

Individualizing Generic Decision Models Using Assessments As Evidence

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Abstract

Complex decision models in expert systems often depend upon a number of utilities and subjective probabilities for an individual. Although these values can be estimated for entire populations or demographic subgroups, a model should be customized to the individual's specific parameter values. This process can be onerous and inefficient for practical decisions. We propose an interactive approach for incrementally improving our knowledge about a specific individual's parameter values, including utilities and probabilities, given a decision model and a prior joint probability distribution over the parameter values. We define the concept of value of elicitation and use it to determine dynamically the next most informative elicitation for a given individual. We evaluated the approach using an example model and demonstrate that we can improve the decision quality by focusing on those parameter values most material to the decision.

Keywords: decision support, medical decision making, expert systems, real-time systems, patient education, healthcare preferences

1 Introduction

Expert systems have been gaining popularity in a number of domains, especially medicine, in which different individuals regularly make similar decisions. Many of these systems are based on probabilistic models of decision under uncertainty. Complex decision models in such expert systems often contain generic utilities and probabilities that represent average values for entire populations or demographic subgroups. Although individuals might have characteristics that match them to a specific population context, they may not have values representative of their group. Because of this, recommendations or insights from using such systems may not be acceptable for such cases [1]. However, it is not always possible to identify *a priori* with which individuals this will occur. Therefore, it is necessary to custom-tailor the model for every individual.

To apply a generic decision model to a specific individual, the parameter values in the model should be customized for that specific individual. Because the number of values these models contain can be quite large and the acquisition of accurate values can be an onerous and inefficient process, more efficient and approximate methods are needed.

Traditional approaches for making decisions based on a rational or normative model require a complete understanding of the parameter values in the model for a specific individual. Although acquiring information about state probabilities or consequence utilities for a population or group only needs to be done once during system development, obtaining knowledge about the values for an individual is a task required every time the system is used.

This assessment process can be challenging for any given individual, even when performed by a human expert. Different techniques yield different values for the same individual and value being assessed [2]. It is not uncommon for assessed values to change after other questions are asked or more information is presented [3]. Often the assessment questions require the individual to assign a value to an “imagined” situation that will occur in the future rather than a state that they have experienced already. This results in an educated guess of the value rather than the true value. After

a while the individual may tire, and the assessments become less coherent, making long assessment processes impractical and erroneous.

Previous approaches to customizing generic models have defined customization tasks as classification problems. The classification approach customizes the model through a series of discriminator questions, often pre-selected. The process seeks to use a minimal number of categorical questions to determine an optimal policy. Classification does not attempt to provide insight into the decision for the decision maker, rather only to determine the optimal decision policy with a minimal amount of information.

Jimison et al. [4] demonstrated that generic decision models can be tailored for individual patients to provide patient-specific educational material. This work introduced a means to use parameter uncertainty as way to custom-tailor explanations of decision models by representing expected utilities in the model as uncertain quantities instead of point estimates. Utilities for an individual were not assessed, but entered into the system by the researchers. The work laid the groundwork for treating parameter values as distributions rather than point estimates. Although it did consider prioritizing assessment order based on elimination of uncertainty in values (parameter values were assumed to have zero variance after assessment) in a pre-computed order, it did not address issues of interactive assessment. Poh and Horvitz [5] also developed a framework for estimating the value of refining the information in and structure of decision models.

Hornberger et al. [6] used classification and regression-tree (CART) analysis [7] to determine the sets of preference in a decision model that most influence the decision. They were able to pre-determine which preferences were most important to obtain for a given model, and then assessed values for those preferences from each patient. Patients were then classified into different policy groups based on the reduced model from the original CART analysis.

Scott et al. [8] demonstrated an approach to optimize the ordering of assessments based on minimization of contributed variance in the expected utility. They assumed that differences be-

tween decision policies were approximately normally distributed and pre-computed the amount of variance each model parameter's uncertainty contributed to the model prediction. Using this information, an optimal assessment ordering for a given set of population priors was selected to maximize the reduction of variance in the model prediction with each assessment.

Chajewska et al. [9] developed an approach that efficiently determines the optimal policy for an individual based upon a categorization process. The approach is similar to that of Hornberger et al. [6], but uses a classification tree that is generated in advance. It represents utilities as uncertain quantities [4] and terminates the assessment process once the difference between the remaining possible policies in the tree falls below a defined threshold. The approach attempts to minimize the number of assessments necessary by asking categorical questions for each parameter in the model, rather than using traditional elicitation instruments [3]. Like the other approaches, it assumes that once a value is observed, it is known with certainty, and does not provide a means for backtracking through the classification tree without starting over from the beginning.

While these approaches have provided a solid foundation to identify an optimal decision policy with minimal information, they do not address some key issues that arise when using such systems for interactive contexts such as automated decision support. The first major drawback of these methods is that they assume assessments are perfectly observed and can only be made once. There is no way to recognize error in the measurement, to explicitly handle errors, or for adjusting the path of the interaction should an assessment error be made. Second, they are not capable of representing uncertainty about a particular parameter value in the model or the decision policy deemed to be optimal. Third, should the model structure or the values of the non-assessable model parameters change, the split points used for the classification sets would need to be recomputed and the individual's information reassessed. Fourth, they do not provide methods for evaluating the optimality of an interactive process, only for determining optimal assessment orderings for such processes.

We developed an approach that extends these methods further to address these new issues. Our approach differs in one very important way: we view parameter assessments as noisy sensors. We propose an alternative implementation that represents all assessable parameters in the model as uncertain quantities and uses a decision model initially parametrized with population priors to guide the customization of the decision model using parameter assessments from an individual as evidence. We view individuals as naïve experts about their values who are challenged in quantifying them. We explicitly model error in the measurements of quantities and incorporate the measurements as evidence rather than instating them as parameter values. We obtain measurements of the individual's values using computer-based versions of standard assessment instruments [3] rather than categorical questions. The answers for these instruments can be more difficult to obtain than categorical approaches, but are less affected by known biases [10] and contain more information.

Lindley et al. [11] developed a framework for integrating observations from noisy sensors to update a joint distribution on a set of parameters, representing probability values. A log-odds transformation enables an efficient multi-variate Gaussian representation for the posterior joint distribution. We extended this representation to apply to parameters in a decision model.

Our approach is designed to make the automated decision support process practical by obtaining a reasonable approximation to an individual's parameter values for any number of assessments via a real-time interaction. We note that our solution manages customization using any of the model parameters, not just the utility values. Our goal is to efficiently provide insight into the decision problem, as well as selecting an optimal policy with an estimate of certainty. We accomplish this by iteratively refining our knowledge of an individual's true values, determining which question to ask next based upon the potential benefit of the response. Using knowledge about the decision to inform the interaction, we can make the individualization of generic decision models more efficient.

Although we do not determine the global optimal assessment order in advance for each individual, we develop a simple algorithm to select the locally optimal order. As we gather evidence about the individual's parameter values, we can ask the most informative question at each stage of assessment based on our current knowledge of the values. Therefore, using a greedy algorithm with myopic search, we try to maximize the efficiency of the individualization process.

Section 2 presents how we represent decisions and values and our uncertainty about them. Section 3 describes our algorithm for efficiently individualizing generic decision models. Section 5 reviews the work upon which this research is built and provides some suggestions for extending it.

