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Feelders, A.J.

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Knowledge-Based Support for Managerial Diagnosis

Ad J. Feelders

Institute for Language Technology and Artificial Intelligence,
Tilburg University, The Netherlands

Abstract

Problem diagnosis is an essential phase in managerial decision making. It has however not received much attention from researchers in the area of Decision Support Systems. First we will discuss the role of diagnosis in the managerial decision making process. In the second chapter we give an overview of diagnostic computer programs in several application areas. We evaluate different kinds of knowledge representation and reasoning. Qualitative reasoning turns out to be an important mode of inference in diagnosis. Finally we present a framework for diagnostic systems to support managerial decision making.

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Chapter 1

Introduction

Problem diagnosis is an important phase in managerial decision-making [13, 21, 27, 6]. Therefore it is surprising that it has received little attention by researchers of Decision Support Systems (DSS) for management [11]. Emory and Niland [13] distinguish three phases in the decision- making process: goal setting, task delineation and task solving. Other authors make similar distinctions [21, 27]. In the goal setting phase the goals that have to be achieved by the manager or organisation concerned are determined. Task delineation is the process of defining those tasks which have to be fulfilled in order to achieve the goals. Diagnosis is a part of the task delineation process, as the following sub-division shows:

- Problem identification
- Diagnosis
- Task setting

Problem identification consists of analysing data in order to detect a deviation between the real situation and the goals that were defined. When this deviation is significant it becomes a problem symptom that has to be analysed. Managers generally use four kinds of models to define their goals [24]: historical models, planning models, e.g. budgets, models of others, e.g. other departments, superiors, and models from the environment of the organisation, e.g. profit of competitors.

Historical models are strongly supported by routine reports. Managers often get monthly reports, of for example sales totals, that only have meaning when compared to historical figures. Planning models contain projections of operating variables for the coming period(s).

The diagnosis phase consists of the generation of an explanation for the observed symptoms. This explanation should contain the base causes of the observed deviation(s). An accurate diagnosis is important because little benefit can be gained from sophisticated solutions to the wrong problem. The problem statement resulting from the diagnostic process becomes the input to the task setting and task solving phase. In the task setting phase it is determined what has to be achieved in order to solve the problems, the how will be determined in the task solving phase.

Chapter 2

Diagnosis

Diagnosis can in general be described as the attempt to identify, given a set of observable symptoms, the state of the underlying system. In medicine diagnosis is defined as the process of identifying the presence of a disease from its symptoms, signs and test findings. Other areas of decision making where diagnosis plays an important role are for example electronic trouble shooting, process control and managerial decision making. This chapter gives an overview of diagnostic methods in several application areas.

2.1 Medical diagnosis

Most research concerning diagnostic reasoning originated from the field of medical decision making. De Vries Robbe [29] gives a comprehensive overview of the methods that have been developed for medical decision support. Clinical decision aids (as de Vries Robbe calls them) can be divided into two groups:

- methods based on structured medical decisions, and
- methods based on structured knowledge of diseases.

Structured decisions are clinical protocols and decision trees. Systems that contain structured medical knowledge are divided into two categories: classification systems and explanatory systems. In classification systems associations are made between disease characteristics and disease categories. Examples of classification systems are rule-based expert systems like MYCIN [12], and systems based on statistical methods, such as Bayes' rule [26].

Explanatory systems on the other hand are based on causal relationships between disease characteristics. Examples are ABEL [23] and CASNET [30]. These systems use a causal model of the disease process to support diagnosis and prediction. De Vries Robbe proposes to make this causal model qualitative, because in medical knowledge the relations between disease chracteristics are often not quantifiable. In the following is a short description of the model structure and diagnostic procedure is given.

2.1.1 Model structure

The model describing the disease process is a signed directed graph (signed digraph). The nodes in the graph represent disease characteristics and the edges possible causal and empirical relations between these characteristics. An edge between nodes is directed from the cause-node to the effect-node.

