The value of information for conservation auctions

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Abstract

Conservation auctions can been used to meet the objectives of natural resource managers and are designed to cost-efficiently protect biodiversity and ecosystem services. In running an auction, an agency seeks to minimize the cost it pays to get the maximum benefit from the assets bought in the auction. When the auction is completed, cost (the total cost of the winning bids) tends to be known with certainty. Often however, benefits are more uncertain (e.g., when the benefits are to be realized in the future, such as in the case of vegetation regeneration). Therefore, there is an imperative on the part of the auction-running agency to spend resources on learning about benefits to make a decision about which bids will be successful and which bids will be unsuccessful. Here we use the concept of expected value of sample information to assess how such an agency should allocate a limited learning budget among bids to conduct a conservation auction that yields the most cost-efficient return on investment. We propose a simple model system where an agent has two or more assets among which they must pick the most cost-efficient to invest in for a forthcoming auction. The cost-efficiency of each asset is more or less uncertain and there is some budget allocated to reduce the uncertainty of the assets. The agent must decide how to allocate the learning budget among the assets in order to maximize the expected benefit of the auction. We describe an analytical solution to the problem when there are two assets and the uncertainty in cost-efficiency is normally distributed. When there are more the two assets in the auction pool, then the analytical solution does not apply. Instead, we propose a heuristic solution to the problem based on optimally ranking the assets in order of cost-efficiency (rather than knowing explicitly, the exact value that determines the ranks). We compare the results of the heuristic solution to a Monte Carlo simulation of the problem to demonstrate that it arrives at the same

optimal allocation of learning resources. In applying our model to case-studies with different numbers of assets and with different prior knowledge of the assets cost-efficiency, we glean a number of rules-of-thumb that may be helpful to agencies conducting conservation auctions. When learning budgets are small then the most optimal strategy is to learn new information about the most marginal assets, that is, the assets about which the probability of being the most cost-efficient is the most uncertain. Then, as the budget increases it becomes more optimal to learn about assets which have uncertain cost-efficiency in the more general sense. Finally, as learning budgets become large enough as to not be limiting, resources can be allocated evenly across all uncertain assets. The model we propose and the analytical, heuristic solutions we apply to its case studies, imply that naive even allocation (or no allocation at all) to learning among assets in a conservation auction may lead to less than cost-efficient outcomes for the agencies that use them.

Introduction

Conservation auctions have become a widespread and established market mechanism aimed at achieving public environmental good by contracting with landholders and managers cost-efficiently (Schomers and Matzdorf, 2013). Conservation auctions include payment for ecosystem services (PES) schemes (Engel et al., 2008), environmental stewardship (Ribaudo et al., 2008) and conservation easement programs (Brown et al., 2011). Some recent examples include the US Water Quality Incentives Program (Kraft et al., 1996), the English Countryside Stewardship Scheme (Lobley and Potter, 1998), and the Bush Tender in Victoria, Australia (Stoneham et al., 2003).

Uncertainty about the benefits resulting from a conservation auction investment is not often addressed. Ignoring uncertainty may be foregoing untapped benefit in the implementation of a conservation auction. If the uncertainty in a conservation auction was reduced then it could potentially be implemented with greater cost-efficiency than it would otherwise. Here we consider the uncertainty in a conservation auction and how resources should be allocated among the assets that are candidates for investment to seeking information. We use the concept of expected value of sample information (EVSI) (Raiffa and Schlaifer, 1961) and a simple auction model to discover the best strategy to allocate resources to learning in a conservation auction. With our model and the solutions we provide below, we derive three guiding principles that will aid an agency undertaking a conservation auction in allocating resources to learning about the cost-efficiency of the assets in their auction pool.

Reverse auctions

Conservation auctions typically take the form of a reverse auction. In a reverse auction, the agency conducting the auction, usually a branch of a government, is the buyer. The bidders are the landholders or land-managers who compete for the pool of funding available by offering to sell some prespecified environmental good desired by auction-conducting agency (McAfee and McMillan, 1987). The environmental good may take the form of land title or a contract to conduct a particular management action. In some cases the outcome of management is the good specified in the contract and the management action is left up to the managers (Hanley et al., 2014). Unlike a standard auction where the buyers are competing and price is maximized, reverse auctions are aimed at reducing the price of the goods being purchased, as it is the sellers who are in competition with one another. In facilitating the competition for a single pool of funding, the auction conducting agent seeks to maximize the environmental benefit it can get for the lowest cost and thus maximize the cost-efficiency of the environmental scheme (Latacz-Lohmann and Van der Hamsvoort, 1997).

