Bayesian Causal Maps as Decision Aids in Venture Capital Decision Making†

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Abstract

Improving venture capitalists' venture assessment processes is key to reducing investment write-off rates and to improving portfolio returns. In this paper we describe the use of a novel method to support and improve venture capital decision making. We combine causal mapping and Bayesian network techniques to construct a Bayesian causal map. The resulting probabilistic model represents salient features of decision makers' mental models and inference processes. We discuss the application of Bayesian causal maps as decision aids, their specific advantages, as well as the limitations and challenges inherent in their construction and use. Suggestions for future research are also offered.

1 Executive summary

A venture capitalist's (VC) success ultimately rests on making the right choice as to whether or not to invest in a venture. Underlying this decision is the ability to correctly assess (or judge) whether a venture is an attractive investment opportunity, whether the VC should invest in that venture given both venture (e.g., management quality, product potential) and venture capital firm characteristics (e.g., preferred time horizon and available funds).

Not surprisingly then, a vast body of work has examined VCs' decision and assessment models, usually in an attempt to describe or generate best practices. However, we believe there can be no universal model, given the heterogeneity of VCs and their firms: some specialize in high technology investments, some in old-line businesses. Some provide early stage seed funding, others invest in the later stages or focus on turnarounds of established companies. Some VCs have enormous funds at their disposal, others have to take into account the risk of dilution. Some prefer to manage their investments hands on, some prefer to be more hands off.

Thus, we join others in calling for a program of research into judgment models as decision aids for venture capitalists to complement the fields' current focus on description and universal prescriptive models. The Judgment Analysis and Multiple Cue Probability Learning literatures provide a solid scientific foundation for such an endeavor.

In this paper we model an individual VC's judgments with respect to venture proposals, i.e. the "Should I invest?" question. We use a novel technique and create a dynamic Bayesian causal map (BCM). This BCM model can help VCs both in making the actual decision, as well as in improving their decision making over time.

In terms of the actual decision, the Bayesian causal map is simply a statistical model of the VC's own decision policy. Such models almost always outperform the VC on which they are based. They can be used to structure and facilitate the initial screening process in particular. The use of the BCM model ensures that factors are weighted systematically rather than arbitrarily. However, even with a decision aid, the VC still needs to make expert judgements about the inputs to the model, for example about the quality of management. For this purpose our dynamic BCM model allows for interactive what-if and sensitivity analyses, helping the VC to isolate the critical factors which need to be scrutinized. Furthermore, the interactive process of building a BCM model in itself can reduce decision making bias.

BCM decision models also aid learning. Learning from outcomes alone is generally very difficult. This is particularly true in a venture capital context, where the relatively small number of funded ventures, the long time horizon, and the numerous factors that intervene between the VC's assessment/decision and any observable outcomes, favor a hypothesis-testing approach which greatly reduces the decision maker's cognitive load. That is, instead of using outcomes to estimate relationships between variables, VCs use outcomes to confirm or disconfirm their beliefs about the true relationships between venture characteristics and outcomes. This process is often subconscious. BCM models make the hypotheses explicit and thus provide a structure against which outcome data can be compared.

In addition to facilitating the processing of outcome feedback, a BCM provides policy feedback to the VC. Assumptions and decision rules are made explicit in the model building process, providing VCs with insights into their cognitive processes. Thus, decision rules move from tacit, taken-for-granted assumptions to visually and quantitatively explicated models that can be actively and consciously scrutinized by decision makers or expert coaches. VCs have imperfect insight into their own decision process. The explication and scrutiny of beliefs is a key first step in belief updating and revision. BCM-based what-if and scenario analyses provide VCs with a deeper understanding of the nature and implications of their decision rules.

This paper argues that in a situation where learning from outcomes is close to impossible, decision aids can be very powerful tools to support VC decision making, learning, and training. BCMs in particular hold significant promise as decision aids due to their enormous flexibility, their foundation in real cases, and their interactive and dynamic nature which allows VCs to explore the consequences and assumptions of their own decision models.

2 Introduction

By most measures, including available capital, number of funded proposals, deal size, number of venture capital firms, and number of venture capitalists (VCs), the venture capital industry has grown rapidly in the last decade. According to figures by the National Venture Capital Association (NVCA), US deal volume has expanded from investments in 1,317 companies totaling $ 3.4 billion in 1990 to investments in 5,458 companies worth $ 103.8 billion in 2000. At the same time, a large number of venture capital backed companies continue to fail, with at least 40% of backed ventures failing to provide a return (Ruhnka, Feldman, & Dean, 1992). Consequently, reducing this failure rate by even small amounts should have a substantial impact on venture portfolio returns (Zacharakis & Meyer, 1998).

One key to reducing VC-backed venture failure rates is to understand and improve venture capitalists' decision and assessment processes. Thus, a large number of studies have attempted to investigate how venture capitalists make decisions (e.g., Hall & Hofer, 1993; Hisrich & Jankowicz, 1990; MacMillan, Siegel, & Narasimha, 1985; MacMillan, Zemann, & Narasimha, 1987; Muzyka, Birley, & Leleux, 1996; Sandberg, Schweiger, & Hofer, 1988; Shepherd, 1999; Shepherd & Zacharakis, 2002; Tyebjee & Bruno, 1984; Zacharakis & Shepherd, 2001; Zacharakis & Meyer, 1995, 1998, 2000).

However, given that VCs and their firms are a very heterogeneous group (e.g., in terms of fund size/horizon, stage of investment, industrial sectors), we believe there can be no universal model for VC venture assessment and decision making. We thus concur with Shepherd and Zacharakis (2002) who argue that decision aids represent a crucial next step in the research agenda on VC decision making. Consequently, while the accurate modeling of key features of a venture capitalist's mental models and decision process is a necessary secondary objective of this paper, the primary objective is to use a novel modeling technique – Bayesian causal maps (BCM) – to create a decision aid that can support and improve VC decision making over time.

This paper argues that in a situation where learning from outcomes is close to impossible, decision aids can be very powerful tools to support VC decision making, learning, and training. BCMs in particular hold significant promise as decision aids due to their enormous flexibility, their foundation in real cases, and their interactive and dynamic nature which allows VCs to explore the consequences and assumptions of their own decision models.