A disease characteristic can be a variable (e.g bloodpressure) or a condition (e.g. headache). With each edge a sign is associated. If a change in the cause makes the effect change in the same direction, a '+' is associated with the edge. If a change in the cause makes the effect change in the opposite direction, a '-' is associated with the edge. The disease characteristics of a specific patient are are represented by positive and negative markings of nodes in the graph. When a node in the graph represents for example blood pressure then the observation 'increased blood pressure' is represented by a positive mark and 'decreased blood pressure' by a negative mark. When a node represents a condition like headache then finding this symptom is represented by marking that node with a positive sign (a condition cannot have a negative sign).

Edges between points represent relations that could be present in some specific case but do not always have to be. This model structure is primarily based on a method called 'cognitive mapping'; see [2].

2.1.2 Diagnostic procedure

A symptom that is found in a specific case is called a search-node. A search node is a marked +, -, or 0 node in the signed digraph. The set of search-nodes is called the search-set. The diagnostic procedure is split into two steps:

1. Searching for relations between symptoms which results in a clustering of symptoms.

2. Searching for causes of the clustered symptoms.

The possible causal chains of a specific symptom are found by constructing the antecedent graph of this node. Using the mark of the search-node and the relevant line-signs the markings of the antecedent nodes are determined. A simple example will serve to illustrate this procedure. In Figure 2.1 a simple model is given. Suppose the findings for a specific patient are that D has decreased and G has decreased. We represent this by the search set D-,G-. Figures 2.2 and 2.3 represent the antecedent graphs for D- and G- respectively. As a first step the intersection of the antecedent graphs is taken; Figure 2.4. Now the 'least causal' node of this intersection is called the minimal cause of the search-set, i.e. B+. This minimal cause can replace the original search-set for the further diagnostic process. Thus a single cause that explains all the symptoms is preferrable to more complex explanations involving more than one cause. This preference for the simplest explanation can also be found in other

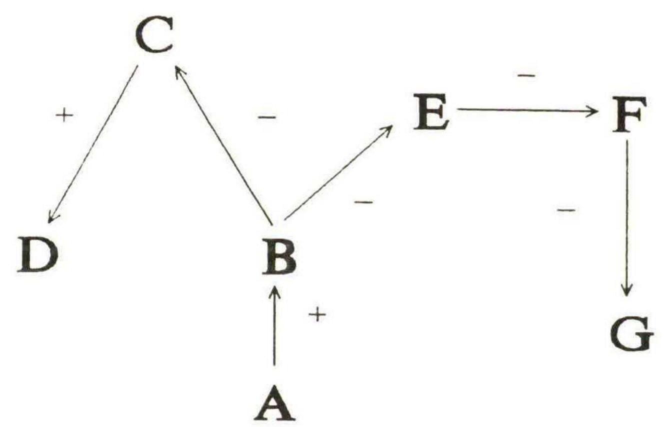

Figure 2.1: A simple causal graph

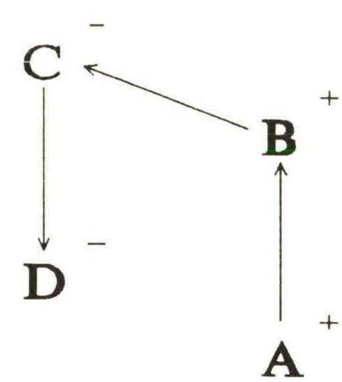

Figure 2.2: Antecedent graph D-

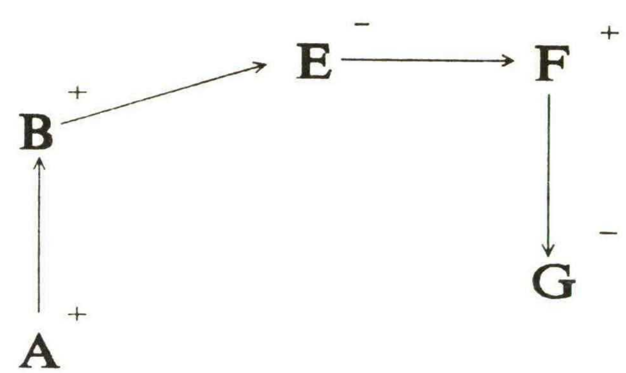

Figure 2.3: Antecedent graph G-

Figure 2.4: Intersection D-, G-

methods of diagnosis, see for example [25]. The diagnostic procedure proposed by De Vries Robbe is more elaborate than this example might suggest (e.g. it also has provisions for cycles occuring in the signed digraph). For details we refer to [29].