2 Modeling Decisions and Values

This section reviews some basic concepts and ideas used in decision and utility theory and how they are modeled and manipulated in the context of a specific example. This overview is not exhaustive and we refer the reader to relevant sources for further discussion.

2.1 Decision Models

Bayesian decision models are mathematical and graphical representations of choice under uncertainty. These models can be represented as trees or influence diagrams [12], directed graph networks representing a choice from the viewpoint of a single decision-maker.

For the evaluation of our algorithm, we used decision models for four different medical decision contexts. One of the contexts was the decision about the treatment of prostate cancer [13; 14; 15] shown in Figure 1. Prostate cancer affects many older men. The prostate gland surrounds the urethra in men and can impinge on the patency of the urethra if enlarged or swollen. Since the urethra transports urine from the urinary bladder to the outside world, stricture or blockage can

result in difficulty starting or stopping urine flow, incontinence, and urinary retention (inability to empty the urinary bladder). Urinary retention results in the perceived need to urinate frequently and often, especially during the night. Prostate cancer might also metastasize, or spread, to other organs in the body. Once the cancer has metastasized, the prognosis of the patient becomes very poor. The decision is one in which there is a tradeoff between the possible side-effects of surgery versus the side-effects of medication. In addition, if the medication fails to prevent the cancer from progressing in the future, the patient might need to undergo surgery at that time. The rate and severity of complications from the surgery increase with patient age.

The model considers the choice between aggressive surgical treatment versus conservative medical treatment. Should the cancer progress with conservative treatment, surgery may be necessary. The prognosis of the patient is modeled using a Markov process. The parameters that are assessable for an individual faced with the testing decision are listed in Table 1.

For any Bayesian decision model, we can define a notation that allows us to describe our method in general. Let D be the set of all decisions in the model domain, $\{d_1, \dots, d_m\}$. Let S be the chance states in the model domain, $\{s_1, \dots, s_n\}$. Let C be the set of mutually exclusive consequences in the model domain, $\{c_1, \dots, c_o\}$. D is completely under the control of the decision maker, while S is uncertain and beyond decision maker's control. The decision maker cares about C and it inherits uncertainty and the decision maker's control through S and D . We can then define Π as the set of decision policies in the model, $\{\pi_1, \dots, \pi_p\}$, such that every member of Π is a sequence of decisions from D , possibly contingent on S . All of the uncertainty about actions can now be isolated unconditionally in S . Therefore, without loss of generality, we obtain the decision model in normal form shown in Figure 2. There is a choice among policies Π , an uncertain state S , and consequence C determined by Π and S .

Utility values are assigned to the consequences, C , and the expected utility is computed for each. The optimal policy is defined to be the policy that maximizes the decision maker's expected

utility for a given parameterization of the model.

2.2 Utility Functions

Utility functions are key component of decision models that describe the value that the decision maker assigns to each of the possible consequences, C , in the model. The utility function for a given element of C can range in complexity from a single number to a complex function of several attributes. Utilities, like probabilities, often exhibit dependence. As the size of C grows and the complexity of its associated utility functions increases, the number of possible assessments grows rapidly. If there is dependence among attributes, the number of assessable states can grow exponentially.

Utility functions have been explicitly assessed [16], determined through meta-analysis [17], observed as revealed preferences through simulated decision scenarios Farr and Shachter [18], or learned from databases of values [19]. Utility functions have also been represented as uncertain quantities and used to provide individualize explanations of decision models [4; 9]. We take the latter route, using a model-based approach that captures the structure of a utility model with parameter values and can be tailored to each individual.

2.3 Parameter Value Assessments

One of the major challenges of assessing values for utilities and subjective probabilities is that individuals have difficulty quantifying their feelings or beliefs. To assist in this task, several standardized methods have been developed to obtain measurements of subjective probability and utility values. Probabilities are often assessed using visual analog scales (VAS) and probability wheels (PW). Utilities are usually assessed using methods such as VAS, standard gamble (SG), and time-tradeoff (TTO).

Examples of these assessment instruments are shown in Figure 3. Figure 3a represents a VAS

instrument [20]. This is usually represented as a horizontal or vertical rule with anchor points at each end. The individual selects a point along the line that best represents the value being assessed. Figure 3b shows a simple SG instrument. It is used to assess an individual's value taking into account the individual's attitude toward risk. Given a preferences order of $a_1 \succ a_2 \succ a_3$, the individual is asked what probability p is the gamble between a_1 with probability p and a_3 with probability $(1 - p)$ equivalent to obtaining a_2 for certain.

Figure 3c depicts a TTO instrument [21]. The TTO measures an individual's value taking into account the time discount rate, the amount the individual devalues future events. Given a preference order $a_1 \succ a_2$, the individual is asked what duration of time, t , with a_2 is equivalent to a set duration of time, t_0 with a_1 . Figure 3d shows a probability wheel. The individual is asked to set the area of the arc p such that it represents the probability being elicited.

2.4 Value Assessments As Evidence

Because of their nature and the manner by which they are obtained, value assessments are imperfect observations of parameter values. Traditionally, they have been treated as direct observations of personal values without regard for any error that might occur in the assessment. Our approach allows us to represent this uncertainty by treating the assessments as imperfect measurements which provide observable evidence of the true values. This has a strong advantage over the traditional approach: we can explicitly represent the error associated with the assessments and efficiently update our beliefs about the values given the observations that we have made.

Let T be the set of all parameters in the model domain, $\{t_1, \dots, t_i\}$. Let E be the set of all evidence, or assessments, $\{e_{1,1}, \dots, e_{i,j}\}$, that we have observed about T , where $e_{i,j}$ is the j th assessment of the i th parameter.

Figure 4 shows an augmented form of the general decision model in Figure 2 demonstrating how assessed values are used as evidence to update our beliefs about the values. It shows the

relationships among the policies, Π , the uncertain states, S , the consequences, C , the values, T , and the evidence, E . Uncertain states are conditioned by the parameters. Some of those parameters describe the utility, so consequences are now a function of parameters as well as policies and states. We have a prior distribution over the parameters and our evidence is comprised of imperfect observations of the parameters. Finally, the arc from E to Π is informational, denoting that E is observed before Π is chosen.

2.5 Representing Parameter Uncertainty

Because we are not obtaining complete information about an individual's parameter values, we represent them in the model as uncertain quantities. Other approaches have used constraints or preference ordering to assess and model parameter values. In this paper, we have chosen to model parameter values as continuous-valued random variables and explicitly ask individuals for an estimate of their own values.

Elicited probability and utility values are subjective estimates that we assume are constrained on the interval $[0,1]$. In many medical decision models, there can be more significance in the distinction between the values of 0.98 and 0.99 than between the values of 0.50 and 0.51. In fact, 0.99 vs. 0.995 can be even more significant than either of them.

To address this, we model parameter values assuming that their log-odds transforms are multivariate Gaussian, where the log-odds, lo , of a parameter value x is $lo(x) = \ln((x)/(1 - x))$. This way, parameter values can be modeled using a multivariate Gaussian probability density function (PDF) while remaining in the $[0,1]$ interval. These measurements tend to have error that is approximately Gaussian in the log-odds space independent of the extremeness of the value [11].

When the log-odds of the parameter values are Gaussian distributed, the distribution for the parameter values is determined. Unfortunately, neither this distribution nor its moments can be represented in closed form. We have developed numerical methods to efficiently estimate the mo-

ments in the natural parameter space. This permits us to assess priors and display posteriors in the parameter's natural space while efficiently representing dependence and updating the distributions in the multi-variate Gaussian space.