Our paper is structured as follows. First, we briefly provide a brief introduction to judgment analysis and Brunswik's Lens Model which provides the theoretical foundation for our work. Second, we develop a probabilistic Bayesian causal map decision model for an experienced venture capitalist. Bayesian causal maps (Nadkarni & Shenoy, 2001), a new causal mapping based form of causal Bayesian networks, combine techniques from the causal mapping and Bayesian Network literatures. We provide some background for both causal maps and Bayesian networks and outline a methodology for constructing Bayesian causal maps. In the first practical application of BCMs, we apply this methodology to the decision model of an experienced venture capitalist specializing in early-stage, high-tech investments. Third, we describe the application of the BCMs as decision aids in venture capital decision making. Fourth, we discuss the specific advantages as well as the challenges and limitations inherent in using Bayesian causal maps for decision modeling. Fifth, suggestions for future research are offered.

3 Judgment analysis

Decision models based on judgement analysis have a long history in the social science literature (e.g., Hoffman, 1960). Judgment analysis is concerned with how people "integrate multiple, probabilistic, potentially conflicting cues to arrive at an *understanding* of the situation, a *judgment"* (Goldstein & Hogarth, 1997:4). This paper examines VCs' judgments of investment opportunities, that is their assessments as to whether they should invest in a venture.

Judgment Analysis is rooted in Egon Brunswik's *Probabilistic Functionalism* (e.g., Brunswik, 1943; Brunswik, 1952) which focuses on the relationship between an organism and its environment. Objects in the environment stimulate perceptual organs (eyes, ears, etc.) to produce cues to the object's identity and properties (e.g., length). However, these cues are inherently ambiguous, i.e. perception is based on fallible and incomplete sensor cues which are only probabilistically related to the identity and properties of the actual object. (Cooksey, 1996; Goldstein & Hogarth, 1997). Hammond (1955) is credited with transferring Brunswik's theory of perception into the realm of decision making. Thus, a VC's judgments about ventures are based on inferences drawn from incomplete and fallible cues, such as profit and market projections.

Brunswik and Hammond's work cumulated in the *Lens Model* which is comprised of two systems (cf. Figure 1). The task system describes the relationship between the ecological variable of interest Y_e (the "true" probability that the investment will be successful), and the cues X_1 to X_n (e.g., the quality of management). The cognitive system, in contrast, describes the relationship between perceived cues and the subjective judgment of a decision maker Y_s (here the VC's perceived probability that he/she should invest). Lens model research usually conceptualizes both the task system and the cognitive system in the form of linear relationships but this is not a necessary feature of the theory.

Insert Figure 1 about here

The primary interest of this paper is in the cognitive systems, i.e. the implicit decision rules used by VCs to arrive at their judgments/assessments. These rules can be elicited in a variety of ways. Studies investigating venture capital decisions have used, for example, participant direct report (e.g., MacMillan et al., 1985; MacMillan et al., 1987; Tyebjee & Bruno, 1984), verbal protocols (e.g., Hall & Hofer, 1993; Sandberg et al., 1988; Zacharakis & Meyer, 1995), repertory grids (e.g., Hisrich & Jankowicz, 1990), and conjoint analysis (e.g., Muzyka et al., 1996; Shepherd, 1999; Shepherd & Zacharakis, 2002; Zacharakis & Meyer, 1998). In contrast, we use a novel methodology, Bayesian causal maps (BCMs; Nadkarni & Shenoy, 2001), which will be discussed in more detail below. BCMs can incorporate both compensatory and non-compensatory relationships and imposes very few a priori restrictions in terms of independence or the nature of interactions.

The lens model also highlights that boundedly rational decision makers (Cyert & March, 1963; Simon, 1955) make decisions based on simplified models of their environment and use only three to seven informational cues at a time (Stewart, 1988). Thus, while quantitative models will never fully capture all the variables and intuitive decision rules of an expert decision makers, there is some suggestion that they can adequately represent the most salient features of actual decision processes.

4 Causal maps and Bayesian networks

Bayesian causal maps incorporate techniques from both the causal mapping and the Bayesian network arena. We will provide a brief theoretical overview for each.

4.1 Causal maps

The use of causal maps to represent individuals' mental models is commonly traced to Tolman (1948) and was popularized in the social sciences by Axelrod (1976). He defined a causal map as "a specific way of representing a person's assertions about some limited domain such as a policy problem. It is designed to capture the structure of the person's causal assertions and to generate the consequences that follow from the assertions." (Axelrod, 1976: 72). Causal maps capture knowledge, expertise, and assumptions in the form of directed cause-effect and means-end relationships between variable-like concepts. A sample map is depicted in Figure 2. The map depicts the expert's assertions that the quality of the science and technology behind a product positively affects product quality. Similarly, the quality of management, product quality, and the appropriate marketing strategy for the product positively influence the product potential (expected market share) in a given market.

Insert Figure 2 about here

Using causal maps in decision analysis rests on three core assumptions about the role of cognition in decision-making. (1) Causal associations are a key way in which decision problems can be described and understood (Huff, 1990); (2) revealed causal maps represent to a significant extent the actual mental models of the decision maker; and (3) these simplified, causality-based representations of the decision environment form the basis for decision making and managerial action. While we cannot present a full discussion here (see Axelrod, 1976; Huff, 1990) there is significant evidence that these assumptions are not unreasonable. There is, for example, evidence for the congruence of external with private statements (Fiol, 1995) as well as the congruence of causal maps with later action (Bonham & Shapiro, 1976).

Causal maps have been used to study a wide variety of phenomena, including strategic change (Barr & Huff, 1997), environmental adaptation (Barr, Stimpert, & Huff, 1992; Fahey & Narayanan, 1989), joint venture formation (Fiol, 1989), software operations support expertise (Nelson, Nadkarni, Narayanan, & Ghods, 2000), and intrapreneurship (Russell, 1999). Another stream of research pioneered by Eden (e.g., Eden, 1991; Eden & Ackermann, 1993) has used causal maps to define the actual decision problem and to reveal hidden decision premises.

