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Engaging Citizen Scientists in Data Collection for Conservation

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Introduction

Big data is becoming increasingly important for monitoring large-scale and complex spatial and temporal ecological processes to support informed decision-making in computational sustainability [Gomes 2009]. Historically, data collection methods for conservation typically involved many hours of field work performed by professional researchers, which could not scale up to meet today's conservation goals. Citizen science programs, on the other hand, engage the general public in the data collection process. With the active participation of thousands of volunteers, citizen science programs have been very successful at collecting rich datasets for conservation, enabling the possibility of conducting ecological surveys across multiple years and at large continental scales. Over the last few years, there have been several successful citizen science programs. For example, in biology, citizen scientists help with bird and arthropod research using eBird [Sullivan et al. 2009] and BugGuide [www.bugguide.net.]. In environmental studies, citizen scientists contribute to monitoring coral bleaching conditions [Marshall et al. 2012]. To attract more people to contribute data, the success of citizen science programs relies on tapping into the intrinsic motivations of citizen scientists. The citizen scientists' contribution cycle is shown in Figure 11.1. The self-fulfillment brought by participation while contributing to science keeps citizen scientists engaged, in return accelerating the whole contribution cycle. In this chapter, we illustrate effective ways to engage citizen scientists in data collection for conservation (Figure 11.2). Our approaches are motivated by our collaborations with two citizen science programs: the eBird and Nchioto projects.

eBird is a citizen science program of the Cornell Lab of Ornithology which engages the general public in bird conservation. To understand the distribution and migration of birds, eBird enlists bird watchers to identify

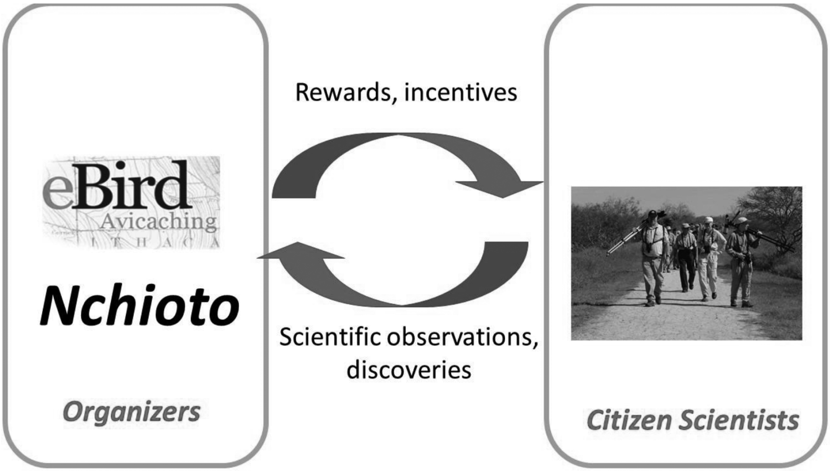

Figure 11.1 Citizen science program cycle. The organizer of a citizen science program uses reward and incentives to stimulate participation. Citizen scientists contribute scientific observations and discoveries to the organizers. Citizen Scientists' photo is from Steve Hillebrand at the U.S. Fish and Wildlife Service. Avicaching banner credit: Ian Davies and Christopher Wood at the Cornell Lab of Ornithology.

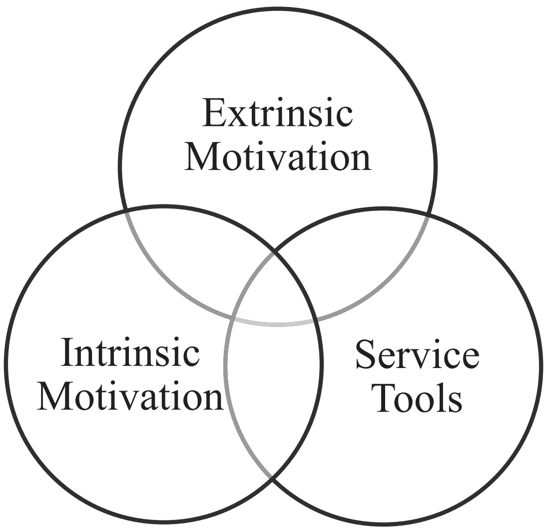

Figure 11.2 Three effective ways to engage citizen scientists in scientific discovery.