3 The Algorithm

Our approach is based on the iterative refinement of our belief about the individual's parameter values through the acquisition of evidence in the form of parameter value assessments. We dynamically determine the assessment question that is likely to provide the most information given the current state of information. This results in an order of assessments that is not pre-computed, but is instead based upon the responses that the individual provides. We describe a greedy algorithm with myopic search. The algorithm can be stopped at anytime to yield insights based on all of the information collected to that point. A greedy search works well for this problem, allowing the system to respond quickly enough for real-time interaction and without imposing requirements about the number of number of questions to be asked. Because of this, we are also able to provide insight at any stopping point, rather than requiring a full set of observations be made.

The algorithm selects a parameter value to assess and updates the parameter distributions based on the assessment. It then calculates the incremental value of obtaining evidence for each possible assessment, which we call the value of elicitation (VOE). It continues to assess and update its knowledge until the net value of elicitation is too small or the user halts the process.

3.1 Initial Conditions

The algorithm starts with a joint prior PDF over the individual's parameter values. This prior may be either non-informative or based on a previous clustering into a studied demographic group. These PDFs can be learned or directly studied in the desired populations as described above.

Since full elicitation of values can be impractical, guidelines are often used in fields such as medicine to avoid assessing values for every individual. In cases where priors are not available, the assumptions used in the guidelines for parameter values can be used as the individual's initial PDF.

3.2 Value of Elicitation

After each assessment is made, it is necessary to determine the net value of an additional assessment. While the value of elicitation is always a non-negative value, it will eventually be too small to make a question worthwhile. The algorithm can stop the interaction at this point, or allow users to determine for themselves the value of continuing the interaction. The user can stop the assessment process at any time or choose to continue it.

We assume a constant cost for an additional elicitation. In general, one could consider such factors as the number of assessments of the current parameter already made, the total number of assessments, the psychological burden of the question and the time required to answer the question.

Traditionally, the expected benefit of obtaining a perfect observation of a point estimate for a parameter value was calculated using the value of information. We have extended this concept to value distributions and noisy observations of those distributions. In order to custom-tailor an assessment ordering for an individual, we must determine the incremental value of obtaining evidence for each possible assessment. That is precisely the value of elicitation, the value of information of an additional noisy measurement. As a result, the value of elicitation captures the anticipated benefit of obtaining an assessment with uncertainty based on our current state of information comprising our prior beliefs and observations to this point. Since the net benefit of elicitation is the potential to change the individual's decision less the constant cost, we can compare different possible assessments based on their value of elicitation.

At any point in the assessment process, we have a joint probability distribution, $p(t)$, over the

values for the parameters in the model, T . For any value t of T there is an optimal policy $\pi(t)$, which is the policy that maximizes expected utility given that $T = t$. Because the value surface for each policy is linear in t , the optimal policy with our current knowledge is $\pi(\mu)$, where μ is the current mean of $p(t)$. We can determine the expected value of observing T before choosing our policy. It is the probability weighted difference between the expected values of the optimal policies with our current knowledge, $\pi(\mu)$, and with perfect knowledge, $\pi(t)$. We define the value of elicitation as

$$VOE = \int_0^{\infty} (E[U | t, \pi(t)] - E[U | t, \pi(\mu)])p(t) dt. \quad (1)$$

Figure 5 graphically represents the value of elicitation for a parameter. The shaded region represents the difference between the locally optimal policy and the globally optimal policy. The PDF for $p(t)$ has been scaled to be visible on the graph. If desired, $p(t)$ can be adjusted to reflect the noise in the observation. The above integral is approximated using numerical methods.

We note that even if the belief about a given value is crude, the refinement of the value is only important to pursue it if it has enough potential to lead to a locally optimal policy other than the current optimal policy in light of the other assessments.

This definition captures several aspects of behavior for each parameter. Whenever the decision is insensitive to a parameter (i.e., there is only one dominant policy over the parameter's PDF), its value of elicitation is 0. It also captures the notion of diminishing returns on assessment of values. If a parameter is assessed more than once, there is less information provided by each additional assessment.

Since the parameters can be dependent, updating the belief for one parameter can impact other parameters. Learning about one value might result in parameters becoming material that previously were not or vice versa. This might be the case when an assessment reveals that the individual falls into a special group that requires information about previously immaterial values, or when the new

evidence suggests that the decision is insensitive to other values.

3.3 Value Assessment Selection

One of the key aspects of our approach is the ability of the algorithm to select the parameter that should next be examined. This selection is made on the basis of which parameter is myopically most material to the decision. It might even be a reassessment of a parameter value.

The selection is based upon the value of elicitation. Since the value of elicitation captures the worthiness of considering the true value of the parameter, it is a natural choice for this task. We select the parameter that has the maximum value of elicitation and, as long as the individual is willing or the value of elicitation is large enough to make the elicitation worthwhile, we assess the value. After a value x is elicited from the individual, we convert the value from the natural space of the parameter into the multi-variate Gaussian space using the log-odds transformation with a mean of $lo(x)$ and the assigned error to the measurement.

3.4 Updating Parameter Values

Whenever we have an observation of a parameter assessment, we treat it as evidence in our model, and use it to obtain a new posterior joint PDF for the parameter values.

Because we model the log-odds of the parameter values as multivariate Gaussians, it is possible to utilize existing representations for continuous-valued influence diagrams [22] and approaches to learning them from data [23]. This representation implicitly maintains a covariance matrix, capturing the dependence among the parameter values. This allows us to model complex dependency relationships between parameter values explicitly within our framework.

4 Experimental Results

We evaluated the algorithm using decision models for four medical treatment decision domains (PSA screening for prostate cancer, benign prostatic hypertrophy management, BRCA screening in high-risk women, and the amniocentesis decision). We simulated six groups of 1000 patients each for the models. The simulates were assigned parameter values randomly sampled from the population priors used to develop each of the models. Value assessments were assumed to have observational error of constant variance at two levels, $\sigma^2 = 0.0$ and 0.1 . We compared our approach to the guideline approach, the full assessment with random ordering approach, and the full assessment with greedy optimal ordering approach.

The guideline approach entailed assigning to each individual the parameter values of the *average* patient in the population. This is analogous to the use of population values in clinical practice guidelines. The full assessment with random ordering approach involved sequentially measuring all quantities of interest once in a random order for each simulate and assigning the measurements as the simulate's true values. A random ordering was used to demonstrate an average case performance of the approach to avoid unintentional positive or negative biases caused by a particular ordering. This is analogous to the current assessment of values using a sequential assessment process. The full assessment with greedy optimal ordering involved sequentially measuring all quantities of interest once in the optimal order for the population based on the decision model and parameter priors used. This is analogous to the methods that pre-compute the optimal assessment ordering for a population.

We defined model customization error as the difference between the expected utility of the optimal policy for an individual given perfect full information and the expected utility for the policy selected given the current state of information. The accuracy of each approach is the error after the final observation. Although our approach is capable of any number of observations, we choose to limit the comparison to the total number of assessable parameter values in each model.

The efficiency of each approach is how quickly the error is reduced (the curve approaches the horizontal axis). The robustness to noise for each approach is its ability to maintain accuracy and efficiency with increases in observation noise.