Causal maps can be derived based on documentary sources (e.g., letters to shareholders, speech and interview transcripts) as well as using more intrusive measures such as card sorts or repertory grids (e.g., Bougon, Weick, & Binkhorst, 1977). Causal maps can also be developed directly by, or in consultation with, the research participant, aided by software such as *Decision Explorer* (Banxia Software Limited, 2000).

4.2 Bayesian networks

Bayesian networks have their roots in attempts to represent expert knowledge in domains where information is uncertain, ambiguous, and/or incomplete. Bayesian networks are based on probability theory. A primer on Bayesian networks can be found in the work of Spiegelhalter and colleagues (Spiegelhalter, Dawid, Lauritzen, & Cowell, 1993).

A Bayesian network model is represented at two levels, the qualitative and the quantitative level. At the qualitative level, a Bayesian network is a directed acyclic graph in which nodes represent variables, and directed arcs describe the conditional independence relations embedded in the model. Figure 3 shows a Bayesian network consisting of four discrete variables: Management Market Know-how (M), Management Quality (Q), Potential Revenue (R), and Decision to Invest (D).

At the quantitative level, the dependence relations are expressed in terms of conditional probability distributions for each variable in the network. Each variable X has a set of possible values, called its state space, that is mutually exclusive and commonly exhaustive. In Figure 3, for example, Management Market Know-how, Management Quality, and Potential Revenue have two states each: 'High' and 'Low.' Decision to Invest has two states: 'Go' and 'No go.' If there is an arc pointing from X to Y, we say X is a parent of Y. For each variable, a probability distribution needs to be specified. For variables with a parent, this takes the form of a table of conditional probability distributions, one for each configuration of states of its parents. Figure 3 shows these tables of (conditional) distributions—P(M), P(Q | M), P(R), and P(D | Q, R)[1]. As can be seen, absent other information, the probability of the management quality being high is 25 %. Similarly, the probability that an investment is made given high revenue potential and high quality of management, is 90 %.

Insert Figure 3 about here
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[1] Notation: P(D | Q, R) specifies the probability distribution for the Decision to Invest (D) given information of about the Management Quality (Q) and Potential Revenue (R).

4.2.1 Semantics of Bayesian networks

A fundamental assumption of Bayesian networks concerns conditional independence relationships in the joint probability distribution. These conditional independence assumptions can be read directly from the Bayesian network graph as follows. Missing arcs (from a node to its successors in the sequence) signify conditional independence assumptions. Thus, in Figure 3, the lack of an arc from M to R signifies that M is independent of R; the lack of an arc from Q to R signifies that Q is independent of R; and the lack of an arc from M to D signifies that D is conditionally independent of M given Q and R. Pearl (1988) and Lauritzen and colleagues (Lauritzen, Dawid, Larsen, & Leimer, 1990) describe other equivalent graphical methods for identifying conditional independence assumptions embedded in a Bayesian network graph.

4.2.2 Conditional independence and causality

Unlike a causal map, the arcs in a Bayesian network do not necessarily imply causality but rather conditional independence assumptions. How are conditional independence and causality related? Conditional independence can be understood in terms of relevance. If Z is conditionally independent of X given Y, then this statement can be interpreted as follows. If the true state of Y is known, then in assigning probabilities to states of Z, the states of X are irrelevant. In practice, the notion of direct causality is often used to make judgments of conditional independence. Consider a situation where X directly causes Y and Y in turn directly causes Z, i.e., the causal effect of X on Z is completely mediated by Y. Then it is clear that although X is relevant to Z, if we know the true state of Y, further knowledge of X is irrelevant (for assigning probabilities) to Z, i.e., Z is conditionally independent of X given Y. This situation is represented by the Bayesian network $X \rightarrow Y \rightarrow Z$ in which there is no arc from X to Z.

4.2.3 Making probabilistic inferences

Inference (also called probabilistic inference) in a Bayesian network is based on the notion of *evidence propagation*. Evidence propagation refers to efficiently computing probabilities for the variables of interest based on observed evidence about the state of one or more other variables (Spiegelhalter et al., 1993). Once a Bayesian network is constructed, it can be used to make inferences about the variables in the model. The conditional probabilities given in a Bayesian network specify the *prior* joint distribution of the variables, e.g., the base line investment probability, given no information about the investment opportunity. If we observe (or learn about) the values of some variables (e.g., quality of management), then a *posterior* joint distribution of the variables can be calculated, including updated probabilities for key variables of interest (e.g., the invest decision). Thus, the joint distribution of variables changes each time we learn new information about the variables.

5 Building a Bayesian causal map

Below, we elaborate the process of constructing a causal map-based Bayesian network (Bayesian causal map) of an expert venture capitalist, implementing for the first time a methodology proposed by Nadkarni and Shenoy (2001). The procedure consists of five steps: (1) elicitation of a raw causal map from an expert venture capitalist, (2) preprocessing of the raw causal map, (3) assignment of states to variables, (4) assignment of probabilities to states, and (5) refinement and validation.

5.1 *Elicitation of the raw causal map*

The first step in building the raw causal map was to interview an expert with knowledge of the domain, in this case an experienced venture capitalist. By using a semi-structured interview, the concepts in the map are allowed to emerge from the data, rather than being predetermined a priori by the researcher (Carley & Palmquist, 1992). In order to elicit the Venture Capitalist's mental model, we not only asked for a general description of the venture capital investment process, but also asked the participant to describe three real world cases to us. These cases involved both successful and unsuccessful investments, as well as a case where the venture capital firm decided not to make an investment after studying the venture. Using case studies is much less intrusive than directly asking experts to explicate a general model of their decision processes. Experts understanding of their own decision models is often limited (e.g., Zacharakis & Meyer, 1998). Thus, a study of *revealed* decision criteria through case descriptions usefully complements the direct elicitation of decision models.

The interview lasted 1.5 hours. The interview was transcribed, yielding in excess of 13,000 words. A revealed causal map was created from this textual base, by (1) identifying the causal statements in the text, and (2) constructing a raw causal map with cause concepts linked to effect concepts by arrows indicating the direction of causality. An excerpt of the raw causal map is shown in Figure 2.

