Building A Decision Analysis Model Using Neural-Network Based Decision Class Analysis

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Abstract

The model construction in practice is known to be a most complicated and burdensome process. It needs much time, efforts, and cost, but the main difficulty is that a constructed decision model such as influence diagrams(IDs) are usually applicable to only one specific problem. Holtzman suggests a decision class analysis (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. To analyze a class of decisions, rule-based system, and neural network based approach have been used. Even though the use of neural networks to generate IDs in the topological level results in a good performance, the generated ID usually is not a well-formed ID.

This research suggests an interactive procedure to build a well-formed ID. The procedure is based on a generated ID from neural network. As an interactive procedure between domain expert(s), the decision analyst, and the decision maker never reach the level of a perfect communication, it will be useful to inexpensively model a decision problem from a cumulative set of decisions at a starting point. Such an ID can be thought of as an approximation of experts' (explicit or implicit) interpretation of decision problem even if it may not be a well formed ID. Based on such an ID, our suggested procedure helps the decision participants to build a well-formed ID. We illustrated the procedure with an analogous land development and conservation problems.

1. Introduction

Two criticisms of decision analysis are that the amount of effort expended and time spent on modeling a problem are too burdensome and that the resulting model is applicable to only one specific problem [3]. The formulation of real decision problems needs much time, efforts, and cost, but the main difficulty is that a constructed decision model such as influence diagrams(IDs) are usually applicable to only one specific problem. Decision participants found that some prior knowledge from the experience to model IDs can be utilized to resolve other similar domain problems.

In order to reduce the burden of modeling decision problem, the concept of decision class analysis (DCA) was proposed a single unit by Holtzman [5]. To analyze a class of decisions, rule-based system [2, 5, 8, 9], and neural network based approach [4] have been used. Even though the use of neural networks to generate IDs in the topological level results in a good performance [4], the generated ID usually is not a well-formed ID. Especially the size of decision class grows larger and larger, the generated ID deviate from a well-formed ID. Decision participants may use the generated ID to communicate each other as a starting model, which can save the time and effort. If the problem size grows larger, an interactive procedure would be necessary to build a well-formed ID based on the ID generated from neural networks.

This research suggests an interactive procedure to build a well-formed ID. The procedure is based on an initial ID which was generated from neural network. As an interactive procedure between the domain experts, the decision analyst, and the decision maker never reach the level of a perfect communication, it will be useful to inexpensively model a decision problem from a cumulative set of decisions at a starting point. Such an ID can be thought of as an approximation of experts' explicit or implicit interpretation of decision problem even if it may not be a well formed ID. Based on such an ID, our suggested procedure helps the decision participants to build a well-formed ID.

This paper unfolds as follows. Influence diagram is reviewed in section 2 .In section 3, we described the concept of DCA and examine ID and neural-network in implementing DCA. Section 4 presents the neural-network based process to build an ID and an interactive procedure which was proposed to reconciling IDs. In section 5, we illustrated the procedure with a real world case that is an analogous land development and conservation problem. Finally, the conclusions are discussed in section 6.

2. Influence diagram

Influence Diagram (ID) is a graphical representation language that represents decision basis [6, 7, 13, 14]. It can be viewed from three levels: topological, functional, and the numerical level. At the topological level, the ID is defined as an acyclic digraph $G = (N, A)$, where N is a finite set of nodes and A is a set of arcs, $A \subseteq N \times N$. Figure 1 represents an influence diagram of a landfill expansion problem.

