A Bayesian model for combating poaching of wild life in the Kruger national park

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Abstract - *Poaching of the elephant for its tusk and the rhinoceros (rhino) for its horn is rampant at the Kruger national park (KNP). An average of 1000 rhinos are killed each year. If there is no additional measures put in place to curb poaching, the rhino will become extinct at the KNP in the next 15 years. A framework for curbing the poaching of wild life has been designed. In addition, a model based on the Bayesian networks has been constructed for predicting poaching activities at the KNP. The implications of the results is that adapting to this framework and model will disrupt poaching activities. This will lead to the conservation of the rhino and the elephant and thus maintain the ecosystem. In addition, more tourists will keep on coming to see these animals roaming in their natural habitat and thus contribute to economic development and also to reducing unemployment.*

Keywords: poaching, d-separation, Markov blanket, maximum a posteriori.

1 Introduction

The Poaching of the elephant for its tasks and the rhino for its horn over the past 3 years claimed an average of 61 elephants and 474 rhinos (from 2014 to 2016) per year at the Kruger National Park (KNP) [8, 9]. The rhino is projected to go into extinction in another two decades if wildlife protection strategies are not scaled up. The KNP measures about 19 485 square kilometers and is difficult to police more so as it shares a border with Mozambique and Zimbabwe. The former has just emerged from a civil war and the weapons of war are now used for poaching. The latter's economy is still emerging from decades of collapse and thus it lacks resources for fighting poachers.

There is a market in Asia for ivory and the rhino horn and a kg of a rhino horn fetches up to US $ 5000 and ivory fetches up to US 2 100 per kg. The Rhino horn weighs up to 4 kg and an elephant tusk weighs up to 45kg.

Currently the Kruger National Park (KNP) is patrolled by Rangers and by helicopters. It tags and relocates some of the endangered animals to private parks for preserving species and to Zoos to recuperate from wounds inflicted by poachers. South Africa might be tempted to profile tourists from the Asian illicit trade source countries. However, these countries can inform their citizens to avoid visiting the KNP and this could result in a loss of hundreds of millions of US dollar in tourist revenue and a loss of tens of thousands of jobs in the tourism value chain. It has been established that for every 13 tourists, one job is created. In addition, some of the Rangers have been implicated in poaching or collision with poachers. This is a dilemma. Poaching thus poses a threat to the wildlife ecosystem. Currently, the KNP has limited wild life poaching protection and prevention systems. Prediction models based on machine learning (ML) can complement current strategies that are used in protecting wildlife from poaching. These models can foretell where next the poaching activities are likely to occur and hence resources can be deployed to pre-empt poaching and thus bring efficiency and effectiveness in the allocation of anti-poaching resources.

2 Literature Review

Gurumurthy et al. [1] using the Bagging Ensemble Decision Tree and Neural Networks on a dataset collected over a period of 5 years in China established that the use of human knowledge is useful in the prediction of poaching activities. Identifying areas within the national park where poaching is likely to occur is important. Using data collected from Ranger-based monitoring over 9 years from Nyungwe National Park in Rwanda, Moore et al. [3] using a link between the number of patrols and poaching activities and dynamic multi-season occupancy models, identified the areas which were at a high risk of poaching. Other tools can be used to complement physical patrols by rangers. Shaffer and Bishop [2] established correlations between roads, water, land and poaching activities. Using data from the Queen

Elizabeth (QE) national park in Uganda collected over a period of 12 years Nguyen et al. [4] developed the Comprehensive Anti-Poaching tool with Temporal and Observation Uncertainty Reasoning (CAPTURE) based on a Dynamic Bayesian Networks. CAPTURE links the patrol strategy to the probability of an attack thereby creating a temporal pattern of poaching activities. Kar et al [7] used poaching data collected from the QE National Park to design an ensemble of trees for predicting poaching. They used a modification of the CAPTURE model [7] of Nguyen et al. [4] called INTERCEPT which obtained better poaching prediction results. Gholami et al. [5] used a dataset from 2003 to 2016 for the QE national park that consisted of patrolling effort, type, location and the date of the poaching incident to construct a hybrid model of the Decision Trees and Markov Random Fields. This model achieved better wild life prediction levels. In 2018, Gholami et al. [6] developed iWare prediction model for wildlife protection using a dataset from 2003 to 2016 for Murchison and QE national parks.

