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A Bayesian Network model to measure project manager's confidence on project execution

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Abstract

Bayesian Networks are a well-recognized decision support tool for a wide range of situations that involve uncertainty and probabilistic reasoning. Projects are not an exception to these situations. They are usually one-off experiences where many data are incomplete, suffer from imprecision and accuracy, and estimations are conditionally dependent on assumptions that are a major source of uncertainty. This uncertainty is present during the different stages of a project where complex causal relationships are involved between uncertainty and project performance. In this complex and uncertain environment many project managers are faced with the question, will the project finish successfully? This paper introduces an approach, using Bayesian Networks to know the project manager's confidence on the future of its project. With this aim, a Bayesian Network is modelled using four earned value management indexes, three financial ratios, and the technical and financial capability of the contractor responsible for the execution of the project.

Keywords: Project Management; Bayesian networks; Uncertainty

1. Main text

Bayesian networks (BNs) also known as belief networks, probabilistic cause-effect networks, or Bayes nets, provide decision support for a wide range of situations involving uncertainty and probabilistic reasoning that require statistical inference. BNs are recognized as a nature formalism for handling causality and uncertainty [1] and as a decision

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support tool, have gained increasing attention when dealing with uncertainty and probabilistic reasoning in many fields of research ranging from medical or machine diagnosis to safety and risk evaluation. In the project management field of knowledge, Khodamari et al. [2] applied a Bayesian network to the traditional Critical Path Method in order to handle the uncertainty associated to estimate the duration of an activity. Jeet et al. [3] combined subjective judgment from experienced project managers and available defect rates data to build a Bayesian network used to forecast control defect rates in software development projects. Barbaros et al. [4] presented a hybrid and dynamic Bayesian network containing both discrete and continuous variables over multiple time stages in order to calculate the costs, benefits, and return on investment based on multiple causal factors. Sánchez et al. [5] developed a method to estimate the impact of project management maturity on project performance using Bayesian networks to formulate experts' knowledge. Khodakarami and Abdollah [6] proposed a quantitative assessment framework integrating the inference process of BNs to the traditional probabilistic risk analysis. Ghosh et al. [7] proposed a Bayesian Belief Network model to update project time and cost estimates when crashing a project. De Melo and Sánchez [8] presented a Bayesian netowrk for maintenance project delays based on specialists' experience and a tool to help in managing software maintenance projects.

In order to model and handling uncertainty during the different stages of a project where complex causal relationships are involved between actions and consequences, BNs are one of the most well-stablished approaches [9,10]. The key benefits of BNs that make them highly suitable for project management are [2,11]: (*i*) Quantify uncertainty and model the causal relations between variables analyzing how much a specific node is influenced by other nodes; (*ii*) Enable reasoning from effect to cause as well as from cause to effect, that is, propagation is both forward and backward; (*iii*) Calculate the probability of events before and after the introduction of evidences updating its predictions and diagnosis, making it possible to overturn previous beliefs in the light of new data; (*iv*) Can be developed combining subjective and objective data (information) and allow variables to be added or removed without significantly affecting the network; (*v*) Enable users to arrive at decisions that are based on visible auditable reasoning; (*vi*) Allow the value of a variable to be extended as a known input or to evaluate the likelihood of a variable as an input.

In this paper a BN is used to know the project manager's confidence on the future of its project. With this aim, the BN is modelled using four earned value management indexes, three financial ratios, and the technical and financial capability of the contractor responsible for the execution of the project. In the next section, the methodology presented in this paper is described. Next, this methodology is applied to a project under execution. Finally, there is a conclusion section with the main findings of the paper.

2. Bayesian Networks

In situations such as machine diagnostics, the probability of machine failure is based on the current knowledge and obtained with the earlier events that have caused the fault. This permits us to obtain the conditional probability, which probability that event A given that event B has occurred. However, in many real-world situations such as the execution of a project, we are more concerned with the reverse situation, what is the probability of an earlier event given that some later one has occurred? What is the probability of project success/failure as the project progresses and information on its performance is obtained and updated? This is known as the a posteriori probability. While the conditional probability is forward in time, the a posterior probability is backward in time. The solution to this problem is given by the Bayes Theorem which provides the probability of truth of some hypothesis H given some evidence E:

$$P(H|E) = \frac{P(H) * P(E|H)}{P(E)} \quad (1)$$

where
$P(H|E)$ = probability that hypothesis H is true given evidence E
$P(H)$ = probability that hypothesis H is true
$P(E|H)$ = probability of observing evidence E when hypothesis H is true
$P(E)$ = probability of evidence E which can also be written as

$$P(E) = P(E|H) * P(H) + P(E|{\sim}H) * P({\sim}H) \tag{2}$$

where $P(E|{\sim}H)$ is the probability that evidence E is true when hypothesis H is false and $P({\sim}H)$ is the probability that hypothesis H is false.