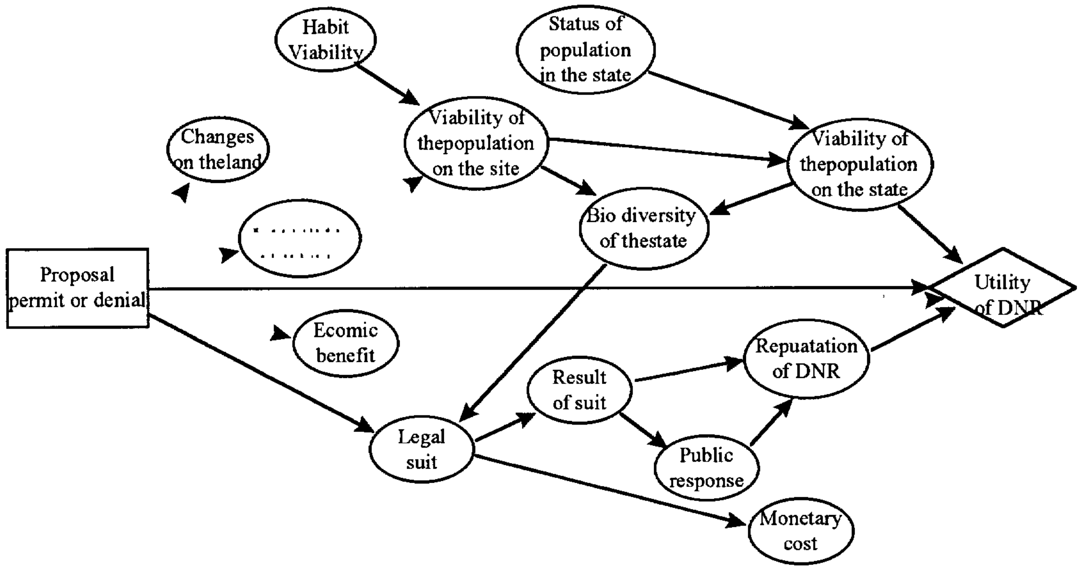

Figure 1. An influence diagram of a landfill expansion problem.

Well-formed Influence diagram (WFID) is a syntactically correct, completely assessed ID whose nodes have fully consistent distributions and outcomes [5]. When a WFID contains at least one decision node directly or indirectly influencing a value node, it is referred to as a well-formed decision influence diagram (WFDID). WFIDs can be evaluated using reversal and removal operations to yield answers to a large class of probabilistic, inferential, and decision questions. WFDIDs can also be evaluated to produce a recommended course of action.

The procedure to generate an influence diagram consists of a sequence of *value-preserving expansion*. The value preserving expansion is a transformation of the influence diagram which maintains feasibility and do not modify the optimal policy or maximal expected value [8]. The process to expand an influence diagram is made through adding a node, and splitting a node procedure. Once the structure is reasonable, the diagram is further refined in more detail using node removal, merging two nodes, and reverse an arc as well as adding and splitting procedures. It was shown that these procedures satisfy the value-preserving expansions by Kim [8, 12].

3. Decision class analysis and neural-network

The process of decision analysis can be viewed as three steps: the formulation of real decision problem, the evaluation of the formulation by a primarily computational process in order to give the decision maker a recommendation, and the appraisal of the analysis to gain insight into the recommendation [1, 10]. The formulation step has been accomplished manually, through lengthy interviews among decision analysts and persons intimately familiar with the problem domain. The model construction in practice is known to be a most complicated and burdensome process. Furthermore, the decision analyst may observe that a constructed decision model such as IDs is usually applicable to only one specific problem [8, 9].

Holtzman describes decision class analysis (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 [5]. Whereas the end result of an individual decision analysis is a decision, the result of a DCA is an individual decision analysis. In contrast with the single decision, DCA implies a deliberate omission of knowledge pertaining to the decision situation. Thus, analyzing a class of decisions occurs at a higher level of abstraction than analyzing a single decision. To analyze a class of decisions, rule-based system [2, 5, 12], and neural network based approach have been used. Rule-based approaches tend to be domain-specific and function extremely well when decision problems as well-defined. It can be a lengthy process depending on the size of the domain and range of cases [4].

