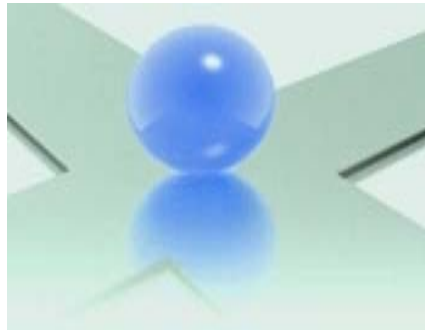


Why Risk Analysis is  
**Difficult**  
*and*  
Some Thoughts on How to Proceed

Yakov Ben-Haim

Technion

Israel Institute of Technology



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# **1** *Highlights*

## § What is

# Risk Analysis?

## § Article titles from *Risk Analysis*:

- Pesticides and Methylmercury  
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-

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## § Goals of risk analysis:

- Improve safety.
- Identify causes of injury.
- Support decision making.



## § Components of risk analysis:

- Models of the **process**.



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- Performance **requirements** or **failure criteria**.
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## § Why is risk analysis hard?

- Complex variable processes.
- Conflicting requirements.
- Lots of **uncertainty**.

## § Other difficulties:

- Psychology.
- Social and cultural issues.
- Institutions.

## Part I

### *Why Risk Analysis is Difficult*



## 2 *A Bit of History*

## § History of human thought:

- Cerebral cortex: many 10,000s of years.
-

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- Agriculture and settlement: 7-8,000 years.
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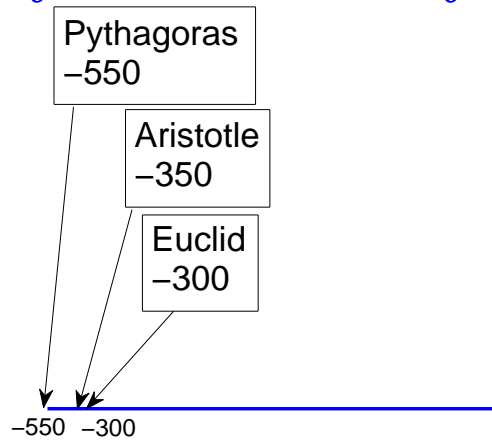
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- Agriculture and settlement: 7-8,000 years.
- Writing: 5,000 years.
- Science:
  - Ancient Greeks had some: 2,000 years.
  - Mostly modern Europe: 500 years.

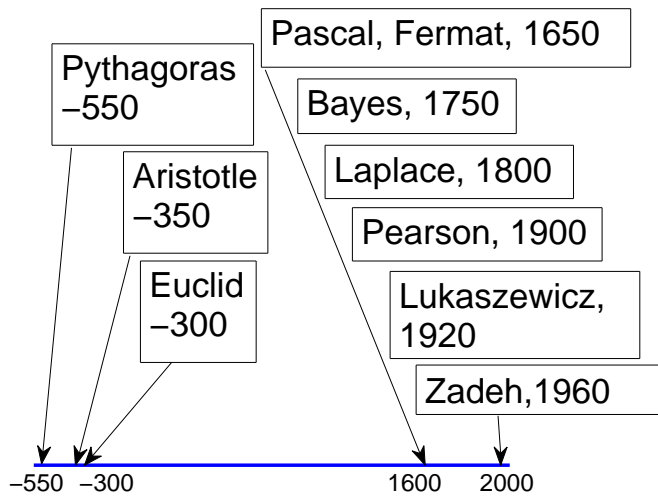
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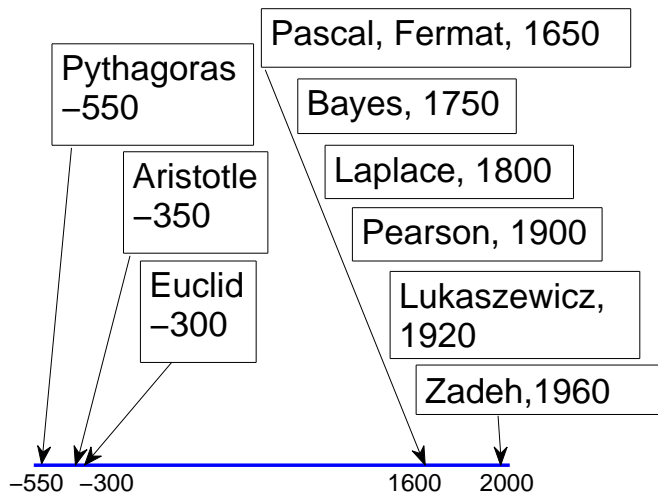


