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**The use of a multi-agent learning system to analyse embedded  
context in qualitative data for decision-making.**

by

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## Acknowledgements

### **The use of a multi-agent learning system to analyse embedded context in qualitative data for decision-making**

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Is my own work and that all sources that I have used or quoted have been indicated and acknowledged by means of complete references.

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## Abstract

### **The use of a multi-agent learning system to analyse embedded context in qualitative data for decision-making**

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Department: Informatics  
Degree: M. Com. (Informatics)

A number of studies have shown that the success of knowledge discovery from data, with an intelligent data analysis tool, is dependent on the combination and integration of individual data mining techniques. The aim of this study was to determine whether an intelligent data analysis tool could successfully be used to analyse the context embedded in a real world data repository. Although the data repository contained both quantitative and qualitative measures, the study only focussed on the qualitative aspects of the data. For example, organisations were characterised in terms of the key technologies that made their products sustainable in the market rather than its market share.

The intelligent data analysis tool was based on a multi-agent learning system that consisted of learning agents or so-called learners grouped into learner teams. A learner team included data mining techniques as well as human learners. These learners interacted with one another and the environment. The interactions between the learners involved learning in a co-operative inductive learning team. This was accomplished by team members sharing their knowledge, i.e. the rules they have acquired during the learning process. The knowledge acquired by each individual learner, as well as the team's knowledge were stored in separate knowledge bases.

The intelligent data analysis tool was evaluated against a data repository developed as part of the National Research and Technology (NRT) Audit conducted for the Department of Arts, Culture, Science and Technology of the South African Government. The results of the cooperative learner teams were verified by the active participation of a human expert, as well as against a synthesis report. This report, which was another major output of the NRT Audit, contained findings of experts that described the current state of science and technology in South Africa. Also, it outlined certain trends that were based on the data collected during the NRT Audit.

Experimental results indicated that the intelligent data analysis tool could be applied successfully to a real-world application. It was concluded that the inclusion of a human learner makes a substantial contribution to a multi-agent learning system. The intelligent data analysis tool can be successfully used by human experts to verify their findings and therefore assist them in gaining confidence in their own interpretation of the data. The results obtained from the application of the tool differed from the opinions of the human experts in some instances, indicating pre-conceived ideas that were erroneously made. The human experts indicated that their inclusion in the learning process was a valuable learning experience.

## Opsomming

### **Die gebruik van 'n multi-agent leerstelsel vir die analise van verskuilde konteks in kwalitatiewe data om besluitneming te ondersteun**

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Verskeie studies het aangetoon dat die sukses van 'n kennisontdekkingstrategie uit 'n data omgewing, met 'n intelligente data analise werktuig, afhanklik is van die kombinasie en integrasie van individuele datamyn tegnieke. Die doel van hierdie studie is om te bepaal of 'n intelligente data analise werktuig toegepas kan word in 'n werklike situasie om die konteks verskuil in 'n databank te kan analiseer en sodoende die besluitnemers te ondersteun. Die databank bevat beide kwalitatiewe sowel as kwantitatiewe maatstawwe. Hierdie studie het gekonsentreer op die kwalitatiewe aspekte. Byvoorbeeld, 'n organisasie is beskou in terme van sleuteltegnologieë wat die firma lewensvatbaar in die mark maak, eerder as die organisasie se markaandeel.

Die intelligent data analise werktuig is gebaseer op 'n multi-agent leerstelsel wat bestaan uit leeragente wat in leerspanne gegroepeer is. 'n Leerspan bestaan uit beide datamyn tegnieke, sowel as kundige individue, wat met mekaar en die omgewing saamwerk. Die interaksie tussen die leeragente behels koöperatiewe leer wat plaasgevind het in spanne en bekend staan as koöperatiewe induktiewe leerspanne. Dit was bewerkstellig deurdat spanlede hulle kennis, die stel reëls wat hulle gegenereer het gedurende die leerproses, met mekaar uitruil. Die kennis wat elke individuele leerder, sowel as die span as geheel ontdek het, is in aparte kennisbasisse gestoor.

Die intelligente data analise werktuig is gebruik om die databank, ontwikkel as deel van die Nasionale Navorsing en Tegnologie (NRT) Oudit van die Departement Kuns, Kultuur, Wetenskap en Tegnologie van die Suid-Afrikaanse Regering, verder te ontleed. Die resultate van die koöperatiewe induktiewe leerspanne is getoets deur die aktiewe deelname van 'n kenner in die gebied, sowel as teen die sintese verslag wat nog 'n uitset van die NRT Oudit was. Hierdie verslag bevat die bevindinge van gebiedskenners wat die huidige stand van die wetenskap en tegnologie in SA beskryf, tesame met sekere tendense bepaal vanaf die data wat gedurende die Audit versamel is.

Die resultate toon dat die intelligente data analise werktuig wel suksesvol in 'n werklike situasie toegepas kan word. In hierdie toepassing het die menslike leerder 'n beduidende bydrae gemaak tot die multi-agent leerstelsel. Die strategie kan gebruik word om die gevolgtrekkings van die kenners betrokke in die analise te bevestig en hulle sodoende te help om vertroue in hulle eie interpretasie van die data op te bou. Die strategie het ook soms verskil van die menings van die betrokke kenners en het daardeur foutiewe aannames uitgewys, wat weer vir die individue 'n waardevolle leerervaring was.

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# Chapter 1

## Introduction

The main application of databases, which have been in use since the early 1970's, is to support the operational aspects of organisations. Here, everyday transactions are captured and processed via standard database queries and reports. More recently, a new use of database systems has emerged. This trend is mainly due to the demand for information made by management. Database systems now also have to support the decision making process. The desire by organisations to gain a competitive advantage using the knowledge from their corporate data has led to the need for business intelligence. Berthold *et al* (1999), defines business intelligence as “*the gathering and management of data, and the analysis of that data to turn it into useful information to improve decision making*”. According to the Palo Alto Management Group the market, by the year 2001, for business intelligence is estimated close to \$70 billion, a huge industry by any measure [Berthold *et al* 1999]. However, existing databases have been designed to automate transaction processing, therefore these databases and traditional database query tools are not well suited for this new task [Inmon 1996]. This shortcoming is addressed through the development of intelligent data analysis tools that extract knowledge from data, as discussed next.

Knowledge Discovery from Data (KDD) focuses on the extraction of knowledge from data repositories i.e. databases and data warehouses, enabling these repositories to support the decision making process of organisations. KDD can be defined as “*the non-trivial extraction of implicit, previously unknown and potentially useful information from data*” [Adriaans *et al* 1996]. In principle, the process of knowledge discovery from data consists of six stages, namely data selection, cleaning, enrichment, coding, knowledge discovery (intelligent data analysis) and reporting. The first four stages concern data pre-processing during which a single, integrated data source for the knowledge discovery phase should be

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built. The fifth stage of the KDD process focuses on the actual process of intelligent data analysis, also referred to as data mining. A number of popular data mining techniques are neural networks, as discussed in Section 2.5.6, decision trees, as discussed in Section 2.5.5, rule induction algorithms, as discussed in Section 2.5.4 and generic algorithms. These tools employ statistics and machine learning to extract knowledge from data. Recently, hybrid systems that combine two or more of these data mining techniques into a single system have gained popularity.

The two main objectives of this study are the creation of an intelligent data analysis tool, which combines more than one data mining technique into a unified framework, and the subsequent application of this intelligent data analysis tool to a real-world application. The real-world application concerns, the National Research and Technology (NRT) Audit, as discussed in Chapter 3. This audit was commissioned by the South African Department of Arts, Culture, Science and Technology (DACST) to better understand the capacity, capability and limitations of the country's science and technology system. The rationale behind the audit is discussed next.

South Africa is facing many new challenges in the 21<sup>st</sup> century – competing in a world economy, growing environmental concerns, social and economic inequalities, an ageing population, low productivity, massive unemployment, and the nation's evolving role in Africa. It is widely recognised in government that the role of technology, defined as *“the set of means embodied in products, processes, machines and related services by which the physical and informational domains are manipulated”* [DACST 1998], is crucial in addressing these challenges. This recognition emphasises the importance of having a robust technology policy. Drucker [in Fairhead 1995] mentioned that the major challenge facing management in developed countries is improving the performance of knowledge and service workers, i.e. the decision makers. However, in a developing country, such as South Africa, the need to improve the performance of decision makers in government is even more important. This improvement will enable decision makers to formulate policies that successfully address the challenges lying ahead. Formulating a technology policy requires a critical assessment of South Africa's strengths and weaknesses in science and technology. This realisation was the reason for the commissioning of the NRT Audit by the South African Government.

This thesis discusses the development of an intelligent data analysis tool and its application to aid decision makers with the interpretation of the findings of the NRT Audit. The tool uses the data repository developed as part of the NRT Audit to verify the findings contained in the synthesis report, Technology and Knowledge [DACST 1998], prepared by the Foundation for Research and Development. In addition, this study investigates the existence of possible additional findings. Here, the use of intelligent data analysis may lead to the discovery of additional conclusions that can be used for decision-making.

The remainder of this chapter provides an introductory overview of the thesis. Section 1.1 contains the problem statement; Section 1.2 briefly outlines the research approach that was followed; and lastly, Section 1.3 presents an outline of the remainder of the thesis.

## 1.1 Problem statement

According to Hand [in Berthold *et al* 1999], intelligent data analysis does not consist of choosing and applying a technique to match a problem at hand. He argues that data analysis is not a collection of isolated techniques, completely different from one another, waiting to be matched to a problem. On the contrary, these techniques have complex interrelationships that can alter the problem being investigated in subtle ways. Furthermore, very rarely is a problem so precisely stated that a single application of one technique will suffice. Hand describes intelligent data analysis as the *“repeated application of techniques, as one attempts to tease out the structure, to understand what is going on. To refine the questions that the researchers are seeking to answer requires painstaking care and, above all, intelligence. It is a carefully planned and considered process of deciding what will be most useful and revealing”* [Berthold *et al* 1999]. A number of studies have been conducted regarding the selection of the best, most useful technique for solving different types of problems, including: Dhar *et al* 1997, Michie *et al* 1994 and Moustakis *et al* 1996. Some studies reported few differences between the various techniques while others reported a distinct advantage using a particular technique. Moustakis *et al's* (1996) survey indicated the following general trends: A classification task, which is a *task that has the ability to classify*



*objects as members of known classes*, is best supported by neural networks. When analysing the generic soybean data set, containing instances describing soybeans with diseases, a neural network will be the best data mining technique to use if the aim of the task is to classify these diseases. Rule induction algorithms best support a problem solving type of task, which is a *task that describes the procedural and algorithmic aspects of problem solving*. When given a set of constraints describing a system, a rule induction algorithm will be best at optimising the system's parameters.

The question now arises, since there are so many techniques that appear to be applicable to a task, which one should be chosen. Furthermore, if the problem consists of more than one type of task which technique should be used? The study by Moustakis *et al* (1996) draws the conclusion that different types of tasks are best supported by different techniques and that a KDD environment's success as an intelligent data analysis tool depends on the combination and integration of individual data mining techniques.

Real-world problems are complex. It takes an infinite number of attributes to accurately describe the problem domain. This complexity can be simplified by a divide and conquer approach. A problem can be broken into smaller problems, each addressing a particular section of the domain. The data describing each section should then be analysed separately. During the analysis of the data describing each of these smaller domains different data mining techniques will be required depending on the type of task. This implies that, when addressing a real-world problem with the use of KDD, an environment consisting of more than one data mining technique is required. Following Moustakis *et al's* (1996) findings, these techniques should be combined and integrated.

The integration and combination of data mining techniques into a single KDD environment can be viewed from three different perspectives. The environment can be seen as a multi-strategy learning system, a multi-agent learning system or a hybrid learning system, as discussed by Viktor (1999), drawn from Kholsa *et al* (1993), Jacobsen (1998), Jennings (1993), Honavar (1995) and Sun (1995):

- A multi-strategy learning system involves the combination of more than one form of learning strategy into a single system. In this way the strengths of each strategy is enhanced and the weaknesses are alleviated.
- The second perspective is that of a multi-agent learning system. According to Russell *et al* (1995), an agent is *"anything that can be viewed as perceiving its environment through sensors and acting upon that environment through effectors"*. In a multi-agent learning system the environment consists of a number of agents, residing in a communal environment, interacting with one another as well as the environment.
- Lastly, when viewing the environment as a hybrid learning system, the different data mining techniques are combined into a single system. Operating side-by-side, the techniques co-operate to solve a problem.

Following Viktor (1999), the KDD environment developed during this study will be viewed from the perspective of a multi-agent learning (MAL) system. This approach is chosen since it does not isolate learning from the environment in which the problem exists, but acknowledges the influence of the communal environment on learning. Weiss (1999) states that a multi-agent learning system offers a natural way to view and characterise learning. Multi-agent systems reflect the insight that, learning, intelligence and interaction are deeply coupled.

The agent and multi-agent learning concepts are based on our perception of how humans learn. Humans do not learn in isolation, but participate with other intelligent agents, i.e. other humans or machine learners, in an environment in which they all co-operate. They interact in many ways and most of what they achieve is a result of these interactions. A multi-agent learning system provides a framework for modelling these interactions. Learning within the MAL system will occur by means of the full co-operation of the participating learning agents, applying inductive learning techniques as described in Section 2.1.

In summary this study investigates the use of a KDD environment in a real-world application, focusing on the following:

- i. The development of an intelligent data analysis tool, modelled as a MAL system that combines more than one data mining technique into a unified framework for decision support.
- ii. The evaluation of the capability of this intelligent data analysis tool, using co-operative inductive learning techniques, in analysing the context as embedded in qualitative data, to be used for decision-making.

The next section discusses the research approach followed during this investigation.

## 1.2 Research approach

The underlying epistemology supporting this study is a combination of a quantitative and qualitative approach to research, by the triangulation of data from different sources [Kaplan *et al* 1988]. The specific research methodology that has been followed is a combination of case study and action research from an interpretative philosophical perspective.

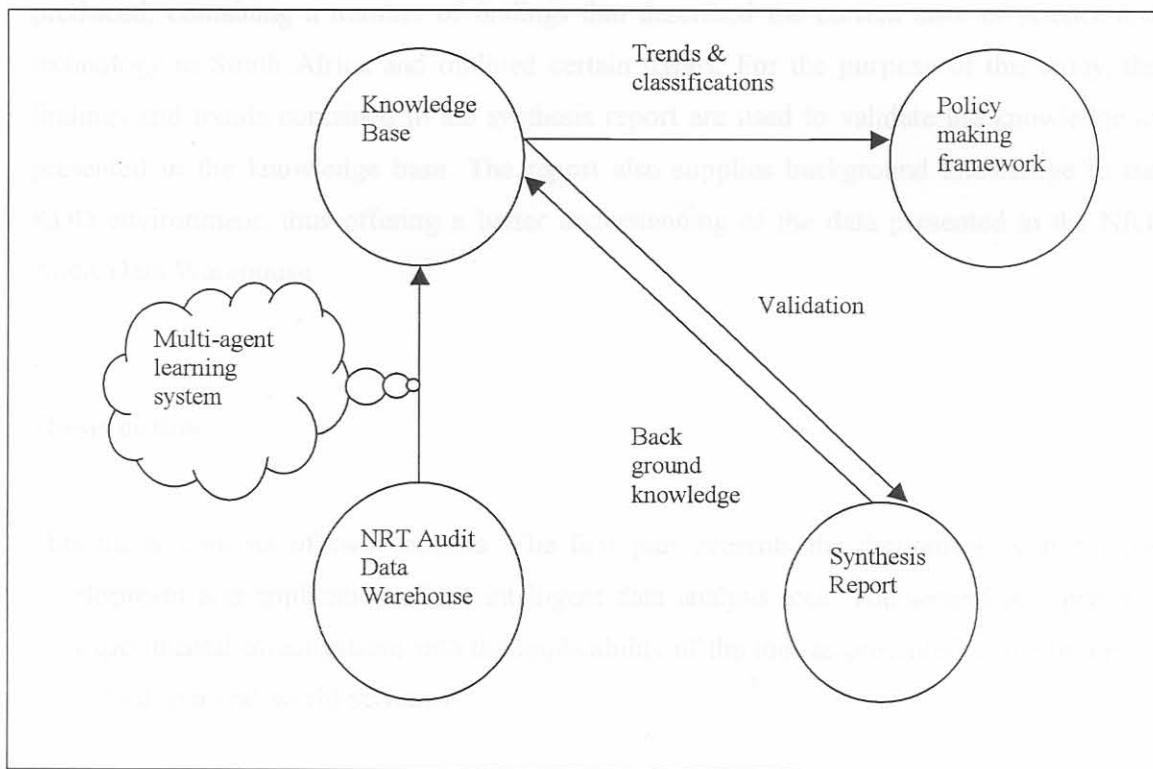
Case study research is the most common qualitative research method used in information systems research. Yin (1994) defines case study research as follows:

*“A case study is an empirical inquiry that:*

- Investigates a contemporary phenomenon within real-life context, especially when*
- The boundaries between phenomenon and context are not clearly evident”*

The phenomenon investigated in this study is thus: the capability of a multi-agent learning system in analysing a complex real-world domain, defined by a set of qualitative data, for decision-making, as discussed next.

The approach to this study is depicted graphically in Figure 1.



**Figure 1 Research Approach**

The real-world domain analysed for this study is the South African Science and Technology System. This science and technology system is defined by a set of qualitative data as contained in, the NRT Audit Data Warehouse. The NRT Audit Data Warehouse is one of the outputs of the NRT Audit and is a data repository of all the data gathered during the audit. Knowledge should be extracted from this data repository by an intelligent data analysis tool and stored into a knowledge base. This knowledge base, containing the potential useful information from the data can then be used as a basis for policy making directed at the development of science and technology in South Africa. The knowledge will be represented by means of rule sets consisting of trends and classifiers, as defined in Section 2.1. Recall that, learning within the MAL system will occur by means of the full co-operation of the participating learning agents, applying inductive learning techniques. Therefore, the intelligent data analysis tool used for extracting the knowledge is modelled as a co-operative inductive learner team - multi-agent learning system (CILT-MAL system), as described in Chapter 2.

During the NRT Audit a synthesis report, Technology and Knowledge [DACST 1998], was produced, containing a number of findings that described the current state of science and technology in South Africa and outlined certain trends. For the purpose of this study, the findings and trends contained in the synthesis report are used to validate the knowledge as presented in the knowledge base. The report also supplies background knowledge to the KDD environment, thus offering a better understanding of the data presented in the NRT Audit Data Warehouse.

### 1.3 Thesis outline

This thesis consists of two sections. The first part presents the theoretical basis for the development and application of the intelligent data analysis tool. The second part presents the experimental investigations into the applicability of the tool as presented in the first part, as applied to a real-world scenario.

Chapter 2 lays the theoretical foundation for the experimental work conducted in Chapters 4 and 5. In Chapter 2 the CILT-MAL system is defined and the learners that participated in the CILT-MAL system are described. Chapter 3 describes the NRT Audit case study. This case study is used for the experimental work as documented in Chapters 4 and 5. Chapter 4 describes the first experiment that used a CILT-MAL system to conduct a classification task required by the audit. Chapter 5 documents the second experiment, the aim of which was to process a problem solving type task, as needed by the audit. Chapter 6 summarises the main results of this thesis and discusses areas of future research.

## 2.1 Co-operative inductive learner teams

# Chapter 2

## Co-operative inductive learning in a multi-agent learning system.

Recall from Chapter 1 that a CILT-MAL system consists of a number of learners, i.e. data mining techniques and human experts. The learners discussed here learned by means of induction to form sets of concept descriptions. The learners did not learn in isolation, but co-operated with one another in teams, hence they formed co-operative inductive learner teams. A co-operative inductive learner team can be modelled as a multi-agent learning system, with co-operative inductive learners participating as learning agents within this multi-agent learning environment.

This chapter is organised as follows. Section 2.1 introduces the concept of inductive learning and discusses co-operative inductive learner teams (CILT). This is followed by Section 2.2, which introduces a multi-agent learning system and the concept of an intelligent data analysis tool. Section 2.3 describes the way in which co-operative inductive learner teams can be modelled as a multi-agent learning system and hence describes the CILT-MAL system used for this study. Section 2.4 discusses the learning process as it occurs within a CILT-MAL system. Finally, Section 2.5 places the learning agents used in this CILT-MAL system, into Langley's framework for machine learning and draws a comparison between the two frameworks.

## 2.1 Co-operative inductive learner teams

In 1912, Russell [in Sestito *et al* 1994] defined the induction principle as:

*“When a thing of a certain sort A has been found to be associated with a thing of a certain other sort B, and has never been found dissociated from a thing of the sort B, the greater the number of cases in which A and B have been associated, the greater is the probability that they will be associated in a fresh case in which one of them is known to be present”.*

Later, in 1988, Honavar and Uhr [in Sestito *et al* 1994] defined the induction process as:

*“A process by which a system develops an understanding of principles or theories that are useful in dealing with the environment by generalization and specialization from the specific examples or instances presented to the system. This includes the process of experimentation and discovery; that is setting the hypothesis and then accumulating evidence to confirm or deny their validity”.*

Inductive learning is *the construction of a description of a problem domain, based on the observations made of that domain, by a learner*. The automation of this construction process is referred to as inductive machine learning [Holsheimer *et al* 1994]. Data mining is a special case of inductive machine learning, where the problem domain is being observed through a data repository. This data repository describes the problem domain in the following way:

Let  $A = \{A_1, A_2, \dots, A_n\}$  be a set of attributes with domains  $Dom_1, Dom_2, \dots, Dom_n$ . A data repository  $S$  is a table over  $A$ , with an example or fact being a tuple in the repository  $S$ . Consider the example in Table 1 :

**Table 1 Vehicle descriptions**

Make	# of wheels	Wings	Class
Toyota	4	No	Car
Boeing	3	Yes	Airplane
Honda	2	No	Motorbike
Sailboat	0	No	Boat

Each attribute in the table describes a type of vehicle using all the properties of the tuple.

$A_1$  is the make,

$A_2$  denotes the number of wheels,

$A_3$  specifies whether it has wings or not, and

$A_4$  the class.

