A Machine Learning Environment
To Determine Novel Malaria Policies

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Abstract
The research and development of new tools and strategies in the fight against malaria, already uses resources, data, and computation spread across numerous institutions and individuals. Whether this is towards an objective such as drug discovery or informing intervention policy, they present common requirements. Such threads may be interwoven to achieve common goals towards malaria eradication. This unifying influence may be the technology of Machine Learning, helping to tie together different efforts, necessitating Novel Exploration Techniques for scientific discovery and an Infrastructure for Research at Scale.

Infrastructure for Research at Scale
Applying computational models and relevant data to interesting malaria settings is often difficult to configure (including acquisition of the requisite data), difficult to execute (especially at scientifically relevant scales), and difficult to interpret. In [1] we demonstrated an approach which addresses this problem, with the emphasis on exploration and interpretation using black-box optimisation techniques. We developed an infrastructure by applying common computing abstractions in software development and deployment, and then applied three classes of AI algorithms to generate insight from the developed infrastructure.

Architecture

- **Worker**: Using containers, we have packaged malaria models in a manner which is easy to deploy at scale, and in multiple types of computing environments. In this container we also couple the model with software to communicate the desired input file, and to process the output files as needed. Together, these tools are referred to as a worker, and multiple workers can be deployed on a single machine or even distributed across the Internet.
- **Task Clerk**: We permit users to define a specific instantiation of a model that they’d like to evaluate. The resulting file is then sent as a task to the worker so that it can be processed. At present we explore two aspects of an intervention policy: the portion of the households using insecticide treated bednets (ITN), and the portion of households where indoor residual spraying (IRS) is applied. Several other interventions may be modelled and comprise future work.
- **Data store**: The results for all evaluated policies are stored in a central repository. The task clerk and all the distributed workers are connected via a common messaging fabric to this data store. Results from the model’s execution are converted through an economical cost-effectiveness analysis, to the cost per Disability Adjusted Life Year averted, in this case providing an engineered scalar reward. This measure is the same as that used in the malaria modeling community for decision-making [2].

Policy Learning from Simulation

- **Action**: Actions on malaria simulation models describe intervention campaigns. Intervention campaigns consist of timed sequences of interventions.
- **Environment**: A parameterised discrete-time simulation model.
- **Reward**: Through a decision may have multiple objectives or rewards, with initial work using single scalar rewards.
- **Context**: The parameterisation of the model defines context; location, resolution (population sizes), reward metric etc.
- **Queue**: Each Agent has a fixed size queue containing simulations to run. A temporal sequence of actions (interventions rather than policies), defined at each discrete simulation time step.
- **State**: The state of the environment is available at each discrete simulation time step (5 days). State is only accessible after a simulation run.

Results

- **State**: The state of the environment is available at each discrete simulation time step (5 days).
- **Policy**: A temporal sequence of actions (interventions rather than campaigns), defined at each discrete simulation time step.
- **Resource**: Feasible Actions should preserve a notion of cost. Each Action has a resource requirement of monetary value. Simulations may be constrained to only contain cost feasible policies.

Figures:
2. Policy Learning from Simulation: Off-Policy Reinforcement Learning
3. Boxplots of Discrete Actions: Multi-armed Bandit
4. Response Surface for Continuous Actions: Multi-armed Bandit + Gaussian Process Regression

References