Next, two new terms are introduced, the Likelihood of Sufficiency and the Likelihood of Necessity. The Likelihood of Sufficiency, *LS*, represents the measure of support for the hypothesis *H* given that evidence *E* is present. That is, how much the prior odds are changed when evidence *E* is present. The Likelihood of Necessity, *LN*, represents the measure of discredit to the hypothesis *H* given that evidence *E* is absent. That is, how much the prior odds are changed when evidence *E* is absent. Both factors, *LS* and *LN* must follow the following conditions:

when $LS > 1$ then, $LN < 1$
when $LS < 1$ then, $LN > 1$
when $LS = 1$ then, $LN = 1$

These *LS* and *LN* values take values between 0 and infinity and their effects on hypothesis *H* are shown in Table 1.

Table 1. Effects of *LS* and *LN* on the hypothesis *H*

LS/LN	Effects of *LS* on hypothesis *H*	Effects of *LN* on hypothesis *H*
0	*H* is false when *E* is true or $\sim E$ is necessary for concluding *H*	*H* is false when *E* is absent or *E* is necessary for concluding *H*
Small	*E* is unfavourable for concluding *H*	Absence of *E* is unfavourable for concluding *H*
1	*E* has no effect for concluding *H*	Absence of *E* has no effect for concluding *H*
Large	*E* is favourable for concluding *H*	Absence of *E* is favourable for concluding *H*
Infinity	Observing *E* means that *H* must be true	Absence of *E* means that *H* must be true

The posterior probability of hypothesis H given evidence E, $P(H|E)$, can be obtained from *LS* and the prior odds on hypothesis *H*, $O(H)$, according to:

$$P(H|E) = \frac{LS * O(H)}{1 + LS * O(H)} \tag{3}$$

where the prior odds on hypothesis *H*, $O(H)$, are given by the following equation

$$O(H) = \frac{P(H)}{P({\sim}H)} = \frac{P(H)}{1 - P(H)} \tag{4}$$

Similarly,

$$P(H|{\sim}E) = \frac{\mathrm{LN} * O(H)}{1 + LN * O(H)} \tag{5}$$

In many situations, establishing $P(E)$, the probability of evidence E being true, may be difficult because project managers may be uncertain about the evidence. In these situations, a certainty measure in the evidence, $C(E|E')$, can be used. It indicates that evidence *E* is dependent upon the observed evidence, E', where E' represents the belief in *E*. The certainty measure lies on a scale from +5 to -5, where +5 corresponds to evidence E being definitely true, -5 corresponds to evidence E being definitely false and 0 corresponds to an unknown situation. On the basis of this expert-provided certainty measure, the probability on the evidence *E* based on the observable evidence E', $P(E|E')$, can be determined according to:

For $C(E|E') > 0$

$$P(E|E') = \frac{C(E|E') * [1 - P(E)] + 5 * P(E)}{5} \tag{6}$$

For $C(E|E') \leq 0$

$$P(E|E') = \frac{C(E|E') * P(E) + 5 * P(E)}{5} \tag{7}$$

The certainty measure, $C(E|E')$, and the probability in the evidence, $P(E|E')$, are mapped according to the following rules:

IF $C(E\|E') = -5$	Definitely false	THEN $P(E\|E') = 0$
IF $C(E\|E') = 0$	Unknown situation	THEN $P(E\|E') = P(E)$
IF $C(E\|E') = 5$	Definitely true	THEN $P(E\|E') = 1$

To take into account the degree of uncertainty in the evidence, the probability of hypothesis *H* given E', is:
For $P(E) \leq P(E|E') < 1$

$$P(H|E') = \frac{P(H) - P(H|E) * P(E)}{1 - P(E)} + P(E|E') * \frac{P(H|E) - P(H)}{1 - P(E)} \tag{8}$$