bird species, a task that is still beyond the capacity of automated technology. Bird watchers report their observations to the centralized eBird database via online checklists that include detailed information about the observed birds, such as the name of the species, number of individuals, gender, and time and location of the observation. eBird has been enormously successful. To date, more than 360,000 individuals have volunteered more than 400 million bird observations, which in terms of person-hours is equivalent to building several Empire State Buildings. Since 2006, eBird data have been used to study a variety of scientific questions, from highlighting the impact of climate change to designing conservation plans [Kelling et al. 2012].

Avicaching is a game that we developed to incentivize bird watchers to collect observations in remote and under-sampled locations in order to reduce bias in eBird data [Xue et al. 2016a, 2016b]. Specifically, Avicaching engages bird watchers by providing rewards in the form of Avicaching points for observations made in remote and under-sampled locations. In a friendly competitive environment, bird watchers compete for Avicaching points through an online leaderboard. At the end of the season, Avicaching players have the chance to win birding gear based on how many points each bird watcher has earned. Avicaching has been very successful among birding communities. In a field study conducted in Tompkins and Cortland County in New York in 2015, the Avicaching game shifted approximately 20 percent of birding effort from traditional hotspots to Avicaching locations, which had not been visited prior to the Avicaching game.

We have also developed Bird-Watcher Assistant [Xue et al. 2013], to further boost eBird participation and scientific discovery. The success of eBird is in part due to a series of service tools for record-keeping, exploration, and visualization, which nurture and reward participation. Bird-Watcher Assistant recommends interesting birding sites in which a diverse set of bird species might be seen. The Bird-Watcher Assistant particularly engages beginner bird watchers, who rely on eBird tools to discover interesting sites. In addition, we recommend locations that are seldom visited through Bird-Watcher Assistant, which helps expand the spatial coverage of eBird into less-populated regions. Recommending tasks that are rewarding to citizen scientists with Bird-Watcher Assistant creates a positive feedback loop, bringing in greater participation, which in turn results in more data, better models, and leads to more accurately recommended tasks.

Nchioto is a crowdsourcing project of the International Livestock Research Institute (ILRI) to monitor rangeland and vegetation conditions in Eastern Africa [Jensen et al. 2017a; Naibei et al. 2017]. In a collaboration with ILRI, we developed AI solutions to incentivize participation in the program.

Nchioto relies on local pastoralists, who live on rangeland themselves, to report information on rangeland and vegetation conditions via an intuitive cellphone application. Nchioto distributes incentives in a monetary form to stimulate participation in under-sampled areas. With a crowdsourcing program, it is important to quantify its elasticity in terms of the reward value, i.e., the extent to which citizen scientists are willing to deviate from their normal everyday path to participate in our data collection program as a function of the rewards. In our work, we showed the potential of large-scale crowdsourcing of environmental information from low-literacy populations, such as the local pastoralists in Eastern Africa. In particular, we showed that participants respond to incentives in a rational way, increasing our confidence that optimally designed incentive schemes will be useful in driving the crowd toward important tasks.

Our tools to support citizen scientists are supported with novel advances in AI technology. In the Nchioto and Avicaching programs, we study the problem of optimal incentive allocation under a game-theoretic setting, taking into account the fact that citizen scientists have their own utility functions, which may not align with the organizers' objectives. Game-theoretic formulations for conservation problems have also been studied in a few related works [Fang et al. 2017; Yadav et al. 2017]. In both applications, we use novel machine learning and constraint programming techniques to capture the citizen scientists' elasticity to rewards and to compute the optimal reward allocation. To solve the two-stage game in both Nchioto and Avicaching programs, we embed agents' decision problem as linear constraints in the master problem, solved by the organizer, therefore reducing a bi-level optimization to a single optimization. In the Bird-Watcher Assistant application, we introduce novel algorithms that assist citizen scientists by recommending locations within a travel budget in which a diverse set of species can be observed. We formalize the problem of recommending these locations as a probabilistic maximum coverage problem, which can be solved by submodular maximization subject to radius locality constraints. We propose several novel algorithms that have constant approximation guarantees and validate their effectiveness empirically.

