Analyzing a Class of Investment Decisions in New Ventures : A CBR Approach

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벤처 투자를 위한 의사결정 클래스 분석: 사례기반추론 접근방법

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Abstract

An application of case-based reasoning is proposed to build an influence diagram for identifying successful new ventures. The decision to invest in new ventures is characterized by incomplete information and uncertainty, where some measures of firm performance are quantitative, while some others are substituted by qualitative indicators. Influence diagrams are used as a model for representing investment decision problems based on incomplete and uncertain information from a variety of sources. The building of influence diagrams needs much time and efforts and the resulting model such as a decision model is applicable to only one specific problem. However, some prior knowledge from the experience to build decision model can be utilized to resolve other similar decision problems. The basic idea of case-based reasoning is that humans reuse the problem solving experience to solve a new decision.

In this paper, we suggest a case-based reasoning approach to build an influence diagram for the class of investment decision problems. This is composed of a retrieval procedure and an adaptation procedure. The retrieval procedure use two suggested measures, the fitting ratio and the garbage ratio. An adaptation procedure is based on a decision-analytic knowledge and decision participants' knowledge. Each step of procedure is explained step by step, and it is applied to the investment decision problem in new ventures.

Keywords: Case-based reasoning, Decision analysis, Influence diagram, Investment decision, Venture

1. Introduction

The investment decisions in new ventures are the problems having followed characteristics such as incomplete information and uncertainty, where some measures of firm performance are quantitative, while some others are substituted by qualitative indicators. Influence diagrams (IDs) can be used as a tool for representing and analyzing the investment decision problems based on incomplete and uncertain information from a variety of sources. The traditional formulation of investment decision problems is done by lengthy interviews between decision maker (DM), domain expert(s), and decision analyst(s). Such a process needs much time, effort, and cost, but the main difficulty is that a constructed decision model such as influence diagrams are usually applicable to only one specific problem (Olmsted, 1984). Decision makers and domain experts found that some prior knowledge from the experience to model IDs can be utilized to resolve other similar decision problems (Kim, 1991). The concept of decision class analysis (DCA) is proposed by Holtzman (1989) to reduce the burden of DM for modeling decision problems, and furthermore to model an ID without the help of other participants. DCA regards

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a decision analysis as an integrator of domain-specific knowledge and decision-analytic knowledge, and treats a set of decisions having some degree of similarity as a single unit. As a methodology to implement DCA, rule-based approach (Chung, 1992; Holtzman, 1989; Kim, 1991), frame-based approach (Chung, 1992; Kim, 1991; Sonnenberg, 1994), and neural network based approach (Kim & Chu, 1998; Kim & Park, 1997) have been used until now. In this research, we propose a case based reasoning (CBR) approach, a methodology to build IDs for investment decision in new venture. The basic idea of case-based reasoning is that humans reuse the problem solving experience to solve a new problem (Kolodner, 1991). The CBR approach regards an ID of one decision problem as a case, so it stores IDs of the venture investment decision problems at a case base. CBR can acquire knowledge with ease using inductive methodology, so it is useful especially when knowledge is incomplete, or evidence is sparse (Kolodner, 1993).

The main task of using CBR is generally the representation of a class, a retrieval procedure, and an adaptation procedure (Kolodner, 1993). In this research, we represent a case as a frame-typed data structure corresponding to a decision situation and an ID. A retrieval procedure is suggested to retrieve one or more cases to model a new investment decision. We suggested also an adaptation procedure of the retrieved IDs to get an ID for the given problem. Our procedure is applied to a decision for software and hardware development ventures.

2. Influence Diagram

Influence diagrams (IDs) are developed as a model for representing complex decision problems based on incomplete and uncertain information from a variety of sources (Howard, 1988). ID is defined as an acyclic digraph, with three types of nodes and two types of arrows. This visual level of the ID explicitly reveals the flow of information, influences, and overall structure of the decision problem. The rectangle symbolizes a *decision node* which represents a variable for the decision maker and contains alternatives to choose. The oval symbolizes a *chance node* which represents events and contains a variable for the event. It contains probabilities assigned to the possible outcomes of the random variable. The rounded rectangle symbolizes a *value node* which represents an objective to maximize or minimize. An arrow into a chance node implies a probabilistic dependency between the nodes. An arrow into a decision node implies that when we make a decision, we have information on the value of the predecessor. Figure 1 shows an example of ID for the venture investment problem.