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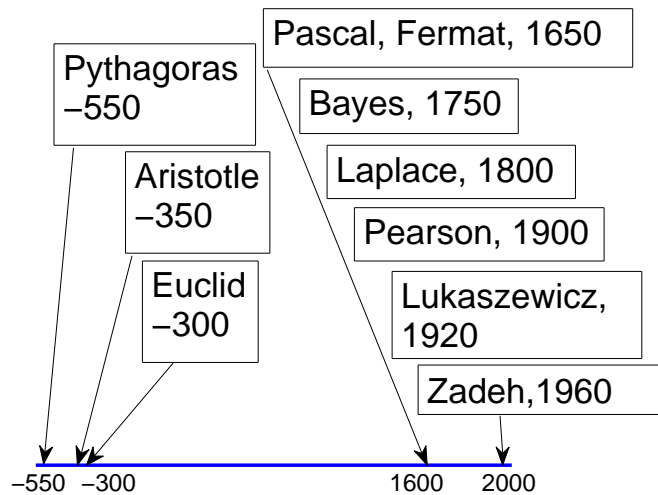
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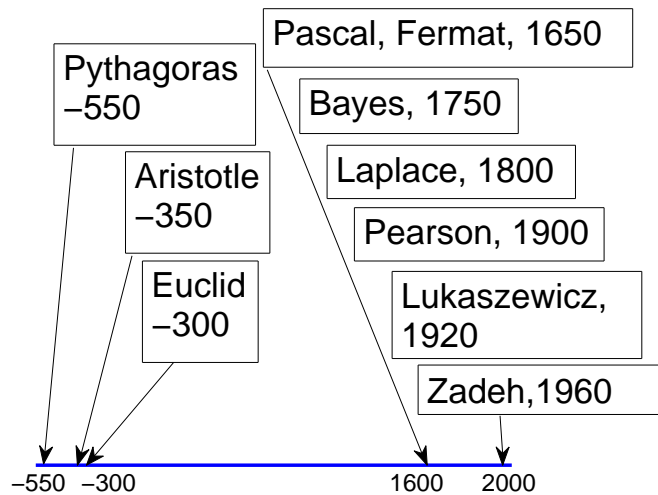


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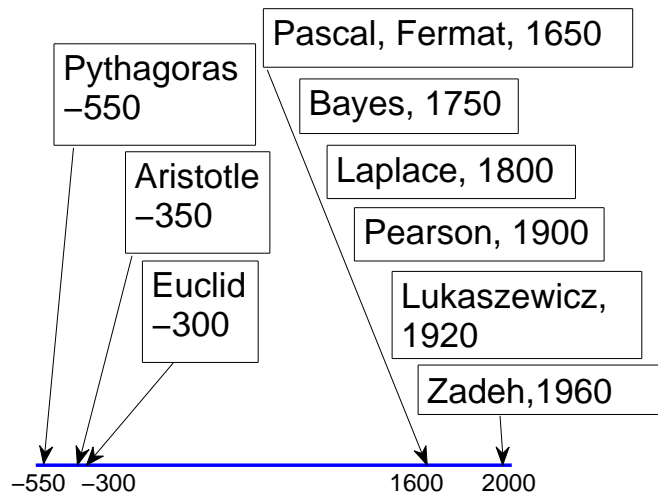


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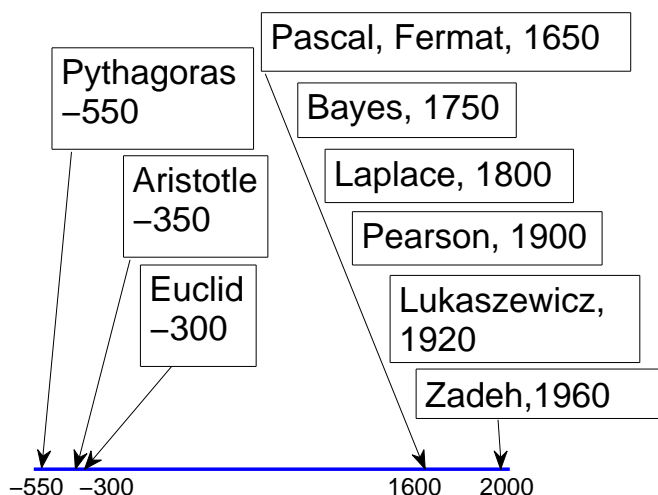