Sometimes there can be inconsistency in the interpretation of a marking of a point in the graph. A positive marking of a variable indicates that the variable has increased. However, as De Vries Robbe notices, it sometimes can be impossible to find out whether a variable or condition has changed because no previous observation of that variable has been made. In these cases normal values and normal conditions have to be taken as reference points for comparison. Thus increased blood pressure now changes to high blood pressure. But this change must lead to an entirely different interpretation of the causal links in the model. The first interpretation refers to the change in a variable whereas the second interpretation refers to its level.

The diagnostic program does not provide a theory for problem detection, as the symptoms that are used by the algorithm have to be provided by the user of the program. This means that the data abstraction which leads to symptoms such as 'increased blood pressure' is not performed by the program, but by human interpretation. In the following section we will describe this problem detection activity.

2.2 Bouwman's research on financial diagnosis

Bouwman [7, 8] uses a qualitative model of the 'typical firm' to simulate the diagnostic behaviour of a financial analyst. The financial diagnostic task required subjects to analyze various 'cases'. These cases were presented in the form of balance sheets, income statements, financial ratios, sales figures and production data, for the past three years of operation of a particular firm. The

```
Market Share = (Basic Market Share - C1 * Relative Price) *
               (1.00 - C2 * Lost Demand)

Relative Price = Sales Price - Average Sales Price
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Figure 2.5: Example of model equations

subjects were asked to 'make a quick evaluation of the position of the firm', and to indicate the underlying problem areas. 'Thinking aloud' protocols were used to record the problem solving of the subjects. The following is a brief description of Bouwman's findings.

2.2.1 Qualitative data abstraction

The first phase of the diagnostic process is problem detection. This is a screening activity that extracts those information items that are judged to be potentially relevant to the formulation of a diagnosis. Although the financial analysts are faced with primarily quantitative data, such as balance sheets and financial ratio's, they translate the series of figures into qualitative terms. The computer program developed by Bouwman uses several operators that translate figures into qualitative terms. Among these operators are the computation of a simple trend (increasing, decreasing) and the comparison against an industry norm. This result can get a further qualification such as large increase, slightly above, etc.. After the qualitative translation, the most significant findings are selected for further processing. Generally, only considerably deviating descriptions, such as large increase or way below industry average may qualify as significant.

2.2.2 A qualitative model of the firm

The knowledge on which diagnostic reasoning is based, is represented as a causal structure that describes the functioning of a typical firm. This model is defined in the program as a series of qualitative equations. The operators in the equations (+, -, *, /, min, max) are qualitative operators, operating on the values up, down, stable, too high and too low. Qualifications (such as large) which were used during problem detection are not applied during diagnostic reasoning. Figure 2.5 gives an example of the expressions in the model. Figure 2.6 gives an example definition of qualitative operators. If X_1 (or X_2) is 'up' then Y is 'up' and if X_1 (or X_2) is 'too low' then Y is 'too low'. The program does not specify what happens when both X_1 and X_2 are given.

Some operators defined are logically correct: they generate all possible results for their input values. Others operators are based on heuristics: they

```
y = f(x);     given x what is the value of y?