For $0 \leq P(E|E') \leq P(E)$

$$P(H|E') = P(H|\sim E) + \frac{P(E|E')}{P(E)} * \left(P(H) - P(H|\sim E)\right) \tag{9}$$

The total updated odds for *H* if all the evidence contributing to *H* are true are obtained from Eq. (10):

$$O\left(H\middle|E'_{1,}\, E'_{2,}\, E'_3\,, \cdots E'_{n,}\ \right) = \prod_{i=1}^{n} LS'_i * O(H) \tag{10}$$

where

$$LS'_i = \frac{O(H|E'_i)}{O(H)} = \frac{P(E_i|H)}{P(E_i|\sim H)} \tag{11}$$

In a similar way, if all the evidences contributing to *H* are false:

$$O\left(H\middle|\sim E'_{1,} \sim E'_{2,} \sim E'_3\,, \cdots \sim E'_{n,}\ \right) = \prod_{i=1}^{n} LN'_i * O(H) \tag{12}$$

where

$$LN'_i = \frac{O(H|\sim E'_i)}{O(H)} = \frac{P(\sim E_i|H)}{P(E\sim_i|H)} \tag{13}$$

The updated certainty factor for the hypothesis, $C(H|E')$, can be obtained from:
For $P(E|E_{total}) > P(E)$:

$$C(H|E') = 5 * \frac{P(H|E'_{total}) - P(E)}{1 - P(E)} \tag{14}$$

For $P(E|E_{total}) \leq P(E)$:

$$C(H|E') = 5 * \frac{P(H|E'_{total}) - P(E)}{P(E)} \tag{15}$$

where

$$P(H|E'_{total}) = \frac{O\left(H\middle|E'_{1,} E'_{2,} E'_{3,\dots}\right)}{1 + O\left(H\middle|E'_{1,} E'_{2,} E'_{3,\dots}\right)} \tag{16}$$

In the case of multiple nodes, $E_1, E_2, \cdots, E_i, \cdots E_n$, affecting a single hypothesis, H, the coupling of these multiple nodes to this single hypothesis is considered as a multi-premise rule, either in a conjunctive or disjunctive way. In the case of a conjunctive way such as IF E_1, AND E_2, AND ⋯THEN H, where all of the evidences E_i, based on the partial evidences E'_i, must be true for the conclusion of the hypothesis H to be true, the *min* function is used to calculate the $P(E|E')$ value:

$$P(E|E') = min\{P(E|E')\} \tag{17}$$

In the case of a disjunctive way such as IF E_1, OR E_2, OR ⋯THEN H, where at least one of the evidences E_i, based on the partial evidences E'_i, must be true for the conclusion of the hypothesis H to be true, the *max* function is used to calculate the $P(E|E')$ value:

$$P(E|E') = max\{P(E|E')\} \tag{18}$$

4. Application

In this section, the methodology presented above will be applied to the Bayesian network shown in Fig.1. To know the project manager's confidence on the future of its project and whether the project will be completed successfully, four earned value management indexes that measure project progress, the Schedule Performance Index (SPI), Schedule Variance time ($SV_t = ES - AT$), Cost Performance Index (CPI), and Schedule Variance cost (SV_c) are used. In addition, three financial ratios, the Liquidity ratio, the Long-term debt to equity and the Debt ratio are used to measure the financial capability of the contractor responsible for the execution of the project. The project manager's perception on project progress and financial capability are established according to the values shown in Table 2. Regarding the technical capability and the experience, the project manager, based on its perception and experience, provides the $C(E_9|E'_9)$, $C(E_8|E'_8)$, LS and LN values for the contractor. All prior probabilities are assumed to be equal to 0.5.

