A Machine Learning Environment
To Determine Novel Malaria Policies

Oliver Bent, Sekou Remy, Nelson Bore, Daniel Nkemelu, Violette Ogega, Komminist Weldemariam & Stephen Roberts
IBM Research Africa and University of Oxford

Contact Information:
Machine Learning Research Group
Eagle House
University of Oxford
25 Walton Well Road, Oxford, OX2 6ED

Phone: +44 (0) 7484 710139
Email: `oetbent@robots.ox.ac.uk`

IBM Research | Africa

UNIVERSITY OF OXFORD

Abstract
The research and development of new tools and strategies in the fight against malaria, already uses resources, data and computation spread across innumerable 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.
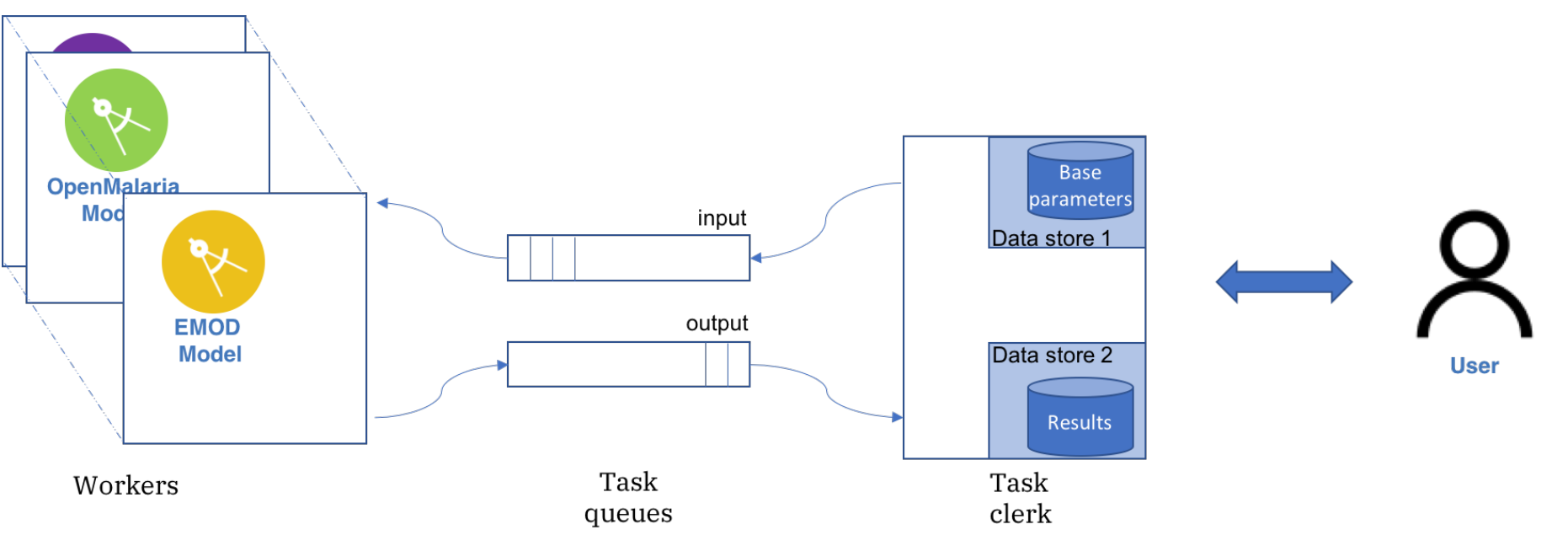
Architecture

Figure 1: Conceptual architecture of the infrastructure.

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 modeled 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].