Well-formed ID is a syntactically correct, completely assessed ID whose nodes have fully consistent distributions and outcomes (Holtzman, 1989). But in this research, we use Well-formed ID to refer a well-constructed decision model from which a decision is made without further modification of the model.

The traditional interactive procedure to generate an ID consists of a sequence of *value-preserving transformation* between domain expert(s), decision analyst(s), and DM (Holtzman , 1989; Kim, 19997). The value preserving transformation is a transformation of the ID which maintains feasibility and do not modify the optimal policy or maximal expected value. The process to expand an ID is made through the repetitive operation of adding nodes, and splitting nodes. Once the structure is reasonable, the diagram is further refined in more detail through the operation of node removal, merging nodes, and reversing an arc as well as adding and splitting nodes. It was shown that these operations satisfy the value-preserving transformation (Chung, 1992; Kim, 1997; Kim et. al, 1999).

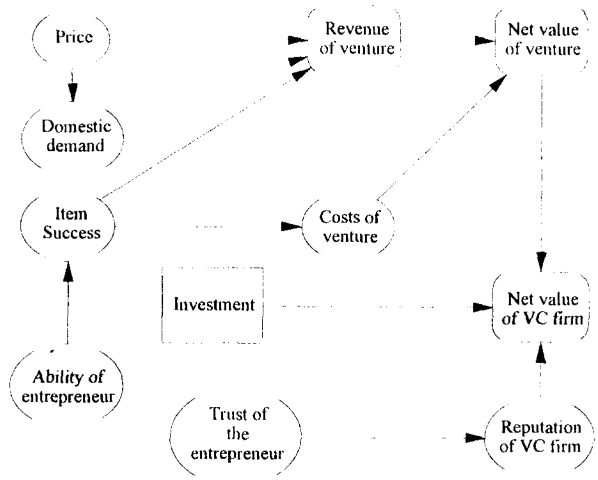


Figure 1. An influence diagram for venture investment

3 Decision Class Analysis

The practical decision analysis process is viewed as a three-stage closed-loop process whose three stages are formulation (i.e., development of a decision model, like influence diagram), evaluation (i.e., computation of a recommendation from the model) and appraisal (i.e., interpretation of the formal recommendation) (Howard, 1984). The closed-loop decision process can be viewed as a conversation involving two key participants: the decision maker (and his/her team of domain expert(s)) and a decision analyst. Most of the insight developed in the closed-loop decision process results from the interchange of information and new knowledge between the DM and the decision analyst. The decision analysts have observed that a constructed decision model such as an influence diagram (ID) is usually applicable to only one specific problem, even if the formulation of a real decision problem needs much time, efforts, and cost. They often investigate that some prior knowledge from the experience of modeling IDs can be utilized to resolve other similar decision problems (Chung, 1992; Howard, 1984; Kim and Chu, 1988).

Holtzman describes DCA which regards a decision analysis as an integrator of decision knowledge and treats a set of decisions having some degree of similarity as a single unit (Holtzman, 1989). In this research, venture investment decision means that the problem belong to the same domain. DCA helps decision analysts to inexpensively model an investment decision problem from a cumulative set of decisions in venture investment.

Variables in the ID are changeable according to the *specific situations*. The specific situations may be decision nodes and decision maker's circumstances, that are called *situation frames* in subsequent descriptions. A class problem consists of a number of individual decision problems, thus the size of a class problem is usually larger than that of each individual decision. When the situation-specific information is given, the DCA should abstract the corresponding specific decision variables for solving the individual problem. In this case, the DCA can be described as a *classification problem*.

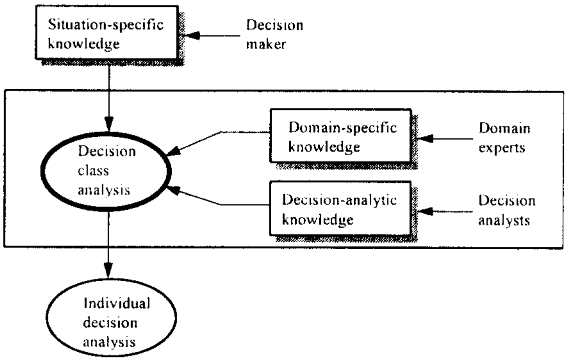


Figure 2. Knowledge for decision class analysis

So the quality of resulting ID depends on the quality of input data given from DM with the help of domain expert(s). Analyzing a class of decisions occurs at a higher level of abstraction than analyzing a single decision. Given the values of situation frames from the DM, the DCA should abstract and refine the corresponding specific decision variables for solving the individual problem. CBR is a general paradigm for reasoning from experience. A case-based reasoner solves a new problem by adapting the solution that was used to solve old problem (Risebeck and Schank, 1989). In this research, we suggest a CB-DCA, which is a methodology using CBR to implement a DCA, i.e., to build a topological level ID. In other words, the role of CB-DCA is to replace the rectangular area in Figure 2.

