The Crayfish Problem

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Outline

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The Problem: Introduction

What is Marmorkrebs?

Origin unknown, first known individuals from pet trade 1990’s.
Can reproduce asexually, high reproduction rate, damages ecosystems.

Ecological Decision Problem

Eradicate invasive marmorkrebs aledgedly observed in a lake

Possible Interventions

(I) Do nothing
(II) Mechanical removal
(III) Drain system and remove individuals by hand
(IV) Drain system, dredge and sieve to remove individuals
(V) Decomposable biocide plus drainage
(VI) Increase pH plus drainage and removal by hand

The Problem: Key Variables & Parameters

Variables

- H = is alien crayfish present?
- E = is alien crayfish observed?
- D = intervention decision
- $\beta(D)$ = probability of erradication
- H' = is alien crayfish present after intervention?
- $A_1, \ldots, A_5$ = features of the intervention

Parameters

- θ = probability of alien crayfish presence
- α = probability of observing crayfish if present

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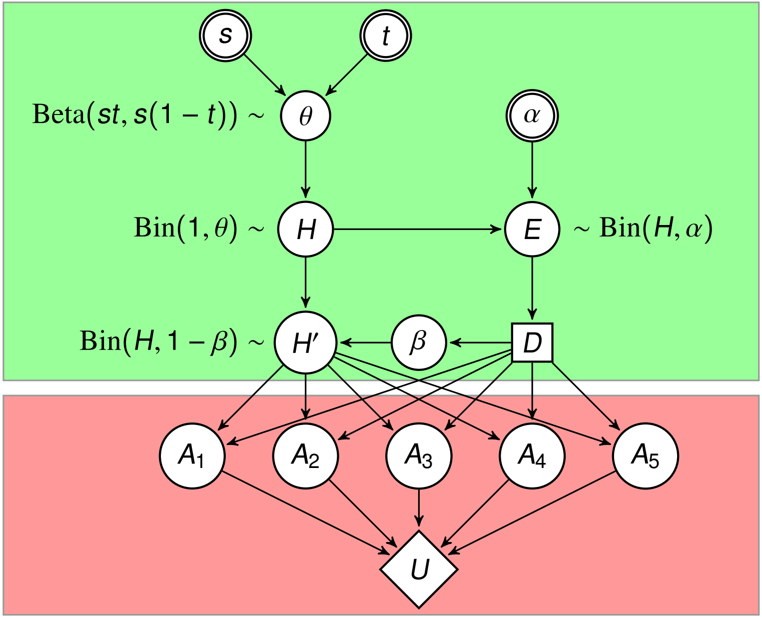
The Model: Overview

uncertainty

value ambiguity



The Model: Features

Learning

- E (observing crayfish or not) tells us something about θ (probability of crayfish)
- put $\mathrm{Beta}(st, s(1-t))$ distribution on θ to allow learning

Severe Uncertainty

- interval analysis for $\alpha \in [0.1, 0.5]$
- interval analysis for $t \in [0.1, 0.9]$

Act-State Dependence

-

	Decision D					
Probability	**I**	**II**	**III**	**IV**	**V**	**VI**
$\underline{\beta}(D)$	0	0.05	0.3	0.4	1.0	0.7
$\overline{\beta}(D)$	0	0.25	0.5	0.7	1.0	0.8

- will need interval dominance (other methods?)

The Model: Features

Utilities For Each Attribute Separately

- marginal utility for each attribute if eradication successful:

Attribute	Worst (score 1)	Best (score 4)	Decision *D* I	II	III	IV	V	VI
Biotic impact	High	Low	4	4	3	3	2	1
Longevity of impacts	Long	Short	4	4	3	3	1	2
Experience	Little	High	4	3	1	4	1	1
Feasibility	Difficult	Easy	4	4	2	3	1	2
Cost	High	Low	4	4	3	1	2	3

- marginal utility for each attribute if eradication fails:

Attribute	Worst (score 1)	Best (score 4)	Decision *D* I	II	III	IV	V	VI
Biotic impact	High	Low	1	1	1	1	1	1
Longevity of impacts	Long	Short	1	1	1	1	1	1
Experience	Little	High	4	3	1	4	1	1
Feasibility	Difficult	Easy	4	4	2	3	1	2
Cost	High	Low	4	4	3	1	2	3

The Model: Features

How to weigh attributes? Severe value ambiguity!