Task queue To tie each of the components together, we use a messaging fabric. The current implementation harnesses AMQP as implemented in the RabbitMQ message queue. The frontend posts jobs to a message queue which are subsequently picked up by idle *workers* of the appropriate type. When the *worker* is complete, the results are posted to a different channel on the same queue. This instantiation permits *workers* to be deployed in a wide range of environments, with little requirements on coordination.
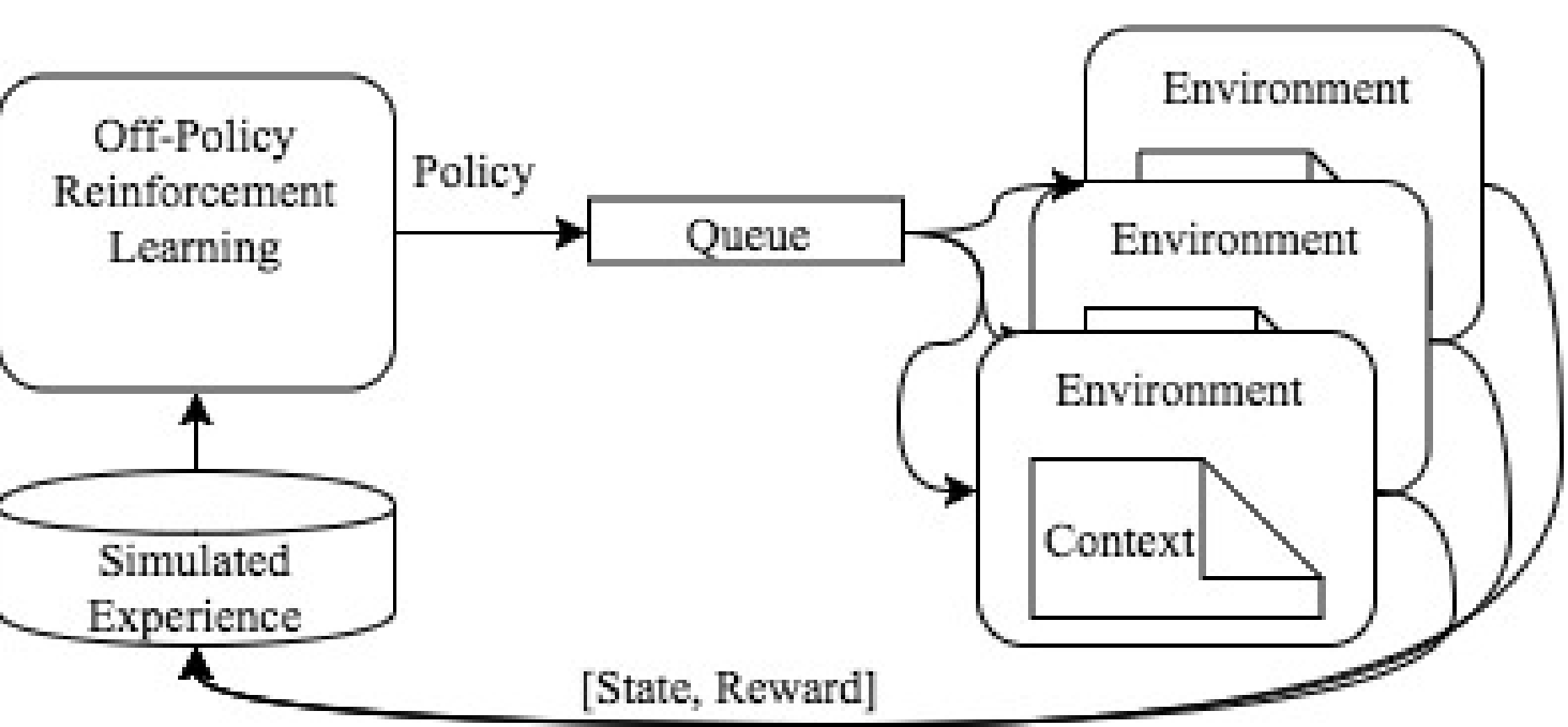
Learning from Simulation

Figure 2: Policy Learning from Simulation: Off-Policy Reinforcement Learning

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 Though 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 be run. The fixed queue size providing some notion of a fixed budget for simulations an agent may run at any time.

Simulated Experience Due to delayed rewards it is necessary for Agents to make use of simulated experience. This may be seeded with similar previously run simulations.

State The state of the environment is available at each discrete simulation time step (5 days). State is only accessible after a simulation run.

