Info-Gap Methods

for

Decision Support

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Contents

1 *HIGHLIGHTS*

§ Info-gaps:

- **Incomplete understanding.**
- **Erroneous data.**
- **Changing conditions.**
- **Sur$_{\mathbf{p}}$rises.**

§ Info-gaps:

- **Incomplete understanding.**
- **Erroneous data.**
- **Changing conditions.**
- **Sur p rises.**

¶ Questions:

- **Updating.**
- **Decision making.**
- **Forecasting.**

2 *BIOLOGICAL CONSERVATION: EXAMPLES*

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2.1 Protection Against Infestation

§ **Danger: Infestation at any point x.**

§ **Resources: q.**

§ **Uncertainties:**

- **Prob. of infestation at x: $p(x)$.**
- **Loss from infestation at x: $L(x, q)$.**

§ **Assessment: Expected loss:**

$$\mathrm{E}(L|p, q) = \int L(x, q)p(x)\,\mathrm{d}x$$

§ Tasks:

- **Allocate resources.**
- **Satisfice expected loss.**
- **Maximize robustness to uncertainty.**

§ Extensions:

- **Strategic opponent,** $p(x, q)$**.**
- **Temporal dynamics,** $p(x, t)$**.**

2.2 Spatial Monitoring

§ **Danger:** Extreme toxin.

§ **Resources:** Measure at N sites.

§ **Uncertainty:** Spatial distribution of toxin.

§ **Remedial action** if
critical toxin level detected.

§ **Tasks:**

- Choose #, place, type of measurements.
- Satisfice level detected.
- Max. robustness to spatial uncertainty.

§ Extensions:

- **Multiple toxins.**
- **Latent toxins.**
- **New (uncertain) toxins.**
- **Transport dynamics (uncertain).**
- **Probabilistic detection.**

2.3 Investment for Bio-Diversity

§ **Goal:** **Enhance bio-diversity.**

§ **Method:** **Invest in land, treatment, etc.**

§ **Problems:**

- **Limited resources,** q**.**
- **Uncertain bio-div return,** $N(q, t)$**.**
- **Returns and resources emerge (uncertainly) over time.**

2.4 Statistical Tests with Distributional Uncertainty

§ **Goal:**

Determine freq. of occurrence of species.

§ **Data:** **Non-random, heterogeneous data.**

E.g. Various observer talent, effort, sites.

§ **Method:** **Statistical test, e.g.** t, χ^2, **etc.**

§ **Problem:** **Distributional uncertainty.**

3 *Setting Conservation Priorities For Land Rehabilitation*

3.1 Models and Uncertainties

§ **The goal:**

- **Bio-diversity and land management.**
- **Enhance number of species by joining remnant land to new patch at specified distance.**

§ **The problem: Uncertain model and data.**

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§ References:

• **Moilanen, Runge, Elith, Tyre, Carmel, Fegraus, Wintle, Burgman and Ben-Haim, Planning for robust reserve networks using uncertainty analysis,** *Ecological Modelling,* **2006.**

• **Moilanen, van Teeffelen, Ben-Haim and Ferrier, How much compensation is enough? A framework for incorporating uncertainty and time discounting when calculating offset ratios for impacted habitat,** *Restoration Ecology,* **2008.**

§ Ecological model:

Increments in # of species:

Remnant : $S_1' - S_1 = \left[(R_1 + A_0)^Z - R_1^Z\right] \mathrm{e}^{-\beta D} \; C$

Patch : $S_0' - S_0 = \left[(R_1 + A_0)^Z - A_0^Z\right] \mathrm{e}^{-\beta D} \; C$

§ Decision variables: $Q = (R_1,\ A_0,\ D)$:

R_1 = **remnant area.**

A_0 = **patch area.**

D = **distance from remnant to patch.**

§ Uncertain variables: $U = (\beta,\ C,\ Z)$.

§ Performance function: # of new species:

$$N(Q, U) = \max[S_0' - S_0,\ \ S_1' - S_1]$$

§ Performance requirement:

Achieve at least minimal growth.

$$N(Q, U) \ \geq \ N_{\mathrm{C}}$$

§ Info-gap model of uncertainty:

- **Uncertain model parameters:** $U = (\beta,\ C,\ Z)$.
- **Best estimates:** $\widetilde{U} = (\widetilde{\beta},\ \widetilde{C},\ \widetilde{Z})$.
- **Unknown fractional errors of estimates:**

$$\left| \frac{U_I - \widetilde{U}_I}{\widetilde{U}_I} \right| \le \alpha, \quad \alpha \ge 0$$

- **Info-gap model:**

$$\mathcal{U}(\alpha, \widetilde{U}) = \left\{ U : \ \left| \frac{U_I - \widetilde{U}_I}{\widetilde{U}_I} \right| \le \alpha, \quad I = 1,\, 2,\, 3 \right\}, \quad \alpha \ge 0$$

Unbounded family of nested sets.

§ Many info-gap models of uncertainty:

$$\mathcal{U}(\alpha, \widetilde{U}) = \left\{ U \in \Re^N : \ \left(U - \widetilde{U}\right)^T W \left(U - \widetilde{U}\right) \le \alpha^2 \right\}, \quad \alpha \ge 0$$

$$\mathcal{U}(\alpha, \widetilde{U}) = \left\{ U(T) : \ \int \left[U(T) - \widetilde{U}(T) \right]^2 \mathrm{d}T \le \alpha^2 \right\}, \quad \alpha \ge 0$$

$$\mathcal{U}(\alpha, \widetilde{P}) = \left\{ P(T) : \ P(T) \in \mathcal{P}, \ \left| \frac{P(T) - \widetilde{P}(T)}{\widetilde{P}(T)} \right| \le \alpha \right\}, \quad \alpha \ge 0$$

Many more . . .