The results of the simulations for the four decision contexts are shown in Figures 6, 7, 8, and 9. The average error was plotted for each approach as a function of the assessment count for the two cases of response noise variance: $\sigma^2 = 0.0$ is shown in the top graphs, $\sigma^2 = 0.1$ is shown in the middle graphs. The value of elicitation as a function of assessment number for both cases of response noise variance is shown in the bottom graphs.

The guideline approach demonstrates the error if no information is gathered about individuals averaging over the population. The plots show that all of the approaches that assess values result in a perfectly customized model for all four decision contexts provided that the response noise variance is zero. The optimal ordering approach is more efficient than the random ordering approach, but our approach is the most efficient for all four decision contexts. Once the observations become noisy, the full assessment approaches become less accurate. Our algorithm required fewer assessments for all four decision contexts and resulted in smaller error regardless of the number of assessments made.

For two of the models (Figures 8 and 9), the value of elicitation can be seen increasing after the first assessment is made, and the error drops more after the second assessment than it does after the first. This is due to the fact that the first assessment makes parameters that were not material to the decision for the population material for the individual's decision, i.e. the most informative question is actually the second question asked conditioned on the answer from the first question. The value of elicitation increases for the next measurement since there was a greater potential for the decision to be affected by the newly considered parameters. The error of the greedy optimal ordering approach also remains high since there is a sub-population for whom the population optimal ordering is not appropriate.

5 Discussion and Extensions

Traditional decision analytic approaches develop a customized model for every individual, often only including states or consequences relevant to the individual. This process, in most cases, is too costly and labor intensive to be practical for everyday use in important personal decisions, such as those in medicine. By developing a consultation system that is based on a generic decision model, we can amortize the cost of model development over many users.

There is a fundamental trade-off in using a generic model versus an individual model. A generic model must be able to consider the states and consequences that would be relevant to any of its potential users. This has the benefit that only one model needs to be developed and maintained. The cost is that it greatly increases the number of parameter values that need to be assessed for each individual. The goal of our algorithm is to minimize this increased burden of assessment required with generic consultation systems.

We have described a novel approach for efficiently individualizing generic decision models based on using assessments of parameter values as evidence of their actual values for a specific individual. We model the uncertainty about the parameter values as Gaussian PDFs of the log-odds transform of the values. This representation lets us represent accurately even extreme values on the $[0,1]$ interval with robust distributions and dependence among parameters. By defining a value and cost of elicitation, we are able to select the optimal assessment to make next and determine when further elicitation is not worthwhile. We believe that this approach will help mitigate the customization burden and allow generic systems to find practical use.

Our results demonstrate that our approach is more efficient than both the standard approach of full assessment and the greedy optimal ordering assessment for four decision context models. In addition, as the noise in the responses increased, our approach retained both its accuracy and efficiency as compared to the full and greedy optimal assessments. We feel that these results show that our implementation can make the customization of a decision model of user preferences

practical, especially in light of noisy observations.

An interesting addition to this is our algorithm's ability to recognize and interact with accordingly individuals whose values place them into subgroups of the population for whom the population as a whole is not representative. In these situations the value of elicitation does not always diminish with each assessment. In fact, it is likely to increase after some assessments are made as is evidenced by the graphs of value of elicitation for breast cancer screening and prenatal testing. The increase in the value of elicitation after the first question is asked indicates that the individuals response to the assessment has made material aspects of the decision that are irrelevant for the average member of the population. By learning more about how an individual's values compare with a demographically matched cohort, our algorithm is able to not only determine whether an individual has a value set that differs significantly from his/her peers, but can also conduct the value assessment interview in an appropriate order for each individual. Those users that have values different from their peers are the individuals that stand to benefit most from such an intervention, as they stand to gain the most value from an individualized decision.

The approach described in this paper has some limitations to its use. First, if the algorithm recommends multiple assessments of the same parameter, we might minimize bias in the user's responses by developing different assessment questions for the parameter. Second, the approach requires that a decision model and prior distributions exist for the decision context to be addressed. Third, a reasonable estimate of the noise in the measurements is required. Finally, the approach only provides a mechanism for incorporating observations from one user at a time.

One natural extension to our method would allow the individual to assign a confidence to the answer to an assessment question. This would permit us to scale the variance of the observed evidence to correspond to the confidence with which it was provided. Another extension would be to use a sliding window for incorporating assessments. As additional assessments are made, earlier ones can be down-weighted or ignored. This would allow the algorithm to incorporate the notion

that as users gain experience in a particular domain, the accuracy of assessments might increase.

We believe that our approach provides a practical solution to the automation of real-time individualization of generic decision models with potentially noisy observations of individual values. By providing a system that is able to acquire evidence about an individual's values in an adaptive way to determine what, if any, meaningful differences exist between the individual's values and the values of his/her peers, we hope to be able to facilitate the inclusion of individual health values into the healthcare decision-making process. Such a step forward might help to make individual values a staple of the patient-physician encounter and has the potential of improving the quality of healthcare while making the delivery of individualized care more efficient.

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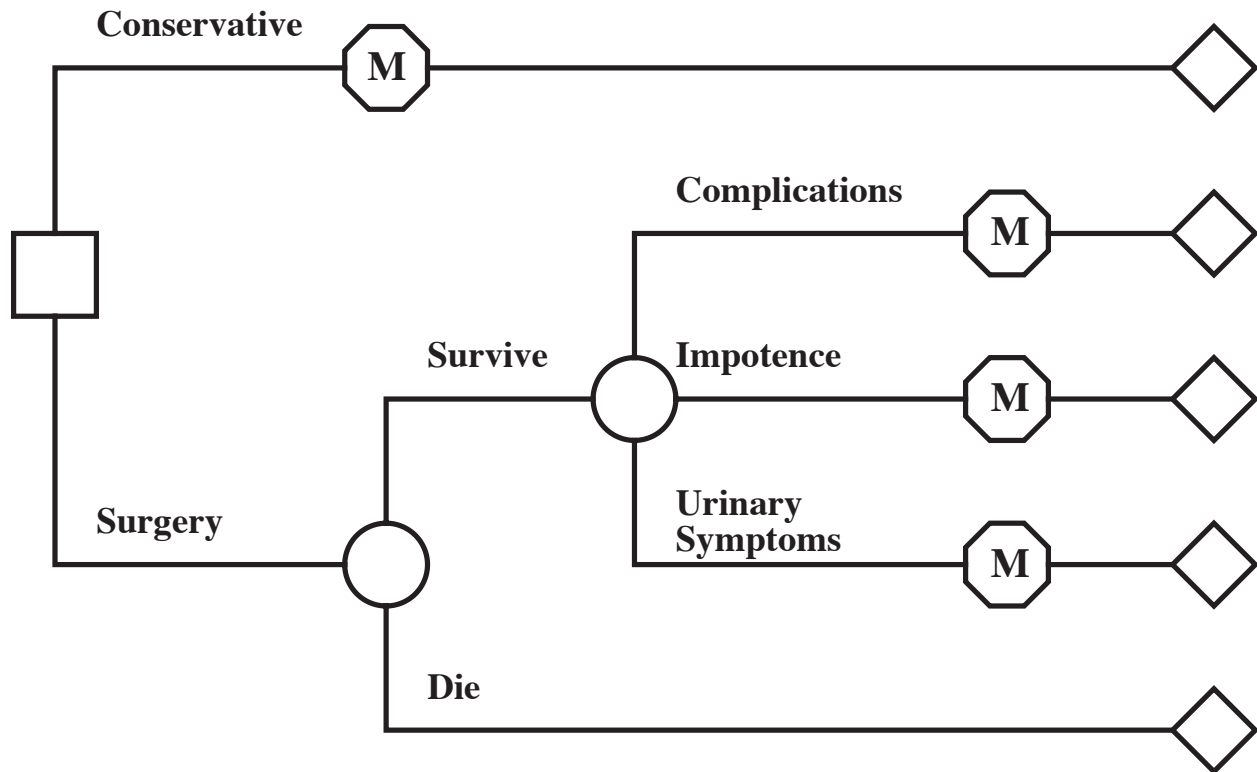


Figure 1: A summary decision model for the prostate cancer treatment decision [13; 14; 15].