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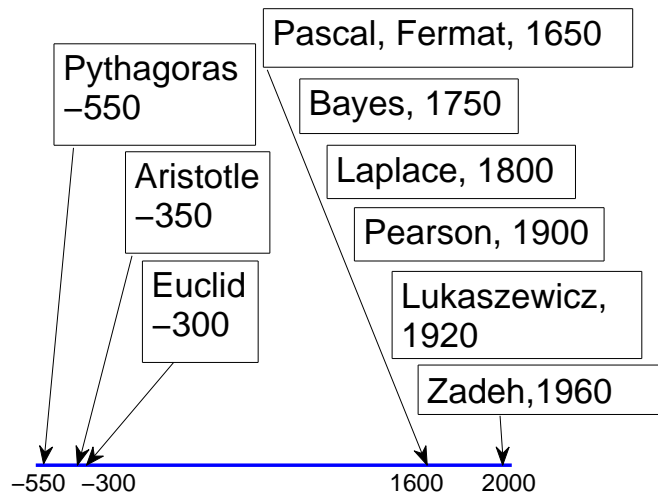
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- Dempster-Shafer. GIT.
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§ **We're just beginning to understand uncertainty.**

### **3** *Shackle-Popper Indeterminism*

### 3.1 *Shackle-Popper Indeterminism*

## § Intelligence:

What people know,  
influences how they behave.

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## § Discovery:

What will be discovered tomorrow  
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## § Indeterminism:

Tomorrow's behavior cannot be  
modelled completely today.

§ **Information-gaps**, indeterminisms,  
sometimes  
cannot be modelled probabilistically.

§ **Ignorance is not probabilistic.**

## § Two types of discoveries:

- Discover what **does exist** (recovery).
  - America.
  - HIV virus.
  - House keys.
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  - Idea of freedom.
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**Closed universe. Creation ended.**
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## § Two corresponding types of universe:

- Discover what **does exist**.  
**Closed universe.** Creation ended.
- Discover what **does not exist**.  
**Open universe.** Creation continues.

## 4 *Hume and the Problem of Induction*



## § Induction:

- Use **evidence** to make new conclusion, generalization, prediction.

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- Use **evidence** to make new conclusion, generalization, prediction.

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- Induction cannot prove validity of induction.
- Knowledge, including science, based on induction.
- **How to justify knowledge?**

## § Hume:

- “[W]e cannot give a satisfactory reason why we believe, after a thousand experiments, that a stone will fall or fire burn”.<sup>1</sup>

- 

---

<sup>1</sup>Hume, D. *An Inquiry Concerning Human Understanding*, 1748, edited by Antony Flew. Collier Books, 1962, p.160.

## § Hume:

- “[W]e cannot give a satisfactory reason why we believe, after a thousand experiments, that a stone will fall or fire burn”.<sup>2</sup>

- “For all inferences from experience suppose, as their foundation, that the future will resemble the past and that similar powers will be conjoined with similar sensible qualities. . . .

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- “It is impossible, therefore, that any arguments from experience can prove this resemblance of the past to the future, since all these arguments are founded on the supposition of that resemblance.”<sup>4</sup>

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## § Hume argues from

**logical** structure of induction.

## § Hume’s justification of induction: **habit**.

Today we’d say: **psychology**.

---

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§ One can also argue from  
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§ One can never test the future:

- All tests occur **now**.
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- **Rug metaphor:**

The future can never be tested,  
just as one can never step on  
the rolled up part of an endless rug  
unfurling always in front of you.<sup>9</sup>

---

<sup>9</sup>Yakov Ben-Haim, 2011, The end of science?  
<http://decisions-and-info-gaps.blogspot.com/2011/10/end-of-science.html>

## § Goodman's green and grue example.

- Examine many emeralds up to time  $t$ .
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- How to decide between  
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- Each is equally supported by evidence.

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- Each is equally supported by evidence.

## § Easy (they say): We know stability of color, chemical properties, etc.

## § No help. Make grue-like hypotheses consistent with current knowledge.

- Past does not constrain the future.
- Hume: “Whatever *is* may *not be*.”<sup>10</sup>

---

<sup>10</sup>Hume, D. *An Inquiry Concerning Human Understanding*, 1748, p.161.

## § Why are Hume's problems important:

- for risk analysis?
- in general?

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- Learn from experience by induction.
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- for risk analysis?
- in general?

## § Induction is important:

- Learn from experience by induction.
- Base decisions on knowledge.

## § We need to know:

- What inferences are valid? (**green** or **grue**)
- What knowledge is warranted.
- What learning algorithms are valid?

## Part II

### *Some Thoughts on How to Proceed*



## 5 *Epistemic Paralysis*

## § Epistemic paralysis (Locke's wingless man):

“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>11</sup>



---

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- Belief and action justified despite uncertainty.

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## § Practical implications:

- Acquire best available “models:”  
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- Acquire best available “models:” data, knowledge, understanding, . . . .
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- Belief and action justified despite uncertainty.

## § Practical implications:

- Acquire best available “models:”  
data, knowledge, understanding, . . . .
- Acknowledge: better models in future.
- Balance between skepticism and action.  
Tools needed for this balancing.