Hence

$$Dom_1 = \{Toyota, Boeing, Honda, Sailboat\},$$

$$Dom_2 = \{4, 3, 2, 0\},$$

$$Dom_3 = \{no, yes, no, no\}, \text{ and}$$

$$Dom_4 = \{car, boat, motorbike, airplane\}.$$

The data repository contains three attributes that denote the class of the tuple, i.e.  $A_1$ ,  $A_2$ , and  $A_3$ . These are called predicting attributes.  $A_4$  is the predicted attribute. A training set, i.e. the set of training examples, is a subset of the repository  $S$  presented to the learners through which the problem domain is being observed. A combination of values for the predicting attributes defines a class. A class  $C_i$  is a subset of the database  $S$ , consisting of all objects that satisfy the conditions,  $cond_i$ , that define the class description  $D_i$  [Holsheimer *et al* 1994]. Therefore, a class  $C_i$  may be expressed as:

$$C_i = \{o \in S / cond_i(o)\}.$$



Inductive machine learning can be defined as *the process where a hypothesis, i.e. a rule or a set of rules, is formed by observing the environment through a data set formatted as (predicting attributes, predicted attribute). The rules describe the input features of a problem domain that will predict a certain output and can be interpreted as classifiers or trends.* All the learners<sup>7</sup>, which participated in this study, learning technique is based on the induction principle, therefore they are referred to as inductive learners.

During this research, the participating learners did not learn in isolation. They co-operated with one another during the learning process. Over the past 12 years there has been a keen interest in applying principles of co-operation into human learning environments (Slavin 1983). Johnson (1994) defines human co-operative learning as *“the instructional use of small teams so that students work together to maximise their own and one another’s learning”*. A wide variety of human co-operative learning techniques have been developed and evaluated. These techniques have two primary components namely, a co-operative incentive structure and a co-operative task structure. Slavin (1983) defines a co-operative incentive structure *“as a structure in which two or more individuals are rewarded based on their performance as a group. Co-operative incentive structures usually involve co-operative task structures, which are situations in which two or more individuals are allowed, encouraged or required to work together to complete a task”*. For example, when three people travelling in a car push the car out of a ditch, all of them benefit from each other’s efforts. Either all of them will be rewarded, by being able to continue their journey, or none of them will be, depending whether they succeed or not. Hence, when these techniques are applied to the world of machine learning, co-operative inductive learning refers to the active co-operation of two or more inductive learners in a learner team, to acquire new knowledge, to maximise their individual and/or combined results. The level of co-operation among the learners in a learner team may differ, for the purpose of this study an approach of full co-operation was used.

## 2.2 Multi-agent learning system

In Section 1.1 it has been stated that learning environments can be viewed from different perspectives and that this study will follow Viktor’s (1999) approach and model co-

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operative inductive learner teams as multi-agent learning systems. Russell *et al* (1995) defines an agent as *"anything that can be viewed as perceiving its environment through sensors and acting upon that environment through effectors"*. An agent that can act rationally at any given time is perceived as being successful. According to Russell *et al* (1995), four factors influence an agent's ability to act rational: A performance measure that determines how successful the agent is; A percept sequence, which includes everything the agent has perceived thus far; The agents background knowledge of the environment; And lastly, the actions that the agent is capable of performing. A rational agent can therefore be defined as *an agent that for each possible percept sequence, will do whatever action is expected to maximise its performance measure, based on the evidence provided by the percept sequence as well as whatever built-in background knowledge of the environment the agent has* (Russell *et al*, 1995;Knapik *et al*, 1998; Jennings *et al*, 1998). A learning agent is a rational agent with the added ability to improve itself by interacting with its environment and by observing its own decision making process.

Weiss (1998) defines a multi-agent learning system *"as a system that consists of a number of learning agents residing in a communal environment that interact with one another as well as the environment"*. Hence, a co-operative inductive learner team can be modelled as a multi-agent learning system, with co-operative inductive learners participating as learning agents that interact with one another by means of full co-operation, as discussed in Section 2.3.

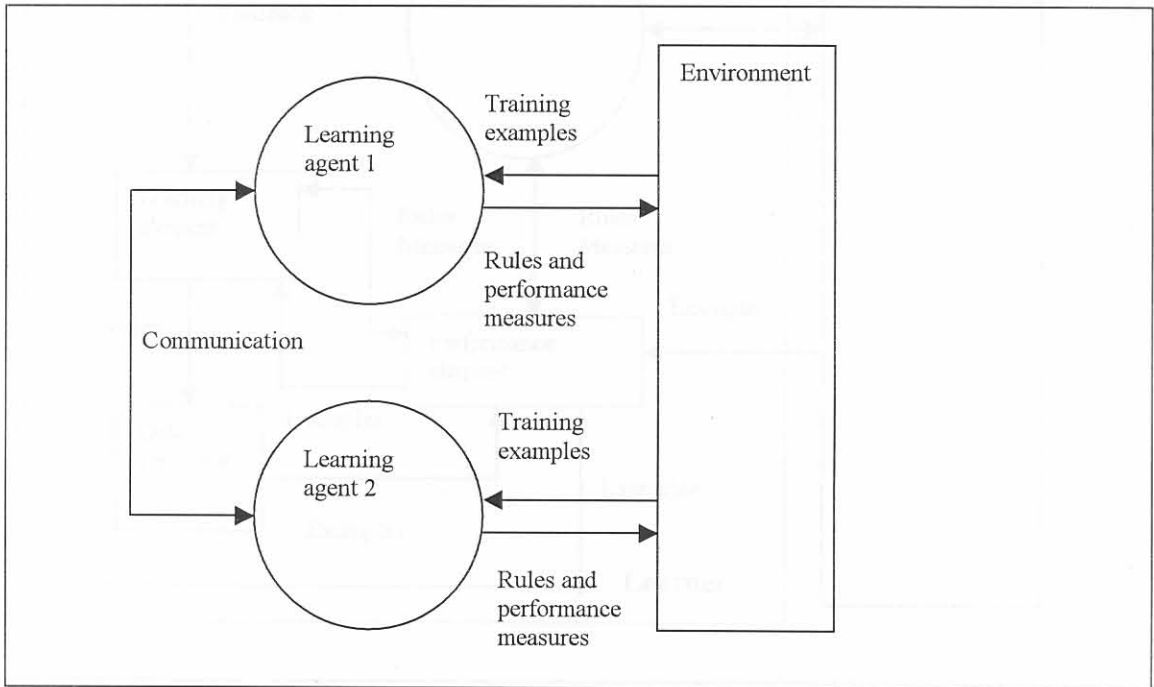
Hand [in Berthold *et al* 1999] argues that intelligent data analysis has two significant parts, one being the learning environment concerned with finding a model for the data, the other concerned with the actual algorithms, i.e. the computational facilitators that enable the environment to analyse the data. The following two sections, Section 2.3 and Section 2.4, address the first significant part, namely defining the learning environment. Section 2.5 addresses the second significant part, the algorithms, by placing the different learning agents into Langley's framework for machine learning. Langley's framework defines machine learners in terms of four components, each describing the key aspects that influence a learner's learning process.

### 2.3 Modelling a co-operative inductive learner team as a multi-agent learning system

Recall from Section 2.2 that, a multi-agent learning system consists of a number of learning agents that reside in a learning environment. The learning agents interact with one another, as well as the environment [Weiss 1998]. Within a co-operative inductive learner team the learners interact with the environment by accepting training material, such as training examples, from the environment and feed discovered knowledge, such as rules induced from the training material, back to the environment. This section gives an overview of the CILT-MAL system.

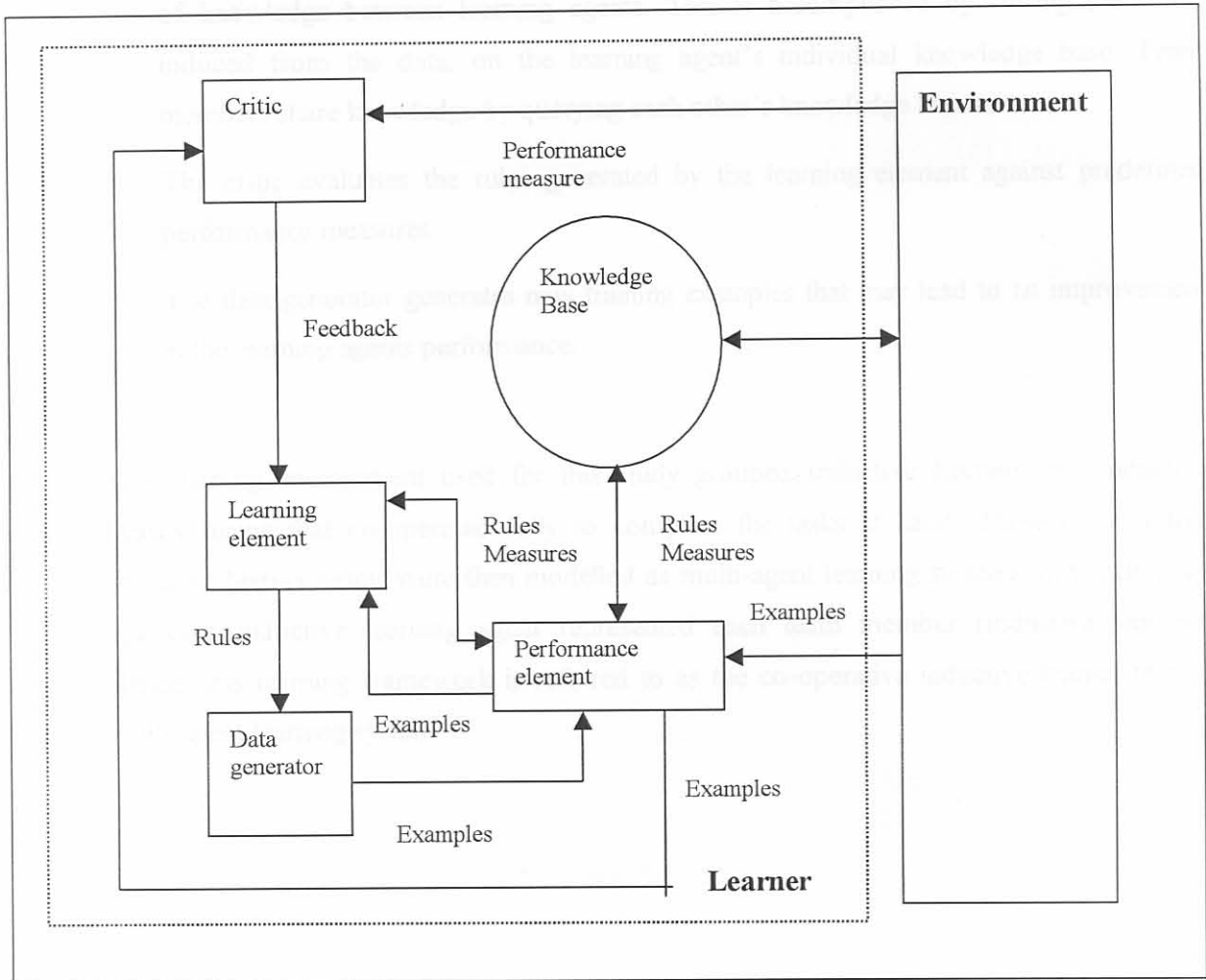
In the CILT-MAL system, the learners interact with one another by means of full co-operation. Viktor (1999) describes full co-operation as *“the method whereby all the participating learners, i.e. members of a learner team, receive the same study material and share the knowledge acquired with one another in such a way that the performance of all the learners in the team improves”*. The inductive learners form co-operative inductive learner teams within which they co-operate fully with one another. This is achieved as follows: all the learners that participate in a learner team are presented with a training set, as defined in Section 2.1. These sets are identical. Each learner executes an individual inductive learning episode, also known as a single-agent episode, during which no communication with other learners occurs, as described in Section 2.4.1. This is followed by the two evaluation episodes of the individual learning phase. Co-operative learning, as described in Section 2.4.2, follows during which the learners, within each co-operative inductive learner team, share the knowledge acquired during their individual learning phase with each other. The learners then re-execute their individual learning phases with the shared knowledge incorporated into each learners training set, which can again be followed by a co-operative learning episode. This iterative process continues until all the learners have mastered the material at hand and each team has reached consensus that the learning episode has successfully been completed. Finally, as a performance measurement, the knowledge acquired by each learner is validated against a set of unseen training examples called the validation set, as described in Section 2.4.3. The validated knowledge generated by the different teams is then fused together to represent the knowledge acquired by the learning environment as a whole.

Learners sharing their acquired knowledge, i.e. induced rules, with one another accomplish full co-operation. Hence, the learners are able to improve their behaviour through the experience gained by learning from the training material as well as the knowledge gained by co-operating with other learners. An inductive learner residing within a co-operative inductive learner team can be modelled as a learning agent residing in a multi-agent learning system, and referred to as a co-operative inductive learning agent, as shown in Figure 2.



**Figure 2 Co-operative learner team modelled as a multi-agent learning system**

Russell *et al* (1995) defined a general model for learning agents. The model divides a learning agent into four conceptual components namely, the learning element, performance element, critic and problem generator. Viktor (1999) adapted Russell *et al*'s general model and defined the inductive machine learning architecture for modelling co-operative inductive learning agents. The inductive machine learning architecture divides each learning agent into five conceptual components namely, the learning element, performance element, critic, data generator and knowledge base. Figure 3 shows the modelling of a co-operative inductive learning agent using the inductive machine learning architecture.



**Figure 3 Model of a co-operative inductive learning agent using the inductive machine learning architecture [Viktor 1999]**

The role of the five components are described as follows [Viktor 1999]:

- The learning element contains the inductive machine learning process that produces sets of rules by observing the environment through a data repository. These rule sets describe the problem domain.
- The performance element controls, monitors and guides the progress of the learning element by accepting training material in the form of training examples from the environment and presenting them to the learning element or critic. It also controls the communication of rules and measures to other components.

- The knowledge base is used for inter learner communication by facilitating the transfer of knowledge between learning agents. This is accomplished by storing the rules, induced from the data, on the learning agent's individual knowledge base. Team members share knowledge by querying each other's knowledge bases.
- The critic evaluates the rules generated by the learning element against predefined performance measures.
- The data generator generates new training examples that may lead to an improvement in the learning agents performance.

The learning environment used for this study grouped inductive learners into inductive learner teams that co-operated fully to complete the tasks at hand. These co-operative inductive learner teams were then modelled as multi-agent learning systems, in which a co-operative inductive learning agent represented each team member (inductive learner). Hence, this learning framework is referred to as the co-operative inductive learner team - multi-agent learning system.

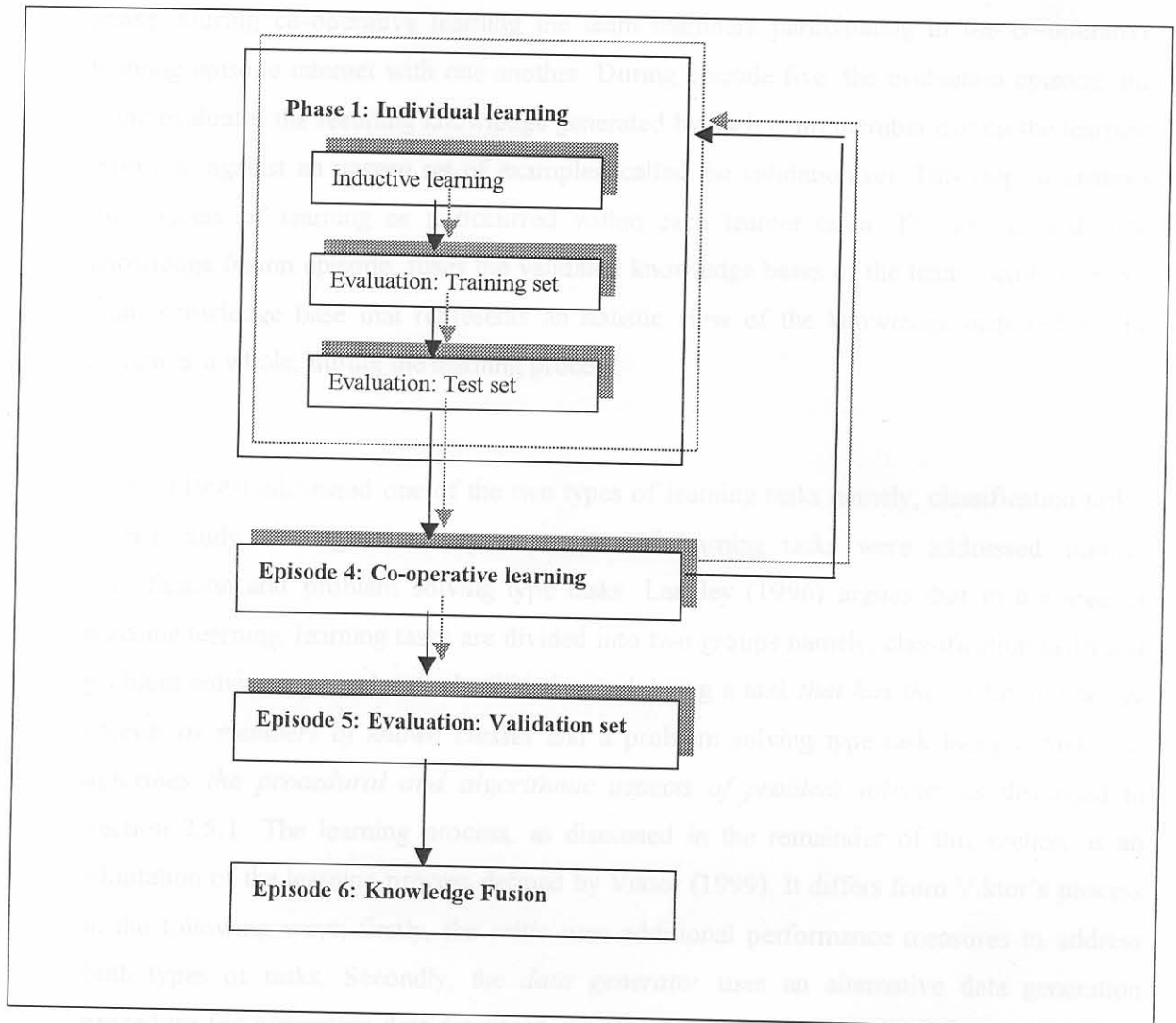


Figure 4 The learning process of the CLT-MAL system

This learning process is controlled by the performance element, which controls and monitors the progress of the learning element. Learning occurs in two phases. The first being individual learning, also known as single-agent learning, during which the learning agent

## 2.4 Learning in the CILT-MAL system

Figure 4 graphically depicts the learning process as it occurs within the CILT-MAL system.



**Figure 4** The learning process of the CILT-MAL system

This learning process is controlled by the *performance element*, which controls and monitors the progress of the *learning element*. Learning occurs in two phases. The first, being individual learning, also known as single-agent learning, during which the learning agents

learn without interacting with team members. The individual learning phase consists of three episodes namely, episode one, the inductive learning episode. Followed by episode two, an evaluation episode during which evaluation occurs against the training set. The individual learning phase concludes with episode three, during which evaluation occurs against the test set.

Co-operative learning, also known as multi-agent learning, follows the individual learning phase. During co-operative learning the team members participating in the co-operative learning episode interact with one another. During episode five, the evaluation episode, the *critic* evaluates the resulting knowledge generated by each team member during the learning episodes, against an unseen set of examples, called the validation set. This step determines the success of learning as it occurred within each learner team. The last episode, the knowledge fusion episode, fuses the validated knowledge bases of the team members into a team knowledge base that represents an holistic view of the knowledge acquired by the system as a whole, during the learning process.

Viktor (1999) addressed one of the two types of learning tasks namely, classification tasks, in her study. During this study two types of learning tasks were addressed, namely classification and problem solving type tasks. Langley (1996) argues that in the area of machine learning, learning tasks are divided into two groups namely, classification tasks and problem solving type tasks. A classification task being a *task that has the ability to classify objects as members of known classes* and a problem solving type task being a *task that describes the procedural and algorithmic aspects of problem solving*, as discussed in Section 2.5.1. The learning process, as discussed in the remainder of this section, is an adaptation of the learning process defined by Viktor (1999). It differs from Viktor's process in the following ways; firstly, the *critic* uses additional performance measures to address both types of tasks. Secondly, the *data generator* uses an alternative data generation procedure for generating data for problem solving type learning tasks. Also, an alternative rule pruning technique for problem solving type learning tasks was added and lastly an additional episode, knowledge fusion, was used at the end of the learning process.



### 2.4.1 Individual learning phase

During single-agent learning all the learners receive the same study material, i.e. an identical training set of examples. This training set should contain 70% of the instances, randomly chosen from the data repository, describing the problem domain [Theron 1993]. Following Theron (1993), each experiment's individual inductive learning episode is repeated at least 10 times, with randomised training sets. Each of the individual *learning elements* analyse their own training set to induce the best, most accurate set of rules describing the problem domain, without any interaction with the other learners. The *critic* then evaluates each rule set against the training set to measure the learners' performance against known cases.

The *critic* uses the following performance measures, determined by the type of learning task, to evaluate the performance of the learners.

- For a classification task the overall rule set accuracy is used as the performance measure. The overall accuracy of a rule set, covering class descriptions  $D_1, D_2, D_3, \dots, D_i$ , describing classes  $C_1, C_2, C_3, \dots, C_i$ , is the number of instances in the set that are covered correctly, expressed as a percentage of the total number of instances in the set. Section 2.5.4.1 contains a detailed description of these measures,
- For problem-solving type tasks the strength, interestingness and consistency of each individual trend are used as the performance measures. The strength of a trend is measured by the percentage positive coverage for that trend. The interestingness of a trend is measured by the difference in the percentage coverage of a trend over different classes, the bigger the difference the more interesting the trend. Lastly, the consistency of a trend is determined in terms of how consistent the strength of the trend is when evaluated against different data sets. A detailed description of these measures can be found in Section 5.4.

Next, the *critic* evaluates each rule set against the unseen test cases. A test set, consisting of 15% of the instances that describes the problem domain, are randomly chosen from the data repository [Theron 1993]. The performance element presents this test set to the *critic*. The *critic* evaluates each rule against the test set, using the above performance measures. The

resulting rule set of each learner as well as the performance measures when evaluated against the test set, are stored in each individual learner's *knowledge base*. Next, the learners engage in co-operative learning.

#### 2.4.2 Co-operative learning episode

Once all the learners have executed their individual learning phases, those participating in co-operative inductive learner teams, engage in the co-operative learning episode. The co-operative learning episode of a multi-agent learning system involves the improvement of the performance measures of individual rule sets through co-operation. This is accomplished by replacing a low quality rule in a learner's knowledge base with a related high quality rule, obtained from a team member's knowledge base. This co-operative learning episode is executed as follows.

