in S_B) \leq \frac{1}{2}$ :

$$\mathbf{Prob}\left(\mathbf{Prob}(p_T \in S_B) > \frac{1}{2}\right) > \frac{1}{2} \implies B \succ_r C \quad (10)$$

§ **This regression can go forever.**

One could claim:

$$\mathbf{Prob}\left(\dots \left[\mathbf{Prob}\left(\mathbf{Prob}(p_T \in S_B) > \frac{1}{2}\right) > \frac{1}{2}\right]\right) > \frac{1}{2} \implies B \succ_r C \quad (11)$$

Converse not necessary at any step.

§ Second question was, Is:

$$p_T \in S_B \quad (12)$$

necessary to motivate robust preferences:

$$B \succ_r C \quad (13)$$

§

§ Second question was, Is:

$$p_T \in S_B \quad (14)$$

necessary to motivate robust preferences:

$$B \succ_r C \quad (15)$$

§ Summary of Q.2 answer:

- Any of an **infinity** of probability beliefs would justify  $\succ_r$  to some extent:

$$\begin{aligned} \text{Prob} \left( \dots \left[ \text{Prob} \left( \text{Prob}(p_T \in S_B) > \frac{1}{2} \right) > \frac{1}{2} \right] \right) > \frac{1}{2} \\ \implies B \succ_r C \end{aligned} \quad (16)$$

•

§ **Second question was, Is:**

$$p_T \in S_B \quad (17)$$

necessary to motivate robust preferences:

$$B \succ_r C \quad (18)$$

§ **Summary of Q.2 answer:**

- Any of an **infinity** of probability beliefs would justify  $\succ_r$  to some extent:

$$\begin{aligned} \text{Prob} \left( \dots \left[ \text{Prob} \left( \text{Prob}(p_T \in S_B) > \frac{1}{2} \right) > \frac{1}{2} \right] \right) > \frac{1}{2} \\ \implies B \succ_r C \end{aligned} \quad (19)$$

- Higher-order probability statements provide weaker justification.
-



§ Second question was, Is:

$$p_T \in S_B \quad (20)$$

necessary to motivate robust preferences:

$$B \succ_r C \quad (21)$$

§ Summary of Q.2 answer:

- Any of an **infinity** of probability beliefs would justify  $\succ_r$  to some extent:

$$\begin{aligned} \text{Prob} \left( \dots \left[ \text{Prob} \left( \text{Prob}(p_T \in S_B) > \frac{1}{2} \right) > \frac{1}{2} \right] \right) > \frac{1}{2} \\ \implies B \succ_r C \end{aligned} \quad (22)$$

- Higher-order probability statements provide weaker justification.
- None of any **finite** sequence of prob beliefs is necessary to justify  $\succ_r$ .
-

§ **Second question was, Is:**

$$p_T \in S_B \quad (23)$$

necessary to motivate robust preferences:

$$B \succ_r C \quad (24)$$

§ **Summary of Q.2 answer:**

- Any of an **infinity** of probability beliefs would justify  $\succ_r$  to some extent:

$$\begin{aligned} \text{Prob} \left( \dots \left[ \text{Prob} \left( \text{Prob}(p_T \in S_B) > \frac{1}{2} \right) > \frac{1}{2} \right] \right) > \frac{1}{2} \\ \implies B \succ_r C \end{aligned} \quad (25)$$

- Higher-order probability statements provide weaker justification.
- None of any **finite** sequence of prob beliefs is necessary to justify  $\succ_r$ .
- At any step, prob belief can be deferred to next higher-order belief.

§

§ **Second question was, Is:**

$$p_T \in S_B \quad (26)$$

necessary to motivate robust preferences:

$$B \succ_r C \quad (27)$$

§ **Summary of Q.2 answer:**

- Any of an **infinity** of probability beliefs would justify  $\succ_r$  to some extent:

$$\begin{aligned} \text{Prob} \left( \dots \left[ \text{Prob} \left( \text{Prob}(p_T \in S_B) > \frac{1}{2} \right) > \frac{1}{2} \right] \right) > \frac{1}{2} \\ \implies B \succ_r C \end{aligned} \quad (28)$$

- Higher-order probability statements provide weaker justification.
- None of any **finite** sequence of prob beliefs is necessary to justify  $\succ_r$ .
- At any step, prob belief can be deferred to next higher-order belief.