---

<sup>15</sup>Locke, John, *An Essay Concerning Human Understanding*, 5th edition, 1706. Roger Woolhouse, editor. Penquin Books, 1997, I.i.5.

## 6 *Models and Robustness*

§ **Avoiding epistemic paralysis: many tools.**

**We focus on concepts of robustness.**

§



§ **Avoiding epistemic paralysis: many tools.**

We focus on **concepts of robustness.**

§ **‘Robust’ means (OED):**

- ‘Strong and hardy; sturdy; healthy’.
- ‘Not easily damaged or broken, resilient’.
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§ **Avoiding epistemic paralysis: many tools.**

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§ **‘Robust’ means (OED):**

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- **Robust statistical test** yields approximately correct results despite falsity of assumptions or data.
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- ‘Strong and hardy; sturdy; healthy’.
- ‘Not easily damaged or broken, resilient’.
- **Robust statistical test** yields approximately correct results despite falsity of assumptions or data.
- **Robust decision:**
  - Outcome is satisfactory despite error.
  - Resilient to surprise.
  - Immune to ignorance.

## § Robustness operationalized in many ways:

- Robust statistics.<sup>16</sup>
- 

---

<sup>16</sup>Huber, Peter J., 1981, *Robust Statistics*, John Wiley, New York.

## § Robustness operationalized in many ways:

- Robust statistics.<sup>17</sup>
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<sup>18</sup>Zhou, Kemin; John C. Doyle, 1997, *Essentials of Robust Control*, Prentice Hall, Upper Saddle River, New Jersey.

## § Robustness operationalized in many ways:

- Robust statistics.<sup>19</sup>
- Robust control.<sup>20</sup>
- Robust decision making.<sup>21</sup>
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- Robust control.<sup>23</sup>
- Robust decision making.<sup>24</sup>
- Robust flexibility.<sup>25</sup>
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<sup>25</sup>Rosenhead, Jonathan, 1989, Robustness analysis: Keeping your options open, in Jonathan Rosenhead, ed. *Rational Analysis For a Problematic World: Problem Structuring Methods For Complexity, Uncertainty and Conflict*, John Wiley, New York.

## § Robustness operationalized in many ways:

- Robust statistics.<sup>26</sup>
- Robust control.<sup>27</sup>
- Robust decision making.<sup>28</sup>
- Robust flexibility.<sup>29</sup>
- Robust economics.<sup>30</sup>
- 

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- Yes, in many (not all) cases.
- Examples (see earlier lecture<sup>61</sup>):
  - Animal foraging.
  - Financial markets.
  - Many engineering designs.
  - ...

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<sup>61</sup>Paradox of Choice: Why More is less, \lectures\talks\lib\pdox-choice01.tex



## § Innovation dilemma:

- 2nd look. (See earlier lecture<sup>62</sup>)
- Is robustness good response to innovation dilemma?

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<sup>62</sup>No-Failure Design and Disaster Recovery Lessons from Fukushima, \lectures\talks\lib\no-fail-disas-rec01.tex

# 7 *Innovation Dilemma*

## § Choose between two options:

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- **Option 1:**
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- **Option 2:**
  - State of the art.
  - Lower uncertainty.

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  - Sensor-based computer control (innov).
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  - Import technology, infrastructure (SotA).
- **Financial investment:**
  - New start-up firm (innov).
  - US Treasury bonds (SotA).
- **Risk taking or avoiding:**
  - Nothing ventured, nothing gained (innov).
  - Nothing ventured, nothing lost (SotA).

## § Decision strategies.

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  - Use models to predict outcomes.
  - Choose predicted best option.
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  - Use models to predict opportuneness.
  - Choose best ops of wonderful outcome.

§

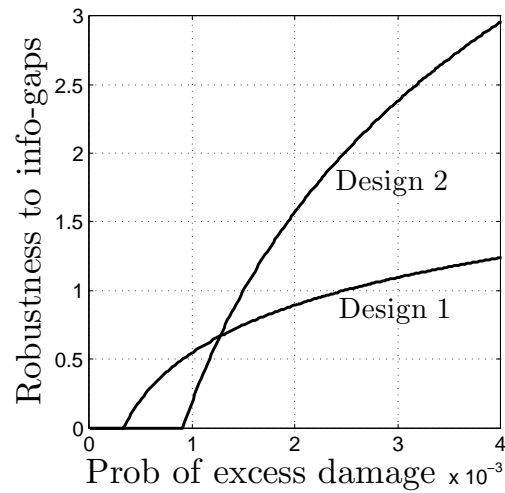
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## § Question:

Which strategy suitable for innovation dilemma?