Causal statements are assertions that can be represented in the form "the more A, the more/less B" (Axelrod, 1976: 258). A concept can therefore be thought of as a variable that is able to take on different values. The following is an example of a causal statement:
"[…] with the name that he had in the pharmaceutical industry. So that was a real asset, that was one of the reasons we made the investment". This is an *explicit* causal statement. However, most

texts also contain a multitude of *implicit* causal statements which are also coded.

A causal statement thus identified is then transformed into a graphical representation in the form of a raw causal map. The map consists of vertices, linked by arrows. The vertices represent the concepts. The relationship between concepts is represented by an arrow in the direction from the cause to the effect concept. The causal relationship is either positive or negative, i.e., the cause has either a promoting or retarding influence on the effect variable (Axelrod, 1976: 10-11). This is represented in the form of a "+" or "–" above the arrow. The totality of all (domain relevant) causal statements in a given text forms a raw causal map[2].

5.2 Preprocessing of the causal map

Before probability values can be assigned to the causal map, the raw causal map has to be preprocessed in order for it to be compatible with Bayesian network theory (Nadkarni & Shenoy, 2001). The four necessary steps are discussed below.

5.2.1 Conditional independence

Causal networks can either be modeled as dependence maps (D-maps) or independence maps (I-maps) (Pearl, 1988). In a D-map, concepts (variables, vertices) connected by arrows are indeed dependent. However, concepts lacking a direct connection may or may not be conditionally independent. In contrast, in an I-map, the absence of a connection between two concepts does indeed imply conditional independence, given the state of other variables in the map, but the presence of a link may or may not imply dependence. Causal maps, by their nature are D-maps, while Bayesian networks are I-maps. Thus, the raw causal map needed to be transformed into an I-map, in consultation with the expert on whom the raw causal map was based. At the end of the procedure, the Bayesian network was both a D-map and an I-map, i.e. a *perfect map*. This step resulted in significant changes to the map, partially also due to the fact that this was the first time the VC was able to see and audit the causal map.

5.2.2 Underlying reasoning

There are two underlying types of reasoning that are relevant in building Bayesian networks: *deductive* and *abductive* reasoning (Charniak & McDermott, 1985; Winston, 1984). Deductive reasoning is reasoning from causes to effects. Abductive reasoning moves from effects to causes. This is illustrated in Figure 4. Observing rain and predicting that the streets will be wet, is an example of deductive reasoning. The abductive reasoning analog would be observing wet streets and inferring that it must have rained. In a spontaneous interview situation, people often use the same causal syntax for both deductive and abductive statements, which means that both representations of our examples can be reasonably expected to occur in a raw causal map. As a consequence, the linkages in the raw causal maps had to be audited and the true direction of causality was established in cooperation with the expert. The direction in causal Bayesian networks should reflect the underlying causality, rather than the language used. This is particularly challenging in the case of latent, unobservable concepts (e.g., ‘management quality’) where reflective and formative indicators are often not easily distinguishable (Hulland, 1999).

[2] For further illustrations and descriptions of how to derive revealed causal maps (including from non-textual sources) see the works by Axelrod (1976), Fahey and Narayanan (1989), Huff (1990), and Eden and Spender (1998).

Insert Figure 4 about here

5.2.3 Direct and indirect relationships

Standard methods for deriving causal maps do not provide for a distinction between ‘direct’ and ‘indirect’ linkages between concepts (Eden, Ackermann, & Cropper, 1992; Laukkanen, 1994). In our experience, people, in conversation, often draw direct linkages, even if they are aware of important mediators, since they want to emphasize the fact *that* two concepts are linked and not necessarily *how* they are linked. Thus, for a given pair of variables both direct and indirect connections often appear in interview transcripts (see Figure 5). However, as discussed above, since a Bayesian network is an I-map, the presence or absence of the direct link between two concepts does have implications in terms of conditional independence. If the relationship between “involvement of strong partner” and “decision to invest” is fully mediated by “confidence in timing”, the direct arrow needs to be removed. Consequently, the exact nature of such relationships had to be discussed and verified with the domain expert since conditional independencies are critical in making inferences in Bayesian networks.

Insert Figure 5 about here

5.2.4 Eliminating circular relationships

The final step in the preprocessing of the raw causal map concerns circular relationships. Causal maps, while directed graphs, have no restrictions with respect to circular relationships. In contrast, Bayesian networks are hierarchical graphs that are by necessity acyclic. Thus, circular relationships need to be removed from the raw causal map. In our raw causal map circular relationships were not present.

At the end of this procedure, the pre-processed map was once again audited by the research participant before probabilities were elicited.

5.3 Assignment of states to variables

Each concept from the raw causal map was assigned two states, such as High/Low, True/False. Due to the complex calculations involved in probabilistic inference, such crude state spaces are often unavoidable (see also, e.g., Shepherd & Zacharakis, 2002 for a similar example using conjoint analysis). However, Bayesian networks allow probabilities to be assigned to each variable state. Thus, once management quality, for example, is observed, it can be set to, say, high – low = 80 % – 20 %, allowing for finely graded judgements by the model user.

5.4 Assignment of probabilities to states

While the procedures outlined above established the structure of the Bayesian network, the inference processed is driven by a set of prior (for nodes without parents) and conditional probabilities (for nodes with at least one parent) that are attached to each state of each variable. As shown in Figure 3, these are contained in tables.

We elicited these probabilities directly from the expert. This is a lengthy and complex task. To facilitate the process and to ensure data quality we employed several techniques. One, we used verbal and experiential anchors since most people do not routinely think in probabilities. Second, we focused on one or two sub-sections of the map at a time. Third, we attempted to exploit noisy-AND or noisy-OR (Henrion, 1989) relationships. This is similar to the ability to reduce the number of attribute combinations that need to be directly assessed in conjoint analysis, given assumptions about orthogonality and interaction effects. However, in our example such modeling was usually inappropriate given the complex and asymmetric interdependencies between variables. Fourth, we continuously checked for unusual results and had them verified by the venture capitalist. Overall, the elicitation process is iterative in nature. The resulting Bayesian network is depicted in Figure 6 and was implemented using Netica (Norsys Software Corp., 1998), a widely used and user friendly Bayesian Network software package. The boxes show the variables (e.g. Management Quality) and their states (here: High/Low). The probabilities attached to each states are shown numerically as well as through a bar graph. Arrows show the directionality of influence. Variables for which actual observations or assessments have been entered to supercede the a priori probabilities are shown in dark gray.