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.
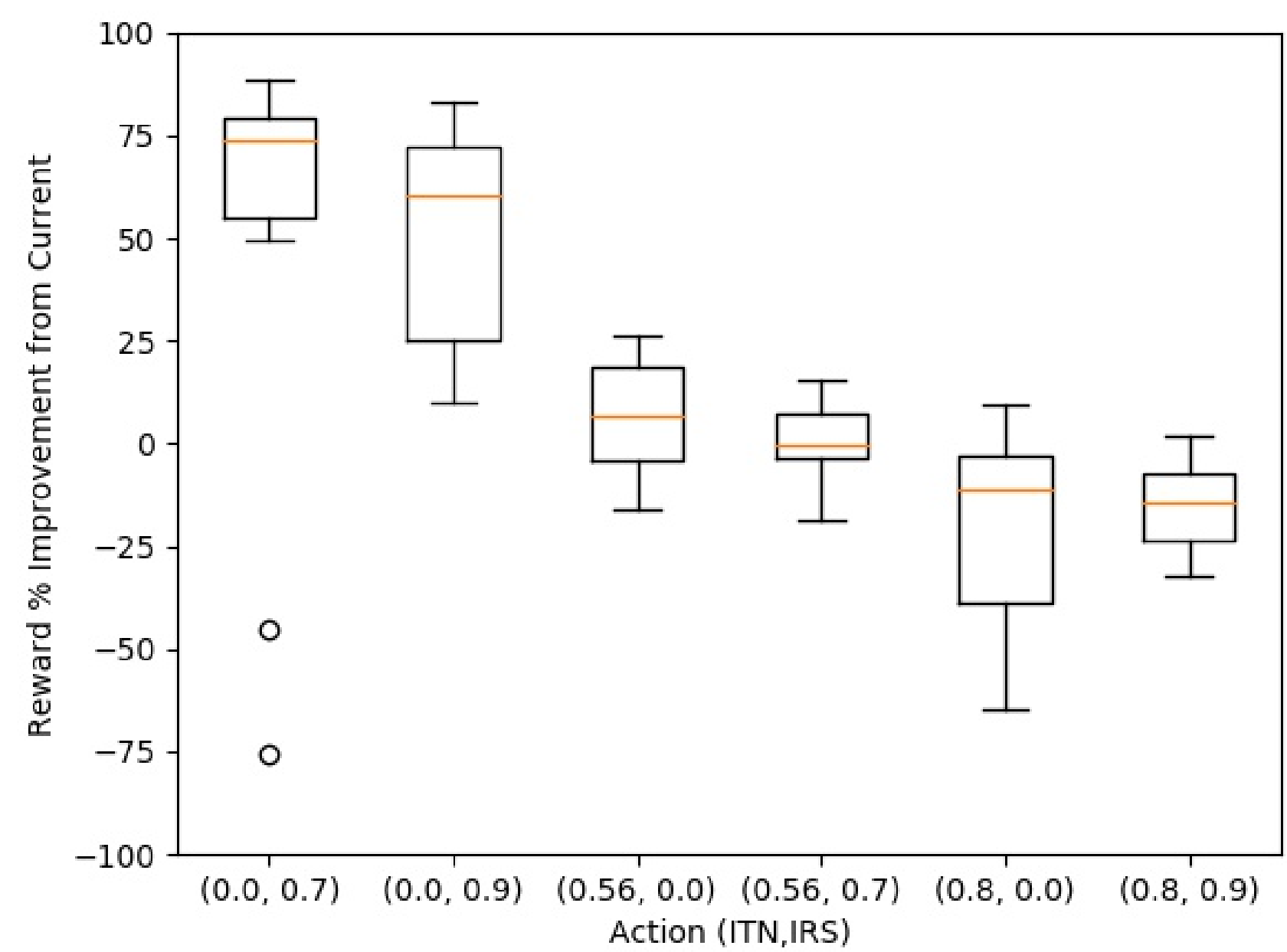
Results