## § Optimize or robust-satisfice?



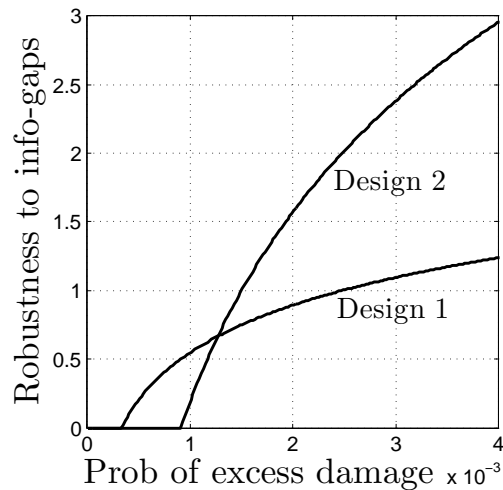
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Des 1 predicted better than Des 2.

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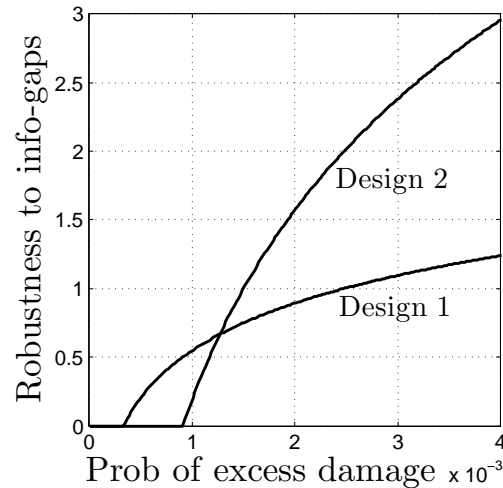
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Design 2 more robust for  $P > P_{\times}$ .

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### § Resolve innovation dilemma:

- Value judgment on outcome requirement.
- Robustly satisfy requirement.

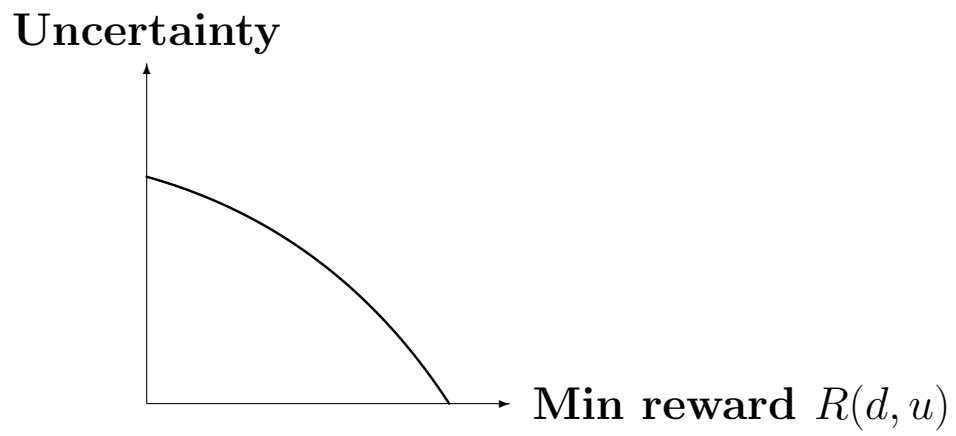
# § Is robustness good response to innovation dilemma?

## 8 *Max-Min and Robust-Satisficing*

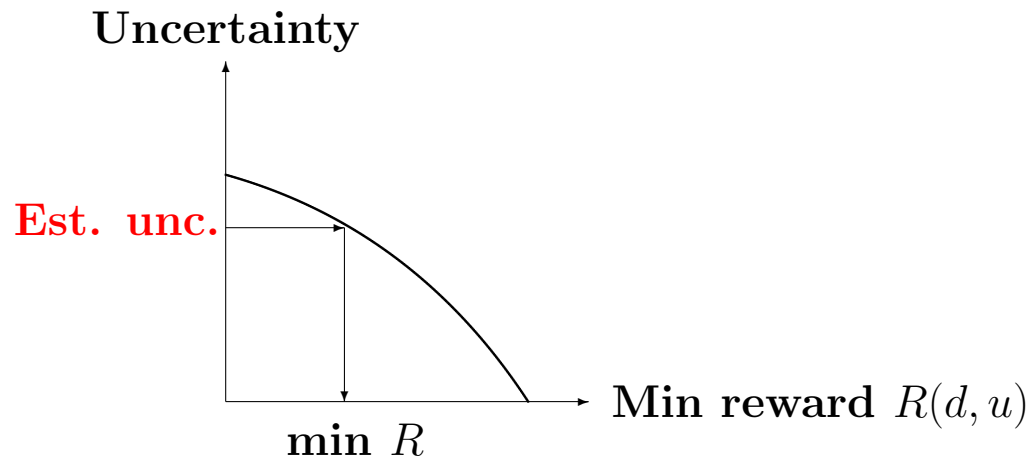
§ **Task:** make a decision.