4. Case Representation and Retrieval

Frame typed knowledge representation method is used to represent the structure of an ID. In CB-DCA, a case is composed of an ID and its corresponding specific situation of one decision problem. In the terminology of DCA, a case is related with decision analysis, whereas a case base is related with decision class analysis. One case of case base contains all the information such as the situations of one specific decision problem, and nodes and influences of the ID. IDs of similar decision problems of a same class is stored in the same case base.

The situation-specific knowledge about decision problem does a very significant role in our approach. When retrieving a case from case base, one of important criteria is the degree of similarity between a given decision problem and the case of case base. Each situation frame has a value. The value of the situation frame is the bipolar, such as "yes" or "no". Whereas the number of decision frame represents the number of similar decision problems of one class, the number of node frames represents the sum of nodes of the IDs in the same class. The arc of an ID is represented using 'PREDECESSORS' and 'SUCCESSORS' of node frame.

Candidates IDs are retrieved from case base one based on the predefined criteria. The criteria are based on the situation frames. For the retrieval of a case, we developed two measures, one is *the fitting ratio of a case* and the other one is *the garbage ratio of a case*. The fitting ratio of a case is used to measure the degree of similarity between the situation of a new problem and those of stored cases. It is related with how well the case stored at case base represents the new decision problem. In this research, as more situation frames between two cases are matched, the two cases are regarded as similar ones. We assumed that each situation frame has equal weight. The garbage ratio of a case is related with how bad the problem model becomes when the case is adapted into the current problem. It measures how many fractions of situation frames of the stored case are not matched with that of a new problem.

For the more detailed explanation, some notations are defined as follows:

N: the number of cases.
$X_1, X_2, \ldots, X_N$: cases
$T=\{S_1, S_2, \ldots, S_N\}$: the set of the situation frames, where S_k is the situation frame of case X_k, $k=1,\ldots, N$.
m: the number of situation frames.
$S_k=(e_{k1}\ e_{k2} \ldots e_{km})$: the situation frame of case X_k, $k=1,\ldots, N$.
$S_0=(e_{01}\ e_{02} \ldots e_{0m})$:the situation frame of the new decision problem.
$R=(r_1\ r_2 \ldots r_m)$: the indicator for covered situation frame of S_0, if situation frame is covered then 1 otherwise then 0, $r_j \in \{0, 1\}, j=1,\ldots,m$.

Definition: $A \otimes B=(c_1\ c_2 \ldots c_m)$ is defined as follows; if $a_j=b_j$ then $c_j=1$, else if $a_j \neq b_j$ then $c_j=0$, where $A=(a_1\ a_2 \ldots a_m)$, $B=(b_1\ b_2 \ldots b_m)$ are situation frames and a_j, b_j are the value of jth situation frame of A and B.

Definition: A AND $B=(c_1, c_2, \ldots, c_m)$ is defined as follows; if $a_j=1$ and $b_j=1$ then $c_j=1$, else then $c_j=0$, where $A=(a_1\ a_2 \ldots a_m)$, $B=(b_1\ b_2 \ldots b_m)$, a_j and $b_j \in \{0, 1\}$, $j=1,\ldots,m$.

Definition: A OR $B=(c_1\ c_2 \ldots c_m)$ is defined as follows: if $a_j=0$ and $b_j=0$ then $c_j=0$, else then $c_j=1$, where $A=(a_1\ a_2 \ldots a_m)$, $B=(b_1\ b_2 \ldots b_m)$, a_j and $b_j \in \{0, 1\}, j=1,\ldots,m$.

Definition: $\bar{A}=(b_1\ b_2 \ldots b_m)$ is defined as follows; if $a_j=0$ then $b_j=1$, else if $a_j=1$ then $b_j=0$, where $A=(a_1\ a_2 \ldots a_m)$, $a_j \in \{0, 1\}, j=1,\ldots,m$.