Ranking auction bids by cost-efficiency

In a typical reverse auction, aimed at getting some public environmental good, the conducting agency will assess the bids by their cost-efficiency. The bids will be ranked from highest to lowest in terms of cost-efficiency (Stoneham et al., 2003). The winning bids will be the most cost-efficient up to some cutoff. The cutoff may be the cumulative total cost of the most cost efficient bids measured against a fixed budget, or it could be a prespecified level of cost-efficiency (Latacz-Lohmann and Van der Hamsvoort, 1997). Time-limited reverse auctions will often use the budget exhaustion method whereas longer-term schemes with repeated rounds might use a cost-efficiency-based cutoff. The rank-by-cost-efficiency strategy is usually near optimal though in some circumstances it can produce non-optimal results and more sophisticated portfolio methods can be used to maximize the total benefit (Hajkowicz et al., 2007).

Conservation auctions and uncertainty

There are multiple sources of uncertainty in a conservation auction that can affect the outcome in a number of ways. Moreover, there a multiple perspectives from which to view uncertainty within the framework of a conservation auction, and the different actors may be affected by different uncertainties about different aspects of the auction. Here we focus only one aspect of uncertainty: uncertainty about the cost-efficiency of bids and only from the perspective of the agency conducting the auction. Other important facets of uncertainty in reverse-auctions, are the knowledge bidders have of one anther's circumstances and intentions and the circumstances of the seller. There is a vast game-theoretic literature dealing with these types of uncertainty in auctions (see for example Hailu and Schilizzi, 2004), but we don't deal with them further here.

After the bids are submitted in an auction, that component of the auction cost will have no uncertainty. So in most conservation auctions the bulk of the uncertainty about cost-efficiency is due to uncertainty about benefits. Conservation benefit of the kind sought after in a reverse auction is inherently uncertain as it is often only realized at some point far in future, long after the auction scheme is implemented. Land regeneration, water or soil quality improvement, or other ecosystem services are some examples of the type of benefit that is payed for at one point in time, while the payoff is not expected until much later on (Vesk et al., 2008). This time-lag in return on investment makes the cost-efficiency of auction bids uncertain. Uncertainty in the individual auction bids then leads to a necessary uncertainty in their ranking. And therefore, the uncertainty in benefits flows through to the cost-efficiency and to the total benefit realized for the conservation auction scheme.

The value of information

Given that the outcome of many conservation auctions maybe uncertain, it may be wise for an auction conducting agency to invest resources in learning about the benefits before they rank the assets and determine the winning bids. If they can increase the probability of correctly ranking the bids in order of cost-efficiency, they could avoid investing in unwarranted assets and increase the total benefits realized after the auction is completed. The performance gain one might expect after learning and a subsequent reduction in uncertainty is known as the expected value of information (Raiffa and Schlaifer, 1961). Decision makers can use an EVI analysis to predetermine the worth of learning about the outcome a decision problem such as a conservation auction. A type of EVI is the expected value of sample information, EVSI, which is the value of reducing uncertainty by some degree, by collecting a sample of data, as opposed to eliminating uncertainty completely, which is the expected value of perfect information (EVPI) (Yokota and Thompson, 2004).

Using the concept of EVSI a conservation auctioneer could work out if it would be worthwhile collecting data to learn about the benefits of a conservation auction and even how much data would be most to appropriate to collect. Here we extend the idea of expected value of sample information for a conservation auction and consider how to allocate the uncertainty reducing sample of information among the different assets available in the auction. The naive solution to problem is simply to allocate learning evenly among the assets and reducing the uncertainty about the benefits of each by the same degree. However, depending on the particular circumstances of the initial levels of uncertainty, this may not be the most optimal allocation of learning resources.