y = x1 + x2
y = x1 * x2

program: given x1: y = x1
         given x2: y = x2
```

Figure 2.6: Definition of qualitative operators '+' and '*'

only generate the most 'likely' possibilities in order to reduce the number of alternatives. This reduction of alternatives brings with it the risk of making wrong inferences. The only justification for these heuristics is that they enable the program to simulate the subject's behaviour.

2.2.3 Diagnostic procedure

The diagnostic procedure consists of two phases: integrating significant findings and formulating problem hypotheses (cf. de Vries Robbe's symptom clustering and searching for causes of clusters).

Integrating significant findings

Given a certain finding the program infers potential consequences through the qualitative model. These consequences are compared with the observed significant findings. If a match occurs a causal link between the two findings is established. In this way the program determines chains and trees of related findings (called clusters) in order to focus the diagnostic process.

Hypothesis formulation

There was no evidence from the protocols that the subject actually performed any hypothesis formulation at all. The formulation of this procedure is based on literature findings and the type of knowledge and reasoning that were used by the subject in the preceding phases.

The program uses the qualitative model of the firm to generate causes that might explain the root of a cluster of significant findings. It then explores the possible causes of those causes etc. In this way a branching tree of causes develops where each node represents a possible explanation of its higher level parent Note that this is equivalent to the antecedent graphs used by de Vries Robbe. Given this collection of problem hypotheses, the program ranks them on the basis of observed significant findings. Some hypotheses can be eliminated because they contradict observed findings. Others get a higher ranking because they are confirmed by observed findings. The result of this evaluation is an ordered list of problem hypotheses.

The model built by Bouwman was based on the study of the diagnostic behaviour of students. He also interviewed expert financial analysts and it is interesting to notice some differences:

- the examinination behaviour of professionals is guided by a check-list which contains standard questions and conditional questions.
- at the beginning of their analysis, professionals formulate a general impression about the kind of company they are dealing with e.g.'expanding', 'declining', 'stalling', etc. They use this impression to assess the significance of observed findings.
- professionals may employ summaries: facts which summarize part of the observed company behaviour. For example, increasing inventory together with declining sales revenues is summarized as 'producing for inventory'.
- professionals have available a list of common financial diseases. This is a list of frequently occurring typical financial problems.
- in contrast to students, professionals do use a process of generating problem hypotheses.

Bouwman's model of financial diagnosis shows some limitations of human diagnostic reasoning. Examples are:

- the limitation of causal chains to a maximum length.
- the restriction of the number of alternative explanations per level in the branching tree of causes.

This can only be justified by the limited capacity of human short-term memory. These shortcoming also suggest where a knowledge-based support system could be of use. Structuring of such a program's processes parallel to human decision-making processes will make it's results more acceptable to the user.

2.3 Diagnosis of technical systems

Diagnostic reasoning systems are often divided into two classes: systems that perform diagnosis from 'first principles' and systems based on 'experiential knowledge' (Also called 'deep' and 'shallow' knowledge respectively [28, 25].) Much work in the first area is concerned with diagnosis of technical systems.

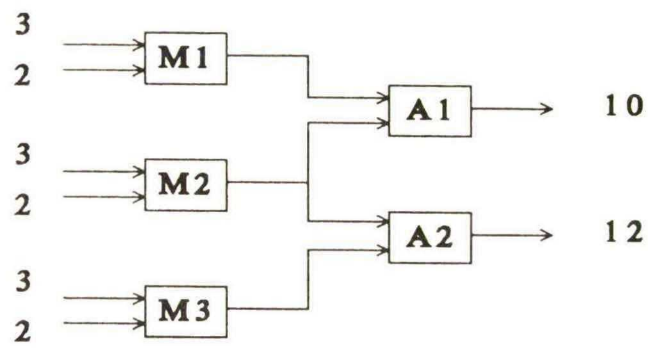

Figure 2.7: A device with observed outputs and inputs

The basic idea of this approach is as follows. One has available a structural description of the system to be diagnosed. In case of a digital circuit this would be a description of the gates (components) the system contains, and how these gates are connected to each other. If the observed system behaviour is logically inconsistent with the system description then there is a diagnostic problem. The problem is to determine the (minimal) set of faulty components that will explain the discrepancy between the observed and correct system behaviour. The following well-known example illustrates the idea; see Figure 2.7. M1, M2, and M3 are multipliers; A1 and A2 are adders.

From the logical description of this device and its observed behaviour the possible diagnoses can be obtained. The method for obtaining these diagnoses is as follows; see [25, 17]. First we define the notion of a conflict set. A conflict set is a set of components that cannot all be functioning correctly ,given the observations of the system. For example: {M1, M2, A2} is a conflict set in the example of Figure 2.7.