3 Methods

The competing techniques for creating the model include the artificial neural networks (ANN) and the naïve Bayes. The data used only consisted of 50 instances and thus the ANN is not suitable as it requires hundreds of instances. The collected data was insufficient to model a ANN model dynamic Bayes model. The Bayesian networks is the tool that was chosen for this work. The use of the Bayesian to solve a problem requires that the nodes in a graph or network are independent or conditionally independent. The independence or conditional independence in Bayesian networks was explained through the use d-separation and the Markov blanket.

3.1 D-Separation

The variables also called nodes X and Y are d-separated if on any undirected path between X and Y there is a variable Z such that:

Z is in a serial or diverging connection and Z is observed.
Z is in a converging connection and neither Z nor any of Z's descendants are observed.

If X and Y are d-separated by Z, then X and Y are conditionally independent.

In this paper d-separation was established using the above recipe. All the triples (X, Y, Z) in the network were examined in this fashion. Once one is satisfied that the network meets the conditional independence requirements, a Bayesian prediction model is constructed as detailed in section 4.

3.2 The Markov Blanket

The Markov blanket says that a node X is conditionally independent of all other nodes given its parents, children and parents of common children or parents sharing a child. Thus when all these nodes are instantiated (i.e. values for children of X, values of parents of X, values variables sharing a child with X are known), then X is d-separated from the rest of network.

4 Experimentation

4.1 Data Collection

Poaching data can be sparse noisy and at times incomplete (Gurumurthy, 2018). A survey design was used for collecting data. During the survey there were challenges in scheduling appointments with participants. In such cases data was collected based on the availability of each participant. Some experts in the national parks related areas were consulted. Some of these experts suggested variables we were not aware of. The survey included some questions on collaboration between stakeholders in fighting poaching, questions on time of the day on which poaching is rampant, questions on benefits accruing to neighbouring communities, questions on collusion with poachers, questions on the disciplines of management and their age were asked, remuneration of Park Rangers, questions around watering holes, questions on a number of each category of endangered species poached per annum, and archived data in particular and questions around the cost of policing the national parks, questions on human resources in place to protect wild life, questions on strategies in place to protect wildlife. These questions were a mixture of closed-ended questions and open-ended questions. The results from the data collection are variables which were used to construct the framework shown in Figure 1.

4.2 Data Pre-processing

The cleaning of data involved discarding responses that were incomplete. Some values were inferred from other given responses. The result is Figure 1.

