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Angela Dalton

Alan Brothers

Stephen Walsh

Paul Whitney

# Expert Elicitation Method Selection Process and Method Comparison

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# Expert Elicitation Method Selection Process and Method Comparison

Angela Dalton, Alan Brothers, Stephen Walsh, Paul Whitney[1]
Fundamental and Computational Sciences Directorate
Pacific Northwest National Laboratory

## Abstract

Research on integrative modeling has gained considerable attention in recent years and expert opinion has been increasingly recognized as an important data source and modeling contributor. However, little research has systematically compared and evaluated expert elicitation methods in terms of their ability to link with computational models that capture human behavior and social phenomena. In this paper, we describe a decision-making process we used for evaluating and selecting a task specific elicitation method within the framework of integrative computational social-behavioral modeling. From the existing literature, we identified the characteristics of problems that each candidate method is well suited to address. A small-scale expert elicitation was also conducted to evaluate the comparative strength and weaknesses of the methods against a number of consensus-based decision criteria. By developing a set of explicit method evaluation criteria and a description characterizing decision problems for the candidate methods, we seek to gain a better understanding of the feasibility and cost-effectiveness of integrating elicitation methods with computational modeling techniques. This serves an important first step toward expanding our research effort and trajectory toward greater interdisciplinary modeling research of human behavior.

## 1. Introduction

Expert judgment is a critical component of forecasting methods and can be implemented by a variety of forecasting tools. Expert judgment has long been employed in computational modeling to develop and structure Bayesian networks (BNs). As the result of advanced computational algorithms that enabled BNs to learn from data, modelers increasingly found expert judgment useful and even crucial in some cases in dealing with data limitation problems and calibrating model parameters (Walsh et al. 2010; Henrion, Breese, and Horvitz 1991). Due to their technical simplicity and methodological transparency, we focused on four forecasting methods: conjoint analysis, probability elicitation, judgmental bootstrapping, and prediction markets. We recognize that different decision-making environments and conditions undergird each of these methods and their application is largely influenced by the characteristics of the research questions at hand. We do not propose to incorporate all judgmental forecasting methods into the integrative framework, or identify the most superior forecasting method, which would be beyond the scope of this project. Our goal is to shed some exploratory light on integrative modeling with the hope of ushering in additional research interests in modeling complex decision making and risk assessments.

[1] paul.whitney@pnl.gov, 509-375-6737

In the following sections, we describe the four candidate methods, their theoretical background, areas of application, empirical successes, and limitations. Then we will identify the characteristics of decision tasks that are suited to each of the methods. In order to understand the feasibility of linking these methods with computational models, we conducted a small-scale elicitation exercise with a group of researchers from PNNL. Based on the evaluation results, we developed a methodological comparison matrix to demonstrate each method's strengths and weaknesses. We conclude by discussing potential applications of integrating expert elicitation with computational frameworks and our research progress to date.

## 2. Methods Overview

### *2.1 Conjoint Analysis*

Conjoint analysis is a form of preference structure measurement (Netzer et al. 2008; Kroes and Sheldon 1988; Srinivasan and Park 1997) that estimates the part-worths of multiple attributes of an alternative product, service or policy option in relation to the overall utility of the product and uses stated preferences to predict choice behavior (Luce and Tukey 1964). Conjoint analysis can be used when: a) the item being selected can be viewed as a combination of the attributes; b) the attributes have some intrinsic exchangeability; c) the utility or likelihood of the overall product or item is related to the bundle of attributes.

In our approach, the scenarios can be constructed and presented as "profiles" in conjoint analysis. Experts will rank or rate each profile in a pairwise fashion. Through an iterative process, experts will express their preferences measured in terms of relative likelihood or probability beliefs for each profile pair. Currently, commercial conjoint analysis tools are widely available and are able to handle complex research designs (Orme, 2009). Computer-based conjoint analysis is highly interactive, capable of producing real time preferences and part-worths, and predicting choice behavior. PNNL researchers recently developed a novel integrative conjoint analysis user interface and algorithms that enable rapid scenario generation and facilitate the integration of data and expert domain knowledge to calibrate Bayesian network model parameters (Walsh et al, 2010). The utilization of this newly developed conjoint analysis tools will help diminish the setup costs of integrated modeling.