In this paper, similarity among decision problems are interpreted in such a way that one or more key variables relevant to a given decision problem are admitted into the model of another decision problem. Specifically, an ID involves one or more nodes being in another ID. We further denote a class of decision problems to be the collection of such IDs that their nodes are partially or entirely owned by each diagram within the class.

At the point of decision making with the ID, variables in the ID are changeable from the current specific situations. The specific situations may be decision nodes, and decision maker's circumstances that are called situation frames in subsequent descriptions. When given the situation-specific information of the decision maker, the DCA should abstract the corresponding specific decision variables for solving the individual problem. In contrast to rule-based systems, neural networks have a broad response capability because of their capability to provide the general classification of a set of inputs [15]. Particularly, multi-layer neural nets which register in their hidden layers important features of the knowledge domain, can use this hidden knowledge to generate non-trivial generalizations[x].

4. Interactive procedure to build an ID

4.1 Neural-network based process to build an ID

In a class of problem, the notation of the ID is defined as follows [4]. On the nodes: decision $d_k \in D$, chance $c_k \in C$ and value $v_k \in V$; the arcs $a_{ij} \in A$ where i and j are the indices of the nodes. Denote a set S in which there are one or more situation frames $s_k \in S$. We further define the following sets:

$DS = \{d_k \in D \mid k = 1, ..., p\} \cup \{s_k \in S \mid k = 1, ..., n\}$,

$CV = \{c_k \in C \mid k = 1, ..., q\} \cup \{v_k \in V \mid k = 1, ..., r\}$,

$DCV = \{d_k \in D \mid k = 1, ..., p\} \cup CV$,

$ARC = \{a_{ij} \in A \mid i < j;\ i = 1, ..., p+q+r\text{-}1;\ j = 2, ..., p+q+r\}$,

where p, q, r, n are respectively the number of decision, chance, value nodes, and situation frames. The size of ARC is $|ARC| = {}_{p+q+r}C_2$ (where C is combination operator). For each node in the ID and $s_k \in S$, we have that its value is either 1 if it is present or 0 otherwise. We have the arc $a_{ij} \in \{-1, 0, 1\}$: If its direction is (i,j) then $a_{ij}=1$, if (j,i) then $a_{ij}= -1$, and if the influence between i and j does not exist then $a_{ij} = 0$.

To obtain a single decision analysis, an ID is built based on the decision and the situation-specific knowledge. First, neural-network I (NN I) is to search for relevant chance and value nodes of the individual ID from the given decision nodes and specific situations (i.e., situation frames). Second, neural-network II (NN II) elicits arcs among the nodes.

4.2 Modification of IDs

Initial ID is generated through the NN I and NN II based on decision class. It is represented as a set of $DCV = \{d_k \in D \mid k = 1, ..., p\} \cup \{c_k \in C \mid k = 1, ..., q\} \cup \{v_k \in V \mid k = 1, ..., r\}$ and a set of $ARC = \{a_{ij} \in A \mid i < j;\ i = 1, ..., p+q+r\text{-}1;\ j = 2, ..., p+q+r\}$, where p, q, r are respectively the number of decision, chance, and value nodes. the arc $a_{ij} \in \{-1, 0, 1\}$.

To build a well-formed ID, the initial ID was modified and expanded by each domain experts and decision makers. This process is to expand and refine the influence diagram. Expanding is made through adding a node, and splitting a node procedure. To maintain reasonable structure, the diagram is refined in more detail using node removal, merging two nodes, and reverse an arc as well as adding and splitting procedures. This process is carried out transformation of the influence diagram under maintains feasibility and do not modify the optimal policy or maximal expected value. So, It is the value-preserving expansion. We already described the value-preserving expansions in section 2.

4.3 An aggregation process

We refer the modified IDs to make agreed well-formed ID by decision participants. However the decision participants usually have different domain knowledge, information, and preference. So each participant may give a different ID. So an interactive procedure becomes necessary to aggregate IDs of each participant.

Three definition need to be give before the resolution procedure for reconciling different structures of influence diagrams can be presented.