Analysis

The Model

Here we describe a simple model of a conservation auction where the cost-efficiency of each asset in the auction pool is uncertain. In our model there are, $n > 1$, assets. The i^{th} $(i = 1...n)$ asset's, A_i, cost-efficiency, c_i, is described by a normal distribution with mean, μ_i and standard deviation, σ_i. There are two separate budgets, one for investing in assets in the reverse auction and a second budget that can be used to reduce the uncertainty about the asset's cost-efficiency. The first budget is large enough to invest in any one of the assets, while the second budget is variable and can be used to collect a sample of data about the cost-efficiency of each individual asset. The total budget for data collection M, may be divided between each of the n assets in the auction with a different proportion, p_i, allocated to each asset where Mp_i is proportional to the sample-size of data collected about the cost-efficiency of the i^{th} asset. Here M can be considered to be the total sample-size given a sampling variance of one. An increase in sample-size or reduction in sampling variance would both increase the effective budget size.

Expected value under uncertainty

Under the initial level of uncertainty a risk-neutral auctioneer would simply rank the assets in order of their expected cost-efficiency and invest in the asset with the largest mean cost-efficiency. This is the expected value under uncertainty or also known as the expected value with original information (EVWOI). More formally,

$$\text{EVWOI} = \max \mu_i \tag{1}$$

Expected value of sample information

Now we turn to the allocation of sampling among the assets in the auction pool and the calculation of the EVSI. In the following sections we outline three solutions to the problem of calculating EVSI for the model above, given a sampling budget and an allocation of the budget among the assets in the auction pool. The first is an analytical solution which applies when $n = 2$. For $n = 3$ we have formulated a heuristic definition. The heuristic definition of EVSI is based on valuing the rank order of cost-efficiency rather than actual benefit achieved. We then compare these solutions to a general solution using Monte Carlo simulation. All analysis has been implemented in the programming language R (R Core Team, 2017) unless otherwise stated.

Analytical solution for $n = 2$

When $n = 2$ there is analytical solution. Its derivation can be found in Moore et al. (2017) where it is defined as:

$$\text{EVSI} = \frac{1}{2}\left(\Theta\sqrt{\frac{2}{\pi}}^{-\frac{\mu_1-\mu_2}{2\Theta^2}} + (\mu_1 - \mu_2)\,\text{erf}\left(\frac{\mu_1-\mu_2}{\Theta\sqrt{2}}\right)\right) \tag{2}$$

where,

$$\Theta = \sqrt{\sigma_1^2 \frac{Mp_1\sigma_1^2}{Mp_1\sigma_1^2+1} + \sigma_2^2 \frac{Mp_2\sigma_2^2}{Mp_2\sigma_2^2+1}} \tag{3}$$

Note that to calculate the EVPI one can replace equation (3) with $\Theta = \sqrt{\sigma_1^2 + \sigma_2^2}$. With the above definition we can find the value of p_1 (where $p_2 = 1 - p_1$) that maximizes EVSI for a given budget, M. To find the optimal solutions we used a combination of golden section search and successive parabolic interpolation (as implemented in Forsythe et al., 1977). In figure 1 we show the results of such an optimization for a case where one asset has high expected cost-efficiency and high uncertainty and the other asset has relatively lower expected cost-efficiency and uncertainty.

Heuristic solution for $n = 3$

As the analytical solution above does not hold for $n > 2$ we propose the following heuristic solution based on valuing the rank order of cost-efficiency of assets in the auction pool. To elaborate, in valuing the assets by rank we mean we assign utilities to choosing an asset that is ranked first, second or third in terms of cost-efficiency. In this sense utility is indifferent to how much better, for example, the first-ranked asset is than the second and only concerned that it is the better of the two assets. With this principle we assign utilities to each combination of asset choice, A_i, and rank order of c_i such that:

$$\begin{gathered}
u(A_1, c_1 > c_2 > c_3) = 1 \\
u(A_1, c_1 > c_3 > c_2) = 1 \\
u(A_1, c_2 > c_1 > c_3) = 0.5 \\
u(A_1, c_3 > c_1 > c_2) = 0.5 \\
u(A_1, c_2 > c_3 > c_1) = 0 \\
u(A_1, c_3 > c_2 > c_1) = 0 \\
u(A_2, c_2 > c_1 > c_3) = 1 \\
\text{etc...}
\end{gathered} \tag{4}$$