In contrast to its major competitor for our considerations (e.g. probability elicitation), computer-based conjoint analysis does *not* require the researcher or facilitator to play an active role in interacting with, motivating, or training domain experts as model information is provided in the user-friendly web-based interface and the procedural instructions are straightforward. Further, probability elicitation commonly employs an exercise, which helps the expert calibrate their opinions and conceptions of a probability. For example, the exercise would help make the distinction between a fairly unlikely event (small probability) vs. an extremely rare even (infinitesimal probability). Conjoint analysis is a clear standout in this regard since relative likelihood is a more natural quantity to conceive for one who is not accustomed to the idea of a probability (*c.f.* Renooij 2001 and Gustafsson et al. 2007 ) .

With regard to linking conjoint analysis to computational models, the methodology has a long history of being applied under regression type models. The success of conjoint analysis under commonly used computational methods such as regression inspired confidence that the methodology could be generalized to elicit a more general probability structure in the form of a Bayes net. Further, the ability to aggregate information across multiple experts is an inherent trait of conjoint analysis.

### *2.2 Probability Elicitation*

Probability elicitation is a formal process of obtaining probability estimates in a manner designed to minimize bias and overconfidence. While there are variations in the method (Morgan and Henrion 1990), the basic procedure, most commonly in use is the SRI/Stanford protocol developed in Spetzler and Stael von Holstein (1975) and Stael von Holstein and Matheson (1979).

The probability elicitation process typically consists of five or six steps (Hora 2007). The process begins with identifying, recruiting, and motivating domain experts, during which the facilitator establishes rapport with the experts and determines if there are any motivational biases that could influence the results. Then, in the structuring phase, experts will identify relevant state and conditioning variables, and agree on the unit of analysis. Next, the experts are trained to be aware of how heuristics and biases can affect their judgment. During the probability encoding stage, probability assessments are elicited from the experts. The method will vary depending on whether the variables on which the probabilities being elicited are discrete or continuous. Direct elicitation techniques such as fixed probability, fixed value, and the PV method (where experts provide both probability and value assessments) as well as indirect techniques such as pairwise betting and a lottery can be used. Probability assessments can be influenced by the elicitation techniques used. Generally, direct probability assessment techniques are more straightforward, efficient, and inexpensive than indirect probability assessment techniques such as betting or lottery (Renooij 2001; Lau and Leong 1999). In the final stage, the facilitator explains and reviews the results with the experts and verifies the consistencies of their assessments. In case of assessment divergence, individual results are shared and discussed with the group to determine if a consensus estimate can be obtained (for a discussion on combining probability elicitation information across experts, see Clemen and Winkler 1999).

Probability elicitation places a considerable emphasis on facilitator-expert interaction, therefore, requiring the facilitator to play an active role throughout the elicitation process. For that reason, Spetzler and Von Holstein (1975) caution against the use of computer-based probability elicitation applications for the loss of facilitators' "balancing effect" with regard to minimizing experts' biases. Probability elicitation requires substantial time commitment from domain experts. The time involved in an elicitation process can be even longer for experts who are unfamiliar with the process. Computer-based applications can enhance the efficiency of elicitation. For example, Lau and Leong (1999) developed an automated system to prompt domain experts to revise their responses in case of inconsistencies in their assessments; in the absence of inconsistencies, the probability responses are directly entered into a theoretic analytic model such as Bayes Nets as prior probabilities. The detection of expert judgmental inconsistencies can be performed by automating the calculation of the Inconsistency Index (Lau and Leong 1999; Saaty 1980).