Definition: $n(A)$ is the number of elements of A, which have "1" value.

Definition: The *fitting ratio*, F_k is the fitting ratio of kth case at current stage. The notation is defined as follows;

$$F_k = \frac{n(\bar{R} \text{ AND } (S_0 \otimes S_k))}{n(\bar{R})}.$$

Definition: The *garbage ratio*, G_k is the garbage ratio of kth case. The notation is defined as follows;

$$G_k = \frac{m - n(S_0 \otimes S_k)}{m}.$$

The value of fitting ratio is calculated between the situation frame of a given problem and that of all the cases which have same decision nodes.

For example let S_0=(H H L L L L) and S_k=(H L H L H L). Let the number of covered situation frame until now be four, i.e., R=(1 1 1 0 0 1). As $\overline{R}$ AND $(S_0 \otimes S_k)$ = (0 0 0 1 1 0) AND (1 0 0 1 0 1)= (0 0 0 1 0 0) and $n(\overline{R})$=2, so F_k=1/2=0.5. As m=6 and $S_k \otimes S_0$ = (1 0 0 1 0 1), G_k=3/6=0.5. Based on these two measures, the retrieval process in CB-DCA is performed as the following two phases. Phase I retrieves all the cases which have the same decision(s) as a new problem. Phase II, the retrieval of the candidate cases for a new problem begins selecting alternative cases from the case base using the fitting ratio measure. The alternative cases may be a predefined number of cases or may be the cases larger than a predefined threshold value. In this research, we used second criteria with θ as a threshold value. The alternative case becomes a candidate case if the garbage ratio is less than a predefined threshold value $\theta\,(0 < \theta < 1)$. If a larger threshold value is used, more cases will be selected as candidate cases. But it is decreased the capability of screening out inappropriate cases.

The procedure of the phase II, i.e., selection of candidate cases is summarized as follows.

T={S_1, S_2, ..., S_N},
$S_0=(e_{01}\ e_{02} \cdots e_{0m})$,
$S_k=(e_{k1}\ e_{k2} \cdots e_{km})$,
$R=(r_1\ r_2 \ldots r_m)$,
$S_k \otimes S_0=(a_1, a_2, \ldots, a_m)$,
MAX(T): the function having return value which is the number of element which have the maximum fitting ratio from the element of the set T.

Step(0) Set r_j=0, j=1,...,m.
Step(1) If T = ∅ then stop
Otherwise calculate F_k, k=1,...,N.
Step(2) Set k = MAX(T) and calculate G_k.
Step(3) If $G_k < \theta$ then select kth case.
Otherwise goto Step(5).
Step(4) Set R = R OR $(S_0 \otimes S_k)$
Step(5) If $n(\overline{R})$ = 0 then stop.
Otherwise set Set T = T-{S_k}, goto Step(1).

5. Case Adaptation

A case adaptation procedure is proposed to build an ID using the retrieved candidate cases. In Figure 2, two kinds of knowledge are necessary for the decision class analysis. Likewise, the adaptation procedure relies on decision-analytic knowledge and domain-specific knowledge of the decision participant. Decision analytic knowledge is the model constraints. Model constraints are used to check whether the resulting ID is well-formed ID or not. Decision analytic knowledge is described and after that in brief. We suggest an adaptation procedure.

Decision analytic knowledge (Model constraint)

To testify that a constructed ID meets the conditions of well-formed ID, we suggest to use the following model constraints:
(1) the directed graph has no cycles,
(2) the value node, if present, has no successors, and
(3) there is a directed path that contains all of the decision nodes. For the further information about this, please refer Shachter (1986).

Several terms are defined such as *core ID*, *super ID*, *supplementary node*.

Definition: A *core ID* is defined as the ID which is the intersection of the candidate IDs selected from the case base.

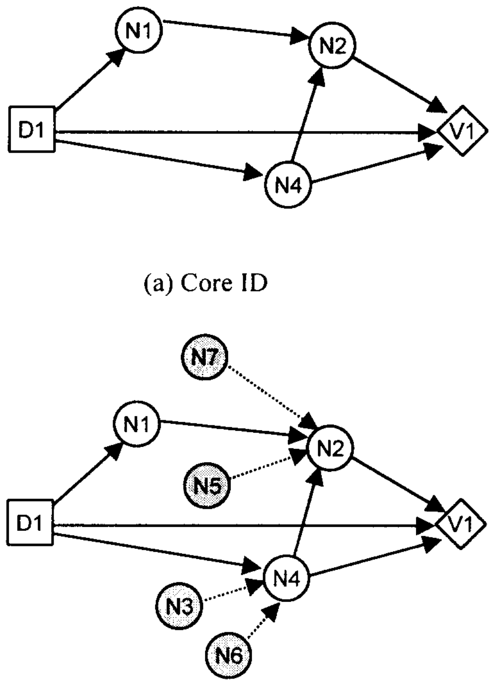
Definition: A *super ID* is the ID which is the union of the candidate IDs.

