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Adaptive web sampling in ecology

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Abstract Adaptive sampling strategies for ecological and environmental studies are described in this paper. The motivations for adaptive sampling are discussed. Developments in this area over recent decades are reviewed. Adaptive cluster sampling and a number of its variations are described. The newer class of adaptive web sampling designs and their spatial sampling uses are discussed. Case studies in the use of adaptive sampling strategies with ecological populations are cited. The nature of optimal sampling strategies is described. Design-based and model-based approaches to inference with adaptive sampling strategies are summarized.

Keywords Sampling · Adaptive sampling · Adaptive cluster sampling · Adaptive web sampling · Optimal sampling strategies · Ecological sampling

1 Introduction

The difficult-to-sample nature of many ecological populations has motivated the development of adaptive sampling strategies. In a typical survey of animals or plants, the population is highly uneven in its distribution, sometimes extremely rare, and may occur in an extremely clustered pattern. If these patterns are known in advance they can be largely accommodated with conventional sampling designs such as stratified sampling or systematic sampling. In many cases the patterns are not known in advance.

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In addition the pattern of the population distribution may change unpredictably between surveys.

Adaptive sampling strategies for ecological or other spatial surveys are surveyed in this paper. Section 2 describes the idea of adaptive sampling in general and what distinguishes an adaptive design from a conventional one. Section 3 describes adaptive cluster sampling and some of its variations. Section 4 describes adaptive web sampling, with particular attention to its spatial sampling uses. Section 5 takes a look at some of the case studies of adaptive designs for ecological surveys. Optimal sampling strategies, which are in general adaptive, are described in Sect. 6. In Sect. 7, approaches to inference with data from adaptive sampling are described.

2 Adaptive sampling

An adaptive sampling design is one in which the procedure for selecting the sample depends on sample values observed during the survey. For conventional survey designs such as simple random sampling, stratified random sampling, two-stage sampling and so on, the procedure for selecting the sample can be characterized by the probability function $p(s)$, $s \in \mathcal{S}$, where s is the sample of units and $\mathcal{S}$ is the collection of all possible samples. For an adaptive design the sample selection probability is $p(s \mid y)$, where y represents the target variable of interest. Sometimes an auxiliary variable x is available, in such a way that the the selection probability is given by $p(s \mid y, x)$; i.e., it also depends on the auxiliary variable x. If x is known before the sample is selected then the design is not necessarily adaptive.

Field studies in ecology have provided a significant part of the motivation for developing adaptive sampling designs and related inference methods. Indeed, many populations of fish, plants, insects, birds, mammals, crustaceans, mollusks, and microorganisms have spatial distributions that are rare, clustered, and unevenly distributed. Adaptive strategies offer a way for the selection of sample sites to depend on the patterns in the population distribution encountered during the survey.

Additional motivation for adaptive sampling methodologies comes from theoretical results showing that in principal the optimal sampling strategy is in most cases an adaptive one.

3 Adaptive cluster sampling

Adaptive cluster sampling was introduced in Thompson (1990) and its follow-ups Thompson (1991a,b). The procedure involves first selecting a conventional sample of units, such as spatial plots, from the study region. When any of these sample plots are found to have interesting values of the variable of interest, such as high abundance of animals, neighboring units are added to the sample. If any of the added units also has values satisfying the condition its neighbors are added as well. This process continues until, for any unit in the sample satisfying the condition, its neighbors have been added as well. In this way, whenever a cluster of high abundance has been encountered in the sampling, the investigators are enabled to explore the surrounding region and so eventually take in the whole cluster.

The advantage of bringing entire clusters or "networks" into the sample is that the procedure allows selection probabilities for many of the units in the sample to be calculated. Exceptions are the edge units brought in at the edge of the natural clusters, around which further exploration was not done. Simple unbiased estimators of population abundance are obtained with this procedure using the inclusion or selection probabilities for those units for which the probabilities can be calculated. These units include all the units of high observed abundance. Typically, the edge units contain zero or very low values, depending on the condition set.

Values of edge units can be incorporated by taking the conditional expectation of the initial estimator given the minimal sufficient statistic, thus forming the Rao–Blackwell improved version of the estimator. These improved estimators were described in Thompson (1990), where they were computed for small sample sizes. Analytical expressions for them were given in Félix-Medina (2000). Further advances using the Rao–Blackwell method to improve estimators in adaptive cluster sampling were given in Salehi (1999) and Chao et al. (2011). A Markov Chain Monte Carlo method for the computation of the Rao–Blackwell estimators for adaptive sampling designs was presented in Thompson (2006).