Table 1: Population values for prostate cancer decision model [13; 14; 15].

| <i>Parameter</i> | <i>Population</i> | <i>Population</i> |
|---|-------------------|-------------------|
| <i>Name</i> | <i>Mean</i> | <i>Variance</i> |
| Utility(Urinary Symptoms) ¹ | 0.741 | 0.025 |
| Utility(Metastastatic Disease) ¹ | 0.509 | 0.025 |
| Utility(Impotence) ¹ | 0.693 | 0.025 |
| Personal Discount Rate ¹ | 0.03 | 0.0012 |

¹ when Utility(Current Health) = 1 and Utility(Death) = 0.

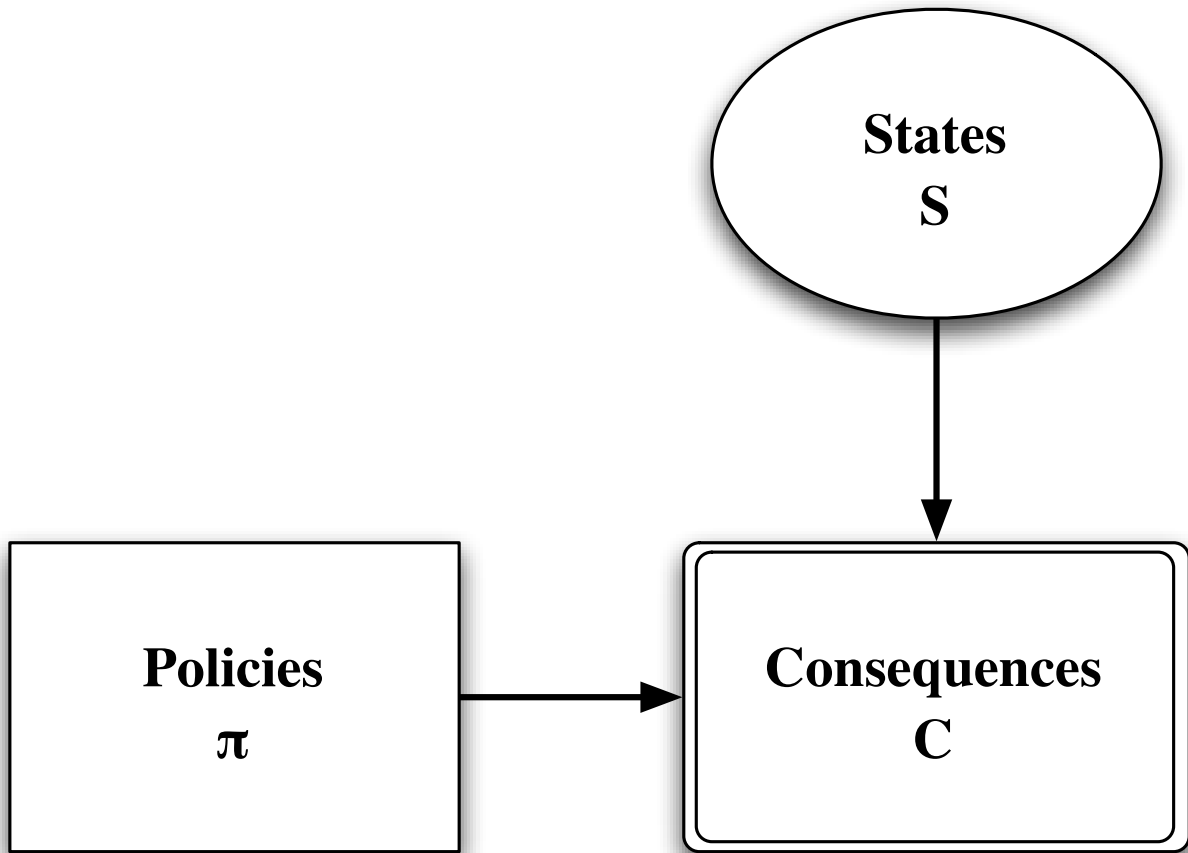


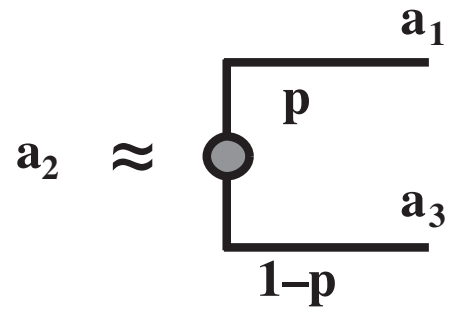
Figure 2: A example of a generic decision model in normal form [24].

a)



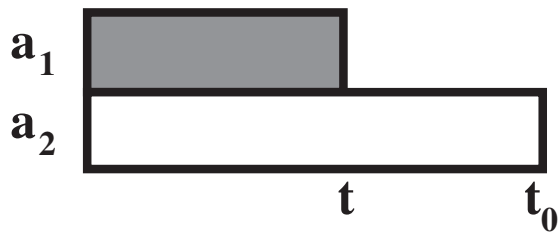
Visual Analog Scale (VAS)

b)



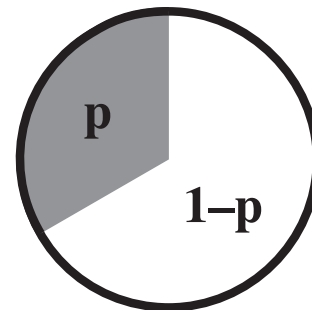
Standard Gamble (SG)

c)



Time Trade-off (TTO)

d)



Probability Wheel (PW)

Figure 3: Examples of assessment instruments: A) Visual Analog Scale (VAS), B) Standard Gamble (SG), C) Time Trade-off (TTO), and Probability Wheel (PW).