Definition: A *supplementary node* is a node which belongs to the super ID but does not belong to the core ID.

The adaptation procedure starts from a super ID and modifies it considering a core ID until the modified super ID is suitable to the given problem. Modification process starts from a supplementary node of super ID and its direct related nodes. If more detailed analysis is necessary, then the supplementary node is accepted, and the decision model is more specialized (i.e., expanded). If the information of that node is unnecessary or insufficient, then it does not accepted, and the decision model can be more aggregated (i.e., abstracted). The adaptation procedure is formally presented as follows:

Step(0) Define super ID and core ID.
Step(1) Select a supplementary node from the super ID. If there are many supplementary nodes, choose one node arbitrary.
Step(2) Modify the successor node of the selected supplementary node and the predecessor nodes of the successor node through aggregation or specialization process considering the level of analysis, the availability of information, and the characteristics of given problems.
Step(3) Check the model constraint whether the resulting ID is well-formed ID or not.
Step(4) If exists another supplementary node, then goto Step(1)
Otherwise stop.

The following example shows the modification process. Two candidate IDs are assumed to be selected by the case retrieval procedure. The core ID and the super ID is obtained as shown in Figure 3. In the super ID, <N3>, <N5>, <N6>, and <N7> are supplementary nodes. To refine the super ID, the supplementary node <N5> is assumed to be selected first. Node <N5> has the successor node <N2>. Node <N2> has the predecessor nodes <N1>, <N4>, <N5>, and <N7>, so node <N2> can be specialized to nodes <N1>, <N4>, <N5>, and <N7>. The DM has to decide whether node <N5> and <N7> are accepted or not, because nodes <N1> and <N4> are already included in the core ID. Next, the other supplementary node <N3> has the successor node <N4>. Node <N4> has the predecessor nodes <D1>, <N3>, and <N6>. So it can be decided whether node <N4> is specialized or not. The core ID can be result ID from the aggregation process. Also, the super ID can be result ID from specialization process. Both of them are testified by the model constraints. Which one of possible resulting IDs becomes the final ID is dependent on the DM's preference, availability of information, characteristics of decision problems such as time pressure and cost.



(b) Super ID

Figure 3. Core ID and super ID

6. Overall Procedure

The implementation of this CBR approach needs four processes (searching process, combining process, modification process, and building process) and two storage (decision analytic knowledge base and case base).

To build an ID of a new decision problem, the DM gives the values of situation frame of a new problem. At the searching process, the proper cases are retrieved and selected through the given retrieval procedure. The ID of selected case is defined as a candidate ID. The combining process combine candidate IDs to generate the core ID and the super ID. To fit them into the specific situation of a given problem, the modification process modifies the super ID by DM and the characteristics of the problem. At the well-formed ID building process, decision analytic knowledge is used to check and to correct whether the modified ID is well-formed ID or not. Finally, the resulting ID is stored at the case base as a new case.

The overall procedure is summarized as follows.

Step(1) Search case base.
- 1.1 Input the value of situation frame of a given decision problem.
- 1.2 Retrieve cases which have same decisions with a given problem.
- 1.3 Select candidate cases using case retrieval procedure based on the fitting ratio and the garbage ratio.

Step(2) Combining candidate IDs.
- 2.1 Obtaion super ID.
- 2.2 Obtaion core ID.

Step(3) Modification of super ID.
- 3.1 Define supplementary nodes using the super ID and the core ID.
- 3.2 Select a supplementary node and its successor node.
- 3.3 Modify the super ID using DM's domain specific knowledge and the characteristics of the problem.
- 3.4 Repeat this step until any supplementary node does not exist.

Step(4) Building well-formed ID
- 4.1 Check model constraints using decision analytic knowledge.
- 4.2 If the ID does not satisfy model constraints, then modify the ID.