§ Axioms of info-gap models of uncertainty:

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

Nesting: $\alpha < \alpha^{\bullet} \quad \Longrightarrow \quad \mathcal{U}(\alpha, \widetilde{u}) \subset \mathcal{U}(\alpha^{\bullet}, \widetilde{u})$

α **is unknown horizon of uncertainty.**

3.2 Robustness to Uncertainty

§ Robustness of design Q:

Max horizon of uncertainty, α,

at which all realizations U

satisfy growth requirement, $N(Q,U) \geq N_{\mathrm{C}}$.

$$\widehat{\alpha}(Q, N_{\mathrm{C}}) = \max\left\{\alpha : \ \left(\min_{U \in \mathcal{U}(\alpha, \widetilde{U})} N(Q,U)\right) \geq N_{\mathrm{C}}\right\}$$

§ Preferences.

Robustness: bigger is better:

$$Q \ \succ \ Q^{\bullet} \quad \textbf{if} \quad \widehat{\alpha}(Q, N_{\mathrm{C}}) > \widehat{\alpha}(Q^{\bullet}, N_{\mathrm{C}})$$

§ Decision strategy: Robust satisficing.

- **Satisfy performance requirements.**
- **Maximize robustness to uncertainty.**

$$\widehat{Q}(N_{\mathrm{C}}) = \arg\max_{Q} \widehat{\alpha}(Q, N_{\mathrm{C}})$$

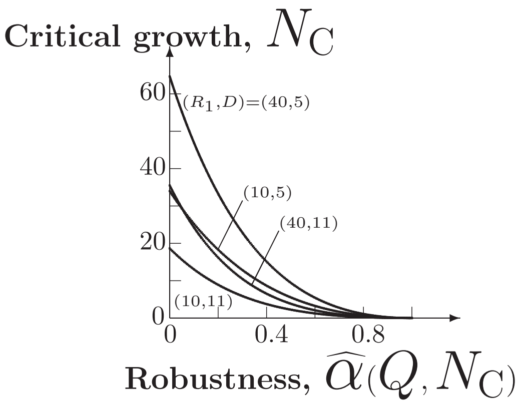
§ Robust-satisficing syllogism:

- **Adequate performance is necessary.**
- **More reliable adequate performance is better than less reliable adeq. perf.**
- **Thus maximum reliability is best.**

§ Trade-off:

$$N_C > N_C^\bullet \quad \textbf{implies} \quad \widehat{\alpha}(Q, N_C) < \widehat{\alpha}(Q, N_C^\bullet)$$

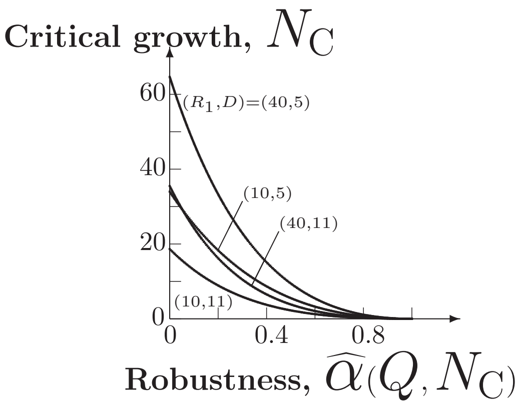
- **More demanding performance:**
  - **Less immunity to uncertainty.**
  - **Less reliable achievement.**



§ Why not optimize with best model?

$$N_{\mathrm{C}} = N(Q, \widetilde{U}) \quad \textbf{implies} \quad \widehat{\alpha}(Q, N_{\mathrm{C}}) = 0$$

- **Performance of best model has zero robustness to model error.**
- **Only lower aspirations have higher robustness.**



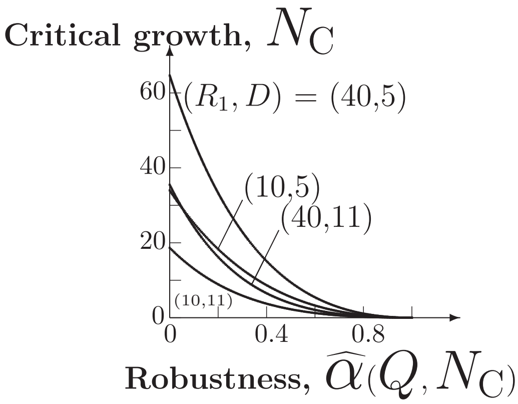
§ Why not optimize with best model?

Best-model optimum:

$$Q^{\star} = \arg\max_{Q} N(Q, \widetilde{U})$$

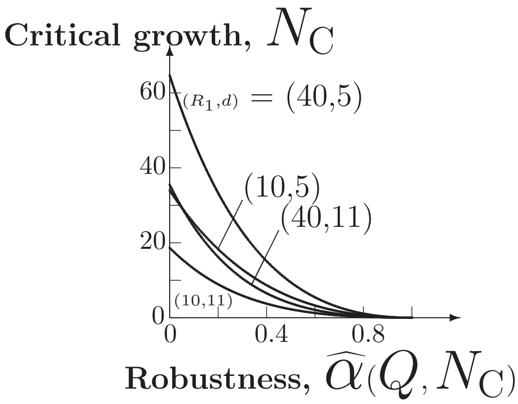
has zero robustness:

$$N_{\mathrm{C}} = N(Q^{\star}, \widetilde{U}) \quad \textbf{implies} \quad \widehat{\alpha}(Q^{\star}, N_{\mathrm{C}}) = 0$$



§ **Decisions: Choose area R_1, distance D. $(A_0 = 1)$**

- **Large R_1 better than small R_1: $40 \succ 10$.**
- **Small D better than large D: $5 \succ 11$.**
- **R_1 trades-off against D: $(10, 5) \approx (40, 11)$.**



§ What does robustness mean?

