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BAYESIAN DISCOVERY SAMPLING: A SIMPLE MODEL OF BAYESIAN INFERENCE IN AUDITING

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Bayesian Discovery Sampling: a simple model of Bayesian Inference in Auditing

by

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Abstract

Once auditors have been convinced of the advantages of Bayesian inference their difficulties in practical applications are not the same as statisticians have. The mathematical formulations of prior and posterior probabilities only need to correspond with the auditor's subjective ideas about the presence of errors in a population to be audited; exact derivations are left to specialists.
The auditor, however, has other problems to solve:

1. How can he objectively specify his prior knowledge about the population?
2. How can he objectively interpret posterior probabilities to decide how to audit this population?

In this paper the above-mentioned questions are answered by showing that the methodology of discovery sampling gives all the information needed to specify the prior and to interpret the posterior densities. This results in a Bayesian version of a methodology that has already been used by auditors for a number of years.

By using the Bayesian model of discovery sampling presented in this paper, auditors are not only able to reduce sample sizes but will also exactly know the importance of the assumptions they have made in order to achieve this efficiency.

1. Introduction

Until a few decades ago, auditors used to examine all entries and records of the company to be audited. Because of the steadily growing size of many corporations, the volume of entries became so large that checking all entries became almost impossible and anyhow uneconomical. Therefore auditors have to rely on the examination of only a portion of the entries to give an opinion about the populations underlying the financial statements. This eventually results into an opinion whether the financial statements show a true and fair view of the size and composition of the assets and liabilities and of the earnings of the corporation. In balancing the resulting level of confidence and precision against costs involved statistical sampling methods have proved to be very useful for both attribute sampling (a.o. discovery sampling) and variable sampling.

The Dutch member firm of Touche Ross International has applied statistical methods in auditing for a period of 30 years. An overall methodology has been designed, including hypothesis testing, error evaluation methods, regression estimators and outgoing quality limit methods, cf. Kriens (1979), Kriens and Dekkers (1979), Kriens and Veenstra (1985), Van Batenburg, Kriens and Veenstra (1987), Kriens (1988).
At the moment progress is made with the implementation of Bayesian inference.To show how fruitful Bayesian inference can be, the Center for Quantitative methods and Statistics of Touche Ross Nederland has built a simple model in which the Bayesian notion of prior and posterior probabilities is combined with the classical method of discovery sampling.
In section 2 of this paper, our version of discovery sampling in the classical manner is presented. In section 3, Bayesian methodology is applied to the parameters of this classical method. Section 4 describes the complete model of Bayesian discovery sampling, and in section 5 some numerical examples are presented to show the efficiency in sample sizes of Bayesian inference over classical methodology.

2. Discovery sampling

In this section, a brief outline of discovery sampling as used by Touche Ross Nederland is presented. This methodology of "testing for major errors" implies a statistical evaluation of those errors that should not be present in the population to be audited. The aim of this paper is not to discuss this methodology, but to show the advantages of Bayesian inference.

Let p be the error fraction in a population. The null hypothesis

$$H_0 : p = 0$$

is tested against

$$H_1 : p > 0.$$

It is obvious to take as the critical region of this test

$$Z = \{k | k \geq 1\},$$

k representing the number of errors in a random sample of size n taken from the population to be audited. By taking this very null hypothesis, standard testing theory is reasonably simplified: the probability of a type I error, α (wrongly rejecting a perfect population) equals zero, so attention can be focused completely on the probability of a type II error. The symbol β is - as usual - given to the probability to accept a population that is not perfect.

The random variable $\underline{k}$ follows a hypergeometric probability function which can often be approximated by a binomial probability function. Using this approximation the probability of a type II error equals:

$$\beta = P(\underline{k} = 0|n,p) = (1-p)^n.$$

The parameters β_0 and p_1 are chosen by the auditor, stating: 'when the true error percentage exceeds p_1, the probability of not noticing this from the sample may not exceed β_0'. Sample sizes can now be deducted:

$$\beta \leqq \beta_0 \text{ when } n \geqq \frac{\log \beta_0}{\log(1-p_1)} .$$

Some interesting minimal sample sizes used for testing in this manner are presented in table 1, to which can be added that in practical applications β_0 is usually chosen to be 1% or 5%, whereas p_1 almost never exceeds 5%.