This chapter is organized as follows. In the next section we describe the Nchioto application, in which we use extrinsic incentives to motivate local pastoralists to monitor vegetation conditions in Eastern Africa. In the third section, we present the eBird Avicaching game and in the fourth section Bird-Watcher Assistant, another tool to further boost eBird participation and scientific discovery. The three sections are organized to illustrate three effective ways to engage citizen scientists, as shown in Figure 11.2. We conclude with a discussion of the relationship among the three incentives and future directions.

Nchioto: Engaging Pastoralists in Eastern Africa with Extrinsic Incentives

The global spread of low-cost mobile phones allows us to communicate effectively in remote and underdeveloped areas. Integrating today's citizen science programs with mobile phones allows us to overcome the gaps in infrastructure that limit the effectiveness of traditional data collection methods. In Kenya, for example, over 80 percent people have access to cellphones, and the percentage of smartphone users is approximately 20 percent and growing.

In collaboration with scientists from the ILRI, we studied the problem of monitoring local vegetation conditions at high spatial and temporal resolution, aggregating responses from local citizen scientists via smartphones. The study area was a 150 km by 155 km region in central Kenya. We recruited volunteers among local pastoralists who spent most of their time herding livestock. We gave pastoralists cellphones, which they used to report vegetation conditions of the local landscape while they were actively herding livestock. Our goal in this study was to see to what extent we could rely on cellphone users on the ground to conduct land survey and monitoring tasks.

Nchioto is a cellphone application that we developed for pastoralists (or herders) to characterize the forage conditions using a short, visually oriented, and geolocated survey (see Figure 11.3) [Jensen et al. 2017a, 2017b; Naibei et al. 2017]. The vegetation survey first asked a few questions, such as whether grass in this area was dense, sparse, or absent; what was the color of the grass; and whether the grass was edible by animals. After these questions, the survey asked participants to estimate the carrying capacity, i.e., the number of livestock that could be supported with the available grass in the local area. All the questions were shown using a graphical interface to overcome language barriers. Questions of similar purpose were asked from different perspectives to guarantee consistency. As the last step, pastoralists were asked to take a picture of the location that they were characterizing before they submitted their report.

Nchioto used extrinsic monetary motivation to stimulate participation. We developed a reward map (Figure 11.3(b)), which gave participants different monetary rewards for observations made in different areas. Through the reward map, participants could see clearly which reward zone they were currently in and information about nearby reward zones. The reward map was based on an AI algorithm, which assigns reward points in an intelligent way to motivate participants toward remote areas where observations are needed the most. The whole reward map was integrated into the Nchioto application.

Through field experiments with interleaved reward treatments, we have been able to capture the reward elasticity of citizen scientists, which captures