- $\widehat{\alpha}(Q, N_C) = 0.4$**:**

  $N(Q, U) \geq N_C$ **is guaranteed**

  for model error $\leq \pm$ 40**%.**
- $\widehat{\alpha}(Q, 15) = 0.4$ **for** $Q = (R_1, A_0, D) = (40, 1, 5)$**.**
- $\widehat{\alpha}(Q, 3) = 0.4$ **for** $Q = (R_1, A_0, D) = (10, 1, 11)$**.**

3.3 Opportuneness from Uncertainty

§ Two faces of uncertainty:

- **Pernicious.**
- **Propitious.**

§ Two decision strategies:

- **Robust satisficing:**
  - **Satisfice the performance.**
  - **Maximize robustness against pernicious uncertainty.**
- **Opportune windfalling:**
  - **Windfall the performance.**
  - **Minimize robustness against propitious uncertainty.**

§ Windfalling:

- N_{W} = **Large number of new species.**
- $N_{\mathrm{W}} \gg N_{\mathrm{C}}$.
- N_{C} **is critical, necessary.**
- N_{W} **is wonderful windfall!**

§ Opportuneness of design Q:

Min horizon of uncertainty, α,

at which at least one realization U

enables windfall: $N(Q,U) \;\geq\; N_{\mathrm{W}}$.

$$\widehat{\beta}(Q, N_{\mathrm{W}}) = \min\left\{\alpha : \left(\max_{U \in \mathcal{U}(\alpha, \widetilde{U})} N(Q,U) \right) \geq N_{\mathrm{W}} \right\}$$

§ Robustness and opportuneness: duality

$$\widehat{\alpha}(Q, N_{\rm C}) = \max\left\{\alpha : \left(\min_{U \in \mathcal{U}(\alpha, \widetilde{U})} N(Q, U)\right) \geq N_{\rm C}\right\}$$

$$\widehat{\beta}(Q, N_{\rm W}) = \min\left\{\alpha : \left(\max_{U \in \mathcal{U}(\alpha, \widetilde{U})} N(Q, U)\right) \geq N_{\rm W}\right\}$$

§ Preferences.

- **Robustness: bigger is better.**

$$Q \succ Q^{\bullet} \quad \textbf{if} \quad \widehat{\alpha}(Q, N_{\rm C}) > \widehat{\alpha}(Q^{\bullet}, N_{\rm C})$$

- **Opportuneness: big is bad.**

$$Q \succ Q^{\bullet} \quad \textbf{if} \quad \widehat{\beta}(Q, N_{\rm W}) < \widehat{\beta}(Q^{\bullet}, N_{\rm W})$$

- **Antagonism or sympathy.**

§ Decision strategy: opportune windfalling.

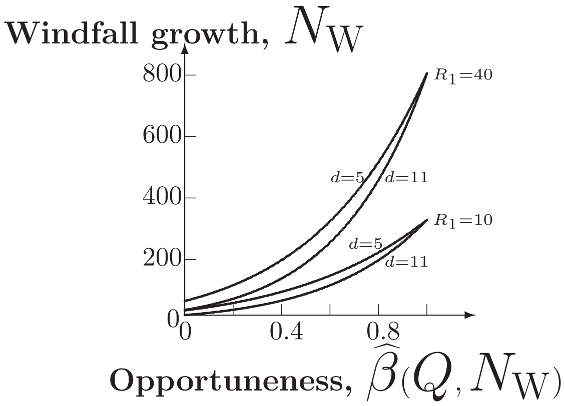
- **Windfall the performance requirements.**
- **Minimize robustness to propitious uncertainty.**

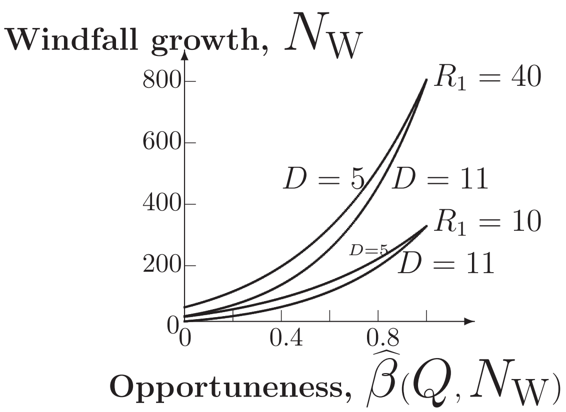
$$\widehat{Q}(N_{\mathrm{W}}) = \arg\min_{Q} \widehat{\beta}(Q, N_{\mathrm{W}})$$

§ Trade-off:

$$N_{\mathrm{W}} > N_{\mathrm{W}}^{\bullet} \quad \textbf{implies} \quad \widehat{\beta}(Q, N_{\mathrm{W}}) > \widehat{\beta}(Q, N_{\mathrm{W}}^{\bullet})$$

- **Wilder windfall performance requires more uncertainty.**





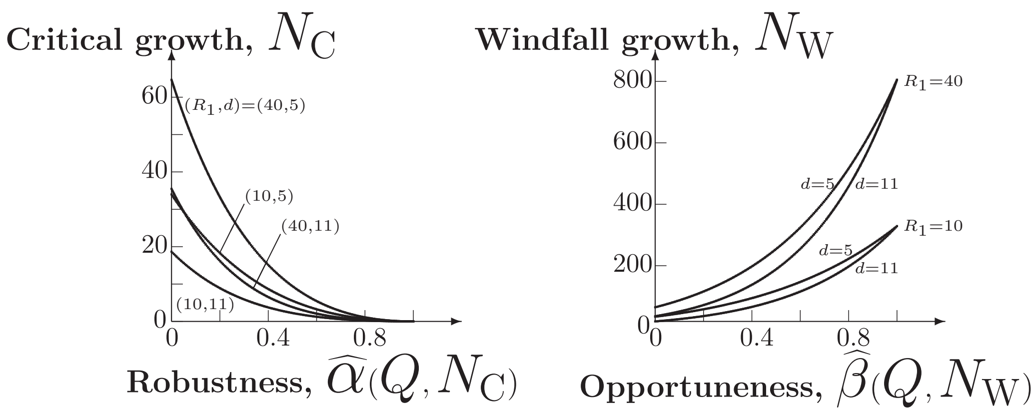
§ What does opportuneness mean?