Table 1. Sample sizes for discovery sampling based on binomial probabilities.*)

p_1 \ β_0	1%	2%	5%
0,1%	4603	3911	2995
0,2%	2301	1955	1497
0,5%	919	781	598
1%	459	390	299
2%	288	194	149
5%	90	77	59
10%	44	38	29

*) Poisson approximations to this formula, often frequented, are mathematically a little simpler but will always result in larger sample sizes.

3. A Bayesian view on the parameters in discovery sampling

The critical error fraction p_1, chosen by the auditor in order to decide on the sample size to be used, together with the maximal probability β_0 of a type II error to be allowed, will also be the outcome of the calculation of the upper limit of the one-sided $100(1-\beta_0)\%$ confidence interval for p given a random sample of size n in which no errors occurred. This can be verified by specifying the formula by which this upper limit is calculated:

$$\mathrm{Min}\{p \mid P(\underline{k}=0) \mid n,p) \leqq \beta_0\}.$$

Assuming one wants to exploit this information from year t in the sampling process for year t+1, it is, from a Bayesian point of view, reasonable to fit a prior distribution (Pr(.)) on $\underline{p}$ for year t+1 such that

$$(3.1) \qquad P(\underline{p}>p_1) = \beta_0.$$

The confidence interval $[0,p_1]$ implies that with a confidence level of $100(1-\beta_0)\%$ only values of p between 0 and p_1 are taken into account; a prior distribution satisfying (3.1) states that with probability $100(1-\beta_0)\%$ the value of $\underline{p}$ is $\leqq p_1$.

The next question is what kind of prior distribution can be used. Because the method is meant to confirm the auditor's belief that no major errors are present, there is a genuine possibility that p = 0 and that small values of p are far more likely than larger ones. Therefore it is obvious to use a prior distribution with $P(\underline{p}=0) = h_0 (> 0)$ and for values of $p > 0$, a beta density with r = 1 and s still to be identified:

$$(3.2) \qquad \begin{aligned} &P(\underline{p}=0) = h_0 \\ &\Pr(p) = \begin{cases} (1-h_0)s(1-p)^{s-1} & 0 < s \leqq 1 \\ 0 & \text{elsewhere.} \end{cases} \end{aligned}$$

For simplicity we avoid problems of estimation and of validation by restraining ourselves to $h_0 = 0$; values $h_0 > 0$ will further reduce the necessary sample sizes.
The parameter s is chosen applying (3.1). Figure 1 gives a rough idea of the prior distribution.

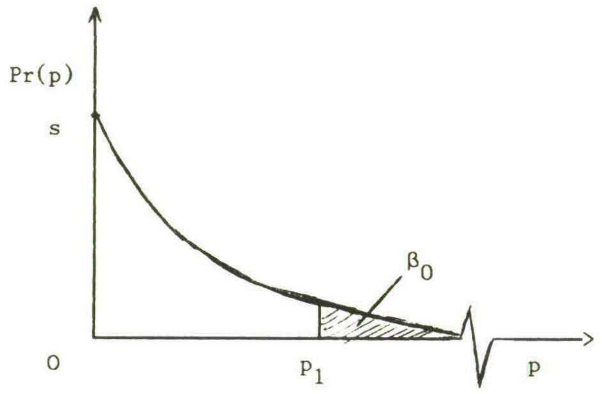

Figure 1. Sketch of a prior distribution for $\underset{\sim}{p}$

The idea to use a beta prior distribution in similar situations is standard; in the context of discovery sampling a more general version of (3.2) was presented by Kriens as early as 1963; cf. Kriens (1963).