Insert Figure 6 about here

5.5 Refinement and validation

In addition to general audits, we used real world cases to verify the face validity of the model. We asked the research participant to think of and describe three actual investment opportunities from the past: one successful, one unsuccessful, and one where he decided not to invest. We conducted two checks.

First, we tested whether the model reflected his decision policy. For each variable for which information was available at the time of the decision, we entered the VC's *original assessment* of the state of those variables into the model. The probability distribution for the variable '[Should] Invest' should now reflect the actual decision and the decision confidence of the research participant. This was indeed the case. Figure 6 shows the probabilities for one of these cases (dark gray boxes denote observed / assessed variables). As can be seen, the 'should invest' probability was 71.4, supporting the original investment decision.

Second, we investigated how well the model correlated with real-world outcomes. This time, however, instead of entering the VC's original subjective assessment, we used *the actual variable state as revealed in hindsight*. For example, in one of the cases the VC (and other industry players) had assessed the market potential as high, although the actual market potential turned out to be very unfavorable. To the extent that the decision maker is indeed a competent venture capitalist, the investment probability should now correspond to the economic fate of the venture. This was the case. In a case from the energy sector, the investment probability based on the information at the time of decision was 57.4, supporting the investment decision. However, merely entering the true information regarding the market potential, reduced the investment probability to 25.4, in line with the disastrous outcome of the actual venture.

The validation process also lead to minor refinements to the model. Throughout the process, the VC commented several times (without prompting) on the sometimes surprising, but after reflection appropriate nature of the Bayesian causal map, further increasing our confidence in the face validity of the model.

6 Applications: Bayesian causal maps as decision aids

Decision aids are methods that attempt to improve decision making. They include a wide variety of tools and techniques, including devils advocacy (e.g., Schwenk, 1984b) and simulation (Hall & Menzies, 1983), for example. Our discussion will focus on formal, quantitative decision and judgment models which also can function as decision aids (Shepherd & Zacharakis, 2002; Zacharakis & Meyer, 1998, 2000).

The term 'decision aid' can sometimes be misleading in that it seems to focus mainly on the immediate process of making the decision at hand. However, in addition to the direct (i.e., the extent to which the outcome prescribed by the decision aid is superior; Humphreys, 1983) and indirect benefits (such as increased understanding and process implications; Humphreys, 1983; Watson & Brown, 1975) that relate directly to the decision, a further benefit lies in the role of decision aids in learning over time.

Decision aids are especially useful in a venture capital context, since in trying to predict future venture success, VCs face a messy, unstructured, complex decision problem. The idiosyncratic nature of investment opportunities, a highly uncertain future, and an almost infinite number of potentially relevant factors pose an immense challenge for VCs and make it tempting to rely purely on intuition.

6.1 Benefits for decision making

While a Venture Capitalist will rarely rely exclusively on the output of a BCM decision model, the fact is, that models (like BCMs) that are based on an individual expert (so called *bootstrapping models*) in almost all cases outperform that expert him/herself (e.g., Brehmer & Brehmer, 1988; Camerer & Johnson, 1997; Yntema & Torgerson, 1961).

The reasons is a reduction of random error through reduction of noise, selective attention, and inconsistent application, for example (e.g., Kleindorfer, Kunreuther, & Schoemaker, 1993). This relates directly to the second benefit of a decision aid for VCs, i.e. the fact that decision aids structure the decision process. This structuring is often an important decision making step because it increases the decision makers' understanding of the problem (Rhodes, 1993: 6).

In addition, the model building process in itself can reduce decision making bias: Hodgkinson and colleagues (1999) report that the mere process of creating a causal map reduced decision bias (framing bias) in a sample of both undergraduate students and senior managers.

The use of models also reduces cognitive load and can be effectively used in the screening process. Business plans passing the first hurdle can then be subjected to thorough what-if analyses with the help of the dynamically updating BCM model. These interactive what-if and sensitivity analyses help the VC to isolate the critical factors which need to be scrutinized in the due-diligence.

So far we have discussed individual decisions. However, decisions are rarely made by one person or without an organizational context to consider. Thus, Fischhoff remarked in interpreting the studies of Watson and Brown (1975), that “the greatest benefits of the analyses seemed to come not from the decisions they recommended, but from their contribution to organizational processes.” (Fischhoff, 1983: 75). For example, Bayesian causal maps can improve the collaboration of partners within a venture capital firm by enabling them to understand their differences in terms of decision models, biases, and focus. Thus, Bayesian causal maps can help to constructively resolve situations in which partners consistently differ in their assessment of an investment opportunity.

6.2 Benefits for learning

Expertise is something that is acquired over time. Thus a large stream on Multiple Cue Probability Learning has emerged within the judgment analysis literature, that investigates how decision makers can improve their judgments/assessments. Kleindorfer and colleagues distinguish three types of feedback that can form the basis for learning (Kleindorfer et al., 1993: 80): (1) *Outcome feedback*; (2) *relationship feedback* (information about how cues are related to outcomes); (3) *policy feedback* (information about how a person combines and weights cues to arrive at a judgment). Relationship and policy feedback, together or by themselves, are also known as *cognitive feedback* in the literature (cf. e.g., Doherty & Balzer, 1988).