A *core ID* is the minimal ID which is the intersection of the modified IDs.
Core DCV = $\bigcap_1^u DCV_k$, where u is the number of domain experts and DCV_k is the ID of kth domain expert.
Core ARC = $\bigcap_1^u ARC_k$, where u is the number of domain experts and DCV_k is the ID of kth domain expert.
A *super ID* is the maximal ID which is the union of the modified IDs.
Super DCV = $\bigcup_1^u DCV_k$, where u is the number of domain experts and DCV_k is the ID of kth domain expert.
Super ARC = $\bigcup_1^u ARC_k$, where u is the number of domain experts and ARC_k is the ID of kth domain expert.
A *disagreed set* is the difference of super ID and core ID.
Disagreed DCV = Super DCV - Core DCV. Disagreed ARC = Super ARC - Core ARC.

The modified IDs may have two kind of disagreement. They are *naming disagreement* and *structural disagreement*. There are two sources of name disagreement: synonyms and homonyms. Synonyms occur when the same nodes of the application domain are represented with different names in the two IDS; homonyms occur when different application nodes of the domain are represented with the same name in the two IDs. Renaming is performed whenever a synonym or a homonym is detected in the IDs.

After performing an resolution of naming disagreements, we achieve *reconciling process* for structural disagreement resolution. There are three types of disagreements: arc path, node expansion, internal structure. The reconciling process is presented as follows.

Step1: Defining the initial *core ID* and the *super ID* from the modified IDs.
Step2: Defining the disagreed sets; *disagreed DCV* and *disagreed ARC.*
Step3: Reconciling the disagreed sets until they become null set and reconciling process and *core ID* is a well-formed ID.
Step4: Evaluating the well-formed ID

To make null sets out of the disagreed sets which have three types of disagreements, the step3 is performed iteratively by the super ID reduction and refining the core ID. We further explain the reconciling process with the example in section 5.

4.4 An interactive procedure to build a WFID

Figure 2 shows the overall interactive procedure to build well-formed influence diagram.

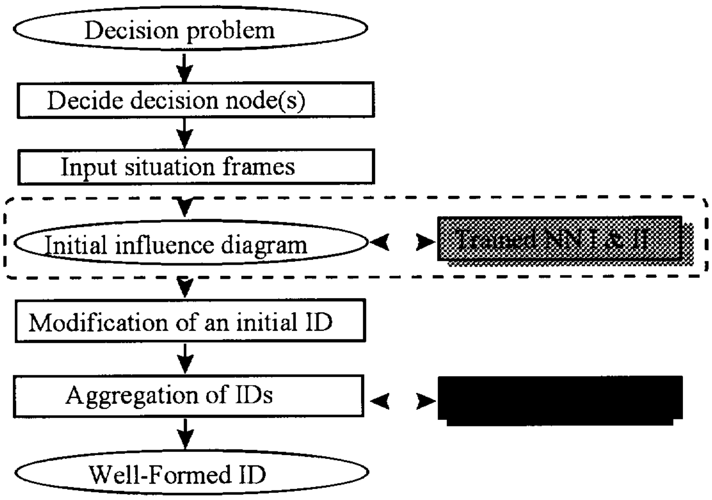

Figure 2. Overall interactive procedure for implementing DCA

The first two steps are performed by the decision makers. The third step is done by two trained feed-forward neural nets (shortly termed NNs). Each decision participant modifies an initial ID to make a well-formed ID using adding nodes and (or) arcs, deleting nodes and (or) arcs, merging nodes, splitting nodes, and reversing arcs, as it was explained previously. Aggregation process is performed based on modified IDs. Reconciling process is carried out to make null sets out of the disagreed sets respectively by decision participants.