### *2.3 Prediction Markets*

Prediction markets are among the highest empirically performing predictors of election outcomes. Prediction markets aggregate diverse opinions and expertise by providing an opportunity to purchase a contract (stock) on a particular outcome. Trading in a prediction market is similar to many market exchanges: buyers and sellers discuss, negotiate, and stall until a mutually agreeable price is reached on the outcome. Prediction markets have been extensively practiced with well-known markets including the Iowa Election Markets, companies such as INTRADE, and the CNN futures market. Yeh (2006) provides a wealth of background information and references on the application of prediction markets. A wide variety of empirical successes of these markets in predicting is well documented (Wolfers and Zitzewitz, 2004; Hayek, 1945). Berg et al. (2001) review the performance of the Iowa Electronic Market and suggest that it outperformed major polling services in predicting presidential elections. Prediction markets also perform well at the more micro-level analysis such as cities and districts where other methods often fail to aggregate information at such levels of analysis (Wolfers and Leigh 2002). In addition, the learning curve required for setting up a prediction market is relatively low. Note, however, the application of prediction markets to policy analysis, particularly pertaining to sensitive policy issues such as terrorism, has been subject to harsh media criticism (Looney 2004; Wolfers and Zitzewitz 2004), thus prompting researchers to give serious consideration to its potential political and ethical consequences.

Depending on the contract structure, the price of the contract at any point in time can be interpreted as the expectation or the probability forecast for the future event. Given this interpretation, it is conceivable that the prediction market can be linked to computational models (such as Bayes nets). For example, we may consider multiple markets, which represent different scenarios under the model and aggregate the market prices of the scenarios into a Bayes net.

### *2.4 Judgmental Bootstrapping*

Judgmental bootstrapping translates experts' assessments into a quantitative model by regressing expert forecasts against the given information. The collection of studies summarized in Armstrong (2001) reviews a number of forecast studies spanning the discipline of psychology, education, personnel, marketing, and finance. Across these 11 studies, the bootstrapping forecast was more accurate than individual expert assessment in eight of 11 of the studies. The rationale behind judgmental bootstrapping is that human judgments are subject to random errors and the model applies expert rules more consistently. Dawes (1971) accomplished seminal work in this area. In later work, Dawes (1979) points out that even quantitative models constructed using "non-optimal" criteria can significantly outperform expert judgment.

This record of accomplishment for judgmental bootstrapping, the technical simplicity, and methodological transparency warrants incorporating such methodology into this project. It is also worth noting that, even with this technical transparency, this model can be viewed similarly as a dynamic Bayes Net (DBN), as a likelihood-based model for summarizing the relationship between the indicators in the narrative and the predictive outputs of interest. We represent this model form, generically, as $p(\cdot|\theta)$, where $\theta$ are model parameters (in this case, the regression model coefficients) and the form of $p(\cdot|\theta)$ is a Gaussian or normal distribution.

## 3. Task Characteristics and Method Selection

We argue that no single probability assessment method discussed above is clearly superior to any other methods with regard to eliciting and aggregating expert opinions and that the choice of methods should be the function of the characteristics of the decision tasks and cost-benefit calculations. Method comparison studies suggest that each judgmental method has its advantages and disadvantages and that method selection should be task specific. For instance, Kadane and Winkler (1988) compared the probabilities elicited from lotteries, scoring rules, and promissory notes under the conditions of non-stake and with-stake elicitations and their results suggest that the elicited probabilities are congruent with experts' utility functions only if experts have no stake in the elicited subject. Camerer (1981) specifies that although judgmental bootstrapping consistently outperforms raw expert opinion, it is more appropriate when the criterion information is sparse and the prediction environment vague. Green et al. (2007) argue that while prediction markets are more appealing than traditional group decision-making procedures and are more likely to reveal real participants' preferences, its predictive accuracy can be influenced by a host of factors such as the transaction volume, framing of bets, and ethical considerations. In Table 3.1, we provide an overview of the task characteristics that are suitable for each judgmental method. Within the framework of integrative modeling with BNs, the elicitation task for different nodes in the BN should be rendered through the method that is most appropriate for attributes of the elicitation tasks and number of experts.