A wide variety of additional adaptive cluster sampling strategies have been developed. Brown (1999), Brown and Manly (1998), Brown et al. (2008) examined and compared a number of adaptive sampling procedures including variations to control sampling effort in adaptive cluster sampling. Christman (2000) reviewed quadrat-based sampling including adaptive cluster sampling for sampling of rare, geographically clustered populations. Christman (2003) introduced adaptive two-stage, one-per-stratum sampling. Christman and Lan (2001) introduced an inverse adaptive cluster sampling design. Christman and Olkin (1997) investigate efficiency of adaptive sampling designs for spatially clustered populations. Christman and Pontius (2004) develop bootstrap confidence intervals for adaptive cluster sampling.

Salehi and Seber (1997a) introduced adaptive cluster sampling without replacement of networks. Salehi (2003) compared Hansen-Hurwitz and Horvitz-Thompson types of estimators for adaptive cluster sampling. Salehi (2006) describe a type of design designated "adaptive cluster row and column elimination sampling+(1) design." Salehi and Seber (1997b) introduce a two-stage adaptive cluster sampling. Salehi and Smith (2005) describe a neighborhood-free adaptive sampling procedure. Salehi (1999) considered the Rao–Blackwell versions of the Horvitz-Thompson and Hansen-Hurwitz in adaptive cluster sampling, while Muttlak and Khan (2002) introduced an adjusted two-stage adaptive cluster sampling design.

Multivariate aspects of adaptive cluster sampling are discussed in Dryver (2003), Gattone and Di Battista (2004) and Thompson (1993). Dryver and Chao (2007) describe ratio estimators in adaptive cluster sampling, and Chao et al. (2011) used the Rao–Blackwell approach to improve ratio estimators in adaptive cluster sampling. Dryver and Thompson (2005) describe some improved unbiased estimators in adaptive cluster sampling. Dryver and Thompson (2007) introduced adaptive sampling without replacement of clusters. Dryver et al. (2012) describe a partial systematic adaptive cluster sampling design. Borkowski (1999) developed Horvitz-Thompson estimation for a type of adaptive simple latin square sampling. Rocco (2003) introduced constrained inverse adaptive cluster sampling. Rocco (2008) describes a two-stage restricted adaptive cluster sampling design. Di Consiglio and Scanu (2001) give some results on asymptotics in adaptive cluster sampling. Pontius (1997) introduced probability-proportional-to-size strip adaptive cluster sampling. Perez and Pontius (2006) compare bootstrap and normal confidence interval estimation under adaptive cluster sampling. An earlier review of adaptive cluster sampling is given in Turk and Borkowski (2005).

4 Adaptive web sampling

Adaptive web sampling was introduced in Thompson (2006) as a way to free adaptive designs in spatial and network settings to be as flexible as desired. All of the adaptive spatial designs described so far can be recast as a network sampling situation. A network has nodes, which here are the sampling units or plots, and links, which represent relationships or connections between nodes. Sampling in networks applies directly to populations having inherent network structure, such as hidden human subpopulations in which social links between subpopulation members are used to add more individuals from the hidden population to the sample. In non-human ecology, network structures are found in studies of habitat patches, which are the nodes, connected by corridors, which serve as the links. Network dynamics are also encountered in studies of epidemics in natural populations, for example in the spread of bark beetles between trees or the spread of simian immunodeficiency virus (SIV) among chimpanzees.

In the spatial setting involving plots and adaptive addition of neighboring plots, an equivalent network structure can be described as follows. The spatial units or plots become the nodes in a network. For a unit that satisfies the condition of interest, such as having high abundance of an animal or plant species, an arrow is drawn from that unit to each of its neighbors. The arrow represents a directional link, or edge, between two units or nodes. If the neighboring unit in turn satisfies the condition then an arrow is drawn from it to each of its neighbors, including the unit that initiated the finding of that neighbor in the first place. In this way the whole population of units superimposed over the unevenly clustered population is translated to a directed graph, having symmetric links between neighboring units satisfying the condition and asymmetric or directed links from any unit satisfying the condition to its neighboring edge units.

In adaptive web sampling, an initial sample of nodes is selected by simple random sampling or other conventional design. The values of these nodes are observed together with the existence or absence of the links out from them. Some of these links go to other units already in the sample, while others lead out from the sample. In simple adaptive web sampling one of these links out is selected at random and followed to bring a new unit into the sample. The added unit in turn may have links and may add to the total set of links out from the current sample. One of these links in turn is selected. In addition, however, with small probability, instead of following a link, a new node is selected at random from the entire population of units not yet included in the sample. In this way the sampling continues step by step until the desired sample size of units is reached. If at any step there are no links out from the current sample, the next unit is selected at random.