In accordance with the arguments given in section 2 the posterior distribution of the random variable $\underset{\sim}{p}$ in year t+1, following from the Bayesian model, is required to satisfy

$$(3.3) \quad P(\underset{\sim}{p}>p_2) = \beta_2,$$

with p_2 and β_2 to be chosen. By stating the classical parameters β_2 and p_2 in the usual way ('when the error fraction exceeds p_2, the probability of not noticing this from the sample may not exceed β_2'), the auditor has declared which posterior probability he wants to achieve using the Bayesian model. This complete model is presented in the next section.

An approach different from (3.3) is also possible; one can require the posterior probability $P(\underline{p}=0|n, k=0)$ to be sufficiently high, say $\geqq h_1$. In this approach all attention is focussed on the point mass in $p = 0$, in stead of on the upper limit of the confidence interval. We use (3.3) because it provides a mean to explicitly use the parameters of discovery sampling which is in agreement with Touche Ross Nederland's practice.

4. The model

4.1. Prior probability for the fraction of errors in year t+1:

$$\Pr(p) = s(1-p)^{s-1} \qquad 0 \leqq p \leqq 1$$

$$= 0 \qquad \text{elsewhere.}$$

4.2. Probability of zero errors in a random sample of size n from a population with error fraction p:

$$L(\underline{k}=0|n,p) = (1-p)^n.$$

4.3. The posterior probability function Po for $\underline{p}$ results from the following calculations:

$$\mathrm{Po}(p|\underline{k}=0,n) = \frac{L(\underline{k}=0|n,p)\Pr(p)}{\int_0^1 L(\underline{k}=0|n,p)\Pr(p)dp}$$

$$= \frac{s(1-p)^{n+s-1}}{\int_0^1 s(1-p)^{n+s-1}dp}$$

$$= (n+s)(1-p)^{n+s-1} \qquad 0 \leqq p \leqq 1.$$

4.4. Prior identification: from the audit of year t a $100(1-\beta_t)\%$ confidence interval is calculated to have one-sided upper limit p_t. Therefore we take:

$$\beta_t = P(\underline{p}_t > p_t) = \int_{p_t}^1 s(1-p)^{s-1}dp = (1-p_t)^s,$$

which results in:

$$s = \frac{\log \beta_t}{\log (1-p_t)}.$$

4.5. Requirements for posterior identification: auditing in year t+1 is started by specifying p_{t+1} and β_{t+1}, which yield:

$$\beta_{t+1} = P(\underline{p}_{t+1} > p_{t+1})$$

$$= \int_{p_{t+1}}^{1} (n+s)(1-p)^{n+s-1}\, dp = (1-p_{t+1})^{n+s},$$

which gives:

$$n+s = \frac{\log \beta_{t+1}}{\log (1-p_{t+1})}.$$

Just as in section 3, an equivalence is created between the parameters of discovery sampling p_{t+1} and β_{t+1} on one hand, and a posterior density that satisfies $P[\underline{p}_{t+1} > p_{t+1}] = \beta_{t+1}$ on the other hand.

4.6. Combining this result for n+s and the expression for s in 4.4, sample size n equals:

$$n = \frac{\log \beta_{t+1}}{\log (1-p_{t+1})} - \frac{\log \beta_t}{\log (1-p_t)}.$$

4.7. The prior density of $\underline{p}$ in year t+1 is derived from the information found in year t. This actually implies that the auditor states that populations to be audited in years t and t+1 are completely equivalent.

This will usually not be true and the population to be audited in year t+1 will only be comparible with the population in year t to a certain extent. As a measure of comparibility a factor f on the interval [0,100%] is introduced, which indicates the auditor's opinion on comparability. If the auditor is of the opinion that both populations are completely equivalent, he gives f the value 100%. However, if he thinks that both populations are completely incomparible the value for f will be 0. The latter may occur if in year t one or more major errors were found; as a consequence measures will have been

taken to improve the situation in such a way that new major errors are considered to be impossible.
Using the factor f sample size n(year t+1) for year t+1 can be calculated as a weighted average between classical and Bayesian sample sizes:

$$n\ (\text{year } t+1) = (1-f).n(\text{year } t+1 \text{ without Bayes}) +$$

$$+ f.n(\text{year } t+1 \text{ with Bayes}) =$$

$$= (1-f).\left[\frac{\log \beta_{t+1}}{\log\ (1-p_{t+1})}\right] +$$

$$+ f.\left[\frac{\log \beta_{t+1}}{\log\ (1-p_{t+1})} - \frac{\log \beta_t}{\log\ (1-p_t)}\right] =$$

$$= \frac{\log \beta_{t+1}}{\log\ (1-p_{t+1})} - f\ \frac{\log \beta_t}{\log\ (1-p_t)}.$$

As was to be expected for f = 0 the sample size equals the value derived in section 2. If f is chosen to be equal to 100% and β_{t+1} and p_{t+1} are chosen equal to β_t and p_t respectively, the necessary sample size equals 0; it is the auditor's responsibility to indicate whether this is acceptable. At the moment, research is carried out in order to find methods to assess specific values of f that are corresponding with the auditor's approach to specific audit situations.

5. Numerical examples

Let us assume that in year t, an auditor has drawn a random sample of 59, in which no errors were found. When deciding on the audit sampling plan for year t+1, the auditor again has to decide on the critical error fraction and the confidence level required. If, for example, the auditor once more decides to take p_{t+1} = 5% and β_{t+1} = 5%, according to section 2, a new sample of 59 is required.
The auditor, however, by using his prior knowledge, can decide if there is a justified reason to choose a value for f. Logically, taking f = 100% results in a zero sample size because this assumption implies that last year's audit sample is completely sufficient for this year's audit.
The bottom row of table 2 shows sample sizes required for this year's audit with β_{t+1} = 5% and p_{t+1} = 5%, depending on the chosen value of f.
Let us furthermore assume that the auditor will take his responsibility for setting f at 70%. He can now decide on three strategies, or even a combination of these:

- a sample size of 18 would be sufficient for discovery sampling with p_{t+1} = 5% and β_{t+1} = 5%;
- by taking a new sample of 59, he can perform discovery sampling with p_{t+1} = 3% and β_{t+1} = 5%, (table 2) which would have required 99 sample items without Bayesian inference;
- by taking a new sample of 50, he can perform discovery sampling with p_{t+1} = 5% and β_{t+1} = 1%, (table 3) which would have required 90 sample items without Bayesian inference.

A combination of these strategies eventually leading to β_{t+k} = 1% and p_{t+k} = 1% in k years, could even be possible. For the moment, no discussions about these strategies have yet been held with auditors: the only objective of this research project was to show the fact that sample sizes can be reduced when using acceptable and well-founded prior information in a Bayesian model.

Table 2. Sample sizes in Bayesian discovery sampling.

prior: upper limit 5%
confidence level 95%
fictive sample size (rounded down) 58

posterior: confidence level 95%

upper limit	sample size without Bayes	Bayesian sample sizes									
		f=100%	90%	80%	70%	60%	50%	40%	30%	20%	10%
1%	299	241	247	253	259	265	270	276	282	288	294
2%	149	91	97	103	109	115	120	126	132	138	144
3%	99	41	47	53	59	65	70	76	82	88	94
4%	74	16	22	28	34	40	45	51	57	63	69
5%	59	1	7	13	19	25	30	36	42	48	54

Table 3. Sample sizes in Bayesian discovery sampling.

prior: upper limit 5% confidence level 95% fictive sample size (rounded down) 58											
posterior: confidence level 99%											
upper limit	sample size without Bayes	Bayesian sample sizes									
		f=100%	90%	80%	70%	60%	50%	40%	30%	20%	10%
1%	459	401	407	413	419	425	430	436	442	448	454
2%	228	170	176	182	188	194	199	205	211	217	223
3%	152	94	100	106	112	118	123	129	135	141	147
4%	113	55	61	67	73	79	84	90	96	102	108
5%	90	32	38	44	50	56	61	67	73	79	85

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