A Multi-Armed Bandit Model to Optimize Entomological Surveys

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Introduction

- The spread of vector-borne infections make it increasingly important to find strategies that accurately and efficiently identify foci of infestation and disease transmission based on limited information.
- We developed a novel strategy to optimize entomological surveys. Our strategy uses a multi-armed bandit (MAB) algorithm to select among a number of proposed search areas each day based on results from previous days.
- The MAB strategy is designed to optimally balance between exploiting known high-prevalence areas and exploring unknown areas that may have a high infestation burden.

The Multi-Armed Bandit Model (MAB)

- On a daily basis, the algorithm stochastically selects an arm to search, and 10 houses within the arm (i.e., area) are surveyed.
- Initially, the algorithm assigns equal probability to each arm but updates the probabilities daily based on the results of the search.
- We compare this algorithm on sets of simulated infestation data to a global search method that does not subdivide the search zone into arms/areas.

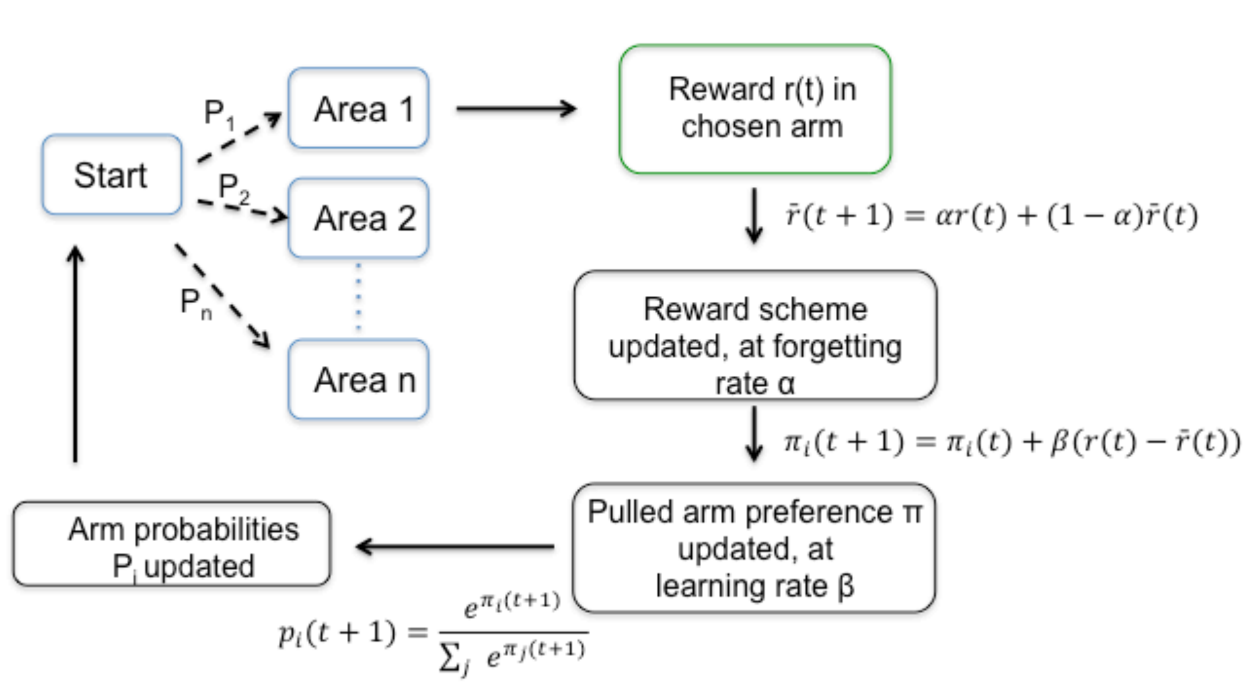


Fig. 1: Reinforcement-Comparison Algorithm for Solving the Multi-Armed Bandit Model
At each time, t, the bandit choses an arm to search based on probabilities P_i. A search is conducted in the chosen arm and rewards R(t) are found. The bandit then updates its account of past rewards and by comparing R(t) to past rewards, the bandit updates its preferences for the chosen arm. Then, using the new preferences, probabilities for all arms are recalculated and the bandit choses a new arm to search.

Fig. 2: Simulated Infestation in Arequipa, Peru – a potential application of MAB to a real-time search
Colors represent potential assigned arms of the bandit, with divisions by neighborhood. Circles are proportional to the number of *T. infestans* based on a simulated infestation.

Design of Simulated Data

- Zone is divided into 2 or more areas
- Infestation in each area starts with 1+ initial foci and then grows to prevalence desired.
- MAB arm is assigned to each area