§ **Answer to second:** Nope.

§

§ **Second question was, Is:**

$$p_T \in S_B \quad (29)$$

necessary to motivate robust preferences:

$$B \succ_r C \quad (30)$$

§ **Summary of Q.2 answer:**

- Any of an **infinity** of probability beliefs would justify  $\succ_r$  to some extent:

$$\begin{aligned} \text{Prob} \left( \dots \left[ \text{Prob} \left( \text{Prob}(p_T \in S_B) > \frac{1}{2} \right) > \frac{1}{2} \right] \right) > \frac{1}{2} \\ \implies B \succ_r C \end{aligned} \quad (31)$$

- Higher-order probability statements provide weaker justification.
- None of any **finite** sequence of prob beliefs is necessary to justify  $\succ_r$ .
- At any step, prob belief can be deferred to next higher-order belief.

§ **Answer to second:** Nope.

§ I'm arguing like Keynes on p.107:

All reasoning (not direct knowledge) is probabilistic.

### 1.7.3 *Third Question*

### § First question:

Does  $B \succ_r C$  need to assume a uniform pdf on the underlying uncertain events?

### § Second question:

Does  $B \succ_r C$  assume *some* probability distribution on the uncertain events?

§

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Does  $B \succ_r C$  need to assume a uniform pdf on the underlying uncertain events?

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§ We answered NO in both cases.

The argument was **deductive, conclusive.**

§

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### § Third question:

Is at least one probability belief, from among the infinite sequence of beliefs:

$$\mathbf{Prob} \left( \dots \left[ \mathbf{Prob} \left( \mathbf{Prob}(p_T \in S_B) > \frac{1}{2} \right) > \frac{1}{2} \right] \right) > \frac{1}{2} \quad (32)$$

necessary in order to justify  $B \succ_r C$ ?

§



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Does  $B \succ_r C$  need to assume a uniform pdf on the underlying uncertain events?

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Does  $B \succ_r C$  assume *some* probability distribution on the uncertain events?

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necessary in order to justify  $B \succ_r C$ ?

### § Answer: **plausibly no**.

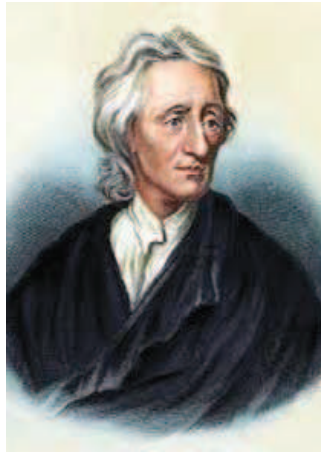


Figure 29: John Locke, 1632–1704.

## § John Locke’s wingless gentleman.

“If we will disbelieve everything, because we cannot certainly know all things; we shall do much what as wisely as he, who would not use his legs, but sit still and perish, because he had no wings to fly.”<sup>9</sup>

§

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<sup>9</sup>John Locke, 1706, *An Essay Concerning Human Understanding*, 5th edition. Roger Woolhouse, editor. Penguin Books, 1997, p.57, I.i.5

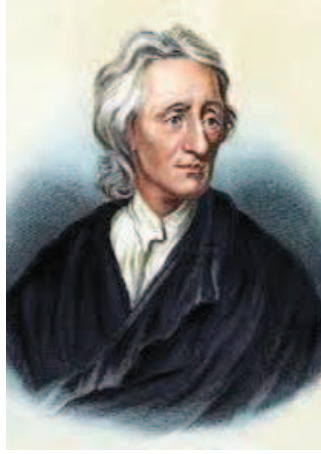


Figure 30: John Locke, 1632–1704.

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### § Our situation:

- If we disbelieve all propositions in eq.(33), rejecting  $\succ_r$  is ‘muchwhat as wise’ as Locke’s wingless gentleman.