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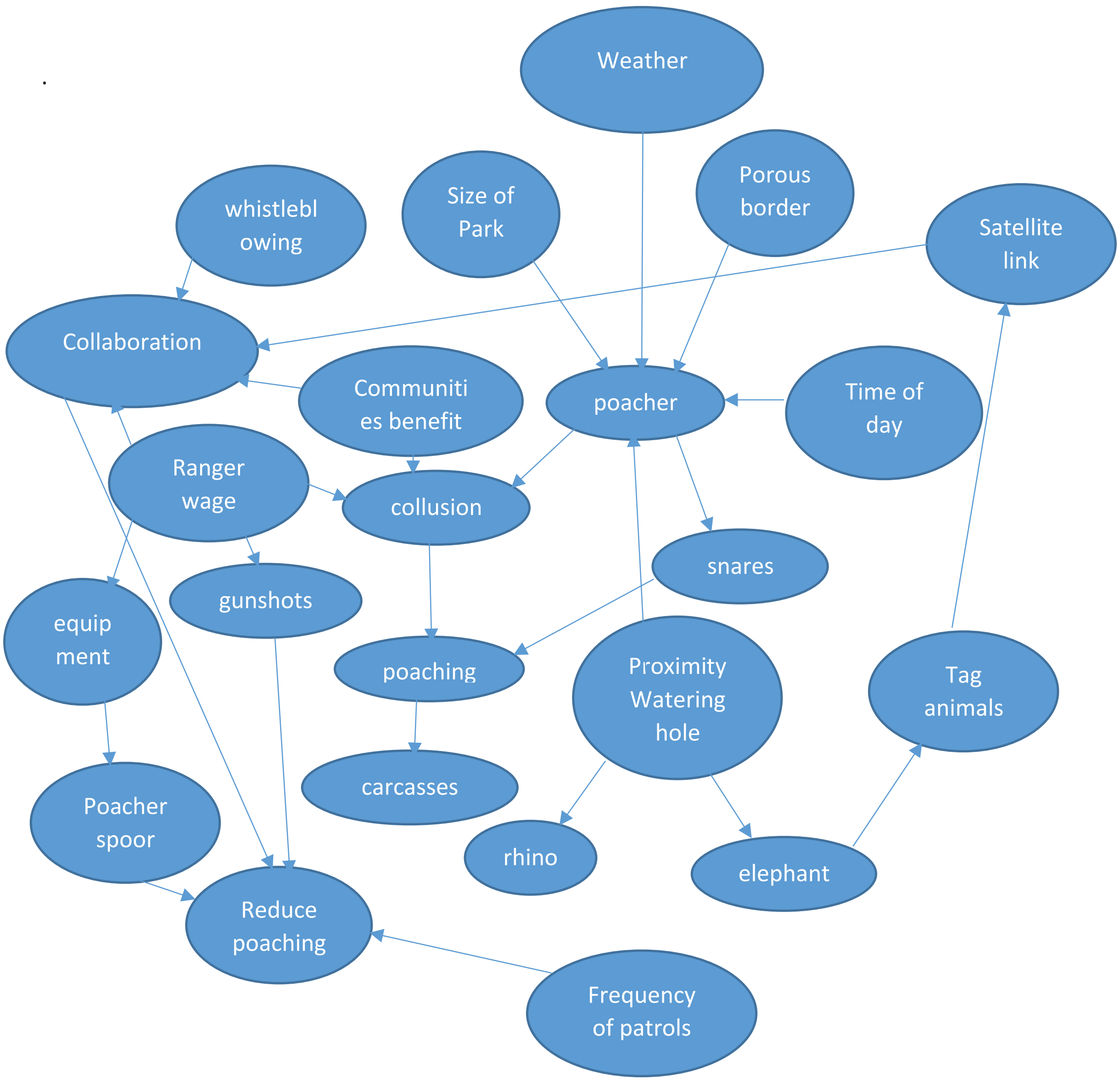


Figure 1: A Framework for reducing poaching

Two or more variables in the framework in Figure 1 were collapsed into one variable which was to be used for constructing the Bayesian network.

4.3 Steps for Constructing a BN

Prediction Model

i. Define from the instance space X, the set of relevant target values X_i .

ii. Provide the training set of the target function

iii. Add the instance, X_i to the network.

iv. Add relations to the node X_i from a set of selected attributes to form a network $P(X_i \mid X_1, X_2.....X_m) = P(X_i \mid Parents(X_i))$ where $X_1, X_2.....X_m$ are all variables preceding X_i that are not in $Parents(X_i)$

v. Determine the conditional probability table (CPT) given by, $P(X_i \mid Parents(X_i))$ for each attribute