- $\widehat{\beta}(Q, N_{\rm W}) = 0.4$**:**

  $N(Q, U) \geq N_{\rm W}$ **is possible**

  only if model errors $\geq \pm\ 40$**%.**

- $\widehat{\beta}(Q, 200) = 0.4$ **for** $Q = (R_1, A_0, D) = (40, 1, 5)$**.**
- $\widehat{\beta}(Q, 200) = 0.75$ **for** $Q = (R_1, A_0, D) = (10, 1, 5)$**.**



§ Robustness and opportuneness:

- **Performance range:**

  $$\widehat{\alpha}(Q, 15) = 0.4 = \widehat{\beta}(Q, 200)$$

  for $Q = (R_1, A_0, D) = (40, 1, 5)$**.**

- **Sympathetic immunities.**

3.4 Robustness and Probability of Design Success

§ Probability of design success

- **Model:** $N(Q, U)$.
- **Use design Q to reach target $N_{\rm C}$.**
- **Require:** $N(Q, U) \geq N_{\rm C}$.
- **U uncertain:**
  - $\mathcal{U}(\alpha, U)$ = **known info-gap model.**
  - $F(U)$ = **unknown prob. distribution.**
- **Probability of design success:**

$$P_{\rm s}(Q, N_{\rm C}) = F[N(Q, U) \geq N_{\rm C}]$$

§ "Theorems":

$$\left(\frac{\partial \widehat{\alpha}(Q, N_{\mathrm{C}})}{\partial Q}\right)\left(\frac{\partial P_{\mathrm{s}}(Q, N_{\mathrm{C}})}{\partial Q}\right) \geq 0$$

- **Robustness proxies for prob. of success.**
- **We can't calculate $P_{\mathrm{s}}(Q, N_{\mathrm{C}})$.**
- **We can calculate $\widehat{\alpha}(Q, N_{\mathrm{C}})$, so**
- **We can maximize $P_{\mathrm{s}}(Q, N_{\mathrm{C}})$.**

4 *MAX-MIN and ROBUST-SATISFICING*

§ Task: make a decision.

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

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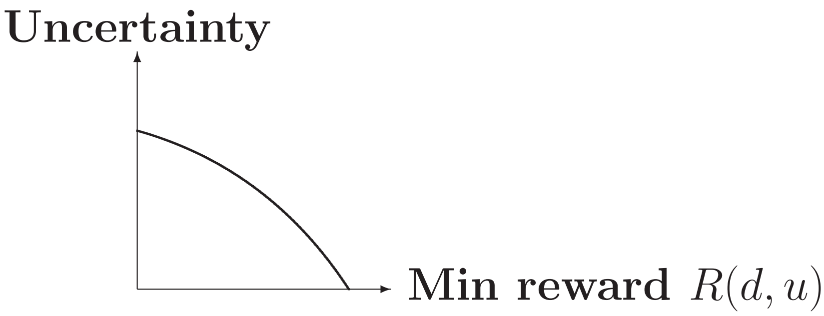
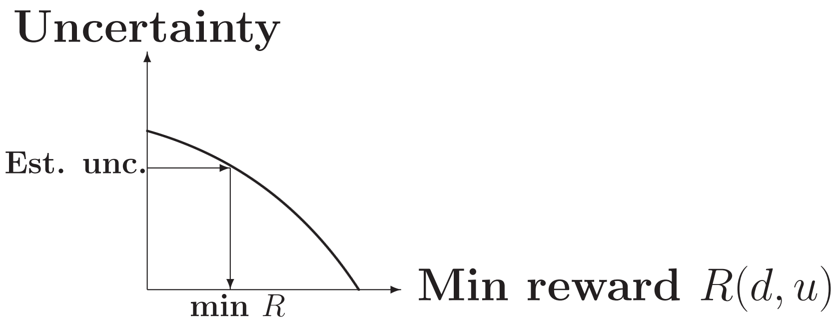
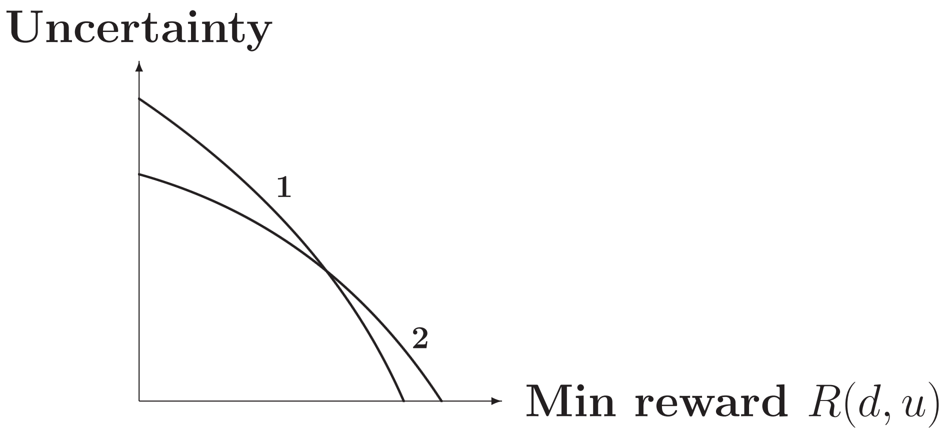
§ Trade-off: uncertainty vs. min reward.