Firstly, each learner evaluates its own knowledge base to identify all the low quality rules, i.e. rules with performance measures below some predetermined threshold value. The learner then queries the knowledge bases of all the other learners in the team for high quality rules, i.e. rules with performance measures above or equal to some predetermined threshold value, related to the low quality rules identified previously. Viktor (1999) categorises related rules into three categories namely, rules that overlap each other, subsume each other or correspond to each other. That is, a low quality rule can be identified as a misconception or being in conflict with a high quality rule and therefore be removed from the learner's knowledge base. These relating high quality rules are then placed on a NewRule list. Hence, all the low quality rules are removed from the knowledge base.

Secondly, the *data generator* subsequently generates new training sets for each rule on the NewRule list in the following way.

- For a classification task, following Viktor (1999), the data generator generates a strongly biased training set for each high quality rule on the NewRule list. Each of the new training sets contain the same class distribution as the original training set, however, the attribute values of those attributes that form part of the high quality rule

are biased towards the new rule. Those attributes that do not form part of the rule's attribute tests are distributed in exactly the same way they were in the original training set. This ensures a new training set strongly biased towards the high quality rules without changing the characteristics of the remainder of the training set.

- However, if the learning task is a problem solving type task one single training set is generated for all the high quality rules on the NewRule list. The approach used for the classification task generates a strong biased data set for each high quality rule on the NewRule list. This leads to the production of rules that do not necessarily reflect the knowledge as contained in the original training set [Viktor 1999]. For a problem solving type task the data is generated in the following way. For any rule  $R_j$  that covers  $[x_j, x_i]$  instances of the training set (where  $x_j$  is the number training instances covering class  $C_j$  and  $x_i$  the number of training instances describing one or more of the other classes  $C_i$  as contained in the data set) the data generator produces a new training set that contains  $x_j$  new occurrences of the class  $C_j$  and  $x_k$  new occurrences of each of the other classes  $C_i$ , where rule  $R_j$  covers  $x_k$  examples of class  $C_i$ . Following this approach, the coverage of the high quality rules double and the remaining instances, which are not covered by the new high quality rules, are left as is. Therefore, instead of generating one strongly biased data set for each high quality rule, one single data set is generated with twice the number of instances covering the high quality rules on the NewRule list. The performance of a problem solving type task is measured by the strength, interestingness and consistency of single trends, which is based on the trends percentage coverage, rather than its prediction accuracy. Therefore, this approach to data generation is better suited for this type of task.

After the data generation process, the learner returns to the individual learning phase to generate new sets of rules by learning from the newly created training sets. This leads to newly generated high quality rules that are then added to the learner's individual knowledge base. The system follows an incremental learning approach where the knowledge bases are improved by adding the high quality results of the various iterations. The co-operative learning episode continues until the solution to the learning problem cannot be improved or a predetermined period of time has elapsed.

Finally, a rule-pruning algorithm is used to simplify the individual knowledge bases. Once again the type of learning task determines the pruning algorithm that will be used.

- For classification type tasks the study follows Viktor (1999) and uses the reduced error-pruning scheme (REP), as introduced by Quinlan (1994).
- For problem solving type tasks performance is measured in terms of each individual trend's qualitative measures namely, strength, interestingness and consistency and not in terms of the overall rule set accuracy as is the case for classification type tasks. This makes the REP pruning algorithm not applicable. When simplifying the knowledge bases of a problem solving type task, duplicate trends should be removed. Any further simplification, for example the combining of trends, is dependent on user needs and not on quantitative measures.

Next, the resulting rule set of each learner as well as the performance measures when evaluated against the validation set, are stored in each individual learner's *knowledge base*.

#### 2.4.3 Evaluation and knowledge fusion episodes

The fifth episode involves the validation of the resulting sets of high quality rules, generated during the co-operative learning episode. These rule sets are evaluated against the previously unseen set of validation, i.e. the remaining 15% of the instances, randomly chosen from the data repository. The performance measures, when evaluated against the validation set, are stored in each individual learner's *knowledge base*.

During the final stage, the high quality rule knowledge bases of each team member are fused together into a team knowledge base. The co-operative incentive structure, as introduced in the beginning of this chapter, of this co-operative learning technique is to acquire new knowledge, for the maximisation of individual and/or combined results. Therefore, each team's knowledge base is pruned and tested against a validation set to determine the team's success as a group. Finally the knowledge bases of the participating teams are fused together into one holistic knowledge base representing the knowledge acquired by the system as a whole.

Recall from Section 2.2 that an intelligent data analysis has two significant parts, one being the learning environment concerned with finding a model for the data, as discussed above. The other concerned with the actual algorithms, i.e. the computational facilitators that enable the environment to analyse the data, as discussed next.

## 2.5 Langley's framework for machine learning

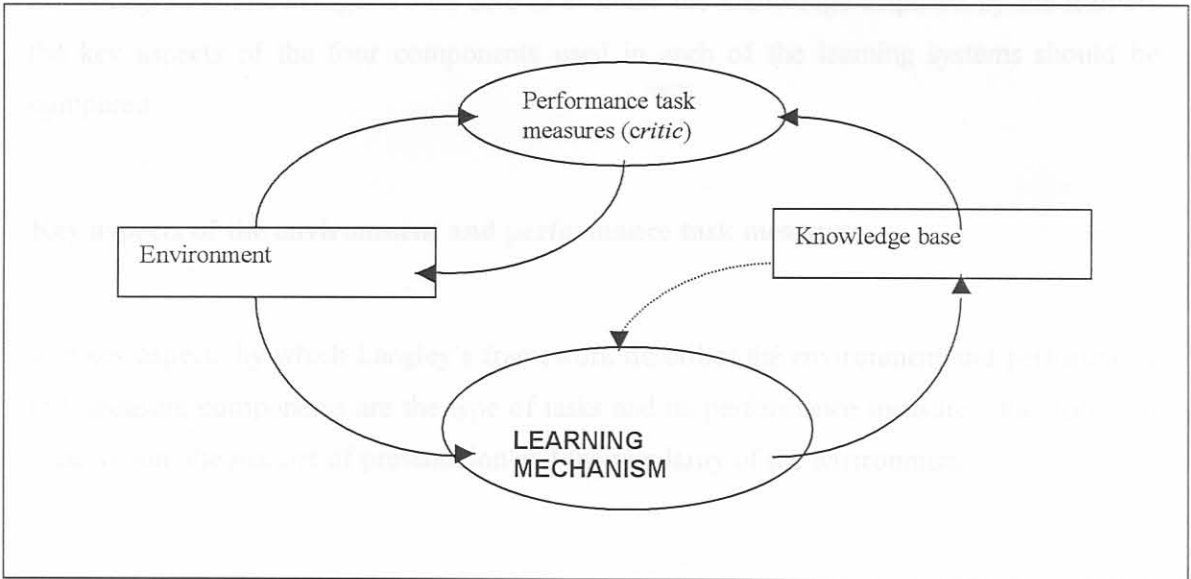
The multi-agent learning systems constructed during this study used a variety of different learning agents. Each learning agent had a learning element component that contained the inductive machine learning process that produced sets of rules that described the problem domain. For the purpose of interpreting and comparing the individual rule sets produced by the different agents, their learning elements, i.e. algorithms, were modelled according to Langley's (1996) framework for machine learning.

Langley (1996) defines machine learning as “*the improvement of performance in some environment through the acquisition of knowledge resulting from experience in that environment*”. Langley describes machine learning as an ongoing process during which a machine learner's execution of a specific task, within a specified problem domain will improve as long as the learner is presented with sufficient data that describes the problem.

Whereas:

- **improvement** involves a desirable change in a performance measure;
- **performance** suggests some quantitative measure of behaviour on a task, such as efficiency, accuracy, or understanding;
- the **environment** is an external setting with regularity;
- **knowledge** as depicted through a kind of internal data structure;
- **experience** requires some processing, depicted by the learning mechanism itself.

According to Langley (1996), learning does not happen in isolation. Rather, it is the intricate interaction between all these components as illustrated in Figure 5.



**Figure 5 Langley’s machine learning framework**

The figure shows that learning always takes place in an environment, about which a learner attempts to learn something. On the other hand, a learner is always linked to a knowledge base from which it can extract previously acquired knowledge or experience (the input to learning), and into which it can store new acquired knowledge (the output of learning). The success of the learning mechanism is measured by the improvement of the task’s performance. The performance task measurer uses the knowledge base to control its interactions with the environment.

Langley uses these four components namely: the environment, performance task measures, learning mechanism and knowledge base to describe a learning system, i.e. a learner or a learning agent. Each one of these components incorporates key aspects that influence the learning process. Langley’s machine learning framework relates to the inductive machine learning architecture, as discussed in Section 2.3, in the following way. The performance task measures correspond to the criteria by which the *critic*, of the inductive machine learning architecture, measures the performance of a *learning element*. The environment corresponds to the *environment* residing outside the learning system. The learning mechanism corresponds to the combined role of the *learning* and *performance elements* of

the inductive machine learning architecture. The knowledge bases contain the acquired knowledge for both of the architectures but differ in the following way, as for Langley's framework the knowledge base also contains previously acquired knowledge or experience i.e. background knowledge. To be able to evaluate the knowledge acquired by the learners the key aspects of the four components used in each of the learning systems should be compared.

### 2.5.1 Key aspects of the environment and performance task measures

The key aspects by which Langley's framework describes the environment and performance task measure components are the type of tasks and its performance measures, the degree of supervision, the manner of presentation and the regularity of the environment.

Firstly, the type of task required and the measures to determine the quality of the performed task are used to describe the learning environment. Learning tasks can be divided into two groups namely, classification tasks and problem solving type tasks i.e. those that use acquired knowledge for classification purposes and those that use the learned knowledge for some form of problem solving [Langley 1996]. A classification task, which is a *task that has the ability to classify objects as members of known classes*, for example, when analysing a soybean data set, containing descriptions of instances carrying different soybean diseases, the aim of the task is to classify the soybeans according to their diseases. A problem solving type task, which is a *task that describes the procedural and algorithmic aspects of problem solving*, for example, when given a set of constraints describing a system, should be able to optimise the system's parameters. The goal of the inductive learners is to increase the accuracy of the performance system, regardless the type of task. For example, the performance measure of a classification task is the accuracy by which it can predict the class of unseen cases.

Secondly, the learning environment is described by means of the degree of supervision. The degree of supervision determines whether supervised or unsupervised learning is occurring. During supervised learning, the learning mechanism (learning element) is presented with the training material that includes both the predicting attributes, as well as a preferred solution

i.e. the predicted attribute, as defined in Section 2.1. The learning element should find a path from the predicting attributes to the preferred solution. However, during unsupervised learning the learning element is presented with training material that includes only the predicting attributes. Hence, the learning element should find the best possible solution as well as the different paths to get from the training material to the solution.

Thirdly, the manner of presentation describes the way in which the training examples are presented to the learning mechanism i.e. how the *performance element* presents the data to the *learning element*. All the examples can be presented simultaneously which is referred to as offline learning, or one at a time, which is referred to as online learning.

Lastly, the regularity of the environment refers to the complexity of the target knowledge that should be acquired based on the number of irrelevant attributes, the amount of noise in the environment and the consistency of the environment over time.

### 2.5.2 Key aspects of the knowledge base

The knowledge base within Langley's framework is responsible for the representation of both experience (input to learning) and acquired knowledge (output of learning), which differs from that of the inductive machine learning architecture. The knowledge base of the inductive machine learning architecture stores the acquired knowledge only, the rule sets and their performance measures.

The first aspect of the knowledge base component is the way in which training; test and validation sets are formatted. For example, it could be in binary format, as a set of nominal attributes, numeric attributes, or as a set of relational literals. The second aspect is the way in which the acquired knowledge produced by the learning mechanism is presented. This representation involves the formulation of a description that can distinguish between instances belonging to a specific class and those that don't. These descriptions are formulated using a concept description language. The interface between the concept description and the actual instances is referred to as an interpreter or matcher. The role of the



interpreter is to use the concept descriptions, described in terms of a concept description language, to classify instances, represented in a specific format.

Interpreters are categorised under one of three approaches, namely, the logical approach, threshold approach or competitive framework. The logical approach uses an “all or none” match to determine whether an instance belongs to a certain class. The threshold approach uses a partial matching process to classify instances, and the competitive framework uses a best-match approach. Langley emphasises that the interpretative approach far outweighs the importance of representation, since different interpreters can yield different meanings for the same representation.

The third aspect is that of organisational structures. In the field of machine learning one of three classes of organisational structures is used to represent the knowledge acquired about static objects. They are decision lists, inference networks or concept hierarchies.

### 2.5.3 Key aspects of a learning mechanism

Langley (1996) argues that learning is a search through a problem domain. He therefore describes the learning element in terms of the incrementality of the learning process, its search technique and search bias. The incrementality of the learning process refers to the manner in which training examples are processed, all at once in a non-incremental manner, or one at a time, in an incremental manner.

The way in which learning agents apply search operators to a problem domain is referred to as the search technique. These search techniques are described firstly, in the way they start the search, secondly, how the search is organised i.e. the search bias and how alternative states are evaluated and finally, when to terminate the search.

Induction methods typically start their search through the problem domain from either the most general or the most specific state, although some may start from a randomly selected state. When starting from the most general state, the concept description describing the

problem domain will cover all of the instances in the training set i.e. the rule set will be empty. When starting from the most specific state, the concept description describing the problem domain will be so specific that it will cover the smallest number of instances in the training set. The search can be organised to explore the search space using exhaustive methods or heuristic methods. Exhaustive searches are inefficient [Russell *et al* 1995] since every possible path is explored. Heuristic methods, also known as informed search methods, are therefore preferred. These methods use an evaluation function that determines the desirability of a specific search path. Heuristic methods sacrifice optimality but in return gain in tractability. Search procedures terminate when no further progress is made or when the method finds a concept description that is entirely consistent with the training data.

A learning system must direct or limit its search through the space of possible concept descriptions. These directions or restrictions are often referred to as the search bias of the system. The bias of the learning element can be a representational bias, which restricts the solution space by limiting the concept description language. Or, the bias may be a search bias, which considers all possible concept descriptions for a given problem domain, but chooses to examine some descriptions earlier than others in the search process. Sometimes these preferences are encoded into the evaluation metric of the learning element, or else they form part of the structure of the search algorithm itself. Another source of bias can be that of background knowledge available to the learning system, which can strongly guide the course of learning.

A co-operative inductive learning agent, as described in Section 2.2, can be modelled using the inductive machine learning architecture, as employed by Viktor (1999). To further define the learning process, with an emphasis on the learning element the learning agents are placed into Langley's machine learning framework. The next four sections describe the four learning agents used for this study, CN2, C4.5, BRAINNE and the human learner, using Langley's machine learning framework.

#### 2.5.4 CN2 – A rule induction learning agent

CN2 is a rule induction program developed by Clark *et al* (1989) designed for the efficient induction of simple, comprehensible rules in problem domains where problems of poor description language and/or noise may be present.

##### 2.5.4.1 Environment and performance task measures

CN2 typically performs classification tasks (as defined in Section 2.5.1). The aim of CN2 is to induce simple concept descriptions that accurately classify novel instances. The input to the system is presented as a training set of examples, where each instance is described as a set of numerical attributes, including an attribute that specifies its class. This indicates that offline supervised learning, as defined in Section 2.5.2, is occurring. The program has an evaluation function that evaluates the accuracy of the individual rules as well as the overall rule set, as follows:

- Individual rule accuracy

As an example the inductive learner generated the following rule during the execution of the problem solving type task, as discussed in Chapter 5.

```

IF    Highest_qualification = Degree
      AND Gender = F
      AND Discipline_specialisation = AMS
THEN  Org_type = Technikon [11 10 12]
  
```

The CN2 evaluation function evaluated the rule, on an unseen validation set consisting of 212 instances, as follows:

```

EVAL> individual
      FIRED?
ACTUAL CLASS Yes  No  Accuracy
Technikon     3   10    23.1 %
Not Techni    2  197    99.0 %
Overall accuracy: 94.3 %
  
```

Where the accuracy of the individual rule is calculated as the sum of the number of correct positive covered instances, i.e. 3, and the correct negative covered instances, i.e. 197, as a percentage of the total number of instances read i.e. 212.

$$(3 + 197)/212 * 100 = 94.3\%$$

- Overall rule set accuracy

As an example the CN2 evaluation function evaluates the overall rule set as follows:

ACTUAL	PREDICTED			Accuracy
	Private	Technik	Univers	
Private	164	0	0	100.0 %
Techniko	10	0	3	0.0 %
Universi	33	0	2	5.7 %
Overall accuracy:	78.3 %			

Where the accuracy of the rule set is calculated as the sum of all the correct positive covered instances, i.e. 100, 0, 2, as a percentage of the total number of instances, i.e. 212.

$$(100 + 0 + 2)/212 * 100 = 78.3\%$$

#### 2.5.4.2 The knowledge base and performance element

CN2 organises its output as a list of if-then rules, also known as a decision list. The concept description language describes each rule induced by CN2 as follows:

- 'if <complex> then predict <class>',
- <complex> is a conjunct of <attribute test>,
- <attribute test> is a test on a single attribute.

For example, the CN2 learner generated the following rule during the analysis of a business classification task, as described in Chapter 4.

```

IF    Process_Capability < 5.50
AND  SIC_Code_Old > 3560.00
THEN company_sector = Product [79 0]
  
```

Where IF  $\text{Process\_Capability} < 5.50$   
AND  $\text{SIC\_Code\_Old} > 3560.00$  is the complex,  
 $\text{Process\_Capability} < 5.50$   
 $\text{SIC\_Code\_Old} > 3560.00$  are attribute tests and  
 $\text{company\_sector} = \text{Product}$  is the class.

The interpreter applied by CN2 falls into the logical class approach, carrying out an “all or none” matching process. Each rule is tried until one is found whose conditions are all satisfied by the instance being classified. If no induced rule is satisfied, the default class, as determined by the learning mechanism as the class that most instances in the data set belongs to, is assigned to the instance.

#### 2.5.4.3 The learning mechanism

The CN2 learning algorithm searches the problem space by means of a pruned general-to-specific search, starting at the most general concept description, as described in Section 2.5.3. At each stage of the search the algorithm retains a size-limited set of best complexes found thus far. The star size parameter (default 5) defines the limit of complexes that are retained during execution. This set is further specialised by applying a beam search to the space of complexes. The complexes are evaluated so that the best, reliable complex may be found. This process iterates until no more good, reliable complexes, as defined next, are found.

The search is directed by two heuristic decisions. Firstly, the quality of the complexes found is assessed. This is done by means of an information-theoretic entropy measure. This measure prefers complexes covering a large number of examples of a single class and few examples of other classes, such as the complex in the above-mentioned example that covers 79 instances of the “Product” class and none of the other classes. Secondly, the significance of the complex is measured. This measure attempts to establish whether a complex reflects a genuine correlation between attribute values and classes, or if the correlation just occurred

by chance. The user can manipulate this relationship by setting the significance threshold (default 0). The two heuristic decisions based on entropy and significance determines whether the complexes found during a search are both of good quality and with high correlation.

### **2.5.5 C4.5 – A decision tree learning agent**

C4.5 is a decision tree generation program developed by Quinlan (1994). C4.5 is an industrial strength version of ID3 developed by Quinlan (1994) to investigate the effect of noise on learning. Recently Quinlan released C5.0 an updated version of C4.5 ([www.rulequest.com](http://www.rulequest.com)).

#### **2.5.5.1 Environment and performance task measures**

The program takes a set of examples as input and generates a decision tree that classifies the training set as output. The program has an evaluation function that evaluates the accuracy of the generated classifier on pre-classified test examples. Since large decision trees are too complex to be understood, C4.5 has a conversion function that re-expresses the generated decision tree as a decision list.

C4.5 is mostly used as a classifier that aims to build a compact decision tree, which is consistent with the training set and reveals the structure of the domain in such a way that it has predictive power. The input set of examples includes an attribute that specifies the class of the instances, which indicates that offline supervised learning is occurring.

#### **2.5.5.2 The knowledge base and performance element**

All the instances in the training set are described as a set of numerical attributes. An attribute may have either a discrete or a numeric value. The class to which the instance belongs must be established beforehand and is denoted as the last attribute value. C4.5 organises the

output as a decision tree, also known as a concept hierarchy, consisting of decision nodes, branches and leaves. The concept description language describes each node or leaf induced by C4.5 in the following format:

- a decision node: specifies a test on a single attribute, with one branch for each possible outcome:
  - ‘<attribute test>
  - <attribute test> / leaf’
- leaf: specifies a test on a single attribute and indicates a class.
  - ‘<attribute test> : predicted class’
- <attribute test> is a test on a single attribute.

For example, the following decision tree was generated by C4.5 during the problem solving type task described in Chapter 5.

```

Gender = M: Engineering (577.0/253.8)
Gender = F:
| Highest_qual = Dipl: APS (53.0/33.9)
| Highest_qual = Postgrad: APS (49.0/34.7)
| Highest_qual = Degree:
| | Race = A: ABS (65.0/37.3)
| | Race = D: APS (9.0/6.4)
  
```

Where <Gender = M: Engineering> is a leaf,  
 <Gender = M: Engineering  
 Gender = F: > is a node and  
 <Highest\_qual = Degree> is an attribute test.

The decision tree interpreter applied by C4.5 decides to which class an unseen instance belongs, given the instance’s attributes. The goals set for the interpreter are to permit the use of imprecise information about attribute values and to estimate the degree of certainty associated with the predicted, most likely class alternatives. The C4.5 decision tree

interpreter falls into the logical class of approaches, carrying out an “all or none” matching process. However, when the soft threshold option is invoked during the construction of the decision tree the interpreter falls into the threshold class of approaches carrying out a partial matching process [Quinlan 1994]. An instance is classified by testing its attribute values against the decision nodes, starting at the root and working its way up the tree until it satisfies the condition of a leaf, at which point the predicted class of that leaf will be assigned to the instance. By taking into consideration the predicted number of errors at a leaf more than one leaf can be satisfied by the attribute values of an instance. Therefore, the interpreter calculates an estimated certainty factor for each possible classification to indicate the most likely class. The interpreter handles imprecise values in a similar way to the learning algorithm’s way of handling unknown values, which is described in the next section. If the soft threshold option is invoked during tree construction a weighting method is used to soften absolute thresholds. For each continuous attribute an interpolation range is calculated, so that if the attribute value lies within the range both outcomes will be explored with a calculated weight assigned to each [Quinlan 1994].

