# MANAGING VENTURE CAPITAL INVESTMENT DECISIONS: A KNOWLEDGE-BASED APPROACH

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## ABSTRACT

In this study, we build a causal map of the investment decision using causal mapping techniques by interviewing venture capitalists (VCs). We convert this map into a causal Bayes net using techniques we developed. Causal Bayes nets are especially suited for domains characterized by high degree of uncertainty. Bayes nets have been recently developed in artificial intelligence and used in medical diagnosis, modeling portfolio risk and return, and new product development. They are based on probability theory. The network of cause-effect relations that constitutes a causal map reflects how individuals view the world and make inferences about the values of some variables in these maps when information is received about other variable in the map.

## 1 INTRODUCTION

In the last decade, the venture capital (VC) industry has grown rapidly by most measures including available capital, number of funded proposals, size of a deal, number of VC firms, and number of venture capitalists. The popularity and attractiveness of the VC market has lured established firms to develop such funds and look at themselves as venture capitalists (Brody and Ehrlich, 1998). A research house estimated that the venture capital-backed investments increased from $14B in 1998 to nearly $36B in 1999 (Smart Business, August 2000). Expectations for 2000 were even higher, about $70B.

As more money is available to the investors/entrepreneurs and as more deals are closed, one would expect that the significant learning would occur in the VC industry. Average returns for VC investments do not reflect this learning (Brody and Ehrlich, 1998). The McKinsey study finds that annual returns for VCs have been dropping since 1995. In fact, in 1997, return for the VCs was even lower than for the S&P 500. Though the industry appears to be doing better than others, there is ample scope for improvement.

The current meltdown in the success of the venture capital-backed businesses is another indication of the lack of development of "better" investing models for the VCs. Clearly there are several reasons for the lack of improvement in the investing returns for VCs. We speculate that one reason for this is that the decision-making models that have been proposed in the literature are based on statistical data from past investments. Such models do not encode a venture capitalist's knowledge and expertise and are primarily static in a rapidly changing business investment environment. Thus, we need to develop investment models that capture the expertise of the venture capitalist and that can be updated whenever new information about the project is available. A "Bayes net" model that captures the expertise of a successful VC will make the decision rules and biases more explicit and consequently, make investments more efficiently. We realize that there will be some factors that may be difficult to elaborate and the venture capitalist will still need to make the decision. The Bayes net models will serve only as aids to this decision.

### 1.1 Practical Contributions

Our hope is to identify the "losers" before any investments are made in them, the "winners" early so that the venture capitalist can partner in their success. For example, typically four out of ten investments are written off. This model could reduce this number of losers. On the other hand, the industry does not want to pass up the several entrepreneurs who become successful without its funding. This would lead to more efficient, and possibly effective, allocation of capital in the industry. In an ideal situation successful ventures would likely be funded, while unsuccessful ones would be less likely to pass through the screen.

### 1.2 Past Research

Noting the importance of venture capitalists in the creation of successful new companies, venture capitalists have been widely researched. Research has looked at investment rates, success rates, return rates, and various aspects of the decision-making models used by the venture capitalists. Earlier research is more about the industry statistics and the structure and governance of the industry (Sahlman, 1990). The attempts to study the decision criteria used in new venture evaluation have been evolving over time. There have been attempts to develop models for venture capitalists' investment activity (e.g., Tyebjee and Bruno, 1984; MacMillan, Siegal, and Narasimha, 1985; MacMillan, Zemann, and Narasimha, 1987). These models are primarily correlation driven and static. Deficiencies of these models and the need for better understanding have led to more research in this area.

More recently, verbal protocols of venture capitalists were studied to evaluate their decision processes (Hall and Hofer, 1993). Baron (1998) studies the thought processes of entrepreneurs and compares them to other people's thought processes. Researchers have revisited the venture capitalists' decision-making problem (e.g., Zacharakis and Meyer, 2000; Zacharakis, Meyer and DeCastro, 1999; Zacharakis and Shepherd, 2001; Shepherd and Zacharakis, 1997; and Shepherd, 1999). They raise the possibility that the statistical models developed in the literature may not be reliable or valid because of inherent decision-making biases, e.g., overconfidence, and they question the usability of actuarial decision models by the VCs.

