Spatio-temporal Model for Wildlife Poaching Prediction Evaluated through a Controlled Field Test in Uganda

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Abstract

Worldwide, conservation agencies employ rangers to protect conservation areas from poachers. However, agencies lack the manpower to have rangers effectively patrol these vast areas frequently. While past work has modeled poachers behavior so as to aid rangers in planning future patrols, those models predictions were not validated by extensive field tests. In my thesis, I present a spatio-temporal model that predicts poaching threat levels and results from a five-month field test in Ugandas Queen Elizabeth Protected Area (QEPA). To my knowledge, this is the first time that a predictive model has been evaluated through such an extensive field test in this domain. These field test will be extended to another park in Uganda, Murchison Fall Protected Area, shortly. Main goals of my thesis are to develop the best performing model in terms of speed and accuracy and use such model to generate efficient and feasible patrol routes for the park rangers.

Introduction

Wildlife poaching continues to be a global problem as key species are hunted toward extinction. For example, the latest African census showed a 30% decline in elephant populations between 2007 and 2014 (Chase et al. 2016). Wildlife conservation areas have been established to protect these species from poachers, and these areas are protected by park rangers. These areas are vast, and rangers do not have sufficient resources to patrol everywhere intensively.

At many sites now, rangers patrol and collect data related to snares they confiscate, poachers they arrest, and other observations. Given rangers' resource constraints, patrol managers could benefit from tools that analyze these data and provide future poaching predictions. However, this domain presents unique challenges. First, this domain's real-world data are few, extremely noisy, and incomplete. To illustrate, one of rangers' primary patrol goals is to find wire snares, which are deployed by poachers to catch animals. However, these snares are usually well-hidden (e.g., in dense grass), and thus rangers may not find these snares and (incorrectly) label an area as not having any snares. Second, poaching activity changes over time, and predictive models must account for this temporal component. Third, because poaching happens in the real world, there are mutual spatial and neighborhood effects that influence poaching activity. Finally, while field tests are crucial in determining a model's efficacy in the world, the difficulties involved in organizing and executing field tests often precludes them.

Related Works

(Nguyen et al. 2016) introduced a two-layered temporal Bayesian Network predictive model (CAPTURE) that was also evaluated on real-world data from QEPA. CAPTURE, however, assumes one global set of parameters for all of QEPA which ignores local differences in poachers' behavior. While CAPTURE includes temporal elements in its model, it does not include spatial components and thus cannot capture neighborhood specific phenomena. In contrast to CAPTURE, (Kar et al. 2017) presented a behavior model, INTERCEPT, based on an ensemble of decision trees and was demonstrated to outperform CAPTURE. While their model accounted for spatial correlations, it did not include a temporal component. In contrast to these predictive models, our model addresses both spatial and temporal components.

In game theory literature, learning adversary models has been mostly done based on simulated games where data is collected by human subject experiments in the laboratory (Gholami et al. 2016) rather than real world poachers. It is vital to validate predictive models in the real world, and both (Critchlow et al. 2016) and (Kar et al. 2017) have conducted field tests in QEPA. (Kar et al. 2017) conducted a one month field test in QEPA and demonstrated promising results for predictive analytics. Unlike the field test we conducted, however, that was a preliminary field test and was not a controlled experiment. On the other hand, (Critchlow et al. 2016) conducted a controlled experiment where their goal, by selecting three areas for rangers to patrol, was to maximize the number of observations sighted per kilometer walked by the rangers. Their test successfully demonstrated a significant increase in illegal activity detection, but they did not provide comparable evaluation metrics for their predictive model. Also, our field test was much larger in scale, involving 27 patrol posts compared to their 9 posts.

Wildlife Crime Dataset

This study's wildlife crime dataset is from two wildlife conservation parks in Uganda. There are several patrol posts situated across the parks from which Uganda Wildlife Authority rangers conduct patrols to apprehend poachers, remove any snares or traps, monitor wildlife, and record signs of illegal activity. Along with the amount of patrolling effort in each area, both datasets contain 14 years (2003-2016) of the type, location, and date of wildlife crime activities.

Rangers lack the manpower to patrol everywhere all the time, and thus illegal activity may be undetected in unpatrolled areas. Patrolling is an imperfect process, and there is considerable uncertainty in the dataset's negative data points (i.e., areas being labeled as having no illegal activity); rangers may patrol an area and label it as having no snares when, in fact, a snare was well-hidden and undetected. These factors contribute to the dataset's already large class imbalance. It is thus necessary to consider models that estimate hidden variables (e.g., whether an area has been attacked). We divide the parks into 1 square kilometer grid cells, and we refer to these cells as targets. Each target is associated with several static geospatial features such as terrain (e.g., slope), distance values (e.g., distance to border), and animal density. Each target is also associated with dynamic features such as how often an area has been patrolled (i.e., coverage) and observed illegal activities (e.g., snares).

Completed Steps

Up to the present, we have provided the following contributions. (1) We introduced a new hybrid model that enhances an ensemble's broad predictive power with a spatio-temporal model's adaptive capabilities. Because spatio-temporal models require a lot of data, this model works in two stages. First, predictions are made with an ensemble of decision trees. Second, in areas where there are sufficient data, the ensemble's prediction is boosted via a spatio-temporal model. (2) In collaboration with the Wildlife Conservation Society and the Uganda Wildlife Authority, we designed and deployed a large, controlled experiment to QEPA. Across 27 areas we designated across QEPA, rangers patrolled approximately 452 kilometers over the course of five months; to our knowledge, this is the largest controlled experiment and field test of Machine Learning-based predictive models in this domain. In this experiment, we tested our model's selectiveness: is our model able to differentiate between areas of high and low poaching activity? In experimental results, (1) we demonstrated our model's superior performance over the state-of-the-art (Kar et al. 2017) and thus the importance of spatio-temporal modeling. (2) During our field test, rangers found over three times more snaring activity in areas where higher poaching activity is predicted. When accounting for differences in ranger coverage, rangers found twelve times the number of findings per kilometer walked in those areas. These results demonstrate that (i) our model is selective in its predictions and (ii) our model's superior predictive performance in the laboratory extends to the real world (Gholami et al. 2017).

Future Works and Progress Schedule

- Develop new problem set-up and a hierarchical model of ensemble of decision trees which not only handles both spatial and temporal dimensions of the problem, but also inherits the fast running time speed of the decision tree based models. However, MRF based models are able to take the hidden states (i.e., actual poaching attacks in our problem) into account but they are relatively slow in training process. So the main challenge is to develop a hybrid of decision trees which possess all positive features of existing best performing models. This step of the project is in progress and will be definitely completed by February 2018.
- Similar to the experiments conducted in QEPA, we are planning to conduct field test in Murchison Fall park to evaluate the selectiveness of our predictive model for that protected area, as well. This step of the project is in progress and will be completed by February 2018.
- Build a patrol planning tool to generate detailed patrol routes for park rangers based on the best performing developed model and conduct field tests to evaluate them. This step of the project will be started in February 2018.

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