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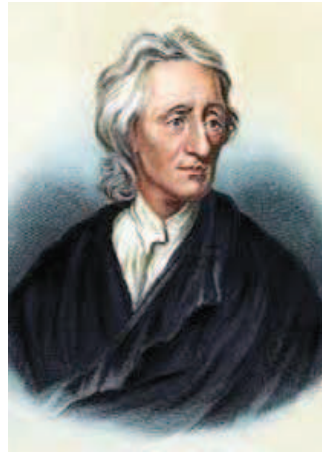


Figure 31: John Locke, 1632–1704.

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“If we will disbelieve everything, because we cannot certainly know all things; we shall do muchwhat as wisely as he, who would not use his legs, but sit still and perish, because he had no wings to fly.”<sup>11</sup>

### § Our situation:

- If we disbelieve all propositions in eq.(33), rejecting  $\succ_r$  is ‘muchwhat as wise’ as Locke’s wingless gentleman.
- Rejecting  $\succ_r$  is **epistemic paralysis**.

---

<sup>11</sup>John Locke, 1706, *An Essay Concerning Human Understanding*, 5th edition. Roger Woolhouse, editor. Penquin Books, 1997, p.57, I.i.5

## § Causes of epistemic paralysis:

- Pdf's not known: Knightian uncertainty, info-gaps.
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Inaction, injury, retrogression, . . . .

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## § Avoiding probabilistic epistemic paralysis:

- Probability is one model of the world.
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- Expand conceptions of uncertainty:  
Adam's 20 images.

§

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## § Answer to Q.3:

- $\gamma_r$  is epistemic last resort.
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Inaction, injury, retrogression, . . . .

## § Avoiding probabilistic epistemic paralysis:

- Probability is one model of the world.
- Other models:
  - Fuzzy, P-box, min-max, info-gap . . . .
- Expand conceptions of uncertainty:  
Adam's 20 images.

## § Answer to Q.3:

- $\succ_r$  is epistemic last resort.
- $\succ_r$  is sometimes best bet.  
(More on this now.)

## 2 *Robustness and Probability:* *A Short Intuitive Introduction to Proxy Theorems*

### § **Is robustness a good bet for “survival”?**

- Is **robustness** a proxy for probability?
- Can we **maximize “survival” probability** without knowing probability distributions?

## § Robustness proxies for probability: Examples.



## § Foraging strategies.

- **Optimizing:** Maximize caloric intake.
-





## § Foraging strategies.

- **Optimizing:** Maximize caloric intake.
- **Robust-satisficing:** survive reliably.
  - Satisfice caloric requirement.
  - Maximize robustness to uncertainty.
-



## § Foraging strategies.

- **Optimizing:** Maximize caloric intake.
- **Robust-satisficing:** survive reliably.
  - Satisfice caloric requirement.
  - Maximize robustness to uncertainty.
- Robust-satisficing **survives in evolution.**



## § Financial market strategies.

- **Optimizing:** Maximize revenue.





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-



## § Financial market strategies.

- **Optimizing:** Maximize revenue.
- **Robust-satisficing:** beat the competition.
  - Satisfice revenue requirement.
  - Maximize robustness to uncertainty.
- **Robust-satisficing survives in competition.**
  - Equity premium puzzle.
  - Home bias paradox.

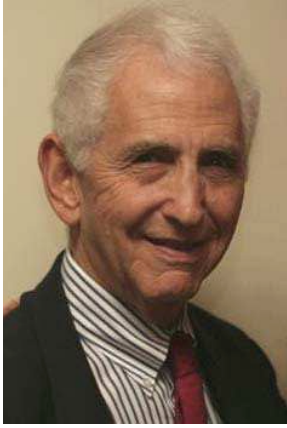


Figure 32: Ellsberg, 1931–.

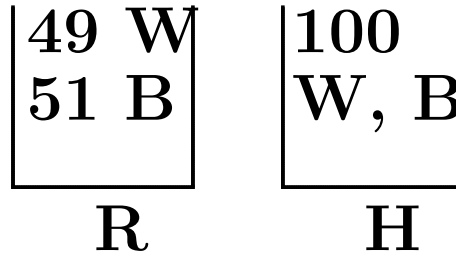


Figure 33: Ellsberg's Urns.