Other techniques such as conjoint analysis (Shepherd and Zacharakis, 1997), have been used to study the importance that VCs place on the factors used in the decision making process. Brody and Ehrlich (1998) suggest various factors VCs look at when making investment decisions. Another area of research that has evolved to study VCs has been the use of *post hoc* analysis of the differences across performance of venture-backed companies (Bygrave, *et al.*, 1998, 1999). We see that the primary models are actuarial and static, and that the research is ongoing to better understand the decision making of VCs.

## 2 METHODOLOGY

In this study, we build a causal map of the investment decision using causal mapping techniques by interviewing VCs. We convert this map into a causal Bayes net using techniques developed by us. Causal Bayes nets are especially suited for domains characterized by high degree of uncertainty. Bayes nets have been recently developed in artificial intelligence and used in medical diagnosis, modeling portfolio risk and return, and modeling new product development. They are based on probability theory. The network of cause-effect relations that constitutes a causal map reflects how individuals view the world. One can make inferences about the true state of some variables in the map when information is received about other variables in the map.

### 2.1 Causal Maps

*Origins.* 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, p. 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 causal map is depicted in Figure 3.

*Assumptions.* The use of 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 (e.g., 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 and Shapiro, 1976).

*Applications.* Causal maps have been used to study a wide variety of phenomena, including strategic change (Barr, 1998; Barr and Huff, 1997), environmental adaptation (Barr *et al.*, 1992; Fahey and Narayanan, 1989; Narayanan and Fahey, 1990), joint venture formation (Fiol, 1989; 1990), and software operations support expertise (Nelson et al., 200).

Another stream of research pioneered by Eden (e.g., Eden, 1991; Eden and Ackermann 1993; 1998) has used causal mapping to define the actual decision problems and to reveal hidden decision premises. Making expertise and decision assumptions explicit has been shown to significantly reduce the occurrence of certain cognitive biases (Hodgkinson *et al*., 1999).

*Derivation.* Causal maps can be derived based on documentary sources (e.g., letters to shareholders, speech and interview transcripts) as well as more intrusive measures such as card sorts or repertory grids (e.g., Bougon, Weick and Binkhorst, 1979). Causal maps can also be developed directly by, or in consultation with, the subject, aided by software, such as Decision Explorer (Banxia, 1999).

*Analysis.* Analysis of causal maps has largely focused on the content and the structure of causal maps. The *content* of maps is usually analyzed largely qualitatively or in a combination of qualitative and quantitative techniques, e.g. in the strategic change and environmental studies cited above. In order to investigate the structural properties of causal maps, researchers have investigated and operationalized constructs such as comprehensiveness (e.g., Langfield-Smith and Lewis, 1989), density (e.g., Calori *et al*., 1994; Eden *et al*., 1981; Laukkanen, 1994) and centrality (e.g. Eden, Jones and Sims, 1983; Fiol and Huff, 1992). The dynamic properties of causal maps, i.e. the direct analysis of implied decision outcomes have received scant attention in the management literature (see Axelrod, 1976 for exceptions from the political science arena).

## 2.2 Bayes Nets

In this section, we briefly describe the semantics of Bayesian networks. A procedure for constructing a Bayesian network starting from a causal map is described in Section 3.

Bayesian networks have their roots in attempts to represent expert knowledge in domains where expert knowledge is uncertain, ambiguous, and/or incomplete. Bayesian networks are based on probability theory. A primer on Bayesian networks is found in (Spiegelhalter *et al*., 1993).

A Bayesian network model is represented at two levels, qualitative and quantitative. At the qualitative level, we have a directed acyclic graph in which nodes represent variables, and directed arcs describe the conditional independence relations embedded in the model. Figure 1 shows a Bayes net consisting of four discrete variables: *Reputation of Management* (M), *Assessment of Management* (A), *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 consists of mutually exclusive and exhaustive values of the variable. In Figure 1, e.g., Reputation of Management has two states: 'high' and 'low;' Assessment of Management has two states: 'high' and 'low;' Potential Revenue has two states: 'high' and 'low;' and 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, we need to specify a table of conditional probability distributions, one for each configuration of states of its parents. Figure 1 shows these tables of conditional distributions—P(M), P(A | M), P(R), and P(D | A, R).