Learning from outcomes alone is generally very difficult (e.g., Klayman, 1988). Especially in a venture capital context, the relatively small number of funded ventures, the long time horizon and the numerous intervening factors (including the involvement of the VC him/herself; Gupta & Sapienza, 1992) that lie between assessment/decision and observable outcomes, make learning from outcomes alone "likely to be prohibitive in terms of complexity of encoding and demands on memory. A hypothesis-testing approach greatly reduces the learner's cognitive load" (Klayman, 1988: 126, speaking in a general context). That is, instead of using outcomes to estimate relationships between variables, VCs use outcomes to confirm or disconfirm their beliefs about the true relationships between venture characteristics and outcomes, although often subconsciously. Bayesian causal map decision aids make these hypotheses explicit and thus provide a structure against which outcome data can be compared. Initial assumptions about the states of the cue variables can be compared to actual outcomes and "wrong" decisions can be traced to specific failures in either (1) the cue variable state assessment (e.g., management quality was overestimated), (2) the overall decision rules (e.g., the model did not consider a key variable or interdependency, or did not weigh its impact correctly) , or (3) the implementation (marketing strategy was correctly assessed as good, but implementation of the marketing campaign was mishandled). Einhorn also emphasizes the need for task structure information (or at least a hypothesis):

> "[W]ithout knowledge of task structure, outcome feedback can be irrelevant or even harmful for correcting poor heuristics. Moreover, positive outcome feedback without task knowledge tends to keep us unaware that our rules are poor because there is very little motivation to question how successes were achieved."
> (Einhorn, 1980: 8)

A Bayesian causal map decision aid provides *policy feedback* to the VC. Assumptions and decision rules are made explicit in the model building process, providing VCs with insights into their cognitive processes. Thus, decision rules move from being tacit, taken-for-granted assumptions to visually and quantitatively explicated models that can be actively and consciously scrutinized by decision makers or expert coaches. There is evidence that VCs have imperfect insight into their own decision process (Zacharakis & Meyer, 1998). The explication and scrutiny of beliefs is a key first step in belief updating and revision. Bayesian causal maps also allow for easy what-if and scenario analyses providing VCs with a deeper understanding of the nature and implications of their decision rules.

Most studies on cognitive feedback confound policy feedback and relationship feedback (Doherty & Balzer, 1988). While *cognitive* feedback generally is more effective than outcome feedback, there is some indication that for maximum effectiveness *policy* feedback may have to be combined with some knowledge about the true relationship between decision cues and outcomes (relationship feedback) (cf. Doherty & Balzer, 1988), even if that relationship may never be fully known as in the VC context. As in the case of outcome feedback, policy feedback enhances the incorporation of other information. For example, Schmitt and colleagues found that the performance of subject's bootstrapping models improved if they were given both policy and relationship feedback (Schmitt, Coyle, & King, 1976). In the VC case, this means combining the use of BCM decision models with expert coaching or other interventions.

BCMs can also be used in collective and collaborative learning. Models can be compared between novices and experts, or between partners of the same firm. Due to their explicit nature they can serve as a point of reference and departure for both individualized coaching as well as group learning in a peer or within-organization context.

7 Advantages of Bayesian causal maps

Bayesian causal maps as decision aids have several advantages. First, in comparison with the hypothetical cases or pure attribute lists employed in many other techniques, the elicitation is based on *real* cases that are meaningful to the respondent, improving the confidence in the meaningfulness of the response.

Second, the elicitation of the initial model structure and pool of variables through causal mapping of multiple case narratives is relatively unobtrusive and less susceptible to bias than direct questions such as: "What factors do you consider when making an investment decision?"

Third, with the exception of circular relationships, the method imposes no a-priori assumptions about the orthogonality of variables or the (non)-existence of interaction terms. As discussed, any independence assumptions in the final model can be read from the structure of the model by visual inspection. In addition, no symmetric or linear relationships are assumed. For example, in Figure 3, the impact of the observed state of Management Market Know-how on Management Quality depends on whether the observed Market Know-how is high or low. The relationship is asymmetric. Thus, complex interdependencies can be modeled. We observed such asymmetries throughout the model.

Fourth, Bayesian networks can accommodate partial information and uncertainty. Full information is not required. The user can enter his or her assessment for only the variables for which information is known. In addition, assessments can be entered in probabilistic rather than absolute terms (e.g., management quality high – low = 60 % – 40 %).

Fifth, the model is dynamic in the sense that it can be easily updated with new information and the impact of such information is automatically propagated through the model.

Sixth, software is readily available to support the creation, and more importantly, the use of the model. Features that support visualization of, and easy mouse-click interaction with, the model are key to user friendliness and actual use of such models as decision aids in real-world settings. The computer implementation facilitates user interaction and experimentation with the model leading to a deeper understanding of its nature and implications.

8 Limitations and challenges

There are several limitations and challenges inherent in the construction and use of Bayesian causal maps for venture capital decision making. First, if done conscientiously, the iterative elicitation process can be quite time consuming. This is potentially problematic, given the time constraints faced by venture capitalists.

Second, depending on the structure of the network, the size of the conditional probability tables may become unmanageable. For a node with 8 parents with 2 states each, 256 conditional probabilities would have to be assessed. However, this problem similarly applies to conjoint analysis and other methods. Given certain assumptions, methods such as noisy-AND/OR do exist to reduce the number of probabilities that have to be elicited (e.g., Henrion, 1989).

Third, in this paper we have chosen to elicit conditional probabilities directly from the VC. Prior research (Zacharakis & Meyer, 1998) shows that while VCs understanding of their own decision processes is overall quite accurate, it is clearly imperfect.

Fourth, the fact that the original model is based on actual cases is in general a benefit. However, it may also cause idiosyncratic learning from these cases to skew the model. For example, issues that are peripheral in every-day decision making (e.g., the technological and market progress of big industry players), may feature prominently in the model, since it featured prominently in one of the real-life cases used to construct the BCM. However, while this may lead to the inclusion of less than salient factors in the model, it does not in itself represent a significant problem.

Fifth, the universe of variables and interdependencies that could be considered is almost limitless. Any model includes only key variables and dependencies and excludes many more. Together with the crude state space (discussed earlier), this may make acceptance of the model by the decision maker more difficult. However, the probabilistic uncertainty that is included in Bayesian causal maps explicitly accounts for such exogenous factors, albeit imperfectly.