The Bayesian network will be used for answering a query from the domain captured by the Bayesian network. Prediction is the foretelling of the occurrence of an event based on historical data. The model in Figure 2 was constructed using variables from the poaching problem domain. This model is able to predict future unseen data (poaching instances) that come from the same distribution as data used to construct the model. This model is then deployed to predict new instances. Thus using the joint probability distribution, which acts as a database, the Bayesian network can be queried provided it captures the problem domain, it will provide the correct answers to the query. Using the chain rule on Figure 2 we get the probability joint distribution:

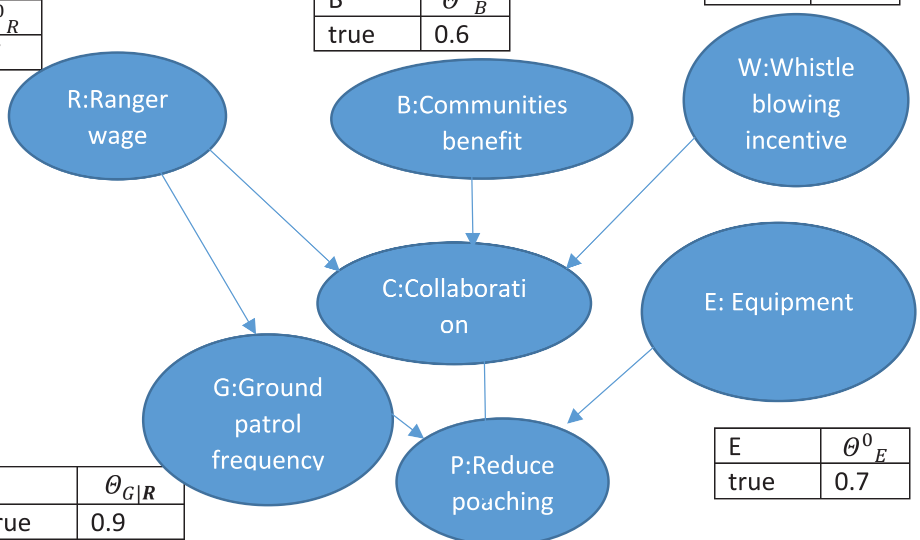
P(B, C, H, G, P, R,T, W) = P(B)P(R)P(T)P(H)P(W)P(C|B,H,R,S,T)P(S|T)P(G|R)P(P|C,G,W)

The Bayesian network in Figure 2 was constructed by linking the nodes (variables). The CPTs for each node in the network were created. The data for populating the CPTs was obtained from responses in the questionnaire. The other data for populating the CPTs was obtained from experts. Some of the values were common knowledge (prior information).

T	$\Theta^0{}_T$
true	0.8

B	$\Theta^0{}_B$
true	0.6

R	$\Theta^0{}_R$
true	0.7



E	$\Theta^0{}_E$
true	0.7

R	G	$\Theta_{G\|\boldsymbol{R}}$
true	true	0.9
false	true	0.3

E	C	G	P	$\Theta_{P\|\boldsymbol{G,E}}$
true	true	true	true	0.95
true	true	false	true	0.65
true	false	true	true	0.68
true	false	false	true	0.3
false	true	true	true	0.75
false	true	false	true	0.35
false	false	true	true	0.55
false	false	false	true	0.5
false	false	false	true	0.1

B	W	R	C	$\Theta_{C\|\boldsymbol{R,B,W}}$
true	true	true	true	0.95
true	true	false	true	0.75
true	false	true	true	0.65
true	False	true	true	0.75
false	true	true	true	0.80
false	true	false	true	0.5
false	false	true	true	0.6
false	false	false	true	0.1

Figure 2: A Bayesian Model for reducing poaching

The equipment includes helicopter, Tagging animals, Satellite, guns among other equipment that they use**.** Once the Bayesian network in Figure 2 was constructed, the first specific query to pose **is** the *maximum a posteriori* (MAP) query. Put in other words, the goal is to instantiate the MAP variables having chosen the evidence variables (variables whose values are known). The evidence variables (whose values are known) and the MAP variables (whose values we want to know) were chosen as shown on Table 1.