**Table 3.1 Task Characteristics and Judgmental Method Selection**

| Method | Task Characteristics | Limitations | Sources |
|---|---|---|---|
| Conjoint Analysis | Appropriate when experts are not comfortable with providing direct probabilistic estimations but are more willing to provide comparative assessments | May not be appropriate if a node's attributes cannot be clearly and reliably identified; Does not provide opportunities for exchanging reasoning and justification; Difficulty for dealing with judgmental inconsistencies | (Bradlow 2005) |
| Probability Elicitation | Appropriate when experts are willing to invest considerable time to participate, have some knowledge of statistics, and are comfortable with providing estimates in probabilistic terms. | Aggregation of opinions to achieve consensus might be challenging; Training sessions might be needed for experts who are not well versed in probabilities and statistics; Time consuming and therefore not suitable if decisions need to be reached within a short time window | Kadane and Winkler (1991); Dewispelare et al. (1995); Renooij (2001) |
| Prediction Markets | When an event can be clearly and specifically defined as contracts; A host of contract formats can be used in prediction markets such as: binary option, index, futures, and spread betting, each of which is designed to provide a different | Not all elicitation problems can be framed as a prediction market contract and even well defined contracts may still have loopholes. Does not provide opportunity for exchange of reasoning and justification, which can be as important as the outcome itself. Thin | Green, et al. (2007); Yeh (2006); Wolfer and Zitzewitz (2004) |

| | | | |
|---|---|---|---|
| | kind of forecast (Green et al. 2008, p. 4). | markets may not perform well. May be open to manipulation and is subject to ethical limitations. | |
| Judgmental Bootstrapping | Suitable when criterion information and prediction environment is vague or limited | Experts must be able to properly specify differential cue weights. Cue information may not exist and cue selection can bias prediction. There is limited generalizability across samples. Misweighting in judgments can result in bias. | Camerer (1981) |

## 4. Method Evaluation and Comparison

When setting up elicitation for parameter estimations, logistical factors such as the costs, technological and human resource requirements, and time commitments are all important decision-making considerations. In conjunction with the task characteristics, these considerations will help modelers and experts choose the most cost-effective method that promises the best possible estimations for computational models.

To evaluate the advantages and limitations of the methods, a group of four researchers conducted a pilot method evaluation. The participants brought a diverse range of expertise to the discussion: mathematics, statistics, computational modeling, psychology, political science, and public policy. The group collectively determined a set of judgmental criteria against which the methods were to be evaluated. Key considerations for elicitation method selection criteria include:

- Interactivity and representation of feedback
- Set up costs; resource requirements
- Linkable with risk analyses available and well understood
- Consistent with good forecasting practices
- Re-usable, updatable as new scenarios are available, as new experts' assessments are rolled on or previous ones updated or removed
- Availability of expertise and technology. Track-record of the technology.

Then the evaluators proceeded to individually rate each method along all the criteria listed above on a Likert scale of 1 to 5 where 1 means the least suitable method while 5 the most suitable. After the ratings were completed, the evaluators discussed their respective scores for each of the criteria and provided a justification and rationale for their scores. Evaluators were allowed to revise their scores based on the discussion and the process was repeated until a group consensus was reached. After the scores for all the criteria were collectively evaluated, these scores were summed to generate an overall score for each method. The overall score provides a quantitative frame of reference for the methods to be compared and assessed in terms of their suitability for integrating with computational modeling methods such as Bayesian network and systems dynamic models. Next, the evaluators were asked to reflect on their justification and scores, and share a final written evaluation of the top two method choices for integrative modeling, in this case, Bayesian network models. The following are the excerpts of the final written evaluation from the evaluators:

"I vote for Conjoint Analysis and Prediction Markets… I believe conjoint analysis and judgmental bootstrapping are similar in that they require attributes and levels to work and that prediction markets and expert elicitation are also similar in that they provide a probability number for a specific outcome. I also believe that conjoint analysis and judgmental bootstrapping give more information about the specific attributes that could be useful, but they may not apply to all types of stimulus sets (in particular not to sets that don't have well defined parts)..."