- imprecise swing weighting method [5]
- results in system of linear constraints on weights
- can enumerate extreme points to propagate easily

	k_1	k_2	k_3	k_4	k_5
1	0.37	0.26	0.19	0.11	0.07
2	0.38	0.27	0.19	0.12	0.04
3	0.40	0.28	0.20	0.04	0.08
4	0.42	0.29	0.21	0.04	0.04
5	0.42	0.29	0.17	0.04	0.08
6	0.43	0.30	0.17	0.04	0.04
7	0.40	0.28	0.16	0.12	0.04
8	0.38	0.27	0.15	0.12	0.08
9	0.42	0.33	0.17	0.04	0.04
10	0.40	0.32	0.16	0.04	0.08
11	0.38	0.31	0.15	0.12	0.04
12	0.37	0.30	0.15	0.11	0.07
13	0.40	0.32	0.20	0.04	0.04
14	0.38	0.31	0.19	0.04	0.08
15	0.37	0.30	0.19	0.11	0.04
16	0.36	0.29	0.18	0.11	0.07

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JAGS code:

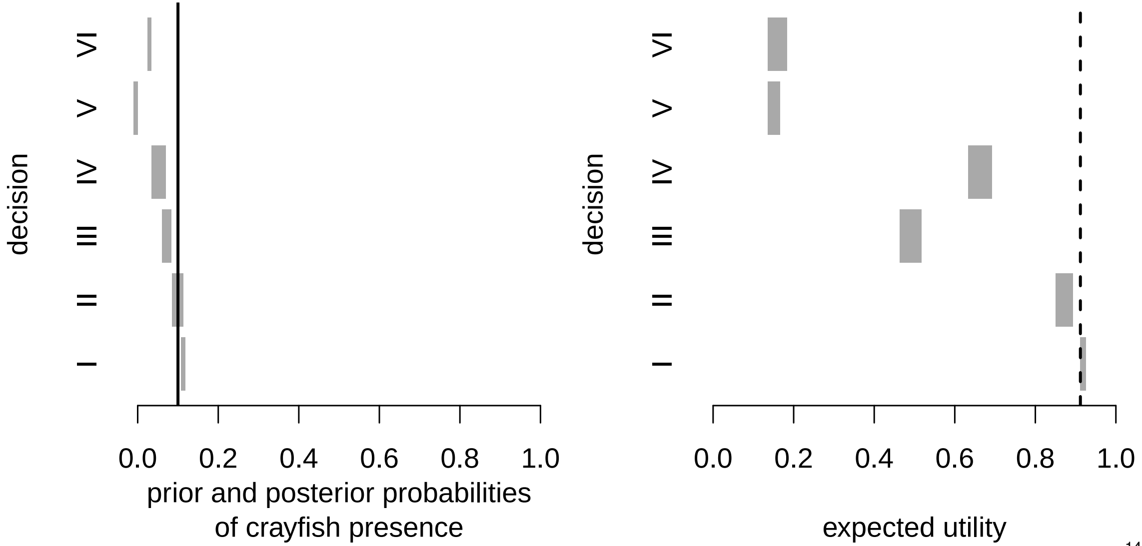
```
theta ~ dbeta(s*t, s*(1-t)) T(0.001,0.999)
H ~ dbinom(theta,1)
E ~ dbinom(alpha,H)
for(D in 1:n_decisions) {
  for(i in 1:n_beta_points) {
    H'[i,D] ~ dbinom(1-beta[i,D],H)
    for (k in 1:n_util_points) {
      U[D,i,k] =
          H'[i,D]        * inprod(util_H'_one [,D], util_weights[k,])
        + (1 - H'[i,D]) * inprod(util_H'_zero[,D], util_weights[k,])
    }
  }
}
```