### 2.2.1 Semantics of Bayes Nets

A fundamental assumption of a Bayesian network is that when we multiply the conditionals for each variable, we get the joint probability distribution for all variables in the network. In Figure 1, e.g., we are assuming that

$$P(M, A, R, D) = P(M) \otimes P(A \mid M) \otimes P(R) \otimes P(D \mid A, R),$$

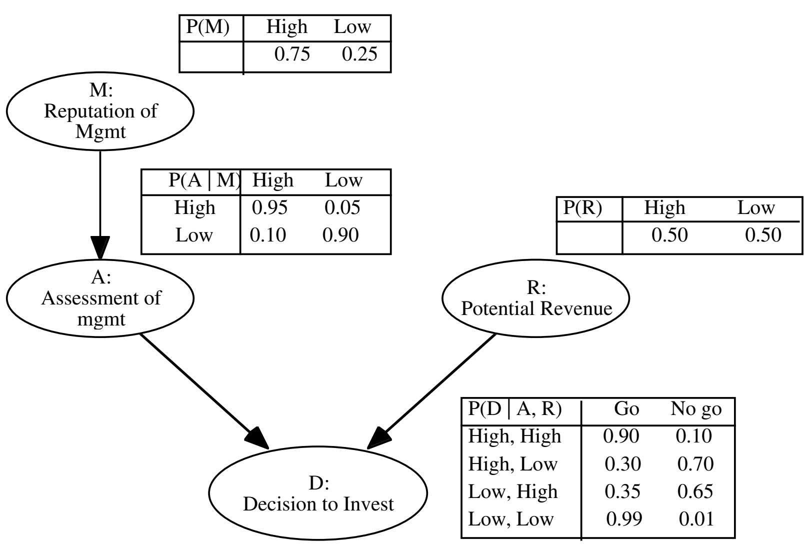
where $\otimes$ denotes pointwise multiplication of tables. The rule of total probability tells us that

$$P(M, A, R, D) = P(M) \otimes P(A \mid M) \otimes P(R \mid M, A) \otimes P(D \mid M, A, R).$$

Comparing the two, we notice that we are making the following assumptions: $P(R \mid M, A) = P(R)$, i.e., R is independent of M and A; and $P(D \mid M, A, R) = P(D \mid A, R)$, i.e., D is conditionally independent of M given A and R.

Notice that we can read these conditional independence assumptions directly from the Bayesian network graph as follows. Suppose we pick a sequence of the variables such that for all directed arcs in the network, the variable at the tail of each arc precedes the variable at the head of the arc in the sequence. Since the directed graph is acyclic, there always exists such a sequence. In Figure 1, e.g., one such sequence is M-A-R-D. Then, the conditional independence assumptions can be stated as follows. For each variable in the sequence, we are assuming it is conditionally independent of its predecessors in the sequence given its parents. The essential point here is that missing arcs (from a node to its successors in the sequence) signify conditional independence assumptions. Thus, the lack of an arc from M to R signifies that M is independent of R; the lack of an arc from A to R signifies that A is independent of R; and the lack of an arc from M to D signifies that D is conditionally independent of M given A and R.

Figure 1. A Bayesian Network with Conditional Probability Tables




| P(M) | High | Low |
|---|---|---|
| | 0.75 | 0.25 |

| P(A \| M) | High | Low |
|---|---|---|
| High | 0.95 | 0.05 |
| Low | 0.10 | 0.90 |

| P(R) | High | Low |
|---|---|---|
| | 0.50 | 0.50 |

| P(D \| A, 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 |

In general, there may be several sequences consistent with the arcs in a Bayesian network. In such cases, the list of conditional independence assumptions associated with each sequence can be shown to be equivalent using the laws of conditional independence (Dawid, 1979). Pearl (1988) and Lauritzen *et al*. (1990) describe other equivalent graphical methods for identifying conditional independence assumptions embedded in a Bayesian network graph.