With adaptive web sampling the sample size may be fixed in advance and it is not necessary to completely sample the encountered clusters or natural aggregations of plants or animals. Encountered aggregations tend to be explored well but not necessarily exhaustively. Rather, the adaptive sampling of clusters is balanced with the random jumps to unexplored areas of the study region. In this way the sampling spreads weblike into interesting areas of the population while never getting stuck in large networks. The balance between the exploration of aggregations spreading the sampling effort more evenly can be set with the probability of the random selections versus neighborhood link tracing.

Many variations and modifications are possible with adaptive web sampling. The sampling can be without replacement, as described above, or with replacement. The sample size can be fixed, or can be based on a criterion such as complete sampling of encountered aggregations. At each step a single unit can be added, or a whole set of units can be added at a time. The links out from the current sample can be selected at random, or selection of links to follow can be with unequal probability based on link weights. The weight can be, for example, proportional to the value of the originating node, so that the neighbors of units having a high abundance of animals are the most likely to be added to the sample. Some of the possible variations with adaptive web sampling are described in Thompson (2011) and Vincent and Thompson (2012).

More generally in adaptive web sampling there is an active set of current sample units from which links are followed, that is, from which neighbors are selected. In the simple version above, the active set is the whole current sample. However, the active set could consist for example of only the most recently selected 10 units.

The simple unbiased estimators of adaptive cluster sampling are not possible with adaptive web sampling in the cases where not all units in an encountered natural aggregation are sampled. Instead, efficient estimation methods use the Rao–Blackwell method and its MCMC computational counterpart or model-based Bayes estimates as described in the section on inference approaches.

Spatial adaptive web sampling was investigated in Thompson (2006) using the wintering waterfowl population data set used by Smith et al. (1995) in their study of adaptive cluster sampling. Using a fixed total sample size, as is possible with adaptive web sampling, initial sample sizes ranged from one unit up to the total sample size. The lowest mean square error of estimates was obtained when the initial sample size in adaptive web sampling was about 65 % of the final sample size, so that adaptive additions made up the remaining 35 % of the sampling effort. The initial sample serves to spread the sample throughout the study region for good overall coverage, while the adaptive part provides needed additional coverage in the high-abundance, high-variability aggregations of birds.

5 Case studies of adaptive sampling in ecology

A number of studies have used and investigated adaptive sampling designs for specific ecological populations. Seber and Thompson (1994) described adaptive sampling applications to ecology in general. McDonald (2004) summarizes the experiences of a number of investigators in practical uses of adaptive cluster sampling. Philippi (2005) examined adaptive cluster sampling for estimation of abundances within local populations of low-abundance plants. Acharya et al. (2000) investigated adaptive cluster sampling for assessment of rare tree species in Nepal. Smith et al. (2003) studied the application of adaptive cluster sampling to low-density populations of freshwater mussels. Su and Quinn (2003) discuss adaptive cluster sampling with order statistics and a stopping rule for a fish population. Mier and Picquelle (2008) compare adaptive sampling with other survey designs for fish populations. Magnussen et al. (2005) describes the use of adaptive cluster sampling for estimation of deforestation rates. Noon et al. (2006) compare the efficiency of adaptive cluster and random sampling of amphibians in a tropical rainforest. Roesch (1993) did a study of cluster sampling for forest inventories, developing in the process a new unequal-probability design variation. Talvitie et al. (2006) examine inventories of sparse forest populations using adaptive cluster sampling. Woodby (1998) examined the use of adaptive cluster sampling to survey red sea urchins, describing an interesting variation with systematic sampling which limits the total sample size. Skibo et al. (2008) describe a further study of adaptive cluster sampling in comparison with other designs for sampling sea urchins. Di Battista (2003) examined a variety of sampling designs including adaptive cluster sampling for estimating dispersion indices. Cabral and Murta (2004) used adaptive cluster sampling among other designs for benthic invertebrates in environmental monitoring studies. Goldberg et al. (2007) describe the application of adaptive cluster sampling for rare subtidal algae species. Khaemba and Stein (2002) describe the use of adaptive sampling for improving airborne surveys of African wildlife.

6 Nature of optimal sampling strategies

An optimal sampling strategy for a given type of population is a design together with an estimation procedure that gives the lowest possible mean square error. Optimal strategies only exist in the model-based sampling setup, in which a statistical model describes the stochastic properties of the population being studied. For ecological populations the appropriate types of models are spatial models allowing for properties such as spatial correlations and clustering. Bayes models provide the fullest and most meaningful context in which to explore optimal sampling strategies.