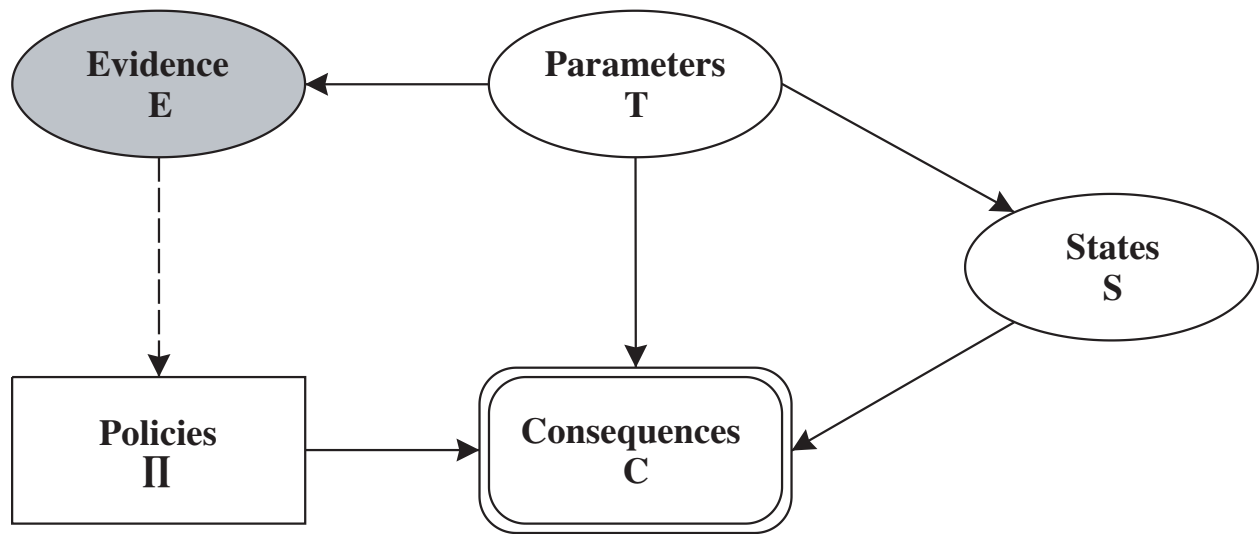


Figure 4: An influence diagram representing how evidence is used to condition the belief about parameter values and affect the policy choice.

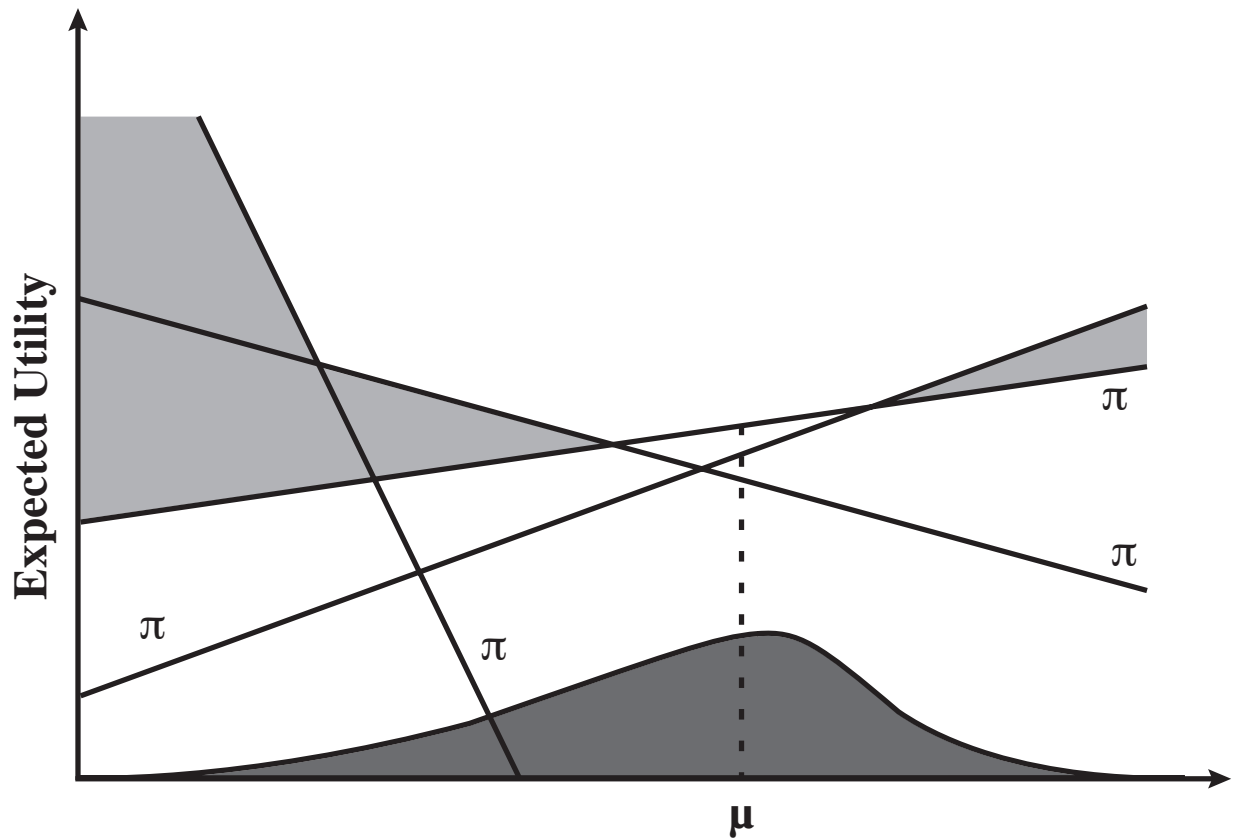


Figure 5: An example of the value of elicitation. The shaded region represents the difference between the locally optimal policy and the expected optimal policy. The parameter distribution has been scaled to be visible.