C4.5 organises the output as an ordered decision list. By invoking the conversion function, called C4.5rules. Each path, from the root of a decision tree to a leaf, will be converted into one initial rule. The concept description language describes each rule in the following format ‘if <complex> then predict <class>’, where <complex> is a conjunct of single attribute tests. The decision list interpreter applied by C4.5 falls into the logical class approach, carrying out an “all or none” matching process. The rules are tried in the specified top-down order until one is found whose conditions are all satisfied by the instance being classified. The interpreter then calculates the estimated certainty factor for the suggested class. The following rules were extracted from the decision tree listed previously in this section.

The final rules from decision tree:

Rule 5:

Highest\_qual = Postgrad

Race = D

-> class APS [41.7%]



Rule 3:  
Highest\_qual = Dipl  
Gender = F  
-> class APS [36.0%]

Rule 2:  
Race = D  
Gender = F  
-> class APS [34.5%]

Rule 4:  
Race = A  
Gender = F  
-> class ABS [32.6%]

Rule 7:  
Highest\_qual = Dipl  
Gender = M  
-> class Engineering [61.1%]

Rule 6:  
Highest\_qual = Degree  
Gender = M  
-> class Engineering [61.1%]

Default class: Engineering

### 2.5.5.3 The learning mechanism

The C4.5 learning algorithm searches the problem space by means of a greedy method that directs the search with an evaluation function. Greedy methods are the simplest form of best-first search strategies. A best-first strategy's decision on which node to expand during a

search, is based on a value produced by an evaluation function. The node obtaining the best evaluation will be expanded first. When the evaluation function evaluates the estimated cost of a path from a node to its goal, the search is conducted by means of a greedy method. That is, the node whose state is judged to be closest to the goal state is always expanded first [Russell *et al* 1995].

C4.5 organises the search from the root node downward, in a divisive manner. The algorithm follows a divide and conquer-approach, in an attempt to partition the training set. Firstly the algorithm creates a partition for each attribute that describes an instance. In each partition the instances are clustered according to their values for that specific attribute. Each partition is then evaluated according to its ability to discriminate between classes. C4.5 requires that any partition in the tree must have at least two outcomes with a minimum number of cases; in other words, the sum of the weights of the cases for at least two of the subsets must attain some minimum. The default minimum is two, but can be changed by the user via the weight parameter. The algorithm selects the best such partition and creates a child decision node for each cluster in the partition, associating the appropriate attribute test to the root node. When all the instances in the cluster belong to the same class the child decision node becomes a leaf, else the process iterates, passing on the instances in the cluster and the unused attributes, to build a sub-tree, with the current child decision node as the root. The process terminates once all the instances have been classified, or all the attributes have been used.

C4.5 learning algorithm's search is directed by two heuristic decisions. Firstly, the simplest, most compact decision tree must be generated and secondly, the decision tree must be consistent with the training environment, and have predictive powers. Quinlan (1994) uses the gain ratio criterion as an evaluation function to direct the search, in his quest to find the most compact, and consistent decision tree. The gain ratio criterion selects the attribute test that will maximise the ratio between the information gained, by partitioning a training set according to the attribute test, and the potential information generated by this partitioning. Therefore, the gain ratio expresses the portion of the information generated by the partitioning that is useful. The C4.5 learning algorithm simplifies its decision tree by means of an error-based pruning technique. This error-based pruning technique allows the algorithm to replace any one of its sub-trees by a leaf, or the most frequently used branch in

the sub-tree, as long as it leads to a lower predicted error rate. A confidence factor is used to estimate this error rate. The default confidence factor is 25% but can be changed by means of the confidence parameter. Redundant complexes are finally pruned; a redundancy factor is used to identify these complexes (default 1.0). The two heuristic decisions based on gain ratio and predicted error rate, determine that the decision tree constructed during a search will be as simple and accurate as possible.

The C4.5 conversion function algorithm, C4.5rules uses the un-pruned decision tree generated by the C4.5 learning algorithm as a starting point. The algorithm rewrites the tree as a collection of rules. One rule is generated for every leaf, by tracing all the test outcomes along the path from the root to that leaf. A rule is induced as a conjunction of these tests. Rules are simplified by removing conditions that do not affect the accuracy of the rule, by means of a pessimistic accuracy estimate. The rules are then grouped according to their predicted classes and those that do not contribute to the accuracy of the rule set as a whole are removed. The rules for the classes are then ordered to minimise false positive errors and a default class is chosen.

## 2.5.6 BRAINNE– an artificial neural network learning agent with rule extraction algorithm

BRAINNE is an artificial neural network (ANN) generator that extracts rules from a trained neural network [Sestito 1994].

### 2.5.6.1 Environment and performance task measures

The input to the system is both the training data set, as well as the structure of the defined inference network. The system generates an inference network, according to the specified structure. This trained inference network will be able to make the most accurate predictions about novel test instances.

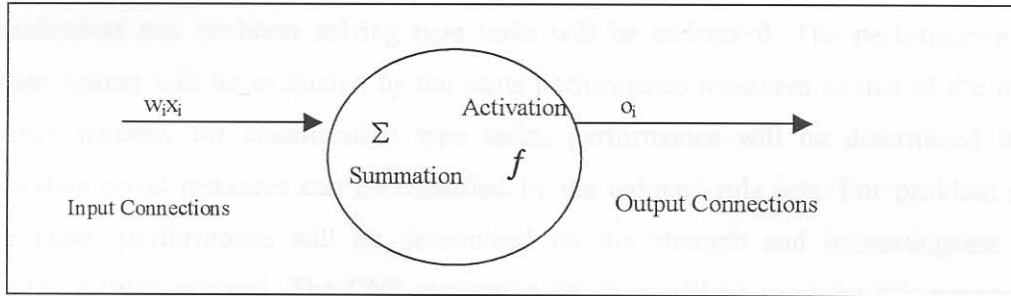
The learning system, presented with one instance from the training set at a time, generates an inference network. Since the instances are presented to the learner one at a time it indicates that a form of online, supervised learning is occurring.

Once training is completed, the trained inference network will be able to classify an unseen instance according to the concept described by the network. In other words, the performance task of the BRAINNE environment is a form of classification. The performance of the network is measured by means of the mean squared error between all the original inputs and the generated outputs, over all the test instances presented.

### 2.5.6.2 The knowledge base and performance element

As mentioned above, the input to the learning system is presented as a set of examples. Every instance in the set is represented by a set of numeric, continuous or discrete attributes describing the instance as well as the class it belongs too. Furthermore, the structure of the inference network must be specified in terms of the number of hidden layers and for each hidden, input and output layer the number of neurones must be specified. Also, the type of activation function, the learning rate and the momentum at which learning should occur must be defined for the learning system. BRAINNE uses the Sigmoid activation function.

The acquired knowledge of an ANN is represented in terms of a weighted value assigned to each connection strength between neurones. BRAINNE organises the output as a multi-layered neural network, also known as an inference network, consisting of neurones, input and output connections and weights. The generated inference network is the input to the rule extraction algorithm. The extraction algorithm then extracts concept descriptions describing the inference network. The concept description language describes the neural network in the format of Figure 6.



**Figure 6 BRAINNE concept description language**

### 2.5.6.3 The learning mechanism

The BRAINNE algorithm searches the complex space by means of an incremental gradient descent method. A linear threshold unit is induced for each class by means of the back propagation algorithm using the least mean square (LMS) as the evaluation function. The aim of the LMS is to minimise the mean squared error between the predicted and the actual classes by adjusting the weights assigned to each attribute. This is done in an iterative process, by specifying the number of epochs, passes through the training set, as well as the learning rate or size of steps through the weighted space. The process terminates once the number of epochs has been reached or the mean square error has decreased to a predefined level.

### 2.5.7 Human learner– learning agent

Viktor (1999) modelled a human learner as a learning agent using the inductive machine learner architecture. The sections that follow cast the human learning agent into Langley’s machine learning framework.

#### 2.5.7.1 Environment and performance task measures

The performance task of the environment that the human learner resides in is complex. The human learner must be able to acquire, generate, analyse, manipulate and structure

information in order to construct knowledge [Alavi 1994]. For the purpose of this study only classification and problem solving type tasks will be addressed. The performance of the human learner will be evaluated by the same performance measures as that of the machine learners namely, for classification type tasks, performance will be determined by how accurately novel instances can be classified by the induced rule sets. For problem solving type tasks, performance will be determined on the strength and interestingness of the individual rules induced. The CN2 evaluation function will be used for this purpose. The human learner that participated in this study made use of both supervised and unsupervised learning, as defined in Section 2.5.1, by using the classified training set, but also ignoring the given classifications at times and generating new classes.

#### 2.5.7.2 The knowledge base and performance element

The input to the human learner is presented as a set of training examples, identical to the set presented to the machine learners. The output of learning i.e. the knowledge acquired by the human learner is transferred into a knowledge base.

This process of capturing knowledge from human learners is referred to as knowledge acquisition. Turban (1995) defines knowledge acquisition as *"the process of extracting, structuring and organising knowledge from one or more sources"*. Knowledge acquisition does not concern only the extraction of acquired knowledge from the learner, but also concerns the transfer of that knowledge to a knowledge base. Many researchers have identified this process, as a bottleneck that hampers the development of artificial intelligence systems [Turban 1995]. The reason being, the nature of the knowledge possessed by humans is often unstructured and inexplicitly expressed which makes it nearly impossible to transfer into a machine-based knowledge base.

In every day life, transferring information from one person to another is difficult. Different media are often used, for example, spoken words, written words and pictures, yet none of them are perfect. The same problems that exist when transferring information from one person to another exist when transferring knowledge from a human to a machine. However,

transferring knowledge from a human learner to a machine-based knowledge base is even more difficult. This task of transferring knowledge is the responsibility of the knowledge engineer. Turban (1995) defines knowledge engineering as “*a process involving the co-operation of human learners and a knowledge engineer in a problem domain, to codify and make explicit the rules that a human learner uses to solve real life problems*”. Sestito *et al* (1996) defines a knowledge engineer as “*the person that communicates with the expert to acquire the relevant knowledge*” and “*... looks at books, manuals, case studies and other material in order to better understand the problem domain*”. The knowledge engineer faces two major obstacles during the process of knowledge acquisition namely, knowledge expression and knowledge transfer. The knowledge that the human learner applies to solve a real life problem must be expressed as a set of rules. However, the process of solving a problem is an internal process. This requires the human learner to be introspective about his/her decision making process. The human learner is often unaware of this detailed process he/she uses to arrive at a conclusion and of the vast amount of previously acquired knowledge influencing his/her decisions. Hence, a different set of rules might be expressed to the knowledge engineer than what is actually used to solve the real life problem. The second obstacle, knowledge transfer, encountered by the knowledge engineer concerns transferring the acquired knowledge to a machine-based knowledge base. Machines express knowledge at a lower, more detailed, level than humans. Humans express knowledge in a compact form and are unaware of all the intermediate steps used by their brain in processing the knowledge. This creates a mismatch between human and machine representation.

Several methods for acquiring knowledge from human learners exist. For the purpose of this study the elicitation of knowledge from the human learner is done manually via structured interviews as described by Turban (1995). Structured interviews places great demands on the human learner who must be able to demonstrate his/her expertise in the problem domain, as well as be able to express it. However, structured interviews reduce interpretation problems and allow the knowledge engineer to prevent distortions caused by the subjectivity of the human learner [Turban 1995].

Once the knowledge engineer acquires knowledge from the human learner it is organised in a chosen configuration. A variety of knowledge representation schemes exist, for example, production rules, decision trees, semantic networks, decision lists and many more. All the

schemes have two things in common, firstly, they can be stored in a machine-based knowledge base and secondly the knowledge base can be manipulated by a learning mechanism to perform an intelligent function. For the purpose of this study the knowledge acquired from the human learner will be converted into decision lists using a concept description language similar to that of CN2, as discussed in Section 2.5.4.2. Decision lists should be used as the knowledge representation scheme because the CN2 evaluation function is used to evaluate the performance of all the learners participating in the CILT-MAL system.

### 2.5.7.3 The learning mechanism

A mother of a one-year-old toddler observes that her child is fussy and irritable for several days. She decides that the child is teething. A one-year-old takes a bath every day, every time the child gets into the bath the mom says “Bath, bath” pointing to the bathtub filled with water. One day the child discovers a swimming pool in the garden. The child points and says “Bath, bath”. These are examples of induction, where the learner learns from example [Johnson-Laird 1988] . Humans understand their environment by creating a simplification of the environment, called a model. A model consists of classes, representing similar objects in the environment, and class descriptions predicting the behaviour of the objects in the different classes [Holsheimer 1994]. The creation of such a model is called inductive learning, as discussed in Section 2.1.

Philosophers, psychologists and researchers of artificial intelligence have spent hundreds of person-years trying to characterise inductive learning, develop learning theories and attempt to program systems to improve themselves. Yet the current research has little in common with the way people actually think and learning theories often fail to represent human thinking [Holland *et al* 1986]. However, what we do know is that “*the human learner observes a series of objects and hence creates a hierarchy that summarises and organises experiences, building a prototypical example of each concept. As the human learner encounters new examples the prototype is refined*” [Gennari *et al* 1989]. Research conducted by Nisbett *et al* (1983) indicated that prior knowledge and experience, i.e. expertise in a problem domain, have a major impact on a human’s inductive learning



process. Those theorists that suggest experts typically do not reason using rules of formal logic but instead rely on memory specific experiences support this theory [Holland *et al* 1986]. The human learner that participated in this study used a combination of inductive learning and relying on his memory in areas of expertise. The human learner most often searched the problem space by means of a general-to-specific search, although this was not always the case. The human learner's searches were directed by heuristics based on the learner's previous experience within the problem domain.

## 2.6 Conclusion

Three different learner teams were used during this study, namely: A machine learner team that consisted of three machine learners, CN2, C4.5 and BRAINNE; A human learner team consisting of a human expert and a report, Technology base of large, medium and small organisations in the South African business sector [AMI 1998]; And a machine-human learner combination team that consisted of a human learner, CN2 and C4.5.

The CILT-MAL system consists of co-operative inductive learning agents that interact with the environment, by accepting training examples and feeding acquired knowledge back. The agents also interact with one another by sharing their individual knowledge bases. Using the inductive machine learner architecture, an agent can be divided into five conceptual components namely, the learning element, performance element, critic, data generator and knowledge base, as described in Section 2.3.

Langley's machine learning framework describes a learning system in terms of four components namely, the environment, performance task measures, learning mechanism and knowledge base. Hence, a learning system described by Langley's machine learning framework, relates to a learning agent, described by the inductive machine learner architecture in the following way: The environment of the one corresponds to the environment of the other. The performance task measures of the one correspond to the critic of the other. The learning mechanism of the one corresponds to the combined role of the

learning and performance elements of the other and lastly the knowledge base of the one corresponds to the knowledge base of the other, as described in Section 2.5.

Within Langley's machine learning framework a learning system interacts with the environment but not with other learning systems. To relate Langley's framework to a multi-agent learning system, the individual learning systems must be able to communicate with one another, as the learning agents do in a MAL system. A learning system has its own knowledge base in which it stores all the knowledge acquired during learning. Sharing their individual knowledge bases will enable the learning systems to communicate. However, this will only be possible under the following two conditions, namely; if the knowledge contained in the knowledge bases are represented in a uniform way across all the learning systems and if a uniform performance task measure is used across all the learning systems. Adhering to these conditions, a learning system will be able to interpret, as well as determine the quality of the knowledge acquired by a team member.

This chapter described co-operative inductive learning and then proceeded to define co-operative inductive learner teams. Co-operative inductive learner teams were then modelled as CILT-MAL systems. Within the CILT-MAL system learners were described using the inductive machine learner architecture. A suitable framework, namely, Langley's machine learning framework, was introduced. This framework was used to better define the learning mechanisms of the learning systems that participated in this study in terms of the key aspects of the framework's four components, which is summarised in Table 2, emphasising their main differences.

**Table 2 Key aspects of the learning agents modelled using Langley's machine learning framework**

Learning agent	Performance task	Degree of supervision	Representation of output	Search technique	Search heuristics
CN2	Classification	Offline supervised	Decision list	General to specific	Information-theoretic entropy measure Significance measure
C4.5	Classification	Offline supervised	Concept hierarchy	Greedy method	Gain ratio criteria Error based pruning
BRAINNE	Classification	Online supervised / unsupervised	Inference network	Incremental gradient descent method	Least mean square error
Human	Classification Problem solving	Online/Offline supervised/ unsupervised	Decision list	General to specific	Previous experience

By focusing on these differences the performance of the different learning systems within the co-operative inductive learner teams, as presented in Chapters 4 and 5, will be better understood.

The next chapter, Chapter 3, describes the NRT Audit case study.

## Chapter 3

# National Research and Technology Audit

This chapter introduces the case study used to illustrate the CILT-MAL system, namely the National Research and Technology Audit commissioned by the Department of Arts, Culture, Science and Technology. Recall from Chapter 1 that this audit was undertaken due to the realisations by the South African Government that science and technology will have a major impact on society in the 21<sup>st</sup> century and that, if a developing nation wants to compete in the world economy, it should have a robust technology policy. Formulating this policy required a critical assessment of South Africa's existing strengths and weaknesses in science and technology.

It is widely recognised that technology, and the science that supports it, are vital contributors to the well-being and economic competitiveness of a nation. Successful nations are those which develop and nurture 'technologising' policies i.e. policies that stimulate the processes whereby knowledge is gained and embodied in people, products and services [DACST 1997]. The South African Government recognised the contribution that science and technology can make to meet the nation's societal needs. Hence, they had to determine whether the country's science and technology system has the capacity and capability to contribute to the national, social and economic well being of the nation.

The forces that shaped the character of science and technology in South Africa have changed significantly over the past six years. New priorities have emerged, placing different demands on the science and technology system. This required an investigation into the capabilities and weaknesses of the system in relation to the new demands. The NRT Audit was commissioned by the government in order to gain an idea of the capacity, capability and

limitations of the science and technology system as they relate to the country's current and future needs.

- The objective of the NRT Audit, as accepted by the Ministers' Committee on Science and Technology, was "*to provide data and information to be used as a basis for policies directed at increasing the effectiveness of technological innovation as a contributor to industrial productivity, economic growth, environmental sustainability and international competitiveness by way of sound recommendations and implementation strategies*" [DACST 1997]. The audit was therefore initiated to support the government in formulating a technology policy framework to create a science and technology system that would be effective, efficient and have a positive cultural impact on the South African society. Furthermore, the system should hold all stakeholders accountable and responsible for the execution thereof. Finally, the system should minimise conflicting interests and objectives [DACST 1997].

In order to achieve these objectives, the audit was planned to assess the strengths and weaknesses of South Africa's science and technology system and determine the efficiency, adequacy and value of the system. It was also intended to develop and communicate a better understanding of the forces that will shape the long-term effectiveness of the nation's science and technology system. Lastly, the audit was to provide direction and guidance on how to maximise the effectiveness of the science and technology system to meet the future challenges facing South Africa [DACST 1997].

The NRT Audit was carried out by conducting five surveys. Each survey collected large amounts of data on the science and technology system and was compiled in stand-alone reports. The data have been captured in a data repository, the NRT Audit Data Warehouse. The Foundation for Research and Development produced a synthesis report, *Technology and Knowledge* [DACST 1998]. This report was produced by human experts who assessed the information and data collected during the audit. The synthesis report describes the current state of science and technology in South Africa and identifies certain trends. This knowledge, as contained in the synthesis report, guides and motivates policy recommendations for the formulation of a Science and Technology Framework for South

Africa. This framework is directed at increasing the effectiveness of technological innovation, as a contributor to industrial productivity, environmental sustainability and international competitiveness [DACST 1997].

The question arises whether the data in the data warehouse support the findings of the synthesis report. It needs to be determined whether the findings are supported by the data, or whether these findings were based on experts' perceptions of the science and technology system in South Africa.

The case study is introduced by describing the five surveys. Furthermore, the conclusions contained in the synthesis report are discussed. Finally the two tasks to be further researched are introduced.

### 3.1 Survey overviews

The surveys conducted during the NRT Audit were contracted out to individual and separate consulting organisations. Each survey covered one of the following subjects:

- Scientific and technological infrastructure
- Human resources and skills in science, engineering and technology
- Research and development outputs
- Technology base of the South African business sector
- Research and training equipment in South Africa

Using January 1996 as the baseline date data were collected on the science and technology system, from participants (respondents) in the following sectors [DACST 1997]:

- Government: complete population of departments involved in science and technology, science councils and statutory and national heritage science and technology institutions
- Higher education: complete population of universities and technikons
- Private, non-profit organisations serving household and serving business (for example, multi-client industrial and services research institutions)
- Business: sample population of technology-driven production and processing enterprises, private and public, within technology-driven market sectors

The data obtained from the five surveys were integrated and stored in the NRT Audit Data Warehouse, covering the following topics for each sector. For government, higher education and non-governmental organisations data relating to their scientific and technological infrastructure, human resources and skills, research and scholarship outputs as well as their research and training equipment were captured. For the business sector, data relating to their market sector of operation, ownership, market share, exports, innovation, new products and processes, profitability, capitalisation and employment were gathered. Descriptions of their core products, dependence on technological knowledge and capabilities and the level and nature of research and development investment made by the company were also included. Furthermore, data on outputs such as patents and technical publications and the company's current and future needs for technical skills were captured [DACST 1997].

The remainder of this section introduces each of the surveys by describing their particular aim and source of data. A complete description of the audit, as well as the complete reports on all of the surveys is available from the following website:

***[www.dacst.gov.za/science\\_technology/nrta](http://www.dacst.gov.za/science_technology/nrta)***.

### **3.1.1 Survey of the scientific and technological infrastructure**

The aim of this survey was to collate, interpret and assess data related to the national pattern of science and technology funding and performing activities in South Africa, excluding the business sector and public corporations. A total of 189 organisations participated in the survey.

For the purpose of this survey scientific and technological infrastructure is defined as *“all activities, which help maintain and/or expand the knowledge base, including, research and development; education and training; the generation of information, development of knowledge, standards and guidelines, patents and licensing”* [DACST 1998].

### **3.1.2 Survey of human resources and skills in science, engineering and technology**

The objective of this survey was to analyse the supply and estimate the demand for science, engineering and technology human resources, as well as to estimate the actual human resources available in research and development. Data supporting this survey were obtained from existing databases of the Human Science Research Council, questionnaires on employment issues completed by organisations actively involved in research and development as well as the GEAR macro-economic strategy.