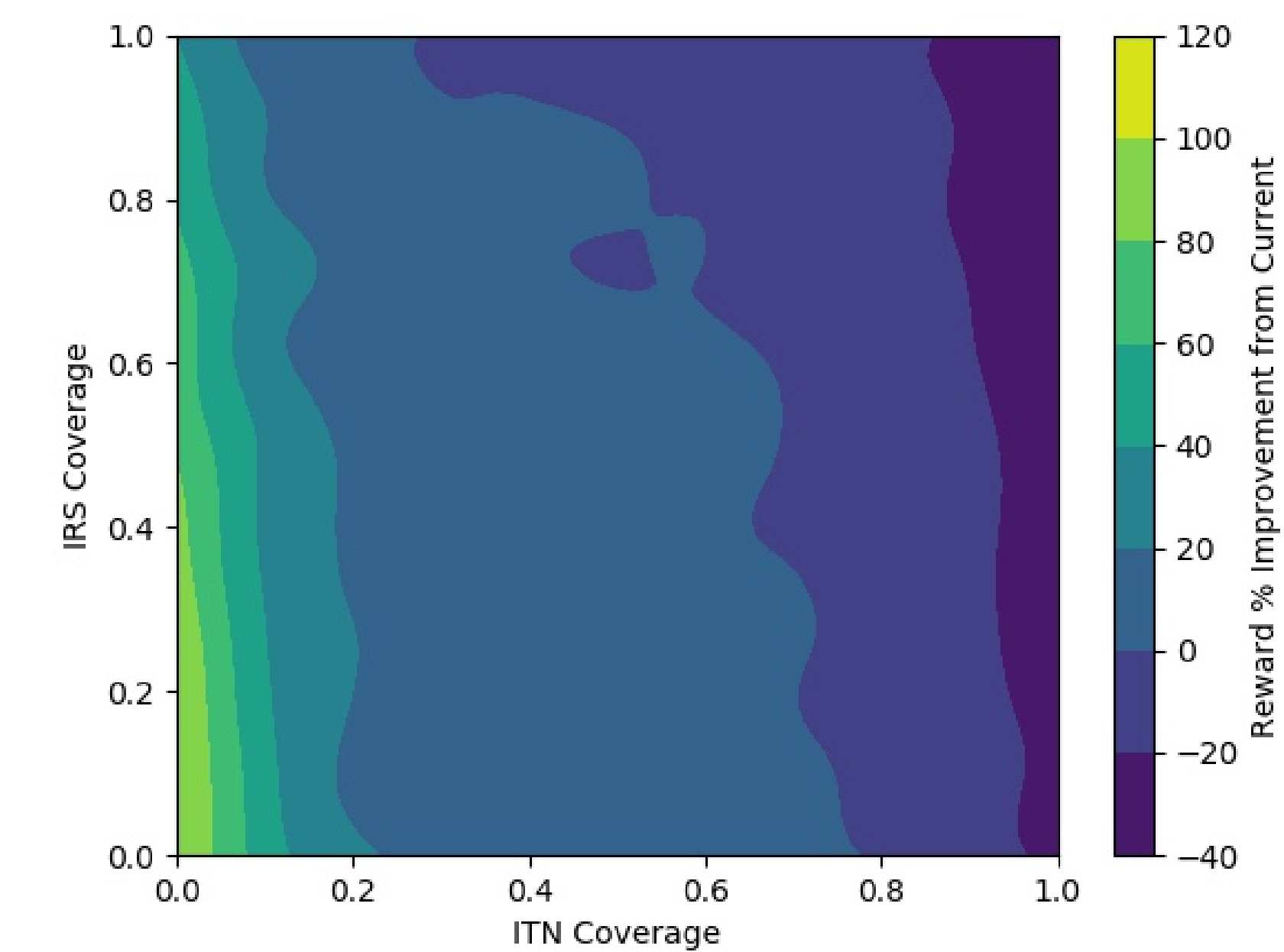**Figure 3:** Boxplots of Discrete Actions: Multi-armed Bandit