5. An illustrative example

5.1 Description of a class problem

A project proposal evaluation problem in the Minnesota Natural Heritage Program (MN NHP): MN NHP has had to make decisions in dilemma situation which often faces administrators and lawmakers throughout the country. The dilemma is of how to balance endangered species protection with land development. The problem arises frequently and it is important that the decision is made in a fashion consistent with the legislative mandate and goals of the decision-makers. Influence diagrams are used to structure the ecological, social and economic, and practical considerations in a value hierarchy and to calculate the preferred alternative. The model used to develop it could be adapted for use with recurring analogous land development and conservation problems.

The Minnesota DNR (Department of Natural Resources) considers a project proposal in that environmental review process. Their considerations when they review a project proposal is as follows: the legal status of the species, the viability of that instance of the species. and effects of changes and species loss on larger ecological community picture. They usually also consider the social and economical benefits and the consequences or legal repercussions for denying the permit. But their main concerns are the effects of project into species on site and MN state. They encounter this decision about two or three times a year. DNRs in other states also consider similar problems. Some of the previous and current decision situations are summarized as follows in the set of situation frame;

S = {Landfill expansion project, Flood control project, Residence project, Factory project, Recreation project, Golf course project, Quality of the site, Rarity of the site, Social pressures, Momentum of the project, Many people involved, , Forest fragmentation, Erosion , Wetland, Sedimentation}

5.2 Demonstration of the procedure

The Minnesota DNR (Department of Natural Resources) was requested considering a project proposal which landfill expansion project. The decision situations are summarized as follows in Table 1.

Table 1. Situation frame of the landfill expansion

Situations	Given status
Quality of the site	Good
Rarity of the site	High
Social pressures	High
Water quality of the site	Good
Momentum of project	Large
Forest fragmentation	Wide

Using given the situation frame, we obtained a initial ID based on decision class analysis which is implemented by the trained neural-network I and II. Figure 1 shows the result of inference based on the NN II. It have two barren nodes without successor, representing a variable irrelevant to the problem. So, the initial ID is not a well-formed influence diagram. The barren nodes are linked another nodes to make a well-formed ID by each decision participant. Some nodes are expanded by adding nodes and arcs. The initial core ID is obtained from the modified IDs. Also, the super ID is obtained as shown Figure 3. In the super ID of the landfill expansion problem, arc path disagreement and node expansion disagreement are occurred. A arc path disagreement are occurred at a_6 and a_7. The node expansion disagreement is occurred at disagreed n_5 and which are called border node belongs to the core and has at least one direct predecessor outside the core. The node n_1 and arc a_1 and a_2 are agreed by all decision participants. The other nodes n_2 , n_3 , and n_4 are belong to the set of disagreed DCV. Also, The disagreed ARC set contain arc a_3 , a_4 , a_5 , a_6 and a_7. The disagreed sets become to null sets by performing reconciling process. The two border nodes are expanded and the arc a_7 is removed by reconciling process.