Sixth, we believe that the final probability for the “invest” variable, calculated by the model, cannot and should not be interpreted as a probability in the classical sense. For one thing, because of the uncertainty included in the conditional probability tables to account for exogenous factors, there is a floor and a ceiling on the probability of investment inherent in each model. For example, in our model these were 2.91 and 81.4 percent respectively.[3] There are several approaches to this problem. (1) One can normalize the final investment probability over the range of possible probabilities: $P_{normalized} = (P_{invest} - P_{floor})/(P_{ceiling} - P_{floor})$. (2) Using real cases and past experience, one can construct a verbal translation of probability ranges (e.g., 60%-70% = invest only after serious due diligence). (3) If used repeatedly for past cases or future projects, the VC will develop his or her own intuition or translation of the meaning attached to the investment probability after using the model (cf. Davis, Fusfeld, Scriven, & Tritle, 2001: 54).

Seventh, our model explicitly models only the salient decision model of a particular VC. That is, any systematic imperfection in his or her expertise is included in the model. Also, the model is not transferable across venture capitalists, venture capital firms, or stage of investing.

[3] Ceilings (floors) were calculated by setting the management quality, product potential, market potential, strong partnerships, and dilution risk variables to their most beneficial (detrimental) state.

In the end, decision aids live and die by their acceptance by the venture capitalists that will use them. Given resistance to objectively superior models in the medical field and the fact that the average business plan initially only receives 8-12 minutes attention (Sandberg, 1986), pragmatic as well social and cognitive legitimacy considerations may well be the biggest obstacle to the application of the present research.

9 Future research

There are several ways the research presented here can be extended. First, the model can be refined to accommodate a wider variety of variables and interdependencies. Second, the modeling exercise could be repeated with a number of participants and systematic differences (across VC firms, novice vs. experts, stage of investment, etc.) could be compared to understand better the heterogeneous nature of VC investing. Third, it would be interesting to compare the performance of expert knowledge based Bayesian causal maps to pure statistical models such as neural networks. Fourth, we believe that combining causal mapping to elicit the network structure with conjoint or regression techniques to elicit the conditional probability relationships would be a very fruitful avenue for future research. Finally, incorporation of insights from Spohn's theory of epistemic beliefs (Spohn, 1988) would allow a decision model based on order of magnitude probabilities which may be easier to elicit than classical probabilities.

10 Conclusion

In this paper we have introduced Bayesian causal maps as a new decision aid in VC decision making. Together with Shepherd and Zacharakis (2002) we are one of the first to move to a critical new step in venture capital decision research and to focus primarily on decision aids and improving decisions rather than focusing on descriptive models. An inspection of the variables included in our VC's model support the validity of prior research (see, e.g., the overview in Zacharakis & Meyer, 1998: 61), but also our assertion that decision models are often idiosyncratic, tailored not just to the person, but the characteristics of the venture capital fund in question (in this case a fund focused on relatively small investments in early stage, high-tech companies) .

This paper also represents the first implementation and application of Bayesian causal maps first proposed by Nadkarni and Shenoy (2001), thus contributing to the causal mapping, artificial intelligence, and decision modeling literatures in addition to entrepreneurship. We believe that the study of decision aids in general, and of Bayesian networks in particular, holds great promise for venture capital research.

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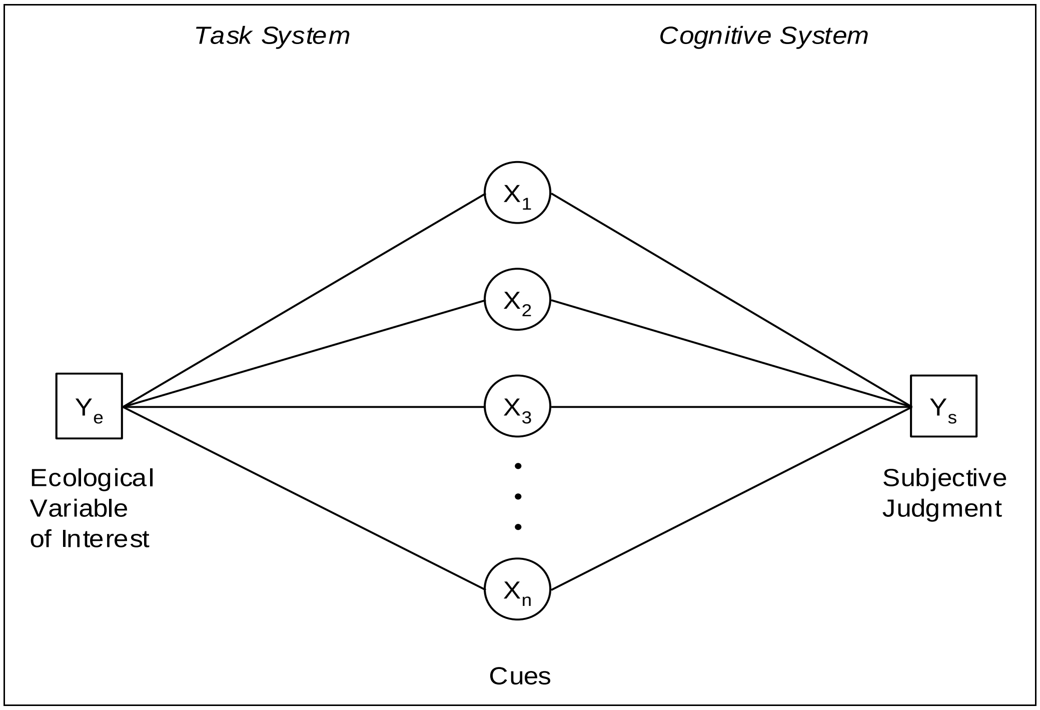
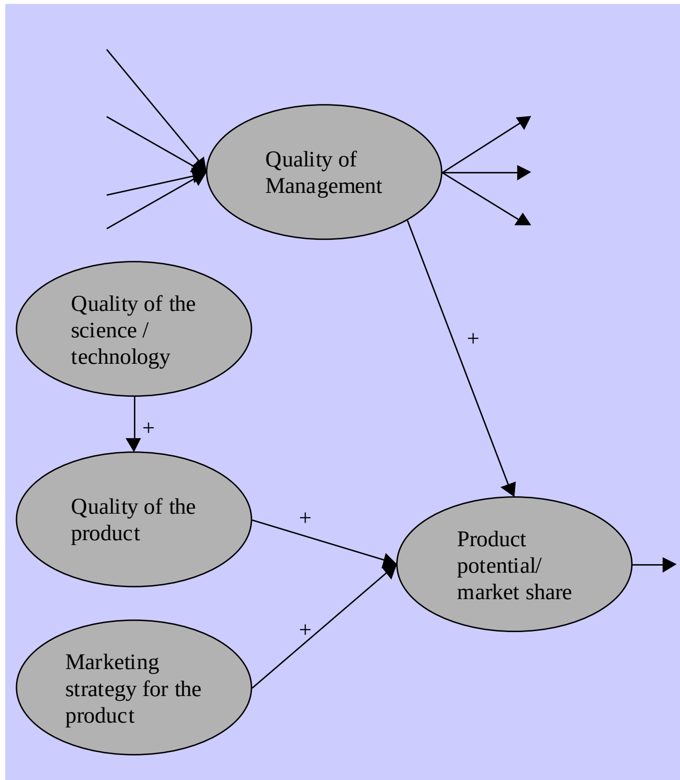
Figure 1: Brunswik's Lens Model