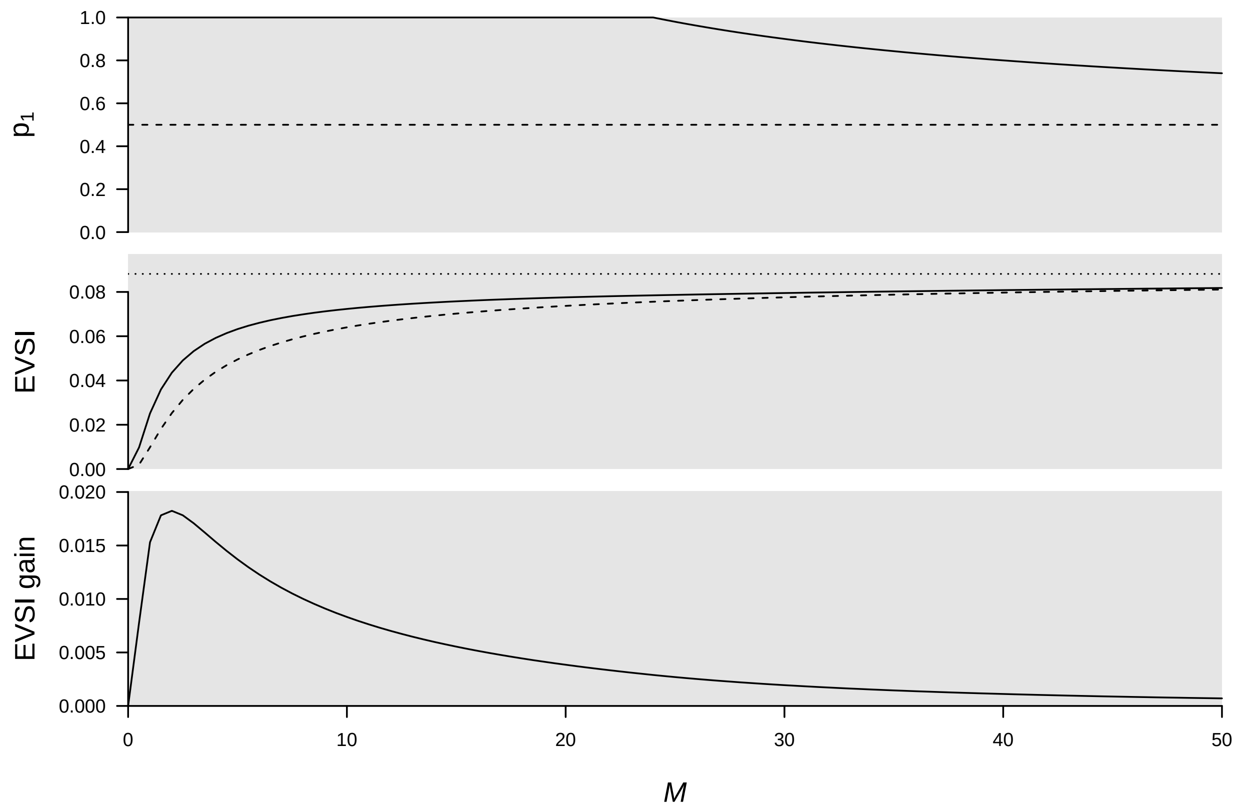

Figure 1: Analytical solution to optimal allocation of sampling between two assets. In this case, the two assets have prior distributions $\mathrm{N}(1, 1)$ and $\mathrm{N}(0, 1/5)$ respectively. The top panel indicates the optimal proportional allocation of sampling between the two assets (black line) as well as the naive allocation with even sampling between two assets (dashed line) . Here p_1 is the proportion allocated to the first asset and M is the total number of samples (the budget). The middle panel shows the EVSI for the optimal and naive sampling strategies of the panel above. The dotted line is the EVPI (0.088). The solid line indicates the EVSI for the optimal allocation while the dashed line is the naive allocation. The bottom panel indicates the gain in EVSI of using the optimal strategy over the naive solution (the difference between the two curves in the middle panel).

Note that the choice of utilities is arbitrary and that a different set of values will change the solution. However, as long as the rank order of the utilities is the same, the general shape of the solution remains. It is this that makes the solution heuristic rather than exact.

To determine EVSI given the above utilities we need only determine the probability of each rank order and calculate the expected utility of choosing each action with either the original or updated knowledge of the asset cost-efficiencies.