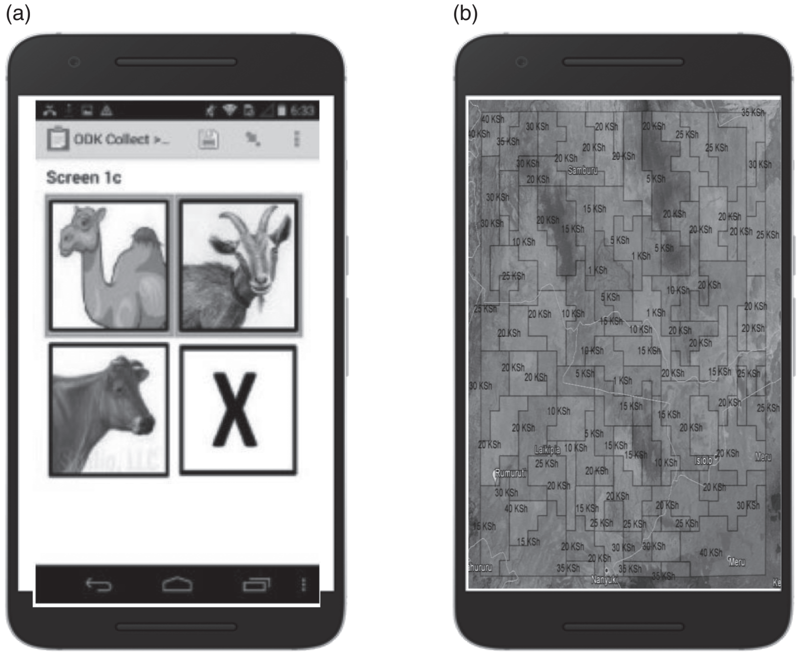

Figure 11.3 The intuitive Nchioto interface allows participants to submit reports monitoring vegetation conditions on the ground via smart phones. (a) The Nchioto interface asks the participants whether the grass on the ground is edible for certain types of animals using graphics that overcomes language barriers. (b) Nchioto shows a map of rewards, motivating participants to conduct land surveys in remote regions with high monetary rewards. Image credit: Andrew Mude, Nathan Jensen at the International Livestock Research Institute.

the percentage increase in participation per unit of reward increase. In terms of individual-level elasticity, we observed that increasing the amount of reward leads to an increase in submissions. In terms of aggregate-level elasticity, we observed that a spatial variant reward treatment designed with AI algorithm, where rewards were biased toward remote and under-sampled locations, performed better than a uniform reward treatment in pushing the crowd to remote areas [Jensen et al. 2017a].

In summary, our results demonstrate that large-scale crowdsourcing of environmental information from low-literacy populations can be feasible. Furthermore, we showed that participants respond to incentives in a rational way, demonstrating the potential impact of optimally designed incentive schemes in driving the crowd toward the most useful tasks.

Avicaching: Tapping into Intrinsic Motivation via Friendly Competition for Uniform Data Collection

Aside from monetary incentives, we engage citizen scientists by tapping into their intrinsic motivation for participation. In this section, we discuss a friendly competition among citizen scientists to shift their effort toward remote and under-sampled areas to reduce the data bias.

Data bias is a common problem in citizen science. To attract large groups of participants, citizen science projects often have few restrictions, leaving many decisions about where, when, and how to collect data up to the citizen scientists. As a result, the data collected by citizen scientists are often biased, aligned with their personal preferences, rather than providing systematic observations across various experimental settings to address scientific goals. Moreover, since participants volunteer their effort, convenience is an important factor that often determines how data are collected. For spatial data, this means more searches occur in areas close to urban areas and roads. See Figure 11.4 for an illustration of the data bias problem in eBird.

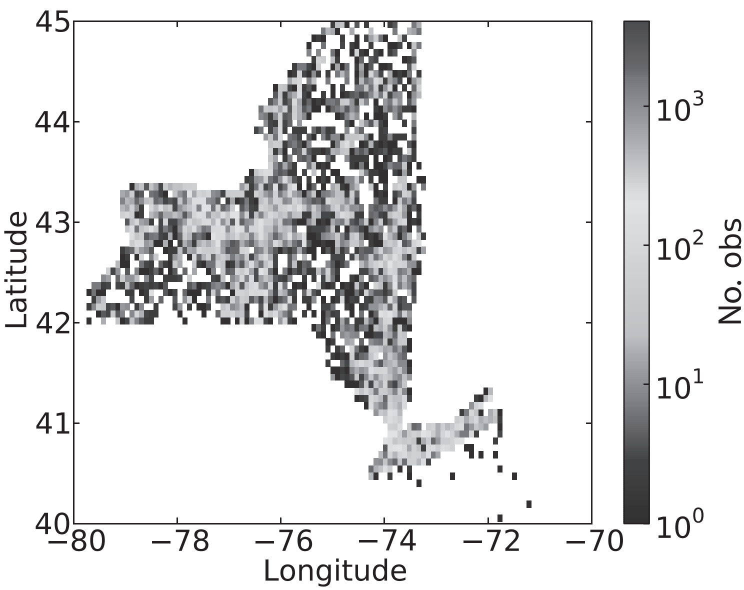

Figure 11.4 Highly biased distribution of eBird observations. This picture shows the number of observations in New York State from May 1 to September 1, 2011. A few locations receive orders of magnitude more observations than other locations.