Table 2. Project manager's perception on project progress and financial capability

Index		Value	Project manager's perception
Schedule Performance Index	$SPI = \frac{ES}{AT}$	> 1	The efficiency in utilizing the time of the project is good
		< 1	The efficiency in utilizing the time of the project is not good
Schedule variance time	$SV_t = ES - AT$	> 0	The project is ahead of schedule
		< 0	The project is behind schedule
Cost Performance Index	$CPI = \frac{EV}{PV}$	> 1	The efficiency in utilizing the resources is good
		< 1	The efficiency in utilizing the resources is not good
Schedule variance cost	$SV_c = EV - PV$	> 0	The project is under budget
		< 0	The project is over budget
Liquidity ratio	$L = \frac{Current\ Assets}{Current\ Liabilities}$	> 1	The company´s ability to pay-off its short-term debt obligations is good
		< 1	The company´s ability to pay-off its short-term debt obligations is bad
Long-term debt to equity	$LtDE = \frac{Long\ Term\ Debt}{Total\ Assets}$	> 0.5	The company's ability to repay long-term debt is bad
		< 0.5	The company's ability to repay long-term debt is good
Debt ratio	$D = \frac{Total\ Liabilities}{Total\ Assets}$	> 1	Total liabilities are higher than total assets
		< 1	Total assets are higher than total liabilities

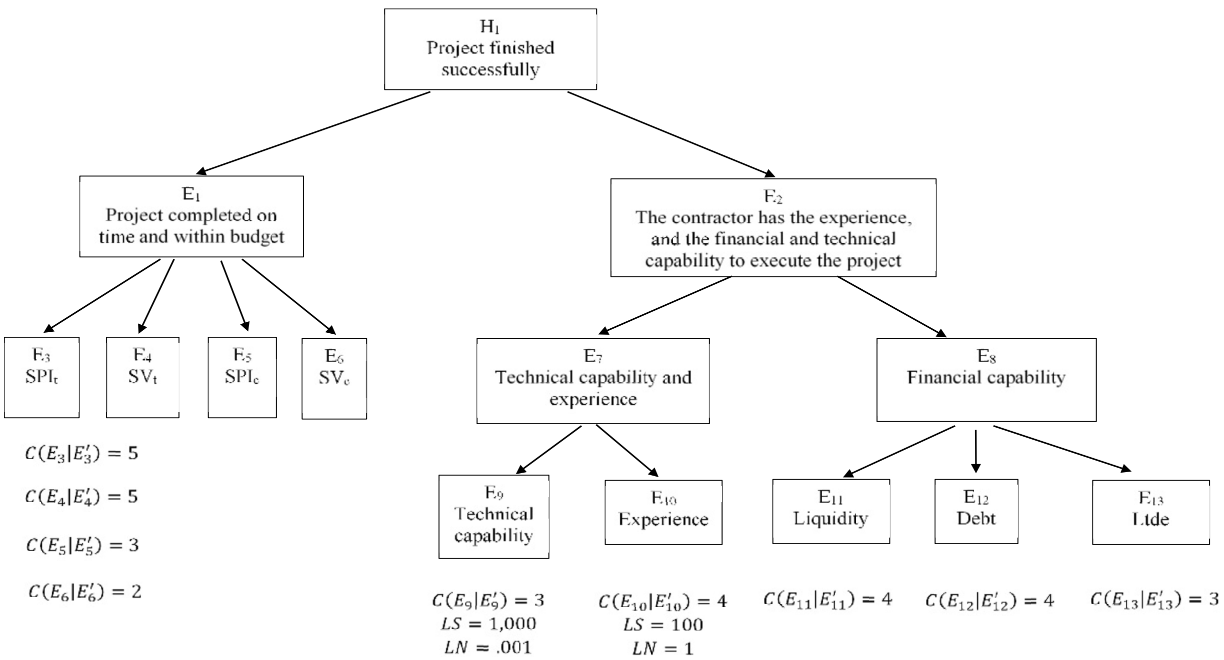

Fig. 1. Bayesian Network.

The Probability that the contractor has the technical capability and the experience to execute the project given the evidence he has the needed resources and the required experience are obtained applying Eq. (9):

$$P(E_9|E_9') = \frac{C(E_9|E_9') * [1 - P(E_9)] + 5 * P(E_9)}{5} = 0.8$$

$$P(E_{10}|E_{10}') = \frac{C(E_{10}|E_{10}') * [1 - P(E_{10})] + 5 * P(E_{10})}{5} = 0.9$$

Next, we calculate $P(E_7|E_9')$, that indicates the probability that the contractor is right given the evidence he/she has technical capability. Applying Eqs. (3) and (4):

$$O(E_7) = \frac{P(E_7)}{1 - P(E_7)} = \frac{0.5}{1 - 0.5} = 1 \qquad P(E_7|E_9) = \frac{LS * O(E_7)}{1 + LS * O(E_7)} = \frac{1{,}000 * 1}{1 + 1{,}000 * 1} = 0.999$$