The calculation of diagnoses is based on the determination of minimal hitting sets of the collection of conflict sets. A hitting set H of a collection of sets C is a set with the following property: for all sets S in C, the intersection of S and H is not empty. Delta is a diagnosis for a device (and observations of it) if and only if Delta is a minimal hitting set for the collection of minimal conflict sets for that device. The two minimal conflict sets for this example are: {M1, M2, A1} and {M1, M3, A1, A2}. The minimal hitting sets (=diagnoses) of these two sets are:{M1}, {A1}, {M2, M3} and {M2, A2}.

The diagnosis {M1} means that M1 being faulty is an adequate explanation of the observed behaviour. Single-fault diagnoses, here {M1} and {A1}, are considered more likely than multiple faults because one normally expects components to fail independently from each other.

To differentiate between these two possible diagnoses additional observations (measurements) are needed. The problem is now to find the best point to make a measurement. It is clear that for example a measurement that

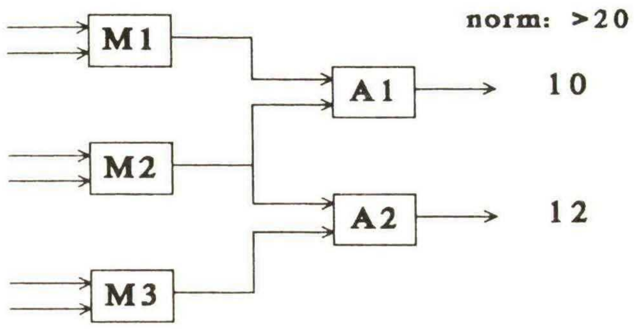

Figure 2.8: A diagnostic situation in management

disconfirms none of the available diagnoses gives no new information.

De Kleer and Williams describe a general minimum entropy technique to determine the best measurement to make next. This technique critically depends on the availability of failure probabilities for the components. In many cases this information may not be available. Therefore de Kleer [18] constructed a probing strategy that works without knowing these probabilities. Despite the intended generality of this approach, it has some characteristics which seem to make it unsuited for the kinds of models and diagnoses in the domain of managerial decision-making. The following comparison should make this clear.

In the domain of diagnosing devices, the intended (desired) behaviour can be derived from the model of the device. This model describes the correct system. A diagnosis is called for when the observed behaviour of the system is inconsistent with the model. The diagnosis states how we should change our model of the system, by assuming some components to be faulty, in order to obtain consistency between the model and observed system behaviour.

In the domain of management decision-making, models usually describe the relations, causal and otherwise, between concepts in the problem domain. A diagnosis is called for when observed behaviour is considered undesirable. Usually this is the case when a specific variable deviates from some normal or desired value(range); see figure 2.8. The undesirability of this behaviour does not follow from the model. The norm values have to be added to the model in order to be able to recognize the need for a diagnosis. Diagnosis in this context, is an explanation of how this undesired behaviour could occur, assuming the correctness of the model. So the model is capable of describing correct and incorrect system behaviour.

2.4 A quantitative approach

Courtney et al. [11, 1] have developed a Decision Support System (DSS) for managerial problem diagnosis. They build on Bouwman's work but also extend it in several ways. Weighted acyclic digraphs are used to represent knowledge of causal relations. Weighted digraphs are directed graphs with numbers assigned to edges to indicate the strength of the relationship between two variables. Thus an edge from variable i to variable j has a number C_{ij} assigned to it. This should be interpreted as follows: a one unit change in variable i causes a C_{ij} unit change in variable j.

The user can select variables in the model that have to be monitored by the system. For every monitored variable the user specifies bounds. These bounds indicate the allowed change from one period to the next for that variable. If the observed change exceeds these bounds the variable and its consecutive values are added to the list of problem symptoms. The result of this problem identification phase is a list of problem symptoms, called the monitor report.

If there are problem symptoms the system enters the 'interactive diagnosis' phase. Now the user can let the program perform several analyses. The first is the computation of the change in a selected node. This change is computed using the weighted digraph model and data base values for the model variables. The change of variable X_i (ΔX_i) between times $t-1$ and t is computed as follows:

$$\Delta X_i = \sum_j C_{ji} \Delta X_j$$

If the computed change is close to the observed change in the value of the selected problem symptom then a diagnosis may be obtained. If not, the model does not represent the problem domain faithfully and an accurate diagnosis is not possible. This analysis can generate explanations such as: 'Variable X_1, X_2, X_3 have contributed V_1, V_2, V_3 to the changes observed in Z (the symptom); the problem would have been worse had it not been for variable Y_1 and Y_2 whose changes have offset the magnitude of the problem'; see [11] p.388. The analysis is only one level deep: it only takes into account the variables that directly influence the problem symptom.

The second analysis generates hypotheses about the problems causes by constructing paths from terminal nodes to the selected node. The paths from terminal nodes to the selected variable are ranked on the basis of their contribution to explaining the problem. If for example the problem variable has declined, the path with the most negative contribution is displayed first. Paths with a positive contribution have actually offset the problem. This analysis is several levels deep: it takes into account variables that are the first node in a path leading to the problem variable.