### **3.1.3 Survey of scholarship, research and development**

The goal of this survey was to collect and analyse data on research projects and their associated resources and funding. It was required to describe South Africa’s research projects in terms of key variables, such as objectives, researchers and financial value, and to classify the projects in terms of dimensions such as socio-economic sector and discipline of specialisation, as well as by main performance sectors.



Data supporting the survey were obtained through personal interviews on research policy as well as from documentation on research policy of surveyed organisations, and questionnaires completed by researchers at higher education institutions, science councils and government departments. Research was classified into three types, namely: basic research, applied research and development research. Basic research includes fundamental and strategic research, whereas applied research is the specific application of the basic research and development research is the actual development of a product and/or service.

### **3.1.4 Survey of the technology base of the South African business sector**

The aim of the survey was to determine the extent to which private firms and public corporations depend on technology and related competencies, investment in research and development as well as reliance on external funding.

Data supporting the survey were obtained from 313 of the most economic significant companies by means of questionnaires and buy-in interviews. The companies were grouped into two sectors, namely: the continuous process and discrete products sectors. Companies were broadly classified as follows into these sectors.

**Table 3 Industry sectors**

Continuous process	Discrete products
Agriculture	Rubber and plastics
Mining	Civil construction
Base metal	Textiles and footwear
Pulp and paper	Electrical and electronic
Power generation	Medical and pharmaceutical
Petrochemicals	Automotive and transport
Glass and non-metallic	Metal products and machinery
Food and beverage	Defence
Water	

### 3.1.5 Survey of research and training equipment in South Africa

This survey was aimed at obtaining, organising and analysing data related to training and research equipment in South Africa. Data were obtained from higher education institutions, research councils, government established research centres and businesses on a sample basis. This was done by means of questionnaires and personal interviews.

### 3.2 Summation of the findings

The function of a nation's science and technology system is to contribute to the future of the country by dealing with problems facing the nation as well as growing the country's economy. Spies (1996) argues that all activities within the system should be judged for relevance, quality, effectiveness and efficiency, against the needs and requirements of both the business sector as well as the social development sector.

### 3.2.2 Relevance of the science and technology system

For the purpose of this study the findings were grouped according to the following categories, the findings relating to the quality of human resources, the findings relating to the relevance of the science and technology system and the findings relating to the effectiveness and efficiency of the science and technology system. The purpose for creating these categories is to integrate the findings of the five surveys, to provide a holistic view of the current status of the country's science and technology system across the partitions created by the surveys and to place the findings within Spies' framework by which the science and technology system should be judged.

#### 3.2.1 Quality of human resources

The findings related to the quality of human resources cover two aspects namely, how well the existing human resources match the needs of the economy and the appropriateness of human resource training. From the five surveys, it is concluded that: The current knowledge and skills of the South African population are altogether inappropriate for a country that aspires to become an industrialised nation; And there is a major mismatch between the needs of the economy and the human resource skills the system is producing. It is crucial that the needs of the economy and the training and development of human resources should be better aligned.

Regarding the appropriateness of human resource training it was concluded that the human resource delivery system is inappropriate. This observation was based on the fact that a large number of new entrants into the job market are not optimally prepared for their new careers. Also, mathematics, technology, science, and language abilities at secondary school level represent an Achilles' heel in the preparation of future generations.

### 3.2.2 Relevance of the science and technology system

From the five surveys, it is concluded that the science and technology system is increasingly moving towards more relevant types of research. However, applied research, as conducted at higher education institutions, does not directly address the technological and information needs of national priorities or resolve salient national problems. The science and technology system is currently not coherently geared to address the critical problems confronting South African society due to the lack of strategic technology management. Lastly, the implementation of technology from local sources by the business sector is weak.

### 3.2.3 Effectiveness and efficiency of the science and technology system

From the five surveys, it is concluded that the effectiveness of the science and technology system in attaining the goals of generating new and relevant knowledge. However, the generation of developing technologies is low in terms of the number of technologies reported. It is assumed that mission-oriented research should lead to higher levels of efficiency. However, when the unfavourable ratio of research output to resource input reported by the audit is considered, it must be concluded that the national system is not operating efficiently. The main reason given is that at higher education institutions the teaching load consumes a disproportionate share of the potential research capacity of the staff. Similarly, the amount of effort and time allocated for marketing in science councils is disproportionate to the time spent on research by the staff. It was also found that there is inefficiency in the collaborative use of resources and that both international and inter-institutional collaboration is lacking. Because of the lack of internal and external linkages the current science and technology system does not achieve its maximum potential.

### 3.3 The two learning tasks

As stated in Section 2.5.1, in the area of machine learning, performance tasks are generally divided into two categories, namely, classification tasks and problem solving type tasks. To determine if the CILT-MAL system is able to analyse context embedded in qualitative data, in a real-world scenario, two experiments to cover each of these task types were formulated.

Firstly, as a classification task, the classification of companies surveyed in the “Survey of the technology base of the South African business sector” into two industry sectors, was investigated. This specific classification task was chosen as all the findings in the synthesis report, based on this survey, were made according to this grouping. An equal important consideration was the completeness and quality of the data collected, which increased the chances of the success of the classification task. Chapter 4 provides a detailed description of the classification task experiment.

Secondly, as a problem-solving type task, the data collected by the surveys dealing with human resources namely the “Survey of human resources and skills in science, engineering and technology”, “Survey of the scientific and technological infrastructure” and the “Survey of scholarship, research and development” were used to investigate the quality of the human resources. The fact that this task was supported by data from multiple surveys increased its complexity. The task required a data pre-processing step during which the data from the different surveys had to be integrated into a single data set, as discussed in Section 5.2. Between 50% and 70% of the total time spent on solving a real world problem is typically spent on data pre-processing [Berthold *et al* 1999]. Therefore, it was necessary to include a task that required a significant amount of data pre-processing. Secondly, the task was also within the human learner’s field of expertise. As discussed in Section 2.5.7.3, expertise in a problem domain has a major impact on a human’s inductive learning process and hence made this task the appropriate choice. This problem solving type task experiment is documented in Chapter 5.

### 3.4 Conclusion

This chapter introduced the five surveys of the NRT Audit and outlined the findings as reported in the synthesis report of the audit. Subsequently the two learning tasks to be addressed were defined.

This concludes the first part of the thesis. The first part presented the theoretical basis for the development of an intelligent data analysis tool to be used in the experimental work that follows. Part one discussed the concept of co-operative inductive learning as it occurs in co-operative inductive learner teams. These teams were then modelled as multi agent learning systems. Langley's framework for machine learning was used to define the learning mechanisms of the learners that participated in the study. The first part concluded by introducing the NRT Audit case study and formulating the two learning tasks to be addressed.

Part two focuses on the experimental work and the results. Chapters 4 and 5 provide a detailed description of the application of a CILT-MAL system in a real-world scenario. Followed by Chapter 6, which discusses the results and presents appropriate conclusions.

## Chapter 4

### **Classification task: Grouping organisations into continuous process and discrete product business-clusters.**

The survey of the technology base of the South African business sector, conducted as part of the NRT Audit, surveyed the technology base of large, medium and small business organisations in South Africa. The survey determined the extent to which private firms and public corporations within the 17 technology-driven industry sectors depend on technology and related competencies. To increase the coverage of the industry sectors the experts involved in producing the synthesis report grouped the companies surveyed into two broad business-clusters. This grouping became the classification task presented to the CILT-MAL system. The aim of the classification task presented in this chapter is to determine the applicability of a CILT-MAL system to a real-world scenario to classify organisations according to main commercial activities.

This chapter is organised as follows. Section 4.1 contains the task description, followed by Section 4.2 discussing the data pre-processing step. The initial exploratory results are introduced in Section 4.3. Section 4.4 introduces the experimental method and performance measures. This is followed by a description of the individual learning phase and co-operative learning episode of two of the co-operative inductive learning teams, as introduced in Section 2.4, namely the machine learner team and the human learner team. The individual and co-operative learning episodes of the machine learner team are described in Section 4.5 and that of the human learner team is described in Section 4.6. Episode five and six of the CILT learning process, namely, evaluation against the validation set and knowledge fusion

are discussed in Section 4.7, followed by a discussion of the results in Section 4.8. Section 4.9 concludes the chapter with a discussion of the success of the CILT-MAL system as a classifier in a real-world application.

#### 4.1 Task description

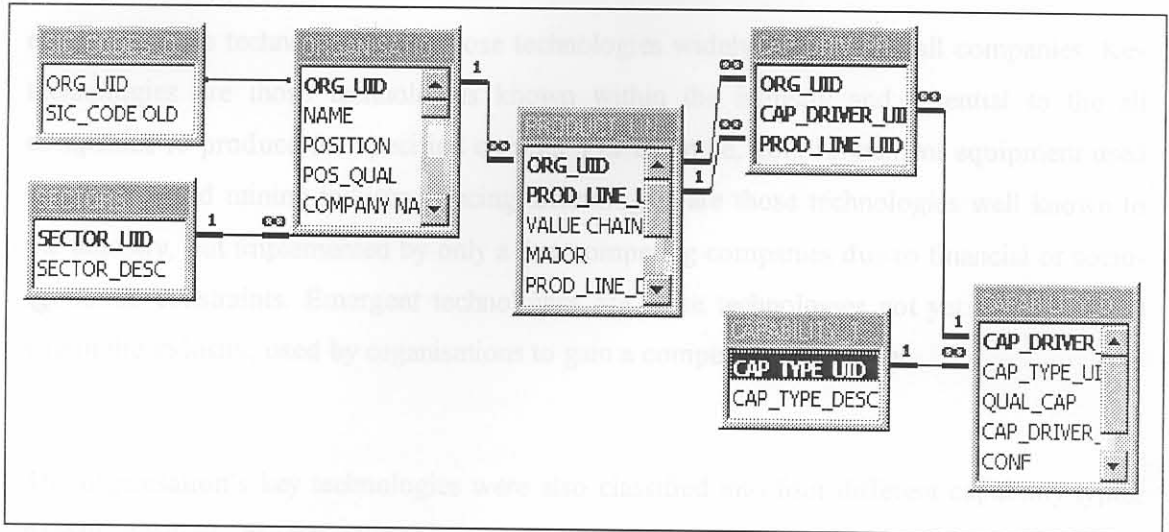
Data supporting the survey were obtained from 313 economically significant companies by means of questionnaires and buy-in interviews. Representative sampling determined that 1 260 companies would constitute the broad sample for a fully representative picture. Only 313 of these companies were considered significant and were interviewed [DACST 1998]. The experts, involved in producing the synthesis report, grouped the 313 companies surveyed, within the 17 technology-driven business sectors, into two broader business-clusters, namely that of continuous processes and discrete products.

Continuous process companies are those organisations that produce commodities that are measured in units of volume, mass, length and area for example gold, water or chemicals. These products have well established international benchmark prices and clear product specifications. Discrete product clustered companies, on the other hand, are those organisations that sell their output as individual items e.g. computers, cars or televisions. Discrete products are complex to manufacture and are produced as an assembly of many different components that are frequently manufactured from different materials. The aim of this learning task was to classify the surveyed organisations into these two broadly defined business-clusters using the data collected during the survey, as stored in the NRT Audit Data Warehouse.

#### 4.2 Data pre-processing

The data collected from the 313 organisations that participated in the survey were stored in the data structure presented in Figure 7.





**Figure 7 Business survey entity relationship diagram**

The organisations as contained in the *Organisation* entity, were described in terms of two main aspects, as shown in Figure 7. Firstly, the key product lines produced by an organisation, as contained on the *Product\_Line* entity, were considered with respect to their position in the value chain hierarchy. These positions denoted the level of sophistication of a product i.e. whether it was a “raw” material, component, sub-product, product, product system or a user system. For example, consider the value chain of a computer network. An organisation producing user systems, will supply customers with a network of computers including all the peripherals e.g. modems, printers, scanners, CD writers, etc, as well as the software and user-training. An organisation producing product systems sell packages, consisting of personal computers and the required software, which form part of the user system. Organisations producing products will, for example, produce printer cartridges used by the printers that form part of the user system. Organisations producing motherboards produce sub-products for personal computers. These sub-products are made up of components, which again are made of raw materials. The characteristics of each product produced by an organisation determine the product’s position in the value chain hierarchy.

Secondly, organisations were characterised in terms of the key technologies (capability drivers) that make their products sustainable in the market, as contained on the *Cap\_Driv\_Prod\_Line* entity. These key technologies were categorised under their technological stages of development. The four stages utilised were base, key, pacing and

emergent. Base technologies, are those technologies widely used across all companies. Key technologies are those technologies known within the industry and essential to the all companies to produce the specified outputs. For example, gold refinement equipment used within the gold mining industry. Pacing technologies are those technologies well known to the industry, but implemented by only a few competing companies due to financial or socio-economic constraints. Emergent technologies are those technologies not yet widely known within the industry, used by organisations to gain a competitive advantage

The organisation's key technologies were also classified into four different capability types, namely product, process, support or informational, as contained in the *Capability\_Type* entity. Product capabilities are those technologies directly related to the performance of a product, e.g. chipboard-covering technology used by the pulp and paper industry. Process capabilities are those technologies directly related to the manufacturing process, e.g. pocketing machines used by the textile industries. Support capabilities are indirectly related to the manufacturing of a product e.g. paper quality measuring machinery used by the paper and pulp industries. Lastly, informational capabilities are those technologies directly associated with the gathering, storage and access of information related to the product, process or within any support function, e.g. a payroll system.

Fayyad *et al* (1996) made the statement that data in real world data repositories are always incomplete due to the fact that the data are usually collected in an ad hoc manner, which causes, for example, missing values. Also, mistakes are made during data entry, which results in poor data being captured. As a result KDD cannot succeed unless the data is first cleaned during the data pre-processing phase [Fayyad *et al* 1996]. For this classification task 64 of the 313 organisations were excluded from the final data set, mainly due to missing values. The next section documents this reduction process.

### 4.3 Initial exploratory results

The 313 organisations surveyed included 928 key product lines and 1048 capability drivers. Since an organisation can be described in terms of its product lines and capability drivers,

---

the first training set had an instance for every product line, capability driver combination, giving a total of 1664 instances. Preliminary analysis by the learners showed that the learners were grouping product lines, into organisations instead of business-clusters. Hence, the organisation identifier was removed from the instances and the data were presented to the learners for preliminary analysis. Using the new data, the learners were grouping product lines into business-clusters, which implied that an organisation could be classified under more than one business-cluster depending on the product lines it carried. However, the aim of the classification task was to classify an organisation as a single unit into a business-cluster, therefore, it was decided to summarise all the data pertaining to an organisation into one instance. This was done in the following manner.

Every instance carried the organisation's details concerning:

- the number of product lines produced by the organisation classified under the four different capability types, as defined in Section 4.2,
- the number of product lines produced by the organisation classified under the four technological stages of development, as described in Section 4.2,
- the number of product lines produced by the organisation per value hierarchy chain position (only the first three stages were included),
- the standard industry code (SIC) the organisation is classified under, and
- the business-cluster the organisation belongs to.

**Table 4 Sample data from the business sector profile data set**

Process Cap	Product Cap	Information Cap	Support Cap	Base	Key	Pacing	Emergent	Product	Product System	User System	SIC	Business Cluster
0	2	0	0	2	0	0	0	0	0	0	3660	Product
1	1	0	0	0	2	0	0	2	0	0	3321	Process
7	5	0	0	0	12	0	0	4	0	0	3353	Product
4	1	0	0	5	0	0	0	0	0	0	?	Product

During preliminary analysis by the individual learners the individual inductive learning episode was repeated at least 10 times, with 10 randomised training sets. Finally a data set, which included 249 instances of the original 313 organisations surveyed, was used for the

experiment. During the preliminary data analysis 64 of the instances were eliminated due to missing values. Only 257 of the 313 organisations had SIC's, five of the organisations did not have any capability drivers, seven had no technological stages of development identified and two had no value chain hierarchies. SIC was indicated as the most significant attribute during preliminary analysis and it was therefore decided not to include the incomplete instances.

#### 4.4 Experimental method and evaluation criteria

Following Theron (1993), the training set contained 70% of the available instances and the test and validation sets each 15% respectively. A total of 167 of the 249 randomly chosen instances were included in the training set, 42 in the test set and the remaining 40 formed the validation set.

Four of the learners introduced in Chapter 2, namely CN2, C4.5, BRAINNE and the human learner, participated in the CILT-MAL system. For the classification task the learners were grouped into two teams namely, the human learner team and the machine learner team. The machine learner team included the three machine learners CN2, C4.5 and BRAINNE. The human learner team consisted of the human learner that participated in the NRT Audit supplemented by the findings as contained in the synthesis report. Co-operative inductive learning, within the teams of this multi-agent system, occurred as described in Section 2.4.

The performances of the learners were evaluated by the CN2 evaluation function. The performance measure was the accuracy by which a learner's rule set was able to predict the class of unseen instances i.e. the overall rule set accuracy, as defined in Section 2.5.4.1. The machine learners applied a reduced error-pruning scheme (REP), as discussed in Section 2.4.2 to prune their rule sets.

## 4.5 Learning of the classification task by the machine learner team

This section describes the individual and co-operative learning phases, as introduced in Section 2.4, of the machine learner team. Three inductive machine learners, CN2, C4.5 and BRAINNE participated in the machine learner team.

### 4.5.1 Individual learning phase

The individual learning phase introduced in Section 2.4.1, consisted of three episodes, the individual inductive learning episode, followed by the evaluation episode against the training set and finally, the evaluation episode against the test set. The three learners, CN2, C4.5 and BRAINNE received the full training set of 167 instances, as described in Section 4.3, and individually proceeded to execute their learning episodes independently of each other.

The parameters of the CN2, C4.5 and BRAINNE algorithms, as introduced in Section 2.5.4, 2.5.5 and 2.5.6, were assigned the following values according to the recommendations made by Theron (1993).

- CN2 algorithm:
  - threshold = 0
  - star size = 5
- C4.5 algorithm:
  - weight = 2
  - confidence = 5%
  - redundancy = 0.5
- BRAINNE algorithm:
  - epochs = 400
  - step = 0.2
  - hidden units = 6
  - momentum = 0.7

After the individual inductive learning episodes were completed, the rule sets, generated by the learners, were evaluated using the CN2 evaluation function and the rules, together with their performance measures, were subsequently placed into their individual knowledge bases. Table 5 shows the overall rule set accuracies obtained by the learners during their individual learning phase. Step one lists the learners' overall rule set accuracies, as evaluated by their own unique evaluation functions, against the training set. Step two lists the rule set accuracies of the same rule sets, as evaluated by the CN2 evaluation function, against the training set. Lastly, step three lists the rule set accuracies of the rule sets, as evaluated by the CN2 evaluation function, against the test set.

**Table 5 Accuracies and rule sets after the individual machine learner episodes**

Step	Overall Rule Set Accuracy			Number of rules in KB		
	CN2	C4.5	BRAINNE	CN2	C4.5	BRAINNE
1	98.2%	97%	81.9%	14	11	5
2	98.2%	94.6%	73.7%	14	11	5
3	81%	83.3%	71.4%	14	11	5

The rule set produced by the C4.5 learner had the highest overall accuracy (83.3%), followed by CN2 (81%). The BRAINNE learner failed to find a highly accurate set of rules, and obtained the lowest overall rule set accuracy of 71.4%. The average rule set accuracy was 80.1% and the average accuracy of the individual rules were 61.2%. These averages were used as the performance threshold values. The evaluation of the individual rule sets showed that the learners learned accurate rules for the discrete product class, but failed to find accurate rules for the continuous process class. This was due to the fact that the training set contained more than twice the number of discrete product instances compared to the number of continuous process instances. This implies that the coverage of the discrete product class was twice as good as that of the continuous process class. The aim of the co-operative learning episode was therefore to improve the individual results and to produce sets of informative rules that describe the continuous process class.

#### 4.5.2 Co-operative learning episode

The BRAINNE high quality rule, with a rule accuracy of 89%, described the company. Next the three learners initiated the full co-operative learning episode, as described in Section 2.4.2. Each team member queried the knowledge base of the other team members to find high quality rules that are related to their own low quality rules. These high quality rules were then used to produce a NewRule list.

#### 4.5.2.1 The CN2 co-operative learning episode

Recall from Section 2.4.2 that low quality rules are the individual rules in a rule set with performance measures below some predetermined threshold value. For this experiment the threshold value was determined by the average accuracy of an individual rule calculated over the accuracies of all the individual rules as contained in the different learners' rule sets. The average individual rule accuracy of the machine learner team was 61.2%. Therefore, any rule with accuracy lower than 61.2% was considered to be of a low quality. CN2 produced 5 low quality rules during the individual inductive learning episode. The CN2 learner engaged in co-operative learning by searching the knowledge bases of the other two team members looking for high quality rules that relates to the five low quality rules. One high quality rule was found on the C4.5 team member's knowledge base. This rule overlapped one of the low quality rules and subsumed another. The CN2 learner also obtained a high quality rule from the BRAINNE team member's knowledge base. This rule was in conflict with a low quality rule produced by CN2. The remaining two low quality rules were classified as misconceptions due to their low coverage. The two new high quality rules were placed on CN2's NewRule list and the five low quality rules were removed from the CN2 knowledge base.

The C4.5 high quality rule described the class discrete products and had a rule accuracy of 76.2%. The rule included the following tests:

Process Capability < 7

SIC < 3520.

The BRAINNE high quality rule, with a rule accuracy of 69%, described the continuous processes class. The rule included the following tests:

Product Capability < 3  
Support Capability < 5  
Product Value Hierarchy < 5  
Key Technology Stage < 9  
Product System Value Hierarchy < 5  
Base Technology Stage < 8  
302 < SIC < 2521.

Next, the data generation process, as introduced in Section 2.4.2, was used to generate two new sets of 167 training instances, one for each rule in the NewRule list. The two new training sets contained the same class distribution as the original training set, with 110 instances belonging to the discrete product class and 57 to the continuous process class.

The first 167 instances generated by the data generator contained 110 examples belonging to the discrete products class, with values:

0 <= Process Capability < 7,  
SIC < 3520

The SICs were randomly chosen, while still representing the distribution of SICs (less than 3520) as contained in the original training set. All the attributes not included in the tests were assigned values distributed similarly to the original training set by ensuring that the mean value and variance of the attributes remained the same.