Since $P(E_9) \leq P(E_9|E_9')$, Eq. (8) is applied.

$$P(E_7|E_9') = \frac{0.5 - 0.999 * 0.5}{1 - 0.5} + 0.8 * \frac{0.999 - 0.5}{1 - 0.5} = 0.7944$$

Similarly, we calculate $P(E_7|E_{10}')$, that indicates the probability that the contractor is right given the evidence he/she has experience. Applying Eq. (3) and Eq. (4):

$$O(E_7) = \frac{P(E_7)}{1 - P(E_7)} = \frac{0.5}{1 - 0.5} = 1 \qquad P(E_7|E_{10}) = \frac{LS * O(E_7)}{1 + LS * O(E_7)} = \frac{100 * 1}{1 + 100 * 1} = 0.999$$

Since $P(E_{10}) \leq P(E_{10}|E_{10}')$, Eq. (8) is applied to calculate $P(E_7|E_{10}')$.

$$P(E_7|E_{10}') = \frac{0.5 - 0.99 * 0.5}{1 - 0.5} + 0.9 * \frac{0.99 - 0.5}{1 - 0.5} = 0.892$$

The updated odds on E_7, contractor is right, based on evidences E_9' and E_{10}' are obtained from Eq. (4)

$$O(E_7|E_9') = \frac{P(E_7|E_9')}{1 - P(E_7|E_9')} = \frac{0.7984}{1 - 0.7984} = 3.96$$

$$O(E_7|E_{10}') = \frac{P(E_7|E_{10}')}{1 - P(E_7|E_{10}')} = \frac{0.892}{1 - 0.892} = 8.259$$

The total updated odds on E_7, contractor is right, based on observing evidences E_9' and E_{10}' jointly are obtained from Eq. (10)

$$O(E_7|E_9', E_{10}') = \frac{O(E_7|E_9')}{O(E_7)} * \frac{O(E_7|E_{10}')}{O(E_7)} + O(E_7) = 33.7$$

Next, $P(E_7|E_9', E_{10}')$ is obtained:

$$P(E_7|E_9', E_{10}') = \frac{O(E_7|E_9', E_{10}')}{1 + O(E_7|E_9', E_{10}')} = 0.97$$

The confidence on E_7, contractor is right, based on evidences E_9' and E_{10}' jointly is obtained from Eq. (6)

$$C(E_7|E_9', E_{10}') = 4.7$$

Our confidence on E_8, and E_2, by noting that evidences E_8, and E_2, are conjunctive are obtained from Eq. (17):

$$C(E_8) = min\{E_{11}|E'_{11};\ E_{12}|E'_{12};\ E_{13}|E'_{13}\} = min\{4; 4; 3\} = 3$$

$$C(E_2) = min\{E_7|E'_9, E'_{10};\ E_8|E'_8\} = min\{4.7; 3\} = 3$$

Similarly, our confidence on E_1 by noting that evidence E_1 is conjunctive and obtained according to project manager's perception on project progress:

$$C(E_1) = min\{E_3|E'_3;\ E_4|E'_4;\ E_5|E'_5;\ E_6|E'_6\} = min\{5;\ 5;\ 3;\ 2\} = 2$$

Finally, the project manager's confidence on hypotheses H_1, the project will be completed successfully, by noting that hypotheses H_1 is disjunctive is obtained from Eq. (18):

$$C(H_1) = max\{E_1|E'_1;\ E_2|E'_2\} = max\{3; 2\} = 3$$

which indicates that the project manager's confidence on the future of its project is 3 on a scale from +5 to -5. The values given by the project manager based on the earned value management indexes, and the financial and technical capability of the contractor responsible for the execution of the project, indicate that the project will be finished successfully.

4. Application

Bayesian Networks are a well-recognized decision support tool that can be used to handle the uncertainty inherent to any project. This paper uses a BN to know the project manager's confidence on the future of its project. Four earned value management indexes, three financial ratios, and the technical capability and experience of the contractor responsible for the execution of the project are introduced in the Bayesian Network. This methodology is extensive to any project. Different indexes about project progress or project managers' perceptions about any aspect of the project or its participants can be introduced in the Bayesian Network in order to know our confidence on the future of a project and therefore if our project will be finished successfully.

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