- $d =$  decision.
- $u =$  uncertain parameters, functs., sets.
- $R(d, u) =$  reward.

## § Trade-off: uncertainty vs. min reward.

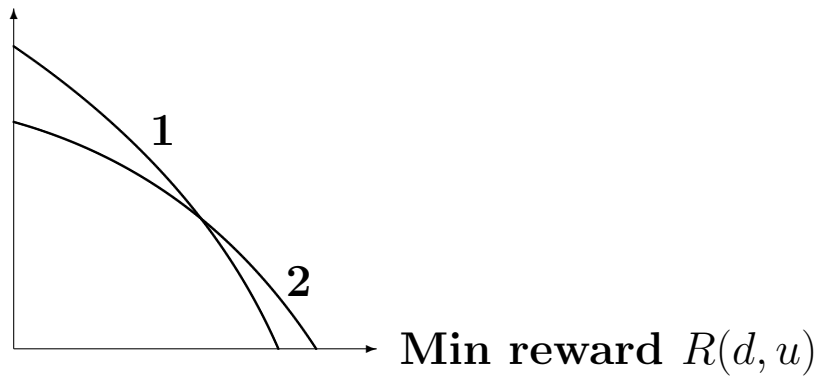


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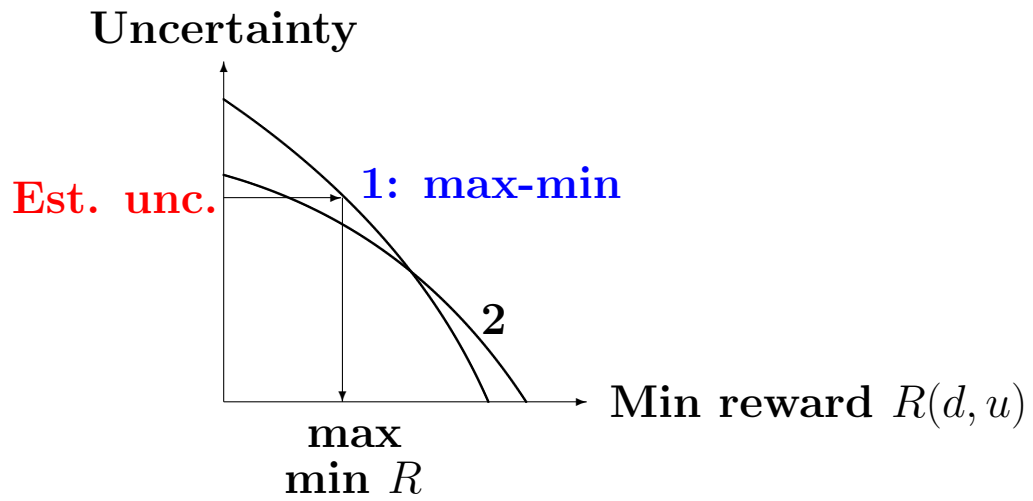