## § Humans and ambiguity: Ellsberg paradox.

- Probabilistic risk vs uncertainty.
- **Optimizing:** Maximize expected utility.
-

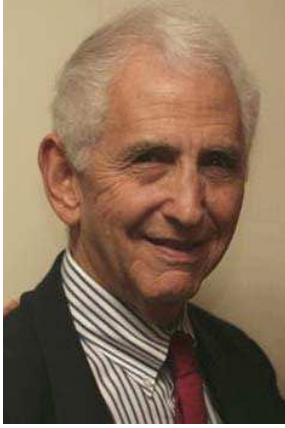


Figure 34: Ellsberg, 1931–.

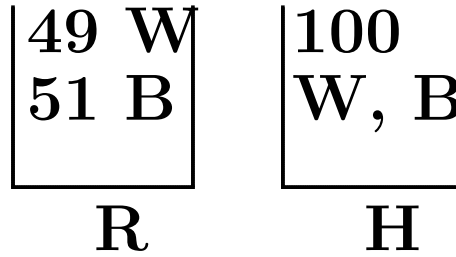


Figure 35: Ellsberg's Urns.

## § Humans and ambiguity: Ellsberg paradox.

- Probabilistic risk vs uncertainty.
- **Optimizing:** Maximize expected utility.
- **Robust-satisficing:** do good enough.
  - Satisfice expected utility.
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-

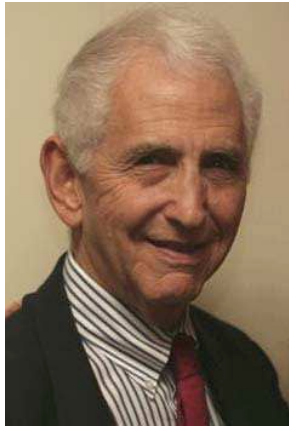


Figure 36: Ellsberg, 1931–.

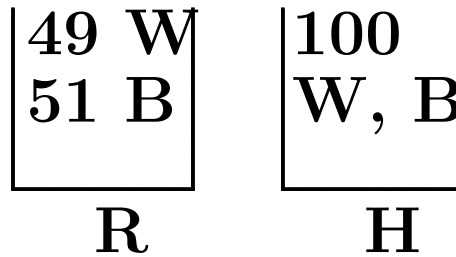


Figure 37: Ellsberg's Urns.

## § Humans and ambiguity: Ellsberg paradox.

- Probabilistic risk vs uncertainty.
- **Optimizing:** Maximize expected utility.
- **Robust-satisficing:** do good enough.
  - Satisfice expected utility.
  - Maximize robustness to uncertainty.
- Robust-satisficers are **happier**.



§ **Proxy theorems:** Robustness proxies for Probability

§ **Robust satisficing** is (often) a better bet than **optimizing**.

### **3** *Robust-Satisficing is a Proxy for Probability of Survival*

## § Decision problem:

- Decision:  $r$ .
- Uncertainty:  $u$ .
- Loss function:  $L(r, u)$ .
- Satisficing:  $L(r, u) \leq L_c$ .

§

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## § Info-gap uncertainty model: $\mathcal{U}(h, \tilde{u})$ , $h \geq 0$ .

- Unbounded family of nested sets.
- Axioms:

$$\text{Contraction: } \mathcal{U}(0, \tilde{u}) = \{\tilde{u}\}$$

$$\text{Nesting: } h < h' \implies \mathcal{U}(h, \tilde{u}) \subset \mathcal{U}(h', \tilde{u})$$

§ **Robustness:** max tolerable uncertainty.

$$\widehat{h}(r, L_c) = \max \left\{ h : \left( \max_{u \in \mathcal{U}(h, \tilde{u})} L(r, u) \right) \leq L_c \right\} \quad (34)$$

§

§ **Robustness: max tolerable uncertainty.**

$$\widehat{h}(r, L_c) = \max \left\{ h : \left( \max_{u \in \mathcal{U}(h, \tilde{u})} L(r, u) \right) \leq L_c \right\} \quad (35)$$

§ **Robust-satisficing preferences:**

$$r \succ_r r' \quad \text{if} \quad \widehat{h}(r, L_c) > \widehat{h}(r', L_c) \quad (36)$$