Uncertainty Quantification: Simulation Methodology

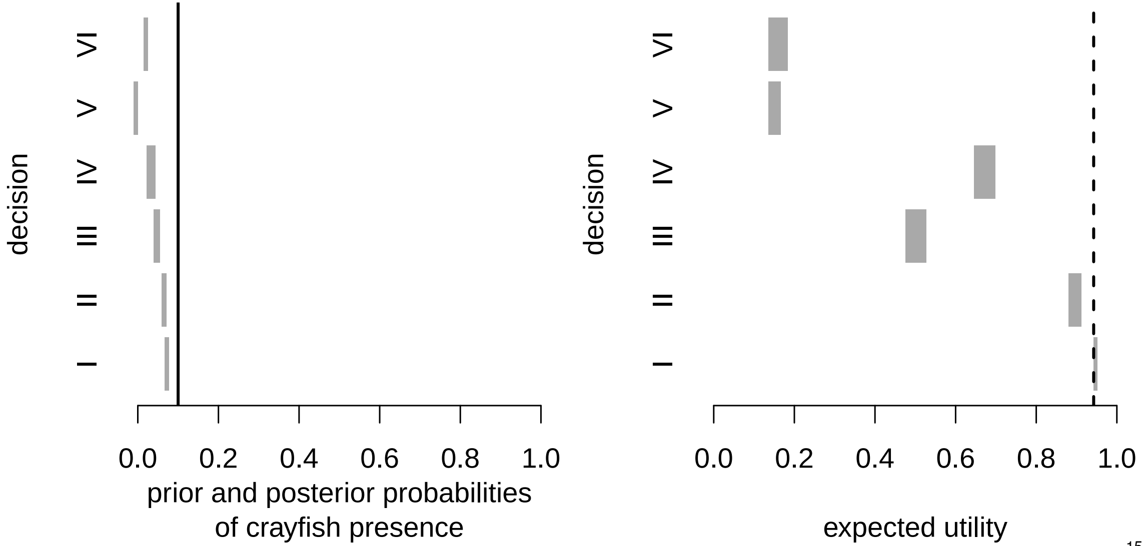
- set up grid for $\beta(D)$
- set up list extreme points of utility weights k
- for each fixed value of t and α within their interval
  - run JAGS code to produce posterior expectation for each $\beta(D)$ and k
  - calculate lower and upper posterior expectation over $\beta(D)$ and k from JAGS output
  - plot results and analyse for interval dominance
- look at all plots, draw conclusions

mixed E-admissiblity / interval dominance criterion!