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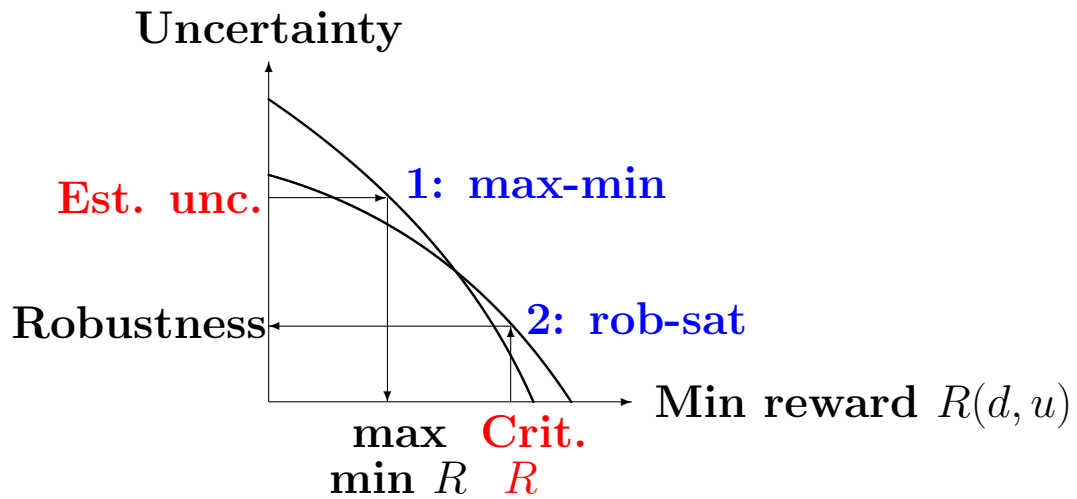
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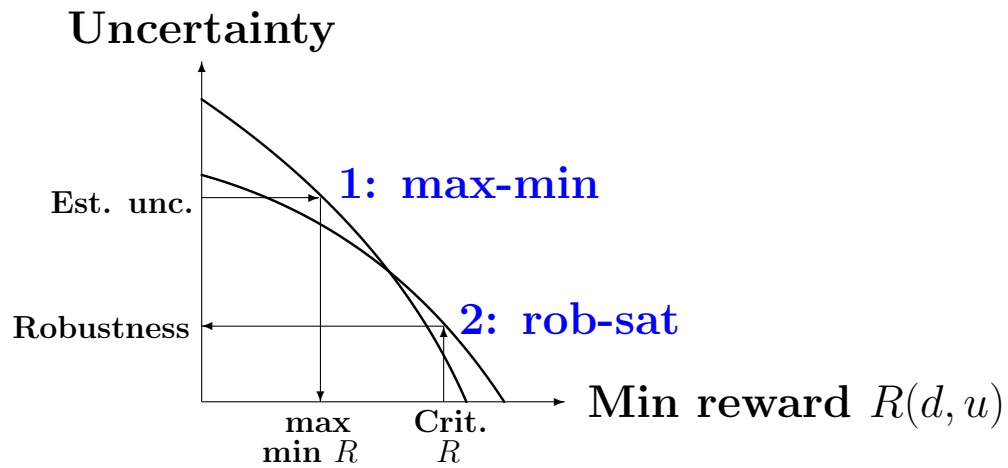


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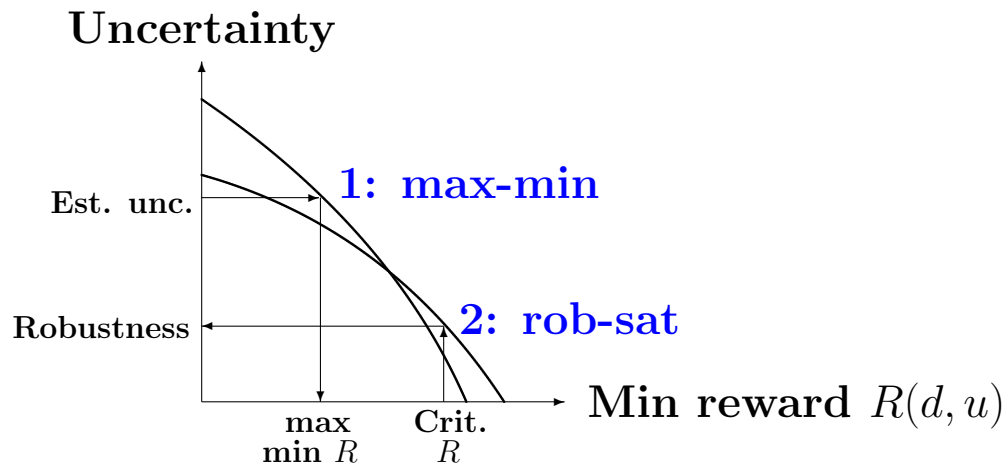
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## § Modeller's equivalence: **description.**

- Max-min can always describe rob-sat (by adjusting prior beliefs).
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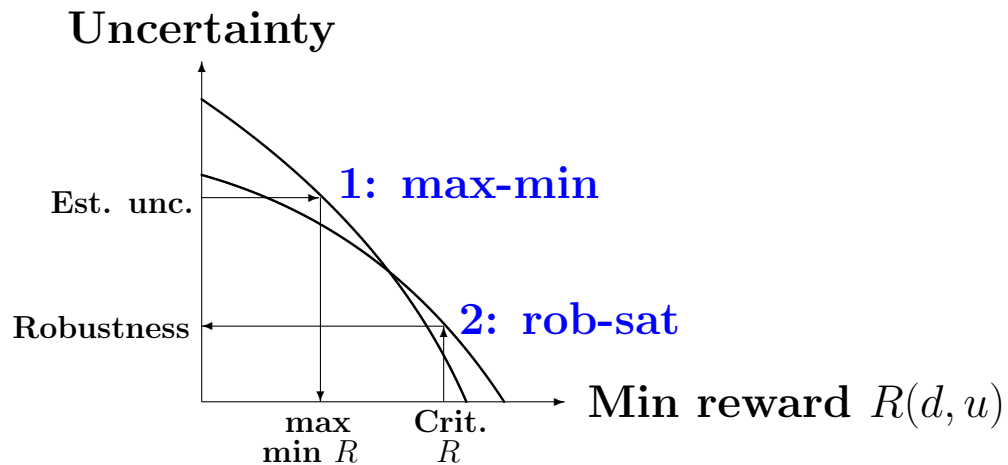
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## § Modeller's equivalence: **description.**