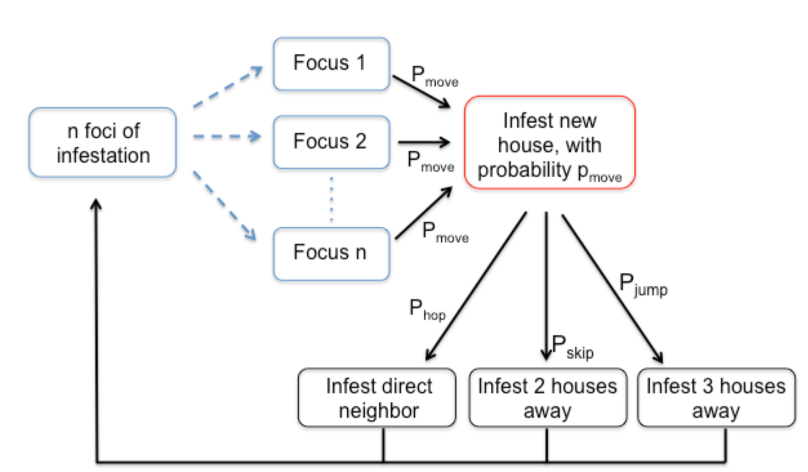
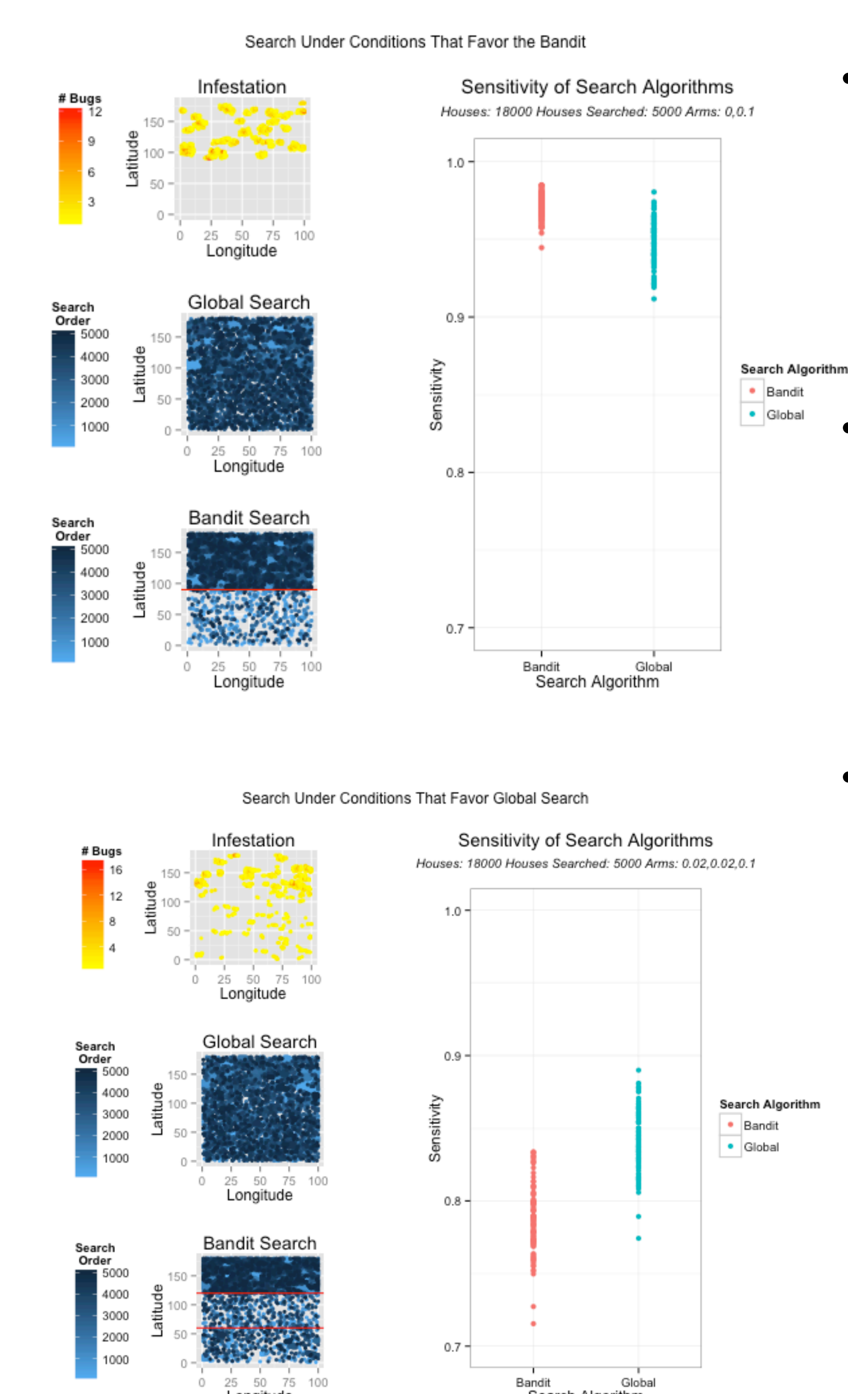


Fig. 3: Algorithm to simulate infestations
The infestation starts with initial set of foci of infestations n_0. At each time t, each focus of infestation can grow with probability p_{move}. A growing infestation can grow by infesting a direct neighbor ("hopping"), infesting a house two houses away ("skipping"), or infesting a house three houses away ("jumping"). Probabilities of hopping, skipping, and jumping based on Barbu et al. (unpublished).

Results From Simulated Infestations



- MAB is more sensitive than global search when distribution very heavily (Prevalences of 10% in Arm 1 and 0% in Arm 2).
- At less skewed distributions (Prevalence of 10% in Arm 1 and 2% in Arms 2 and 3) MAB is less sensitive.
- MAB explores early on, but quickly localizes to the highest prevalence arm

Fig. 4: Results from simulated Infestations
Total search area of 18,000 houses, divided equally into 2 or 3 arms

Conclusions and Future Directions

- MAB algorithms provide a mechanism through which to optimize entomological surveys. MAB often correctly identifies the area with highest prevalence, and in certain conditions outperforms random search.
- MAB algorithms have a tendency to over-explore an area, and thus give performance inferior to random search, particularly when the prevalence is similar in the different areas, but this could be addressed with more advanced MAB algorithms.
- In the future, we plan to apply this model to retrospective entomological search data and then use it for prospective data collection. The MAB could also be used to optimize between competing search strategies rather than search areas.

References

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