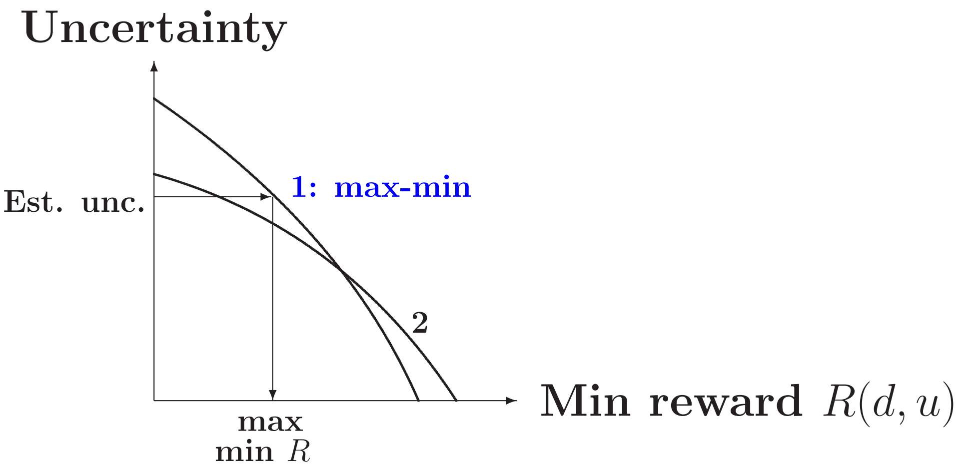
§ Trade-off: uncertainty vs. min reward.



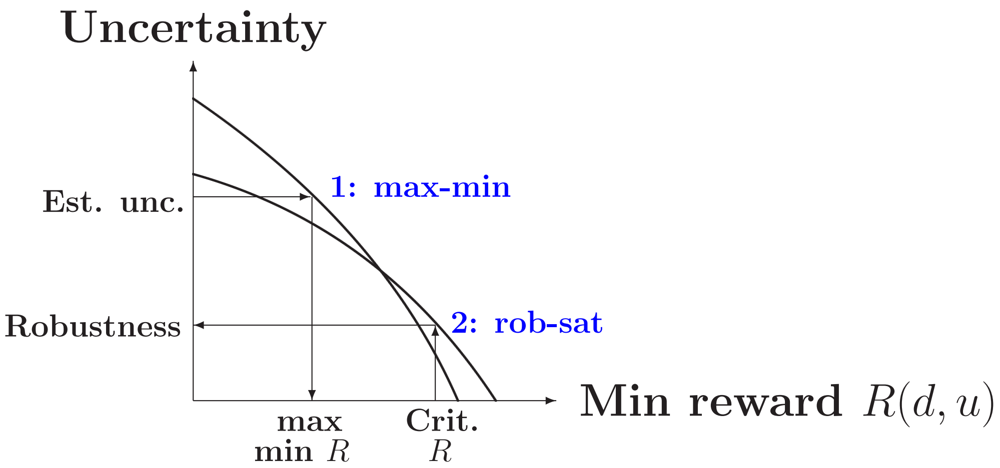
§ Choose from 2 decisions: d_1, d_2.



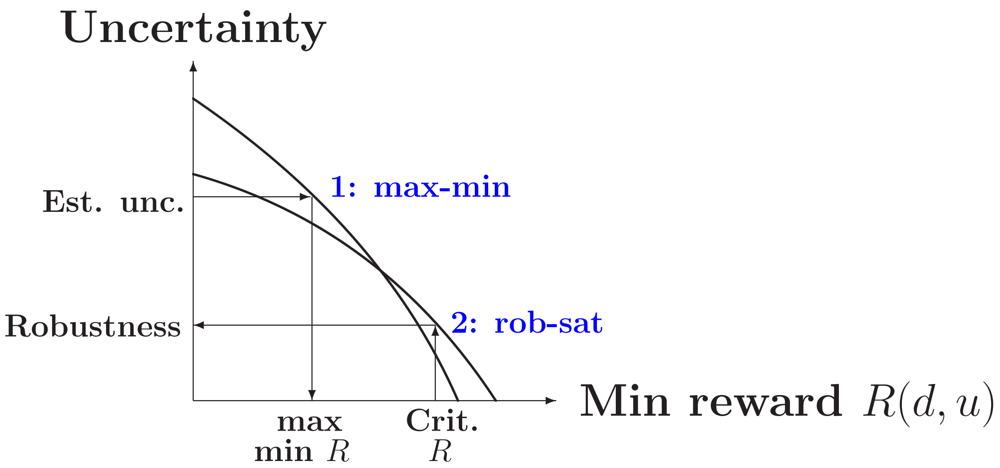
§ Choose from 2 decisions: d_1, d_2.



§ Choose from 2 decisions: d_1, d_2.



§ Choose from 2 decisions: d_1, d_2.

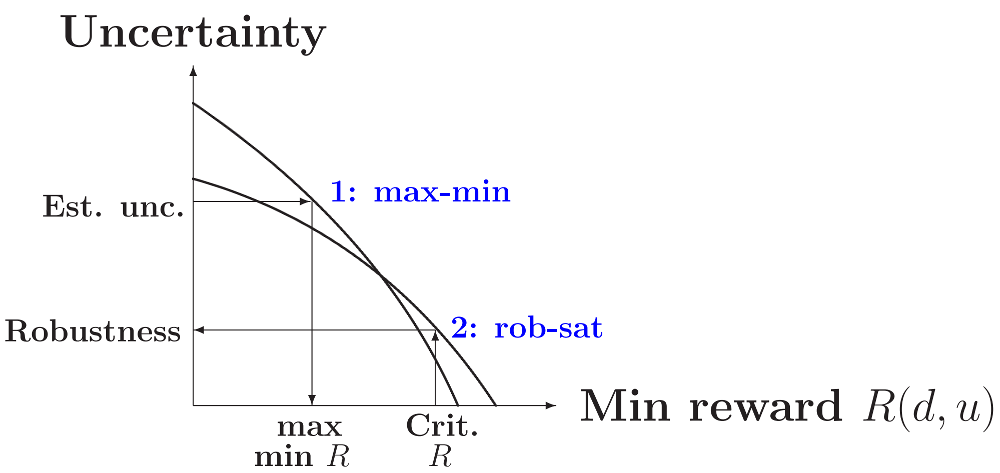


§ Modeller's equivalence:

Max-min can always describe rob-sat.