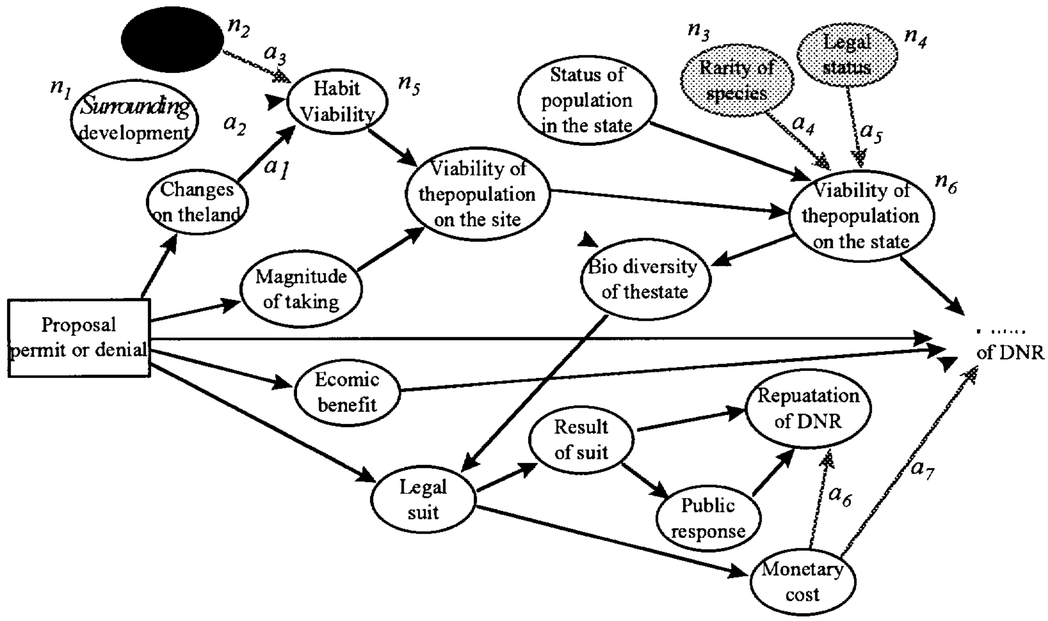

Figure 3. Super ID of the landfill expansion problem.

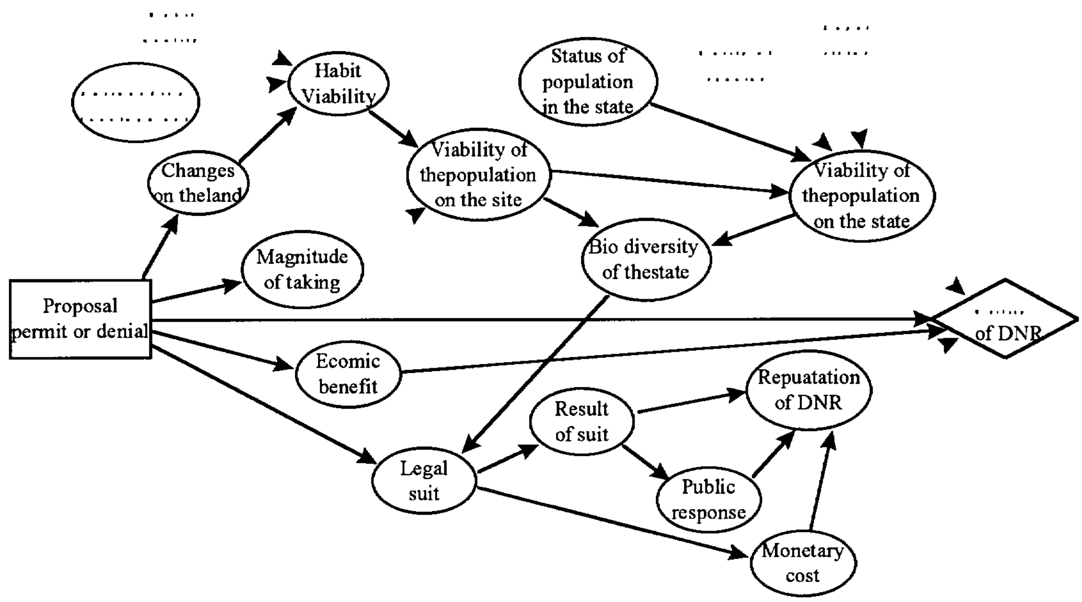

Figure 4. Agreed Well-Formed ID of the landfill expansion problem.

Finally, we obtain the well-formed influence diagram for landfill expansion problem as shown Figure 4.

6. Conclusions

The interactive procedure, building an well-formed influence diagram of an initial ID which generated from neural-network based decision class analysis, is suggested. Once the DCA is implemented using neural nets, we can greatly reduce the time and save large amounts of duplicate efforts for a single decision. This paper proposed reconciling process to aggregate the disagreements of decision model which are made by decision participants.

Two concern existed in the paper that are to combine a case based reasoning approach to define a class of decision and to support adaptation or reconciling process using classified domain knowledge.

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