The 57 examples, belonging to the continuous process class, were generated with values distributed similarly to the original training set, by ensuring that the mean value and variance of the attributes remained the same.

The resultant 167 training instances produced by the data generator were added to the original 167 instance in the training set. In this way, a training set biased to the high quality rule was created, while maintaining the original distribution of the attributes that were not included in the rule. Similarly, a second, new training set was generated, biased towards the BRAINNE high quality rule on the NewRule list.

The CN2 learner then completed two iterations of the individual learning phase to extract new sets of rules from the new training sets. After two iterations the CN2 learner generated two new high quality rules, namely:

```
If      Process Capability < 6
and     3551.5 < SIC < 4380.5
then    business sector = Product ,
with a 73.8% accuracy
```

and

```
If      744.5 < SIC < 3082
then    business sector = Process ,
with a 76.2% accuracy.
```

CN2 produced a rule set of 9 high quality rules with an overall rule set accuracy of 85.7%, improving its original overall rule accuracy by 4.7%. The resulting high quality rule set was pruned and then tested against the test set, giving an overall rule set accuracy of 88.1% and average rule accuracy of 66.4%.

At the end of the individual learning phase, described in Section 4.5.1, the CN2 learner's discrete product concept description was 100% accurate compared to that of the continuous process concept description which was 50% accurate. During the co-operative learning episode, the overall rule set accuracy of the discrete product concept description could not be improved, since it was already 100%. However, the individual rule accuracies of the discrete product concept description improved, which in turn improved the average rule accuracy. The continuous process concept description's accuracy improved from 50% to 68.8%. The highest accuracy of a continuous process concept description generated by the machine-learner team, during their individual learning phase, was 68.8%. The CN2 learner was able to improve its continuous process concept description accuracy to 68.8%, but not higher, confirming Viktor's (1999) finding that co-operative learning cannot negate the effect of poor quality rules. This implied that the overall rule set accuracy of 88.1% could not be improved.

#### 4.5.2.2 The C4.5 co-operative learning episode

During the individual learning phase, C4.5 produced four low quality rules describing the discrete products class but no low quality rules describing the continuous process class.

The C4.5 learner engaged in co-operative learning and obtained two high quality rules from its CN2 team member describing the discrete product class. These rules overlapped C4.5's four low quality rules. The two new high quality rules were placed in C4.5's NewRule list and the four low quality rules were removed from C4.5's knowledge base.

The CN2 high quality rules describing the discrete products class that were included on the NewRule list were:

```
If      Process Capability < 9.5
and     3551.50 < SIC < 4380
then    business sector = Product,
```

with a rule accuracy of 73.8%

and

```
If    Process Capability < 0.5
and   Key < 3
and   Emergent < 1
then  business sector = Product,
```

with a rule accuracy of 64.3%

The C4.5 data generator proceeded by using the rules in the NewRule list to generate two new sets of 167 training instances each. The two new training sets contained the same class distribution as the original training set, with 110 instances belonging to the discrete product class and 57 to the continuous process class.

The first 167 instances generated by the C4.5 data generator contained 110 examples belonging to the discrete product class, with values:

```
0 <= Process Capability < 9.5,
3551.5 < SIC < 4380
```

where the SICs were randomly chosen, but still representing the distribution of SICs between 3552 and 4380 as contained in the original training set. All of the attributes not included in the attribute value tests received values distributed in exactly the same way as in the original training set, by ensuring that the original mean value and variance of the attributes remained the same.

A total of 57 new instances belonging to the continuous process class were generated. These values were added to the original training set and the data generator produced a new training set with 334 instances. Similarly, a second new training set was generated, biased towards the second CN2 high quality rule on the NewRule list.

After two individual learning phases, the C4.5 learner produced one new high quality rule, with 64.3% accuracy, namely:

```

If      Process Capability < 1
and    Key < 4
and    Emergent < 1
then   business sector = Product ,
  
```

C4.5 produced a new rule set with eight high quality rules and an overall rule set accuracy of 83.3%, as measured against the test set, therefore not improving its overall rule set accuracy. The resulting high quality rule set was pruned by applying the REP rule-pruning algorithm. The pruned rule set, consisting of four high quality rules, was tested against the test set, resulting in an overall rule set accuracy of 90.5% and an average rule accuracy of 75.6%, thus, improving its overall rule set accuracy by 7.2%.

The C4.5 learner generated the most accurate continuous process concept description during the individual learning phase, with an accuracy of 68.8% with no low quality rules, when measured against the test data set. When there is a limited amount of data available inductive learners tend to overfit data, especially decision tree generation algorithms, due to their greedy search method as described in Section 2.5.5.3. Overfitting is a phenomenon during which an algorithm lacks the ability to distinguish between data trends that a rule set should be modelled on and random outliers that should be ignored [Fayyad *et al* 1996]. As mentioned in Section 4.5.1, the training set had limited data covering the continuous process class. Hence, C4.5, a decision tree algorithm, overfitted the instances describing the continuous process class and generated the most accurate rule set as evaluated against the training set.

Co-operative learning therefore only affected the discrete product class. During the co-operative learning episode, the learner was not able to improve the rule set accuracy for the discrete product concept description. This explains why the overall rule set accuracy did not

change. However, the new rule set contained eight high quality rules, compared to the 11 original rules consisting of four low quality and seven high quality rules. After rule pruning, the overall rule set accuracy increased by 7.2%, resulting in an overall rule set accuracy of 90.5%. The discrete product concept description was 100% accurate when applied to the test set whereas the continuous process concept description was only 75% accurate against the test set. This increase in accuracy can be explained by the fact that C4.5, a decision tree generation algorithm, overfitted the data in the training set, which implies that the model, i.e. rule sets, generated by C4.5 were not general enough. Where a general model means that the rule sets, derived from the training set, apply equally well to new sets of data from the same problem not included in the training set [Berthold *et al* 1999]. Pruning is a technique used to generalise concept descriptions by preventing recursive splitting on attributes that are not clearly relevant [Russell *et al* 1995]. Hence, the pruning algorithm generalised the concept descriptions, generated by the C4.5 learner, by removing irrelevant attribute tests. The increase in accuracy, after the rule set was pruned, implies that the concept descriptions generated by C4.5 overfitted the training data and therefore was too specific. By pruning the rule set, the individual rules became more general and therefore the rule set performed significantly better.

#### 4.5.2.3 The BRAINNE co-operative learning episode

BRAINNE produced two low quality rules during the individual inductive learning episode, one describing each class. The BRAINNE learner engaged in co-operative learning and obtained two high quality rules, one from the CN2 team member, which overlapped a low quality rule, and the other from the C4.5 learner that subsumed a low quality rule. The two new high quality rules were placed in BRAINNE's NewRule list and the two low quality rules were removed from BRAINNE's knowledge base.

The CN2 high quality rule describing the continuous processes class that was included in the NewRule list was:

```
If Process Capability > 8.5
```

```
and Emergent < 5
and SIC > 3180
then business sector = Process,
with a rule accuracy of 66.7%
```

The C4.5 high quality rule describing the discrete product class that was placed in the NewRule list was:

```
If Process Capability < 7
and SIC > 3520
then business sector = Product
with a rule accuracy of 76.2%.
```

The BRAINNE data generator used the rules contained in the NewRule list to generate two new sets of 167 training instances each. The two new training sets contained the same class distribution as the original training set, with 110 instances belonging to the discrete product class and 57 to the continuous process class.

The first 167 instances generated by the BRAINNE data generator contained 57 examples belonging to the class continuous processes, with values:

```
8.5 <= Process Capability <= 28,
0 <= Emergent < 5
3180 < SIC <= 4911
```

with the SICs randomly chosen, but still representing the distribution of SICs between 3180 and 4911 as contained in the original training set. All the attributes not included in the tests received values distributed in exactly the same way as in the original training set by ensuring that the mean value and variance of the attributes remained the same.

The 110 examples belonging to the discrete product class were generated with values distributed in the same way as in the original training set, by ensuring that the original mean value and variance of the attributes remained the same.

The resultant 334 training instances included the 167 produced by the data generator and the original 167 from the training set. In this way, a training set biased to the high quality rule was created. Similarly a second new training set was generated, biased towards the second C4.5 high quality rule in the NewRule list.

The individual inductive learning episode was re-iterated twice and the BRAINNE learner produced two new high quality rules, namely:

```
If      17 < Process Capability < 29
and     7 < Base < 29
and     Emergent < 5
and     2511 < SIC < 4888
then    business sector = Process ,
```

with a 61.9% accuracy and

and

```
If      8 < Process Capability < 29
and     0 < Base < 13
and     Emergent < 5
and     3020 < SIC < 4897
then    business sector = Process ,
```

with a 61.9% accuracy and

The BRAINNE learner produced a rule set containing five high quality rules with an overall rule set accuracy of 71.4%, therefore not improving its overall rule accuracy. The resulting

high quality rule set was pruned by applying the REP rule-pruning algorithm. The pruned rule set, consisting of three high quality rules was tested against the test set, resulting in an overall rule set accuracy of 78.6%. The BRAINNE learner improved its overall rule set accuracy by 7.2%.

BRAINNE was the weakest performer in the machine learner team, with an overall rule set accuracy significantly lower than that of the other members. Co-operative learning enabled the BRAINNE learner to improve its performance significantly. However, the learner was unable to improve its performance to the same accuracy level as its team members. The artificial neural network trained by BRAINNE, using the training set, had an overall rule set accuracy of 82%. The rule set extracted by the BRAINNE rule extraction algorithm had an overall rule set accuracy of 73% on the same training set. According to Craven *et al* (1993), the aim of a rule extractor can be described as “*given a trained neural network and the examples used to train it, the rule extractor should produce a concise and accurate description of the network*”. The performance of a rule extractor is measured in terms of a degree of fidelity, where fidelity is measured by comparing the classification performance of the rule set to that of the trained neural network from which the rules were extracted. The accuracy of the set of rules was 9% lower than that of the trained neural network, indicating that the rule set does not model the trained neural network to a comparable degree of fidelity. This indicates that the rule extractor did not model the trained neural network accurately.

Table 6 summarises the results of the co-operative learning episode. Step one lists the results before pruning and step two lists the results after pruning, as tested against the test set using the CN2 evaluation function.

**Table 6 Accuracies and rule sets after the co-operative learning episode**

Step	Overall Rule Set Accuracy			Number of rules in KB		
	CN2	C4.5	BRAINNE	CN2	C4.5	BRAINNE
1	85.7%	83.3%	71.4%	9	8	5
2	88.1%	90.5%	78.6%	9	4	3



## 4.6 Learning of the classification task by the human learner team

The human learner team consisted of a human expert that participated in NRT Audit supplemented with reference material i.e. the synthesis report. A knowledge engineer, as defined in Section 2.5.7.2, played the role of the performance element, as defined in Section 2.3. The knowledge engineer presented the learning element i.e. human learner, with the training set. The knowledge engineer then scheduled an interview with the human learner for a later date. A week later the knowledge engineer met with the human learner for a structured interview during which the relevant knowledge pertaining to the classification task was acquired from the learner.

### 4.6.1 Individual learning phase

The human learner presented the knowledge engineer with two concept descriptions, one for each class. The human learner's concept descriptions were expressed explicitly in terms of the attributes and their values that were present in the training set. During the interview it became clear that the human learner based his decisions on which attribute and attribute value to use for describing a class often on memory of specific experiences, rather than the actual data as represented in the training set. With the assistance of the knowledge engineer, the human learner transferred these concept descriptions into decision lists i.e. rule sets that can be interpreted by the critic, the CN2 evaluation function.

The major obstacle the knowledge engineer encountered during the knowledge acquisition process was that of knowledge transfer, as discussed in Section 2.5.7.1. Sestito *et al* (1996) describes this mismatch in knowledge representation as *the difference between the structures of human expert's knowledge compared to the representation of knowledge by a program*. The human learner that participated in the learning episode created concept descriptions by means of a set of disjunctive rules. The CN2 concept description language, as defined in Section 2.5.4.2, only supports conjunctive rules. However, the CN2 evaluation function evaluates the overall rule set as one disjunctive rule. Therefore, the human expert's concept descriptions were represented as disjunctive rule sets consisting of individual conjunctive rules expressed in terms of the CN2 concept description language. Each individual rule had

low individual rule accuracy, because of the limited coverage of each section of the disjunctive rule set. But the overall rule set, representing the disjunctive rule, had a high overall rule set accuracy, since the overall rule set accuracy measurement took the disjunctive nature of the rule set into consideration.

This can be explained as follows:

A training set  $T$ , consists of 50 instances describing class  $Y$  and a learner extracts the following rules describing class  $Y$ :

$$R_1 : (x > a) \Rightarrow Y$$

$$R_2 : (z < b) \Rightarrow Y$$

If  $R_1$  covered 10 of the 50 instances describing class  $Y$  then  $R_1$ 's correct positive coverage will be 20%. If  $R_2$  covered 5 of the 50 instances describing class  $Y$  then  $R_2$ 's correct positive coverage will be 10%. However, the overall rule set accuracy, as calculated by the CN2 evaluation function will be  $(10 + 5) / 50 * 100 = 30\%$ . Therefore, the following disjunctive rule,  $R_3$ , which is represented by the above rule set, is:

$$R_3 : (x > a) \cup (z < b) \Rightarrow Y$$

$$= R_4 : R_1 \cup R_2 \Rightarrow Y$$

has an individual rule set accuracy of 30%, compared to the 10% and 20% accuracies of the individual rules,  $R_1$  and  $R_2$ .

This implies that a disjunction of low accuracy rules could be as accurate as a single disjunctive high accuracy rule. This explains why the overall rule set accuracy of the concept description generated by the human learner was high, even though the average individual rule accuracies were low. Table 7 compares the individual learning phases of the

four learners in the two teams, as evaluated by the CN2 evaluator. First, the rule sets were evaluated against the training set, followed by the evaluation against the test set.

**Table 7 Accuracies and rule sets after the individual learning phase of both teams**

Set	Overall Rule Set Accuracy				Number of rules in KB			
	CN2	C4.5	BRAINNE	Human	CN2	C4.5	BRAINNE	Human
Training	98.2%	94.6%	73.7%	91%	14	11	5	9
Test	81%	83.3%	71.4%	88.1%	14	11	5	9

During the evaluation of the four learners' rule sets against the training set, as generated during the individual inductive learning episodes, CN2 scored the highest overall rule set accuracy, followed by C4.5 and then the human learner. However, when the same rule sets were evaluated against unseen instances the human learner scored the highest overall rule set accuracy followed by C4.5 and CN2. CN2 and C4.5's performance measure dropped by 17% and 11% respectively, but the human learner had a fluctuation of only 3%. This result emphasises the value of the background knowledge the human learner possesses within this problem domain. With the help of this knowledge, the human learner was able to construct concept descriptions that included knowledge extracted from prior experience, not necessarily reflected by the instances in the training set. However, the machine learners were restricted to the knowledge embedded in the training set and generated concept description reflecting that. Hence, when the data set changed the new knowledge in the test set is not reflected in the machine learner's concept descriptions and therefore the decrease in the machine learners' performance.

#### 4.7 Validation evaluation episode and knowledge fusion

Full co-operation involves the active participation of all the team members during co-operative learning. The individual and team results are evaluated by considering the improvement over past performances and/or the actual final mark achieved. In a machine learning environment, the individual learner's final rule sets are evaluated against a validation set and the accuracy's are placed in each learner's knowledge base. Next, these knowledge bases of the individual team members are fused together into a team knowledge

base. The purpose of this step was to produce, for each full co-operative learner team, an integrated knowledge base that contains the results of the team effort. These team knowledge bases were subsequently pruned and validated against the validation set. Table 8 compares the overall rule set accuracies of the individual learners knowledge bases after the co-operative learning episode, to that of the team knowledge bases after knowledge fusion, as tested against the validation set. Lastly, the two team's knowledge bases were fused together into a final knowledge base. The result of the knowledge fusion episode is summarised in Table 9.

**Table 8 Accuracies and rule sets after validation and knowledge fusion**

Pruned	Overall Rule Set Accuracy (Number of rules in KB)				
	CN2	C4.5	BRAINNE	Machine learner team	Human learner team
No				77.5% (16)	80% (9)
Yes	85% (9)	72.5% (4)	67.5% (3)	82.5% (5)	

**Table 9 Final accuracies and rule sets of fused knowledge bases**

	Overall Rule Set Accuracy (Number of rules)		
	Machine learner team	Human learner team	Machine and human learner team results fused together
Un-pruned	77.5% (16)	80% (9)	87.5% (14)
Pruned	82.5% (5)		87.5% (11)

The continuous process concept description generated by the machine learning team during knowledge fusion had an accuracy of 83.3% when evaluated against the validation set. The next best performing description is that of the CN2 learner, with an accuracy of 58.3%. This implies that, by means of full co-operation, the machine learner team was able to improve its predictive accuracy of the continuous process concept description by at least 25%. This team achieved the goal of the co-operative learning episode namely, to produce sets of informative rules that describe the continuous process class. The discrete product concept description accuracy also showed a slight improvement of 6.8%, from 82.5% to 89.3%. The final knowledge base created by the fusion of the human and machine learner team's pruned rule sets had the highest overall rule set accuracy of 87.5%. This result highlights the

success of human-computer collaboration. It emphasises the importance of determining what the human learner is good at and what the machine learners are good at, so that a collaborative strategy focussing on the strengths of the teams can emerge. Most importantly, these results indicated that in a real-world scenario, full co-operation is preferred over individual learning.

#### 4.8 Discussion

This section highlighted the knowledge acquired during the learning of a classification task. It discussed how the rule sets, obtained through co-operative learning, in some instances supported the findings of the human experts, while in others contradicted the findings of the human experts. It went on to describe new additional findings that were made during the learning process, which could have been considered when the human experts compiled the synthesis report.

The following knowledge acquired by the CILT-MAL system supported some of the findings of the human experts. The human experts were of the opinion that technologies in the key stage of sophistication are more dominant in the discrete product companies compared to the continuous process companies. On the other hand, technologies in the base or emergent stage of sophistication are more dominant in the continuous process companies. Continuous process companies, who are competing for an increased market share internationally, use emergent technologies in order to minimise production costs and increase profit margins. Therefore, these companies have to combine basic technologies with “cutting-edge” technologies in a well-balanced manner to maximise their profit margin. The international prices and manufacturing specifications of the products produced by the continuous process companies are usually internationally determined, e.g. gold and steel. However, according to the data, a total of 62% of the discrete product companies used technologies in the key technological stage of sophistication, compared to only 46% of the continuous process companies. In addition, 26% of the continuous process companies employed technologies in the emergent technological stage of sophistication, compared to only 6% of the discrete product companies. This indicates that the rules, as produced during co-operative learning, supported the human expert’s opinions as stated above.

In some instances the results of the CILT-MAL system contradicted the opinions of the human experts. For example, knowledge acquired by the CILT-MAL system showed that 97.5% of the continuous process companies employ process type technologies. Process type technologies are those technologies and competencies directly related to the manufacturing process. On the other hand, only 42% of the discrete product industry employs process type technologies. The human experts were of the opinion that, when it comes to process type technologies, there should be no significant difference in their use within the two business-clusters. The finding by the CILT-MAL system indicates that discrete product companies do not rely on process type technologies during the final stages of production. This approach leads to job creation, an important issue in South Africa and one of the many challenges facing the country in the 21<sup>st</sup> century, as discussed in Chapter 3. However, this approach leads to an increase in the production cost of goods, which has a negative influence on the selling price of the product and eventually the competitiveness in the market.

Co-operative learning highlighted new, additional findings. For example, the companies within the textile and footwear industry are unique compared to the other discrete product companies. During all stages of learning a dedicated rule was generated for the leather and footwear industry companies. This rule indicated that these companies did not adhere to the general concept description of the discrete product cluster. Further investigation discovered that more than 20% of these companies were not able to adequately describe their technologies in the survey [AMI 1998]. This indicated a low level of technological orientation in this sector. Only 12% of the companies could specify their research and technology outputs [AMI 1998], which indicated a lack of technology management in these organisations. The major technology types identified within this industry were of the product and process capability type. Even within these major technology types, the companies identified less than the average number of technologies identified across the business-cluster [AMI 1998]. The textile and footwear industry sector indicate that the biggest threat to their competitive environment is illegal imports into South Africa [AMI 1998]. This, in turn pressurises their pricing structure. To overcome this hurdle, productivity must be increased, by investing in new technologies, enabling them to reduce overall cost and lower the price of merchandise. The CILT-MAL system identified the textile and footwear sector companies as being different compared to the other discrete product companies. After

further investigation of the data the following problem was identified. Currently, many of the companies in this sector are struggling to survive because of their high production costs and therefore the inability to price their products competitively. One cannot help wondering if this could have been prevented if the cost trends were identified at an earlier stage.

Lastly, it was established that the most significant attribute enabling learners to distinguish between the two business-clusters was the SIC attribute. The SIC's, identifying discrete product companies, were grouped into three ranges. These ranges were imbedded within the six ranges that identify the continuous process companies. According to Langley's machine learning framework, one of the key aspects of the environment is the representation of knowledge, of both input to learning and output of learning. The combination of the input to learning not being in continuous ranges and CN2's inability to formulate disjunctive rules i.e. not being able to represent the three ranges as a disjunctive rule restricted the learners ability to learn.

#### 4.9 Conclusion

This chapter presented a classification type task in a real-world application. This task concerned the grouping of organisations into business-clusters by means of co-operative learning in a multi-agent learning environment, as described in Section 4.1. In Sections 4.2 and 4.3 the data selection process that divided the data into three sets, i.e. a training, test and validation set, was discussed. The experimental method and evaluation criteria were presented in Section 4.4. Section 4.5 and 4.6 introduces the teams and showed how co-operative inductive learning manifested within the MAL system. The next section, Section 4.7, presented the way in which the knowledge bases were fused together and discussed the success of the knowledge fusion episode. The chapter concludes with a discussion of the major trends discovered during the co-operative learning episode.

When comparing the major trends discovered by the CILT-MAL system to the findings of the synthesis report, regarding this specific classification task, one comes to the following conclusion. That, the human experts involved in producing the synthesis report grouped the

companies surveyed into two broad business-clusters, the two clusters were defined as continuous process industries and discrete product industries. To adhere to these definitions, companies should have been categorised according to the characteristics of their major product lines. Knowledge, as contained in the knowledge base of the CILT-MAL system, showed that the groupings were made instead according to the organisation's SIC. There is no indication that the level of sophistication of the products played a role in the classification, as one would have expected from the definition of the two clusters.