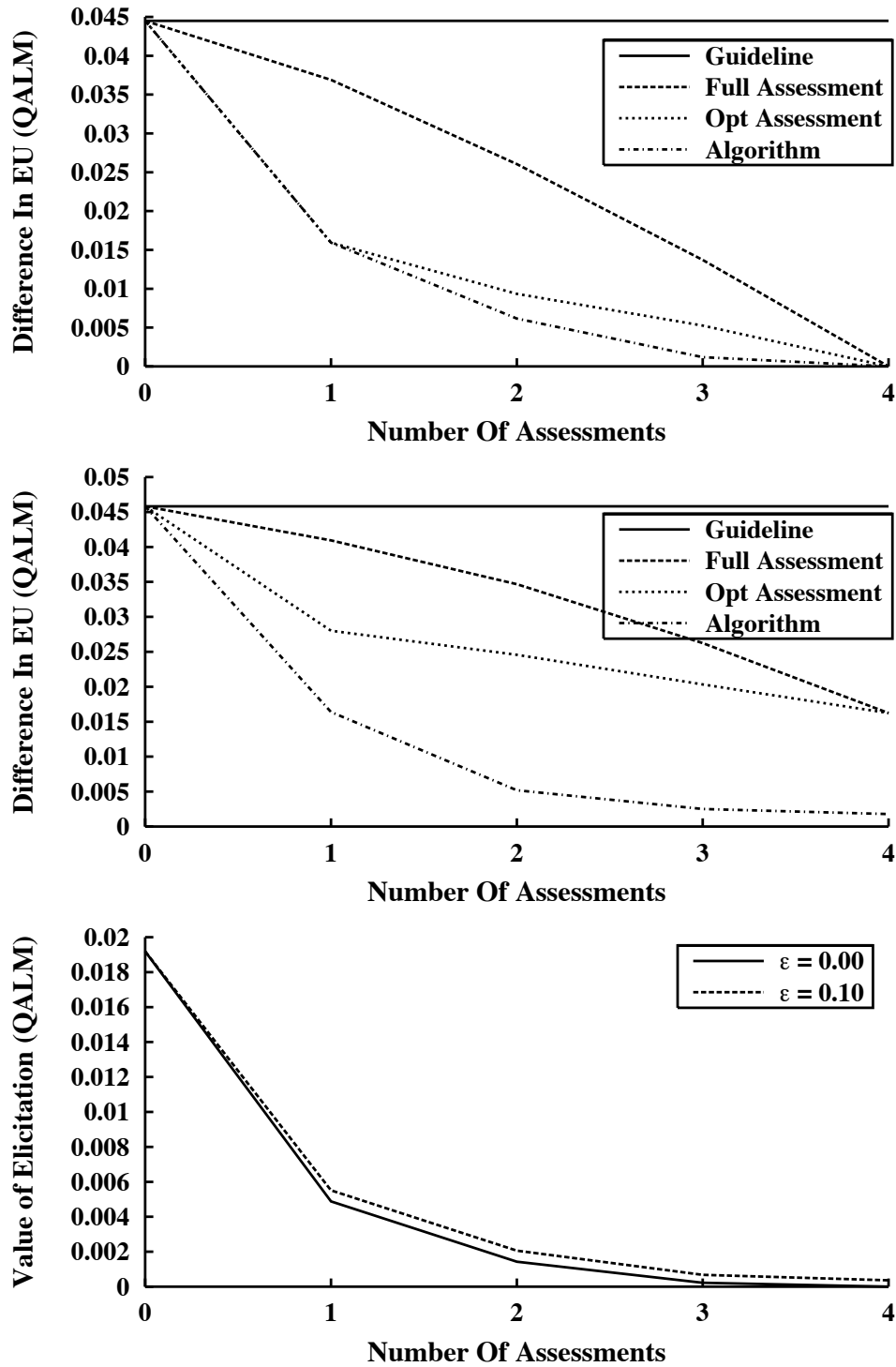


Figure 6: Comparison of error in quality-adjusted life months (QALM) for our algorithm, guideline, full assessment, and greedy optimal solutions for the prostate cancer decision context with response noise of variance $\sigma^2 = 0.0$ (top) and 0.1 (middle). Value of elicitation is shown as a function of assessments for both noise levels (bottom).

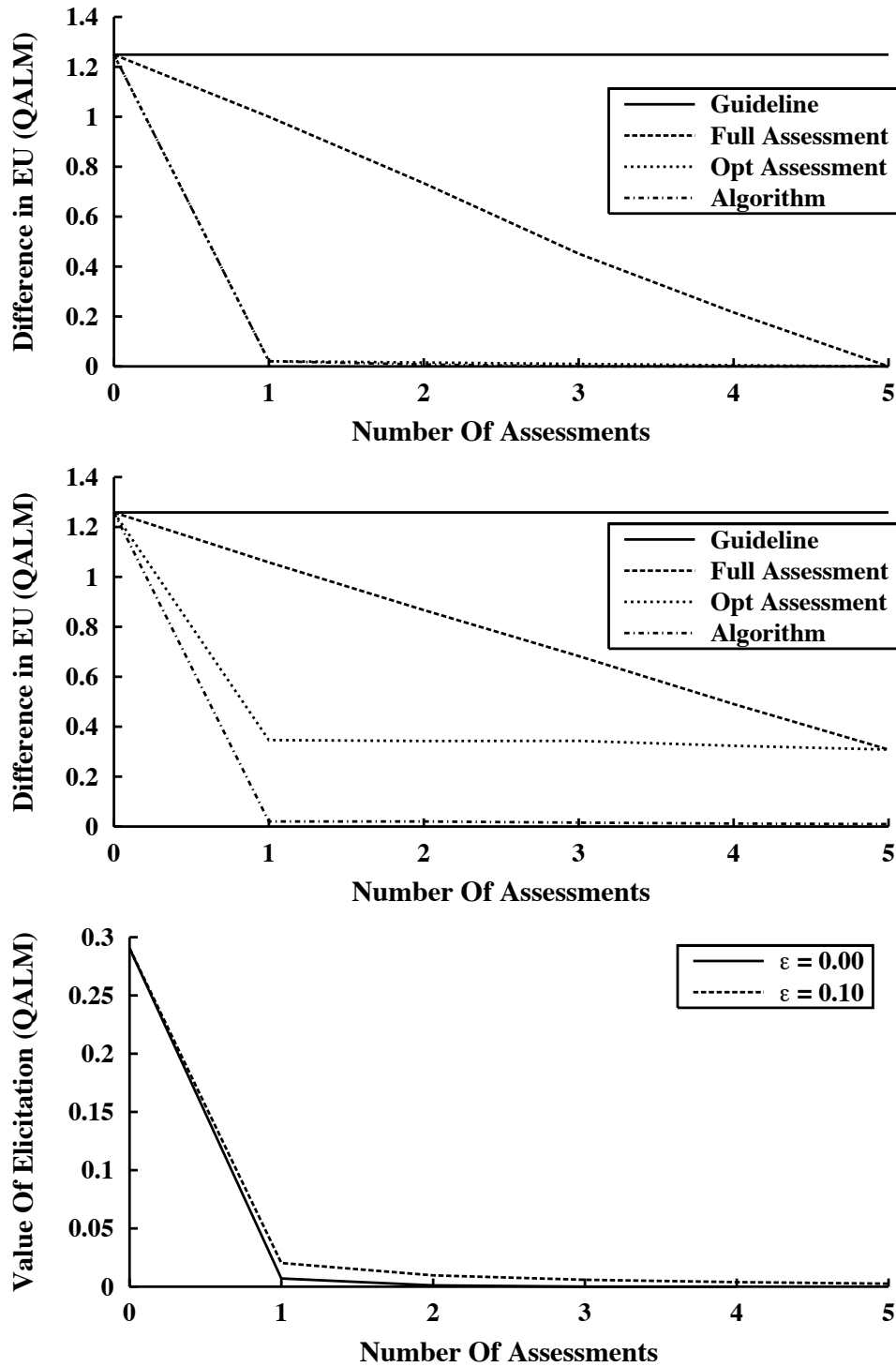


Figure 7: Comparison of error in quality-adjusted life months (QALM) for our algorithm, guideline, full assessment, and greedy optimal solutions for the benign prostatic hypertrophy decision context with response noise of variance $\sigma^2 = 0.0$ (top) and 0.1 (middle). Value of elicitation is shown as a function of assessments for both noise levels (bottom).