Citizen scientists often join the program with very commendable goals; they would like to contribute in a meaningful way to science. The best way to motivate them, in this case, is to nurture their intrinsic motivation, by creating ranked lists and milestones, which will engage them in a healthy, competitive environment, to see more and rare bird species.

To address the data bias problem in citizen science, and particularly in eBird, we proposed a game called Avicaching, which motivates the participants by tapping into their intrinsic motivation via friendly competition (see Figure 11.5). We reward citizen scientists with additional Avicaching points for observations conducted in remote and under-sampled areas. Avicaching points, in this case, represent how much effort each bird watcher has expended. We maintain a leaderboard to document how many Avicaching points each

Figure 11.5 The Avicaching game motivates bird watchers to explore remote and under-sampled locations by tapping into their intrinsic motivation via a friendly competition. Bird watchers compete on how many Avicaching points they have earned in an online ranking list (a reward map in the lower left; a ranking list in the lower right). At the end of each season, bird watchers have an opportunity to win birding gear in a lottery drawn based on the number of Avicaching points earned. Avicaching banner credit: Ian Davies and Christopher Wood at the Cornell Lab of Ornithology.

participant has earned, viewable by all participants. At the end of the season, Avicaching players have the chance of winning a prize, such as a pair of binoculars, which is determined by how many Avicaching points one has earned.

The Avicaching game is supported by novel AI technologies in multi-agent systems and game theory. We formalize Avicaching as a two-stage game, which can be represented by the following bi-level optimization:

$$\begin{array}{lll} \text{(Organizer) :} & r \leftarrow \operatorname{argmin}_r V_{\text{org}}(v, r), & \\ \text{subject to} & B_{\text{org}}(r), & \\ & v \leftarrow \operatorname{argmax}_v U_a\,(v, r) & \text{(Agents)} \\ & B_a(v). & \end{array} \tag{11.1}$$

The agents of this game are citizen scientists, who maximize their total utility function $U_a\,(v, r)$, which includes their intrinsic utilities, combined with the incentives distributed by the game organizer, subject to a budget constraint $B_a(v)$. v is the optimal action of the agents, which in this game is the set of locations that agents choose to visit. r denotes a vector of rewards that the organizer allocates to different locations. The agents' intrinsic utilities include the birding quality of the location, such as how many bird species can be seen in one location, as well as the convenience factor of the location. The organizer in our two-stage game corresponds to an organization with notable influence on the citizen scientists, such as the eBird program. The organizer factors in the reasoning of the citizen scientists to propose an optimal incentive allocation r which maximizes his/her objective function $V_{\text{org}}(v, r)$. In our setting, since the organizer would like to induce a uniform data collection process, $V_{\text{org}}(v, r)$ is an objective function that measures the spatial and temporal uniformity of the data collected.

There are two aspects to consider in solving the two-stage game. The first aspect is to design a behavioral model in order to learn citizen scientists' utility function $U_a\,(v, r)$. Citizen scientists do not reveal their reward preferences to the organizer directly. Instead, the organizer must infer the agents' utility functions based on their response to different reward treatments. According to the formulation in equation 11.1, v is the response that maximizes the citizen scientists' utility function. Assuming v^* is the optimal response of one agent, the following inequalities

$$U_a\left(v^*, r\right) \geq U_a\,(v, r) \tag{11.2}$$

hold for every action v that the agent can possibly take. Motivated by this idea, we formalize the problem of fitting the behavioral model as a structured learning problem, in which we search for model parameters that satisfy as many inequalities of type 11.2 as possible. We first proposed a structural SVM approach for behavioral modeling [Xue et al. 2016a]. We also proposed a refined dynamic discrete choice model [Xue et al. 2016b]. We refer the reader to these two papers for mathematical details.

The second aspect is to solve the two-stage game, given the behavioral model of the agents. This is challenging because it is a bi-level optimization, in which the organizer needs to solve his/her own optimization problem, taking into account that agents are also optimizing for their own reward functions. In other words, there is a sub-optimization (shown in the box of equation 11.1) embedded in the global optimization problem. We devised several novel algorithms to solve the two-stage game.