(by adjusting prior beliefs)

§ Choose from 2 decisions: d_1, d_2.



§ Modeller's equivalence:

Max-min can always describe rob-sat.

(by adjusting prior beliefs)

§ Decision-maker's duality:

Max-min and rob-sat differ if:

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

§ Evolutionary advantage of robustness:

Robustness is a proxy for

Probability of survival.

§ **Evolutionary advantage of robustness:**

Robustness is a proxy for

Probability of survival.

§ **Survival:** $R(d,u) \geq R_{\rm c}$.

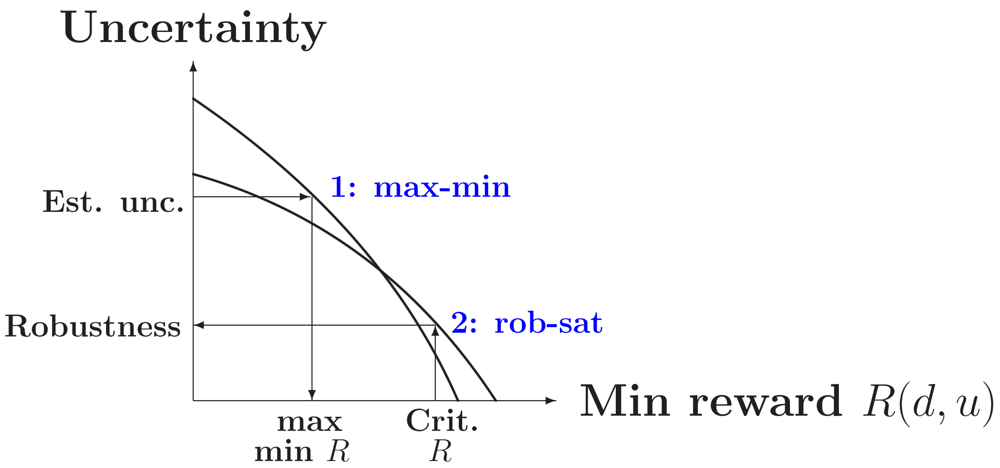
§ **Probability of survival:** $P_{\rm s}(d, R_{\rm c}) = \int_{R \geq R_{\rm c}} p(u)\, {\rm d}u$

§ **Robustness:** $\widehat{\alpha}(d, R_{\rm c})$.

§ **Proxy Theorem:**

$$\left(\frac{\partial \widehat{\alpha}(d,u)}{\partial d} \right) \left(\frac{\partial P_{\rm s}(d,u)}{\partial d} \right) \geq 0$$

§ **Choose from 2 decisions:** d_1, d_2.



§ **Modeller's equivalence:**

Max-min can always describe rob-sat.

§ **Decision-maker's duality:**

Max-min and rob-sat differ if:

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

§ **Rob-sat beats max-min in competition.**

5 *FAULT DETECTION*

§ The goal:

Distinguish between

No Fail (NF) and Fail (F).

§ Use vector measurement x.

- **Declare NF if $x \in D$.**
- **Declare F if $x \notin D$.**

§ Choose D for:

- **Small probability of missed detection.**
- **Small probability of false alarm.**

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§ Uncertain pdfs:

- **Estimated:** **Actual:**
  - **NF:** $\pi_0(x)$. $p_0(x)$.
  - **F:** $\pi_1(x)$. $p_1(x)$.
- **Info-gap models:**
  - **NF:** $\mathcal{U}_0(\alpha, \pi_0)$, $\alpha \ge 0$.
  - **F:** $\mathcal{U}_1(\alpha, \pi_1)$, $\alpha \ge 0$.

Unbounded families of nested sets of pdfs.

- **E.g. fractional-error info-gap model:**

$$\mathcal{U}_i(\alpha, \pi_i) = \left\{ p(x) : \ p(x) \in \mathcal{P}_i, \ |p(x) - \pi_i(x)| \le \alpha \pi_i(x) \right\}, \ \alpha \ge 0$$

Unbounded uncertainty. No worst case.

§ Performance functions:

- **Probability of missed detection:**

$$P_0(p) = \mathbf{Pr}(x \in D | \mathrm{F})$$

- **Probability of false alarm:**

$$P_1(p) = \mathbf{Pr}(x \notin D | \mathrm{NF})$$

§ Performance spec. Choose D so that:

- $P_0(p) \le P_{0\mathrm{c}}$
- $P_1(p) \le P_{1\mathrm{c}}$.

§ The problem: $p(x)$ highly uncertain.