We can express the probability of the assets being in a given rank order as the probability of two differences being less than zero. Such that, for example,

$$\Pr(c_1 > c_2 > c_3) = \Pr(c_2 - c_1 < 0, c_3 - c_2 < 0) \tag{5}$$

Following this we define two new variables, z_1 and z_2 where

$$\begin{aligned} z_1 &= c_2 - c_1, \\ z_2 &= c_3 - c_2 \end{aligned} \tag{6}$$

When c_i are uncorrelated then the covariance of z_1 and z_2 is $-\sigma_2^2$ and they will have a joint distribution defined as:

$$\begin{bmatrix} z_1 \\ z_2 \end{bmatrix} \sim \mathrm{N}\left(\begin{bmatrix} \mu_2 - \mu_1 \\ \mu_3 - \mu_2 \end{bmatrix}, \begin{bmatrix} \sigma_1^2 + \sigma_2^2 & -\sigma_2^2 \\ -\sigma_2^2 & \sigma_2^2 + \sigma_3^2 \end{bmatrix} \right) \tag{7}$$

Given this joint distribution we can calculate $\Pr(c_1 > c_2 > c_3)$ by evaluating the multivariate cumulative distribution function, $\Phi(z_1, z_2)$ within the limits, $-\infty$ and 0, using the algorithm of Genz (Genz, 1992).

With the above we can calculate the EVWOI, which is the maximum of the expected utilities of choosing the i^{th} asset:

$$\text{EVWOI} = \max(\text{E}[u(A_i)]) \tag{8}$$

where each expected value is the sum of the utilities assigned for that choice of asset, multiplied by the rank order probabilities defined above. For example,

$$\begin{aligned}\text{E}[u(A_1)] = & 1 \times \Pr(c_1 > c_2 > c_3) + 1 \times \Pr(c_1 > c_3 > c_2) + \\ & 0.5 \times \Pr(c_2 > c_1 > c_3) + 0.5 \times \Pr(c_3 > c_1 > c_2) + \\ & 0 \times \Pr(c_2 > c_3 > c_1) + 0 \times \Pr(c_3 > c_2 > c_1)\end{aligned} \tag{9}$$

To calculate the EVSI we need not only know the EVWOI but also the expected value with sample information (EVWSI), for EVSI is the magnitude of their difference:

$$\text{EVSI} = \max(\text{E}[u(A'_i)]) - \max(\text{E}[u(A_i)]) \tag{10}$$

Where EVWOI relied on the expected utilities under the prior knowledge of cost efficiency ranking, the EVWSI relies on the expected utility under the posterior (after knowledge of cost efficiency ranking has been improved). To go from the expected utility under the prior, $\text{E}[u(A_i)]$, to expected utility under the posterior, $\text{E}[u(A'_i)]$, we need to adjust the variances in equation (7) from σ_i^2 to σ'^{2_i}, where

$$\sigma_i'^2 = \frac{\sigma_i^2}{Mp_i\sigma_i^2 + 1} \tag{11}$$

which accounts for the new information given the sampling allocation Mp_i.

Given the above, we can find the optimal values of p_i for any given learning budget, M, and set of prior distributions describing uncertainty in cost-efficiency, c_i. To find the optimal allocation of M we performed a constrained optimization using the algorithm of Nelder and Mead (1965). Figure 2 shows such an optimal allocation of M for a case where the expected cost-efficiency declines along with the level of uncertainty across the three assets.