A drawback of this approach is the massive need for quantitative data to be able to generate a problem diagnosis. Inherently qualitative variables cannot be included in the model. Furthermore the system is limited to acyclic graphs. The authors indicate variance analysis in accounting system as a possible application area for their program [11].

Chapter 3

Evaluation of different diagnostic approaches

Several conclusions can be drawn from the overview in the foregoing paragraph. Firstly it has been shown that qualitative reasoning appears to be an important mode of inference in diagnosis. The studies of Bouwman [8] and de Vries Robbe [29] make this point clear. Secondly the kind of model that is used for diagnosis differs between and within the application areas studied. This is partly explained by the fact that only particular kinds of models are available in that application domain. For technical systems design descriptions are often available, in contrast to medical diagnosis where only a mapping between symptoms and diseases is partly known. The reasons are obvious. A technical device is defined by its design description. In medicine the system to be diagnosed is the human body, or part of it, for which no adequate description for diagnostic purposes exists. On the other hand physicians have been able to collect knowledge about disease processes over a long period. This is partly due to the uniformity of the system to be diagnosed, the human body. In managerial diagnosis it is more difficult to construct mappings between diseases and their symptoms. This is caused by the diversity and dynamics of organizational structures.

The merits of several models have been studied in literature. Diagnostic programs based on quantitative models have some disadvantages:

- the unability to adequately represent causalities.
- difficulties in representing incomplete knowledge about the phenomena considered.

The unability to represent causality stems from the symmetry of mathematical equations. The equation $Y = f(X_1, \ldots, X_n)$ has often the implicit meaning that $X_1, \ldots, X_n$ are the causal influences and Y is the effect. Economists often call this 'the reading of the model'. However during formal manipulation with the equations the intended causal direction is lost. The difficulty with representing incomplete knowledge is caused by the requirement to specify the precise numeric value of system parameters. Explanatory paths, based on cause-effect relations, are important for the justifications of decisions. Furthermore they can be of value in the therapy phase. Consequently systems based on mathematical models have not been used much in real-world decision making [8]. Difficulties in representing incomplete knowledge were demonstrated in the approach of Courtney et al..

Diagnostic systems based on (heuristic) classification [10] do also have some shortcomings. These systems primarily contain knowledge of associations between problem features and problem solutions. This is often called 'shallow' knowledge. Some disadvantages of this shallow knowledge are [28]:

- problem solving is rather 'brittle'.
- explanation of results is not satisfactory.

Problem solving is called brittle because the system fails completely if there isn't a total match between the features of a specific problem and one of the patterns in its knowledge-base. Explanation of results is not satisfactory because causal relations are often not represented by classification systems. 'Deep' models on the other hand represent the causal or structural knowledge that underlies this shallow knowledge [28]. The theory of qualitative reasoning forms a theoretical framework to represent deep models and serves as a formal basis for describing causality. In the following chapter we give an overview of this research area.

Chapter 4

Qualitative reasoning

Recently, the attempts to construct deep models for knowledge-based systems have lead to a new research area in Artificial Intelligence, known as Qualitative Reasoning [5]. Research on qualitative reasoning has primarily tried to develop a theory for predicting and explaining the behaviour of physical systems in qualitative terms. A main objective of this field is to provide a theory which is far simpler than classical physics but still retains all the important distinct physical behaviours (e.g oscillation, momentum, etc.). Furthermore the theory must be able to produce causal explanations that are easy to understand.

In qualitative reasoning the variables that are used to describe the behaviour of the system can only take on a small number of values. This set of values is called the quantity space of the variable. For example the quantity space used in the approach of de Kleer and Brown [19] is {-, 0, +}. The usual mathematical equations expressing physical laws are expressed by restrictions on the qualitative values of the parameters. These restrictions are called confluences. In the approach of Kuipers [20] the quantity space for a variable can be extended during simulation of the qualitative system. The simulation algorithm can discover new 'landmark values' for a variable. The set of landmark values for a variable is a totally ordered set. A variable is in this approach represented by a tuple {QVAL, QDIR}. QVAL represents the value of a variable, and QDIR represents the direction of change of the variable. QVAL can be either a landmark value or the interval between two adjacent landmarks. QDIR takes its value from the fixed quantity space increasing, steady, decreasing. Forbus [15] uses a process-oriented description. A survey of the state of the art of qualitative reasoning can be found in [9].