Theoretical results showing that in most cases the optimal sampling strategy is a sequential or adaptive one were given by Zacks (1969) and Basu (1969). Some explanation and extension of these results is given in Thompson and Seber (1996), Chap. 10. Chao and Thompson (2001) computed sample-selection efficiency results of optimal spatial selection of sampling sites, illustrating the selection patterns graphically. Computational advances are described in Chao (2003). The model used was a spatial log-Gaussian model with covariance function decreasing with distance. Small population and sample sizes and a two-phase adaptive design were used because of the computational intensity, a problem anticipated by Zacks (1969). Nonetheless the results were highly evocative. The characteristics of the optimal adaptive sample selections can be described as seeking a balance between exploring the conditionally most promising areas of the study region given the sample observations so far and spreading the remaining sample into the areas least sampled so far. The first characteristic calls for adaptive selection of new sample sites near high observed values, while the second calls instead for space-filling selections. The optimal strategy emerges between the push and pull between these competing objectives. The mean square error in estimating the population mean in the Chao and Thompson (2001) study for the optimal adaptive strategy was about one-seventh that of the optimal conventional design (which with that model is a systematic one).

Adaptive designs such as adaptive cluster sampling and adaptive web sampling, while not optimal, capture much of the spirit of the optimal strategies. The adaptive addition of neighboring or linked units near high observed values explores promising areas of the study region taking account of what has been observed so far. The countervailing space-filling is provided by the selection of the initial sample and the small-probability random selections at each step.

7 Approaches to inference in adaptive web sampling

Adaptive sampling procedures typically increase the yield of a sample. That is, a sample is obtained that most often has higher values on average of the variable of interest than is representative of the population as a whole. More precisely, the adaptive procedure produces more than the average number of units satisfying the condition for the adaptive selections. In ecological studies, most often the condition of interest is high abundance values.

While high-yield designs have many advantages in their own right, for example giving botanists a better knowledge of the distribution of a rare species, producing more observations on the behavior of animals, or revealing the patchy locations of insect infestations, the sample mean with such a design does not give an unbiased estimate of the population mean. Effective estimation procedures require that the adaptive selection procedure be taken into account at the estimation stage.

The two main approaches used to obtain effective estimates of population quantities from adaptively selected sample data are design-based and model-based. In the design-based approach, the population is viewed as having fixed but unknown values of the variable of interest. Uncertainty arises because of the selection of only a sample of those units. Inference properties are determined by the design-induced selection probabilities.

In the model-based view, the values or the variables associated with the units in the population are modeled as random variables, not necessarily independent of one another, having a statistical distribution that may depend on unknown parameters. The objective is to estimate or predict the actual population total, mean or other characteristic realized from these random variables, based on the sample data.

The interconnection between these views in relation to adaptive sampling is described in Thompson and Seber (1996). An advantage of the design-based approach is that it does not rely on modeling assumptions about the characteristics of the population. With ecological populations, realistic modeling of the population and its spatial characteristics is often difficult. The model-based approach, although requiring that the population be modeled, has the advantage that considerable flexibility can then be allowed in how the design is done.

7.1 Design-based approach

Many of the practical inference methods developed so far for adaptive sampling are design-based. Adaptive cluster sampling uses the complete selection of networks of units underlying clusters to enable calculation of unit selection probabilities. For edge units for which these probabilities could not be calculated using sample data, Rao–Blackwell improvement of the initial estimator is possible, with which edge units are weighted into the estimator. The initial estimators are constructed using variations on the Hansen-Hurwitz, Horvitz-Thompson, Das Raj, and Murthy estimators.

For estimation with adaptive web sampling four types of initial design-based estimators are given in Thompson (2006). The first is based on the initial, conventionally selected sample. The other three are based on that together with the conditional selection probabilities involved in selecting the remaining the rest of the sample. Each of these estimators can be improved with the Rao–Blackwell method. A Markov Chain Monte Carlo method makes the Rao–Blackwell estimation practical.

7.2 Model-based approach

Some general ideas about model-based inference approaches for adaptive sampling were examined in Thompson and Seber (1996), Chap. 3. There it was determined that among model-based approaches, the likelihood-based approaches such as maximum likelihood and Bayes estimation or prediction would be more promising with adaptive sampling than would frequentist model-based approaches such as minimum variance unbiased estimation. In many cases the adaptive designs, such as adaptive cluster sampling and adaptive web sampling, are "ignorable" selection mechanisms for likelihood-based inference but nonignorable for frequentist-based inferences.

Since then model-based, Bayes inference methods for adaptive designs have been developed in works including Thompson and Frank (2000), Chow and Thompson (2003), Kwanisai (2005, 2006), Rapley and Welsh (2008), Conroy et al. (2008), and Handcock and Gile (2010). Except in fairly simple cases, the practical implementation of these approaches involves the use of Markov Chain Monte Carlo in a computational Bayes approach.

8 Discussion

The direction of progress in the development of adaptive sampling strategies has focused on obtaining increasingly effective sampling methods for inherently hard-to-survey populations. Objectives have included increased flexibility in implementation of the designs, the development of a variety of inference approaches, improvements in computational methods for inference, and increased simplicity of designs. Each of these areas are amenable to improvements with future research.

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