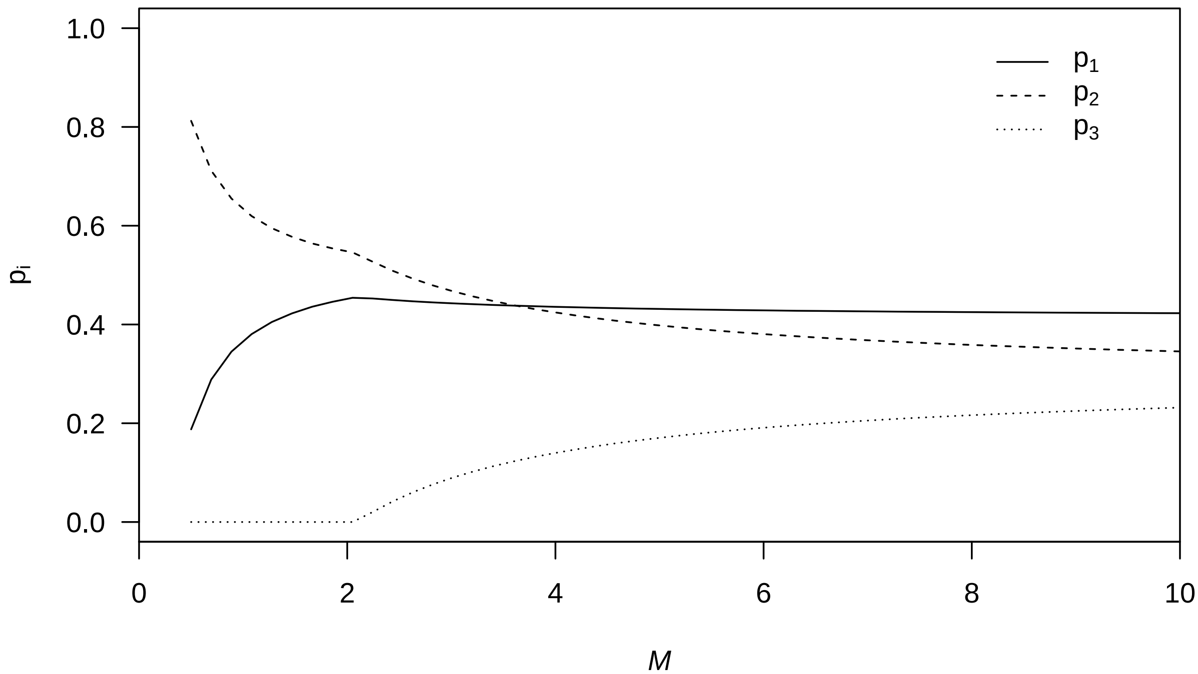

Figure 2: Heuristic solution to the optimal allocation of sampling among three assets. In this case the assets have prior distributions of $N(2, 4/5)$, $N(1/2, 5/4)$ and $N(1/2, 3/4)$ describing the uncertainty in the cost-efficiency respectively. The curves show the optimal allocation p_i of the sampling budget, M, to the first (solid line), second (dashed line) and third (dotted line) assets.

Monte Carlo Simulation

Finally we present a general solution to calculate the EVSI for the model with Monte Carlo simulation. The simulation uses an algorithm we have implemented in the programming language Julia (Bezanson et al., 2017) and presented in the pseudo code below.

Begin outer loop: for s of 1 to S, simulations

Begin inner loop: for i of 1 to n assets

1. Draw a *true* value, $c^*_{s,i}$, at random from prior distribution $\mathrm{N}(\mu_i, \sigma_i)$
2. Draw a sample mean, $y_{s,i}$, at random from $\mathrm{N}(c^*_{s,i}, \sqrt{\frac{1}{Mp_i}})$
3. Calculate a posterior mean μ'_i as weighted sum of prior and sample means $\mu_i \frac{\frac{1}{\sigma_i}}{Mp_i + \frac{1}{\sigma_i}} + y_{s,i} \frac{Mp_i}{Mp_i + \frac{1}{\sigma_i}}$

End inner loop

4. Calculate value given sample information, v_s, as *true* value of asset with largest posterior mean $c^*_{s,\mathrm{argmax}_i(\mu'_i)}$

End outer loop

5. Calculate EVSI as expected value given sample information, $\frac{1}{S}\sum_{s=1}^{S} v_s$, minus expected value given prior information, $\max_i \mu_i$

While the algorithm is relatively simple to implement and gives accurate estimates of EVSI, it is computationally expensive and the estimates are relatively imprecise. Moreover the impact of this imprecision becomes more profound as M increases, as changes in EVSI in response to changes in p_i are more subtle for larger budgets. Therefore, we use the simulation as a tool to validate assertions about optimal allocation of learning resources based on the heuristic solution above. Figures 3 and 4 illustrate the application of the simulation solution to the same case studies outline in figures 1 and 2 respectively.