Adapted from Cooksey (1996: 12) and Shepherd and Zacharakis (2002: 5). All graphical representations of the lens model ultimately are based on Brunswik's own representation, most notably in *The Conceptual Framework of Psychology* (1952: 20).

Figure 2: Raw Causal Map



Note: To improve readability, only an excerpt is presented. The structure of the total map is shown below. The focal variable (decision to invest) is shown as a rectangle.

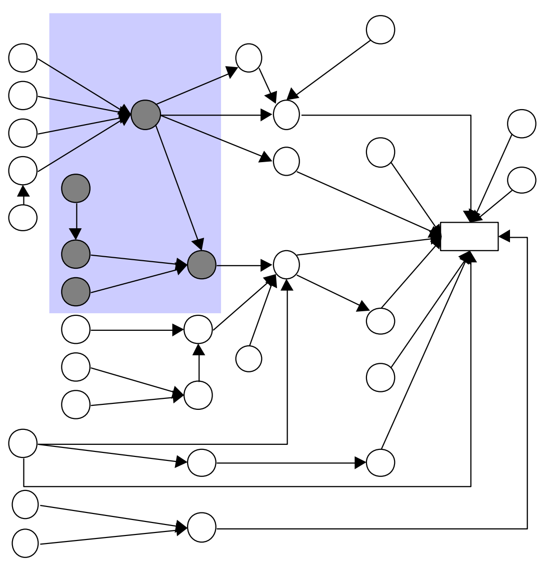
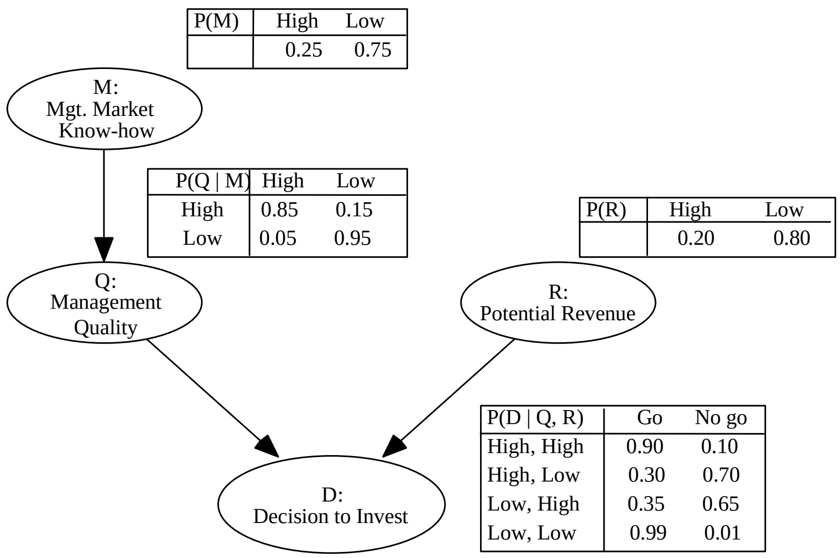


Figure 3: A Bayesian Network with Conditional Probability Tables



P(M)	High	Low
	0.25	0.75

P(Q | M)	High	Low
High	0.85	0.15
Low	0.05	0.95

P(R)	High	Low
	0.20	0.80

P(D | Q, R)	Go	No go
High, High	0.90	0.10
High, Low	0.30	0.70
Low, High	0.35	0.65
Low, Low	0.99	0.01

Figure 4: Examples of Deductive and Abductive Reasoning

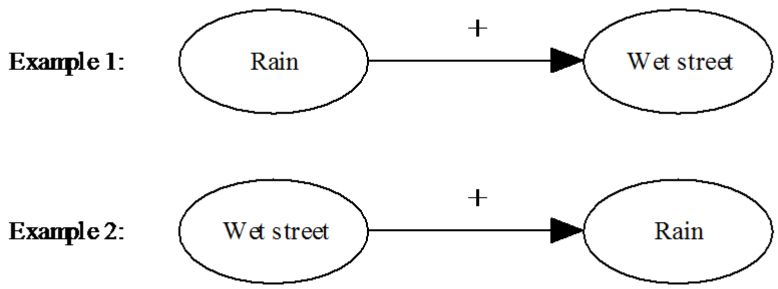


Figure 5: An Example of Direct and Indirect Reasoning

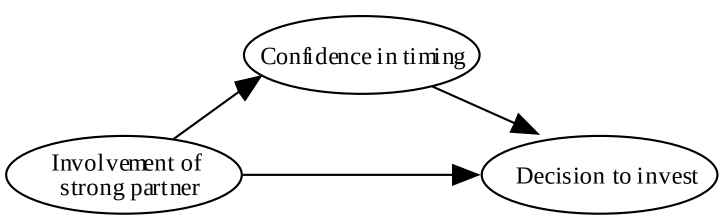


Figure 6: BCM - Chemical industry case