The results indicated that a KDD environment, modelled as a MAL system, could be used successfully for a real-world application. In this case, through the construction of a knowledge base, a valuable tool in developing a technology policy framework was provided. This can be attributed to the following: [Viktor *et al* 2000]:

- Human experts have seen that they can successfully verify their results against the data. This helps building experts confidence in their own pre-empted ideas and also changing their ideas where being proved to be incorrect.
- The results as contained in the team knowledge base confirmed certain pre-empted ideas from experts, but also showed where the pre-empted ideas were wrongfully made. The approach can therefore be used to ensure that decisions are taken according to correct assumptions.
- The KDD process provided a tool that should enable government to make sense of the large amount of data produced by the NRT Audit. The socio-economic threats of the incorrect application of a Science and Technology policy in South Africa can, if care is not taken, widen the gap between the economic 'haves' and 'have-nots'. With this in mind, it is very important to consider the way in which policy will be formulated in South Africa. These inputs can sensibly be used to ensure that the policy forming is not top-down driven, but rather a bottom-up approach.

The next chapter presents the application of the CILT-MAL system to a problem solving type task concerning the quality of human resources, in scarce disciplines of specialisation, as introduced in Section 3.3.



## Chapter 5

### Problem solving type task: Discovering trends in the human resources for research and technology

This chapter presents an investigation into the capability of the CILT-MAL system to perform a problem solving type task. This task concerns trend analysis with regards to the quality of human resources, in scarce disciplines of specialisation for research and technology in the current science and technology system of South Africa. Where scarce disciplines of specialisation are defined as *those disciplines in which participating organisations experience difficulty to find suitable staff*. Data supporting three of the surveys, conducted as part of the NRT Audit, were used for this investigation.

The goal of the intelligent data analysis presented here is to show that a CILT-MAL system can be used successfully for problem solving type tasks. The chapter is organised as follows: Section 5.1 outlines the task on hand; Section 5.2 discusses the data pre-processing step, followed by Section 5.3 that introduces the initial exploratory results. Section 5.4 explains the experimental method and evaluation criteria used for the analysis. The actual learning by the system is presented in Section 5.5, followed by the validation and knowledge fusion episodes in Section 5.6. The chapter concludes with, Section 5.7, a discussion of the results produced by the CILT-MAL system and Section 5.8, the conclusions drawn from the intelligent data analysis.

## 5.1 Task description

The following three surveys, conducted during the NRT Audit, were used to investigate the quality of human resources, in scarce disciplines of specialisation, namely:

- Data from the Survey on human resources and skills in science, engineering and technology [DACST 1998], focusing on human resource delivery to the current science and technology system. A census of all the participants in the higher education system was conducted to obtain this data.
- Data from the Survey on scholarship, research and development [DACST 1998], focusing on the human resources related to the research and technology output of the current science and technology system. Data supporting this survey was obtained from a representative sample of organisations.
- Lastly, data from the Survey on the technology base of the South African business sector [AMI 1998], focusing on the economic relevance, effectiveness and efficiency of the human resources employed by the business sector. Data supporting this survey was also obtained from a representative sample of organisations.

## 5.2 Data pre-processing

The data collected by the three surveys were carried on different entities in the NRT Audit Data Warehouse. The entities are related to one another as shown in Figure 8.

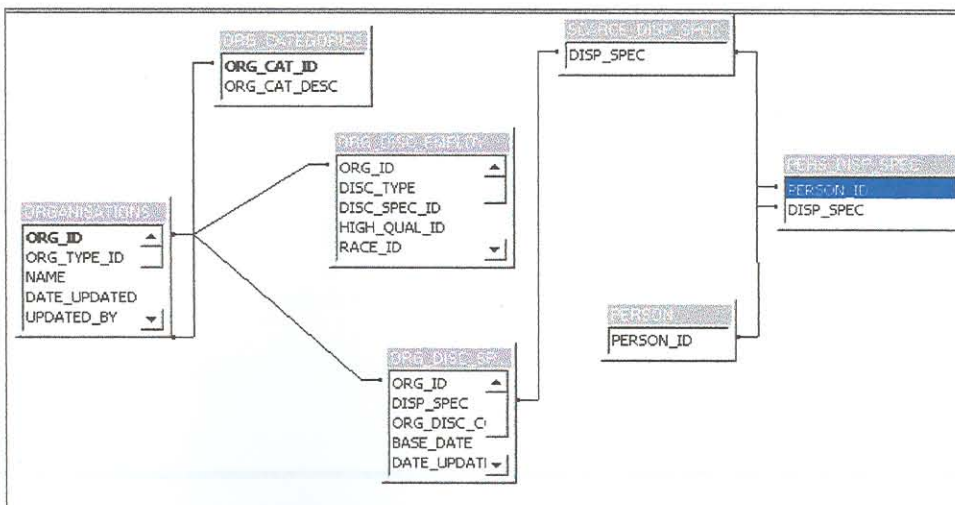


Figure 8 Human resources data structure

The data pertaining to this analysis were extracted from the different entities and integrated into one data set, as discussed next. Each organisation or functional unit was represented by one instance on the *Organisation* entity. The unique identifier for an organisation and the organisation's type describes this instance. Instances on the *Org\_Dispatch\_Employ* entity describe the number of employees within an organisation in terms of the employee's discipline of specialisation, gender, race and highest qualification. The *Org\_Dispatch\_Employ* entity contains data supporting only the survey of the technology base of the South African business sector, i.e. data covering the private sector. The *Scarce\_Dispatch\_Spec* entity listed all the disciplines in which participating organisations experience difficulty to find suitable staff for, as indicated during interviews or on returned questionnaires. Since this task investigated the quality of human resources, in scarce disciplines of specialisation, only data pertaining to these scarce disciplines were included. The *Person* entity contains data describing employees in the public sector including universities, technikons and scientific councils. These instances were described by their gender, race and highest qualification. The *Person\_Dispatch\_Spec* entity contains the specific disciplines of specialisation for all the employees on the *Person* entity. Again, only data associated with people in the scarce disciplines, as indicated by participating organisations, were included. Table 10 lists these scarce disciplines.

**Table 10 Scarce disciplines of human resources in research and technology**

Applied Biological Sciences	Applied Mathematical Sciences	Applied Physical Science	Engineering
Agricultural economics	Information and computer science	Chemical sciences	Engineering sciences
Agriculture	Computer networks	Analytical sciences	Chemical engineering
Food science & technology	Information systems	Chemistry, general	Civil engineering
Forest science	Programming systems	Applied chemistry	Electronical engineering
Horticulture		Polymers	Electronic engineering
Wood science		Textiles	Mechanical engineering
Biochemistry		Material sciences & technology	Manufacturing & process technology
Viticulture			Production management
Oenology			

Table 10 shows that the scarce disciplines identified by the organisations predominantly reside under the applied science categories. To ensure sufficient coverage for the disciplines of specialisation, the disciplines were grouped under four major applied science categories, namely applied biological sciences, applied mathematical sciences, applied physical sciences, and engineering.

The instances in the integrated data set were described by the following attributes:

Gender: male or female,

Race: advantaged or disadvantaged,

Discipline of specialisation: applied biological sciences (ABS), applied physical sciences (APS), applied mathematical sciences (AMS) or engineering,

Highest qualification: diploma, 4 year degree, or an advanced degree; and

Organisation type: private sector, university, technikon or science council.

**Table 11 Sample data from the employee-profile data set**

Highest qualification	Race	Gender	Discipline specialisation	Organisation type
Postgrad	A	M	ABS	Private
Diploma	A	M	Engineering	Private
Degree	A	M	ABS	Private
Diploma	D	M	Engineering	Private
Postgrad	A	F	APS	Private
Degree	A	M	Engineering	Technikon
Postgrad	A	M	Engineering	University

The employee-profile data set contained 1422 instances. The aim of the learning task was to identify trends in this employee-profile data set of employees in scarce disciplines.

### 5.3 Initial exploratory results

The learning task, to identify trends in this employee-profile data set of employees in scarce disciplines, was not a typical supervised learning task. Recall, from Section 2.5.1 that, during supervised learning the learning element is presented with a training set which describes each instance by both the predicting attributes, as well as its predicted attribute, i.e. class. The task of the learning element is to generate a class description for each domain value of the predicted attribute. In contrast, this learning task described here involved the identification of unknown trends as well as generating descriptions for them. The performance element does not only have to generate a class description for each domain value of the predicted attribute, but first had to identify the best possible predicted attribute from the set of attributes. This is an example of an unsupervised induction problem, as defined in Section 2.5.1, where both the classes and their corresponding descriptions are unknown.

The CN2 induction algorithm was adapted from a supervised method to an unsupervised method. This enabled the system to determine the strongest and most interesting set of

predicting attributes and the associated predicted attribute. CN2 was adapted in the following way: *Given  $k$  attributes, the algorithm executes  $k$  times. In each case with a different attribute playing the role of the predicted attribute. This results in  $k$  different classifiers, each designed to accurately predict the predicted attribute as a function of the remaining predicting attributes* [Langley 1998]. From the results obtained by the execution of the above-mentioned procedure, the knowledge engineer, after consulting the human expert, identified the organisation type as the strongest and most interesting predicted attribute. The strength of the classifier was measured by means of its degree of correlation i.e. overall rule set accuracy as determined by the CN2 evaluation function. In addition, the human expert evaluated the interestingness of the generated rule set. The employee-profile data set with organisation type as predicted attribute was chosen to be further processed.

#### 5.4 Experimental method and evaluation criteria

From the employee-profile data set, randomly chosen training, test and validation sets were generated. Following Theron (1993), the training set contained 70% of the available instances and the test and validation sets comprised of 15% respectively. Only five of the 1422 instances describe the science council organisation type. Due to this low occurrence, these instances were removed from the data set.

The CILT-MAL system consisted of two machine learners, CN2 and C4.5, together with a human learner. Preliminary training showed that the BRAINNE learner was unsuitable due to its low fidelity. Recall that the fidelity refers to the extent in which the accuracy of rule extraction matches that of the original trained neural network. Here, the neural network was 82% accurate, whilst the BRAINNE system was 73% accurate.

Each of the three participating learners was presented with the full training set of 993 instances and the test set of 212 instances. The learners proceeded by executing their individual inductive learning episodes as described in Section 2.4.1, followed by the evaluation step. All trends were evaluated by the CN2 evaluation function, and converted to the performance measures for problem solving type tasks. These performance measures

were determined in collaboration with the human expert during preliminary data analysis and are defined as follows:

- **Strength:** *The percentage positive coverage of a trend is defined as the total number of positive instances covered by the rule divided by the total number of instances.* For example, if  $R_1$  classifies 95 instances correctly and 4 instances incorrectly the strength of the trend will be 95.96%. The trend will be deemed strong when the calculated strength is higher than the average percentage positive coverage as calculated over all the trends in the rule sets generated by the learners, which are participating in the CILT-MAL system.
- **Interestingness:** *The difference between the percentage positive coverage of a trend over the different classes.* For example, the training set has 754 instances belonging to class A, 66 belonging to class B and 173 belonging to class C.  $R_1$  covers 95 of the class A instances, two of class B's and two of class C's instances positively. The percentage positive coverage for each class is thus 13%, 3% and 1% respectively. A significant difference between the relative coverage exists. This implies that the identified trend ( $R_1$ ) is a common trend of class A when compared to the other classes, which makes it interesting and worthwhile to investigate further. As a pre-requisite the highest percentage positive coverage must be that of the assigned class.
- **Consistency:** *Consistency is determined in terms of how consistent the strength of a certain trend is when it is evaluated against different data sets.* For example, the strength of trend  $R_1$  measures 96% on the training set, 100% on the test set, and 93.3% on the validation set. The discrepancy value of the trend is  $\Delta$ strength on the test and validation sets, calculated as follows:

$$100 - 93.3 = 6.7,$$

a low discrepancy value indicates a consistent trend. This measure ensures that a trend is not just a one-off occurrence within one data set, but occurs with similar strength in all the data sets.

These performance measures differ significantly from that of the classification task presented in Chapter 4. Recall that the goal of the classification task is to generate rule sets that can accurately predict the class of unseen instances. Therefore, performance is measured

in terms of overall rule set accuracy. However, the main goal of a problem solving type task is to find strong, consistent and interesting individual trends within a given data set. The significance of the trends as a disjunctive set with predictive power, measured by means of the overall rule set accuracy, is therefore irrelevant. The unique performance measures, as defined above, were determined by analysing the results of the individual inductive learning episodes, in collaboration with the human expert. Pazzani (2000) is of the opinion that most KDD papers contain unfounded assumptions about “interestingness”. For example, the paper, “Mining the most interesting rules” by Bayardo and Agrawal [Bayardo *et al* 1999] presents an algorithm that searches the space of association rules with metrics involving the confidence of the rules. However, the paper does not show that any of these metrics correlates with user judgements of what is interesting [Pazzani 2000]. Therefore, when the performance measures for this specific problem solving type task were defined it was done in collaboration with the human expert. Bollacker *et al* (2000) accomplished this type of collaboration, when determining the interestingness of new scientific literature on the web, by calculating the interestingness of a new paper as a weighted sum of the relatedness between the new paper and existing papers in a user’s profile. When the interestingness is greater than a certain threshold value the system, CiteSeer, recommends the new paper to the user. The user could then manually adjust the calculated relatedness of the new paper added to his/her profile [Bollacker *et al* 2000].

The remainder of this chapter describes the learning as it occurred within the CILT-MAL system. The chapter concludes with a discussion of the resulting trends.

## **5.5 Learning of the problem solving type task by the combined machine-human learner team**

This section describes the individual and co-operative learning of the combined machine-human learner team. Two inductive machine learners, CN2 and C4.5 and a human learner participated in the combined machine-human learner team.

### **5.5.1 Individual learning phase**

The three learners, i.e. the CN2, C4.5 and human learner, received the full set of 993 training instances and proceeded with the individual inductive learning episode. The



knowledge engineer, as introduced in Section 2.5.7.2, transferred the knowledge acquired by the human learner into a decision list consisting of 20 trends.

The evaluation steps, using the training and test data sets, followed the inductive learning episode. The trends generated by each learner with their resulting evaluation measures were added to the learner's individual knowledge bases. Table 12 summarises the results of the individual learning phase.

**Table 12 Strengths and interestingness of trends after the individual learning phase**

Learner	Strength		Interestingness		Total	High quality trends
	Strong	Weak	Interesting	Uninteresting		
CN2	15	22	15	22	37	9
C4.5	8	0	4	4	8	4
Human learner	14	6	10	10	20	6

The average strength of the trends, evaluated against the test set, was 49.7%. The trends had an average consistency of 86.4%. The CN2 learner produced the highest number of trends, followed by the human expert and then C4.5. The C4.5 learner produced eight trends during the individual inductive learning episode, compared to CN2's 37 trends. The CN2 learner produced nine strong and interesting trends, compared to C4.5's four strong and interesting trends and the human learner's six. The average class coverage of the trends, generated by the C4.5 learner, for the different classes were, 15% for a trend describing private organisations, 0% for a trend describing technikons and 21% for one describing universities. On the other hand, the CN2 learner's average class coverages for the respective types of organisations were 7%, 3% and 7%.

This indicated how the differences in the performance elements, i.e. a general-to-specific search directed by information theoretic entropy and significance measures of CN2, as described in Section 2.5.4, compared to a greedy search directed by gain ratio criteria and error-based pruning of C4.5, as described in Section 2.5.5, of the two learners influence the

way they perceive the problem domain. The CN2 learner generated the highest number of rules with a low average class coverage, indicating more specific trends compared to the C4.5 learner's lower number of rules with a significant higher average class coverage, indicating more general trends.

For example, the following high quality trend was generated by CN2:

```

IF    Highest_qualification = Diploma
    AND Race = D
THEN  Org_type = Private  [95 2.50 0.50]
  
```

FIRED?			
ACTUAL CLASS	Yes	No	Accuracy
Private	95	659	12.6 %
Not Privat	3	236	98.7 %
Overall accuracy: 33.3 %			

compared to a high quality trend generated by C4.5 for the same class

```

IF    Highest_qualification = Diploma
THEN  Org_type = Private  [297 24 2]
  
```

FIRED?			
ACTUAL CLASS	Yes	No	Accuracy
Private	287	467	38.1 %
Not Privat	26	213	89.1 %
Overall accuracy: 50.4 %			

Note the difference in coverage, for the "Private" class, 95 instances were covered by the rule produced by the CN2 learner compared to 297 instances covered by the trend discovered by the C4.5 learner.

The human learner created more or less one trend for every possible attribute test combination. This limited the coverage of the trends, similar to that of the CN2 learner, creating strong uninteresting trends.

## 5.5.2 Co-operative learning episode

The three learners then engaged in co-operative learning, querying the knowledge bases of the other members for high quality trends related to their own low quality trends, as described in Section 2.4.2.

The problem solving data generation approach, as introduced in Section 2.4.2, was executed next. Using this approach, only one single new training set based on all the high quality trends contained in the NewRule list was generated. The coverage of the high quality rules that need to be learned in the new training set has doubled and the remaining instances, which were not covered by the new high quality rules, were left as is. Therefore, instead of generating one strongly biased data set for each high quality rule, one single data set was generated with twice the number of instances covering each high quality rule on the NewRule list. This new training set was merged with the original training set and presented to the learners.

### 5.5.2.1 The CN2 co-operative learning episode

The CN2 learner obtained three high quality trends from the human learner's knowledge base and four from the C4.5 learner's knowledge base. These seven high quality trends were added to the CN2 NewRule list and the 28 low quality trends were removed from CN2's knowledge base. Table 13 contains six of the 28 low quality trends generated by the CN2 learner:

**Table 13 Low quality trends generated by the CN2 learner**

Rule	Highest qualification	Gender	Race	Discipline specialisation	Organisation type	Positive coverage
16	Diploma	Male		AMS	Technikon	0%
19	Diploma	Female	Adv	ABS	Technikon	0%
23	Diploma	Male	Adv	Engineering	Technikon	25%
24	Diploma	Male	Adv	Engineering	Technikon	15.8%
26	Diploma	Male	Adv	APS	Technikon	0%
29	Diploma	Female		AMS	University	0%

These trends were in conflict with the C4.5 high quality trend, namely

If Highest qualification = Diploma

Then Organisation type = Private [287 24 2],

strength 92.6% (on test set).

The C4.5 high quality trend indicates that, if a person's highest level of qualification is a diploma, then the person will most likely be working in the private sector. The six low quality trends in Table 13, generated by CN2, indicated that, if a person's highest level of qualification was a diploma, then the person would most likely be working at a university or technikon. These trends are in direct conflict.

The data generator proceeded to generate 313 new instances to cover the C4.5 high quality trend on the NewRule list. Of the 313 instances, 287 were of the private organisation type, 24 were technikons and 2 universities, similar to the original distribution. The attribute values were distributed in such a manner that the mean values and variances were the same as that of the original 313 instances. The 313 new instances were added to the original training set. Similarly, data was generated for all the other high quality trends on the NewRule list and added to the training set. The CN2 learner was then presented with this

new training set consisting of 1 758 instances, including the 993 instances of the original training set. CN2 then generated the high quality trends shown in Table 14.

**Table 14 Trends generated by the CN2 learner during the co-operative learning episode**

Rule	Highest qualification	Gender	Race	Discipline specialisation	Organisation type	Positive coverage
1	Diploma		Disadv	APS	Private	100%
2	Diploma	Male		ABS	Private	100%
4	Diploma		Disadv	Engineering	Private	100%
5	Diploma	Female			Private	92%
6	Diploma	Male	Adv		Private	90%

CN2 generated five individual high quality trends. The five rules can be combined into a single rule,  $R_{new}$  as follows:

$$(R_1 \cup R_2 \cup R_4 \cup R_5 \cup R_6) \Rightarrow R_{new}$$

where  $R_{new}$ : If Highest qualification = Diploma  
 and Discipline specialisation in (APS,ABS,Engineering)  
 Then Organisation type = Private.

$R_{new}$  resembles the C4.5 high quality trend on the NewRule list:

If Highest qualification = Diploma  
 Then Organisation type = Private.

$R_{new}$  differs from the trend on the NewRule list, in that the CN2 learner excluded the applied mathematical science's (AMS) discipline from the concept description. On further investigation, it was found that only seven of the 313 instances covered by the trend were from AMS. This low coverage was the reason why CN2's search algorithm excluded this discipline.

After completing the co-operative learning episode, the CN2 knowledge base consisted of nineteen high quality trends. The CILT learning system subsequently applied a rule-pruning algorithm to simplify the knowledge base. As discussed in Section 2.2.2, when simplifying the knowledge bases of a problem solving type task, duplicate trends are removed. Any further simplifications, for example the combination of trends, depended on the user's needs and not quantitative measures. In this study, all the duplicate trends were removed from the CN2 knowledge base.

### 5.5.2.2 The C4.5 co-operative learning episode

During the individual learning phase, C4.5 produced eight trends of which four were strong and interesting. The uninteresting trend,

```
If Highest qualification = Degree
```

```
Then Organisation type = Private,
```

was not removed from the C4.5 knowledge base. This was due to the fact that this trend had the highest percentage class coverage, 69%, for technikons, with a percentage coverage discrepancy of 26% and 32% for private sector and universities respectively. This indicates a strong trend for technikons, although the classification was incorrect. Implying that the majority of academic staff, employed by technikons in South Africa, highest level of education is a four-year degree, although most of the four-year degree employees are to be found in the private sector. The remaining three low quality trends were removed from the C4.5 knowledge base since no other high quality trends related to these low quality trends could be found.

### 5.5.2.3 The human learner co-operative learning episode

The human learner generated six high quality and 14 of low quality trends during the individual learning phase. During the co-operative learning episode six high quality trends

were added to the NewRule list. These trends related to the fourteen low quality trends and were selected from both the CN2 and C4.5 knowledge bases.

The human learner, with the assistance of the knowledge engineer, removed seven trends, including three of low quality, from the knowledge base and added one from the NewRule list that corresponded to the combined criterion of the seven individual trends. Four misconceptions were removed from the knowledge base and replaced by two trends from the NewRule list. A high quality trend contained in the NewRule list that overlapped with two low quality trends, was added to the knowledge base. The two low quality trends were removed. This resulted in a human learner knowledge base consisting of seven high quality trends. Table 15 summarises the results of the co-operative learning episodes.