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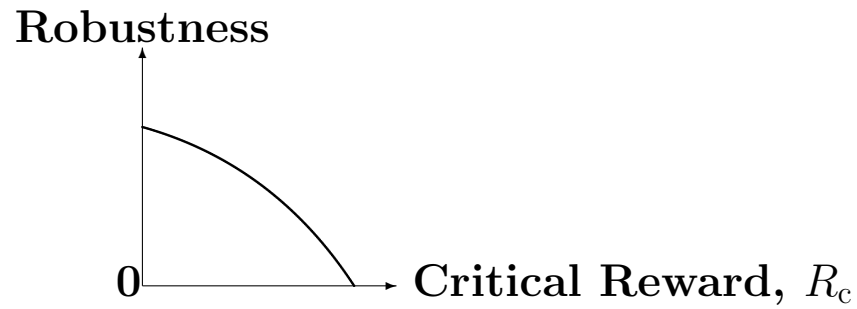
§ Modeller's equivalence: **description.**

§ Decision-maker's duality: **prescription.**

Max-min and rob-sat **differ** if:

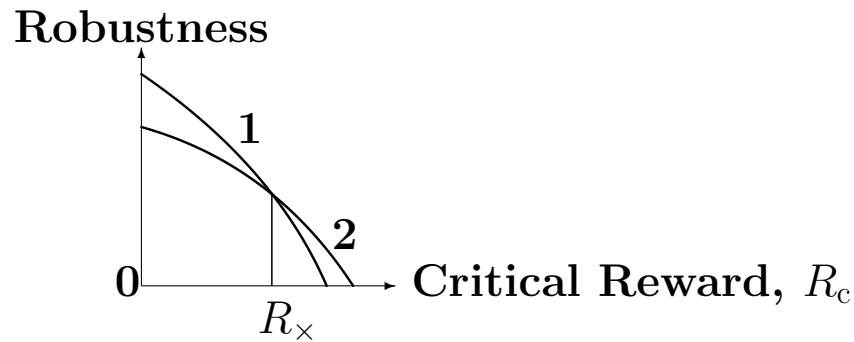
- Max-min gain too low, or,
- Worst case is uncertain.

## § Optimizing vs Robustifying



- **Trade off:** Robustness vs performance.
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- **Trade off:** Robustness vs performance.
- **Zeroing:** No rbs of predicted reward.
- **Predicted optimum:** 2.
- **Robust-satisficing optimum:** 2 iff  $R_c > R_x$ .

§ Info-gap robustness is **non-probabilistic**.

Is it a **good bet**?

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§ **Evolutionary advantage of robustness:**

- Robustness may **proxy for**  
Probability of survival.
- Proxy theorems.

# 9 *Opportuneness*



## § Risk analysts:

- Prevent high-consequence adverse events in critical technologies.
- Are risk averse.

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- Converses.
- Risk analysts mainly use robustness.
- Opportuneness has 3 supporting roles.

## § Utility of opportuneness analysis:

- Choose from 2 options w/ similar rbs.

Opportuneness can **break the tie**.

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- Robustness and opportuneness:

- Not necessarily **antagonistic**.
- May be **sympathetic**.

- If rbs and ops are **antagonistic**:

**Trade some robustness for opportuneness.**

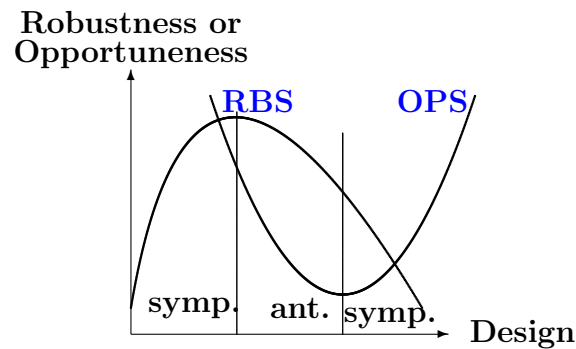


Figure 1: Robustness and opportuneness curves.

## 10 *Conclusion*

## § Risk analysis is hard because:

- **Knowledge** is limited.
- **Uncertainty** is **unlimited**.
- **Other factors:**  
resources, psychology, institutions, . . . .

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- **Robustness**: protect against unknown.
- **Opportuneness**: exploit the unknown.
- **Methodological** pluralism.