§ Info-gap robust-satisficing:

- **Given specs $P_{0\text{c}}$ and $P_{1\text{c}}$ choose D to:**
- **Satisfice performance.**
- **Maximize robustness.**

§ Robustness to $\mathcal{U}_0(\alpha, \pi_0)$, $\mathcal{U}_1(\alpha, \pi_1)$, $\alpha \geq 0$:

$$\widehat{\alpha}(D, P_{0\text{c}}, P_{1\text{c}}) = \max \left\{ \alpha : \quad \left(\max_{p \in \mathcal{U}_1(\alpha, \pi_1)} P_0(p) \right) \leq P_{0\text{c}}, \quad \left(\max_{p \in \mathcal{U}_0(\alpha, \pi_0)} P_1(p) \right) \leq P_{1\text{c}} \right\}$$

§ Robust-satisficing design:

$$\widehat{D}(P_{0\text{c}}, P_{1\text{c}}) = \arg \max_{D} \widehat{\alpha}(D, P_{0\text{c}}, P_{1\text{c}})$$

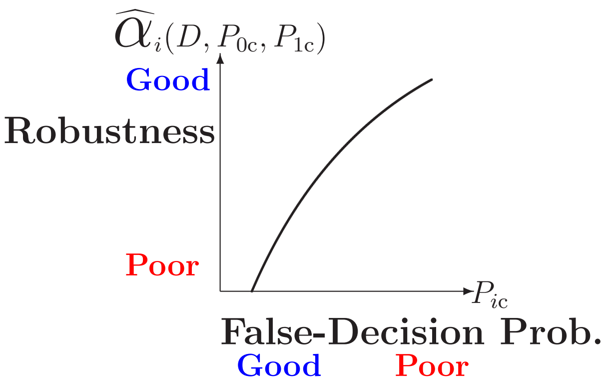
§ Trade-off:

- **Better perf. $\Longleftrightarrow$ Lower robustness:**
  - **Missed-detection performance trade-off:**

$$P_{0c} < P'_{0c} \quad \textbf{implies} \quad \widehat{\alpha}(D, P_{0c}, P_{1c}) \le \widehat{\alpha}(D, P'_{0c}, P_{1c})$$

  - **False-alarm performance trade-off:**

$$P_{1c} < P'_{1c} \quad \textbf{implies} \quad \widehat{\alpha}(D, P_{0c}, P_{1c}) \le \widehat{\alpha}(D, P_{0c}, P'_{1c})$$

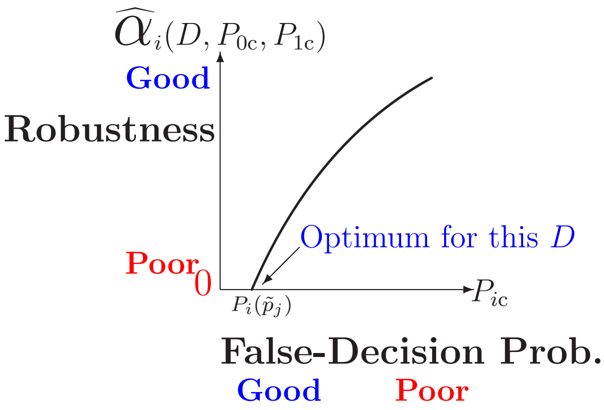


§ Trade-off:

- **Better perf. $\Longleftrightarrow$ Lower robustness.**
- **Estimated perf. has zero robustness:**

$$\widehat{\alpha}(D, P_{0c}, P_{1c}) = 0 \quad \textbf{if} \quad P_{0c} = P_0(\pi_1) \quad \textbf{or if} \quad P_{1c} = P_1(\pi_0)$$

- **Pareto optimum has zero robustness.**



§ **Robust-satisficing may differ from Pareto optimization.**

§ **Pareto optimal design, $D^\star$:**

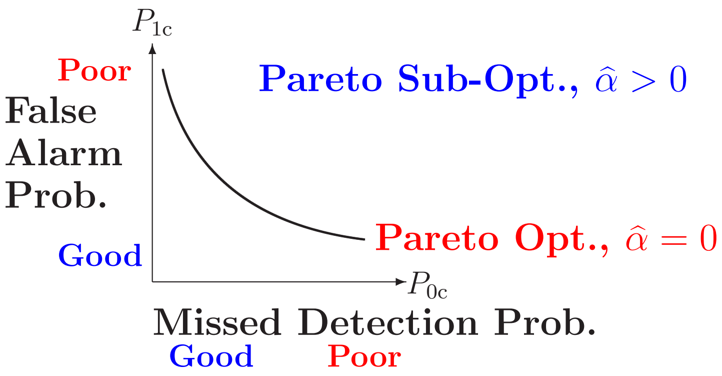
Any change reducing one failure prob. increases the other.

§ **Estimated error probabilities with $D^\star$:**

$$P_0^\star = P_0(\pi_1, D^\star), \qquad P_1^\star = P_1(\pi_0, D^\star)$$

No robustness of estim. Pareto optimum:

$$\widehat{\alpha}(D^\star, P_0^\star, P_1^\star) = 0$$



§ **Estimated error probabilities with $D^\star$:**

$$P_0^\star = P_0(\pi_1, D^\star), \qquad P_1^\star = P_1(\pi_0, D^\star)$$

- **No robustness of Pareto optima:**

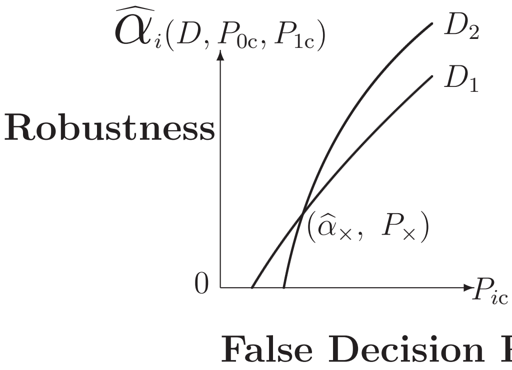
$$\widehat{\alpha}(D^\star, P_0^\star, P_1^\star) = 0$$

- **Positive robustness of Pareto sub-optima:**

$$\widehat{\alpha}(D, P_{0c}, P_{1c}) > 0$$

Preference Reversal

§ Two designs: D_1 and D_2:



§ Preferences:

- **Nominal:** $D_1 \succ D_2$.
- **Low robustness:** $D_1 \succ D_2$.
- **High robustness:** $D_2 \succ D_1$.