Unlike a causal map, the arcs in a Bayesian network do not necessarily imply causality. The (lack of) arcs represent 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. As another example, consider the situation where X directly causes Y and X also directly causes Z. Although knowledge of Y is relevant to Z (if Y is true then it is more likely that X is true which in turn means that it is more likely that Z is true), once we know the true state of X, then further knowledge of Y is irrelevant to Z, i.e., Y is conditionally independent of Z given X. This situation is represented by the Bayesian network $Z \leftarrow X \rightarrow Y$ in which there is no arc from Y to Z or vice-versa. Finally as a third example, consider the situation where X and Y are two independent direct causes of Z, i.e., X and Y are unconditionally independent. But if we learn something about the true state of Z, then X and Y are no longer irrelevant to each other (if Z is believed to be true and X is false, then it is more likely that Y is true), i.e., Y is not conditionally independent of X given Z. This situation is represented by the Bayesian net $X \rightarrow Z \leftarrow Y$ in which there is no arc from X to Y or vice-versa.

### 2.2.2 Making Probabilistic Inferences

Inference (also called probabilistic inference) in a Bayesian network is based on the notion of *evidence propagation*. Evidence propagation refers to an efficient computation of marginal probabilities of variables of interest, conditional on arbitrary configurations of other variables, which constitute the observed evidence (Spiegelhalter et al., 1993). Once a Bayesian network is constructed, it can be used to make inferences about the variables in the model. The conditionals given in a Bayesian network representation specify the *prior* joint distribution of the variables. If we observe (or learn about) the values of some variables, then such observations can be represented by tables where we assign 1 for the observed values and 0 for the unobserved values. Then the product of all tables (conditionals and observations) gives the (un-normalized) *posterior* joint distribution of the variables. Thus, the joint distribution of variables changes each time we learn new information about the variables.

## 3 A CAUSAL MAP FOR VENTURE CAPITAL DECISION MAKING

We use a causal mapping-based approach to constructing an expert Bayesian network, implementing for the first time a methodology described by Nadkarni and Shenoy (2001). The procedure consists of three broad steps: (1) Elicitation of a raw causal map from an expert venture capitalist; (2) pre-processing of the raw causal map into a Bayesian causal map; and (3) assignment of probabilities.

### 3.1 Eliciting the raw causal map

The first step in building the raw causal map was to interview a subject with expert 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 and Palmquist, 1992). In order to elicit the Venture Capital's mental model, we not only asked him to give a general description of the venture capital investment process, but also asked him to describe three real world cases to us. These cases involved both successful and unsuccessful investments, as well as a case where the venture capitalist firm decided not to make any investments 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 often have a limited understanding of their own decision models (e.g., Zacharakis and 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 13000 words. A revealed causal map was created from this textual base, by (1) identifying causal statements in the text, and (2) constructing a raw causal map with cause concepts linked to effect concepts by arrows indicating direction of causality. The raw causal map is shown in Figure 2.

Causal statements are assertions that can be represented in the format "the more A, the more/less B" (Axelrod, 1976, p. 258). A concept can thus 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".

A causal statement thus identified in step one above is then transformed in step two 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, p. 10f.). This is represented in the form of a "+" or "–" above the arrow. An example appears in Figure 3.