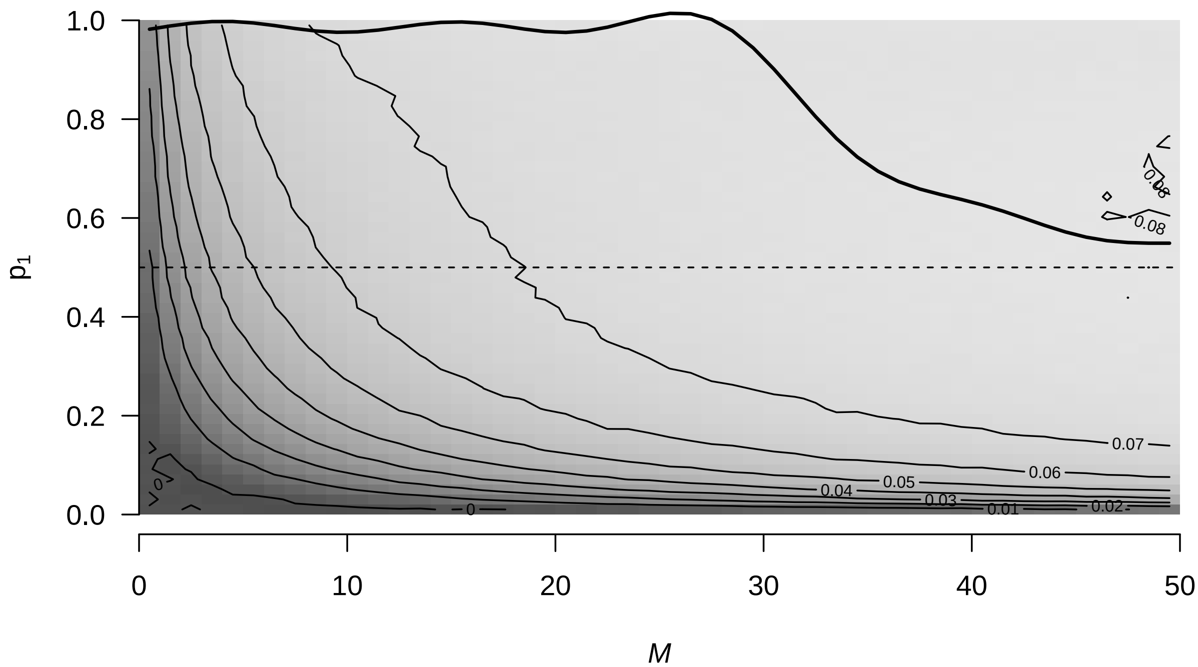

Figure 3: Simulation of EVSI for different allocations of sampling effort with increasing budget. Again, the two assets have prior distributions N(1, 1) and N(0, 1/5) respectively. Contours and shading indicates the estimated EVSI for the given allocation and budget. Dark black line is a smoothed curve fit to the optimal (maximum EVSI) value of p_1 for each budget. Note that this curve is more or less the same shape as the top panel of figure 1.