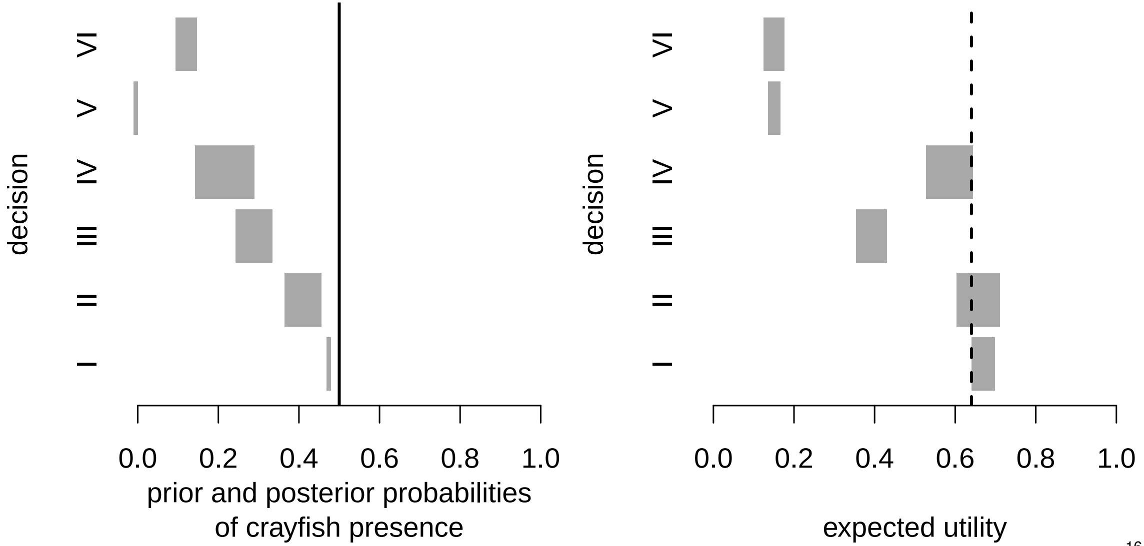
Results: $t = 0.1$, $\alpha = 0.1$



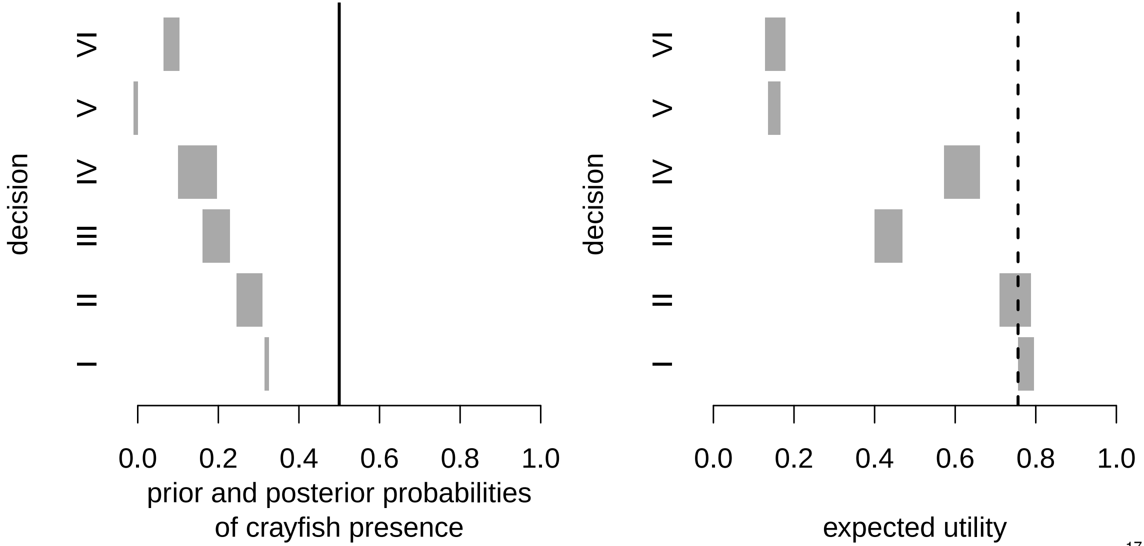
Results: $t = 0.1$, $\alpha = 0.5$



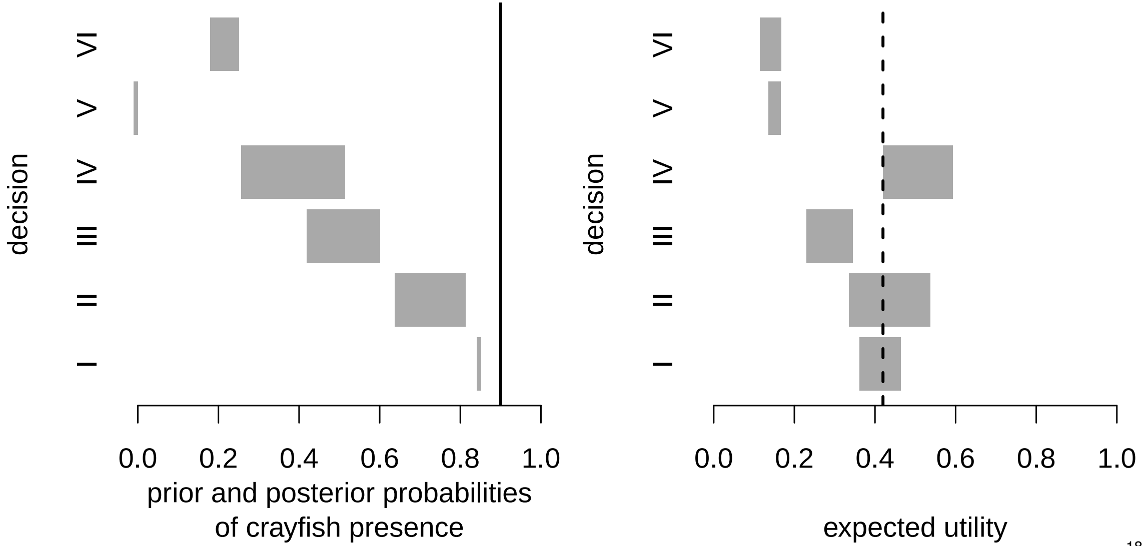
Results: $t = 0.5$, $\alpha = 0.1$



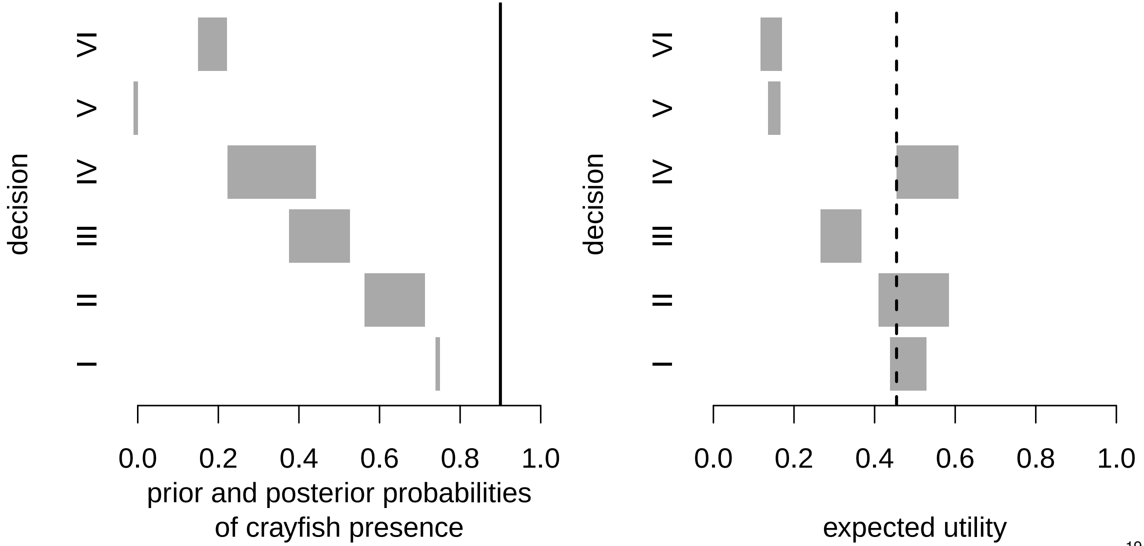
Results: $t = 0.5$, $\alpha = 0.5$



Results: $t = 0.9$, $\alpha = 0.1$



Results: $t = 0.9$, $\alpha = 0.5$



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Open Questions

- Graphical models are very useful: easy to evaluate posterior
- Dealing with interval uncertainty in JAGS is not straightforward
  - No optimisation routines within JAGS (or STAN, ...)
  - Brute force appropriate for low dimensional problems only
- Graphical presentation of results?
- Formalisation of act-state dependent choice functions?
  - Not all variables/parameters are affected by the decision
  - Important for reliability and risk analysis:
    decision meant to affect future state, but cannot affect past states
  - Concern:

$$\bigcup_{t \in \mathcal{T}} \mathrm{Ch}_t(\mathcal{X}) \neq \mathrm{Ch}_{\mathcal{T}}(\mathcal{X}) \tag{1}$$

Thank you for listening!

References I

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[3] Matthias C. M. Troffaes.
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[4] Matthias C. M. Troffaes and John Paul Gosling.
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