Since the information contained in a qualitative description results in an incomplete description of a state of the system this may lead to several possible behaviours. So the celebrated uniqueness theorems for solutions of differential equations are no longer valid in qualitative physics.

Some attempts have been made to apply the methods developed in qualitative physics to economic reasoning [3, 4, 14, 31]. Berndsen and Daniels [3, 4] adjust the approach of Kuipers to make it suited for the qualitative simulation of economic systems. Also they explicitely represent causal relations between variables. Woon and Coxhead [31] use the approach of de Kleer and Brown for financial analysis. They use the quantity space {low, normal, high} for variables, like profit, sales, etc., to explain departure from normality. Research on qualitative reasoning is of relevance to the development of decision support in managerial diagnosis because it can provide a formal basis for reasoning over qualitative models.

Chapter 5

A framework for managerial diagnosis systems

From the foregoing we can formulate some general requirements for managerial diagnosis systems. An adequate explanation of the programs results is of crucial importance to its use in practice. To be able to achieve good explanations the programs knowledge representation and reasoning should be similar to that of the human decision maker. Causal relations are frequently used in problems in the business domain. Therefore the use of a causal model seems appropriate for a managerial diagnosis system. We formulate a general framework for managerial diagnosis systems based on the study of management decision making and the different diagnostic models from other application areas. An information system for the support of managerial diagnosis could have the following components:

- A descriptive model.
- A normative model.
- A data base.

The descriptive model is a specification of the relations between variables in the problem domain, for example a qualitative causal model represented by a signed digraph or qualitative equations. The normative model is the definition of the desired situation. It can be based on historical data, budgets, industry averages, etc. More general it is a set of constraints defined over a subset of the variables in the descriptive model. The data base contains values of variables in the model, or these values can be inferred from it. Furthermore the system will contain the following procedures:

- Data abstraction.
- Problem identification.

- Diagnosis.

Data abstraction is the conversion of quantitative data into qualitative terms. Examples are the derivation of historical trends (increasing, decreasing), or a comparison with an industry average (above, below average). Problem identification is the comparison of the desired situation with reality. For a specified set of variables, called indicators, a difference between reality and norm is considered a symptom. Finally the diagnostic procedure gives an explanation for the observed symptoms.

The interaction between these components and procedures is as follows. Problem identification consists of a comparison between the normative model and the real values of the indicators stored in the data base. The normative model was defined as a set of constraints over model variables. Any constraint not satisfied by the data base defines a problem symptom. Often it is, from a cost point of view, not possible to monitor all model variables; see for example Bonge [6]. Therefore it is important that managers identify those variables that are most critical to the achievement of their goals. This part of the system could benefit from work done on exception reporting information systems, for example [16, 22].

After qualitative abstraction the problem symptoms are passed to the descriptive model. The descriptive model is used by the diagnostic procedure to generate possible explanations for the symptoms. These possible explanations (hypotheses) have to be checked against data concerning the variables in the descriptive model. Hypotheses that contradict with the data base values are rejected. We don't assume that the database contains the values for all variables in the descriptive model. Thus it can happen that we cannot check a hypothesis against the data base. In this case competing hypotheses may induce a search for additional information by the system user.

This backward reasoning in the causal model will in the ideal case continue until a point is reached at which taking corrective action is possible. This is the case as soon as we can identify a controllable variable through which we can influence the beginning of the causal chain. The output of the diagnostic process should be a problem statement that can serve as an input to further problem solving activities.

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ITK: P.O. BOX 90153 5000 LE TILBURG THE NETHERLANDS