Step(5) Stopping rule
- 5.1 If DM is not satisfied with the resulting ID then goto Step(3).
- 5.2 Store the resulting ID and the relevant situation frames to the case base as a new case.

7. Description of a Decision Class Problem

A venture evaluation problem of the venture capitalists (VC) is introduced to explain the suggested CBR approach. VC has had to make investment decisions under risk. IDs are used to structure the economic and practical considerations in a value hierarchy and to calculate the preferred alternative. The ID used to develop it could be adapted for use with recurring venture evaluating problems.

VC investment activity about the venture evaluation has five stages. The five stages they identified were: deal origination, or the search for prospective investment; screening, in which most proposal are rejected based on the venture capital firm's investment criteria; evaluation, during which the proposed venture is examined in detail; deal structuring, during which the VC and the entrepreneur agree to specific financial arrangements: and post-investment activities, which encompasses the VC's involvement in the management of the new venture. They usually consider the economical benefits and the consequences for denying the permit. They encounter this decision about five or six times a month. So these problem are to be modeled using DCA. The situations of the decision class problem are summarized as in Table 1. The situation frames of this problem are classified into two kinds of categories, situation frames related with the *industry* project and related with the business environment. The situation frame of the venture represents the type of industry whether it is Internet business, software development, hardware development, semi conductor development, or telecommunication project. The value of these situation frames has 'yes' or 'no'. In this research we restricted the followings as business environmental situation frames. Business environmental situation frames have two kinds of values, which are shown at Table 1.

Table 1. Situation frames

	Situation frame	Value
Situations about the industry	Internet business	yes/no
	Software	yes/no
	Hardware	yes/no
	Semi conductor	yes/no
	Telecommunication	yes/no
Situations of the business environmental	Target market	domestic/global
	Major competitor	yes/no
	Strength of competition	high/low
	Maturity stage of venture	early/maturity
	Maturity level of the target market	early/maturity
	Saturation level of the target market	high/low

8. Building an ID for the Venture Investment

Table 2 shows the description of the situation frames of a given decision problem. It is a semi conductor venture, and its business environmental situations are shown at Table 2. The VC has to permit or deny the proposal.

Table 2. The value of the new venture

	Situation frame	Value
Situations about the industry	Internet business	no
	Software	no
	Hardware	no
	Semi conductor	yes
	Telecommunication	no
Situations of the business environmental	Target market	global
	Major competitor	yes
	Strength of competition	high
	Maturity stage of venture	early
	Maturity level of the target market	early
	Saturation level of the target market	low

Based on these situation values, two candidates IDs are retrieved from the case base. They are represented at Figure 1 and Figure 4.

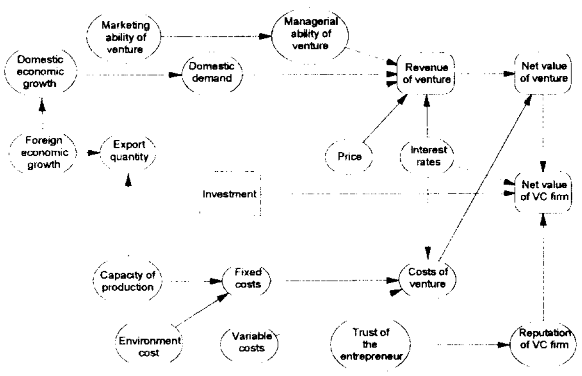


Figure 4. A candidate ID

A super ID and a core ID are generated by the combination of the two candidates IDs. Next, The supplementary nodes of the super ID are accepted or not by DM.

9. Conclusions

A decision class refers decision problems sharing common domain-specific knowledge among the problems. So DCA tries to model a decision problem conveniently and efficiently based on previous experience of modeling decision problems. CBR is a methodology which is to solve a new problem through the retrieval of appropriate cases and adaptation them using appropriate procedures. In this research, we suggested a CBR approach to implement DCA. Contrast to other methodologies, like neural-networks, CBR is believed to be a better methodology for DCA. Because CBR does not needs many similar decision problems, and works well in domains that are poorly understood. The suggested CBR approach consists of the following functions: the retrieval of candidate cases using suggested two measures, adaptation then to the specific situation of a given problem and storing the result as a new case.

We explained each step of the CBR approach in detail and applied it to a real investment decision class problem. It will be interesting to apply to other domain problems. The evaluation of the CBR approach will be a promising research area. Developing a group decision support system will be helpful for applying our suggested methodology to real world problems.

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