

Robust detection of exotic infectious diseases in animal herds: A comparative study of two decision methodologies under severe uncertainty

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Problem Description

Inspection Protocols

- animals are transported and pass through customs
- some of them may have dangerous infectious diseases
- **how many animals to test, yet avoid cataclysmic events?**



Model

extension of [2]

- allow for **imperfect testing**
- cost term for terminating the herd
- diseased animals modelled as **binomial process**
- worst-case assumption of independence between animals

Model Parameters

- n animals, of which m are to be tested
- d diseased animals (uncertain, see r)
- p test sensitivity, q test specificity
- r probability that a single animal is infected

$$\begin{aligned} n &= 250 \\ p &= 0.9999 \\ q &= 0.999 \end{aligned}$$

Model Loss Function

- $c(m)$ cost of testing m animals
- $a(d)$ cost of d diseased animals passing inspection
- $t(n)$ cost of terminating n animals

$$\begin{aligned} c(m) &= 1000 - 2000m + 1000m^2 \\ a(d) &= \begin{cases} 0 & \text{if } d = 0 \\ a & \text{if } d \geq 1 \end{cases} \quad (a = 10\,000\,000) \\ t(n) &= 400n = 100\,000 \end{aligned}$$

References

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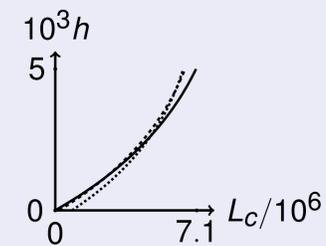
Comparison of Methodologies

Info-Gap Analysis [1]

**select decision which meets a given performance criterion L_C
under the largest possible range of r**

$$\hat{h}(m, L_C) = \max_{h \geq 0} \left\{ h : \max_{r \in [0, h]} L(m|r) \leq L_C \right\}$$

robustness curve: $\hat{h}(m, L_C)$ as a function of L_C



$m = 1$ (solid), $m = 15$ (dashed), and $m = 30$ (dotted).

$L_C/10^6$	m^*	$10^3 \hat{h}(m^*, L_C)$
0.5	2	0.207
1.5	5	0.661
2.5	8	1.184
3.5	11	1.803

Maximality [3]

- m dominates m' when $\min_{r \in [0, h]} [L(m'|r) - L(m|r)] > 0$
- pick one of the undominated options, i.e. any m for which

$$\min_{m' \in \{0, 1, \dots, n\}} \max_{r \in [0, h]} [L(m'|r) - L(m|r)] \geq 0$$

m	0.207	0.661	1.184	1.803
0	-0.9	-0.9	-0.9	-0.9
1	1.1	1.1	1.1	1.1
2	1.4	3.1	3.1	3.1
3	-0.6	4.9	5.1	5.1
4	-3.1	2.9	7.1	7.1
5	-7.7	0.9	7.0	9.1
6	-14.3	-1.1	5.0	11.1
7	-22.9	-4.3	2.9	9.9
8	-33.4	-9.5	0.9	7.9
9	-46.0	-16.6	-1.1	5.8
10	-60.6	-25.9	-4.3	3.7
11	-77.2	-37.1	-9.5	1.7
12	-95.8	-50.3	-16.8	-0.4
13	-116.4	-65.6	-26.1	-2.9
14	-139.1	-82.9	-37.4	-7.4
15	-163.7	-102.2	-50.8	-14.1

Discussion

- info-gap and maximality give essentially the same result
- **this is not a coincidence!**

Info-Gap–Maximin Theorem

The info-gap solution $D^*(L_C)$ coincides with Γ -minimax solution with respect to \bar{P}_h whenever the following conditions are satisfied:

- 1 for all $d \in D$, $\bar{P}_h(L(d, \cdot))$ is strictly increasing as a function of h , and
 - 2 it holds that $L_C = \min_{d \in D} \bar{P}_h(L(d, \cdot))$.
- (so, 'free' to choose L_C under the additional assumption of continuity)

Info-Gap–Maximality Theorem

Let $L_C(h) = \min_{d \in D} \bar{P}_h(L(d, \cdot))$.

Then, for all $h' \leq h$, every info-gap decision $d^* \in D^*(L_C(h'))$ is maximal with respect to \bar{P}_h .

Final Remarks

- info-gap yields an elegant approach to capture maximal solutions
- info-gap gives rough idea of the size of the maximal set
- info-gap is a graphically appealing way to represent maximal solution
- robustness curves show trade-off between uncertainty and cost