Our novel contribution is to embed (an approximation of) the agents' problems into the organizer's problem. The core idea is to approximate the agents' reasoning process with a tractable algorithm. We then compile this algorithm as a set of linear constraints. The compilation process mimics exactly the execution of the algorithm, introducing one constraint for each operation. After obtaining all the linear constraints, we embed them in the bi-level optimization, collapsing the entire problem to a single optimization. To be more specific, we consider different objectives for the organizer, corresponding to different measures of data uniformity, using mixed integer programming and mixed integer quadratic programming formulations. We also consider different levels of rationality for the agents. For the scenario in which the agents have unbounded rationality, we developed an iterative row generation method to avoid the potentially exponential number of constraints induced by agents' optimization problems. We also consider the case in which the agents have bounded rationality. In this scenario, we embed the agent decision process as linear constraints into the global bi-level optimization problem, and therefore the entire problem can be solved by a single optimization.

The Avicaching game has been very popular among citizen scientists and has received an amazing field response. In a study conducted in Tompkins and Cortland Counties in New York in 2015, the Avicaching game was able to shift approximately 20 percent of birding effort from traditional hotspots to Avicaching locations, which had not been visited prior to the Avicaching game. Many participants revealed that indeed it is both the intrinsic motivations to make contributions to science, and the honor and fulfillment of ranking highly in the final list that have kept them competing in the Avicaching game.

Bird-Watcher Assistant: Engaging Participants with Service Tools

Rather than using incentives, in this section we explore the possibility of engaging citizen scientists by developing service tools that render participation more enjoyable and rewarding. Service tools bring value to the citizen science community and are appreciated by the participants. Successful citizen science programs often emphasize service tools to the participants. For example, in eBird, many useful tools have been built over the years, such as eBird bar charts, top 100 lists and Merlin [Wood et al. 2011; http://merlin.allaboutbirds.org.].

We focus on building a set of service tools for recommending interesting birding sites to bird watchers, encapsulated in an application that we call Bird-Watcher Assistant, to further boost participation in eBird. Figure 11.6 shows snapshots of our application on a cellphone. Bird-Watcher Assistant is especially targeted at beginner bird watchers, whose continuous participation depends on discovering interesting birding sites and therefore building reputation and skills within the birding community. To increase their participation,

Figure 11.6 Bird-Watcher Assistant brings back value to bird watchers by making birding activities fun and enjoyable. (a) Bird-Watcher Assistant recommends a few locations in a small region under a travel budget. A diverse set of species can be seen by visiting these locations. (b) A large-scale variant in which Bird-Watcher Assistant recommends locations within the travel budget in a sub-region (shown in the blue circle) of the entire area.

we suggest birding sites that they may not have known about, based on their limited experience.

Bird-Watcher Assistant makes use of information from spatio-temporal species distribution models [Fink et al. 2010], which predict species occurrence at a given location and time based on the associations between current eBird observations and local environmental data. These species distribution models inform the selection of the most desirable or useful new tasks for the citizen scientists. Besides engaging participants, another goal is to build a loop for active learning, in which our Bird-Watcher Assistant recommends locations that are most informative for addressing eBird's scientific goal. Active learning is a popular research direction in machine learning and artificial intelligence, where one seeks to select the set of unlabeled data points that would have the most significant impact on the fitted predictive model when added to the labeled training data. In the context of citizen science, however, one cannot simply maximize the information content of the tasks but should take into account the interests of the citizen scientists to make the recommended tasks enjoyable.