Figure 2. A Raw Causal Map of a VC's Decision Model

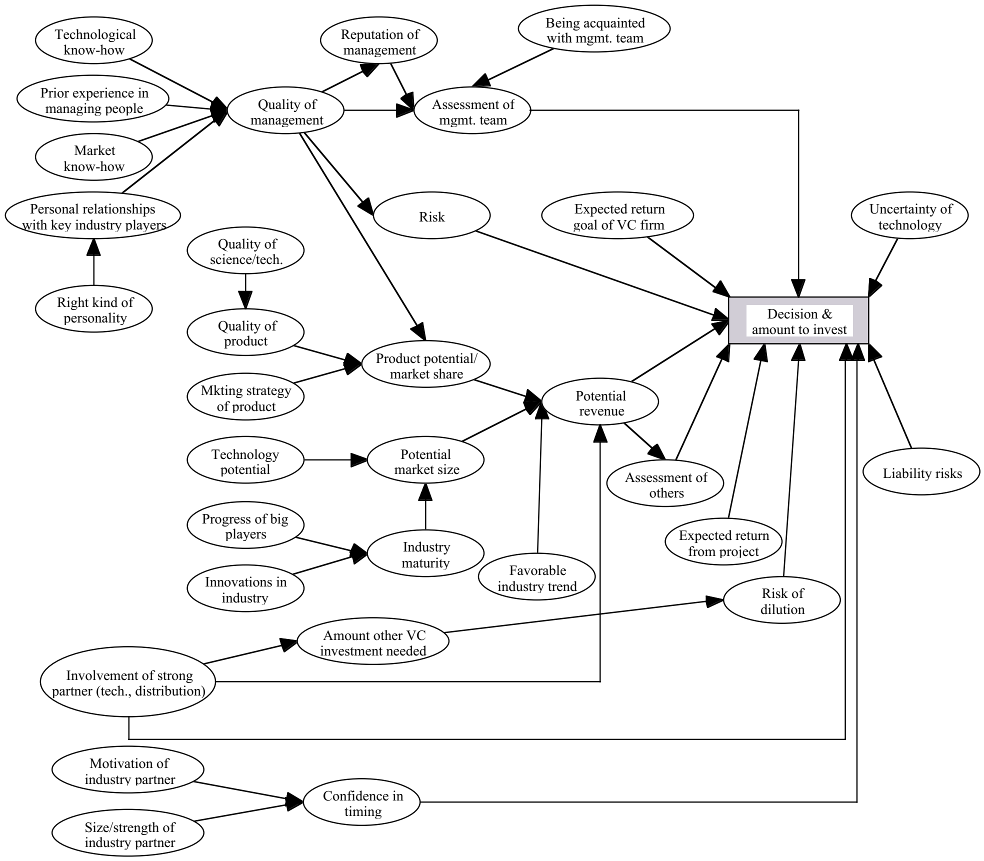
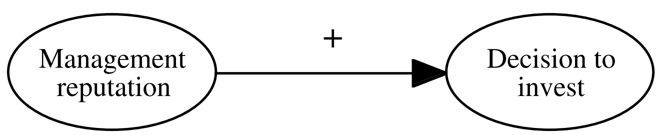



Figure 3. A Positive Causal Relation Between Two Variables




The totality of all (domain relevant) causal statements in a given text forms a raw causal map[1].

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[1] For further illustrations and descriptions of how to derive revealed causal maps (including from non-textual sources) see (Axelrod, 1976; Eden and Spender, 1998; Huff, 1990; and Nelson *et al*., 2000).

The example above was an extreme case of an *explicit* causal statement. However, semi-structured interviews and other texts also contain a multitude of *implicit* causal statements. It was here, where we slightly deviated from standard causal mapping methodology. While the coding of implicit causal statements is standard practice (cf. Wrightson, 1976), researchers generally favor a conservative approach to including questionable causal statements. In our case, there were to reasons that let us err on the side of inclusion. (1) As we will discuss below, in Bayesian networks, counter to causal maps, the absence of linkages has meaning (conditional independence), thus it is important to represent all linkages present. (2) The methodology for constructing Bayesian causal maps necessarily includes a feedback process, where the original interviewee is asked to verify the map and certain linkages, something that is often not possible in the case of many causal mapping studies who thus need to be more conservative.

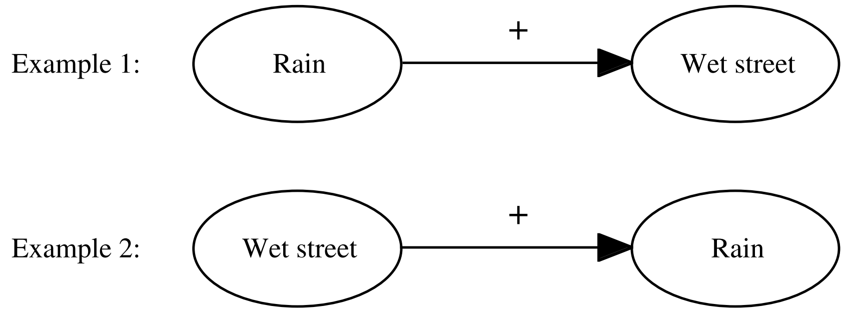
### 3.2 Preprocessing of the Causal Map into a Bayes Net

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

*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 Bayes nets are I-maps. Thus, the raw causal map needs to be made into an I-map, usually in consultation with the subject on which the raw causal map is based. This can be done by either using a grid-based technique in which the concepts from a map are arranged along two dimensions and the expert is asked to indicate the (non)existence and direction of a relationship on each intersection between two variables. Alternatively, the expert can be asked to audit the raw causal map directly, with direct instructions given regarding conditional independence. Both techniques require the raw causal map to be of manageable size. This is even more true for grid-based techniques, given the exponentially increasing number of grid-intersections. At the end of the procedure, the Bayes net is both a D-map and an I-map, i.e. it is a *perfect map*.