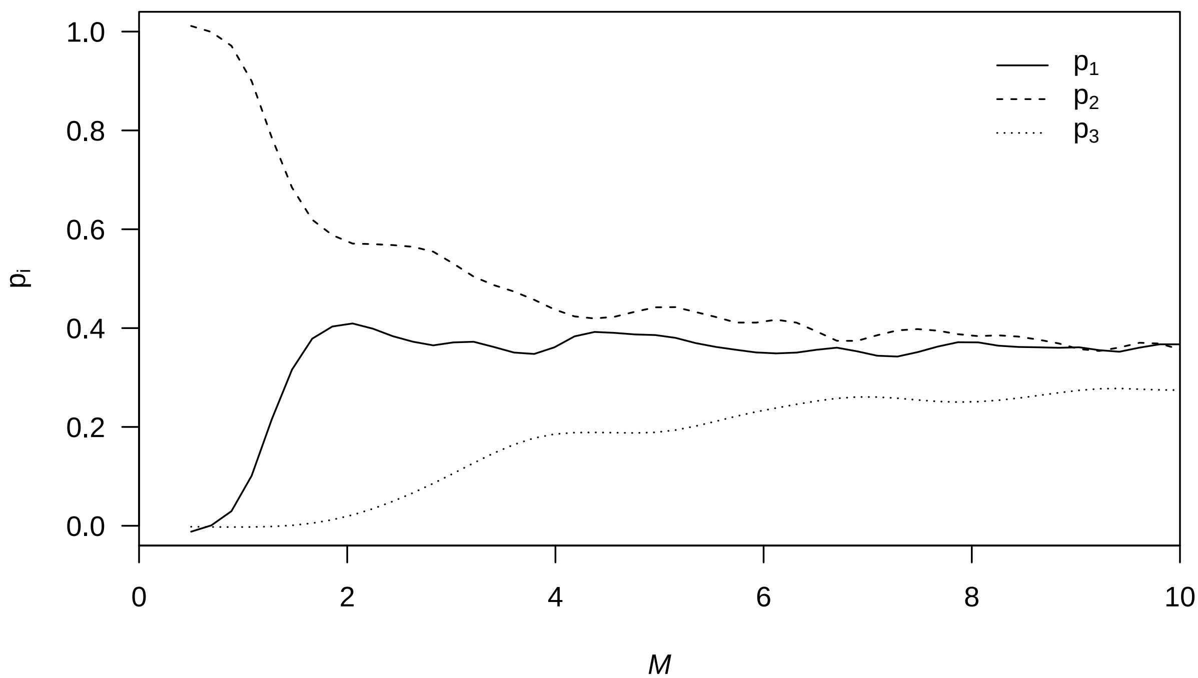

Figure 4: Simulation of optimal allocation of sampling among three assets. Prior distributions of the three assets are as in figure 2. Curves are smooth splines of the value of p_i that maximizes the simulated EVSI for a given budget level of M. Note that the three curves are broadly similar to the heuristic solution of figure 2.

Principles

From the solutions to our simple model we can glean a number of rules of thumb that agencies conducting conservation auctions should consider. By examining the analytical solution to the two asset problem we can learn a number of things, some of which hold when we increase the complexity by adding a third asset and some of which don't. In examining both the two asset and three asset solutions we have elucidated the following principles guiding the allocation of learning resources in a conservation auction.

Principle 1: Unequal sampling allocation

In general an optimized unequal allocation of sampling among the assets in an auction will have greater EVSI and result in a more cost-effective auction than simply allocating sampling equally among the assets. However, the larger the budget for learning, the less having an optimal allocation matters. For example, in the case study of figure 1 we see that the peak of expected gain from sampling optimally is for a small budget that is expected to return an EVSI about half the EVPI. As the budget increases and with it EVSI approaches EVPI asymptotically, the difference between an optimal allocation of learning and a naive, even allocation becomes negligible. When considering two assets, this principle only applies when the uncertainty around each asset's cost-efficiency is unequal. Even if each asset has a different expected cost-efficiency it is only optimal to unevenly allocate learning if the variance of their prior cost-efficiencies is unequal. However, when we consider a case with three assets, then it is only optimal to allocate evenly when all the prior means and all the prior variances are the same. That is to say, we should only allocate learning equally when we are completely in the dark about the rank order of asset cost efficiencies.

Principle 2: Learn first at the margin

Knowing that it is probably sub-optimal to allocate learning equally among assets is only useful if one knows in what way they should otherwise distribute sampling effort. The second principle is that given a relatively small to moderate budget and some state of uncertainty about the cost-efficiency of auction assets, it is wisest to prefer allocation to assets on the margin. By on the margin we mean assets that are borderline cases for potential investment. If the prior knowledge of an asset is it that is unlikely to be cost-efficient enough to warrant being a winning bid, or if the prior knowledge is that is highly likely to warrant investment, then learning about these classes of assets is less preferential than the more marginal case. In figure 2 this principle is illustrated by the fact that assets 1 and 2 demand greater allocation of sampling than asset 3, as asset 3 has the lowest prior mean cost-efficiency as well as the greatest certainty. Further, for small budgets investment in learning about asset 1 is preferred over asset 2 even though asset 2 has a greater uncertainty.

Principle 3: Learn about the more uncertain assets

Again, figure 2 highlights the final principle. Given the choice among to assets with similar cost-efficiency, it is more optimal to learn about the more uncertain. This third principle is however, superseded by the second, as it is only preferential to learn about asset 2 (the most uncertain cost-efficiency) once the budget is large enough to also satisfy the demand to learn about asset 1. What is also clear from figure 2 is that principles two and three are interactive. For when the budget is large enough the allocation to learning about asset 2 compensates for learning about asset 1.

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