The maximum a posteriori (MAP)

Step 1: given the set of ALL variables X

Step 2: M is a subset of variables in step 1 (M < X)

Step3: Given evidence **e**

Step4: find an instantiation m of variables **M** for which Pr **(m|e)** is maximal

Any instantiation **m** that satisfies step 4 is called a maximum a posteriori (MAP) hypothesis. The variables in **M** are known as MAP variables.

By carrying out the experimentation as shown in Table 1 and only given values for the second column and variables whose values we want to know shown in the first column of Table 1, we were able to get values shown in columns 3, 4, 5 and 6. It can be seen in Table 3 in the first row that for MAP variables {C, W, G, E, P} we get the instantiation C = yes, W = yes, G = yes, E = yes, P = yes which has a probability 46% given evidence R = yes; B = yes. Since this is the highest probability of 46% (0.45480) shown in Table 1, these results mean that C,W,G,E,P are MAP variables given that we know that rangers get a high wage and that the community collaborates fully with the rangers. By summing out non-MAP variables, we compute the joint marginal Pr(MAP, e)**.** But Pr(m|e) = Pr(m,e)/Pr(e). Pr (e) is independent of the instantiation m**.**

Table 1: Instantiation of variables (MAP query) given evidence **e**. In P(m|e), m is MAP

MAP Variables	Given Evidence variables	Instantiation by SamIam	P(**m**|e)	P(**m**,e)	P(e)
C,W,G,E,P	R = yes, B = yes	C = yes, W = yes,G=yes,E=yes,P=yes	0.4548	0.1910	0.4199
C,W,G,E,P	R = yes, B = no	C = yes, W = yes, G=yes,E=yes,P=yes	0.383	0.1072	0.28
C,W,R,B,P	G = yes, E = yes	C = yes, W = yes, R=increase,B=yes,P=yes	0.2995	0.0646	0.216
C,W,R,B,P	G = yes, E = no	C= yes, W = yes, R=increase,B=yes,P=yes	0.3551	0.2556	0.719
C,W,R,B,P	G= no, E = no	C= yes, W = yes, R=decrease,B=yes, P=yes	0.1310	0.0366	0.28
G,P,W,B,C	R = yes, E = yes	G = high, P = yes, W=yes, B=yes,C=yes	0.389	0.1910	0.49
G,P,W,B,C	R = yes, E = no	G = high, P = yes	0.3779	0.0646	0.21
G,P,W,B,C	R = no, E = no	G=low,P=no,W=yes, B=yes,C=yes	0.1419	0.0127	0.09

Pr(e) means asking for the probability of some variable instantiation **e,** P (**e**). The P (e) is the probability of evidence query corresponding to the instantiation of variables as shown in Table 1. P (e) is independent of the instantiation m. Community initiated projects that get funding from the national parks would make the community to appreciate the value of wildlife and thus become partners in its preservation.

5 Discussions

The results mean that the framework if followed could have an impact on anti-poaching activities in the Kruger National Park. The results mean that a Bayesian model can answer the queries posed to the model. The results are what they are because it is likely that there are still variables that we were not aware of (missing data) and thus they were not captured for use in constructing the framework.

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Once deployed, a comparison can be made with strategies used East African countries of Kenya, Rwanda and Uganda.

The implications of the results is that adapting this framework will disrupt poaching activities at the Kruger National Park. This will lead to an increase in the number of threatened species and thus maintain the ecosystem. In addition, more tourists will keep on coming to see these animals roaming in their natural habitat and thus contribute to economic development and also in reducing unemployment in South Africa.

6 Conclusions

A Bayesian prediction model that predicts the movement of poachers has been constructed. In addition a framework for reducing poaching has been constructed. The model and the framework can potentially play a big role in complementing current efforts on reducing poaching in the Kruger national park and beyond.

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