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Efficient computation of partial expected value of sample information using Bayesian approximation

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Abstract

We describe a novel process for transforming the efficiency of partial expected value of sample information (EVSI) computation in decision models. Traditional EVSI computation begins with Monte Carlo sampling to produce new simulated data-sets with a specified sample size. Each data-set is synthesised with prior information to give posterior distributions for model parameters, either via analytic formulae or a further Markov Chain Monte Carlo (MCMC) simulation. A further 'inner level' Monte Carlo sampling then quantifies the effect of the simulated data on the decision. This paper describes a novel form of Bayesian Laplace approximation, which can be replace both the Bayesian updating and the inner Monte Carlo sampling to compute the posterior expectation of a function. We compare the accuracy of EVSI estimates in two case study cost-effectiveness models using 1st and 2nd order versions of our approximation formula, the approximation of Tierney and Kadane, and traditional Monte Carlo. Computational efficiency gains depend on the complexity of the net benefit functions, the number of inner level Monte Carlo samples used, and the requirement or otherwise for MCMC methods to produce the posterior distributions. This methodology provides a new and valuable approach for EVSI computation in health economic decision models and potential wider benefits in many fields requiring Bayesian approximation.

JEL classification: I18

Keywords: Bayesian decision theory; Value of information; Uncertainty; Sensitivity analysis; Sample size; Clinical trial design; Stochastic CEA; Approximate Bayesian inference

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1. Introduction

1.1. Expected value of sample information

Global investment in biomedical research was estimated at around US$80 billion during 2001/2002 (Lewison et al., 2004). Investment by governmental bodies, pharmaceutical companies and non-profit organizations aims to develop and test health technologies and to have an effect on healthcare investment decisions. The efficiency of this research investment is therefore an important issue.

Expected value of sample information (EVSI) was developed within decision theory (Raiffa and Schlaiffer, 1967). The central concept of EVSI is to quantify the expected value to the decision maker which might be gained by obtaining sample information before making a large decision (e.g. test drilling for oil before setting up a major oil platform). In health economics, the use of value of information methods in general is an active area of methodological development, with authors investigating and promoting their use in sensitivity analysis and to quantify the value of research (Claxton and Posnett, 1996; Claxton, 1999; Thompson and Graham, 1996; Felli and Hazen, 1998; Meltzer, 2001; Brennan et al., 2002c; Coyle et al., 2003; Tappenden et al., 2004; Yokota and Thompson, 2004a,b). EVSI in particular is under discussion as a tool for quantifying the societal value of expensive medical research projects and for determining optimum sample sizes and allocation rates in randomized clinical trails and other research studies (Claxton and Thompson, 2001; Chilcott et al., 2003; Brennan et al., 2002a,b, and Ades et al., 2004). One can use EVSI as a form of sensitivity analysis, quantifying how much of the decision uncertainty is a consequence of our current uncertainty around particular parameters, and how amenable to reduction the uncertainty might be via realistically-sized data collection exercises. One can also perform quantified trade-offs of the 'per person' value of the proposed data multiplied by the cohort of people affected over the 'lifetime' of the decision choice versus the absolute expected costs of the proposed research. The substance of this paper relates to the means of calculation of the per person EVSI.

We begin with a mathematical description of EVSI using the context of health economics (Brennan et al., 2002b; Ades et al., 2004). We assume a decision model with uncertain parameters θ, for which we have a multi-variate probability distribution based on current evidence $p(\theta)$. There is a decision to be made between a fixed number of treatment strategies $t = 1, 2, \ldots, T$. Each treatment delivers expected utility gains measured in quality adjusted life years (QALYs), with an associated expected cost. We adopt a net benefit approach to the cost-effectiveness analysis (Stinnett and Mullahy, 1998), whereby health gains are monetarised by multiplying by the decision maker's willingness to pay per additional QALY (λ_w). NB (t, θ) is the net benefit of treatment t if the parameters take the value θ. The net benefit for treatment t is thus $\text{NB}(t, \theta) = \lambda_w U(t, \theta) - C(t, \theta)$ where the functions C and U give the costs and the QALYs under treatment t.

The optimal decision given the current information is the decision that yields the highest expected net benefit. Using expectation notation, we write this highest expected net benefit as,

$$\text{Expected Net Benefit}|\text{Current Information} = \max_t E_\theta \text{NB}(t, \theta)$$

Assume that a particular research study is being considered. The new study will provide new data relating to a subset of parameters of interest θ_I. The data obtained from the proposed study X_{θ_I} will update our knowledge concerning the parameters of interest θ_I, and if parameters are correlated, may additionally tell us something about the complementary set of parameters θ_I^c, i.e.