Spatial sampling for vector-borne diseases using multi-armed bandit methodology

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1 Overview

In this study, we apply the multi-armed bandit algorithm to optimize the detection of houses infected with T. infestans bugs. The algorithm would be used to solve the high-level planning problem of choosing between promising but untested detection strategies. The algorithm would be integrated with the work of a field epidemiology team.

2 Background

Generally, search for T. infestans in human communities is a complex multi-level multi-period optimization problem. The ultimate optimization algorithm, if we could build it, would integrate all the available knowledge and guide the search to the level of individual house. To be specific, there are many types of information available:

- detection of previous sites of infestation, including location, dates and confidence level.
- known control measures, such as spraying over multiple years
- non-geographic characteristics of the site, such as square area, presence of any animals or terrain features, willingness to cooperate with previous visits, reports from neighbors
- characteristics of the T. infestans host, as estimated statistics (including likelihood and synthetic likelihood methods)

All of the above information might be relevant for the optimization problem, and it is highly challenging to fully incorporate it into a unified framework. Some of the complexity in optimization includes:

- the best search would involve spatial coordination between choices, similarly to the game of Battleship where a regular spatial grid is used to find the 4-deck ship

- the search strategy has multiple periods (time steps), and any long term plans would quickly become suboptimal in light of new information
- information during the search informs parameter estimates, which inform future steps of the search

Thus, an approach such as greedy search for highest-probability house is inherently myopic because it does not consider the long-term information value of non-detection, while an approach such as grid search seems to ignore the information discovered from recent detections. Various search strategies appear to solve one aspect of the problem, while ignoring the others. For example, a maximal mutual information search (which we originally proposed) is suitable in light of existing information, but completely ignores any information that might be discovered in the process.

It is proposed here that high search efficiency could be achieved using a hierarchical approach as follows. The idea is to construct a hierarchy of two or more algorithms, in which each of the algorithms considers part of the data or the decision. There are multiple ways of dividing the problem:

- divide the decision into a high level (strategy) and a low level (individual house).
- divide the decision by time: immediate decision and longer-term decision
- divide the data by type and integrate them together

Concretely:
Here we propose to use a multi-armed bandit algorithm at the high level of decision. The bandit would determine which, of several lower-level search strategies is the best one. Or alternatively, given a set of search areas, determine which has the highest number of infested houses.

Theory to compare alternative hypotheses in real-time has developed around the multi-armed bandit problem and its various extensions. A ‘one-armed bandit’ is a slot machine, and the multi-armed bandit problem consists of identifying how to optimally play a slot machine with multiple levers (arms) that have different and unknown probabilities of yielding a reward. Bandit strategies have been used to guide experiments, including numerous clinical trials. The core tension in the bandit problem is the tradeoff between gathering additional data to better determine the value of a strategy (exploration) and acting on existing information (exploitation).

3 Methods

Our method would use the bandit strategy as the high level decision algorithm. At the lower level, we will decide which house (i.e. premises or site) to search.

3.1 Bandit algorithm for selection among search strategies

Consider a set of S strategies which are considered viable for detection of infested houses. A priori we may believe that the strategies might be equally likely to produce fairly high probability of detection. Two such strategies are (and there are many others):

- R1: Inspect any infected premises and then each its neighbors in a ring. If no such premises are known, select randomly.
- R2: Inspect any infected premises and then perform search the immediate ring of neighbors, and secondary ring. If no such premises are known, select randomly.

The traditional approach to decide between the strategies might be to search n infestations with each strategies, and then perform hypothesis testing. This approach is wasteful since it may become quickly apparent which of the strategies is more suitable. Instead, we will use the bandit approach where the arms correspond to the strategies.

Each of the strategies $s \in S$ would be initialized, i.e. applied to search up to k_s premises. The number k_s would be adjusted for fairness of effort: Because R1 searches approximately 9 houses, while R2 searches 25 (for a new hotspot), fairness means that the rewards u should be computed by repeating R1 approximately three times (to be more precise, 11 times R1 for every 4 times of R2).

At this point we will include the data in a bandit algorithm, which will decide which strategy to use in the next week of searches. We already have an implementation of the bandit algorithm (see code/bandit.R including examples)

3.2 Bandit algorithm for selection among search areas

The idea here is similar to the above, but instead of decision among strategies, we will decide among geographic areas. The high level problem is to find the most houses in the setting where we do not know which zone has more infestation.

To be more concrete, select on a single search strategy, such as R1 above. A neighborhood of the city would be divided among a set of zones Z such that the number of infested houses is the same in expectation, a priori, in all of the zones. The task is to find the most infested houses using a limited number of steps, e.g. a month of field work.

We will use the bandit algorithm, where the zones correspond to arms of the bandit. We will sample from each of the zones to initialize the algorithm, and then use the algorithm to plan the next week of searches.

3.3 Validation

We would perform preliminary evaluation of our method using two strategies:

1. consider a synthetic infestation problem on a grid, where we generate an infestation and then simulate the search
2. empirically, we would perform the search and then visit also the non-visited houses to determine the maximum possible outcome.

4 Results

We find ...

5 Discussion

We were right, homefully!

References