Example

§ Estimated Exponentials:

$$\pi_i(x) = \lambda_i \mathrm{e}^{-\lambda_i x}, \quad i = 0,\ 1$$

$\lambda_0 > \lambda_1$. NF: 0. F: 1.

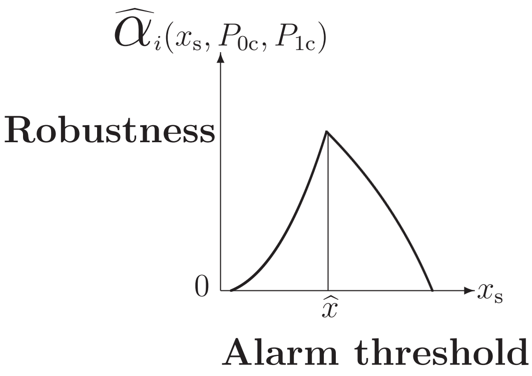
§ NF decision region:

$$D = [0, x_{\rm s}]$$

§ Choose x_s to:

- **Satisfice performance.**
- **Maximize robustness.**

$$\widehat{x}(P_{0\mathrm{c}}, P_{1\mathrm{c}}) = \arg\max_{x_\mathrm{s}} \widehat{\alpha}(x_\mathrm{s}, P_{0\mathrm{c}}, P_{1\mathrm{c}})$$



Optimize or Robust-Satisfice?

§ Optimization syllogism:

- **Outcome is valuable.**
- **More value is better than less value.**
- **Most valuable outcome is best.**

§ Implicit optimization syllogism:

- **Outcome values are uncertain.**
- **High value safer than low value.**
- **Highest value safest.**

§ Robust-satisficing syllogism:

- **Critical value necessary for survival.**
- **High reliability of critical value better than low reliability.**
- **Max reliability of critical value is best.**

Why Robustness?

§ **Adequate error probabilities:**

$P_0(p) =$ **missed detection prob.** $\leq P_{0c}$.

$P_1(p) =$ **false alarm probability** $\leq P_{1c}$.

for greater range of pdfs.

§ **More confidence in outcome.**

§ **Greater probability of success.**

Probability of Successful Detection

§ $p(x)$ **random function; distribution** $\Pi(p)$**.**

§ $p(x)$ **info-gap-uncertain.**

§ **Probability of success:**

$$P_{\rm s}(D) = \Pi(P_0(p) \le P_{0{\rm c}},\ P_1(p) \le P_{1{\rm c}})$$

§ **Theorems. Robustness and success prob:**

$$\frac{{\rm d}\widehat{\alpha}(D, P_{0{\rm c}}, P_{1{\rm c}})}{{\rm d}D} \ge 0 \quad \textbf{if and only if} \quad \frac{{\rm d}P_{\rm s}(D)}{{\rm d}D} \ge 0$$

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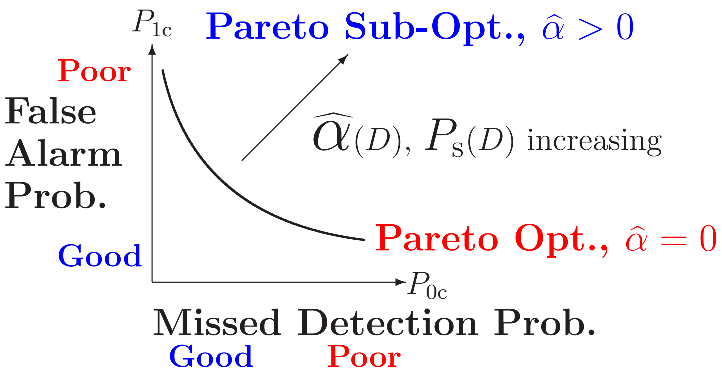

Summary

§ **Models (pdfs):**

Attributes of model correspond to attributes of reality.

§ **Model-based design:**

Adapt design, D, to attributes of model.

§ **Optimization:**

Use best model to choose design with best outcome.

§ Uncertainty:

- **Randomness: structured uncertainty.**
- **Info-gaps: surprises, ignorance.**

§ Fallacy of optimal model-based design:

- **Severe uncertainty:**
  - **Best models err seriously.**
  - **Some model attributes are correct.**
  - **Some model attributes err greatly.**
- **Best-model optimization**
  - **exploits all model attributes to extreme.**
  - **Vulnerable to model error.**

§ Resolution: Info-gap decision theory.

- **Satisfice performance.**
- **Maximize robustness to uncertainty.**
- **Model and manage sur^p^rises.**

§ Robust-satisficing syllogism:

- **Adequate performance is necessary.**
- **More reliable adequate performance is better than less reliable adeq. perf.**
- **Thus maximum reliability is best.**

§ Theorems:

- **Positive robustness only for Pareto sub-optima.**
- **Increasing probability of success with increasing robustness.**

6 *SUMMARY*

§ **Models:**

Attributes of model correspond to attributes of reality.

§ **Model-based decision:**

Adapt decision to attributes of model.

§ **Optimization:**

Use best model to
choose decision with best outcome.

§ Uncertainty:

- **Randomness:** **structured uncertainty.**
- **Info-gaps:** **surprises, ignorance.**

§ Fallacy of optimal model-based decision:

- **Severe uncertainty:**
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§ Resolution: Info-gap decision theory.

- **Robust-satisficing.**
- **Opportune-windfalling.**
- **Model and manage sur^{p}rises.**

§ Proxy theorems:

max robustness ≡ max survival prob.

§ Applications:

- Engineering design.
- Forecasting.
- Biological conservation.
- Medical decisions.
- Homeland security.
- Resource economics.
- Monetary policy.
- Financial economics.
- Ellsberg and Allais paradoxes.
- Foraging by animals.
- Quantum indeterminacy.