*Underlying reasoning*. There are two underlying types of reasoning that are relevant in building Bayes nets: *deductive* and *abductive* reasoning (Charniak and McDermott, 1985; Winston, 1984). Deductive reasoning is reasoning from causes to effects. Abductive reasoning moves from effects to causes. Thus, 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.

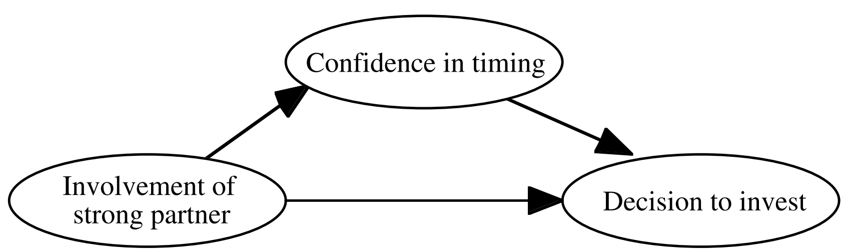
Figure 4. Examples of Deductive and Abductive Reasoning




Thus, the linkages in raw causal maps often need to be audited and the true direction of causality established, in cooperation with the expert. The direction in causal Bayes nets should reflect the underlying causality, rather than the language used. Not surprisingly, in real-life raw causal maps the true direction is not always easy to ascertain. For example, are "people skills" a constituent cause or an indicative result of "management quality?" The question of direction is much more difficult to solve in this example.

*Direct and Indirect Relationships*. Standard methods for deriving causal maps do not provide for a distinction between 'direct' and 'indirect' linkages between concepts (Eden et al., 1992; Laukkanen, 1996). 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 a long interview transcript:

Figure 5. An Example of Direct and Indirect Reasoning




However, as discussed above, since a Bayesian network is an I-map, the presence or absence of the direct link between two concepts does carry 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. Thus, the exact nature of such relationships needs to be discussed and verified with the domain expert since conditional independencies are critical in making inferences in Bayes nets.

*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. Assuming correct coding, loops in causal maps usually are the result of dynamic relationships between variables across multiple time periods (Nadkarni and Shenoy, 2001). Usually these can be resolved by disaggregating a concept into two concepts at different time periods. Thus e.g., if a startup's strong alliances induces VC investment and VC investment in turn encourages alliance partners to partner with the venture, leading to a circular relationship between "strong alliances" and "VC investment" this circular relationship can be resolved by disaggregating "strong alliances" into two concepts "alliances at time $t_1$" and alliances at time $t_2$".

Attention and resolution of the four critical issues outlined above results in the transformation of the raw causal map into a preprocessed Bayes net to which probability values can be assigned and which allows for evidence propagation like any other Bayes net. For the causal map that was elicited from a VC and shown in Figure 2, we have yet to convert it to a Bayes net. We plan to meet with the VC and do the conversion in the next stage of our project.

### 3.3 Assessment of Probabilities

The next step is to populate the Bayes net with probabilities as described in Nadkarni and Shenoy (2001). We plan to do this in the next stage of our project.

## 4 RESULTS AND IMPLICATIONS

Our project has major theoretical and practical contributions. First, it will contribute to the literature on constructing Bayes nets. Our proposed method for constructing Bayes nets starting from causal maps has never been attempted for a real project. Second, the proposed Bayes net of VC decision is the first application of Bayes net in this domain. Bayes net modeling technique makes it possible to integrate expert knowledge as well as data from past projects. We use expert knowledge to construct the structure of a Bayes net and use either subjective assessments or statistical data to estimate the numerical parameters of the model. The development of such models and their subsequent incorporation in the decision making sequence of VCs should increase the likelihood of picking winners. This should lead to a more effective and efficient allocation of capital to the available projects.

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