**Table 15 Results of the co-operative learning episodes**

Learner	Strong	Interesting	Total	Number of rules in knowledge base
CN2	18	13	13	13
C4.5	5	5	5	5
Human expert	7	6	7	6

Notice that at this time the consistency has not been determined since it can only be calculated after the validation episode. This is due to the fact that strength measurements against both the test and validation set are necessary for the calculation.

## 5.6 Validation episode and knowledge fusion

During the validation episode, the final knowledge bases of the team members participating in co-operative learning were evaluated against the validation data set. The third performance measure, namely, consistency was used at this time. This was done to ensure that the high quality trends were not co-incidental, but consistent over the two randomly chosen unseen data sets namely the test and validation set. The consistency of the trends were calculated at this point and not earlier, because only at this point were strength measurements available as evaluated against the test and validation set that could be

compared. The average consistency of all the trends in the high quality knowledge bases was 92.8%. Trends, with a consistency higher than the average, are deemed to be consistent, as defined in Section 5.4. However, the trends with a lower than average consistency need to be further investigated. Due to the fact that the test and validation sets are smaller than the original training set, a one-instance difference in coverage, of a trend with low class coverage, can make a significant difference in the consistency of the trend. For a well-informed decision, both the actual positive and negative coverage as well as the percentages should be taken into consideration. For example the C4.5 trend:

If      Highest qualification = Postgrad  
and     Discipline specialisation = APS  
Then    Organisation type = Private,

with a (private, technikon, university) [59 1 11], [13 0 5] and [9 0 1] coverage over the training, test and validation sets respectively, had a 17.8 discrepancy value, calculated as follows:

$$|13/18*100 - 9/10*100| = 17.8$$

The consistency value of the trend is therefore,  $100 - 17.8 = 92.2\%$ . However, the following trend was found to be more consistent than the above-mentioned trend although its consistency value, calculated as follows, was lower:

If      Highest qualification = Postgrad  
and     Race = Disadvantaged  
and     Gender = Male  
and     Organisation type = Private,

with a [9 0 4], [1 0 0] and [3 0 1] coverage over the training, test and validation sets. The discrepancy value 25 was calculated as follows:

$$|1/1*100 - 3/4*100| = 25.$$

The consistency value of the trend is therefore,  $100 - 25 = 75\%$ . The coverage of this trend is lower than for the previous case and therefore the only one instance that was misclassified resulted in a lower calculated consistency.



Finally, the knowledge bases of the individual team members were fused together into one integrated knowledge base, consisting of 21 trends, which contained the results of the team effort. The team knowledge base was then pruned for duplicates, removing six trends, resulting in a 15 high quality trend team knowledge base.

## 5.7 Discussion

This section highlights the main findings as contained in the team knowledge base. The human expert's perspectives were obtained by an interview as well as by consulting the synthesis report. The trends, as contained in the knowledge bases, in some instances supported the findings of the human expert while contradicting the expert in other cases. There were newly discovered trends of which the human expert was not aware.

The knowledge acquired by the learning system supported the human expert on the following trends. Firstly, that there is a significant difference in the type of organisation where a person will be employed depending on his/her highest qualification. Persons with a four-year degree or diploma, as defined in Section 5.2, are predominantly employed by the private sector. Within the private sector and technikons the percentage of employees with diplomas are identical. However, the technikons dominate with a significant higher percentage of employees with a four-year degree compared to the universities and private sector that are similar. This confirmed the human expert's opinion that, within a technikon, a person with a four-year degree can obtain a more senior position.

Secondly, that the lack of presence of postgraduate engineers in the private sector is due to the weakness of the South African industry's own process development initiatives. The knowledge base indicated that universities, as tested against the test set, employ 90% of the advantaged, male, engineers. The human experts were of the opinion that the South African industry prefers to buy in processes by licensing (AMI 1998). However, postgraduate engineering courses train people for product development, without the South African industry having the required maturity to compete internationally with new products. This indicates a mismatch in the needs of the industry and the focus of the higher education

system. However, disadvantaged engineers with a Masters or Doctorate are absorbed by the private sector. The knowledge base indicates that 75%, as tested against the test set are employed within the private sector. This could be due to the imbalance in the production of engineers from disadvantaged backgrounds. This imbalance is most prominent in this field. This is amplified by the fact that the higher education system cannot compete with the salaries offered by the private sector and therefore the trend becomes more prominent.

Lastly, that the working conditions in the information technology industry are the least suited to that of a working mother. Therefore, females with advanced degrees in applied mathematical sciences, for example information technology, prefer working at universities, even though there are plenty of opportunities for employment within the private sector. This was confirmed by a similar trend in the knowledge base.

Some of the opinions of the human expert were, contradicted by trends contained in the knowledge base, highlighting preconceived biases of the human expert. For example, the strongest trends based on gender were for females in applied physical science, females with degrees in the applied biological sciences and females with Masters or Doctorates in the applied mathematical science, as listed below.

```
IF      Gender = F
      AND Discipline_specialisation = APS
THEN   Org_type = Private [54 2 1]
```

```
IF      Highest_qualification = Degree
      AND Gender = F
      AND Discipline_specialisation = ABS
THEN   Org_type = Private [31 0 0]
```

```
IF      Highest_qualification = Postgrad
      AND Gender = F
      AND Discipline_specialisation = AMS
THEN   Org_type = University [0 0 2]
```

These trends confirmed the human expert's opinion that females in the applied physical science work in the private sector. These females are responsible for most of the routine work, such as conducting tests in analytical laboratories and quality control. However, the human expert was convinced that females in the applied biological sciences would not be employed by the private sector since biotechnology within South Africa is dominated by the government sector. However, the trends in the team knowledge base contradicted the expert and indicated that the food processing industry is a major employer of females trained in this discipline.

Some trends discovered by the CILT-MAL system were new to the human expert as they were previously unknown and potentially useful information was discovered by the intelligent data analysis tool. For example, the trend that employees with an advanced degree, i.e. a Masters or Doctorate, in the applied physical sciences were strongly absorbed by the private sector compared to, for example engineers. This is due to the fact that the scarce applied physical sciences discipline was dominated by chemistry. The South African chemical industry is recognised as an international competitive industry, competing with its own products. Because of its sophistication, this industry employs human resources similarly distributed to corresponding organisation types in Germany and the United States (Synthesis Report). This implies that the chemical industry can offer postgraduate qualified candidates better career opportunities and therefore becomes their major employer.

## 5.8 Conclusion

This chapter presented a problem solving type task, executed by a CILT-MAL system, applied to a real-world scenario. Section 5.1 described the task that concerned the discovery of trends in the human resources for research and technology, in the scarce disciplines of specialisation, by means of co-operative learning in a multi-agent learning environment. Section 5.2 discussed the integration of the data from the different surveys into a single data set. Section 5.3 explained how the CN2 learner was adapted from a supervised to an unsupervised learning algorithm. The experimental method and evaluation criteria were introduced in Section 5.4. Section 5.5 introduced the machine-human learner combination team and showed how co-operative inductive learning manifested within the MAL system.

Next, the knowledge fusion episode was discussed in Section 5.6. The chapter concludes with a discussion of the major trends discovered during the co-operative learning episode.

Results indicated that a CILT-MAL system could be successfully applied to a real-world problem solving type task. However, for the CILT-MAL system to be successful the following had to be defined; a new set of performance measures; an alternative method for the data generator to generate data with; as well as a trend pruning algorithm. Once again, the results as contained in the team knowledge base confirmed some findings of the experts, but also showed where the findings were wrongfully made, making it a valuable learning experience to both the experts and the learners.

Problem solving type tasks are more complex than classification tasks, due to the multiple steps involved. Therefore, executing this type of task becomes a more time consuming process. The CILT-MAL system could be a valuable tool assisting the human expert during his/her execution of the task, saving the expert time as well as verify his/her findings.

## Chapter 6

### Summary and conclusion

Recall from Section 1.1 that this study investigated the use of a KDD environment in a real-world scenario, focusing on the following:

- i. The development of an intelligent data analysis tool, modelled as a MAL system that combines more than one data mining technique into a unified framework for decision support.
- ii. The evaluation of the capability of this intelligent data analysis tool, using co-operative inductive learning techniques, in analysing the context as embedded in qualitative data, to be used for decision-making.

This was addressed by the construction of an intelligent data analysis tool based on the philosophy of co-operative learning, applied to machine learning techniques as well as a human expert. The intelligent data analysis tool consisted of co-operative inductive learner teams operating in an environment modelled as a multi-agent learning system. Three different teams were constructed namely, a machine learner team, consisting of three inductive machine learners; a human learner team, consisting of a human expert and of a synthesis report written by experts; and lastly, a machine, human learner team combination, consisting of two inductive machine learners and a human expert.

During the study the human expert changed roles, from that of a traditional onlooker to an active participant within the system. This study focussed on the qualitative aspects of the data describing the problem domain compared to the traditional quantitative aspects. The human learner is an expert within this domain with background knowledge pertaining to the problem. To ensure that this knowledge is incorporated within the learning process the human learner had to actively participate in it. By this active participation the CILT-MAL system as a whole, as well as the individual machine learners benefited as follows. For the classification task, the human learner and machine learners participated in separate teams. The results of the classification task showed that the final knowledge base created by the fusion of the human and machine learner team's rule sets obtained the highest overall rule set accuracy. This highlighted the success of human-machine collaboration by the active participation of the human in the learning process. For the problem solving type task, the human and machine learners participated within the same team, hence they had access to each other's knowledge bases and were able to benefit from each other in a more direct way during the co-operative learning episode.

The success of the intelligent data analysis tool was determined by its ability to address two types of tasks within a real-world scenario namely, a classification task and a problem solving type task.

## 6.1 Summary

This thesis was organised as follows:

- Chapter 1, 2 and 3 formed part of the theoretical basis of the work presented. Chapter 1 introduced the aim of the study and outlined the research approach used during the study.
- Chapter 2 concerned multi-agent learning by means of co-operation. This chapter described co-operative inductive learning and hence proceeded to define co-operative inductive learner teams. Co-operative inductive learner teams were then modelled as a CILT-MAL system. Within the CILT-MAL system learning agents

were described using the inductive machine learner architecture. A new architecture, namely, Langley's machine learning framework, was introduced. This framework was used to better define the learning mechanisms of the learners that participated in this study.

- Chapter 3 introduced the case study i.e. the National Research and Technology Audit. This chapter provided background on the different surveys that made up the audit and gave a summation of the findings. The chapter concluded by introducing the subjects for intelligent data analysis.
- Chapter 4 and 5 presented the experimental work done during the study. Chapter 4 presented the execution of the classification task namely, grouping organisations into business-clusters using two learner teams in a CILT-MAL system. The chapter concluded with a discussion of the knowledge discovery that occurred.
- Chapter 5 presented the execution of the problem solving type task namely, discovering trends in the human resources for research and technology using a combined machine/human learner team in a CILT-MAL system and concluded with a discussion of the knowledge discovery that occurred.

## 6.2 Concluding remarks

Experimental results showed that the CILT-MAL system was able to successfully address both types of performance tasks, namely, a classification as well as problem solving type task. This study created a new framework for learning as it occurs during a problem solving type task, within the CILT-MAL system.

A number of the findings supported the conclusions of the human experts, as presented in the synthesis report. However, a number of findings contradicted their opinions, making it a valuable learning experience to both the intelligent data analysis tool as well as the human experts. This study showed how intelligent data analysis could enrich the conclusions made by the human experts, assisting them to gain confidence in their own areas of expertise, but also indicating their weaknesses.

Fusing the knowledge bases of the two inductive learner teams during the classification task showed the power of co-operation. This fused knowledge base obtained the highest level of overall rule set accuracy compared to all the other knowledge bases. Having a human learner participate in the co-operative learning environment proved to be very valuable. Each time a human learner or human learner team was added to the CILT-MAL system a significant improvement in performance occurred.

Comparing the findings of the CILT-MAL system, as contained in the knowledge bases, to those of the synthesis report, two dominant conclusions can be made. Firstly, for the classification task, the human experts involved in producing the synthesis report, grouped the companies surveyed into two broad business-clusters, for data analysis purposes. The two clusters were defined as continuous process industries and discrete product industries. To adhere to these definitions, companies had to be categorised according to the characteristics of their major product lines. However, the knowledge as contained in the knowledge base showed that the groupings were made according to SICs and there is no indication that the sophistication level of the products played a role in the classification, as one would have expected from the definition of the two clusters.

Secondly, the findings in the synthesis report, as related to the problem solving type task, state that there is a major mismatch between the needs of the economy and the human resource skills that the system is producing. It is crucial that the needs of the economy and the training and development of human resources be better matched. However, the knowledge as contained in the knowledge base indicates not a mismatch but more a communication gap between the human resource delivery system and the needs of the economy. The human resource delivery system is producing according to the trends of the future knowledge needs of a competitive market system. This is not communicated to the business sector therefore; the efforts of the delivery system are not being appreciated. For example, the opinion that there is an overproduction of social scientists compared to the technology related human resources might be a dangerous generalisation of the current situation that is not in line with the prediction of the complexity of the economic problems of the future. Success in the future will be dependent on the ability of intelligent technology



to interact with knowledgeable people, the latter depending on a strong social science involvement, which the market demand will rely on.

A number of inadequacies of the intelligent data analysis tool constructed for this study came to light, which should be addressed in future work: Firstly, the inability of the CN2 machine learner to represent input as a combination of conjunctive and disjunctive attribute tests within a rule. This restriction on knowledge representation was a major drawback for representing the human learner's knowledge. Secondly, the inflexibility of the performance measures generated by the CN2 evaluation function had a negative effect on the efficiency of the system. Different types of tasks require different performance measures. Therefore, evaluation functions used to address real world problems must be able to accommodate a variety of measures as required by the specific performance tasks.

The NRT Audit Data Warehouse contains a wealth of useful information that could be used by decision makers, when creating a policy framework for research and technology in South Africa. The CILT-MAL system approach to knowledge discovery in data may be the key to unlock this source of information.

[Clark et al. 1991] P. Clark and T. Niblett, 1989. The CN2 Induction Algorithm. *Machine Learning*, 3, pp. 261-283.

[Cohen et al. 1993] M.W. Cohen and J.W. Shiple, 1993. Learning neural networks using genetic artificial neural networks. *Proceedings of the tenth international conference on machine learning*, Ashland, USA, pp.79-95.

[DACST 1997] Department of Arts, Culture, Science and Technology, 1997. *South African Research and Technology Audit*, Pretoria: South Africa.

[DATSI 1998] Department of Arts, Culture, Science and Technology, 1998. *Knowledge and Knowledge, synthesis report of the National Research and Technology Audit*, Pretoria: South Africa.

[Dhar et al. 1997] V. Dhar and R. Stein, 1997. *Seven methods for transforming corporate data into business intelligence*, France Hall, USA.

## Bibliography

- [Adriaans *et al* 1996] P Adriaans and D Zantinge, 1996. Data mining, Addison-Wesley, Harlow: England
- [Alavi 1994] M Alavi, 1994. Computer-mediated collaborative learning: An empirical evaluation, MIS quarterly, 18 (2), pp.160-173.
- [AMI 1998] Access Market International, 1998. Technology base of large, medium and small organisations in the South African business sector, DACST: Pretoria.
- [Bayardo *et al* 1999] R Bayardo and R Agrawal, 1999. Mining the most interesting rules, Proceedings of the fifth ACM SIGKDD international conference on KDD, ACM Press: New York
- [Berthold *et al* 1999] M Berthold and D Hand, 1999. Intelligent data analysis, an introduction, Springer: Berlin.
- [Bollacker *et al* 2000] KD Bollacker, S Lawrence and CL Giles, 2000. Discovering relevant scientific literature on the web, IEEE Intelligent systems, Data mining II, March/April 2000, pg 42-46.
- [Clark *et al* 1989] P Clark and T Niblett, 1989. The CN2 Induction Algorithm, Machine learning , 3, pp.261-283.
- [Craven *et al* 1993] MW Craven and JW Shlavik, 1993. Learning symbolic rules using artificial neural networks, Proceedings of the tenth international conference on machine learning, Amherst: USA, pp.79-95.
- [DACST 1997] Department of Arts, Culture, Science and Technology, 1997. National Research and Technology Audit, Pretoria: South Africa.
- [DACST 1998] Department of Arts, Culture, Science and Technology, 1998. Technology and knowledge, synthesis report of the National Research and Technology Audit, Pretoria: South Africa.
- [Dhar *et al* 1997] V Dhar and R Stein, 1997. Seven methods for transforming corporate data into business intelligence, Prentice Hall: USA.

- [Fairhead 1995] N Fairhead, 1995. Data warehouses increasing the value of your decision makers, *Business quarterly*, 60 (2), pg. 89.
- [Fayyad *et al* 1996] UM Fayyad, G Piatesky-Shapiro, P Smyth and R Uthurusamy, 1996. *Advances in knowledge discovery and data mining*, AAAI Press: USA
- [Gennari *et al* 1989] J Gennari, P Langley and D Fisher, 1989. Models of incremental concept formation, *Artificial Intelligence*, 40, pp.11-61.
- [Holland *et al* 1986] JH Holland, KJ Holyoak, RE Nisbett and PR Thagard, 1986. *Induction. Processes of inference, learning and discovery*, MIT Press: Cambridge, USA.
- [Holsheimer *et al* 1994] M Holsheimer and APJM Siebes, 1994. *Data mining the search for knowledge in databases*, Centrum voor wiskunde en informatica rapport, Amsterdam: Stichting Mathematisch Centrum.
- [Honavar 1995] Honavar, 1995. *Symbolic artificial intelligence and numeric artificial neural networks: towards a resolution of the dichotomy*, Computational architecture integrating neural and symbolic processes, Kluwer Academic Publishers, Boston: USA.
- [Inmon 1996] WH Inmon, 1996. *Building the data warehouse*, second edition, John Wiley & Sons, Inc: USA.
- [Jacobsen 1998] HA Jacobsen, 1998. A generic architecture for hybrid intelligent systems, *Proceedings of the 1998 international joint conference on neural networks (IJCNN'98)*, Alaska: USA, pp.709-714.
- [Jennings 1993] NR Jennings, 1993. Commitments and Conventions: The foundations of coordination in multi-agent systems, *The knowledge engineering review*, 2(3), pp.223-250.
- [Jennings *et al* 1998] NR Jennings and MJ Woodridge (editors), *Agent technologies: Foundations, Applications and Markers*, Springer Verlag, Berlin: Germany.
- [Johnson 1994] J Johnson, 1994. *In [Sharan 1994]*, Greenwood Press: USA.
- [Johnson-Laird 1988] PN Johnson-Laird, 1988. *The computer and the mind: an introduction to cognitive science*, Harvard University Press: Cambridge, Mass., USA.

- [Kaplan *et al* 1988] B Kaplan and D Duchon, 1988. Combining Qualitative and quantitative methods in information system research: Case study, *MIS Quarterly* 12(4), pg.571-586.
- [Kholisa *et al* 1993] R Kholisa and T Dillon, 1998, Engineering intelligent hybrid multi-agent systems, Kluwer Academic Publishers, Norwell : USA.
- [Knapik *et al*] M Knapik and J Johnson, 1998. Developing intelligent agents for distributed systems, McGraw-Hill, New York: USA, 1998.
- [Langley 1996] P Langley, 1996. Elements of machine learning, Morgan Kaufmann Publishers: USA.
- [Michie *et al* 1994] D Michie, DJ Spiegelhalter and CC Taylor, 1994. Machine learning neural and statistical classification, Ellis Harwood.
- [Moustakis *et al* 1996] V Moustakis, M Letho and G Salvendy, 1996. Survey of expert opinion: Which machine learning method may be used for which task?, *International journal of human-computer interaction*, 8 (3), pg. 221-236.
- [Nisbett *et al* 1983] RE Nisbett, DH Krantz, D Jepson, and Z Kunda, 1983. The use of statistical heuristics in everyday inductive reasoning, *Psychological Review*, 90, pg 339-363.
- [Pazzani 2000] MJ Pazzani, 2000. Knowledge discovery from data?, *IEEE Intelligent systems*, Data mining II, March/April 2000, pg 10-11.
- [Quinlan 1994] JR Quinlan, 1994. C4.5: Programs for machine learning, Morgan Kauffmann, California: USA.
- [Russell *et al* 1995] SJ Russell and P Norvig, 1995. Artificial Intelligence: A modern approach, Prentice Hall, New Jersey: USA
- [Sestito *et al* 1994] S Sestito and TS Dillon, 1994. Automated knowledge acquisition, Prentice-Hall, Sydney: Autralia
- [Sharan 1994] S Sharan (editor), 1994. Handbook of co-operative learning methods, Greenwood Press: USA.
- [Slavin 1983] RE Slavin, 1983. When does cooperative learning increase student achievement? *Phsycolgical Bulletin*, 94, pg. 429-445.

- [Spies 1996] PH Spies, 1996. Scoping Socio-economic Trends in South Africa: a Technological Perspective, Institute for future research, University of Stellenbosch: South Africa.
- [Sun 1995] Sun, 1995. An introduction: on symbolic processing in neural networks, computational architectures integrating neural and symbolic processes, Kluwer Academic Publishers, Boston: USA. [Theron 1993] H Theron, 1993. Specialisation by exclusion: An approach to concept learning, PhD dissertation, Department of Computer Science, University of Stellenbosch, Stellenbosch: South Africa.
- [Turban 1995] E Turban, 1995. Decision support and expert systems, Fourth edition, Prentice Hall: New Jersey, USA
- [Viktor 1999] HL Viktor, 1999. Learning by co-operation: An approach to rule induction and knowledge fusion, PhD dissertation, Department of Computer Science, University of Stellenbosch, Stellenbosch: South Africa.
- [Viktor *et al* 2000] HL Viktor and H Arndt, 2000. Enhancing government decision making through knowledge discovery from data, eight European conference on information systems (ECIS-00), Vienna: Austria, July 4-6, 2000.
- [Weiss 1998] G Weiss, 1998. Adaption and learning in multi-agent systems: Some remarks and a bibliography, adaption and learning in a multi-agent system, Proceedings of the IJCAI'95 Workshop, Montreal, Canada, August 1995, Springer Verlag Lecture Notes in artificial intelligence, Vol. 1042, pp1-21.
- [Weiss 1999] G Weiss, 1999. Multi-agent systems, MIT Press: Massachusetts, USA.
- [Yin 1994] RK Yin, 1994. Case study research, design and methods, 2<sup>nd</sup> ed. Sage Publications Newbury Park:UK.