"My top two choices are Prediction markets and Conjoint Analysis because they are:
1. Entertaining
2. Excellent empirical record of accomplishment
3. This is a new research area and we can contribute to this line of research through our project
4. Flexibility
5. Can be linked to BN
6. Instant feedback possible
7. Strong theoretical foundation."

"I like Prediction Markets and Conjoint Analysis. Reasons include:

- PM and CA offer "different" output
- Group discussions communicated to me more enthusiasm for CA and PM
- Both seem easily implementable."

Table 4.1 provides an overview of the method evaluation. Special attention was paid to key factors, such as the degree of interactivity with end users/decision makers, costs, suitability for tasks, resource requirements, linkage with BN, forecasting success, and political considerations. These characteristics should provide helpful guidance for matching specific decision tasks with appropriate methods. For example, if a problem has a short decision-making time window without substantial resources for building original software, then using commercial conjoint analysis tools would be suitable. If a decision problem involves politically sensitive information, then caution should be exercised when considering prediction markets.

**Table 4.1: Method Integration Criteria Comparison**

| | **Conjoint Analysis** | **Probability Elicitation** | **Prediction Markets** | **Judgmental Bootstrapping** |
|---|---|---|---|---|
| Interactivity, level of engagement | Medium-high; interpersonal and computer-expert interaction | High; Extensive interaction between facilitators and experts | Medium; User-market instrument interaction | Low-medium |
| Setup Costs/Resource | Low-medium; commercial service/tools readily available | Medium-high | Medium-high if markets are created anew | Medium |
| Linkage with BN | Mathematically feasible; | Readily linkable and has been done | Mathematically feasible | Mathematically feasible; |

| | Conjoint Analysis | Probability Elicitation | Prediction Markets | Judgmental Bootstrapping |
|---|---|---|---|---|
| Empirical track record – known successes in forecasting | Good performance well documented | Perform well but subject to heuristic biases | Outperforms opinion polls in predicting elections, etc. | Performs well than unaided expert assessment |
| Political sensitivity or ethical considerations | Minimal | Minimal | Could be controversial | Minimal |

## 5. Conclusion

As a critical first step toward advancing the integrative social-behavioral modeling framework, we demonstrated a consensus-based decision-making approach to evaluating and selecting expert elicitation methods in view of their suitability for linking with computational modeling methods. We examined the strengths and weaknesses of linking four well-established elicitation methods: conjoint analysis, probability elicitation, prediction markets, and judgmental bootstrapping, with computational models. We identified elicitation task characteristics and limitations for each method. We also conducted an evaluation study to assess methodological and logistical advantages and disadvantages of the four methods to provide a relatively comprehensive view and a deeper understanding of the feasibility and effectiveness of method integration. As a follow up to this initial phase of research, PNNL researchers have developed a web-based conjoint analysis user interface and algorithms that successfully incorporated subject matter experts' opinion through the interface to calibrate Bayes net models that were developed by Whitney et al. at PNNL (Walsh, et al. 2010). The next phase of the project will advance the social-behavioral modeling research thrust and expand our integrative modeling endeavor to include additional elicitation methods and apply our research outcome to a broader range of social-behavioral research inquiries.

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UNIVERSITY OF SIENA
PIAZZA S. FRANCESCO, 7 53100 SIENA (ITALY)
http://www.labsi.org labsi@unisi.it