Learning about a Moving Target in Resource Management: Optimal Bayesian Disease Control

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Overview

Resource managers are faced with difficult choices regarding imperfectly observed and dynamically changing systems. Existing techniques required modifications to address disease management problems.

Testing for subclinical infections disallows selective culling and provides information that improves the efficiency of subsequent applications of broad-based controls, e.g., additional testing and monitoring.

We apply our methodology to the control of bovine tuberculosis in New Zealand’s cattle herds and compare to less comprehensive approaches. Bovine tuberculosis represents a subclinical disease with complex transmission dynamics.

We extend the existing literature of optimal control of disease by allowing for uncertainty regarding the state of the system.

Objectives

1. Compare the value of accounting for physical dynamics and learning in disease management
2. Develop and refine a methodology for assessing dynamic decision making under uncertainty when the uncertain state is changing and continues

Methods

- We extend the existing literature of optimal control of disease by allowing for uncertainty regarding the state of the system.
- We apply our methodology to the control of bovine tuberculosis in New Zealand’s cattle herds and compare to less comprehensive approaches.

Physical Dynamics

- Meta-population model
- Kernel reaction (both among cattle and between cattle and disease vector populations (e.g. possums)).
- Comprehensive approaches.

Information Dynamics

- Behaviors about prevalence are modeled as a beta diet.
- Updating in two steps.
- Density projection to account for newly infected from known physical dynamics.

Manager Comparison: Testing Rate, Prevalence and Belief Error

We examine four managers that update their beliefs differently based on new infections and test results.

- All managers account for prevalence reductions resulting from selective culling of identified facilities.
- Initial beliefs are shared across managers.
- Managers:
  1. Naive manager: considers both test results and infections.
  2. Partial (Bayesian learner): considers test results but not infections.
  4. Optimal manager: considers both test results and infections.

Welfare Comparison

The distinct testing rate paths result in qualitatively different cumulative welfare (measured in producer profits minus testing costs) trajectories. We compare each of these trajectories to the Naive manager in percentage terms.

Model Performance Comparison: Optimal vs. Stochastic Programmer

- Concern: average percentage differences in cumulative welfare are driven by outliers.
- We compare the present value of cumulative welfare across the most successful managers (Optimal and Stochastic Programmer).

Conclusion

- Stochastic gains are realized from accounting for both physical dynamics and learning lead to substantial system change at the cost of excessive testing.
- Accounting for physical dynamics is more important than accounting for learning and uncertainty.
- Learning allows managers to compensate for miscalculation in beliefs and fundamental errors in understanding of the physical system.

Manager:
- Naive: 
  - High initial testing rate that declines over time.
  - Prevalence quickly declines (similar to optimal).
  - Beliefs are the most inaccurate.
- Partial learner:
  - Moderate test rates throughout.
  - Beliefs are somewhat inaccurate.
- Stochastic programmer:
  - Moderate test rates throughout.
  - Beliefs are moderately inaccurate.
- Optimal manager:
  - High test rates throughout.
  - Prevalence quickly takes off.
  - Beliefs are the most inaccurate.

Model Performance Comparison: Optimal vs. Stochastic Programmer

- Important features:
  - Accounting for physical dynamics leads to higher initial testing rates.
  - High initial testing that declines as prevalence takes off.
  - Partially alleviated by testing.

- Stochastic programmers successfully stress down prevalence, but at the cost of excessive testing.
- Be in absence of learning, high testing rates induce prevalence for a while before initial epidemics.
- Gains from learning are immediate and grow over time.

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