In order to improve the bird watchers' chances of seeing a diverse set of species, the Bird-Watcher Assistant is designed to recommend locations based on the solution to the following problem: given a set of locations, select a subset of size k, such that the bird watchers maximize the expected number of observed species by visiting such locations. We consider two variants of this problem: (1) a local-scale variant (Figure 11.5(a)), in which we are choosing among birding sites that are within a given region, for example when planning a birding trip within a county; and (11.2) a large-scale variant (Figure 11.5(b)), in which we want to choose a sub-region (with a given radius) from a given larger region, from which we want to choose the set of locations to visit. For example, bird watchers might want to fly to Colombia and visit a subset of birding sites within a sub-region of Colombia. We formalize the first small-scale problem as the probabilistic maximum coverage problem. Mathematically, it can be represented as:

$$\text{(probabilistic maximum coverage)}$$
$$\text{maximize}\, f(S), \;\; \text{subject to} \;\; |S| \leq k.$$

Here, S is the set of locations that we recommend to the user. $f(S)$ is the objective function that captures the expected number of species that one can see by visiting all locations in S. We formalize the second large-scale problem as probabilistic maximum coverage with locality constraints, which is:

(probabilistic maximum coverage with locality constraints)

$$\text{maximize}\, f(S), \ \text{subject to} \ |S| \le k \text{ and}$$
$$\text{all locations in } S \text{ are covered by a circle of radius } r.$$

In addition to the primary objective of maximizing the expected number of observed species, we also consider a secondary objective that gives preference to birding sites not previously visited, when in the presence of multiple solutions with a comparable number of expected species. This secondary objective helps expand the spatial coverage of eBird by promoting new birding sites, typically in less-populated areas. Observations made at the Bird-Watcher Assistant recommended sites will help mitigate the spatial bias in eBird, where observations are concentrated toward regions with high human density.

The first problem of probabilistic maximum coverage can be formulated as maximizing a submodular function, subject to cardinality constraints. While the problem is NP-hard, we can use the classical $(1 - 1/e)$ approximation algorithm to solve the problem. The second probabilistic maximum coverage with locality constraints problem is a submodular optimization subject to both cardinality and locality constraints, specified by a given radius. To our knowledge, the most similar problem studied previously concerns submodular optimization subject to a path length constraint [Chekuri and Pal 2005; Singh et al. 2009]. The state-of-the-art for that problem is a quasi-polynomial-time algorithm with a logarithmic approximation bound. In contrast, we show that the probabilistic maximum coverage problem with radius locality constraints admits a strongly polynomial $(1 - 1/e)$ approximation bound. The high-level idea of our algorithm is to consider all location sets covered by circles of radius r, and then select the k best locations from each location set. To consider all possible location sets, it turns out to be sufficient to only consider circles of radius r that pass through all pairs of locations that are at most $2r$ apart.

We evaluated the performance of the proposed algorithms in the context of eBird. At the local scale, we considered Tompkins County, NY, the home of the Cornell Lab of Ornithology and eBird. To test the performance of Bird-Watcher Assistant, we compared locations recommended by our model to locations recommended by a set of expert bird watchers. Qualitatively, the locations suggested by our model were judged to be of high quality by the domain experts. Quantitatively, the locations suggested by our model achieve higher expected numbers of species than the locations suggested by the experts. The locations suggested by Bird-Watcher Assistant systematically covered the three most important habitat types for birds while promoting increased spatial coverage of the county. At a larger scale, we considered planning birding trips across multiple states, spanning more than 70,000 potential locations.

Overall, our algorithms are remarkably fast and provide high-quality birding site recommendations.

Conclusion

Citizen science programs are an effective way to engage the general public in data collection for conservation. To make citizen science programs enjoyable, this chapter presented three effective ways to stimulate participation, namely with extrinsic motivation, intrinsic motivation, and service tools. We discussed the Nchioto application, in which we used extrinsic incentives to motivate local pastoralists to monitor vegetation conditions in Eastern Africa. We then described a two-stage game called Avicaching in eBird, where we encouraged bird watchers to conduct bird observations in remote and under-sampled locations, with intrinsic motivations via friendly competitions. In addition, we discussed Bird-Watcher Assistant, a service tool to help bird watchers discover interesting and enjoyable birding locations and to further boost participation and scientific discovery. The success of each of these citizen science programs depends on novel contributions from game theory, machine learning, and combinatorial optimization of artificial intelligence. On the other hand, artificial intelligence benefits enormously from novel problems and concepts from conservation. We see the integration of artificial intelligence and conservation as a very promising interdisciplinary research direction that benefits both fields, showing the great impact of artificial intelligence to conservation.

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