§

§ **Robustness: max tolerable uncertainty.**

$$\widehat{h}(r, L_c) = \max \left\{ h : \left( \max_{u \in \mathcal{U}(h, \tilde{u})} L(r, u) \right) \leq L_c \right\} \quad (37)$$

§ **Robust-satisficing preferences:**

$$r \succ_r r' \quad \text{if} \quad \widehat{h}(r, L_c) > \widehat{h}(r', L_c) \quad (38)$$

§ **Probability of survival:**

$$P_s(r) = \mathbf{Prob}[L(r, u) \leq L_c] = \int_{L(r, u) \leq L_c} p(u) \, du \quad (39)$$

§

§ **Robustness: max tolerable uncertainty.**

$$\widehat{h}(r, L_c) = \max \left\{ h : \left( \max_{u \in \mathcal{U}(h, \tilde{u})} L(r, u) \right) \leq L_c \right\} \quad (40)$$

§ **Robust-satisficing preferences:**

$$r \succ_r r' \quad \mathbf{if} \quad \widehat{h}(r, L_c) > \widehat{h}(r', L_c) \quad (41)$$

§ **Probability of survival:**

$$P_s(r) = \mathbf{Prob}[L(r, u) \leq L_c] = \int_{L(r, u) \leq L_c} p(u) \, du \quad (42)$$

§ **Probabilistic preferences:**

$$r \succ_p r' \quad \mathbf{if} \quad P_s(r) > P_s(r') \quad (43)$$



§ **Robustness: max tolerable uncertainty.**

$$\widehat{h}(r, L_c) = \max \left\{ h : \left( \max_{u \in \mathcal{U}(h, \tilde{u})} L(r, u) \right) \leq L_c \right\} \quad (44)$$

§ **Robust-satisficing preferences:**

$$r \succ_r r' \quad \text{if} \quad \widehat{h}(r, L_c) > \widehat{h}(r', L_c) \quad (45)$$

§ **Probability of survival:**

$$P_s(r) = \mathbf{Prob}[L(r, u) \leq L_c] = \int_{L(r, u) \leq L_c} p(u) \, du \quad (46)$$

§ **Probabilistic preferences:**

$$r \succ_p r' \quad \text{if} \quad P_s(r) > P_s(r') \quad (47)$$

§ **Do  $\succ_r$  and  $\succ_p$  agree?**

- $\widehat{h}(r, L_c)$  proxies for  $P_s(r)$ ???
- $\widehat{h}(r, L_c) > \widehat{h}(r', L_c)$  implies  $P_s(r) \geq P_s(r')$ ???

## Why $\succ_r$ and $\succ_p$ Are Not Necessarily Equivalent

§ **Two actions**,  $r_1$  and  $r_2$ , with robustnesses:

$$\widehat{h}(r_1, L_c) < \widehat{h}(r_2, L_c) \quad (48)$$

Denote  $\widehat{h}_i = \widehat{h}(r_i, L_c)$ ,  $\mathcal{U}_i = \mathcal{U}(\widehat{h}_i, \tilde{q})$ .

§  $\mathcal{U}_i$  are nested:

$$\mathcal{U}_1 \subseteq \mathcal{U}_2 \quad \text{because} \quad \widehat{h}_1 < \widehat{h}_2 \quad (49)$$



$\mathcal{U}_i$  reflect agent's beliefs.

## § Survival set:

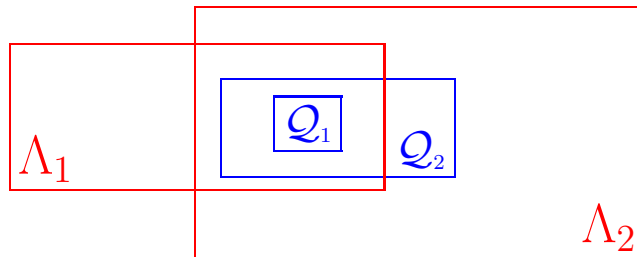
$$\Lambda(r, L_c) = \{u : L(r, u) \leq L_c\} \quad (50)$$

## § Prob of survival:

$$P_s(r) = \mathbf{Prob}[\Lambda(r, L_c)] \quad (51)$$

## § Survival sets:

- Need not be nested.
- Do not reflect agent's beliefs.