Figure 4: Response Surface for Continuous Actions: Multi-armed Bandit + Gaussian Process Regression
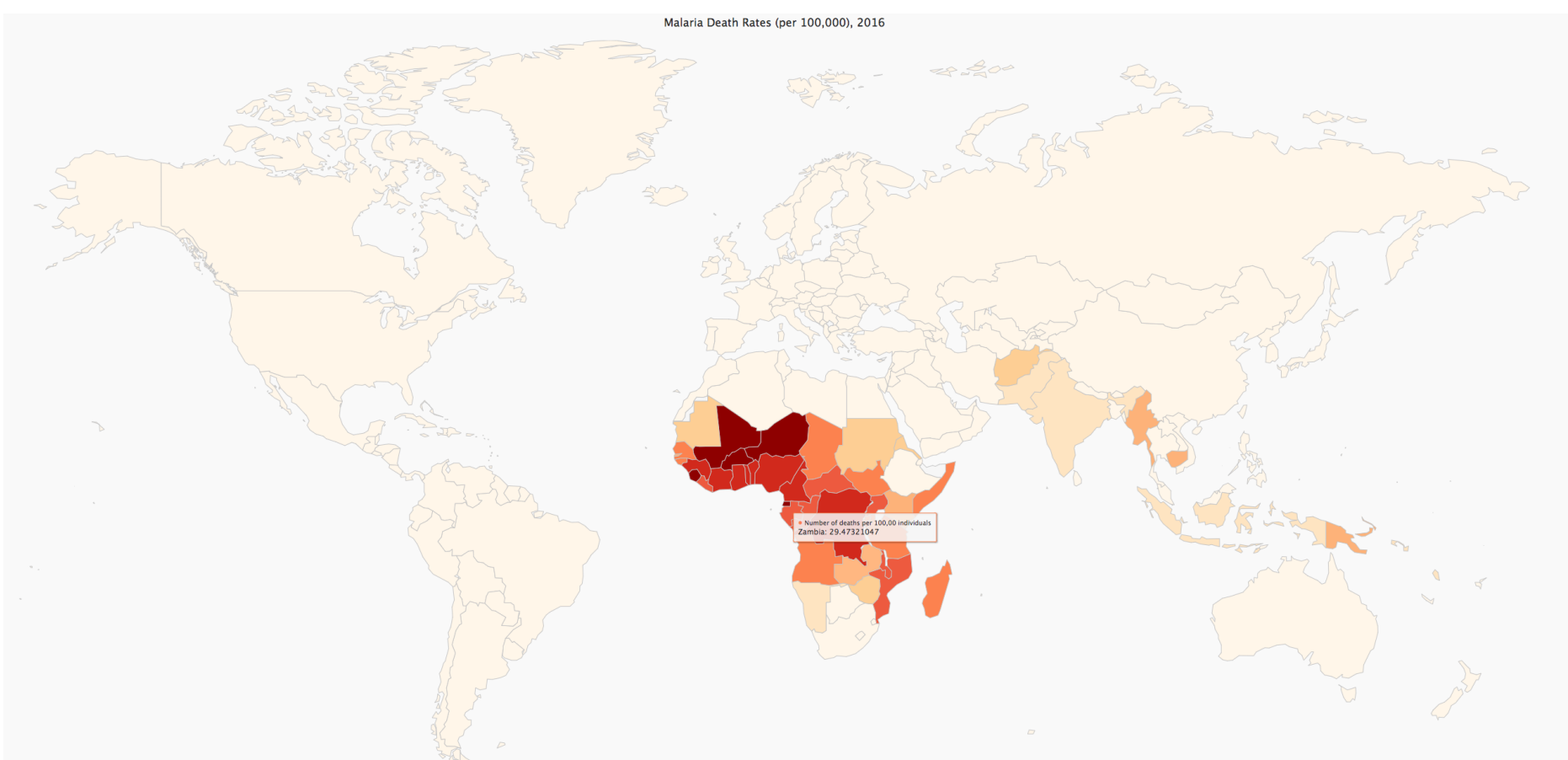

Figure 5: Demo Landing Page

API

```
In [1]: locationId = libs.location.getLocationId(locations, 'nips_demo')
        envId = libs.environment.initEnv(locationId, userId, baseuri)
        action = [0.55, 0.70] #[ITN, IRS]
        reward = libs.environment.postAction(envId, action, baseuri)
        rewards = np.append(action, reward)
```

Figure 6: Open API to access Infrastructure and Learning from Simulation

Follow-up:

https://tinyurl.com/ml4malaria

References

[1] Oliver Bent, Sekou L. Remy, Stephen Roberts, and Aisha Walcott-Bryant. Novel exploration techniques (nets) for malaria policy interventions. In *Proceedings of the Thirtieth Conference on Innovative Applications of Artificial Intelligence*, 2018.

[2] Erin M Stuckey, Jennifer Stevenson, Katya Galactionova, Amrish Y Baidjoe, Teun Bousema, Wycliffe Odongo, Simon Kariuki, Chris Drakeley, Thomas A Smith, Jonathan Cox, and Nakul Chitnis. Modeling the cost effectiveness of malaria control interventions in the highlands of western Kenya. *PLoS ONE*, 9(10), 2014.