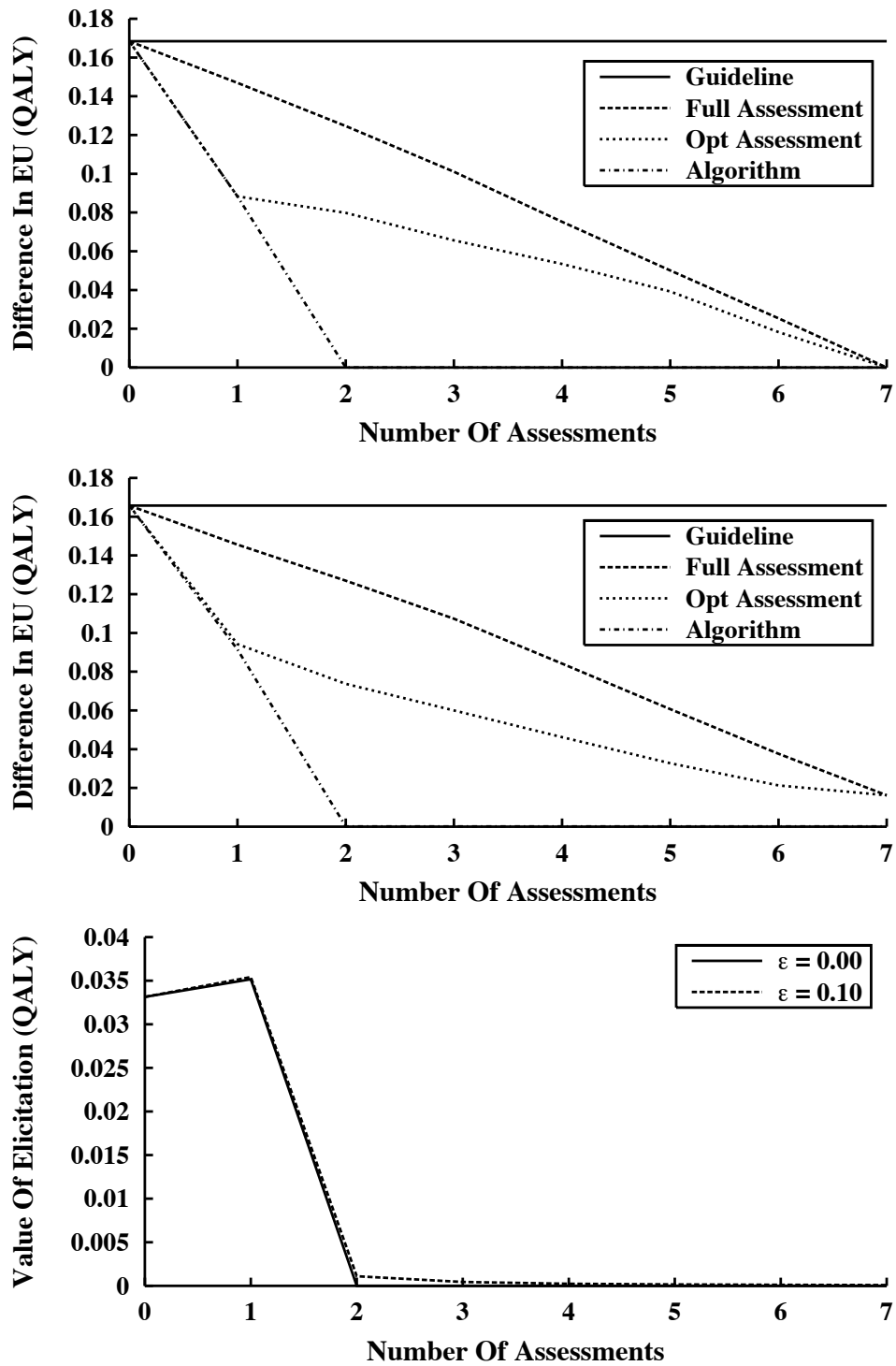


Figure 8: Comparison of error in quality-adjusted life years (QALY) for our algorithm, guideline, full assessment, and greedy optimal solutions for the breast cancer screening decision context with response noise of variance $\sigma^2 = 0.0$ (top) and 0.1 (middle). Value of elicitation is shown as a function of assessments for both noise levels (bottom).

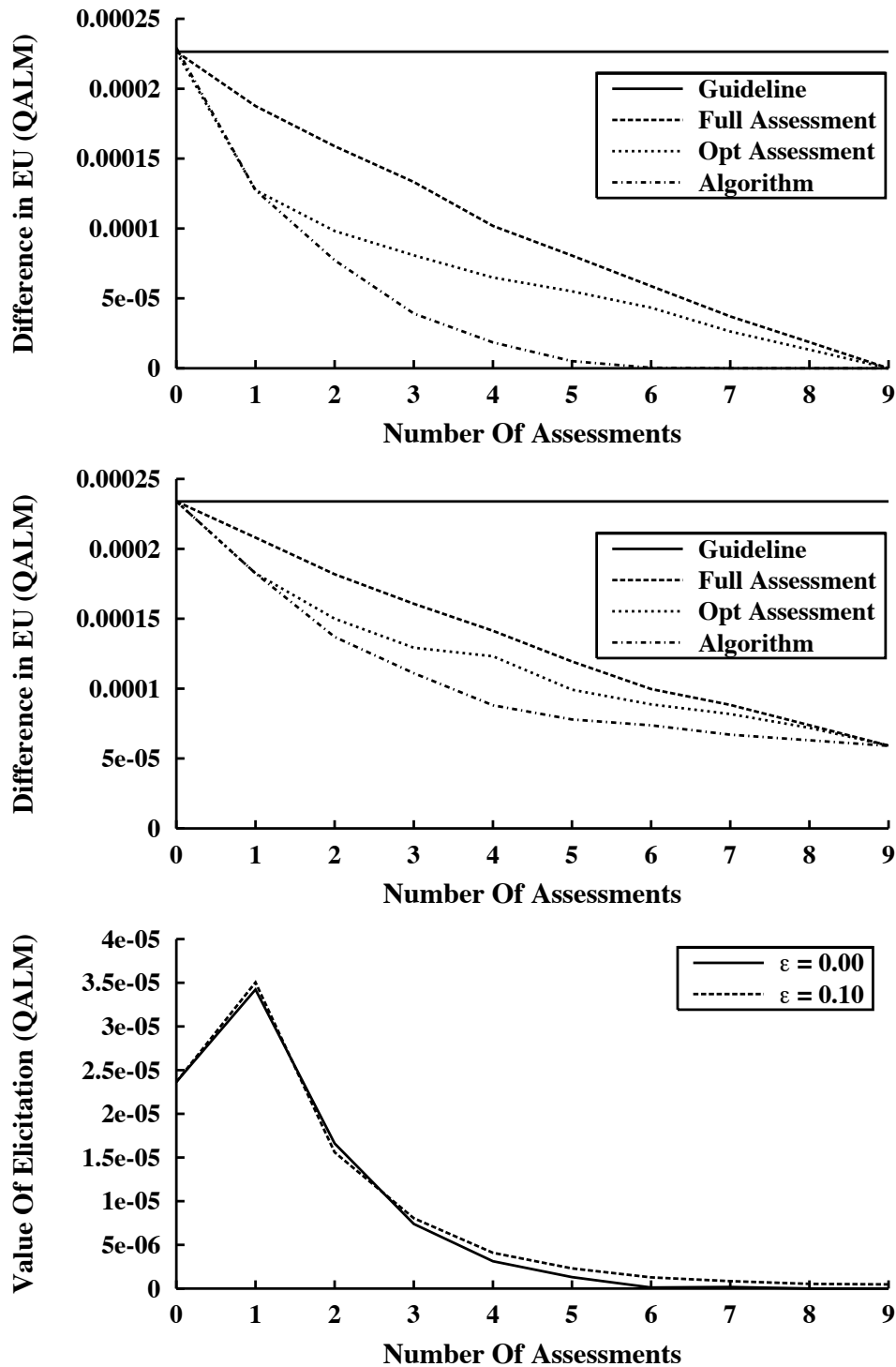


Figure 9: Comparison of error in quality-adjusted life months (QALM) for our algorithm, guideline, full assessment, and greedy optimal solutions for the prenatal testing decision context with response noise of variance $\sigma^2 = 0.0$ (top) and 0.1 (middle). Value of elicitation is shown as a function of assessments for both noise levels (bottom).