## § Proxy theorem need not hold.

## Systems with Proxy Theorems

(Each theorem with its own “fine print”)

## § Uncertain Bayesian mixing of 2 models.

- Decision  $r$ .
- Outcome depends on which of 2 models,  $A$  or  $B$ , is true.
- $u$  is uncertain probability that  $A$  is true.
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- $\hat{h}(r, L_c)$  is **robustness** for satisficing at  $L_c$ .
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- $\hat{h}(r, L_c)$  is a **proxy** for  $P_s(r)$ :

Any change in  $r$  that **increases  $\hat{h}$**  cannot decrease  $P_s$ .



## § Risky and risk-free assets.

- $r$  is fraction of budget invested in risky assets.
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Is the grass really **greener?**

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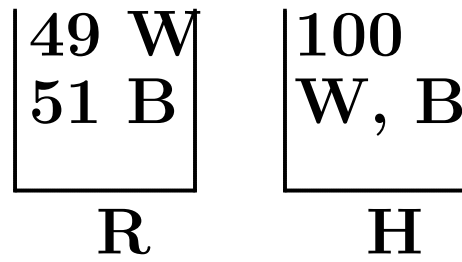


Figure 38: Ellsberg's Urns.

## § Ellsberg's paradox.

- 2 lotteries: 1 **risky**, 1 **ambiguous**.
- 2 experiments: 'win on black' or 'win on white'.
-

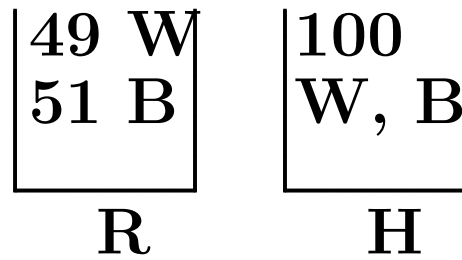


Figure 39: Ellsberg's Urns.

## § Ellsberg's paradox.

- 2 lotteries: 1 **risky**, 1 **ambiguous**.
- 2 experiments: 'win on black' or 'win on white'.
- Choice between **risk** and **ambiguity**.
- Ellsberg's agents prefer risky lottery both times.
-

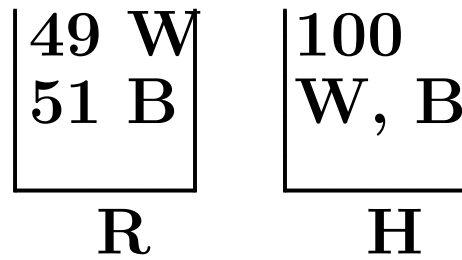


Figure 40: Ellsberg's Urns.

## § Ellsberg's paradox.

- 2 lotteries: 1 **risky**, 1 **ambiguous**.
- 2 experiments: 'win on black' or 'win on white'.
- Choice between **risk** and **ambiguity**.
- Ellsberg's agents prefer risky lottery both times.
- Ellsberg's agents are robust-satisficers because:
- **Robustness is a proxy for probability**, so:
  - Agents maximize probability of adequate return.

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- Many systems **have** proxy property.
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- How prevalent is the proxy property?
  - **Human:** economic competition.
  - **Biological:** foraging.
  - **Physical:** quantum uncertainty.

## 4 *Robust Satisficing: Normative or Prescriptive?*

### § **Main Source:**

Barry Schwartz, Yakov Ben-Haim, and Cliff Dacso, 2011, What Makes a Good Decision? Robust Satisficing as a Normative Standard of Rational Behaviour, *The Journal for the Theory of Social Behaviour*, 41(2): 209-227.

Pre-print to be found on:

<http://info-gap.com/content.php?id=23>

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Describe how DM's decide.
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Establish **norm, gold standard** for decision making.
- **Prescriptive:**  
Specify **implementable strategies**  
given human and epistemic limitations.



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- Utility optimizing was the ideal norm.
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**don't have info and ability to optimize.**
- If they did have, they would optimize:
  - Moral imperative.
  - Competitive advantage.

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  - Facilitate decision making (36 jellies).
- Explains the **paradox of choice**:  
Why aiming at **more** yields **less**.

*In Conclusion*

Human decision making  
under **uncertainty**  
is  
**In**te**re**st**i**Ng

